A Framework for Fast Polarity Labelling of Massive Data Streams

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ABSTRACT
Many of the existing sentiment analysis techniques are based on supervised learning, and they demand the availability of valuable training datasets to train their models. When dataset freshness is critical, the annotating of high speed unlabelled data streams becomes critical but remains an open problem. In this paper, we propose PLStream, a novel Apache Flink-based framework for fast polarity labelling of massive data streams, like Twitter tweets or online product reviews. We address the associated implementation challenges and propose a list of techniques including both algorithmic improvements and system optimizations. A thorough empirical validation with two real-world workloads demonstrates that PLStream is able to generate high quality labels (almost 80% accuracy) in the presence of high-speed continuous unlabelled data streams (almost 16,000 tuples/sec) without any manual efforts.

CCS CONCEPTS
• Computing methodologies → Massively parallel algorithms; Natural language processing.

KEYWORDS
sentiment classification, stream processing, distributed computing

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1 INTRODUCTION
Companies have utilized sentiment analysis [12] in many business services to gain useful insights, such as the opinions of new products. Although unsupervised methods exist, many sentiment analysis tasks still work with supervised learning models [46]. Their effectiveness thus highly depends on the quantity and quality of training data. Despite the popularity of applying unsupervised pre-trained models such as GPT-3 and BERT [15] in sentiment analysis,

Figure 1: Comparing the performance of polarity labelling of increasing volume of datasets on 48 cores: an existing approach (Self-learning), and our framework PLStream.

a supervised downstream fine-tuning task is still required to achieve outstanding performance, such as model fine-tuning for sentiment analysis. A large amount of labelled datasets is still required, and it is costly to label the datasets with human efforts.

Motivated by such a demand, Iosifidis et al. [21] have recently introduced a semi-supervised labelling approach to annotate polarity labels. However, their are focusing on theoretical accuracy guarantees with self-learning and co-training techniques, but overlook the annotating speed as well as the generality of the algorithm. In particular, it is a well-established industry practice to use the most recent data to train machine learning models [36]. New datasets are continuously generating in the form of data streams, such as twitter tweets and online customer reviews. When dataset freshness is critical to sentiment analysis, frequent offline label retraining and deployment are constrained by the cost of manual labelling, limited computation and storage resources.

Figure 1 further shows the evaluation results of the existing self-learning approach [21] to annotate polarity labels of tweets. We let it first train an initial model with 5000 labelled data. Then, it uses the high-confidence predicted results as new training datasets to train their models. When dataset freshness is critical to sentiment analysis, frequent offline label retraining and deployment are constrained by the cost of manual labelling, limited computation and storage resources.

In this work, we propose PLStream, a novel framework that continuously annotates high quality labels to massive ongoing streams of opinions. As Figure 1 shows, PLStream is
able to achieve steady high throughput when annotating polarity labels of data streams. The key of PLStream is a novel online sentiment learning paradigm, which updates a word-embedding model (e.g., word2vec [28]) incrementally and generates labels by referencing the learned vector representations to a small reference table of vocabularies with assumed polarities. A list of algorithmic improvements and system optimization are further developed to help PLStream achieve both high performance and high labelling correctness. To ensure its high scalability and robustness, we have implemented PLStream on top of Apache Flink [13] – a production level data stream processing system (DSPS). Nevertheless, our proposed solution is general and can be applied to other DSPSs such as Spark [43] with marginal programming efforts.

For a comprehensive comparison, we have further implemented several alternative methods, including statistics-based [24], lexicon-based [30] and clustering-based [23] unsupervised sentiment classification algorithms in PLStream for labelling data streams without labelled datasets. The experimental evaluation shows that our proposed solution is able to continuously generate high quality labels (almost 80% accuracy) to high-speed continuous data streams (almost 16,000 tweets/s). Compared to the alternative approaches, PLStream improves labelling accuracy by more than 20%, and achieves more than 50% improvements in terms of both latency and throughput.

In summary, we make the following technical contributions:

1. We design a scalable and robust framework (Section 4), PLStream for annotating unlabelled data streams based on a production-level data stream processing system, Apache Flink. We open-source our system.

2. We propose and evaluate several algorithmic and system optimizations in PLStream including (i) fast similarity-based labelling (Section 4.1), (ii) temporal trend detection (Section 4.2), and (iii) tunable model management (Section 4.3) that help PLStream to achieve high performance and high labelling accuracy.

3. To the best of our knowledge, this is also the first empirical study that ensures a fair comparison among alternative approaches on annotating unlabelled data streams on modern parallel hardwares (Section 5), as we eliminate the performance difference caused by different compilers and runtime by implementing all alternative solutions inside the same framework.

2 RELATED WORK

We discuss related work comes from three key areas: sentiment classification, large scale annotations and stream processing.

Sentiment classification is an application of natural language processing (NLP) that analyzes subjective texts with emotions to determine the views, preferences, and tendencies of a text. Most prior works [7, 17–19, 31] belong to supervised sentiment learning, which typically requires a training phase that trains a classifier with labelled training texts followed by an inference phase that identifies the polarity of a testing text based on the trained classifier. Their primary concern is to obtain a high accuracy classifier from a large set of collected and labelled datasets, assuming infinite time and resource budgets. Zimbra et al. [46] reviewed 28 existing techniques of sentiment classification across five distinctive twitter data sets, and are mostly supervised approaches. Unsupervised methods, such as lexicon-based approaches [8, 37] have been proposed. However, lexicon-based approaches only deal with novel vocabulary and contextual information in a limited way as they rely on domain-dependent opinion words and aspect-dependent opinion words [16]. Probabilistic models, such as LDA [24], target learning from a large set of words from documents, while we target processing data streams, like tweets, which are written in a unique conversational style particular to the brevity of the Twitter medium (i.e., 280 character limit per tweet).

Large scale annotations of unlabelled datasets is not a new demand. Early work by Pak and Paroubek [32] utilizes emoticons to infer labels from tweets and is limited with their application scenarios. Closely related to our work, a recent work [21] applies Multinomia Naive Bayes (MNBs) as the based model to annotate sentiment datasets. Combined the MNBs model with a confidence threshold, they use the classification results as new training data to incrementally train the model offline until the accuracy converges. However, we haven shown in Section 1 that, such an offline approach is not applicable to annotate high-speed data streams due to the exponentially increasing computational complexity. To the best of our knowledge, how to ensure high accuracy of polarity labelling of massive unlabelled data streams such as social media opinions, so far has been an unsolved problem.

Most existing sentiment analysis techniques have emphasized algorithmic accuracy. They have not focused on utilizing parallel hardware resources. Although there are general-purpose data stream processing systems (DSPSs) that can provide fast stream computations (e.g., Apache Spark streaming [3] and Apache Flink [13]), they have not been designed nor optimized for the tasks of sentiment analysis. This had motivated a distributed online sentiment analysis system as proposed by Amir et al. [35]. Liu et al. [26] have described a standalone system that supports real-time unsupervised machine learning tasks such as lexicon-based sentiment analysis. We evaluate the lexicon-based sentiment classification as an alternative approach in our experiments. Recently, Ramanath et al. [36] have proposed a library called Lambda Learner, which trains sequential bayesian logistic regression models by incremental updates in response to mini-batches from data streams. In contrast, our work strictly focuses on fast polarity labelling of massive data streams.

3 PRELIMINARY

In this section, we present the preliminary knowledge of basic concepts in word embedding and the data stream processing systems.

**Word Embedding.** To analyze unstructured natural language texts, a common step is to first convert vocabulary into a vector of numeric values. Two classical word representation algorithms are one-hot encoding and bag of words [9]. However, one-hot encoding will lead to a dimension explosion when the vocabulary size becomes larger, while bag of words does not consider the context information in one sentence. Another advanced word vector representation technique, word embedding, is to find a mapping or
function to generate an expression in vector space. Representative recent word embedding tool include Word2Vec \cite{34}, Glove \cite{34}, BERT \cite{15} and their variants \cite{22}. Glove combines local contextual information with overall statistics of the corpus, while word embedding with pre-trained model BERT provide richer embedded vectors, where BERT uses deep bidirectional transformer \cite{38} components to build the entire model with bidirectional contextual information, i.e., each word has different vector representations in different context. However, the training of Glove and BERT are batch-based, requiring the presence of the entire input datasets and cannot be applied to learn from on-going input streams. In contrast, Word2Vec \cite{28} is able to learn incrementally, and is thus adopted in our framework.

**DSPSs.** With the explosion of information, being able to process data streams efficiently in real time is perceived as a major challenge. In the last decade, data stream processing systems (DSPSs) have received considerable attention. Many DSPSs have been proposed, such as Apache Flink \cite{13}, Apache Storm \cite{2}, and Spark Streaming \cite{3}. We leverage Apache Flink for stream processing due to its capability of expressive, declarative, and efficient data analysis on data streams \cite{13}, with high-level programming language API support such as the Python API \cite{4}. Nevertheless, our proposed solution is general and can be applied to other DSPSs with similar characteristics.

### 4 INCREMENTAL POLARITY LEARNING

We propose PLStream, a novel framework that learns and identifies the polarity of fast ongoing data streams. We summarize the notations used throughout this paper in Table 1. We define a tuple (denoted as $T_i$) as a timestamp $t_i$ associated with a finite number of vocabularies (i.e., $v_1 \sim v_n$). The input stream is a list of tuples chronologically arriving at the system, denoted as $S = \{T_1, \ldots, T_N\}$, where $N$ goes to infinity. In PLStream, every input tuple functions as both the training and testing datasets. The goal of PLStream can be thus defined as follows.

**DESIGN GOAL** 1. *Given an input stream $S$, PLStream learns and identifies the polarity of $T_i \in S$ as soon as $T_i$ arrives without relying on any offline training phase with labelled datasets.*

An overview of PLStream is depicted in Figure 2. It is implemented on top of Apache Flink as a chain-topology stream application with three stream operators. Each operator can be carried by multiple threads to run concurrently to improve system throughput. It is noteworthy that, PLStream is continuously updated and can be used to label sentences with even unforeseen vocabularies. This differs significantly from offline approaches \cite{7, 19}, where the pre-trained model can quickly become outdated, as both the vocabulary and the polarity model evolve, requiring periodically re-training with labelled datasets.

First, it continuously batches a tunable number ($b$) of tuples from the input data stream and extracts useful vocabulary to feed to the subsequent operators. To reduce the processing workload, information that have nothing to do with emotions, such as numbers, stopwords, usernames, etc. is filtered out. For example, in Figure 2, `#COVID, I and !` are removed because they are unrelated to sentiment. It is noteworthy that we retain as much as possible of the words that constitute the sentence to provide contextual information. This contradicts to some prior work \cite{37}, which only retain adjectives and adverbs. For example, the noun "criminal" is more likely to appear in negative texts.

Second, PLStream performs an incremental word embedding based on Word2Vec as it captures the vector representation of each vocabulary with local information involving low computational costs compared to alternative embedding approaches like BERT \cite{15}. It continuously trains and updates vector representations (VRs) of input tuples and help make high-accuracy polarity predictions by extracting both contextual and temporal information from opinionated streams. For example, in Figure 2, weight matrix $M$ is incrementally trained and each row stands for the VR for one word.

Third, with the learned vector representation of each word, PLStream classifies the polarity of each input tuple without manual labelling efforts. For example, in Figure 2, the polarity of four input tuples (i.e., tweets) are labelled through similarity-based computations. To improve the system performance and labelling accuracy, PLStream adopts a fast cosine similarity computation method to estimate the polarity label of the sentences and enhance it further with a temporal trend detection mechanism, to be covered in Section 4.1 and 4.2, respectively.

During the second step, the learned VRs may be stored locally by each thread or in Redis for shared access by multiple threads. When VRs are shared among threads, continuously updating VRs potentially leads to huge overhead, especially the communication overhead between two systems, i.e., Flink and Redis. To this end, we further develop several alternative model merging approaches, detailed in Section 4.3.
Table 1: Notations used in this paper. Parameter value ranges used in our experiments are also shown.

| Name             | Notation | Description                                                                 |
|------------------|----------|-----------------------------------------------------------------------------|
| Tuple            | $T = \{o_1, o_2, ..., o_n\}$ | A timestamped (t) finite number n of words $o_i$ with a polarity to be identified |
| Input stream     | $S = \{T_1, ..., T_N\}$   | A list of tuples chronologically arriving at the system to be analyzed       |
| Weight Matrix    | $M_{ad}$, where each element in $M$ is denoted as $m_{ij}$ | The vector representation of a list of words, where $m$=number of words, and $d$=number of features |
| Vector lookup table | $V$ : word $\rightarrow m_i$ | A lookup table of trained words (key) with corresponding vector representation in $M$ (value) |
| Window           | $w = 1 \sim 10$   | A tunable training window size calculated by Word2Vec to capture contextual information |
| Vector Dimension | $d = 10 \sim 500$ | A tunable feature size used by Word2Vec training                           |
| Batch size       | $B = 200 \sim 5000$ | A tunable size of batched tuples being collected before training            |
| Trend Detection Window | $TDW = 200 \sim 2000$ | A tunable window size for polarity trend detection                           |
| Model Merging Periodic | $p = 20 \sim 90$(seconds) | Model merging frequency                                                     |

Table 2: Reference table used in our experiments

| Positive          | dazzling, brilliant, phenomenal, fantastic, excellent, cool, gripping, mesmerizing, riveting, spectacular |
| Negative          | sucks, terrible, awful, unwatchable, hideous, bad, cliche, boring, stupid, slow, worst, waste, unexciting, rubbish, tedious, unbearable, pointless, cheesy |

Example Input Tuple T1:

![Example Matrix and Table](image)

Figure 3: Example of similarity-based labelling

4.1 Fast Similarity-based Labelling

After getting the learned vector representation of each word, instead of relying on supervised training progress for polarity identification, we propose to rely on text similarity \[29, 40, 41\] to infer the polarity of input tuples based on a list of reference words with assumed polarity [24] listed in Table 2. The reference table may become outdated as well. In practice, one may periodically update the table, which involves minor labor efforts compared to manually labelling training datasets.

Intuitively, we can compute the cosine similarity between each word of the input tuple and the reference words as the quantitative relative polarity of each word. We can then compared the sum of the quantitative polarity of all words to get the polarity score of an input tuple. However, such a simple solution leads to significant computational overhead as it involves multiple cosine similarity computations for every word in each input tuple.

We leverage a simple yet effective word centroid distance (WCD) calculation approach. For illustration, we show our running example in Figure 3. First, we obtain the vector representation of the input tuple by calculating the arithmetic mean of the learned vector representation of all words. As illustrated in the example, for the input tuple “hate mask”, we calculate the mean of each dimension ($d = 3$) of two words ($S = 2$) to obtain a new vector $V = \{v_1, v_2, ..., v_d\}$, where $v_i = \sum_{j=1} m_{ij}$ and $d = 3$, $S = 2$. Then, we perform cosine similarity computation (CSC) between $V$ and all reference positive or negative words to obtain the aggregated sum $SUM_{pos}$ and $SUM_{neg}$. Finally, we compare $SUM_{pos}$ and $SUM_{neg}$ to infer the polarity of the input tuple entirely. Our extensive experimental results confirm the superiority of such a simple solution in terms of both significantly reduced computational effort and higher prediction accuracy compared to alternative solutions.

4.2 Temporal Trend Detection

The conventional way of training word2vec assumes that an entire dataset is trained at once and does not consider the temporal attribute. It hence overlooks important information, such as temporally skewed opinions, which we call temporal semantic aggregation. For example, there may be more positive texts (e.g. live tweets) timely aggregated because of an unbelievable shot in a football match. In addition, in product-level applications, continuously capturing trend can also help one keep an eye on real-time sentiment trends (such as latest reviews of a product). To capture such important information, we leveraged a temporal trend detection mechanism that helps our learning algorithm achieve higher prediction accuracy.

We illustrate the whole process of trend detection with an example of two trend detection windows ($TDW_s$), shown in Figure 4. In each iteration, we identify the polarity of the current window of recent inputs (i.e., 100 tuples in this example). The trend detection results are used to feedback the classification of the next window of inputs by tuning the calculation of cosine similarity. For example, when the current window has a tendency to accumulate higher positive polarity, the weighted coefficient (WC) for calculating the positive polarity will become larger in the next window. Both the
trend detection window and the weighted coefficient adjustment step size are tunable, and we will evaluate the effect of TTD in our experiments (Section 5.4).

4.3 Periodical Model Merging

A major limitation of modern DSPSs is the lack of support for shared mutable state [44], i.e., a shared memory that multiple application threads can access and update concurrently. Shared state is crucial for PLStream as parallel training requires multiple threads to access and update the trained embedding model. This is not supported by Flink by default. Commonly, one will leverage a key value store (KVS) to maintain such shared mutable states for stream processing. Typical examples of such KVS systems include Redis [6] and RocksDB [5]. As our experimental results will demonstrate, naively relying on a KVS to manage the access and update of a trained classifier leads to a huge run-time overhead.

We propose three alternative model management strategies in PLStream, as depicted in Figure 5. 1) local model: we can maintain the model locally at each thread. This promises the best system performance as it does not involve costly Redis access. However, it raises the problem of divergence among learned models at each thread, and it can lead to lower prediction accuracy. Deploying the system in a distributed environment with multiple nodes would further exacerbate the problem. 2) global model: we can share the learned model of word2vec among threads. This ensures a global model in the system that promises higher prediction accuracy. However, when the input stream is processed in a parallel fashion, different processing threads may subsequently access the same model concurrently, which can lead to significant access contention overheads. And 3) hybrid model: we can periodically merge models among threads using a customizable frequency that allows users to trade-off accuracy for performance on demand. In particular, we compute the mean of two vectors as the new vector representation of the corresponding word. Other pooling mechanisms [11] may be also applied such as min and max.

5 EVALUATION

In this section, we show that PLStream manages to achieve much better prediction accuracy, higher throughput, and lower processing latency compared to the state-of-the-art through a detailed experimental evaluation.

5.1 Experimental Methodology

In this section, we first introduce the benchmark workloads and evaluation metrics, followed by the discussion of several alternative approaches that we implemented in the same system to validate the efficiency of our proposal.
is no lexicon that can cover all words because a lexicon is costly to build and requires intensive manual maintenance if it needs to be updated. Text-Blob [27], VADER [20] and SentiWordNet [8] are three well-known lexicons for unsupervised sentiment classification. Among them, the Vader lexicon contains only 7,500 features, while SentiWordNet consists of more than 100,000 words and has a better ability to cover large-scale data than Vader and other lexicons. Therefore, we have implemented and evaluated SentiWordNet in our experiments.

LDA. Latent dirichlet allocation (LDA) [10] is widely used for processing large-scale corpora. LDA determines the topic of each document in the document set in the form of a probability distribution. Based on LDA, Lin et al. [24] proposed a Joint Sentiment Topic (JST) model that can infer sentiment by adding an additional sentiment layer between the document and topic layers. In conjunction with prior information from lexicons, JST has shown great performance on the IMDB movie reviews dataset (document-level) with an overall accuracy of 82%, close to the performance of supervised approaches. In our experiments, we have implemented and evaluated the performance of JST [1].

Clustering. Data clustering aims at grouping data such that objects in the same group are similar to each other and those in different groups are dissimilar according to the properties of the instances. In the literature, some have used clustering for unsupervised sentiment classification [23, 47]. We have implemented the clustering-based approach based on streaming K-means, and set the $K$ parameter to 2 (i.e., either positive or negative) as another baseline method for sentiment classification in our evaluation.

5.1.4 Experimental Setup. We have deployed our experiments on a prototyping cluster with four nodes. Each node is equipped with 3.6GHz Intel(R) Xeon(R) CPU E5-1650 with 12 cores and 125GB RAM. The network bandwidth is 1Gb/s. We have evaluated the system performance up to 48 working threads. We have used Flink v1.12.0 with Java 8 (Oracle JVM), Python 3.7 and Redis v6.0.6. Finally, Table 2 summarizes the hyperparameters of PLStream and their default values.

5.2 Overall Performance Comparison

In this section, we compare algorithms on processing benchmark workloads in terms of throughput, latency, and accuracy. Each algorithm is experimentally tuned to its best-performing configuration.

Throughput and Latency. Figure 6a shows the throughput of alternative approaches on processing two datasets when the system is stable. The LDA-based method has the highest throughput because it only involves a simple inference stage in this case. Its performance may drop significantly when the prior information (i.e., the probability distribution) it requires needs to be re-calculated. On the contrary, PLStream continuously updates its learned vector representation from new data, which introduces unavoidable overhead. Nevertheless, PLStream’s throughput is still promising, reaching 9877 tuples/second (Sentiment140) and 7182 tuples/second (Yelp Review) respectively. Lexicon-based and clustering-based approaches achieve poor performance because the former involves costly lookups from the lexicon, while the latter involves a costly clustering computation process for every batch of input stream. Figure 6b shows that PLStream achieves the lowest processing latency confirming the effectiveness of its fast incremental word embedding and low overhead similarity-based classification mechanisms. We will demonstrate the impact of each optimization techniques in detail later in Section 5.3.

Accuracy. Figure 7 shows the evaluation of labelling accuracy. There are three key observations. First, we can see that the accuracy of PLStream increases with more input tuples, since it can incrementally learn from new data, i.e., the quality of the vector representation improves gradually. Starting from 360,000 and 480,000 input tuples, the accuracy begins to converge, reaching an average accuracy of 79.2% and 68.8% for Yelp Review and Sentiment140, respectively. Second, the LDA-based method, which is sometimes treated as the representative unsupervised sentiment classification algorithm [25], achieves an accuracy of 68.3% on average for handling the Yelp Review dataset. Its accuracy is even poorer when processing Sentiment140 (61.3%), because it relies on a larger corpus for distribution computations of vocabulary and topics, while Sentiment140 contains mostly short texts. Third, the clustering-based approach achieves the worst accuracy on both datasets. It achieves an average accuracy of 52.3% and 51.9% for Sentiment140 and Yelp Review, respectively. This is because the topics involved in the input stream are relatively random, and the text lacks important clustering features required for it to be effective.

5.3 Impact of Optimizations

A series of system optimization strategies further improve PLStream in terms of both accuracy and performance. In this section, we study the effectiveness of the key optimization techniques. Unless otherwise stated, we evaluate the labelling accuracy of PLStream on Yelp Review Polarity. We tune each optimization technique to its optimal configuration experimentally.

Impact of Temporal Trend Detection (TTD). We have generated datasets with more or less positive texts based on the Yelp Review dataset. The generated datasets have proportions of positive texts ranging from 0-100%. We have evaluated the performance of various algorithms on these regenerated datasets in terms of accuracy and $F1 − score$. It can be observed from Figure 8 that the
accuracy of PLStream becomes higher with a more skewed polarity distribution. This is due to the temporal trend detection technique employed by PLStream, which is able to react well to temporal semantic aggregation and improves the classification accuracy by up to 5.2%. In contrast, the accuracy of lexicon- and LDA-based algorithms, is clearly lower for negative samples than for positive samples. This indicates that they misclassified a large number of samples, resulting in many false positives. This is also reaffirmed by the F1-score shown in Table 3. Specifically, the Lexicon- and LDA-based algorithms have an F1-score of less than 0.7 for the dataset with low positive samples, whereas PLStream outperforms all of them with an F1-score greater than 0.8.

Our further investigation found that the trend detection window (TDW) has a significant impact on the effectiveness of the temporal trend detection technique. Specifically, the system performance with a smaller size TDW (such as 10 or 20) becomes unstable. This is because prediction accuracy may be low in a small window, leading to low trend detection accuracy, which continuously affects the classification accuracy of subsequent windows. On the contrary, an oversized TDW may miss the semantic aggregation. Automatically choosing the right size of TDW is important and possible [42], and we leave its tuning as a future work due to its considerable complexity.

Impact of Model Merging. Figure 9 clearly shows the trade-offs among three model management strategies in terms of accuracy and throughput. There are three observations. First, the global model strategy achieves the highest prediction accuracy, as it generates the most comprehensive vector representations in the system. However, its throughput is the worst due to the contended global model updates to Redis. Second, unlike the global model strategy, there is no communication between threads in the local model strategy, which leads to significantly higher throughput. However, it achieves the lowest classification accuracy and slowest convergence speed since the model on each thread can only learn from the data that is distributed to it. Third, as expected, the hybrid model achieves reliable accuracy and relatively good system performance at the same time. Our further evaluation has confirmed the clear trade-off of varying model merging frequency from 20 to 90 seconds. Higher frequency leads to better accuracy, but lower performance as frequent model merging can bring down the system performance. In the following experiments, we apply a hybrid model merging strategy with a merging frequency of 30 seconds.

5.4 System Sensitivity Study

In this section, we present the effectiveness of tuning various hyperparameters of PLStream in detail.

Impact of Adaptive Batching. A larger batch size allows PLStream to learn from more input tuples at a time. Hence, it achieves a faster convergence speed, lower latency, and higher throughput with amortized function call cost, as shown in Figure 10. However, there is a clear decrease in system performance when b exceeds 2000. The reason is that each thread in PLStream needs to
wait for more tuples to start training, resulting in more system idle time.

The Effect of Varying Vector Dimension ($d$). We may tune the number of features (i.e., vector dimension $d$) used in word2vec training. The common wisdom is that a large vector dimension ($\sim 500$ [28, 33]) helps to obtain a better quality vector representation. Figure 11 (a) illustrates how the classification accuracy changes by varying $d$ from 10 to 500. We can see that the converged accuracy (when the number of processed input tuples=30k) increases from $d = 10$ to $d = 20$. This matches the previous findings [33]. However, the classification accuracy does not increase and sometimes even drops once $d$ exceeds 20. This is due to the well-known curse of dimensionality [39] problem raised during our similarity-based classification. In particular, when the dimensionality is high, data points (i.e., vector representations in our case) are mostly sparse and dissimilar, which prevents reliable detection of data points of similar properties. Figure 11 (b) and (c) show that as the vector dimension becomes higher, PLStream achieves lower throughput and higher processing latency. This is due to the increasing cost spend in matrix multiplications during incremental word vectorization, as well as the costly similarity-based classification.

5.5 Solution Scalability

In this section, we evaluate the scalability of PLStream with respect to hardware resources and workload complexity.

Hardware Resource Scalability. Our next experiment shows that PLStream scales effectively, when we increase the number of CPU cores. In this experiment, PLStream is configured with hybrid model strategy and LRU-based model pruning technique. Figure 12 (a) shows that as the number of threads increases, PLStream needs to process more tuples to achieve accuracy convergence. This is expected, as each thread learns less with increasing number of threads. In contrast, PLStream’s processing and incremental learning at different threads are mostly independent with little contention among others. In particular, we can see from Figure 12(b) that the processing latency of PLStream does not vary with the different number of cores in one node. The processing latency increases marginally when PLStream is deployed on multiple nodes due to the additional network communication overhead. Figure 12 (c) further shows that the throughput of PLStream improves significantly when increasing the number of cores from 2 to 12 cores (one node), up to 48 cores (four nodes), reaffirming its good scalability. Nevertheless, further exploration is required to improve the system towards linearly scale-up.

Workload Complexity Scalability. Data streams such as reviews have longer text, whereas tweets, for example, are dominated by short text. We now examine our annotating effect in terms of text length. We selectively pick texts of varying length from the two benchmark workloads to regenerate the input stream for this experiment. Figure 13 shows the converged accuracy of each algorithm on the data set of different text lengths. We have repeated each experiment three times and report the average result. We have four major observations. First, it can be observed that the accuracy of PLStream always outperforms other algorithms. Interestingly, in the dataset with a text length of less than 30, the accuracy of all algorithms is poorer. This is because, unlike paragraphs or documents, short texts are more ambiguous: they do not contain enough contextual information, which poses a great challenge for classification [14]. Second, the accuracy of the LDA-based algorithm
improves with increased text length. This is expected, as the LDA-based approach is designed for document-level sentiment analysis [24]. Third, the accuracy of the lexicon-based algorithm also increases initially due to the increased contextual information in the input workloads. However, its accuracy decreases when the text length exceeds 300. This is due to the increasing noise interfering with its scoring process. For example, one input tuple may contain multiple opinions. Fourth, in contrast, varying text length shows no impact on the clustering-based approach. This is again due to the lack of important clustering features in our benchmark workloads.

6 CONCLUSION

We have presented PLStream, a new framework designed for annotating fast ongoing unlabelled data streams at scale on modern parallel machines. PLStream encompasses several algorithmic and system architectural innovations, that reduce workloads, enhance learned embedding models incrementally, and control model management overhead. Based on extensive experiments with two real-world workloads, we demonstrate PLStream’s high labelling accuracy, system throughput, and low processing latency. In practice, users can further use a confidence threshold to control the labelling of the vast majority of the data with high confidence by PLStream and leave the rest to human experts. Labelled datasets can be immediately consumed by subsequent supervised learning tasks and reduce the development cost of sentiment analysis services. In the future, we plan to further exploiting "auto-ML" techniques to identify the optimal value of the various tuning knobs of PLStream.

REFERENCES

[1] Last accessed by 11 November 2021. Joint sentiment topic code, https://github.com/bhayani/JST_model-on-MR.
[2] Last accessed by 14 August 2021. Apache Storm, https://storm.apache.org/.
[3] Last accessed by 14 August 2021. Spark Streaming, https://spark.apache.org/streaming/.
[4] Last accessed by 16 September 2021.
[5] Last accessed by 14 August 2021. Pyflink overview, https://nightlies.apache.org/flink/flink-docs-release-1.13/docs/dev/python/overview/.
[6] Last accessed by 24 August 2021. RocksDB key value store, https://rocksdb.org.
[7] Last accessed by 24 June 2021. Redis key value store, https://redis.io/topics/introduction.
[8] B. Agarwal and N. Mittal. 2016. Machine Learning Approach for Sentiment Analysis. Springer International Publishing. 21–45 pages.
[9] Stefano Baccianella and et al. 2010. Sentiwordnet 3.0: an enhanced lexical resource for sentiment analysis and opinion mining. In Lrec, Vol. 10. 2200–2204.
[10] S Selva Birunda and R Kanniga Devi. 2021. A Review on Word Embedding Techniques for Text Classification. In Innovative Data Communication Technologies and Application. Springer, 267–281.
[11] David M Blei, Andrew Y Ng, and Michael I Jordan. 2003. Latent dirichlet allocation. in Proceedings of the 2003 conference on uncertainty in artificial intelligence. 2. 526–533.
[12] Ankkara Ortigosa and et al. 2014. Sentiment analysis in Facebook and its application to e-learning. Computers in human behavior 31 (2014), 527–541.
[13] Alvaro Ortigosa and et al. 2014. Sentiment analysis in Facebook and its application to e-learning. Computers in human behavior 31 (2014), 527–541.
[14] Jindong Chen and et al. 2019. Deep Short Text Classification with Knowledge Powered Attention. AAAI’19 (July 2019).
[15] Jacob Devlin and et al. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805 (2018).
[16] Yang Gao and et al. 2015. Pattern-based Topics for Document Modelling in Information Filtering. TKDE’15 (2015).
[17] Rohan Ramanath and et al. 2021. Lambda Learner: Fast Incremental Learning on Big Data Streams. In IJCAI’21.
[18] Alvaro Ortigosa and et al. 2014. Sentiment analysis in Facebook and its application to e-learning. Computers in human behavior 31 (2014), 527–541.
[19] Tanjim Ul Haque and et al. 2018. Sentiment analysis on large scale Amazon product reviews. In ICRRD. IEEE, 1–6.
[20] Clayton Hutto and Eric Gilbert. 2014. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In AAAI’14, Vol. 8.
[21] Shuankai Liu and Ermin Nsouli. 2017. Large scale sentiment learning with limited labels. In KDD’17. 1823–1832.
[22] Quoc Le and Tomás Mikolov. 2014. Distributed Representations of Sentences and Documents. In ICML’14.
[23] Jie Li and Wei Liu. 2014. Sentiment analysis based on clustering: a framework in improving accuracy and recognizing neutral opinions. Applied intelligence 40, 3 (2014), 441–452.
[24] Chenghua Lin and Yulan He. 2009. Joint sentiment/topic model for sentiment analysis. In CICM’09. 375–384.
[25] Bing Liu and Lei Zhang. 2012. A survey of opinion mining and sentiment analysis. In Mining text data. Springer, 415–463.
[26] Qingyuan Liu and et al. 2015. FLORIN - A System to Support (Near) Real-Time Applications on User Generated Content on Daily News. Proc. VLDB Endow. 8 (2015), 1944–1947.
[27] Steven Loria. 2018. textblob Documentation. Release 0.15.2 (2018), 269.
[28] Nicola Capuano and et al. 2021. Sentiment analysis for customer relationship management. in Proceedings of the 10th International Conference on Multimedia Information Processing and Retrieval. Springer International Publishing. 21–45 pages.
[29] Bruno Obana and Brendan Tierney. 2009. A review and benchmark evaluation. In LREC’10.
[30] Kevin Patel and Pushpak Bhattacharyya. 2017. Towards Lower Bounds on Number of Dimensions for Word Embeddings. In IJCNLP’17.
[31] J. Pennington and et al. 2014. Glove: Global Vectors for Word Representation. In EMNLP’14.
[32] Amir Hossein Akhavan Rahnama. 2014. Distributed real-time sentiment analysis for big data social streams. In CoDIT’14. IEEE, 789–794.
[33] Rohan Ramanath and et al. 2021. A Preliminary Study of Fast Incremental Learning on Big Data Streams. In KDD’21.
[34] Mohammad Shafiei and et al. 2018. SentiWordNet: A Lexical Resource for Opinion Mining and Sentiment Analysis. In LREC’18.
[35] Tanjim Ul Haque and et al. 2018. Sentiment analysis on large scale Amazon product reviews. In ICRRD. IEEE, 1–6.
[36] Ashish Vaswani and et al. 2017. Attention is all you need. In ICLR’18.
[37] Jindong Chen and et al. 2019. Deep Short Text Classification with Knowledge Powered Attention. AAAI’19 (July 2019).
[38] Xiang Zhang and et al. 2015. Character-Level Convolutional Networks for Text Classification. In ICML’15.
[39] Shuhao Zhang and et al. 2020. Towards concurrent stateful stream processing on modern parallel machines. PLStream, a new framework designed for annotating fast ongoing unlabelled data streams at scale on modern parallel machines. PLStream encompasses several algorithmic and system architectural innovations, that reduce workloads, enhance learned embedding models incrementally, and control model management overhead. Based on extensive experiments with two real-world workloads, we demonstrate PLStream’s high labelling accuracy, system throughput, and low processing latency. In practice, users can further use a confidence threshold to control the labelling of the vast majority of the data with high confidence by PLStream and leave the rest to human experts. Labelled datasets can be immediately consumed by subsequent supervised learning tasks and reduce the development cost of sentiment analysis services. In the future, we plan to further exploiting "auto-ML" techniques to identify the optimal value of the various tuning knobs of PLStream.

Figure 13: Accuracy on different text length.