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ANALYSIS OF MEDICAL REFERRAL PATTERNS BETWEEN PRIMARY CARE PHYSICIANS AND SPECIALIST CARE PHYSICIANS

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Abstract

The study represents a master dissertation, that is a research project with objective is to identify the referral pattern between primary care physicians and specialists using network science. The referral network represents significant impact on improving healthcare effectiveness. Understanding powerful features that have stronger clustering effect on referral network and the referral patterns differed from physician needs and geographical characteristics can predict an adequate referral relationship. Graph Neural Networks model was applied on this study which conducted a social network consists of nodes to be physicians, edges are the referrals from one physician to another and the shared patients represents weights of edges.

Keywords: Big data analysis, GraphSAGE, Data visualization, Medical referral network, Healthcare

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1. Introduction

The referral process holds substantial influence over outcomes, including the cost and quality of care. Proper utilization of referrals promotes timely and accurate diagnosis and treatment of conditions, while also granting primary care physicians' access to specialized expertise they may lack. Conversely, inappropriate use of referrals can lead to unnecessary expenses and inefficiencies due to excessive testing and procedures (Nutting, Franks, and Clancy, 1992). To this end, medical referral has become a significant concern in the advancement of managed care within the United States.

The relationship between primary care provider (PC) and specialist care provider (SC) of care and effective communication during consultations significantly affects the improvements of patient outcomes and physician satisfaction. Function of communication facilitates seamless and efficient healthcare delivery, benefiting both patients and healthcare professionals (O'Malley & Reschovsky, 2011). According to this, recognizing the importance of such coordination (Mendes & Almeida, 2020b), gaining a thorough understanding of its nature can yield valuable knowledge regarding the emergence of local practice patterns and the diffusion of healthcare practices, and this understanding, in turn, has the potential to inform health policy decisions aimed at effectively influencing physicians' behavior.

Physicians exist in a network of relationships, interacting with a diverse range of other doctors. These connections, or ties, with other physicians create an intricate graph in which they are embedded (Barnett, Landon, O'Malley, Keating, & Christakis, 2011). Networks among physicians have been regarded as the influential factors in the successful adoption and diffusion of new technologies. (Keating, Ayanian, Cleary, & Marsden, 2007), likely by establishing effective communication, shaping philosophies, preferences and sharing of new information and benefits. Similarly, physician opinion leaders have been shown to be effective in speeding adoption of clinical guidelines (Bertakis, 2009).

In this study, I analyzed patterns of medical referrals for Medicare beneficiaries in the current (managed care) health care system. To reach it, I propose a novel GNN based framework to provide personalized medical referral recommendations for patient care according to the features of original referral record. I use shared patient records to link the two types of physicians and the method of social network analysis to explore the features of referrals between PCs and SCs. First I searched about the referral mechanism in the healthcare system in the United States and defined the network structure. Then constructed the network of influential factors depending on this practice together with data processing and explored further analysis of characteristics in the network graph, including specialty types, as well as demographic factors such as gender and practice year. In the end, I applied GraphSAGE model making the classification that select features from what obtained from the previous network to make further research that evaluated the assumption that social features of physicians influence the referral process.

In this dissertation, some hypotheses was proposed regarding the relationships between PCs and SCs: (1)referral collaboration between physicians can reflect the patient's medical trajectory as well as diagnostic and treatment needs; (2) the referral patterns differed from physician needs and geographical characteristics; (3) powerful features have stronger clustering effect.

2. Literature review

2.1 Healthcare Industry

The healthcare industry is highly regarded and valued across the world, all people have a right to health care provided by their government (Basch, 1999). In 2015, the World Health Organization documented that Member States unanimously adopted the United Nations Sustainable Development Goals, which serve as a global call-to-action aimed at ensuring universal health, peace, and prosperity for all by the year 2030. A Deloitte report on the global healthcare industry highlights significant growth anticipated in the coming years (Deloitte, 2022), driven by notable trends in investment and profitability. The report specifically identifies the pharmaceutical, medical device, and hospital industries as experiencing high investment returns.

The United States stands out in terms of healthcare, renowned for its complex healthcare system. The healthcare system in America has been in existence, in various forms, since the era when the founding fathers were battling for independence from Great Britain. Throughout the past two centuries, healthcare in the U.S. has undergone a complex history, with notable successes and setbacks. These range from the challenges of confronting racism against the formerly enslaved to the significant enactment of the Affordable Care Act. (Push, 2022)

There are four primary healthcare models with different legislative and practical approaches globally. The US healthcare model incorporates aspects of all four, with most Americans covered under the Bismarck model through employers. The Veterans Health Administration leans toward the Beveridge model and Medicare serves as a single-payer service for the elderly. In contrast, Canada offers national health insurance, China uses an out-of-pocket model, and Europe offers various versions of the Beveridge and Bismarck models. Despite progress with the Affordable

Care Act, 8.6% of Americans lack health insurance, highlighting the difficulty of achieving universal healthcare amidst opposition from lobbyists and politicians. (Push, 2022)

2.2 Medical Referral

Medical referral serves as a formal mechanism in the healthcare system to address patients' need for specialized care. It involves the transfer or sharing of responsibility for a patient's healthcare from a primary care physician to a specialist doctor (Shortell & Anderson, 1971).

The referral describes a medical care process that links the primary care physician, the patient, and the specialist, all three of which interact with each other. The referral of patients from primary care physicians to specialists can have an impact on patient evaluation, treatment, continuity of care, clinical outcomes, and costs. In the United States, Primary care physicians face the decision of whether to refer a patient to a specialist and, in addition, must choose which specialist would be most suitable to see the patient (Kinchen, 2004). In part, this can impact the effectiveness of medical referral services.

In a recent analysis by the Commonwealth Fund placed U.S. last in effectiveness of care among the 10 countries investigated (Schneider et al., 2021). One study conducted by O'Malley and Reschovsky (O'Malley & Reschovsky, 2011) revealed that, in the U.S., 69.3% of PCs reported "always" sending notification of a patient's history and reason for consultation to specialists, whereas only 34.8% of specialists indicated receiving such notification. This unbalanced situation of referral delivery is the cause of inefficient health care. The referral process between physicians reflects their attitudes and sentiments towards each other, it involves overt behavior and can be observed (S M Shortell & O W Anderson, 1971), and medical referrals rely on physicians' personal social networks, and that physicians generally prefer referral relationships from which they can derive benefit. Meanwhile, they are more likely to recommend consultants with whom they already have an established relationship, whether it is a previous referral relationship or a personal connection (Anthony, 2003).

I propose a versatile framework, GraphSAGE (SAmple and aggreGatE), for inductive node embedding. Unlike traditional embedding techniques that rely on matrix factorization, this approach leverages node features such as text attributes, node profile information, and node degrees. By incorporating these features, we can learn an embedding function that is capable of classifying and representing to unseen nodes. This enables us to generate embeddings for nodes that were not part of the initial training set, expanding the applicability of the model to handle novel or unknown nodes.

2.3 Centers for Medicare & Medicaid Services (CMS) in US

Using methods adopted from social network analysis, I used open-source data derived from Centers for Medicare & Medicaid Services (CMS). CMS is a federal agency under the United States Department of Health and Human Services (HHS). It is responsible for the administration of the Medicare program and collaborates with state governments to administer Medicaid, the Children's Health Insurance Program (CHIP), and health insurance portability standards. (CMS, 2019), it has had a positive impact on the US healthcare system.

CMS aims to make their data readily available in open, accessible, and machine-readable formats. This initiative enables to promote transparency, accountability and innovation in healthcare industry, would be useful for data entrepreneurs, for software and application development, and for research training purposes. Those open-source data from CMS U.S. contribute to the advancement of healthcare research, policy development, and the overall understanding of the U.S. healthcare system (CMS, 2023).

2.4 Medical Claims

CMS open-source data comes from the Medicare/Medicaid programs, so Medical Claims are the best representation of the referral process and physician-patient situation. In the claims, providers, in other words, physicians, are the healthcare professionals or institutions that deliver medical services to Medicare beneficiaries. Beneficiaries or patients are the individuals who are eligible for Medicare coverage. The roles of providers and beneficiaries in the Medicare claims process are interconnected, as providers submit claims for reimbursement for services they provide to beneficiaries. (CMS, 2008).

The relationship between providers and beneficiaries in the Medicare claims process is complex. Medicare assigns a unique identification number (NPI) to each provider, which is used in the claims process. Providers submit claims to Medicare on behalf of beneficiaries for services provided to them. The beneficiary is responsible for paying their share of the costs for services received, such as copayments, deductibles, and coinsurance. Providers cannot charge beneficiaries for services that Medicare covers and the payment process depends on the type of Medicare coverage that the beneficiary has, and can involve direct billing by providers or reimbursement through private insurance companies (CMS, 2012).

2.5 Graph Neural Networks (GNN)

The delay in accessing medical specialty care, driven by limitations in clinicians' time and resources, has been linked to higher mortality rates, early prediction of procedures needed during initial outpatient specialty consultations can improve specialist access and decision-making processes. While artificial intelligence (AI) has achieved success in solving healthcare problems, its potential in addressing this task remains largely unexplored (Fouladvand et al., 2022). Graph structures are a natural representation for data in various domains such as proteomics, image analysis, scene description, software engineering, and natural language processing (Scarselli, Gori, Ah Chung Tsoi, Hagenbuchner, & Monfardini, 2009). Graph Neural Networks (GNNs) were introduced in Gorietal.(2005) and Scarsellietal.(2009) as a generalization of recursive neural networks that can directly deal with a more general class of graphs, e.g.cyclic, directed and undirected graphs (Veličković et al., 2018). Fouladvand et al., 2022 demonstrated in their research that embedding graph neural network models into health care can improve digital specialty referral systems and expand the access to quality medical expertise.

3. Methodology

3.1Data collection and data processing

The data gathered about the physician's business practice information that were done till 2023, includes over 11 million unique physicians. With around 8.9 million referrals from PC to SC with number of nearly 1.9 million physicians that involved totally over 400 million patient visits. Note, the analysis uses only the physician data information for further exploration. With the intention for processing the physician's information data, I proposed following criteria: (1) physicians have taxonomy code is equal to 207Q00000X or 208D0000X[1] are primary care physicians (PC), the others are specialist care physicians (SC); (2) the specialties of physicians are derived from the academic subject divisions in Allopathic and Osteopathic[2]; (3) the selected physicians only represent individuals not any organization or sole proprietor instead. By the considering these criteria, I have access to information about each physician: gender,

[1] In taxonomy code classification regulations of US, 208D0000X represents general practice, which is more likely to provide referral services. 207Q00000X represents family medicine, which is a family doctor in a broad sense, providing basic medical services as well as medical consultation and providing referral services (NUCC, 2023).

[2] Osteopathic medicine and allopathic medicine are two branches in the American medical system (Johnson & Kurtz, 2002).

enumeration year, first-second care, primary specialty, the place where they work, practice year (Table 1). The data processing was performed by generating several relevant subsets of categorical data. Features were extracted from multiple categorical datasets of different sources.

Table 1 Datasets features

Categories	Features	Description	Source
Physician information	NPI	Unique identifier of the health provider (physicians) in US	CMS
	Gender	Gender of each physician	
	Enumeration year	The year the NPI was assigned to each physician.	
	Is Sole Proprietor	If the corresponded physician represents an organization	
	First-second care	The corresponded physician is PC or SC	
	Specialty	Primary specialty of the physician	
	Practice Location State	The state name of practice location of physicians	
Referral shared relationship	NPI1	The initial physician provides medical services	
	NPI2	The secondary physician provides medical services	
	Bene Count	Number of shared unique patient	
	Pair Count	Times that shared patients	
	Same Day Count	Number of same day visits	
Taxonomy classification	Taxonomy code[3]	The code in classifying specialties	National Uniform Claim Committee (NUCC)
	Grouping	Groups for medical specialties	
	Specialization	Medical specialization	

[3] Taxonomy code is a specialized code used to categorize healthcare providers. It consists of a unique alphanumeric code that is 10 characters long. (NUCC, 2023).

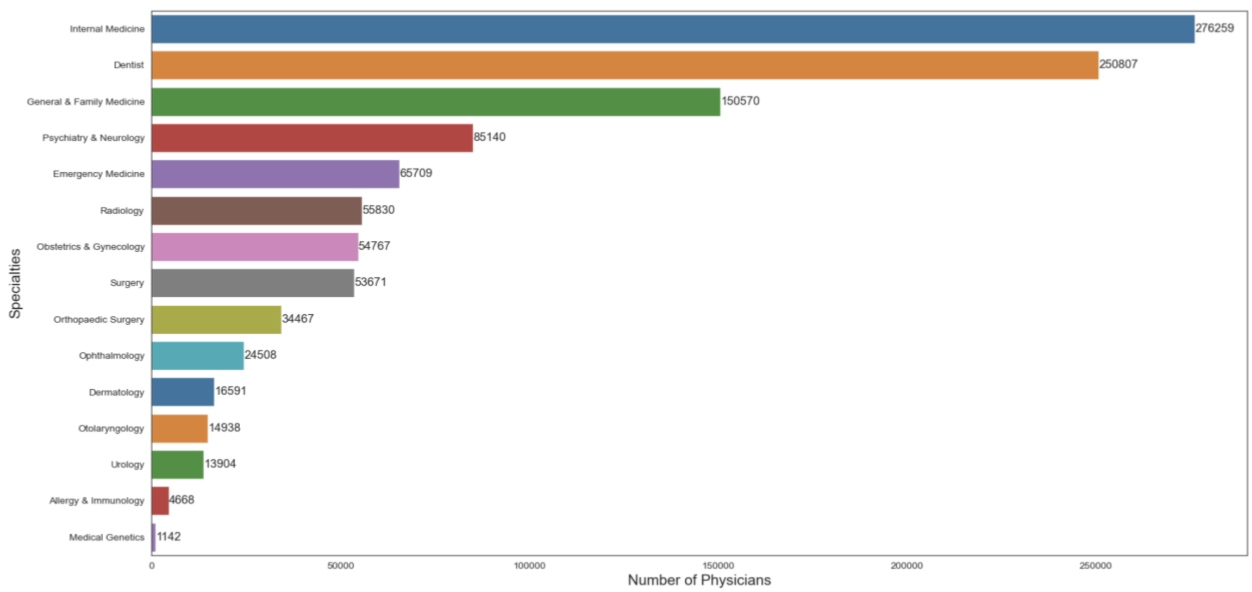
The physician information data demonstrated some distinct distributional characteristics in general, which were developed and assembled naturally by physician’s specific feature during real referral process.

Specialization distribution. The overall distribution of the number of physicians engaged in the specialty shows a large variation, ranging from around 1,000 to 2.7 million (see Fig.1). Internal medicine is the top-ranked medical specialty possibly due to its broad range of disease treatment and non-surgical approach. According to the growth forecast made by the Bureau of Labor Statistics in 2018, employment opportunity for internal medicine doctors is expected to increase by 13 percent through 2026, surpassing the 7 percent growth rate of other occupations. This growth is driven by the increasing demand for healthcare services, particularly from the aging population. Also, due to its multi-function, internists played a vital role for COVID-19 prevention, essential care coordinators, providers of care continuity, and sources of scientific information, testing, and vaccination (Di Ciaula, Moshammer, Lauriola, & Portincasa, 2022). Gynecology, surgery and radiology are almost equal. It is worth mentioning that psychiatry & neurology becomes the fourth largest professional group.

This occurrence does not seem unusual in today's post-covid-19 era. Studies have shown that fatigue was the most frequent symptom of neurological post-COVID-19 syndrome, brain fog, sleep disturbances and memory issues were similarly frequent (Premraj et al., 2022). Dentist ranks #2, this provides an expanded insight. The universality of dentistry is the high-end pursuit of people's appearance, from extensive beauty of appearance to the control of details, and the appearance is no longer limited to a single visual stimulation but gradually shifted to the overall transmission of temperament. And people's concern and research on mental illness may be the product of the increasingly intensified social conflicts. There is a potential market demand for genetic genetics and allergy & immunology, among others. Medical genetics is 11 (the last).

Specialists significantly outnumber primary care physicians (see Fig. 3). In the medical system professional classification Allopathic and Osteopathic medicine in the United States, around 87% individual physicians are SC, which is almost eight times as many as PC, which only accounts for 12.9%. In his study Harold S. Luft, referring to the bad sign of the large gap between PC and SC in the US health care system, said that the unattractiveness of primary care is due to three factors: a. PCs' income is not proportional to the medical services that they provided; b. it is difficult to establish longstanding relationships with patients due to the change relates to employers or payers; c, the schedule time of PCs is not manageable to accommodate changing family structure in the US.

Fig.1. Number of physicians per specialization till 2023



Gender distribution. There is a notable disparity between male and female physicians, with a larger representation of male practitioners. This trend is especially pronounced in fields where the proportion of physicians of a particular specialty can represent the one of its male physicians. For example, among the physicians with valid information in the open-source data provided by CMS till 2023 in the United States, 65% were male in a range of nearly 5 million unique physicians, which is almost 2 times as the number of female physicians that is 35% (Fig.2.); male SCs take up nearly 60% of SCs (see detail at Fig.3.). This imbalance in the ratio of male to female physicians is even more obvious when compared to different specialties. Of the more than one million physicians involved in the specialty selected for this study, the proportion of male physicians was 1~3 times higher in all cases, and even 4 times higher in emergency medicine (4.87% of men and 1.78% of women). However, there are still several specializations where the proportion is more balanced: dermatology, allergy & immunology, medical genetics, psychiatry & neurology and obstetrics & gynecology among which, female SCs of obstetrics & gynecology even outnumbered males (men: 2.04%, women: 2.93%).

Fig. 2. Physicians general gender distribution

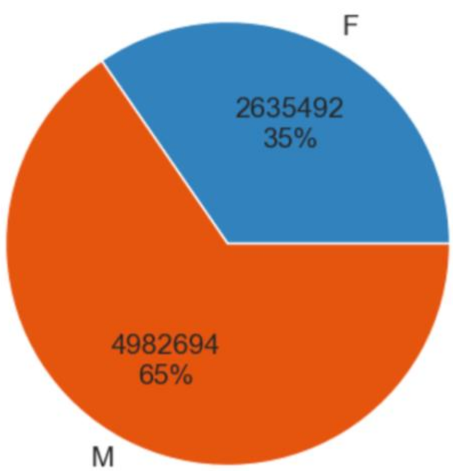
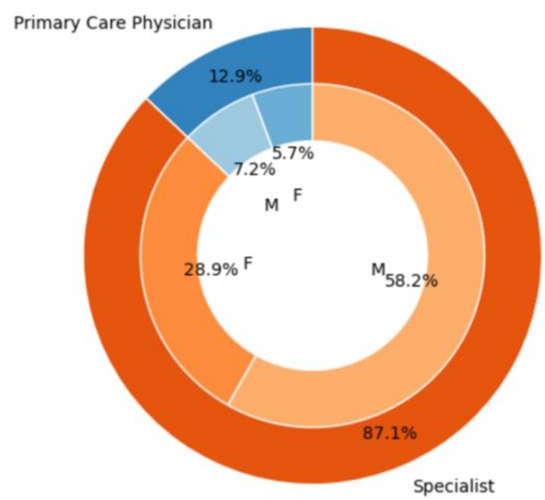
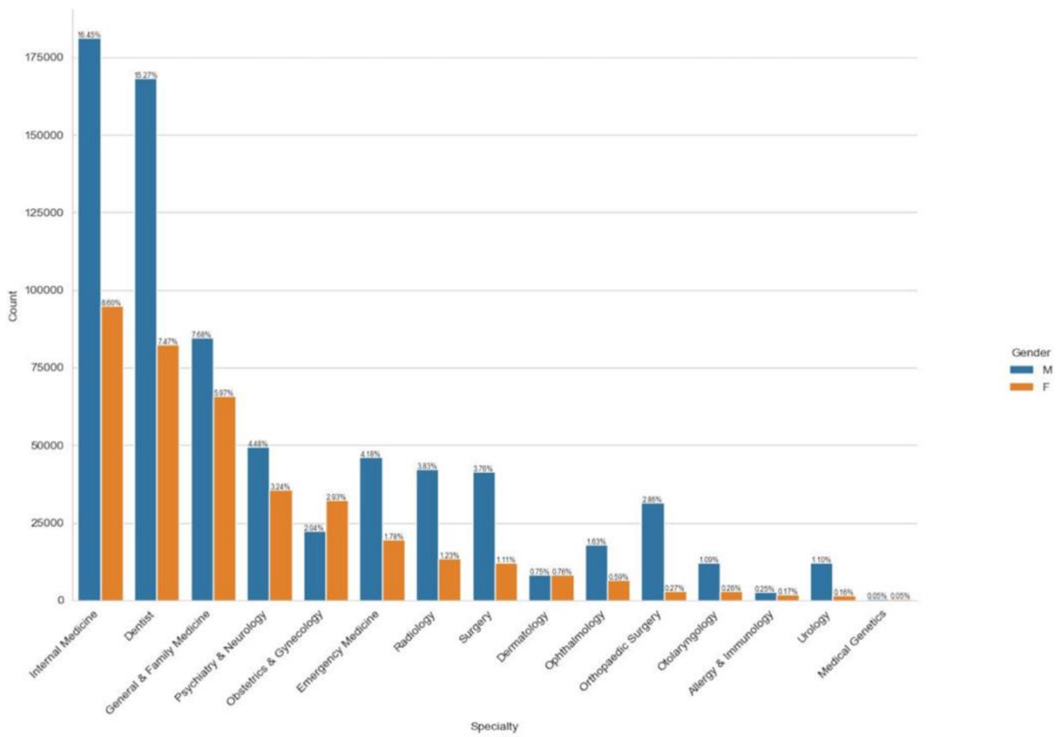


Fig.3. First-second care complemented with gender distribution



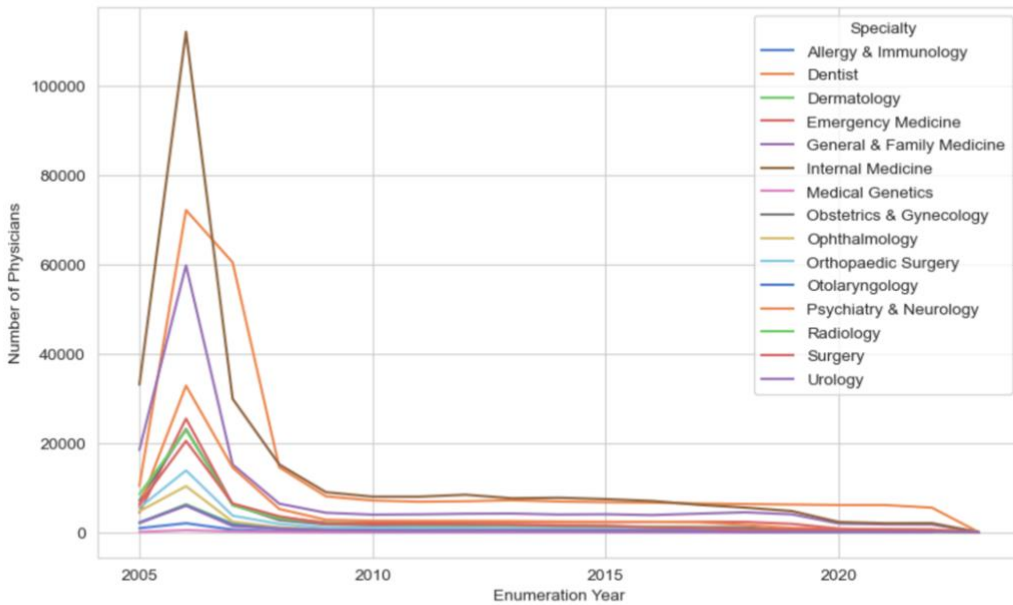
The phenomenon regarding the ratio of men to women in the physician profession stems from differences in medical services styles, the need for professional rewards, and the personal preferences of patients in choosing a physician thereby increasing patient satisfaction. For gynecological care, patients prefer female PCs, cause most gynecological and obstetric consultations include pelvic examinations, so female patients prefer female obstetricians and gynecologists, and it is the fact that less male residents are now starting careers in obstetrics and gynecology (Gerber & Sasso, 2006). Research (Riska, 2001) concluded that women are fairly well represented in specialties that have a significant impact on women's health and children's health (e.g., obstetrics and gynecology, pediatrics). On the other hand, women physicians are overrepresented in medical practice and health care services, and they have less impact than their male colleagues in changing the overall conditions of medical work (health centers). However, the increase in the number of female doctors in administration, research and teaching can be found in the Finnish data, which is a new trend that indicates a change in the status of women in the medical field.

Fig.4. Gender distribution on different specialties



Enumeration Year. How long have the physicians been practicing demonstrates the profession demand in one specialty. I use the year in which the physician received their NPI number as a reference for how long they have been practicing. Clearly, the largest number of physicians in each specialty received an NPI is in around 2006 (Fig.5.). Since CMS's healthcare programs provides a precise insight that is targets a specific population (see details in 2.3) and the NPI qualification doesn't require professional practice time, I can determine that physician professional experience, while extremely influential in numerous studies, was still influential in the characteristics of the data in this study. As the most populous internal medicine department, the demand for experienced physician resources is also very high, and with the aging population, internists' activity scope tends to be increasing.

Fig.5. Enumeration year distribution of each physician



3.2 Social network construction

I constructed a social network to analyze the referral patterns between physicians, focusing on their interactions and shared patients. In this network, physicians are represented as nodes, and the referrals from one physician to another are represented as weighted and directed edges. The weight of each edge corresponds to the number of shared patients between the two physicians. To understand the social behaviors influencing physician referrals, I considered two important network features: in-degree and weighted in-degree. The in-degree of a physician is the number of edges directed towards them, regardless of the edge weights. On the other hand, the weighted in-degree is the sum of the weights of the edges directed towards a physician, reflecting their popularity and prestige within the referral network. By analyzing these network features, we can gain insights into the prominence of physicians in terms of referral interactions. The social network construction focused on physician referral network between Primary Care Physicians (PC) and Specialists (SC) across the United States. The construction of the referral network followed several criteria: (1) the node features selection should effectively represent the professional characteristics of the physicians, such as gender, specialty, and more; (2) referrals were traced only from PCs to SPs; (3) the referral graph was formed based on interactions occurring within a 30-day timeframe; (4) two different physicians share a patient and neither physician in the same pair withdraws. By adhering to these specific criteria, I used libirary NetworkX (NetworkX, 2023) to conduct this operation. The related referral observations were as described in 3.1. The social network included unique physicians and the referral frequencies of different specialization varied (Table 2).

Table 2 2015 - Unique physician number and referral frequencies of different specialties across from the U.S.

	Unique physician number	*Referral frequencies*
Internal Medicine	62798	307790
General & Family Medicine	41206	297536
Radiology	20141	124328
Emergency Medicine	15517	53255
Psychiatry & Neurology	6475	20904
Surgery	6225	19810
Orthopaedic Surgery	5475	19527
Ophthalmology	4937	16302
Urology	3391	13107
Dermatology	2687	10481
Otolaryngology	1763	5080
Obstetrics & Gynecology	452	708
Allergy & Immunology	159	346
Dentist	22	27
Medical Genetics	3	3

Network graph and metrics. according to the summarized network metrics that resulting the referral networks of different specialties, the nodes degree distribution displayed a power-law pattern, indicating that (1) the presence of medical referral clusters takes specific physician as center: a small group of physicians received a great volume of referrals (SC node - centered) or that referred to a great body of specialists (PC node centered). (2) one-to-one cooperation: the majority of SCs primarily received referrals from only one PC, while PCs typically referred to only one SC. This can be attributed to some reasons: SCs with a high in-degree considerably are more influential within the network, while PCs with a low out-degree may have fewer social activities. Additionally, I calculated the average clustering coefficient (Girvan and Newman, 2002) of the referral network to be 0.222, suggests that there is some tendency for physicians to cluster together within the network, indicating the presence of local referral patterns and relationships among physicians. However, the network is not highly clustered, indicating that there are also connections between physicians outside of these local clusters, demonstrating a small-world network structure.

Fig.6. Obstetrics & Gynecology

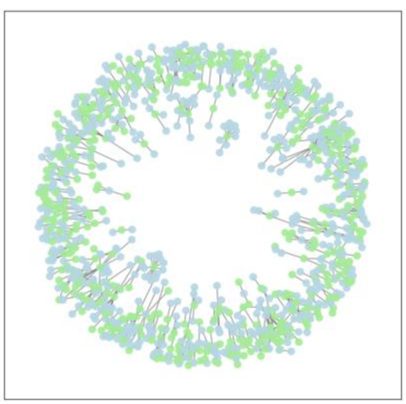


Fig.7. Allergy & Immunology

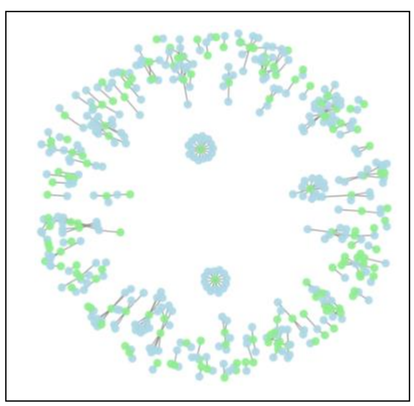
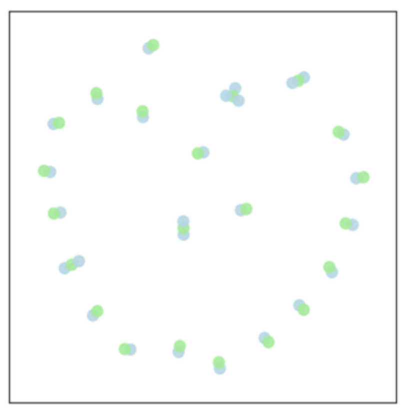


Fig.8. Dentist



By understanding better of it, four distinct social network centrality measurements were computed: In-out degree, Betweenness Centrality, Closeness Centrality and Eigenvector Centrality. The distribution (Fig.7.) of all four centrality appears to be very prominent in a certain bin specially the distribution of eigenvector, which indicates the existence of extreme value. The closeness and betweenness centrality distribution in another aspect shows that the not too many physicians included in clusters. In terms of in-out degree, it is possible to observe that a slight skewed distribution to the right of in-degree, symmetric distribution on out-degree. Therefore, in the referral between PC and SC, there are 2 kinds of cluster patterns: a certain SC or PC dominates the whole cluster, or a one-to-one long-term cooperation. Fig.6. is the spring layout graph of Obstetrics & Gynecology, Allergy & Immunology and Dentist, which shows clearly that small number of clusters surrounded by one-to-one referral type.

Based on the above analysis, I extracted the clusters with the most referrals in each specialty, the center of these clusters is regarded as "Influencer". There are 14 influencers in total, 12 of them are sole proprietor, 2 from State of Taxas and 2 from NE, OMAHA city, all of them are female physicians (detail information see appendix Table.1., f.1.).

3.3 GraphSAGE Classification Model

In the case of the referral network, node embeddings would be generated using the GraphSAGE model, which incorporates both node attributes and the graph structure to learn the characteristics of each node's neighborhood and the distribution of node features within that neighborhood. Node embeddings are vector representations derived from graph-structured data, capturing the local neighborhood information of each node.

These embeddings have demonstrated their usefulness in various machine learning tasks, including node classification, clustering, dimensionality reduction, and link prediction. To create node embeddings for the referral network, this GraphSAGE model utilizes a classification task that involves classifying the likelihood of co-occurrence between pairs of nodes during random walks on the graph. Positive node pairs are generated through random walks, while negative pairs are randomly selected based on a specific distribution. By employing this approach, the model can learn mappings from node attributes and their neighboring nodes to generate informative node embeddings while preserving the structural similarities of nodes and their associated features (Hamilton, Ying, & Leskovec, 2017).

Embedding Algorithm. A supervised learning approach was conducted for the established relationship from first medical care to secondary care, and I extracted node pairs whose first care is only PC and secondary care is only SC. I use Stellargraph library, which is a Python-based machine learning tool specifically designed for graph and network analysis. The library provides pre-built GraphSAGE models that can be readily employed for link prediction and node embedding tasks. By leveraging this powerful tool, I can streamline the research process and effectively explore the referral behavior regarding the influence of physician features during the referral process (Stellargraph, 2017).

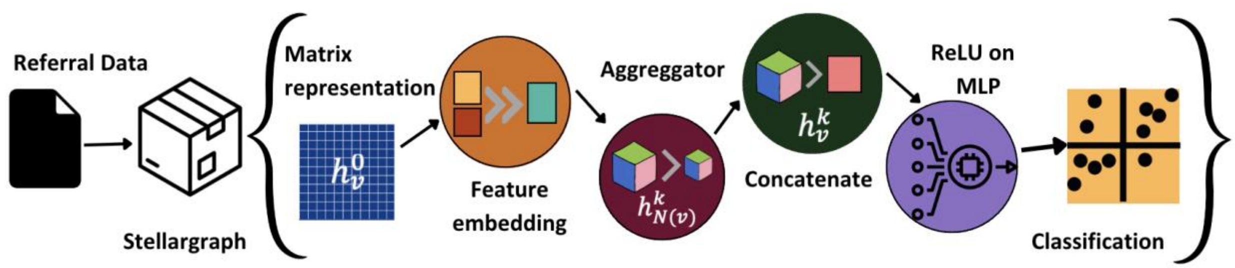
As mentioned previously, the Stellargraph provides the GaphSAGE model algorithms, the embedding process (Fig.9) as general cases did was saved, such as from features and edge adjacency matrices representation to the aggregation from local features to neighbor as it represents $h_{N(v)}^{k}$[4] and finally concatenate these aggregation results as h_v^k. Further, to classify the existed edge between two nodes to maximize the positive prediction results that the existence of referral relationship between PCs and SCs, I adopted a binary cross-entropy loss function:

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

[4] $h_{N(v)}^{k}$where h represents the hidden state or feature representation of a node or set of nodes in a graph; k signifies the number of iterations or steps of information propagation or message passing in a graph neural network; $N_{(v)}$represents the neighborhood of a particular node v in the graph. i.e., the nodes that are directly connected to it by an edge; $h_{N(v)}$denotes the hidden state or feature representation of the nodes in the neighborhood *N(v).*

where y is the label to represent 1 as positive 0 as negative. p(y) equals to the predicted possibility of the point being positive for all N point. Here for each positive point (y=1), it adds log(p(y)) to the loss, that is, the log possibility of it being positive. Conversely, it adds log(1-p(y)), that is, for each negative point (y=0) the log probability of it being negative (Godoy, 2018). The ReLU activation function is used in the full connected layers (also known as MLP) on the output to lift the probability of positive results (SHARMA, 2017). Minibatches of 'training' links were generated on demand and fed into the model for training. Those Node embeddings captured from the encoder part can be leveraged in downstream tasks.

Fig.9. Embedding model process



Hyperparameter tuning. For this study, I aim to improve the accuracy and efficiency of the classification model. To gain further insights from it, I chose data from one additional state, Arizona, the predication modeling results of two location range were regarded as a comparative validation experiment. I learned an supervised graph representation of the referral network.

To optimize the performance of the model, I conducted a thorough tuning process on several key hyperparameters. Take the data across from the U.S. as an example. The learning rate was set to 0.0001, striking a balance between training speed and model quality. This choice allowed the algorithm to converge effectively during training, ensuring efficient utilization of computational resources. By fine-tuning the learning rate, I aimed to enhance the model's training efficiency without compromising its predictive accuracy. Next, I explored the vector dimensions. Higher dimensions generally result in more expressive embeddings, capturing finer details of the data. However, there exists diminishing returns point, where further increasing the dimensionality may yield marginal improvements. I experimented with dimensions of 64 by 64, the results revealed that the embeddings with 100 dimensions achieved the highest prediction accuracy for the downstream task compared to other dimension options.

Table 3 Parameters of GNN model training

Location	**Graph information**	**Node features**	**Hyper-parameters**	**Loss function**	**Batch size**	**Num samples**	**Layer activation function**
The U.S.	Nodes: 192,571 Edges: 889,204	Specialty Gender First-second care	64 by 64 layers Epochs 20 Dropout 0.15 Adam learning rate 0.0001	Binary cross entropy	1000	[50,50]	ReLU
The state of Arizona	Nodes: 2,844 Edges: 7,349	Specialty Gender First-second care	32 by 32 layers Epochs 20 Dropout 0.2 Adam learning rate 0.005	Binary cross entropy	50	[10,10]	ReLU

3.4 Node embeddings and Clustering

Node embeddings. The previous section (refer to section 3.2) demonstrated that the referral social network exhibits clustering characteristics and follows a power-law distribution, indicating similarities between primary care (PC) and specialists (SC) nodes. The classification model developed earlier can be utilized to predict referral patterns, leveraging the similarity between nodes in the referral network. To achieve this, I employed the node encoder component of the trained model to evaluate node embeddings, aiming to identify similarities in referral social network patterns among numerous interactions. These embeddings were obtained as activations from the GraphSAGE layer stack. To facilitate further analysis of the evaluated node embeddings, I employed UMAP (Bratanic, 2020) to create a visual representation of the embeddings, with nodes colored according to their subject labels .

HDBSCAN Clustering. The neural network embeddings generated from the GNN model encode all the attributes and topological structures of the referral connections. (Pealat, Bouleux, & Cheutet, 2021), a density-based clustering algorithm. HDBSCAN creates a density-based clustering hierarchy, where each cluster is represented by a tree structure, then it uses an approach called "condensed tree" to extract a set of stable clusters from the hierarchical structure. It identifies the clusters by finding the most persistent clusters in the condensed tree, which are regions of high-density points, which allows it to ignore small clusters that may be considered noise. It also handles clusters of varying densities, making it robust to different cluster shapes and sizes. My embeddings encode the social network connectivity and the social network structure. Hence, the HDBSCAN clustering approach is a proper approach to cluster the physicians based on their vector representations.

4. Findings

4.1 Referral Prediction using Graph Embeddings

The outcomes of medical referral classification of GraphSAGE model in Table 4, displaying ROC, PR and F1 score on the test set of two different location range, and the Fig.10 shows the training process. It is clearly that the model in the nation-wide range is able to effectively capture and learn the underlying patterns in the medical referral network data and has a good ability to distinguish between different referral patterns, as reflected in the high ROC AUC score. The state of Arizona seems to be not good, since its PR score is low while the ROC (Receiver Operating Characteristic) score and F1 score are higher, it suggests that the classification model performs well in terms of overall accuracy and the trade-off between precision and recall. The insufficient data sample may cause this issue, since the positive instances are limited. However, the model can still gain valuable insights and make informed decisions in the healthcare domain.

Fig.10. Model training records – nation-wide

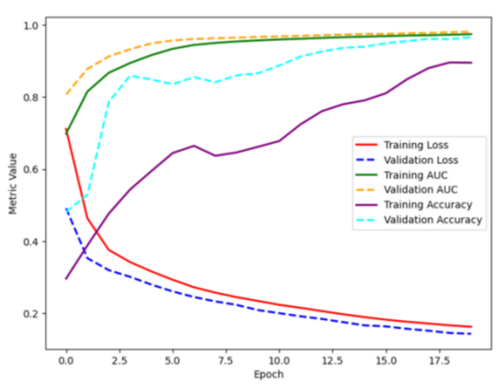


Table 4 Modeling performance

Location	ROC	PR	F1
The U.S.	0.871	0.607	0.967
The state of Arizona	0.684	0.351	0.770

4.2 Node Embeddings and clustering

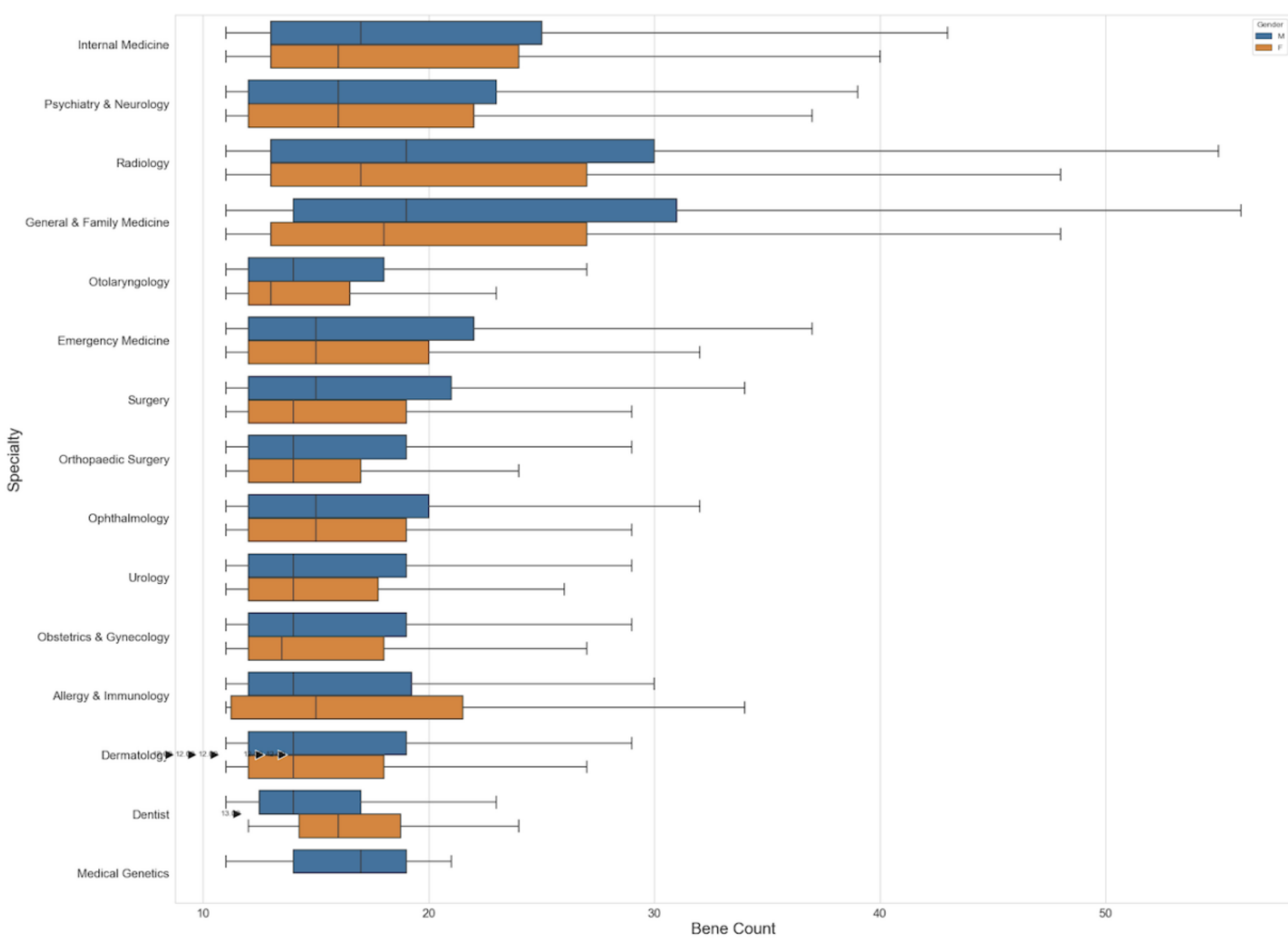
Both of two location exhibits a highly clustered visualization in the embedding model (Appendix.fig 2). The main findings are as follows:, I generated a in the perspective of state of Arizona :(1) first-second care distributed less power on forming clusters and well-distributed presence of both PC and SC physicians across the primary clusters of the embeddings, (2)as well as the female-male physicians, but the distribution is tended to be clustered (as Fig.10. showing); (3) each specialty represents a particular cluster; from the U.S. nationwide, I adjusted the model: eliminated the node feature of first-second care, set the focus is the network pattern under the influence of gender and specialty, and let these two features were observed together, the embedding model presents a more complete pattern. The distribution characterized by clusters: a. largest clusters like male-General & Family Medicine, male internists and male radiologists; b. 'elite' clusters with smaller volume such as male-Orthopedic surgery, female internists; c. common clusters consist of a few scattered dots or crosses (see APPENDIX fig.3). d. fragmented distribution of single dots.

The characteristics of clusters are gender-based, doctors of the same gender tend to be in a cluster, the cluster of specialties is basically related to the number of physicians in the specialty. Clusters that only consist of physicians of general & family medicine are the most; internists are more likely to form a cluster with whom has same specialty; only cluster #13 included physicians of different genders, but male physicians also account for most of the number of the cluster; female physicians of general & practice medicine have 6 clusters which are the majority, followed by male physicians of general & practice medicine; male physician's specialty is dermatology have 4 clusters. In addition,

4.3 Statistics in Referral network

For both male and female patients, General & Family Medicine (GFM) specialists have the highest median and upper quartile values, indicating that GFM physicians have shared the most patients with PC doctors. Conversely, the lowest median and upper quartile values belong to Medical Genetics (MG) specialists, indicating that MG doctors have shared the least number of patients with PC doctors. In referral medical networks, the connection between SCs and PCs is communal and cluster-like, and this network characteristic implies the presence of influencer, i.e., the center of the cluster, among physicians. Overall, the vast majority of referring physicians received a range of 10-50 unique patients. A small number of SCs such as SCs of MG have no female physicians, while 75% of male GFM physicians receive more than 50 patients. however, due to the large sample size, there is still a very significant fraction of physicians who receive many times that number, as shown in the box plot of whisker and outlier points, with extreme values above 2000 for Radiology and Family Medicine. This suggests that this referral process for medical referrals is uneven and that the linkage between SC and PC is more limited.

Fig.11. Referrals general statistics



5. Conclusion

Medical referral networks are influenced by both the social network structure and the personal characteristics of physicians. Primary care physicians (PCs) tended to be individually due to the nature of their work, while physicians of the same gender are more likely to have connections. Gender has been a topic of interest in medical care research, as patients may have preferences based on gender. Studies have shown that female patients prefer female doctors, and female PCs are often consulted for women's health issues (Brink-Muinen, Bakker, & Bensing, 1994), (Phillips, 1998).

The characteristics of physicians and the patients they serve also play a role in the network. Physicians with more practice activities have a stronger influence in the network and can become "influencers." By visualizing the node embeddings, we can observe a structured pattern, especially when incorporating social features. The embeddings generated with different features reveal a detailed cluster structure, providing evidence of specific relationship patterns between different types of physicians. Additionally, in the visualization, we can see that specialist care physicians (SCs) tend to form clusters, as most data points are individually scattered around. This aligns with the referral process, where referrals typically occur from a PC to an SC doctor. To make sense, a cluster should contain both types of doctors who share referrals.

The findings suggest that the utilization of node embeddings and considering social features can enhance our understanding of the referral patterns in medical networks. This granular representation may contribute to the success of tasks such as link prediction, particularly when specific relationship patterns exist between different types of physicians.

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APPENDIX

fig.1 Centrality Distribution

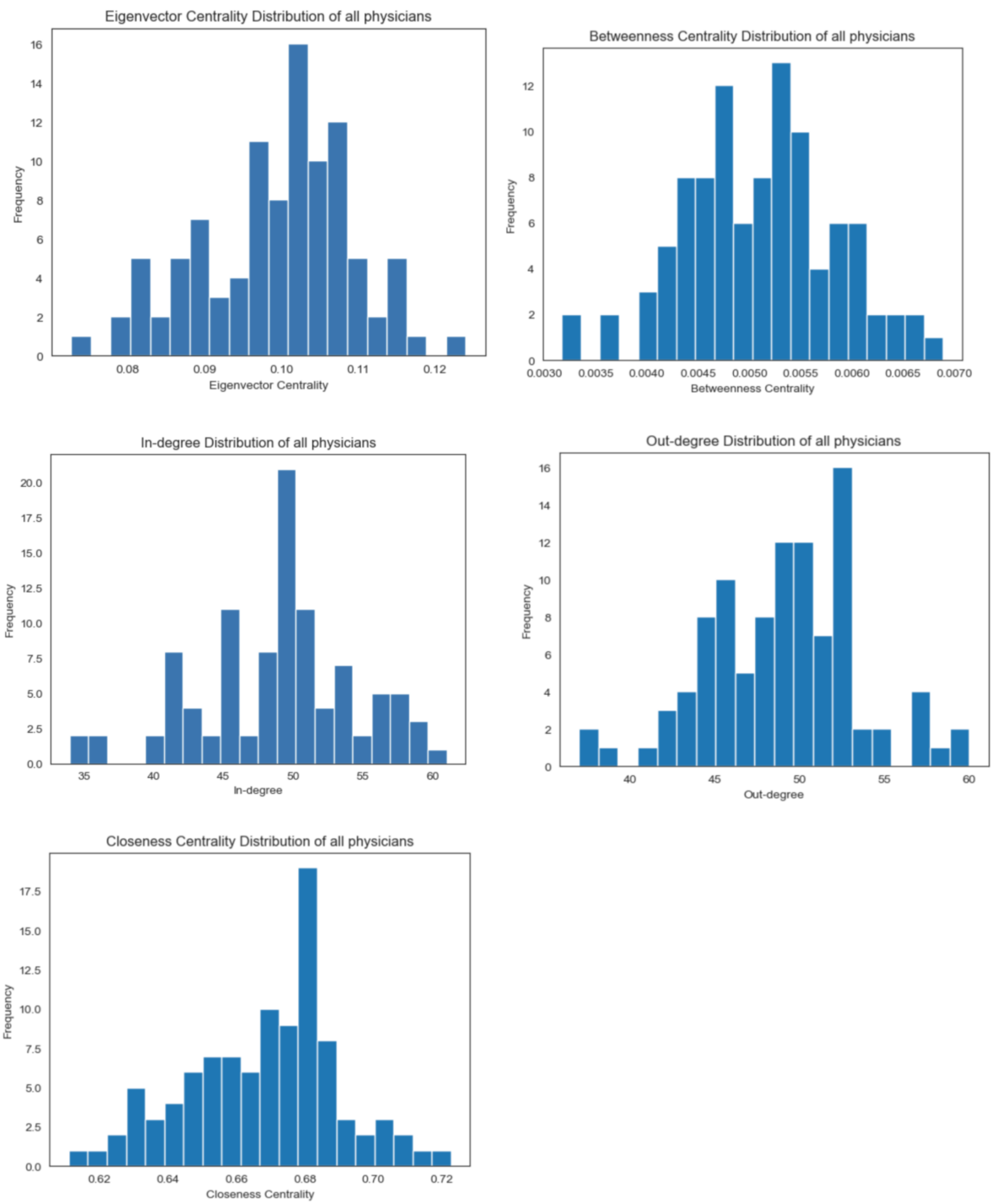


fig.2 Node Embedding Visualization of the state Arizona

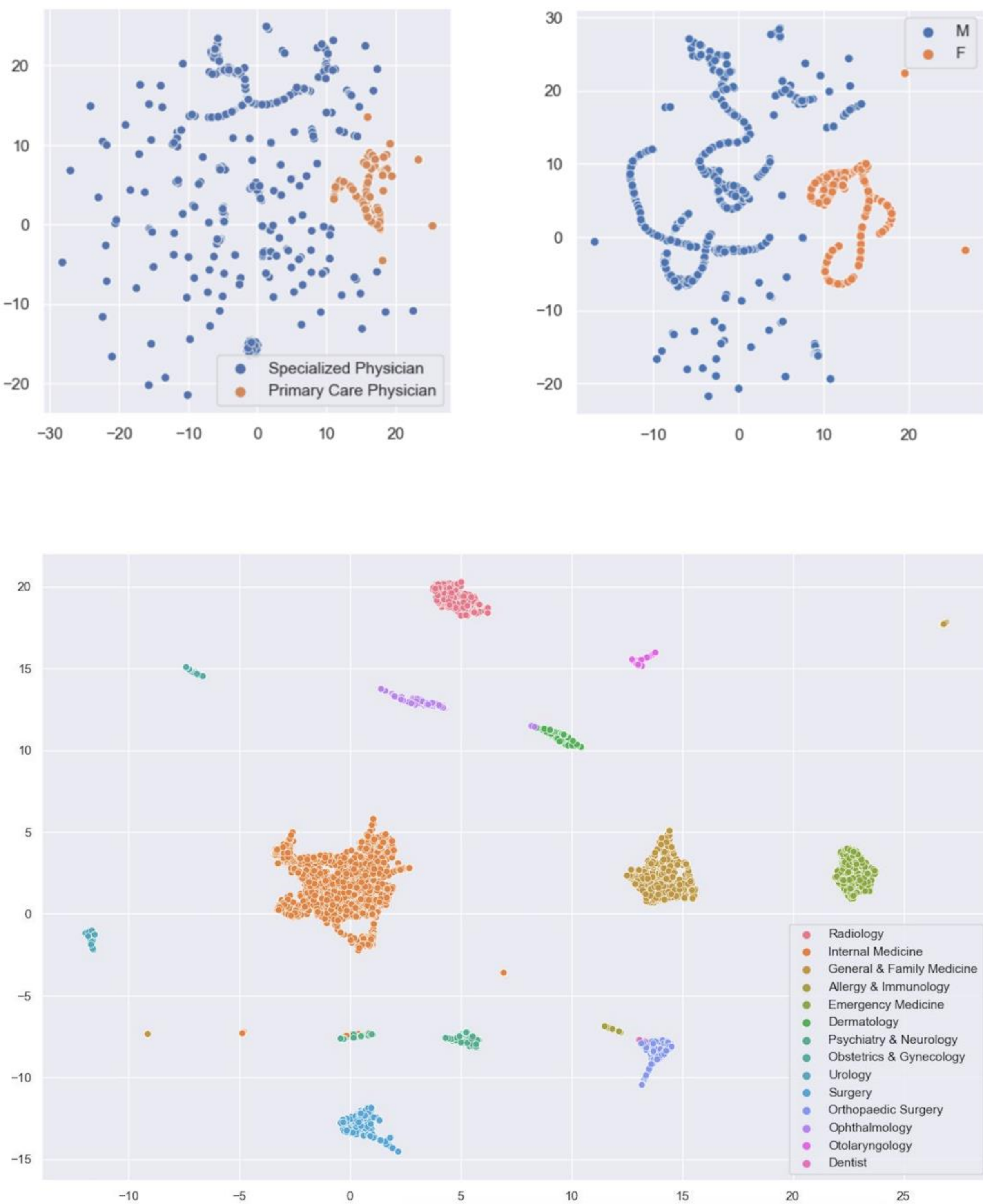


fig.3 Node Embedding of the U.S. nation wide

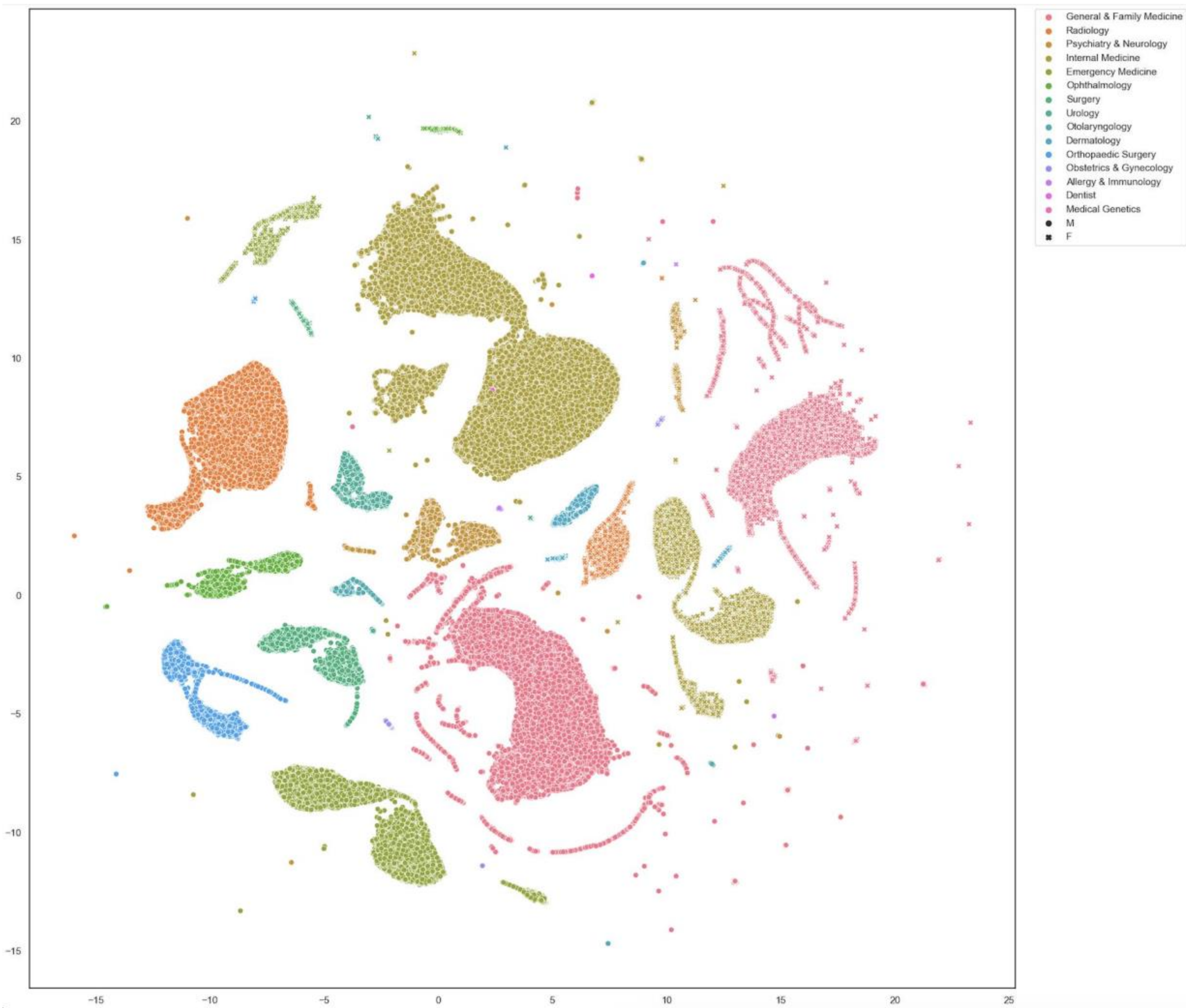
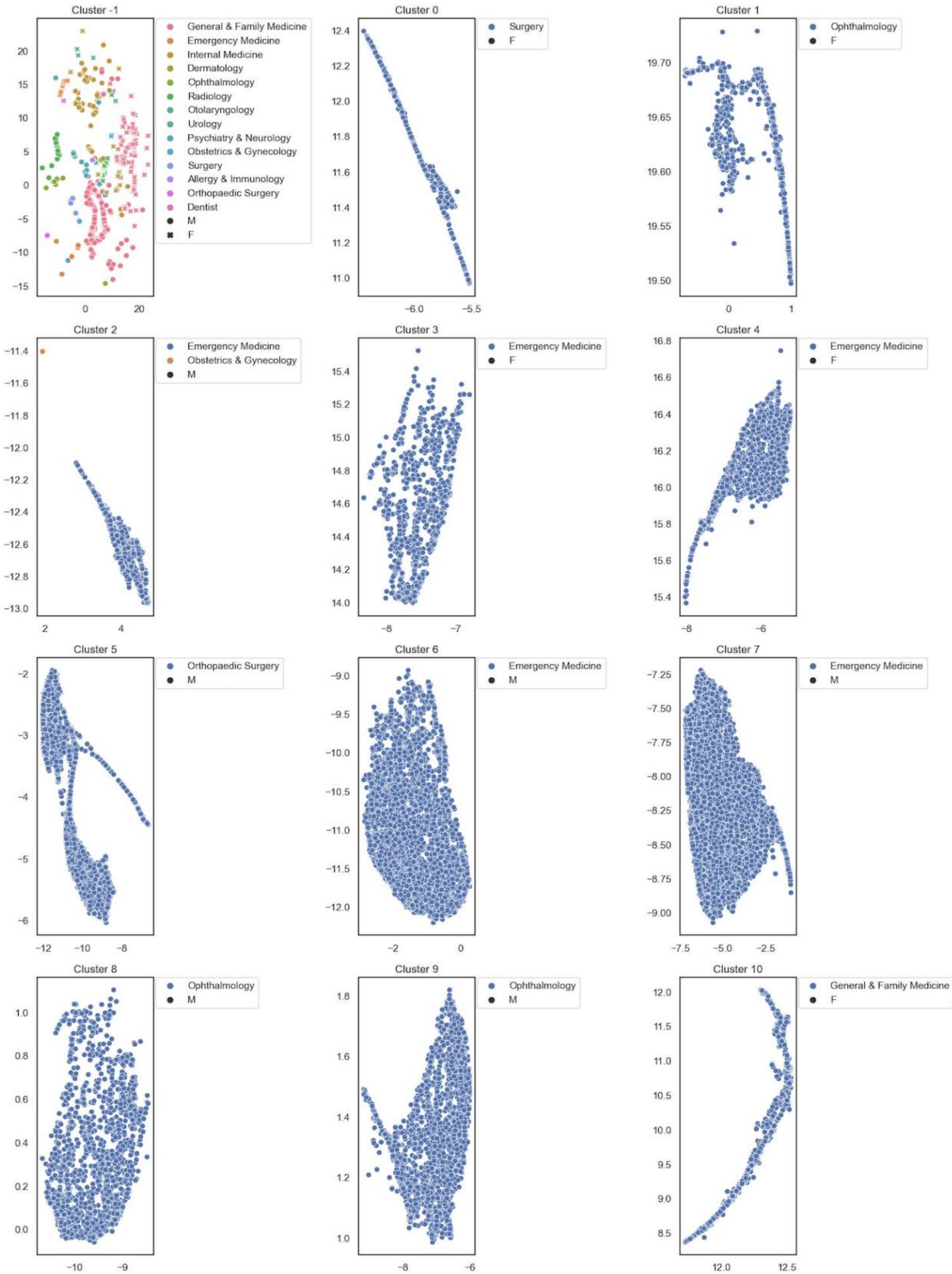
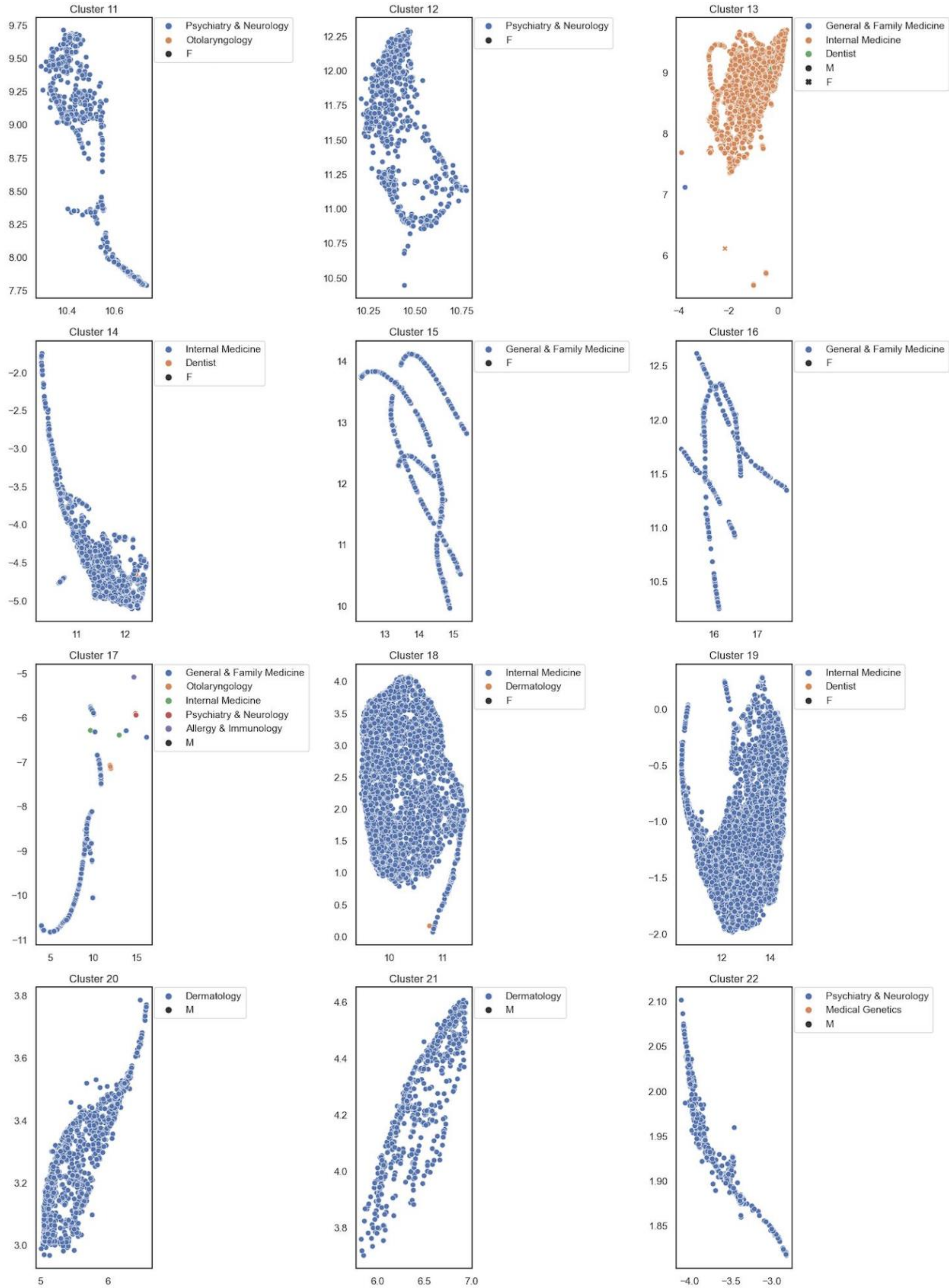


fig.4 HDBSCAN Clustering Visualization

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Internal Medicine
Dentist
F
Cluster 15
General & Family Medicine
F
Cluster 16
General & Family Medicine
F
Cluster 17
General & Family Medicine
Otolaryngology
Internal Medicine
Psychiatry & Neurology
Allergy & Immunology
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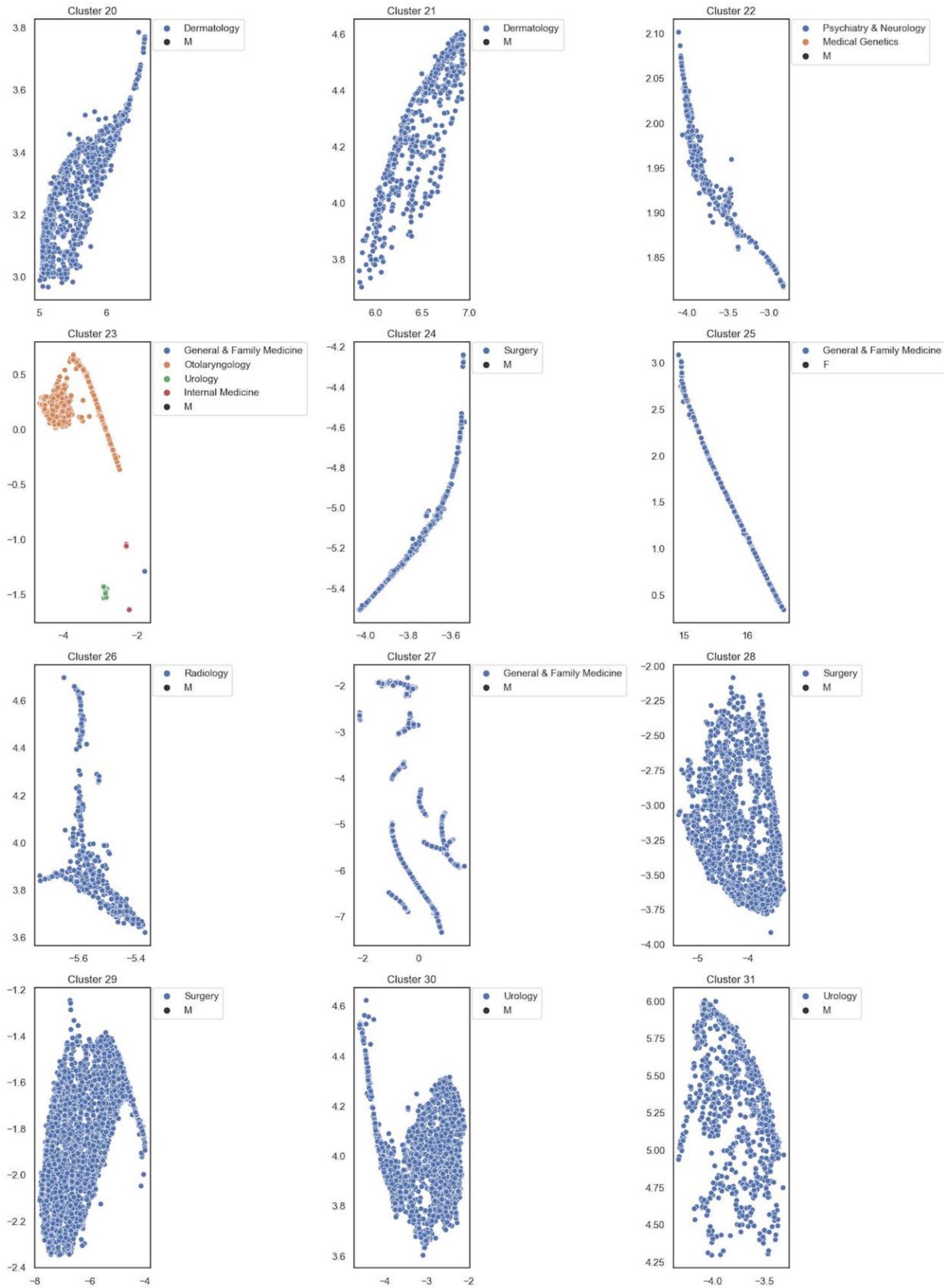
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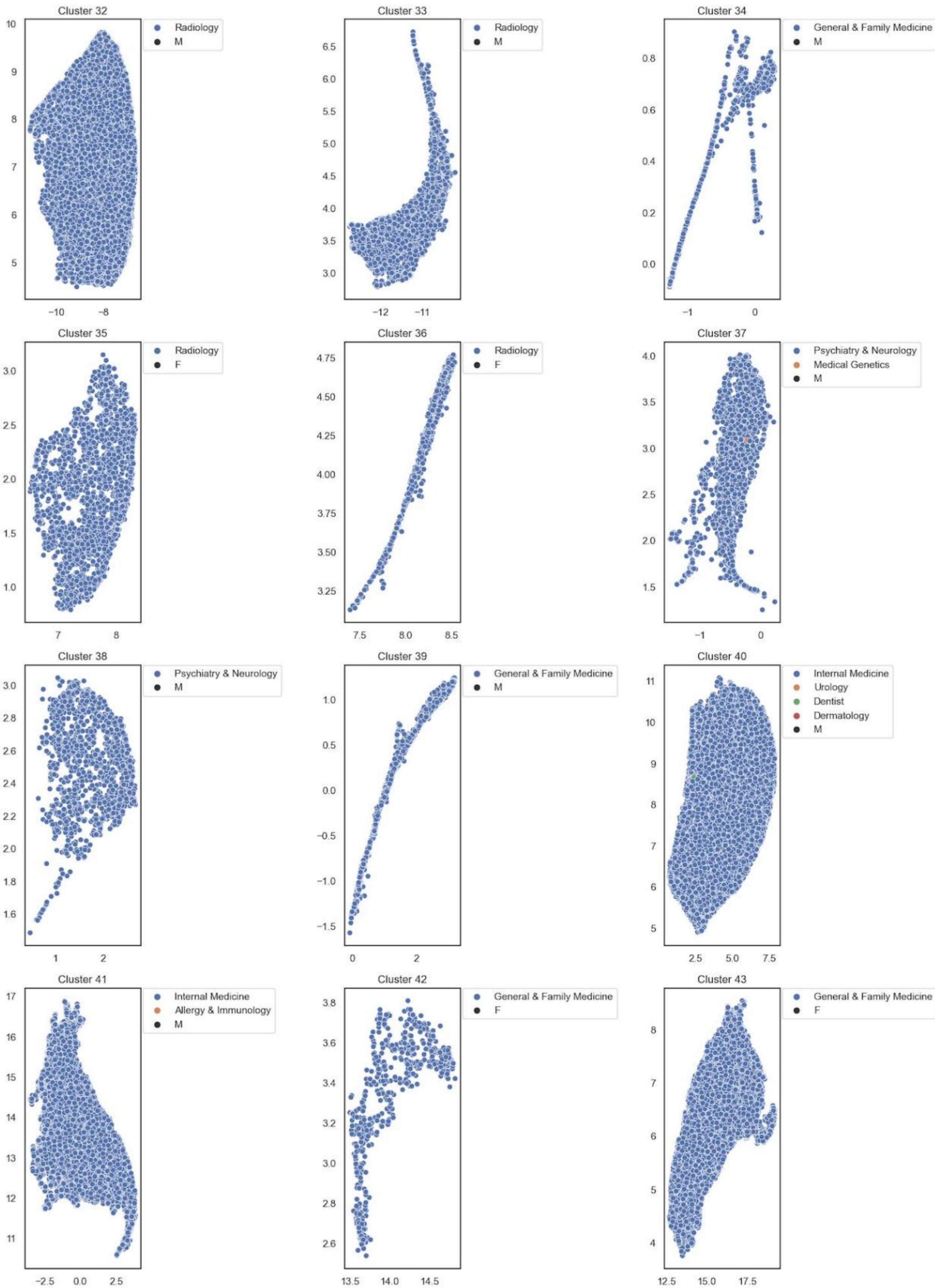
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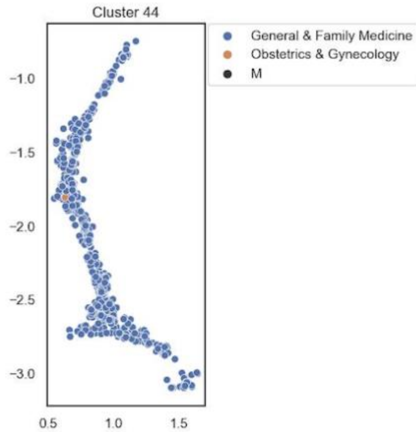
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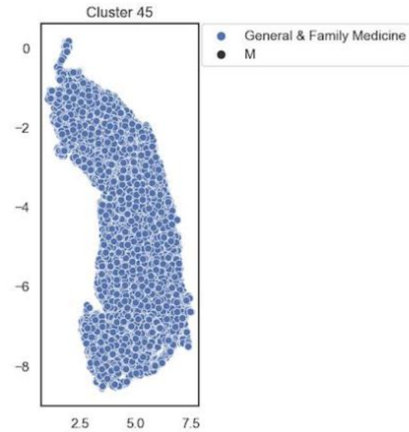
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Limitations

Although the database used in this study is based on the open-source data provided by CMS, the matching medical referral file only covers the year 2015. As a result, the study may not include physicians who have recently enrolled or deactivated their accounts, and those who have seen more patients over the years. Additionally, any changes to the healthcare system during this time frame may also affect the network structure, leading to potential bias in the results. It's important to note that this bias only represents a time lag in the results, and updating the database regularly is crucial for machine learning models to accurately capture the relevant features.

When building a network of physician relationships, patient data information is the medium that connects the referral, acting as an edge between the two physicians. Patient information provides a more comprehensive understanding of the impact of the referral or the disease, whether the referral works in real situations, whether the medical referral changed by disease of patient. Therefore, the physician's social network is inseparable from the patient. However, due to the protection mechanism of patient information, this project only takes the physician's perspective to obtain values to build the network, so it has some bias and incompleteness in the analysis.