Analyzing Software using Deep Learning

Lecture 2:
RNN-based Code Completion and Repair

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Plan for Today

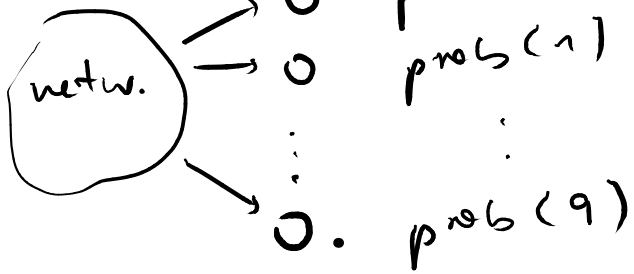
- **Deep learning basics**
  - Finish up last lecture
- **Recurrent neural networks (RNNs)**
- **Code completion with statistical language models**

  Based on PLDI 2014 paper by Raychev et al.
- **Repair of syntax errors**

  Based on ”Automated correction for syntax errors in programming assignments using recurrent neural networks” by Bhatia & Singh, 2016

Learning: Cost Function

- Cost fct. = feedback on how good the output is for a given input
- Example:



If digit is known to be 6, want output

$y(x) = (0,0,0,0,0,0,1,0,0,0)^T$

Actual output maybe:

$a = (0,0,0,0.2,0,0,0.7,0.1,0,0)^T$

Length of vector: $\|(x,y,z)\| = \sqrt{x^2+y^2+z^2}$

$$C(w,b) = \frac{1}{2n} \cdot \sum_x \| y(x) - a \|^2$$

... quadratic cost fct. (or: mean squared error)

- nb. of training inputs
- desired output
- output of network

Quiz: Cost Function

- **Recognition of hand-written digits**
- **Only digits 0, 1, and 2**
- **Training examples:**

Example	Actual	Desired
1	$(0, 1, 0)^T$	$(0.5, 0.5, 0)^T$
2	$(1, 0, 0)^T$	$(1, 0, 0)^T$

- **What is the value of the cost function?**

Quiz: Cost Function

$$C(w, b) = \frac{1}{2 \cdot n} \cdot \sum_x \| y(x) - a \|^2$$

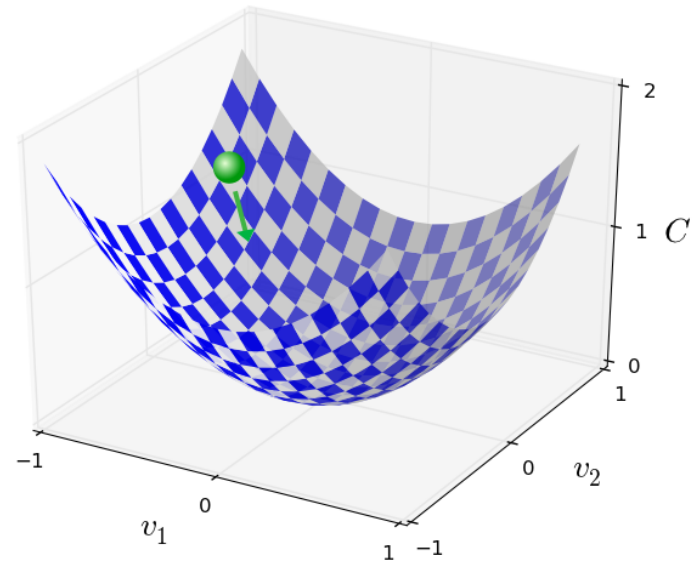
$$= \frac{1}{2 \cdot 2} \cdot \left(\| (-0.5, 0.5, 0)^T \|^2 + \| (0, 0, 0)^T \|^2 \right)$$

$$= \frac{1}{4} \cdot (0.5 + 0) = 0.125$$

.

Goal: Minimize Cost Function

- **Goal of learning: Find weights and biases that minimize the cost function**
- **Approach: Gradient descent**
  - Compute gradient of C: Vector of partial derivatives
  - ”Move” closer toward minimum step-by-step
  - Learning rate determines step size



Training Examples

- **Effort of computing gradient depends on number of examples**
- **Stochastic gradient descent**
  - Use small sample of all examples
  - Compute estimate of true gradient
- **Epochs and mini-batches**
  - Split training examples into k mini-batches
  - Train network with each mini-batch
  - Epoch: Each mini-batch used exactly once

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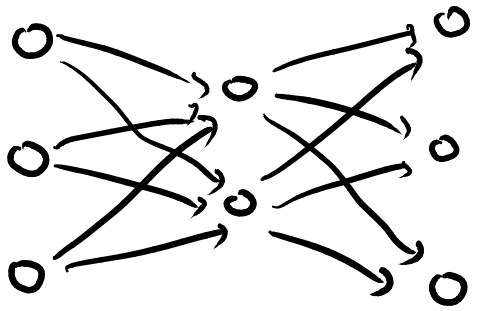
From Neurons to Layers

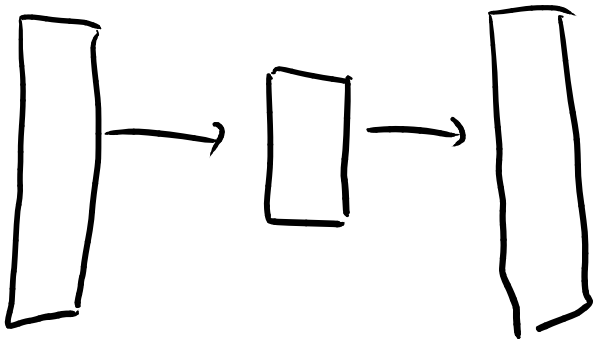


For each neuron:

$$\text{output} = f(w \cdot x + b)$$

x, f, b ... scalars, e.g., in $\mathbb{R}$

w ... vector, e.g., in $\mathbb{R}^n$



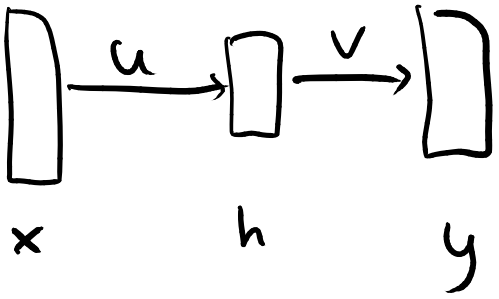
For each layer:

$$\text{output} = f(W \cdot x + b)$$

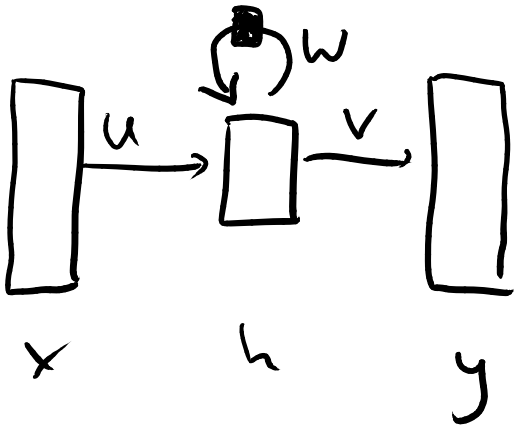
f, x, b ... vector, e.g., in $\mathbb{R}^n$

W ... matrix, e.g., in $\mathbb{R}^{m \times n}$

Feedforward networks



Recurrent networks



x, h, y .. input layer, hidden layer, output layer

U, V, W ... weight matrices

⟶ .. function

⟶ .. function with delay of single time step

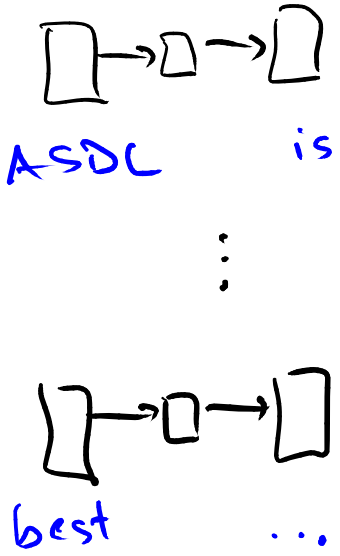
→ useful for representing sequences of inputs & outputs

→ store information about previous inputs

Example: Predict next word in sentence

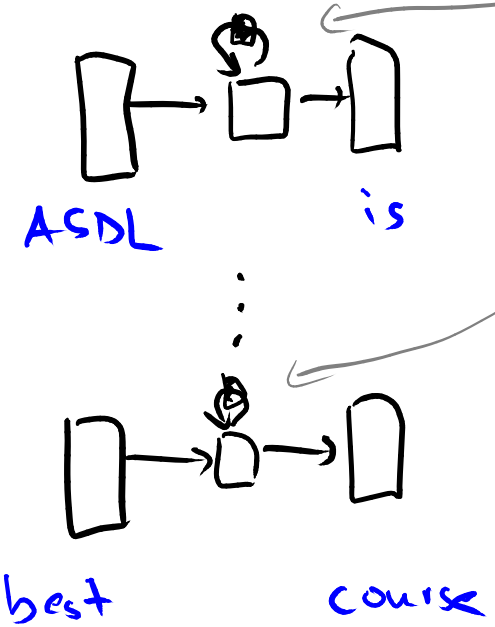
ASDL is the best ... (course)

Feedforward:



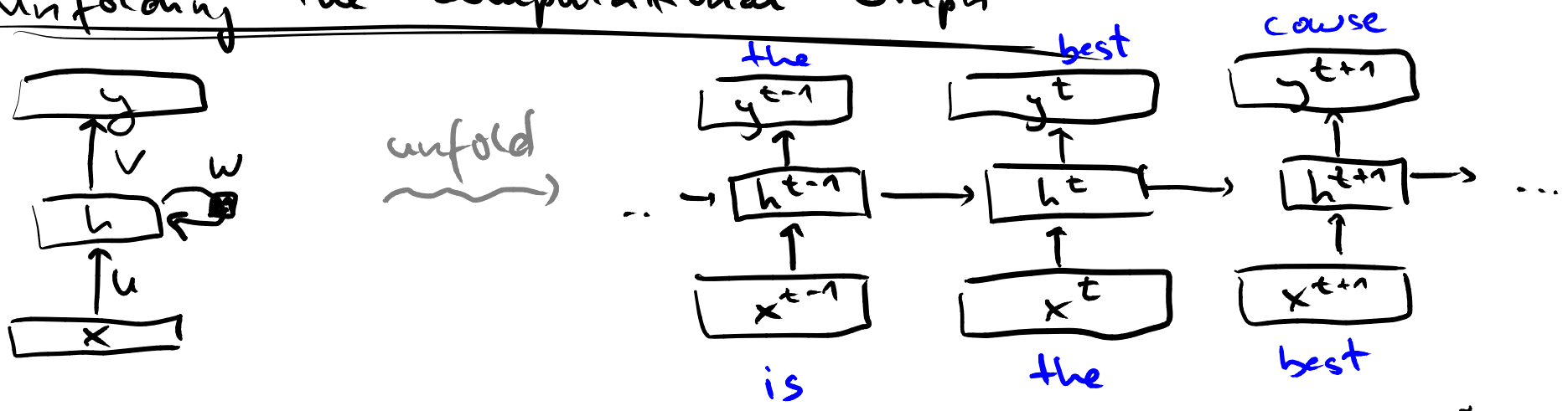
time = 1

Recurrent



Recurrent connections remember the beginning of the sentence

Unfolding the Computational Graph

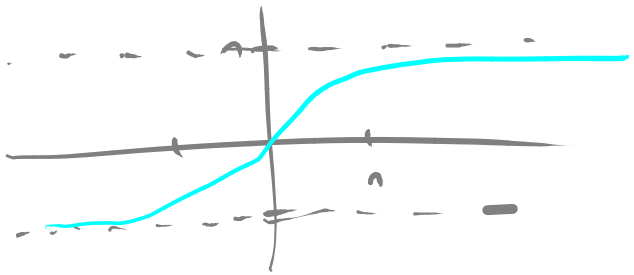


$$h^t = f(h^{t-1}, x^t)$$

$$y^t = f(h^t)$$

e.g. $h^t = \tanh(W \cdot h^{t-1} + U \cdot x^t + b)$

e.g. $y^t = \text{softmax}(V \cdot h^t + c)$



Softmax Function

- Goal: Interpret output vector as a probability distribution
- "Squashes" vector of k values $\in \mathbb{R}$ into vector of k values $\in [0, 1]$ that sum up to 1
- Definition:

$$\sigma(y)_j = \frac{e^{y_j}}{\sum_i^k e^{y_i}} \text{ for } j = 1, .., k$$

- Example:

$$\sigma([1, 2, 3, 4, 1, 2, 3]) =$$
$$[0.024, 0.064, 0.175, 0.475, 0.024, 0.064, 0.175]$$

Quiz

Which of the following vectors may be the output of the softmax function?

1.) $y = [0.0, 0.0, 0.0, 0.0]$

2.) $y = [0.0, 0.25, 0.25, 0.5]$

3.) $y = [0.0, 1.0, 0.0, 0.0]$

4.) $y = [0.1, 0.1, 0.2, 0.3]$

Quiz

Which of the following vectors may be the output of the softmax function?

1.) ~~$y = [0.0, 0.0, 0.0, 0.0]$~~ **sum is not 1**

2.) $y = [0.0, 0.25, 0.25, 0.5]$

3.) $y = [0.0, 1.0, 0.0, 0.0]$

4.) ~~$y = [0.1, 0.1, 0.2, 0.3]$~~ **sum is not 1**

Applications of RNNs

Useful for tasks where the input (and maybe also the output) is a sequence

Examples:

- Unsegmented connected handwriting recognition
- Machine translation of natural languages
- Video classification by frames
- Speech recognition
- Sentiment analysis of twitter messages

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Code Completion

- Given: Partial program with one or more holes
- Goal: Find suitable code to fill into the holes
- Basic variants in most IDEs
- Here: Fill holes with sequences of method calls
  - Which methods to call
  - Which arguments to pass

Example

```
SmsManager smsMgr = SmsManager.getDefault();
int length = message.length();
if (length > MAX_SMS_MESSAGE_LENGTH) {
  ArrayList<String> msgList =
      smsMgr.divideMsg(message);
  // hole H1
} else {
  // hole H2
}
```

Statistical Language Models

- Dictionary of words
- Sentences: sequences of words
- Model: Probability distribution over all possible sentences

Example: English

$Pr(\text{"hello world"}) > Pr(\text{"world hello"})$

- Most basic model: Predict next word based on all previous words

$$Pr(s) = \prod_{i=1}^{m} Pr(w_i \mid h_{i-n})$$

where $s = w_1 \cdots w_m$

$h_i = w_1 \cdots w_i$

Model-based Code Completion

- Program code $\approx$ sentences in a language
- Code completion $\approx$ Finding the most likely completion of the current sentence

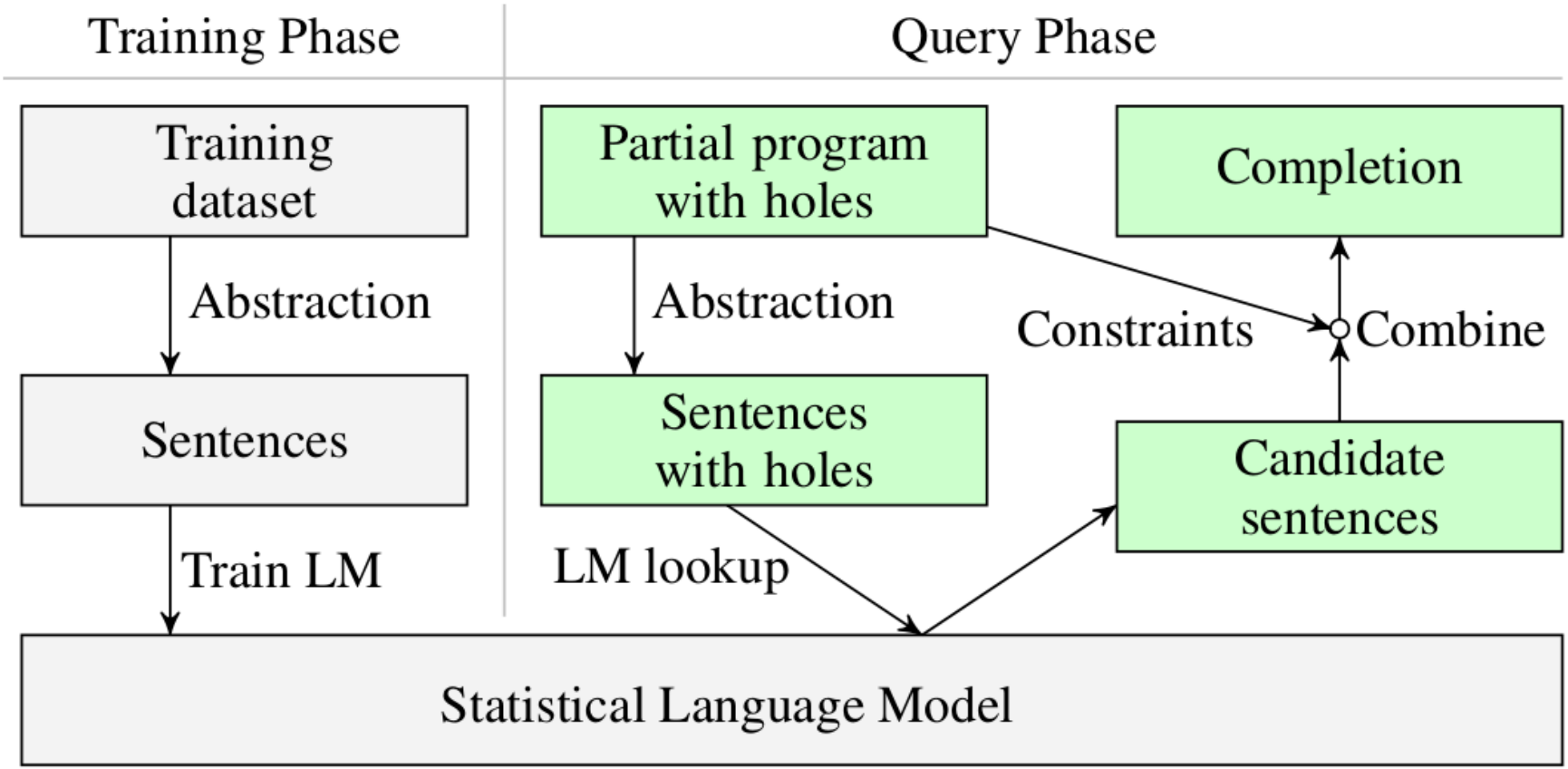
Model-based Code Completion

- **Program code ≈ sentences in a language**
- **Code completion ≈ Finding the most likely completion of the current sentence**

Challenges

- How to abstract code into sentences?
- What kind of language model to use?
- How to efficiently predict a completion

Overview of SLANG Approach



From ”Code Completion with Statistical Language Models” by Raychev et al., 2014

n-gram Language Model

Problem of "all history" model: Training data may not contain anything about h_i

Idea: Next word depends on n-1 previous words

$$Pr(s) = \prod_{i=1}^{m} Pr(w_i \mid w_{i-n+1} \cdots w_{i-1})$$

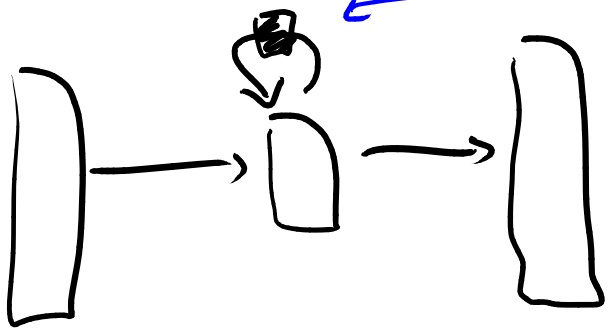
Example: $Pr(\text{to} \cdot \text{be} \cdot \text{or} \cdot \text{not} \cdot \text{to} \cdot \text{be})$ $\quad n = 3$

$= Pr(\text{to} \mid \varepsilon) \cdot Pr(\text{be} \mid \text{to}) \cdot P(\text{or} \mid \text{to} \cdot \text{be})$

$\cdot \ldots \cdot Pr(\text{be} \mid \text{not} \cdot \text{to})$

Probability of n-grams: Estimated from corpus of training examples

RNN-based Model



stores information about (all) previous words

previous word

next word

encoded as vector:
- length = size of dictionary
- all values zero except position of word set to one

} "one hot encoding"

Sequences of Method Calls

Abstracting code into sentences

- Method call $\approx$ word
- Sequence of method calls $\approx$ sentence
- Separate sequences for each object
- Objects can occur in call as base object, argument, or return value

Option 1: Dynamic Analysis

Execute program and observe each method call

Advantage:

- Precise results

Disadvantage:

- Only analyzes executed code

```
if (getInput() > 5) {  // Suppose always taken
  obj.foo();           // in analyzed execution
} else {
  obj.bar();  // Never gets analyzed
}
```

Option 2: Static Analysis

Reason about execution without executing the code

Advantage:

- Can consider all execution paths

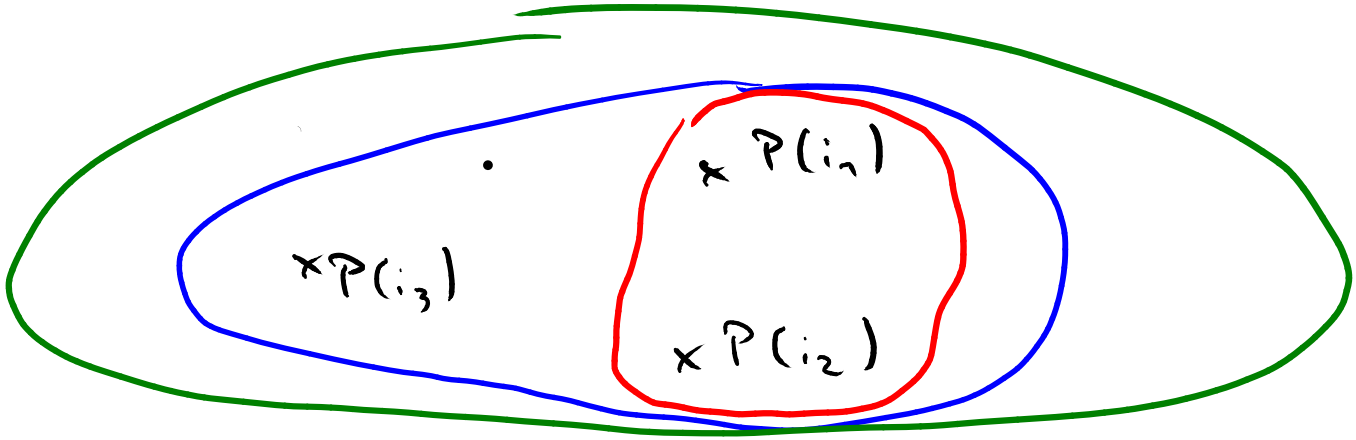
Disadvantage:

- Need to abstract and approximate actual execution

```
if (getInput() > 5) {
  a.foo();  // Does this call ever get executed?
}
b.bar();    // May a and b point to the same object?
```

Over- & Underapproximation

Program P, Input i, Behavior $P(i)$



All possible behaviors (what we want to analyze, ideally)

Underapproximation (most dynamic analyses)

Overapproximation (most static analyses)

Static Analysis of Call Sequences

SLANG approach: Static analysis

- Bound the number of analyzed loop iterations
- On control flow joins, take union of possible execution sequences
- Points-to analysis to reason about references to objects

Example

```
SmsManager smsMgr = SmsManager.getDefault();
int length = message.length();
if (length > MAX_SMS_MESSAGE_LENGTH) {
  ArrayList<String> msgList =
      smsMgr.divideMsg(message);
} else {}
```

Example

```
SmsManager smsMgr = SmsManager.getDefault();
int length = message.length();
if (length > MAX_SMS_MESSAGE_LENGTH) {
  ArrayList<String> msgList =
      smsMgr.divideMsg(message);
} else {}
```

5 sequences:

Object	Calls
smsMgr	(getDefault, ret)
smsMgr	(getDefault, ret) · (divideMsg, 0)
message	(length, 0)
message	(length, 0) · (divideMsg, 1)
msgList	(divideMsg, ret)

Training Phase

- Training data used for paper:
  3 million methods from various Android projects
- Extract sentences via static analysis
- Train statistical language model
  - Both n-gram and RNN model

Query Phase

- Given: Method with holes
- For each hole:
  - Consider all possible completions of the partial call sequence
  - Query language model to obtain probability
    - Average of n-gram and RNN models
- Return completed code that maximizes overall probability

Example

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int length = message.length();
if (length > MAX_SMS_MESSAGE_LENGTH) {
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  // hole H1
} else {
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}
```

Example

```
SmsManager smsMgr = SmsManager.getDefault();
int length = message.length();
if (length > MAX_SMS_MESSAGE_LENGTH) {
  ArrayList<String> msgList =
      smsMgr.divideMsg(message);
  smsMgr.sendMultipartTextMessage(..., msgList, ...);
} else {
  smsMgr.sendTextMessage(..., message, ...);
}
```

Scalability Tricks

Search space of possible completions:
Too large to explore in reasonable time

Refinements to reduce space

- Users may provide hints
  - How many calls to insert
  - Which objects to use
- Replace infrequent words with ”unknown”
- Obtain candidate calls using bi-gram model
- Query language model only for candidates

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