# Preference learning

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## Story so far

Q: How well can we capture structure of natural language?

- Shannon's N-gram model and basic learning objective
  - Very easy to understand, but quite limited in power
- Neural language models
  - Exploit word embeddings + neural computation models
  - Some coarse- and fine-grained understanding of what they can do
  - Fairly robust understanding of learnability/generalization theory
  - Very preliminary understanding of efficient training algorithms (commensurate with how well we understand training for other neural nets)

## LLM training

- Pre-training
  - Shannon's objective (a special case of "self-supervised learning")
- <u>Training</u>
- Post-training
  - Supervised fine-tuning
    - Labeled examples (prompt x, response y)
    - Train model to predict desired responses to prompts
  - Instruction-tuning
    - Labeled examples (instructions i, prompt x, format f)
    - Train model so predicted responses match the desired format as instructed
  - Both of these "post-training" methods are (just) standard supervised learning

E.g., questions are not always followed-up with correct answers in natural language text

Handle custom instructions and response formats

## Preference-tuning

How to make a language model polite?

- <u>Solution 1</u>: supervised fine-tuning on prompts with polite answers
  - Requires a polite person to write these polite answers
- Solution 2: supervised fine-tuning that rewards polite answers
  - Requires a polite person to judge whether answers are polite or not
    - How polite is polite enough? What is politeness level 7?
    - People tend to be better at comparing answers than giving absolute grades
  - Use pairwise preference comparisons to learn a reward function, which in turn is used with supervised learning

### Reward model

• <u>Classical models (like BTL)</u>: parameterized by quality score  $w_i \ge 0$  for each item *i* 

$$\Pr(i \succ j) = \frac{w_i}{w_i + w_j}$$

• <u>Models with features</u>: each item *i* has a feature vector  $v_i$ , and (log) quality score is  $\log w_i = \langle \theta, v_i \rangle$  for some model parameter vector  $\theta$ 

$$\Pr(i \succ j) = \frac{1}{1 + \exp(-\langle \theta, v_i - v_j \rangle)}$$

Models with context-dependent features:

$$\Pr(i \succ j | x) = \frac{1}{1 + \exp(-\langle \theta, \phi(v_i, x) - \phi(v_j, x) \rangle)}$$

• ...