Text Compression for Sentiment Analysis via Evolutionary Algorithms

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Abstract—Can textual data be compressed intelligently without losing accuracy in evaluating sentiment? In this study, we propose a novel evolutionary compression algorithm, PARSEC (PARts-of-Speech for sEntiment Compression), which makes use of Parts-of-Speech tags to compress text in a way that sacrifices minimal classification accuracy when used in conjunction with sentiment analysis algorithms. An analysis of PARSEC with eight commercial and non-commercial sentiment analysis algorithms on twelve English sentiment data sets reveals that accurate compression is possible with (0%, 1.3%, 3.3%) loss in sentiment classification accuracy for (20%, 50%, 75%) data compression with PARSEC using LingPipe, the most accurate of the sentiment algorithms. Other sentiment analysis algorithms are more severely affected by compression. We conclude that significant compression of text data is possible for sentiment analysis depending on the accuracy demands of the specific application and the specific sentiment analysis algorithm used.

Index Terms—sentiment analysis, evolutionary algorithm, compression

I. INTRODUCTION AND RATIONALE

Sentiment analysis is the automated detection of emotions and attitudes towards a particular subject, event or entity, and has received an increasing amount of interest since the year 2000 [1], [2]. Sentiment analysis has been applied to many problem domains; for instance, determining sentiments of consumers towards products, or mining social media to gain an understanding of the public’s opinion on matters such as corruption [1]–[3].

In this study, we propose a novel evolutionary algorithm (EA) which is tasked with compressing text, whereby the objective is to retain the correct sentiment classification of the compressed text. To achieve this, the EA makes use of POS (Parts of Speech) to determine which POS can be removed from the text without hindering the classification performance. EAs [4], [5] – inspired by nature – make use of a population of individuals which are evolved over several iterations to solve optimisation problems.

To illustrate the idea, consider the sentence “I went home yesterday, opened the door and was immediately faced with a terrible shock”. The key sentiment-encoding phrase is “terrible shock”. We thus want to propose an algorithm that can learn to evolve rules that can effectively do this compression. The remaining words in the sentence do not contain any useful information in determining the sentiment expressed, and thus the rules can discard those words.

Feng et al. [6] proposed a Chinese text compression method with the objective of preserving the opinions expressed in the text to retain the sentiment, and to ensure that the compressed sentence is grammatically correct. The authors propose a score function which takes into consideration three primary functions; namely a word significance, a linguistic and an opinion scoring function. The word significance function makes use of the word frequency properties to allocate a score to each word. The scores were obtained by processing a corpus containing 30,000 documents. The linguistic score was obtained using a n-gram probabilistic function which made use of Google search results. The opinion score made use of an opinion lexicon to allocate a value to each word based on the frequency of the word. The authors created the lexicon from three different sources and the resulting lexicon contained 32,051 words for which the sentiment (positive, neutral or negative) was known. A dynamic programming algorithm was used in order to determine how many words should be present in a compressed sentence by evaluating several candidate compressed sentences. The score function was applied to each candidate sentence and the result was divided by the number of words in the compressed sentence. The compressed sentence with the highest value after this operator was deemed to be the final compressed sentence for a given uncompressed sentence. One Chinese data set of compressed sentences was manually created to evaluate their proposed approach. The study revealed that their proposed approach was able to outperform a traditional sentence compression method when the sentences were evaluated - in terms of the opinion and grammar - by a human.

Che et al. [7] also proposed a text compression method for sentiment analysis. In their study, they make use of 10 features (which are determined for every word) to perform the compression. The features are grouped into basic, sentiment related, semantic and syntactic features. The basic features include the words before and after the word for which the sentiment is known. A binary field denoting if the word is a perception word and if it is a polarity word. These words were obtained from an existing lexicon. The semantic features include prefix and suffix characters and also Brown word features which helps identify that words which are written differently represent the
same thing. They also include word embedding which makes use of Word2Vec [8] to determine if two words have a similar meaning. The syntactic feature makes use of a single feature which indicates the relationship between the words in the sentence. The sentence compression is conducted prior to the sentiment analysis.

With the limited amount of existing work in this field, we propose and investigate PARSEC (PARts-of-Speech for sEntiment Compression), which makes use of an EA to achieve text compression with minimal loss in sentiment accuracy.

II. PARTS-OF-SPEECH

POS, in languages, are defined as the primary groups of words that are grammatically similar. Common POS include, but are not limited to: adjective, verb and noun. For example, the words “dog”, “house” and “student” are examples of nouns.

In this study, the Stanford Log-linear Part-Of-Speech Tagger [9] was used to convert the original data sets into their corresponding POS tags. Thus, each word in a dataset was converted into a POS tag, and the length of each sentence in the original dataset was identical to that of the POS tagged dataset. For example, if the following sentence was found in the original dataset: “this is a great product”, it would be converted into “DT VBZ DT JJ NN” (which corresponds to the POS equivalent) in the POS tagged dataset.

We used the Penn Treebank tag set [10], [11]. This set contains 36 tags and an additional 12 tags to denote certain characters such as comma, semi-colon and other characters.

III. PROPOSED COMPRESSION METHOD

A. Compressor

This study proposes a new type of individual for EAs – referred to as a compressor – which reduces the length of sentences when applied to a dataset. The compressor is made up of several rules, and in turn, each rule is made up of a sequence of POS tags and a decision. The decision is applied whenever it’s sequence of POS tags matches the POS tags in the data. The decisions represent the indices of the words which will be removed in the matched sequence. Figure [1] illustrates an example of a compressor.

![Compressor](image)

Fig. 1. An example of a PARSEC compressor with 10 rules.

In the following explanation, let $X$ denote some original dataset for which PARSEC is being applied to, and let $Y$ denote the equivalent POS dataset. Furthermore, let $X_{i,j}$ denote sentence $i$ and word $j$ in $X$, and $Y_{i,j}$ denote sentence $i$ and word $j$ in $Y$.

The compressor in the figure has 10 rules denoted as $R_1$, $R_2$, $R_3$, ..., $R_{10}$. The first rule, $R_1$, has 2 tags which are represented by the sequence “JJ, NN”. This rule has one decision, and that is, to delete the word at index 0. This implies that when this particular compressor is applied, rule $R_1$ will find POS tags in $Y$ corresponding to the sequence “JJ NN”. Let $Y_{i,m}$ and $Y_{i,m+1}$ denote two consecutive words in $Y$ which have the sequence “JJ NN”. The decision in $R_1$ is to delete index 0, thus $R_1$ will delete $Y_{i,m}$ and consequently it will delete $X_{i,m}$. Thus, the size of $X$ and $Y$ has been reduced by one. Each time $R_1$ finds the exact sequence “JJ NN”, the POS tag and word corresponding to “JJ” (index 0) in $Y$ and $X$ are deleted.

Similarly for $R_{10}$. Let $Y_{i,m}$, $Y_{i,m+1}$ and $Y_{i,m+2}$ denote three consecutive words in $Y$ which have the sequence “NN VB RB”. The decision in $R_{10}$ is to delete index 0 and 2, thus $R_{10}$ will delete $Y_{i,m}$, $Y_{i,m+2}$, $X_{i,m}$ and $X_{i,m+2}$ from $Y$ and $X$ respectively for each occurrence of the POS tags “NN VB RB”.

When a rule is being processed, if a punctuation mark occurs, then the rule evaluation immediately stops. This mechanism was incorporated so that the sequence of tags – which is encapsulated by a rule – is applied to a single sentence and is not applied across two separate sentences. For example, consider the two following sentences “This book was really funny. Great, tomorrow is Friday.” which corresponds to: “DT NN VBZ DT JJ NN”. Assume that some rule has the following tags “JJ JJ” and the decision is to delete both indices. If the punctuation marks are not taken into consideration, then the rule will match with the words “funny” and “great”. This will result in “This book was really , tomorrow is Friday.” Consequently, the sentiments in these two sentences are no longer positive. However, if punctuation is taken into consideration, then the rule will not delete any words since the full stop separates the two sentences.

In this study, we define the term ‘wildcard’, which represents the notion of ‘any POS’ tag and is denoted with a ‘*’ symbol. Thus, when a rule is being evaluated, the wildcard POS can match with any POS in the POS dataset. For example, if a rule has the following tags: “JJ * NNP”, then any POS sequence that has ‘JJ’, followed by any POS, followed by ‘NNP’ will cause the rule to match with that POS sequence.

Algorithm [1] presents the generalized pseudocode to match the tags in a rule with the POS tags in the POS dataset. The algorithm also presents how to delete words from the original and POS dataset once a rule matches with a sequence.

B. PARSEC initial population generation

The pseudocode for creating an initial population of compressors is presented in algorithm [2]. Several individuals are created based on a predefined user parameter, namely the population size. Several rules have to be created for each compressor. There must be at least one rule, and a user-defined
parameter, namely max\textsubscript{rules}, is implemented to restrict the total number of rules. When creating the rules, the algorithm iterates until it has reached max\textsubscript{rules}, and a probability value of 0.5 was set to determine if a rule was to be created or not, as can be seen on line 9 in algorithm 2. Each rule consists of two primary parts, namely the tags and the decisions, the pseudocode for the creation of those respective parts are presented in algorithms 3 and 4.

### C. PARSEC fitness function

The pseudocode for the fitness evaluation of a compressor is presented in algorithm 5. Each instance in the dataset is considered in turn. The sentiment for each instance in the original dataset is computed using algorithm 3. When a compressor is evaluated, it is applied to each instance and a compressed sentence is created. The sentiment of each compressed sentence is computed using algorithm 5. The compressed sentiment is then compared to the original sentiment. If these are the same then the compressed sentence has had no effect on the sentiment when compared to the original. Conversely, if the values are different, then there are two possibilities. Either the compressed sentiment is equal to the correct sentiment as labelled in the training data (in which case the compressor is rewarded) or it is not (in which case the compressor is penalised). Thus, the fitness function takes

\begin{algorithm}
\caption{Algorithm 1: Pseudocode to apply a compressor to a sentence and compress the text.}
\begin{algorithmic}[1]
\setlength{\algorithmicindent}{0em}
\Function{compress}{\text{compressor}, \text{original}\text{sentence}}
\For{\text{\textbf{each} rule \text{in} \text{compressor}}} \label{line:compressor}
\State \text{tag\_in\_rule} ← \text{the tags inside rule}
\State \text{rule\_decisions} ← \text{the decisions inside rule}
\For{i ← 0 \text{to} \text{length}\text{sentence}} \label{line:rule}
\State \text{match} ← \text{true}
\For{j ← 0 \text{to} \text{length} (\text{tag\_in\_rule})} \label{line:tag}
\If{\text{tag\_in\_rule}[j] \neq \text{POS} \text{sentence}[i+j]} \label{line:if}
\State \text{match} ← \text{false}
\State \text{break loop and go to line 5}
\EndIf
\EndFor
\If{\text{match} = \text{true}} \label{line:match}
\For{k ← 0 \text{to} \text{length} (\text{rule\_decisions})} \label{line:decision}
\State \text{flag original\_sentence} [i+k] = 1 \label{line:flag}
\EndFor
\State \text{compressed\_sentence} ← \text{delete all words in original\_sentence that have been flagged.}
\EndIf
\EndFor
\EndFor
\State \Return \text{compressed\_sentence}
\EndFunction
\end{algorithmic}
\end{algorithm}

\begin{algorithm}
\caption{Algorithm 2: Pseudocode to create the initial population of compressors.}
\begin{algorithmic}[1]
\setlength{\algorithmicindent}{0em}
\Function{CreateCompressor}{\text{population\_size}}
\For{i ← 0 \text{to} \text{population\_size}} \label{line:create}
\State \text{CreateCompressor()}
\State \text{Evaluate compressor.}
\State \text{Add compressor to the initial population.}
\EndFor
\State \Return \text{new\_compressor}
\EndFunction
\end{algorithmic}
\end{algorithm}

\begin{algorithm}
\caption{Algorithm 3: Pseudocode to create POS tags.}
\begin{algorithmic}[1]
\setlength{\algorithmicindent}{0em}
\Function{CreatePOS}{\text{minimum\_tags}, \text{maximum\_tags}}
\State \text{pos\_list} ← \{ \}
\State \text{number\_tags} ← \text{random}[\text{minimum\_tags}, \text{maximum\_tags}]
\For{i ← 0 \text{to} \text{number\_tags}} \label{line:create}
\If{i = 0} \label{line:if}
\State Create a tag (excluding wildcard) and add it to pos\_list
\ElseIf{i = \text{number\_tags\_1}} \label{line:else}
\State Create a tag (excluding wildcard) and add it to pos\_list
\Else
\State Create a tag (including wildcard) and add it to pos\_list
\EndIf
\EndFor
\State \Return \text{pos\_list}
\EndFunction
\end{algorithmic}
\end{algorithm}
Twelve data sets were created by randomly selecting reviews from corresponding Amazon review datasets [12]. For each created data set, 1000 positive and 1000 negative reviews were randomly selected from the larger corresponding Amazon data set. The larger Amazon data sets were obtained from [12], [13]. The data sets were: Amazon Instant Video (AIV), Apps for Android, Automotive, Baby, Beauty, Digital Music, Health and Personal Care, Musical Instruments (MI), Patio Lawn and Garden, Pet Supplies, Tools and Home Improvement, and Toys and Games.

We propose a set of experiments whereby the compression rate is a user parameter and PARSEC must generate compressors that can compress the original datasets to reach the specified compression rate.

To achieve this, a lower and upper user-defined compression bound were defined. The lower compression bound (LCB) was implemented to ensure that the compressors did not result in a compression ratio less than the specified value. Similarly, the upper compression bound (UCB) ensured that the compressors did not result in a compression ratio greater than the specified value. Thus, every compressor in the EA population had to have a compression rate between the LCB and UCB.

Furthermore, two additional user-defined parameters were implemented to ensure that the total number of rules within each compressor remained within a certain bound. The two parameters were named compressionRules\textsubscript{min} and

\begin{algorithm}
\begin{algorithmic}
\State \textbf{input:} number\textsubscript{\text{tags}} the number of tags
\begin{algorithmic}[1]
\State \textbf{begin}
\For{$i \leftarrow 0$ to number\textsubscript{\text{tags}}}
\If{random[0,1] $< 0.5$}
\State Add \text{\textit{i}} to \text{\textit{decision\_list}}
\EndIf
\EndFor
\State \textbf{return} \text{\textit{decision\_list}}.
\end{algorithmic}
\end{algorithmic}
\end{algorithm}

\begin{algorithm}
\begin{algorithmic}
\State \textbf{output:} The sentiment for the evaluated sentence \text{\textit{sentence}}
\begin{algorithmic}[1]
\State \textbf{input:} \text{\textit{sentence}}, \text{\textit{dictionary}} the dictionary of sentiment words, \text{\textit{negation\_words}} the list of negation words
\State \textbf{begin}
\State sentiment\textsubscript{\textit{score}} $\leftarrow 0$
\State negation $\leftarrow$ false
\For{\textit{each word in the sentence}}
\If{\textit{word is in dictionary} and \textit{negation is true}}
\State sentiment\textsubscript{\textit{score}} $\leftarrow$ sentiment\textsubscript{\textit{score}} + (-1 \times \textit{word’s sentiment value})
\EndIf
\If{\textit{word is in dictionary} and \textit{negation is false}}
\State sentiment\textsubscript{\textit{score}} $\leftarrow$ sentiment\textsubscript{\textit{score}} + \textit{word’s sentiment value}
\EndIf
\If{\textit{word is in negation\_words}}
\State negation $\leftarrow$ swap polarity
\Else
\State negation $\leftarrow$ false
\EndIf
\EndFor
\State \textbf{return} sentiment\textsubscript{\textit{score}}
\end{algorithmic}
\end{algorithmic}
\end{algorithm}

A multi-objective fitness function was created to combine the fitness, the average reduction in terms of the length of the sentences before and after compression, and the size of the compressor in terms of the number of rules. Thus, the objective was to maximize the fitness and average reduction in sentences, and to minimize the size of the compressor.

\section{Experimental Setup}

\subsection{Datasets and Setup}

Twelve data sets were created by randomly selecting reviews from corresponding Amazon review datasets \cite{12}. For each created data set, 1000 positive and 1000 negative reviews were randomly selected from the larger corresponding Amazon data set. The larger Amazon data sets were obtained from \cite{12}, \cite{13}. The data sets were: Amazon Instant Video (AIV), Apps for Android, Automotive, Baby, Beauty, Digital Music, Health and Personal Care, Musical Instruments (MI), Patio Lawn and

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\State \textbf{output:} The sentiment for the evaluated sentence \text{\textit{sentence}}
\begin{algorithmic}[1]
\State \textbf{input:} \text{\textit{sentence}}, \text{\textit{original\_lengths}} a list of lengths for each sentence in the original data set
\State \text{\textit{original\_sentiments}} a list of sentiment values determined by applying algorithm \text{\textbf{5}} on the original data set
\State \text{\textit{correct\_sentiments}} a list of correct sentiment values for the original data set
\State \text{\textit{number\_rules}} the number of rules that \text{\textit{compressor}} has
\State \textbf{begin}
\For{$i \leftarrow 1$ to number\textsubscript{\text{of\_sentences}}}
\State compressed\textsubscript{\textit{sentence}} $\leftarrow$ apply compression to sentences \text{\textit{[i]}}
\State compressed\textsubscript{\textit{sentiment}} $\leftarrow$ apply algorithm \text{\textbf{5}}
\If{compressed\textsubscript{\textit{sentiment}} is not equal to original\textsubscript{\textit{sentiments}} \text{\textit{[i]}}}
\If{compressed\textsubscript{\textit{sentiment}} is equal to correct\textsubscript{\textit{sentiments}} \text{\textit{[i]}}}
\State raw\textsubscript{\textit{fitness}} $\leftarrow$ raw\textsubscript{\textit{fitness}} + 1
\Else
\State raw\textsubscript{\textit{fitness}} $\leftarrow$ raw\textsubscript{\textit{fitness}} - 1
\EndIf
\EndIf
\State average\textsubscript{\textit{change}} $\leftarrow$ average\textsubscript{\textit{change}} + \left(\textit{Length(\textit{sentences} \text{\textit{[i]}})} - \textit{Length(\textit{compressed\_sentence})}\right)
\Stateraw\textsubscript{\textit{fitness}} $\leftarrow$ raw\textsubscript{\textit{fitness}} + [0.5 \times (average\textsubscript{\textit{change}}/ \text{\textit{number\_of\_sentences}})] - (0.1 \times \text{\textit{number\_rules}})
\EndFor
\State \textbf{return} \text{\textit{raw\_fitness}}
\end{algorithmic}
\end{algorithmic}
\end{algorithm}

into consideration the number of new instances for which the compressor produces the correct result.

We propose a set of experiments whereby the compression rate is a user parameter and PARSEC must generate compressors that can compress the original datasets to reach the specified compression rate.

To achieve this, a lower and upper user-defined compression bound were defined. The lower compression bound (LCB) was implemented to ensure that the compressors did not result in a compression ratio less than the specified value. Similarly, the upper compression bound (UCB) ensured that the compressors did not result in a compression ratio greater than the specified value. Thus, every compressor in the EA population had to have a compression rate between the LCB and UCB.

Furthermore, two additional user-defined parameters were implemented to ensure that the total number of rules within each compressor remained within a certain bound. The two parameters were named compressionRules\textsubscript{min} and

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\State \text{\textit{correct\_sentiments}} a list of correct sentiment values for the original data set
\State \text{\textit{number\_rules}} the number of rules that \text{\textit{compressor}} has
\State \textbf{begin}
\For{$i \leftarrow 1$ to number\textsubscript{\text{of\_sentences}}}
\State compressed\textsubscript{\textit{sentence}} $\leftarrow$ apply compression to sentences \text{\textit{[i]}}
\State compressed\textsubscript{\textit{sentiment}} $\leftarrow$ apply algorithm \text{\textbf{5}}
\If{compressed\textsubscript{\textit{sentiment}} is not equal to original\textsubscript{\textit{sentiments}} \text{\textit{[i]}}}
\If{compressed\textsubscript{\textit{sentiment}} is equal to correct\textsubscript{\textit{sentiments}} \text{\textit{[i]}}}
\State raw\textsubscript{\textit{fitness}} $\leftarrow$ raw\textsubscript{\textit{fitness}} + 1
\Else
\State raw\textsubscript{\textit{fitness}} $\leftarrow$ raw\textsubscript{\textit{fitness}} - 1
\EndIf
\EndIf
\State average\textsubscript{\textit{change}} $\leftarrow$ average\textsubscript{\textit{change}} + \left(\textit{Length(\textit{sentences} \text{\textit{[i]}})} - \textit{Length(\textit{compressed\_sentence})}\right)
\State raw\textsubscript{\textit{fitness}} $\leftarrow$ raw\textsubscript{\textit{fitness}} + [0.5 \times (average\textsubscript{\textit{change}}/ \text{\textit{number\_of\_sentences}})] - (0.1 \times \text{\textit{number\_rules}})
\EndFor
\State \textbf{return} \text{\textit{raw\_fitness}}
\end{algorithmic}
\end{algorithmic}
\end{algorithm}
TABLE I
THE LOWER (LCB) AND UPPER (UCB) COMPRESSION BOUND CONSTRAINT THE ALGORITHM BY ENSURING THAT THE COMPRESSION RATE FOR EACH COMPRESSOR IS BETWEEN THE TWO VALUES RESPECTIVELY. THE TABLE PRESENTS THE LCB AND UCB VALUES (%) ALONG WITH THE MINIMUM AND MAXIMUM NUMBER OF RULES USED IN THE EXPERIMENTS. THESE SET COMPRESSION RATES WERE ENFORCED AND THE PERFORMANCE OF PARSEC WAS MEASURED ON SEVERAL DATASETS. THE VALUES FOR THE MINIMUM AND MAXIMUM NUMBER OF RULES WERE DETERMINED BY ADDITIONAL TRIAL RUNS. IT WAS OBSERVED THAT A GREATER NUMBER OF RULES WERE NEEDED TO ACHIEVE HIGHER COMPRESSION RATES.

| LCB (%) | UCB (%) | compressionRules min | compressionRules max |
|---------|---------|----------------------|----------------------|
| 10      | 13      | 5                    | 50                   |
| 15      | 18      | 10                   | 70                   |
| 20      | 13      | 20                   | 90                   |
| 25      | 28      | 40                   | 120                  |
| 30      | 33      | 90                   | 150                  |
| 50      | 53      | 350                  | 500                  |

compressionRules max. The compressionRules max parameter prevents compressors from having an extremely large number of rules. Both parameters aid in restricting the search space in terms of the number of rules to create and maintain for each compressor during the evolutionary process. The initial population generation had to respect the LCB and UCB, and respect the minimum and maximum number of rules. The mutation operator also had to respect these constraints.

B. Sentiment analysis algorithms

Several sentiment analysis algorithms were applied to the original and compressed datasets to determine the difference in accuracy and to investigate the performance of PARSEC. The following algorithms were used: SentiStrength [14], [15], MeaningCloud [16], Vivek [17], Stanford [18], uClassify [19], Sentiment140 [20], Intellexer [21] and LingPipe [22].

C. Execution of experiments

We first applied the sentiment analysis algorithms described in section IV-B to the original datasets and record the test accuracy. Then, we ran PARSEC using the baseline evaluation to create compressor rules. Once the compressors were created, we applied the compressors to the original datasets to generate the compressed data. We applied the sentiment analysis algorithms on the compressed data and recorded the test accuracy. In the following section we report on the change in accuracy between the compressed and original data. PARSEC evolved a population of 250 compressors over 100 generations, the crossover rate was 60% and mutation rate was 40%.

V. RESULTS AND CONCLUSION

Figure 2 shows the average change in test accuracy across the different methods based on the compression rates. The general trend is a decrease in performance with the largest decrease in performance observed by Sentiment140. LingPipe and SentiStrength were the only two methods that achieved a positive change in performance (on certain datasets) on compression rates of 10% and 15% respectively. When experimenting with PARSEC we posed the following question. For a predetermined drop in accuracy, how much compression is achievable by PARSEC? For a threshold of -1% compression, Vivek and LingPipe were able to achieve up to 30% compression. For this same threshold five methods could achieve up to 20% compression rate. Regardless of the compression rate used, both Stanford and Sentiment140 did not obtain any result less than -1%. These two algorithms produced the weakest performance with PARSEC.

Fig. 2. Change in average test accuracy across the different sentiment analysis algorithms for different compression rates enforced by PARSEC, averaged across all the data sets. A higher positive value indicates a better result. The various sentiment analysis technologies are denoted as follows: IN, LP, MC, S140, SS, ST, uC and V refer to Intellexer, LingPipe, MeaningCloud, Sentiment140, SentiStrength, Stanford, uClassify and Vivek respectively. The accuracy obtained by LingPipe outperformed all the other methods. Furthermore, LingPipe obtained an average positive change in accuracy of 0.1% for 10% compression. At a compression rate of 50%, LingPipe obtained an change in accuracy of -1.2% averaged over all the datasets, illustrating that it works well with PARSEC.

For a threshold of -2%, five algorithms could achieve up to 30% compression rate and LingPipe was able to achieve up to 50% compression. When the threshold is set to -3% four methods could achieve up to 50% compression.

We additionally wanted to determine the change in test accuracy when a much larger compression rate was used. Table IV presents the results when a compression rate of 75% was used. Only certain algorithms were tested due to our limited access to the sentiment analysis algorithms. These results reveal that a large compression rate is achievable without a
great loss in test accuracy: LingPipe obtained a loss of -3.3% accuracy.

An example of PARSEC compression is as follows. The original sentence (which contains 56 words and is already stemmed): “this be a wonderful movie involve fascinating people who be such great actor and actress. the event be interesting and I never get tire of watch the episode. I be so sad to see that they be not go to keep go with the life of all these inhabitant of Lark rise and candleford. Mrs. Hamlin”. The compressed sentence (22 words): “this be wonderful movie involve fascinating people who actress. get tire. so sad to see not keep go rise candleford. Mrs. Hamlin”.

| Algorithm      | Change in Test Accuracy | Original Accuracy | Compressed Accuracy |
|---------------|-------------------------|-------------------|---------------------|
| LingPipe      | -4.2                    | 79.7              | 76.4                |
| MeaningCloud  | -6.4                    | 67.8              | 60.8                |
| SentiStrength | -6.9                    | 80.7              | 74.3                |

Below are four rules which were randomly selected from a PARSEC model to illustrate some of the evolved rules. This model had a total of 38 rules. The POS tags are presented in order of appearance between square brackets. The indices start from zero. Rule 1 denotes that if the POS “NNP” is followed by “JJ”, then delete both words. Rule 4 denotes that if “IN” is followed by any POS and then followed by “VB”, then delete the word at index 1.

- Rule 1: [NNP, JJ]. Number of decisions: 2.
  Decisions: [0, 1]
- Rule 2: [VBG, NNP]. Number of decisions: 2.
  Decisions: [0, 1]
- Rule 3: [IN, CC]. Number of decisions: 2.
  Decisions: [0, 1]
- Rule 4: [IN, *, VB]. Number of decisions: 1.
  Decisions: [1]

This study empirically demonstrates that machine learning can reduce the amount of data needed to determine the sentiments within sentences with little loss in accuracy. To achieve this, we proposed an evolutionary algorithm, PARSEC, which evolves a population of chromosomes which encode rules for compression based on the removal of POS.

We studied the test accuracies achieved by the eight algorithms when set compression rate thresholds were enforced. Two algorithms showed marginal improvements in accuracy on several data sets for a compression rate of 15%. Additionally, there were 9 data sets whereby some of the algorithms were able to yield an improvement in accuracy for a compression rate of 30%. At a threshold of -1% sentiment accuracy loss, two methods were able to achieve up to 30% compression, five methods up to 20% compression, and six methods up to 10% compression. The best performing algorithm, LingPipe, showed only modest losses in accuracy even at high compression: 3.3% for a four-fold data compression.

It would be of interest to incorporate the PARSEC algorithm directly into a sentiment analysis algorithm instead of via a simple dictionary approach. One could achieve this by replacing the fitness function used in the evolutionary phase with a more sophisticated sentiment analysis algorithm. This would allow the emergence of an algorithm where the compression and sentiment analysis are mutually optimised for best performance.

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### TABLE II

Average change in test accuracy (%) across all the data sets when PARSEC models were created for 75% compression rate.

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Table III to VIII present the difference in test accuracy results for the various compression rates. The various sentiment analysis algorithms are abbreviated as follows: IN, LP, MC, S140, SS, ST, uC and V refer to Intellexer, LingPipe, MeaningCloud, Sentiment140, SentiStrength, Stanford, uClassify and Vivek respectively. For a compression rate of 10%, the best and worst change in accuracy were obtained by LingPipe and Sentiment140 respectively. Based on all the findings for 10 percent compression, there were 21 cases across all the methods and data sets whereby the change in accuracy was greater than zero. For a compression rate of 15% the number of cases was 17 whereby LingPipe obtained the best average change in accuracy with a value of 0.0%.

The best change in accuracy for 20% compression rate was obtained by uClassify with a value of 0.7 on two data sets. There were six data sets for which uClassify reduced the data up to 20% and for which the test accuracy on the compressed data was better than on the original data. Additionally, there were 14 cases in total across all the algorithms whereby the change in accuracy was greater than zero for 20% compression.

The findings revealed that for the compression rate of 25% there were 14 cases for which the change was greater than zero, and the best change in average accuracy was obtained once again by LingPipe with a value of -0.3%. There was a reduction performance in terms of the number of cases having a change greater than zero when a compression of 30% was used; notably 9 cases. uClassify however, on 5 datasets, had a test accuracy greater than zero. Finally, only two algorithms were able to obtain improvements in terms of the changes for a compression rate of 50%, namely uClassify and LingPipe, with changes in 3 and 2 data sets respectively.

APPENDIX

TABLE III

| Method       | IN   | LP   | MC   | S140 | SS   | ST   | uC   | V   |
|--------------|------|------|------|------|------|------|------|-----|
| AIV          | -1.1 | -1.1 | -0.2 | -2.7 | 0.1  | -3.2 | -2.0 | -0.7|
| MI           | 1.1  | 0.5  | 0.2  | 2.9  | 0.8  | -0.2 | 1.3  | 0.8 |
| Digital Music| -1.6 | 0.4  | -0.7 | 3.6  | 0.5  | -2.3 | 1.2  | 2.1 |
| Baby         | 0.0  | -0.9 | -0.5 | -2.4 | 0.2  | -2.0 | 0.6  | -0.1|
| Patio & Garden| -0.3 | -0.4 | -0.3 | -3.5 | -0.6 | -1.2 | 0.5  | -1.0|
| Automotive   | -1.4 | 0.6  | -1.0 | -2.8 | -0.3 | -2.2 | 0.9  | -0.8|
| Pet Supplies | -1.1 | 0.6  | -0.2 | -3.8 | -0.6 | -1.3 | 0.2  | -2.9|
| Apps for Android| -1.7 | -0.3 | -0.9 | -4.2 | -0.5 | -3.4 | -1.0 | -3.2|
| Beauty       | -0.9 | -0.3 | -0.7 | -3.5 | -0.2 | -1.3 | -1.8 | -1.2|
| Tools & Home | -0.2 | 0.0  | 0.0  | -3.0 | -0.3 | -1.7 | 1.2  | 0.7 |
| Toys & Games | -1.3 | -0.2 | -1.2 | -1.6 | -0.1 | -1.1 | -0.8 | -1.8|
| Health & Personal | 0.1  | 0.0  | -0.6 | -2.8 | -0.5 | -2.6 | 0.2  | -0.4|
| Average      | -0.7 | 0.0  | -0.6 | -3.0 | -0.3 | -1.8 | -0.3 | -1.2|

TABLE IV

| Method       | IN   | LP   | MC   | S140 | SS   | ST   | uC   | V   |
|--------------|------|------|------|------|------|------|------|-----|
| AIV          | 0.0  | -0.4 | 0.1  | -2.3 | 0.4  | -3.0 | -1.9 | 0.9 |
| MI           | 0.0  | 0.2  | -0.7 | -1.9 | -0.4 | 0.5  | -0.4 | -1.4|
| Digital Music| -1.0 | 0.2  | -0.3 | -2.5 | -0.1 | -1.9 | -0.4 | -2.0|
| Baby         | 0.0  | 0.4  | -0.2 | -2.7 | 0.0  | -1.2 | 0.3  | 0.2 |
| Patio & Garden| -0.1 | -0.4 | -0.2 | -2.1 | -0.2 | -0.7 | 0.9  | -0.9|
| Automotive   | -1.1 | 0.4  | -0.5 | -2.1 | 0.0  | -1.1 | 0.7  | -0.9|
| Pet Supplies | -1.2 | 0.3  | -0.4 | -2.9 | -0.4 | 0.3  | 0.0  | -1.6|
| Apps for Android| -1.4 | 0.0  | -0.5 | -2.5 | -0.3 | -3.5 | 0.0  | -1.6|
| Beauty       | -0.5 | 0.0  | 0.2  | -1.2 | 0.0  | -0.5 | -0.7 | -0.4|
| Tools & Home | 0.8  | -0.1 | -1.0 | -2.3 | -0.6 | -1.7 | 0.5  | 0.0 |
| Toys & Games | -0.5 | 0.0  | -1.5 | -1.8 | 0.2  | -3.1 | -0.1 | -1.4|
| Health & Personal | 0.4  | 0.1  | -0.4 | -1.6 | -0.3 | -1.4 | 0.5  | -0.4|
| Average      | -0.4 | 0.1  | -0.4 | -2.1 | -0.2 | -1.4 | 0.0  | -0.9|

DIFFERENCE BETWEEN THE COMPRESSED AND ORIGINAL TEST ACCURACY WHEN A COMPRESSION RATE BETWEEN 10% AND 13% WAS IMPOSED.

DIFFERENCE BETWEEN THE COMPRESSED AND ORIGINAL TEST ACCURACY WHEN A COMPRESSION RATE BETWEEN 15% AND 18% WAS IMPOSED.
### Table V

**Difference between the compressed and original test accuracy when a compression rate between 20% and 23% was imposed.**

| Category          | IN  | LP  | MC  | S140 | SS  | ST  | uC  | V  |
|-------------------|-----|-----|-----|------|-----|-----|-----|----|
| AIV               | -1.7| -1.2| 0.3 | -4.0 | -0.4| -3.1| -1.8| -1.8|
| MI                | 0.2 | 1.1 | -1.1| -2.5 | -0.6| 0.4 | -1.2| -1.4|
| Digital Music     | -2.2| -0.4| -0.2| -3.5 | -1.2| -3.1| -1.7| -2.0|
| Baby              | -0.7| -0.4| -0.4| -2.7 | -0.8| -2.2| 0.5 | -1.1|
| Patio & Garden    | -0.9| -1.1| -1.2| -3.7 | -0.5| -2.2| 0.5 | -0.9|
| Automotive        | -1.6| 0.2 | -0.3| -3.5 | -0.9| -2.8| 0.3 | -1.7|
| Pet Supplies      | -1.0| 0.4 | -1.3| -3.5 | -0.4| -2.1| 0.7 | -2.2|
| Apps for Android  | -1.7| -0.1| -1.6| -4.8 | -0.4| -4.5| -1.7| -1.8|
| Beauty            | -1.1| 0.2 | -0.6| -4.0 | -1.0| -1.1| -1.2| -1.2|
| Tools & Home      | 0.6 | -0.1| -1.2| -4.4 | -0.7| -1.9| 0.0 | -1.5|
| Toys & Games      | -1.5| 0.0 | -0.4| -3.3 | -0.2| -2.8| -1.5| -1.9|
| Health & Personal | 0.0 | -0.4| -1.0| -4.2 | -1.2| -1.7| 0.7 | -0.9|
| **Average**       | -0.9| -0.1| -0.7| -3.7 | -0.7| -2.2| -0.5| -1.6|

### Table VI

**Difference between the compressed and original test accuracy when a compression rate between 25% and 28% was imposed.**

| Category          | IN  | LP  | MC  | S140 | SS  | ST  | uC  | V  |
|-------------------|-----|-----|-----|------|-----|-----|-----|----|
| AIV               | -2.4| -1.6| -0.6| -3.7 | -0.2| -6.0| -2.5| -2.0|
| MI                | -0.6| 1.0 | -0.1| -4.8 | -1.0| -1.6| -0.1| -1.8|
| Digital Music     | -1.9| -0.1| -0.5| 25.1 | -0.5| -2.4| -2.9| -3.5|
| Baby              | 0.1 | -0.9| 0.5 | -4.4 | -0.5| -2.6| -0.4| -0.6|
| Patio & Garden    | -0.9| -1.4| 0.1 | -4.7 | -0.9| -1.5| 0.6 | -1.6|
| Automotive        | -2.0| 0.1 | 0.1 | -3.3 | -1.5| -4.2| 0.5 | -0.4|
| Pet Supplies      | -0.8| 0.0 | -0.1| -5.3 | -0.6| -1.7| 0.0 | -0.4|
| Apps for Android  | -2.4| -0.4| -1.4| -6.7 | -0.9| -3.4| -0.9| -3.4|
| Beauty            | -1.1| 0.2 | -0.7| -5.5 | -0.6| -2.1| -1.8| -2.4|
| Tools & Home      | -0.8| -1.0| -1.6| -5.2 | -1.1| -3.6| 0.0 | -0.3|
| Toys & Games      | -1.2| -0.5| -1.1| -5.7 | -0.2| -2.7| -1.0| -3.6|
| Health & Personal | 0.3 | 0.9 | 0.0 | -3.9 | -0.3| -2.8| -0.9| -1.1|
| **Average**       | -1.1| -0.3| -0.5| -2.3 | -0.7| -2.9| -0.7| -1.9|

### Table VII

**Difference between the compressed and original test accuracy when a compression rate between 30% and 33% was imposed.**

| Category          | IN  | LP  | MC  | S140 | SS  | ST  | uC  | V  |
|-------------------|-----|-----|-----|------|-----|-----|-----|----|
| AIV               | -2.3| -2.1| -0.1| -8.2 | -1.3| -7.0| -2.3| -2.5|
| MI                | -0.5| 0.6 | -1.1| -6.9 | -1.6| -2.4| -1.9| -2.8|
| Digital Music     | -3.3| -1.1| -1.0| -6.2 | -1.7| -3.6| -2.8| -4.9|
| Baby              | -0.8| -0.7| 0.2 | -6.1 | -1.1| -5.3| 0.7 | -1.3|
| Patio & Garden    | -1.8| -1.2| -1.7| -6.6 | -1.5| -4.3| -0.3| -2.2|
| Automotive        | -1.2| -0.4| -0.9| -4.8 | -1.5| -4.7| 0.8 | -2.6|
| Pet Supplies      | -2.2| -0.9| -1.1| -5.8 | -1.0| -4.4| 1.6 | -2.8|
| Apps for Android  | -3.0| 0.0 | -2.1| -7.7 | -1.1| -6.4| -2.1| -5.3|
| Beauty            | -2.4| -0.2| -1.1| -7.7 | -1.2| -4.6| -1.9| -3.2|
| Tools & Home      | -0.9| 0.0 | -1.3| -5.9 | -1.5| -5.0| 0.4 | -1.1|
| Toys & Games      | -2.2| 0.0 | -1.6| -6.0 | -0.2| -5.0| -0.7| -3.0|
| Health & Personal | -0.6| -0.3| -0.60| -6.10| -0.70| -5.30| 0.70| -2.00|
| **Average**       | -1.8| -0.5| -1.0| -6.5 | -1.2| -4.8| -0.6| -2.8|

### Table VIII

**Difference between the compressed and original test accuracy when a compression rate between 50% and 53% was imposed.**

| Category          | IN  | LP  | MC  | S140 | SS  | ST  | uC  | V  |
|-------------------|-----|-----|-----|------|-----|-----|-----|----|
| AIV               | -5.8| -4.2| -1.8| -15.6| -3.4| -13.2| -7.8| -8.2|
| MI                | -1.9| 0.8 | -0.9| -15.1| -2.6| -6.9 | -5.9| -7.6|
| Digital Music     | -5.5| -1.3| -1.9| -15.3| -3.5| -9.9 | -5.5| -9.0|
| Baby              | -1.4| -1.4| -1.7| -12.4| -2.4| -11.2| -1.5| -5.6|
| Patio & Garden    | -3.8| -1.8| -2.1| -13.9| -2.5| -10.1| -0.5| -4.7|
| Automotive        | -3.7| -2.4| -1.9| -12.6| -2.8| -7.9 | 0.1 | -4.6|
| Pet Supplies      | -1.8| -1.6| -2.2| -14.9| -2.5| -8.0 | 0.6 | -6.2|
| Apps for Android  | -6.2| -1.6| -4.8| -17.1| -4.4| -12.4| -4.3| -11.0|
| Beauty            | -3.0| -0.1| -1.8| -15.3| -3.0| -8.7 | -4.1| -7.8|
| Tools & Home      | -2.2| 0.1 | -2.2| -14.3| -3.6| -9.5 | 1.0 | -4.9|
| Toys & Games      | -4.8| -1.2| -2.0| -12.7| -1.8| -10.1| -4.3| -7.2|
| Health & Personal | -2.2| -0.2| -2.0| -12.1| -2.2| -10.1| -1.1| -5.0|
| **Average**       | -3.5| -1.2| -2.1| -14.3| -2.9| -9.8 | -2.6| -6.8|