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Skipping Chit-chat with ChatGPT: Large Language Models and Structured Outputs

Ondřej Dušek

Machines That Understand?
7.12.2023

Thanks: Vojtěch Hudeček, Zdeněk Kasner, Ondřej Plátek, Patrícia Schmidtová, Mateusz Lango, Jonáš Kulhánek, Tomáš Nekvinda, Ioannis Konstas

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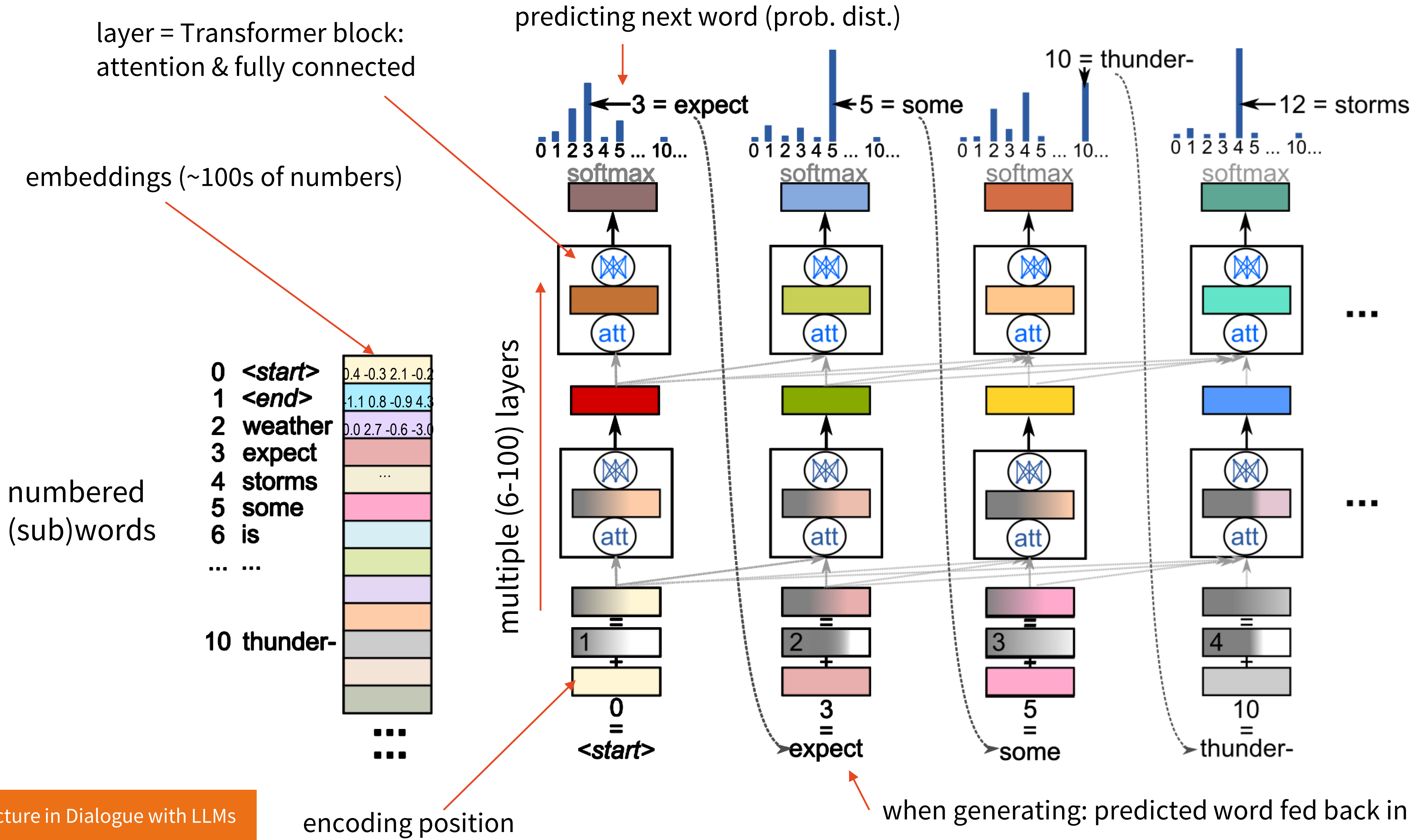
Neural Language Generation

- **End-to-end**
  - feed some input data (linearized), context or prompt
  - neural network handles everything
  - directly generates output text word-by-word, left-to-right
- **Transformer** neural architecture (see→)
- Very **fluent** & convincing outputs

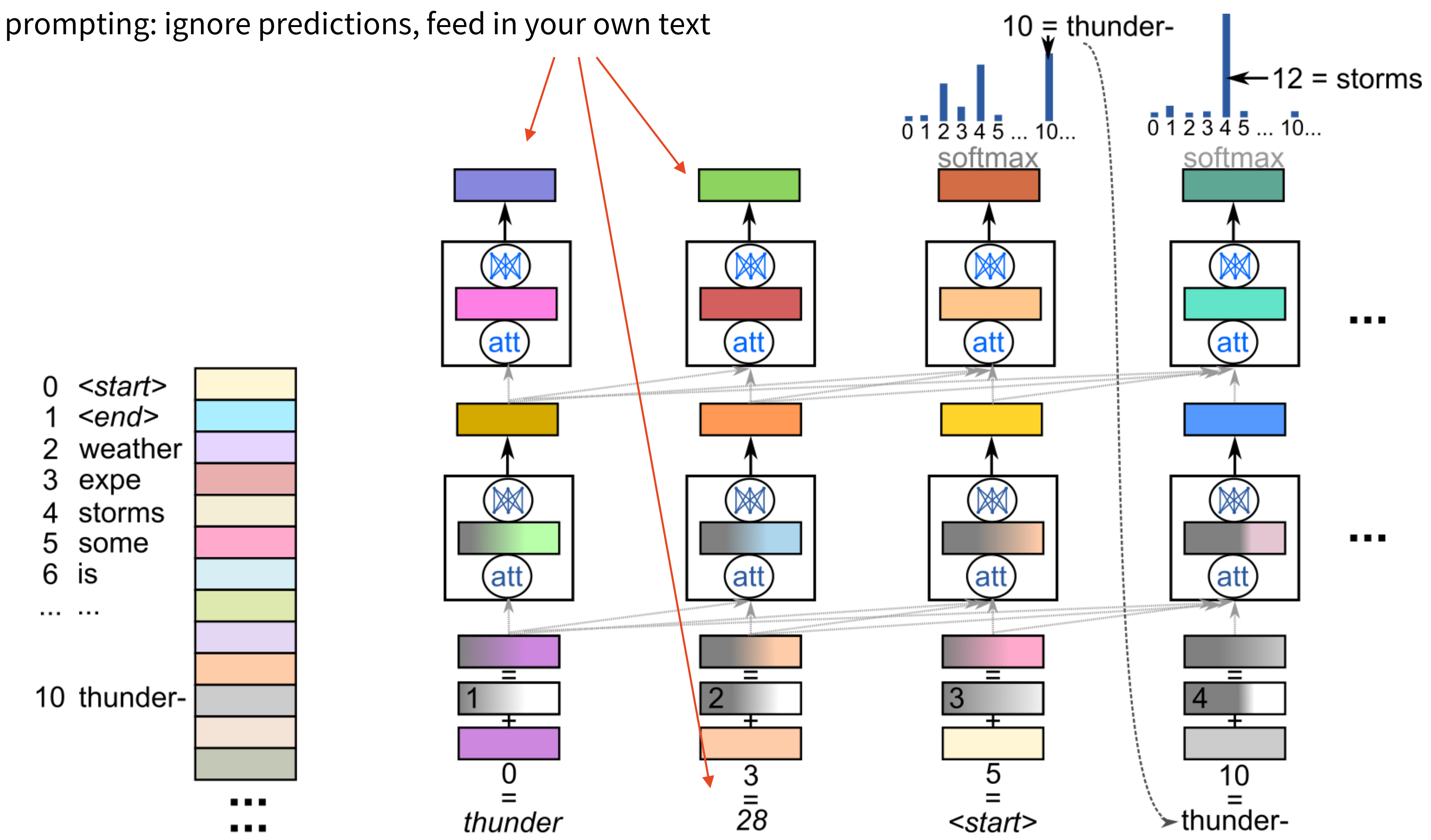
x

- Opaque & has **no guarantees on accuracy**
  - used essentially as a black box, internals unknown

Transformer neural language model

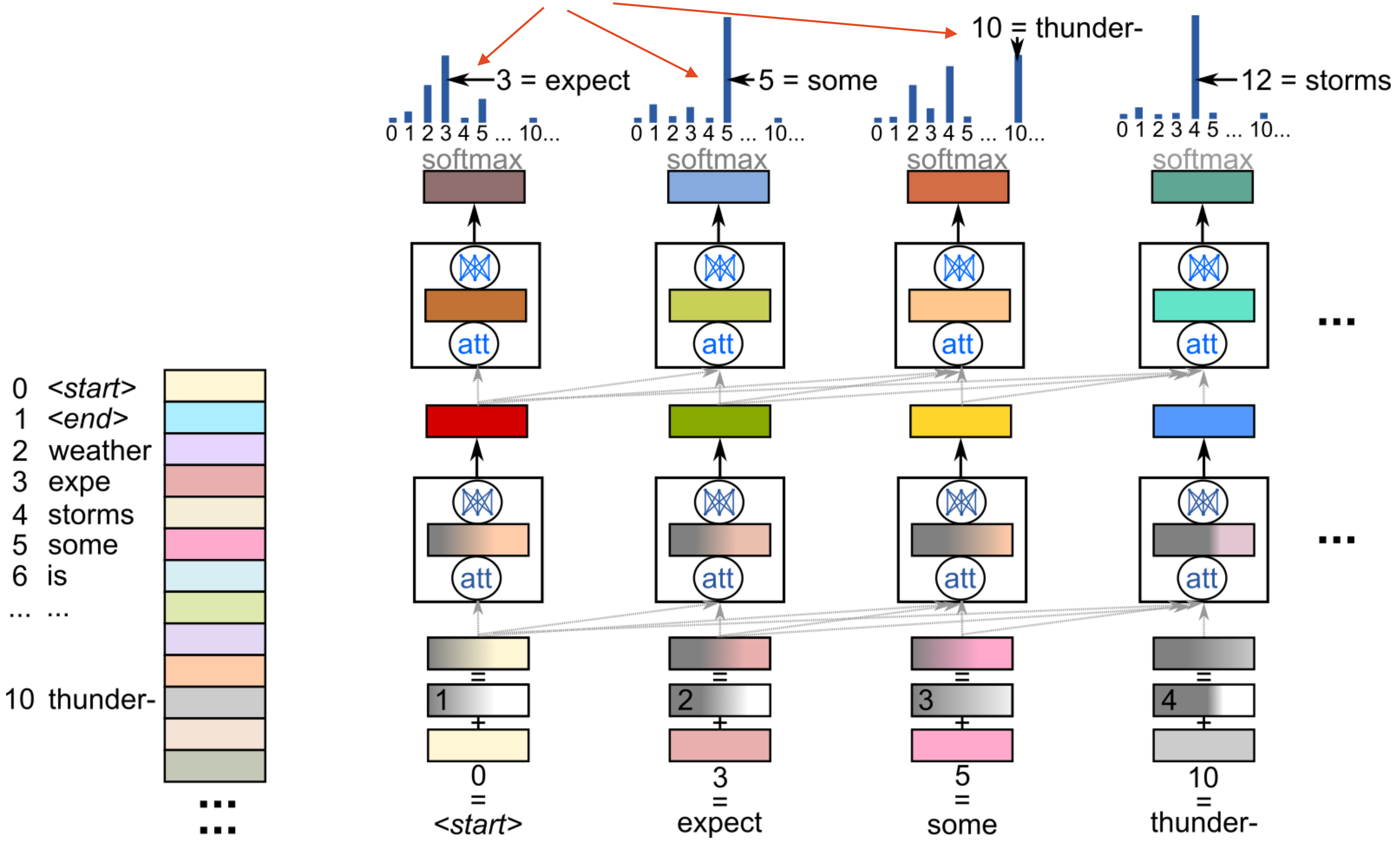


Transformer neural language model



Transformer neural language model

training: train to predict just 1 next word, feed training data (in parallel)



Training a Neural NLG System

- Reproduce sentences from data
  - replicate exact word at each position
- Fully trained from data
  - initialize model with random parameters
  - input example: didn’t hit the right word → update parameters

Blue Spice | price | expensive → NLG → *Blue Spice is* *expensive*

cheap

pricey

in the expensive price range

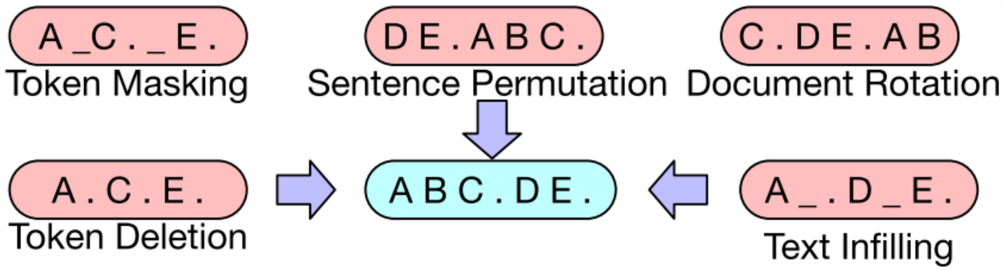
reference:

Blue Spice is expensive

- Very **low level**, no concept of sentence / text / aim

Pretraining & Finetuning

1. **Pretrain** a model on huge data (simple language-based tasks)
   - predicting next word
   - reconstructing garbled texts
2. **Fine-tune** on your smaller data
   - same as training, but starting from a better model



(Lewis et al., 2020)
https://www.aclweb.org/anthology/2020.acl-main.703

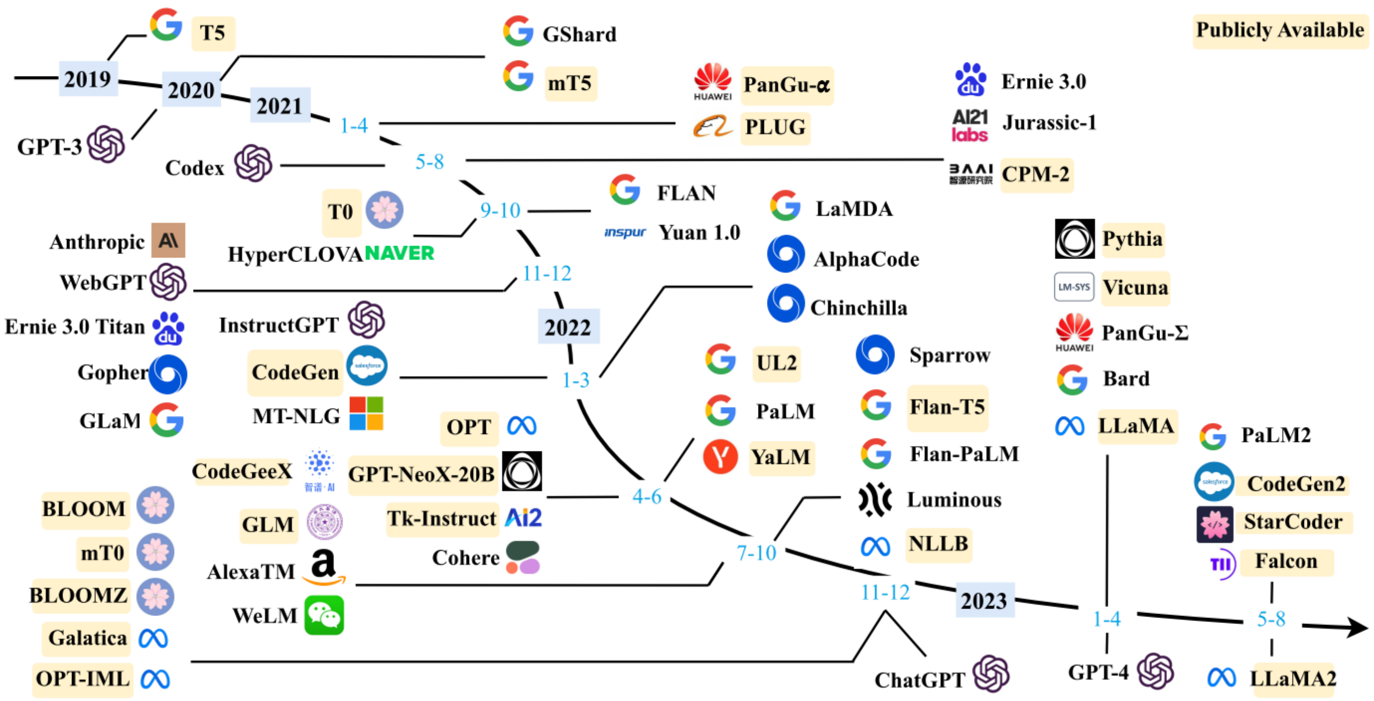
- Models free for download (https://huggingface.co/)
  - BERT/RoBERTa, GPT-2, BART, T5…
  - 100k-1B parameters – runs easily on regular GPUs

https://jlibovicky.github.io/2023/02/07/Otazky-a-odpovedi-o-ChatGPT-a-jazykovych-modelech.html

Large language models (LLMs): Pretrain & Prompt

(Zhao et al., 2023)
http://arxiv.org/abs/2303.18223

- Today's large models:
  10-100B parameters
  - hard(er) to run (OPT, LlaMa, Falcon…)
  - or API only (GPT-3/4, ChatGPT, Bard…)
- architecture mostly the same
- pretrained on more data

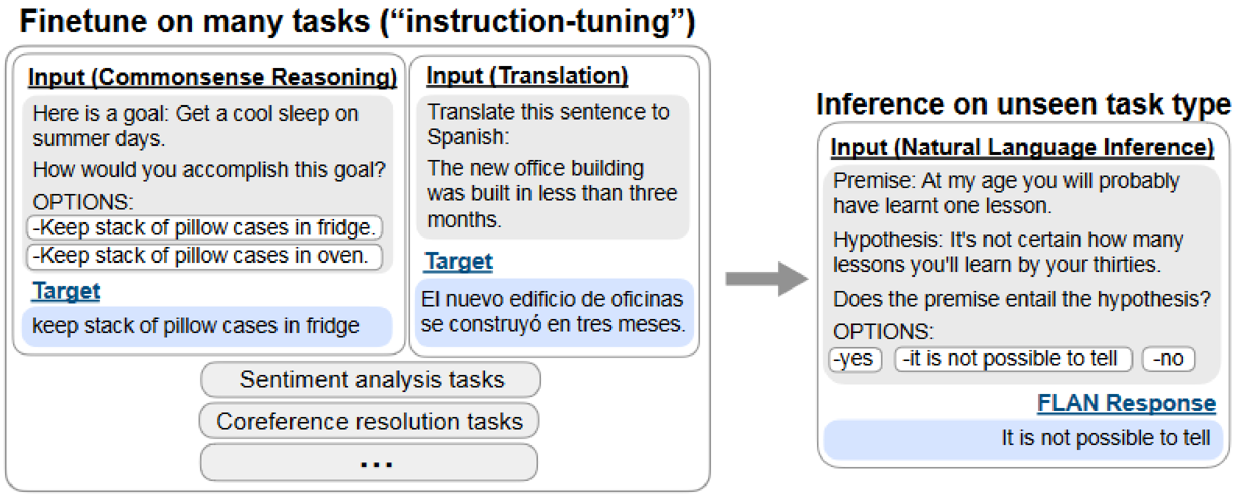


- often no need to finetune
- **prompting:** feed in context / few examples / ask question, get reply
  - finetuning can help, but it's expensive & has less effect than in smaller LMs
  - **prompt engineering** may be required
  - still the same problems– hard to control

Instruction Tuning / RL from Human Feedback

(Wei et al., 2022) https://arxiv.org/abs/2109.01652

- LLMs finetuned for prompting
  - **instructions** (task description) **+ solution** in prompts
  - "in-domain" for what it's used later
  - Datasets available with many tasks



- RL improvements on top (~InstructGPT/ChatGPT/…):
  1) generate lots of outputs for instructions
  2) have humans rate them
  3) learn a rating model (another LM: instruction + solution → score)
  4) use rating model score as reward in RL
  - main point: **reward is global** (not token-by-token) – RL-free alternatives exist
  - somewhat safer (low reward for bad behavior)

(Ouyang et al., 2022) http://arxiv.org/abs/2203.02155
https://openai.com/blog/chatgpt
(Rafailov et al., 2023) http://arxiv.org/abs/2305.18290

https://nlpnewsletter.substack.com/p/instruction-tuning-vol-1

LLMs Caveats

- Training scheme ~ Be **convincing** but **not necessarily true**
- !Not reliable for QA: only uses information it memorized, “hallucinates”

Who is Ondřej Dušek?

16, depending how you count

Ondřej Dušek is a researcher and academic in the field of natural language processing (NLP). He is currently an Assistant Professor at the Faculty of Mathematics and Physics, Charles University, Prague, Czech Republic.

no other tasks than generation & dialogue

Dušek's research focuses on developing computational models and algorithms for natural language generation, dialogue systems, and machine learning approaches for NLP tasks. He has published several research papers in top-tier NLP conferences and journals, and he has also served as a reviewer and program committee member for these conferences.

no PhD graduate yet

I only teach dialogue systems

In addition to his research, Dušek is also actively involved in teaching and mentoring students in the field of NLP. He has supervised several Master's and PhD theses, and he teaches courses on topics such as computational linguistics, NLP, and machine learning.

- Can use information provided in the prompt though (→ →)

Describing relations with LMs

(Kasner et al., 2023)
https://arxiv.org/abs/2210.07373

- Can we use LMs/LLMs to verbalize simple facts?
  - single subject – relation – object triple (RDF)
  - expressing the relations may be hard

relation	possible verbalization
is part of	X is part of Y.
duration	X lasted for Y.
platform	X is available on Y.
	X runs on Y.
country	X was born in Y.
	X is located in Y.
parent	X is the parent of Y.
	Y is the parent of X.
ChEMBL	X has an id Y in the ChEMBL database.

Rel2Text:

- we collected a new dataset to test this
  - current sets were not diverse enough
- 1.5k relations / 4k examples from Wikidata/YAGO/DBPedia
- crowdsourced + manual checks
- It's actually hard for people (our checks removed ~45% data)

Evaluating LMs on Rel2Text

- Testing on unseen relations only
- **Finetuning** BART ("old-school" PLM)
  - training on Rel2Text works well
  - WebNLG (old, less relations) OK (esp. on correctness)
  - ~hundreds of examples needed to work well
- **Prompting** ChatGPT
  - requires carefully crafted prompts
  - chattier outputs (~less control)
- Error analysis
  - **Unclear relation labels lead to semantic errors**
  - Still some "unprovoked" semantic errors
  - BART + Rel2Text & ChatGPT produce nicer, less literal verbalizations

	~overlap with human	~correctness	~fluency
Rel2Text data	**BLEU**	**% Log. Entail**	**PPL↓ (GPT2)**
Human	-	-	5.88
Copy baseline	29.04	91.21	7.55
BART/WebNLG	41.99	89.39	5.65
BART/Rel2Text	52.54	91.85	5.89
ChatGPT	38.23	88.58	5.68

(Kasner et al., 2023) https://arxiv.org/abs/2210.07373

Task-oriented Dialogue

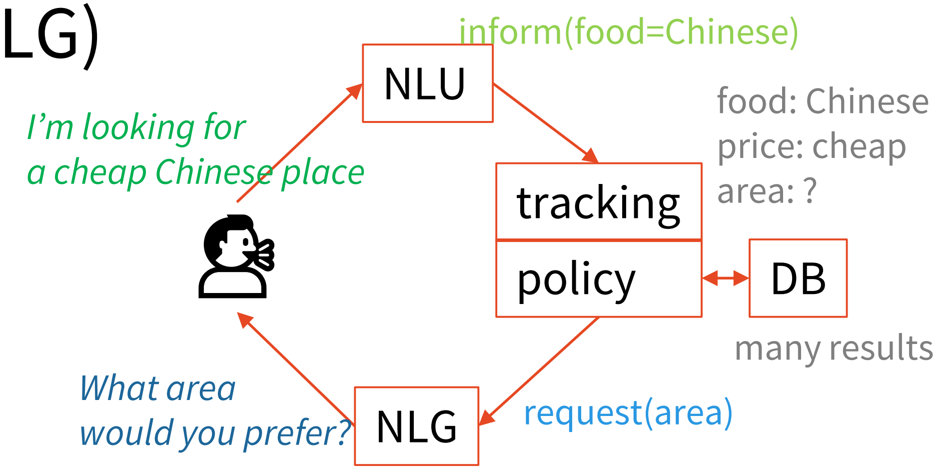
- **Assistant:** fulfill user requests (book a hotel/restaurant/taxi etc.)
- MultiWOZ: benchmark for multiple connected domains
  - 10k dialogues, extensive annotation (but noisy!)

(Budzianowski et al., 2018)
https://aclanthology.org/D18-1547/

1. user: I am looking for a train from Cambridge to London Kinks Cross.
   state: *{train {departure = cambridge, destination = london kings cross}}*
   DB: *{train (70) {…}}*
   system: There are 70 [count] trains departing from Cambridge [departure] to London Kings Cross [destination]. What day would you like to travel?
2. user: I would like to leave on Saturday after 18:45.
   state: *{train {day = saturday, departure = cambridge, destination = london kings cross, leave at = 18:45}}*
   DB: *{train (3) {arrive by = 19:51,21:51,23:51; id = TR0427,TR0925,TR4898; leave at = 19:00,21:00,23:00; … }}*
   system: TR0427 [id] leaves at 19:00 [leave_at] and arrives by 19:51 [arrive_by]. Would you like to book this train?
3. user: Yes, I would like to book it for eight people.
   system: I have booked it for you. Your reference number is 00000057 [reference]. Is there anything else I can help you with?
4. user: I am also looking for an expensive restaurant in the centre.
   belief: *{restaurant {area = centre, price range = expensive} train {...}}*
   DB: *{restaurant (33) {area = centre (33); name=Curry Garden, ...; ...}, ...}*
   system: There are 33 [count] expensive [price_range] restaurants in the centre [area]. Is there a particular type of food you would like?

End-to-end Neural Dialogue

- Traditional: separate components (NLU→DM→NLG)
  - trained separately, possibly optimization by RL
- **End-to-end models**
  - single neural LM for NLU&DM&NLG
  - word-by-word response generation



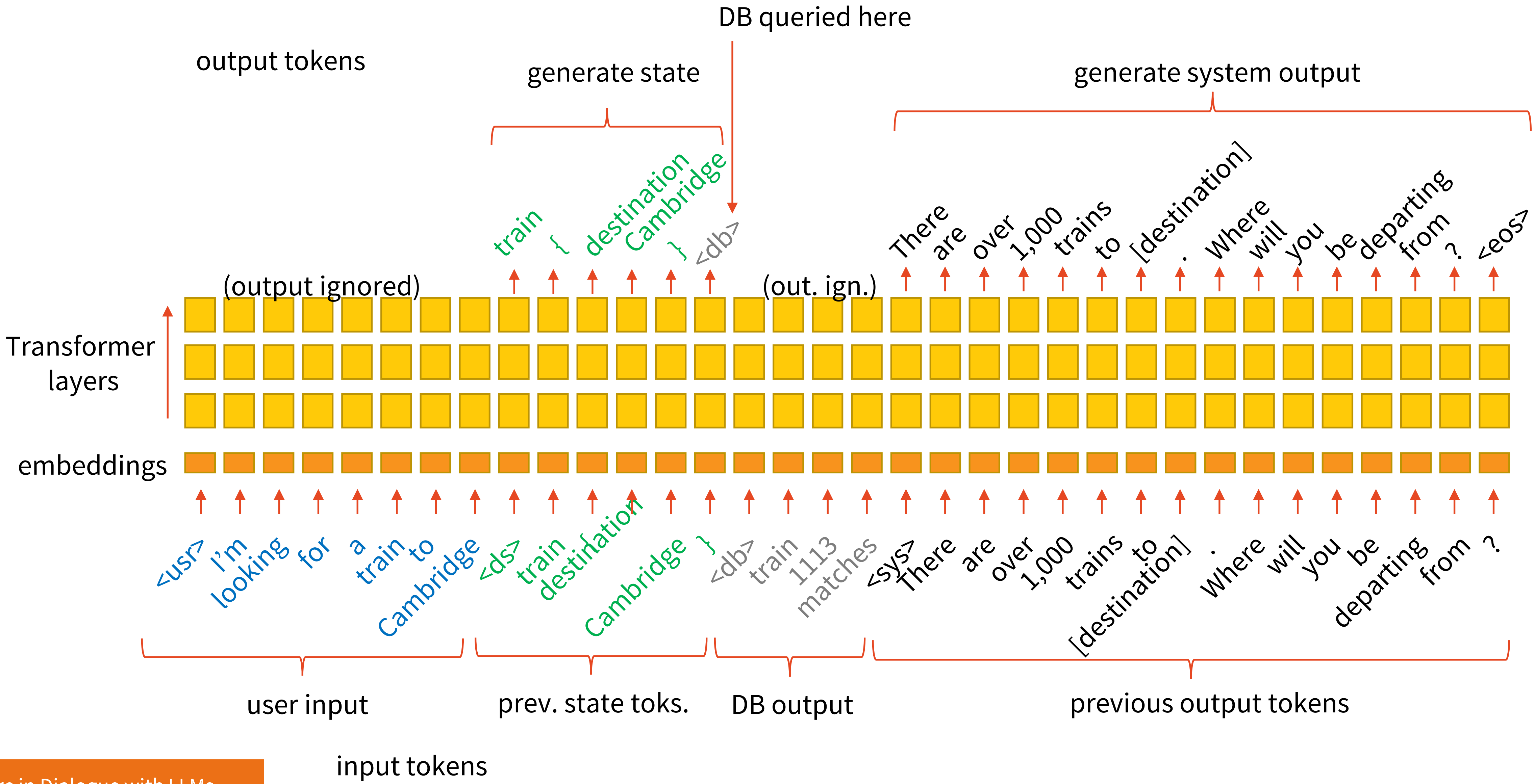
AuGPT: finetuned GPT-2 LM (~100M params)

- Multi-step, all word-by-word:
  1. feed in dialogue context
  2. generate dialogue state (as text)
  3. query DB, feed in DB results as text
  4. generate response

(Kulhánek et al., 2021)
http://arxiv.org/abs/2102.05126
https://github.com/ufal/augpt

End-to-end Neural Dialogue with GPT-2

(Kulhánek et al., 2021)
http://arxiv.org/abs/2102.05126



Performance

- Dialogue success (=user gets what they wanted)
  - 1-step (corpus-based): 67%
  - crowdsourced human eval: 82% perceived, 62% w/DB
  - expert eval – if you try hard: 87%
- **Hallucinates** sometimes
  - may generate factually incorrect outputs, hard to control
  - → data cleaning, consistency checks
- **Needs a lot of data** & annotation (MultiWOZ = 10k)
  - costly, may be noisy
  - → transfer learning, data augmentation
  - … or **LLM prompting**?

Dialogue with LLMs

(Hudeček & Dušek, 2023)
https://aclanthology.org/2023.sigdial-1.21

- How good are LLMs if we require structure?
  - slots / DB are given
  - no finetuning? → **prompting only**
  - ChatGPT, Tk-Instruct, Alpaca… (7-20B params)
- Zero/few-shot (FAISS context store, 10 ex./domain)
  - little to no data needed: wide potential
- Still the same idea: **context** → **state** → **DB** → **response**
  - additional step needed: domain detection

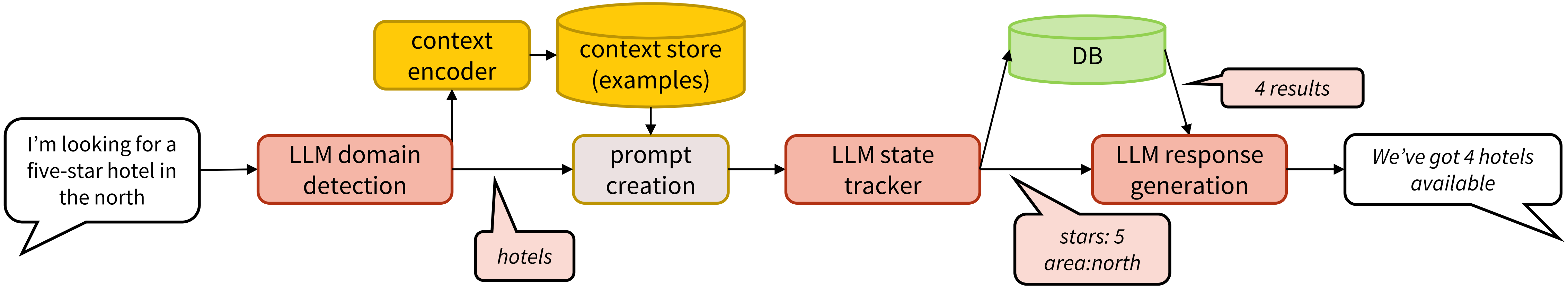
instruction: Definition: Capture values from a conversation about hotels. Capture pairs "entity:value" separated by colon and no spaces in between. Separate the "entity:value" pairs by hyphens. Values that should be captured are:

domain description:
- "pricerange": the price of the hotel
- "area": the location of the hotel
…

examples:
--- Example 1 ---
…
---

dial. history: Assistant: "Hello, how can I help you?"
…

user input: Customer: "I am looking for a five-star hotel in the north"



Results

- Domain detection ~ 70%+
  - Alpaca & TkInstruct OK, ChatGPT almost perfect
- Belief state – not great
  - much worse than SotA
  - examples help (ChatGPT, TkInstruct: ~50-60% F1, Alpaca 8%), 10 ex./domain enough
- Responses: OKish

Dialogue Success		ChatGPT	TkInstruct
1-step (corpus)	predicted state	44%	19%
	gold state	68%	46%
expert eval (end-to-end, with recoveries)		76%	64%

- More potential with better prompt engineering

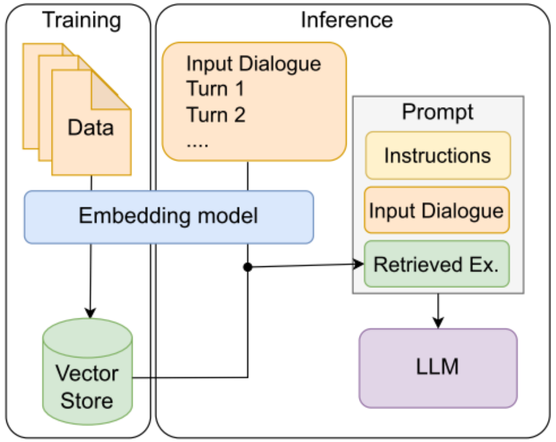
Chat Evaluation with LLMs

(Plátek et al., 2023)
https://aclanthology.org/2023.dstc-1.14

- Evaluating NLG is hard, metrics are inaccurate, humans are expensive
- Can we use LMs to evaluate instead?
- Free chat (non-task-oriented)
- Checking **appropriateness**, **relevance**, **diversity** of responses on **1-5** scale

Chat Turns		Appr	Rel	Div
A	do you have any pets?	5	-	4
B	I am retired so I love to travel so pets would slow me down	4	4	4
A	I understand that my idea of traveling is a hot hot bubble bath	3	2	4
B	Yes I have dogs and cats I like to take them with me on trips	2	2	4

Evaluating Chat



Approach

- Same as previous: LLM prompting
  - few-shot examples in DB
  - LLM asked to provide a score given response in context
- Alternative: LLMs as embeddings & regression on top
  - finetuned on few-shot data
- Checking correlation with humans

Results

- LLM prompting better than prev. SotA (with ChatGPT, Llama2 close, others fail)
- Prompt formulation matters, examples useful
  - but maybe static examples are enough

Appr	Rel	Div	ø
49%	36%	45%	42%

Conclusions

- LLMs are powerful & can work well…
  - if you provide data on the input
  - if you optimize your prompts
- So far, ChatGPT/GPT4 are better than open LLMs
  - new LLMs coming up every week (Llama2, Falcon, Mistral, …)
  - OpenAI closed models may have seen some of the data (~is it zero-shot?)

Future work

- look into data leakage effect
- more transparency ~ prompting, interpretable latents
- constraining – alignments, decoding-time "critic"

(Lango & Dušek, 2023)
https://arxiv.org/abs/2310.16964

Thanks

Contacts:

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Links

These slides: https://bit.ly/mtu23-od

Relations: https://aclanthology.org/2023.eacl-main.176

Dialogue: http://arxiv.org/abs/2102.05126
https://aclanthology.org/2023.sigdial-1.21

Evaluation: https://aclanthology.org/2023.dstc-1.14

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