

**MSc in Data Science**

**Deree The American College of Greece**

Applied machine learning

**- Final Report -**

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# Introduction

**Machine learning** is a subfield of artificial intelligence that enables computers to learn and improve from experience without being explicitly programmed. It is a rapidly growing field that involves training a computer system using a dataset and algorithms to identify patterns in the data and make accurate predictions or decisions based on new data. Machine learning can be divided into several categories, including supervised learning, unsupervised learning, and reinforcement learning. Clustering, classification, regression, and prediction are four popular types of machine learning techniques that are used to extract insights from data.

**Clustering** is a technique used in unsupervised learning that involves grouping similar data points together. The goal of clustering is to identify patterns or relationships in the data that may not be apparent to the human eye. Clustering can be used in a variety of applications, such as client segmentation, image processing, and anomaly detection.

**Classification** is a technique used in supervised learning that involves predicting the category or class of a new data point based on its features. The goal of classification is to build a model that accurately maps input data to output labels. Classification can be used in a variety of applications, such as spam detection, sentiment analysis, and medical diagnosis.

**Regression** is a technique used in supervised learning that involves predicting a continuous numerical value based on input features. The goal of regression is to build a model that can accurately predict the value of an unknown variable based on known data. Regression can be used in a variety of applications, such as stock price prediction, sales forecasting, and weather forecasting.

**Prediction techniques** in machine learning involve using algorithms to make predictions about future events or outcomes based on historical data. These techniques can be applied to a variety of applications, such as demand forecasting, fraud detection, and client churn prediction. Prediction techniques can involve both supervised and unsupervised learning, and can use a variety of algorithms, including neural networks, decision trees, and support vector machines.

The aim of this report is to explore different types of machine learning techniques in order to address three machine learning problems (market segmentation analysis, prediction of house prices and prediction of annual income of a person). The evaluation of the techniques is an important factor analyzed in this report, in order to decide which is the best model for each problem.

# Clustering: Market Segmentation: Unsupervised learning

## Data source

The source of the data set used for the analysis is presented below:

[UCI Machine Learning Repository: Wholesale customers Data Set](https://archive.ics.uci.edu/ml/datasets/Wholesale+customers)

## Description of data

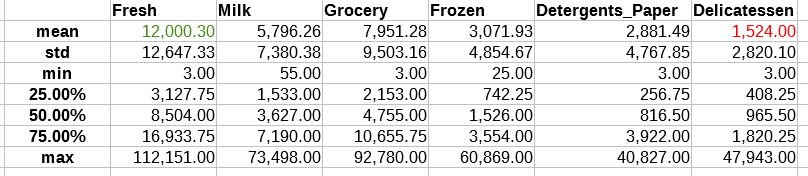
The data set includes information about the annual spending on different product categories and it refers to clients of a wholesale distributor.

It consists of 8 columns in total. The 6 of them represent the different categories of products such as fresh, milk, grocery, frozen, detergents\_paper, delicatessen, 1 column represents the channel, that refers to the method or platform through which the annual spending were made and 1 column represents the region of these transactions. Also, the dataset has 440 rows, that summarize the annual spending per client in each category.

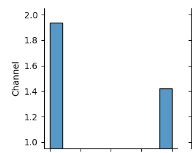
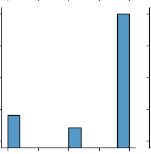
The 6 columns (fresh, milk, grocery, frozen, detergents\_paper, delicatessen) consist of continuous numerical data (amount of money in monetary units (m.u.)) and the two (channel, region) include categorical data, as per below:

* CHANNEL: Channel – Horeca (Hotel/Restaurant/Café) (1) or Retail channel (2)
* REGION: Lisnon (1), Oporto (2) or Other (3)

In the below table, some basic statistics for the numerical data are provided:



For the categorical data, in the below charts, the distribution of the data points within the different classes is presented:

## Data pre-processing

Data preprocessing is a crucial step in any machine learning project. It involves cleaning and preparing the data so that it can be properly analyzed and used to train machine learning models.

Steps followed:

1. Handling missing values: no missing values were detected in the data set.
2. Data standardization: StandardScaler () was used for transforming the data in order to have mean=0 and std=1, for better analysis of the data from the algorithm.
3. Split of data: the column “Region” was used as a target variable for the classification and it was excluded from the analysis. The rest of the columns (saved in a X variable) were used for the classification and the clustering.
4. Feature selection: mutual\_info\_classif (X,y) was used for each feature to identify the most informative features for predicting the target variable. The scores indicated that some features are more informative than others and might be beneficial to focus on these features when building the classification model.

The results from the mutual information implementation on the data set are summarized below:

Graphical user interface, text, application, chat or text message

Description automatically generated

1. Split of data into training and test set: train\_test\_split(X, y, test\_size=0.2, random\_state=42) was used, determining the size of the test set to 20% of the whole sample, with random\_state = 42 in order to get the same train and test sets across different executions.

## Algorithm description

For this problem, were used three classifier models to predict the column “Region” of the clients: Decision Tree, Random Forest, and Neural Network.

In addition, two clustering techniques were applied to the dataset: K-means clustering and Agglomerative (hierarchical) clustering. The performance of each technique was evaluated using the silhouette score.

### Optimal number of clusters and evaluation of performance

The silhouette score was used for the evaluation of the performance of the model. This score ranges from -1 to 1, with a score of 1 indicating that a data point is very similar to its own cluster and very dissimilar to other clusters.

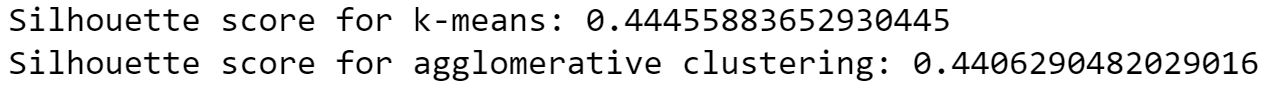
According to the silhouette score, the optimal number of clusters for this particular dataset is two -2-. However, knowing that there are three Regions where clients belong to, as optimal number of clusters is considered the three. The same number of clusters was also used for applying the agglomerative clustering.

For 3 clusters, the silhouette scores for K-means and Agglomerative clustering are presented below:

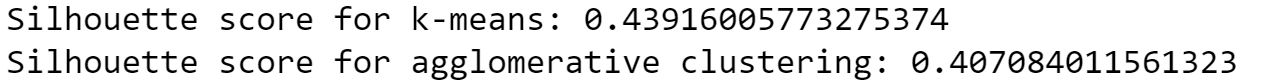


Results of different number of clusters:

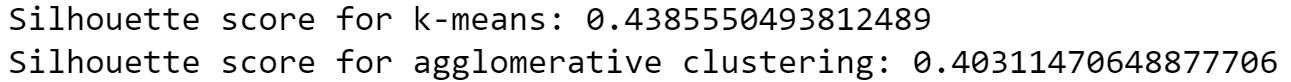
* For 2 clusters the evaluation of performance of each method is the following:



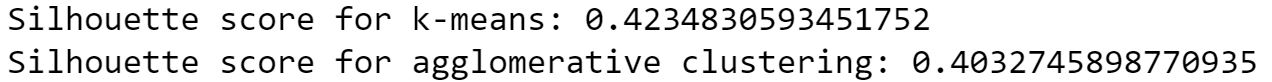
* For 3 clusters the evaluation of performance of each method is the following:



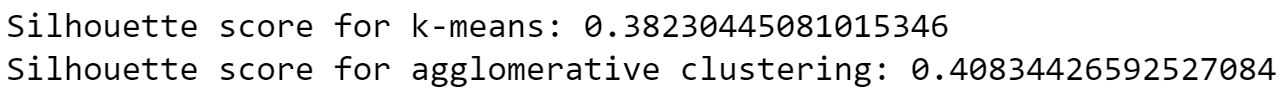
* For 5 clusters the evaluation of performance of each method is the following:



* For 7 clusters the evaluation of performance of each method is the following:



* For 9 clusters the evaluation of performance of each method is the following:



A visual representation of the created clusters was performed for both techniques, in order to check the distribution of the data points into the created clusters, as seen below:

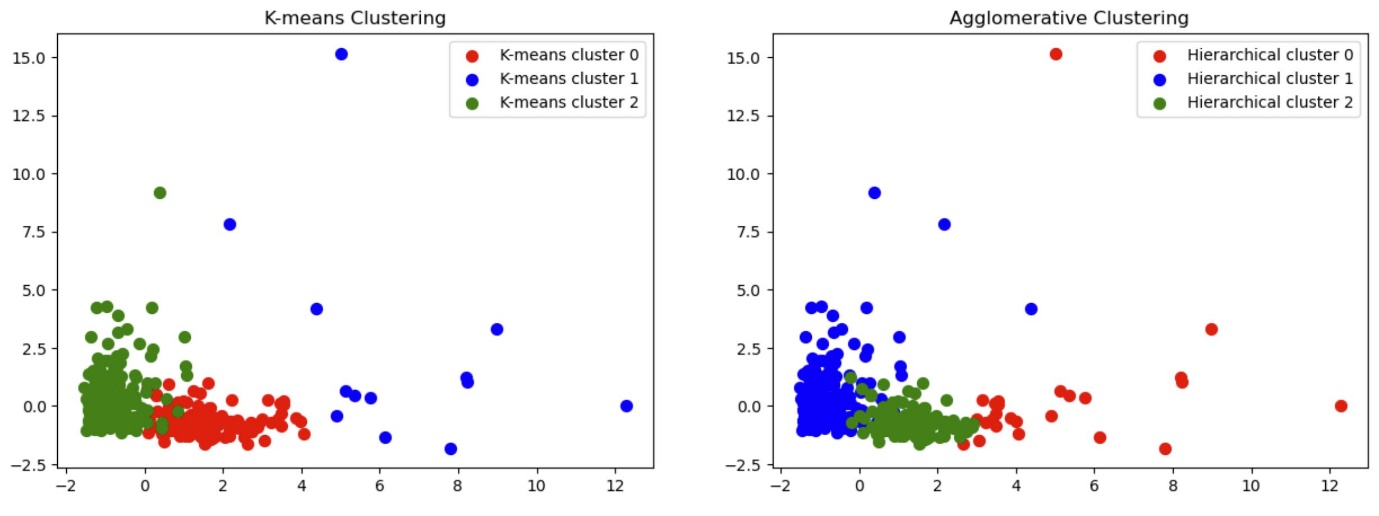


Figure . Visual representation of clusters.

### Classifier Performance Evaluation

The classifier models’ performance was evaluated using F1 score, precision and recall. According to the following results, the Random Forest classifier outperformed both the Decision Tree and Neural Network classifiers based on the aforementioned metrics.

|  |  |  |  |
| --- | --- | --- | --- |
| **Classification methods** | **Metrics** | | |
| **F1 score** | **Precision** | **Recall** |
| **Decision Tree** | 0.6611184778586406 | 0.7281468531468532 | 0.6136363636363636 |
| **Random Forest** | 0.756818181818182 | 0.704016913319239 | 0.8181818181818182 |
| **Neural Network** | 0.756818181818182 | 0.704016913319239 | 0.8181818181818182 |

### Clustering Performance Evaluation

According to the silhouette scores, both K-means and agglomerative clustering methods have similar silhouette scores indicating that their performance in clustering the data was comparable.

* Silhouette score for k-means: 0.43916005773275374
* Silhouette score for agglomerative clustering: 0.407084011561323

### Hyperparameter Tuning and Cross-Validation

A grid search was performed for each classifier model to find the best hyperparameters, followed by 5-fold cross validation to validate their performance. The mean F1 scores from cross-validation were used to compare the classifiers’ performance. The results of this process are summarized in the figure below.

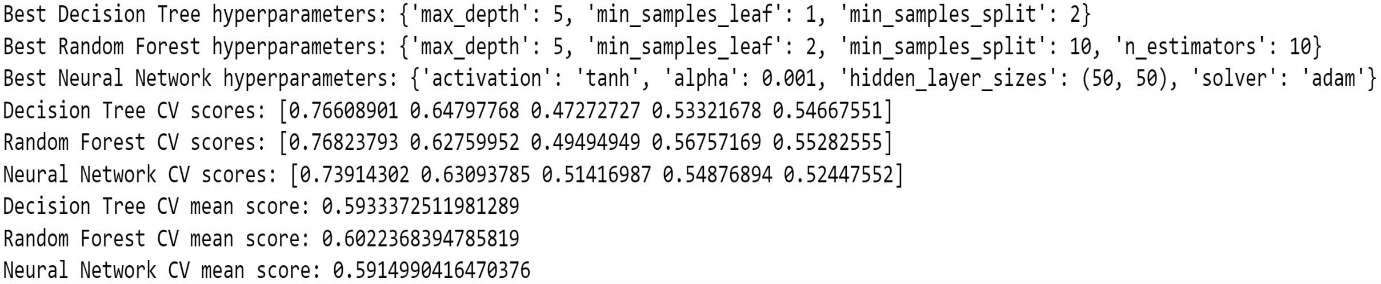


Figure . Hyperparameter Tuning and Cross-Validation

### Characterization of clusters

Pair plots and box plots for both K-means and Agglomerative Clustering methods, elbow method plot for K-means clustering and scatter plot of data points with cluster colors (after PCA) are represented below for better understanding of the data.

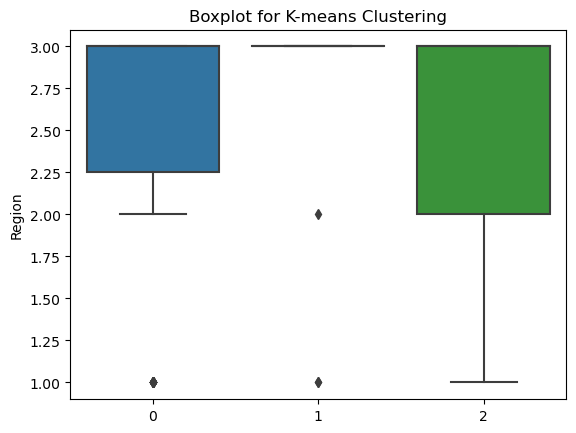


Figure . Box-plot for K-means clustering.

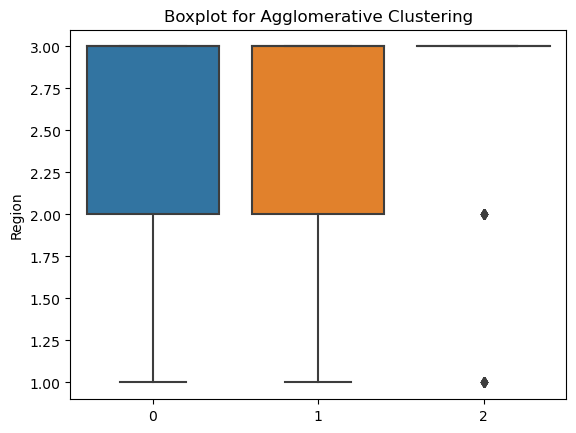


Figure . Box-plot for Agglomerative clustering. (βάσει των box plot ανά cluster, το δεύτερο cluster θα έπρεπε να έχει το visual του τρίτου για το agglomerative clustering. Τώρα φάινεται το πρώτο και το δεύτερο να έχουν ίδιο representation, δε μου φαίνεται πολύ σωστό???)

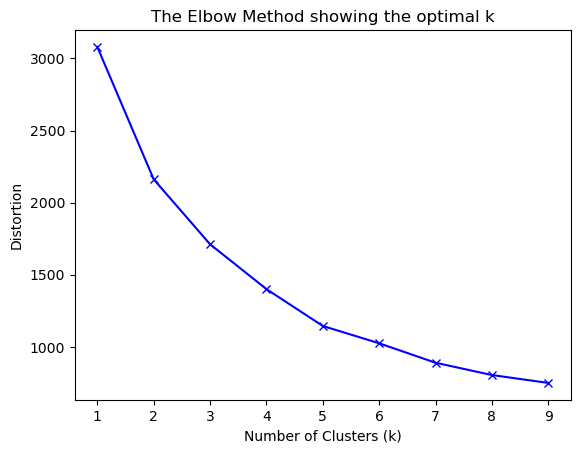


Figure . Elbow method plot for K-means clustering.

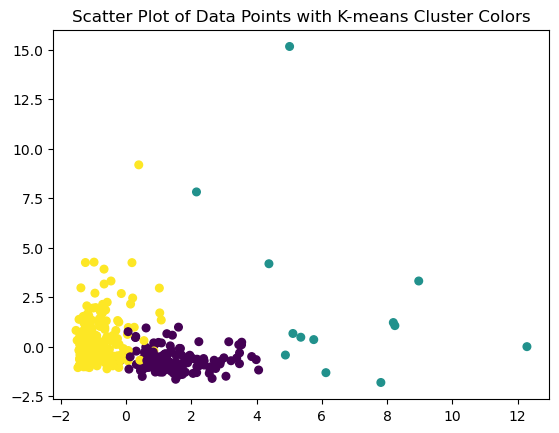


Figure . Scatter plot of data points with K-means cluster. Αυτό είναι το plot μετά το PCA, αλλά μου φαίνεται το ίδιο με το figure 1 για K-means??

Also, the figures below represent the confusion matrices for each classifier model. In addition, there are ROC curves for each classifier that evaluate the performance of classifiers in terms of true positive rate and false positive rate.

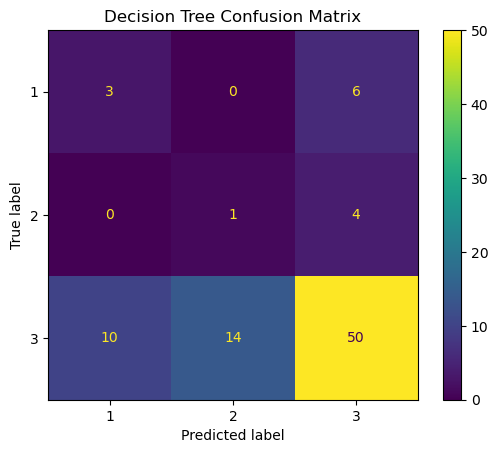


Figure . Confusion Matrix of Decision Tree.

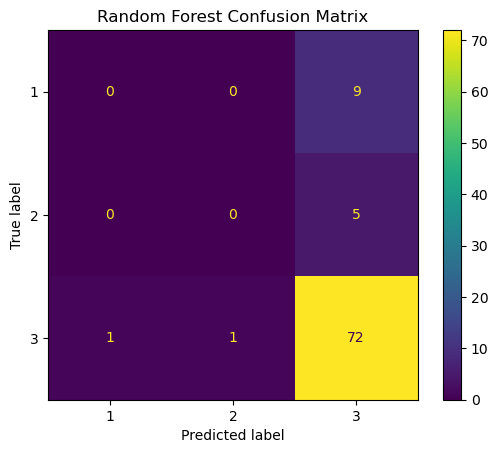


Figure . Confusion Matrix of Random Forest.

Chart

Description automatically generated

Figure . Confusion Matrix of Neural Network.

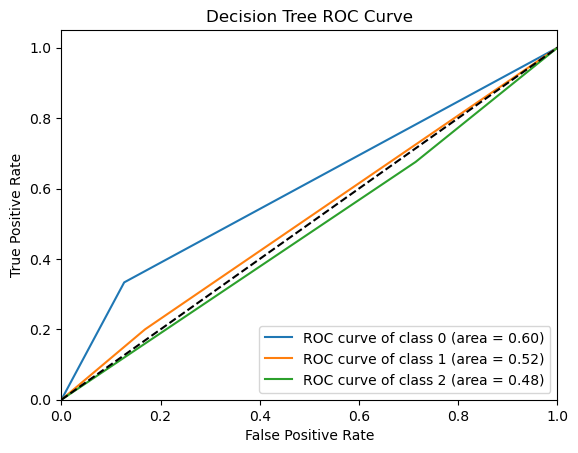


Figure . ROC curve of Decision Tree.

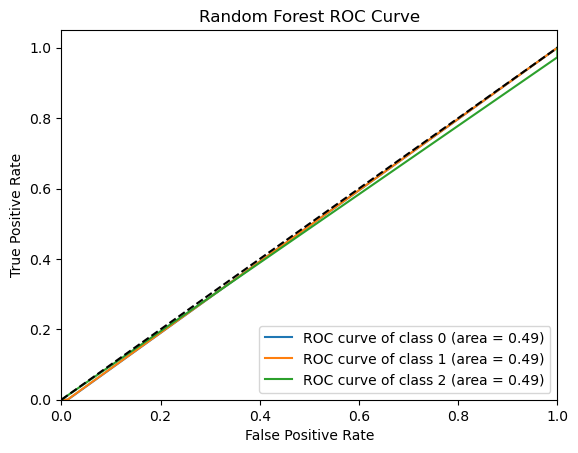


Figure . ROC curve of Random Forest.

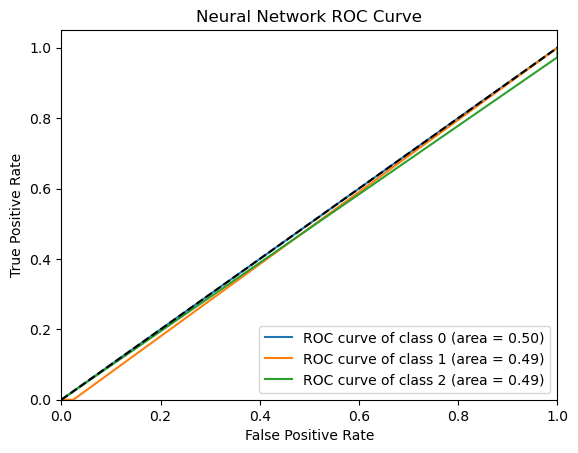


Figure . ROC curve of Neural Network.

For the characterization of each cluster created by each clustering technique, a box plot per cluster was created, as shown in the below figures:

Chart, box and whisker chart

Description automatically generated

Figure 13. Box plot for the first cluster, using K-means clustering

Chart, box and whisker chart

Description automatically generated

Figure 14. Box plot for the second cluster, using K-means clustering

Chart, box and whisker chart

Description automatically generated

Figure 15. Box plot for the third cluster, using K-means clustering

Chart, box and whisker chart

Description automatically generated

Figure 16. Box plot for the first cluster, using Agglomerative clustering

Chart, box and whisker chart

Description automatically generated

Figure 17. Box plot for the second cluster, using Agglomerative clustering

Chart, box and whisker chart

Description automatically generated

Figure 17. Box plot for the third cluster, using Agglomerative clustering

### Conclusions

* Concerning the different classifiers, the Random Forest classifier performs better that the other two, the Decision Tree and the Neural Network classifier, based on the F1 score, precision and recall. As a result, this is more reliable in predicting the “Region” of customers based on their spending habits.
* Both K-means and Agglomerative clustering can be used effectively for clustering, as they have similar silhouette scores. The score is relatively big, indicating that the three clusters could be representative of the distribution of the data points and that the model performed relatively well on segmenting the clients of the wholesale distributor into Regions.
* By focusing on the features that are more informative according to the mutual information scores (Milk and the Detergents\_paper columns), it is feasible to improve the classifier models and their performance.
* The visualizations of box plots per cluster for both clustering methods indicate that the second cluster includes the most outliers in the majority of the analyzed features. This observation, in addition to the observation that the optimal number of clusters is two according to the silhouette score, might indicate that the second cluster could be omitted and the clustering to two clusters might be more appropriate for the data set.

Also, comparing the two techniques, it seems that the **first cluster** of the **K-means** clustering is more similar to the **third cluster** of the **Agglomerative** clustering according to the distribution of the data points within the classes (similar mean, max, min, std) and the third cluster of the K-means clustering is more similar to the first cluster of the Agglomerative clustering, accordingly.

For the most informative features (Milk and Detergent\_paper) the results are summarized below:

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **K-means** | | | **Agglomerative Clustering** | | |
|  | **median** | **50% of data** | **max value** | **median** | **50% of data** | **max value** |
| **Milk** | 0.25 | 0.1-0.75 | 1.5 | 2.5 | 2-3.1 | 5.5 |
| **Detergent\_paper** | 0.5 | 0.2-0.9 | 2.25 | 3 | 2-4.1 | 5.1 |
| **Milk** | 2.7 | 2.5-5 | 6.2 | 0.25 | 0.1-0.75 | 1.5 |
| **Detergent\_paper** | 4 | 3.5-4.9 | 5.1 | 0.5 | 0.2-0.9 | 1.9 |

* Both clustering methods indicate that the second cluster consists of outliers
* Oι ROC curves για τις τρεις τεχνικές classification βγάζουν πολύ κακό αποτέλεσμα και η καλύτερη φαίνεται να είναι αυτή του Decision tree, που δε συμφωνεί με τα υπόποιπα αποτελέσματά μας που λένε ότι η καλύτερη classification technique είναι η Random Forest. Μήπως να τις αφαιρέσουμε???
* Κάπως να σχολιάζαμε τα confusion matrices που βάλαμε??
* Τα decision trees να τα προσθέσουμε γιατί δεν μου τα εμφάνιζε

# Regression

## Data source

The source of the data set used for the analysis is presented below:

<https://www.kaggle.com/datasets/camnugent/california-housing-prices?fbclid=IwAR125Veohw-zpmmCWRj9_SZ8_zvADMfUy2ji3AKpTe-nIFG9w5RY2aDSm7I>

## Description of data

The data set includes information about the houses in a given California district and some summary stats about them based on the 1990 census data.

It consists of 10 columns and 20.640 rows in total. The following table describes the content of each column.

|  |  |
| --- | --- |
| **Column** | **Description** |
| 1. longitude | A measure of how far west a house is; a higher value is farther west. |
| 1. latitude | A measure of how far north a house is; a higher value is farther north. |
| 1. housingMedianAge | Median age of a house within a block; a lower number is a newer building. |
| 1. totalRooms | Total number of rooms within a block. |
| 1. totalBedrooms | Total number of bedrooms within a block. |
| 1. population | Total number of people residing within a block. |
| 1. households | Total number of households, a group of people residing within a home unit, for a block. |
| 1. medianIncome | Median income for households within a block of houses (measured in tens of thousands of US Dollars) |
| 1. medianHouseValue | Median house value for households within a block (measured in US Dollars) |
| 1. oceanProximity | Location of the house w.r.t ocean/sea. |

## 

The aim of the analysis is to predict the price of a house, given its features.

## Data pre-processing

For the cleaning and the pre-processing of the data set, the below steps were followed:

1. Keep only the columns that contain numerical values (ποιο feature δεν περιέχει numerical values??)
2. Remove rows and columns that would lead to df being singular
3. Keep only the columns that have more than one unique values
4. Reduce the number of columns for matrix inversion of kernel density plots
5. The ocean\_proximity column includes categorical data. In order to process the information included in this column, one hot encoding is used
6. Inspect if there are any missing values and replace the missing values with the median of the column
7. Define the target column (median\_house\_value) and remove it from the dataframe
8. Split the data into train and test sets (test\_size=0.3)

## Algorithm description

For this problem, a regression analysis was performed, using Linear Regression, Random Forest Regression, Polynomial Regression (2nd and 3rd degree) and Elastic Net. In order to investigate if the model improves with Regularization, the Lasso and Ridge Regressors were also used, with alpha = 0.5 for both methods.

Firstly, one model was **initialized** for each of the 6 Regressors.

The **fitting** step followed, for the training of the models.

Afterwards, the **predictions** were obtained for each model.

The final step of the analysis was the **evaluation**, which was performed by calculating the R2 scores and the MSE.

For each model, the coefficients and the intercepts of the Regressors were calculated and displayed in order to define the final equation.

## Results

The visual representation of the results is shown below:

Chart, scatter chart

Description automatically generated

Chart, scatter chart

Description automatically generated

Chart, scatter chart

Description automatically generated

A picture containing graphical user interface

Description automatically generated

Chart

Description automatically generated

In the below table, the R2 scores and the MSE for each model are summarized:

|  |  |  |
| --- | --- | --- |
|  | **R2 score** | **MSE** |
| **Linear Regression** | 0.65036 |  |
| **Ridge Regression** | 0.65039 |  |
| **Lasso Regression** | 0.65036 |  |
| **Random Forest Regression** | 0.82251 |  |
| **Polynomial Regression (Degree 2)** | -7913406.303 | 104447803085970000.00 |
| **Polynomial Regression (Degree 3)** | -50.56649 | 680617920332.76 |
| **Elastic Net Regression** | 0.62475 | 5063640312.02 |

There are several reasons why a regression model may produce a negative R2 score. One possibility is that the model is misspecified, meaning that it does not accurately capture the underlying relationships between the features and the target. Another possibility is that the data may be noisy or have high variability, making it difficult to accurately predict the target variable.

In any case, a negative R2 score indicates that the model is not useful for making predictions, and should be reevaluated or redesigned to improve its performance.

## Conclusions

Based on the above calculations, the regression model that explains the better the variance of the variables in the data set is the Random Forest Regressor.

There is a linear correlation between the features of the data set.

A Linear Model could explain approximately 65 % of the variance of the data set.

No significant improvement by applying Regularization techniques, such as Lasso and Ridge Regression.

# Predicting outcome

## Data source

The sources of the data set used for the analysis is presented below:

[UCI Machine Learning Repository: Adult Data Set](https://archive.ics.uci.edu/ml/datasets/adult)

## Description of data

The data set includes general personal information about people and the objective is to predict their income. Specifically, this problem aims to predict whether the income is above 50.000$ per year.

There are 14 columns (attributes) in the data set and 48842 rows (inputs).

The attributes are presented below:

age: continuous numerical  
workclass: categorical  
fnlwgt: continuous numerical  
education: categorical  
education-num: continuous numerical  
marital-status: categorical  
occupation: categorical  
relationship: categorical  
race: categorical  
sex: categorical binary

capital-gain: continuous numerical  
capital-loss: continuous numerical  
hours-per-week: continuous numerical  
native-country: categorical

income: continuous numerical

There are two data sets, one for train and one for test.

Since the are many categorical data in the data set, that have to be transformed to numerical in order to be used in Python, both are loaded for preprocessing.

## Data pre-processing

Steps followed:

1. Read and clean the adult.data
2. Read and clean the adult.test
3. Create two new dataframes with the train and the test data, after the cleaning
4. Use one hot encoding for handling of the categorical data
5. Separate the features (X) and the target (y) in both datasets

## Algorithm description

For this problem, Logistic Regression, Random Forest and K-Nearest Neighbor classifier was used.

Random Forest Classifier method applies multiple decision tree classifiers on different sub sets of the whole data set and, by averaging the results of each iteration, improves the model and prevents over fitting.

Firstly, one model was **initialized** for each of the 3 classifiers.

The **fitting** step followed, for the training of the models.

Afterwards, the **predictions** were obtained for each model.

The evaluation metrics used for this analysis is the Accuracy, the precision, the recall and the F-1 score.

The confusion matrix for each model was depicted and the feature importance of each feature (for the Random Forest model) was plotted in a bar chart.

## Results

The results obtained after the evaluation are summarized in the below table:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | | **Logistic Regression** | **Random Forest** | **K-Nearest Neighbor** |
| **accuracy** |  | 0.793 | 0.845 | 0.769 |
| **precision** | **0 class** | 0.8 | 0.88 | 0.81 |
| **1 class** | 0.71 | 0.72 | 0.55 |
| **recall** | **0 class** | 0.96 | 0.92 | 0.91 |
| **1 class** | 0.27 | 0.62 | 0.33 |
| **f-1 score** | **0 class** | 0.88 | 0.9 | 0.86 |
| **1 class** | 0.39 | 0.66 | 0.41 |

The confusion matrices for each model are depicted below:

Chart, treemap chart

Description automatically generated

Chart, treemap chart

Description automatically generated

Chart, treemap chart

Description automatically generated

Also, in the below diagram, the importance of each feature for the Random Forest classifier is plotted:

Chart, funnel chart

Description automatically generated

From the evaluation metrics, the overall result is that Random Forest performs best in the data set.

This is also confirmed by the confusion matrices,

## Explainable AI (XAI)

### SHapley Additive exPlanation (SHAP)

Shapley Additive Explanation (SHAP) is a popular and widely used method for explaining the output of black box machine learning models and for the interpretation of predictions of LM models through Shapely values, that introduced by Lundberg and Lee in 2017**(1).** It provides a way to quantify the contribution of each input feature to the final prediction of a model, which can be helpful in understanding how the model is making its decisions.

The core idea behind SHAP is to assign a value to each input feature based on its contribution to the model's output. The value assigned to each feature is a function of the feature's impact on the model's prediction when compared to all possible combinations of features. This approach is based on cooperative game theory, specifically the Shapley value, which assigns a fair and consistent contribution to each player in a game.

To calculate the SHAP value for a particular feature, the model is run multiple times with different permutations of features. The contribution of each feature to the model's output is then calculated and averaged over all possible combinations of features. The resulting SHAP value for each feature represents its average contribution to the model's output, relative to other features.

![Graphical user interface, diagram, application

Description automatically generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEA8ADwAAD/4REARXhpZgAATU0AKgAAAAgABAE7AAIAAAASAAAISodpAAQAAAABAAAIXJydAAEAAAAkAAAQ1OocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFRoZW9kb3JhIEJvdHNpYWxhAAAFkAMAAgAAABQAABCqkAQAAgAAABQAABC+kpEAAgAAAAMxOAAAkpIAAgAAAAMxOAAA6hwABwAACAwAAAieAAAAABzqAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA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Figure . Descriptive process of SHAP to obtain Shapley values from an ML model. (1)

One of the main benefits of SHAP is that it provides an intuitive and understandable way to explain the predictions of complex models. By breaking down the contribution of each feature to the model's output, SHAP can help users understand which factors are driving the predictions and why. This can be particularly useful in applications where the model's predictions have significant real-world consequences, such as in healthcare or finance.

However, one limitation of SHAP is that it can be computationally expensive to calculate, particularly for models with a large number of input features. Additionally, SHAP may not always provide a complete understanding of how a model is making its predictions, as it only considers the impact of individual features and not their interactions.

In conclusion, SHAP provides a way to quantify the contribution of each input feature to the model's output, which can help users understand how the model is making its decisions, but it is important to consider the limitations of SHAP and use it in conjunction with other methods for interpreting and explaining machine learning models.

### Explanation of results

In order to obtain results regarding the way the model works, the SHAP library was installed and the SHAP values were calculated.

A picture containing graphical user interface

Description automatically generated

In the summary plot, each dot represents a single sample, with the position of the dot on the x-axis indicating the impact of the feature on the prediction, and the color indicating the value of the feature for that sample. Features that are associated with higher predicted outcomes are shown in red, while features that are associated with lower predicted outcomes are shown in blue. The plot can be used to identify which features are most important to the model's predictions and to understand the direction and magnitude of each feature's effect.

The direction of the SHAP value is also important. A positive SHAP value indicates that the feature is associated with higher predicted outcomes, while a negative SHAP value indicates that the feature is associated with lower predicted outcomes.

It's also important to look at the distribution of SHAP values across the feature values. If the distribution is uniform or random, it may indicate that the feature is not important to the model's predictions. However, if the distribution is skewed or concentrated in certain regions of the feature space, it may indicate that the feature is highly informative.