Welcome to Advisen’s Predictive Modeling Insights Conference

Opening Remarks

David Bradford
Co-Founder & Chief Strategy Officer
Advisen

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PIVOTPOINT RISK ANALYTICS

PREMONITION™

Keynote Address

Richard Clarke
Head of Insurance Advanced Analytics
McKinsey & Company

The Analytics Journey

PREDICTIVE MODELING INSIGHTS CONFERENCE

JANUARY 14, 2016 | NEW YORK, NY

The Analytics Journey

Kimberly Holmes
Global Head of Strategic Analytics
XL Catlin
Moderator

The Analytics Journey

- **Kimberly Holmes**, Global Head of Strategic Analytics, XL Catlin (Moderator)
- **Riccardo Baron,** Big Data & Smart Analytics Lead, Americas, Swiss Re
- **Libbe Englander**, CEO & Founder, Pharm3r
- **Jonathan Laux,** Senior Consultant, Cyber Risk Analytics Leader, Aon Benfield
- **Jim Paugh,** SVP and Co-Founder, Care Bridge International, Inc.

The Analytics Journey





Morning Break

Coming up next: “Beyond the GLM – Using Advanced Analytics Methods for Insurance”

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PIVOTPOINT RISK ANALYTICS

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Advisen Transforming • Insurance™

Beyond the GLM - Using Advanced Analytics Methods for Insurance

Chris Cooksey
Chief Actuary
EagleEye Analytics

PREDICTIVE MODELING INSIGHTS CONFERENCE

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BEYOND THE GLM

Using Advanced Analytics Methods for Insurance

Christopher Cooksey, FCAS, MAAA
Chief Actuary
eagleeye ANALYTICS

AGENDA

1) Beyond the GLM?
2) Ensembles
3) Objections to ensembles
4) Understanding the Journey

BEYOND THE GLM?

Generalized Linear Modeling is “State of the Industry” among actuaries in P&C insurance.

WHY?

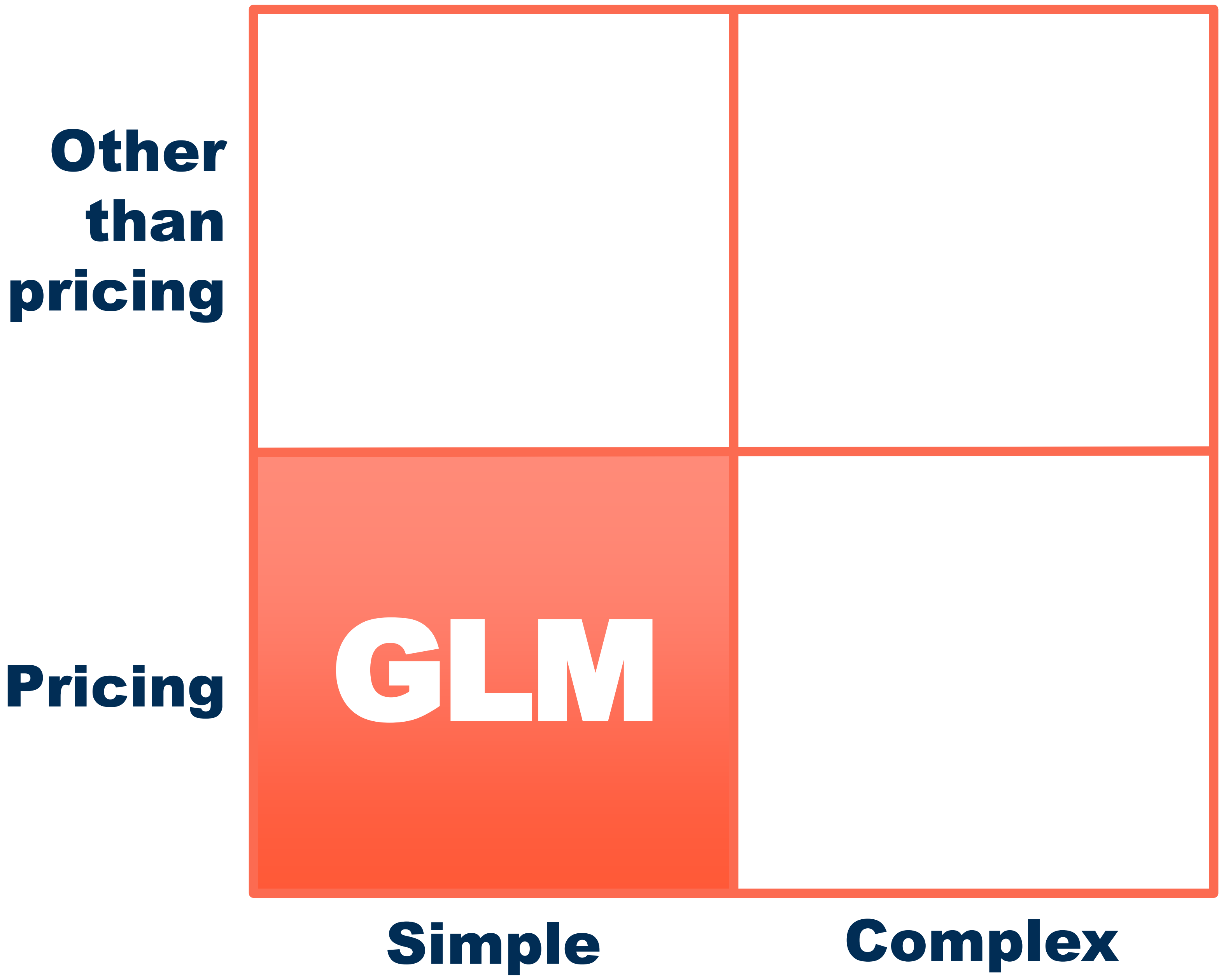
GLM is a flexible regression approach with error distributions appropriate to insurance.

And the output looks like a rating algorithm.

BEYOND THE GLM?

GLM models are not complex. The modeler retains control over what is in the model and the effect of each predictor can be evaluated separately.

Given the GLM's similarity to pricing algorithms, and the insurance industry's famously conservative nature, what is the potential to push into other quadrants?



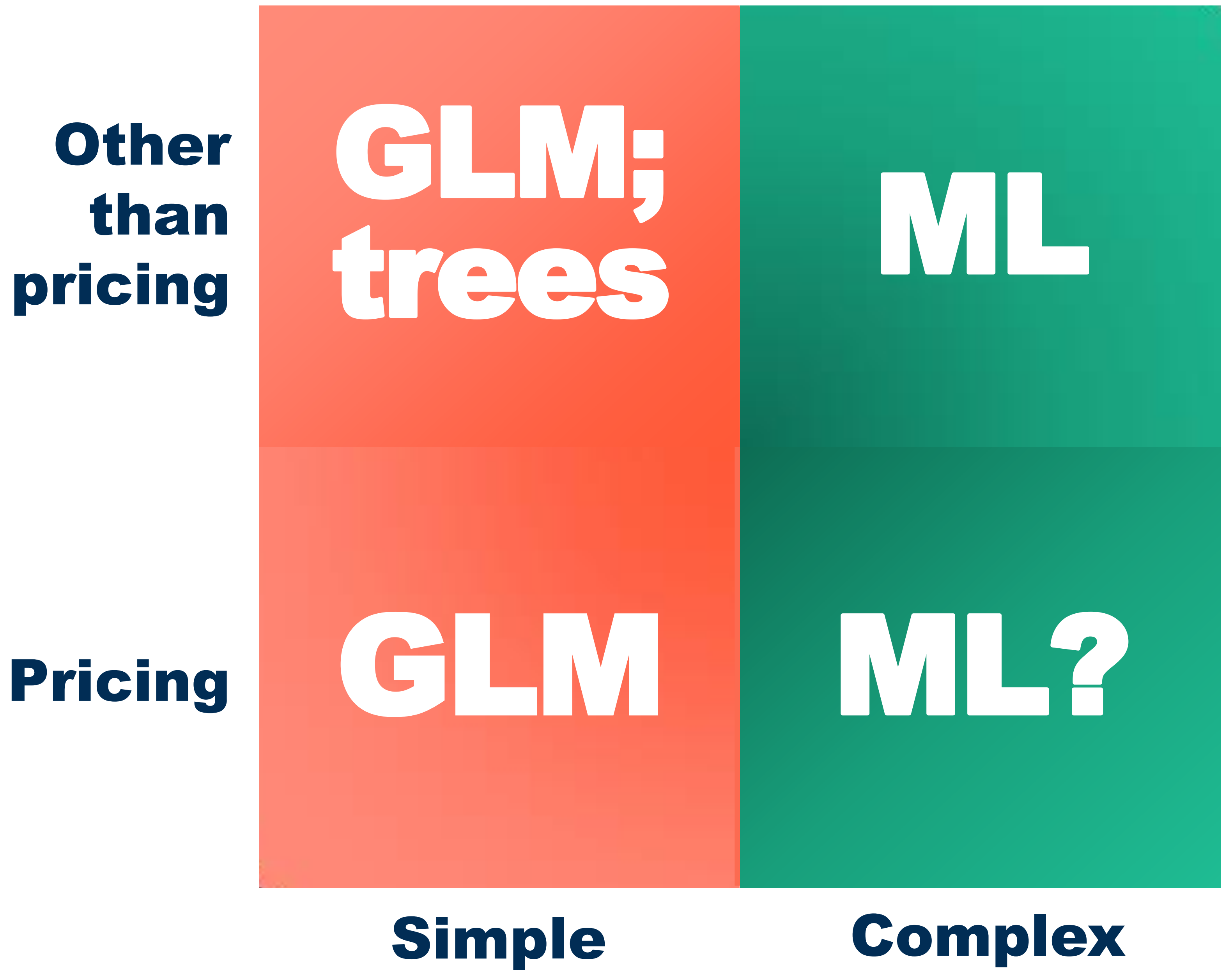
BEYOND THE GLM?

A number of companies are pushing GLMs into other areas. Trees are also readily understood, with applications beyond pricing.

But what about complex Machine Learning ("ML") models?

Can they be made accessible?

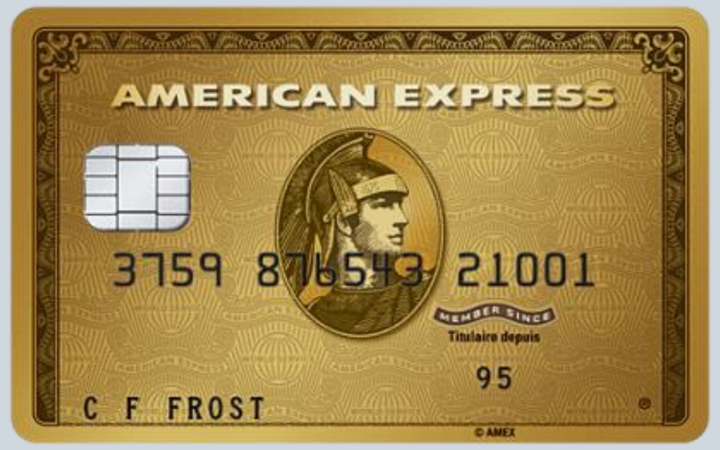
Can they be implemented?



Predictive Policing reduced burglaries 33% & violent crime 21%.

Predictive algorithm analyzes a quintillion variables to deliver consistent flavor in each batch, regardless of supply chain conditions.

MACHINE LEARNING BEYOND INSURANCE



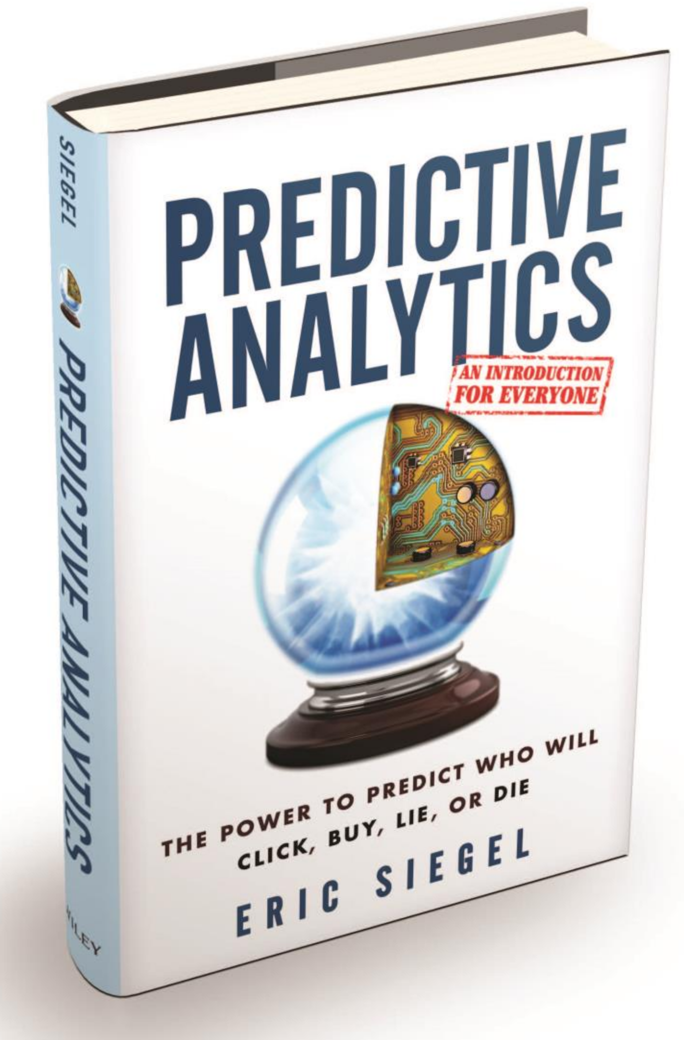
Predictive models identify at-risk accounts and help prevent churn.

Route optimization balances efficiency with service levels.

MACHINE LEARNING

- Neural Networks
- Decision Trees
- Support Vector Machines
- Genetic Algorithms
- Artificial Immune Systems
- Ensembles

ENSEMBLES



Ensemble modeling has taken the [Predictive Analytics] industry by storm.

It's often considered the most important predictive modeling advancement of this century's first decade.

Siegel, E. (2013). *Predictive Analytics.*

MULTIPLICITY OF MODELS

"…there is often a multitude of different descriptions [equations f(x)] in a class of functions giving about the same minimum error rate."

Breiman, L. (2001). Statistical Modeling: The Two Cultures. *Statistical Science*, Vol. 16, No. 3.

"Data will often point with almost equal emphasis on several possible models, and it is important that the statistician recognize and accept this."

McCullagh, P. and Nelder, J. (1989). *Generalized Linear Models*.

AN UNREALISTIC ILLUSTRATION

Ground Rules

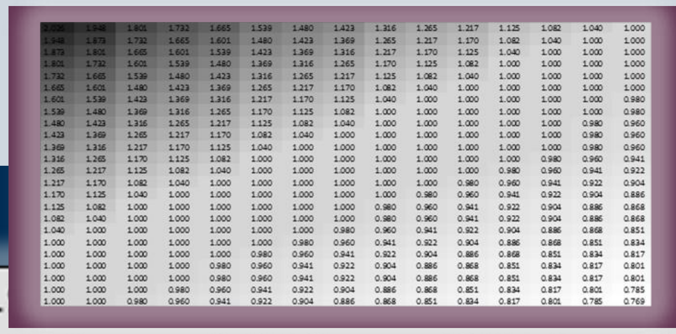
1. We get to know reality & compare our models directly.
2. Assume the numbers are frequency relativities.
3. Volume is limited; we can only divide the data into three equally-sized groups.
4. Model predictions are just the average for each defined group.

AN UNREALISTICILLUSTRATION

2.026	1.948	1.801	1.732	1.665	1.539	1.480	1.423	1.316	1.265	1.217	1.125	1.082	1.040	1.000
1.948	1.873	1.732	1.665	1.601	1.480	1.423	1.369	1.265	1.217	1.170	1.082	1.040	1.000	1.000
1.873	1.801	1.665	1.601	1.539	1.423	1.369	1.316	1.217	1.170	1.125	1.040	1.000	1.000	1.000
1.801	1.732	1.601	1.539	1.480	1.369	1.316	1.265	1.170	1.125	1.082	1.000	1.000	1.000	1.000
1.732	1.665	1.539	1.480	1.423	1.316	1.265	1.217	1.125	1.082	1.040	1.000	1.000	1.000	1.000
1.665	1.601	1.480	1.423	1.369	1.265	1.217	1.170	1.082	1.040	1.000	1.000	1.000	1.000	1.000
1.601	1.539	1.423	1.369	1.316	1.217	1.170	1.125	1.040	1.000	1.000	1.000	1.000	1.000	0.980
1.539	1.480	1.369	1.316	1.265	1.170	1.125	1.082	1.000	1.000	1.000	1.000	1.000	1.000	0.980
1.480	1.423	1.316	1.265	1.217	1.125	1.082	1.040	1.000	1.000	1.000	1.000	1.000	0.980	0.960
1.423	1.369	1.265	1.217	1.170	1.082	1.040	1.000	1.000	1.000	1.000	1.000	1.000	0.980	0.960
1.369	1.316	1.217	1.170	1.125	1.040	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.980	0.960
1.316	1.265	1.170	1.125	1.082	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.980	0.960	0.941
1.265	1.217	1.125	1.082	1.040	1.000	1.000	1.000	1.000	1.000	1.000	0.980	0.960	0.941	0.922
1.217	1.170	1.082	1.040	1.000	1.000	1.000	1.000	1.000	1.000	0.980	0.960	0.941	0.922	0.904
1.170	1.125	1.040	1.000	1.000	1.000	1.000	1.000	1.000	0.980	0.960	0.941	0.922	0.904	0.886
1.125	1.082	1.000	1.000	1.000	1.000	1.000	1.000	0.980	0.960	0.941	0.922	0.904	0.886	0.868
1.082	1.040	1.000	1.000	1.000	1.000	1.000	1.000	0.980	0.960	0.941	0.922	0.904	0.886	0.868
1.040	1.000	1.000	1.000	1.000	1.000	1.000	0.980	0.960	0.941	0.922	0.904	0.886	0.868	0.851
1.000	1.000	1.000	1.000	1.000	1.000	0.980	0.960	0.941	0.922	0.904	0.886	0.868	0.851	0.834
1.000	1.000	1.000	1.000	1.000	0.980	0.960	0.941	0.922	0.904	0.886	0.868	0.851	0.834	0.817
1.000	1.000	1.000	1.000	0.980	0.960	0.941	0.922	0.904	0.886	0.868	0.851	0.834	0.817	0.801
1.000	1.000	1.000	1.000	0.980	0.960	0.941	0.922	0.904	0.886	0.868	0.851	0.834	0.817	0.801
1.000	1.000	1.000	0.980	0.960	0.941	0.922	0.904	0.886	0.868	0.851	0.834	0.817	0.801	0.785
1.000	1.000	0.980	0.960	0.941	0.922	0.904	0.886	0.868	0.851	0.834	0.817	0.801	0.785	0.769

Reality

AN UNREALISTIC ILLUSTRATION



Reality

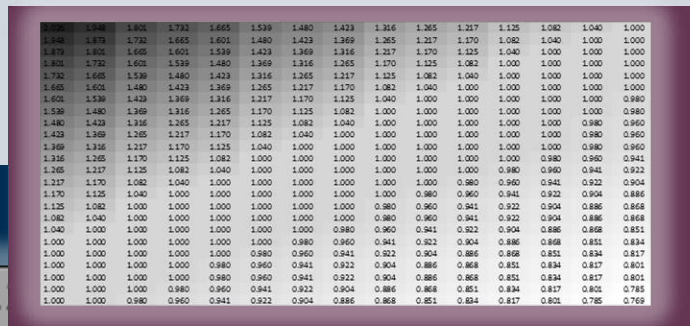
MODEL 1

Group relatively homogeneous business together.

Sum of the squared error = 13.48

1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.	[illegible]	[illegible]	[illegible]
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944
1.260	1.260	1.260	1.260	1.260	1.059	1.059	1.059	1.059	1.059	0.944	0.944	0.944	0.944	0.944

AN UNREALISTIC ILLUSTRATION



MODEL 2

A different way of splitting the data.

Sum of the squared error = 11.63

1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.			
1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287
1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287
1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287
1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287
1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287
1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287
1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287	1.287
1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048
1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048
1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048
1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048
1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048
1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048
1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048
1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048	1.048
0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929
0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929
0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929
0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929
0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929
0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929
0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929
0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929

AN UNREALISTIC ILLUSTRATION

ENSEMBLE Models 1 & 2

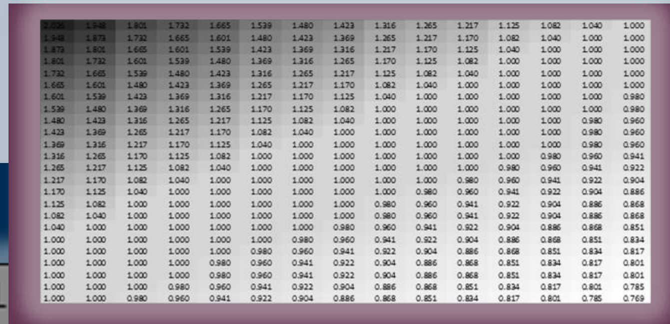
Combining information from models 1 & 2. NOT dividing the data 9 ways.

Sum of the squared error = 9.02

Reality

1.274	1.274	1.274	1.274	1.274	1.173	1.173	1.173	1.173	1.173	1.116	[illegible]	[illegible]	[illegible]	[illegible]
1.274	1.274	1.274	1.274	1.274	1.173	1.173	1.173	1.173	1.173	1.116	1.116	1.116	1.116	1.116
1.274	1.274	1.274	1.274	1.274	1.173	1.173	1.173	1.173	1.173	1.116	1.116	1.116	1.116	1.116
1.274	1.274	1.274	1.274	1.274	1.173	1.173	1.173	1.173	1.173	1.116	1.116	1.116	1.116	1.116
1.274	1.274	1.274	1.274	1.274	1.173	1.173	1.173	1.173	1.173	1.116	1.116	1.116	1.116	1.116
1.274	1.274	1.274	1.274	1.274	1.173	1.173	1.173	1.173	1.173	1.116	1.116	1.116	1.116	1.116
1.274	1.274	1.274	1.274	1.274	1.173	1.173	1.173	1.173	1.173	1.116	1.116	1.116	1.116	1.116
1.274	1.274	1.274	1.274	1.274	1.173	1.173	1.173	1.173	1.173	1.116	1.116	1.116	1.116	1.116
1.154	1.154	1.154	1.154	1.154	1.053	1.053	1.053	1.053	1.053	0.996	0.996	0.996	0.996	0.996
1.154	1.154	1.154	1.154	1.154	1.053	1.053	1.053	1.053	1.053	0.996	0.996	0.996	0.996	0.996
1.154	1.154	1.154	1.154	1.154	1.053	1.053	1.053	1.053	1.053	0.996	0.996	0.996	0.996	0.996
1.154	1.154	1.154	1.154	1.154	1.053	1.053	1.053	1.053	1.053	0.996	0.996	0.996	0.996	0.996
1.154	1.154	1.154	1.154	1.154	1.053	1.053	1.053	1.053	1.053	0.996	0.996	0.996	0.996	0.996
1.154	1.154	1.154	1.154	1.154	1.053	1.053	1.053	1.053	1.053	0.996	0.996	0.996	0.996	0.996
1.154	1.154	1.154	1.154	1.154	1.053	1.053	1.053	1.053	1.053	0.996	0.996	0.996	0.996	0.996
1.154	1.154	1.154	1.154	1.154	1.053	1.053	1.053	1.053	1.053	0.996	0.996	0.996	0.996	0.996
1.094	1.094	1.094	1.094	1.094	0.994	0.994	0.994	0.994	0.994	0.937	0.937	0.937	0.937	0.937
1.094	1.094	1.094	1.094	1.094	0.994	0.994	0.994	0.994	0.994	0.937	0.937	0.937	0.937	0.937
1.094	1.094	1.094	1.094	1.094	0.994	0.994	0.994	0.994	0.994	0.937	0.937	0.937	0.937	0.937
1.094	1.094	1.094	1.094	1.094	0.994	0.994	0.994	0.994	0.994	0.937	0.937	0.937	0.937	0.937
1.094	1.094	1.094	1.094	1.094	0.994	0.994	0.994	0.994	0.994	0.937	0.937	0.937	0.937	0.937
1.094	1.094	1.094	1.094	1.094	0.994	0.994	0.994	0.994	0.994	0.937	0.937	0.937	0.937	0.937
1.094	1.094	1.094	1.094	1.094	0.994	0.994	0.994	0.994	0.994	0.937	0.937	0.937	0.937	0.937
1.094	1.094	1.094	1.094	1.094	0.994	0.994	0.994	0.994	0.994	0.937	0.937	0.937	0.937	0.937

AN UNREALISTIC ILLUSTRATION



Reality

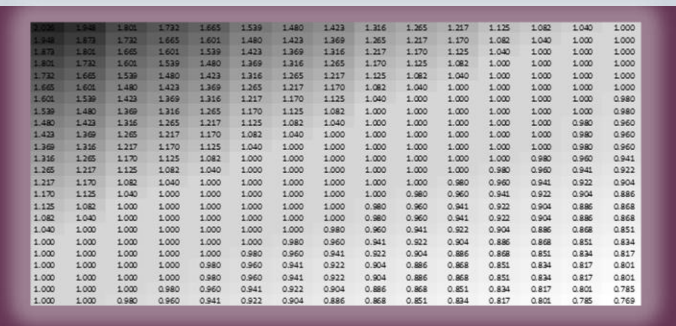
ENSEMBLE Models 1 - 5

Combining information from models 1 -5.

Sum of the squared error = 8.47

1.278	1.278	1.278	1.278	1.259	1.218	1.218	1.164	1.164	1.164	1.141	[illegible]	[illegible]	[illegible]	[illegible]
1.278	1.278	1.278	1.278	1.259	1.218	1.218	1.164	1.164	1.164	1.141	1.141	1.063	1.063	1.063
1.278	1.278	1.278	1.278	1.259	1.218	1.218	1.164	1.164	1.164	1.141	1.141	1.063	1.063	1.063
1.278	1.278	1.278	1.278	1.259	1.218	1.218	1.164	1.164	1.164	1.141	1.141	1.063	1.063	1.063
1.278	1.278	1.278	1.278	1.259	1.218	1.218	1.164	1.164	1.164	1.141	1.141	1.063	1.063	1.063
1.278	1.278	1.278	1.278	1.259	1.218	1.218	1.164	1.164	1.164	1.141	1.141	1.063	1.063	1.063
1.278	1.278	1.278	1.278	1.259	1.218	1.218	1.164	1.164	1.164	1.141	1.141	1.063	1.063	1.063
1.278	1.278	1.278	1.278	1.259	1.218	1.218	1.164	1.164	1.164	1.141	1.141	1.063	1.063	1.063
1.230	1.230	1.230	1.230	1.211	1.170	1.170	1.116	1.116	1.116	1.093	1.093	1.015	1.015	1.015
1.230	1.230	1.230	1.230	1.211	1.170	1.170	1.116	1.116	1.116	1.093	1.093	1.015	1.015	1.015
1.172	1.172	1.172	1.172	1.152	1.058	1.058	1.058	1.058	1.058	1.015	1.015	1.015	1.015	0.975
1.172	1.172	1.172	1.172	1.112	1.018	1.018	1.018	1.018	1.018	0.975	0.975	0.975	0.975	0.975
1.172	1.172	1.172	1.172	1.112	1.018	1.018	1.018	1.018	1.018	0.975	0.975	0.975	0.975	0.975
1.172	1.172	1.172	1.172	1.112	1.018	1.018	1.018	1.018	1.018	0.975	0.975	0.975	0.975	0.975
1.172	1.172	1.172	1.172	1.172	1.054	0.994	0.994	0.974	0.974	0.952	0.952	0.952	0.952	0.952
1.172	1.172	1.172	1.172	1.172	1.054	0.994	0.994	0.974	0.974	0.952	0.952	0.952	0.952	0.952
1.148	1.148	1.148	1.148	1.070	1.030	0.970	0.970	0.951	0.951	0.928	0.928	0.928	0.928	0.928
1.148	1.148	1.148	1.148	1.070	1.030	0.970	0.970	0.951	0.951	0.928	0.928	0.928	0.928	0.928
1.148	1.148	1.148	1.148	1.070	1.030	0.970	0.970	0.951	0.951	0.928	0.928	0.928	0.928	0.928
1.148	1.148	1.148	1.148	1.070	1.030	0.970	0.970	0.951	0.951	0.928	0.928	0.928	0.928	0.928
1.148	1.148	1.148	1.148	1.070	1.030	1.030	0.970	0.951	0.951	0.928	0.928	0.928	0.928	0.928
1.070	1.070	1.070	1.070	1.070	1.030	1.030	0.970	0.951	0.951	0.928	0.928	0.928	0.928	0.928
1.070	1.070	1.070	1.070	1.070	1.030	1.030	0.970	0.951	0.951	0.928	0.928	0.928	0.928	0.928
1.070	1.070	1.070	1.070	1.070	1.030	1.030	0.970	0.951	0.951	0.928	0.928	0.928	0.928	0.928

AN UNREALISTIC ILLUSTRATION



ENSEMBLE
Models 1 - 9

Combining information from models 1 -9.

Sum of the squared error = 7.35

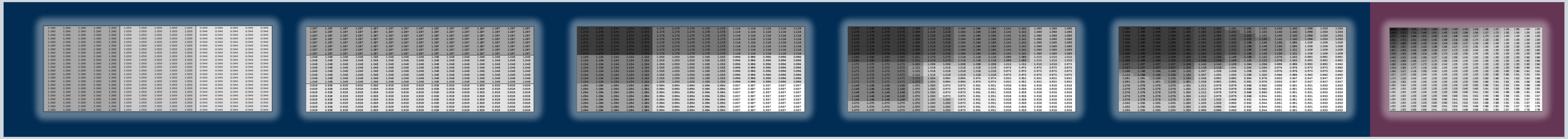
1.296	1.296	1.296	1.296	1.285	1.262	1.262	1.191	1.191	1.152	1.140	[illegible]	[illegible]	[illegible]	[illegible]
1.296	1.296	1.296	1.296	1.285	1.262	1.262	1.232	1.191	1.152	1.140	1.140	1.096	1.053	1.053
1.296	1.296	1.296	1.296	1.285	1.262	1.262	1.232	1.232	1.152	1.140	1.140	1.096	1.053	1.053
1.296	1.296	1.296	1.296	1.285	1.262	1.262	1.232	1.232	1.193	1.140	1.140	1.096	1.053	1.053
1.296	1.296	1.296	1.296	1.285	1.262	1.262	1.232	1.196	1.148	1.136	1.095	1.009	1.009	1.009
1.296	1.296	1.296	1.296	1.285	1.262	1.262	1.232	1.196	1.148	1.136	1.095	1.009	1.009	1.009
1.296	1.296	1.296	1.296	1.285	1.262	1.262	1.232	1.196	1.148	1.136	1.101	1.009	1.009	1.009
1.296	1.296	1.296	1.296	1.285	1.262	1.262	1.232	1.196	1.148	1.136	1.101	1.009	1.009	1.009
1.269	1.269	1.269	1.269	1.258	1.236	1.236	1.169	1.169	1.122	1.076	1.042	0.992	0.992	0.982
1.269	1.269	1.269	1.269	1.258	1.236	1.236	1.169	1.130	1.122	1.076	1.042	0.992	0.992	0.982
1.237	1.237	1.237	1.237	1.226	1.140	1.140	1.103	1.064	1.056	0.998	0.998	0.992	0.992	0.960
1.237	1.237	1.237	1.237	1.203	1.118	1.118	1.042	1.042	1.034	0.976	0.976	0.970	0.970	0.960
1.166	1.166	1.166	1.166	1.133	1.047	1.008	1.008	1.008	1.000	0.976	0.976	0.970	0.970	0.960
1.124	1.166	1.166	1.166	1.133	1.047	1.005	1.005	1.008	1.000	0.966	0.966	0.960	0.960	0.960
1.091	1.091	1.133	1.133	1.133	1.026	0.992	0.992	0.984	0.976	0.953	0.947	0.947	0.947	0.947
1.091	1.091	1.091	1.133	1.091	1.026	0.992	0.992	0.981	0.976	0.953	0.947	0.947	0.947	0.947
1.078	1.078	1.078	1.078	1.035	1.012	0.979	0.979	0.968	0.960	0.938	0.931	0.931	0.933	0.933
1.078	1.078	1.078	1.078	1.035	1.012	0.979	0.979	0.968	0.960	0.931	0.931	0.931	0.933	0.933
1.078	1.078	1.078	1.078	1.035	1.012	0.979	0.979	0.968	0.960	0.931	0.931	0.931	0.933	0.933
1.078	1.078	1.078	1.078	1.035	1.012	0.979	0.979	0.968	0.954	0.931	0.931	0.931	0.933	0.933
1.078	1.078	1.078	1.078	1.035	1.003	1.003	0.969	0.952	0.944	0.931	0.931	0.931	0.933	0.933
1.035	1.035	1.035	1.035	1.035	1.003	1.003	0.963	0.952	0.944	0.931	0.931	0.931	0.933	0.933
1.035	1.035	1.035	1.035	1.035	1.003	0.996	0.963	0.952	0.944	0.931	0.931	0.931	0.933	0.933
1.035	1.035	1.035	1.035	1.035	0.996	0.996	0.963	0.952	0.944	0.931	0.931	0.931	0.933	0.933

A REALISTIC EFFECT

"Ensembles remain robust even as they become increasingly complex.

They seem to be immune to this limitation, as if soaked in a magic potion against overlearning."

Siegel, E. (2013). *Predictive Analytics.*



OBJECTIONS TO ENSEMBLES

Resistance usually centers around complexity.

Simpler is preferred in the absence of certainty, when multiple models perform equally well.

But if an ensemble performs better, then it is simply the better model.

OBJECTIONS TO ENSEMBLES

"Framing the question as the choice between accuracy and interpretability is an incorrect interpretation of what the goal of a statistical analysis is.

The point of a model is to get useful information about the relation between the response and predictor variables. Interpretability is a way of getting information."

Breiman, L. (2001). Statistical Modeling: The Two Cultures. *Statistical Science*, Vol. 16, No. 3.

OBJECTIONS TO ENSEMBLES

"All machine learning techniques are equally difficult to explain.
(Consider neural nets vs. trees)

Departments of insurance won't accept them.

Because it can't be explained in simple terms, there is no opportunity for insight."

Anything that is theoretically possible will be achieved in practice, no matter what the technical difficulties are, if it is desired greatly enough.

~ Arthur C Clarke ~

OBJECTIONS TO ENSEMBLES

Don’t think a complex model will be accepted for pricing in your underwriting-driven culture?

Context & Needs for Predictive Analytics in Insurance	
Underwriting	Claims management
Marketing	Internal monitoring

The JOURNEY

to Becoming a Data & Analytics-Driven Organization

DATA-DRIVEN ORGANIZATION

Business Sponsor: Real-time dashboard reporting

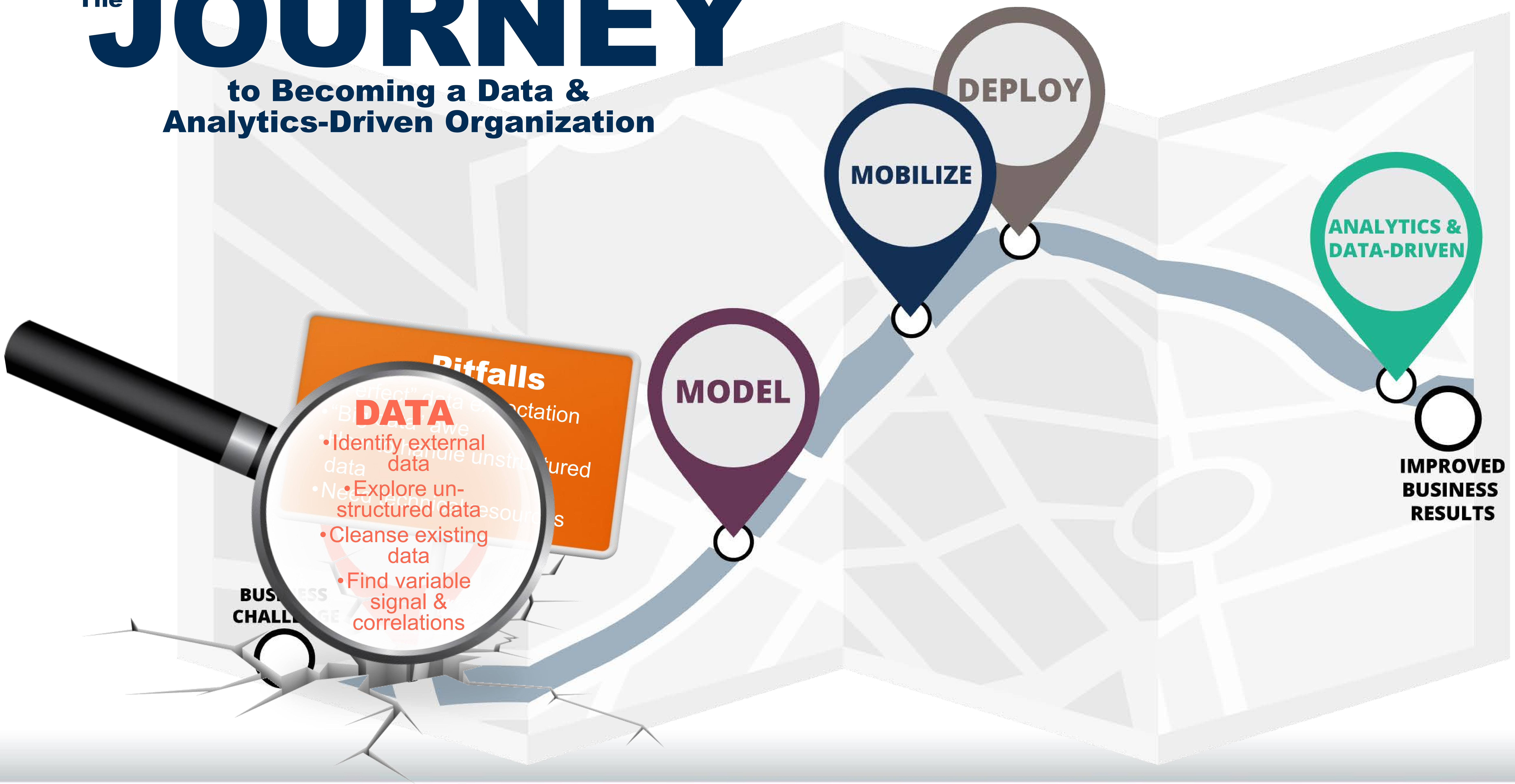
Modeling Team: Real-time analysis-level information

Front line, Claims/Underwriting: Real-time evaluations of quotes, policies, claims with reason codes

Technology Staff: Analytic model control panel, automated error checking, release manager, infrastructure

The JOURNEY

to Becoming a Data & Analytics-Driven Organization



The JOURNEY
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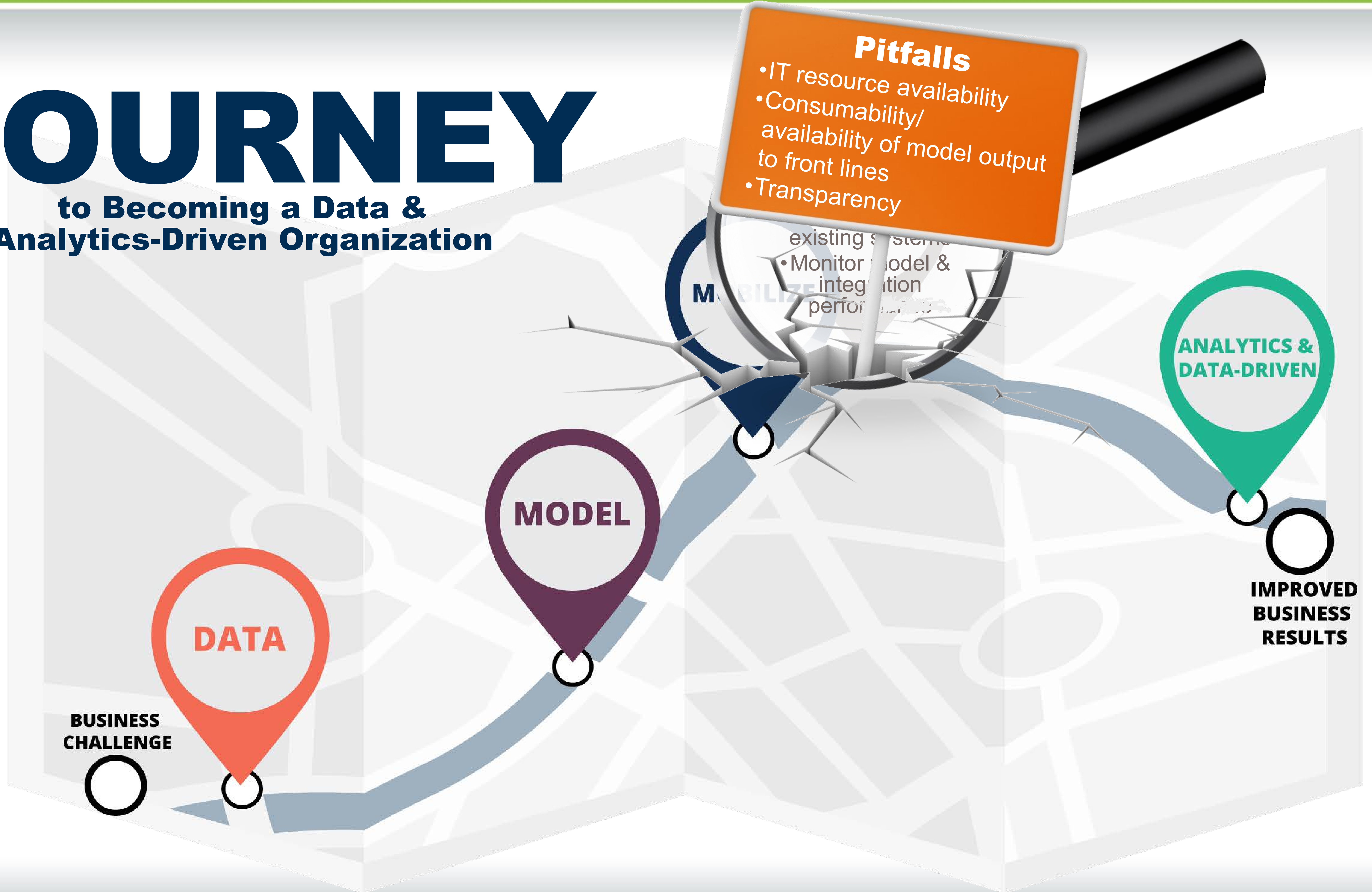

DATA-DRIVEN CULTURE

If the leadership team insists on "going with its gut," analytics can only validate what the team has already decided.

Genuine data cultures will shift course based on what analytics teams discover.

Baseline Magazine

TAKEAWAYS

1) Complex models can be used within insurance companies. The complexity of the models can be dealt with if we choose to deal with it.
2) Ensembles extract more information from data without paying the expected pricing in over fitting.
3) Results from ensemble approaches are transforming other industries and are worth the effort for insurance predictive modelers to explore.
4) The difficulties around model complexity include more than just understanding. The entire analytical journey should be considered so that using complex models leads to actual benefits.

eagleeye ANALYTICS | Talon®

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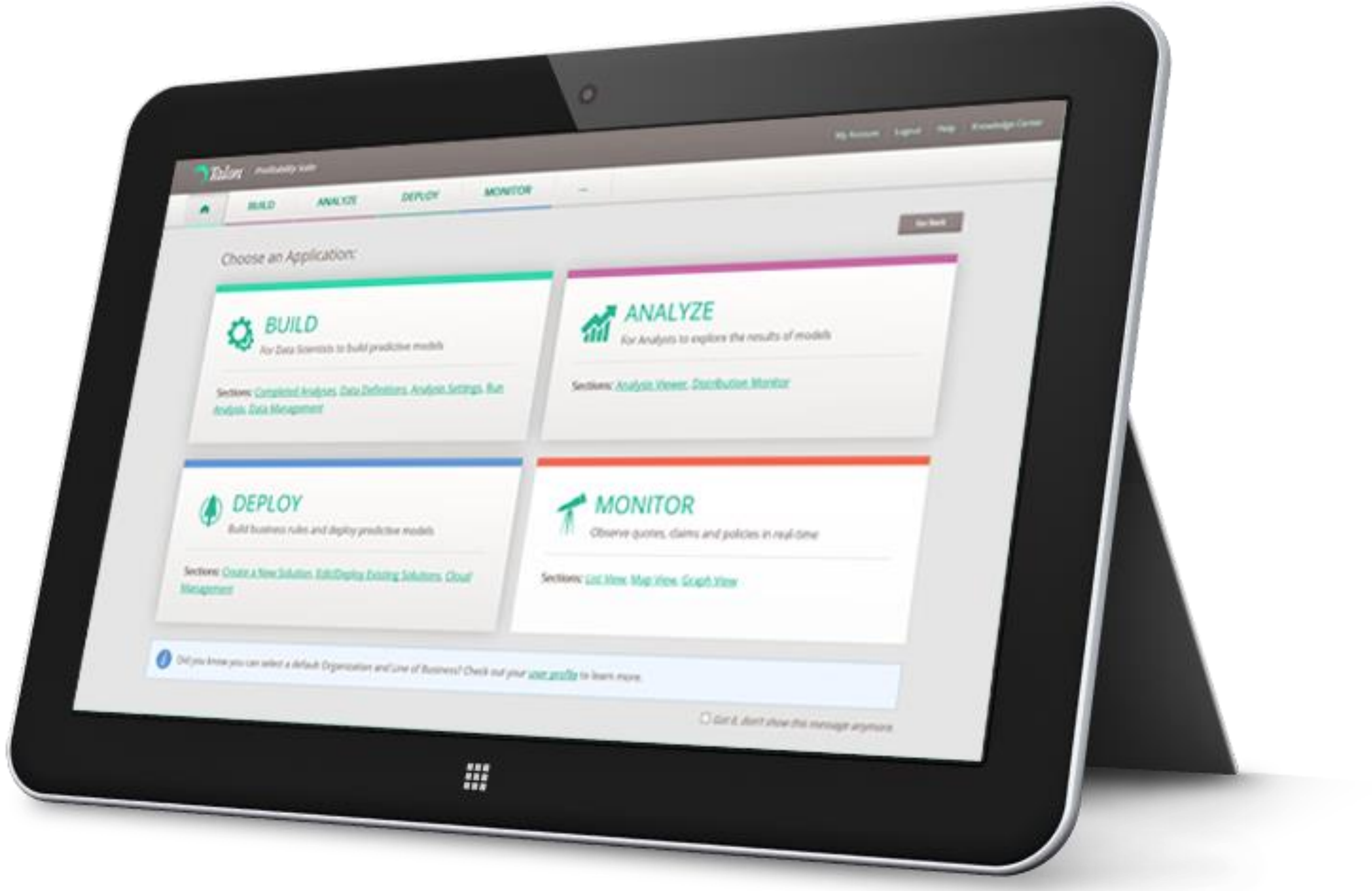

Conference Luncheon

Coming up next: “Focus on Casualty: Examples of Predictive Models in WC Claims Handling”

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PIVOTPOINT RISK ANALYTICS

PREMONITION™

Focus on Casualty: Examples of Predictive Models in WC Claims Handling

Keith Higdon
VP, Claims Data Analytics, Global Claims
ACE Group

Defining predictive modeling

- Predictive modeling is a group of statistical techniques designed to identify patterns in data that the human eye cannot discern through standard reporting and data visualization.
  - Predictive modeling finds the opportunity, it is NOT the action
  - Predictive modeling supports the product/offering, it is NOT the product/offering
  - Predictive modeling provides insight into what will likely occur, it is NOT a reflection of what has occurred
- Predictive modeling is a tool. When used correctly, it fills the gaps of human experience. **Predictive modeling enhances experience, it does not replace experience.**

Utilizing predictive modeling

- Additional information – large scale application of supplementary data that supports the decision process
- Targeted intervention – identification of a small subset of claims focusing on added resources to drive specified outcomes
- Best practice alignment/foundation – large scale change in process effecting all or a majority of claims

Utilization Example

FNOL
(added information)

nurse case mgt.
(targeted intervention)

12 month unrecognized severity
(targeted intervention)

Occurrence

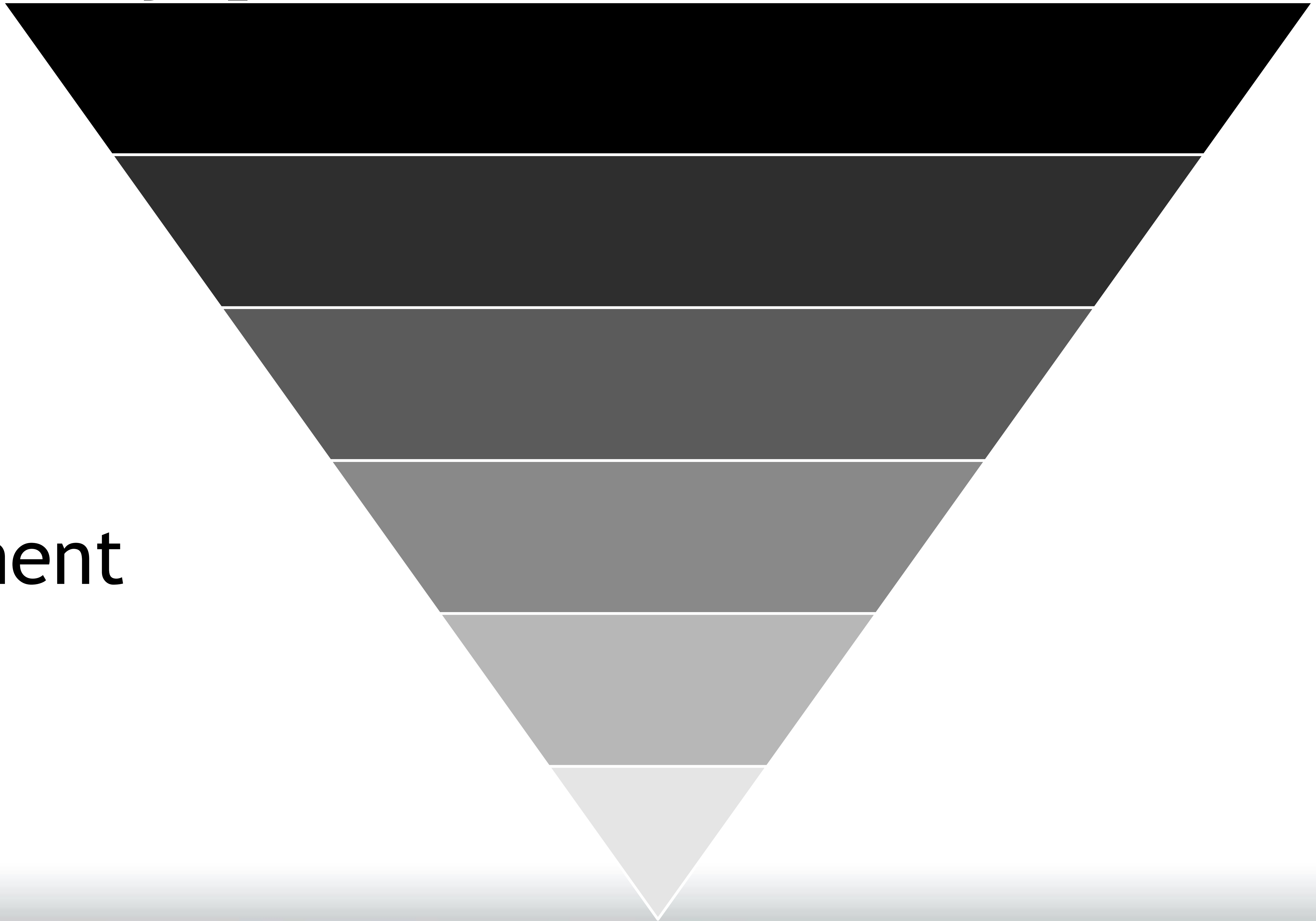
Management

Resolution

supervisor involvement (best practice)

Common model types in claims

- Fraud or SIU referral
- Severity
- Subrogation
- Litigation/Attorney involvement
- Surgery
- Reserve guidance



Implementing predictive models

Develop → Optimize → Execute → Measure → Develop

- **Develop**: Build the model
- **Optimize**: Systems, people, and process
- **Execute**: Consistent action
- **Measure**: Monitor consistency and assess impact

Severity segmentation

50% of claims

Level 1: Lowest Severity

4.4% of dollars

25% of claims

Level 2: Mid-tier Severity

13.2% of dollars

25% of claims

Level 3: Highest Severity

82.4% of dollars

Program example

- Program/Line of coverage: Workers' Compensation
- Model type: Likely severity measured at 12 months (individual claim anniversary from entry into the claim system to 12 months)
- Intervention: ACE claim review and oversight at 10% chance of claim exceeding retention level
- Monitoring compliance: Over 85% across offices
- Time frame: 20 months of program run time and 18 month of additional development for a range of 30-50 months of total claim development
- Number of claims = approximately 700 in the intervention period
- Outcomes: $10.2 million dollars saved; ROI 20:1

Technical Future

- BIG Data eruption continues requiring ongoing focus on storage and access facilities – cloud approaches; traditional data warehousing; and extraction, transformation, and loading (ETL) tools
- Analytic tools will follow the path of BI and visualization products toward increased access by business analysts – oversight and tool management approach for base levels of modeling

Claims future

- Models will become embedded into the claims process and drive best practices over targeted interventions – acceptance of the partnership between the model and adjuster experience
- Redefinition of the concept of "claim type" and further refinement of adjuster roles and responsibilities

Thank you

Customer Information and Privacy Laws

Customer Information and Privacy Laws

Laurie Kamaiko
Partner
Sedgwick LLP
Moderator

Customer Information and Privacy Laws

- **Laurie Kamaiko**, Partner, Sedgwick LLP (Moderator)
- **Randi Singer,** Partner, Weil, Gotshal & Manges LLP
- **Grant Petersen**, Shareholder, Olgetree Deakins

Customer Information and Privacy Laws



CONSUMER INFORMATION & PRIVACY LAWS
General Theme: Consumer Protection

Privacy

Security

Fairness In Use

Disclosure of Practices

THE LEGAL LANDSCAPE
Regulations, Agency Guidelines Governing Data Security

The U. S. does not (yet) have a comprehensive federal privacy and data security statute.

Instead, there are sector-specific laws, regulations and agency guidelines governing privacy and data security, including:

- **Medical**
  - Healthcare Insurance Portability & Accountability Act (HIPAA)
  - HITECH/GINA
  - FDA Guidelines
- **Telecommunications**
  - Federal Communications Commission
  - Telemarketing & Consumer Fraud & Abuse Prevention Act
  - Telemarketing Sales Rule / TCPA / CAN-SPAM / Video Privacy Protection Act, etc.

THE LEGAL LANDSCAPE
Regulations, Agency Guidelines Governing Data Security *(con't)*:

- **Financial**
  - Fair Credit Reporting Act (FCRA/FACTA)
  - Equal Credit Opportunity Act (ECOA)
  - Gramm-Leach Bliley (GLB)
  - Dodd-Frank
- **Overall Regulation of Businesses**
  - Federal Trade Commission Act Sec. 5
  - SEC (public companies)
- **Others**
  - Electronic Communications Privacy Act
  - Presidential Executive Orders

THE LEGAL LANDSCAPE
Regulations, Agency Guidelines Governing Data Security *(con't)*:

❑ **States**

There are also state laws, regulations and agency guidelines governing privacy and data security:

- 47 states (plus DC, PR, Guam and VI) with notification laws for breach of statutorily defined Personal Information, many with data security requirements
- Definitions of Personal Information vary
- States also starting to regulate collection and disclosure practices

THE LEGAL LANDSCAPE
Regulations, Agency Guidelines Governing Data Security *(con't)*:

- **Equal Opportunity & Employment**
  - Title VII of the Civil Rights Act
  - Equal Credit Opportunity Act (ECOA)
  - ADA and other anti-discrimination laws
  - Dodd-Frank
  - Employment laws governing hiring, monitoring, investigation of employees
- **Laws Pertinent to Minors**
  - Family Educational Rights & Privacy Act (FERPA)
  - Children's Online Privacy Protection Action (COPPA) – governing online companies' collection of information regarding/targeting minors

THE LEGAL LANDSCAPE
Regulations, Agency Guidelines Governing Data Security *(con't)*:

- **Additional Governance of Insurance:**
  - NAIC – Cyber security task force
    - consumer cybersecurity bill of rights
    - cybersecurity framework for regulators
- Department of Treasury/FIO
- State regulators – scrutiny of insurer practices

Who Regulates and Enforces In the U.S.?

- ❑ Federal Trade Commission (FTC)
- ❑ Consumer Financial Protection Bureau
- ❑ Federal Communications Commission
- ❑ Department of Commerce
- ❑ Department of Treasury
- ❑ Department of Health & Human Services
- ❑ Federal Reserve/Consumer Financial Protection Board (CFPB)
- ❑ Comptroller of the Currency
- ❑ Department of Labor
- ❑ Equal Employment Opportunity Commission (EEOC)
- ❑ Securities and Exchange Commission (SEC)
- ❑ National Labor Relations Board
- ❑ Department of Justice
- ❑ State Attorneys General
- ❑ Self-Regulatory Programs
- ❑ Plaintiff Class Action Attorneys

- **FTC Highly Active In Regulation of Privacy & Usage of Consumer Data**
  - Issues numerous Guidances and Reports on consumer data collection, usage, security and in particular use of data analytics (including last week)
  - Active in Enforcement
- **Federal Trade Commission Act Section 5**
  - Section 5 broadly prohibits "unfair or deceptive ads or practices in or affecting commerce:
    - Deception: a material misrepresentation or omission that is likely to mislead consumers acting reasonably under the circumstances
    - Unfairness: practices that cause or are likely to cause substantial injury to consumers that are not outweighed by countervailing benefits to consumer or competition and are not reasonably avoidable by consumers
  - Flexible law that can be applied to many difference situations, entities and technologies

- **The Increasing Focus on Disparate Treatment/Impact on a Protected Class**
  - FTC Report, January 2016:
    - Big Data: A Tool for Inclusion or Exclusion?
    - Understanding the Issue
  - Concern about Digital Redlining

- **But Is All Disparate Impact Unlawful?**
  - Does it serve a legitimate business need?
  - Can the need be reasonably achieved by another means with a smaller disparate impact?

Impact of Rise of Data Security Laws, Regulations, Contractual Requirements

- Usefulness of information vs. risks of long-term retention
- Security in transfer of information
- Anonymization – is it really?
- Erasure – is it really?
- Security of practices in event of a breach or regulatory review
- Due Diligence of your vendors' practices
- Due diligence of those providing information to you
- Contractual assumption of liabilities/indemnity

- **Litigation**
  - **Theories/Examples:**
    - Data Security failure
    - Discrimination
    - Anonymization failure
    - Collection without due consent
    - Misrepresentation
    - Violations of privacy laws
    - Violation of data security laws
    - Violation of consumer protection laws, unfair competition, deceptive trade practices
    - Implied warranty of merchantability
    - Bailment
    - Unjust enrichment
- **Challenge of Establishing Injury/Damages**

GOOD THINGS GONE BAD
Examples Where The Legal Framework Can Come Into Play

- Determining markets/geographic areas in which to promote products, deals
- Factors used in pricing for different groups of consumer
- Determining where to deploy services
- Employment recruitment, screening, hiring, retention, promotion, termination

HYPO

- Company uses an application that connects to wearable devices that record, collect and analyze data of users' heart rate, body temperature, activity level (steps, etc.), geolocation, and skin surface detectable hormonal responses.
- What are the potential privacy concerns?
- Do the concerns change if application records the user's:
  - Driving patterns
  - On line purchases
  - Banking information or insurance purchases
  - Music preferences
  - Home security system
  - Television viewing habits
  - Sleeping patterns
  - Weight loss/gain
  - Other personal habits/preferences

- **What if:**
  - Offers made to some consumers but not others based on information provided
  - Discounts offered to some but not others
  - Representations made about how information collected will be used differs from how actually used
- What regulatory bodies would be involved
- What statutory schemes apply
- What remedies are available to adversely affected consumers

Framework for Best Practices

- Privacy by Design
- Simplified Choice for Business and Consumer
- Greater Transparency
- Awareness/mitigation of potential for discriminatory treatment/impact
    - By business itself
    - By those providing data to a business
    - By those to whom the business provides data

Fun and Games with Massively Parallel Processing

Fun and Games with Massively Parallel Processing

Jim Blinn
EVP & Global Product Manager
Advisen
Moderator

Fun and Games with Massively Parallel Processing

- **Jim Blinn**, EVP & Global Product Manager, Advisen (Moderator)
- **Drew Farris**, Lead Associate, Booz Allen Hamilton
- **Mary Kotch**, EVP, Group Chief Information Officer, Validus Holdings
- **Marcelo Rocha**, Vice President Technical Services, 5Fathom Ltd.

Fun and Games with Massively Parallel Processing

Data Store Classification

5 FATHOM

	Relational/SQL	NoSQL
Analytical	Oracle, Actian, Microsoft SQL Server 2014, Teradata, Netezza an IBM Company	hadoop, Hive, Spark
Operational	Oracle, PostgreSQL, Microsoft SQL Server 2014, MySQL	mongoDB, Cassandra, Couchbase, Apache HBase

Data Store Popularity

db-engines.com

Select a ranking

- Complete ranking
- Relational DBMS
- Key-value stores
- Document stores
- Graph DBMS
- RDF stores
- Search engines
- Object oriented DBMS
- Time Series DBMS
- Multivalue DBMS
- Native XML DBMS
- Wide column stores
- Content stores
- Event Stores
- Navigational DBMS

Special reports

- Ranking by database model
- Open source vs. commercial

Featured Products

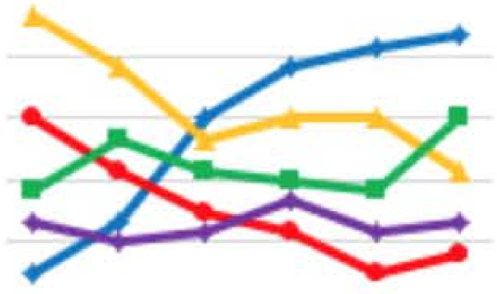
Ranking > Complete Ranking

RSS Feed

DB-Engines Ranking

The DB-Engines Ranking ranks database management systems according to their popularity. The ranking is updated monthly.

Read more about the method of calculating the scores.



trend chart

282 systems in ranking, September 2015

Rank			DBMS	Database Model	Score		
Sep 2015	Aug 2015	Sep 2014			Sep 2015	Aug 2015	Sep 2014
1.	1.	1.	Oracle	Relational DBMS	1463.37	+10.35	-3.53
2.	2.	2.	MySQL	Relational DBMS	1277.75	-14.28	-19.39
3.	3.	3.	Microsoft SQL Server	Relational DBMS	1097.83	-10.83	-111.04
4.	4.	↑ 5.	MongoDB	Document store	300.57	+5.91	+59.58
5.	5.	↓ 4.	PostgreSQL	Relational DBMS	286.18	+4.31	+30.38
6.	6.	6.	DB2	Relational DBMS	209.14	+7.91	+12.11
7.	7.	7.	Microsoft Access	Relational DBMS	146.00	+1.79	+5.52
8.	8.	↑ 9.	Cassandra	Wide column store	127.60	+13.60	+39.74
9.	9.	↓ 8.	SQLite	Relational DBMS	107.66	+1.84	+15.04
10.	10.	↑ 12.	Redis	Key-value store	100.65	+1.85	+26.05
11.	11.	↓ 10.	SAP Adaptive Server	Relational DBMS	86.52	+1.41	+1.10
12.	12.	↓ 11.	Solr	Search engine	81.94	+0.04	+6.17

Afternoon Break

Coming up next: “Analytics in Fraud Detection”

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- **David Bradford**, Co-Founder & Chief Strategy Officer, Advisen (Moderator)
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Closing Remarks

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