CS388: Natural Language Processing
Lecture 10: Evaluation Principles and Dataset Artifacts

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Announcements

- Final project proposals due next Thursday
- P3 released next week

Recap

- **Pretraining** (BERT):
  - Train a big model to fill in masked-out words, then adapt it to other tasks. Led to big gains in **question answering** and **NLI** performance. BART/T5, GPT-3, etc. push this further and extend it to other tasks
- **Decoding methods:** nucleus sampling > greedy for open-ended tasks
- **Two tasks we'll focus on today: Question answering** (QA)…
  - "What was Marie Curie the first female recipient of?"
    -> "The Nobel Prize" (find this span in a document)
- …and **NLI**
  - "But I thought you'd sworn off coffee."
    contradicts "I thought that you vowed to drink more coffee."

Today

- Finish prompting
- Ethical issues
- Evaluation in NLP: benchmarks and generalization
- Spurious correlations / dataset artifacts
- Debiasing

Prompts

Prompting demo:
QA, Math QA, etc.

Brown et al. (2020)

Ethical Issues

Bias and Toxicity

- "Toxic degeneration": systems that generate toxic stuff

- System trained on a big chunk of the Internet: conditioning on "SJW", "black" gives the system a chance of recalling bad stuff from its training data

https://toxicdegeneration.allenai.org/

Stochastic Parrots (about LMs generally)

- Paper (that included authors at Google who were subsequently fired) about dangers of large language models
- **Claim 1**: environmental cost is disproportionately born by marginalized populations, who aren't even well-served by these tools
- **Claim 2**: massive data is fundamentally challenging to audit, contains data that is biased and is only a snapshot of a single point in time
- **Claim 3 (what we'll focus on today)**: these models are not grounded in meaning — when they generate an answer to a question, it is merely by memorizing cooccurrence between symbols

Bender, Gebru, McMillan-Major, Shmitchell (2021)

Stochastic Parrots

Question: What is the name of the Russian mercenary group?
Answer: Wagner group.

Question: Where is the Wagner group?
Answer: In Syria.

Question: Who is the leader of the Wagner group?
Answer: A Russian citizen, Dmitry Utkin. He was born in 1971 and lives in Moscow. He has been a member of the Russian parliament since 2016. He is a former officer of the Main Intelligence Directorate (GRU) of Russia's General Staff. He was also a commander of the special forces unit "Vostok" (East). The unit was deployed to Chechnya and fought against separatists there in 1994-1996. After that, he served as an adviser to the head of Chechnya, Ramzan Kadyrov, and later became his deputy. In 2004-2005, he

- We are likely to assume the model is producing factual information and presenting it in a coherent way, but this is our interpretation we project on the model

Bender, Gebru, McMillan-Major, Shmitchell (2021)

Cross-Dataset Evaluation

Principles of Evaluation Suites

- Training and testing on i.i.d. data with big neural models often yields very high performance
- "Solving" a task (getting human-level performance) may be useful, but often can't tell us about our models more broadly
- To assess big models, we need **evaluation suites (benchmarks)** like GLUE
- What makes a good evaluation suite of tasks?

Principles of Evaluation Suites

- Difficulty: even if some task can be solved by hand-engineering, it should be hard to solve all *N* tasks
  - SWAG: multiple-choice commonsense reasoning, was designed to be hard for ELMo but ended up being easy for BERT (solved before the conference talk)
  - GLUE was the first evaluation suite to be solved very quickly…so a new one was needed!
- Diverse: doing well on it should say something useful
- Good "yardstick": should understand where human performance is and what good performance on the task would mean

Alex Wang et al., 2019

SuperGLUE: Task Requirements

- Task substance: "*Tasks should test a system's ability to understand and reason about texts in English.*"
- Task difficulty: "*Tasks should be beyond the scope of current state-of-the-art systems, but solvable by most college-educated English speakers.*" (notably they excluded domain-specific tasks, which have become more popular these days, e.g., the bar exam)
- Evaluatable: this is challenging to find!
- Public dataset, good license, etc.

Alex Wang et al., 2019

SuperGLUE: Performance

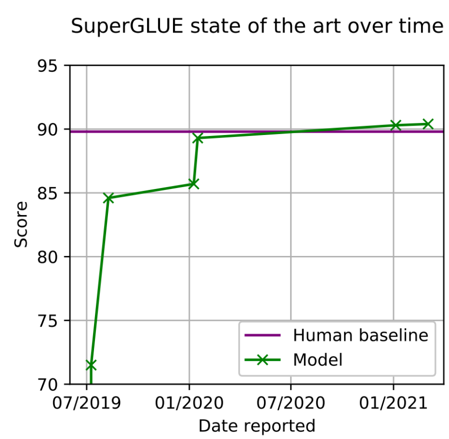
Model Metrics	Avg	BoolQ Acc.	CB F1/Acc.	COPA Acc.	MultiRC $F1_a$/EM	ReCoRD F1/EM	RTE Acc.	WiC Acc.	WSC Acc.	AX_b MCC	AX_g GPS Acc.
Most Frequent	47.1	62.3	21.7/48.4	50.0	61.1 / 0.3	33.4/32.5	50.3	50.0	65.1	0.0	100.0/ 50.0
CBoW	44.3	62.1	49.0/71.2	51.6	0.0 / 0.4	14.0/13.6	49.7	53.0	65.1	-0.4	100.0/ 50.0
BERT	69.0	77.4	75.7/83.6	70.6	70.0 / 24.0	72.0/71.3	71.6	**69.5**	**64.3**	23.0	97.8 / 51.7
BERT++	**71.5**	79.0	**84.7/90.4**	73.8	70.0 / 24.1	72.0/71.3	79.0	**69.5**	**64.3**	38.0	99.4 / 51.4
Outside Best	-	**80.4**	- / -	**84.4**	**70.4*/24.5***	**74.8/73.0**	**82.7**	-	-	-	- / -
Human (est.)	89.8	89.0	95.8/98.9	100.0	81.8*/51.9*	91.7/91.3	93.6	80.0	100.0	77.0	99.3 / 99.7

- RoBERTa in 2019: 84.6
- DeBERTa in 2020: 90.3. **Even SuperGLUE was solved quickly!**

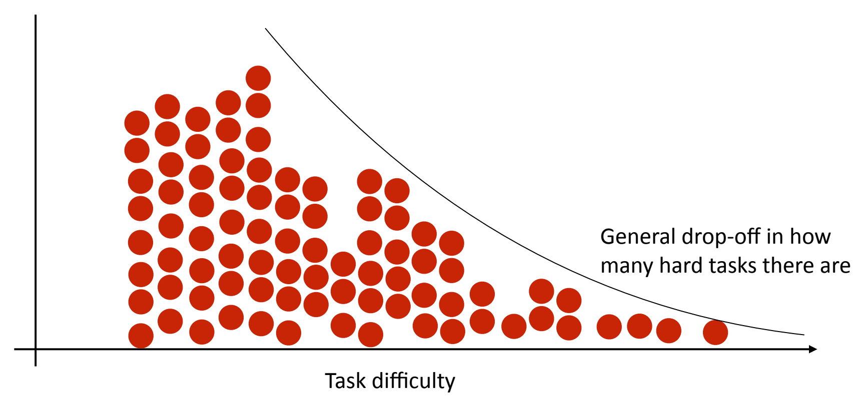
Alex Wang et al., 2019

SuperGLUE: Performance

As reported in BIGBench:



Intuition



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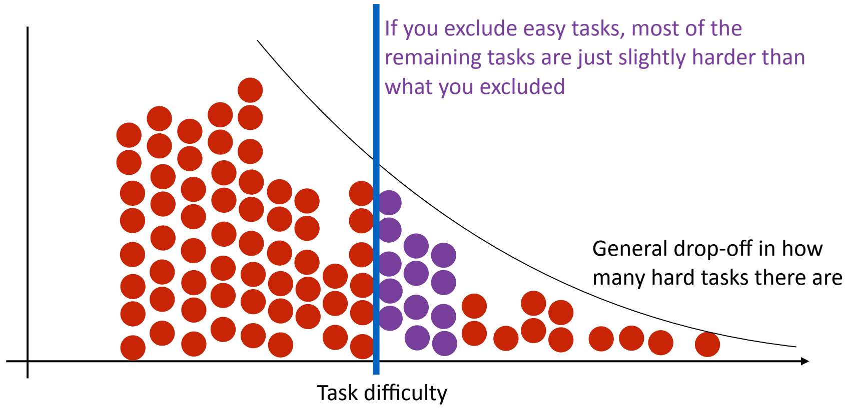
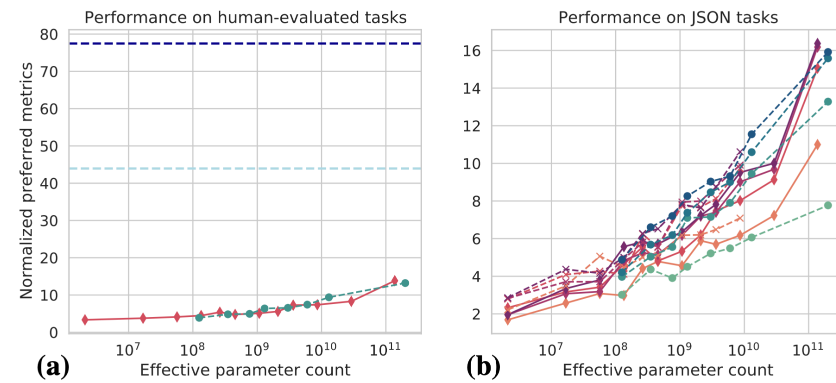


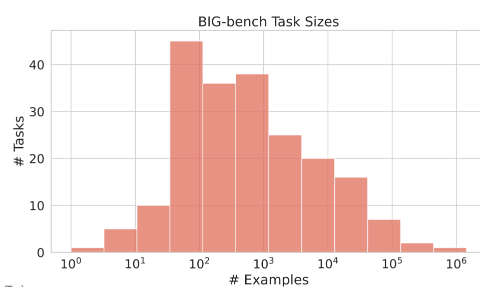
BIG-bench

- 204 tasks, 444 authors



BIG-bench

- "Beyond the Imitation Game" — aim to learn more than what's possible from model vs. human performance
- Particular emphasis on scaling
- Primarily for pre-trained models without fine-tuning. Therefore, not all tasks have large training (or even test!) sets



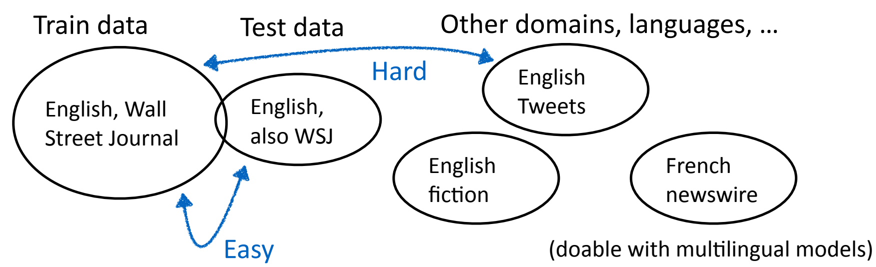
Evaluation Under Distribution Shift

Model Performance

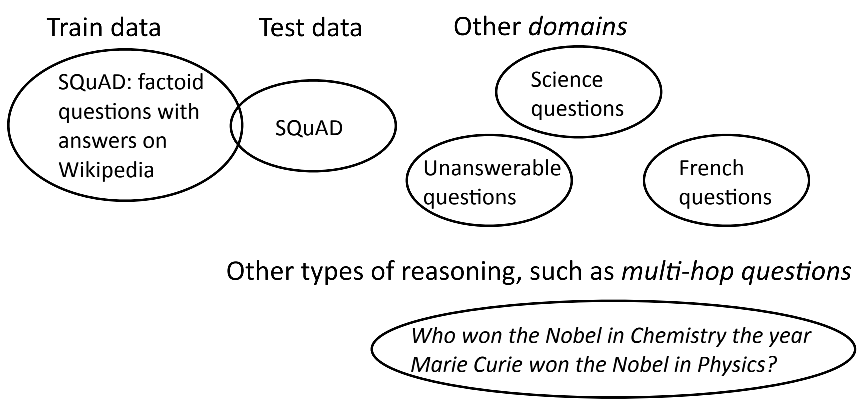
- If models can be fine-tuned on each of n tasks in an evaluation suite and perform very well on the held-out test dataset, have we solved everything we want?
- What can go wrong?

Generalization

- If a model does well on train but poorly on test data, it *doesn't generalize*
- A model can do well on its test data and still fail to generalize *out of distribution* — arguably an even more important notion
- Many notions of generalization. Example: POS tagging



Generalization: QA



Generalization

- Just doing well on a single test set **is not that useful**
- We want POS taggers, QA systems, and more that can generalize to new settings so we can deploy them in practice
- Sometimes, you can get **very good test performance** but the model **generalizes very poorly**. How does this happen?

Annotation Artifacts, Reasoning Shortcuts: QA

Annotation Artifacts

- Some datasets might be easy because of how they're constructed, especially in QA and NLI

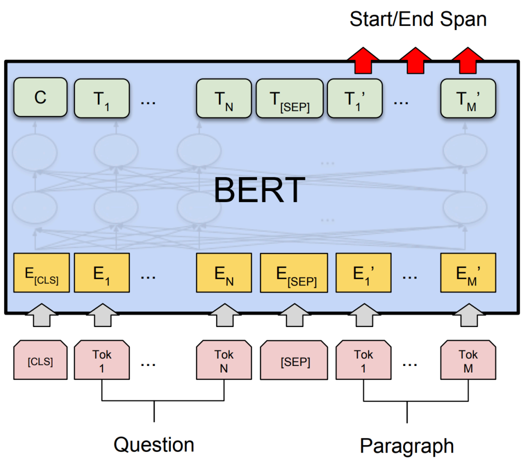
  What becomes of Macbeth?

  What does Macduff do to Macbeth?

  What violent act does Macduff perform upon Macbeth?

- All questions have the same answer. But some are more easily guessable

Reminder: QA with BERT



Devlin et al. (2019)

QA: Answer Type Heuristics

What degree did Martin Luther receive on October 19, 1512?

On October 19, 1512, Luther was awarded his doctorate of theology and, on October 21, 1512, was received into the senate of the theological faculty of the University of Wittenberg. He spent the rest of his career in this position at the University of Wittenberg.

- What should the model be doing? Corresponding Martin Luther with Luther, matching October 19, 1512 between question and passage

QA: Answer Type Heuristics

What degree did Martin Luther receive?

What degree ___?

On October 19, 1512, Luther was awarded his doctorate of theology and, on October 21, 1512, was received into the senate of the theological faculty of the University of Wittenberg. He spent the rest of his career in this position at the University of Wittenberg.

- Only one possible degree here! Model only needs to see "what degree" and will not learn to use the rest of the context!

QA: Answer Type Heuristics

- Question type is powerful indicator. Only a couple of locations in this context!

Where ____?

On October 19, 1512, Luther was awarded his doctorate of theology and, on October 21, 1512, was received into the senate of the theological faculty of the University of Wittenberg. He spent the rest of his career in this position at the University of Wittenberg.

Who ____?

When ____?

QA: Answer Type Heuristics

- Question type is powerful indicator. Only a couple of locations in this context!

Where ____? *Who ____?* *When ____?*

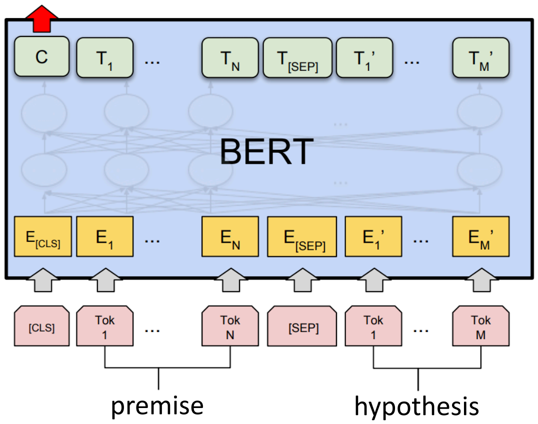
On October 19, 1512, Luther was awarded his doctorate of theology and, on October 21, 1512, was received into the senate of the theological faculty of the University of Wittenberg. He spent the rest of his career in this position at the University of Wittenberg.

- What will happen if we train on this data?
  - Will loss decrease?
  - How will the model learn to "behave"?

Annotation Artifacts, Reasoning Shortcuts: NLI

Reminder: NLI with BERT

entailed/neutral/contradiction



Devlin et al. (2019)

NLI: Hypothesis-only Baselines

Premise: *A woman on a deck is selling bamboo sticks.*

Label?

Hypothesis: *A man is selling bamboo sticks*

Hypothesis: *A man is juggling flaming chainsaws*

Hypothesis: *Eighteen flying monkeys are in outer space*

- Not all of these things have the same likelihood of being true a priori
- What might the model learn to do in this case?

NLI: Hypothesis-only Baselines

Premise	A woman selling bamboo sticks talking to two men on a loading dock.
Entailment	There are **at least** three **people** on a loading dock.
Neutral	A woman is selling bamboo sticks **to help provide for her family.**
Contradiction	A woman is **not** taking money for any of her sticks.

- What's different about this neutral sentence?
  - To create neutral sentences: annotators *add information*
- What's different about this contradictory sentence?
  - To create contradictions: annotators *add negation*
- These are not broadly representative of what can happen in other settings. There is no "natural" distribution of NLI, but this is still very restrictive

NLI: Hypothesis-only Baselines

Premise	A woman selling bamboo sticks talking to two men on a loading dock.
Entailment	There are **at least** three **people** on a loading dock.
Neutral	A woman is selling bamboo sticks **to help provide for her family.**
Contradiction	A woman is **not** taking money for any of her sticks.

- Models can detect new information or negation easily
- Models can do very well ***without looking at the premise***

Performance of models that only look at the hypothesis: ~70% on 3-class SNLI dataset

	Hyp-only model	Majority class	
SNLI	69.17	33.82	+35.35
MNLI-1	55.52	35.45	+20.07
MNLI-2	55.18	35.22	+19.96

Gururangan et al. (2018); Poliak et al. (2018)

NLI: Heuristics (HANS)

Heuristic	Definition	Example
Lexical overlap	Assume that a premise entails all hypotheses constructed from words in the premise	**The doctor** was **paid** by **the actor**. $\xrightarrow[\text{WRONG}]{}$ The doctor paid the actor.
Subsequence	Assume that a premise entails all of its contiguous subsequences.	The doctor near **the actor danced**. $\xrightarrow[\text{WRONG}]{}$ The actor danced.
Constituent	Assume that a premise entails all complete subtrees in its parse tree.	If **the artist slept**, the actor ran. $\xrightarrow[\text{WRONG}]{}$ The artist slept.

- Word overlap supersedes actual reasoning in these cases
- They create a test set (HANS) consisting of cases where heuristics like word overlap are misleading. Very low performance

McCoy et al. (2019)

Evidence of Spurious Correlations: Contrast Sets

- How do we control for annotation artifacts? Things like "premises and hypotheses overlap too much" aren't easy to see!
- For any particular effect like lexical overlap, we could try to annotate data that "breaks" that effect
- Issue: breaking one correlation may just result in another one surfacing. How do we "break" them all at the same time?
- Solution: construct new examples through *minimal edits that change the label.*

Gardner et al. (2020)

Evidence of Spurious Correlations: Contrast Sets

Hardly one to be faulted for his ambition or his vision, it is genuinely unexpected, then, to see all Park's effort add up to so very little. . . . The premise is promising, gags are copious and offbeat humour abounds but it all fails miserably to create any meaningful connection with the audience.
(Label: Negative)

Hardly one to be faulted for his ambition or his vision, **here we see all Park's effort come to fruition.** . . . The premise is **perfect**, gags are **hilarious** and offbeat humour abounds, **and it creates a deep** connection with the audience.
(Label: Positive)

- By minimally editing an example, we control for pretty much all of the possible shortcuts that apply to the original.
- E.g., [summary starts with "*Hardly*" -> negative] is a pattern that could not hold anymore

Gardner et al. (2020)

Evidence of Spurious Correlations: Contrast Sets

Dataset	# Examples	# Sets	Model	Original Test	Contrast	
NLVR2	994	479	LXMERT	76.4	61.1	(–15.3)
IMDb	488	488	BERT	93.8	84.2	(–9.6)
MATRES	401	239	CogCompTime2.0	73.2	63.3	(–9.9)
UD English	150	150	Biaffine + ELMo	64.7	46.0	(–18.7)
PERSPECTRUM	217	217	RoBERTa	90.3	85.7	(–4.6)
DROP	947	623	MTMSN	79.9	54.2	(–25.7)

Gardner et al. (2020)

Solutions

Broad Solutions

- Most solutions involve changing what data is trained on
  - Subset of data
  - Soft subset (i.e., reweight the existing examples)
  - Superset: add adversarially-constructed data, contrast sets, etc.
- For subsets: what do we train on?
  - Don’t train on stuff that allows you to cheat
  - Train on examples that teach the real task rather than shortcuts

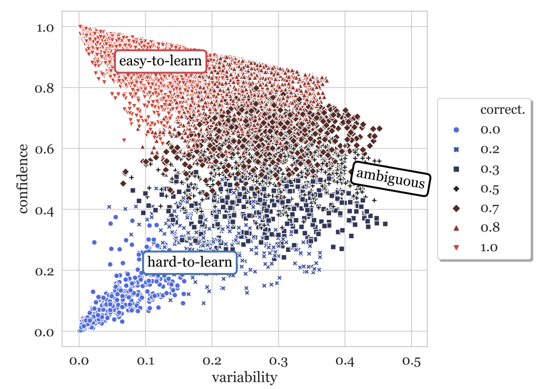
Dataset Cartography

- What happens with each particular example during training?
- Spurious correlations are *easy to learn*: a model should learn these early and always get them right
- Imagine a very challenging example
  - Model prediction may change a lot as it learns this example, may be variable in its predictions
- Imagine a mislabeled example
  - Probably just always wrong unless it gets overfit

Swayamdipta et al. (2021)

Data Maps

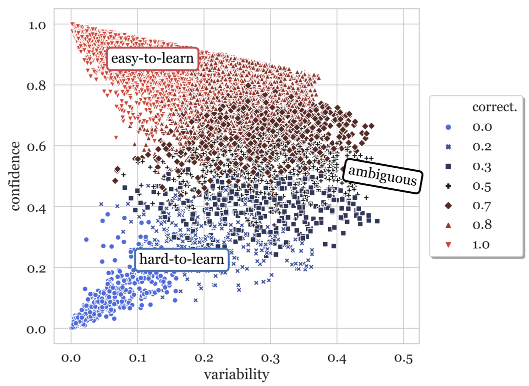
- Confidence: mean probability of correct label
- Variability: standard deviation in probability of the correct label
- Ambiguous examples: possible learnable (model knows it sometimes but not other times), but hard!



Swayamdipta et al. (2021)

Data Maps

- What to do with them?
- Training on hard-to-learn or ambiguous examples leads to better performance out-of-domain



Swayamdipta et al. (2021)

Debiasing

- Other ways to identify easy examples other than data maps
- Train some kind of a weak model and discount examples that it fits easily

one-hot label vector

log probability of each label

$$\mathcal{L}(\theta_d) = -(1 - p_b^{(i,c)})y^{(i)} \cdot \log p_d$$

probability under a copy of the model trained for a few epochs on a small subset of data (bad model)

Utama et al. (2020)

Debiasing

Method	MNLI (Acc.) dev	HANS	Δ
BERT-base	84.5	61.5	-
Reweighting known-bias	83.5‡	69.2‡	+7.7
Reweighting self-debias	81.4	68.6	+7.1
Reweighting ♠ self-debias	82.3	69.7	**+8.2**

- On the challenging HANS test set for NLI, this debiasing improves performance substantially
- In-domain MNLI performance goes down

Utama et al. (2020)

Debiasing

- Other work has explored similar approaches using a known bias model

$$\hat{p}_i = softmax(\log(p_i) + \log(b_i))$$

probabilities from learned bias model — like the weak model from Utama et al. (prev. slides), but you define its structure

- *Ensembles* the weak model with the model you actually learn.
- Your actual model learns the *residuals* of the weak model: the difference between the weak model's output distribution and the target distribution.
- This lets it avoid learning the weak model's biases!

He et al. (2019), Clark et al. (2019)

Takeaways

- Strong neural models trained on "tough" datasets may fail to generalize because they learn annotation artifacts
- By reweighting data or changing the training paradigm, you can learn a model that generalizes better
- Most gains will show up **out-of-domain**. Very hard to get substantial improvements on the same dataset, unless you consider small subsets of examples (e.g., the toughest 1% of examples by some measure)
- Next time: back to prompting, further understanding in-context learning