Evolution of Semantic Parsing (& modern testing)

CS395T - Communicative and Grounded AI Agents
UT Austin, Fall 2025

Presented by Rishabh Mediratta

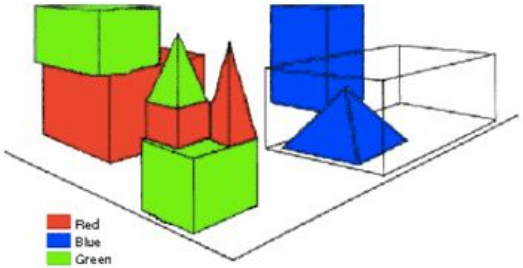
The Big Picture before we begin

Keep this in mind as we go through this presentation - evolution of the task of natural language to a formal machine-understandable representation moving from symbolic rule-based to modern data-driven systems

The pioneer - SHRDLU

The idea - talk to a machine about a world it understands

In this case, the world was a simulated micro block world with a hand and limited set of actions available



Person: Pick up a big red block.
Computer: OK.
Person: Grasp the pyramid.
Computer: I don't understand which pyramid you mean.

https://cryptlabs.com/understanding-shrdlu-a-pioneering-ai-in-language-and-reasoning/

SHRDLU capabilities

- Commands to actions
  - “Pick up a red block” -> MOVETO, GRASP, UNGRASP
  - Used planner to plan
- Resolve ambiguity with context
  - “Grasp the pyramid” -> if unclear, ask for clarification
- Remember dialogue history
  - Dialogue manager
- Explain actions
  - "Why did you pick up the pyramid?" -> "SO THAT THE GREEN BLOCK WOULD BE CLEAR"

Moving to learning

SHRDLU played a part in popularizing natural language interfaces for machines

Key limitation - hand-programmed - every rule, action, etc all by Winograd; limited context - block world

New question - instead of defining rules manually - can a machine learn how to do this?

Learning to Parse Database Queries Using Inductive Logic Programming

- Shift to learning instead of creating

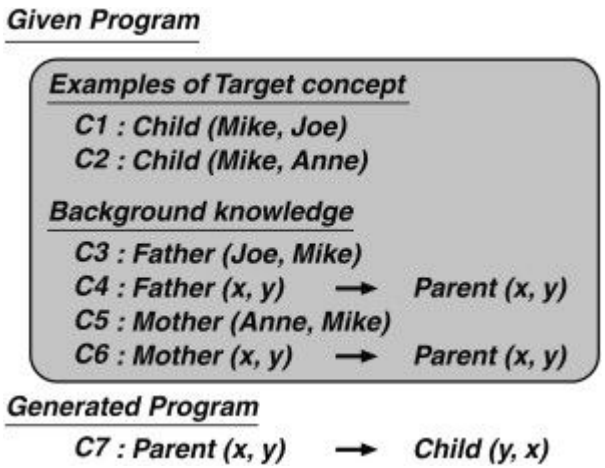
- Natural Language interface for DB queries with a system called CHILL

- Given question-query pairs, learn to create a parser automatically

Inductive Logic Programming primer

Given a set of facts, find a general rule that explains the facts

For question-query pairs, learn rules that translate english sentences to DB queries



https://www.sciencedirect.com/topics/computer-science/inductive-logic-programming

CHILL

The domain: US geography dataset called Geobase with the query language being Geoquery

Data: question-query pairs

What are the major cities in Kansas?

```
answer(C, (major(C), city(C), loc(C,S),
equal(S,stateid(kansas)))).
```

Goal: Learn a parser capable of taking in a new question about geography and producing the correct query

How: ILP

Results: 225-25 train-test split. Outperforms existing system on 175 or more queries. Also produced fewer spurious parses.

The next frontier

CHILL proved that data can be used for this parsing problem to produce effective solutions for generalized problems

Previous bottleneck - Handwritten rules. New bottleneck - Data.

Next problem - data synthesis.

The next frontier

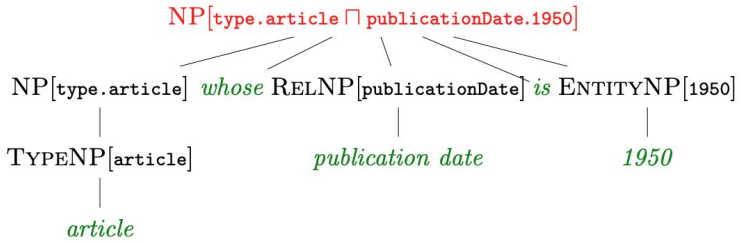
How do you build a parser for a new domain with no training examples?

Tradition data collection is slow and expensive

“Building a semantic parser overnight” introduces a 4-step method to generate the necessary data

The 2 core ideas you need - Idea 1 - Canonical Compositionality

Compositionality - Complex expressions are defined by the meanings of its parts and the rules to combine them. The paper assumes for any complex logical expression, it is possible to get a (somewhat awkward) English phrase based on some rules (this English phrase is called canonical utterance)



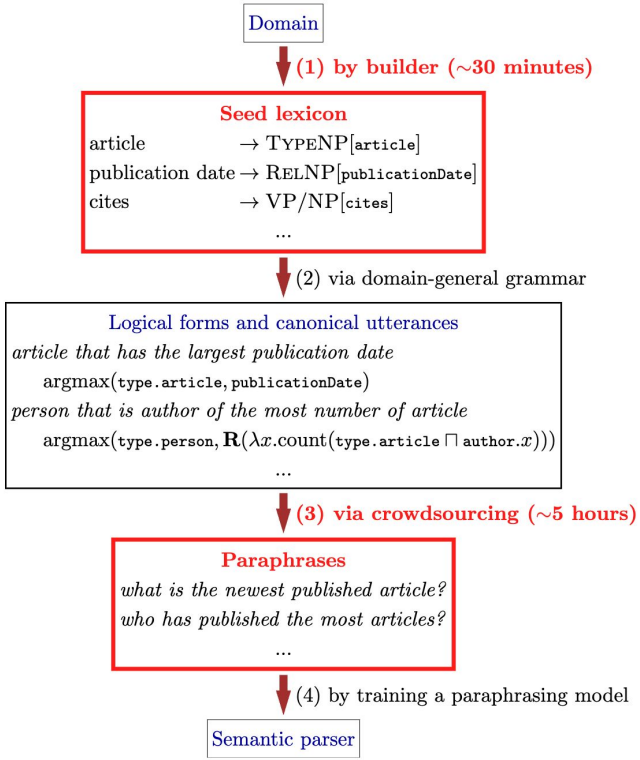
The 2 core ideas you need - Idea 2 - Bounded Non-Compositionality

Canonical utterances correspond to logical structure but natural language often does not

For eg, “co-author of X” is the natural language version of “person that is author of paper whose author is X” (this is why I said awkward)

The “Bounded” assumption - these non-compositional chunks are bounded (limited). A limited number of examples will let a model learn to map from canonical utterances to natural language.

4-step process



4-step process

1. Create a seed lexicon - eg DB property publicationDate is mapped to publication date
2. Generate logical forms and canonical utterances - using the domain general grammar and seed lexicon, logical forms and canonical utterances are produced. Eg - NP[x] that has the largest RELNP[r] → NP[arg max(x, r)]. substitute article for NP and publicationDate for RENLP
3. Crowdsource canonical utterance -> natural language (authors use Amazon MT), create (natural_language, canonical_utterance, loacl_form) triplets
4. Train a log-linear model to find correct logical form given natural language (generate candidates with beam search and keep based on similarity between input query and canonical utterances)

Results

Avg accuracy of 58.8% across all domains

Overnight experiment - parser built within 24 hours got to 70.8%

An experiment on the CALENDAR domain confirms bounded non-compositionality hypothesis

Different ablations prove that implemented steps of the system are useful. Important ablation - removing domain specific features drop occurrence significantly

Yet another frontier

Now that the model and data problems have been explored, how do we push systems?

The next step is establishing a benchmark to measure the performance of modern semantic parsers (spoiler - a lot of these modern systems are LLM-based and the task is to parse natural language to SQL)

Late 2010s

- Models were performing very well on tasks like GeoQuery (> 80%)
- Problems with existing datasets
  - Single DB for both training and testing
  - Same queries appeared in both train and test (with different questions)
  - Tasks like WikiSQL were large but simple queries

The need for a large scale and complex task hence arose

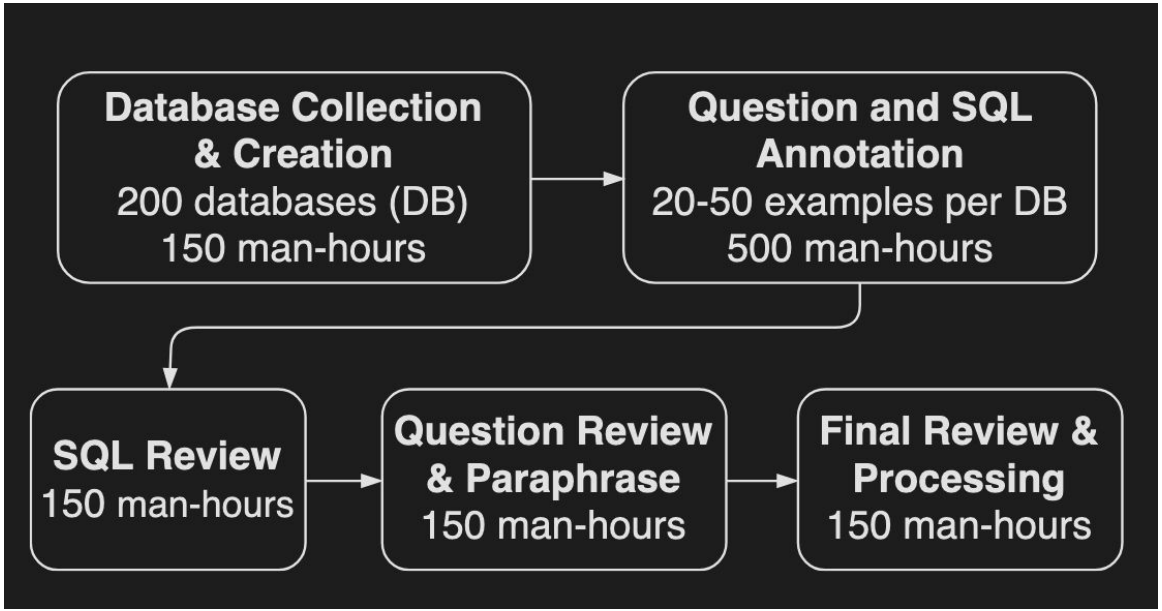
Spider - Yale Semantic Parsing and Text-to-SQL Challenge

Large scale, complex, cross-domain human annotated text-toSQL dataset

200 databases with multiple tables and foreign key relations within tables, 138 domains, 10181 natural language questions, 5693 unique complex SQL queries labeled by 11 CS students investing >1000 man hours

Corpus Creation

WikiSQL + online, multiple domains



SQL with complex structure (LIKE, JOIN, nested queries, UNION, etc) + no ambiguous or out of knowledge-base questions allowed

Spider as compared to other datasets

Dataset	# Q	# SQL	# DB	# Domain	# Table /DB	ORDER BY	GROUP BY	NESTED	HAVING
ATIS	5,280	947	1	1	32	0	5	315	0
GeoQuery	877	247	1	1	6	20	46	167	9
Scholar	817	193	1	1	7	75	100	7	20
Academic	196	185	1	1	15	23	40	7	18
IMDB	131	89	1	1	16	10	6	1	0
Yelp	128	110	1	1	7	18	21	0	4
Advising	3,898	208	1	1	10	15	9	22	0
Restaurants	378	378	1	1	3	0	0	4	0
WikiSQL	80,654	77,840	26,521	-	1	0	0	0	0
Spider	10,181	5,693	200	138	5.1	1335	1491	844	388

Databases in the test set do not appear in the training set

Evaluation Metrics

- Correctness
  - Component Matching - whether the generated query has the right clauses (SELECT, WHERE) with the right features (student_id, room_number) - follows a set based comparison, different order not penalized
  - Exact Match - every component must match in the generated and gold query. Here, the specific values usually required in a query is not required, the structure alone suffices.
  - Execution accuracy - to test whether does the query actually runs. Model is given the correct values to fill in the right placeholders.
- SQL Hardness
  - 4 levels: easy, medium, hard, extra hard based on the number of SQL components, selections, and conditions

Extra Hard

What is the average life expectancy in the countries where English is not the official language?

```
SELECT AVG(life_expectancy)
FROM country
WHERE name NOT IN
   (SELECT T1.name
    FROM country AS T1 JOIN
    country_language AS T2
    ON T1.code = T2.country_code
    WHERE T2.language = "English"
      AND T2.is_official = "T")
```

Results

	Test					Dev
	Easy	Medium	Hard	Extra Hard	All	All
Example Split						
Seq2Seq	22.0	7.8	5.5	1.3	9.4	10.3
Seq2Seq+Attention (Dong and Lapata, 2016)	32.3	15.6	10.3	2.3	15.9	16.0
Seq2Seq+Copying	29.3	13.1	8.8	3.0	14.1	15.3
SQLNet (Xu et al., 2017)	34.1	19.6	11.7	3.3	18.3	18.4
TypeSQL (Yu et al., 2018)	47.5	38.4	24.1	14.4	33.0	34.4
Database Split						
Seq2Seq	11.9	1.9	1.3	0.5	3.7	1.9
Seq2Seq+Attention (Dong and Lapata, 2016)	14.9	2.5	2.0	1.1	4.8	1.8
Seq2Seq+Copying	15.4	3.4	2.0	1.1	5.3	4.1
SQLNet (Xu et al., 2017)	26.2	12.6	6.6	1.3	12.4	10.9
TypeSQL (Yu et al., 2018)	19.6	7.6	3.8	0.8	8.2	8.0

Table 2: Accuracy of Exact Matching on SQL queries with different hardness levels.

Modern-ish Results

Leaderboard - Execution with Values

Our current models do not predict any value in SQL conditions so that we do not provide execution accuracies. However, we encourage you to provide it in the future submissions. For value prediction, your model should be able to 1) copy from the question inputs, 2) retrieve from the database content (database content is available), or 3) generate numbers (e.g. 3 in "LIMIT 3"). *Notice:* Test results after May 02, 2020 are reported on the new release (collected some annotation errors).

Rank	Model	Test
1 Nov 2, 2023	MiniSeek *Anonymous* Code and paper coming soon	**91.2**
1 Aug 20, 2023	DAIL-SQL + GPT-4 + Self-Consistency *Alibaba Group* (Gao and Wang et al.,'2023) code	**86.6**
2 Aug 9, 2023	DAIL-SQL + GPT-4 *Alibaba Group* (Gao and Wang et al.,'2023) code	**86.2**

Leaderboard - Exact Set Match without Values

For exact matching evaluation, instead of simply conducting string comparison between the predicted and gold SQL queries, we decompose each SQL into several clauses, and conduct set comparison in each SQL clause. Please refer to the paper and the Github page for more details. *Notice:* Test results after May 02, 2020 are reported on the new release (collected some annotation errors).

Rank	Model	Dev	Test
1 Nov 2, 2023	MiniSeek *Anonymous* Code and paper coming soon	80.3	**81.5**
1 Sep 13, 2022	Graphix-3B + PICARD (DB content used) *Alibaba DAMO & HKU STAR & SIAT* (Li et al., AAAI'2023) code	77.1	**74.0**
2 Sep 14, 2022	CatSQL + GraPPa (DB content used) *Anonymous*	78.6	73.9

Actual modern benchmark

Spider 2.0 - move to real-world enterprise-level workflows

Larger and more complex tables with metadata - multiple TBs

More comprehensive task - read documentations, work with retrieved data, transformation, analysis, understand codebase

More data storage systems - Snowflake, BigQuery and more SQL dialects (Postgres, DuckDB)

Not solved

Spider 2.0-Snow | Spider 2.0-lite | Spider 2.0-DBT

Spider 2.0-Snow is a self-contained text-to-SQL task that includes well-prepared database metadata and documentation, includes **547** examples, all hosted on *Snowflake*, which offers participants free quotas.
Methods with -* use special settings (ground-truth tables) and are not included in the ranking.

Rank	Method	Score
1 Aug 14, 2025	PAI-DataSurfer Agent *Alibaba Cloud Computing Platform*	**59.78**
2 Aug 8, 2025	WindAgent + Claude-4-Sonnet *MeiTuan AI For FinData*	**59.05**
3 Aug 6, 2025	Ask Data with Relational Knowledge Graph *AT&T CDO & RelationalAI*	**57.77**

Spider 2.0-Snow | Spider 2.0-lite | Spider 2.0-DBT

Spider 2.0-Lite is a self-contained text-to-SQL task that includes well-prepared database metadata and documentation. This setup enables a text-in, text-out approach, facilitating faster development and evaluation. Spider 2.0-lite, which has **547** examples, is designed to handle queries for *BigQuery*, *Snowflake*, and *SQLite* databases.

Rank	Method	Score
1 Aug 7, 2025	AgenticData + Qwen3 *Tsinghua University* [Sun et al. '25]	**44.5**
2 May 22, 2025	ReFoRCE + o3 *Hao AI Lab x Snowflake* [Deng et al. '25]	**37.84**
3 Aug 7, 2025	ReFoRCE + Qwen3 *Tsinghua University* [Sun et al. '25]	**35.6**

Spider 2.0-Snow | Spider 2.0-lite | Spider 2.0-DBT

Spider 2.0-DBT is a comprehensive code generation agent task that includes **68** examples. Solving these tasks requires models to understand project code, navigating complex SQL environments and handling long contexts, surpassing traditional text-to-SQL challenges.

Rank	Method	Score
1 Jul 26, 2025	Shadowfax-DBT-Agent + GPT-5 *Shadowfax Data*	**41.18**
2 Aug 9, 2025	Spider-Agent-Extended + GPT-5 *Woods, A. '25.*	**39.71**
3 Jun 25, 2025	DAQUV_QUVI_Agent *DAQUV*	**17.65**

Closing Thoughts

Problems arose in Spider with models not generating the correct SQL - how to fix that?

Is translating directly to SQL the best approach? Or will some intermediate representation help?

How to tackle the challenges posed by Spider 2.0 and allow models to use multiple tools to tackle the challenges it presents?

Spoiler - all these will be addressed next

References

https://dspace.mit.edu/handle/1721.1/7095

https://www.cs.utep.edu/nigel/papers/shrdlu.pdf

https://cdn.aaai.org/AAAI/1996/AAAI96-156.pdf

https://aclanthology.org/P15-1129.pdf

https://aclanthology.org/D18-1425/

https://arxiv.org/abs/2411.07763

https://yale-lily.github.io/spider

https://spider2-sql.github.io/

Semantic Parsing - Part II

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3rd year CS PhD working on Agent Orchestration

Quick Recap: Semantic Parsing

Definition:

Mapping **natural language utterance** to **executable logical forms**.

Where was the director of film "2001 space odyssey" born?

Semantic Parsing

```
SELECT DISTINCT ?e_2 WHERE { ?e <instance_of> ?c .
?c <name> "film". ?e <name> "2001: A Space Odyssey" .
?e <director> ?e_1 . ?e_1 <place_of_birth> ?e_2 }
```

Execution

New York City.

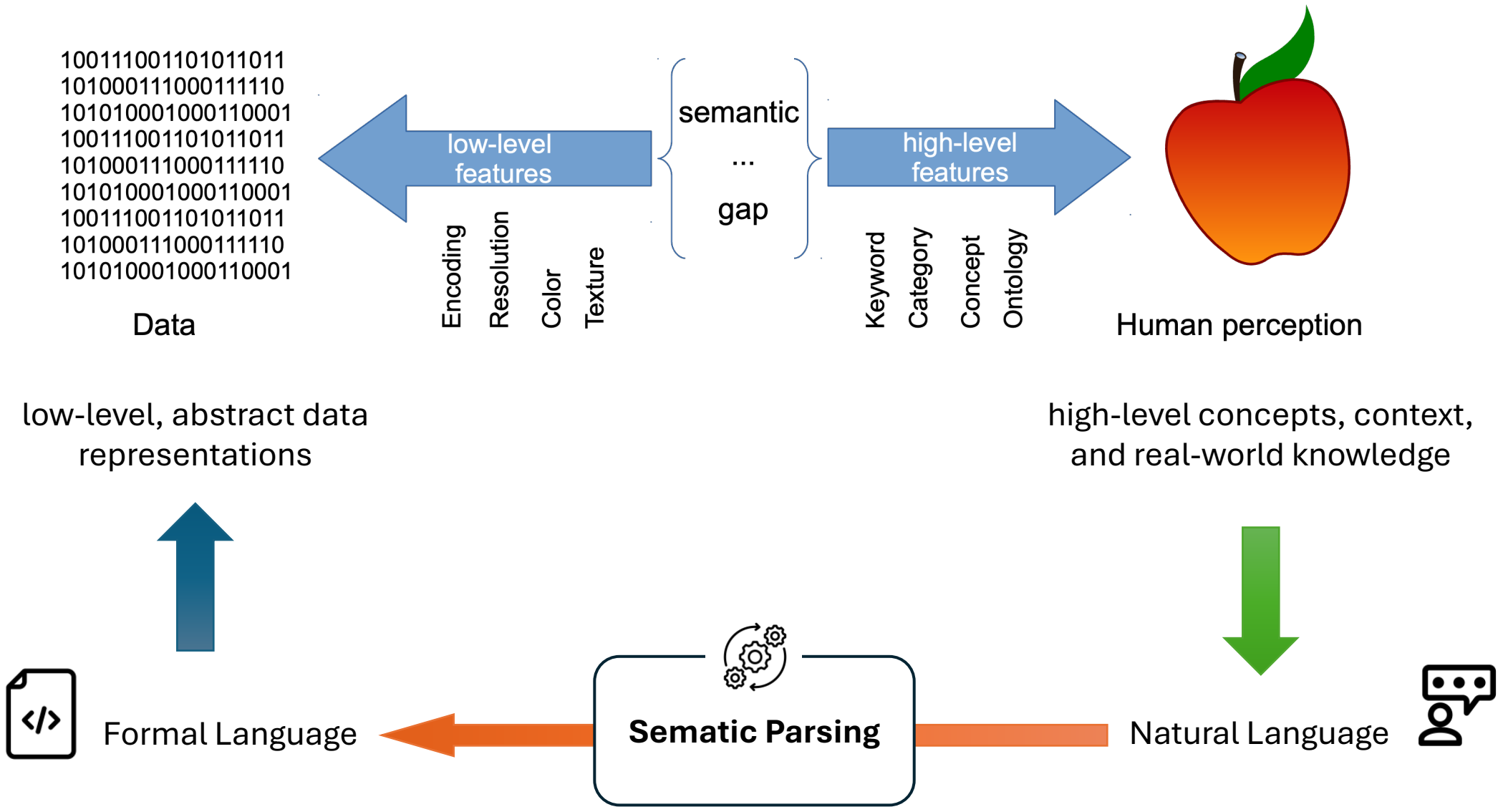
Applications:

DB/KB Query

Virtual Assistant

Robot Control

Code Generation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101010001000110001
Data
low-level features
Encoding
Resolution
Color
Texture
semantic
...
gap
high-level features
Keyword
Category
Concept
Ontology
Human perception
low-level, abstract data representations
high-level concepts, context, and real-world knowledge
Formal Language
Sematic Parsing
Natural Language

Semantic Gap

- LMs used to be trained on natural language corpus and are not familiar with code (formal language).

The **semantic gap** between natural language and formal language is the major challenge.

- Natural language user query:

  How many films has Stanley Kubrick directed? / Tell me the total number of movies directed by Stanley Kubrick.

- SPARQL:

  SELECT (COUNT(DISTINCT ?e) AS ?count) WHERE { ?e instance_of ?c . ?c name “film" . ?e director ?e_1 . ?e_1 name “Stanley Kubrick“ }

- Cypher:

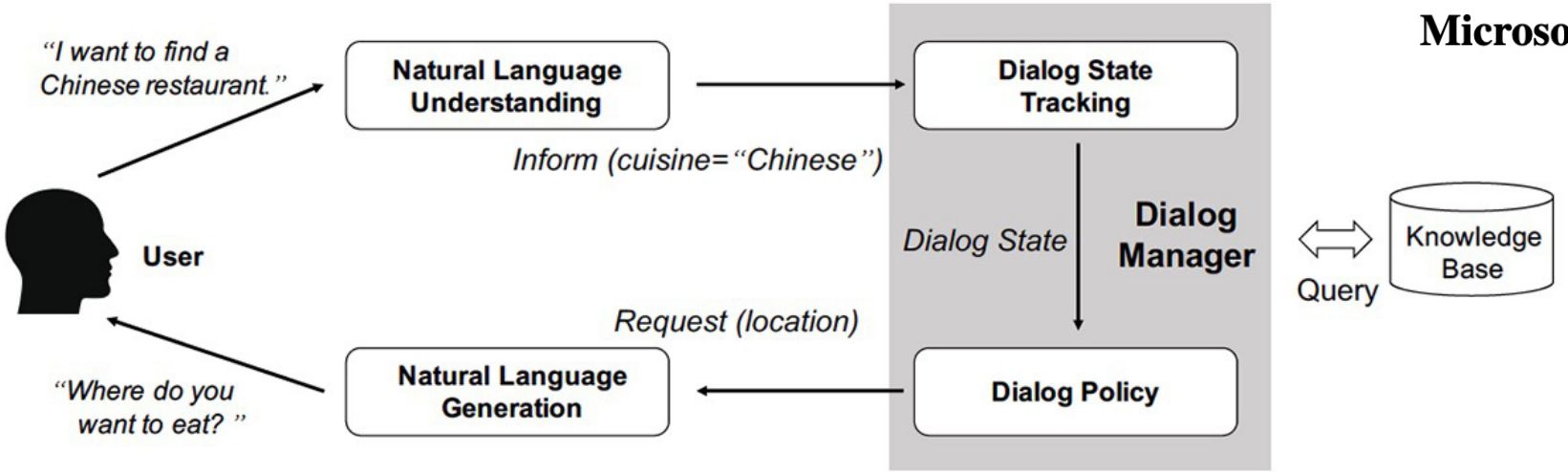
  MATCH (n1)<-[:DIRECTOR]-(n2) WHERE n1:Film AND n2.name=‘Stanley Kubrick’ RETURN COUNT(DISTINCT n1)

Bridging the Gap

- Symbolic methods
  - Interpretable
  - Verifiable
  - Structured Domain Knowledge
  - Data efficient
- Neural methods
  - Scalable
  - Flexible
  - Handles messy data
  - Easy to get started (need data!)

- Symbolic heuristics
  - Execution-guided
  - Grammar Constrained-decoding
- Better neural networks
  - Advanced model architecture
  - Scaled Pretraining
- Neurosymbolic combinations
  - Data Augmentation with SCFG
  - Intermediate Representations

Task-oriented Dialogue as Dataflow Synthesis



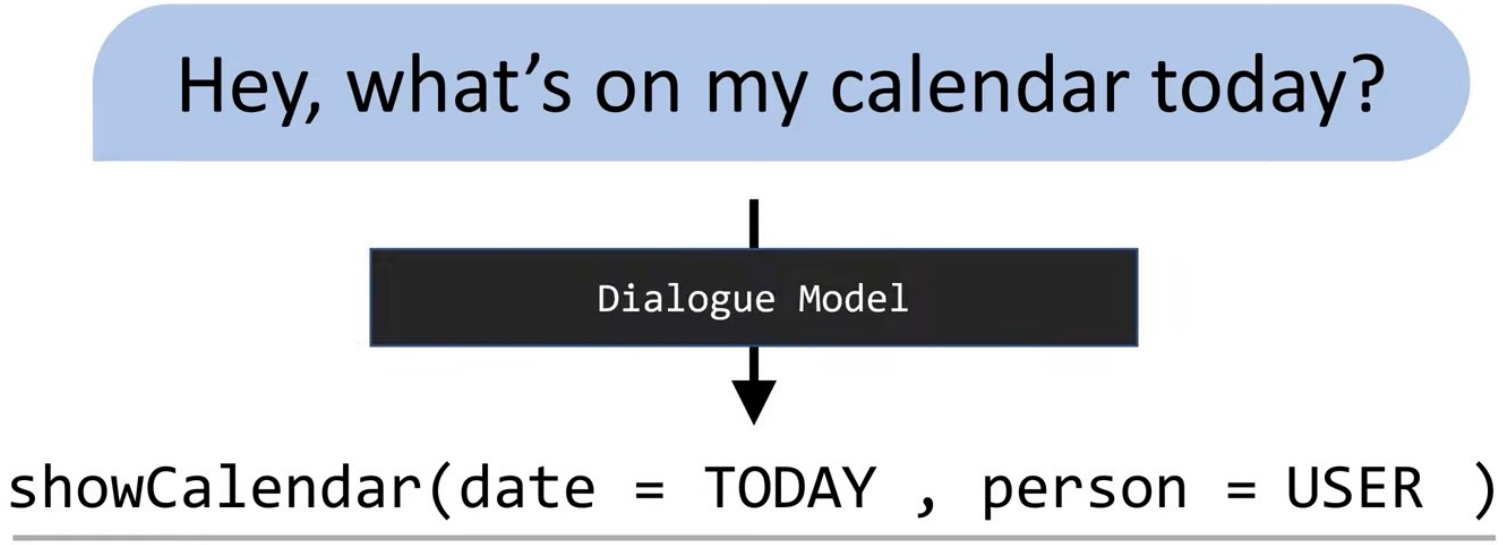
Microsoft Semantic Machines*

TACL 2020

- Problem: how to represent & track user goals and requests?
  - Slot-filling isn't enough: users sometimes request complex new values, **refer** to old values, and **revise** previous plans
- Proposed solution: Dialogue as **Dataflow**
  - A single dataflow graph records all grounded computations so far. Dialogue agents synthesize programs that extend the graph as they listen, act, and respond to users, using meta-computation operators to retrieve and transform earlier computations.

Answering Simple Query

Slot filling: e.g. Bobrow et al. 1977, Liu & Lane 2016



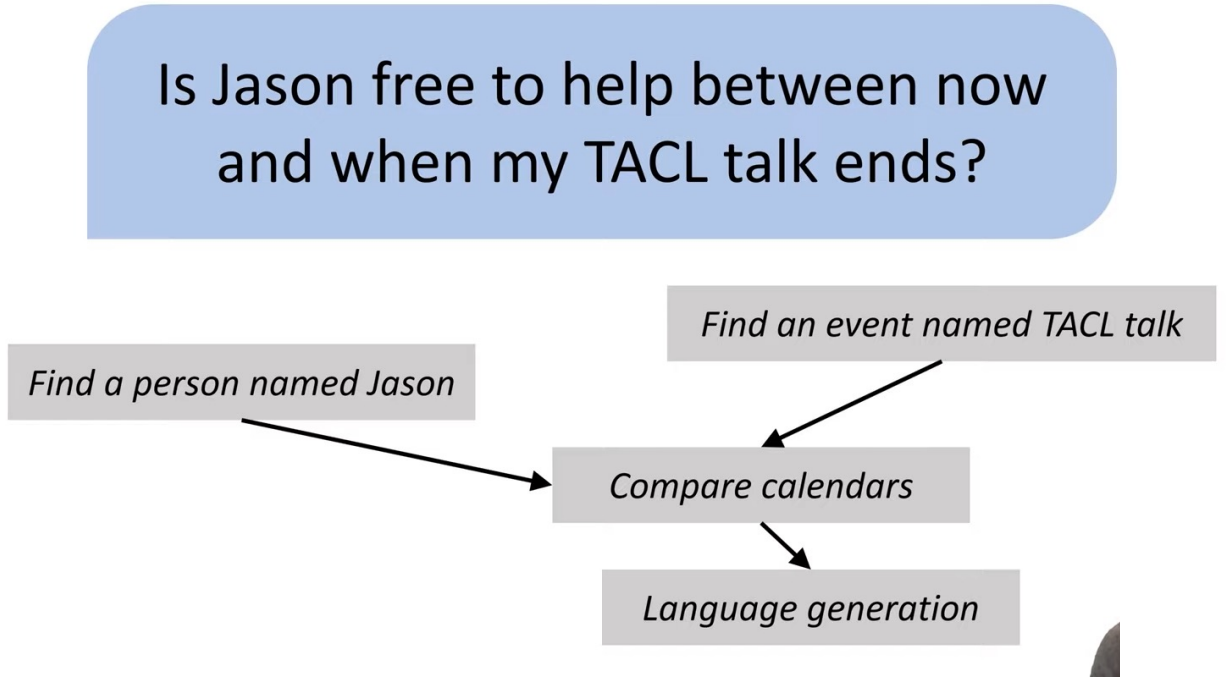
Core Challenge: Diversity in User Requests

- **Diverse goals.**
  - *Book a meeting with Megan.*
  - *Book a meeting with Megan on Tuesday.*
  - *Book a meeting with Megan the first morning she's free after Labor Day.*
- **Diverse language for the same request.**
  - *What's tomorrow's weather?*
  - *What'll it be like out tomorrow?*
  - *Do I need a jacket for the hike?*
- **Diverse contexts of the same sentence --** *How about three?*
  - Following *Megan is busy at 2:00, do you have other suggestions?*, it's a proposal to move a meeting.
  - Following *The forecast for noon is cloudy*, it's a query about the weather.
  - Following *Rivoli has a table for two available*, it's a request to increase the size of a dinner reservation.

Answering Complex User Requests

A specialized function? `freeBetweenNowAndEndOfEvent`

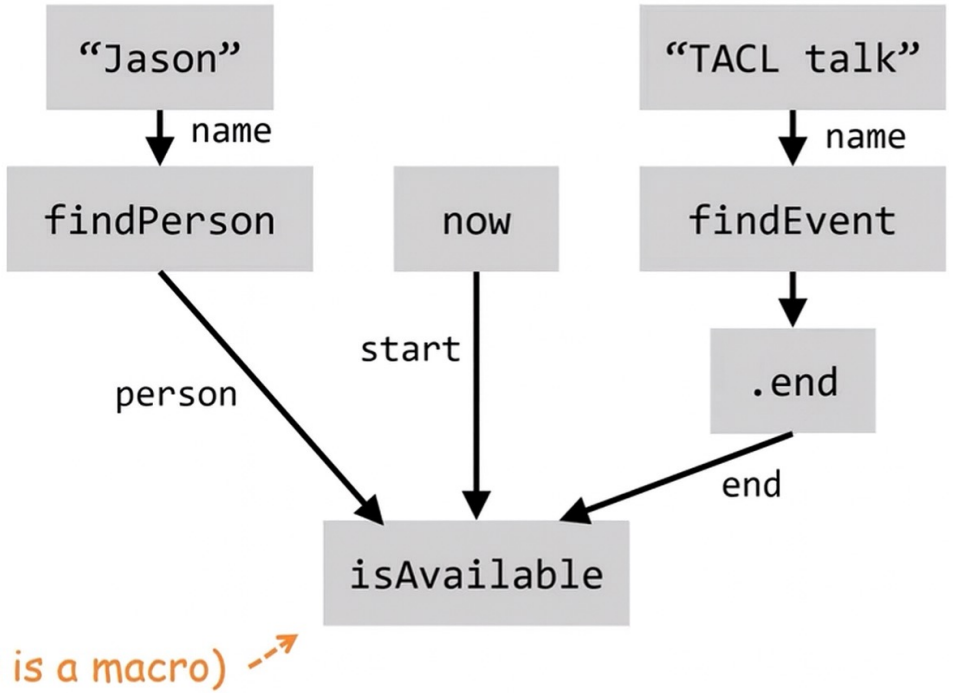
Answering **complex** user requests



Decomposition into a Dataflow Graph

Is Jason free to help between now and when my TACL talk ends?

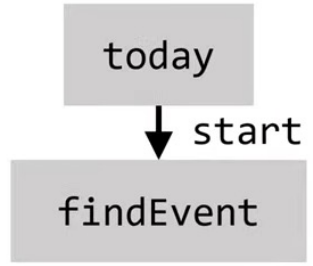
```
isAvailable(
  person=findPerson(
    name="Jason"),
  start=now(),
  end=findEvent(
    name="TACL talk"
  ).end
)
```



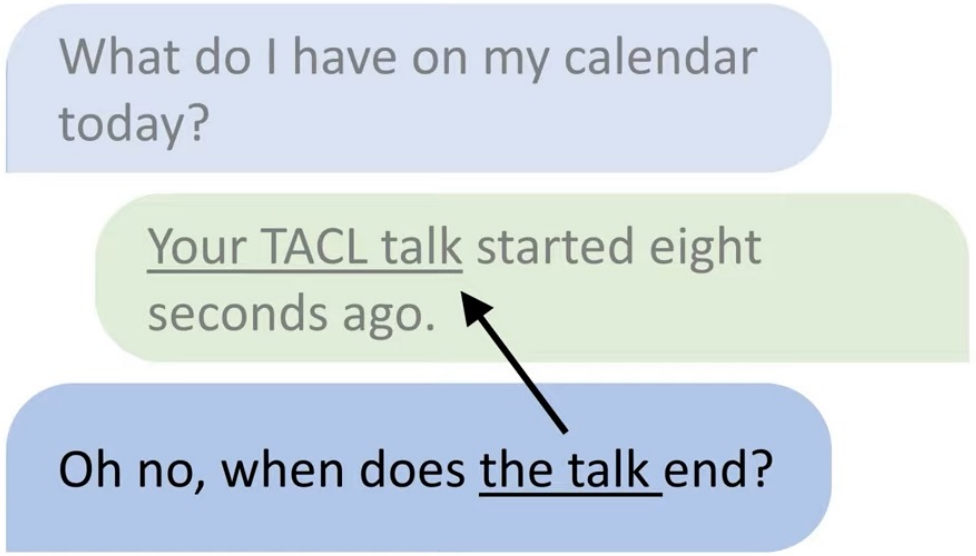
Dialogue as Interactive Programming

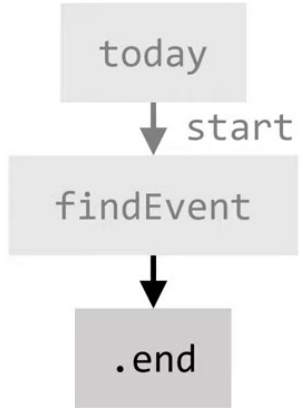
What do I have on my calendar today?

Your TACL talk started eight seconds ago.

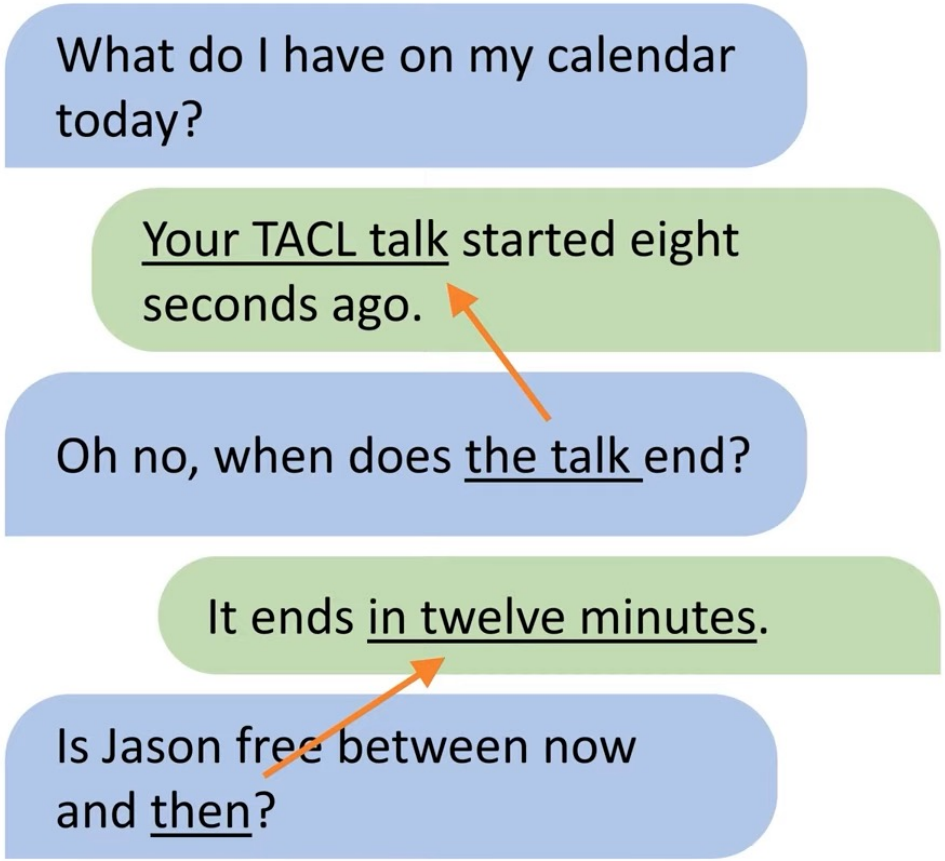


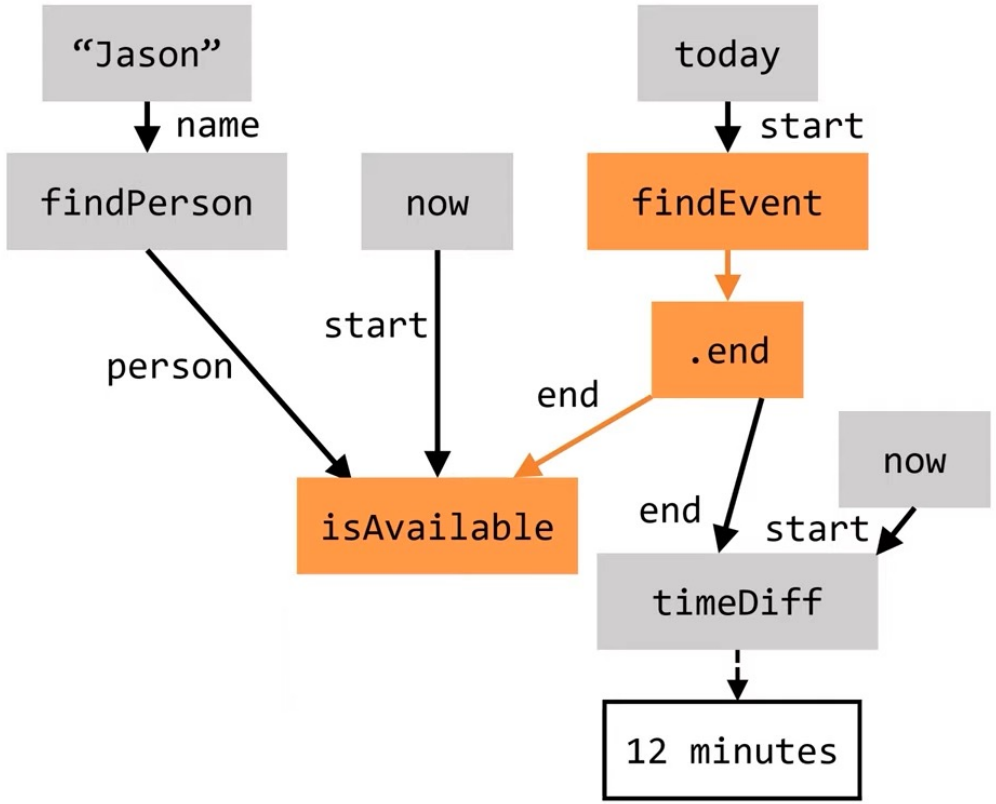
Dialogue as Interactive Programming





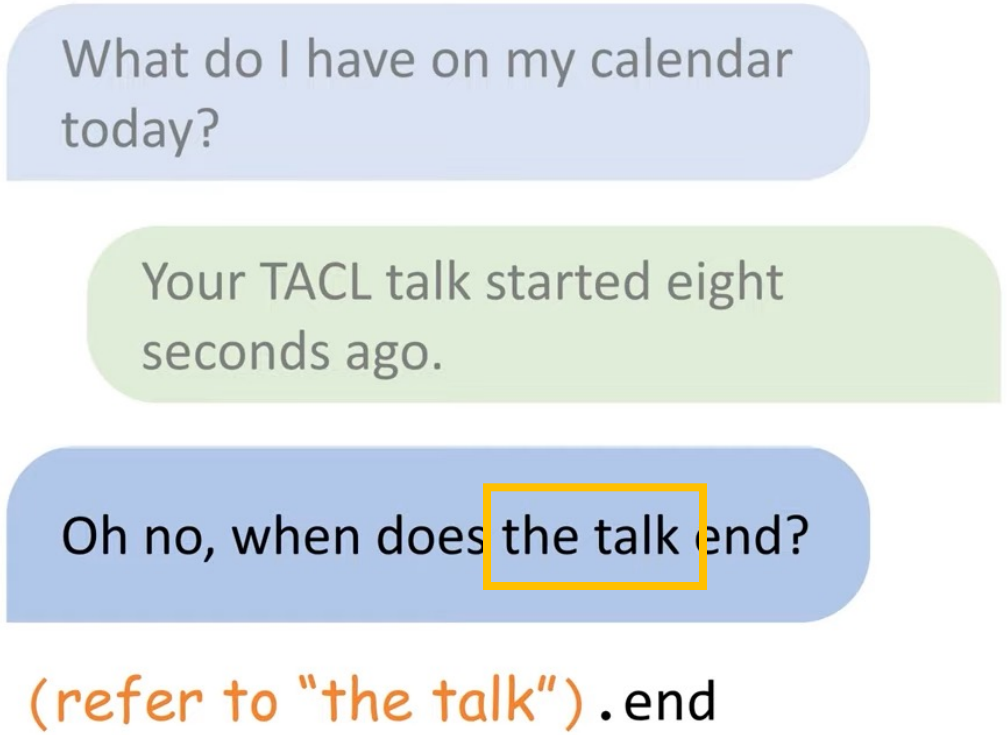
Dialogue as Interactive Programming

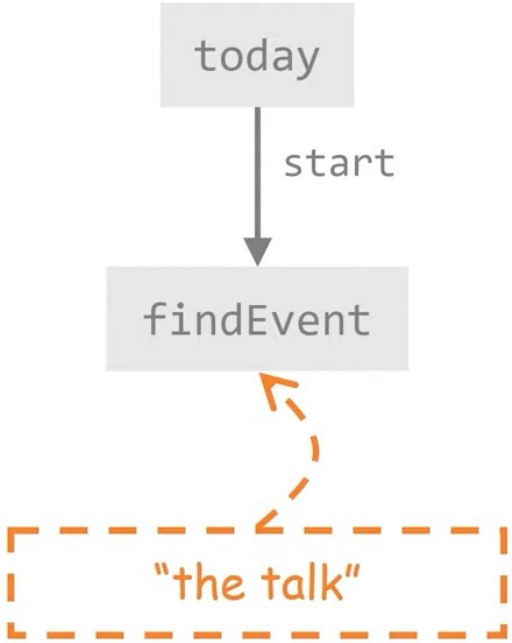




Complex actions are built by **composing** simpler ones rather than defining a large set of top-level behaviors

Graph Transformation I: Reference





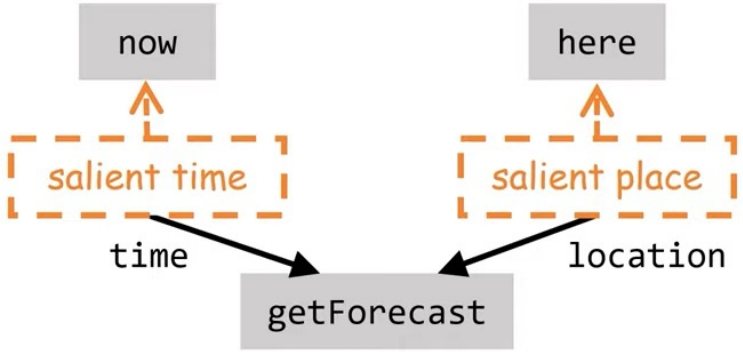
Metacomputation Operator 1: `Refer`

Reference Resolution: Salience

Good morning, Jacob!

What's the weather going to be like?

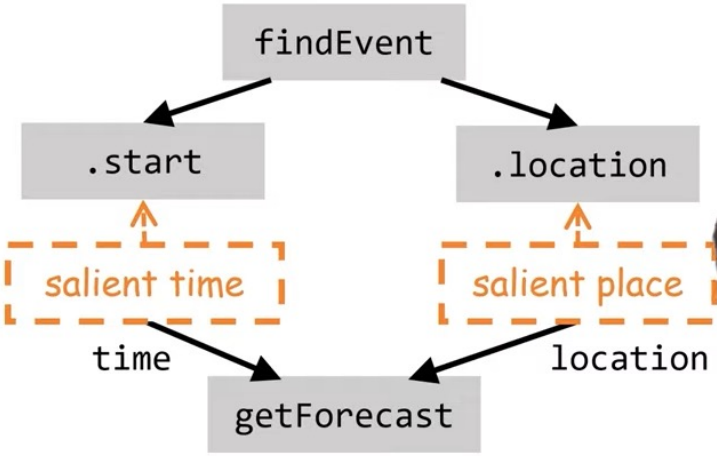
The forecast in Cambridge this afternoon is sunny with a high of 76.



Your dinner is at Café Sushi.

What's the weather going to be like?

The forecast there at 7 pm is cloudy with a high of 55.



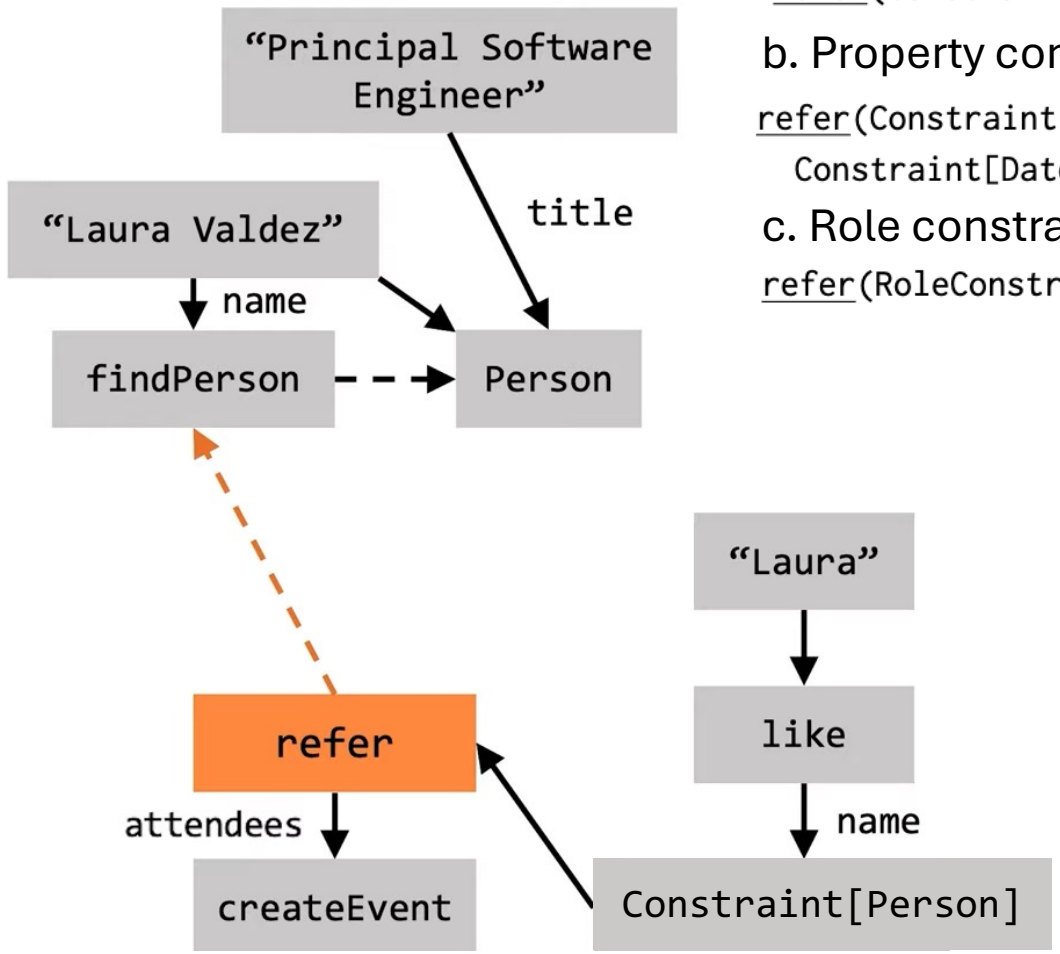
Reference Resolution: Constraints

Most cases are easy: type constraints + recency + executability → 84—98% accuracy!

Is Laura Valdez free today?

Schedule a meeting with Laura

```
createEvent(attendees=
  refer(Constraint[Person](
    name=like("Laura"))))
```



a. Type constraint

```
refer(Constraint[Event]()).
```

b. Property constraint

```
refer(Constraint[Event](date=
  Constraint[DateTime](weekday=thurs)))
```

c. Role constraint

```
refer(RoleConstraint([date,weekday]))
```

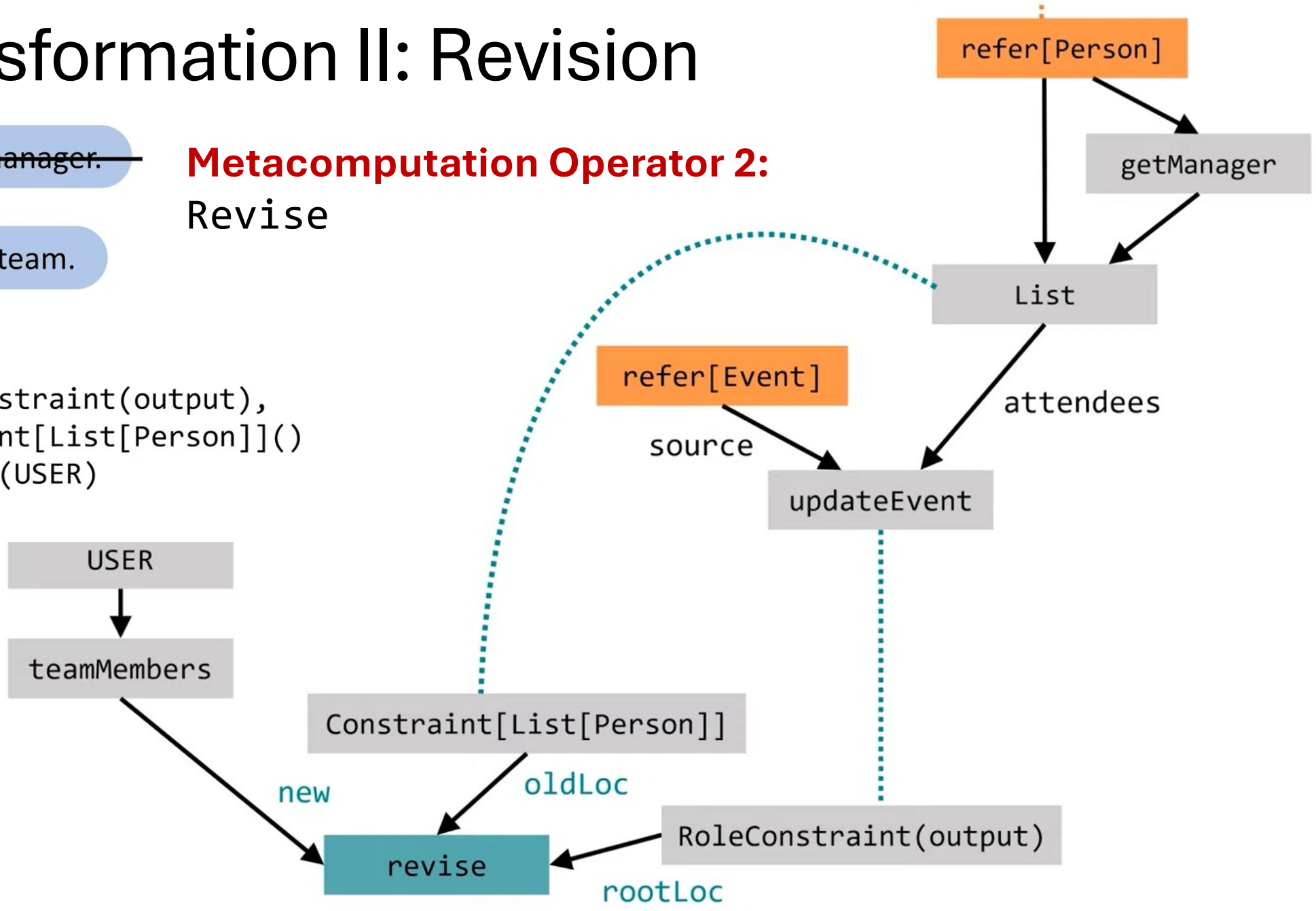
Graph Transformation II: Revision

~~Invite him and his manager.~~

Actually, the whole team.

Metacomputation Operator 2:
`Revise`

```
revise(
  rootLoc=RoleConstraint(output),
  oldLoc=Constraint[List[Person]]()
  new=teamMembers(USER)
)
```



Graph Transformation III: Recovery

User: *Book a meeting for me.*
Agent: *When should the meeting start?*

```
=> UnderconstrainedException
```

User: *Who is coming to the planning meeting?*
Agent: *Susan Chu and Susan Brown.*
User: *What is Susan's email?*

```
=> MultipleMatchesFoundException
```

User: *When is my first meeting on February 30?*

```
=> InvalidValueException
```

Things can go wrong.

User: *Create a meeting.*

```
createEvent()
--> UnderconstrainedException!(name)
```

Agent: *What should it be called?*
User: *Planning meeting.*

```
revise(rootLoc=RoleConstraint(output),
  oldLoc=RoleConstraint(name),
  new='Planning meeting')
--> UnderconstrainedException!(start)
```

Agent: *When should it start?*

Revision on dataflow graph!

The SMCalFlow dataset: **stats**

microsoft.github.io/task_oriented_dialogue_as_dataflow_synthesis

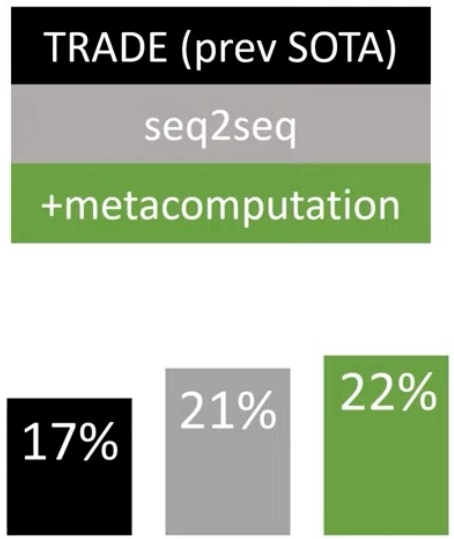
41,517 dialogues
155,923 turns
338 library functions

median utterance length: **8 words**
median program length: **40 tokens**

The SMCalFlow dataset: **evaluation**

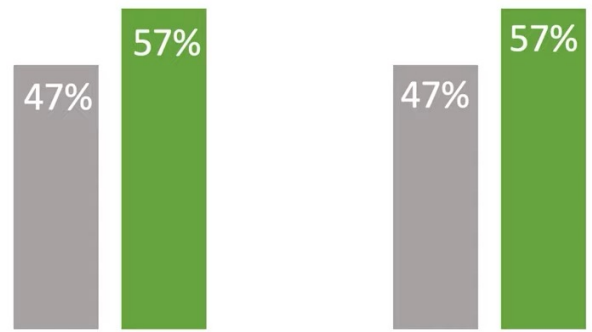
microsoft.github.io/task_oriented_dialogue_as_dataflow_synthesis

SMCalFlow
(Turn exact match)



MultiWoZ
(Dialogue exact match)

MultiWoZ: Budzianowski et al. 2018
TRADE: Wu et al. 2019



Turns with reference Turns with revision

	Full		Ref. Turns		Rev. Turns	
	dev	test	dev	test	dev	test
# of Turns	13,499	21,224	3,554	8,965	1,052	3,315
Dataflow	**.729**	**.665**	**.642**	**.574**	**.697**	**.565**
inline	.696	.606	.533	.465	.631	.474

Key Takeaways

- Alignment with High-level User Intent
  - Break complex queries into decomposed operations
  - Simplified Meta-operators: Refer & Revise
- Heuristics from Symbolic Execution
  - Constraint-based Reference & Revision
  - Runtime-exception-guided Recovery

What if the neural models fail in generating correct syntax/schema?

Constrained Decoding in Language Models

Constrained Language Models Yield Few-Shot Semantic Parsers

Richard Shin, Christopher H. Lin, Sam Thomson, Charles Chen,
Subhro Roy, Emmanouil Antonios Platanios, Adam Pauls,
Dan Klein, Jason Eisner, Benjamin Van Durme
Microsoft Semantic Machines
sminfo@microsoft.com

EMNLP 2021

- Language Models in 2020: GPT-2, GPT-3, T5, BART, etc.
- Better at generating natural language, but not good at domain-specific formal language

Synchronous Context-Free Grammar (SCFG)

Rules in SCFG apply to two languages at the same time, capturing grammatical structures that are each other's translations.

	[glue]	
(G1)	ENTITYNP$[x]$	$\rightarrow$ NP$[x]$
(G2)	TYPENP$[x]$	$\rightarrow$ NP[type.x]
(G3)	NP$[x]$ CP$[f]$ (and CP$[g]$)*	$\rightarrow$ NP$[x \sqcap f \sqcap g]$
	[simple]	
(R0)	that VP$[x]$	$\rightarrow$ CP$[x]$
(R1)	whose RELNP$[r]$ CMP$[c]$ NP$[y]$	$\rightarrow$ CP$[r.c.y]$
	is|is not|is smaller than|is larger than|is at least|is at most	$\rightarrow$ CMP$[= \mid \neq \mid < \mid > \mid \leq \mid \geq]$
(R2)	that (not)? VP/NP$[r]$ NP$[y]$	$\rightarrow$ CP$[(\neg)r.y]$
(R3)	that is (not)? RELNP$[r]$ of NP$[y]$	$\rightarrow$ CP$[(\neg)\mathbf{R}(r).y]$
(R4)	that NP$[y]$ (not)? VP/NP$[r]$	$\rightarrow$ CP$[(\neg)(\mathbf{R}(r).y)]$
	[counting]	
(C1)	that has CNT$[c]$ RELNP$[r]$	$\rightarrow$ CP$[\mathbf{R}(\lambda x.\text{count}(\mathbf{R}(r).x)).c]$
(C2)	that VP/NP$[r]$ CNT$[c]$ NP$[y]$	$\rightarrow$ CP$[\mathbf{R}(\lambda x.\text{count}(y \sqcap \mathbf{R}(r).x)).c]$
(C3)	that is RELNP$[r]$ of CNT$[c]$ NP$[y]$	$\rightarrow$ CP$[\mathbf{R}(\lambda x.\text{count}(y \sqcap r.x)).c]$
(C4)	that CNT$[c]$ NP$[y]$ VP/NP$[r]$	$\rightarrow$ CP$[\mathbf{R}(\lambda x.\text{count}(y \sqcap r.x)).c]$
	(less than|more than) NUM$[n]$	$\rightarrow$ CNT$[(< .\mid > .)n]$
	[superlatives]	
(S0)	NP$[x]$ that has the largest RELNP$[r]$	$\rightarrow$ NP$[\arg\max(x, r)]$
(S1)	NP$[x]$ that has the most number of RELNP$[r]$	$\rightarrow$ NP$[\arg\max(x, \mathbf{R}(\lambda y.\text{count}(\mathbf{R}(r).y)))]$
(S2)	NP$[x]$ that VP/NP$[r]$ the most number of NP$[y]$	$\rightarrow$ NP$[\arg\max(x, \mathbf{R}(\lambda y.\text{count}(\mathbf{R}(r).y)))]$
(S3)	NP$[x]$ that is RELNP$[r]$ of the most number of NP$[y]$	$\rightarrow$ NP$[\arg\max(x, \mathbf{R}(\lambda z.\text{count}(y \sqcap r.z)))]$
(S4)	NP$[x]$ that the most number of NP$[y]$ VP/NP$[r]$	$\rightarrow$ NP$[\arg\max(x, \mathbf{R}(\lambda z.\text{count}(y \sqcap r.z)))]$
	[transformation]	
(T1)	RELNP$[r]$ of NP$[y]$	$\rightarrow$ NP$[\mathbf{R}(r).y]$
(T2)	$\text{RELNP}_0[h]$CP$[f]$ (and CP$[g]$)*	$\rightarrow$ NP$[\mathbf{R}(h).(f \sqcap g)]$
(T3)	RELNP$[r]$ of $\text{RELNP}_0[h]$ NP$[x]$ CP$[f]$ (and CP$[g]$)*	$\rightarrow$ NP$[\mathbf{R}(r).(h.x \sqcap f \sqcap g)]$
(T4)	NP$[x]$ or NP$[y]$	$\rightarrow$ NP$[x \sqcup y]$
	[aggregation]	
(A1)	number of NP$[x]$	$\rightarrow$ NP[count(x)]
(A2)	total|average RELNP$[r]$ of NP$[x]$	$\rightarrow$ NP[sum|average(x, r)]

Canonical Utterance ⇔ Formal Logical Form

Example
x: *"Show me meetings after the weekly standup day"*
c: *"meeting whose date is at least date of weekly standup"*
z: `type.meeting` $\sqcap$ `date.` $>$ $\mathbf{R}$(`date`)`.weeklyStandup`
x: *"Select the brick that is to the furthest left."*
c: *"block that the most number of block is right of"*
z: `argmax`(`type.block`, $\mathbf{R}(\lambda x.$`count`$(\mathbf{R}$(`right`$).x))$)
x: *"Housing that is 800 square feet or bigger?"*
c: *"housing unit whose size is at least 800 square feet"*
z: `type.housingUnit` $\sqcap$ `area.` $>$ `.800`
x: *"What restaurant can you eat lunch outside at?"*
c: *"restaurant that has outdoor seating and that serves lunch"*
z: `type.restaurant` $\sqcap$ `hasOutdoorSeating` $\sqcap$ `serveslunch`
x: *"Who has co-authored articles with Efron?"*
c: *"person that is author of article whose author is efron"*
z: `type.person` $\sqcap$ $\mathbf{R}$(`author`)`.(type.article` $\sqcap$ `author.efron)`
x: *"When did alice start attending brown university?"*
c: *"start date of student alice whose university is brown university"*
z: $\mathbf{R}$(`date`)`.(student.Alice` $\sqcap$ `university.Brown)`
x: *"How many fouls were played by Kobe Bryant in 2004?"*
c: *"number of fouls (over a season) of player kobe bryant whose season is 2004"*
z: count($\mathbf{R}$(`fouls`)`.(player.KobeBryant` $\sqcap$ `season.2004)`

Paraphrasing is easier than Semantic Parsing

- Natural Language Utterance u
  who has published the most articles?

$$u \mapsto c \mapsto m$$

Pretrained LM — Equiv. SCFG

- Canonical Utterance c
  person that is author of the most number of article

- Meaning Representation (Formal Language) m
  $\text{argmax}(\texttt{type.person}, \mathbf{R}(\lambda x.\text{count}(\texttt{type.article} \sqcap \texttt{author}.x)))$

Paraphrasing is easier than Semantic Parsing

By Prompting LMs:

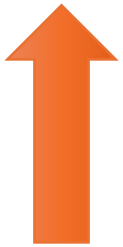
$$u \mapsto c \mapsto m$$

Pretrained LM

Equiv. SCFG

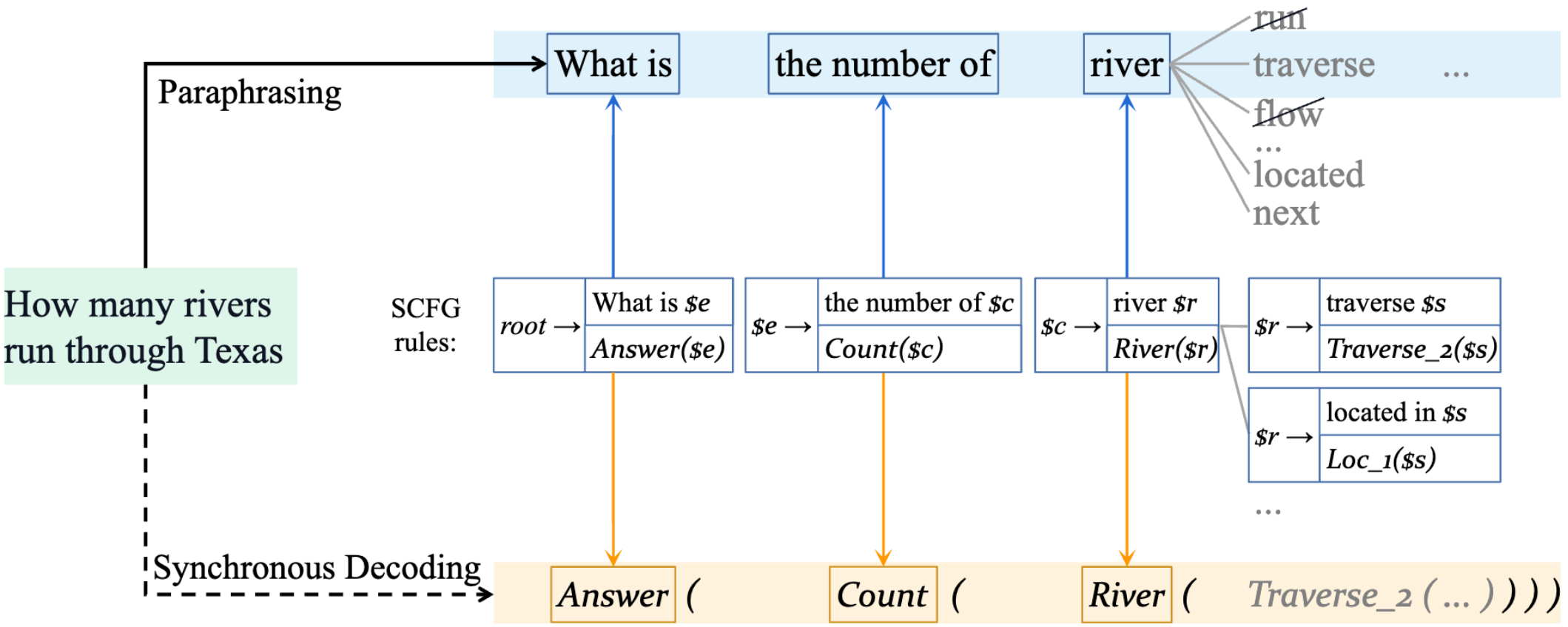
```
Let's translate what a human user says into
    what a computer might say.

   Human: when is the weekly standup
Computer: start time of weekly standup
   Human: what date is the weekly standup
Computer: date of weekly standup
              ...
   Human: how long is the weekly standup
Computer:
```

Few-shot Examples



Retrieved from a database based on similarity (Retrieval-augmented Generation)

Grammar-constrained Decoding



Results

Overnight:

Ablation:
a) Canonical > Meaning
b) Constrained >> Unconstrained

Model	Train n	Basketball	Blocks	Calendar	Housing	Publications	Recipes	Restaurants	Social
GPT-3 Constrained Canonical	200	**0.80***	**0.62***	**0.82***	**0.71***	0.79*	**0.84***	**0.89***	**0.72***
GPT-3 Constrained Meaning	200	0.68*	0.53*	0.68*	0.58*	0.63*	0.75*	0.78*	0.63*
GPT-3 Unconstrained Canonical	200	0.76*	0.46*	0.68*	0.56*	0.58*	0.74*	0.74*	0.55*
GPT-3 Unconstrained Meaning	200	0.56*	0.39*	0.50*	0.42*	0.46*	0.66*	0.58*	0.48*
GPT-3 Constrained Canonical	20	**0.80***	0.55*	0.67*	0.68*	**0.81***	0.60*	0.76*	0.67*
BART^f Constrained Canonical	200	**0.85**	**0.58**	**0.85**	0.73	0.76	**0.77**	**0.83**	**0.73**
BART^f Constrained Meaning	200	0.83	0.56	0.77	**0.75**	**0.79**	0.76	0.81	0.69
BART^f Unconstrained Canonical	200	0.83	0.56	0.80	0.67	0.72	0.75	0.81	0.65
BART^f Unconstrained Meaning	200	0.82	0.55	0.76	0.71	0.77	0.73	0.80	0.63
Cao et al. (2019)	640–3535	**0.880**	**0.652**	**0.807**	**0.767**	**0.807**	**0.824**	**0.840**	**0.838**
BERT-LSTM (Xu et al., 2020)	640–3535	0.875	0.624	0.798	0.704	0.764	0.759	0.828	0.819

Key Takeaways

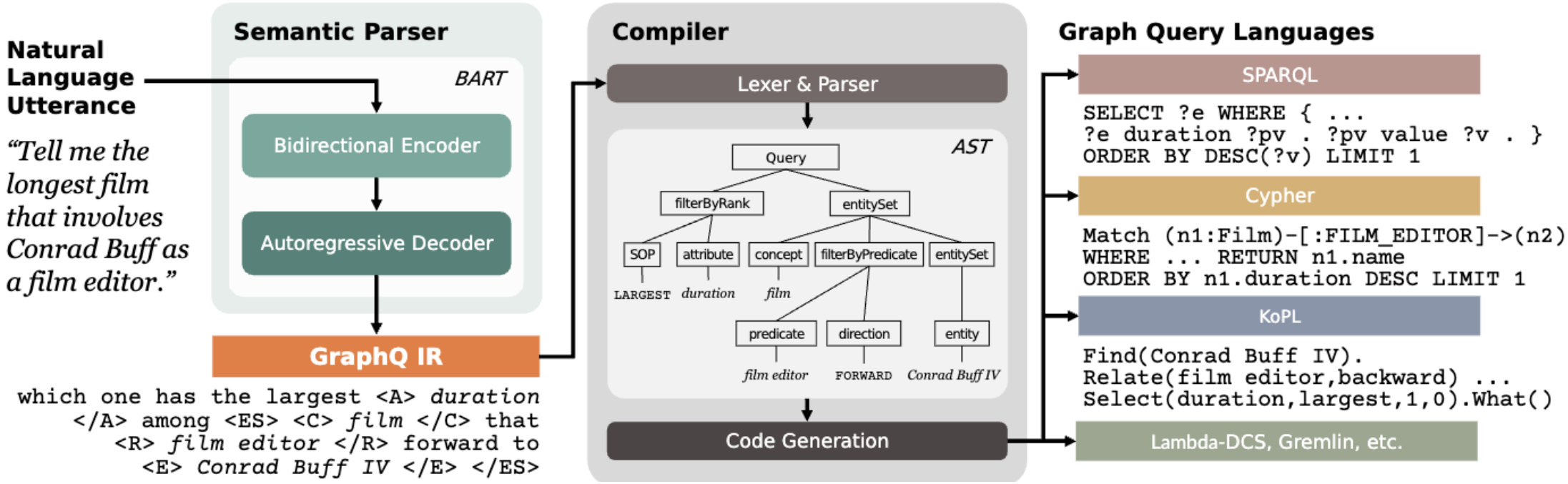
- Alignment with Neural Model Strengths
  - Language models are better at paraphrasing than code generation
  - Canonical utterance plays as the intermediate representation (IR) to bridge the Semantic Gap
- Symbolic Heuristics
  - Grammar constraint-based decoding

Can we utilize the **Intermediate Representation** to improve **knowledge transferability** and **low-resource** semantic parsing?

GraphQ IR: Unifying the Semantic Parsing of Graph Query Languages with One Intermediate Representation

EMNLP 2022

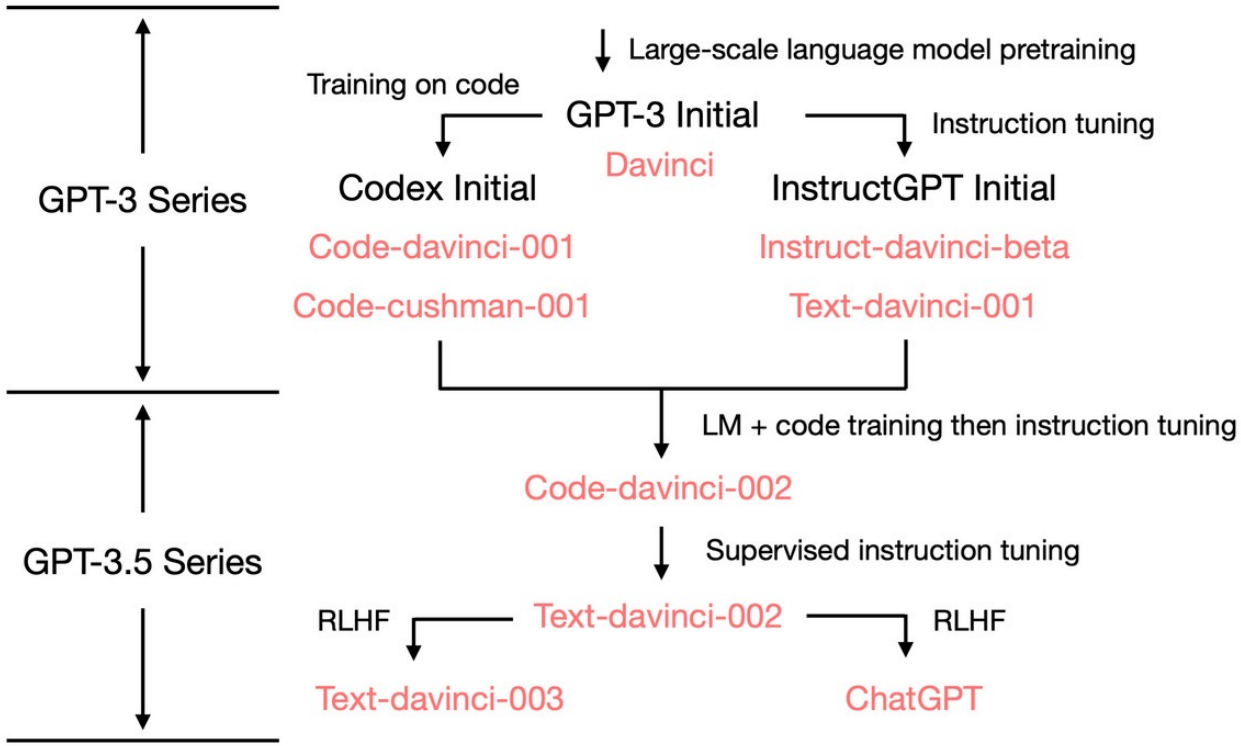
Lunyiu Nie[1], **Shulin Cao**[1], **Jiaxin Shi**[2], **Jiuding Sun**[1],
Qi Tian[2], **Lei Hou**[1], **Juanzi Li**[1], **Jidong Zhai**[1]



	Bas.	Blo.	Cal.	Hou.	Pub.	Rec.	Res.	Soc.	Overall
Baselines									
SPO (Wang et al., 2015)	46.3	41.9	74.4	54.0	59.0	70.8	75.9	48.2	58.8
CrossDomain* (Su and Yan, 2017)	88.2	62.2	**82.1**	78.8	80.1	86.1	83.7	83.1	80.6
Seq2Action (Chen et al., 2018a)	88.2	61.4	81.5	74.1	80.7	82.9	80.7	82.1	79.0
DUAL (Cao et al., 2019)	84.9	61.2	78.6	67.2	78.3	80.6	78.9	81.3	76.4
2-stage DUAL* (Cao et al., 2020)	87.2	**65.7**	80.4	75.7	80.1	86.1	82.8	82.7	80.1
Our Approach									
GraphQ IR	88.2	64.7	78.6	72.0	77.6	83.3	84.9	81.6	79.5
GraphQ IR*	**88.2**	65.4	81.6	**81.5**	**82.6**	**92.9**	**89.8**	**84.1**	**82.1**

Cross-domain training on SPARQL annotations

From Semantic Parsing to Agent Tool Use



As pretraining scales up & on code corpus, today's LLMs can handle code generation very well

Fu, Yao; Peng, Hao and Khot, Tushar. (Dec 2022).
How does GPT Obtain its Ability? Tracing Emergent Abilities of Language Models to their Sources.

From Semantic Parsing to Agent Tool Use

Toolformer: Language Models Can Teach Themselves to Use Tools

Timo Schick **Jane Dwivedi-Yu** **Roberto Dessì**[†] **Roberta Raileanu**
Maria Lomeli **Luke Zettlemoyer** **Nicola Cancedda** **Thomas Scialom**

Meta AI Research [†]Universitat Pompeu Fabra

NeurIPS 2023

(Post-ChatGPT

Answers from ChatGPT 5

ChatGPT Limitations

Who is the current President of the United States?

Searching the web

The current President of the United States is **Donald J. Trump**,

As an AI language model, I don't have real-time data or internet access, and my knowledge was last updated in September 2021. [...]

What day of the week is it today?

Today is **Monday, September 1, 2025.** ✅

As an AI language model, I do not have the capability to access current time or date information. [...]

What is the result of 3435 * 235 / 9?

Let's carefully calculate step by step:

.....

✅ Final Answer:

89,691 remainder 6

or ≈ **89,691.67** in decimal.

This is approximately 89,937.22.

True answer: 89691.66

Toolformer Tools/APIs

What other name is Pittsburgh known by?

The Steel City

War memorial Flodden

[...] was created in memory of the Battle of Flodden.

3435 * 235 / 9

89691.67

Ø

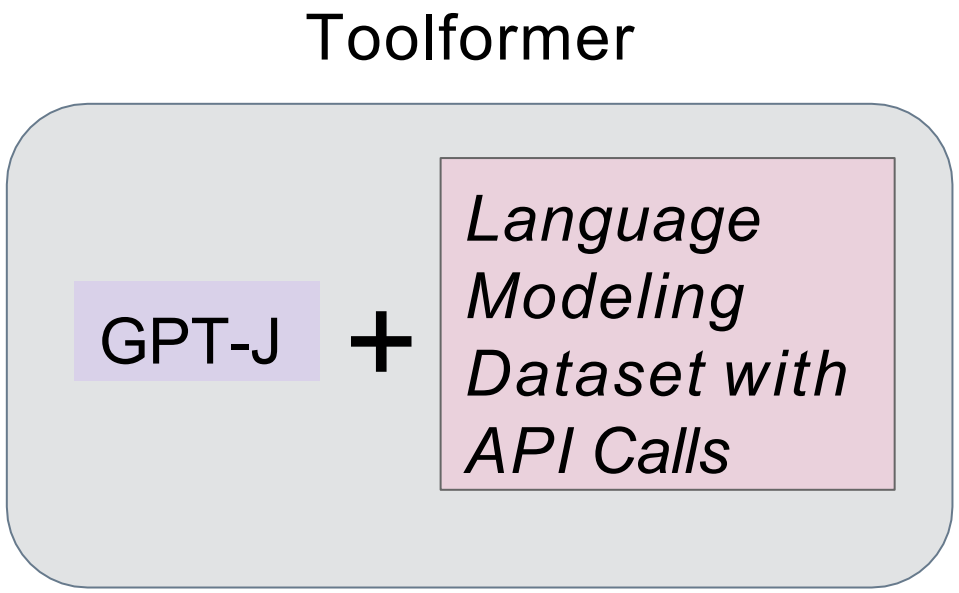
Thursday, March 10, 2019

Os Melhores Escolas em Jersey

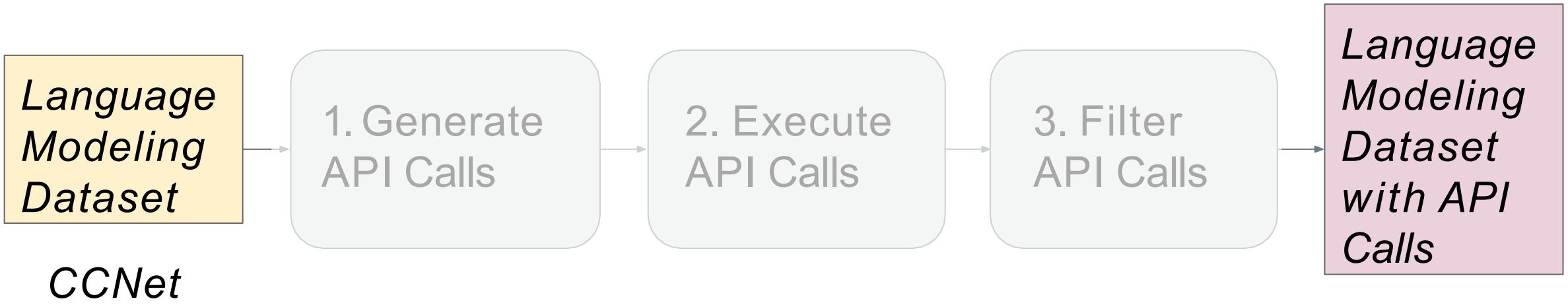
The Best Schools in Jersey

Steps to Create Toolformer

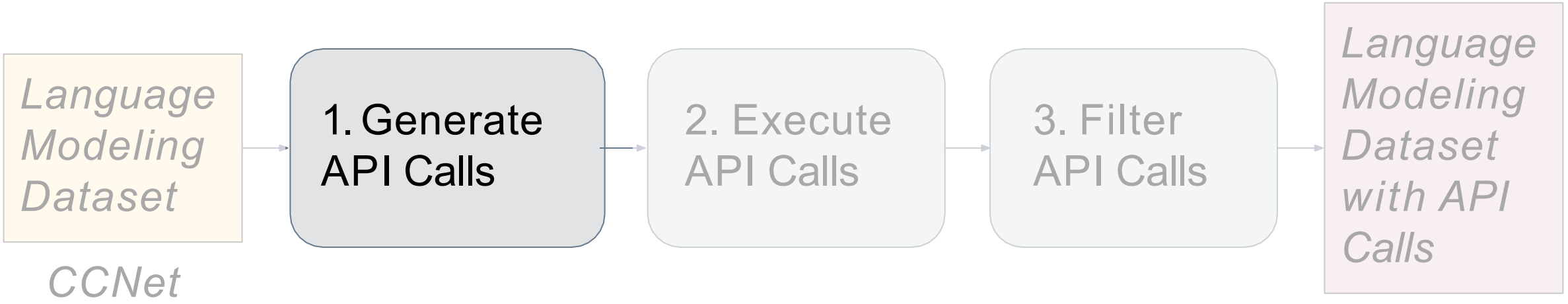
1. Creating a new training dataset augmented with API calls
2. Finetune GPT-J using this new dataset



Creating the Training Dataset



Creating the Training Dataset



Prompting the Model to Generate API Calls

Your task is to add calls to a Question Answering API to a piece of text. The questions should help you get information required to complete the text. You can call the API by writing "[QA(question)]" where "question" is the question you want to ask. Here are some examples of API calls:

Input: Joe Biden was born in Scranton, Pennsylvania.
Output: Joe Biden was born in [QA("Where was Joe Biden born?")] Scranton, [QA("In which state is Scranton?")] Pennsylvania.

Input: *${input}*
Output:

Examples of Generated API Calls

Your task is to add calls to a QA API to a piece of text [...]

Input: Pittsburgh is known as the Steel City.

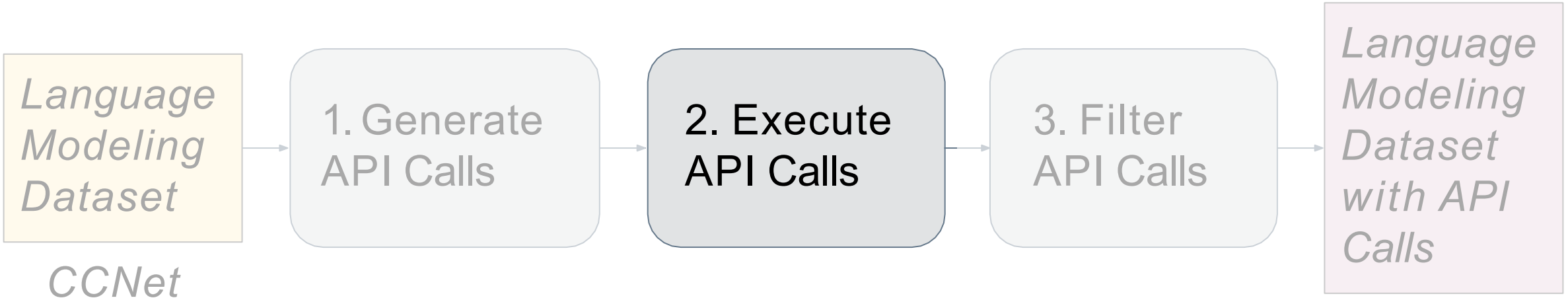
Output:

Pittsburgh is known as [QA("In which state is Pittsburgh?")] the Steel City.

Pittsburgh is known as [QA("What other name is Pittsburgh known by?")] the Steel City.

Pittsburgh is known as [QA("What is the second city in Pennsylvania?")] the Steel City.

Creating the Training Dataset



Execute the API Calls

In which state is Pittsburgh? →  → Pennsylvania

What other name is Pittsburgh known by? →  → The Steel City

What is the second city in Pennsylvania? →  → Pittsburgh

Execute the API Calls

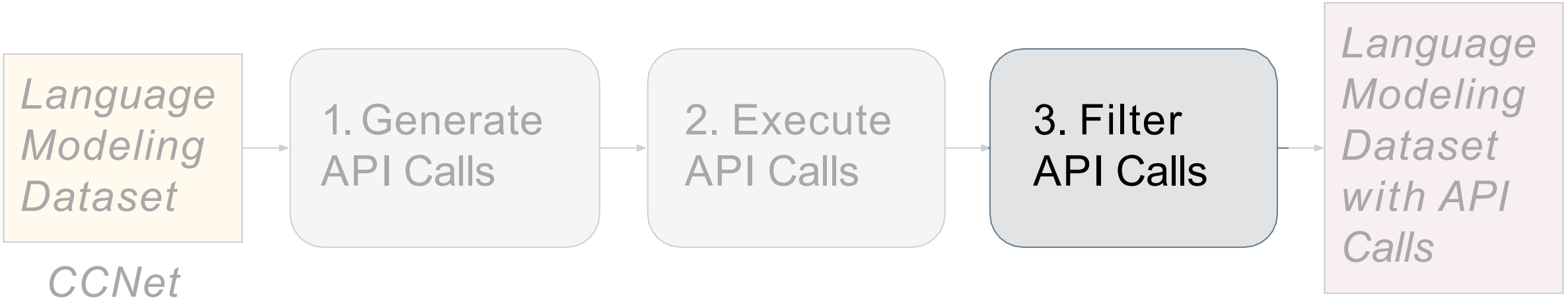
In which state is Pittsburgh? →  → Pennsylvania

Pittsburgh is known as the Steel City.

Pittsburgh is known as [QA("In which state is Pittsburgh?")]

Pittsburgh is known as [QA("In which state is Pittsburgh?") → Pennsylvania] the Steel City.

Creating the Training Dataset



Filter the API Calls using Model-based Perplexity

$L_{\bullet}(PREFIX) = -\log p(\text{the Steel City.} \mid PREFIX)$

A. No API Call — $L_A(\textit{Pittsburgh is known as}) = \mathbf{2.5}$

B. Non-executed API Call — $L_B(\textit{Pittsburgh is known as [QA("What other name is Pittsburgh known by?") → ?]}) = \mathbf{2.1}$

C. Executed API Call — $L_C(\textit{Pittsburgh is known as [QA("What other name is Pittsburgh known by?") → Steel City]}) = \mathbf{0.8}$

$$\text{Usefulness} = \min(L_A, L_B) - L_C = \min(2.5, 2.1) - 0.8 = 1.3$$

Usefulness Examples

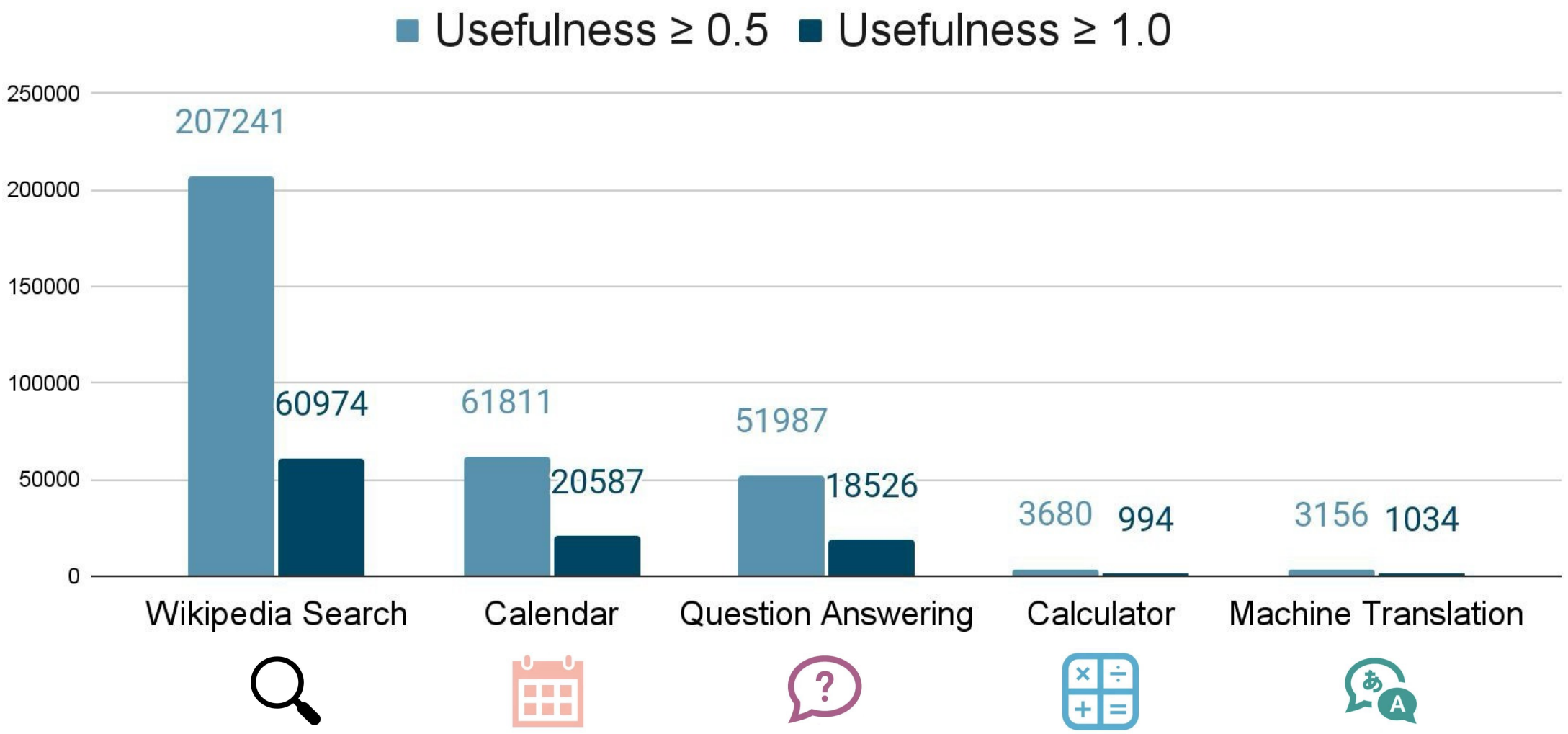
2.11

The WL will be open on Friday, [Calendar() → Today is Thursday, March 9, 2017.] March 10, and Sunday, March 19 for regular hours.

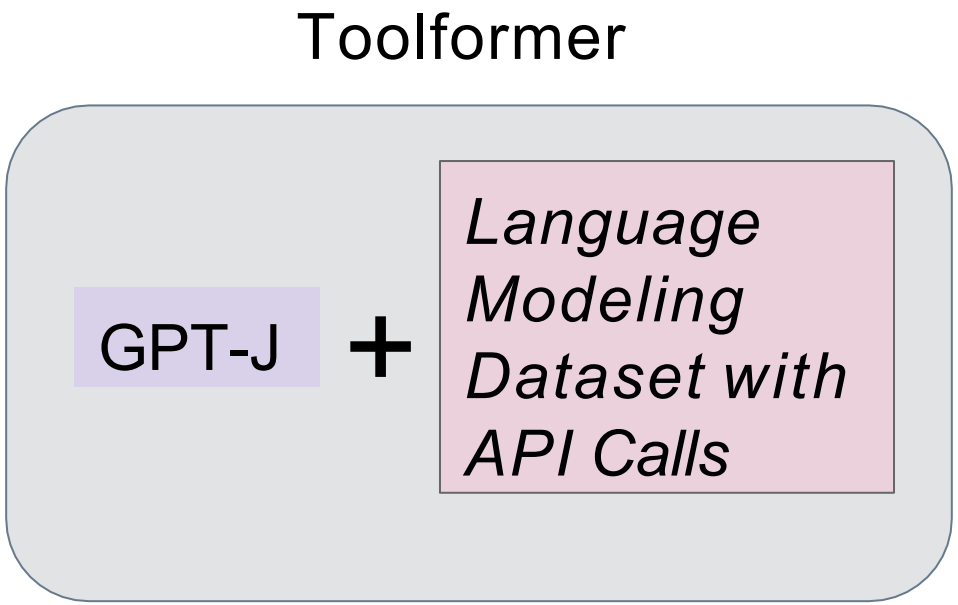
-0.02

85 patients (23%) were hospitalised alive and admitted to a hospital ward. Of them, [Calculator(85 / 23) → 3.70] 65% had a cardiac aetiology.

Number of Tool-Usage Samples After Filtering



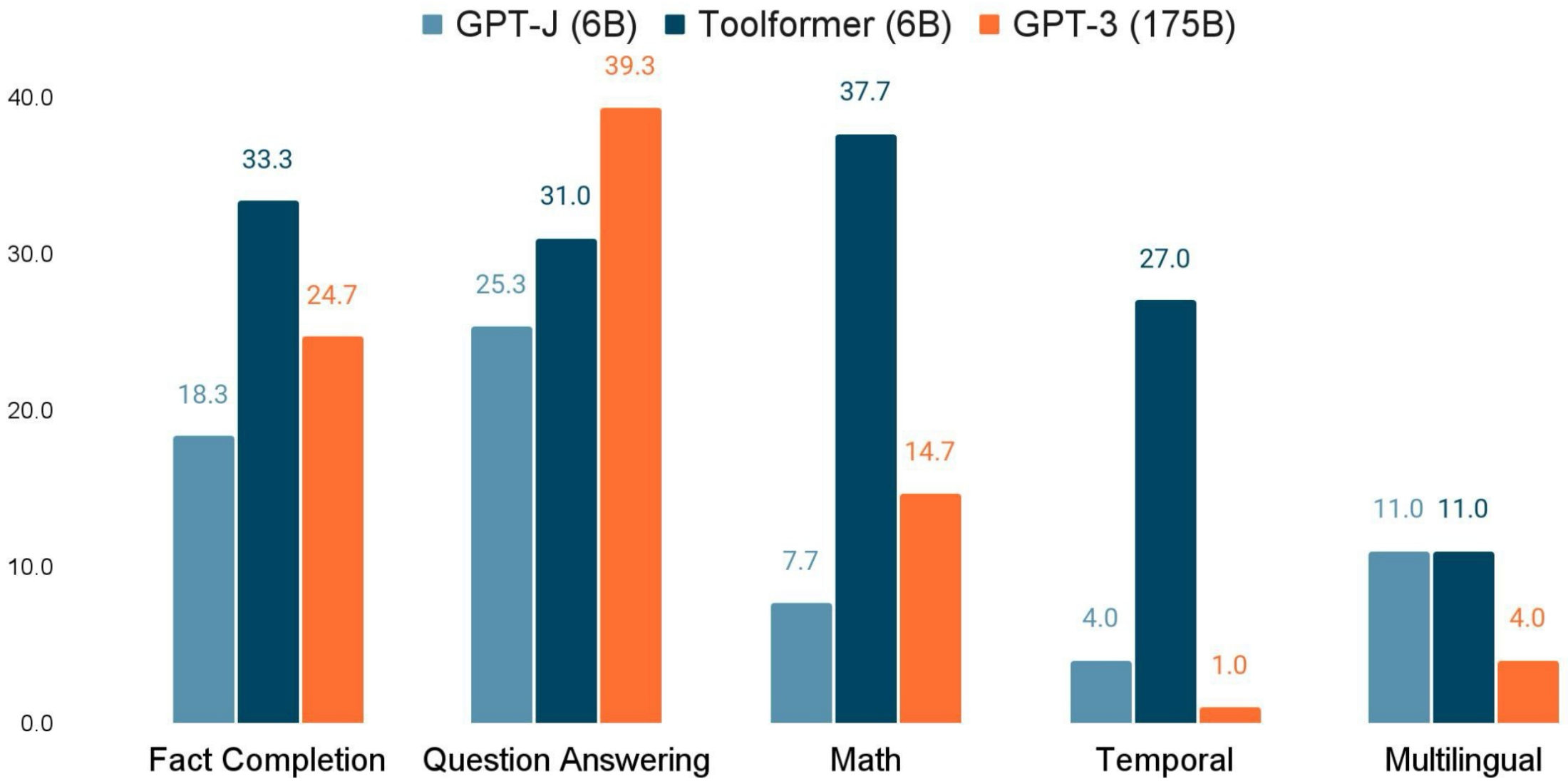
Fine-tuning Toolformer



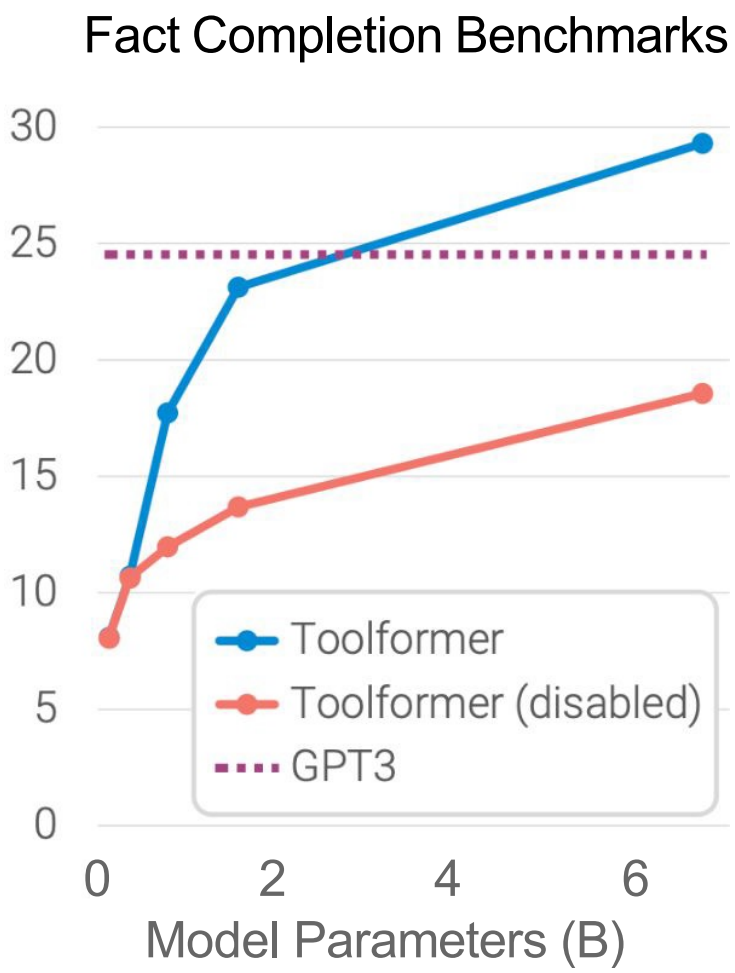
Evaluation Tasks

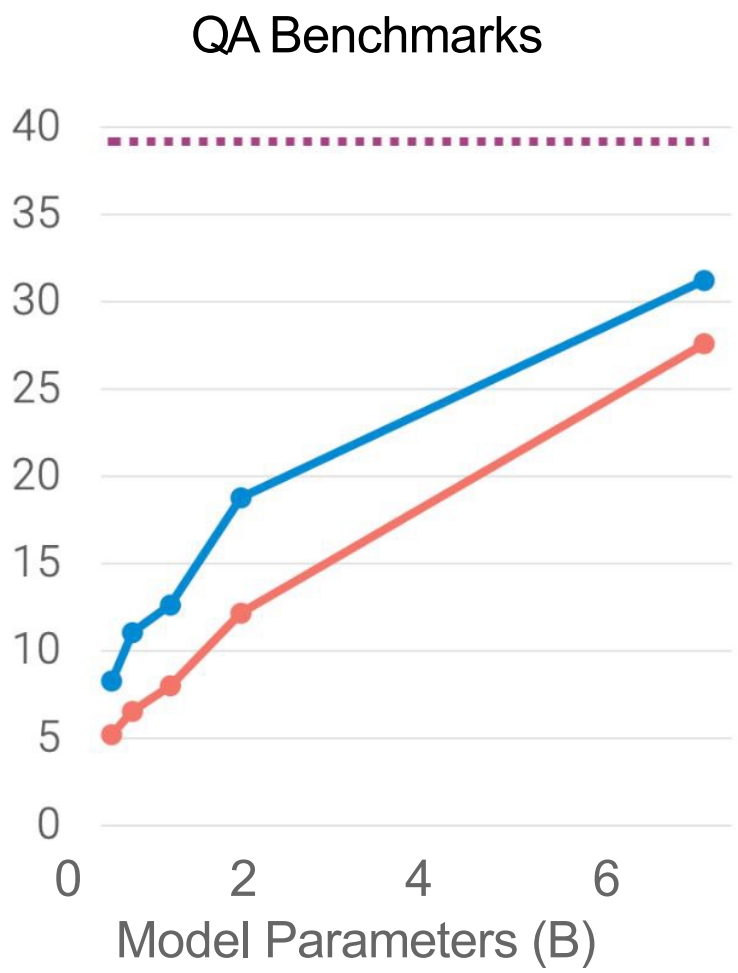
1. Fact Completion/Question Answering
    a. “The theory of relativity was developed by _____”
    b. “In Greek Mythology, who is the goddess of spring growth?”
2. Math Computations
3. Multilingual Questions
    a. Context is given in English, question is multilingual.
4. Temporal Questions
    a. How many days is it until Christmas?

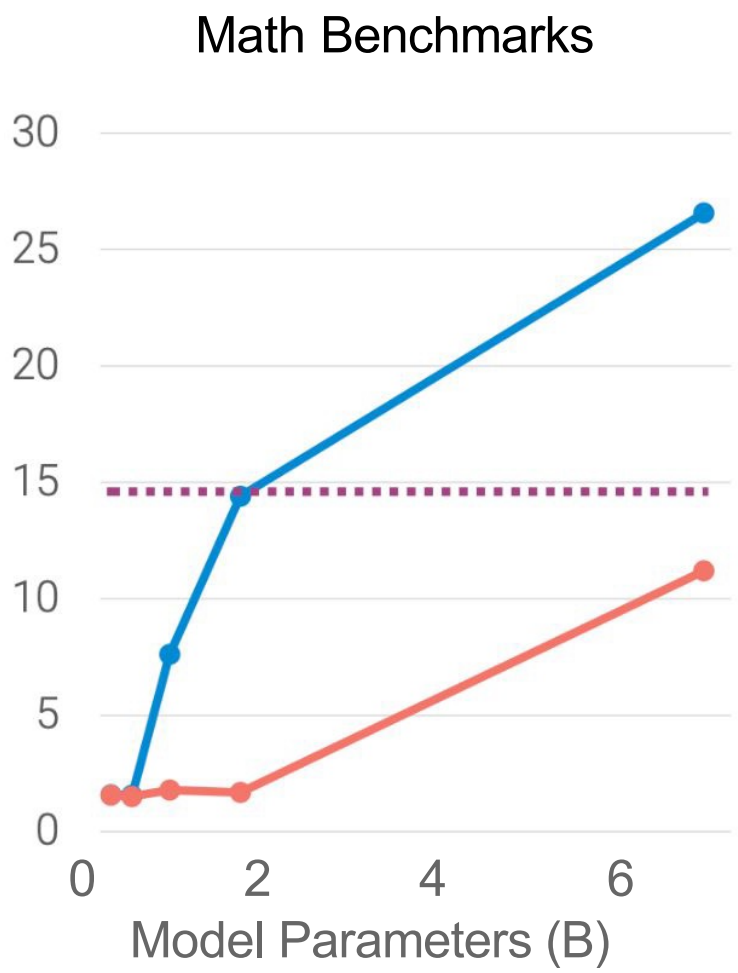
Results


GPT-J (6B)
Toolformer (6B)
GPT-3 (175B)
40.0
30.0
20.0
10.0
0.0
18.3
33.3
24.7
25.3
31.0
39.3
7.7
37.7
14.7
4.0
27.0
1.0
11.0
11.0
4.0
Fact Completion
Question Answering
Math
Temporal
Multilingual

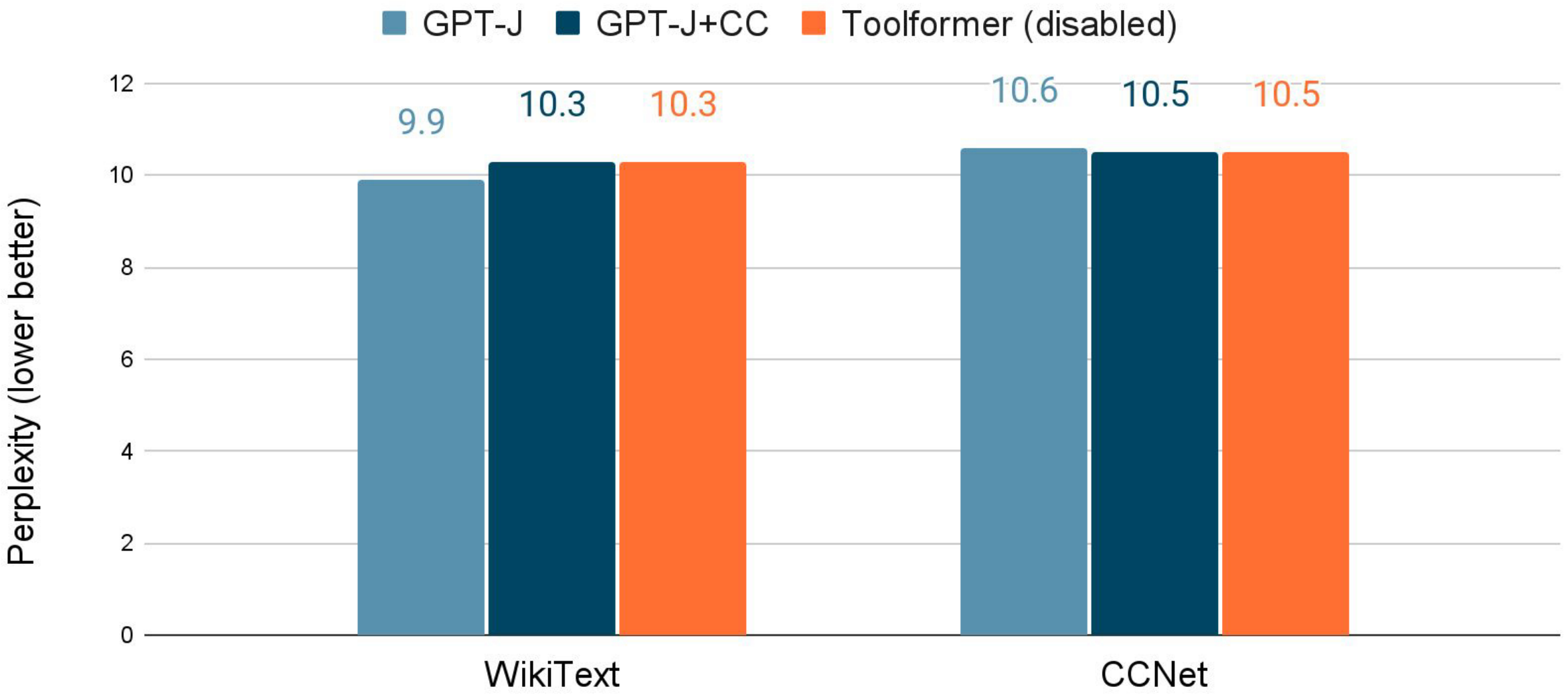
Can small models effectively use tools?







Is Toolformer still a good language model?



What Old-School Semantic Parsing can teach us in the Age of LLMs

- Symbolic methods
  - Interpretable
  - Verifiable
  - Structured Domain Knowledge
  - Data efficient
- Neural methods
  - Scalable
  - Flexible
  - Handles messy data
  - Easy to get started (need data!)

- Symbolic heuristics
  - Execution-guided
  - Grammar Constrained-decoding
- Better neural networks
  - Advanced model architecture
  - Pretraining
- Neurosymbolic combinations
  - Data Augmentation with SCFG
  - Intermediate Representation

Discussion

- What key challenges from early semantic parsing (ambiguity, compositionality, grounding, etc.) still matter for LLMs today?
- How can structured meaning representations complement LLMs?
- Could semantic parsing ideas help reduce hallucinations or improve reasoning?
- How might symbolic constraints or grammar-driven parsing improve the reliability of LLM outputs?
- What role could hybrid models (symbolic + neural) play in bridging old and new paradigms?