

## Agenda

- 1. Prohibited Fields
- 2. Generalization Power
- 3. Model Validation





# **Prohibited Fields**

It is the responsibility of insurance companies and those who work for them to be aware of predictors that are prohibited or limited in their use.

Has advanced analytics changed this?

No, but now we have the possibility of "replacing" fields.



## ANALYTICS & REGULATION - MODELER'S PERSPECTIVE

#### Prohibited Fields

What is meant by "replace"?



Similar amount of signal? Uses same underlying fields (credit report) or different fields? Similar impact on current customers? Similar impact on protected groups?







#### **Generalization Power**

Fundamental Modeling Question:

How do we know that the model is any good?

What do we mean by "good"?

How do we know that the model will apply correctly to future data that is collected?

This fundamental question speaks directly to the issue of generalization power, and it exists regardless of what modeling technique is used.

#### ANALYTICS & REGULATION - MODELER'S PERSPECTIVE



Modeling in general is a constant balancing act between underfitting and over-fitting the data.

•"Fit" – how well does the model match the given data? •"Generalization" – how well *will* the model fit new data?

Noise will vary between datasets, but real signal will be constant.



Fit versus Generalization Power – these are NOT co-equal goals!

Underfit – Signal left on the table, but generalizes well. Overfit – All the signal extracted (and more!), but the model under-performs on new data.





Model validation uses unseen data in order to test the model. It is the most direct way to test a model's generalization power. It is the most direct way to show proof that the "model is any good".

Regulators are really the last person you have to convince...



#### ANALYTICS & REGULATION - MODELER'S PERSPECTIVE

Many of the metrics used to evaluate models are not tests against hold-out data.

- P-values, confidence intervals, etc. are a direct consequence of an assumed error distribution.
   Many times only one predictor is being evaluated
  - Many times only one predictor is being evaluated.
    Not all modeling techniques make this assumption.
- Whole mode metrics like AIC and BIC attempt to measure performance on unseen data, but do so indirectly through a complexity penalty.

These approaches only use training data.



# Severity – Forward Regression – AIC & BIC Improvement





# ANALYTICS & REGULATION - MODELER'S PERSPECTIVE

## Severity – Forward Regression – Deviance Improvement



## ANALYTICS & REGULATION - MODELER'S PERSPECTIVE

## Hold-out datasets

Two main methods -

• Out of sample: randomly trained on 70% of data; validated against remaining 30% of data.



#### Hold-out datasets

- Two main methods -
  - Out of sample: randomly trained on 70% of data; validated against remaining 30% of data.
  - Out of time: trained against older years of data; validated against newest years of data.



#### **ANALYTICS & REGULATION - MODELER'S PERSPECTIVE**



#### **ANALYTICS & REGULATION - MODELER'S PERSPECTIVE**

The use of hold-out data suggests two powerful ideas.

First, models can and should be evaluated in their entirety. How well does the whole model perform on unseen data?

Second, there is a distinction between the inner workings of the model and its output.

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- How the model works may be proprietary How the model works may be complicated to explain
- Input to the model should be understood and specified to regulators
- Performance of the model on unseen data should be shared • and available

Eagle Eye Analytics