SENTIMENT ANALYSIS ON MOVIE REVIEWS BY RECURRENT NEURAL NETWORKS AND LONG SHORT-TERM MEMORY

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Specially dedicated
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ABSTRACT

Sentiment analysis has become important tool that can analyse review on any product or service that can be reviewed. Same goes to movie, all the audient are freely to make their own reviews on the movie that they watch and the reviews can be positive or negative based on audient satisfactions. Automated sentiment analysis is very important to make sure the analysis produce an accurate result and in faster time. By using the deep learning as the based to create the automated sentiment analysis it will be the great decision because of the deep learning structure that have multilevel of layer that can have sensitive process to classify the data. Upgrading the sentiment analysis using Recurrent Neural Networks (RNNs) and addition of Long Short-term Memory (LSTM) and also some modification on the number of layer with the mathematical calculation can improve the analysis accuracy. The dataset of the movie reviews will be collected on IMDB movie reviews database.

ABSTRAK

Analisis sentimen telah menjadi alatan penting untuk menganalisis pandangan pengguna terhadap produk barangan mahupun perkhidmatan. Ini juga boleh terjadi terhadap filem, penonton bebas untuk memberikan pandangan terhadap filem yang mereka tonton dan pandangan yang diberi boleh menjurus kepada positif ataupun negatif bergantung kepada keppuasan penonton. Menganalisis sentimen secara automatik adalah sangat penting untuk memastikan analisis yang dihasilkan adalah tepat dan juga mengambil masa yang singkat untuk memperoleh keputusan analisis. Dengan menggunakan deep learning sebagai asas untuk menghasilkan analisis sentimen secara automatik, ia adalah keputusan yang tepat kerana struktur deep learning mempunyai pelbagai lapisan yang mempu memproses untuk mengkasifikasi data yang sangat sensitif. Menambah baik analisa sentimen dengan menggunakan RNN dan tambahan dari LSTM dan juga modifikasi kepada bilangan lapisan dengan munggunakan pengiraan matematik mampu memperbaiki ketepatan analisis. Set data untuk pandangan filem akan diambil dari pengkalan data IMDB.

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LIST OF ABBREVIATION

CNN	-	Convolutional Neural Network
LSTM	-	Long Short-term Memory
NLP	-	Natural Language Processing
RNN	-	Recurrent Neural Network
SDRNN	-	Supervised dual recurrent neural network
IMDB	-	Internet Movie Database
SVM	-	Support Vector Machine
GloVe	-	Global Vector for Word Representation

LIST OF SYMBOLS

h_t	-	Hidden state vector / output vector of LSTM bock
σ	-	Sum of two term
W^H	-	Recurrent weight matrix multiply with hidden state vector
W^X	-	Weight matrix multiply with input vector
h_{t-1}	-	Hidden state vector at previous time
x_t	-	Input vector / input vector to LSTM block
f_t	-	Forget gate's activation vector
i_t	-	Input gate's activation vector
o_t	-	Output gate's activation vector
c_t	-	Cell state vector
$W\&U_{f,i,o,c}$	-	Weight matrices
σ_g	-	Sigmoid function
$\sigma_c\&\sigma_h$	-	Hyperbolic tangent function
$b_{f,i,o,c}$	-	Bias vector
$\odot$	-	Multiplication point by point

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Nowadays monitoring customer feedback and reviews is considered an important tool from a business perspective such as in the film industry. Filmmakers can create and present their masterpieces to the audience but getting timely reviews is a major input to planning the next business move. To overcome this issue the filmmaker need to analyse the movie reviews and identify the audience sentiment from the good and bad reviews. Sentiment analysis or opinion mining enable the filmmaker to analyse the reviews from social media websites automatically. Sentiment analysis also can be applied in many products or services. Therefore, developing automated tools for sentiment analysis is a big step in business.

Lately, deep learning is a popular research topic in natural language processing. Deep learning is an improvement from the machine learning. Deep learning is about learning multiple level of the architecture that help to make sense of data such as text, image and sound. Currently, deep learning applied to many natural language processing area such as text, voice and speech and come out with a good result. One of the deep learning algorithm is Recurrent Neural Networks (RNNs) deep learning.

Although many researcher have applied automated sentiment analysis using the deep learning, the accuracy can still be improved. Figure 1.1 shows an example of movie review that randomly pick from the datasets. Based on current trend the

automated sentiment analysis with good accuracy is really important to improve the movie quality that been produce.

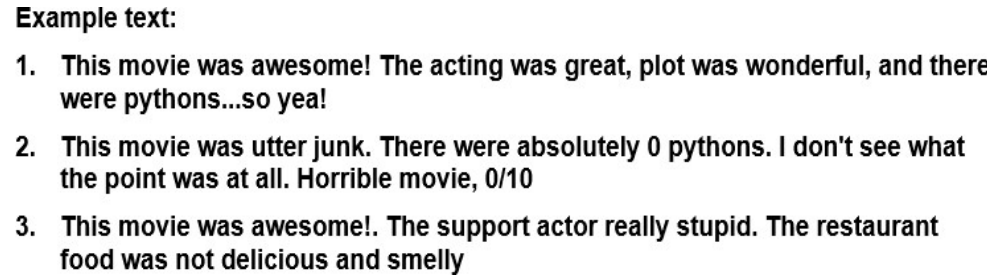

Figure 1.1 : Sample of movie reviews

1.2 Problem Statement

Movie reviews produce a lot of data. Reaching up to millions of reviews for one movie, analysing all the reviews manually will consume a lot of time. Manual analysis also can have problem on miss count the number of reviews because it will have some of human error. This is a challenging issued on sentiment analysis effectiveness. Although there are some researcher that create automated sentiment analysis using machine learning and deep learning, the accuracy is still relatively low. This issues arises because the machine learning algorithms used cannot process the big sized data that need to be analysed. Deep learning is able to address the big data issue, but the deep neural network architectures can be improved to increase the accuracy on the analysis. Some work on deep learning by recurrent neural networks (RNNs) have been done and the results achieve good accuracy, but RNNs itself have some issue on the memory side. RNNs alone will create problem called vanishing gradient and exploding gradient which can reduce the accuracy on learning side. When the learning of the model has issues, it will affect the inference process, and this will drop the RNNs accuracy during the sentiment analysis.

1.3 Research Aim and Objective

The aim of this research is to produce accurate sentiment analysis on movie reviews by recurrent neural networks and long short-term memory. The research objectives are:

- To investigate the previous sentiment analysis works and use as benchmarking
- To design sentiment analysis using RNNs and LSTM model.
- To evaluate the accuracy of the sentiment analysis using propose architecture.

1.4 Scope of Project

The scope of the study are as below:

i) Datasets use from the movie reviews that extract from IMDB.
ii) Word vector get from glove and prepared by Stanford NLP.
iii) Language use to train and test the model is in English.
iv) Deep learning system is based on RNNs and LSTM architecture.
v) Using python as the only programming language in this project.
vi) ANACONDA is use as the simulation software in the analysis process.

1.5 Organization of Thesis

Chapter 1 represent the background of study, problem statement, objectives of project, scope of project, and project limitation.

Chapter 2 describes the literature review of sentiment analysis, for both machine learning and deep learning method.

Chapter 3 illustrate the design methodology proposed based on deep neural networks using RNNs and LSTM. Also cover the project flowchart.

In chapter 4, present the preliminary result, analysis and discussion of the work done in this research.

Lastly in chapter 5, a conclusion of the research work is given. The discussion on the recommendation for future work and contribution will also include in this last chapter.

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