A Work Project, presented as part of the requirements for the Award of Master's degree in Business Analytics from the NOVA – School of Business and Economics

HyperML and Deep Interest Network to build a Recommender System for Modatta: Data Privacy with GAN

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Abstract

This work project intends to propose a privacy-based system to Modatta, a start-up focused on monetising users' data, eliminating the concerns of data leakage. The system consists of the following techniques: Deep Interest Network (DIN)/ Hyperbolic Embedding (HE), Generative Adversarial Network (GAN) and Federated Learning (FL), providing a recommender system and protecting the users' privacy. Data protection has been a hotly debated topic in society for many years, especially the adverse social effects caused by the misuse of user privacy by technology giants. This report will show that GAN is one of the feasible solutions to tackle these concerns.

Keywords

Machine Learning, Deep Learning, Hyperbolic Embeddings, Data Monetization, Recommender System, Generative Adversarial Network, Synthetic Data

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1. Introduction

This study was conducted in collaboration with Modatta, a Lisbon (Portugal) based startup company that aims to help European Union (EU) citizens to better manage and monetize their data under EU's digital laws.

Modatta was founded in 2019 by Rodrigo Moretti and Eduardo Pinto Basto who saw benefit in creating an app under the EU General Data Protection Regulation (GDPR) to give its users more control over how their data is collected, used, and protected online. This is accomplished with the creation of a community of potential clients willing to share their information for a fair compensation and companies wanting to reduce the cost of attracting customers while promoting a positive relationship based on respect with their audience.

Today, our data and the valuable insights that comes from it are stored and used by big technological companies to gain a competitive advantage over others, and where consumers lose influence to make decisions about their own personal information. Modatta's goal is to allow everyone – both companies and citizens – to benefit from sharing their own data, meanwhile promoting privacy, transparency and a fair share of value.

Moving forward, this study intends to first, investigate how to incorporate modatta users' historical interests, as well as their personal data, to find meaningful representations of the users in a fully privacy-preserving approach. For that, two different Deep Learning approaches will be followed – Hyperbolic Embeddings and Deep Interest Network. Furthermore, a Recommender System is built to recommend users new interests that they are likely to have interest in.

The implementation of these two representation learning approaches is the first step of the whole process to be developed, where the final goal is to allow the deployment of an utterly privacy-based system that will help Modatta to bring the list of potential customers to marketers

while giving users the opportunity to learn about their data, always keeping their privacy.

1.1 Problem definition and Objectives

Identifying the problems that need to be addressed and the goals to be achieved is the first step of any project. With this project, our main goal is to help Modatta to build a marketplace for both users and marketers, where both have the opportunity to get valuable insights from data. While users have total control over their own data and can still learn more about it, companies who want to target users with particular attributes will be able to do it in a much easier and less costly way, and never accessing users' data.

As we need to keep data privacy, as mentioned above, the first problem we face throughout this study is the access to real data. To comply with the GDPR, we don't have access to users' data, meaning that the data cannot be inspected.

To overcome this problem, we need to use techniques that allow us to work with the data we have access to. For this reason, we propose dividing our project into 2 Deep Learning approaches: Hyperbolic Embedding and Deep Interest Network (DIN). While the first is using the hierarchical information from Facebook pages categories to get a representation of the user on the Hyperbolic Space, the second is using synthetic users' data and trying to find a way of capturing the similarities between users by learning a latent and abstract representation of them.

The rest of the first part of this paper is structured as follows:

- Section 2 describes the Hyperbolic Embedding and Deep Interest Network approaches.
- Section 3 presents the implementation process of both approaches.
- Section 4 describes the evaluation of both methods.
- Section 5 defines the next steps to be taken.

2. Deep Learning Approaches

Recently, learning embeddings from data such as text, graphs and multi-relational data has become a central topic in Machine Learning (ML), as well as Artificial Intelligence (AI), since most ML models can´t read and understand linguistic associations in the human sense. Therefore, the learning representations algorithms that characterize semantically meaningful dense vectors shows a response to an increased necessity to the challenges of Natural Language Processing (NLP).

Moreover, Deep Learning based methods have been recently proposed for tackling click-through-rate (CTR) prediction tasks in online advertising, where embedding vectors are used to represent large scale sparse input features, and then are transformed into fixed-length vectors that will work together to learn the nonlinear relations among the features. (Zhou, et al. 2018) In this project, instead of clicking in an advertisement that is displayed on a website, the prediction task can be defined as whether a Modatta user is interested in a particular insight or not.

To understand how these methods could be used to tackle the problem of this study, two different approaches will be followed to train models that are then used to find meaningful representations of the users' interests and predict new recommendations of the insights and categories that the users are most likely to be interested in.

2.1 Hyperbolic Embedding

In the context of extracting knowledge from symbolic objects, such as words, entities and concepts, hyperbolic embeddings present properties able to capture excellent quality hierarchy information in a few dimensions with arbitrarily low distortion. Even though, the Euclidean geometry is widely used, it is shown that linear embeddings of graphs require higher dimensionality that normally is outperformed by lower dimensionality of hyperbolic embeddings, in terms of both the similarity between objects (distances), and their relative depths in the hierarchy (in their norms). (Maximilian e Kiela 2017)

The constant negative curvature of the hyperbolic space in the area of a circle or volume of a sphere, which may be expanded exponentially with its radius, can be used to model complex networks with hierarchical data structures. Meaning that the distance between two objects is well preserved, giving a measure of their similarity, thus, reflecting their semantic or functional relationship.

In this sense, the Poincaré Ball model is the most adequate in learning hierarchical representations, as it offers to conform mapping between hyperbolic and Euclidean space, i.e., the angles between adjacent vectors indicate to be similar to angles in Euclidean geometry, although the length of their vector is not, but can be illustrated by the hyperbolic distance [Appendix A1 – Equation 1].

This equation exemplifies the utility of implementing Poincaré embeddings, due to their ability to preserve original graph distances to capture the hierarchy of objects, as a result of their norm. Additionally, the dataset used in this study comprises multiple latent hierarchies, which the Poincaré ball is better suited as a larger embedding is needed to model more complex structures such that the difficulty for an optimization method is decreased. (Maximilian e Kiela 2017)

In this sense, the Riemannian SGD optimization involves computing the Riemannian gradient (a scaled version of the Euclidean gradient) with respect to the loss, performing a gradient-descent step and projecting any embeddings that move outwards within its boundary. (Bhuwan, et al. 2018)

To evaluate the hierarchical embeddings, the same approaches were used as described by (Maximilian e Kiela 2017): **Reconstruction** error in relation to the embedding dimension, that is, reconstruction of a hierarchy from the embedding to evaluate the representation capacity. **Link prediction** by splitting the data into a train, validation and a test set to evaluate the generalization performance.

PoincareKMeans

Clustering is one of the most common approaches to identify subgroups in the data showing similar characteristics (Jin X. 2011). To create some groups from the performed embeddings

over Poincaré ball, the group resorted to a different version of the K-Means algorithm because of the Euclidean based distance as a similarity measure. The context of the hyperbolic space prohibits the use of linear spaces to determine in its most accurate sense comparable features without exhausting the original graph distances. Thus, the PoincareKMeans will be used. (AlexPof 2021)

Recommendation system

Across the literature, we can find a variety of machine learning models applying Recommender Systems based on metric learning models concerned with designing matching functions between users and items. However, the gross of these examples only encompasses user-item representations in the Euclidean space.

To explore the notion of learning user-item representations with more complex relationships and still preserving their distances when performing embeddings in the hyperbolic space, it was proposed a HyperML model that is able to maintain valuable representations of user-item pairs in the hyperbolic space. (Vinh Tran, et al. 2020) A Recommender System was developed to overcome the limitations of the Poincaré model that unable the option to obtain the relations between categories and users. The Recommender System will then get new insights based on the similarity of the categories and also, on the similarity of the users.

2.2 Deep Interest Network

As referred, our goal is to predict whether users would be interested in the insights that we recommend to them. Many models could do similar work to what we intend to, such as Wide & Deep Learning (Cheng, et al. 2016) or Youtube Recommendation (Covington, Adams e Sargin 2016) for the CTR model. These models share a similar structure [Appendix A2 – Figure 2]: to learn the non-linear relations among the users' features, first projecting extensive sparse features – which are the historical behaviors of users in this study – into lower-dimensional embedding vectors, which are subsequently modified into fixed-length vectors, and lastly concatenated together to be fed into fully connected layers. However, although these models

allow reducing the engineering workload significantly, there are still some drawbacks that cannot be compensated, mainly due to the diversity of users' interests. The above-mentioned models are not capable enough to express these users' diverse interests, as they learn the representation of all the interests by compressing the user historical behaviors into embedding vectors, and then obtaining a fixed-length vector by pooling them using Equation 3 in Appendix A2. Essentially, to make these models able to get a representation sufficient enough to express all the users' interests, the fixed-length vectors would need to be broadly enlarged. Consequently, it would significantly expand the size of the learning parameters, increasing the risk of overfitting under limited data. (Zhou, et al. 2018)

Thus, to overcome this problem, a model called Deep Interest Network for Click Through Rate (DIN-CTR) was created by Alibaba Group in 2018 (Zhou, et al. 2018), improving the defects of the models mentioned above. Considering that users may have a great range of vast interests among Facebook pages, to express this interests' diversity, DIN uses a multimodal distribution in which each peak represents a user's interest. Also, users may show interest in the insights that we recommend to them only depending on a small portion of the historical interests instead of the entire historical behavior. For example, imagine a person who loves animals and has liked a dog photo, Trump's scandal, and a post of Marvel's movies. Now we would like to recommend a cat-related insight to him/her, and whether he/she will be interested in this insight or not is uncorrelated to whether he/she has liked Trump's scandal or Marvel's movies before – it is related to his/her previous like of a dog's photo. In other words, in this CTR estimation, some historical data played a decisive role, while the others did not contribute to the prediction.

For this reason, DIN introduced an innovative designed local activation unit adapted from Neural Machine Translation task (Bahdanau, Cho e Bengio 2015) to the structures of models mentioned above [Appendix A2 – Figure 3], maintaining the representative vector of users the same. Activation units are applied to the user behavior features, paying more attention to the related user interests by soft-searching for proper insights of historical behaviors, then taking weight sum pooling to adaptively calculate user representation given a candidate

recommendation [Appendix A2 – Equation 4]. Also, as the input of DIN is highly sparse, which is a vector consisting of many zeros, resulting in many parameters, a significant amount of them appears several times, adding extra noises to training. Thus, the model can be easily overfitted. DIN proposed a productive mini-batch aware regularizer to mitigate the overfitting. In every mini-batch, it calculates the L2-norm over the parameters of sparse features [Appendix A2 – Equation 5]. Finally, a last introduced innovative technique was the Dice activation function [Appendix A2 – Equation 6], instead of applying PReLU activation function. The PReLU takes a hard rectified point with a value of 0, which may be inappropriate when the distributions of inputs of each layer are different. The idea of Dice is to adaptively adjust the rectified point according to the distribution of input data, whose value is set to be the mean of input.

3. Implementation

3.1 Hyperbolic Embeddings

The process of implementation of the Hyperbolic Embeddings approach was structured by the following steps: Preprocessing and curation of the data, Generation of a synthetic data of users, implementation of the Poincaré model for learning hierarchical representation, execution of the PoincareKMeans model to obtain clusters, represent the users in the space, and the last part, the deployment of a Recommender System. For more information, check Appendix A1 – Exhibit 1.

The preprocessing of the data was the curation of Facebook categories of users' preferences into tuples fit to serve as input on the Poincaré model [Appendix B1 – Figure 6], as well as an additional dataset to be used as a test set containing information from one of the members of the group to evaluate the model along the whole process. Furthermore, it was necessary to generate a synthetic dataset, which can be read about in Appendix B1.

The Poincaré model takes the hierarchical data coming from Facebook's categories and performs embeddings into the hyperbolic space. The Poincaré is represented as a circle, where the categories that are on the high-level of the hierarchy are laid closer to the center and lower-

level categories (child-nodes) shifted to the end of the circumference. The end result illustrates a tree-like structure where similar categories are put nearer each other and the less similar ones farther away [Appendix B1 – Figure 7].

The outcome of the Poincaré model is a set of vectors or coordinates of each category on the hyperbolic space, which is useful to calculate the distances between categories to get similar (closer) categories or else, check the ranks (relationship) between two variables [Appendix B1 – Figures 8 & 9]. To note that from the distances between the categories we can also get new insights for the users, as can be seen in Appendix B1 – New Insights for Users.

Since the Poincaré model shows to be incredibly useful for learning the latent hierarchical embeddings, it enabled to represent the user into the hyperbolic space. Firstly, each user was represented into the space by calculating an average of their interests and characteristics, creating one unique vector. Additionally, to represent the embeddings of the users into the space, the creation of target groups through the PoincareKMeans, would group users that have similar characteristics together. That way, the characteristics of the targeted group create an avatar of the users that were targeted.

By representing the embeddings of the users into the space, the closeness between them would posteriorly, create target groups of users, in which the users that have similar characteristics will be grouped into a cluster. For more details, check Appendix B1 – Representation of the User into the Space. The implementation of the PoincareKMeans allowed to create 6 target groups [Appendix B1 - Figure 13], enabling the suggestion to a specific user, certain categories that he/she might like, because the users of their cluster (that are similar to he/she) like them too.

It is worth highlighting, the Poincaré model is not able to get relations between users and categories, so until this instant, the focus was on the underlying relationship between categories.

Nevertheless, the necessity for a Recommender System able to perform in the hyperbolic space as well as, exploring the notion of relationships between categories and users let us to the next, and final step. Its implementation. We used the aforementioned model, HyperML, by means of a tensorflow package, called CurvLearn, providing the framework for training deep learning models in non-Euclidean spaces (Alibaba 2021). The Recommender System will outcome the recommendations of insights to users.

3.2 Deep Interest Network

Input Data

As this project is done on a data privacy basis, there is no access to Modatta users' data. However, to train a Deep Interest Network, data about users' profile and previous interests needs to be inputted to the model. So before starting the training process, synthetic data had to be created to train and test the models. The generated data is divided into three main sections:

Insight features, which contains a list of insights that the users may be interested in (originated by the users' likes in Facebook pages), associated with the correspondent categories. **User profile features**, which corresponds to synthetic data that has the profile information about each user. **User historical behavior features**, which has the historical behavior of each user, containing data about whether the user has interest in a particular insight.

Besides creating the synthetic data, we are also using one of our members' consented data to validate the recommendations with real data. To a better understanding of all the data we have generated in each section, further details are given in Appendix B2 – Generated Data section.

Implementation

To implement the models under this approach, a Kaggle example of Ad CTR Prediction using the DIN model (Sanagapati 2019) was followed to understand how the data should be handled. Likewise, the DeepCTR documentation was studied for a better understanding of how to approach the model training (Shen 2021). To start the training process, several models were tried and the model that produced the best results was the already explained DIN model. To

choose which model should be used, several parameters were changed, and overfitting tried to be reduced as much as we could [Appendix C2].

After having the best model trained, two different approaches were followed to build the recommendation system and get insights recommendations for Modatta users. While the first consists of directly using the *model.predict* method to recommend some of the unknown insights to the users as individuals, the second approach lies in getting the embedding weights for each user in the dataset and using them to find similarities between users.

Individual Recommendation

In this approach, the predict method was applied to the *x_unlabeled* data and the probabilities of recommendation were assigned to each *user_id – insight_id* observation. Then, to get the insights that a particular user might like, one should just get the ones with the highest probability of recommendation. The results of applying this approach to the real user's (Emila's) data can be found in Appendix B2 –Table 16.

Besides recommending particular insights, another recommendation system was built to get the insight categories that the users are more likely to have an interest in [Appendix B2 – Table 17]. This is because the insights are very specific, and we can get more accurate results by aggregating them by their categories.

Finding Users Representation

The second approach consists of finding users' representations based on their embedding weights (which represent a mapping of the categorical variables to a vector of continuous numbers). These vectors will then be used to identify which users are more similar to each other, through a clustering technique: K-Means. This information can then be used to target groups of users with new insights or new offers, based on characteristics of the target audience.

Step 1 – Retrain the model

To develop this approach, there was a need for a different split of the data on the user side. Only

some of the users were used to train the model and then a function was defined to obtain the embedding weights for the new users. For this reason, the previous model needs to be fitted again, now with the new training and test split.

Step 2 – Find representations for the different users

In this step, the embedding weights for the different users were obtained and the profile data of each user was merged with the embedding weights, so that we have a more complete representation of the users. As the users' profile data is categorical, one hot encoder was used to transform them, so that later on, when analyzing the cluster centroids, valuable information can be extracted from the values that are shown for each variable.

Step 3 – K-Means clustering

In this section, the clustering technique K-Means is used to get the clusters for each of the users present in the dataset, based on the previously created representations. The optimal number of clusters was found with *KElbowVisualizer* and the users were assigned to each cluster. *Umap* technique was used to reduce the dimension of the data so that it could be easily visualized in the 2-D space [Appendix B2 – Figure 16]. The profile distribution of the users within the clusters was also plotted so that one could get a clear picture of how the clusters are defined [Appendix B2 – Figures 17, 18 and 19]. Different functions were created to get: **1.** the cluster assigned to each user; **2.** the centroids for each cluster; **3.** the users and correspondent liked insights and categories for each cluster.

By analyzing the centroids for each cluster, one could check the average profile information characterizing each group of users. The results comparing Emila's data and the cluster he/she is inserted in can be found in Appendix B2 –Table 18 and Figure 20. Getting the users for each cluster allows us to find the insights and insight categories that are the most liked inside each cluster. By doing that, one could then get recommendations for a new user.

Lastly, a final recommendation system was built for this approach, and the results of applying

it to Emila's data can be found in Appendix B2 –Tables 19 and 20.

4. Evaluation

Throughout the process of implementation of the techniques previously stated, some evaluation procedures were undertaken to assure the outcomes succeeded to translate meaningful conclusions. Conclusions that can afterwards be successfully implemented by Modatta.

4.1 Poincaré model and HyperML

The first step in the evaluation process occurred in the Poincaré model aimed at choosing the best model for a set of hyperparameters displaying the most adequate learning hierarchical representation. In order to find the best model, it was done a series of experiments to fine tune the model's hyperparameters [Appendix C1 – Figure 21], to which the evaluation assumed two approaches, mentioned before: **Reconstruction** and **Link Prediction**. These two approaches can be determined by two methods:

- **Mean Rank**: the average of the ranks for all observations within each sample.
- **MAP**: refers to Mean Average Precision, which is a metric that captures how well each vertex's neighborhoods are preserved.

Table 1 - Poincaré Ball Evaluation

	Reconstruction				**Link Prediction**			
	25D	50D	100D	200D	25D	50D	100D	200D
Mean Rank	2.59	2.55	**2.50**	2.53	3.19	2.98	3.07	**2.76**
MAP	0.534	0.534	0.536	**0.54**	0.413	0.418	0.416	**0.538**

The results of the Implementation of the Poincaré Ball can be seen on the table above. Looking at the Reconstruction, one can check that the values vary slightly, specially the MAP values that only increase from 0.53 to 0.54. However, looking at the Link Prediction values, the Mean Rank had 3.2 on 25 dimensions and decreased to 2.76 as well as the MAP value got from 0.41 to 0.538, showing a substantial increase on the Link Prediction. Therefore, the best one had the following characteristics: **20 negatives** sample to use, **0 number of epochs** to use in burn-in

initialization, no regularization, **200 epochs**, in a **200-dimensional space**.

Moreover, the PoincareKMeans model is in its essence an unsupervised learning algorithm, where the evaluation metrics for clustering analysis is still very shy. The choice for the number of clusters came down mostly to domain knowledge and intuition, so the number of clusters chosen after a series of attempts was 12.

The last step regarded the evaluation of the Recommender System with the Hit Rate (HR) metric, measuring the fraction of users for which the right answer is in fact included in the suggestion by the recommendation system. The final **HR@10** was of **0.77**, which is a good result, as compared with the results from HyperML experiments (Vinh Tran, et al. 2020). The parameters are represented in Appendix C1 – Figure 23.

To understand if the Recommender System was deploying the intended results, we experimented with a test set containing information from one of the members. The final results were presented as insights as well as master categories [Appendix C1 – Table 19 & 20].

4.2 DIN

During the training process of the DIN model, some problems of overfitting emerged, meaning that the model was able to get very accurate predictions for the training set but when applied to new data the evaluation was not that good. Thus, to overcome the overfitting the model was suffering from, L2 regularization and Dropout parameters were changed, having the final values for these parameters been defined as follows:

- l2_reg_dnn = 0.01
- dnn_dropout = 0.03

To evaluate the model as a regression problem, the two metrics used were log Loss and AUC, however, to get more interpretable results, we have also transformed it into a classification problem and calculated accuracy, recall and precision metrics. In this case, recall is our most important metric, as we want to minimize the number of False Negatives (insights that users

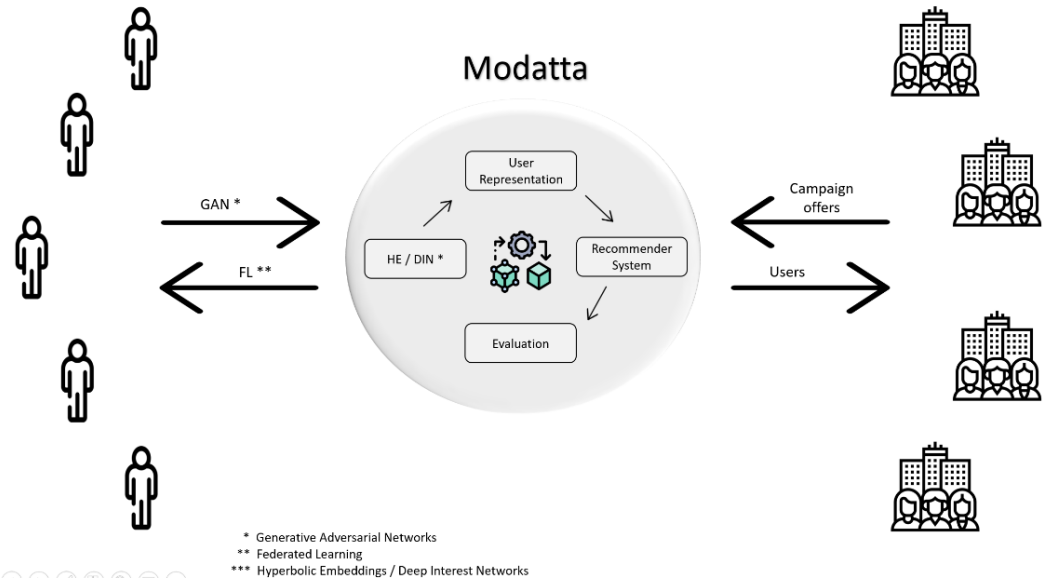
would be interested in, but we predict as non-liked insights, and so don't recommend them to the user), even if we have some False Positives (insights that users would not be interested in, but we wrongly recommend them because we predicted as liked insights). This way, when recommending a wrong insight, the user can tell us if it is not true, but if we don't recommend it at all we are not getting any information from the user side. Thus, the model was chosen mainly based on the recall metric. As we can see in Table 11 below, the model is not overfitting and the recall score is pretty good, meaning that the model is correctly predicting the majority (88%) of insights the users are interested in. More details concerning the best model evaluation can be found in Appendix C2.

Table 2 - Best DIN model Evaluation

Metric	Training set	Test set
Log loss	0.619	0.620
AUC	0.547	0.545
Recall	0.878	0.876

5. Next Steps

Figure 1 - Diagram representation of the system to be developed



Above, the figure shows a diagram of the overall system intended to be developed after

applying the models before described in this paper so far. To do so, in the next phases, there is a need to implement the following steps:

1. Identify a user-base for a campaign offer, making sure that marketers target the users that are more prompt to accept the offer, as well as users get the campaigns they want and need.
2. Generative Adversarial Networks implementation for generating synthetic data to feed to the model, preventing users' privacy from the potential data leakages.
3. Federated Learning implementation to demonstrate an alternate approach to the traditional centralized learning, aimed at leveraging communication efficacy and defense techniques to ensure data privacy.
4. Evaluate the effectiveness of the campaign, accounting for both the profile and interests' distribution of the targeted users and use the results to improve the targeting strategy.

The implementation of these four steps together will then allow the deployment of an utterly privacy-based system that will help Modatta achieve its goal of guaranteeing privacy-preserving for the users and bringing the list of potential customers to marketers.

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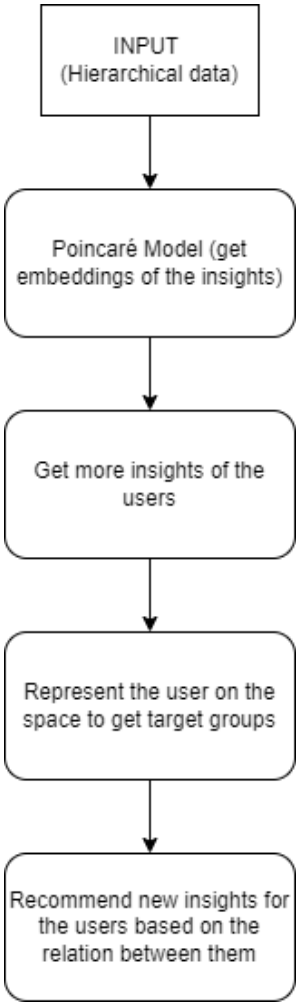
Appendix

A – Introduction to Hyperbolic Embeddings and Deep Interest Network

A1 – Hyperbolic Embeddings Approach

Exhibit 1 – Diagram of the Hyperbolic Embeddings Approach



Above, the diagram shows a flow of the overall system of the Hyperbolic Embedding Approach. It starts with the implementation of the Poincaré Model and ends up with the deployment of a Recommender System.

Formula of distance on Hyperbolic Space

$$d_H(x,y) = acosh\left(1 + 2\frac{\|x-y\|^2}{(1-\|x\|^2)(1-\|y\|^2)}\right)$$

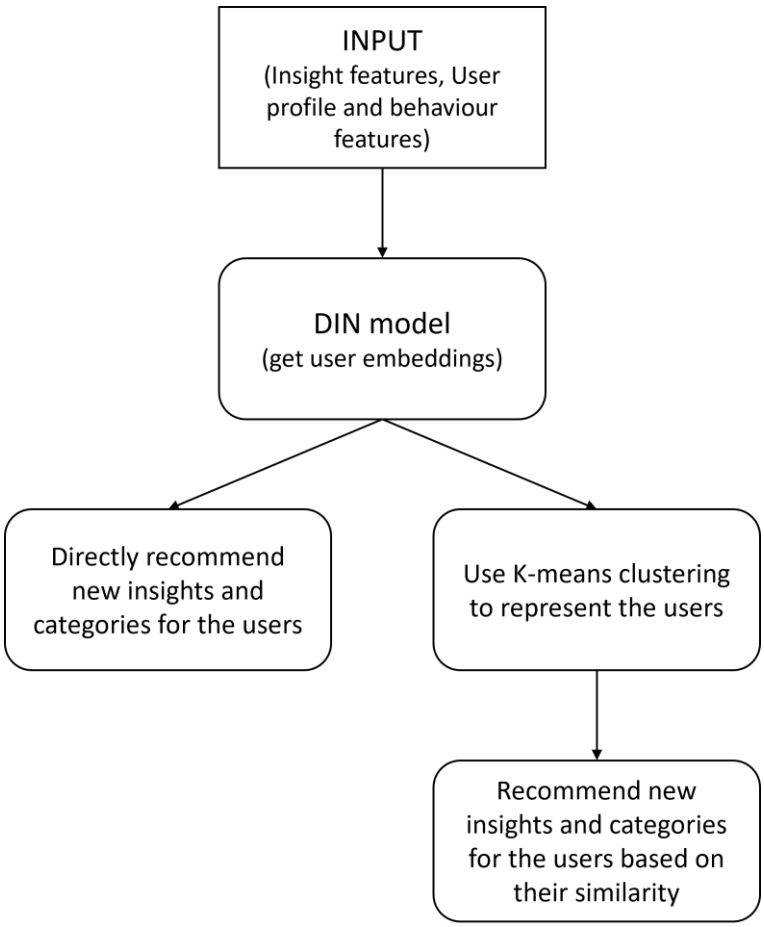
Equation 1 – Formula of distance on Hyperbolic Space

The formula above calculates the distance between 2 points, x and y, on the hyperbolic space.

The hyperbolic distance within the Poincaré ball varies smoothly with the position of *x* and *y*. Suppose three points, x and y, are the children of a parent z, placed at the origin 0. When the points move towards the edge of the disk, i.e. x -> 1, in the Euclidean space, the ratio $\frac{d_E(x,y)}{d_E(x,0)+d_E(0,y)}$ remains a constant. By contrast, the ratio $\frac{d_H(x,y)}{d_H(x,0)+d_H(0,y)}$ in the hyperbolic space gets closer to 1, giving the most approximate distance to the original graph distance ratio. This experiment exemplifies the utility for implementing Poincaré embeddings, due to their ability to preserve original graph distances to capture hierarchy of objects, as a result of their norm.

A2 – Deep Interest Network Approach

Exhibit 2 – Diagram of the Deep Neural Networks Approach

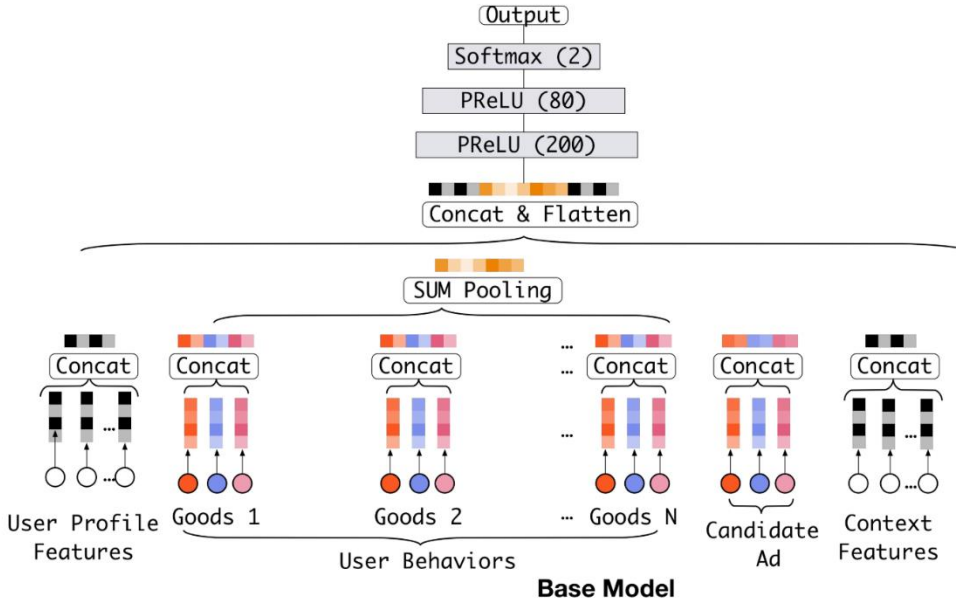


Above, the diagram shows the process of implementing the Deep Neural Networks Approach. It starts with the deployment of the DIN Model, splits into two different recommendation methods, individual and clustering.

Deep Neural Networks Models

Base model

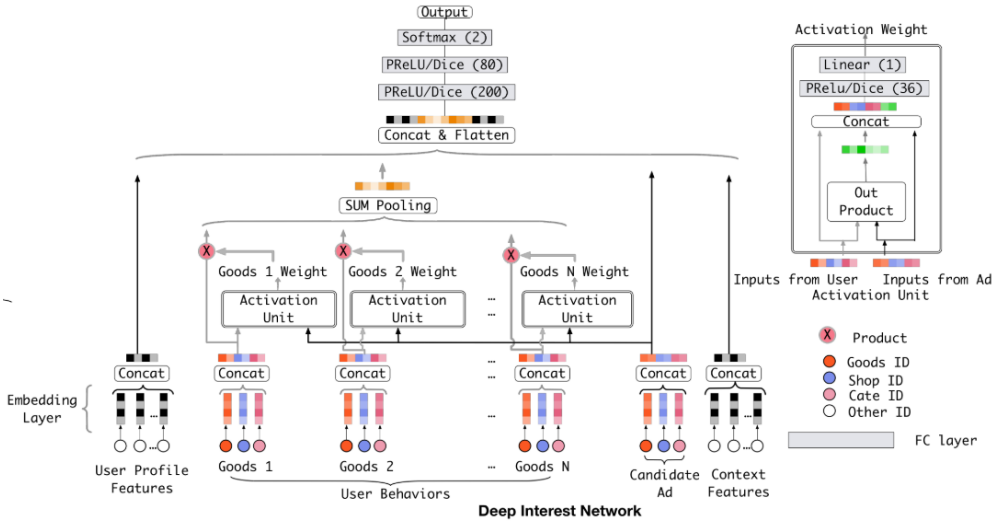
Figure 2 - The architecture of Base models



The architecture of Base models consists of several parts: Embedding layer, Pooling layer, Concat layer and multi-layer perceptro.

DIN Model:

Figure 3 - The architecture of DIN



The architecture of DIN has almost the same architecture as the base model. Introduced an innovative local activation unit function.

Loss function for both models:

$$L = -\frac{1}{N}\sum_{(x,y)\in S}^{n}(\mathrm{y}\ log_{p(x)} + (1-y)log_{(1-p(x))}$$

Equation 2 – Formula of Loss function

S denotes the training set of size N, with x as the input of the network and $y \in \{\mathbf{0}, \mathbf{1}\}$ is the label of training set, p(x) is the output of the model, which is the predicted probability of sample x being clicked.

Base models Pooling:

$$\mathrm{e_i} = \mathrm{pooling}(\mathrm{e_{i_1}}, \mathrm{e_{i_2,\ldots,e_{i_k}}})$$

Equation 3 - Pooling layer for base models

Where e_i represents a single embedding vector.

Local activation unit:

$$u_U = f(u_A, e_1, e_2, \ldots, e_H) = \sum_{j=1}^{H} a(e_j, u_A)\, e_j = \sum_{j=1}^{H} w_j\, e_j$$

Equation 4 - Local activation unit for DIN model

Where $\{e_1, e_2, \ldots, e_H\}$ is a list of embedding vectors of behaviors of user U with a length of H, u_A is the embedding vector of ad A, a(·) is a feed-forward network with output as the activation weight. With constrains: $\sum_{j=1} Wi = 1$.

Mini-batch aware regularizer:

Let $\mathbf{W} \in \mathbb{R}^{DxK}$ denote parameters of the whole embedding dictionary, with D as the dimensionality of the embedding vector and K as the dimensionality of feature space.

$$w_j \leftarrow w_j - \eta \left[\frac{1}{|ß_m|} \sum_{(x,y) \in ß_m} \frac{\partial L(p(x), y)}{\partial w_j} + \lambda \frac{\alpha_{mj}}{nj} w_j \right]$$

Equation 5 - Mini-batch aware regularization formula

Where $w_j \in \mathbb{R}^D$ denotes the j-th embedding vector, nj denotes the number of occurrence for feature id j in all samples, $ß_m$ denotes the m-th mini-batch and $\alpha_{mj} = max_{(x,y)} \in ß_m \, I(x_j \neq 0)$ if there is at least one instance having the feature id j in mini-batch $ß_m$.

Dice activation function:

$$fx{=}ps \cdot s + 1 - psf(x) = p(s) \cdot s + \big(1 - p(s)\big) \cdot \alpha s \,,$$

$$p(s) = \frac{1}{1 + e^{-\frac{s - E[s]}{\sqrt{Var[s] + \epsilon}}}}$$

Equation 6 - Dice activation function

Where in the training phase, E[s] and Var[s] is the mean and variance of input in each mini batch. In the testing phase, E[s] andVar[s] is calculated by moving averages E[s] andVar[s] over data. ϵ is a small constant which is set to be 10^{-8}.

B – Implementation

B1 – Hyperbolic Embeddings Approach

Generated Data

As there is no access to data from users, it was necessary to generate a synthetic dataset, with 10.000 users, with specific interests and profiles, selected at random, to replicate the information Modatta's app receives from each user without breaching any privacy regulation set by the GDPR. The following figure shows the generated dataset of the interests of users.

Figure 4 - Sample of the Insights Dataframe

	Interest	Interest | Literary arts	Interest | Performance art	Interest | Performing arts	Interest | Science	Interest | Sports	Interest | Visual arts	Community organisation	Community organisation | Armed forces	Community organisation | Charity organisation	...	Other | TypeAhead | Pet Tricks	Other | TypeAhead | Public figure type	Other | TypeAhead | Concentration or Major	Other | TypeAhead | Degree	Other | TypeAhead | Work position type	Other | TypeAhead | Year	Ur
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
1	0	1	0	0	0	0	0	0	0	0	...	0	0	0	1	0	0	
2	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	...	0	1	0	0	0	0	
4	0	0	0	0	0	1	0	0	0	0	...	0	0	0	0	0	0	
5	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
6	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
7	0	0	0	0	0	0	0	0	0	0	...	0	0	1	0	0	0	
8	0	0	0	0	0	1	1	0	0	1	...	0	0	0	0	0	0	
9	0	0	1	0	0	0	0	0	0	0	...	-1	0	0	0	0	0	

10 rows × 1563 columns

In order to get new insights, we need to have some users with specific interests. In addition, we need to take into consideration the interests of the users:

- The user has a real interest in a category: **1**
- The user does not have an interest (explicit): **-1**

The other categories that aren't filled with 1 or -1, are considered an unknown interest (value = 0), which means that we do not know if the user does have an interest or not.

Data Dictionary for *Insights'Dataframe*

The names of the columns are the Facebook' categories, that englobes the 3 levels of hierarchy. There is a total of 1563 categories. Below, one can find an example of 5 of them.

Table 3 - Example of Facebook Insights

Facebook Insights
Interest
Interest | Performance art
Community organisation | Charity organisation
Other | TypeAhead | Pet Tricks
Other | TypeAhead | Public figure type

Below, Figure 5 represents the dataset that was generated with some profile data for users, containing especially demographic characteristics.

Figure 5 - Sample of the Customers' Dataframe

	user_id	Birth year	Gender	Home country	Civil status	Number of children	Degree	Professional status	Annual income	Practice sports	Smokes
0	0	1936	male	AE	married	1	2	2	45	yes	no
1	1	1919	male	NP	single	2	3	5	70	yes	yes
2	2	1939	male	AD	widow	10000	1	3	70	yes	yes
3	3	1984	female	IS	single	1	0	3	100	yes	yes
4	4	1995	male	MQ	married	10000	0	3	70	no	yes
...	...	...	...	...	...	...	...	...	...	...	...
9995	9995	1948	male	BL	married	1	4	1	70	no	no
9996	9996	1950	non_binary	IO	single	0	2	6	15	yes	yes
9997	9997	1947	male	CN	married	0	2	1	15	no	no
9998	9998	1942	male	AM	single	0	2	2	10000	yes	yes
9999	9999	2017	male	TK	widow	0	4	2	15	yes	yes

Table 4 - Data Dictionary for Customers'Dataframe

Column Name	Description	Values
user_id	Unique identifier of a Modatta's user	0 to 9999
Birth_year	Birth year of the user	1900 to 2019
Gender	Gender of the user	-
Home country	Home country of the user	-
Civil_status	Civil status of the user	-
Number of children	Number of children of the user	-
Degree	Degree of the user	0 to 6
Professional_status	Professional status of the user	0 to 6
Annual_income	Annual income of the user	-
Practice_sports	Binary variable saying if the user practices sports	Yes or No
Smokes	Binary variable saying if the user smokes	Yes or No

Features Data Dictionary

Gender

Value
Male
Female
Non-binary

Civil_status

Value
Divorced
Married
Single
Widow

Degree

Value	Label
0	Other
1	High school diploma
2	Technical degree
3	Bachelor degree

Professional_status

4	Major degree
5	Master degree
6	Doctor degree

Value	Label
0	Unemployed
1	Student
2	Retired
3	Freelancer
4	Fixed term contract
5	Permanent contract
6	Business owner

Annual_income

Value	Label
15	Less than 15000€
30	Between 15000€ and 30000€
45	Between 30000€ and 45000€
70	Between 45000€ and 70000€
100	Between 70000€ and 100000€
10000	More than 100000€

Practice_sports

Value
No
Yes

Number of children

Value	Label
0	No children
1	Has 1 children
2	Has 2 children
1000	Has 3+ children

Smokes

Value
No
Yes

For simplicity purposes, the Home Country is not referred, as it has 249 values. Those values are country names. Below one can find an example of 4 of them.

Value	Label
PT	Portugal
ES	Spain
UK	United Kingdom
US	United States

Poincaré Model: Implementation

Table 5 - Tuples of Categories' Dataframe

Child	Parent
Literary arts	Interest
Performance art	Interest

Performing arts	Interest
Science	Interest
Sports	Interest
Visual arts	Interest
Armed forces	Community organisation
Charity organisation	Community organisation
Country club/Clubhouse	Community organisation
Community group	Community organisation
Environmental conservation organisation	Community organisation
Government organisation	Community organisation
Intergovernmental organisation	Community organisation
Trade union	Community organisation
Political organisation	Community organisation
Political party	Community organisation
Private members club	Community organisation
Religious organisation	Community organisation
Social club	Community organisation
Sorority & fraternity	Community organisation

Table 8 represents the data frame created to be an input for Poincaré Model. Later, it will be transformed into tuples.

Figure 6 - Input for the Poincaré Model

```
tuples
```

```
[('Literary arts', 'Interest'),
 ('Performance art', 'Interest'),
 ('Performing arts', 'Interest'),
 ('Science', 'Interest'),
 ('Sports', 'Interest'),
 ('Visual arts', 'Interest'),
 ('Armed forces', 'Community organisation'),
 ('Charity organisation', 'Community organisation'),
 ('Country club/Clubhouse', 'Community organisation'),
 ('Community group', 'Community organisation'),
 ('Environmental conservation organisation', 'Community organisation'),
 ('Government organisation', 'Community organisation'),
 ('Intergovernmental organisation', 'Community organisation'),
 ('Trade union', 'Community organisation'),
 ('Political organisation', 'Community organisation'),
 ('Political party', 'Community organisation'),
 ('Private members club', 'Community organisation'),
 ('Religious organisation', 'Community organisation'),
 ('Social club', 'Community organisation'),
 ('Sorority & fraternity', 'Community organisation'),
 ('Sports club', 'Community organisation'),
 ('Youth organisation', 'Community organisation'),
 ('Art', 'Media'),
```

To implement the Poincaré Model, there was a need to transform the Facebook' categories into tuples, in order to represent the hierarchical structure of the categories. The tuple represented on Figure 6 is composed by (child, parent) nodes.

Figure 7 - Representation of the Poincaré Embeddings in 2D

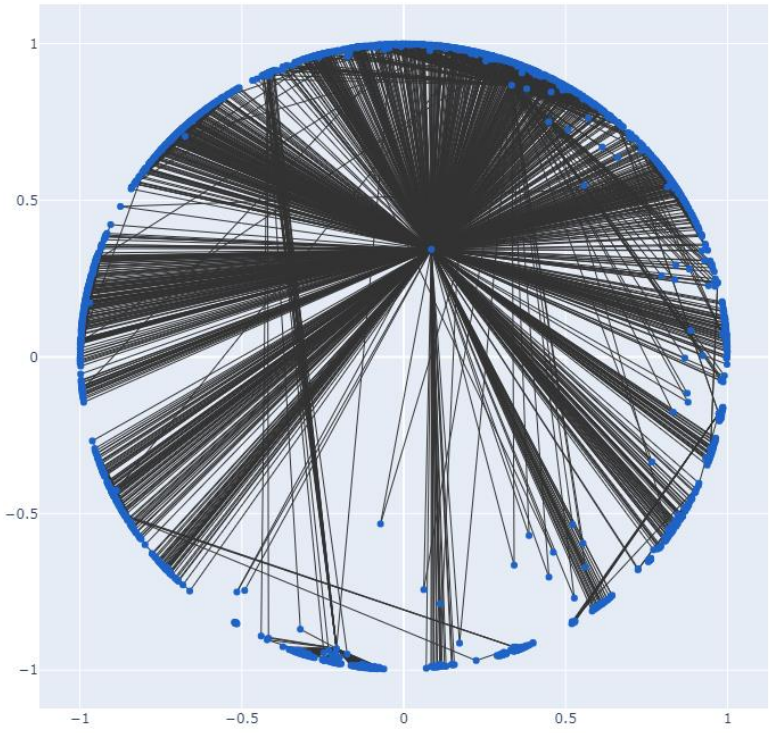


Figure 7 represents all the embeddings resulting from the implementation of the Poincaré Model. Each blue dot represents a category that has a unique representation into the space. The straight black lines represent the relations between the levels of the categories.

The categories that are on the high-level of the hierarchy are laid closer to the center and lower-level categories (child-nodes) shifted to the end of the circumference. Finally, similar categories are put nearer each other and the less similar ones farther away. This representation was created using the parameters of the best model, changing the dimensions from 200 to 2.

Figure 8 - Example of Closer Categories

```
]: print("The category Music is most similar to:")
   model.most_similar('Music')

   The category Music is most similar to:

]: [('Playlist', 1.8499834460025835),
    ('Music award', 1.8929040891332125),
    ('Music chart', 2.446066311528132),
    ('Podcast', 2.5070578937722567),
    ('Musical genre', 2.5715183839839804),
    ('Album', 2.742832353196168),
    ('Record label', 3.3631610546738644),
    ('Music video', 3.461160005308079),
    ('Choir', 3.856084689279786),
    ('Song', 3.873946372133142)]
```

From the Poincaré model, a set of vectors or coordinates of each category on the hyperbolic space, let us check which are the coordinates closer to a specific category. On Figure 8, we used the category *Music* as an example. From the results, one can see that *Playlist* and *Music Award* are the insights closer to this category. This tuple also returns the distance between the category chosen and another category. As we can see, the closest categories mentioned before, have a hyperbolic distance below 2.

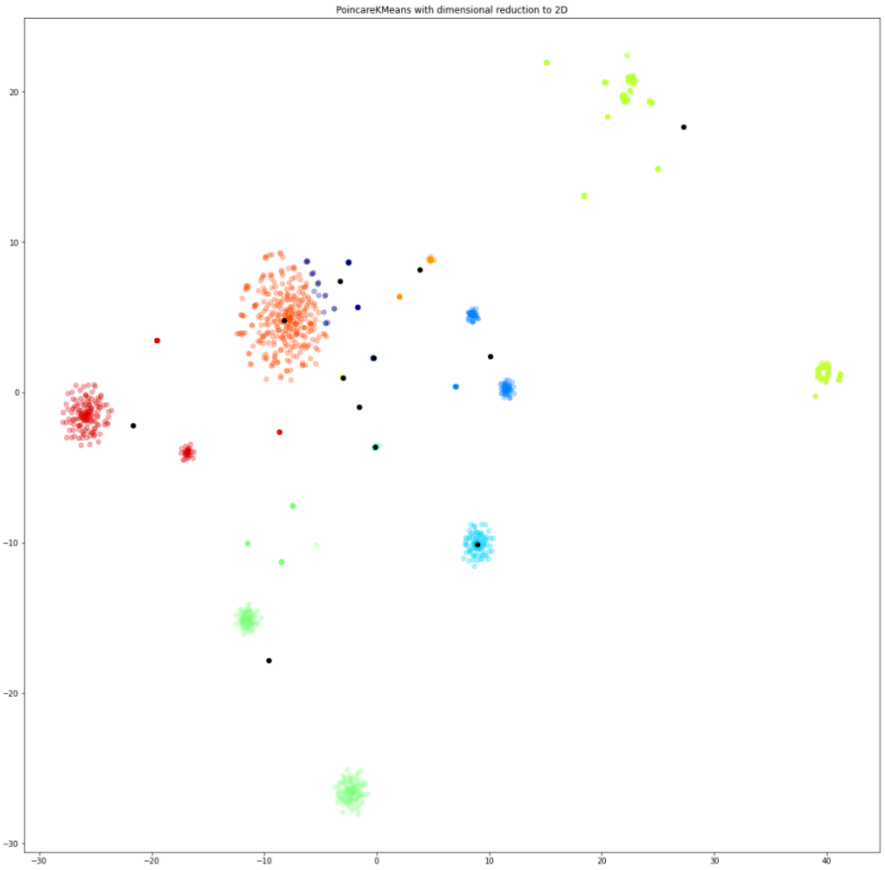
Figure 9 - Example of Rank between 2 Categories

```
[31]: # Rank of distance of node 2 from node 1 in relation to distances of all nodes from node 1
      print("The category Music is at the second position of Song (most similar)")
      model.rank('Song', 'Music')
      # In Song, the Music is at 2st place on the most similar

      The category Music is at the second position of Song (most similar)
[31]: 2
```

Figure 9 shows an example of a rank of distance between 2 categories, that demonstrates their relationship. As an example, we have *Song* and *Music*. The rank function calculates the distance from all categories to the category *Song* and then it will see at each position is *Music*. We can see that it is at the second position, but that doesn't mean that vice versa the same number will be 2. When calculating the rank between *Music* and *Song*, meaning that were calculating the distance from all categories to the category *Music*, *Song* is in 10th.

Figure 10 - PoincareKMeans in 2D



The implementation of the PoincareKMeans, even though, doesn't have a clear influence on our final goal, allowed us to analyze the categories in each cluster. Figure 10 illustrates the grouping of the vectors of each category that was created by implementing the Poincaré Model. Therefore, it shows the different centroids (black dots) and their clusters, that are assigned with a different color. Because the best model has 200D, we used it on our project, but as a mean of visualization, the dimension was reduced to 2D.

Looking at the figure, you will notice some clusters without any category. This may be due to the context of performing computations in the hyperbolic space, which may hold back some centroids to find any category.

New Insights for Users

From the Poincaré Model, it's possible to use the most similar function, aforementioned, that will give us the categories that are most similar to the interests of the user. So, for each category, one can check which are the categories closer, and recommend those for the user. Once again, we're using insights of the Emila' data. Below we can find the categories of insights that our real user has showed interest or disinterest in:

Figure 11 - Interests and disinterests that the user has

[50]:

	POSITIVE INSIGHTS	NEGATIVE INSIGHTS
0	Businesses | Education | State school	Community organisation | Armed forces
1	Community organisation	
2	Non-business places	
3	Businesses	
4	Other | Brand | Health/Beauty	
5	Other | Community	
6	Other | Brand	
7	Other | Brand | Electronics	
8	Businesses | Beauty, cosmetic & personal care	
9	Businesses | Shopping & retail | Swimwear shop	
10	Non-business places | Campus building	
11	Businesses | Beauty, cosmetic & personal care ...	
12	Businesses | Arts & entertainment	
13	Businesses | Food & drink | Family-style resta...	
14	Other | Brand | Entertainment website	
15	Businesses | Media/news company	
16	Media | TV & film | TV Programme	
17	Businesses | Sport & recreation	
18	Businesses | Education | University	
19	Businesses | Non-profit organisation	
20	Media | TV & film | TV	
21	Businesses | Shopping & retail | Mobile phone ...	
22	Media | Books & magazines	
23	Other | Brand | Product/Service	
24	Businesses | Education | Higher education	
25	Businesses | Food & drink | Cocktail bar	
26	Community organisation | Social club	
27	Public figure | Comedian	

Table 6 - Predicting new insights

New Insights	Distances
Social club	0.305306
Sorority & fraternity	0.403680
Fashion model	0.552897
Political organisation	0.603168
Gaming video creator	0.684306
Orchestra	0.769347
Sportsperson	0.848823
Public figure	0.881704
Books & magazines	0.883995
Newspaper	0.883995
Visual arts	0.933503
Article	0.959758
Science	0.999553
TV network	1.770001
Other	1.974406
Brand	1.974406
Art	2.040909
Theatrical play	2.158405

New Insights	Distances
Book series	2.192080
Language	2.589027

For getting the new insights, we used a test set from a member of our group, Emila, that contains some positive and negative interests. Table 9 shows the new insights for this user as well as their distances between the category that the user is interested in and the new insight recommended. As we want the categories that are most similar, we got 20 new insights sorted by ascending distances.

Explicit Negative Interests

Notice that, if the user does have a negative interest in some category, the model makes sure that there is an impact on the final new insights, meaning that the negative interests and their similar ones, will not be on the new insights derived from the model.

Imagine we have a user that doesn't like Soccer. We are going to make sure that the insights derived from the model will not get categories that are related with Soccer, but also, be aware that even though this user doesn't like soccer, he can like other type of sports. Not limiting all the choices of Sports (the parent node).

Representation of the User into the Space

Doing an average of the coordinates of each user, allowed to represented each user into the space. This means that, based on the interests of the user, the embeddings of each interest is retrieved and then it's applied an average on those embeddings, creating one unique vector that will represent each user.

Below one can see the representation of 7000 users in a 2D visualization. For reducing from 200D to 2D, UMap was used as a dimensional reduction technique.

Figure 12 - Representation of the users into the space

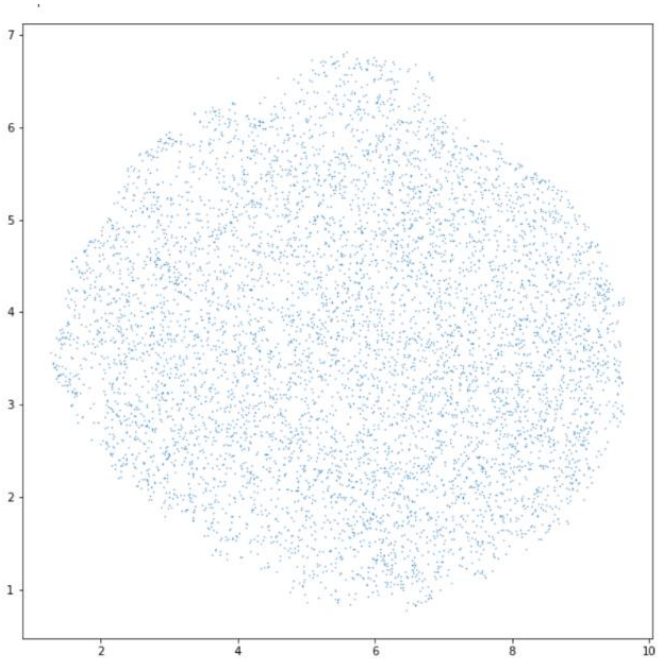


Figure 13 - KMeansPoincare for Representing users

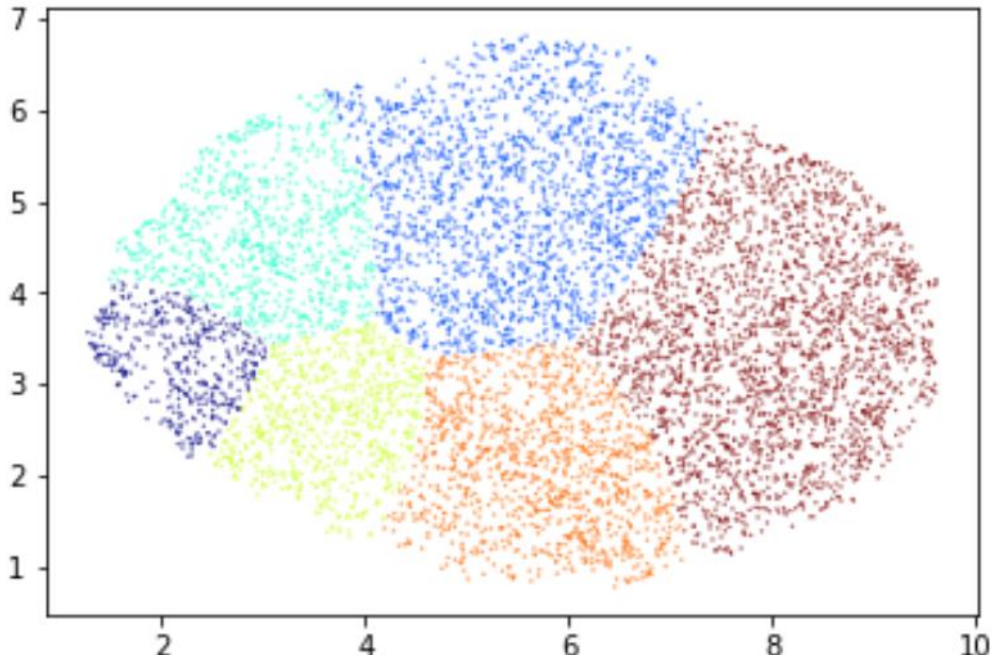


Figure 13 shows 6 target groups created by implementing PoincareKMeans on the representation of the users.

Having target groups, will allow us to suggest to a specific user a certain category that he/she might like, because of the cluster he's in.

In order to understand the target groups, we had to analyze each cluster and understand their characteristics. This was done by going to each user, in a specific cluster, and calculate the insights that appear the most, meaning that the users that are on that cluster are characterized by those attributes.

The following tables identify the main characteristics of each cluster. The target groups are characterized as follows:

Cluster 1

Users in cluster 1 tend to like Real State and Media.

Businesses – Property
Businesses – Media/news company
Businesses – Arts & Entertainment

Cluster 2

Businesses – Commercial & industrial
Businesses – Medical & health
Non-business places - religious
Businesses - Sports & Recreation
Businesses - Food & Drink

Users in cluster 2 are interested in commerce, sports centers, cinema, food and drink and religious places.

Cluster 3

Businesses - Education
Businesses - Finance
Businesses - Science, technology & engineering

Users in cluster 3 are interested in Education, finance services and telecommunication companies.

Cluster 4

Businesses - Food & Drink
Businesses - Vehicle, aircraft and boat
Businesses - Sport & recreation
Shopping & Retail

Users in cluster 4 like to go to Restaurants, all types of cars, motorcycles and boats. They also like sports.

Cluster 5

Other - Brand
Businesses - Food & Drink
Businesses - Travel & Transport
Media

Users like all types of brands, like to buy all kind of things and travel. Like books and music.

Cluster 6

Users in cluster 6 are into

Businesses - Medical & health
Shopping & Retail
Businesses - Food & Drink
Sports

Medical and health; Like to shop, and go to restaurants.

In order to evaluate the representation of the user, we predicted the cluster of Emila, as we have been doing before. From the prediction, Emila belongs to cluster 1. We believe that the results indicate to be good, as she is interested on Real State, Media and Entertainment.

Having groups of users together, we are able to identify people more similar to each other. Therefore, it will allow us to suggest to a specific user a certain category that he/she might like, because the users of their cluster (that are similar to he/she), like them too. Below, we have an example of user 1000, where it outputs their closest / similar users.

Figure 14 - Closest Users to user 1000

x 1000

```
[[('User 2598', 0.08168382446355738)],
 [('User 6644', 0.08659737440963623)],
 [('User 5454', 0.08699786909174022)],
 [('User 1414', 0.08776293177995817)],
 [('User 1476', 0.08814171036714673)],
 [('User 4763', 0.09036007364312187)],
 [('User 1497', 0.09059016391621268)],
 [('User 5262', 0.09076536525640845)],
 [('User 6983', 0.09091308487799786)],
 [('User 6160', 0.09126500366380853)],
 [('User 2093', 0.09129561814139267)]]
```

B2 – Deep Interest Network Approach

Generated Data

Insight features

This section comprises data that is related to the insights information that we have access to. **Insights** are particular interests that the users are able to get when connecting their Facebook data with their Modatta app. These insights are particular categorizations of the Facebook pages the users like. Then each insight is assigned with a more general **category**, which will be used later on to find more meaningful recommendations. It is important to note that only each user has control over their own data, and neither Modatta nor the marketeers can access it.

Table 7 - Insight features datasets description

Data	Description
insight_dic	dictionary for the insights data, where each *insight_id* is assigned to its correspondent label
insight_cat_dic	dictionary for the insights' categories data, where each cat_id is assigned to its correspondent label
insight_features_df	dataset with each *insight_id* assigned to its correspondent *cat_id*

User profile features

In this section, synthetic user profile data was created. The following variables were chosen to represent a user's profile: *Birth year*, *Gender*, *Civil status*, *Degree*, *Professional status*, *Annual income*, and *Practice sports*.

Table 8 - User profile features datasets description

Data	Description
labeled_user_profiles	synthetic data created to represent 10 000 users with random profile data. This data frame contains the labeled data
user_profile_df:	*labeled_user_profiles* with the labels transformed into codes, so that it can be easily read by the model later on
labeled_new_profiles	real data that comes from a new profile (in this case, we are using Emila's consented data). This data frame contains the labelled data
new_profiles_df	*labeled_new_profiles* with the labels transformed into codes, so that it can be easily read by the model later on
final_profile_df	*user_profile_df* merged with the *new_profiles_df*

Table 9 - Data Dictionary for final_profile_df

Column Name	Description	Values
user_id	Unique identifier of a Modatta's user	0 to 10000
Birth_year	Birth year of the user coded into bins	0 to 8
Gender	Code for identifying the gender of the user	0 to 2
Civil_status	Code for identifying the civil status of the user	0 to 3
Degree	Code for identifying the degree of the user	0 to 6
Professional_status	Code for identifying the professional status of the user	0 to 6
Annual_income	Code for identifying the annual income of the user	0 to 5
Practice_sports	Binary variable saying if the user practices sports	0, 1

Features Data Dictionary

Birth_year

Value	Label
0	Birth year between 1900 and 1920
1	Birth year between 1921 and 1940
2	Birth year between 1941 and 1960
3	Birth year between 1961 and 1970
4	Birth year between 1971 and 1980
5	Birth year between 1981 and 1990
6	Birth year between 1991 and 2000
7	Birth year between 2001 and 2010
8	Birth year between 2011 and 2021

Gender

Value	Label
0	Male
1	Female
2	Non-binary

Civil_status

Value	Label
0	Divorced
1	Married
2	Single
3	Widow

Degree

Value	Label
0	Other
1	High school diploma
2	Technical degree
3	Bachelor’s degree
4	Major degree
5	Master’s degree
6	Doctor degree

Professional_status

Value	Label
0	Unemployed
1	Student
2	Retired
3	Freelancer
4	Fixed term contract
5	Permanent contract
6	Business owner

Annual_income

Value	Label
0	Less than 15000€
1	Between 15000€ and 30000€
2	Between 30000€ and 45000€
3	Between 45000€ and 70000€
4	Between 70000€ and 100000€
5	More than 100000€

Practice_sports

Value	Label
0	No
1	Yes

User historical behavior features

In this section, the user behaviors dataset, which represents the historical association between the **users** and the **insights**, has been created. When building this data frame, each user (previously created and stored with a unique *user_id*) has some insights associated and a value saying if:

1. the user shows interest in the insight: **True = 1 & False = 0**
2. the user is not interested in the insight: **True = 0 & False = 1**
3. we don't have information about whether the user is interested: **True = 0 & False = 0**

Table 10 - User historical behavior datasets description

Data	Description
user_behaviors_df	synthetic data created to represent 1000000 "behaviors" for the 10000 created users – 1000000 interactions between a user and an insight
new_users_behavior	real data that comes from a new profile (in this case, Emila's data is used). This data frame has information about which insights the new user is interested in, is not interested at all and the insights we don't any have information about for the users
final_behaviors_df	*user_behaviors_df* merged with the *new_users_behavior* data frame

Table 11 - Data Dictionary for final_behaviors_df

Column Name	Description	Values
user_id	Unique identifier of a Modatta's user	0 to 10000

insight_id	Unique identifier of an insight that may be of the user's interest	0 to 1563
True	Binary variable saying if the user is interested in the insight	0, 1
False	Binary variable saying if the user is not interested in the insight	0, 1

Detailed explanation of True / False values

True

Value	Label
0	We may not know if the user is interested in the insight; or the user is not interested at all
1	We know explicitly that the user is really interested in the insight

False

Value	Label
0	We may not know if the user is interested in the insight; or the user is really interested
1	We know explicitly that the user is not interested in the insight at all

Final dataset

Finally, the three datasets – *insight_features_df*, *final_profile_df* and *final_behaviors_df* – are merged into one final data frame – *final_df*. This is how the data that will be inputted to the model looks like:

Figure 15 - Final dataset (all the previous generated final datasets merged)

```
final_df
```

	user_id	insight_id	True	False	Birth_year	Gender	Civil_status	Degree	Professional_status	Annual_income	Practice_sports	c
0	235	1153	1	0	1	1	0	4	2	0	1	
1	6285	1153	1	0	3	0	3	5	4	3	0	
2	431	1153	1	0	5	0	3	5	4	1	0	
3	2244	1153	0	1	1	2	0	1	2	2	0	
4	1214	1153	1	0	0	1	3	4	0	1	0	
...	...	...	...	...	...	...	...	...	...	...	...	
1001559	6690	1444	0	0	2	0	0	5	4	4	1	
1001560	5193	1444	1	0	1	0	3	5	0	5	1	
1001561	4211	1444	1	0	7	0	1	6	1	2	0	
1001562	2878	1444	1	0	8	2	3	0	4	4	1	
1001563	10000	1444	0	0	6	1	2	5	1	0	1	

1001564 rows × 14 columns

Emila's TRUE and FALSE insight categories

Below we can find the categories of insights that our real user has showed interest or disinterest in:

Table 12 - Interests and disinterests of our Emila

TRUE	FALSE
ARTS	ARMED FORCES
BEAUTY AND PERSONAL CARE	
COMEDY	
COMMUNITY SERVICES	
ENTERTAINMENT	
FASHION	
FOOD AND DRINK	
GADGETS	
HEALTH AND FITNESS	
JOURNALISM	
LITERATURE	
NON-PROFIT ORGANIZATION	
Non-business places	
PHOTOGRAPHY	
SCIENCE AND TECHNOLOGY	
SHOPPING AND DEALS	
SPORTS	
TEACHING AND EDUCATION	
TV	

DIN Model Implementation

Individual Recommendation

Table 13 - Recommending Insights

Insight	Category
Businesses | Sport & recreation | Baseball field	SPORTS
Businesses | Local service | Veterinarian	PETS AND ANIMALS
Businesses | Beauty, cosmetic & personal care | Threading service	BEAUTY AND PERSONAL CARE
Businesses | Beauty, cosmetic & personal care | Image consultant	BEAUTY AND PERSONAL CARE
Businesses | Medical & health | STD testing centre	HEALTH AND FITNESS
Public figure | Author	LITERATURE
Businesses | Travel & transport | Private bus service	TRAVEL
Businesses | Shopping & retail | Outdoor equipment shop	SHOPPING AND DEALS
Businesses | Medical & health | Medical device company	HEALTH AND FITNESS
Other | Brand | Website	COMPUTER AND TECHNOLOGY
Businesses | Travel & transport | Tour guide	TRAVEL
Businesses | Food & drink | Hot pot restaurant	FOOD AND DRINK
Businesses | Food & drink | Rajasthani restaurant	FOOD AND DRINK
Businesses | Shopping & retail | Women's clothes shop	SHOPPING AND DEALS
Businesses | Shopping & retail | Rent-to-own shop	SHOPPING AND DEALS
Businesses | Food & drink | Padangnese restaurant	FOOD AND DRINK
Businesses | Sport & recreation | Football pitch	SPORTS
Businesses | Food & drink | Goan restaurant	FOOD AND DRINK

As we are first recommending particular insights that the users may be interested in, when looking at the categories assigned to each of the recommended insights for our real user, one can see that the majority of them fall into categories that the user has already shown interest in (SPORTS, BEAUTY AND PERSONAL CARE, HEALTH AND FITNESS, LITERATURE, SHOPPING AND DEALS, FOOD AND DRINK), while only four insights are assigned with new categories (PETS AND ANIMALS, TRAVEL and COMPUTER AND TECHNOLOGY). This makes sense, as our goal is to find new interests that the user may have and thus it is realistic that these new interests are similar to the ones the user likes.

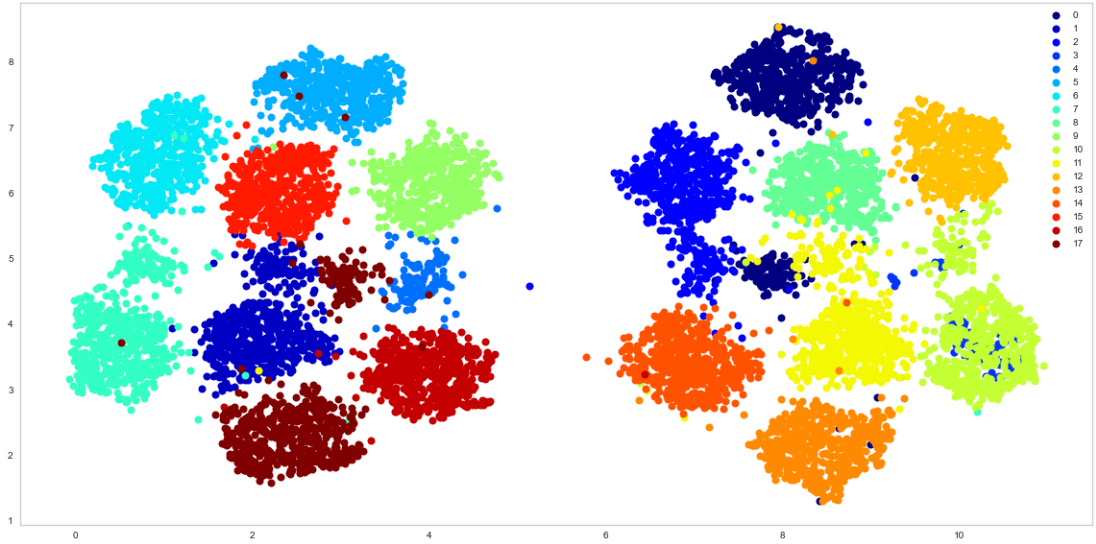
Table 14 - Recommending Categories Insights

Category
COMPUTER AND TECHNOLOGY
POLITICS
HISTORY
PETS AND ANIMALS
FINANCE
GAMING
MOTOR VEHICLES
HOSPITALITY AND TOURISM
MUSIC
ENVIRONMENT
RELIGION
DESIGN
TRAVEL
REAL ESTATE

By grouping the insights per category and trying to find the right categories of insights to recommend, besides the ones the user has already shown interest in, these are the results of applying the model to Emila's data. As expected from the previous recommendations, COMPUTER AND TECHNOLOGY and PETS AND ANIMALS are part of the first categories to be recommended. From the remaining ones, we know that at least FINANCE, MUSIC and TRAVEL would be positively validated by the user concerned, while the others, despite their probable non direct validation, could be hidden interests that the user might explore in more detail when being shown these recommendations by the app.

Clustering Recommendation

Figure 16 - Kmeans Clusters Visualization



These are the clusters resulting from applying the K-Means clustering and UMAP dimensionality reduction techniques. As we can see, the users are grouped into well-defined clusters, with a low dispersion of users between clusters.

An interesting analysis one could do is to look at the distribution of users by their profile features. By analyzing some of the variables, it is possible to note a clear distribution based on three determinant features: users' gender, users' civil status and whether they practice sports or not. Let's plot the clusters distributed by these three features, one by one:

Figure 17 - Distribution by Gender

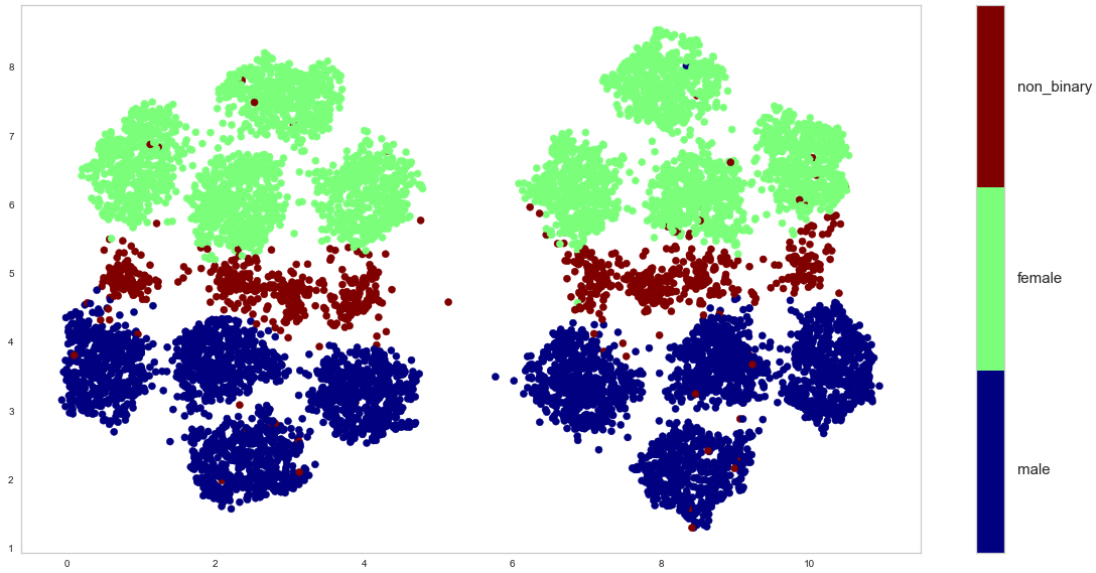


Figure 18 - Distribution by Civil Status

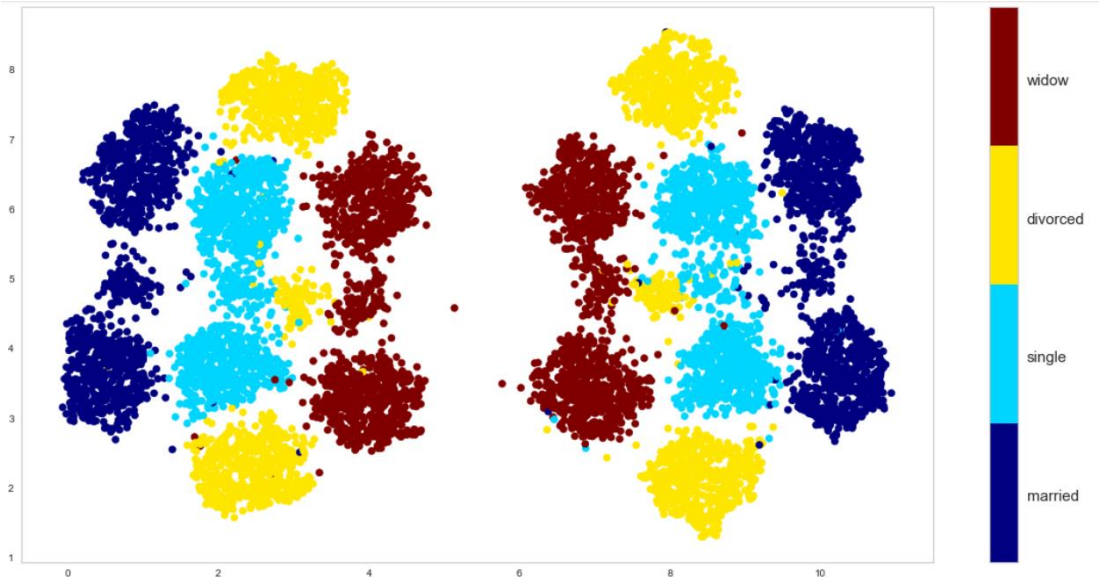
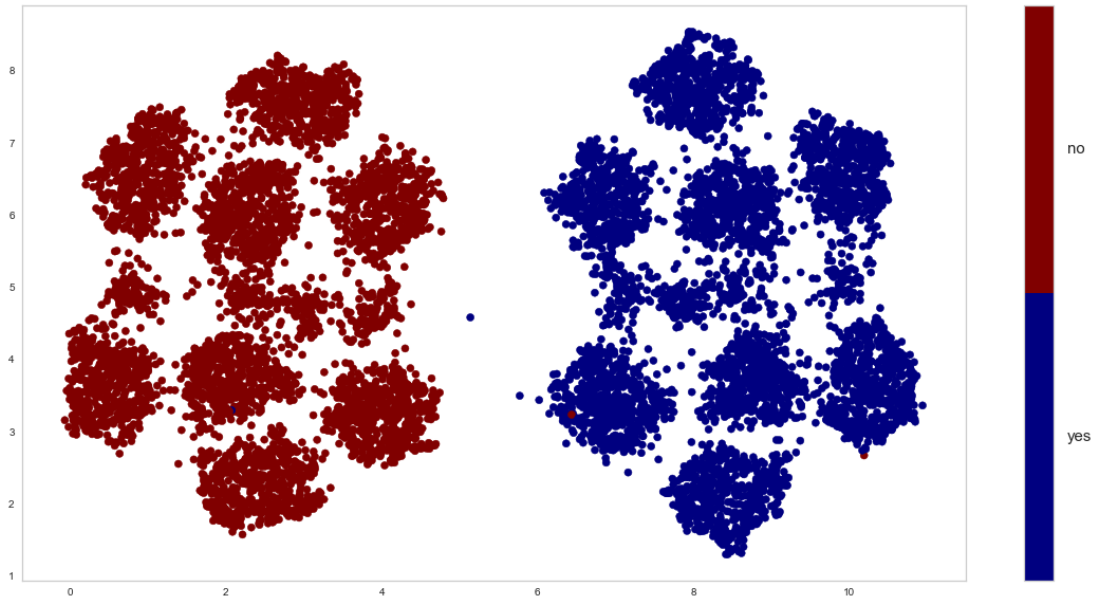


Figure 19 - Distribution by Sports Practice



Concluding, this clusters' division is being highly determined by these three variables, while the others play a secondary role in the groups' definition.

Validating cluster distribution with Emila's data:

Let's now check a particular example by comparing our real user's data with the distribution of the cluster she is inserted in.

Table 15 – Emila's profile data

Value	Label
Birth_year_6	1991 – 2000
Gender_1	Female
Civil_status_2	Single
Degree_5	Master's Degree
Professional_status_1	Student
Annual_income_0	Less than 15000€
Practice_sports_1	Yes

Figure 20 - Emila's cluster distribution

	distribution
Birth_year_2	0.1775
Birth_year_1	0.1618
Birth_year_0	0.1596
Birth_year_3	0.0899
Birth_year_5	0.0876
Birth_year_7	0.0854
Birth_year_8	0.0809
Birth_year_4	0.0787
Birth_year_6	0.0787

	distribution
Civil_status_2	1.0
Civil_status_0	-0.0
Civil_status_1	-0.0
Civil_status_3	0.0

	distribution
Gender_1	1.0
Gender_0	0.0
Gender_2	-0.0

	distribution
Degree_0	0.1820
Degree_3	0.1461
Degree_2	0.1438
Degree_5	0.1393
Degree_6	0.1371
Degree_4	0.1303
Degree_1	0.1213

	distribution
Practice_sports_1	1.0
Practice_sports_0	0.0

	distribution
Professional_status_4	0.1551
Professional_status_5	0.1528
Professional_status_2	0.1483
Professional_status_6	0.1438
Professional_status_0	0.1371
Professional_status_1	0.1348
Professional_status_3	0.1281

	distribution
Annual_income_3	0.1865
Annual_income_2	0.1820
Annual_income_1	0.1730
Annual_income_0	0.1596
Annual_income_4	0.1551
Annual_income_5	0.1438

As we had already concluded, Gender, Civil status and Practice sports are the determinant factors in the cluster definition. For the other variables the distribution is quite disperse, and we

can even see that Emila is in the group with the lowest % for birth year.

Final Recommender System

A final Recommender System was built based on the second approach, so that we could take advantage of the information that is gained by considering the similarity between users to represent them into clusters. Thus, as for the first approach, we have recommendations for both particular insights and categories of insights:

Table 16 - Recommending Insights

Insight	Category
Businesses | Vehicle, aircraft and boat | Aviation repair station	AVIATION
Other | TypeAhead | Coming of age	Other
Businesses | Shopping & retail | Rent-to-own shop	SHOPPING AND DEALS
Businesses | Food & drink | Xinjiang restaurant	FOOD AND DRINK
Non-business places | Outdoor recreation | Pond	Non-business places
Other | TypeAhead | Holiday	TRAVEL AND VACATIONS
Businesses | Local service | Personal assistant	PERSONAL IMPROVEMENT
Other | Brand | Musical instrument	MUSIC
Businesses | Hotel & B&B	HOSPITALITY AND TOURISM
Other | Brand | Society & culture website	CULTURE
Businesses | Food & drink | Asian restaurant	FOOD AND DRINK
Businesses | Vehicle, aircraft and boat | Marine supply shop	MOTOR VEHICLES
Businesses | Local service | Animal shelter	PETS AND ANIMALS
Businesses | Arts & entertainment | Decorative arts museum	DESIGN
Businesses | Shopping & retail | Fishing shop	SHOPPING AND DEALS

By comparing the insights obtained with the individual recommendation with these insights, it is notable that the categories of the latest are way more diverse and different from the ones that Emila has already shown interest in. This is because we are now trying to recommend insights not only based on the user's personal interests but on his/her peers' interests, with peers being the most similar users that are inserted in the same cluster. This is an interesting result since our goal is exactly to try to predict possible hidden insights that the users may like, so even

though at first the users might find it intriguing to be recommended with insights they had never considered to like, they might end up discovering new insights that they are really interested in.

Table 17 - Recommending Categories of Insights

Category
AGRICULTURE
MUSIC
REAL ESTATE
HISTORY
MOTOR VEHICLES
DESIGN
HOSPITALITY AND TOURISM
FINANCE
AVIATION
RELIGION
ENVIRONMENT
COMPUTER AND TECHNOLOGY
TRAVEL
PETS AND ANIMALS
MOVIES

Regarding the recommendation of categories of insights, the results are very similar to the ones obtained with the individual recommendation. The main difference is the order of recommendations – for instance, COMPUTER AND TECHNOLOGY was the first category to be recommended individually, however it is now the 12th; the same for MUSIC, which was previously the 9th and now it's the second most likely to be of the user's interest.

C – Evaluation

C1 – Hyperbolic Embeddings Approach

Poincaré Model: Evaluation

Figure 21 - Fine-tuning of parameters on Poincaré Model

```
negatives_array=[10, 20]
dimensions = [5, 25, 50, 100, 200]
epochs_array = [50, 100, 150, 200]
burn_in_array = [0, 10]
regularization_coeff = [0, 1]

# Try the different values of the parameters;

for neg in negatives_array:
    for di in dimensions:
        for epo in epochs_array:
            for burn in burn_in_array:
                for reg in regularization_coeff:
                    model = Model(negative = neg, size = di, epochs = epo, burn_in=burn, regularization_coeff=reg )
```

On our code, we created a function called *Model* implementing the Poincaré Model, based on some parameters that will be evaluated in order to get the best model possible.

In this case, we are going to fine tuning the following:

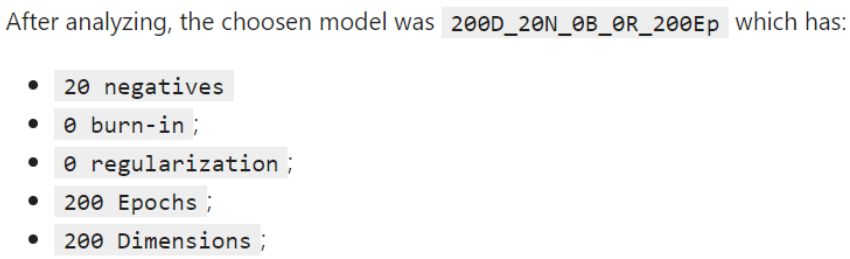
- **Negative:** Number of negative samples to use.
- **Size**: Number of dimensions of the trained model
- **Burn-in**: Number of epochs to use for burn-in initialization (0 means no burn-in)
- **Regularization_coeff**: Coefficient used for l2-regularization while training (0 effectively disables regularization)
- **Epochs:** hyperparameter that controls the number of complete passes through the training dataset.

To get the best model, we are going to fine tuning the parameters described above. The values for the parameters are the following:

- **Negatives:** 10, 20;
- **Dimensions:** 5, 25, 50, 100, 200;
- **Epochs:** 50, 100, 150, 200;
- **Burn-in:** 0, 10;
- **Regularization coeff:** 0, 1;

Figure 21 illustrates the code that was built to apply these parameters. In Figure 22, it is shown the best model hyperparameters.

Figure 22 - Best Model Parameters



For evaluation on Link Prediction, it was required a test set. This test set was transformed into tuples, as explained before.

To check the results on real data, we used data from one of our members, Emila. Table 21 shows the tuples of Emila's data.

This data allowed us to evaluate the generalization performance of the Poincaré Model.

Table 18 - Tuples of Emila's data

Child	Parent
Books & magazines	Media
TV & film	Media
Comedian	Public figure
Brand	Other
Media/news company	Businesses
Education	Businesses
Non-profit organisation	Businesses
Community	Other
Just for fun	Other
Arts & entertainment	Businesses
Beauty, cosmetic & personal care	Businesses
Youth organisation	Community organisation
Local service	Businesses
Sport & recreation	Businesses
Food & drink	Businesses
Shopping & retail	Businesses

Social club	Community organisation
Campus building	Non-business places
Video creator	Public figure
Magazine	Books & magazines

Recommender System: Implementation and Evaluation

Figure 23 - Parameters used on HyperML

```
training_config = {
    "manifold"            : PoincareBall(),  # The manifold to be used in the model
    "init_curvature"      : -1.0,  # Default value of the curvature of the manifold
    "trainable_curvature" : True,  # Whether the curvatures are trainable

    "training_steps"      : 1000,  # Steps for training
    "log_steps"           : 100,  # Log intervals during training
    "eval_steps"          : 100,  # Evaluation intervals during training

    "batch_size"          : 60,  # Batch size used in training
    "learning_rate"       : 0.001,  # Learning rate of training
    "optimizer"           : RAdam,  # The optimizer to be used in training

    "dim"                 : 25, # Dimension of the embedding tables
    "margin"              : 1.0,
    "candidate_num"       : 10,  # Sampled negative candidates for evaluation
    "K"                   : 10,  # Metric of HR@K

    "gamma"               : 0.1,  # Multi-task learning rate between the two types of loss
    "epsilon"             : 1e-9,  # Small value for avoiding dividing zeros in distortion optimization (loss)

    "embedding_initializer": tf.initializers.glorot_uniform(),  # Initializer for the embedding tables
    "shuffle_buffer"      : 10000,  # Buffer size for TF's shuffling over the dataset
}
```

Figure 23 illustrates the parameters used on the implementation of HyperML.

The final HR@10 result was of 0.77, which demonstrated to be more desirable given previous results.

Table 19 - Top 10 Recommendations of Insights

Top 10 item Recommendations
Businesses | Food & drink | Scandinavian restaurant
Businesses | Food & drink | Café
Businesses | Arts & entertainment | Museum
Businesses | Shopping & retail | Beauty supply shop
Businesses | Food & drink | Ice cream shop
Businesses | Arts & entertainment | Amusement & theme park
Public figure | Talent agent
Businesses | Sport & recreation | Volleyball court
Businesses | Vehicle, aircraft and boat | Wheel & rim repair service
Businesses | Travel & transport | Private bus service

Table 20 - Recommendations of Master Categories

Master Categories Recommendations
FOOD AND DRINK
TEACHING AND EDUCATION
BEAUTY AND PERSONAL CARE
TRAVEL
AVIATION
GAMING
MUSIC
FASHION
WINE
ENTERTAINMENT
THEATRE
POLITICS
TV
PUBLIC FIGURE
JOURNALISM
ARTS
PETS AND ANIMALS
LITERATURE
MOVIES
MOTOR VEHICLES
SPORTS

Tables 22 and 23 shows the results of the Recommender System for Emila's test set. The final results were presented as insights, as well as master categories.

The use of master categories made sense as a way to obtain new insights of users in broader terms, which can later benefit organizations when looking for new users that have some specific but wide-ranging characteristics.

C2 – Deep Interest Network Approach

DIN model parameters and evaluation

After trying to overcome the overfitting the model was suffering from, we have decided to keep the following parameters for the best model:

- dnn_use_bn = True
- dnn_hidden_units = (200, 80)
- dnn_activation = "relu"
- att_hidden_size = (40, 20)
- att_activation = "dice"
- att_weight_normalization = False
- l2_reg_dnn = 0.01
- l2_reg_embedding = 1e-6
- dnn_dropout = 0.03
- seed = 1024
- task = "binary"

Table 21 - Best DIN model Evaluation

Metric	Training set	Test set
Log loss	0.619	0.620
AUC	0.547	0.545
Recall	0.878	0.876

As we can see from the above, the model is not overfitting and the recall score is pretty good, meaning that the model is correctly predicting the majority (88%) of insights the users are interested in.

When retraining the model for the clustering recommendation, the results were very similar, showing a Log loss of 0.543 on the training set and 0.569 on the test set, and a recall of 0.852

and 0.849 on the training and test sets, respectively.

6. Step 2 :Introduction

This study was conducted in collaboration with Modatta, a Lisbon (Portugal) based startup company that aims to help European Union (EU) citizens to better manage and monetize their data under EU's digital laws.

Modatta was founded in 2019 by Rodrigo Moretti and Eduardo Pinto Basto who saw benefit in creating an app under the EU General Data Protection Regulation (GDPR) to give its users more control over how their data is collected, used, and protected online. This is accomplished with the creation of a community of potential clients willing to share their information for a fair compensation and companies wanting to reduce the cost of attracting customers while promoting a positive relationship based on respect with their audience.

Today, our data and the valuable insights that comes from it are stored and used by big technological companies to gain a competitive advantage over others, and where consumers lose influence to make decisions about their own personal information. Modatta's goal is to allow everyone – both companies and citizens – to benefit from sharing their own data, meanwhile promoting privacy, transparency and a fair share of value.

Moving forward, this study intends to first, investigate how to incorporate modatta users' historical interests, as well as their personal data, to find meaningful representations of the users in a fully privacy-preserving approach. For that, two different Deep Learning approaches will be followed – Hyperbolic Embeddings and Deep Interest Network. Furthermore, a Recommender System is built to recommend users new interests that they are likely to have interest in.

The implementation of these two representation learning approaches is the first step of the whole process to be developed, where the final goal is to allow the deployment of an utterly privacy-based system that will help Modatta to bring the list of potential customers to marketers while giving users the opportunity to learn about their data, always keeping their privacy.

6.1 Problem definition and Objectives

Identifying the problems that need to be addressed and the goals to be achieved is the first step of any project. With this project, our main goal is to help Modatta to build a marketplace for both users and marketers, where both have the opportunity to get valuable insights from data. While users have total control over their own data and can still learn more about it, companies who want to target users with particular attributes will be able to do it in a much easier and less costly way, and never accessing users' data.

As we need to keep data privacy, as mentioned above, the first problem we face throughout this study is the access to real data. To comply with the GDPR, we don't have access to users' data, meaning that the data cannot be inspected.

To overcome this problem, we need to use techniques that allow us to work with the data we have access to. For this reason, we propose dividing our project into 2 Deep Learning approaches: Hyperbolic Embedding and Deep Interest Network (DIN). While the first is using the hierarchical information from Facebook pages categories to get a representation of the user on the Hyperbolic Space, the second is using synthetic users' data and trying to find a way of capturing the similarities between users by learning a latent and abstract representation of them.

The rest of the first part of this paper is structured as follows:

- Section 2 describes the Hyperbolic Embedding and Deep Interest Network approaches.
- Section 3 presents the implementation process of both approaches.
- Section 4 describes the evaluation of both methods.

- Section 5 defines the next steps to be taken.

7. Deep Learning Approaches

Recently, learning embeddings from data such as text, graphs and multi-relational data has become a central topic in Machine Learning (ML), as well as Artificial Intelligence (AI), since most ML models can´t read and understand linguistic associations in the human sense. Therefore, the learning representations algorithms that characterize semantically meaningful dense vectors shows a response to an increased necessity to the challenges of Natural Language Processing (NLP).

Moreover, Deep Learning based methods have been recently proposed for tackling click-through-rate (CTR) prediction tasks in online advertising, where embedding vectors are used to represent large scale sparse input features, and then are transformed into fixed-length vectors that will work together to learn the nonlinear relations among the features. (Zhou, et al. 2018) In this project, instead of clicking in an advertisement that is displayed on a website, the prediction task can be defined as whether a Modatta user is interested in a particular insight or not.

To understand how these methods could be used to tackle the problem of this study, two different approaches will be followed to train models that are then used to find meaningful representations of the users' interests and predict new recommendations of the insights and categories that the users are most likely to be interested in.

7.1 Hyperbolic Embedding

In the context of extracting knowledge from symbolic objects, such as words, entities and concepts, hyperbolic embeddings present properties able to capture excellent quality hierarchy information in a few dimensions with arbitrarily low distortion. Even though, the Euclidean geometry is widely used, it is shown that linear embeddings of graphs require higher dimensionality that normally is outperformed by lower dimensionality of hyperbolic

embeddings, in terms of both the similarity between objects (distances), and their relative depths in the hierarchy (in their norms). (Maximilian e Kiela 2017)

The constant negative curvature of the hyperbolic space in the area of a circle or volume of a sphere, which may be expanded exponentially with its radius, can be used to model complex networks with hierarchical data structures. Meaning that the distance between two objects is well preserved, giving a measure of their similarity, thus, reflecting their semantic or functional relationship.

In this sense, the Poincaré Ball model is the most adequate in learning hierarchical representations, as it offers to conform mapping between hyperbolic and Euclidean space, i.e., the angles between adjacent vectors indicate to be similar to angles in Euclidean geometry, although the length of their vector is not, but can be illustrated by the hyperbolic distance [Appendix A1 – Equation 1].

This equation exemplifies the utility of implementing Poincaré embeddings, due to their ability to preserve original graph distances to capture the hierarchy of objects, as a result of their norm. Additionally, the dataset used in this study comprises multiple latent hierarchies, which the Poincaré ball is better suited as a larger embedding is needed to model more complex structures such that the difficulty for an optimization method is decreased. (Maximilian e Kiela 2017)

In this sense, the Riemannian SGD optimization involves computing the Riemannian gradient (a scaled version of the Euclidean gradient) with respect to the loss, performing a gradient-descent step and projecting any embeddings that move outwards within its boundary. (Bhuwan, et al. 2018)

To evaluate the hierarchical embeddings, the same approaches were used as described by (Maximilian e Kiela 2017): **Reconstruction** error in relation to the embedding dimension, that is, reconstruction of a hierarchy from the embedding to evaluate the representation capacity. **Link prediction** by splitting the data into a train, validation and a test set to evaluate the generalization performance.

PoincareKMeans

Clustering is one of the most common approaches to identify subgroups in the data showing similar characteristics (Jin X. 2011). To create some groups from the performed embeddings over Poincaré ball, the group resorted to a different version of the K-Means algorithm because of the Euclidean based distance as a similarity measure. The context of the hyperbolic space prohibits the use of linear spaces to determine in its most accurate sense comparable features without exhausting the original graph distances. Thus, the PoincareKMeans will be used. (AlexPof 2021)

Recommendation system

Across the literature, we can find a variety of machine learning models applying Recommender Systems based on metric learning models concerned with designing matching functions between users and items. However, the gross of these examples only encompasses user-item representations in the Euclidean space.

To explore the notion of learning user-item representations with more complex relationships and still preserving their distances when performing embeddings in the hyperbolic space, it was proposed a HyperML model that is able to maintain valuable representations of user-item pairs in the hyperbolic space. (Vinh Tran, et al. 2020) A Recommender System was developed to overcome the limitations of the Poincaré model that unable the option to obtain the relations between categories and users. The Recommender System will then get new insights based on the similarity of the categories and also, on the similarity of the users.

7.2 Deep Interest Network

As referred, our goal is to predict whether users would be interested in the insights that we recommend to them. Many models could do similar work to what we intend to, such as Wide & Deep Learning (Cheng, et al. 2016) or Youtube Recommendation (Covington, Adams e Sargin 2016) for the CTR model. These models share a similar structure [Appendix A2 – Figure 2]: to learn the non-linear relations among the users' features, first projecting extensive sparse

features – which are the historical behaviors of users in this study – into lower-dimensional embedding vectors, which are subsequently modified into fixed-length vectors, and lastly concatenated together to be fed into fully connected layers. However, although these models allow reducing the engineering workload significantly, there are still some drawbacks that cannot be compensated, mainly due to the diversity of users' interests. The above-mentioned models are not capable enough to express these users' diverse interests, as they learn the representation of all the interests by compressing the user historical behaviors into embedding vectors, and then obtaining a fixed-length vector by pooling them using Equation 3 in Appendix A2. Essentially, to make these models able to get a representation sufficient enough to express all the users' interests, the fixed-length vectors would need to be broadly enlarged. Consequently, it would significantly expand the size of the learning parameters, increasing the risk of overfitting under limited data. (Zhou, et al. 2018)

Thus, to overcome this problem, a model called Deep Interest Network for Click Through Rate (DIN-CTR) was created by Alibaba Group in 2018 (Zhou, et al. 2018), improving the defects of the models mentioned above. Considering that users may have a great range of vast interests among Facebook pages, to express this interests' diversity, DIN uses a multimodal distribution in which each peak represents a user's interest. Also, users may show interest in the insights that we recommend to them only depending on a small portion of the historical interests instead of the entire historical behavior. For example, imagine a person who loves animals and has liked a dog photo, Trump's scandal, and a post of Marvel's movies. Now we would like to recommend a cat-related insight to him/her, and whether he/she will be interested in this insight or not is uncorrelated to whether he/she has liked Trump's scandal or Marvel's movies before – it is related to his/her previous like of a dog's photo. In other words, in this CTR estimation, some historical data played a decisive role, while the others did not contribute to the prediction.

For this reason, DIN introduced an innovative designed local activation unit adapted from Neural Machine Translation task (Bahdanau, Cho e Bengio 2015) to the structures of models mentioned above [Appendix A2 – Figure 3], maintaining the representative vector of users the

same. Activation units are applied to the user behavior features, paying more attention to the related user interests by soft-searching for proper insights of historical behaviors, then taking weight sum pooling to adaptively calculate user representation given a candidate recommendation [Appendix A2 – Equation 4]. Also, as the input of DIN is highly sparse, which is a vector consisting of many zeros, resulting in many parameters, a significant amount of them appears several times, adding extra noises to training. Thus, the model can be easily overfitted. DIN proposed a productive mini-batch aware regularizer to mitigate the overfitting. In every mini-batch, it calculates the L2-norm over the parameters of sparse features [Appendix A2 – Equation 5]. Finally, a last introduced innovative technique was the Dice activation function [Appendix A2 – Equation 6], instead of applying PReLU activation function. The PReLU takes a hard rectified point with a value of 0, which may be inappropriate when the distributions of inputs of each layer are different. The idea of Dice is to adaptively adjust the rectified point according to the distribution of input data, whose value is set to be the mean of input.

8. Implementation

8.1 Hyperbolic Embeddings

The process of implementation of the Hyperbolic Embeddings approach was structured by the following steps: Preprocessing and curation of the data, Generation of a synthetic data of users, implementation of the Poincaré model for learning hierarchical representation, execution of the PoincareKMeans model to obtain clusters, represent the users in the space, and the last part, the deployment of a Recommender System. For more information, check Appendix A1 – Exhibit 1.

The preprocessing of the data was the curation of Facebook categories of users' preferences into tuples fit to serve as input on the Poincaré model [Appendix B1 – Figure 6], as well as an additional dataset to be used as a test set containing information from one of the members of the group to evaluate the model along the whole process. Furthermore, it was necessary to generate a synthetic dataset, which can be read about in Appendix B1.

The Poincaré model takes the hierarchical data coming from Facebook's categories and performs embeddings into the hyperbolic space. The Poincaré is represented as a circle, where the categories that are on the high-level of the hierarchy are laid closer to the center and lower-level categories (child-nodes) shifted to the end of the circumference. The end result illustrates a tree-like structure where similar categories are put nearer each other and the less similar ones farther away [Appendix B1 – Figure 7].

The outcome of the Poincaré model is a set of vectors or coordinates of each category on the hyperbolic space, which is useful to calculate the distances between categories to get similar (closer) categories or else, check the ranks (relationship) between two variables [Appendix B1 – Figures 8 & 9]. To note that from the distances between the categories we can also get new insights for the users, as can be seen in Appendix B1 – New Insights for Users.

Since the Poincaré model shows to be incredibly useful for learning the latent hierarchical embeddings, it enabled to represent the user into the hyperbolic space. Firstly, each user was represented into the space by calculating an average of their interests and characteristics, creating one unique vector. Additionally, to represent the embeddings of the users into the space, the creation of target groups through the PoincareKMeans, would group users that have similar characteristics together. That way, the characteristics of the targeted group create an avatar of the users that were targeted.

By representing the embeddings of the users into the space, the closeness between them would posteriorly, create target groups of users, in which the users that have similar characteristics will be grouped into a cluster. For more details, check Appendix B1 – Representation of the User into the Space. The implementation of the PoincareKMeans allowed to create 6 target groups [Appendix B1 - Figure 13], enabling the suggestion to a specific user, certain categories that he/she might like, because the users of their cluster (that are similar to he/she) like them too.

It is worth highlighting, the Poincaré model is not able to get relations between users and categories, so until this instant, the focus was on the underlying relationship between categories. Nevertheless, the necessity for a Recommender System able to perform in the hyperbolic space as well as, exploring the notion of relationships between categories and users let us to the next, and final step. Its implementation. We used the aforementioned model, HyperML, by means of a tensorflow package, called CurvLearn, providing the framework for training deep learning models in non-Euclidean spaces (Alibaba 2021). The Recommender System will outcome the recommendations of insights to users.

8.2 Deep Interest Network

Input Data

As this project is done on a data privacy basis, there is no access to Modatta users' data. However, to train a Deep Interest Network, data about users' profile and previous interests needs to be inputted to the model. So before starting the training process, synthetic data had to be created to train and test the models. The generated data is divided into three main sections:

Insight features, which contains a list of insights that the users may be interested in (originated by the users' likes in Facebook pages), associated with the correspondent categories. **User profile features**, which corresponds to synthetic data that has the profile information about each user. **User historical behavior features**, which has the historical behavior of each user, containing data about whether the user has interest in a particular insight.

Besides creating the synthetic data, we are also using one of our members' consented data to validate the recommendations with real data. To a better understanding of all the data we have generated in each section, further details are given in Appendix B2 – Generated Data section.

Implementation

To implement the models under this approach, a Kaggle example of Ad CTR Prediction using the DIN model (Sanagapati 2019) was followed to understand how the data should be handled. Likewise, the DeepCTR documentation was studied for a better understanding of how to

approach the model training (Shen 2021). To start the training process, several models were tried and the model that produced the best results was the already explained DIN model. To choose which model should be used, several parameters were changed, and overfitting tried to be reduced as much as we could [Appendix C2].

After having the best model trained, two different approaches were followed to build the recommendation system and get insights recommendations for Modatta users. While the first consists of directly using the *model.predict* method to recommend some of the unknown insights to the users as individuals, the second approach lies in getting the embedding weights for each user in the dataset and using them to find similarities between users.

Individual Recommendation

In this approach, the predict method was applied to the *x_unlabeled* data and the probabilities of recommendation were assigned to each *user_id – insight_id* observation. Then, to get the insights that a particular user might like, one should just get the ones with the highest probability of recommendation. The results of applying this approach to the real user's (Emila's) data can be found in Appendix B2 –Table 16.

Besides recommending particular insights, another recommendation system was built to get the insight categories that the users are more likely to have an interest in [Appendix B2 – Table 17]. This is because the insights are very specific, and we can get more accurate results by aggregating them by their categories.

Finding Users Representation

The second approach consists of finding users' representations based on their embedding weights (which represent a mapping of the categorical variables to a vector of continuous numbers). These vectors will then be used to identify which users are more similar to each other, through a clustering technique: K-Means. This information can then be used to target groups of users with new insights or new offers, based on characteristics of the target audience.

Step 1 – Retrain the model

To develop this approach, there was a need for a different split of the data on the user side. Only some of the users were used to train the model and then a function was defined to obtain the embedding weights for the new users. For this reason, the previous model needs to be fitted again, now with the new training and test split.

Step 2 – Find representations for the different users

In this step, the embedding weights for the different users were obtained and the profile data of each user was merged with the embedding weights, so that we have a more complete representation of the users. As the users' profile data is categorical, one hot encoder was used to transform them, so that later on, when analyzing the cluster centroids, valuable information can be extracted from the values that are shown for each variable.

Step 3 – K-Means clustering

In this section, the clustering technique K-Means is used to get the clusters for each of the users present in the dataset, based on the previously created representations. The optimal number of clusters was found with *KElbowVisualizer* and the users were assigned to each cluster. *Umap* technique was used to reduce the dimension of the data so that it could be easily visualized in the 2-D space [Appendix B2 – Figure 16]. The profile distribution of the users within the clusters was also plotted so that one could get a clear picture of how the clusters are defined [Appendix B2 – Figures 17, 18 and 19]. Different functions were created to get: **1.** the cluster assigned to each user; **2.** the centroids for each cluster; **3.** the users and correspondent liked insights and categories for each cluster.

By analyzing the centroids for each cluster, one could check the average profile information characterizing each group of users. The results comparing Emila's data and the cluster he/she is inserted in can be found in Appendix B2 –Table 18 and Figure 20. Getting the users for each cluster allows us to find the insights and insight categories that are the most liked inside each

cluster. By doing that, one could then get recommendations for a new user.

Lastly, a final recommendation system was built for this approach, and the results of applying it to Emila's data can be found in Appendix B2 –Tables 19 and 20.

9. Evaluation

Throughout the process of implementation of the techniques previously stated, some evaluation procedures were undertaken to assure the outcomes succeeded to translate meaningful conclusions. Conclusions that can afterwards be successfully implemented by Modatta.

9.1 Poincaré model and HyperML

The first step in the evaluation process occurred in the Poincaré model aimed at choosing the best model for a set of hyperparameters displaying the most adequate learning hierarchical representation. In order to find the best model, it was done a series of experiments to fine tune the model's hyperparameters [Appendix C1 – Figure 21], to which the evaluation assumed two approaches, mentioned before: **Reconstruction** and **Link Prediction**. These two approaches can be determined by two methods:

- **Mean Rank**: the average of the ranks for all observations within each sample.
- **MAP**: refers to Mean Average Precision, which is a metric that captures how well each vertex's neighborhoods are preserved.

Table 22 - Poincaré Ball Evaluation

	Reconstruction				**Link Prediction**			
	25D	50D	100D	200D	25D	50D	100D	200D
Mean Rank	2.59	2.55	**2.50**	2.53	3.19	2.98	3.07	**2.76**
MAP	0.534	0.534	0.536	**0.54**	0.413	0.418	0.416	**0.538**

The results of the Implementation of the Poincaré Ball can be seen on the table above. Looking at the Reconstruction, one can check that the values vary slightly, specially the MAP values that only increase from 0.53 to 0.54. However, looking at the Link Prediction values, the Mean Rank had 3.2 on 25 dimensions and decreased to 2.76 as well as the MAP value got from 0.41 to

0.538, showing a substantial increase on the Link Prediction. Therefore, the best one had the following characteristics: **20 negatives** sample to use, **0 number of epochs** to use in burn-in initialization, no regularization, **200 epochs**, in a **200-dimensional space**.

Moreover, the PoincareKMeans model is in its essence an unsupervised learning algorithm, where the evaluation metrics for clustering analysis is still very shy. The choice for the number of clusters came down mostly to domain knowledge and intuition, so the number of clusters chosen after a series of attempts was 12.

The last step regarded the evaluation of the Recommender System with the Hit Rate (HR) metric, measuring the fraction of users for which the right answer is in fact included in the suggestion by the recommendation system. The final **HR@10** was of **0.77**, which is a good result, as compared with the results from HyperML experiments (Vinh Tran, et al. 2020). The parameters are represented in Appendix C1 – Figure 23.

To understand if the Recommender System was deploying the intended results, we experimented with a test set containing information from one of the members. The final results were presented as insights as well as master categories [Appendix C1 – Table 19 & 20].

9.2 DIN

During the training process of the DIN model, some problems of overfitting emerged, meaning that the model was able to get very accurate predictions for the training set but when applied to new data the evaluation was not that good. Thus, to overcome the overfitting the model was suffering from, L2 regularization and Dropout parameters were changed, having the final values for these parameters been defined as follows:

- l2_reg_dnn = 0.01
- dnn_dropout = 0.03

To evaluate the model as a regression problem, the two metrics used were log Loss and AUC, however, to get more interpretable results, we have also transformed it into a classification

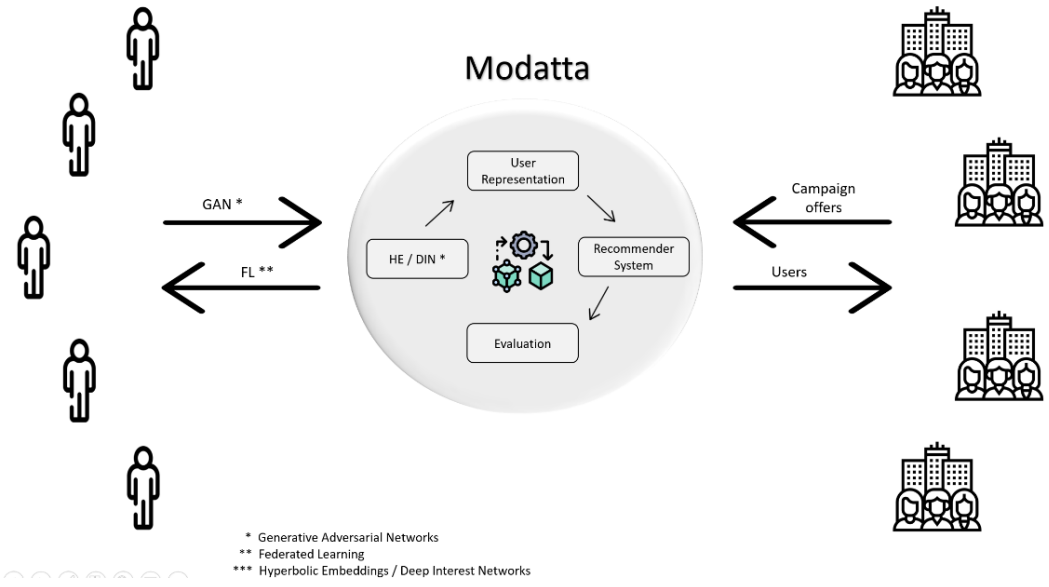
problem and calculated accuracy, recall and precision metrics. In this case, recall is our most important metric, as we want to minimize the number of False Negatives (insights that users would be interested in, but we predict as non-liked insights, and so don't recommend them to the user), even if we have some False Positives (insights that users would not be interested in, but we wrongly recommend them because we predicted as liked insights). This way, when recommending a wrong insight, the user can tell us if it is not true, but if we don't recommend it at all we are not getting any information from the user side. Thus, the model was chosen mainly based on the recall metric. As we can see in Table 11 below, the model is not overfitting and the recall score is pretty good, meaning that the model is correctly predicting the majority (88%) of insights the users are interested in. More details concerning the best model evaluation can be found in Appendix C2.

Table 23 - Best DIN model Evaluation

Metric	Training set	Test set
Log loss	0.619	0.620
AUC	0.547	0.545
Recall	0.878	0.876

10. Next Steps

Figure 24 - Diagram representation of the system to be developed



Above, the figure shows a diagram of the overall system intended to be developed after applying the models before described in this paper so far. To do so, in the next phases, there is a need to implement the following steps:

5. Identify a user-base for a campaign offer, making sure that marketers target the users that are more prompt to accept the offer, as well as users get the campaigns they want and need.
6. Generative Adversarial Networks implementation for generating synthetic data to feed to the model, preventing users' privacy from the potential data leakages.
7. Federated Learning implementation to demonstrate an alternate approach to the traditional centralized learning, aimed at leveraging communication efficacy and defense techniques to ensure data privacy.
8. Evaluate the effectiveness of the campaign, accounting for both the profile and interests' distribution of the targeted users and use the results to improve the targeting strategy.

The implementation of these four steps together will then allow the deployment of an utterly privacy-based system that will help Modatta achieve its goal of guaranteeing privacy-preserving for the users and bringing the list of potential customers to marketers.

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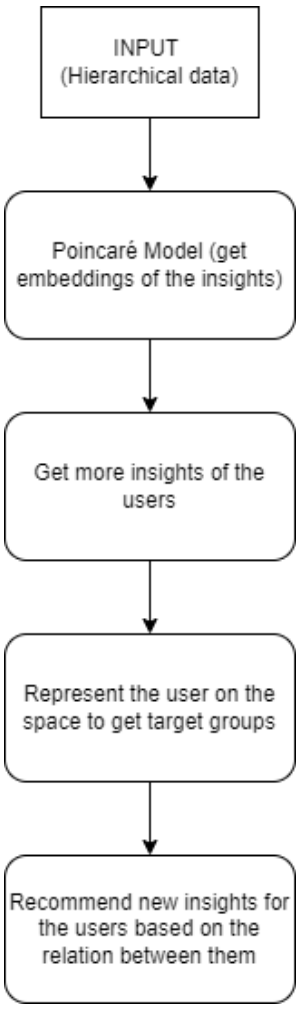
Appendix

A – Introduction to Hyperbolic Embeddings and Deep Interest Network

A1 – Hyperbolic Embeddings Approach

Exhibit 3 – Diagram of the Hyperbolic Embeddings Approach



Above, the diagram shows a flow of the overall system of the Hyperbolic Embedding Approach. It starts with the implementation of the Poincaré Model and ends up with the deployment of a Recommender System.

Formula of distance on Hyperbolic Space

$$d_H(x,y) = acosh\left(1 + 2\frac{\|x-y\|^2}{(1-\|x\|^2)(1-\|y\|^2)}\right)$$

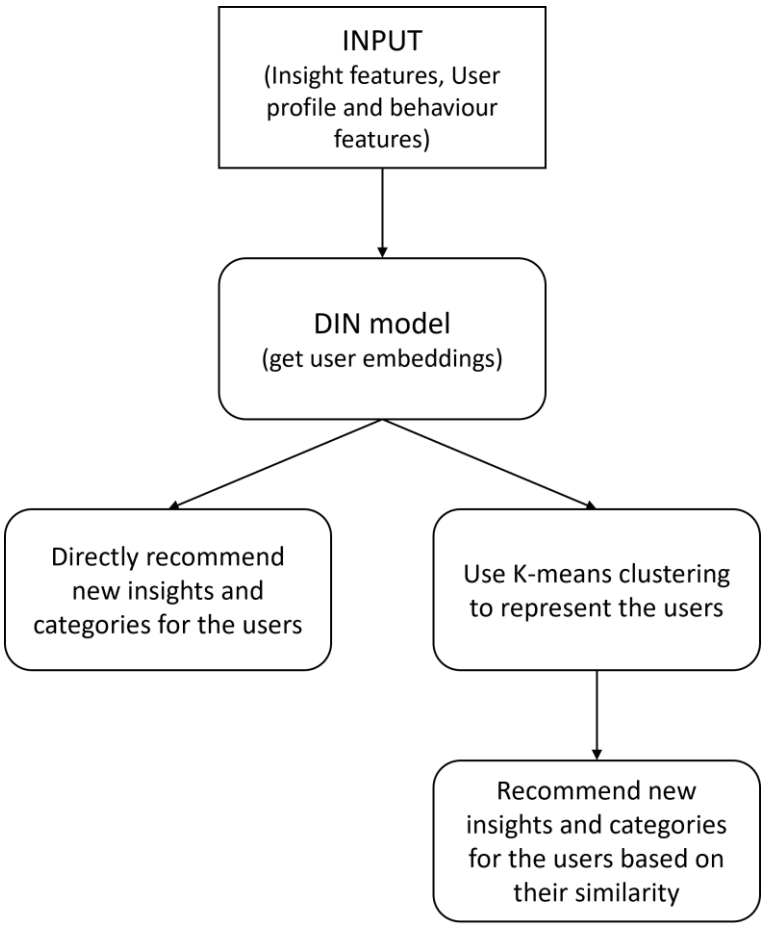
Equation 7 – Formula of distance on Hyperbolic Space

The formula above calculates the distance between 2 points, x and y, on the hyperbolic space.

The hyperbolic distance within the Poincaré ball varies smoothly with the position of *x* and *y*. Suppose three points, x and y, are the children of a parent z, placed at the origin 0. When the points move towards the edge of the disk, i.e. x -> 1, in the Euclidean space, the ratio $\frac{d_E(x,y)}{d_E(x,0)+d_E(0,y)}$ remains a constant. By contrast, the ratio $\frac{d_H(x,y)}{d_H(x,0)+d_H(0,y)}$ in the hyperbolic space gets closer to 1, giving the most approximate distance to the original graph distance ratio. This experiment exemplifies the utility for implementing Poincaré embeddings, due to their ability to preserve original graph distances to capture hierarchy of objects, as a result of their norm.

A2 – Deep Interest Network Approach

Exhibit 4 – Diagram of the Deep Neural Networks Approach

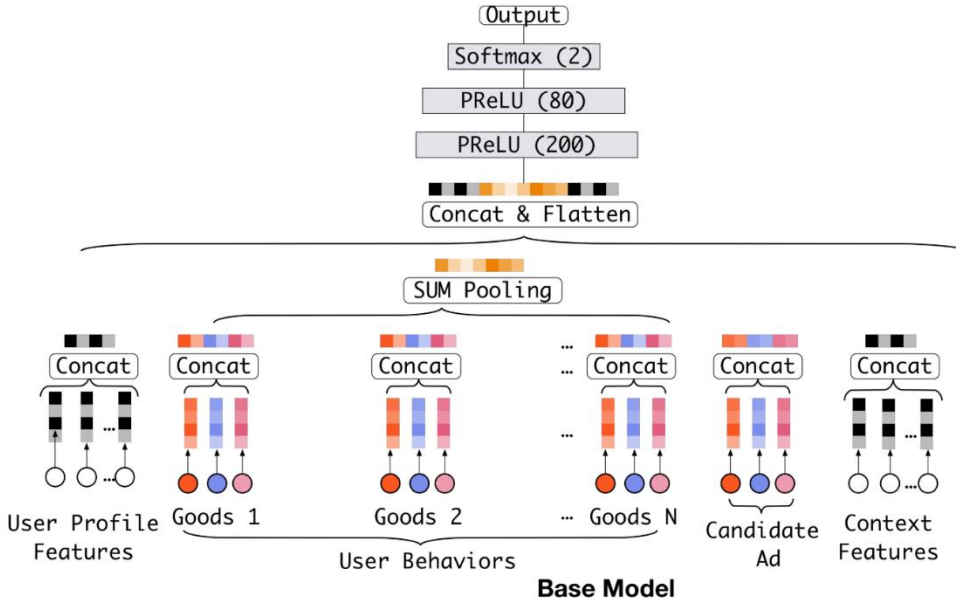


Above, the diagram shows the process of implementing the Deep Neural Networks Approach. It starts with the deployment of the DIN Model, splits into two different recommendation methods, individual and clustering.

Deep Neural Networks Models

Base model

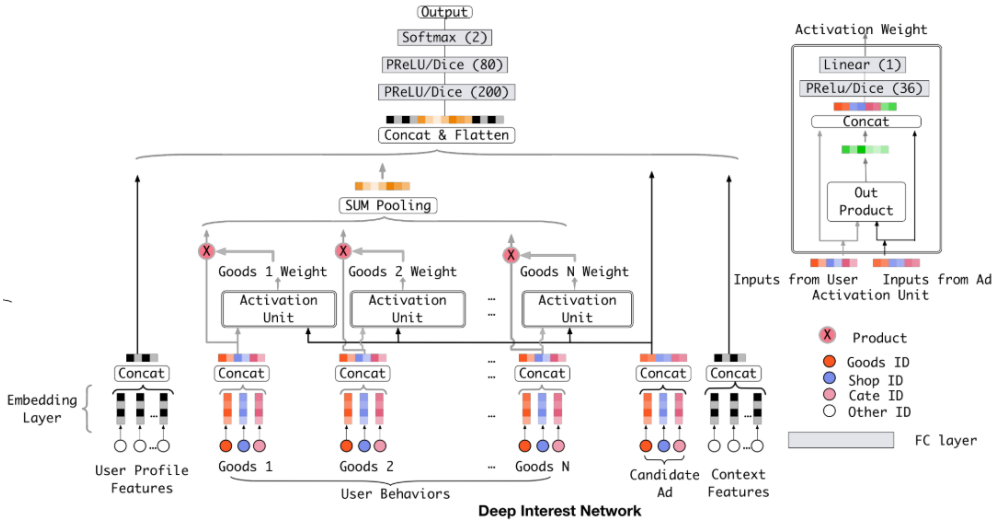
Figure 25 - The architecture of Base models



The architecture of Base models consists of several parts: Embedding layer, Pooling layer, Concat layer and multi-layer perceptro.

DIN Model:

Figure 26 - The architecture of DIN



The architecture of DIN has almost the same architecture as the base model. Introduced an innovative local activation unit function.

Loss function for both models:

$$L = -\frac{1}{N}\sum_{(x,y)\in S}^{n}(\mathrm{y}\ log_{p(x)} + (1-y)log_{(1-p(x))}$$

Equation 8 – Formula of Loss function

S denotes the training set of size N, with x as the input of the network and $y \in \{\mathbf{0}, \mathbf{1}\}$ is the label of training set, p(x) is the output of the model, which is the predicted probability of sample x being clicked.

Base models Pooling:

$$\mathrm{e_i} = \mathrm{pooling}(\mathrm{e_{i_1}}, \mathrm{e_{i_2,\ldots,e_{i_k}}})$$

Equation 9 - Pooling layer for base models

Where e_i represents a single embedding vector.

Local activation unit:

$$u_U = f(u_A, e_1, e_2, \ldots, e_H) = \sum_{j=1}^{H} a(e_j, u_A)\, e_j = \sum_{j=1}^{H} w_j\, e_j$$

Equation 10 - Local activation unit for DIN model

Where $\{e_1, e_2, \ldots, e_H\}$ is a list of embedding vectors of behaviors of user U with a length of H, u_A is the embedding vector of ad A, a(·) is a feed-forward network with output as the activation weight. With constrains: $\sum_{j=1} Wi = 1$.

Mini-batch aware regularizer:

Let $\mathbf{W} \in \mathbb{R}^{DxK}$ denote parameters of the whole embedding dictionary, with D as the dimensionality of the embedding vector and K as the dimensionality of feature space.

$$w_j \leftarrow w_j - \eta \left[\frac{1}{|ß_m|} \sum_{(x,y) \in ß_m} \frac{\partial L(p(x), y)}{\partial w_j} + \lambda \frac{\alpha_{mj}}{nj} w_j \right]$$

Equation 11 - Mini-batch aware regularization formula

Where $w_j \in \mathbb{R}^D$ denotes the j-th embedding vector, nj denotes the number of occurrence for feature id j in all samples, $ß_m$ denotes the m-th mini-batch and $\alpha_{mj} = max_{(x,y)} \in ß_m I(x_j \neq 0)$ if there is at least one instance having the feature id j in mini-batch $ß_m$.

Dice activation function:

$$fx=ps \cdot s + 1 - psf(x) = p(s) \cdot s + \big(1 - p(s)\big) \cdot \alpha s ,$$

$$p(s) = \frac{1}{1 + e^{-\frac{s - E[s]}{\sqrt{Var[s] + \epsilon}}}}$$

Equation 12 - Dice activation function

Where in the training phase, E[s] and Var[s] is the mean and variance of input in each mini batch. In the testing phase, E[s] andVar[s] is calculated by moving averages E[s] andVar[s] over data. ϵ is a small constant which is set to be 10^{-8}.

B – Implementation

B1 – Hyperbolic Embeddings Approach

Generated Data

As there is no access to data from users, it was necessary to generate a synthetic dataset, with 10.000 users, with specific interests and profiles, selected at random, to replicate the information Modatta's app receives from each user without breaching any privacy regulation set by the GDPR. The following figure shows the generated dataset of the interests of users.

Figure 27 - Sample of the Insights Dataframe

	Interest	Interest | Literary arts	Interest | Performance art	Interest | Performing arts	Interest | Science	Interest | Sports	Interest | Visual arts	Community organisation	Community organisation | Armed forces	Community organisation | Charity organisation	...	Other | TypeAhead | Pet Tricks	Other | TypeAhead | Public figure type	Other | TypeAhead | Concentration or Major	Other | TypeAhead | Degree	Other | TypeAhead | Work position type	Other | TypeAhead | Year	Ur
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
1	0	1	0	0	0	0	0	0	0	0	...	0	0	0	1	0	0	
2	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	...	0	1	0	0	0	0	
4	0	0	0	0	0	1	0	0	0	0	...	0	0	0	0	0	0	
5	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
6	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
7	0	0	0	0	0	0	0	0	0	0	...	0	0	1	0	0	0	
8	0	0	0	0	0	1	1	0	0	1	...	0	0	0	0	0	0	
9	0	0	1	0	0	0	0	0	0	0	...	-1	0	0	0	0	0	

10 rows × 1563 columns

In order to get new insights, we need to have some users with specific interests. In addition, we need to take into consideration the interests of the users:

- The user has a real interest in a category: **1**
- The user does not have an interest (explicit): **-1**

The other categories that aren't filled with 1 or -1, are considered an unknown interest (value = 0), which means that we do not know if the user does have an interest or not.

Data Dictionary for *Insights'Dataframe*

The names of the columns are the Facebook' categories, that englobes the 3 levels of hierarchy. There is a total of 1563 categories. Below, one can find an example of 5 of them.

Table 24 - Example of Facebook Insights

Facebook Insights
Interest
Interest | Performance art
Community organisation | Charity organisation
Other | TypeAhead | Pet Tricks
Other | TypeAhead | Public figure type

Below, Figure 5 represents the dataset that was generated with some profile data for users, containing especially demographic characteristics.

Figure 28 - Sample of the Customers' Dataframe

	user_id	Birth year	Gender	Home country	Civil status	Number of children	Degree	Professional status	Annual income	Practice sports	Smokes
0	0	1936	male	AE	married	1	2	2	45	yes	no
1	1	1919	male	NP	single	2	3	5	70	yes	yes
2	2	1939	male	AD	widow	10000	1	3	70	yes	yes
3	3	1984	female	IS	single	1	0	3	100	yes	yes
4	4	1995	male	MQ	married	10000	0	3	70	no	yes
...	...	...	...	...	...	...	...	...	...	...	...
9995	9995	1948	male	BL	married	1	4	1	70	no	no
9996	9996	1950	non_binary	IO	single	0	2	6	15	yes	yes
9997	9997	1947	male	CN	married	0	2	1	15	no	no
9998	9998	1942	male	AM	single	0	2	2	10000	yes	yes
9999	9999	2017	male	TK	widow	0	4	2	15	yes	yes

Table 25 - Data Dictionary for Customers'Dataframe

Column Name	Description	Values
user_id	Unique identifier of a Modatta's user	0 to 9999
Birth_year	Birth year of the user	1900 to 2019
Gender	Gender of the user	-
Home country	Home country of the user	-
Civil_status	Civil status of the user	-
Number of children	Number of children of the user	-
Degree	Degree of the user	0 to 6
Professional_status	Professional status of the user	0 to 6
Annual_income	Annual income of the user	-
Practice_sports	Binary variable saying if the user practices sports	Yes or No
Smokes	Binary variable saying if the user smokes	Yes or No

Features Data Dictionary

Gender

Value
Male
Female
Non-binary

Civil_status

Value
Divorced
Married
Single
Widow

Degree

Value	Label
0	Other
1	High school diploma
2	Technical degree
3	Bachelor degree
4	Major degree
5	Master degree
6	Doctor degree

Professional_status

Value	Label
0	Unemployed
1	Student
2	Retired
3	Freelancer
4	Fixed term contract
5	Permanent contract
6	Business owner

Annual_income

Value	Label
15	Less than 15000€
30	Between 15000€ and 30000€
45	Between 30000€ and 45000€
70	Between 45000€ and 70000€
100	Between 70000€ and 100000€
10000	More than 100000€

Practice_sports

Value
No
Yes

Number of children

Value	Label
0	No children
1	Has 1 children
2	Has 2 children
1000	Has 3+ children

Smokes

Value
No
Yes

For simplicity purposes, the Home Country is not referred, as it has 249 values. Those values are country names. Below one can find an example of 4 of them.

Value	Label
PT	Portugal
ES	Spain
UK	United Kingdom
US	United States

Poincaré Model: Implementation

Table 26 - Tuples of Categories' Dataframe

Child	Parent
Literary arts	Interest
Performance art	Interest
Performing arts	Interest
Science	Interest
Sports	Interest
Visual arts	Interest
Armed forces	Community organisation
Charity organisation	Community organisation
Country club/Clubhouse	Community organisation
Community group	Community organisation
Environmental conservation organisation	Community organisation
Government organisation	Community organisation
Intergovernmental organisation	Community organisation
Trade union	Community organisation
Political organisation	Community organisation
Political party	Community organisation
Private members club	Community organisation
Religious organisation	Community organisation
Social club	Community organisation
Sorority & fraternity	Community organisation

Table 8 represents the data frame created to be an input for Poincaré Model. Later, it will be transformed into tuples.

Figure 29 - Input for the Poincaré Model

```
tuples
```

```
[('Literary arts', 'Interest'),
 ('Performance art', 'Interest'),
 ('Performing arts', 'Interest'),
 ('Science', 'Interest'),
 ('Sports', 'Interest'),
 ('Visual arts', 'Interest'),
 ('Armed forces', 'Community organisation'),
 ('Charity organisation', 'Community organisation'),
 ('Country club/Clubhouse', 'Community organisation'),
 ('Community group', 'Community organisation'),
 ('Environmental conservation organisation', 'Community organisation'),
 ('Government organisation', 'Community organisation'),
 ('Intergovernmental organisation', 'Community organisation'),
 ('Trade union', 'Community organisation'),
 ('Political organisation', 'Community organisation'),
 ('Political party', 'Community organisation'),
 ('Private members club', 'Community organisation'),
 ('Religious organisation', 'Community organisation'),
 ('Social club', 'Community organisation'),
 ('Sorority & fraternity', 'Community organisation'),
 ('Sports club', 'Community organisation'),
 ('Youth organisation', 'Community organisation'),
 ('Art', 'Media'),
```

To implement the Poincaré Model, there was a need to transform the Facebook' categories into tuples, in order to represent the hierarchical structure of the categories. The tuple represented on Figure 6 is composed by (child, parent) nodes.

Figure 30 - Representation of the Poincaré Embeddings in 2D

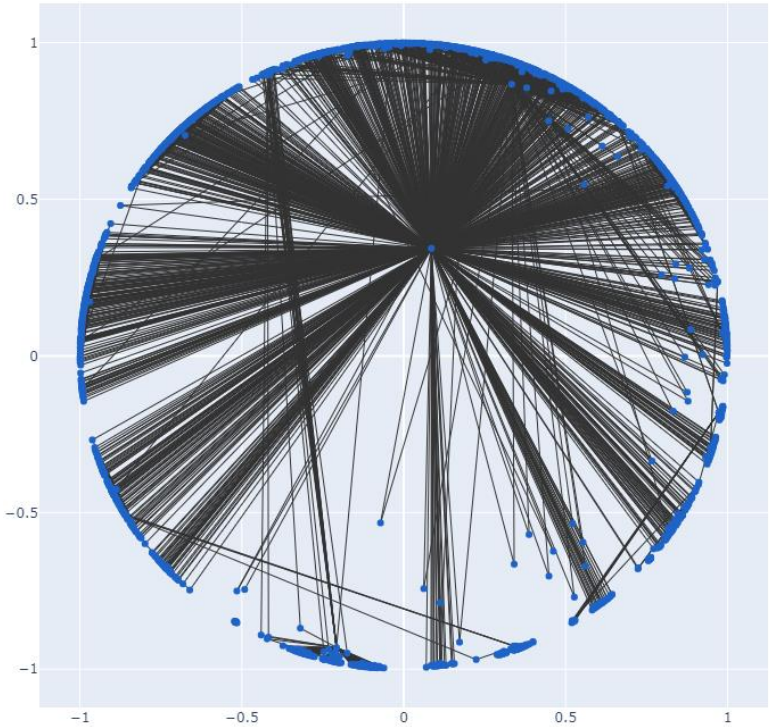


Figure 7 represents all the embeddings resulting from the implementation of the Poincaré Model. Each blue dot represents a category that has a unique representation into the space. The straight black lines represent the relations between the levels of the categories.

The categories that are on the high-level of the hierarchy are laid closer to the center and lower-level categories (child-nodes) shifted to the end of the circumference. Finally, similar categories are put nearer each other and the less similar ones farther away. This representation was created using the parameters of the best model, changing the dimensions from 200 to 2.

Figure 31 - Example of Closer Categories

```
]: print("The category Music is most similar to:")
   model.most_similar('Music')

   The category Music is most similar to:

]: [('Playlist', 1.8499834460025835),
    ('Music award', 1.8929040891332125),
    ('Music chart', 2.446066311528132),
    ('Podcast', 2.5070578937722567),
    ('Musical genre', 2.5715183839839804),
    ('Album', 2.742832353196168),
    ('Record label', 3.3631610546738644),
    ('Music video', 3.461160005308079),
    ('Choir', 3.856084689279786),
    ('Song', 3.873946372133142)]
```

From the Poincaré model, a set of vectors or coordinates of each category on the hyperbolic space, let us check which are the coordinates closer to a specific category. On Figure 8, we used the category *Music* as an example. From the results, one can see that *Playlist* and *Music Award* are the insights closer to this category. This tuple also returns the distance between the category chosen and another category. As we can see, the closest categories mentioned before, have a hyperbolic distance below 2.

Figure 32 - Example of Rank between 2 Categories

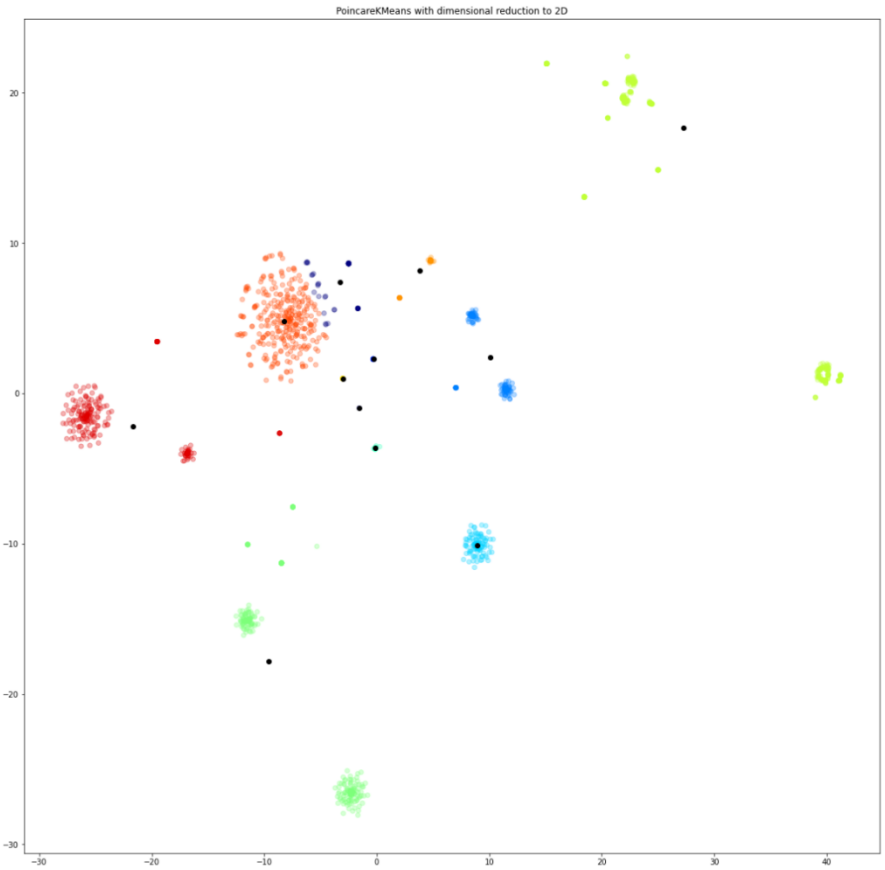
```
[31]: # Rank of distance of node 2 from node 1 in relation to distances of all nodes from node 1
      print("The category Music is at the second position of Song (most similar)")
      model.rank('Song', 'Music')
      # In Song, the Music is at 2st place on the most similar

      The category Music is at the second position of Song (most similar)

[31]: 2
```

Figure 9 shows an example of a rank of distance between 2 categories, that demonstrates their relationship. As an example, we have *Song* and *Music*. The rank function calculates the distance from all categories to the category *Song* and then it will see at each position is *Music*. We can see that it is at the second position, but that doesn't mean that vice versa the same number will be 2. When calculating the rank between *Music* and *Song*, meaning that were calculating the distance from all categories to the category *Music*, *Song* is in 10th.

Figure 33 - PoincareKMeans in 2D



The implementation of the PoincareKMeans, even though, doesn’t have a clear influence on our final goal, allowed us to analyze the categories in each cluster. Figure 10 illustrates the grouping of the vectors of each category that was created by implementing the Poincaré Model. Therefore, it shows the different centroids (black dots) and their clusters, that are assigned with a different color. Because the best model has 200D, we used it on our project, but as a mean of

visualization, the dimension was reduced to 2D.

Looking at the figure, you will notice some clusters without any category. This may be due to the context of performing computations in the hyperbolic space, which may hold back some centroids to find any category.

New Insights for Users

From the Poincaré Model, it's possible to use the most similar function, aforementioned, that will give us the categories that are most similar to the interests of the user. So, for each category, one can check which are the categories closer, and recommend those for the user. Once again, we're using insights of the Emila' data. Below we can find the categories of insights that our real user has showed interest or disinterest in:

Figure 34 - Interests and disinterests that the user has

[50]:

	POSITIVE INSIGHTS	NEGATIVE INSIGHTS
0	Businesses | Education | State school	Community organisation | Armed forces
1	Community organisation	
2	Non-business places	
3	Businesses	
4	Other | Brand | Health/Beauty	
5	Other | Community	
6	Other | Brand	
7	Other | Brand | Electronics	
8	Businesses | Beauty, cosmetic & personal care	
9	Businesses | Shopping & retail | Swimwear shop	
10	Non-business places | Campus building	
11	Businesses | Beauty, cosmetic & personal care ...	
12	Businesses | Arts & entertainment	
13	Businesses | Food & drink | Family-style resta...	
14	Other | Brand | Entertainment website	
15	Businesses | Media/news company	
16	Media | TV & film | TV Programme	
17	Businesses | Sport & recreation	
18	Businesses | Education | University	
19	Businesses | Non-profit organisation	
20	Media | TV & film | TV	
21	Businesses | Shopping & retail | Mobile phone ...	
22	Media | Books & magazines	
23	Other | Brand | Product/Service	
24	Businesses | Education | Higher education	
25	Businesses | Food & drink | Cocktail bar	
26	Community organisation | Social club	
27	Public figure | Comedian	

Table 27 - Predicting new insights

New Insights	Distances
Social club	0.305306
Sorority & fraternity	0.403680
Fashion model	0.552897
Political organisation	0.603168

New Insights	Distances
Gaming video creator	0.684306
Orchestra	0.769347
Sportsperson	0.848823
Public figure	0.881704
Books & magazines	0.883995
Newspaper	0.883995
Visual arts	0.933503
Article	0.959758
Science	0.999553
TV network	1.770001
Other	1.974406
Brand	1.974406
Art	2.040909
Theatrical play	2.158405
Book series	2.192080
Language	2.589027

For getting the new insights, we used a test set from a member of our group, Emila, that contains some positive and negative interests. Table 9 shows the new insights for this user as well as their distances between the category that the user is interested in and the new insight

recommended. As we want the categories that are most similar, we got 20 new insights sorted by ascending distances.

Explicit Negative Interests

Notice that, if the user does have a negative interest in some category, the model makes sure that there is an impact on the final new insights, meaning that the negative interests and their similar ones, will not be on the new insights derived from the model.

Imagine we have a user that doesn't like Soccer. We are going to make sure that the insights derived from the model will not get categories that are related with Soccer, but also, be aware that even though this user doesn't like soccer, he can like other type of sports. Not limiting all the choices of Sports (the parent node).

Representation of the User into the Space

Doing an average of the coordinates of each user, allowed to represented each user into the space. This means that, based on the interests of the user, the embeddings of each interest is retrieved and then it's applied an average on those embeddings, creating one unique vector that will represent each user.

Below one can see the representation of 7000 users in a 2D visualization. For reducing from 200D to 2D, UMap was used as a dimensional reduction technique.

Figure 35 - Representation of the users into the space

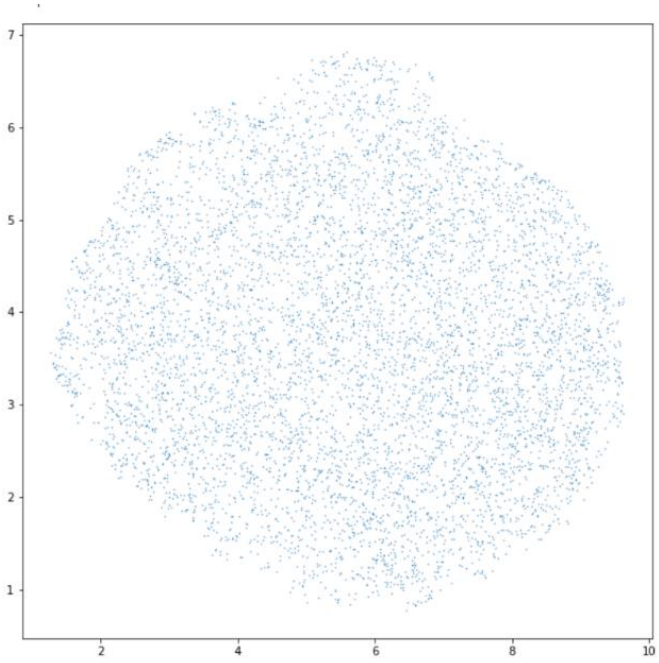


Figure 36 - KMeansPoincare for Representing users

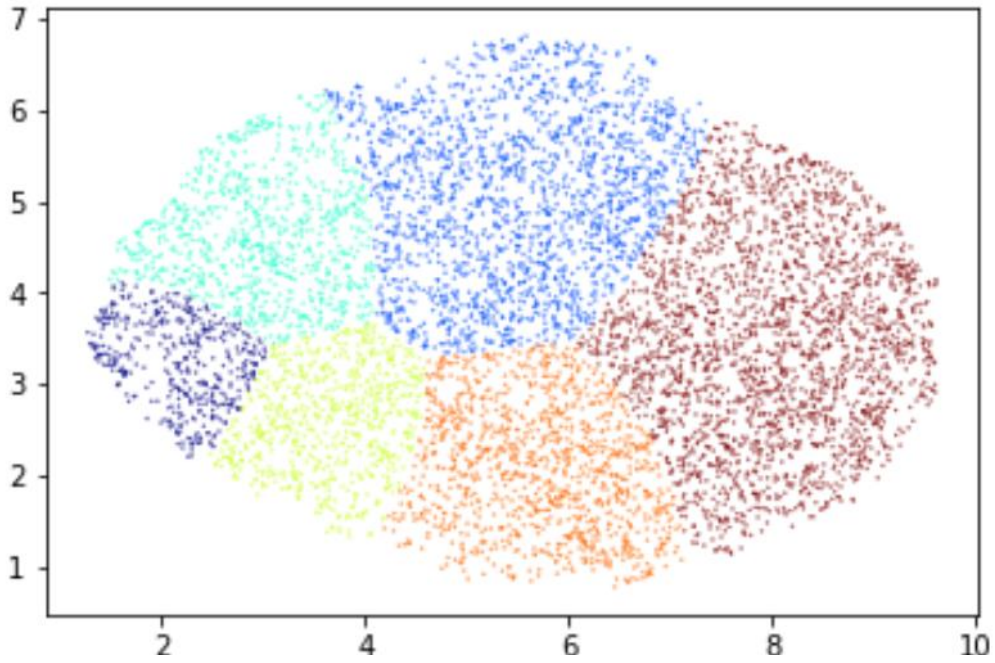


Figure 13 shows 6 target groups created by implementing PoincareKMeans on the representation of the users.

Having target groups, will allow us to suggest to a specific user a certain category that he/she might like, because of the cluster he's in.

In order to understand the target groups, we had to analyze each cluster and understand their characteristics. This was done by going to each user, in a specific cluster, and calculate the insights that appear the most, meaning that the users that are on that cluster are characterized by those attributes.

The following tables identify the main characteristics of each cluster. The target groups are characterized as follows:

Cluster 1

Users in cluster 1 tend to like Real State and Media.

Businesses – Property
Businesses – Media/news company
Businesses – Arts & Entertainment

Cluster 2

Businesses – Commercial & industrial
Businesses – Medical & health
Non-business places - religious
Businesses - Sports & Recreation
Businesses - Food & Drink

Users in cluster 2 are interested in commerce, sports centers, cinema, food and drink and religious places.

Cluster 3

Businesses - Education
Businesses - Finance
Businesses - Science, technology & engineering

Users in cluster 3 are interested in Education, finance services and telecommunication companies.

Cluster 4

Businesses - Food & Drink
Businesses - Vehicle, aircraft and boat
Businesses - Sport & recreation
Shopping & Retail

Users in cluster 4 like to go to Restaurants, all types of cars, motorcycles and boats. They also like sports.

Cluster 5

Other - Brand
Businesses - Food & Drink
Businesses - Travel & Transport
Media

Users like all types of brands, like to buy all kind of things and travel. Like books and music.

Cluster 6

Businesses - Medical & health
Shopping & Retail
Businesses - Food & Drink
Sports

Users in cluster 6 are into Medical and health; Like to shop, and go to restaurants.

In order to evaluate the representation of the user, we predicted the cluster of Emila, as we have been doing before. From the prediction, Emila belongs to cluster 1. We believe that the results indicate to be good, as she is interested on Real State, Media and Entertainment.

Having groups of users together, we are able to identify people more similar to each other. Therefore, it will allow us to suggest to a specific user a certain category that he/she might like, because the users of their cluster (that are similar to he/she), like them too. Below, we have an example of user 1000, where it outputs their closest / similar users.

Figure 37 - Closest Users to user 1000

```
x 1000
[[('User 2598', 0.08168382446355738)],
 [('User 6644', 0.08659737440963623)],
 [('User 5454', 0.08699786909174022)],
 [('User 1414', 0.08776293177995817)],
 [('User 1476', 0.08814171036714673)],
 [('User 4763', 0.09036007364312187)],
 [('User 1497', 0.09059016391621268)],
 [('User 5262', 0.09076536525640845)],
 [('User 6983', 0.09091308487799786)],
 [('User 6160', 0.09126500366380853)],
 [('User 2093', 0.09129561814139267)]]
```

B2 – Deep Interest Network Approach

Generated Data

Insight features

This section comprises data that is related to the insights information that we have access to. **Insights** are particular interests that the users are able to get when connecting their Facebook

data with their Modatta app. These insights are particular categorizations of the Facebook pages the users like. Then each insight is assigned with a more general **category**, which will be used later on to find more meaningful recommendations. It is important to note that only each user has control over their own data, and neither Modatta nor the marketeers can access it.

Table 28 - Insight features datasets description

Data	Description
insight_dic	dictionary for the insights data, where each *insight_id* is assigned to its correspondent label
insight_cat_dic	dictionary for the insights' categories data, where each cat_id is assigned to its correspondent label
insight_features_df	dataset with each *insight_id* assigned to its correspondent *cat_id*

User profile features

In this section, synthetic user profile data was created. The following variables were chosen to represent a user's profile: *Birth year*, *Gender*, *Civil status*, *Degree*, *Professional status*, *Annual income*, and *Practice sports*.

Table 29 - User profile features datasets description

Data	Description
labeled_user_profiles	synthetic data created to represent 10 000 users with random profile data. This data frame contains the labeled data
user_profile_df:	*labeled_user_profiles* with the labels transformed into codes, so that it can be easily read by the model later on
labeled_new_profiles	real data that comes from a new profile (in this case, we are using Emila's consented data). This data frame contains the labelled data
new_profiles_df	*labeled_new_profiles* with the labels transformed into codes, so that it can be easily read by the model later on
final_profile_df	*user_profile_df* merged with the *new_profiles_df*

Table 30 - Data Dictionary for final_profile_df

Column Name	Description	Values
user_id	Unique identifier of a Modatta's user	0 to 10000
Birth_year	Birth year of the user coded into bins	0 to 8
Gender	Code for identifying the gender of the user	0 to 2
Civil_status	Code for identifying the civil status of the user	0 to 3
Degree	Code for identifying the degree of the user	0 to 6
Professional_status	Code for identifying the professional status of the user	0 to 6
Annual_income	Code for identifying the annual income of the user	0 to 5
Practice_sports	Binary variable saying if the user practices sports	0, 1

Features Data Dictionary

Birth_year

Value	Label
0	Birth year between 1900 and 1920
1	Birth year between 1921 and 1940
2	Birth year between 1941 and 1960
3	Birth year between 1961 and 1970
4	Birth year between 1971 and 1980
5	Birth year between 1981 and 1990
6	Birth year between 1991 and 2000
7	Birth year between 2001 and 2010
8	Birth year between 2011 and 2021

Gender

Value	Label
0	Male
1	Female
2	Non-binary

Civil_status

Value	Label
0	Divorced
1	Married
2	Single
3	Widow

Degree

Value	Label
0	Other
1	High school diploma
2	Technical degree
3	Bachelor's degree
4	Major degree
5	Master's degree
6	Doctor degree

Professional_status

Value	Label
0	Unemployed
1	Student
2	Retired
3	Freelancer
4	Fixed term contract
5	Permanent contract
6	Business owner

Annual_income

Value	Label
0	Less than 15000€
1	Between 15000€ and 30000€
2	Between 30000€ and 45000€
3	Between 45000€ and 70000€
4	Between 70000€ and 100000€
5	More than 100000€

Practice_sports

Value	Label
0	No
1	Yes

User historical behavior features

In this section, the user behaviors dataset, which represents the historical association between the **users** and the **insights**, has been created. When building this data frame, each user (previously created and stored with a unique *user_id*) has some insights associated and a value saying if:

4. the user shows interest in the insight: **True = 1 & False = 0**
5. the user is not interested in the insight: **True = 0 & False = 1**
6. we don't have information about whether the user is interested: **True = 0 & False = 0**

Table 31 - User historical behavior datasets description

Data	Description

user_behaviors_df	synthetic data created to represent 1000000 "behaviors" for the 10000 created users – 1000000 interactions between a user and an insight
new_users_behavior	real data that comes from a new profile (in this case, Emila's data is used). This data frame has information about which insights the new user is interested in, is not interested at all and the insights we don't any have information about for the users
final_behaviors_df	*user_behaviors_df* merged with the *new_users_behavior* data frame

Table 32 - Data Dictionary for final_behaviors_df

Column Name	Description	Values
user_id	Unique identifier of a Modatta's user	0 to 10000
insight_id	Unique identifier of an insight that may be of the user's interest	0 to 1563
True	Binary variable saying if the user is interested in the insight	0, 1
False	Binary variable saying if the user is not interested in the insight	0, 1

Detailed explanation of True / False values

True

Value	Label
0	We may not know if the user is interested in the insight; or the user is not interested at all
1	We know explicitly that the user is really interested in the insight

False

Value	Label
0	We may not know if the user is interested in the insight; or the user is really interested
1	We know explicitly that the user is not interested in the insight at all

Final dataset

Finally, the three datasets – *insight_features_df*, *final_profile_df* and *final_behaviors_df* – are

merged into one final data frame – *final_df*. This is how the data that will be inputted to the model looks like:

Figure 38 - Final dataset (all the previous generated final datasets merged)

```
final_df
```

	user_id	insight_id	True	False	Birth_year	Gender	Civil_status	Degree	Professional_status	Annual_income	Practice_sports	c
0	235	1153	1	0	1	1	0	4	2	0	1	
1	6285	1153	1	0	3	0	3	5	4	3	0	
2	431	1153	1	0	5	0	3	5	4	1	0	
3	2244	1153	0	1	1	2	0	1	2	2	0	
4	1214	1153	1	0	0	1	3	4	0	1	0	
...	...	...	...	...	...	...	...	...	...	...	...	
1001559	6690	1444	0	0	2	0	0	5	4	4	1	
1001560	5193	1444	1	0	1	0	3	5	0	5	1	
1001561	4211	1444	1	0	7	0	1	6	1	2	0	
1001562	2878	1444	1	0	8	2	3	0	4	4	1	
1001563	10000	1444	0	0	6	1	2	5	1	0	1	

1001564 rows × 14 columns

Emila's TRUE and FALSE insight categories

Below we can find the categories of insights that our real user has showed interest or disinterest in:

Table 33 - Interests and disinterests of our Emila

TRUE	FALSE
ARTS	ARMED FORCES
BEAUTY AND PERSONAL CARE	
COMEDY	
COMMUNITY SERVICES	
ENTERTAINMENT	
FASHION	
FOOD AND DRINK	
GADGETS	
HEALTH AND FITNESS	
JOURNALISM	

LITERATURE
NON-PROFIT ORGANIZATION
Non-business places
PHOTOGRAPHY
SCIENCE AND TECHNOLOGY
SHOPPING AND DEALS
SPORTS
TEACHING AND EDUCATION
TV

DIN Model Implementation

Individual Recommendation

Table 34 - Recommending Insights

Insight	Category
Businesses | Sport & recreation | Baseball field	SPORTS
Businesses | Local service | Veterinarian	PETS AND ANIMALS
Businesses | Beauty, cosmetic & personal care | Threading service	BEAUTY AND PERSONAL CARE
Businesses | Beauty, cosmetic & personal care | Image consultant	BEAUTY AND PERSONAL CARE
Businesses | Medical & health | STD testing centre	HEALTH AND FITNESS
Public figure | Author	LITERATURE
Businesses | Travel & transport | Private bus service	TRAVEL
Businesses | Shopping & retail | Outdoor equipment shop	SHOPPING AND DEALS
Businesses | Medical & health | Medical device company	HEALTH AND FITNESS
Other | Brand | Website	COMPUTER AND TECHNOLOGY
Businesses | Travel & transport | Tour guide	TRAVEL
Businesses | Food & drink | Hot pot restaurant	FOOD AND DRINK
Businesses | Food & drink | Rajasthani restaurant	FOOD AND DRINK
Businesses | Shopping & retail | Women's clothes shop	SHOPPING AND DEALS
Businesses | Shopping & retail | Rent-to-own shop	SHOPPING AND DEALS
Businesses | Food & drink | Padangnese restaurant	FOOD AND DRINK
Businesses | Sport & recreation | Football pitch	SPORTS
Businesses | Food & drink | Goan restaurant	FOOD AND DRINK

As we are first recommending particular insights that the users may be interested in, when looking at the categories assigned to each of the recommended insights for our real user, one can see that the majority of them fall into categories that the user has already shown interest in (SPORTS, BEAUTY AND PERSONAL CARE, HEALTH AND FITNESS, LITERATURE, SHOPPING AND DEALS, FOOD AND DRINK), while only four insights are assigned with new categories (PETS AND ANIMALS, TRAVEL and COMPUTER AND TECHNOLOGY). This makes sense, as our goal is to find new interests that the user may have and thus it is realistic that these new interests are similar to the ones the user likes.

Table 35 - Recommending Categories Insights

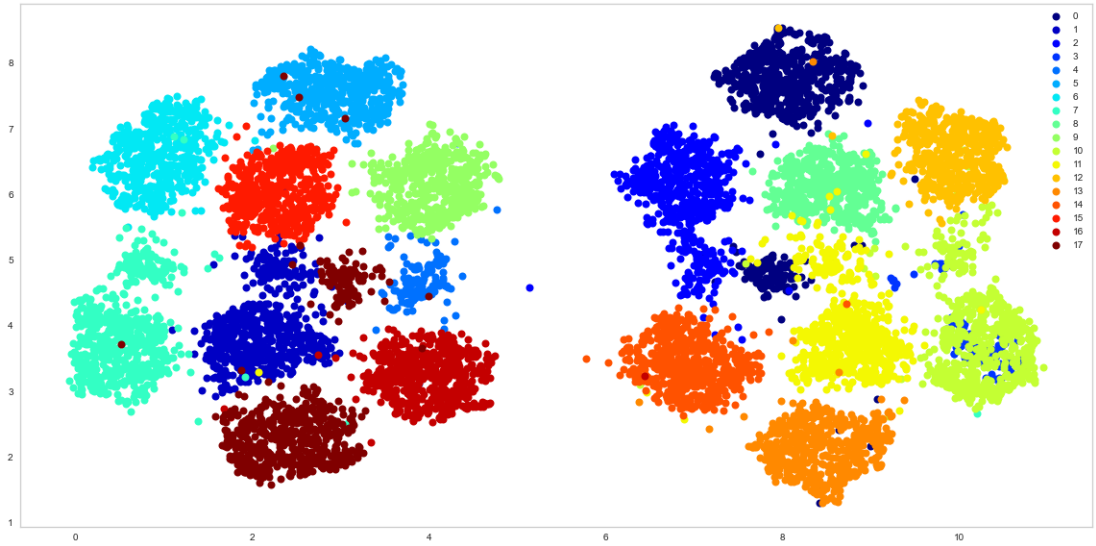
Category
COMPUTER AND TECHNOLOGY
POLITICS
HISTORY
PETS AND ANIMALS
FINANCE
GAMING
MOTOR VEHICLES
HOSPITALITY AND TOURISM
MUSIC
ENVIRONMENT
RELIGION
DESIGN
TRAVEL
REAL ESTATE

By grouping the insights per category and trying to find the right categories of insights to recommend, besides the ones the user has already shown interest in, these are the results of applying the model to Emila's data. As expected from the previous recommendations, COMPUTER AND TECHNOLOGY and PETS AND ANIMALS are part of the first categories to be recommended. From the remaining ones, we know that at least FINANCE, MUSIC and TRAVEL would be positively validated by the user concerned, while the others, despite their

probable non direct validation, could be hidden interests that the user might explore in more detail when being shown these recommendations by the app.

Clustering Recommendation

Figure 39 - Kmeans Clusters Visualization



These are the clusters resulting from applying the K-Means clustering and UMAP dimensionality reduction techniques. As we can see, the users are grouped into well-defined clusters, with a low dispersion of users between clusters.

An interesting analysis one could do is to look at the distribution of users by their profile features. By analyzing some of the variables, it is possible to note a clear distribution based on three determinant features: users' gender, users' civil status and whether they practice sports or not. Let's plot the clusters distributed by these three features, one by one:

Figure 40 - Distribution by Gender

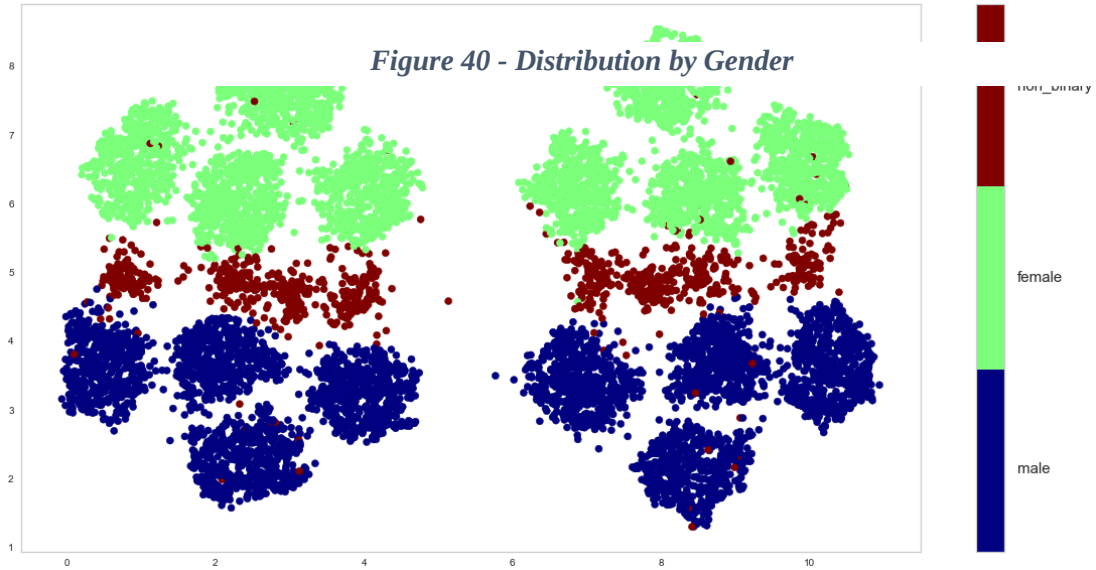


Figure 41 - Distribution by Civil Status

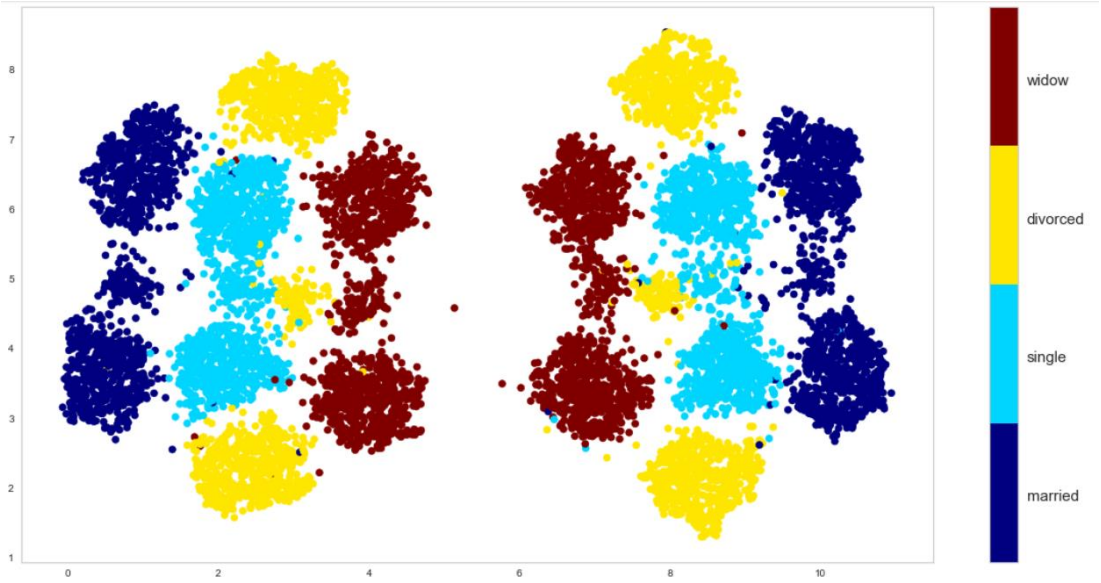
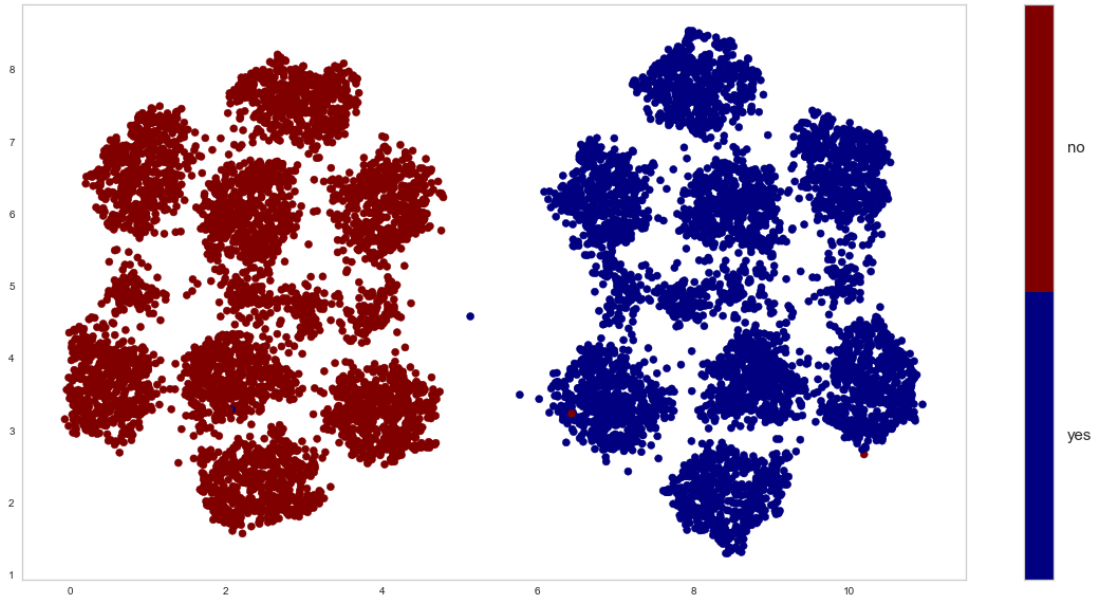


Figure 42 - Distribution by Sports Practice



Concluding, this clusters' division is being highly determined by these three variables, while the others play a secondary role in the groups' definition.

Validating cluster distribution with Emila's data:

Let's now check a particular example by comparing our real user's data with the distribution of the cluster she is inserted in.

Table 36 – Emila's profile data

Value	Label
Birth_year_6	1991 – 2000
Gender_1	Female
Civil_status_2	Single
Degree_5	Master's Degree
Professional_status_1	Student
Annual_income_0	Less than 15000€
Practice_sports_1	Yes

Figure 43 - Emila's cluster distribution

	distribution
Birth_year_2	0.1775
Birth_year_1	0.1618
Birth_year_0	0.1596
Birth_year_3	0.0899
Birth_year_5	0.0876
Birth_year_7	0.0854
Birth_year_8	0.0809
Birth_year_4	0.0787
Birth_year_6	0.0787

	distribution
Civil_status_2	1.0
Civil_status_0	-0.0
Civil_status_1	-0.0
Civil_status_3	0.0

	distribution
Gender_1	1.0
Gender_0	0.0
Gender_2	-0.0

	distribution
Degree_0	0.1820
Degree_3	0.1461
Degree_2	0.1438
Degree_5	0.1393
Degree_6	0.1371
Degree_4	0.1303
Degree_1	0.1213

	distribution
Practice_sports_1	1.0
Practice_sports_0	0.0

	distribution
Professional_status_4	0.1551
Professional_status_5	0.1528
Professional_status_2	0.1483
Professional_status_6	0.1438
Professional_status_0	0.1371
Professional_status_1	0.1348
Professional_status_3	0.1281

	distribution
Annual_income_3	0.1865
Annual_income_2	0.1820
Annual_income_1	0.1730
Annual_income_0	0.1596
Annual_income_4	0.1551
Annual_income_5	0.1438

As we had already concluded, Gender, Civil status and Practice sports are the determinant factors in the cluster definition. For the other variables the distribution is quite disperse, and we

can even see that Emila is in the group with the lowest % for birth year.

Final Recommender System

A final Recommender System was built based on the second approach, so that we could take advantage of the information that is gained by considering the similarity between users to represent them into clusters. Thus, as for the first approach, we have recommendations for both particular insights and categories of insights:

Table 37 - Recommending Insights

Insight	Category
Businesses | Vehicle, aircraft and boat | Aviation repair station	AVIATION
Other | TypeAhead | Coming of age	Other
Businesses | Shopping & retail | Rent-to-own shop	SHOPPING AND DEALS
Businesses | Food & drink | Xinjiang restaurant	FOOD AND DRINK
Non-business places | Outdoor recreation | Pond	Non-business places
Other | TypeAhead | Holiday	TRAVEL AND VACATIONS
Businesses | Local service | Personal assistant	PERSONAL IMPROVEMENT
Other | Brand | Musical instrument	MUSIC
Businesses | Hotel & B&B	HOSPITALITY AND TOURISM
Other | Brand | Society & culture website	CULTURE
Businesses | Food & drink | Asian restaurant	FOOD AND DRINK
Businesses | Vehicle, aircraft and boat | Marine supply shop	MOTOR VEHICLES
Businesses | Local service | Animal shelter	PETS AND ANIMALS
Businesses | Arts & entertainment | Decorative arts museum	DESIGN
Businesses | Shopping & retail | Fishing shop	SHOPPING AND DEALS

By comparing the insights obtained with the individual recommendation with these insights, it is notable that the categories of the latest are way more diverse and different from the ones that Emila has already shown interest in. This is because we are now trying to recommend insights not only based on the user's personal interests but on his/her peers' interests, with peers being the most similar users that are inserted in the same cluster. This is an interesting result since our goal is exactly to try to predict possible hidden insights that the users may like, so even

though at first the users might find it intriguing to be recommended with insights they had never considered to like, they might end up discovering new insights that they are really interested in.

Table 38 - Recommending Categories of Insights

Category
AGRICULTURE
MUSIC
REAL ESTATE
HISTORY
MOTOR VEHICLES
DESIGN
HOSPITALITY AND TOURISM
FINANCE
AVIATION
RELIGION
ENVIRONMENT
COMPUTER AND TECHNOLOGY
TRAVEL
PETS AND ANIMALS
MOVIES

Regarding the recommendation of categories of insights, the results are very similar to the ones obtained with the individual recommendation. The main difference is the order of recommendations – for instance, COMPUTER AND TECHNOLOGY was the first category to be recommended individually, however it is now the 12th; the same for MUSIC, which was previously the 9th and now it's the second most likely to be of the user's interest.

C – Evaluation

C1 – Hyperbolic Embeddings Approach

Poincaré Model: Evaluation

Figure 44 - Fine-tuning of parameters on Poincaré Model

```
negatives_array=[10, 20]
dimensions = [5, 25, 50, 100, 200]
epochs_array = [50, 100, 150, 200]
burn_in_array = [0, 10]
regularization_coeff = [0, 1]

# Try the different values of the parameters;

for neg in negatives_array:
    for di in dimensions:
        for epo in epochs_array:
            for burn in burn_in_array:
                for reg in regularization_coeff:
                    model = Model(negative = neg, size = di, epochs = epo, burn_in=burn, regularization_coeff=reg )
```

On our code, we created a function called *Model* implementing the Poincaré Model, based on some parameters that will be evaluated in order to get the best model possible.

In this case, we are going to fine tuning the following:

- **Negative:** Number of negative samples to use.
- **Size**: Number of dimensions of the trained model
- **Burn-in**: Number of epochs to use for burn-in initialization (0 means no burn-in)
- **Regularization_coeff**: Coefficient used for l2-regularization while training (0 effectively disables regularization)
- **Epochs:** hyperparameter that controls the number of complete passes through the training dataset.

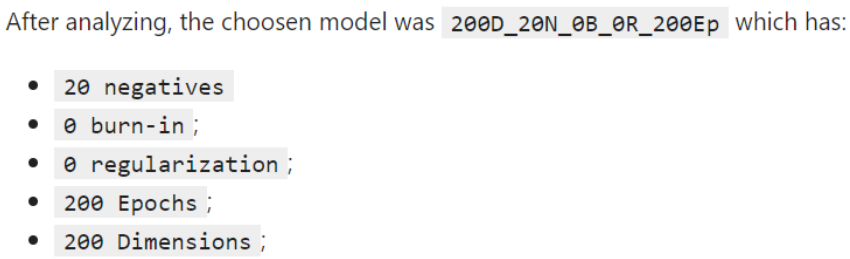
To get the best model, we are going to fine tuning the parameters described above. The values for the parameters are the following:

- **Negatives:** 10, 20;
- **Dimensions:** 5, 25, 50, 100, 200;

- **Epochs:** 50, 100, 150, 200;
- **Burn-in:** 0, 10;
- **Regularization coeff:** 0, 1;

Figure 21 illustrates the code that was built to apply these parameters. In Figure 22, it is shown the best model hyperparameters.

Figure 45 - Best Model Parameters



For evaluation on Link Prediction, it was required a test set. This test set was transformed into tuples, as explained before.

To check the results on real data, we used data from one of our members, Emila. Table 21 shows the tuples of Emila's data.

This data allowed us to evaluate the generalization performance of the Poincaré Model.

Table 39 - Tuples of Emila's data

Child	Parent
Books & magazines	Media
TV & film	Media
Comedian	Public figure
Brand	Other
Media/news company	Businesses

Education	Businesses
Non-profit organisation	Businesses
Community	Other
Just for fun	Other
Arts & entertainment	Businesses
Beauty, cosmetic & personal care	Businesses
Youth organisation	Community organisation
Local service	Businesses
Sport & recreation	Businesses
Food & drink	Businesses
Shopping & retail	Businesses
Social club	Community organisation
Campus building	Non-business places
Video creator	Public figure
Magazine	Books & magazines

Recommender System: Implementation and Evaluation

Figure 46 - Parameters used on HyperML

```
training_config = {
    "manifold"            : PoincareBall(),  # The manifold to be used in the model
    "init_curvature"      : -1.0,  # Default value of the curvature of the manifold
    "trainable_curvature" : True,  # Whether the curvatures are trainable

    "training_steps"      : 1000,  # Steps for training
    "log_steps"           : 100,  # Log intervals during training
    "eval_steps"          : 100,  # Evaluation intervals during training

    "batch_size"          : 60,  # Batch size used in training
    "learning_rate"       : 0.001,  # Learning rate of training
    "optimizer"           : RAdam,  # The optimizer to be used in training

    "dim"                 : 25, # Dimension of the embedding tables
    "margin"              : 1.0,
    "candidate_num"       : 10,  # Sampled negative candidates for evaluation
    "K"                   : 10,  # Metric of HR@K

    "gamma"               : 0.1,  # Multi-task learning rate between the two types of loss
    "epsilon"             : 1e-9,  # Small value for avoiding dividing zeros in distortion optimization (loss)

    "embedding_initializer": tf.initializers.glorot_uniform(),  # Initializer for the embedding tables
    "shuffle_buffer"      : 10000,  # Buffer size for TF's shuffling over the dataset
}
```

Figure 23 illustrates the parameters used on the implementation of HyperML.

The final HR@10 result was of 0.77, which demonstrated to be more desirable given previous results.

Table 40 - Top 10 Recommendations of Insights

Top 10 item Recommendations
Businesses | Food & drink | Scandinavian restaurant
Businesses | Food & drink | Café
Businesses | Arts & entertainment | Museum
Businesses | Shopping & retail | Beauty supply shop
Businesses | Food & drink | Ice cream shop
Businesses | Arts & entertainment | Amusement & theme park
Public figure | Talent agent
Businesses | Sport & recreation | Volleyball court
Businesses | Vehicle, aircraft and boat | Wheel & rim repair service
Businesses | Travel & transport | Private bus service

Table 41 - Recommendations of Master Categories

Master Categories Recommendations
FOOD AND DRINK
TEACHING AND EDUCATION
BEAUTY AND PERSONAL CARE
TRAVEL
AVIATION
GAMING
MUSIC
FASHION
WINE
ENTERTAINMENT
THEATRE
POLITICS
TV
PUBLIC FIGURE
JOURNALISM
ARTS
PETS AND ANIMALS
LITERATURE
MOVIES
MOTOR VEHICLES
SPORTS

Tables 22 and 23 shows the results of the Recommender System for Emila's test set. The final results were presented as insights, as well as master categories.

The use of master categories made sense as a way to obtain new insights of users in broader terms, which can later benefit organizations when looking for new users that have some specific but wide-ranging characteristics.

C2 – Deep Interest Network Approach

DIN model parameters and evaluation

After trying to overcome the overfitting the model was suffering from, we have decided to keep the following parameters for the best model:

- dnn_use_bn = True
- dnn_hidden_units = (200, 80)
- dnn_activation = "relu"
- att_hidden_size = (40, 20)
- att_activation = "dice"
- att_weight_normalization = False
- l2_reg_dnn = 0.01
- l2_reg_embedding = 1e-6
- dnn_dropout = 0.03
- seed = 1024
- task = "binary"

Table 42 - Best DIN model Evaluation

Metric	Training set	Test set
Log loss	0.619	0.620
AUC	0.547	0.545
Recall	0.878	0.876

As we can see from the above, the model is not overfitting and the recall score is pretty good, meaning that the model is correctly predicting the majority (88%) of insights the users are interested in.

When retraining the model for the clustering recommendation, the results were very similar, showing a Log loss of 0.543 on the training set and 0.569 on the test set, and a recall of 0.852 and 0.849 on the training and test sets, respectively.

1. Step 2 Introduction

Privacy-preserving has been a challenge since the beginning of the "Big data era". On the one hand, Giant Company collects the users' data to feed their recommending algorithm to send commercial delivery accurately to make a considerable profit. On the other hand, there is always the risk of users' data leakage, causing irretrievable damage. Therefore, many techniques were introduced to protect privacy, such as de-identification techniques (k-anonymization, l-diversity, and k-closeness); yet, these are vulnerable to re-identification attacks. Other similar methods are removing identifies (such as tax number, ID number), altering quasi-identifiers (such as Gender, Name, Post Code) and perturb values. However, these are also not the most reasonable. Due to the following reasons: 1- Attackers could still retrieve the private data if they acquire some background information, 2 - These methods could damage the utility of the released data, and it is problematic to achieve a good performance in privacy-preserving and utility simultaneously. The privacy level and data utility are inversely proportional, i.e., when privacy is well preserved, its utility is usually unsatisfactory, vice-verse.

A generative adversarial networks (GANs) model was proposed to tackle these challenges. GAN has made a massive breakthrough in synthesizing high-quality artificial samples by capturing the distribution of the original training data, from which it is quasi-impossible to distinguish whether it is artificial or genuine. In recent years,

GAN has presented an excellent achievement in generating images and in other areas (such as video generation, music generation, etc).

Image 1 shows an example of a realistic synthetic portrait of humans:

Image 47 - Portraits generated by StyleGAN2. Photo credits: Connor Shorten/Towards Data Science

Images can be represented as a combination of numbers: zero's and one's, and in this report, the main objective are to synthesize the user's data (to substitute the original one), which are categorical variables also represented by integers. Thus, theoretically, GAN should apply the synthetic data set to achieve the goal.

2. Related Work

Some literature surveys were performed and, in this section, will present some recent works accomplished by employing advanced GAN, providing a privacy protector layer for those domains that face data leakage threats. A variation called table-GAN (Park,

Mohammadi, & Gorde, 2018) was modified from DCGAN (Chintala, Radford, & Metz, 2016), which is considered the most sophisticated (Arjovsky & Bottou, 2017) model and many variations diversify from it. The table-GAN aims to synthesize relational tables (consists of different data types) and are statistically identical to the original table, based on convolutional neural networks, avoiding information leakages.

GAN also has a significant role to play in the medical industry, for instance, in generating artificial patient electronic health records (EHRs). EHRs have a remarkable attribution to the medical industry, from developing new medicine to exploring a new disease. medGAN (Choi, et al., 2018) was introduced and had a good result in generating EHRs. Afterwards, some improvements were realized, medWGAN and medBGAN (Baowaly, Lin, Liu, & Chen, 2018) were proposed to generate more realistic EHRs. These methods aim to create a genuine HER data set (preventing patient data leakage) and simultaneously promote the medical industry.

A new variation - CTGAN (Xu, Skoularidou, Cuesta-Infante, & Veeramachaneni, 2019) - aims to synthesize Tabular data, consisting of continuous and discrete columns by using a conditional generator (a deep neural network intended to generate artificial data). The challenge CTGAN faces is that discrete columns are occasionally imbalanced, and continuous columns may have numerous nodes, adding complexity to modelling. The performance of CTGAN is favourable, outperforming the Bayesian methods on most of the real datasets.

3. Generative Adversarial Network

The principal idea of GAN is to train two neural networks simultaneously: 1- a Generator (G), which generates synthetic data by capturing the distribution of the training data, providing negative training examples for the discriminator. 2- a

Discriminator (D) distinguishes fake data from authentic data, penalizing G for providing fake samples. One could interpret G as a student and D as a teacher. The teacher provides feedback to the student regarding the quality of the work.

Figure 2 shows the complete system of GAN:

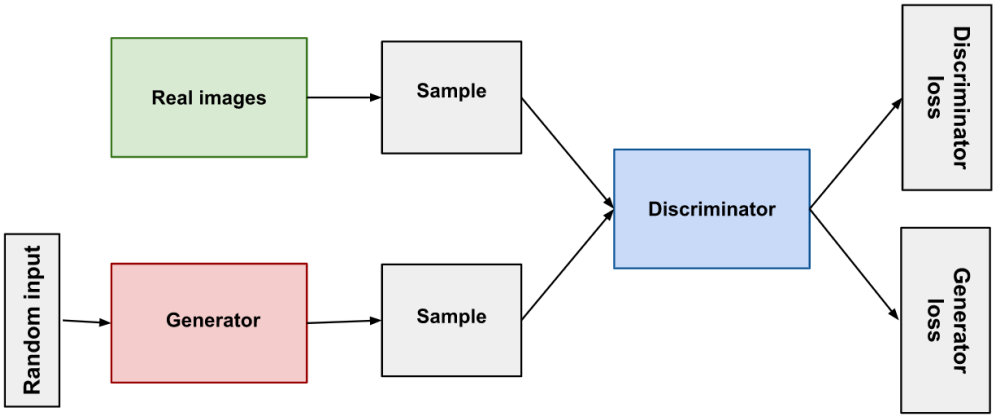


Figure 2- Architecture of GAN

And the following equation shows the loss function of GAN, consisting of two target functions:

$$min_G max_D V(G,D) = \mathbb{E}_{x\sim p_{data}(x)}[logD(x)] + \mathbb{E}_{z\sim p_z(z)}[log\ (1 - D(G(z)))]$$

Equation 13 - Loss Function of GAN

Where $p_{data}(x)$ denotes the original data distribution and $p_z(\mathrm{z})$ is the simple noise distribution (we used normal distribution). $\mathbb{E}_{x\sim p_{data}(x)}$represents the expected value in all instances of original data, and $\mathbb{E}_{\mathrm{z}\sim \mathrm{p}_z(\mathrm{z})}$ represents the expected value over all random inputs to the Generator.

The Discriminator receives two input data during the training process: 1-real data from the original data set and 2-synthetic data created by the Generator. Next, the Discriminator classifies synthetic data a real or fake. If misclassified, the Discriminator will be penalized by the discriminator loss. Lastly, the hyperparameters get updated

through backpropagation, adjusting the weights of hyperparameters in the correct direction. This process is repeated until the convergence of discriminator loss, minimizing the probability of making mistakes.

Unlike the Discriminator, the Generator cannot be trained standalone. After the Generator created a synthetic sample by inputting a random noise and feeding it to the Discriminator, an evaluation from the Discriminator is required to update the Generators' hyperparameters. It suffers penalization by providing a sample that the Discriminator classifies as artificial. The Generator's capacity is highly dependent on the effectiveness of the Discriminator. Therefore, backpropagation starts at the output of the Discriminator and returns through it into the Generator. Figure 3 shows the training algorithm:

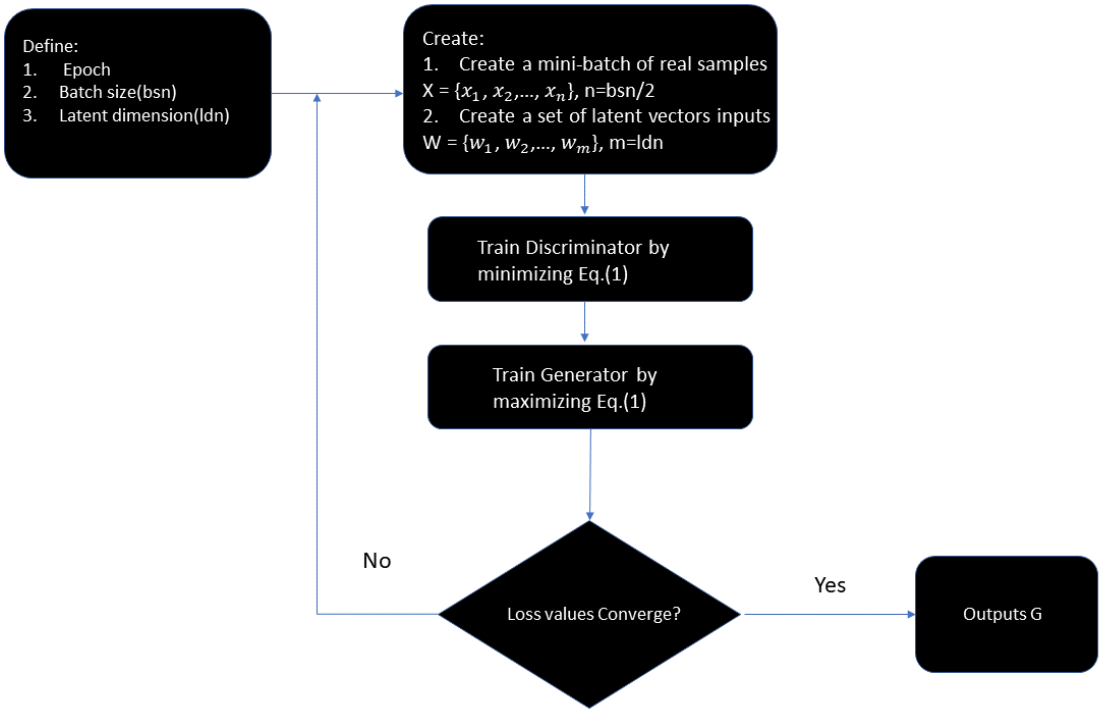


Figure 3 - GANs' training process

Note: Epochs is a hyperparameter of gradient descent that defines the number of training passes. Moreover, Batch size is a hyperparameter of gradient descent that

defines the number of samples during the training process.

4. Implementation

In section 2, some sophisticated GAN models were presented. However, this section will not introduce any new variation. Instead, some modifications were performed by adapting the architecture of the existing GAN [Appendix Figure 4] to make the training process possible. Due to time limitations, only a demonstration of GAN's feasibility to generate synthetic users' data is presented.

The code from the website Machine Learning Mastery (Brownlee, 2020) was referenced to make the training successful, keeping the code almost unchanged. A new architecture for G and D was created [see the original architecture in Appendix], shown in Figure 4:

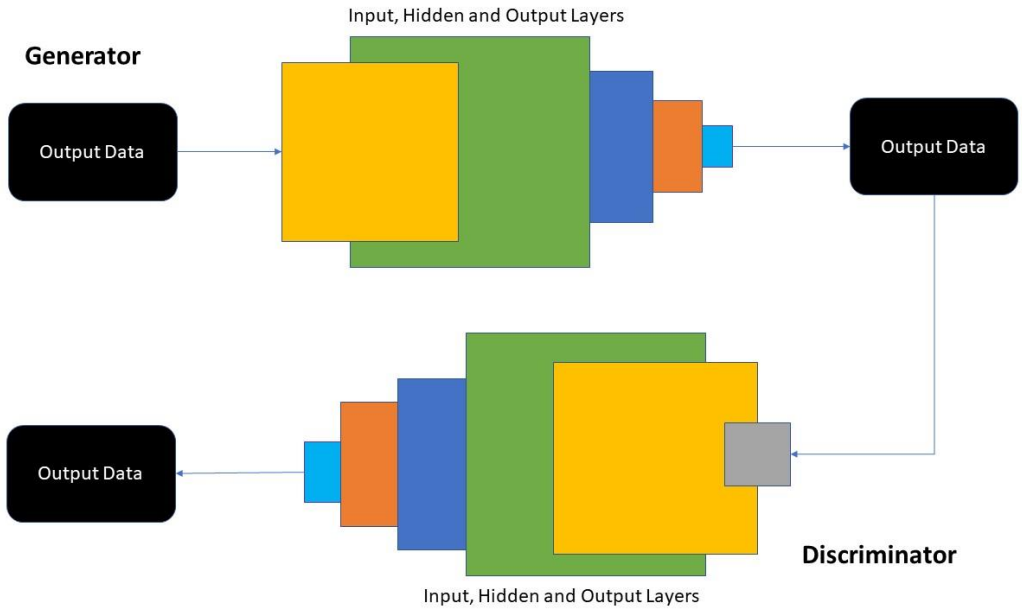


Figure 4-Architecture of Generator and Discriminator

In the new architecture, G consists of one input layer and three fully connected hidden

layers to capture possible correlations between variables and one output layer. The activation function LeakyReLU was applied for all the hidden layers and a tanh for the output layer. In addition, for D, there is one input layer, four fully connected hidden layers and one output layer. The following activation functions were applied: LeakyReLU for all the hidden layers, Sigmoid function to the output layer, Dropout to avoid the overfitting and Adam version of stochastic gradient descent with a learning rate of 0.0002 and a momentum of 0.5. For more details, see Figure 5 in Appendix.

The data set used for training is the one that was randomly generated for the DIN model (since the access to the real users' data was limited) after applying the one-hot encoding technique, as shown in Table 1:

	user_id	insight_id	True	False	Birth_year	Gender	Civil_status	Degree	Professional_status	Annual_income	Practice_sports
0	235	1149	1	0	1	1	0	4	2	0	1
1	5056	1149	1	0	0	1	2	5	6	3	0
2	5374	1149	1	0	7	0	0	0	4	0	1
3	753	1149	0	1	1	2	0	5	2	1	0
4	9719	1149	1	0	2	1	3	1	0	2	0

Table 43- Columns represents the user profile and historical behaviours and row represents the user-id

Note: cat_id was not considered to the train set for avoiding possible confusion, as each insight has its corresponding cat_id. Afterwards, cat_id will be concatenated to the result after the training.

Before starting the training process, a standardization was performed to the original data set, using the function StandardScaler from Sklearn preprocessing module, due to the following reasons: 1- Standardizing the data would accelerate the training process. 2- the output results range from [-1, 1] and [0, 1] for tanh and sigmoid functions, respectively. Thus, a standardization was performed to maintain all the parameters in the same order of magnitude.

After several experiments, the following values for the hyperparameters were chosen: n_epochs = 50, batch_size = 50 and latent_dim = 100 for the training process.

Table 2 shows the results after the training:

	user_id	insight	True	False	Birth_year	Gender	Civil_status	Degree	Professional_status	Annual_income	Practice_sports
0	1.000000	-0.845067	0.999998	-0.497486	0.999726	0.963554	-0.107356	0.999848	1.000000	0.978093	0.999151
1	0.999998	-0.866893	0.526793	-0.531801	0.999999	0.999156	-1.000000	-0.999991	1.000000	0.999972	0.999557
2	1.000000	-0.583935	0.923556	-0.239171	0.994375	-0.999933	0.999959	-0.999938	0.999993	-0.947586	-0.999995
3	0.990746	-0.754724	0.999996	-0.535204	0.997373	-0.976575	0.999996	-0.998929	0.996577	0.997952	-0.726533
4	1.000000	-0.979748	1.000000	-0.813957	0.999374	0.748914	1.000000	1.000000	0.999489	0.639002	0.999980
...	...	...	...	...	...	...	...	...	...	...	...
9995	-0.930661	-0.971160	1.000000	-0.641737	-0.999631	-0.369774	-0.999581	0.914149	-0.996376	0.999999	-0.999781
9996	-0.998592	0.852033	-1.000000	-0.704185	1.000000	0.970593	-0.999191	-1.000000	1.000000	0.998447	-0.950965
9997	-0.999183	0.791789	1.000000	-0.597315	0.086268	0.658265	-0.935611	-0.999754	-0.616301	1.000000	-0.892437
9998	1.000000	-0.870286	-0.999926	-0.466694	-0.996973	0.965498	-1.000000	-1.000000	1.000000	0.896432	-0.985427
9999	-0.999982	-0.986584	1.000000	-0.670771	0.998167	0.999725	-1.000000	-0.963877	-1.000000	1.000000	-1.000000

10000 rows × 11 columns

Table 44 – Standardized Synthetical user profile data

The inversed operation was performed to retrieve the real value, and labels were assigned to each data point, as shown in Table 3:

	user_id	True	False	Birth_year	Gender	Civil_status	Degree	Professional_status	Annual_income	Practice_sports	category	insight
0	7917.0	1.0	-0.0	1991 - 2000	Male	Widow	high school diploma	student	15K - 30K	Yes	Businesses	Businesses | Local service | Tree cutting service
1	2105.0	0.0	1.0	1961 - 1970	Male	Widow	high school diploma	permanent contract	70K-100K	Yes	Businesses	Businesses | Local service | Self-storage faci...
2	2168.0	1.0	-0.0	1921 - 1940	Male	Married	master degree	student	15K - 30K	Yes	COMEDY	Public figure | Comedian
3	2133.0	0.0	0.0	1991 - 2000	Female	Divorced	master degree	student	15K - 30K	Yes	Businesses	Businesses | Local service | Septic tank service
4	7918.0	1.0	0.0	1921 - 1940	Female	Widow	master degree	student	15K - 30K	No	DESIGN	Public figure | Designer

Table 45 – Original values for the synthetic user profile data

5. Evaluation

The existing measurement to measure the performance of GANs could divide into two different types of research: quantitative (accuracy, recall, f1-scores and precisions) and qualitative (Nearest Neighbors and Rapid Scene Categorizations).

However, in this case, none of these methods is suitable for applying to the model as generating the synthetic data is not the final objective. These data will then be fed to the DIN model created in the collective group work. Hence the performance of the GAN highly depends on the results after applying the DIN to the synthetic data.

Therefore, the trained DIN model's hyperparameters were loaded to predict the probability of artificial users' like the recommended insights or categories. In addition, some analyses were performed by comparing these results with the previous ones obtained by applying the trained DIN model to the original data set. Table 4 summarizes all the results:

	Original Data Set		**Synthetic Data set**
Metric	**Training set**	**Test set**	
Log loss	0.619	0.620	0.55
AUC	0.547	0.545	0.504
Recall	0.878	0.876	0.872

Table 46 - Scores of metrics for evaluating the DIN model's result

The prediction results using synthetic data are comparable to the original prediction. The recall scores are similar, and the log loss is even better than the original ones. However, all the AUC scores are unfavourable; the synthetic one is nearly 0.5, which indicates a random guess, worse than the others. Nonetheless, the results are reasonably acceptable.

6. Conclusion

A privacy-based system was proposed for Modatta to accomplish its primary objective: Users can be confident in providing their personal data, and these will not be compromised in the hands of Modatta. In return, users will benefit by receiving the

recommendations and allowance in commercial products they may be interested in. On the other hand, marketers will gain a representation of potential customers to reach out to them accurately—the system support Modatta to create a win-win situation for all stakeholders.

In this report, a feasible approach was introduced to the first step of the whole system: Using GAN to generate a synthetic user profile from the original data set to mask up the real users, preventing them from conceivable attacks mentioned in the first section. These data will then be used to train the DIN model, getting similar results as the original data set.

7. Limitations and future works

The nature restrains the capacity of GAN in generating categorical data. Instead, GAN-based methods perform adequately in generating continuous data. Furthermore, GAN does not consider the problem of imbalance in the categorical variables. The generator may not be trained accurately if the randomly sampled variables with minor instances are not adequately represented during the training process.

Afterwards, to overcome these difficulties, one could perform some experiments applying variations of GANs mentioned previously: medWGAN and medBGAN to achieve more satisfactory results in generating categorical data, and CTGAN to tackle the imbalance of the data set. In addition, a different architecture could also be designed for the GAN applied in this report, adding more hidden layers with different dimensions.

References

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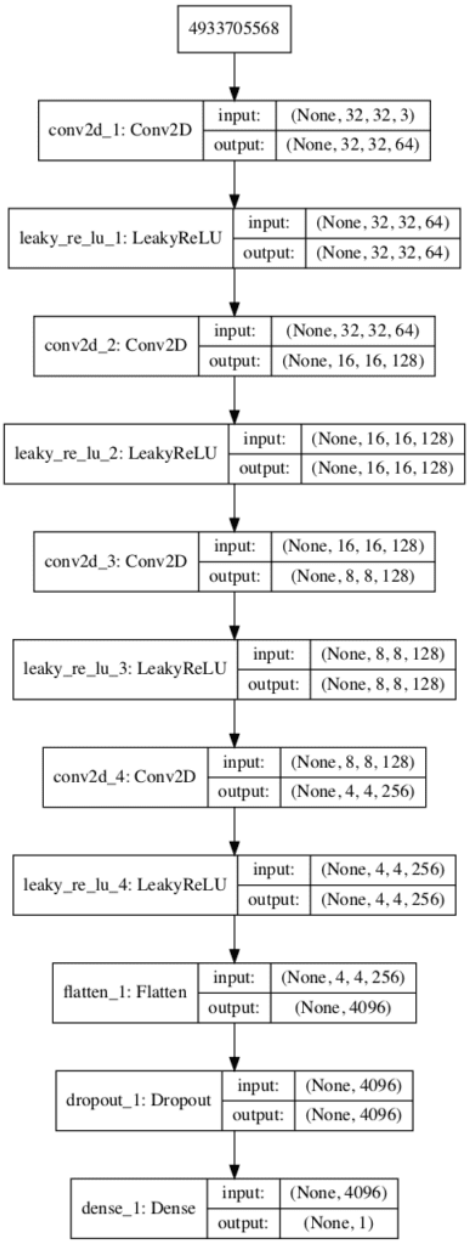
Appendix



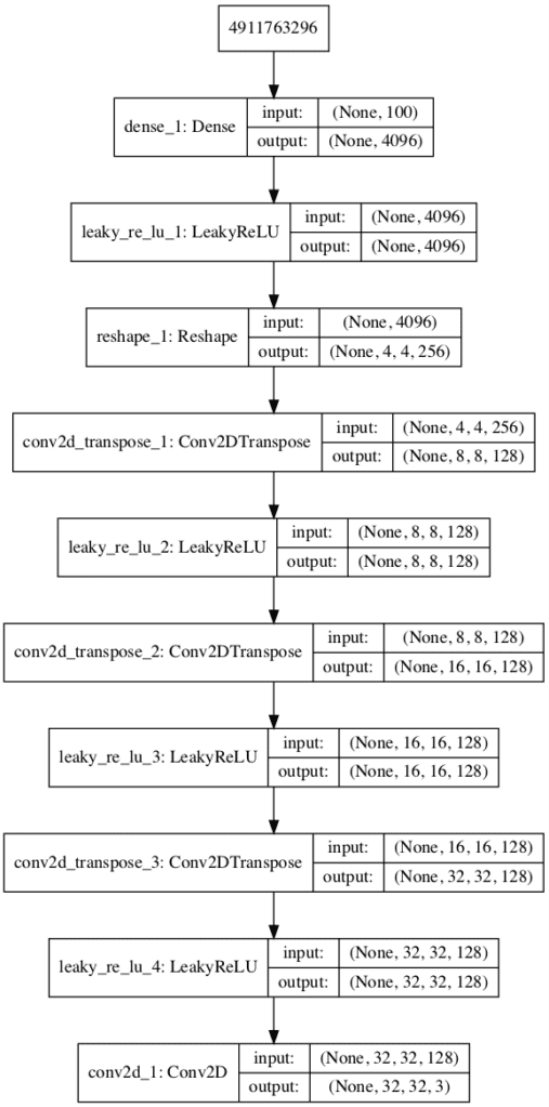


Figure 4 - Architecture of Standard GAN

Model: "Discriminator"

Layer (type)	Output Shape	Param #
dense_7 (Dense)	(None, 11)	132
leaky_re_lu_6 (LeakyReLU)	(None, 11)	0
dropout_5 (Dropout)	(None, 11)	0
dense_8 (Dense)	(None, 100)	1200
leaky_re_lu_7 (LeakyReLU)	(None, 100)	0
dropout_6 (Dropout)	(None, 100)	0
dense_9 (Dense)	(None, 150)	15150
leaky_re_lu_8 (LeakyReLU)	(None, 150)	0
dropout_7 (Dropout)	(None, 150)	0
dense_10 (Dense)	(None, 50)	7550
leaky_re_lu_9 (LeakyReLU)	(None, 50)	0
dropout_8 (Dropout)	(None, 50)	0
dense_11 (Dense)	(None, 30)	1530
leaky_re_lu_10 (LeakyReLU)	(None, 30)	0
dropout_9 (Dropout)	(None, 30)	0
dense_12 (Dense)	(None, 10)	310
leaky_re_lu_11 (LeakyReLU)	(None, 10)	0
dense_13 (Dense)	(None, 1)	11

Total params: 25,883
Trainable params: 25,883
Non-trainable params: 0

Model: "Generator"

Layer (type)	Output Shape	Param #
dense_214 (Dense)	(None, 50)	5050
leaky_re_lu_177 (LeakyReLU)	(None, 50)	0
dense_215 (Dense)	(None, 150)	7650
leaky_re_lu_178 (LeakyReLU)	(None, 150)	0
dense_216 (Dense)	(None, 80)	12080
leaky_re_lu_179 (LeakyReLU)	(None, 80)	0
dense_217 (Dense)	(None, 15)	1215
leaky_re_lu_180 (LeakyReLU)	(None, 15)	0
dense_218 (Dense)	(None, 11)	176

Total params: 26,171
Trainable params: 26,171
Non-trainable params: 0

Figure 5 – Detailed information for architecture of Generator and Discriminator