

# Beyond Reliability: Advanced Analytics for Predicting Quality

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#### Office Locations

Arlington, VA  
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# Who Should Attend?

## Job Titles:

- Statisticians
- Researchers
- Managers
- Lean professionals
- Process improvement team members
- Continuous improvement managers
- Master Black Belts
- Six Sigma Black Belts



# When Individual Entities Matter



- **Context**
  - Natural Gas Wells in Wyoming
- **Problem: Well “Freezing”**
  - Costly to send maintenance into the field to prevent
  - Lost production during downtime

**When should they go?**

**Where should they go?**

# What do maintenance crews need to know?

- Which well has stopped producing?
- Why has this well stopped producing?
- What is the nature of the failure?
- What service has already been performed?



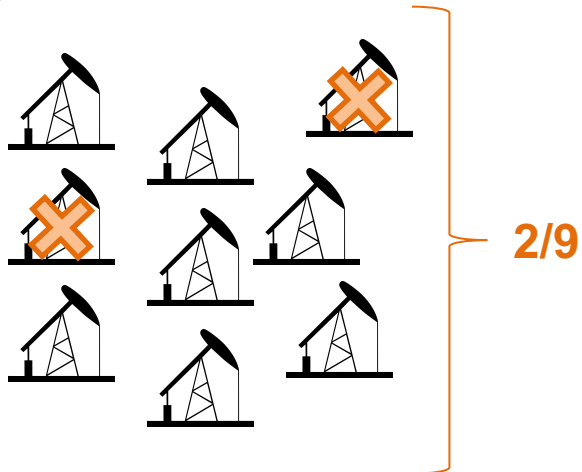
# Reliability: A Question of Questions

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Which question is more important?

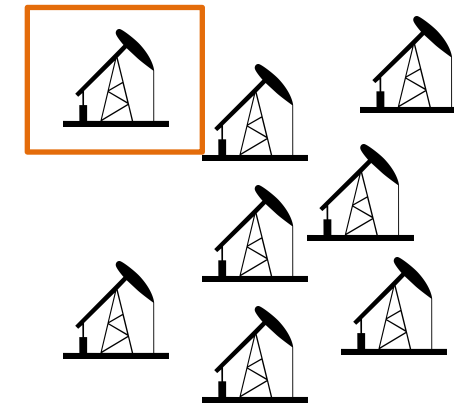
**“Traditional”**

What proportion of wells will have an equipment failure in the next 180 days?



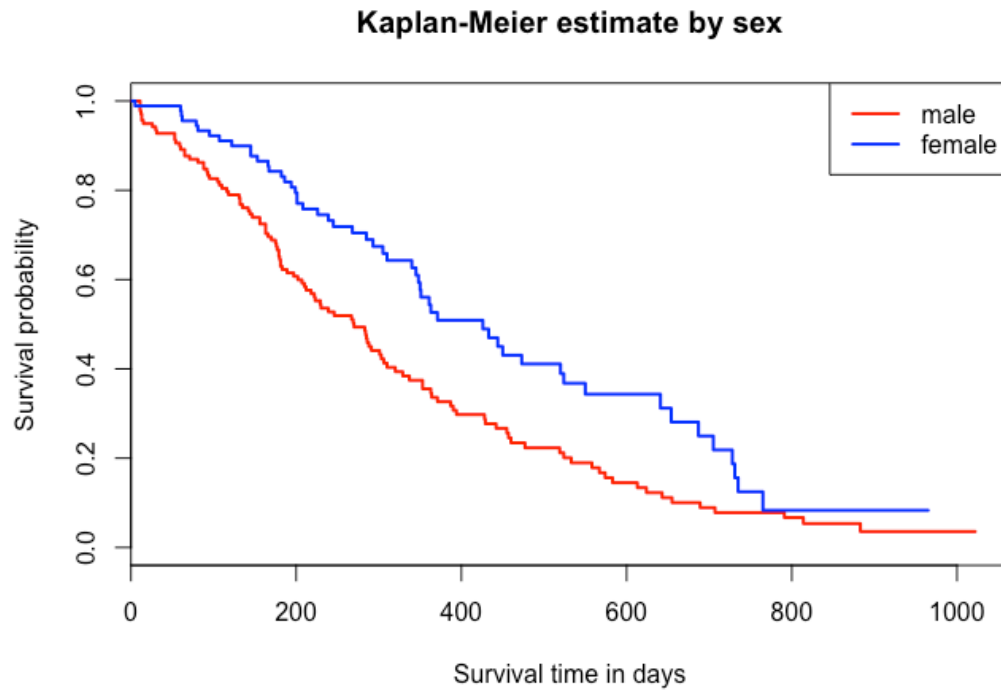
**Predictive Analytics**

What is the likelihood that *this particular* well will require maintenance in the next 180 days?

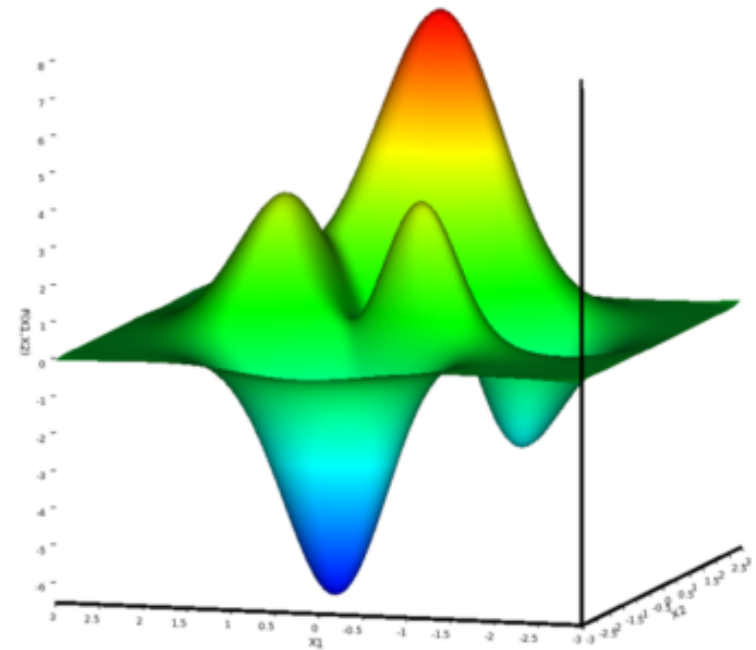


# Traditional Paradigms

## Kaplan-Meier/Cox Regression

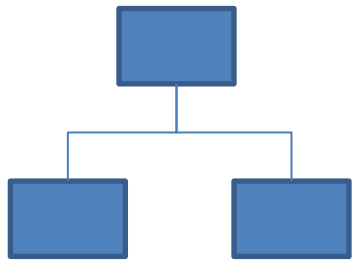


## Design of Experiments

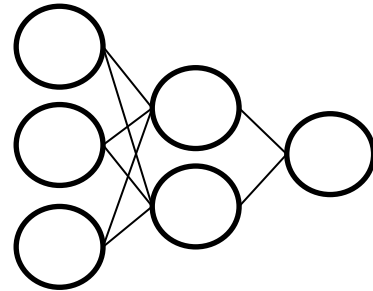


# Predictive Analytics Methods

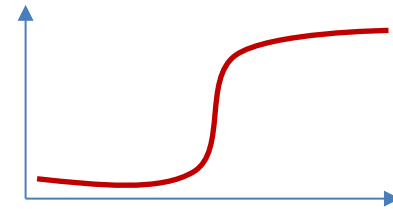
**Decision  
Trees**



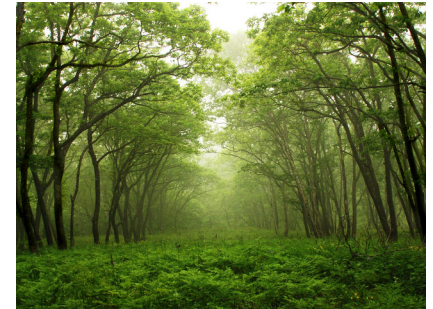
**Neural  
Networks**



**Regression  
Analysis**



**Random  
Forests/  
Ensembles**





# The Strengths of Traditional Methods

- We want to make a decision based on the reliability (or quality) of a *population*
  - How many or how much...?
- Possible applications:
  - Estimating fleet overall performance
  - Budgeting for field maintenance
  - Population health management
  - Life/Long-Term Care portfolio analysis



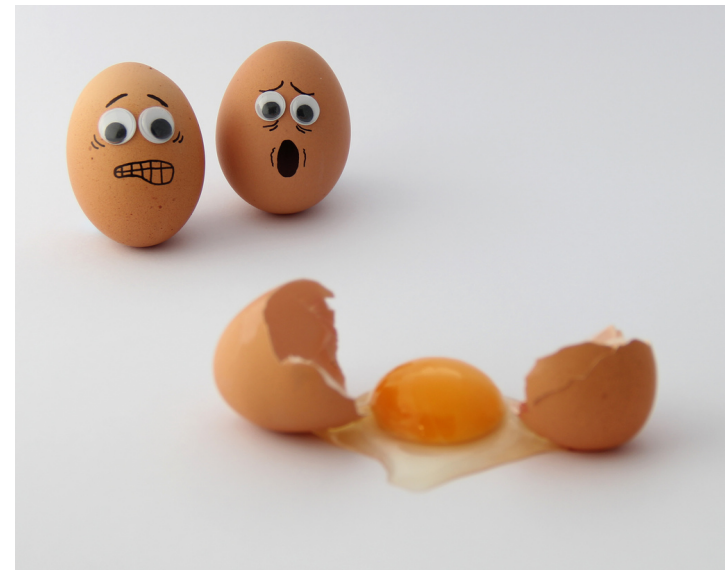
# What do the traditional methods tell us about the wells?

## Kaplan-Meier/Cox Regression

We might know what proportion of wells make it to a given life, but we may not know what contributes to the likelihood of failure for a **particular** well

## Design of Experiments

We might know something about the wells in the center of our DoE, but we will know very little about the performance in extreme cases.



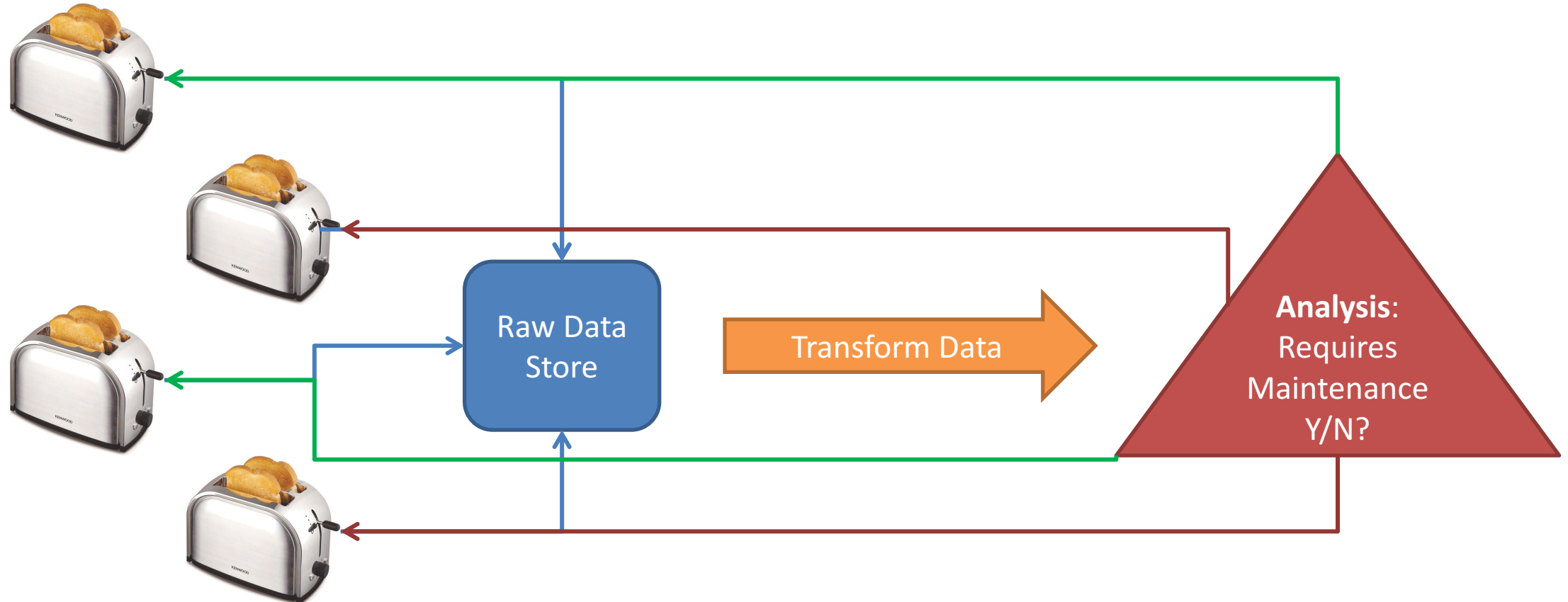
# Predictive Analytics: A Complementary Paradigm

# Case Study: Connected “Toasters”

- **Client:** Connected “Toaster” Manufacturer
- **Goal:** use data as an asset for competitive advantage
- **Identified Opportunity:** preventative maintenance of “toasters”
- **Our Engagement:** Third-Party Validation



# Unpacking the Opportunity



# Elements of the “Toaster” Solution

- **Need:** Select/create variables related to maintenance and failures
- **Analysis Method:** Kaplan-Meier
  - Stratified by:
    - Date of Manufacture
    - Design
    - ...
- **Goal:** Optimize for Consumer’s Risk of devices



# Burnt “Toast”: Limitations with Traditional Methods

- **Average** survival was correct, but **particular** survival probabilities did not match observations
- Some strata had no failures at all (e.g., newer “toasters”)
- Excessive Stratification → Small samples!
- Assumptions for missing data grossly overestimated failures



# Two Questions Again!

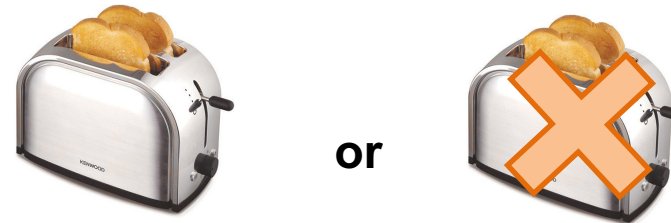
## Our client's question

*How many “toasters” can we afford to bring back for maintenance? How many failures in the field can we afford to have?*



## Their customer's question

*Does **my** toaster need maintenance?*





# Applying Predictive Analytics to “Toaster” Data

- **Problem:** Classification
  - Does *this* “toaster” require maintenance: Y/N?
- **Method:** LASSO Regression
  - Combined variable selection and prediction
  - Mitigate overfit through regularization
- **Benefit:** also can estimate aggregate Consumer’s Risk

**How did we compare?**



# Combining Traditional Methods with Predictive Analytics

- **Complementary Validation**
  - Identified similar feature space
  - Consumer's Risk still matters!
- **Entity Failure Probabilities**
  - Likelihood of failure for individual "toasters"
  - Closer to user needs
- **Integration of Historical Performance**
  - Historical data for *each "toaster"* used to assess model performance



# Back to Wyoming

# The Old Challenges of Found Data

- >1 TB of *ugly* data

## Some Challenges Included:

- Difficult integration
- Missing/sparse data
- Information unavailable until end of project (e.g., “freeze”)
- No information on well treatment (i.e., methanol pour-down)



# More on “Freezing”

- **Initially:** well is “frozen”
- **Evolution 1:**
  - Subsurface Freezing  
(**more costly**)
  - Above-Ground Freezing
- **Evolution 2:** *any* downtime  
(including scheduled maintenance!)



# Starting Traditionally

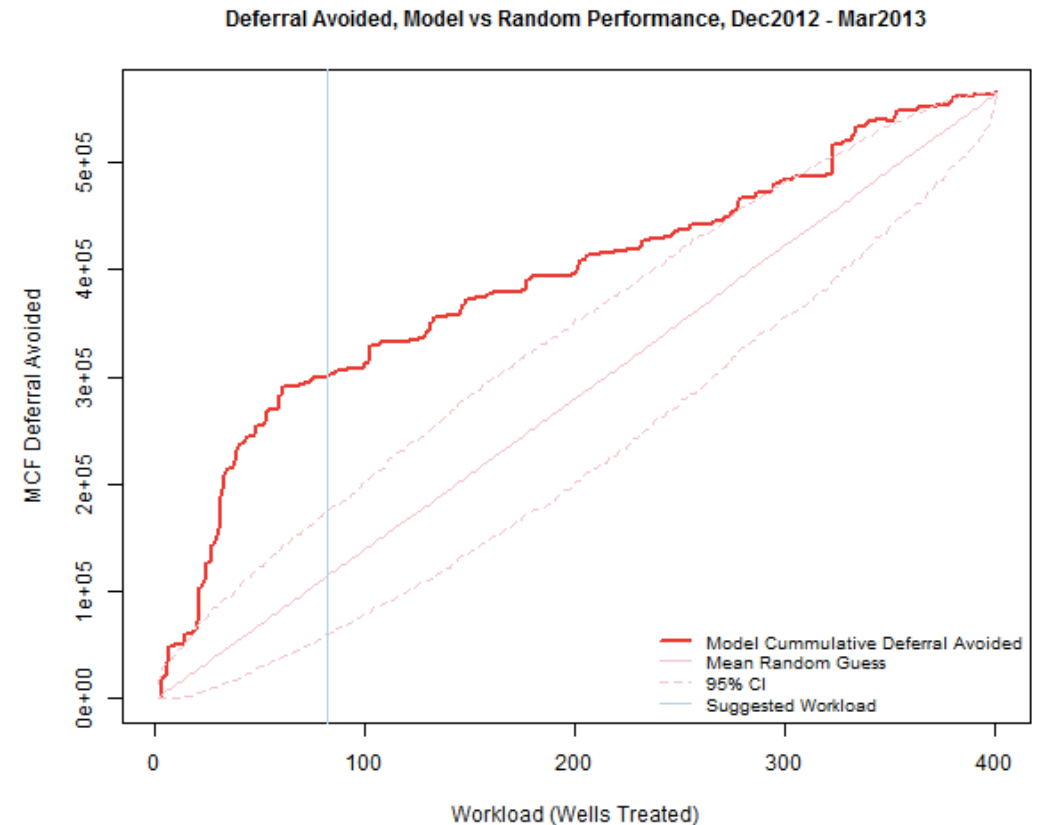
- **Initial Analysis:** Kaplan-Meier
- **Key Insights:**
  - Field-level statistics still matter for resourcing/budgeting decisions
  - Fast and efficient statistics on aggregate well behavior
  - Repeat “freeze” 10x more likely after first freeze



# Finishing with Predictive Analytics

- **Problem:** Classification
  - How likely is *this* well to freeze in the next 180 days?
- **Method:** Logistic Regression
- **Key Insights:**
  - Aggregated entity probabilities were more accurate than K-M
  - Significant additional effort

**3x improvement over random baseline (at 20% workload)**



# Success?





# Summary

# If the problem looks like this. . .

- **Who. . .?**
- **Which. . .?**
- **Where. . .?**
- **When. . .?**



# . . . then predictive analytics may help like this

- **Who. . .?**
  - Prioritization of people for expert review
- **Which. . .?**
  - Highlight products of interest
- **Where. . .?**
  - Narrow geographical focus
- **When. . .?**
  - Likelihood of event in a given window of time



# Reliability/Quality: Complementary Decisions

## Traditional Methods

- **Decisions/Actions that Affect Groups**
  - High-level planning and cost analysis
  - Resource forecasting
  - “Portfolio” analysis

## Predictive Analytics

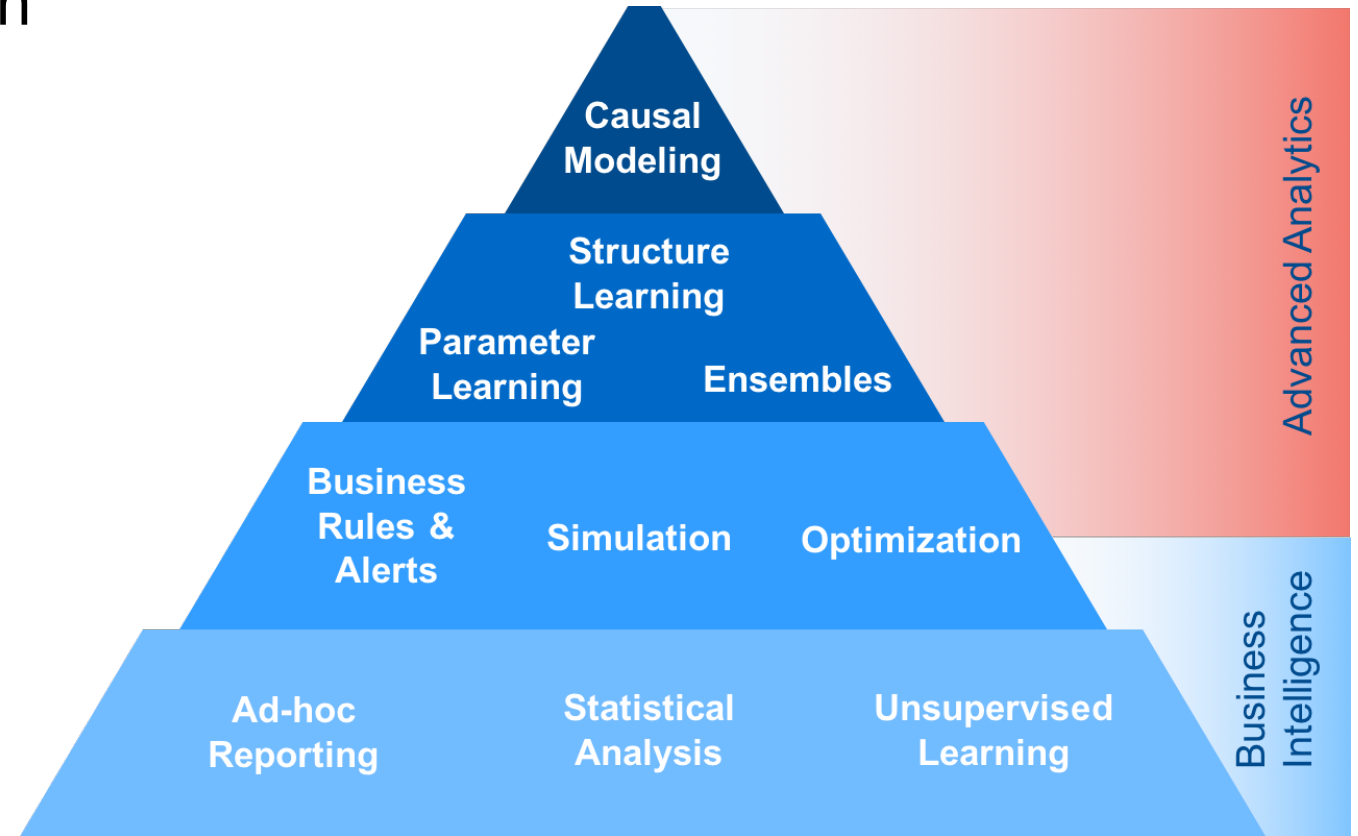
- **Decisions/Actions that Affect Entities**
  - Maintenance Recommendations
  - Prioritization of Investigations/Audits
  - Resource scheduling



# About Our Company

# About Elder Research

- Founded in 1995 by Dr. John Elder
- **Offices:**
  - Charlottesville (HQ)
  - Arlington
  - Baltimore
  - Raleigh
- **Areas of Expertise:**
  - Data Science
  - Text Mining
  - Data Infrastructure
  - Data Visualization



# Appendix

# What is LASSO?



- **Least Absolute Shrinkage and Selection Operator**
- Generalized Linear Model (Logistic Regression is related)
- **Key Features:**
  - Budget on the sum of coefficients
  - “Regularization” term
- **Result:** prevents overfit, and helps select inputs!



# About Me



Dr. William Goodrum is a Data Scientist with Elder Research; one of the oldest predictive analytics consultancies in North America. At Elder Research, Dr. Goodrum has led teams of Data Scientists and Software Engineers on a variety of different projects including analytics strategy development, predictive model validation, and predictive model building. These projects have been in industries as diverse as philanthropic development, maritime risk assessment, and connected device maintenance. He is also a frequent contributor to the company blog on analytics and analytics strategy.

Dr. Goodrum holds a B.S. in Mechanical Engineering from the University of Virginia, and a PhD in Engineering from Cambridge University.