### PromptSource: IDE + repo for natural language prompts

What it is Why it is needed

Paper: S. Bach et al., "PromptSource: An Integrated Development Environment and Repository for Natural Language Prompts", ACL Demo (2022)

### Motivation Prompting: represent task as an utterance maps to E.g. text classification prompt: "This video class label describes PromptSource. It is about..." <a href="https://www.ncb.nlm.n enables adapting LMs to ad hoc tasks Prompt applications sample efficiency in low data regimes Prompt engineering can have a major influence Training on prompts can enable task generalisation

### But how can we enable users to: refine prompts? share create PromptSource IDE (Web GUI) Shared repo Elements of design: simple but flexible Template language Prompt management support browsing/iteration Community-driven standards evolved guidelines Stats: 2087 prompts across 180 datasets

#### References:

V. Sanh et al., "Multitask Prompted Training Enables Zero-Shot Task Generalization", ICLR (2021)

Public Pool of Prompts (P3)

T. Brown et al., "Language models are few-shot learners", NeurIPS (2020)

T. Schick et al., "It's Not Just Size That Matters: Small Language Models Are Also Few-Shot Learners", NAACL-HLT (2021) Le Scao et al., "How many data points is a prompt worth?", NAACL-HLT (2021)

### Prompt creation $\neq$ traditional NLP annotation

### What makes prompt creation different?

Functions, not labels

Prompts are functions that map examples to input/target pairs - how expressive should format be?

Datasets, not examples

Unlike labels, prompt design must consider all dataset examples - what interface will support this?

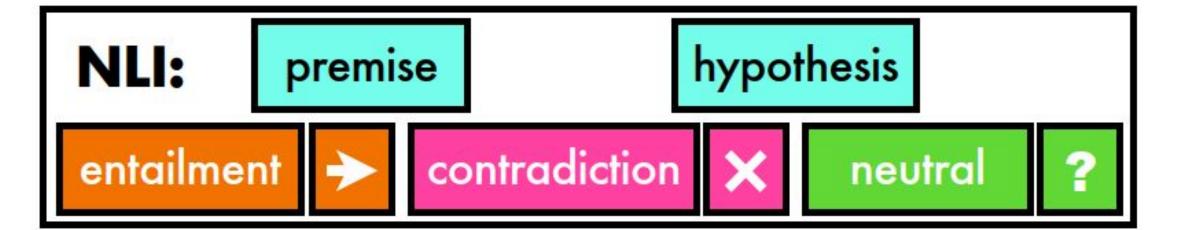
Variation is desirable

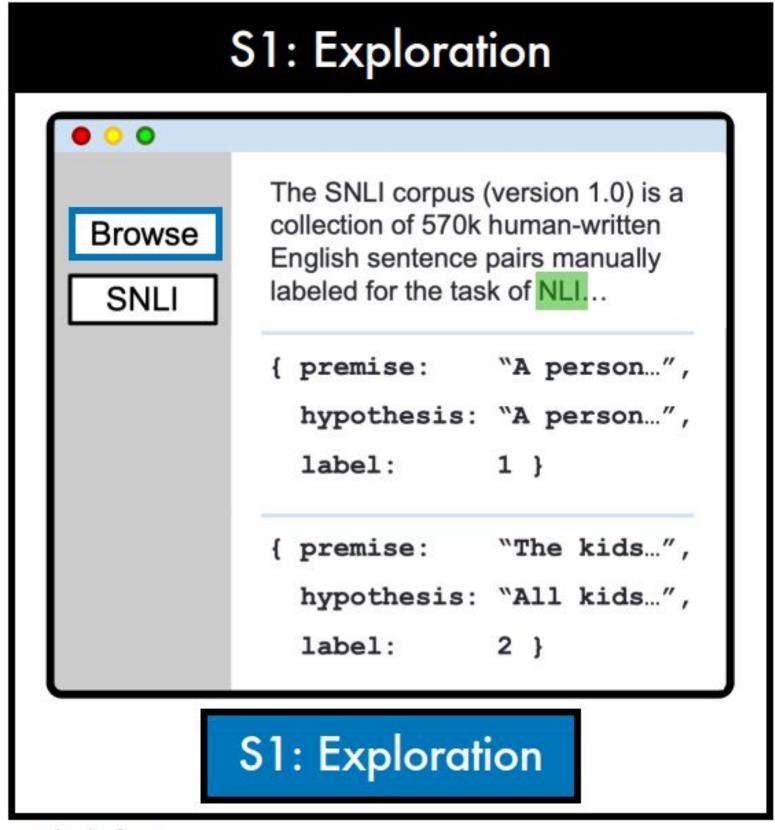
Label variation generally undesirable but prompt variation has benefits - how can this be supported?

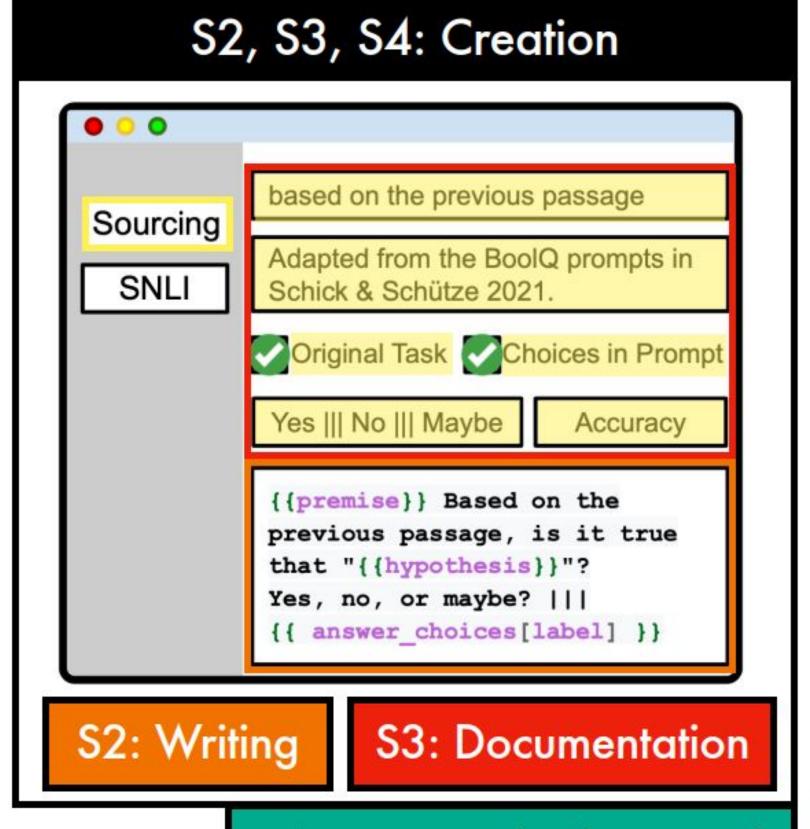
## The PromptSource workflow

Example Task: design prompt query for SNLI

Require answers that can map to SNLI classes







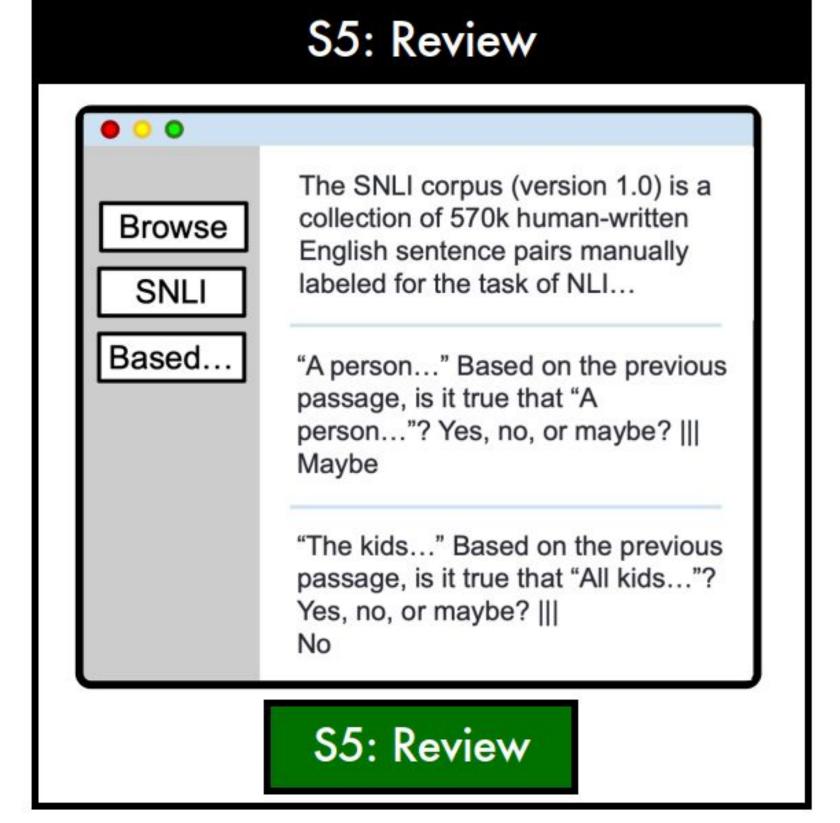


Image credits/Reference:

S4: Iteration (with variety)

S. Bach et al., "PromptSource: An Integrated Development Environment and Repository for Natural Language Prompts", ACL Demo (2022)

# PromptSource plays nicely with Bource plays

### Practical usage

#### Import libraries

```
from promptsource.templates import DatasetTemplates
from datasets import load_dataset
```

### Fetch prompt by name

```
prompts = DatasetTemplates("snli")
prompt_key = "based on the previous passage"
p = prompts[prompt_key]
```

#### Load example

```
dataset = load_dataset("snli", split="train")
example = dataset[0]
```

### Apply to an example

```
result = p.apply(example)
print("INPUT: ", result[0]) A person ....? Yes, no, or maybe?
print("TARGET: ", result[1]) Maybe
```

## Prompt Template Engine: Jinja2

### Jinja2 template engine used for prompts

- More flexible vs rule-based generation
- Simpler than pure Python code

#### Example prompt:

```
If {{premise}} holds, does {{hypothesis}}
also hold? | | | {{entailed}}
```

Placeholder refer to fields in example dict

Separator between condition and completion

Jinja2 enables some fancy string manipulation In practice, simple manipulations suffice

### Useful idioms

Template may not be applicable for all examples

Conditionals can be used to skip examples (empty)

Examples can generate multiple training instances

Elements can be selected with the choice function

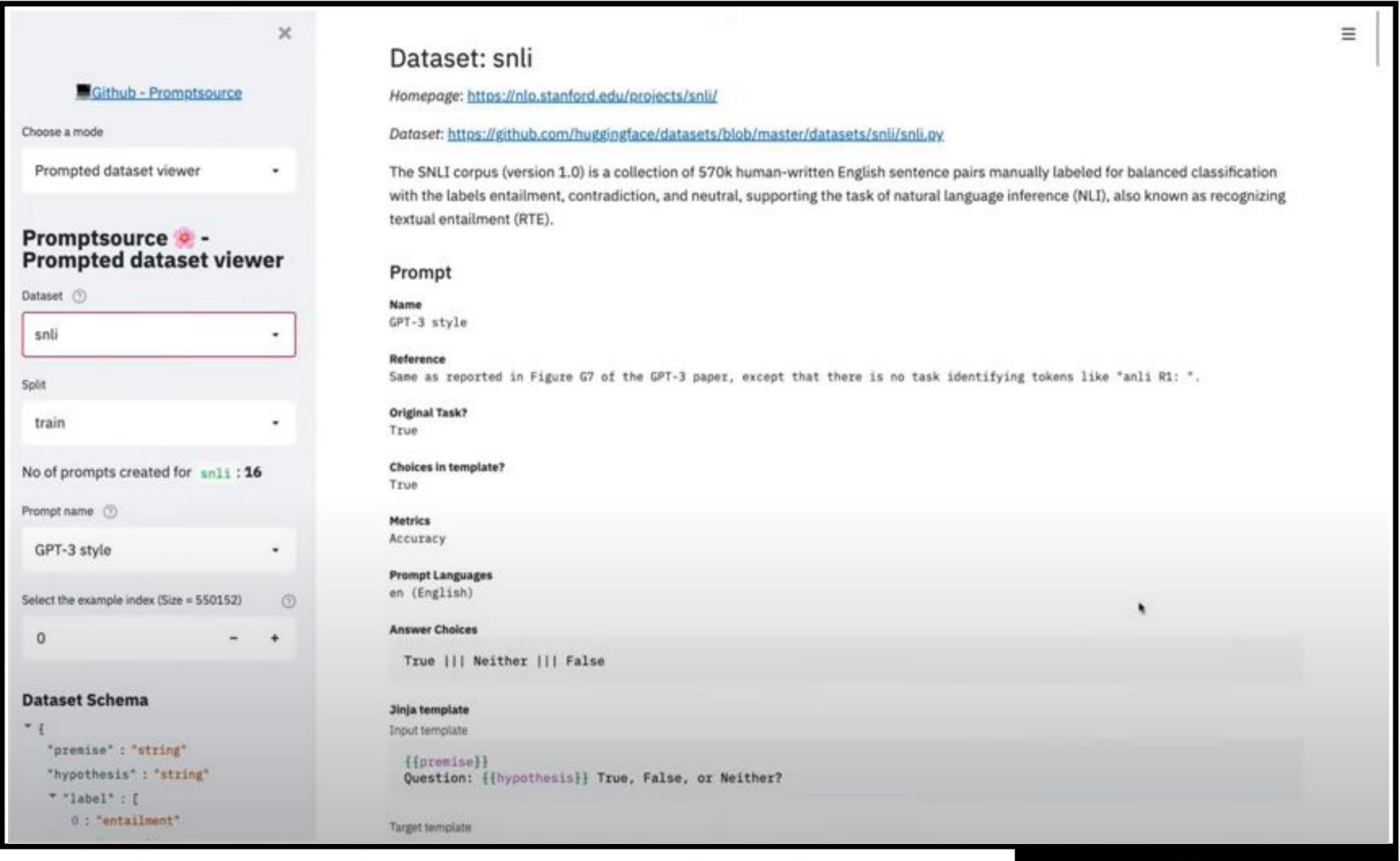
Some examples may have multiple valid completions

These can be specified as a separate field

### User Interface: Dataset Browsing

useful for verifying prompts across many examples

Built with Streamlit

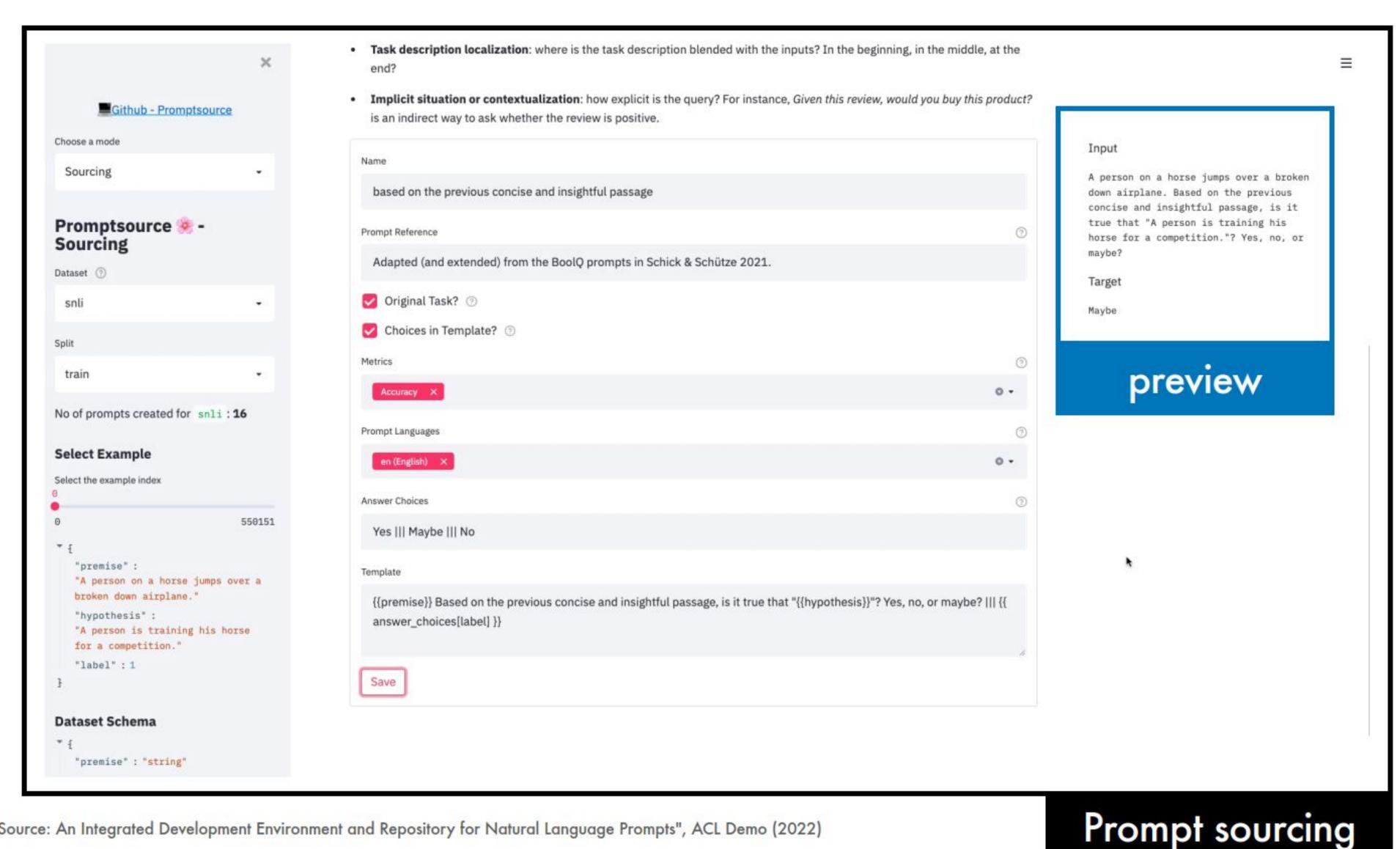


References:

S. Bach et al., "PromptSource: An Integrated Development Environment and Repository for Natural Language Prompts", ACL Demo (2022) <a href="https://github.com/streamlit">https://github.com/streamlit</a>

Dataset browsing

# User Interface: Sourcing



## User Interface: Helicopter view



## Community Guidelines

Describing what makes a good prompt is hard Community guidelines evolved through iteration Key objectives for guidelines:

- Standardised vocab & minimum requirements
- Highlight common errors & best practices
- Gather useful metadata for future research

The guidelines cover templates and metadata

#### Encourage:

- explicitly state possible completions
- remove spurious ambiguity from targets
- creation of multiple prompt variants

#### Require:

- only natural language prompts allowed
- inclusion of metadata (e.g. reference paper)

## Case Studies with PromptSource

#### Massively multitask prompted training

TO (Sanh et al., 2021) uses a multitask mixture of prompts for training to boost generalisation Training and evaluation use P3

### Multilingual prompting

XGLM (Lin et al., 2021) train on

30 languages to study cross-

lingual generalisation

P3 - quality English prompts

### Priming (in-context learning)

MetalCL (Lin et al., 2021) train

on a multitask mixture with in-

context learning examples

Instructions from P3 bring gains



#### References:

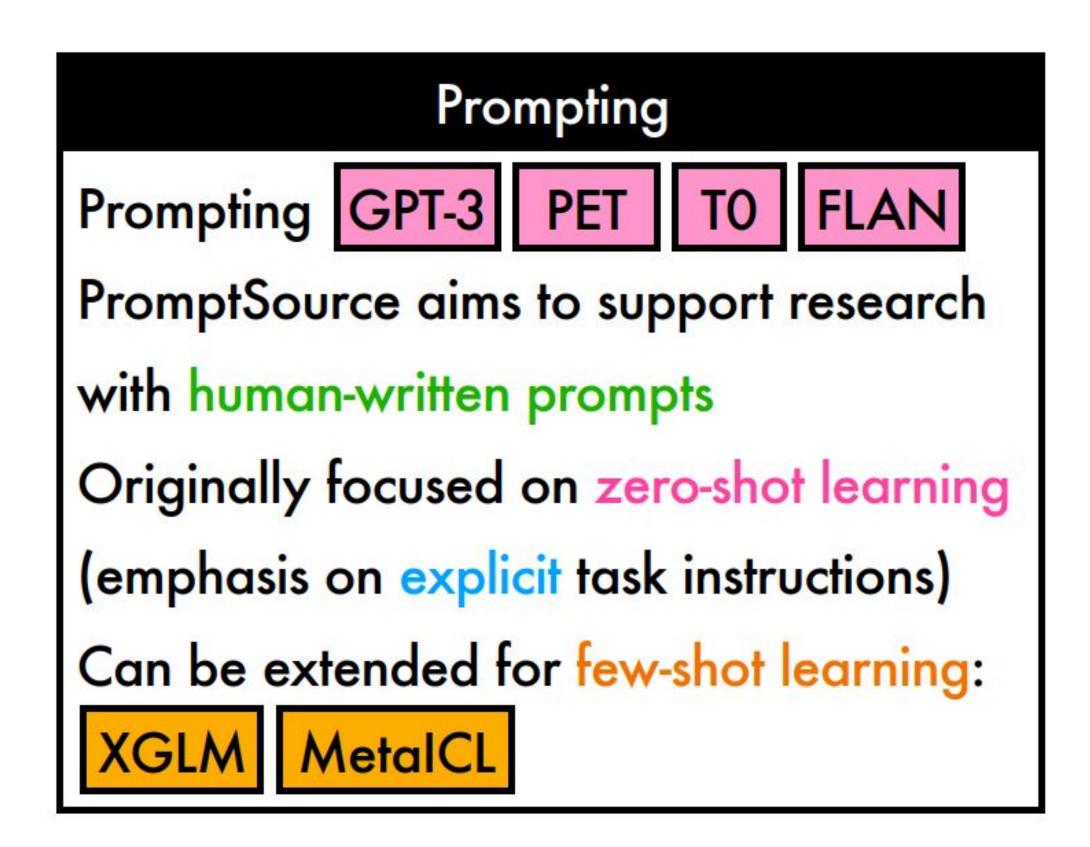
S. Bach et al., "PromptSource: An Integrated Development Environment and Repository for Natural Language Prompts", ACL Demo (2022)

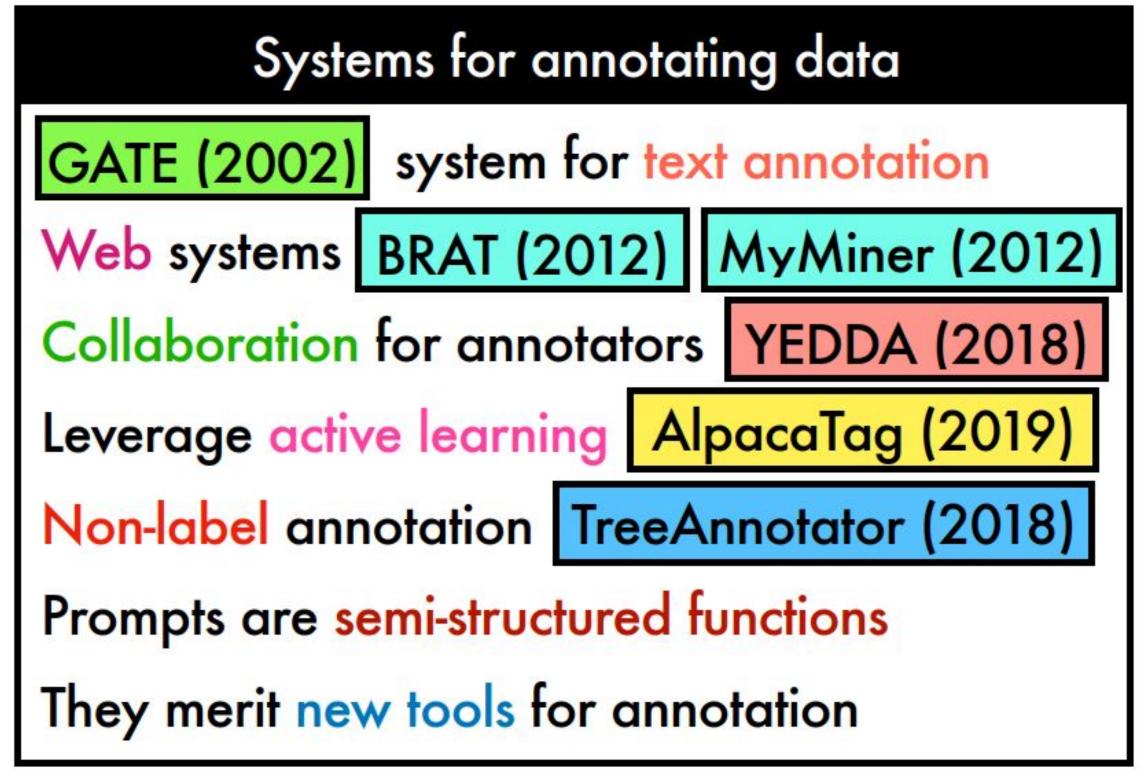
V. Sanh et al., "Multitask Prompted Training Enables Zero-Shot Task Generalization", ICLR (2021)

V. Lin et al., "Few-shot learning with multilingual language models", arXiv (2021)

S. Min et al., "MetalCL: Learning to learn in context", arXiv (2021)

### Prior work





#### References:

S. Bach et al., "PromptSource: An Integrated Development Environment and Repository for Natural Language Prompts", ACL Demo (2022) (GPT-3) T. Brown et al., "Language models are few-shot learners", NeurIPS (2020)

(PET) T. Schick et al., "Exploiting Cloze-Questions for Few-Shot Text Classification and Natural Language Inference", EACL (2021)

(TO) V. Sanh et al., "Multitask Prompted Training Enables Zero-Shot Task Generalization", ICLR (2021)

(FLAN) J. Wei et al., "Finetuned Language Models are Zero-Shot Learners", ICLR (2021)

(XGLM) V. Lin et al., "Few-shot learning with multilingual language models", arXiv (2021)

(MetalCL) S. Min et al., "MetalCL: Learning to learn in context", arXiv (2021)

(GATE) H. Cunningham, "GATE, a general architecture for text engineering." Computers and the Humanities (2002) (BRAT) P. Stenetorp et al., "BRAT: a web-based tool for NLP-assisted text annotation", EACL (2012)

(MyMiner) D. Salgado et al., "MyMiner: a web application for computer-assisted biocuration and text annotation", Bioinformatics (2012)

(YEDDA) J. Yang et al., "YEDDA: A Lightweight Collaborative Text Span Annotation Tool", ACL (2018)

(AlpacaTag) B. Lin et al., "AlpacaTag: an active learning-based crowd annotation framework for sequence tagging", ACL (2019)

(TreeAnnotator) P. Helfrich et al., "TreeAnnotator: versatile visual annotation of hierarchical text relations", LREC (2018)

# Thank You