

# **Analyzing Software using Deep Learning**

**Sequence-to-Sequence Networks  
and their Applications**

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# Overview

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- **Sequence-to-sequence networks**
- **API usage sequences for natural language queries**

Based on "Deep API learning" by Gu et al., 2016

- **Interpreting Python programs**

Based on "Learning to execute" by Zaremba and Sutskever, 2014

# Sequence-to-Sequence

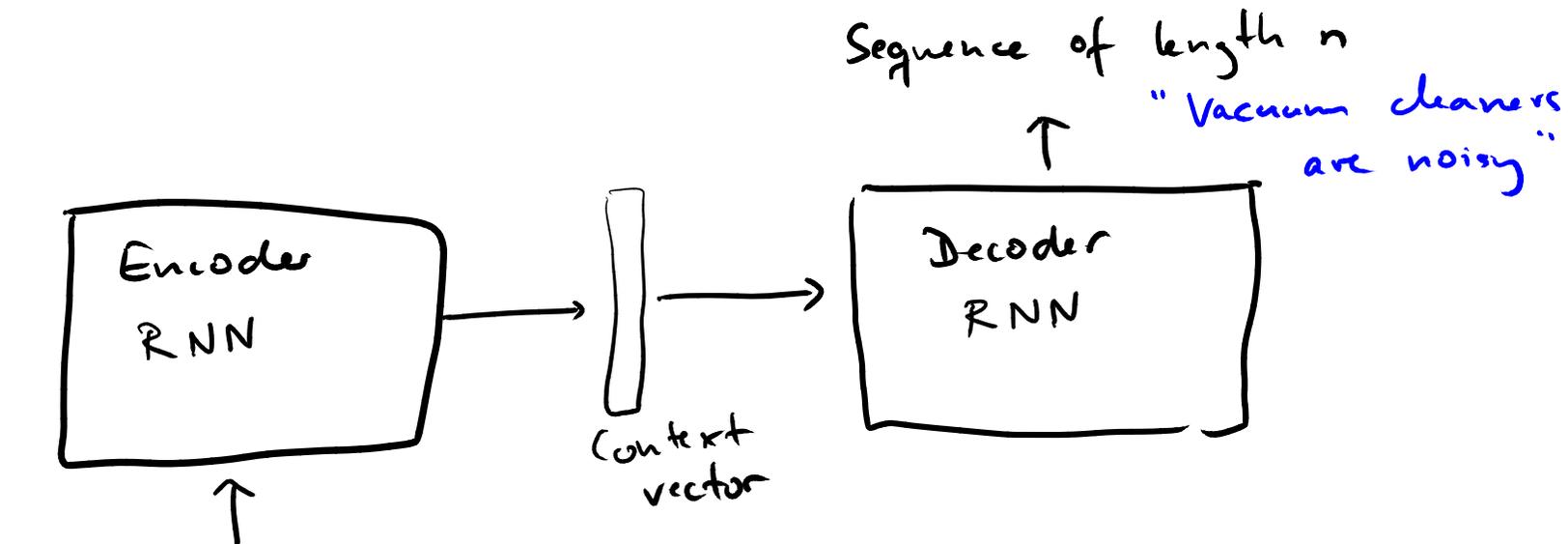
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**Goal: Translate sequence of items into another sequence of items**

## **Various applications**

- Translation between natural languages
- Generate image captions
- Summarize videos into text
- Answer natural language questions

## Overview of Sequence-to-Sequence Architecture

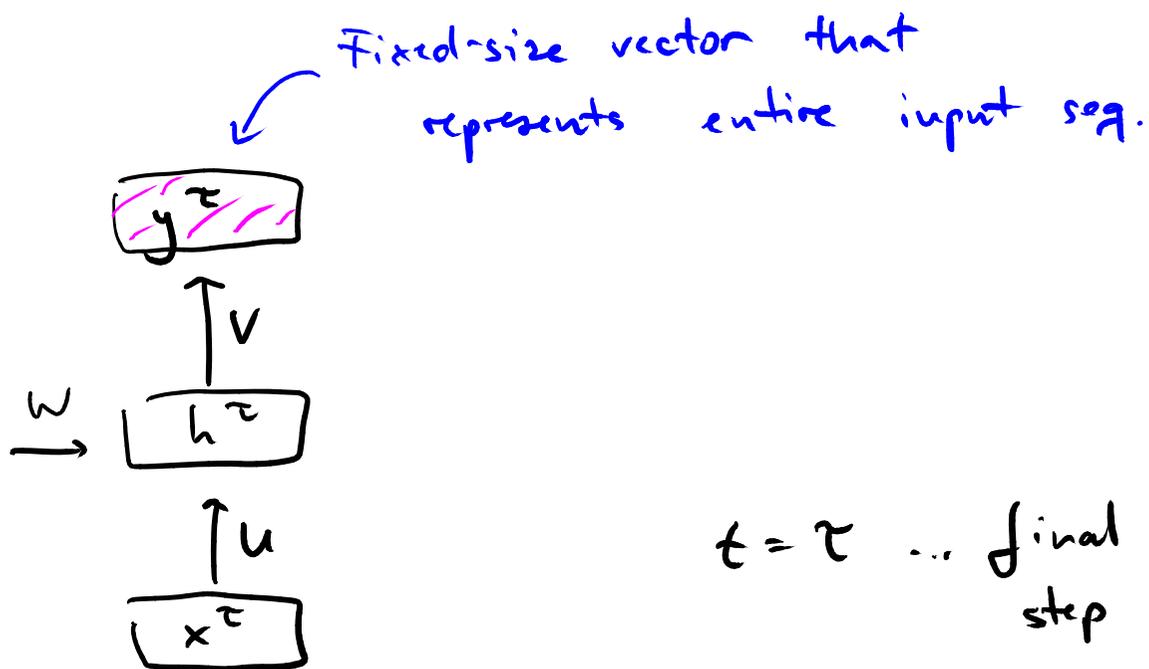
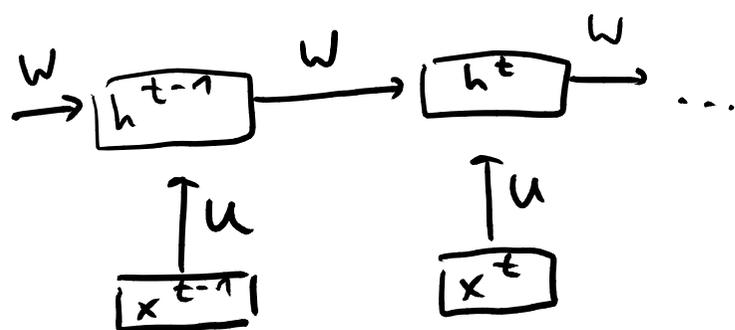


Sequence of length  $m$   
 "Staubsauger sind laut"

- $m$  may be different from  $n$
- both networks are trained jointly
- context vector: summary of input suitable to generate output

## Encoder RNN

Time-unfolded network:

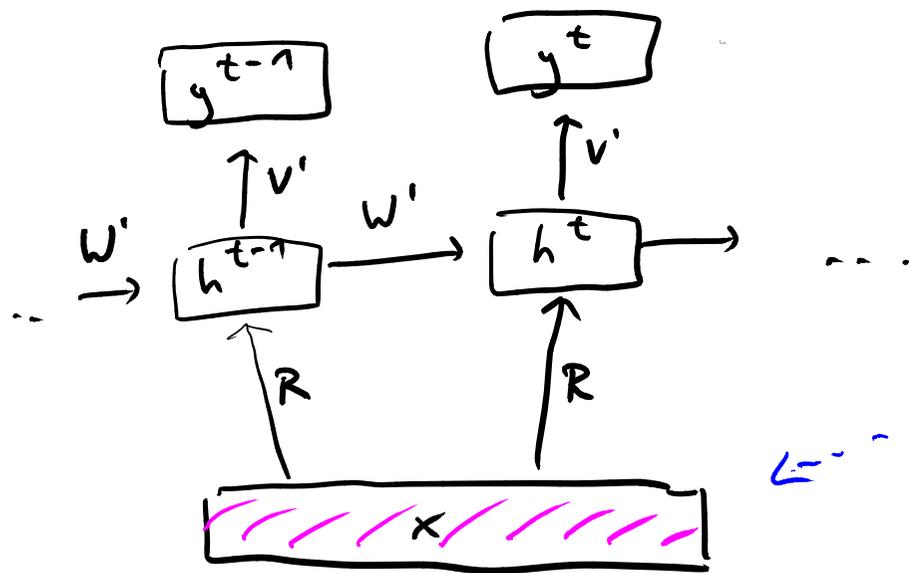


$$h^t = \tanh(W \cdot h^{t-1} + U \cdot x^t + b)$$

$$y^z = V \cdot h^z + c$$

or any other activation fct.

## Decoder RNN



← Fixed-size used to generate entire output sequence

$$h^t = \tanh(W' \cdot h^{t-1} + R \cdot x + b')$$

$$y^t = \text{softmax}(V' \cdot h^t + c')$$

## Training

Training data:  $N$  pairs of sequences  $(x_i, y_i)$  for  $i=1, \dots, N$   
 $\hookrightarrow$  End of sequence marked with  $\langle \text{EOS} \rangle$

Example:

$x_1 = \text{Staubsauger, sind, laut, } \langle \text{EOS} \rangle$

$y_1 = \text{Vacuum, cleaners, are, noisy, } \langle \text{EOS} \rangle$

Goal of training:

$$\text{Minimize } \frac{1}{N} \sum_{i=1}^N \sum_{t=1}^T -\log \Pr(y_{it} | x_i)$$

where  $T$ ... length of output sequences

$\Pr(y_{it} | x_i)$ ... prob. of word  $y_{it}$  given input seq.  $x_i$

# Translation

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For many applications, want  $k$  **most likely translations**

Use left-to-right **beam search**

- For every word, consider  $k$  most likely alternatives
- Extend partial sentence in  $k$  ways
- After each time step, keep only  $k$  most likely partial sequences



# Quiz

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Which of following sentences is correct (multiple sentences may be correct)?

- The context vector is a potential bottleneck that may prevent the network from effective learning.
- The length of the input sequence must be the same across all instances of the training set.
- The length of the output sequence must be the same across all instances of the training set.
- Each instance in the training set must contain two sequences (input and output).

# Quiz

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Which of following sentences is correct (multiple sentences may be correct)?

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# Motivation

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## **APIs** are difficult to use

- Which **methods** to call?
- In what **order** to call them?

## Developers **ask questions**, e.g., on **stackoverflow.com**

- Human effort required to answer them

**Goal: Automatically suggest API usages based on natural language query**

# Idea

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## Formulate the problem as a **translation problem**

- Input: Sequence of **natural language words**
- Output: Sequence of **API method calls**
- Train and query sequence-to-sequence neural network

# Example

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**Natural language query:**

**”match regular expressions”**

**Sequence of API calls expected as  
(possible) answer:**

**Pattern.compile, Pattern.matcher,  
Matcher.group**

# Training Data

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- Analyze 443.000 Java projects from GitHub
- Focus on JDK = APIs of Java standard library
- Extract pairs of annotation and call sequence
- About 7 million extracted pairs
- Use 10.000 for testing and others for training

# Example

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```
/**
 * Copies bytes from a large (over 2GB) InputStream to an
 * OutputStream. This method uses the provided buffer, so
 * there is no need to use a BufferedInputStream.
 * @param input the InputStream to read from
 * . . .
 */
public static long copyLarge(final InputStream input,
final OutputStream output, final byte[] buffer)
    throws IOException {
    long count = 0;
    int n;
    while (EOF != (n = input.read(buffer))) {
        output.write(buffer, 0, n);
        count += n;
    }
    return count;
}
```

# Example

---

```
/**
 * Copies bytes from a large (over 2GB) InputStream to an
 * OutputStream. This method uses the provided buffer, so
 * there is no need
 * @param input the
 * . . .
 */
public static long
final OutputStream
    throws IOExce
    long count = 0;
    int n;
    while (EOF != (n = input.read(buffer))) {
        output.write(buffer, 0, n);
        count += n;
    }
    return count;
}
```

## Annotation:

”copies bytes from a large inputstream  
to an outputstream”

## Call sequence:

InputStream.read , OutputStream.write

# Extracting Annotations

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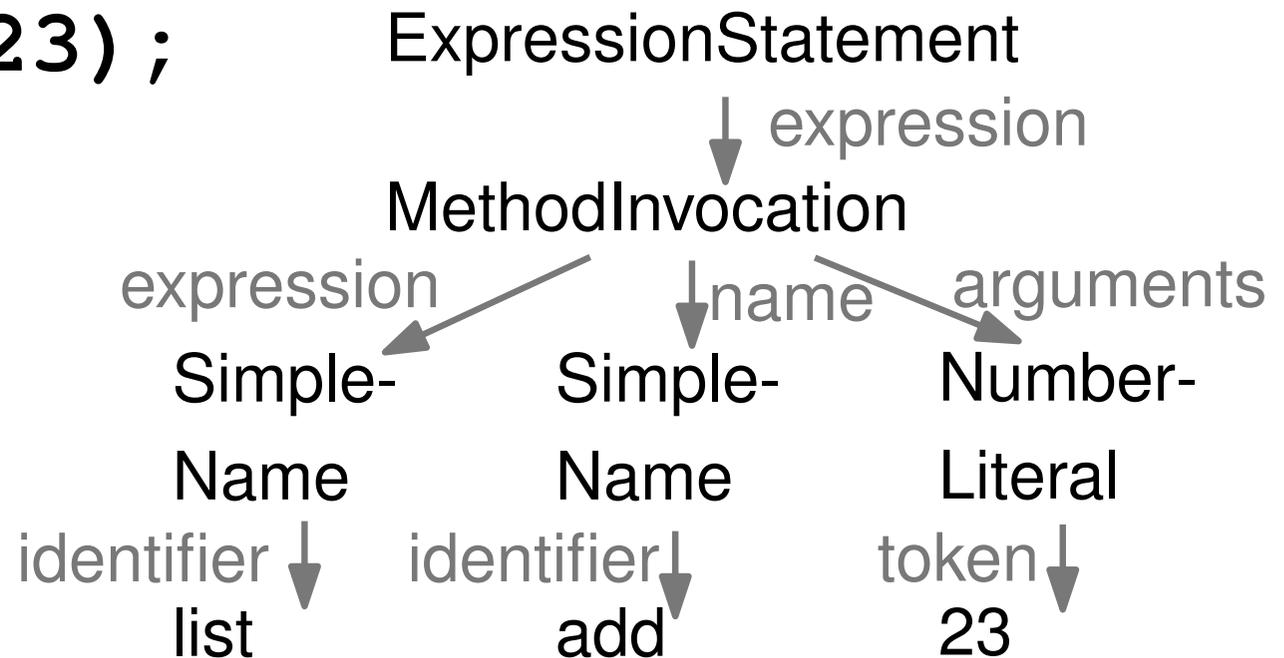
- Extract **JavaDoc** of each method
- Extract **first sentence**
- Ignore methods without JavaDoc
- Ignore annotations with "irregular" comments, e.g., `TODO: . . .`

# Extracting Call Sequences

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- Goal: Lightweight analysis that scales to millions of code files
- **Static, AST-based analysis** with **type bindings**
- Example:

**list.add(23);**



# AST-based Extraction (1)

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- **Constructor call:**

`new C ()`  $\rightarrow$  `C.new` (if `C` is JDK class)

- **Method call:**

`obj.m ()`  $\rightarrow$  `C.m` (if type of `obj` is JDK class)

- **Call expressions as arguments:**

`o1.m1 (o2.m2 ())`  $\rightarrow$  `C2.m2, C1.m1`

# AST-based Extraction (2)

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- **Sequence of statements:**

`o1.m1 (); o2.m2 ();` → C1.m1, C2.m2

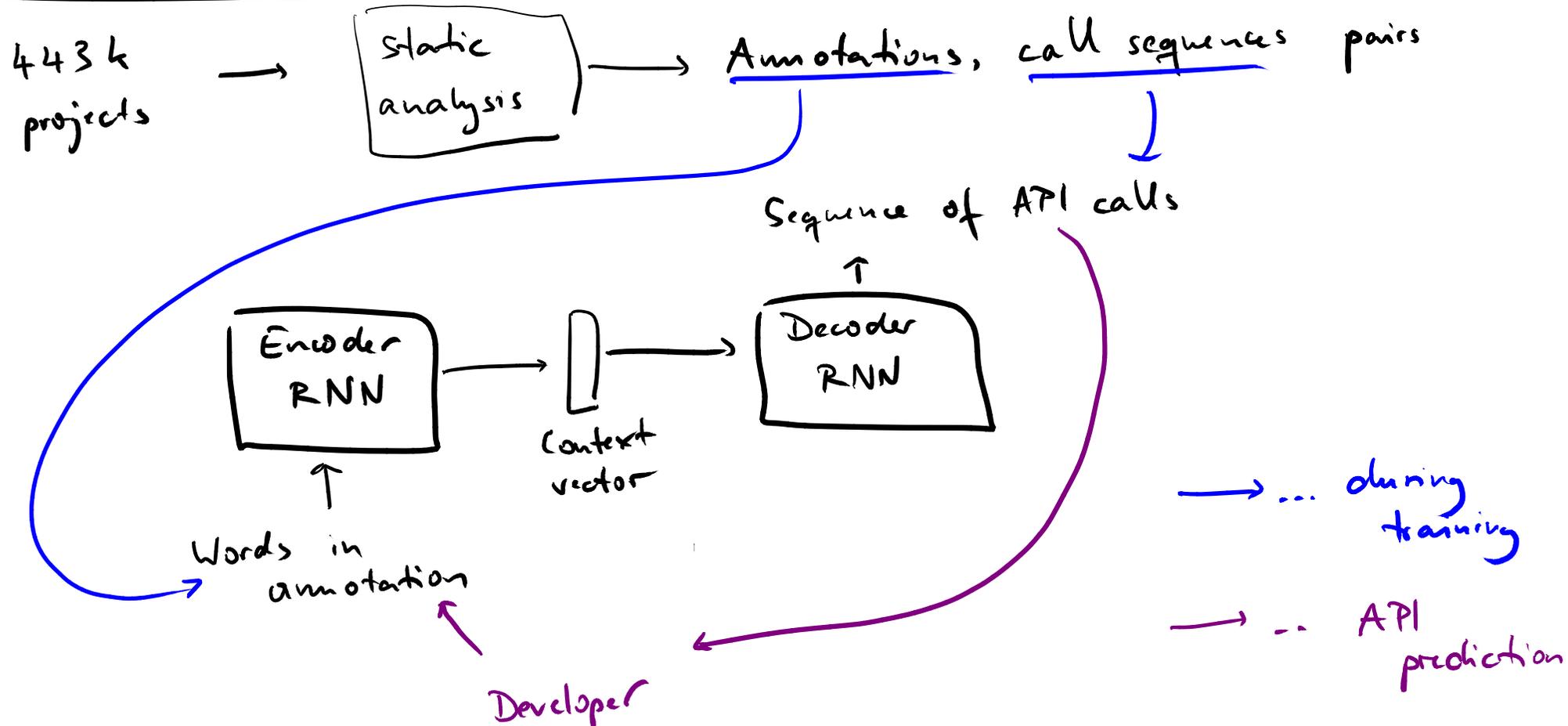
- **Conditionals:**

```
if (o1.m1 ()) {  
    o2.m2 ();  
} else {  
    o3.m3 ();  
} → C1.m1, C2.m2, C3.m3
```

- **Loops:**

```
while (o1.m1 ()) { o2.m2 (); }  
→ C1.m1, C2.m2
```

## Putting Everything Together



# Examples

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- "generate md5 hash code"
  - ↳ MessageDigest.getInstance,  
MessageDigest.update, MessageDigest.digest
- "convert int to string"
  - ↳ Integer.toString
- "get files in folder"
  - ↳ File.new, File.list, File.new, File.isDirectory

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# Motivation

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**In principle, neural networks can express arbitrary computations**

**Can they **interpret a program**?**

- Real-world interpreters are complex pieces of software
- Non-trivial task

# Idea

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## Formulate as sequence-to-sequence translation problem

- Input: Sequence of characters of the source code
- Output: Sequence of characters of the program output
- Here: Restricted set of programs
  - Can evaluate with single left-to-right pass using constant memory

# Example

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## Program:

```
j=8584
for x in range(8):
    j+=920
b=(1500+j)
print ( (b+7567) )
```

## Expected result:

25011

# Another Example

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## Program:

vqppkn

sqdvfljmnc

y2vxdddsepnimcbvubkomhrpliibtwztljipcc

## Expected result:

hkhpg

Characters are obfuscated to illustrate  
difficulty faced by neural network

# Training Data

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## Inputs:

- Automatically **generated Python programs**
  - Addition, subtraction, multiplication
  - Variable assignments
  - If statements
  - For loops, but not nested loops
  - Ends with `print` statement

## Outputs:

- Behavior of **traditional Python interpreter**

# Results

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- Prediction **accuracy between 36% and 84%**
- Depends on size and complexity of programs
- Example of inaccurate prediction:

```
e=6653
```

```
for x in range(14):e+=6311
```

```
print(e)
```

- Predicted output: 94103
- Actual output: 95007

# Summary

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## Sequence-to-sequence networks

- Two jointly trained RNNs combined through context vector
- Translation with arbitrary length of sequences

## Applications

- Predict API call sequences for natural language queries
- Interpret programs and predict their output