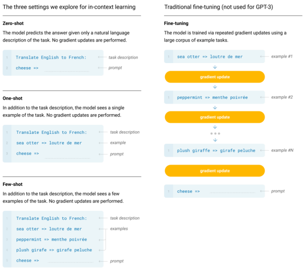
Basics

Learning Paradigms



Learning goals

- Understand the different learning paradigms
- Relate type of learning to amount of labeled data required

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

EMBEDDING

Problem statement

- Words are discrete units composed of characters
- We can represent them as (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)

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

EMBEDDING

Problems of one-hot embeddings

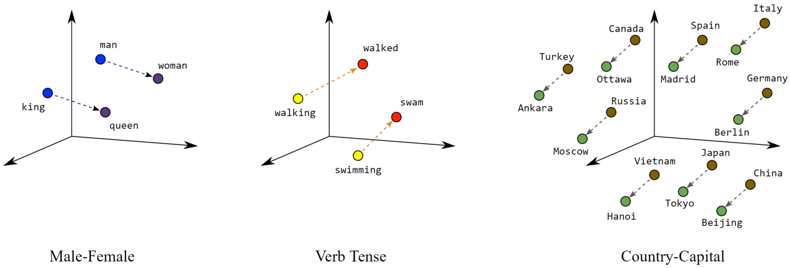
- high dimensionality
- *Again:* not possible to measure similarity
- *Alternative:* Dense embeddings

Example (dense embedding)

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

EMBEDDING

Measuring similarity now possible:

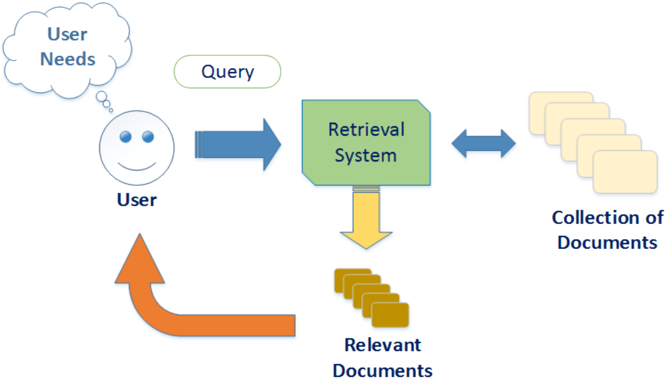


▸ Source: Google

EMBEDDING

Not only possible for words, but for whole documents:

Use Case: **Document retrieval**



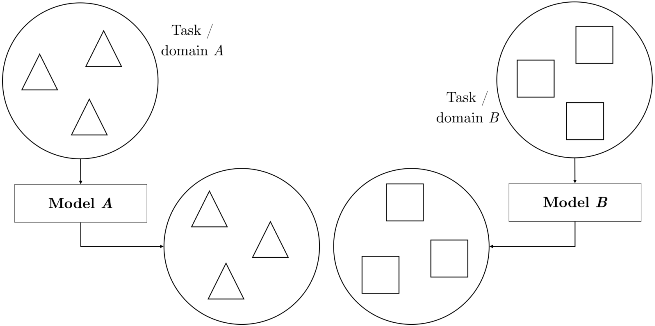
Source: Analytics Vidhya

PRE-TRAIN/FINE-TUNE

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:
  Number of speakers (of a language) $\neq$ *Amount of available written text*
- Unlabeled (English) text data is ubiquitous

PRE-TRAIN/FINE-TUNE



▸ Classical Machine Learning (Source: Ruder, 2019)

PRE-TRAIN/FINE-TUNE

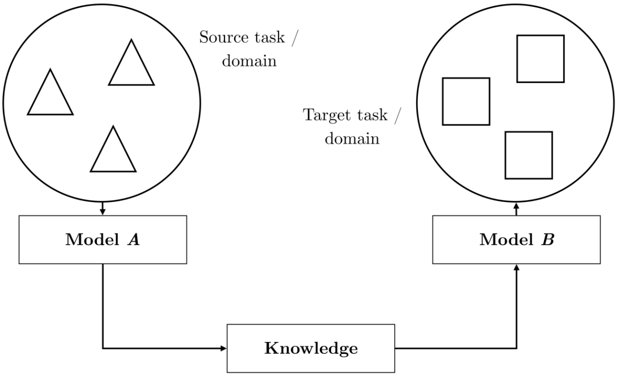
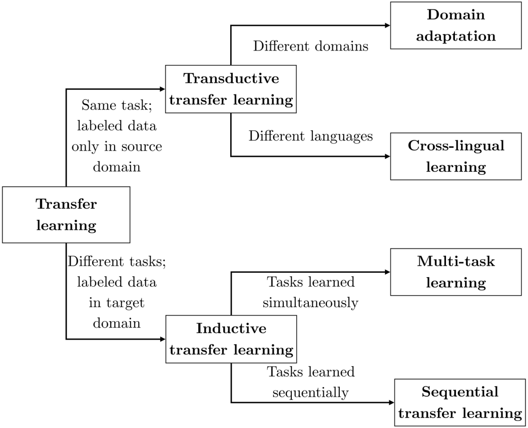


FIGURE 3.2: The transfer learning setup.

▸ Transfer Learning (Source: Ruder, 2019)

PRE-TRAIN/FINE-TUNE



▸ Taxonomy of transfer learning (Source: Ruder, 2019)

PRE-TRAIN/FINE-TUNE

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
  - *Example 1:* predict next work in a sentence
  - *Example 2:* masked word prediction

PRE-TRAIN/FINE-TUNE

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

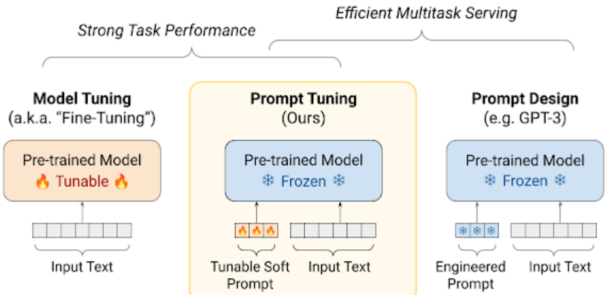
PROMPTING

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:



▸ Source: Google

CHATTING / GENERATION

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 "knowledge"

CHATTING / GENERATION

Interacting with the model: *Persona-Chat Benchmark*

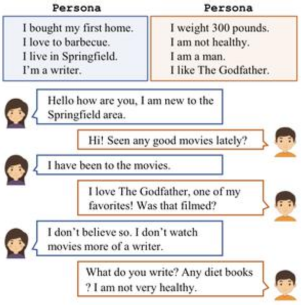
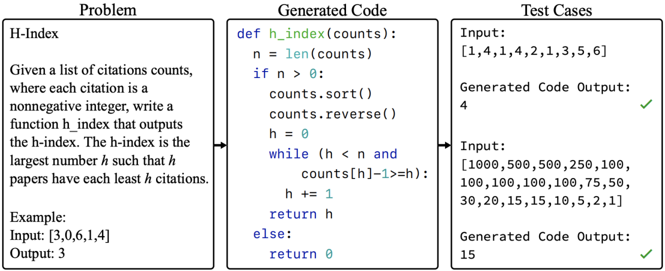


Figure 1: A clippled dialogue from PERSONA-CHAT.

▸ Source: Papers with code (example for `Persona-Chat`)

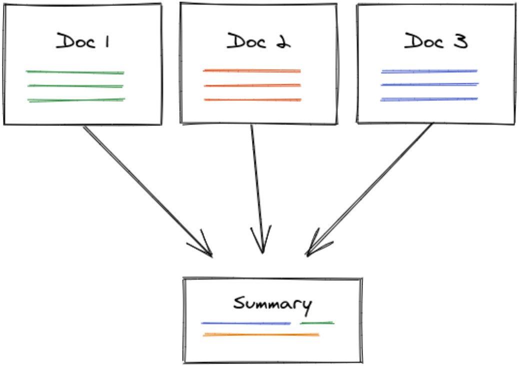
Code generation



Source: Papers with code

CHATTING / GENERATION

(Multi-)Document summarization



▸ Source: Aylien

OUTLOOK

Agents

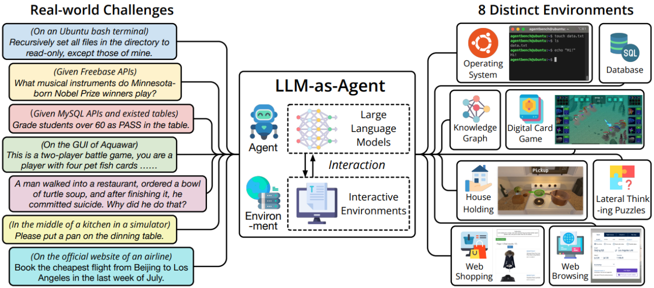


Figure 2: AgentBench is the first systematic benchmark to evaluate LLM-as-Agent on a wide array of real-world challenges and 8 distinct environments. In total, 25 LLMs are examined in its first edition.

▸ Source: Liu et al., 2023