

SENTIMENT ANALYSIS OF NEWS ARTICLES USING BIDIRECTIONAL
RECURRENT NEURAL NETWORKS

ALEXANDER TAN KA JIN

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Literature Review

Polarity of language within politics

Politics heavily uses language. The subject of politics is mainly communicated using language, politicians utilize certain words for their rhetoric, media can manipulate sentences to paint a different picture for or against a cause, languages and mannerism to shape and influence public support for policies and discourse within politics is frequently a site of analysis for many journalists and political analysts. This language can have various sentiments, ranging from anger to hope, parties, politicians and citizens can have strong opinions on these subjects and is communicated through textual opinions on various forms of media. Given this, the analysis of these opinions is done through the analysis of the language of politics like in (Orellana & Bisgin, 2023) where opinions can be classified in terms of importance to a given political group. A significant amount of these opinions are communicated through online social media platforms and newspaper like Twitter (now also known as X), which provides an opportunity for textual analysis. (Németh, 2023)'s review of political polarity research using Natural Language Processing (NLP) notes that sentiment polarity often uses political polarity as a basis for it's measurement, even though political polarity is not a well-defined term. Such political polarity measures include the four measures by (DiMaggio et al., 1996), 1. variance of opinion, 2. bimodality of opinion, 3. ideological constraint of opinion, 4. differences in in-group opinion. From there, sentiment polarity can be measured as the propensity for political groups to hold to a certain group. That being said, most papers utilize sentiment polarity as the strength and attitude of a given opinion between negative opinion and positive opinion such as (Alshutayri et al., 2022).

Sentence	Polarity
Stupid storm. No river for us tonight	Negative
that's great!! weee!! visitors!	Positive
looking forward to body works today	Neutral

Table 1 Examples of sentiment from tweets on Twitter. Gathered from Kaggle Dataset: (<https://www.kaggle.com/datasets/abhi8923shriv/sentiment-analysis-dataset> Accessed 22:50 14/12/2024)

Natural Language Processing and it's challenges

(Nadkarni et al., 2011) notes in their introduction that NLP originated as the intersection of artificial intelligence (AI). (Liddy, 1998) describes NLP as a range of techniques for processing natural text in hopes of achieving human-like text comprehension. This subject was initially distinct from Information Retrieval (IR), which was concerned with efficiently identifying and querying large corpora of text. It's integration with IR occurred with a need for identifying underlying meanings of text, often in regards to text that contain non-conventional uses of language such as sarcasm or irony that contain semantics outside of it's literal meaning. Similarly in Text Mining, the identification of irony and sarcasm is crucial to yielding accurate results from analysis of data like Twitter data.

Irony and sarcasm has been traditionally the main obstacle to sentiment analysis within social media where sentences may be more opinionated and more subjective. Within news media however, journalists are expected to maintain an objective form of writing that removes the presence of irony. Instead, news media will utilize methods such as loaded language, appeal to authority or obfuscation as a means of introducing bias and persuading people into supporting certain causes. (Da San Martino et al., 2019)

Text Mining

Similar to IR, Text Mining is the discovery of patterns within unstructured textual data, it deals with the processing and comprehension of complex textual patterns in order to uncover hidden trends. Like IR, Text Mining deals with large corporea of text and is concerned with the complexities of language.(Stavrianou et al., 2007) The rules of language can be complex and change frequently to fit the cultural context of it's speakers. (AbuSa'aleek, 2015) notes that internet users have a change in words and expression in English internet discourse ranging from shortening of words to the use of emoticons while (Bengio et al., 2000) mentions that traditional language models suffer greatly from the curse of dimensionality and have decreases

in efficiency owing to the number of words in a given vocabulary. The analysis of text has to adjust to these changes in both morphology and semantics while also accommodating the diversity of expressions and words.

Due to the complexities of text, much of NLP have moved away from statistical models (n-gram, maximum entropy) into the domain of Machine Learning utilizing the presence of larger corpora with the development of models like BERT and GPT-3, achieving higher results than traditional models. (Wei et al., 2023) The use of Machine Learning helps tremendously with pattern recognition and mining of textual data. Still, more research is to be done on more complicated use of words in different languages and context (such as humour or disgust and hate) (Farabi et al., 2024).

Semantics

This thesis concerns mainly with the semantics of language. Semantics is one of the main disciplines of language along with phonetics (individual sounds), phonology (the organization of sounds), morphology (the formation of sound into words), syntax (the structure of sentences), pragmatics (how information is conveyed through language), discourse (use of language in conversations) and socio-linguistics (how society influences language). These components of language are listed in the Handbook of Linguistics (Aronoff & Rees-Miller, 2020), where semantics is listed as the study of meaning developed through words and sentences. Though semantics is mainly thought to come from words and phrases, the meaning of a given sentence can change depending on any of the other components of language like discourse, phonology and socio-linguistics.

Sentiment Analysis

Sentiment is the emotional reaction of a given person. In text, we often communicate our emotions and opinions using words with specific connotations we learn. Examples of words that communicate strong sentiment may include direct

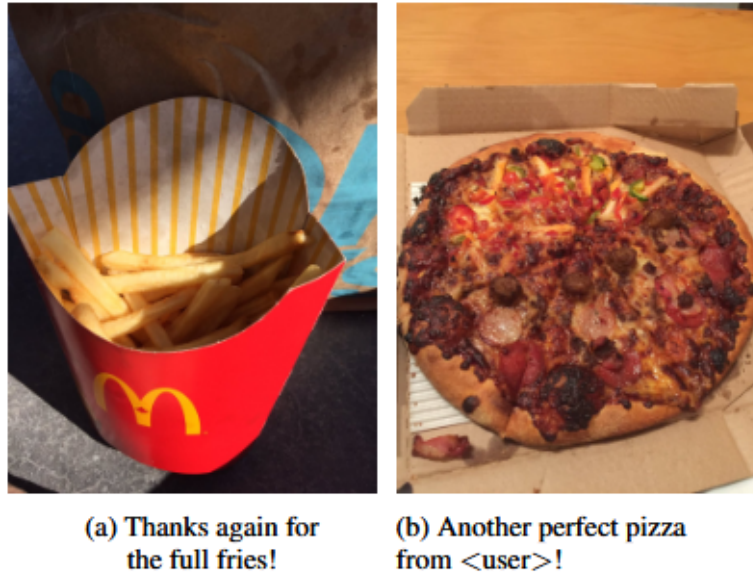


Figure 1 Examples of how social media users may post sarcastic messages. The semantics of the sentence may be literal but is rendered not due to the juxtaposition of the images. Similarly, the discussion surrounding a conversation may render a message sarcastic. (Farabi et al., 2024)

emotions (Happy, Sad, Afraid), objects that evoke emotions (Baby, Rain, Rainbow) or adjectives (Cool, Warm, Bitter). These opinions can be all sorts of different emotions ranging from anger, sadness to joy and surprise and of different polarities from extremely negative to extremely positive (Taboada, 2016).

Goal of Sentiment Analysis

The purpose of Sentiment Analysis (also known as Opinion Mining) is to uncover and summarize the various opinions hidden within large corpora of text in order to discover cultural and societal opinions on subjects. Papers such as (Singh et al., 2022) classified tweets on Twitter during the Covid-19 pandemic with the labels of joy,sad,fear and anger using various machine learning models in order to help organizations adapt to current world events. From sentiment analysis, research can uncover the trends in opinion within given subjects like pandemics or opinions on political/cultural issues such as dementia.(Kong et al., 2022)



Figure 2 Examples of various emotional sentiments in Weibo messages and their sentiment labels. (Li & Li, 2023)

Machine Learning based Sentiment Analysis

Of the methods in sentiment analysis, two are most significant, Machine Learning approaches and Lexicon-Based approaches.(Taboada, 2016) A majority of Sentiment Analysis utilizes Machine Learning/Deep Learning methods. These methods utilize a textual dataset that is transformed by Feature Engineering to emphasize relevant information. The machine learning models then train and classify based on the transformed dataset. Machine learning approaches are more popular within the domain. As (Rodríguez-Ibáñez et al., 2023) notes, machine learning became more popular when vector embedding was introduced where words are transformed into vector space, allowing a mathematical representation of language. Deep learning, SVMs and Bayesian methods are some of the most commonly used techniques for sentiment analysis with more recent deep learning models like Long Short-term Memory (LSTM) and Transformers like Generative Pre-trained Transformers (GPT) and Bidirectional Encoder Representations from Transformers (BERT) achieving higher results. This thesis will use this branch of sentiment analysis and several deep learning and machine learning models will be discussed in detail later in the thesis.

Lexicon-based Sentiment Analysis

These methods differs from lexicon based approaches that develop rules based on dictionaries and text and separate the data according to the rules. Mentioned in (Sabeti & Saad, 2017), a lexicon-based method like semantic orientation would use k-means clustering to group documents and sentences based on a set of positive/negative words to form a dictionary, the text would be then be weighted upon using term frequency-inverse document frequency (TF-IDF) and a voting technique to measure it's importance and fine-tune the dictionary. The key advantage that Lexicon-based approaches have was their ability to be applied to a wide variety of corpora without changes to the dictionary (Taboada et al., 2011) allowing for easy reuse. But with increases in computational capabilities, recent research is heavily skewed towards Machine Learning methods.

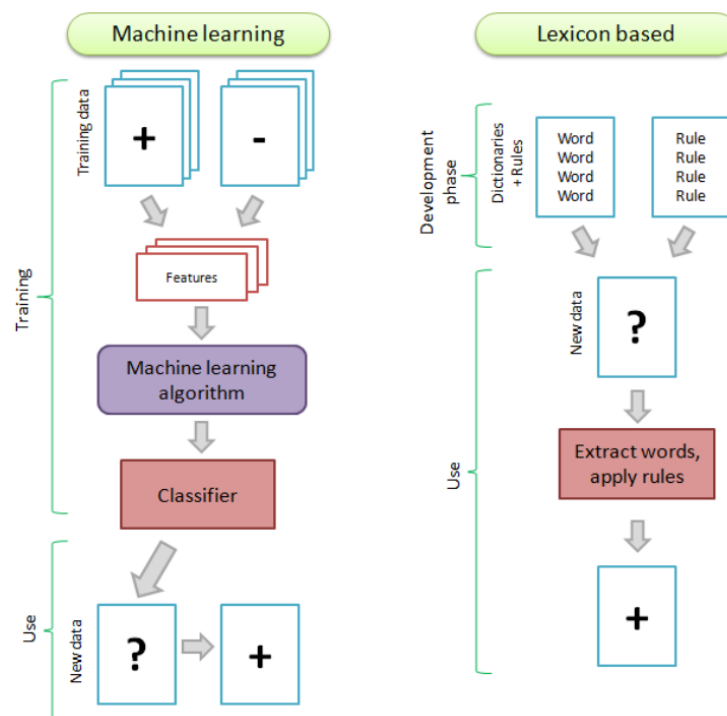


Figure 3 Difference between Machine Learning methods and Lexicon-based methods. (Taboada, 2016)

Challenges and Research Gaps of Sentiment Analysis

The main challenge to all sentiment analysis is non-literal use of language. As stated above, sarcasm, irony and satire all use language in a way that communicates the opposite of it's literal meaning. (Maynard & Greenwood, 2014) analysed tweets using labels of polarity, strength of opinion and sarcasm and showed that accounting for sarcasm could have an improvement on Text Mining systems. In terms of political humour, (Frenda et al., 2018) noted that aspects of bigotry like misogyny are often transmitted through sarcastic jokes, identification of sarcasm and correct labelling of sentiment may be important for political jokes that demean groups of people.

Machine Learning/Deep Learning Classification Models

The domain of Artificial Intelligence (AI) is largely split between two types of classifications. (Janiesch et al., 2021) distinguishes these two classifications as the model type (Machine Learning (ML) methods which includes Artificial Neural Networks (ANN) which includes Deep Learning (DL) methods) and the learning type (supervised, unsupervised, semi-supervised and reinforcement learning).

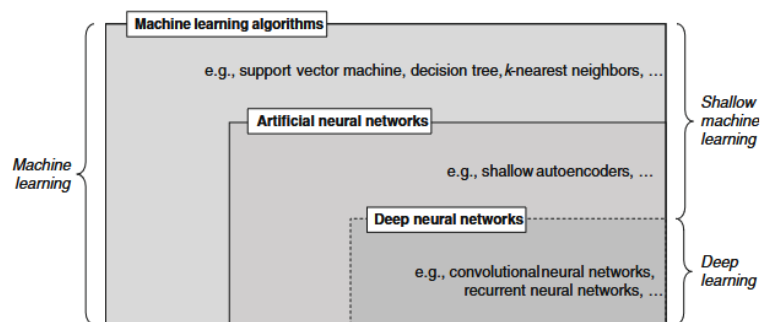


Figure 4 Venn diagram grouping on ML Methods. DL is a subset of ML that utilizes complicated neural networks. (Janiesch et al., 2021)

Much of sentiment analysis is done through supervised classification ML/DL such that the model is able to recognize the concept of polarity and emotional labels. This type of learning occurs when models are first trained on a set of data with labelled outputs

(positive/negative, emotional labels, etc) and then utilized for use and evaluation in unlabelled data. In general, both supervised ML and DL follow the same basic methodology:

1. Labelled Data Input

Data is labelled with it's correct output and fed to the model. This directs the model so that it is useful for classification.

2. Model Training

The model is trained to identify patterns within the data provided. The results of the model are transformed by the loss function into a value that is gradually optimized. For deep learning models this is usually a form of gradient descent. (Andrychowicz et al., 2016) The next sections will go into detail on how ML/DL models are gradually trained to identify patterns and the specific architecture of these models.

3. Model Evaluation

The model is evaluated based on it's performance. Common evaluation metrics for classification models include Precision, Recall, Accuracy, F1-score and Receiver Operating Characteristic(ROC)-Curve

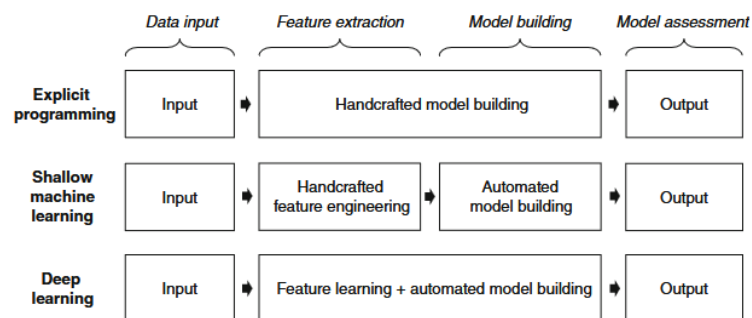


Figure 5 Comparison of explicit programming methods, machine learning and deep learning. (Janiesch et al., 2021)

Neural Networks

Artificial Neural Networks (ANN) are at the heart of deep learning. They are composed of several layers of artificial neurons within hidden layers. Each neuron has weight inputs and transforms them via an activation function of choice (sigmoid, tanh, softmax, so on.) The output weight is then fed to the next layer, continuing until it reaches the end of network where the value of the prediction is calculated by a loss function (usually Mean Square Error) against it's training dataset. (Zakaria et al., 2014) The network "learns" and self-corrects by performing back-propagation. Starting from the output layer, back-propagation derives every layer in order to minimize the loss of the model.

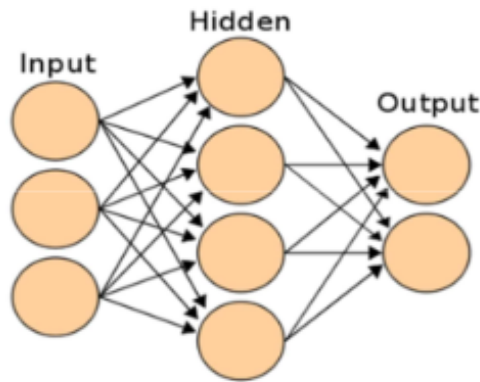


Figure 6 Illustration of a simple ANN model. (Islam et al., 2019)

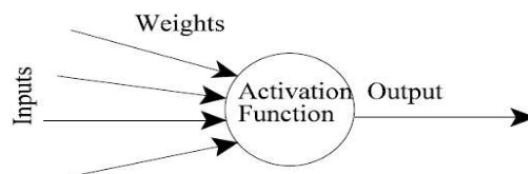


Figure 7 Illustration of an artificial neuron. The neuron is fed weights from previous layers and transforms it into an output by an activation function. (Zakaria et al., 2014)

Feature Extraction Methods

The main distinction of DL methods from other ML methods like Support Vector Machines (SVM) is the reduced need for feature engineering, that is the preprocessing of data in order to reduce the dimensionality of it such that the ML model can achieve suitable accuracy. (Zebari et al., 2020) DL Models do not suffer from the requirement of feature engineering due to it's ability to find features by itself. As (LeCun et al., 2015) notes, DL models operate on successive feature extraction layers which can find significant features of data by continuously abstracting from higher representative patterns. Given that textual data and language contains high dimensional data such that multiple factors can affect the semantics of a given sentence, it is easy to see how the self extraction of significant features in DL can result in improved performances in both Sentiment Analysis and NLP. That being said, DL methods still require the use of feature extraction in order to convert textual data into mathematical representations before the DL model can extract more abstract features. (Chaudhary et al., 2023)'s overview of Machine Learning and Deep Learning method in Sentiment Analysis for Twitter data noted that a majority of Deep Learning methods utilize Word2Vec, TF-IDF and GloVe in order to transform text into mathematical representations.

Term Frequency-Inverse Document Frequency (TF-IDF)

TF-IDF weights words based on their importance within a given document. This is based on the frequency of the word within the document and within the corpus. The weight of the word is increased based on it's frequency of within the document while simultaneously decreased by it's frequency within the wider corpus.(Lubis et al., 2021) The total equation is given as:

$$TF - IDF_{t,d} = tf_{t,d} \cdot idf_t$$

For word t in document d , $tf_{t,d}$ is the weight of importance based on it's frequency within document d while idf_t is the inverse weight of a term based on df_t , the frequency of documents that contain word t against the number of documents within

the corpus, N . There are a variety of different methods to calculate the two terms:

Term Frequency $tf_{t,d}$		Inverse Document Frequency idf_t	
natural	$f_{t,d}$	no frequency	1
logarithmic	$1 + \log(f_{t,d})$	idf	$\log \frac{N}{df_t}$
augmented	$0.5 + \frac{0.5f_{t,d}}{mode_d}$	probabilistic	$\max\{0, \log \frac{N-df_t}{df_t}\}$
boolean	$f(x) = \begin{cases} 1 & \text{if } f_{t,d} > 0 \\ 0 & \text{otherwise} \end{cases}$		

Table 2 List of tf-idf methods documented by (Schütze et al., 2008)

For $f_{t,d}$ being the frequency of term t in document d , $mode_d$ being the count of the most frequent term in document d . N being the total number of documents in the corpus, df_t being the number of documents containing term t .

A common method of calculating $tf_{t,d}$ is the logarithmic method, where the importance of words is not measured linearly like in natural count. Another method is by augmented $tf_{t,d}$ where the weight of importance is measured against the frequency of the most common word in the document.

Word2Vec

Until Word2Vec, most techniques for extracting textual features ignore the surrounding context of a given word like TF-IDF. Word2Vec is a technique for transforming text into representational vectors that utilizes one of two simple neural network models, Continuous Bag of Words (CBOW) and Skip-gram. (Ma & Zhang, 2015) notes that CBOW predicts the appropriate words given adjacent words (word order does not matter) and Skip-gram does the opposite, predicting the adjacent words using the words given. Using either of the two models, Word2Vec constructs a lexicon of words from the dataset and then assigns weight to each word to a point in vector space, such that similar words are placed closed to each other while dissimilar words are placed further apart. Due to it's ability to consider the context of a word, Word2Vec has been popularly adopted as a feature extraction method for many NLP

tasks.

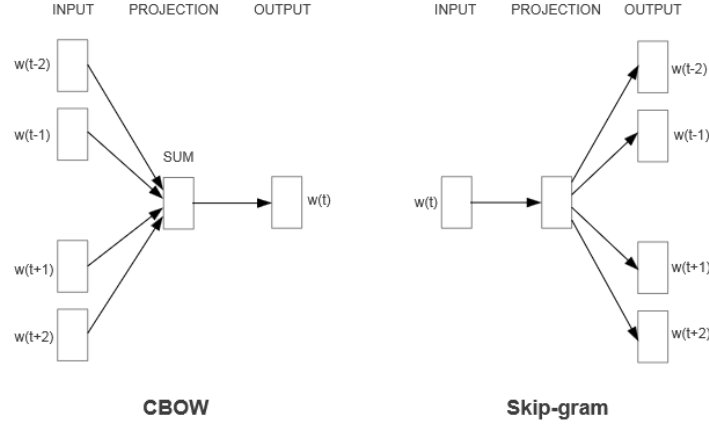


Figure 8 Illustration of Word2Vec’s two models, CBOW and Skip-gram. CBOW takes words and predicts the most appropriate word in the context. Skip-gram takes a word and generates the most appropriate words outside of the input word. Both of these methods will produce a vector of weights that represents it’s similarity to other words in vector space. (Mikolov, 2013)

Global Vectors (GloVe)

Word2Vec is a powerful method for feature extraction of text, but it focuses on small windows of words and ignore the global view of how words interact. As introduced in (Pennington et al., 2014), GloVe is a method that uses a large global matrix to represent the probability of any given word co-occurrence represented by the conditional probability:

$$g_{i,j} = P(w_i|w_j) = \frac{P(w_i \cap w_j)}{P(w_j)}$$

For i -th row, j -th column within the GloVe matrix, $g_{i,j}$ is represented by the probability that words w_i and w_j co-occur in a sentence/phrase over the probability that word w_j is present with a sentence. The matrix is then factorized by the equation to extract the weights of the words in a given sentence. This allows for extraction of the weights

through a simple mathematical operation at the cost of utilizing large matrices that scale quickly with the number of words in a given corpus.

$$\begin{matrix} \text{The} \\ \text{Cat} \\ \text{Sat} \\ \text{On} \\ \text{Mat} \end{matrix} \begin{bmatrix} 5 \\ 3 \\ 4 \\ 3 \\ 1 \end{bmatrix} = \begin{matrix} & \text{the} & \text{cat} & \text{sat} & \text{on} & \text{mat} \\ \text{the} & 2 & 1 & 2 & 1 & 1 \\ \text{cat} & 1 & 1 & 1 & 1 & 0 \\ \text{sat} & 2 & 1 & 1 & 1 & 0 \\ \text{on} & 1 & 1 & 1 & 1 & 1 \\ \text{mat} & 1 & 0 & 0 & 1 & 1 \end{matrix} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

Figure 9 Demonstration of matrix factorization for GloVe Matrices. The importance of each word is extracted given that words "the" "cat" "sat" (represented as the vector on the right) appear within a sentence. This example may be misleading as it is preferable to understand co-occurrence matrices as a matrix of conditional probabilities. Example GloVe co-occurrence matrix given by (Hindocha et al., 2019)

Recurrent Neural Networks (RNN)

Although the utilization of ANNs within NLP and consequently, sentiment analysis, have been massive benefits in identifying patterns within unstructured textual data. That being said, ANNs do not have the ability to remember information from previous contexts. This makes the recognition of patterns in highly dynamical systems of information (such as language or speech recognition) achieve less than desirable accuracy. Due to this, the use of RNN is deemed to be an improvement on these subjects. The main modification of RNNs is the presence of prior knowledge from previous layers, which allows RNNs to have limited knowledge of previous words and phrases and making use of the order of sentences and words. (Tarwani & Edem, 2017)

Some recent studies have been using bidirectional RNNs that promised increased results compared to single directional RNNs, at the expense of increased computational time during back-propagation. (Mahadevaswamy & Swathi, 2023)

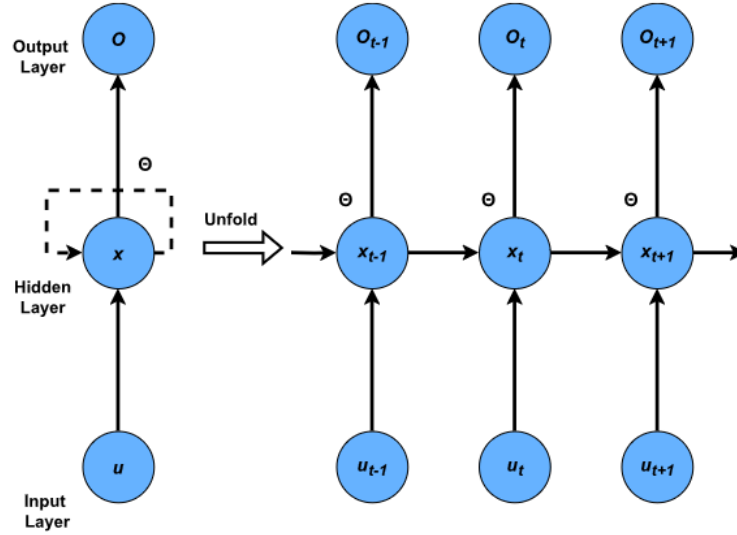


Figure 10 Illustration of RNN architecture. The left image depicts the neural network containing a hidden layer that loops back information from the previous step. When unfolded, information from time $t - 1$ is fed to the RNN at time t . Information at time t is fed to time $t + 1$ and so on. (Alhajeri et al., 2024)

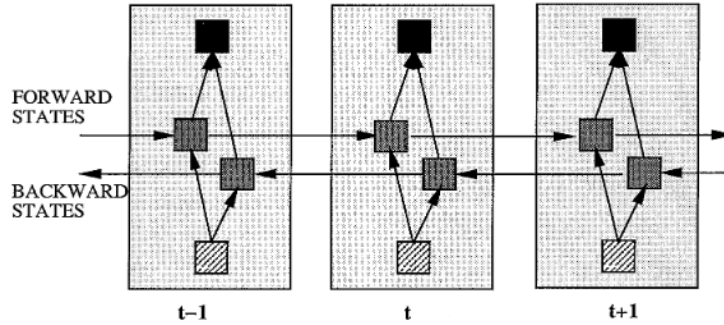


Figure 11 Illustration of Bidirectional RNNs, this applies to subsequent models like LSTM and GRU. The information is passed through two RNNs understanding context from two directions. (Schuster & Paliwal, 1997)

Long Short-Term Memory (LSTM)

(Noh, 2021) noted that the standard RNN model has difficulty learning information in the long run. The training improvement will gradually vanish and long term training of RNNs will bring about increasingly diminishing returns. Similarly, the RNN may explode in learning gradient that equally leads to a lack of training progress. These two issues were described by (Bengio et al., 1994). The problem comes with the use of back-propagation, the gradient during back-propagation. (Pascanu et al., 2013)

examined the gradient of back-propagation in RNNs and highlighted that the cause of vanishing/exploding gradients was due to repeated multiplications in the differential between RNN states. A common solution to this is to utilize a variant of RNN called

$$\frac{\partial \mathcal{E}}{\partial \theta} = \sum_{1 \leq t \leq T} \frac{\partial \mathcal{E}_t}{\partial \theta} \quad (3)$$

$$\frac{\partial \mathcal{E}_t}{\partial \theta} = \sum_{1 \leq k \leq t} \left(\frac{\partial \mathcal{E}_t}{\partial \mathbf{x}_t} \frac{\partial \mathbf{x}_t}{\partial \mathbf{x}_k} \frac{\partial^+ \mathbf{x}_k}{\partial \theta} \right) \quad (4)$$

$$\frac{\partial \mathbf{x}_t}{\partial \mathbf{x}_k} = \prod_{t \geq i > k} \frac{\partial \mathbf{x}_i}{\partial \mathbf{x}_{i-1}} = \prod_{t \geq i > k} \mathbf{W}_{rec}^T \text{diag}(\sigma'(\mathbf{x}_{i-1})) \quad (5)$$

Figure 12 The issue with back-propagation in RNNs as highlighted by (Pascanu et al., 2013). In the general back-propagation chain, $\frac{\partial \epsilon}{\partial \theta}$, it is required that it also account for the gradient between two states of a RNN, $\frac{\partial \mathbf{x}_t}{\partial \mathbf{x}_k}$. This differential is comprised of only multiplications of gradient between the two states, making it susceptible to greatly amplifying/diminishing the gradient of the network over time.

LSTM (Hochreiter, 1997). LSTM does not address with the exploding gradient, again as noted by (Pascanu et al., 2013), but it does adequately address the vanishing gradient problem by providing a long term memory channel, allowing the results of older states to leak into new states. The model utilizes two channels, a long term memory channel c_t and a short term memory channel, h_t (illustrated in Figure 13 as the top channel and bottom channel respectively). The model is designed such that the results of long term memory will leak into short term memory and short term memory will modify long term memory. This allows for a broader view than RNNs and allows significant words and phrases in the beginning of a sentence/document to have greater effect on the prediction overall. (Lakretz et al., 2019) notes that LSTMs are able to capture specific linguistic information, that models contain units that are able to capture information such as subject-verb dependency.

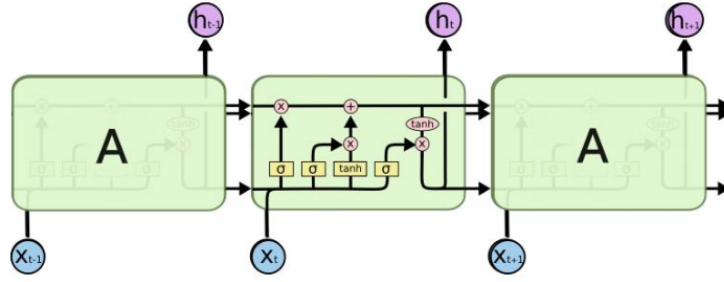


Figure 13 Simplified illustration of the LSTM model. (Tarwani & Edem, 2017)

Gated Recurrent Units (GRU)

GRUs are a subset of LSTMs that are simpler than the traditional LSTM model. The main difference is the combination of the long-term memory channel and short-term memory channel into a single channel. The model is worse than LSTM by a bit, but has demonstrated improved running times. (Shewalkar et al., 2019)

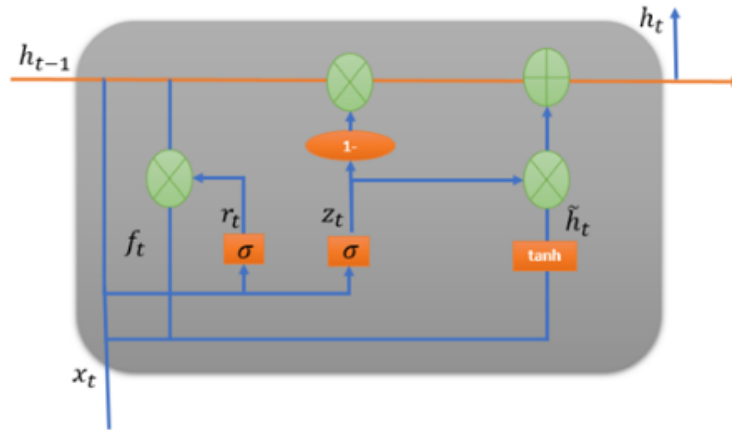


Figure 14 Simplified illustration of the GRU model. (Mateus et al., 2021)

Literature of LSTM use in sentiment analysis

From the table, we can see that LSTMs are effective at classifying text into sentiment with most models reaching 80% to 90% in evaluation metrics. In a survey of sentiment analysis methods, (Wankhade et al., 2022) noted the effectiveness of

Paper	Dataset Language	Model	Accuracy	Precision	Recall
(Singh et al., 2022)	English	LSTM-RNN with attention mechanism	0.8456	0.8234	0.8212
(Said et al., 2023)	English	LSTM-2BiGRU	0.9246	0.9297	0.9194
(Mu et al., 2024)	English	IDBO-CNN-BiLSTM	0.8033	0.8235	0.8207
(Eyvazi-Abdoljabbar et al., 2024)	Farsi	Ensemble of CNN and LSTM Hybrid models	0.7234	0.72069	0.72198
(Halawani et al., 2023)	English	ABiLSTM	0.8425	0.8583	0.8637
(Yin et al., 2023)	English	DPG-LSTM		0.842	0.845
(Li & Li, 2023)	Chinese	CNN-BiLSTM	0.8778	0.8946	0.8841
(Nguyen, 2024)	English	BiLSTM, with GloVe	0.8218	0.8219	0.8218
(Kastrati et al., 2024)	English with Emojis	BiLSTM with attention mechanism	0.7022	0.7093	0.7091
(Vernikou et al., 2022)	English	LSTM with BERT tokenizer	0.91	0.91	0.91
(Vanam & Raj, 2023)	English	BET Tokenizer and H-LSTM	0.99	0.98	0.97
(Lin et al., 2023)	Chinese	BiGRU-Att	0.9758	0.98	0.98
(Tabinda Kokab et al., 2022)	English	BERT embedding and BiLSTM	0.95	0.96	0.97

Table 3 List of LSTM/GRU models used in literature.

BiLSTM models in comparison to other types of models but the training cost and time is higher compared to other models, the same paper also noted that semi-supervised training is the best at handling ambiguous text while the more commonly used supervised training is effective at handling subjectivity. That being said most of the recent models utilize a hybrid model with the only non-hybrid model being BiGRU and BiLSTM. From the table, some of the best performing models are relatively simple LSTM/BiLSTM and BiGRU models.

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