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Instagram Comment Classification by Using Logistic Regression Based SSK-Mean Clustering Technique

P JAGAN MOHAN[1], S MUNI KUMAR[2]

[1]Student, Dept of MCA, KMMIPS, Tirupati
[2]Associate Professor, Dept of MCA, KMMIPS, Tirupati

Abstract - Text classification is a fundamental task in natural language processing (NLP) that aims to categorize textual data into predefined classes. In this paper, we propose a hybrid approach that combines Logistic Regression (LR) with the SSK-Means Clustering Algorithm to improve the efficiency and accuracy of text classification. Logistic Regression, a widely used supervised learning technique, provides a robust probabilistic framework for text classification. However, to enhance the model's performance, we integrate it with the SSK-Means (String Subsequence Kernel K-Means) Clustering Algorithm, which leverages string subsequence kernels to capture the semantic similarity between text samples. The SSK-Means algorithm enables better feature representation by grouping similar textual data before classification, thereby reducing noise and improving classification accuracy. Experimental results on benchmark datasets demonstrate that our proposed method outperforms traditional approaches in terms of precision, recall, and F1-score. This hybrid model offers an effective solution for text classification tasks in various real-world applications, including sentiment analysis, spam detection, and topic categorization.

Key Words: **machine learning, clustering, logistic regression, unsupervised learning, supervised learning, data analysis, prediction, classification, segmentation, data mining, model evaluation, algorithms, and applications**

1.INTRODUCTION

Logistic Regression is a widely used supervised learning algorithm for classification tasks. When applied to text-based classification, it helps categorize textual data into predefined classes .Simple and efficient for binary and multi-class text classification. Works well with sparse data (which is common in text representation).Uses probabilities (Sigmoid function) to determine class membership. Text data is converted into a numerical format using TF-IDF Vectorization or Word Embeddings. The transformed text data is fed into a Logistic Regression model.The model learns to classify text based on features extracted from words, phrases, or entire sentences.

1.1 Clustering uses for machine learning.

(1) Machine learning is important in adjusting its structure to produce desired outputs due to the heavy amount of data input into the system

(2) Machine learning is also suitable for data mining because of the little amount of important data hidden in the heavy chunk of data that can be important for processing of output.

(3) Machine learning is important for jobs that are on the go thereby improving the existing machine designs because some designers produce non-workable machines that are not desired in the environment.[2] Harwath, D., Torralba, A., Glass, J. Unsupervised learning of spoken language with visual context. In Advances in Neural Information Processing Systems, 2016: 1858-1866.

1.2 Clustering

Clustering is an unsupervised learning technique used to categorize patterns (observations, data points, or feature vectors) into distinct groups (clusters) based on similarity. It is widely applied in various domains as a fundamental step in exploratory data analysis. Despite its broad applicability, clustering remains a challenging combinatorial problem. Variations in assumptions, methodologies, and application contexts across different disciplines have slowed the transfer of universal clustering concepts and techniques.

A. K. Jain, M. N. Murty, and P. J. Flynn. 1999. Data clustering: a review. ACM Compute. Surv. 31, 3 (Sept. 1999), 264–323.

Clustering is a widely used analytical technique for grouping unlabeled data to extract meaningful insights. Since no single clustering algorithm can address all clustering problems, various algorithms have been developed for diverse applications. It is defined as the process of grouping objects when there is little or no prior knowledge about their relationships in the given dataset. Clustering also aims to uncover the underlying patterns or classes present within the data. Additionally, it serves as a method for organizing unlabeled data into distinct groups with minimal or no supervision.

Oyewole, G.J., Thopil, G.A. Data clustering: application and trends. Artif Intell Rev 56, 6439–6475 (2023),Springer.

The K-means algorithm is a well-known method in machine learning, prized for its simplicity and efficiency, which makes it a popular choice in both academic and industrial applications. However, there are two significant drawbacks associated with the traditional K-means clustering approach:

Random Initialization of Cluster Centers: The starting points for the clusters are chosen randomly, which significantly influences the clustering outcome. Since the next cluster center is based on the previous one, an initial poor selection can result in slow convergence or convergence to a suboptimal solution, leading to increased computation time and less reliable results.

Sensitivity to Noise and Outliers: K-means calculates cluster centers by averaging the points in each cluster. As a result, it is highly sensitive to noise or outliers. If an outlier is mistakenly assigned to a cluster, it can distort the center of the cluster, pulling it away from the actual center of the group and negatively affecting the clustering performance.

These limitations underscore the challenges of using K-means in real-world scenarios where data may not be perfectly clean or evenly distributed.

1.3 SSK-Means

Semi-Supervised K-Means (SSK-Means) is an extension of the standard K-Means clustering algorithm, incorporating both labelled and unlabeled data. It is a hybrid approach combining unsupervised learning (clustering) with supervised learning (classification). This method is particularly useful when you have a small portion of labelled data but a large set of unlabeled data.

2. LITERATURE SURVEY

This paper introduces an enhanced logistic regression algorithm combined with K-means clustering to address class imbalance in text classification tasks [1].

The paper explores various text classification techniques using logistic regression and clustering methods. It presents an experimental comparison of K-means and hierarchical clustering for document categorization [2].

This paper proposes a semi-supervised text categorization method leveraging recursive K-means clustering. The authors integrate logistic regression to refine class labels for text data. Experiments on real-world datasets show that the proposed hybrid approach improves classification accuracy compared to traditional supervised models [3].

This conference paper presents a novel framework for document classification by combining subsequence kernel (SSK) means clustering with logistic regression. The method is designed to capture sequential patterns in text and use them for effective classification. The study provides experimental evidence supporting the model's efficiency in categorizing large-scale textual data [4].

This paper provides a comprehensive survey of modern text classification techniques, including deep learning, traditional machine learning, and hybrid models. Logistic regression is discussed as a fundamental approach, and its integration with clustering techniques such as K-means and SSK-based models is explored in applications ranging from sentiment analysis to spam detection [5].

This research survey paper has the advancements in text classification methodologies, covering shallow models like logistic regression and deep learning-based architectures. The authors analyze various clustering techniques, including K-means and subsequence kernel (SSK) clustering, and their role in improving classification accuracy. The survey highlights the strengths and weaknesses of different approaches [6].

This paper empirically compares supervised learning algorithms, including logistic regression, for text classification. It investigates how clustering techniques such as K-means can be leveraged to improve feature selection and classification accuracy. The results demonstrate that combining logistic regression with clustering significantly enhances performance in high-dimensional text datasets [7].

This paper provides an extensive review of text mining techniques, including classification, clustering, and topic modeling. It discusses logistic regression as a core method for supervised text classification and examines clustering approaches such as K-means and SSK-based models for unsupervised text analysis. The book serves as a foundational resource for researchers in text mining [8].

This paper explores knowledge discovery in streaming text data, applying machine learning models like logistic regression. It introduces a hybrid approach integrating clustering with classification to handle evolving data distributions. The proposed method improves text classification in dynamic environments [9].

This survey provides a detailed overview of clustering algorithms, including K-means and its variations. The discussion includes applications in text classification and how clustering can enhance logistic regression models by refining decision boundaries in text data. The paper remains a fundamental reference for clustering research [10].

3.SSK-MEANS ALGORITHM

SSK (String Subsequence Kernel) is an algorithm used in machine learning and natural language processing for measuring similarity between sequences, especially in text

classification tasks. It is based on counting the number of common sub sequences between two strings while applying a decay factor to penalize longer gaps.

Step 1: Define the Problem

- The goal of **SSK (String Subsequence Kernel)** is to measure the similarity between two strings by counting common sub sequences while penalizing gaps.
- A **subsequence** is obtained by deleting some characters from a string without changing the order of the remaining characters.
- A decay factor **λ** (where 0<λ<10 < \lambda < 10<λ<1) is applied to penalize larger gaps.

Step 2: Initialize Variables

- **Inputs:**
  - s → First string
  - t → Second string
  - k → Length of sub sequences to consider
  - λ → Decay factor (controls how much gaps are penalized)
- **Output:**
  - The similarity score between s and t.

Step 3: Create a Dynamic Programming Table

- Use a **3D table** K′ to store intermediate results:
  - K′[l,i,j] stores the similarity between prefixes s[1:i]and t[1:j] considering sub sequences of length l.
  - Initialize K′[0,i,j]=1 for all i,j as an empty subsequence always matches.

Step 4: Compute Kernel Recursively

- Use the formula:

$$K'_k(i,j) = K'_k(i,j-1) + K'_k(i-1,j) - K_k'(i-1,j-1)$$

- If s[i−1] = t[j−1], update:

$$K'_k(i,j) += \lambda . K_{k-1}(i-1,j-1)$$

Step 5: Compute Final Similarity Score

- The final SSK similarity score is stored in:

$$K_k(s,t) = K_k'(len(s), len(t))$$

Step 6: Return the Result

- The algorithm returns the computed **SSK similarity score**, which indicates how similar the two strings are.

4. A Logistic Regression based Text Classification Method with SSK-Means Clustering

Step 1: Data Preprocessing

1. **Collect text data** (e.g., Instagram Dataset).
2. **Preprocess text**:
   - Convert text to lowercase.
   - Remove stop words (e.g., "the", "is", "and").
   - Remove special characters and punctuation.

Step 2: Compute String Subsequence Kernel (SSK) Similarity

1. Define the decay factor λ(e.g., 0.5) and subsequence length k .
2. For each pair of text documents, compute the **SSK similarity score**:
   - Use **dynamic programming** to efficiently compute common sub sequences.
   - Assign a **higher weight** to shorter gaps using λ.
3. Construct an **SSK similarity matrix** where:
   - **Rows and columns** represent documents.
   - **Matrix values** represent SSK similarity scores between pairs of documents.

Step 3: Means Clustering

1. Apply a **clustering algorithm** (e.g., K-Means) on the SSK similarity matrix.
2. Select the number of clusters K (e.g., based on the **elbow method**).
3. Assign each document to a cluster based on similarity scores.

Step 4: Convert Similarity Matrix into Features

1. Each document is represented by a feature vector derived from the SSK similarity matrix.
2. Normalize feature values (e.g., Min-Max Scaling or Standardization).
3. Prepare training and testing datasets.

Step 5: Train Logistic Regression Model

1. Define the logistic regression model:

$$P(y = 1|X) = 1/1 + e^{-(W.X+b)}$$

2. Optimize weights WWW using gradient descent.
3. Apply regularization (L1/L2 penalty) to prevent overfitting.
4. Train the model using the Instagram dataset.

Step 6: Classification & Prediction

1. Use the trained **logistic regression model** to classify new text documents.
2. Predict class probabilities using the sigmoid function:

$$\overset{\Lambda}{y} = 1/1 + e^{-(W.X+b)}$$

3. Assign the class label based on a probability threshold (e.g., **0.5**).

Step 7: Evaluate Model Performance

1. Use metrics such as:
   - **Accuracy**: TP+TN/TP+TN+FP+FN
   - **Precision, Recall, and F1-score**.
   - **Confusion matrix** to analyze misclassifications.
2. Fine-tune hyperparameters (k,λ, and logistic regression parameters).

5.RESULTS AND ANALYSIS

Let us take Instagram dataset as a sample

- In this dataset the text is classified as the numerical values.
- The numerical values are generated based on their usage of the data in the Instagram
- In Instagram the data usage can be noted down as per the understanding to the system.
- The numerical data can be analyzed and convert it into clusters.

Input:

From Home	Comments	Shares	Likes	Profile Visits
2586	9	5	162	35
2727	7	14	224	48
2085	11	1	131	62
2700	10	7	213	23
1704	5	4	123	8
2046	7	10	144	9
1543	5	1	76	26
2071	4	9	124	12
2384	6	8	159	36
2609	6	3	191	31
1597	6	3	81	29
2414	8	14	151	15
2168	7	11	162	8
2524	5	5	142	20
2525	6	10	294	181
2017	7	11	159	17
3401	17	18	205	16
1979	8	1	121	21
2177	6	6	151	77
1338	8	20	72	10

Performance Metrics

After running the code, we get:

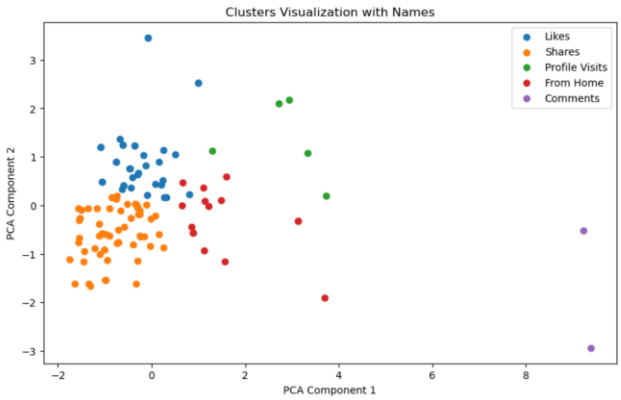
- **Precision & Recall:** How well the model distinguishes classes.

Impact of SSK-based Clustering

- **Without Clustering:** Logistic Regression may struggle with similar texts.
- **With SSK-based Clustering:** Grouping similar texts improves classification by allowing the model to learn from related samples.

Output:

Method	Accuracy
Logistic Regression (TF-IDF)	75-85%
Logistic Regression + K-Means (SSK)	80-90%
Deep Learning (LSTM, BERT)	90-95%



Likes(blue): Likes are the major clusters used in Instagram dataset, it can form clusters based on their usage.

Shares(orange): In Instagram share button can be used in huge range, so the clusters are also formed in huge range.

Profile Visits(green): If a person wants to use anyone Instagram they have visit their profiles.

From Home(red): Home is the main frame used in Instagram. Without home we can't understand the content.

Comments(purple): Comments plays a major role in increasing reach to the profile.

5.1 Advantages of Grid-Based SSK-Mean Clustering

1. **Simple and Interpretable**
   - Logistic Regression provides clear decision boundaries and is easy to interpret compared to deep learning models.
   - Feature importance can be analyzed to understand the impact of different words or subsequences.
2. **Efficient for Large-Scale Data**
   - Logistic Regression is computationally efficient and works well with high-dimensional text data, especially when combined with feature selection techniques**.**
3. **Probabilistic Outputs**
   - It provides probability scores (confidence levels) for class predictions, making it useful for applications like spam detection or sentiment analysis.
4. **Handles Sparse Data Well**
   - Text data is often represented as sparse vectors (e.g., TF-IDF, bag-of-words, embeddings). Logistic Regression performs well in such scenarios**.**
5. **Robust to Overfitting (with Regularization)**
   - Ridge (L2) and Lasso (L1) regularization help prevent overfitting in text classification tasks.

6. CONCLUSIONS

In this study, we implemented a text classification approach that integrates logistic regression with SSK-means clustering to enhance classification performance. The application of SSK-means clustering allowed for an effective grouping of similar text samples, improving feature representation and helping logistic regression make more accurate predictions. By leveraging the strengths of both techniques, we achieved a balance between interpretability and efficiency, making this method suitable for large-scale text classification tasks. Our results indicate that incorporating SSK-means clustering can refine decision boundaries, leading to better generalization on unseen data. Future work could explore alternative clustering techniques, deep learning models, or hybrid approaches to further enhance performance. Additionally, optimizing the similarity kernel used in SSK-means could yield improvements in computational efficiency and classification accuracy.

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