

# Annotation and Evaluation

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COLLEGE OF  
INFORMATION  
STUDIES

- Solutions posted
- Most missed question: “One coin in a collection of 9 has two heads. The rest are fair. If a coin, chosen at random from the lot and then tossed, turns up heads 3 times in a row, what is the probability that it is the two-headed coin?”

# Exam

- Solutions posted
- Most missed question: “One coin in a collection of 9 has two heads. The rest are fair. If a coin, chosen at random from the lot and then tossed, turns up heads 3 times in a row, what is the probability that it is the two-headed coin?”

## Solution

Let  $A$  be the event that the two-headed coin was selected. Let  $B$  be the event that three heads were observed.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} = \frac{1 \cdot 1/9}{1/9 + 8/9 \cdot (1/2)^3} = \frac{1/9}{2/9} = 1/2 \quad (1)$$

## Homework 2

- Some very imaginative
- Too open ended answers: more next time
- Need to be very careful about what data you collect features from and which dataset you report on!

# Free-response Questions

- SVM
  - ▶ Diagonal line does better than axis-aligned
  - ▶ Most who attempted it did fine
- Suicide
  - ▶ Not enough training data
  - ▶ Baseline: always say no
- Decision Tree
  - ▶ Wrong base
  - ▶ Math errors

## Rest of this course

- Less time with me lecturing
- Use the class time to connect with your project teammates to work on project
- But don't forget about HW3

1 **Annotation**

2 Agreement

3 Evaluation

# Where do labeled data come from?

- For supervised classification, we've assumed that our data are already available
- Not always the case
- This comes from **annotation**



# Examples of annotation

- Whether an e-mail is spam or not
- Whether a document is relevant to a court case (e-Discovery)
- Which meaning the noun “break” has
  - ▶ A time where you're not working
  - ▶ A stroke of luck
  - ▶ A fracture or other discontinuity
  - ▶ A change in how things are done
- Whether an image has a van or not

# Why do we annotate?

We manually annotate texts for several reasons

- to understand the nature of text (e.g., what % of sentences in news articles are opinions?)
- to establish the level of human performance (e.g., how well can people assign POS tags?)
- to evaluate a computer model for some phenomenon (e.g., how often does my tagger or parser find the correct answer?)

# The process of annotation

- Develop a set of annotations
- Define each of the annotations
- Have annotations annotate the **same** data
- See if they agree (more on this later)
  - ▶ If not, go back to Step 1
  - ▶ Why not?
    - ★ Bad annotators?
    - ★ Bad definitions?
    - ★ Unexpected data?

# Who does the annotation?

- Undergrads
- Grad students
- Crowdsourcing
  - ▶ Scammers
  - ▶ Diverse population
    - ★ Worldwide
    - ★ Bored office workers
    - ★ Individuals at home
  - ▶ Equity issues
- Users
  - ▶ Reviews
  - ▶ Blog categories
  - ▶ Metadata
  - ▶ Often noisy

# Why is it important to have agreement?

- Think about what happens to a classifier if it has inconsistent data (same data, different annotations)

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- Think about what happens to a classifier if it has inconsistent data (same data, different annotations)
  - ▶ For an SVM: there's separating hyperplane
  - ▶ For a decision tree: decreases information gain of all the features
- Your classifier is only as good as the data it gets
- If your annotators only agree on 40% of the data, your accuracy will be less than 40%
- Common problem: disagreement is undetected because each item is only annotated once
- Resulting complaint: machine learning sucks

# Annotation Tools

- WordFreak (for text)
- LabelMe (for images)
- OpenAnnotation (an XML framework)
- Bamboo (visualization and annotation for humanists)

# Outline

1 Annotation

**2 Agreement**

3 Evaluation



# What does agreement mean?

- Simple answer: how often do two annotators give the same answer
- More complicated: above, **adjusting for chance agreement**
- Most important for class-imbalanced data

# Computing Agreement

$$\kappa = \frac{P_a - P_c}{1 - P_c} \quad (2)$$

- $P_a$ : Probability of coders agreeing
- $P_c$ : Probability of coders agreeing by chance

## Agreement example

Annotator A	Annotator B		
	Y	N	
Y	20	5	25
N	10	15	25
	30	20	

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$$P_a = \frac{15+20}{50} = 0.7$$

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### Chance agreement

- A says yes with probability .5
- B says yes with probability .6
- The probability that both of them say yes (assuming independence) is .3; the probability both say no is .2. The probability of chance agreement is then  $P_c = 0.2 + 0.3$ .

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Agreement:

$$\kappa = \frac{.7 - .5}{1 - .5} = .4 \quad (3)$$

Typically, you want above 0.7 agreement.

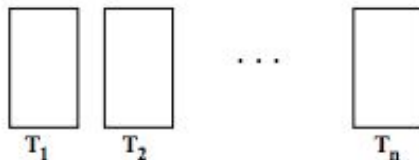
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# Cross Validation



- Split your data into  $N$  folds
- For each fold:
  - ▶ Train your data on all the **other** folds
  - ▶ Compute accuracy/precision/recall on this fold
- Average over all folds
- Uses all available data

# Intrinsic vs. Extrinsic Evaluation

- We've focused on **intrinsic** evaluation
  - ▶ Correctly predicting spoilers
  - ▶ Assigning words/documents to correct category
  - ▶ Detecting whether an image has a cow in it
- More realistic: **extrinsic** evaluation
  - ▶ Number of spoilers seen by social media user
  - ▶ Number of relevant documents returned by IR system
  - ▶ Throughput of automatic cow milking system
- Bottom line: extrinsic evaluations are harder, but they're more often the thing you care about.

# Convincing Results

- Give baseline performance
  - ▶ Most frequent class
  - ▶ Random guessing
  - ▶ Current “best practice”
- Give qualitative results
  - ▶ Examples that were right / wrong
  - ▶ Error analysis
  - ▶ Tell a story
- Give “blue sky” bounds
  - ▶ Oracle results for pipeline systems
  - ▶ Human ability

# Takeaways

- Effective data science depends not just on algorithms, but also having good data
- Agreement measures the quality of the inputs into algorithms
- Effective evaluation is important for communicating your results