UNIVERSITY OF TROMSØ

Python potential in Data Science field: Norwegian salmon farming analysis.

by

Andrea Spreafico

A thesis submitted in partial fulfillment for the degree of Computer Science
Computer Science

in the
Faculty of Computer Science
Department of Computer Science

May 2017

Abstract

The term Data Science refers to the collection of knowledges and skills, mainly about statistics and computer science, that allow to collect, analyze and display data in order to understand actual phenomena. Since there isn't a default technique to extract informations from the data this study investigates about the possibility of using Python in order to realize a system able to analyze, display and forecast data.
This kind of systems are commonly used to elaborate data coming from high-interest area; for instance, during this work was used a dataset about the Norwegian aquaculture industry, since Norway represents the forefront of innovation and development in this area, in particular about the Norwegian salmon farming, and also because this business produces a lot of unstructured and not interpreted data.
The implementation procedure reported in this study reveals that Python provides several modules and packages that could be useful for a data analysis and displaying on dataset coming from any kind of area of interest.
Further more, this thesis provides several analysis results about each single norwegian county involved in the Norwegian aquaculture business, such as graphics, correlation coefficients, trend line indicators and prediction of the future.

Acknowledgements

I would like to offer my special thanks to my supervisor Ståle Walderhaug.
I would like to express my very great appreciation to Bård Johan Hanssen.
I am particularly grateful to Sara Björk.
I am grateful for the support and good times given by the staff of SINTEF Nord.

My special thanks are extended to:
- My family.
- Università di Milano Bicocca.
- UiT, Universitetet i Tromsø.

Contents

List of Figures

List of Tables

Abbreviations

SIA	**S**ingle **I**nput **A**nalyzer
MIA	**M**ultiple **I**nput **A**nalyzer
AR	**A**uto **R**egressive
MA	**M**oving **A**verage
ARMA	**A**uto **R**egressive **M**oving **A**verage
ARIMA	**A**uto**R**egressive **I**ntegrated **M**oving **A**verage
MAPE	**M**ean **A**verage **P**ercentage **E**rror

Chapter 1

Introduction

During the last few years we have witnessed an ever-increasing production of data in any sector all around the world. For this reason instruments and techniques for analyzing and understanding these data are becoming more and more indispensable, in order to extract useful information that might be used to improve business strategies or people's life condition.

Data Science is a recent launch field which contains processes and systems that could be used to extract knowledge from data, either structured or unstructured. Since the newness of this field, would be very interesting to test and evaluate different ways to apply daily technologies to its procedures and systems.

Python is a simple interpreted, object-oriente and high-level programming language that has a easy to learn syntax. Since it provides severals modules and package, the use of Python during a Data Science process could be very productive.

The processes and systems which belong to the Data Science field might be applied to high-interest economic areas, such as the Aquaculture industry in Norway. This business, in particular the Norwegian salmon farming, has a big economic repercussions on the country, and at the same time is producing a huge amount of data, so it would be very helpful to restructure and analyze it.

This thesis will contributes providing a documented implementation of an analysis, displaying and prediction system using Python applied to the Norwegian salmon farming.

1.1 Aim of the study

The focus of this study will be on:

- Initial approach with Data Science field, in order to investigate and document possible techniques, methods and approaches.
- Testing Python potential in Data Science field, describing implementation procedures and reporting pro and cons.
- Report the initial analysis and displaying results about Norwegian salmon farming, in order to provide structured, described and readable data that might be used for future works.

1.2 Research Objectives

The above aim will be accomplished by fulfilling the following research objectives:

1) Collect as much data about aquaculture in Norway as possible.

- Which kind of data is possible to obtain about aquaculture general statistics in Norway? Where is possible to find it? Are that available for everyone?
- Which kind of data is possible to obtain about aquaculture of single locations in Norway? Where is possible to find it? Are that available for everyone?

2) Increase accessibility and availability of the data.

- How you can create a unique dataset that contains and summarize all the data previous collected?
- Which kind of structure allows to the total dataset to be more accessable and readadble than the original single sources?

3) Analyze and display the data.

- Which kind of Python functions is possible to use for analyze and displaying data?
- Which kind of requirements does it need and how is possible to implement it?
- Why Python could be a good solution for data analysis and displaying?
- Which kind of relationships and patterns about the data is possible to identify using the result graphics? How is possible to identify it?
- How is possible to check out the data trend line?
- Which kind of informations have been reported for future reuse? How it's possible to access it? (Informations such as correlation coefficients, trend line equations,..)

4) Extract information from the data.

- Which parameters about aquaculture in Norway are increasing? How fast are they increasing/decreasing?
- How you can compare different parameters trend line?
- Which kind of correlations is possible to find out between different parameters? How is possible to show it? What is possible to extract from that?

5) Prediction of values about the data.

- Which kind of Python utilities is possible to use for time series predictions?
  - How Python works for time series prediction systems implementation?
  - Which kind of accuracy it provides about the predicted values?
  - Would it be a good way for let the people get some experience with the machine learning field?
- Would be useful to have the possibility of forecasting some future data?
- Which kind of data might be the most useful to know for people into the Aquaculture field?

6) Recommendations to future work and extra ideas.

- How it could be possible to improve the Anaysis and Displaying system?
- How it could bee possible to improve the Forecasting system?
- Which kind of services is possible to provide using the collected informations and the implemented systems?
  - How you can provide the analysis system like a service?
  - How you can provide the prediction system like a service?

1.3 Previous Works

The implementation of the prediction system in this thesis was based on a previous work, which provides a basic implementation of a forecasting system with Python.
That particular work was showing how to create a general ARIMA Model for Time Series Forecasting with Python. During this study that implementation has been improved, customized and applied to the current context.

The previous work source website is named "machinelearningmastery.com", and here's the reference: [1]

Chapter 2

Background Theory

2.1 Data science

It's really important to have a general idea about what "Data Science" means since this thesis procedure is strongly based on the classic Data Science Process.

We can define Data Science like a "concept to unify statistics, data analysis and their related methods" in order to understand and analyze actual phenomena with data.[2] It includes theories drawn from many field within the broad areas of mathematics, statistics, information science and computer science.

In the computer science area are particular important the subdomains of:

- Machine learning
- Classification
- Cluster Analysis
- Data mining
- Databases
- Visualization

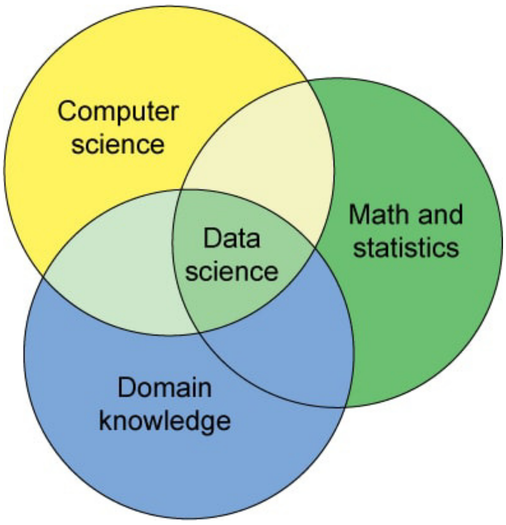


FIGURE 2.1: Data science concept

Here is reported a short definitions about the main subdomains considered by this study:

- **Data mining**: Is the computing process of discovering patterns in large data sets. The overall goal of the data mining process is to extract information from a data set and transform it into an understandable structure for further use.
- **Data Visualization**: It involves the creation and study of the visual representation of data. The primary goal of data visualization is to communication information clearly and efficiently via graphics and plots.
- **Machine learning**: Is a subfield of computer science that gives computers the ability to learn without being explicitly programmed.[3] More useful specific informations about this field are provided in the following section [2.2].

The follow image represents the "Blitzstein and Pfister's framework" and provides a clear overview of the Data Science process.

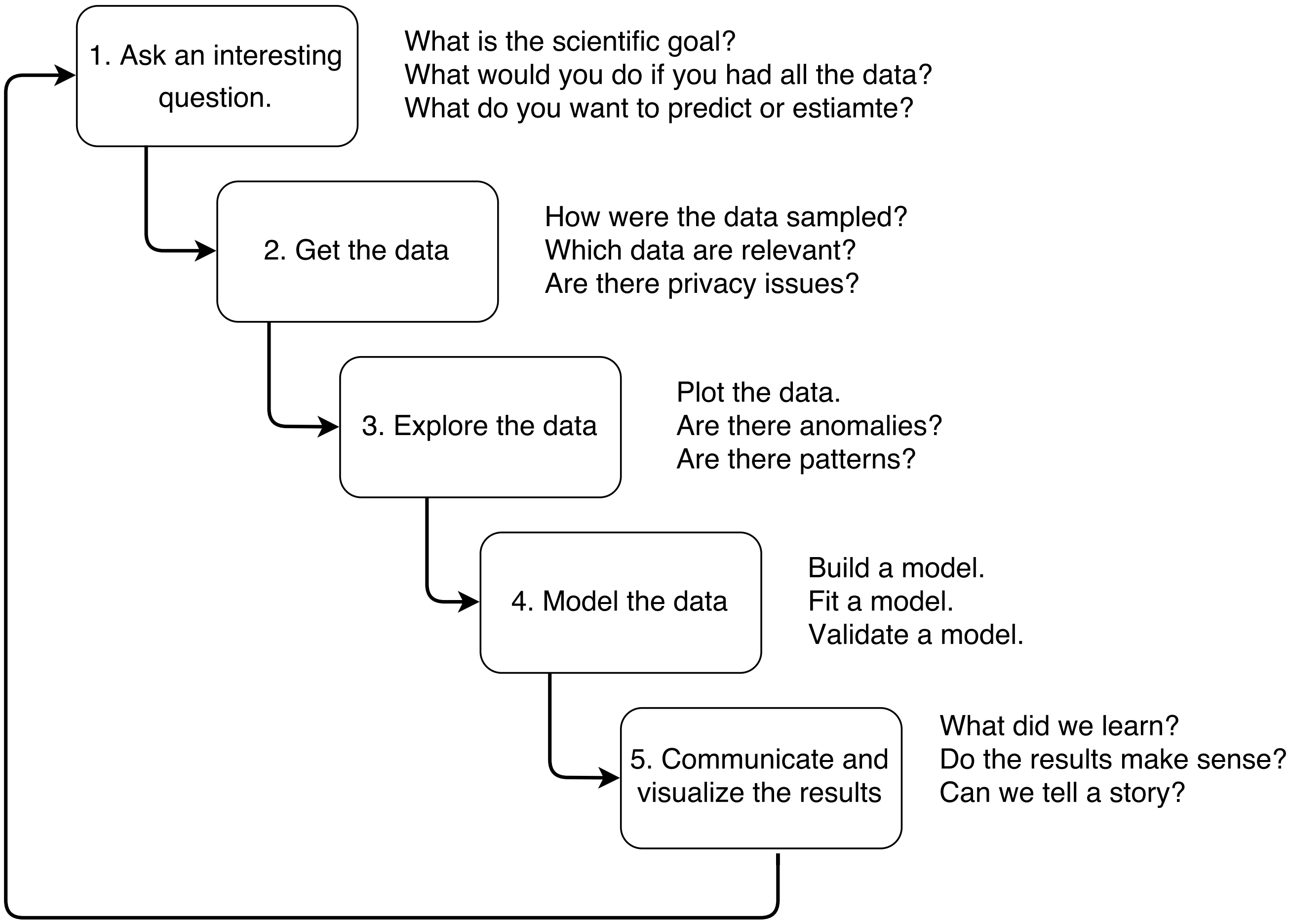


FIGURE 2.2: Data science process

2.2 Machine learning

How is reported in the previous section, this subfield of computer science gives ”computers the ability to learn without being explicitly programmed”.
Machine learning explores the study and construction of algorithms that can learn from and make predictions on data.

There are several machine learning algorithm, each one of them is used for a different purpose and a different domain. For examples:

- Deep Learning
- Neural Network
- Regularization
- Clustering
- **Regression**: This specific domain contains the model used in this study.
- Bayesian

2.2.1 Time Series analysis and predictions

Time Series forecasting is an important area of machine learning, but that is often neglected. Is that important mainly beause there are so many prediction problems that involve a time component, and these problems are neglected because it is this time component that makes time series problems more difficult to handle.[4]

” A time series is a sequence of observations taken sequentially in time. ”[5]

Classic example of a time series dataset:

Date	**Paramater**
Time #1	observation
Time #2	observation
Time #3	observation

Understanding a dataset is called time series analysis and it can helps to make better prediction, but sometimes it's not required and can result in a large of technocal investment in time and expertise.

Making predictions could be called time series forecasting and it involves taking models fit on historical data and using them to predict future observations.

2.2.2 Autoregressive integrated moving average (ARIMA)

Since this a very complicated and deep topic, this study provided just an initial implementation and descripton of it. During this section are provided some basic definitions and overviews enough to understand the general logic behind a forecasting system. If you are particular interested in this topic my suggestion is to read more about it, in the specific the mathematic side.

AR model: an autoregressive model is a representation of a type of random process; as such, it is used to describe certain time-varying processes in nature, economics, etc. The autoregressive model specifies that the output variable depends linearly on its own previous values and on a stochastic term (an imperfectly predictable term); thus the model is in the form of a stochastic difference equation.[6]

MA model: a moving-average model is a common approach for modeling univariate time series. The moving-average model specifies that the output variable depends linearly on the current and various past values of a stochastic (imperfectly predictable) term.[7]

ARMA model: an autoregressive-moving-average model provides a parsimonious description of a stationary stochastic process in terms of two polynomials, one for the autoregression and the second for the moving average. Basically it combines both AR and MA models into a unique representation.[8]

ARIMA model: is a generalization of an autoregressive moving average (ARMA) model. Both of these models are fitted to time series data either to better understand the data or to predict future points in the series (forecasting).
This model is applied in some cases where data show evidence of non-stationarity, where an initial differencing step (corresponding to the "integrated" part of the model) can be applied one or more times to eliminate the non-stationarity.[9]

ARIMA(p, d, q)

- **p** is the number of autoregressive terms (How many preceding values are examinated for the current value's forecast).
- **d** is the number of nonseasonal differences needed for stationarity.
- **q** is the number of lagged forecast errors in the prediction equation.

2.3 Aquaculture in Norway

During the last years there has been a very rapid development of Norway's aquaculture industry, and the production of Atlantic salmon has grown to become a major sector of its economy. The industry is now an economic pillar for several Norwegian coastal communities.[10]

The Aquaculture industry in Norway is dominated by its finfish sector, with Atlantic salmon and Rainbow trout accounting for 93.9% and 5.8% respectively of total volume produced.

This business takes place in the counties along most of the country's coastline. In the finfish sector Nordland is the dominant producer county, with Hordaland coming second, Møre og Romsdal third, and Troms fourth.

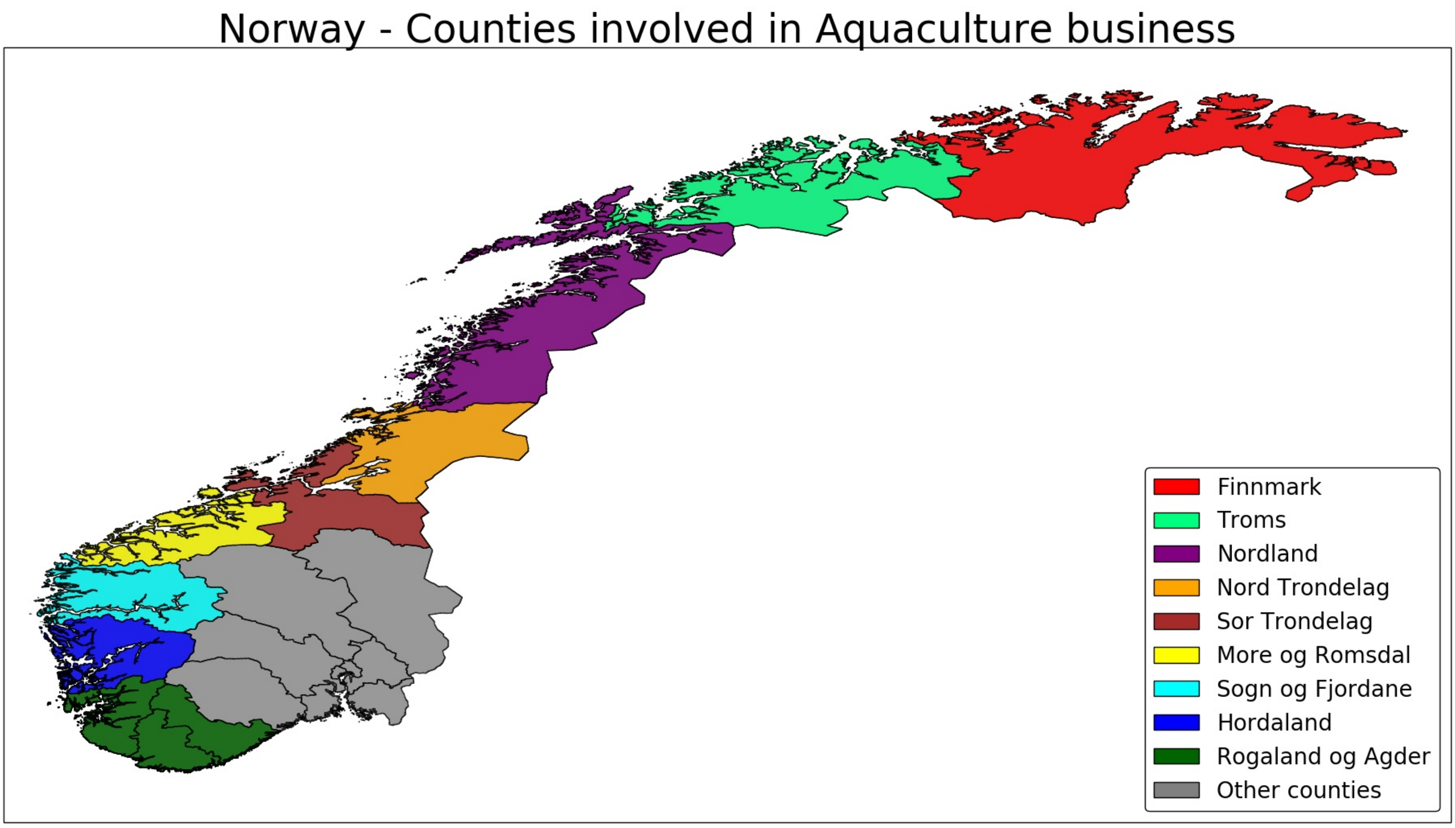


FIGURE 2.3: Norwegian counties involved in aquaculture business

Chapter 3

Approach and Design

3.1 Development Flow

I Part: Data collection and validation

- Collect as many useful data as possible.
- Create a structured dataset that contains the collected data.
- Let the new data structure be accessable, available and readable.
- Let the data structure be an appropriate input to the analysis system used during the study.

II Part: Systems implementation

- Analysis and displaying system implementation and results collection..
- Informations extraction.
- Prediction system implementation and results collection.

III Part: Result, Discussion and Conclusions

- Results:
- Discussion:
- Conclusions:

IV Part: Full code Implementation

——¿ I PART During this phase the most important thing is to gather as much data as possible. The data have to be of course related with the current area of interest and they should be considered somehow useful for asnwering the initial questions of the study.
At the same time they should be as much reliable as possible since they are indispensable for the next phases and in particular for the final results and conclusions.
The data's reliability mainly depends by which source they are coming from.
Then you should elaborate the data that you collected in order to: ——¿ II PART This phase of the work will investigate about different ways for understanding and extracting information from the data. For instance, the data will be displayed on different kind of graphics in order to increase their readable. Further more, several coefficients will be calculated and reported, always to allow the informations extraction from the data.
During this phase the main purpose is to predict some kind of useful data about the current dataset. To reach this goal, is first of all indispensable to choose a prediction system to implement.
Once the prediction system has been implemented, it's time to apply it on the current data and try to get as much evidences as possible.

——¿ III PART The results part contains

The purpose of the discussion is to interpret and describe the significance of this thesis results. Further more, has to be reported a critical evaluation about the work done and explain any kind of limitations found during the procedure. The conclusion part has to contains a summarize about what was done in this thesis, and then figure out some other extra ideas, implementations or recommendations to future work about this thesis.

3.2 Important recommendation

Before start to read the implementation procedure about this work, it's important to know that is possible to find the system's full implementation on Github.
I **strongly recommend** to check it out and download the following repository. It allows to test the system and better understand how it is structured and how it works.
Further more, it's possible to find inside the same repository all the needed datasets and a "Manual" wich contains the instructions about how to use it.

The Github repository is:
https://github.com/Sprea22/Python_Systems

The direct Zip file download is:
https://codeload.github.com/Sprea22/Python_Systems/zip/master

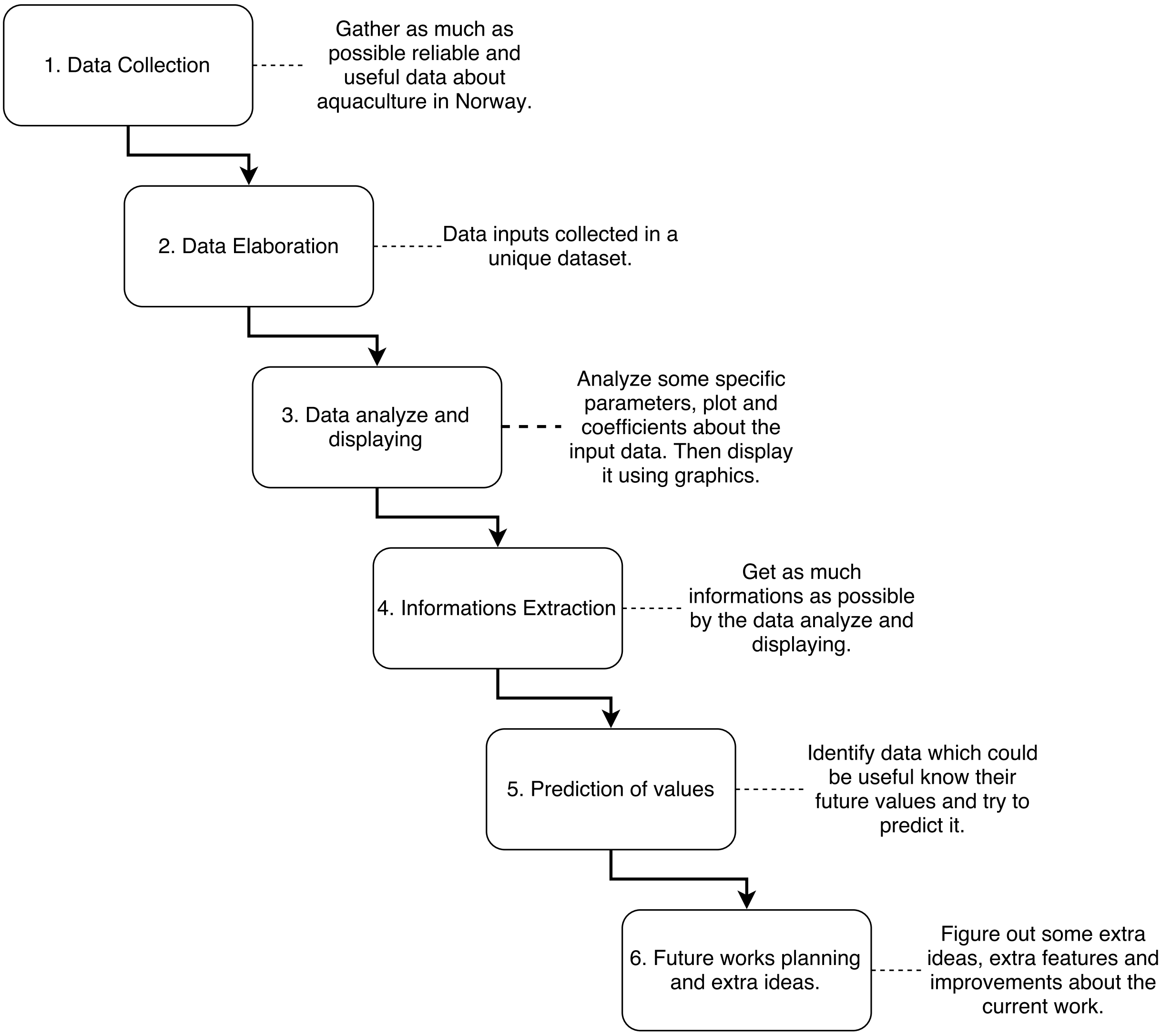


FIGURE 3.1: Plan flow chart

Part I

Data Collection and Validation

Chapter 4

Data Sources and Elaboration

4.1 Data Sources

The collection of the data has been an important phase during this work.
Several sources have been checked and consulted in order to find reliable and useful data for the final purpose of this thesis.
In this particular case the main data collection way was internet, but some important data have been provided also from SINTEF Nord.

4.1.1 Data from SINTEF Nord

Some of the data used during this thesis were provided from the team members of the eSushi project team at SINTEF Nord.
The data are about each single norwegian county and with the following details:

Input	**Content**	**Unit**	**Frequency**	**Available Period**
1. Average Sea Temperature	Reported number of cages with salmon and rainbow trout.	Celsius	Monthly	January 2007 - April 2014

Table 4.1: Data provided from SINTEF Nord.

4.1.2 Data from Fiskeridir

The current website has been the main data source for this work. It provides several statistics about Aquaculture in Norway.
The data inputs from the current website used for this thesis are reported below, and they are available for each single county in Norway involved in Aquaculture business:

Input	**Content**	**Unit**	**Frequency**	**Available Period**
1. Cages	Reported number of cages with salmon and rainbow trout.	Number	Monthly	January 2005 - April 2017
2. Localities	Reported number of localities with salmon and rainbow trout.	Number	Monthly	January 2007 - April 2017
3. Feed consumption	Reported feed consumption for Salmon.	Tonnes	Monthly	January 2007 - April 2017
4. Restock	Fish restock reported for Salmon.	1000 pcs	Monthly	January 2007 - April 2017
5. Withdrawals	Withdrawals of Salmon for slaughter.	Tonnes	Monthly	January 2007 - April 2017
6. Biomass	Reported biomass of Salmon.	Tonnes	Monthly	January 2007 - April 2017
7. Salmon Number	Reported number of Salmon.	Number	Monthly	January 2007 - April 2017

Table 4.2: Data provided from Fiskeridir.

About the current data source is also important to know that:

- The data are available from 2005 to 2017.
- The data are uploaded once per month.
- The data are reported and available just in XLSX format.
- The data are available just in Norwegian.
- Is not possible to implement an automatic download script.

4.1.3 Data from Indexmundi

Is possible to find data about fish (salmon) monthly price, Norwegian Krone per KG.

Input	**Content**	**Unit**	**Frequency**	**Available Period**
1. Export Salmon Price	Reported farm bred Norwegian Salmon export price.	NOK/KG	Monthly	January 2005 - April 2017

TABLE 4.3: Data provided from Indexmundi.

4.2 Increase accessibility and availability of data

In order to increase the accessibility and availability of the row data have been downloaded from the above reported sources, during this phase the main goals were:

- provide an accurate description (in English, since it was available just in Norwegian)
- Report the data in a standard and reusable standard (CSV).
- Design and build a easily readable dataset structure.

The final decision about the datasets set up during this thesis provided the followng list of datasets, where the structure can be checked in the following two pages:

- Overview Dataset: Norway.csv
- County 1 Dataset: Finnmark
- County 2 Dataset: Troms
- County 3 Dataset: Nordland
- County 4 Dataset: Nord Trondelag
- County 5 Dataset: Sor Trondelag
- County 6 Dataset: More og Romsdal
- County 7 Dataset: Sogn og Fjordane
- County 8 Dataset: Hordaland
- County 9 Dataset: Rogaland og Agder

4.2.1 Dataset about Norway

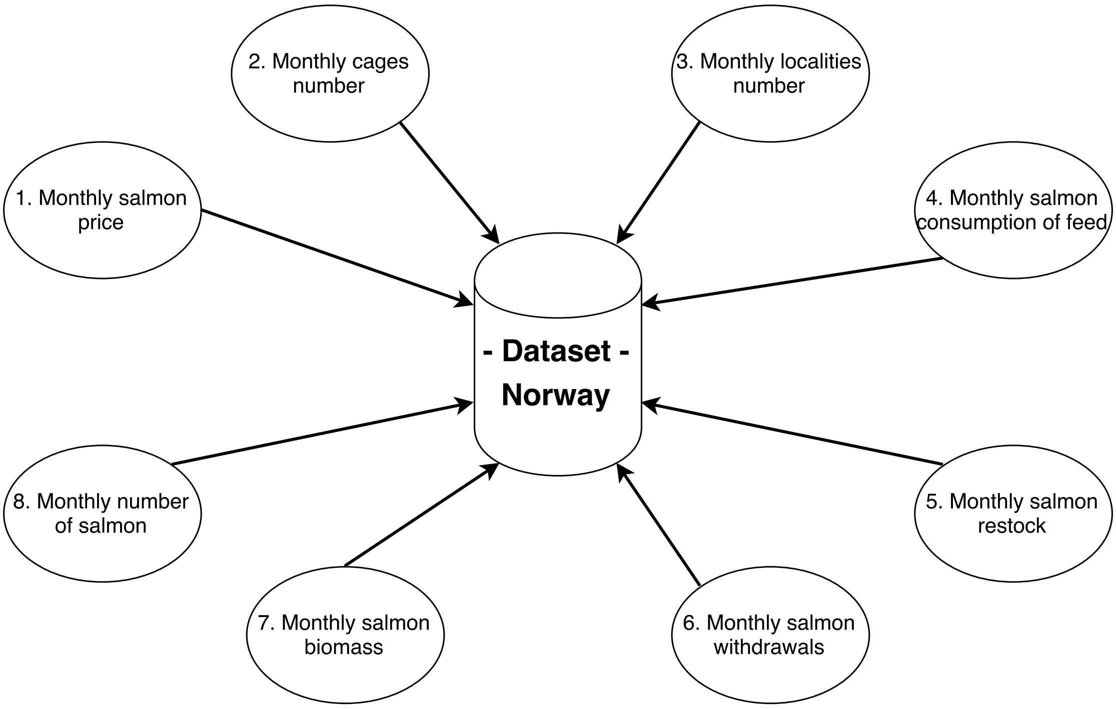


FIGURE 4.1: Dataset structure.

Input	Frequency	Period	Location
1. Export Salmon Price	Monthly	January 2005 - December 2016	Norway
2. Cages	Monthly	January 2005 - December 2016	Norway
3. Localities	Monthly	January 2005 - December 2016	Norway
4. Feed consumption	Monthly	January 2005 - December 2016	Norway
5. Restock	Monthly	January 2005 - December 2016	Norway
6. Withdrawals	Monthly	January 2005 - December 2016	Norway
7. Biomass	Monthly	January 2005 - December 2016	Norway
8. Salmon Number	Monthly	January 2005 - December 2016	Norway

TABLE 4.4: Structure of the dataset about Norway.

4.2.2 Dataset about single county

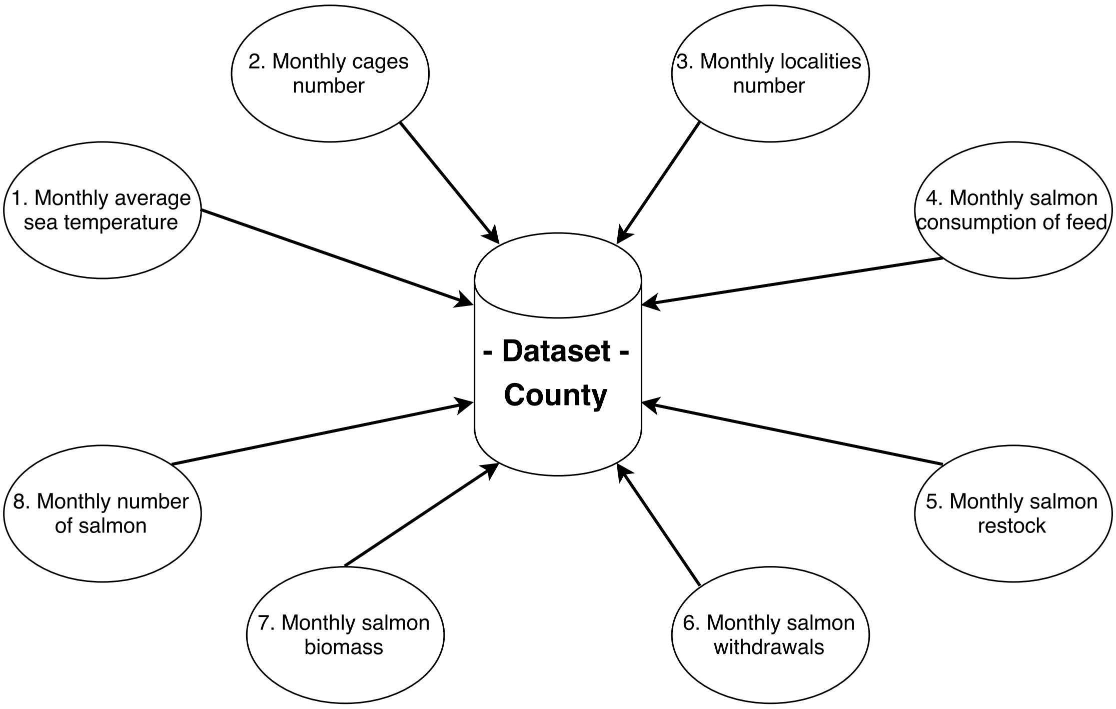


Figure 4.2: Dataset structure.

Input	Frequency	Period	Location
1. Average Sea Temperature	Monthly	January 2007 - December 2014	Single county
2. Cages	Monthly	January 2007 - December 2014	Single county
3. Localities	Monthly	January 2007 - December 2014	Single county
4. Feed consumption	Monthly	January 2007 - December 2014	Single county
5. Restock	Monthly	January 2007 - December 2014	Single county
6. Withdrawals	Monthly	January 2007 - December 2014	Single county
7. Biomass	Monthly	January 2007 - December 2014	Single county
8. Salmon Number	Monthly	January 2007 - December 2014	Single county

Table 4.5: Structure of the dataset about each norwegian county.

Part II

Implementation

Chapter 5

Analyzer System

Total implementation link for data analyzer :
https://github.com/Sprea22/Python_Systems

During this part the main purpose is to analyze the whole dataset in order to find some kind of useful informations later on.

The system that it's going to be implemented during this part of the work could be divided in two subsystems, with the relative outcomes:

- Single Input Analyzer (SIA): Used for analyze a single data input.
  - Total graphic of the input data for the whole period.
  - Graphic of the input data for each single year.
  - Correlation matrix between different months of the same input.
  - Correlation matrix between different years of the same input.
- Multiple Inputs Analyzer (MIA): Used for analyze multiple data inputs.
  - General correlation matrix between all the different inputs.
  - Graphic of the normalized angular coefficients of all the inputs.

5.1 Requirements for reusability

Both the analysis systems that are going to be implemented during this phase of the work will need for just one requirement about the input dataset:

- Monthly frequency of data values.

5.2 System requirements

It's important to remind that this phase can be implemented in different ways and with different programming language;
This proceure will describes the system implentation using Python, so be sure to have installed all the necessary for compile and execute Python code on your platform.

```
Current development environment:
Python version: 2.7.12
Linux kernel version number: Linux Asus 4.4.0-71-generic SMP
```

5.3 Single Input Analyzer

It's possible to check out the total implementation code of the SIA in the appendice [A]. The implementation of this Analyzer can be divided in the following parts:

- SIA imported libraries.
- SIA part I: Generate and display a graphic about current input with total data.
- SIA part II: Generate and display a graphic about current input for each year.
- SIA part III: Generate and display a graphic that contains the correlation matrix between each single year of the current input.
- SIA part IV: Generate and display a graphic that contains the correlation matrix between each single months of the year of the current input.
- SIA part V: Generate and display a single overview image for the current input.

5.3.1 SIA: Imported libraries

Specific Python libraries have been imported for the implementation of this system. It's possible to find out a list of this libraries with a specific description for each of them in the appendice [A.1].

5.3.2 SIA section I: Total graphic for all the years

Goal:

Generate and display the total graphic about current input, and then calculate and display the trend line as well. Trend line angular coefficient has to be save in a document.

Requirements:

The current data input has to be with a monthly frequency.

Implementation:

To reach the current goal have been used two main functions of the "pandas" library. They allow to read the data values from the dataset and display it on a graphic.

```
series = pandas.read_csv()
seris.plot()
```

It's possible to check out the full commented implementation in the appendice: [A.3]

Results:

With this first part of the code has been reached the first goal of displaying and saving the basic graphic about the current input, with also the relative trend line and saving it angular coefficient in a document, that looks like:

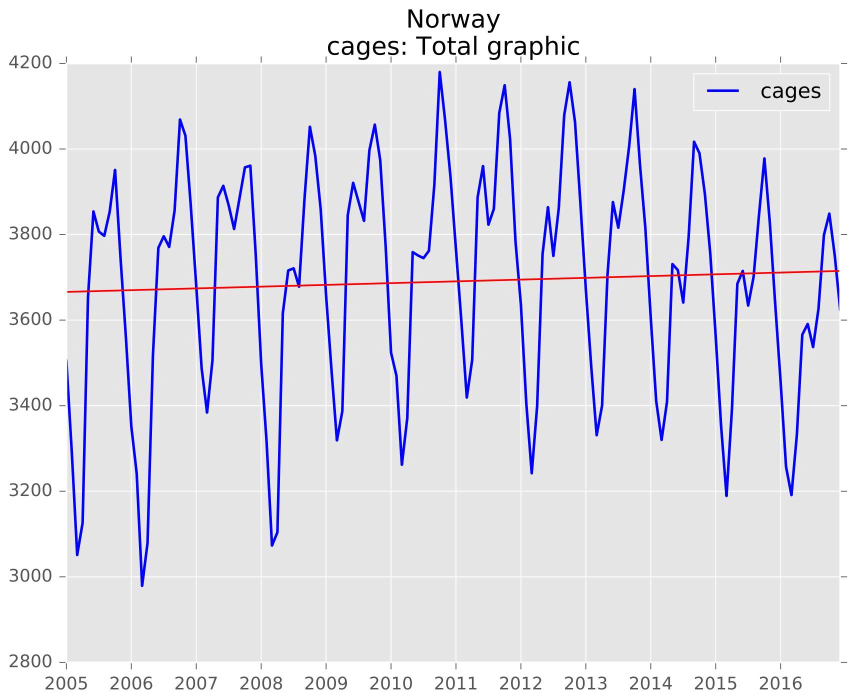


FIGURE 5.1: Total graphic about current input over the whole period.

5.3.3 SIA section II: Single graphics for each year

Goal:

Generate and display a graphic that contains the plots of each single year over the whole period of the current input.

Requirements:

The current data input has to be with a monthly frequency.

Implementation:

To reach the current goal have been used two main libraries.

The "pandas" library allows to read the data values from the dataset and return it like "ndarray" type, then the library "pyplot" allows to display it on a graphic.

```
series = pandas.read_csv()
series.values()
pyplot.plot()
```

It's possible to check out the full ccommented code in the appendice: [A.4]

Results:

With this second part of the code has been reached the goal of displaying and saving the graphic of the plots for each single year of the current input, that looks like:

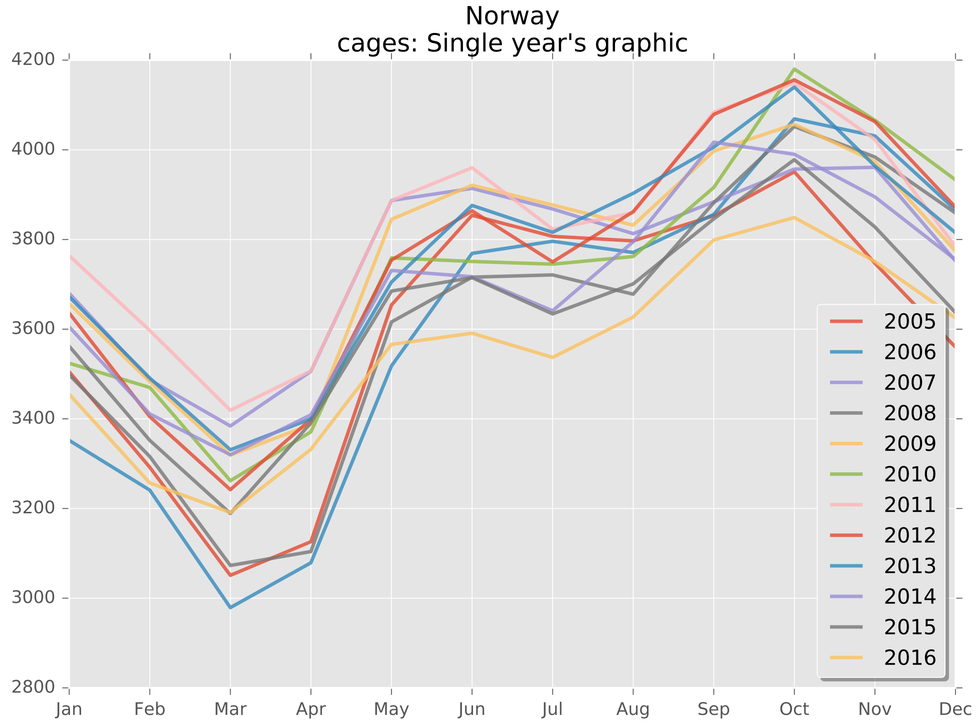


FIGURE 5.2: Graphics for each single year of the current input data.

5.3.4 SIA section III: Correlation matrix between years

Goal:

Calculate and save the correlation coefficients between each single year over the whole period of the current input and then display it with a correlation matrix.

Requirements:

The current data input has to be with a monthly frequency.

Implementation:

To reach the current goal have been used the scientific computing library ”numpy”, that allows to calculate the correlation coefficients between data. Then the library ”pyplot” has been used to display the results on a matrix.

```
numpy.corrcoef()
figure = pyplot.figure()
ax = figure.add_subplot()
ax.matshow()
```

It’s possible to check out the full ccommented code in the appendice: [A.5]

Results:

With this part of the code have been calculated and displayed the correlation coefficients between each single year of the current input, that looks like:

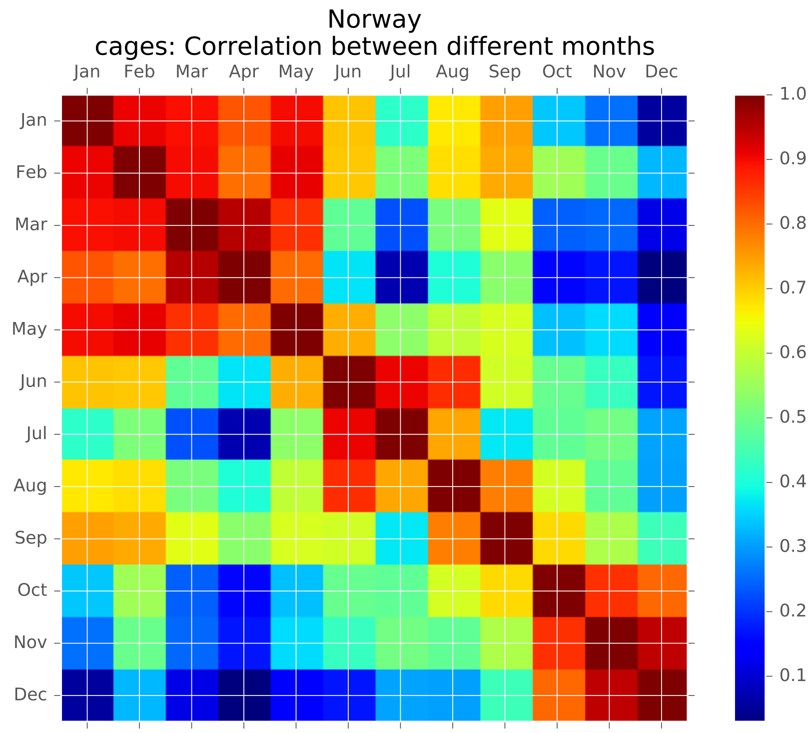


Figure 5.3: Correlation matrix between different months of the same input

5.3.5 SIA section IV: Correlation matrix between months

Goal:

Calculate and save the correlation coefficients between each single month of the current input and then display it with a correlation matrix.

Requirements:

The current data input has to be with a monthly frequency.

Implementation:

To reach the current goal have been used the scientific computing library ”numpy”, that allows to calculate the correlation coefficients between data. Then the library ”pyplot” has been used to display the results on a matrix.

```
numpy.corrcoef()
figure = pyplot.figure()
ax = figure.add_subplot()
ax.matshow()
```

It’s possible to check out the full ccommented code in the appendice: [A.6]

Results:

With this part of the code have been calculated and displayed the correlation coefficients between each single month of the current input, that looks like:

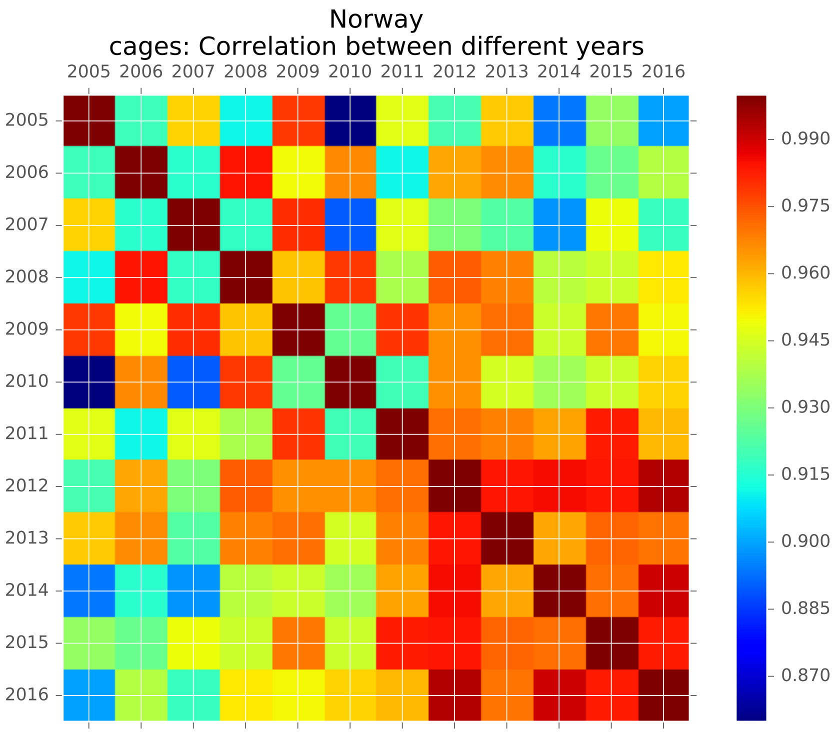


Figure 5.4: Correlation matrix between different years of the same input

5.3.6 SIA section V: Single overview

Goal:

Generate and display a single overview image that contains all the graphics previous calculated about the current input.

Requirements:

All the graphics about the current input have to be already calculated and saved.

Implementation:

During this part of the implemented system has been indispensable the Python Imaging Library, called also PIL.

```
from PIL import Image
```

It basically allowed to create a new ”empty” image and then create a sort of collage pasting the already calculated graphic’s images on it.

```
new_im = Image.new()
new_im.paste()
```

The following method contains the full code that allows to create the overview image.

```
def create_single_overview(cols, rows, dest, width, height, listofimages):
```

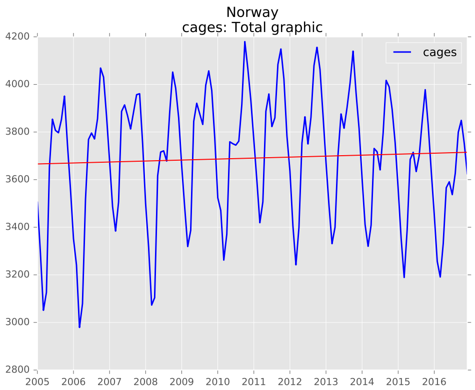
The output of this phase depends by the input to this method, that are basically the list of image and the preferences about the collage’s structure.

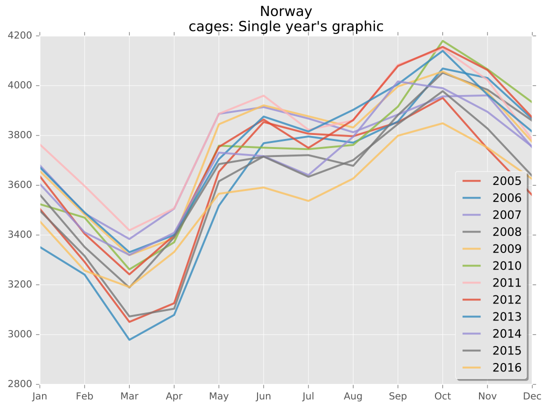
Is possible to view the final result of this phase in the next page and is possible to check out the full ccommented code in the appendice: [A.7]

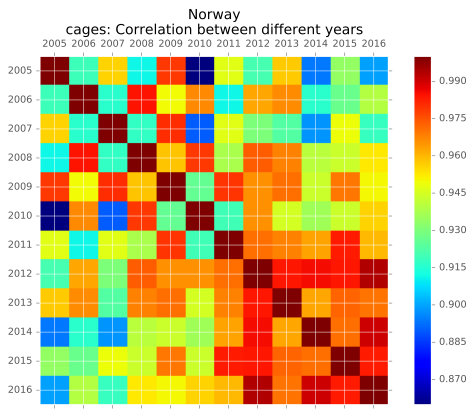
Results:

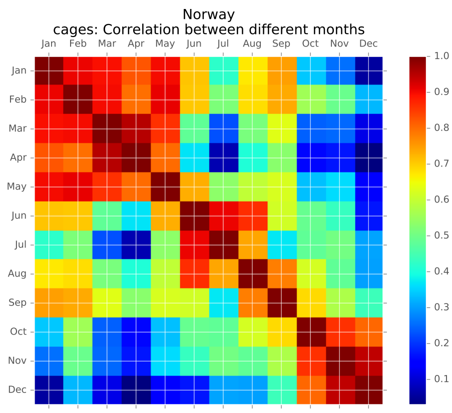
With this part of the code it's possible to have a single overview image about the current input, that basically allows to compare all the graphics already calculated about this input. The general overview graphic contains:

- Total graphic of the input data for the whole period.
- Graphic of the input data for each single year.
- Correlation matrix between different months of the same input.
- Correlation matrix between different years of the same input.









5.4 Multiple Inputs Analyzer

The implementation of this Analyzer can be divided in the following parts:

- MIA imported libraries.
- MIA part I: Calculate the correlation coefficients between the different input of a dataset, save the result and display it in a matrix.
- MIA part II: Display the comparison graphic between the different input's trend line normalized angular coefficients.

It's possible to check out the total implementation of the MIA in the appendice [B].

5.4.1 MIA: Imported libraries

Specific Python libraries have been imported for the implementation of this system. It's possible to find out a list of this libraries with a specific description for each of them in the appendice [B.1].

5.4.2 MIA section I: Total Correlation Coefficients

Goal:

Calculate and save the correlation coefficients between different inputs of the current dataset and then show it with a matrix.

Requirements:

To let the MIA system works in a proper way, is necessary that the current dataset has been already analyzed from the SIA system.

Implementation:

To reach the current goal have been used the scientific computing library "numpy", that allows to calculate the correlation coefficients between data. Then the library "pyplot" has been used to display the results on a matrix.

```
numpy.corrcoef()
figure = pyplot.figure()
ax = figure.add_subplot()
ax.matshow()
```

It's possible to check out the full ccommented code in the appendice: [B.2]

Results:

This part of the MIA implementation allows to calculate the correlation coefficients value between each single inputs and then also to display and save it. It looks like:

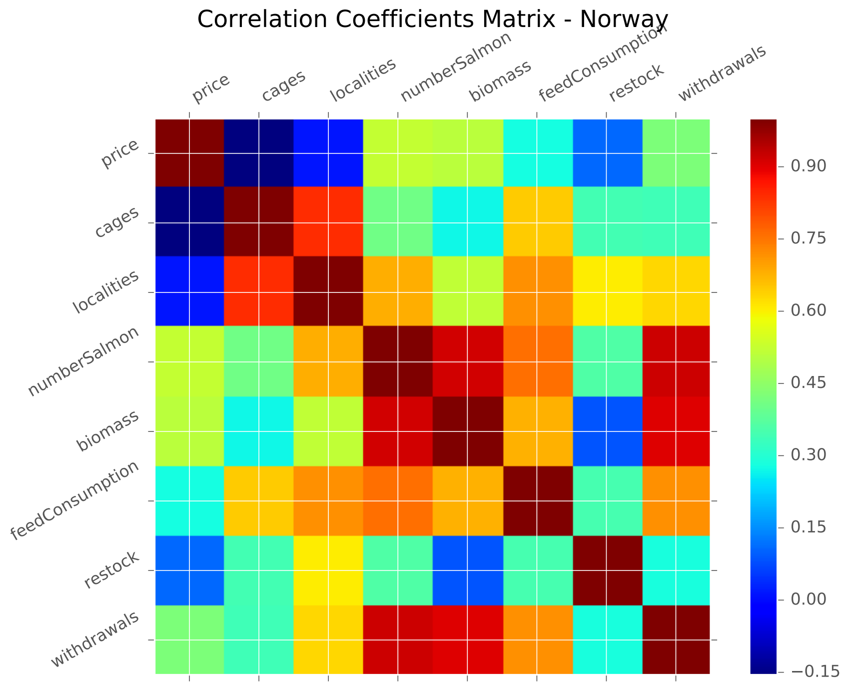


FIGURE 5.7: Correlation matrix between different inputs with data.

5.4.3 MIA section II: Normalized Angular Coefficients

Goal:

Display the comparison graphic between the normalized angular coefficient of each input trend line.

Requirements:

To let the MIA system works in a proper way, is necessary that the current dataset has been already analyzed from the SIA system.

Implementation:

Also to reach this goal have been used the two libraries ”pandas” and ”pyplot”. The first one allows us to read the values that the library ”pyplot” will display, in this case in a histogram.

```
pandas.read_csv()
pyplot.barh()
```

It’s possible to check out the full ccommented code in the appendice: [B.3]

Results:

This part of the MIA implementation allows to display a graphic that compare the normalized angular coefficients for each single input that have been already calculated and reported in a document. The result graphic look like:

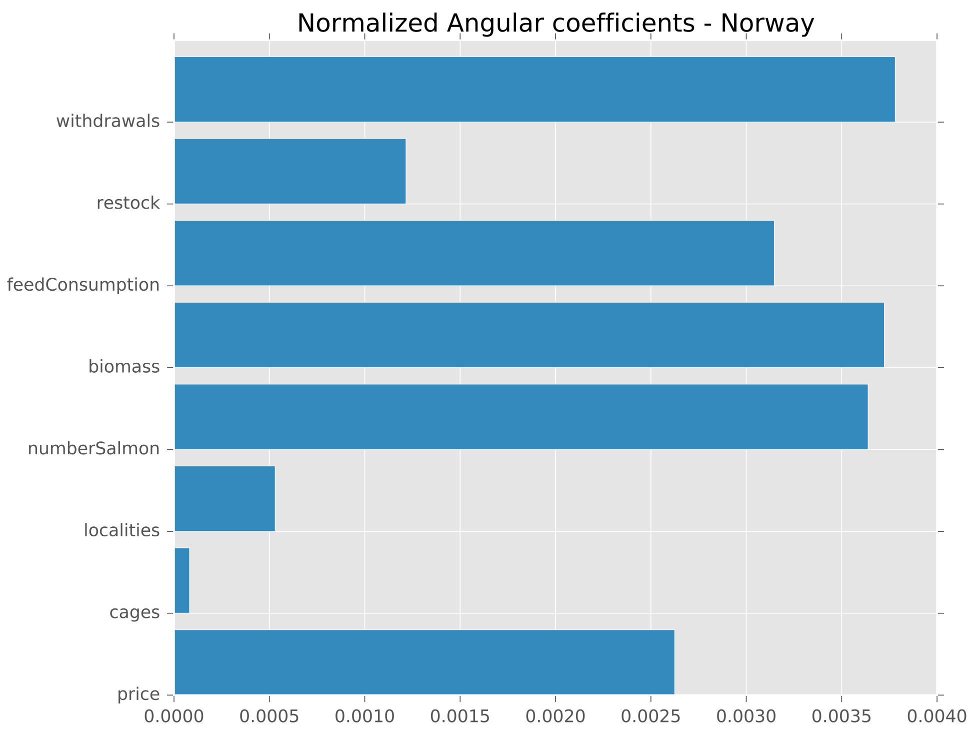


FIGURE 5.8: Normalized angular coefficients of each input’s trendline.

5.5 Data Displaying on a map

Goal:
The main goal of this phase is to find a way to visualize some data values on a map graphic using Python. In this particular case the map graphic has to represents the Norway territory and its every single county.

Requirements:
This displaying system was implemented just for displaying data about Norway, that means it's not reusable for other input datasets.

During this work has been created a specific dataset for test the system works. It contains the average value of a specific input about a single county on the whole available period. The following table shows some examples about the dataset structure: for each county has been calculated the average value from 2007 to 2014 of different parameters.

county	**averageSeaTemp**	**cages**	**localities**	**...**	**feedConsumption/biomass**
Finnmark	5.2128134819	257.2395833333	33.8333333333	...	0.1611964666
Troms	6.2185416667	393.3958333333	52.1666666667	...	0.1831404686
Nordland	6.8333444959	804.5104166667	109.0208333333	...	0.1849358645
Nord-Trondelag	7.322600258	231.6875	30.3645833333	...	0.1852350478
Sor-Trondelag	7.5381376237	306.9479166667	51.3645833333	...	0.1862036956
More_og_Romsdal	8.0087820154	347.3229166667	59.5729166667	...	0.1831662176
Sogn_og_Fjordane	8.1081250683	318.9583333333	52.5	...	0.1863151035
Hordaland	7.8033025443	738.8854166667	131.1770833333	...	0.1925203347
Rogaland_og_Agder	7.1951075619	338.53125	53.0416666667	...	0.1840209916

Implementation:
During the implementation was used the library "cartopy", that provdes cartographic tools for Python.
In this particular case has been useful use the library "cartopy.io.shapereader" that allows to read the extension file ".shp", which in this particular case contains the Norway's shape.

```
import cartopy.io.shapereader as shpreader
shpreader.Reader(filename).geometries()
```

Then the input shapely geometries were displayed to the axes using the "matplotlib".

```
plt.figure()
ax = plt.axes()
axes.add_geometries
```

Once displayed the geometries on the map, is possible to set their colors based on some input values with the library ”matplotlib”.

```
plt.get_cmap
matplotlib.colors.Normalize
```

It’s possible to check out the full ccommented code in the appendice: [C]

Results:

During this implementation was implemented a cartographic representation of some parameters about each single county involved in the Norwegian aquaculture business, but is possible to use the reported library to implement a system about an another territory or an another country.

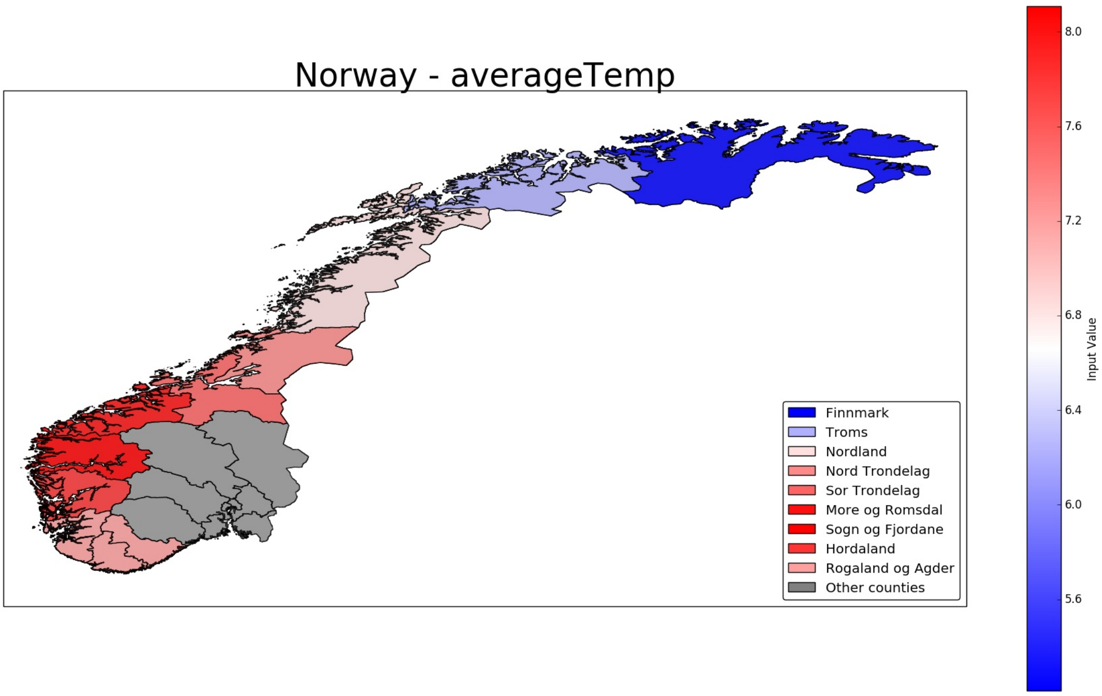


FIGURE 5.9: Average Sea Temperature from 2007 to 2014 in Norway.

5.6 Extract information from data

Chapter 6

Prediction System

Some basic and general goals were defined before starting this phase, with the idea of "doing as much as possible".
The main purpose was the one of, after the previous analysis, predict some values and evaluate the quality of the results. This prediction system was not defined with some specific requirements, so the first main problem was to find a reliable, accurated and user-friendly way to predict and display prediction of values.

Since the current dataset can be considered like a time series, in this phase we will develop the data prediction system using an ARIMA machine implemented in python.

The ARIMA machine can be configured with several configurations, it allows you to have more accurated results; so the first thing was to find the right configuration of the ARIMA machine of each single input which we are interested to forecast.

During this phase of the work have been implemented 3 different subsystems for different purposes:

1. Evaluating System
2. Prediction System

6.1 Evaluating System

Goal:

Used for evaluate different configurations of ARIMA machine.
It tests 112 different configurations for the current input that we would like to forecast and report the results with each MAPE (Mean Average Percentage Error) values.

Requirements:

There are not any kind of needed requirements. It's possible to use this system on dataset of arbitrary length.

Code implementation:

It's possible to check out the full implemented code in the appendice: D.1

The most important part of the code about the Evaluating System is the following.
Basically the method ARIMA() allows to train a model based on historic values (history) and a specific order (p,d,q). After that it's possible to call the method forecast() through the trained model and having some predictions like result.

```
model = ARIMA(history, order=arima_order)
model_fit = model.fit(disp=0)
yhat = model_fit.forecast()[0]
```

More in the specific, the 112 different ARIMA configurations that were tested are all the possible combinations between the following three parameters values:

```
p_values = [0, 1, 2, 4, 6, 8, 10]
d_values = [0, 1, 2, 3]
q_values = [0, 1, 2, 3]
```

Results:

The system will display the MAPE between real value and predicted values for each of the 112 tested ARIMA machine. In particular, once tested all the configurations, the system will provide the configuration that gave the best MAPE result.
All these results have been reported in a document that is possible to check for check out the different configurations result.

The following graphic display the different ARIMA configurations tested, providing also:

- General overview about MAPE values for each single tested configuratons.
- Best configuration with relative MAPE value.
- Color legend, where the red means lower MAPE, so more accurate predictions, and blue means higher MAPE, so less accurate predictions.

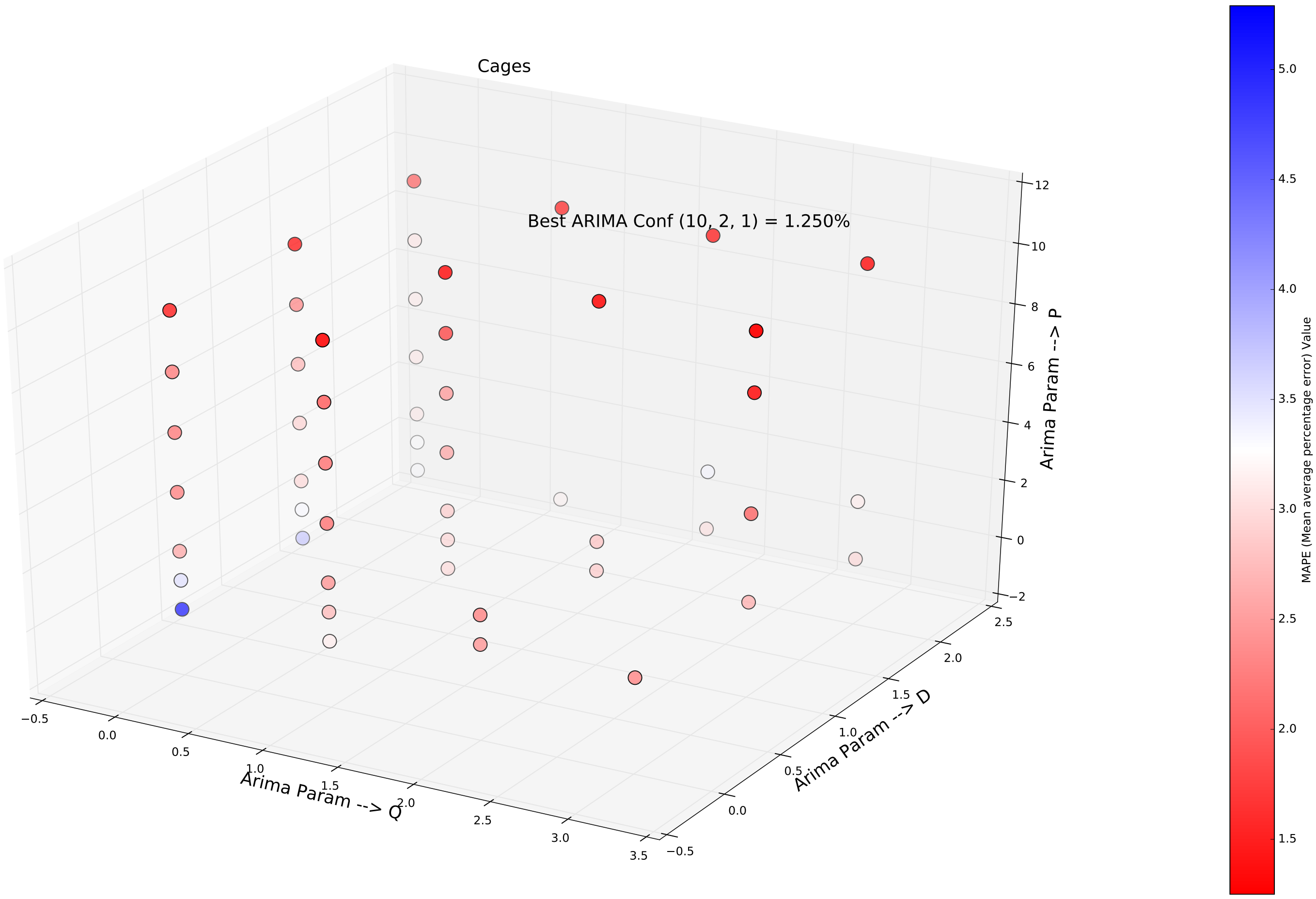


Figure 6.1: Graphic that displays different MAPE values for each ARIMA order.

6.2 Prediction System

Goal:

This system has three main goals:

- Testing a specific ARIMA configuration on a particular data input, and display how much accurate it is (MAPE).
- Predict some future value with the same ARIMA configuration.
- Display the historic data together with the testing and future predictions.

Requirements:

There are not any kind of needed requirements. It's possible to use this system on input dataset of arbitrary length.

Code implementation:

To reach the first of the goals reported above the system will divide the input dataset in two parts, train and test. It allows to train the ARIMA model with just the "train" part of the dataset, that usually is 66% of the whole dataset, and then try to predict the rest of the dataset values, comparing in the end with the values contain in the "test" part to have a general idea about the accuracy.

The method ARIMA() allows to train a model based on historic values (history) and a specific order (p,d,q). After that it's possible to call the method forecast() through the trained model and having some predictions like result.

```
model = ARIMA(history, order=arima_order)
model_fit = model.fit(disp=0)
yhat = model_fit.forecast()[0]
```

Then the system will also predict a number of future values choosen by the system user.

```
model = ARIMA(dataset, order=order)
model_fit = model.fit(disp=0)
forecast = model_fit.forecast(int(sys.argv[3]))[0]
```

The final step is to display the historic data together with the test prediction and the future prediction on the same graphic.

```
# Plot current input's historic values
series.plot(color="blue", linewidth=1.5, label="Series: "+sys.argv[1])

# Plot current input's test prediction
predHistoric.plot(color="red", linewidth=1.5, label="Prediction test:")

# Plot current input's future prediction
predFuture.plot(color="green", linewidth=1.5, label="Future Prediction:")
```

Results:

This system will automatically generate two documents that contain:

- Test predictions values
- Future predictions values

And then it provides also the possibility to visualize the historic, test and future predictions values on the same graphic, that looks like the following example:

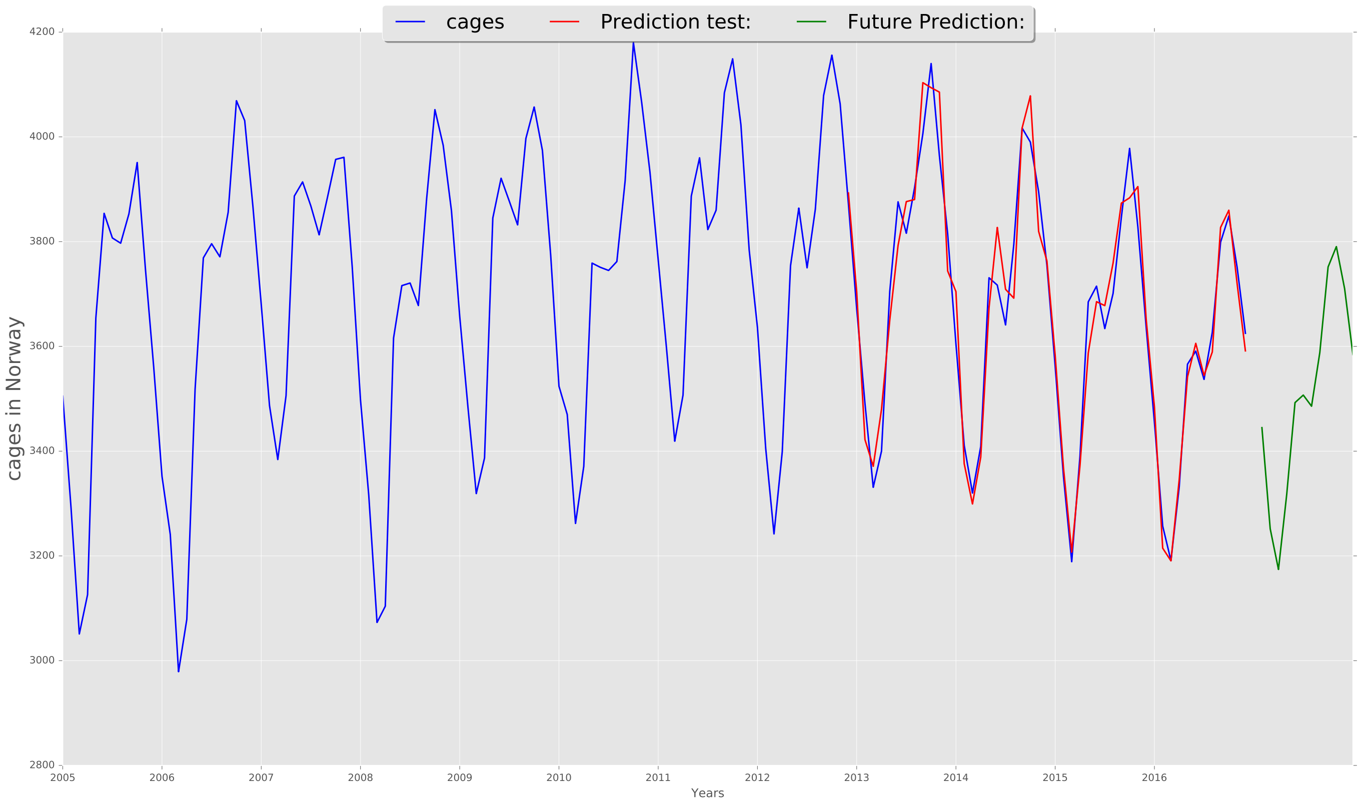


Figure 6.2: Graphic that display historic, future and predicted values of a input.

Part III

Discussion, Evaluations and Conclusions

Chapter 7

Discussion and Evaluations

The results obtained are actually providing an answer to the initial questions of this thesis. In particular:

——¿ Initial approach with Data Science field, done?

- The working procedure that has been followed during this work allows to have an initial approach with the data science field, since have been reported INITIAL considerations about any step of the general data science process. (Data colleciton, analysis, displaying, extraction, forecasting..)

——¿ Test the Python potential in Data Science field, done? - The results reported during this thesis are actually showing the Python potential in data analysis, displaying and forecast.

——¿ Are the data about Norwegian salmon farming structured, described and readable? - This study process actually changed the structure of the data. From the original data sources to the final dataset, with relative descriptions, graphics, coefficients,.. there is a big different that could be helpful for future reuse of the data for more specific analysis.

Interpret and explain your results

Answer your research question

Justify your approach

7.1 Evaluation and limitations of the study

- The implemented Python system can be reused for any kind of input dataset (with just the monthly frequency requirement). It allows to make some analysis done during this thesis about other dataset in a fast and easy way.

- All the systems implemented in this thesis are probably efficient and productive for a personal use. That's because there is no GUI implemented and to customize the output graphics in a better way you have to know Python language.

- Not enough informations have been extracted from the data cause of a lack in the background theory about Norwegian salmon farming, and not enough time to document myself in a proper way.

- Not enough informations about machine learning field, so during this thesis was implemented just a basic implementation of the forecasting system, just to give an idea about how it works and give the possibility to improve it in future works.

The purpose of the discussion is to interpret and describe the significance of your findings in light of what was already known about the research problem being investigated, and to explain any new understanding or insights about the problem after you've taken the findings into consideration. The discussion will always connect to the introduction by way of the research questions or hypotheses you posed and the literature you reviewed, but it does not simply repeat or rearrange the introduction; the discussion should always explain how your study has moved the reader's understanding of the research problem forward from where you left them at the end of the introduction.

Chapter 8

Conclusion

8.1 Summary

8.2 Recommendations to future work

8.2.1 Improve the dataset content

8.2.2 Visualization of the data

8.2.3 Improve the prediction system

8.2.4 System as a service

This system has been developed with the idea that it could become a ”Service system”, that is basically a configuration of technology and organizational networks designed to deliver services that satisfy the needs or wants of customers. Since the prediction system implemented during this work is almost 100% reusable, it could be used from people for prediction about any kind of data.

Basically the idea is to create a web application that allows to let you upload your own dataset, choose your own preferences and prediction settings, and then the system will calculate and display prediction of the current values in the future together with the MAPE (Mean Average Percentage Error) to have an idea bout how accurate are the.

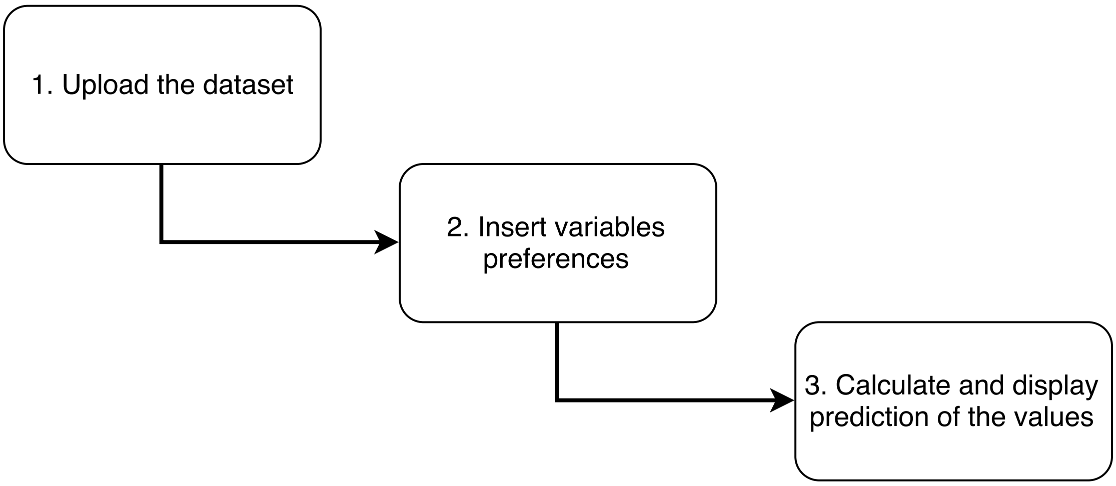


FIGURE 8.1: Idea of the Servie System for predictions.

Part IV

Full Code Implementation

Appendix A

SIA Implementation code

A.1 SIA: Imported libraries

The library "os" is really important since provides a waay of using operating system dependent functinality.

```
import os
```

Also the library "sys" would be very useful for test and execute the program, mainly because it allows to input directly from terminal.

```
import sys
```

The "pandas" library will be very useful for read the data from CSV dataset and setup the plot abut it.

```
import pandas as pd
```

The "numpy" library it's used for mathematic purpose, such as calculating the correlation coefficent between two series.

```
import numpy as np
```

The "pyplot" library it's used for basic graphic displaying and customization, easy to use but very efficent.

```
import matplotlib.pyplot as pyplot
```

The library "PIL" supports many file formats, and provides powerful image processing and graphics capabilities.

```
from PIL import Image
```

A.2 SIA: Implemented methods

This pyplot style configuration allows to customize the graphic desig. In this case was used ggplot, a popular plotting package.

```
pyplot.style.use('ggplot')
```

The two methods reported below here were used for calculating the trend line angular coefficients and the normalized one. In order to reach this goal is used the python library "numpy".

```
def trendline(x, y, col):
    z = np.polyfit(x, y, 1)
    p = np.poly1d(z)
    pyplot.plot(x,p(x), c=col)
    z2 = trendlineNorm(x, normalization(y))
    return z[0], z2

def trendlineNorm(x, y):
    z = np.polyfit(x, y, 1)
    return z[0]
```

The following method was used for normalize the input values, that means adjusting values measured on different scales to a notionally common scale , in this case (0,1).

```
def normalization(values):
    column = list(float(a) for a in range(0, 0))
    val = np.array(values)
    val.astype(float)
    column = val / val.max()
    return column
```

The following code shows the code of the two methods that are allowing to save images and matrix values to the library "os".

```
def saveFigure(descr):
     script_dir = os.path.dirname(__file__)
     results_dir = os.path.join(script_dir, "Results/" + sys.argv[1] + "/" +
      sys.argv[2]+"/")
     if not os.path.isdir(results_dir):
          os.makedirs(results_dir)

def saveMatrix(corrRes, dest):
    mat = np.matrix(corrRes)
    dataframe = pd.DataFrame(data=mat.astype(float))
    dataframe.to_csv(dest, sep=',', header=False, float_format='%.2f', index
     =False)
```

The following code represents the method that was used for creating the overview image generated by the SIA system, that is basically a collage of all the generated graphics about a particular parameter of the current input dataset. In order to reach this goal has been strongly used the library "PIL", that allows image elaboration using Python, and the libary "OS", for saving the results.

```
def create_single_overview(cols, rows, dest, width, height, listofimages):
    thumbnail_width = width//cols
    thumbnail_height = height//rows
    size = thumbnail_width, thumbnail_height
    new_im = Image.new('RGB', (width, height))
    ims = []
    for p in listofimages:
        im = Image.open(p)
        im.thumbnail(size)
        ims.append(im)
    i = 0
    x = 0
    y = 0
    for col in range(cols):
        for row in range(rows):
            new_im.paste(ims[i], (x, y))
            i += 1
            y += thumbnail_height
        x += thumbnail_width
        y = 0
    if dest==0:
      script_dir = os.path.dirname(__file__)
      results_dir = os.path.join(script_dir, "Results/" + sys.argv[1]+"/"+sys.argv[2]+"/")
      if not os.path.isdir(results_dir):
         os.makedirs(results_dir)
        new_im.save(results_dir+"/"+ sys.argv[1] +"_"+sys.argv[2]+"_Graphics_Overview.jpg")
        new_im.show()
    if dest==1:
      script_dir2 = os.path.dirname(__file__)
      results_dir2 = os.path.join(script_dir2, "Results/" + sys.argv[1]+"/Total_Evidences/Single_Inputs")
      if not os.path.isdir(results_dir2):
         os.makedirs(results_dir2)
        new_im.save(results_dir2+"/"+ sys.argv[1] +"_"+sys.argv[2]+"_Overview.jpg")
```

A.3 SIA section I: Total graphic for all the years

Code implementation:

During this section of the code was used "pandas" library for read the dataset.

```
series1 = pd.read_csv("Datasets/" + sys.argv[1]+".csv", usecols=[1,sys.argv
    [2]])
```

Then using the "pyplot" library has been possible to setup the plot of the input data.

```
series1.plot(color="blue", linewidth=1.5)
```

Thera are some settings about the axis x just to display the data in the right format, are easy to change and to costume.

```
years = []
j = 0
for i in range(len(yearInput)):
    if j==11:
        years.append(yearInput.values[i][0])
        j=0
    else:
        j=j+1
x = range(0, len(yearInput.values))
pyplot.xticks(np.arange(min(x), max(x)+1, 12.0), years)
pyplot.title(sys.argv[1] + "\n" + sys.argv[2]+ ": Total graphic")
```

Once setted up the plot of the current data, the next step was to display the trendline of the current graphic.

At this point the current data values have been read again and passed to the method just impleneted above for calculating the trendline.

```
series1 = pd.read_csv("Datasets/" + sys.argv[1]+".csv", usecols=[sys.argv
    [2]], squeeze=True)
z1, z2 = trendline(x, series1.values.astype(float), "red")
saveFigure("_Total.jpg")
results_dir = "Results/" + sys.argv[1]+"/"+sys.argv[2]+"/"+sys.argv[1]+"_"+
    sys.argv[2]+"_AngCoeff.csv"
with open(results_dir, "w") as text_file:
    text_file.write("," + sys.argv[1] + "-" + sys.argv[2]+"\n")
    text_file.write("," + "Ang_Coeff " + "," + str(z1)+"\n")
    text_file.write("," + "Norma_Ang_Coeff " + "," + str(z2)+"\n")
```

A.4 SIA section II: Single graphics for each year

Code implementation:

During this section of the code was used "pandas" library for read the dataset.

```
series2 = pd.read_csv("Datasets/" + sys.argv[1]+".csv", index_col=['month'
    ], usecols=[0,1,sys.argv[2]])
```

Some initialization of variables that are going to be useful.

```
fig2 = pyplot.figure()
ax = fig2.add_subplot(111)
months = ["Jan","Feb","Mar","Apr","May","Jun","Jul","Aug","Sep","Oct","Nov"
    ,"Dec"]
x_pos = np.arange(len(months))
```

The following code allows the system to split the values and display them in the right way: that means that are going to be splitted for each single year and then plotted on the same graphic.

```
tempValues = []
j = 0
for i in range(len(series2.values)):
    if j in range(12):
        tempValues.append(series2.values[i][1])
        j = j + 1
        if(i == len(series2.values)-1):
            pyplot.plot(x_pos, tempValues, linewidth=2, alpha=0.8, label = int
    (series2.values[i-1][0]))
    else:
        pyplot.plot(x_pos, tempValues, linewidth=2, alpha=0.8, label = int(
    series2.values[i-1][0]))
        tempValues = []
        tempValues.append(series2.values[i][1])
        j = 1
```

These are some personalization settings that could be easily changed as you want.

```
ax.legend(loc=4, ncol=1, fancybox=True, shadow=True)
pyplot.xticks(x_pos,months)
pyplot.xlim(0,11)
pyplot.title(sys.argv[1] + "\n" + sys.argv[2]+ ": Single year's graphic")
pyplot.tight_layout()
```

There is the possibility to save the graphic like an image and/or display it.

```
saveFigure("_Years.jpg")
```

A.5 SIA section III: Correlation matrix between years

Code implementation:

During this section of the code was used "pandas" library for read the dataset.

```
series3 = pd.read_csv("Datasets/" + sys.argv[1]+".csv", index_col=['month'], usecols=[0,1,sys.argv[2]])
```

```
corr = []
tempValues = []
j = 0
# Collecting the correct values to elaborate.
for i in range(len(series3.values)+1):
    if j in range(12):
        tempValues.append(series3.values[i][1])
        j = j + 1
    else:
        corr.append(tempValues)
        tempValues = []
        if i in range(len(yearInput)):
            tempValues.append(series3.values[i][1])
            j = 1
```

With the library "numpy" is possible to calculate the correlation coefficents between all the variables in the series just read.

```
corrRes = np.corrcoef(corr)
```

Setup the figure that will display the correlation matrix using the library "pypot".

```
fig3 = pyplot.figure()
ax = fig3.add_subplot(111)
```

Creating the correlation matrix using the already calculated correlation coefficents.

```
cax = ax.matshow(corrRes, interpolation='nearest')
```

Settings for display the matrix in the right way, in particular for the values to display on both the axis x and y, in this case every single year from 2005 to 2016

```
pyplot.title(sys.argv[1] + "\n" + sys.argv[2]+ ": Correlation between different years")
x_pos = np.arange(yearsLen)
y_pos = np.arange(yearsLen)
pyplot.yticks(y_pos,years)
pyplot.xticks(x_pos,years)
pyplot.colorbar(cax)
```

Adding a title to the graphic that we are going to display and also a bar that works like a legend for the colors of the matrix, allowing the reader to better understand the values reported inside the matrix.

```
pyplot.tight_layout()
saveFigure("_years_Matrix.jpg")
saveMatrix(corrRes, "Results/"+sys.argv[1]+"/"+sys.argv[2]+"/"+sys.argv[1]+
    "_"+sys.argv[2]+"_years_CorrCoeff.csv")
```

A.6 SIA section IV: Correlation matrix between months

Code implementation:

During this section of the code was used "pandas" library for read the dataset.

```
series4 = pd.read_csv("Datasets/" + sys.argv[1]+".csv", usecols=[0,1,sys.
    argv[2]])
```

```
corr = []
for month, year in series4.groupby(["month"], sort=False):
    corr.append(year[sys.argv[2]].values)
corrRes = np.corrcoef(corr)
```

Setup the figure that will display the correlation matrix using the library "pypot".

```
fig4 = pyplot.figure()
ax = fig4.add_subplot(111)
```

Creating the correlation matrix using the already calculated correlation coefficents.

```
cax = ax.matshow(test, interpolation='nearest')
```

Settings for display the matrix in the right way, in particular for the values to display on both the axis x and y, in this case every single months of the year.

```

months = ["Jan","Feb","Mar","Apr","May","Jun","Jul","Aug","Sep","Oct","Nov"
    ,"Dec"]
x_pos = np.arange(len(months))
y_pos = np.arange(len(months))
pyplot.yticks(y_pos,months)
pyplot.xticks(x_pos,months)
```

Adding a title to the graphic that we are going to display and also a bar that works like a legend for the colors of the matrix, allowing the reader to better understand the values reported inside the matrix.

```
pyplot.title(sys.argv[1] + "\n" + sys.argv[2]+ ": Correlation between different months")
pyplot.colorbar(cax)
```

There is the possibility to save the correlation matrix like an image and/or display it.

```
pyplot.tight_layout()
saveFigure("_months_Matrix.jpg")
saveMatrix(corrRes, "Results/"+sys.argv[1]+"/"+sys.argv[2]+"/"+sys.argv[1]+"_"+sys.argv[2]+"_months_CorrCoeff.csv")
```

A.7 SIA section V: Single overview

Code implementation:

create_single_overview() : this method will use the "Image" library for autogenerate a collage of the current input's graphics and save it like an overview image. The content of the params will basically decide how the "Current input overview image" will looks like.

It uses each single "current input overview image" of all the inputs and the "correlation matrix between all the inputs image" for combine them in a unique "total overview" and save it using the PDF format.

```
listofimages=["Results/" + sys.argv[1]+"/"+sys.argv[2]+"/"+sys.argv[1]+"_"+sys.argv[2]+"_Total.jpg",
            "Results/" + sys.argv[1]+"/"+sys.argv[2]+"/"+sys.argv[1]+"_"+sys.argv[2]+"_years_Matrix.jpg",
            "Results/" + sys.argv[1]+"/"+sys.argv[2]+"/"+sys.argv[1]+"_"+sys.argv[2]+"_years.jpg",
            "Results/" + sys.argv[1]+"/"+sys.argv[2]+"/"+sys.argv[1]+"_"+sys.argv[2]+"_months_Matrix.jpg"]

create_single_overview(4, 1, 1, 3200, 600, listofimages)
create_single_overview(2, 2, 0, 1600, 1200, listofimages)
```

Appendix B

MIA Implementation code

B.1 MIA: Imported libraries

The "pandas" library will be very useful for read the data from CSV dataset and setup the plot abut it.

```
import pandas as pd
```

The "numpy" library it's used for mathematic purpose, such as calculating the correlation coefficent between two series.

```
import numpy as np
```

Also the library "sys" would be very useful for test and execute the program, mainly because it allows to input directly from terminal.

```
import sys
```

This pyplot style configuration allows to customize the graphic desig. In this case was used ggplot, a popular plotting package.

```
pyplot.style.use('ggplot')
```

The "pyplot" library it's used for basic graphic displaying and customization, easy to use but very efficent.

```
import matplotlib.pyplot as pyplot
```

B.2 MIA section I: Total Correlation Coefficients

During the first part of the implementation of this system was used again the "pandas" library for reading all the values of each single paramaeter of the current input dataset.

```
series = pd.read_csv("Datasets/" + sys.argv[1]+".csv", usecols=range(2,10),
    header=0)
corr = []
for column in series:
    corr.append(series[column].values)
```

Then, once read and organized the values, are calculated all the correlation coefficients between each single paramater values

```
corrRes = np.corrcoef(corr)
mat = np.matrix(corrRes)
dataframe = pd.DataFrame(data=mat.astype(float))
```

The resulting correlation coefficients values are reported in a CSV output file.

```
dataframe.to_csv("Results/"+sys.argv[1]+"/Total_Evidences/"+sys.argv[1]+"
    _CorrCoeff.csv", sep=',', header=False, float_format='%.2f', index=
    False)
```

The final step of this first part of the MIA implementation is to display the calculated correlation coefficients on a correlation matrix. The following code show how to set it up, customize both the tick labels and in end how to save it.

```
fig = pyplot.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(corrRes, interpolation='nearest')
labels = []
j = 1
for i in range(len(series.columns)+1):
    if i == 0:
        labels.append("")
    else:
        labels.append(series.columns[i-1])
ax.set_xticklabels(labels)
ax.set_yticklabels(labels)
pyplot.setp(ax.get_xticklabels(), rotation=30, horizontalalignment='left')
pyplot.setp(ax.get_yticklabels(), rotation=30, horizontalalignment='right')
pyplot.colorbar(cax)
pyplot.title("Correlation Coefficients Matrix - " + sys.argv[1], y=1.15)
pyplot.tight_layout()
pyplot.savefig("Results/" + sys.argv[1]+"/Total_Evidences/"+sys.argv[1]+"
    _Total_Matrix.jpg", format="jpg")
```

B.3 MIA section II: Normalized Angular Coefficients

During this part of the code the system will read for each single paramater of the current input dataset the trend line normalized angular coefficient. The coefficients values are organized and saved in a temporary data structure.

```
temp = []
for i in series.columns:
    index = sys.argv[1]+"-"+i
    tempSeries = pd.read_csv("Results/"+sys.argv[1]+"/"+i+"/"+sys.argv[1]+"_"+i+"_AngCoeff.csv", header=0)
    temp.append(tempSeries[index].values[1])
```

Once the values are ready to be elaborated, the system displays it on a horizontal bar plot using the library "pyploy".

```
fig2 = pyplot.figure()
ax2 = fig2.add_subplot(111)
x = range(len(series.columns))
pyplot.barh(x, temp)
```

Last part of the code was used for graphic's customization and for saving it.

```
pyplot.yticks(x,series.columns)
pyplot.title("Normalized Angular coefficients - " + sys.argv[1])
pyplot.tight_layout()
pyplot.savefig("Results/"+sys.argv[1]+"/Total_Evidences/"+sys.argv[1]+"_Norm_Ang_Coeffs.jpg", format="jpg")
```

Appendix C

Norway's Map System Implementation Code

```
import os
import sys
import matplotlib
import pandas as pd
import cartopy.crs as ccrs
import matplotlib.cm as cmx
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
import cartopy.io.shapereader as shpreader
```

```
def add_geom(axes, shapeInput, labelInput, colorInput):
    axes.add_geometries(shapeInput, ccrs.Robinson(), edgecolor='black',label
      = labelInput, facecolor=colorInput, alpha=0.8)
    return mpatches.Rectangle((0, 0), 1, 1, facecolor=colorInput)
```

```
def main():
# Downloaded from http://biogeo.ucdavis.edu/data/gadm2.8/shp/NOR_adm_shp.
    zip
    fname = 'Datasets/NOR/NOR_adm1.shp'
    NOR_shapes = list(shpreader.Reader(fname).geometries())
    plt.figure()
    ax = plt.axes(projection=ccrs.Robinson())
    ax.coastlines(resolution='10m')
    ax.set_extent([4, 32, 57, 72], ccrs.Robinson())

    colMap='bwr'
    dataInput = sys.argv[1]
    inputSeries = pd.read_csv("Datasets/countiesAverages.csv")

```

```python
    inputValues = [inputSeries[dataInput][0], inputSeries[dataInput][1], inputSeries[dataInput][2], inputSeries[dataInput][3],
    inputSeries[dataInput][4], inputSeries[dataInput][5],inputSeries[dataInput][6], inputSeries[dataInput][7], inputSeries[dataInput][8]]

    cm = plt.get_cmap(colMap)
    mininputValues = min(inputValues)
    cNorm = matplotlib.col.Normalize(vmin=mininputValues, vmax=max(inputValues))
    scalarMap = cmx.ScalarMappable(norm=cNorm, cmap=cm)
    col = scalarMap.to_rgba(inputValues)
    scalarMap.set_array(inputValues)
    plt.colorbar(scalarMap,label='Input Value')
    norway = add_geom(ax, NOR_shapes, "Norway", "gray")
    finnmark = add_geom(ax, NOR_shapes[4], "Finnmark", col[0])
    troms = add_geom(ax, NOR_shapes[16], "Troms", col[1])
    nordland = add_geom(ax, NOR_shapes[9], "Nordland", col[2])
    nord_trondelag = add_geom(ax, NOR_shapes[8], "Nord Trondelag", col[3])
    sor_trondelag = add_geom(ax, NOR_shapes[13], "Sor Trondelag", col[4])
    more_og_romsdal = add_geom(ax, NOR_shapes[7], "More og Romsdal", col[5])
    sogn_og_fjordane = add_geom(ax, NOR_shapes[14], "Sogn og Fjordane", col[6])
    hordaland = add_geom(ax, NOR_shapes[6], "Hordaland", col[7])
    rogaland_og_agder = add_geom(ax, NOR_shapes[2], "Rogaland og Agder", col[8])
    rogaland_og_agder = add_geom(ax, NOR_shapes[12], "Rogaland og Agder", col[8])
    rogaland_og_agder = add_geom(ax, NOR_shapes[17], "Rogaland og Agder", col[8])

    plt.title('Norway - '+sys.argv[1] , fontsize=35)
    labels = ['Finnmark', 'Troms', 'Nordland','Nord Trondelag', 'Sor Trondelag', 'More og Romsdal', 'Sogn og Fjordane', 'Hordaland', 'Rogaland og Agder','Other counties', ]
    plt.legend([finnmark, troms, nordland, nord_trondelag, sor_trondelag,
        more_og_romsdal, sogn_og_fjordane, hordaland, rogaland_og_agder, norway],
        labels, loc='lower right', fancybox=True)
    manager = plt.get_current_fig_manager()
    manager.resize(*manager.window.maxsize())
    plt.show()

if __name__ == '__main__':
    main()
```

Appendix D

Prediction System Implementation code

D.1 Evaluating System

D.2 Prediction System

Bibliography

[1] Jason Brownlee. How to create an arima model for time series forecasting with python. http://machinelearningmastery.com/arima-for-time-series-forecasting-with-python/, January 9, 2017. Online.

[2] Wikipedia. Data science — wikipedia, the free encyclopedia, 2017. [Online].

[3] Arthur Samuel, 1959.

[4] Jason Brownlee. Machine learning mastery, 2017.

[5] Time series analysis: Forecasting and control. [page 1].

[6] Wikipedia. Autoregressive model — wikipedia, the free encyclopedia, 2017. [Online].

[7] Wikipedia. Moving-average model — wikipedia, the free encyclopedia, 2017. [Online].

[8] Wikipedia. Autoregressive–moving-average model — wikipedia, the free encyclopedia, 2017. [Online].

[9] Wikipedia. Autoregressive integrated moving average — wikipedia, the free encyclopedia, 2017. [Online].

[10] Standing Senate Committee on Fisheries and Oceans. Volume two - aquaculture industry and governance in norway and scotland, June 2016. [Online].