Transfer Learning

DSCC/LING 251/451: Machine Learning with Limited Data

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Roadmap

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  - (Semi-Supervised Learning, Active Learning, Weak Supervision)

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  - (Semi-Supervised Learning, Active Learning, Weak Supervision)
- Today: how can you leverage **distinct but related data?**
  - (or models trained on that data)
- Approaches like this fall under the umbrella of **Transfer Learning**
  - This is a **very overloaded term**: refers to a **very wide range of techniques**
  - Today we'll examine a **taxonomy of approaches** in this space

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- Train an LLM on **30 tasks simultaneously** (e.g. T5 or FLAN models)
- **Distill** GPT-4 into a **compact model** (e.g. to fit on a phone)

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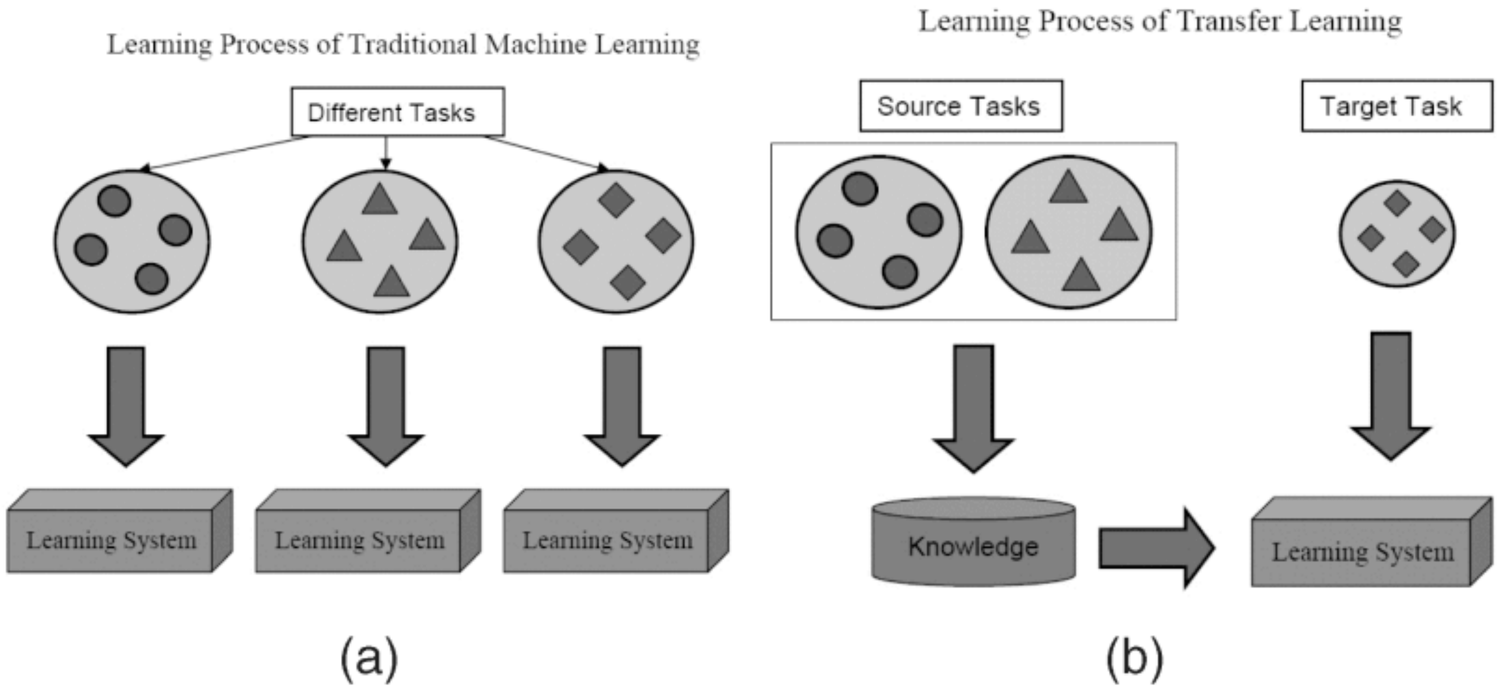
- This definition is **still very broad!**

Transfer Learning Schematic



Pan and Yang (2010)

Axes of Transfer

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- **Knowledge transfer:** transfer model behavior/decisions rather than parameters
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- These are **not mutually exclusive:** fine-tuning a pre-trained NN is both representation and parameter transfer

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- **Simultaneous:** train on source and target at the **same time**
  - Example: **multi-task learning**
- **Continual:** keep transferring to **more tasks over time**
  - Can be hard to prevent **forgetting previous tasks**

Mapping the Opening Examples

Example	What Differs	What Transfers	When
ResNet > X-Rays	domain	params, features	sequential
BERT > task	task	params, features	sequential
English task > Swahili	domain (language)	params, features	sequential
T5/FLAN	tasks (multiple)	params, features	simultaneous
GPT-4 > small version	model	knowledge	sequential

Pre-training + Fine-tuning

(Sequential Transfer)

Pre-training as Transfer

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- We've already seen sequential transfer in **self-supervised pre-training**
  - Source task: the **pretext / surrogate task** (LM, SimCLR, etc.)
  - Target task: the **actual downstream problem** (classification, QA, etc.)
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  - What transfers: the **parameters** and **representations of the data**
- Before about 2018, "transfer learning" in NLP meant using **pre-trained word vectors** (word2vec, GloVe)
  - Howard & Ruder (2018), ULMFiT: pre-train an LM then **fine-tune on many tasks**
  - BERT (2019): shifted to **pre-train + fine-tune** as the **default paradigm**

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- For well-constructed pretext tasks, model has to learn **general-purpose representations of the data**
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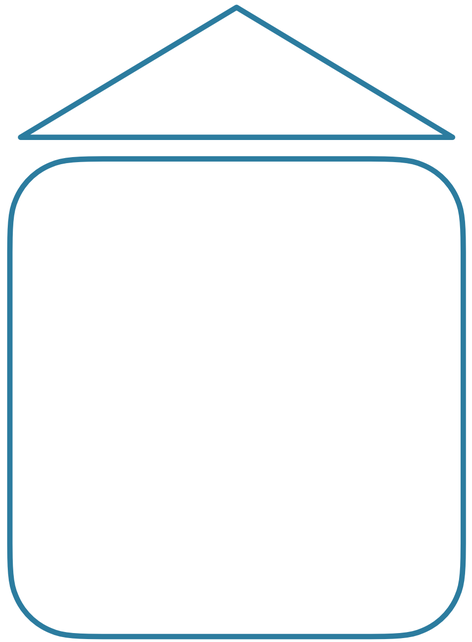
  - These features give a **head-start for solving downstream tasks**
- Sometimes fine-tuning involves **freezing the pre-trained model** and **only training task-specific layers**
  - Shows the main model functions as a **general-purpose feature extractor**
  - Different downstream tasks make use of the **shared feature space**

Traditional Learning

Task 1 outputs



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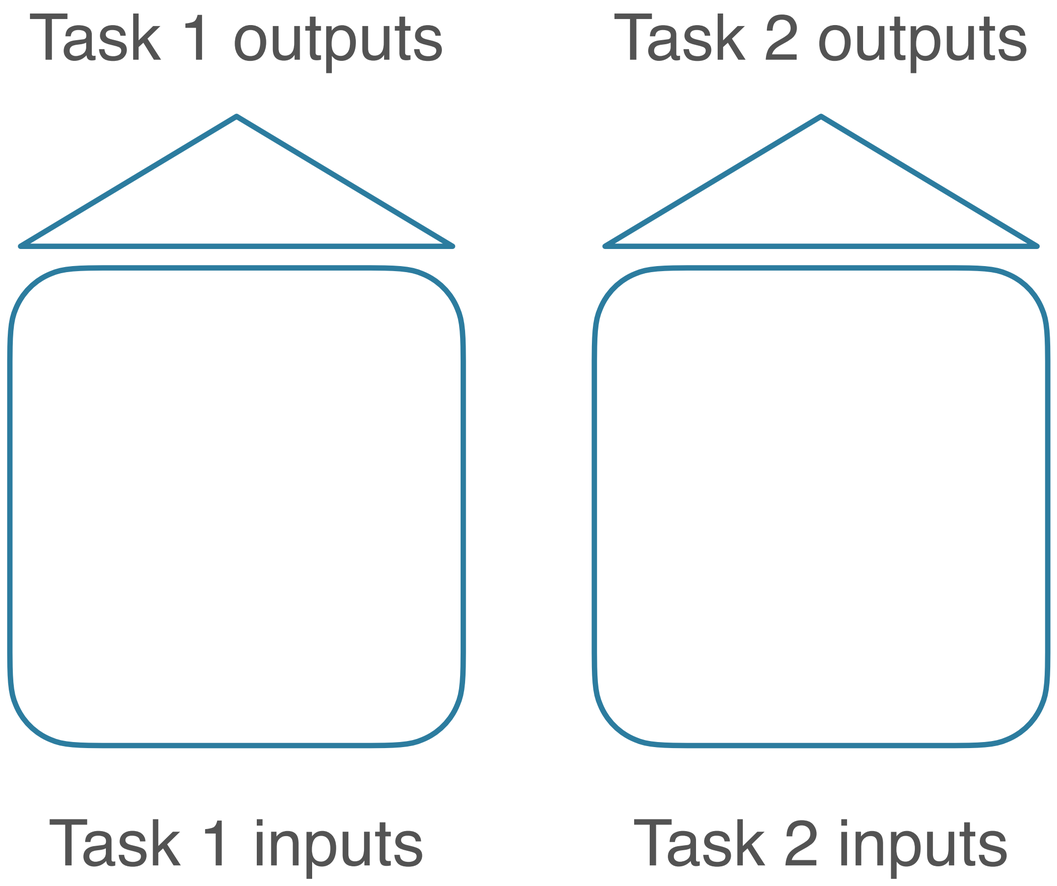

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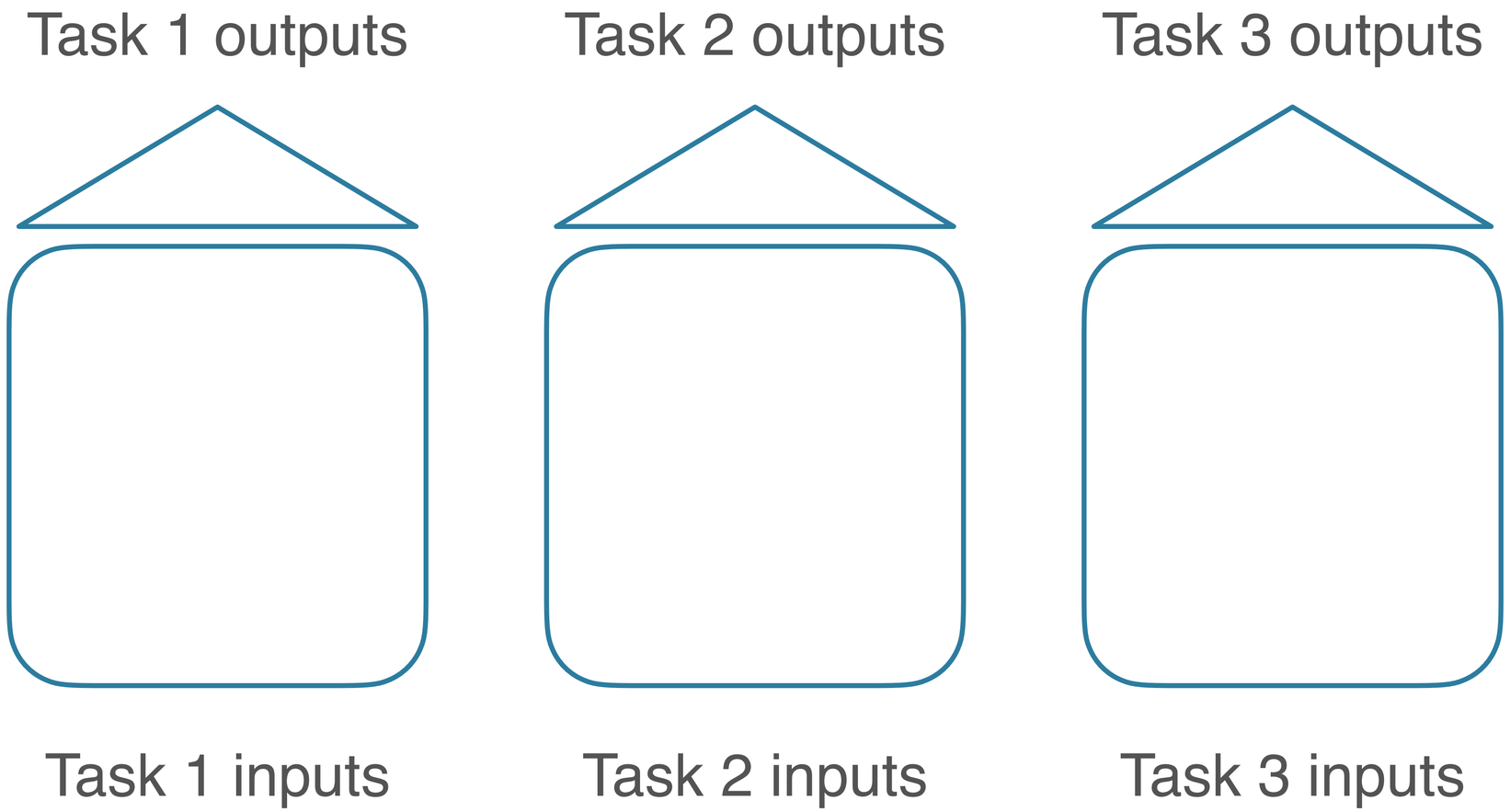

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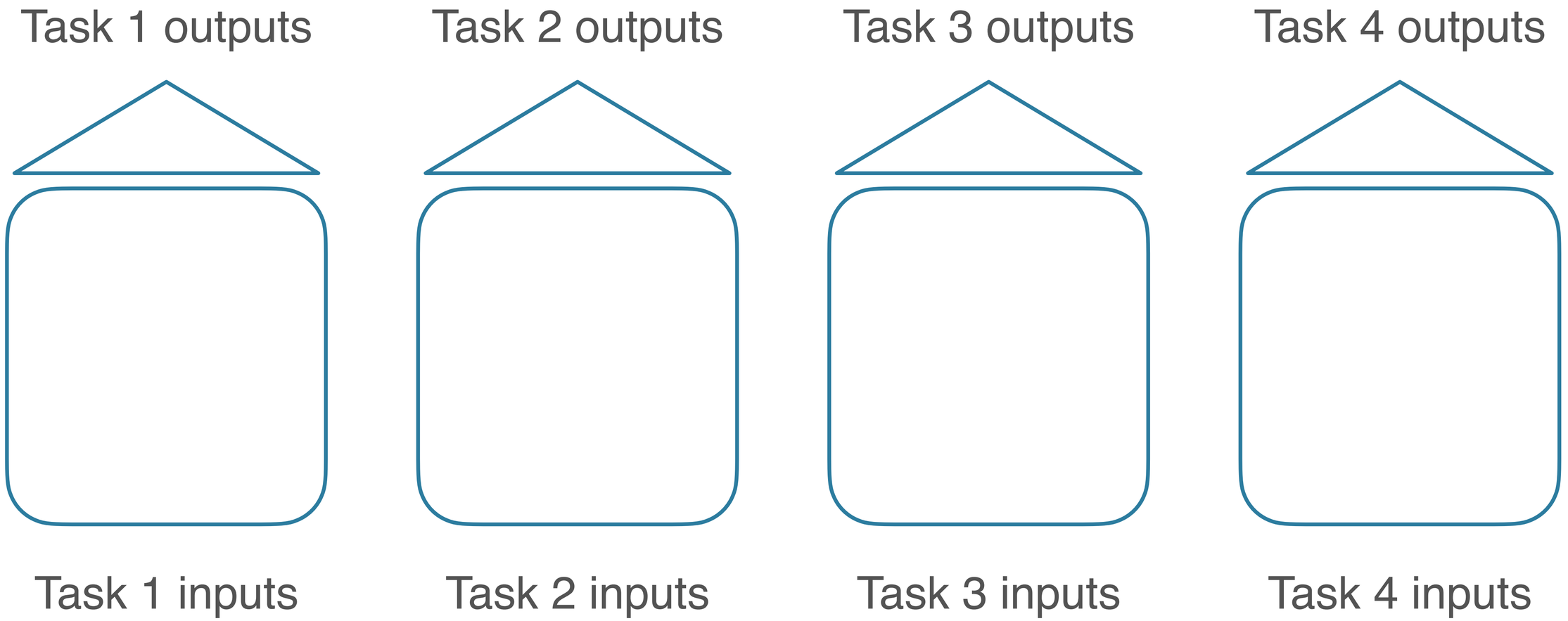

Pre-training / Representation Learning

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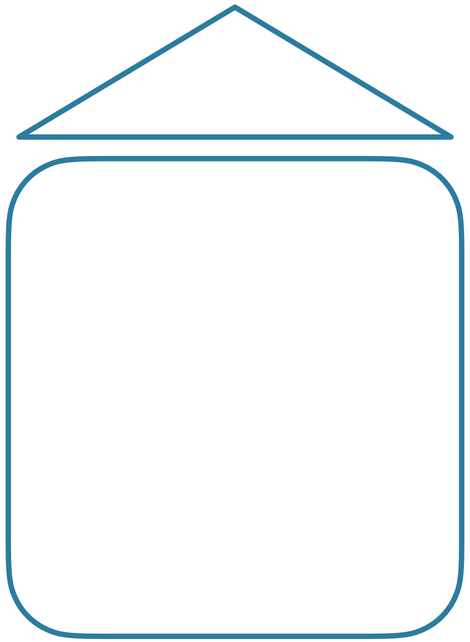

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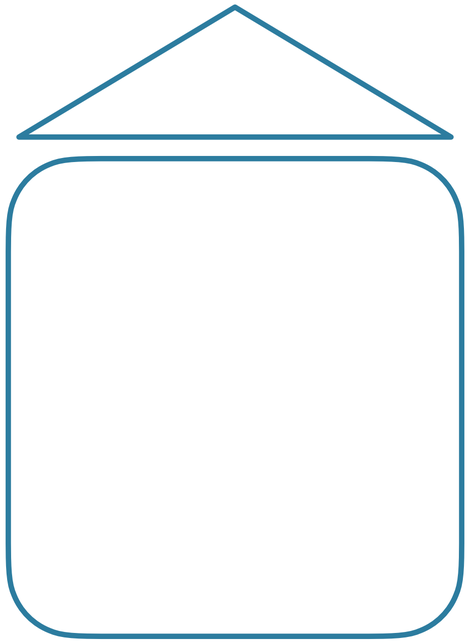

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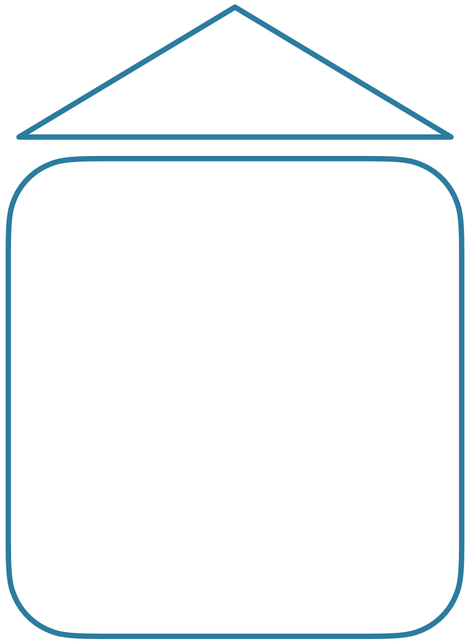

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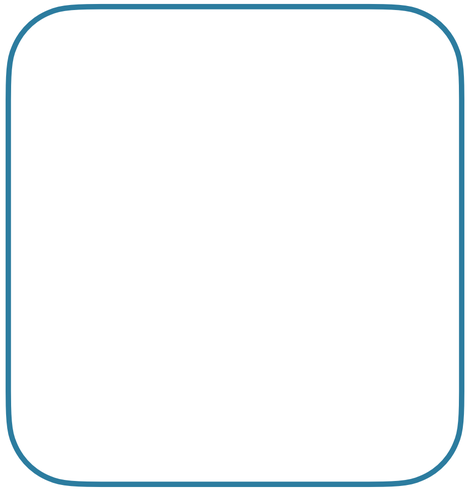

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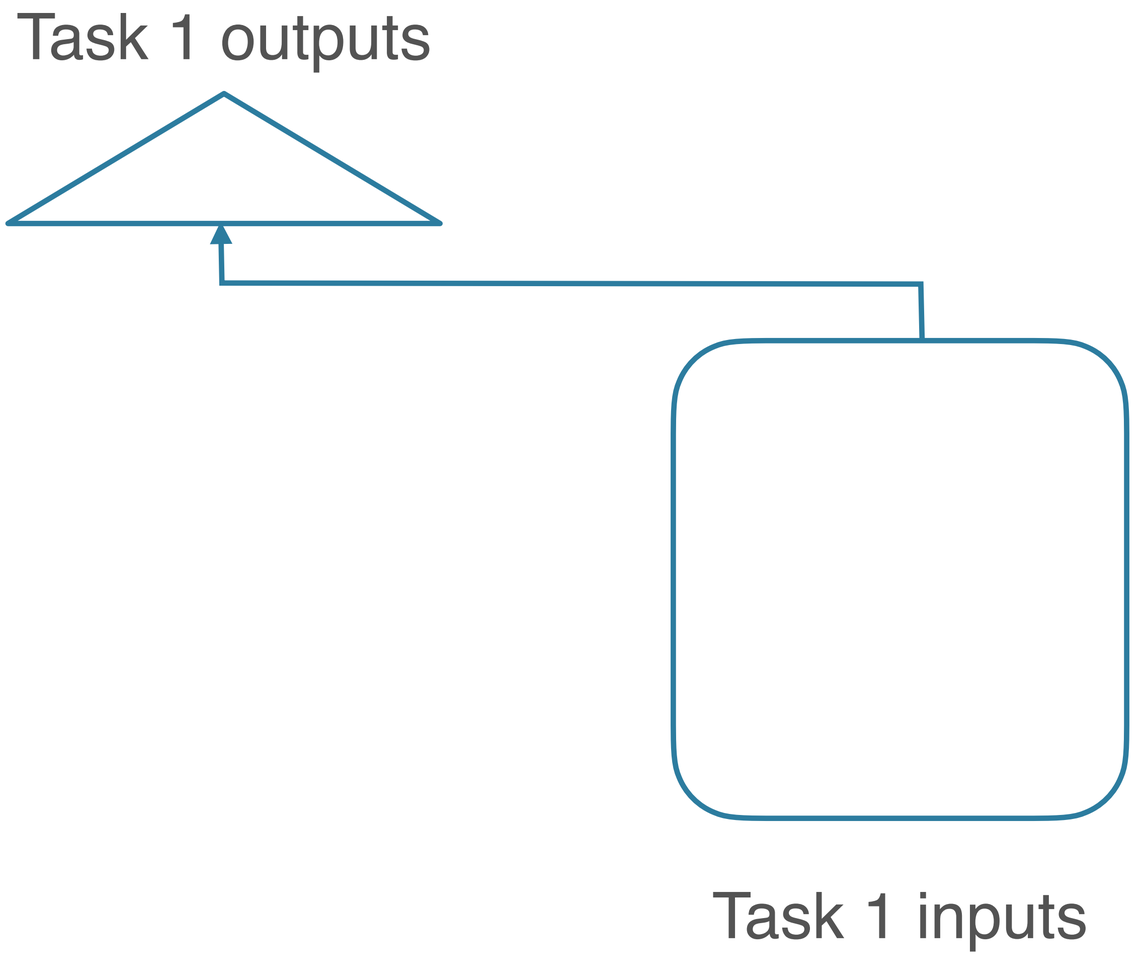

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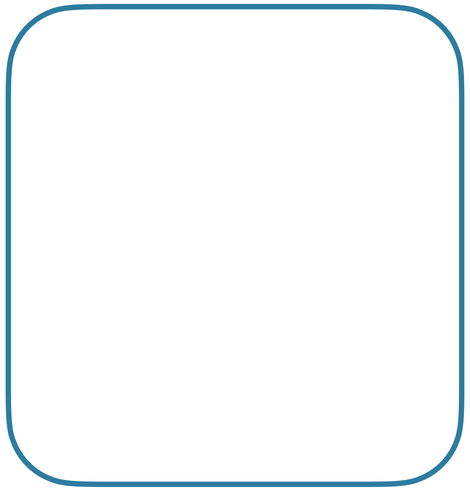

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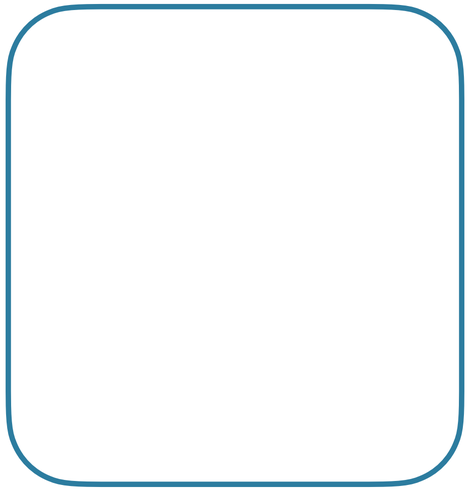

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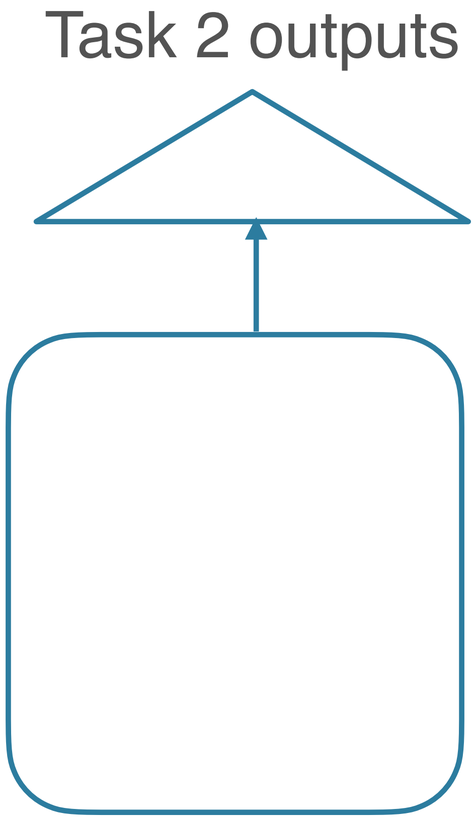

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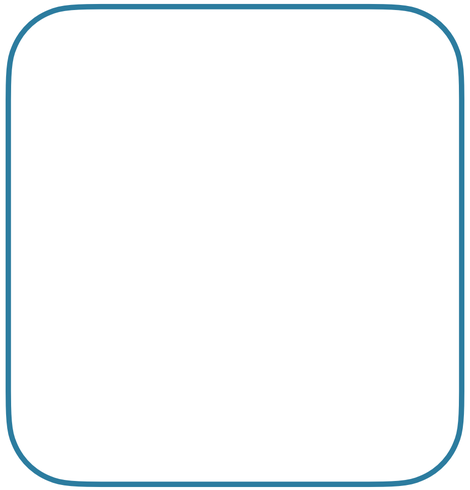

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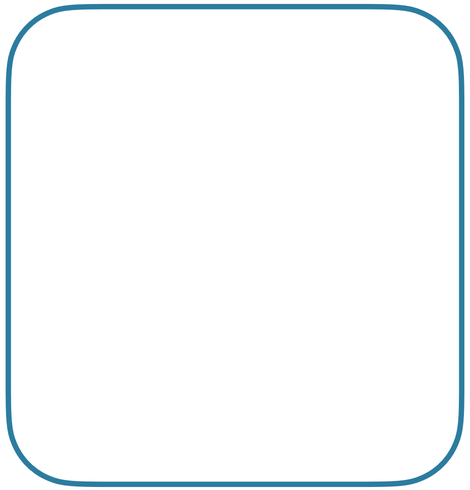

Task 3 inputs

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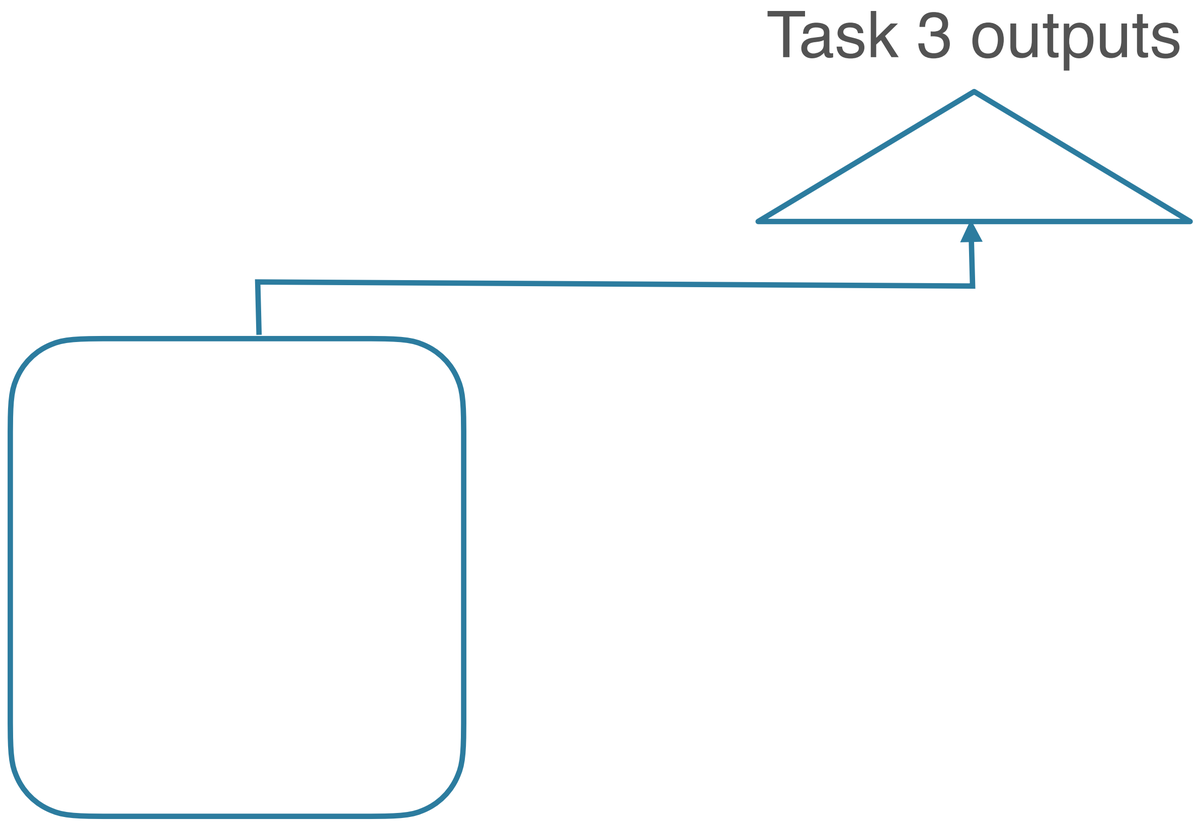

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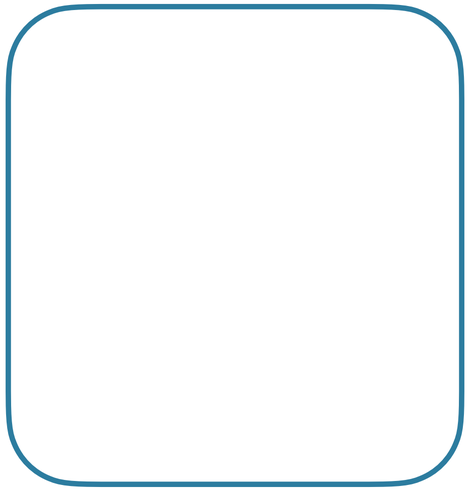

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- Generally **relatedness** between source and target is important. But what kind?
  - Picking the **wrong source** can sometimes hurt transfer (**negative transfer**)

Cross-lingual Transfer

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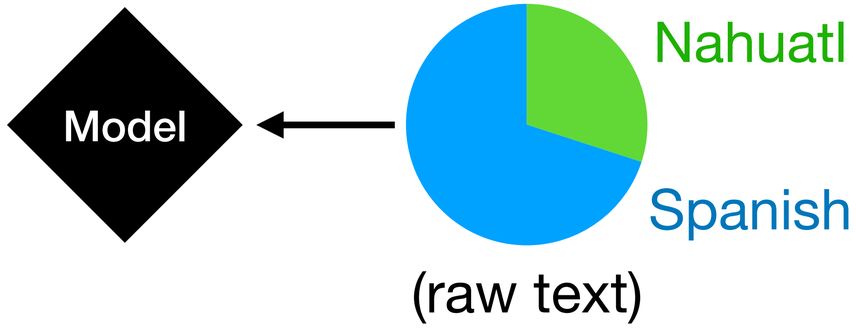

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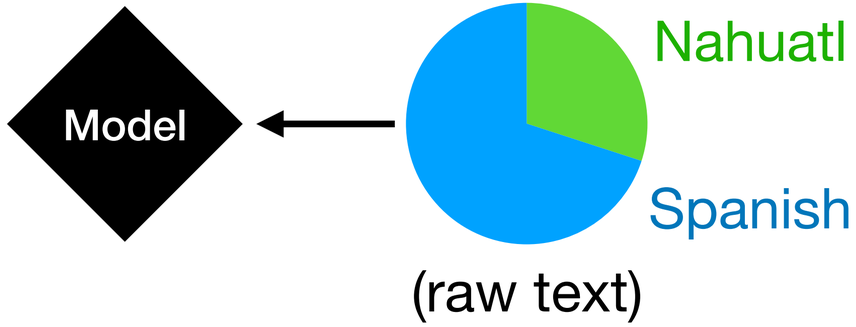

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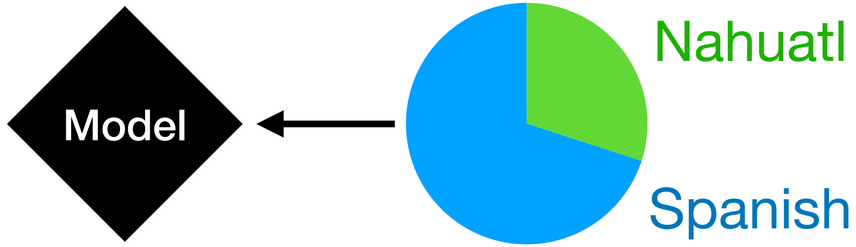

(raw text)

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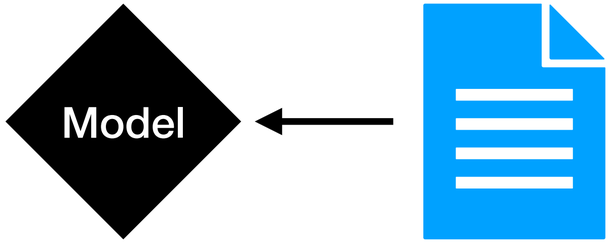

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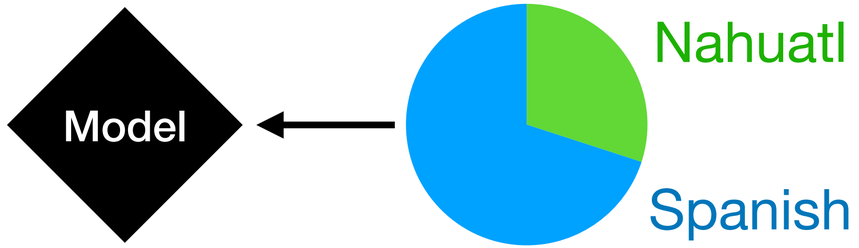

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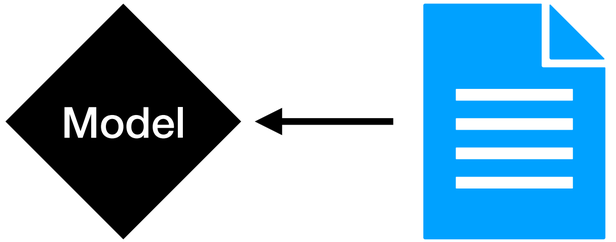
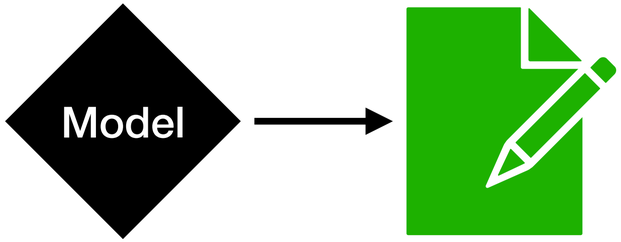


Spanish task training data

3. Transfer to Nahuatl task



Nahuatl task test data

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- **Shared model parameters:** all languages are processed by the same weights, model needs at least some **language-general representations**
- **Shared linguistic structure:** there is **some universal structure** to languages, and **related languages** share much more than the minimum

What enables this?

- **Shared (sub-word) vocabulary**: different languages share at least some units that the model uses to build text
  - Especially beneficial for languages with **shared scripts, cognates, borrowings**
- **Shared model parameters:** all languages are processed by the same weights, model needs at least some **language-general representations**
- **Shared linguistic structure:** there is **some universal structure** to languages, and **related languages** share much more than the minimum
- Where does it **not work?**
  - Typologically **distant/dissimilar languages**
  - Languages with **very little pre-training data** (which is most of them)

Multi-Task Learning

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$$\mathscr{L}_{\text{MTL}} = \sum_{t=1}^{T} \lambda_t \mathscr{L}_t(\theta_{\text{shared}}, \theta_t)$$

θ_{shared}: shared parameters

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- Instead of training on source then target, train on **multiple tasks at once**
- Key point: tasks **share model parameters** (sometimes all of them)
- Why should this help?
  - **Implicit regularization:** each task is a different "view" of the data
  - **Attention focusing:** different tasks can help the model notice important features
  - A hard task might **benefit from easier task training**

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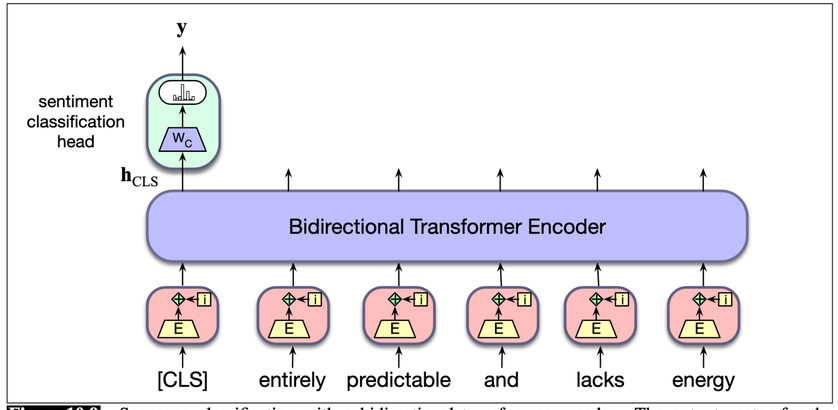

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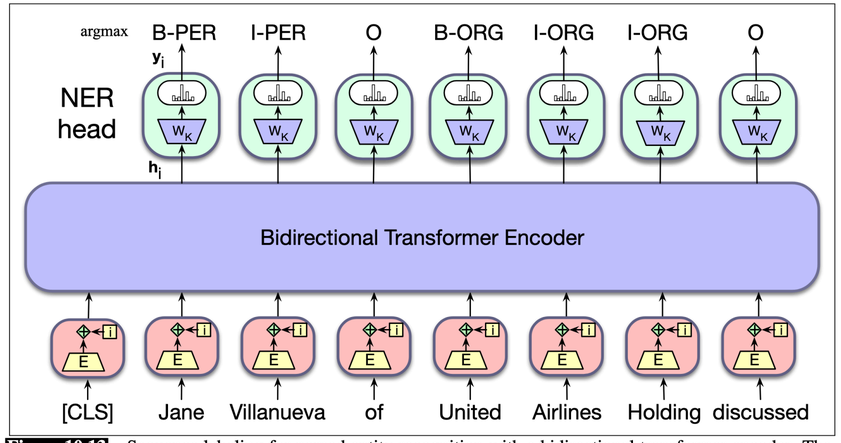

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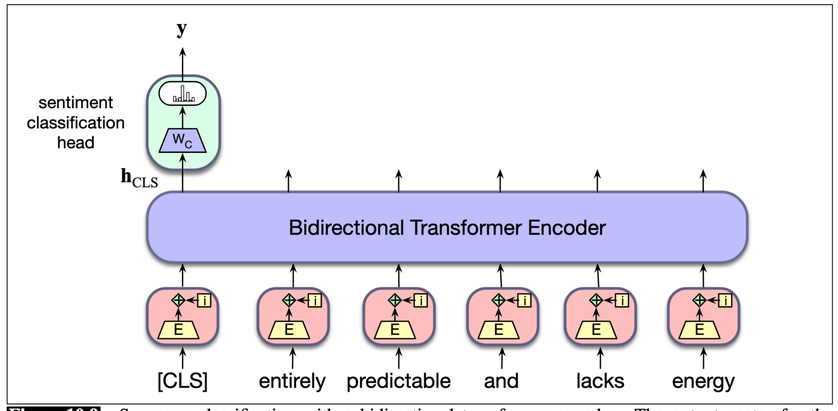

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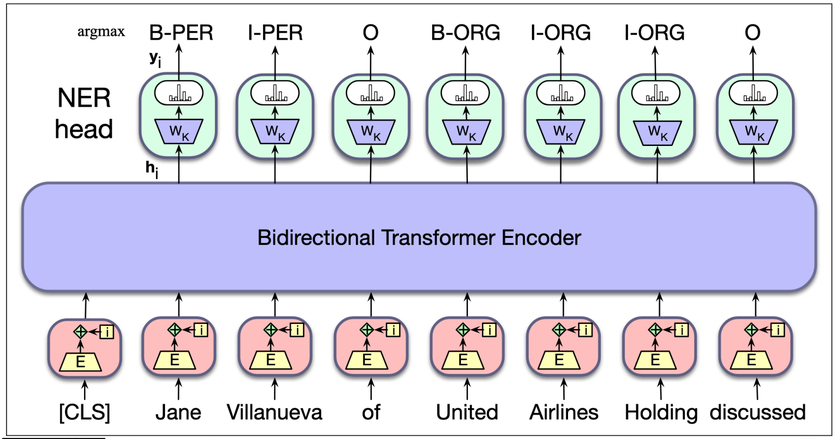

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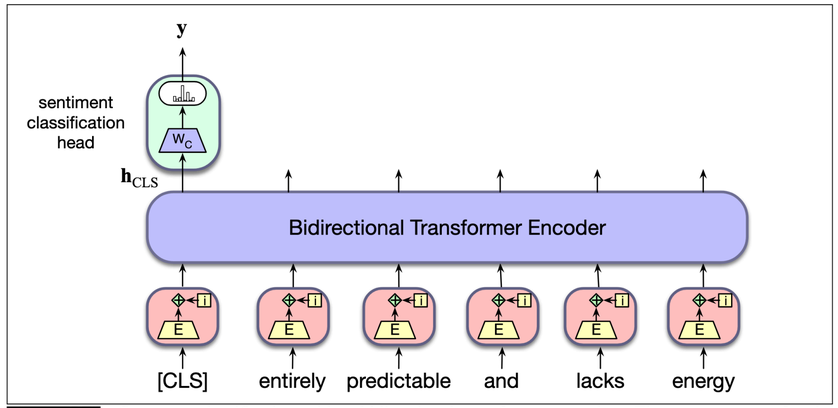

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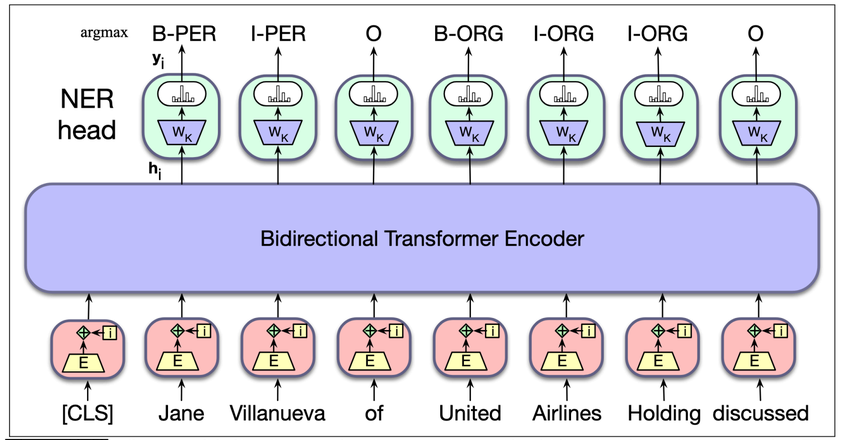

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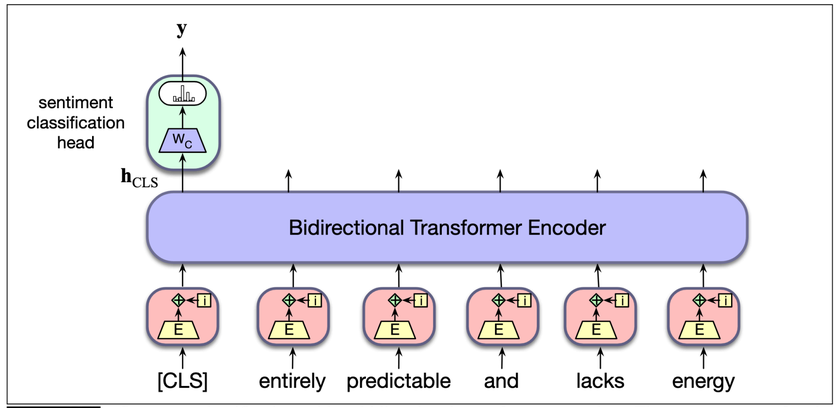

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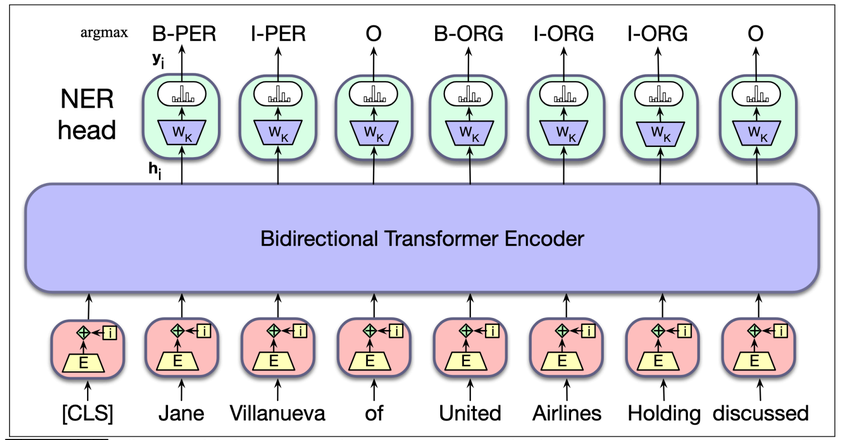

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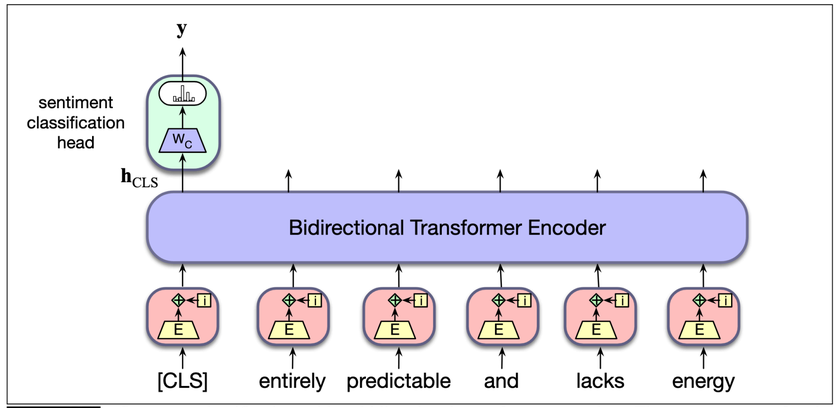

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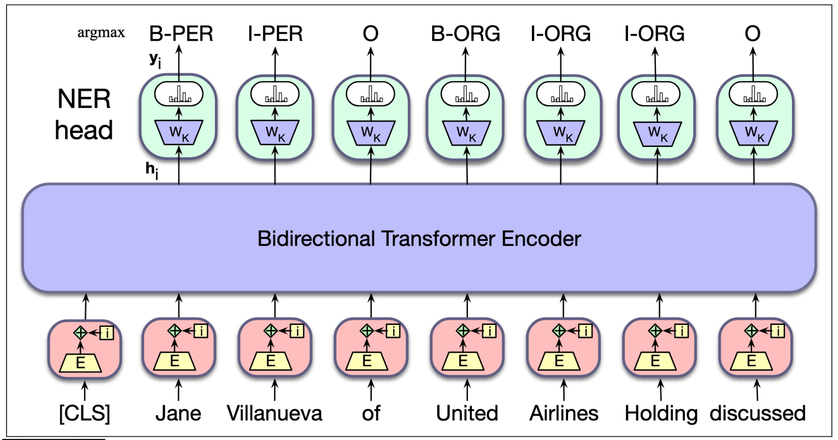

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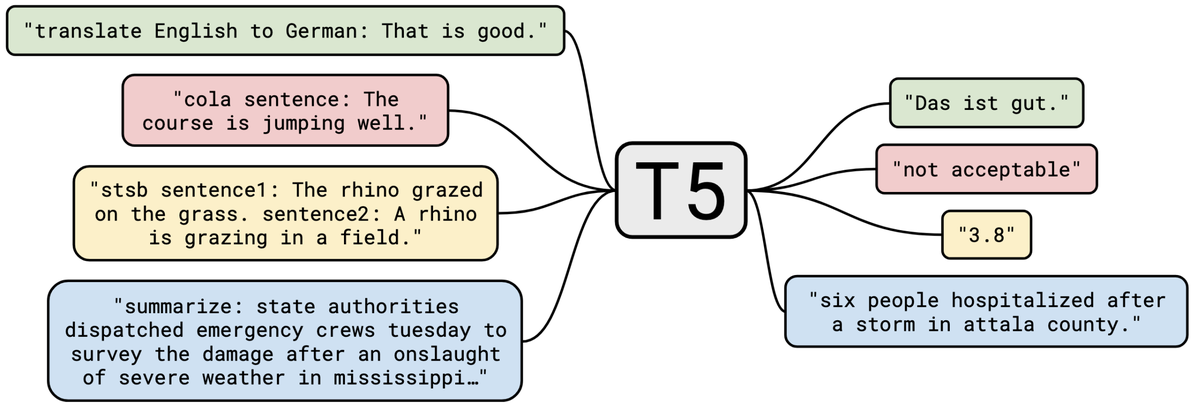

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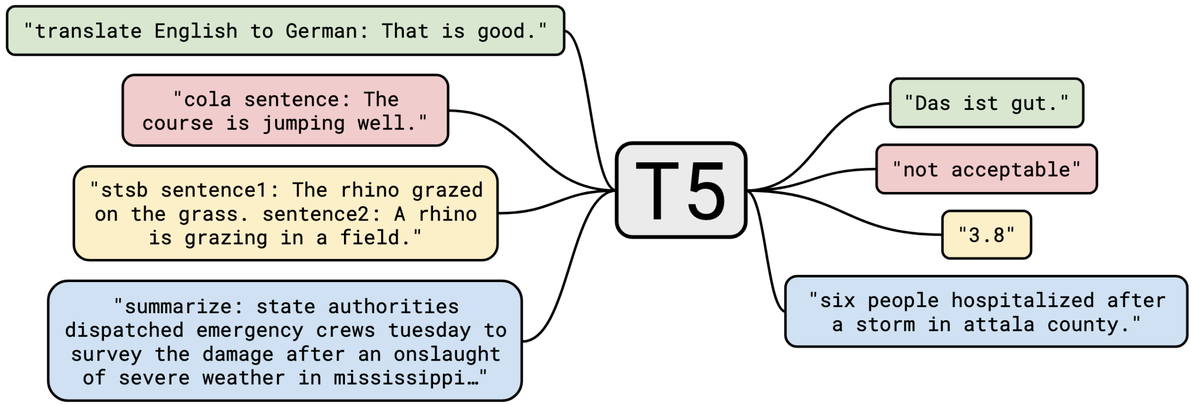

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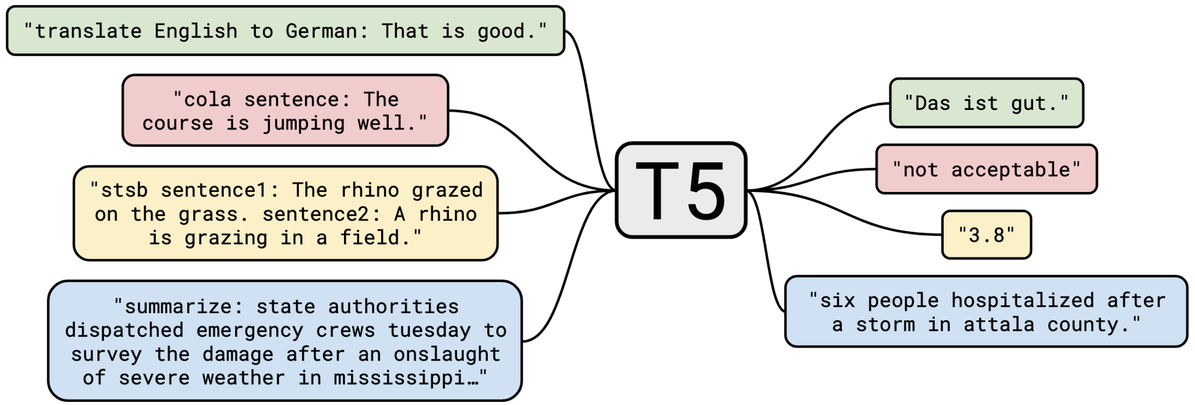

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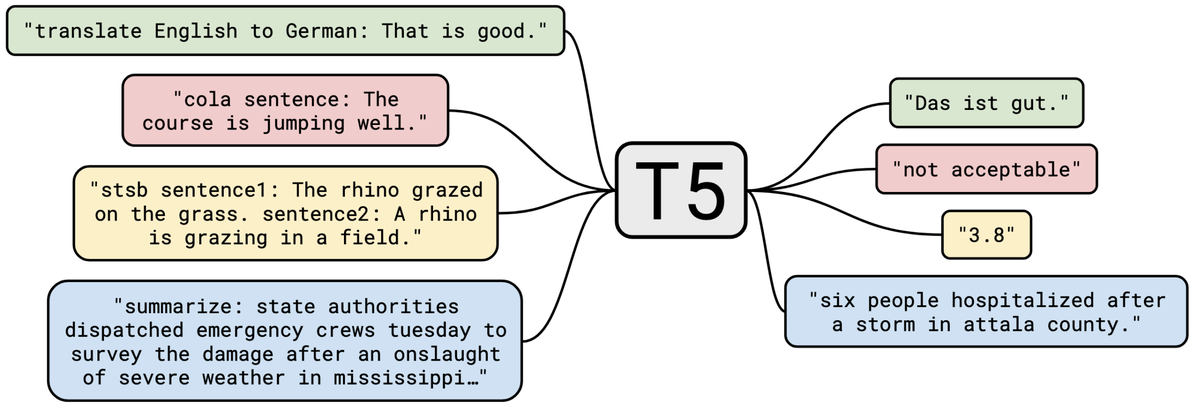
  - "**T**ext-**t**o-**T**ext **T**ransfer **T**ransformer"



Converting Tasks to Language Modeling

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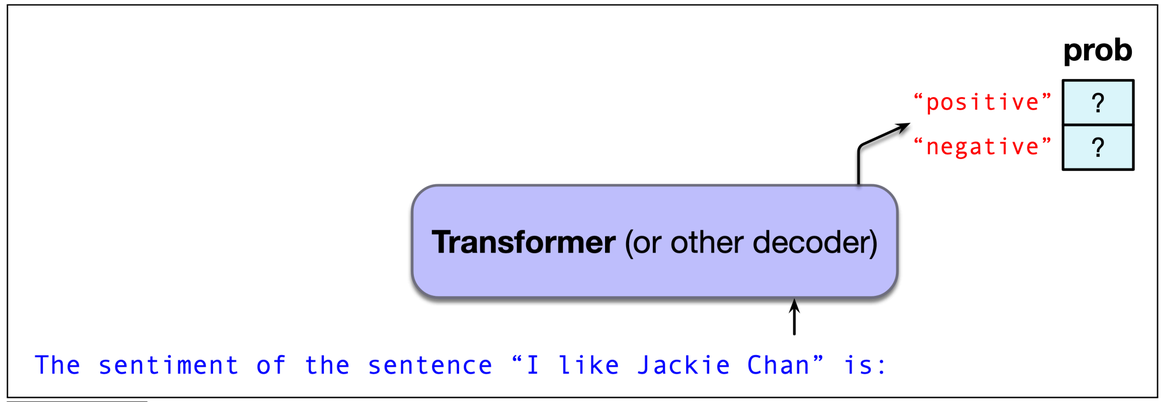

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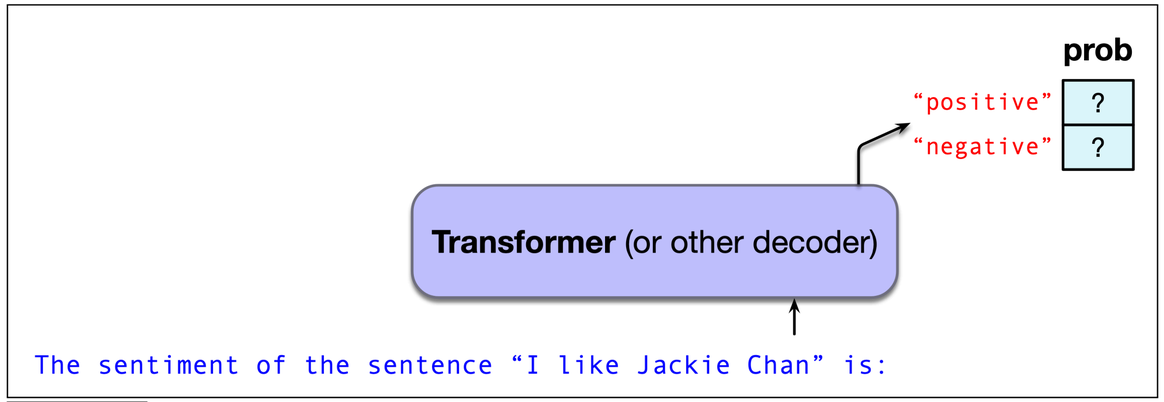

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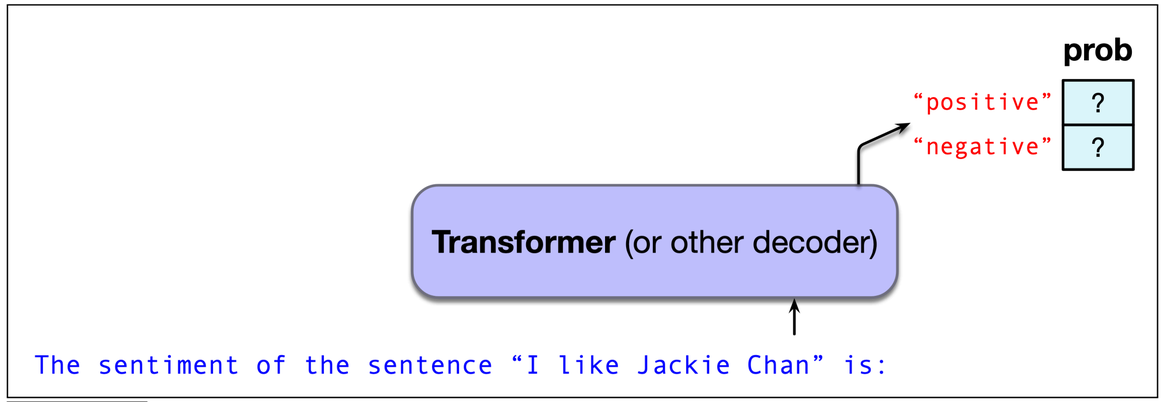

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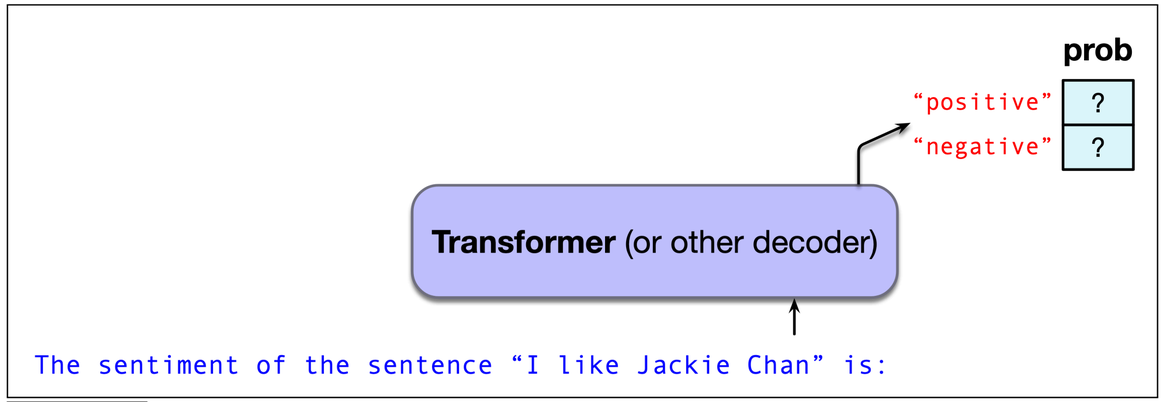

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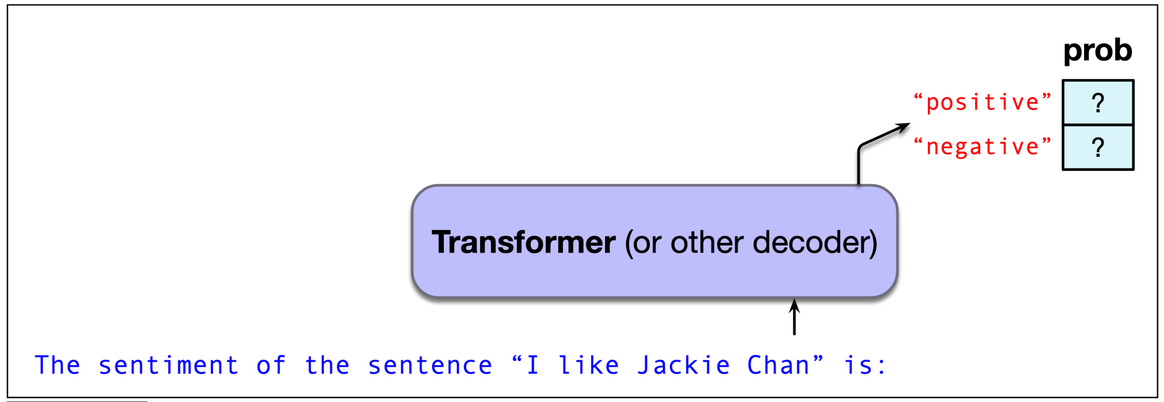

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- Other times this is with more **"meta"** text like `sentence1:` , `sentence2:`

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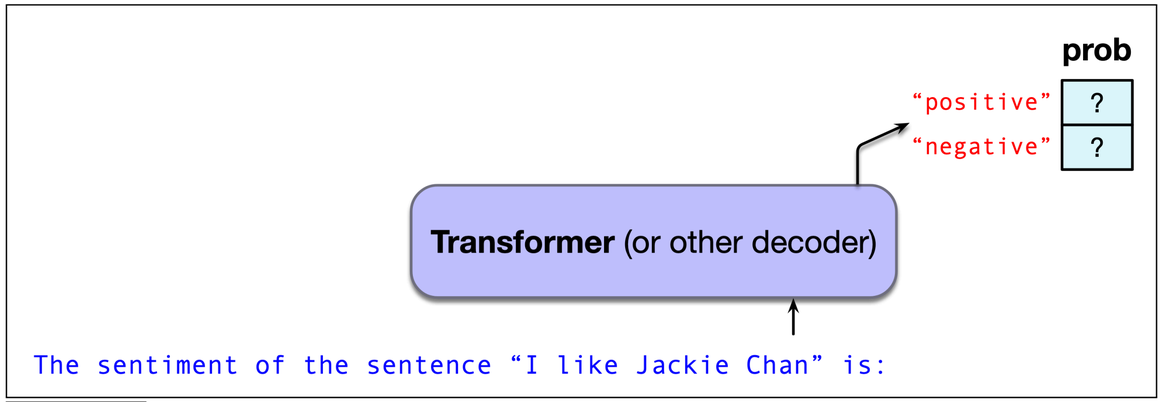

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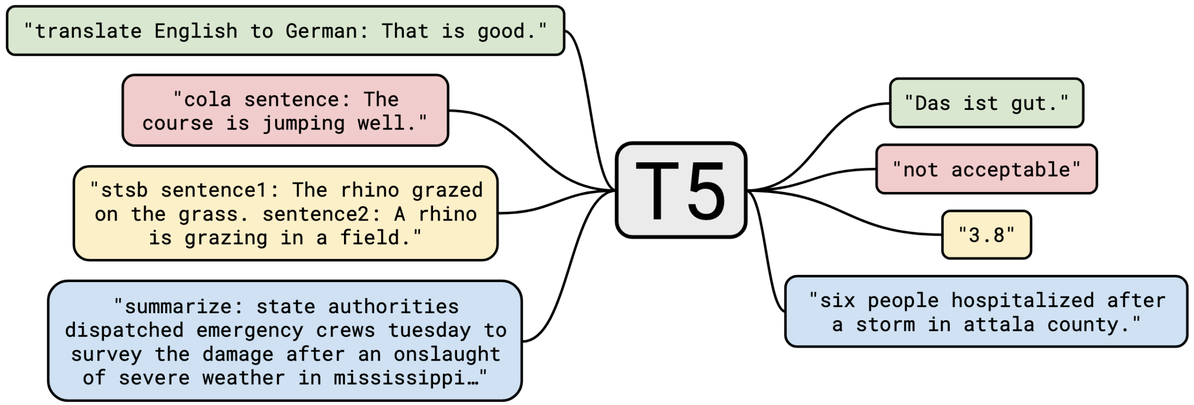

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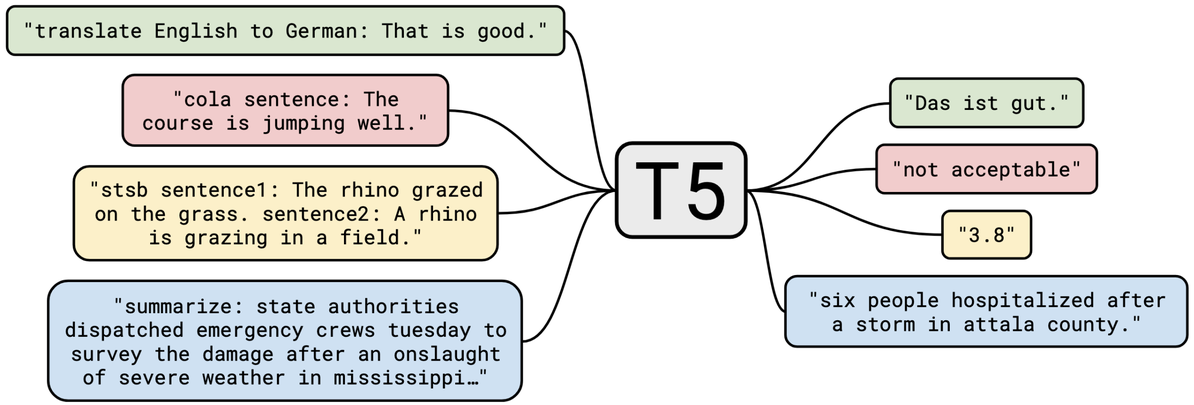

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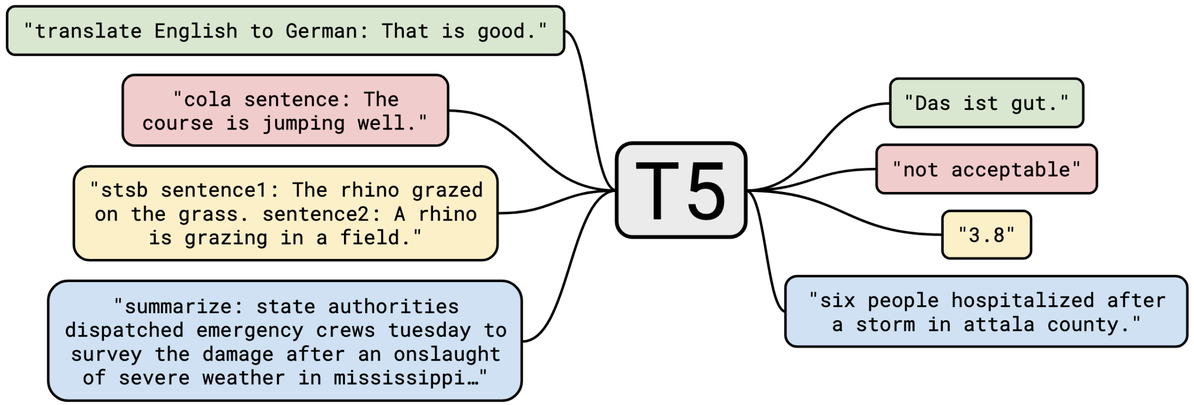

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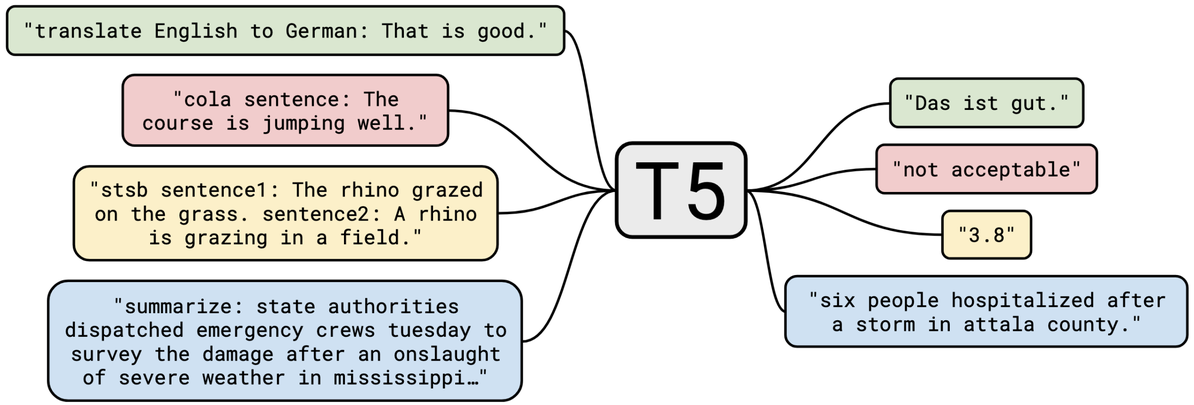

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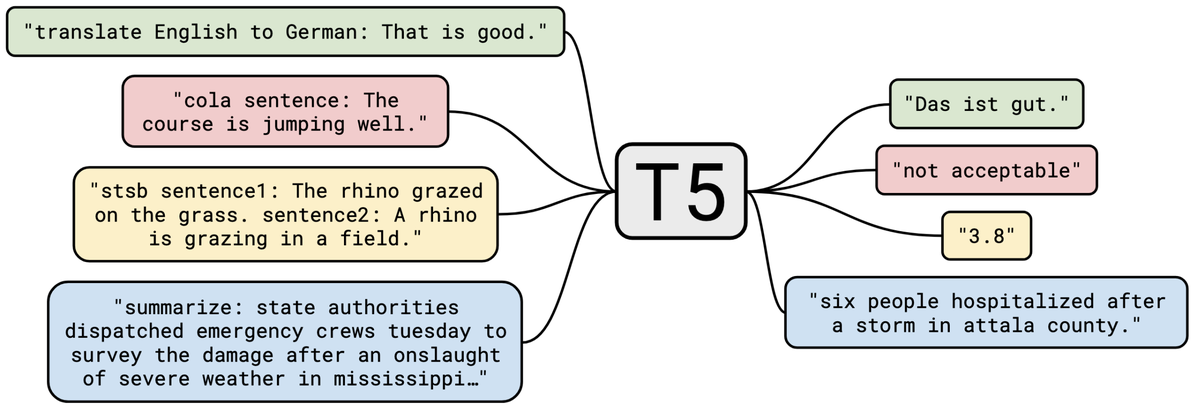

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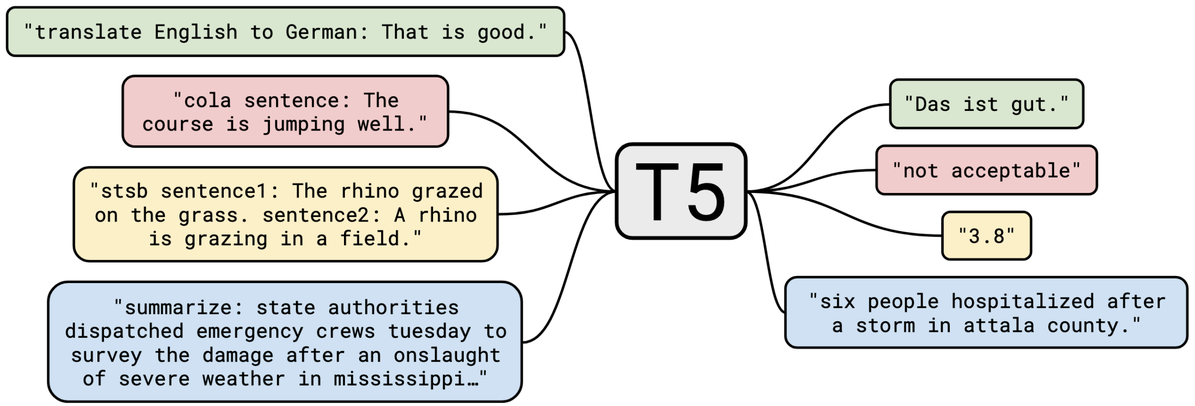

Task Inventories

(a) SUP-NATINST (this work)

(b) NATINST

(c) PROMPTSOURCE (T0 subset)

(d) FLAN

(e) INSTRUCTGPT

Figure 2: Compared to other datasets, SUP-NATINST covers a more diverse range of task types. InstructGPT reports a very coarse categorization of their task types. Bubble size represents the number of tasks of each type in log scale.

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- This type of interference is called **Negative Transfer**
  - Important and active field of research

How much to transfer?

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- **Feature Extraction:** (aside from an optional task head) **everything is frozen**
  - Pre-trained model used as a **fixed feature extractor**
  - **Low risk** of overfitting or forgetting

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- **LoRA (Low-Rank Adaptation):** essentially, learn a **compact offset to the pre-trained weights** $W' = W + BA$
  - B and A are **low-rank matrices**, containing **strictly less information** than W

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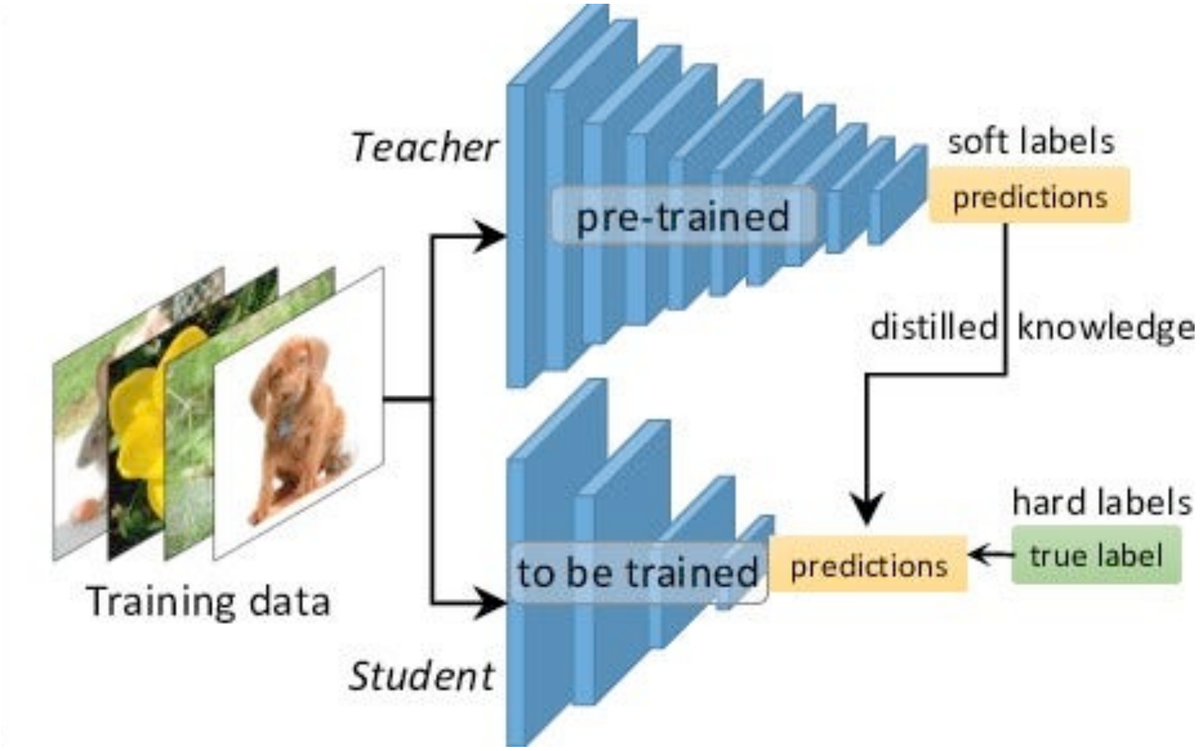
- $\mathscr{L}_{\text{distill}} = (1-\alpha)\cdot\mathscr{L}_{\text{CE}}(y,\hat{y}_S) + \alpha\cdot \text{KL}\left(\sigma(z_T/\tau)\|\sigma(z_S/\tau)\right)$
  - KL: **KL Divergence** between **teacher and student probability dists.**
  - L_CE: normal **classification loss**

Distillation Visualized



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- DistilBERT: 97% of BERT's performance at only **60% parameter size**

When use distillation?

- Example: you have a **powerful model** (e.g. LLM), but you **can't afford to deploy it** (because of latency, cost, privacy, etc.)
- Distillation transfers the capability to a **smaller, deployable model**
  - For instance, many models that are **deployed to smartphones**
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- Teacher predictions can be seen as **information-rich labeling functions**