CS769 Advanced NLP

Prompting

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Slides adapted from Pengfei, Graham

https://junjiehu.github.io/cs769-fall24/

Goals for Today

- Prompting vs other machine learning paradigms in NLP
- General Workflow of Prompting
- Key Components of Prompting
  1. Pre-trained Model Choice
  2. Prompt Engineering
  3. Answer Engineering
  4. Expanding the Paradigm
  5. Prompt-based Training Strategies

Recommended Reading

Pre-train, Prompt, and Predict: A Systematic Survey of Prompting Methods in Natural Language Processing

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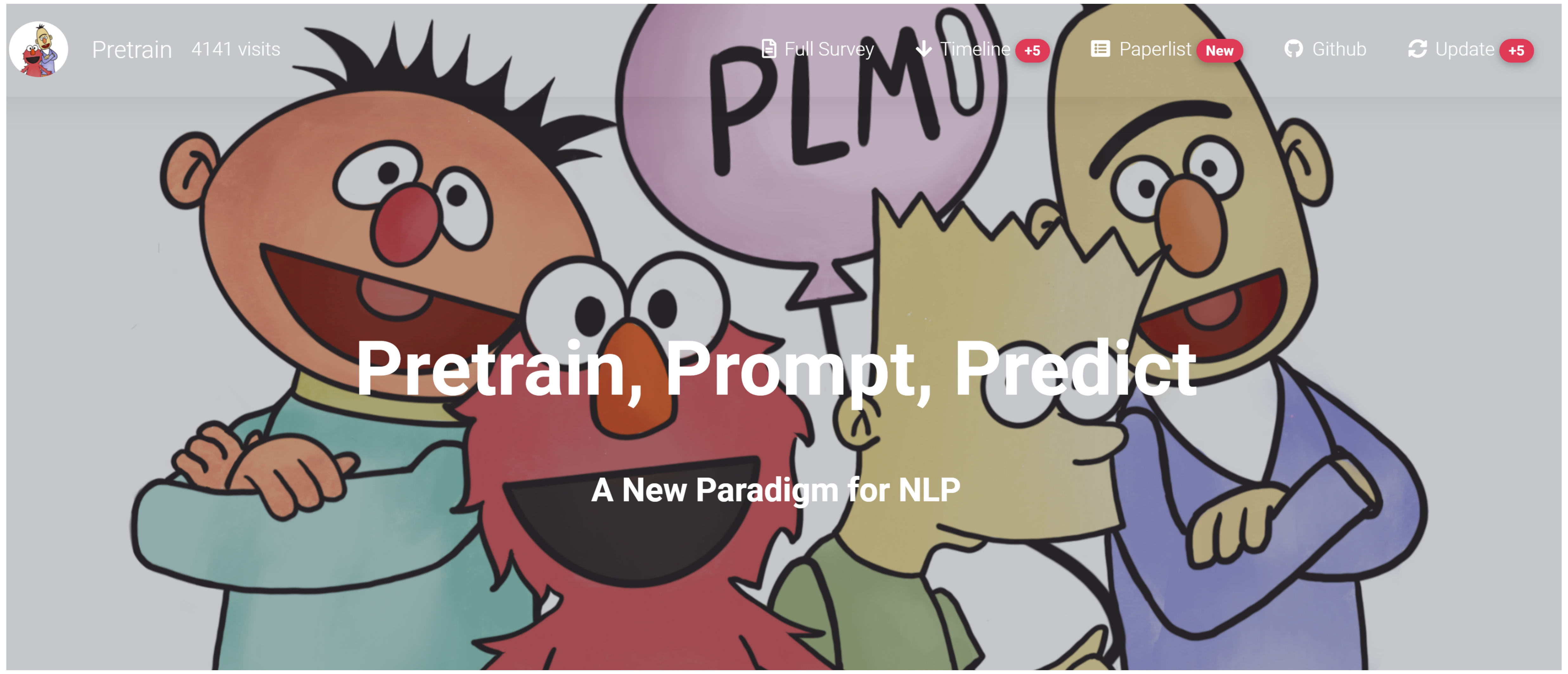


Four Paradigms of NLP Technical Development

- Feature Engineering
- Architecture Engineering
- Objective Engineering
- Prompt Engineering

Feature Engineering

- **Paradigm**: Fully Supervised Learning (Non-neural Network)
- **Time Period:** Most popular through 2015
- **Characteristics**:
  - Non-neural machine learning models mainly used
  - Require manually defined feature extraction
- **Representative Work**:
  - Manual features -> linear or kernelized support vector machine (SVM)
  - Manual features -> conditional random fields (CRF)

Architecture Engineering

- **Paradigm**: Fully Supervised Learning (Neural Networks)
- **Time Period**: About 2013-2018
- **Characteristics**:
  - Rely on neural networks
  - Do not need to manually define features, but should modify the network structure (e.g.: LSTM v.s CNN)
  - Sometimes used pre-training of LMs, but often only for shallow features such as embeddings
- **Representative Work**:
  - CNN/LSTM for Text Classification
  - Transformer for Machine Translation

Objective Engineering

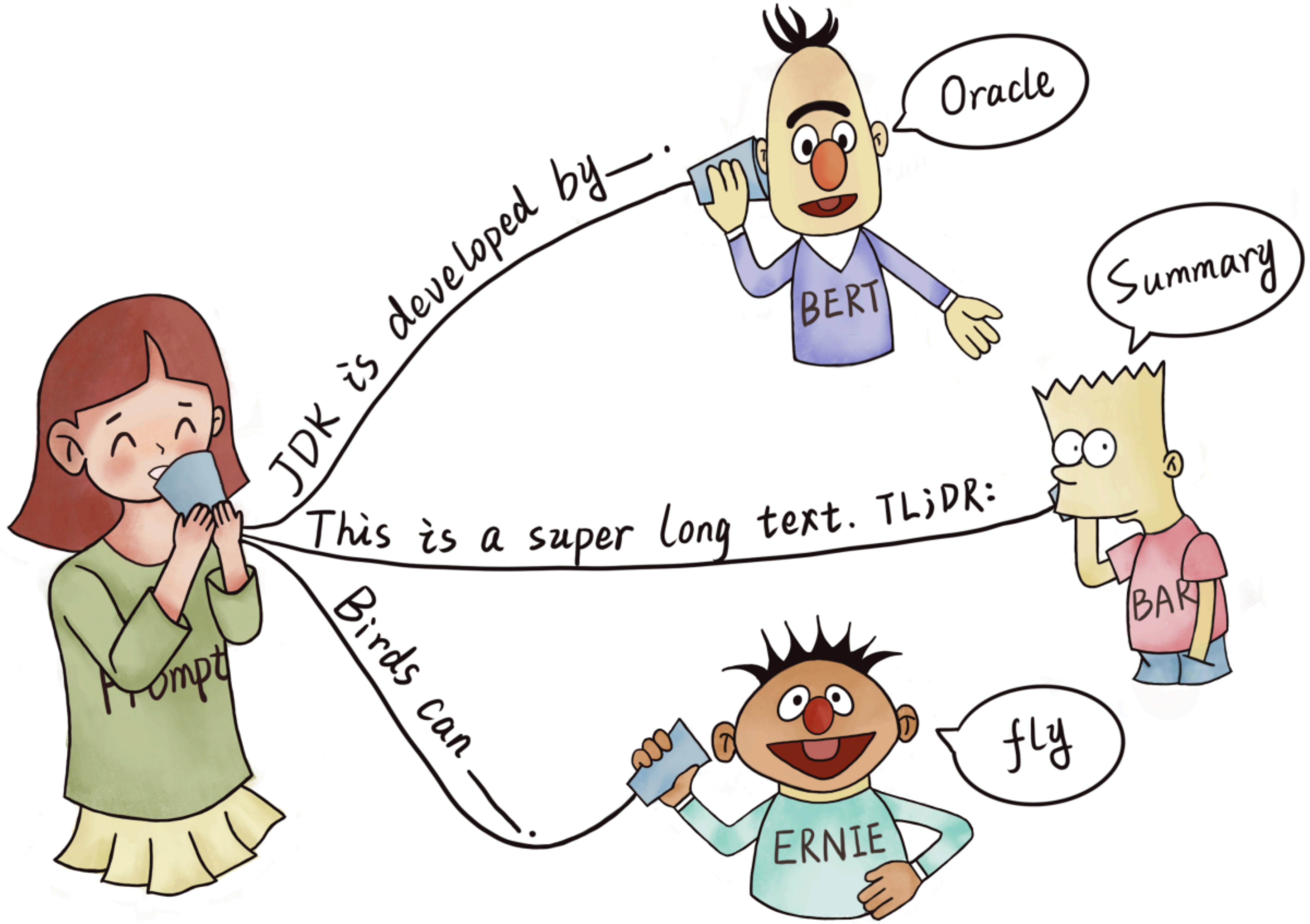
- **Paradigm**: Pre-train, Fine-tune
- **Time Period**: 2017-Now
- **Characteristics**:
  - Pre-trained LMs (PLMs) used as initialization of full model - both shallow and deep features
  - Less work on architecture design, but engineer objective functions
- **Typical Work**:
  - BERT → Fine Tuning

Prompt Engineering

- **Paradigm**: Pre-train, Prompt, Predict
- **Date**: 2019-Now
- **Characteristic**:
  - NLP tasks are modeled entirely by relying on LMs
  - The tasks of shallow and deep feature extraction, and prediction of the data are all given to the LM
  - Engineering of prompts is required
- **Representative Work:**
  - GPT3, GPT4, ChatGPT

What is Prompting?

- Encouraging a pre-trained model to make particular predictions by providing a "prompt" specifying the task to be done.



What is the general workflow of Prompting?

- Prompt Addition
- Answer Prediction
- Answer-Label Mapping

Prompt Addition

- **Prompt Addition**: Given input x, we transform it into prompt x' through two steps:
  - Define **a template** with two slots, one for input [x], and one for the answer [z]
  - Fill in the input slot [x]

Example: Sentiment Classification

Input: x = "I love this movie"

⇩

Template: [x] Overall, it was a [z] movie

⇩

Prompting: x' = "I love this movie. Overall it was a [z] movie."

Answer Prediction

- Answer Prediction: Given a prompt, predict the answer [z]
  - Fill in [z]

Example

Input: x = “I love this movie”

⇩

Template: [x] Overall, it was a [z] movie

⇩

Prompting: x’ = “I love this movie. Overall it was a [z] movie.”

⇩

Predicting: x’ = “I love this movie. Overall it was a fantastic movie.”

Mapping

- Mapping: Given an answer, map it into a class label

Example

Input: x = “I love this movie”

⇩

Template: [x] Overall, it was a [z] movie

⇩

Prompting: x’ = “I love this movie. Overall it was a [z] movie.”

⇩

Predicting: x’ = “I love this movie. Overall it was a fantastic movie.”

⇩

Mapping: fantastic => Positive

Types of Prompts

- Cloze Prompt: **I love this movie. Overall it was a [z] movie**
  Example outputs:
  - **I love this movie. Overall it was a boring movie**
  - **I love this movie. Overall it was a fantastic movie**

- Prefix Prompt: **I love this movie. Overall this movie is [z]**

Design Considerations for Prompting

- Pre-trained Model Choice
- Prompt Template Engineering
- Answer Engineering
- Expanding the Paradigm
- Prompt-based Training Strategies

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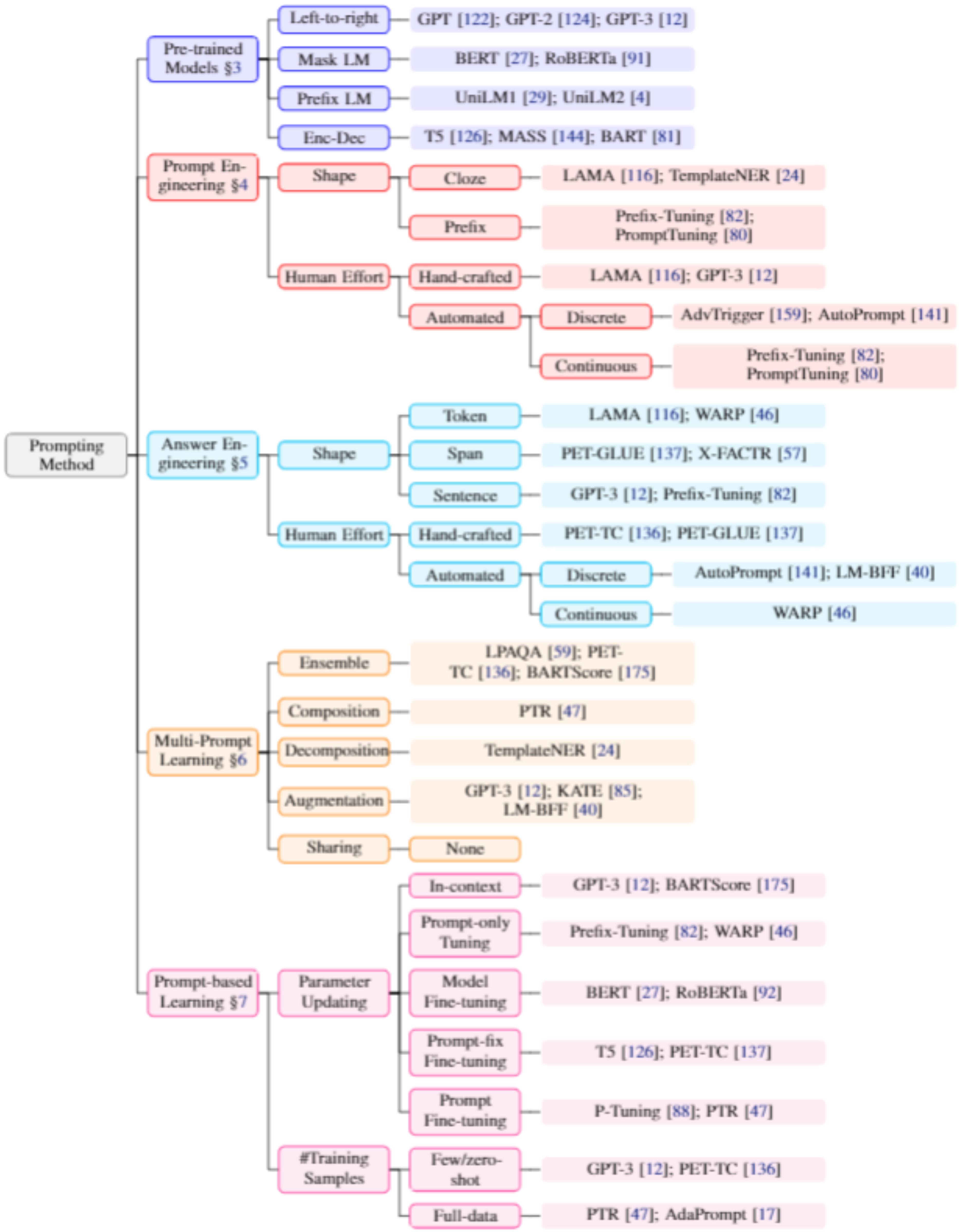

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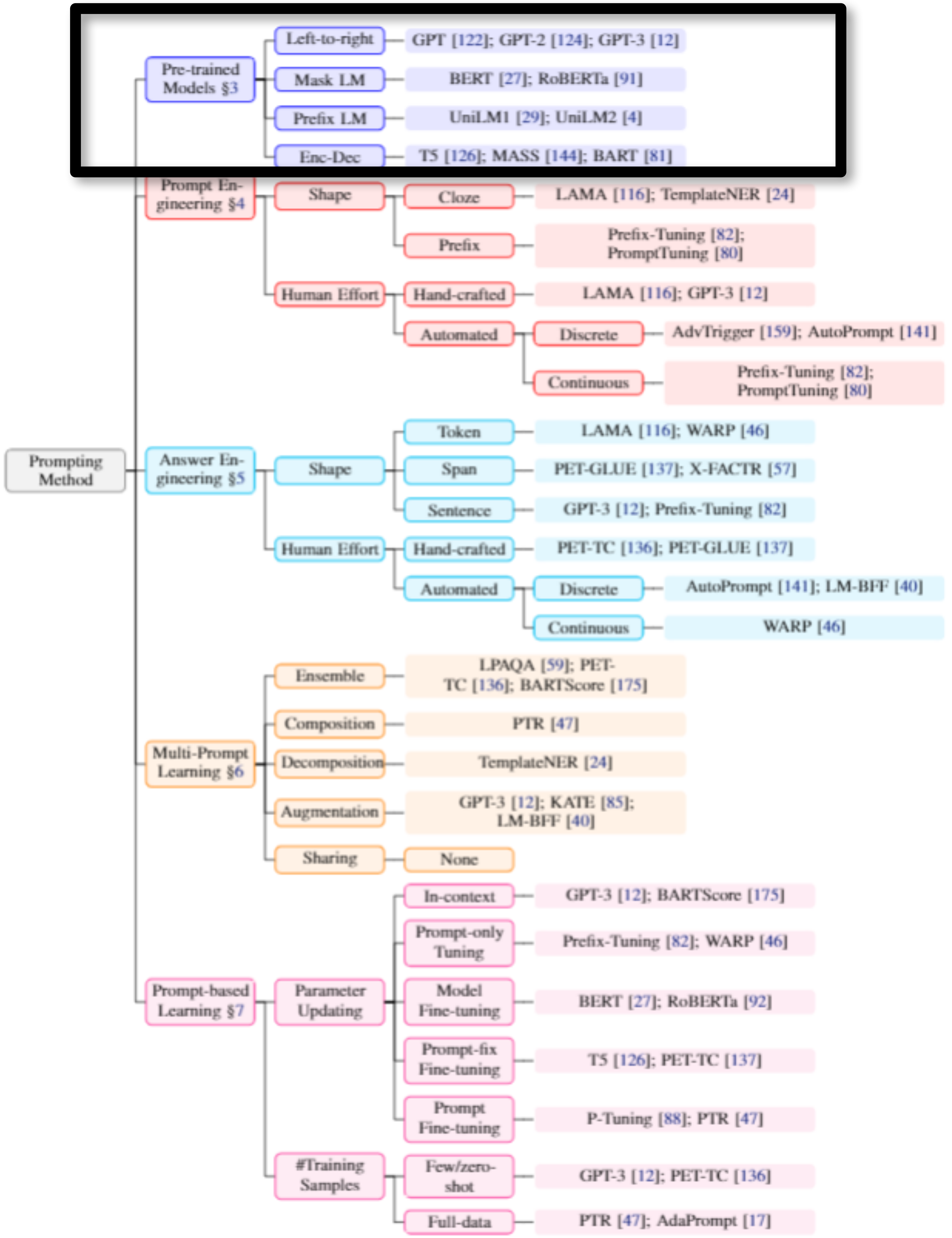


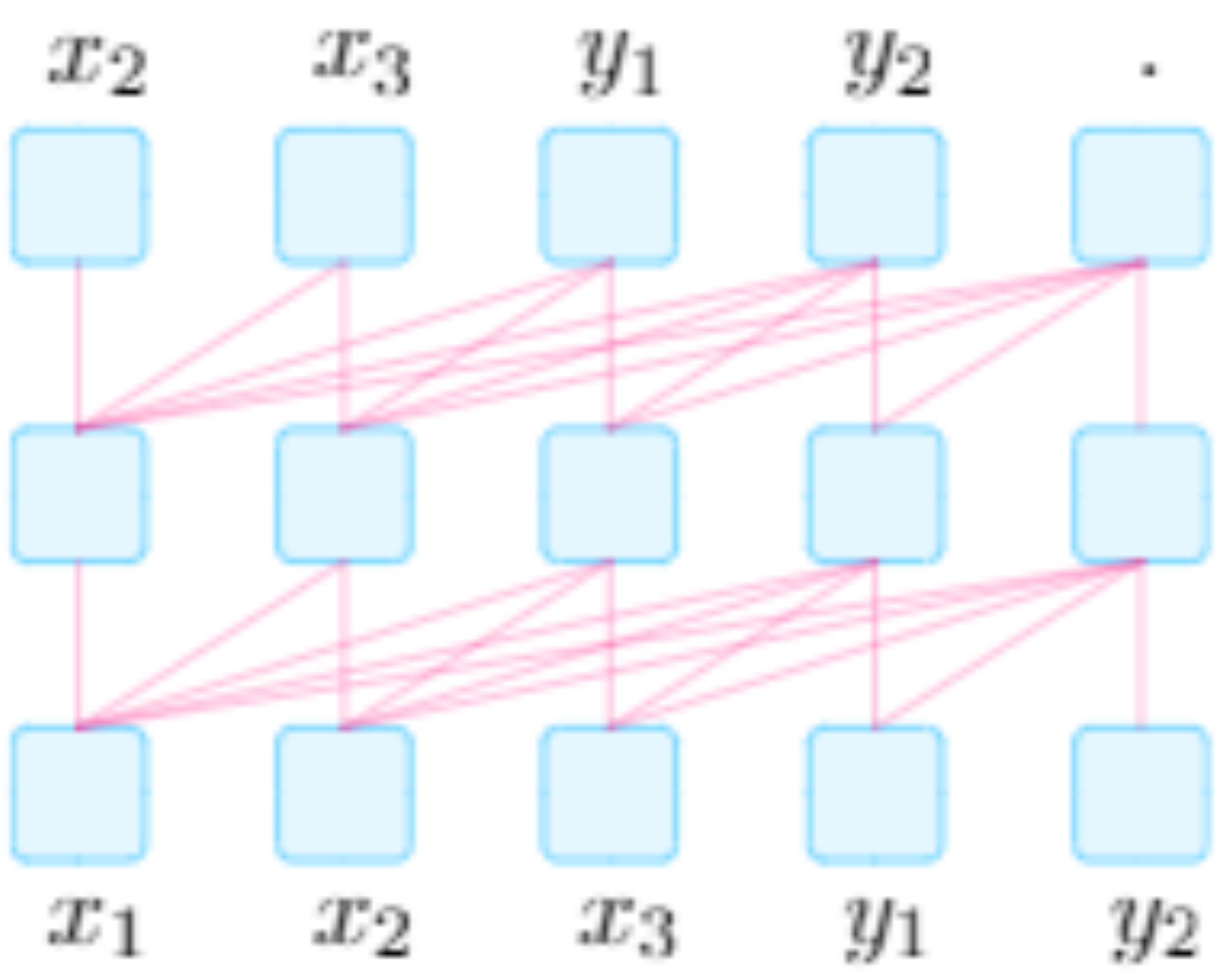
Pre-trained Language Models

Popular Frameworks

- (Left-to-Right) Autoregressive LM
- Masked LM
- Prefix LM
- Encoder-decoder LM

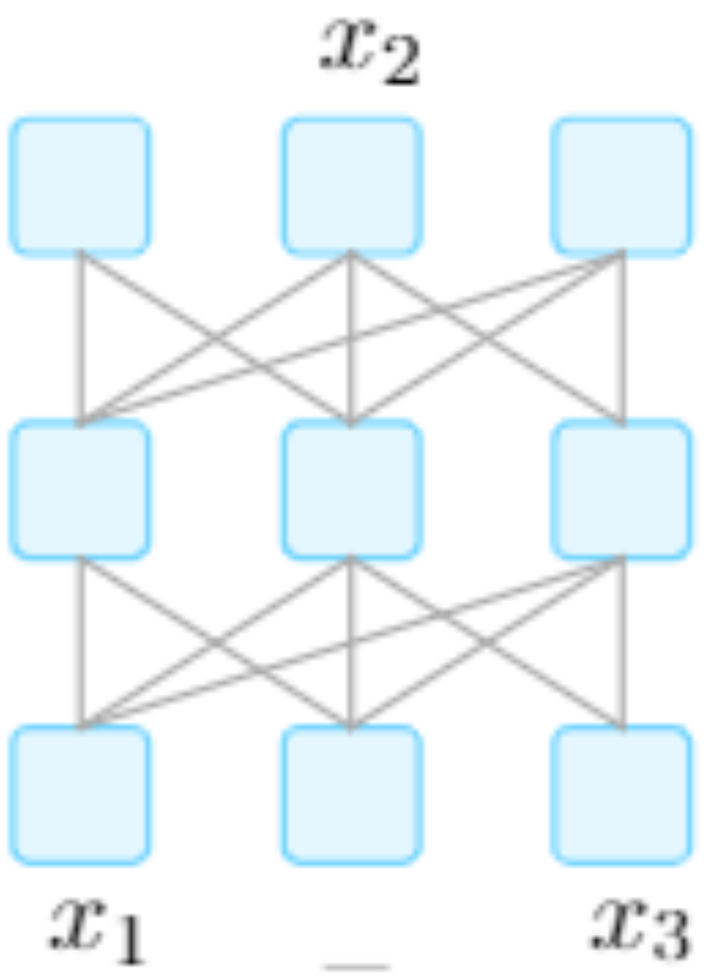
(Left-to-right) Autoregressive Language Model

- **Characteristics**:
  - First proposed by Markov (1913)
  - Count-based-> Neural network-based
  - Specifically suitable to highly larger-scale LMs
- **Example**:GPT-1,GPT-2,GPT-3, GPT-4
- Roles in Prompting Methods
  - The earliest architecture chosen for prompting
  - Usually equipped with prefix prompt and the parameters of PLMs are fixed



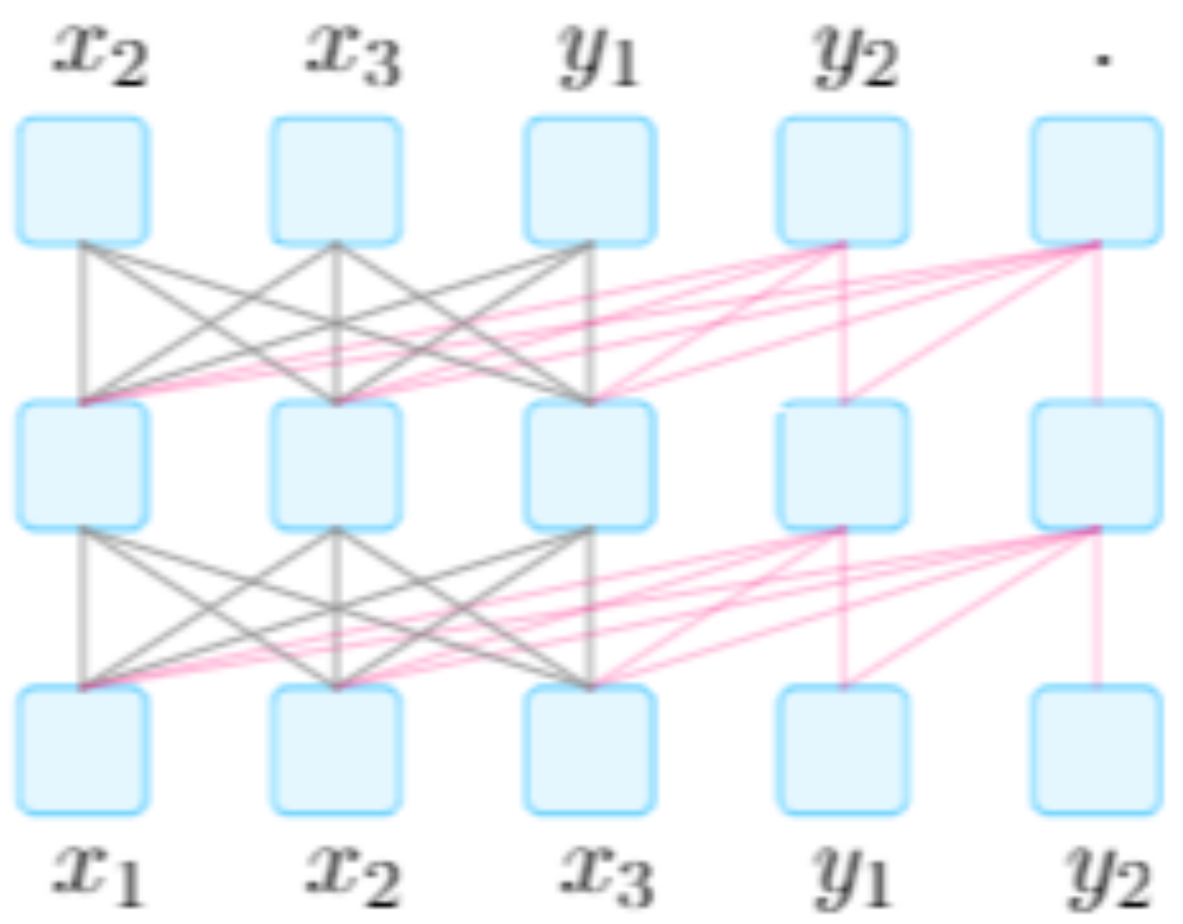
Masked Language Model

- Characteristics:
  - Unidirectional -> bidirectional prediction
  - Suitable for NLU tasks
- Example:
  - BERT, ERNIE
- Roles in Prompting Methods
  - Usually combined with Cloze prompt
  - Suitable for NLU tasks, which should be reformulated into a cloze task



Prefix Language Model

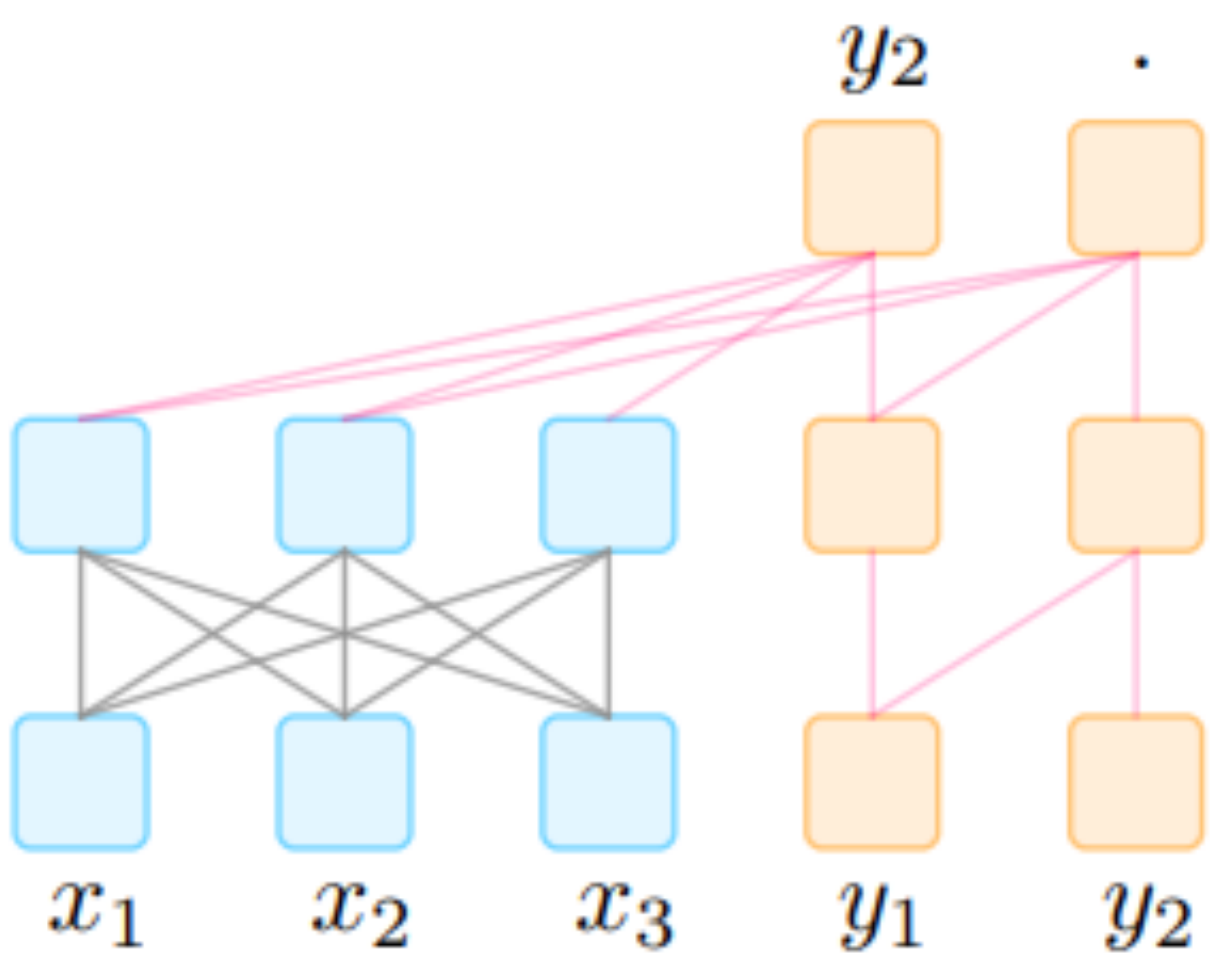
- Characteristics:
  - A combination of Masked & Left-to-right
  - Use a Transformer but two different mask mechanisms to handle text X and y separately
  - Corruption operations can be introduced when encoding X



- Examples:
  - UniLM 1,2, ERNIE-M

Encoder-Decoder LM

- Characteristics:
  - A denoised auto-encoder
  - Use two Transformers and two different mask mechanisms to handle text X and y separately
  - Corruption operations can be introduced when encoding X
- Examples:
  - BART, T5



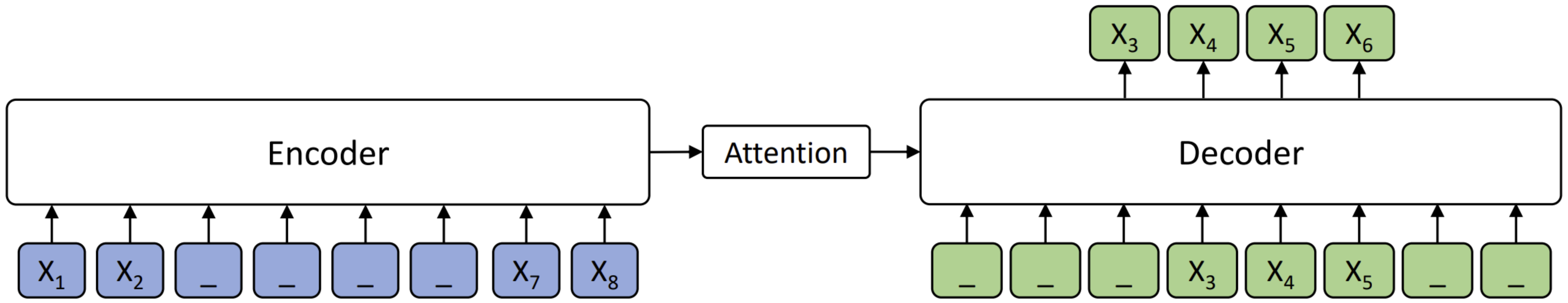
Encoder-Decoder Pre-training Methods

Representative Methods

- MASS
- BART (mBART)
- UniLM
- T5 (mT5, FlanT5)

MASS

(Song et al. 2019)

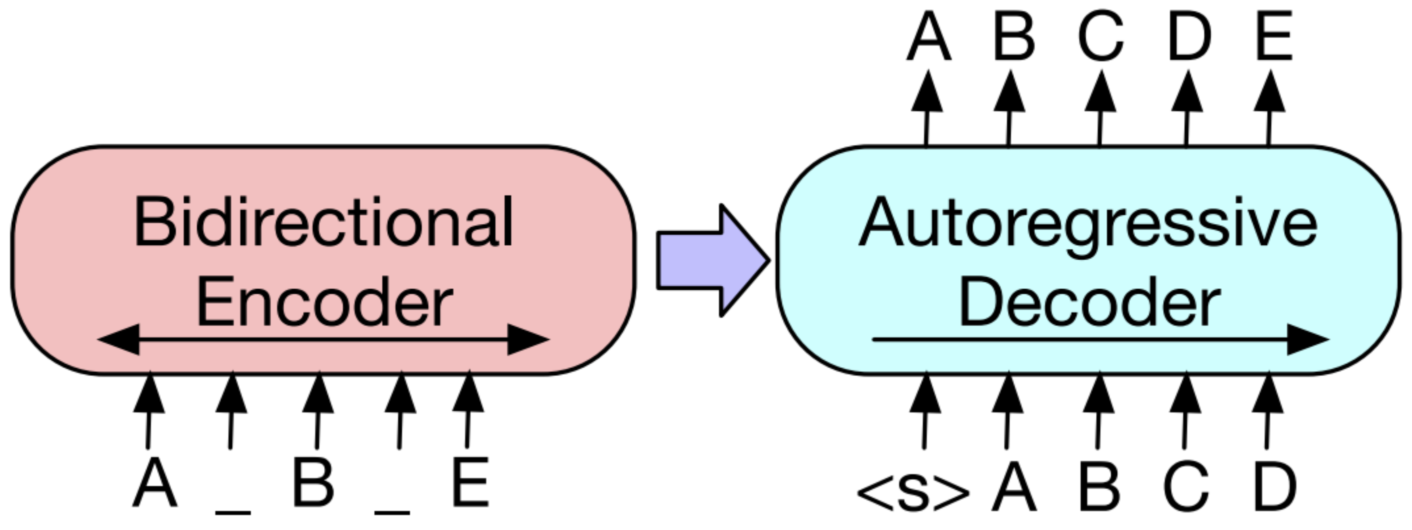


- Model: Transformer-based Encoder-decoder
- Objective: *only* predict masked spans
- Data: WebText

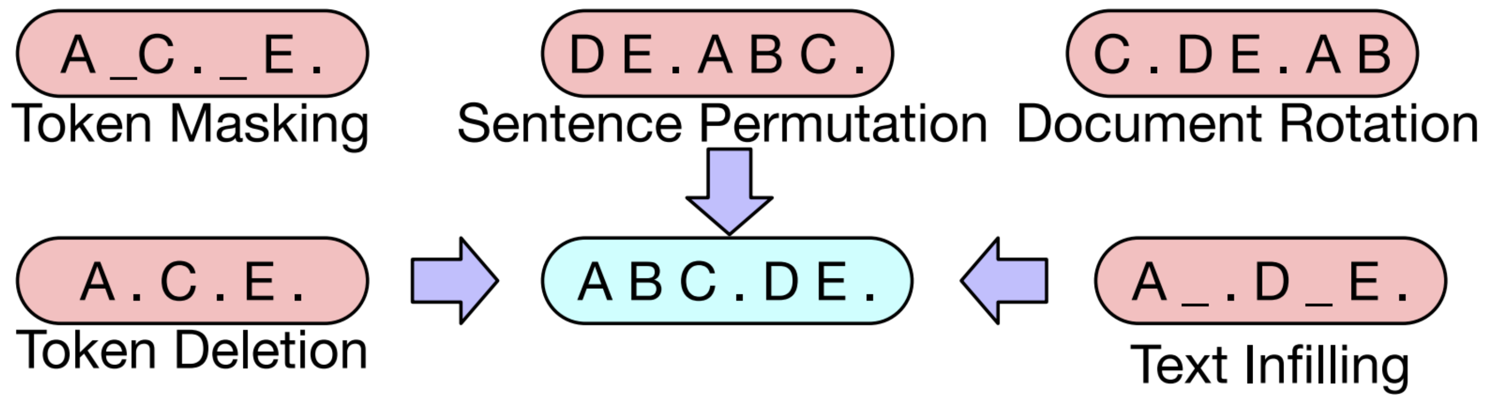
BART

(Lewis et al. 2019)

Framework

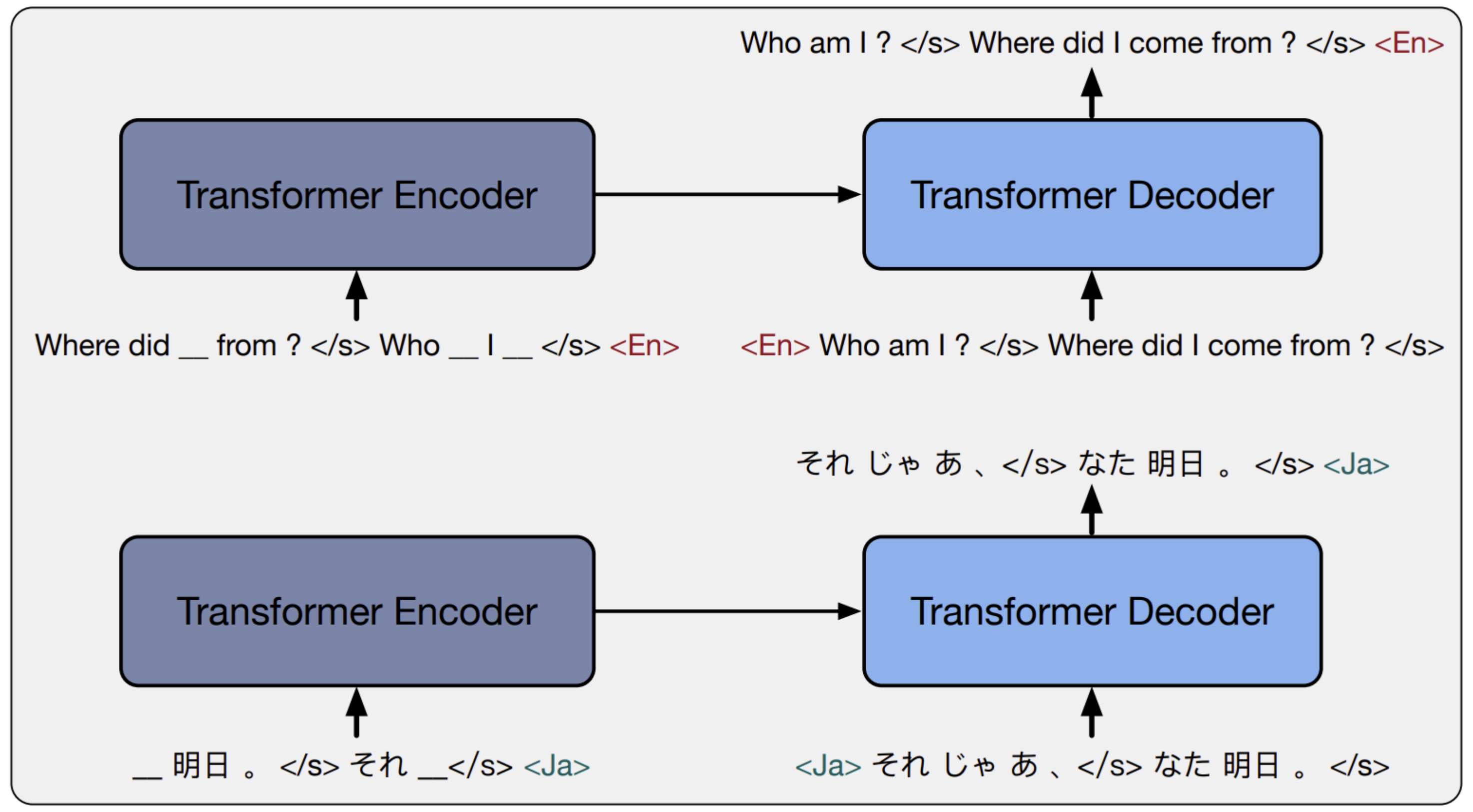


Different Corruption



- Model: Transformer-based encoder-decoder model
- Objective: Re-construct (corrupted) *original sentences*
- Data: similar to RoBERTa (160GB): BookCorpus, CC-NEWs, WebText, Stories

mBART (Liu et al. 2021)



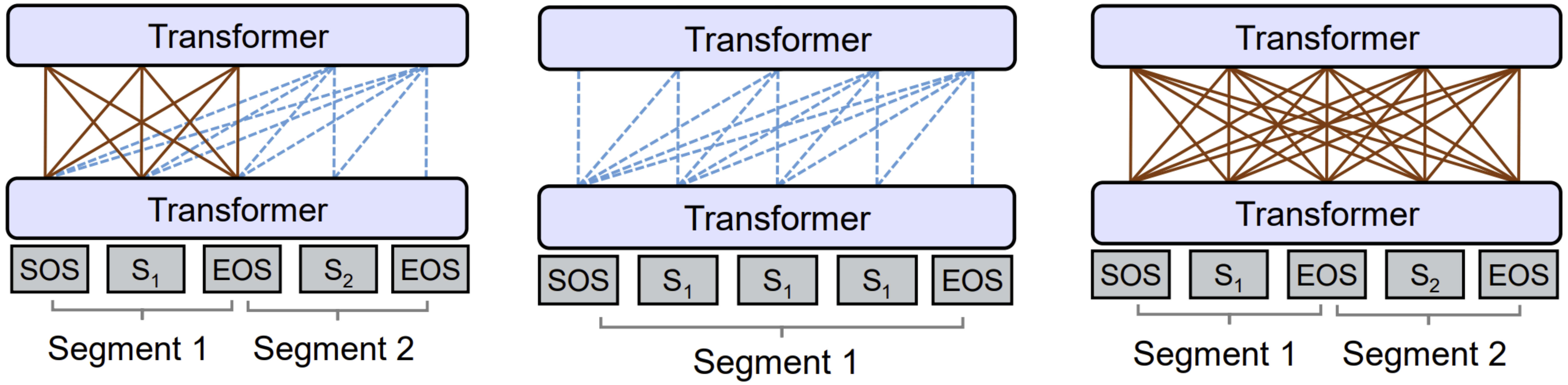
- Model: Transformer-based *Multi-lingual Denoising* auto-encoder

- Objective: Re-construct (corrupted) *original sentences*

- Data: CC25 Corpus (25 langauges)

UNiLM

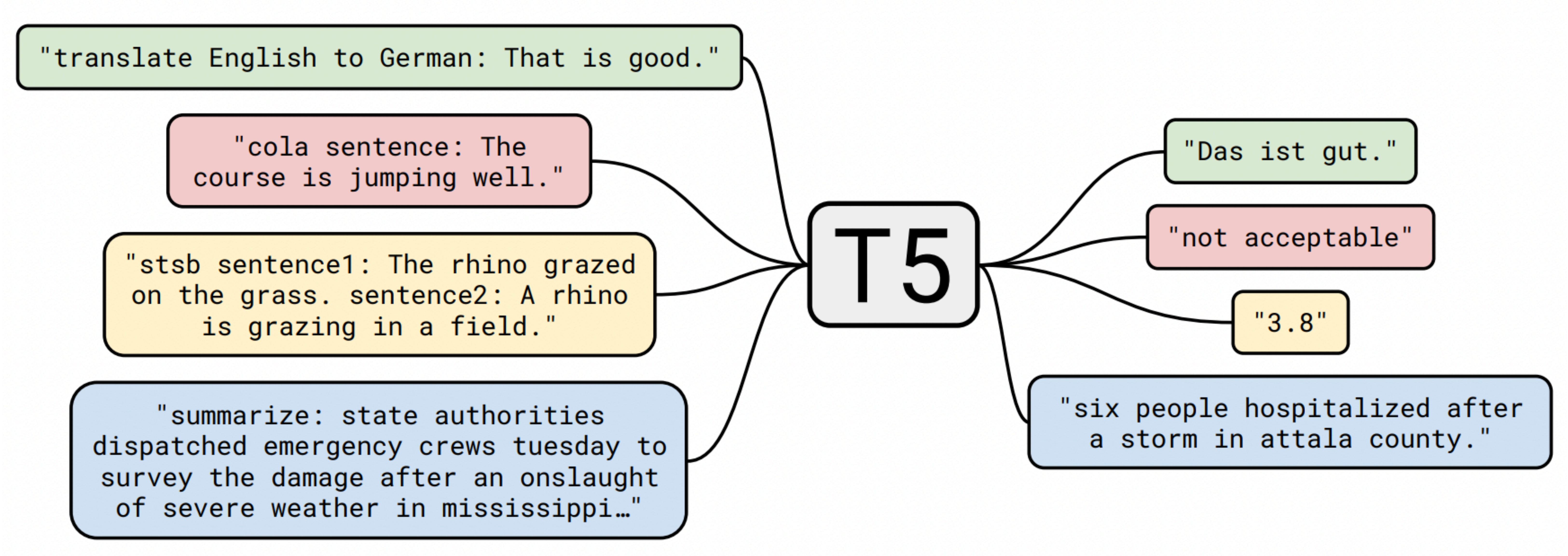
(Dong et al. 2019)



- Model: Prefix LM (a.k.a. Seq2seq LM), left-to-right LM, Masked LM
- Objective: three types of LMs, *shared* parameters
- Data: English Wikipedia and BookCorpus

T5

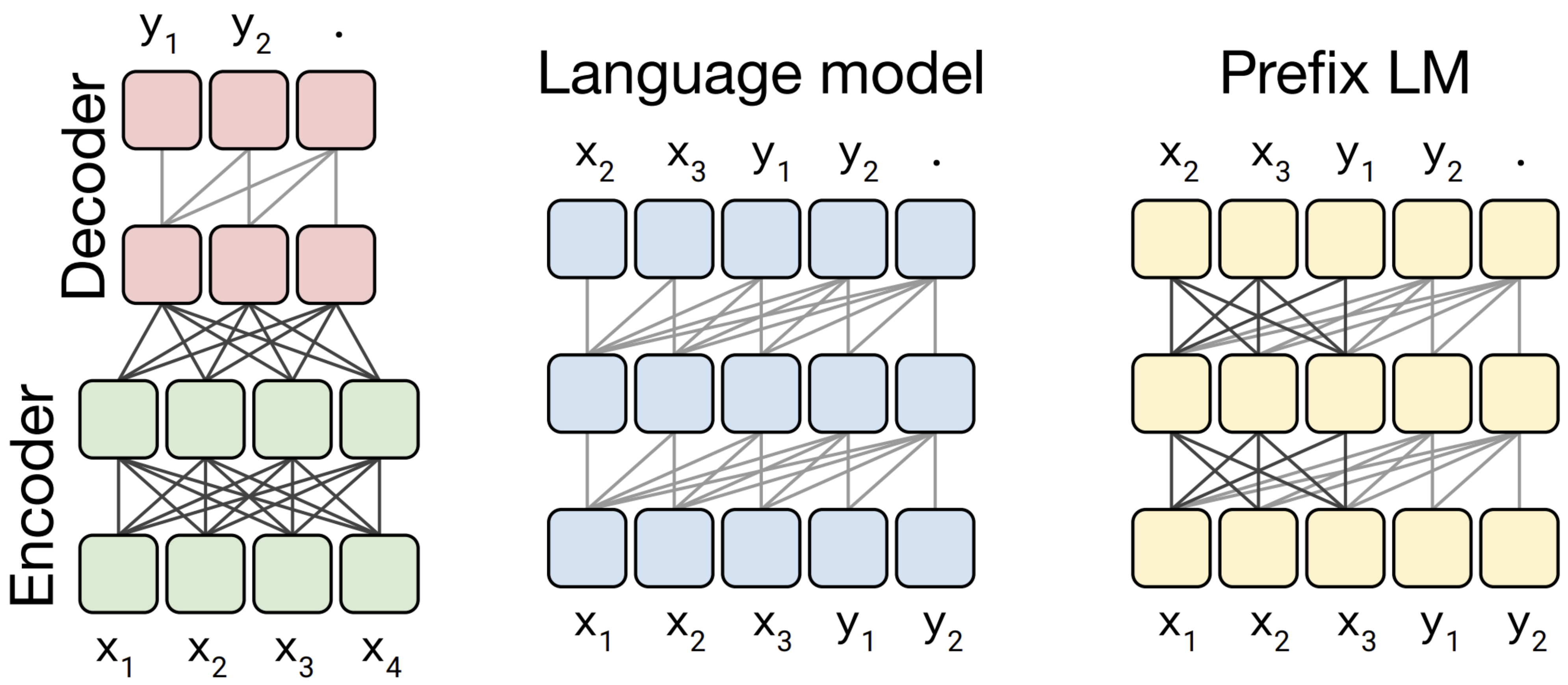
(Raffel et al. 2020)



- Convert all tasks to sequence-to-sequence prediction

T5

(Raffel et al. 2020)



- Model: left-to-right LM, Prefixed LM, encoder-decoder
- Objective: explore different objectives respectively
- Data: C4 (750G) + Wikipedia + RealNews + WebText

T5

(Raffel et al. 2020)

Objective	Inputs	Targets
Prefix language modeling	Thank you for inviting	me to your party last week .
BERT-style Devlin et al. (2018)	Thank you <M> <M> me to your party apple week .	*(original text)*
Deshuffling	party me for your to . last fun you inviting week Thank	*(original text)*
MASS-style Song et al. (2019)	Thank you <M> <M> me to your party <M> week .	*(original text)*
I.i.d. noise, replace spans	Thank you <X> me to your party <Y> week .	<X> for inviting <Y> last <Z>
I.i.d. noise, drop tokens	Thank you me to your party week .	for inviting last
Random spans	Thank you <X> to <Y> week .	<X> for inviting me <Y> your party last <Z>

- Model: left-to-right LM, Prefix LM, encode-decoder
- Objective: explore different objectives respectively
- Data: C4 (750G) + Wikipedia + RealNews + WebText

Application of Prefix LM/Encoder-Decoders in Prompting

- Conditional Text Generation
  - Translation
  - Text Summarization
- Generation-like Tasks
  - Information Extraction
  - Question Answering

Design Considerations for Prompting

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- Answer Engineering
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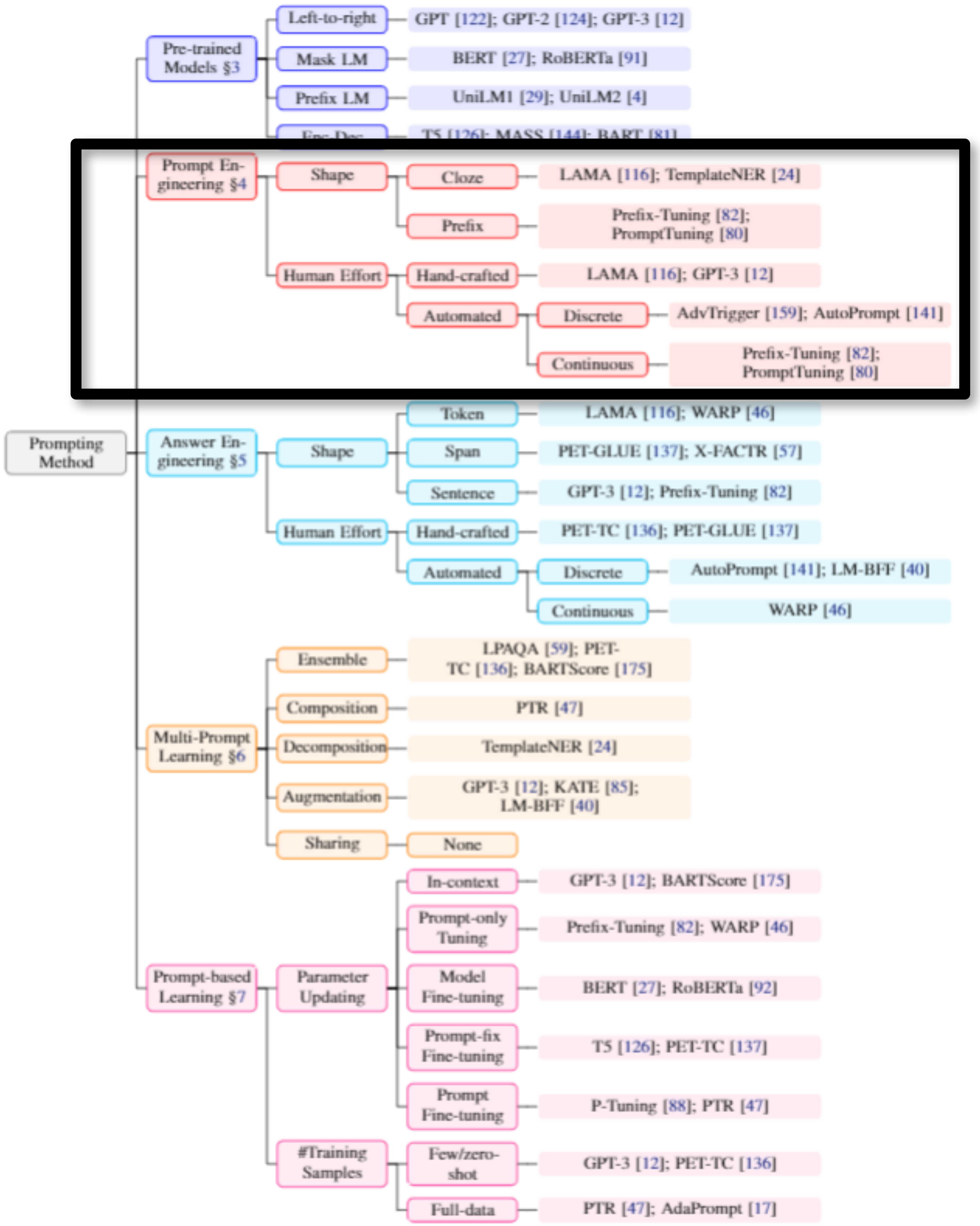

Traditional Formulation V.S Prompt Formulation

Traditional Formulation

Input: x = “I love this movie”

Predicting: y = Positive

Prompt Formulation

Input: x = “I love this movie”

Template: [x] Overall, it was a [z] movie

Prompting: x’ = “I love this movie. Overall it was a [z] movie.”

Predicting: x’ = “I love this movie. Overall it was a fantastic movie.”

Mapping (answer -> label):
fantastic => Positive

Traditional Formulation V.S Prompt Formulation

Input: x = "I love this movie"

⇩

Predicting: y = Positive

Input: x = "I love this movie"

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Template: [x] Overall, it was a [z] movie

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Prompting: x' = "I love this movie. Overall it was a [z] movie."

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Predicting: x' = "I love this movie. Overall it was a fantastic movie."

⇩

Mapping (answer -> label):
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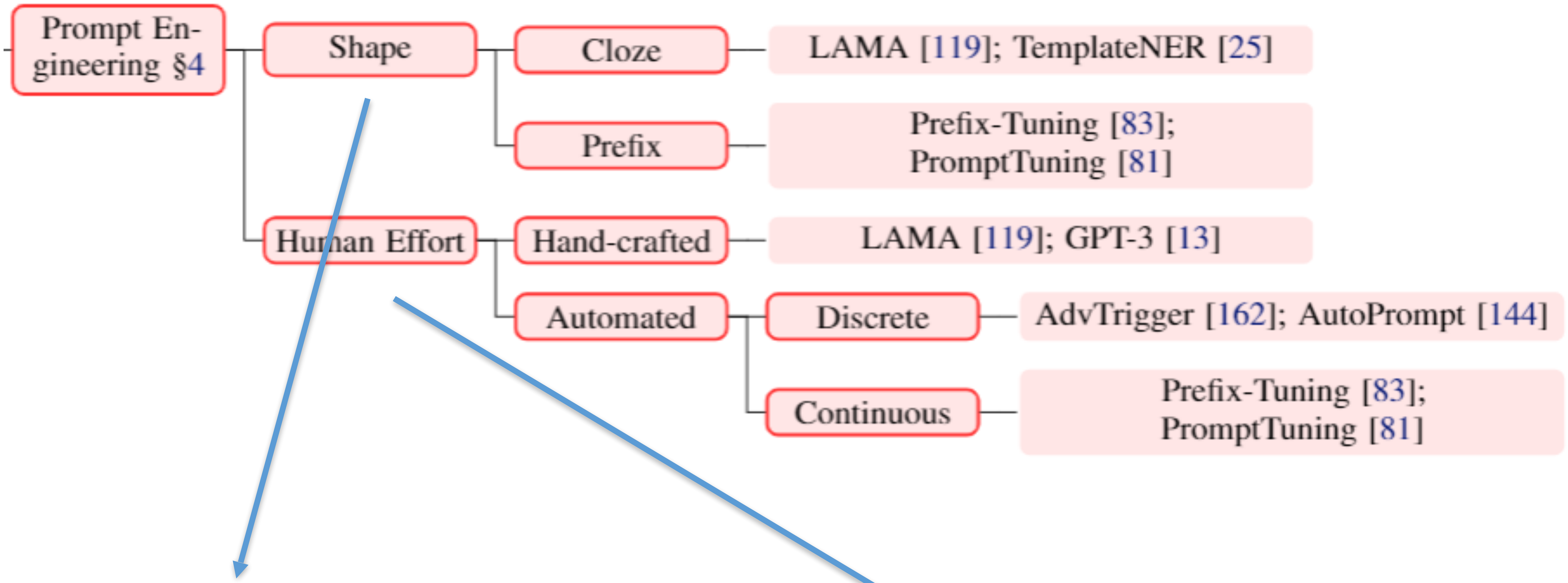
How to define a suitable prompt template?

Prompt Template Engineering



How to define the shape of a prompt template?

How to search for appropriate prompt templates?

Prompt Shape

- Cloze Prompt
  - prompt with a slot [z] to fill in the middle of the text as a cloze prompt,

I love this movie. Overall it was a [z] movie

- Prefix Prompt
  - prompt where the input text comes entirely before slot [z]

I love this movie. Overall this movie is [z]

Design of Prompt Templates

- Hand-crafted
  - Configure the manual template based on the characteristics of the task
- Automated search
  - Search in discrete space
  - Search in continuous space

Representative Methods for Prompt Search

- Prompt Mining
- Prompt Paraphrasing
- Gradient-based Search
- Prompt/Prefix Tuning

Prompt Mining (Jiang et al. 2019)

- Mine prompts given a set of questions/answers
- **Middle-word**

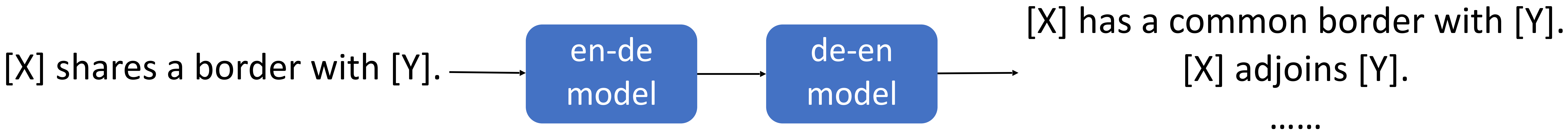
  Barack Obama was born in Hawaii. → [X] was born in [Y].

- **Dependency-based**

  The capital of France is Paris. → capital of [X] is [Y].

Prompt Paraphrasing (Jiang et al. 2019)

- **Paraphrase an existing prompt to get other candidates**
- e.g. back translation with beam search

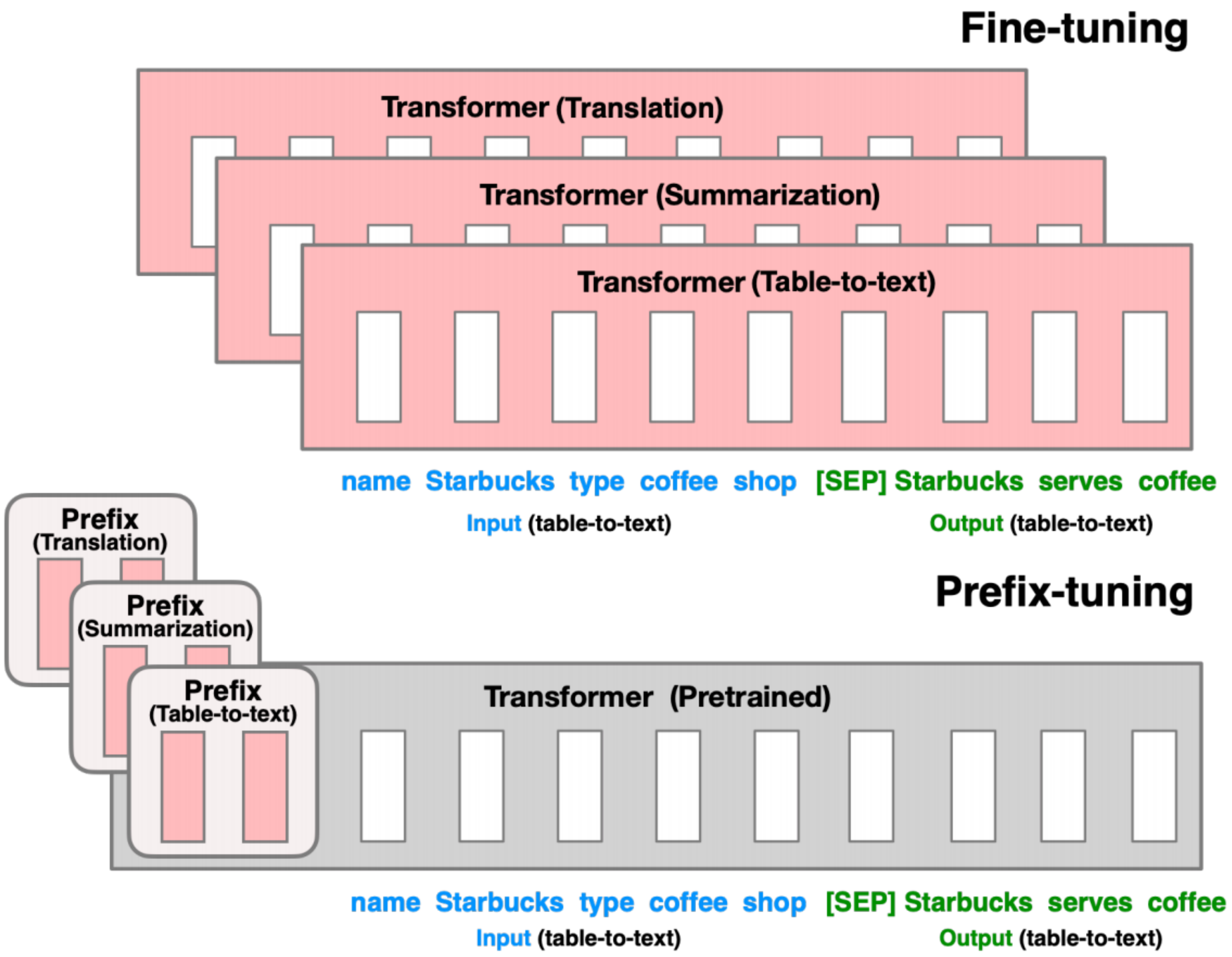


Gradient-based Search —AutoPrompt (Shin et al. 2020)

- Automatically optimize arbitrary prompts based on existing words

Prefix/Prompt Tuning (Li and Liang 2021, Lester et al. 2021)

- Optimize the embeddings of a prompt, instead of the words.
- "Prompt Tuning" optimizes only the embedding layer, "Prefix Tuning" optimizes prefix of all layers



Design Considerations for Prompting

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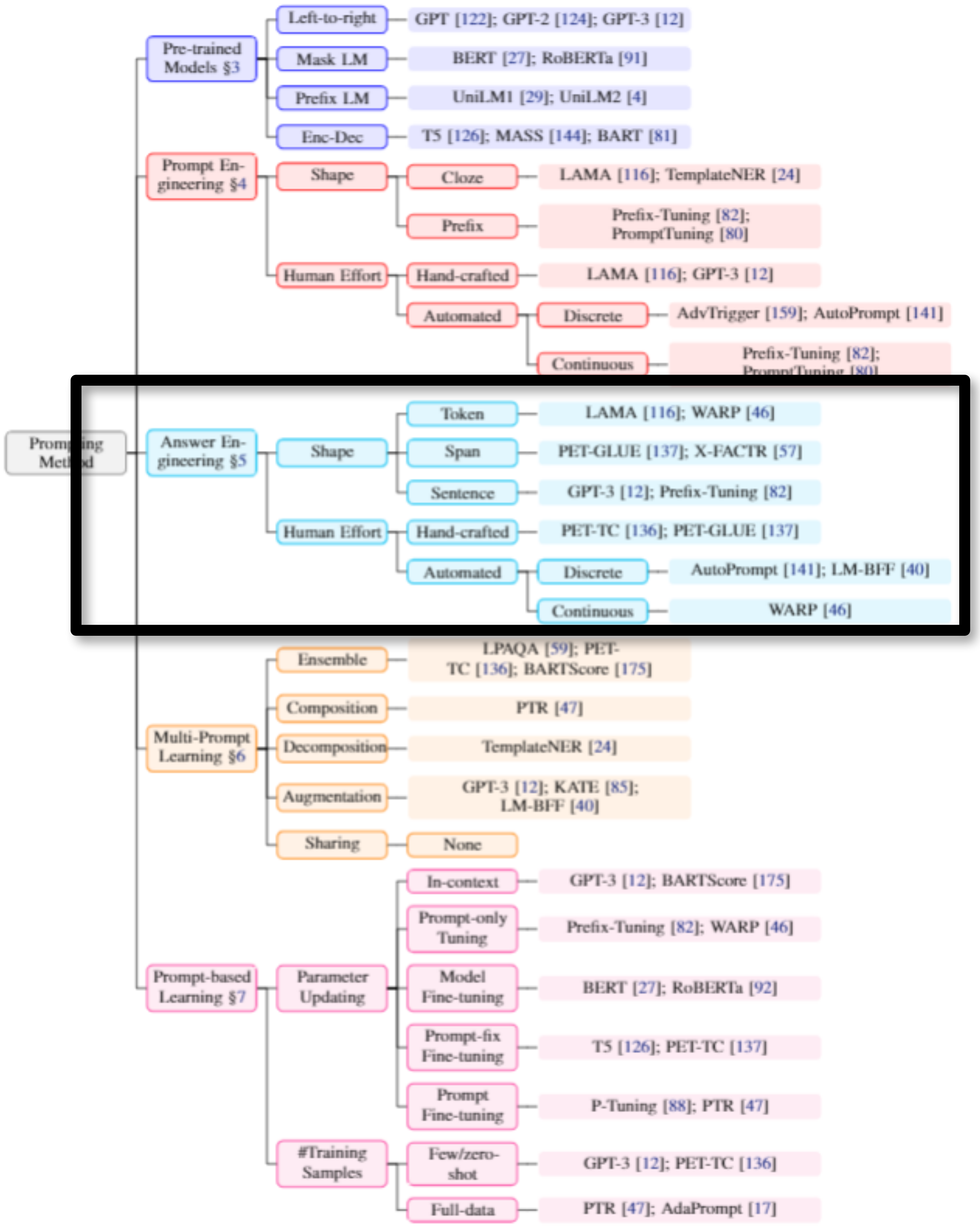

Answer Engineering

- Why do we need answer engineering?
  - We have reformulated the task! We also should re-define the “ground truth labels”

Traditional Formulation V.S Prompt Formulation

Input: x = "I love this movie"

Predicting: y = Positive

Input: x = "I love this movie"

Template: [x] Overall, it was a [z] movie

Prompting: x' = "I love this movie. Overall it was a [z] movie."

Predicting: x' = "I love this movie. Overall it was a fantastic movie."

Mapping (answer -> label):
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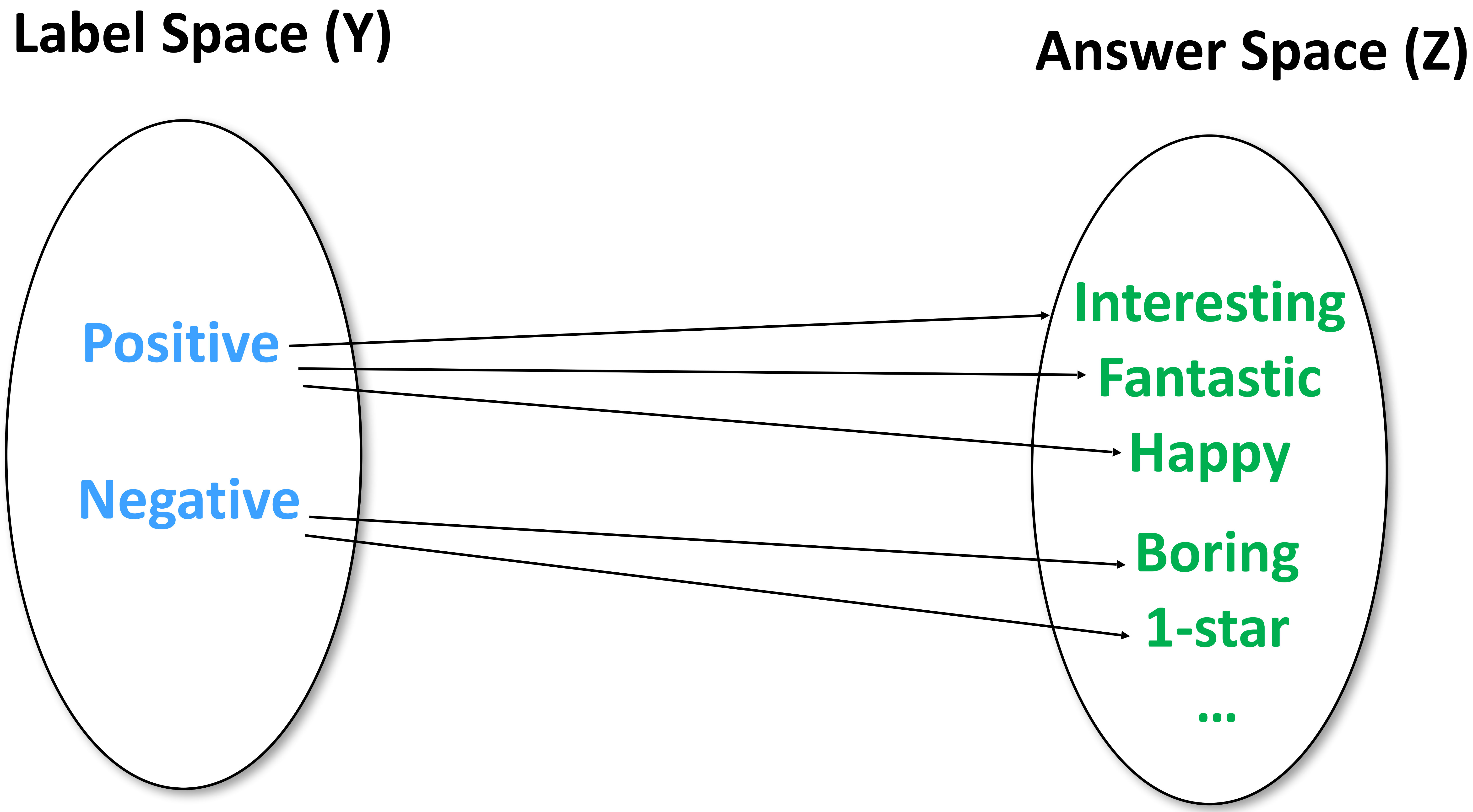
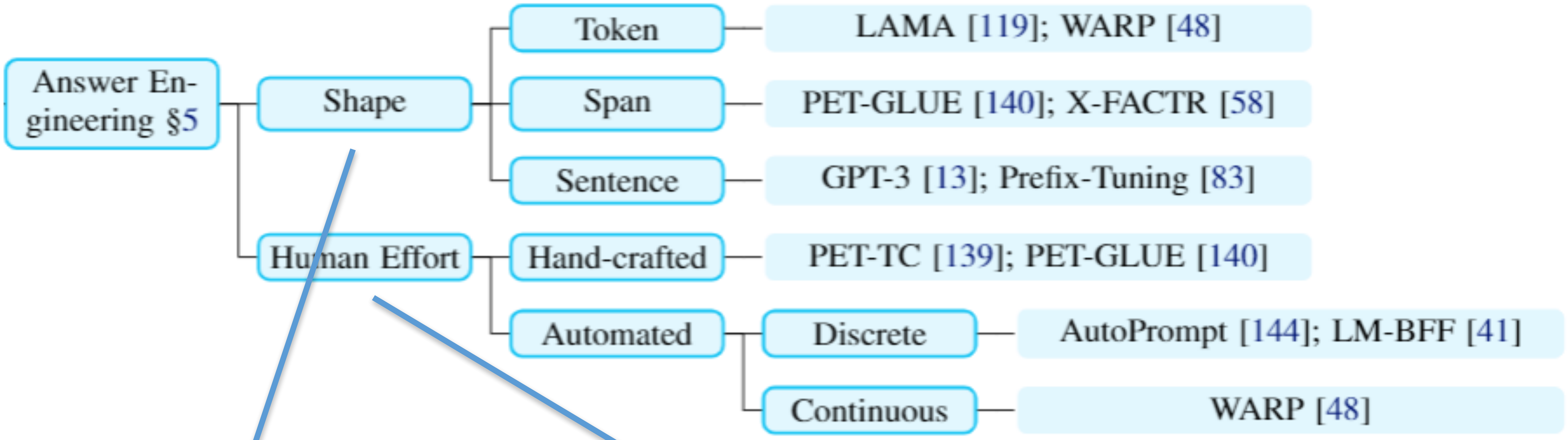
Traditional Formulation V.S Prompt Formulation



Answer Engineering

- Why do we need answer engineering?
  - We have reformulate the task! We also should re-define the “ground truth labels”
- Definition:
  - aims to search for an answer space and a map to the original output Y that results in an effective predictive model

Design of Prompt Answer



How to define the shape of an answer?

How to search for appropriate answers?

Answer Shape

- **Token**: Answers can be one token in the pre-trained language model vocabulary
- **Chunk**: Answers can be chunks of words made up of more than one tokens
  - Usually used with the Cloze prompt
- **Sentence**: Answers can be a sentence of arbitrary length
  - Usually used with prefix prompt (seq2seq LM for generative tasks)

Answer Shape

Type	Task	Input ([X])	Template	Answer ([Z])
Text CLS	Sentiment	I love this movie.	[X] The movie is [Z].	great fantastic ...
	Topics	He prompted the LM.	[X] The text is about [Z].	sports science ...
	Intention	What is taxi fare to Denver?	[X] The question is about [Z].	quantity city ...
Text-span CLS	Aspect Sentiment	Poor service but good food.	[X] What about service? [Z].	Bad Terrible ...
Text-pair CLS	NLI	[X1]: An old man with ... [X2]: A man walks ...	[X1]? [Z], [X2]	Yes No ...
Tagging	NER	[X1]: Mike went to Paris. [X2]: Paris	[X1] [X2] is a [Z] entity.	organization location ...
Text Generation	Summarization	Las Vegas police ...	[X] TL;DR: [Z]	The victim ... A woman ... ...
	Translation	Je vous aime.	French: [X] English: [Z]	I love you. I fancy you. ...

token

Token or span

sentences

Answer Search

- Hand-crafted
  - Infinite answer space (e.g., summarization, machine translation): Map the predicted tokens as the final answers ($z \rightarrow y$)
  - Finite answer space (e.g., text classification, sequence labeling): Map a finite set of words to labels (e.g., "anger", "sadness", "fear" to "negative")
- Automated Search
  - Discrete Space
  - Continuous Space

Discrete Search Space

- Answer Paraphrasing
  - start with an initial answer space,
  - then use paraphrasing to expand this answer space
- Prune-then-Search
  - an initial pruned answer space of several plausible answers is generated
  - an algorithm further searches over this pruned space to select a final set of answers
- Label Decomposition
  - decompose each relation label into its constituent words and use them as an answer
    - per:city_of_death => {person, city, death}

Chain-of-Thought Prompting

- Instead of searching for the answer directly, and manually add some intermediate reasoning steps in the prompt to guide the model derive the answer

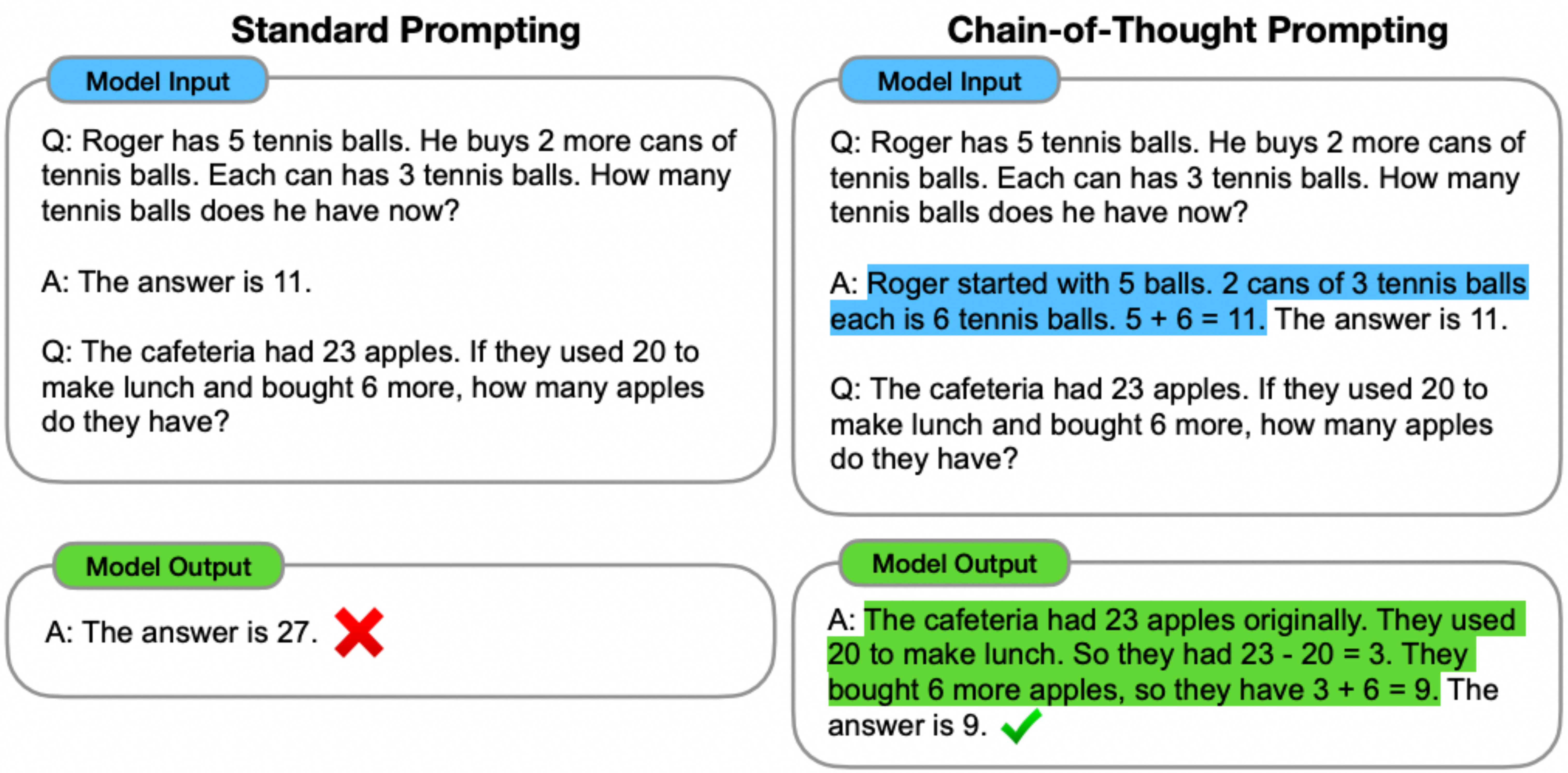
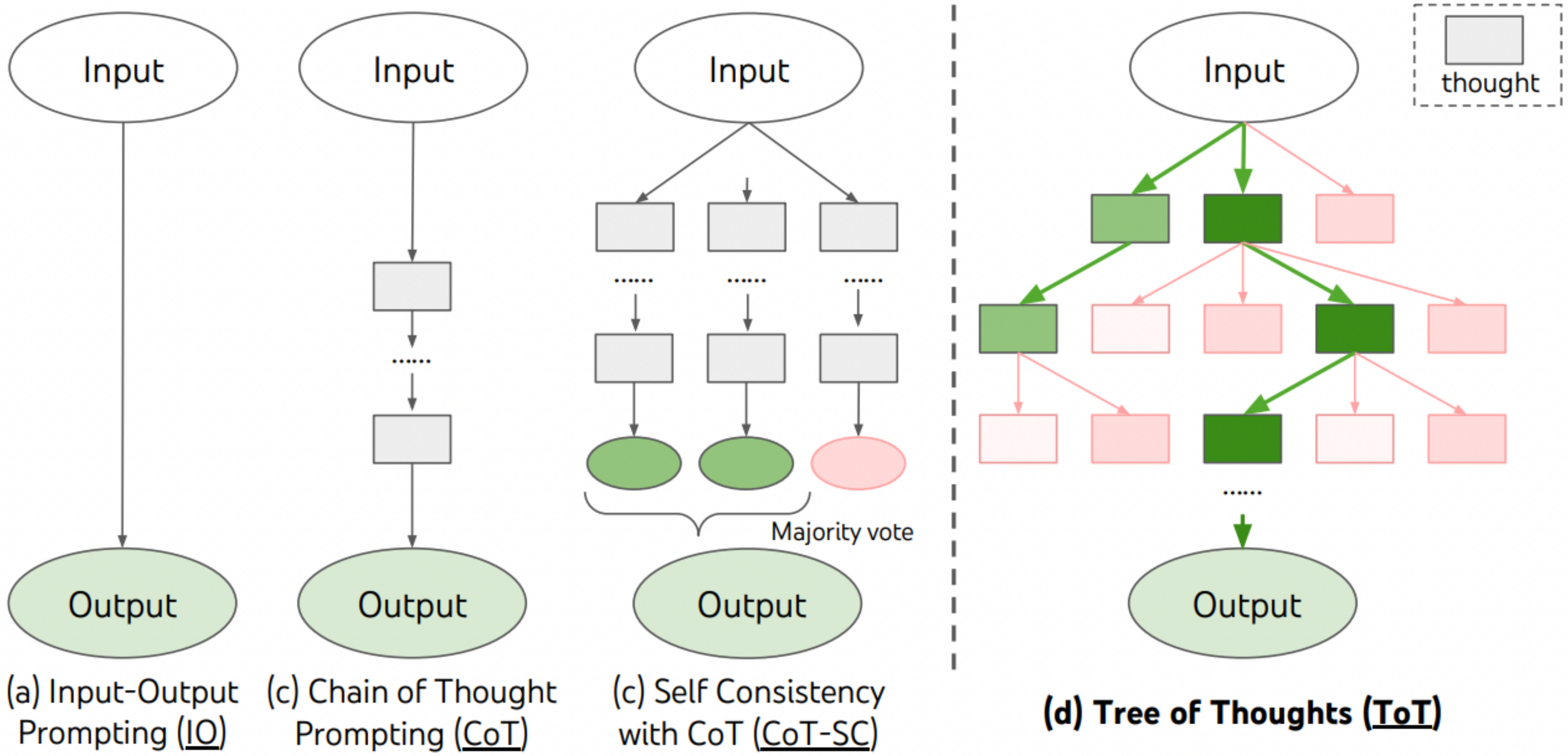


Figure 1: Chain-of-thought prompting enables large language models to tackle complex arithmetic, commonsense, and symbolic reasoning tasks. Chain-of-thought reasoning processes are highlighted.

Tree-of-Thought

- Instead of search the answer using a linear chain structure, prompt the output sequence to follow a tree structure



Tree of Thought: Example

- Game of 24 is a mathematical reasoning challenge, where the goal is to use 4 numbers and basic arithmetic operations (+-*/) to obtain 24. For example, given input “4 9 10 13”, a solution output could be “(10 - 4) * (13 - 9) = 24”.

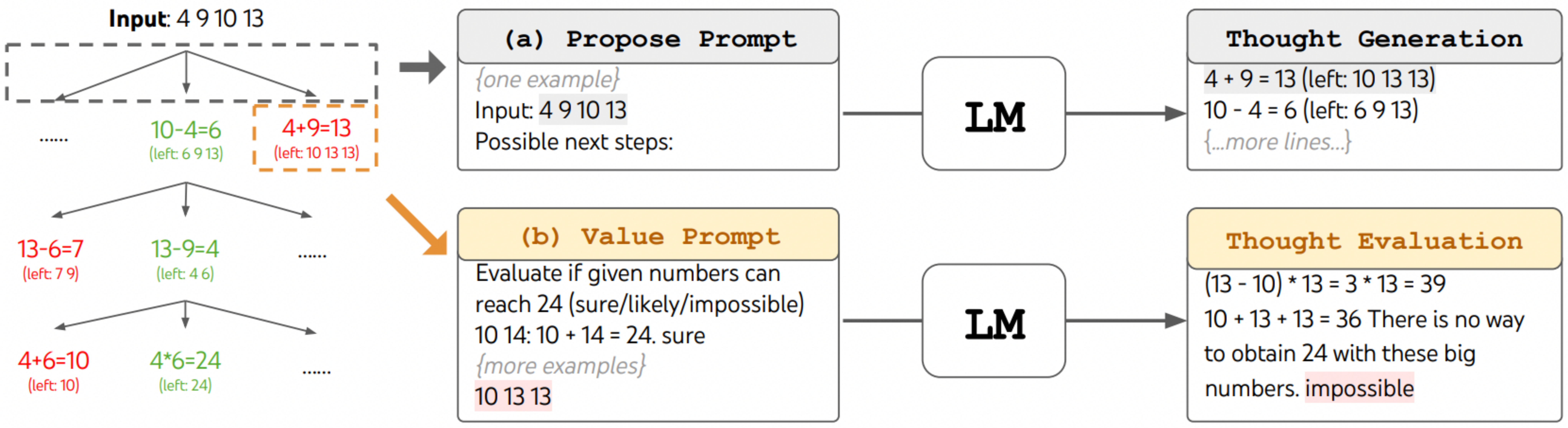
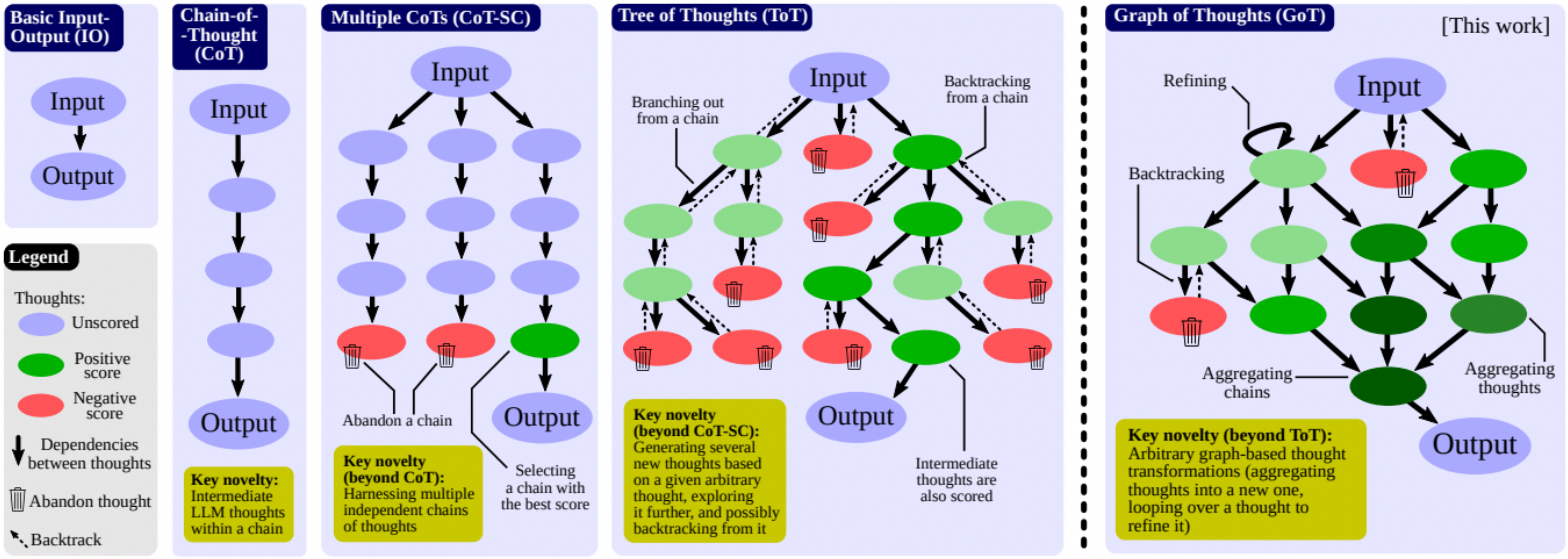


Figure 2: ToT in a game of 24. The LM is prompted for (a) thought generation and (b) valuation.

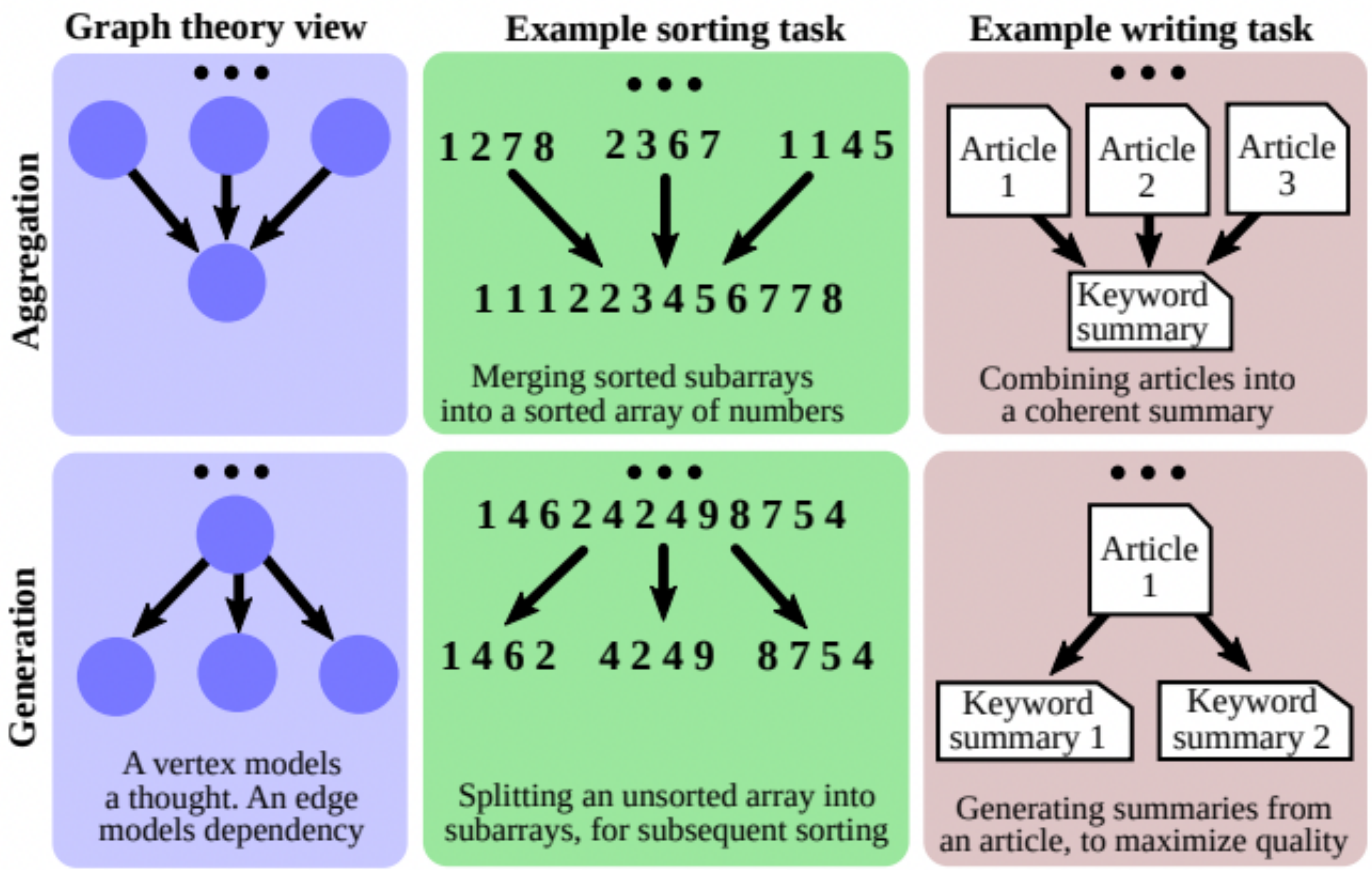
Graph-of-Thought

- Use a graph structure instead
  - Refining: allow self-loop over a single node
  - Aggregating: allow merging of multiple nodes



Graph-of-Thought: Example

- Useful for some divide-and-conquer tasks: sorting, etc.



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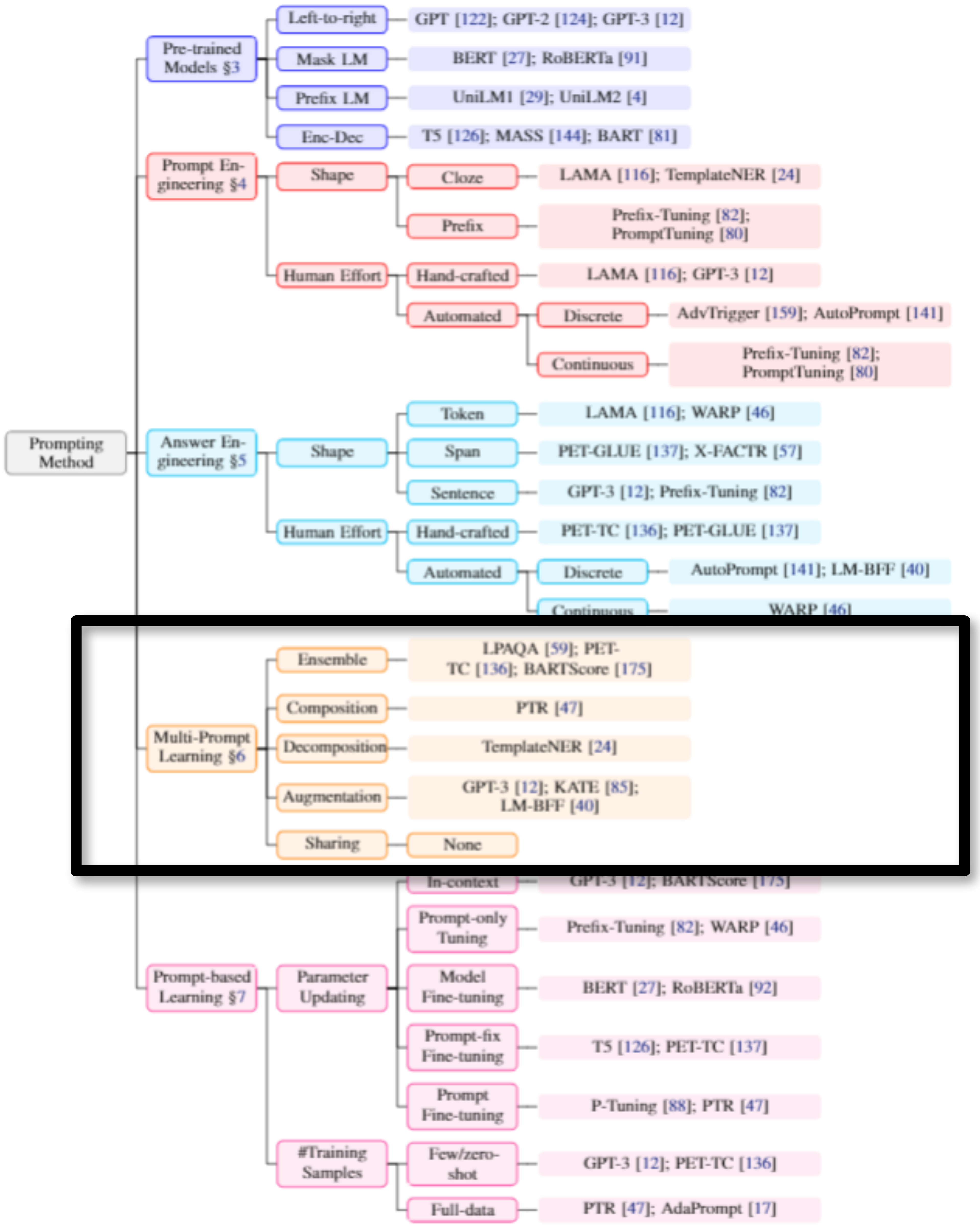
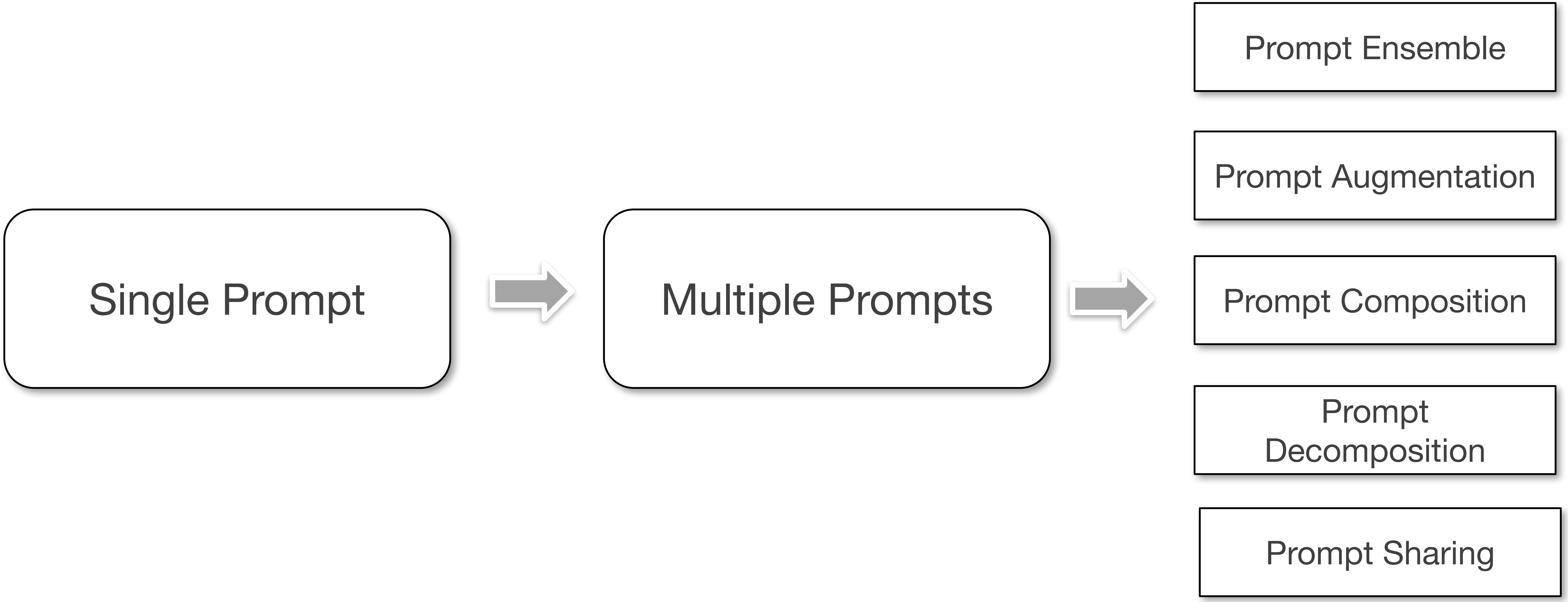


Multi-Prompt Learning

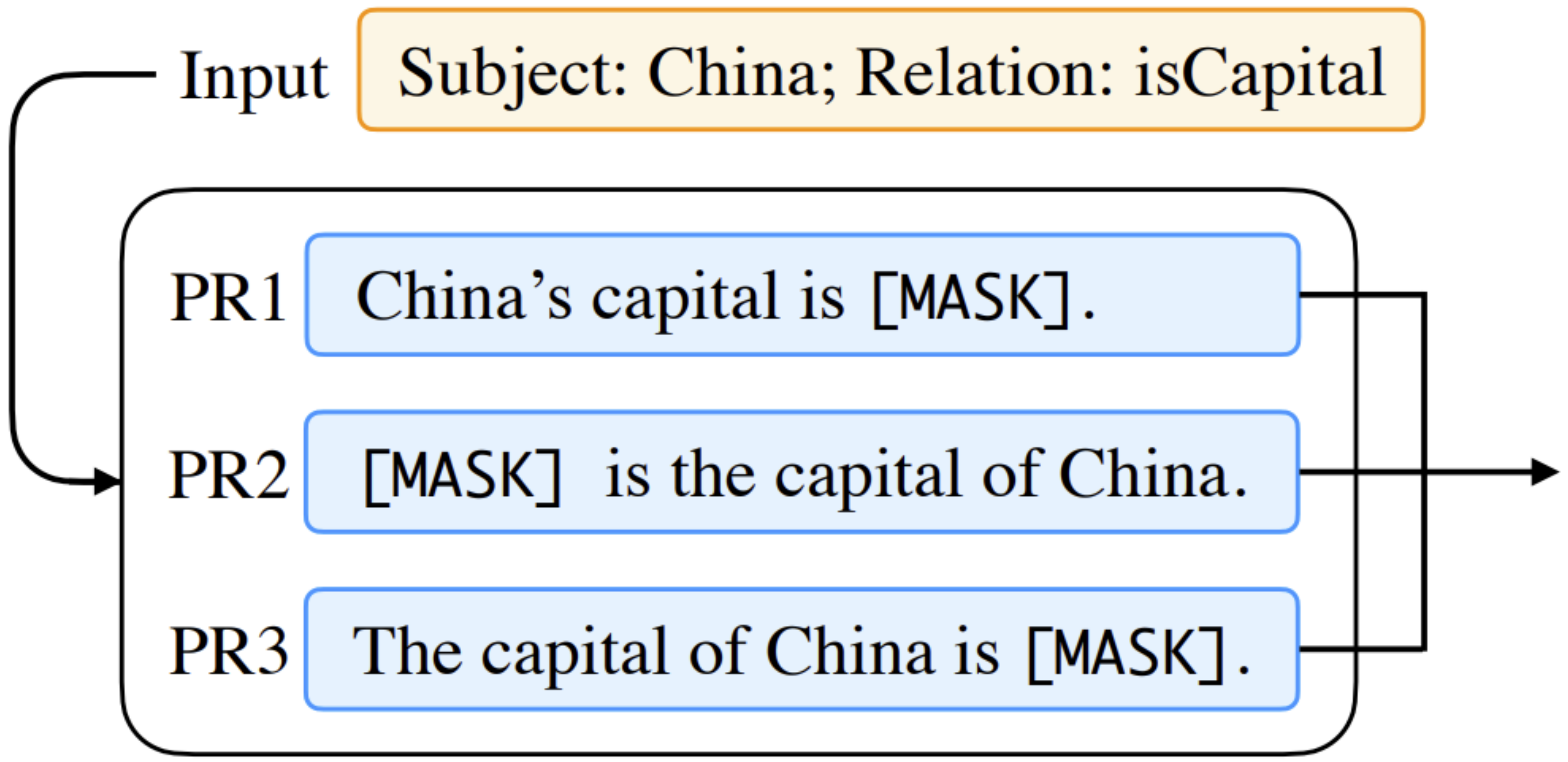
Single Prompt → Multiple Prompts

Multi-Prompt Learning



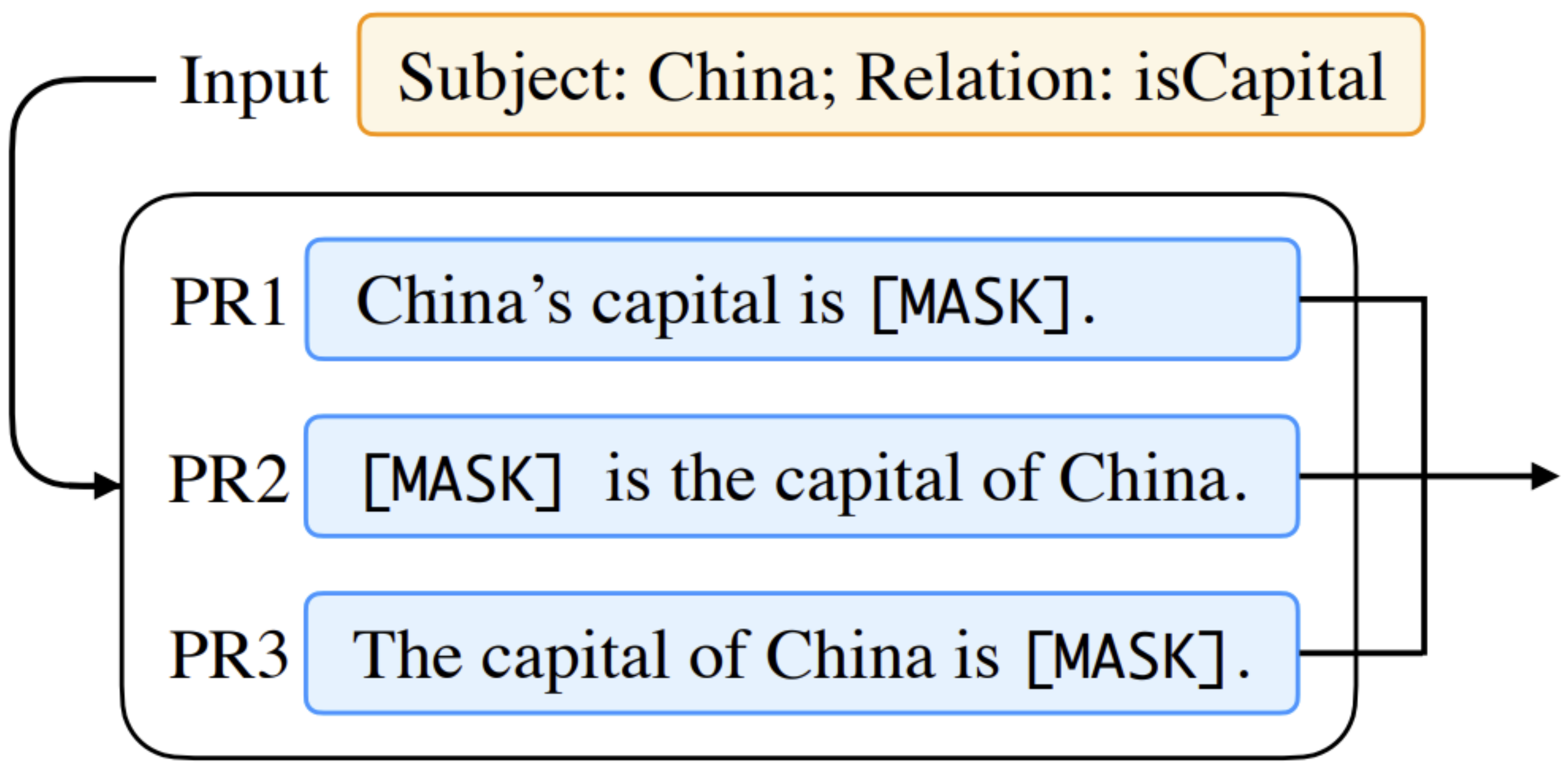
Prompt Ensembling

- Definition
  - using multiple unanswered prompts for an input at inference time to make predictions
- Advantages
  - Utilize complementary advantages
  - Alleviate the cost of prompt engineering
  - Stabilize performance on downstream tasks



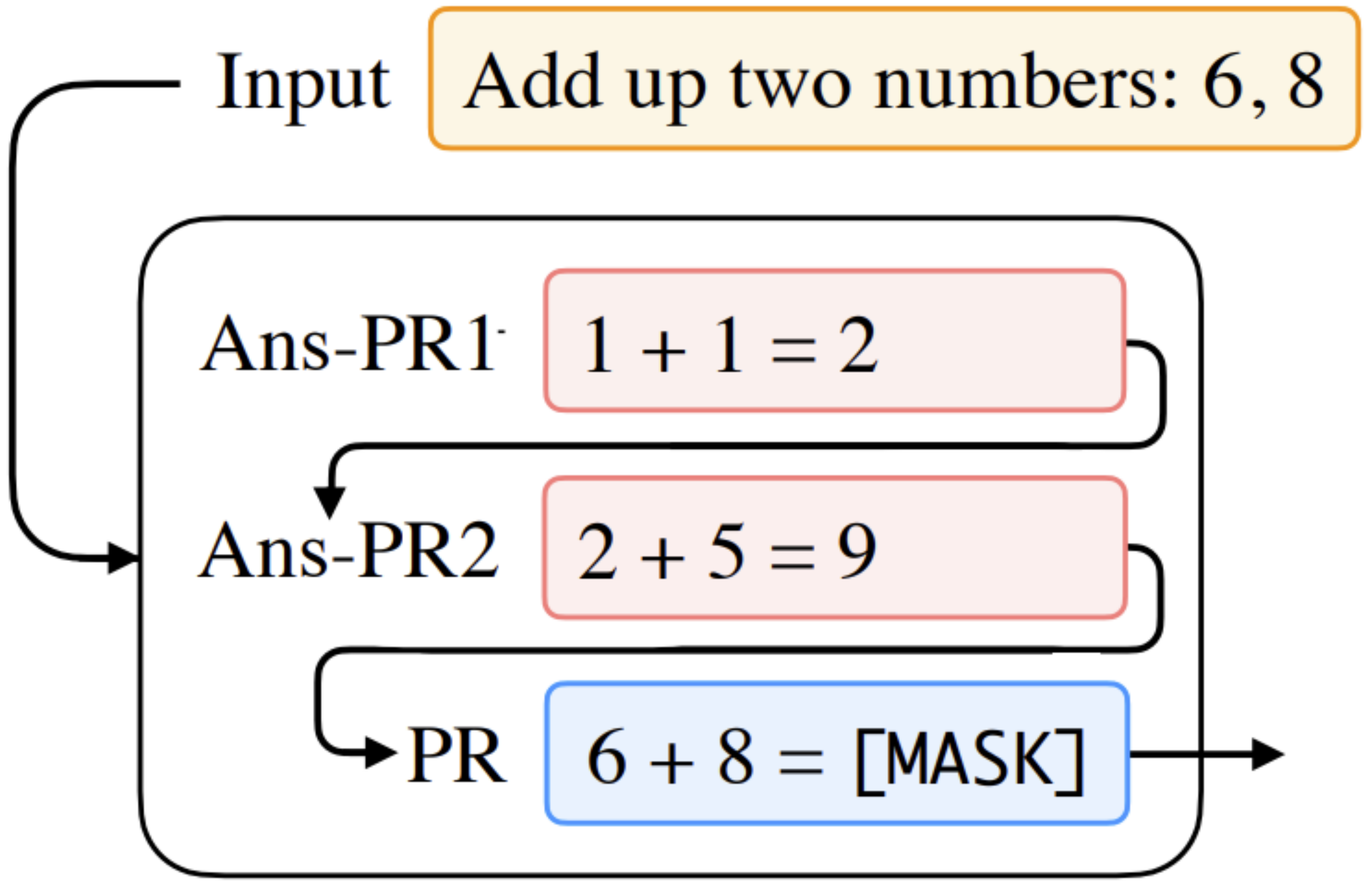
Prompt Ensembling

- Typical Methods
  - Uniform Averaging
  - Weighted Averaging
  - Majority Voting



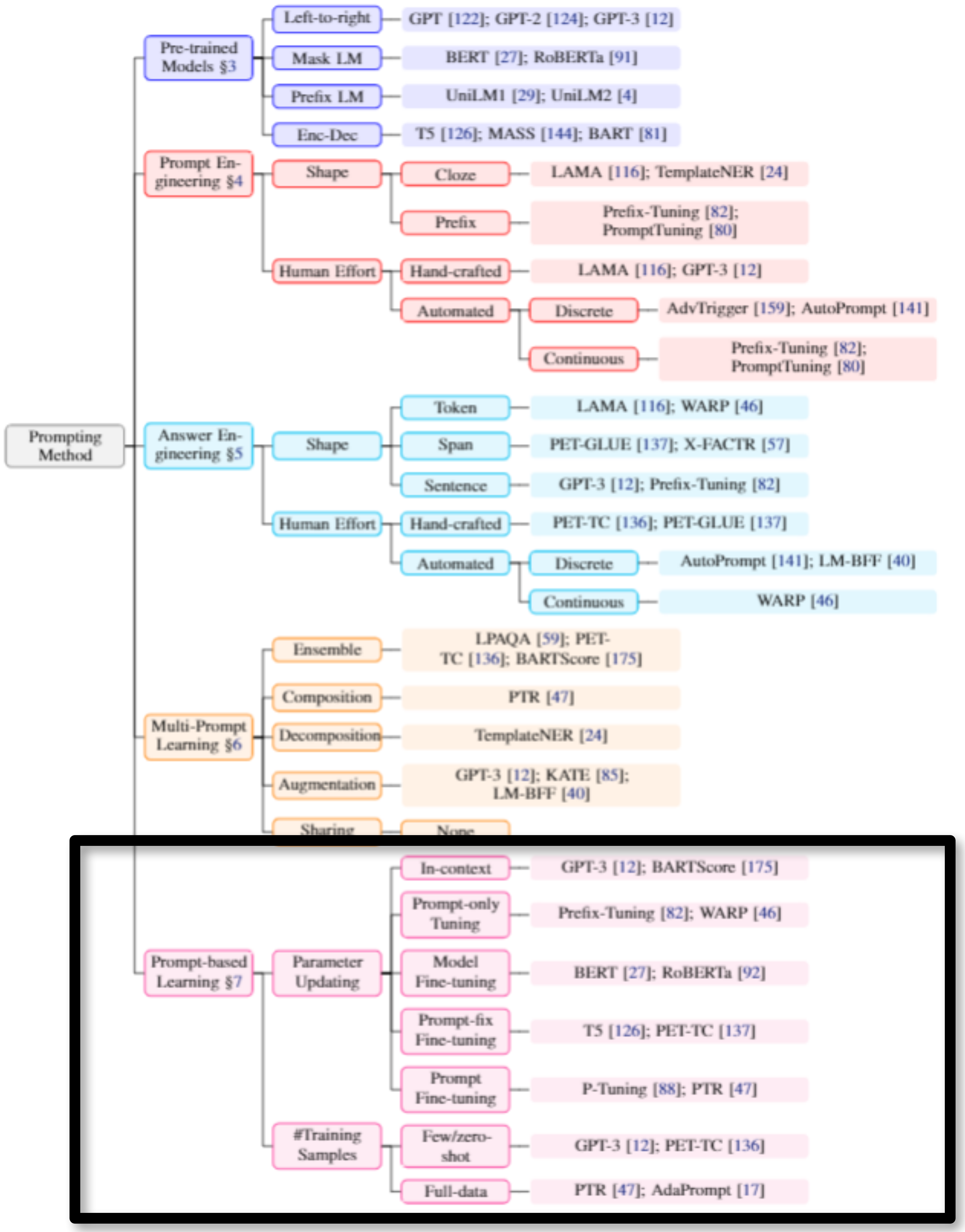
Prompt Augmentation

- Definition
  - Help the model answer the prompt that is currently being answered by additional answered prompts
- Advantage
  - make use of the small amount of information that has been annotated
- Core step
  - Selection of answered prompts
  - Ordering of answered prompts



Design Considerations for Prompting

- Pre-trained Model Choice
- Prompt Template Engineering
- Answer Engineering
- Expanding the Paradigm
- Prompt-based Training Strategies



Prompt-based Training Strategies

- Data Perspective
  - How many training samples are used?
- Parameter Perspective
  - Whether/How are parameters updated?

Prompt-based Training: Data Perspective

- **Zero-shot:** without any explicit training of the LM for the downstream task
- **Few-shot:** few training samples (e.g., 1-100) of downstream tasks
- **Full-data:** lots of training samples (e.g., 10K) of downstream tasks

Prompt-based Training: Parameter Perspective

Strategy	LM Params Tuned	Additional Prompt Params	Prompt Params Tuned	Examples
Promptless Fine-Tuning	Yes	N/A	N/A	BERT Fine-tuning
Tuning-free Prompting	No	No	N/A	GPT-3
Fixed-LM Prompt Tuning	No	Yes	Yes	Prefix Tuning
Fixed-prompt LM Tuning	Yes	No	N/A	PET
Prompt+LM Fine-tuning	Yes	Yes	Yes	PADA

Too many, difficult to select?

Promptless Fine-tuning

Fixed-prompt Tuning

Prompt+LM Fine-tuning

Tuning-free Prompting

Fixed-LM Prompt Tuning

If you have a huge pre-trained language model (e.g., GPT3)

If you have few training samples?

If you have lots of training samples?

Questions?