

# CS388: Natural Language Processing

## Lecture 9: Annotation + Dataset Bias

Greg Durrett



## Administrivia

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- ▶ OPTIONAL LECTURE; normal lectures resume on Thursday
- ▶ Mini 2 due March 2
- ▶ +3 slip days
- ▶ Rest of the course pushed back



## This Lecture

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- ▶ Annotation practices + examples
- ▶ Datasheets for datasets
- ▶ Annotation artifacts, evolving datasets



## Annotation

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- ▶ A **critical** part of the ML pipeline
- ▶ Powerful models like neural networks (and BERT specifically) can learn patterns in the data — we need the right datasets to teach them the right patterns!
- ▶ **How do we build a good dataset?**

## Annotation Practices

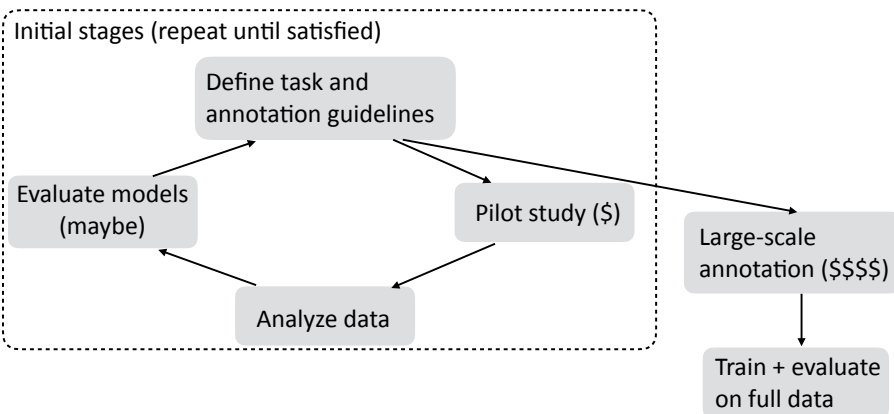


## Annotating a Dataset

- ▶ Who's involved?
  - ▶ Researchers: you!
  - ▶ Annotators: typically people you hire, might be workers on platforms like Amazon Mechanical Turk
  - ▶ Stakeholders: whose data are you annotating / who will be impacted by the system?



## Annotation Lifecycle



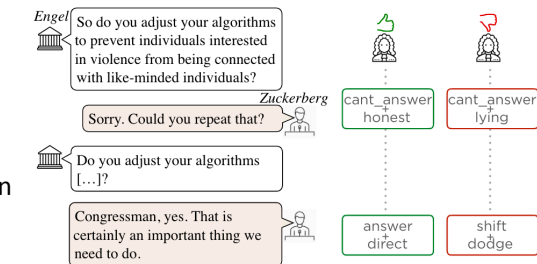
## Defining the Task

- ▶ What is the goal of the annotation?
- ▶ How can you explain the task to annotators?
  - ▶ If using non-experts, how can linguistic tasks be communicated?



## Example: Discourse Acts

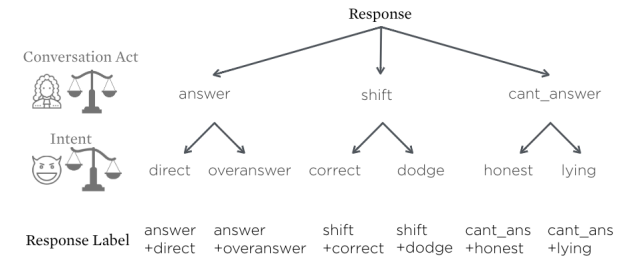
- Annotate *perceived conversational intents* in Congressional hearings
- Annotators: workers on MTurk
- Stakeholders: researchers on discourse, social scientists
- Key focus: natural disagreement between the annotators based on their views of the speakers



Elisa Ferracane, Greg Durrett, Junyi Jessy Li, Katrin Erk. In submission



## Example: Discourse Acts



- Other labels are possible (stalling), or more complex linguistic notions, but annotators then struggled to apply these consistently
- It is not easy to come up with the correct taxonomy here!

Elisa Ferracane, Greg Durrett, Junyi Jessy Li, Katrin Erk. In submission



## Defining the Task

- What is the goal of the annotation?
- How can you explain the task to annotators?
  - If using non-experts, how can linguistic tasks be communicated?
- How to make the task more engaging for annotators? Asking them to do something creative or a "challenge" is best!



## Example: Regex Descriptions

Lines starting with a capital letter not containing the string "dog"

seq2seq model

`concat(<cap>, .*) & ~contain("dog")`

- Goal: collect pairs of (English description, regex code)
- Annotators: MTurk; Stakeholders: people who use regexes who need a system to generate them
- How to get such pairs from non-programmers? How to ensure these pairs are realistic?

Xi Ye, Qiaochu Chen, Isil Dillig, Greg Durrett. ACL 2020



## Example: Regex Descriptions

The input will be in the form a **colon (:) separated tuple of three values**. The **first value** will be an integer (potentially a long in terms of size/length), with **the other two values** being either numeric or a string.

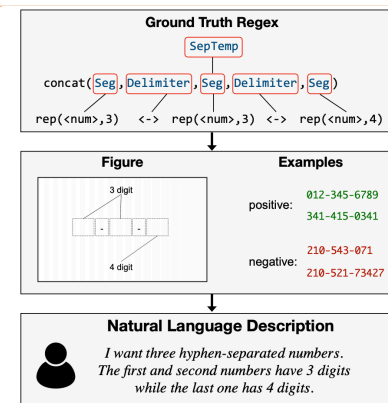
- ▶ Realistic examples contain **referring expressions**, new **abstract constructs**
- ▶ How to get complex, realistic examples like this and not simple examples? If you ask people to write down a random regex task, they will come up with something simple
- ▶ We need to structure this task appropriately!

Xi Ye, Qiaochu Chen, Isil Dillig, Greg Durrett. ACL 2020



## Example: Regex Descriptions

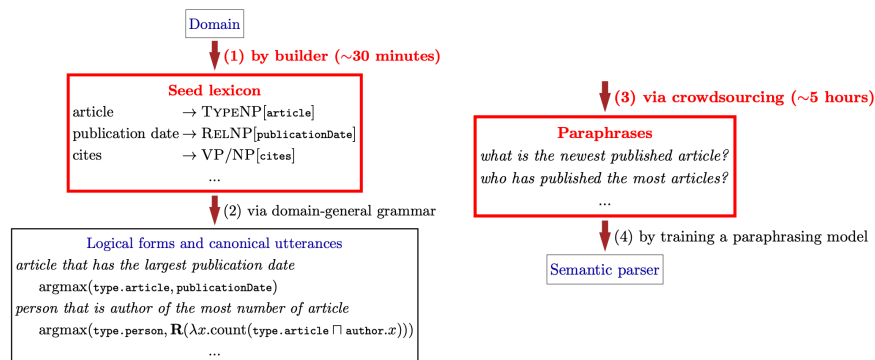
- ▶ Generate the ground-truth regex **first**, draw it as a figure, get people to describe it
- ▶ Annotators enjoyed this task (they emailed us!) and came up with creative descriptions



Xi Ye, Qiaochu Chen, Isil Dillig, Greg Durrett. ACL 2020



## Data Collection “Overnight”



Yushi Wang et al. (2015)



## Pilot Studies

- ▶ Usually start with a small group of experts (e.g., the researchers and their colleagues/friends) and scale out to a group of non-experts
- ▶ Aim: collect enough data to assess annotator agreement and to tell what pitfalls might exist in the data

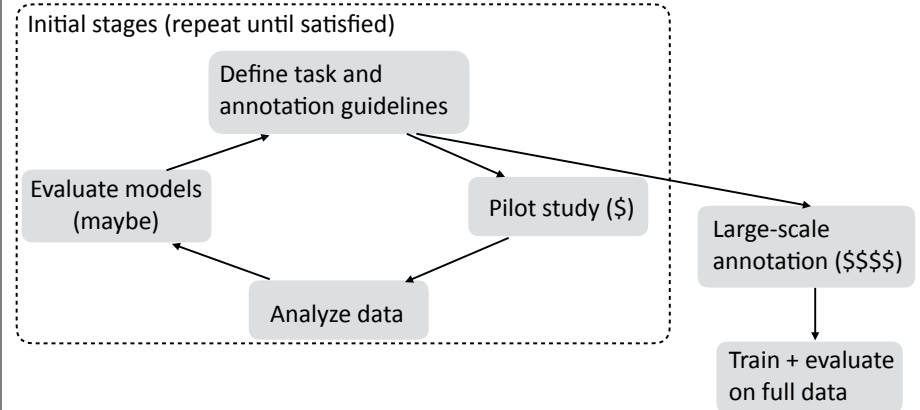


## Analyzing Data

- ▶ How well do annotators agree?
- ▶ Metrics for categorical labels (e.g., multiclass problems): Krippendorff's alpha, Fleiss's kappa
  - ▶ 0-1 measures where 0 is the agreement of random chance
  - ▶ For the conversations: overall Krippendorff's alpha = 0.494 ("moderate")
  - ▶ Conversation act: 0.652. Intent: 0.376. Intents are more subjective, so we expect higher disagreement here!
- ▶ Metrics for real-valued ratings: Spearman's rho (corrects for different scales of different annotators)



## Annotation Lifecycle



## Datasheets for datasets



## Datasheets for Datasets

- ▶ Framework for describing why a dataset was created, what's in it, how it was collected, etc.
- ▶ Motivation
  - **For what purpose was the dataset created?** Was there a specific task in mind? Was there a specific gap that needed to be filled? Please provide a description.
  - **Who created the dataset (e.g., which team, research group) and on behalf of which entity (e.g., company, institution, organization)?**
  - **Who funded the creation of the dataset?** If there is an associated grant, please provide the name of the grantor and the grant name and number.



## Datasheets for Datasets

- ▶ Composition
  - ▶ Questions about type of data, subsampling, nature of the labels
  - ▶ Train/dev/test splits
  - ▶ Noise/errors
  - ▶ Confidential/sensitive data, data about vulnerable subpopulations, identifiability
  - ▶ Dangerous/upsetting data

Gebru et al. (2018)



## Datasheets for Datasets

- ▶ Collection process
  - ▶ How was the data acquired?
  - ▶ Who was involved in the process?
  - ▶ Was consent obtained to collect the data?
  - ▶ Was IRB approval obtained?

Gebru et al. (2018)



## Datasheets for Datasets

- ▶ Preprocessing
- ▶ Uses
- ▶ Distribution
- ▶ Maintenance
- ▶ **Datasheets outline a good set of questions to consider when undertaking an annotation effort**

Gebru et al. (2018)

## Annotation Artifacts



## Natural Language Inference

- ▶ NLI, also called textual entailment: three class classification task over pairs of sentences

- ▶ Entailment: premise *implies* hypothesis
- ▶ Neutral: premise *is unrelated* to hypothesis
- ▶ Contradiction: hypothesis *cannot be true* if premise is true

<b>Premise</b>	A woman selling bamboo sticks talking to two men on a loading dock.
<b>Entailment</b>	There are <b>at least</b> three <b>people</b> on a loading dock.
<b>Neutral</b>	A woman is selling bamboo sticks <b>to help provide for her family</b> .
<b>Contradiction</b>	A woman is <b>not</b> taking money for any of her sticks.

- ▶ Caveat: these sentences are understood to be about the same scenario. And the judgments are usually somewhat subjective



## Natural Language Inference

<b>Premise</b>	A woman selling bamboo sticks talking to two men on a loading dock.
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Gururangan et al. (2018)

- ▶ Why is something entailed?
- ▶ Hypernymy: *A woman is doing X -> A person is doing X*
- ▶ Quantification: *Everybody is selling X -> Someone is selling X*
- ▶ Commonsense: *A woman is selling bamboo sticks -> A woman wants to earn money*
- ▶ Temporal: *A woman is selling X all day -> A woman is selling X at 2pm*



## Natural Language Inference

<b>Premise</b>	A woman selling bamboo sticks talking to two men on a loading dock.
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Gururangan et al. (2018)

- ▶ Why is something contradicted? Actually this is pretty specific!
- ▶ *A man is selling iced tea*: this could be true! Not a contradiction
- ▶ Negation: *A woman is not selling bamboo sticks*: we have to assume it's the same woman, which we typically assume
- ▶ Commonsense: *A woman is relaxing, doing nothing*
- ▶ Quantification: *No woman is selling bamboo sticks*



## Natural Language Inference

- ▶ How was the dataset annotated?

We will show you the caption for a photo. We will not show you the photo. Using only the caption and what you know about the world:

- Write one alternate caption that is **definitely** a **true** description of the photo. Example: For the caption "Two dogs are running through a field." you could write "There are animals outdoors."
- Write one alternate caption that **might be a true** description of the photo. Example: For the caption "Two dogs are running through a field." you could write "Some puppies are running to catch a stick."

- Write one alternate caption that is **definitely** a **false** description of the photo. Example: For the caption "Two dogs are running through a field." you could write "The pets are sitting on a couch." This is different from the maybe correct category because it's impossible for the dogs to be both running and sitting.

- ▶ Very clever protocol! But the open-endedness + the given examples lead annotators into certain patterns!

Bowman et al. (2015)



## Natural Language Inference

Gururangan et al. (2018); Poliak et al. (2018)

<b>Premise</b>	A woman selling bamboo sticks talking to two men on a loading dock.
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- ▶ To create neutral sentences: annotators *add information*
- ▶ To create contradictions: annotators *add negation*

- ▶ Models can do very well  
*without looking at the premise*

	Hypothesis-only	Majority	
SNLI	69.17	33.82	<b>+35.35</b>
MNLI-1	55.52	35.45	<b>+20.07</b>
MNLI-2	55.18	35.22	<b>+19.96</b>



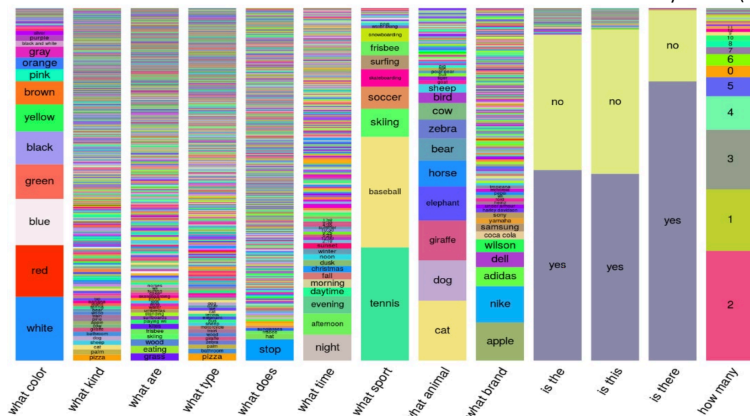
## What do we do?

- ▶ Why is this a problem? Because our models learn these simple cues and not actually the hard task we want them to learn
- ▶ They don't generalize to challenging new examples without these patterns — understanding this behavior is crucial to explaining what our models are doing!
- ▶ Solutions: build harder tasks, tweak data or training objective to inoculate models against this (many proposals)



## Bias in Visual Question Answering

Goyal et al. (2018)



## Visual Question Answering

- ▶ They collected multiple images with different answers for every question. Now the dataset is more balanced



Figure 1: Examples from our balanced VQA dataset.

Goyal et al. (2018)





## Contrast Sets

- Construct *controlled* datasets that test what we want
- Perturb examples to highlight similar distinctions as in VQA

**Original (Negative):** I had quite high hopes for this film, even though it got a bad review in the paper. I was extremely **tolerant**, and sat through the entire film. I felt quite **sick** by the end.

**New (Positive):** I had quite high hopes for this film, even though it got a bad review in the paper. I was extremely **amused**, and sat through the entire film. I felt quite **happy** by the end.

Gardner et al. (2020)



## Contrast Sets

**Original (Positive):** This is the **greatest** film I saw in 2002, whereas I'm used to mainstream movies. It is **rich and makes a beautiful artistic act** from these 11 short films. From the technical info (the chosen directors), I feared it would have an anti-American basis, but ... it's a kind of (11 times) **personal tribute**. **The weakest point** comes from Y. Chahine : he does not manage to "swallow his pride" and considers this event as a well-merited punishment ... It is **really the weakest** part of the movie, but this testifies of a real freedom of speech for the whole piece.

**New (Negative):** This is the **most horrendous** film I saw in 2002, whereas I'm used to mainstream movies. It is **low budgeted and makes a less than beautiful artistic act** from these 11 short films. From the technical info (the chosen directors), I feared it would have an anti-American basis, but ... it's a kind of (11 times) **the same**. **One of the weakest point** comes from Y. Chahine : he does not manage to "swallow his pride" and considers this event as a well-merited punishment ... It is **not the weakest** part of the movie, but this testifies of a real freedom of speech for the whole piece.

Gardner et al. (2020)



## Dynamic Datasets

- Adversarial filtering (Le Bras et al., 2020): filter out data that is easily fit due to dataset biases
- Dynabench (FAIR): adaptive benchmarks with new data being collected to highlight errors
- Lots of ongoing work here!



## Takeaways

- We looked at the basic procedures for constructing a dataset
- Lots of guiding frameworks, such as datasheets, for thinking about both data quality as well as possible ethical issues
- Dataset *biases*: these will come up again later!