And The Winner Is...? How to Pick a Better Model

Model Lift – 2016 CAS RPM Seminar

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Motivation

- Models that appear to be strong may have weaknesses
  - Fit may not be good
  - Model may be overfit
  - Wrong distribution may have been chosen
  - Results may not be stable across data subsets or over time
  - Results may be highly influenced by several records
  - Model may underperform the status quo

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Some Models Used by Actuaries

- Linear regression
- Exponential regression
- Logistic regression
- Minimum bias procedures
- Generalized linear models
- Classification and regression trees
- Clustering procedures

Understanding & Validating a Model

- Model Lift
  - How well does the model differentiate between best and worst risks?
  - Does the model help prevent adverse selection?
  - Is the model better than the current rating plan?
- Goodness of Fit
  - What kind of model statistics are available, and how do you interpret them?
  - What kind of residual plots should you consider, and how do you interpret them?
  - What are some considerations regarding actual versus predicted plots?
- Internal Stability
  - How well does the model perform on other data?
  - How will the model perform over time?
  - How reliable are the model's parameter estimates?

Model Lift

- Ability to differentiate between low and high cost policyholders
  - Sometimes called the “economic value” of the model

- Some tools for measuring and illustrating model lift
  - Simple Quantile plots
  - Double lift charts
  - Gini index
  - Loss ratio charts

Model Lift – Simple Quantile Plots

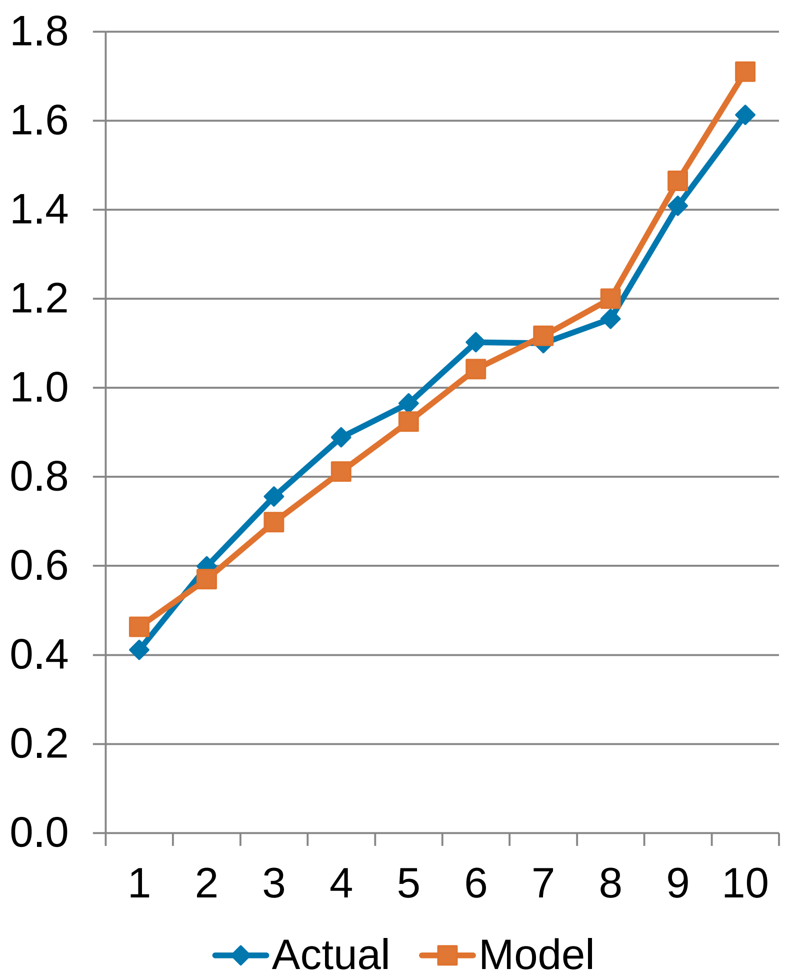
- Creating a quantile plot
  - Use holdout sample.
  - Sort data based on predicted value (frequency, severity, loss cost).
  - Subdivide sorted data into quantiles (quartiles, quintiles, deciles) with equal weight (exposure, claim count).
  - Calculate average actual value and predicted value for each quantile and index to overall average.

Decile	Actual Pure Premium	Model Pure Premium	Actual Index	Model Index
1	41.10	47.23	0.411	0.463
2	59.90	58.14	0.599	0.570
3	75.60	71.20	0.756	0.698
4	88.90	82.82	0.889	0.812
5	96.50	94.25	0.965	0.924
6	110.20	106.28	1.102	1.042
7	110.00	113.93	1.100	1.117
8	115.50	122.40	1.155	1.200
9	140.90	149.43	1.409	1.465
10	161.30	174.42	1.613	1.710
All	100.00	102.00		

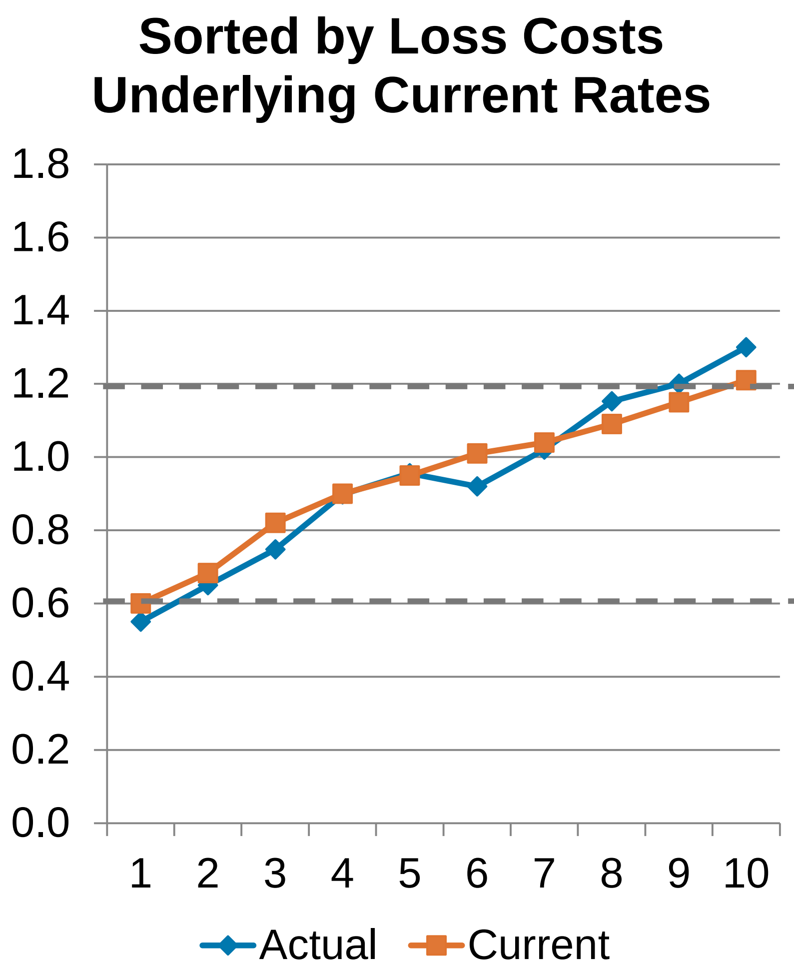
Hypothetical

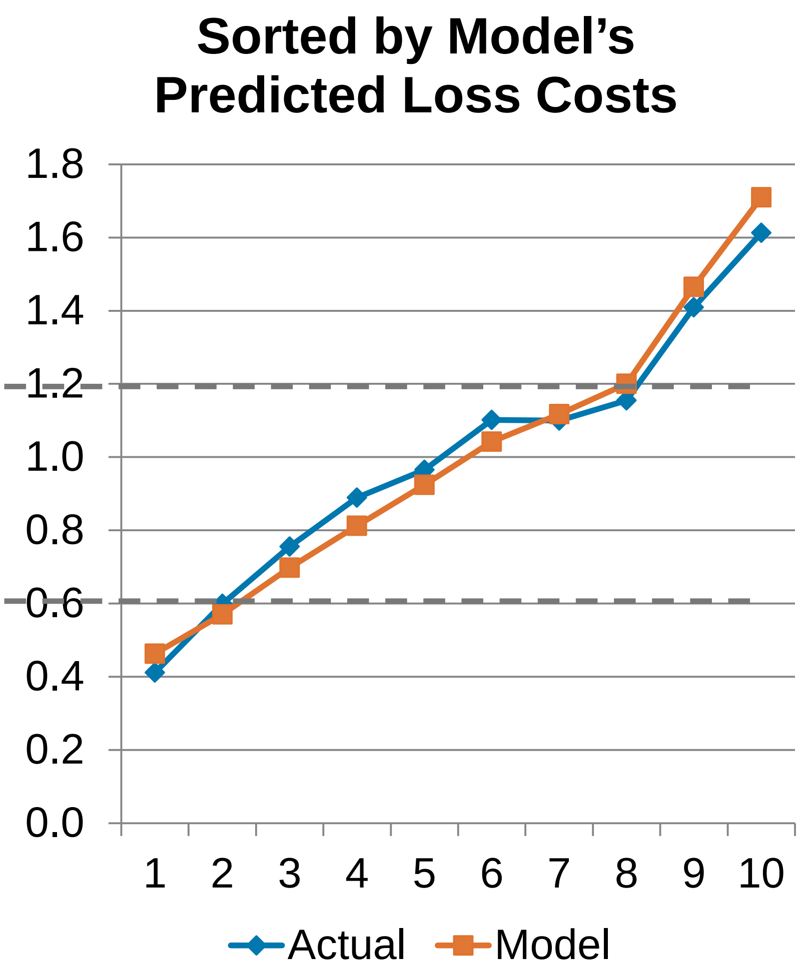
Model Lift – Simple Quantile Plots

- Checking a quantile plot
  - Is there a close match between actual and predicted values?
  - Are values increasing monotonically or with few reversals?
  - How well does the model distinguish between low cost and high costs policyholders?



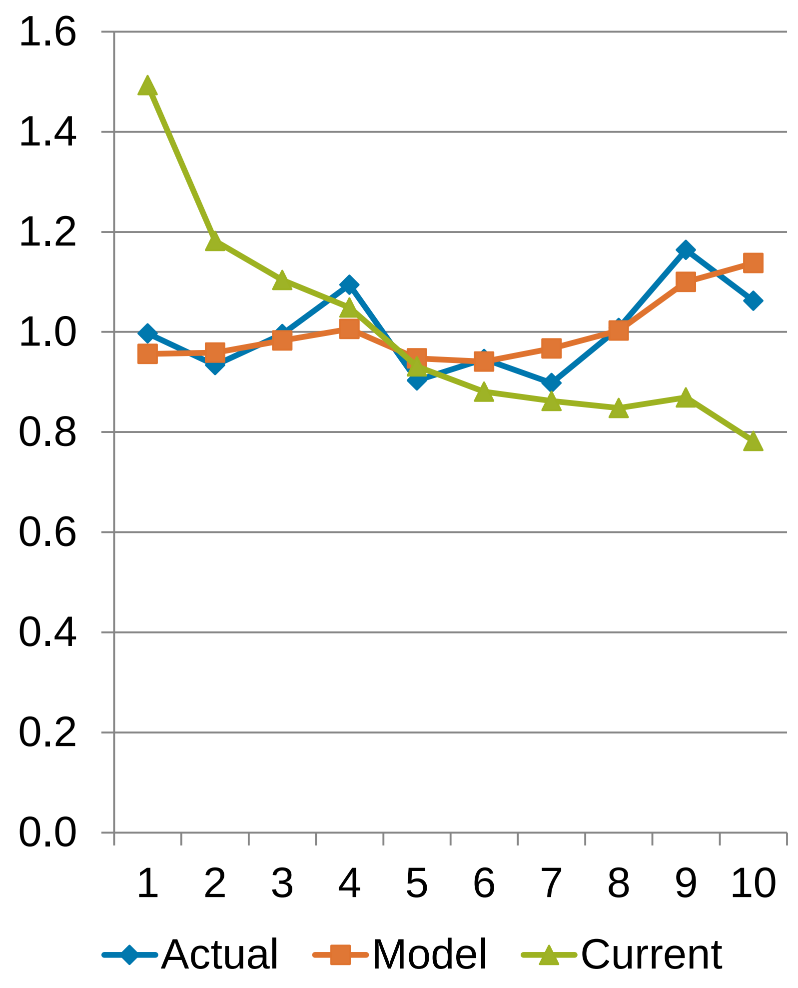
Model Lift – Simple Quantile Plots





Model Lift – Double Lift Charts

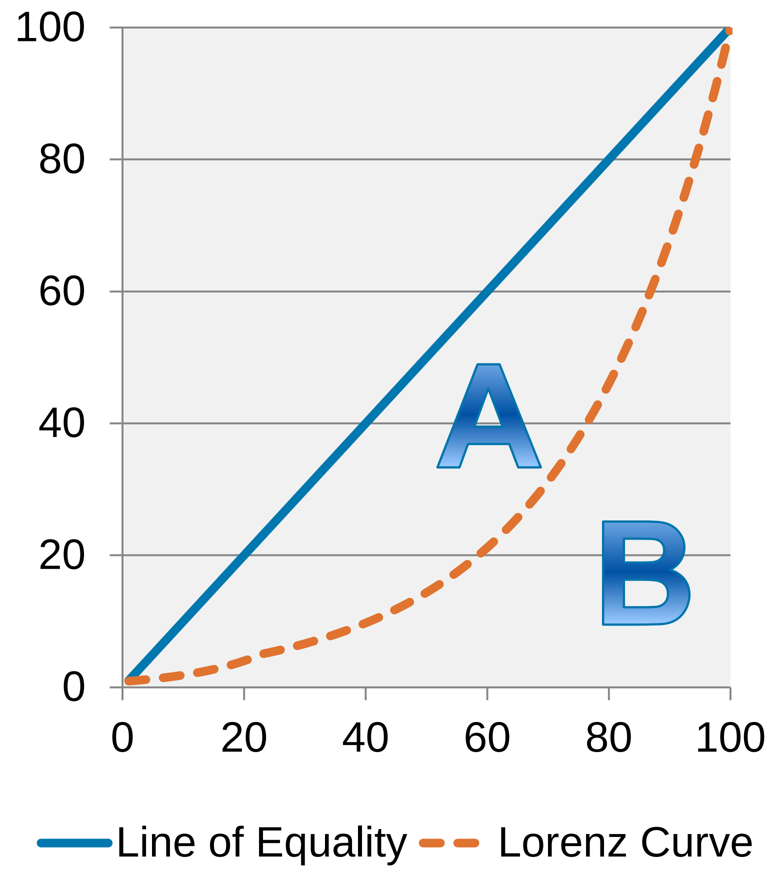
- Creating a double lift chart
  - Sort data by ratio of model prediction to current premium.
  - Subdivide sorted data into quantiles with equal exposure.
  - For each quantile calculate average actual loss cost, average model predicted loss cost and the average loss cost underlying the current manual premium .
  - Index the quantile averages to the overall averages.



Economics – The Gini Index

- Gini coefficient or Gini ratio
  - Named after Corrado Gini

- Measure of income inequality
  - Horizontal axis = percentage of country's population
  - Vertical axis = percentage of country's income
  - A = Area between line of equality and Lorenz Curve
  - B = Area beneath Lorenz Curve
  - Gini index = A / (A + B)



Model Lift – Simple Gini Index

Binary Response

- SAS Proc Logistic
- t = total pairs with different responses
- n_c = concordant pairs
- n_d = discordant pairs
- $t - n_c - n_d$ = tied pairs
- Sommer's D

  = Gini's coefficient

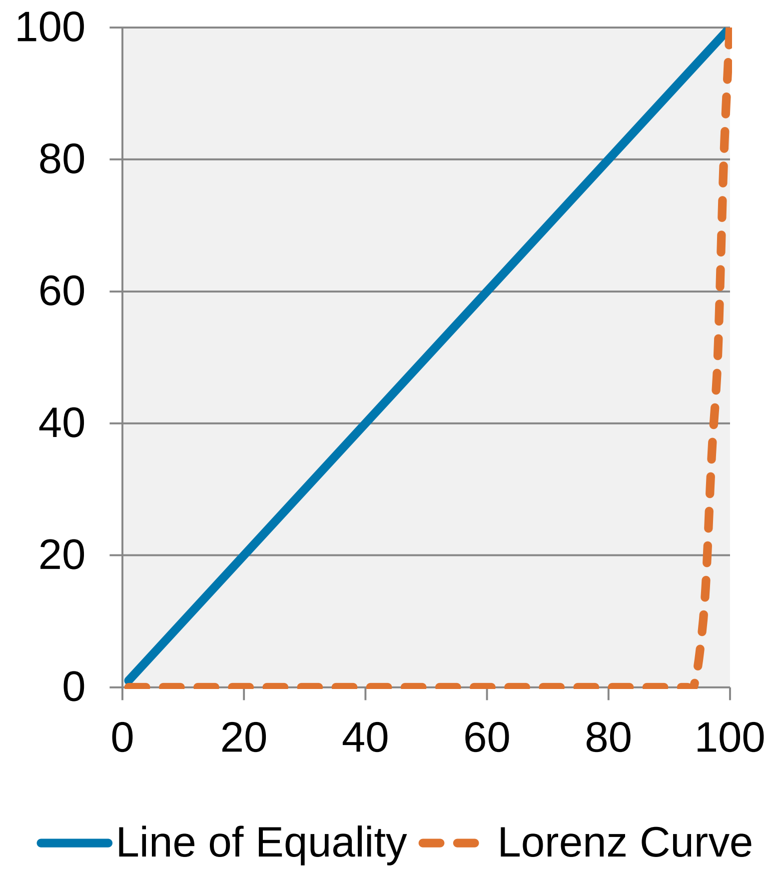
  $= (n_c - n_d) / t$

Lorenz Curve for Loss Cost

- Sort holdout data by predicted loss cost
- Calculate cumulative percentages for actual incurred loss and exposure
- Plot
  - Cumulative exposure in horizontal axis
  - Cumulative loss in vertical axis

Model Lift – Simple Gini Index

- Adapting to car insurance
  - Assume claim frequency = 5%
- "The perfect model"
  - Prediction = actual loss, which is $0 for 95% of vehicles insured.
  - Sort holdout data set by model prediction.
  - Horizontal axis = percentage of total earned car years.
  - Vertical axis = Percentage of total incurred loss.
  - Gini Index = A / (A+ B) is very high.



Model Lift – Simple Gini Index

- Exercise:
  - Model X prediction = expected loss cost
  - Model Y prediction = 0.5 (expected loss cost)
  - Model Z prediction = 2.0 (expected loss cost)
  - Which model has the highest Gini index?

- Model A has a Gini index of 15.9 and B has a Gini index of 15.4
  - Is that difference significant, or is it just a quirk of the holdout data?

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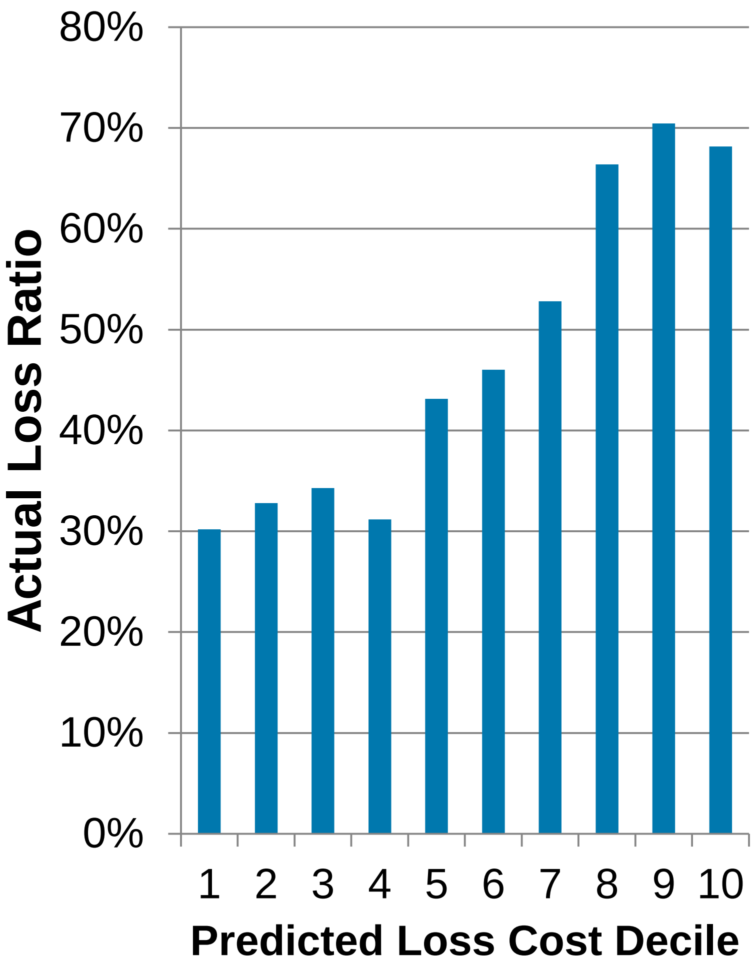
Model Lift – Loss Ratio Charts

- Lift charts and Gini index
  - May be unfamiliar to some stakeholders
- Loss ratios
  - Widely used and understood in the industry
- Ranking by predicted loss cost
  - Rank data into quantiles by predicted model loss cost
  - Calculate loss ratio for each quantile



Model Lift – Summary

- Simple Quantile plots
  - Illustrate how well the model helps prevent adverse selection
- Double lift charts
  - Compare competing models
  - Compare new model against current rating plan
- Simple Gini Index
  - Summarizes model lift into one number
- Loss ratio charts
  - Puts lift in context most people in insurance industry can understand
  - Can be distorted by redundancy or inadequacy of current rating plan

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