



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
 - Denote dependent variable “PoorCare” by y
 - $P(y = 1)$
- Then $P(y = 0) = 1 - P(y = 1)$
- Independent variables x_1, x_2, \dots, x_k
- Uses the Logistic Response Function

Poor Care = 1
Good Care = 0

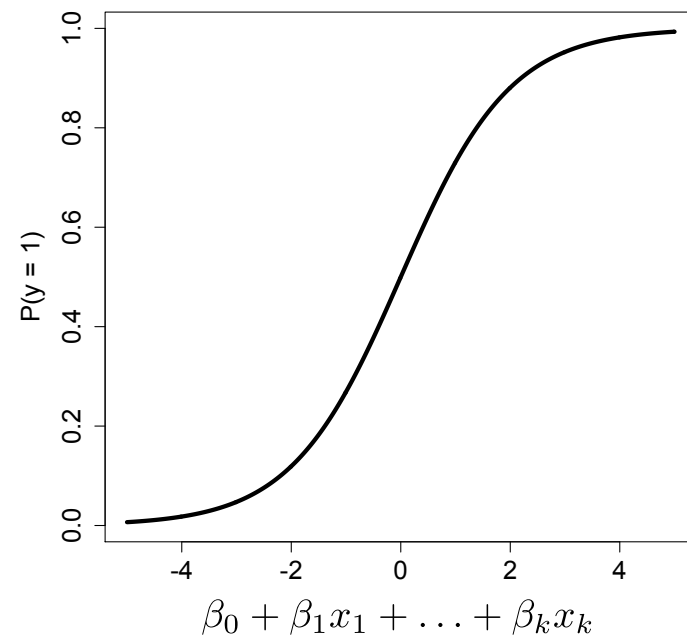
$$P(y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k)}}$$

- 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)

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

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

The Logit

- It turns out that

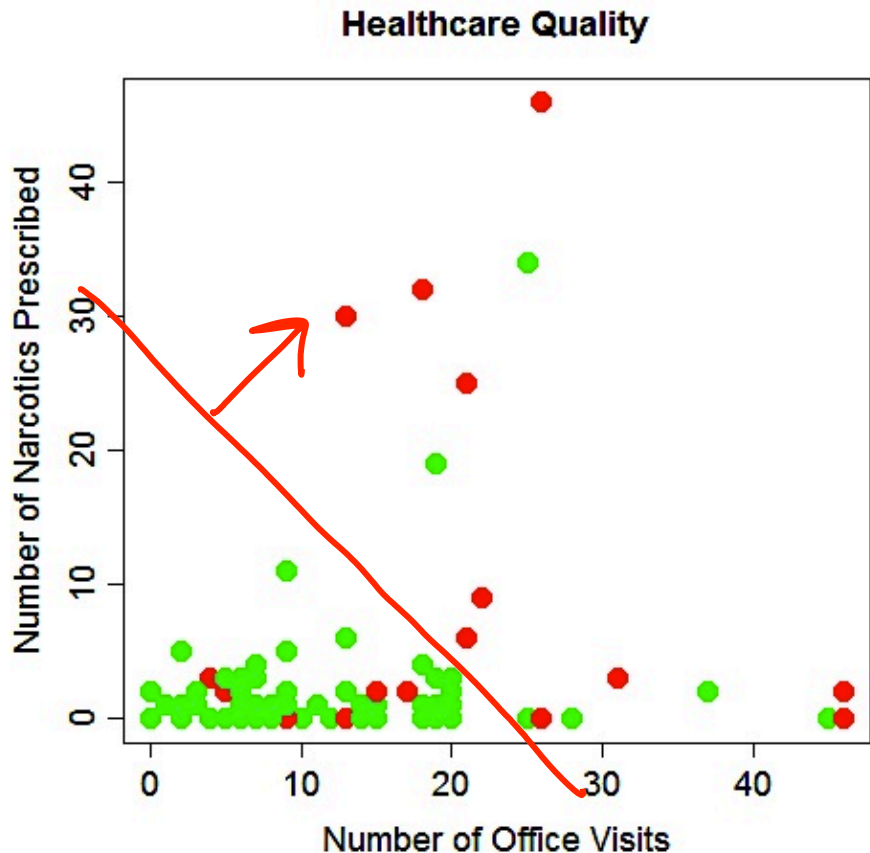
$$\text{Odds} = e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k}$$

$$\log(\text{Odds}) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k$$

- 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 $P(\text{PoorCare} = 1) \geq t$, predict poor quality
- If $P(\text{PoorCare} = 1) < t$, 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*)

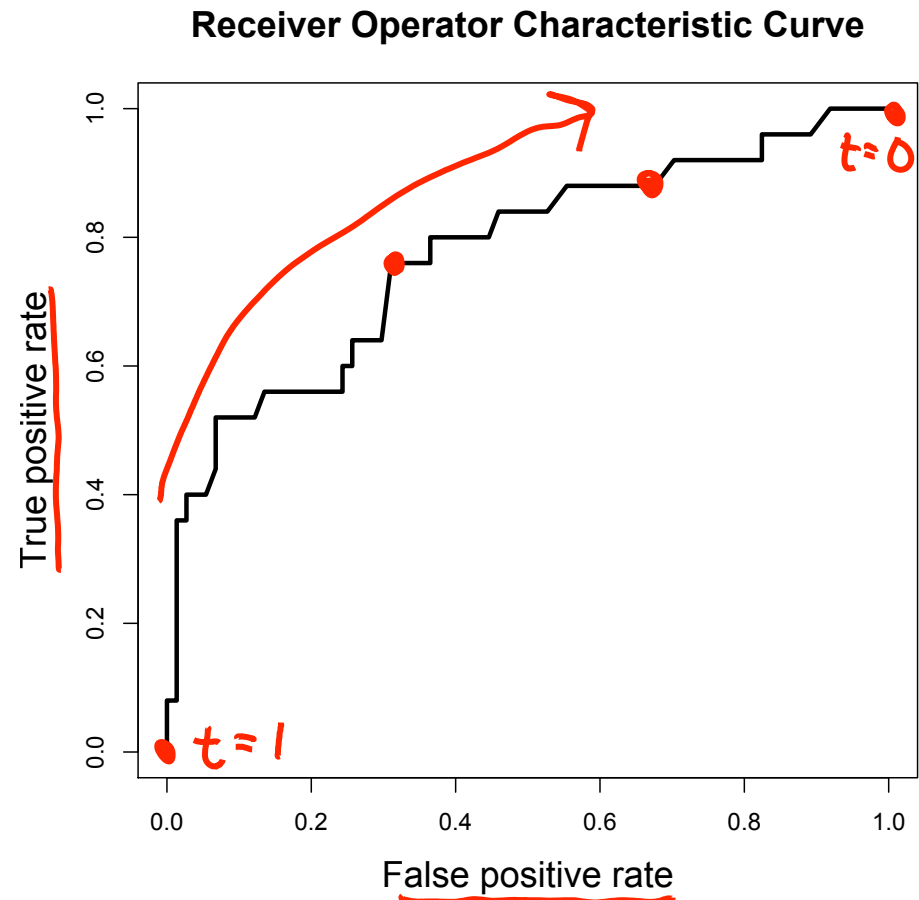
	Predicted = 0	Predicted = 1
Actual = 0	True Negatives (TN)	False Positives (FP)
Actual = 1	False Negatives (FN)	True Positives (TP)

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

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

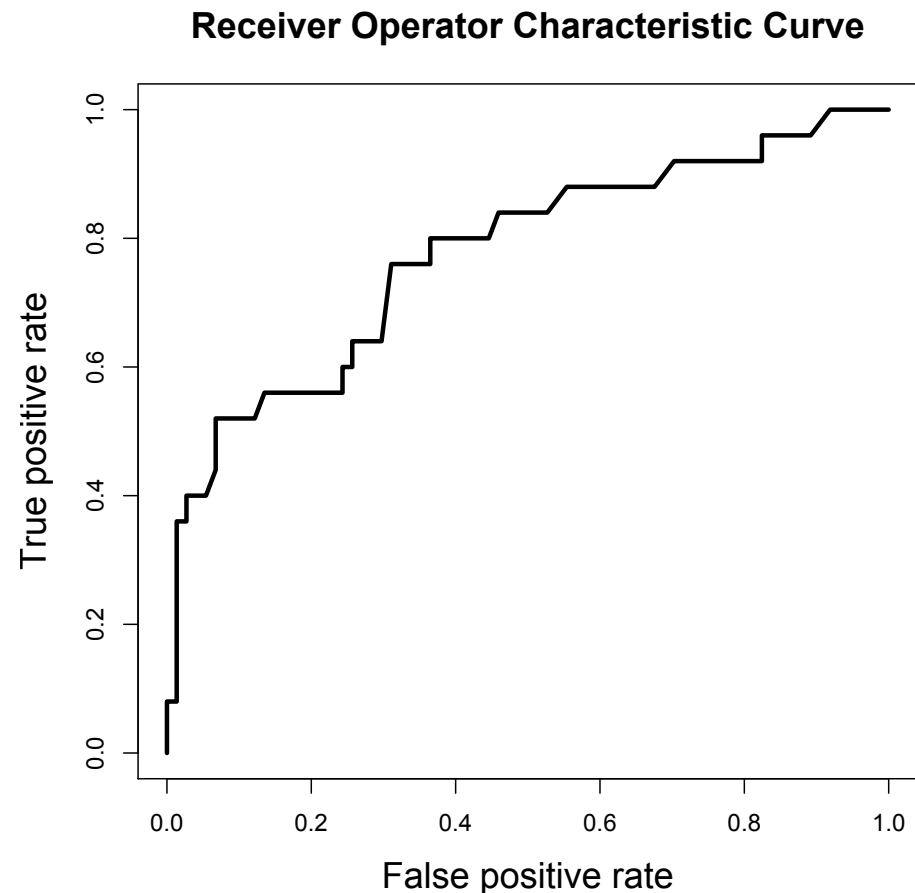
Receiver Operator Characteristic (ROC) Curve

- 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



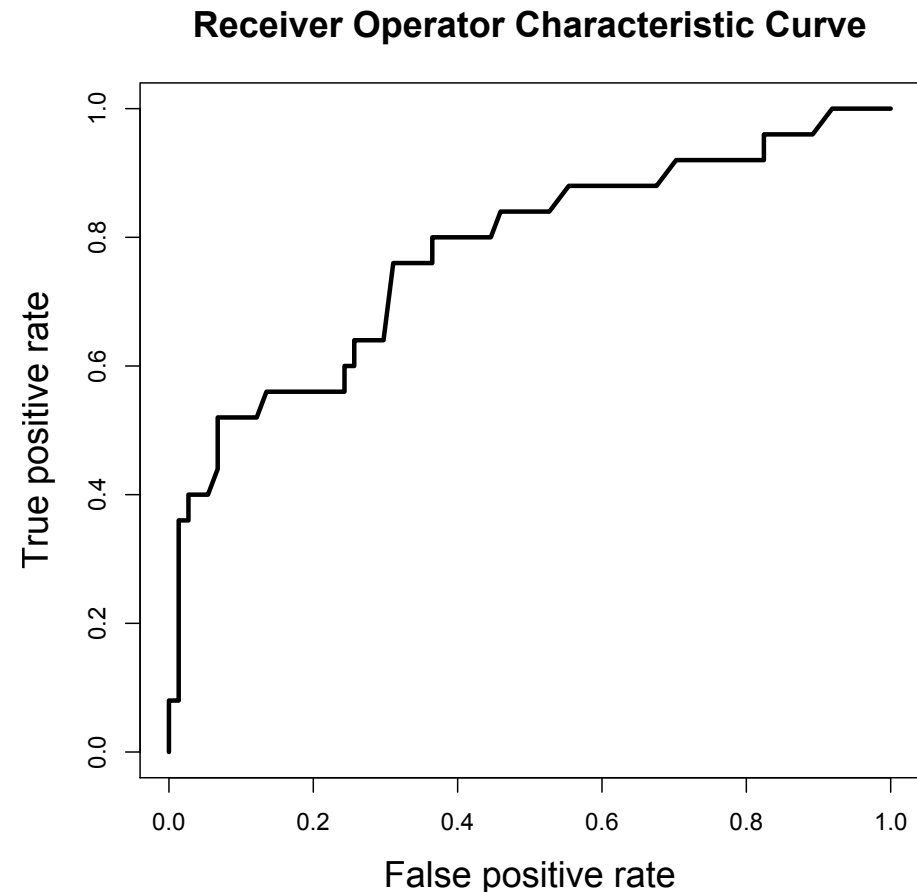
Selecting a Threshold using ROC

- Captures all thresholds simultaneously
- **High threshold**
 - High specificity
 - Low sensitivity
- **Low Threshold**
 - Low specificity
 - High sensitivity



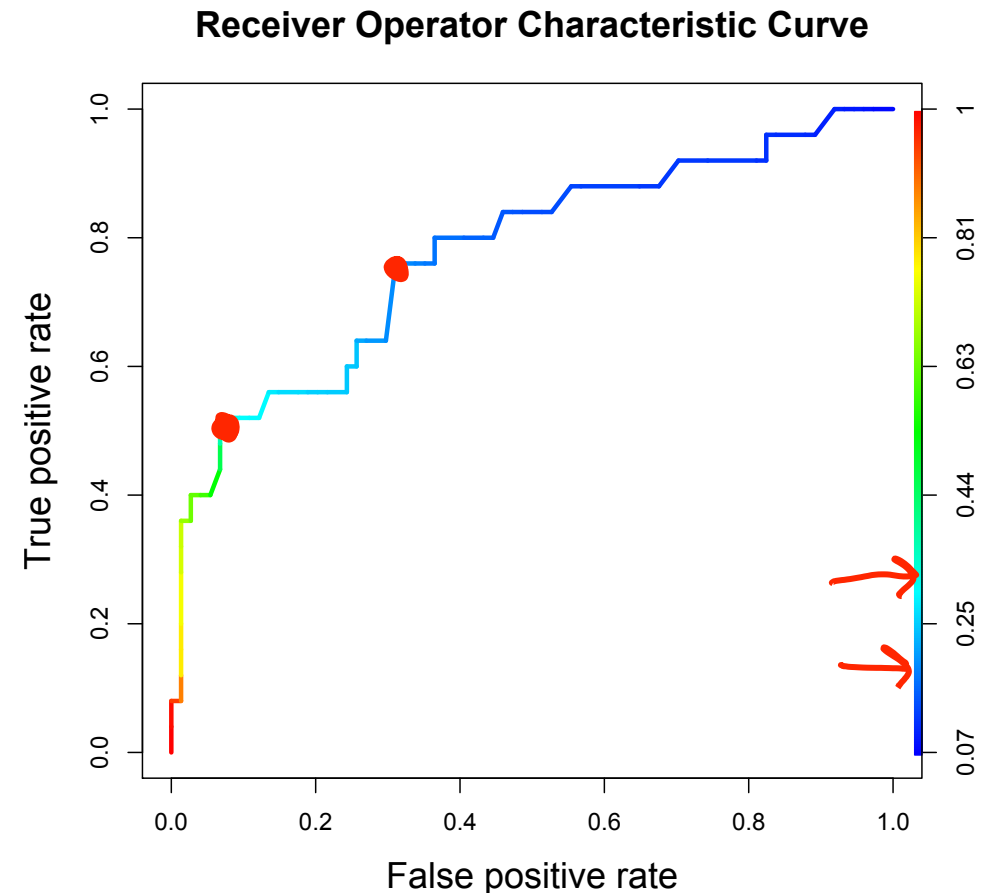
Selecting a Threshold using ROC

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



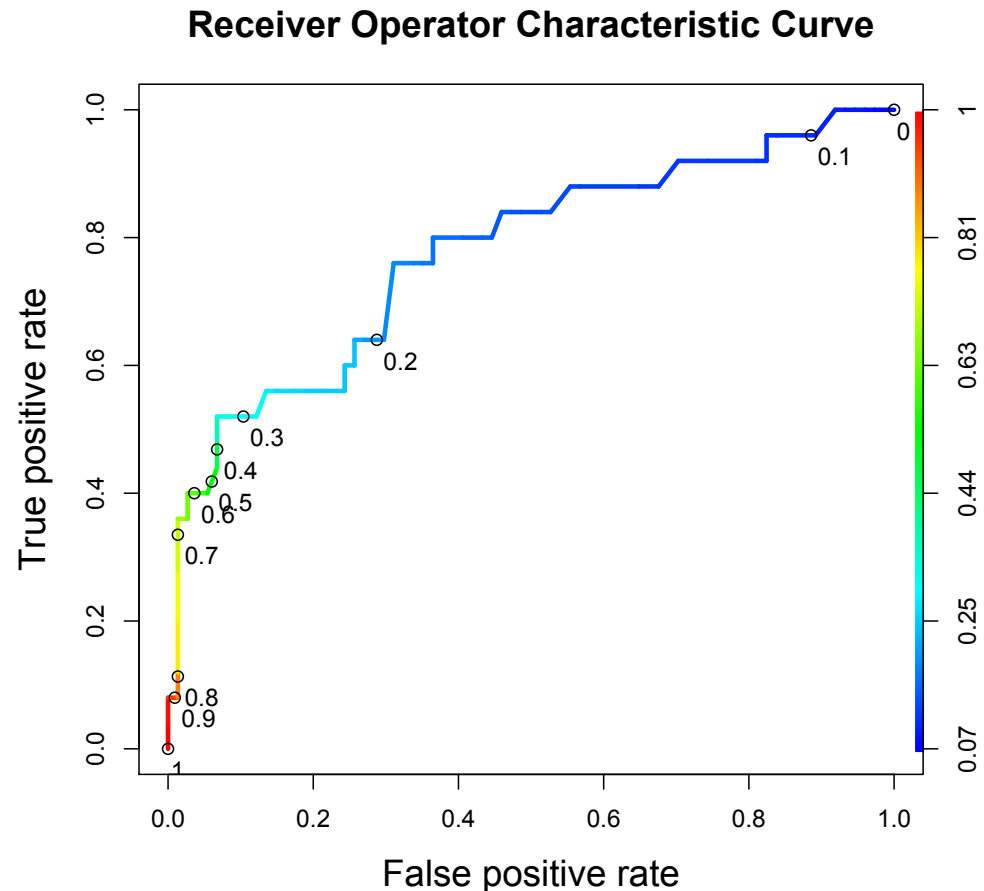
Selecting a Threshold using ROC

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



Selecting a Threshold using ROC

- 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

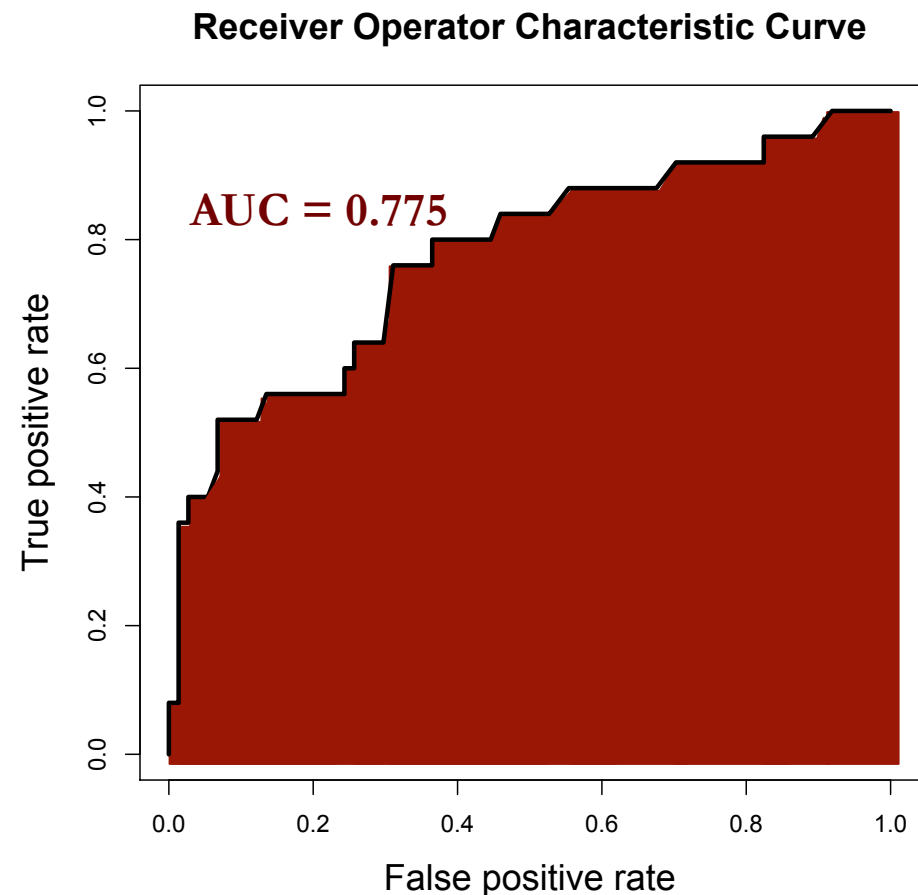
- Just like in linear regression, we want to make predictions on a test set to compute out-of-sample metrics

```
> 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

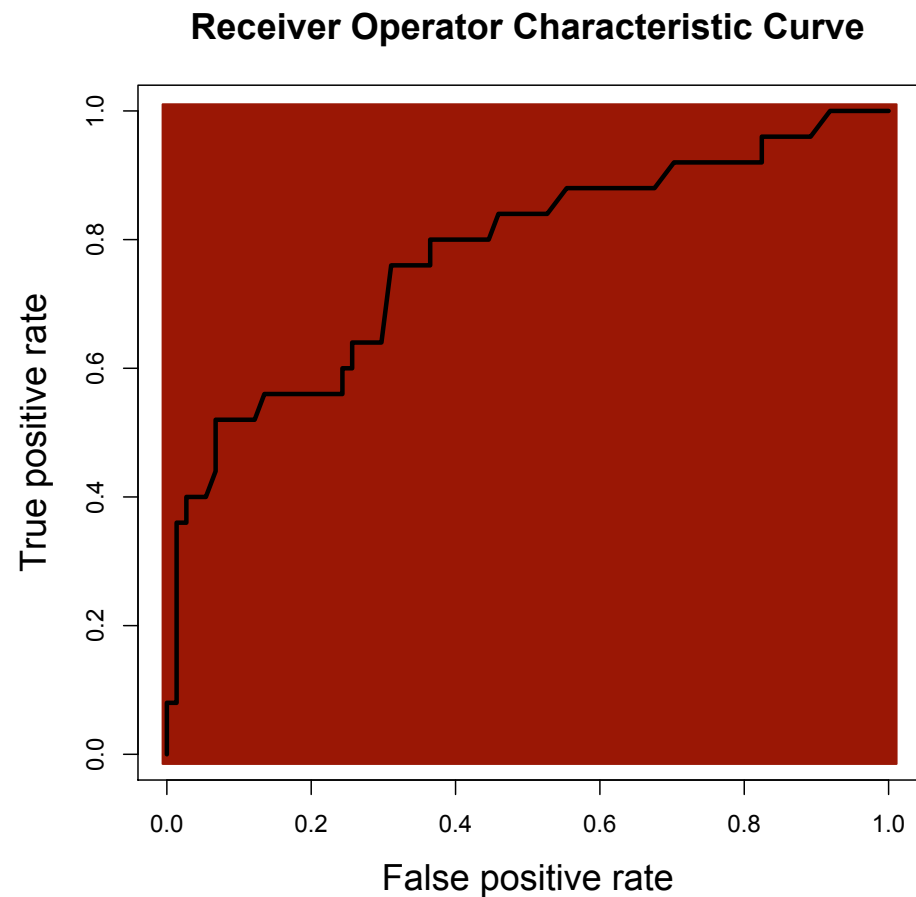
Area Under the ROC Curve (AUC)

- 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



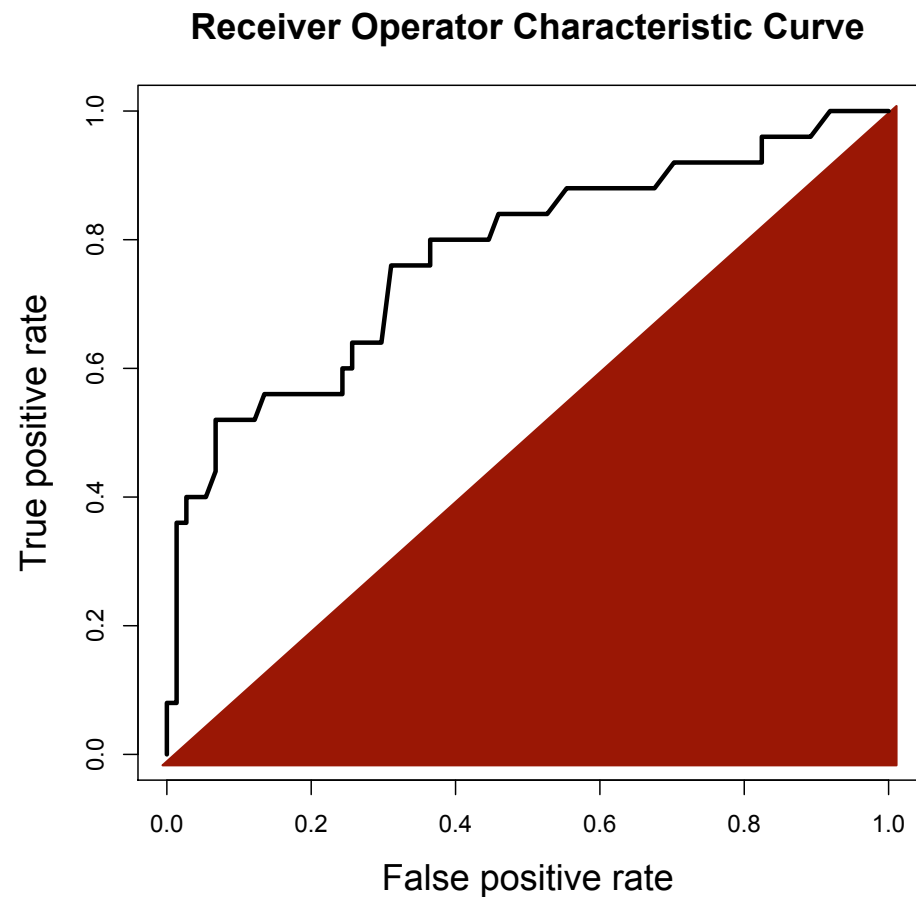
Area Under the ROC Curve (AUC)

- 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