PART 02

# Tasks and Datasets

Adopted from Spring2023 Section03 Slides by Nitish

# NLP Datasets

- Datasets in NLP, and useful resources to use them.
- Considerations when choosing a dataset.
- Challenges in data collection.

# Individual Task Benchmarks

- Tasks: Machine Translation,Question Answering, Sentiment Analysis, Common Sense Reasoning, Summarization etc.

- http://nlpprogress.com - Useful resource to track datasets for different tasks in NLP

# Individual Task Benchmarks

What is different in all the benchmarks for the same task (say QA)?

- Domain (e.g. sports domain vs legal domain)
- Fine-grained phenomena (e.g. short answers vs long answers)
- Language
- Evaluation Metric (e.g. exact span match vs multiple-choice)
- etc.

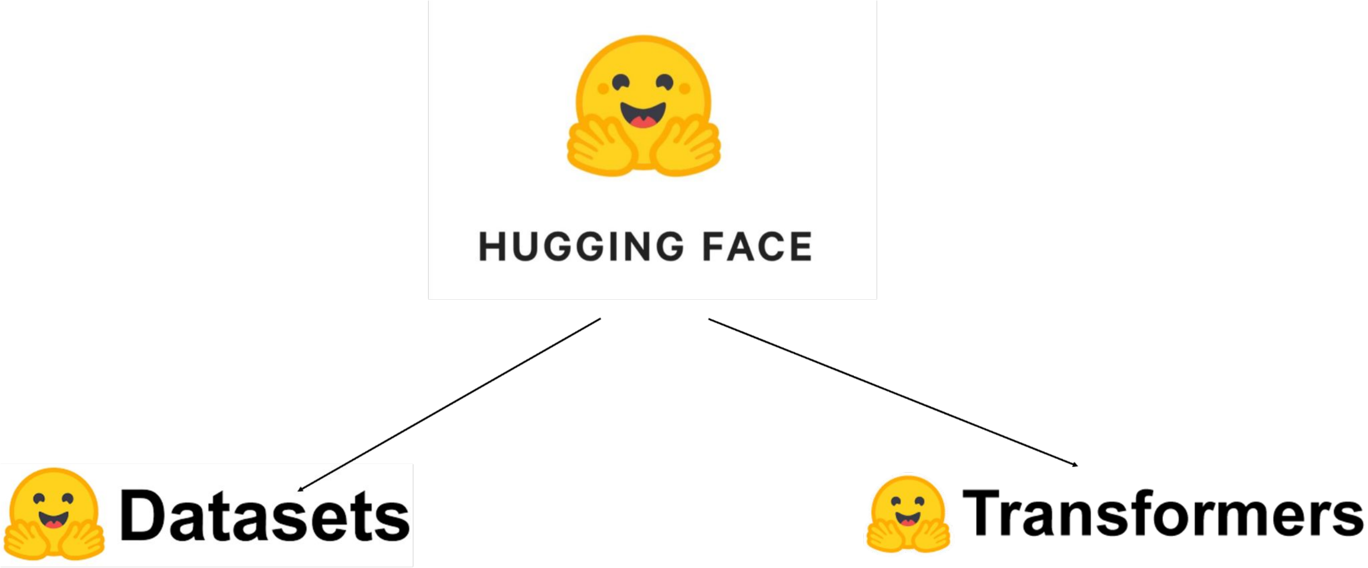
# Individual Task Benchmarks

- GLUE and SuperGLUE include a suite a tasks designed to test natural language understanding
  - Tasks: Sentiment analysis, paraphrase detection, natural language inference etc.
- Highly influential in recent developments in NLP (BERT, GPT-2 etc) and developed at NYU!!

# Multi-Task Benchmarks

- BigBench: create a collaborative benchmark.
- Spans 204 diverse tasks including linguistics, common-sense reasoning, social bias, math etc.
- Influential in recent developments in large language models like GPT-3. (More later in the course!)

# Useful Resources




Today!

Next week!

# Datasheets for Datasets

- Analogous to the datasheets common in electronic components (e.g. operating characteristics, usage etc.)
- Why? Increases transparency and accountability.
- Standardizes dataset documentation along: Creation Composition Intended uses Maintenance

# Datasheets for Datasets

### Motivation for Dataset Creation

**Why was the dataset created?** (e.g., were there specific tasks in mind, or a specific gap that needed to be filled?)

**What (other) tasks could the dataset be used for?** Are there obvious tasks for which it should *not* be used?

### Data Collection Process

**How was the data collected?** (e.g., hardware apparatus/sensor, manual human curation, software program, software interface/API; how were these constructs/measures/methods validated?)

**Who was involved in the data collection process?** (e.g., students, crowdworkers) How were they compensated? (e.g., how much were crowdworkers paid?)

**Over what time-frame was the data collected?** Does the collection time-frame match the creation time-frame?

### Dataset Composition

**What are the instances?** (that is, examples; e.g., documents, images, people, countries) Are there multiple types of instances? (e.g., movies, users, ratings; people, interactions between them; nodes, edges)

**Are relationships between instances made explicit in the data** (e.g., social network links, user/movie ratings, etc.)?

**How many instances of each type are there?**

Gebru et al., 2019

# Datasheets for Datasets

### Dataset Distribution

**How is the dataset distributed?** (e.g., website, API, etc.; does the data have a DOI; is it archived redundantly?)

**When will the dataset be released/first distributed?** (Is there a canonical paper/reference for this dataset?)

### Data Preprocessing

**What preprocessing/cleaning was done?** (e.g., discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values, etc.)

**Was the "raw" data saved in addition to the preprocessed/cleaned data?** (e.g., to support unanticipated future uses)

### Legal & Ethical Considerations

**If the dataset relates to people (e.g., their attributes) or was generated by people, were they informed about the data collection?** (e.g., datasets that collect writing, photos, interactions, transactions, etc.)

**If it relates to other ethically protected subjects, have appropriate obligations been met?** (e.g., medical data might include information collected from animals)

**If it relates to people, were there any ethical review applications/reviews/approvals?** (e.g. Institutional Review Board applications)



Gebru et al., 2019

# Challenges in Dataset Construction

- Annotation Artifacts in Datasets (Gururangan et al., 2018)
- Annotators might use simple rules or heuristics to create the examples
- Task: Given a premise p write three hypothesis h such that:

| | |
|---|---|
| **Entailment** | $h$ is definitely true given $p$ |
| **Neutral** | $h$ might be true given $p$ |
| **Contradiction** | $h$ is definitely **not** true given $p$ |

# Challenges in Dataset Construction

**Contradiction:**

*Premise*: The woman was standing near the shop.
*Hypothesis*: The woman was **not** near the shop.

*Premise*: She is selling bamboo sticks.
*Hypothesis*: She is **not** taking money for the bamboo sticks.

*Premise*: It was raining heavily today.
*Hypothesis*: There was **no** water on the ground today.

Annotators tend to add negation words in contradiction

# Challenges in Dataset Construction

**Contradiction:**

*Premise*: The woman was standing near the shop.
*Hypothesis*: The woman was **not** near the shop.

*Premise*: She is selling bamboo sticks.
*Hypothesis*: She is **not** taking money for the bamboo sticks.

*Premise*: It was raining heavily today.
*Hypothesis*: There was **no** water on the ground today.

- Models trained on this data may predict contradiction whenever negation word is present.
- Why might this be bad?

# Challenges in Dataset Construction

| Heuristic | Definition |
| --- | --- |
| Negation Word | Assume that the label is contradiction whenever a negation word is present in the hypothesis. |

Might work sometimes

But not in all cases

*Premise*: The woman was standing near the shop.
*Hypothesis*: The woman was not near the shop.
Label: Contradiction

*Premise*: The actor paid by the doctor.
*Hypothesis*: The doctor did not treat the actor.
Label: Neutral

# Challenges in Dataset Construction

| Heuristic | Definition |
|---|---|
| Lexical overlap | Assume that a premise entails all hypotheses constructed from words in the premise |

Might work sometimes

But not in all cases

*Premise*: The woman was standing near the shop.
*Hypothesis*: The woman was near the shop.
Label: Entailment

*Premise*: The doctor was paid by the actor.
*Hypothesis*: The doctor paid the actor.
Label: Not Entailment

# Spurious Correlations in Datasets

- Certain input features (e.g. negation words) are highly correlated with a certain label (e.g. contradiction).
- Is my model right the right reasons? (McCoy et al., 2019)
- If the model relies on the spurious correlations, then it may not generalize well when used in practice!

# Summary

- Single-task vs Multi-task benchmarks
- Huggingface Datasets Library
- Datasheets for Datasets
- Challenges in data collection — annotator artifacts.