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# Revealing Physicians Referrals from Health Insurance Claims Data ☆

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ABSTRACT

Health insurance companies in Brazil have their data about claims organized having the view only for service providers. In this way, they lose the view of physicians' activity and how physicians share patients. Partnership between physicians can be seen as fruitful, when they team up to help a patient, but could represent an issue as well, when a recommendation to visit another physician occurs only because they work in same clinic. This work took place during a short-term project involving a partnership between our lab and a large health insurance company in Brazil. The goal of the project was to provide insights (with business impact) about physicians' activity from the analysis of the claims database. This work presents one of the outcomes of the project, i.e., a way of modeling the underlying referrals in the social network of physicians resulting from health insurance claims data. The approach considers the flow of patients through the physician–physician network, highlighting connections where referrals between physicians potentially occurred. We present the results from the analysis of a claims database (detailing 18 months of activity) from the health insurance company we partnered with. The main contribution presented in this paper is the model to reveal *mutual referrals* between physicians. Results show the proposed model reveals underlying characteristics of physicians' activity from real health insurance claims data with multiple business applications.





## 1. Introduction

Health insurance costs are a main issue of concern in almost every country in the world as budget constraints impact directly on the quality of the service. As a result, health insurance companies have been extensively trying to reach a trade-off between offered services and costs as a way to meet budget constraints.

One way for health insurance companies to address those issues is to better understand the complex relationships among the diverse participants of the healthcare systems, including patients, physicians, hospitals, and other service providers. To support this quest, healthcare insurance companies and other health service providers have often a wealth of data from their own operations at their disposal, especially transactional data.

In the case of health insurance companies, an important piece of transactional data involves the claims presented by their ecosystem of providers. In the present work, a claim represents a report from a physician or a healthcare service provider to a health insurance company requesting some form of fee related to a patient's consultation with a physician, a clinical exam, or a medical procedure. Even though claims data may vary, it generally contains at least the ID of the healthcare professional involved in the procedure (it may also be a group of professionals), the ID of the patient, the type of procedure, and time information related to the event. It may include other types of information such as location of the service, pre-authorization codes, etc.

Traditionally the analysis of claims data is based on applying statistics and Data Mining methods to the individual elements of the system (physicians, service providers, patients) or to the set of claims. However, healthcare is often provided by collaborative teams of physicians, nurses, and technicians which are connected to each other by often strong professional relationships. Physicians that refer patients to other physicians have clear preferences about who they want to team up with for specific procedures and often are involved in master-apprentice structures. Physicians also have preferences for specific service providers such as hospitals and clinical analysis laboratories. Those recommendations could be good for building patient trust or indicate a fraud when this is not the patient's will. Similarly, patients establish bonds of trust and reliance with specific physicians or group of physicians.

In practice, mining claims is difficult because claims are paid to a wide variety of providers, such as hospitals, clinics, or even

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physicians registered as small companies. A single patient can consult a physician through all those channels. It could be even difficult to know who exactly is taking care of a given patient, since that there are cases in which the physician ID used in a claim is from a professional registered in the health care provider system, but the one taking care of the patient is an unregistered physician. Moreover, claims contain no information about referrals and often the connections among service provider team members are not recorded explicitly in claims. It is also well known that claims data is riddled with errors and unreliable information. Despite all those difficulties, we show in this paper that meaningful and reliable insights about the flow of patients through the network of physicians and how physicians refer each other can be inferred from claims data.

This study took place during a partnership, in a short-term project, between our lab and a major Brazilian health insurance company involving the analysis of their claims database. The main challenge the insurance company brought to our team was to identify physicians that excel at medicine by using the claims database. After decomposing this challenge considering the health insurance workflow, the following components were identified as key factors for outstanding professionals, defined by the health insurance company: physicians referred by peers, relative importance in the network of physicians, and returning behavior of patients. The need for modeling referrals emerged during interactions with the health insurance company staff as a way of identifying physicians that excel in a certain specialty and are referred by their peers. These interactions occurred weekly, fomenting discussions between our team and subject matter experts, IT specialists, analytics team, and the superintendent of the health insurance company. Hence, this work aims at presenting a way of modeling mutual referrals in a physician–physician network, which connects to the hypothesis studied in this work: *H1) It is possible to identify underlying physicians' referrals from claims data.*

The main contribution of this work is a way of modeling mutual referral patterns in the physician–physician network. The method can therefore be used by health insurance companies to better manage the physicians they have businesses with, nurturing the experience of registered physicians and inviting unregistered physicians that collaborate with registered ones. It can also be used to support patients to receive more integrated care from a group of physicians and service providers.

This paper is organized as follows: section 2 describes the related work, section 3 details the database analyzed, section 4 presents the proposed model for highlighting mutual referrals, section 5 discusses the obtained results, and section 6 concludes and points to future works.

## 2. Related work

Healthcare data is heralded as the key element in the quest to improve efficiency and reduce costs in healthcare systems [1]. This trend is becoming more pronounced as multi-scale data generated from individuals is continuously increasing, particularly due to new high-throughput sequencing platforms, real-time imaging, and point-of-care devices, as well as wearable computing and mobile health technologies [2].

In healthcare, data heterogeneity and variety arise as a result of linking the diverse range of biomedical data sources available. Sources of quantitative data (e.g., sensor data, images, gene arrays, laboratory tests) and qualitative data (e.g., diagnostics, free text, demographics) usually include both structured and unstructured data, normally under the name of Electronic Health Records. Additionally, the possibility to process large volumes of both structured and unstructured medical data allows for large-scale longitudinal studies, useful to capture trends and to propose predictive models [3].

One of the most useful and commonly used datasets are claims databases. Claims data records are often rich in details, as they describe important elements of the events taking place around the healthcare professional and the patient, e.g., timestamps, geographical location, diagnosis codes, associated expenses, among others. The use of claims data in healthcare studies has been scrutinized in [4] and [5], providing a set of good practices and outlining the shortcomings of claims-based research.

Social network analysis has proven to be a useful analysis tool in this context, allowing for insights difficult to reach by traditional descriptive statistics as presented in [5]. For instance, social network analysis has been used to study comorbidity, the simultaneous presence of two chronic diseases or conditions in a patient. By structuring diseases as a network, it is possible to quantify some of the aspects of the complex interactions between conditions in the different patient populations. A number of studies have focused on extensive claims datasets to examine and understand comorbidity networks. In [6], the authors study a diffusion process on a comorbidity network to model the progressive spreading of diseases on a population depending on demographic data. In [7], the authors study how a given chronic disease (diabetes) correlates with age and gender, spanning almost 2 million patients from an entire European country. Such comorbidity networks have also been proposed as models to understand the connection between genetic and environmental risk factors for diseases [8].

Beyond clinical purposes, claims data have also been studied to understand the complex interactions of different organizational structures and management relationships involved in patient care processes. For instance, in [9], temporal patterns in electronic health records were modeled in order to present useful information for decision-making. The authors developed a data representation for knowledge discovery so as to extract useful insights on latent factors of the different processes involving a patient, aiming at improving workflows.

Another important trend is the understanding of the relationship among healthcare professionals, in particular the physicians. In [10], the authors apply social network analysis to mine networks of physicians which might be used to improve the designation of middle-sized administrative units (accountable care organizations). Sauter et al. [11] use social network analysis to understand networks of healthcare providers which share patients, providing insights in the interplay between general practitioners, internal specialists, and pediatricians. Also, the network structure of different healthcare providers taking care of a given individual can show important variability of the healthcare system [12].

Social networks have also been used to understand the state of coordination of healthcare actors. In [13], the authors describe a complex network approach applied to health insurance claims to understand the nature of collaboration among physicians treating in-hospital patients and to explore the impact of collaboration on cost and quality of care. Also, in [14], the authors study the social network structure in hospitals among healthcare professionals to understand which variables affect patient care efficiency measures. The idea is further developed in [15] from a statistical point of view in a medium-sized number of hospitals, through the analysis of temporal patterns and costs.

The medical referral system in the Canadian healthcare system is studied in [16], where the authors map and analyze the network between general practitioners and specialists. In [17], the authors describe the condition of the basic medical insurance for urban and rural residents in China, then they demonstrate that social network analysis can be used in the health insurance claims data to support better understanding of patients transfers among hospitals.



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Social network visualization methods can also be powerful to explore and analyze healthcare information, in particular to depict the relationship among healthcare professionals [18].

Finally, this work differs from the previous ones as it combines social network analysis, graph mining, and information visualization. This combination fomented the conversion of a visual pattern identified in the data exploration phase into a network model that reveals underlying mutual referrals from claims database, allowing an in depth scalable analysis of such relationships.

## 3. The insurance claims database

The data used in this study was provided by a large Brazilian health insurance company we partnered with. The database contains information about services and materials of 108,982,593 instances of claims paid by the health insurance company to service providers covering 18 months of activity (about 200,000 claims per day). The database names 279,085 physicians, of which 81% are considered valid, that is, the physician register ID is well formed. Moreover, during the project we had access to information about 2,243,198 patients and 26,033 service providers. The database contained only claims related to medical consultations performed by physicians, i.e., it does not include claims related to clinical analysis, image-based exams, or hospitalizations. Considering ethical and data protection, the terms of access to database were covered by the contract between our lab and the health insurance company. In addition, given the goals of the project, related to the understanding of physicians' activity, patient sensitive information was not available to our team.

Two important aspects related to the quality of the data need to be mentioned. First, approximately 25% of the data do not contain information about state (location) in which the service was performed. This proportion increases when the data is modeled as a graph, since that missing state value in one or both nodes (representing physicians) may hinder an important piece of the analysis. Another important aspect of the data is related to the distribution of physicians' specialties. This attribute is important to correlate with physicians' relationships and crucial to the proper understanding of the results. However, because of the large amount of missing values, the use of this information in the data analysis had limited scope.

As mentioned before, the dataset analyzed contains only claims related to procedures performed by physicians. Therefore, the claims data can be mapped into a social network by considering connections among healthcare professionals or patients. Moreover, additional bits of information in the data may be included in the graph in the form of edges' weights, for instance, the number of events connecting the two nodes, the total expense, etc. For the nodes, the attributes to be included in the network involve demography, specialty, location, etc. Both weights and attributes may be represented visually by mapping their values to colors or sizes in the case of nodes, or colors and widths in the case of links.

In this work we focus on the relationships between physicians within the health insurance company network. Thus, two physicians are considered related if they have a common patient, that is, a patient that had a consultation with both physicians (i.e., a physician–physician network). This does not indicate a direct relationship, but, for large number of common patients (represented here as an outlier), there is a high likelihood that these physicians have some kind of relationship, be it a similar profile, same provider, similar location, similar education background, etc. This signals the possibility that they know each other and have referred their patients to one another.

In order to model the flow of patients throughout the physician–physician network, we consider the graph $G(V, E, w)$, where the $|\mathcal{V}| = N$ denotes the set of nodes that represent physicians and

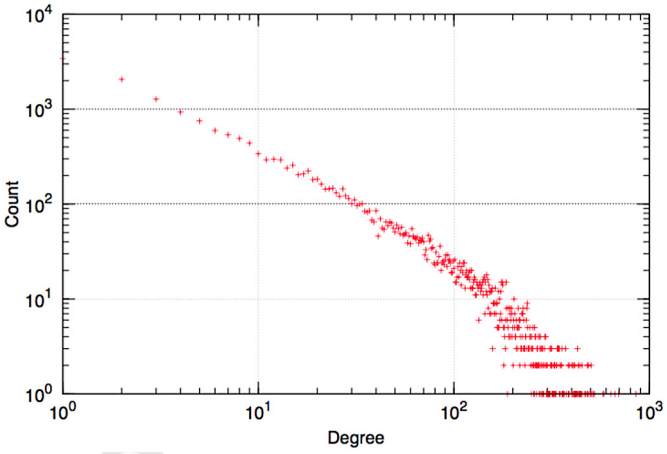


**Fig. 1.** Node degree distribution of the physician–physician network.

$|\mathcal{E}| = M$ denotes the edges that connect physicians that have in common consultations claim of a certain patient. Moreover, node $v_i \in V$ and edges $e_{ij} \neq e_{ji} \in E$. Each edge $E$ has an associated weight $w : E \rightarrow \mathbb{R}^+$ equal to the number of patients that consulted with physician $v_i$ and subsequently with $v_j$, denoted as $w_{ij}$.

The advantage in using a social network to model the relationships among physicians involves the several ways to quantify the relative importance of the physicians and to visually represent multiple physicians' connections and attributes. For example, social network analysis allows for individualization of physicians that are in a prominent position in the network be it due to the relationship with his/her peers, due to her connections with influential physicians, or because without the physician the topology of the network would change substantially (e.g., by increasing the number of connected components).

Fig. 1 shows the node degree distribution of the physician–physician network. As we can see, the tail of the distribution follows approximately a power-law, pointing to the fact that the relationship between physicians has a structure also commonly found in other real networks, such as social networks [19]. Here, most physicians are connected to only a few other physicians while a small number of physicians are very well connected in the network.

In the next sections we describe in detail the model proposed to better understand the physicians' referral behavior in this type of network.

## 4. Modeling mutual referrals

This section details the proposed way of modeling mutual referrals between physicians from health insurance claims data. It considers healthcare service relationships to identify the underlying referral network among physicians.

Identifying physicians that work together, especially for consultations, is of great business value for health insurance companies. Physicians working together may be due to several reasons. On the one hand, it could be positive for medical care professionals to treat patients together and be able to work as a team, building trust. On the other hand, this pattern could also point to a misuse of health insurance resources. For instance, it could be the case that every time a patient visits a given clinic or physician, she/he is redirected to another physician, even if there is no need to do so. Other situations could involve physicians benefiting certain colleagues by issuing unnecessary referrals, possibly under terms of reciprocity.

The data analysis of the physician–physician network started from the overview of the whole network, followed by zoom and

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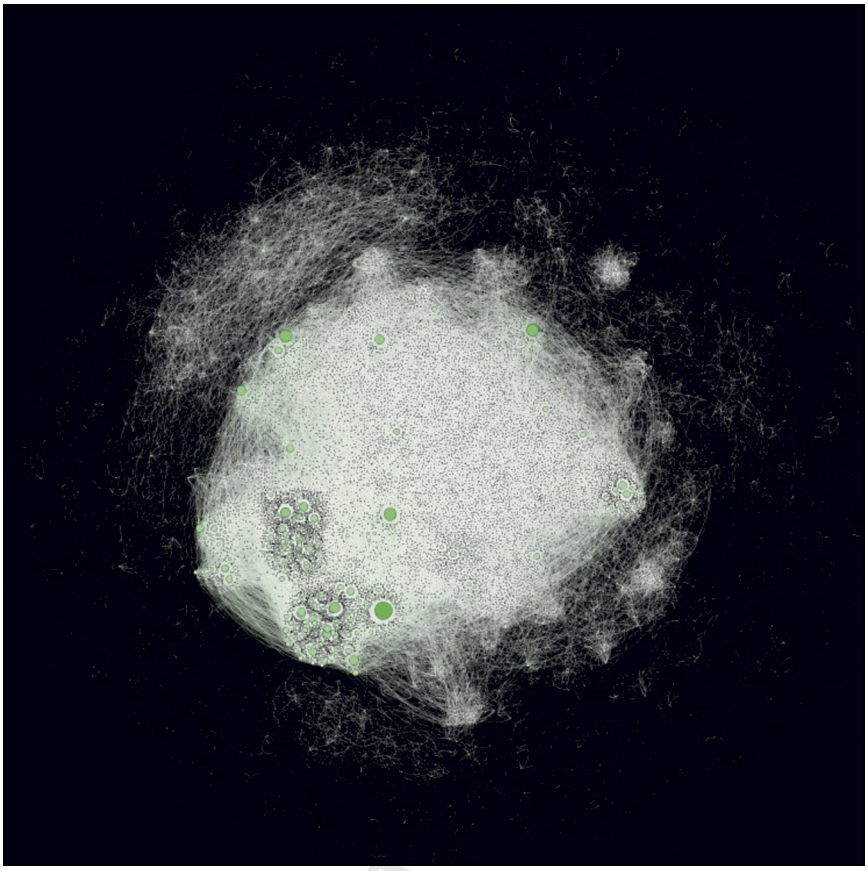

**Fig. 2.** Directed graph showing the physician–physician network and the flow of consultations. Two physicians ($P_1$ and $P_2$) are connected if a patient visited first ($P_1$ and then $P_2$). The graph counts on 19,424 nodes, 386,204 edges, has diameter of 20, average path length of 4.71, average degree of 19.34, average weighted degree of 32.12, and density of 0.001. In this visualization, edges' opacity was set to maximum to highlight how the mutual referral visual pattern was identified in the peripheral connected components of the graph, although this opacity hindered connection patterns occurring in the core of the network.

filter, and details on-demand, as proposed by Shneiderman [20]. By visualizing the whole network, it was possible to identify interesting topological characteristics and visual patterns. The mutual referral model focuses on identifying nodes that are part of a visual pattern that emerged during the first visualizations of the network. Fig. 2 shows the whole physician–physician network where connections represent the consultations of shared patients (as detailed in Section 3). In the network it is possible to see the small components at the border of the network and how the connections occur in a reciprocal way between multiple pairs of physicians.

The visual pattern connecting pairs of physicians was clearer when the nodes with small degree (less than the 2nd decile) were filtered (Fig. 3). Fig. 4 shows an example of the same visual patterns for the state of São Paulo, now in a circular layout. In Fig. 4 it is also possible to identify the pairs of mutual connections and degree distribution. These initial results from visual analysis fomented the creation of the proposed model.

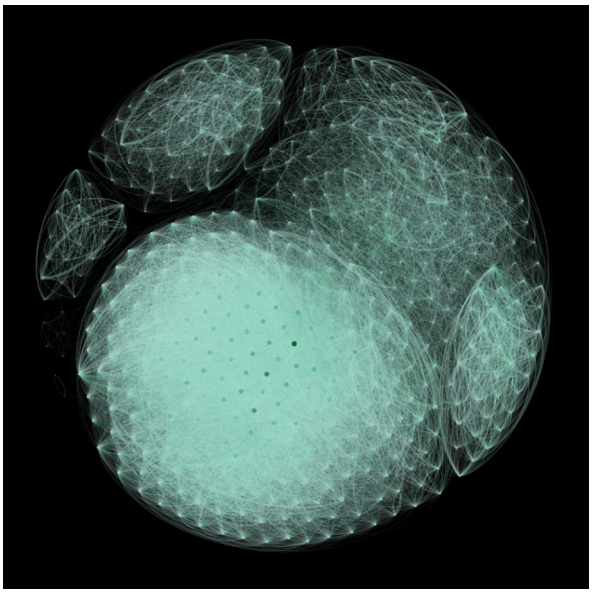

**Fig. 3.** Directed graph showing the physician–physician network for consultations after filtering nodes with degree smaller than the 2nd decile (270).

**Definition 1** *(Mutual Referral).* The *Mutual Referral* focuses on identifying pairs of nodes $v_i$ and $v_j$ (where $i, j \in [1, N]$ being $N$ the total number of nodes in the network $G$) connected by edges $e_{ij}$ and $e_{ji}$, where the weights $w_{ij}$ and $w_{ji}$ are high (the metric increases proportionally to the weights) and, at the same time, as similar as possible to each other (the metric decreases as weights differ):

$$mr(v_i, v_j) = w_{ij} + w_{ji} - |w_{ij} - w_{ji}|,$$

where $mr(v_i, v_j) = mr(v_j, v_i)$. The metric is symmetric to $i, j$, as expected for a variable describing a property of a given pair of nodes. Note that the second term in $mr(v_i, v_j)$ represents a penalty for those pairs of edges not similar to each other, thus the metric scores higher in case of symmetrical relationships.

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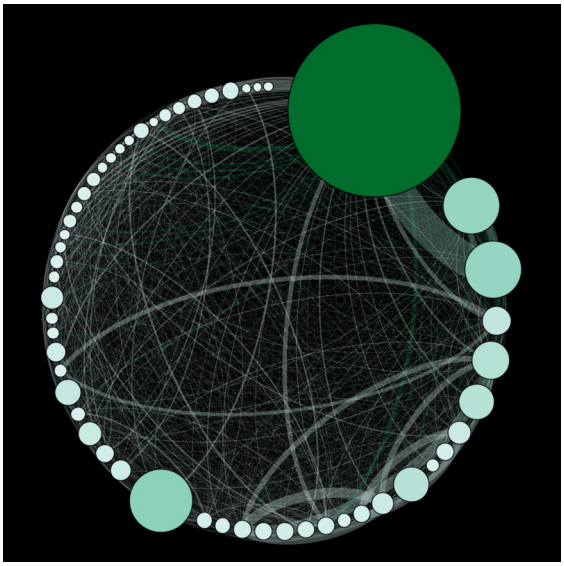

**Fig. 4.** Directed graph with top 50 physicians in the state of São Paulo in a circular layout. Node color and node diameter represent degree.

To allow for the possibility of a global comparison between pairs of nodes, we defined a mutual referral score (*mrs*), by normalizing by the maximum value of *mr* across the complete graph $G$.

**Definition 2** *(Mutual Referral Score).* The *Mutual Referral Score* measures, in the unit range $[0, 1]$, the relationship between each pair of nodes $v_i$ and $v_j$, relative to the maximum mutual referral identified in the directed graph $G$, represented by $max(mr(v_s, v_t))$, $\forall s, t \in [1, N]$. Thus, for any pair of nodes $v_i$ and $v_j$ in $G$, the mutual referral score is defined as:

$$mrs(v_i, v_j) = \frac{mr(v_i, v_j)}{max(mr(v_s, v_t))}, \ \forall s, t \in [1, N],$$

where again $mrs(v_i, v_j) = mrs(v_i, v_j)$.

Aiming at identifying connections among physicians when the studied settings change (e.g., population, availability of health services, socioeconomic levels), analyses were performed considering the top 20 and top 50 physician IDs with strongest mutual referral scores from five Brazilian states containing the most claims.

Fig. 5 presents a visualization of five Brazilian states that have different characteristics not only in terms of population, but also in per capita income and healthcare services availability. São Paulo and Rio de Janeiro have the larger population numbers, per capita income, and healthcare services offerings. Nodes represent physicians, nodes' size and color are proportional to node degree, larger/darker nodes represent degrees of higher value. The health insurance company has an important presence in São Paulo and Rio de Janeiro, which can be observed looking at the top 20 physicians in these states. Because of the number of physicians is larger in these states, patients have more options to choose, but they usually choose physicians working with a particular group of other physicians (mainly associated with regions and well-known service providers).

On the other hand, in other states such as Bahia, Pernambuco and Distrito Federal, the presence of the health insurance company is sparser; there are less physicians that work with this company, meaning less options for patients and in consequence more evenly distributed degrees, which can also be identified in the density values of the network (see Fig. 5).

We observe an unusual case in Distrito Federal, where two pairs of heavily connected physicians have the median of days between two consultations equal to zero days, meaning that half or more patients consulted both physicians in the same day. This could represent physicians that work in the same healthcare provider, for example, a cardiologist that executes an electrocardiogram and another cardiologist that analyzes the results right after the exam. However, in both cases we did not have the physicians' specialty information. Actually, most of the physicians that are strongly connected with others do not specify their specialty, which hinders details regarding the context in which the connection occurred.

Table 1 shows the strongest pairs of physicians in the studied database. Except the top pairs from the state of Mato Grosso do Sul, $P_{MS}028$ and $P_{MS}027$, all the other physicians are from the 5 states represented in Fig. 5. Physicians $P_{MS}028$ and $P_{MS}027$ have 205 same-patient consultations (first with $P_{MS}028$ and then with $P_{MS}027$) and 196 consultations (first $P_{MS}027$ and then $P_{MS}028$). None informed their specialty, but with this information, subject matter experts can analyze in detail the highlighted relationships, identifying groups of physicians that work together, misuse health insurance resources by forcing unnecessary referrals, or cases of referral/counter-referral.

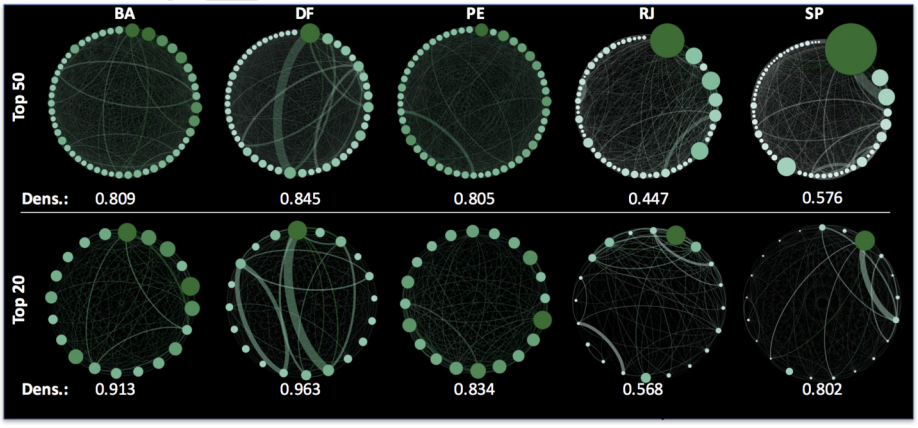


**Fig. 5.** Directed graphs showing top 50 and 20 physicians with highest mutual referral score from the following Brazilian states: Bahia (BA), Distrito Federal (DF), Pernambuco (PE), Rio de Janeiro (RJ), and São Paulo (SP).

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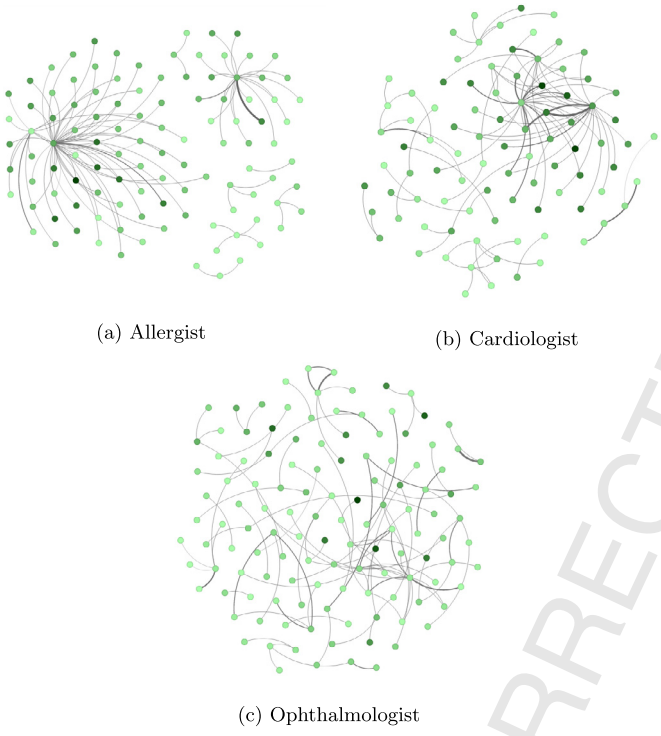
**Table 1**
The top 10 mutual referral scores in the database; physicians' IDs are anonymized and state codes are used to allow interpretation considering different Brazilian states.

| | | Consultations | | |
|---|---|---|---|---|
| $P_1$ | $P_2$ | $P_1 \rightarrow P_2$ | $P_2 \rightarrow P_1$ | $mrs(P_1, P_2)$ |
| $P_{MS}028$ | $P_{MS}027$ | 205 | 196 | 1.000 |
| $P_{DF}010$ | $P_{DF}009$ | 267 | 108 | 0.551 |
| $P_{SP}022$ | $P_{SP}021$ | 103 | 102 | 0.520 |
| $P_{SP}139$ | $P_{SP}138$ | 92 | 72 | 0.367 |
| $P_{DF}057$ | $P_{DF}056$ | 73 | 71 | 0.362 |
| $P_{SP}141$ | $P_{SP}140$ | 72 | 70 | 0.357 |
| $P_{SP}139$ | $P_{SP}140$ | 73 | 66 | 0.337 |
| $P_{SP}024$ | $P_{SP}023$ | 92 | 63 | 0.321 |
| $P_{SP}143$ | $P_{SP}142$ | 73 | 63 | 0.321 |
| $P_{SP}145$ | $P_{SP}144$ | 70 | 62 | 0.316 |



(a) Allergist (b) Cardiologist

(c) Ophthalmologist

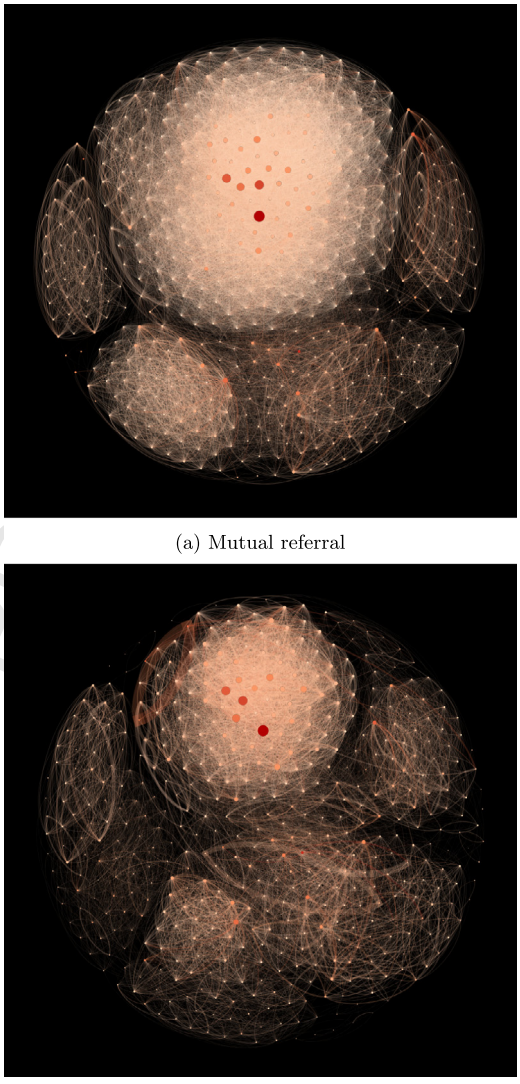
**Fig. 6.** Undirected graphs showing the top 100 mutual referral scores connected to the following specialties: allergist, cardiologist and ophthalmologist.

Considering the whole network, analysis of those pairs of physicians with highest mutual referral score and with informed specialties revealed the following common specialties referrals:

- Ophthalmologist ↔ ophthalmologist;
- Cardiologist ↔ cardiologist/vascular surgery[1];
- Acupuncture/pediatrician ↔ allergist;
- Cardiology ↔ hematology/clinical pathology;
- Dermatology ↔ cardiology.

Based on the identified connections considering specialties, the next step considered verifying differences regarding the mutual referrals for physicians with informed specialties. Interesting aspects were revealed considering connections of allergists, cardiologists and ophthalmologists. Fig. 6 shows the network for the top 100 mutual referral scores for different specialties. We can see that in the studied database the referral behavior is different when considering specialty.

[1] Physicians can have more than one specialty informed.



(a) Mutual referral

(b) PageRank

**Fig. 7.** Directed graphs of top 500 nodes selected by the mutual referral (a) and the top 500 nodes selected by PageRank algorithm (b), both from the physician–physician network generated from the claims database. The graph in (a) counts on 38,597 edges and has density of 0.158 while the graph in (b) counts on 18,099 edges and has density of 0.072. Node size represents in-degree and node color represents PageRank value.

For allergists (Fig. 6a) there are two main physicians connected with several other physicians from different specialties, most of them pediatricians. Thus, it is possible to infer that these two allergists are recommended by most of their pediatrician colleagues. Hence, for this physician–physician network losing these two allergists would cause a negative impact on the network and likely on the health insurance company.

For cardiologists (Fig. 6b) there are two physicians that are strongly connected with several other physicians and nine other cardiologists that have a small number of other physicians connected to them. Finally, the network is different for ophthalmologists (Fig. 6c) in which almost no other physician is strongly connected to multiple physicians. They work mostly in pairs (usually the other ophthalmologist is a surgeon, or a peer responsible for running certain types of exams). Thus, the health insurance company now knows that approaching an ophthalmologist either for registering or improving his/her experience with the company means approaching also his/her peer.

Fig. 7 shows the comparison between our proposal for modeling mutual referrals and the PageRank algorithm [21], both applied

to the same physician–physician network. The PageRank algorithm aims at providing a proxy for nodes' reputation, allowing this reputation to be propagated when nodes with higher reputation "refer" to nodes with smaller reputation values. In the context of health insurance claims data, PageRank would support identifying a new physician in the network being referred by a physician with high reputation in the network. However, PageRank algorithm does not support selecting pairs of physicians highly connected, even in cases that they are disconnected from physicians with high reputation in the network, but, to the best of our knowledge, this is the closer technique to compare considering referrals. This effect can be seen in Fig. 7a. It shows the resulting graph using mutual referral model with a higher number of pairs strongly connected and with higher density (0.158) than in PageRank graph (0.072). On the other hand, Fig. 7b shows the resulting graph using the PageRank algorithm, in which fewer edges are connecting the nodes, but, in turn, existing connections allow for the selection of physicians without mutual relationships to physicians highly referred.

Lastly, the mutual referral model suggests that some physicians consider their own connections to indicate patients. Hence, in situations where the health insurance company wants to improve the relationship with physicians, it could consider an approach involving groups of doctors that already act together, increasing the involvement of the group as a whole with the health insurance company and its services. More generally, this metric could support decision-making processes involving increasing or reducing the network of accredited physicians/service providers. Connecting to our hypothesis (i.e., *it is possible to identify underlying physicians' referrals from claims data*). The pairs of physicians emerging from the visual analysis, the connections between specialties, and the relationship involving location of the service provider are all in accordance to facts highlighted by subject matter experts.

## 5. Discussion of results

The results show interesting aspects related to social network analysis, information visualization, and the healthcare insurance business. Considering the main contribution of the paper, the proposed model represents a step forward towards revealing underlying characteristics of physician–physician networks and physicians' referral behavior in the context of private healthcare services.

The study was conducted considering multiple problems the health insurance company presented us in the context identifying physicians that excel in their daily work. After multiple interactions with subject matter experts, this goal was decomposed in minor challenges, one of them being the referral. The importance for the health insurance company in improving the relationship with professionals involves increasing the quality of service as whole.

The model for mutual referrals proposes a proxy for identifying how physicians refer peers to their patients. The act of referring a physician occurs informally and is not coded anywhere in the data. The presented approach not only was able to detect those relationships but also provided insights considering social ties, time between referrals, location, and specialty attributes. Moreover, the mutual referral can be used as a metric in any type of service involving people at both ends (provider and consumer) and where this informal referral between peers might occur.

The comparison between the mutual referral and the PageRank algorithm [21] in the selection of the top 500 physicians highlighted the main differences between them. On the one hand, mutual referral supports selecting pairs of physicians that are not connected to the core of the physician–physician network. This case is interesting for health insurance companies with country-wide operations, when the resulting graph might result in a network with multiple connected components with multiple locally important connections. On the other hand, PageRank supports the identification of physicians that are new in the network and that are referred by a physician highly influent in the network. However, in the context of physician–physician network, such connections could also occur by chance, scenario that is reduced in the case of mutual referral given the nature of the model to value reciprocity. Finally, the use of mutual referral approach or PageRank algorithm in the context of health insurance data depends on the question to answer. If the question involves identifying pairs of mutual relationships, the mutual referral can be used as a starting point for highlighting such underlying relationship. If the question involves identifying how physicians highly important in the network refer physicians recently added ones, then PageRank seems an appropriate first step for such analysis.

## 6. Conclusion

In this work we have shown how information visualization and social networking techniques can be applied to the analysis of health insurance claims data, mainly by mapping physicians using shared patients as a proxy for a relationship between them. The resulting model provided useful insights to the health insurance company we partnered with. The way of identifying mutual referrals improved the understanding of important characteristics both from physicians and the flow of patients considering consultations, specialty, location, and time between the consultations. Those insights can have multiple business applications such as to detect frauds or to improve the relationship between the health insurance company and important physicians for the company.

We demonstrated, by the analysis of a real database of claims from a large Brazilian healthcare insurance company, how health insurance data can be modeled as a social network supporting a structural analysis as opposed to traditional transactional approaches. Moreover, our results point out that the complex physician–physician network derived from the health insurance claims database has characteristics similar to a social network, opening multiple paths for this research to follow, in particular, considering theories and techniques from Social Network Analysis.

The data analysis and the value of the model for the business of the health insurance company we partnered with were validated through weekly meetings involving our team and the health insurance company staff, including physicians, process analysts, and IT specialists. Those interactions with subject matter experts were key for the proper understanding of the database, processes, and the identification of the most important cases in terms of decision-making support and business value. The company was already performing analysis of high cost procedures and flow of patients throughout the health insurance services. However, our results provided them with new tools for performing analysis at scale, considering the data they have at their own disposal.

Future works involve a more detailed study of the proposed approach, including authorization processes and clinical exams/surgeries. Moreover, building on the presented results, we plan to apply Social Network Analysis algorithms (e.g., community detection, link prediction, among others) in order to deepen the analysis involving groups of physicians that work together.

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