

# Genetic Algorithms

# Announcements

- Lab4 due Sunday
- HW2 Posted
  - Assertion inference
  - Optionally work with a partner

# Outline

- HW2 Overview and Assertion Generation Review
- Review: Randoop
- Genetic algorithms

# HW2: Assertion Generation Techniques

## Part 1: Neural Approach

- a. LLM unconstrained outputs
- b. Grammar based

## Part 2: IR Based Approach

# HW2: Assertion Generation Techniques

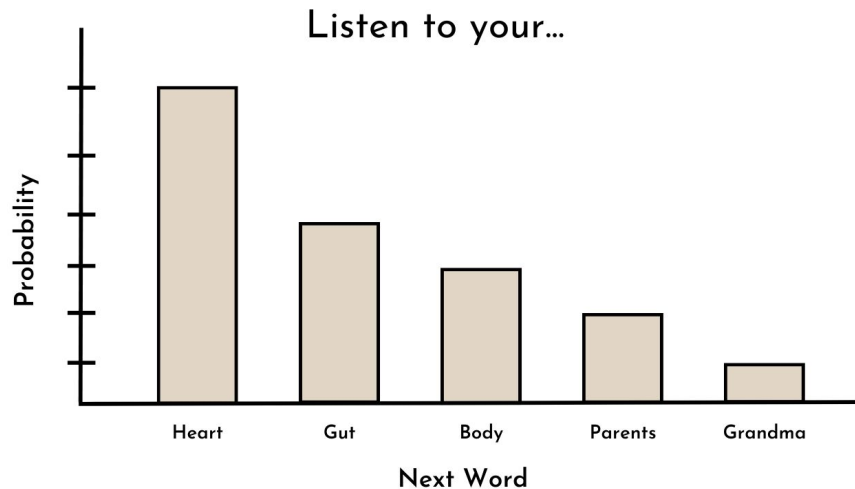
## Part 1: Neural Approach

- a. **LLM unconstrained outputs**
- b. Grammar based

## Part 2: IR Based Approach

# Task Independent Autocomplete

The core task for most state-of-the-art LLMs is word prediction. Given a sequence of words, what is the probability distribution of the next word?



# Prompt Engineering

- The practice of designing inputs (prompts) to effectively communicate with LLMs
  - Usually involves tinkering with the prompts and observing the outputs
- <https://platform.openai.com/docs/guides/prompt-engineering>
- <https://www.promptingguide.ai>

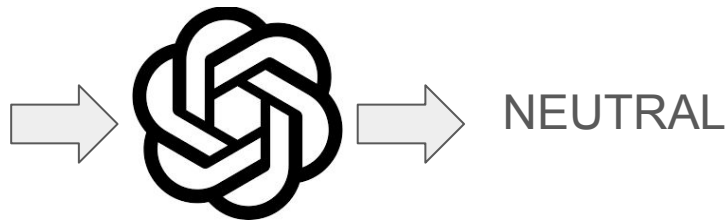
# Prompting Techniques

**Sentiment analysis:** determine whether the writer's attitude towards a particular topic, product, etc. is positive, negative, or neutral.

```
Classify the text into neutral,  
negative or positive.
```

```
Text: I think the vacation is okay.
```

```
Sentiment:
```





# One-shot prompting

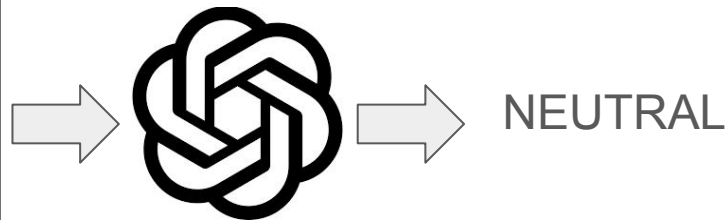
Classify the text into neutral,  
negative or positive.

Text: This is awesome!

Sentiment: Positive

Text: I think the vacation is okay.

Sentiment:



# Few-shot prompting

Classify the text into neutral, negative or positive.

Text: This is awesome!

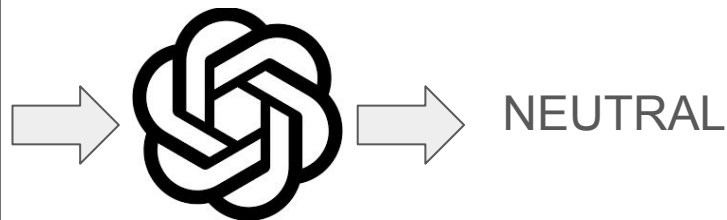
Sentiment: Positive

Text: Wow that movie was bad...

Sentiment: Negative

Text: I think the vacation is okay.

Sentiment:



# Prompting Techniques

1. **Zero-shot prompting** – No examples, direct query.
2. **One-shot prompting** – Single example provided.
3. **Few-shot prompting** – Multiple examples provided.

Pros and cons?

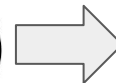
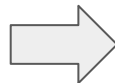
Con: Might overfit to the examples

Con: Might follow implicit patterns in the input

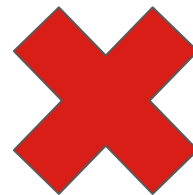
# Chain of Thought Prompting

- Enables complex reasoning capabilities through intermediate reasoning steps.

I went to the market and bought 10 apples. I gave 2 apples to the neighbor and 2 to the repairman. I then went and bought 5 more apples and ate 1. How many apples did I remain with?



11 apples



# Chain of Thought Prompting

- Enables complex reasoning capabilities through intermediate reasoning steps.

I went to the market and bought 10 apples. I gave 2 apples to the neighbor and 2 to the repairman. I then went and bought 5 more apples and ate 1. How many apples did I remain with?

*Let's think step by step.*



First, you started with 10 apples.  
You gave away 2 apples to the neighbor and 2 to the repairman, so you had 6 apples left.  
Then you bought 5 more apples, so now you had 11 apples.  
Finally, you ate 1 apple, **so you would remain with 10 apples.**

# Chain of Thought Prompting

~10k citations

On “grade school math word problems”

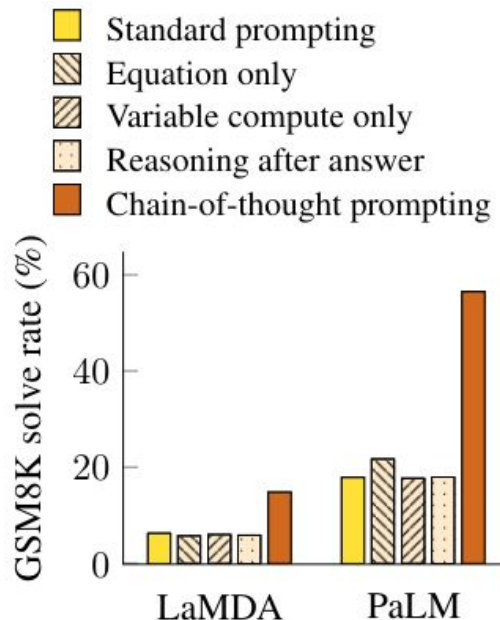
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## Chain-of-Thought Prompting Elicits Reasoning in Large Language Models

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Jason Wei    Xuezhi Wang    Dale Schuurmans    Maarten Bosma  
Brian Ichter    Fei Xia    Ed H. Chi    Quoc V. Le    Denny Zhou

Google Research, Brain Team  
{jasonwei,dennyzhou}@google.com



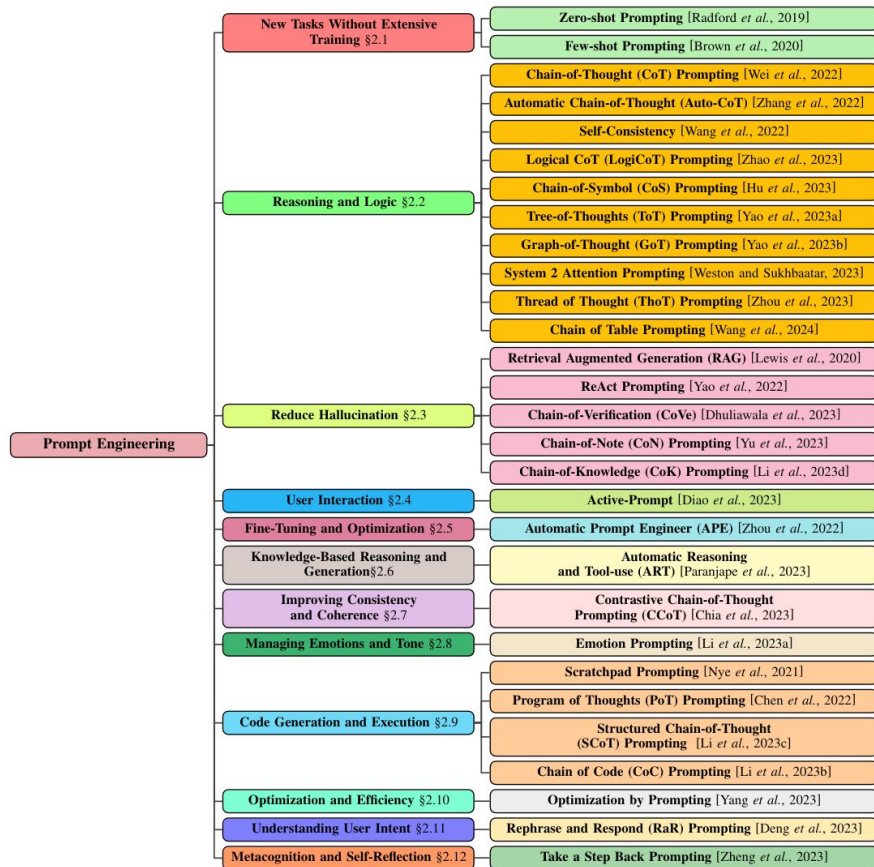


Figure 2: Taxonomy of prompt engineering techniques in LLMs, organized around application domains, providing a nuanced framework for customizing prompts across diverse contexts.

# HW2: Assertion Generation Techniques

## Part 1: Neural Approach

- a. LLM unconstrained outputs
- b. **Grammar based**

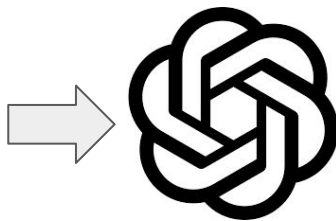
## Part 2: IR Based Approach



# Grammar Based Assertion Generation

Can you suggest a valid assertion to insert at the  
<AssertPlaceholder> ?

```
testStack ( ) { Stack<Integer> s = new  
Stack<Integer>(); s.push(0); s.push(1); Integer  
result = s.pop(); <AssertPlaceholder> ; }
```



**assertTrue (stack.size() == 0);**

# Grammar Rules

1. `A -> assertEquals(const, var)`
2. `A -> assertTrue(var)`
3. `A -> assertFalse(var)`
4. `A -> assertNull(var)`
5. `A -> assertNotNull(var)`
6. `const -> 0 | 1 | 5`
7. `var -> type matching var from the prefix`

```
testStack ( ) {  
    Stack<Integer> s = new Stack<Integer>();  
    s.push(0);  
    s.push(1);  
    Integer result = s.pop();  
    <AssertPlaceholder> ;  
}
```

Exhaustively enumerate the possible assertions and query LLM to rank rather than generate

```
assertEquals(0, result);    assertNull(s);  
assertEquals(1, result);    assertNotNull(s);  
assertEquals(5, result);    assertNull(result);  
                             assertNotNull(result);
```

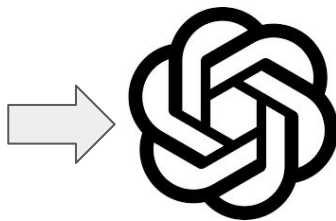
# Grammar Based Assertion Generation

Can you suggest a valid assertion to insert at the  
<AssertPlaceholder> ?

```
testStack ( ) { Stack<Integer> s = new Stack<Integer>();  
s.push(0); s.push(1); Integer result = s.pop();  
<AssertPlaceholder> ; }
```

Select an assertion from this list:

```
assertEquals(0, result);  
assertEquals(1, result);  
assertEquals(5, result);  
assertNull(s);  
assertNotNull(s);  
assertNull(result);  
assertNotNull(result);
```



**assertEquals(1, result);**

# What if this was our prefix?

1. `A -> assertEquals(const, var)`
2. `A -> assertTrue(var)`
3. `A -> assertFalse(var)`
4. `A -> assertNull(var)`
5. `A -> assertNotNull(var)`
6. `const -> 0 | 1 | 5`
7. `var -> type matching var from the prefix`

```
testStack ( ) {  
    Stack<Integer> s = new Stack<Integer>();  
    s.push(100);  
    s.push(42);  
    Integer result = s.pop();  
    <AssertPlaceholder> ;  
}
```

# HW2: Assertion Generation Techniques

## Part 1: Neural Approach

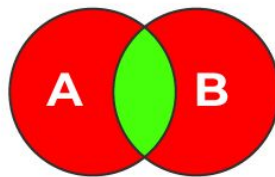
- a. LLM unconstrained outputs
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## Part 2: IR Based Approach

# Similarity Metric - Jaccard

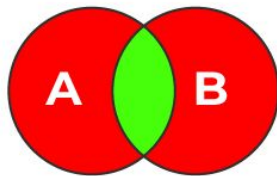
- Measures similarity between two sets
- Values range from 0 (no similarity) to 1 (identical sets)

$$J(X, Y) = |X \cap Y| / |X \cup Y|$$



$$\text{Jaccard} = \frac{\text{Intersection (A, B)}}{\text{Union (A, B)}}$$

# Jaccard Coefficient



$$\text{Jaccard} = \frac{\text{Intersection (A, B)}}{\text{Union (A, B)}}$$

**D1:**

“Information Retrieval is useful”

**D2:**

“Retrieval of information is important”

{ information, retrieval, is useful }

{ retrieval, of, information, is, important }

$$\begin{aligned}(A \cap B) &= 3 \\ (A \cup B) &= 6\end{aligned}$$

$$J(D1, D2) = 3 / 6 = 0.5$$

# Randoop Review

A randomized algorithm for generating tests

Randomly select a method call and select arguments from components

Iteratively build up *valid* test prefixes

What are used for assertions?



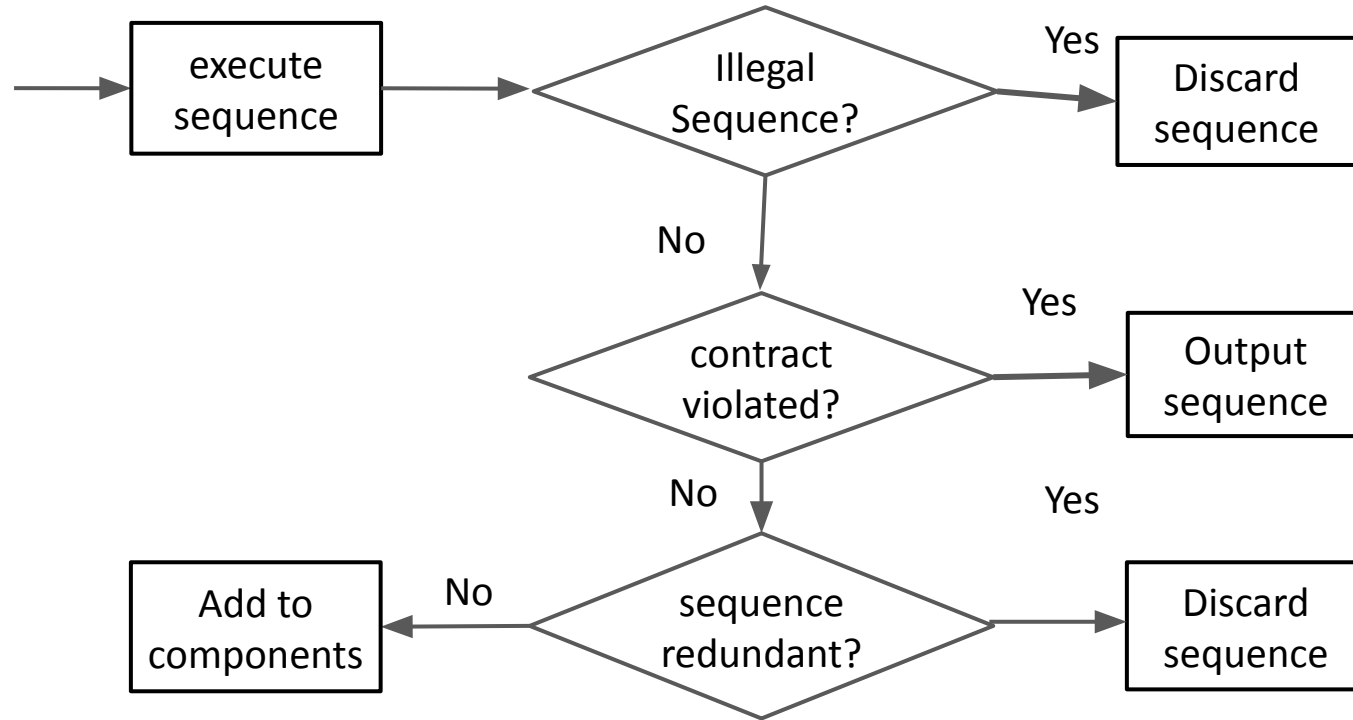
# Randoop Algorithm

components = { int i = 0;    boolean b = false;    ... }

Repeat until time limit expires:

- Create a new sequence
  - Randomly pick a method call  $T_{ret} \ m(T_1, \dots, T_n)$
  - For each argument of type  $T_i$ , randomly pick sequence  $S_i$  from components that constructs an object  $v_i$  of that type
  - Create  $S_{new} = S_1; \dots; S_n; T_{ret} \ v_{new} = m(v_1, \dots, v_n);$
- Classify new sequence  $S_{new}$ :
  - discard / output as test / add to components

# Classifying a Sequence



# Randoop Drawbacks

1. Assertions...
2. Poor coverage! Only feedback is that the prefix is valid

# Generating Tests From a Different Perspective..

# Search Based Software Testing

Idea: A test exists in a finite space of all possible Java tests. We just need to find the one which triggers the bug.

This requires two things

- 1) Prefix
- 2) Assertion

## A note on this field...

So far we've discussed the **problem** of **test oracle generation** and the **tools** to solve it: **neural**, **neural constrained by grammar**, **NL parsing**, and **IR**.

Now we are going to discuss the **problem** of **search based software testing** and the tools to solve it: **feedback directed** (randoop), **genetic algorithms** (EvoSuite), and **coverage guided** (AFL).

# Genetic Algorithms

- Search technique used to find true or approximate solutions to search or optimization problems
  - What are some optimization problems you know?
- Use techniques inspired by evolutionary biology:
  - Selection
  - Mutation
  - Crossover
- Motivating Example: Imagine you're trying to create a **meal plan** that meets daily nutritional requirements while **minimizing cost**. This is an **optimization problem** where we search for the best combination of foods.

# Genetic Algorithms

## Selection (Survival of the Fittest)

- **Biology:** In nature, organisms that are better adapted to their environment are more likely to survive and reproduce. This is known as **natural selection**.
- **Optimization:** In evolutionary algorithms, the best-performing candidate solutions (individuals) are selected from a population based on their "fitness" (how well they solve the problem). These individuals are more likely to contribute to the next generation.



# Genetic Algorithms

## Crossover (Genetic Recombination)

- **Biology:** During reproduction, genetic material from two parents combines to create offspring with traits inherited from both, leading to increased genetic diversity.
- **Optimization:** In evolutionary algorithms, crossover combines parts of two parent solutions to create a new solution (offspring) that may inherit beneficial traits from both parents, improving the search process.
- **Meal plan example - what would crossover look like? Breakfast from M1 lunch from M2**

# Genetic Algorithms

## Mutation (Genetic Variation)

- **Biology:** Mutations are random changes in an organism's DNA that introduce genetic diversity. While some mutations may be harmful, others can offer advantages that improve survival.
- **Optimization:** In evolutionary algorithms, mutation introduces small random changes to candidate solutions to maintain diversity and prevent the algorithm from getting stuck in local optima.
- **Meal plan example - what would mutation look like? Maybe swap out breakfast**

# Genetic Algorithms

- Start with a population of randomly generated individuals
- Works in multiple “generations”
  - Select individuals for breeding based on “fitness”
  - Mutation + crossover creates individuals for the next generation
  - Used in the next iteration

# Genetic Algorithm

**Termination:** The algorithm terminates when either:

- A max number of iterations have been reached or
- Timeout or
- A satisfactory fitness level has been achieved

**NO CONVERGENCE GUARANTEES**

# Vocabulary

- **Individual** - Any possible solution (also called chromosome)
- **Population** - Group of all individuals
- **Fitness** – Target function that we are optimizing (each individual has a fitness)

# Genetic Algorithms

To adapt GA to test generation (or any other task) we need to define the following:

1. What is a chromosome / individual in the population?
  - a. This is a potential solution
2. How are individuals selected for breeding?
3. What happens during crossover?
4. What happens during mutation?
5. How is fitness evaluated?
  - a. How do we measure how “good” a chromosome / individual is?
  - b. Called the *fitness function*

# Meal Example

1. What is a chromosome?
  - a. Meal plan with one option for breakfast and one for dinner
2. How are individuals selected?
  - a. Probabilistically based on their fitness function
3. What happens during crossover?
  - a. The new individual has breakfast from one plan and lunch from another
4. What happens during mutation?
  - a. Breakfast is swapped out
5. Fitness function?
  - a.  $F(\text{meal}) = \text{nutrition} - (0.5 \times \text{cost})$
  - b.  $F(\text{mealplan}) = F(\text{breakfast}) + F(\text{lunch})$

# Basic Genetic Algorithm

- Start with a large “population” of randomly generated “attempted solutions” to a problem
- Repeatedly do the following:
  - Evaluate each of the attempted solutions
  - (probabilistically) keep a subset of the best solutions
  - Use these solutions to generate a new population
- Quit when you have a satisfactory solution (or you run out of time)



# Summary

Genetic Algorithms are search and optimization techniques inspired by natural selection and evolution.

Effective for complex, non-linear problems.

Explores a vast solution space efficiently.

Next week we will see how GAs are used to generate tests