

MODELING THE EXPERT

An Introduction to Logistic Regression

15.071 – The Analytics Edge

Ask the Experts!

- Critical decisions are often made by people with expert knowledge
- Healthcare Quality Assessment
 - Good quality care educates patients and controls costs
 - · Need to assess quality for proper medical interventions
 - No single set of guidelines for defining quality of healthcare
 - Health professionals are experts in quality of care assessment

Experts are Human

- Experts are limited by memory and time
- Healthcare Quality Assessment
 - Expert physicians can evaluate quality by examining a patient's records
 - This process is time consuming and inefficient
 - Physicians cannot assess quality for millions of patients

Replicating Expert Assessment

- Can we develop analytical tools that replicate expert assessment on a large scale?
- Learn from expert human judgment
 - Develop a model, interpret results, and adjust the model
- Make predictions/evaluations on a large scale
- Healthcare Quality Assessment
 - Let's identify poor healthcare quality using analytics

Claims Data

Medical Claims

Diagnosis, Procedures, Doctor/Hospital, Cost

Pharmacy Claims

Drug, Quantity, Doctor,
Medication Cost

- Electronically available
- Standardized
- Not 100% accurate
- Under-reporting is common
- Claims for hospital visits can be vague

Creating the Dataset – Claims Samples

Claims Sample

- Large health insurance claims database
- Randomly selected 131 diabetes patients
- Ages range from 35 to 55
- Costs \$10,000 \$20,000
- September 1, 2003 August 31, 2005

Creating the Dataset – Expert Review

Claims Sample

Expert Review

 Expert physician reviewed claims and wrote descriptive notes:

"Ongoing use of narcotics"

"Only on Avandia, not a good first choice drug"

"Had regular visits, mammogram, and immunizations"

"Was given home testing supplies"

Creating the Dataset – Expert Assessment

Claims Sample

Expert Review

Expert Assessment

 Rated quality on a two-point scale (poor/good)

"I'd say **care was poor** – poorly treated diabetes"

"No eye care, but overall I'd say high quality"

Creating the Dataset – Variable Extraction

Claims Sample

Expert Review

Expert Assessment

Variable Extraction

- Dependent Variable
 - Quality of care
- Independent Variables
 - ongoing use of **narcotics**
 - only on Avandia, not a good first choice drug
 - Had regular visits, mammogram, and immunizations
 - Was given home testing supplies

Creating the Dataset – Variable Extraction

Claims Sample

Expert Review

Expert Assessment

Variable Extraction

- Dependent Variable
 - Quality of care
- Independent Variables
 - Diabetes treatment
 - Patient demographics
 - Healthcare utilization
 - Providers
 - Claims
 - Prescriptions

Predicting Quality of Care

- The dependent variable is modeled as a binary variable
 - 1 if low-quality care, 0 if high-quality care
- This is a categorical variable
 - A small number of possible outcomes
- · Linear regression would predict a continuous outcome
- How can we extend the idea of linear regression to situations where the outcome variable is categorical?
 - Only want to predict 1 or 0
 - Could round outcome to 0 or 1
 - But we can do better with logistic regression

Logistic Regression

Predicts the probability of poor care

- Poor Care = 1 Good Care = 0
- Denote dependent variable "PoorCare" by \boldsymbol{y}
- P(y=1)
- Then P(y=0) = 1 P(y=1)
- Independent variables x_1, x_2, \ldots, x_k
- Uses the Logistic Response Function

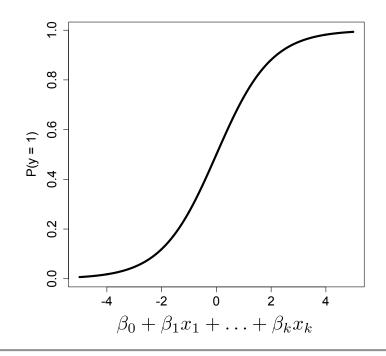
$$P(y=1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k)}}$$

• Nonlinear transformation of linear regression equation to produce number between 0 and 1

Understanding the Logistic Function

$$P(y=1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k)}}$$

- Positive values are predictive of class 1
- Negative values are predictive of class 0



Understanding the Logistic Function

$$P(y=1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k)}}$$

- The coefficients are selected to
 - Predict a high probability for the poor care cases
 - Predict a low probability for the good care cases

Understanding the Logistic Function

$$P(y=1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k)}}$$

We can instead talk about Odds (like in gambling)

$$Odds = \frac{P(y=1)}{P(y=0)}$$

- Odds > 1 if y = 1 is more likely
- Odds < 1 if y = 0 is more likely

The Logit

• It turns out that

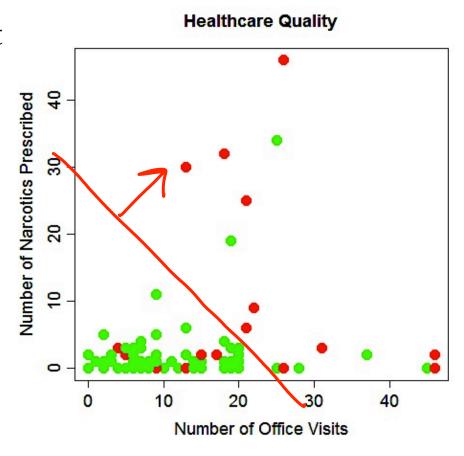
Odds =
$$e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k}$$

$$log(Odds) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k$$

- This is called the "Logit" and looks like linear regression
- The bigger the Logit is, the bigger P(y=1)

Model for Healthcare Quality

- Plot of the independent variables
 - Number of Office Visits
 - Number of Narcotics Prescribed
- Red are poor care
- Green are good care



Threshold Value

- The outcome of a logistic regression model is a probability
- Often, we want to make a binary prediction
 - Did this patient receive poor care or good care?
- We can do this using a threshold value t
- If $P(PoorCare = 1) \ge t$, predict poor quality
- If P(PoorCare = 1) < t, predict good quality
- What value should we pick for t?

Threshold Value

- Often selected based on which errors are "better"
- If t is **large**, predict poor care rarely (when P(y=1) is large)
 - More errors where we say good care, but it is actually poor care
 - Detects patients who are receiving the worst care
- If t is **small**, predict good care rarely (when P(y=1) is small)
 - · More errors where we say poor care, but it is actually good care
 - Detects all patients who might be receiving poor care
- With no preference between the errors, select t = 0.5
 - Predicts the more likely outcome

Selecting a Threshold Value

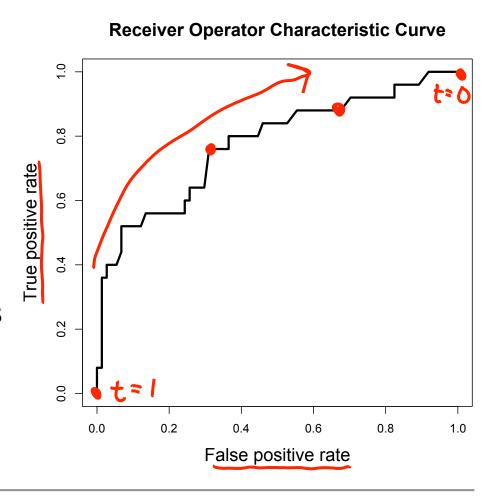
Compare actual outcomes to predicted outcomes using a confusion matrix (classification matrix)

	Predicted = 0	Predicted = 1
Actual = 0	True Negatives (TN)	False Positives (FP)
Actual = 1	False Negatives (FN)	True Positives (TP)

Sensitivity =
$$\frac{TP}{TP + FN}$$

Specificity = $\frac{TN}{TN + FP}$

- True positive rate (sensitivity) on y-axis
 - Proportion of poor care caught
- False positive rate
 (1-specificity) on x-axis
 - Proportion of good care labeled as poor care



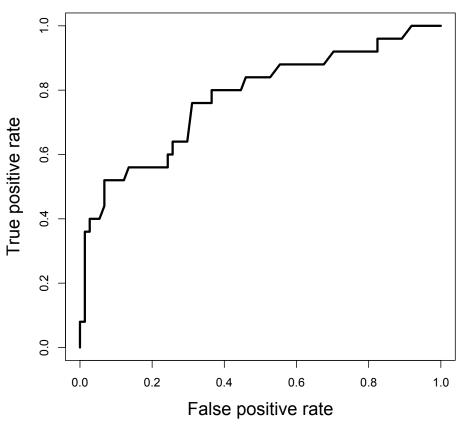
Captures all thresholds simultaneously

High threshold

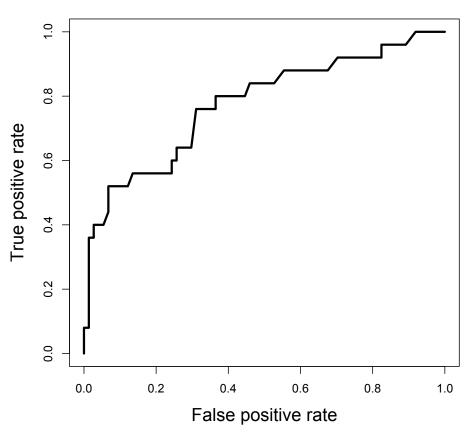
- High specificity
- Low sensitivity

Low Threshold

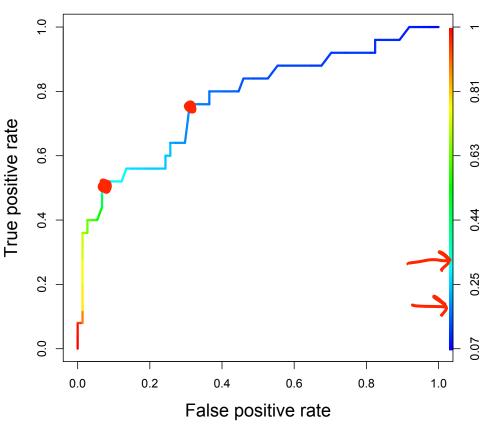
- Low specificity
- High sensitivity



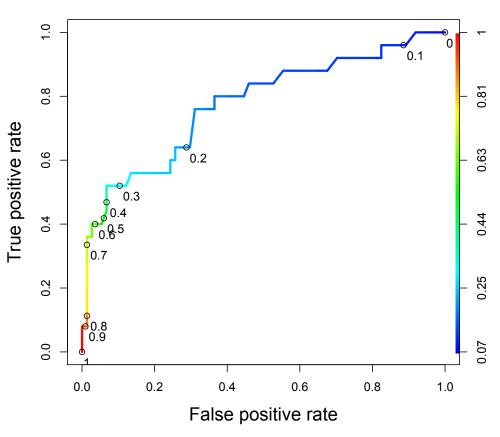
- Choose best threshold for best trade off
 - cost of failing to detect positives
 - costs of raising false alarms



- Choose best threshold for best trade off
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- Choose best threshold for best trade off
 - cost of failing to detect positives
 - costs of raising false alarms



Interpreting the Model

- Multicollinearity could be a problem
 - Do the coefficients make sense?
 - Check correlations
- Measures of accuracy

Compute Outcome Measures

Confusion Matrix:

	Predicted Class = 0	Predicted Class = 1
Actual Class = 0	True Negatives (TN)	False Positives (FP)
Actual Class = 1	False Negatives (FN)	True Positives (TP)

N = number of observations

Overall accuracy =
$$(TN + TP)/N$$
 Overall error rate = $(FP + FN)/N$

Sensitivity =
$$TP/(TP + FN)$$
 False Negative Error Rate = $FN/(TP + FN)$

Specificity =
$$TN/(TN + FP)$$
 False Positive Error Rate = $FP/(TN + FP)$

Making Predictions

• Just like in linear regression, we want to make predictions on a test set to compute out-of-sample metrics

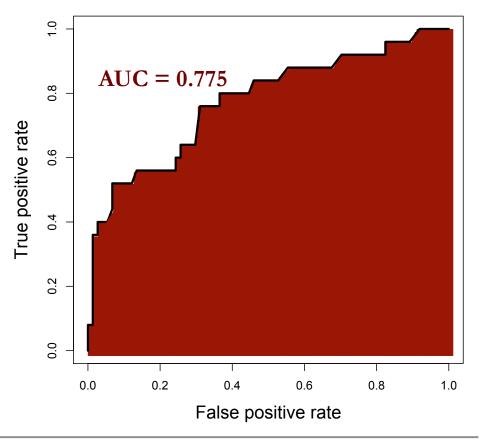
```
> predictTest = predict(QualityLog,
type="response", newdata=qualityTest)
```

- This makes predictions for probabilities
- If we use a threshold value of 0.3, we get the following confusion matrix

	Predicted Good Care	Predicted Poor Care
Actually Good Care	19	5
Actually Poor Care	2	6

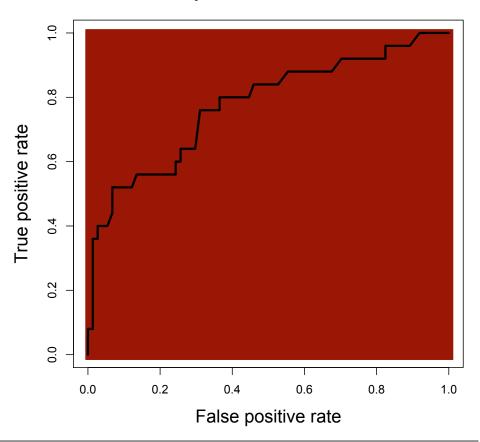
Area Under the ROC Curve (AUC)

- Just take the area under the curve
- Interpretation
 - Given a random
 positive and negative,
 proportion of the time
 you guess which is
 which correctly
- Less affected by sample balance than accuracy



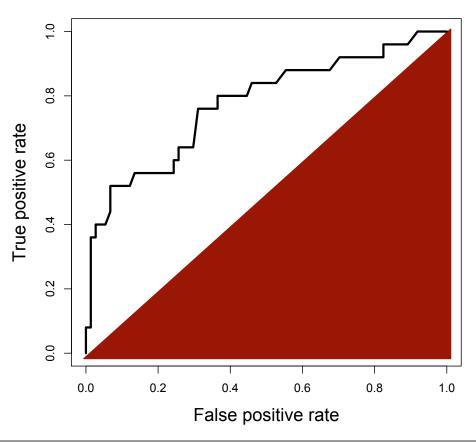
Area Under the ROC Curve (AUC)

- What is a good AUC?
 - Maximum of 1 (perfect prediction)



Area Under the ROC Curve (AUC)

- What is a good AUC?
 - Maximum of 1 (perfect prediction)
 - Minimum of 0.5 (just guessing)



Conclusions

- An expert-trained model can accurately identify diabetics receiving low-quality care
 - Out-of-sample accuracy of 78%
 - Identifies most patients receiving poor care
- In practice, the probabilities returned by the logistic regression model can be used to prioritize patients for intervention
- Electronic medical records could be used in the future

The Competitive Edge of Models

- While humans can accurately analyze small amounts of information, models allow larger scalability
- Models do not replace expert judgment
 - Experts can improve and refine the model
- Models can integrate assessments of many experts into one final unbiased and unemotional prediction