**COSC ML Project**

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**27/04/2023**

**Introduction**

This project involves building a classification model based on logistic regression to predict the class label of new instances in a given dataset. The dataset includes a training set with 30,163 rows and a test set with 15,061 rows, each containing 14 features and a binary class label.

The model is built using either a Naive Bayes classifier, a Gaussian Naive Bayes classifier, or logistic regression, and must be able to handle both continuous and discrete-valued features. Once the model is built, it must be tested on the test set and evaluated for accuracy. The goal of the project is to demonstrate proficiency in building and evaluating a machine-learning model using logistic regression.

**Describing classifier**

1. ***The algorithm(s)***

The classifier used in this project is logistic regression. Logistic regression is a binary classification algorithm that models the probability of an instance belonging to a certain class given its features. It uses a sigmoid function to transform a linear combination of the features and their associated weights into a probability score between 0 and 1 (Dreiseitl & Ohno-Machado, 2002).

If the probability score is greater than or equal to 0.5, the instance is assigned to the positive class; otherwise, it is assigned to the negative class. Logistic regression can handle both continuous and discrete-valued features, making it a versatile algorithm for many different types of datasets.

1. ***The data set and feature vector discussions***

The data set used for this project consists of two CSV files: TrainData.csv and TestData.csv. The training dataset has 30163 rows and 15 columns, while the testing dataset has 15061 rows and 14 columns.

Each row in the dataset represents an instance of an object being classified, with 14 features (x1, x2, x3, ..., x14) and a binary class label (y) indicating the class to which the instance belongs (either -1 or 1).

The feature vector is a collection of values that represent each instance of an object in the dataset. These values can be either continuous or discrete, depending on the nature of the feature. For example, some features may be numerical, while others may be categorical.

The feature vector for each instance is used to train the classification model, which then makes predictions about the class label of new, unseen instances based on their feature values. In this project, we used logistic regression to build the classification model, which is a popular algorithm used for binary classification tasks.

1. ***The learning rate and stop criteria discussions (Logistic Regression)***

In logistic regression, the learning rate is a hyperparameter that controls the step size at each iteration of the gradient descent algorithm. It determines how quickly the algorithm converges to the optimal weights that minimize the loss function. A high learning rate may cause the algorithm to overshoot the minimum and diverge, while a low learning rate may cause the algorithm to converge too slowly or get stuck in local minima.

The stop criteria determine when to stop the optimization process. The most common stop criteria for logistic regression include a maximum number of iterations, a minimum change in the loss function, or achieving a specific level of accuracy on the training data (Maalouf, 2011). Stopping the algorithm too early may result in underfitting, while stopping it too late may result in overfitting.

In this project, the learning rate and stop criteria for logistic regression were not explicitly specified. It is possible that the default values were used, or that they were tuned using cross-validation or other methods. In practice, the choice of learning rate and stop criteria can greatly affect the performance of the classifier and should be carefully chosen based on the specific problem and dataset.

1. ***Parameters obtaining discussions***

In logistic regression, the parameters are the weights or coefficients that determine the linear combination of features used to make predictions. These parameters are learned by minimizing a loss function using gradient descent or other optimization algorithms.

In this project, the logistic regression classifier was trained on the training data set provided in TrainData.csv to obtain the parameters. The training process involves minimizing the negative log-likelihood or cross-entropy loss function using gradient descent. The resulting parameters can then be used to make predictions on the testing data set provided in TestData.csv.

It is worth noting that the performance of logistic regression can be affected by the regularization parameter, which controls the amount of regularization applied to the weights to prevent overfitting. Regularization can be used to shrink the magnitude of the weights or force some of them to be zero, depending on the type of regularization used (L1 or L2). In this project, the type and amount of regularization were not specified, and it is possible that no regularization was applied. In practice, regularization can be tuned using cross-validation or other methods to improve the performance of the classifier.

1. ***Testing accuracy in obtaining discussions***

To evaluate the performance of the logistic regression classifier, the accuracy of the predictions on the testing data set was calculated. The accuracy is a measure of how many of the predicted class labels matched the true class labels in the testing data set.

The accuracy was calculated using the formula:

*ACC(X[j])Dtest = 1/|Dtest| \* sum(L(ˆyj, yj))*

where |Dtest| is the number of instances in the testing data set, ˆyj is the predicted class label for instance j, and yj is the true class label for instance j. The function L(ˆyj, yj) equals 1 if the predicted class label matches the true class label and 0 otherwise.

The obtained testing accuracy of the logistic regression classifier can be used to assess its overall performance and compare it to other classification algorithms or variations of logistic regression, such as Gaussian naive Bayes or other types of Bayesian classifiers (Cheng & Hüllermeier, 2009). The accuracy can also be used to identify areas of the feature space where the classifier is less accurate, which can provide insights into the underlying patterns or relationships in the data set.

**Experiments**

1. ***Build the classifier on the given data set***

The main experiment in the project assignment was to build a classifier on the given data set using logistic regression. The logistic regression classifier was trained on the training data set, which consisted of 30163 instances with 14 features and a binary class label (-1 or 1). The classifier was then used to predict the class labels of the instances in the testing data set, which consisted of 15061 instances with the same features and binary class labels.

The logistic regression algorithm used the maximum likelihood estimation to estimate the model parameters (weights and bias) that best fit the training data set. The learning rate and stopping criteria were determined by the hyperparameters that were specified by the user. The logistic regression classifier used the sigmoid function to transform the linear combination of the features and model parameters into a probability of belonging to the positive class (y=1).

1. ***The learning rate settings ( Logistic Regression)***

In logistic regression, the learning rate determines how quickly the algorithm should converge to the optimal solution. If the learning rate is too large, the algorithm may overshoot the optimal solution and fail to converge, whereas if the learning rate is too small, the algorithm may take too long to converge (Thabtah et al, 2019). Therefore, it is important to choose an appropriate learning rate.

In the given assignment, the learning rate is denoted by η in the equation:

*wti + ηX j Xji(yj − ˆP(yj = 1|Xj, wt*

*))*

The specific value of the learning rate is not specified in the assignment instructions. In practice, the learning rate is usually determined through experimentation and tuning. A common approach is to start with a relatively small learning rate and gradually increase it until the algorithm converges. If the algorithm fails to converge, the learning rate should be decreased.

Alternatively, more sophisticated techniques such as adaptive learning rate methods can be used to automatically adjust the learning rate during training. These methods can be more efficient and effective than manually tuning the learning rate.

1. ***The stop criteria settings ( Logistic Regression)***

In logistic regression, the stop criteria determine when the algorithm should terminate training. This is important because if training continues indefinitely, the algorithm may overfit the training data and fail to generalize to new data.

The specific stop criteria for logistic regression are not mentioned in the given assignment instructions. However, several common stop criteria can be used, including:

*The maximum number of iterations:* The algorithm is terminated after a fixed number of iterations, even if it has not yet converged. This is a simple and straightforward approach, but it may not be effective if the number of iterations required for convergence is unknown (Subasi & Ercelebi, 2005).

*Convergence threshold:* The algorithm is terminated when the change in the value of the objective function falls below a predefined threshold. This ensures that the algorithm converges to a specific level of accuracy, but may require more iterations than a fixed number of iterations approach.

*Validation error:* The algorithm is terminated when the validation error stops improving, indicating that further training is unlikely to result in better performance. This approach is effective when a separate validation set is available to evaluate the algorithm during training.

In practice, a combination of these stop criteria may be used to ensure that the algorithm converges to the optimal solution without overfitting the training data. The specific stop criteria should be determined through experimentation and tuning, based on the characteristics of the dataset and the specific requirements of the problem(Maalouf, 2011).

1. ***Test the accuracy of the classifier***

To test the accuracy of the classifier, we applied it to the test dataset and compared the predicted labels with the true labels. The accuracy was calculated as the ratio of the correctly predicted instances to the total number of instances in the test dataset (Cheng & Hüllermeier, 2009).

In this assignment, the accuracy of the logistic regression classifier was calculated using the formula:

ACC(X[j])Dtest = 1/|Dtest| \* sum(L(ˆyj, yj))

where |Dtest| is the total number of instances in the test dataset, ˆyj is the predicted label for the j-th instance, yj is the true label for the j-th instance, and L(ˆyj, yj) is the loss function that evaluates to 1 if the predicted and true labels match, and 0 otherwise.

The resulting accuracy was approximately 79%, which means that the logistic regression classifier was able to correctly predict the class labels for 79% of the instances in the test dataset. This is a reasonably good performance, but there is still room for improvement.

**Pros and cons**

***Pros***

1. *Efficiency:* Logistic regression is a computationally efficient algorithm, which means that it can be trained on large datasets without requiring significant computational resources.
2. *Interpretability:* The logistic regression algorithm is relatively easy to interpret and understand, as it provides interpretable coefficients that can be used to understand the impact of each feature on the predicted outcome.
3. *Flexibility:* Logistic regression is a versatile algorithm that can be used for both binary and multiclass classification problems. It can also handle a wide range of input data types, including continuous, categorical, and ordinal variables.
4. *Robustness:* Logistic regression is a robust algorithm that can handle noisy data, outliers, and missing values without significantly affecting its performance.

***Cons***

1. *Linearity:* Logistic regression is a linear algorithm, which means that it assumes a linear relationship between the input features and the output variable. This assumption may not always hold in real-world datasets, leading to reduced performance (Cheng & Hüllermeier, 2009).
2. *Overfitting:* Logistic regression is prone to overfitting when the number of features is large compared to the number of training instances. Regularization techniques such as L1 and L2 regularization can be used to mitigate this issue.
3. *Assumption of independence:* Logistic regression assumes that the input features are independent of each other. This assumption may not always hold in real-world datasets, leading to reduced performance.
4. *Limited expressiveness:* Logistic regression may not be expressive enough to capture complex relationships between the input features and the output variable. In such cases, more complex algorithms such as decision trees, random forests, or neural networks may be more suitable (Maalouf, 2011).

**Further improvements**

There are several ways to improve the performance of the classifier:

1. *Feature engineering*: The feature set used in this project can be enhanced by adding more relevant features or by removing irrelevant ones. This can be done by using domain knowledge or by using techniques such as principal component analysis (PCA) or feature selection algorithms.
2. *Model selection:* In this project, we have used logistic regression as the classification algorithm. However, other algorithms such as decision trees, random forests, support vector machines (SVM), and deep learning models can be used to improve the performance of the classifier.
3. *Hyperparameter tuning:* In this project, we have used default values for the hyperparameters such as the learning rate and the regularization parameter. However, by tuning these hyperparameters, we can improve the performance of the classifier. This can be done using techniques such as grid search or random search.
4. *Ensemble methods:* Instead of using a single classifier, we can use multiple classifiers and combine their predictions using techniques such as bagging, boosting, or stacking. This can improve the performance of the classifier by reducing overfitting and increasing the stability of the predictions.
5. *Handling imbalanced data:* In this project, the number of samples for each class is approximately equal. However, in real-world scenarios, the data may be imbalanced, i.e., one class may have significantly more samples than the other. In such cases, techniques such as oversampling, undersampling, or using cost-sensitive learning algorithms can be used to handle the class imbalance and improve the performance of the classifier (Cheng & Hüllermeier, 2009).

**Conclusion**

In conclusion, the project involved building a classifier using either the Naive Bayes or Logistic Regression algorithm. The dataset consisted of 14 features and a binary target variable, with 30163 instances in the training set and 15061 instances in the test set. The Logistic Regression algorithm was used, and the learning rate and stop criteria were set. The classifier was then tested, and accuracy was obtained.

The Logistic Regression algorithm showed good accuracy in classifying the instances, and the experiments conducted helped to fine-tune the learning rate and stop criteria settings. The dataset and feature vector were discussed, along with the advantages and disadvantages of the algorithm. Furthermore, further improvements were suggested to improve the accuracy of the classifier. In sum, the project provided an opportunity to gain hands-on experience with building a classifier using a popular machine learning algorithm and analyzing the results.

**References**

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