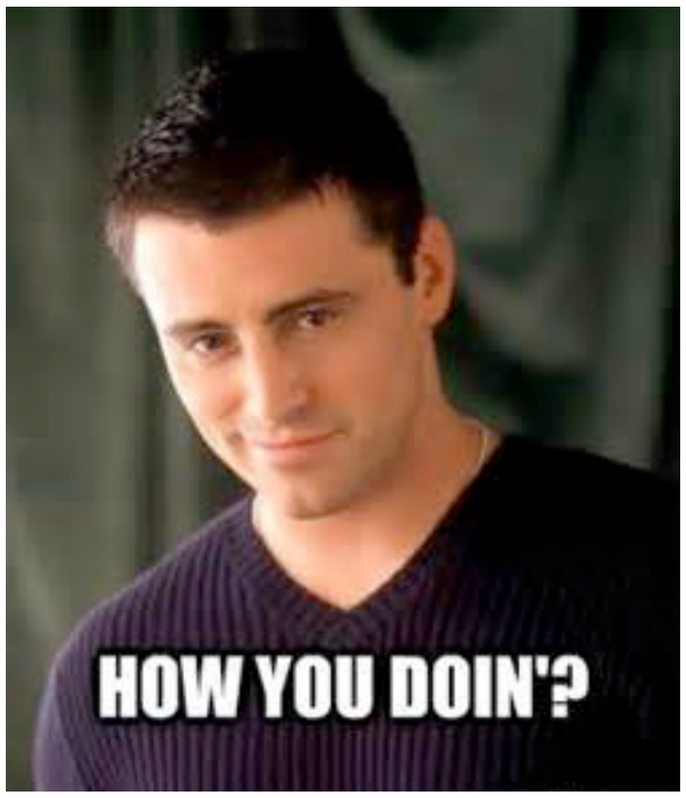
HUDK 4050:CORE METHODS IN EDM

12/1/16 8:25 AM

Diagnostic Metrics



How to determine how well your model is doing

Diagnostic Metrics

Classification

- Accuracy
- Cohen's Kappa
- ROC/AUC/A'
- Correlation
- RMSE

Regression

- MAE/RMSE
- Pearson's Correlation/R^2
- AIC/BIC

Terms

- **Ground truth**: data that is available, relevant, and most trustworthy to train your model

- **Baseline**: initial measurement

- **Gold standard**: (expensive) comparative measurement

- **Inference**: data that is inferred from logic + data

Diagnostics for Classifiers

Accuracy

- $\frac{\text{correct predictions}}{\text{total predictions}}$

- Gotcha: unequal categories

- EG - Predicting fraudulent credit card transactions

- False positives/negatives (over/ under predict)

Precision & Recall

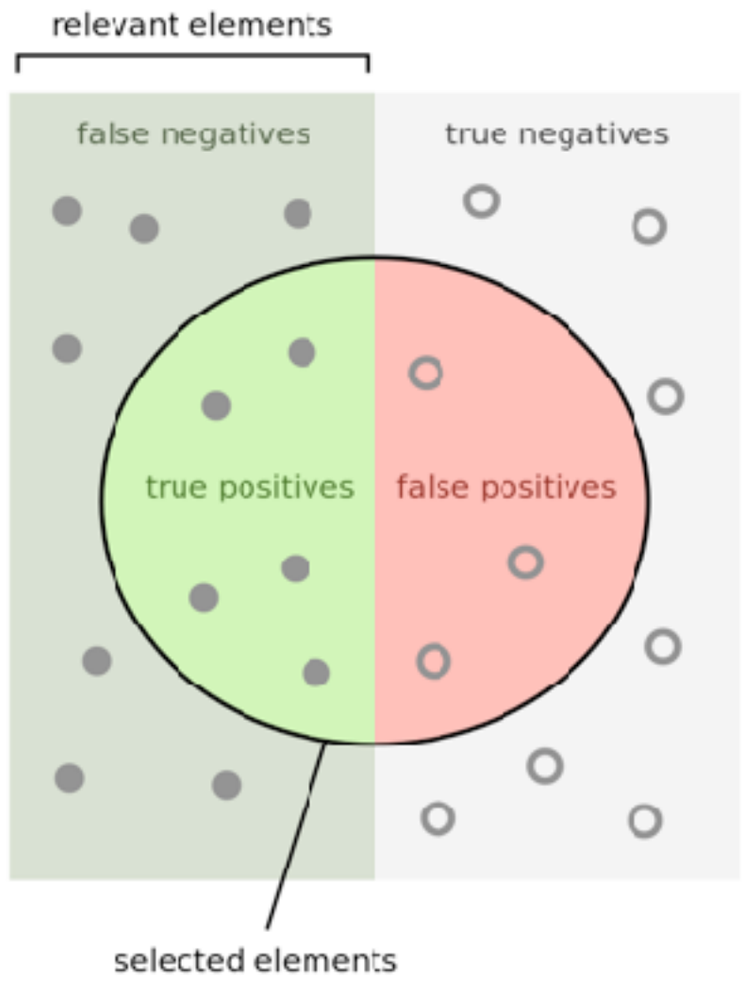
$$\textbf{Precision} = \frac{\text{True Positive}}{\text{True Positive + False Positive}}$$

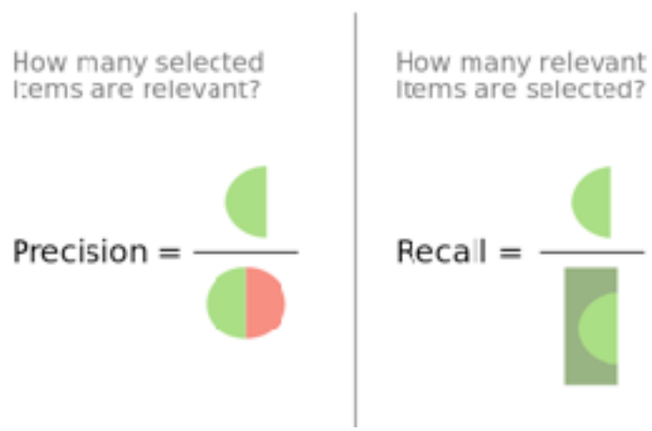
$$\textbf{Recall} = \frac{\text{True Positive}}{\text{True Positive + False Negative}}$$

Precision & Recall

Precision
The fraction (probability) of predictions that are ***relevant***

Recall
The fraction (probability) of relevant instances that are ***predicted***





Walber, 2014

Cohen's Kappa (κ)

- Traditionally used for inter-rater reliability
- We will use it to look at the reliability between the data and our model

$$\kappa = \frac{p_o - p_e}{1 - p_e}$$

Observed Agreement

Expected Agreement

(hypothetical probability of chance agreement)

		Model		
		Yes	No	
Data	Yes	4	2	6
	No	3	3	6
		7	5	12

$p_o = (4 + 3)/12 = 0.58$

$p_e = (7/12) \times (6/12) + (5/12) \times (6/12) = 0.5$

$\kappa = (0.58 - 0.5)/(1 - 0.5) = 0.16$

Is this good? Depends on the context

Gotchas with Kappa

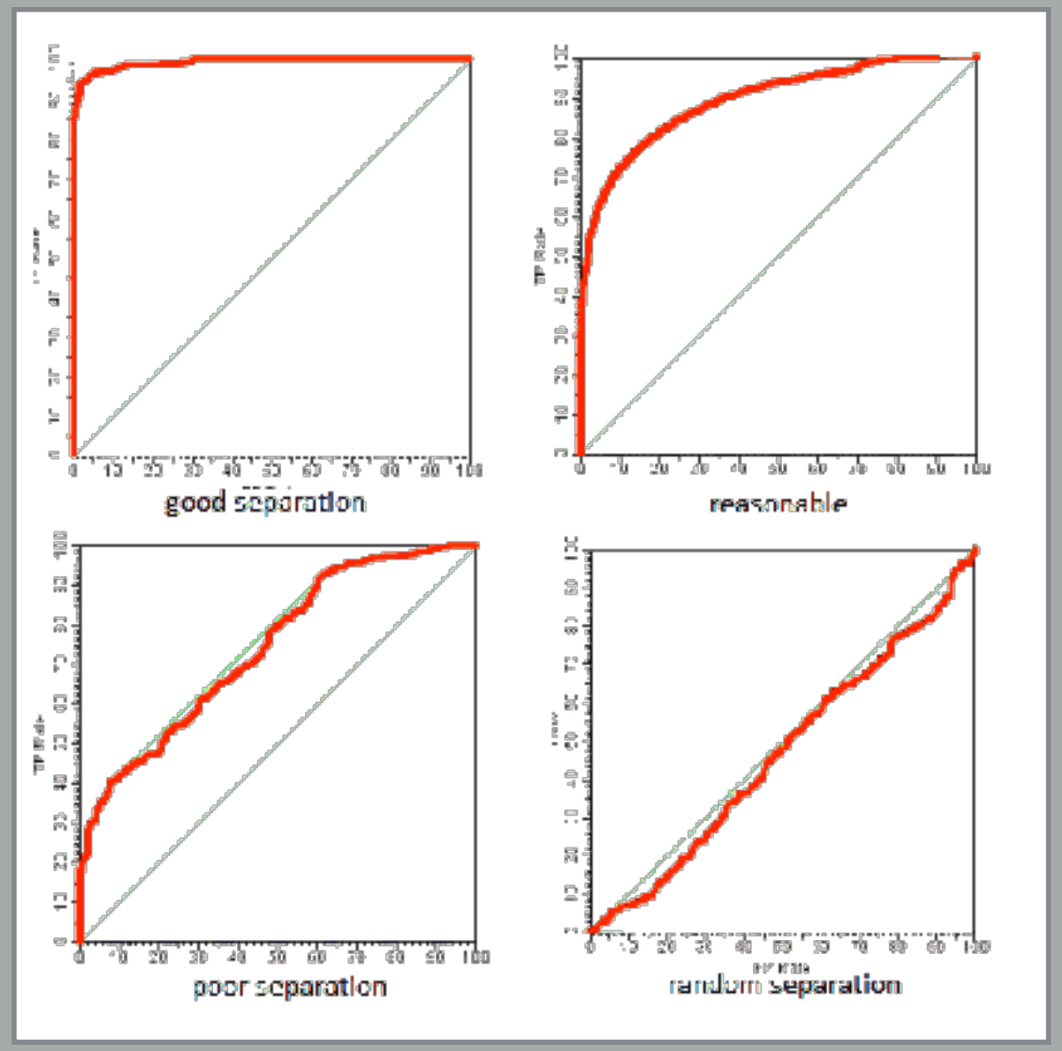
- Again, rare categories pose a problem and will incur a higher penalty than common categories
- Does the marginal probability represent “chance”?

Probabilities

- Model assigns a probability of belonging to a class, rather than a class directly
- Then choose a probability threshold to assign to a class
- Allows us to choose a preference based on the consequences of false positives/negatives
- http://www.navan.name/roc/

Receiver Operating Characteristic (ROC)

- Relationship between the false positive and the true positive rates
- World War II for detecting enemy objects on radar in response to Pearl Harbor
- Demonstrates the sensitivity vs specificity tradeoff



Receiver Operating Characteristic (ROC)

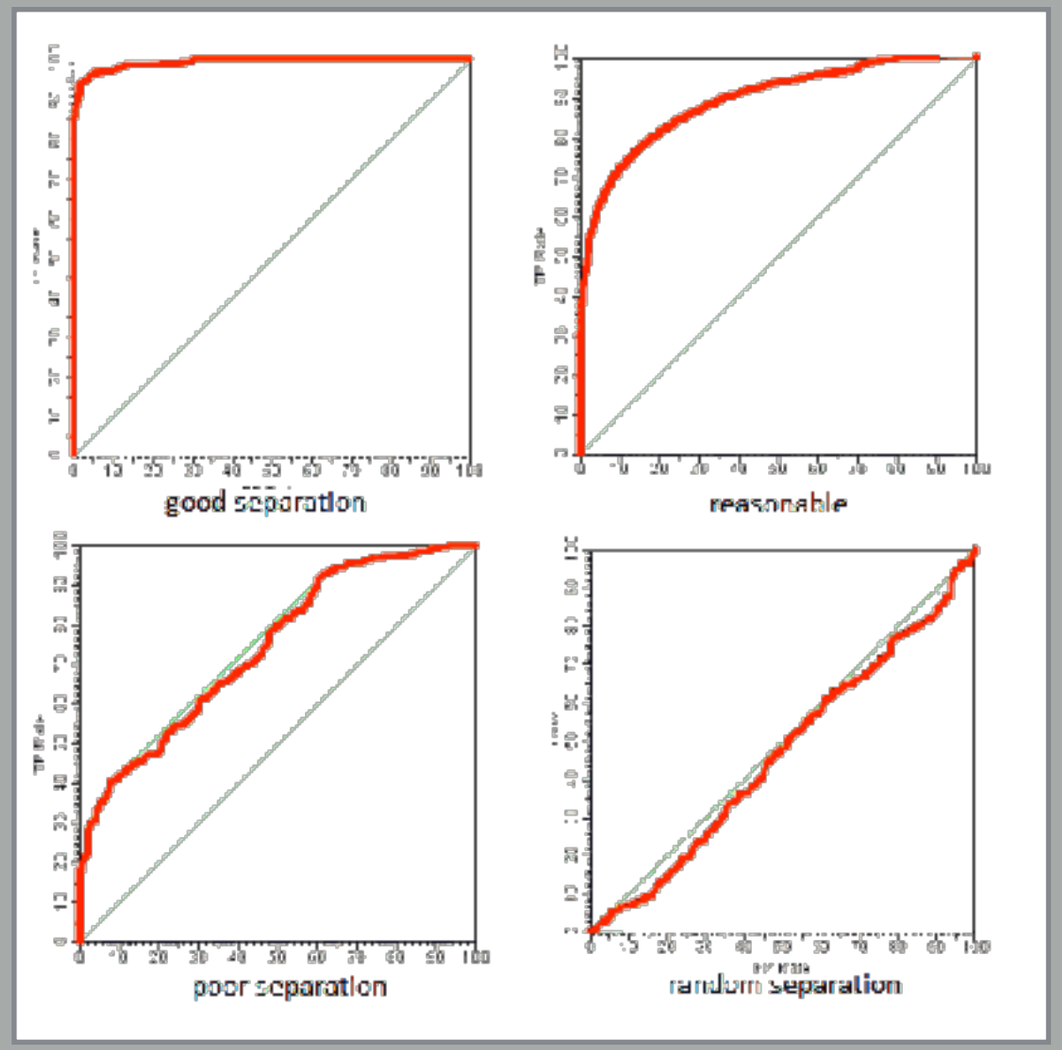
<u>Area Under the ROC Curve:</u>

- AUC is the collapsed metric to compare models

- AUC is the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one

- It is equivalent to the Wilcoxon Sum-Rank Test and can therefore generate a probability test

- Is sometimes called A' (A Prime) depending on how it is calculated



Diagnostics for Regressors

Mean Absolute Error

- Mean of observed values minus predicted values

MAE = $\frac{\sum|x - \overline{x}|}{n}$

Root Mean Squared Error

- Square root of the observed values minus predicted values squared

RMSE = $\sqrt{\frac{\sum_{i=1}^{n}(p_i - a_i)^2}{n}}$

Pearson's Correlation

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

- Measure of the linear dependence between two variables
- Covariance between two variables divided by the product of the standard deviation of those variables
- Development began ~ 1880s by Galton and then Pearson
- Gotcha: must be a linear relationship

Denis Boigelot, 2011

r^2

- The proportion of the variance in the dependent variable that is predicted from the independent variable
- There are several ways to calculate R^2
- If it involves two variables it is the square of the correlation (OLS classes will go more in depth)

Akaike Information Criterion (AIC)

AIC = number of parameters - goodness of fit

- Developed by Akaike in 1971 based on thermodynamics
- Relative estimate of the information lost when a given model is used to represent the process that generates the data
- Model with lowest AIC “wins”
- Represents the trade off between goodness-of-fit with model complexity
- It compares models, cannot give an estimate of model fit in an absolute sense
- Gatcha: Software implementation was not always reliable

Bayesian Information Criterion (BIC)

BIC = number of parameters x sample size - goodness of fit

- Developed by Schwarz in 1978
- Uses Bayes Theorem to penalize the addition of parameters
- Penalty for adding parameters is great than in AIC
- Represents the trade off between goodness-of-fit with model complexity
- Lowest BIC “wins”
- Gotcha: Does poorly when dealing with many parameters