Experiments with a PCCoder extension

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Abstract

Recent research in synthesis of programs written in some Domain Specific Language (DSL) by means of neural networks from a limited set of inputs-output correspondences such as DeepCoder (Balog et al., 2017) and its PCCoder (Zohar and Wolf, 2018a) reimplementaiton/optimization proved the efficiency of this kind of approach to automatic program generation in a DSL language that although limited in scope is universal in the sense that programs can be translated to basically any programming language.

We experiment with the extension of the domain specific language (DSL) of DeepCoder/PCCoder with symbols IFI and IFL which denote functional expressions of the If ramification (test) instruction for types Int and List. We notice an increase (doubling) of the size of the training set, the number of parameters of the trained neural network and of the time spent looking for the program synthesized from limited sets of inputs-output correspondences.

The result is positive in the sense of preserving the accuracy of applying synthesis on randomly generated test sets.

1 Introduction

The task of automatically finding a program in some underlying programming language that satisfies the user intent expressed in the form of some specification, i.e., program synthesis, has been considered ‘the holy grail’ of Computer Science ever since the inception of Artificial Intelligence (AI) in the 1950’s. It was Alonzo Church who defined the problem to synthesize a circuit from mathematical requirements during the Summer Institute of Symbolic Logic at Cornell University in 1957. With the revival of artificial Neural Networks during the last decade the issue of applying deep learning techniques to such an old problem finally percolated in the last two years, as illustrated by the papers listed in the bibliography section (Bavishi, 2019; Cai et al., 2017; Chen et al., 2019; Ellis et al., 2019; Kalyan et al., 2018; Polosukhin and Skidanov, 2018; Shin et al., 2019). This basically started with the initial success of Balog et. al. (Balog et al., 2017) from Google Brain. The reimplementation and adaptation of Zohar and Wolf (Zohar and Wolf, 2018a) added further depth by using a second neural network for pruning and thus extending the length of generated programs.

In their 2017 survey (Gulwani et al., 2017), Gulwani, Polozov and Singh present a review of state of the art techniques for program synthesis that include in Section 6.4 the approach called Neural Program Synthesis which employs Neural Networks
in one of two ways: either new neural architectures learn the behavior of a program that is consistent with a given set of input-output examples or the neural systems do perform effective program synthesis by returning an interpretable program that matches the desired specification behavior. The first approach is also called ‘program induction’ and comes with the shortcoming that no interpretable model of the learnt program is generated while large computational resources and several thousands of input-output examples per synthesis task are required.

We are thus concerned with the second approach of which Flash Fill is a successful example that has already been implemented in Microsoft Excel. Given the Flash Fill domain specific language (DSL), the Flash Fill neural system learns a generative model of programs in the DSL which is conditioned on the input-output examples. The neural system is made from two networks: the I/O encoder and the R3NN (Recursive-Reverse-Recursive Neural Network) which incrementally synthesizes a program in the DSL given a continuous representation of the input-output examples.

Other, non-neural approaches to program synthesis include: enumerative search, constraint solving, stochastic search, and deduction-based programming by examples (see, e.g., (Knoth et al., 2019)).

2 Deep Coder - PC Coder

In their paradigm-shifting approach (Balog et al., 2017), Balog et al. achieve the goal of integrating neural network architectures with search-based techniques (rather than replace them) for the objective of program induction: they illustrate the use of a corpus of program induction problems in learning strategies that generalize across problems. They manage to define a programming language that is expressive enough to include real-world programming problems while being high-level enough to be predictable from inputs-output examples.

They generate models for mapping sets of inputs-output examples to program properties and they perform experiments that show an order of magnitude speedup over standard program synthesis techniques, which makes their approach feasible for solving problems of similar difficulty as the simplest problems that appear on programming competition websites.

In their PCCoder reimplementation (Zohar and Wolf, 2018a), Zohar and Wolf optimize and extend the performance of DeepCoder by employing a stepwise approach to the program synthesis problem. Given the current state, the main neural network directly predicts the next statement, including both the function (operator) and parameters (operands). A beam search is then performed, based on the network’s predictions, reapplying the neural network at each step. The more accurate the neural network, the less programs one needs to include in the search before identifying the correct solution. Since the number of variables increases with the program’s length, some of the variables in memory need to be discarded. Therefore a second network is trained to predict the variables that are to be discarded. Training the new network does not only enable to solve more complex problems, but serves also as an auxiliary task that improves the generalization of the statement prediction (main) network.

The DSL from (Balog et al., 2017; Zohar and Wolf, 2018a) is a small purely functional language with basic types Bool, Int and List where the latter are vectors of at most 20 Int and the functions are divided into three categories: first-order,
higher-order and lambdas. Each line of instruction is given by a function name followed by arguments 0,1,2,.. where each natural represents the n-th (previous) instruction (result) or one of the inputs: 0 identifies the first input, 1 the second input (if it exists), 2 the third input or the result of the first instruction (if our program only takes two inputs). Thus no constants are allowed in their language, as these natural literals are reserved for positions in the instruction stack. The outcome of the program is the result of the application of the last instruction in the stack.

The DSL of PCCoder is yet the same as the one of DeepCoder and currently cannot express solutions to many problems. Complex problems require more complex algorithmic solutions like dynamic programming and search, which are currently beyond reach for such DSL.

It is therefore important to attempt the extension of the DSL with branching and loop constructs and investigate how this would complicate the task of program synthesis in terms of the increase in search complexity. We previously demonstrated that at least allowing more function symbols appears to be feasible, without much complexity increase, see Section 3.

We experimented with the addition of the branching command If expressed functionally for types Int and List. We thus extended the DSL with symbols IFI and IFL which denote functional expressions of the If ramification (test) instruction for types Int and respectively List:

IFI = Function('IFI', lambda f, n, x, y: x if f(n) else y, (FunctionType(INT, BOOL), INT, INT, INT), INT)

IFL = Function('IFL', lambda f, n, x, y: x if f(n) else y, (FunctionType(INT, BOOL), INT, LIST, LIST), LIST)

We noticed an increase in the size of the training set $T_n$ (basically a doubling in size) for programs of length at most $n$ (e.g., $n = 5$) and correspondingly an increase (doubling) of the number of parameters of the neural network $R_n$ trained from $T_n$. All this also brings a doubling of the execution time of the search script for solutions from examples. The maximum length of a program was not affected, as networks could be generated even for $n \geq 20$.

We also noticed the generalization capacity of the result in the sense that, e.g., the network $R_5$ has a success rate of $\geq 90\%$ for a randomly generated test set of programs of length 6, a success rate of $\geq 70\%$ for programs of length 8 and $\approx 50\%$ for programs of length 14. In general, the network $R_n$ has a 99% success rate for programs of length at most $n$, also for the extended DSL.

3 MNIST classification

We first demonstrated a simpler (from a complexity viewpoint) extension of the DSL, namely with function symbols for Python implemented functions. This may have at most a linear impact on the complexity, as the new symbol may be included in the programs of a certain maximal length generated for training the network later used in the program synthesis search for a program compatible with a certain given set of inputs-output pairs.

We exemplify with a function that is complex enough in order to be interesting
but also has a fairly simple implementation in Python (using the \texttt{sklearn} library), namely a function for MNIST classification.

We thus extended the DSL of DeepCoder/PCCoder with a function symbol \texttt{MNIST} which takes as input a list of 8 integers between 0 and 255 and returns an integer between 0 and 9 or 10 as error. Each of the 8 integers represents a line in the 8x8 matrix of the input drawing, with the integer value between 0 and 255 coding the columns marked with 1 in the binary representation where a point is drawn (on that line).

We can thus take advantage of the Python library \texttt{sklearn's datasets.load_digits()} training dataset for digits classification where each datapoint is a 8x8 image of a digit (we also transform the standard values 0 to 16 to a binary 0/1).

Thus for MNIST we use 8x8 images with binary pixel values (1 for black and 0 for white) which come at input as one-byte unsigned integer arrays of length 8: the one-byte translates to integers in the range $[0,\ldots, 255]$.

Here is the code that we add to \texttt{dsl/impl.py}:

```python
from sklearn.datasets import load_digits
from sklearn.ensemble import RandomForestClassifier
import numpy as np

def bin(n):
    if n<8:
        return 0
    else:
        return 1

def bin2dec(a):
    r=0
    for i in range(8):
        r+=a[i]*(2**i)
    return r

digits = load_digits()
data=digits.data
labels=digits.target
m=data.shape[0]
n=data.shape[1]

for i in range(m):
    for j in range(n):
        data[i][j]=bin(data[i][j])

data=np.reshape(data,(m,8,8))
d=[[0 for x in range(8)] for y in range(m)]

for i in range(m):
    for j in range(8):
        d[i][j]=bin2dec(data[i][j])

clf_rf = RandomForestClassifier()
```

clf_rf.fit(d, labels)

def mnist(tx):
    if len(tx)! = 8:
        return 10
    for k in range(8):
        if tx[k]<0 or tx[k]>255:
            return 10
    print("predict BEGIN")
    y_pred_rf = clf_rf.predict([tx])
    print("predict END")
    return int(y_pred_rf[0])

In the file dsl/impl.py we also add the following line in the section outlined by "# first-order functions":

MNIST = Function('MNIST', mnist, LIST, INT)

In the file dsl/constraint.py we also need to replace

elif f in [impl.MINIMUM, impl.MAXIMUM]:
    # list constrained to int constraint
    return [ListConstraint(int_constraints=[constraint] * L)]

with (just add 'impl.MNIST' to the list)

elif f in [impl.MINIMUM, impl.MAXIMUM, impl.MNIST]:
    # list constrained to int constraint
    return [ListConstraint(int_constraints=[constraint] * L)]

We only need to generate DSL programs of length at most 2, as our target is a program of length 1 (which simply applies mnist on its LIST input to return an INT). After training the two networks on the set of generated programs, we run scripts/gen_programs.py on the following test set of ten correspondences of label (one of 0,...,9) to image (array of 8 integers from 0 to 255):

{"examples": [{"inputs": [24, 60, 100, 100, 100, 36, 52, 24],
"output": 0}, {"inputs": [24, 56, 24, 28, 24, 24, 24, 56],
"output": 1}, {"inputs": [48, 56, 60, 48, 28, 14, 60, 112],
"output": 2}, {"inputs": [24, 22, 24, 24, 48, 96, 100, 56],
"output": 3}, {"inputs": [16, 16, 8, 104, 44, 60, 48, 16],
"output": 4}, {"inputs": [12, 60, 60, 28, 32, 96, 48, 60],
"output": 5}, {"inputs": [24, 24, 12, 12, 12, 60, 120, 56],
"output": 6}, {"inputs": [120, 96, 48, 60, 28, 8, 12, 4],
"output": 7}, {"inputs": [28, 60, 44, 56, 24, 60, 100, 60],
"output": 8}, {"inputs": [12, 60, 60, 52, 60, 96, 48, 28],
"output": 9}]

It is sufficient to only search for programs of length 1 and we quickly (a few seconds) obtain the following DSL program:

{"result": "LIST[MNIST,0]", "num_steps": 27, "time": 2.6361,
"beam_size": 200, "num_invalid": 3, "width": 20}
4 Extension with ramification instructions

Since the DSL of DeepCoder/PCCoder is essentially functional, in order to add the ramification (test) instruction If-Then-Else we had to consider its functional versions IFI and IFL for types Int and List respectively.

The test value is of type Bool and is obtained as function of an Int which in the DSL can be one of the three comparisons to 0 or an even/odd test:

\[
\begin{align*}
\text{EQ0} &= \text{Function}(\text{'=0'}, \text{eqZero}, \text{INT}, \text{BOOL}) \\
\text{GT0} &= \text{Function}(\text{>'0'}, \text{gtZero}, \text{INT}, \text{BOOL}) \\
\text{LT0} &= \text{Function}(\text{'<0'}, \text{ltZero}, \text{INT}, \text{BOOL}) \\
\text{EVEN} &= \text{Function}(\text{'EVEN'}, \text{isEven}, \text{INT}, \text{BOOL}) \\
\text{ODD} &= \text{Function}(\text{'ODD'}, \text{isOdd}, \text{INT}, \text{BOOL})
\end{align*}
\]

Notice that EQ0 was not part of the original DSL, we added it for increasing the expressivity of the language. The Python functions are defined as expected (but not using lambdas as in (Zohar and Wolf, 2018a), due to technical problems)

```python
def eqZero(x): return bool(x==0)
def gtZero(x): return bool(x>0)
def ltZero(x): return bool(x<0)
def isEven(x): return bool(x%2==0)
def isOdd(x): return bool(x%2==1)
```

We present the steps of operation of the PCCoder implementation (Zohar and Wolf, 2018b). First a sufficiently large training set is generated (and eventually also a smaller test set) with the option of loading a cache of previously generated training set (of programs of smaller maximal length).

```
python -m scripts.gen_programs --num_train=100000 --num_test=500 --train_output_path=train_dataset --test_output_path=test_dataset --max_train_len=12 --test_lengths="5 9" --num_workers=20
```

Here num_train is the raw number of programs generated before eliminating equivalent programs, num_test is the number of test programs for each length given to test_lengths; num_workers is the number of processes tasked to concurrently execute the workload, train_dataset is the file name of the train dataset and test_dataset is the file name of the test dataset. Also max_train_len is the maximal length of a generated program and there is also the optional parameter cache that gives the file name of a previously generated train dataset. The script will first find the maximal length of a program from the cache database and proceed with further generation only if this is strictly lower than max_train_len.

The parameter num_train should not be larger than the number of all possible raw generated programs and therefore has to be fixed for small max_train_len values such as 1 and 2. It is possible to find the maximal values for 1 and 2 by running the script with a large num_train and noting the number of raw programs generated before the script stops, e.g., the following line is written in the preamble of scripts/gen_programs.py for the DSL without IFI and IFL

```
KNOWN_TRAIN_SIZES = {1: 44, 2: 2561}
```

whereas for the richer DSL with IFI and IFL we have more possibilities:
KNOWN_TRAIN_SIZES = {1: 123, 2: 15000}

Already for max_train_len=3 many more programs of length 3 can be generated in the richer DSL; note that it is recommended to include virtually all programs of length 3 in the training set for an improved accuracy of the trained network.

By testing we established that num_train=100000 for the original DSL that ships with PCCoder and num_train=300000 for the DSL with IFI and IFL:

```python
python -m scripts.gen_programs --num_train=300000
--train_output_path=tt5nif_3 --test_output_path=tt5test
--max_train_len=3 --num_workers=20 --cache=tt5nif_2
Loading program cache... 6628\6629
Generating programs of length 3 (current dataset size: 6629)
Generating programs... 300000\300000
Generating examples... 298578\300082 (remaining programs: 267583)
Discarding identical programs... 267393\267577
Finished generation. Total programs: 90214
Writing 90214 train programs to tt5nif_3

The script thus generates (after more than 2 hours) a number of 90214 program examples of length at most 3 in the extended DSL. We proceed to further generate program examples of length at most 5, raising the cap of raw generated programs to 600000:

```python
python -m scripts.gen_programs --num_train=600000
--train_output_path=tt5nif_5 --test_output_path=tt5test
--max_train_len=5 --num_workers=20 --cache=tt5nif_3
Loading program cache... 90213\90214
Generating programs of length 4 (current dataset size: 90214)
Generating programs... 600100\600100
Generating examples... 597900\600446 (remaining programs: 483158)
Discarding identical programs... 482731\483104
Generating programs of length 5 (current dataset size: 158177)
Generating programs... 600100\600100
Generating examples... 596906\601198 (remaining programs: 388298)
Discarding identical programs... 387830\388043
Finished generation. Total programs: 174958
Removed 2525 programs
Writing 172433 train programs to tt5nif_5

Thus (again after more than 2 hours) the script generates another 67963 program examples of length 4 and another 14256 program examples of length 5, to a total of 172433 programs examples of length at most 5.

In comparison, for the original DSL it takes at least 4 hours to generate the set of 42730 program examples of length at most 3; we here had to opt for the smaller 100000 cap since it was hardly attained due to the less expressive (original) DSL.
Generating programs of length 3 (current dataset size: 1586)
Generating programs... 100000\100000
Generating examples... 99308\100013 (remaining programs: 80603)
Discarding identical programs... 80411\80592
Finished generation. Total programs: 42730
Writing 42730 train programs to t5nif_3

hence the size of the training set is slightly less than half the one for the extended DSL. Going further for program examples of length at most 5 we get

```bash
python -m scripts.gen_programs --num_train=150000
--train_output_path=t5nif_5 --test_output_path=t5test
--max_train_len=5 --num_workers=20 --cache=t5nif_3
Loading program cache... 42729\42730
Generating programs of length 4 (current dataset size: 42730)
Generating programs... 150100\150100
Generating examples... 149123\150180 (remaining programs: 116402)
Discarding identical programs... 116276\116375
Generating programs of length 5 (current dataset size: 72480)
Generating programs... 150100\150100
Generating examples... 149206\150289 (remaining programs: 80598)
Discarding identical programs... 80453\80487
Finished generation. Total programs: 80494
Removed 423 programs
Writing 80071 train programs to t5nif_5

hence a set of 80071 train programs, slightly less than half the number for the extended DSL (adding 29750 of length 4 and 7591 of length 5). By raising the cap of num_train to 200000 we get 95734 train programs (adding 42068 of length 4 and 10936 of length 5). It is important not to raise the cap too much in order to allow the generation of programs of longer length, as the generation script cannot produce more than a bit over 200000 train programs altogether.

So if one is interested in programs of smaller length then it's ok to raise the cap as much as possible, but otherwise it's better to proceed gradually.

The next step is to train a network from the generated training set, via

```bash
python -m scripts.train dataset model
```

where model is the prefix name of the model file (a file model_i is saved after each training epoch i) and dataset is the previously generated training dataset, e.g., t5nif_5 for the original DSL or tt5nif_5 for the extended DSL. The number of epochs is given by a parameter num_epochs from the preamble of scripts/train.py which by default is 40.

For the original DSL the training of m5 from t5nif_5 takes less than 4 minutes per epoch, hence roughly two hours to get m5. 39. For the extended DSL the training of mm5 from tt5nif_5 takes 7 minutes per epoch, hence four hours to get mm5. 39.

At last we can proceed to test the program synthesis component, via

```bash
python -m scripts.solve_problems dataset result model 60 5
--num_workers=8
```

Here dataset is a file of inputs-output pairs, one for each line representing problems to solve, given a timeout in seconds (here 60) and the maximal length of the
sought program (here 5). The script will display the number of problems that it could solve and the number of those who failed to be solved (by the timeout). At the end it will give the number and the list of actual programs in the result file.

We thus obtain, for the original DSL

```
python -m scripts.solve_problems t5test_6 res-test-6
m5.39 3000 6 --num_workers=40
Solving problems... 100 (failed: 5)
Solved: 94\100: 94.0%
```

meaning that programs were synthesized for 94 out of 100 sets of five inputs-output pairs for test programs of length 6, in one case the timeout of 3000 seconds was overpassed and for 5 sets the script directly failed to produce a program.

When given test sets of programs of length at most 4 the success rate was 99%.

The generalization capacity of this program synthesis method is illustrated when the network trained on programs of length at most 5 yields a success rate of over 70% on sets of test programs of length 8 (in this case an astounding 80%):

```
python -m scripts.solve_problems t5test_8 res-test-8
m5.39 2000 8 --num_workers=40
Solving problems... 100 (failed: 19)
Solved: 80\100: 80.0%
```

Even more, for a randomly generated test set of programs of length 14 the success rate was of 50%. In the case of the extended DSL we found by similar experiments that same (minimal) percentages hold for the success rate, namely at least 99% for programs of length at most 5, at least 90% for programs of length 6, at least 70% for programs of length 8 and \approx 50% for programs of length at most 14.

## 5 Conclusion

The work of (Balog et al., 2017) brings a novel approach to program synthesis from inputs-output pairs, also called programming-by-example (PBE) in that it uses a neural network to guide the search for programs compatible with the input set of inputs-output examples. The authors manage to synthesize programs of length at most 5 in a DSL that satisfy sets of 5 examples and their implementation is feasible for programs of length at most 8.

They use a trained neural network to predict an order on the program space and show how to use it to guide search-based techniques that are common in the programming languages community (enumerative search and SMT-based solver). They thus bring a neural-guided solution to the Inductive Program Synthesis (IPS) problem. While the approach of Balog et al. works for short programs, the number of possible solutions grows exponentially with program length, thus rendering the identification of the solution based on global properties infeasible.

The work of (Zohar and Wolf, 2018a) brings a step-wise approach to the program synthesis problem. Given the current state, their neural network directly predicts the next statement, including both the function (operator) and parameters (operands). They perform a beam search based on the network’s predictions, reapplying the neural network at each step. The more accurate the neural network, the less programs one needs to include in the search before identifying the correct solution. They also train a second network to predict the variables that are to be
discarded, as the number of variables increases with the program’s length and some of them may no longer be in use. Training the new network serves as an auxiliary task that improves the generalization of the statement prediction network.

Both (Balog et al., 2017) and (Zohar and Wolf, 2018a) generate the train and test data in the same manner. First, generate random programs from the DSL. Then, prune away programs that contain redundant variables, and programs for which an equivalent program (possibly shorter) already exists in the dataset. Equivalence is approximated by identical behavior on a set of inputs-output examples. Valid inputs for the programs are generated by bounding their output value to the DSL’s predetermined range and then propagating these constraints backward through the program.

We successfully proved that the (Zohar and Wolf, 2018a) implementation can be extended to include symbols for branching instructions that can be added to the DSL language with only a linear increase of the complexity of program search, but maintaining the accuracy of the search procedure.

We also extended the DSL language of DeepCoder/PCCoder with symbols for more complex functions for which we have a (Python) implementation and saw whether the 1-instruction programs for such functions can be deduced by the learning algorithm based on the two neural networks of PCCoder from limited sets of inputs-output correspondences.

We obtained a genuinely positive result for the case of a complex MNIST classification function.

6 Future work

We can identify three directions for future research concerning synthesis of programs from inputs-output examples. First the DSL language may be extended with constructs allowing for cycling commands such as repeat; here we prefer the variant of adding recursion to the language, by first allowing subroutines and then recursive procedure calls. For this we can get inspiration from the recent paper (Cai et al., 2017) (see also (Chen et al., 2019)) that achieved results in synthesizing complex sorting algorithms in the Neural Programming Architecture.

The second direction concerns experiments with different neural network topologies for the training part. So far we only used the PCCoder (Zohar and Wolf, 2018b) Dense network with a number of layers given as programmable parameter. Originally 10 layers were used in (Zohar and Wolf, 2018b) but we obtained the same results with 5 layers and half the original output_size and growth_size parameters. Different topologies may bring different results in terms of accuracy and generalizability.

Last but not least, a third direction is concerned with different program search algorithms. In (Zohar and Wolf, 2018b) beam search is used by default and Depth-First search is provided as alternative via the search_method parameter for the solve_problems script. Recent work by Safari (Safari, 2019) goes exactly in this direction, with preliminary results indicating an increase in the speed of program search.
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