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THE POWER OF PREDICTIVE MODELS IN WORKERS' COMPENSATION CLAIMS HANDLING

WORKERS' COMPENSATION: PART-ART, PART-SCIENCE

November 2015

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WORKERS' COMPENSATION: PART-ART, PART-SCIENCE

As an employer, the financial burden of benefits, costs, and coverage for workers' compensation programs is high – and rising.

According to the National Academy of Social Insurance[1], there were 128 million covered workers in Workers' Compensation (WC) programs in the US in 2012, costing employers around $1.32 in every $100 of covered wages in that year.

The research, published in 2014, shows that employer's costs were up almost seven percent year-on-year, to $83.2 billion nationwide.

It is no surprise, therefore, that employers – and their insurers – pour resources into devising efficient methods for identifying, tracking and mitigating claims to get the best outcomes for the employee and employer alike.

One significant development arising out of recent research is the use of predictive models in WC claims administration – a tool that has already yielded concrete results and looks poised to transform the process of claims handling and cost mitigation in the WC sector.

Current WC claims adjusting techniques employ part-art and part-science, which produces mixed results for carriers, employers, and workers over time.

Structured data capture is limited and greatly enhanced by an adjuster's individual case notes and professional experience. Inevitably, this combination creates opportunities for potentially severe claims to be missed within the management process.

This paper will address how the creation and correct application of predictive models in WC claims management can help to catch patterns and trends in claims data and identify potentially serious claims before they get out of hand.

The paper will address topics including:

- Why build a model? What is the business case?
- What data is out there and how easy is it to capture?
- How do you get people to believe in a model and apply its recommendations?
- Case studies will show real results in the Worker's Compensation sector

THE BUSINESS CASE FOR PREDICTIVE MODELS

There are a plethora of different definitions of predictive analytics and modeling in the WC insurance sector, and each corporation builds its own business case for applying scarce resources to the development of models and analytics to improve WC claims administration.

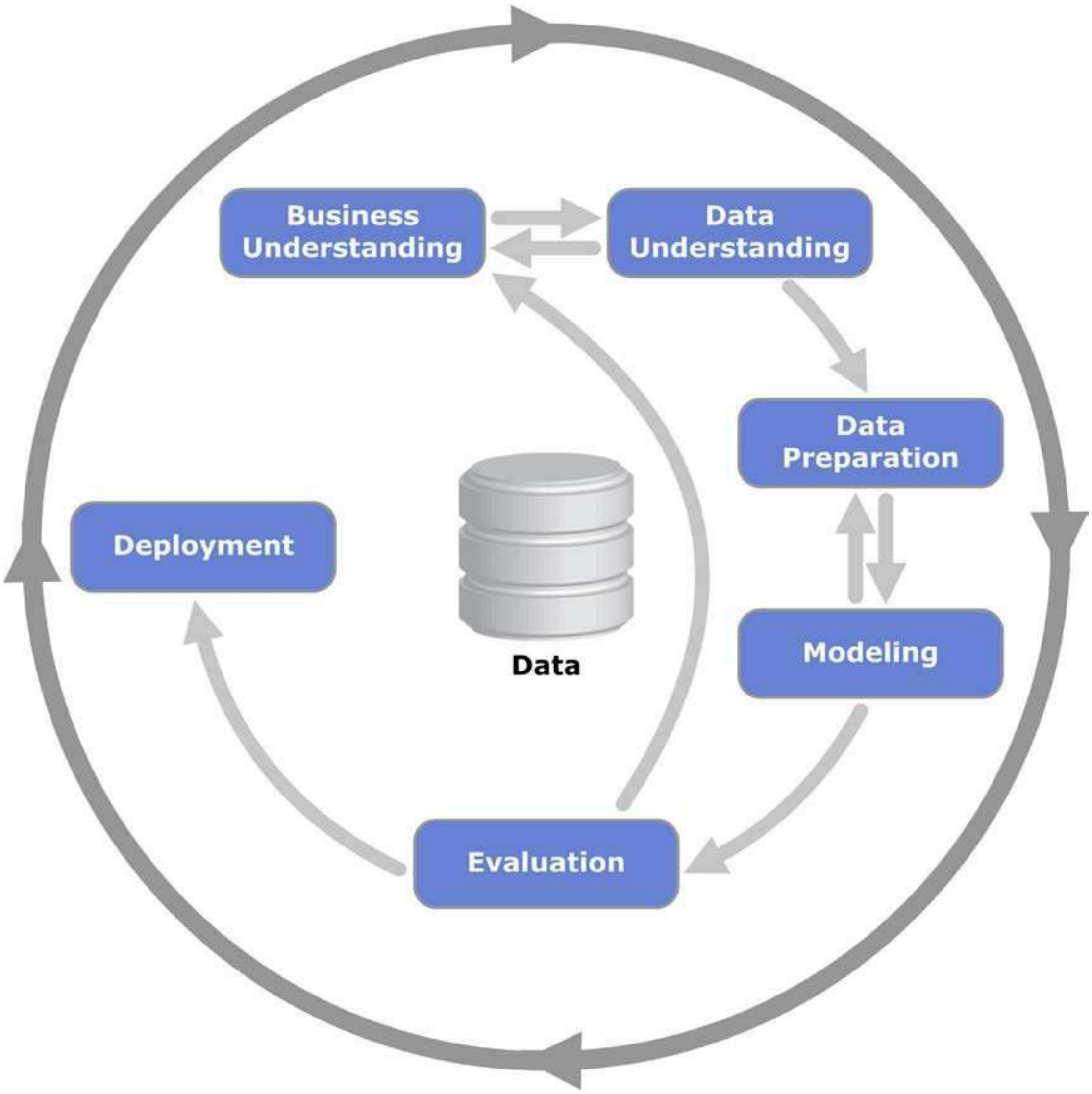
But, a corporate-wide belief in the power of analytics must lie at the heart of every business decision to adopt the strategy.

A model should be considered as a potentially powerful tool in the organizations' belt, but by itself does not save money or lower claims durations.

[1] https://www.nasi.org/sites/default/files/research/NASI_Work_Comp_Year_2014.pdf

There must be a cultural commitment to taking the information highlighted by models and applying it in the work process to effect an improvement in outcomes.

The widely accepted basis for most modeling projects is the Cross Industry Standard Process for Data Mining (CRISP-DM) platform, developed in the late 1990's and describes commonly used approaches that data mining experts use to tackle problems. (see box-out).



Source: https://the-modeling-agency.com/crisp-dm.pdf]

THE CRISP-DM WAY…

Developed by a cross-industry team in the late 1990's, CRISP-DM outlines six major phases in data modeling:

BUSINESS UNDERSTANDING

This initial phase focuses on understanding the project objectives and requirements from a business perspective, and then converting this knowledge into a data mining problem, and a preliminary plan designed to achieve the objectives.

DATA UNDERSTANDING

The data understanding phase starts with an initial data collection and proceeds with activities in order to get familiar with the data, to identify data quality problems, to discover first insights into the data, or to detect interesting subsets to form hypotheses for hidden information.

DATA PREPARATION

The data preparation phase covers all activities to construct the final dataset (data that will be fed into the modeling tool(s)) from the initial raw data. Data preparation tasks are likely to be performed multiple times, and not in any prescribed order. Tasks include table, record, and attribute selection as well as transformation and cleaning of data for modeling tools.

MODELING

In this phase, various modeling techniques are selected and applied, and their parameters are calibrated to optimal values. Typically, there are several techniques for the same data mining problem type. Some techniques have specific requirements on the form of data. Therefore, stepping back to the data preparation phase is often needed.

EVALUATION

At this stage in the project you have built a model (or models) that appears to have high degree of benefit, from a data analysis perspective. Before proceeding to final deployment of the model, it is important to more thoroughly evaluate the model design and review the steps executed to construct the model. A key objective is to determine if there is some important business issue that has not been sufficiently considered. At the end of this phase, a decision on the use of the data mining results should be reached.

DEPLOYMENT

Creation of the model is generally not the end of the project. Even if the purpose of the model is to increase knowledge of the data, the knowledge gained will need to be organized and presented in a way that is useful to the customer. Depending on the requirements, the deployment phase can be as simple as generating a report or as complex as implementing a repeatable data scoring (e.g. segment allocation) or data mining process. In many cases it will be the customer, not the data analyst, who will carry out the deployment steps. Even if the analyst deploys the model it is important for the customer to understand up front the actions which will need to be carried out in order to actually make use of the created models.

The very first step in this process is 'Business Understanding', defined as the need to thoroughly understand, from a business perspective, what the corporation wants to accomplish. The CRISP-DM creators warned that "a possible consequence of neglecting this step is to expend a great deal of effort producing the right answers to the wrong questions"[2].

Keith Higdon, vice president of claims data analytics at ACE Group, summarized his firm's business understanding of creating models for WC claims:

"We first discover the pain points for our clients in WC claims and consider how to ease those frictions. We firmly believe that analytics can further refine claim segmentation to better align claim-handling resources, with the goal to getting better outcomes."

Hidgon outlined three primary business reasons for building a WC model to influence the outcome of these types of claims:

1. Developing new services for an existing product to drive revenue generation. An example would be offering nurse case management on an a-la-carte basis.
2. Cost savings, either by preventing losses or by identifying how to reallocate existing claim-handling resources. Models can both prevent losses from escalating and also improve efficiencies for adjusters in handling caseloads, thus improving profit margins.
3. Enhancing partnerships – delivering better outcomes to employers from WC claims translates into better relationships with clients. Insurers who add value to their relationships using these types of tools increase their competitive advantage when the client is considering its renewal options.

ACE Group senior vice president, Jeff Block explained his company's philosophy:

"We seek to identify those long-term expensive claims sooner and devise different strategies and best practices to resolve them as expeditiously and effectively as possible."

Once a company has defined its business case for investing in predictive modeling and analytics, the project is passed to the modelers, whose job is to translate the business problem into a useable tool. This involves defining what data is available, how to translate that data into the tool and then to work jointly with the business owners on how best to implement the model in the daily workflow.

WHERE'S THE BEST DATA?

Generally, there is sufficient data available at the claim level to efficiently administer the case and produce the best outcome for employers and employees alike.

That data can be found in both a structured form – that which is entered into formatted fields (dollar figures, claimant demographics, categories for injury type and cause, etc.) – and in additional case notes and experience brought to bear by the individual claims administrator.

However, with huge volumes of crucial data being held in an unstructured format and experience not captured by

[2] https://the-modeling-agency.com/crisp-dm.pdf

formal claims systems, many triggers that could provide an early alert to potentially large claims, can easily go unnoticed even when the claims handler is diligently managing a claim in the normal course of business.

The human mind can only process a finite amount of data at one time – leading the way for models to complement that data processing task.

Predictive models use tools such as text-mining techniques to extract some of these key unstructured data points. However, these tools have to be married with statistical techniques in order to bring the full picture of a claim into focus.

Such data, for instance, may include information indicating that a WC claimant recently put on a lot of weight or is under severely stressful conditions at home or at work. Maybe the claimant a short time ago started taking a prescription medication that is unrelated to the claim, but has claim-related ramifications. The medication could influence the treatment plan, return-to-work options, and claim duration. Perhaps the claimant recently separated or divorced a spouse. This may affect the physical and emotional support he or she was to receive at home, with resulting claims implications.

Not all of the above examples will be present on enough claims to include in a predictive model, but the goal is to identify as many as possible and test each as to how they relate to claim outcomes.

THE 4D APPROACH

ACE Group has invested heavily in predictive modeling, rolling out its 4D approach for its third party administrators (TPAs) and employer clients to apply to claims handling processes.

ACE's 12-month severity model processes more than 20 variables pertaining to a claim and produces a probability score of that claim breaching a $250,000 – or 10 percent of the insurance deductible - threshold .

The claim adjuster receives a report on the claim, including detailed information on the driving variables, offering an indication of how much each variable contributes to the loss.

With typical insured retention levels sitting well in excess of $250,000, the model has proved most useful to employers and TPAs administering claims at the lower levels.

The 4D model is not a catastrophe model, nor a frequency model, but is designed to "find the anomaly – that needle in the haystack that could signal a potentially severe claim in the making", said ACE's Jeff Block.

"Broad claim categories are better defined and taking a subset of those that can most significantly drive costs can have greater impact," he added.

THE HUMAN TOUCH

Having developed a predictive model, the next challenge lies in integrating the tool with claims administrators and employer work processes.

"Predictive models are tools for adjusters and team leaders and can only work if combined with their experience and judgement," said ACE's Keith Higdon.

Models bring important information to the attention of adjusters and it is a prompt for them to think differently about a claim, to ask probing questions and possibly adjust a strategy, Higdon explained.

Higdon addressed two common misconceptions raised by adjusters when first presented with predictive models:

- Severe claims are recognizable from the outset: The basis of a 'predictive' model is that the turning point likely hasn't yet happened. The claim may look fine from a processing perspective when it is first presented, but the model is indicating that in 1,2 or 6 months from now historically claims with similar characteristics have grown significantly worse. Now is the time to change the direction of the claim.
- Adjusters tend to assume 'auto adjudication'. This is not the case. WC predictive models are built around partnership between the adjuster's experience and insight, and the model's ability to impartially process large volumes of data. Successful implementation blends trust in the capabilities of the model and the adjuster's trust in their own judgment.

Frank Murray, senior vice president at ESIS - a TPA and part of ACE Group – has adopted ACE's 4D model in his business and with a number of his clients. He explains his experience of implementing a predictive model:

"At the outset, we had to educate the claims adjusters on the context and rationale behind the model and explain how it could transform their efficiency in WC claims handling," Murray said. "Once they understood the model and the variables it was processing to produce the probability score, their reaction was 'wow!'."

"Claims adjusters live with certain frustrations – in their view, there may be no logical reason why a claim may stay open for 2-3 years. Models help to unlock those difficult cases and offer insights into why they are behaving as they are. Once this information is mingled with the adjuster's experience, a different outcome may be achieved."

The timing of an adjuster's intervention in a claim is just one part of success in WC claims. Predictive models can only be successful if the adjuster applies the information appropriately, ACE's Jeff Block said.

"Precision in execution requires the adjuster to ask if they are using the right strategy in handling a case: if surgery is recommended, for example, 'should I get a second opinion?' or 'does this doctor have the required experience, given the other factors affecting this case?' We want adjusters to use the model to develop their strategy and ask the right questions and solicit the right information to use in the case."

MEASURES OF SUCCESS

Intervention targets are often small as a program looks to drive better outcomes on the highest dollar claims. This creates a challenge when measuring results. For instance the ACE 4D 12-month Workers' Compensation program targets claims that are open on their 12-month anniversary with a 10 percent probability of exceeding the claims retention level in order to identify those that have unrecognized severity. The 12-month anniversary and 10 percent criteria greatly shrinks the target population. That said, using a dual intervention approach with both ACE Claims and ESIS examiners results over a 16 month period show claims cost saving of $8.26 million across 703 claims. Given that the 10 percent threshold is much lower than the average insurance program retention, 97 percent of the cost saving went directly back to the employers, ACE said.

While average savings are small, there are certain significant case studies that demonstrate the potential of using predictive models (see box out).

CLAIMS CASE STUDIES

EXAMPLES OF ACE/ESIS-MANAGED CASES ABOVE A 10 PERCENT INSURED DEDUCTIBLE THRESHOLD

2011, Illinois chemical waste/recycling business

- 42 year old operator injured shoulder/neck lifting vacuum hoses, resulting in potential Permanent Total Disability (PTD)
- Predictive model high risk indicators: employee was obese, had a high 'pain' count, had neurological issues and spine stimulator history
- 12-month predictive model breach score 29 percent
- TPA changed strategy to focus on settlement of claim rather than pursue less productive medical management strategies

Result: Settled at $100,000, when exposure for wage differential could have potentially projected to $320,000 if the claim had not been managed in concert with guidance from predictive modeling

Louisiana petroleum transport and logistics business

- 59 year old maintenance worker injured shoulder/lifting a tailgate, resulting in potential Permanent Total Disability (PTD)
- Predictive model high risk indicators: claim open 12 months at cost of $312,000, two prior surgeries, high frequency of doctor visits, co-morbid factors (smoker, high blood pressure etc.)
- 12-month predictive model breach score 13 percent
- TPA changed strategy to focus on settlement of claim. Further surgery unlikely to result in return to work

Result: Settlement resulted in net exposure savings of $500,000 off the projected potential PTD exposure, not including future medical exposure

Illinois chemical manufacturing business

- 46 year old operator injured neck reaching overhead, resulting in potential Permanent Total Disability (PTD)
- Predictive model high risk indicators: prior injuries, fast attorney representation, high frequency of doctor visits, high 'pain' count, neurological issues
- 12 month predictive model breach score 54 percent
- TPA introduced surveillance, screening for fluid on neck and activities outside of permanent restrictions, independent medical exam, prior and subsequent injuries discovered. Prompted aggressive negotiation strategy to reach fair resolution

Result: Settled at $240,000. Potential exposure could have been in the $700,000 range

2013 Oklahoma network communication provider

- 57 year old service technician injured back lifting generators in an ice storm, resulting in potential Permanent Total Disability (PTD)
- Predictive model high risk indicators: high medical spend over 6 months, minimal outstanding reserves
- 12-month predictive model breach score 11 percent
- TPA determined file was under-reserved. Pushed for settlement, rather than continued litigation and ineffective medical management strategies

Result: Settled at $60,000. Potential exposure could have been in the $183,000 range

BEHAVIOURAL CHANGES

TPAs and employers are beginning to see behavioural changes in the way claims are handled with a predictive model in place.

ESIS's Frank Murray reported two main changes:

- Employers using the model's probability scores to select which claims files to review with TPA'. Rather than taking a random selection of files, or ones that had been open for a certain amount of time, some employers are using the model data to determine which files to review with a TPA. They may set the threshold at cases with a 10 percent probability score of reaching the $250,000 threshold, for example. Murray notes that this increases efficiency and helps clients to focus on potentially troublesome claims.
- Changing claims handling strategy based on predictive model's probability scores. Murray notes seeing employers and adjusters change their proposed plan on a claim file based on a new probability score for that claim reaching $250,000. Clients have either moved to settle a claim sooner, if long-term medical care is highlighted as a critical factor in the claim, or may re-consider their litigation strategy in light of new information presented through predictive modeling exercises.