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AUXILIARY-BASED EXTENSION OF MULTI-TASKING SEQUENCE-TO-SEQUENCE MODEL FOR CHATBOT ANSWERS

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By

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AUXILIARY-BASED EXTENSION OF MULTI-TASKING SEQUENCE-TO-SEQUENCE MODEL FOR CHATBOT ANSWERS

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December 2021

Chair : Nurfadhlina Mohd Sharef, PhD
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Chatbots that can answer user questions have a great future to assist humans to be very productive. Question-answering (QA) chatbots can be implemented using machine learning (ML) or rules. ML chatbots are better compared to rule-based chatbots because ML chatbots are expandable with continuously training. Since its inception for the machine-learning-based translation problem domain in 2014, the sequence-to-sequence (Seq2Seq) training approach has shown remarkable progress in developing chatbots. Nevertheless, Seq2Seq chatbots have a weakness whereby it tends to produce irrelevant responses and is not meaningful hence may reduce the chatbot acceptance. The flaw is caused by three factors: “Language Model Influence”, “Question Encoding Overfitting”, and “Answer Generation Overfitting”. Besides, many chatbots are developed using the single-task learning (“STL”) method which executes only the response generation task. Recent works utilize multi-task learning (MTL) to overcome the weakness, but they still produce generic answers which are not consistent with the questions. Therefore, this research presents “SEQ2SEQ++”. “SEQ2SEQ++” is a Seq2Seq MTL learning method which comprises of four (4) components (“Multi-Functional Encoder” (MFE), “Answer Decoder”, “Answer Encoder”, “Ternary-Classifier” (TC)) and is trained using “Dynamic Weights” algorithm and “Comprehensive Attention Mechanism” (CAM). All these methods and mechanisms are novel approaches proposed in this work. Experiments were conducted on two (2) publicly available published academic datasets (SQuAD and NarrativeQA) to measure the performance of the suggested method against two current MTL methods (“MTL-LTS” and “MTL-BC”). “MTL-BC” executes response generation and binary question-response categorization in parallel. “MTL-LTS” executes first-word generation subsequently response generation in sequential order. Experiment outcomes show that “SEQ2SEQ++” outexecutes the benchmark works on all assessment metrics used in this study. For the “BLEU” metric, “SEQ2SEQ++” performed 44.42% superior to “MTL-BC” on NarrativeQA and 17.31% superior to “MTL-BC” on SQuAD correspondingly. On “WER”, “SEQ2SEQ++” performed 58.83% superior to “MTL-LTS” on

NarrativeQA and 37.26% superior to “MTL-BC” on SQuAD correspondingly. As for “Distinct-2”, “SEQ2SEQ++” performed 0.73% superior to “MTL-BC” on NarrativeQA and 0.21% superior to “MTL-LTS” on SQuAD correspondingly.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

MODEL JURUTAN-KE-JURUTAN BERASASKAN PELBAGAI TUGAS LANJUTAN UNTUK JAWAPAN ROBOT PERBUALAN

Oleh

KULOTHUNKAN A/L PALASUNDRAM

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Pengerusi : Nurfadhlina Mohd Sharef, PhD
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Robot perbualan atau lebih dikenali sebagai *chatbot* mempunyai potensi besar untuk melengkapkan manusia dalam pelbagai bidang dan melakukan tugas seperti menjawab soalan. *Chatbot* penjawab soalan dilaksanakan sama ada dengan sistem berasaskan peraturan atau pembelajaran mesin. Tidak seperti sistem berasaskan peraturan, *chatbot* berasaskan pembelajaran mesin dapat belajar dan menjadi lebih pintar dari masa ke masa dan lebih senang ditingkatkan. Pembelajaran urutan-ke-urutan (*Seq2Seq*) adalah salah satu pendekatan yang paling popular dalam *chatbot* berasaskan pembelajaran mesin dan menunjukkan kemajuan yang besar sejak diperkenalkan pada tahun 2014. Walau bagaimanapun, *chatbot* berdasarkan pembelajaran Seq2Seq menunjukkan kelemahan di mana ia cenderung menghasilkan jawapan yang umum dan tidak konsisten dengan soalan, sehingga menjadi tidak bermakna dan oleh itu, dapat menurunkan kadar penggunaan *chatbot*. Kelemahan ini boleh dikaitkan dengan tiga masalah: pengekodan soalan terlebih sesuai (*question overfit*), penjanaan jawapan terlebih sesuai (*"answer generation overfitting"*), dan pengaruh model bahasa (*"language model influence"*) . Selain itu, kebanyakan *chatbot* dibangunkan berdasarkan kaedah satu-tugas (*single-task learning* - "STL") yang hanya melakukan tugas penjanaan jawapan. Beberapa penyelidikan terkini menggunakan kaedah pembelajaran pelbagai-tugas (*multi-task learning* - MTL) untuk mengatasi kelemahan tersebut. Walau bagaimanapun, kaedah MTL yang sedia ada menunjukkan peningkatan yang sangat sedikit berbanding "STL" di mana mereka masih menghasilkan jawapan yang umum dan tidak konsisten. Oleh itu, penyelidikan ini mencadangkan pendekatan baru untuk Seq2Seq berdasarkan MTL yang disebut SEQ2SEQ ++ yang terdiri daripada *"Multi-Functional Encoder" (MFE), "Answer Decoder", Answer Encoder,* dan *"Ternary-Classifier" (TC).* Selain itu, SEQ2SEQ ++ menggunakan mekanisma *dynamic task loss weight* dan mekanisma *"Comprehensive Attention Mechanism" (CAM)*. Eksperimen ke atas set data NarrativeQA dan SQuAD telah dijalankan untuk mengukur prestasi kaedah yang dicadangkan berbanding dua kaedah sedia ada iaitu "MTL-BC" dan "MTL-

LTS”. Kedua-dua “MTL-BC” dan “MTL-LTS” adalah kaedah MTL. “MTL-BC” melaksanakan tugas penjanaan jawapan dan klasifikasi soalan-jawapan binari manakala “MTL-LTS” melaksanakan ramalan perkataan pertama dan kemudian penjanaan jawapan. Hasil kajian menunjukkan bahawa peningkatan yang signifikan secara statistik berbanding dua kaedah sedia ada untuk semua metrik yang digunakan untuk kajian ini. Untuk metrik “BLEU”, “SEQ2SEQ++” menunjukkan prestasi 44.42% lebih baik daripada “MTL-BC” atas set data NarrativeQA dan 17.31% lebih baik daripada “MTL-BC” atas set data SQuAD. Untuk metrik WER, “SEQ2SEQ++” menunjukkan prestasi 58.83% lebih baik daripada “MTL-LTS” atas set data NarrativeQA dan 37.26% lebih baik daripada “MTL-BC” atas set data SQuAD. Bagi metrik “Distinct-2”, “SEQ2SEQ++” menunjukkan prestasi 0.73% lebih baik daripada “MTL-BC” atas set data NarrativeQA dan 0.21% lebih baik daripada “MTL-LTS” atas set data SQuAD.

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfillment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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AL	Adversarial learning
BC	Binary Classifier
BLEU	Bilingual Evaluation Understudy
CAM	Comprehensive Attention Mechanism
CNN	Convolution Neural Network
DL	Dynamic Task Loss Weight Algorithm
DRL	Deep Reinforcement Learning
GAM	Global Attention Mechanism
GAN	Generative Adversarial Network
GRU	Gated Recursive Units
LSTM	Long Short-Term Memory
MDP	Markov Decision Process
MFE	Multi-Functional Encoder
MMI	Maximum Mutual Information
MTL	Multi-task Learning
MTL-BC	Multi-task Learning Model with Binary Classifier
MTL-BC-CAM	Multi-task Learning Model with Binary Classifier and Comprehensive Attention Mechanism
MTL-BC-DL	Multi-task Learning Model with Binary Classifier and Dynamic Task Loss Weight Algorithm
MTL-LTS	Multi-task Learning Model with First-Word Prediction
MTL-MFE	Multi-task Learning Model with “Multi-Functional Encoder”
MTL-TC	Multi-task Learning Model with Binary Classifier
NLP	Natural Language Processing

RL	Reinforcement Learning
RNN	Recurrent Neural Network
Seq2Seq	Sequence to sequence
STL	Single-task Learning
STL-CAM	Single-Task Learning Model with Comprehensive Attention Mechanism
TC	Ternary Classifier
WER	Word Error Rate

CHAPTER 1

INTRODUCTION

1.1 Motivation

Chatbots are artificially intelligent systems that can communicate with humans using normal language. Alan Turing, who asked "Can machines think?" in his paper "Computing Machinery And Intelligence," is credited with creating interest in chatbot development (Turing, 1950). A chatbot named "ELIZA" was created in 1966 to research natural language communication between humans and machines. (Sharma et al., 2017; Shum et al., 2018; Weizenbaum, 1966). Since then, hundreds of thousands of chatbots have been created with the help of proprietary and independent chatbot platforms developed by technology firms for instance Microsoft, Google, and Amazon (Walker, 2018).

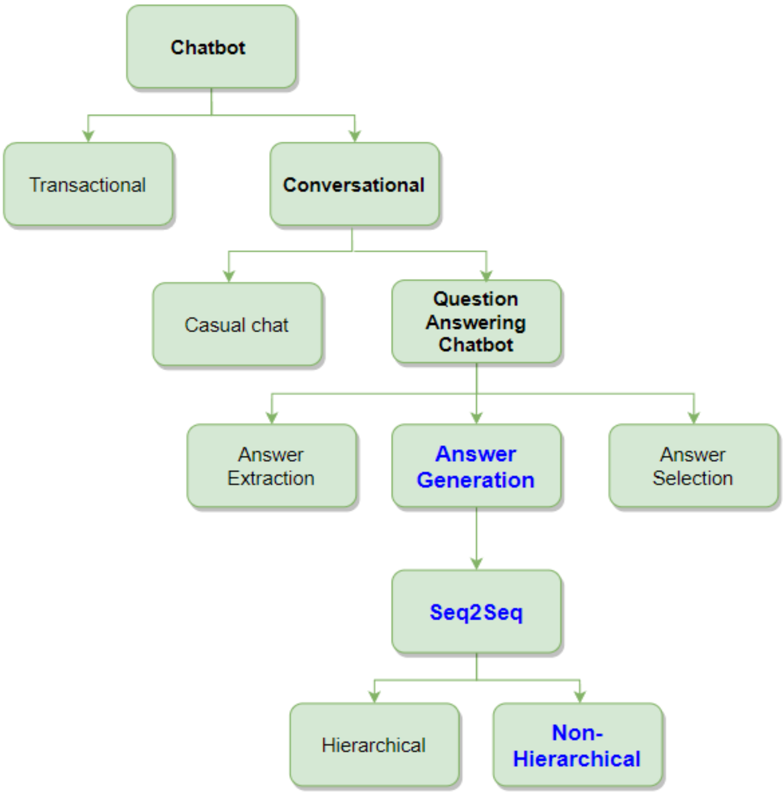

Figure 1.1: Types of Chatbots

Transactional and conversational chatbots are the two types of chatbots (Figure 1.1). Users use transactional chatbots to complete a specific job, for-instance booking restaurant or hotel reservations, to achieve a specified goal. Casual and more formal question-answering (QA) chatbots are two types of conversational chatbots. Casual chatbots (language models) can converse with people and act as a friend for humans. A language model is a machine learning algorithm that learns to predict the likelihood of a sequence of words. It guesses the next word based on the words it has already generated. One of the most recently proposed language models, the GPT-3 (Brown et al., 2020) has shown great potential in chatbot modeling. Language models for instance GPT-3 can converse in natural language on general everyday conversation topics. The more formal QA chatbots aim at providing specific answers to questions based on the knowledge gathered by learning the facts from a structured knowledge base (KB) or unstructured documents. Therefore, a QA chatbot is more targeted to provide concise answers for a specific question in domains for instance customer support it was trained on (Andrenucci & Sneiders, 2005). Artificial intelligent (AI) chatbots could scale much more quickly compared to humans. As a result, QA chatbots are quickly gaining traction in areas including help desk, general queries, and education (Palasundram et al., 2019). Chatbots also help to keep expenses down when compared to using humans via a variety of channels like phone, email, live chat, and message boards (Hardalov et al., 2018).

Extraction, generation, and selection are three methods to obtain a chatbot answer (Figure 1.1). The process of separating an answer from a text paragraph is known as extraction. Selection is the process of ranking and picking an answer from a set of options. The task of creating a series of words to make a response is called generation. Sequence to sequence (Seq2Seq) learning is a popular technique for generating natural answers. The Seq2Seq based models are first trained with question-response pairs. Once training is completed, the chatbot can provide answers to user queries. Even though the Seq2Seq based models can generate words that make up the answer, some of the generated words may be unrelated which makes the answers meaningless and irrelevant to the question. This issue is discussed further in more detail in the next section.

1.2 Problem Statement

Numerous studies (Huang & Zhong, 2018; Liu et al., 2019; Peng et al., 2019; Y. Wang et al., 2019; Yang et al., 2018) show that the Seq2Seq method (Cho et al., 2014) tends to generate high-frequency words as the answer which may not be relevant to the question. This weakness can be imputed to “language model influence”, “answer generation overfitting”, and “question encoding overfitting”. The following points provide a more detailed explanation of the three (3) issues.

Issue 1: Language Model Influence

After model training, the RNN decoder acquires language model capability which means it can generate a word or sequence of words based on the preceding words even without being given a question. Eventually, the decoder's capability to generate words on its own overtakes the question's influence when generating the answer and could cause the model to produce irrelevant responses. To address “language model influence”, attention mechanisms are utilized for decoding. Using the attention mechanism, a model executes computation to identify which part of the question is important to generate the response. The benchmark works “MTL-BC”(Huang & Zhong, 2018) and “MTL-LTS” (Zhu et al., 2016) utilized the global attention mechanism (GAM) as proposed in (Bahdanau et al., 2015)**.**

Nevertheless, this attention mechanism concentrates only on the decoder’s latest encoding when performing attention computation on the question encoding. Even though the decoder’s latest encoding constitutes past states, the influence of earlier states diminishes towards the end. The produced words from earlier time steps lose their influence as the decoding advances. Even though the purpose of the attention mechanism is to allow a greater influence of the question (make decoder concentrate on a particular section of the questions) during response generation, existing attention mechanisms create an imbalance where the question’s influence becomes much greater compared to the decoder’s which makes the model unable to cope well with unseen questions. This presents an opportunity to search for an attention mechanism that can balance the decoder's influence with the question at hand, resulting in a more relevant and meaningful response.

Issue 2: Answer Generation Overfitting

The Seq2Seq approach finds the optimal sequence of words that comprises the response by lowering cross-entropy loss. Inconsistent word frequency, in contrast, drives the Seq2Seq model to produce high-frequency words, resulting in “answer generation overfitting”.

There are several popular methods to address “answer generation overfitting” for-instance multitask learning (MTL) (Huang & Zhong, 2018; R. Zhang et al., 2017), reinforcement learning (RL) (Asghar et al., 2017; Li, Monroe, et al., 2016; Yang et al., 2018) and adversarial learning (AL) (Tuan & Lee, 2019; Xu et al., 2020). Even though popular, reinforcement and adversarial learning approach learning can be unstable, most methods are still dependent on warm start using cross-entropy loss functions. The loss function used for one dataset may not be suitable for another dataset. It also requires custom reward functions to evaluate the model. A more practical approach is the MTL method. In MTL, additional tasks are learned together with the response generation task. Nevertheless, a constant tasks loss weight approach is employed to calculate the MTL loss in current Seq2Seq MTL models. The additional task is often allocated a small constant like 0.01 and 0.1 (Huang & Zhong, 2018).

Nevertheless, because there are no defined guidelines or formulae for establishing the actual number to be used, finding the weight for each task is a difficult process. Before a task's final weight can be determined, random values must be assigned and tested. Before arriving at a specific value for the task loss weights, researchers must conduct multiple trial and error studies. For example, in “MTL-BC”(Huang & Zhong, 2018), the task loss weight used for the auxiliary task (binary categorization) is 0.1. This value was determined after many trials by the author. There may also be a better value compared to 0.1 for instance 0.08 or 0.12 for example. Furthermore, various datasets may need the usage of different values. The weights that work for one dataset might not work for another. This method of trial and error is very tedious. When there are greater two (2) tasks, it gets significantly more difficult, if not impossible. This provides a research opportunity to identify a more competent approach to determine the weights for the auxiliary tasks.

Issue 3: Question Encoding Overfitting

Seq2Seq QA models are routinely trained with specialized datasets albeit limited amount of data, for-instance the knowledge base for frequently asked questions and can cause question encoder to overfit. When dealing with unknown questions, “question encoding overfitting” leads the model to suffer.

Existing MTL approaches (Ghazvininejad et al., 2018; Liu et al., 2019; Ren et al., 2019) require additional input for instance facts, emotion, or conversation topics categories to train the additional tasks. In contrast, additional inputs may not be practical or obtainable for all question-answering instances. As a result, a strategy that can address model overfit without relying on extra input is required. “MTL-BC”(Huang & Zhong, 2018) and “MTL-LTS” (Zhu et al., 2016) are the only two MTL methods known to this author that doesn’t depend on any additional input.

“MTL-BC” utilizes binary question-response categorization as a supplementary task. This categorization task is trained together to reduce model overfit. Binary categorization refers to an action whereby an answer is categorized as either right or wrong. Nevertheless, this is not the natural way to categorize an answer because a generated response can also be half-correct. This provides a research opportunity to identify a more appropriate response categorization method.

“MTL-LTS” is a sequential MTL training strategy in which the model learns to generate the first word before moving on to generate a full answer in two phases.

To reduce model overfitting, this is a fantastic concept. Sequential MTL, in contrast, faces a "negative transfer" issue that is a circumstance in which mastering the first assignment may jeopardize mastering the second (Pan & Yang, 2010). This provides a research opportunity in Identifying a more appropriate method to include first-word generation into an MTL model.

1.3 Research Objectives

This research aims to resolve response generation issues to create a model that can produce relevant answers. Four (4) objectives are identified to fulfill the aim. They are: -

i) To present the **"Comprehensive Attention Mechanism" (CAM)** as a novel attention mechanism for decoding answers as an alternative to the widely used GAM.

ii) To resolve the overfitting issue during response generation by proposing a novel MTL loss computation algorithm called **"Dynamic Weights" (DL)** which automatically computes and assigns weights for each task.

iii) To present innovative methods called **"Multi-Functional Encoder" (MFE)** and **"Ternary Classifier" (TC)** to tackle the "question encoding overfitting" issue.

iv) To propose a Seq2Seq based MTL model (**"SEQ2SEQ++"**) and a new training algorithm to integrate **CAM, DL, MFE, and TC** to capitalize on each method's strengths

1.4 Research Scope

1.4.1 Methods

This work focuses on question-answering (response generation) as a single turn conversation task (a pair of question and response) under the MTL framework as defined in (Huang & Zhong, 2018) that is a key reference for this research. The MTL framework was chosen since it was discovered throughout the literature research that it can address Seq2Seq model issues from various angles such as language model influence and question and response encodings. Attention mechanism, beam search, and additional embedding can all be combined with the MTL approach to increase the quality of the answers generated.

Three areas of improvement were identified which are attention mechanism, question encoding, and response generation Existing models that were used for comparing results are: -

i) **"STL"**: A single-task model utilizing GAM (Bahdanau et al., 2015). that is the most popular attention mechanism used in Seq2Seq learning. It was selected to study the limitations and effects of existing attention mechanisms in response generation. This is also used as the control method for this study.

ii) **"MTL-LTS"**: "MTL-LTS" is a two-phased MTL method that uses a sequential MTL methodology and GAM. The model learns to generate first-word only in phase one subsequently full response in phase two (Zhu et al., 2016). It was selected to study the limitations and effects of sequential against parallel multi-task learning for response generation.

iii) **"MTL-BC"**: A MTL approach with constant weights and a binary question-response classifier and GAM (Huang & Zhong, 2018). It was selected to study the limitations and effects of question-response categorization as an auxiliary task in multi-task learning for response generation.

1.4.2 Datasets

The datasets used in this research are NarrativeQA (Kočiský et al., 2017) and SQuAD (Rajpurkar et al., 2016) which are state-of-art for reading comprehension-based questions answering where the question, answer, and paragraph with the answer is provided. A detailed description of these datasets is provided in chapter 3 section 3.3.

1.4.3 Assessment Metrics

To measure each model performance, Bilingual Evaluation Understudy ("BLEU") (Papineni et al., 2002), Word Error Rate ("WER") (Mikolov et al., 2010), and "Distinct-2" (Li, Galley, Brockett, Gao, et al., 2016) metrics have been utilized. A detailed description of these metrics is provided in section 3.2.

1.5 Research Contributions

The primary contribution of this research work are:-

i) proposal of four (4) new methods as listed below

a. “Comprehensive Attention Mechanism” (CAM) that is presented as a replacement for existing attention mechanisms to resolve the “language model influence” problem

b. Dynamic Weights (DL) algorithm to overcome the “answer generation overfitting” problem. It is a novel computation algorithm that replaces the constant weights methodology. It's a way of calculating and implementing the weight for each task loss automatically.

c. “Multi-Functional Encoder” (MFE) and “Ternary-Classifier” (TC) to resolve the “question encoding overfitting” issue. Besides question encoding and first-word generation, a new task called last-word prediction is introduced in this work as part of MFE. Additionally, this work also introduces another new task called TC.

ii) proposal of a new Seq2Seq based MTL model (“SEQ2SEQ++”) and a new training algorithm to integrate all the newly suggested methods to capitalize on each method’s strengths to all resolve chatbot response generation issues.

1.6 Thesis Outline

The rest of this thesis is organized as follows: -

Chapter 2 provides a comprehensive literature review of the Seq2Seq model including design, implementation, and training algorithm, issues in Seq2Seq based response generation, and the existing approaches to address those issues including datasets utilized for training and metrics used to measure the performance. The strengths and weaknesses of the existing methods are discussed. Chapter 2 ends with the identification of gaps of existing approaches in addressing the issues in Seq2Seq learning.

Chapter 3 presents the methodology applied to perform this research work. The research phases undergone are explained in detail. The dataset identified to perform the experiments and the metrics utilized to measure the performance of the experimental models are also elaborated in chapter 3.

Chapter 4 discusses the design and implementation of the “Comprehensive Attention Mechanism” (CAM) that is suggested to resolve the “language model influence” issue. Design and implementation of benchmark works (Bahdanau et al., 2015; Huang & Zhong, 2018) are also discussed for detailed comparison and analysis. Experiments conducted for SQuaD and NarrativeQA datasets and their results are presented and discussed.

Chapter 5 discusses the design, implementation, and training algorithm called Dynamic Weights (DL) that is suggested to resolve “answer generation overfitting” in a Seq2Seq based MTL model. The design and implementation of the benchmark model (Huang & Zhong, 2018) which utilizes constant tasks loss weight mechanism are also discussed. Experiments conducted for SQuaD and NarrativeQA datasets and their results are presented and discussed.

Chapter 6 discusses the design, implementation, and training algorithms of the “Multi-Functional Encoder” (MFE) and Ternary Classifier (TC). Both methods are suggested to resolve “question encoding overfitting” in a Seq2Seq model. The design and implementation of the auxiliary tasks in the benchmark works (Huang & Zhong, 2018; Zhu et al., 2016) are also discussed. Experiments conducted for SQuaD and NarrativeQA datasets and their results are presented and discussed.

Chapter 7 discusses the design of “SEQ2SEQ++”, its implementation, and the training algorithm. “SEQ2SEQ++” implements CAM, DL, MFE, and TC as discussed in chapters 4, 5, and 6 respectively. Experiments were conducted against benchmark works (Bahdanau et al., 2015; Huang & Zhong, 2018; Zhu et al., 2016) for SQuaD and NarrativeQA datasets, and their results are presented and discussed.

The conclusion for this thesis research which includes a summary of the literature review, experiments conducted, results from the experiments, and analysis as well as the future work recommendations are presented in the final chapter 8.

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