

An Analysis of Machine Learning and Deep Learning Techniques for Detecting Sarcasm in Online Text

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Abstract —

Context / Background – Sarcasm detection is a relatively new research topic that has recently gained interest due to the increased use of sentiment analysis and social media analytics. Sarcasm is a unique form of language that cannot be interpreted at surface-level, therefore detecting sarcasm proves a significant challenge for traditional sentiment analysers and humans alike. This highlights the scope for innovative machine learning and deep learning solutions to this ill-structured problem.

Aims – The ultimate aim of this project is to develop a tool that can detect sarcasm in online text from multiple domains with a *high degree* of accuracy. We aim to determine whether deep neural network architectures are more effective than machine learning classifiers for this task, and to what extent manually extracted sentiment features can be used to improve machine learning classification. Finally, we aim to highlight tokens that correlate more to sarcastic labels.

Method – We gather labelled datasets from online sources containing Amazon reviews, Twitter data and News headlines. Multiple vectorisation approaches are used to transform text into numerical representations, including a state-of-the-art contextualised embedding approach (ElMo). These vectors are used to train various machine learning and deep learning classifiers to detect the presence of sarcasm. In addition, an attention mechanism is incorporated to localise the presence of sarcasm within a passage of text.

Results – Through extensive experimentation, we show that

Conclusions – In summary, we conclude that

Keywords — Machine learning, Deep learning, Sarcasm Detection, Sentiment, Classification

INTRODUCTION

Sarcasm is a complex linguistic phenomenon, which when present in text indicates that the literal interpretation differs from the implied meaning. Sarcasm is prevalent in online user-generated content, and poses a significant challenge within the field of natural language processing, specifically within sentiment analysis, as it inverts the sentiment-polarity of a positive or negative utterance. Sentiment analysis is the task of deducing the sentiment polarity of text - typically whether the author is in favour of, or against, a certain subject. It is increasingly common for organisations to use sentiment analysis in order to gauge public opinion on their products and services; however, classic sentiment analysers cannot deduce the implicit meaning of sarcastic text and will wrongly classify the author's opinion. Hence, any tool that strives to accurately determine the meaning of user-generated text must be capable of detecting sarcasm. The phenomenon of sentiment incongruity often lies at the heart of sarcasm, therefore advancements in

automatic sarcasm detection research have the potential to vastly improve the task of sentiment analysis in opinion mining.

A Problem Background

As sarcasm is multi-faceted, this makes its detection a unique and interesting challenge. It can be both explicit and implicit; oftentimes, contextual cues are more powerful indicators of sarcasm than the words themselves. However we often lose this context, and hence the sarcastic undertones, in transcription. Consider the scenario where a person is congratulated on their hard work, despite the obviousness of them having not worked hard at all. Or perhaps a customer thanking a waiter for the delicious food, even though they sent it back to the kitchen. In isolation, the speech is not enough to convey the sarcastic intent. Furthermore, even humans struggle to consistently recognise sarcasm; due in part to the lack of an all-encompassing, universal definition¹. In a 2011 study, González-Ibáñez et al. [5] found low agreement rates between human annotators when classifying statements as either sarcastic or non-sarcastic, and in their second study, three annotators unanimously agreed on a label less than 72% of the time. Truly, the existence of sarcasm can only be conclusively affirmed by the author. Additionally, developmental differences such as autism, as well as cultural and societal nuances cause variations in the way different people define and perceive sarcasm.

These factors make sarcasm detection an extremely complex task for both humans and computers. Despite this, *most* humans can recognise sarcastic intent *most* of the time. We strive to replicate this performance, or even perhaps improve upon it, in order to move towards a more concrete definition of what *makes* a statement sarcastic. This highlights the scope for automating this process, and the need for an innovative solution.

Early rule-based approaches introduced the idea that the sentiment contained within text can be indicative of sarcasm, although exploring these sentiment features using more complex machine learning and deep learning architectures is a novel approach to the problem. The first deep learning approach to sarcasm detection was used in Poria et al. (2017) [17] to produce state of the art results.

B Research Questions and Objectives

The **research questions** guiding this project are as follows –

- *Can handcrafted sentiment features improve sarcasm predictions?*
- *Do deep learning techniques perform better than machine learning approaches?*
- *Can a custom model identify which linguistic cues correlate more to sarcastic labels?*

The following objectives are designed to address these specific research questions, and are divided into three categories depending on their priority level and difficulty.

The **minimum** objectives of this project are to evaluate, compare and clean high-quality datasets, as well as to employ machine learning models and evaluate the effectiveness of these architectures on our chosen datasets. We found that a logistic regression model trained on ELMo vectors performed best for all three datasets, achieving F_1 scores of 84.6%, 81.3% and _%.

The **intermediate** objectives of this project are to experiment with and evaluate deep learning

¹www.dictionary.cambridge.org/dictionary/english/sarcasm

models on the chosen datasets, and to determine which is the best performing solution. Additionally, we evaluate the model against unseen data. This is achieved by ...

The **advanced** objectives of this project are to implement an attention-based neural network in order to identify words that correlate more to sarcastic labels, in order to produce a visualisation of attention words. We implement a custom attention layer using keras, and apply our trained model to a number of sentences to illustrate its effectiveness.

This is achieved by...

RELATED WORK

In this section, we report on the architectural design of solutions used specifically in sarcasm detection research, as well as techniques that have seen success in other natural language processing (NLP) classification tasks. Oftentimes, sarcasm detection is treated as a binary classification problem, in which text is grouped into two categories - sarcastic and non-sarcastic. It is otherwise treated as a multi-class problem where the extent to which a statement is sarcastic is ranked on a discrete scale, e.g. 1 to 5. In similar studies, the terms irony and sarcasm are used synonymously [23], although their definitions differ slightly (*table 1*). Both definitions capture the humorous intent in both sarcasm and irony, however sarcasm includes the potential for mockery and criticism - often present in opinion-based content such as product reviews.

Table 1: Definition of Irony and Sarcasm

| Term | Definition |
|---------|---|
| Irony | A subtle form of humour which involves saying things that you do not mean. ¹ |
| Sarcasm | Speech or writing which actually means the opposite of what it seems to say, usually intended to mock or insult someone. ² |

A Rule-based Classifiers

A number of naïve approaches have been used in previous research, where text is classified based on a set of linguistic rules. Rule-based techniques are fairly primitive when compared to their modern, deep learning counterparts, as each rule-set must be generated manually for each unique dataset. An early example of a rule-based approach is displayed in Veale and Hao (2010a) [24], yielding an F_1 score of 0.73 in the irony detection task. They collect a corpus of 15039 phrases that match the wildcarded query “* as a*”, applying a nine-step procedure which filters ironic similes out of the corpus at each stage.

Maynard and Greenwood (2014) [12] proposed that the sentiment contained in hashtags can indicate the presence of sarcasm in tweets, such as #notreally in the example “*I love doing the washing-up #notreally*”. They used a rule-based approach, whereby if the sentiment of a tweet contradicts that of the hashtag, it is labelled sarcastic. They reported an F_1 score of 91.03% on a random sample consisting of 400 tweets.

Bharti et al. (2015) [2] proposed two rule-based approaches - the first approach (IWS) classifies tweets that begin with interjections, such as “wow” and “yay”, as sarcastic, and the second approach uses a parsing based lexical generation algorithm (PBLGA) to recognise sentiment-bearing situation phrases juxtaposed with contrasting sentiment phrases. When tested on 1500

¹<https://www.collinsdictionary.com/dictionary/english/irony>

²<https://www.collinsdictionary.com/dictionary/english/sarcasm>

tweets containing #sarcasm, the IWS and PBLGA approaches yielded F_1 scores of 0.90 and 0.84, respectively.

B Machine-Learning Classifiers

Machine learning algorithms do not rely upon a static linguistic rule-set. Instead, they can learn patterns that are associated with each class, allowing them to separate unseen data into these categories. There are a number of commonly used architectures, including Naïve Bayes classifiers, Support Vector Machines (SVMs) and Logistic Regression classifiers, although not all approaches fit neatly into these categories.

An early approach, Tsur et al. (2010) [23], proposed a novel semi-supervised algorithm, *SASI*, for sarcasm identification; trained on a small balanced seed of 160 reviews (80 sarcastic and 80 non-sarcastic) from a corpus of 66000 human-annotated Amazon product reviews. In order to mimic the ambiguous and spectral nature of sarcasm, a discrete score between 1 (non-sarcastic) and 5 (definitely sarcastic) is assigned to each sentence; scores of 3 and higher indicate sarcasm. Syntactic and pattern-based features are extracted and fed to a classifier which utilises a strategy similar to K-Nearest Neighbours (kNN), whereby a sarcasm score is assigned to an unseen vector based upon the weighted average of the k closest vectors from the training set. They reported an F_1 score of 82.7% on the binary classification task.

In Riloff et al. (2013) [20], sarcasm is described as a contrast between positive sentiment e.g. "*i love*", in reference to a negative situation, e.g. "*being ignored*". They use a bootstrapping algorithm to extract positive verb phrases and negative situation phrases from a Twitter corpus and used these to train a hybrid model consisting of an SVM and a contrast method which classifies text as sarcastic if a positive sentiment phrase precedes a negative situation. This yielded an F_1 score of 51%.

Reyes et al. (2013) [19] used a naïve bayes and decision trees algorithm in order to detect irony which is closely related to sarcasm. They experimented with balanced and unbalanced distributions (25% ironic tweets and 75% other), achieving an F-score of 0.72 on the balanced distribution, dropping to 0.53 for the imbalanced distribution. In a similar vein, Barbieri et al. (2014) [1] used random forest and decision tree classifiers, also for the detection of irony. They used six types of features in order to represent tweets, and recorded results over three categories of training data - education, humor and politics.

González-Ibáñez et al. (2011) [5] used a Support Vector Machine (SVM) with sequential minimal optimisation, as well as Logistic Regression, on lexical (e.g. unigrams) and pragmatic (e.g. emoticons) features. They achieved 71% accuracy using an SVM trained on unigrams.

Ptáček et al. (2014) [18] also used SVM and Maximum Entropy classifiers. They also performed classification on balanced and imbalanced distributions.

C Deep-Learning Classifiers

Deep neural networks (DNNs) are increasingly being used in text classification tasks [17, 27]. Though there are many forms of DNN, two commonly used architectures are Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs). Oftentimes, deep neural networks require a lot more training data than machine learning algorithms, but have been shown to produce state-of-the-art results in several domains. If the training data is high-quality and plentiful, then the model can begin to make accurate predictions.

One particularly interesting technique is the *Hierarchical Attention Network (HAN)* defined in Yang et al. (2016) [25] - an attention-based LSTM. The intuition is that certain words and

sentences in a document contribute more to its overall meaning, and this is highly context dependent. They included one attention mechanism at word-level and another at sentence-level, and this allowed them to determine which words and phrases correlate more to certain labels. Using a similar approach in the domain of sarcasm may allow me to highlight the attention-words that are strongly influence the level of sarcasm. A similar technique was applied in *Ghosh et al. 2018*) [4] where they concluded that emoticons such as ':' and interjections e.g. "ah", "hmm" correspond with highly weighted sentences. Gated Recurrent Units (GRUs) are another type of RNN used to overcome the vanishing gradient problem. *Zhang et al. (2016)* [26] used a bidirectional gated RNN to capture local information in tweets, as well as a pooling neural network to extract context from historic tweets, achieving 78.55% accuracy.

Convolutional Neural Networks allow us to extract higher-level features, and they are based on the mathematical operation of convolution. *Zhang et al. (2015)* [27] explored the used of character-level convolutional neural networks for text classification. This network consists of 6 convolutional layers and 3 fully-connected layers. They found that it showed better performance on raw texts such as an Amazon product review corpus.

In *Poria et al. (2017)* [17], cited as the first study to use deep learning for sarcasm

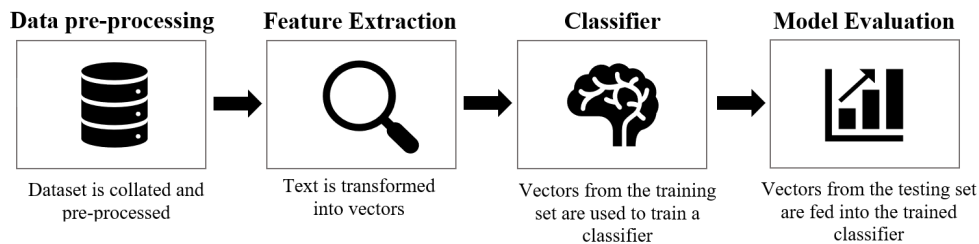
CNNs have been previously used in sarcasm detection. For example, *Poria et al. (2017)* [17] describes a convolutional neural network (CNN) for sarcasm detection.

SOLUTION

This project addresses a binary classification problem, aiming to determine if an unseen snippet of text is sarcastic or non-sarcastic. Our sarcasm detection tool employs trained classification models which form predictions based on knowledge gained from features encountered during training. Developing highly accurate classification models remains the greatest challenge in this project, therefore it is the central focus of our solution. Model performance is strongly dependent on the data pre-processing and feature extraction techniques employed, as well as the choice of model architecture and training procedures.

In our solution, high quality datasets are first collected and pre-processed. During feature extraction, the textual training data is transformed into numerical vectors and these features are used to train a classification model. The trained classifier is then carefully evaluated in order to account for potential overfitting. The following figure outlines the model pipeline, and each of these stages are further addressed in the remaining sections.

Figure _: Overview of the solution



A Implementation Tools

This project is majoritively written in **Python**, as it has an abundance of open-source libraries well-suited to machine learning and deep-learning tasks. Additionally, Python is very readable, making it easy for others to interpret, test and reproduce code. We use **pandas** for manipulating the datasets, as it provides functionality for applying functions globally across the dataset. We use **pickle** to store the vectorised datasets in memory. Vectorisation is a costly process, therefore writing the files to memory reduces long-term time demands during the experimentation and testing phases. We also incorporate **SpaCy** when cleaning and tokenising the data.

In terms of *classification*, we implement most of the machine learning architectures using **scikit-learn** - an open-source machine learning library. For constructing deep learning models, we use **keras**, as its modular structure allows for extensive experimentation and simplifies tweaking of model architectures.

B Datasets

We utilise three publically available datasets, and a statistical analysis of their properties is provided in *figure 2*. This includes the number of instances in the dataset, the average number of tokens per instance and a benchmark score where the dataset was used in the original paper to train one or more classifiers. This data is collected from multiple domains and online platforms, including Twitter, Amazon, and online news outlets; providing broad coverage of sarcasm usage in both formal and informal media.

1. **News Headlines Dataset For Sarcasm Detection** - *Misra et al. (2019)* [14] collected thousands of news headlines from two sources - *The Onion*³ (renowned for posting satirical news) and *The Huffington Post*⁴. News headlines are written formally, hence there is little noise in this dataset due to the absence of erroneous spelling. These headlines are self-contained, unlike tweets which may be in response to another tweet thereby excluding necessary context. Misra et al. (2019) [14] used a hybrid neural network architecture and achieved an *accuracy* of 0.897.
2. **Sarcasm Amazon Review Corpus** - *Filatova (2012)* [3] used crowdsourcing to collect Amazon reviews, human-labelled by 5 annotators. The number of stars given to a review, as well as the title and content are provided. These reviews are typically longer than the average tweet, which is capped at 280 characters. The author's punctuation and spelling is preserved, therefore this data is very messy. This is the smallest of the three datasets. This dataset was not used by its compilers for classification, hence there is no score available for comparison.
3. **Ptáček et al. (2014)** - One of three datasets collated in *Ptáček et al. (2014)* [18], we use a balanced dataset of 100000 English tweet ids, whereby the original tweet must be scraped using the Twitter API. Of this original corpus, 17.28% of the original tweets remain available to access on Twitter, therefore all others are omitted from the compiled dataset. This dataset is messy, as sarcastic instances are those that include *#sarcasm*, and non-sarcastic instances are selected arbitrarily from the set of all other tweets. Hence, some of the sarcastic instances may not be sarcastic, and some non-sarcastic instances may be sarcastic. We take a subset of the remaining

³www.theonion.com

⁴www.huffpost.com

tweets (7500 from each class) to form a smaller balanced corpus. Ptáček et al. (2014) [18] achieved an F_1 score of 0.947.

Figure -: Statistical breakdown of the datasets used in this project

| Dataset | Dataset Size | Composition* | Avg. tokens | Benchmark Score |
|----------------|--------------|--------------------------|-------------|-----------------|
| News Headlines | 28619 | pos: 47.6% neg: 52.4% | 11.2 | 0.897 |
| Amazon Reviews | 1254 | pos: 34.9% neg: 65.1% | 276.4 | N/A |
| Twitter Data | 17280 | pos: 50.4% neg: 49.6% | 19.8 | 0.947 |

**pos* indicates positive instances (sarcastic) and *neg* indicates negative instances (non-sarcastic)

Each of these datasets are sufficiently large enough to provide a representative view of their respective data sources, without exceeding our computational resources. However, we augment the *Amazon Reviews* corpus using a synonym replacement strategy to increase the amount of data used in deep learning as this improves training stability and model performance. Adjectives and nouns are chosen at random from each snippet of text and are substituted with a synonym so as not to alter the syntax but not the semantics of the text. This procedure is repeated to produce 8 variations of each snippet; hence, the final size of the dataset is 10032.

Most of the datasets are approximately balanced; despite the fact that sarcasm is used infrequently in real-life. On an unbalanced dataset, a classifier can achieve high accuracy simply by annotating each data instance with the majority class label. As most machine learning algorithms are designed to optimise overall accuracy, it is important to provide them with approximately equal amounts of both sarcastic and non-sarcastic data, to prevent them from overfitting to either class.

C Data Pre-Processing

Datasets of user-generated content are inherently noisy and ill-structured, as users are free to include spelling errors and inconsistent capitalisation. Pre-processing is necessary for removing as much of this noise as possible to reduce sparsity in the feature space; although, we must be careful not to remove useful features.

On Twitter, users can include hyperlinks and references to other users in their tweets; however, this can be a source of noise in the dataset therefore we remove them using regular expressions. In Ptáček et al. (2014) [18], hashtags are removed in pre-processing. However, Liebrecht et al. (2013) [10] showed that the sentiment contained in hashtags can be used to indicate sarcasm, such as the use of #not to suggest insincerity. In the simplest case, single-word hashtags can be included simply by removing the # symbol, however multi-word hashtags must first be parsed to separate the tokens. As this is beyond the scope of this project, we remove all hashtags with the exception of #not (which we substitute with *not*).

Punctuation is removed and text is transformed to lowercase in order to reduce sparsity induced by the optional inclusion of punctuation and variations in letter capitalisation. This ensures that there are fewer representations of the same word, as tokens such as 'CAN'T', 'can't', and 'Cant' are all mapped to the same single token - 'cant'. However, punctuation and capitalisation can

be used for emphasis, which may in turn be indicative of sarcasm. Hence, we re-introduce this meaning in the form of additional lexical features using a procedure outlined in the feature extraction section. Finally, we remove numbers and stopwords, such as '*the*', '*in*' and '*an*', as they provide little additional meaning to a sentence despite the number of times they occur.

Figure -: Proportion of tokens represented in the GloVe dictionary

| Dataset | Original data | Processed data |
|----------------|---------------|----------------|
| News Headlines | 97.71% | 97.71% |
| Amazon Reviews | 83.17% | 98.22% |
| Twitter Data | 89.62% | 96.43% |

Figure _ shows the proportion of GloVe-representable tokens before and after processing, where the same processing techniques are applied to each dataset. GloVe is a word-embedding technique, detailed in the feature extraction section, where tokens are encoded as pre-computed numerical vectors. We use the number of tokens represented in the GloVe dictionary (containing 27 billion tokens) as a measure of quality, as uncommon or ill-formed tokens are omitted from this dictionary. The quality of the Amazon and Twitter data vastly improved after processing, however the quality of the news headlines corpus remained consistent as the original data is written formally and in lowercase.

D Feature Extraction

Extracting meaningful data from large corpora is a complex task, however in order to do this successfully, we first construct word vectors that capture semantic and syntactic relationships. The textual data is transformed into numerical vectors, so as to encapsulate the seminal features of language.

D.1 Main Features

Traditional Approaches – We utilise the *Bag of Words (BOW)* and *Term Frequency-Inverse document frequency (TF-IDF)* [21] vectorisation approaches. In BOW, text is encoded as a single vector containing a count of the number of occurrences of each word. TF-IDF extends the BOW model by providing each word with a score that reflects its importance based upon its frequency within the document. These approaches create sparse inefficient representations, where each vector is the size of the vocabulary. Additionally, vectors produced in this way do not preserve the context within which words are found, although sarcasm is a highly contextual phenomenon. These approaches are used as a baseline against which to compare more advanced techniques.

Word Embedding – Introduced in Mikolov et al. (2013a) [13], *Word2Vec* describes a group of related models that were the first to produce high-quality vector representations of words, known as word embeddings. Word2Vec consists of a shallow (two-layer) neural network that takes a large corpus and produces lower-dimensional vectors than the sparse representations generated by BOW and TF-IDF; however, intrinsic statistical properties of the training corpus, which were key to earlier techniques, are neglected, therefore global patterns may be overlooked. To mitigate this, we use the *GloVe* [15] approach, which generates word embeddings by constructing an explicit word co-occurrence matrix for the entire corpus. Word embeddings appear in a

high-dimensional vector space, whereby words that share a similar context are clustered together.

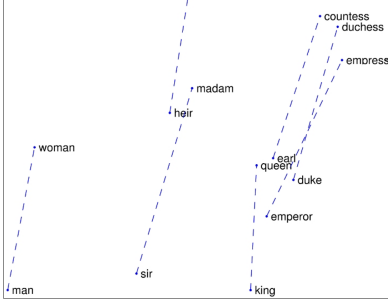


Figure -: GloVe substructure⁵

GloVe is able to preserve the semantic relationships between words, even constructing analogies by composing vectors e.g. $king - man + woman \approx queen$. Likewise, it captures syntactic regularities such as the singular to plural relationship e.g. $cars - car \approx apples - apple$. GloVe is used in this project to produce word embeddings for each corpus, however it does not accommodate polysemy, which describes the co-existence of alternative meanings for the same word, and cannot generalise to words that were not specifically included in the training set.

Contextualised Word Embedding – Peters et al (2018) [16] introduced the *ELMo* model, and showed that ELMo markedly improved the state-of-the-art in a number of NLP tasks.

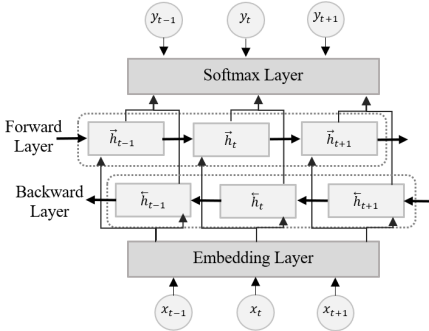


Figure -: ELMo model pipeline

ELMo utilises a bi-directional LSTM (*long short-term memory*) model, concatenating the left-to-right and right-to-left LSTM in order to produce deep contextualised word representations. They are character based, therefore robust representations can be constructed for out-of-vocabulary tokens. However, rather than 'looking-up' pre-computed embeddings, ELMo generates them dynamically. Hence, it can disambiguate the sense of a word given the context in which it was found. These state-of-the-art contextualised embeddings are used in this project as the most advanced method of feature extraction.

D.2 Miscellaneous Features

While deep learning algorithms are able to extract useful higher-level features from dense vectors (such as ELMo and GloVe), machine learning classifiers may require additional handcrafted features to better inform their predictions. We consider miscellaneous features as well as those produced by the aforementioned techniques - including lexical (punctuation) features, topic features and sentiment features. We produce low-dimensional feature vectors for each of our datasets, concatenating those that are shown to improve classification scores with existing vectors.

1. Punctuation features – We extract punctuation features following the procedure outlined in Tsur et al. (2010) [23]. Five lexical features are combined to produce a 1×5 dimensional vector for each text snippet, including the length of the snippet in tokens, as well as the number of: "!" characters, "?" characters, quotations and tokens that include at least one capitalised character. These features are normalised by dividing them by the (maximal observed value · average maximal value of remaining feature groups).

2. Topic features – We use Latent Dirichlet Allocation (LDA) to perform topic modelling - this is an unsupervised machine learning technique where a fixed number of abstract "topics" are identified in a corpus. Each instance in a dataset is represented as the distribution of its topics,

⁵<https://nlp.stanford.edu/projects/glove/>

relative to the topics in the global dataset. The intuition is that positive and negative instances may each contain their own distinct assortment of topics, thereby informing future predictions on unseen sarcastic and non-sarcastic data.

3. Sentiment features – We produce sentiment features using the state-of-the-art *SentimentAnnotator* [22] by Stanford CoreNLP [11]. This model uses a Recursive Neural Tensor Network to assign a discrete sentiment label to text, where 0 is very negative and 4 is very positive.

Example: "i love when my train is late"

| Tokens | i | love | when | my | train | is | late |
|-----------|---|------|------|----|-------|----|------|
| Sentiment | 2 | 4 | 2 | 2 | 2 | 2 | 1 |

| Sentiment | 0 | 1 | 2 | 3 | 4 |
|------------|---|-------|-------|---|-------|
| Frequency | 0 | 1 | 6 | 0 | 1 |
| Proportion | 0 | 0.125 | 0.750 | 0 | 0.125 |

Overall sentiment: 3.0

Feature vector: [0.0, 0.125, 0.750, 0.0, 0.125, 3.0]

For each instance in the dataset, we collect the sentiment values for each of the individual tokens, as well as the overall sentiment of the snippet. We construct 1×6 dimensional feature vectors, where values 0 - 4 show the distribution of sentiment classes for tokens in the snippet, and value 5 shows the overall sentiment label.

E Classification

In this section, we describe the machine-learning and deep-learning classification models that are used in this project. These algorithms are trained a set of rich features as outlined in the previous section.

E.1 Machine Learning Models

We experiment with five candidate machine learning classifiers, evaluating each of them when trained on four types of features. Each of these supervised models perform binary classification, where unseen samples are predicted to be sarcastic or non-sarcastic. Brief descriptions of the models are provided below.

1. **K-Nearest Neighbours (KNN)** – The KNN classifier is a non-parametric model which uses lazy learning at the time of prediction. An unseen sample is assigned the most common class label amongst its k nearest neighbours, where k is a hyperparameter to be finetuned.
2. **Naïve Bayes Classifier** – This is a probabilistic model derived from Bayes theorem, where all features are assumed to be independent of one another. Naïve Bayes classifiers are supervised algorithms that use bayes theorem to make predictions. Commonly used in the document classification problem, we calculate $P(\text{Sarcastic}|\text{features})$. This is the probability of an outcome A (i.e. statement is sarcastic), given its feature vector, x. There are a number of variations of Naïve Bayes - including Multinomial, Bernoulli and Gaussian.
3. **Support Vector Machine (SVM)** – SVMs use a kernel functions to draw hyperplanes which divide a space into subspaces. In our experiments, a single hyperplane is drawn such that the positive and negative features are partitioned into two groups. The features at the shortest euclidean distance to the hyperplane are known as support vectors, and their distance from the

hyperplane is known as the margin. An SVM attempts to maximise this margin in order to create a decisive boundary between the sarcastic and non-sarcastic data. SVMs can be effective when smaller amounts of training data are available, however they require more computational resources than naïve bayes.

4. **Logistic Regression** – A statistical model that aims to predict the likelihood of an event occurring given some previous data. It works with binary data, i.e. is the statement sarcastic or not. It is a more advanced approach than linear regression, which aims to model data using a linear equation.
5. **Random Forest Classifier** – An ensemble learning method, the random forest classifier fits a number of decision tree classifiers on subsamples of the training set. The decision trees are fairly independent of one another, and this low correlation allows them to produce ensemble predictions that outperform their individual predictions. Where one model goes wrong, the others are able to contradict this incorrect prediction.

E.2 Deep Learning Models

Deep learning classifiers do not require the hand-crafted features used in supervised classifiers, and are instead capable of learning higher-level features from dense vectors such as ELMo and GloVe. We focus on two categories of neural networks - Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN). While it is beyond the scope of this paper to describe in detail each of the model architectures used in this project, we provide a brief explanation of the basic concepts involved in CNNs and RNNs. As we are performing binary classification, we use the Binary Cross-Entropy loss function.

E.2.1 Recurrent Neural Networks – As in all neural networks, input vectors are modified by weighted nodes as they travel through the network. However, in a Recurrent Neural Network (RNN), there is an additional hidden state that is updated as inputs are fed through the network. This hidden state represents the context based on prior inputs, giving rise to the *temporal dimension* in RNNs which allows them to take into account time and sequencing.

In a RNN, there is an additional hidden state which represents the context based on prior inputs. The hidden state is h_t . This leads to the interesting property that the same input could produce a different output depending on the previous inputs given to the RNN.

In a vanilla RNN, the input and hidden state are simply propagated through a single tanh layer. However in a Long Short Term Memory model (LSTM), three gates are introduced, as well as a cell state, allowing an LSTM to better preserve long-term dependencies.

1. **Vanilla Recurrent Neural Network** –
2. **Vanilla Gated Recurrent Unit** –
3. **Long Short-term Memory (LSTM)** – three gates are introduced, as well as a cell state, allowing an LSTM to better preserve long-term dependencies
4. **Bidirectional Long Short-term Memory (BiLSTM)**

RNNs have been successfully applied to language-related tasks. Often, we may require more context than just the most recent surrounding text. The gap between the most relevant information needed to form a prediction can be very wide, if the relevant contextual information was given at the beginning of the paragraph. LSTMs are especially suited to processing sequential, or time-series, information such as text. This is due to the fact that RNNs have a 'memory', in that the input to the current step is the output from the previous step. However, they suffer from the vanishing gradient problem. This is where gradient values get smaller as it backtracks through lower layers, making it harder for the network to update weights and causing calculations to take longer. Recurrent Neural Networks are not very good at remembering long term dependencies, therefore in this instance we can use *Long short-term memory (LSTM)* models [7] instead which are more effective at preserving long term dependencies.

E.2.2 Convolutional Neural Networks – A Convolutional Neural Network (CNN) [9] is a specialised form of neural network. They were popularised for their applications in computer vision, hence they are designed to be used with two-dimensional image data [8], but have since been adapted for text-based classification tasks. CNNs consist of a few layers of convolutions with non-linear activation functions - they have fewer layers than typical neural networks, where each layer applies different filters and combines their result. The convolution operation is very fast, therefore many convolutional layers can be used in a single network.

$$\begin{bmatrix} w_{1,1} & w_{1,2} & \dots & w_{1,N} \\ w_{2,1} & w_{2,2} & \dots & w_{2,N} \\ \vdots & \vdots & \vdots & \vdots \\ w_{M,1} & w_{M,2} & \dots & w_{M,N} \end{bmatrix}$$

Figure -: $m \times n$ feature vector

Each token in a sentence is represented independently by a fixed-size n -dimensional vector; as such, the sentence is represented by an $m \times n$ vector of feature weights, where m is the number of tokens in the sentence. This feature vector is used as input to the convolutional neural network.

Convolutional layers compute the dot product of a kernel vector of k weights with k rows in the feature vector (representing k -tokens in the input sentence), producing a new sequence of features. The convolution filter is repeatedly applied to overlapping sections of the matrix, and a max pooling operation is applied over each resulting feature map. Tokens in a sentence occur on a time axis, as the order that the tokens appear in gives rise to their meaning; hence, the filter slides downwards over the rows of the vector. Applying *maximum pooling over time* produces a single output value following each convolution, such that the feature corresponding to a particular vector is the maximum activation in the feature map. Producing a fixed-size output matrix means that variable size sentences and variable size filters can be used to obtain features with the same output dimensions. This is especially useful for classification tasks, where the desired output is a fixed-sized vector indicating which class the input vector belongs to.

1. Convolutional Neural Network (CNN)
2. Deep Convolutional Neural Network (DCNN)

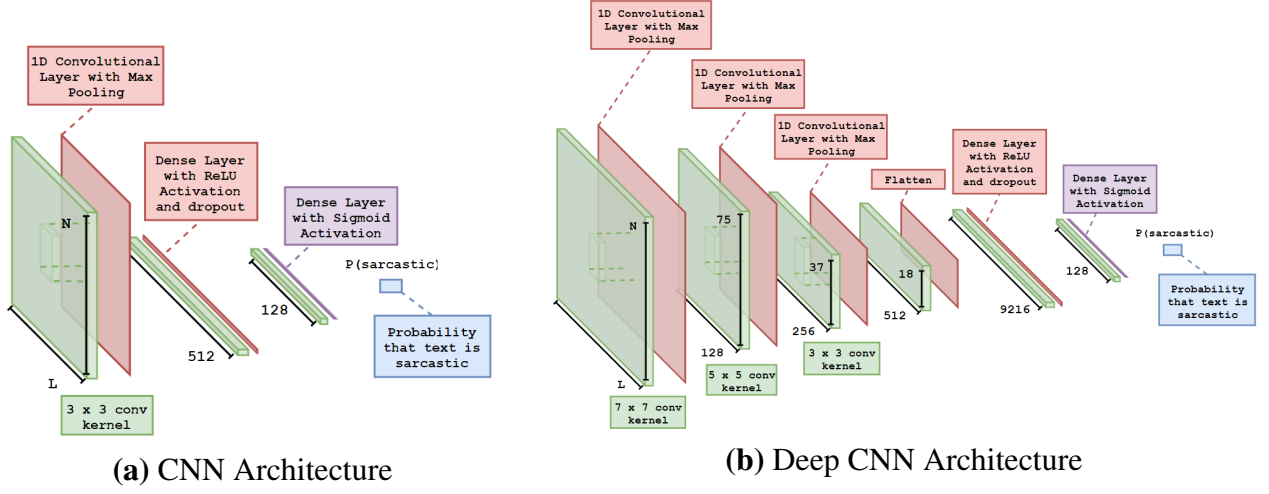


Figure -: Illustration of Convolutional Neural Network Architectures

F Attention

Extending our binary classification solution to incorporate attention allows us to answer the re-search question: *Can a custom model identify which linguistic cues correlate more to sarcastic labels?* We add an attention layer to our best performing lstm-based model. This allows us to

RESULTS

A Evaluation Method

This section discusses our approach to evaluating the performance of the trained models. Each trained model makes predictions on labelled unseen data, and these predictions are compared to the corresponding ground truth labels. From this, we extract the number of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN). We use four metrics that leverage this data differently to produce an evaluation of the trained models.

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F_1 \text{ Score} = \frac{2 \times precision \times recall}{precision + recall}$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

In the domain of sarcasm detection, precision refers to the proportion of the classified-sarcastic data that is *truly sarcastic* i.e. how many of the positives are true positives, and recall describes the proportion of the truly sarcastic data in the corpus that is *classified* as such i.e. how many true positives are labelled as positives. We mostly use the F_1 score i.e. the harmonic mean of precision and recall, where scores range from 0 (worst) to 1 (best). This metric has faced some criticism for giving equal weight to both precision and recall [6], therefore we also consider these measures separately. We also use the Matthews correlation co-efficient (MCC). This is a balanced measure which only shows high scores if the true positive and negative rates are high, and if the false positive and negative rates are low - taking into account all four quadrants of a confusion matrix.

B Analysis of Miscellaneous Features

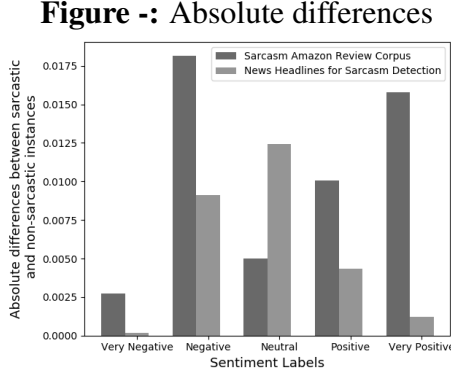
We analyse the effectiveness of the hand-crafted features, sentiment, punctuation and topic modelling, on each of the three datasets. As the feature vectors are small, we use logistic regression for this task. We train three logistic regressors (one for each dataset) separately, using each feature type in isolation, then use 5-fold cross-validation to compute the F_1 scores of the trained models. This enables us to assess whether these features alone are indicative of sarcasm in different media types. We deem scores above 0.5 to be indicative of useful features, particularly for scores significantly greater than this baseline.

Figure -: F_1 score of logistic regression models trained on hand-crafted features

| Dataset | Feature Type | | |
|--------------------------------------|--------------|-------------|-------|
| | Sentiment | Punctuation | Topic |
| News Headlines for Sarcasm Detection | 0.516 | 0.344 | 0.525 |
| Sarcasm Amazon Review Corpus | 0.685 | 0.394 | 0.520 |
| Ptáček et al. (2014) | 0.593 | 0.611 | 0.530 |

Our results show that sentiment features are indicative of sarcasm when extracted from the Sarcasm Amazon Review Corpus, however when extracted from the News Headlines for Sarcasm

Detection, they were ineffective. To further examine this relationship between sarcasm and sentiment, we compute the mean proportion of tokens in each sentiment class for sarcastic and non-sarcastic instances. We then compute the absolute differences of these values between the sarcastic and non-sarcastic classes - the intuition being that it is simpler for a classifier to separate samples where there is a clearer distinction between the expected features of each class. Hence, where the absolute difference in the mean proportion of tokens between sarcasm classes is higher, a classifier is better able to correctly annotate samples. A visualisation of these results is given in the figure below.



For the Sarcasm Amazon Review Corpus, within most sentiment classes there is a greater difference in the proportion of tokens for non-sarcastic and sarcastic instances. This indicates that sarcastic and non-sarcastic instances are easier to distinguish, given that their sentiment compositions are more distinct. The News Headlines for Sarcasm Detection results displays the opposite, and this explains why the logistic regression classifier trained on this data achieved an F_1 score of only 0.515, as the features for each class are very similar.

C Binary Classification

We train each machine learning classifier independently on each of our datasets, vectorised using Bag of Words, TF-IDF, GloVe and ELMo vectors. We also experiment with miscellaneous features, combining useful features with our best performing machine learning classifier on each dataset. Additionally, we train each deep learning model separately on each of the three datasets, using glove vectors and elmo vectors. Sparse feature representations such as tf-idf and bag of words are not used to train our deep learning models, as training neural networks on very high dimensional data is computationally intractable. For both our machine learning and deep learning classifiers, we report only a subset of our most informative results, including the result of the best classifier. The precision, recall and F_1 scores of the trained models are provided to 3 significant figures, and the scores of the best-performing machine learning and deep learning models are highlighted for each dataset.

Experimental Settings for Machine Learning – 5-fold cross validation was employed to ensure reproducibility and consistency of results. We allocate 80% of data to the training set, and the remaining 20% to the testing set for each of the five folds. For the K-Nearest Neighbours algorithm, the hyperparameter k is set to 5, as this is found to be a good balance between the computational cost of a large amount of neighbours and increased noise and bias associated with small values of k . Our Support Vector Machine uses a linear kernel as this model performed better than the SVM with radial basis function (RBF) kernel.

Experimental Settings for Deep Learning– The upper-bound on the number of training epochs is 300, although this is seldom reached due to the use of the Early Stopping callback function. Preliminary experimentation showed that model performance peaked early in the training pro-

cess for all models, although there was some fluctuation in the optimal number of epochs for different model types, hence early stopping is incorporated to stop training once model performance begins to plateau. The patience is set to 20, and this is the number of epochs for which no improvement can be seen before the training is prematurely terminated. However, setting the patience too low can hamper a model that plateaus for a while before continuing to improve.

1. **Early stopping** – Training is interrupted when the validation loss stops declining, using thins to determine the appropriate number of epochs.
2. **Model Checkpointing** – We track and save the weights of the best performing model during training; the model with the lowest validation loss.

Preliminary experimentation showed that the training process on the Sarcasm Amazon Review corpus was very unstable as this dataset is small. Results varied widely, and model scores were significantly lower. We augment this particular dataset using a synonym replacement strategy, whereby for each instance of the dataset, a new instance is added.

C.1 News Headlines Dataset

Figure -: F_1 scores of Machine Learning classifiers on the *News Headlines for Sarcasm Detection* dataset

| Machine Learning Model | Feature(s)* | Precision | Recall | F_1 Score |
|--------------------------|--------------|-----------|--------|-------------|
| Random Forest Classifier | GloVe | 0.774 | 0.735 | 0.754 |
| Support Vector Machine | TF-IDF | 0.688 | 0.751 | 0.718 |
| Random Forest Classifier | ElMo | 0.801 | 0.793 | 0.797 |
| Logistic Regression | ElMo | 0.840 | 0.852 | 0.846 |
| Logistic Regression | ElMo + S + T | 0.843 | 0.851 | 0.847 |
| Deep Learning Model | Feature(s) | Precision | Recall | F_1 Score |
| LSTM | ElMo | 0.843 | 0.878 | 0.860 |
| Bidirectional LSTM | GloVe | 0.855 | 0.873 | 0.864 |
| Vanilla GRU | ElMo | 0.889 | 0.877 | 0.883 |
| Deep CNN | ElMo | 0.873 | 0.869 | 0.871 |

*S refers to sentiment features and T refers to topic features

The table above Deep learning models routinely outperform Machine learning models. Logistic regression with ElMo vectors was the best performing machine learning model, and a slight improvement of 0.1

C.2 Amazon Reviews Dataset

Figure -: F_1 scores of Machine Learning classifiers on the *News Headlines for Sarcasm Detection* dataset

| Machine Learning Model | Feature(s)* | Precision | Recall | F ₁ Score |
|------------------------|--------------|-----------|--------|----------------------|
| Support Vector Machine | TF-IDF | 0.679 | 0.903 | 0.775 |
| K-Nearest Neighbours | ElMo | 0.742 | 0.636 | 0.685 |
| Support Vector Machine | BOW | 0.710 | 0.764 | 0.736 |
| Logistic Regression | ElMo | 0.799 | 0.819 | 0.809 |
| Logistic Regression | ElMo + S + T | 0.806 | 0.830 | 0.818 |
| Deep Learning Model | Feature(s) | Precision | Recall | F ₁ Score |
| CNN | GloVe | 0.833 | 0.821 | 0.827 |
| Vanilla RNN | ElMo | 0.814 | 0.810 | 0.812 |
| LSTM | GloVe | 0.835 | 0.841 | 0.838 |
| Deep CNN | ElMo | 0.869 | 0.851 | 0.860 |
| Bidirectional LSTM | ElMo | 0.859 | 0.865 | 0.862 |

*S refers to sentiment features and T refers to topic features

C.3 Twitter Dataset

Figure -: F_1 scores of Machine Learning classifiers on the *News Headlines for Sarcasm Detection* dataset

| Machine Learning Model | Feature(s)* | Precision | Recall | F ₁ Score |
|--------------------------|------------------|-----------|--------|----------------------|
| Gaussian Naïve Bayes | Bag of Words | 0.677 | 0.685 | 0.681 |
| Random Forest Classifier | GloVe | 0.669 | 0.623 | 0.645 |
| Support Vector Machine | ElMo | 0.722 | 0.789 | 0.754 |
| Logistic Regression | ElMo | 0.758 | 0.766 | 0.762 |
| Logistic Regression | ElMo + S + T + P | 0.794 | 0.786 | 0.790 |
| Deep Learning Model | Feature(s) | Precision | Recall | F ₁ Score |
| Vanilla RNN | ElMo | 0.834 | 0.801 | 0.817 |
| Bidirectional LSTM | GloVe | 0.829 | 0.815 | 0.822 |
| CNN | ElMo | 0.851 | 0.814 | 0.832 |
| Bidirectional LSTM | ElMo | 0.847 | 0.851 | 0.849 |
| Long Short-Term Memory | GloVe | 0.837 | 0.845 | 0.841 |

*S refers to sentiment features, T refers to topic features and P refers to punctuation features

Interestingly, the Random Forest Classifier was the best performing model using GloVe vectors. GloVe performance was weak on this particular dataset, and this could be due to the fact that this dataset has the lowest percentage of tokens present in the GloVe dictionary; hence, we lose the meaning of these tokens in the embedding input.

C.4 Cross-Dataset Evaluation

Given that the following model performed best, trained separately on all three datasets. We evaluate which of these models had the best performance on the other two datasets - this gives us an indication of which model is more likely to generalise to unseen data in multiple forms of media (i.e. which model is most adaptable, therefore the most suitable to be used in our tool)

EVALUATION

In the following section, we analyse the effectiveness of the solution, discussing its strengths and weaknesses and evaluating to what extent it satisfies the research questions and deliverables.

A *Solution Strengths*

We found that sentiment features can be useful predictors of sarcasm in *some* forms of media. This may be due to the fact that sarcasm must be more overt in product reviews in order to mock the product, rather than the subtle, more contextualised instances in News Headlines.

B *Solution Limitations*

It was only feasible to evaluate a small range of online media types, however surveying a broader range of media types could give us a wider perspective of sarcasm in online media.

C *Lessons learnt*

We learned that

D *Project organisation and approach*

CONCLUSIONS

In terms of satisfying the objectives, this project was an overall success. With an interactive console, it may be useful to individuals who struggle to detect sarcasm in their daily-life, or for the industrial applications of enhanced opinion mining.

The main contributions of this project are as follows: sentiment features are combined with state-of-the-art vectorisation approaches.

For future work, it would be interesting to explore the use of sarcasm in a wider variety of media types, and to extend support to additional non-English languages. Exploring the use of transfer learning with Transformers (BERT) may also produce interesting results.

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Table 1: SUMMARY OF PAGE LENGTHS FOR SECTIONS

| | Section | Number of Pages |
|------|--------------|-----------------|
| I. | Introduction | 2–3 |
| II. | Related Work | 2–3 |
| III. | Solution | 4–7 |
| IV. | Results | 2–3 |
| V. | Evaluation | 1-2 |
| VI. | Conclusions | 1 |

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