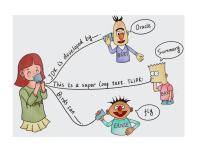
Basics

Learning Paradigms



Learning goals

- Understand the different learning paradigms
- Linguistic tasks vs. higher-level tasks

CATEGORIZATION OF LEARNING

Disclaimer:

- This categoriazation is rather coarse
- The list of paradigms is extendable
- Not everything is unambiguous, there might be overlap

Connection to tasks/data:

- Given the task, some paradigms are more suitable
- Given the amount of data, a specific paradigm might be preferrable
- Presence/Absence of labels makes certain paradigms (in)feasible

CATEGORIZATION OF LEARNING

Distinction between:

- Embedding texts
- Pre-training & fine-tuning a model
- Prompting
- Interaction & Generation
- Agents

Problem statement

- Words are discrete units composed of characters
- We can represent them (high-dimensional) one-hot vectors
- This makes it difficult/impossible to e.g. capture similarity between synonyms
- Documents can be represented as a vector of word occurrences (bag-of-words)

Example (one-hot)

$$ec{w}^{(\text{football})} = [0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0] \\ ec{w}^{(\text{basketball})} = [0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]$$

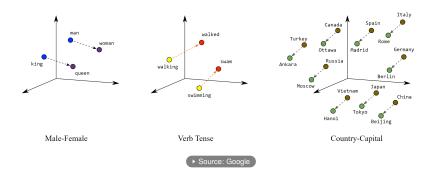
Problems of one-hot embeddings

- high dimensionality
- not possible to measure similarity

Example (dense embedding)

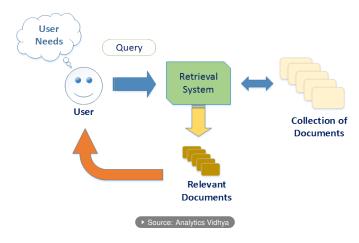
$$ec{w}^{(\text{football})} = egin{bmatrix} 0.359 \\ -0.174 \\ 0.701 \\ \vdots \\ 0.445 \\ -0.123 \\ 0.509 \end{bmatrix}$$

Measuring similarity



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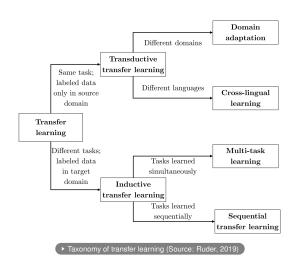
Document retrieval



© Basics - 6 / 18

Problem statement

- The larger the models, the more data is needed to train them
- (Labeled) Data is scarce and expensive!
- Many languages in the world are highly underrepresented in terms of existing resources
 - Often: Number of speakers \neq Amount of available written text
- Unlabeled (English) text data is ubiquitous



Pre-training:

- Using unlabeled corpora in conjunction with self-supervised objectives is commonly referred to as Pre-Training the model
- Generation of samples for pre-training basically effortless, exploiting the inherent structure of the text
- Construction of different self-supervised objectives, which are assumed
 - to cover different phenomena better than the others
 - to work more efficiently for learning

Fine-tuning:

- The second phase of transfer learning, i.e. adapting the pre-trained model to a labeled data set for a specific downstream task is referred to as Fine-Tuning
- Far less labeled data required compared to a scenario w/o pre-training

PROMPTING

Accessing pre-trained models:

- Fine-tune them
- Also possible: No fine-tuning, but ...
 - Zero-Shot Transfer w/o ANY labeled data
 - Few-Shot Transfer w/ FEW labeled data points
- In both of the latter cases, good pre-training becomes even more important

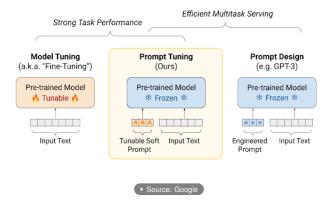
PROMPTING

Definition(s):

- GPT-3 paper:
 "Task Description" (accompanied by samples + labels)
- Prompt: Describing the task the model is expected to perform
- Prompt Engineering:
 Finding the best prompt(s) for one (or across multiple) task(s)
- Prompt Tuning:
 Add trainable weights ("soft prompt") to inputs and fine-tune

PROMPTING

Differences:



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Interacting with the model

- Larger model sizes, reduced latency and improved training regimes enable conversations with the models
- Enables the user to ..
 - .. have multi-turn conversations, with the model "remembering" previous inputs
 - .. refine the prompt in case of unsatisfactory output
 - .. used increased context sizes for the prompts
- Still: Static, pre-trained model with with "knowledge"

Interacting with the model

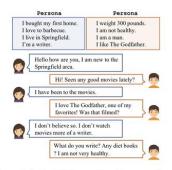
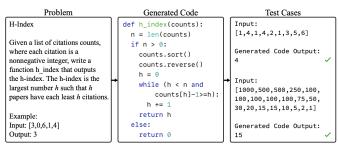


Figure 1: A clippled dialogue from PERSONA-CHAT.

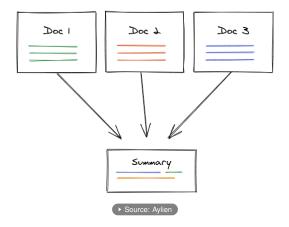
Source: Papers with code (example for Persona-Chat

Code generation



► Source: Papers with code

(Multi-)Document summarization



OUTLOOK

Agents

- Example: LangChain
- Goal: The agent is able to solve complex task using tools and/or accessing the internet

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