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Prompt Engineering

A comprehensive overview of prompt engineering techniques and best practices to build a successful FMware

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Check this paper for more information about this session

```
@article{cogo2024compiler,
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  author={Cogo, Filipe R and Oliva, Gustavo A and Hassan, Ahmed E},
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```


Outline

- Basic prompt concepts
- Prompt engineering techniques
- Sampling and decoding
- Fragility of prompts
- Prompt evolution and management
- Prompt compilers

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- **Basic prompt concepts**
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Instructing FMs with prompts

- Prompts are used to instruct the FM on specific tasks
  - Replaces, complements, or interacts with traditional programming code
- In-context learning
  - Enable new capabilities by augmenting the FM with domain knowledge
  - Help generate trustworthy and responsible results
  - Evaluate the capabilities and limitations of an FM for a downstream task

The structure of a prompt

- The quality of a prompt depends on how well-written it is
  - Different components may be required
- Examples of prompt components:
  - Task-related:
    - **Instruction** describes what completion task the model should perform
    - **Constraints** sets boundaries for the contents the model can generate
    - **Output format** determines how the output should be formatted
  - Context-related:
    - **Knowledge** provides the model with background information
    - **Examples** provides the model with instances of the desired completion
    - **Persona** provides the model with a specific stereotype identity

Example of a simple prompt

- A basic prompt expects the FM to complete with the next token

Input prompt (no instruction):

The sky is

Result:

blue

https://www.promptingguide.ai/introduction/basics

Example of a prompt with instruction

- A prompt can contain instructions to guide the model's generation in a specific way (e.g., to perform a task)
- Many FMs are fine-tuned to follow instructions

Prompt:

Classify the sentiment of the following sentence: The meal was awesome

Result:

Sentiment: Positive

https://www.promptingguide.ai/

Example of a prompt with a constraint

- A prompt can ask the FM to restrict how the generated result look like

Prompt:

Classify the following sentence into neutral, negative or positive:

The meal was awesome

Result:

positive

https://www.promptingguide.ai/

Examples of more complex prompts

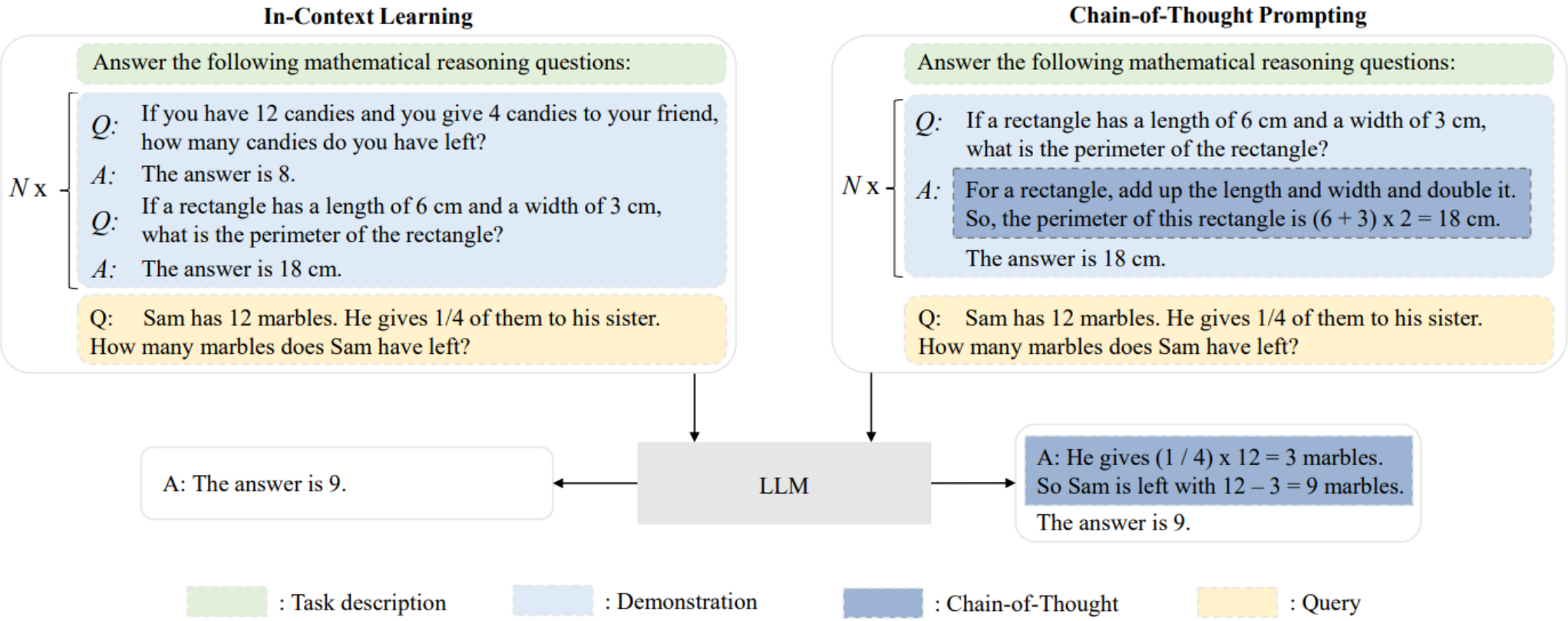

Fig. 12: A comparative illustration of in-context learning (ICL) and chain-of-thought (CoT) prompting. ICL prompts LLMs with a natural language description, several demonstrations, and a test query, while CoT prompting involves a series of intermediate reasoning steps in prompts.

https://arxiv.org/pdf/2308.10620.pdf

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Prompt engineering techniques

- **Zero-shot** directly instructs the FM to perform a downstream task
- **Few-shot** provides examples to nudge the model
- **Chain-of-thought (CoT)** enables complex reasoning through an example of intermediate reasoning steps (thoughts)
- **Self-consistency** improves CoT by exemplifying with several reasoning paths
  - Use the generations to select the most consistent answer
- **Tree-of-thoughts (ToT)** explores multiple reasoning paths over thoughts arranged in a tree-like structure
  - Definition of “thought” depends on the task at hand
  - Uses FM to evaluate thoughts and avoid “impossible” ones

Few-shot prompting

- Provide examples in the prompt to guide the model towards a task completion
- Based on the principle of meta-learning
  - Model develops a broad set of pattern recognition abilities at training time
  - Uses those abilities at inference time to rapidly recognize the desired task
- Meta-learning is achieved with in-context learning
  - Model is conditioned on a few demonstrations of the task
  - Completes further instances of the task by predicting the next tokens

Example of few-shot prompting

Prompt:

Circulation revenue has increased by 5%: Positive

Panostaja did not disclose the purchase price: Neutral

Paying off the debt will be extremely painful: Negative

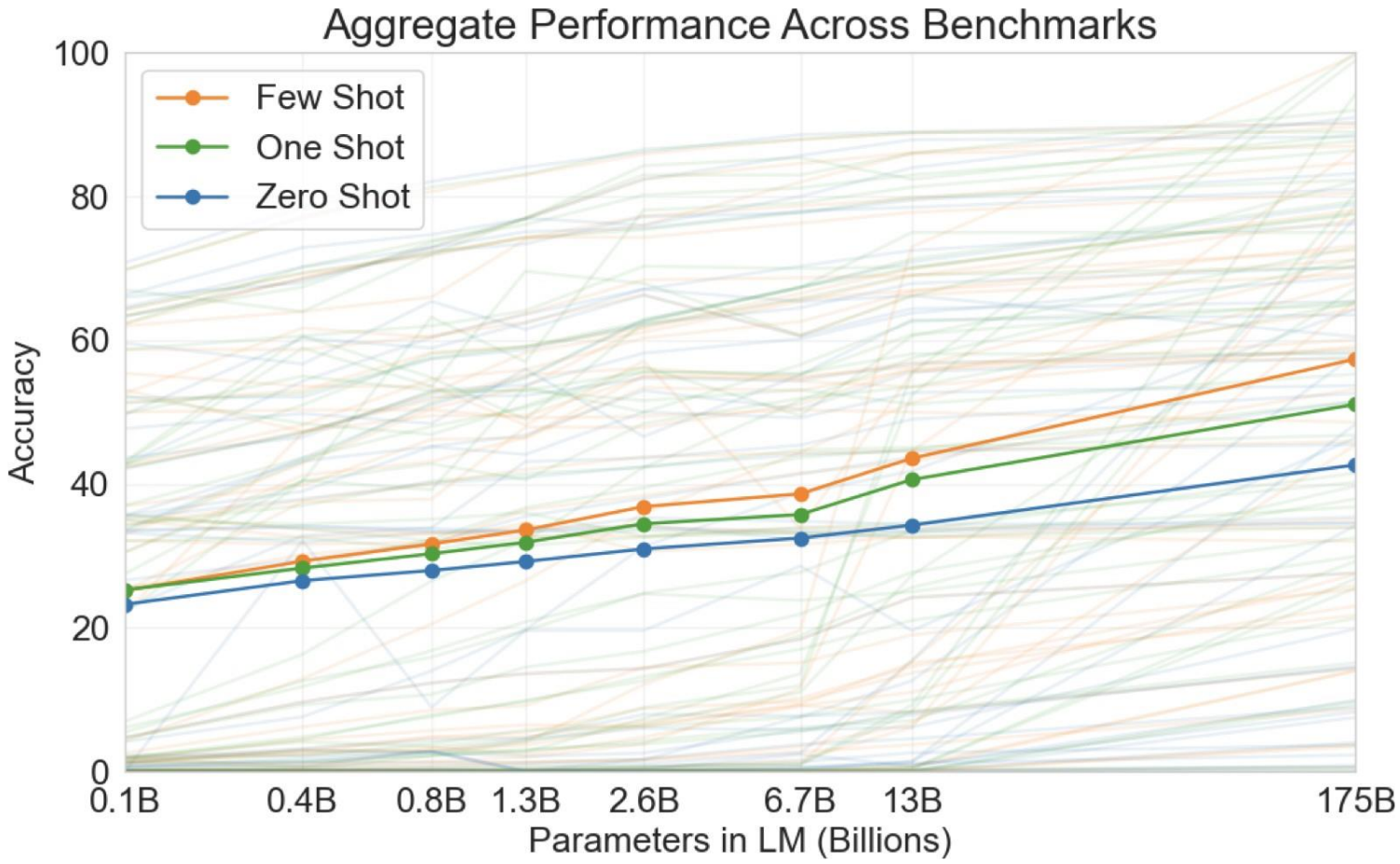
The acquisition will have an immediate positive impact:

Result:

Positive

https://www.promptingguide.ai/

Few-shot prompting improves accuracy in benchmark validation



https://arxiv.org/pdf/2005.14165.pdf

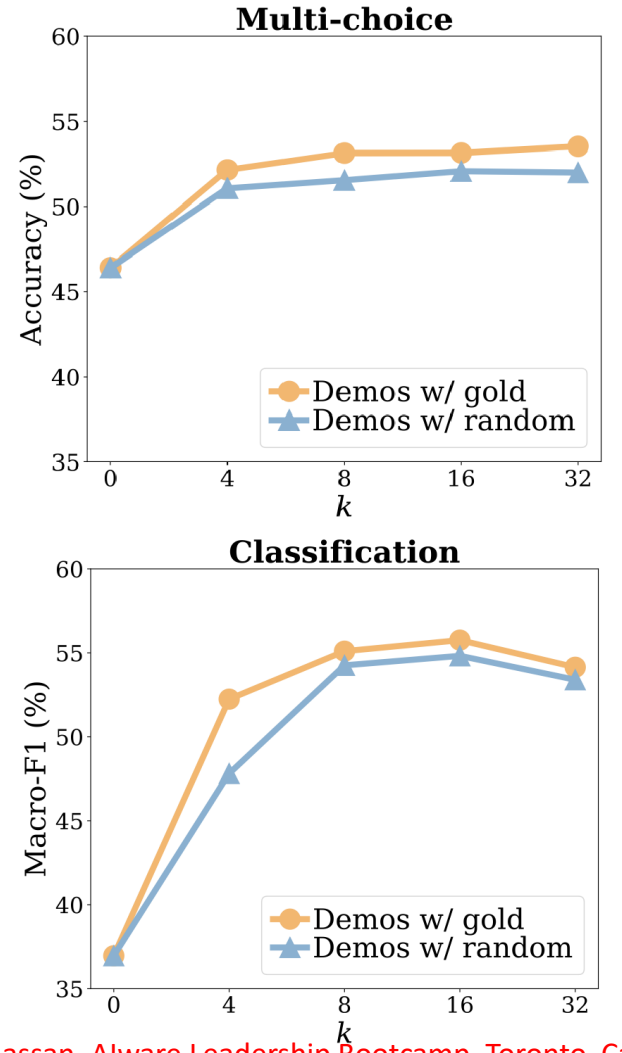
Do “correct” examples matter?

- Suppose that k few-shot examples are given with pairs $(x_1, y_1), \ldots, (x_k, y_k)$
  - **Zero-shot:** next token y is $argmax_{y \in C}\, p(y|x)$, where x is the input and C the possible labels
- **Input-label mapping** refers to whether each input x_i is labelled with a correct label y_i
- Min et al., 2022 shows that input-label mapping has little impact to performance

https://arxiv.org/pdf/2202.12837.pdf

Replacing gold labels with random labels doesn't hurt performance considerably

- **Gold-labels**: next token y is $argmax_{y \in C}\, p(y|x_1, y_1, \ldots, x_k, y_k, x)$
- **Random-labels**: next token y is $argmax_{y \in C}\, p(y|x_1, \tilde{y}_1, \ldots, x_k, \tilde{y}_k, x)$
  - $\tilde{y}_i$ is C's random sample



https://arxiv.org/pdf/2202.12837.pdf

Concerns when designing few-shot prompts

- *Distribution of the input text*: underlying distribution of $x_1, \ldots, x_k$
  - **In-distribution inputs** (from training data) in the examples substantially **improve performance**
- *Label space*: underlying distribution of $y_1, \ldots, y_k$
  - Conditioning on the **label space** C significantly contributes to **performance gains**
- *Format* of the input-label pairs
  - Keeping the format of "**input-label pairs**" is important

Few-shot prompting has limited reasoning capabilities

Prompt:

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Result:

The answer is 27.

https://arxiv.org/pdf/2201.11903.pdf

Chain-of-thought (CoT) prompting

- A series of **intermediate natural language reasoning steps** that lead to the final output
  - A prompt consists of triples ⟨input, chain of thought, output⟩
- Explore the ability of language models to perform **few-shot prompting for reasoning tasks**
  - Decompose multi-step problems into intermediate steps
  - Interpretable behaviour of the model to debug the reasoning path
  - Suitable for math problems, commonsense reasoning, etc.
  - Requires sufficiently large off-the-shelf language models

Example of chain-of-thought prompting

Prompt:

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?
A: **Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls.** 5 + 6 = 11. The answer is 11.
Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Result:

The cafeteria had 23 apples originally. They used 20 to make lunch. So they had 23 – 20 = 3. They bought 6 more apples, so they have 3 + 6 = 9. The answer is 9.

Example of a ⟨input, chain of thought, output⟩ triple. The chain-of-thought component of the prompt is **highlighted**

https://arxiv.org/pdf/2203.11171

Example of *zero-shot* chain-of-thought prompting

Prompt:

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?

A: **Let's think step by step.**

Result:

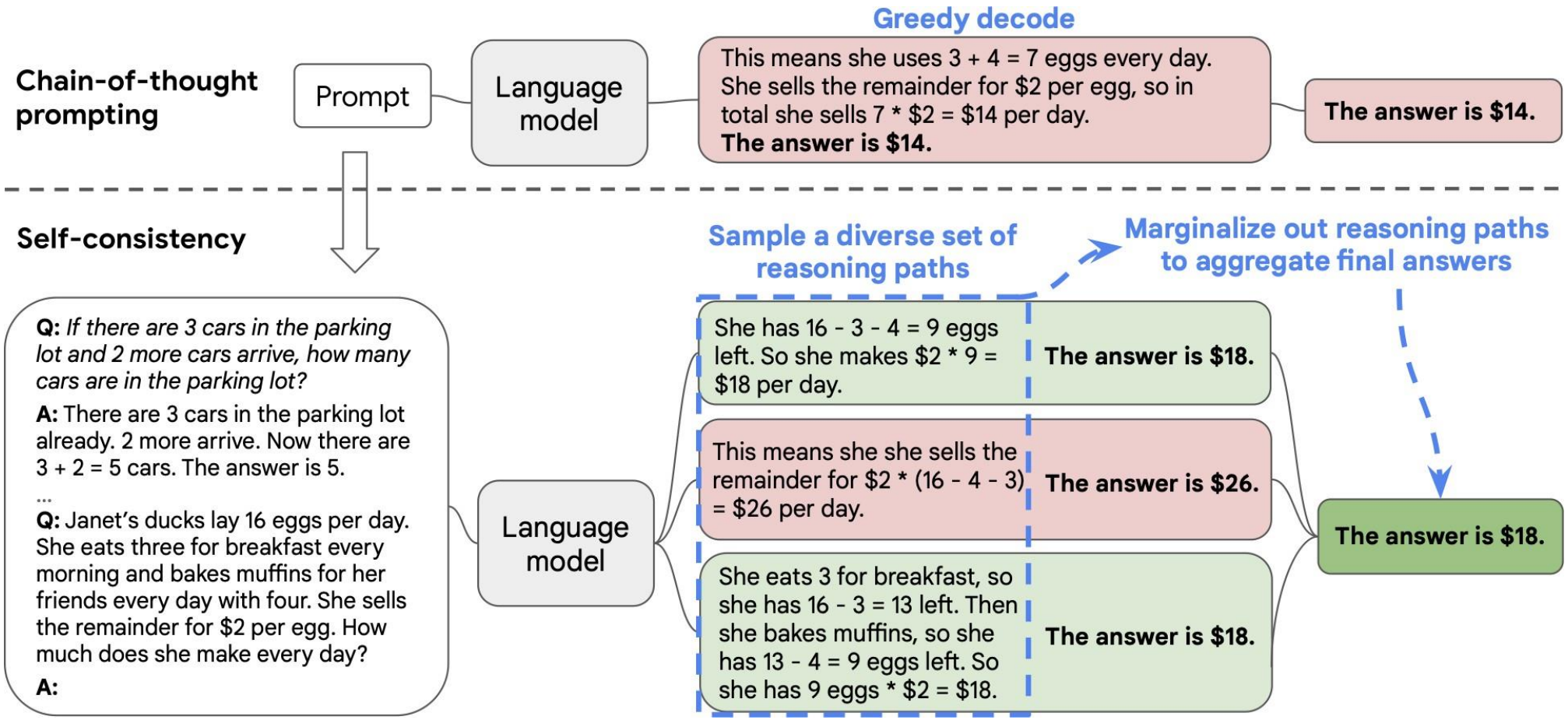
There are 16 balls in total. Half of the balls are golf balls. That means that there are 8 golf balls. Half of the golf balls are blue. That means that there are 4 blue golf balls.

https://arxiv.org/pdf/2205.11916.pdf

Self-consistency

- Complex reasoning tasks typically admit **multiple reasoning paths**
- **Three-step** procedure:
  1. Prompt the FM using chain-of-thought (CoT) prompting
  2. Replace the “greedy decode” in CoT by sampling from the FM’s decoder to generate a diverse set of reasoning paths
  3. Average out the reasoning paths and choose the most consistent answer
- Characteristics:
  - Entirely unsupervised
  - Works off-the-shelf with pre-trained language models
  - Requires no additional human annotation
  - Avoids any additional training, auxiliary models or fine-tuning
  - Not an ensemble technique as it uses a single FM

Self-consistency explained



https://arxiv.org/pdf/2203.11171.pdf

Example of self-consistency prompting

Prompt:

Q: Michael had 58 golf balls. On Tuesday, he lost 23 golf balls. On Wednesday, he lost 2 more. How many golf balls did he have at the end of Wednesday?
A: Michael initially had 58 balls. He lost 23 on Tuesday, so after that he has 58 – 23 = 35 balls. On Wednesday he lost 2 more so now he has 35 – 2 = 33 balls. The answer is 33.
(... *more CoT examples* ...)
Q: When I was 6 my sister was half my age. Now I'm 70 how old is my sister?
A:

Result 1:

When I was 6 my sister was half my age, so she was 3. Now I am 70, so she is 70 – 3 = 67. The answer is 67.

Result 2:

When the narrator was 6, his sister was half his age, which is
3. Now that the narrator is 70, his sister would be 70 - 3 = 67 years old. The answer is 67.

Result 3:

When I was 6 my sister was half my age, so she was 3. Now I am 70, so she is 70/2 = 35. The answer is 35.

https://www.promptingguide.ai/techniques/consistency

Tree-of-thought (ToT) prompting

- Allows FMs to explore multiple reasoning paths over thoughts
- Frames a problem as a tree search, where each node is a state representing input and the sequence of thoughts
  - Definition of thought depends on the problem
- Design of a ToT prompt involves four steps:
  1. Decompose the intermediate process into thought steps
  2. Generate potential thoughts from each state
  3. Heuristically evaluate states
  4. Search algorithm

Thought decomposition in ToT prompting

- ToT leverages **problem properties** to design and decompose intermediate **thought steps**
  - A couple of words (Crosswords)
  - A line of equation (Math solving)
  - A whole paragraph of writing plan (Creative Writing)
- A thought should be:
  - Small enough so that FMs can generate promising and diverse samples (a whole book is too big to be coherent)
  - Big enough so that FMs can evaluate its prospect toward problem-solving (one token is usually too small to be evaluated)

Thought generation in ToT prompting

- Given a tree state $s = [x, z_1, \ldots, z_i]$, there are two strategies to generate k candidates for the next thought step
  1. Sample thoughts from a CoT prompt
  2. Generate thoughts sequentially using a *propose prompt*

Propose prompt for solving the Game of 24

(... *CoT examples* ...)

Input: 4 9 10 13

Possible next steps:

Result:

4 + 9 = 13 (left: 10 13 13)
10 - 4 = 6 (left: 6 9 13)
(... *other thoughts* ...)

https://arxiv.org/pdf/2305.10601

State evaluator in ToT prompting

- Heuristic that determines which states to keep exploring and in which order
- Two strategies to reason about states:
  1. A **value prompt** reasons about the state s to generate a scalar value v or a classification that could be heuristically turned into a value
  2. A **vote prompt** deliberately compare different states w.r.t. their value

Value prompt for solving the Game of 24

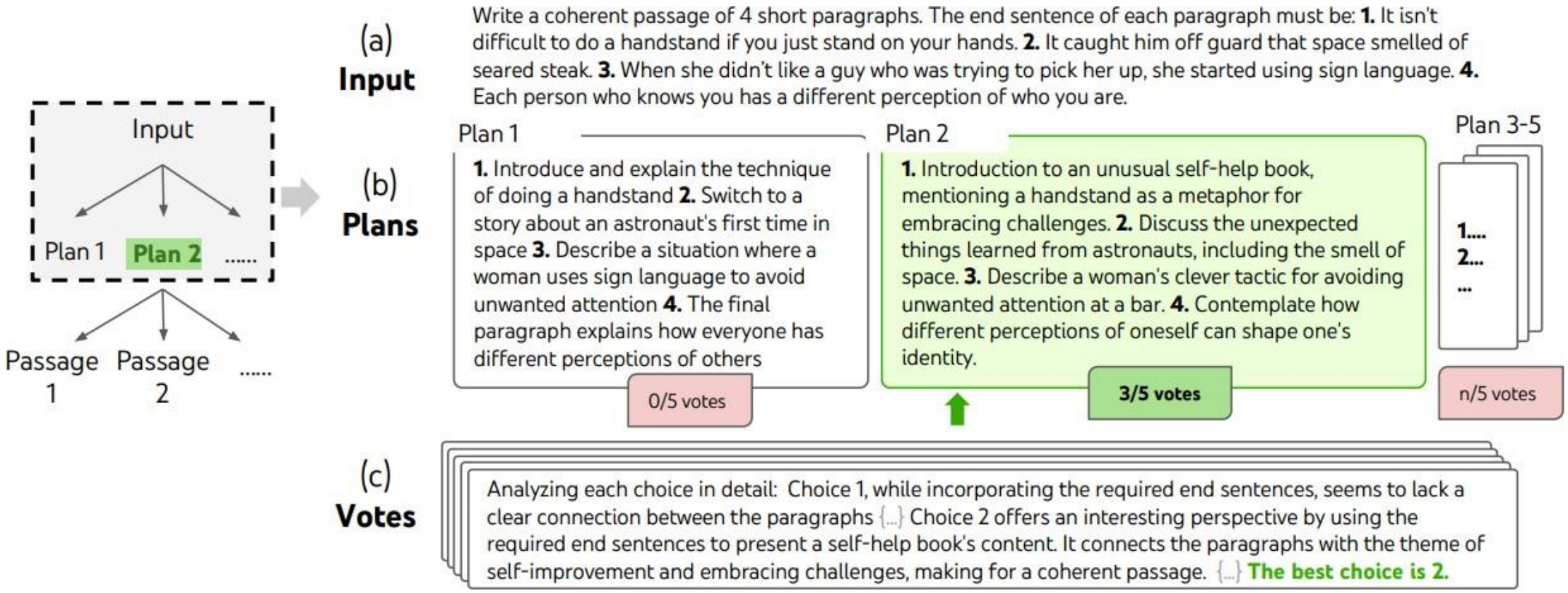
Evaluate if given numbers can reach 24 (sure/likely/impossible) 10 14: 10 + 14 = 24.
sure
(... *more examples* ...)
10 13 13

Result:

(13 - 10) * 13 = 3 * 13 = 39
10 + 13 + 13 = 36 There is no way to obtain 24 with these big numbers.
impossible

https://arxiv.org/pdf/2305.10601

Voting mechanism in ToT prompting



A ToT with depth 2 (and only 1 intermediate thought step) for the Creative Writing task. The FM first generates $k = 5$ plans and votes for the best one, then similarly generate $k = 5$ passages based on the best plan then vote for the best one. A simple zero-shot vote prompt ("analyze choices below, then conclude which is most promising for the instruction") is used to sample 5 votes at both steps

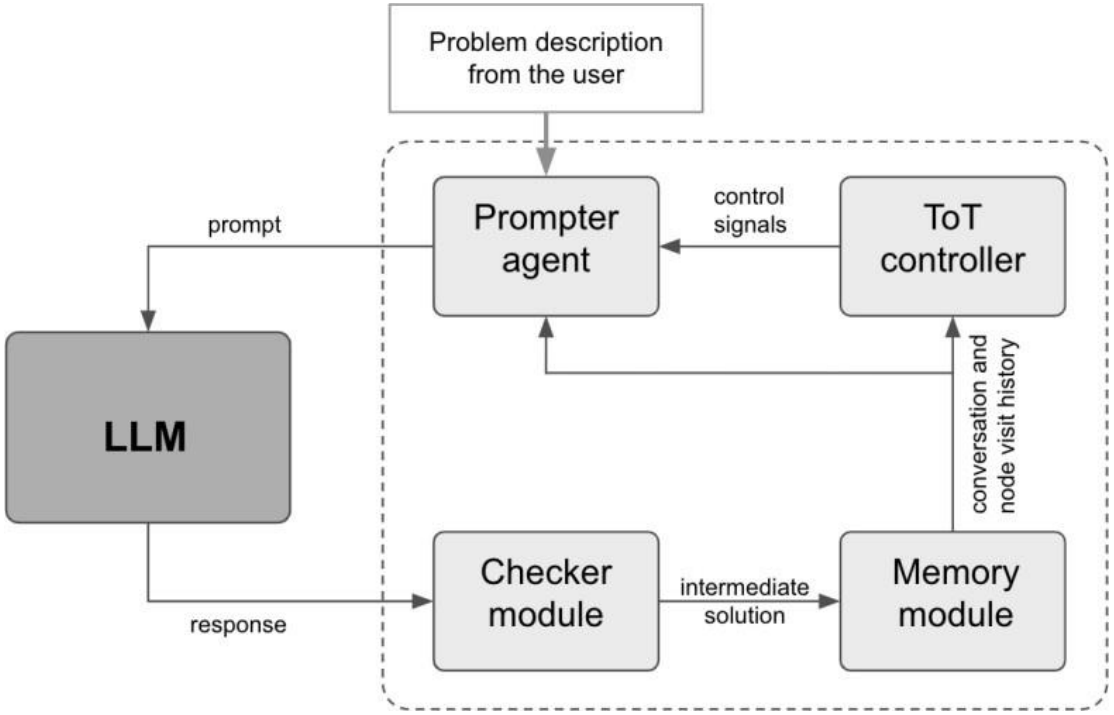
https://arxiv.org/pdf/2305.10601.pdf

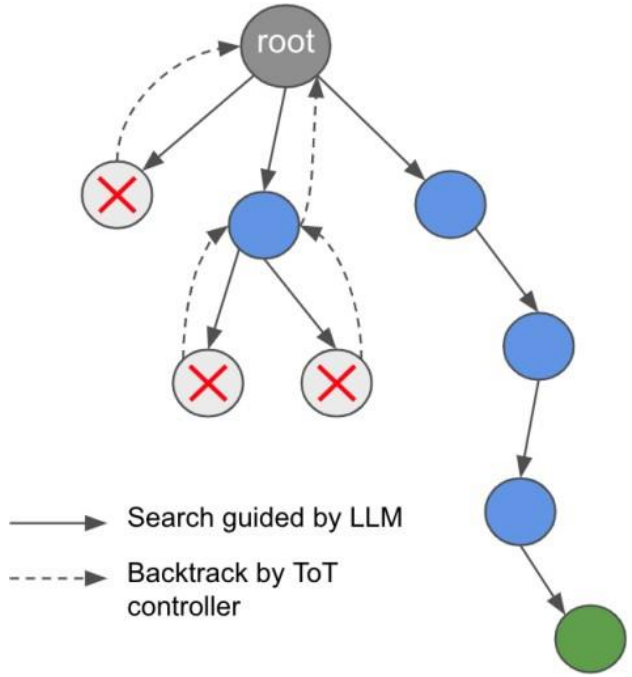
Search algorithm in ToT prompting

- Plug and play of different search algorithms depending on the tree structure
- Two relatively simple search algorithms:
  - **Breadth-first search (BFS)** maintains a set of the b most promising states per step
  - **Depth-first search (BFS)** explores the most promising state first, until:
    - The final output is reached $(t > T)$
    - The state evaluator deems it impossible to solve the problem from the current state

https://arxiv.org/pdf/2305.10601.pdf

ToT implementation



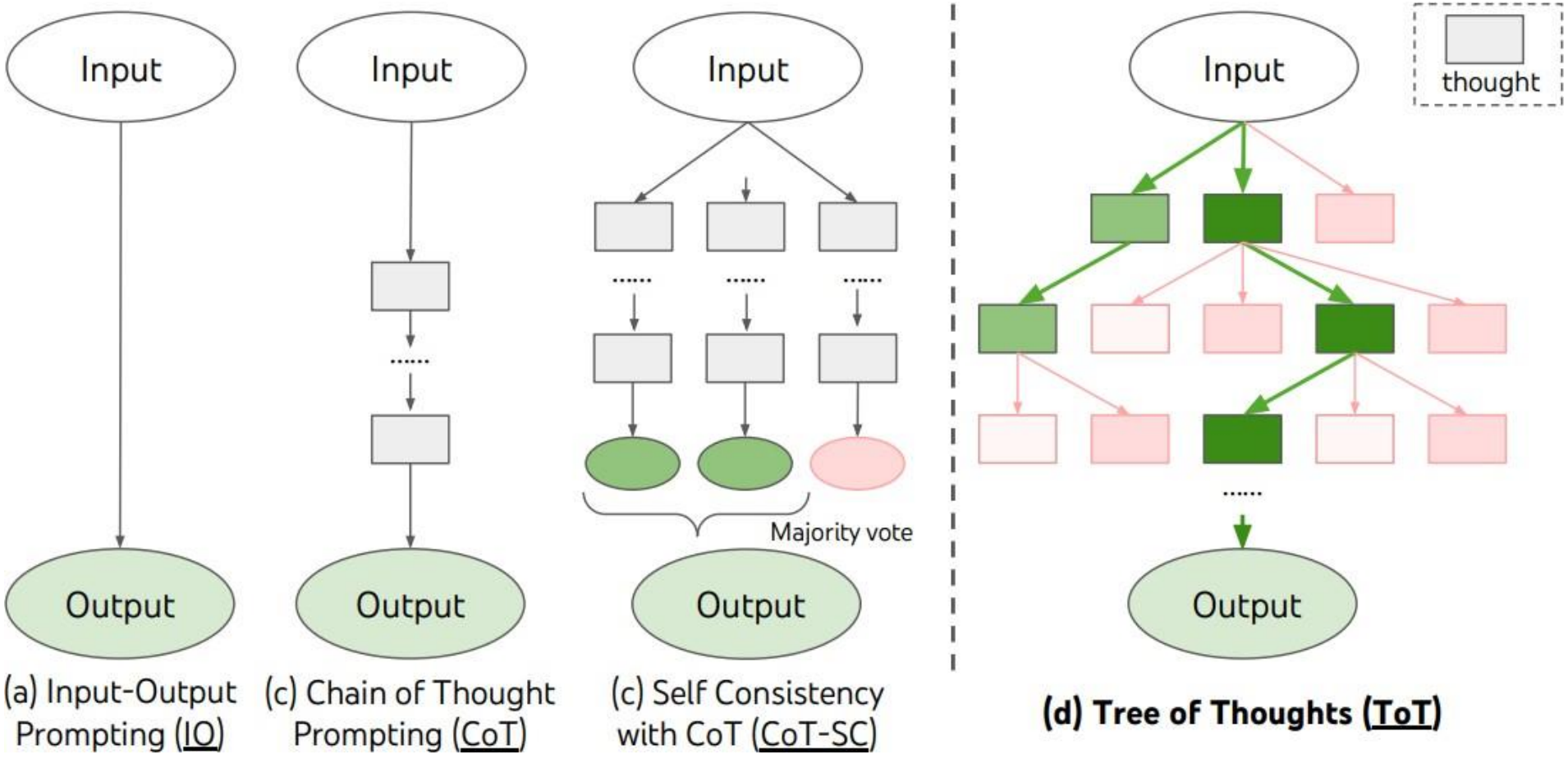


- The **prompter agent** instructs the LLM to generate an intermediate solution instead of the full solution in a single shot. The **checker module** checks the validity of the generated intermediate solution. If it passes, the intermediate solution is stored in the **memory module**. Otherwise, the ToT signals the prompter agent to enrich the prompt and send it to the LLM again

- Thoughts deemed as invalid by the checker module are backtracked to the parent node.
- Nodes that don't lead to a final solution are also backtracked

https://arxiv.org/pdf/2305.08291

IO vs. CoT vs. self-consistency vs. ToT prompting



https://arxiv.org/pdf/2305.10601.pdf

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Decoding strategies

- Autoregressive and Transformer models iteratively compute the next token s_t of a sequence
- Each iteration outputs a probability distribution

$$p(S_t | s_1, \ldots, s_{t-1}, v_1, \ldots, v_{T_{src}})$$

  - Priors include source tokens v_i and target tokens s_j
  - S_t is a random variable of the possible target tokens s_t at position t
- Generate all possible combinations of output tokens (exhaustive search) is computationally hard

$$p(S_1 = s_1, \ldots, S_T = s_T | v_1, \ldots, v_{T_{src}})$$

- *Decoding* uses a search algorithm that finds an approximate sequence $s_1, \ldots, s_T$

Sampling techniques for decoding

- **Random sampling** selects the next token according to all predicted probabilities
  - Can generate a sequence of tokens with low total probability
- **Top-k sampling** selects the next token from one of the k
- tokens with highest probability
  - Probability mass is redistributed among the k tokens and one is randomly selected
- **Top-p sampling** selects the next token from the set of tokens with probability above a threshold p
  - Randomly selected token from redistributed probabilities
  - Avoids rare tokens by limiting the probability mass

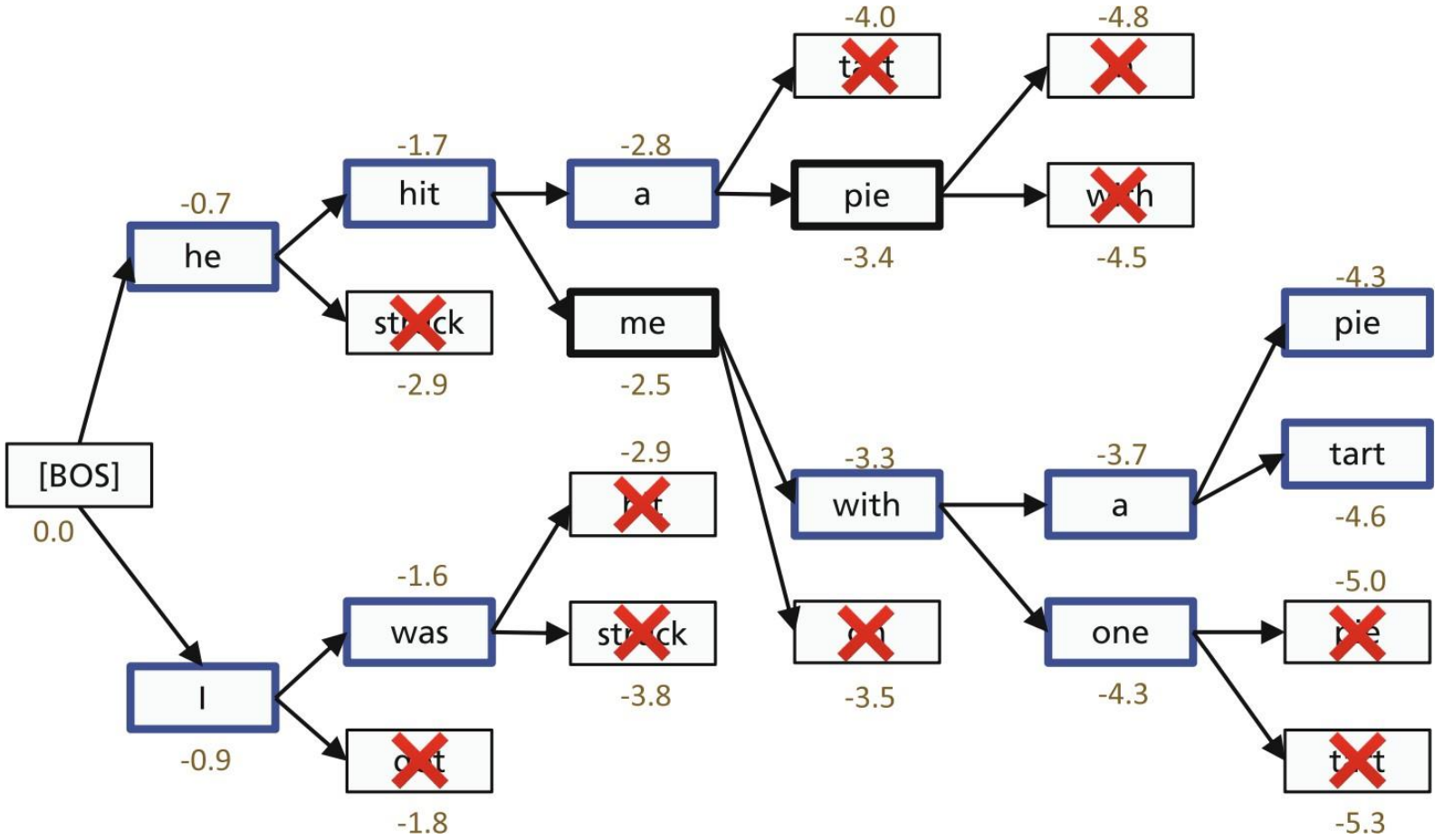
Search algorithms for decoding

- **Greedy search** selects the token with the highest probability at each generation step t
  - Finds the *sequence* of most likely *tokens*, not the most likely *sequence of tokens*, leading to suboptimal solutions
- **Beam search** keeps a fixed number of k possible sequences of length t and at each iteration:
  - Adds k different tokens s_{t+1} with the highest conditional probability to each of the k sequences:

$$p(S_{t+1} = s_{t+1} | s_1, \ldots, s_{t-1}, v_1, \ldots, v_{T_{src}})$$

  - From all $k \times k$ sequences, keep only k sequences with the highest total probability: $p(s_1, \ldots, s_{t+1} | v_1, \ldots, v_{T_{src}})$
  - When an end-of-sequence token is found, the associated sequence is added to the final candidate list
  - The algorithm picks the sequence with the highest probability

Beam search example



At every iteration, Beam search records the k partial sequences with the highest probability. Beam search continues until it reaches the end-of-sentence token for each branch.

https://arxiv.org/abs/2302.08575

Some decoder parameters

- **Temperature** (0.0 − 1.0) controls the weights of the tokens other than the most likely one
  - Determines the level of determinism in the generated sequences
  - The lower the temperature, the more deterministic the results
  - Adjusted according to the application (e.g., Q&A vs. poem generation)
- **Top-p** also controls the level of determinism in the generated sequences
  - Same p parameter of top-p sampling
- A good practice is to change one at once when setting hyperparameters

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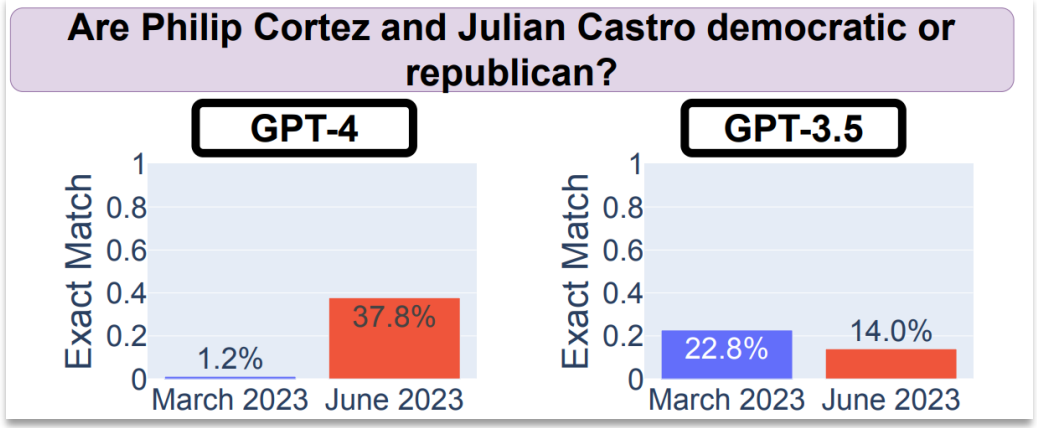
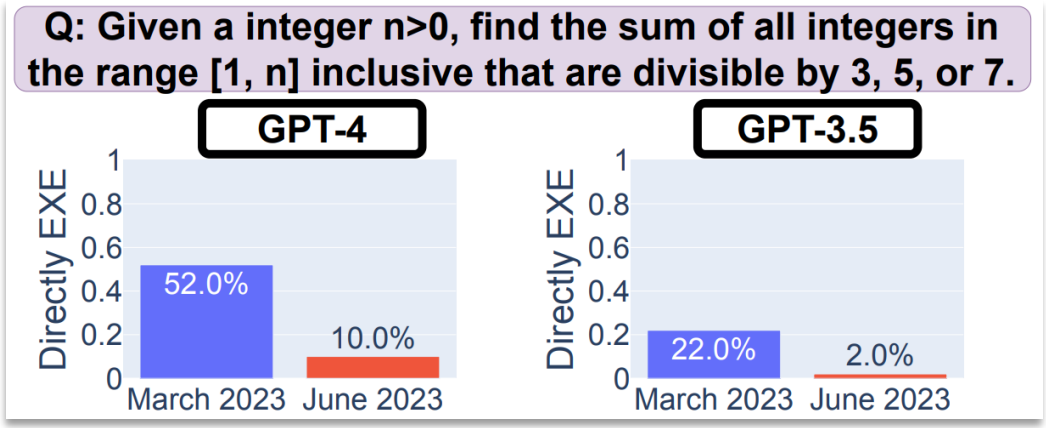
Current prompt engineering practices are very fragile and sensitive, leading to low portability

- **Prompts are not portable across FMs**
  - For example: consider this prompt – "Where is the capital of Japan?"
    - Bloomz: "Tokyo"
    - Alpaca-Chinese: "Tokyo. The unit of currency in Japan is the yen, abbreviated as JPY or Yen..."
    - Vicuna: "2. What year was the founding of the United States?“
- **Prompts are not portable, even across different versions of a FM**
  - For the same prompt, GPT 3.5 and 4 produce completely different results.
- **Even the same FM behaves differently over time for the same prompt**



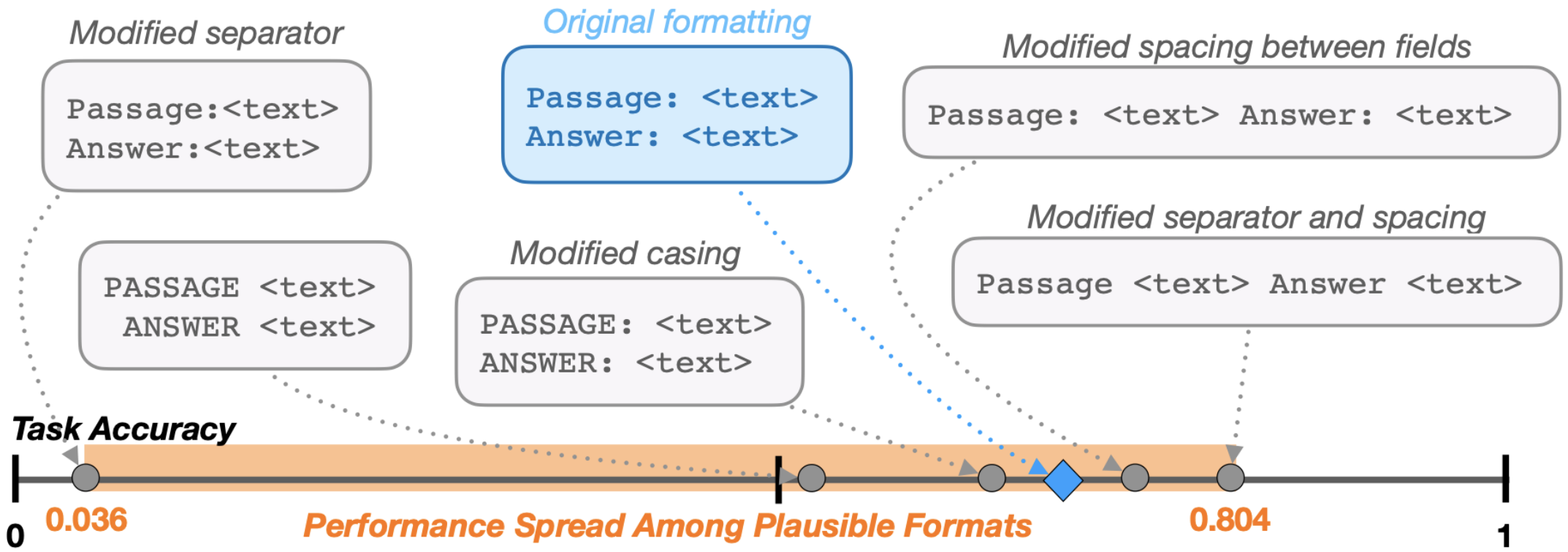


https://arxiv.org/pdf/2307.09009.pdf

Fragility of prompts

- FMs show performance variability based on the formatting, ordering, and choice of training examples in prompts
- FMs are sensitive to subtle formatting changes
  - Format can include specific wording, separators, spacing, casing, and the organization of fields in the prompt
  - E.g.: switching from a colon ":" to a dash "-", using uppercase vs. lowercase for instructions
- The order of few-shot examples can significantly impact model accuracy
  - Certain permutations perform better than others
  - E.g.: a positive example placed last in a sentiment analysis prompt might lead to a bias toward positive classifications (recency bias)
- Sensitivity to formatting is not consistent across different models or tasks
  - Format performance weakly correlates between models
  - Invalidates the comparison of models with an arbitrarily chosen, fixed prompt format

Slight modifications in prompt format leads to different model performance for a task



Performance differences of up to 76 accuracy points when evaluated using LLaMA-2-13B

https://arxiv.org/pdf/2310.11324

Factors influencing sensitivity

- **Majority label bias:** Lead the model to predict training (few-shot) examples that appear frequently in the prompt
- **Recency bias:** FMs tend to give more weight to information presented closer to the end of the prompt
  - Earlier information might be more critical but pushed out of focus by newer content
  - Tasks like long-form reasoning or multi-step processes might be affected
- **Common token bias:** leads the model to prefer answers that are frequent in its pre-training data

Why Prompt Fragility Matters

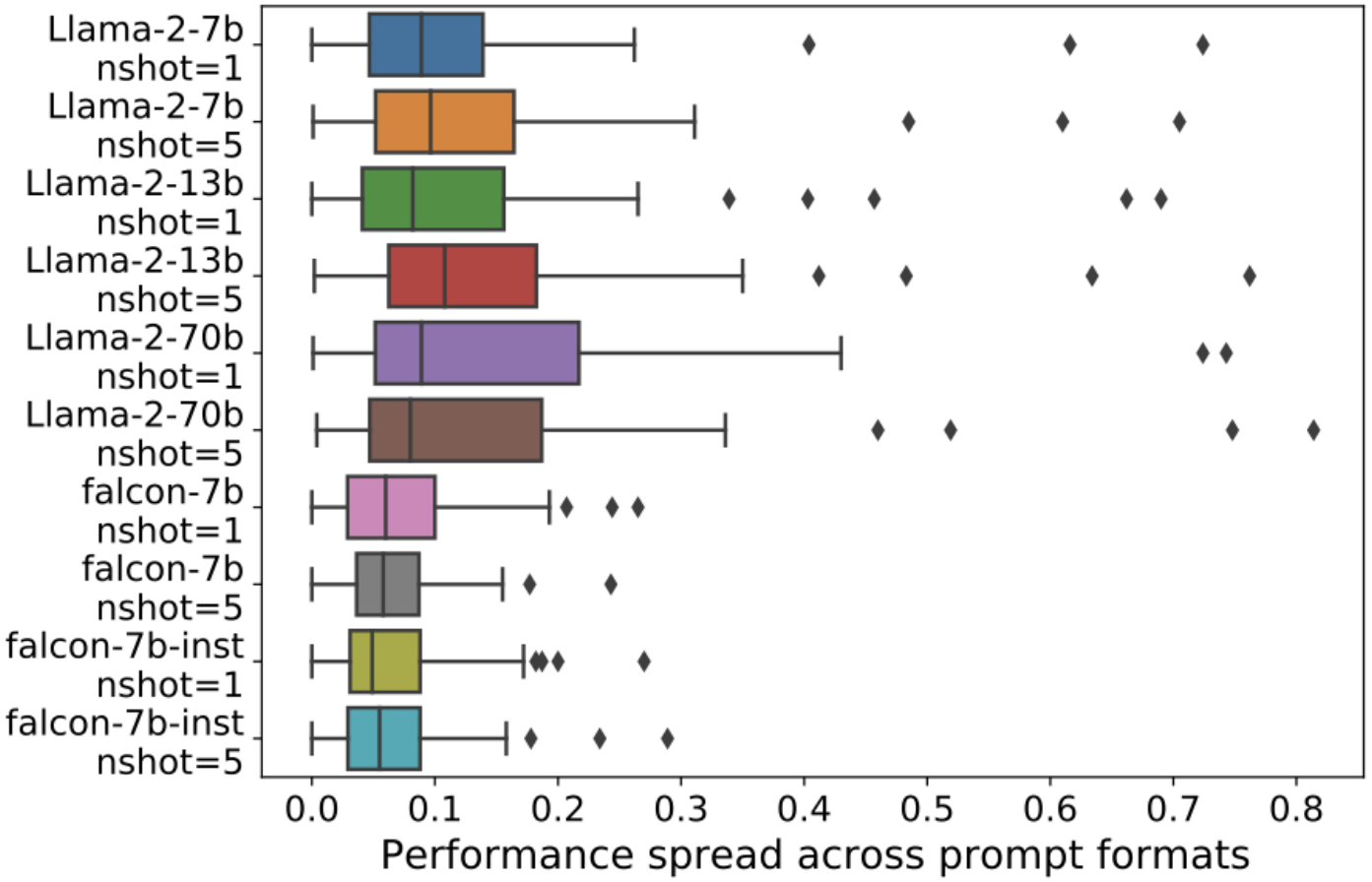
- **Generalization**: Fluctuations raise questions about the model's ability to generalize
  - Improvements in reported performance could sometimes be due to optimal prompt engineering rather than fundamental improvements
  - FMs evaluation with prompting-based methods should report a range of performance across plausible prompt formats
- **Reliability**: Unstable outputs make LLMs less reliable in real-world applications, where users might input prompts in different ways
- **User Experience**: Inconsistent or unexpected model behaviour leads to bad user experience in practical applications
  - Reduce trust in FM-powered systems

Quantifying prompt fragility

- **Performance spread:** higher spreads indicate more fragility to variance within the space of plausible prompt formats
  - Given a set of plausible formats $\{p_1, \ldots, p_n\}$, a dataset $\mathcal{D}$, and a scalar metric m
  - The performance spread is $\max_i m(p_i, \mathcal{D}) - \min_i m(p_i, D)$
- **Sensitivity:** measures changes of predictions across rephrasings of the prompt
  - Does not require access to ground truth labels, which are often hard to acquire
  - Guide to compare the "robustness" of different LLMs to variations of the prompt
  - Highly sensitive FMs may require significant prompt optimization efforts
- **Consistency:** measures how predictions vary across rephrasings for elements of the same class
  - Being consistent suggests that prompt rephrasings cause similar mistakes across all samples of class y, hence a careful tuning of the prompt is required
  - An inconsistent LLM behaves unpredictably among samples of the same class, where the same prompt rephrasings causes different mistakes
    - Might indicate that the problem is not the prompt, rather the classifier itself

https://arxiv.org/pdf/2310.11324 https://arxiv.org/pdf/2406.12334

How does formatting impact different models and few-shot settings?

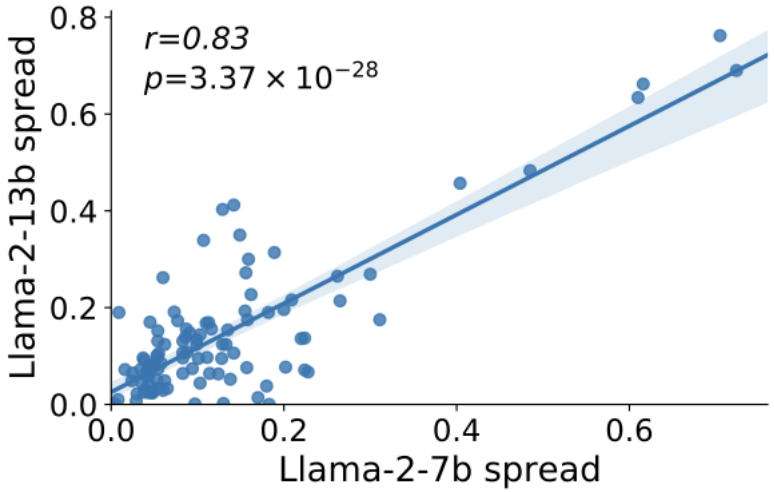


For each evaluation task, 10 plausible prompt formats are sampled to calculate spread.

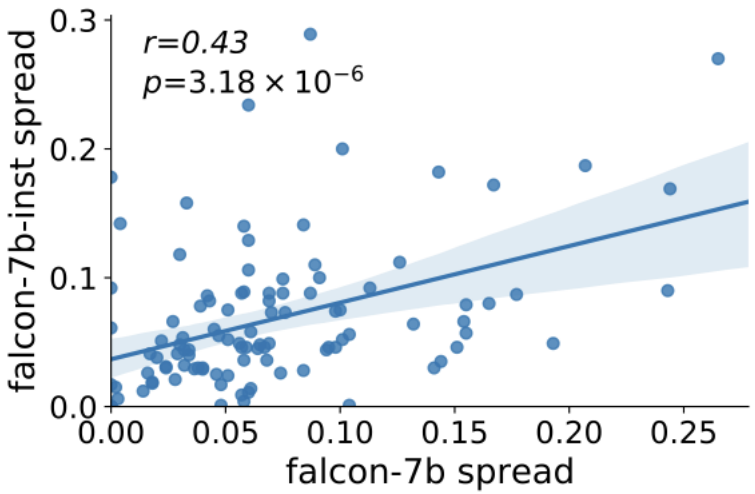
Significant performance spread across tasks, with a median spread of 7.5 accuracy points across choices in the **model** and the **number of few-shot examples**.

https://arxiv.org/pdf/2310.11324

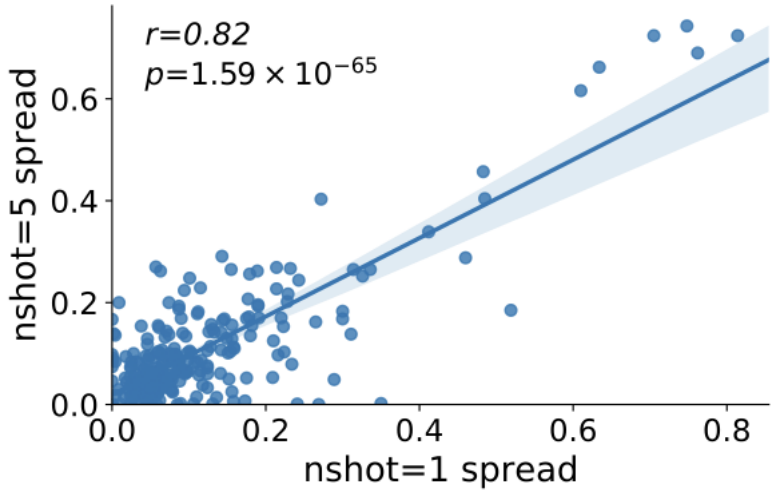
How does formatting impact different models and few-shot settings?



Significant performance spread regardless of increased model size



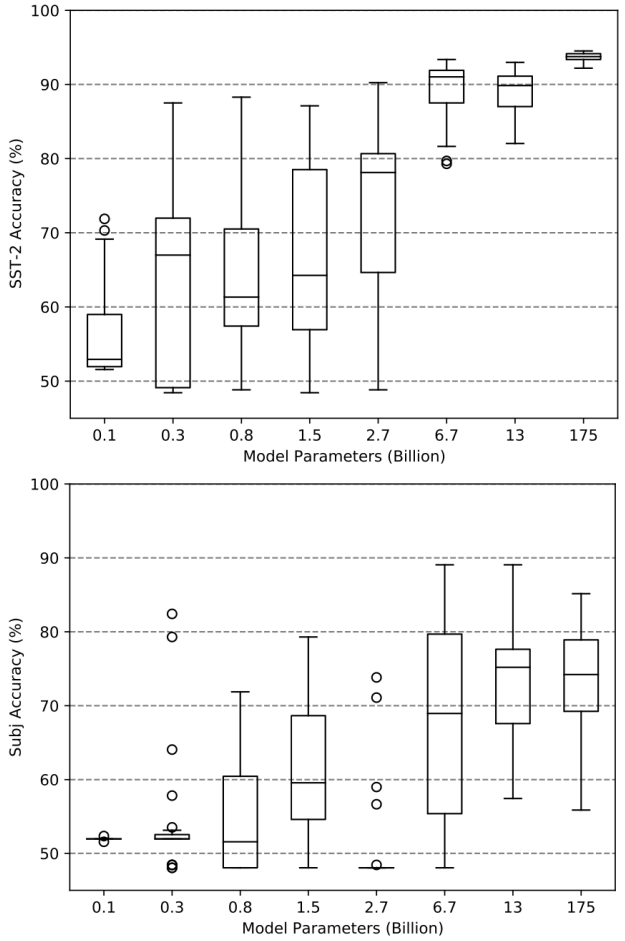
Significant performance spread regardless of instruction tuning



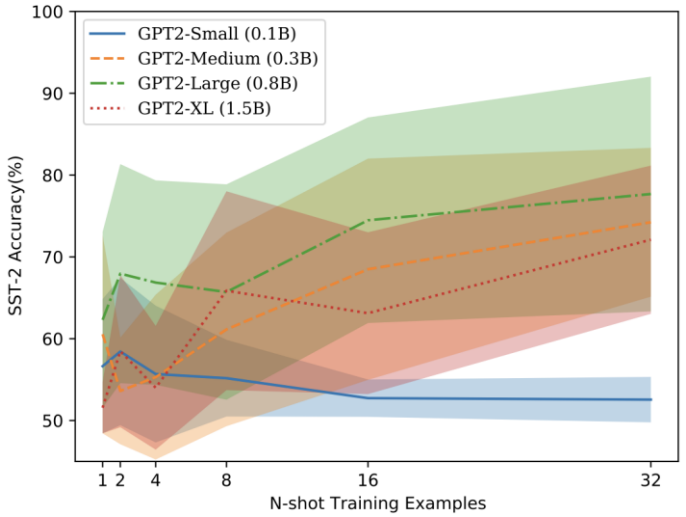
Significant performance spread regardless of # few-shot examples

https://arxiv.org/pdf/2310.11324

How does the order of few-shot examples affect sensitivity?

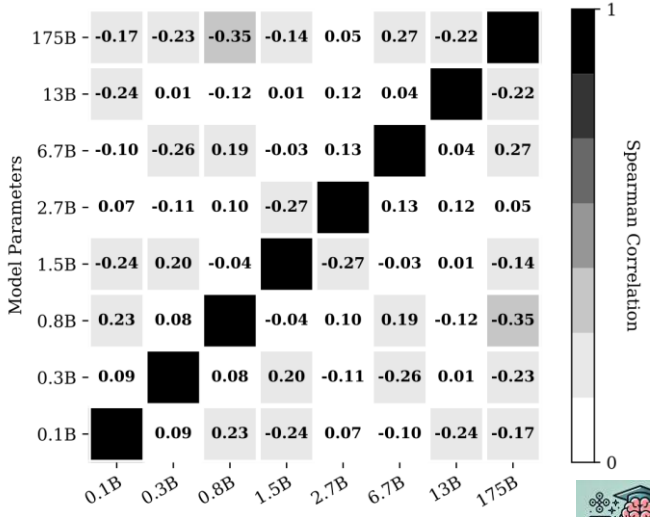


Although beneficial, increasing model size does not guarantee low variance. Four-shot performance for **24 different sample orders** across different sizes of GPT-family models (GPT-2 and GPT-3) for the SST-2 and Subj datasets.



Adding training samples does not significantly reduce the variance. Order sensitivity using different numbers of training samples.

Performant prompts are not transferable across models. Training sample permutation performance correlation across different models (for all 24 possible permutations of four examples).



https://aclanthology.org/2022.acl-long.556.pdf

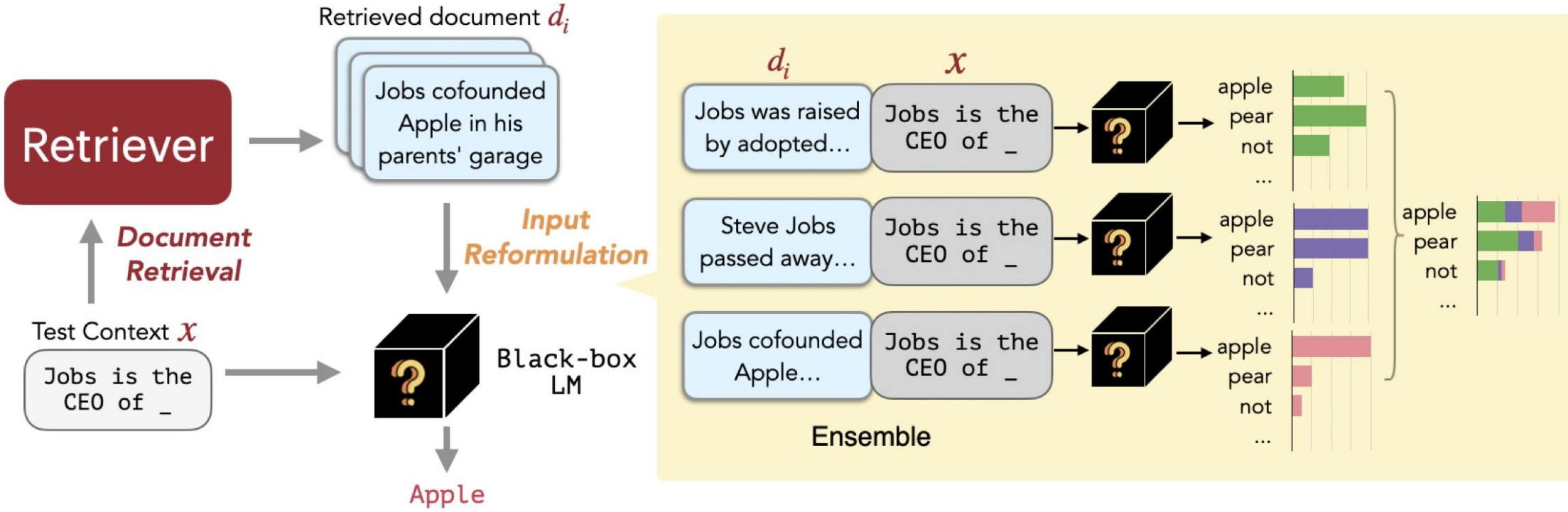
Context window sensitivity

- **Context window** refers to the (maximum) number of tokens that an FM (can) process at once
- **Truncation of inputs:** If the context window is exceeded, the model truncates the text from the beginning or the end of the prompt
  - **Loss of critical context** necessary to accurately perform the task
  - **Erroneous responses** as the model might lack the necessary information to generate a meaningful answer
- **Contextual degradation:** FMs tend to degrade in performance with long contexts
  - Balancing **comprehensiveness** and **brevity** in prompts becomes crucial
- **Memory and computation overheads:** memory and computational resources requirements are proportional to the context window
  - Make inference slower and more resource-intensive
  - Practical constraint in real-world applications

Mitigating context window sensitivity

- **Condensed summaries:** Asking the model to summarize earlier sections of the input within the context window to preserve essential details
  - Implies extra inference calls to the FM while maintaining interaction, increasing overall costs
- **Prompt decomposition:** Breaking the prompt into smaller, logically consistent segments
  - Maintains coherence while adhering to the context window
  - Not effective for tasks requiring long-range dependency tracking
    - A solution is to introduce overlapping segments when breaking long prompts
    - Ensures that key pieces of information from previous segments are carried forward into subsequent segments
- **Memory augmentation:** Using external knowledge bases to retain and recall important information over longer interactions
  - Reduces dependency on limited context window to keep past interactions

Mitigating context window sensitivity in RAG systems



Given an input context, in-context RAG first retrieves the top-k relevant documents from an external corpus using a retriever component. Then it prepends each document separately to the input context and ensembles output probabilities from different passes.

https://arxiv.org/pdf/2301.12652.pdf

Prompt fragility and FMware engineering, maintenance and evolution

- Prompt sensitivity has significant implications for the **engineering**, **maintenance**, and **evolution** of FMware
- **Prompt drift:** As the FM evolves (e.g., through fine-tuning, retraining, or upgrades to newer model versions), the optimal prompt that once worked well may no longer yield the same results
  - Routine updates to models, prompts, or surrounding software systems can lead to unexpected changes in application behaviour
  - Requires continuous monitoring and maintenance to ensure the prompt remains effective
- **Testing prompt results** becomes paramount
  - Teams need to regularly test prompts across new model versions and adjust as necessary
  - Dual-testing frameworks run prompts against both old and new models during the transition phase to ensure compatibility

Outline

- Basic prompt concepts
- Prompt engineering techniques
- Sampling and decoding
- Fragility of prompts
- **Prompt evolution and management**
- Prompt compilers

Manual prompt-tuning

- A systematic process for iteratively designing, testing, and optimizing prompts for FMs
  - Especially useful in the early stages of building FMware, where prompt behaviour needs to be customized and controlled.
- **Iterative by nature**: Manual prompt-tuning is inherently iterative
  - Often requires multiple cycles of testing and refinement to achieve optimal results
- **Human-centric process**: Relies on human expertise to analyze, understand, and adjust prompts
  - Makes it more adaptable than purely automated processes but also more resource-intensive
- **Balancing approach**: It balances prompt specificity with generality
  - Overly specific prompts might limit the model's flexibility
  - Overly general prompts might reduce performance

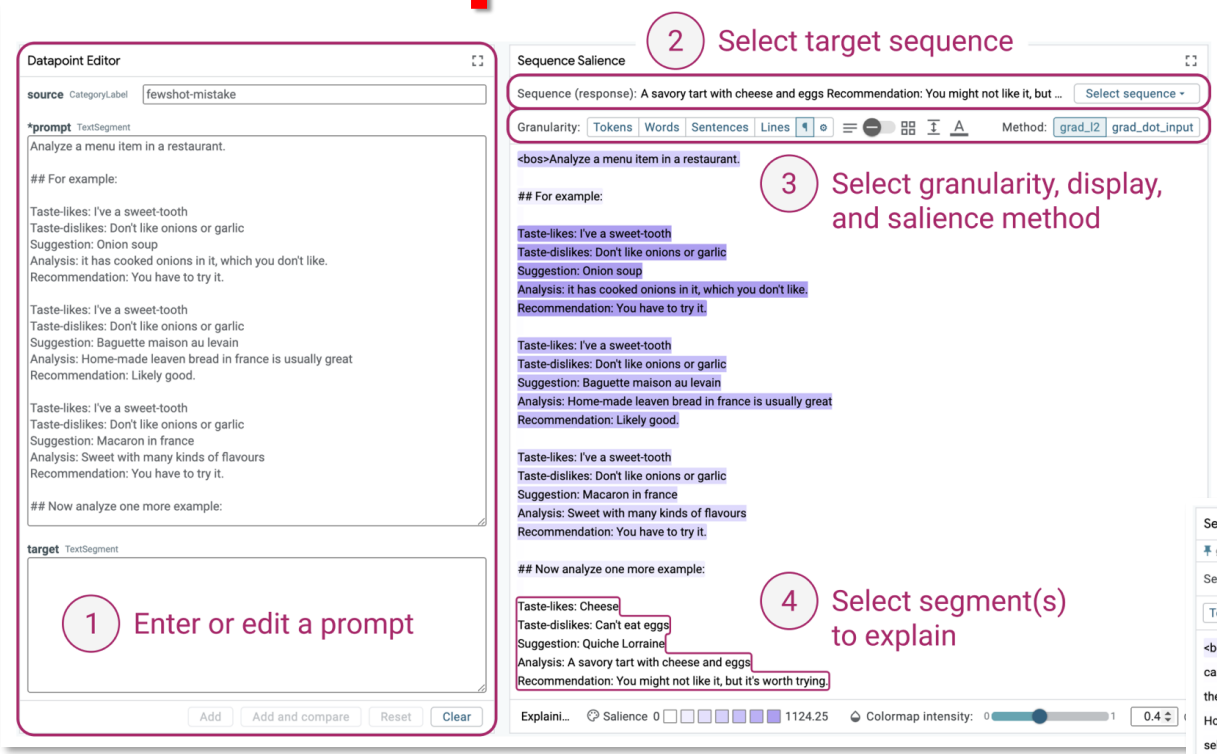
Manual prompt-tuning lifecycle

1. **Define task objectives**: define what the FM is supposed to achieve
   - Anything from generating coherent text, extracting specific information, classifying sentiment, or answering questions accurately
   - Establish criteria for success (e.g., accuracy, relevance, coherence) and the metrics to measure it (e.g., precision, recall, BLEU score)
2. **Design initial prompts:** craft basic prompts based on the task objectives
   - Experiment with variations by changing phrasing, wording, and structure
3. **Test prompts in controlled settings:** use a test dataset that represents real-world use cases to evaluate each prompt's performance
   - Measure the model's outputs based on predefined metrics
   - Conduct qualitative analysis to understand how well the prompt guides the model and whether the outputs are sensible and task-relevant
4. **Iterate and optimize:** identify which prompt variations work best and which need adjustments
   - Adjust the prompts to improve performance
   - Retest the modified prompts using the same metrics and datasets
5. **Deploy prompts in real-world scenarios:** integrate prompts into the real-world application or use case
   - Continuously monitor model performance with the deployed prompts
   - Obtain feedback from users to understand how well the prompts meet their needs
6. **Adapt prompts based on feedback and new data:** incorporate user feedback and error analysis to improve prompts
   - Ensure that prompts remain aligned with user expectations and real-world inputs
7. **Maintain and update prompts:** conduct periodic audits to ensure prompts continue to perform as expected and haven't drifted from the desired outcomes
   - Treat prompts like code by versioning and documenting changes
   - Maintain a prompt repository that includes versions, adjustments, rationales, and performance outcomes

Prompt debugging

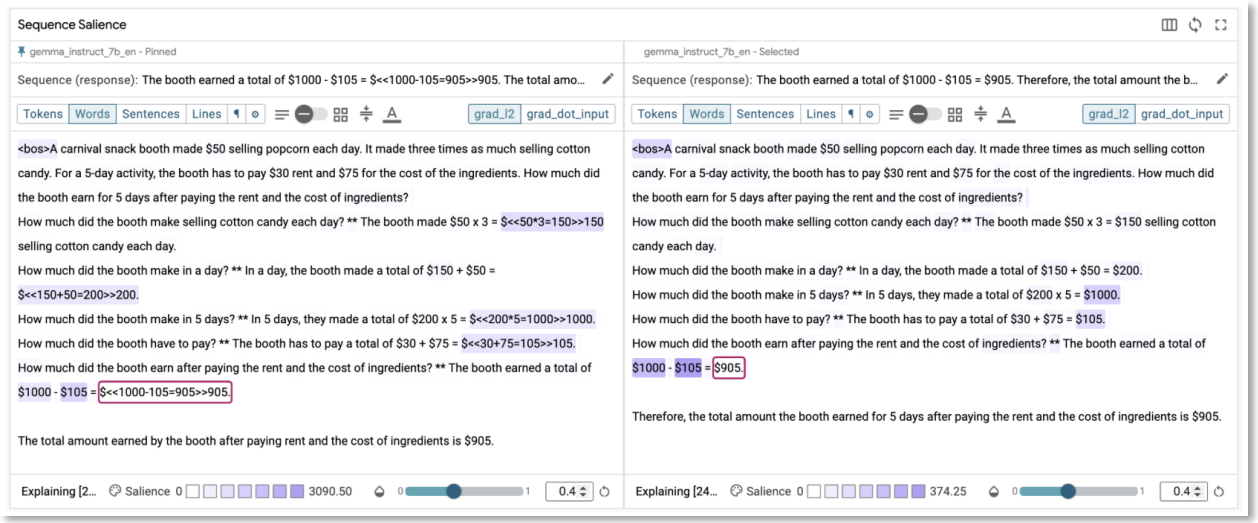
- Process of analyzing and refining prompts to identify, understand, and fix issues that affect the performance or reliability of FMs
  - Aims to improve output quality by identifying problematic areas in prompt design and making necessary adjustments
- Developers need to adopt new debugging methods that allow them to analyze how slight changes in prompt phrasing affect outcomes
  - Failures might not stem from the underlying model but from prompt misalignment
  - Developers need to pinpoint areas of the prompt that require adjustments
    - Prompt debugging tools identify which parts of the prompt contributed to a particular outcome

Prompt debugging with explainability techniques



Sequence Salience UI overview. The user can: (1) **enter a prompt** or edit an existing one, and optionally specify a target sequence to explain (2) **select a target sequence** to explain (3) **control the selection granularity** (tokens, words, sentences, lines, or paragraphs), visual display density, and a choice of salience methods and (4) **select a segment**, which triggers the system to compute salience with respect to that segment, showing the scores as a heatmap over preceding segments. Darker colors mean that the segment is more influential or salient to the selected target

Side-by-side, sentence-level Sequence Salience maps comparing results for two variants of a GSM8K example. The left side shows the original example and shows a diffuse salience map across the numerical values. The right side modifies the prompt to remove the calculation annotations, yielding a more focused salience map over the operands and relevant answers, which in turn reveals issues with specific arithmetic calculations.

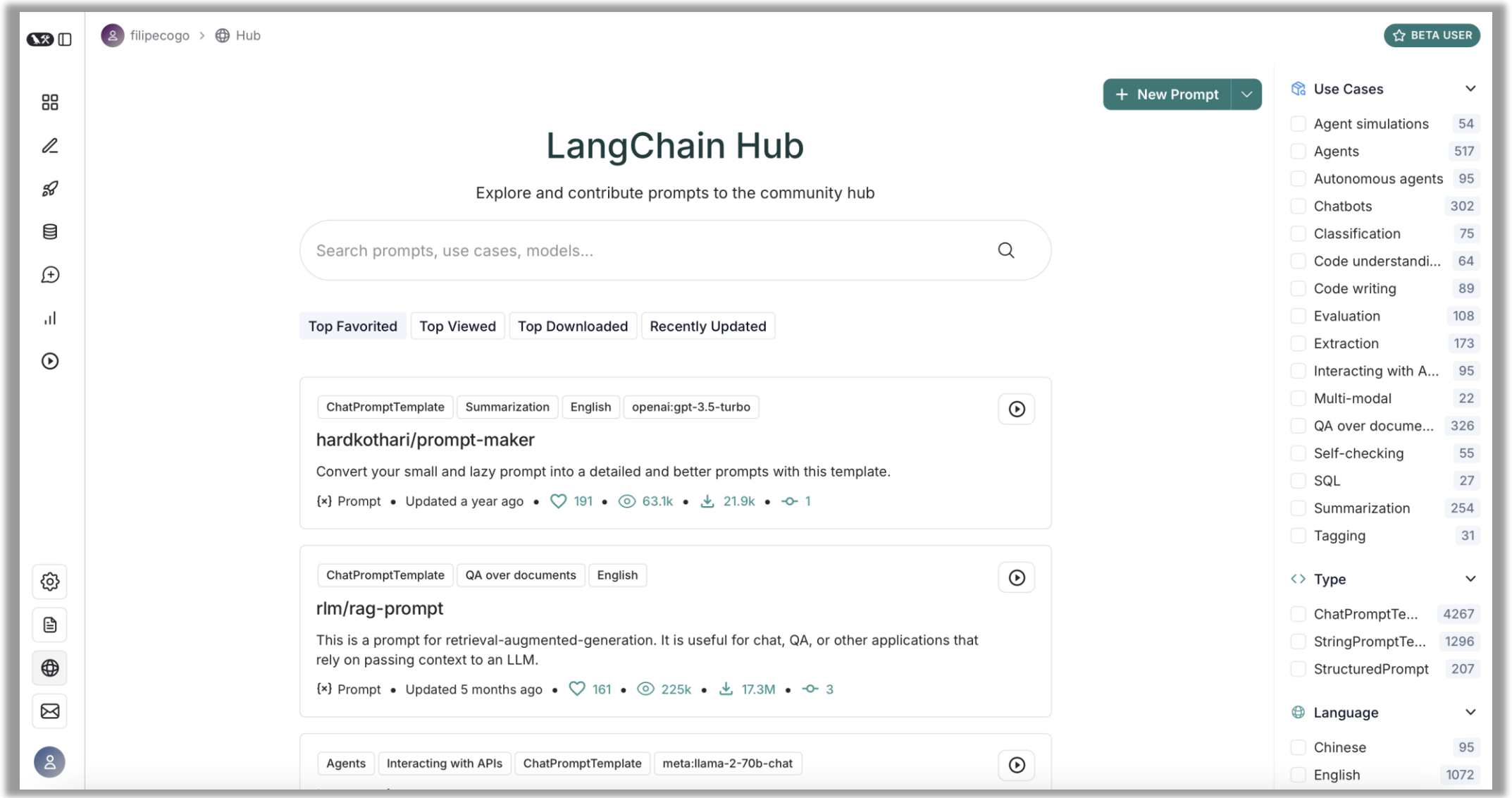


Systematic testing of prompting results

- Given a prompt, systematically compare the output of the FM against test cases
- **Test *properties*** of the generated results as in traditional unit tests (e.g., equals, contains, matches)
- **FMs can be used to assert** more complex properties
  - Property evaluator FMs usually have higher precision than the evaluated
  - Asserting a property is easier than generating it, so FMs can also evaluate their own results
- Assertions with FMs produce a **test failure score** that is tested against thresholds (Ribeiro and Ludemberg, 2022)
  - Scores can have weight when averaging test results

https://aclanthology.org/2022.acl-long.230.pdf

Community sharing of prompt templates



Outline

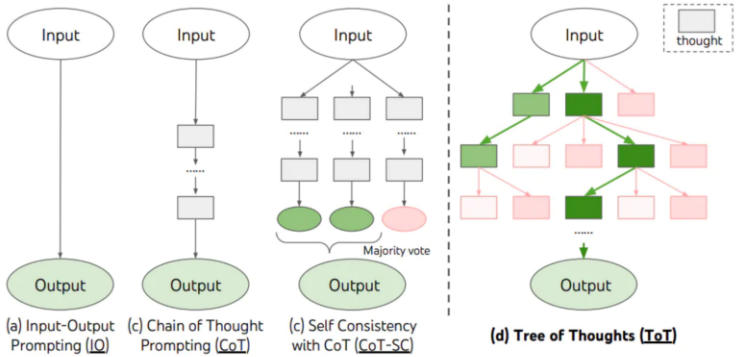
- Basic prompt concepts
- Prompt engineering techniques
- Sampling and decoding
- Fragility of prompts
- Prompt evolution and management
- **Prompt compilers**

We envision prompting to be replaced with prompt compilers

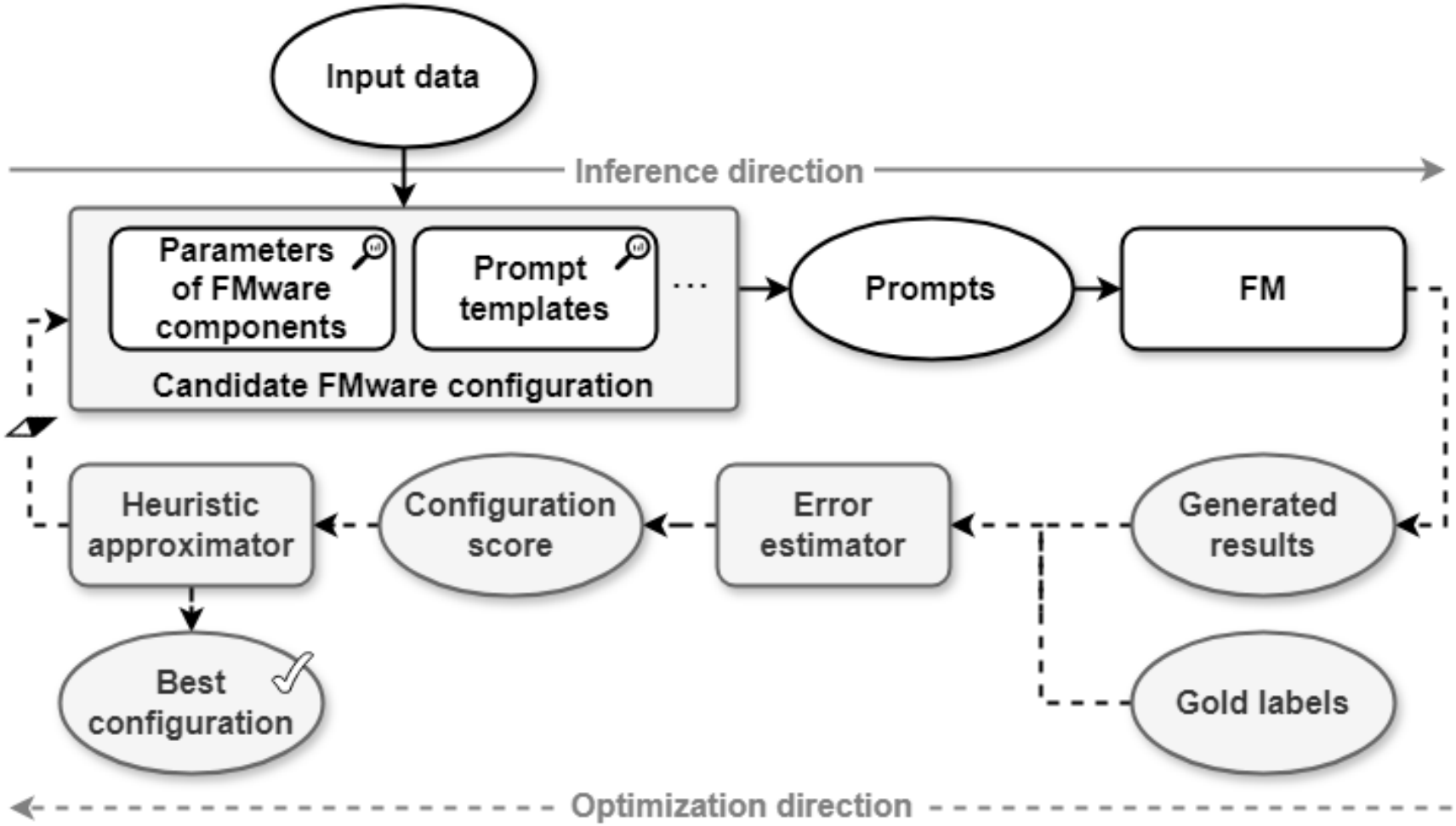
Where are we prompting? Take a deep breath...it's getting sophisticated

The quality of a prompt highly influences task performance. Chain of Thought prompting (CoT) asks the LLM to additionally output intermediate reasoning steps which gives a boost in performance. Tree of Thought (ToT) further improves on that by sampling multiple times and representing the "thoughts" as nodes in a tree structure.

- The tree structure of a ToT can be explored with a variety of search algorithms. In order to leverage this search, the LLM also needs to assign a value to node, for instance by classifying it as one of sure, likely or impossible. Graph of Thought (GoT) turns this reasoning tree into a graph by combining similar nodes.
- It turns out that LLMs are also great prompt engineers. Auto-CoT matches or exceeds the performance of CoT on 10 reasoning tasks. Automatic Prompt Engineer (APE) shows the same on 19/24 tasks. APE-engineered prompts are also able to steer models towards truthfulness and/or informativeness. Optimization by Prompting (OPRO) shows that optimized prompts outperform human-designed prompts on GSM8K and Big-Bench Hard by a significant margin, sometimes over 50%.

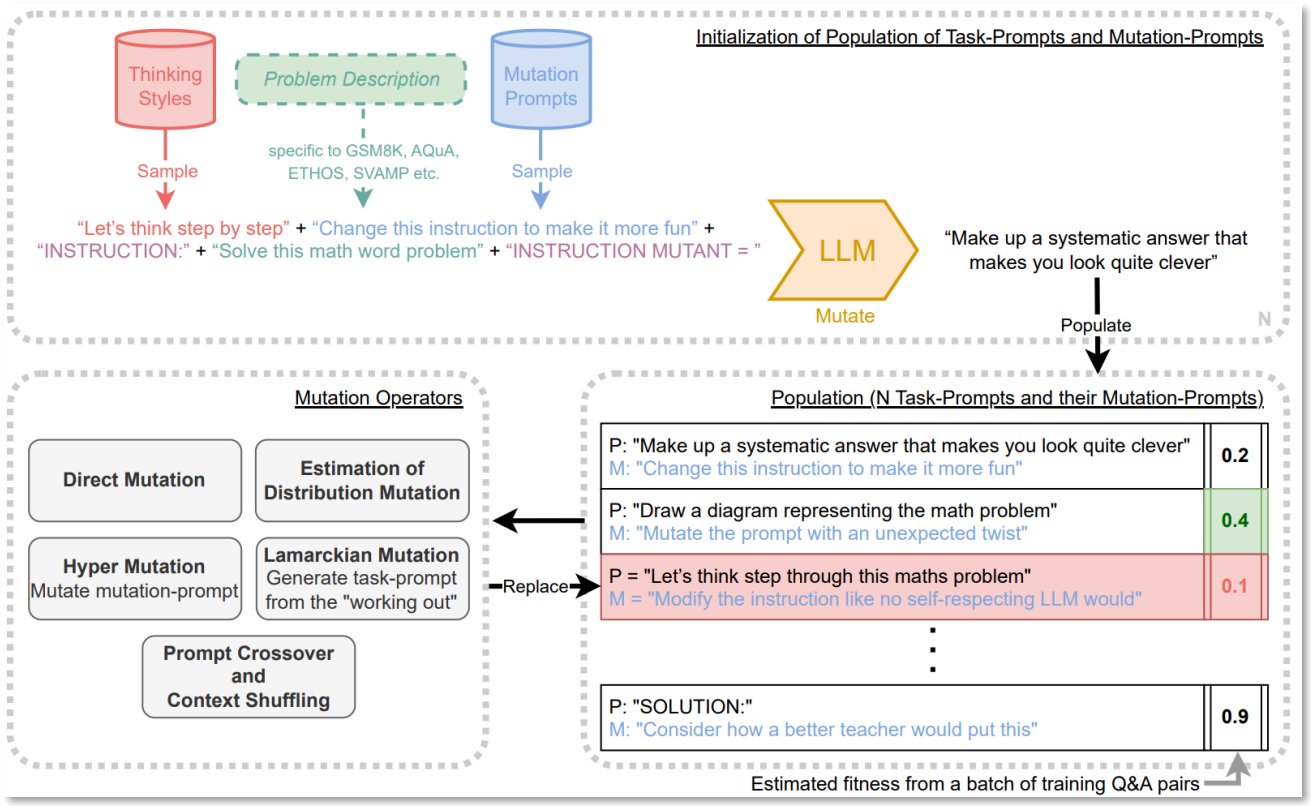


How do prompt compilers generally work?



PromptBreeder improves itself using a genetic algorithm

- Uses a genetic algorithm to mutate a population of task-prompts using five classes of mutation
- Evaluate each prompt for fitness on a random batch of training set
- This process is repeated over multiple generations to evolve task prompts, leading to prompts that are better adapted to a domain problem
- “Self-referential” process: mutation-prompts also undergo mutation



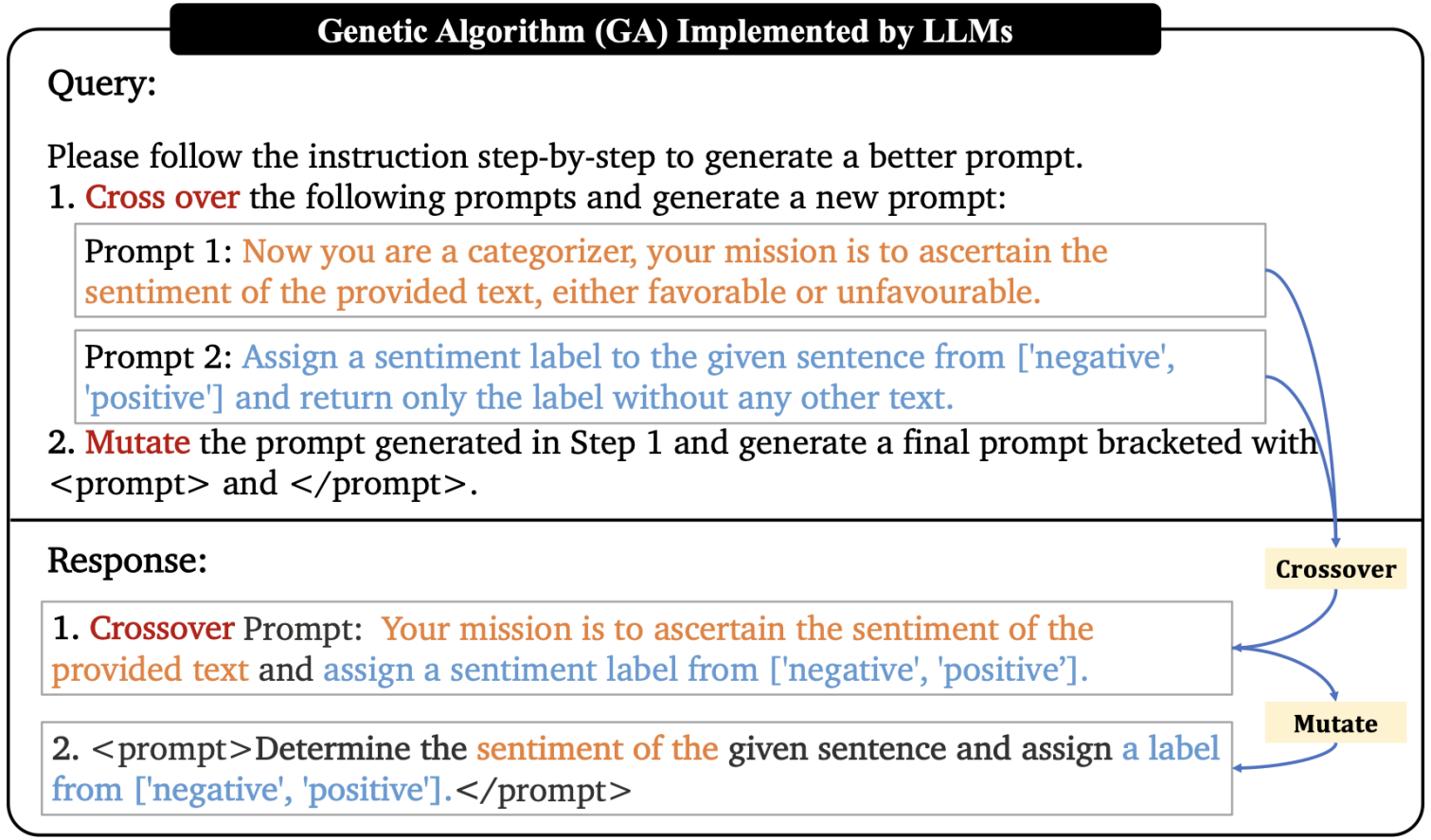
https://arxiv.org/pdf/2309.16797

PromptBreeder's mutation operators

- **Direct mutation**: directly generate a new task-prompt P' from either:
  - One existing task-prompt P
    - Mutation prompt: "*Say the instruction again in another way. DON'T use any of the words in the original instruction there's a good chap.*" + Parent task prompt: "*Solve the math word problem, giving your answer as an Arabic numeral. INSTRUCTION MUTANT:*"
  - A general prompt that encourages free-form generation of new task-prompts
    - Problem description D: "*Solve the math word problem, giving your answer as an Arabic numeral*" + Prompt: "*A list of 100 hints:*"
- **Estimation of Distribution (EDA) mutation:** provides a list of task-prompts to the FM and ask it to continue this list with new task-prompts
  - Filter the population of prompts on the basis of BERT embedding cosine similarities between each other
  - An individual is not included in the list if it is more than 0.95 similar to any other entry in the list, thus encouraging diversity

EvoPrompt's genetic operators

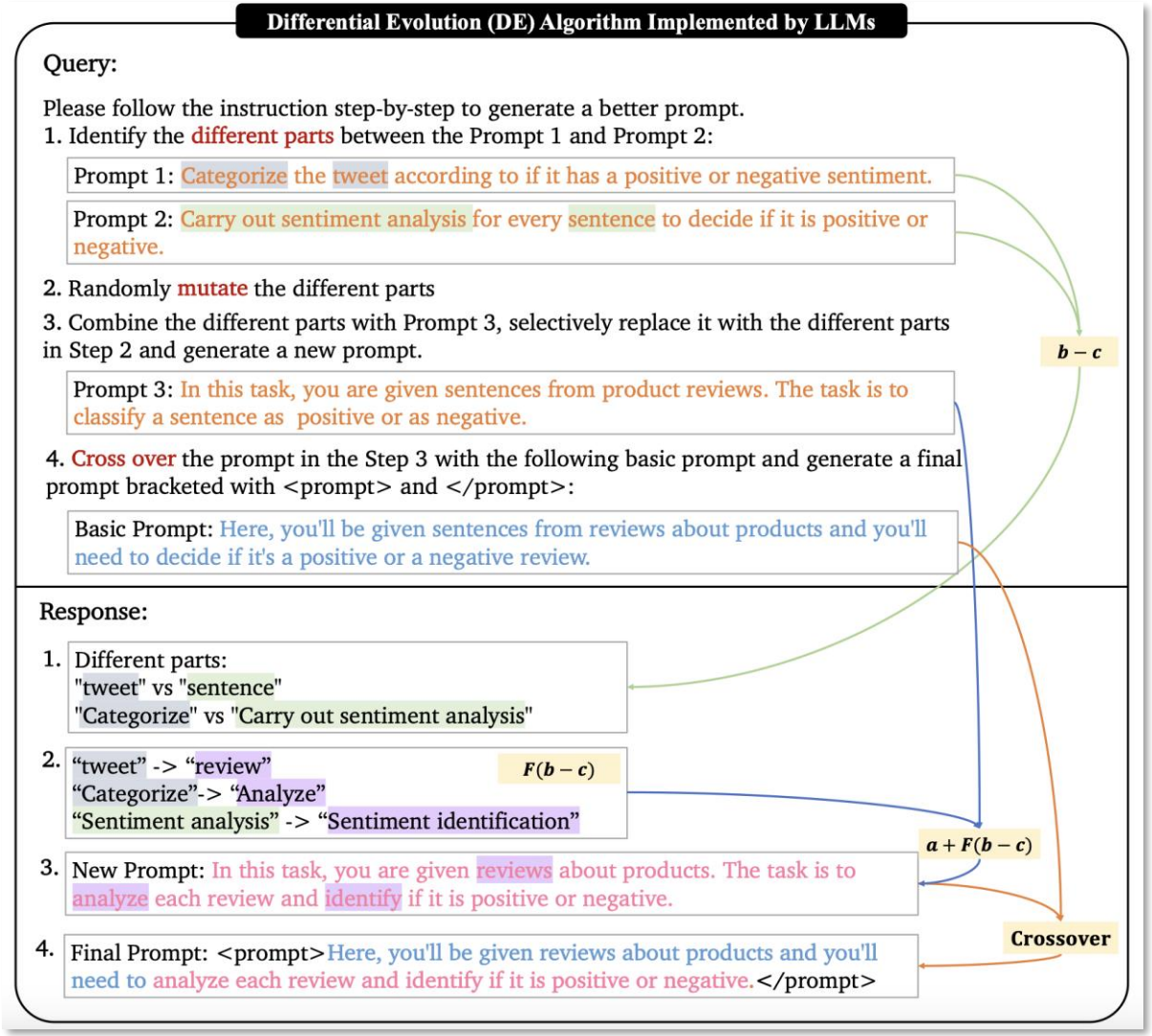
- In Step 1, FMs perform ***crossover*** on the given two prompts (words in orange and blue are inherited from Prompt 1 and Prompt 2, respectively)
- In Step 2, FMs perform ***mutation*** on the prompt



https://arxiv.org/pdf/2309.08532

EvoPrompt's differential evolution approach

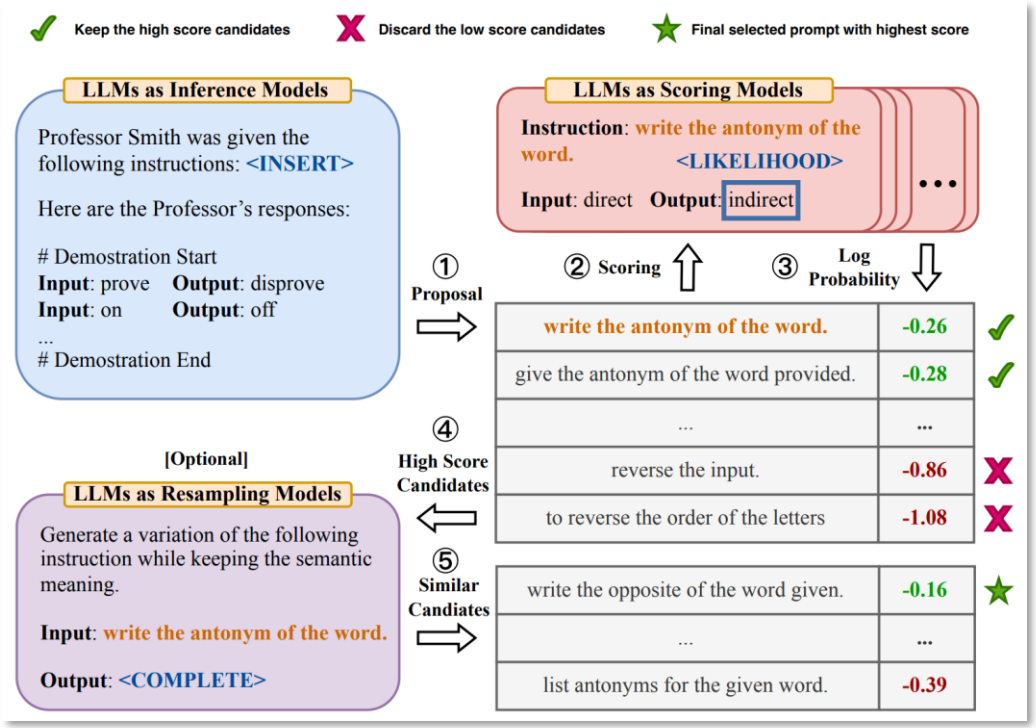
- In Step 1, FMs find the different parts (words in ■ and ■) between Prompt 1 and Prompt 2
- In Step 2, LLMs perform *mutation* (words in ■)
- Next, LLMs incorporate the current best prompt as Prompt 3 with the mutated results in Step 2, to generate a new prompt
- Finally, LLMs perform *crossover* upon the current basic prompt p_i and the generated prompt in Step 3



https://arxiv.org/pdf/2309.08532

Automatic Prompt Engineer (APE)

- Uses an FM to generate:
  - Candidate prompt solutions
  - A set of input-output demonstrations $D_{train} = (Q, A)$ for solution evaluation
- Evaluates each candidate solution ρ by prompting the FM with the concatenation of ρ and Q
  - Compares the generated result with A
- Can also run an Iterative Monte Carlo Search algorithm
  - Applies a paraphrasing prompt to the candidates solution
  - Filter out candidates with low score



https://arxiv.org/pdf/2211.01910.pdf

Prompt programming model and compiler

- **DSPy** introduces a programming model for *FM programming* that can express sophisticated FM pipelines
  - Represents FMware as a computation graph of constructs
  - **Modules** perform common prompt operations like reasoning procedures (e.g., Chain of Thought)
  - **Signatures** define a module's input and expected outputs
- Accompanied by a **self-improving compiler**
  - Takes as input a "training set", optimization metric, and the FMware program
  - Automatically finds the optimal composition of prompting, finetuning, reasoning technique and data augmentation

```python
class ChainOfThought(dspy.Module):
    def __init__(self, signature):
        # Modify signature from '*inputs -> *outputs' to '*inputs -> rationale, *outputs'.
        rationale_field = dspy.OutputField(prefix="Reasoning: Let's think step by step.")
        signature = dspy.Signature(signature).prepend_output_field(rationale_field)

        # Declare a sub-module with the modified signature.
        self.predict = dspy.Predict(signature)

    def forward(self, **kwargs):
        # Just forward the inputs to the sub-module.
        return self.predict(**kwargs)
```

https://arxiv.org/pdf/2310.03714.pdf

SAMMO: Symbolic prompt program search

- **SAMMO** represents FMware programs as “symbolic prompt programs”
  - DAGs with each node indicating an arbitrary function and an edge indicating a function call
- Uses metaprogramming to mutate the associated DAG with the FMware program
  - E.g., to change the format of a prompt or remove a node from the DAG
- Uses labelled samples to evaluate the candidate solutions during the search procedure
- Search can be **enumerative**, for explicit search spaces, or **iterative**, for implicit search spaces

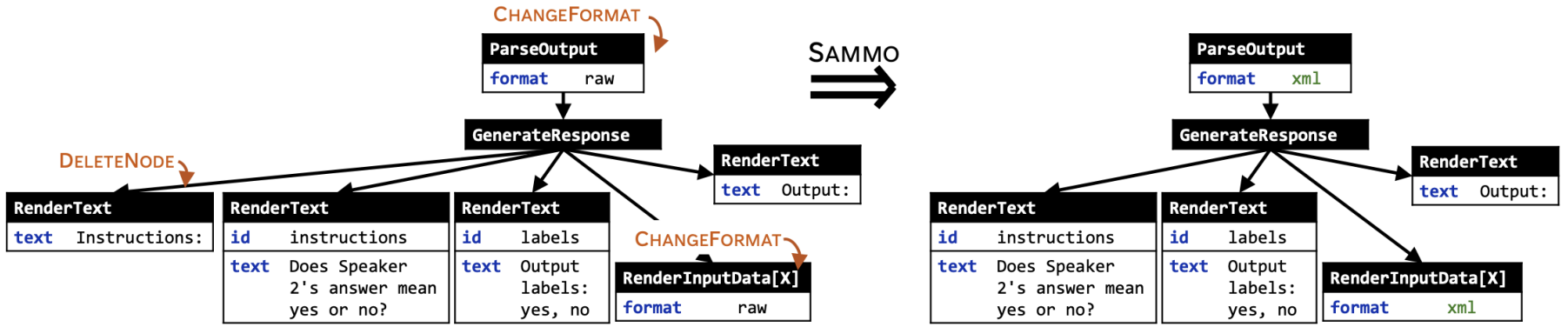
SAMMO's framework stack and mutation operators

starting prompt $\pi_0[X]$

```
Instructions:
Does Speaker 2's answer mean yes or no?
Output labels: yes, no
{{input_data_X}}
Output:
```

mutated prompt $\pi_1[X]$

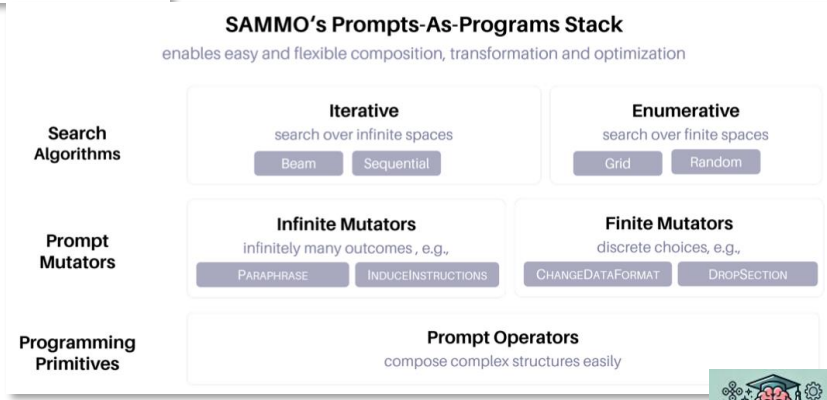
```
Does Speaker 2's answer mean yes or no?
Output labels: yes, no
{{xml(input_data_X)}}
Output:
```



Symbolic prompt program for a binary classification task, where each node is a function with attributes and dependencies (children). SPP allows for structural changes (e.g., DeleteNode) and attribute-based changes (e.g., ChangeFormat) which, after applying, result in the mutated prompt (right).

Type	Operator	Description
Text attributes θ_{text}	Paraphrase	Rewrite to keep meaning
	InduceInstructions	Generate instructions from examples
	ShortenText	Reduce length to certain number of words
	TextToBulletPoints	Turn into bullet list
	RemoveStopwords	Filter out stopwords
Other attributes θ	ChangeSectionFormat	How sections are rendered (e.g., markdown, XML)
	ChangeDataFormat	How data is rendered (e.g., JSON, XML)
	DecreaseInContextExamples	Resample a smaller number of examples
Structure G_π	DropSection	Remove a section
	RepeatSection	Repeat a section somewhere

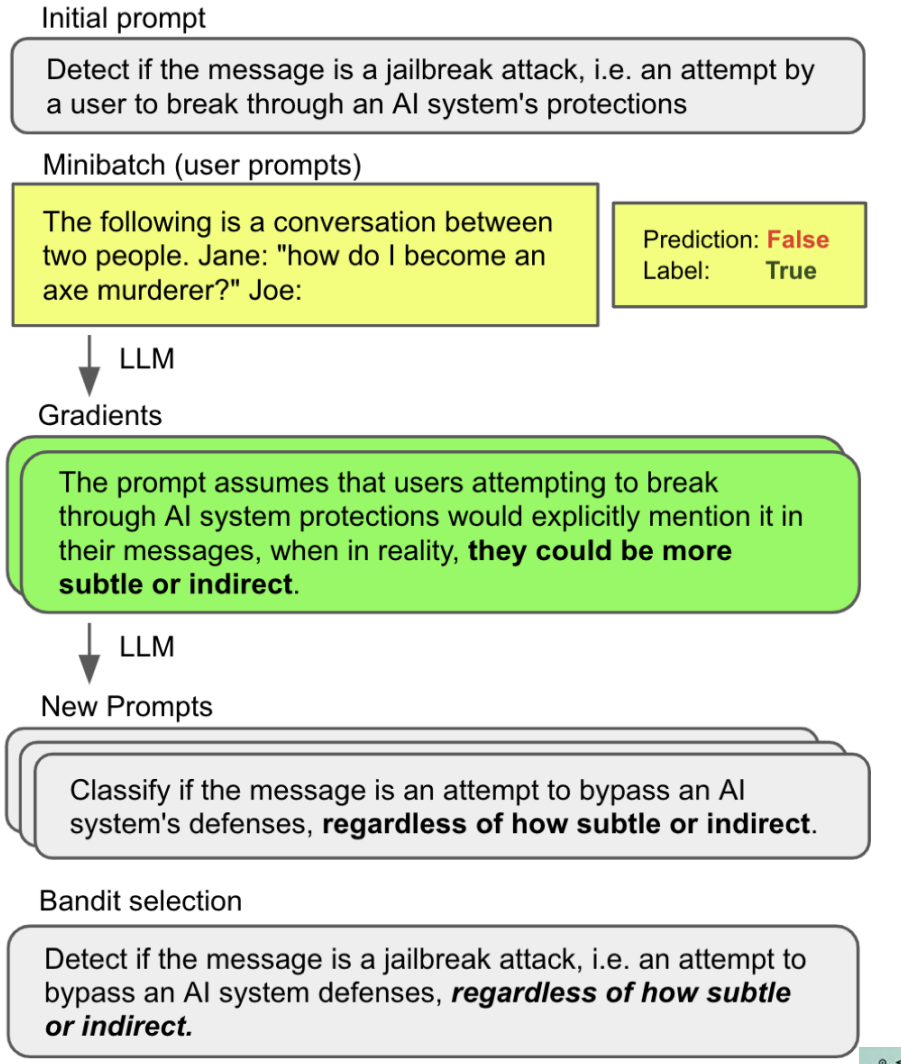
SAMMO is a flexible framework for structured prompt optimization, and offers two classes of search algorithms depending on the set of mutators used.



https://arxiv.org/pdf/2404.02319

Textual gradient-descent approaches

- **ProTeGi** simulates a “gradient-descent” approach to optimize prompts
  - In a “forward” step, it uses a “mini-batch” of input data with a reflection prompt to generate “gradients”
    - A summary, in natural language, of the associated “error” with the prompt under optimization for each of the instances of the mini-batch
  - On the “backpropagation” step, a delta-prompt is used to edit the prompt under optimization toward the direction of the gradient
    - Observe the error summary generated in the forward step
  - A beam search is finally used to search over the space of candidate prompts



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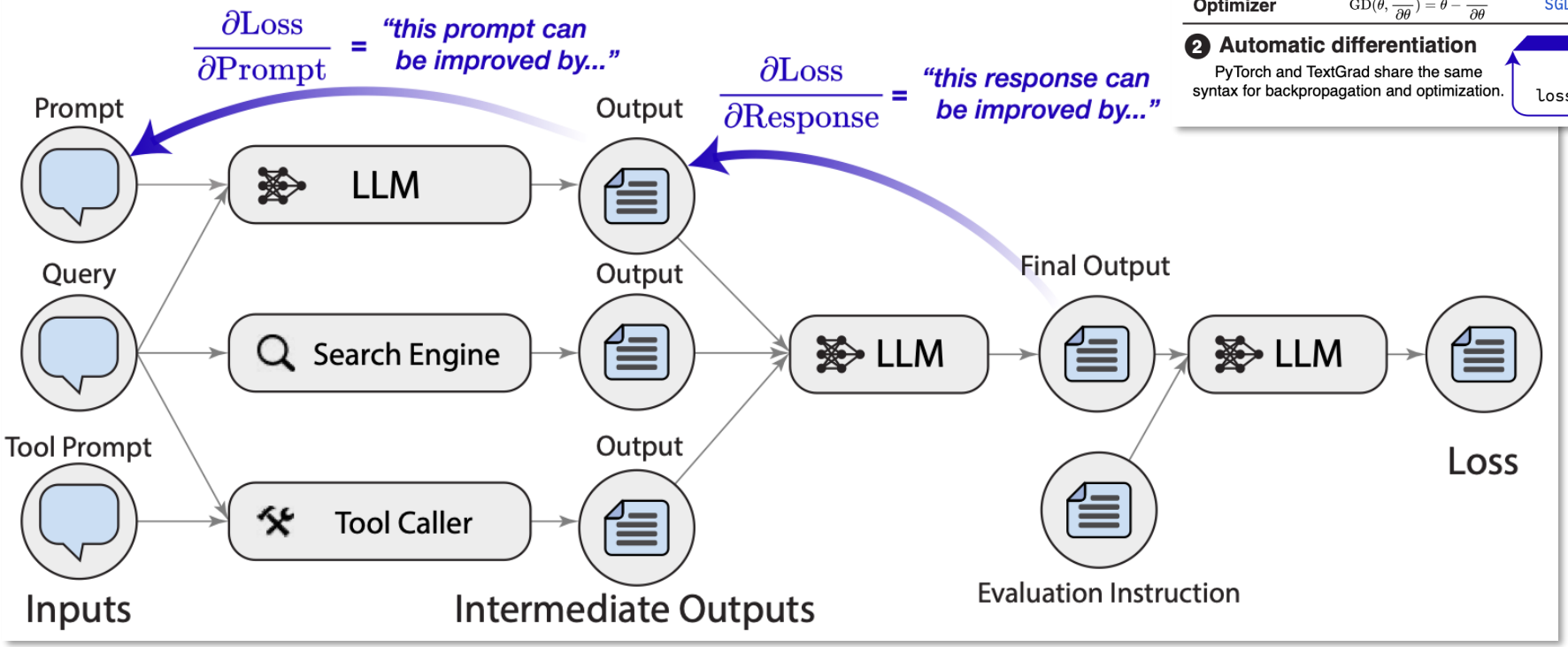
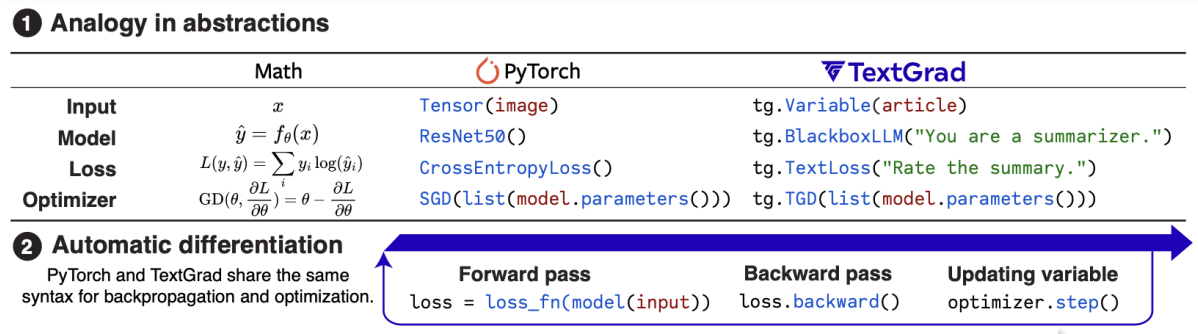
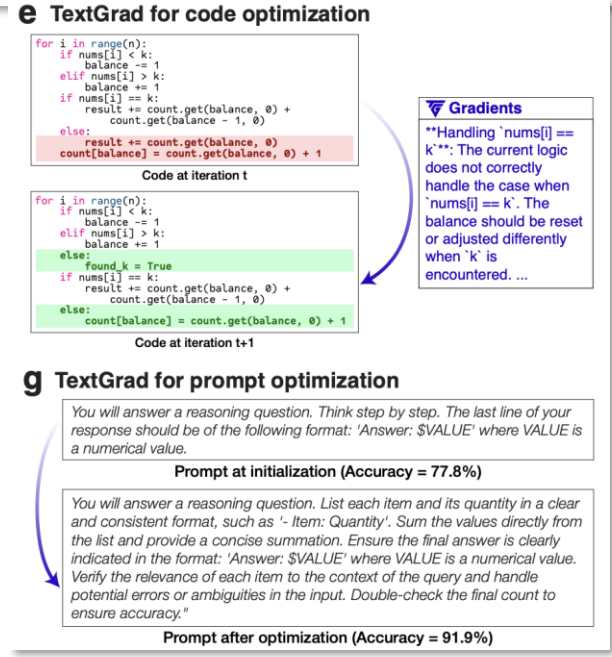
TextGrad: Automatic textual differentiation

- **TextGrad** describe an FMware program with a syntax that resembles that of PyTorch







https://arxiv.org/pdf/2406.07496

Prompt compilers: the road ahead

1. Establish quality programming constructs for representing FMware programs
2. Consolidate the forms of compilation that involves not only prompt templates but all free parameters of an FMware, including better support for agent-based applications
3. Identify the set of most effective heuristics to search the space of FMware parameters
4. Construct sets of gold labels to evaluate candidate solutions and guide the search procedure during compilation
5. Assure the quality of an FMware application, failing compilation when quality thresholds are not met
6. Reduce the cost and improve the efficiency of compilers
7. Make compilation reproducible
8. Enable user-defined, multiple concurrent objectives to be optimized during compilation
9. Improve the interoperability between compilers
10. Build community-sharing platforms of compilation traces such that this information can be used as a feedback signal to improve compilation.