Legal, Compliance, & Regulatory

ILTCI 2014

The Rise of Technology: Impact of Data Aggregation & Analysis on LTC Insurers

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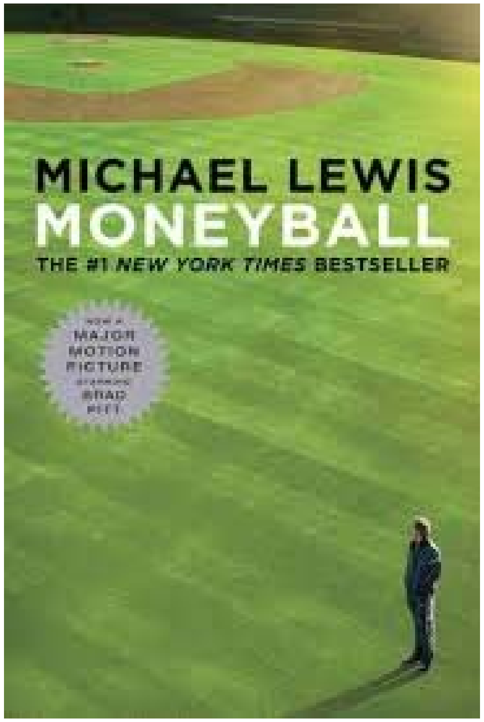
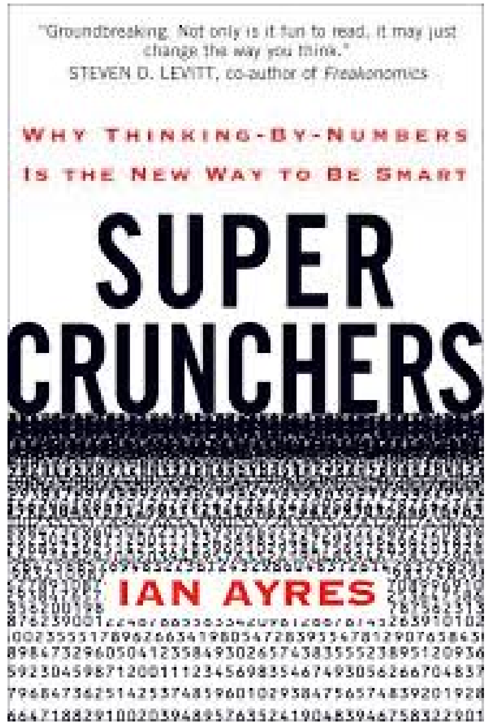
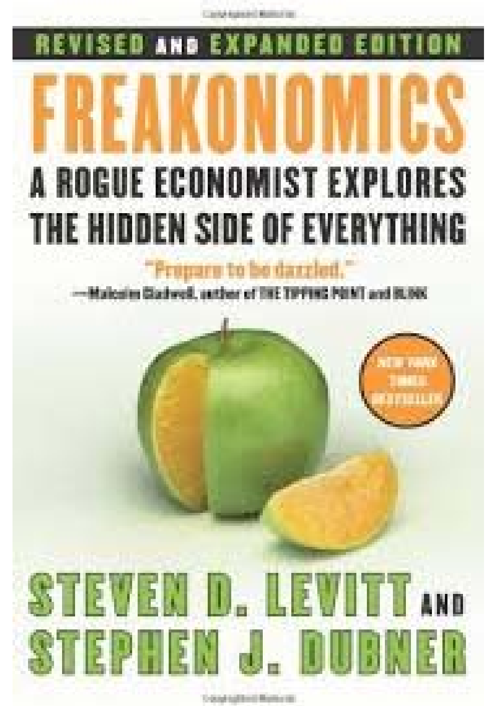
ILTCI

Predictive Analytics in the Mainstream







"Over and over the old scouts will say, 'The guy has a great body,' or 'This guy may be the best body in the draft.' And every time they do, Billy will say, 'We're not selling jeans here.'" Moneyball

How do predictive models work?

- Data analytics identifies correlations between variables and can help suggest outcomes. It interrogates data in an objective and unbiased way, enabling clusters and sometimes unexpected relationships to be identified.
- By using historic data to identify and quantify patterns and trends, future behavior can be predicted.
- Such analytical techniques are completely objective and unbiased in identifying correlations.

Deloitte Financial Services Risk and Regulatory Review Dec. 2012/Feb. 2013

The Potential Benefits of Predictive Analytics

Data analytic techniques have enabled carriers to:

- Weigh their own data against industry data at a detailed level
- Gain a better understanding of claims and claim drivers
- Improve underwriting
- Make more precise financial projections
- Set reserves more accurately

Insurance-Techonoloy.com Mar. 19, 2012

Predictive Analytics and the Bottom Line

Data analytics techniques have been used to improve business decision making which can:

- Reduce cost
- Improve profitability
- Diversify and improve portfolios
- Market to optimal customers
- Enhance customer experience

Financial Services Risk and Regulatory Review Dec. 2012/Feb. 2013

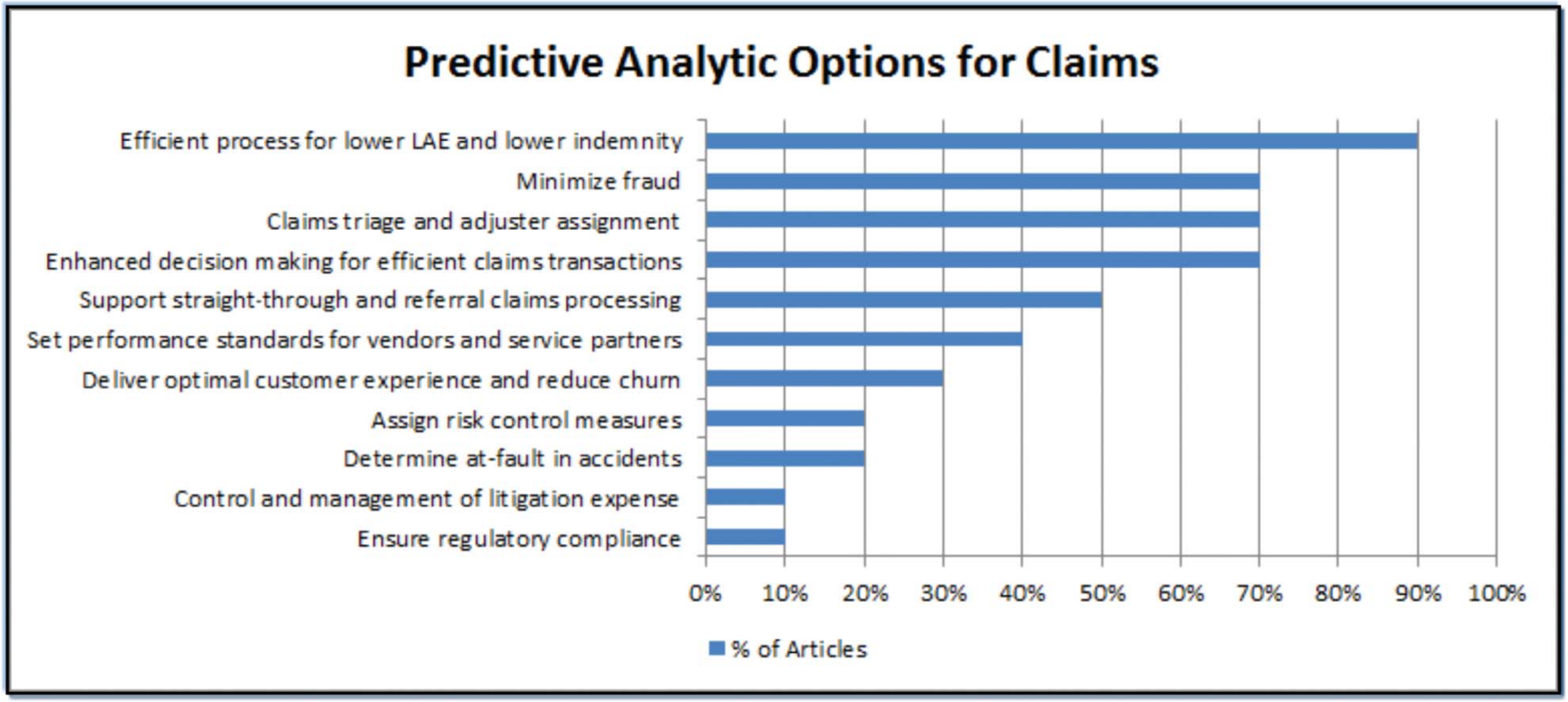
Revolutionizing the Industry through Analytics

Use of Predictive Modeling by Claims Professionals

Analytics supplement the experience of the claims professional by:

- Helping the claims professionals get a better sense of the potential severity of the claim
- Informing the claims professionals of the probabilities of subrogation and litigation
- Assisting the claims professionals in recognizing fraud
- Identifying subrogation and triaging related to the claim

Uses for Predictive Analytics in Claims



SAS: Building Believers: How to Expand the Use of Predictive Analytics in Claims

Better Fraud Detection

Propertycausalty360.com Oct. 1, 2012

Improved Underwriting with Predictive Analytics

- Underwriting is about grouping applicants into segments and deciding whether they should be treated as standard risks, or whether they belong in some other risk categories.
- By combining application data with other available data sources about the applicant, inferences can be made about the applicant's risk profile based on results from similar applicants.
- Data analytics does not remove the need for experienced underwriters as part of the application process. However, the benefit is that underwriters can spend their time on the most deserving cases.
- The underwriting process can be completed faster, more economically, more efficiently, and more consistently when a predictive model is used to analyze a limited set of underwriting requirements and inexpensive third-party marketing data sources to provide an early glimpse of the likely underwriting result.

Deloitte Financial Services Risk and Regulatory Review Dec. 2012/Feb. 2013
Deloitte: Predictive Modeling for Life Insurance Apr. 2010

Use of Traditional Data Sources v. Non-traditional Data Sources

- Traditional Data Sources
  - Application form
  - Medical history
- Non-traditional Data Sources
  - Lifestyle
  - Purchasing
  - Household
  - Social network data
- Shortcomings of traditional underwriting:
  - Expensive
  - Time-consuming
  - Invasive procedures
  - Lack of consistency due to subjective nature of process
  - Diminished customer experience

Deloitte Financial Services Risk and Regulatory Review Dec. 2012/Feb. 2013

Combining Traditional and Non-traditional Data Offers the Most Complete Approach

- Traditional Underwriting data:
  - Low blood pressure and cholesterol
  - No adverse lab results
  - Application information confirmed by para-med report
  - Clean credit report
- Non-traditional Underwriting data:
  - 25 years of work experience with same employer
  - Manager level position
  - Owns home
  - Has lived in hometown all his life
  - Commuting distance – 6 miles
  - Runner and swimmer
  - Married with three children
  - Little to no television consumption

Use of Analytics for In-Force Policyholder

Ways that data analytics can be used to improve the performance of an in-force portfolio:

- Segmentation analysis can be used to identify groups of members with high risk behaviors such as unusual claim payments or identifying the policies which are most at risk of lapsing.
- It may be possible to identify policies that are about to lapse by monitoring policyholder behaviors around premium anniversary dates such as repeated requests for surrender values or by noting numerous missed or late premiums.

Deloitte Financial Services Risk and Regulatory Review Dec. 2012/Feb. 2013

Application for In-Force Policyholder

A company may choose to focus its retention strategies on those at risk of lapsing and who are profitable to the company. Alternatively, a company may decide that some policyholders are no longer desirable.

When one of the less desirable people misses a premium, the lapse would be allowed to take its natural course. This will enable a company to spend its retention efforts on those policies they want to keep.

Deloitte Financial Services Risk and Regulatory Review Dec. 2012/Feb. 2013

Use of Analytics in Management of Reserves

- Managing reserves by:
  - Enhanced actuarial models to improve understanding of risk with claims and reserves
  - Preparing for the unexpected (what-if forecasting for claims rates)
  - Outcomes analysis
  - Encouraging wellness programs and improving Customer Relationship Management

Teradata 2012

Analytics in Marketing

Using analytics to score the entire marketing pool and employ a targeted approach should help reduce the dollars spent marketing to those who will later be declined or less likely to accept an expensive offer, and result in an applicant pool that contains more insurable candidates.

Deloitte: Predictive Modeling for Life Insurance Apr. 2010

Target Marketing

- Insurance customers often have undergone recent life-changing events such as getting married, having children, or purchasing a house.
- A predictive model can be built to identify which characteristics are most highly correlated with the purchase of life insurance.
- Scoring a direct marketing database can help a life insurer determine where to focus limited resources for marketing and sales.

Deloitte: Predictive Modeling for Life Insurance Apr. 2010

Potential Legal Risks of Analytics

How do we safely harness a predictive machine that foresees things such as an individual's life expectancy, propensity for illness, likelihood of job resignation, pregnancy and crime without putting civil liberties at risk?

3 Focus Areas:

- Discrimination
- Fair Credit Reporting Act
- Privacy concerns

Discrimination

- Anti-discrimination policies typically ensure that predictive models exclude characteristics such as race, and (depending on the situation) age, gender, sexual orientation, etc.
- However, there is a large and contentious gray area concerning other variables that may be directly predictive but may also serve as proxies for these omitted characteristics.
- Issue arises frequently in:
  - major insurance markets
  - administration of public assistance programs
  - college admissions
  - mortgage pricing

American Economic Journal: Economic Policy 3 Aug. 2011

Discrimination Example – Proposition 103

- California's Proposition 103 limited the variables that insurance companies could use in pricing automobile insurance.
- Most of the debate surrounded the use of location controls (e.g., ZIP code) and credit scores.
- The insurers argued that these types of variables were directly predictive of losses.
- Consumer advocates argued that these variables were clearly correlated with race and income (which are banned from use in insurance pricing) and were serving as proxies for the omitted characteristics.

American Economic Journal: Economic Policy 3 Aug. 2011

Discrimination Example Cont.

- In the case of Proposition 103, the arguments that the variables were proxies won the day, and the state mandated that insurers price their policies on a very small range of variables that excluded ZIP codes or credit scores.
- Some experts in the field contend that predictive models can be written to allow the direct predictive power of contentious variables (e.g., ZIP codes, credit scores) to be captured, while at the same time ensuring that their predictive strength does not capture a proxying effect for omitted characteristics.

American Economic Journal: Economic Policy 3 Aug. 2011


klossner
www.jklossner.com
"I'M SURPRISED. WITH SUCH EXTENSIVE EXPERIENCE IN PREDICTIVE ANALYTICS YOU SHOULD HAVE KNOWN THAT WE WOULDN'T HIRE YOU."

Fair Credit Reporting Act

History: In the1960s lawmakers became concerned with the availability of data collection and worried that the rapidly developing computing industry would vastly expand its influence, and lead to potential abuses. As a result, the Fair Credit Reporting Act ("FCRA") of 1970 was enacted.

Deloitte: Predictive Modeling for Life Insurance Apr. 2010

Fair Credit Reporting Act Cont.

- Lenders, insurers, employers, and landlords want faster and more efficient analytics and demographics tools for assessing a consumer's background, predicting risk, and maximizing profitability.
- Practically every aspect of consumers' transactional lives is now subject to scrutiny and sale—what they buy, what they sell, how much they make, how much they save, how much they owe, who they buy from, and whether those behaviors have changed in the last 90 days to six months.

American Bar Association: The FCRA: A Double-Edged Sword for Consumer Data Sellers Vol. 29 No. 6

Fair Credit Reporting Act Cont.

- Since metadata used in analytics is analyzed without displaying or distributing the originating data, the third-party marketing data does not face explicit FCRA or signature authority legal restrictions.
- However, FCRA provisions kick in when “adverse action” is taken against a person, such as a decision to deny insurance or increase rates. The law requires that people be notified of any adverse action and be allowed to dispute the accuracy or completeness of data.
- Therefore, to avoid possible exposure, data profiles should not be used to make final decisions about applicants.

WSJ: Insurers Test Data Profiles to Identify Risky Clients Nov. 19, 2010   Deloitte: Predictive Modeling for Life Insurance Apr. 2010

Privacy Concerns

The data used in predictive modeling is often gathered online with consumers only vaguely aware that separate bits of information about them are being collected and collated in ways that can be surprisingly revealing.

WSJ: Insurers Test Data Profiles to Identify Risky Clients Nov. 19, 2010


W184

3 Potential Privacy Pitfalls

1) Personal data: analytics' use of personal data may result in an inference that is correct or faulty, which could be damaging to an individual. (e.g., Target Example)
2) Law Enforcement: as crime-predicting computers emerge in the law enforcement world, the risk comes not when prediction is right but when it's wrong.
3) Employment: analytics' use of data to predict which employees are most likely to leave their jobs. (e.g., Hewlett Packard Example)

Analytics Magazine: Hewlett-Packard's prediction of employee behavior Oct. 23, 2013

Target Example

- Target creatively collated scattered pieces of data about individuals' changes in shopping habits to predict the delivery date of pregnant shoppers – so that they could then be targeted with relevant advertisements.
- One of the company's data analysts noticed that some women customers were stocking up on supplements such as calcium, magnesium and zinc. When someone suddenly starts buying lots of scent-free soap and extra-big bags of cotton balls, in addition to hand sanitizers and washcloths, it signaled they could be getting close to their delivery date.
- Negative backlash: many customers were very upset and felt that Target invaded their privacy related to a very personal issue.

Analytics Magazine Dec. 2013

The Guardian.com Technology Oct. 2013

Predictive Policing

- A timely and complete analysis of the thousands of incident reports, crime tips, 911 calls and other pieces of information that law enforcement professionals confront everyday is critical to fighting crime.
- The massive volume of data can benefit from data mining and predictive analytics.
- Law enforcement analytics can forecast outcomes based on times and locations of previous crimes, combined with sociological information about criminal behavior and patterns.

CNN: Police embracing tech that predicts crime Jul. 9, 2012

Santa Cruz Example

- Santa Cruz police department used the software to estimate where home, car and vehicle burglaries might take place, handing printouts of the maps to officers at the start of their shifts. Later it expanded it to bike thefts, battery, assault and prowling.
- The city saw a 19% reduction in burglaries during the year it was implemented.
- Criticisms:
  - Profiling based on sociological factors and/or criminal history;
  - Analytics' impacts on probable cause

Investigative Database: Predictive Policing Continues to Gain Wide Acceptance   CNN: Police embracing tech that predicts crime Jul. 9, 2012

Hewlett Packard Example

- In an effort to minimize turnover, HP implemented its Flight Risk Program to predict which of its team members were most likely to quit.
- HP's analytics workers pulled together two years of employee data such as salaries, raises, job ratings and job rotations. Then they tacked on, for each employee record, whether the person had quit. Compiled in this form, the data served to train a Flight Risk detector that recognizes combinations of factors characteristic to likely HP defectors.
- The point of making data-driven decisions is to move away from the gut and more toward empirically validated decisions.
- HP's Flight Risk prediction capability promises $300 million in estimated potential savings with respect to staff replacement and productivity loss globally.

Analytics Magazine: Hewlett Packard's prediction of employee behavior Oct. 23, 2013

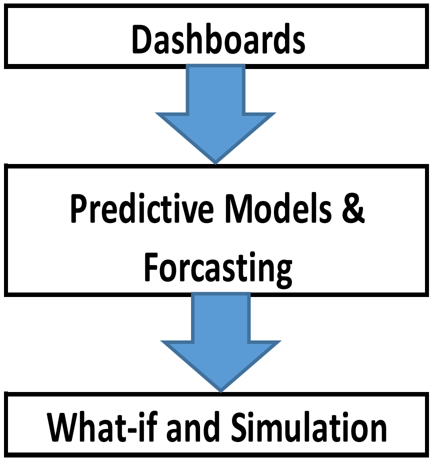
Predictive/Reporting Types

- Predictive methods can be placed into 3 types of solutions based on resources and available data.
- Dashboards and KPI (key performance indicators) are generally used by companies to determine the current standings of the company. Most of the predictive power here comes from the business insight.
- Predictive models and forecasting is used for companies to determine what are the main factors affecting business KPI's and help the company understand what is expected to happen based on past data.
- What-if analysis and simulations are used to evaluate business decisions and what they will do to KPI's and business practices. These models can also help address what will happen given changes in the standard processes.

Predictive Hierarchy

Drivers that moves a company predictive stage.

- Management/Customer buy in
- Cost of predictive project
- Amount of data that can be captured
- Available resources with predictive skills or cost of tools
- Success or failure of a model
- Economic times and need for cost reduction.



Dashboards – Predictive Data

- The audience for a dashboard can be anyone and there are usually many dashboards designed for different audiences with a company. Most of the predictive power of a dashboard comes from the experience of the audience to understand what the metrics are and how day to day decisions affect them.
- Dashboards help management understand how the company or department is performing but can be used to start to understand how different KPI's react to one another.
- With data getting larger and larger, dashboards are good to understand the company better and to help management understand the need for predictive models and get the much needed buy in from the needed management within a company.

Dashboards - Decisions

- Dashboards usually are used to monitor the heath of a company or department so decisions are done to address the symptoms and less about the cause. This is similar to giving medication to a patient to address high blood pressure without looking for the cause.
- Decisions are made to keep the “status quo” and less about helping determine what areas can be improved from what history has shown.
- Dashboards can also help determine where programs need to be implemented and what metrics may be needed to determine the success or failure of a program, such as a fall prevention program or a vitamin program to increase health.
- Dashboards usually do not determine what company “side effects” may occur due to a program or study.

Dashboards – Benefits/Limits

- Dashboard Benefits
  - Dashboards are simple to create and most time invested should be in the KPI's that are monitored.
  - The tools are cheap and usually done in Microsoft Office.
  - There are many non-technical books on dashboards and KPI's, ranging in level of difficulty, such as "The Balanced Scorecard" by Kaplan and Norton
- Dashboard Limits
  - Predictive power comes from business experience and not data element relations.
  - Difficult to understand how business changes will effect the business.
  - Puts a company in reactive mode rather than a proactive position.

Predictive Models & Forecasting

- Predictive and forecasting models can also be of interest to many audiences but most are interested in the results rather than the process. The process can lead to a greater understanding of the business and what drives things such as claims, complaints, and a host of other business aspects.
- Predictive models can help one understand why decisions made in the past failed or succeeded and overall effect on the business from these decisions.
- Predictive analytics can lead one to understand what part of the business can change and have little effect on the bottom line and which can have more drastic effects.

Predictive Models & Forecasting - Decisions

- With a greater understanding of the business from the predictive analytics one can make more sound decisions. If one decides to change a process in the operations of claims, such as receiving the claims into another department, one can determine the overall affect.
- One can determine which programs will have the most effect on the business and allow one to have a greater understanding of the overall effect on the ROI. If management determines there is a great benefit to a free drug program to fight off different diseases one can use predictive analytics to determine which is likely to effect future claims more and lower the overall cost.
- Predictive analytics determine likely events based on historical relationships and when making decisions this should be keep in mind.

Predictive Models & Forecasting – Benefits/Limits

- Predictive Model Benefits
  - Can provide greater insight into the company and how decisions effect the company.
  - Can identify key drivers to help determine company programs, such as fall prevention, or focused groups within a program.
  - Better tools for decisions and ease of use with big data.
- Predictive Model Limits
  - Can be expensive and time consuming.
  - Generally requires predictive experience and statisticians.
  - Expanded amount of tools to use causing great risk in choosing the right tool, due to cost of most tools.

Predictive Models & Forecasting – Example

- Model Variables – Claims inventory
  - Lag time from date of service to receive date.
  - Lag time from receipt to payment.
  - Seasonality and trending based on the last two years.
  - All variables were put together to mimic the system and once evaluated the model was a ARIMA model.
- Learning points
  - The model took about 6 months to create and would not have been done if there was not buy in from the operations.
  - When the model was completed there was little interest in it as the inventories were at a good level until they spiked 2 weeks later as the model predicted they would.

Simulations and What-if models

- Simulations and what-if analysis requires a greater understanding of the business and not just what effects the KPI's but also what are the interactions between the variables, similar to the covariance between two variables.
- There can be significant amount of development put into a simulation model, some are less sophisticated than others. Most require some kind of programming language.
- Simulation analysis requires a predictive model to have been developed and validated, even if the model is basic in nature.
- The best use for simulations is for helping with decisions and understanding the sensitivity to different variables a KPI has.

Simulations and What-if - Decisions

- Simulations help management understand the likely outcome of different decisions.
- One of the best uses of simulations and what-if analysis is to do sensitivity testing for KPI’s. A good example is creating sensitivity around reserves to understand how much they can swing from the predicted reserve level.
- Simulations can take a long time to develop but can lead to much better decisions and also help locate variables that can be added to predictive models to increase accuracy. They can also indicate when there is no real value to add to a predictive model where the remaining error is basically random.

Simulations and What-if – Benefits/Limits

- Simulation Benefits
  - Can help determine possible effects of business decisions.
  - Can help create a greater understanding of the business.
  - Allows management to understand differences between results and predictions, such as swings in reserves.
  - Helps determine when processes and programs can be improved verses general random effects.
- Simulation Limits
  - Requires strong understanding between relationships in business metrics.
  - Requires a significant amount of data.
  - Most simulations have to be home built as fewer tools are available.

For Further Questions

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