And The Winner Is…? How to Pick a Better Model – Part 1

2017 CAS RPM Seminar

ISO
Verisk Insurance Solutions

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Motivation

- Models that appear to be strong may have weaknesses
  - Fit may not be good enough
  - 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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Understanding & Validating a Model

- Model Lift
  - How well does the model differentiate between best and worst risks?
  - Does the model help prevent adverse selection?
  - Does the model improve the 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?

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Model Lift

- Ability to differentiate between low and high cost policyholders
  - Sometimes called the "economic value" of the model
- Some tools for illustrating model lift
  - Simple quantile plots
  - Double quantile charts
  - Loss ratio charts

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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.
- 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 cost policyholders?

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Quantile Chart Examples Using Simulated Data

```
#
# Simulate data
#
# use a seed value to make results reproducible
set.seed(2017)
# simulate data and store in data frame
d <- data.frame(
     policy_number = c(1:240000, 1:240000),
     year = c(rep(2015, 240000), rep(2016,240000)),
     group = rep(c(rep('G1', 80000), rep('G2', 80000), rep('G3', 80000)), 2),
     age = rep(c(rep(1, 20000), rep(2, 20000), rep(3, 20000), rep(4, 20000)), 6),
     exposure = rep(1, 480000),
     claim_count = c(rpois(480000,
                         c(rep(0.0100, 20000), rep(0.0200, 20000), rep(0.0400, 20000), rep(0.0800, 20000),
                           rep(0.0300, 20000), rep(0.0525, 20000), rep(0.0919, 20000), rep(0.1608, 20000),
                           rep(0.0600, 20000), rep(0.0900, 20000), rep(0.1350, 20000), rep(0.2025, 20000)))),
     stringsAsFactors = TRUE
)
```


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An Example of Overfitting

- Model 1

```
#
# Model 1: predicted claim count equals claim count in training sample
#
Training$m1_claim_count <- Training$claim_count
Testing$m1_claim_count <- Training$claim_count
```


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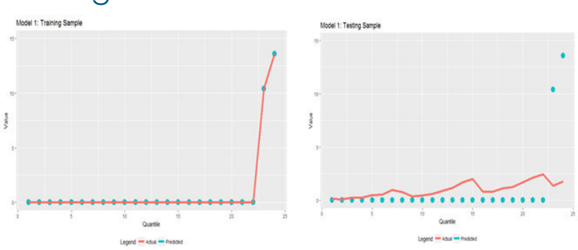
Quantile Chart Examples Using Simulated Data



Model 1: For each policy, predicted claim count equals claim count in training data.

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Alternative Models

- Models 2 and 3

```
#
# Model 2: group only
#
m2 <- glm(claim_frequency ~ group,
                 family = poisson(link = log),
                 data = Training, weights = exposure)
summary(m2)
Testing$m2_frequency <- round(predict(m2, newdata = Testing, type = 'response'), 6)
Testing$m2_claim_count <- Testing$exposure * Testing$m2_frequency
#
# Model 3: group and age
#
m3 <- glm(claim_frequency ~ group + age,
        family = poisson(link = log),
        data = Training, weights = exposure)
summary(m3)
Testing$m3_frequency <- round(predict(m3, newdata = Testing, type = 'response'), 6)
Testing$m3_claim_count <- Testing$exposure * Testing$m3_frequency
```


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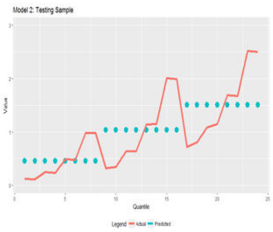
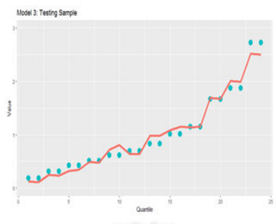
Quantile Chart Examples Using Simulated Data





Model 2: Group
Model 3: Group and Age

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Model Lift – Double Quantile Charts

- Creating a Double Quantile chart
  - Sort data by ratio of model prediction to current premium.
  - Subdivide the sorted data into quantiles with equal exposure.
  - For each quantile calculate average actual loss cost (frequency or severity), average model predicted value, and the average value underlying the current manual premium.
  - Index the quantile averages to the overall averages.

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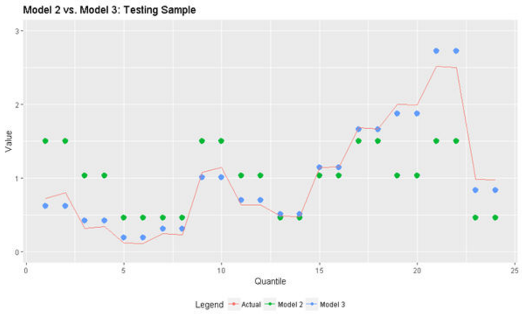
Double Quantile Chart Example Using Simulated Data



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Alternative Models

- Models 3 and 4

```r
#
# Model 3: group and age
#
m3 <- glm(claim_frequency ~ group + age,
          family = poisson(link = log),
          data = Training, weights = exposure)
summary(m3)
Testing$m3_frequency <- round(predict(m3, newdata = Testing, type = 'response'), 6)
Testing$m3_claim_count <- Testing$exposure * Testing$m3_frequency
#
# Model 4: group, age and interaction
#
m4 <- glm(claim_frequency ~ group + age + group*age,
          family = poisson(link = log),
          data = Training, weights = exposure)
summary(m4)
Testing$m4_frequency <- round(predict(m4, newdata = Testing, type = 'response'), 6)
Testing$m4_claim_count <- Testing$exposure * Testing$m4_frequency
```


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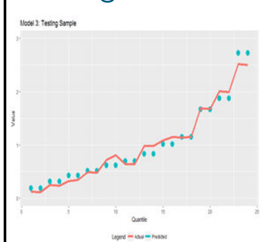
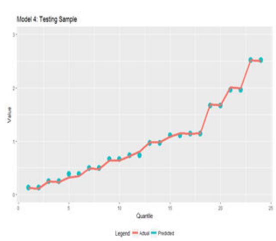
Quantile Chart Examples Using Simulated Data





Model 3: Group and Age
Model 4: Group, Age, and interaction

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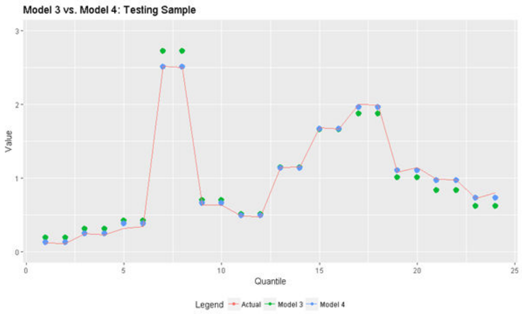
Double Quantile Chart Example Using Simulated Data



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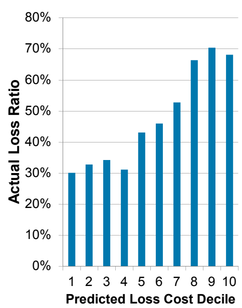
Model Lift – Loss Ratio Charts

- Quantile charts and Double Quantile charts may be unfamiliar to some stakeholders
- Loss ratios are 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



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Model Lift – Summary

- Simple Quantile plots
  - Illustrate how well the model helps prevent adverse selection
- Double Quantile charts
  - Compare competing models
  - Compare new model against current rating plan
- 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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References

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