A Work Project presented as part of the requirements for the Award of a Master's degree in Business Analytics from the Nova School of Business and Economics.

Website Networks and Keyword Distances

Defining the E-commerce Dynamics Through the Identification of Direct and Indirect Competitors

Fridtjov Höyerholt Stokkeland (52922)

Work project carried out under the supervision of:

Qiwei Han, Alessandro Gambetti, Maximilian Kaiser

20/12/2023

Abstract:

This study explores the intricate web of competition in e-commerce, utilizing advanced methods in natural language processing and machine learning. This analysis delves into previously undiscovered competitor networks, deciphering apparent and concealed competition using advanced techniques such as Word2Vec and Graph Neural Networks. The research uncovers the covert strategies of advertisement poaching, offering a rare glimpse into the more intricate dynamics of digital marketing. It serves as a symbol of innovation offering important knowledge for understanding the competitive landscape of internet commerce.

Keywords:

Natural Language Processing, Network Analysis, Competitive Landscape Analysis, Knowledge Graph, FastText, E-Commerce, Bipartite Networks, Advertisement Poaching, Search Engine Optimization, Word2Vec, Minimum Spanning Trees

This work used infrastructure and resources funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019 and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722 and Social Sciences DataLab, Project 22209) and POR Norte (Social Sciences DataLab, Project 22209)

1. Introduction: Competitor identification in Search Engine Optimization

In today’s e-commerce landscape, for businesses to thrive it is necessary to ensure that their online presence is substantial, and their visibility is enhanced. The budgetary allocation to online advertisement is a significant investment from a company perspective (Erdmann, Arilla and Ponzoa 2022). This is reflected by the resilience of the Digital Advertising Industry in the past few years, whose revenue trends reflect the increasing investment in internet advertising by companies (Appendix I) (PwC 2023). To maximize the effectiveness of their investment, companies must ensure that their spending on digital advertising yields the desired brand visibility. Simultaneously, it is crucial to focus on minimizing these expenses, emphasizing the importance of cost-effective strategies. Search Engine Optimization (SEO) is the unpaid practice of enhancing a website's content and structure to increase its visibility in search engine results (Ologunebi and Obafemi Taiwo 2023). Chaffey and Ellis-Chadwick (2019) discovered that 63% of marketers perceive SEO generated organic website traffic effectively, emphasizing on the role of SEO in brand visibility. In the SEO Starter Guide, Google provides suggestions and requirements for E-commerce players to have a positive influence in their websites position in Search Engine Results Page (SERP) through SEO (Google for Developers 2023). Aside from the necessary requirements, these recommendations stress the creation of high-quality and people-centric content (Google for Developers (b) 2023). Google for Developers (b) (2023) encourages using relevant keywords that potential customers may use to search for content. Strategically placing these keywords in the title, main header, alt text, and link text of the web page. This strategy ensures that the content is not only user-focused but also optimized for search engines, thereby improving its visibility and accessibility.

Although this approach is crucial for optimal positioning in SERP, it does not ensure a positive desired visibility. This is caused by the complexity of the competitive landscape within the context. Given these circumstances, this study will focus on competitor identification within the landscape of SEO. Central to this investigation is the question: 'How does competition among online retailers emerge in the dynamics derived from organic search engine optimization?' This inquiry will guide the structure of the analysis, delving into the multifaceted interactions and strategies that shape the competitive e-commerce environment.

As a preliminary step in the analysis of competitor identification and network analysis this work will propose several methods of how NLP and Machine Learning can be applied towards the identification of competitors. First, a way to identifying the key clusters within the e-commerce space. Thereafter two ways of identifying direct and indirect competition is proposed. The first of these utilize Word2Vec and PCA, whereas the second utilize Minimum Spanning Trees to map the overall network of domains.

Building upon the identification of clusters and competitors, the study will redirect the focus on a specific practice in digital marketing commonly referred in the literature as competitive poaching. According to a study by Bhattacharya, Gong, and Wattal from 2022, competitive poaching refers to the marketing tactic where a brand uses a competitor's advertising keywords with the aim of attracting their customers. Throughout this research, this practice will be investigated in the context of SEO and will be referred to as advertisement poaching. The occurrence of this strategy will be observed within and across the clusters found in the preliminary part of the study and will be the basis for comparison on cluster identification.

Another path of analysis of this paper aims to develop a bipartite network graph which nodes (vertices of the graph structure) represents features of the data, such as products, retailers' domains, and keywords terms. The graph's edges not only connect properly the nodes interactions, but also contains weights that leverages numerical features of the interaction, such as cost-per-click (CPC), number of impressions and monthly search volume. This section og the work was developed based on the fact that retailers harvest on considerable advancements in computational power and can gather astounding amounts of high-quality data, as the e-commerce companies and search engines ads generate millions of user interactions on a daily basis. What can be leveraged into knowledge for better decision making to the ones that are capable to perform the necessary transformations and analysis (Gabel, S., Guhl, D., and Klapper, D. 2019; Li, Z., et al. 2020).

2. Related work

The intricate competitive landscape of the e-commerce sector necessitates the implementation of sophisticated analytical methods and strategic decision-making regarding customer acquisition, supplier selection, and product assortment. The significance of product category selection and range is emphasized by Kolk, Fisher, and Vaidyanathan (2015); it has a direct bearing on a company's capacity to attract a wide variety of consumer segments. Aligned with this notion, Gabel (2019) presents a retailer-centric methodology that evaluates competitiveness via product substitutions, thereby providing valuable perspectives on the impact of product diversity on market positioning. Gerling (2023) and Fang et al. (2012), on the other hand, argue that predefined classification systems are inadequate for capturing emergent trends in such dynamic industries and propose more flexible, adaptive alternatives.

Similarly, Gerling (2023) emphasizes the significance of quantitatively representing businesses in order to identify minute distinctions and parallels among them. The aforementioned method, which is vital for acquiring customers and selecting suppliers, is enhanced by the semantic vector representations that Mikolov et al. introduced. The aforementioned factors highlight the intricacy and ever-changing nature of the e-commerce industry's competitive environment, underscoring the importance of employing strategic judgment when it comes to product assortment, adaptive classification systems, quantitative representation, and advanced modeling.

The illustration of how clustering techniques can be effectively utilized in the extraction of social media data by Meng, Tan, and Wunsch provides additional credence for their incorporation into e-commerce (Meng, Tan og Wunsch 2019). Difficulties such as organizing web images, integrating multi-modal data, identifying user communities, conducting sentiment analysis, and detecting social network events are all tackled by clustering methodologies. In the domain of e-commerce, where they are capable of interpreting consumer behaviors, market trends, and competitive environments, their adaptability and proficiency in managing complex data sets are especially practical. This information is of immense value when it comes to making strategic decisions in the e-commerce industry, drawing parallels with the difficulties encountered in social media regarding the analysis of extensive data and comprehension of nuanced consumer interactions and market dynamics.

In addition, the report "Automated Competitor Analysis Using Big Data Analytics: Evidence from the Fitness Mobile App Business" analyzes the competitive landscape of the fitness mobile app industry using Natural Language Processing (NLP) effectively (Yin og Lu 2017). The potential of natural language processing in the wider e-commerce sector is underscored by its application in automated competitor identification. This utilizes substantial amounts of unstructured data to efficiently extract profound insights regarding consumer behavior and market trends. The ability to comprehend the competitive e-commerce environment is of utmost importance as it facilitates strategic positioning and achieves success in the market. The findings presented in this report underscore the significance of advanced data analytics in the realm of electronic commerce and offer a strategic framework for organizations seeking to improve their approaches to competitive analysis in a constantly changing market.

Besides how clustering techniques can be used in pair with Natural Language Processing to identify competitors, other techniques like Minimum Spanning Trees can be of great help too. (Zhou 2009), (Battiston, et al. 2012), and (Gofman 2017) show graph theory can be enhanced with Natural Language Processing and other numerical features to determine different relationships among firms in the financial industry which can be translated into different industries to assess network structures as important players in a certain market, connectivity among companies/domains and potential snowball effects that can start with a company/domain in a certain node and then be translated to subsequent nodes or direct/indirect competitors.

3. Dataset & Methodology

This study is based on a dataset sourced from Grips, a German start-up whose mission is to ‘illuminate blind spots and create a comprehensive map of online commerce for retailers and brands’ (Grips 2023). Grips Competitive Intelligence strives to help retailers and brands understand the e-commerce market, uncover winning solutions, and further maximize their clients' potential income trajectory.

3.1 Dataset

The dataset entails observations representing products offered by diverse retailers, providing insights into organic SEO and the position in the SERP. It consists of approximately 48M observations and 16 features, with each individual row representing a distinct product for a specific domain, covering around ~50.000 unique domains. The primary information sources are Grips, Keyword Planner, and predictions made by Grips (Appendix II for data dictionary and sources). The features aim to convey various aspects of the products being showcased and promoted online, encompassing attributes of the products themselves as well as their placement in the advertising marketplace. Product features derived from metadata such as title, category, brand, and price in USD significantly influence market placement and consumer appeal (Vinutha and Prajwal 2023). Moreover, keyword-related features like keyword, estimated cost-per-click (CPC), impressions, and position in SERP play a significant role in a product's potential and visibility online. Keywords, integral to SEO, determine the positioning of digital content, influencing consumer behavior considerably (Hee Park and Agarwal 2018).

Grips' dataset provides an overview of the product offering, keywords per product, and SERP information. The extensive data allows for a myriad of analytical opportunities. For the specified research question, 'How does competition among online retailers emerge in the dynamics derived from organic search engine optimization?', variable selection, data aggregation, and feature generation have been employed to refine the dataset, detailed further in the ensuing section. In summary, this dataset offers a thorough perspective on various facets of products' online behavior, including their attributes and visibility in digital searches, aiding a comprehensive examination of their online performance.

3.2 Data Preparation

To enhance algorithmic efficiency and competitor analysis, the dataset undergoes a series of data cleaning and processing steps, tailored to the nature of the variables. Textual variables are standardized by trimming spaces, converting to lowercase, and applying lemmatization, enhancing domain comparability and NLP algorithm effectiveness. Instances of blank values erroneously recorded instead of 'None' are corrected to minimize noise. Additionally, non-ASCII characters identified during data screening are removed, ensuring data uniformity and algorithm compatibility.

After the textual data is cleansed, a comprehensive evaluation is performed on all columns to determine their sufficiency for further analysis and to address any missing values. This process, detailed in Appendix III, involves assessing the proportion of missing values in each column. Notably, columns 'low_top_of_page_bid' and 'high_top_of_page_bid' exhibit 50% missing values, leading to their removal since 'cpc_1' adequately represents the estimated CPC. Additionally, rows missing key data in 'avg_monthly_search_volume,' 'predicted_productssold,' 'impressions,' and 'producttitle' are eliminated due to the impracticality of estimation and their limited occurrence.

3.3 Feature Generation

Following initial data cleaning, the final Dataframe is built to construct algorithms on. To identify respective competitors, a feature representing the domain prefix was generated. The feature allows for a more comprehensive and integrated overview of the single retailers within each specific domain. By grouping by this feature, the count of products associated to retailers is performed, providing an overview of the brand recurrence and volume. The operations relating to the grouping of the features allows for completeness and reduced information loss. To aggregate the quantitative variables, summary statistics such as average, mean, and standard deviation, along with the count of unique brands (NuBrands) and unique keywords (NuKeywords) are calculated. The textual characteristics are subjected to a procedure of eliminating stopwords and performing lemmatization in order to maintain uniformity and minimize noise. The final dataset is aggregated per domain containing the aforementioned numeric variables and lists of all string components (e.g., brands, categories, and producttitles).

4. Harnessing FastText and UMAP for Building Clusters

As the number of e-commerce platforms grows, identifying clusters of similar domains becomes both difficult and important. The ability to categorize these offerings based on their characteristics can provide significant insights into market niches and possible competitors, allowing to precisely identify and analyze market moves. For this part of the report a cluster is defined as a group of similar e-commerce operators that share numeric or textual characteristic, representing a differentiating segment or niche within the e-commerce world. The combination of FastText and UMAP provides an innovative and efficient way for delineating these clusters in this setting.

4.1 FastText: Beyond Simple Vectorization

FastText is an NLP algorithm from from Meta's AI Research lab, that enhance word embeddings by leveraging subword information to grasp linguistic nuances (Bojanowski, Joulin, & Mikolov, 2016). Its capacity to encode morphological nuances distinguishes it from other NLP techniques, particularly when dealing with the varied textual material in e-commerce:

1. **Embedding Generation:** FastText is used to encode product titles, categories, and keywords into the shape om embeddings, which are a combination of technical terminology, product information, brand names, and colloquial English. The subword information ensures that even out-of-vocabulary words (which are widespread in the e-commerce area due to developing jargons, brand names, and so on) be represented meaningfully. (Bojanowski, Joulin, & Mikolov, 2016)
2. **Dimensionality Reduction with SVD:** Using SVD on FastText embeddings is critical because textual data, especially when transformed into embeddings, often has significant redundancy and noise. This is efficiently reduced by SVD, which pinpoints and preserves the most latent features, resulting in representations that are both compact and intelligible. SVD, on the other hand, is not used on quantitative data in this instance, to ensure the preservation of the original context and meaning of these. In this instance the silhouette-score was used to identify the optimized number of clusters for the data, which was nine.

4.2 UMAP: Crafting Cohesive Clusters

In the domain of dimensionality reduction approaches, Uniform Manifold Approximation and Projection (UMAP) stands out (McInnes, Healy, & Melville, 2020). Its superiority over classic methods such as PCA or T-SNE is based on its unique ability to preserve data topology, making it particularly suitable for clustering in complex contexts such as e-commerce:

1. **Integration of Numeric and Textual Data:** UMAPs key benefit is its ability to retain data's topological structure, making it particularly well-suited for the sophisticated clustering scenarios typical in e-commerce (McInnes, Healy, & Melville, 2020). UMAP's ability to handle multimodal data is a tribute to its prowess: it smoothly mixes

textual and numeric formats. A detailed domain representation is required prior to using UMAP (Becht, et al., 2019). Numeric attributes scaled using Min-Max merge with SVD-reduced FastText embeddings in this case, resulting in a balanced representation that captures both quantitative and qualitative domain features.

2. **Tuning UMAP for Optimal Clustering:** Aside from its ability to handle a wide range of data, UMAP provides parameter adjustment freedom. The settings within the UMAP function are adjusted to optimize the silhouette score to achieve optimal clustering. A high silhouette score indicates clusters that are not only internally coherent but also well separated from surrounding clusters—an essential condition for accurate competitor identification (Rousseeuw, 1987).

For this methodology, the synergy between FastText and UMAP enables for efficient and meaningful clustering across domains in the e-commerce market. FastText's ability to generate subtle embeddings, along with UMAP's topological clustering, provides a solid technique for demarcating clusters, laying the groundwork for further competitor research.

4.3 Visualizing the E-commerce Terrain

The world of e-commerce is vast and varied, and as with any expansive landscape, visualization is key to truly grasping its intricacies. The provided UMAP plot, a result of the advanced methodologies, paints a vivid picture of the e-commerce domain landscape, clustered by competitive similarity.

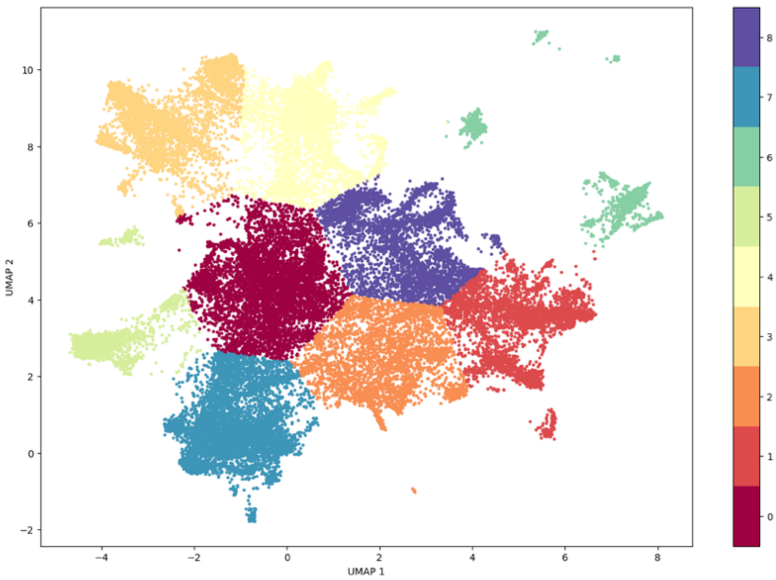


Figure 1 - Domain Clusters

From the onset, it's evident that this methodology provides a clear representation of domain proximity. Through the combination of textual (product titles, categories, and SEO keywords) and numeric data, domains have been mapped into nine differentiating clusters. This gives rise to a spectrum where domains sharing semantic similarity, whether they offer similar products, use akin marketing strategies, or have similar numeric attributes, are nestled together. Such clustering not only underscores direct competitors but also elucidates the nuanced niches within the e-commerce space.

Diving deeper into the visualization, the intricacy of the e-commerce domain landscape unveils itself. The multitude of clusters, each distinguished by unique colors, is indicative of the diversity in the market. Each of these clusters can potentially represent a distinct product niche or category. The density of these clusters, juxtaposed with their spread, becomes a commentary on market saturation and the intensity of competition. Where dense clusters might suggest fiercely contested segments, sparser regions can hint at untapped market opportunities, awaiting savvy entrepreneurs.

For businesses, the visualization is a strategic goldmine. By locating themselves within this mapped terrain, they can discern their competitive positioning. Are they ensconced within the heart of a bustling cluster, surrounded by rivals vying for the same customer base? Or do they find themselves on the fringes, pioneers in a relatively uncharted niche? Such insights can profoundly influence their market strategies, from how they differentiate their products to where they channel their marketing energies. Additionally, a closer examination of domains within specific clusters can serve as a valuable blueprint for businesses. By studying what similar domains are executing, whether in terms of product offerings, marketing campaigns, or customer engagement strategies, businesses can glean actionable insights. Identifying patterns of success within these clusters could guide a domain to tweak its strategy, adapting best practices to increase revenue and market share. Conversely, observing recurrent pitfalls can act as cautionary tales, steering businesses away from potential missteps.

In essence, this visualization serves as a compass in the vast ocean of e-commerce. By succinctly mapping domains based on their textual data, it provides businesses with a clear vantage point, from where they can chart their course with clarity and confidence, and simultaneously adapt strategies for revenue growth and market dominance.

4.4 Analysis of defined clusters

To further understand the defined clusters an analysis of the domains and overarching categories have been completed. This can be seen in Appendix IV, with the key trends and market segments of each cluster summarized below:

Table 4.4.1

Overview of clusters and key characteristics

Cluster	Definition
0	Niche markets, collectibles, and hobbies
1	Technology and electronics sector
2	Sports, active lifestyle, and outdoor equipment market
3	Cosmetics and personal care products
4	Food and beverage retailers and specialty goods
5	Luxury brands and high-end products
6	Home and lifestyle goods
7	Fashion, accessories, and products
8	Office, home appliances and furnishing

Each cluster, as revealed through the analysis of e-commerce data, symbolizes a specific segment, reflecting the varied characteristics and market dynamics in e-commerce. Now, evaluating the key numeric characteristics, found in Appendix V, of each cluster there are clear patterns that are well in line with the characteristics and segmentations. To begin with cluster 5, representing the luxury segment on average have a lower monthly search volume, which is in line with previous research on luxury consumers and their preference for in-store shopping (BOF Insights 2023). Similarly, the average price is also way above others, with only cluster 1 (technology) coming close. The opposite trend can be seen with cluster 1 where monthly search volume on average is the highest across all clusters. Analyzing key numeric attributes attest to the findings of the clusters and serve as a verification of the algorithms ability to correctly classify similar e-commerce operators.

5 Uncovering Underlying Dynamics Among Competitors in the Digital World

5.1. Background

The modern business environment has experienced a significant transformation due to the digital age. Previously, competition was primarily based on geographic proximity and similarities in products or services. However, the rise of online commerce and the importance of search engines have created a complex, digital competitive landscape. In this era, businesses not only vie for market share but also compete for visibility on search engine result pages (SERPs). This shift necessitates a more nuanced approach to identifying competitors, as traditional methods focused on product similarity or location fall short. The research presented aims to redefine competitor identification by recognizing the importance of understanding the competitive dynamics in the pursuit of visibility on SERPs, prompting the exploration of innovative approaches in this evolving landscape.

5.2. Problem

The digital age has transformed business competition, emphasizing the importance of visibility on search engine results pages (SERPs). Traditional methods, like keyword-based SEO analyses, struggle to capture the complexity of digital competition. Identifying competitors based solely on product similarity is no longer adequate, and the intricate relationships among businesses in the digital space are often overlooked. In response, the research proposes innovative approaches, such as Minimum Spanning Trees (MSTs) and network analysis, to redefine competitor identification and address the critical challenge of contemporary digital marketing and competition analysis.

5.3. Improving the accuracy and quality of competitors identification

This research seeks to develop a more precise and comprehensive method for identifying competitors. It aims to go beyond simplistic classifications based only on standard features. Instead, the goal is to provide businesses and digital marketers with a refined understanding of their competitive landscape, considering the complex interaction of digital elements. By doing so, its aims to equip professionals with the insights needed to improve their strategic decisions and optimize their digital marketing efforts.

5.4. Methodology

The analytical approach outlined in this section comprises two main steps. The first step involves creating numerical features at the domain level, derived from quantitative variables at the product level. Simultaneously, textual features are extracted using FastText to generate vector representations for each domain, capturing rich textual characteristics. Singular Value Decomposition (SVD) is then employed for dimensionality reduction, making the dataset manageable and informative.

The concept of Minimum Spanning Trees (MSTs) is introduced for network analysis, serving a crucial role in competitor mapping. MSTs offer a practical approach to unveil complex relationships among domains, distinguishing between direct and indirect competitors. This is especially vital in digital competition, where traditional methods struggle with intricate interdependencies. The discussion explores the significance of MSTs and their potential in interpreting competitive dynamics.

The combined use of FastText, SVD, and MSTs is deemed essential for a comprehensive understanding of competitive dynamics in the digital realm. These techniques enable the capture of both quantitative and textual characteristics, providing effective navigation through the complexities of modern digital competition.

5.5 Text embeddings and MST

In shaping our analytical approach, we place significant emphasis on leveraging text embeddings and Minimum Spanning Trees (MSTs) to gain nuanced insights into the digital competitive landscape.

5.5.1 Text Embeddings

Our approach involves utilizing FastText to extract rich textual features and generate embeddings. FastText's unique ability to consider subword information, treating words as bags of character n-grams, proves invaluable. This approach captures the intricate morphological structures and variations within short, informal texts—common characteristics in our dynamic dataset, which includes domain names and product descriptions.

5.5.2 Minimum Spanning Trees (MSTs) in Network Analysis

MSTs, drawn from graph theory, serve as a foundational tool in our network analysis. By connecting nodes (representing domains or entities) with the minimum total edge weight, MSTs simplify the intricate web of relationships into a more understandable structure. In the realm of digital competition, where traditional methods may fall short, MSTs offer a unique advantage. They enable us to distinguish between direct and indirect competitors, revealing the underlying structure of competitive relationships in a particularly relevant and insightful way.

5.5.3 Integration and Impact

The combination of text embeddings and MSTs forms a robust analytical framework. FastText allows us to represent domain-specific textual elements comprehensively, while MSTs distill complex relationships among domains, offering a clear delineation between direct and indirect competitors. This integrated approach equips us with a powerful means to navigate and understand the competitive dynamics within the digital space, contributing to a more informed and strategic analysis. In this way, we can create a rich representation of each company and build a correlation and distance matrix that can differentiate similar companies for later used to identify potential competitors across companies.

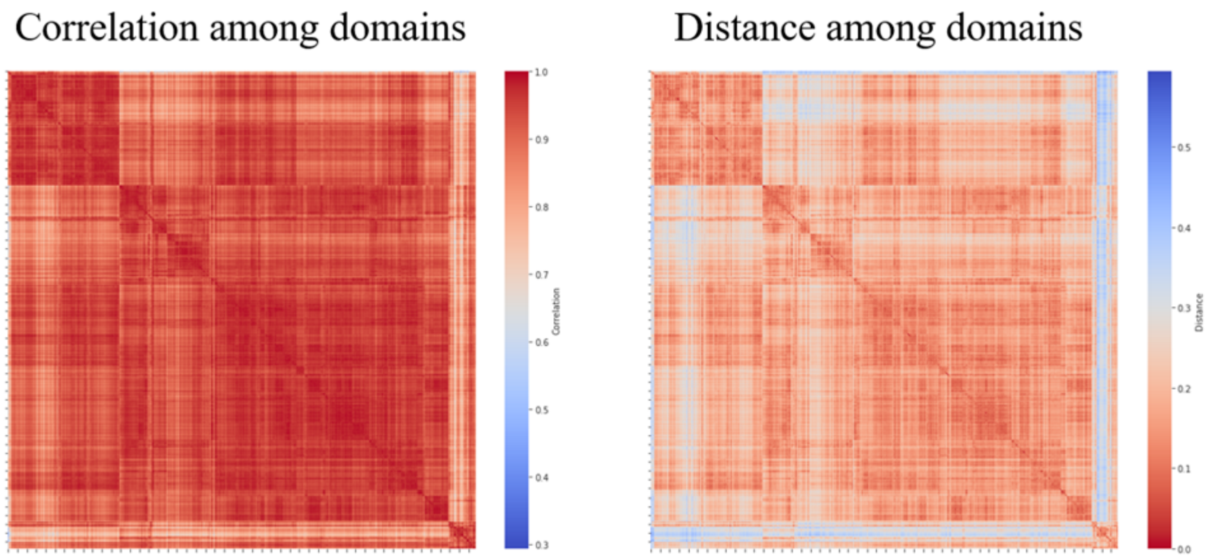


Figure 2 - Correlation vs. Distance Matrix among Domains

Note: Sample for the top 20k domains based on number of products available.

5.5.4 MST direct and indirect competitors

A deeper exploration of peer-to-peer dynamics becomes essential. To minimize the influence of irrelevant relationships between domains, we employ the shortest path algorithm (Mehlhorn and Sanders 2008) to avoid irrelevant connections among domains. This analysis helps to identify both direct and indirect competitors, significantly impacting strategic decision-making and marketing tactics. This analysis goes beyond the mere identification of competitors, shedding light on the intricate interactions that shape market dynamics. To exemplify the application of our findings, we use the prominent retail brand, Adidas. After reducing the number of connections through our previous analysis, we unveil a revealing structure of competitors. It is important to note that this approach let us discover direct and indirect competitors for different companies right away, further analyses should be considered whenever we need to have a deeper understanding of dynamics among them to polish better strategies.

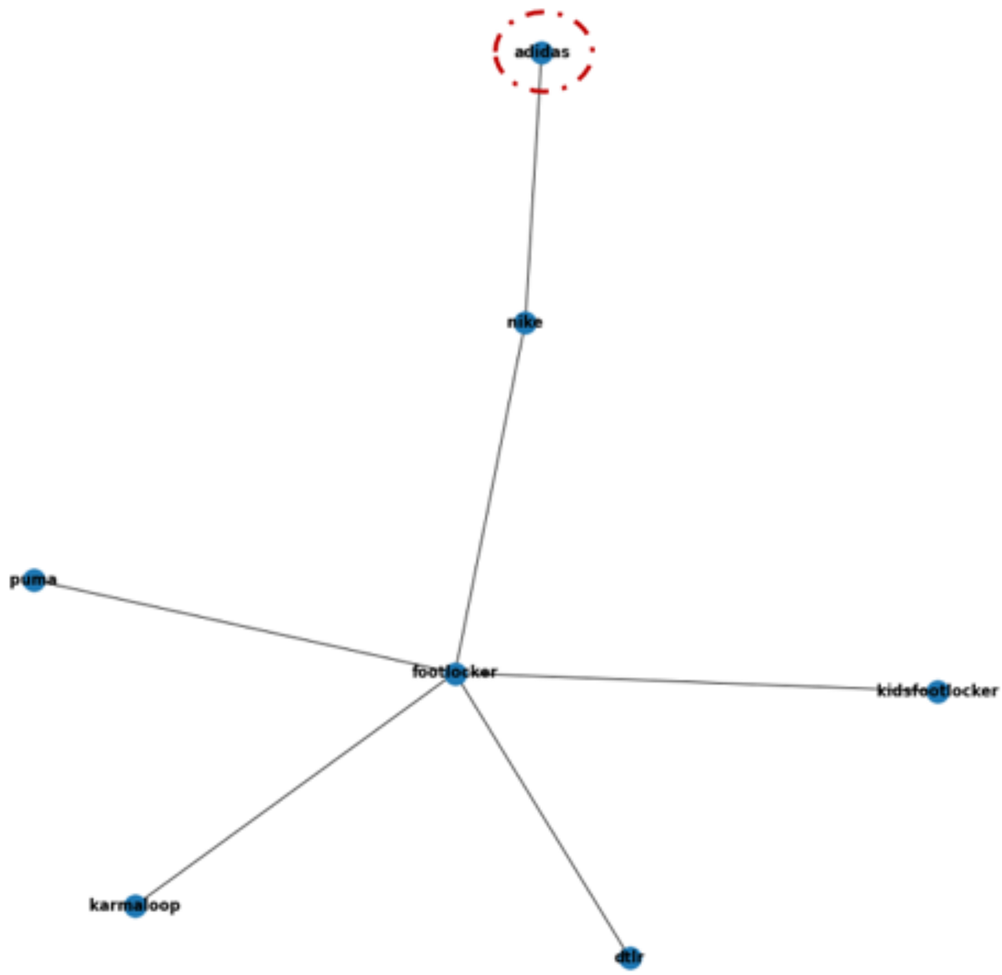


Figure 3 - Potential direct and indirect competitors for Adidas

Note: The target company is circled in red.

Some companies might look familiar right away when analyzing the competitors map for Adidas at first sight, while others might not be that familiar. To have a better understanding of why they are related in the digital world we could explore the semantic similarity behind direct and indirect competitors to understand why they are related in the digital or physical world.

6. Advertisement Poaching and Brand Dynamics in E-commerce

6.1 Introduction to Competitive Poaching in E-commerce

Building upon the robust clustering framework established in Section 4.3, which utilizes FastText and UMAP to categorize e-commerce platforms into distinct market niches, this section delves into the dynamics of competitive poaching within these clusters. As revealed through the findings, these clusters not only highlight direct competitors but also set the stage for understanding intricate competitive strategies such as advertisement poaching in the SEO landscape.

In the highly competitive landscape of e-commerce, the act of advertisement poaching, especially in the context of SEO, presents a distinct and significant challenge. E-commerce retailers use competitor names as keywords and backlinks to redirect traffic, resulting in complex patterns of influence and competitiveness within the network as identified in the clusters (referenced in Section A.4.1). This practice is both employed in organic SEO as well as Search Engine Marketing (SEM).

The subsequent sections will be structured as following. The first part of this paper will present findings on advertisement poaching within and across the previously defined clusters. This will allow the identification of players that engage in the strategy and how the occurrence of this changes across clusters. Furthermore, this research aims to observe the phenomenon's patterns through network analysis, focusing on establishing communities based on the frequency of advertisement poaching and comparing them to clusters identified in part 4.4.

6.2 Methodological Framework for Analyzing Advertisement Poaching

6.2.1 Data Collection on Retailer Keyword Usage

To investigate advertisement poaching in online retail, the frequency at which one retailer's name appears in another's keywords is analyzed. This is reflected in a dataset with variables such as *Retailer_From*, *Retailer_To*, *Cluster_From*, *Cluster_To*, and *Count*, illustrating instances of this practice. Specifically, it shows when a retailer (Retailer_To) uses another's name (Retailer_From) in their associated SEO keywords, with 'Count' denoting the frequency of these occurrences. This analysis sheds light on the competitive strategies in the digital marketplace, where retailers may use competitors' names within their SEO strategy to draw or redirect traffic to their sites. The subsequent analysis focuses on the prevalence of this phenomenon across different clusters, each representing a specific industry (refer to 4.1. for details on cluster-specific industries).

6.2.2 Filtering Criteria for Enhanced Data Accuracy

To enhance the accuracy of this investigation on advertisement poaching, a targeted filtering process was implemented. This approach specifically excludes domains where retailer names are ambiguous, serving both as product descriptors and keywords. This measure is crucial to ensure that the analysis accurately captures instances where retailers deliberately engage in advertisement poaching as a strategic SEO tactic, rather than accidental overlaps. Examples of excluded domains are provided in Appendix VI, ensuring a focus on deliberate strategies in competitive dynamics in e-commerce.

6.3 Quantitative Insights into Advertisement Poaching.

6.3.1 Comparative Analysis of Within-Cluster and Across-Cluster Poaching

A comprehensive analysis of advertisement poaching reveals significant insights into its prevalence both within and across the e-commerce clusters defined in Section 4.3. This practice, where retailers use the names of other retailers in their SEO strategies, varies in frequency and intensity depending on the cluster context and industry.

Within clusters, the investigation reveals a substantial occurrence of poaching. The resulting findings stem from 62,480 instances of poaching, with an average of 36 occurrences per instance. The standard deviation is at 316, indicating significant variation in the frequency of poaching within clusters. The range of occurrences spans from a minimum of 1 to a maximum of 21,634, underscoring some extreme cases of poaching within specific clusters.

In contrast, when looking *across different clusters*, 93,706 instances are observed, with a lower average count of 24.53 occurrences per instance. This suggests that while poaching is still prevalent across clusters, it happens less frequently on average compared to within clusters. The maximum count in across-cluster poaching, however, peaks at an even higher value of 39,736, indicating that in some cases, the extent of poaching across clusters can be significantly high. This result can be attributed to SEO practices of larger online marketplaces.

6.3.2 Notable Retailers in Poaching Dynamics

Exploring the details, some retailers are particularly notable when it comes to advertisement poaching. For instance, 'Apple' and 'Amazon' are the most frequently appearing names used by other retailers in their SEO strategies, with counts of 2,121 and 1,872 respectively as Retailer_From. On the other side, 'Amazon' appears to be the most common Retailer_To, involved in 4,696 instances of poaching, suggesting its significant prominence as a target in

SEO poaching strategies. Other notable mentions include 'Ebay', 'Walmart', and 'Sears', indicating their roles either as common targets or users of others' names.

6.3.4 Implications of the Findings

These findings indicate a strategic pattern in the use of competitors' names in SEO, reflecting a competitive landscape where retailers frequently resort to using the names and backlinks of more prominent or directly competing businesses to enhance their own visibility. The higher frequency of poaching within clusters could suggest a more intense competitive atmosphere among closely related retailers. Conversely, the lower average yet higher peak in across-cluster instances might reflect occasional but very aggressive strategies employed by retailers when targeting businesses outside their immediate cluster.

The significant presence of leading retailers like 'Apple' and 'Amazon' in these poaching activities, both as targets and perpetrators, highlights their centrality in the competitive dynamics of the retail market. This trend raises questions about the competitive implications of SEO strategies in digital marketing and indicates a need for a more detailed understanding of online competitive practices.

6.3.5 Prevalence of Poaching within E-Commerce Clusters

The analysis of within-cluster advertisement poaching practices uncovers differences in the choice of integrating the strategy in their SEO across industries. As shown by Figure X, clusters 1 and 6 exhibit the highest relative frequency of poaching, possibly indicating more aggressive SEO competition or larger market sizes in these industries. Examining individual clusters allows to gain insight into the strategic grounds of SEO techniques in different retail sectors.

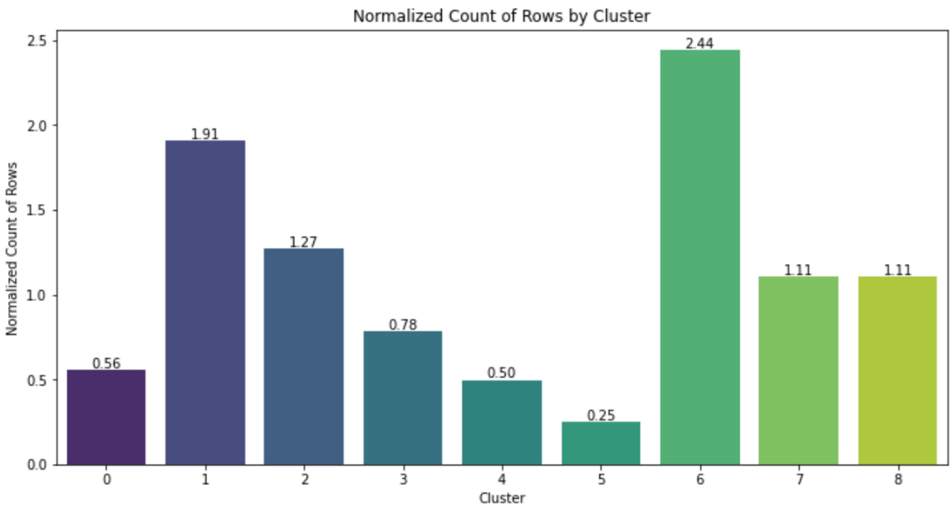


Figure 4: Counts of Advertisement Poaching by Cluster (normalized by cluster size)

Highly Competitive and Popular Sectors (Clusters 2, 3, 7, 1): In clusters related to sports and outdoor equipment, cosmetics, fashion, and technology, there's a significant trend of larger retailers like REI, Dick's Sporting Goods, Ulta, Sephora, RunRepeat, Nordstrom, B&H Photo Video, and Best Buy targeting well-known brands such as Vans, Oakley, Nike, Adidas, Clinique, and HP. This indicates a strategic focus on poaching from high-value, popular brands in highly competitive markets, reflecting the intense struggle for online dominance in these sectors.

Specialized and Niche Markets (Clusters 0, 5): Niche markets, collectibles, hobbies, and luxury brands (like Funko, Lego, Pandora, and Movado) are also prime targets for advertisement poaching. Retailers such as StockX, HotTopic, and BeCharming are leading the charge in these sectors, demonstrating a specific interest in capitalizing on the niche appeal and dedicated consumer bases of these brands.

Home, Lifestyle, and Everyday Goods (Clusters 6, 8, 4): In clusters dealing with home and lifestyle goods, home appliances, and food and beverage, the trend is towards poaching from a broader range of brands (e.g., KitchenAid, Frigidaire, Kroger, Tesco). Key players in poaching here include Amazon, eBay, and Jewel-Osco, pointing to a strategy of capturing traffic across a wide spectrum of everyday consumer products.

Overall, these findings highlight a landscape where larger retailers and online marketplaces are actively engaging in SEO poaching across various sectors. They tend to target both high-profile brands in competitive markets and specialized or niche brands, aiming to capitalize on their established market presence and dedicated customer bases. This underscores the importance of robust and defensive SEO strategies for brands across all sectors.

6.3.6 Implications of Cluster-Specific Poaching and Overall Trends

The detailed analysis of advertisement poaching within specific e-commerce clusters sheds light on the competitive dynamics and SEO strategies prevalent in different retail sectors. By assessing the brands that are commonly targeted for poaching, the investigation reveals insights into how retailers strategically leverage the brand equity of recognized names to their advantage. In each cluster, the prevalence of poaching highlights the importance of brand visibility and recognition in SEO strategies. For example, in technology and electronics, the focus on brands like 'HP' and 'Samsung' underlines the industry's reliance on brand reputation for attracting consumer interest. Similarly, in fashion and apparel, targeting brands like 'Nike' and 'Adidas' points to the competitive nature of the industry, where brand visibility is a key driver for consumer choices.

A pervasive trend observed across all clusters is the prominent role of online marketplaces and multi-brand retailers, often referred to as 'aggregators'. Considering the multitude terminologies employed for describing these types of retailers, this study will utilize the terms 'aggregators' and 'third-party resellers' synonymously. These entities, which offer a diverse array of brands under a single platform, consistently emerge as the most active in employing advertisement poaching strategies. This approach suggests that aggregators leverage the recognition and trust associated with established brand names not just for redirecting traffic, but also as a crucial element in enhancing their own SEO and market visibility. Their strategies indicate a keen understanding of the consumer's search behavior and the importance of brand association in the digital marketplace.

This analysis underscores the multifaceted nature of SEO strategies in the e-commerce sector, highlighting the intricate interplay between brand recognition, consumer behavior, and competitive positioning. It also raises questions about the ethical and strategic implications of such tactics in digital marketing, suggesting the need for ongoing scrutiny and adaptation of SEO practices in light of evolving market dynamics.

6.4 Network Analysis of Advertisement Poaching.

6.4.1 Methodology: Community Detection via Network Analysis

To investigate competitive dynamics of advertisement poaching among online retailers., network analysis is applied. This approach complements the FastText and UMAP clustering by providing a nuanced view of retailer interactions within these clusters. The network is visualized as a series of nodes (retailers) connected by weighted edges (indicating poaching counts), creating a bidirectional flow representing the dual role of retailers as perpetrators and victims of poaching. The networks complexity is underlined by the network's sparsity, quantified at approximately 0.000298 (for visual representation, see Appendix VII). This figure highlights the scarcity of direct connections relative to all potential connections, a state which significantly impacts algorithm choice for community detection. The chosen Community Infomap method is particularly effective for sparse networks, as it simulates the movement of information through random walks. This approach is detailed by Rosvall and Bergstrom 2008 and further emphasized by Fortunato (2010). The algorithm's effectiveness was quantitatively assessed using the Adjusted Rand Index (ARI), a measure of the similarity between two data clustering that accounts for chance groupings. An ARI of 1 suggests perfect correspondence, whereas 0 or below indicates random or discordant clustering.

6.4.2 Results and Interpretations from Network Analysis

Referencing the original clusters identified using FastText, embeddings, and UMAP in A.4.1, the network analysis via the Community Infomap algorithm illuminates the complexity and competitiveness of advertisement poaching. The obtained ARI for Cluster_From (0.5525) suggests a moderate correlation with the originally established clusters, implying a degree of consistency in the targets of advertisement poaching. In contrast, the lower ARI for Cluster_To (0.0250) reveals a broad spectrum of poaching strategies deployed by retailers, pointing to a more dispersed and individualistic set of tactics. Such divergence in ARI scores brings to light the intricate and multifaceted nature of advertisement poaching strategies within the competitive online retail sector.

The combination of network sparsity and bidirectional connections affects the detection of uniform poaching patterns. The impact of data filtering, aimed at eliminating ambiguity from commonly used keywords, also plays a role in these findings. Together, these factors highlight the dynamic and strategic nature of SEO poaching, underlining the complex interactions between the targets and initiators of these maneuvers within the retail sector.

6.5. Conclusion: Understanding the Network of Competitive Poaching

The examination of advertisement poaching within e-commerce has revealed a dynamic interplay of competitive strategies, with a pronounced role of aggregator retailers in the use of this practice. The investigation has uncovered the variance of poaching within and across different retail clusters, indicating industry-specific strategic approaches. The findings underscore the strategic application of competitor names in SEO campaigns, suggesting a more intense competitive environment within clusters and a diverse set of tactics across clusters. Notably, the prominence of certain retailers as frequent targets points to their centrality within the digital marketplace.

7. Graph Neural Networks in E-commerce

The primary objective of this section aims to develop a comprehensive framework for analyzing the competitive landscape in the e-commerce using a Graph Neural Network. The study starts by constructing a heterogenous graph that accurately represents several e-commerce entities such as domains, keywords, products, and categories, along with their interrelationships by relying on weighted edges which leverages relevant information regarding the given relations. The advent of Graph Neural Networks (GNNs) has opened new avenues for data analysis, particularly in understanding complex relationships within large datasets. In recent years, GNNs have become an important topic that rises interest among the research community, several papers are dedicated to effectively learn node embeddings over different graph-based representations. The neural network treats the underlying graph as a computation graph and generates individual node embeddings by passing, transforming, and aggregating node's features present in the given graph. Later, the generated embedding can be widely used to downstream tasks such as classification, recommendation, or prediction. **(**Li, Z., et al. 2020)**.**

7.1 FastText Training and Most Similar Method

The next step relied on training a FastText model which was developed by Facebook AI Research (Bojanowski et al., 2017) which is designed to efficiently learn word representations and sentence classification. FastText works by treating each word as a bag of character n-grams, allowing it to capture the meaning of shorter words and understand suffixes and prefixes, making it especially useful for processing text with misspellings or mixed languages. The model is a state-of-the-art word embedding technique that extends the Word2Vec model to incorporate subword information. This approach offers richer semantic representations as FastText generates embeddings that capture not just the semantic meaning of a word but also the meaning of subword units (n-grams). The model is also capable of handling occurrences of Out-of-Vocabulary (OOV) words unlike traditional word embeddings algorithms as Word2Vec by combining the embeddings of their subword units. This feature is relevant in the context of the dataset of this project as not only the vocabulary in products is constantly evolving but also there are specific words that aren't trivial for a usual vocabulary, such as brand or domains names.

The first step to train the model was to tokenize the text variables which previously were submitted to the process of stop word removal and lemmatization. Namely this step was done for the variables: domain, keyword, product and category. Then one model was trained for each of the variables. The FastText model was configured for 256, 128 and 64 features (or embedding dimensions). The final dimensionality was chosen to balance the richness of the representation in terms of performance levels, methodology to be detailed further on this paper, against the computational efficiency. A higher number of dimensions can capture more detailed semantic relationships but at the cost of increased computational complexity.

Specifically, for the variable keywords the FastText "most_similar" method was used, the core if this process was to leverage the function to identify similar words to every keyword in the dataset. A threshold of 0.8 was set to determine the degree of semantic closeness required for words to be considered in the graph structure, by setting it the focus were exclusively on words that had substantial degree of similarity ensuring relevance and accuracy on the words that will be connected on the graph. The choice of the threshold was done arbitrary based on the analysis of the output of the code to a significant number of keywords, it was observed that around this level there was a good balance of number of similar words and relevancy. The process resulted in a curated list of related words and their respective similarity score. The idea behind this feature was to enhance the graph structure which was not just structural but also conceptual, providing a more intricate and interconnected representation of keyword relationships as it is expected to allow further universal applications and enhances interpretability (Gerling, 2023).

7.3 Knowledge Graph Construction for E-Commerce Data

The initial phase of the methodology of this works involves constructing a graph that accurately represents the relationship of the variables within the dataset. This graph is not just a simple network but a heterogeneous one, meaning it includes multiple types of nodes and edges, each representing different entities and relationships. For this the Deep Graph Library (DGL) was used to build the bipartite graph whose nodes represents unique values for variables that represent components of the search engine keywords and its results as it excels in processing large-scale graph data and its optimized data structures and operations are specifically designed for graph neural networks. The total number of nodes is 4.5 million and they are divided as: 2.5 million nodes represent unique keywords, 80.1 thousand related words, 20.2 thousand domains, 8 thousand categories and 1.9 million products. Each node is enriched with a n-dimension vector build from the correspondent previously trained FastText models. These embeddings capture the semantic essence of the text variable represented by the nodes providing a rich representation of its meaning. The nodes were then connected by weighted edges which translates various types of relationships and interactions among the nodes, examples include 'belongs to' relationships (linking products to categories), 'connects to' (associating keywords with domains or products), and other relevant e-commerce interactions. To encapsulate the strength and nature of the relationships, edges were assigned weights based on metrics like cost per click, number of impressions and monthly search volume. These weights play a crucial role in the analysis, as they quantify the intensity and significance of the connections within the network. By leveraging DGL's capabilities to handle heterogeneous graphs and enriching the node and edge representations with relevant features and weights, a detailed and nuanced graph of the e-commerce domain was created. This graph serves as the backbone of the analysis, enabling a deep dive into the complex web of relationships that define the competitive landscape in e-commerce.

Then, once the representations are available the use of GNNs is enabled. The idea is to create a embedding of the network structure that translates the competitive landscape at domain and keyword level. These embeddings will make possible downstream tasks to competitor retrieval and keyword recommendations for better SEO management. The evaluation of the tasks will be further described on section D of this paper.

7.4 Cluster Analysis

Cluster analysis was conducted to the embeddings generated out the GNN model for the domain’s nodes to distinct the competitive categories aiming to uncover underlying structures and relationships within the e-commerce landscape. For this purpose, the k-means algorithm was chosen for the task. This algorithm partitions the nodes into k clusters in which each node belongs to the cluster with the nearest mean, the algorithm was chosen due to its efficiency and effectiveness in handling large datasets, it is notably well-suited for grouping data points, domains embeddings in this particular case. There are a few methods for determining the optimal number of clusters in a given dataset, for this step the elbow method and silhouette analysis were performed. The elbow method consists in plotting the explained variance as a function of the number of clusters and choosing the elbow of the curve as the number of clusters to use. The elbow point represents where the marginal gain in explained variance begins to diminish, indicating an optimal cluster count. To obtain additional validation to the number of clusters obtained the silhouette analysis comes handy, it measures how similar an object is to its own cluster compared to other clusters. A high silhouette score indicates that the object is well matched to its own cluster and poorly matched to neighboring clusters. After evaluation, the number of clusters were set to 3 (k = 3).

The subsequent cluster analysis, leveraging K-means clustering and validated through the elbow and silhouette methods, segmented specifically the domains embeddings generated with the GNN architecture into distinct groups. This segmentation enabled the development of a method to be described further on this report to understand of how different domains interact and compete in this space.

7.5 Top-N Recommendation Algorithm

An algorithm was created to address the goal of retrieving the most related nodes to within its type, which translates to the understanding which nodes can be considered competitors to a given vertices for the domain use case, or which are the most similar keywords in terms of graph structure and node centrality when that is the node type inserted in the analysis. The algorithm employs the embeddings generated from the GNN to compute similarity scores and identify the most relevant embeddings related to the node of analysis.

For evaluation purposes, the algorithm applied to the domain’s nodes required an initial step involving the creation of a mapping between domains and their associated keywords, what will enable the notion of the shared portion of a retailer’s keyword portfolio to the competitor recommended by the algorithm. For the case of keywords, the metric suffered a slight change, the whole list of domains for a specific keyword was treated as the portfolio for that entry and the shared portion computed.

The algorithm starts by iterating to each of the node out of all of its type to retrieve its embedding. Cosine similarity is then computed between the nodes and all the nodes in the set. The cosine similarity measurement captures the degree of resemblance between the nodes in the multidimensional embedding space of the graph structure. For the additional layer of analysis, the algorithm measures the portion of shared keywords or domains, depending on the use case. The output of the algorithm is a comprehensive dataset of records about the nodes of analysis, including information such as the node, its top related nodes, similarity scores, combined scores and the overlap metrics.

The Top-N Recommendation Algorithm is a sophisticated tool in the arsenal of e-commerce competitive analysis. By integrating advanced machine learning techniques with traditional competitive analysis metrics, it provides a nuanced understanding of the competitive landscape and is able to provide recommendations for keyword bidding strategy. The algorithm's focus on cosine similarity ant is supplemented by keyword overlap analysis, offers a multi-dimensional view of the landscape.

8. Limitations

During this research, many constraints within the provided dataset and methodology were identified that are crucial to acknowledge. In the first place, the dataset utilized has limitations pertaining to the data. There is a significant lack of uniformity across many domains and brands. The inconsistency primarily arises from the precision of web scraping, as being the basis of Grips methodology (Grips 2023). These inconsistencies provide interference during the process of training the algorithm, despite that attempts have been made to reduce the impact of unusual data and limited data from specific domains.

Moreover, the assessment of the results generated by the algorithms presents substantial difficulties. An important concern revolves around the ambiguous delineation of 'competition,' which can significantly differ depending on the context. It is crucial to recognize that the notion of 'competition' in this context is subjective and can vary considerably among individuals. Moreover, the lack of true labels limits an accurate assessment of the algorithms' performance.

Additionally, when it comes to analyzing data in the field of e-commerce, it is crucial to consider various inherent restrictions. The dataset, obtained from numerous e-commerce operators, offers a fixed representation of specific domains rather than up-to-date, dynamic data appropriate for comparison analysis. The data quality in these multiple domains varies, which may introduce additional noise to the computational models. The variability in data quality is closely related to the reliability of online scraping techniques (Grips 2023).

Furthermore, the ever-changing nature of Search Engine Result Pages (SERPs), which adapt based on different domain features as of 2023, introduces an additional level of complexity to the analysis. The rapid evolution of both specific fields and combined sets of data presents a difficulty in continuously assessing the quality and uniformity of the results. The rapid and dynamic nature of this change not only makes it challenging to consistently evaluate existing models, but also makes it difficult to assess any enhancements that may arise from algorithmic adjustments.

9. General Discussion & Conclusion

The initial approach allowed the identification of competitors under different definitions and methodologies. It has been shown that the identification of competitors is possible based on similarities using clustering and network analysis techniques. Both methodologies will dig deeper into different nuances that can be used to assess and craft better strategies for different companies and their positioning in the Search Engine Ranking

The research found a dynamic interplay in advertisement poaching among e-commerce competitors, heavily influenced by aggregator retailers. It identified industry-specific poaching tactics within and across different retail clusters. The use of competitor names in SEO campaigns suggested intense competition within clusters and varied tactics across them. Notably, frequent targeting of certain retailers indicated their market centrality. Network analysis using Community Infomap algorithm, referencing original clusters from FastText embeddings and UMAP, showed moderate to diverse advertisement poaching strategies, with varying ARI scores indicating complexity and individualistic tactics in the online retail sector. This complexity is further highlighted by the impact of network sparsity, bidirectional connections, and data filtering on the detection of poaching patterns, underscoring the strategic nature of SEO poaching.

As a final step, the study explores an innovative approach to leverage the creation of knowledge graphs and Graph Neural networks to address the proposal of this research. The methodology proposes to combine the structural features of the graph into single embeddings which can be used not only to retrieve competitors, but also to recommend keywords for better management of advertising strategies.

In addressing the research question 'How does competition among online retailers emerge in the dynamics derived from organic search engine optimization?', this study comprehensively demonstrates that the intricacies of SEO metrics, such as keyword usage, search volume, and domain interaction patterns, are pivotal in unveiling the competitive landscape of online retail. It extends beyond the confines of advertisement poaching to explore how these SEO dynamics facilitate the identification of both direct and indirect competitors. By delving into the complex interplay of these metrics, the research sheds light on the strategic maneuvers employed by online retailers to gain an edge in a highly competitive digital marketplace. The findings underscore the multifaceted nature of e-commerce competition, where SEO proficiency not only influences visibility but also defines the contours of rivalry in the online domain.

A. Defining the E-commerce Dynamics Through the Identification of Direct and Indirect Competitors

A.1. Introduction: The E-commerce Landscape and the Necessity of Competitor Identification

In recent years, the e-commerce landscape has undergone seismic changes, expanding enormously in both breadth and scale, with expected growth of ~30% globally by 2026 (Statista 2022). E-commerce is no longer relegated to the outskirts of the retail sector; it has become an essential borderless component of the global economic system. This is an evolution spurred by the convergence of technological advancements – enabling even the smallest enterprises to be born global (Manyika, et al. 2016). The shift is mainly driven by changes in customer behavior and massive advances in tech and data (Arora, et al. 2022). The extraordinary circumstances caused by global events such as the COVID-19 pandemic have further propelled the adoption of online commerce, compelling businesses of all sizes to rethink their strategy and strengthen their online presence (Sirimanne 2021). (Briedis, Kronschnabl og Rodriguez 2020) (Morgan Stanley 2022)

This vibrant digital marketplace is providing great opportunities, but it is a challenging environment in constant change, where time preference is shorter than ever. Businesses originate and evolve at an incredible rate, with barriers-to-entry significantly lower than traditional brick-and-mortar companies (Xero u.d.). This constant state of flux creates an environment in which recognizing one's market position becomes critical (Grewal, Roggeveen og Nordfält 2017). Furthermore, because e-commerce is digital, it allows for rapid modifications, allowing businesses to modify strategy on the fly in reaction to evolving market dynamics (Verlhoef, Kannan og Inman 2015). As a result, unlike traditional marketplaces, where changes are more gradual, e-commerce is in constant motion, necessitating agility.

In the midst of this, competitor identification becomes increasingly important. Understanding competitors in a crowded market entails not only recognizing risks, but also uncovering opportunities. When a company can identify its direct and indirect competitors, it can:

1. **Benchmark performance:** Companies can utilize the vast arrays of existing data to compare against peers and thereby uncover direct improvement opportunities in pricing, products, marketing, and much more. (Smith 2022)
2. **Anticipate market moves:** Businesses can respond to or change their strategy by monitoring competitors' actions, whether they are product launches, marketing initiatives, or strategic partnerships.
3. **Identify market gaps:** Businesses can identify unmet customer demands and innovate to fill those gaps by examining the products and services supplied by competitors.
4. **Optimize marketing and ad spending:** Businesses that gain knowledge of their competitors' marketing methods can better deploy their ad spending, targeting niches that their competitors have missed.
5. **Refine product offerings:** Businesses can better cater to customer needs by understanding the strengths and weaknesses of competitors.

Traditional ways of identifying competitors, which rely on manual processes, small datasets, or simple criteria, are not well-suited to handle the complexity of the e-commerce ecosystem (Kumar og Reinartz 2012). Because of the huge amount of data, the intricate interplay of numerous variables (from product listings to keywords), and the speed with which market changes occur, a more sophisticated, data-driven approach is required (Henke, et al. 2016). This is where cutting-edge strategies, such as those described earlier in this report, come into play, utilizing powerful machine learning techniques to condense the intricacies of the digital marketplace into usable insights.

Progressing through this report, the complexities of these approaches will be investigated, demonstrating their effectiveness in navigating the e-commerce world. The goal is to understand not just the "who" of competitors, but also the "why" and "how" - why specific domains emerge as competitors and how they affect one's market strategy.

A.2. Theoretical Framework and Significance of NLP Techniques

Natural Language Processing (NLP) stands at the intersection of computational linguistics and artificial intelligence, aiming to facilitate machine comprehension, interpretation, and generation of human language. Drawing from linguistics, computer science, and cognitive psychology, NLP's primary ambition is to harmonize human communication with machine understanding (Bird, Klein og Loper 2009).

A.2.1. The Relevance and Rise of NLP in E-commerce

NLP has numerous possible uses in e-commerce, some of which are described below:

1. **Identifying Competitors:** NLP can parse massive volumes of textual data to discover competitors based on parameters like brands, products, keywords, or services. This data-driven strategy assists firms in identifying both direct and indirect competitors, allowing them to strategize successfully.
2. **Keyword Optimization:** NLP can discover trending keywords and search queries by evaluating real market data. E-commerce platforms can use this data to improve the visibility and searchability of their content.

3. **Content Curation and Strategy:** NLP can extract patterns, topics, and interests from massive databases. This knowledge can be used to influence product and content strategy, assuring relevancy and engagement.
4. **Understanding User Sentiment:** Businesses can extract information from products, reviews, comments, and social media mentions using NLP to determine customer sentiment. This knowledge aids in the refinement of product strategy and the fast resolution of any issues.

A.2.2. Significance of NLP Techniques in Competitor Identification

Using NLP to identify competitors provides a revolutionary advantage over traditional techniques. Here's how the strategy applies NLP's fundamental competencies:

1. **Deep Embeddings for Semantic Analysis:** Traditional approaches frequently stop at surface-level keyword matches. However, the approach, which makes use of FastText and Word2Vec, delves into the complex domain of semantic analysis. It is not only necessary to recognize identical terms, but also to comprehend their contextual meanings. This ensures that semantic similarities and discrepancies are captured even if two e-commerce domains utilize different terminology for their products or SEO efforts. This in-depth knowledge aids in accurately recognizing competitors based on the underlying information of their products, rather than simply lexical matches.
2. **Topic Modeling and Market Trend Identification:** NLP is used to sift through textual data to identify latent themes or subjects. This topic modeling is critical for identifying broader storylines in e-commerce. Businesses can obtain insights into industry trends, prospective niches, or even oversaturated areas by identifying what themes competitors are focused on.

3. **Extraction of Relationships for Comprehensive Market Views:** Beyond individual competitors, the market's web of inter-relationships provides a comprehensive view. The technique deciphers these complex interactions using NLP. Understanding these relationships provides e-commerce operators with a broad range of beneficial opportunities. For instance, it allows to strategize more effectively, optimize keywords amongst competitors to better target customers, identify potential product niches that are not yet popularized, and identify direct and indirect competitors, which enable a more complete understanding of the market and the key performance factors.

The competitor identification process not only simplifies the intricacies of the e-commerce industry but also gives deeper, more actionable insights by going beyond traditional analysis. Businesses may proactively navigate the digital marketplace by harnessing the depth and breadth of insights provided by NLP, assuring resilience and growth in a dynamic environment.

A.3. Unveiling Competitors: Methodology and Approach

Identifying competitors in the difficult terrain of e-commerce necessitates a complex blend of natural language processing and data transformation techniques. This section explains the unique process, which combines the capabilities of PCA-reduced Word2Vec embeddings, aggregated numeric attributes for each domain, and Cosine Similarity to identify top direct and indirect within-cluster competitors for each domain in the dataset.

A.3.1. Precision through Word2Vec and Cosine Similarity

Previously the groundwork was laid by clustering the e-commerce space, thus mapping out the expansive competitive landscape. By identifying top direct and indirect competitors inside these clusters, deeper insights into the subtleties of competition can be identified. This approach has been developed to distinguish and characterize the intricate web of competitive relationships with more sensitivity by leveraging the deep semantic understanding of Word2Vec and the precision of Cosine Similarity.

A.3.1.1. Word2Vec: Delving Deeper with Contextual Embeddings

Word2Vec, an innovative word embedding method developed by the team at Google, presents words as vectors of numbers. Its key advantage lies in its ability to capture semantic relationships based on the context in which words appear:

1. **Contextual Awareness:** Unlike FastText, which considers morphological nuances (Bojanowski, Joulin og Mikolov 2016), Word2Vec emphasizes contextual relationships (Mikolov, et al. 2013). This is vital when trying to understand the subtle differences between domains within a cluster, where context might differentiate competitors from non-competitors.
2. **Embedding Creation:** Product titles, keywords, and categories for all domains are encoded into embeddings using Word2Vec. This approach ensures a deep semantic understanding, focusing on the contextual relationships between words in each variable.
3. **PCA for Dimensionality Reduction:** The richness of Word2Vec embeddings is undeniable, but their high dimensionality can pose challenges, especially when it comes to computational efficiency. PCA stands out as a solution to these challenges. By transforming the original data into a new coordinate system where the basis vectors align with the directions of maximum variance, PCA condenses the information into fewer dimensions. It prioritizes components that explain the most variance, ensuring that the essence of the data is captured even in its reduced form. This facilitates a clearer understanding of data relationships. (Jolliffe og Cadima 2016)

In essence, the PCA-reduced Word2Vec embedding provide a sophisticated mechanism for deciphering the complex semantic web within the e-commerce scene. This methodology not only improves competitor identification precision, but it also delivers deeper insights into the small but critical differentiators in a highly competitive digital industry.

A.3.1.2. Cosine Similarity: Identifying Close Competitors

Cosine Similarity is a similarity measurement that can be used to evaluate the similarity of two vectors. In this context, it provides a metric for the semantic closeness of domains, as a measurement of their overall similarity:

1. **Creating the Final Embedding:** Numeric attributes that have previously been scaled via Min-Max scaling are combined with PCA-reduced Word2Vec embeddings. This final embedding represents a thorough representation that includes both numerical and contextual domain features – allowing for a complete picture of domain similarity.
2. **Computing Similarity within Clusters:** Cosine similarities between domains are computed within each UMAP-defined cluster. Examining these data reveals domains that are not just in the same cluster but also semantically near, indicating it as a potential competitor based on key selected features. To avoid insignificant competitors, competition is only classified if cosine-similarity is above 0.8 and restricting outputted list of competition to at most ten domains.
3. **Unraveling indirect competition:** Beyond this, the sophisticated algorithms further delve into these relations, uncovering a web of indirect competitors. By cross-referencing the competitors of each domain and filtering out those with less than 0.9 in cosine-similarity the full competitive network is effectively mapped. This approach ensures the understanding of the direct competition, while also granting the opportunity to dive into the web of indirect competition. An understanding of both direct and indirect

competition not only broadens one's understanding of the complexity of the e-commerce industry, but also provides operators with insights into strategic alignment, market positioning, and possible areas for innovation. Businesses can foresee market trends, adjust to growing customer needs, and uncover possibilities for differentiation by studying the mechanics of indirect competition, eventually fostering a proactive rather than reactive approach to market difficulties.

Identifying competitors within clusters involves the use of technologies that provide both semantic depth and precision. This is accomplished by the combination of PCA-reduced Word2Vec embeddings, aggregated domain-specific numeric attributes, and Cosine Similarity, which allows firms to pinpoint competitors with more accuracy. This strategy not only distinguishes competitors, but it also gives information that can be used to guide product strategies, pricing decisions, and marketing campaigns.

A.3.2 Synergizing techniques: The Strategic Integration of FastText and Word2Vec

In the preceding section clusters within the e-commerce space was discovered through the strategic use of SVD-reduced FastText embeddings in conjunction with aggregated numerical attributes for each domain, which were processed via UMAP. This combination expertly blends the richness of textual data with the objectivity of numerical measures, allowing us to discover different market clusters as well as larger competitor categories. This stage's clusters provide a macroscopic perspective of the e-commerce world, grouping comparable domains.

As the analysis progresses to the second phase, it gets more focused. In this section, the previously formed clusters is used to investigate within-cluster competitors. To acquire a more comprehensive picture of direct and indirect competition within each cluster, this stage leverages PCA-reduced Word2Vec embeddings, supplemented once more with aggregated numerical attributes. The use of Word2Vec enables a more in-depth investigation of contextual similarities between domains, improving the ability to determine not just who the competitors are, but also how closely they align in terms of product offering, market strategies, and client targeting.

This two-step technique ensures a thorough understanding of e-commerce competition dynamics. The clustering phase lays the basis by mapping out the larger competitive environment. Subsequently, the focus on within-cluster competition provides detailed insights into direct and indirect competitors, revealing the intricate web of competition that each domain is a part of. Businesses can gain a strategic edge by discovering these correlations, allowing them to customize their strategy to the complexities of their individual market sectors and competitor profiles.

A.4. Insights and Findings: Translating Technique to Business Intelligence

As powerful as data analytics techniques are, their value is only accentuated when translated into actionable business intelligence. The complicated web of competitors is highlighted, both direct and indirect, by using Word2Vec within the defined clusters. These insights provide e-commerce operators with an in-depth overview of their competitive landscape, as well as practical tactics for navigating and growing in the digital marketplace.

A.4.1. Delving into Competitor Identifications

After laying out the vast e-commerce terrain, it's essential to zoom in and focus on the micro-level intricacies that shape a business's immediate environment. Here, the identification of competitors plays a pivotal role. But understanding who your competitors are is only half the battle; the other half is recognizing the depth and nuances of this competition. First, an investigation of the direct relationship and the existing overlap between domains and their recognized competitors will be put forward:

Table 4.1.1

Summary statistics amongst top three competitors for Callaway, Footlocker, and Staples

Domain	Competitor Domain	Cat. Overlap %	Keyword. Overlap %	Prod. Overlap %
callawaygolf	cobragolf	83.3%	30.8%	30.4%
callawaygolf	maplehillgolf	100.0%	63.1%	66.1%
callawaygolf	americangolf	100.0%	67.7%	60.1%
footlocker	puma	100.0%	31.2%	26.0%
footlocker	ycmc	75.0%	34.6%	32.3%
footlocker	hibbett	100.0%	61.2%	62.5%
staples	officedepot	90.4%	73.7%	54.1%
staples	barcodesinc	30.1%	13.2%	9.3%
staples	office-partner	26.0%	22.7%	17.1%

The significant cross-domain category overlap shows that many e-commerce businesses target similar market niches. *callawaygolf*, for example, has a 100% category overlap with both *maplehillgolf* and *americangolf*, signifying significant direct competition. Such high levels of overlap highlight the necessity of differentiation in other areas. The variance in keyword overlaps among domains, on the other hand, indicates potential different marketing or SEO techniques. While certain domains, such as *footlocker* and *puma*, have a high level of category overlap, their keyword divergence implies that they are using different techniques to reach their target audience.

Close connection between keyword and product overlaps shows a strategic alignment between marketing activities and product offerings. However, differences in these overlaps, such as the one seen between *staples* and *officedepot*, reveal chances for differentiation and market expansion. While this analysis provides insight into direct overlap, the advanced competitor identification utilizing Natural Language Processing (NLP) goes much beyond these characteristics. NLP allows for a more detailed understanding of the various relationships and distinctions between competitors, putting light on small, but potentially influential, dynamics.

Finally, as indicated by domain overlaps, the e-commerce competitive landscape is multidimensional. While numerous businesses compete in similar categories, their disparate methods to keyword targeting and product offerings create a complex web of direct and indirect competition. Following this examination, the research will go deeper into the direct and indirect rivals identified by the computational approach. This second investigation will provide a more detailed insight of competitive dynamics and prospective market leadership tactics by identifying common keywords and products among competitors, both direct and indirect. An illustration for *callawaygolf* is provided below to demonstrate how the approach identifies both direct and indirect competitors in a 'competitor web'.

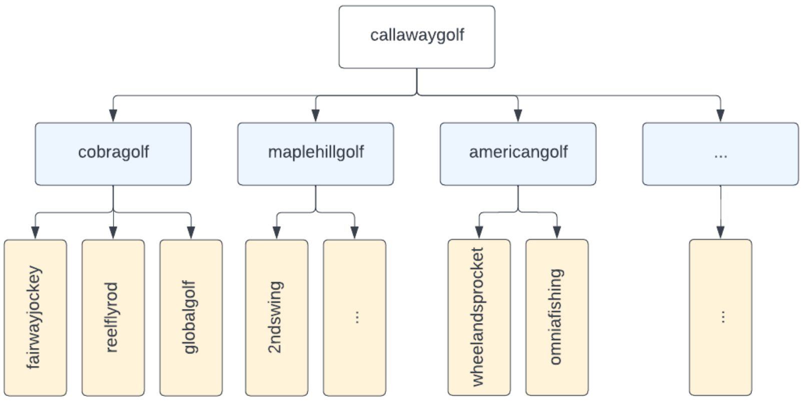


Figure 4.1.1: callawaygolf competitor tree

The use of dendrograms in this study allows for a more sophisticated analysis of market segmentation and the proximity of competitors in e-commerce. This methodology is demonstrated through an in-depth evaluation of three e-commerce operators: *callawaygolf*, *staples*, and *footlocker*, as well as their top three competitors. The analysis demonstrates that *callawaygolf's* close placement to competitors such as *maplehillgolf* and *americangolf* suggests a shared customer base, highlighting the importance of brand differentiation initiatives. Similarly, the proximity of *footlocker* to *ycmc* and *puma* underlines the presence of a strongly competitive environment, demanding specific marketing techniques to obtain an advantage. In contrast to these patterns, *staples* has a close competitive proximity to *officedepot*, indicating a highly competitive area that may demand strategic differentiation. This contrasts with the relatively distant connection to *barcodesinc*, which could imply that *staples* have room to maneuver and develop within the market. Thus, the strategic use of dendrogram analysis provides e-commerce operators with a tool for effectively aligning their market strategy, addressing both the immediate competition landscape and broader market trends.

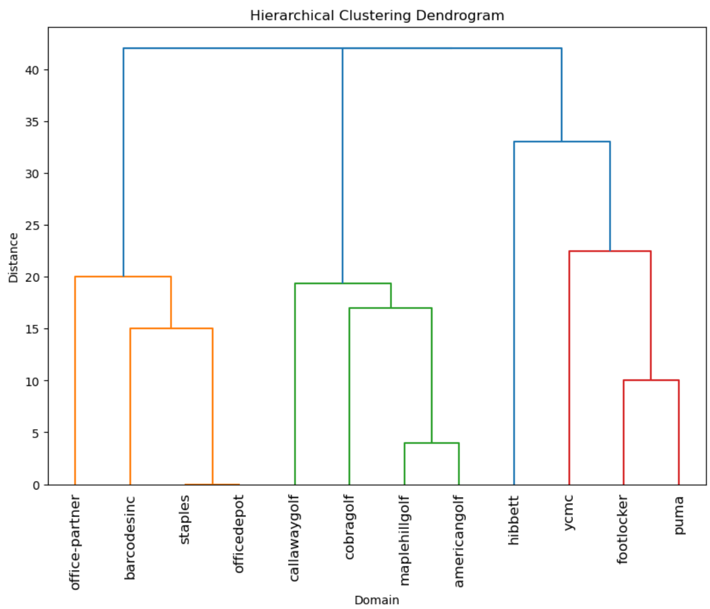


Figure 4.1.2: dendrogram for callawaygolf, staples, footlocker, and top three competitors

To further grasp this web of competition, lets evaluate the most important semantics behind *callawaygolf's* direct and indirect competitors. This analysis seeks to comprehend competitors' strategies to provide an overview of keywords, items, and categories that influence the presence of competition.

Table 4.1.2

Semantics behind competition for Callaway, Top-N words

Keywords	Products	Categories
wood	wood	outdoor
stratum	stratum	golf
hybrid	16piece	recreation
men	hybrid	sporting
bertha	men	club
diamond	bertha	good
complete	lab	
fairway	face	
bag	complete	

To summarize the findings, the e-commerce competitive landscape is profoundly affected by both direct and indirect competitors. The technique used decipher the various methods and elements used by each retailer by combining modern analytical approaches with NLP and multimodal data. Direct competitors, defined by their immediate overlaps in categories, items, and keywords, highlight the market's immediate competition. Understanding their dynamics is critical for survival. However, indirect competitors have more nuanced influences. Even if they do not directly compete for the same product offerings or keywords, their strategies have a substantial impact on market dynamics. It is critical to identify and interpret these indirect tactics for long-term success and carving out a dominant market niche. Finally, understanding both direct and indirect competitors provides a comprehensive view of the digital competitive landscape, providing firms with the strategic acumen required to thrive in the ever-changing e-commerce industry.

A.5. Navigating Ahead: Conclusions, Pitfalls, and Horizons

This study used innovative methods to identify within-cluster competitors in the e-commerce space. Utilizing the defined clusters, the web of direct and indirect competition was defined using PCA-reduced Word2Vec embeddings and cosine similarity. This approach has unearthed some critical insights to aid in strategic decision-making and e-commerce success:

- Created a simple and informative way of identifying both direct and indirect within-cluster competitors.
- Provided e-commerce operators a way to retrieve a deeper and more meaningful understanding of the dynamics and how to succeed, differentiate, and gain market share within their respective category and niche (cluster).

The utilization of PCA-reduced Word2Vec embeddings and cosine similarity in the analysis of e-commerce competitors possesses the capacity to significantly alter the dynamics of the market. The provision of a detailed perspective on the competitive environment empowers organizations to proactively adapt to shifts in the market, consequently upsetting established market norms. By adopting a strategic positioning and differentiated marketing approach, it enables e-commerce operators to compete with established firms. This is consistent with the disruptive innovation theory as described in Christensen's seminal work, ‘The Innovator’s Dilemma: When New Technologies Cause Great Firms to Fail’ (Christensen 1997).

In a practical sense, these findings provide actionable intelligence for e-commerce operators. By conducting competitor network mapping, organizations can enhance their ability to target specific market segments, optimize their marketing spending, and customize their product offerings. These tactics align with the data-driven marketing methodologies emphasized by Kotler and Keller as critical for modern businesses to succeed (Kotler og Keller 2016).

The adoption of these insights has the potential to revolutionize competitive strategies, cultivating a market atmosphere in which the ability to adjust and comprehend data are not only beneficial but critical for ongoing operations and growth.

Following on the positive findings it is further possible to enhance these by implementing the following recommendations:

- Implementing Siamese networks can improve domain comparison by capitalizing on their expertise in detecting small differences, paving the path for more nuanced competitor differentiation within e-commerce.
- Consider using semi-supervised learning in conjunction with accumulated data to fine-tune competitor classifications. With more labeled data, the model may make more informed predictions, focusing on the subtle differences that distinguish direct from indirect competitors.
- Utilize the identified competitive clusters to optimize search engine marketing strategy through a recommender system based on advertisement poaching.

Bibliography

Bojanowski, Piotr, Armand Joulin, and Tomas Mikolov. 2016. *Meta.* August 18. https://research.facebook.com/blog/2016/8/fasttext/.

Statista. 2022. *Statista.* September 21. https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales/.

Briedis, Holly, Anne Kronschnabl, and Alex Rodriguez. 2020. *McKinsey & Company.* May 14. https://www.mckinsey.com/industries/retail/our-insights/adapting-to-the-next-normal-in-retail-the-customer-experience-imperative.

Xero. n.d. *Xero.* https://www.xero.com/hk/reports/online-vs-bricks-and-mortar-business/.

Morgan Stanley. 2022. *Morgan Stanley.* June 14. https://www.morganstanley.com/ideas/global-ecommerce-growth-forecast-2022.

Manyika, James, Susan Lund, Jacques Bughin, Jonathan Woetzel, Kalin Stamenov, and Dhruv Dhing. 2016. *McKinseya.* February 14. https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/digital-globalization-the-new-era-of-global-flows.

Sirimanne, Shamika N. 2021. *UNCTAD.* March 11. https://unctad.org/system/files/official-document/dtlstict2020d13_en_0.pdf.

Grewal, Dhruv, Anne L Roggeveen, and Jens Nordfält. 2017. *The Future of Retailing.* Journal of Retailing.

Verlhoef, Peter C, P.K. Kannan, and Jeffrey J Inman. 2015. *From Multi-Channel Retailing to Omni-Channel Retailing: Introduction to the Special Issue on Multi-Channel Retailing.* Journal of Retailing.

Smith, Jess. 2022. *Meltwater.* March 17. https://www.meltwater.com/en/blog/competitor-benchmarking-what-it-is-and-why-it-is-important.

Kumar, V, and Werner Reinartz. 2012. *Customer Relationship Management: Concept, Strategy, and Tools.* Springer.

Henke, Nicolaus, Jacques Bughin, Michael Chui, James Manyika, Tamim Saleh, Bill Wiseman, and Guru Sethupathy. 2016. *McKinsey & Company.* December 7. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-age-of-analytics-competing-in-a-data-driven-world.

Mikolov, Tomas, Ilya Sutskever, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. "Distributed Representations of Words and Phrases and their Compositionality."

Jolliffe, Ian T, and Jorge Cadima. 2016. "Principal component analysis: a review and recent developments."

Arora, Arun, Roberto Longo, Candace Lun Plotkin , Tatiana Sivaeva , and Kevin Wei Wang. 2022. *Becoming indispensable: Moving past e-commerce to NeXT commerce.* McKinsey & Company.

Bird, Steven, Ewan Klein, and Edward Loper. 2009. *Natural Language Processing with Python.* O'Reilly Media, Inc.

Mehlhorn, Kurt, and Peter Sanders. 2008. "Shortest paths." In *Algorithms and Data Structures: The Basic Toolbox*, by Kurt and Sanders, Peter Mehlhorn, 191-215. Springer.

BOF Insights. 2023. *The Evolving Art of Luxury Experiential Retail.* Business of Fashion.

Christensen, Clayton M. 1997. *The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail (Management of Innovation and Change).* Boston: Harvard Business Review.

Kotler, Philip, and Kevin K Keller. 2016. *Marketing Management.* Accessed December 2023. https://nscpolteksby.ac.id/ebook/files/Ebook/Business%20Administration/Kotler%20and%20Keller%20Marketing%20Management%2014th%20Edition%20(2012)/Chapter%209%20-%20Creating%20Brand%20Equity.pdf.

Erdmann, Anett, Ramón Arilla, and José M. Ponzoa. 2022. “Search Engine Optimization: The Long-Term Strategy of Keyword Choice.” *Journal of Business research.*

PwC. 2023. *IAB.* 12 April. Accessed November 2023. https://www.iab.com/insights/internet-advertising-revenue-report-full-year-2022/.

Ologunebi, John, and Ebenezer Obafemi Taiwo. 2023. “The Importance of SEO and SEM in improving brand visibility in E-commerce industry; A study of Decathlon, Amazon and ASOS.” *MPRA Paper* (University Library of Munich, Germany).

Google for Developers. 2023. *SEO Starter Guide: The Basics.* December. Accessed December 2023. https://developers.google.com/search/docs/fundamentals/seo-starter-guide.

Google for Developers (b). 2023. *Google Search Essentials (Formerly Webmaster Guidelines).* December. Accessed December 2023. https://developers.google.com/search/docs/essentials.

Meng, Lei, Ah-hwee Tan, and Donald C Wunsch. 2019. *Clustering and its extensions in the social media domain.* Singapore Management University.

Yin, Lei, and Ruodan Lu. 2017. *Automated Competitor Analysis Using Big Data Analytics: Evidence from the Fitness Mobile App Business.* Business Process Management Journal.

Zhou, Chen. 2009. "Are banks too big to fail? Measuring systemic importance of financial institutions." *Measuring Systemic Importance of Financial Institutions.*

Battiston, Stefano, Michelangelo Puliga, Rahul Kaushik, Paolo Tasca, and Guido Caldarelli. 2012. "Debtrank: Too central to fail? financial networks, the fed and systemic risk." *Scientific reports* (Nature Publishing Group UK London) 2: 541.

Gofman, Michael. 2017. "Efficiency and stability of a financial architecture with too-interconnected-to-fail institutions." *Journal of Financial Economics* (Elsevier) 124: 113--146.

Grips. 2023. Accessed 2023. https://gripsintelligence.com/data-methodology.

—. 2023. https://gripsintelligence.com/about.

Vinutha, M. S., and M. R. Prajwal. 2023. "A Survey on Search Engine Optimization-Types, Techniques and Factors." *International Journal of All Research Education and Scientific Methods (IJARESM)* 1933-1938.

Hee Park, Chang, and Manoj K. Agarwal. 2018. "The Order Effect of Advertisers on Consumer Search Behavior in Sponsored Search Markets." *Journal of Business Research.*

Appendix

Appendix I: Internet Advertising Revenue trend (2020-2022)

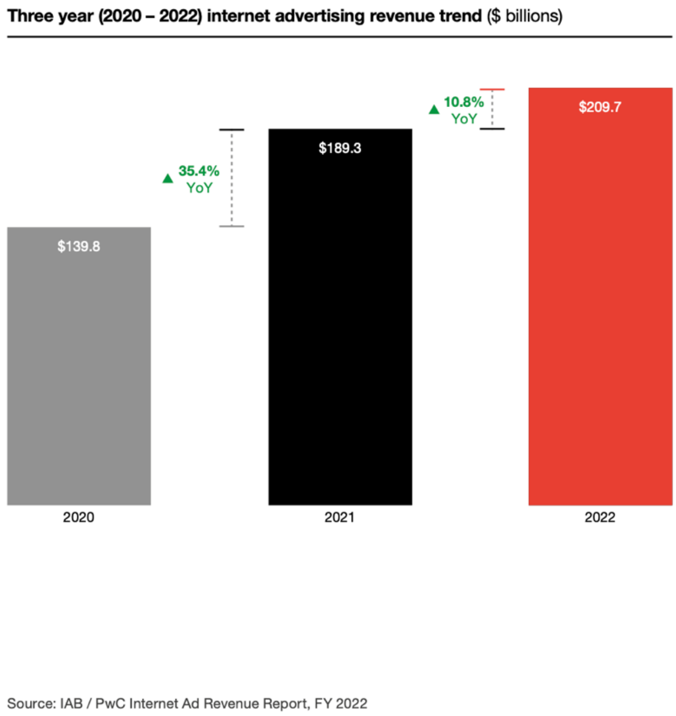


Figure 5 - Internet Advertising Revenue. Source: IAB/PwC Internet Ad Revenue report, FY 2022

Appendix II: Data Dictionary

Variable	Data Type	Description	Source
Keyword	Categorical variable	Stands for the term inserted in the search engine related to products that are shown. The column contains one or more keywords.	Grips
Domain	Categorical variable	Indicates the "top level domain of the website".	Grips
Line_ID	Numerical Value	Used for identification of the product, however not standardized across retailers.	Grips
URL	String variable	Represents the web address of the specific product.	Grips
Position	Numerical Variable	When a specific term is searched, this feature shows the product URL's rank or position on the Search Engine Results Page (SERP). The position is represented by a positive number, where "1" is the SERP's top result.	Grips
Branded	Numerical Variable	Represented as an integer indicating the quantity of keywords that are connected to a particular brand.	Grips
CPC	Numerical continuous variable	Quantifies an estimated amount to be spent by brands/suppliers/retailers whenever a person clicks on the link showcased by the search engine.	Grips
Low_top_of_page_bid	Numerical variables	Represents the lower boundary for the amount bidders are willing to pay for clicks based on specific variables.	Keyword Planner (Google)
High_top_of_page_bid	Numerical variables	Numerical variables that represent the upper boundary for the amount bidders are willing to pay for clicks based on specific variables.	Keyword Planner (Google)
Avg_monthly_search_volume	Continuous variable	Average number of times the keyword is searched per month.	Keyword Planner (Google)
Product Title	String variable	The title given to a product.	Scraped from metadata
Brand	String variable	Name of the brand	Scraped from metadata
Price (USD)	Continuous Numerical variable	Price of the product sold	Scraped from metadata
Category	Categorical variable, string	Product hierarchy of the respective product	Prediction by Grips
Predicted Products Sold	Continuous numerical variable	Serves for the estimation of sales of the product under the given keyword.	Grips
Impressions	Continuous variable	Represents a monthly estimation of products sold.	Grips

Appendix III: Data Cleaning

Variable	Percentage of missing values
low_top_of_page_bid	47.2%
high_top_of_page_bid	47.2%
brand	30.8%
category	11.1%
avg_monthly_search_volume	2.6%
predicted_productssold	0.1%
impressions	0.05%
producttitle	0.05%

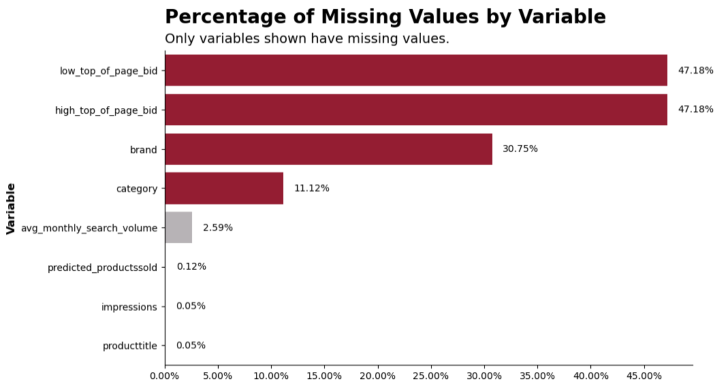
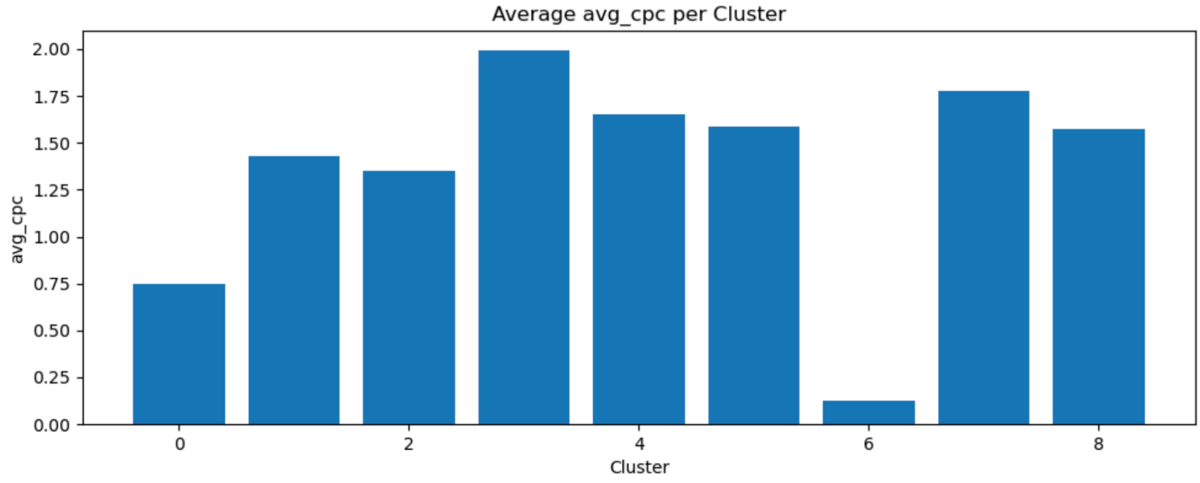


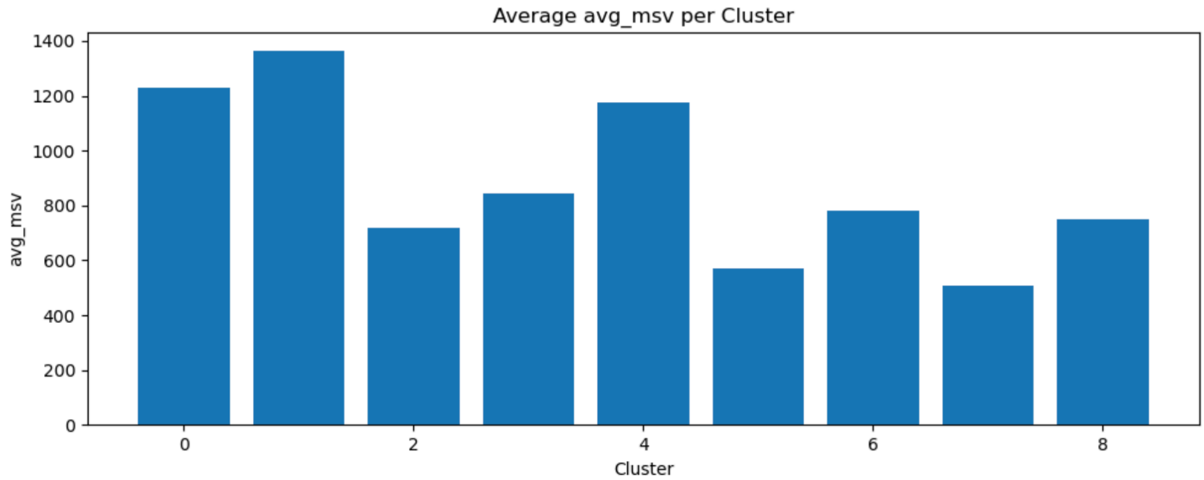
Figure 6 - % of Missing Values within dataset

Appendix IV: Overview of clusters, selected domains, and top categories

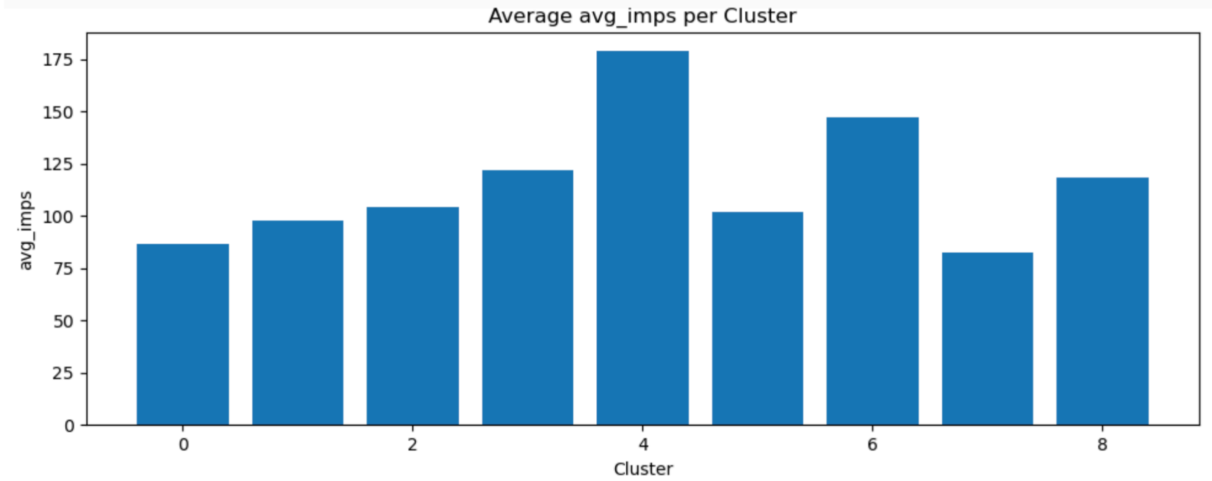
Cluster	Selected Domains	Top Categories
0	StockX, Lego, Scrapbook, Bigbadtoystore, …	Art, Entertainment, Medium, Hobby, …
1	HP, Samsung, Canon, Asus, Dell, Apple, …	Accessory, Electronics, Part, …
2	Vans, Oakley, Wilson, Ping, Burton, Titleist, Evo, …	Sporting, Good, Outdoor, …
3	Chanel, Olay, Dermalogica, Skinceuticals, …	Health, Care, Beauty, Personal, …
4	Tesco, Nespresso, Sodastream, Totalwine, …	Food, Beverage, Tobacco, Item, …
5	Pandora, Cartier, Tiffany, Swarowski, …	Apparel, Jewelry, Accessory, Necklace, …
6	Ikea, Petsafe, Bauhaus, Ebay, Mediamarkt, …	Accessory, Medium, Supply, Garden, …
7	Nike, Adidas, Converse, Ugg, Birkenstock, …	Accessory, Apparel, Clothing, …
8	Kitchenaid, Weber, Dyson, Walmart, …	Garden, Home, Accessory, Kitchen, …

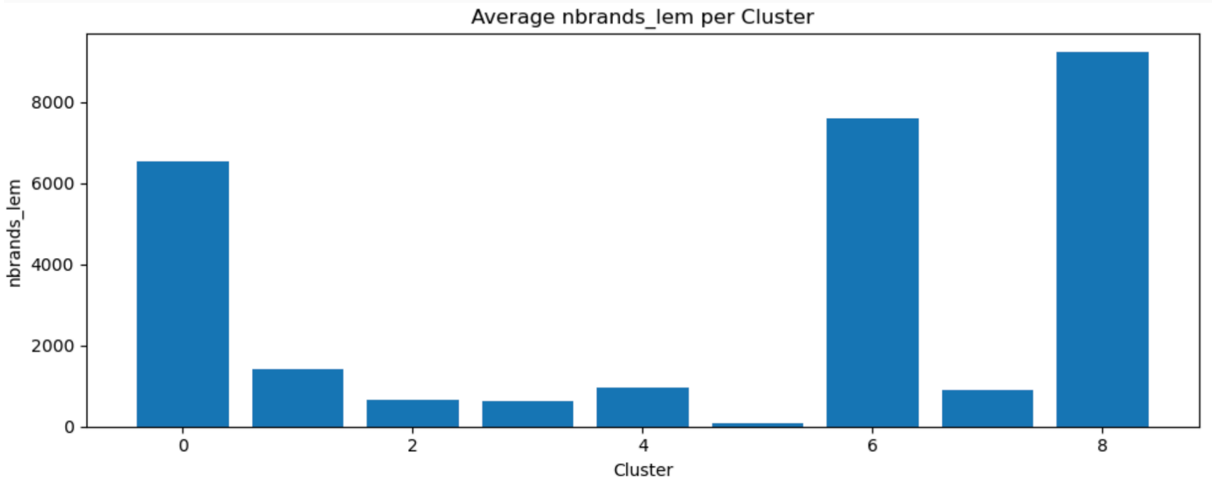
Appendix V: Average numerical statistics per cluster

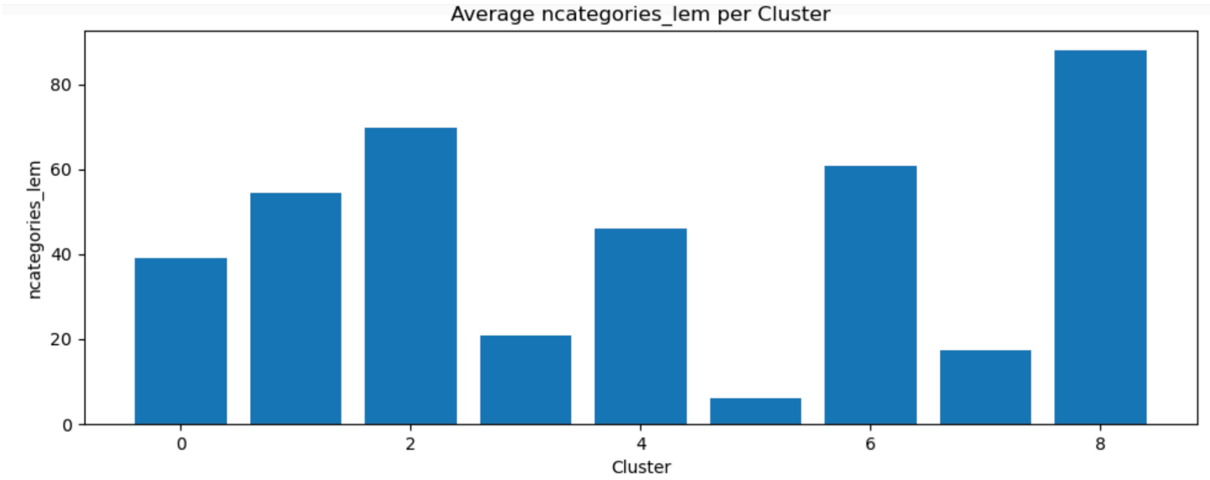


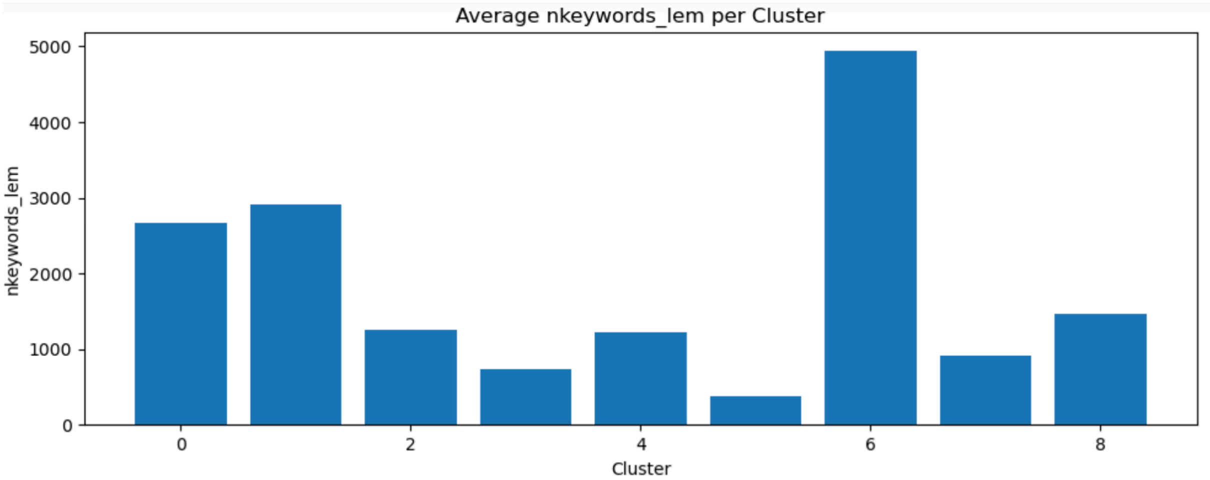


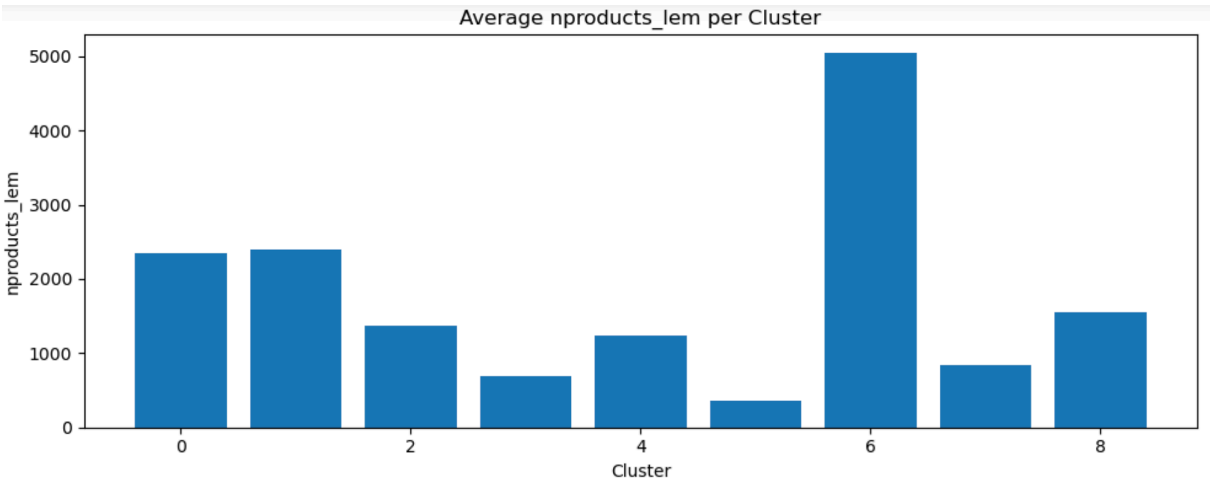

Average avg_predq per Cluster
avg_predq
Cluster
0.0
0.1
0.2
0.3
0.4
0.5
0
2
4
6
8


Average avg_imps per Cluster
avg_imps
Cluster
0
25
50
75
100
125
150
175
0
2
4
6
8


Average nbrands_lem per Cluster
nbrands_lem
Cluster
0
2000
4000
6000
8000
0
2
4
6
8


Average ncategories_lem per Cluster
ncategories_lem
Cluster
0
20
40
60
80
0
2
4
6
8


Average nkeywords_lem per Cluster
nkeywords_lem
Cluster
0
1000
2000
3000
4000
5000
0
2
4
6
8


Average nproducts_lem per Cluster
nproducts_lem
Cluster
0
1000
2000
3000
4000
5000
0
2
4
6
8

Appendix VI: Filtered Derived Retailer Names

Category	Example Retailer Name
Numeric Keywords	220, 1928, 686, 8020, 925
Common Adjectives/Adverbs	did, in, one, only, no, easy, my, at, very
Common Product Names	keyboard, spoon, stethoscope, oven, ring, canoe, headphones, thermometer, fridge, glasses, wigs
Activity/Sport Related	soccer, browning, pilates, bowling
Geographical Locations	uk, eu
Currency Names	euro, dollar
Religious/Spiritual Terms	christ, dame, angel, catholic
Animals and Personas	teenage, animale, corgi, frog, rhino, singer, seals, bird

Appendix VII: Advertisement Poaching Network Sparsity

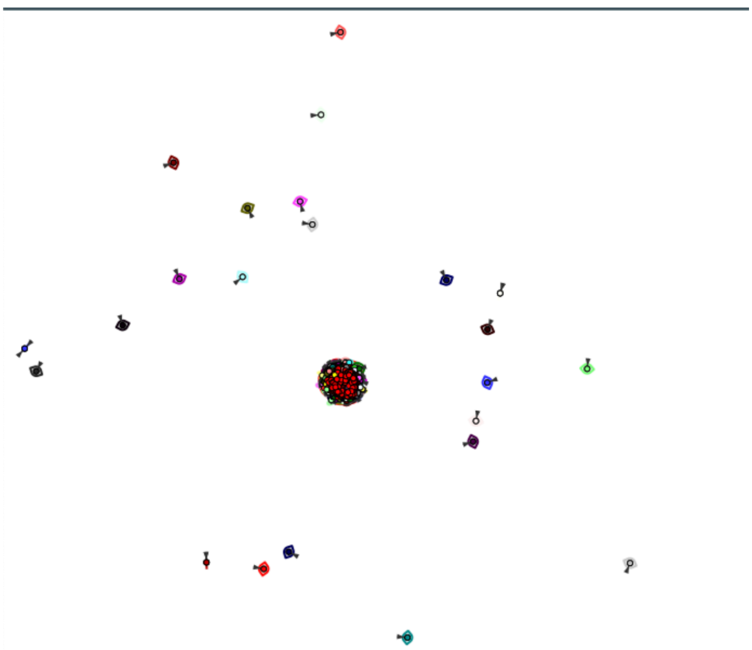


Figure 7 - Visual Representation Of Network Sparsity