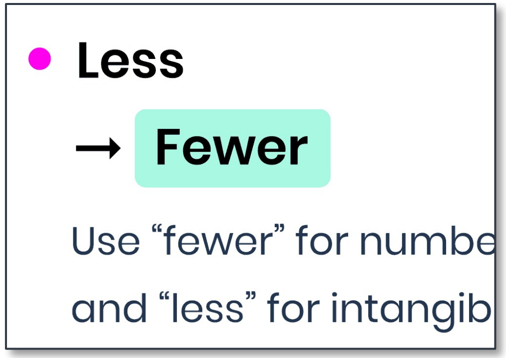
# The Quest Toward Generality in Natural Language Understanding

Daniel Khashabi

Allen Institute for AI

# AI-driven Language Interfaces

... are everywhere!





# AI-driven Language Interfaces

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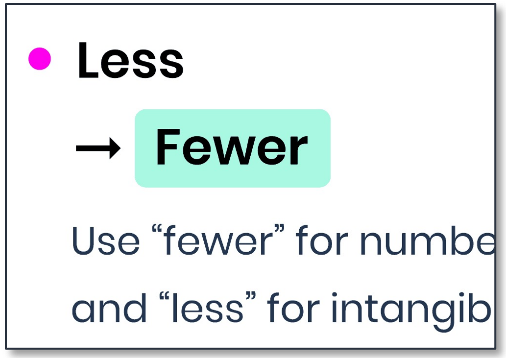



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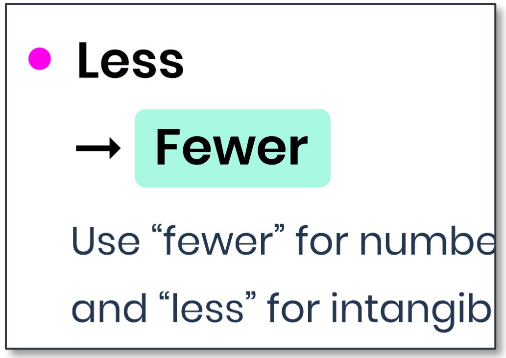



Why no single “general” system?

# AI's Inception w/ a Broad Vision

*"By 'general intelligent action' … a behavior appropriate to the ends of the system and adaptive to the demands of the environment can occur."*


[Newell and Simon, 1959 & 1976]

# AI’s Inception w/ a Broad Vision

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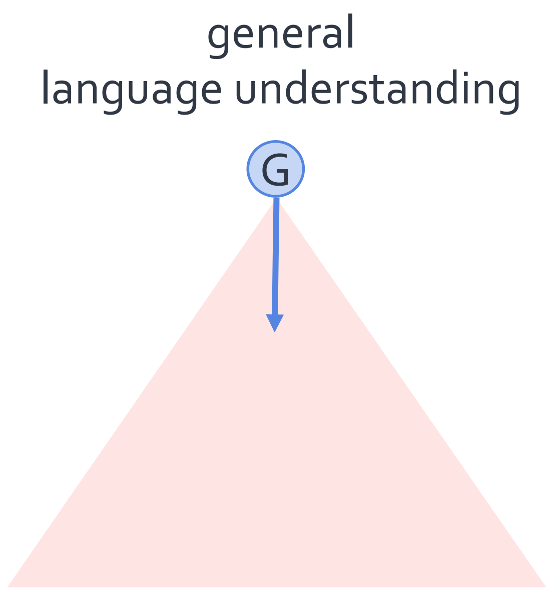
General Problem Solver

[Newell and Simon, 1959 & 1976]

# The Great Separation

- "General language understanding" broken into many narrowed tasks



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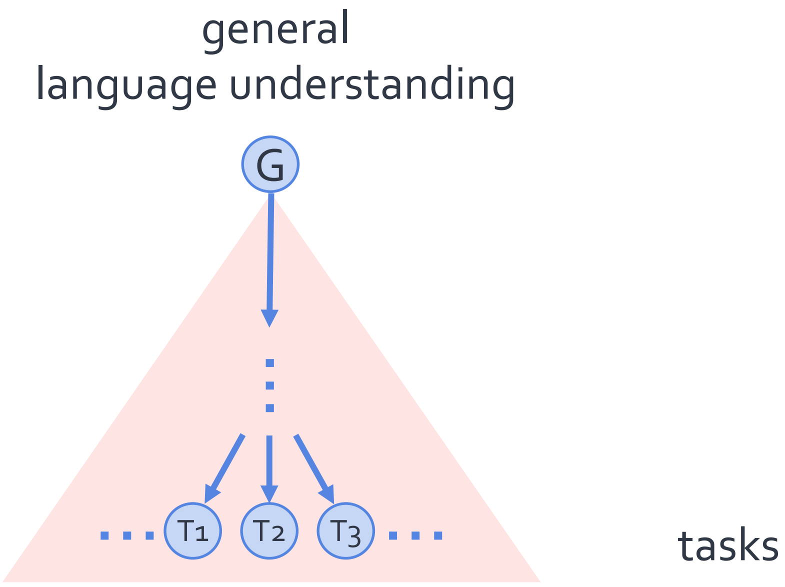


Generalization Hierarchy [Chollet, '19]

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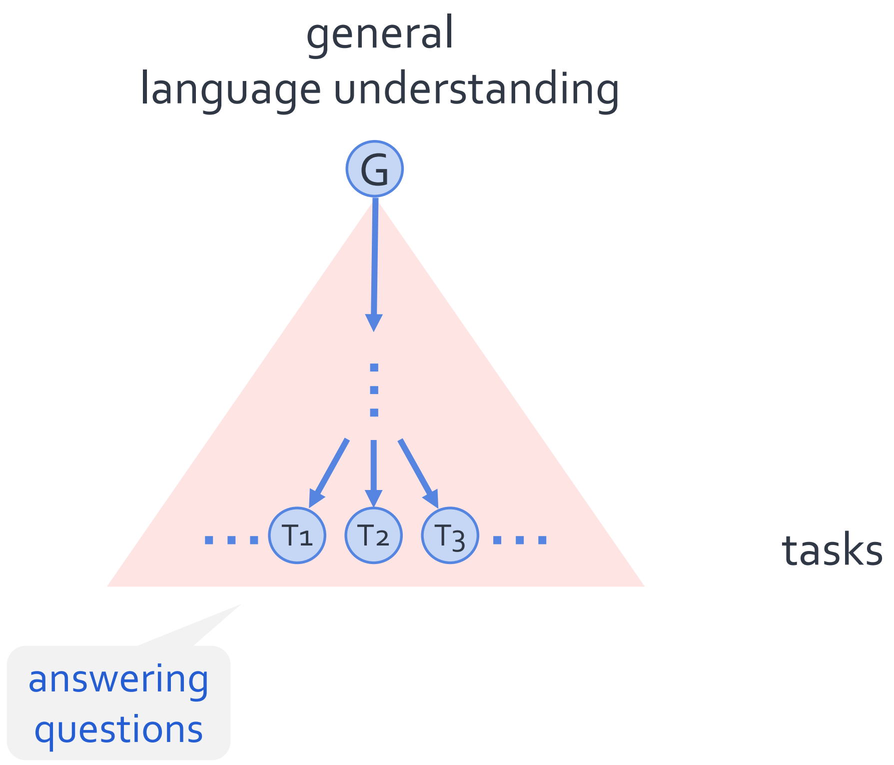
$\mathbf{x}$ = "How long did ....." $\longrightarrow$ $\mathbf{y}$ = "2 years"

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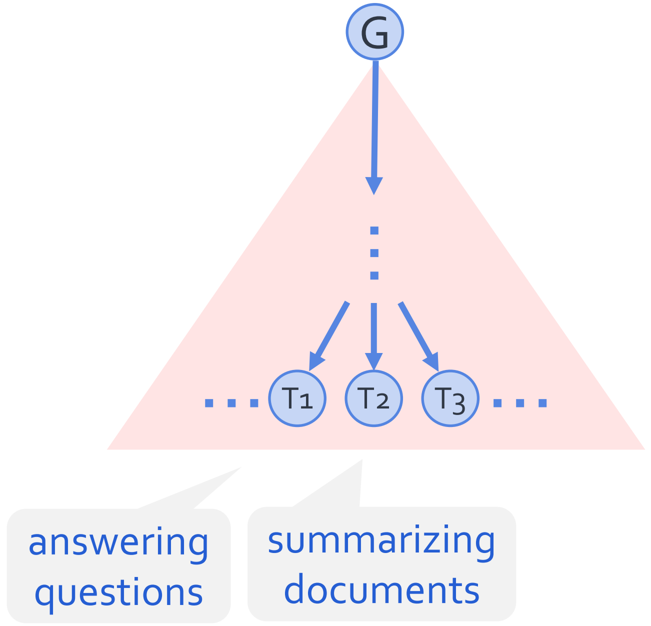
$\mathbf{x}$ =   $\longrightarrow$  $\mathbf{y}$ = " U.S. troops will …"

general
language understanding




tasks

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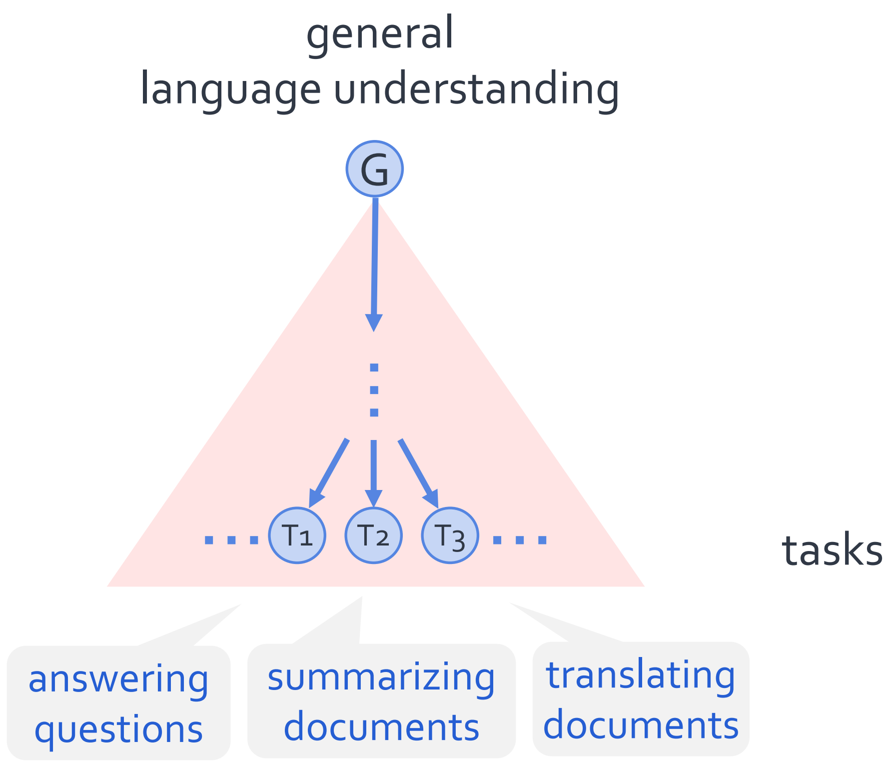
$\mathbf{x} =$ "Enjoyed ... ! " $\longrightarrow$ $\mathbf{y} =$ "¡Disfruté ...!"

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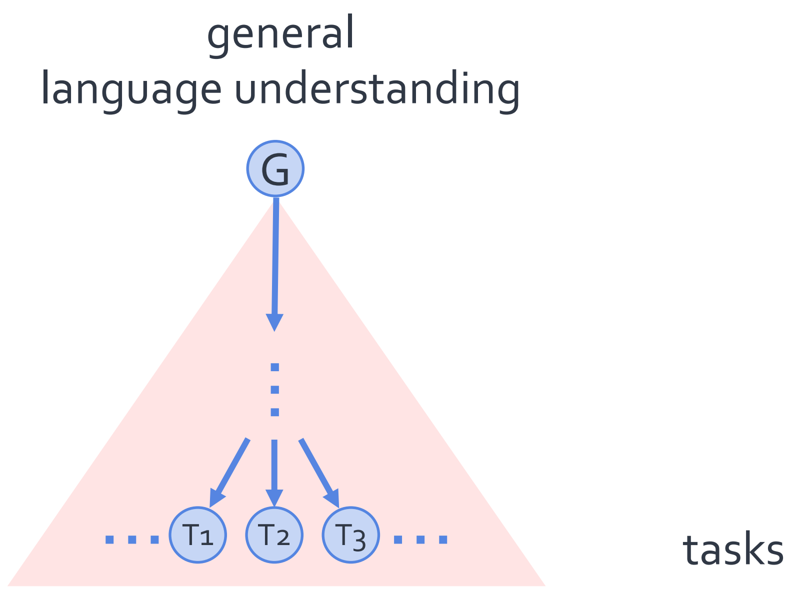


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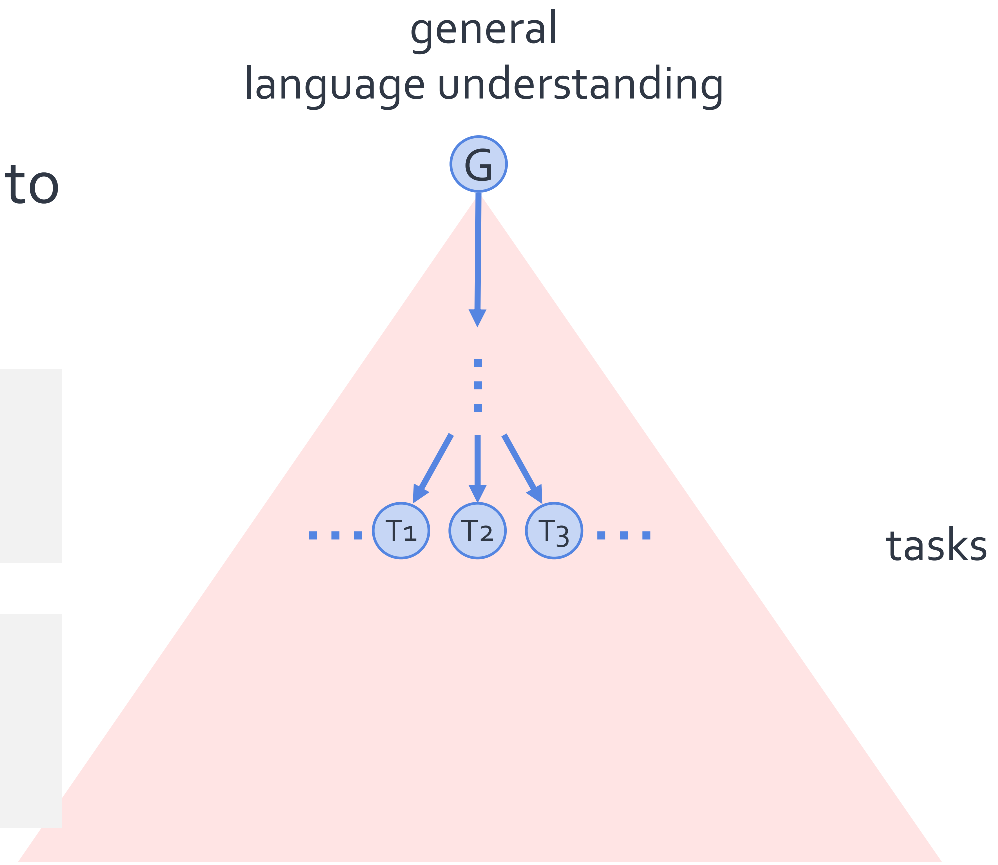


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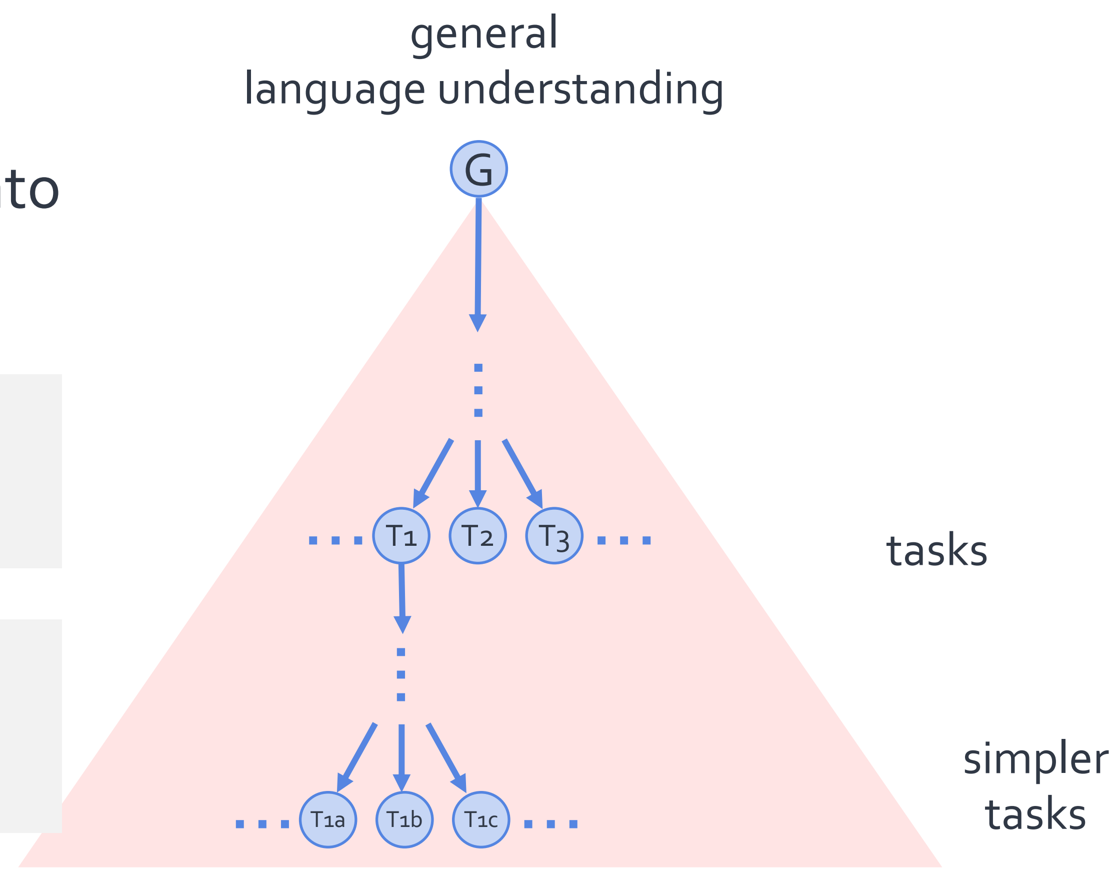


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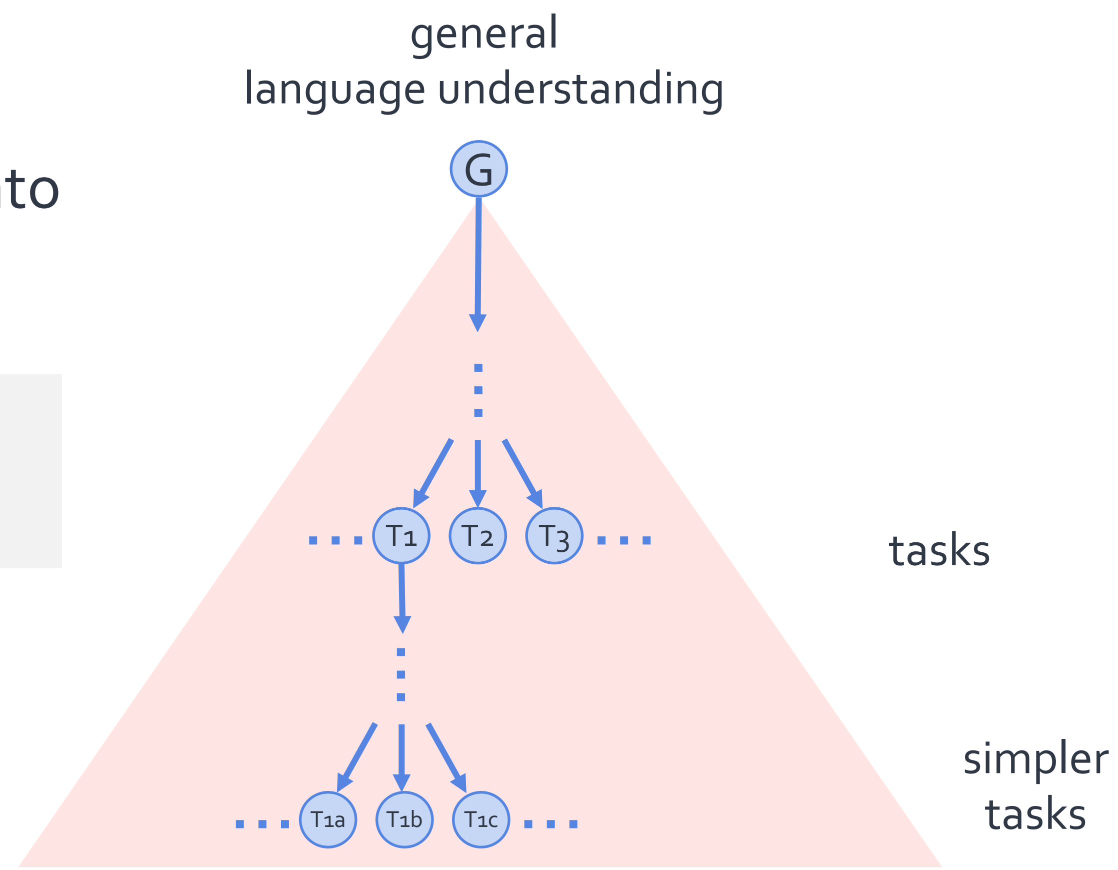


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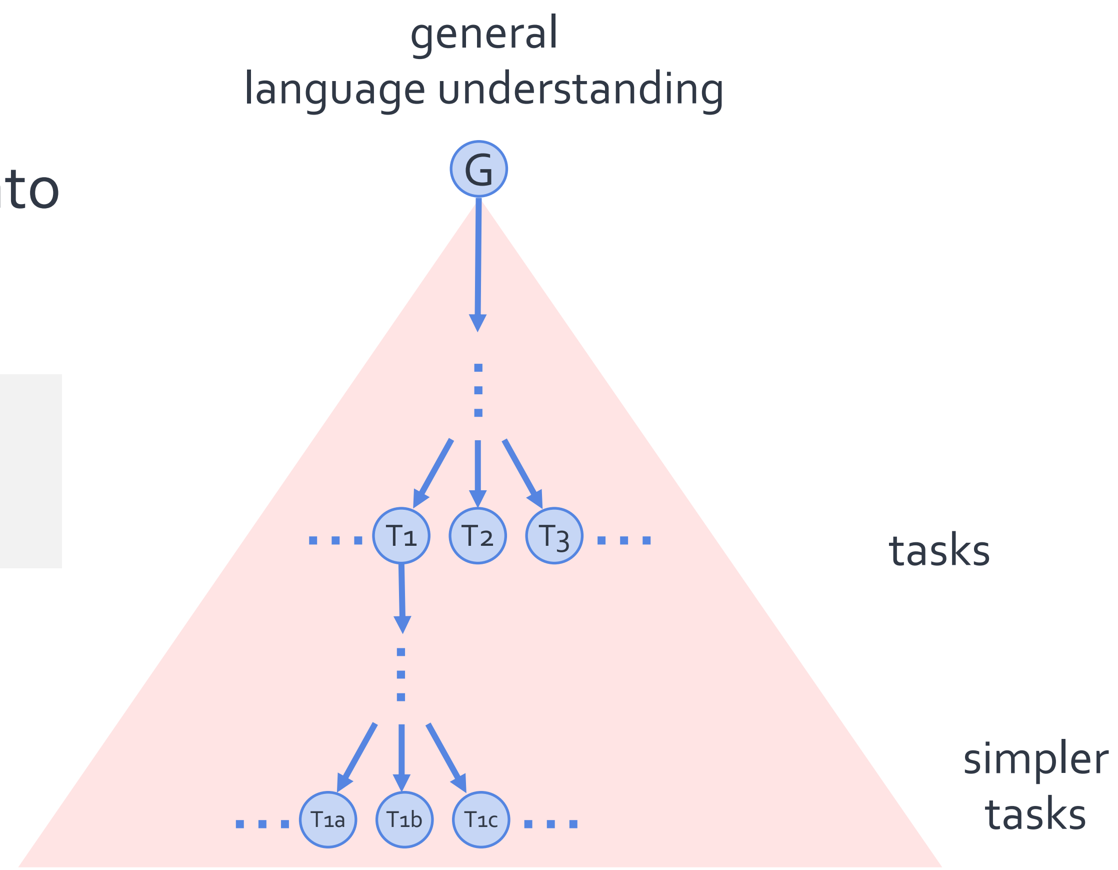
T1a answering simple factual questions

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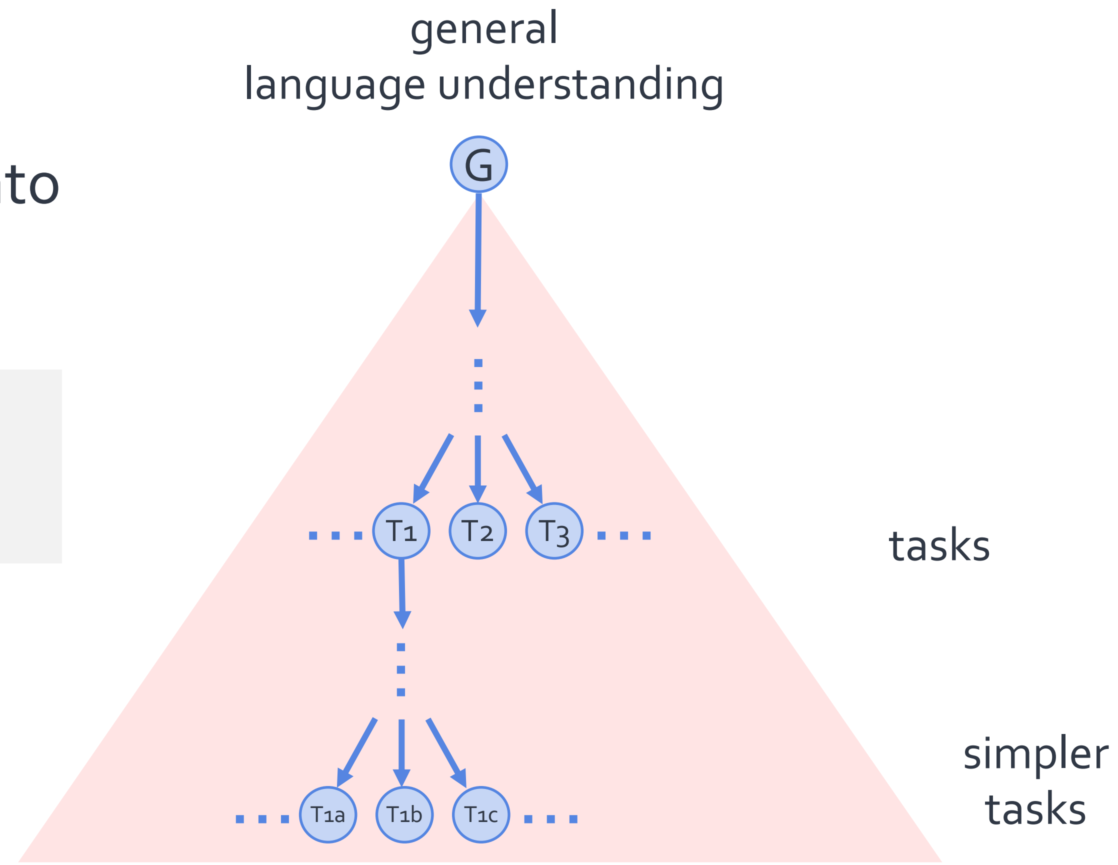
T1b answering algebra questions

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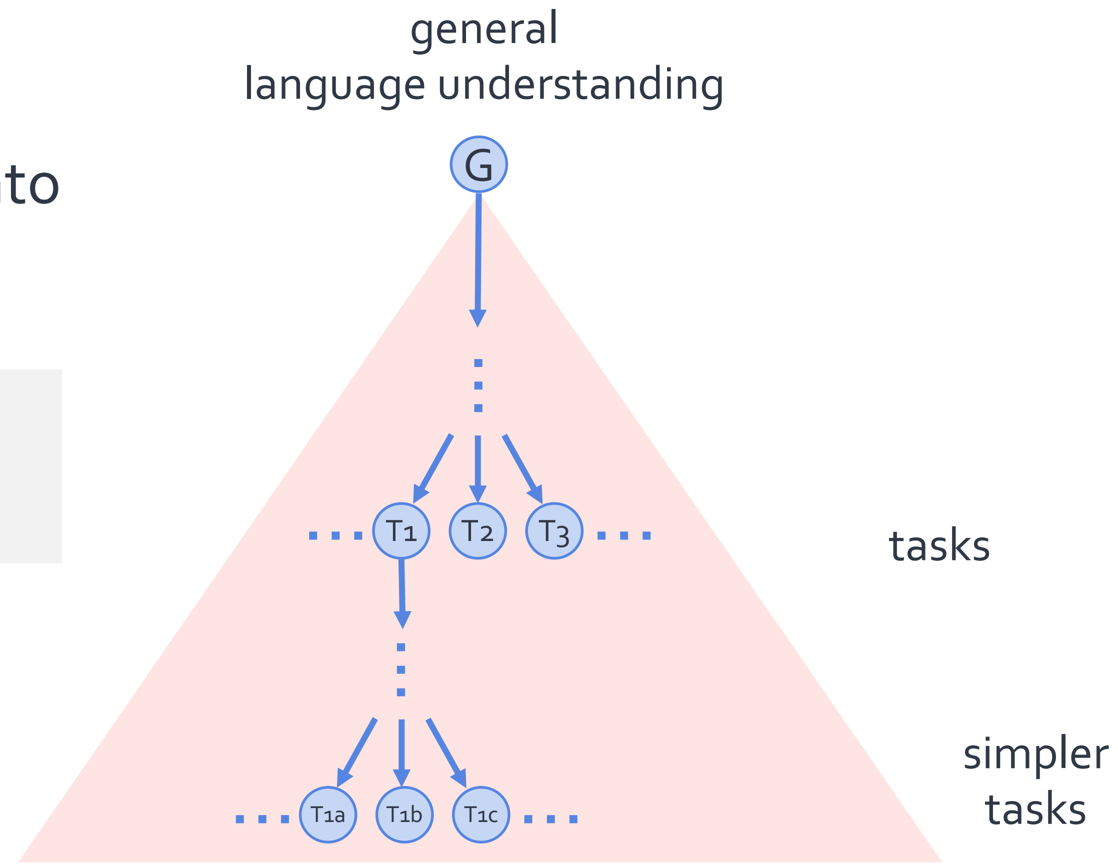
T1b answering algebra questions

T1b answering elementary school questions

⋮

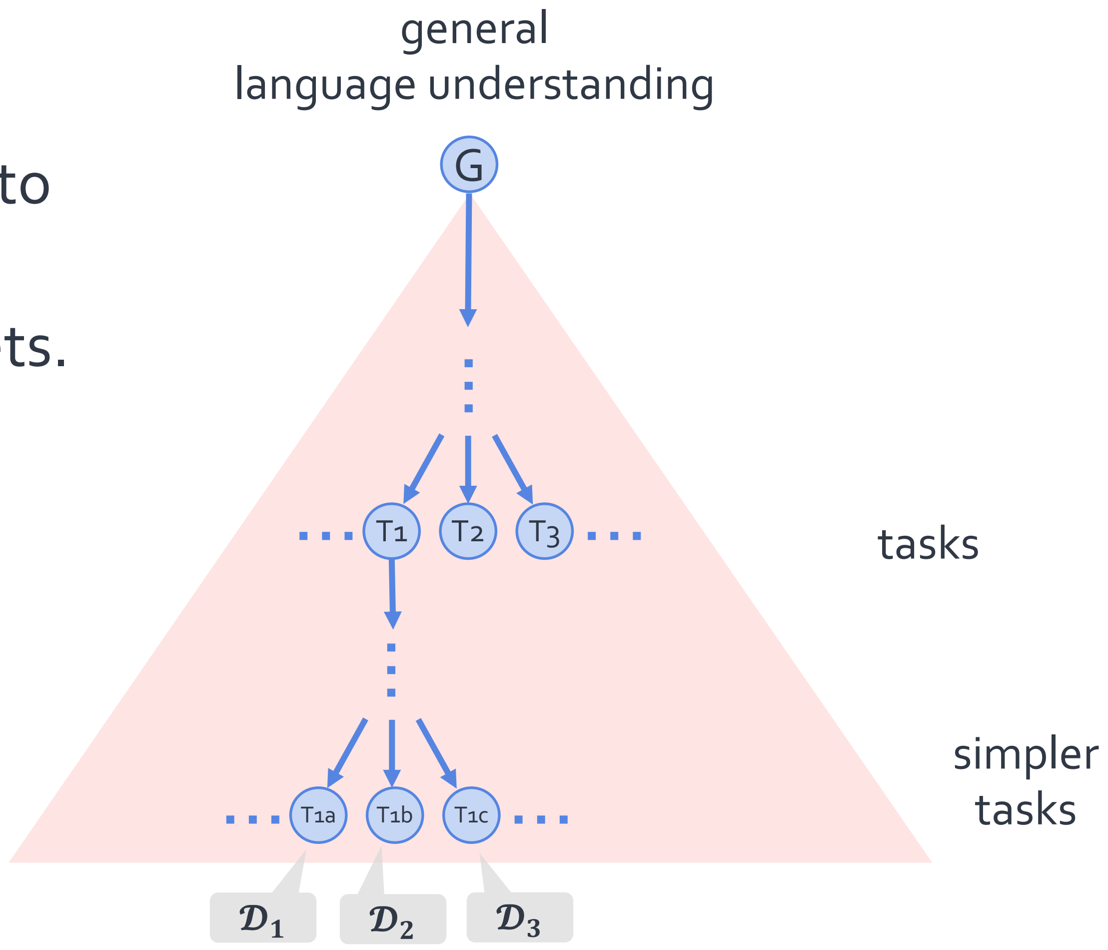



Generalization Hierarchy [Chollet, '19]

# The Dataset Heaven

- "General language understanding" broken into many narrowed tasks
- Subtasks instantiated as input-output datasets.

$$(\mathbf{x}, \mathbf{y}) \sim \mathrm{T} \quad \rightarrow \mathcal{D} = \{(\mathbf{x}, \mathbf{y})\}$$




Generalization Hierarchy [Chollet, '19]

# Success at Dataset Level

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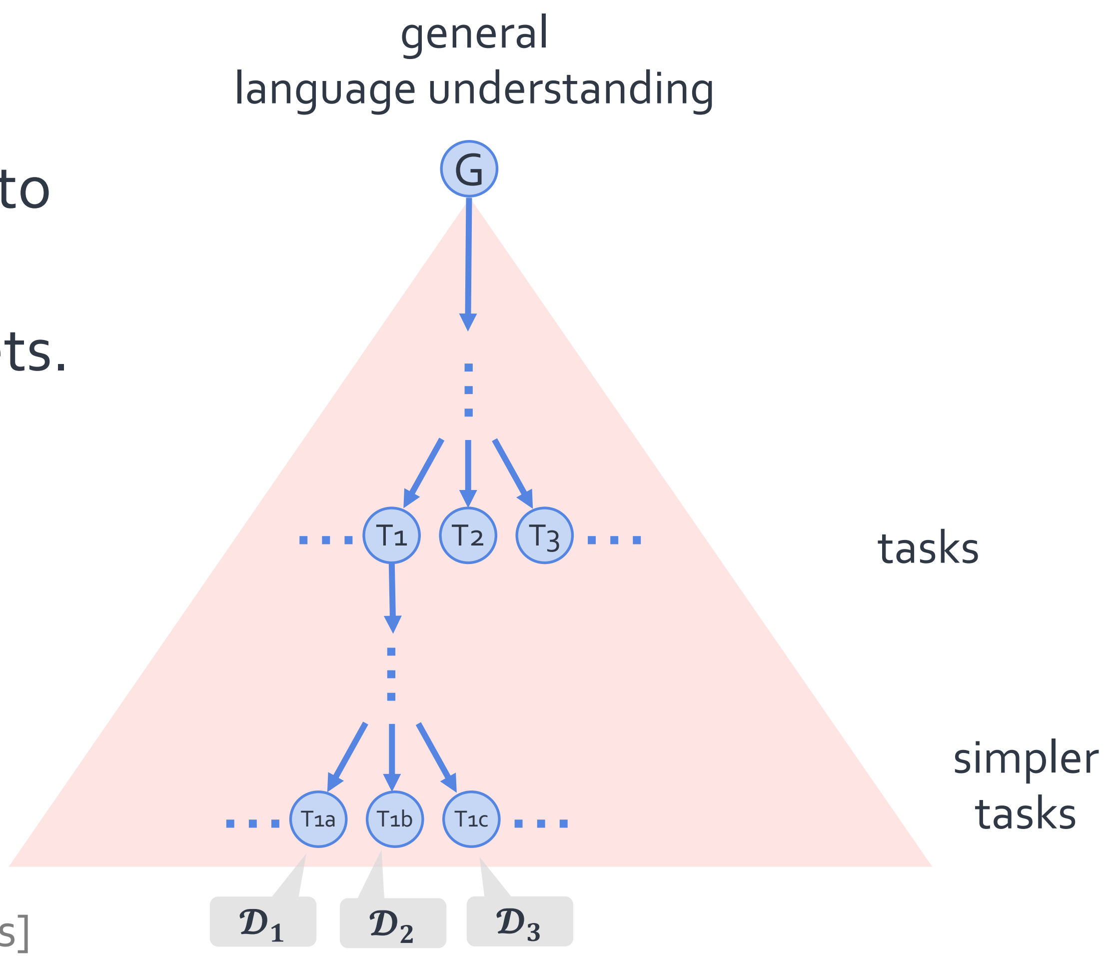
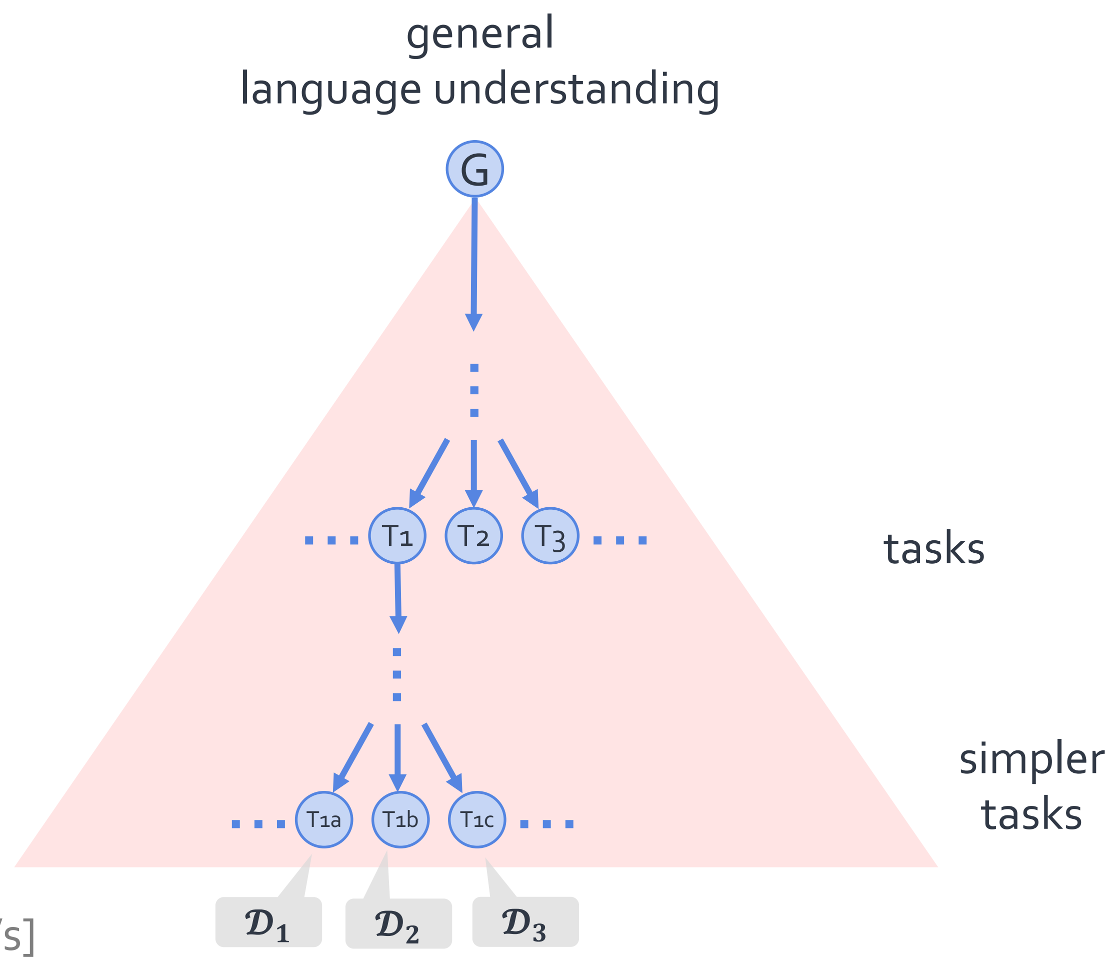
- Statistical models [Brown, Jelinek and others, late 80's]
  - Fitting a parameterized model to datasets



# Success at Dataset Level

**Neural Language Models**

[Bengio et al. '04, Peters et al. '18, Raffel et al. '20, Brown et al. '20, …]

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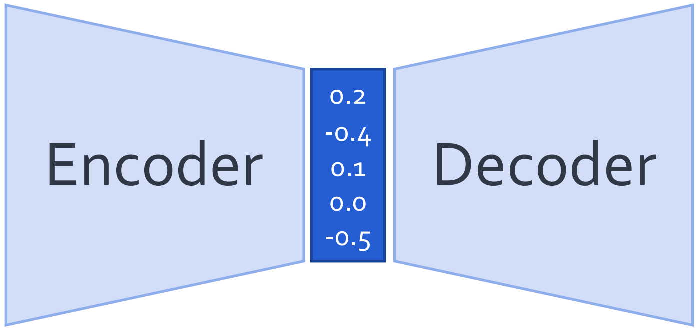


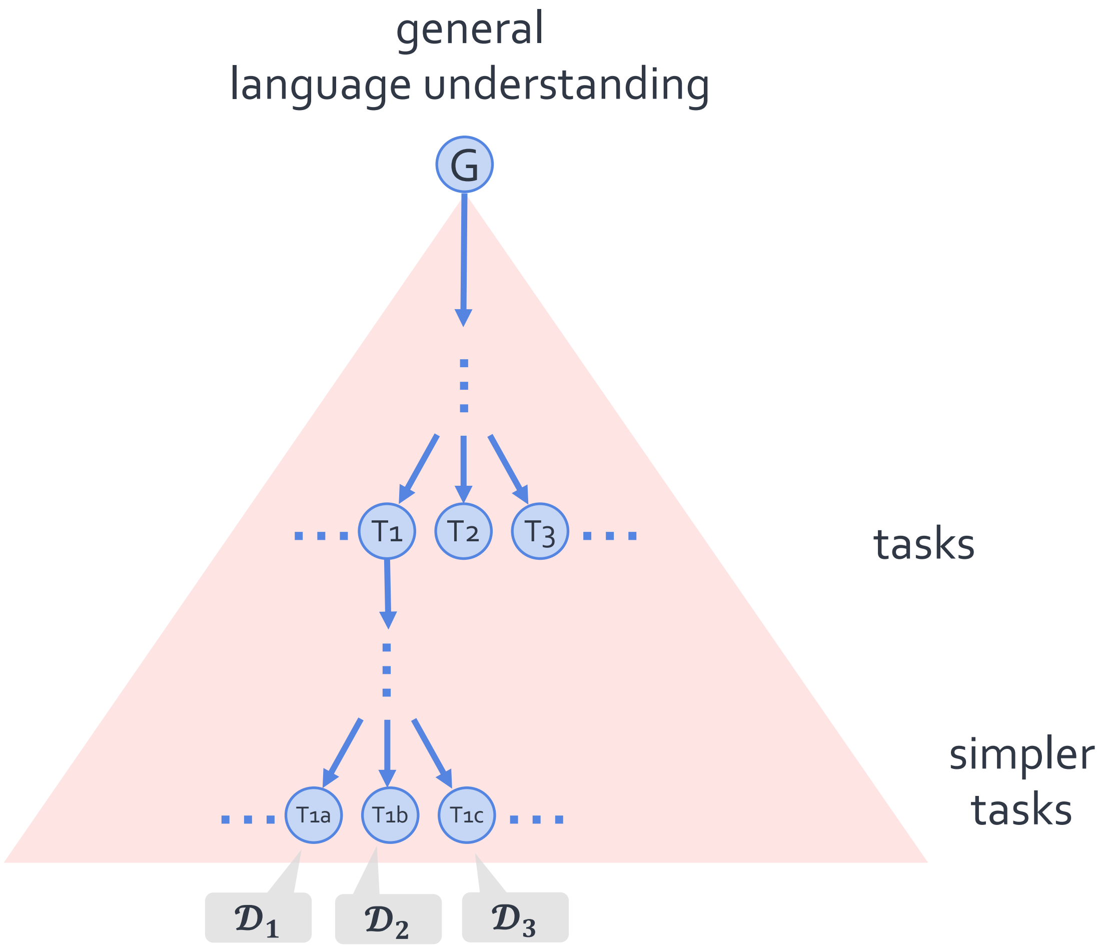

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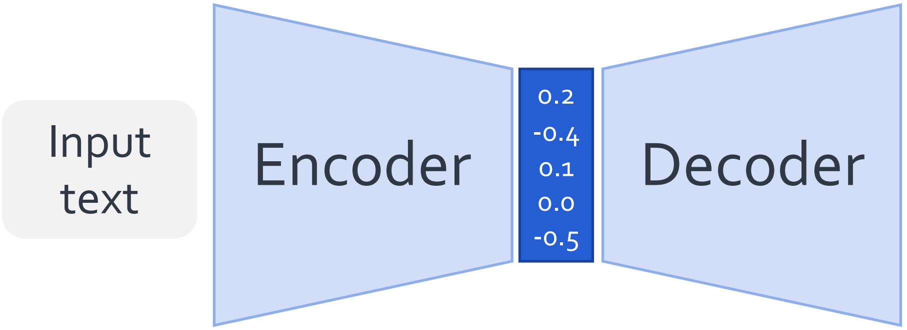


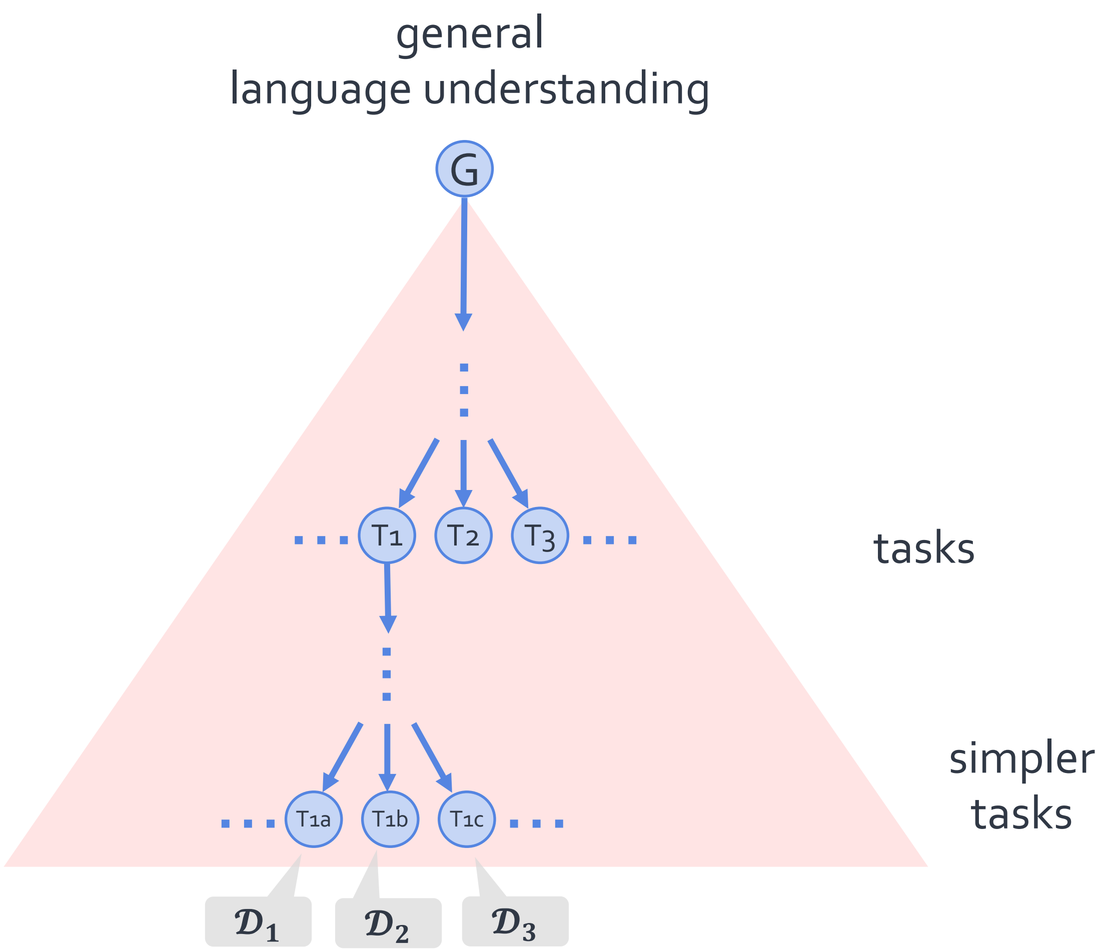

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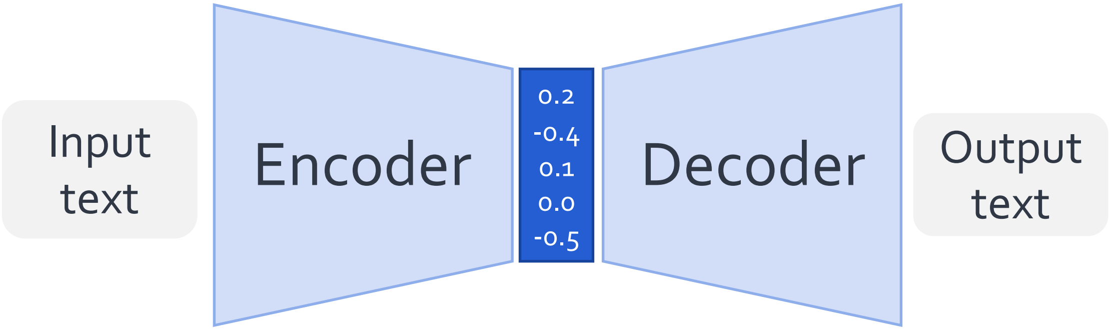


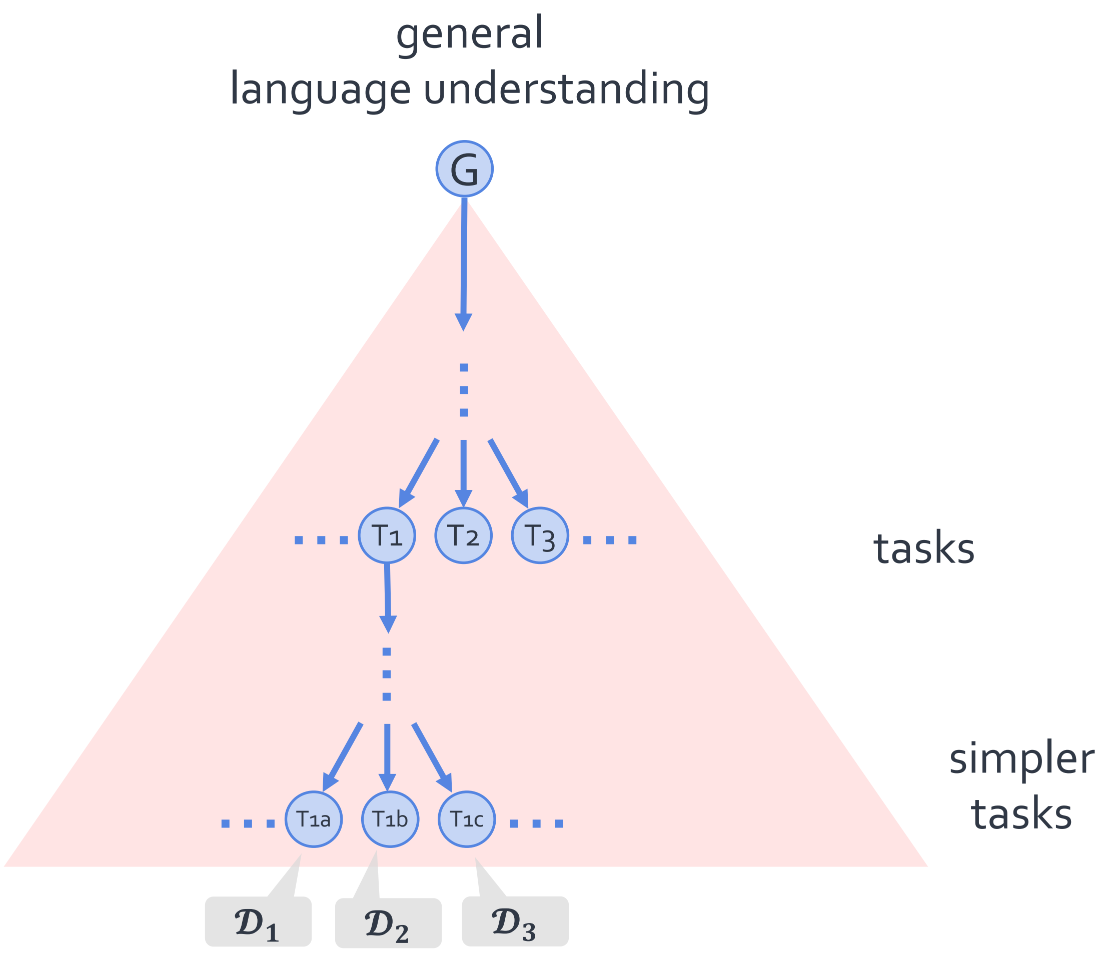

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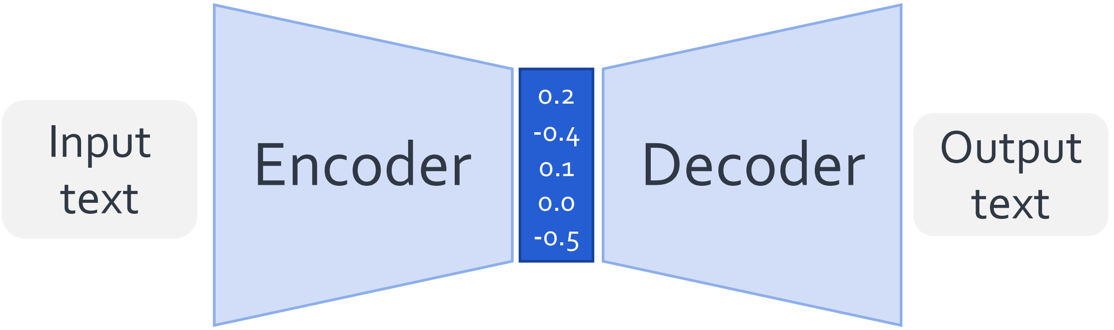
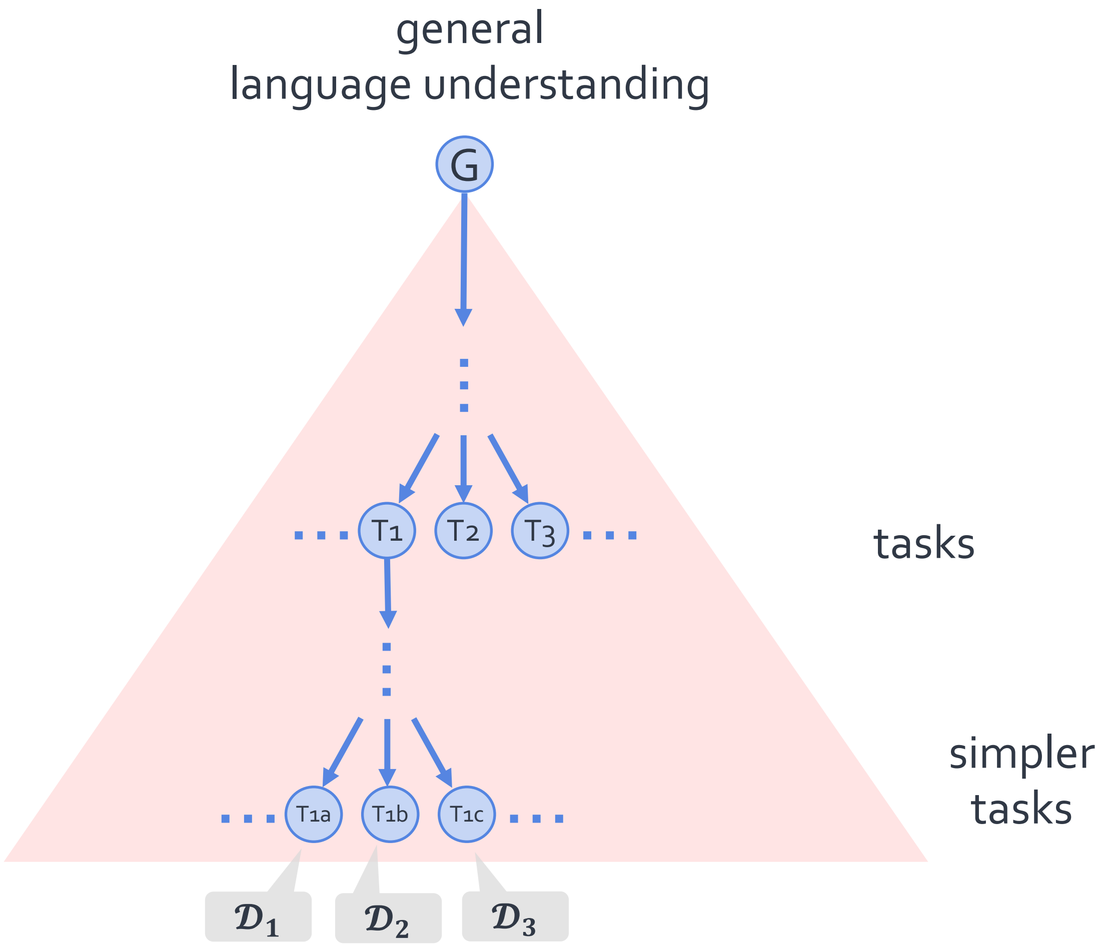



**T5**

Google AI

**GPT-3**

OpenAI



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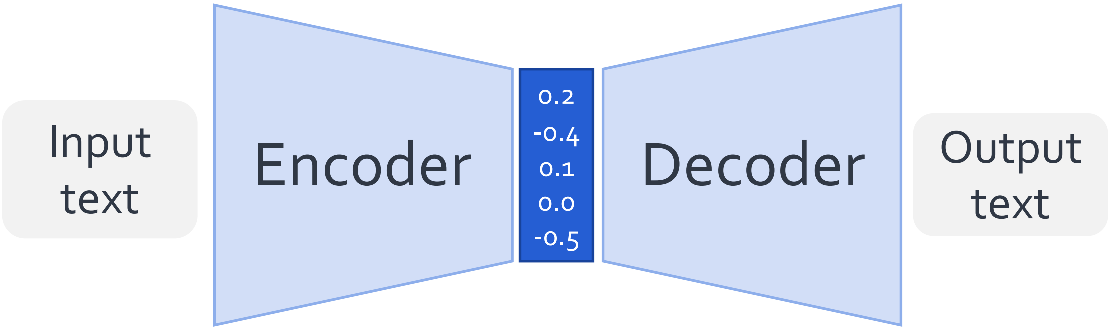


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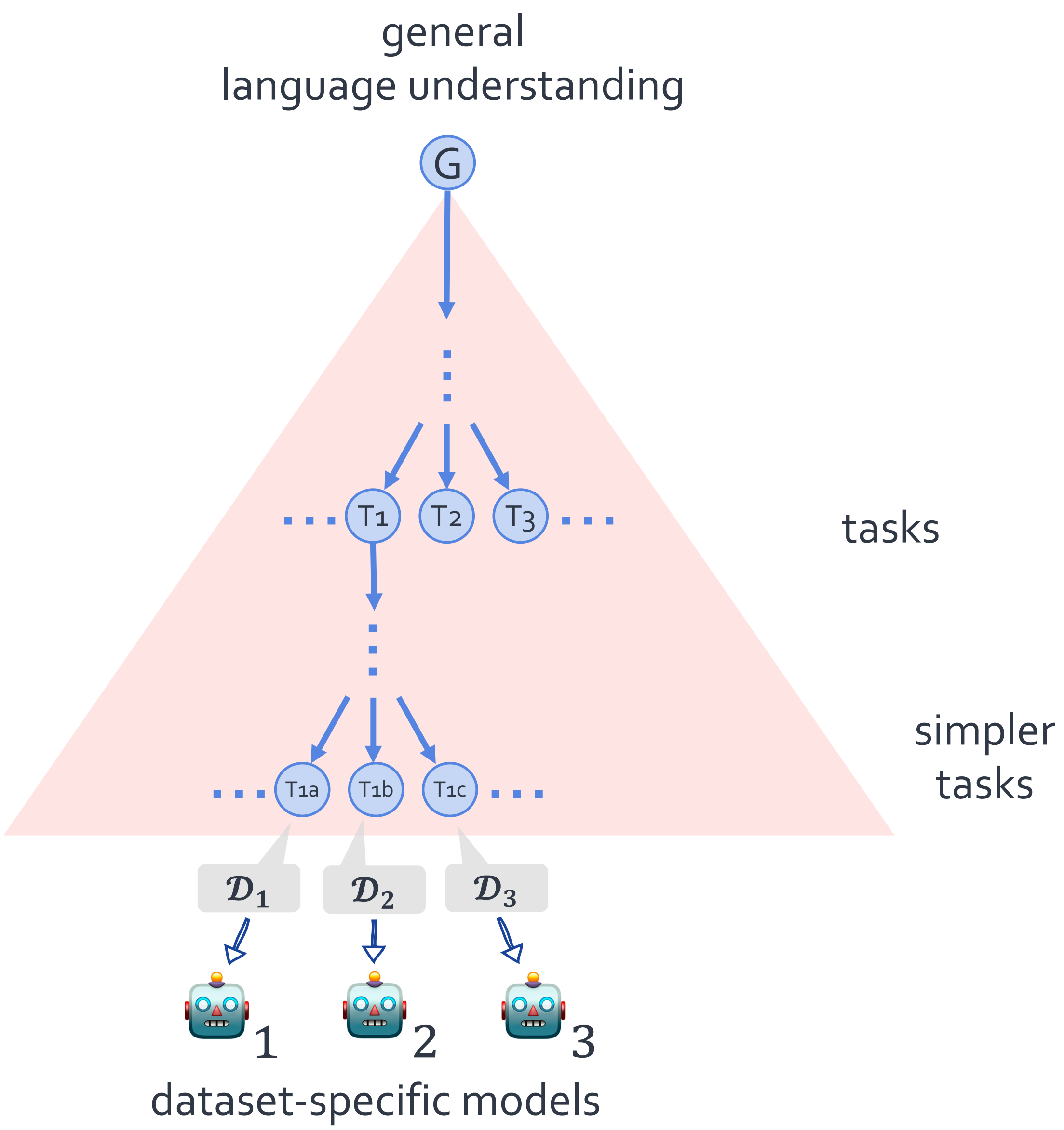

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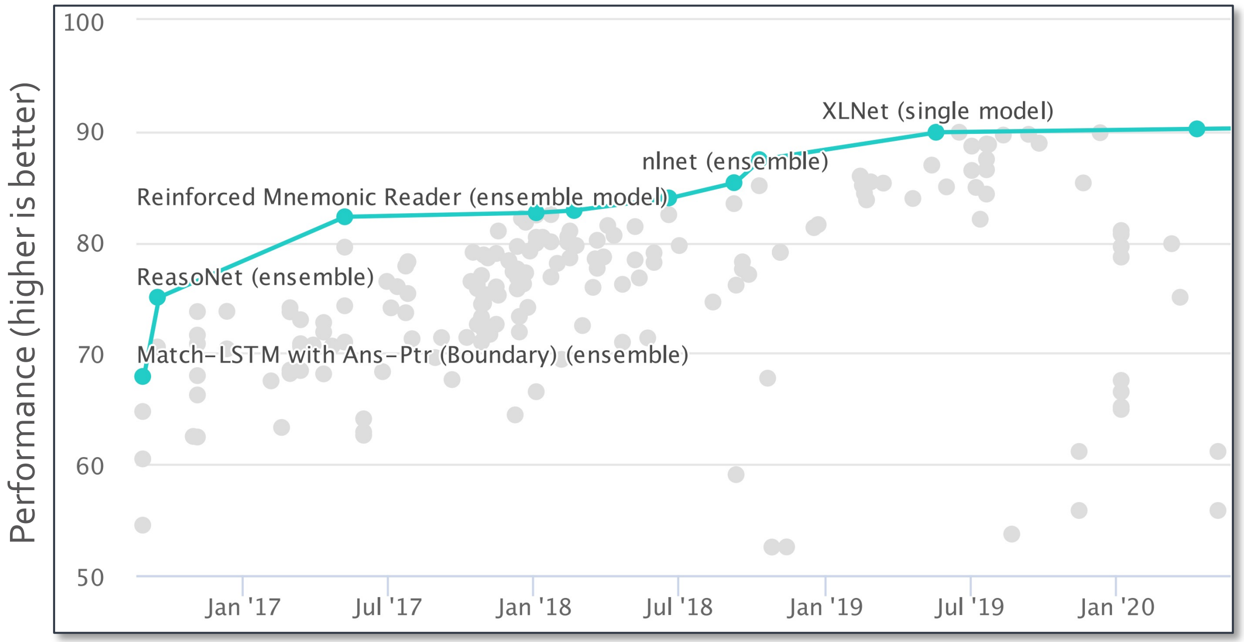
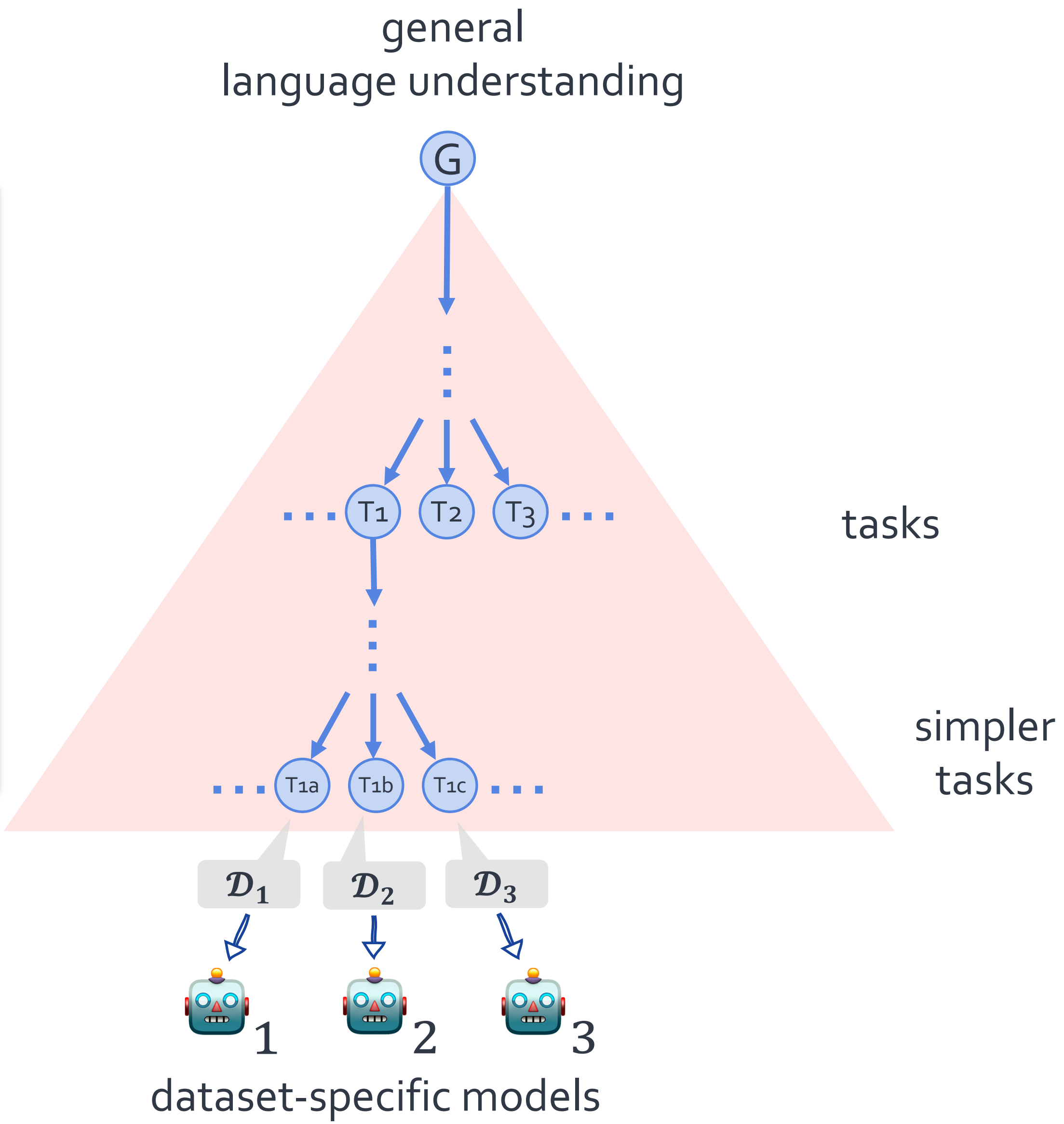
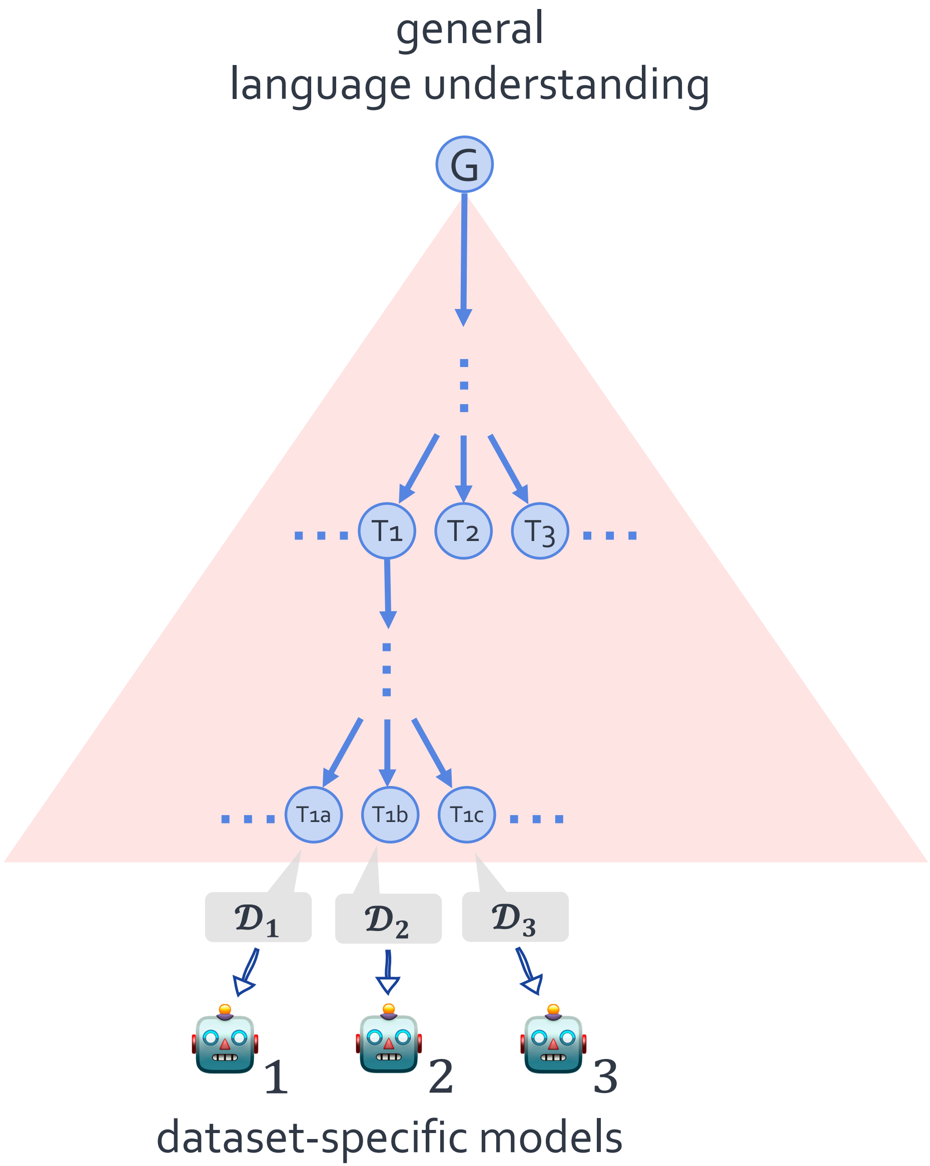



progress over time
on a question answering benchmark
[Rajpurkar et al. '16]



# Limits of Success at Dataset Level



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- Success at dataset level is not enough!
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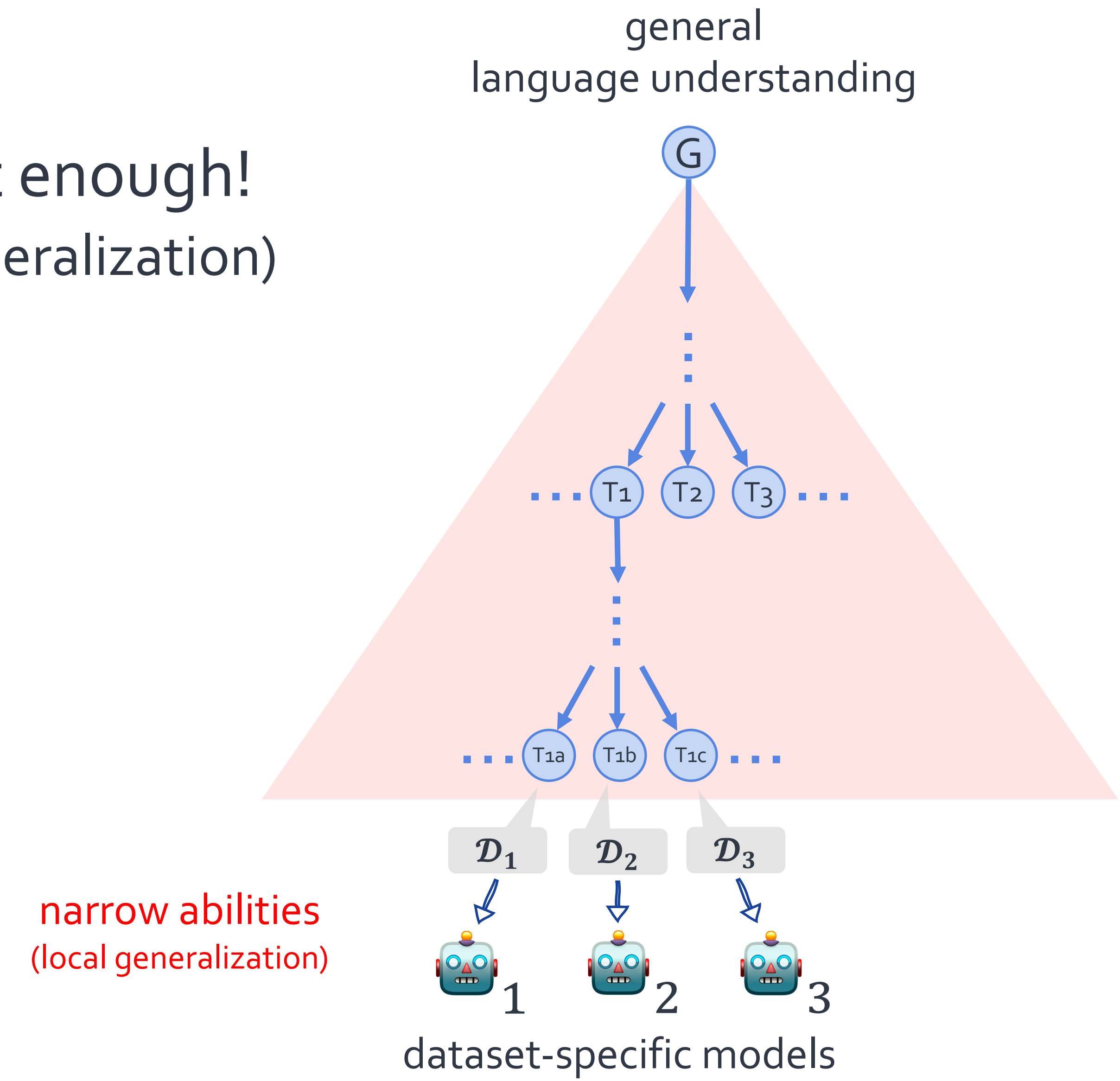

# Quest Toward "Generality"

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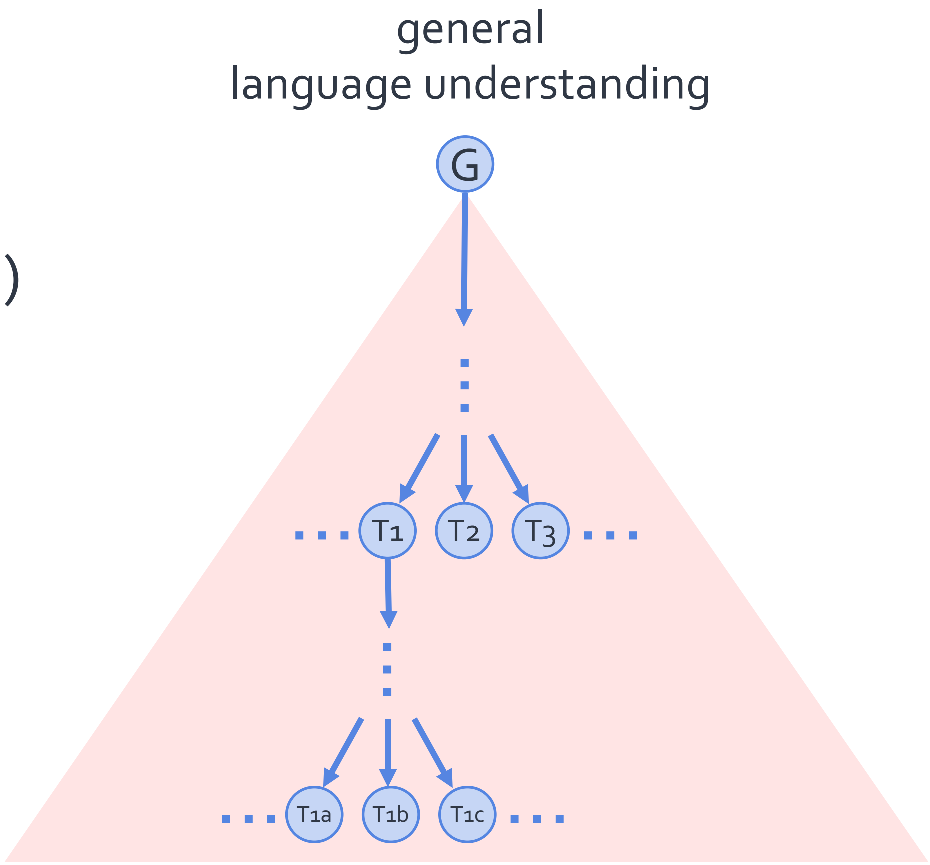

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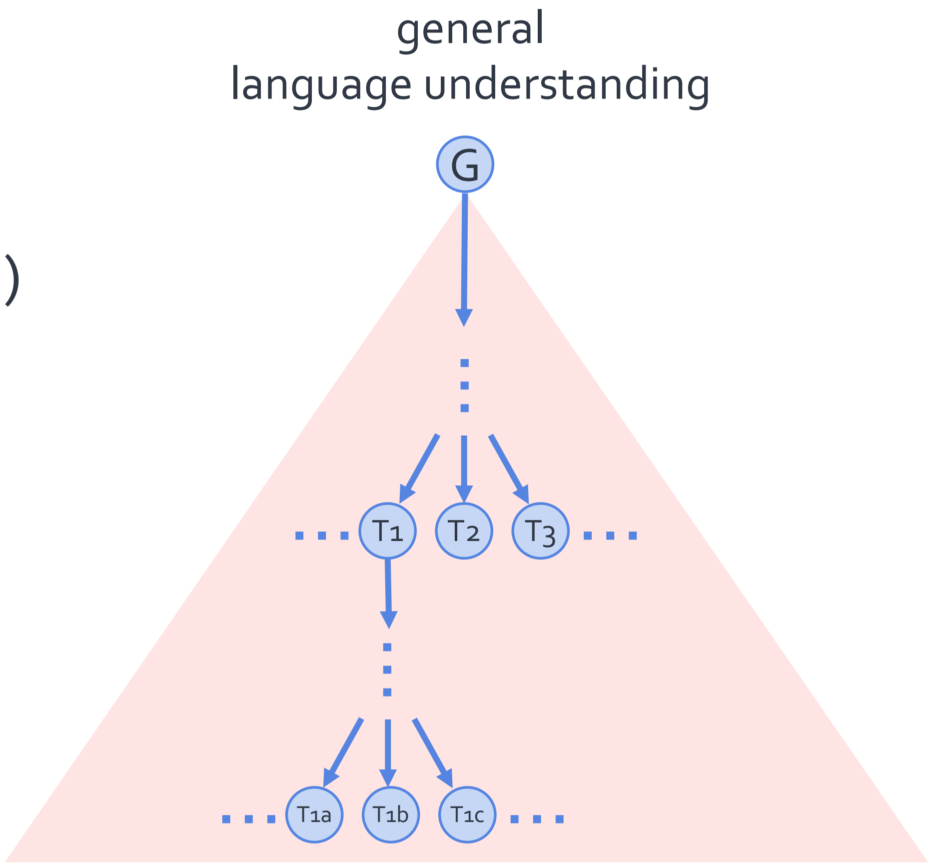
- "Generality" necessitates models that capture broader range of abilities.



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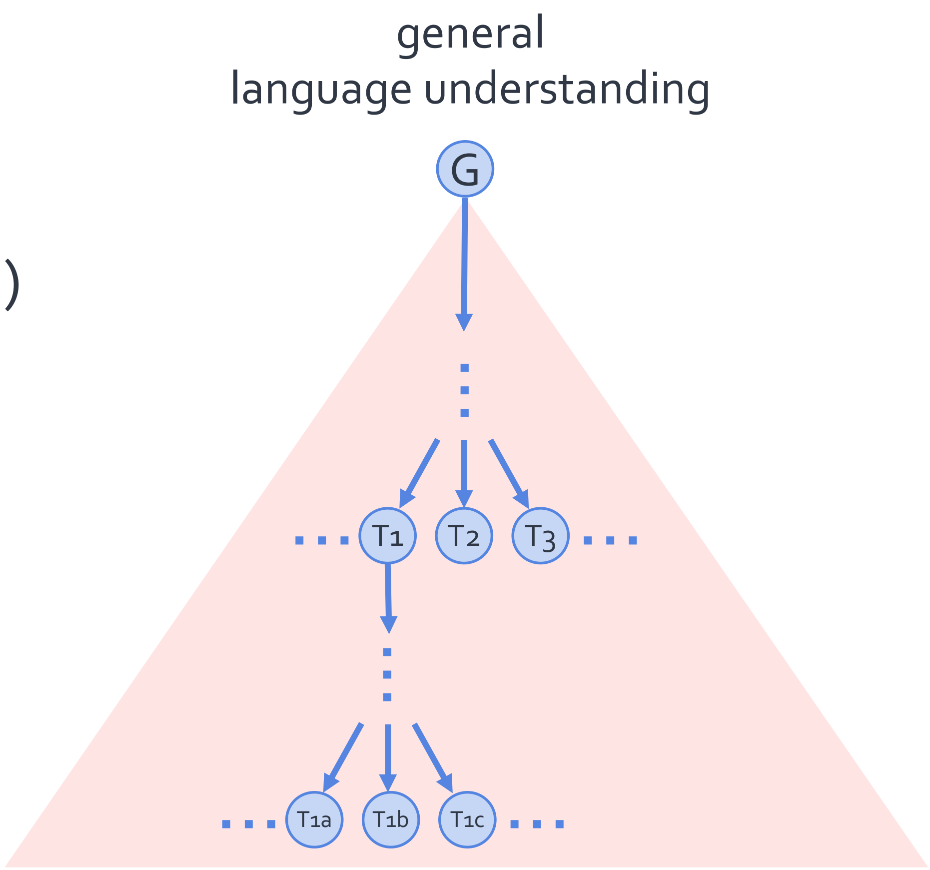

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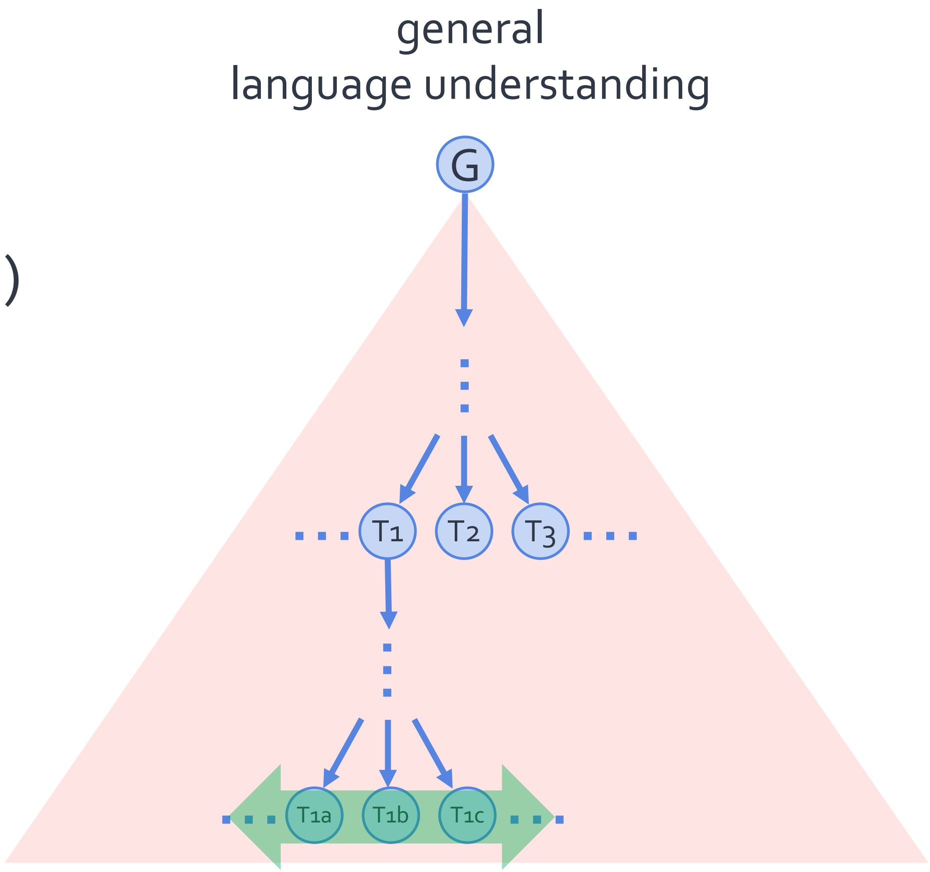

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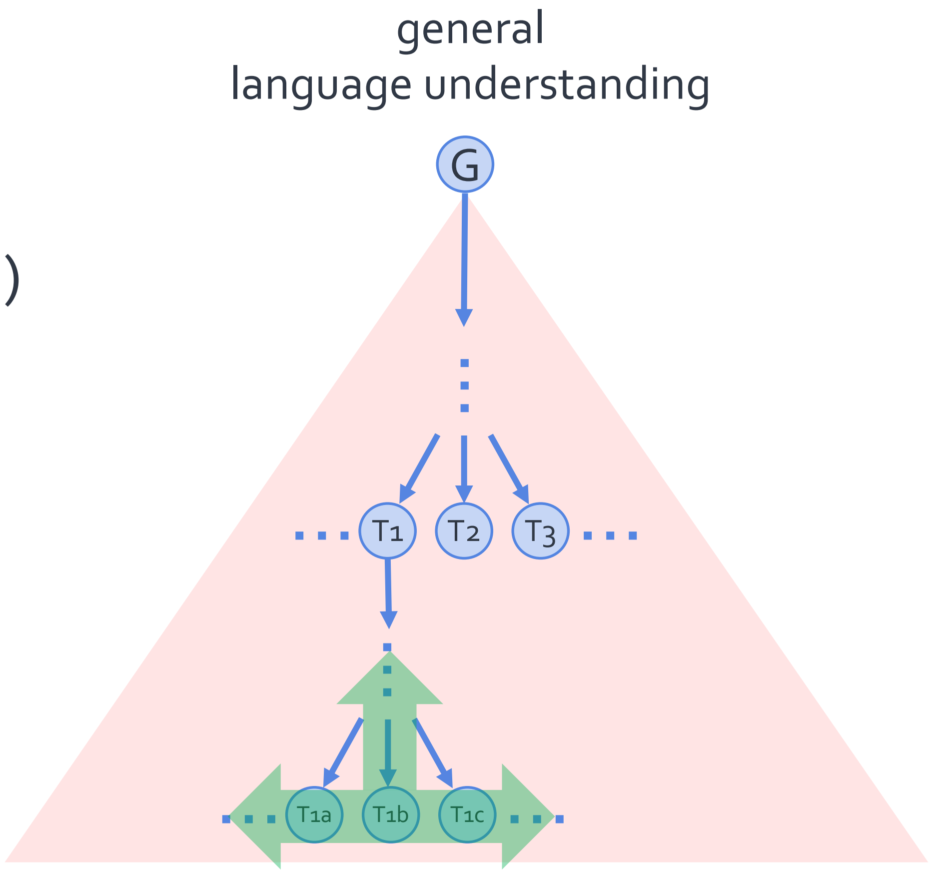

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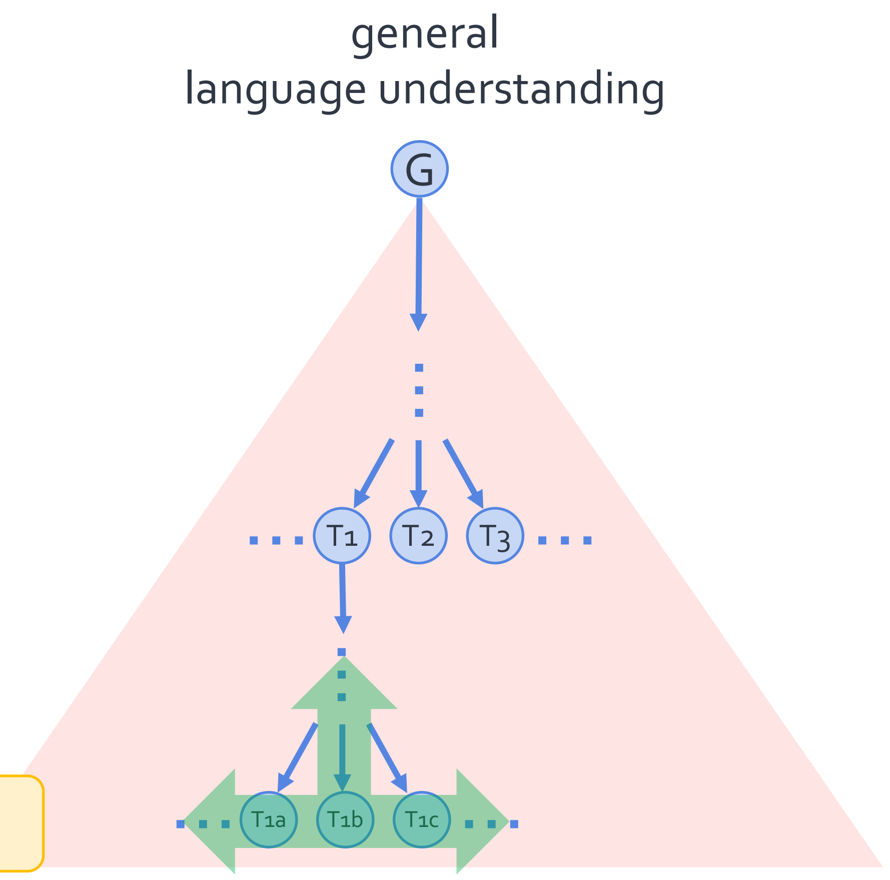
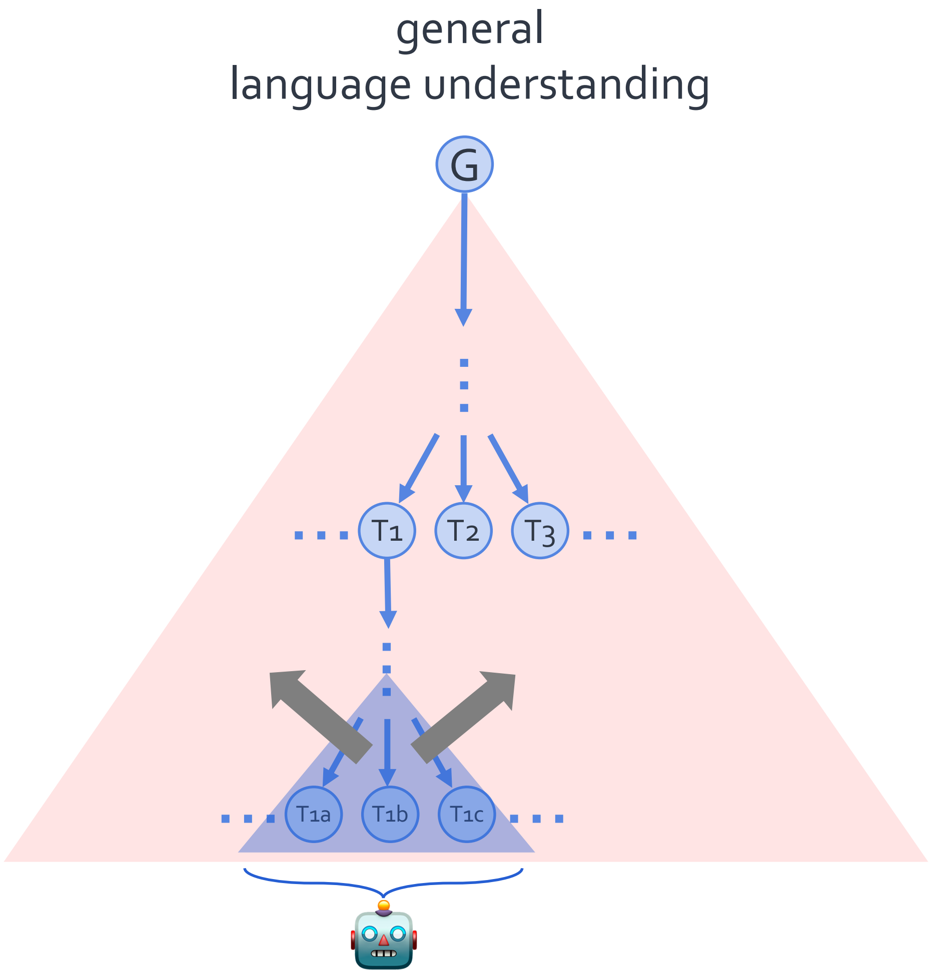
First part

Second part



# Research Goal

**Long-term goal:** more general natural language processing (NLP) systems through unified algorithms and theories.



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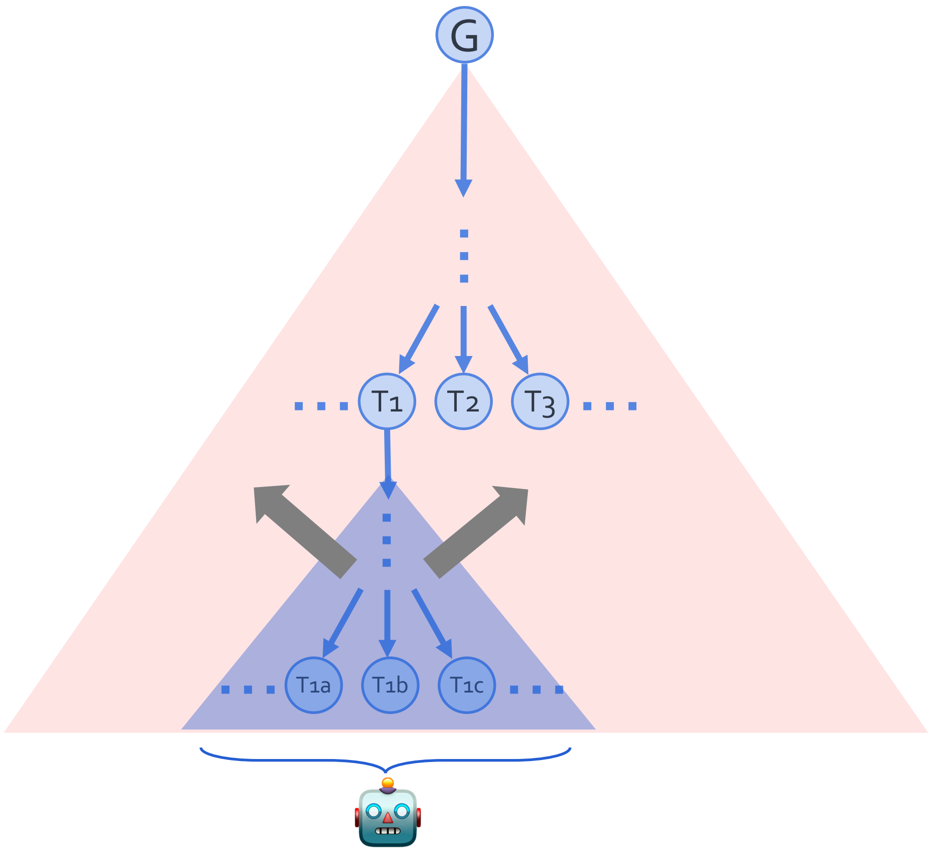
general
language understanding



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**Why?** AI-driven language interfaces that increasingly integrate in our life need to be versatile.



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Generalization in "breadth"

Natural Instructions
*ACL '22*

UnifiedQA
*EMNLP Findings '20*

Contrast-Sets
*EMNLP Findings '20*

Natural Perturbations
*EMNLP '20*

ZOE
*EMNLP '18*

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  - ZOE *EMNLP ’18*
- Generalization in “depth”
  - ModularQA *NAACL ’21*
  - StrategyQA *TACL ‘21*
  - MultiRC *NAACL ’18*
  - SemanticILP *AAAI ’18*
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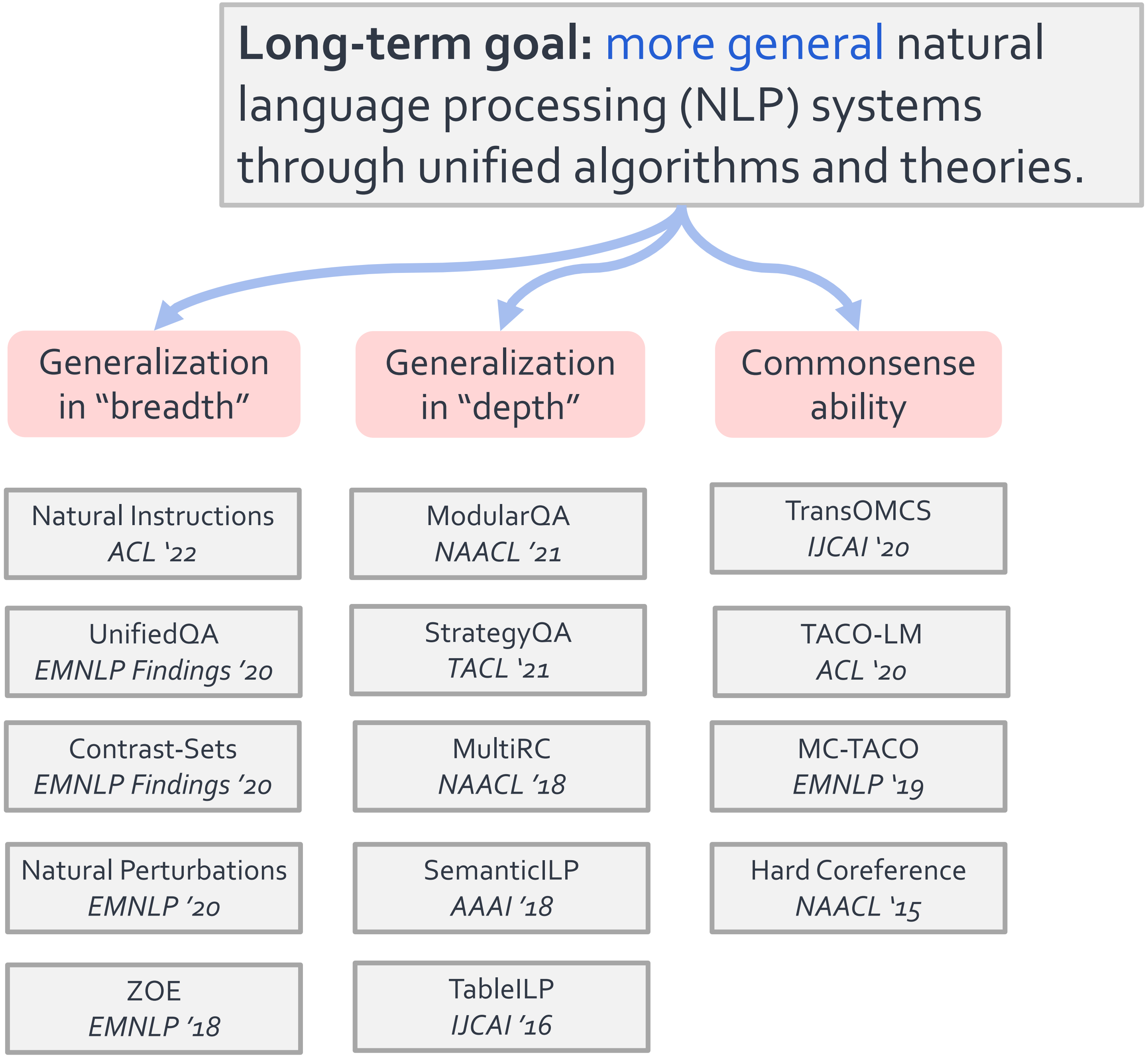
**Long-term goal:** more general natural language processing (NLP) systems through unified algorithms and theories.
Generalization in "breadth"
Generalization in "depth"
Commonsense ability
Natural Instructions *ACL '22*
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TACO-LM *ACL '20*
MC-TACO *EMNLP '19*
Hard Coreference *NAACL '15*

**Long-term goal:** more general natural language processing (NLP) systems through unified algorithms and theories.

| Generalization in "breadth" | Generalization in "depth" | Commonsense ability | Alignment with societal values |
|---|---|---|---|
| Natural Instructions *ACL '22* | ModularQA *NAACL '21* | TransOMCS *IJCAI '20* | Ethical Advice Taker *ACL Findings '21* |
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**Diagnosis**

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**Diagnosis**

**Problem Definition**

**Long-term goal:** more general natural language processing (NLP) systems through unified algorithms and theories.

| Generalization in "breadth" | Generalization in "depth" | Commonsense ability | Alignment with societal values |
|---|---|---|---|
| Natural Instructions<br>*ACL '22* | ModularQA<br>*NAACL '21* | TransOMCS<br>*IJCAI '20* | Ethical Advice Taker<br>*ACL Findings '21* |
| UnifiedQA<br>*EMNLP Findings '20* | StrategyQA<br>*TACL '21* | TACO-LM<br>*ACL '20* | UnQover<br>*EMNLP Findings '20* |
| Contrast-Sets<br>*EMNLP Findings '20* | MultiRC<br>*NAACL '18* | MC-TACO<br>*EMNLP '19* | Perspectrum<br>*NAACL '19* |
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## Generalization in "breadth"

- Natural Instructions — *ACL '22*
- UnifiedQA — *EMNLP Findings '20*
- Contrast-Sets — *EMNLP Findings '20*
- Natural Perturbations — *EMNLP '20*
- ZOE — *EMNLP '18*

## Generalization in "depth"

- ModularQA — *NAACL '21*
- StrategyQA — *TACL '21*
- MultiRC — *NAACL '18*
- SemanticILP — *AAAI '18*
- TableILP — *IJCAI '16*

## Commonsense ability

- TransOMCS — *IJCAI '20*
- TACO-LM — *ACL '20*
- MC-TACO — *EMNLP '19*
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## Alignment with societal values

- Ethical Advice Taker — *ACL Findings '21*
- UnQover — *EMNLP Findings '20*
- Perspectrum — *NAACL '19*

**Diagnosis**

**Problem Definition**

**Solution**

# Talk Outline

Generality in "breadth" — tackling a variety of tasks

Generality in "depth" — tackling more complex tasks

*Future work:* Toward broad, interactive reasoning

UnifiedQA
*EMNLP Findings '20*

Natural Instructions
*ACL '22*

ModularQA
*NAACL '21*

# Talk Outline

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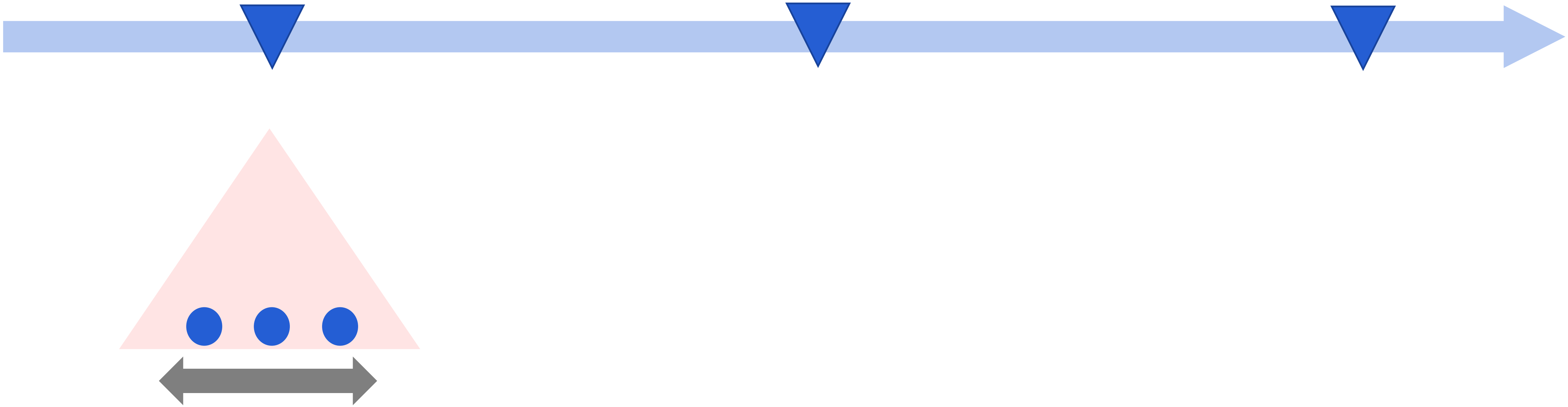

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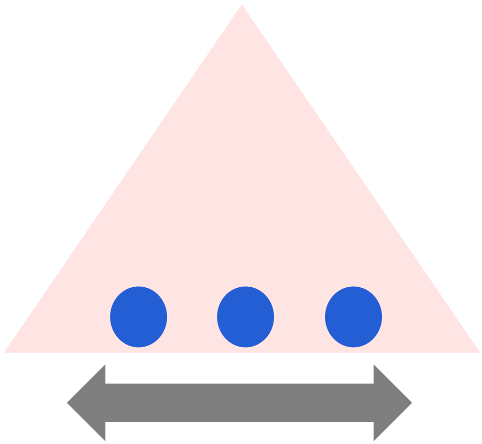

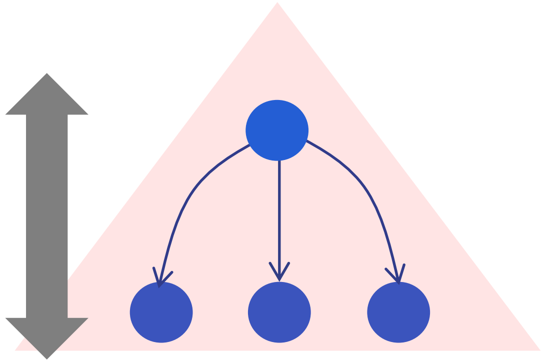

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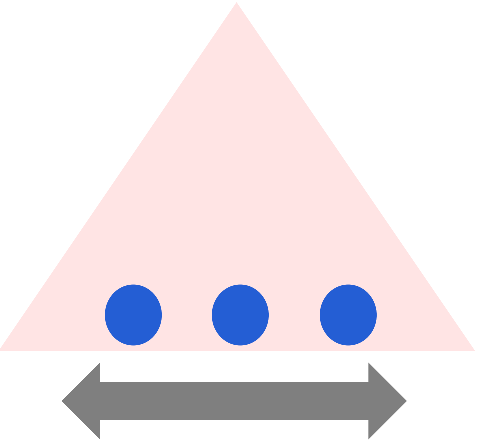

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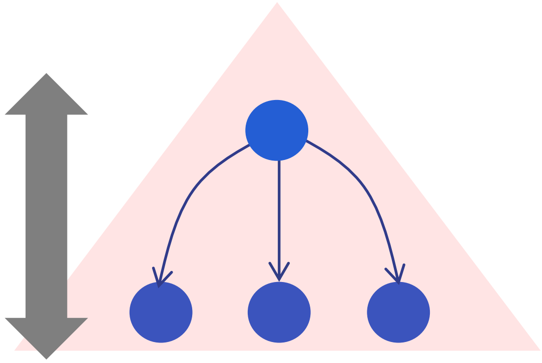

ModularQA
*NAACL '21*

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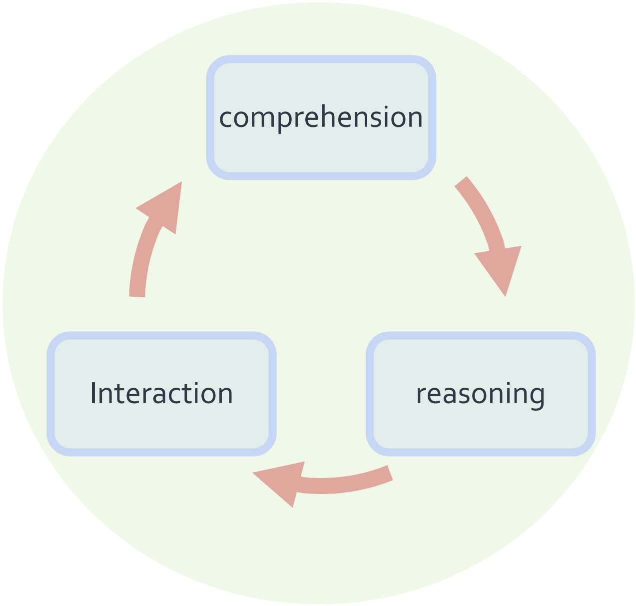

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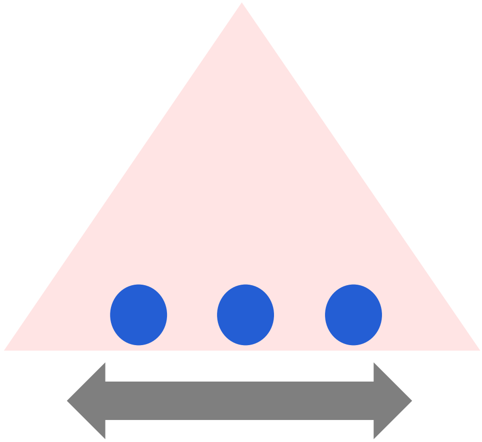

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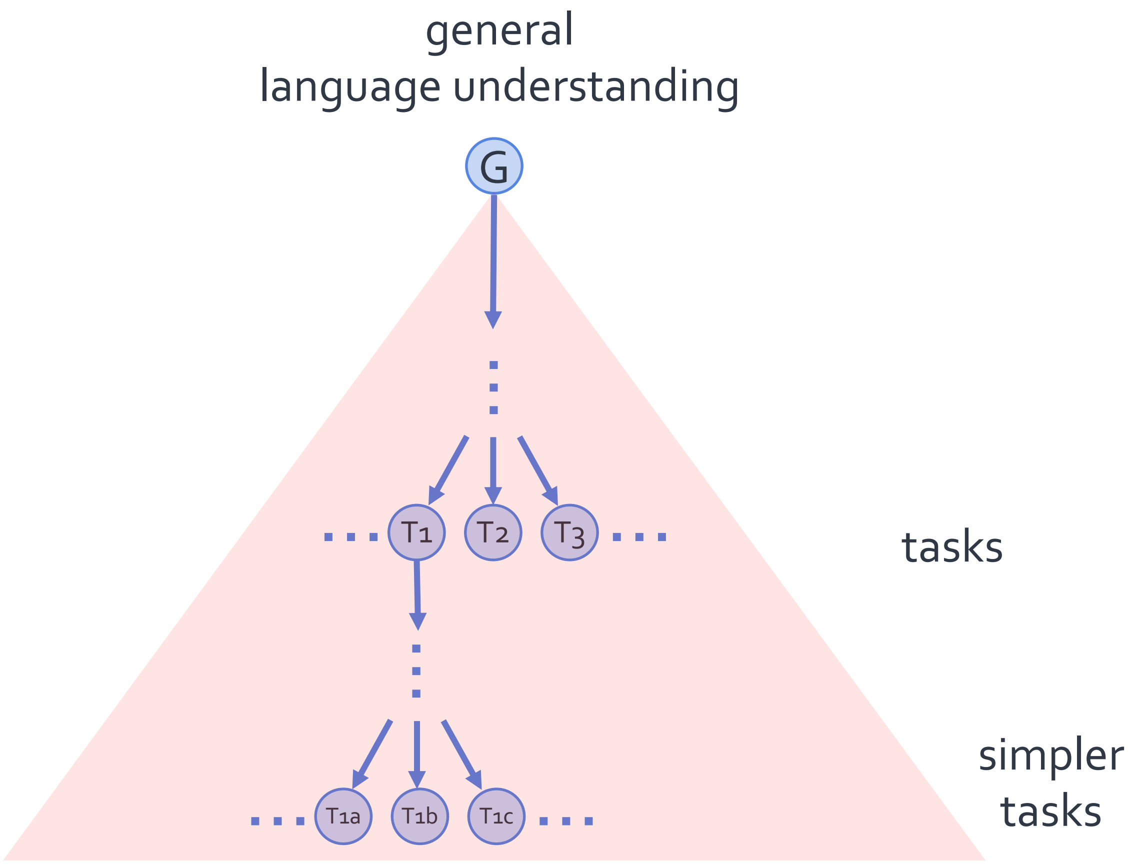
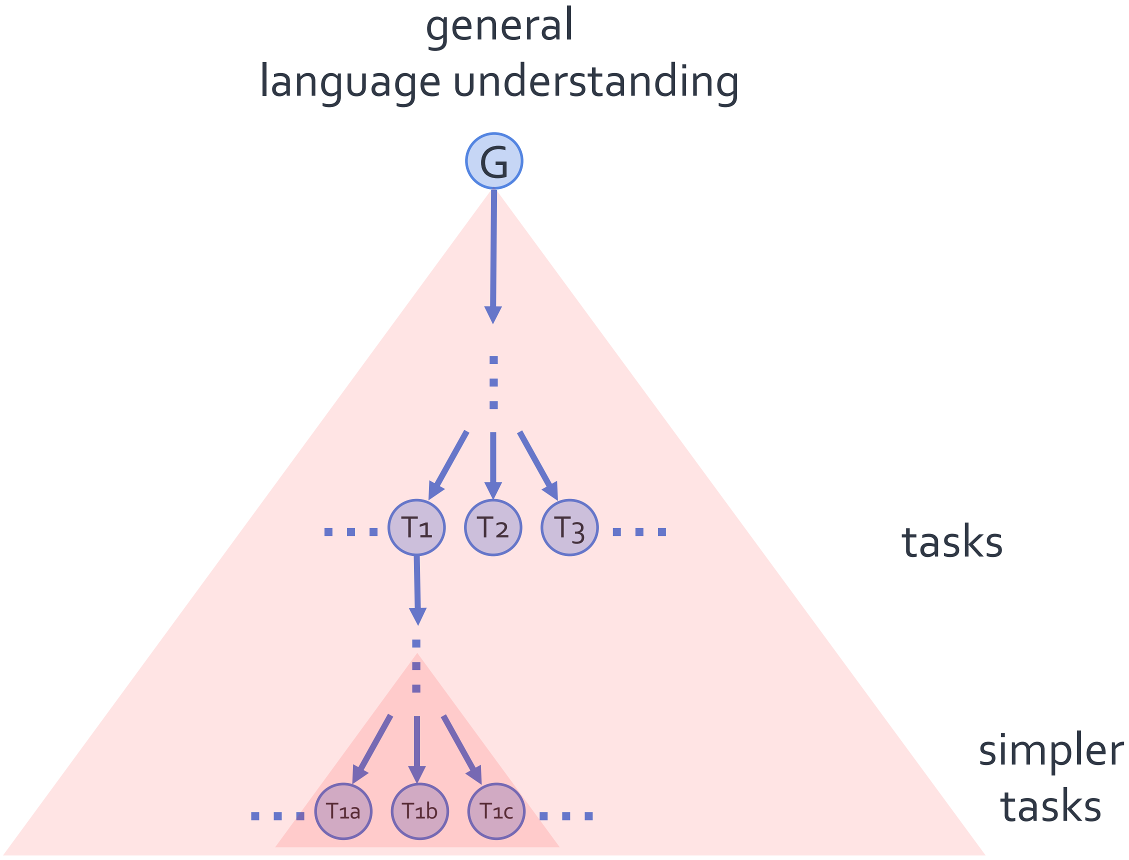

general
language understanding
G
T1
T2
T3
tasks
T1a
T1b
T1c
simpler
tasks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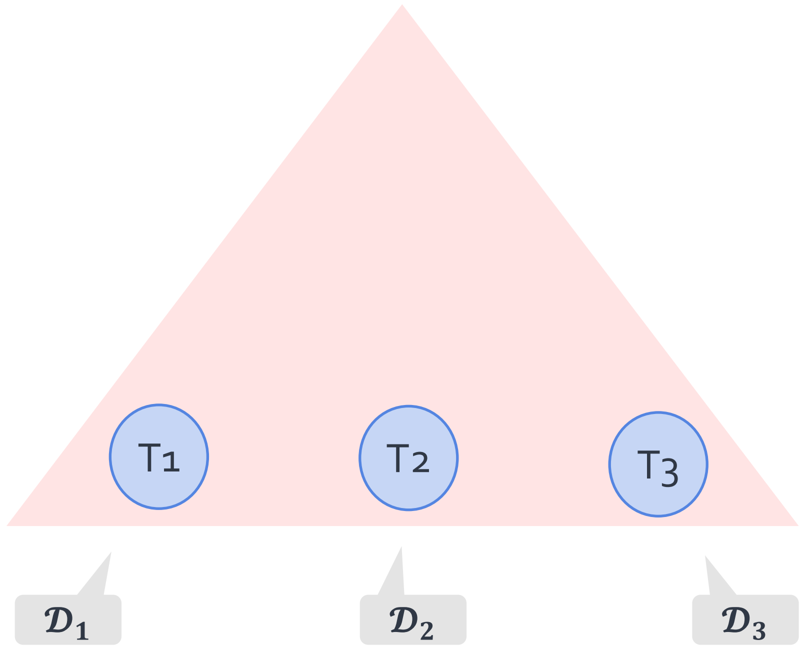
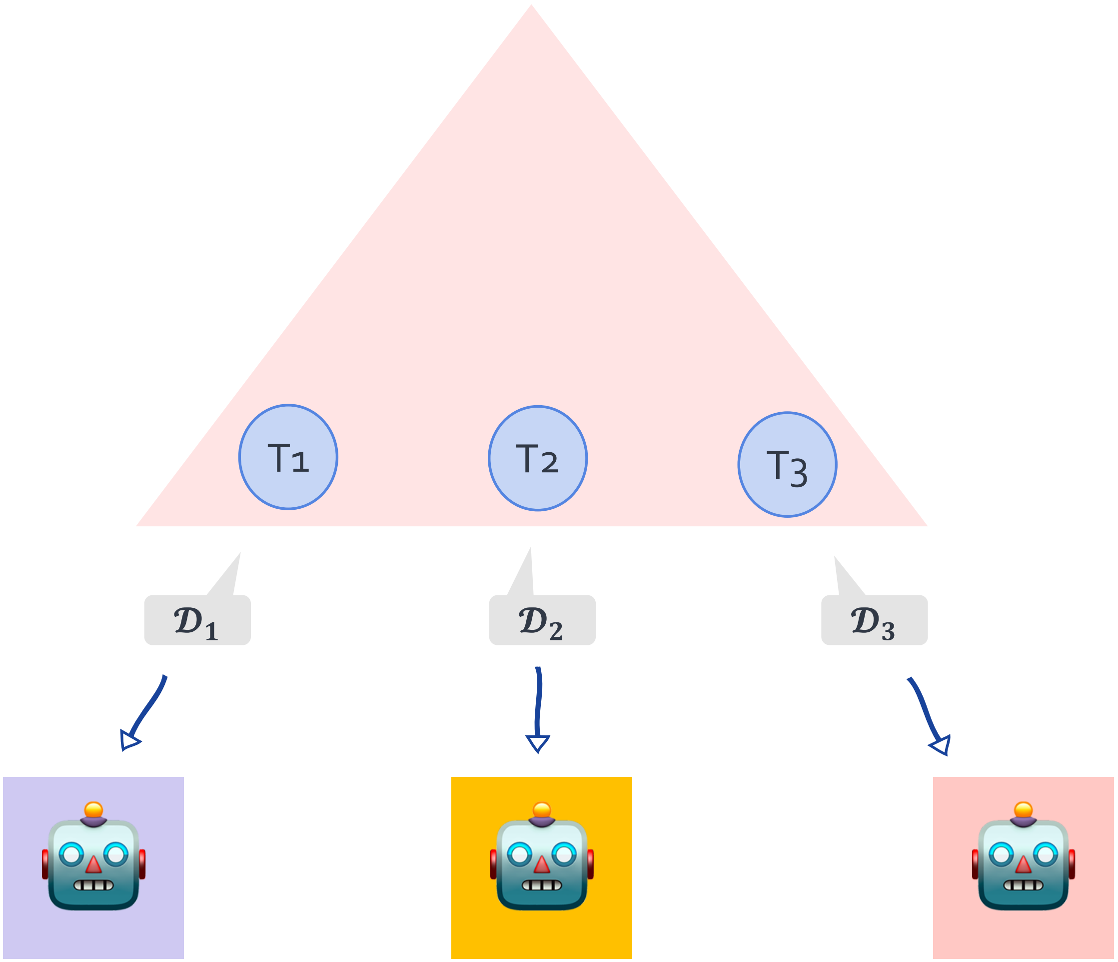
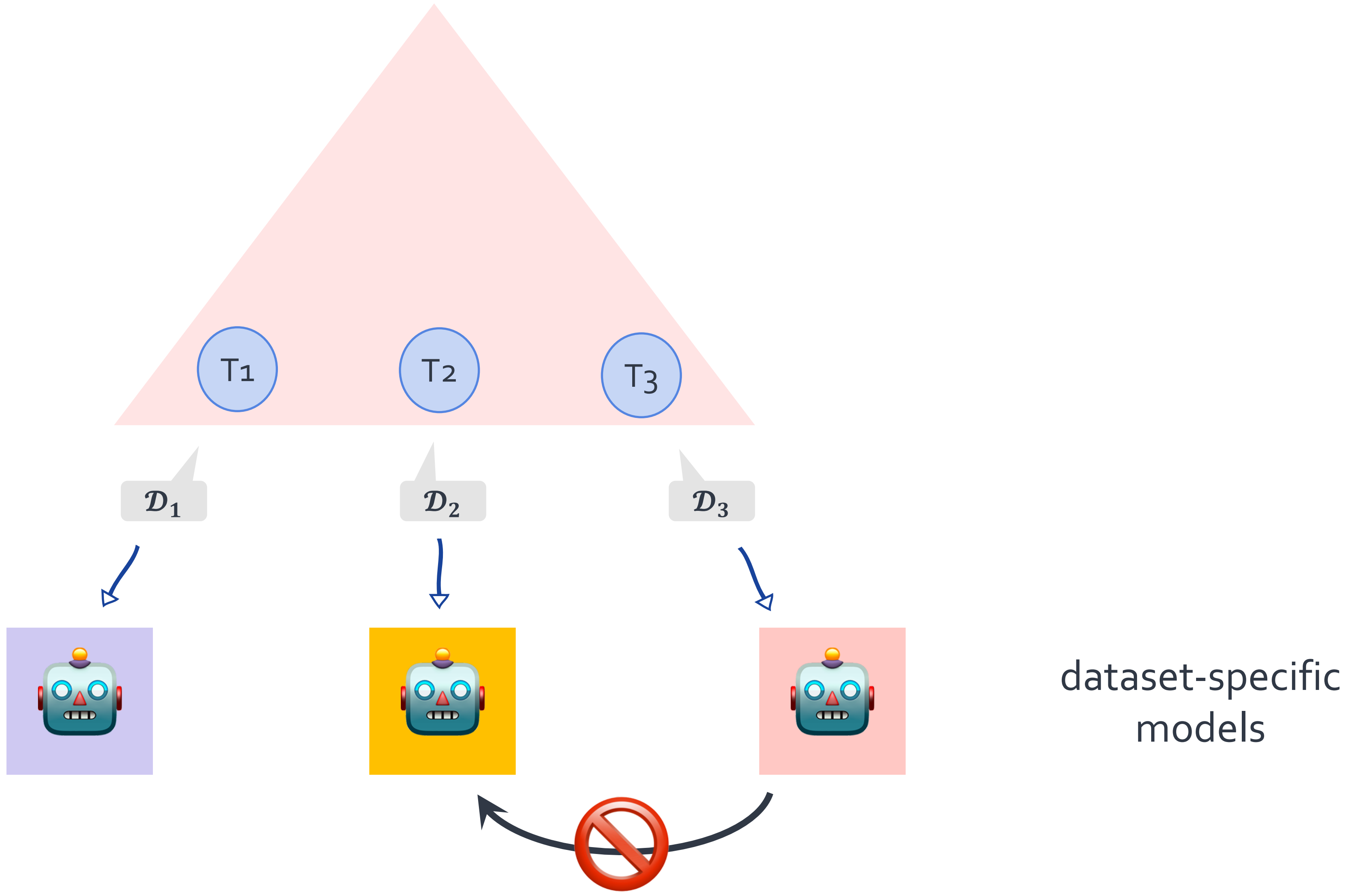
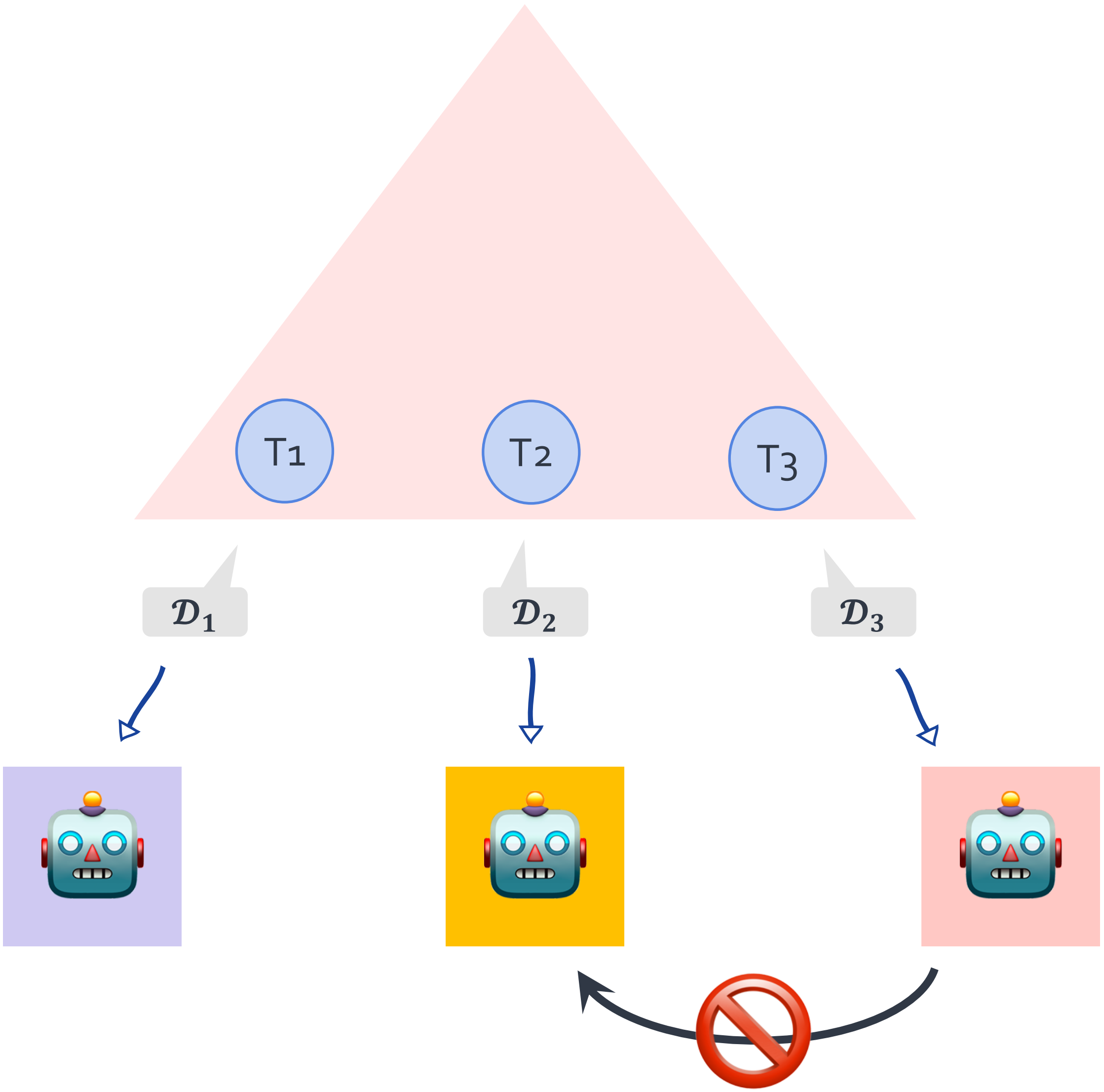

T1
T2
T3
$\mathcal{D}_1$
$\mathcal{D}_2$
$\mathcal{D}_3$




dataset-specific
models




Task specific assumptions prevent generalization!




dataset-specific
models

There are MANY tasks
— this is not scalable!

Task specific assumptions
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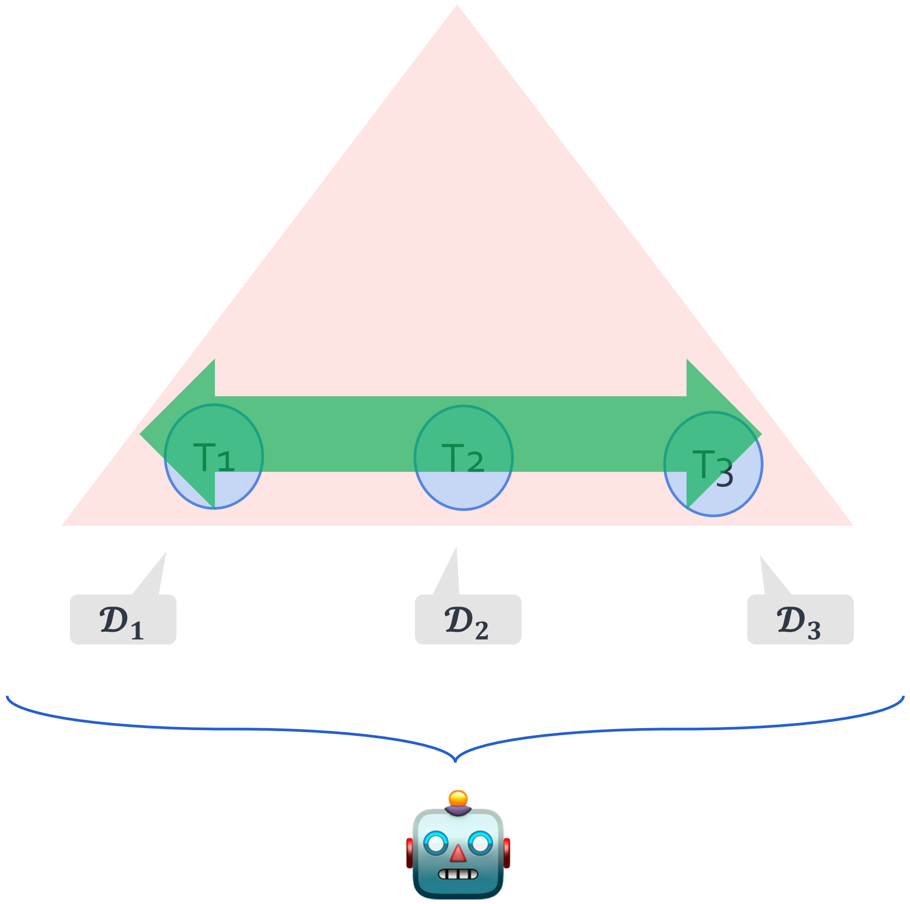
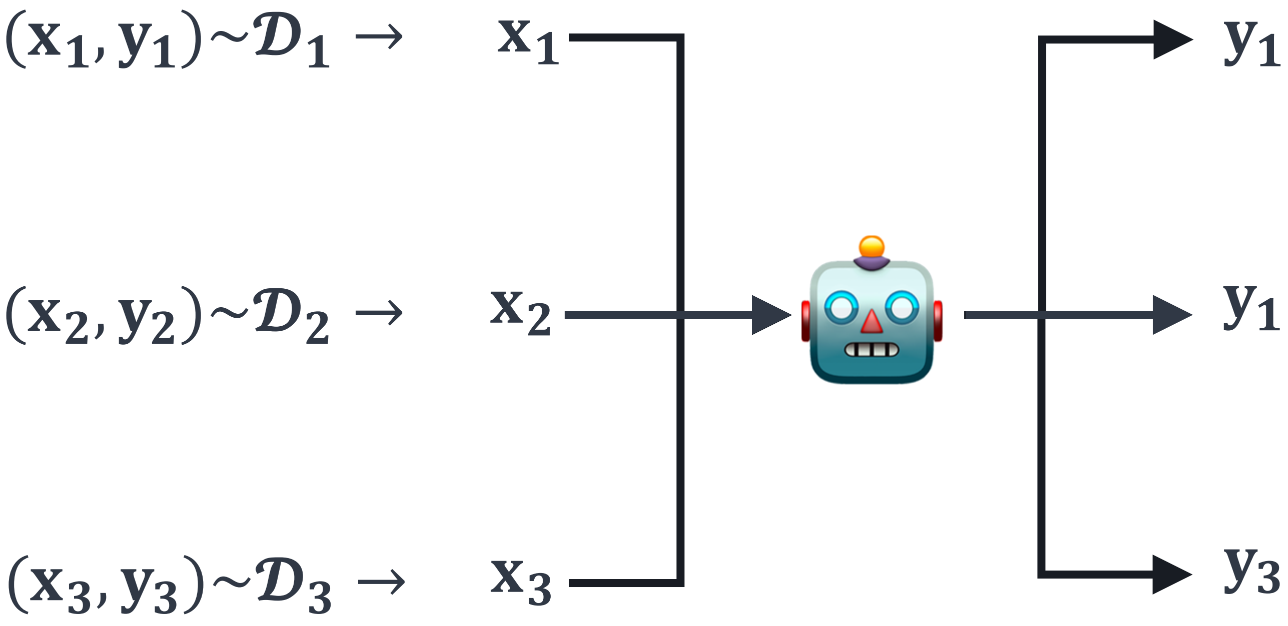
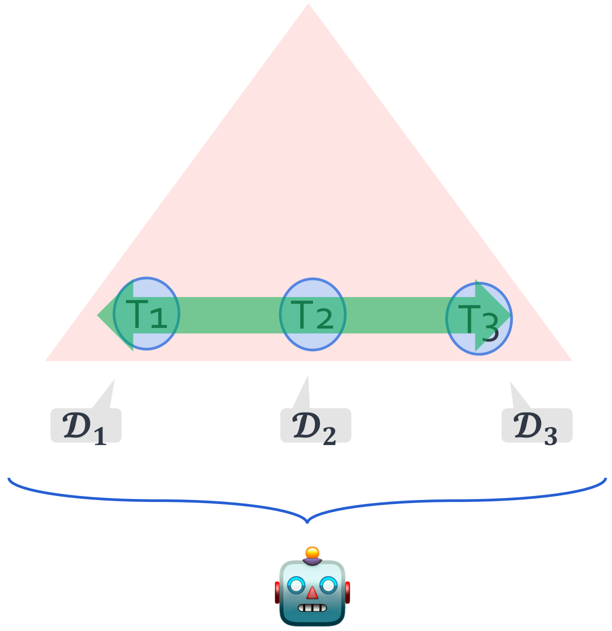



**Research questions:** How can we build a system that tackles a variety of language tasks?

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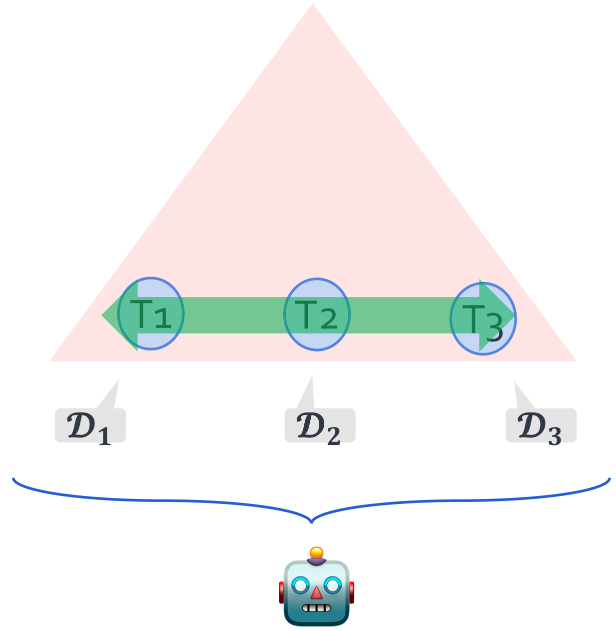
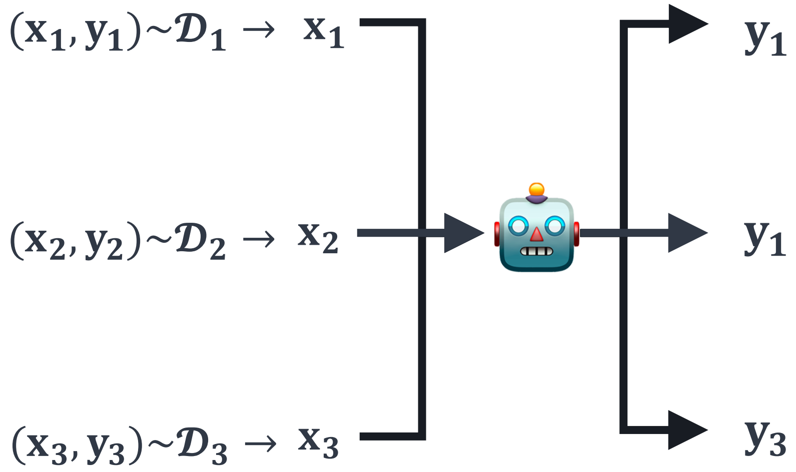
- Multi-task learning [Caruana '97; McCann et al. '18]



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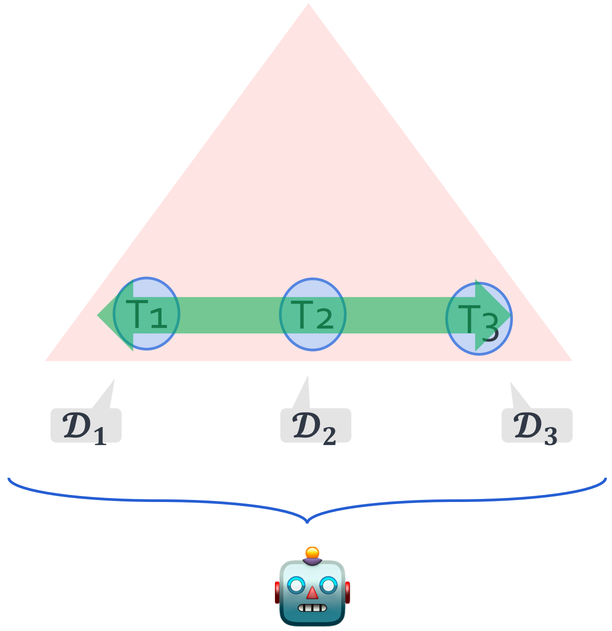
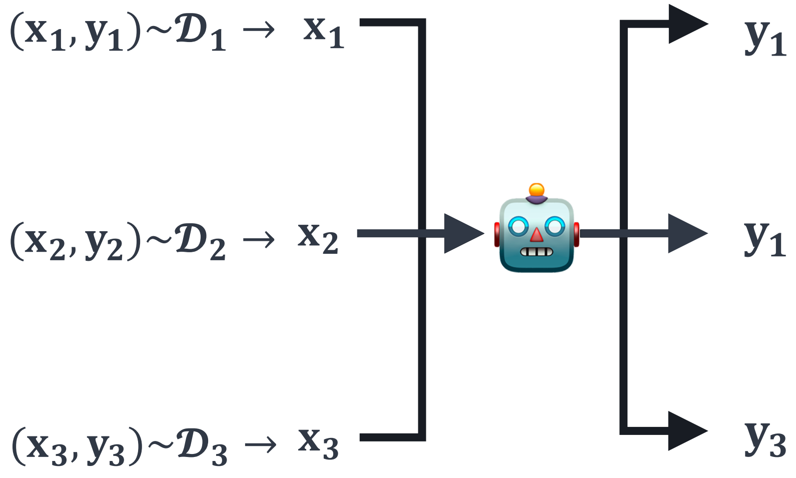
***Solving multiple learning tasks at the same time,***
*while exploiting commonalities across tasks.*



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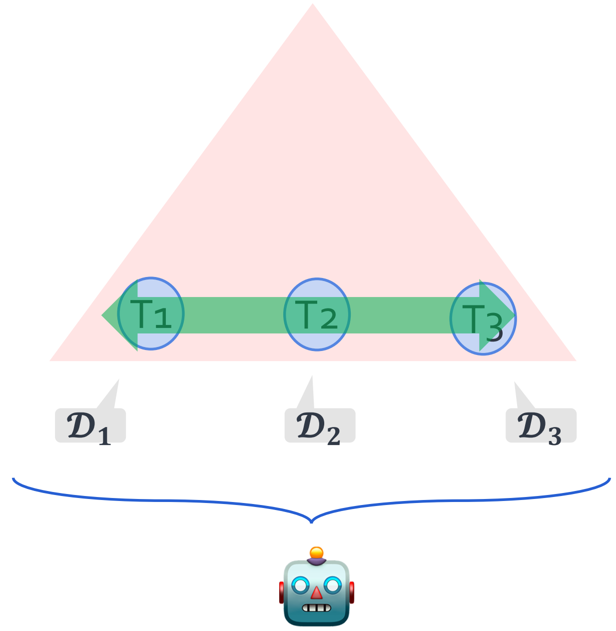


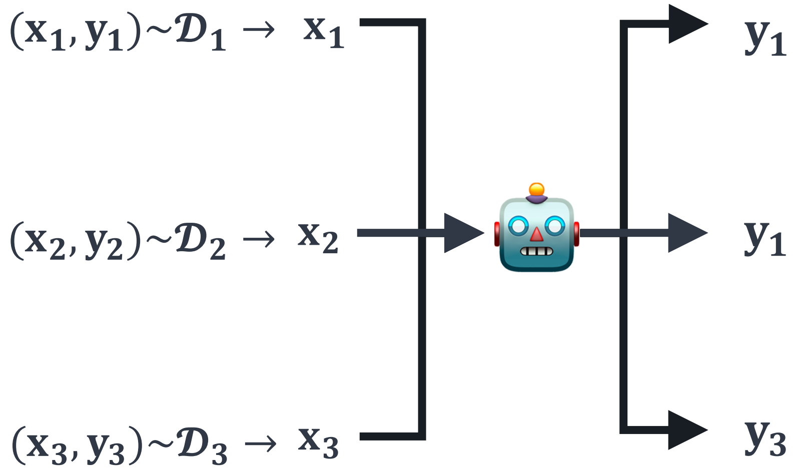

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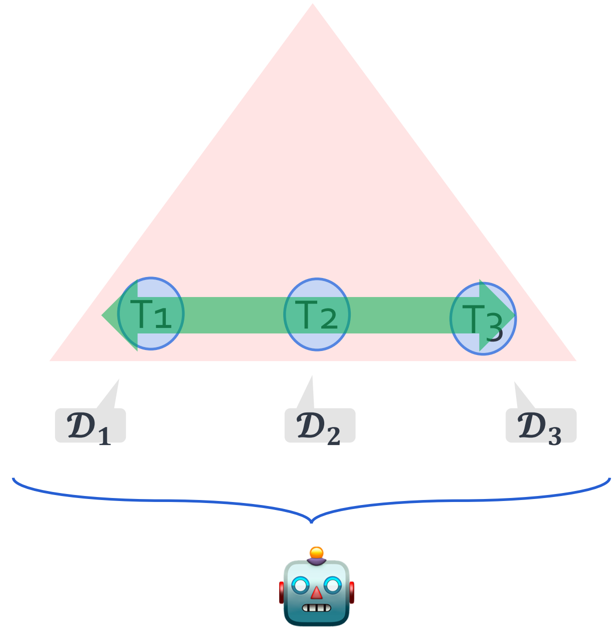


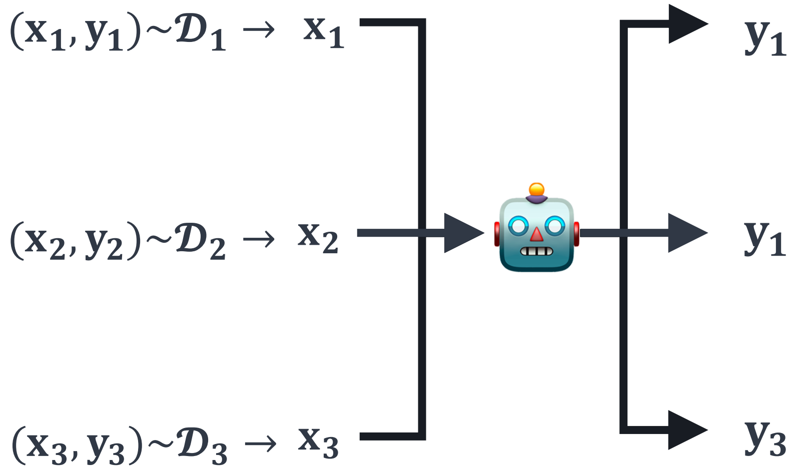

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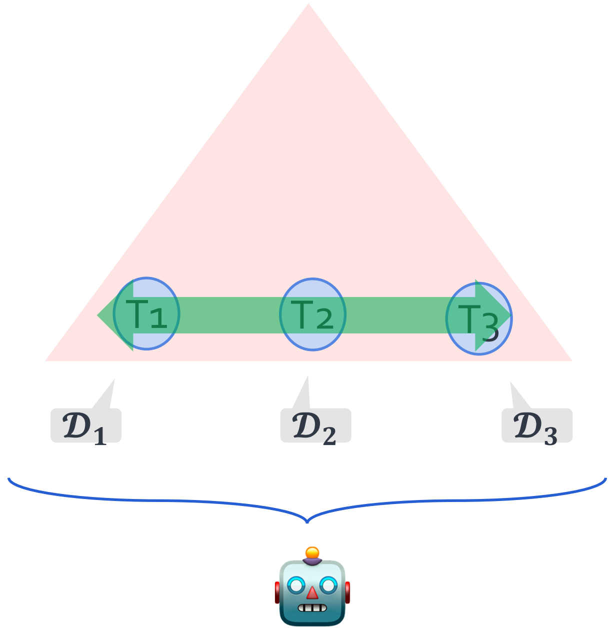
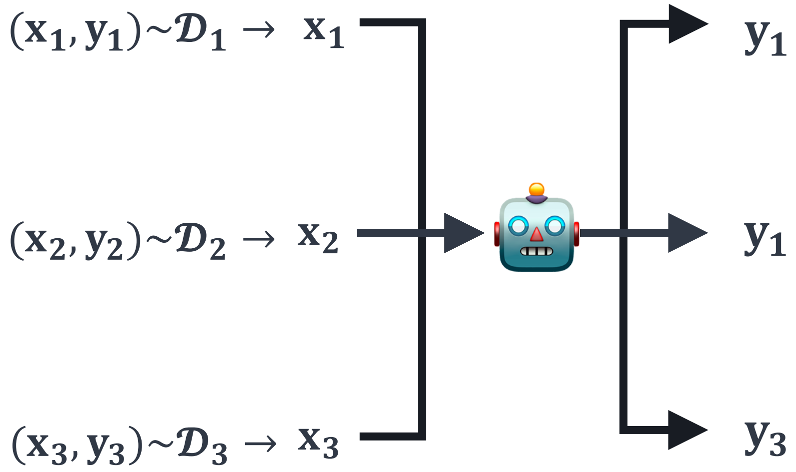
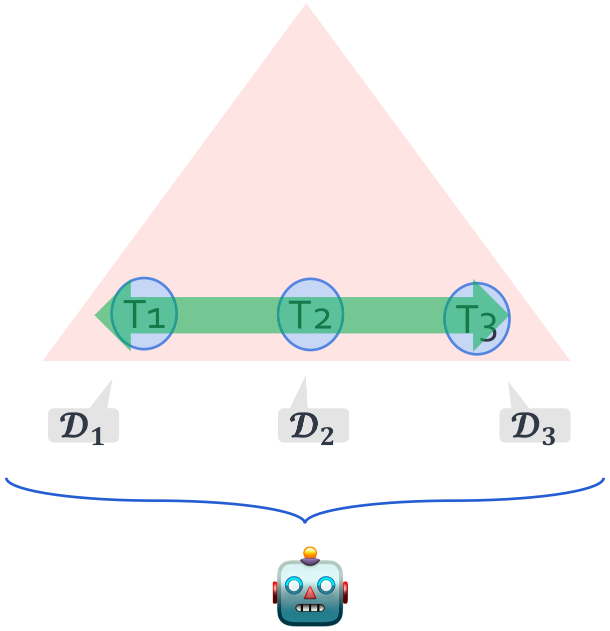
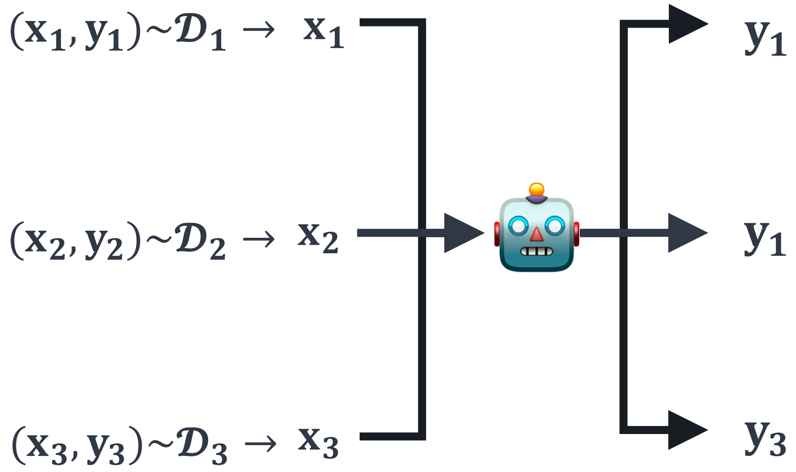
**Multi-Task Learning in NLP:**
How can we leverage (or induce) commonalities among language tasks?



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Answering Questions

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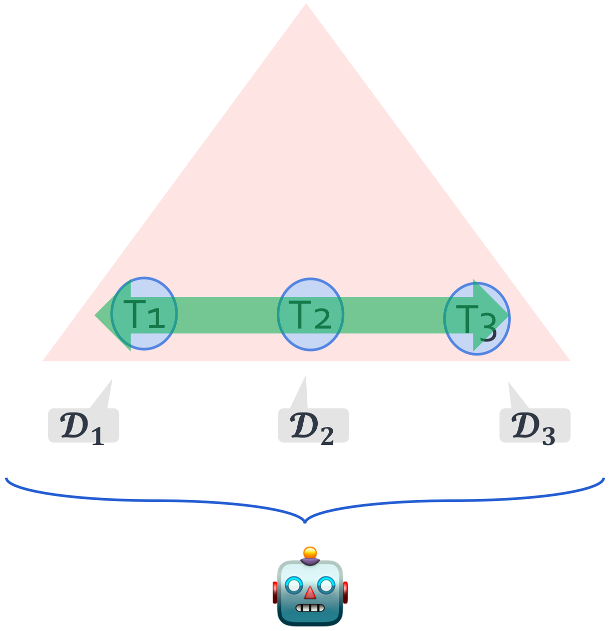


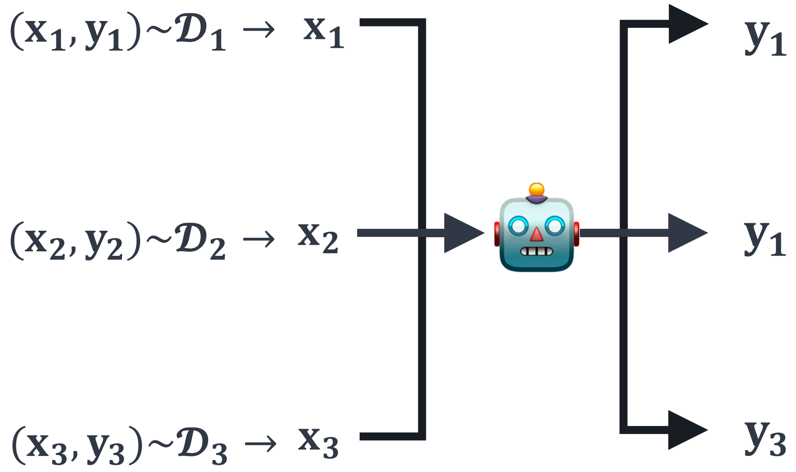


Answering Questions

Common NLP tasks

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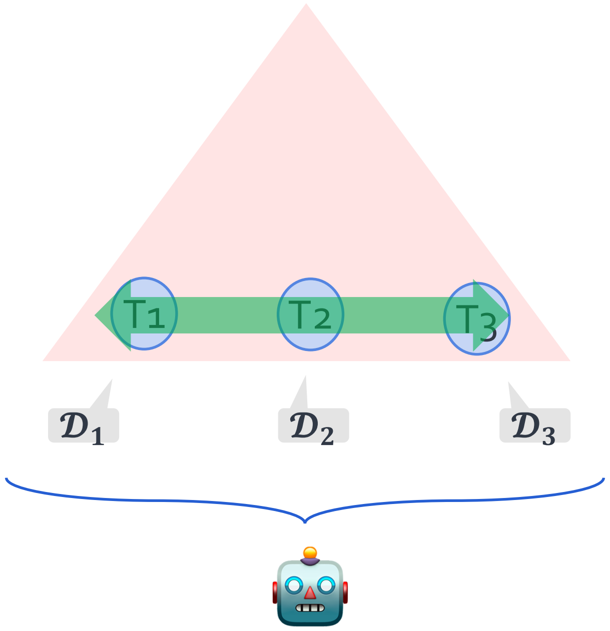
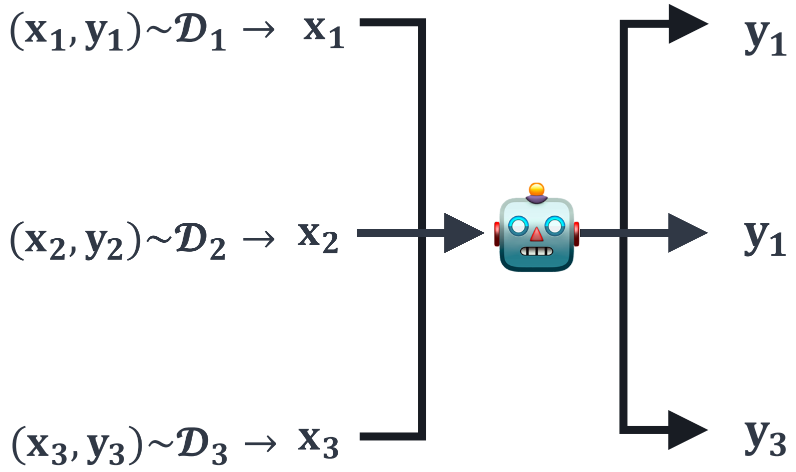


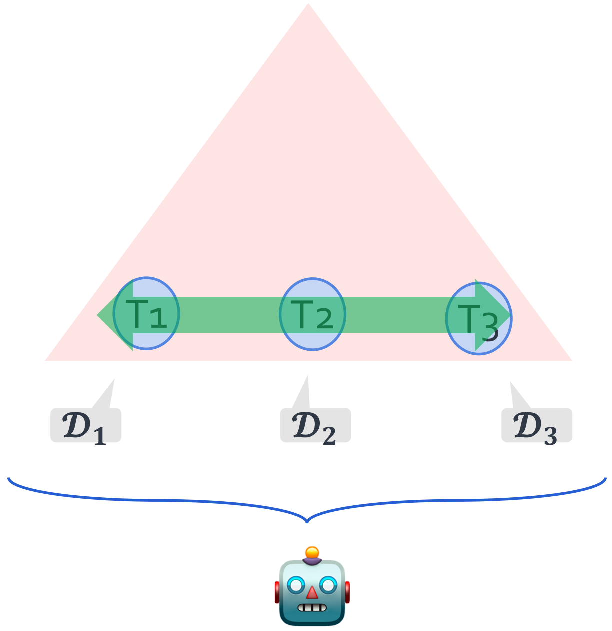



[Raffel et al. 2020]

**Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer**

**T5**

Google AI





Answering Questions

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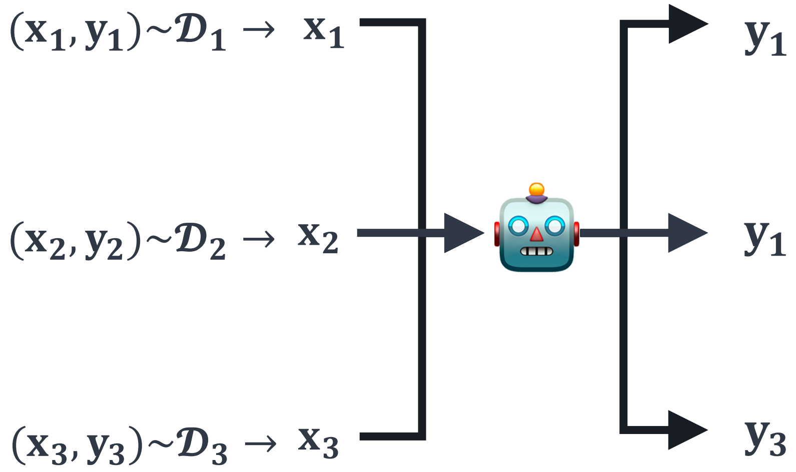

"…. *we find that* ***multi-task training*** ***underperforms*** ***fine-tuning on most tasks***"

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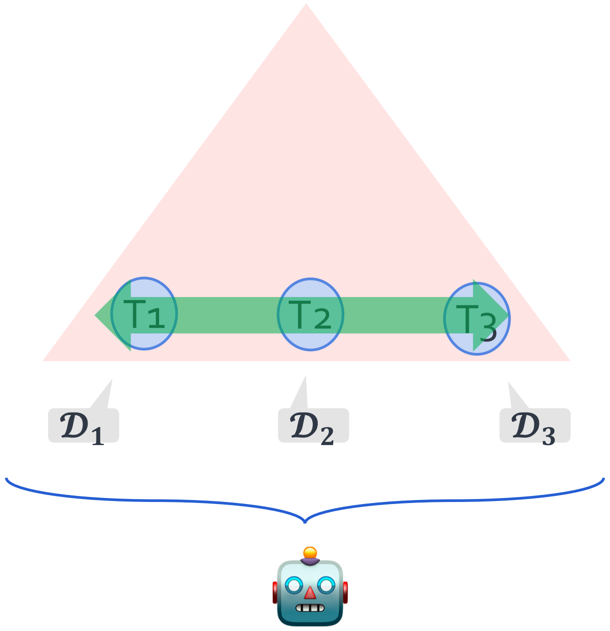



Answering Questions

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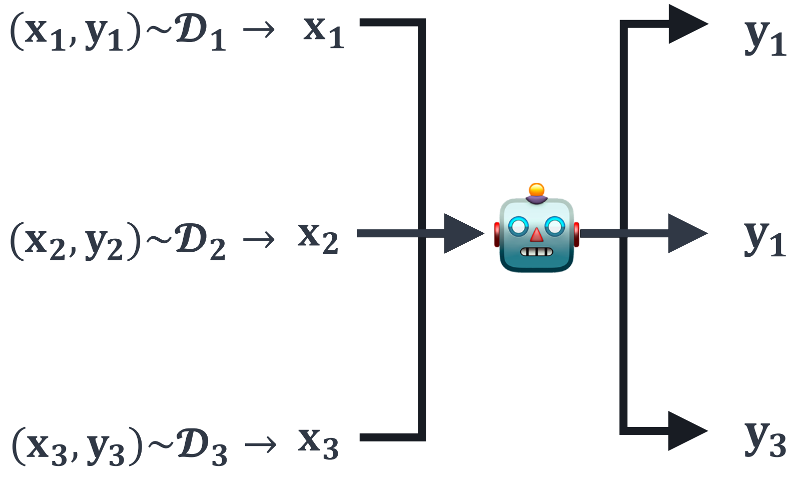

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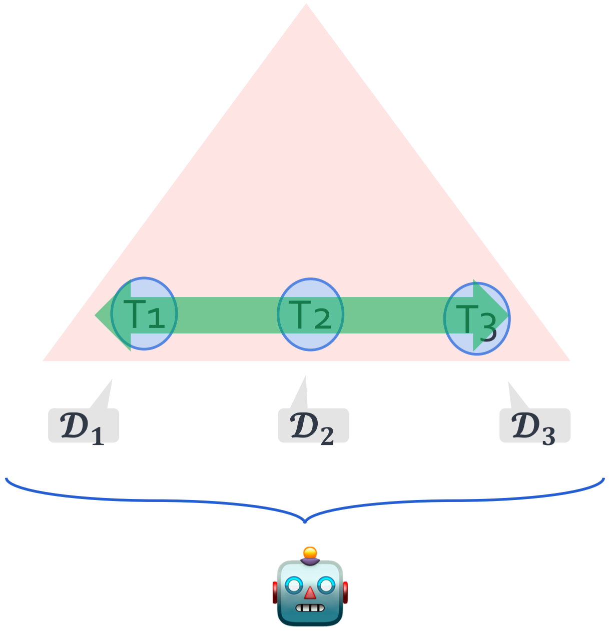



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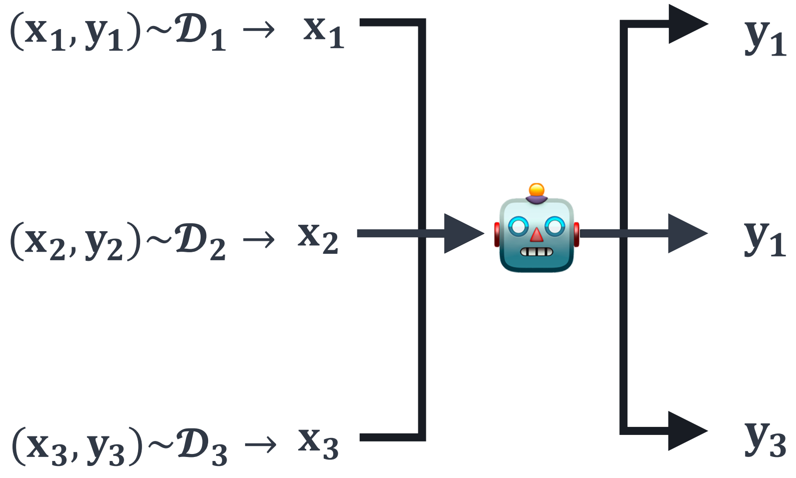


# UnifiedQA

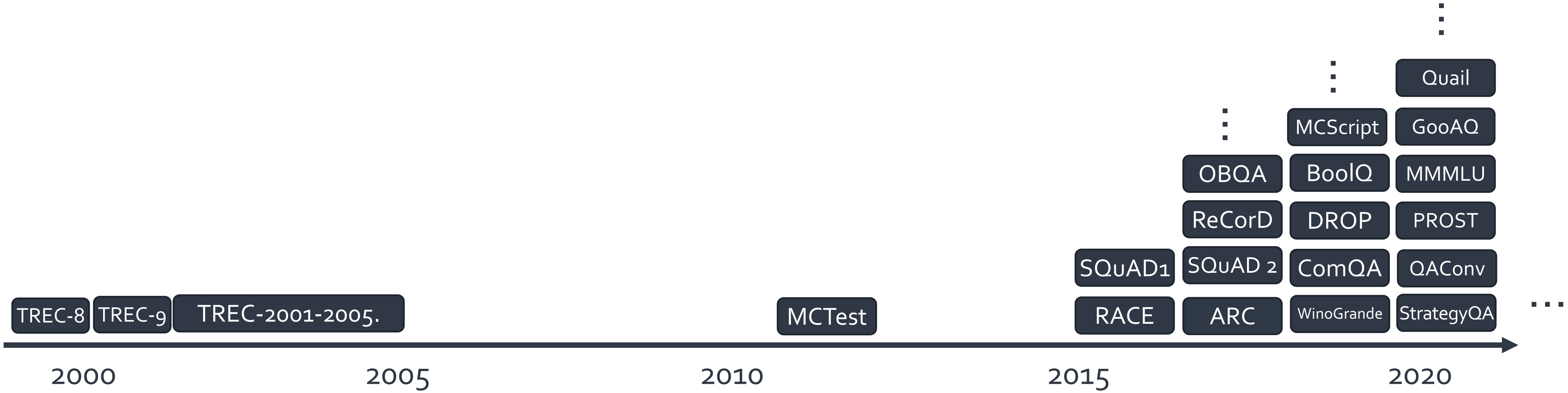
## Answering a broad range of questions with a single system

**Daniel Khashabi**, Sewon Min, Tushar Khot, Ashish Sabharwal
Oyvind Tafjord, Peter Clark and Hannaneh Hajishirzi

*EMNLP Findings 2020*

# Answering Questions: Sub-tasks



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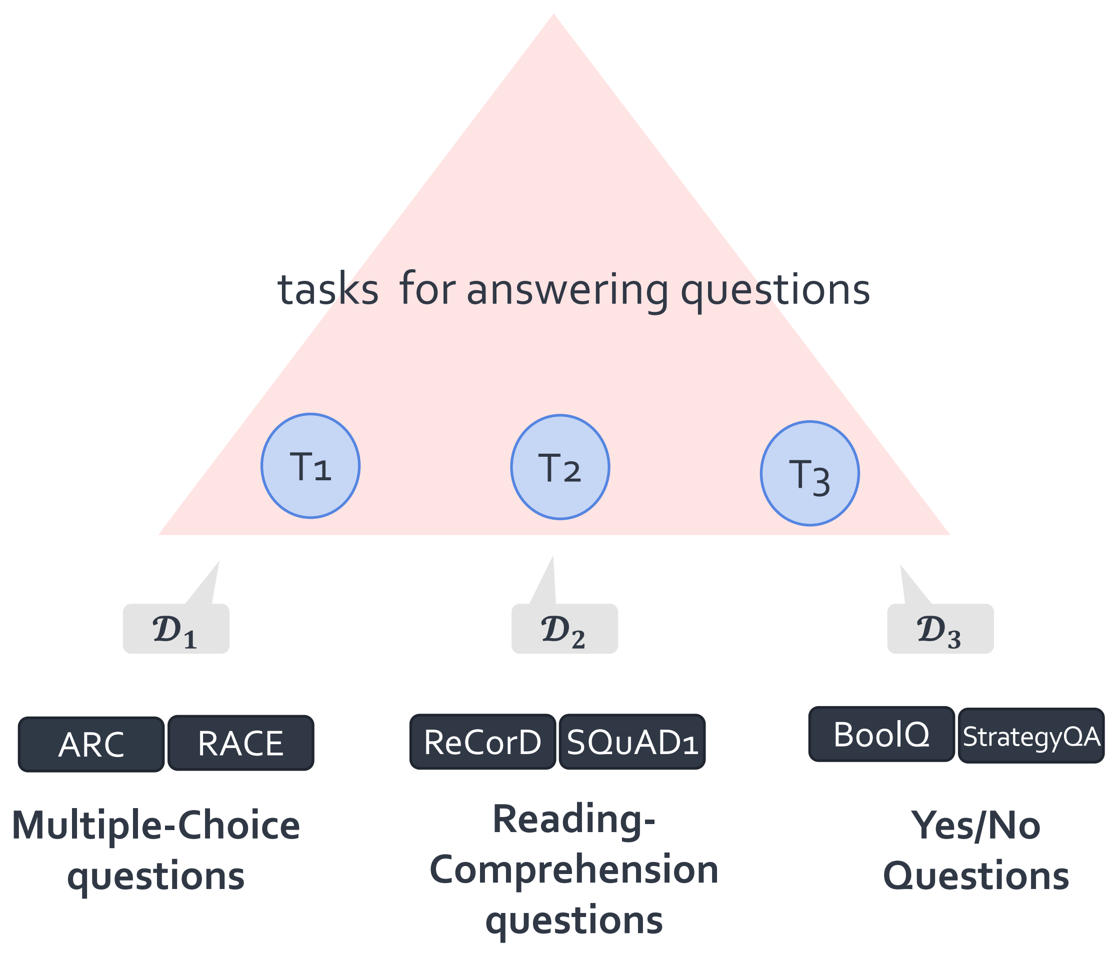

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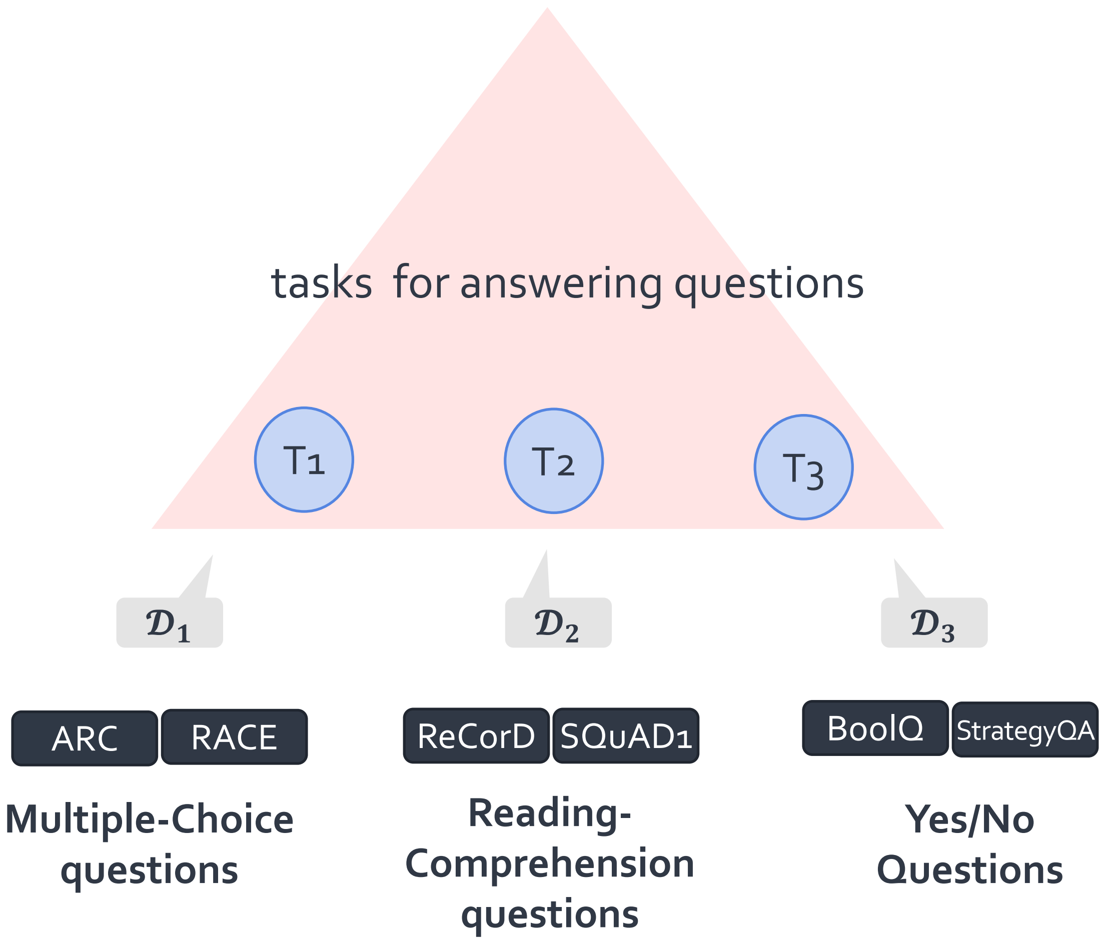


# Answering Questions: Sub-tasks

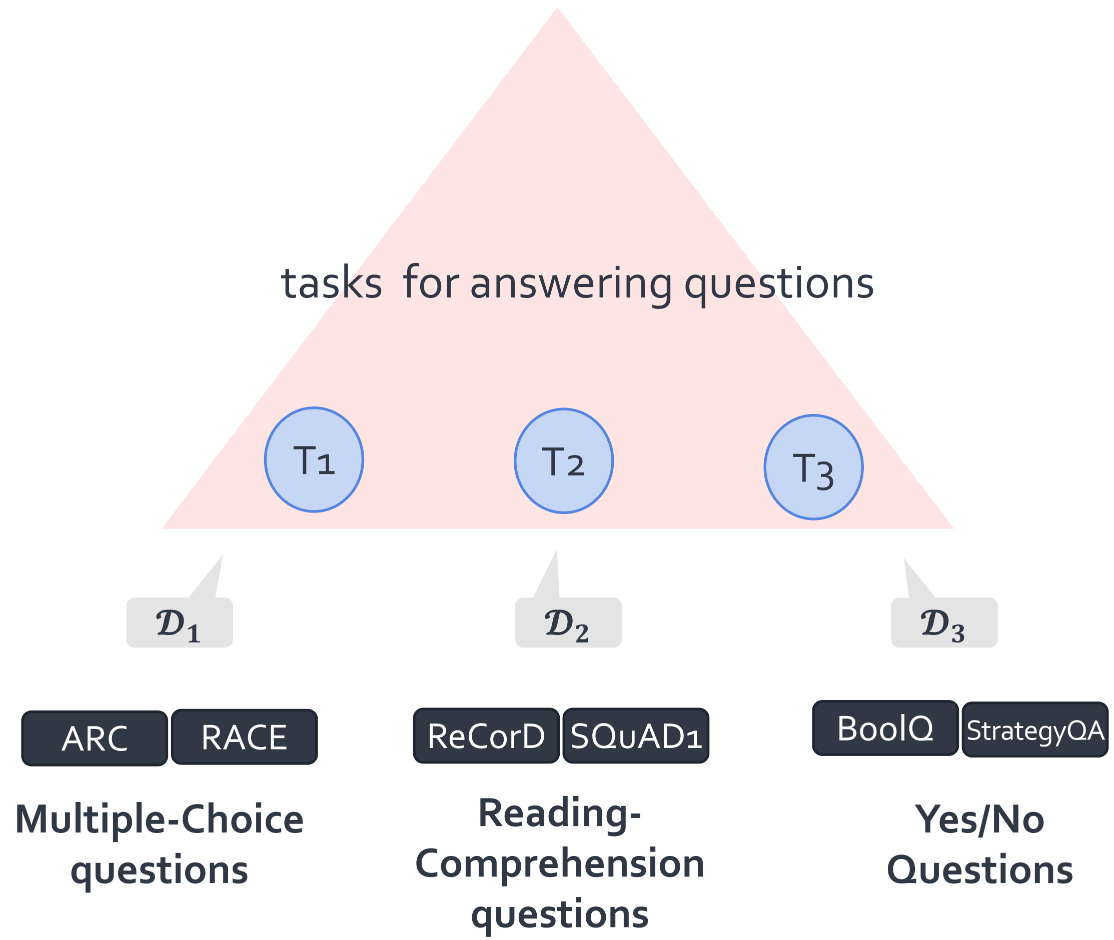
$\mathbf{x} =$ **Question:** *"What does photosynthesis produce that helps plants grow?"*

**Candidates:** *(A) water* *(B) oxygen* *(C) protein* *(D) sugar*

$\rightarrow$ $\mathbf{y} =$*"oxygen"*

multiple-choice

[Clark et al. 18]



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$\mathbf{x} =$ **Question:** *"At what speed did the turbine operate?"*

**Context:** *On his 50th birthday in 1906, Tesla demonstrated ....*

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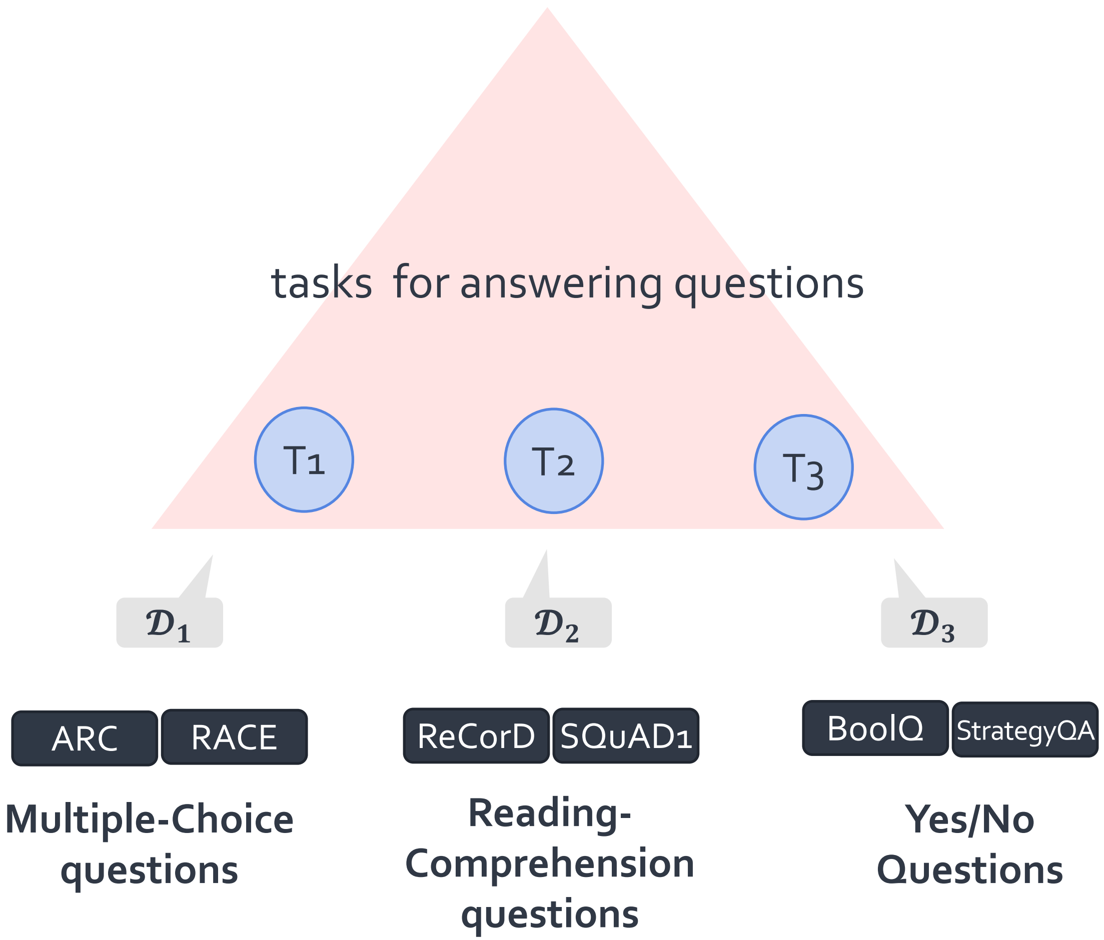
reading-comprehension
[Rajpurkar et al. '16]



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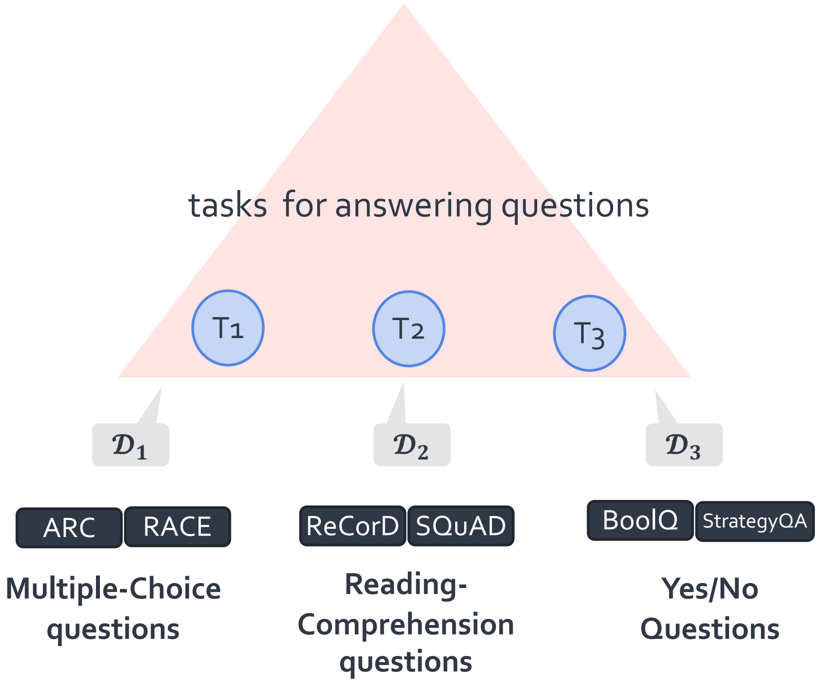

# Toward Unified Question Answering

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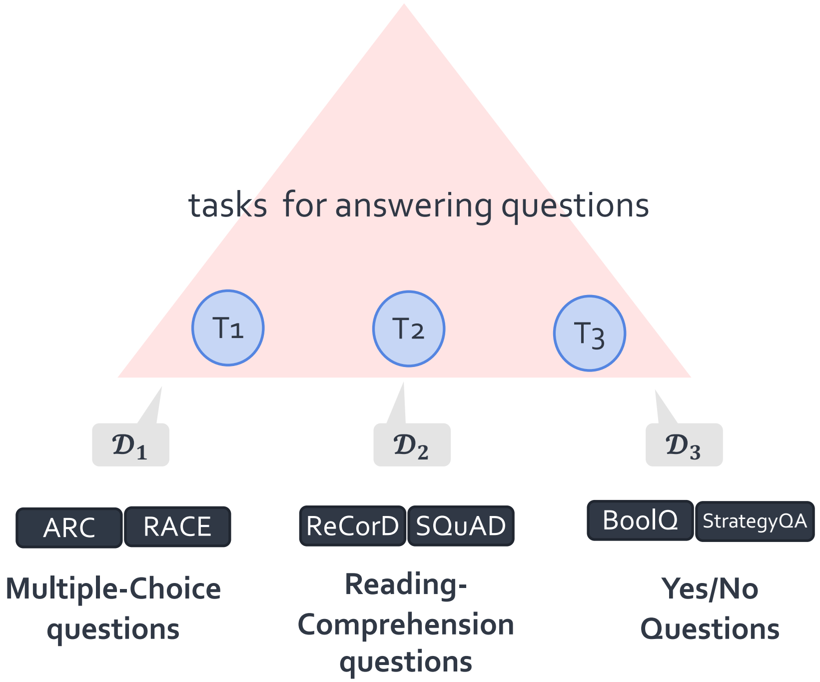


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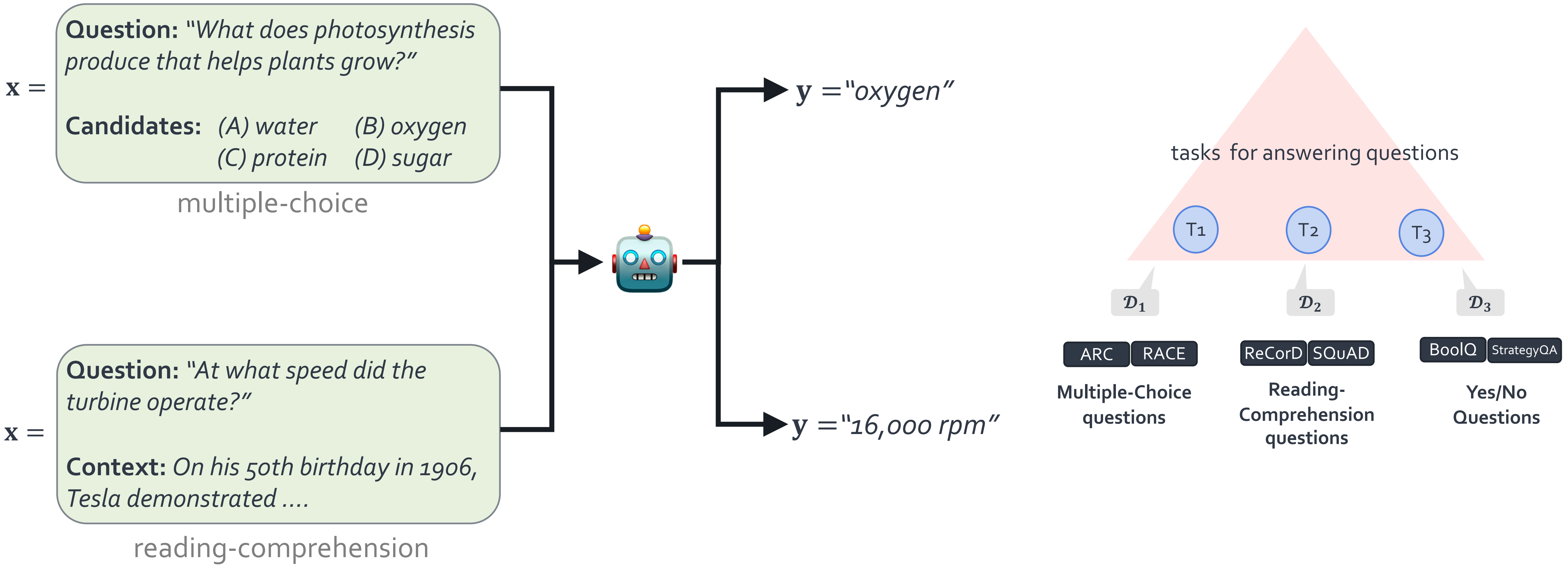

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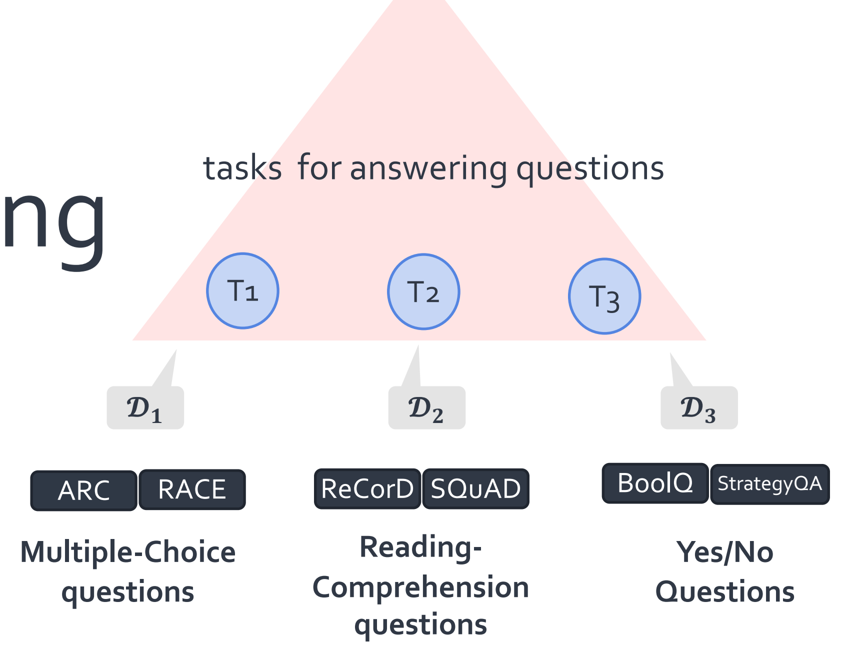


**Multi-Task Learning in NLP:**
How can we leverage (induce) commonalities among ~~language~~ tasks?

*Question Answering*

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multiple-choice

**different but relevant**

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tasks for answering questions

T1 T2 T3

$\mathcal{D}_1$ $\mathcal{D}_2$ $\mathcal{D}_3$

ARC RACE

**Multiple-Choice questions**

ReCorD SQuAD

**Reading-Comprehension questions**

BoolQ StrategyQA

**Yes/No Questions**

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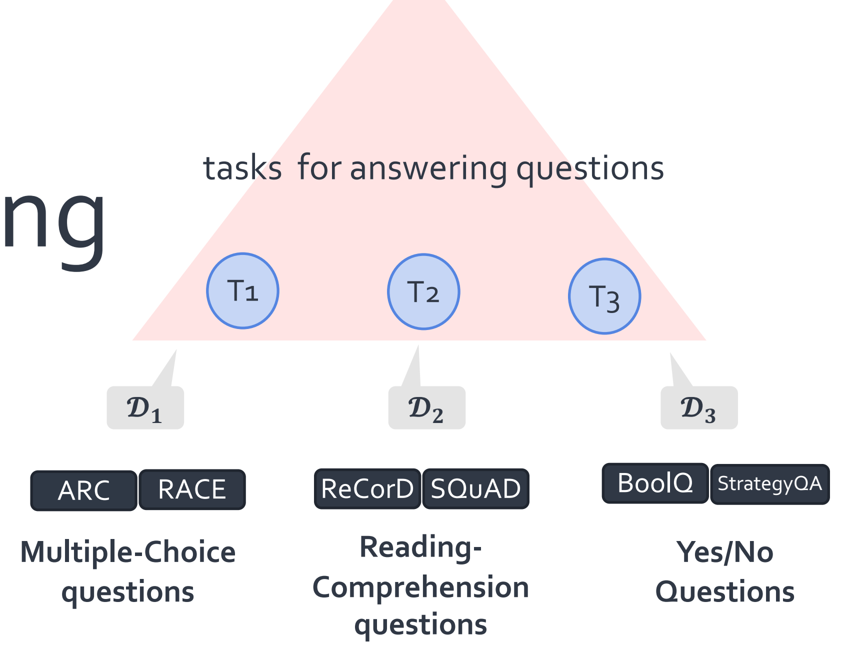
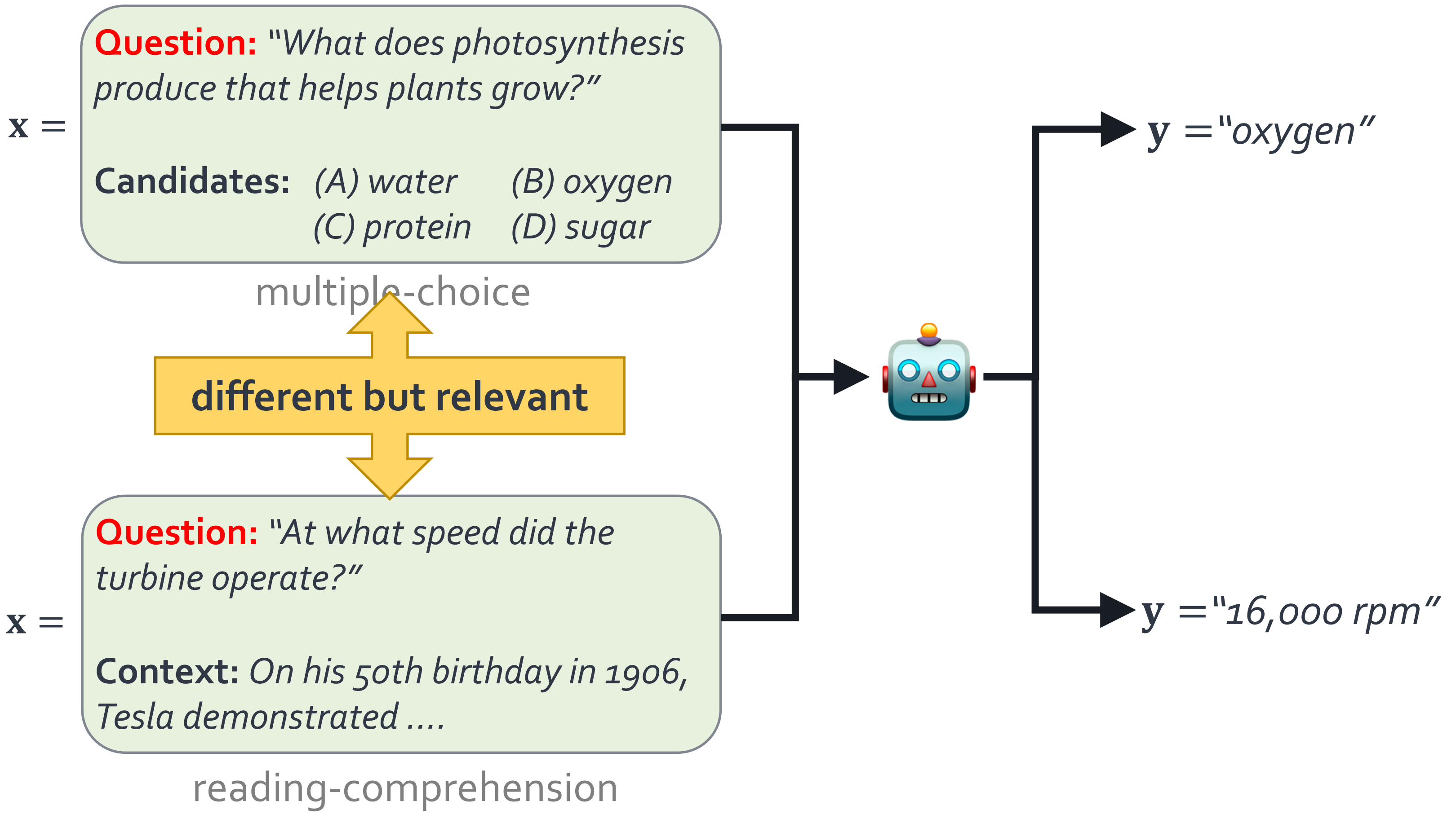
How can we leverage (induce) commonalities among language tasks?

*Question Answering*

# Toward Unified Question Answering

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**Multi-Task Learning in NLP:**
How can we leverage (induce) commonalities among ~~language~~ tasks?

*Question Answering*

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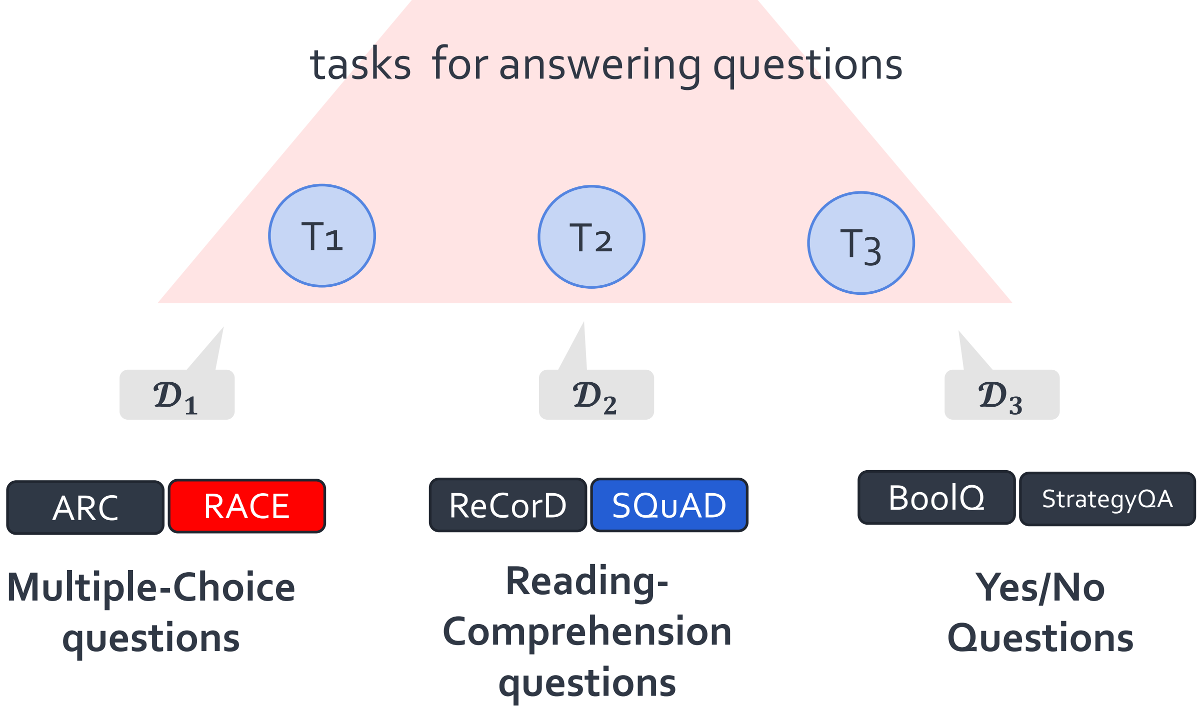

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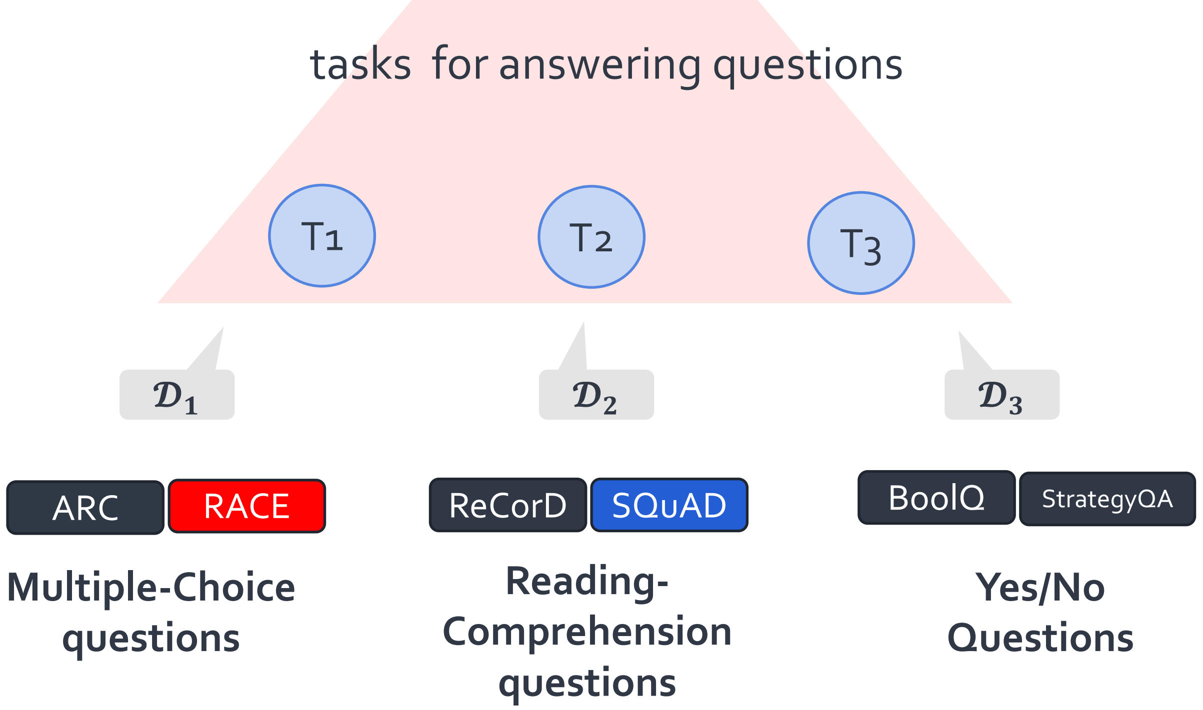

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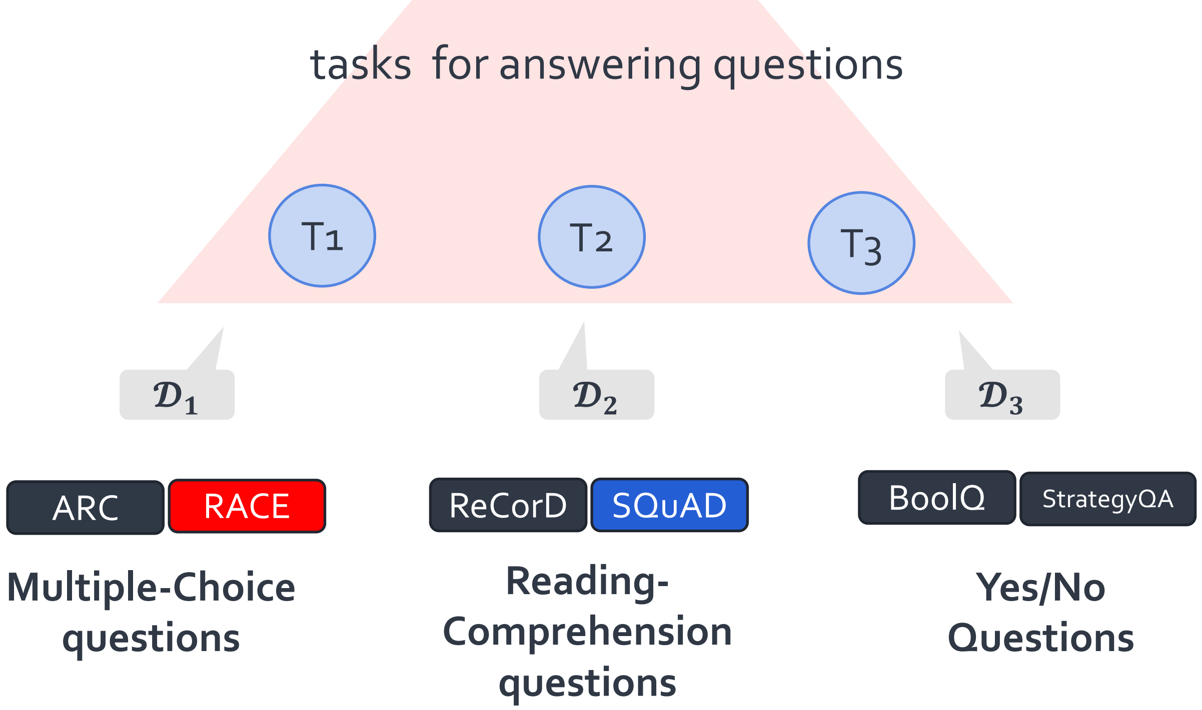


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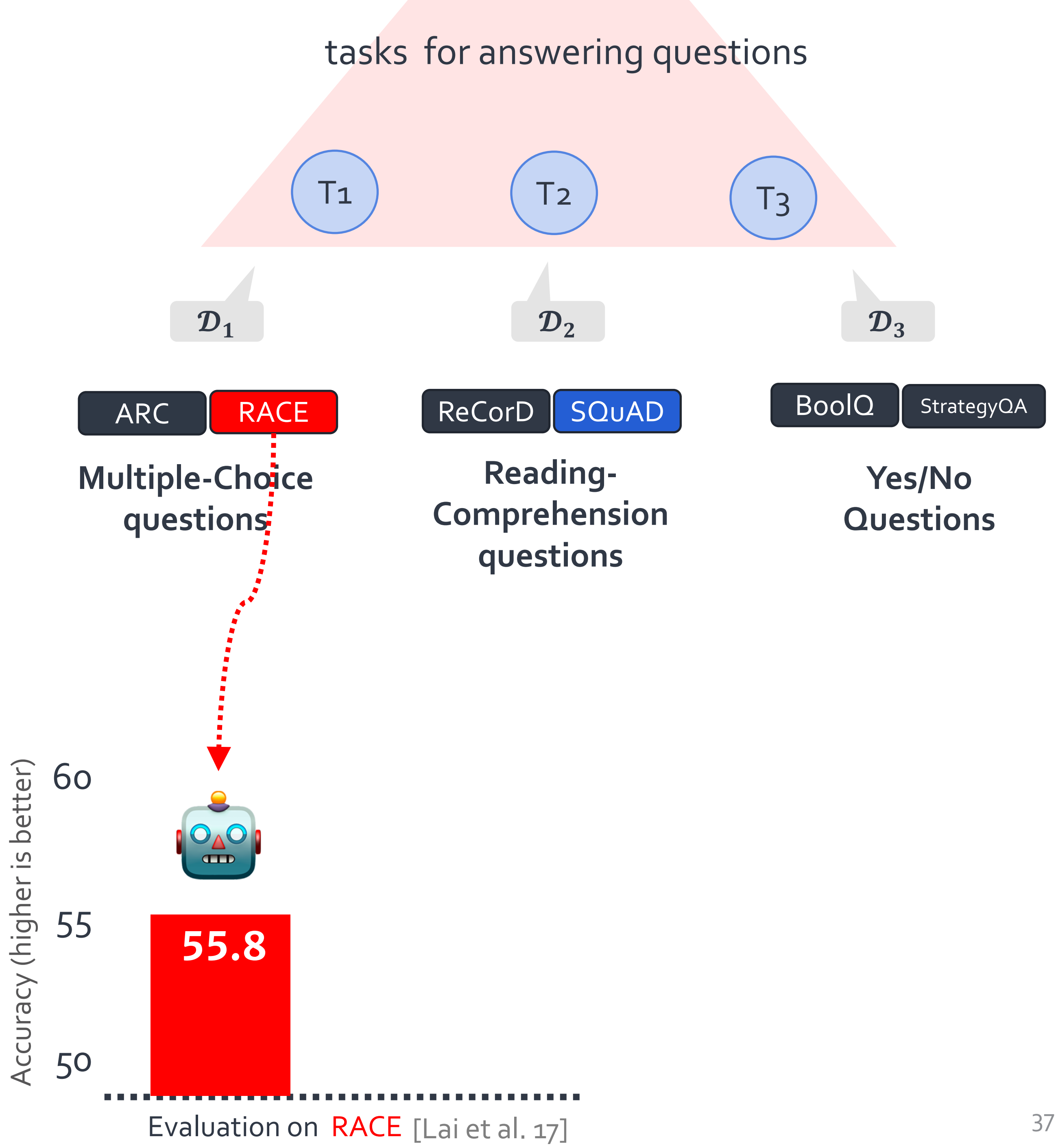

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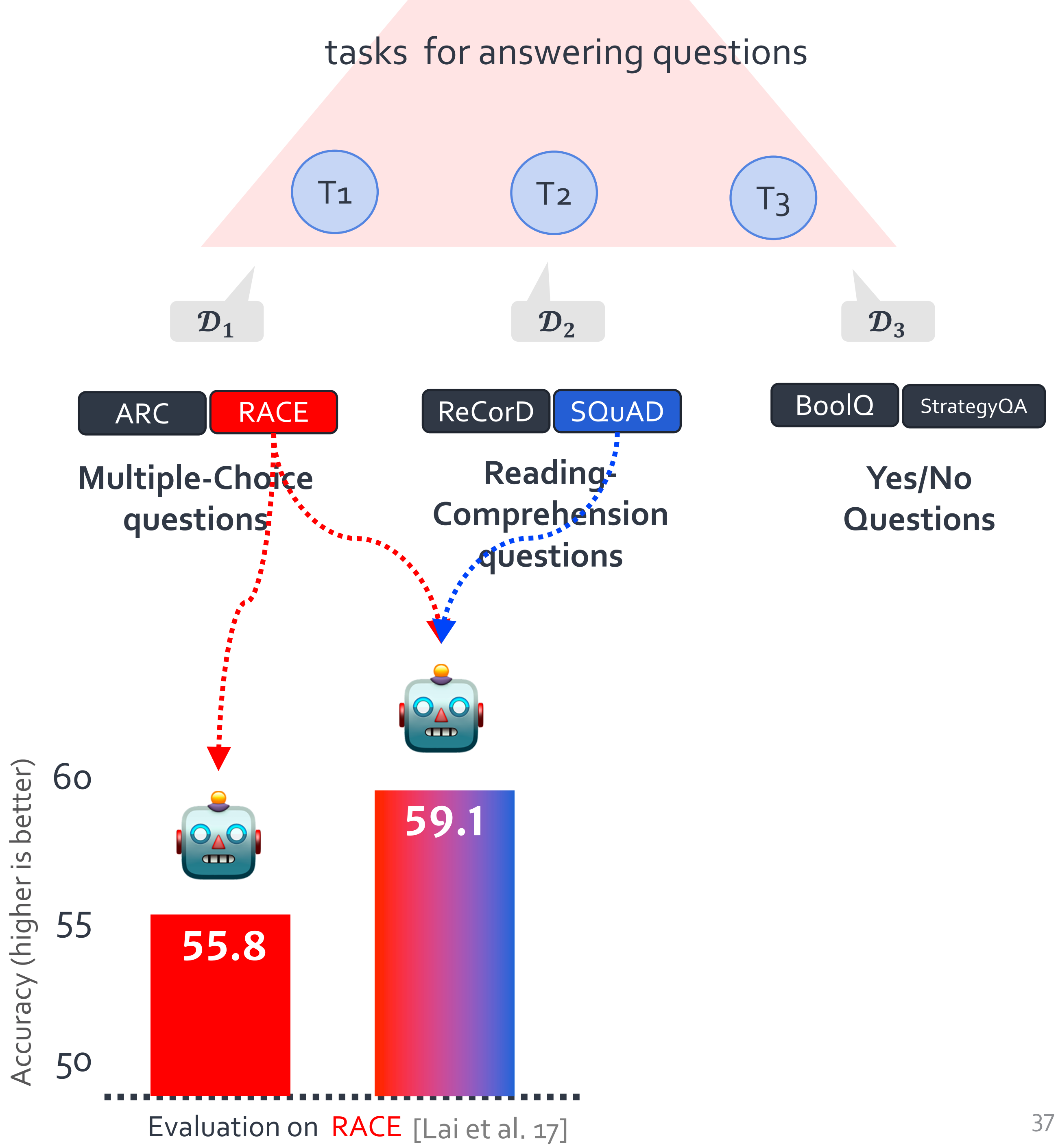

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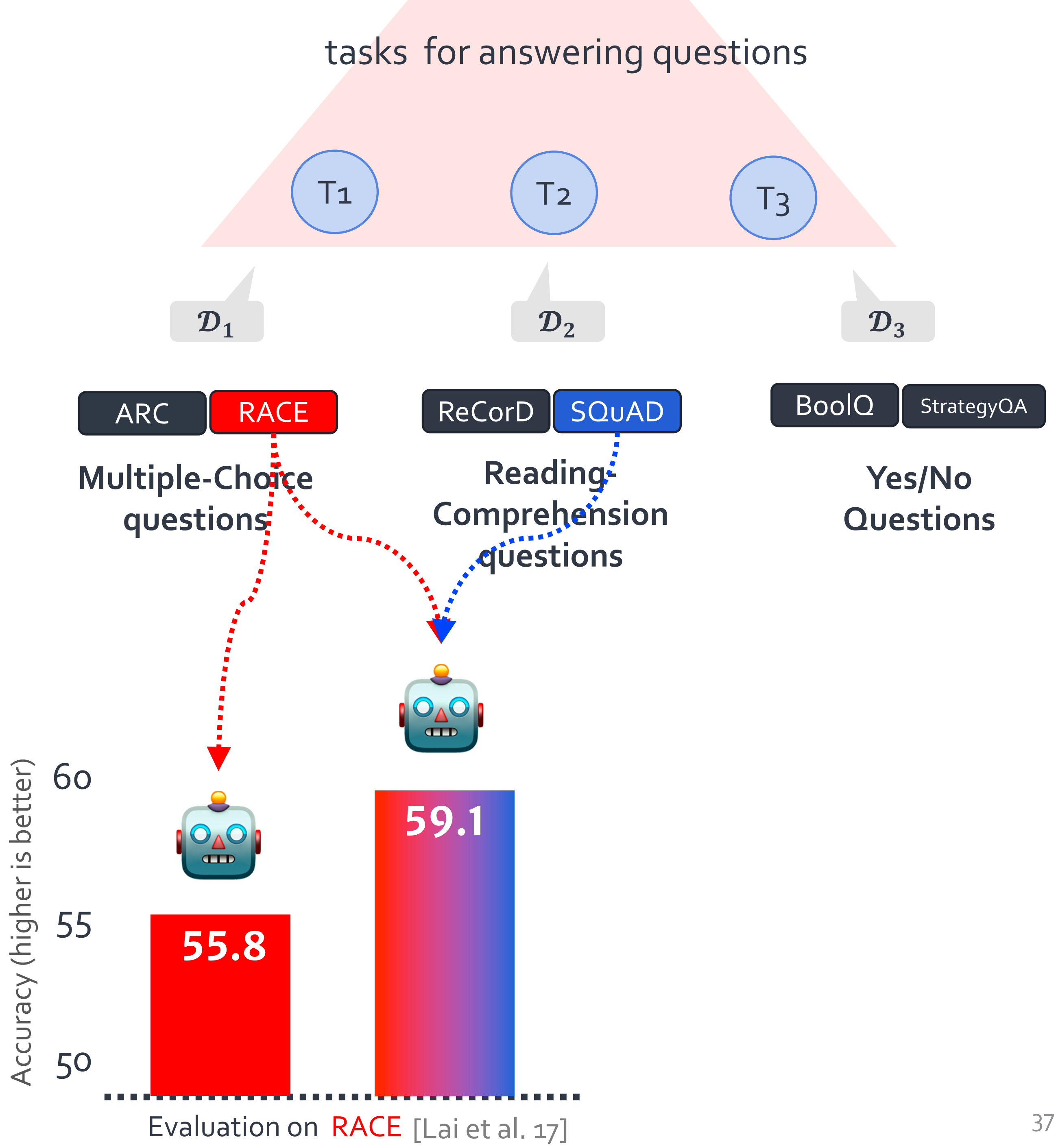

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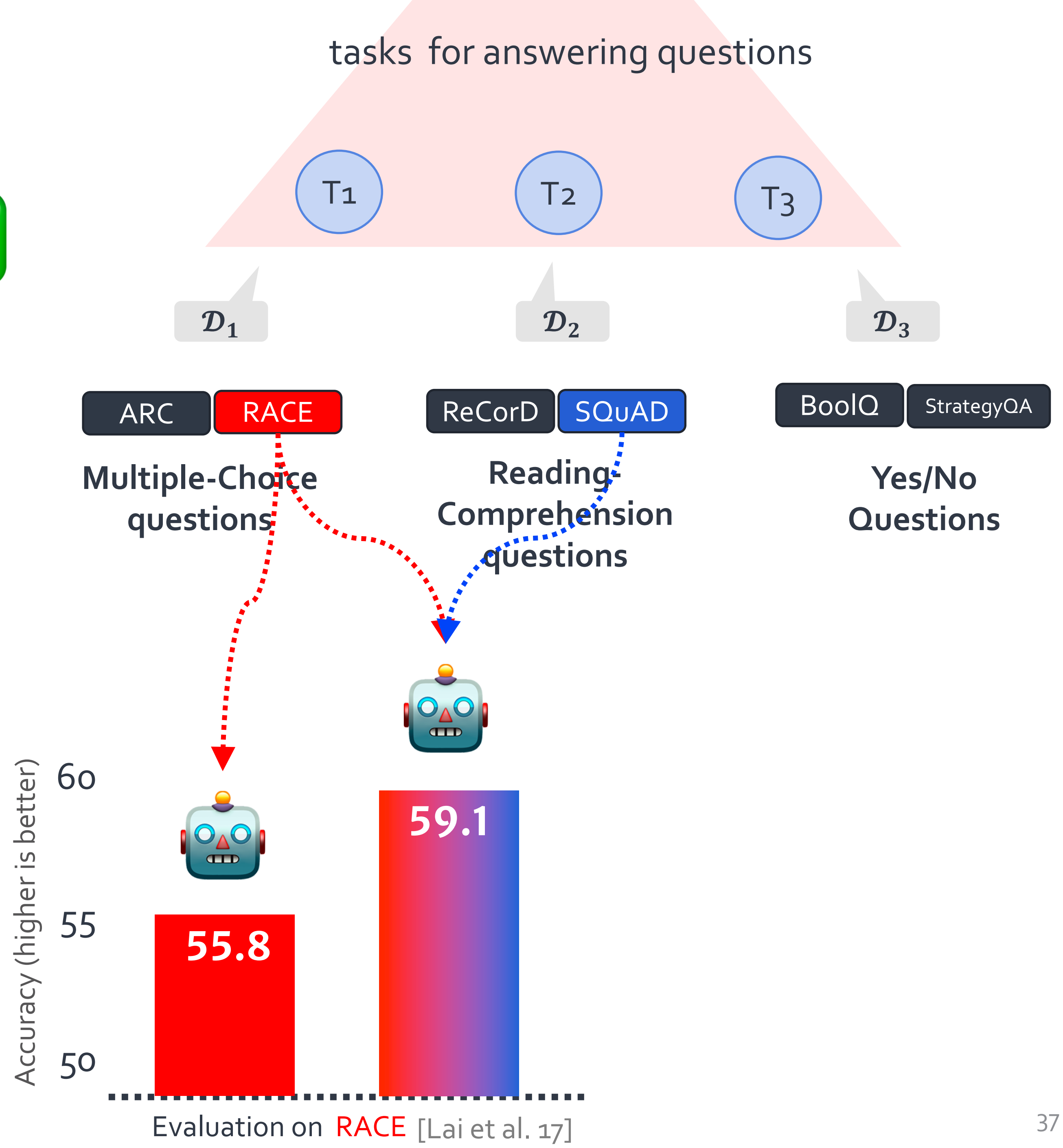
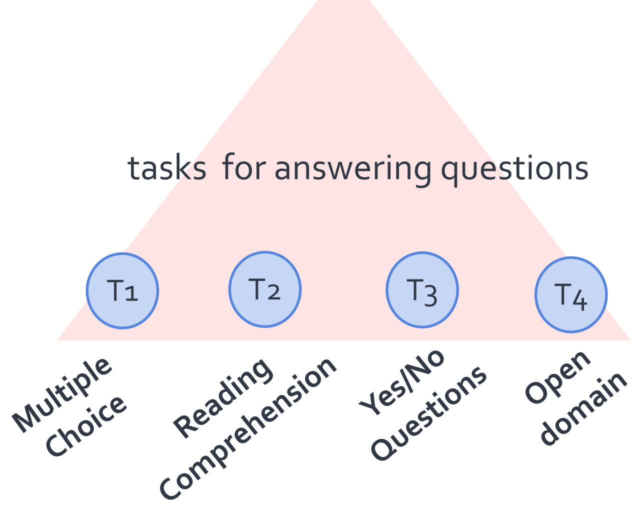


# A Single Unified Model for QA



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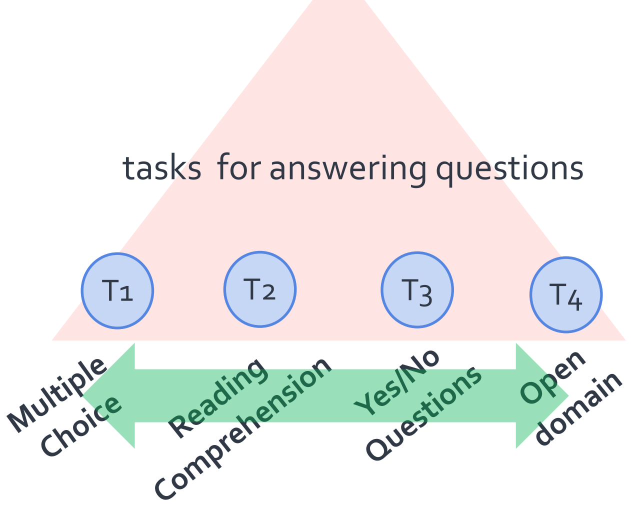


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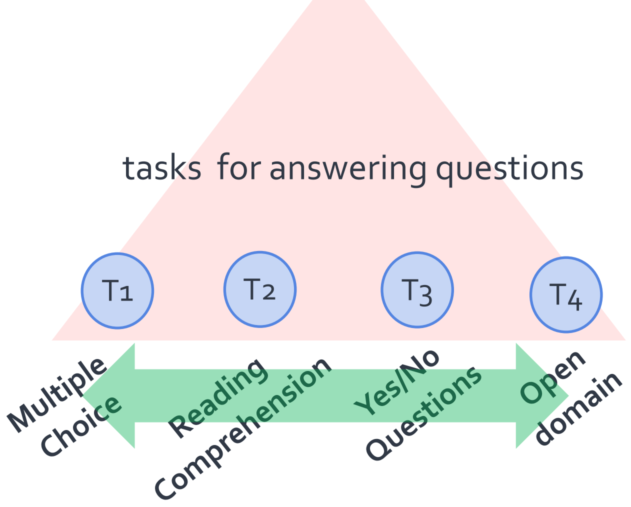


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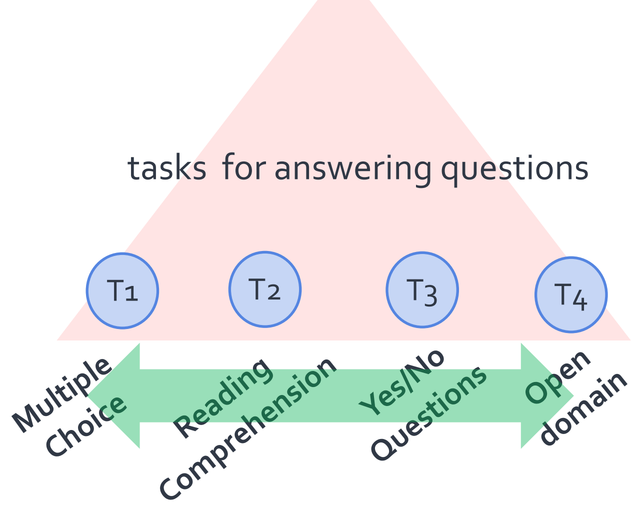


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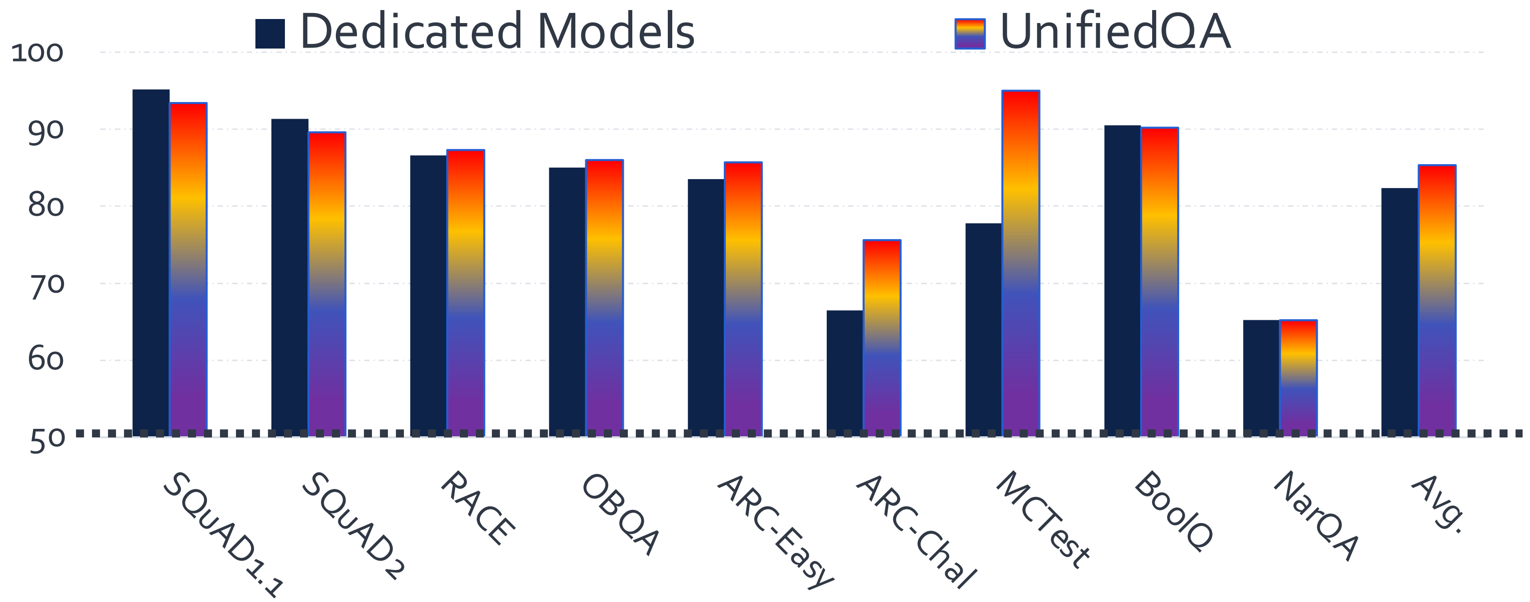


"UnifiedQA: Crossing Format Boundaries With a Single QA System." **Khashabi** and others EMNLP-Findings '20

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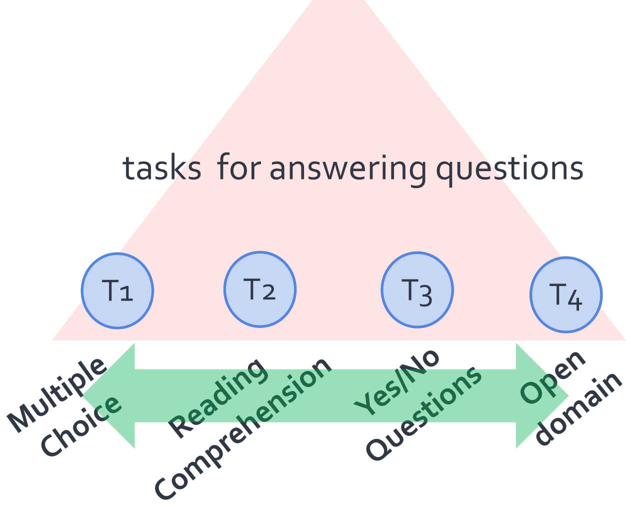


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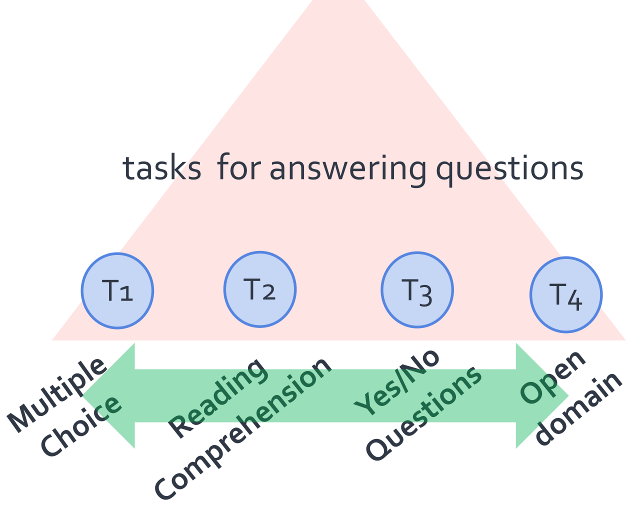


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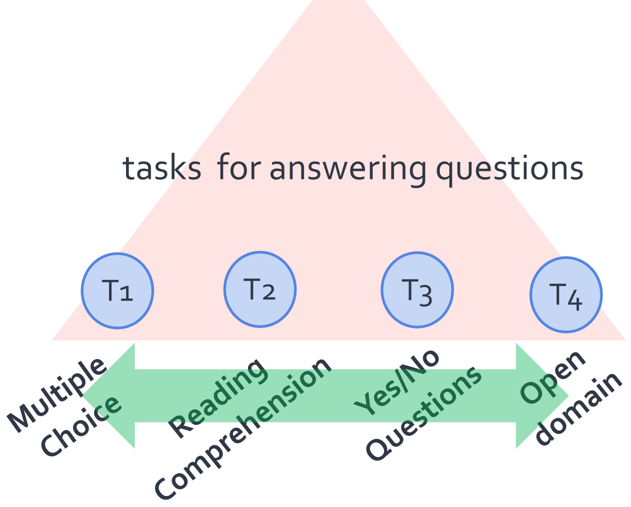


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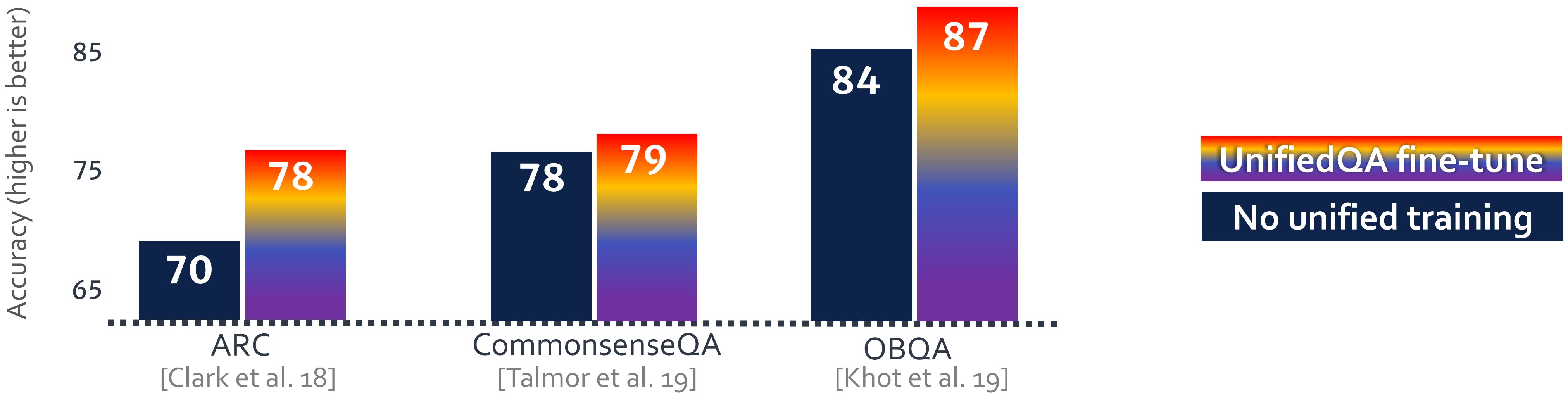


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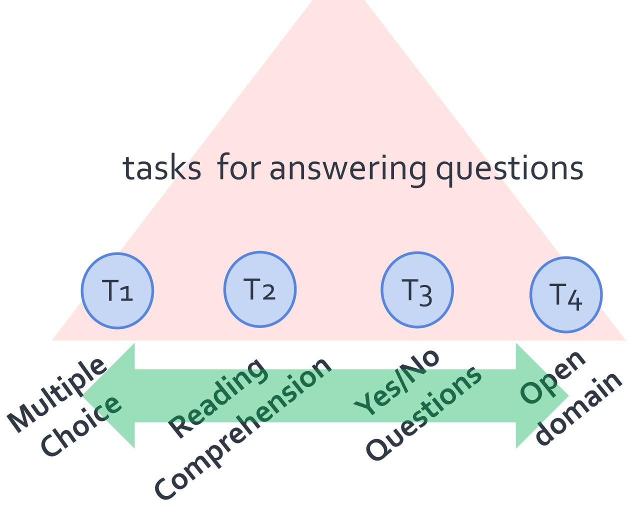


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  - Strong generalization to *unseen* datasets.

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# UnifiedQA: Impact

- Its empirical success was reproduced on new datasets.

[Bragg et al. '21; Wu et al. '21; Zhong et al. '21, …]

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| Model | Answer $F_1$ Span | Answer $F_1$ Abstractive | Answer $F_1$ Overall |
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| LED-base | 54.20 | 24.95 | 44.96 |
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Qasper [Dasigi et al. '21]

| Model | Average |
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| GPT-3 X-Large (few-shot) | 43.9 |

MMMLU [Hendrycks et al. '21]

| | Zero-Shot | | |
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| | **EM** | **F1** | **FZ-R** |
| Human Performance | 79.99 | 89.87 | 92.33 |
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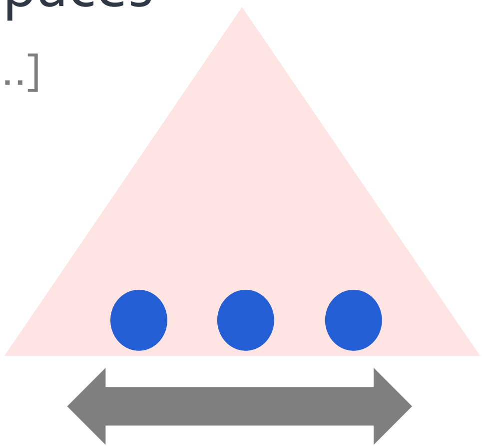
- Helped alleviated the conceptual barriers for building broader models.
  - Follow-ups works have applied these ideas to different problem spaces

    [Aghajanyan et al.'21, Gupta et al.'21, Jiang et al.21, Bragg et al. ‘21, Aribandi et al. 21, …]



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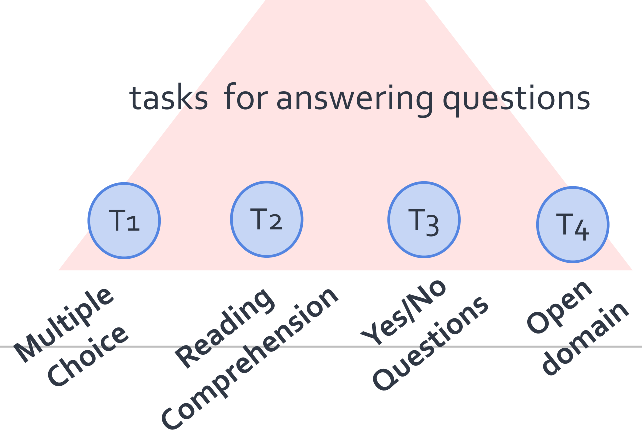


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- Yes we can!
- Added incentive: there is value in mixing QA tasks.
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- **Open questions:**
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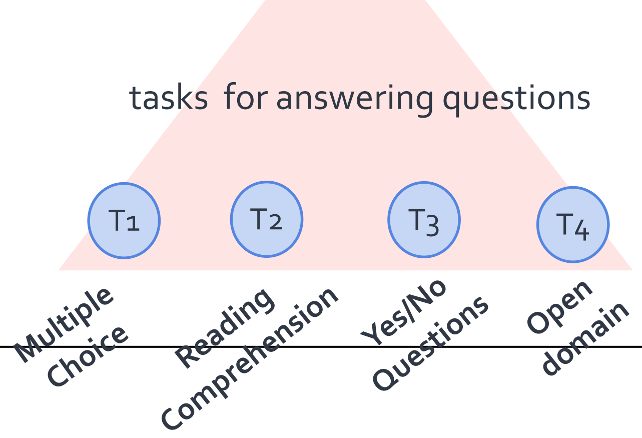


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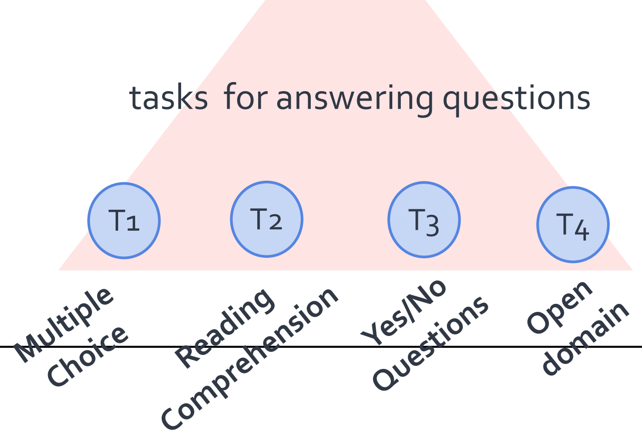


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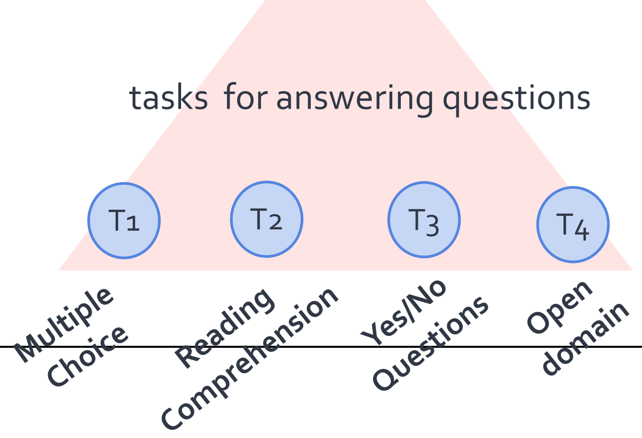


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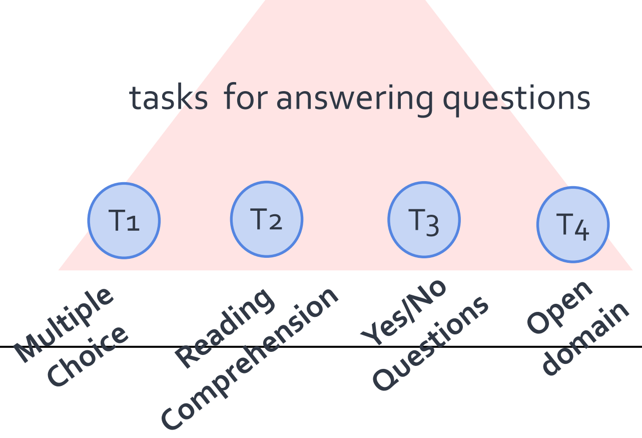


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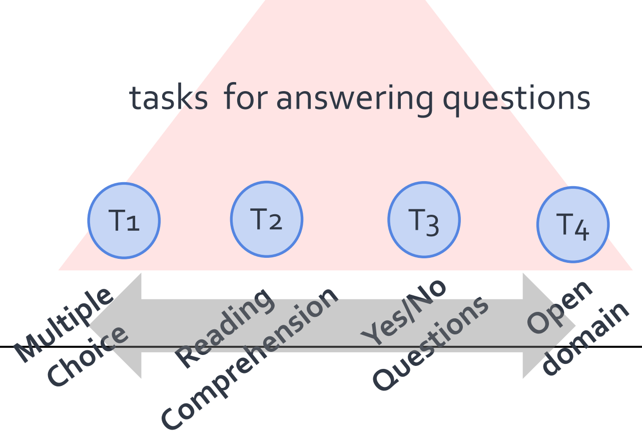


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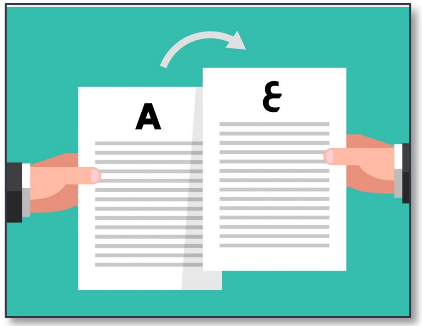


**Grammar Check**

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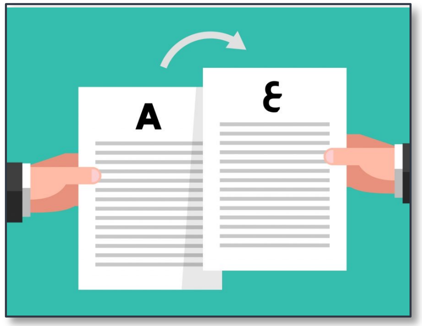



**Grammar Check**

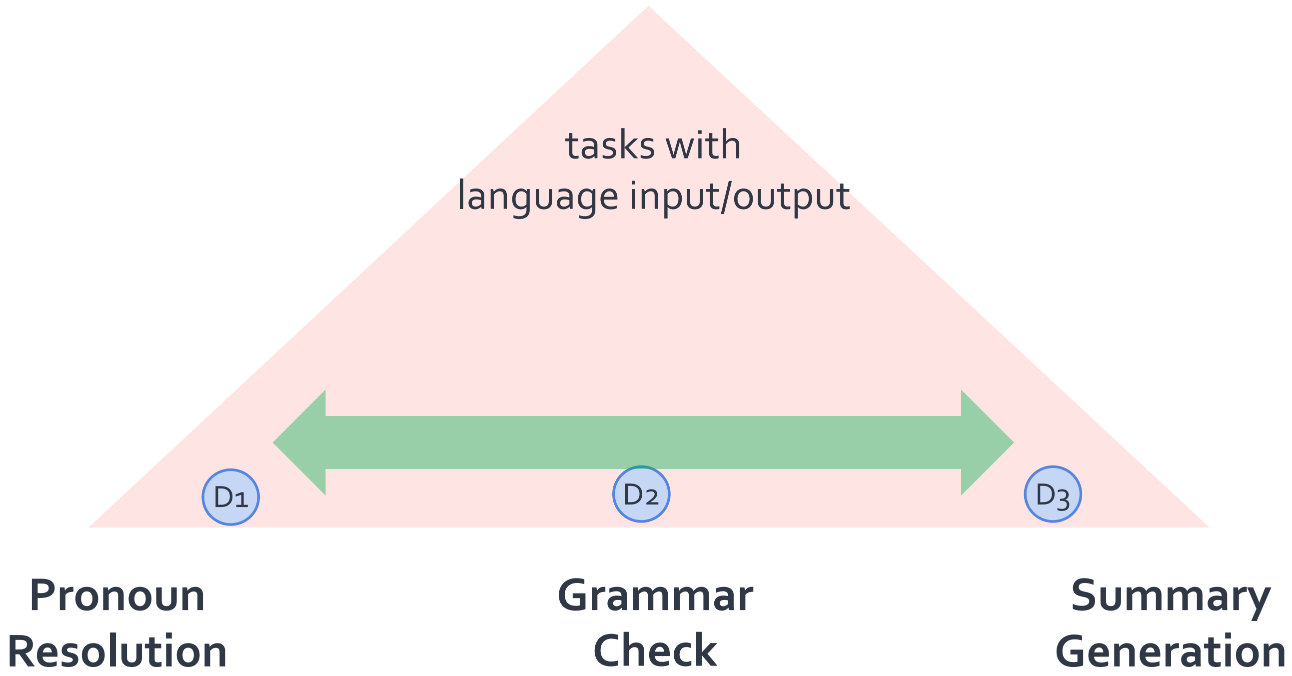
**Summary Generation**

*"Jack fired James but he did not regret it."*

*" … he ~~does~~ not regret."*

*not grammatical*

*"In summary, Jack …."*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D1
D2
D3
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Resolution
Grammar
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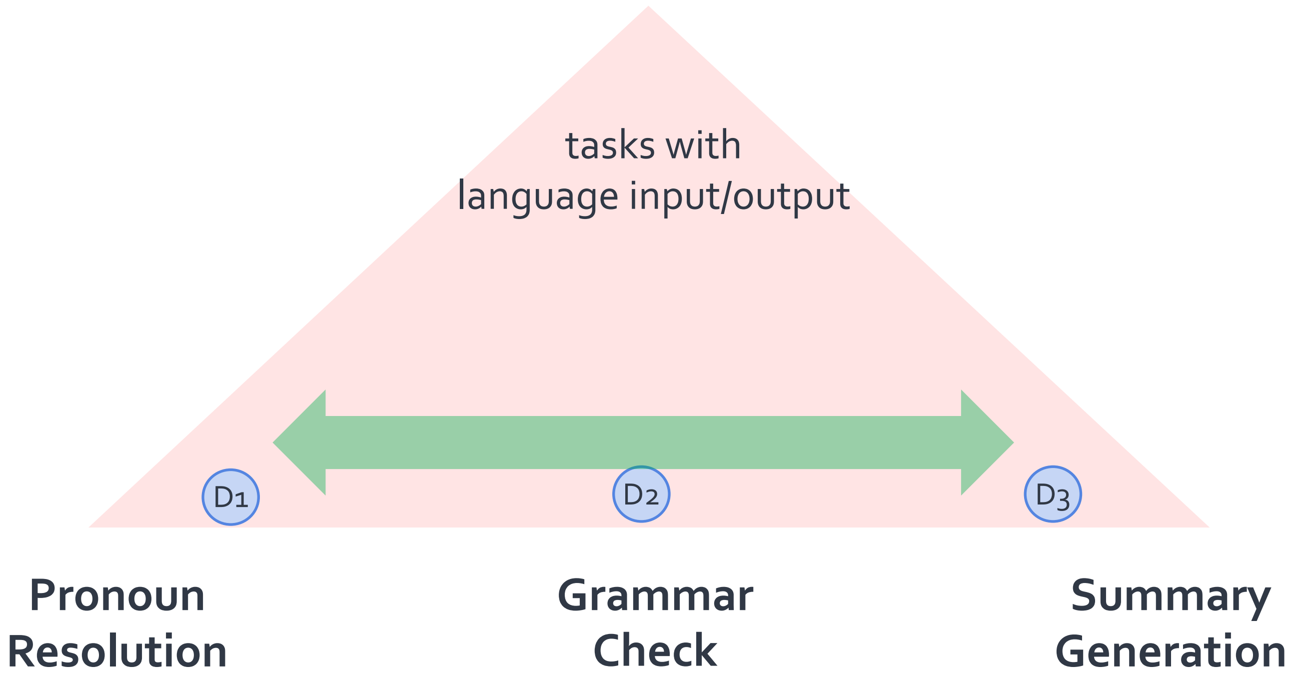
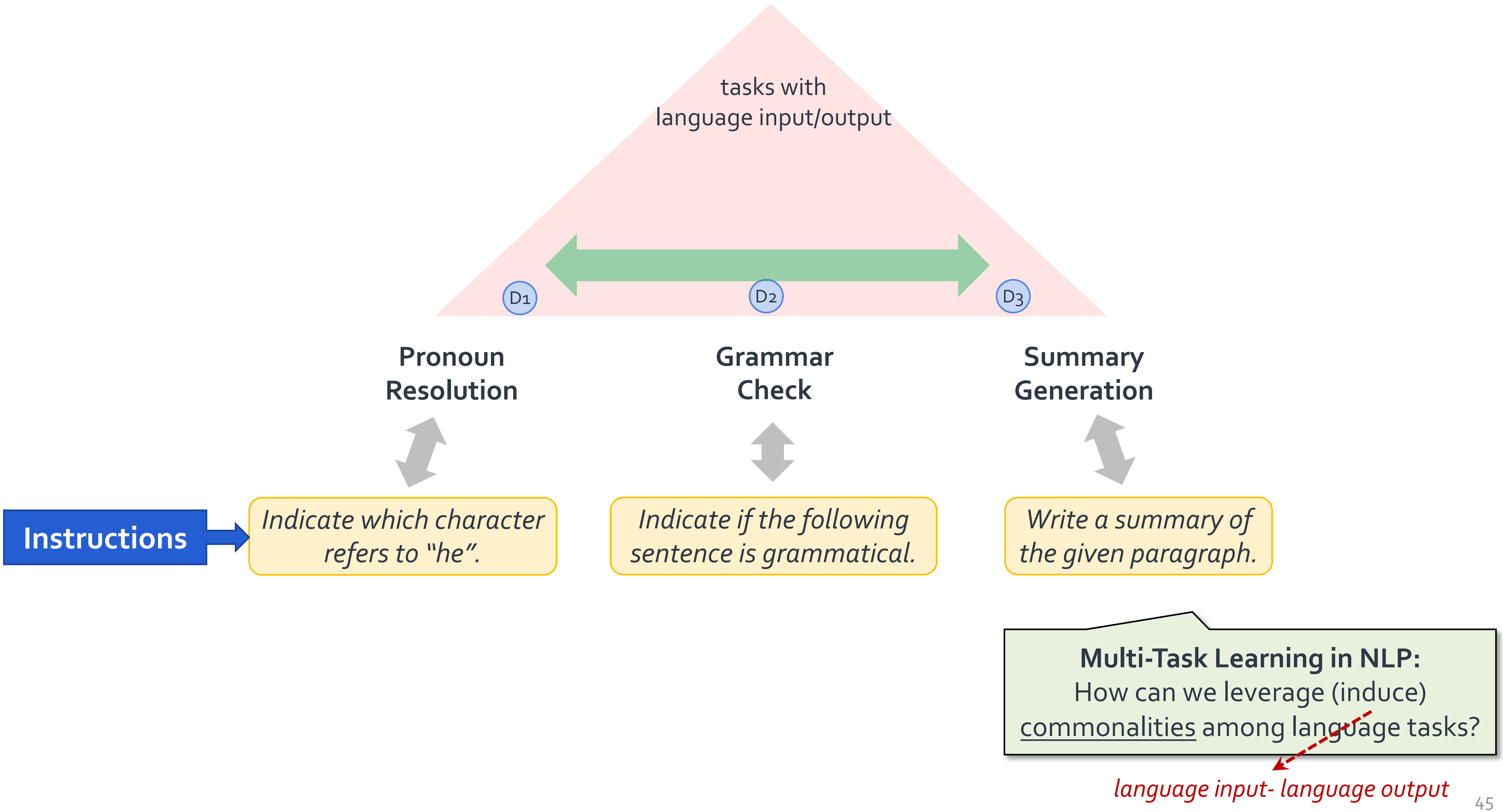



**Multi-Task Learning in NLP:**
How can we leverage (induce) commonalities among language tasks?

*language input- language output*



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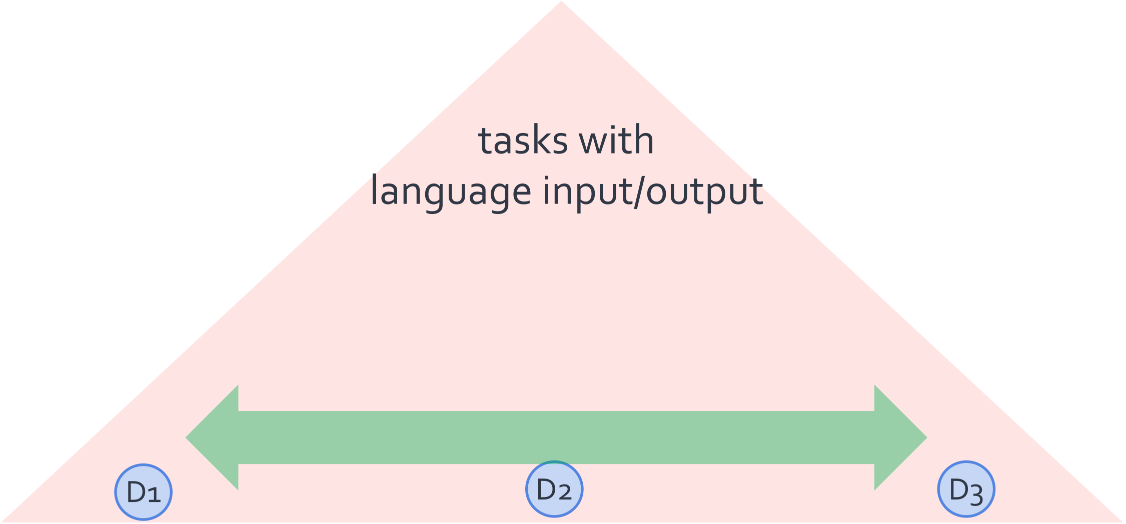


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**Hypothesis:** Task "instructions" are enough to induce sharedness among them.

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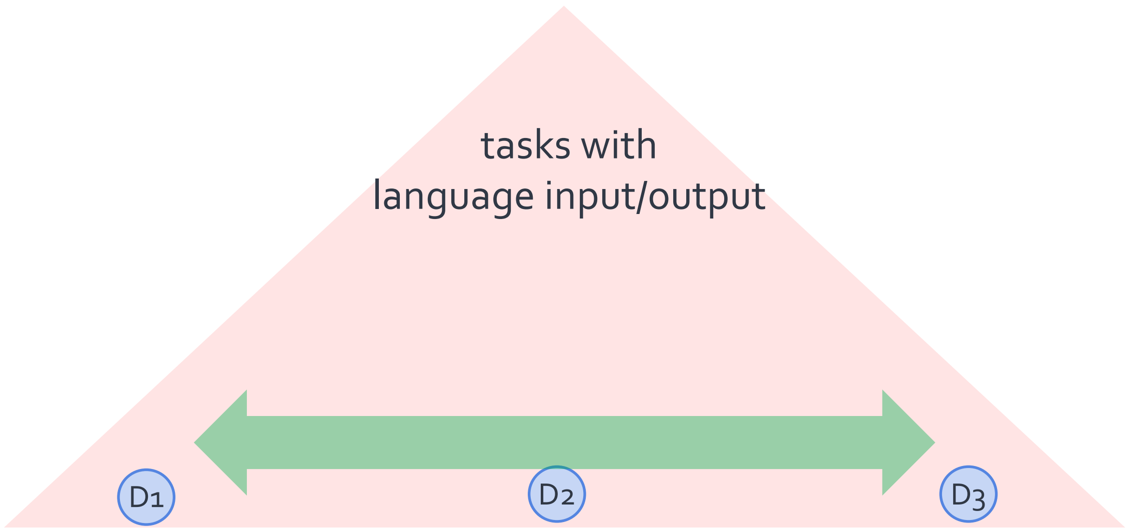
# Generalization via Task Instructions

solving language tasks
via language instructions

Swaroop Mishra, **Daniel Khashabi**, Chitta Baral, Hannaneh Hajishirzi

*ACL 2022*

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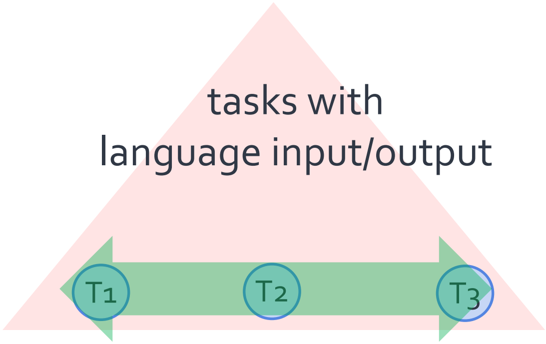


Pronoun Resolution

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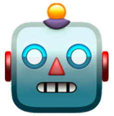
Summary Generation

*Input text*



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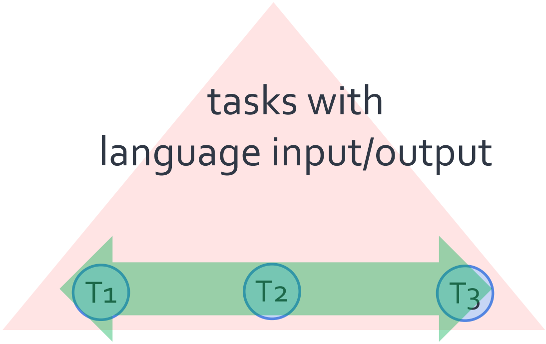


human readable definitions;
fully define the task

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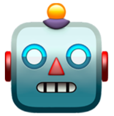
**Grammar Check**

**Summary Generation**

***Input text***



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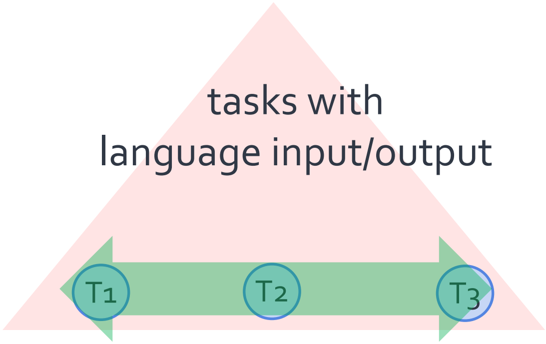


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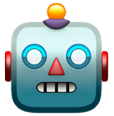

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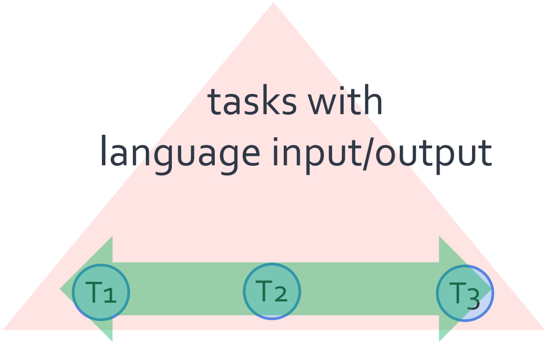


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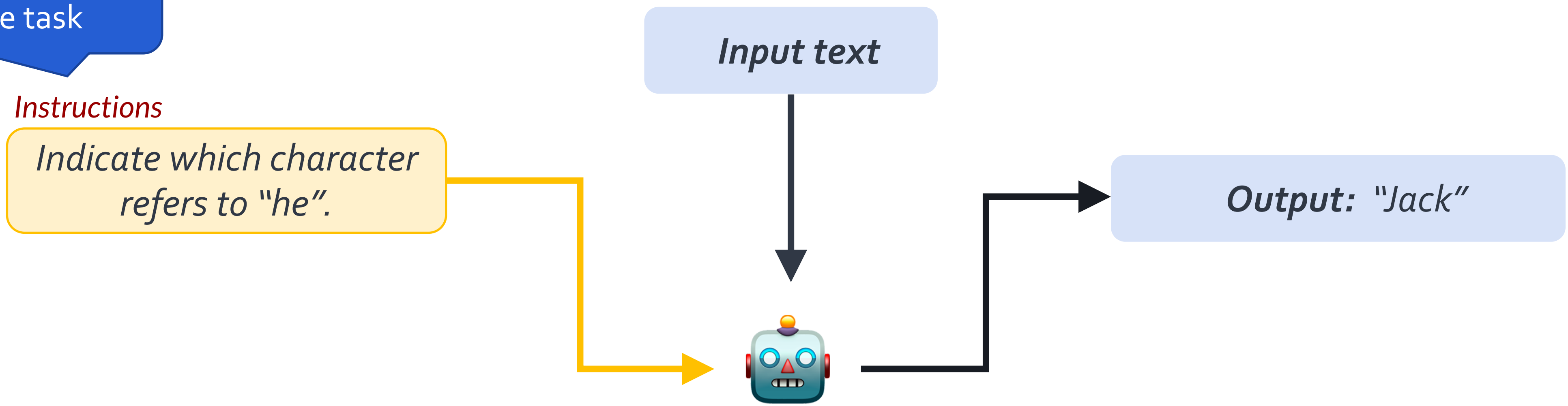


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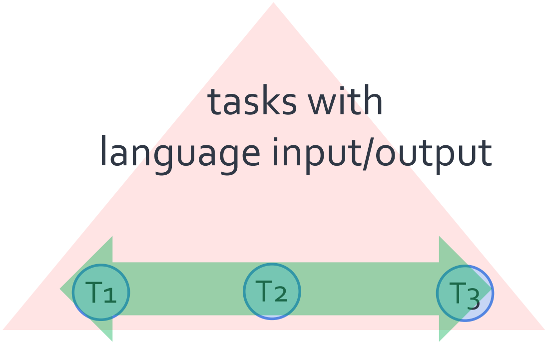


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**Grammar Check**

*Instructions*

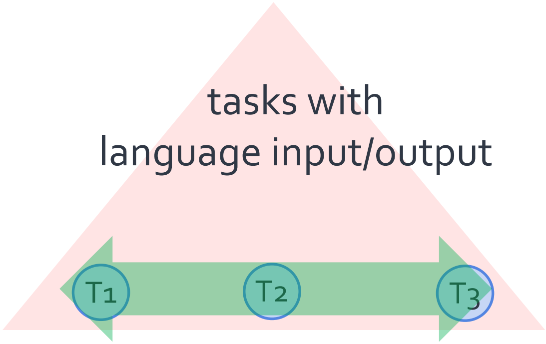
*Indicate if the following sentence is grammatical.*

**Summary Generation**

***Input text***

***Output:** "Jack"*

# Beyond Task-Specific Models




human readable definitions; fully define the task

Input text

**Pronoun Resolution**

*Instructions*

*Indicate which character refers to "he".*

*Output: "Jack"*

**Grammar Check**

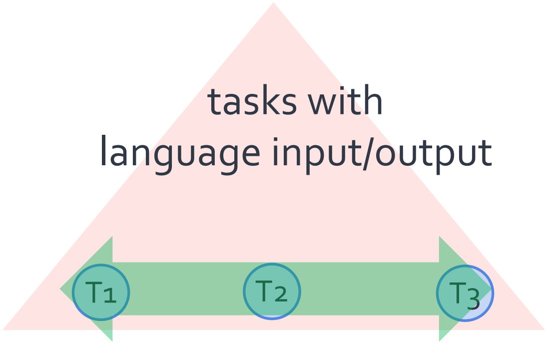
*Instructions*

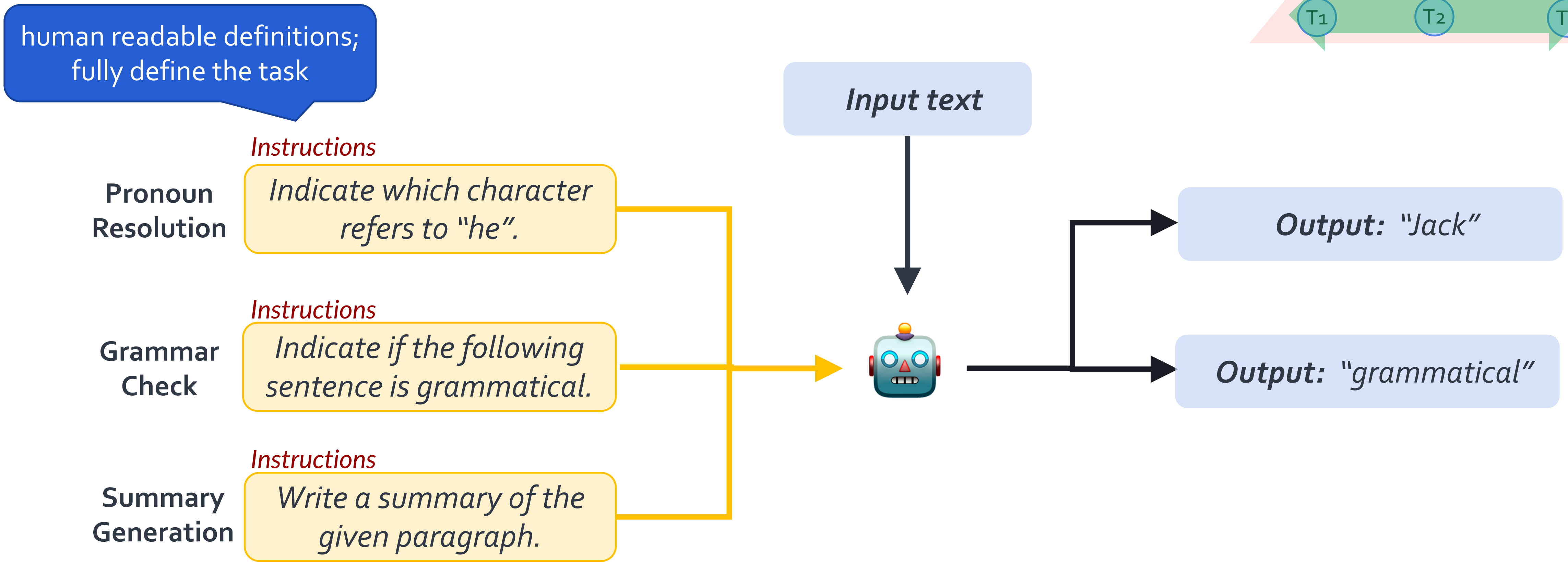
*Indicate if the following sentence is grammatical.*

*Output: "grammatical"*

**Summary Generation**

# Beyond Task-Specific Models



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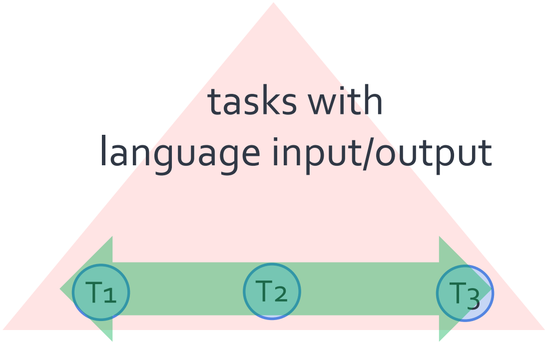
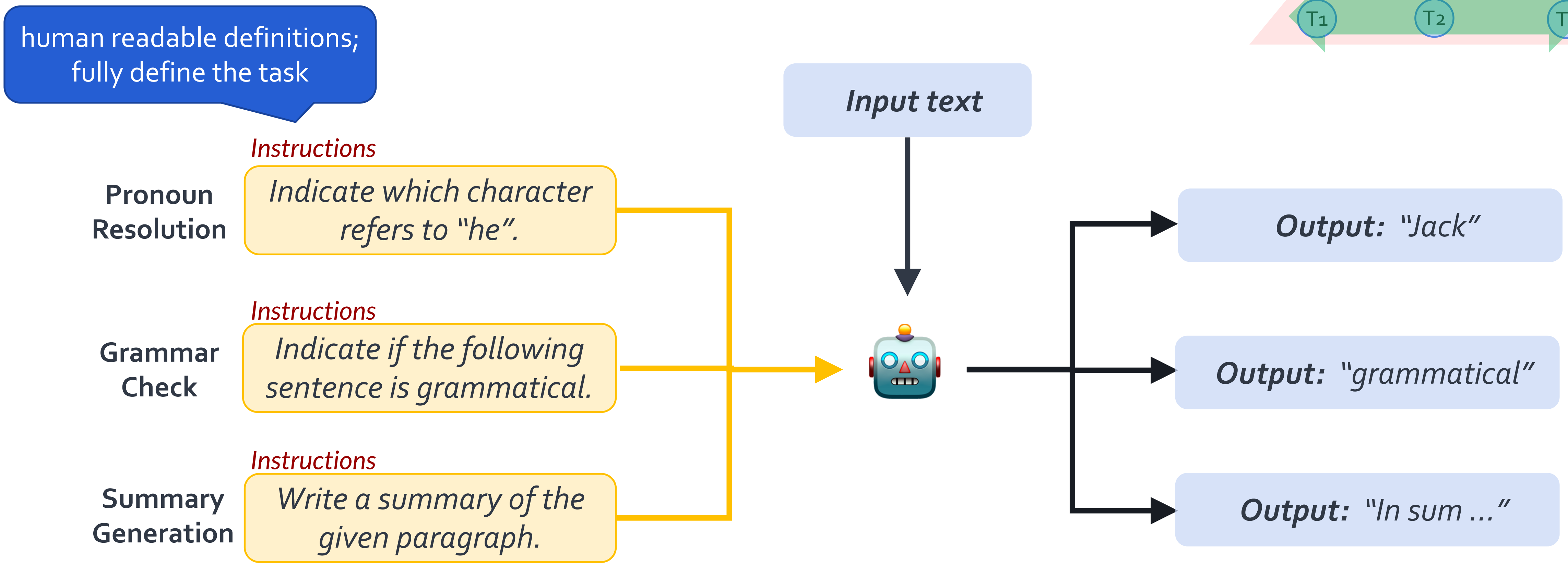
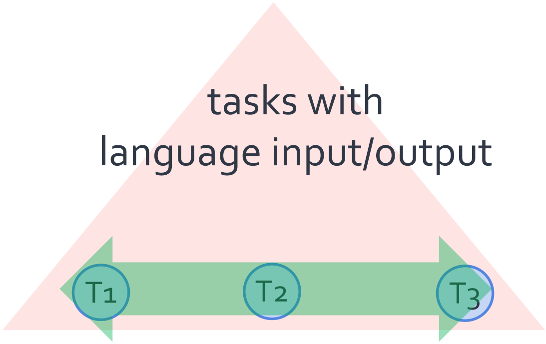
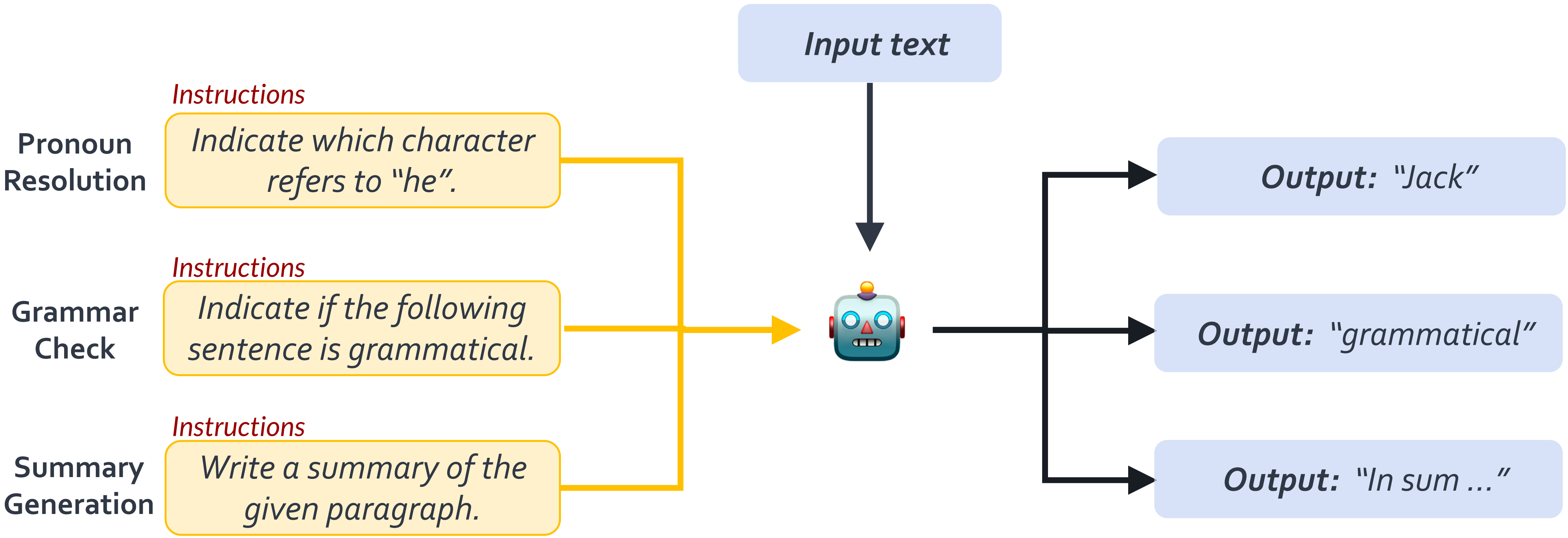


# Cross-Task Generalization



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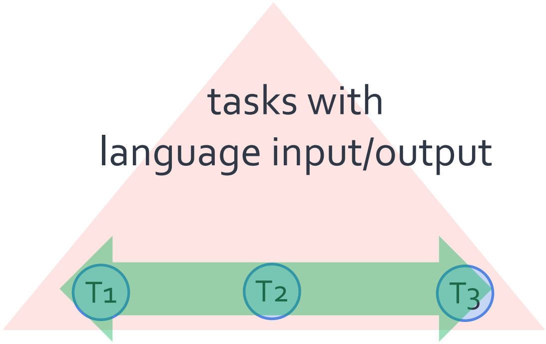


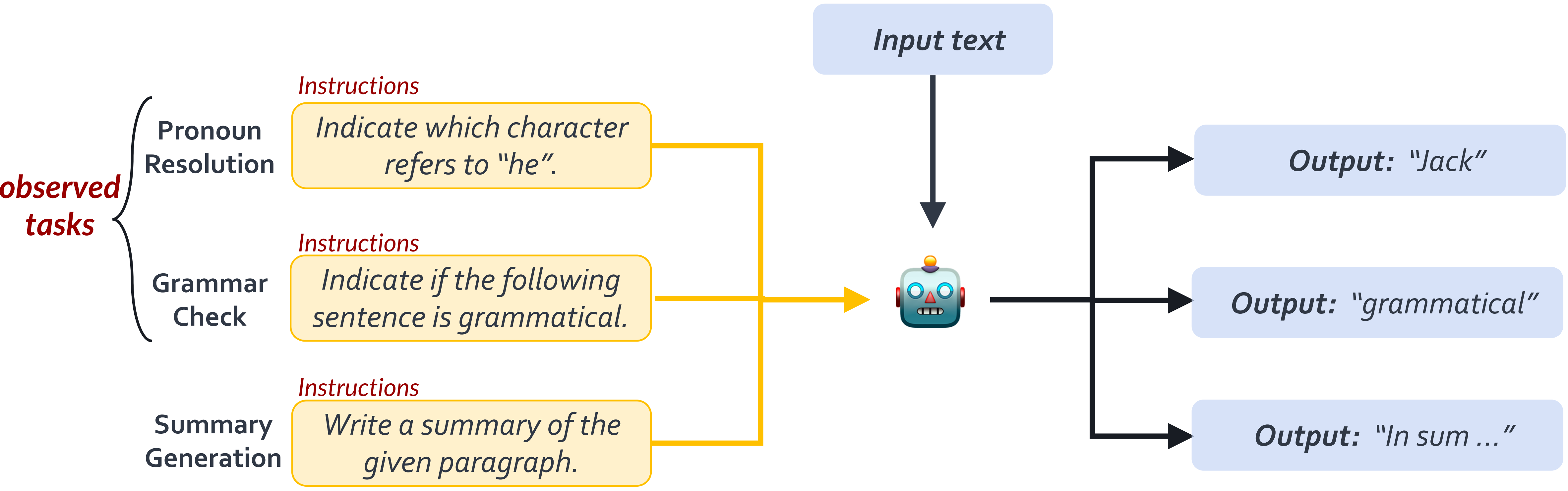

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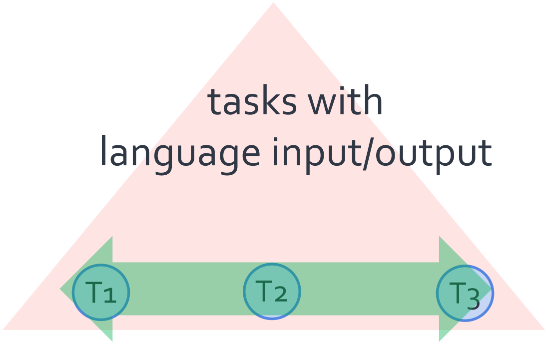


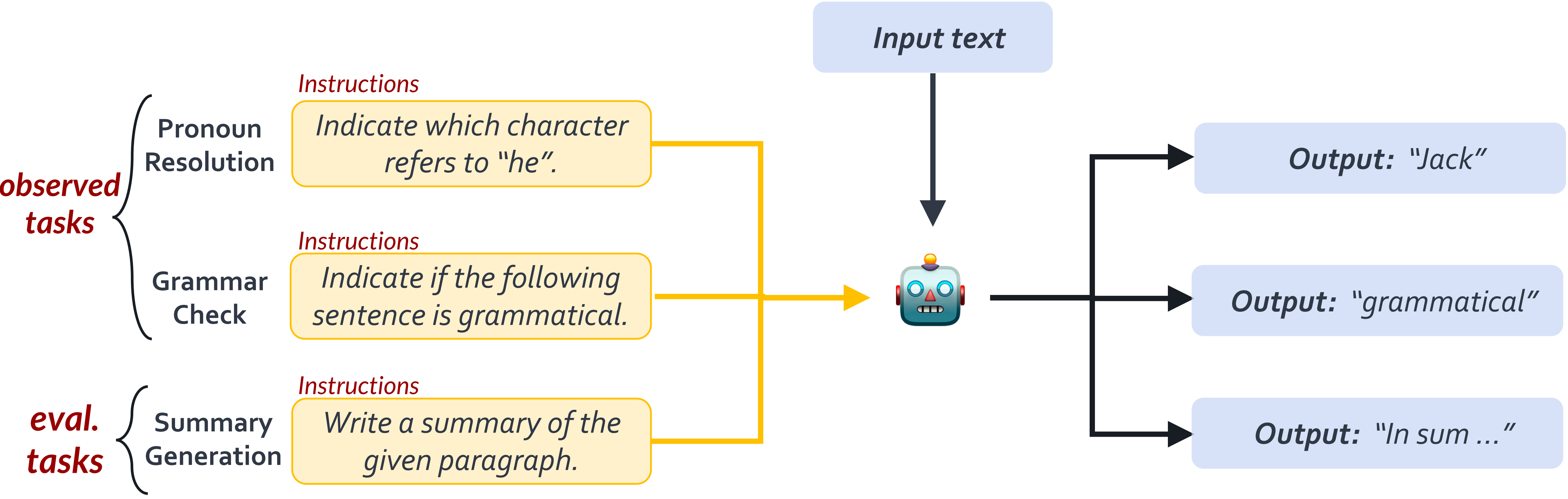

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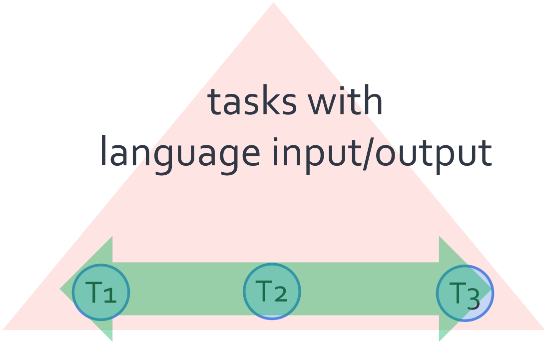


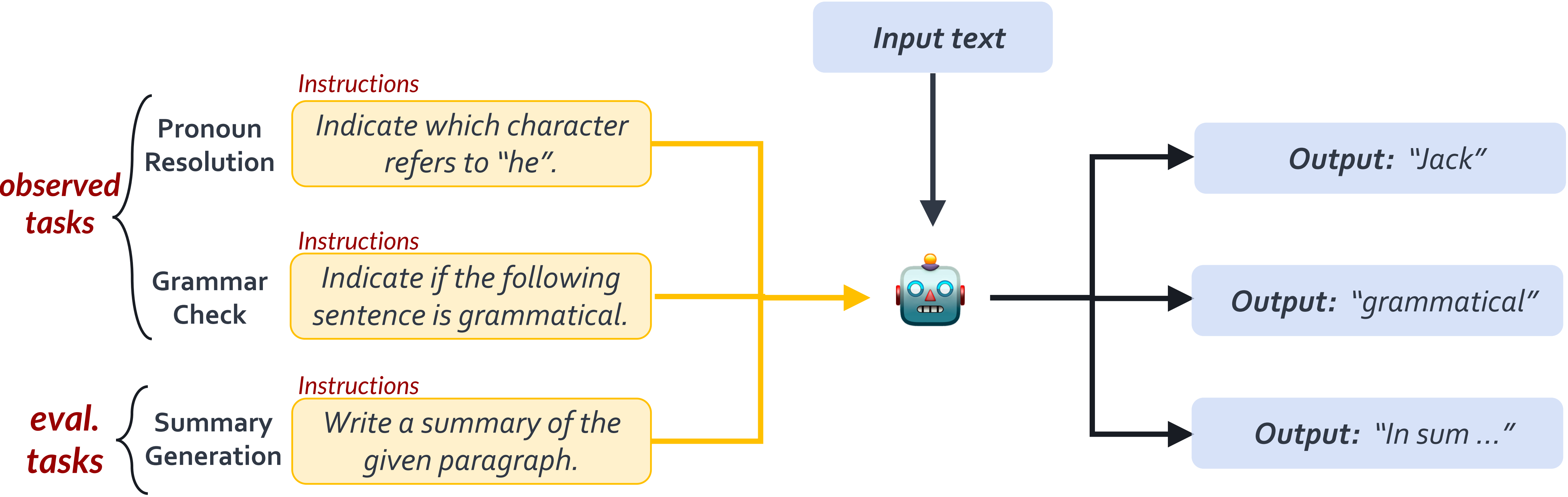


Done on "Natural Instructions" — a meta-dataset of tasks and their language instructions.

https://instructions.apps.allenai.org/

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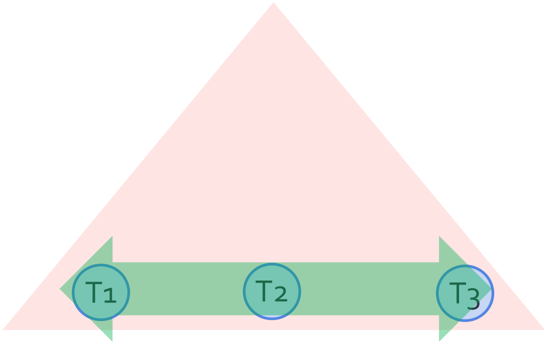


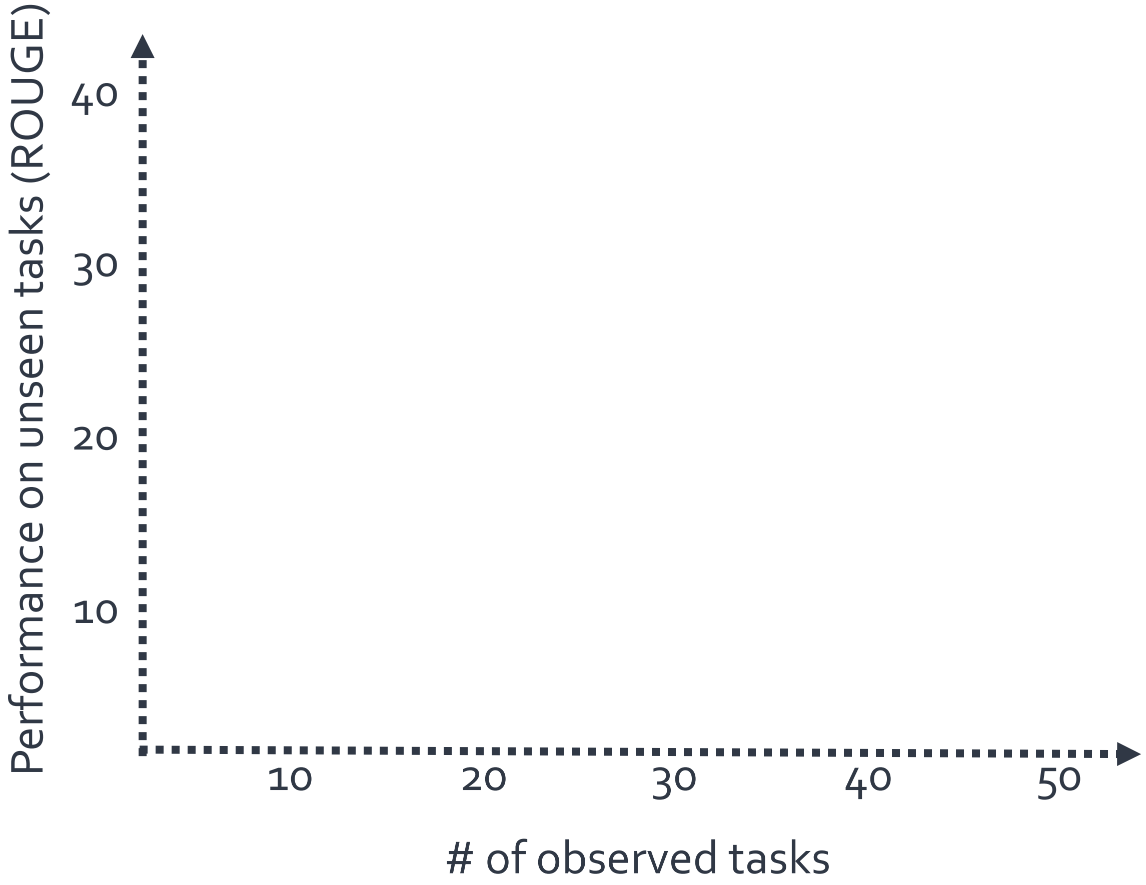


“Cross-Task Generalization via Natural Language Crowdsourcing Instructions.” Mishra, **Khashabi**, Baral, Hajishirzi, ACL’22

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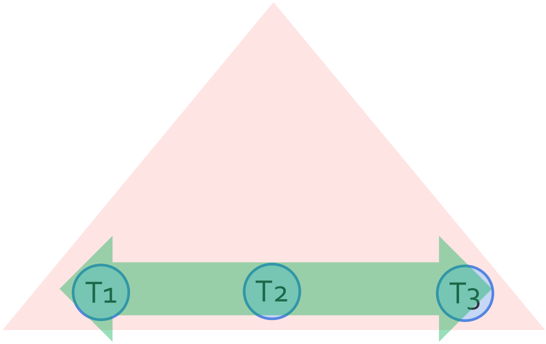


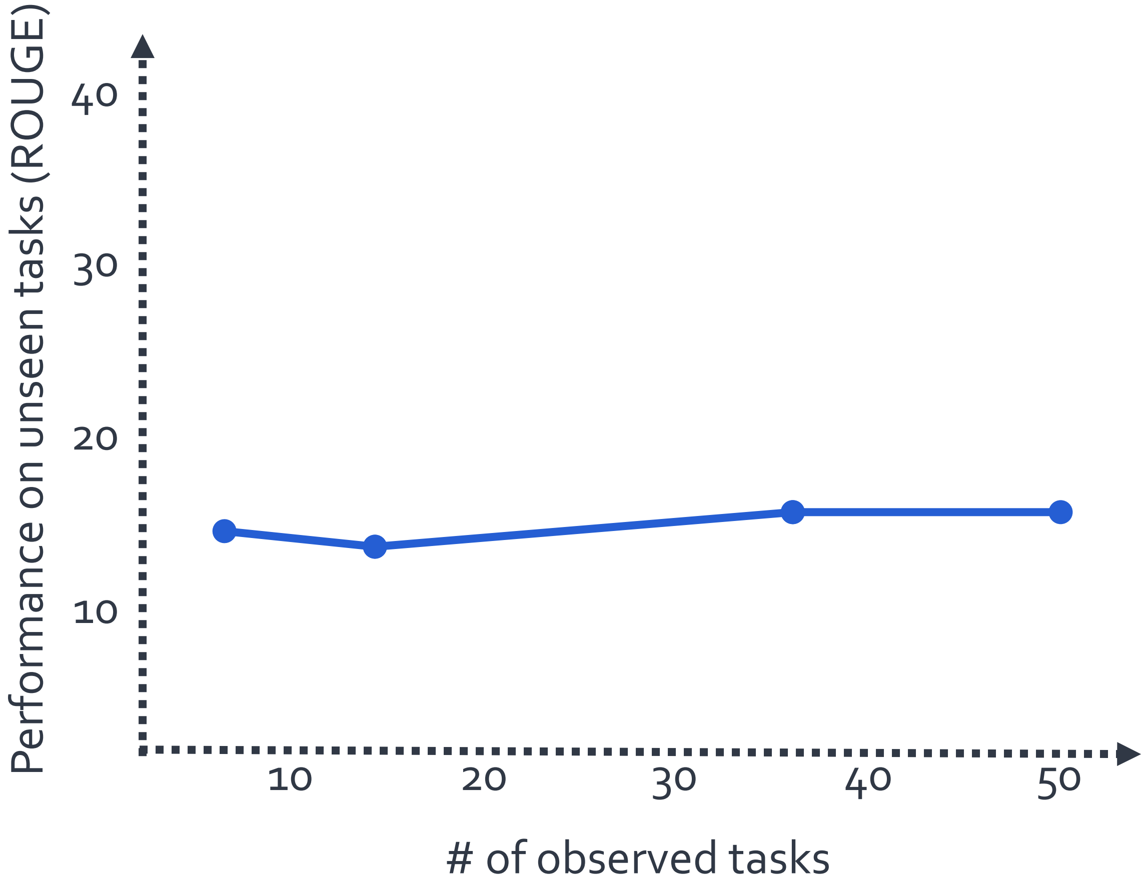


**without** Instructions

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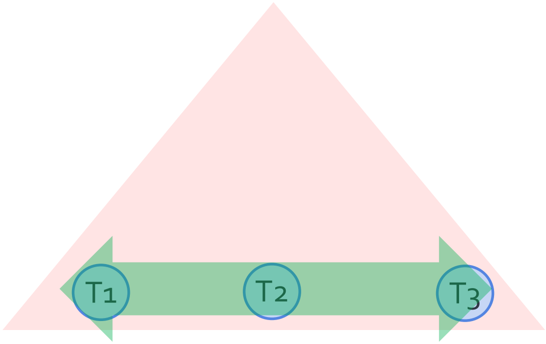


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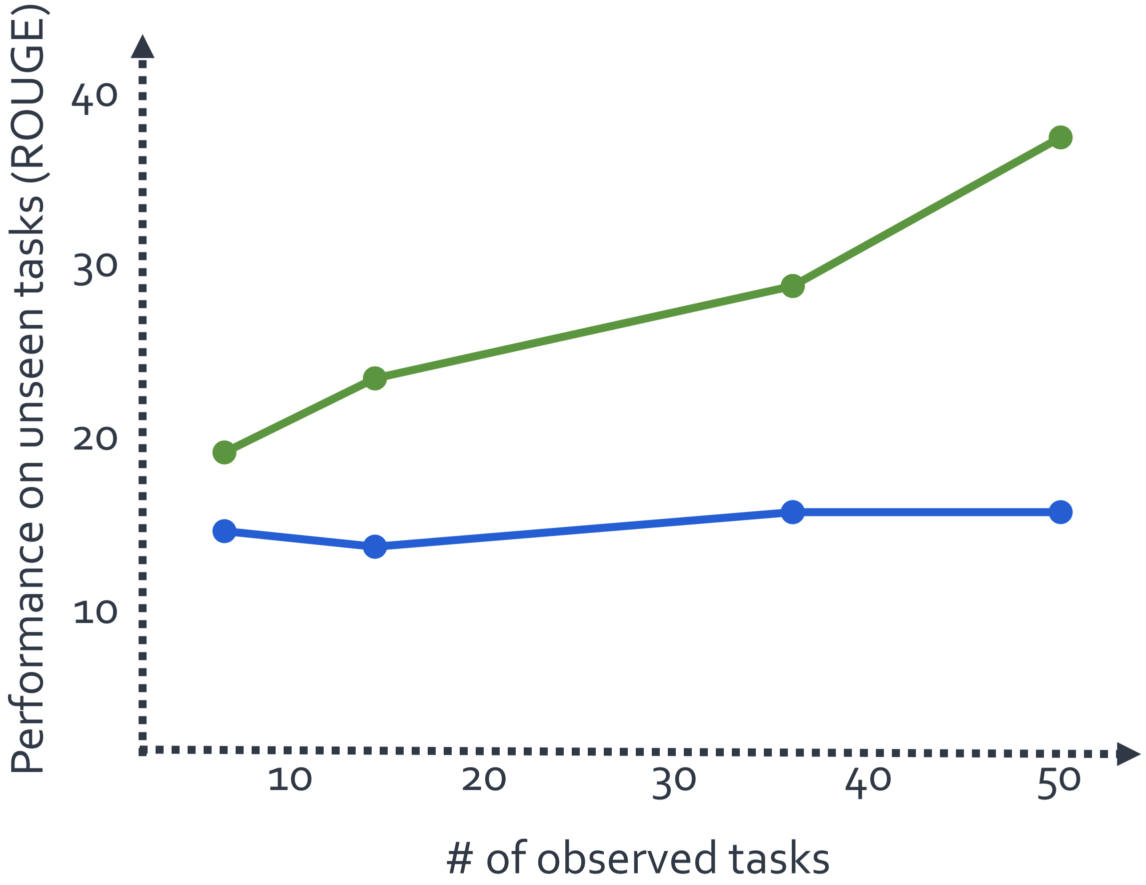
  - **improves** with **more** observed tasks
  - when using **instructions**!

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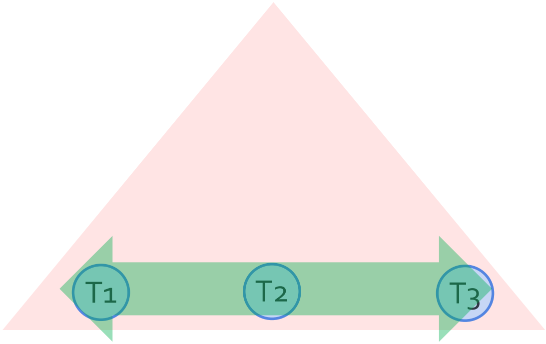


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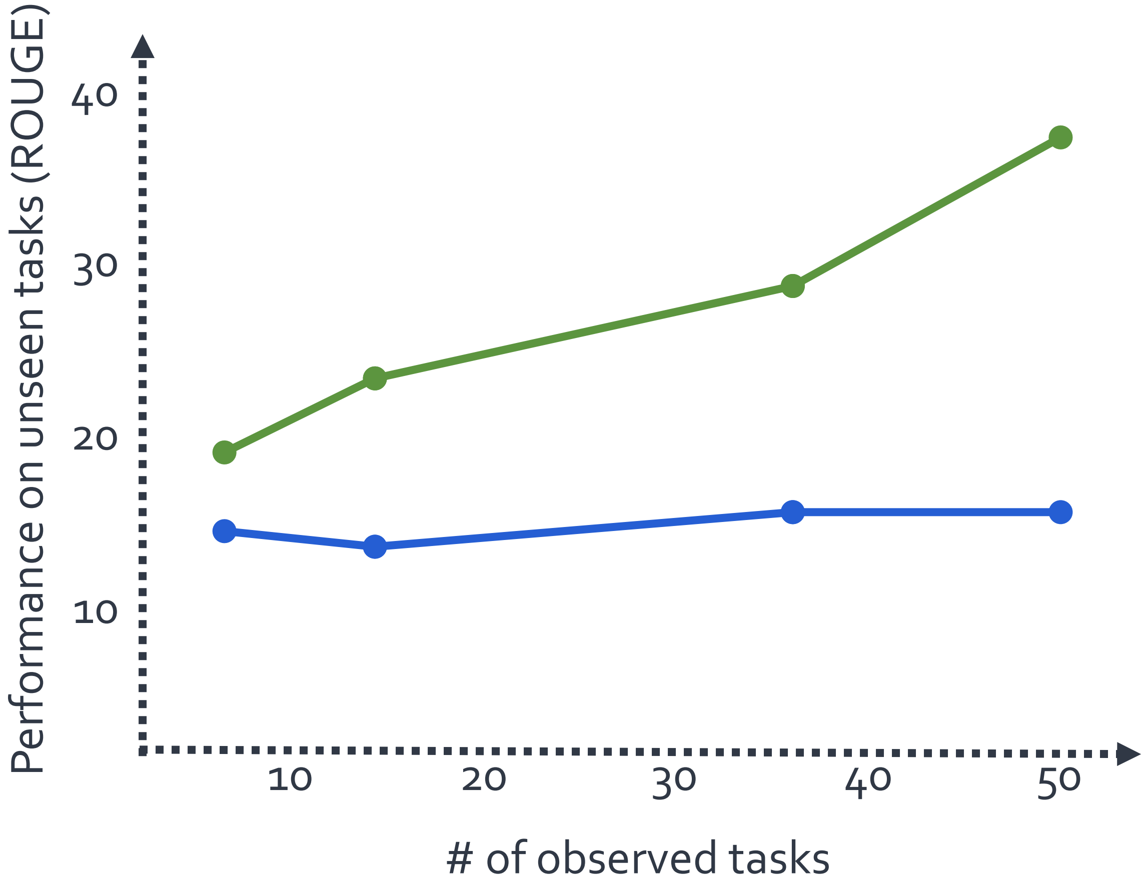
✅ **Hypothesis:** Task "instructions" are enough to induce sharedness among them.

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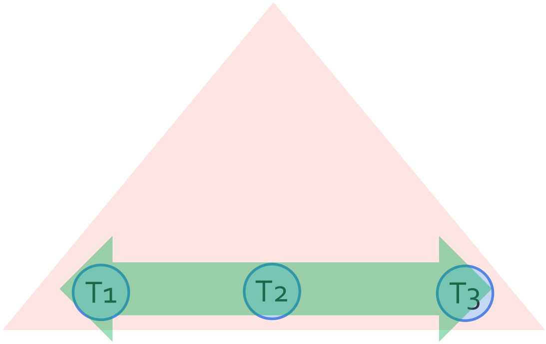


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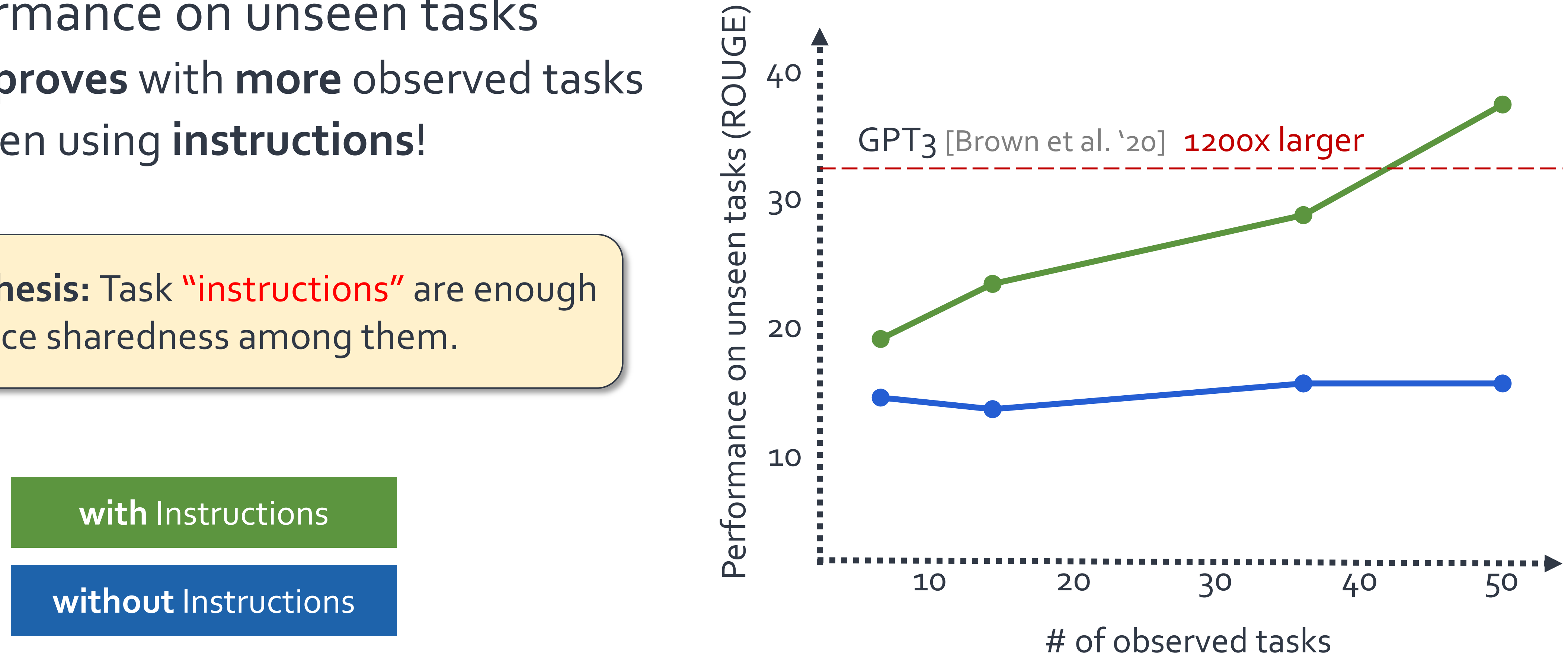


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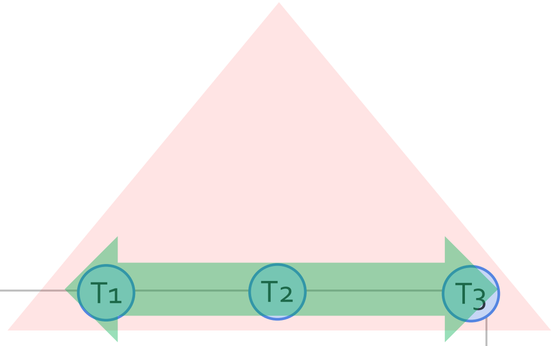
# Summary




- **Motivating Question:** Can we build a single model that generalizes to unseen tasks?
- Generalization to unseen tasks improves when utilizing instructions.
- Toward systems w/ better "alignment" with human asks. [Christian '20]
- **Open questions:**
  - When does this generalization work? When does it not?

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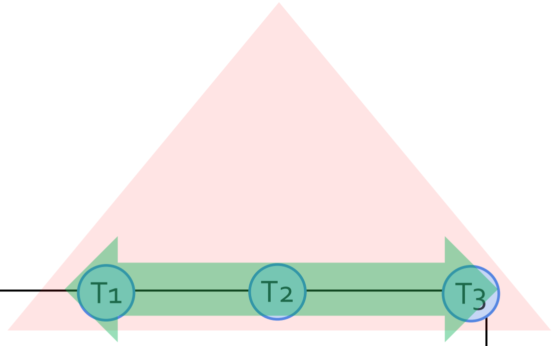


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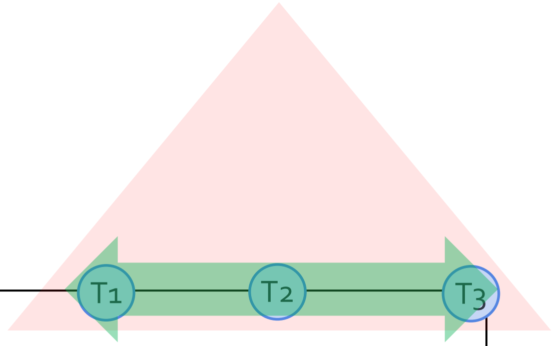


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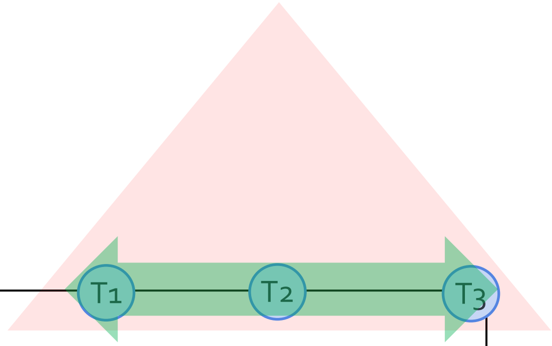


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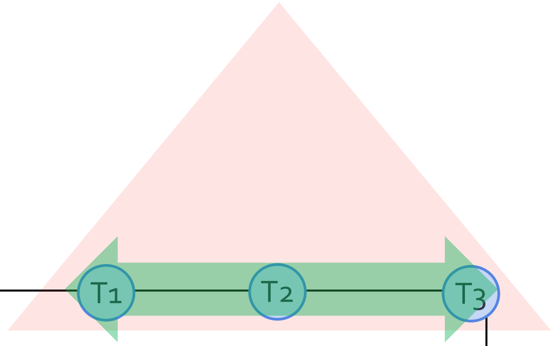


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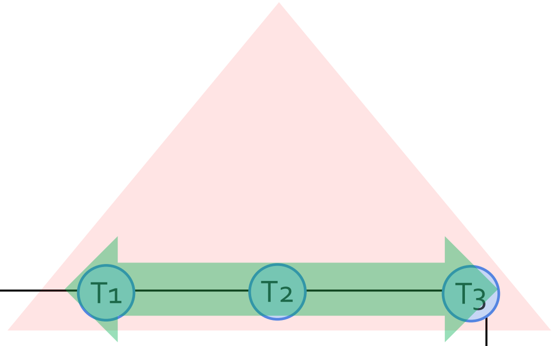


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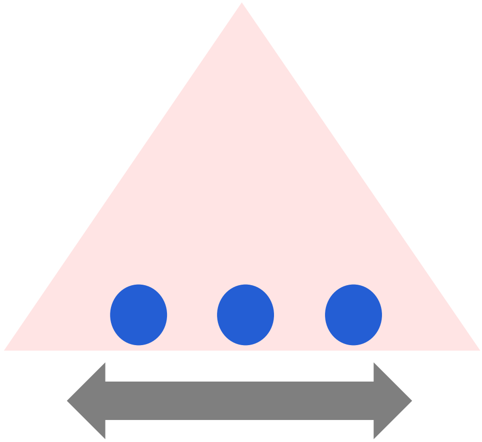
# Talk Outline

Generality in “breadth” — tackling a *variety* of tasks

Generality in “depth” — tackling more *complex* tasks

*Future work:* Toward broad, interactive reasoning








UnifiedQA
*EMNLP Findings ’20*

Natural Instructions
*ACL ‘22*

ModularQA
*NAACL ’21*

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UnifiedQA *EMNLP Findings '20*

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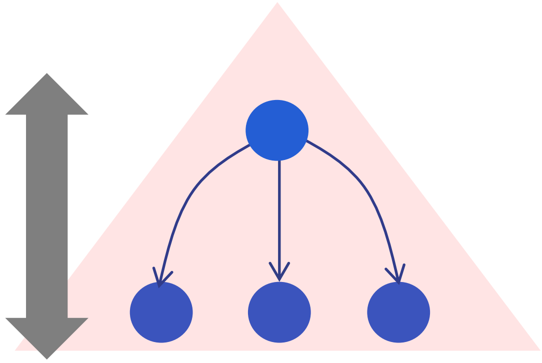
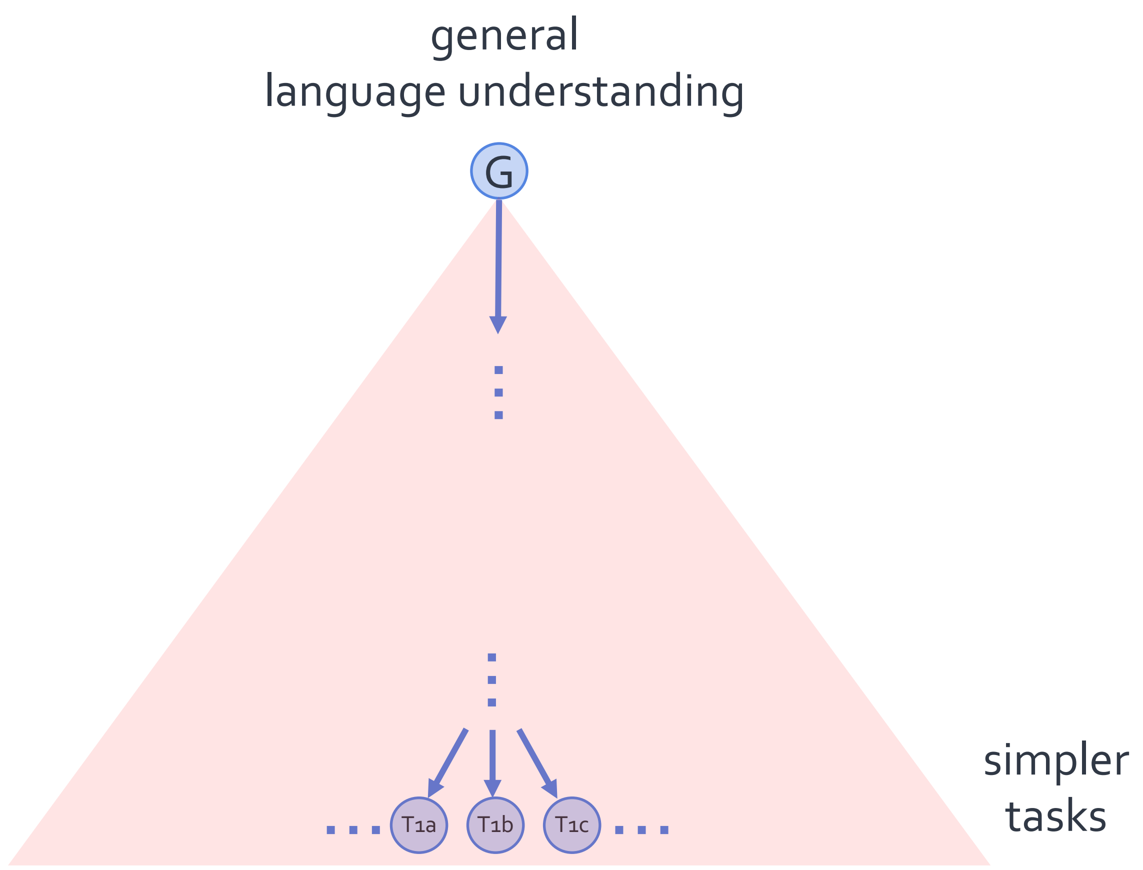


ModularQA *NAACL '21*


general
language understanding
G
T1a
T1b
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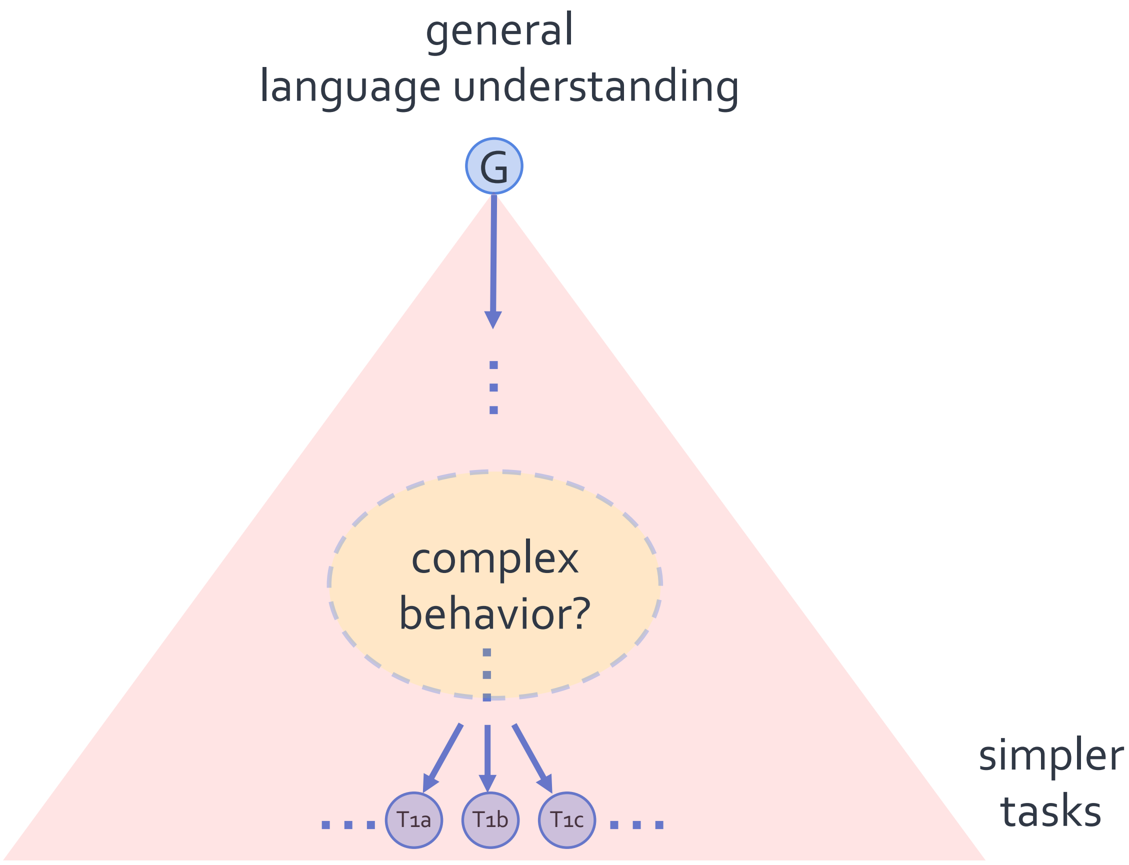
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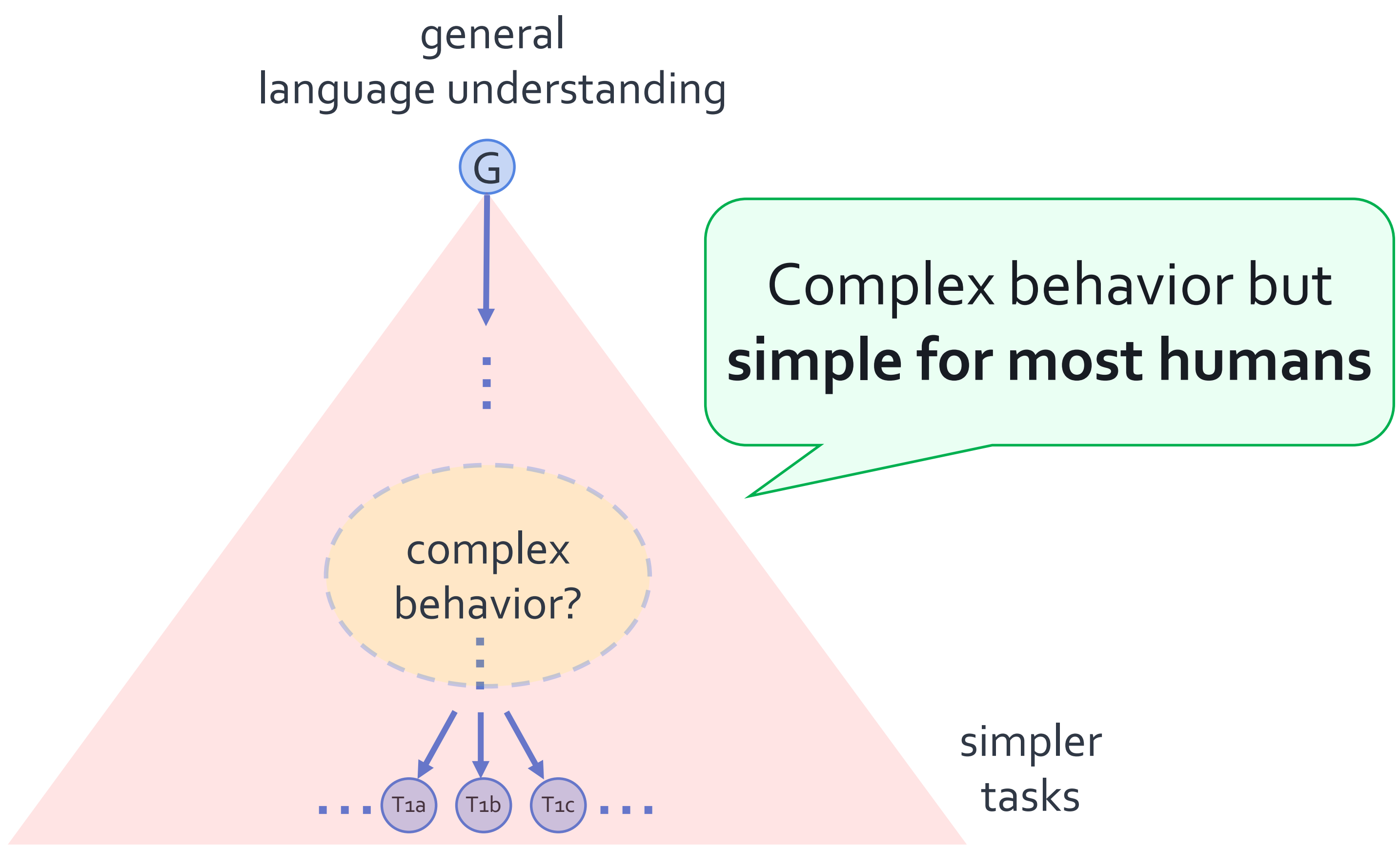
general
language understanding
G
complex
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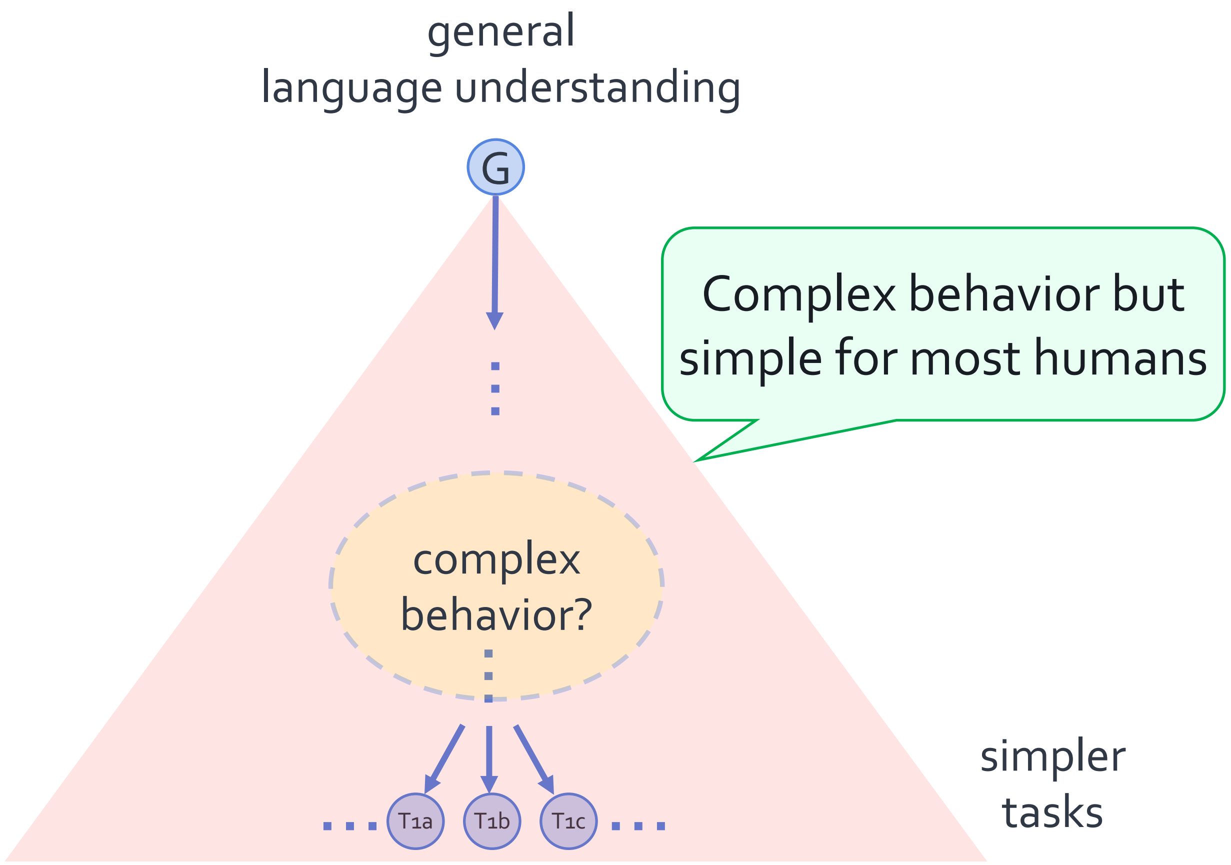
T1a
T1b
T1c
simpler
tasks
Complex behavior but
**simple for most humans**

- **Interactivity** — can lead to complex phenomena, through simple steps.



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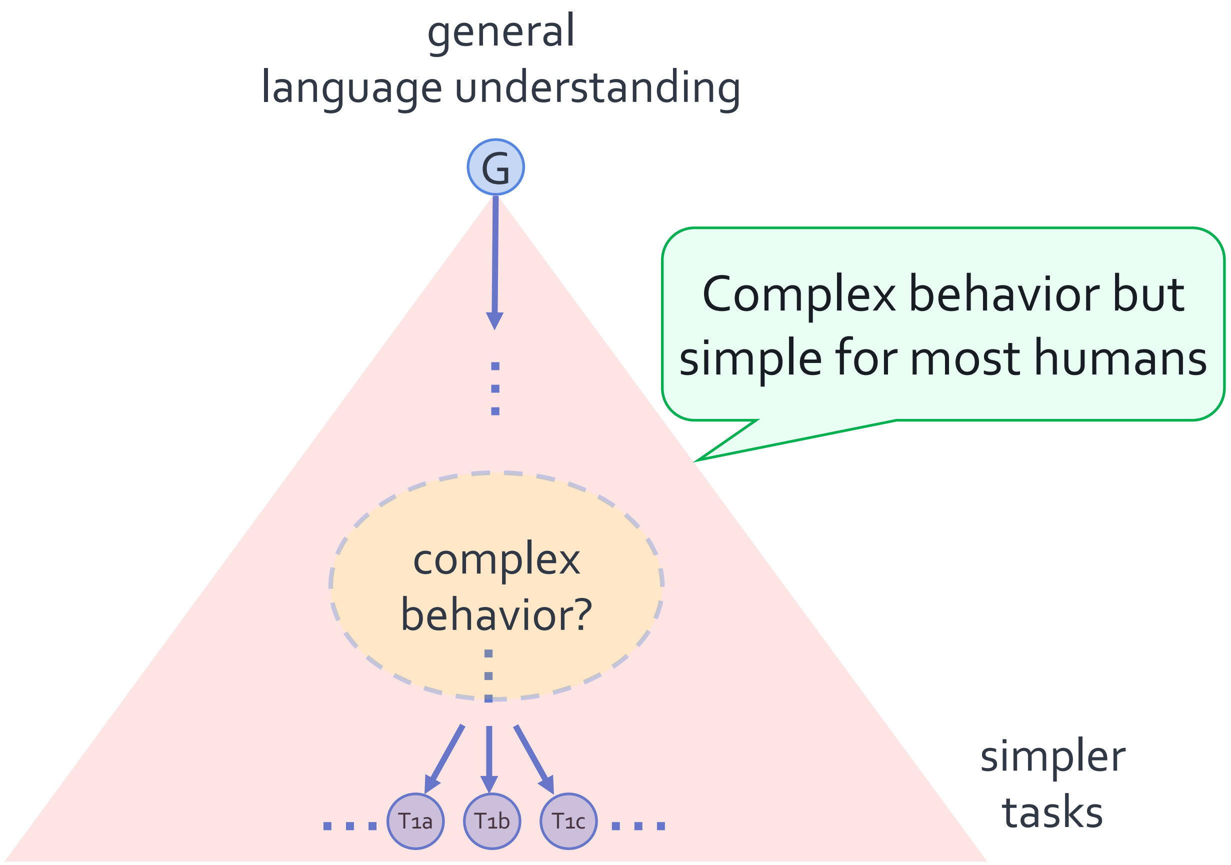

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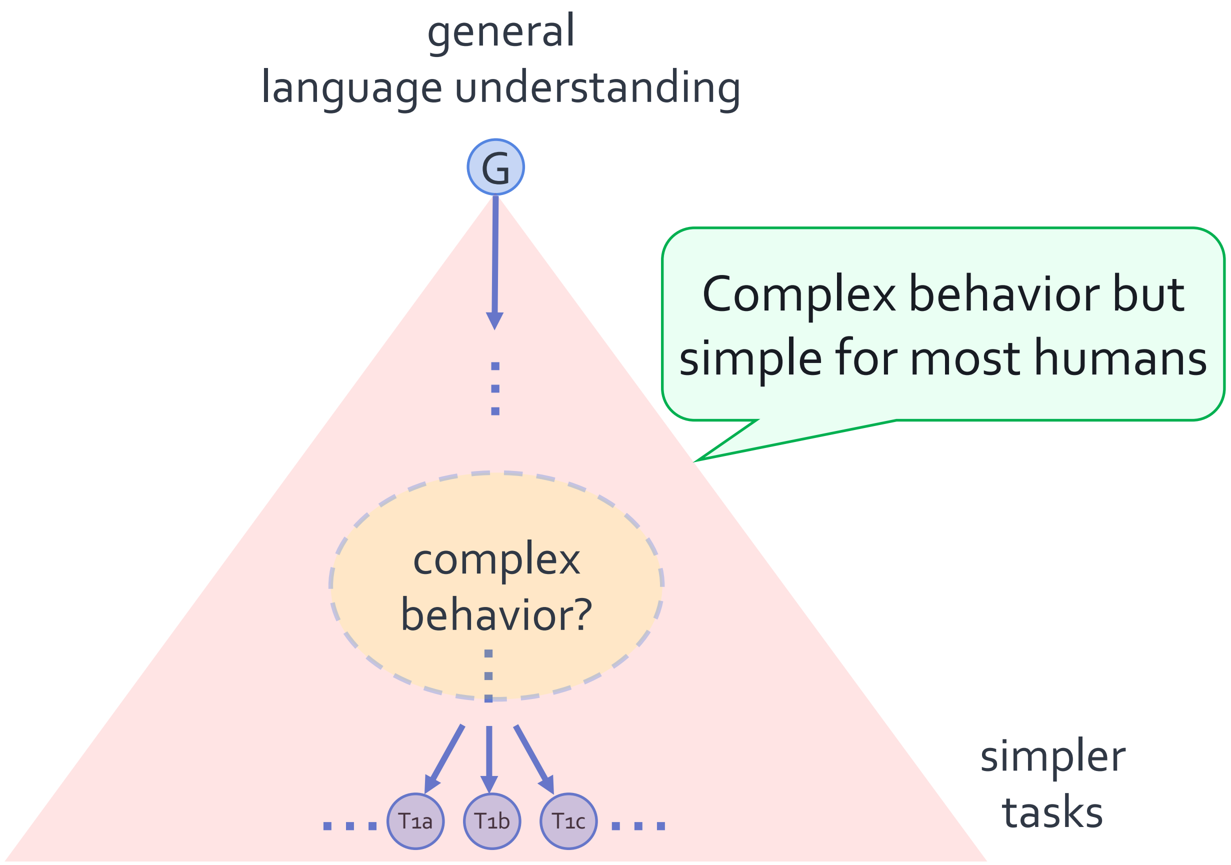

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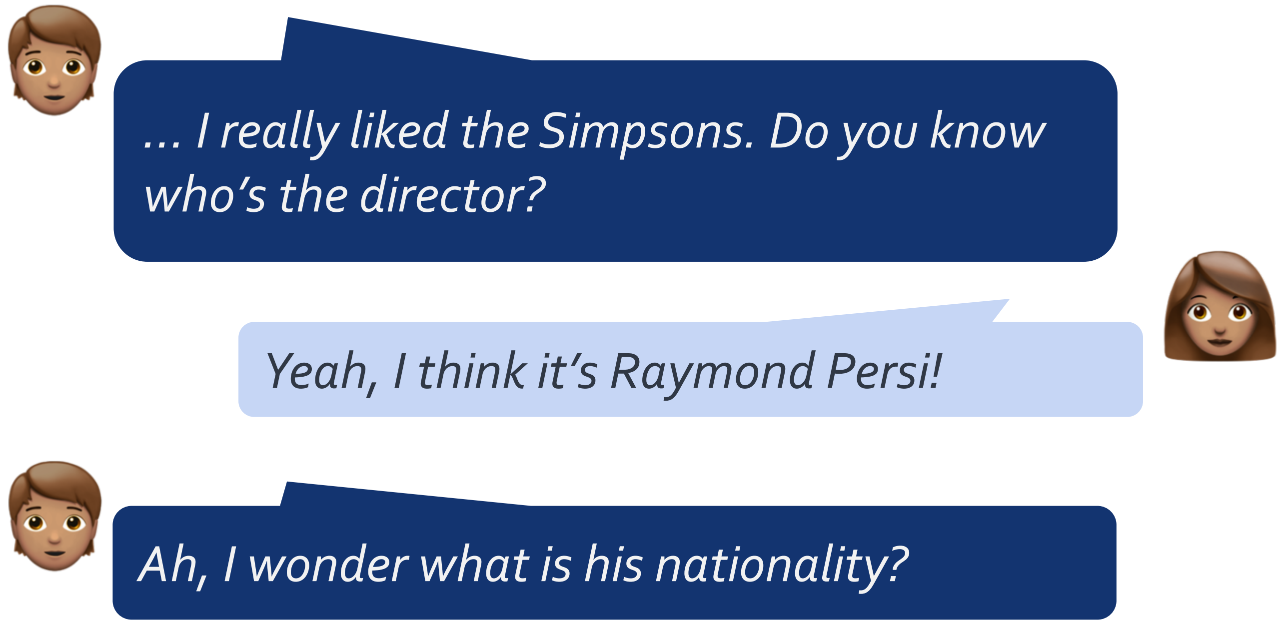


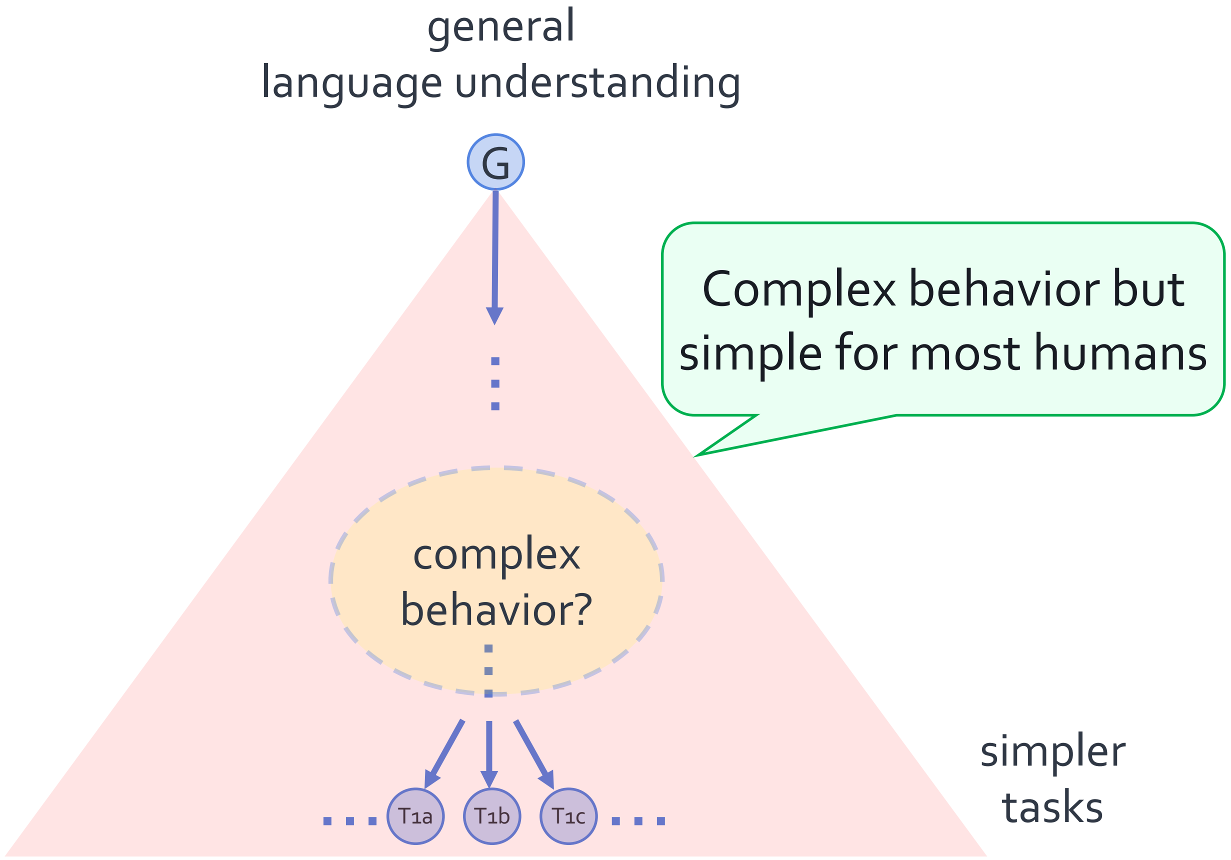

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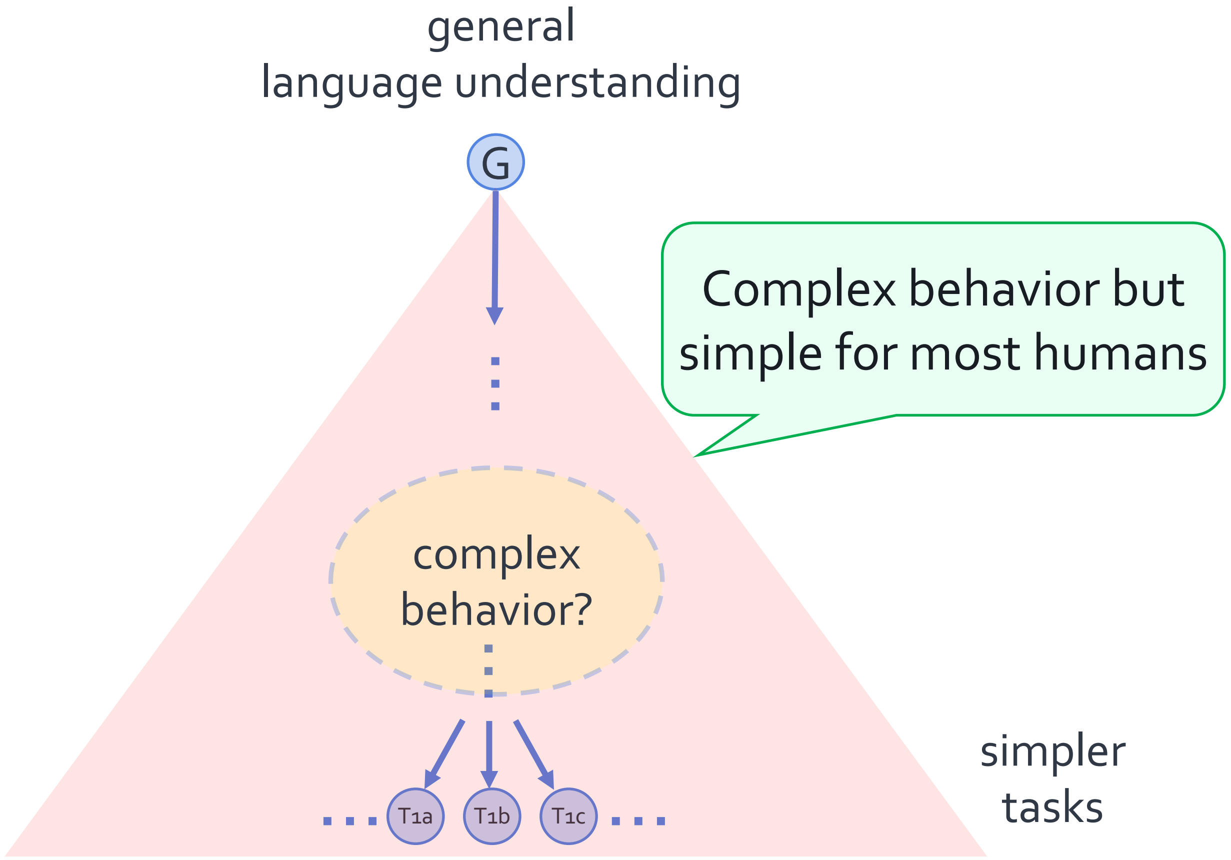

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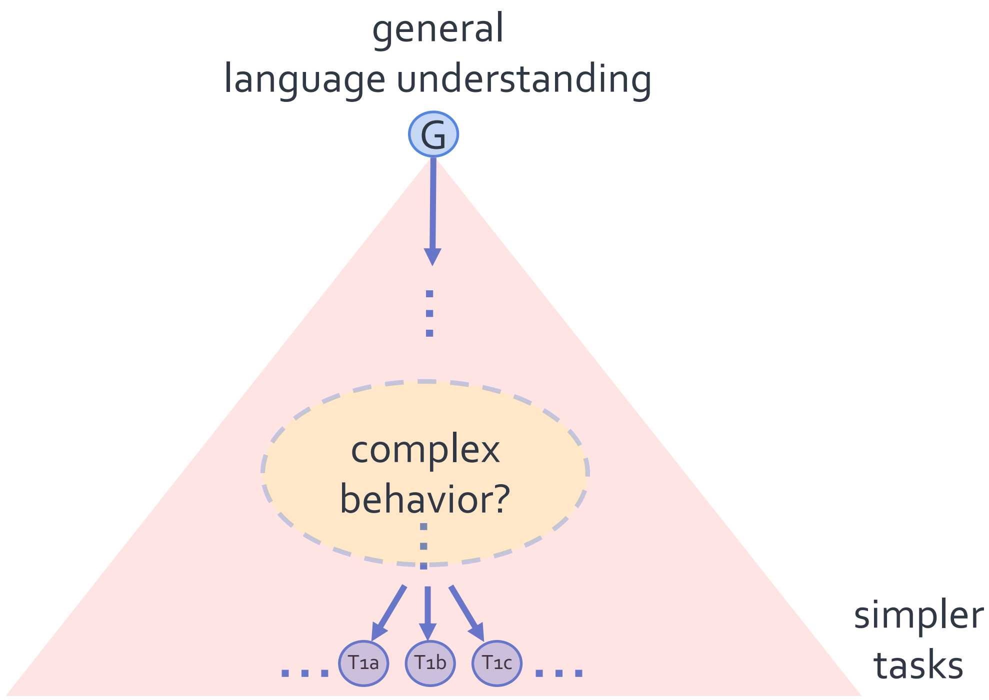

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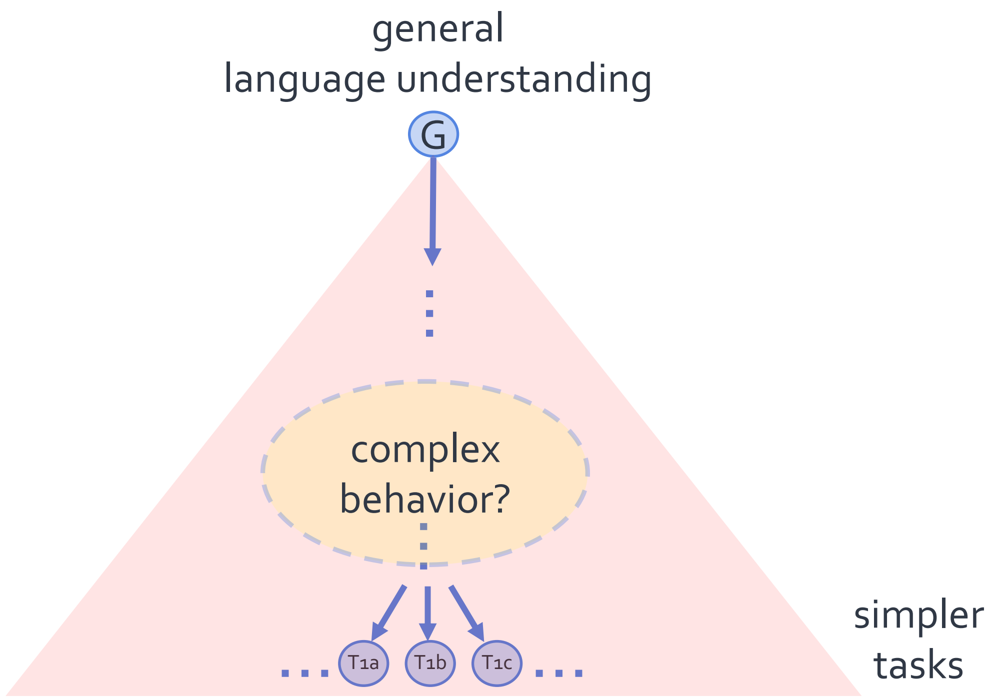


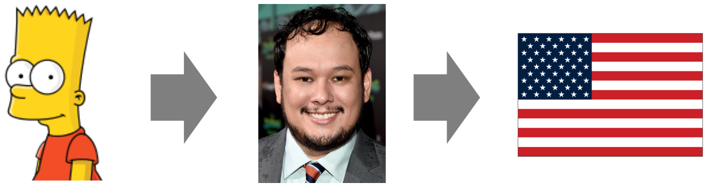

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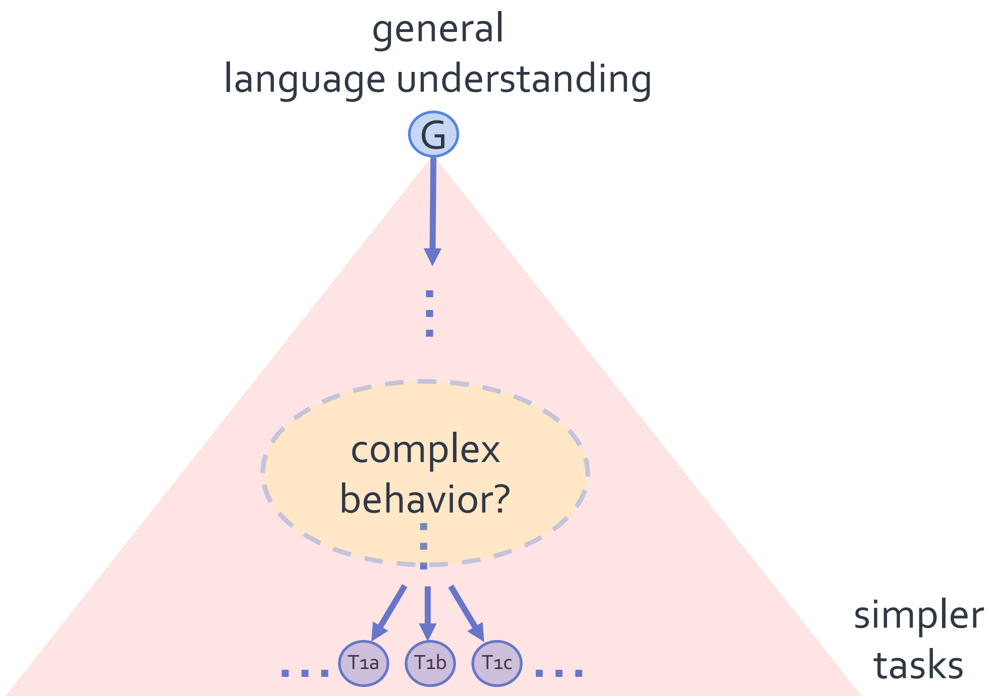


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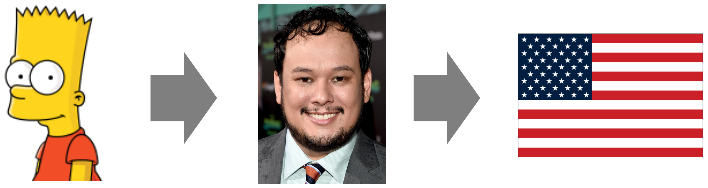
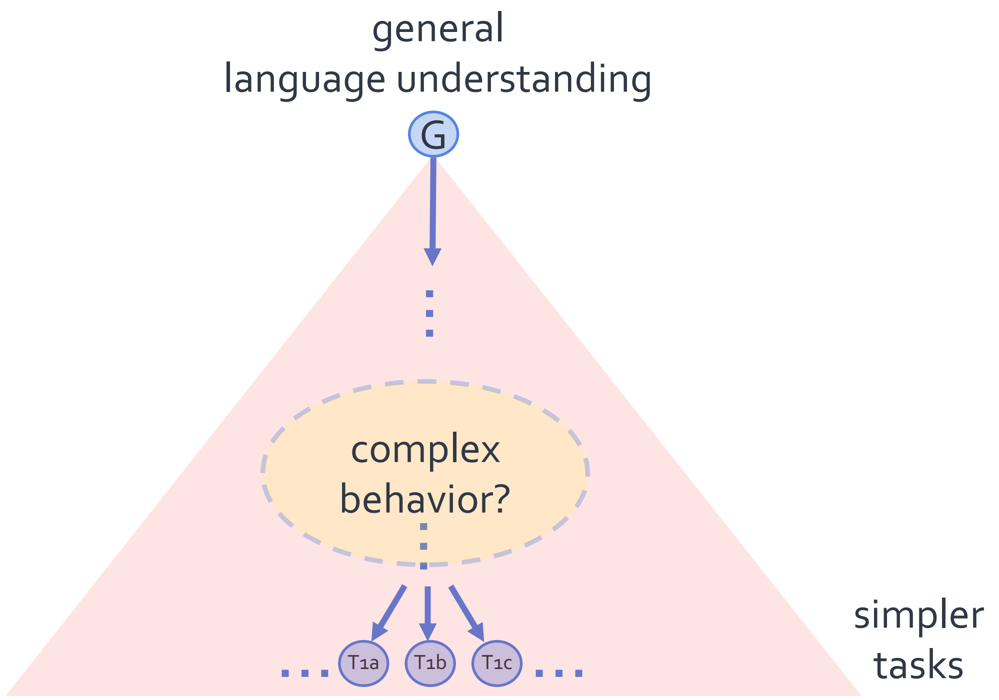
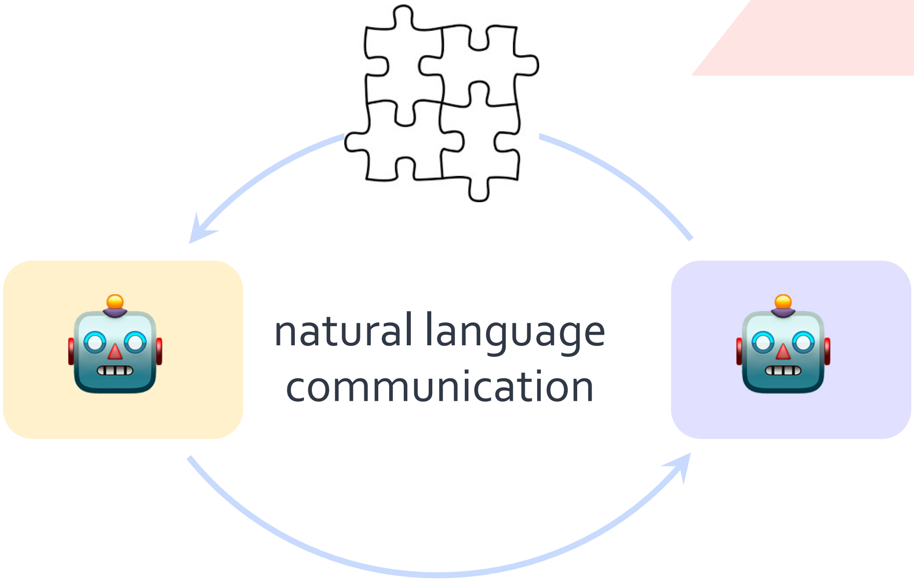


*complex question*

*"What is the nationality of the Simpsons director?"*

- **Interactivity** — can lead to complex phenomena, through simple steps.
- **Setup:**
    - Communications between models
    - Goal oriented



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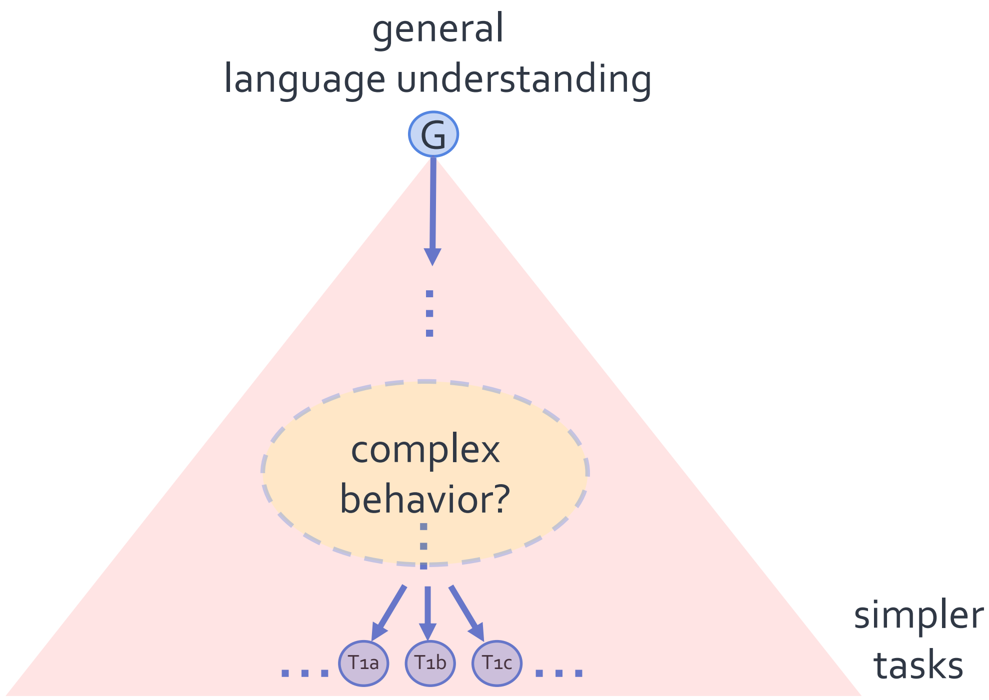

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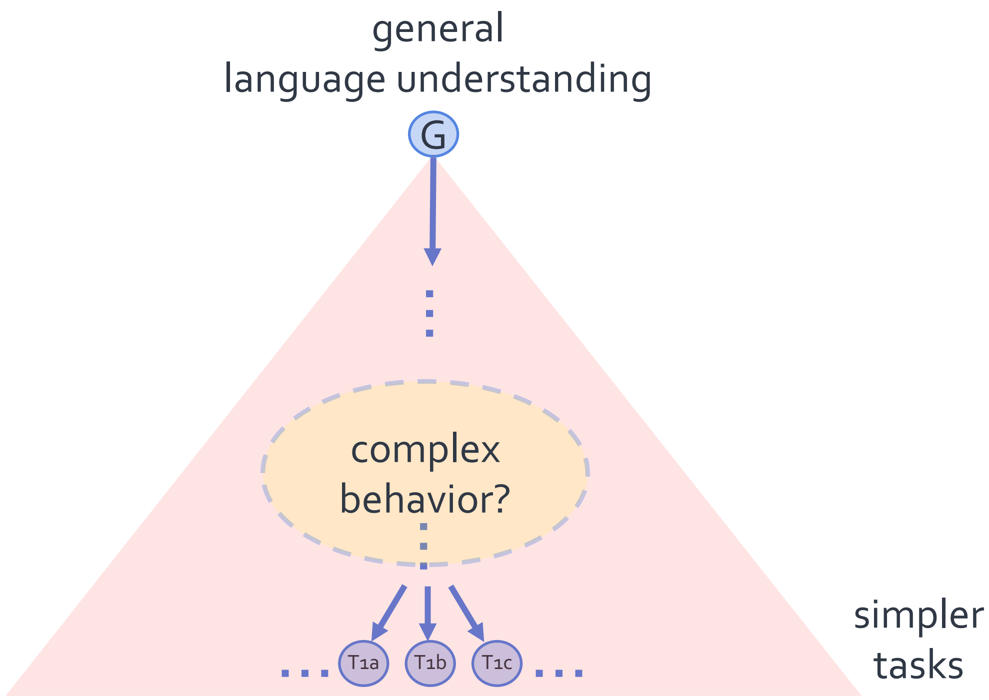
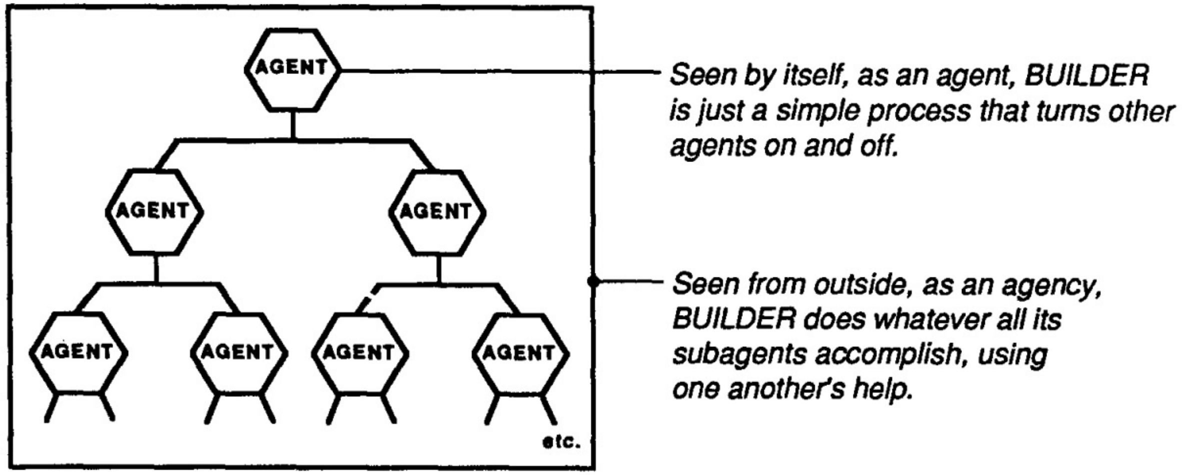
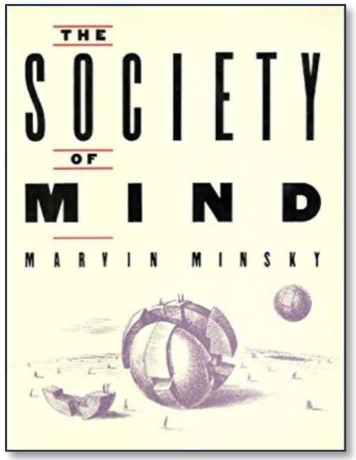



*"human intelligence … built up from the interactions of simple parts called agents"*

[Minsky, '70s]

# Text Modular Networks

Interactive communication
for solving complex questions

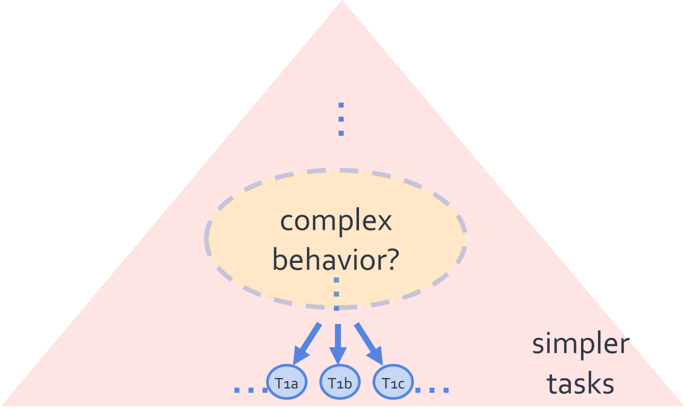
Tushar Khot , **Daniel Khashabi**, Kyle Richardson
Peter Clark and Ashish Sabharwal

*NAACL 2021*





# Complex Problem Solving As Communication

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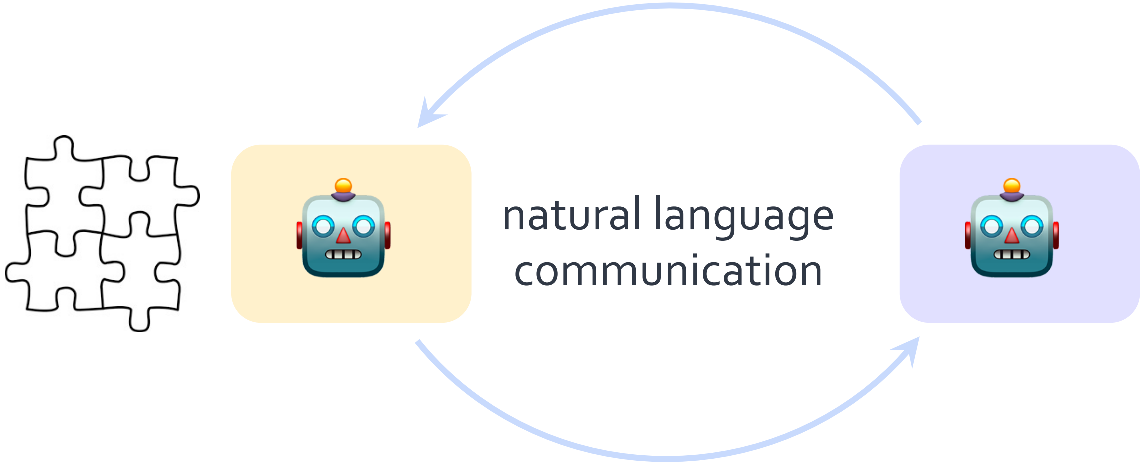

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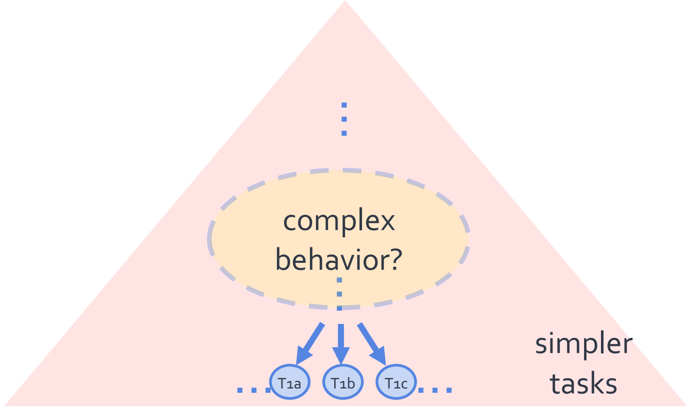
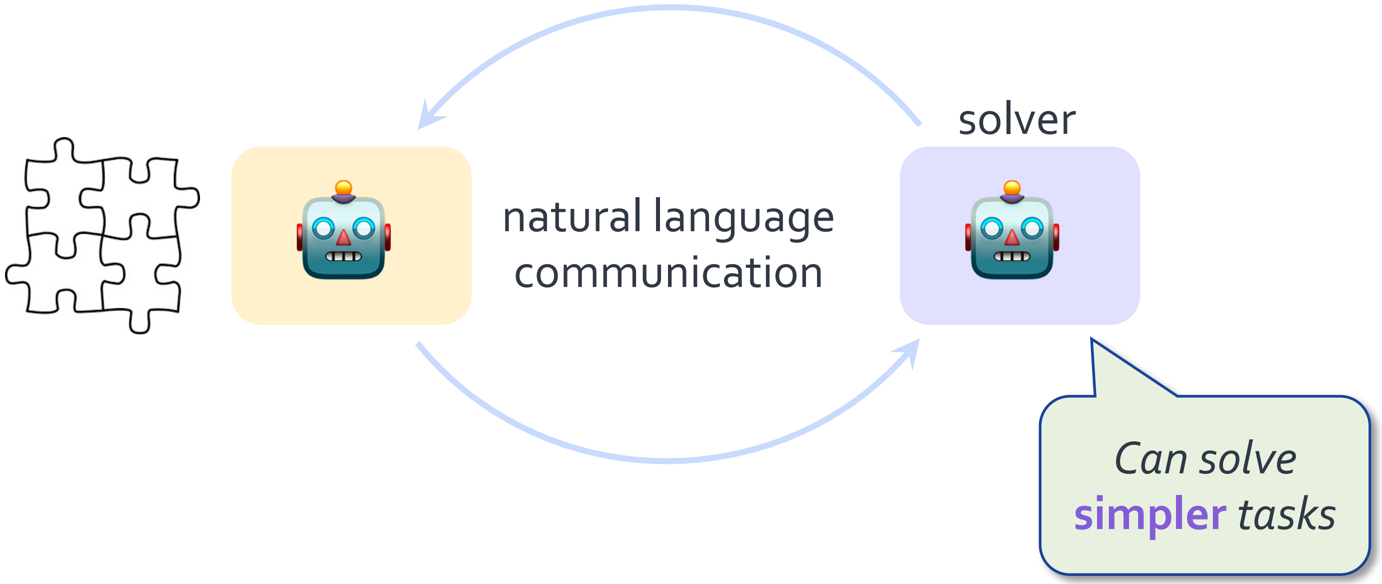



- **Setup:**
  - Communications between models
  - Goal oriented
  - Roles: solver and …



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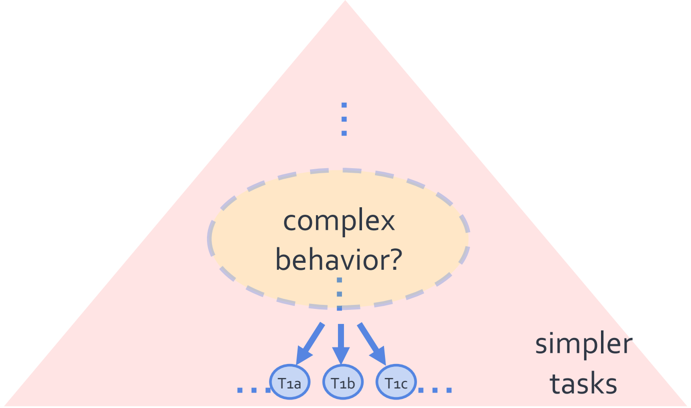


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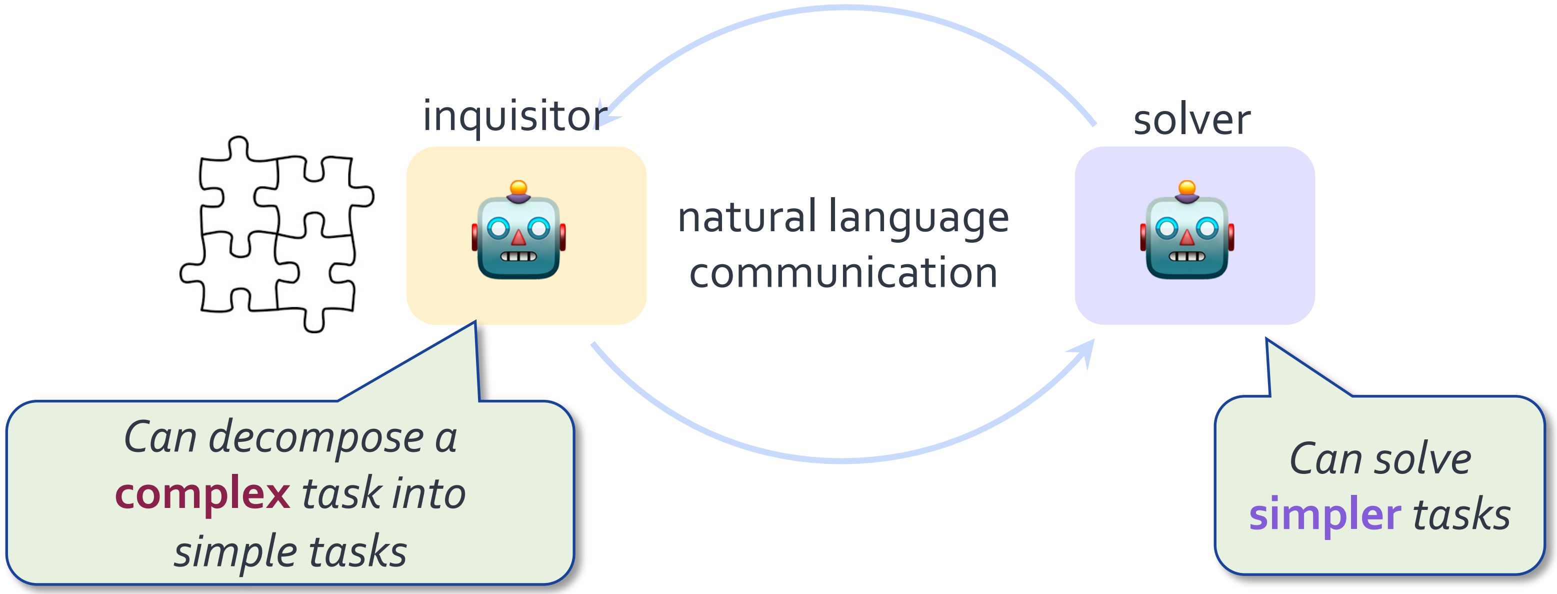
  - Roles: solver and inquisitor



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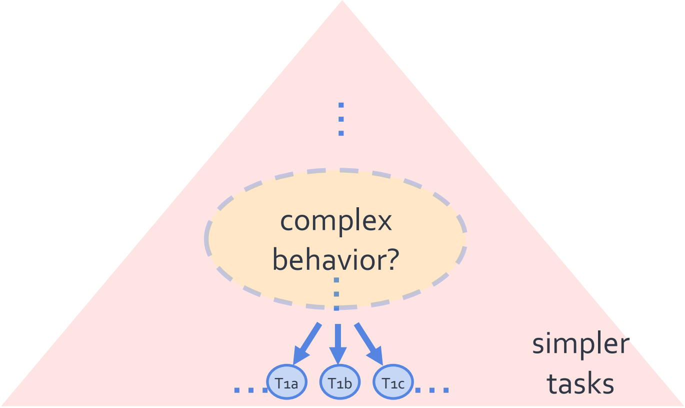
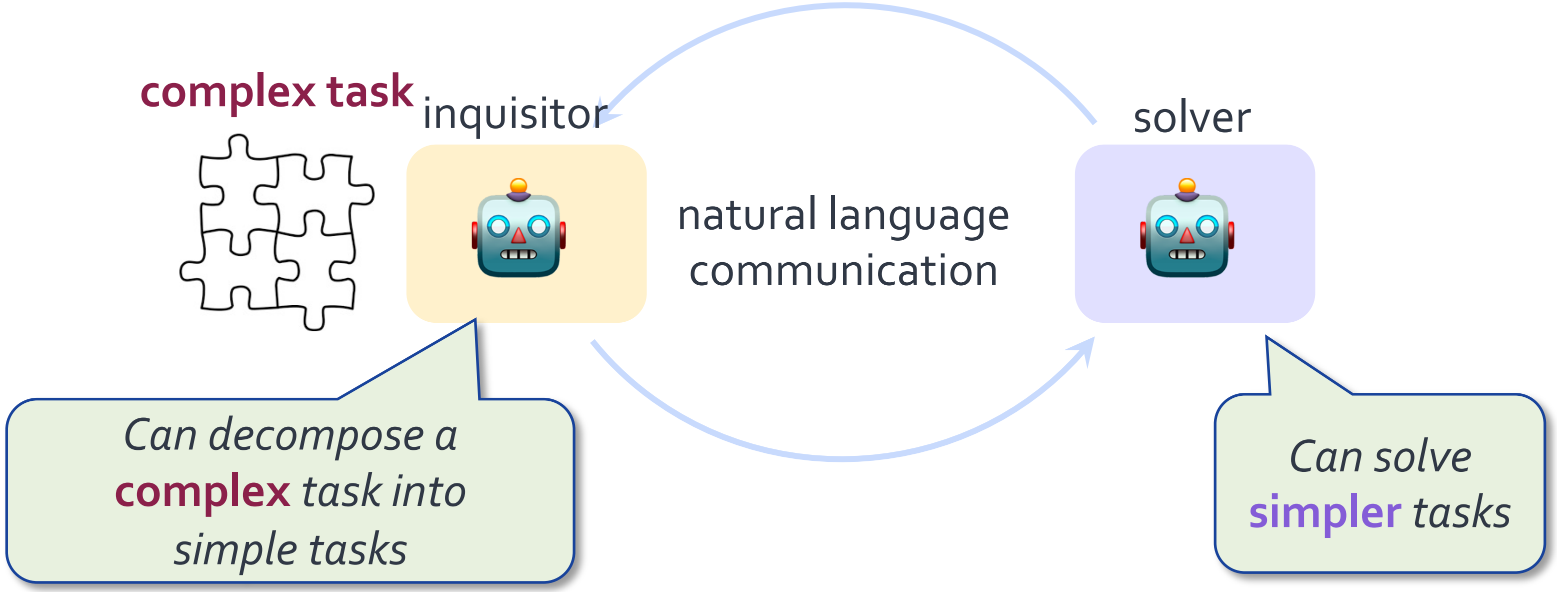



- **Setup:**
  - Communications between models
  - Goal oriented
  - Roles: solver and inquisitor



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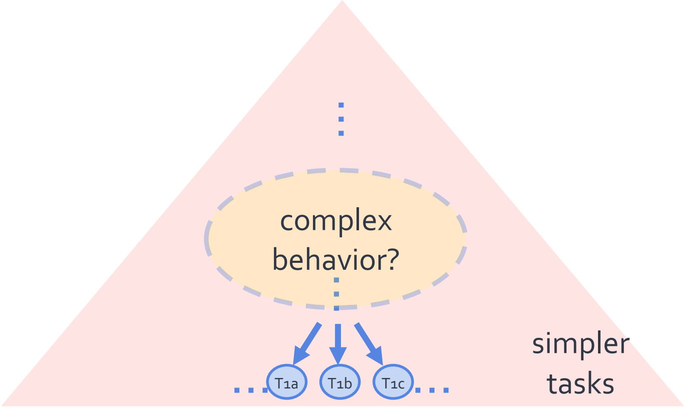


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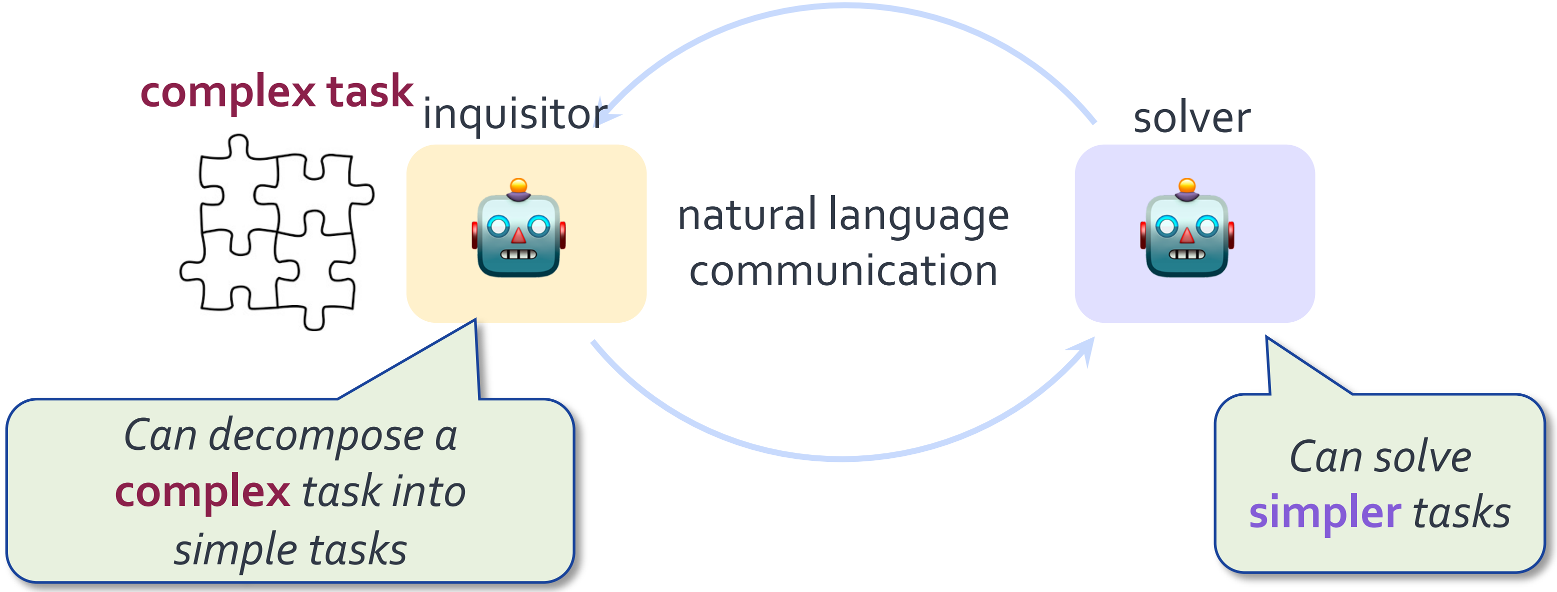

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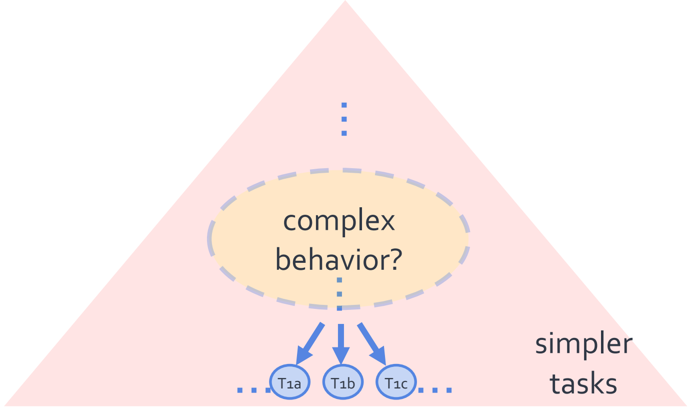


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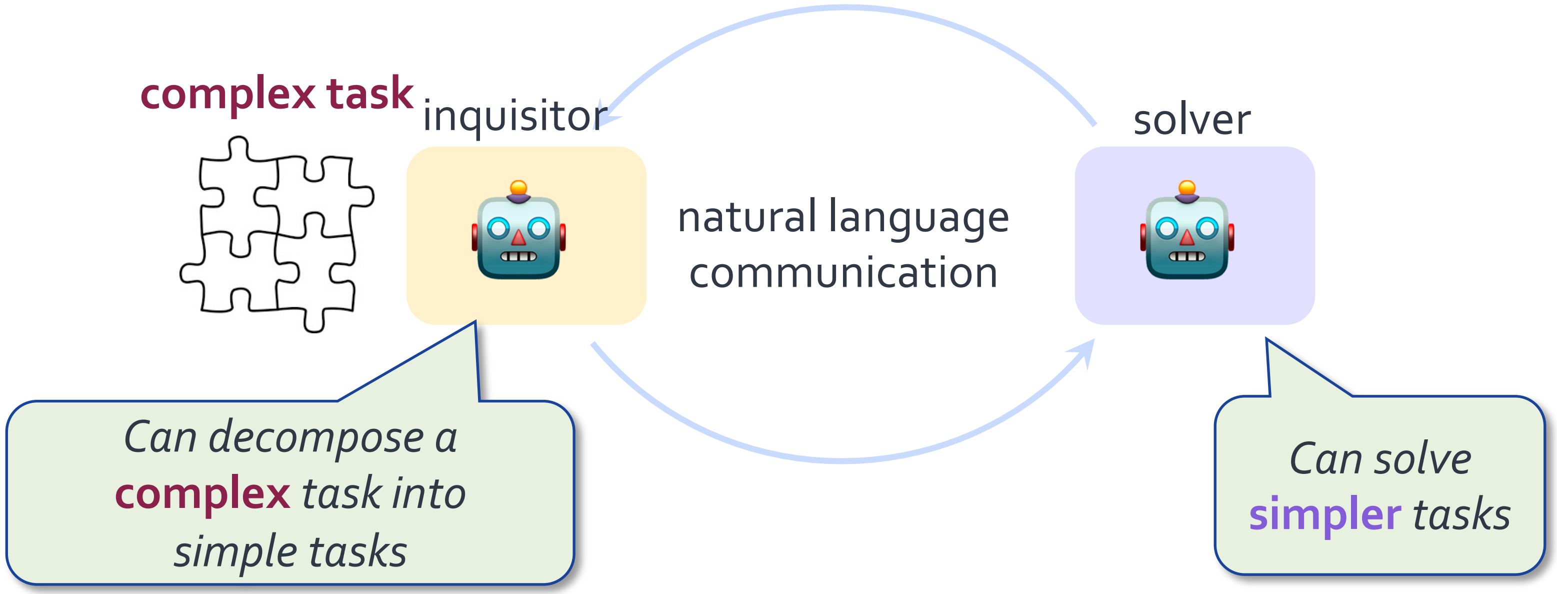

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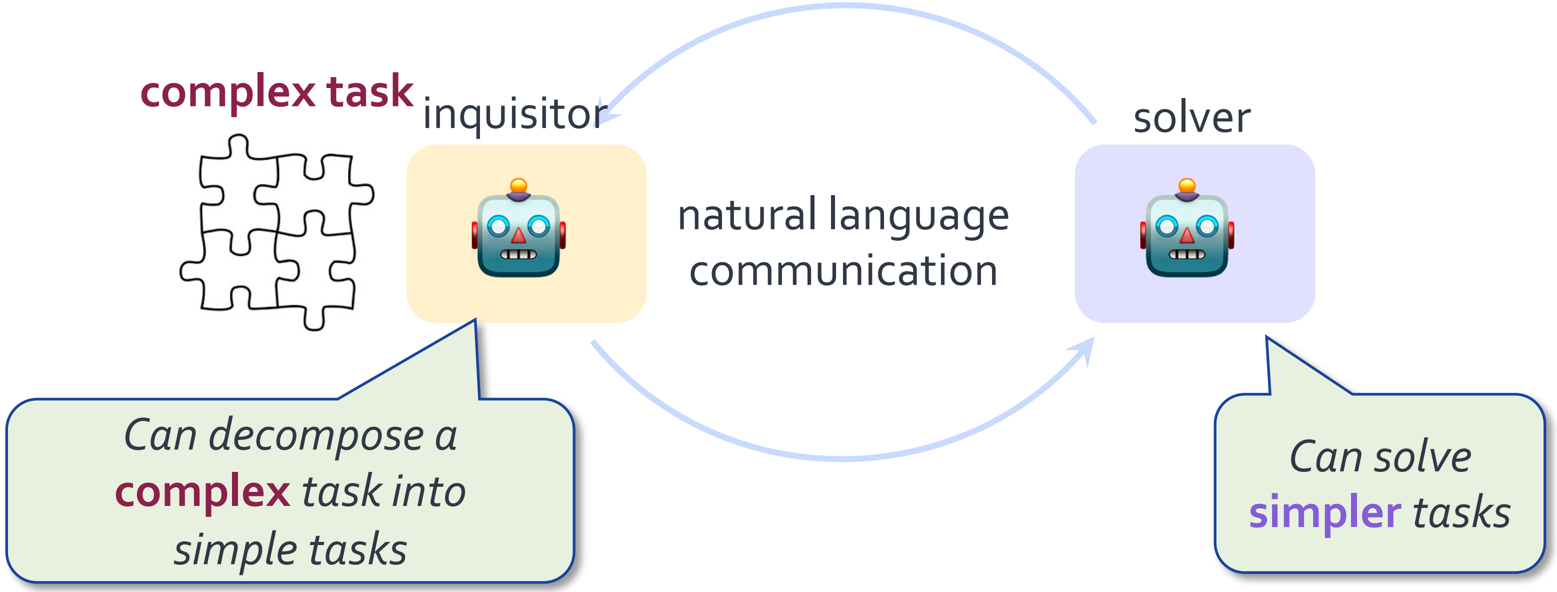

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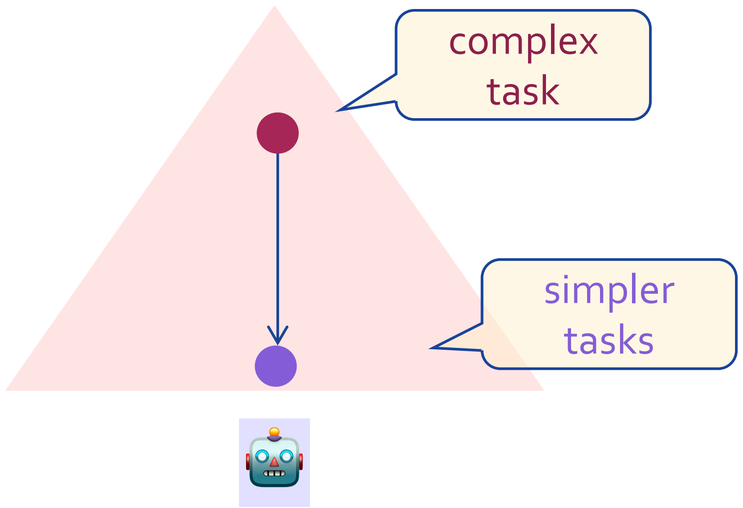


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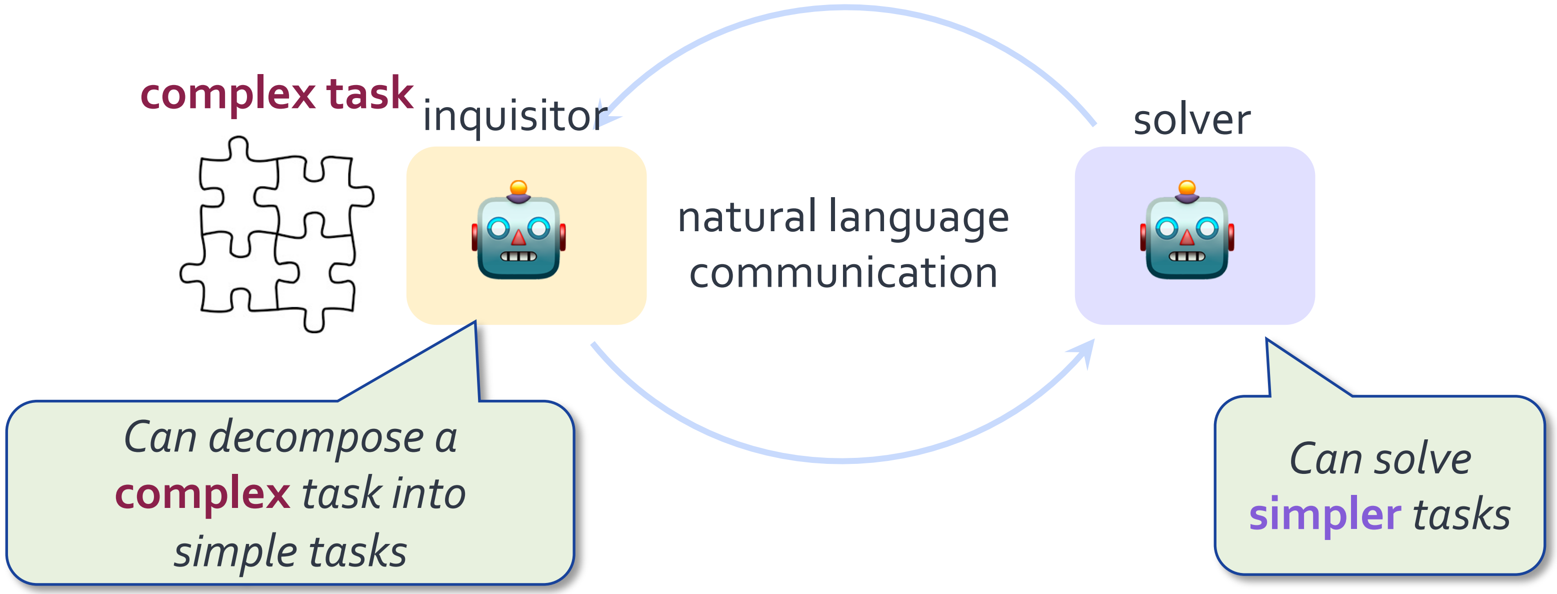
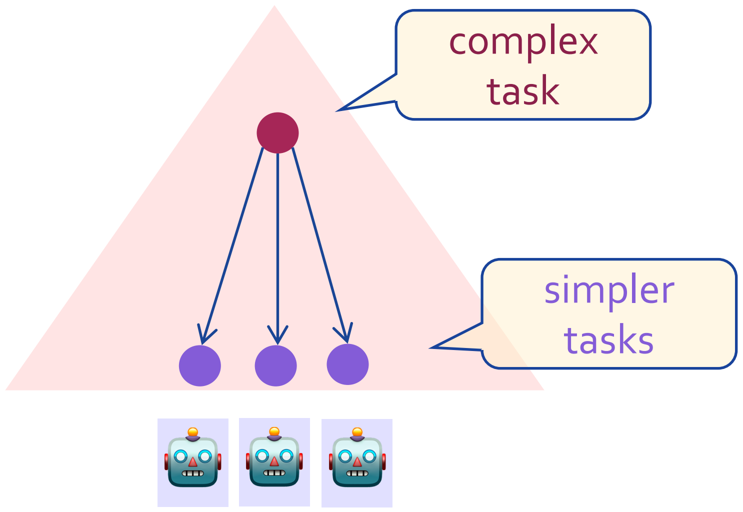
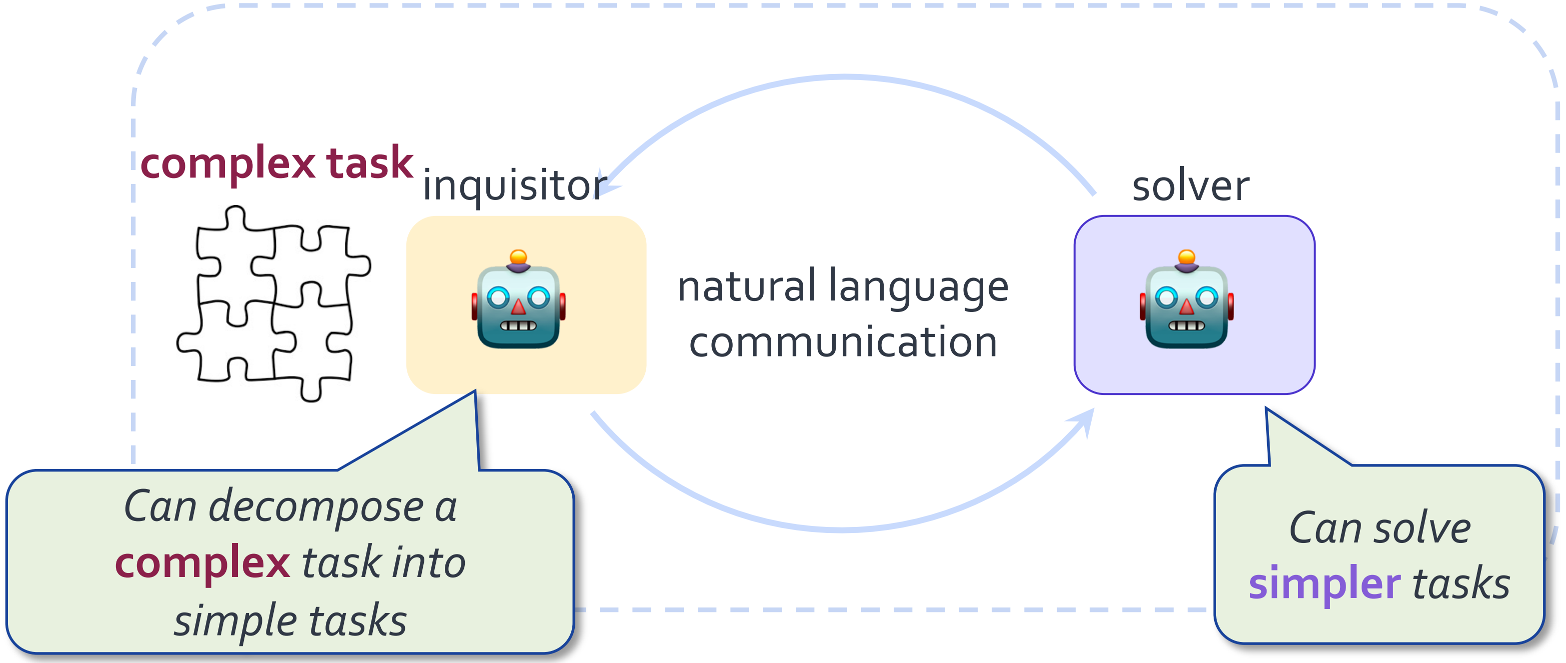


# Text Modular Networks (TMN)




A general framework that leverages existing simpler models –neural or symbolic– through interactive communication.



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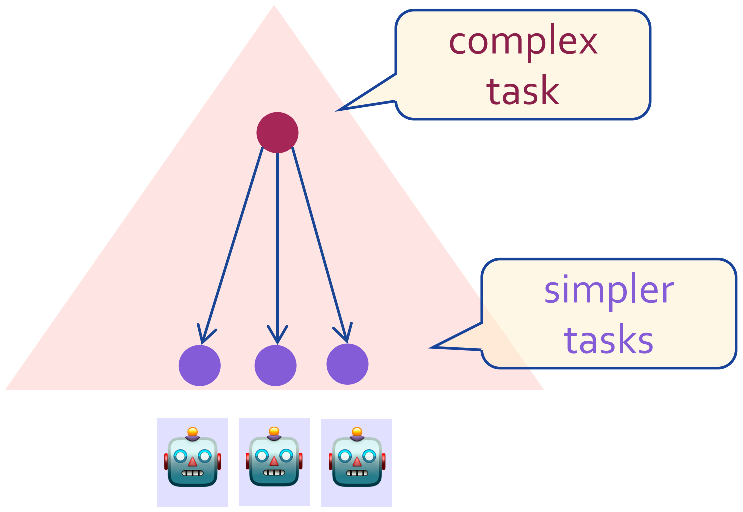


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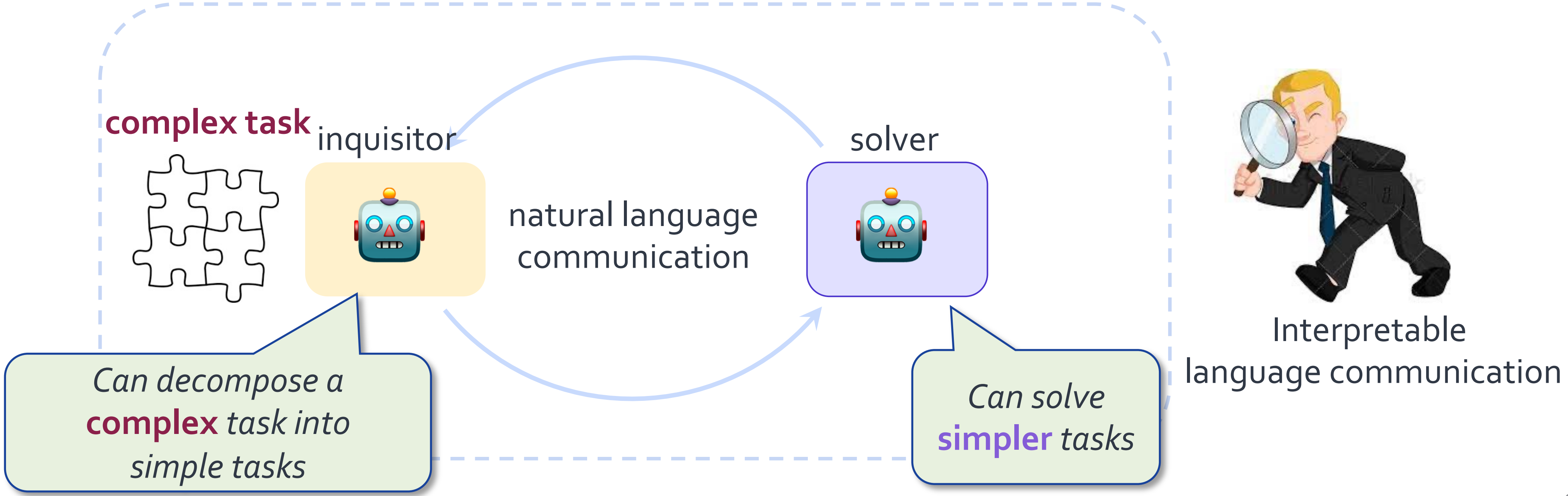

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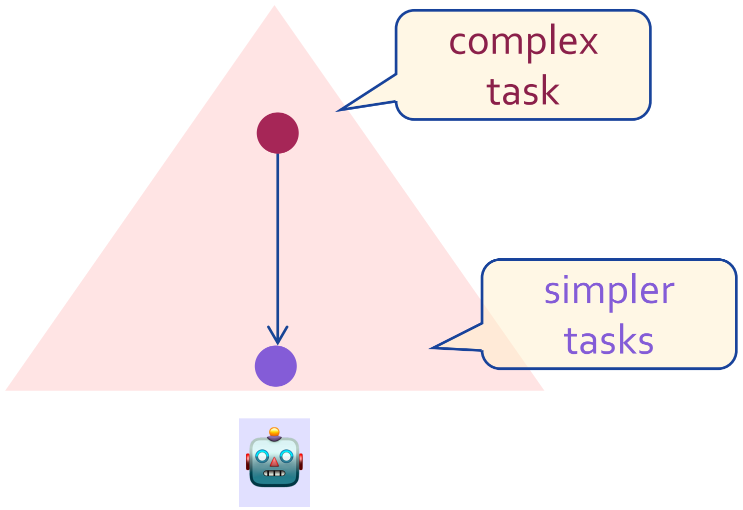

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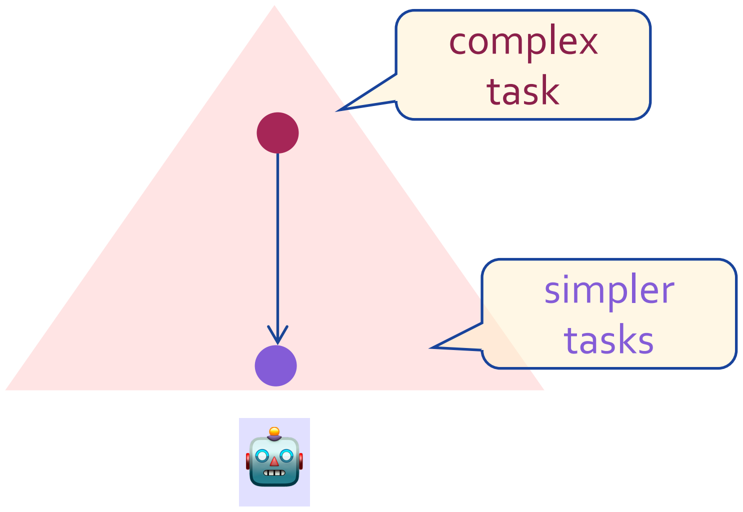
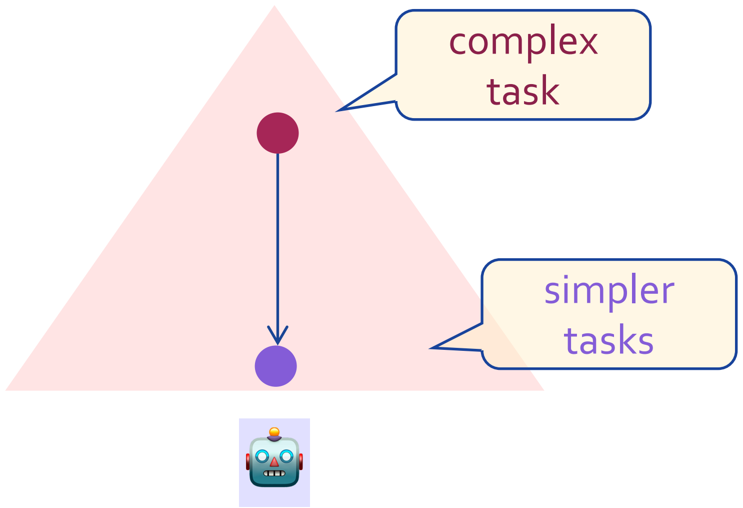



*complex question*

*"What is the nationality of the Simpsons director?"*

# Text Modular Networks (TMN)

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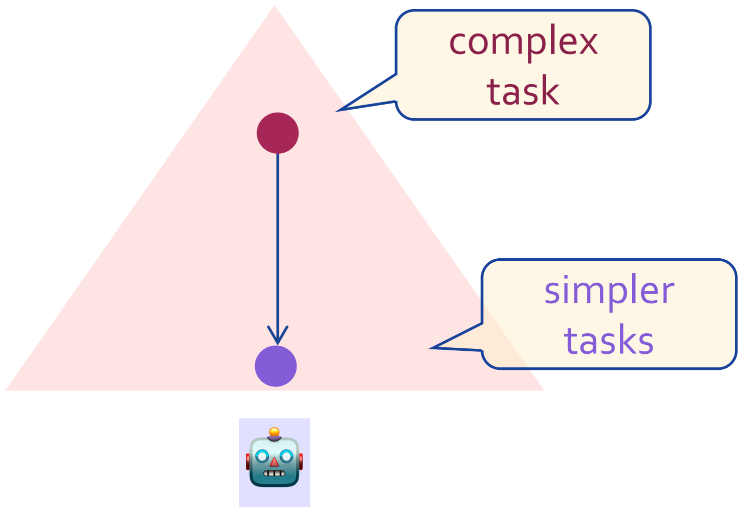



*complex question*

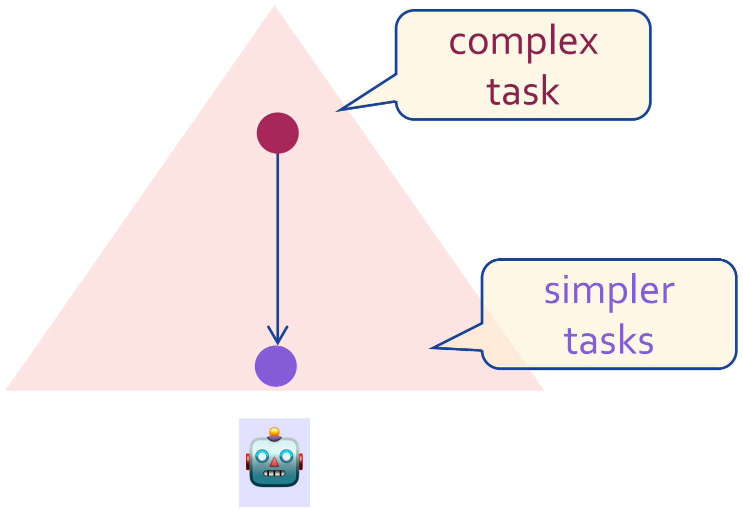
*"What is the nationality of the Simpsons director?"*

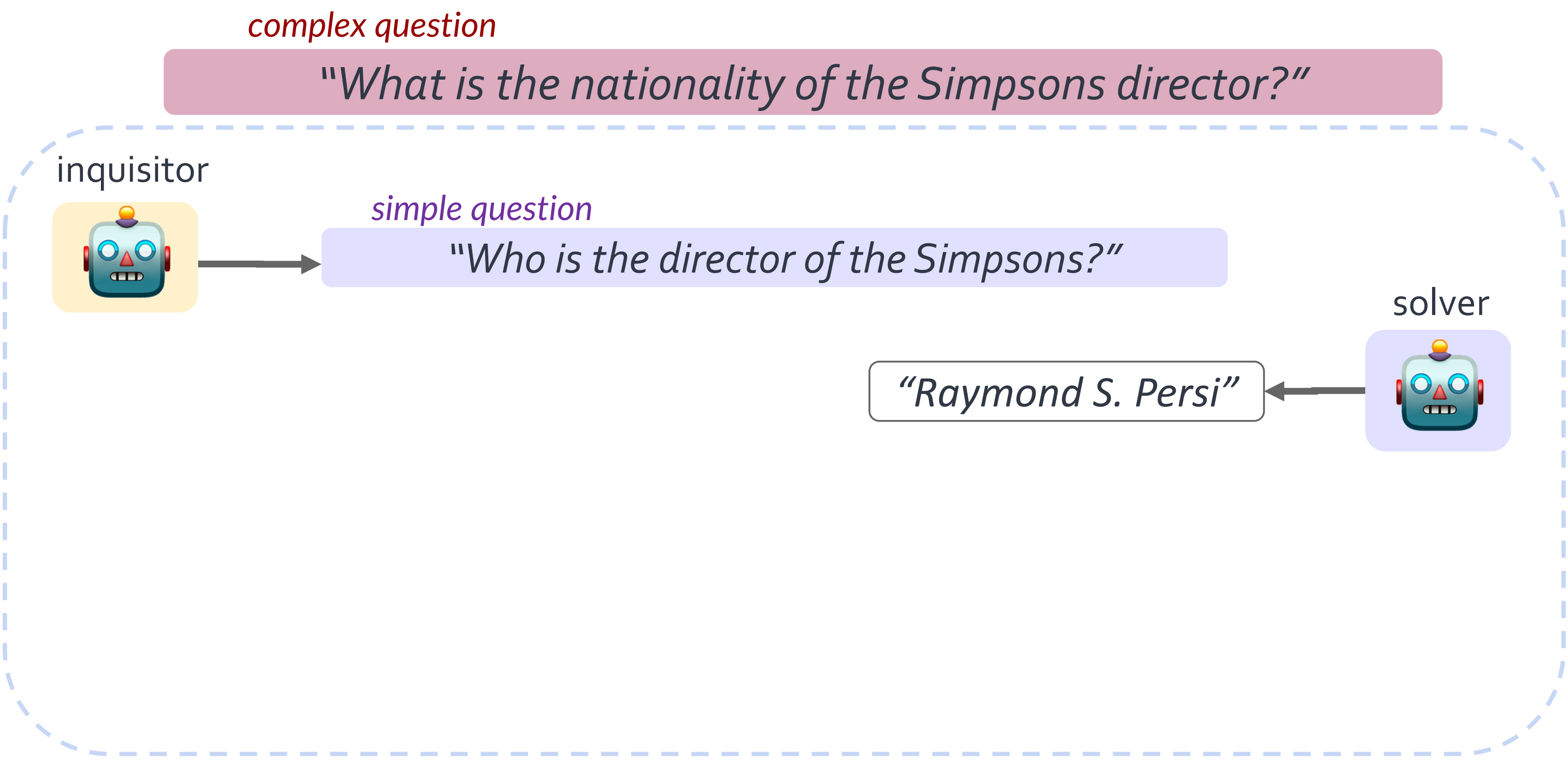
inquisitor

*simple question*

*"Who is the director of the Simpsons?"*

# Text Modular Networks (TMN)



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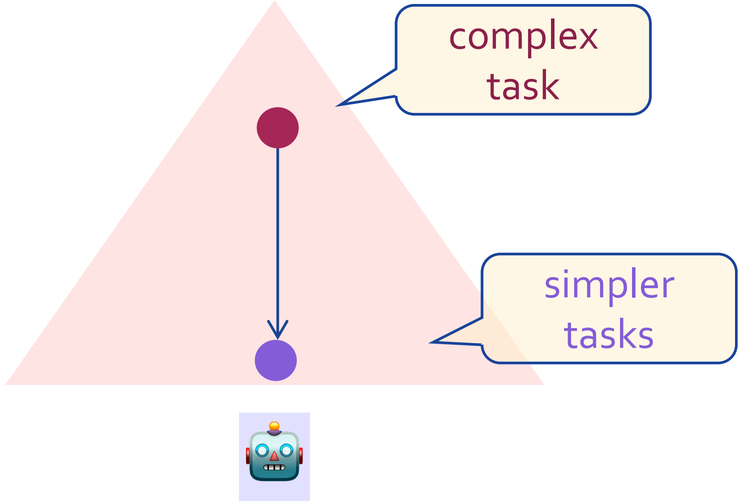


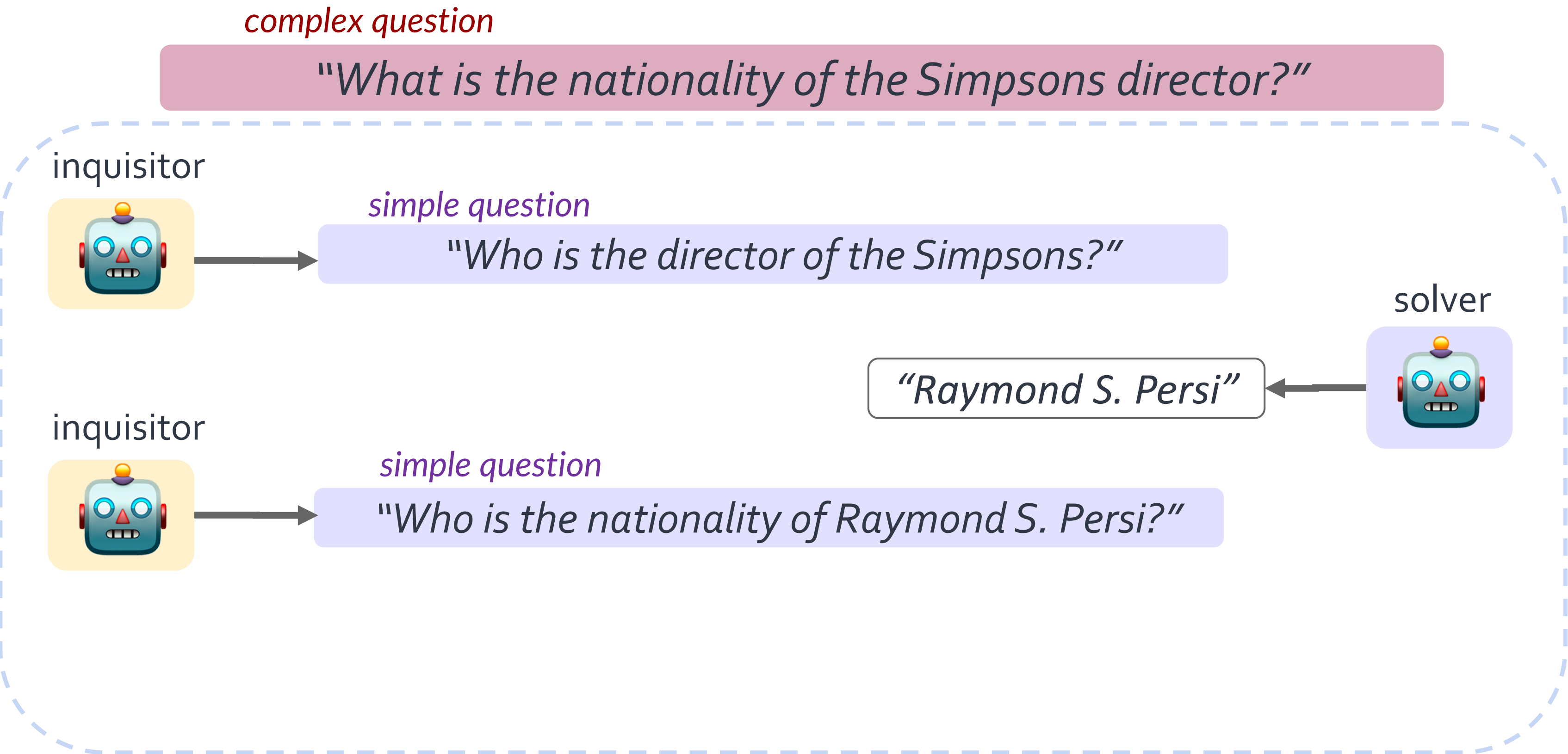

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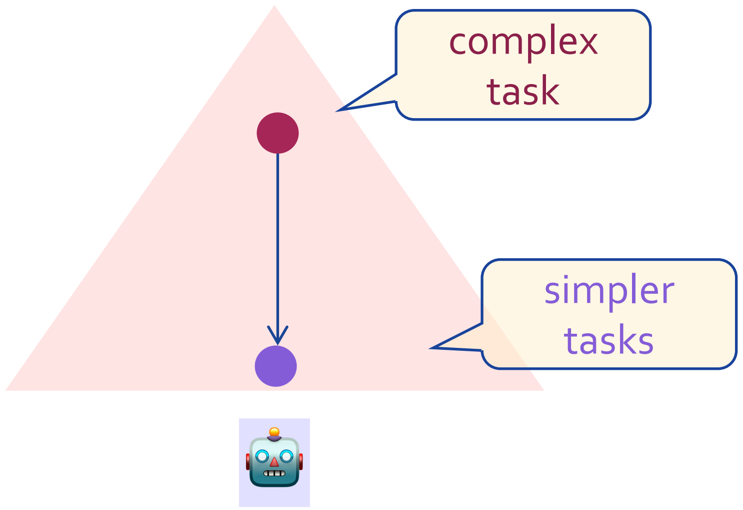
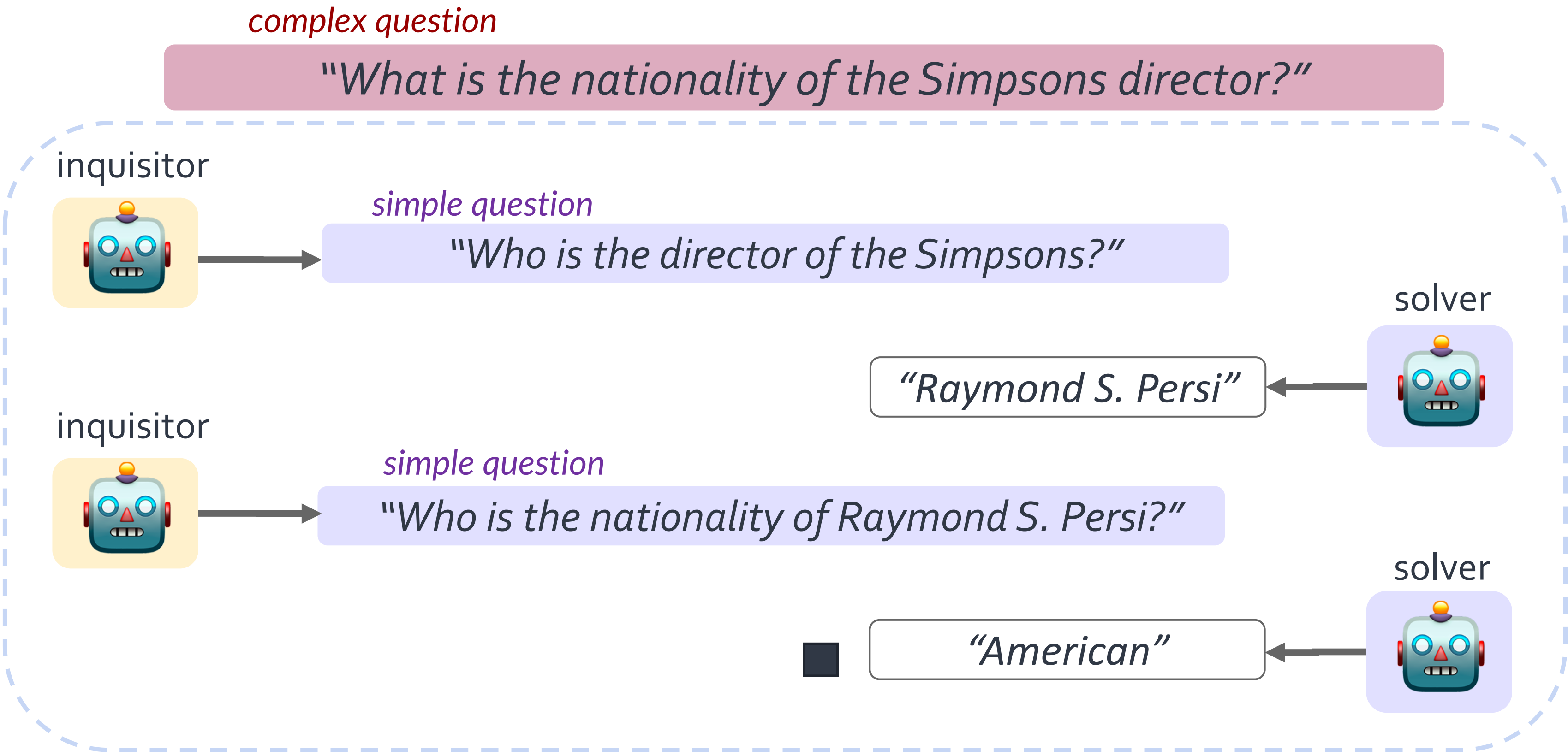


# Demo

https://modularqa-demo.apps.allenai.org/

Selected Reasoning [Ans: **American** ] 0.0044

**Question: What is the nationality of Simpson's "Little Big Girl" director?**

Who was the director of "Little Big Girl"? Curr. Penalty: 0.0000

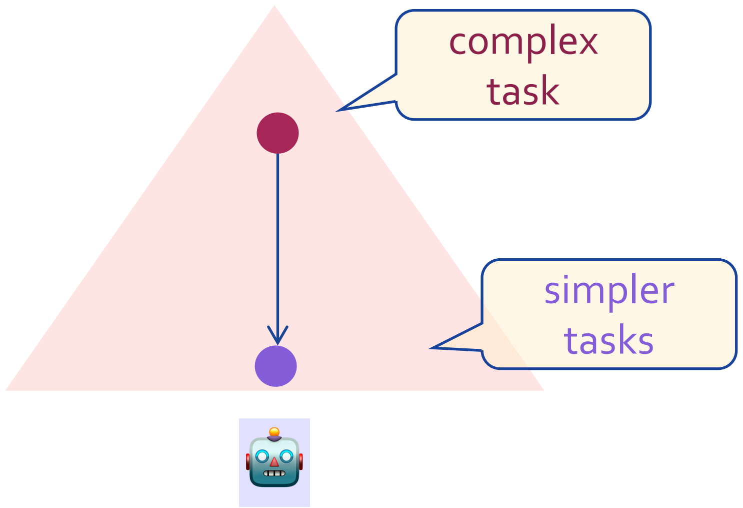
Raymond S. Persi via module: SQUAD QA

What is Raymond S. Persi's nationality? Curr. Penalty: 0.0000

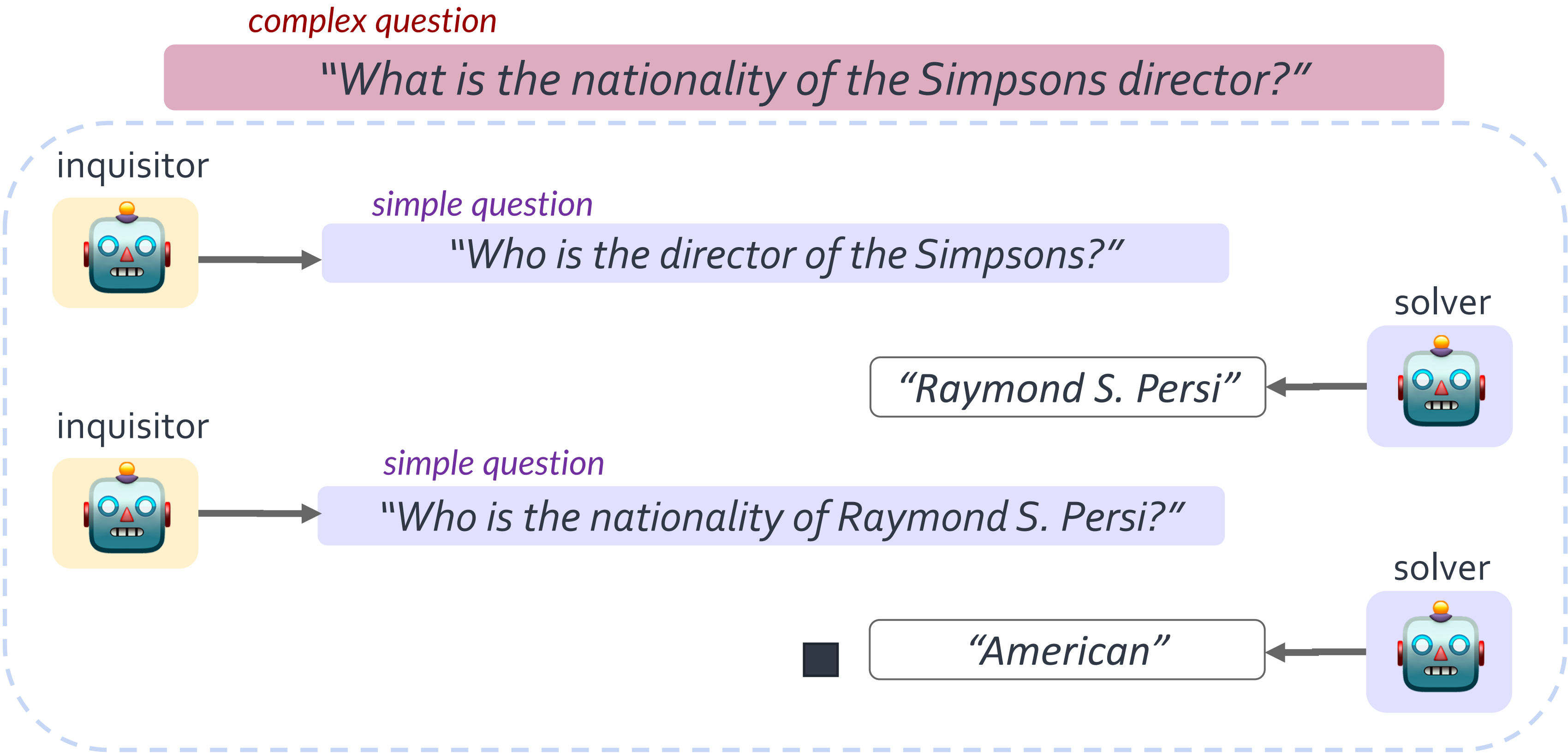
American via module: SQUAD QA

**Answer: American** Final Penalty: 0.0044

# Text Modular Networks (TMN)




**Research question:** Can we learn to solve complex questions via language interactions with existing, simpler models?



# Text Modular Networks (TMN)

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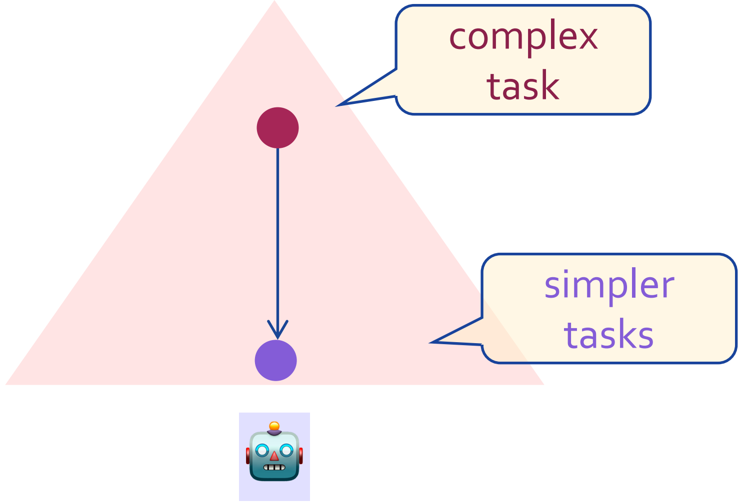


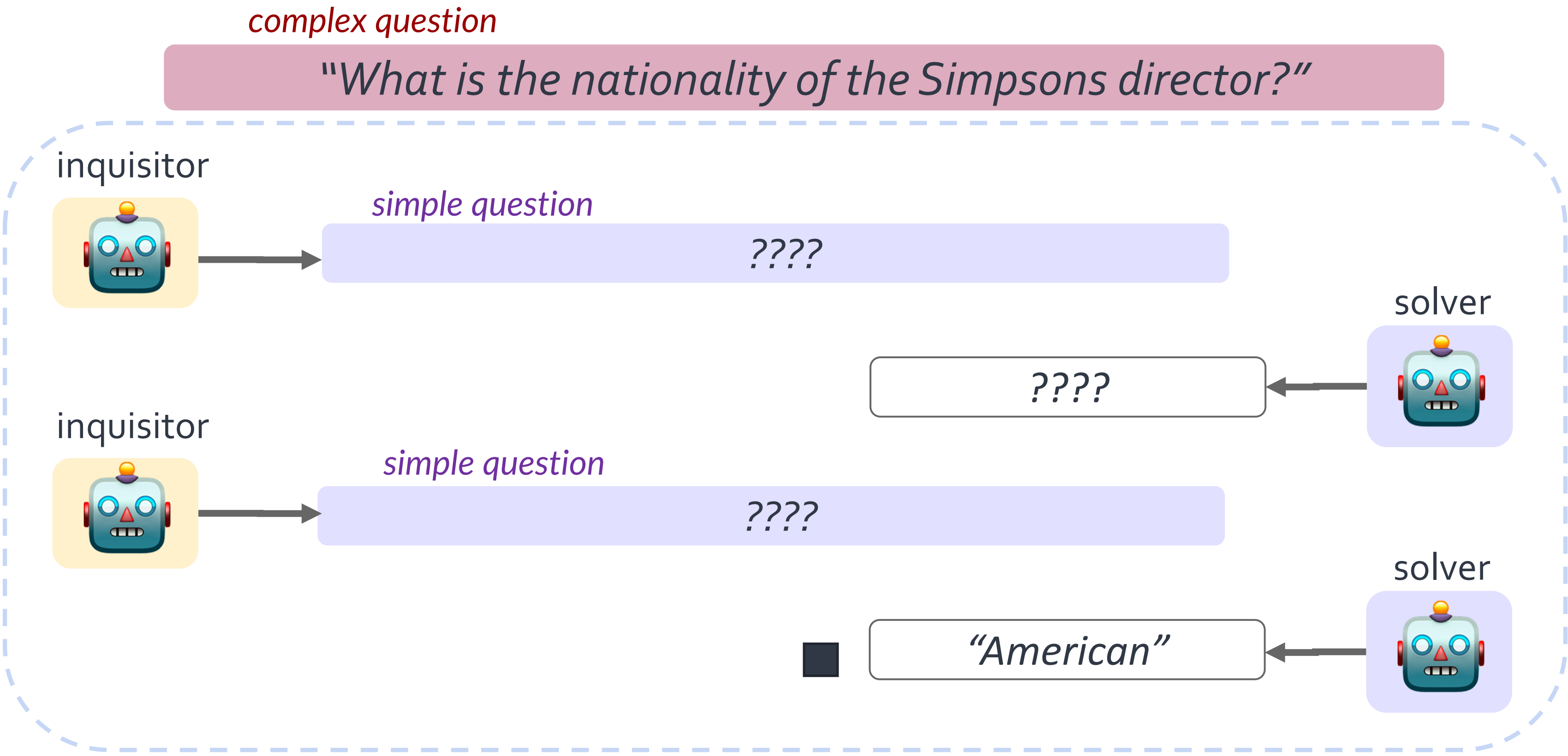

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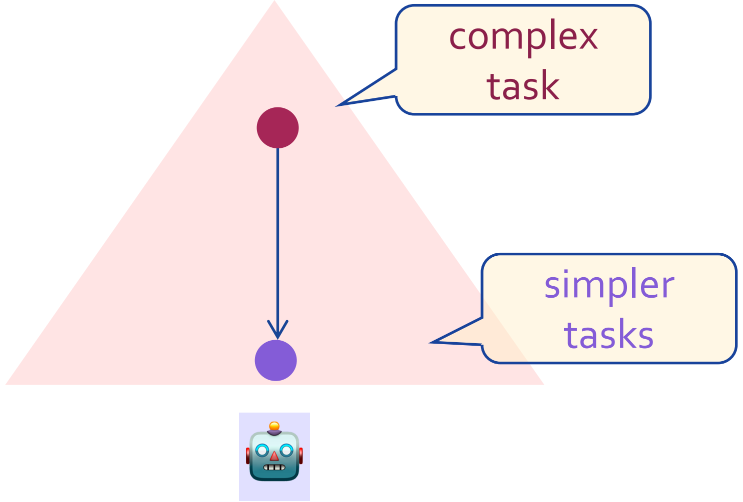


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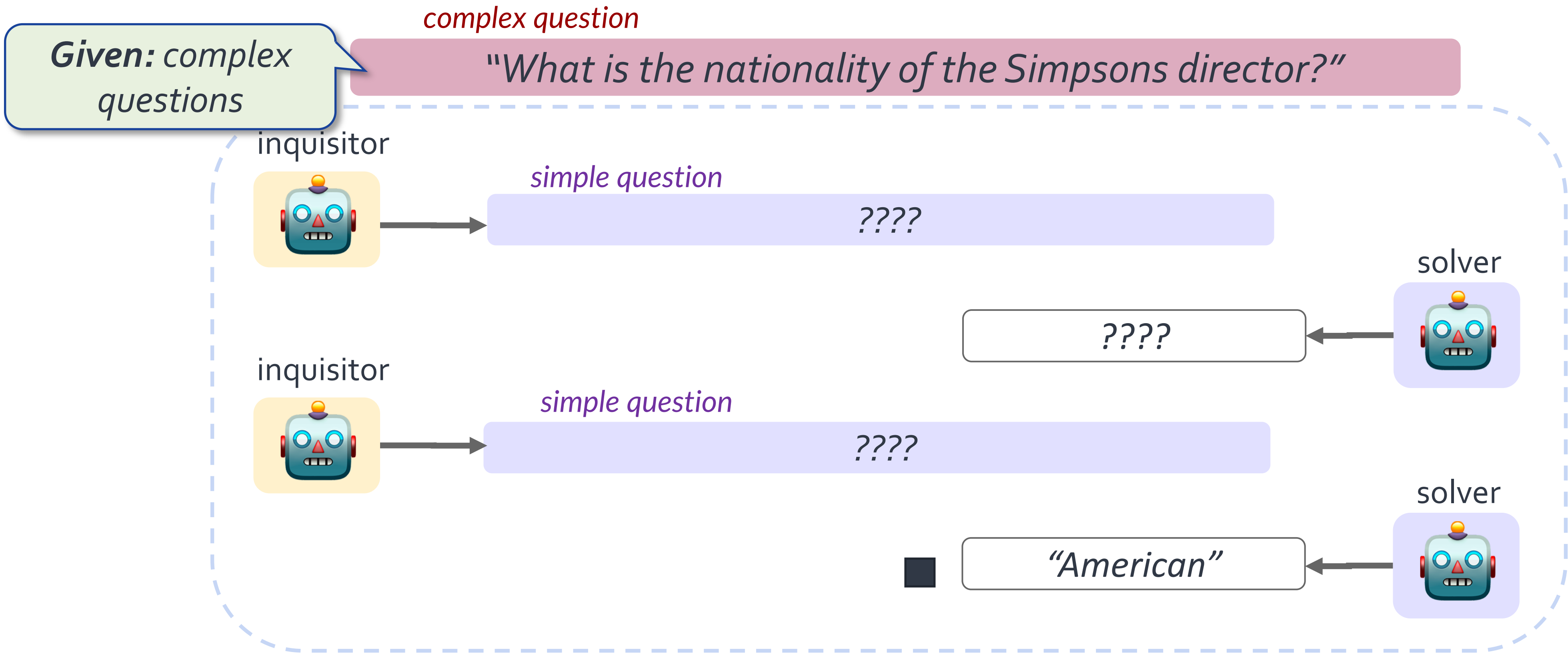

# Text Modular Networks (TMN)

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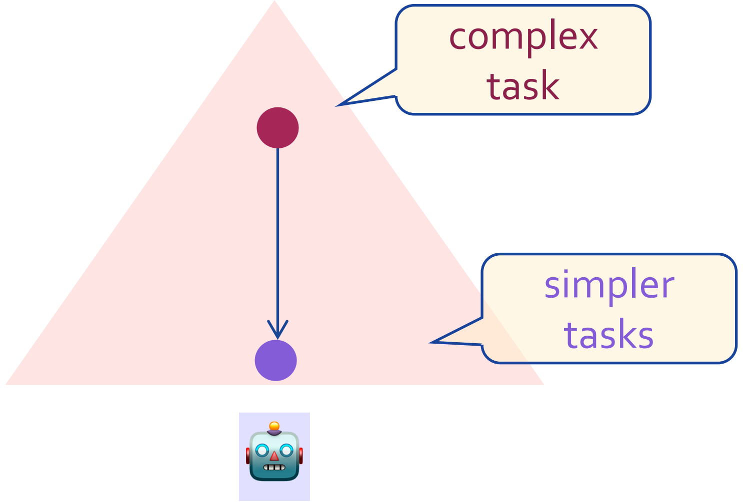
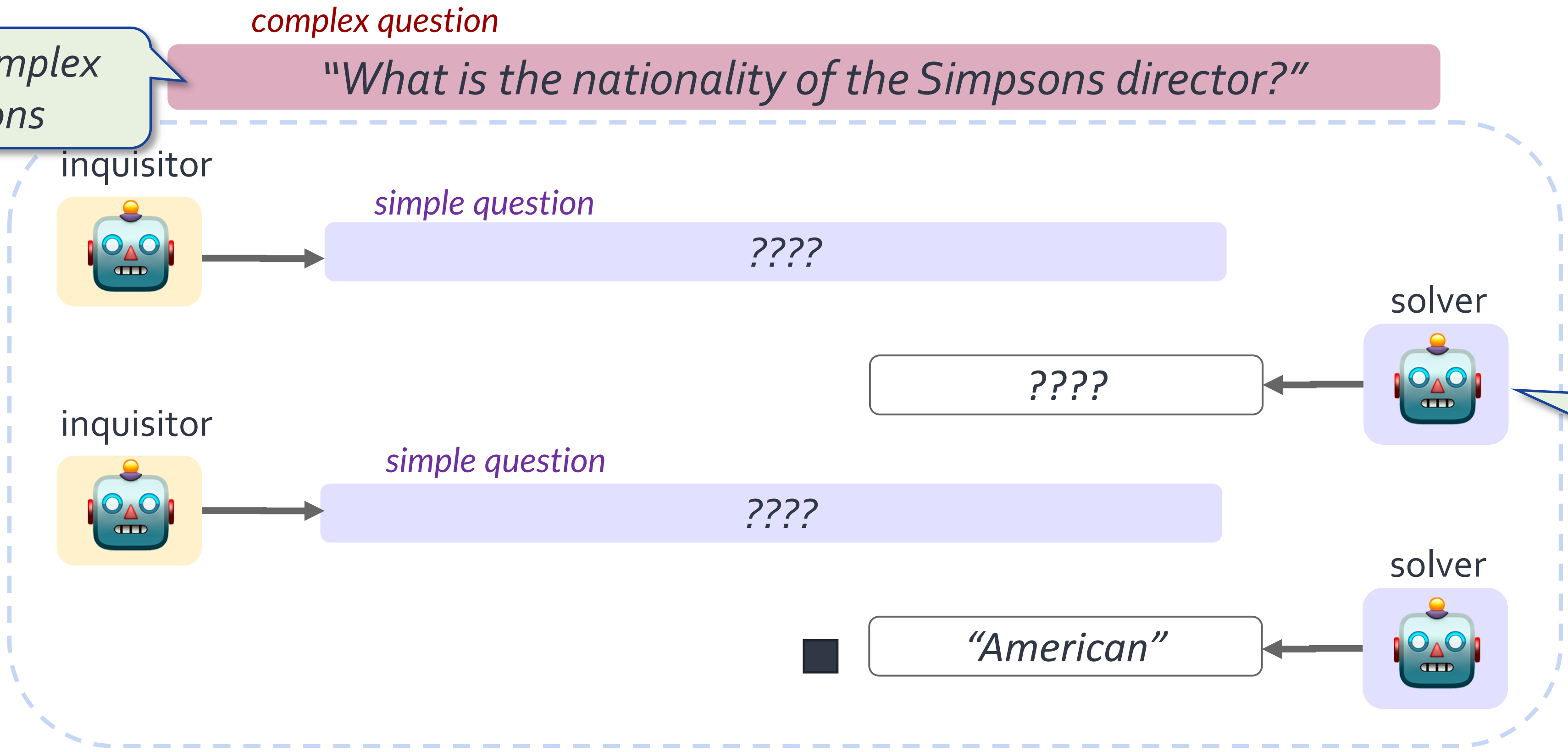
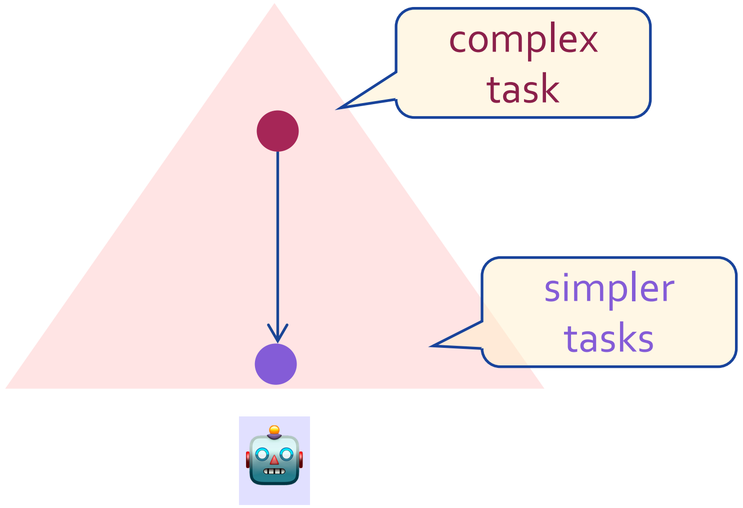



***Given:*** *complex questions*




***Given:*** *fixed QA solvers for simpler questions*

# Text Modular Networks (TMN)

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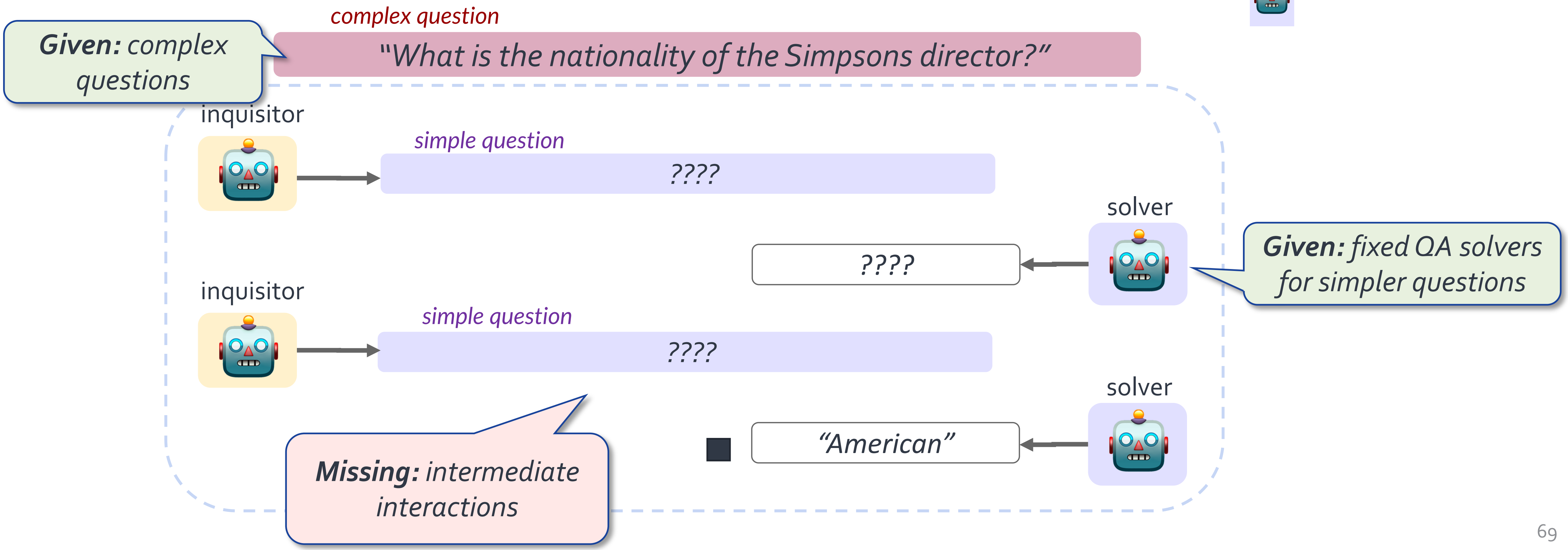
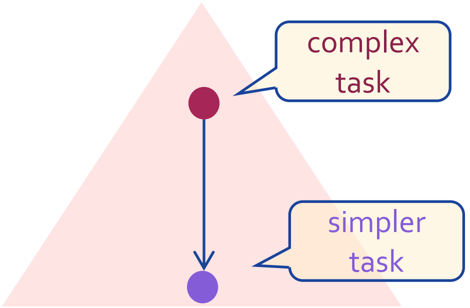
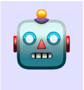


# Approach: Overview

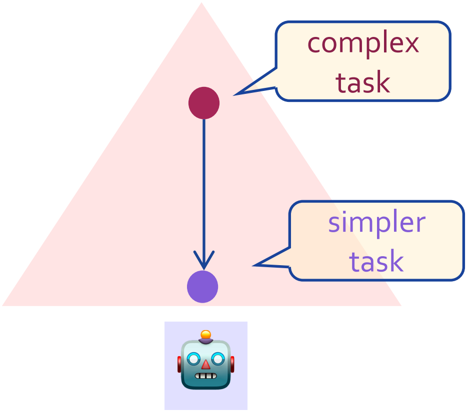



complex question "*What is the nationality of the Simpsons director?*"



answer "*American*"

# Approach: Overview




complex question

*"What is the nationality of the Simpsons director?"*

candidate decompositions
(simple questions)

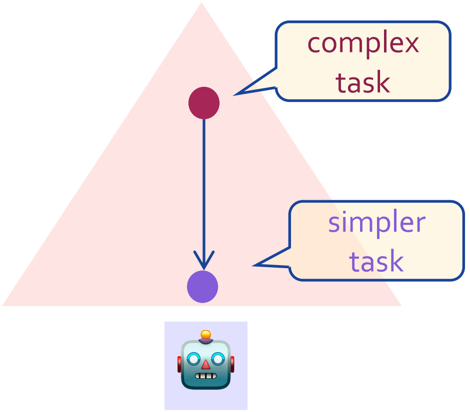
*Who…?* *When…?* *Where…?* *What…?* …

Need to be understandable to the simple models.

answer

*"American"*

# Approach: Overview




complex question

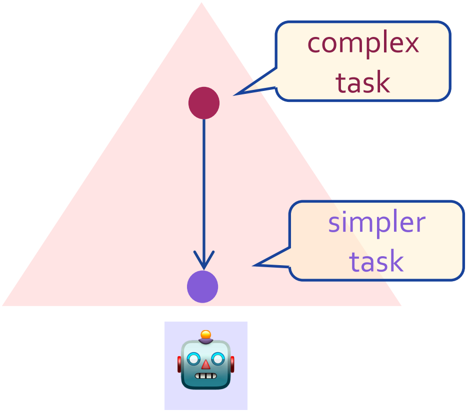
*"What is the nationality of the Simpsons director?"*

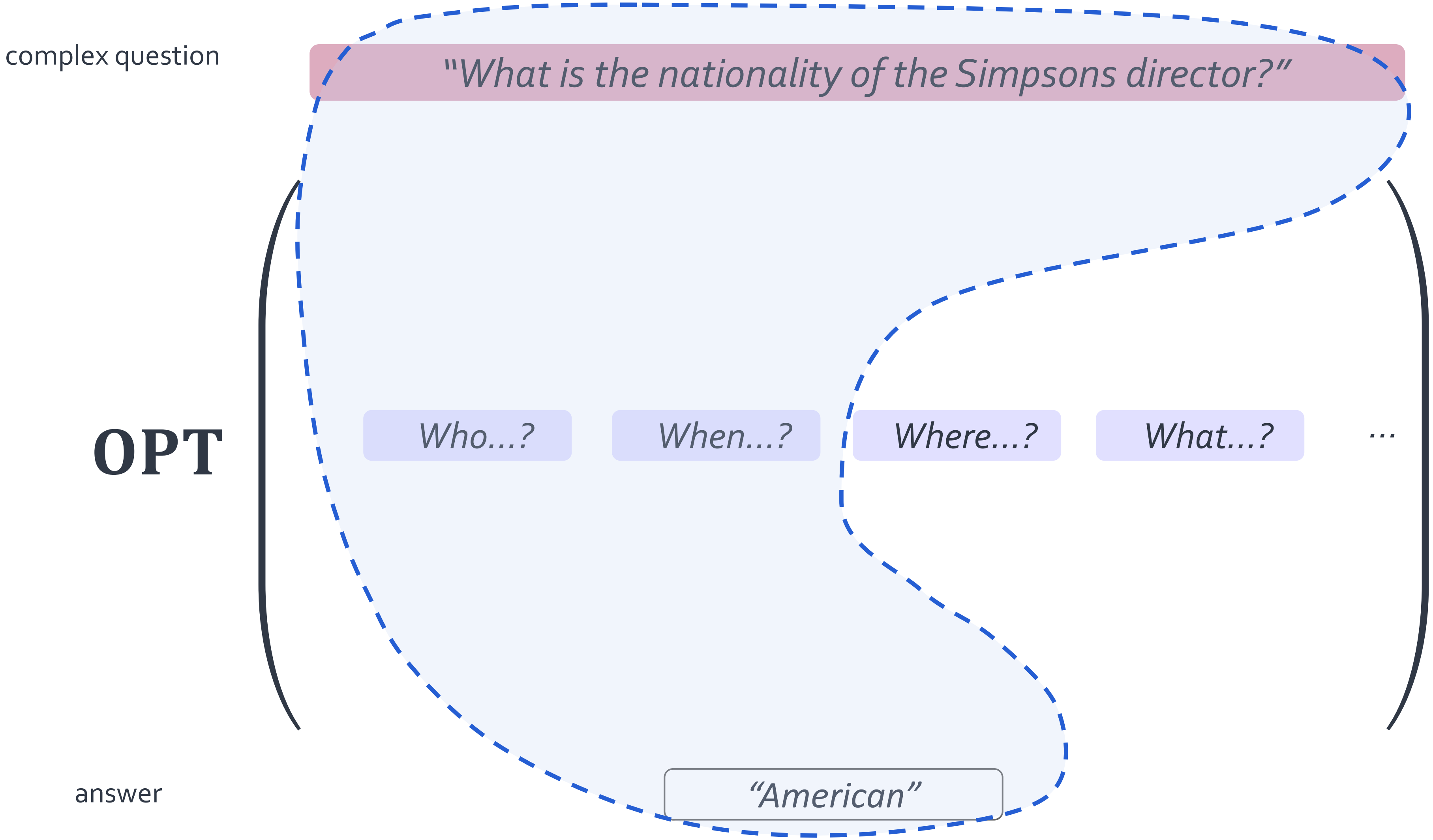
*Who...?* *When...?* *Where...?* *What...?* ...

answer

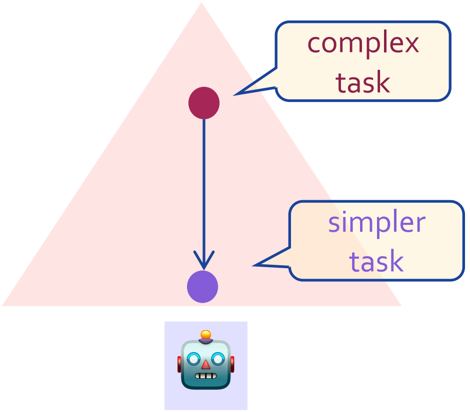
*"American"*

# Approach: Overview



# Step 1: Relevant Documents



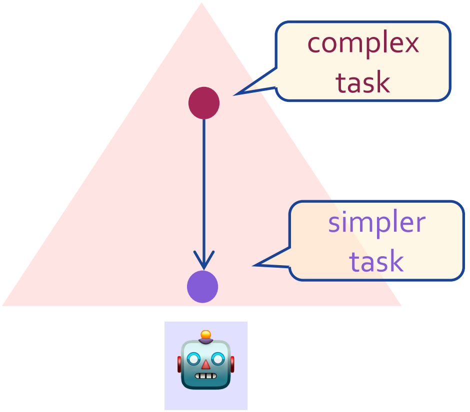

complex question

*"What is the nationality of the Simpsons director?"*

answer

*"American"*

Step 1: # Relevant Documents




complex question

*"What is the nationality of the Simpsons director?"*

*"Little Big Girl" is the twelfth episode of "The Simpsons"'s eighteenth season. It originally aired on the Fox network in the United States on February 11, 2007. It was written by Don Payne, and directed by Raymond S. Persi. Natalie Portman guest starred as a new character, Darcy. The title is a play on the Dustin Hoffman movie "Little Big Man". The last time the title was parodied was in season 11's "Little Big Mom."*

*album with his own rendition of "Iisa Lang Tayo". ....*

*Never-Ending Story". Persi went on to work as a sequence director ...*

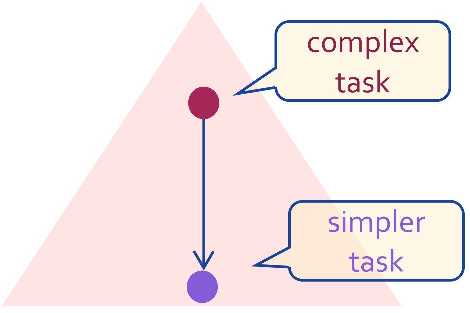
*and the last episode directed by Wes Archer. ...*

*meaning "ineffectual or weak, someone failing to show ....*

answer

*"American"*

# Step 2: Language of Simple QA Models




complex question

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*album with his own rendition of "Iisa Lang Tayo". ....*

*on to work as a sequence director ...*

*Archer. ...*

*meaning "ineffectual or weak, so*

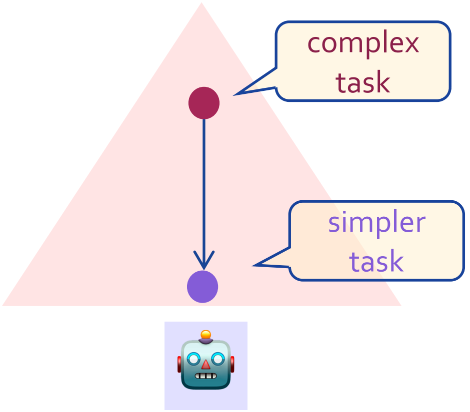
*"Who is the director of Simpson's 'Little Big Girl'?"*

Understandable to the simple models.

answer

*"American"*

# Step 2: Language of Simple QA Models




complex question

*"What is the nationality of the Simpsons director?"*

| | |
|---|---|
| *"Little Big Girl" is in which season of "the Simpsons"'s?* → | *eighteenth* |
| *"Who is the director of Simpson's 'Little Big Girl'?"* → | *Raymond Persi* |
| *"Little Big Girl" is which episode of "the Simpsons"'s?* → | *twelfth* |
| *When was 'Little Big Girl' aired in USA?* → | *February 11, 2007* |
| *Who is the writer of 'Little Big Girl' episode?* → | *Don Payne* |
| ⋮ | ⋮ |

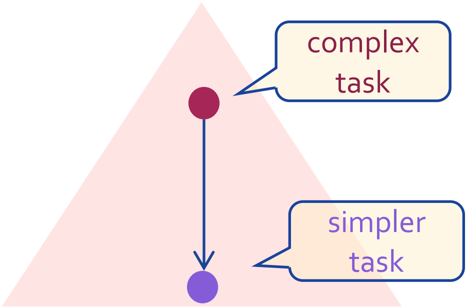
question-answers as an expressive knowledge representation medium.

[He et al., '15, FitzGerald et al. '18]

answer

*"American"*

# Step 3: Subset Selection via Optimization




complex question

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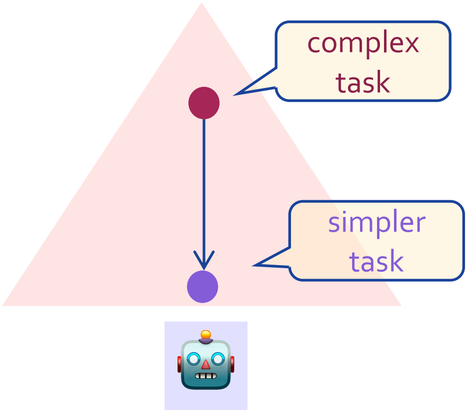
| *Who is the writer of 'Little Big Girl' episode?* → | *Don Payne* |
| ⋮ | ⋮ |

answer

*"American"*

# Step 3: Subset Selection via Optimization




complex question

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| ⋮ | ⋮ |

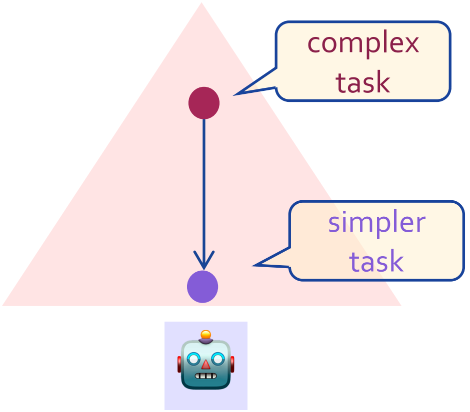
$$\begin{cases} \text{maximize} & \boldsymbol{c}^T\boldsymbol{x} \\ \text{subject to} & \boldsymbol{A}\boldsymbol{x} \le \boldsymbol{b} \\ & \boldsymbol{x} \ge \boldsymbol{0} \\ & \boldsymbol{x} \in \mathbb{Z}^n \end{cases}$$

discrete constrained search

answer

*"American"*

# Step 3: Subset Selection via Optimization




complex question

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| | |
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⋮

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discrete constrained search

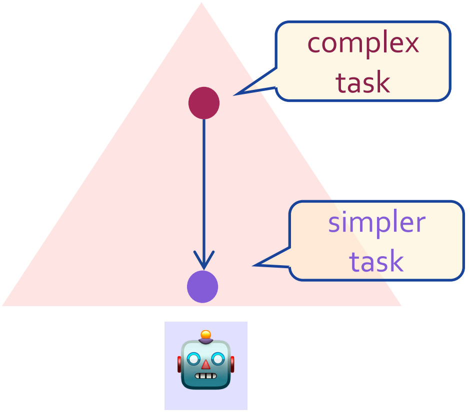
Find a subset of the questions, such that:

1. form a "desirable reasoning structure".

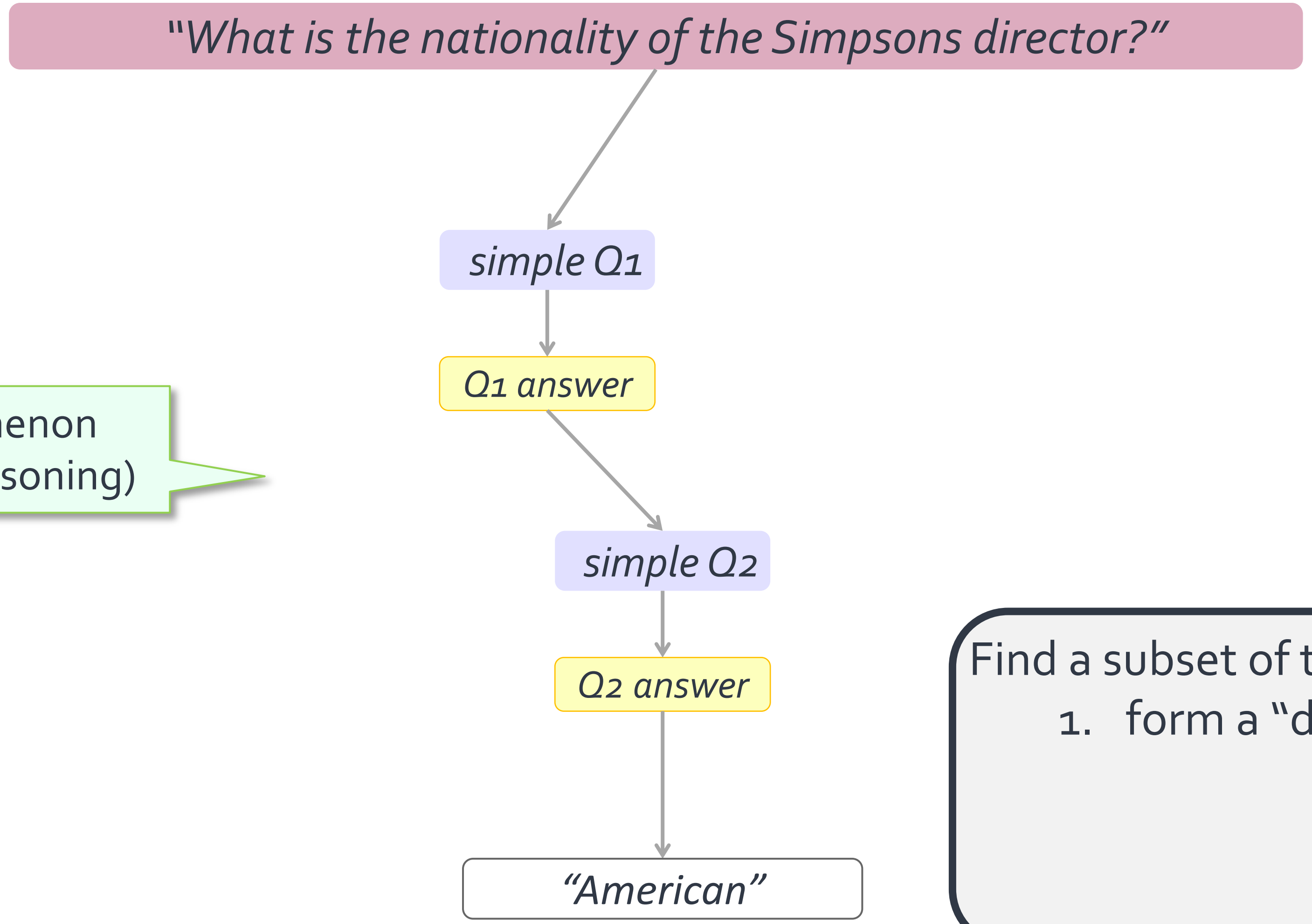
answer

*"American"*

# Step 3: Decomposition via Optimization




complex question




answer

Bridging phenomenon (e.g., deductive reasoning)

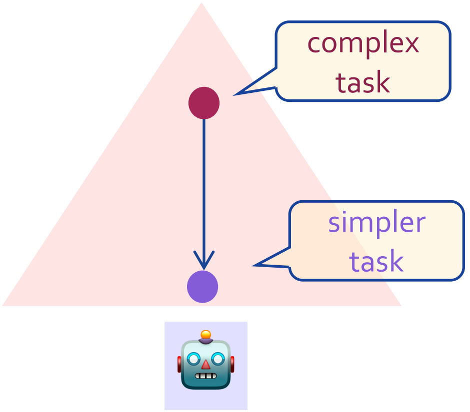
$$
\begin{cases}
\text{maximize} & \boldsymbol{c}^T\boldsymbol{x} \\
\text{subject to} & \boldsymbol{A}\boldsymbol{x} \le \boldsymbol{b} \\
 & \boldsymbol{x} \ge \boldsymbol{0} \\
 & \boldsymbol{x} \in \mathbb{Z}^n
\end{cases}
$$

discrete constrained search

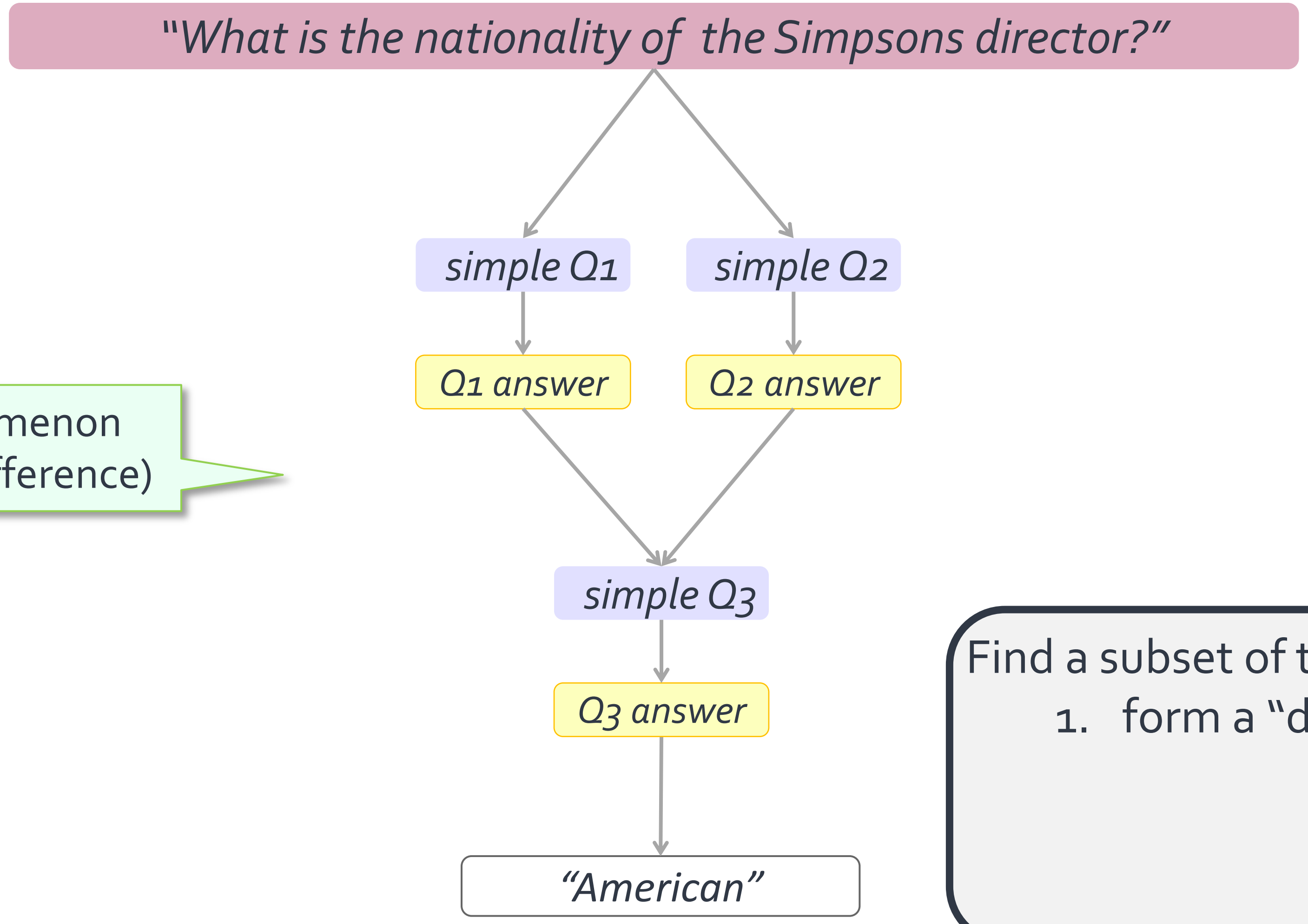
Find a subset of the questions, such that:

1. form a "desirable reasoning structure".

# Step 3: Decomposition via Optimization




complex question




answer

Comparison phenomenon
(e.g., conjunction, difference)

$$\begin{cases} \text{maximize} & \boldsymbol{c}^T \boldsymbol{x} \\ \text{subject to} & A\boldsymbol{x} \leq \boldsymbol{b} \\ & \boldsymbol{x} \geq \boldsymbol{0} \\ & \boldsymbol{x} \in \mathbb{Z}^n \end{cases}$$

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Find a subset of the questions, such that:

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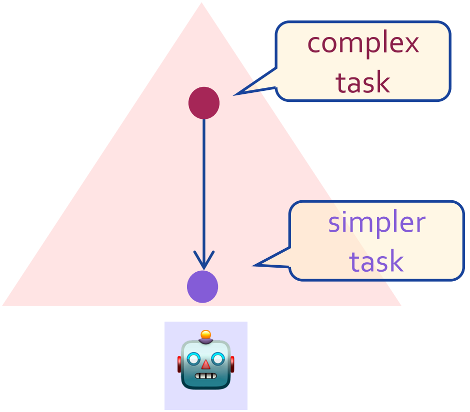
# Step 3: Decomposition via Optimization




complex question

*"What is the nationality of the Simpsons director?"*

*"Who is the director of the Simpsons?"*

*"Raymond Persi"*

*"What is the nationality of Raymond S. Persi?"*

*"American"*

answer

*"American"*

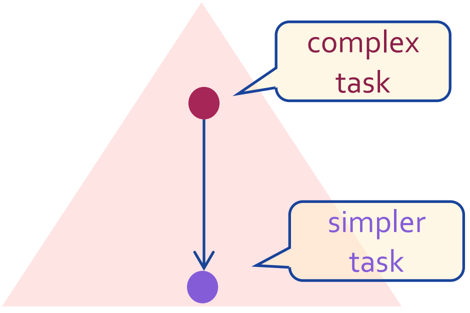
$$\begin{cases} \text{maximize} & \boldsymbol{c}^T\boldsymbol{x} \\ \text{subject to} & \boldsymbol{A}\boldsymbol{x} \leq \boldsymbol{b} \\ & \boldsymbol{x} \geq \boldsymbol{0} \\ & \boldsymbol{x} \in \mathbb{Z}^{\boldsymbol{n}} \end{cases}$$

discrete constrained search

Find a subset of the questions, such that:

1. form a "desirable reasoning structure".

# Step 3: Decomposition via Optimization




complex question

*"What is the nationality of the Simpsons director?"*

*"Who is the director of the Simpsons?"*

*"Raymond Persi"*

*"What is the nationality of Raymond S. Persi?"*

*"American"*

answer

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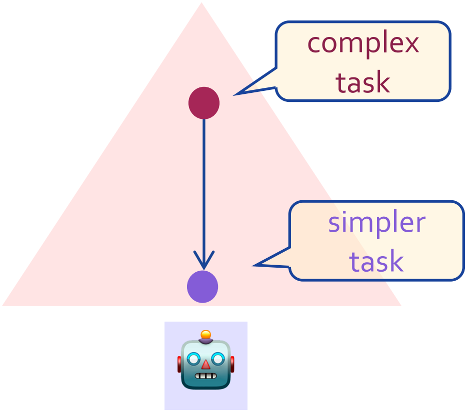
discrete constrained search

Find a subset of the questions, such that:

1. form a "desirable reasoning structure".
2. satisfy sparsity/regularization factors:
   - Small pairwise overlap.
   - Cover the complex question.

Step 4: **Learn to Decompose**

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*"What is the nationality of the Simpsons director?"*

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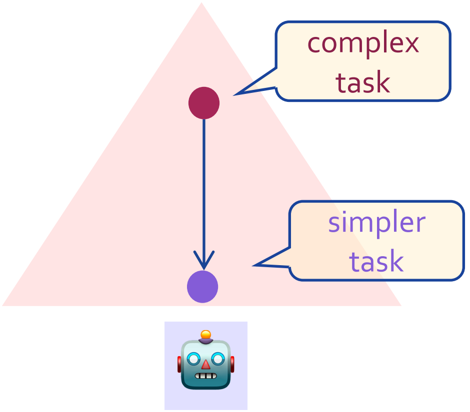
# Step 4: Learn to Decompose

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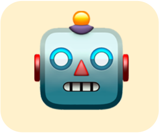
answer

"American"

inquisitor



Trained on [noisy] decompositions

**No decomposition annotation needed!**

# Summary of Empirical Observations

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|---|---|---|
| NumNet [Ran et al. 19] | 92 | 🤔 |
| Quark [Groeneveld et al. 20] | 🤔 | 76 |
| TMN [this work] | 88 | 62 |

- **Competitive** with dataset-specific.

“Text Modular Networks: Learning to Decompose Tasks in the Language of Existing Models.” Khot, **K**, Richardson, Sabharwal NAACL‘21

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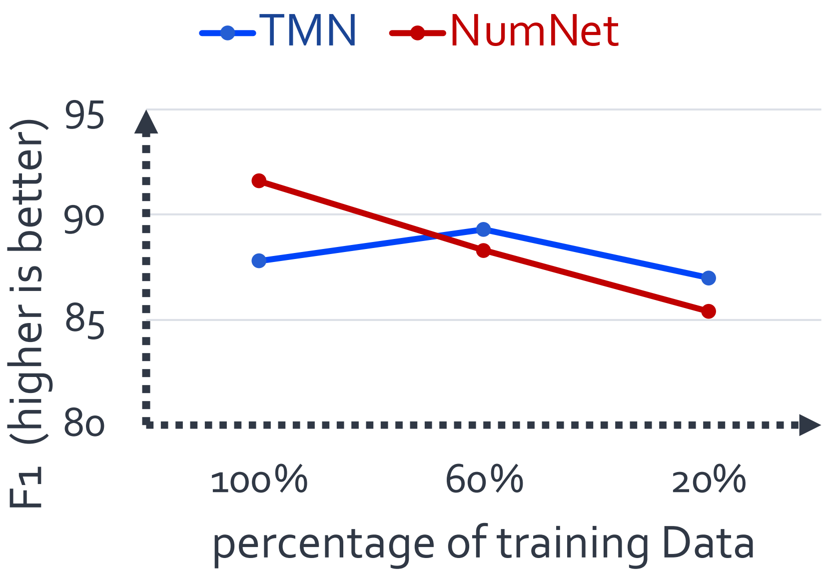


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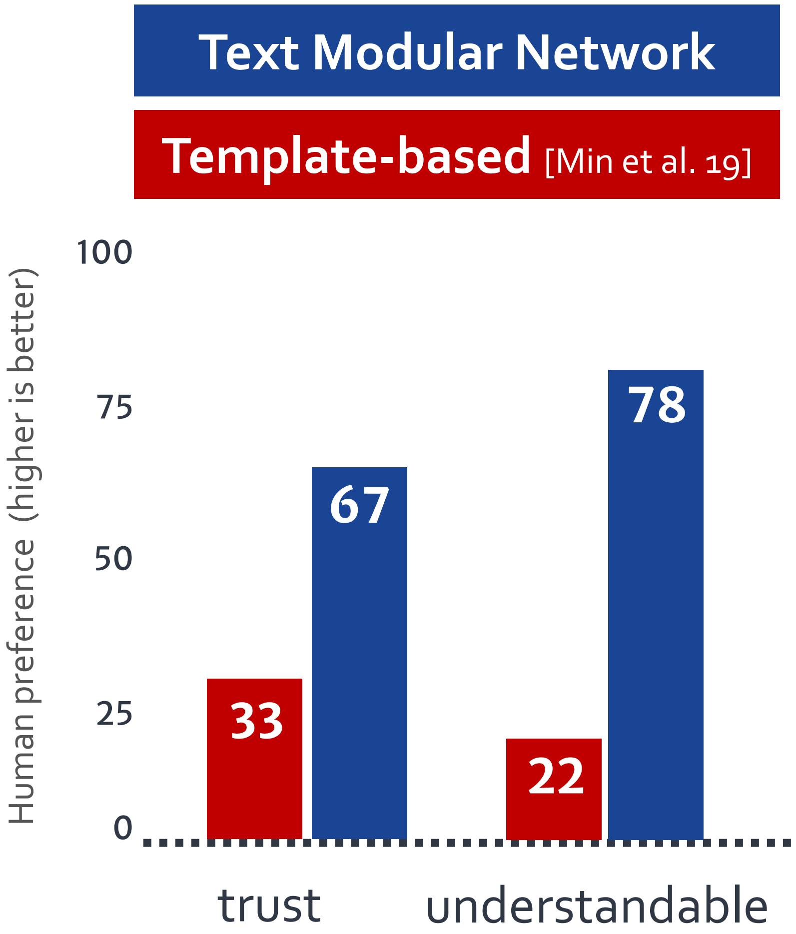


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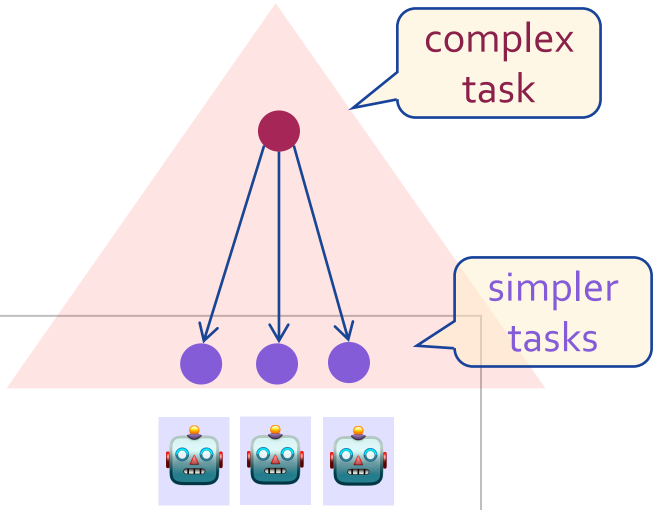


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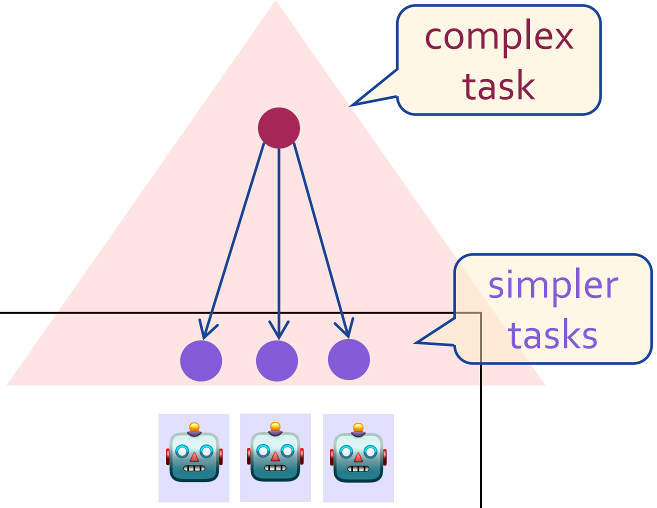


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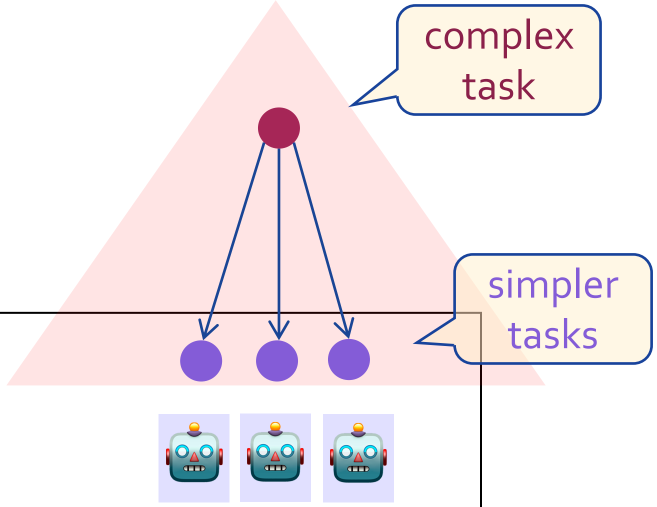


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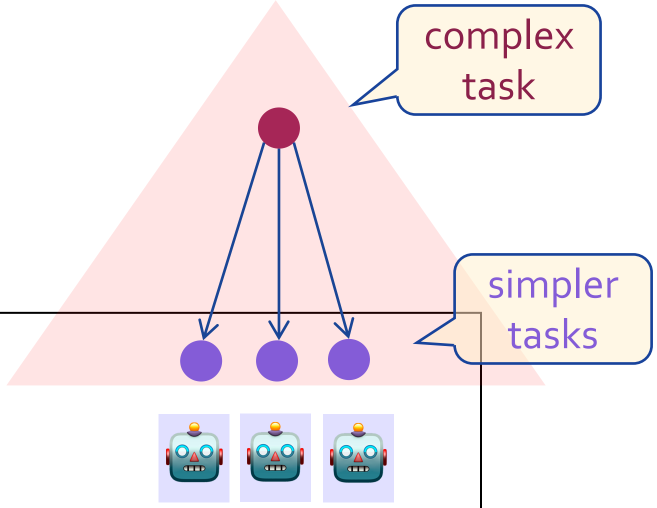


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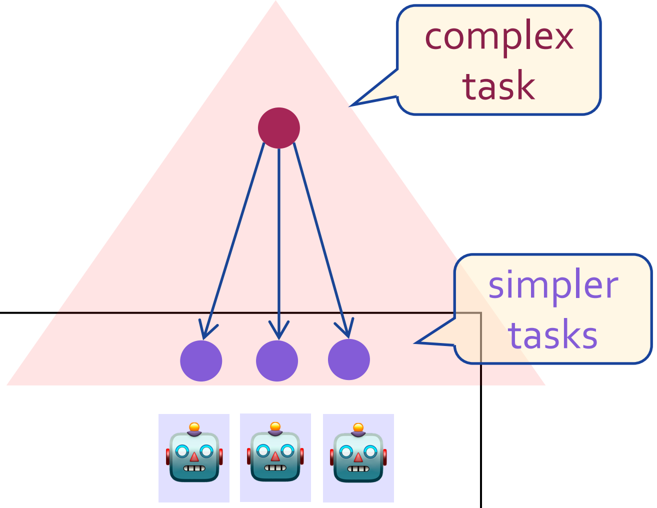


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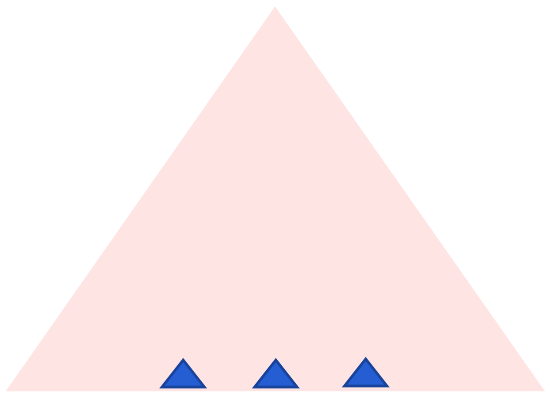
# Tying the Loose Ends



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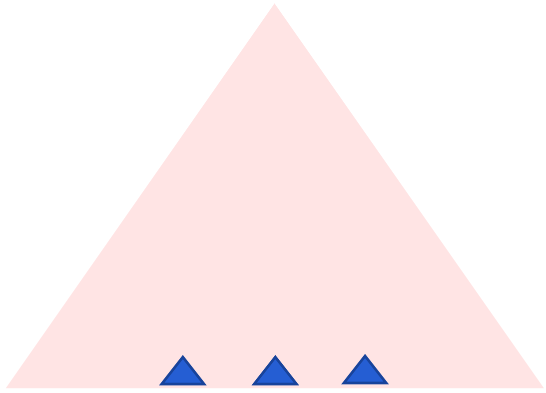

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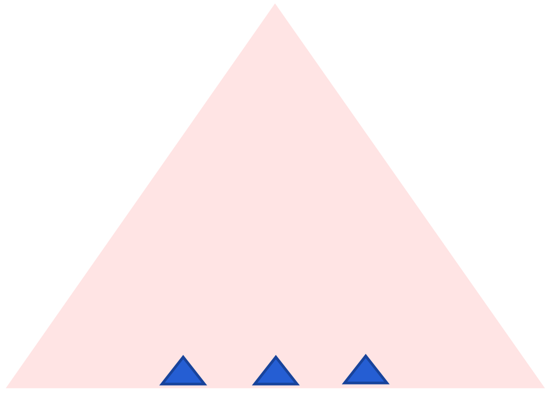

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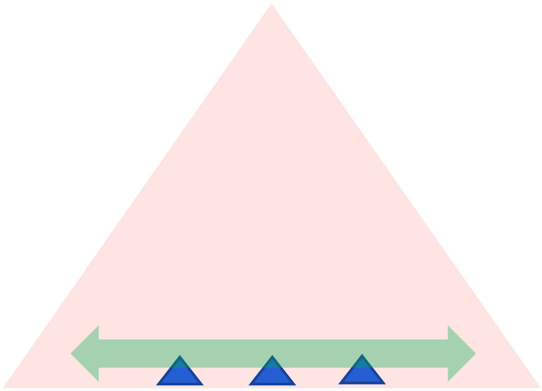

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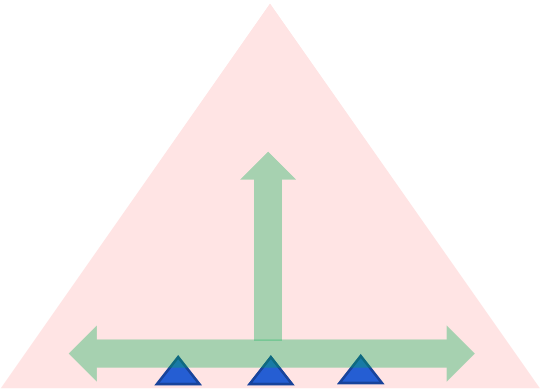


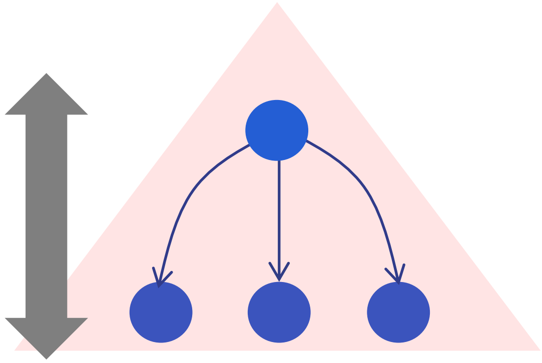
# Talk Outline

Generality in "breadth" — tackling a variety of tasks

Generality in "depth" — tackling more complex tasks

*Future work:* Toward broad, interactive reasoning








UnifiedQA *EMNLP Findings '20*

Natural Instructions *arXiv '21*

ModularQA *NAACL '21*

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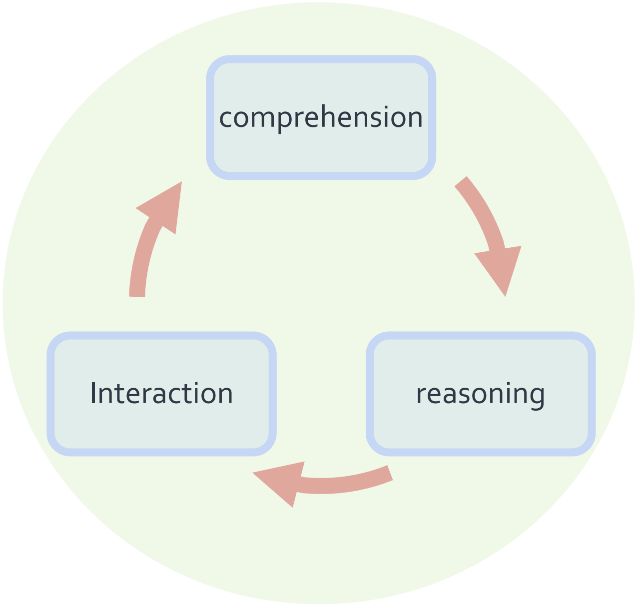


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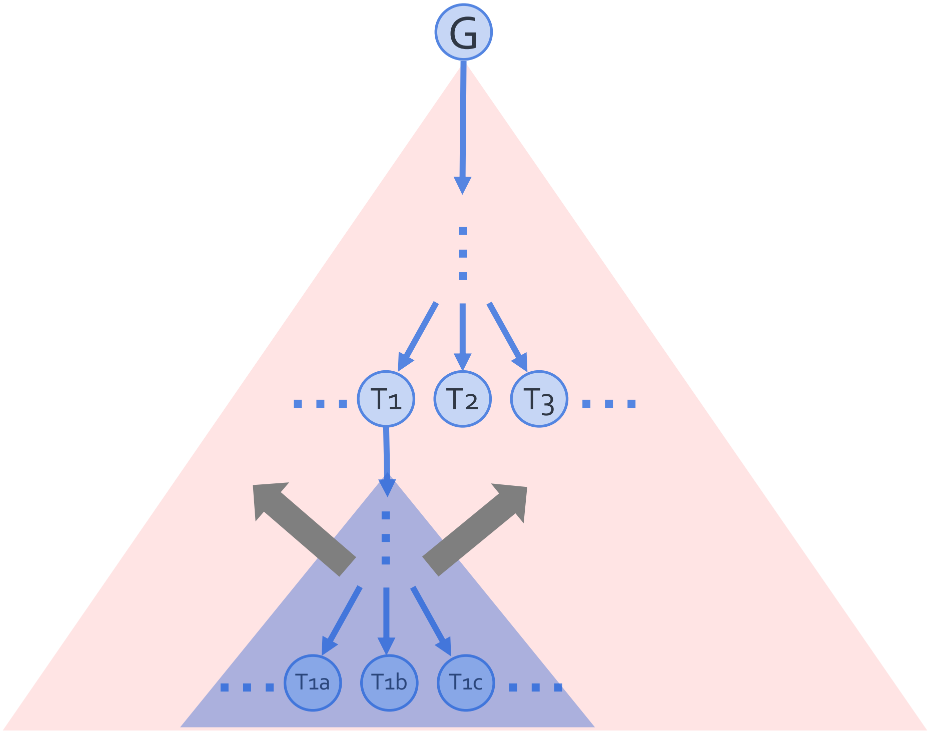
**Long-term goal:** more general natural language processing (NLP) systems through unified algorithms and theories.

general
language understanding



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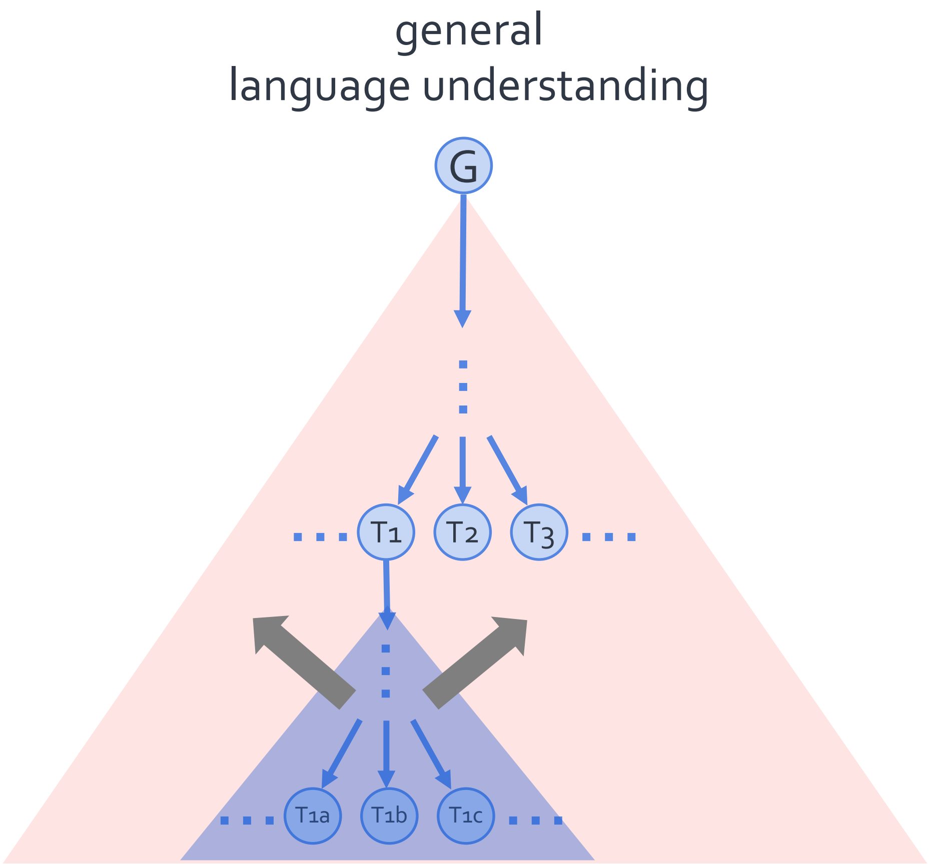

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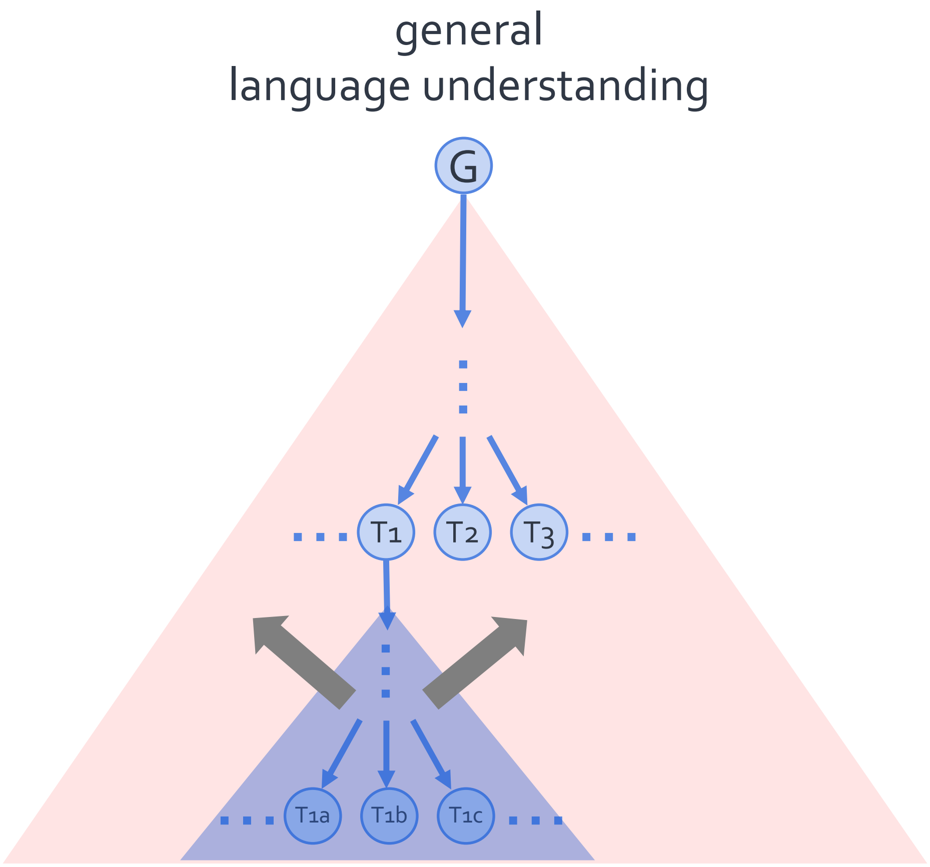


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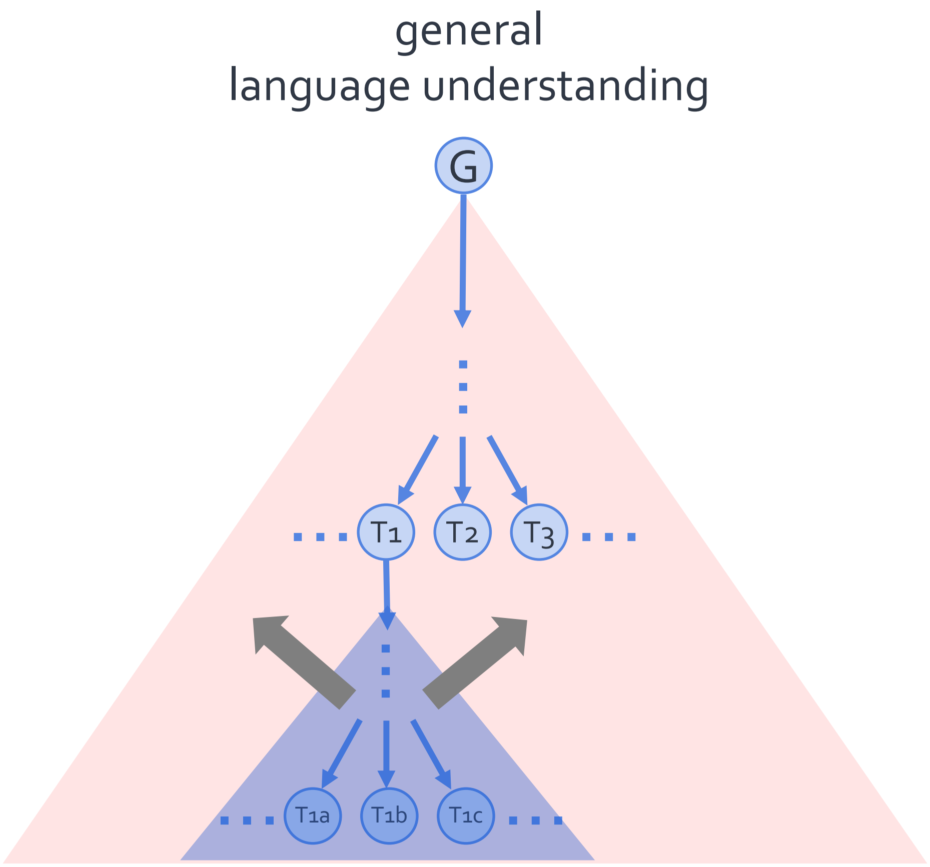


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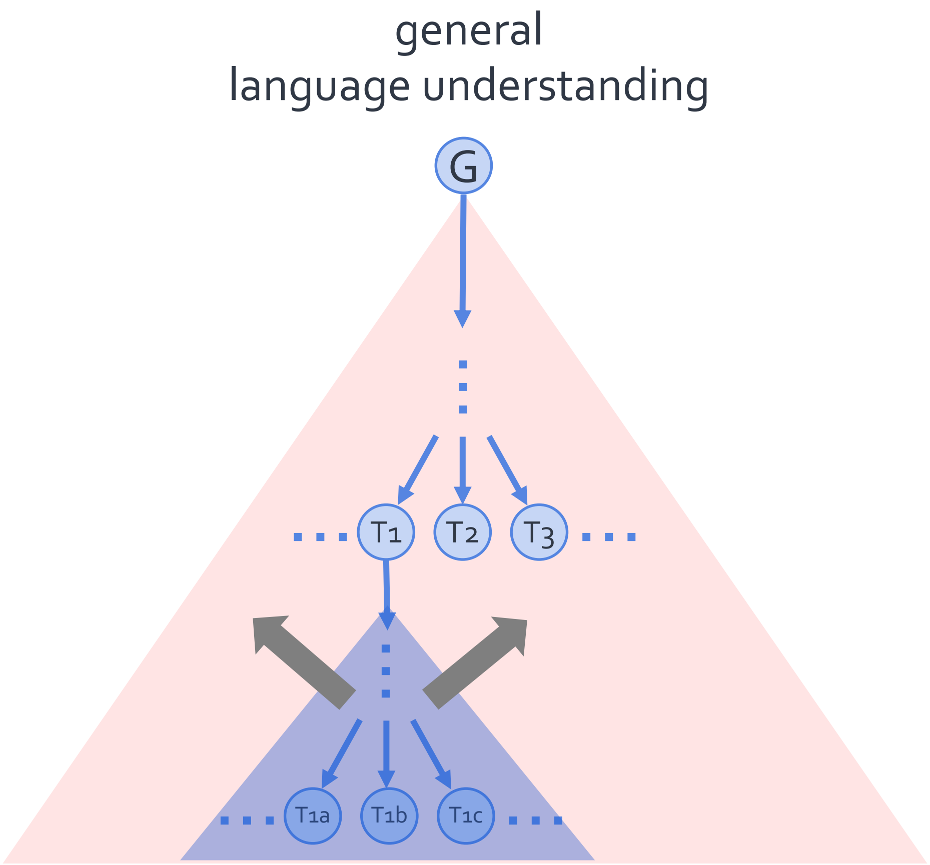
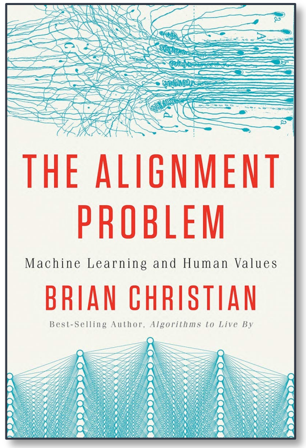



(I) Comprehension

(II) Reasoning

(III) Interaction

# Alignment with Abstract Statements



# Alignment with Abstract Statements

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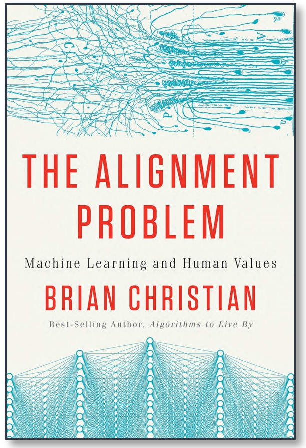

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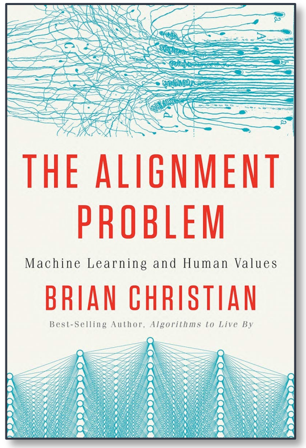

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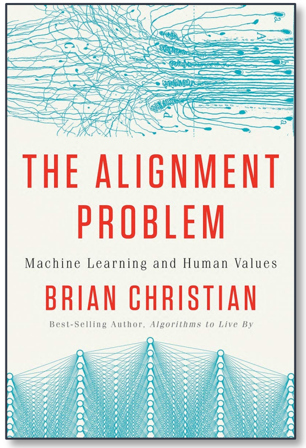

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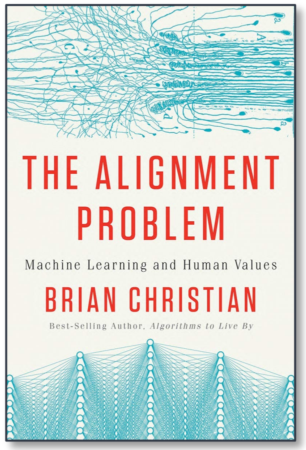


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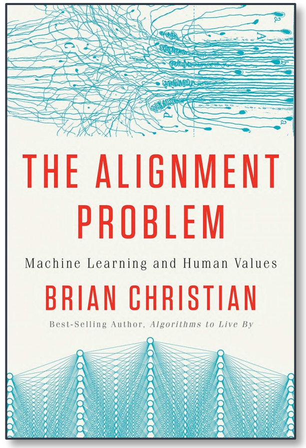


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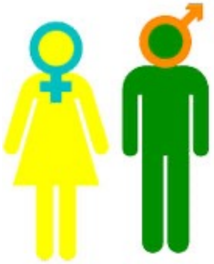

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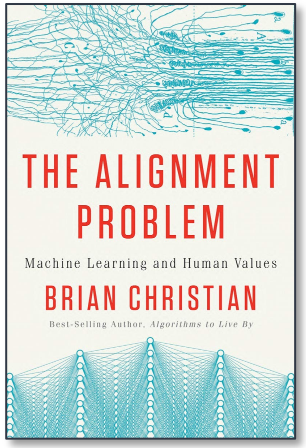


"Do Language Models Understand Natural Language Interventions?" Zhao, **Khashabi**, Khot, Sabhwaral, Chang, Findings of ACL '21

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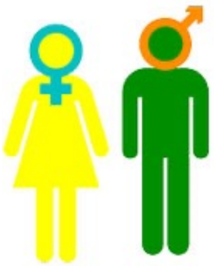

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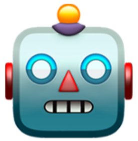

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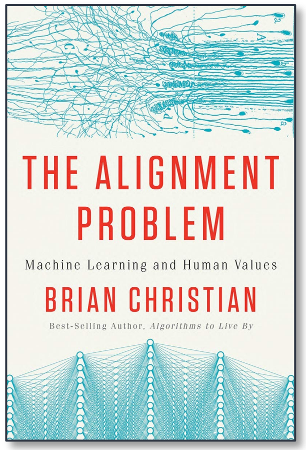


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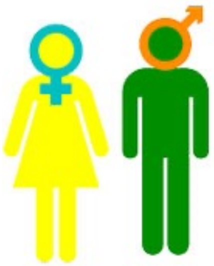

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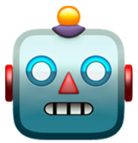

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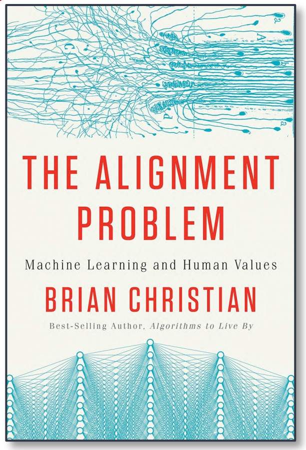

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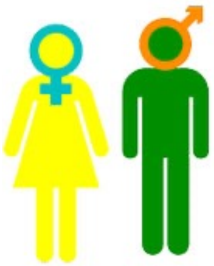

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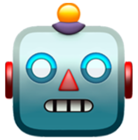

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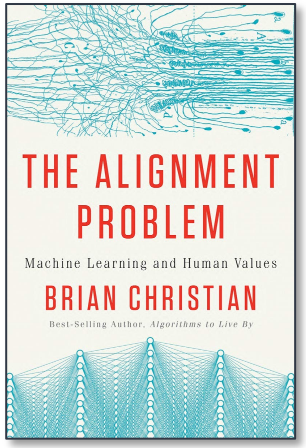


***Future work:*** *understanding and improving generalization over <u>abstract</u> language*

# Models with Commmonsense

- Commonsense — knowledge of everyday situations and events.

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*typical duration of dinner?*


*Few minutes?* *Few hours?* *Few days?*

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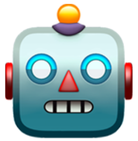
*Do we have time to eat dinner before the movie?*



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# Models with Commmonsense

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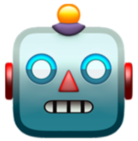
- **Challenge:** reporting bias [Gordon and Van Durme, '13]

*Do we have time to eat dinner before the movie?* →  → ???

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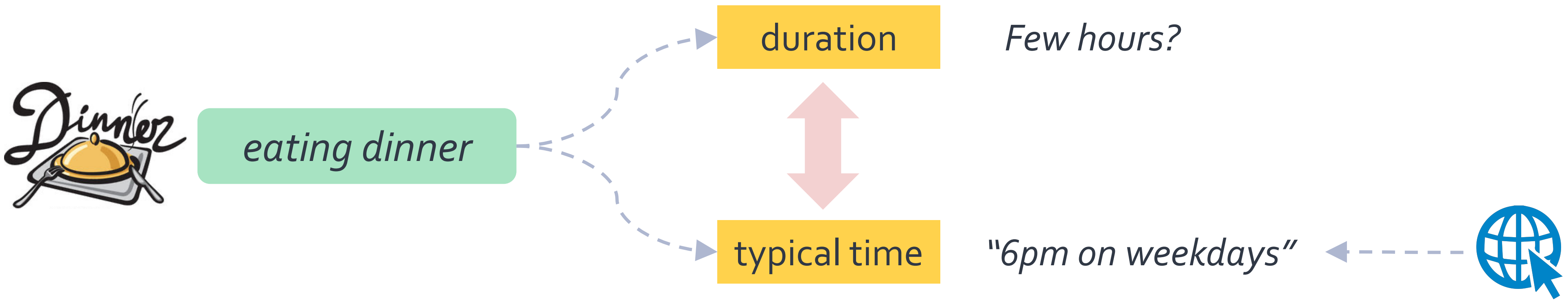


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"Temporal Commonsense Acquisition with Minimal Supervision." Zhou, Ning, **Khashabi**, Roth, ACL '20

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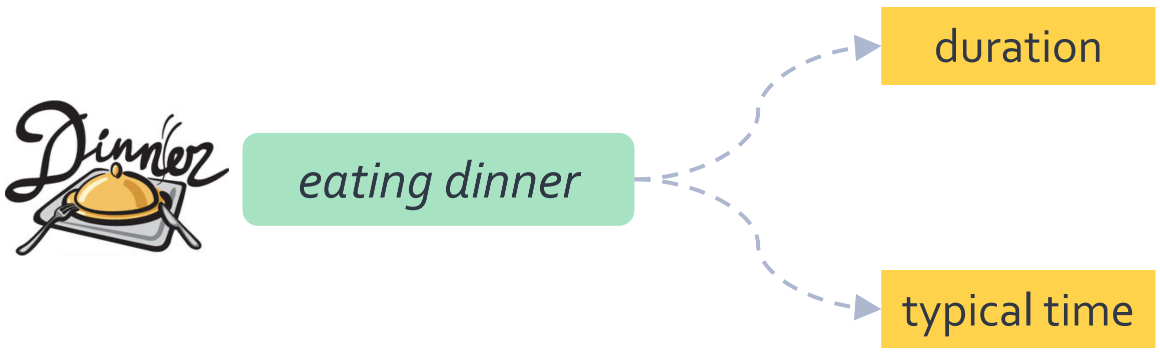


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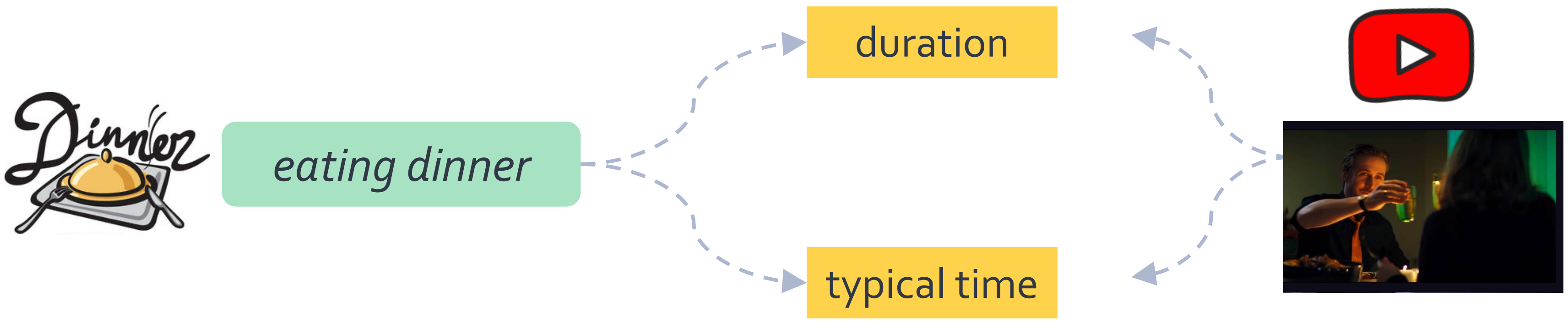
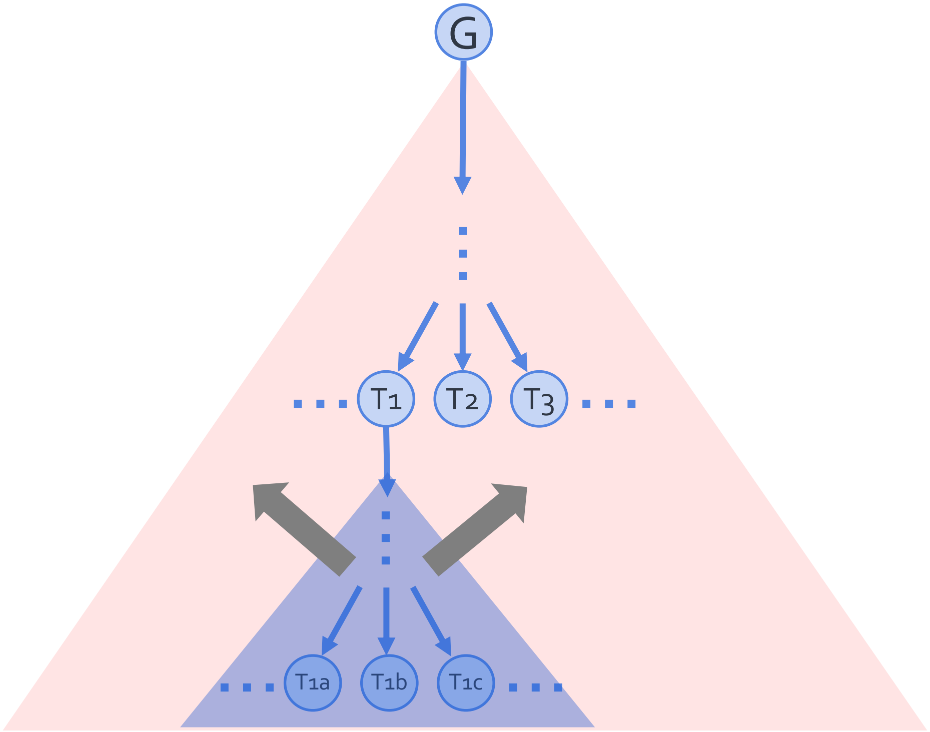



***Future work:** inducing commonsense knowledge in our models*

**Long-term goal:** more general natural language processing (NLP) systems through unified algorithms and theories.




(I) Comprehension

(II) Reasoning

(III) Interaction

# Reasoning with Implicit Compositions

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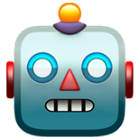
***implicit***

*Did Aristotle use a laptop?*



"Did Aristotle Use a Laptop? A Question Answering Benchmark with Implicit Reasoning Strategies" Geva, **Khashabi**, et al. TACL '21

# Reasoning with Implicit Compositions

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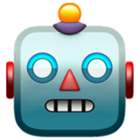
***implicit***

*Did Aristotle use a laptop?*

***explicit***

*Were laptops invented before Aristotle was born?*



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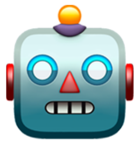

***Future work:*** *robust reasoning for* *implicit compositional statements*

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# Non-monotonic Reasoning

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What happened next?

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She decided to cut her walk short.

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???

She was all freshened up to continue her walk.

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***Future work:** characterizing <u>non-monotonicity</u> in language problems and tackling it*

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***Future work:*** *characterizing non-monotonicity in language problems and tackling it*

"Energy-based Constrained Text Generation with Langevin Dynamics." Qin, Welleck, K, Choi, arXiv pre-print '22

# Non-monotonic Reasoning

constraint text generation as sampling from an energy function

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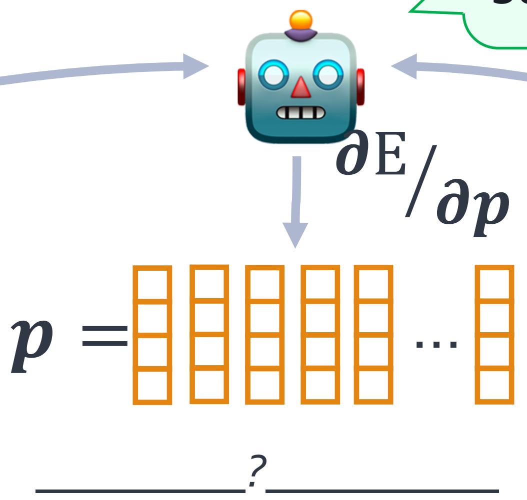


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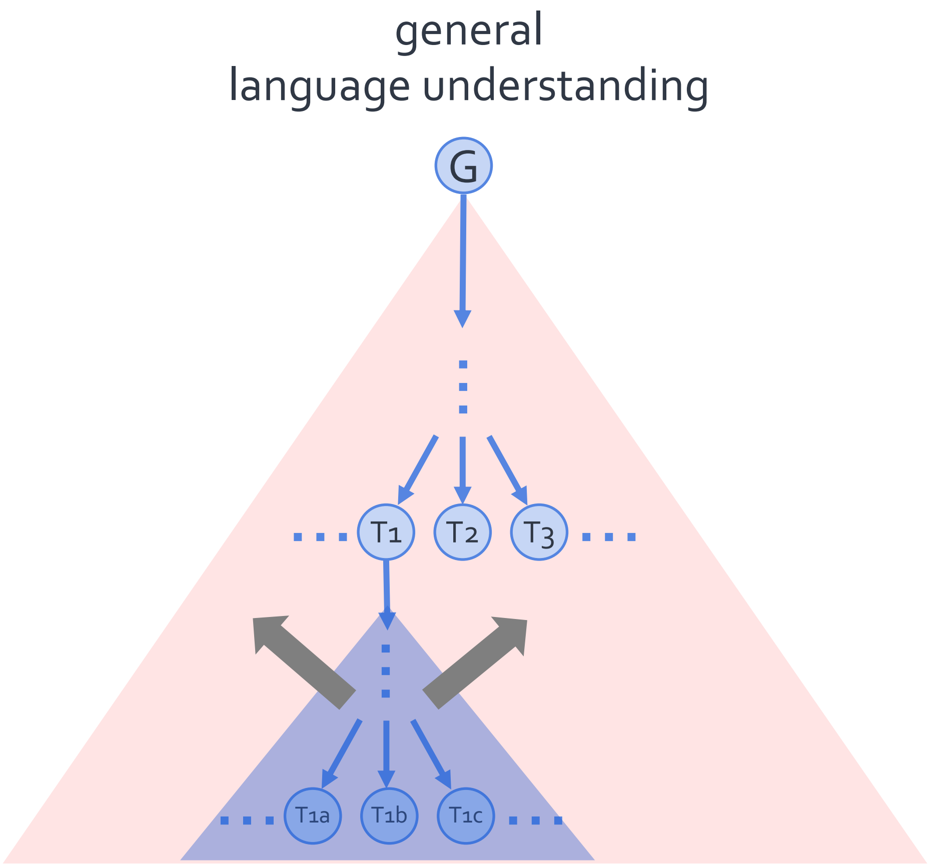


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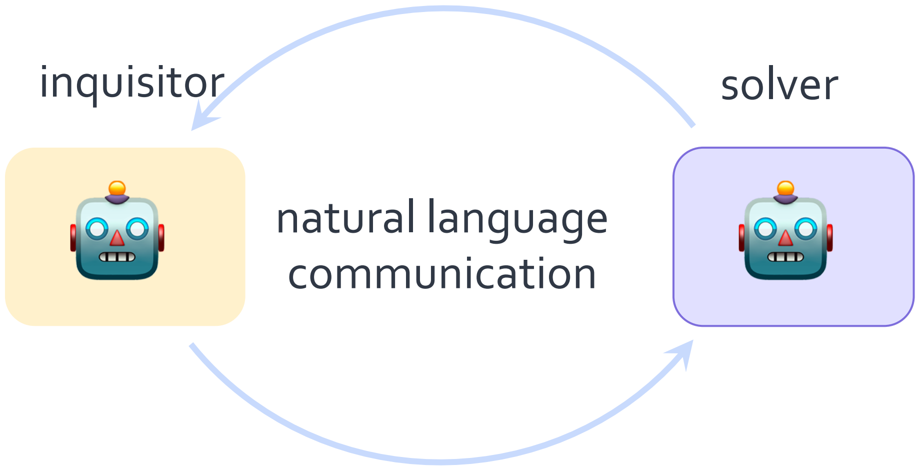
# Reasoning in Language Interaction

- Language interactions is a key medium in which "reasoning" emerges.



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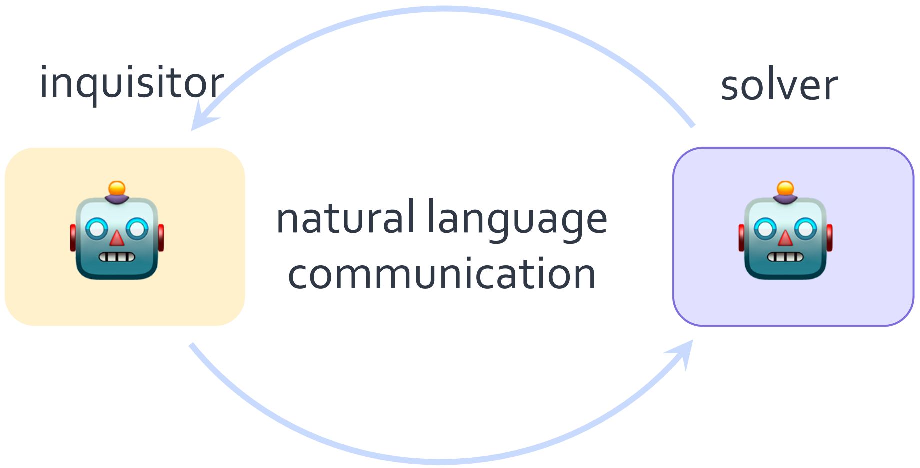
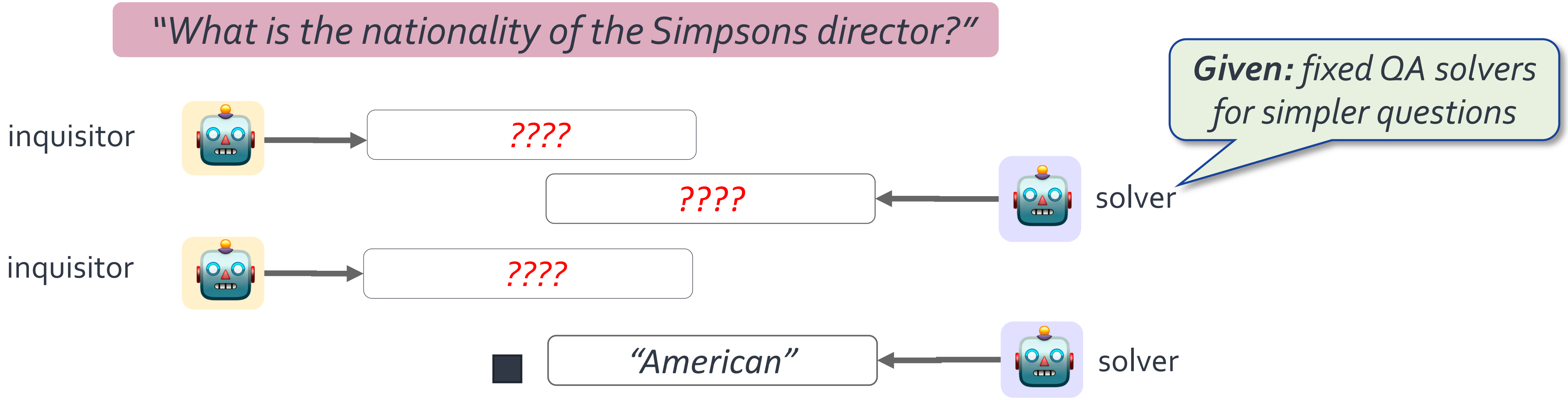
- Text Modular Networks



# Learning Language Interaction

- **Challenge:** assumptions used for learning decompositions in TMN can be limiting.



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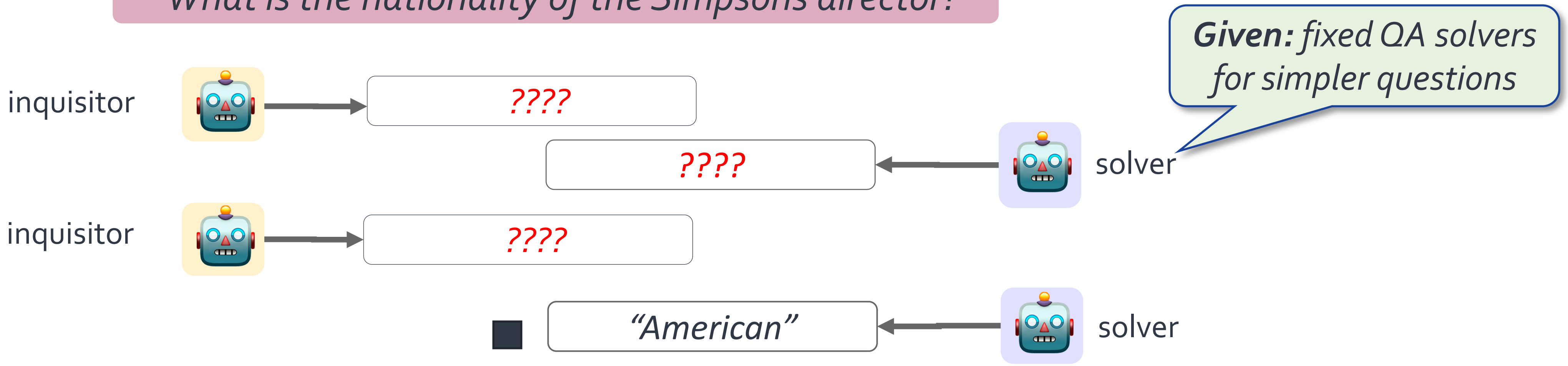
*"What is the nationality of the Simpsons director?"*

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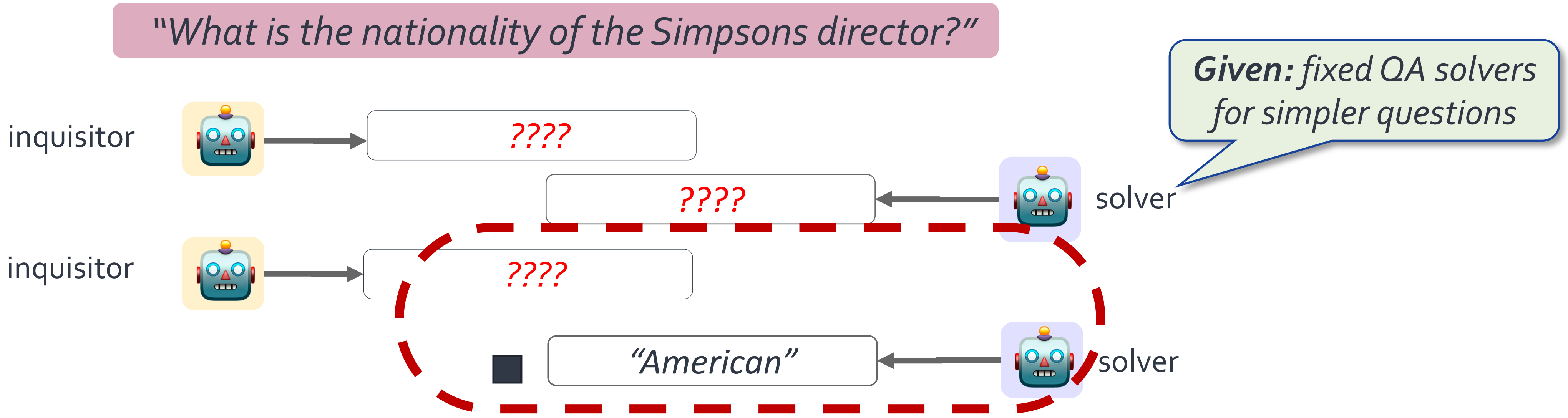


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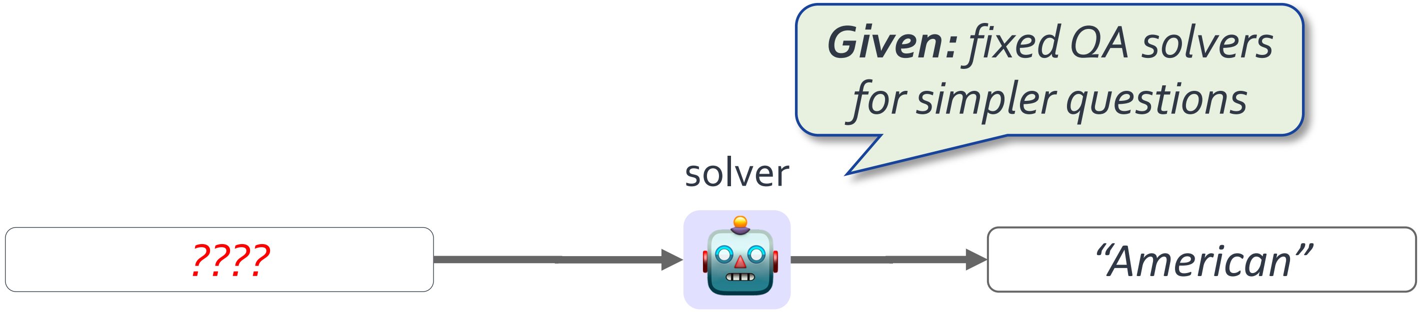


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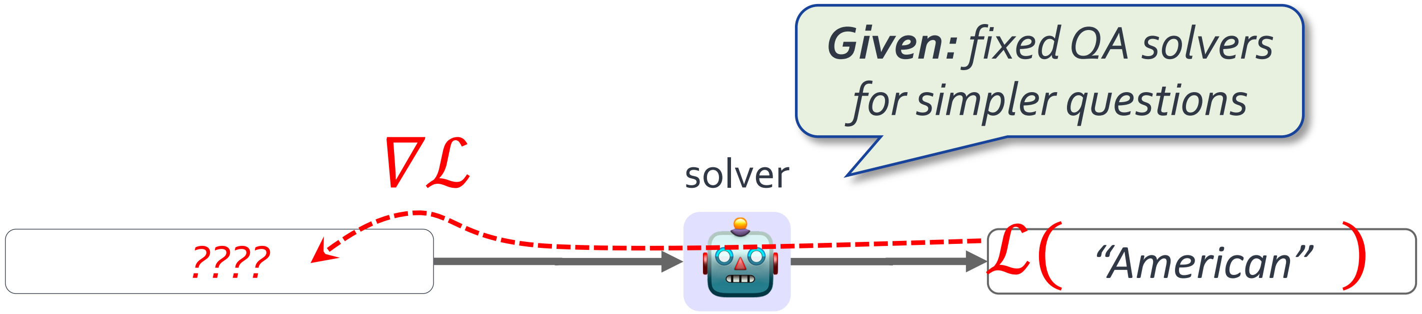


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"Promp Waywardness: The Curious Case of Discretized Interpretation of Continuous Prompts." **Khashabi** and others, arXiv pre-print '22 

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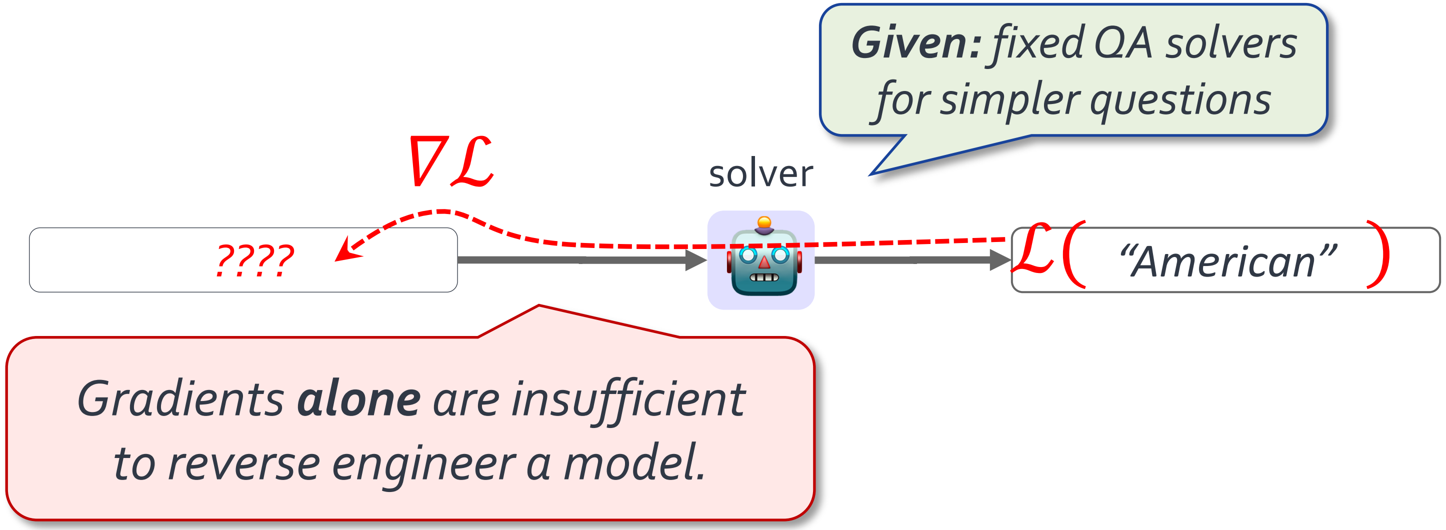


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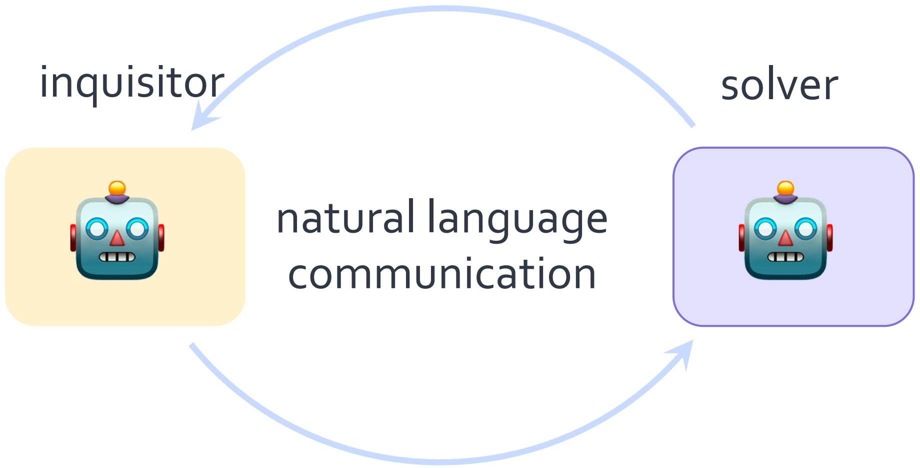
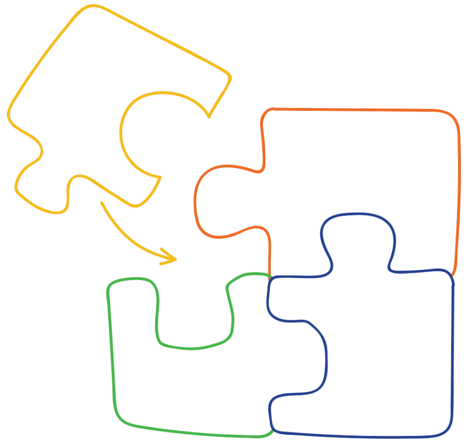
# Extensible Language Interaction

- Extensible Text Modular Networks



"Learning to Solve Complex Tasks by Talking to Agents." Khot, Richardson, **Khashabi** and Sabharwal, ACL Findings '22

# Extensible Language Interaction

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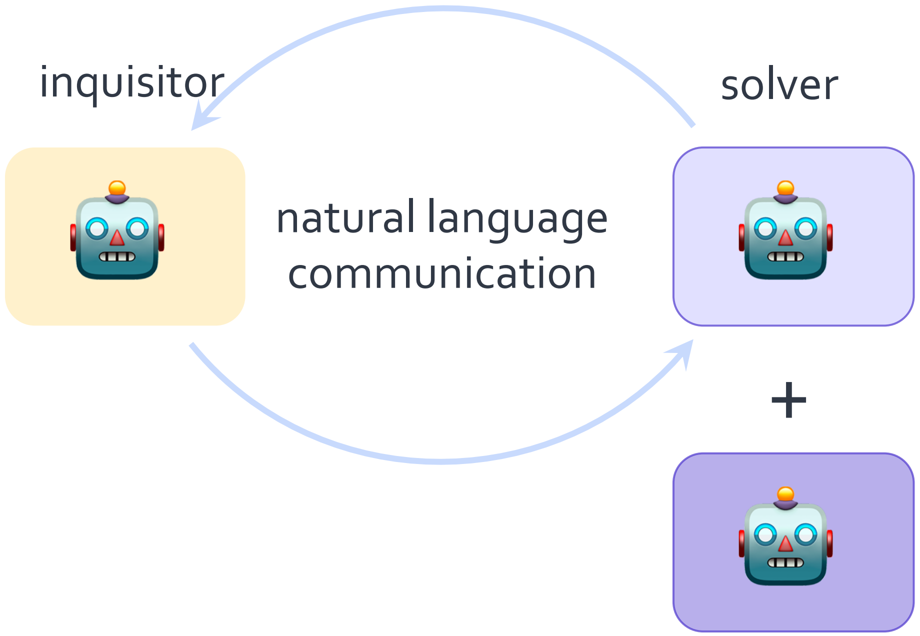


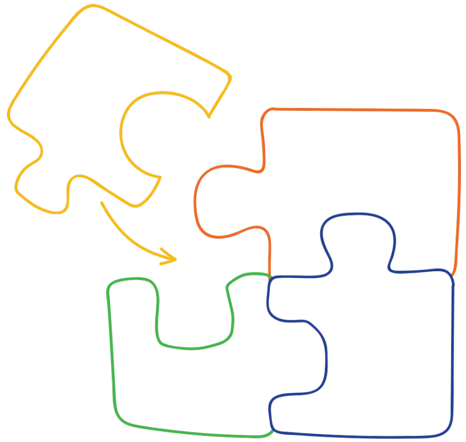

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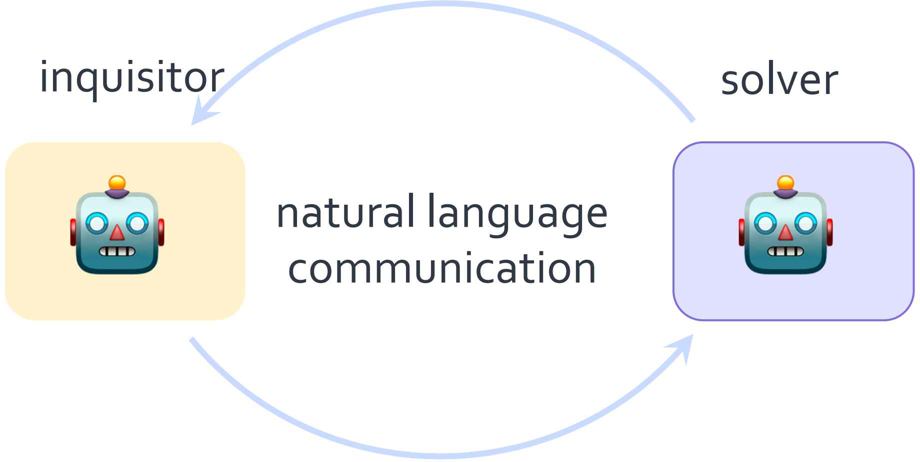


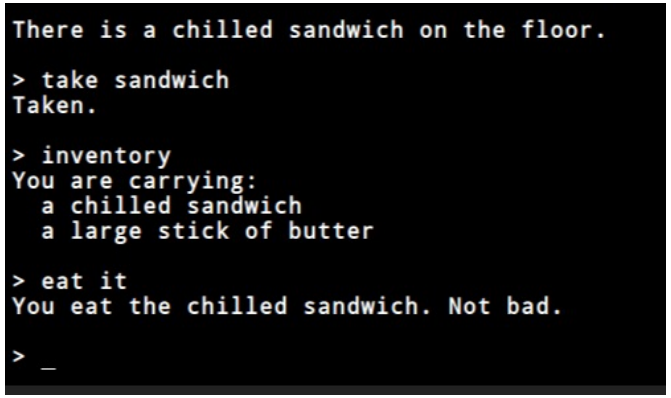


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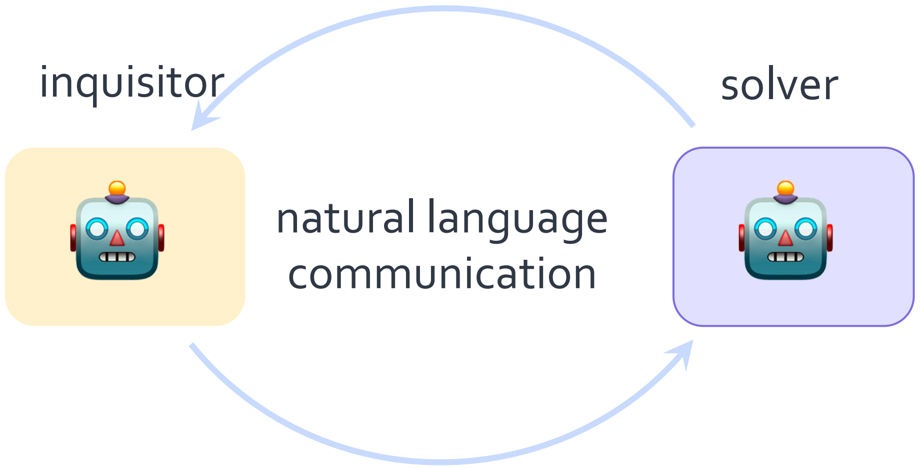



***Future work:*** *interactive goal-driven language communication in <u>partially-known environments</u>*

Ai2 Allen Institute for AI

Penn
University of Pennsylvania







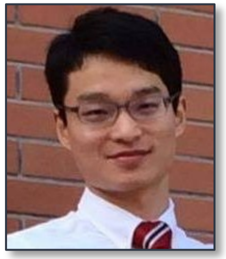


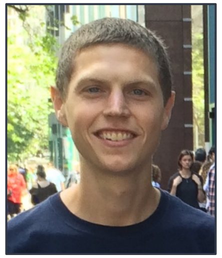
האוניברסיטה העברית בירושלים
THE HEBREW UNIVERSITY OF JERUSALEM

# *Thanks to my collaborators!*

NYU


ASU Arizona State University



W University of Washington