

#### The Problem of Classification

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#### Classification

- Predicting group membership
- Simplest version: binary dependent variable
- Can also be used for ordinal data (ranked, but nonnumeric)
- Can also be used for categorical data (any of a large number of discrete groups)

#### Conditional Mean as a Classifier

- We can continue to use conditional means as a classifier.
- It gives surprisingly good answers.
- But the curse of dimensionality is always with us.

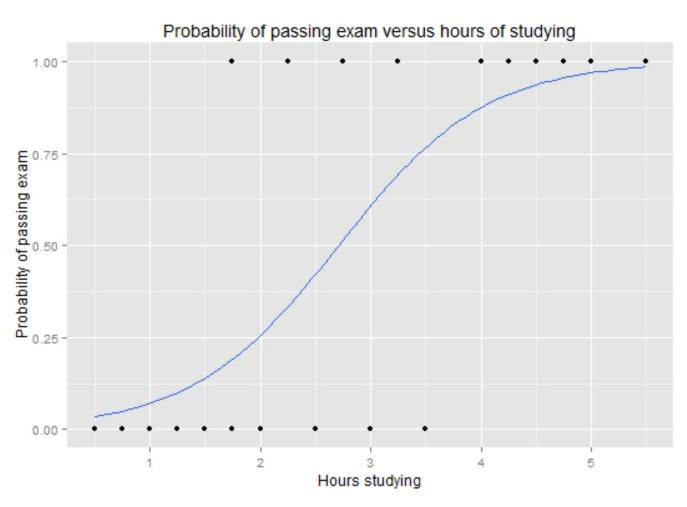
#### Linear Regression as a Classifier

- Linear regression can be used as a classifier for binary group membership.
- It is known as a "linear probability model."
- Real-world performance is often quite good.
- It can generate probabilities lower than 0, greater than 1 (not good).
- Performance is poor when there are a lot of respondents in one group or another (Pr (y = 1) < .05, Pr (y = 1) > .95)

### Logistic Regression as a Classifier

- One of a family of generalized linear models
- Uses maximum likelihood estimation (doesn't directly compute estimates, but chooses estimates which maximize probability of data)
- Parameter estimates can't be directly interpreted on a probability scale

# Visualizing Logistic Curve



Source: https://upload.wikimedia.org/wikipedia/commons/6/6d/Exam\_pass\_logistic\_curve.jpeg





## **Evaluating Classifiers**

Sensitivity and Specificity

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## **Evaluating Classifiers**

- A good classifier will accurately predict group membership.
- There are well-known trade-offs in creating classifiers.
- Some classifiers are very good at predicting group membership. This is called having high sensitivity.
- Some classifiers are very good predicting when someone is **not** in a group. This is called having high specificity.

# Example: Purchasing a Product

| Actual outcome:<br>Purchased | Actual outcome:<br>Did not purchase |
|------------------------------|-------------------------------------|
| 25                           | 75                                  |

# Example: Purchasing a Product Classifier Is Sensitive but Not Specific

|                                     | Actual outcome:<br>Purchased | Actual outcome:<br>Did not purchase |
|-------------------------------------|------------------------------|-------------------------------------|
| Predicted outcome:<br>Purchased     | 25                           | 75                                  |
| Predicted outcome: Did not purchase | 0                            | 0                                   |

# Example: Purchasing a Product Classifier Is Specific but Not Sensitive

|                                     | Actual outcome:<br>Purchased | Actual outcome:<br>Did not purchase |
|-------------------------------------|------------------------------|-------------------------------------|
| Predicted outcome:<br>Purchased     | 0                            | 0                                   |
| Predicted outcome: Did not purchase | 25                           | 75                                  |

## Sensitivity and Specificity

- A good classifier will be both sensitive and specific.
- But it's not easy.
- We can vary the model of course.
- We can also vary the classification threshold from 0 to 1.

#### Receiver Operator Characteristic Curve

- Calculates sensitivity and 1—specificity over a range of classification thresholds.
- Thresholds go from 0–1.
- The measure of AUC (area under curve) measures how well the model classifies at every threshold.
- A perfect classifier will have an AUC of 1 (never actually happens).
- A random classifier will have an AUC of .5.

### ROC and AUC

