CS 2731
Introduction to Natural Language Processing

Session 6: Classifier evaluation

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Course logistics

- Homework 1 **due this Thu Sep 19**
  - Feel free to ask questions in the Canvas discussion forum, email Jayden or Michael
- Project idea submission form **due this Fri Sep 20 (pushed back)**
  - All students must submit one idea for credit
  - You can submit one of the example project ideas from the website
  - Ideas do not need to be fully developed

Lecture overview: classifier evaluation

- Overview of CRC resources, including using GPU (Jayden)
  - Jupyter OnDemand manual: https://crc-pages.pitt.edu/user-manual/web-portals/jupyter-ondemand/
  - Resources on the gpu cluster are described here, https://crc.pitt.edu/resources/computing-hardware
- Precision, recall, f1-score
- Train/dev/test and cross-validation sets
- Statistical significance testing between models
- Harms in classification
- Coding activity
  - Clickbait classification with Naive Bayes

CRC

FOR DUMMIES®

A Reference for the Rest of Us!®

First: Know what you need!

- Training a bigram model? CR-SEE ya!
- Training a sentiment classifier? Yah, a 1080 would do you well.
- Training a 7b+ parameter language model: an a100 is your friend
- Training GPT5? Please save some GPU for the rest of us.

Disclaimer: if these words are not familiar, that’s okay! That’s what this class is for.

CRC Basics

- CRC is served on a queue- you may have to wait!
- The more resources you request, the more likely you’ll have to wait.
  - See previous slide!!!
- You have to request a certain amount of time. Request enough such that you can train what you need to train. Don’t request too much because I want some time too.
- **DO NOT DO NOT** run **any** jobs on login nodes (ie: the node you connect to in the next step)
  - Simple tasks like what we will do are fine

Setting up Conda

1. SSH into **h2p.crc.pitt.edu**

```
> ssh jas644@h2p.crc.pitt.edu
```

1. Create a conda environment for this class

```
> conda create -n nlp python==3.10
```

1. Install necessary packages

```
> conda install jupyterlab pytorch torchvision torchaudio 
pytorch-cuda=11.8 -c pytorch -c nvidia
```

Setting up your Jupyter Server

1. Open **ondemand.htc.crc.pitt.edu**
2. Select Apps > All Apps > Jupyter on GPU
   a. DO NOT SELECT JUPYTER FROM THE DROPDOWN, IT WILL NOT HAVE GPU SUPPORT
3. Python version: “Custom conda environment”
4. Conda environment location:

   /ihome/cs2731_2024f/jas644/.conda/envs/nlp

1. Cuda version: 11.8
2. For GPU settings, please reference the second slide on what you need. In general, try to only use 1 GPU. Using multiple GPUs is a bit hard.
   a. If you need more VRAM you can request an 80gb a100 by selecting **a100_nvlink** and changing the constraint, otherwise you can just select a100 or gtx1080, whichever is necessary.

Connecting

- At any point in time, you can connect to your instance by navigating to the same link as before and clicking “My Interactive Sessions”
- A button will appear by the job you started that allows you to connect to the jupyter server you’ve launched.

How to evaluate your classifier

Gold labels and predicted labels

Document	gold label	predicted label
just plain boring	–	–
entirely predictable	–	–
no surprises and very few laughs	–	+
very powerful	+	–
the most fun film of the summer	+	+

The **gold** label is the label that a human assigned to the document.

The **predicted** or **hypothesized** label is the label that the classifier assigned to the document.

Slide credit: David Mortensen

We Can Evaluate a Classifier Using Accuracy

Accuracy is our first shot.

- Accuracy:

$$\mathrm{A}(\texttt{classify}) = \sum_{\substack{\boldsymbol{d} \in \mathcal{V}^+, \ell \in \mathcal{L}, \\ \texttt{classify}(\boldsymbol{d}) = \ell}} p(\boldsymbol{x}, \ell) \tag{1}$$

  where p is the true distribution over data.
- Error is $1 - A$.
- Accuracy is estimated using a test set $\{(\bar{\boldsymbol{d}}_1, \bar{\ell}_1), (\bar{\boldsymbol{d}}_2, \bar{\ell}_2), \cdots, (\bar{\boldsymbol{d}}_m, \bar{\ell}_m)\}$

$$\hat{\mathrm{A}}(\texttt{classify}) = \frac{1}{m} \sum_{i=1}^{m} \{\texttt{classify}(\bar{\boldsymbol{d}}_i) = \bar{\ell}_i\} \tag{2}$$

Slide credit: David Mortensen

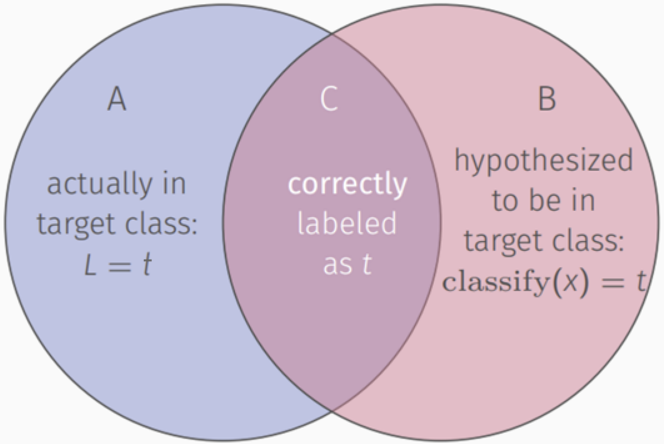
Issues with using test set accuracy

- Imagine an “important email” classifier that notifies you when you get an important email
- Suppose that 99% of the messages you receive are junk and not important (we’re being realistic here)
- An easy important email classifier: classify **nothing** as important
  - You would get lots of work done, because you wouldn’t be distracted by email
  - The email classifier would have an accuracy of ~99%
  - Everybody would be happy except for your boss
- You must take the relative importance of the classes into account, and the cost of the error types

Slide adapted from David Mortensen

Evaluation in the Two-class case

- Suppose we have one of the classes $t \in \mathcal{L}$ as the target class.
- We would like to identify documents with label t in the test data.
- We get

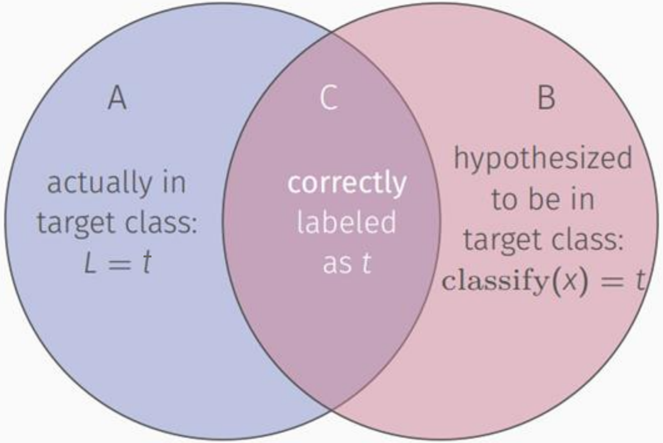


A
actually in target class: $L = t$
C
correctly labeled as t
B
hypothesized to be in target class: $\text{classify}(x) = t$

- Precision $\hat{P} = \frac{C}{B}$ (percentage of documents `classify` correctly labeled as t)
- Recall $\hat{R} = \frac{C}{A}$ (percentage of actual t labeled documents correctly labeled as t)
- $F_1 = 2\frac{\hat{P} \cdot \hat{R}}{\hat{P} + \hat{R}}$

Slide credit: David Mortensen

A Different View – Contingency Tables



A

actually in target class: $L = t$

C

correctly labeled as t

B

hypothesized to be in target class: $\mathrm{classify}(x) = t$

	$L = t$	$L \neq t$	
$\texttt{classify}(X) = t$	C (true positives)	$B \setminus C$ (false positives)	B
$\texttt{classify}(X) \neq t$	$A \setminus C$ (false negatives)	(true negatives)	
	A		

precision = tp/(tp+fp)

recall = tp/(tp+fn)

Slide credit: David Mortensen

Why precision and recall

○ 2-way precision and recall are specific to a target class

- Accuracy=99% on important email detection

  but

- Recall = 0 (out of all actually important emails, got none)
- Precision and recall, unlike accuracy, emphasize true positives: finding the things that we are supposed to be looking for

Slide adapted from Jurafksy & Martin

A combined measure: F

F measure: a single number that combines P and R:

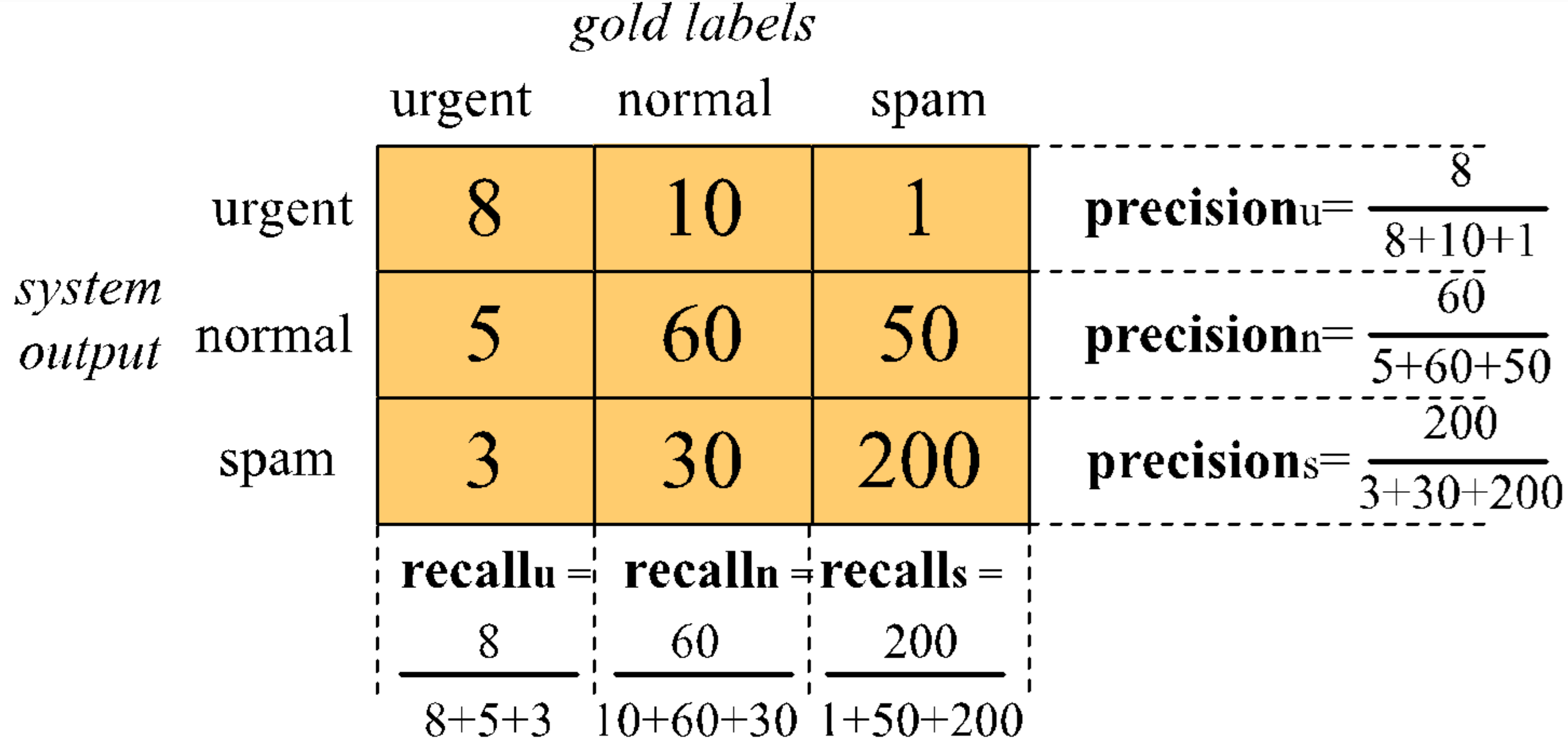
$$F_\beta = \frac{(\beta^2 + 1)PR}{\beta^2 P + R}$$

We almost always use balanced F_1 (i.e., β = 1)   . Harmonic mean

$$\mathrm{F}_1 = \frac{2PR}{P + R}$$

Slide adapted from Jurafksy & Martin

Confusion matrix for 3-class classification



		gold labels		
		urgent	normal	spam
system output	urgent	8	10	1
	normal	5	60	50
	spam	3	30	200

$$\textbf{precision}_{u} = \frac{8}{8+10+1}$$

$$\textbf{precision}_{n} = \frac{60}{5+60+50}$$

$$\textbf{precision}_{s} = \frac{200}{3+30+200}$$

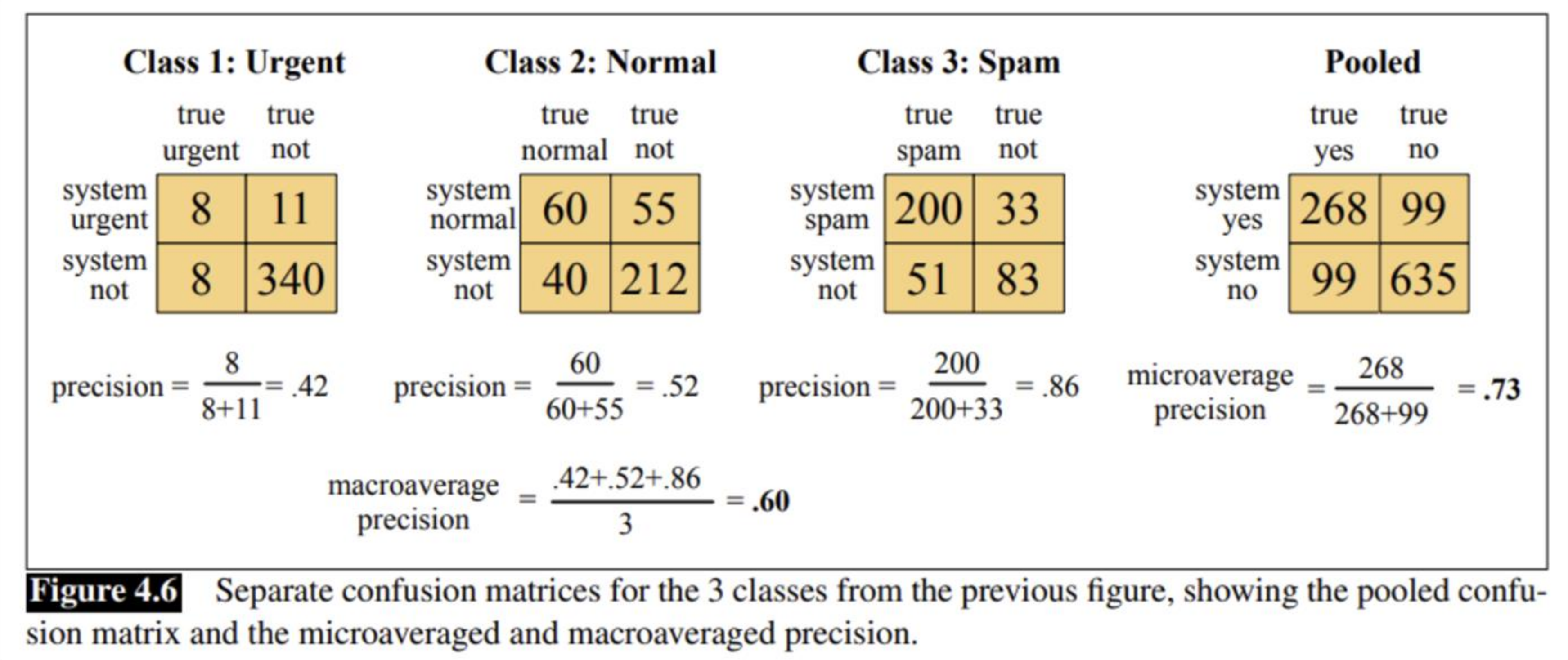
$$\textbf{recall}_{u} = \frac{8}{8+5+3} \qquad \textbf{recall}_{n} = \frac{60}{10+60+30} \qquad \textbf{recall}_{s} = \frac{200}{1+50+200}$$

Slide adapted from Jurafksy & Martin

Evaluation with > 2 Classes

- **Macroaveraged precision and recall**: let each class be the target and report the average $\hat{P}$ and $\hat{R}$ across all classes.
- **Microaveraged precision and recall**: pool all one-vs.-rest decisions into a single contingency table, calculate $\hat{P}$ and $\hat{R}$ from that.

Example of more than two classes



Class 1: Urgent

	true urgent	true not
system urgent	8	11
system not	8	340

$$\text{precision} = \frac{8}{8+11} = .42$$

Class 2: Normal

	true normal	true not
system normal	60	55
system not	40	212

$$\text{precision} = \frac{60}{60+55} = .52$$

Class 3: Spam

	true spam	true not
system spam	200	33
system not	51	83

$$\text{precision} = \frac{200}{200+33} = .86$$

Pooled

	true yes	true no
system yes	268	99
system no	99	635

$$\begin{array}{c}\text{microaverage}\\ \text{precision}\end{array} = \frac{268}{268+99} = \mathbf{.73}$$

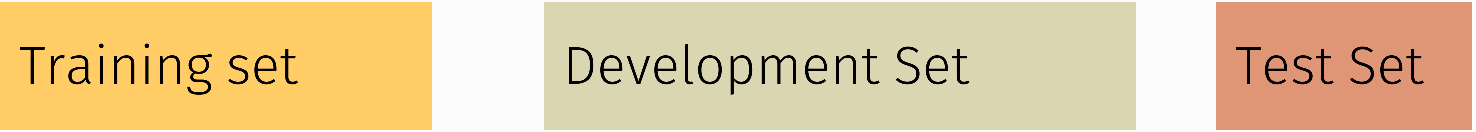
$$\begin{array}{c}\text{macroaverage}\\ \text{precision}\end{array} = \frac{.42+.52+.86}{3} = \mathbf{.60}$$

Figure 4.6 Separate confusion matrices for the 3 classes from the previous figure, showing the pooled confusion matrix and the microaveraged and macroaveraged precision.

Slide credit: David Mortensen, Jurafksy & Martin

Train/dev/test splits and cross-validation

Development Sets ("Devsets") and Cross-validation



Training set

Development Set

Test Set

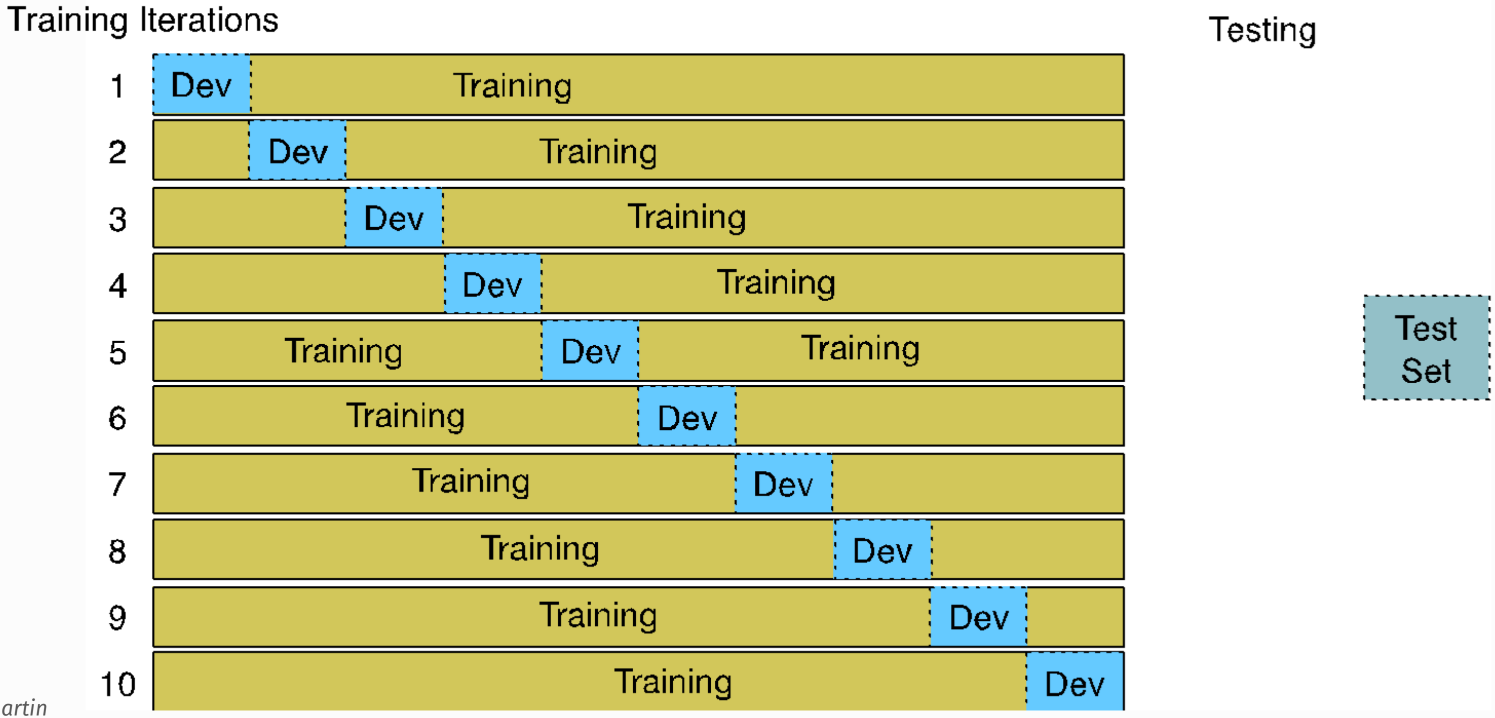
Train on training set, tune on dev set, report on test set

- **Do not look at test set**
- Using a dev set avoids overfitting (‘tuning to the test set’)
- More conservative estimate of performance
- But paradox: want as much data as possible for training, and as much for dev; how to split?

Slide adapted from Jurafksy & Martin

Cross-validation: multiple splits

- Pool results over splits, Compute pooled dev performance
- Good for when you don’t have much data (<10k instances rule of thumb)



Training Iterations

1 Dev Training

2 Dev Training

3 Dev Training

4 Dev Training

5 Training Dev Training

6 Training Dev

7 Training Dev

8 Training Dev

9 Training Dev

10 Training Dev

Testing

Test Set

Slide adapted from Jurafksy & Martin

Statistical significance testing among models

How do we know if one classifier is better than another?

Given:

- Classifier A and B
- Metric M: M(A, x) is the performance of A on test set x
- δ(x): the performance difference between A, B on x:
- δ(x) = M(A,x) – M(B,x)

We want to know if δ(x)>0, meaning A is better than B

- δ(x) is called the effect size
- Suppose we look and see that δ(x) is positive. Are we done?
- No! This might be just an accident of this one test set, or circumstance of the experiment. Instead…

Slide adapted from Jurafksy & Martin

Statistical Hypothesis Testing

Consider two hypotheses:

- Null hypothesis: A isn't better than B
- A is better than B

$$H_0 \ : \ \delta(x) \leq 0$$
$$H_1 \ : \ \delta(x) > 0$$

We want to rule out H_0

We create a random variable X ranging over test sets

And ask, how likely, if H_0 is true, is it that among these test sets we would see the δ(x) we did see?

- Formalized as the p-value:

$$P(\delta(X) \geq \delta(x) | H_0 \text{ is true})$$

Slide adapted from Jurafksy & Martin

Statistical Hypothesis Testing

$$P(\delta(X) \geq \delta(x) | H_0 \text{ is true})$$

- In our example, this p-value is the probability that we would see δ(*x*) assuming H_0 (=*A* is not better than *B).*
  - If H_0 is true but δ(*x*) is huge, that is surprising! Very low probability!
- A very small p-value means that the difference we observed is very unlikely under the null hypothesis, and we can reject the null hypothesis
  - Very small: .05 or .01
- A result (e.g., "*A* is better than *B*") is **statistically significant** if the δ we saw has a probability that is below the threshold and we therefore reject this null hypothesis.

Slide adapted from Jurafksy & Martin

Statistical Hypothesis Testing

How do we compute this probability?

- In NLP, we don't tend to use parametric tests (like t-tests)
- Instead, we use non-parametric tests based on sampling: artificially creating many versions of the setup.
- For example, suppose we had created zillions of test sets x' with an assumption that the null hypothesis is true
  - Now we measure the value of δ(x') on each test set
  - That gives us a distribution
  - Now set a threshold (say .01).
  - So if we see that in 99% of the test sets δ(x) > δ(x’)
    - We conclude that our original test set delta was a real delta and not an artifact.

Slide adapted from Jurafksy & Martin

Bootstrap test [Efron & Tibshirani 1993]

Can apply to any metric (accuracy, precision, recall, F1, etc).

Bootstrap means to repeatedly draw large numbers of smaller samples with replacement (called **bootstrap samples**) from an original larger sample.

See the textbook section 4.9 for further details (or ask me later!)

Slide adapted from Jurafksy & Martin

Harms in classification in NLP

Harms in sentiment classifiers

Kiritchenko and Mohammad (2018) found that most sentiment classifiers assign lower sentiment and more negative emotion to sentences with African American names in them.

This perpetuates negative stereotypes that associate African Americans with negative emotions

Slide adapted from Jurafksy & Martin

Harms in toxicity classification

Toxicity detection is the task of detecting hate speech, abuse, harassment, or other kinds of toxic language

But some toxicity classifiers incorrectly flag as being toxic sentences that are non-toxic but simply mention identities like blind people, women, or gay people.

This could lead to censorship of discussion about these groups.

Slide adapted from Jurafksy & Martin

What causes these harms?

Can be caused by:

- Problems in the training data; machine learning systems are known to amplify the biases in their training data.
- Problems in the human labels
- Problems in the resources used (like lexicons)
- Problems in model architecture (like what the model is trained to optimized)

Mitigation of these harms is an open research area

Can’t fully “remove” bias because exists in societies that produced texts we use

So need to be explicit about what those biases may be through **data statements** and **model cards**

Slide adapted from Jurafksy & Martin

Data statements [Bender & Friedman 2018]

For each dataset you release, document:

- Curation rationale: why were certain texts selected
- Language variety
- Speaker demographic
- Annotator demographic
- Speech situation
  - Time and place, modality, scripted vs spontaneous, intended audience
- Text characteristics
  - Genre, topic
- Recording quality (for speech)

Slide adapted from Jurafksy & Martin

Model cards [Mitchell et al. 2019]

For each algorithm you release, document:

- training algorithms and parameters
- training data sources, motivation, and preprocessing
- evaluation data sources, motivation, and preprocessing
- intended use and users
- model performance across different demographic or other groups and environmental situations

Discussion

In an area of research or industry you are familiar with (in CS or outside CS), do you see issues with transparency of data and/or models?

Is it clear under what circumstances datasets were collected? Are the intended uses of machine learning models clearly stated?

Questions?

Homework 1 due this Thu Sep 19