ErrorDeep: Using an Artificial Neural Network to Detect Syntax Errors and Suggest a Fix

Dhvani Patel, Eddie Santos, Joshua Campbell, Dr. Abram Hindle
University of Alberta, Dept. of Computing Science, Software Engineering Lab

Introduction

- Current tools for interpreting human-written source code (parsers) provide misleading information given an unexpected input.
- Novice programmers thus find it difficult to use the information provided by the parsers to fix their broken code [1], [2], [3].

Purpose

- Provide the location (line number) and fix token given a source file with a single token syntax error
- Use an artificial neural network to automatically find the error

Method

- In order to train the neural network, we needed a large dataset of positive and negative samples.

Collect ~450,000 syntactically-valid JavaScript files

Files were tokenized and standardized to a set vocabulary of 88 tokens.

Chosen sample size for training: 2000
Token Batch Size: 66
Window Size: 10

Method Continued

- Wrote script to mutate the sample size
- 3 types of mutations were created.

Total Training Data: *8000 files*

Input: *Window with 10 Tokens*

if	(	Identifier	==	Identifier	{	Identifier	=	True	;

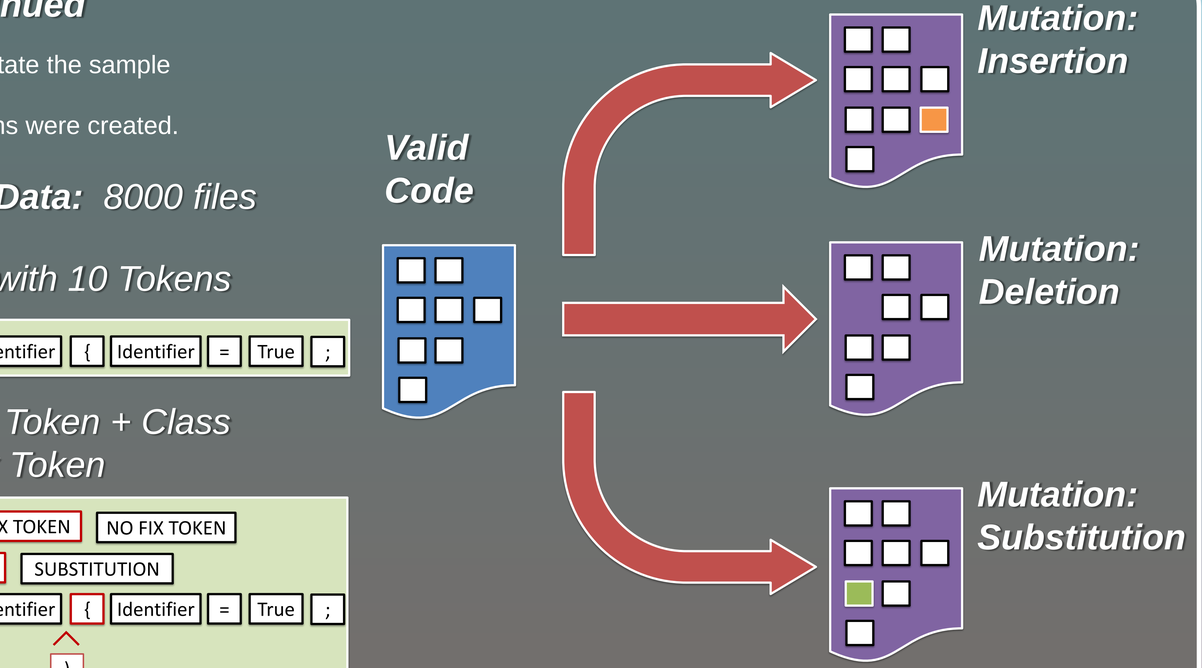
Output: *Error + Token + Class + Location + Fix Token*

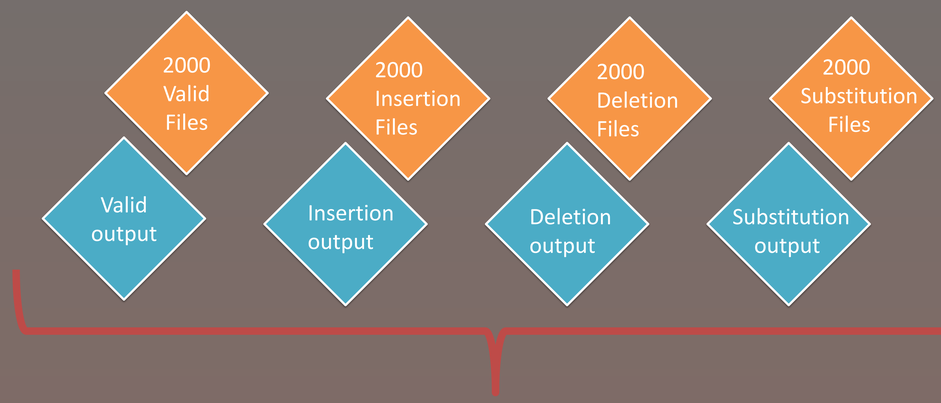
ERROR	NO ERROR	FIX TOKEN	NO FIX TOKEN

INSERTION	DELETION	SUBSTITUTION

if	(	Identifier	==	Identifier	{	Identifier	=	True	;

)





Keras[4] Model Architecture:

Input: One-hot matrix

Layers:

Type	Output dim.	Activation
Dense	4	ReLU
Flatten		
Dense	128	ReLU
Dense	128	ReLU
Dropout		Rate: 0.5
Dense	4	ReLU
Dropout		Rate: 0.5
Activation		softmax

Backend: Theano [5]

Output: Categorical distribution

Loss: Categorical cross-entropy

Optimizer: RMSprop[6], initial learning rate = 0.001, momentum = 0.3

Test Model
Takes future, unknown data and produces the same output format as training.

Results

Conclusions

- Mutations created randomly do not truly represent real errors.
- Machine learning can take a long time to train.
- The model needs more training data and neurons to better learn the language.
- Learning about different types of mistakes will allow for future improvement in teaching programming to others.

References

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