
PROGRAM INDUCTION USING NEURAL PROGRAM-INTERPRETER

NOVEL APPLICATION

Souradeepta Biswas
Department of Computer Science
Syracuse University
sobiswas@syr.edu

Ritesh Nair
Department of Computer Science
Syracuse University
rgnair@syr.edu

Sanman Yadav
Applied Data Science
School of Information Studies
Syracuse University
smyadav@syr.edu

ABSTRACT

Our motivation to work on Neural Program-Interpreter (NPI) has been because it can learn programs in very dissimilar environments with different affordances. In the context of sorting, the authors showed that NPI exhibits very strong generalization in comparison to sequence-to-sequence LSTMs. They discuss how a trained Neural Program-Interpreter with a xed core can continue to learn new programs without forgetting already learned programs. We are attempting to use this architecture to teach the NPI how to program Merge Sort, Arithmetic Question Answering and Card Matching. Our estimation is that the Neural network will be able to train on our generated datasets with their execution traces to be able to solve the three tasks with low loss value. We see that the NPI is able to solve addition and card matching problems with high accuracy. But we face problems when it comes to more complex tasks like merge sort. Developing environment for a recursive solution proves to be challenging.

Keywords Neural Program Interpreter(NPI) · Long Short Term Memory(LSTM) · Merge Sort · Card Matching · Arithmetic Answering(Addition)

1 Introduction

Training neural networks to synthesize robust programs from a small number of examples is a challenging task. The space of possible programs is extremely large, and composing a program that performs robustly on the infinite space of possible inputs is difficult—in part because it is impractical to obtain enough training examples to easily disambiguate amongst all possible programs. Nevertheless, we would like the model to quickly learn to represent the right semantics of the underlying program from a small number of training examples, not an exhaustive number of them[1]. For this the authors propose the architecture neural programmer-interpreter(NPI) which is a recurrent and compositional neural network that learns to represent and execute programs. In NPI, the core module is an LSTM-based sequence model that takes as input a learnable program embedding, program arguments passed on by the calling program, and a feature representation of the environment. The output of the core module is a key indicating what program to call next, arguments for the following program and a flag indicating whether the program should terminate. In addition to the recurrent core, the NPI architecture includes a learnable key-value memory of program embeddings. This program-memory is essential for learning and re-using programs in a continual manner.[2]. For our project we implement Neural Programmer-Interpreter (NPI) to solve three problems. To solve Merge Sort, Arithmetic Question Answering and Card Matching. This application falls under novel application, where in we use the existing architecture of NPI and solve the above mentioned three tasks. We chose these tasks since these tasks were solved on other neural architectures and we wanted to see if NPI would be able to solve this. Our code can be found at [11]

2 Methods

This architecture sub-section focuses on the NPI architecture in depth. Plus this also focuses on the architecture for the 3 novel tasks. The experimental tasks subsection focuses on the novel tasks in depth and shed a light on the data-set used for the project.

2.1 Architecture

The NPI core is a long short-term memory (LSTM) network that acts as a router between programs conditioned on the current state observation and previous hidden unit states. At each time step, the core module can select another program to invoke using content-based addressing. It emits the probability of ending the current program with a single binary unit. If this probability is over threshold, control is returned to the caller by popping the caller's LSTM hidden units and program embedding off of a program call stack and resuming execution in this context.

LSTM's basic unit is called a memory cell. Within each memory cell, there is a linear unit with a fixed-weight self-connection. This enforces constant, non exploding, non-vanishing error flow within the memory cell. A multiplicative input gate unit learns to protect the constant error flow within the memory cell from perturbation by irrelevant inputs. Likewise, a multiplicative output gate unit learns to protect other units from perturbation by currently irrelevant memory contents . stored in the memory cell. The gates learn-to open and close access to constant error flow. Why is constant error flow important? For instance, with conventional "back-propagation through time", error signals "flowing backwards in time" tend to vanish: the temporal evolution of the back-propagated error exponentially depends on the size of the weights.[8]

Our architecture also consists of following:

- Program Termination Network: Feed-Forward Network (fend), takes LSTM Controller hidden state h_t and outputs a probability of terminating execution.
- Subroutine Lookup Network: Feed-Forward Network (fprog), takes LSTM Controller hidden state h_t and outputs a key embedding k_t to look up next subroutine to be called.
- Argument Networks: Feed-Forward Networks (farg), takes LSTM Controller hidden state h_t and outputs subroutine arguments $a(t + 1)$.

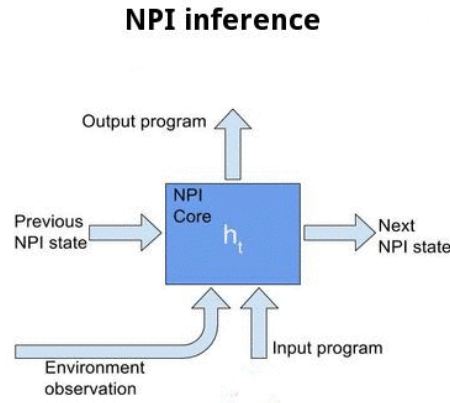


Figure 1: NPI Architecture

The training procedure consisted of Adam optimizer and Stochastic Gradient Descent(SGD). The Adam optimization algorithm is an extension to stochastic gradient descent that has recently seen broader adoption for deep learning applications in computer vision and natural language processing. Adam is an optimization algorithm that can be used instead of the classical stochastic gradient descent procedure to update network weights iteratively based on training data. In gradient descent, a batch is the total number of examples you use to calculate the gradient in a single iteration. So far, we've assumed that the batch has been the entire data set. Stochastic gradient descent (SGD) takes this idea to the extreme—it uses only a single example (a batch size of 1) per iteration.

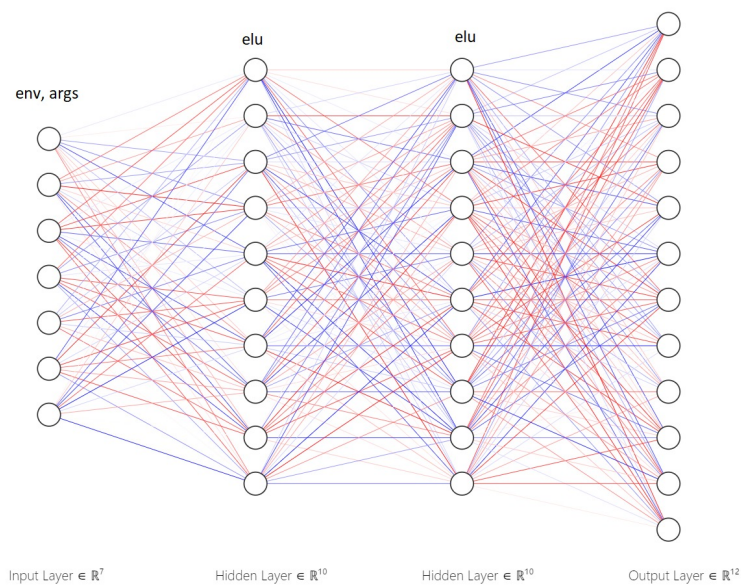


Figure 2: Environment Encoder Network

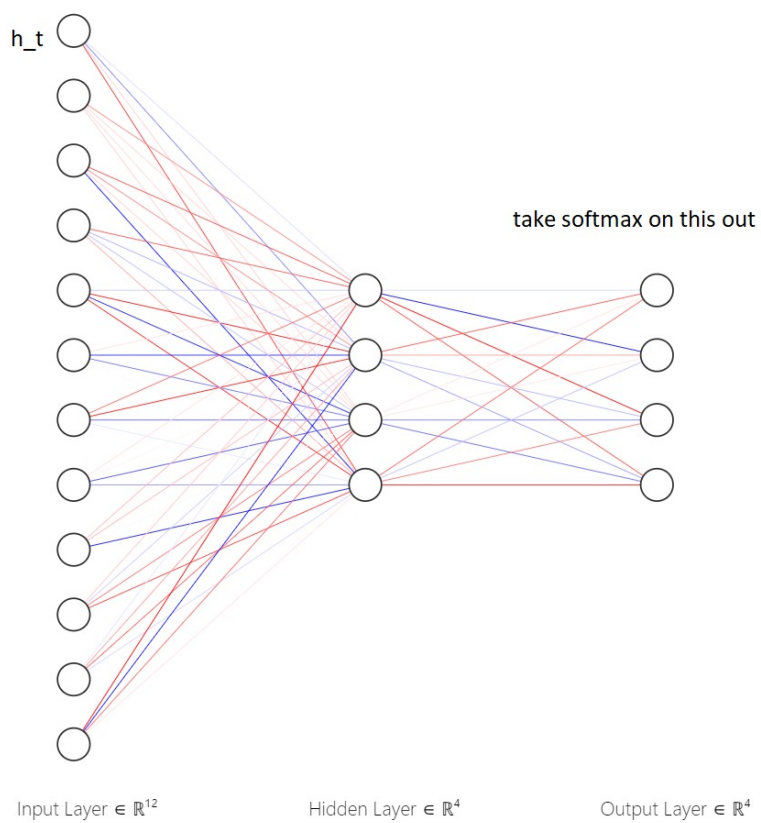


Figure 3: Program Encoder Network

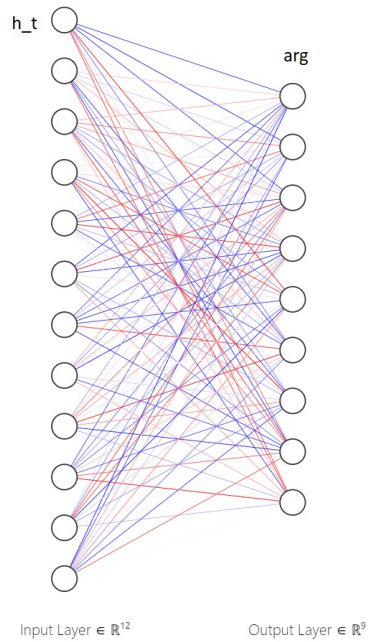


Figure 4: Feed Forward Argument Network

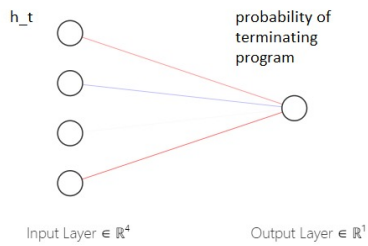


Figure 5: Program Termination Network

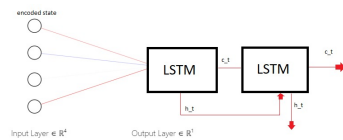


Figure 6: Neural Programmer-Interpreter Core

Layer (type)	Output Shape	Param #
state_input (InputLayer)	(1, 70)	0
dense_1 (Dense)	(1, 100)	7100
dense_2 (Dense)	(1, 100)	10100
encoded_state (Dense)	(1, 128)	12928
Total params: 30,128		
Trainable params: 30,128		
Non-trainable params: 0		

Figure 7: State Encoder

Layer (type)	Output Shape	Param #
lstm_input (InputLayer)	(1, 1, 129)	0
lstm_1 (LSTM)	(1, 1, 256)	395264
final_lstm_state (LSTM)	(1, 256)	525312
dense_precitions (Dense)	(1, 256)	65792
Total params: 986,368		
Trainable params: 986,368		
Non-trainable params: 0		

Figure 8: NPI Core

2.2 Experimental Tasks

In this section we will go in depth of the three tasks that have been mention. We will talk about the tasks it self, some example of how the input and output of the task should look like and about the dataset used for the tasks.

Addition - Sanman Yadav In [2] the author discuss the capability of NPI to perform grade-school addition algorithm. However, in the Neural Programmer paper experiments show the Neural Programmer to give results for arithmetic in question-answer format. We would like to train NPI to learn a program which can answer such arithmetic questions like addition. For the scope of the project we are only focusing on the NPI’s ability to perform basic addition of two numbers. As the digit size goes on increasing the complexity of addition also increases so here we are only focusing on 2 to 3 digit addition.

Table 1: Addition Example

Input		Output
Number1	Number2	
9	9	18
22	8	30
21	21	42

Merge Sort - Souradeepta Biswas In [2] the authors demonstrate how they train NPI to program sorting using bubble sort. We plan to increase the complexity of this task and train NPI to learn Merge Sort. Merge Sort is a sorting algorithm, which is commonly used in computer science. Merge Sort is a divide and conquer algorithm. It works by recursively breaking down a problem into two or more sub-problems of the same or related type, until these become simple enough to be solved directly. The solutions to the sub-problems are then combined to give a solution to the original problem. So Merge Sort first divides the array into equal halves and then combines them in a sorted manner. Steps of Merge Sort: 1. If it is only one element in the list it is already sorted, return. 2. Divide the list recursively into two halves until it can no more be divided. 3. Merge the smaller lists into new list in sorted order.

Card Matching - Ritesh Nair In Engineering neural systems for high-level problem solving, the authors demonstrate how their neural framework GALIS solves the Card Matching problem. In similar veins, it would be interesting to see how the NPI can be trained to program a pattern matching algorithm for Card Matching.

3 Results

3.1 Addition - Sanman Yadav

We were able to train the model to correctly give us the addition of two numbers of variable size.

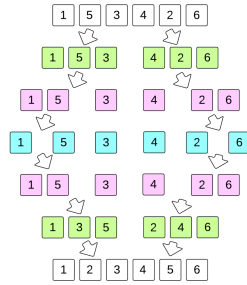


Figure 9: Merge Sort Example

3.1.1 Errors

3.2 Merge Sort - Souradeepta Biswas

Our execution trace was written but development of the environment was challenging.

3.3 Card Matching - Ritesh Nair

We were able to train the model to correctly match two suits of cards.

```

WTF_Arch_X86_CWypackages\WTFproject\WTF-python_main.py
Installing C++ Runtime Matching Code:
C:\Users\user\AppData\Local\Temp\WTF_Arch_X86\wtf_packages\tensorflow\python\wtf_packages\variable_ops.py:15: colocate_with (from tensorflow
Instructions for updating:
Instructions tend to be automatically by place.
Installing WTF Model:
C:\Users\user\AppData\Local\Temp\WTF_Arch_X86\wtf_packages\tensorflow\python\wtf_packages.py:306: io_to_string (from tensorflow.python.ops.mat
Instructions for updating:
C++ test data:
2018-05-08 03:58:03.92510: I tensorflow/core/platform/cpu_feature_guard.cc:141 You GPU supports instructions that tensorflow binary was not compiled to use: AVX2
Epoch 01 Step 001 Default Step Loss 0.569792, Argument Step Loss 0.566679, Argument Step 0.000000, Arg 0.333333, Arg 0.466667, Arg 0.466667, Arg 0.466667
Epoch 01 Step 001 Default Step Loss 0.567612, Argument Step Loss 0.4132040, Temp: 0.933333, Arg 0.066667, Arg 0.833333, Arg 0.833333, Arg 1.0
Epoch 01 Step 001 Default Step Loss 0.568656, Argument Step Loss 0.406498, Temp: 0.933333, Arg 0.066667, Arg 1.0, Arg 1.0, Arg 1.0, Arg 1.0, Arg 1.0
Epoch 01 Step 001 Default Step Loss 0.568656, Argument Step Loss 0.547477, Temp: 0.933333, Arg 0.066667, Arg 1.0, Arg 1.0, Arg 1.0, Arg 1.0, Arg 1.0
Epoch 01 Step 004 Default Step Loss 0.483044, Argument Step Loss 0.502087, Temp: 0.933333, Arg 0.200000, Arg 0.750000, Arg 0.750000, Arg 0.750000, Arg 1.0
Epoch 01 Step 004 Default Step Loss 0.483044, Argument Step Loss 0.496498, Temp: 0.933333, Arg 0.200000, Arg 0.750000, Arg 0.750000, Arg 0.750000, Arg 1.0
Epoch 01 Step 004 Default Step Loss 0.483044, Argument Step Loss 0.268880, Temp: 0.933333, Arg 0.200000, Arg 0.250000, Arg 0.250000, Arg 0.250000, Arg 1.0
Epoch 01 Step 004 Default Step Loss 0.483044, Argument Step Loss 0.268880, Temp: 0.933333, Arg 0.200000, Arg 0.250000, Arg 0.250000, Arg 0.250000, Arg 1.0
Epoch 01 Step 009 Default Step Loss 0.220901, Argument Step Loss 0.2664430, Temp: 0.933333, Arg 0.200000, Arg 0.833333, Arg 0.833333, Arg 0.833333, Arg 1.0
Epoch 01 Step 009 Default Step Loss 0.220901, Argument Step Loss 0.2664430, Temp: 0.933333, Arg 0.200000, Arg 0.833333, Arg 0.833333, Arg 0.833333, Arg 1.0
Epoch 01 Step 010 Default Step Loss 0.203889, Argument Step Loss 0.185716, Temp: 0.933333, Arg 0.200000, Arg 0.750000, Arg 0.750000, Arg 0.750000, Arg 1.0
Epoch 01 Step 010 Default Step Loss 0.203889, Argument Step Loss 0.185716, Temp: 0.933333, Arg 0.200000, Arg 0.750000, Arg 0.750000, Arg 0.750000, Arg 1.0
Epoch 01 Step 012 Default Step Loss 0.197362, Argument Step Loss 0.1495053, Temp: 0.933333, Arg 0.200000, Arg 0.816667, Arg 0.816667, Arg 0.816667, Arg 1.0
Epoch 01 Step 012 Default Step Loss 0.197362, Argument Step Loss 0.1495053, Temp: 0.933333, Arg 0.200000, Arg 0.816667, Arg 0.816667, Arg 0.816667, Arg 1.0
Epoch 01 Step 014 Default Step Loss 0.190785, Argument Step Loss 0.1491121, Temp: 0.933333, Arg 0.200000, Arg 1.000000, Arg 1.000000, Arg 1.000000, Arg 1.0
Epoch 01 Step 014 Default Step Loss 0.190785, Argument Step Loss 0.1491121, Temp: 0.933333, Arg 0.200000, Arg 1.000000, Arg 1.000000, Arg 1.000000, Arg 1.0
Epoch 01 Step 016 Default Step Loss 0.190478, Argument Step Loss 0.127837, Temp: 0.933333, Arg 0.400000, Arg 0.816667, Arg 0.816667, Arg 0.816667, Arg 1.0
Epoch 01 Step 016 Default Step Loss 0.190478, Argument Step Loss 0.127837, Temp: 0.933333, Arg 0.400000, Arg 0.816667, Arg 0.816667, Arg 0.816667, Arg 1.0
Epoch 01 Step 018 Default Step Loss 0.189444, Argument Step Loss 0.098613, Temp: 0.933333, Arg 0.400000, Arg 0.816667, Arg 0.816667, Arg 0.816667, Arg 1.0
Epoch 01 Step 018 Default Step Loss 0.189444, Argument Step Loss 0.098613, Temp: 0.933333, Arg 0.400000, Arg 0.816667, Arg 0.816667, Arg 0.816667, Arg 1.0
Epoch 01 Step 020 Default Step Loss 0.184604, Argument Step Loss 0.0952258, Temp: 0.933333, Arg 0.400000, Arg 0.816667, Arg 0.816667, Arg 0.816667, Arg 1.0
Epoch 01 Step 020 Default Step Loss 0.184604, Argument Step Loss 0.0952258, Temp: 0.933333, Arg 0.400000, Arg 0.816667, Arg 0.816667, Arg 0.816667, Arg 1.0
Epoch 01 Step 022 Default Step Loss 0.181035, Argument Step Loss 0.084646, Temp: 0.933333, Arg 0.400000, Arg 0.816667, Arg 0.816667, Arg 0.816667, Arg 1.0
Epoch 01 Step 022 Default Step Loss 0.177107, Argument Step Loss 0.080322, Temp: 0.933333, Arg 0.400000, Arg 1.000000, Arg 1.000000, Arg 1.000000, Arg 1.0
Epoch 01 Step 022 Default Step Loss 0.177107, Argument Step Loss 0.072787, Temp: 0.933333, Arg 0.400000, Arg 1.000000, Arg 1.000000, Arg 1.000000, Arg 1.0
Epoch 01 Step 023 Default Step Loss 0.170723, Argument Step Loss 0.733449, Temp: 0.933333, Arg 0.400000, Arg 0.816667, Arg 0.816667, Arg 0.816667, Arg 1.0
Epoch 01 Step 023 Default Step Loss 0.170723, Argument Step Loss 0.701392, Temp: 0.933333, Arg 0.400000, Arg 0.816667, Arg 0.816667, Arg 0.816667, Arg 1.0
Epoch 01 Step 027 Default Step Loss 0.168383, Argument Step Loss 0.679470, Temp: 0.933333, Arg 0.400000, Arg 1.000000, Arg 1.000000, Arg 1.000000, Arg 1.0
Epoch 01 Step 027 Default Step Loss 0.168383, Argument Step Loss 0.679470, Temp: 0.933333, Arg 0.400000, Arg 1.000000, Arg 1.000000, Arg 1.000000, Arg 1.0
Epoch 01 Step 029 Default Step Loss 0.163666, Argument Step Loss 0.633430, Temp: 0.933333, Arg 0.400000, Arg 1.000000, Arg 1.000000, Arg 1.000000, Arg 1.0
Epoch 01 Step 029 Default Step Loss 0.163666, Argument Step Loss 0.613255, Temp: 0.933333, Arg 0.400000, Arg 1.000000, Arg 1.000000, Arg 1.000000, Arg 1.0
Epoch 01 Step 031 Default Step Loss 0.164021, Argument Step Loss 0.601139, Temp: 0.933333, Arg 0.400000, Arg 0.816667, Arg 0.816667, Arg 0.816667, Arg 1.0
Epoch 01 Step 031 Default Step Loss 0.164021, Argument Step Loss 0.601139, Temp: 0.933333, Arg 0.400000, Arg 0.816667, Arg 0.816667, Arg 0.816667, Arg 1.0
Epoch 01 Step 033 Default Step Loss 0.157616, Argument Step Loss 0.557729, Temp: 0.933333, Arg 0.400000, Arg 1.000000, Arg 1.000000, Arg 1.000000, Arg 1.0

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Figure 10: Model Running Logs 01

[illegible]

Figure 11: Model Running Logs 02

Epoch	Step	Size	Unit	Default	Step Loss	Loss	0.000001	Argument	Step Loss	Loss	0.000001	Term	1.000000	VRatio	1.000000	Arg1	1.000000	Arg2	1.000000	Arg3	1.000000	Arg4	1.000000	Arg5	1.000000	Arg6	1.000000	Arg7	1.000000	Arg8	1.000000	Arg9	1.000000	Arg10	1.000000	Arg11	1.000000	Arg12	1.000000	Arg13	1.000000	Arg14	1.000000	Arg15	1.000000	Arg16	1.000000	Arg17	1.000000	Arg18	1.000000	Arg19	1.000000	Arg20	1.000000	Arg21	1.000000	Arg22	1.000000	Arg23	1.000000	Arg24	1.000000	Arg25	1.000000	Arg26	1.000000	Arg27	1.000000	Arg28	1.000000	Arg29	1.000000	Arg30	1.000000	Arg31	1.000000	Arg32	1.000000	Arg33	1.000000	Arg34	1.000000	Arg35	1.000000	Arg36	1.000000	Arg37	1.000000	Arg38	1.000000	Arg39	1.000000	Arg40	1.000000	Arg41	1.000000	Arg42	1.000000	Arg43	1.000000	Arg44	1.000000	Arg45	1.000000	Arg46	1.000000	Arg47	1.000000	Arg48	1.000000	Arg49	1.000000	Arg50	1.000000	Arg51	1.000000	Arg52	1.000000	Arg53	1.000000	Arg54	1.000000	Arg55	1.000000	Arg56	1.000000	Arg57	1.000000	Arg58	1.000000	Arg59	1.000000	Arg60	1.000000	Arg61	1.000000	Arg62	1.000000	Arg63	1.000000	Arg64	1.000000	Arg65	1.000000	Arg66	1.000000	Arg67	1.000000	Arg68	1.000000	Arg69	1.000000	Arg70	1.000000	Arg71	1.000000	Arg72	1.000000	Arg73	1.000000	Arg74	1.000000	Arg75	1.000000	Arg76	1.000000	Arg77	1.000000	Arg78	1.000000	Arg79	1.000000	Arg80	1.000000	Arg81	1.000000	Arg82	1.000000	Arg83	1.000000	Arg84	1.000000	Arg85	1.000000	Arg86	1.000000	Arg87	1.000000	Arg88	1.000000	Arg89	1.000000	Arg90	1.000000	Arg91	1.000000	Arg92	1.000000	Arg93	1.000000	Arg94	1.000000	Arg95	1.000000	Arg96	1.000000	Arg97	1.000000	Arg98	1.000000	Arg99	1.000000	Arg100	1.000000	Arg101	1.000000	Arg102	1.000000	Arg103	1.000000	Arg104	1.000000	Arg105	1.000000	Arg106	1.000000	Arg107	1.000000	Arg108	1.000000	Arg109	1.000000	Arg110	1.000000	Arg111	1.000000	Arg112	1.000000	Arg113	1.000000	Arg114	1.000000	Arg115	1.000000	Arg116	1.000000	Arg117	1.000000	Arg118	1.000000	Arg119	1.000000	Arg120	1.000000	Arg121	1.000000	Arg122	1.000000	Arg123	1.000000	Arg124	1.000000	Arg125	1.000000	Arg126	1.000000	Arg127	1.000000	Arg128	1.000000	Arg129	1.000000	Arg130	1.000000	Arg131	1.000000	Arg132	1.000000	Arg133	1.000000	Arg134	1.000000	Arg135	1.000000	Arg136	1.000000	Arg137	1.000000	Arg138	1.000000	Arg139	1.000000	Arg140	1.000000	Arg141	1.000000	Arg142	1.000000	Arg143	1.000000	Arg144	1.000000	Arg145	1.000000	Arg146	1.000000	Arg147	1.000000	Arg148	1.000000	Arg149	1.000000	Arg150	1.000000	Arg151	1.000000	Arg152	1.000000	Arg153	1.000000	Arg154	1.000000	Arg155	1.000000	Arg156	1.000000	Arg157	1.000000	Arg158	1.000000	Arg159	1.000000	Arg160	1.000000	Arg161	1.000000	Arg162	1.000000	Arg163	1.000000	Arg164	1.000000	Arg165	1.000000	Arg166	1.000000	Arg167	1.000000	Arg168	1.000000	Arg169	1.000000	Arg170	1.000000	Arg171	1.000000	Arg172	1.000000	Arg173	1.000000	Arg174	1.000000	Arg175	1.000000	Arg176	1.000000	Arg177	1.000000	Arg178	1.000000	Arg179	1.000000	Arg180	1.000000	Arg181	1.000000	Arg182	1.000000	Arg183	1.000000	Arg184	1.000000	Arg185	1.0000
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Figure 12: Model Running Logs 03

Epoch	Step	1494 default	Step Loss	0.000000	Argument	Step Loss	0.000000	Term	1.000000	Frq	1.000000	Ad1	1.000000	Ad2	1.000000	Ad3	1.000000	Ad4	1.000000	Ad5	1.000000	Ad6	1.000000	Ad7	1.000000	Ad8	1.000000	Ad9	1.000000	Ad10	1.000000	Ad11	1.000000	Ad12	1.000000	Ad13	1.000000	Ad14	1.000000	Ad15	1.000000	Ad16	1.000000	Ad17	1.000000	Ad18	1.000000	Ad19	1.000000	Ad20	1.000000	Ad21	1.000000	Ad22	1.000000	Ad23	1.000000	Ad24	1.000000	Ad25	1.000000	Ad26	1.000000	Ad27	1.000000	Ad28	1.000000	Ad29	1.000000	Ad30	1.000000	Ad31	1.000000	Ad32	1.000000	Ad33	1.000000	Ad34	1.000000	Ad35	1.000000	Ad36	1.000000	Ad37	1.000000	Ad38	1.000000	Ad39	1.000000	Ad40	1.000000	Ad41	1.000000	Ad42	1.000000	Ad43	1.000000	Ad44	1.000000	Ad45	1.000000	Ad46	1.000000	Ad47	1.000000	Ad48	1.000000	Ad49	1.000000	Ad50	1.000000	Ad51	1.000000	Ad52	1.000000	Ad53	1.000000	Ad54	1.000000	Ad55	1.000000	Ad56	1.000000	Ad57	1.000000	Ad58	1.000000	Ad59	1.000000	Ad60	1.000000	Ad61	1.000000	Ad62	1.000000	Ad63	1.000000	Ad64	1.000000	Ad65	1.000000	Ad66	1.000000	Ad67	1.000000	Ad68	1.000000	Ad69	1.000000	Ad70	1.000000	Ad71	1.000000	Ad72	1.000000	Ad73	1.000000	Ad74	1.000000	Ad75	1.000000	Ad76	1.000000	Ad77	1.000000	Ad78	1.000000	Ad79	1.000000	Ad80	1.000000	Ad81	1.000000	Ad82	1.000000	Ad83	1.000000	Ad84	1.000000	Ad85	1.000000	Ad86	1.000000	Ad87	1.000000	Ad88	1.000000	Ad89	1.000000	Ad90	1.000000	Ad91	1.000000	Ad92	1.000000	Ad93	1.000000	Ad94	1.000000	Ad95	1.000000	Ad96	1.000000	Ad97	1.000000	Ad98	1.000000	Ad99	1.000000	Ad100	1.000000	Ad101	1.000000	Ad102	1.000000	Ad103	1.000000	Ad104	1.000000	Ad105	1.000000	Ad106	1.000000	Ad107	1.000000	Ad108	1.000000	Ad109	1.000000	Ad110	1.000000	Ad111	1.000000	Ad112	1.000000	Ad113	1.000000	Ad114	1.000000	Ad115	1.000000	Ad116	1.000000	Ad117	1.000000	Ad118	1.000000	Ad119	1.000000	Ad120	1.000000	Ad121	1.000000	Ad122	1.000000	Ad123	1.000000	Ad124	1.000000	Ad125	1.000000	Ad126	1.000000	Ad127	1.000000	Ad128	1.000000	Ad129	1.000000	Ad130	1.000000	Ad131	1.000000	Ad132	1.000000	Ad133	1.000000	Ad134	1.000000	Ad135	1.000000	Ad136	1.000000	Ad137	1.000000	Ad138	1.000000	Ad139	1.000000	Ad140	1.000000	Ad141	1.000000	Ad142	1.000000	Ad143	1.000000	Ad144	1.000000	Ad145	1.000000	Ad146	1.000000	Ad147	1.000000	Ad148	1.000000	Ad149	1.000000	Ad150	1.000000	Ad151	1.000000	Ad152	1.000000	Ad153	1.000000	Ad154	1.000000	Ad155	1.000000	Ad156	1.000000	Ad157	1.000000	Ad158	1.000000	Ad159	1.000000	Ad160	1.000000	Ad161	1.000000	Ad162	1.000000	Ad163	1.000000	Ad164	1.000000	Ad165	1.000000	Ad166	1.000000	Ad167	1.000000	Ad168	1.000000	Ad169	1.000000	Ad170	1.000000	Ad171	1.000000	Ad172	1.000000	Ad173	1.000000	Ad174	1.000000	Ad175	1.000000	Ad176	1.000000	Ad177	1.000000	Ad178	1.000000	Ad179	1.000000	Ad180	1.000000	Ad181	1.000000	Ad182	1.000000	Ad183	1.000000	Ad184	1.000000	Ad185	1.000000	Ad186	1.00
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Figure 13: Model Running Logs 04

4 Discussion

The main goal of the project was to tweak the NPI architecture to make it learn addition, merge sort and card matching. In this project we take an NPI architecture which had an LSTM as the core. Of the three mentioned tasks, addition and card matching were done successfully. The important results are summerized below.

The most challenging thing we had to deal with was making the NPI architecture understand what we were doing. In the beginning we were working on the simple problem of making the architecture understand how to do addition. But when it came to card matching we had to make different traces for it. Building totally different traces for the card matching problem was a different problem altogether. After making the traces for card matching we thought that the same architecture of the addition. But after trying seeing the training errors we came to an understanding that we again need to tweak the NPI architecture a bit. But the problem wasn't solved there, it wasn't easy to find the proper combination of traces and NPI architecture to get the testing error as low as possible. When we thought we were done with card matching, we had to face the problems of making the merge sort work. Figuring out the merge sort was a different problem altogether, because here the list size was not constant. So for different splits we had to write different splits. Then as the split lists were also of different sizes, this added to the complexity of building the traces. The traces it-self were the hardest part of this project. The addition task was the easiest of the three tasks and its were we had the most success.

4.1 Model performance

The execution traces executed successfully for all the tasks.

```

## Example 1 ##
### Card 1: 2 of spades , Card 2: 2 of spades ###

Card 1 : 022
Card 2 : 022
-----
Output : 000

Card 1 : 022
Card 2 : 022
-----
Output : 000

Card 1 : 022
Card 2 : 022
-----
Output : 000

{
  'card1': {'suit': 'spades', 'rank': '2'},
  'card2': {'suit': 'spades', 'rank': '2'},
  'traces': [
    (('CMP', 2), [], False),
    (('USUB1', 3), [], False),
    (('WRITE', 1), [0, 0], False),
    (('MOVE_PTR', 0), [0, 0], False),
    (('MOVE_PTR', 0), [1, 0], False),
    (('MOVE_PTR', 0), [2, 0], False),
    (('USUB1', 3), [], False),
    (('WRITE', 1), [0, 0], False),
    (('MOVE_PTR', 0), [0, 0], False),
    (('MOVE_PTR', 0), [1, 0], False),
    (('MOVE_PTR', 0), [2, 0], False),
    (('USUB1', 3), [], False),
    (('WRITE', 1), [0, 0], False),
    (('MOVE_PTR', 0), [0, 0], False),
    (('MOVE_PTR', 0), [1, 0], False),
    (('MOVE_PTR', 0), [2, 0], True)
  ]
}

```

Figure 14: Result 01

```

## Example 2 ##
### Card 1: 7 of diamonds , Card 2: 6 of diamonds ###

Card 1 : 074
Card 2 : 064
-----
Output : 000

Card 1 : 074
Card 2 : 064
-----
Output : 010

{
  'card1': {'suit': 'diamonds', 'rank': '7'},
  'card2': {'suit': 'diamonds', 'rank': '6'},
  'traces': [
    (('CMP', 2), [], False),
    (('USUB1', 3), [], False),
    (('WRITE', 1), [0, 0], False),
    (('MOVE_PTR', 0), [0, 0], False),
    (('MOVE_PTR', 0), [1, 0], False),
    (('MOVE_PTR', 0), [2, 0], False),
    (('USUB1', 3), [], False),
    (('WRITE', 1), [0, 1], False),
    (('MOVE_PTR', 0), [0, 0], False),
    (('MOVE_PTR', 0), [1, 0], False),
    (('MOVE_PTR', 0), [2, 0], True)
  ]
}

```

Figure 15: Result 02


```

## Example 3 ##
### Card 1: 9 of hearts , Card 2: A of clubs ###

Card 1 : 091
Card 2 : 013
-----
Output : 002

{
  'card1': {'suit': 'hearts', 'rank': '9'},
  'card2': {'suit': 'clubs', 'rank': 'A'},
  'traces': [
    (('CMP', 2), [], False),
    (('USUB1', 3), [], False),
    (('WRITE', 1), [0, 2], False),
    (('MOVE_PTR', 0), [0, 0], False),
    (('MOVE_PTR', 0), [1, 0], False),
    (('MOVE_PTR', 0), [2, 0], True)
  ]
}

```

Figure 16: Result 03

4.2 Ablation Studies

In this project we tried to do ablation on addition task. But due to the complexity of the architecture we were getting inconsistent results which did not conform to our understanding. Hence we did not continue with ablation.

4.3 Future work

If this project were to be continued in the future, following are some of the things we would give the highest priority:

- Building proper traces for Merge Sort.
- Tweaking the current NPI architecture for it to learn Merge Sort.
- In the beginning we thought that we will try a one hat fits all approach, ie, for the NPI architecture we wanted to have an generalized NPI to do all the three tasks in one architecture. So if this project was continued in the future, this is something we would like to work on the this aspect particularly.
- The card matching was done on a smaller scale, in future we want to do it on a larger scale so that that card matching is done on a bigger stack of cards.

5 Challenges

The first challenge we faced was with the libraries to use for building the NPI core. We started by building the core using vanilla Tensor flow. However, this initial attempt failed due to lack of knowledge with the library coupled with the complex nature of the architecture. We later tried to build the core using TFLearn but eventually settled with building the core using Keras. We have adapted our code based on [10]

The second challenge was compilation of the traces. We were able to come up with the traces for card pattern matching but as discussed earlier due to recursive nature of the merge sort we could not build its traces.

Finally, for the card pattern matching problem we were able to successfully train the model. However, we were not able to run our predictions on the training data set.

Given time and more familiarity with the helper libraries, we should be able to come up with a working prediction for the models.

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