Context discovery and cost prediction for detection of anomalous medical claims, with ontology structure providing domain knowledge

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Abstract: Medical fraud and waste is a costly problem for health insurers. Growing volumes and complexity of data add challenges for detection, which data mining and machine learning may solve. We introduce a framework for incorporating domain knowledge (through the use of the claim ontology), learning claim contexts and provider roles (through topic modelling), and estimating repeated, costly behaviours (by comparison of provider costs to expected costs in each discovered context). When applied to orthopaedic surgery claims, our models highlighted both known and novel patterns of anomalous behaviour. Costly behaviours were ranked highly, which is useful for effective allocation of resources when recovering potentially fraudulent or wasteful claims. Further work on incorporating context discovery and domain knowledge into fraud detection algorithms on medical insurance claim data could improve results in this field.

1 INTRODUCTION

Due to the beneficent nature of healthcare, providers are generally expected to behave with integrity, perhaps more so than in other industries (Couffinhal and Frankowski, 2017). In practice, complex cost drivers in the healthcare industry create opportunities for fraudulent or wasteful conduct, and OECD healthcare organizations typically lose 3-8% of expenditure to fraudulent claims (Gee and Button, 2015; Couffinhal and Frankowski, 2017). The cost of monitoring and detecting fraud and waste can impact payer incentive to take action, as not every investigation will result in recovery of funds, and investigations can involve substantial human time and expertise (Couffinhal and Frankowski, 2017). With the ever-increasing volume of data being recorded, new approaches to data analysis are necessary (Krumholz, 2014; Ekin et al., 2018). Research on medical fraud detection typically involves large amounts of data, so machine learning approaches have been widely investigated Couffinhal and Frankowski (2017); Ekin et al. (2018). Since the more commonly used supervised machine learning methods require class labels, which can have a high cost in human effort, research focus has moved to unsupervised methods, although direct comparison where class labels are available shows that there is room for improvement (Bauder and Khoshgoftaar, 2017; Ekin et al., 2018). Typically, unsupervised methods for fraud detection depend on anomaly detection, either with clustering or outlier identification (Ekin et al., 2018). However, many studies have focused on a single provider specialty or item.

Variation is common in medicine, and health conditions, along with their presentation and treatment, are heterogenous by nature (Ekin et al., 2018). Medical insurance claim items are written to cover a variety of situations in a complex, changing environment. Some items may be claimed in a variety of medical situations, and, conversely, similar situations may generate quite different sets of legitimate claims. Some item specifications are written broadly and are claimed by many providers across a range of specialties, whereas others are very specific and may only oc-

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cur infrequently. These characteristics make anomaly detection from raw claims data difficult, because the *context* in which items can and should occur (as seen through their relationship to other items) can be difficult to determine without domain knowledge.

1.1 Challenges in medical claim anomaly detection

Difficulties in analysing large datasets are common, including, but not limited to, the variability of data sources and features.[1] Despite costs in the order of A$35 billion, and an historically low fraud detection rate (Australian Government, 2017), relatively few studies have examined the Australian Medicare Benefits Schedule (MBS) data (Ng et al., 2010; Mendis et al., 2011; Tang et al., 2010; Shan et al., 2008, 2009; Hu et al., 2011; Yamanishi et al., 2004). MBS claims have several characteristics which make anomaly detection difficult, some of which may be shared across medical claims datasets, and some which may be unique. We note two broad categories: heterogeneity of the data, and information available to analysts.

1.1.1 Claim heterogeneity

Many items, such as professional attendance items, are ubiquitous and may be claimed in quite varied circumstances, whereas others may be very specific in use. There is a high degree of overlap between many specialities and sub-specialities. Some items allow for figurehead billing, a practice whereby the claims of multiple providers are filed under a single identifier (Australian Government Department of Health, 2019). Provider claims may not be an exact representation of service provided; aside from potentially fraudulent billing practices such as upcoding, unbundling, and bundling (Couffinhal and Frankowski, 2017), administration errors can lead to valid claims not being filed, incorrect items being claimed, or claims being ascribed to the wrong patients or providers.

Practices for similar events can vary by region or training school. For example, in surgeries in metropolitan areas, there will usually be a trained anaesthetist administering anaesthetic. However, in regional areas where capacity is limited, surgeons or other hospital staff may be cross-trained to some extent, leading to mixed types of claims. Co-claiming some services is explicitly disallowed by the MBS, but may be manually over-ridden by Services Australia (an agency of the Australian Federal Government) during the claiming process in some circumstances.

1.1.2 Information availability

Information relevant to verifying claims, such as patient case notes, is usually unavailable to analysts, and an audit of the provider may be required to gain all the relevant information. Providers have up to two years to file a claim, so relevant information such as co-claimed items and items claimed by other providers for the same patient may be missing when an analysis is conducted (Australian Government Department of Health, 2019).

Interpreting whether an item is being claimed appropriately can require domain knowledge. Administrative understanding and acceptance often moves slower than current medical practice, leading to imprecise or out of date mappings between claims and the services they represent.

There is an inherent tension in the system between ensuring that services which are legitimately required are paid for and available to all eligible persons equally, and ensuring that fraudulent or wasteful services are not unduly burdensome on the financing of the healthcare system. Service payment is the primary focus of the MBS, and analysis for fraudulent or wasteful services is a secondary activity. As such, the available data is not designed for that purpose.

1.2 Research goals

With such characteristics, identifying appropriate and inappropriate behaviour from patterns in the data alone is not straightforward. Ideally, an algorithm should be able to process multiple contexts and learn to separate them, so that similar providers are compared with each other and outliers from any group flagged. An additional concern is that unusual behaviour does not necessarily warrant attention. Due to the large amount of intrinsic variation in medicine, medical claims do not lend themselves to neat segregation, and anomalies are to be expected. Audits or other interventions can be costly, and time and resources available to conduct them are limited. Therefore, an additional driver for flagging outliers is potential returns; an effective algorithm should maximise the return on investment in the investigation and intervention process.

1.2.1 Graphical Association Analysis

In previous work we developed a method based on creating directed graphs (digraphs) of association rules for claim-item pairs, which we call Graphical

[1] The reader is referred to Sivarajah et al. (2017) for a more complete discussion of big data challenges.

Association Analysis (GAA). GAA was able to identify typical provider claims for joint replacement procedures, and variation from learned reference models, across all provider roles and item types which may be involved. In brief[2], two-item association rules are learned from all pairs of item codes in each set of per-provider, per-patient claims on a single day of service. This process is applied to each provider (creating a model for typical claims of that provider), as well as for the claim set as a whole (creating a typical model across all providers). The association rules, which can be interpreted as directed edges, are converted into a graph structure. In the all-provider model, different provider roles may be seen in the separate graph components. Individual provider models are compared with the closest component in the all-provider model, and excess costs used to rank the providers for potential recovery. In learning the provider roles within the procedure, and the items which contribute to those roles, this method is able to function as a topic-modelling method, with the advantage of easy visualisation using the graph structure which can help with human interpretability.

While this method is generalisable to any single-day procedure, downsides include that the context is specified in relation to a single item – the particular procedure item under investigation. That is, it is only able to learn the typical claim patterns for a single procedure at a time. Using excess typical costs as a metric meant that total recoverable costs for a high-ranking provider were low if a provider only performed a handful of procedures. Further work is therefore required to compare provider behaviour across a range of procedures, so that comparisons can be made both within and between contexts, and to rank providers on total recoverable costs.

1.2.2 Knowledge-based role and cost discovery

In order to achieve these goals, we incorporate domain knowledge in a low-effort, machine-friendly manner by utilising the structure of the MBS ontology in combination with topic modelling, to assist in learning context and predict claim costs. Ontological structures are difficult to create and maintain, but are able to specify domain knowledge in a structure that is simple for both humans and computers to interpret, and they have become prominent in biomedical applications (Konopka, 2015; Ivanović and Budimac, 2014). For our purposes, the claims ontology offers a simple way to define item relationships based on medical reasoning, rather than attempting to find the relationships through clustering. We propose ranking providers by the median of the difference between a provider's actual fees and predicted fees, weighted by their number of procedures, in order to find behaviour which is repeatedly costly and unusual. This method could be useful as part of a decision support system in two ways: it can prioritise potential targets for audit, as well as identify previously unknown patterns of potential fraud and waste for further investigation or potential policy change.

2 Related work

Utilising methods to predict costs of claims and examine the discrepancy between actual costs has been proposed by several authors and implemented on U.S. Medicare and Medicaid data, with promising results.

Thornton et al. (2014) included, among other analyses, a linear regression model of reimbursement amount compared with number of claims by dentists, with a standard deviation threshold to detect outliers. Ko et al. (2015) performed a similar analysis on urology claims, using number of patient visits instead of number of claims. Bauder and Khoshgoftaar (2016) generalised the concept to other provider types, comparing five different regression models within their proposed framework to predict reimbursement depending on the procedure/provider type combination among five different provider specialties. Six features were incorporated, each statistically significantly different between at least most of the provider specialties, and thresholds of error were set to flag outlying providers. However, in each of these works only one provider specialty could be analysed at a time, and for provider specialties with a high degree of overlap, or for procedure item codes which may legitimately co-occur, such a method may not be feasible as reliably segregating providers and procedures can be difficult.

Weiss et al. (2015) discuss the importance of identifying costly outliers from peer groups, and used patient demographic and diagnostic information in order to predict provider prescriptions of Oxycodone (using volume as a proxy for cost). Providers with high volumes of prescriptions that were predicted to be in a low-volume demographic were flagged as anomalous. This method relies on access to patient information which may not be available to the insurance provider; typically such information is held in the medical provider's local database, and there may be legal restrictions on its access.

[2] Full details of this method are currently in the publication review process.

3 Methods

3.1 Data

The Medicare Program in Australia provides reimbursement for medical services and hospital care for Australian residents and some visitors. Eligible services and reimbursement amounts are defined by the MBS as an ontology with a tree structure representing the relationship between items (Australian Government Department of Health, 2019). The tree comprises five levels: *Category* → *Group* → *Subgroup* → *Subheading* → *Item* (with subgroup and subheading being optional). Reimbursement claims are recorded as rows in a tabular dataset, containing a claim for a single professional service performed according to the MBS, with information such as provider and patient identifiers, date of service, the item code (representing the service performed), and other relevant details. Multiple services may be claimed on the same date, e.g., it may be appropriate for a consultation to occur before a surgery, both of which are separate items in the MBS. For this study, we used MBS claims data from 01-Oct-2019 to 30-Sep-2020.[3] As far as we know, this is the first time a full dataset from the Department of Health (DoH) has been made available to outside researchers to study compliance analytics.

3.2 Data extraction

To provide real-world relevance to the project and enable comparison with currently used approaches (see Section 3.6.2), *target items* were chosen to match those of an existing investigation within the Compliance Analytics team at the DoH. The target items were all those related to either hand surgery (MBS Category 3: Therapeutic Procedures, Group T8: Surgical Operations, Subgroup 14: Hand Surgery), or orthopaedic surgery (MBS Category 3: Therapeutic Procedures, Group T8: Surgical Operations, Subgroup 15: Orthopaedic).

From the claim dataset, we first create a set of *patient events*. A patient event contains all claim rows for a single patient which shared the date of service for at least one claim of a target item for that patient, i.e., all claims for a patient on the day of a procedure of interest. Table 1 shows an example where patient events for two fictitious patients are identified for target items. In this example the first patient event for Patient 1 is identified due to the claim of a knee replacement procedure (item code 49518) on January 30. Three further items for Patient 1 claimed on the same date are also included in the patient event (note that two providers are involved). Patient 1 also has a second patient event based on the claim of a different target item, a shoulder replacement procedure (item code 48918) on August 1. On the same date a different patient event is identified, a knee replacement for Patient 2, with three different providers included in this patient event.

We define *episode pairs*, based on patient events, where each pair contains a *provider episode* and an *ontology episode*. A provider episode contains the list of items from a patient event claimed by a single provider. For example, if three providers were involved in a patient event, the items from the patient event would be split into three separate provider episodes, each containing the list of items claimed by that provider. Table 2 shows the three provider episodes that would be generated from the patient event for Patient 2 in Table 1.

An ontology episode contains a set of features denoting the *ontology location* of each item in the corresponding provider episode. For a given item, its ontology location is automatically derived by mapping the item code to a tuple containing, in order, its respective ancestors in the ontology tree, i.e., the item's Category, Group, Subgroup, and Subheading in the MBS ontology (see Figure 1). Each tuple is converted to a single string, i.e., a feature, for the purposes of input to a learning algorithm to enable role modelling (see Section 3.3). This mapping reduced the 5953 individual item codes to 551 ontology locations (Australian Government Department of Health, 2019). Using the MBS ontology structure in this way creates a natural and interpretable prioritisation of relationships by innately identifying some close connections. In terms of feature construction, the ontology locations represent the least generalisation of item codes with respect to the MBS ontology (Han et al., 2011).

3.3 Role modelling

Topic modelling identifies themes and the relationships between them within documents, and is then able to classify documents according to those themes. Patient claims can be viewed as documents, and themes based on item relationships discovered using topic modelling. To give an initial context to the patient claims, the data was first grouped by the likely primary surgery. Episode pairs were assigned to a *subheading collection* by finding the ontology location of the highest-cost hand surgery or orthopaedic item within the parent patient event. The hand surgery group has no subheadings, and the orthopaedic group

[3] Owing to privacy concerns it will not be possible to release this dataset. Source code is available: https://github.com/jpkemp/anomaly_detection_framework

Table 1: An example of claim rows (fictitious data) showing items claimed for two patients identified by target item (Knee or Shoulder replacement) and separated by date and patient ID to create three patient events involving four providers (see text for details).

Patient ID	Provider ID	Item Code	Item Summary	Date
1	1	49518	Knee replacement	30-Jan
1	2	17610	Anaesthetic consultation	30-Jan
1	2	21402	Anaesthetic initiation	30-Jan
1	2	22031	Pain management	30-Jan
1	1	48918	Shoulder replacement	01-Aug
1	2	17610	Anaesthetic consultation	01-Aug
1	2	21622	Anaesthetic initiation	01-Aug
2	3	49518	Knee replacement	01-Aug
2	3	105	Professional attendance	01-Aug
2	2	17610	Anaesthetic consultation	01-Aug
2	2	21402	Anaesthetic initiation	01-Aug
2	4	51303	Surgical assistant	01-Aug

Table 2: Fictitious claim rows illustrating how claims in a patient event are separated by provider ID. Provider episodes are created from the items in the separated claim rows for each (Patient ID, Provider ID) pair on a given date of service.

Patient ID	Provider ID	Item Code	Item Summary	Date
2	3	49518	Knee replacement	01-Aug
2	3	105	Professional attendance	01-Aug
2	2	17610	Anaesthetic consultation	01-Aug
2	2	21402	Anaesthetic initiation	01-Aug
2	4	51303	Surgical assistant	01-Aug

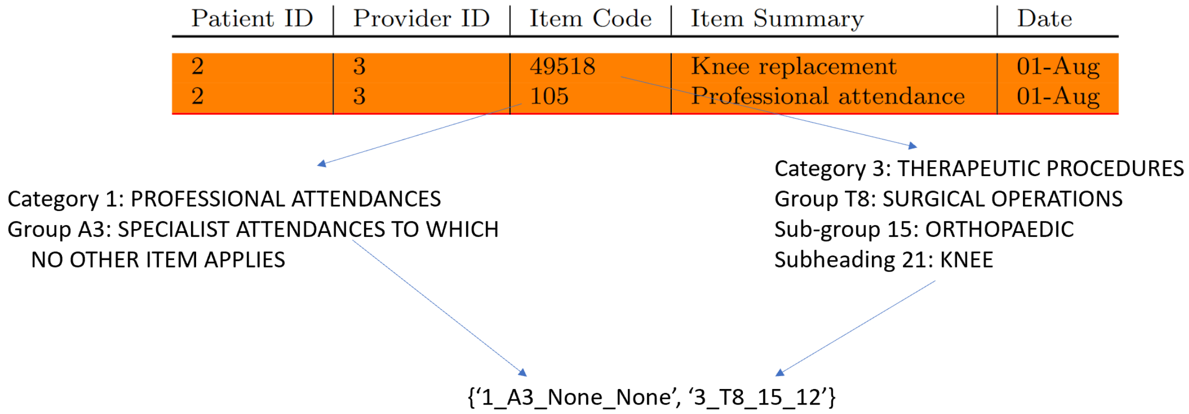
has 21 subheadings, resulting in 22 potential subheading collections. The *episode cost* for an episode pair was calculated by summing the schedule fees for the items in the provider episode. Several fee-based features are available in each claim row in the MBS. The schedule fee is the base fee rate for an item, before incentive payments or variable provider charges are applied. Given that there is legitimate variation in fees, using other fee types such as the total benefits paid can lead to spurious results. For example, in the MBS, variation in benefits paid to providers making the same claims can be on orders of magnitude due to government incentives with respect to location or other factors. The schedule fee is therefore the most comparable fee type for examining wasteful claims.

For each subheading collection, the associated episode pairs were passed to a *role modelling algorithm*. Two algorithms were examined for the purpose of context discovery: GAA (see Section 1.2.1 and Latent Dirichlet Allocation (LDA) (Blei et al., 2003). We use the term context discovery, as GAA is not strictly a topic modelling algorithm in that it is not a probabilistic generative model. Other topic modelling or context discovery algorithms may also be effective, but were not examined for this study. While the approach in each method is quite different, they can both be used to perform the same task. Essentially, typical roles within a surgery – e.g., surgeon, anaesthetist, assistant, etc. – were learned from the ontology episodes by finding relationships between the ontology locations contained in the ontology episodes.

GAA works by finding pairwise item association rules with association analysis (Tan et al., 2005), and constructing a graph from those rules. When applied to the ontology episodes, the association rules identify connections between ontology locations of items. Because the ontology episodes are constructed on a per-patient, per-provider basis, and because different provider roles within a procedure utilise items from different ontology locations within the MBS, components of the graph indicate different provider roles within the procedure (see Figure 2). Episode pairs were assigned to a role based on the closest matching component (i.e. the most matching ontology items).

LDA is a Bayesian probabilistic graphical model which uses mixture models of items in collections over a set number of hidden topics (Blei et al., 2003). Similarly to GAA, when applied to ontology episodes, modelled topics will find probabilities for ontology locations appearing in documents within that topic (see Table 3). Episode pairs were assigned to a role by finding the closest matching topic, i.e., the discovered topics define the provider roles. We arbitrarily assigned 5 topics, based on examination of the GAA results.

The *expected cost* for a role within a context, re-



Patient ID	Provider ID	Item Code	Item Summary	Date
2	3	49518	Knee replacement	01-Aug
2	3	105	Professional attendance	01-Aug

Category 1: PROFESSIONAL ATTENDANCES
Group A3: SPECIALIST ATTENDANCES TO WHICH NO OTHER ITEM APPLIES
Category 3: THERAPEUTIC PROCEDURES
Group T8: SURGICAL OPERATIONS
Sub-group 15: ORTHOPAEDIC
Subheading 21: KNEE
{'1_A3_None_None', '3_T8_15_12'}

Figure 1: Depiction of the items in a provider episode being mapped to their ontology locations in order to create an ontology episode.

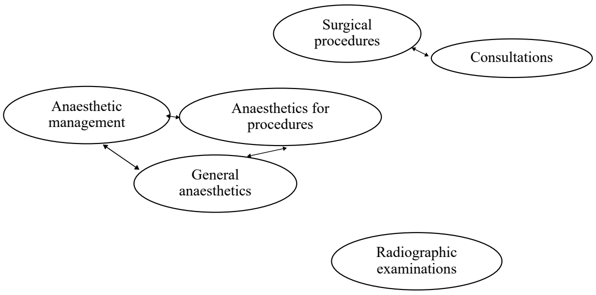


Figure 2: Fictitious graph illustrating how GAA can learn provider roles. The 2-item component represents surgeon claims, the 3-item component represents anaesthetist claims, and the 1-item component represents radiologist claims.

Item	Topic 1	Topic 2	Topic 3
Surgical procedures	0.800	0.001	0.001
Consultations	0.150	0.001	0.050
Anaesthetics management	0.001	0.400	0.001
Anaesthetics for procedures	0.001	0.280	0.001
General anaesthetics	0.001	0.310	0.050
Radiographic examinations	0.047	0.048	0.897

Table 3: Fictitious LDA topics illustrating how provider roles are learned. Topic 1 represents surgeon claims, topic 2 represents anaesthetist claims, and topic 3 represents radiologist claims

gardless of the topic modelling algorithm, was calculated by taking the mean of the episode costs from the episode pairs associated with the role in a given context.

3.4 Provider ranking

Each provider was assigned a *suspicion score*. For the n_p episode pairs associated with a given provider p, episode cost e_i for the i^{th} episode and expected cost r_i for the role to which the episode pair is assigned, the suspicion score s is

$$s_p = n_p \times \text{median}\left(\sum_{i=1}^{n} \max(e_i - r_i, 0)\right) \tag{1}$$

Providers were then ranked by their suspicion score, with higher suspicion scores indicating possible repeated, expensive, and unusual activity as the median represents the typical provider behaviour which is then weighted by the number of episodes for the provider. Note that this score is designed to overcome the limitations of our previous method which focused solely on *items*, which does not adequately represent potential recoverable costs, as discussed in 1.2.2. The weighting by the number of episodes assists with determining total benefit paid to the provider, while use of the median represents their typical costs which assists in preventing unusual, costly patients unduly skewing the representation of their normal behaviour.

3.5 Process summary

The modelling and ranking process is summarised as follows:

1. Identify context
   (a) Identify the ontology location of the patient's primary surgery
      i. E.g., knee, hip, shoulder
   (b) Identify the provider's role within the patient event

i. E.g., surgeon, anaesthetist, assistant

2. Calculate the typical fee for each role in each subheading collection
3. Calculate the suspicion score for each provider
   (a) Calculate the differences between the episode cost and the typical cost of the assigned role for each episode pair
   (b) Take the median difference for the episode pairs for each provider and weight by their total number of claims
4. Rank providers by the suspicion score

3.6 Validation

Due to the volume of data both as input and output to these methods, validating the results is difficult. In order to determine whether the method is producing useful results, known anomalous providers as well as high-scoring, previously unknown providers were examined.

3.6.1 LDA repeatability

As LDA is a stochastic method, the topics produced vary run to run, resulting in different episode role assignments. To reduce the effect of the variation, the LDA method was run multiple times, and the mean suspicion scores were used to determine the final rank. Two-way mixed effects intra-class correlation coefficients for both single fixed and average fixed raters (ICC3 and ICC3k) were used to measure the variation in the scores across the LDA runs, treating the providers as raters (Koo and Li, 2016). ICC3 measures within-rater reliability of a fixed group of raters over multiple ratings, whereas ICC3k measures mean rating score from a fixed group of raters over multiple ratings. In this way we can infer LDA consistency from the reliability of the provider scores produced across the runs. The ICCs were tested on log-transformed data, as the raw scores were highly right-tailed. Descriptive statistics were done on the largest change in score for all providers as a proportion of the total schedule fees for their claims, i.e.

$$\text{changes} = \frac{\max(s_{i,p}) - \min(s_{i,p})}{\text{total\_fees}(p)} \forall p \qquad (2)$$

where $s_{i,p}$ is the score for a given provider p in a single test run i, and total_fees is the sum of the provider's fees across all their episodes.

Rank-biased overlap (RBO) was used to measure the differences in the rankings across the LDA runs, as changes in the scores will affect the ranking. RBO is a metric for determining rank-ordered list overlap which has several advantages over similar metrics, including being symmetric, top-weighted, and not tail-dominated, which are consistent with the requirements for ranking in this study (Webber et al., 2010). RBO was applied to all pairwise combination of ranks from the 10 runs. RBO was also used to compare the rankings of the top 100 providers from the LDA and GAA methods. A weight parameter of 0.99 was used with RBO to give 85% of the weight to the top 100 providers.

3.6.2 Comparison of provider ranking to existing information

Provider IDs were obtained for 100 surgical providers recently flagged as anomalous by the Compliance Analytics team at the DoH. These providers made claims from across the orthopaedic and hand-surgery MBS items, over the same time period as the data we used. They were identified using a variety of statistical analyses focusing on item claim and co-claim counts. We will refer to these 100 providers as the *anomalous set*. Each of the mean LDA and GAA rankings was segmented into 100 even sections. The number of anomalous set providers in each cumulative section was determined. That is, if we call the first segment i_0, and the second set i_1, the first overlap calculated would be the count of intersection between anomalous set and the set of providers in i_0, and the second calculation would be between the intersection of the anomalous set and the union of the set of providers in i_0 and i_1. As well as the intervals described above, the number of overlapping providers in the top 100 was calculated. This analysis indicated whether the ranking provided by our method is able to pick up known anomalies.

3.6.3 In-depth examination of previously unidentified cases

High-scoring providers in our ranking who did not appear in the anomalous set were examined against their peers with methods currently in use at the DoH. As the method incorporates cost into the ranking, it is possible that the high-ranking providers were specialists working on more complicated patients instead of abusing the system. The DoH assigns an in-house provider specialty label (PSL) to its providers based on the provider's registered specialty and their item claims over a quarter. We obtained the PSL for the top 20 providers in the GAA rankings which were not in the anomalous set; we will refer to these providers as the *high-scoring set*. Counts of item claims and co-claims were compiled from the provider episodes for all providers in each PSL, where provider episodes existed (i.e., the providers had claims in the extracted data from section 3.2). For each of the high-scoring set providers, the number of claims and percentile of claims for each item and item co-claim was examined by hand to determine whether the provider was making unusual claims.

Outlying item counts for items claimed by at least 10 providers were also flagged using an adjusted boxplot outlier formula. By inspection, many of the items had a right-tailed, zero-inflated Poisson distribution. That is, a high proportion of providers did not claim given items at all. Typical outlier detection methods do not work well with skewed, zero-inflated data (Templ et al., 2020). The outlier cutoff c was therefore calculated only on the positive-valued data, using the following formula to account for skew (Yang et al., 2011; Templ et al., 2020):

$$c = Q_3 + 1.5 \times IQR \times e^{3MC}, \tag{3}$$

where MC is the medcouple. The medcouple measures univariate distribution skewness, reducing the impact of outliers compared to the classical skewness coefficient (Brys et al., 2004).

This analysis indicated whether the previously unidentified providers were making unusual claims or merely expensive ones.

3.7 Results

The extracted data comprised 1,918,643 claim rows from 31,306 providers covering 331,323 patient events. For the LDA runs, ICC3 on the log-transformed provider scores was 0.035 whereas ICC3k was > 0.99. This shows low consistency within the provider scores across the LDA runs, but good consistency in the mean scores. As a proportion of total costs, the median change was 0.12, the mean change was 0.15, and the maximum change was 0.97. That is, most provider scores changed by only a small amount across the LDA runs, but some providers changed by a large amount. This is due to the episode assignment to roles changing as the topics change. Providers with many episodes which border on two different roles will have large changes in score as the role cost to which their episodes are compared changes. For example, if a provider typically claims episodes which contain both surgical and anaesthetic items (an uncommon edge case), as the topic weightings change the bulk of their episodes might be assigned to the topic representing the surgeon role, or the topic representing the anaesthetist role. As surgical procedure items tend to be relatively expensive, the episode costs may be close to the mean if they are assigned to the surgical role, but much higher than the mean if they are assigned to the anaesthetist role. This provider could then have either a low score or a high score, depending on the learned topics.

The RBO between the rankings from the LDA runs ranged from 0.51 to 0.86, with a mean of 0.74. This shows that the provider ranks can vary due to the stochastic nature of LDA, but in spite of the variation of the within-provider scores, agreement between the rankings is generally good. The RBO between the ranking from the GAA method and the combined ranking from the LDA method was 0.81, also showing good agreement.

3.7.1 Known anomalous providers

Plots of the ranking overlap with the anomalous set are shown in Figures 3 and 4 for the GAA and LDA methods respectively[4]. Of the 100 top-scoring providers from the GAA ranking, 28 were part of the anomalous set, and in the LDA results 33 of the top 100 were from the anomalous set. Most of the anomalous set providers ranked within the top 10% with both methods. The LDA method produced a steeper curve, ranking more of the anomalous higher than the GAA method. In both methods some of the anomalous providers ranked low, with a score of 0. From the plots, it can clearly be seen that the providers who have ranked high are those with both more episodes and a higher cost per episode. This is in line with the objective of ranking providers based on potential return, rather than solely on anomalous behaviour.

3.7.2 High-scoring providers

For privacy reasons we will only discuss the results in general terms – the points noted will also apply to other similar providers. The high-scoring sets included cardio-thoracic surgeons, general surgeons, orthopaedic surgeons, plastic and reconstructive surgeons, and anaesthetists. Seventeen providers overlapped in the GAA and LDA high-scoring sets, totalling twenty-three providers examined. The results are summarised in Table 4

Two of the providers displayed behaviour that had previously been investigated; the quantity and type of items they claimed are common in a particular subspeciality, and are unlikely to be an abuse of the system. Had this previous investigation not occurred, these surgeons would have been considered worth further investigation. Four providers, while high-volume

[4] Note the number of providers in the GAA and LDA results is different due to GAA assigning some providers to no role, which was not assessed. The number of providers in each interval is therefore also different.

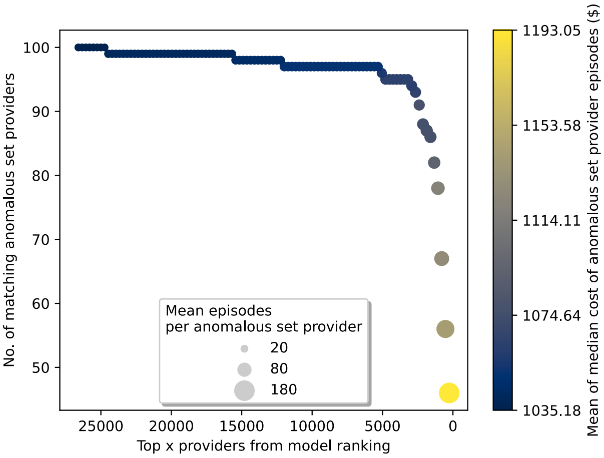


Figure 3: GAA provider rankings showing the overlap with the anomalous set, with each circle representing 100%, 99%, 98%, and so on of the assessed providers. The anomalous set providers ranked more highly by the GAA method have more, and more expensive, episodes than the other anomalous set providers as indicated by the larger, lighter coloured circles as lower-ranked providers drop out of the cumulative analysis.

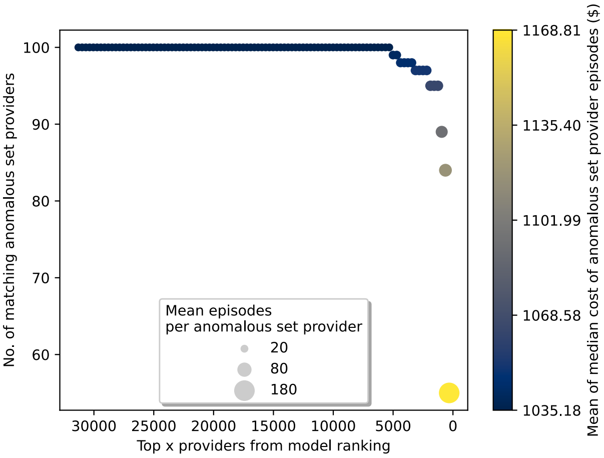


Figure 4: LDA provider ranking overlap with the anomalous set at even intervals. The plot is constructed as per Figure 3

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claimants of some items, were either not clearly differentiated from their near-peers, or were not engaging in potential upcoding or unusual co-claiming behavior, and for a conservative estimate were considered likely to be senior practitioners rather than potentially abusing the system.

The providers we considered unusual were in the top percentiles of claimants in their PSL for co-claimed items or items indicating potential upcoding or unbundling, with a large increase in number of claims from the percentiles below. Upcoding occurs when a similar, higher value claim is made in place of another service (Couffinhal and Frankowski, 2017). Upcoding patterns can also potentially indicate claims from senior consulting physicians who only take complex patients, however it is not possible to assess the difference from the claims data alone, and further investigation would be required. Unbundling occurs when multiple codes are billed in place of a cheaper ‘bundled’ item which is intended to cover the collection of services, and is a common target for recovery (Couffinhal and Frankowski, 2017).

Method	By hand	By formula	Assessed
GAA only	3	3	3
LDA only	2	3	3
Both	12 (14)	11	17
Total	17 (19)	17	23

Table 4: High-scoring set providers confirmed as unusual.

Similar numbers of providers were detected by the adjusted outlier detection formula as by hand. However, we found outlier detection on positive-valued data is quite conservative and not always appropriate. For example, one provider had several hundred claims of an item. The value at the 99th percentile (including 0-valued data) was around 16, but the provider was not flagged as an outlier. With most providers within a PSL not claiming that item, such a high volume of claims was considered of interest. The outlier formula is not always calculable, as the medcouple can go to infinity; alternate outlier thresholds should be considered if automated classification is required.

4 Discussion

Data mining and statistical learning has a history of use in aiding decision-making (Sivarajah et al., 2017; Ekin et al., 2018). The method we propose here is able to automatically group procedures and provider roles within procedures from medical claims by incorporating domain knowledge encoded within the claim ontology structure. It then ranks providers based on the magnitude of the difference from their peers, thereby incorporating potential return in the anomaly detection mechanism. The results showed that the method was able to detect both previously identified and novel patterns of potential fraud and waste. This method is therefore suitable as a decision-support tool for prioritisation of potential cases for audit, and for identifying patterns that can be encoded in other decision-support tools and used for identifying groups of providers exhibiting similar behaviour.

4.1 Underlying challenges

Not all the providers who ranked highly displayed patterns considered to be potentially fraudulent or wasteful. This is inevitable in an area as heterogeneous as medical claims. Some of the patterns identified will be “red herrings” with the providers involved being specialists of some kind. Specialists might perform more expensive services than their peers working in a similar context. It is not possible to determine whether a provider is a specialist or engaging in abusive claiming practices from the data alone. Other providers might perform services which border two different roles in a procedure, and depending on the role to which they are allocated, they might appear normal or expensive. This was highlighted by the high change in costs for some providers over repeated LDA runs. However, the most appropriate role cannot be determined from the data alone; expert assessment is required for these edge cases. Any clustering approach will have the same problem on data with a high degree of overlap; some misclassification is inevitable, and no one tool is likely to be able to capture all fraudulent or wasteful practices (Kose et al., 2015). It may be possible to assign multiple roles to an episode based on probabilities or perhaps Bayesian priors, however the method would need to be significantly extended to account for multiple potential scores. We consider some false-positives acceptable in a first stage decision-support tool, as the behaviours can then be identified, investigated, and assessed appropriately. Later-stage tools could incorporate known non-abuse patterns as a filter, or the knowledge could be fed back into the ontology structure to help group the providers more appropriately. Generally, the frequency of the patterns identified here were shown to be anomalous compared with the peer groups, as well as being expensive behaviours.

4.2 Cost as a metric

Some providers engaging in known anomalous behaviour were ranked very low by the algorithm. Those providers were involved in cheaper procedures; while they exhibited some unbundling behaviour, their total costs were lower than their peers. Moreover, they were generally involved in fewer procedures than their peers. The providers who ranked highly were those involved in more, and more expensive, procedures. This is in accordance with the design goal of ranking by potential for return. Finer granularity in the MBS ontology could help better group the procedures so that complex, expensive procedures are not compared with simple ones.

4.3 Model comparison

Both topic modelling methods performed well, discovering unusually costly providers with both known and unknown patterns of anomalous behaviour. There are advantages and disadvantages to each.

GAA offers the ability to drop episodes which do not fit the topics - classing them as not belonging to a role, which are not assessed - whereas LDA provides the most likely result. This classification could be useful as part of a decision-support suite, where episodes outside the typical part of a procedure could be sent to a different tool for further analysis. A threshold for similarity could be set to provide the same behaviour for LDA if required. The best approach may vary depending on the claims involved.

The GAA method is able to learn the number of roles, whereas LDA requires it to be specified beforehand. In this case the number set was based on visual examination of the GAA modelled roles. The best number of roles may not be fixed. In both cases, roles would need expert examination for suitability in a decision-support system; if the typical claims modelled by the topic-modelling algorithm did not make sense to subject-matter experts, the results of the ranking may not be appropriate.

4.4 Limitations

The model design is based on two assumptions which do not hold. The first assumption is that providers working within a similar area - i.e. a subheading collection - will see a similar distribution of patients and behave in a comparable manner. That is, it is assumed each provider will claim a similar range of cheap and expensive items within the subheading collection. In practice, distributions vary in part due to specialisation and seniority of the providers, meaning that the comparison between providers is not completely like-to-like. Junior practitioners will typically perform a far greater number of simple procedures, while senior practitioners and specialists will be involved in higher numbers of complex procedures, which would be more expensive. As mentioned, this problem is inherent to data with a high degree of overlap, and is difficult to overcome.

The second assumption is that the ontology structure is consistent, i.e. that items within a subheading are equally related to each other and equally distant from items in a different subheading. Similarly, subheadings within a subgroup are assumed to be equally similar to each other, and equally distant from subheadings in a different subgroup. In practice, items do not function equivalently, and the structure of the ontology is not formulated for this purpose. However, it was a simple and effective way of incorporating domain knowledge which is difficult to learn from the data due to its innate heterogeneity.

Validation of the models was necessarily limited through lack of availability of subject-matter experts able to review the results. Two fields of knowledge are required for these experts: specialist medical knowledge of the procedures, and knowledge of the legislation and policies that drives further action in recovering potentially fraudulent and wasteful claims. Few such people are employed by the DoH, and none were available for in-depth analysis, though they did provide assistance with our questions. The process for recovery is lengthy, and results based on outcomes of that process are also impractical to obtain at this stage. Review by data analysts at the DoH was considered to be adequate as the intent of the method is for a decision-support tool, and the data analysts would be the end-users, however a more thorough review would be beneficial. Use of the PSL for comparison purposes is not ideal, as it is known to be an imperfect tool for grouping similar providers. However, it is the tool that is currently in use, and as with all clustering problems there are multiple possible solutions each with advantages and disadvantages dependent on the use-case (Estivill-Castro, 2002).

4.5 Future Work

Additional validation, such as ablation studies or further examination of the rankings and provider roles, including true negatives and mis-classified providers, may help improve the approach. However, due to resource constraints this was not possible for this study.

Further research could focus on better segregating similar providers. There are at least two ways this could be done. One option would be to make use of the cost distribution. Instead of using the median, it may be possible to examine distance from cost peaks. That may allow for different sub-specialties/seniority of providers working on a similar subheading collection. However, it may also lead to more blurring as low-scoring providers working similarly to providers from an expensive peak overlap with high-scoring providers working similarly to providers working from a cheaper peak. Another option would be to work on the ontology, providing a more suitable structure for this use case. Our key domain-knowledge input to the algorithm is the ontology, and the flaws are partly a fault of the ontology structure rather than the algorithm itself. Learning similar role and procedure separation without the ontology would require extensive extra features and possibly semi-supervised or active learning. Weakly-supervised or seeded LDA would enable expert opinion to be included. Better incorporating domain knowledge into the ontology structure or the model would facilitate better results.

Another line of research would be in extending the algorithm to sequential data. It may be possible to treat each day of an ongoing treatment as an input to the role-modelling algorithm. Patterns over time could then be identified, perhaps at the subheading collection level, and significant or expensive variations from those patterns flagged for further investigation.

5 Conclusion

We proposed a model that can automatically learn procedure and role contexts by utilising topic modelling and the MBS ontology, and then rank providers by potential for recovery of costs based on magnitude and quantity of difference to typical costs within the given contexts. This model was able to detect both known and novel patterns of potentially fraudulent and wasteful behaviour, and was found to be suitable for use as an early-stage decision support tool in the claim-recovery process. For our methods we found the MBS ontology structure to be a useful way of incorporating domain knowledge. To the best of our knowledge, this is the first tool of its kind that is able to learn the context for comparison at both the procedure and role level for this type of claim data.

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