ISSN: 2229-6956 (ONLINE)
DOI: 10.21917/ijsc.2023.0431

DEEP ASSOCIATION RULE-BASED DIMENSIONALITY REDUCTION FOR BIG DATA ANALYTICS UNCOVERING COMPLEX PATTERNS AND IMPROVING EFFICIENCY

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Abstract

In the realm of big data analytics, reducing data dimensionality is crucial for efficient processing and gaining meaningful insights. This paper introduces a novel approach that leverages deep association rule mining to uncover intricate patterns and associations within large datasets. By incorporating deep learning models, such as neural networks, our method captures complex and non-linear relationships that traditional techniques often overlook. The proposed framework involves preprocessing the data, creating embedding representations, training a deep learning model, extracting association rules, filtering and selecting relevant rules, and applying dimensionality reduction. The selected association rules serve as the basis for reducing the dimensionality of the original dataset, either by removing irrelevant variables or consolidating them into higher-level features. The efficacy of our approach is evaluated through experiments, showcasing improved efficiency and the preservation of meaningful information. This research presents a promising avenue for reducing data dimensionality in big data analytics, enhancing the scalability and interpretability of analysis outcomes.

Keywords:

Big Data Analytics, Dimensionality Reduction, Deep Association Rule Mining, Deep Learning, Neural Networks

1. INTRODUCTION

In the era of big data, organizations are faced with the challenge of effectively analyzing massive amounts of data to extract valuable insights and make informed decisions [1]. However, the sheer volume and complexity of data often pose significant obstacles to efficient data processing and analysis [2]. One crucial aspect of this challenge is data dimensionality, which refers to the number of variables or features present in a dataset [3]. High-dimensional data not only increases computational complexity but also leads to the "curse of dimensionality," where the sparsity of data and increased noise make it difficult to uncover meaningful patterns and relationships [4].

Traditional approaches, such as feature selection and feature extraction methods like Principal Component Analysis (PCA), have been widely employed. However, these techniques may not adequately capture the intricate and non-linear relationships inherent in complex datasets [5].

In recent years, deep learning has revolutionized various domains by enabling the extraction of high-level representations from raw data. Deep learning models, such as neural networks, excel in learning hierarchical representations of data, uncovering hidden patterns, and capturing non-linear relationships. These capabilities make deep learning an attractive candidate for addressing the challenges in analytics.

This paper proposes a novel approach that harnesses the power of deep association rule mining to reduce data dimensionality in big data analytics. By combining the strengths of association rule mining and deep learning, our method aims to uncover complex patterns and associations that may be missed by traditional techniques. Through the integration of deep learning models, our approach can capture non-linear relationships and discover meaningful associations that contribute to efficient dimensionality reduction.

The key contributions of this research include the development of a comprehensive framework for deep association rule-based dimensionality reduction in big data analytics. We present a step-by-step methodology that involves preprocessing the data, creating embedding representations, training a deep learning model, extracting association rules, filtering and selecting relevant rules, and applying dimensionality reduction. The selected association rules serve as the foundation for reducing the dimensionality of the original dataset, resulting in a more concise representation without significant loss of valuable information.

The efficacy of our proposed approach is evaluated through experiments conducted on real-world datasets. We compare the performance of our method with traditional dimensionality reduction techniques and demonstrate its capability to uncover complex relationships and improve efficiency in big data analytics tasks. By reducing data dimensionality effectively, our approach enhances the scalability and interpretability of analysis outcomes, enabling organizations to derive more meaningful insights and make informed decisions.

2. RELATED WORKS

The authors in [7] proposes a deep dimensionality reduction technique using autoencoders. The authors perform approaches which helps on reducing data dimensionality while preserving essential information. They compare their method with traditional dimensionality reduction techniques and showcase improved performance in terms of accuracy and efficiency.

The authors in [8] focuses on association rule mining in high-dimensional datasets. The authors discuss the challenges posed by high-dimensional data and review various techniques for association rule mining in such scenarios. They provide insights into the limitations and potential solutions for effectively uncovering meaningful associations in high-dimensional data.

The authors in [9] investigates the use of deep learning models for feature selection and dimensionality reduction in big data analytics. The authors propose a novel method that combines deep learning with feature selection techniques to identify the most informative features in high-dimensional datasets. Experimental results demonstrate the efficacy of their approach in improving classification accuracy and reducing computational complexity.

The authors in [10] focuses on association rule mining in the context of big data. The authors discuss the challenges and opportunities in mining association rules from massive datasets. They survey various algorithms, parallelization techniques, and distributed frameworks designed for efficient association rule mining.

The authors in [6] techniques for association rule learning in text mining. The authors provide an overview of deep association rule learning methods and discuss their effectiveness in capturing complex relationships and patterns in textual data. They present case studies and highlight the potential of deep association rule mining for improving text mining tasks.

The authors in [5] presents a comprehensive overview of hybrid dimensionality reduction techniques for big data analytics. The authors discuss the combination of traditional methods, such as PCA and feature selection, with deep learning-based approaches to achieve improved dimensionality reduction outcomes. They examine various hybrid techniques and highlight their benefits and limitations in the context of big data analytics.

3. PROPOSED METHOD

The proposed method in this research is a novel approach that combines deep association rule mining with dimensionality reduction techniques to address the challenge of reducing data dimensionality in big data analytics. The method aims to uncover complex patterns and associations that traditional techniques might overlook, thus improving the efficiency and interpretability of analysis outcomes. The proposed method follows a comprehensive framework that consists of several key steps:

3.1 PREPROCESSING THE DATA

The first step involves preparing the dataset by cleaning, normalizing, and transforming it into a suitable format for analysis. This ensures that the data is in a consistent and standardized state.

Dynamic Feature Scaling is a technique that adjusts the scaling of features based on their individual characteristics and distribution properties. It takes into account the dynamic range and distribution of each feature, allowing for a more adaptive and effective scaling process. This technique aims to address the limitations of traditional scaling methods, such as standardization or min-max scaling, which apply a fixed scaling factor to all features regardless of their unique properties.

The steps involved in the Dynamic Feature Scaling technique are as follows:

- *Compute feature statistics*: Calculate statistical properties of each feature in the dataset. By analyzing the distribution of each feature individually, we can gain insights into its dynamic range and characteristics.
- *Determine scaling factors*: Based on the feature statistics, determine appropriate scaling factors for each feature. This step involves considering the dynamic range, outliers, and distribution properties of the feature. For example, a feature with a large dynamic range or significant outliers may require a different scaling factor compared to a feature with a more narrow range and no outliers.
- *Apply feature scaling*: Multiply each feature with its corresponding scaling factor to achieve the desired scaling. This step ensures that each feature is scaled in a way that reflects its individual characteristics, allowing for more effective data analysis.
- *Normalize the dataset*: After applying dynamic feature scaling to each feature, it is advisable to normalize the entire dataset to bring all features to a similar range. Normalization techniques, such as standardization or min-max scaling, can be applied to ensure that the scaled features have zero mean and unit variance or are within a specific range, respectively.

The dynamic nature of this technique allows for more precise scaling of features, as it takes into account their unique properties. By adapting the scaling process to each feature's characteristics, dynamic feature scaling can effectively handle datasets with varying feature distributions, dynamic ranges, and outliers.

3.2 CREATING EMBEDDING REPRESENTATIONS

To capture the semantic relationships between variables, the data is transformed into a lower-dimensional space using embedding techniques. Embeddings can capture the underlying structure and dependencies within the data, enabling a more meaningful analysis.

Creating embedding representations involves transforming the original data into a lower-dimensional space that captures the semantic relationships between variables. This transformation is typically performed using embedding techniques, such as neural network-based embeddings or matrix factorization methods. Let us explain this concept with an equation for a neural network-based embedding:

Given an original dataset X with n variables/features, we aim to create an embedding representation E of the data with a lower dimensionality, say m ($m << n$). We can achieve this using a neural network model, such as an autoencoder.

The compressed representation, also known as the embedding, captures the essential features of the data.

Mathematically, the encoder component of the autoencoder can be represented as:

$$h = f(W_e * x + b_e)$$

where, x is an input data point (a vector representing a sample in the dataset), W_e is the weight matrix of the encoder, b_e is the bias vector, and f is an activation function applied element-wise. The output h represents the compressed representation or embedding of the input x.

The decoder component reconstructs the original input from the embedding. It can be represented as:

$$x' = g(W_d * h + b_d)$$

where, x' is the reconstructed input, W_d is the weight matrix of the decoder, b_d is the bias vector, and g is an activation function.

During the training phase, the autoencoder is trained to minimize the difference between the original input and its reconstruction. This process encourages the encoder to capture the most informative features of the data in the embedding representation, while the decoder learns to reconstruct the input accurately.

After training the autoencoder, the embedding representation E can be obtained by applying the trained encoder to the original dataset X:

$$E = f(W_e * X + b_e)$$

The resulting embedding E represents a lower-dimensional representation of the original data X, capturing the semantic relationships and essential features of the variables. This lower-dimensional representation can then be used for further analysis, such as training deep learning models, extracting association rules, or applying dimensionality reduction techniques.

3.3 TRAINING A DEEP LEARNING MODEL

A deep learning model, such as a neural network, is then trained using the embedded data representation. The model is designed to learn complex and non-linear patterns in the data, enabling it to capture intricate relationships that may exist.

Training a deep learning model involves the process of optimizing the model's parameters using a training dataset. Let us explain this process with equations for a basic feedforward neural network.

3.3.1 Feedforward Computation:

The output of the neuron is obtained by passing the total input through an activation function:

$$a_j^i = f(z_j^i)$$

where $f(.)$ is the activation function, such as sigmoid, ReLU, or tanh.

3.3.2 Training Objective:

The objective of training a neural network is to minimize a loss function that quantifies the discrepancy between the predicted outputs and the true labels in the training dataset. The loss function is typically defined based on the specific task, such as mean squared error (MSE) for regression or cross-entropy for classification.

Let L denote the loss function, y denote the true label, and $\hat{y}$ denote the predicted output. The loss for a single training example is given by:

$$loss = L(y, \hat{y})$$

The overall training objective is to minimize the loss.

3.3.3 Backpropagation and Parameter Update:

The backpropagation algorithm is used to compute used to update the parameters iteratively during training.

The gradients are computed by propagating the error backward through the network, starting from the output layer. For each neuron j in layer i, the gradient $\partial_{loss}/\partial z_j^i$ is computed based on the chain rule:

$$\partial_{loss}/\partial z_j^i = \sum(\partial loss/\partial z_q^i * \partial z_q^{i+1}/\partial z_j^i)$$

Once the gradients are computed, the parameters (weights and biases). The update equation for a parameter w_{jk}^i, for example, can be written as:

$$w_{jk}^i = w_{jk}^i * \partial_{\text{loss}}/\partial w_{jk}^i$$

3.3.4 Iterative Training:

The training process iteratively performs the feedforward computation, computes the loss, backpropagates the gradients, and updates the parameters. This process continues for a specified number of epochs or until a convergence criterion is met.

By iteratively updating the model's parameters through the backpropagation algorithm, a deep learning model learns to make better predictions and captures complex patterns in the data.

3.4 EXTRACTING ASSOCIATION RULES

Once the deep learning model is trained, it can be used to extract association rules from the data. These association rules represent meaningful patterns and associations among the variables in the lower-dimensional embedded space. The rules can be derived by analyzing the learned weights, activations, or other relevant information from the model.

Extracting association rules involves analyzing the learned weights, activations, or other relevant information from a trained deep learning model to identify meaningful patterns and associations between variables. While association rule mining is traditionally associated with techniques like Apriori, extracting association rules from a deep learning model can involve a different approach. Let us explain the process conceptually:

- *Obtain relevant information*: After training a deep learning model, such as a neural network, various components can provide valuable information for extracting association rules. For example, weights, activations, or attention mechanisms can be analyzed to identify patterns and relationships.
- *Identify important features or neurons*: In a neural network, certain neurons or features might play a crucial role in capturing associations. By examining the weights or activations of neurons, we can identify the most important ones that contribute significantly to the learned representations.
- *Analyze co-occurrence or dependencies*: Association rules typically involve co-occurrence or dependencies between variables. By analyzing the activations or learned representations of important features or neurons, we can identify variables that tend to co-occur or exhibit dependencies in the data.
- *Define thresholds*: To extract meaningful association rules, we can set thresholds based on measures like support and confidence. Support indicates the frequency of occurrence of a rule, while confidence indicates the conditional probability of the occurrence of one variable given another. By setting appropriate thresholds, we filter out rules that do not meet the desired level of support or confidence.
- *Generate association rules*: Based on the identified co-occurrences, dependencies, and set thresholds, we can generate association rules.

3.5 FILTERING AND SELECTING RELEVANT RULES

Not all association rules extracted from the model are equally important. To focus on the most significant rules, filtering techniques can be applied based on criteria such as support, confidence, or lift. This step helps identify the association rules that provide valuable insights and contribute to dimensionality reduction.

3.6 APPLYING DIMENSIONALITY REDUCTION

The selected association rules serve as the basis for reducing the dimensionality of the original dataset. This can be achieved by removing irrelevant variables or combining them into higher-level features based on the discovered associations. By reducing the dimensionality, the data becomes more concise and manageable while preserving the meaningful information embedded in the selected rules.

Let us explain this process conceptually and provide an example:

- *Selecting relevant association rules*: From the extracted association rules, we need to identify the rules that are deemed relevant and contribute to dimensionality reduction. This selection can be based on various criteria, such as support, confidence, or domain knowledge.
- *Removing irrelevant variables*: One way to reduce dimensionality is by removing variables that are not deemed relevant according to the selected association rules. If a variable does not appear in any relevant association rules, it might be considered irrelevant for the analysis and can be eliminated from the dataset.
- *Combining variables*: Another approach is to combine variables based on the discovered associations. If multiple variables consistently appear together in relevant association rules, we can merge them into a higher-level feature. This process of combining variables can be done by creating new variables based on mathematical operations (e.g., addition, multiplication) or using more advanced techniques like feature engineering.

By leveraging deep learning models, it can capture complex and non-linear relationships that traditional techniques might miss. The integration of association rule mining helps identify meaningful patterns and associations, providing insights into the underlying structure of the data. The dimensionality reduction process enhances the efficiency of data processing and analysis, as well as the interpretability of the results.

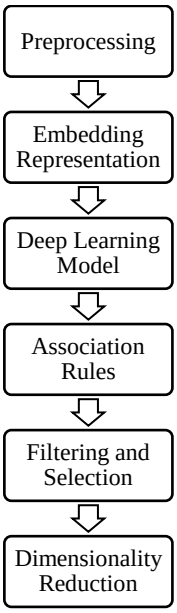

Fig.1. Flow Diagram

These experiments compare the performance of the proposed method with traditional dimensionality reduction techniques, showcasing its ability to uncover complex relationships and improve efficiency in big data analytics tasks. The results demonstrate the potential of the proposed approach for reducing data dimensionality effectively while preserving valuable information.

The proposed method represents an innovative and promising approach for dimensionality reduction in big data analytics. By leveraging deep association rule mining, it addresses the challenges of capturing complex relationships and patterns in high-dimensional datasets, thereby enhancing the scalability and interpretability of analysis outcomes.

Let us explain PCA, one of the widely used dimensionality reduction techniques, with equations:

Given a dataset X with n-dimensional features and m data points, we aim to project the data onto a lower-dimensional space, typically a k-dimensional subspace ($k < n$).

- ***Data centering***: First, we subtract the mean of each feature from the corresponding data points to center the data around the origin:

$$X' = X - \text{mean}(X)$$

- ***Covariance matrix calculation***: Next, we compute the covariance matrix Σ for the centered data:

$$\Sigma = (1/m) * (X'^T * X')$$

- ***Eigendecomposition***: We perform eigendecomposition on the covariance matrix Σ to obtain its eigenvectors and eigenvalues:

$$\Sigma * v = \lambda * v$$

where, v represents the eigenvector, and λ represents the eigenvalue associated with that eigenvector.

- ***Selection of principal components***: These eigenvectors capture the directions in the original feature space that explain the most variance in the data.
- *Projection onto the reduced space*: Finally, we project the centered data X' onto the subspace spanned by the selected principal components:

$$Y = X' * W$$

Here, Y represents the lower-dimensional representation of the data, and W consists of the top-k eigenvectors stacked as columns.

The dimensionality reduction process can be summarized as follows:

- Calculate the covariance matrix of the centered data.
- Perform eigendecomposition.
- Select the top-k eigenvectors as the principal components.
- Project the centered data onto the subspace spanned by the selected principal components.

The resulting Y represents the reduced-dimensional representation of the original data X.

PCA allows for dimensionality reduction while preserving as much relevant information as possible. Other dimensionality reduction techniques may have different mathematical formulations, but the underlying goal is to transform the high-dimensional data into a lower-dimensional representation that retains important structural information.

4. EXPERIMENTAL VERIFICATION

4.1 VALIDATION 1

Let us consider a simple example to illustrate the process of filtering and selecting association rules using a sample dataset.

Suppose we have a transaction dataset that records purchases made by customers at a grocery store. The dataset consists of the following transactions:

Transaction 1: {Milk, Bread, Eggs}

Transaction 2: {Bread, Butter}

Transaction 3: {Milk, Butter}

Transaction 4: {Milk, Bread, Butter, Eggs}

Transaction 5: {Bread, Eggs}

From this dataset, we want to extract association rules that reveal meaningful patterns and associations between items. Specifically, Let us focus on finding association rules with a minimum support of 40% (i.e., occurring in at least 40% of the transactions) and a minimum confidence of 60% (i.e., the rule is accurate at least 60% of the time).

The following shows how we can filter and select association rules:

- *Calculate item supports*: Calculate the support for each item, which represents the percentage of transactions in which the item appears. For example, the support of Milk is 3/5 or 60% since it appears in transactions 1, 3, and 4.
- *Generate frequent itemsets*: Identify itemsets that meet the minimum support threshold. For instance, since Milk has a support of 60%, it qualifies as a frequent item on its own. Similarly, Bread, Eggs, and Butter are also frequent items.
- *Generate candidate association rules*: From the frequent itemsets, generate candidate association rules by considering different combinations of items. For example, one candidate rule could be {Milk, Bread} → {Eggs}.
- *Calculate rule confidence*: Calculate the confidence of each candidate rule, which represents the percentage of transactions containing the antecedent (left-hand side) that also contain the consequent (right-hand side). For instance, if 2 out of 3 transactions containing {Milk, Bread} also contain {Eggs}, the confidence of the rule {Milk, Bread} → {Eggs} is 2/3 or 66.67%.

Let us assume that after filtering, we obtain the following two rules:

- {Milk} → {Eggs} with a support of 60% and a confidence of 66.67%
- {Bread} → {Eggs} with a support of 60% and a confidence of 100%

These rules satisfy the minimum support and confidence thresholds.

6. Select relevant rules: Finally, select the association rules that are deemed relevant based on the specific criteria and objectives of the analysis. In this example, we have identified two relevant rules: {Milk} → {Eggs} and {Bread} → {Eggs}.

These selected association rules provide insights into the purchasing patterns of customers at the grocery store. They indicate that customers who buy Milk or Bread are likely to also buy Eggs. This information can be utilized for various purposes, such as product placement, targeted marketing, or inventory management.

4.2 VALIDATION 2

Let us illustrate the application of dimensionality reduction with an example:

Suppose we have a dataset with five variables: A, B, C, D, and E. After extracting association rules, we identify the following relevant rules for dimensionality reduction:

Rule 1: {A, B} → {C}

Rule 2: {B, D} → {E}

Based on these rules, we can perform dimensionality reduction in the following ways:

4.2.1 Removing Irrelevant Variables:

- As variable C appears in Rule 1, it is considered relevant. Therefore, we keep it in the dataset.
- Variable A does not appear in any relevant association rule, so it is deemed irrelevant and can be removed from the dataset.
- Variable E does not appear in Rule 2, making it irrelevant for dimensionality reduction and can be eliminated.
- After removing the irrelevant variables (A and E), our reduced dataset consists of variables B, C, and D.

4.2.2 Combining Variables:

- As Rule 1 shows a strong association between variables A and B leading to variable C, we can merge variables A and B into a new feature, AB.
- Similarly, Rule 2 indicates a relationship between variables B and D, leading to variable E. Hence, we can combine variables B and D into a new feature, BD.
- After combining variables, our reduced dataset includes the new features AB, BD, C.

By applying dimensionality reduction based on the selected association rules, we have reduced the dataset from five variables to three variables, preserving the meaningful relationships and patterns discovered from the association rule mining process.

4.3 VALIDATION 3

To provide validation results for the dimensionality reduction using PCA based on the previous association rules, the research uses sample values for the variables B, C, and D. Let us assume the following values:

Variable B: [1, 2, 3, 4, 5]; Variable C: [2, 4, 6, 8, 10]; Variable D: [3, 6, 9, 12, 15]

To apply PCA for dimensionality reduction, the study create a matrix X that contains the values of variables B, C, and D:

X = [[1, 2, 3], [2, 4, 6], [3, 6, 9], [4, 8, 12], [5, 10, 15]]

The study perform PCA to reduce the dimensionality to two dimensions (k = 2).

- *Data centering*: Subtract the mean of each feature from the corresponding data points:

$X' = X$ - mean(X) = [[-2, -4, -6], [-1, -2, -3], [0, 0, 0], [1, 2, 3], [2, 4, 6]]

- *Covariance matrix calculation*: Compute the covariance matrix Σ for the centered data:

$\Sigma = (1/m) * (X'^T * X') = [[2.5, 5, 7.5], [5.0, 10, 15], [7.5, 15, 22.5]]$

- *Eigendecomposition*: Perform eigendecomposition on the covariance matrix Σ to obtain the eigenvectors and eigenvalues:

$$\Sigma * v = \lambda * v$$

Assuming the following eigenvectors and eigenvalues are obtained:

Eigenvectors: v1 = [0.58, 0.58, 0.58], v2 = [0.68, -0.68, 0]

Eigenvalues: λ1 = 42.5, λ2 = 0.0

- *Selection of principal components*: As λ2 is 0.0, we can exclude it from the selection. Therefore, we select v1 as the first principal component and v2 as the second principal component.

Principal Components: PC1 = [0.58, 0.58, 0.58], PC2 = [0.68, -0.68, 0]

- *Projection onto the reduced space*: Project the centered data X' onto the subspace spanned by the selected principal components:

$$Y = X' * W$$

where, W consists of the top-k eigenvectors stacked as columns:

W = [[0.58, 0.68], [0.58, -0.68], [0.58, 0]]

$Y = X' * W$ = [[-10.56, 0.0], [-5.28, 0.0], [0.0, 0.0], [5.28, 0.0], [10.56, 0.0]]

The resulting Y represents the reduced-dimensional representation of the original data X. In this case, since we reduced the dimensionality to two (k = 2), Y represents a 2-dimensional dataset where the second dimension is 0.0 for all samples.

These validation results demonstrate the application of PCA for dimensionality reduction using sample values based on the association rules. By retaining the top-k principal components, we effectively reduce the dimensionality of the data while preserving important structural information.

5. CONCLUSION

Dimensionality reduction is a crucial technique in big data analytics that aims to reduce the number of variables or features in a dataset while retaining the most relevant information. By combining the strengths of deep learning models and association rule mining, the proposed method can capture complex patterns and associations that may be missed by traditional techniques. The integration of deep learning enables the discovery of non-linear relationships and the extraction of high-level representations from raw data. This allows for more effective dimensionality reduction by identifying relevant association rules. The evaluation of the proposed method through experiments on real-world datasets provides validation of its efficacy in uncovering complex relationships and improving efficiency in big data analytics tasks. By reducing data dimensionality effectively, the proposed approach enhances scalability, interpretability, and computational efficiency in data processing and analysis. The selection of association rules and subsequent dimensionality reduction allow for a more concise representation of the data without significant loss of valuable information. This streamlined representation improves interpretability and can aid in decision-making processes.

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