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Predictive Modeling: Tips for Data Scientists and Actuaries and How to Implement a Predictive Model

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Agenda

The End-to-End Modeling Journey

Helpful Hints

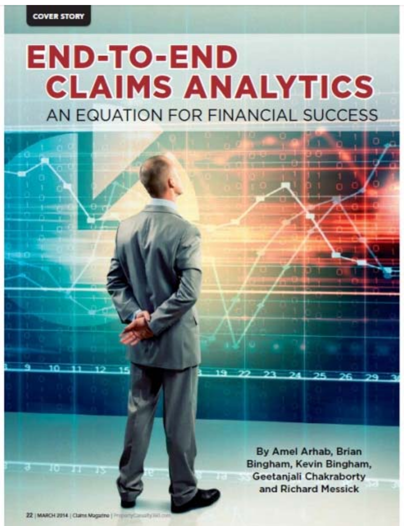
Decision Driven Framework for Analytics

Red Flags and Warning Signs

The End-to-End Journey

The End-to-End Analytics Journey

1. Model Deployment Strategy → 2. Predictive Model Development → 3. Scoring Engine and Technical Integration → 4. Business and Operational Implementation → 5. Organizational Change Management → 6. Performance Management & Loopback Improvement



In the end, a claims predictive model deployment is more than just a bunch of actuaries, statisticians and PhD’s having fun with numbers. The end-to-end analytics journey includes:

1. Model deployment strategy
2. Claims predictive model development
3. Scoring engine development and technical integration
4. Business and operational implementation
5. Organizational change management
6. Performance management and loopback improvement

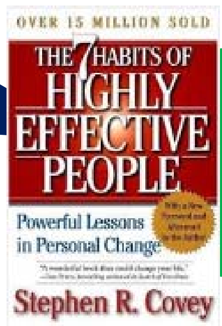
Source: Claims Magazine, March 2014, http://www.propertycasualty360.com/2014/02/03/reaping-the-financial-rewards-of-end-to-end-claims

Begin With Your Modeling Mission in Mind

1. Model Deployment Strategy
2. Predictive Model Development
3. Scoring Engine and Technical Integration
4. Business and Operational Implementation
5. Organizational Change Management
6. Performance Management & Loopback Improvement

The most important step, in any predictive modeling journey, is articulating the business challenges you are trying to solve. Using modeling terminology, we are defining the "target variable". The target variable is what the insurance company hopes to predict and ultimately influence through tactical business decisions.

"To begin with the end in mind means to start with a clear understanding of your destination."



Stephen Covey
The 7 Habits of Highly Effective People

Don't end up with the world's most expensive calculator collecting dust. Have a clear vision of how the end users will use the model in their day to day activities. From there, you can begin turning raw data into actionable predictions and insights that enable better business decisions.

Predictive Models
“Eye Glasses” for The Human Being’s Mind

1. Model Deployment Strategy
2. Predictive Model Development
3. Scoring Engine and Technical Integration
4. Business and Operational Implementation
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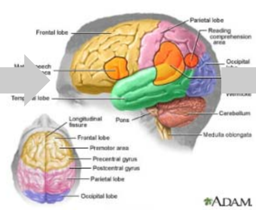
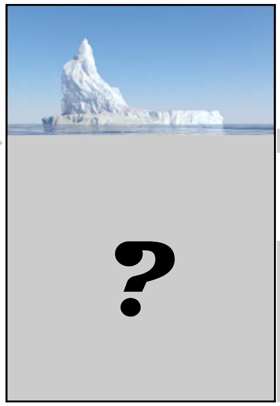
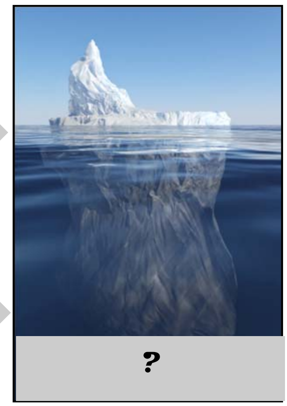
6. Performance Management & Loopback Improvement





$$Y = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + ... + \beta_n * X_n$$

Predictive Modeling Reflecting Internal, External & Synthetic Data



CLARITY BEFORE LEVERAGING ANALYTICS

CLARITY AFTER LEVERAGING ANALYTICS


REVVING YOUR ANALYTIC HORSEPOWER
The Claims IT Journey Continues

“In the end, predictive models can essentially act as decision support “eye glasses” for the claims adjuster’s mind.”

Source: Claims Magazine, November 2011, http://www.propertycasualty360.com/2011/10/26/revving-your-analytic-horsepower

Predictive Models Fall Short Without Business Implementation

1. Model Deployment Strategy → 2. Predictive Model Development → 3. Scoring Engine and Technical Integration → **4. Business and Operational Implementation** → 5. Organizational Change Management → 6. Performance Management & Loopback Improvement

It is important to note the development of predictive models is only one piece of an effective analytics journey. Even the most accurate predictive model has minimal business value if it cannot be successfully incorporated into the day-to-day workflow of the insurance company's end user (e.g., underwriter, claim adjuster, medical specialist, etc.).

A well-defined business implementation plan dictates how:

- The model will be used
- How the model output will be presented to end users
- How the underwriting or claim process will be enhanced to incorporate model output and insights

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Active End-User Involvement Helps Drive Success

1. Model Deployment Strategy
2. Predictive Model Development
3. Scoring Engine and Technical Integration
4. Business and Operational Implementation
5. Organizational Change Management
6. Performance Management & Loopback Improvement

When it comes to end-user adoption, obtaining user buy-in through effective communications and leveraging key claims or underwriting advocates is critical. Organizational change management focuses on the development and delivery of communications and training to achieve stakeholder buy-in and enable end-users to use the predictive modeling tools. Key aspects include:

- Involvement of end-users from day one
- Define detailed communication and training strategy
- Conduct a variety of communication activities (e.g., presentations, newsletters, FAQs, etc.)
- Defined target interventions for high risk areas
- Identify key “evangelists” who will help build buy-in and drive adoption
- Share results and success stories to promote organizational buy-in
- Measure effectiveness of change activities and make changes as needed

Measuring and Monitoring Success

Creating a performance metrics plan is critical to evaluate the performance of your predictive models in production against the insurance company's business objectives.

Key performance indicators (KPIs) can be used to monitor pre- and post-production results. In addition to the traditional KPIs focused on loss & ALAE, fraud & recoveries, claims volume and quality, insurers can also measure detailed model performance KPIs such as:

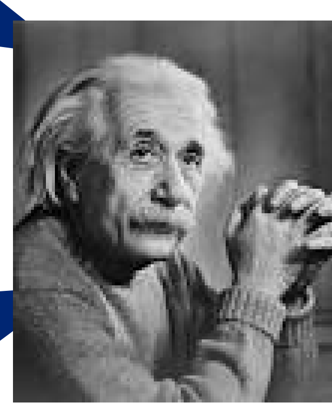
- Score distribution by decile
- Reason code distribution by decile
- Claim score migration through time (a/k/a, "decile drift")
- Adjustor inventory detail

Measuring and monitoring success is critical aspect of a successful analytics journey.

The Importance of Imagination

"Imagination is everything.
It is a preview of life's coming attractions."

"Logic will get you from A to B. Imagination will take you everywhere."



Albert Einstein
Father of Modern Day Physics

The end-to-end modeling journey requires using your imagination throughout the entire process.

Helpful Hints

Tips for Successfully Completing the End-to-End Analytics Journey

The Challenges of Implementing Advanced Analytics

By Kevin Bingham, John Lucker, Laura Ward and Stacey Peterson

Becoming analytics-enabled is perhaps one of the most important evolutionary steps forward an organization can make. The rewards of data-driven decision-making can be a powerful boost to the bottom line. For insurance companies, this may include using underwriting predictive models to increase profitability through more granular pricing, driving a six to eight-point reduction in loss ratios. On the claims side, predictive models have helped insurers better segment and triage high severity workers' compensation and bodily injury claims, driving a four to 10-point reduction in claims spend.

An important part of the analytics journey is overcoming the numerous challenges an organization encounters when experiencing the end-to-end development and deployment of predictive models. Model development (e.g., data assessment, data acquisition, data cleansing), scoring engine development (e.g., scoring engine and database design, development, testing, deployment), and business implementation (e.g., strategy formation, change management, tools for measuring business) are some of the common questions organizations should consider.

Business Issues

Some of the concerns the authors have observed in the development and implementation of advanced analytics include:

1. Executive Ownership

Without buy-in from senior leadership and a clear corporate strategy for integrating predictive models, advanced analytics efforts can end up stalled at model development. In order to be effective, analytics efforts should involve the key executives who can help drive acceptance

24 | OCTOBER 2014 | Claims Magazine | PropertyCasualty360.com

"An important part of the analytics journey is overcoming the numerous challenges an organization encounters when experiencing the end-to-end development and deployment of predictive models."

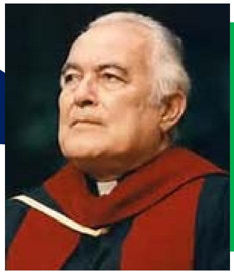
1. Executive ownership
2. IT involvement
3. Available production data vs. cleansed modeling data
4. Project management office
5. End user involvement and buy-in
6. Change management
7. Explainability vs. the "perfect lift"

Source: Claims Magazine, October 2014, http://www.propertycasualty360.com/2014/10/01/the-challenges-of-implementing-advanced-analytics

Executive Ownership

- Without buy-in from senior leadership and a clear corporate strategy for integrating predictive models, advanced analytics efforts can end up stalled at model development.
- In order to be effective, analytics efforts should involve the key executives who can help drive acceptance and change throughout the organization. Senior leaders should insist there be a clear correlation between the actions to be taken through model implementation and the expected business benefits to be realized.
- Without accountability for a targeted return on investment, organizations risk spending a lot of time “doing” versus “getting things done.”

“The very essence of leadership is that you have to have a vision. It’s got to be a vision you articulate clearly and forcefully on every occasion. You can’t blow an uncertain trumpet.”

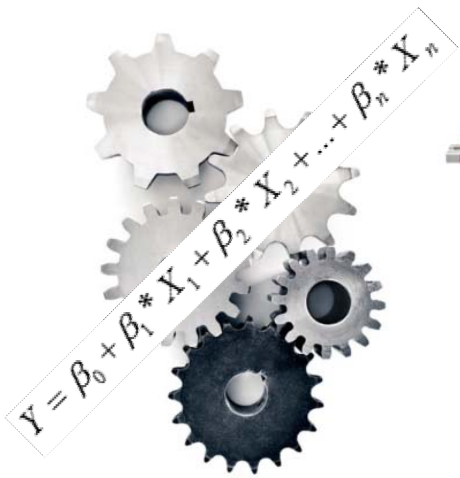


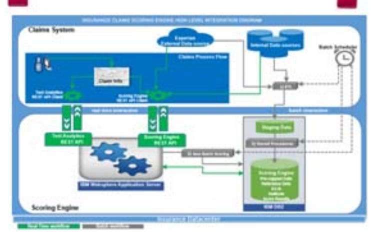
Reverend Theodore Hesburgh

IT Involvement

- Failure to involve IT from the very beginning of the analytics journey can lead to significant issues down the road if technology gaps and limitations aren’t understood up front. Modelers may find a way to get access to internal and external data, but without the help and involvement of IT, it is almost impossible to bring the models to life in the day-to-day operation of the organization.

MODEL → IT → END USER





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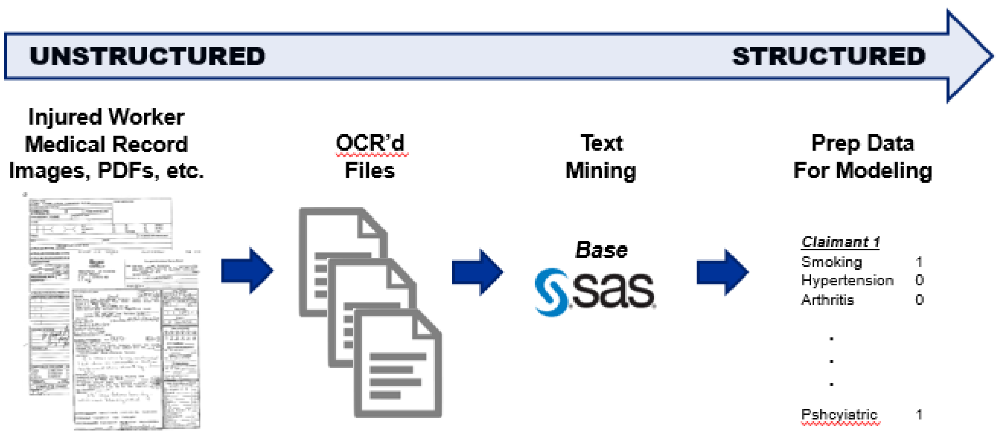
Available Production Data vs. Cleansed Modeling Data

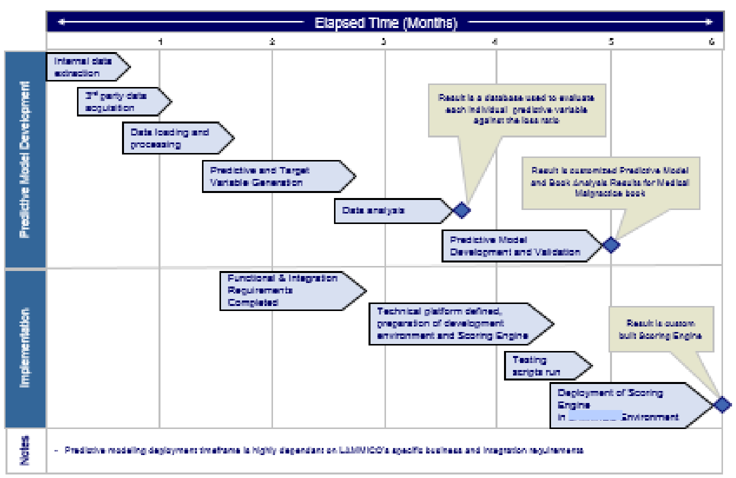
- Access to historical data for model development is very different from access to real-time data in production, and a strong model is only as good as its ability to be practically implemented within the technology infrastructure.
- Real life limitations may restrict the data that's available for historical modeling. Sometimes a proxy variable can be used for modeling until the data is available.
- Analytics initiatives often risk being stymied by the belief that data for modeling must be perfectly clean and organized. Predictive model development is not an accounting exercise, but rather a statistical process where numerous techniques allow the "dirt in data to be washed away."



Source: Claims Magazine, October 2014, http://www.propertycasualty360.com/2014/10/01/the-challenges-of-implementing-advanced-analytics

The Importance of a Project Management Office (PMO)

- Lack of clear ownership of the end-to-end journey is a common stumbling block for organizations that have struggled (and failed) in implementing their predictive models.
- Without the right project management structure in place, a clear cadence of project milestones, and the ownership of deliverables by pre-identified business owners, the project could be doomed before it starts. Most importantly, the PMO must be able to connect with all interested parties and adopt an agile approach.

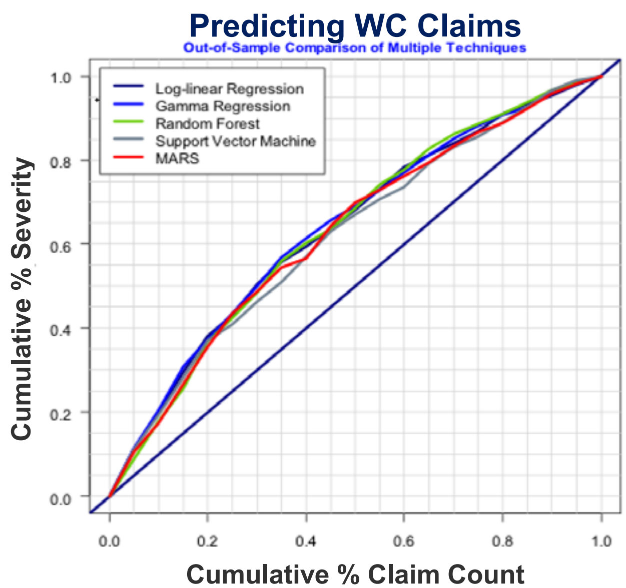


- Project team structure
- Roles & responsibilities by department
- Project timeline by:
  - Stream
  - Task
    - Start date, finish date, duration
    - Key sign offs and milestones

Source: Claims Magazine, October 2014, http://www.propertycasualty360.com/2014/10/01/the-challenges-of-implementing-advanced-analytics

Explainability vs the "Perfect Lift"

- It is important to balance building a precise statistical model with the ability to explain the model and how it produces results. What good is using a non-linear model or complicated machine learning method if the end user has no way to translate the drivers of the score and reason codes into actionable business results?
- Experience shows that a less complex statistical model development method yields results similar to those from more complex approaches, and a small sacrifice of predictive power can result in marked improvement in the explainability of technical model recommendations for end users.



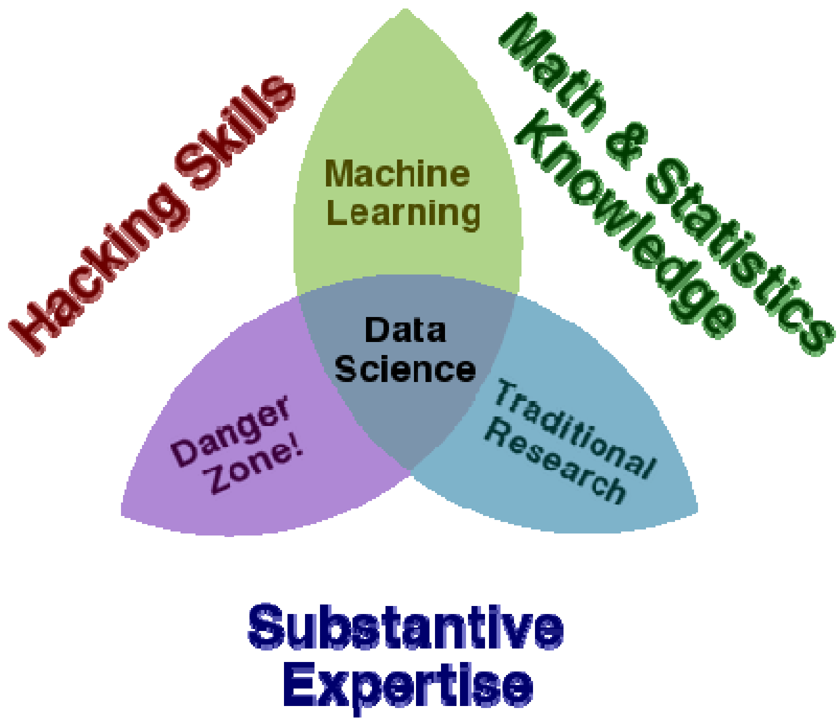
"Explainability trumps lift 95 times out of 100."

Kevin Bingham

Decision-Driven Framework for Analytics

What is an "Analytics Project Anyway"
Comparing Statistics to Analytics (or Data Science)

Drew Conway's Data Science Venn Diagram



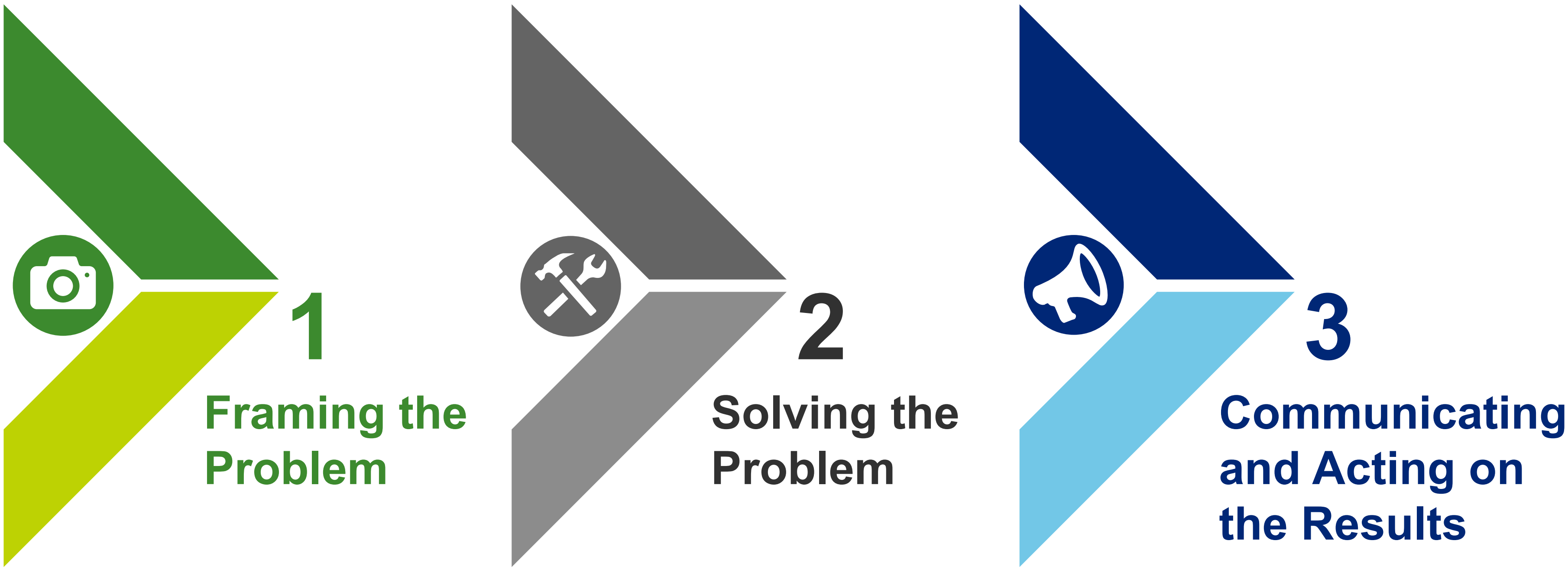
Analytics projects…

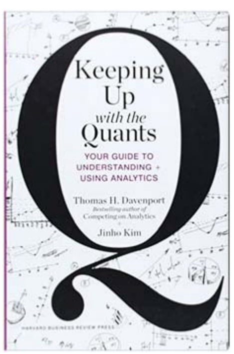
1. Involve data analysis in helping to improve decision making.
2. Often utilize statistical models, methods, and tools.
3. May lead to findings reports or insights.
4. May lead to transformational change for a business process (i.e., better decision making).
5. Can be "exploratory", "confirmatory" or both!

Source: http://drewconway.com/zia/2013/3/26/the-data-science-venn-diagram

Phases of Analytics Projects

Analytics projects often involve the following components.





Davenport, Kim, 2013

Deloitte.

Role of the {Actuary, Data Scientist, Statistician}

Framing

- Collaborate with business experts.
- Translate the business question into a statistical one.
- Plan for and design the solution (e.g., confirmatory vs. exploratory).

Solving

- Select data sources.
- Perform EDA.
- Decide on model or algorithm.
- Understand privacy implications.

Communicating / Acting

- Document of findings.
- Visualize and present data.
- Advise and guide technology decisions during implementation.

Framing the Issue as a Decision to be Improved

What decision is being improved?	▪ What choices are being faced that require a decision? ▪ What's the organizational context of the decision?
Who is deciding?	▪ Who is making the decision to be improved? ▪ Who are the stakeholders, influencers and decision makers?
What is the value of an improved decision?	▪ How should decision improvement be measured? ▪ How good is the current decision? ▪ How much should we invest in improving this decision?

Source: David Steier, A Decision-Drive Framework for Managing Analytics Projects

Red Flags and Warning Signs

Before the Project Starts

Set up your analytics project for success.

Recommendations

Resources

- Planning, Budgeting, Staffing
- Tools and infrastructure (e.g., computing power, software, databases, disk space)

Executive Support

- Single point of contact
- Steering committee
- Demonstrated support

Data Stewards / Key SMEs

- Who owns or controls the data?
- Availability, vacation, competing priorities

Red Flags / Warning Signs

- Requirements are very high level
- Unrealistic expectations
- Multiple sponsors
- Nobody proposing the project has seen the data
- Key experts not involved (or are leaving)
- No representation by end users
- No consideration of privacy for sensitive data or results
- Lack of legal review for project risks

During the Project

Cruise in-flight.

Recommendations

Choice of Model / Algorithm

- **Implementable**
- **Simple**: Occam's Razor
- **Interpretable**: Rashomon Multiplicity

Communication

- There is no such thing as over-communication.

Documentation

- Insufficient understanding
- Hand-off between teams (and skill-sets)

Red Flags / Warning Signs

- Not enough time in the project schedule for testing, iterations, documentation.
- Access to the data is constantly delayed.
- Key elements of data are missing or worse quality than expected.
- Single source for key project elements.
- Major unanticipated shifts in scope.
- Lack of progress/schedule for status reporting or follow-up.
- Analytics runs take much longer than expected.
- Reliance on unverified vendor claims.
- No case studies demonstrating success.
- Stakeholders unavailable.
- No hold out data.

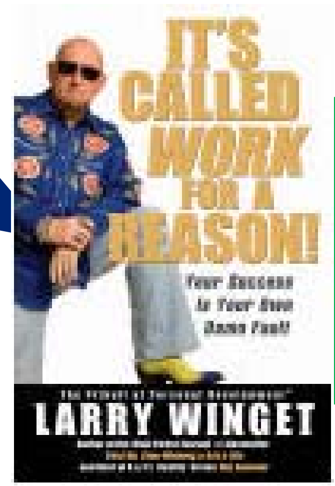
After the Project

Close out and debrief

Recommendations	Questions to Ask
Close-out ▪ Gather feedback ▪ Deliver and document Impact analysis ▪ Assist with the estimation of benefit/impact ▪ Visualize and explain the data for non-technical audiences.	▪ Are the results being used to improve the targeted decisions? ▪ Are the end users applying the analytics as intended? ▪ Have the decision improvements met expectations? ▪ Have there been any unintended consequences? ▪ Are there follow-on opportunities?

The Importance of Implementing the Model

"Knowledge is not power; the implementation of knowledge is power."



Larry Winget
It's Called Work For a Reason

Building cool models is only part of the journey. You have to turn the model into actionable business insights through a successful business implementation.

Questions

Q & A

Speaker Bio

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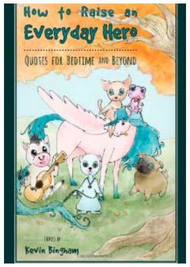
- Co-chairperson, Casualty Actuarial Society's Innovation Council
- Leader of Deloitte Consulting's MPL practice and claim predictive modeling practice
- Past chairperson, Casualty Practice Council Medical Professional Liability (MPL) Subcommittee
- Official spokesperson for the American Academy of Actuaries in Washington
- Advisory board member and chairman of the annual MPL ExecuSummit
- Speaker, trainer and regular contributor to Contingencies Magazine, Inside Medical Liability Magazine, Claims Magazine and other publications on industry issues
  - To date, Mr. Bingham has published over 70 articles/papers and has spoken at more than 100 conferences/seminars/webinars

  - Author of the 155 page children book titled "How to Raise an Everyday Hero: Quotes for Bedtime and Beyond."



Speaker Bio

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- Mike is a data scientist with Deloitte's Advanced Analytics & Modeling practice, based in Boston. For over 10 years he has designed, built, and implemented predictive and behavioral analytics solutions to help organizations in the public and private sector improve business processes, operations, and/or profitability.
- Mike holds an AB in Mathematics from the University of Chicago, and an AM in Statistics from Harvard University. He has been a member of the American Statistical Association since 2003 and proudly knows more computer languages than spoken languages.
- Co-author of *Managing Analytics Projects*
- Specialties
  - Predictive modeling
  - Statistical analysis
  - Ricing and optimization
  - Risk modeling
  - Advanced analytics
  - Exploratory data analysis
  - Bayesian statistical analysis

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Nudging New Mexico
Kindling compliance among unemployment claimants

BY JOY FOREHAND AND MICHAEL GREENE
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Managing Analytics Projects

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Abstract
Analytics projects are often undertaken by statistical consultants in the business sector. Unfortunately many business analytics projects fail to achieve their goals. Often, we statisticians focus on aspects such as the lift curve or the model fit while ignoring critical aspects of managing the project, such as gathering requirements, engaging stakeholders, and choosing between infrastructure platforms. Statisticians could play many roles throughout the project life cycle and, we believe, improve analytic project chances for success. We illustrate these roles by describing business analytics projects, typical project activities and opportunities for statisticians. We will discuss positive (and negative) outcomes of these topics, illustrated through case studies and experience on analytics projects. The paper includes an extensive listing of red flags and warning signs and follow-up questions to assist the analytics practitioner or statistical consultant in navigating the dangers to successfully land the project.

Key Words: Statistical Consulting, Analytics Projects, Project Management

1. Introduction

In recent years, the business community has demonstrated unprecedented demand for use of analytics: the application of rigorous quantitative thinking to improve business decision-making and operations. Businesses now use predictive models for applications as diverse as targeting potential customers, underwriting financial risk, and even focusing retention efforts on employees who are the most likely to quit. This demand for analytics stems from the exponential increase in data collected, economic success of analytics-based business, the increased prevalence of basic statistical training in businesses, and the increasing accessibility of tools for data analysis and visualization.

Statisticians are naturally suited to play crucial roles throughout such analytics projects, from framing the problem to choice of model through the implementation of the analytics within the business. Unfortunately, when trained statisticians are involved at all, they often participate in only a small subset of these activities. And, perhaps not coincidentally, the majority of business analytics projects fail (Demirkan & Dal, 2014). Of course, failure can have many definitions. In this context, failure means not succeeding in meeting the business goals or objectives. In this paper, we describe the roles that statisticians can, and we believe should, play in managing analytics projects. This guide is not intended as a comprehensive discussion of analytics projects. Rather, we aim to help statisticians make analytics projects more successful with suggestions and recommendations on how to navigate the business environment.