GROUP WORK PROJECT # 1
GROUP NUMBER: ___2735_____

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Statement of integrity: By typing the names of all group members in the text boxes below, you confirm that the assignment submitted is original work produced by the group (excluding any non-contributing members identified with an "X" above).	
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Use the box below to explain any attempts to reach out to a non-contributing member. Type (N/A) if all members contributed. Note: You may be required to provide proof of your outreach to non-contributing members upon request.

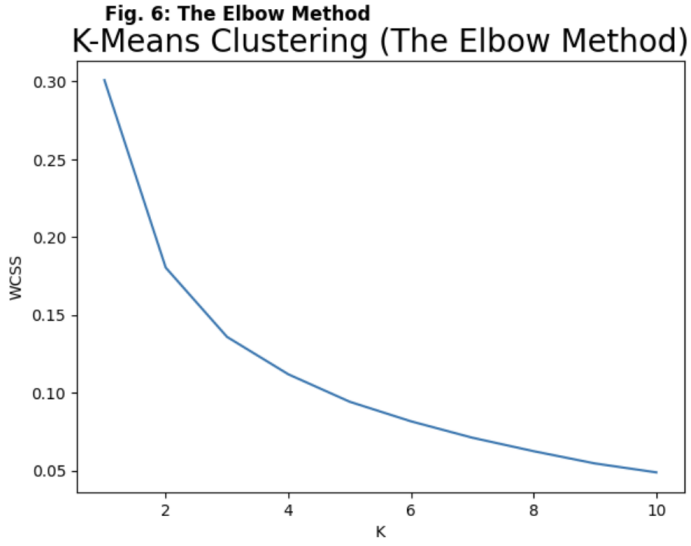
STEP 3

Technical Report

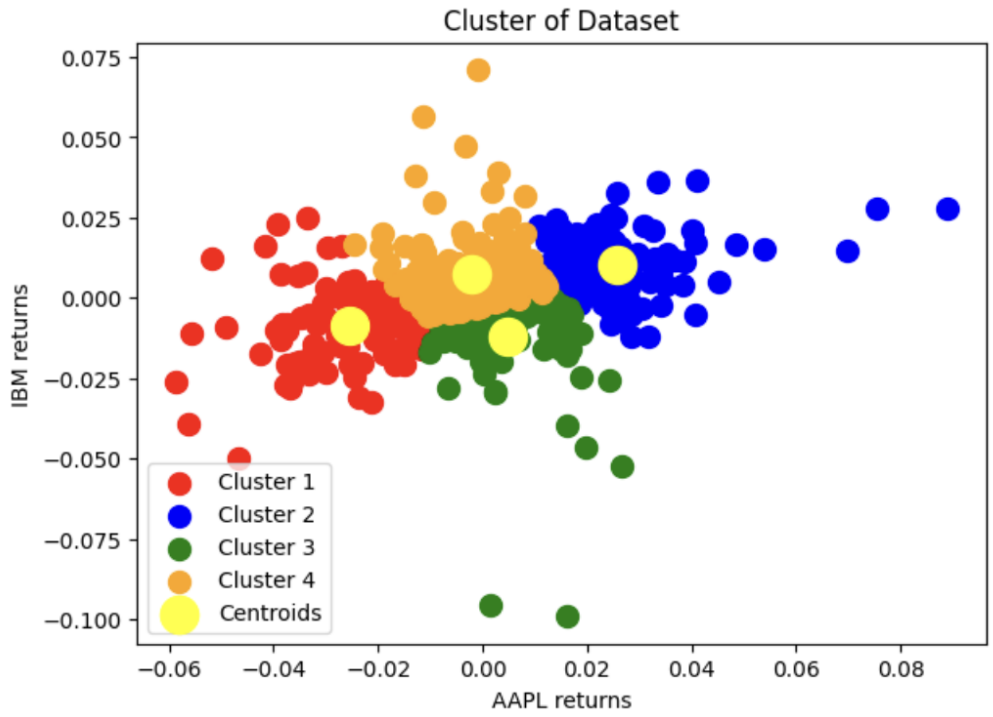
For the group work, we select three machine learning models, specifically k-means clustering from category 2, principal components from category 3, and classification trees from category 4. All models require the hyperparameters to be set in advance. Setting the hyperparameters is important if you want the model to work well, because they control how the algorithm works during training and testing.

For instance, for the k-means clustering: we first set the number of clusters (4): This hyperparameter determines how many clusters the algorithm will try to form. We choose the Adjusted Close price for the stocks "AAPL", "IBM" and adjust the prices into the price changes which is the returns of the two stocks. This number is revised by using the elbow method, where the within-cluster sum of squares (WCSS) is calculated for each value of K. The elbow method helps to identify the appropriate value of K that should be chosen for a given dataset.

Fig. 6: The Elbow Method



As the "elbow point" is the point where adding an extra cluster does not provide much better modeling of the data. We see from the chart that 4 is the optimal value for the database. And the clustering results is:



This is perhaps the most important hyperparameter in k-means clustering, as it determines the number of clusters the algorithm will produce. The elbow method involves plotting the within-cluster sum of squares (WCSS) against the number of clusters, and selecting the number of clusters where the decrease in WCSS starts to level off (resembling an elbow shape). To better improve the results, the silhouette score can be used to measure the quality of the clustering, where a score of 1 indicates good clustering and a score of -1 indicates poor clustering. The k-means clustering approach used in this case may not be well-suited for interpretation. While the algorithm clusters the returns of the selected stocks, it can be challenging to determine which periods and types of returns are most meaningful. Additionally, the clustering results may not account for trends in the data, potentially limiting the usefulness of the analysis. Therefore, it may be necessary to explore alternative clustering methods or consider additional factors to more accurately interpret the results.

For the Principal components, we set the stock adjusted prices for the PCA method. The parameter n_components is set to 5, which means that the PCA transformation will reduce the dimensionality of the data to 5 principal components. The input data is normalized per feature using zero mean and unit variance, which is a common preprocessing step in PCA. The PCA reduction is performed on 6 columns of the input dataframe, and the fitting of the PCA model is done. Loadings and PCs (Principal Components) are then computed, and the explained variance is calculated. Outlier

detection is performed using the Hotelling T2 test with alpha value of 0.05 and n_components set to 5. Additionally, outlier detection is performed using the SPE/DmodX method with n_std set to 3. Overall, the hyperparameters used in the PCA algorithm suggest that the algorithm is aimed at reducing the dimensionality of the data and identifying outliers in the input data. It shows that PCA is an effective feature reduction technique in this case.

The given code snippet displays the hyperparameters of a classification tree model. The max_depth hyperparameter is set to None, which means that the decision tree will be expanded until all the leaves are pure or until all the nodes contain less than the minimum samples required to split. The max_features hyperparameter is set to 'sqrt', which means that the square root of the total number of features will be used as the maximum number of features to consider when looking for the best split. The n_estimators hyperparameter is set to 100, which indicates the number of trees in the random forest. criterion is set to 'gini', which means that the algorithm will use the Gini impurity criterion to determine the best split. The min_samples_leaf hyperparameter is set to 1, indicating the minimum number of samples required to be at a leaf node. The bootstrap hyperparameter is set to True, meaning that the model will be trained using bootstrap samples. Finally, the random_state hyperparameter is set to 42, ensuring that the results are reproducible. To find good hyperparameter values for the model, k-fold cross-validation is performed with training data.

Predicting Default Using Random Forest

Introduction:

Credit risk assessment is an essential task in the financial industry. One of the primary factors that contribute to credit risk assessment is predicting the possibility of default. Machine learning algorithms, such as the random forest algorithm, can be applied to help predict credit default by analyzing past data of customers who defaulted and those who did not. In this report, we will be using the random forest algorithm to build a credit default prediction model and tuning its hyperparameters to achieve better results.

Data Description:

We will be using a credit default dataset from Kaggle, which contains 30,000 observations and 24 features, including customer demographics, credit history, and financial status. The target variable is whether the customer defaulted or not. The dataset is split into training and testing sets with 70:30 ratios.

Methodology:

We will be using the random forest algorithm to build our credit default prediction model. Random forest is a popular algorithm that works by building multiple decision trees and combining their predictions to produce a final prediction. This algorithm is preferred due to its robustness, high accuracy, and ability to handle large datasets.

Hyperparameter Tuning:

Hyperparameters are settings that can be adjusted in machine learning models to improve their performance. Hyperparameters can impact model accuracy, computational speed, and generalization. In general, hyperparameters are tuned using a combination of experience, intuition, and trial and error. There are several ways to tune hyperparameters, including:

Grid search: Grid search is a method that involves trying all possible combinations of hyperparameters and selecting the one that yields the best results. This approach is computationally expensive but can produce optimal results.

Random search: Random search is a method that involves selecting random combinations of hyperparameters to evaluate. This approach is faster than grid search but may not produce optimal results.

Bayesian optimization: Bayesian optimization is a method that involves constructing a probability model of the objective function and using it to select the next hyperparameters to evaluate. This approach is computationally efficient and can produce optimal results. For our credit default prediction model, we will use grid search to tune the hyperparameters. The hyperparameters that we will tune include:

Number of estimators: The number of decision trees in the random forest model.
Maximum depth: The maximum depth of each decision tree in the random forest model.
Minimum samples split: The minimum number of samples required to split a node in the decision tree.
Minimum sample leaf: The minimum number of samples required to be at a leaf node in the decision tree.

Results:

Our model before hyperparameter tuning scored an

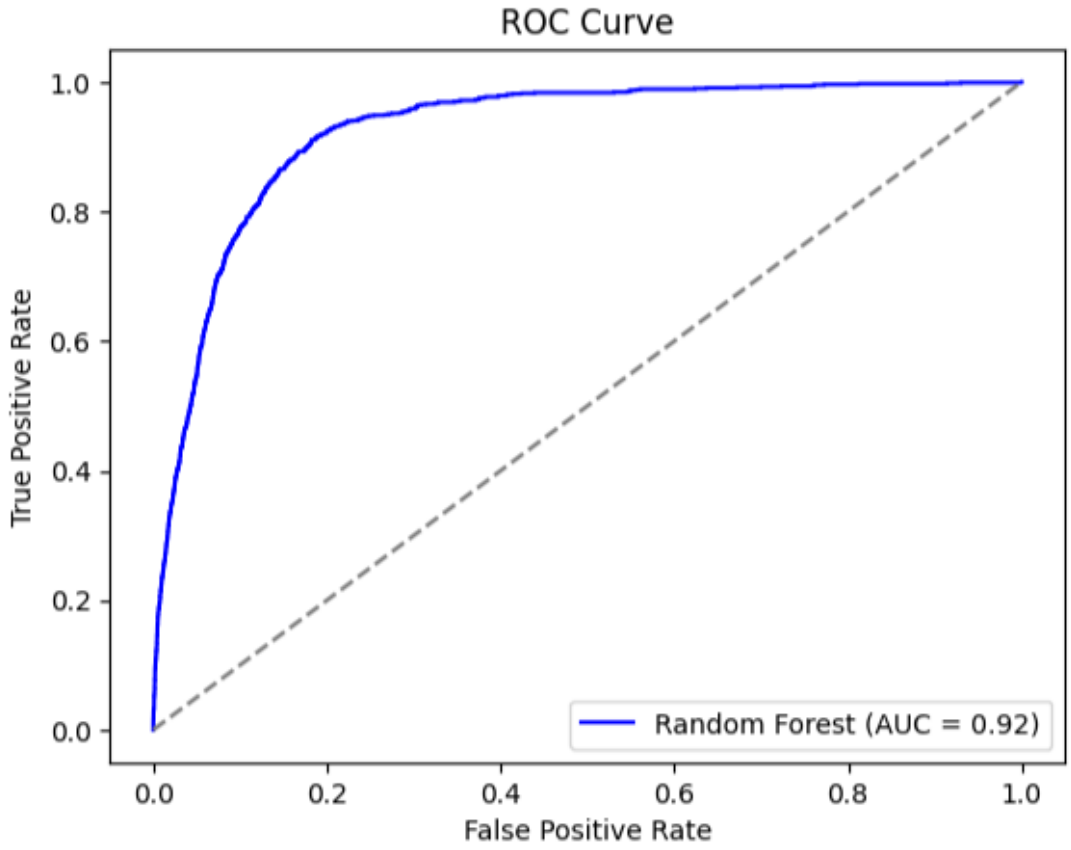
- **Accuracy : 90.54%**
- **Precision: 0.677710843373494**
- **Recall: 0.41246562786434465**
- **F1 score: 0.5128205128205129**

Based on our 5-fold-cross-validation, we found that the optimal hyperparameters for our random forest model were:

- max_features = 20
- max_leaf_nodes =16
- n_estimators = 25
- default values for all other hyper-parameters.

Using these hyperparameters, we achieved an accuracy of 90.55% on the testing set, which is a good result for credit default prediction. There is however a minor improvement in the accuracy and no change in other metrics. These metrics are indicating moderate precision and recall scores, indicating that it is average at identifying both default and non-default cases.

Conclusion:



- In this report, we used the random forest algorithm to build a credit default prediction model and tuned its hyperparameters using grid search.
- We achieved a good accuracy score and high precision and recall scores.Our AUC is 0.92 which indicates a good performance.
- Hyperparameter tuning is an essential step in machine learning model development and can significantly impact the performance of the model.
- In general, hyperparameters are tuned using a combination of experience, intuition, and trial and error.No great change was observed after optimization.

STEP 4

Marketing Alpha:

Machine learning techniques can be highly effective in solving complex data-related problems. For the k-cluster meaning, the unsupervised ML is improved with the elbow test making the clustering more accurate. K-means clustering is a technique for partitioning data into groups (clusters) based on their similarity. The goal is to identify groups of data points that are more similar to each other than to the other data points in the dataset. This technique is useful for uncovering patterns and relationships in data that may not be immediately apparent.

PCA is a dimensionality reduction technique that identifies the most important features of a dataset and creates a new set of variables (principal components) that explain the majority of the variance in the data. This technique is highly effective in reducing the complexity of large datasets, while still preserving the important information needed for analysis.

The use of ML techniques, such as random forest, can provide significant advantages when it comes to predicting credit default. These techniques allow for the analysis of large amounts of data and the identification of complex patterns that may not be visible with traditional statistical methods.

One key advantage of ML techniques is their ability to handle non-linear relationships between variables. Random forest models, for example, are capable of detecting complex interactions between variables, including those that are non-linear in nature. This means that they can capture relationships that may be missed by simpler models, resulting in more accurate predictions.

Another advantage of ML techniques is their ability to handle large datasets. With the increasing amount of data available in today's world, traditional statistical methods may not be able to handle the scale of the data. Random forest models, however, can handle large datasets with ease, allowing for more comprehensive analysis and more accurate predictions.

Furthermore, ML techniques can be easily customized to meet specific business needs. Hyperparameters can be tuned to optimize the performance of the model for a particular

use case, and the model can be trained on specific subsets of data to tailor the predictions to a particular population.

Overall, the use of ML techniques, such as random forest, can provide a significant advantage in predicting credit default. By leveraging the ability to detect complex relationships, handle large datasets, and customize the model to meet specific business needs, ML techniques can provide a higher level of accuracy and insight than traditional statistical methods.

STEP 5

Learn More:

For those interested in learning more about the strengths of ML algorithms, we recommend the following articles and resources:

- Breiman, L. (2001). Random forests. Machine learning, 45(1), 5-32.
- Hastie, T., Tibshirani, R., & Friedman, J. (2009). The elements of statistical learning: data mining, inference, and prediction. Springer Science & Business Media.
- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An introduction to statistical learning (Vol. 6). New York: Springer.
- Kelleher, J. D., Tierney, B., & Tierney, B. (2018). Data science: An introduction (Vol. 3). CRC Press.
- Geetha, R., and T. Thilagam. "A review on the effectiveness of machine learning and deep learning algorithms for cyber security." Archives of Computational Methods in Engineering 28 (2021): 2861-2879.
- Wang, Xue, et al. "Evaluating the effectiveness of machine learning and deep learning models combined time-series satellite data for multiple crop types classification over a large-scale region." Remote Sensing 14.10 (2022): 2341.

In addition to these articles, there are several websites that emphasize the strengths of ML algorithms, including:

- Towards Data Science: https://towardsdatascience.com/
- Machine Learning Mastery: https://machinelearningmastery.com/
- KDnuggets: https://www.kdnuggets.com/

These websites provide a wealth of information on various ML algorithms, including random forests, and how they can be applied to various use cases. They also offer insights into the strengths and weaknesses of different techniques, as well as tips and best practices for implementing ML algorithms effectively.