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Quantum Semantic Textual Similarity for NISQ era

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Abstract of Bachelor's Thesis of Academic Year 2021

Quantum Semantic Textual Similarity for NISQ era

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Summary

Natural language processing research and applications have been advancing rapidly. Pre-trained models such as GPT-3 [3] and BERT [8] have achieved state-of-the-art results on different kinds of NLP tasks. But [23] pointed out that existing representation models encode more syntactic than semantic information. And these large-scale pre-trained models need huge computational resources on parameter training. On the other hand, quantum computer has advantages of their computational power which can reduce the computation complexity exponentially and provide higher dimensional space for word embedding which can improve the accuracy of the result. Recently, Cambridge Quantum Computing (CQC) has implemented experiments of question-answering tasks on quantum computer which shows the possibility that quantum computers can do well on Natural Language Processing (NLP), and possibly better than classical methods in the long term. This work explores the possibilities to use quantum computers and quantum-based language models for Sentence Similarity task. Sentence Similarity task takes an important role in Natural Language Understanding (NLU), and it can also improve the performance of machine translation and search. This work is based on the distributional compositional categorical (DisCoCat) semantics and python library lambeq which is developed for Quantum Natural Language Processing (QNLP) and created by [14]. The result shows this approach owns an acceptable accuracy and can be applied to any DisCoCat style model and the performance can be improved by future quantum hardware devices.

Keywords:

Quantum computing, Quantum natural language processing, Quantum machine learning

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Contents

1 Introduction **1**

1.1. Background 1

1.2. Research Contribution 1

1.3. Thesis Structure 2

2 Preliminary **3**

2.1. Quantum Computing 3

2.1.1 Quantum Circuit 3

2.1.2 ZX-calculus 4

2.1.3 Quantum machine learning: Parameterized Quantum Circuits 4

2.2. Natural Language Processing(NLP) 4

2.2.1 Computational Linguistics 5

2.2.2 Sentence Similarity Task 5

2.3. Quantum NLP(QNLP) 5

2.3.1 DisCoCat model of meaning 6

3 Related work **7**

3.1. Sentence Classification tasks with quantum computers 7

3.2. Machine Translation with quantum computers 7

4 Proposal **9**

4.1. Problem definition 9

4.2. Workflow 9

4.3. From sentence to quantum circuit 10

4.4. Parameterization 11

4.5. Training 11

5 Experiments and Evaluation **14**

5.1. Setup 14

5.2. Result and Evaluation 14

6 Conclusion and Future Works **18**

Acknowledgements **19**

References **20**

List of Figures

2.1 DisCoCat Diagram for ”He likes cat.” 6

4.1 Project components 9
4.2 QNLP pipline (source: Cambridge Quantum Computing, 2021 [14]) 10
4.3 Sample code for generating a quantum circuit 11
4.4 IQPAnsatz for ”He likes cat.” 12
4.5 Gate-based quantum circuit for the sentence ”He likes cat.” . . . 13

5.1 SPSA optimization result of GS2011 dataset on Qiskit's Aer simulator. 15
5.2 SPSA optimization result of KS2013-CoNLL dataset on Qiskit's Aer simulator. 16
5.3 IQPAnsatz for ”A plane is taking off” 17

List of Tables

2.1 Sample of Semantic Text Similarity Dataset 5

5.1 Details of experiment data sets(A:adjective,S:subject,V:verb,O:object). 14

Chapter 1

Introduction

1.1. Background

Recently, Cambridge Quantum Computing (CQC) has implemented experiments of question-answering task on quantum computer [18] which shows the possibility that quantum computers can do well on Natural Language Processing (NLP), and possibly better than classical methods in the long-term. Quantum computer has advantages of their computational power which can reduce the computation complexity exponentially and provide higher dimensional space for word embedding which can improve the accuracy of the result. Current leading quantum devices are known as Noisy Intermediate-Scale Quantum (NISQ)devices [21] which means that the performance could be affected by the noise and the number of qubits is in the range from 50 to a few hundred. Due to the limitation of NISQ devices, NLP tasks on quantum computers performs not as competitive as those on classic computers. But the development of quantum hardware is very fast which shows that developing general approach for NLP tasks on quantum devices at now is meaningful.

1.2. Research Contribution

This work explores the possibilities to use quantum computers and quantum based language models for Semantic Textual Similarity tasks.The result shows this approach has acceptable accuracy and can be applied to any DisCoCat style model. This research will helps machine translation task and search task on quantum computers.

1.3. Thesis Structure

The structure of this thesis is as follows. Background information about quantum computing is shown in Chapter 2.1, which explains basic knowledge about what is quantum computing and provides the basic knowledge and notations which is needed for understanding this work. Background information about classical NLP is shown in 2.2 and quantum NLP in 2.3. The related work of this thesis is summarized in chapter 3, In chapter 3, the related works of CQC's question-answering task based on DisCoCat diagram and machine translation experiment on quantum computers are listed which are the basis of the proposed method. Chapter 4 shows the proposal of this thesis which contains the problem definition, the workflow of this work. Chapter 5 shows the performance of the proposed approach on IBM's quantum simulator,where the performance of different length data set is compared in detail. Finally, Chapter 6 concludes this thesis and several future works are given.

Chapter 2

Preliminary

2.1. Quantum Computing

While classical computers use bits that can be either in state 0 or 1 and information is stored in binary, quantum computers use qubits, which carry physical properties that allow more powerful computational models. A simple example would be a spin-1/2 system of an electron. Such a system has two eigenstates, a qubit is a two level quantum system that assume states 0, 1 or a combination of both. In this manner, a pair of qubits can be in any quantum superposition of four states and n qubits will be in any superposition of 2^n states. Qubits also have vector representation which looks like:

$$|\psi\rangle = \alpha |0\rangle + \beta |1\rangle = \begin{pmatrix} \alpha \\ \beta \end{pmatrix}$$

with $\alpha, \beta \in \mathbb{C}$ and $|\alpha|^2 + |\beta|^2 = 1$. Measuring the state will get a 0 with probability $|\alpha|^2$ and a 1 with probability $|\beta|^2$.

2.1.1 Quantum Circuit

The quantum circuit is a quantum computation model which is similar to classical logic circuits. Quantum circuit maps quantum gates from left to right which also shows the computation order. These quantum gates are operators represented by unitary matrices.

2.1.2 ZX-calculus

ZX-calculus [16] is a graphical language that extracts the compositional structure of quantum circuits and represented it as ZX-diagrams. By following the rule sets of ZX-calculus we can rewrite ZX-diagrams. Due to ZX-calculus is good at T-count reduction and gate compilation, it can be used in quantum circuit optimization which aims to improve the performance by reducing the amounts of quantum gates.

2.1.3 Quantum machine learning: Parameterized Quantum Circuits

Currently,Parameterized Quantum Circuits(PQCs) is a general way which used as a quantum machine learning model [2]. The main approach is to convert the task into a variational optimization problem that can be solved by using hybrid systems of both quantum and classical hardware to find the optimal solutions. PQCs can reduce the requirement of quantum hardware so it is suitable for current NISQ devices. This hybrid algorithmic approach could solve NISQ algorithm such as*variational quantum eigensolver(VQE)* [20] and *Quantum Approximate Optimization Algorithm(QAOA)* [9] and performs well. Learning in this model means updating the parameters to reach the goal.

2.2. Natural Language Processing(NLP)

Natural language processing (NLP) is the artificial intelligence concerned with the interactions between computers and human language which aims to let computers to process and analyze natural language data. Nowadays, the mainstream NLP focuses on building pre-trained language models through large neural networks. Those models are trained on vast data sets such as the whole Wikipedia. The state-of-the-art models like BERT [8] or GPT-3 [3] are both follows this approach and it works very well for diverse kinds of NLP tasks (question and answering, machine translation, text generation etc.).

2.2.1 Computational Linguistics

Computational linguistics (CL) as a subdomain of artificial intelligence, aims to find out the laws of natural language, build calculation models, and finally allow computers to analyze, understand and process natural language. CL can be applied in various applications such as *speech recognition*,*machine translation* and *text generation*.

2.2.2 Sentence Similarity Task

Word-similarities are usually calculated through the cosine similarity. Semantic Textual Similarity benchmark [13] produced a general way to evaluate the performance of Sentence Similarity Task.The data set are pairs of sentences which labeled by hand from 0 to 5 shows the similarity of that pair of sentence.

Sentence 1	Sentence 2	Similarity scores by human hand
A man is dancing.	A man is talking.	0.6
A man is playing a guitar.	A girl is playing a guitar.	2.8
A man is playing the drums.	A man plays the drum	5.0

Table 2.1: Sample of Semantic Text Similarity Dataset

2.3. Quantum NLP(QNLP)

Quantum NLP can be understood as the conversion of classical NLP algorithms to quantum in order to be executed on a quantum computer, or by considering that the mathematics of the text structure is quantum-like. Quantum Natural Language Processing sees sentences as networks of words. Words are connected and combined to build the meaning of a sentence as a whole, and they are described as operators. This is opposed to how classical NLP sees sentences as just a structureless "bag of words" [11] containing the meanings of individual words, and words are considered to be vectors. In this work, we have followed the approach of considering that language can be expressed mathematically and it can be seen as quantum. A categorical based framework for Quantum NLP is the categorical compositional distributional (DisCoCat) semantics model, developed by the authors in ref [6], it is based on the formal quantum-like nature of word interactions [19].

2.3.1 DisCoCat model of meaning

DisCoCat and DisCoPy are based on pregroup grammar, which is a mathematical model introduced by [17]. In this pregroups grammar types are used to analyse the syntax of natural languages using simple algebra .The meanings of words are vectors which contains in the vector space and their grammatical roles are types in a pregroup and tensor product of vector spaces [6].

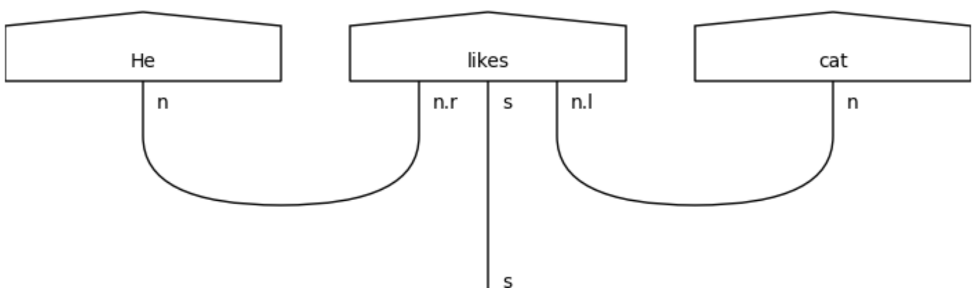

Figure 2.1: DisCoCat Diagram for ”He likes cat.”

Chapter 3

Related work

3.1. Sentence Classification tasks with quantum computers

Cambridge Quantum Computing(CQC) [18] presented two complete medium-scale experiments of Question-Answering tasks on quantum hardware. They represent sentences based on DisCoCat model [6] and mapping it to quantum circuits. They use these representations to implement and successfully train two NLP models that solve simple sentence classification tasks on quantum hardware. The experiments are performed on an IBM NISQ computer provided by the IBM Quantum Experience platform. They proposed this approach as the general pipline for QNLP in the NISQ era.

My work also follows this pipline and aims to solve Sentence Similarity task which need to concerned about mapping two sentences and comparing their quantum states while training.

3.2. Machine Translation with quantum computers

This paper [24] explored the field of Quantum Machine Translation.They evaluated if the framework could handle translation by testing sentences in both

Spanish and English.They also tested different frameworks to decide which one is usable for developing a quantum translation machine. The problem is that they fail to map negative sentence diagram to a quantum circuit using DisCoPy

My work use a more data-driven approach which the functor learns words from the data itself which can avoid mapping negative sentences.

Chapter 4

Proposal

4.1. Problem definition

This work aims to develop a general approach based on quantum computers and quantum based language models for Semantic Textual Similarity tasks.

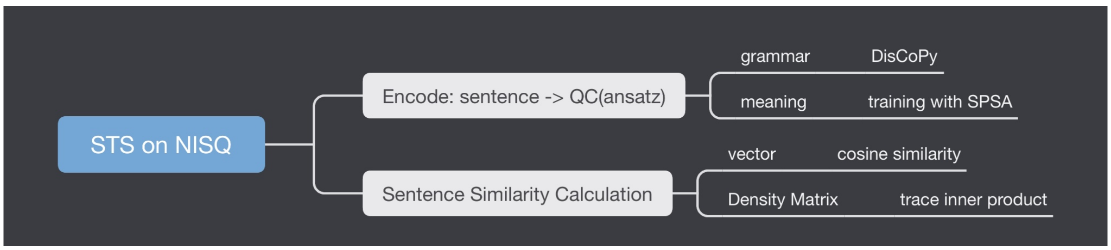

Figure 4.1: Project components

4.2. Workflow

The datasets in this paper is extracted from [13] which are pairs of sentences with similarity scored by hand. We defined their DisCoCat diagrams by a CCG parser, then converted the diagrams into quantum circuits (ansatz) and we executed those sentences on simulators.

4.3. From sentence to quantum circuit

The pipeline of transforming a sentence into quantum circuit representation has introduced in [14].

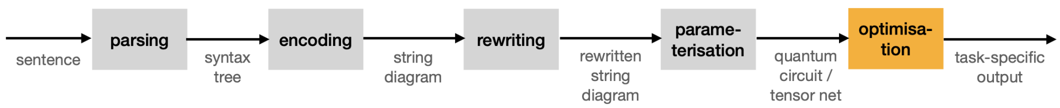

Figure 4.2: QNLP pipline (source: Cambridge Quantum Computing, 2021 [14])

The steps are as follows:

Step 1: **Process sentence into a pregroup parser to get the syntax tree.** Parsing means codifying the sentence into its constituents and the connections between each words. We use a state-of-the-art CCG parser developed by [27] in this work.

Step 2: **Convert syntax tree into string diagram.** Basically, this process can be seen as wearing up the sentence by the relationships between the words. Details are described in [26]. We use DisCoPy [7] which is a python library desinged for this purpose.

Step 3: **Rewrite string diagram to reduce post-selection in the circuit, for faster execution.**

Step 4: **Map rewritten string diagram onto quantum circuit.** This mapping is based on choosing concrete parameterised quantum states and proper ansatze to represent word states. According to the grammar type we can define quantum gates for noun, verb, preposition, etc. That means sentences with same structure such as noun + verb + noun can be represented in the same kinds of quantum gates. Encoding meaning of each words means learning a list of parameters that lets the circuit resulting in a expected quantum state.

```python
from lambeq.ccg2discocat import DepCCGParser
from lambeq.circuit import IQPAnsatz
from lambeq.core.types import AtomicType
from pytket.extensions.qiskit import tk_to_qiskit

# Parsing sentence to get a string diagram
depccg_parser = DepCCGParser()
diagram = depccg_parser.sentence2diagram('He likes cat')

# Convert string diagram to quantum circuit by building IQPAnsatz
ansatz = IQPAnsatz({AtomicType.NOUN: 1, AtomicType.SENTENCE: 1},
                   n_layers=1, n_single_qubit_params=3)
discopy_circuit = ansatz(diagram)

# Convert to a executable quantum circuit form
tket_circuit = discopy_circuit.to_tk()
qiskit_circuit = tk_to_qiskit(tket_circuit)
```

Figure 4.3: Sample code for generating a quantum circuit

4.4. Parameterization

We shows how we actually use the toolkits to generate the IQPAnsatz and executable quantum circuit in *tket* or *qiskit* form in Figure 4.3. We assinging 1 qubit to the noun type and 1 qubit to the sentence type and for each noun we set 3 parameters. The IQPAnsatz for "He likes cat." shows in Figure 4.4 and *qiskit* form in Figure 4.5. As an example, "*He*" can be represented with "*He*" = Ket 0 $\gg$ Rx(phase) $\gg$ Rz(phase) $\gg$ Rx(phase). The wires in Figure 2.1 are represented with Controlled NOT gate.

4.5. Training

Encoding meaning of words in this model means updating the parameters to reach the goal quantum state. We defined the cost function by Mean Squared Error(MSE):

$$J(s_1, s_2) = \frac{1}{2}\|score - cos(s_1, s_2)\|^2 \tag{4.1}$$

with *score* normalized from the similarity label of sentence pair, and $cos(s_1, s_2)$ can be calculated by the cosine similarity between the quantum states of sentence

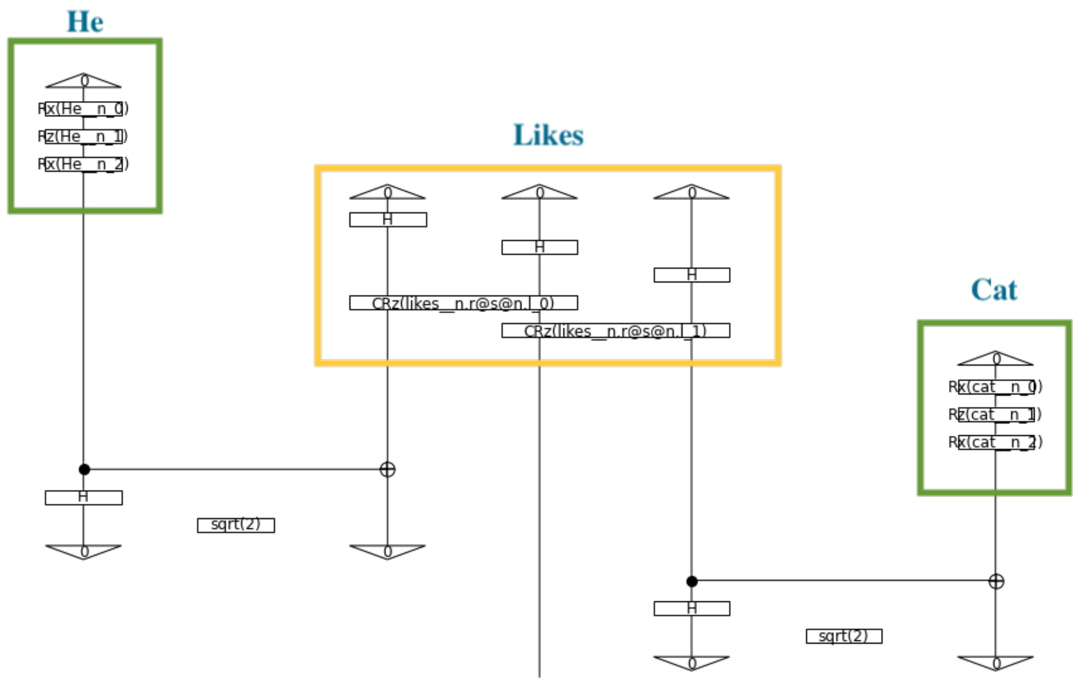

Figure 4.4: IQPAnsatz for "He likes cat."

pair. Learning in this model means updating the parameters to reduce the MSE. To optimize the parameters, we use the *Simultaneous Perturbation Stochastic Approximation* (SPSA) algorithm developed by Spall [22]. SPSA can be used in optimizing noisy functions with multiple unknown parameters. Meichanetzidis et al. [19] has proved the validity of SPSA for for quantum circuits.

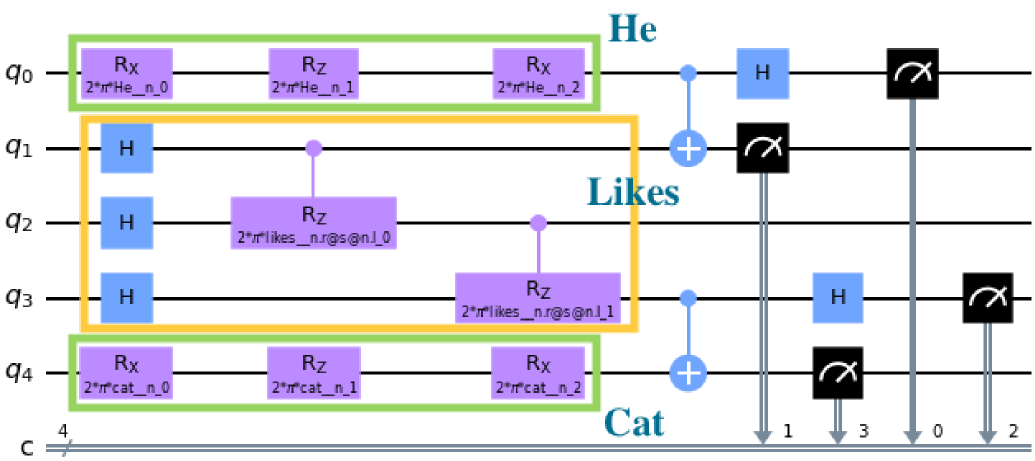

Figure 4.5: Gate-based quantum circuit for the sentence "He likes cat."

Chapter 5

Experiments and Evaluation

In this chapter, we explain the setup of experiments and present the results of the experiments. We care about the MSE introduced in Chapter 4.4.

5.1. Setup

We used lambeq version 0.1.2 [14], depccg version 1.1.0 [27], DisCoPy version 0.3.7.1 [7], Noisyopt version 0.2.2, Qiskit version 0.32.1, Python version 3.9.7 and Apple M1 Max to evaluate proposed method.

We build two datasets which is selected from GS2011 [10] and KS2013-CoNLL [15]. KS2013-CoNLL is more complicated than GS2011.

Dataset	Format	Sentence example	#train_set	#dev_set	#test_set
GS2011	SVO	Man write song. Man publish song.	40	10	10
KS2013-CoNLL	ASVAO	Black dog lick cold water. Black dog wash cold water.	40	10	10

Table 5.1: Details of experiment data sets(A:adjective,S:subject,V:verb,O:object).

5.2. Result and Evaluation

We shows the SPSA optimization results of two datasets on quantum simulator.

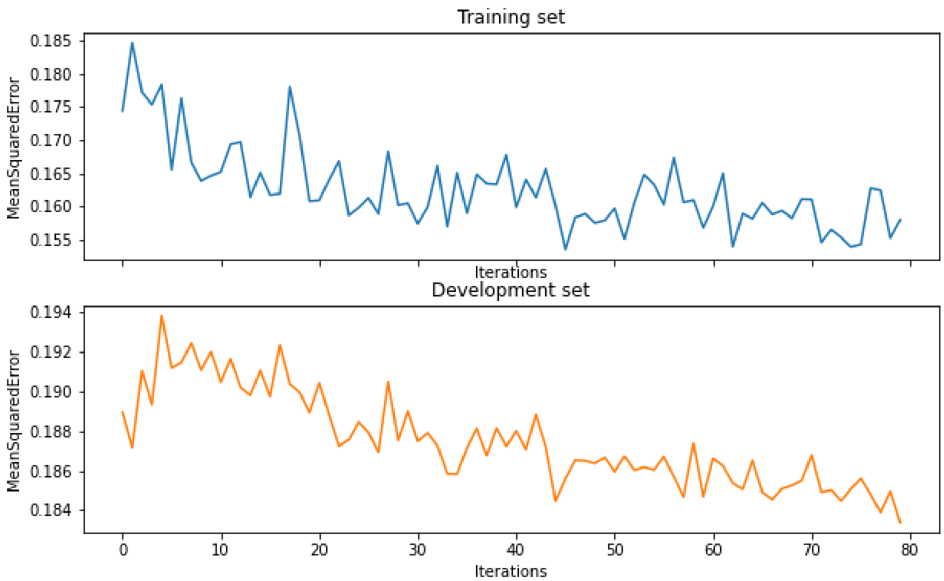

Figure 5.1: SPSA optimization result of GS2011 dataset on Qiskit's Aer simulator.

Figure 5.1 shows the SPSA optimization result of GS2011 dataset on Qiskit's Aer simulator. X-axis shows the iterations of training. Y-axis shows the Loss which is the MSE results of the pairs of sentences with the function in Function 4.1. We used the MSE of the test data set for evaluation, and the result of GS2011 dataset was 0.116. The parameter set we used in *minimizeSPSA* was "a" = 0.15 which is scaling parameter for step size and "c" = 0.05 which is scaling parameter for evaluation step size. Since the MSE of the training set tends to decrease, it means that the distance between the quantum states shows high similarity with the similarity score by human hand.

Figure 5.2 shows the SPSA optimization result of KS2013-CoNLL dataset on Qiskit's Aer simulator. X-axis shows the iterations of training. Y-axis shows the Loss which is the MSE results of the pairs of sentences with the function in Function 4.1. MSE result of KS2013-CoNLL test data set was 0.133. The parameter set we used in *minimizeSPSA* was "a" = 0.15 which is scaling parameter for step size and "c" = 0.05 which is scaling parameter for evaluation step size. MSE of the training set also tends to decrease but MSE of the development set

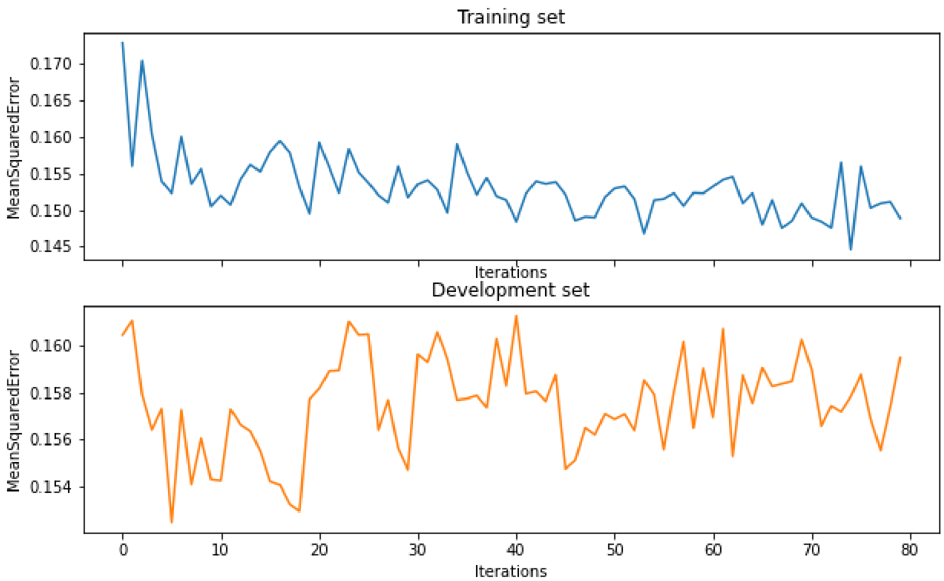

Figure 5.2: SPSA optimization result of KS2013-CoNLL dataset on Qiskit's Aer simulator.

was not ideal. The reason for the unstable result of the development set might be overfitting. Because the size of the data set was small, some words appear in the training set only a few times so the parameters of these words haven't been fully optimized. KS2013-CoNLL data set is in ASVAO format which means adjective words also need to be learned, that's why the unstable result of the development set didn't appear in GS2011 data set which is SVO format.

As Figure 5.3 We also tried SemEval-2017 which is a general STS benchmark dataset [4], however the format of sentences were flexible , resulting that the quantum circuits get quite different from each other and the sentence similarity calculation could not manage this kind of case.

The result of Quantum Semantic Textual Similarity proved the validity of my proposal. Increasing the number of sentences, trying other compositional semantics structures may improve the performance.

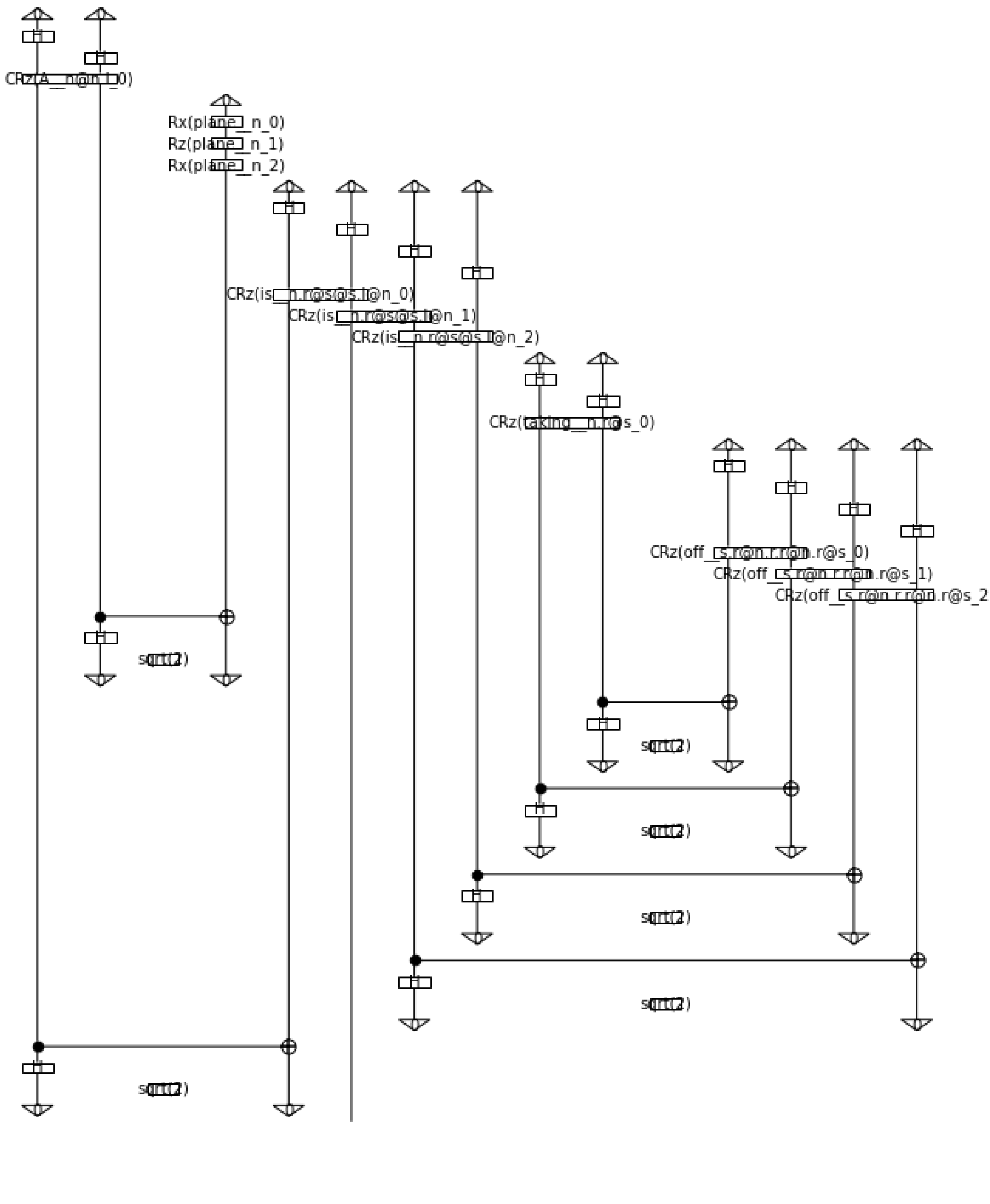

Figure 5.3: IQPAnsatz for "A plane is taking off"

Chapter 6

Conclusion and Future Works

This project explored the field of Quantum Semantic Textual Similarity and tested different datasets to evaluate if DisCoCat model could handle sentence similarity tasks. We used mean squared error as the loss function which aims to let the distance of quantum states close to the similarity score we labeled. We used SPSA as the optimization approach because it can be used in optimizing noisy functions with multiple unknown parameters. Finally, the results show that using a quantum model for Semantic Textual Similarity is feasible. Encoding grammar classically is exponentially expensive [5], but the quantum computer has the advantage of linguistic structure. That's why Natural Language Processing is "quantum-friendly".

This model can be executed in a classical computer and it can also be run on real quantum devices. The experiments were executed on simulators. For future work, we will do experiments on real quantum devices such as IBMQ devices. Building larger datasets and future quantum hardware devices could help with the result performance. Trying other compositional semantics structures will also help with handling real-world datasets.

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