

Group Project  
Documentation: part 3

Authors: *Agata Makarewicz, Jacek Wiśniewski*

Thesis title: *Application for Analysis of the Economic Growth   
Indexes for European Countries*  
Supervisor: *Agnieszka Jastrzębska, Ph.D. Eng.*

version 1.0

20.11.2021

Table of Contents

[1 Abstract 3](#_Toc87292433)

[1.1 History of changes 3](#_Toc87292434)

[2 Vocabulary 4](#_Toc87292435)

[3 Solution Proposal 5](#_Toc87292436)

[4 Data understanding and preparation 5](#_Toc87292437)

[4.1 Collect initial data 5](#_Toc87292438)

[4.2 Describe data 7](#_Toc87292439)

[4.3 Explore data 7](#_Toc87292440)

[4.4 Data quality 8](#_Toc87292441)

[4.5 Construct data 9](#_Toc87292442)

[4.6 Integrate data 9](#_Toc87292443)

[4.7 Select data 9](#_Toc87292444)

[4.8 Preprocess data 10](#_Toc87292445)

[5 GUI Design 12](#_Toc87292446)

[6 Technology selection 14](#_Toc87292447)

[7 References 14](#_Toc87292448)

[8 Bibliography 14](#_Toc87292449)

# Abstract

This document contains model descriptions for the engineering group diploma thesis entitled “Application for Analysis of the Economic Growth Indexes for European Countries”. It consists of the following parts:

* Solution proposal – short description of the project flow
* Data understanding and preprocessing – detailed information about first steps in the project
* GUI design - user interface vision
* Technology selection - languages, libraries, platforms and other technologies used

As the continuation of the previous document „Group Project Documentation: part 2”, mentioned chapters provide more detailed information about the realisation of the project. The aim is to give guidance to the potential developer so that it is possible to reconstruct the process from scratch. Furthermore, there is a whole chapter dedicated to data understanding and preprocessing which are the steps in the Cross-industry standard process for data mining (CRISP-DM) method.

## History of changes

|  |  |  |  |
| --- | --- | --- | --- |
| **Date** | **Author** | **Description** | **Version** |
| 14.11.2021 | Agata Makarewicz | Template | 1.0 |
| 20.11.2021 | Agata Makarewicz,  Jacek Wiśniewski |  | 1.1 |
|  |  |  | 1.2 |
|  |  |  | 1.3 |

Obraz zawierający tekst

Opis wygenerowany automatycznieObraz zawierający tekst

Opis wygenerowany automatycznie

# Vocabulary

**Homepage** - a webpage presented after turning on the application. It will have all of the functionalities like filtering data and generating the report.

**“Read about the project" page** – a webpage that will present all of the information about the project, authors and contact email addresses.

**Report –** content from homepage consisting of charts and results of clustering algorithms with comments.

**Clustering** - the task of dividing a set of objects into several groups called clusters in such a way that objects within the same cluster are more similar to each other than to objects in other clusters.

**Business cycle** - intervals of expansion followed by a recession in economic activity. Fluctuations are usually characterized by general upswings and downturns in a span of macroeconomic variables.

**Segmentation** – i.e. **time-series segmentation** is a method of [time-series analysis](https://en.wikipedia.org/wiki/Time_series#Analysis) in which an input time-series is divided into sub-series (sequences) with hypothetically homogeneous statistical properties.

**Model** – machine learning algorithm used for clustering.

**Cross-industry standard process for data mining (CRISP-DM) –** process model with six phases describing standard data mining methodology

**K Nearest Neighbors (KNN) –** imputation algorithm. K chosen neighbours’ values are used to calculate new estimates to be imputed.

**Mean squared error –** error measure. It is calculated by the equation

**Interpolation –** imputation algorithm. It has different methods specifying how the data should be imputed. For instance, the linear method fills the gap between known data linearly.

**Correlation** - statistical relationship between two random variables. In this project it is calculated using Pearson’s coefficient, defined as follows: , where X,Y represent variables, σ - standard deviation, and *cov* stands for covariance

**Correlation matrix** – table containing correlation for pairs of variables

**UNDP** – United Nations Development Programme, a United Nations organization which is helping countries eliminate poverty, exclusion and inequalities

**HDI** – Human Development Index, a summary measure of health, education, and economic conditions, developed by UNDP

**PWT** – Penn World Table, a dataset containing many important economic indicators, developed by researchers from the University of Groningen and University of California

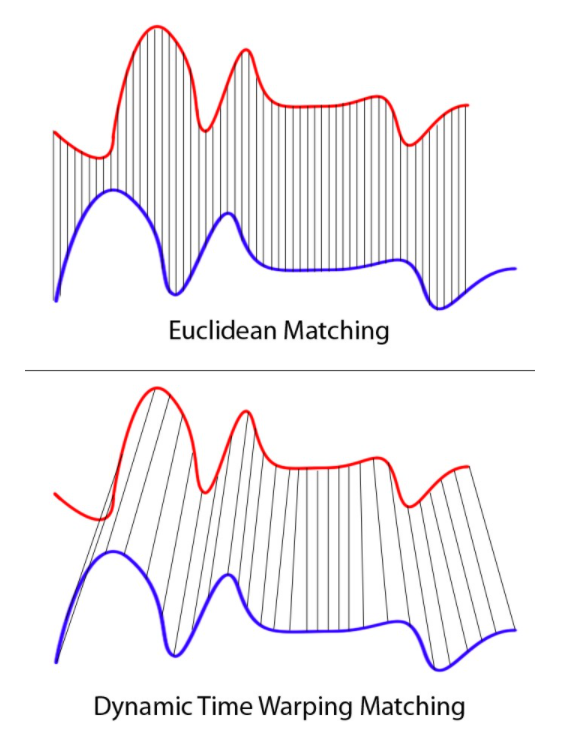
**ISO Code** – 3-letter (alpha-3) country code defined by ISO 3166-1 standard

# Model descriptions

This chapter explains three clustering algorithms that are to be used in the final application. Each of them belongs to a different group of clustering algorithms:

* **Centroid-based algorithms** organize data into non-hierarchical clusters around the closest central vector.
* **Hierarchical algorithms** create trees with hierarchical clusters.
* **Density-based algorithms** connect areas with high example density into clusters.

To extract full information from multivariate time series data, It is essential to change the default Euclidean metric in the algorithms to a more adequate Dynamic Time Warping (DTW) metric. DTW is an algorithm that can measure similarity or distance between two sequences that may vary in length. This key feature comes from the enabled in the algorithm one-to-many and many-to-one connections which help DTW to search for similar patterns in time series with different lengths of periods. The difference between Euclidean and DTW metrics is presented in *Figure x.*

**

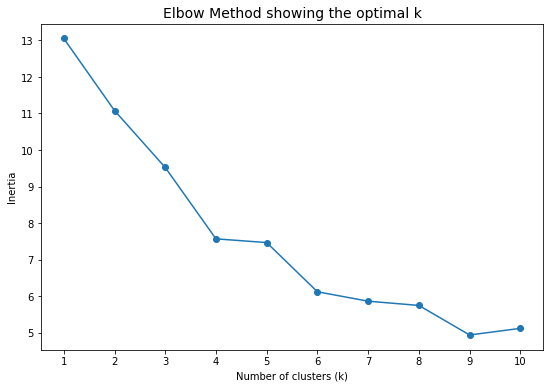
*Figure x: Difference between Euclidean Matching and DTW Matching*

Finally, the algorithms need to be evaluated and compared. For this task there is used Silhouette score which is created to evaluate the goodness of a clustering. It is calculated by the formula:

Where “a” stands for the average distance between points in the cluster, “b” stands for the average distance between cluster “i” and other clusters and sum is over all clusters created.

## K-Means

The centroid-based algorithm used in the application to cluster countries is K-means. Its purpose is to partition n countries into k, previously chosen, clusters selecting the closest cluster center. It achieves the result by iterative relocating cluster centers and reassigning countries to newly created ones. Distance between countries and cluster centers is calculated with DTW. To choose an optimal number of clusters k, there is used an elbow method presented in *Figure x*.



*Figure x: Selection of the best number of clusters in K-means based on the Elbow method.*

The *Figure x* presents the plot of inertia by a number of clusters chosen in the K-means algorithm. Inertia is calculated by summing square distances between data points and cluster centers. A good clustering algorithm should have low inertia and a low number of clusters. According to the Elbow method, the best number of clusters in the K-means algorithm is the one that relates to the point in *Figure x* where inertia starts to decrease slower – in this case, it might be 4.

Obraz zawierający mapa

Opis wygenerowany automatycznie

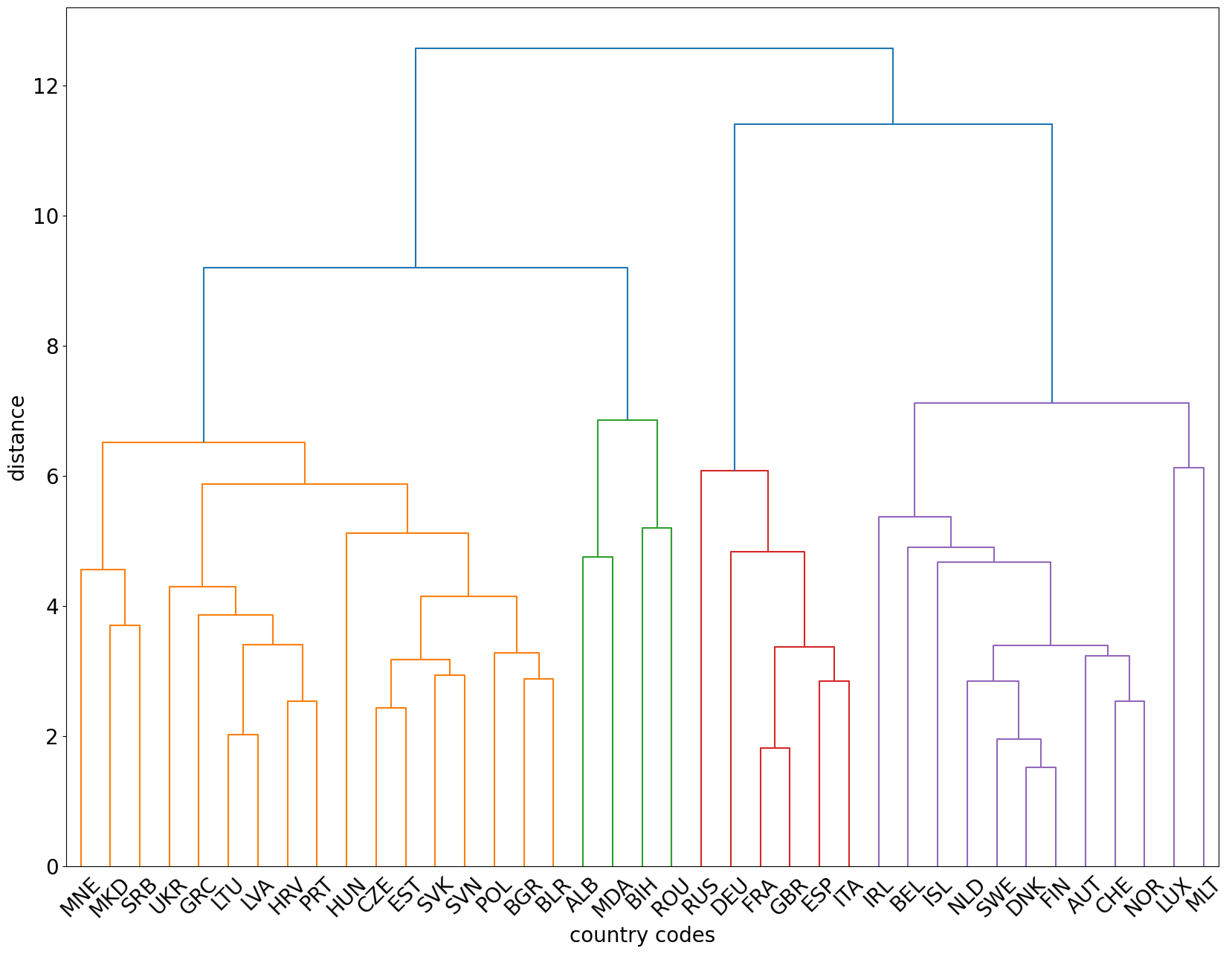
*Figure x: Results of K-means clustering with 4 clusters declared*

## Agglomerative clustering

Agglomerative clustering is hierarchical algorithm that will be an option in the final application. It has two parameters that are needed to be passed:

* **n\_clusters**– number of clusters to form
* **linkage** – type of linkage criterion, i.e. the approach to be used for computing the distance between two clusters; the pairs of clusters that minimize this criterion (are closest to each other due to chosen criterion) are merged
  + *“average”* – uses the average of the distances of each observation of the two sets.
  + *“complete”* – maximum value of all pairwise distances between the elements in first cluster and the elements in second cluster
  + *“single”* – minimum value of all pairwise distances between the elements in first cluster and the elements in second cluster
  + *“ward”* – minimizes the variance of the clusters being merged.

Agglomerative clustering firstly assign each observation (country) to its own cluster. In the next steps  
recursively merges pair of clusters that have the shortest distance between each other until there is only one cluster containing all the countries. The result of this algorithm is a tree based structure showing different possible options to group data into different number of clusters. Dendrogram created with agglomerative clustering is presented in *Figure x*.



*Figure x: Dendrogram presenting results of agglomerative clustering algorithm*

The optimal number of clusters, based on dendrogram*,* is the one, where the following merge happens after the largest distance. Regarding *Figure x* there could be two candidates for the optimal number of clusters – three or four clusters. For a better comparison with K-means results, *Figure x* presents results for four clusters.

Obraz zawierający mapa

Opis wygenerowany automatycznie

*Figure x: Results of Agglomerative clustering algorithm for four clusters*

## DBSCAN

DBSCAN is density-based clustering algorithm that is used in the application. It requires two parameters:

* **Eps** – maximum distance between two points to consider one as a part of the other’s neighbourhood.
* **Min\_samples** – minimum number of points in the neighbourhood to consider the point as a part of the cluster.

DBSCAN groups points from the same neighbourhood (defined by parameters) and creates clusters. The rest of the points that do not belong to any of the clusters are considered outliers. Distance between points is calculated with DTW. To find the best parameters for this algorithm, there has been tested all combinations, where eps is from 0.1 to 10 and min\_samples is from 2 to 39. Finally, results has been evaluated with silhouette score which led to the best parameters – eps = 3.2 and min\_samples = 2.

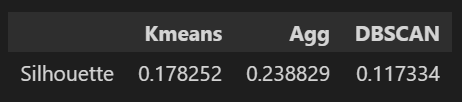
Obraz zawierający mapa

Opis wygenerowany automatycznie

*Figure x: Results for DBSCAN for eps = 3.2 and min\_samples = 2*

## Evaluation

Having all of the algorithms implemented, there is a time to evaluate the results. As mentioned at the beginning of the chapter, the silhouette score is to be used for it. The results are presented in *Figure x*.



*Figure x: Silhouette score for K-means, Agglomerative algorithm and DBSCAN*

# References

[1] Kaushik, S. (2016). *Analytics Vidhya*. An Introduction to Clustering and different methods of clustering: https://www.analyticsvidhya.com/blog/2016/11/an-introduction-to-clustering-and-different-methods-of-clustering/

[2] Robert C. Feenstra, Robert Inklaar, Marcel P. Timmer. (2021). *Penn World Table*. Pobrano z lokalizacji https://www.rug.nl/ggdc/productivity/pwt/

[3] *United Nations Development Programme*. https://www.undp.org/

[4] *Wikipedia*. Business cycle: https://en.wikipedia.org/wiki/Business\_cycle

# Bibliography

1. Aghabozorgi, Saeed, Shirkhorshidi, Ali S., and Wah, Teh Y. Time-series clustering – A decade review. Information Systems 53 16-38, 2015.
2. Gräbner, C., Heimberger, P., Kapeller, J., and Schütz B. Structural change in times of increasing openness: assessing path dependency in European economic integration. Journal of Evolutionary Economics 30, 1467–1495, 2020.
3. Bartlett, W. and Prica, I. Interdependence between Core and Peripheries of the European Economy: Secular Stagnation and Growth in the Western Balkans. LSE‘Europe in Question’ Discussion Paper Series, LEQS Paper No. 104/2016, 2016.
4. Hamilton, James Douglas Time Series Analysis. Princeton University Press, 1994.
5. Pal, Avishek, Prakash, PKS. Practical Time Series Analysis. Master Time Series Data Processing Visualization and Modelling Using Python. Packt, 2017
6. Fu-Lai Chung, Tak-Chung Fu, V. Ng and R. W. P. Luk, "An evolutionary approach to pattern-based time series segmentation," in IEEE Transactions on Evolutionary Computation, vol. 8, no. 5, pp. 471-489, Oct. 2004.