# Annotations, Evaluation, and Generalization

CS 485, Fall 2023
Applications of Natural Language Processing <a href="https://people.cs.umass.edu/~brenocon/cs485\_f23/">https://people.cs.umass.edu/~brenocon/cs485\_f23/</a>

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- Annotations
  - Chance-adjusted calculation
  - Practical ethics example in ChatGPT
- Evaluation
  - Held-out data and overfitting
  - Classification metrics
  - Statistical testing (J&M 4.9) hold off until later in course

## Cohen's Kappa for IAA

- If some classes predominate, raw agreement rate may be misleading
- Idea: normalize accuracy (agreement) rate such that answering randomly = 0.
  - From psychology / psychometrics / content analysis
- Chance-adjusted agreement:

po: observed agreement rate

pe: expected (by chance) rate

Other chanced-adjusted metrics: Fleiss, Krippendorff... see reading

## When is annotating ethical?

### Human labeling is key to ChatGPT

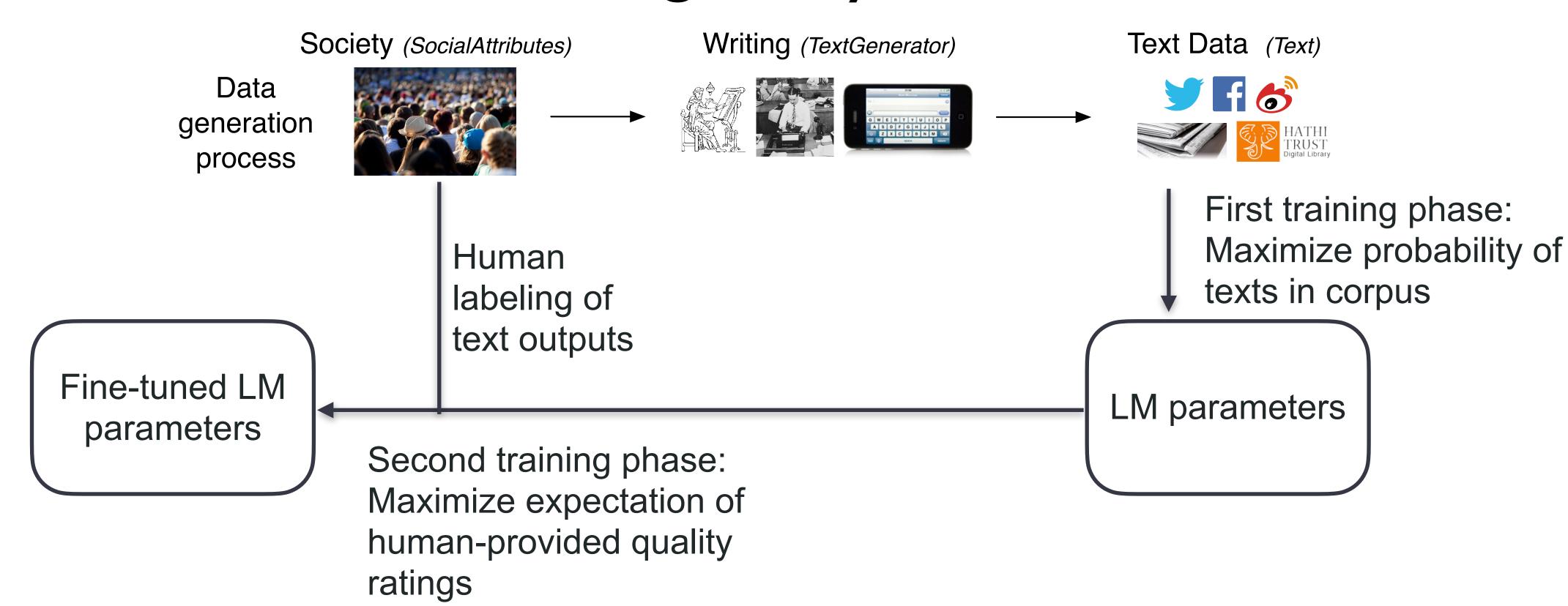
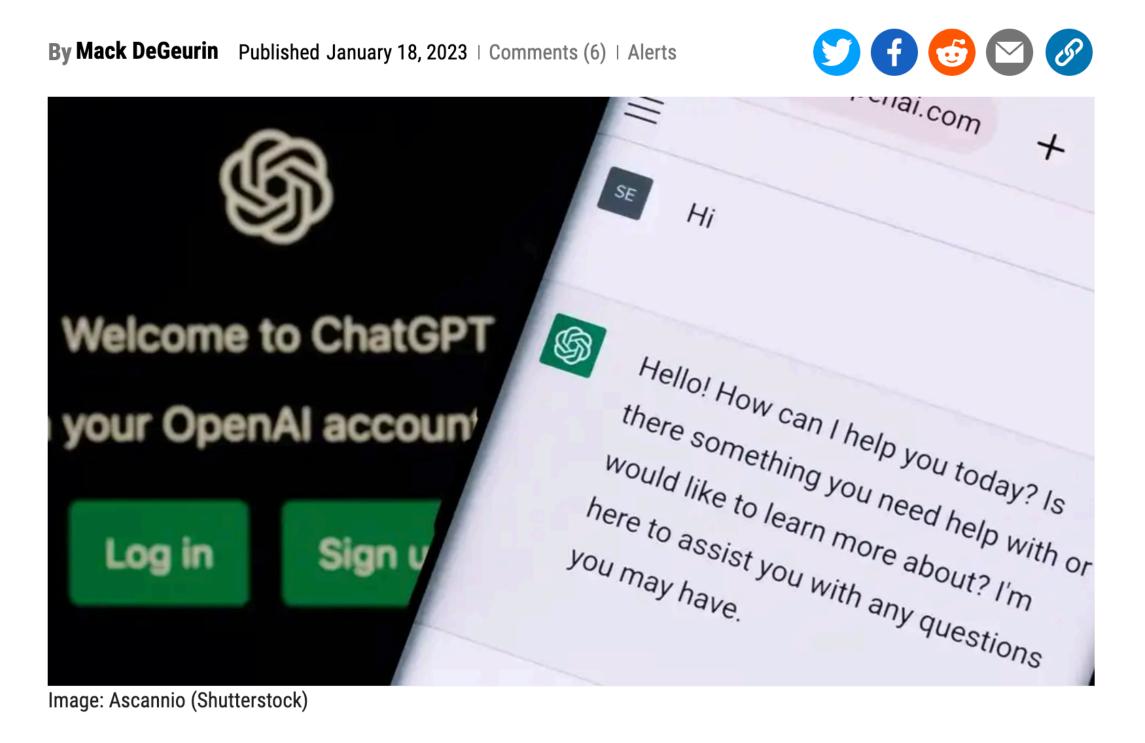


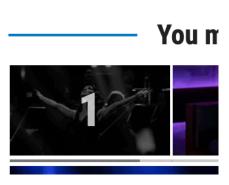
Table 3: Labeler-collected metadata on the API distribution.

Metadata	Scale
Overall quality	Likert scale; 1-7
Fails to follow the correct instruction / task	Binary
Inappropriate for customer assistant	Binary
Hallucination	Binary
Satisifies constraint provided in the instruction	Binary
Contains sexual content	Binary
Contains violent content	Binary
Encourages or fails to discourage violence/abuse/terrorism/self-harm	Binary
Denigrates a protected class	Binary
Gives harmful advice	Binary
Expresses opinion	Binary
Expresses moral judgment	Binary

#### 'That Was Torture;' OpenAl Reportedly Relied on Low-Paid Kenyan Laborers to Sift Through Horrific Content to Make ChatGPT Palatable

The laborers reportedly looked through graphic accounts of child sexual abuse, murder, torture, suicide, and, incest.





#### Held-out data for evaluation

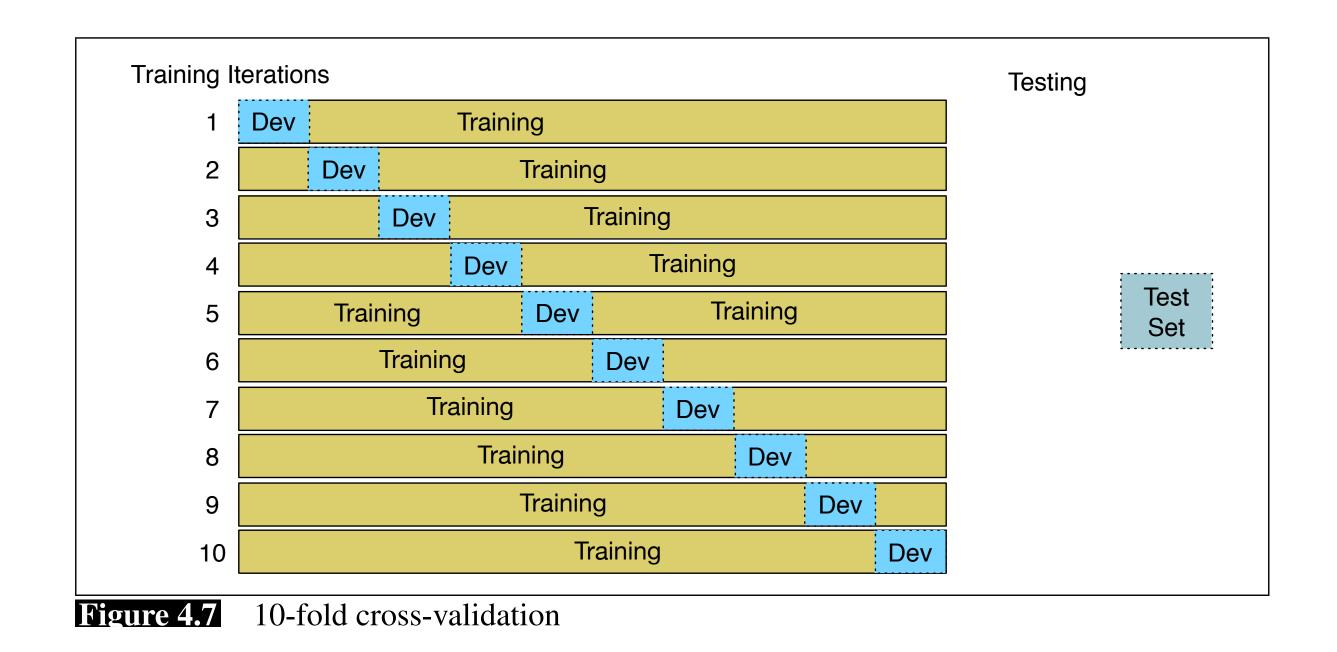
- How well will my classifier work in the future?
  - Can we look at classifier accuracy on training data?

#### Held-out data for evaluation

- Need to diagnose how much your model is overfitting the training set
- Data splits are key. Some ways to split:
  - Training set -vs- test set
  - Training set -vs- "validation"/"development" set -vs- test set
  - Cross-validation (within training set) -vs- test set

#### Cross-validation

• Cross-validation (within training set) -vs- test set



## Regularization in Naive Bayes

## Regularization in logistic regression

- If "dog" only occurs for class **k**, what weight will it get?
- Consider MLE training:

• Solution: regularized training for logistic regression

## Regularization tradeoffs

No regularization
 Very strong regularization

## Do I have enough labels?

- For training, hundreds to thousands of annotations may be needed for reasonable performance
  - Current work: how to usefully make NLP models with <10 or <100 training examples. "Few-shot learning"
- Exact amounts are difficult to know in advance. Can do a learning curve to estimate if more annotations will be useful.

#### Evaluation metrics

Accuracy =

gold standard labels							
		gold positive	gold negative				
system output	system positive	true positive	false positive	$\mathbf{precision} = \frac{tp}{tp+fp}$			
labels	system negative	false negative					
		$\mathbf{recall} = \frac{\mathbf{tp}}{\mathbf{tp} + \mathbf{fn}}$		$accuracy = \frac{tp+tn}{tp+fp+tn+fn}$			

Figure 4.4 A confusion matrix for visualizing how well a binary classification system performs against gold standard labels.

- But do we care about false positives and negatives equally?
- What about rare classes?

## Precision, recall, F1

gold standard labels							
		gold positive	gold negative				
output posit	system positive	true positive	false positive	$\mathbf{precision} = \frac{\mathrm{tp}}{\mathrm{tp+fp}}$			
	system negative	false negative	true negative				
		$recall = \frac{tp}{tp+fn}$		$accuracy = \frac{tp+tn}{tp+fp+tn+fn}$			

Figure 4.4 A confusion matrix for visualizing how well a binary classification system performs against gold standard labels.

• macro vs. micro F1