Code Language Models

Guest Lecture @ HKU

Yale NLP

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Why Build Code Language Models

- Quick Poll
  - GitHub Copilot
  - OpenAI ChatGPT

Why Build Code Language Models

- How to automatically write programs is one of the ***oldest*** and ***hardest*** problems in AI and CS:

> *This process of constructing instruction tables should be very fascinating. There need be no real danger of it ever becoming a drudge, for any processes that are quite mechanical may be turned over to the machine itself.*
> — *Alan Turing (1945)*

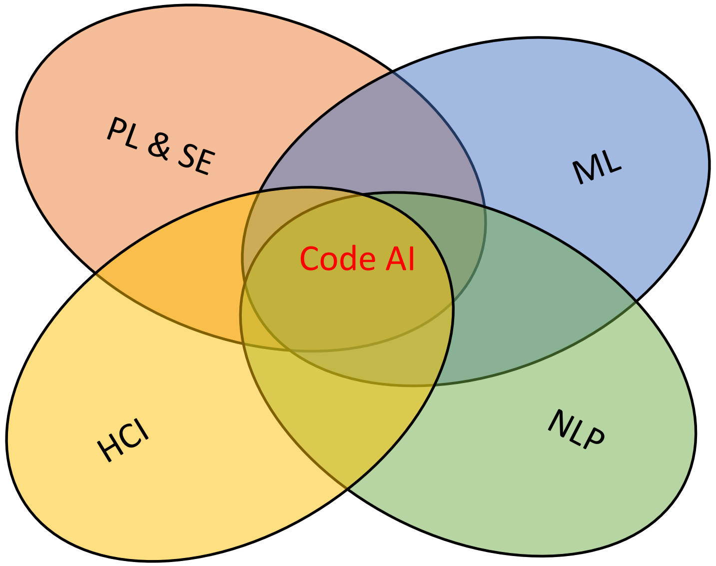
Programming Languages — D. Gries, Editor

Toward Automatic Program Synthesis

Zohar Manna
Stanford University,* Stanford, California
and
Richard J. Waldinger
Stanford Research Institute,†
Menlo Park, California

Why Build Code Language Models

- They relate to several important areas in CS
  - Programming Languages (PL)
  - Software Engineering (SE)
  - Machine Learning (ML)
  - Natural Language Processing (NLP)
  - Human-Computer Interaction (HCI)
  - …



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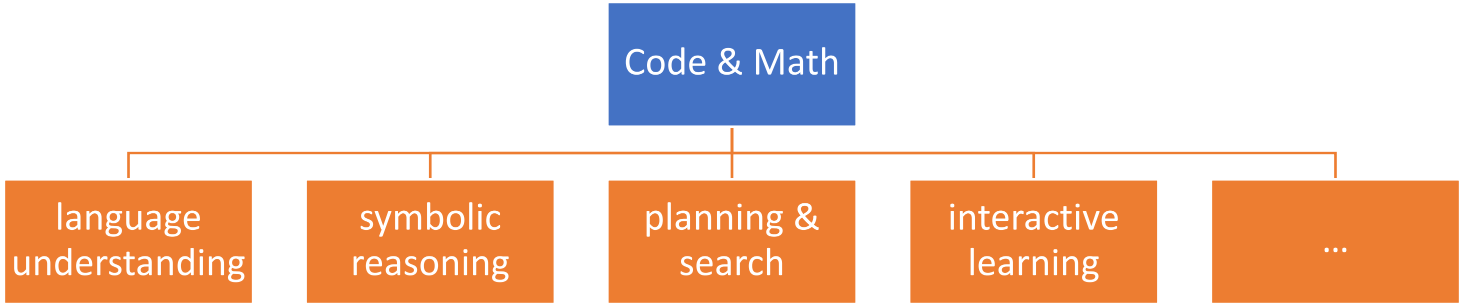
Why Build Code Language Models

- Code generation is a great **testbeds for *intelligence***:
  - language understanding
  - symbolic reasoning
  - planning & search
  - interactive learning
  - …



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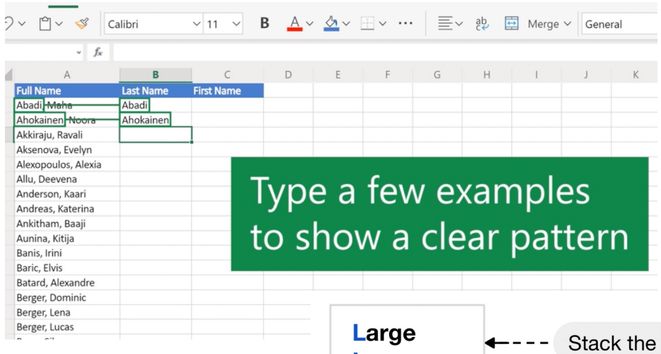
Why Build Code Language Models

- They empower many real-world applications:



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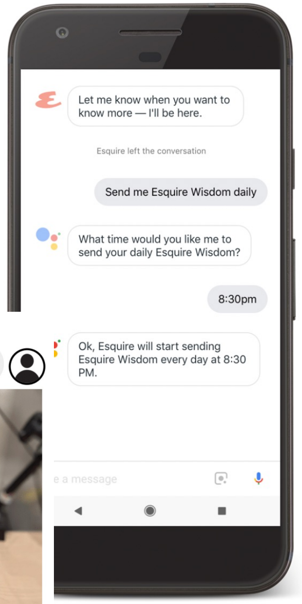

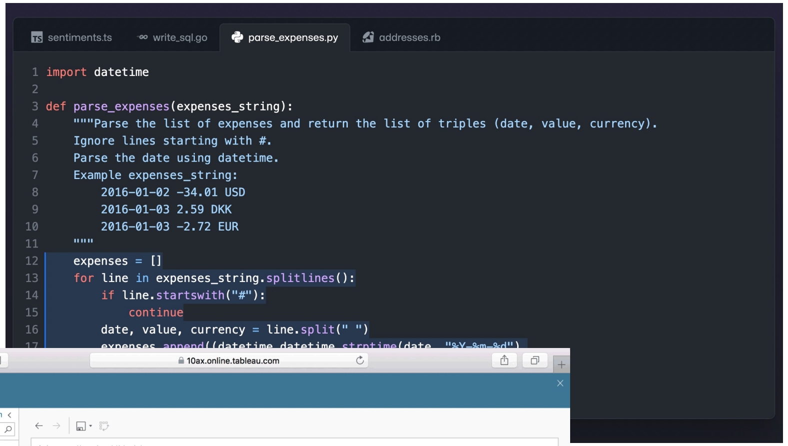

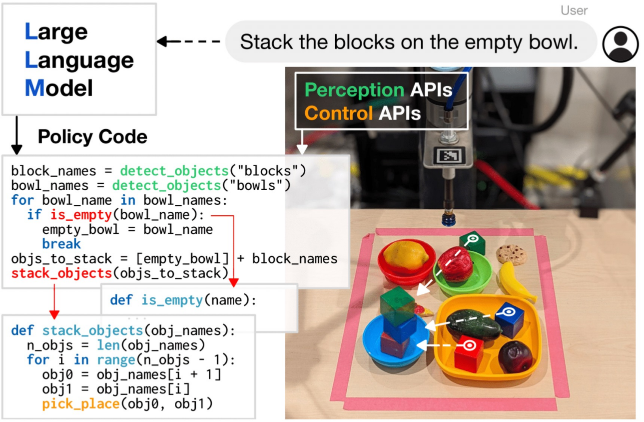

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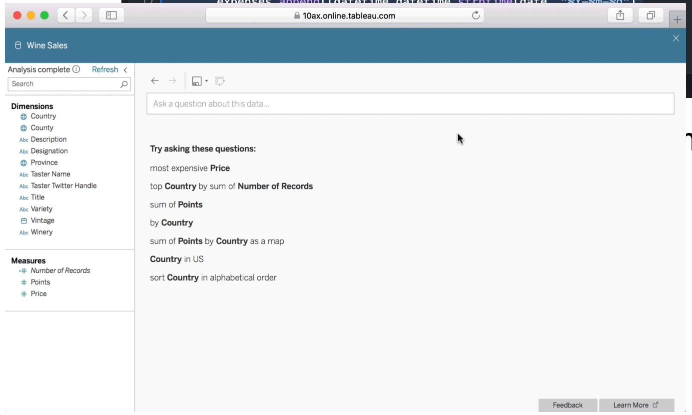

Robotics Control

Database Query and Visualization

Images from: https://developers.googleblog.com/2018/03/new-creative-ways-to-build-with-actions.html; https://support.microsoft.com/en-us/office/save-time-with-flash-fill-9159216a-75a0-4c11-82e6-8eca29cb3b89; https://github.com/features/copilot; https://code-as-policies.github.io/; https://www.tableau.com/blog/ask-data-simplifying-analytics-natural-language-98655

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Before we start…

Preliminaries

- Assume basic knowledge on terms in NLP and related to LLMs
  - E.g., BERT, GPT, prompting, autoregressive, retrieval, etc
- Mixing of terms
  - Foundation Models $\approx$ LM $\approx$ LLM
  - Code LM/LLM: Language models that have seen code during training
- Code and Math LMs
  - They are deeply connected as
    - Both are formal languages;
    - Both require symbolic reasoning
  - This lecture mostly focuses on code LMs but many methods apply for math LMs as well

Outline

- A brief history of code LMs
- Data collection, filtering and tokenization
- Training of code LLMs
  - Decoder-only models and code infilling
  - Encoder-only models;
  - Encoder-decoder models;
  - Reinforcement Learning
- Post-training methods for code LLMs
  - Neuro-symbolic approaches
  - Prompting methods for code
  - Retrieval-augmented generation for code

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A Brief History of LMs for Code

Key Events (2020-2021)

- Feb 2020: CodeBERT [1]
  - *First attempt -- 16 months after original BERT paper*
  - *125M parameters*
- May 2020: GPT-3 [2]
  - *People find that GPT-3 has some coding abilities*
  - *Though it is not specifically trained on code*
- Jun 2021: GitHub Copilot
  - *Revolutionary performance*
  - *Multi-line, whole function completion for the first time*
- Jul 2021: Codex [3]
  - *First 10B+ model trained specifically for code*
  - *Hero behind GitHub Copilot*

[1] Feng et al. (2020), *"CodeBERT: A Pre-Trained Model for Programming and Natural Languages."*
[2] Brown et al. (2020), *"Language Models are Few-Shot Learners."*
[3] Chen et al. (2021), *"Evaluating Large Language Models Trained on Code."*

Key Events (2022)

- Feb 2022: AlphaCode [1]
  - *Claims 54.3% rankings in competitions with human participants*
  - *Up to 41B, model not released nor publicly accessible*
- Mar 2022: CodeGen [2]
  - *Open-source 10B+ code LM*
  - *Later found that the model is severely under-trained (later CodeGen2)*
- Apr 2022: PaLM [3]
  - *PaLM-Coder is a 540B code model*
  - *The models are also severely under-trained (later PaLM-2)*
- Nov 2022: The Stack [5]
  - *3TB of permissively licensed code data*
  - *Foundational data work for many code LMs in the future*

[1] Li et al. (2022), "*Competition-Level Code Generation with AlphaCode.*"
[2] Nijkamp et al. (2022), "*CodeGen: An Open Large Language Model for Code with Multi-Turn Program Synthesis.*"
[3] Chowdhery et al. (2022), "*PaLM: Scaling Language Modeling with Pathways.*"
[4] Kocetkov et al. (2022), "*The Stack: 3 TB of permissively licensed source code.*"

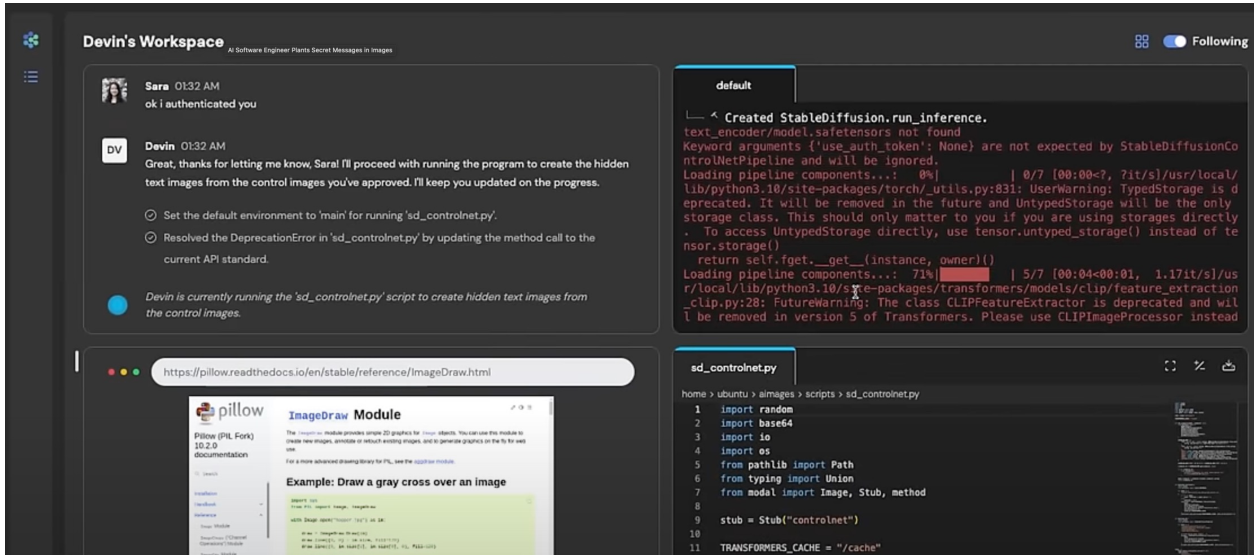
Key Events (2023)

- Feb 2023: LLaMA [1]
  - *Trained with more data (1T tokens)*
  - *Not as large but more performant than larger models*
- Mar 2023: GPT-4 [2]
  - *State-of-the-art in every aspect, coding included*
- May 2023: StarCoder [3]
  - *SoTA in open-source, matches Codex-12B in performance*
  - *Trained on the Stack*
- Aug 2023: CodeLLaMA [4]
  - *Shortly after the release of LLaMA 2 in Jul 2023*
  - *Continued training of LLaMA 2 on code*
- Dec 2023: Gemini [5] and AlphaCode 2 [6]
  - AlphaCode 2 scores 85th percentile on codeforces

[1] Touvron et al. (2023), "*LLaMA: Open and Efficient Foundation Language Models.*"
[2] OpenAI. (2022), "*GPT-4 Technical Report.*"
[3] BigCode. (2022), "*StarCoder: May the source be with you!*"
[4] Rozière et al. (2023), "*Code Llama: Open Foundation Models for Code.*"
[5] Gemini Team (2023), "*Gemini: a family of highly capable multimodal models.*"
[6] AlphaCode Team (2023), "*AlphaCode 2 Technical Report.*"

Entering 2024…

- Feb 2024: StarCoder 2 and Stack v2 [1]
  - Add more data (notebooks, PRs, Code docs…)
  - Improved performance (StarCoder2-15B rivals CodeLLaMA-34B)
- Mar 2024: Devin
  - Coding agent
  - ”First AI software engineer”



[1] Lozhkov et al. (2023), “*StarCoder 2 and The Stack v2: The Next Generation.*”
[2] Cognition AI. (2022), “*https://www.cognition-labs.com/introducing-devin.*”

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Data Collection, Filtering and Tokenization

Code Data Collection and Filtering

- **Data Sources:**
  - Mostly GitHub and similar platforms;
  - More recently:
    - Kaggle Notebooks
    - Software Documentation
    - Commits, issues, pull requests
- **Quality Filtering** (take [1] as an example):
  - GitHub stars >= 5
  - 1% <= Comment-to-code ratio <= 80%
- **License:**
  - Only permissive licensed open-source repo may be used;
  - E.g., MIT, Apache 2.0

[1] Ben Allal et al. (2023), *"SantaCoder: Don't Reach for the Stars!"*

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Deduplication and De-contamination

- **Deduplication:**
  - Remove (near-)duplicated files from the training data;
  - **Why:** repeated training data can significantly hurt the performance [1]
- **Decontamination:**
  - Remove the files that contain solutions to benchmarks used for evaluation;
  - **Why:** better measure generalization ability of trained LMs
- **Methods:**
  - Exact match
  - Near-deduplication

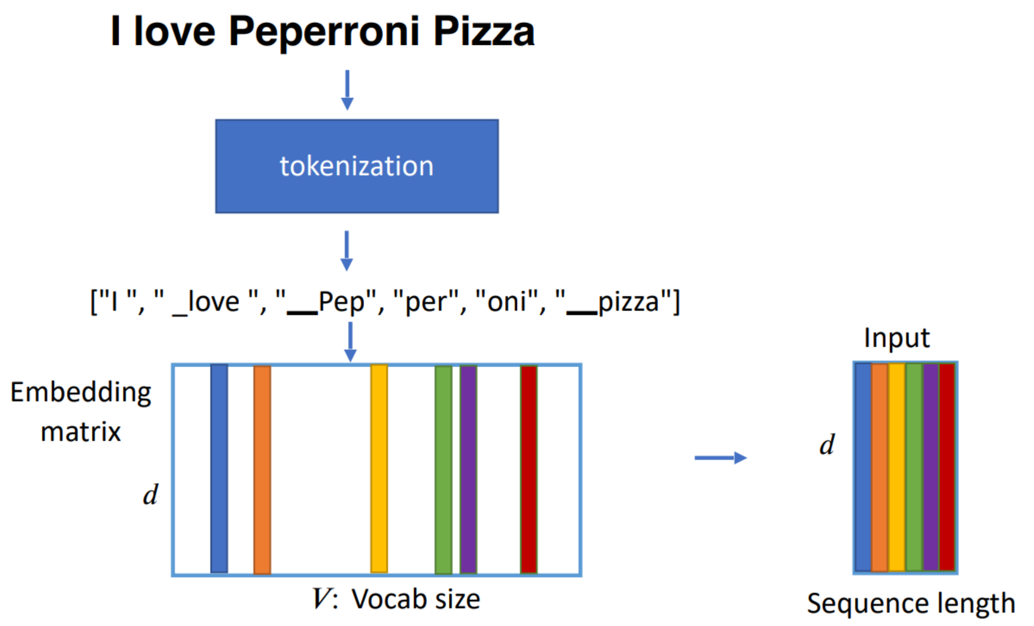
Model	Dataset Deduplication Method
InCoder Fried et al. (2022)	Exact Match (alphanumeric token sequence)
CodeGen (Nijkamp et al., 2022)	Exact Match (sha-256)
AlphaCode (Li et al., 2022)	Exact Match (non-whitespace text)
PolyCoder (Xu et al., 2022a)	Exact Match (hash)
PaLM Coder (Chowdhery et al., 2022)	Near-deduplication (Levenshtein distance)
CodeParrot (Tunstall et al., 2022)	Near-deduplication (MinHash)
Codex (Chen et al., 2021)	Exact Match (”unique python files”)

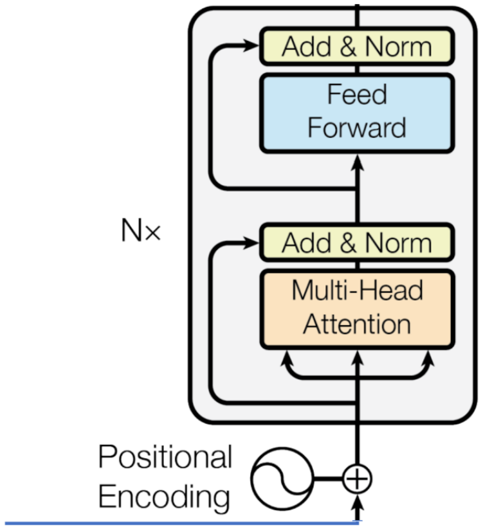
Table 4: Various deduplication methods adopted for different model training data.

[1] Hernandez et al. (2023), *“Scaling laws and interpretability of learning from repeated data.”*
[2] Ben Allal et al. (2023), *“SantaCoder: Don’t Reach for the Stars!”*

Tokenization for Code LM (1)

- Tokenization for LMs





- Tokenization is a ***big deal*** for coding task

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Tokenization for Code LM (2)

- Tokenization is a ***big deal*** for coding task
- Code looks very similar but also very different than natural language:
  - **Similar**: semantic meaning of variable/function/class names
    - E.g., "is_correct", "AttentionLayer", "compute_perplexity"
  - **Different:** Whitespace characters, punctuation, indentations
    - E.g., "df.shape[1]", "def f(x):\n\tif x>0:\n\t\treturn x\n\telse:\n\t\treturn x+1"
- Trade-off between:
  - Vocabulary size
  - # tokens needed to encode the same sequence
  - Generalization ability for different tasks

Tokenization for Code LM (3)

- Trade-off between:
  - Vocabulary size
  - # tokens needed to encode the same sequence
  - Generalization ability for different tasks → downstream performance

Lev.	Description	Example
0	Whitespaces in the middle of tokens are prohibited and each punctuation char is treated as a separate token (except ‘_’)	[‘for’, ‘i’, ‘in’, ‘range’, ‘(’, ‘df’, ‘.’, ‘shape’, ‘[’, ‘1’, ‘]’, ‘)’, ‘:’, ‘NEW_LINE’, ‘INDENT’, ‘print’, ‘(’, ‘i’, ‘)’, ‘NEW_LINE’, ‘print’, ‘(’, ‘df’, ‘.’, ‘columns’, ‘[’, ‘i’, ‘]’, ‘)’]
1	Similar to Level 0, but tokens consisting of several punctuation chars are allowed	[‘for’, ‘i’, ‘in’, ‘range’, ‘(’, ‘df’, ‘.’, ‘shape’, ‘[’, ‘1’, ‘]) :’, ‘NEW˙LINE INDENT’, ‘print’, ‘(’, ‘i’, ‘) NEW˙LINE’, ‘print’, ‘(’, ‘df’, ‘.’, ‘columns’, ‘[’, ‘i’, ‘])’]
2	Similar to Level 1, but dots are allowed in tokens	[‘for’, ‘i’, ‘in’, ‘range’, ‘(’, ‘df’, ‘.shape’, ‘[’, ‘1’, ‘]) :’, ‘NEW˙LINE INDENT’, ‘print’, ‘(’, ‘i’, ‘) NEW˙LINE’, ‘print’, ‘(’, ‘df’, ‘.columns’, ‘[’, ‘i’, ‘])’]
3	Whitespaces and single punctuation chars allowed in tokens, except `NEW_LINE`	[‘for i in range’, ‘(df’, ‘. shape [1’, ‘]) :’, ‘NEW˙LINE INDENT’, ‘print’, ‘(i’, ‘) NEW˙LINE’, ‘print’, ‘(df’, ‘. column’, ‘s [i’, ‘])’]
4	Composite tokens of arbitrary complexity are allowed	[‘for i in range’, ‘(df’, ‘. shape’, ‘[1]’, ‘)’, ‘: NEW˙LINE’, ‘INDENT print’, ‘(i)’, ‘NEW˙LINE print’, ‘(df’, ‘. columns’, ‘[i])’]

[1] Chirkova and Troshin (2023), *“CodeBPE: Investigating Subtokenization Options for Large Language Model Pretraining on Source Code.”*

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Training of Code LLMs

Decoder-only (GPT) Models

- Model architecture and pretraining objectives:
  - Mostly follow those of general-purpose LLMs, e.g., Codex follows the GPT-3
- Multi-stage training:
  - Some models are based off a general-purpose LM
  - E.g., [1] CodeGen-NL→CodeGen-Multi→CodeGen-Mono
  - E.g., [2] LLaMA 2→CodeLLaMA

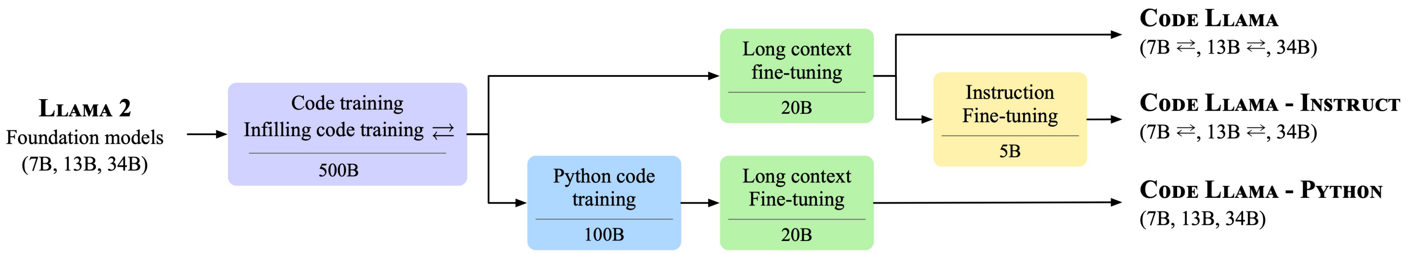

Figure 2: **The Code Llama specialization pipeline**. The different stages of fine-tuning annotated with the number of tokens seen during training. Infilling-capable models are marked with the ⇄ symbol.

[1] Nijkamp et al. (2023), "*CodeGen: An Open Large Language Model for Code with Multi-Turn Program Synthesis.*"
[2] Rozière et al. (2023), *"Code Llama: Open Foundation Models for Code."*

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Code Infilling: Fill in the middle

- Infilling task:
  - <prefix>, <suffix> → <middle>
- Trained via data augmentation [1]:
  - Preprocessing:
    - Special tokens <IF>
    - <prefix>, <middle>, <suffix>
    - <prefix>,<IF>, <suffix>,<IF>, <middle>
  - Mixing with original data
  - Training with normal autoregressive objectives

Docstring Generation

```python
def count_words(filename: str) -> Dict[str, int]:
    """
    Counts the number of occurrences of each word in the given file.

    :param filename: The name of the file to count.
    :return: A dictionary mapping words to the number of occurrences.
    """
    with open(filename, 'r') as f:
        word_counts = {}
        for line in f:
            for word in line.split():
                if word in word_counts:
                    word_counts[word] += 1
                else:
                    word_counts[word] = 1
    return word_counts
```

A use case of infilling [2]

[1] Bavarian et al. (2022), *"Efficient Training of Language Models to Fill in the Middle."*
[2] Fried et al. (2022), *"InCoder: A Generative Model for Code Infilling and Synthesis."*

Encoder (BERT) Models for Code (1)

- Aka ***code representation learning***
- Code is *multi-modal* and it's usually *automatic* to obtain other modalities
- Other modalities of code may better capture the semantics of code

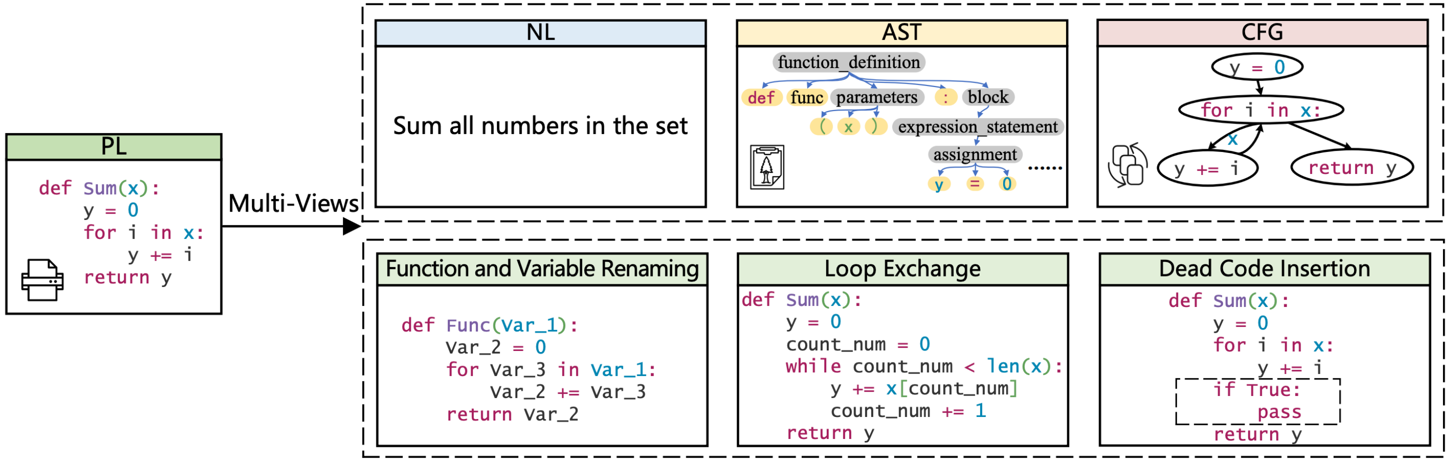
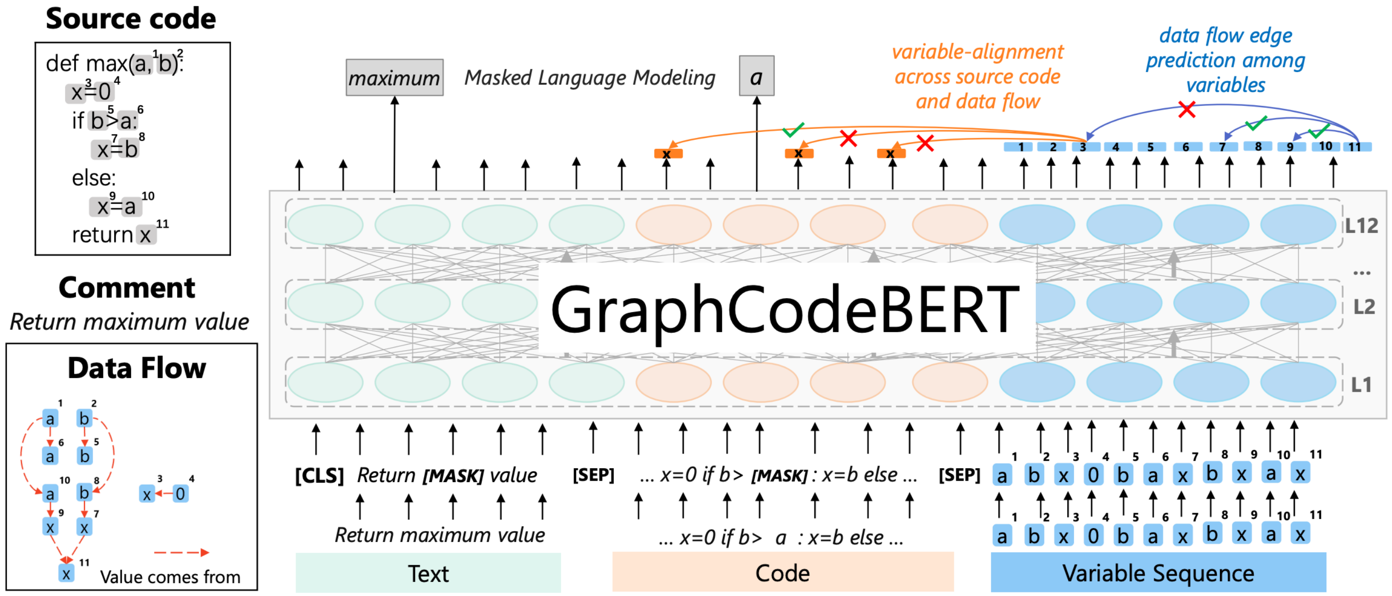


Figure 2: Multiple views of source code.

[1] Wang et al. (2022), "*CODE-MVP: Learning to Represent Source Code from Multiple Views with Contrastive Pre-Training.*"

Encoder (BERT) Models for Code (2)

- Code is *multi-modal*
  - Natural language;
  - Surface form;
  - Control flow graph;
  - Abstract-syntax-tree (AST);
  - Data flow graph;
  - Dependency graph;
  - Compiled machine code;
  - …



Using Data Flow Graph

- **General idea**: *jointly encode* other modalities with surface form

[1] Guo et al. (2021), *"GraphCodeBert: Pre-training Code Representations with Data FLow."*

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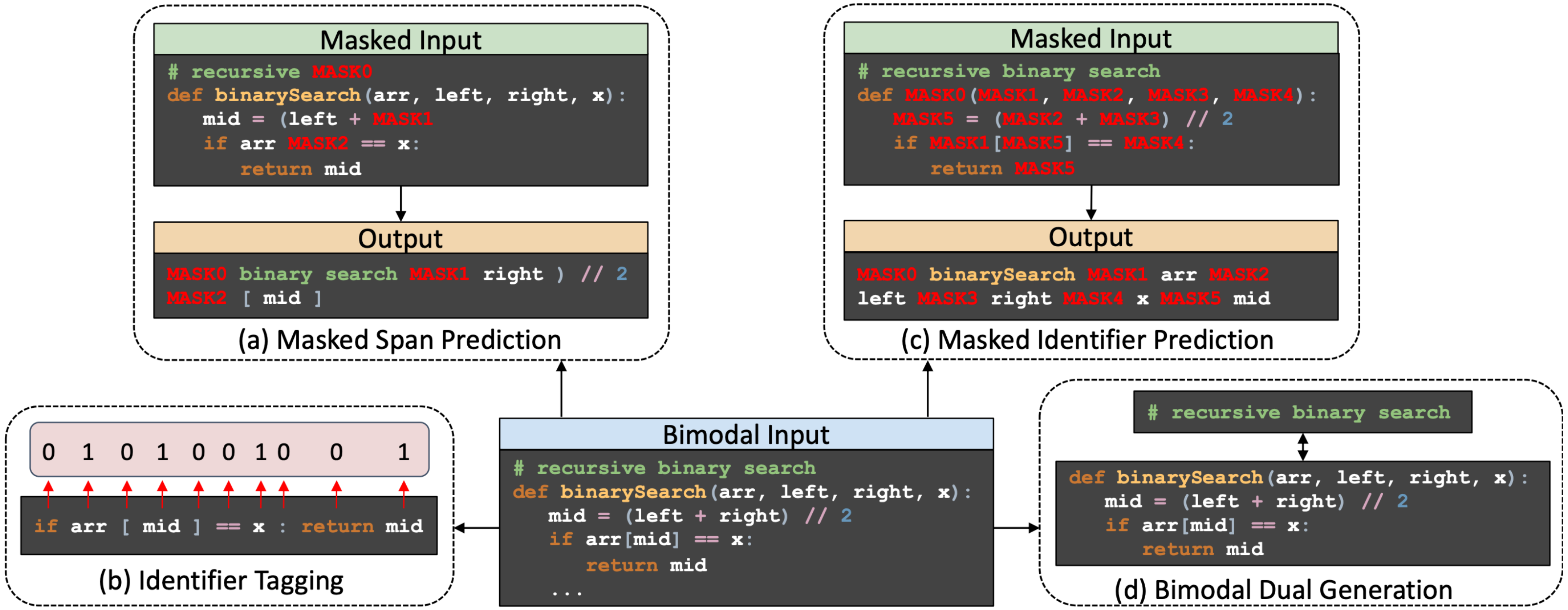
Encoder-Decoder (BART/T5) Models for Code

- A mixture of **classification and generation tasks** for code are typically used during pretraining
  - Researchers get very creative in proposing new pretraining tasks
- E.g., CodeT5 [1]



[1] Wang et al. (2021), *"CodeT5: Identifier-aware Unified Pre-trained Encoder-Decoder Models for Code Understanding and Generation."*

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Reinforcement Learning (1)

- Code generation is a natural task to apply RL as we can automatically obtain *feedback from* ***computers***:
  - Pass/fail a parser;
  - Pass/fail compilation;
  - With/without runtime error;
  - Pass/fail test cases
- Examples:
  - CodeRL [1] (offline actor-critic)
  - RLTF [2] (online w/ feedback from compiler)

$$r(W^s) = \begin{cases} \text{-1.0} & \text{, if } W^s \text{ cannot be compiled (i.e. compile error)} \\ \text{-0.6} & \text{, if } W^s \text{ cannot be executed with unit tests (i.e. runtime error)} \\ \text{-0.3} & \text{, if } W^s \text{ failed any unit test} \\ \text{+1.0} & \text{, if } W^s \text{ passed all unit tests} \end{cases}$$

Rewards used for CodeRL

[1] Le et al. (2021), *"CodeRL: Mastering Code Generation through Pretrained Models and Deep Reinforcement Learning."*
[2] Liu et al. (2023), *"RLTF: Reinforcement Learning from Unit Test Feedback."*

Reinforcement Learning (2)

- Benefits of using RL:
  - Not limited to learning from a single solution from the dataset;
  - Release the dependency for annotated solutions;
  - Able to directly incorporate fine-grained preferences as reward function;
- Limitations:
  - Insufficient test cases may lead to false positives [1]
  - Rewards are typically sparse and underspecified [2];
    - Especially if we start with a weaker model
  - It usually involves exploration (sampling) with LMs, which are expensive

[1] Smith et al. (2015), *"Is the Cure Worse Than the Disease? Overfitting in Automated Program Repair."*
[2] Agarwal et al. (2019), "*Learning to Generalize from Sparse and Underspecified Rewards*."

Post-Training Methods for Code LLMs

Neuro-Symbolic Approaches (1): Incorporating Code Execution

- In addition to providing RL learning signal at training time
- **Execution information** can also help improve models **at test time**
- Methods:
  - Sampling + filtering (codex [1])
    - Sampling solutions then filter out those fail to pass a small subset of test cases

	Introductory	Interview	Competition
GPT-Neo 2.7B raw pass@1	3.90%	0.57%	0.00%
GPT-Neo 2.7B raw pass@5	5.50%	0.80%	0.00%
1-shot Codex raw pass@1	4.14% (4.33%)	0.14% (0.30%)	0.02% (0.03%)
1-shot Codex raw pass@5	9.65% (10.05%)	0.51% (1.02%)	0.09% (0.16%)
1-shot Codex raw pass@100	20.20% (21.57%)	2.04% (3.99%)	1.05% (1.73%)
1-shot Codex raw pass@1000	25.02% (27.77%)	3.70% (7.94%)	3.23% (5.85%)
1-shot Codex filtered pass@1	22.78% (25.10%)	2.64% (5.78%)	3.04% (5.25%)
1-shot Codex filtered pass@5	24.52% (27.15%)	3.23% (7.13%)	3.08% (5.53%)

Codex-12B on APPs. Filtered Pass@k is significantly better

[1] Chen et al. (2021), *"Evaluating Large Language Models Trained on Code."*

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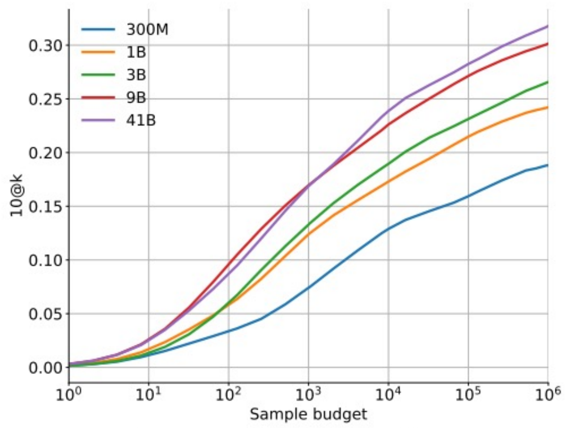
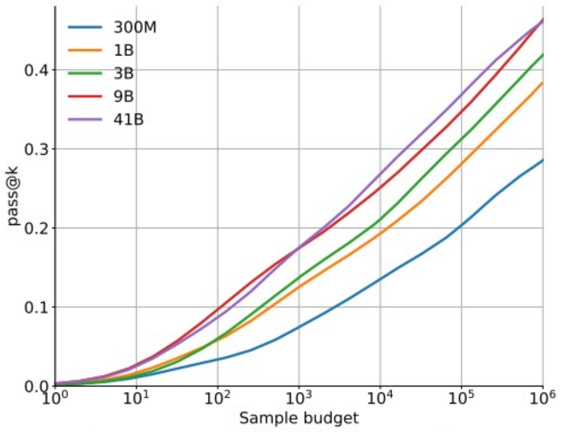
Neuro-Symbolic Approaches (1): Incorporating Code Execution

- Methods:
  - Sampling + filtering (codex [1])
  - Sampling + filtering + clustering (AlphaCode [2])
    - Sample lots of diversified program candidates (i.e., up to 1M)
    - Filter using open test cases
    - Diversify the picked candidates by clustering and selecting from different clusters



(a) 10 attempts per problem



(b) Unlimited attempts per problem

[1] Chen et al. (2021), *"Evaluating Large Language Models Trained on Code."*
[2] Li et al. (2022), *"Competition-Level Code Generation with AlphaCode."*

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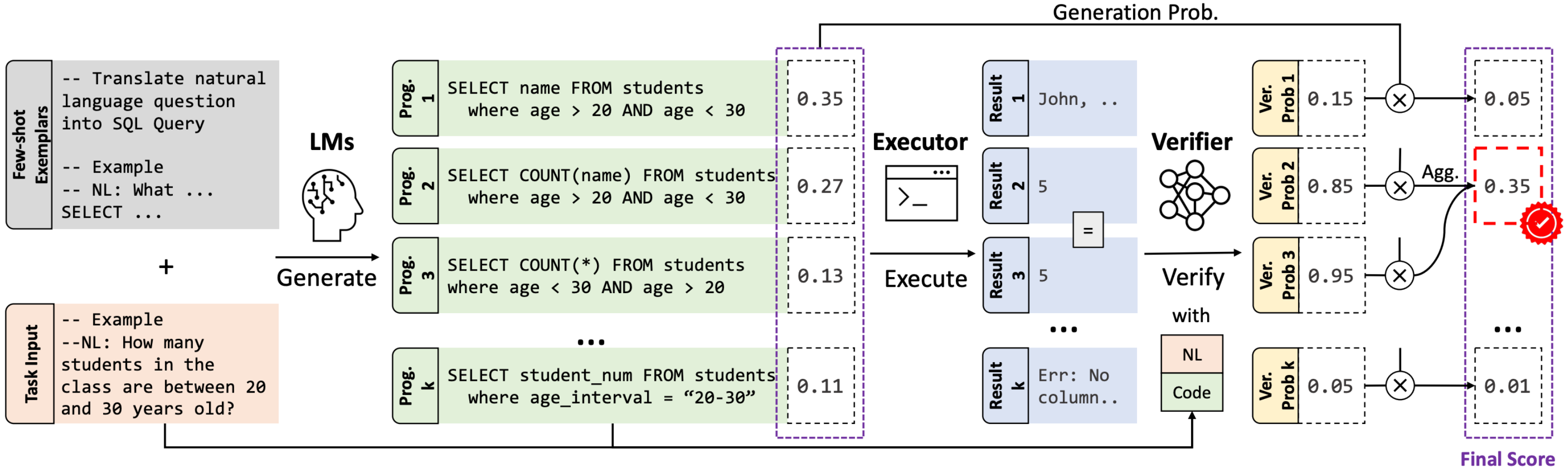
Neuro-Symbolic Approaches (1): Incorporating Code Execution

- Methods:
  - Sampling + filtering (codex [1])
  - Sampling + filtering + clustering (AlphaCode [2])
  - Sampling + verification + voting (LEVER [3])
    - Train a verifier to verify the program with its execution results
    - Aggregate the probability from programs that reach the same execution results



[1] Chen et al. (2021), *"Evaluating Large Language Models Trained on Code."*
[2] Li et al. (2022), *"Competition-Level Code Generation with AlphaCode."*
[3] Ni et al. (2023), *"LEVER: Learning to Verify Language-to-Code Generation using Execution."*

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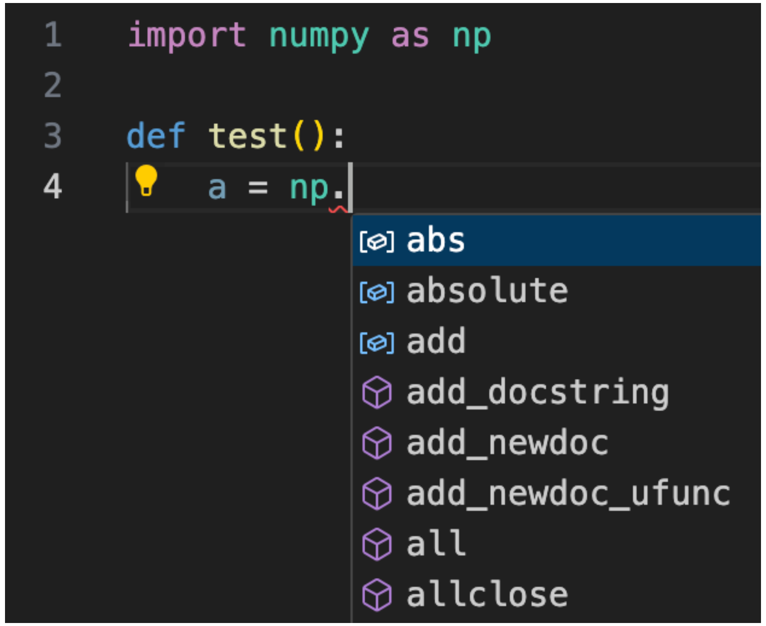
Neuro-Symbolic Approaches (2): Constraint Decoding

- How does code completion work before LLMs?
  - Remember: programs are in *formal languages*, which means that they are regulated by **strict grammar**;
  - Completion Engine (CE): tells you the valid next tokens w/ static analysis
    - Sounds a lot like a language model, right?
    - But it is a *symbolic* process

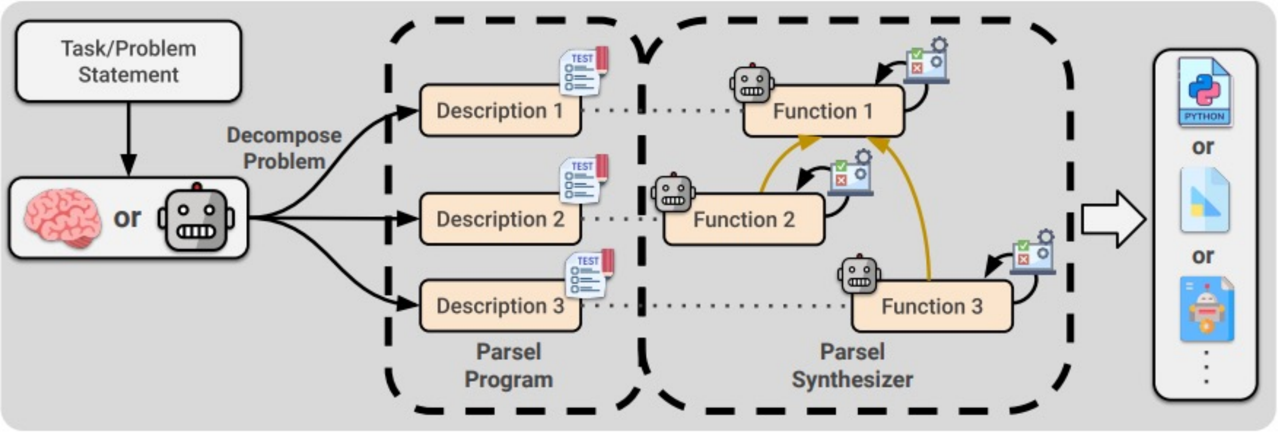


- Combining LM with CE [1]:
  - Filter out next token from the LM that are not approved by CE
  - Best of both worlds!

[1] Poesia et al. (2022), *"Synchromesh: Reliable code generation from pre-trained language models."*

Neuro-Symbolic Approaches (3): Planning and Search

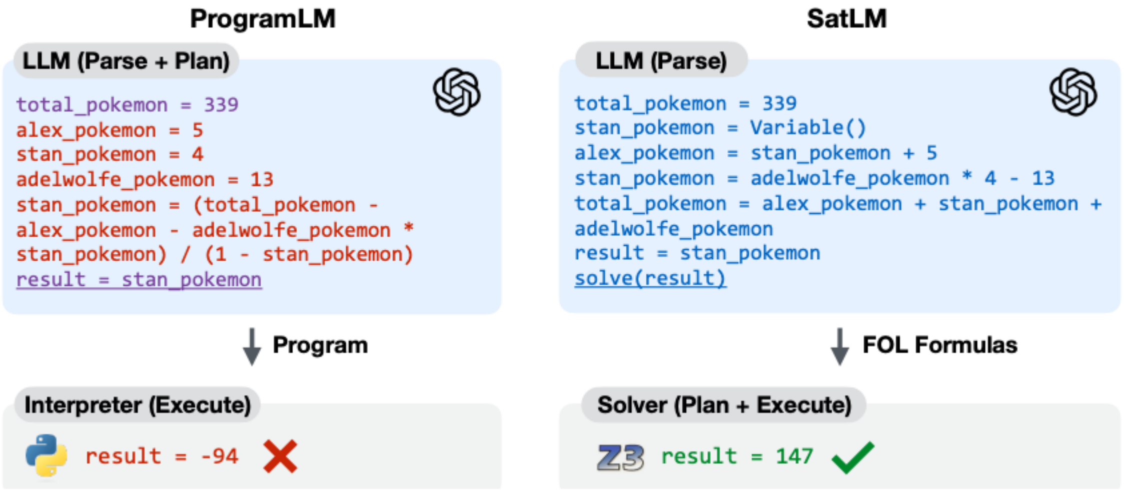
- Programs are ***compositional*** by design
  - Human programmers typically decompose the problem into smaller parts and write functions to solve each of them → ***Planning + Implementation***
  - Given the components (e.g., individual functions), we can use a *solver* to find out if they are sufficient in completing the task → ***Search***
- Example 1: **Parsel** [1]



[1] Zelikman et al. (2022), *"Parsel : Algorithmic Reasoning with Language Models by Composing Decomposition."*

Neuro-Symbolic Approaches (3): Planning and Search

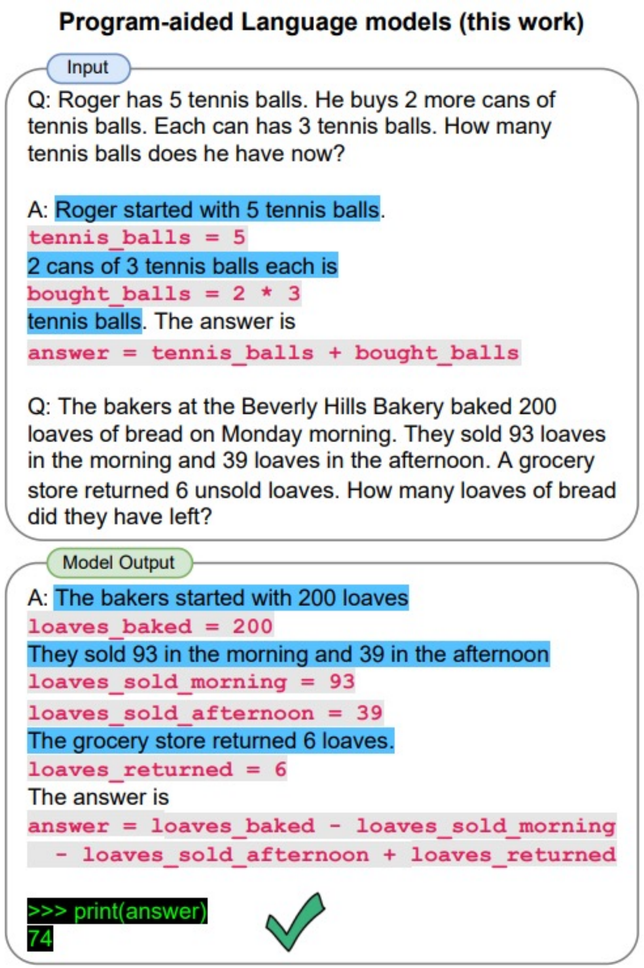
- Programs are ***compositional*** by design
  - Human programmers typically decompose the problem into smaller parts and write functions to solve each of them → ***Planning + Implementation***
  - Given the components (e.g., individual functions), we can use a *solver* to find out if they are sufficient in completing the task → ***Search***
- Example 2: **SatLM** [1]



[1] Xi et al. (2023), "SATLM: Satisfiability-Aided Language Models Using Declarative Prompting."

Prompting Methods using Code for LLMs

- Chain-of-thought (CoT) prompting [1]
  - Explicitly write the reasoning process as **natural language**
- Program-of-thought (PoT) prompting [2] and Program-aided LM (PAL) [3]
  - Explicitly write the reasoning process as a **program**
  - Use *program execution* to obtain the final answer
- Works well with math and other symbolic reasoning tasks
- Also closely related to *tool-use* of LLMs



[1] Wei et al. (2022), *"Chain-of-Thought Prompting Elicits Reasoning in Large Language Models."*
[2] Chen et al. (2022), *"Program of Thoughts Prompting: Disentangling Computation from Reasoning for Numerical Reasoning Tasks."*
[3] Gao et al. (2022), *"PAL: Program-aided Language Models."*

Retrieval Augmented Generation for Code

- Retrieval-augmented generation (RAG)
  - Retrieves relevant pieces of information from some knowledge base and include them in the prompt
- When programmers code, we look at:
  - Current file (e.g., defined variables, function, classes)
  - Documentation of external libraries ← "DocPrompting" [1]
  - Definitions of imported functions and classes ← "Repo-level Prompt Generator" [2]
  - Github, StackOverflow, geeksforgeeks… ← "REDCODER" [3]
- We should give such information to the LLMs as well!

[1] Zhou et al. (2022), *"DocPrompting: Generating Code by Retrieving the Docs."*
[2] Shrivastava et al. (2023), *"Repository-Level Prompt Generation for Large Language Models of Code."*
[3] Parvez et al. (2021), *"Retrieval Augmented Code Generation and Summarization."*

Summary

- A brief history of code LMs
- Data collection, filtering and tokenization
- Training of code LLMs
  - Decoder-only models and code infilling
  - Encoder-only models;
  - Encoder-decoder models;
  - Reinforcement Learning
- Post-training methods for code LLMs
  - Neuro-symbolic approaches
  - Prompting methods for code
  - Retrieval-augmented generation for code

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Extended Readings

- Interdisciplinary applications
  - Code as Policies: Language Model Programs for Embodied Control (2023)
  - Large Language Models for Compiler Optimization (2023)
- Self-Improvement with code LLMs
  - STaR: Bootstrapping Reasoning With Reasoning (2022)
  - CodeT: Code Generation with Generated Tests (2022)
  - Teaching Large Language Models to Self-Debug (2023)
  - DSPy: Compiling Declarative Language Model Calls into Self-Improving Pipelines (2023)
- More ways to learn a code LLM
  - Show Your Work: Scratchpads for Intermediate Computation with Language Models (2021)
  - Learning Math Reasoning from Self-Sampled Correct and Partially-Correct Solutions (2022)

Hope you enjoyed the lecture!

Questions?