Reliable and Interpretable Artificial Intelligence

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Machine Learning (ML) + Synthesis

So far we looked at "program synthesis in the small", meaning we did not leverage knowledge of prior, similar programs, when synthesizing a new program. In this lecture, we are going to study both directions:

Part I: Leverage ML models to enable program synthesis. This will involve learning from a new kind of data sets (e.g., now programs themselves are examples). Motivated by this we will move to **Part II**

Part II: Leverage synthesis to build more interpretable ML models. An alternative to attention mechanism in neural networks. Applies the iterative synthesis (oracle-based) loop concepts from previous two lectures to learn ML models. The techniques here apply beyond learning from code but natural language and other data.

Probabilistic Learning from Code

Task → **Probabilistic Tool** → **Solution**

ML model

15 million repositories

Billions of lines of code

High quality, tested, maintained programs

Why now?

Advances in Programming Languages
[Automated Reasoning, Synthesis, Constraint Solving]

Confluence of streams

Advances in Machine Learning
[Deep Learning, Graphical Models, Language Models]

machine learning-based programming tools
new rules, new ideas, new opportunities

Data
[> 15 million public repositories]

Machine Learning for Programming

Applications	Code synthesis; Deobfuscation; Program repair; Feedback generation; Translation
Intermediate Representation	Sequences (sentences); Trees; Translation Table; Graphical Models (CRFs); Feature Vectors
Semantic Analysis	typestate analysis; scope analysis; control-flow analysis; alias analysis
Train Model (ML)	Neural Networks; N-gram language model; SVM; Structured SVM
Query Model (ML)	argmax P(y | x), y ∈ Ω; Greedy MAP inference

More information: http://plml.ethz.ch

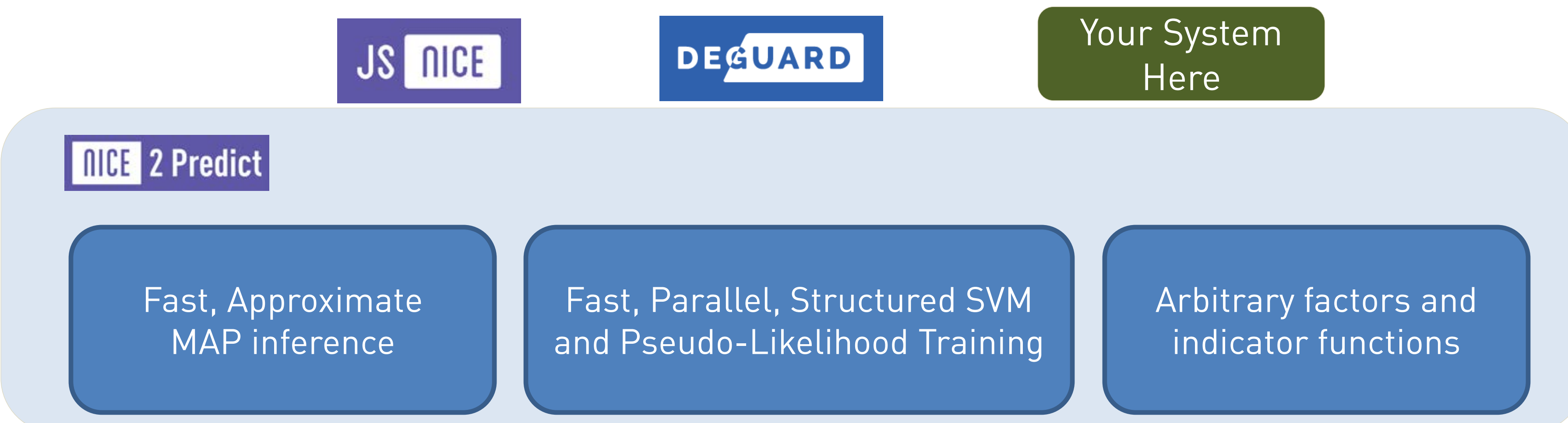
ML Systems we have built, such as jsnice.org and apk-deguard.com have > 300,000 users...

Nice2Predict.org:

scalable structured prediction framework

fully, open sourced, Apache license

used by various groups worldwide



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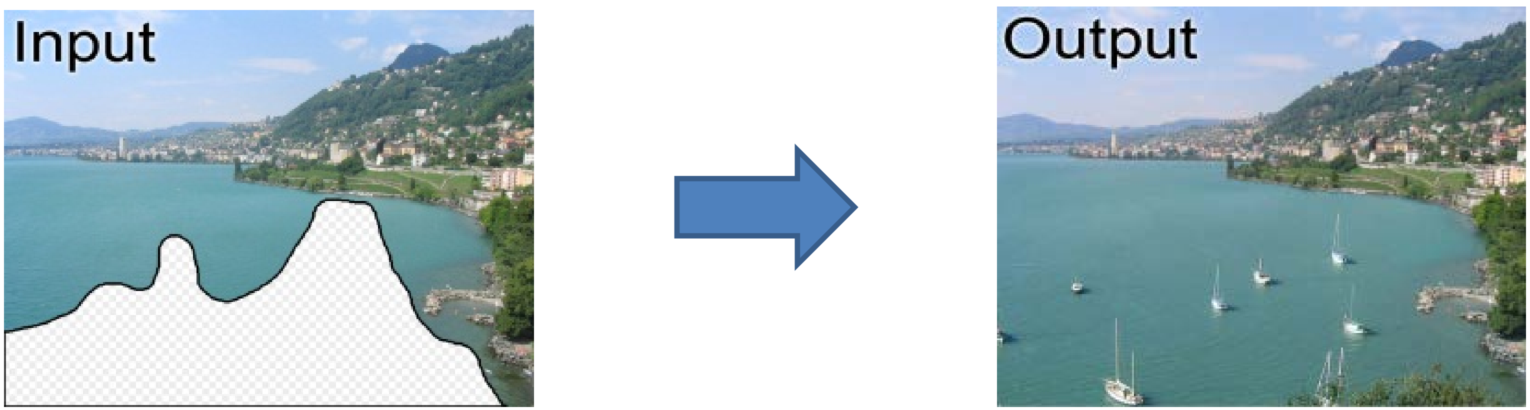
Intuition: Scene Completion



“Scene Completion Using Millions of Photographs”, J. Hays, A. Efros, ACM SIGGRAPH 2007

Statistical Code Synthesis

[Code Completion with Statistical Language Models, ACM PLDI 2014]

```
Camera camera = Camera.open();
camera.setDisplayOrientation(90);
```

?

```
MediaRecorder rec = new MediaRecorder();
```

?

```
rec.setAudioSource(MediaRecorder.AudioSource.MIC);
rec.setVideoSource(MediaRecorder.VideoSource.DEFAULT);
rec.setOutputFormat(MediaRecorder.OutputFormat.MPEG_4);
```

?

```
rec.setOutputFile("file.mp4");
...
```

Statistical Code Synthesis

[Code Completion with Statistical Language Models, ACM PLDI 2014]

```
Camera camera = Camera.open();
camera.setDisplayOrientation(90);

camera.unlock();

MediaRecorder rec = new MediaRecorder();

rec.setCamera(camera);

rec.setAudioSource(MediaRecorder.AudioSource.MIC);
rec.setVideoSource(MediaRecorder.VideoSource.DEFAULT);
rec.setOutputFormat(MediaRecorder.OutputFormat.MPEG_4);

rec.setAudioEncoder(1);
rec.setVideoEncoder(3);

rec.setOutputFile("file.mp4");
...
```

Infers sequences not in training data

Handles multiple objects

Infers multiple statements

Key Insight

Regularities in code are similar to regularities in natural language

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Regularities in code are similar to regularities in natural language

We want to learn that

```
MediaRecorder rec = new MediaRecorder();
```

is before

```
rec.setCamera(camera);
```

Key Insight

Regularities in code are similar to regularities in natural language

We want to learn that

```
MediaRecorder rec = new MediaRecorder();
```

is before

```
rec.setCamera(camera);
```

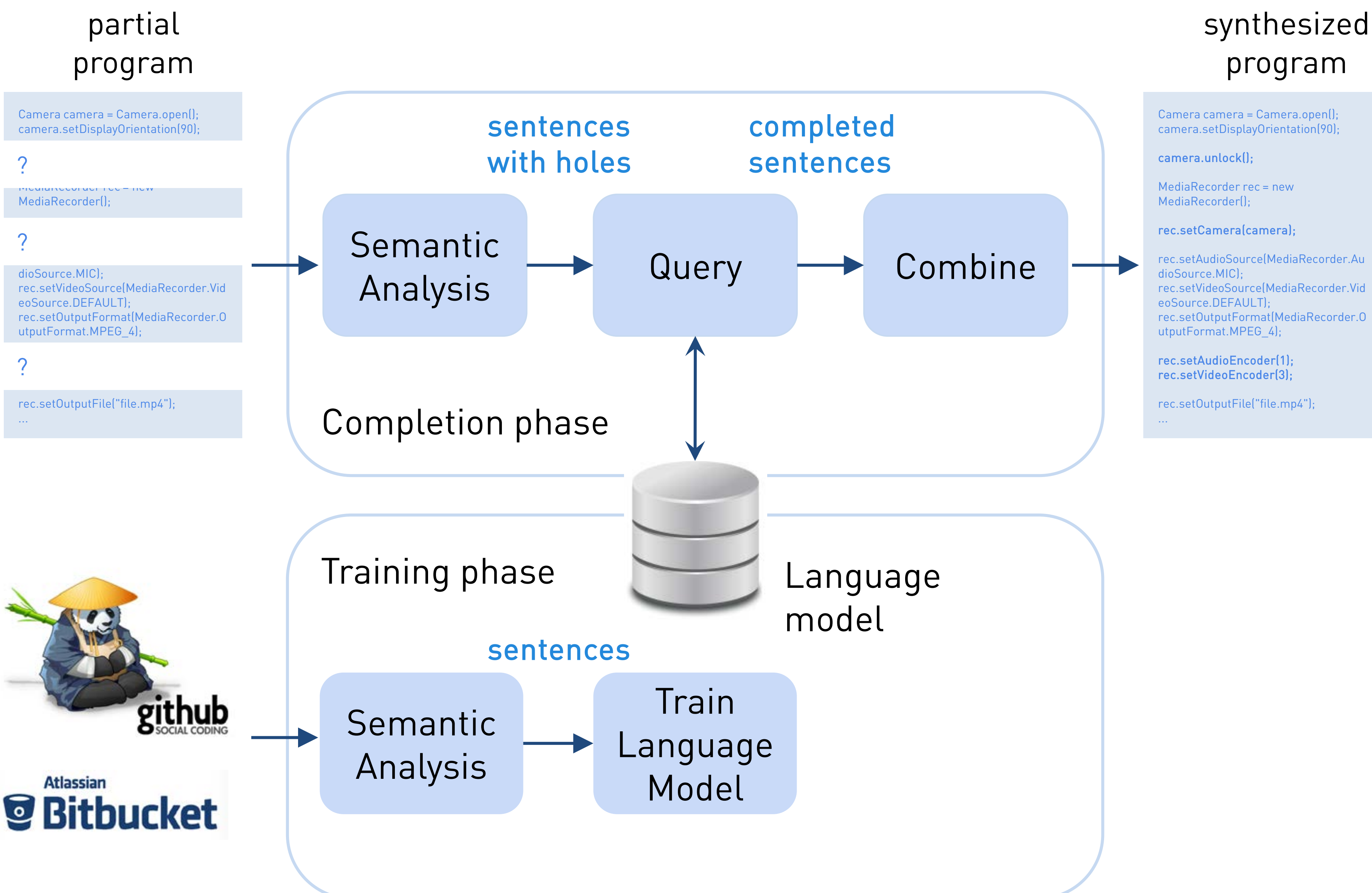
like in natural languages

Hello

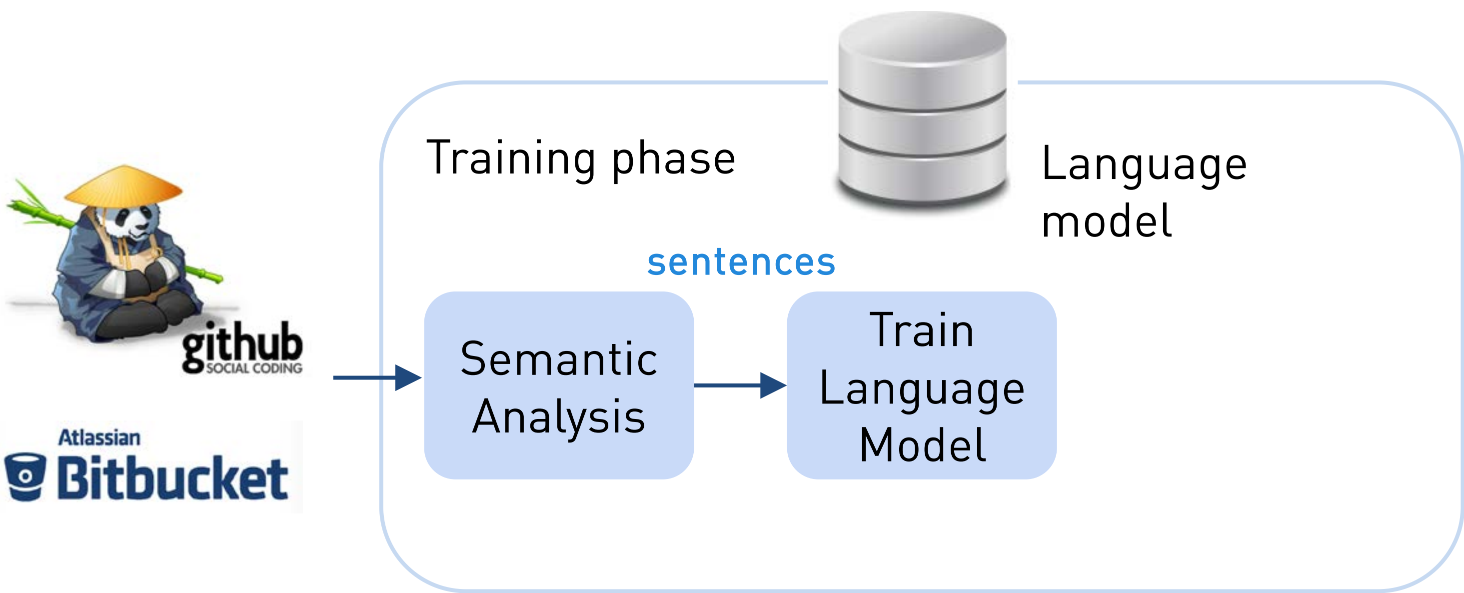
is before

World !

The SLANG System



The SLANG System



Step1: From Programs to Sentences

```
she = new X();
me = new Y();

me.sleep();
if (random()) {
  me.eat();
}
she.enter();
me.talk(she);
```

A note on:

learning from code vs.
learning from natural language (NLP):

Unlike natural language, code has formal semantics that one can benefit from if they have a way to automatically extract these…

This means that with code the actual data can be:

<u>Choice 1</u> (*Syntactic*): a sequence of tokens (words) that make up the program. This follows the NLP mindset.

<u>Choice 2</u> (*Semantic*): a sequence of words where each word captures something about the semantics of the program

Lets see how Choice 2 works…

From Programs to Sentences

```
she = new X();
me = new Y();

me.sleep();
if (random()) {
  me.eat();
}
she.enter();
me.talk(she);
```

We get 3 sequences:

for abstract object **me**:

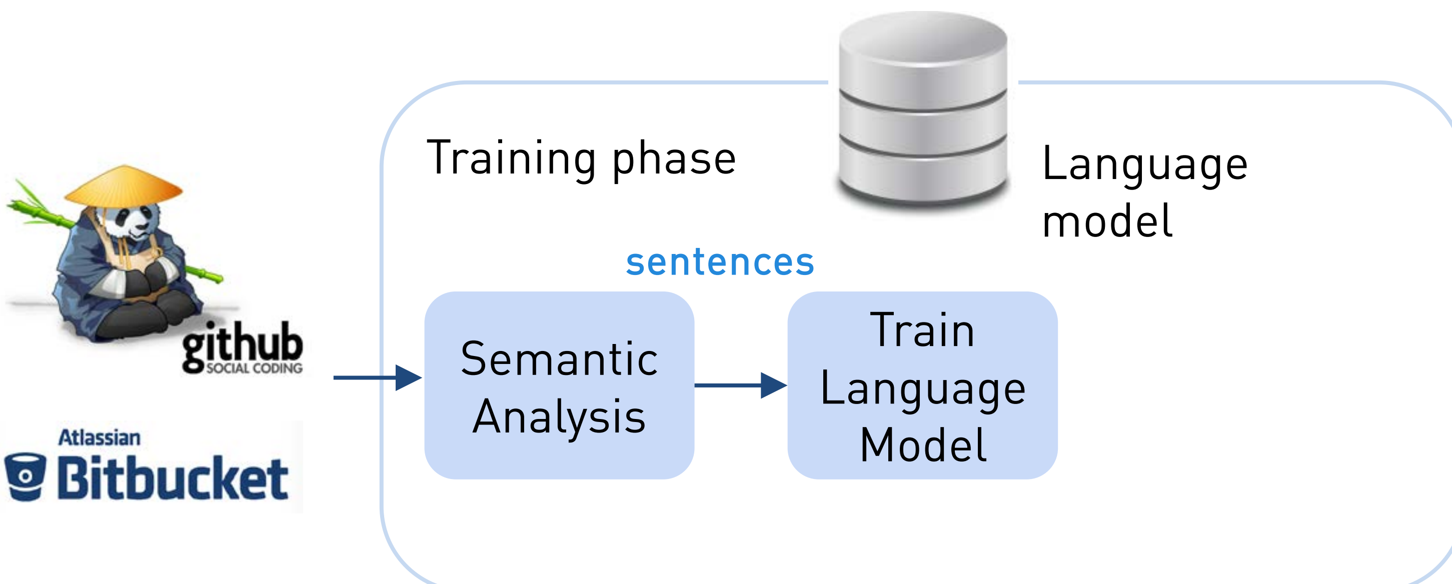
Y_{init} sleep talk
Y_{init} sleep eat talk

for abstract object **she**:

X_{init} enter $talk_{param1}$

abstract (semantic) object:
think of it as the variable denoting all concrete objects assigned to that variable. So many objects assigned to the **she** variable will all be mapped to the same **she** abstract object. In our example we only have 1 concrete object but if we had a loop around **she**=new X(), we would have more concrete objects but still only 1 abstract object.

Step 2: Learn Regularities in Sentences



Learn Regularities

Learn regularities in obtained sentences

Regularities in sentences ⇔ regularities in code usage

If we see many sequences like:

X_{init} enter $talk_{param1}$

then we should learn that $talk_{param1}$ is often after enter

Statistical Language Models

Given a sentence $s = w_1\ w_2\ w_3 \ldots\ w_n$

estimate $\mathbf{P}(\ w_1\ w_2\ w_3 \ldots\ w_n\ )$

Decomposed to conditional probabilities

$$\mathbf{P}(\ w_1\ w_2\ w_3 \ldots\ w_n\ ) = \prod_{i=1..n} \mathbf{P}(\ w_i \mid w_1\ \ldots\ w_{i-1}\ )$$

Statistical Language Models

Given a sentence $s = w_1\, w_2\, w_3 \ldots w_n$

estimate $\mathbf{P}(\, w_1\, w_2\, w_3 \ldots w_n\,)$

Decomposed to conditional probabilities (via chain rule):

$$\mathbf{P}(\, w_1\, w_2\, w_3 \ldots w_n\,) = \prod_{i=1..n} \mathbf{P}(\, w_i \mid w_1 \ldots w_{i-1}\,)$$

P(The quick brown fox jumped) =

P(The) **P**(quick | The) **P**(brown | The quick) **P**(fox | The quick brown) **P**(jumped | The quick brown fox)

Choice I: N-gram language model

Conditional probability based only on previous n-1 words

$$\mathbf{P}(\, w_i \mid w_1 \;\ldots\; w_{i-1}\,) \approx \mathbf{P}(\, w_i \mid w_{i-n+1} \;\ldots\; w_{i-1}\,)$$

N-gram language model

Conditional probability based only on previous n-1 words

$$\mathbf{P}(\, w_i \mid w_1 \; \ldots \; w_{i-1} \,) \approx \mathbf{P}(\, w_i \mid \underbrace{w_{i-n+1} \; \ldots \; w_{i-1}}_{\text{n-1 words}} \,)$$

N-gram language model

Conditional probability based only on previous n-1 words

$$P(w_i \mid w_1 \ldots w_{i-1}) \approx P(w_i \mid \underbrace{w_{i-n+1} \ldots w_{i-1}}_{\text{n-1 words}})$$

Training is achieved by counting n-grams, called MLE = maximum likelihood estimation. E.g., with 3-gram language model, we get:

$$P(\text{jumped} \mid \text{The quick brown fox}) \approx P(\text{jumped} \mid \text{brown fox}) \approx \frac{\#(\text{brown fox jumped})}{\#(\text{brown fox})}$$

#(n-gram) - number of occurrences of n-gram in training data

Time complexity for each word encountered in training is constant, so training is usually fast.

* technicality: to actually get a probability distribution across all sentences we typically add N-1 start symbols and N-1 end symbols </s> to each sentence.

3-gram language model: example

$$P(w_1 \cdot w_2 \cdot w_3 \cdot \ldots w_n) \sim= P(w_1) * P(w_2 \mid w_1) * P(w_3 \mid w_1 \cdot w_2) * \ldots * P(w_n \mid w_{n-2} \cdot w_{n-1})$$

3-grams	# of occurrences
brown fox jumped	125
brown fox walked	45
brown fox snapped	30

P (jumped | brown fox) ~= 125/200 ~= 0.625

P (brown fox jumped) ~=

P (brown)	*	P (fox | brown)	*	P (jumped | brown fox)	
200 / 600	*	200 / 200	*	125 / 200	~= 0.208

Key Problem: Sparsity of Data

What if this number is 0?

$$P(\text{ jumped } | \text{ brown fox }) \approx \frac{\#(\text{ brown fox jumped })}{\#(\text{ brown fox })}$$

The problem of sparsity gets worse as the size of the n-gram becomes larger.

We need to handle n-grams with 0 or few occurrences in the training data.
Techniques that can do that are: **smoothing**, **discounting**

Solution: Smoothing Techniques

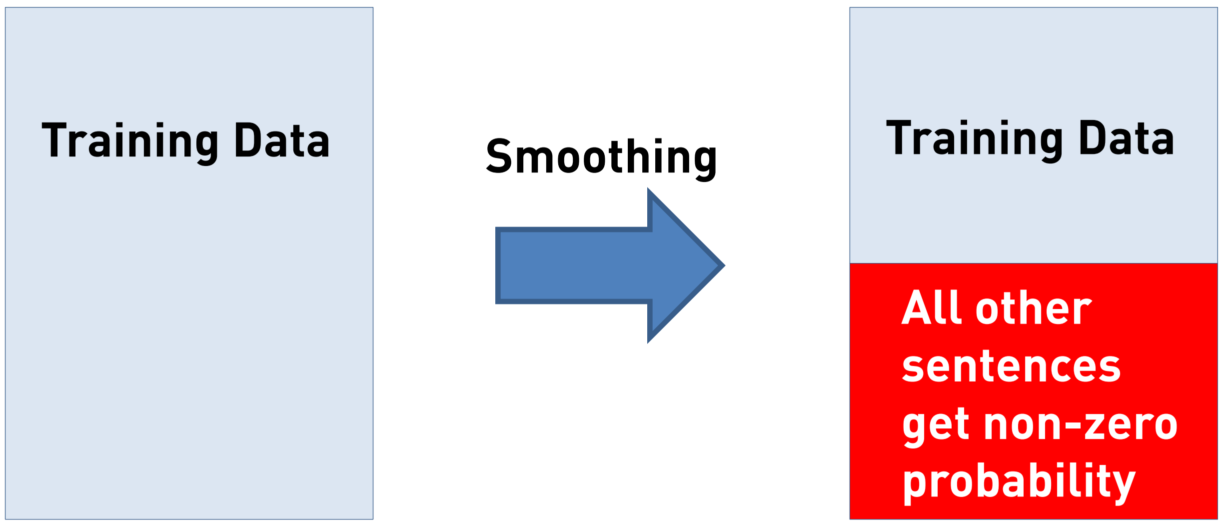
- Smoothing techniques give non-zero probability to n-grams not in the training data.
- Essentially, they try to estimate how likely it is that the n-gram is missing due to the limited size of the training data.
- They work by taking the probability mass of the existing n-grams and redistributing that mass over n-grams that occur zero times.
- Typically, probability of such n-grams is estimated by looking at the probabilities of n-1 grams , n-2 grams, unigrams, etc.

Example smoothing techniques are: Witten-Bell Interpolated (WBI), Witten-Bell Backoff (WBB), Natural Discounting (ND), Stupid-Backoff (SB)`

Smoothing: Intuitively

Distribution of probability mass before smoothing

Distribution of probability mass after smoothing



All other sentences get 0 probability

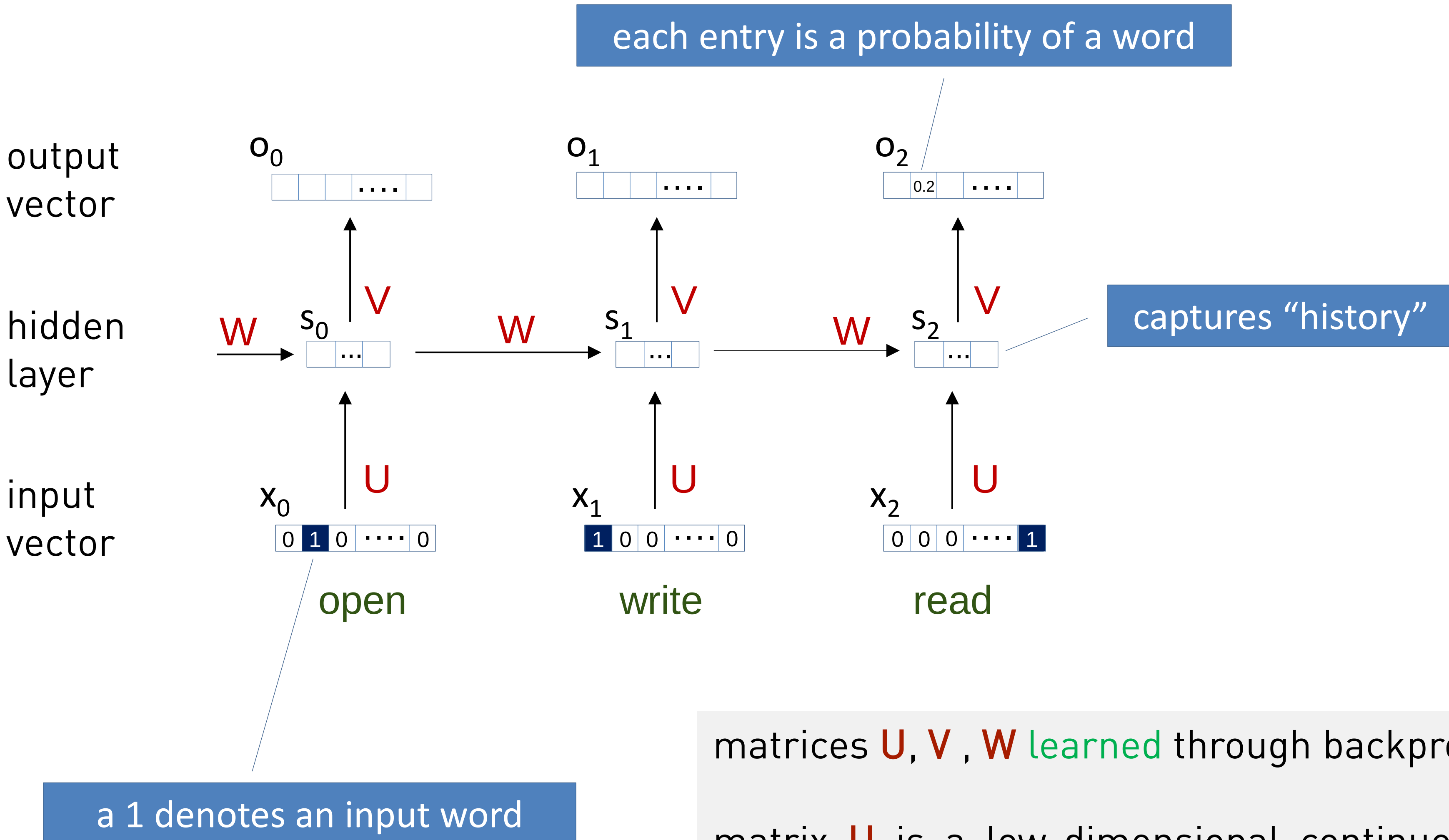
N-gram language model

Conditional probability only on previous n-1 words

$$\mathbf{P}(\,w_i \mid w_1 \;\ldots\; w_{i-1}\,) \approx \mathbf{P}(\,w_i \mid \underbrace{w_{i-n+1} \;\ldots\; w_{i-1}}_{\text{n-1 words}}\,)$$

Existing library implementing language models is SRILM:
http://www.speech.sri.com/projects/srilm/

Choice II: Recurrent Neural Networks (RNN)

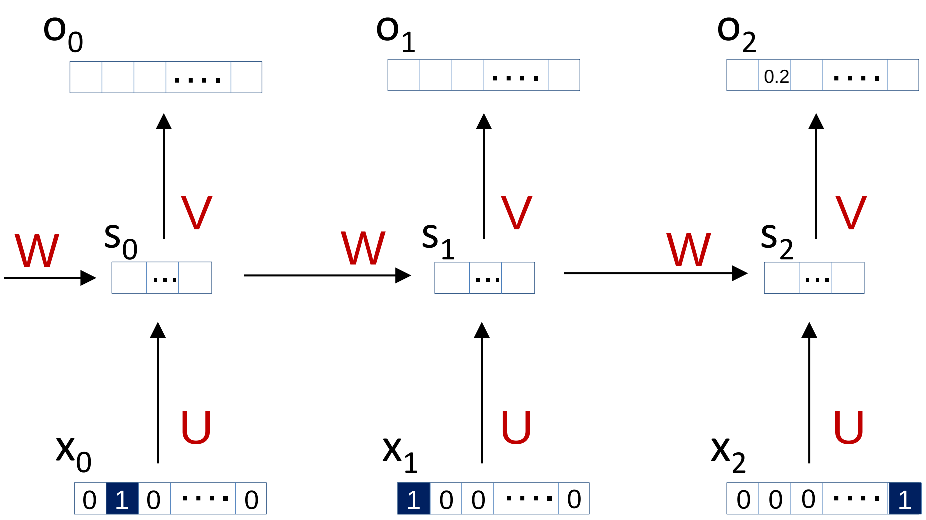


matrices U, V , W learned through backprop

matrix U is a low-dimensional continuous vector representation of input words, also referred to as "word embedding"

RNNs: more details on board

Choice II: Recurrent Neural Networks (RNN)



+ can learn dependencies beyond the prior several words (e.g., LSTM)
+ learns continuous representation of vocabulary (helps avoid sparsity)
- slow and tricky to train
- predictions hard to explain

RNNLM-40 Download: http://rnnlm.org/

TensorFlow https://www.tensorflow.org/

ML-based Code Synthesis

```
smsMgr = SmsManager.getDefault();
int length = message.length();
if (length > MAX_SMS_MESSAGE_LENGTH) {
  list = smsMgr.divideMessage(message);
  ? {smsMgr, list} // (Hole H1)
} else {
  ? {smsMgr, message} // (Hole H2)
}
```

ML-based Code Synthesis

```
smsMgr = SmsManager.getDefault();
int length = message.length();
if (length > MAX_SMS_MESSAGE_LENGTH) {
  list = smsMgr.divideMessage(message);
  ? {smsMgr, list} // (Hole H1)
} else {
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}
```

Abstract object **smsMgr**:

$\text{getDefault}_{\text{result}}$ divideMessage H1

$\text{getDefault}_{\text{result}}$ H2

Abstract object **list**:

$\text{divideMessage}_{\text{result}}$ H1

Abstract object **message**:

length $\text{divideMessage}_{\text{param1}}$

length H2

ML-based Code Synthesis

$\text{getDefault}_{\text{result}}$ divideMessage **H1**	

$\text{getDefault}_{\text{result}}$ **H2**	

$\text{divideMessage}_{\text{result}}$ **H1**	
length **H2**	

ML-based Code Synthesis

	Completion probability
getDefault$_{result}$ divideMessage **sendMultipartTextMessage**	0.0033
getDefault$_{result}$ divideMessage **sendTextMessage**	0.0016

getDefault$_{result}$ **sendTextMessage**	0.0073
getDefault$_{result}$ **sendMultipartTextMessage**	0.0010

divideMessage$_{result}$ **sendMultipartTextMessage$_{param3}$**	0.0821

length **length**	0.0132
length **split**	0.0080
length **sendTextMessage$_{param3}$**	0.0017

ML-based Code Synthesis

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getDefault$_{result}$ divideMessage **sendMultipartTextMessage**	0.0033
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getDefault$_{result}$ **sendMultipartTextMess**	
divideMessage$_{result}$ **sendMultipartTextMes**	
length **length**	
length **split**	0.0080
length **sendTextMessage**$_{param3}$	0.0017

Not a feasible solution: completions disagree on selected method

The solution must satisfy program constraints

ML-based Code Synthesis

	Completion probability
getDefault$_{result}$ divideMessage **sendMultipartTextMessage**	0.0033
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getDefault$_{result}$ **sendTextMessage**	0.0073
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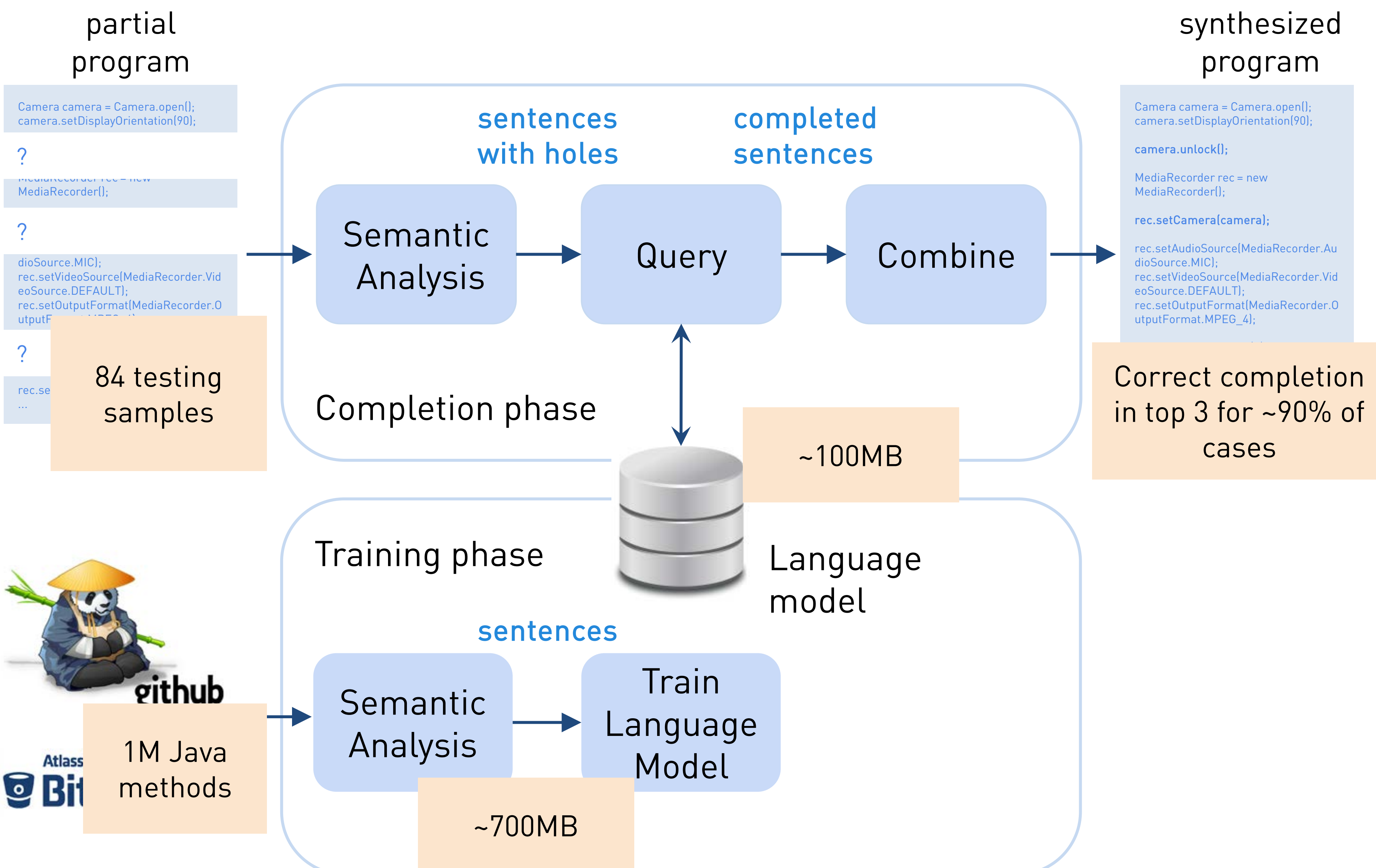
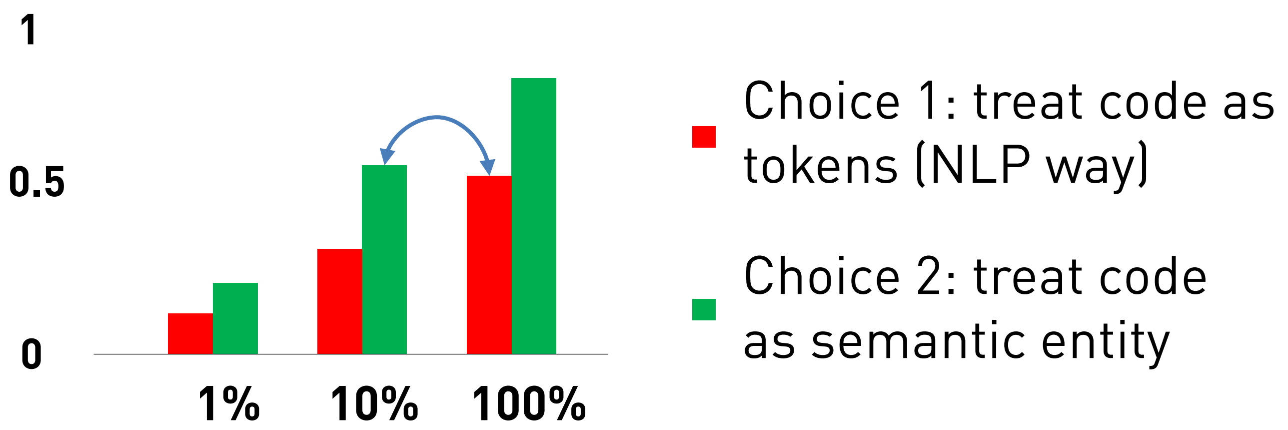
} else {
  smsMgr.sendTextMessage(...message...);
}
```

The SLANG System



Do semantics help?

precision vs. % **of data used**



*need to decide what to ``compile'' into a word

semantic analysis benefit = 10x more data

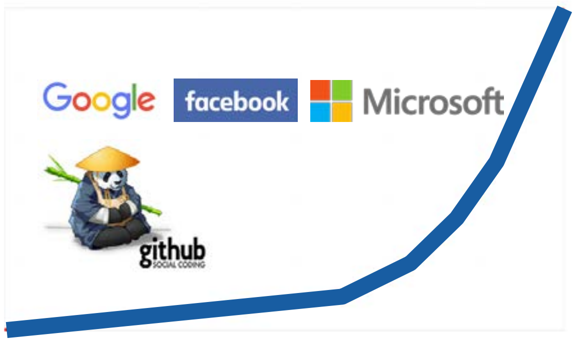
Next: Synthesis for Interpretable ML

Fundamental Question

Data

Learning

Model



Probabilistic Model

Widely Applicable

Efficient Learning

High Precision

Interpretable Model