▼ 15주차 예습과제

1. Extremely large models and GPT3

about GPT3

- -Better than other models at language modeling and related tasks such as story completion
- -GPT-3 demonstrates some level of fast adaptation to completely new tasks.
- -The language model training(outer loop) is learning how to learn from the context limitations and open questions about GPT-3
- -Seems to do poorly on more structured problems that involve decomposing into atomic / primitive skills
- -Performing permanent knowledge updates interactively is not well studied
- -Doesn't seem to exhibit human like generalization (systematicity)
- -Language is situated and <u>GPT</u>-3 is merely learning from text without being exposed to other modalities.
- 2. Compositional Representations and Systematic Generalization

<u>Systematicity</u>: The ability to produce/understand some sentences is intrinsically connected to ability to produce/understand certain others. This means there is a "definite and predictable pattern among the sentences we understand"

E.g. any speaker that understands the sentence "John love Mary" should be able to understand "Mary loves John"

-Compositionality of representations is a helpful prior that could lead to <u>systematicity</u> in behavior.

-Do neural networks generalize systematically on challenging benchmarks involving realistic language?

· Basic Machinery for producing compositionally challenging splits

Let $\mathscr{F}_A(\mathsf{data}) \equiv \mathsf{normalized}$ frequency distribution of atoms Let $\mathscr{F}_C(\mathsf{data}) \equiv \mathsf{normalized}$ frequency distribution of compounds Define atom and compound divergence as:

$$\mathcal{D}_A (\text{train} | | \text{test}) = 1 - C_{0.5} (\mathcal{F}_A (\text{train}) | | \mathcal{F}_A (\text{test}))$$

 $\mathcal{D}_C (\text{train} | | \text{test}) = 1 - C_{0.1} (\mathcal{F}_C (\text{train}) | | \mathcal{F}_C (\text{test}))$

where,

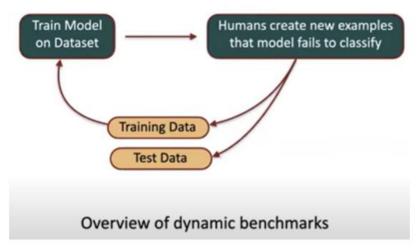
$$C_a(P \mid \mid Q) = \sum_{k} p_k^{\alpha} q_k^{1-\alpha}$$

is the chernoff coefficient between two categorical distributions that measures similarity.

 goal: split data into train/test such that compound divergence is maximized and atom divergence is minimized 3. Improving how we evaluate models in NLP

While we are making progress in terms of <u>perfromance</u> on benchmarks, it's unclear if the gains are coming from spurious correlations or real task understanding

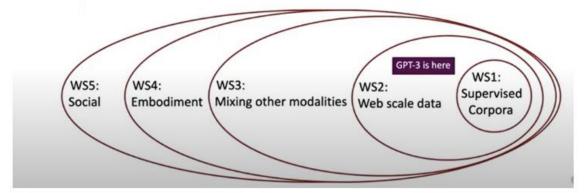
-Instead of testing models on static benchmarks, evaluated on an ever changing dynamic benchmark.



- -main challenges: ensuring that humans are able to come up with hard examples and we are not limited by creativity.
- -current approaches use examples from other datasets for the same task as prompts
- 4. Grounding language to other modalities

Grounding Language to other modalities

- Many have articulated the need for using modalities other than text
- Bender and Koller [2020]: Impossible to acquire "meaning" (communicative intent of the speaker) from form (text / speech signal) alone
- Bisk et al [2020]: Training on only web-scale data limits the world scope of models.



[serious progress in the last decade thanks to data+hardware+neural networks] we now have amazing technologies such as GPT-3 that can do truly exciting things in the short term:

Scaling helps, so perhaps even larger models?

Scaling requires very non-trivial <u>enginerring</u> efforts so a lot of interesting systems work to be done here

in the long term:

making progress towards systematicity, fast adaptation, generalization

Improved evaluation so we can trust benchmarks

Figuring out how to move beyond text in a tractable way