UNIVERSITY OF TROMSØ

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

by

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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. To extract the needed informations from the data there isn't a default technique. This study investigates about the possibility of implementing an informations extraction system using Python. This kind of systems might be used for high interest area, such as the Aquaculture industry, that is a particular relevant industry in the norwegian economy, since Norway represents the forefront of innovation and development in this area.

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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 kind of field and sectors all around the world. For this reason an instrument or techniques for analyzing and understanding these data have been more and more needed, 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-oriented, high-level programming language that has a easy to learn syntax. It might provides a high productivity and severals modules and package.

The processes and systems provided from this field might be applied to areas of high economic interest, such as the Aquaculture industry in Norway. This business area is producing a big amount of data about every single locality or about national statistcs, but most of the time this data are difficult to understand and not analyzed at all.

1.1 Aim of the study

The main purposes of this thesis are basically:

- Initial approach with Data Science field.
- Test and show Python potential in Data Science field.
- Report an initial analysis of data about Norwegian Salmon Farming.

For achieve the goals reported above, this thesis will provide:

- Implementation and description of a procedure that can be used for realize a Python system able to do an automatic initial analysis of big datasets and display the obtained results.
- Implementation and description of a procedure that can be used for make a Python system able to predict future's values using a regression model.

1.2 Initial Goals

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

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.
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

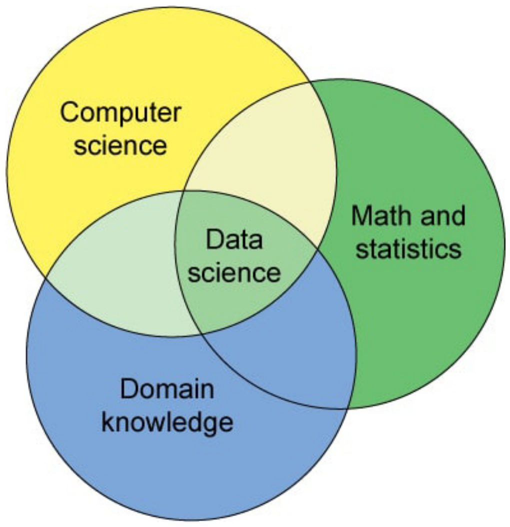


FIGURE 2.1: Data science concept

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, according to Arthur Samuel in 1959, gives computers the ability to learn without being explicitly programmed. 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.

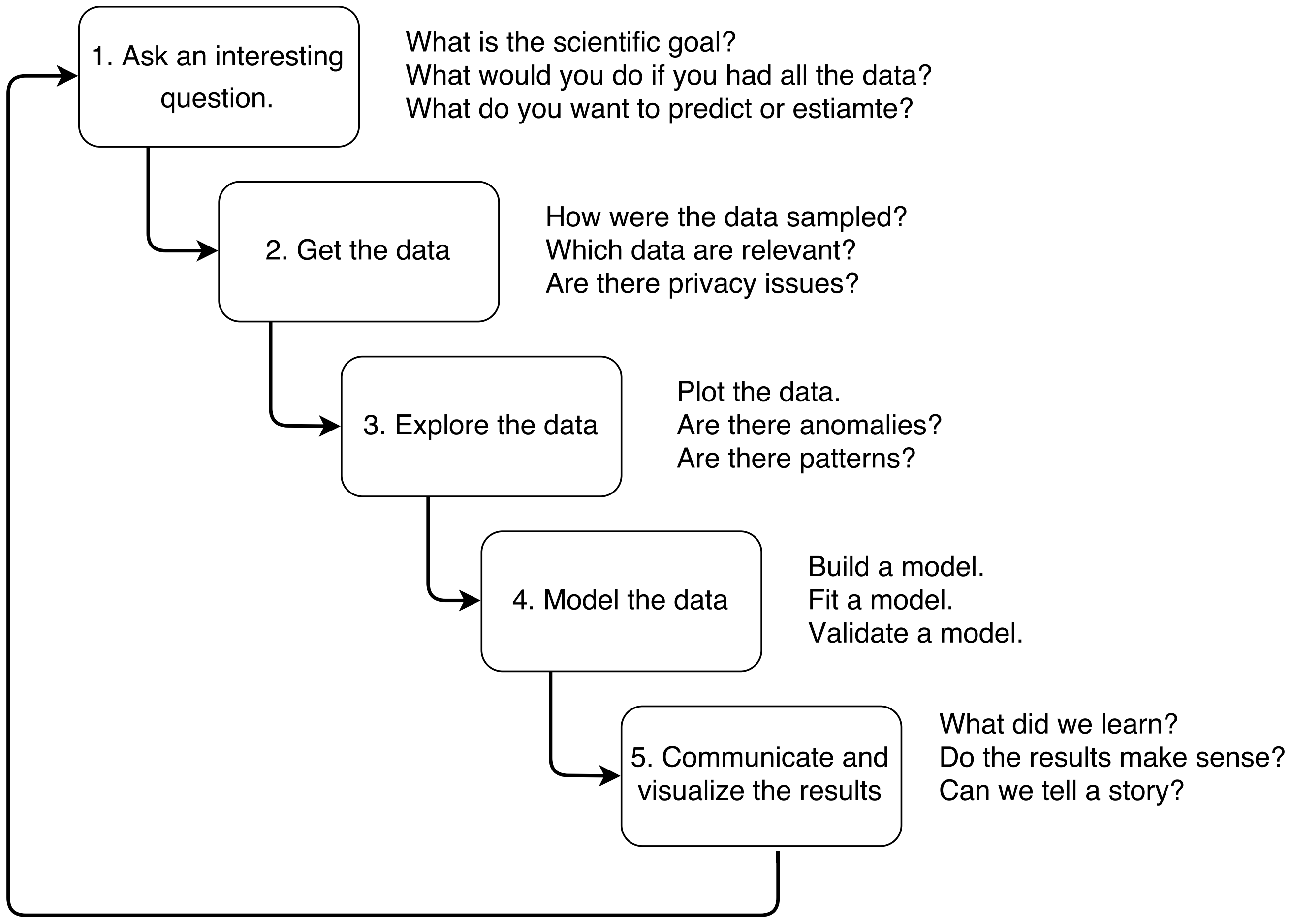

1. Ask an interesting question.
What is the scientific goal?
What would you do if you had all the data?
What do you want to predict or estiamte?
2. Get the data
How were the data sampled?
Which data are relevant?
Are there privacy issues?
3. Explore the data
Plot the data.
Are there anomalies?
Are there patterns?
4. Model the data
Build a model.
Fit a model.
Validate a model.
5. Communicate and visualize the results
What did we learn?
Do the results make sense?
Can we tell a story?

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.

” A time series is a sequence of observations taken sequentially in time. ”
Quoted — Page 1, Time Series Analysis: Forecasting and Control.

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.

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.

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.

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.

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

Is the aquaculture business in Norway growing?

Aquaculture, also known as aquafarming, is the farming of fish, crustaceans, molluscs, aquatic plants, algae, and other aquatic organisms.

Aquaculture would be the future of fish: In 2030, according to the World Bank, aquaculture will supply:

- 93.6 Million tonnes of fish per year
- 25 percent less wild fish will be available
- 62 percent of the fish we eat will come from farms

s

Chapter 3

Approach and Design

3.1 Development Flow

1st Phase: Data collection and validation
During this phase the most important thing is to gather as much as possible data, but they must be as much as possible reliable and useful since they are going to be indispensable for the next phases and in particular for the final results and conclusions. The data's reliability mainly depend by the kind of sources where you're able to mine.
Then you should customize the unstructured data that you collected.
This data's customizing has the main purposes of:

- Let the data structure be a summarize of all the data inputs previous collected.
- Let the new data structure be easier to access and read.
- Follow some kind of setting and standard needed in the system that will be implemented.

2nd Phase: Data Analysis and Displaying
During this phase the first thing that you're going to do is to decide some kind of analysis results that you would like to have.
Once you decided which kind of results you might reach, you will start with the analysis system implementation and meanwhile saving eviences of it.
Once the general analysis of the data is finished, and evidences have been collected, it's time to analyze it and try to extract information about it.

3rd Phase: Data Prediction

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.

4th Phase: Results, Discussion and Conclusions

During this phase of the work all the obtained results will be reported and discussed, trying to figure some useful conclusions.

5th Phase: Future Works

The last but not least phase is to watch at the future: try to figure out some other extra implementations about this thesis.

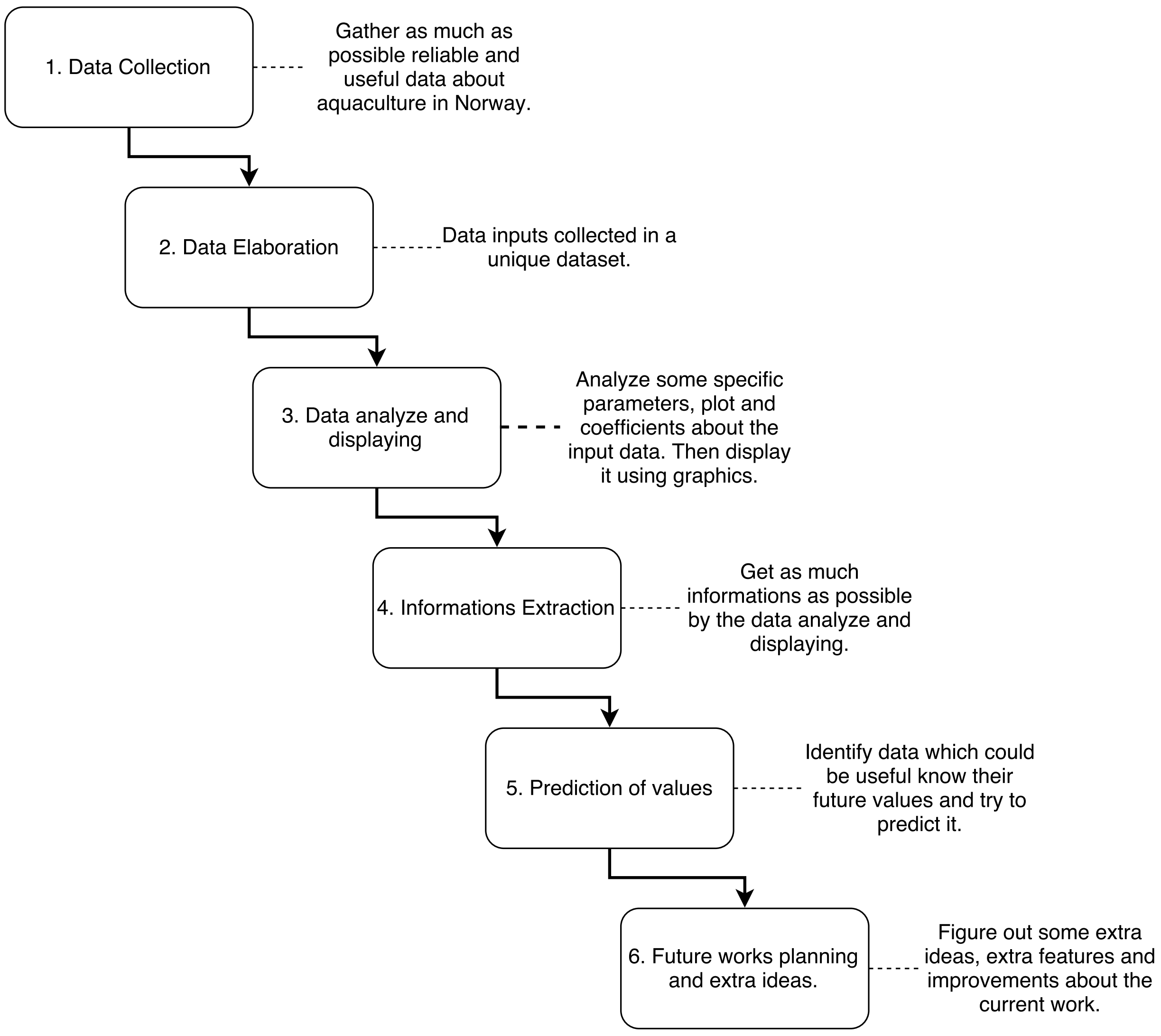

1. Data Collection
Gather as much as possible reliable and useful data about aquaculture in Norway.
2. Data Elaboration
Data inputs collected in a unique dataset.
3. Data analyze and displaying
Analyze some specific parameters, plot and coefficients about the input data. Then display it using graphics.
4. Informations Extraction
Get as much informations as possible by the data analyze and displaying.
5. Prediction of values
Identify data which could be useful know their future values and try to predict it.
6. Future works planning and extra ideas.
Figure out some extra ideas, extra features and improvements about the current work.

FIGURE 3.1: Plan flow chart

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

Part I

Data collection

Chapter 4

Description and collection of the data

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

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

It's also important to know that the following informations about this current data source:

- 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

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

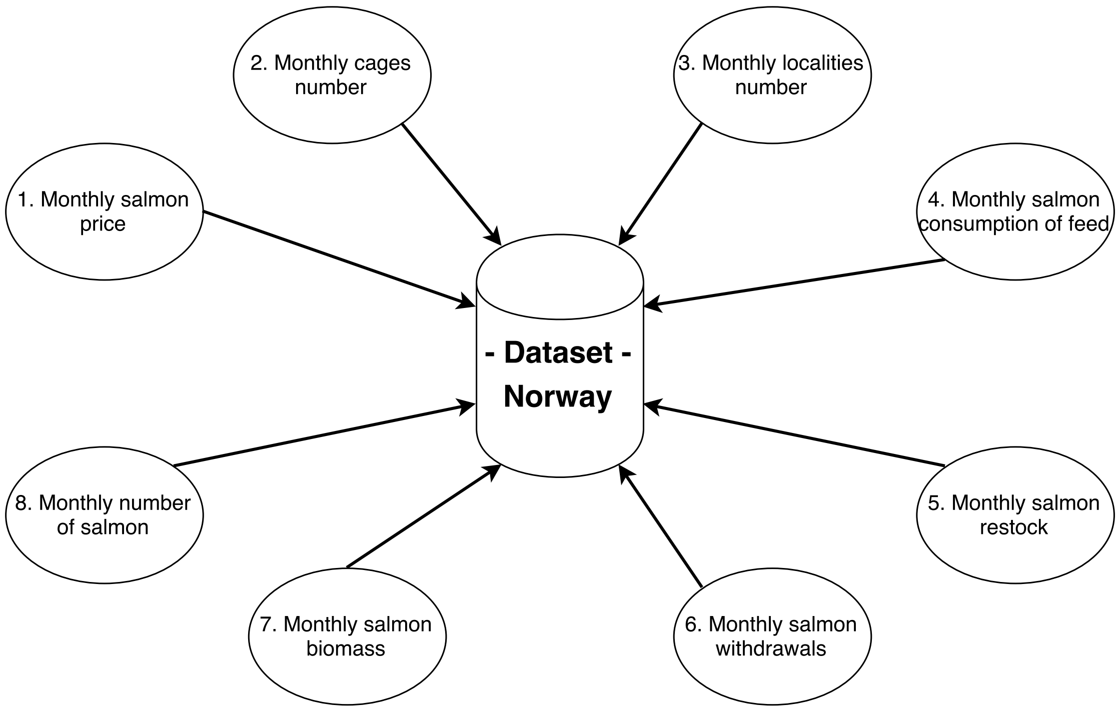

- Dataset - Norway
1. Monthly salmon price
2. Monthly cages number
3. Monthly localities number
4. Monthly salmon consumption of feed
5. Monthly salmon restock
6. Monthly salmon withdrawals
7. Monthly salmon biomass
8. Monthly number of salmon

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

4.2.2 Dataset about single county

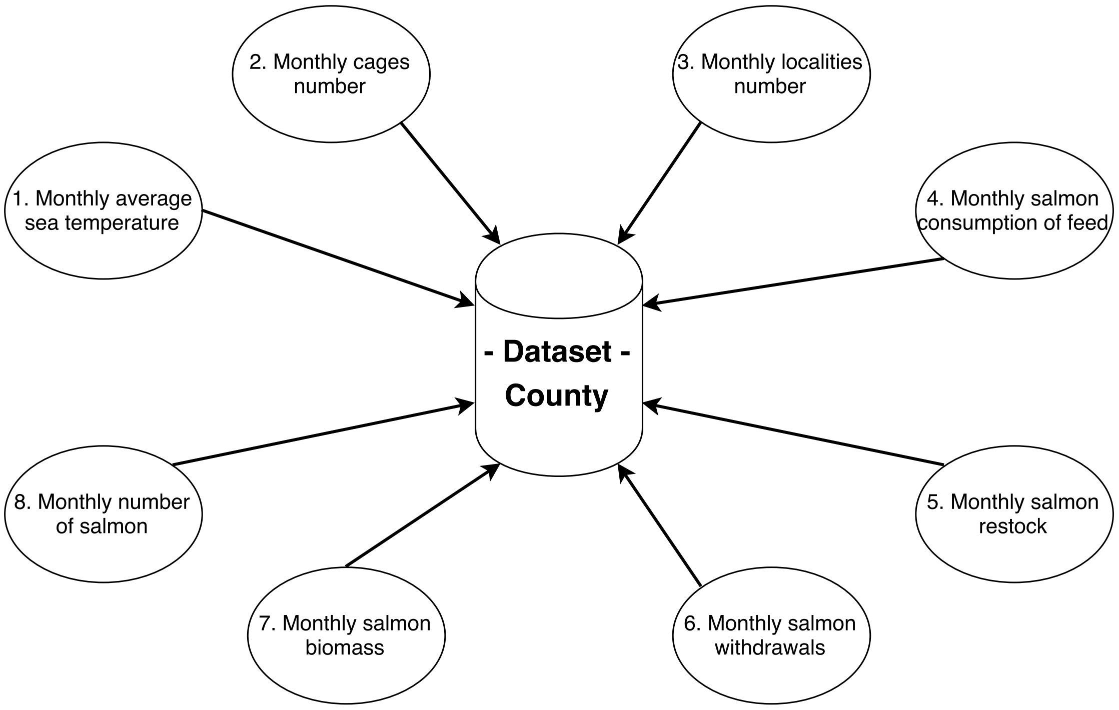

2. Monthly cages number
3. Monthly localities number
1. Monthly average sea temperature
4. Monthly salmon consumption of feed
- Dataset - County
8. Monthly number of salmon
5. Monthly salmon restock
7. Monthly salmon biomass
6. Monthly salmon withdrawals

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

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 contained.

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:

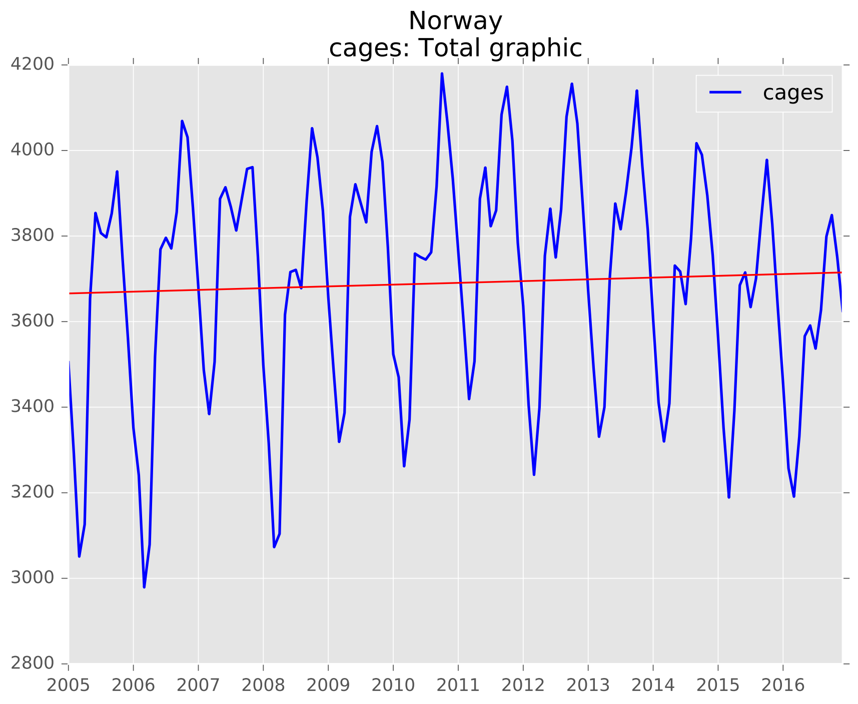


FIGURE 5.1: Total graphic about current input over the whole period.

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:

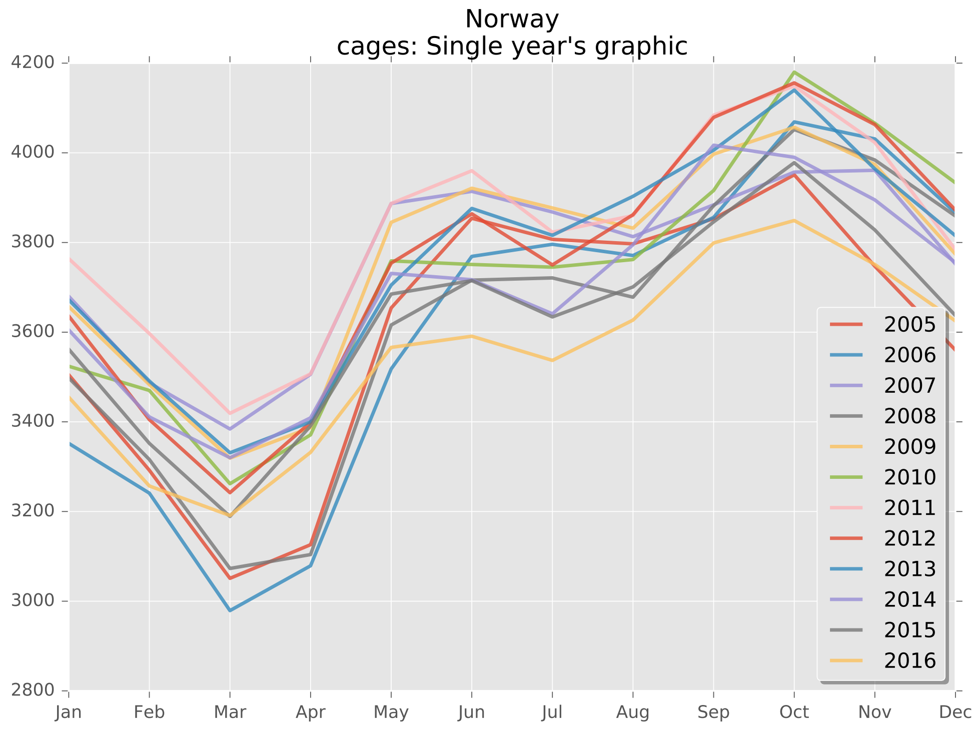


FIGURE 5.2: Graphics for each single year of the current input data.

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:

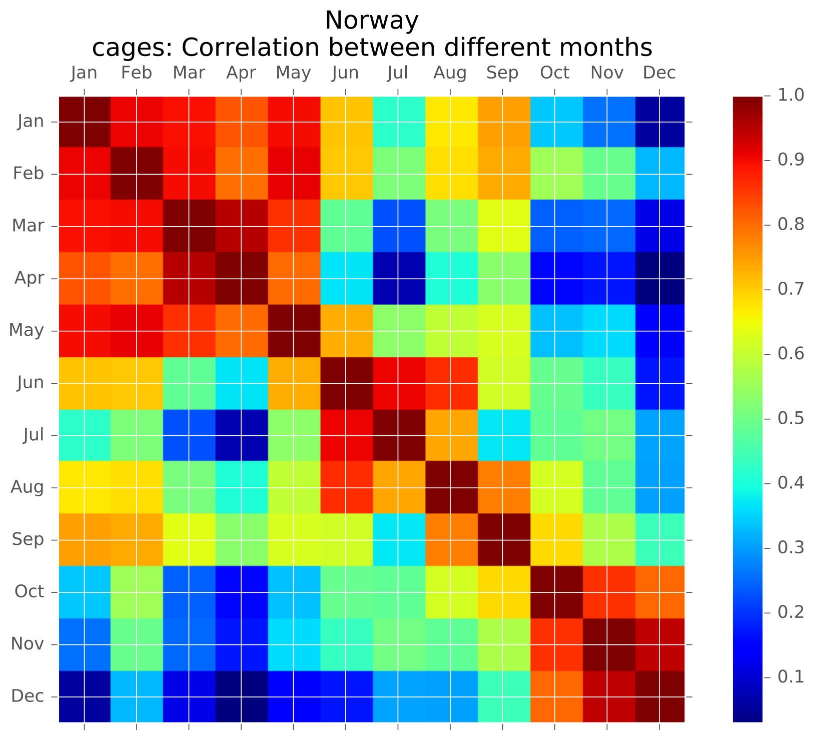


FIGURE 5.3: Correlation matrix between different months of the same input

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:

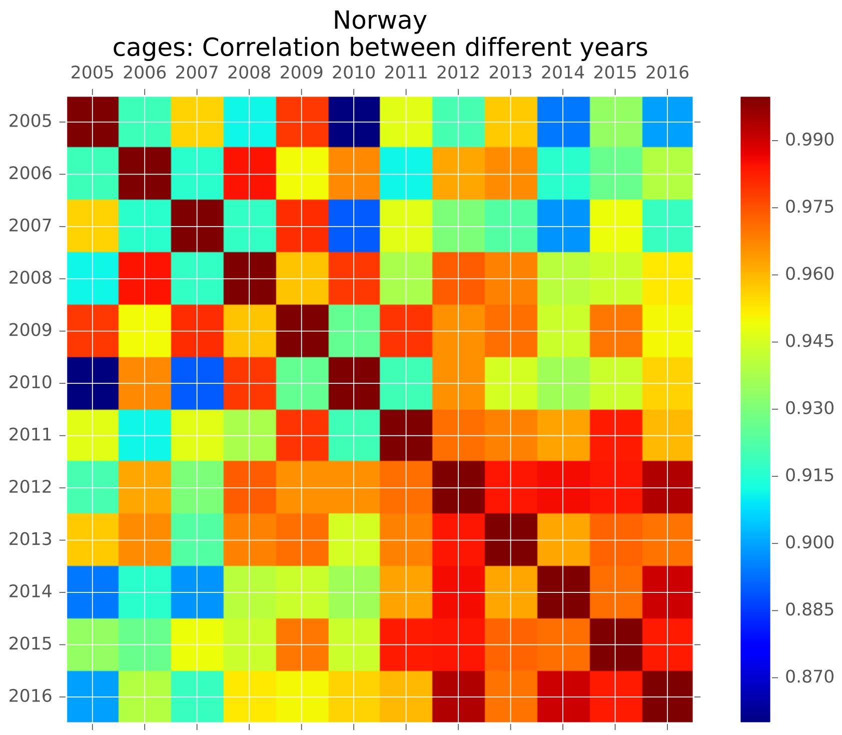


FIGURE 5.4: Correlation matrix between different years of the same input

5.3.6 SIA section V: Single overview

Goal:

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

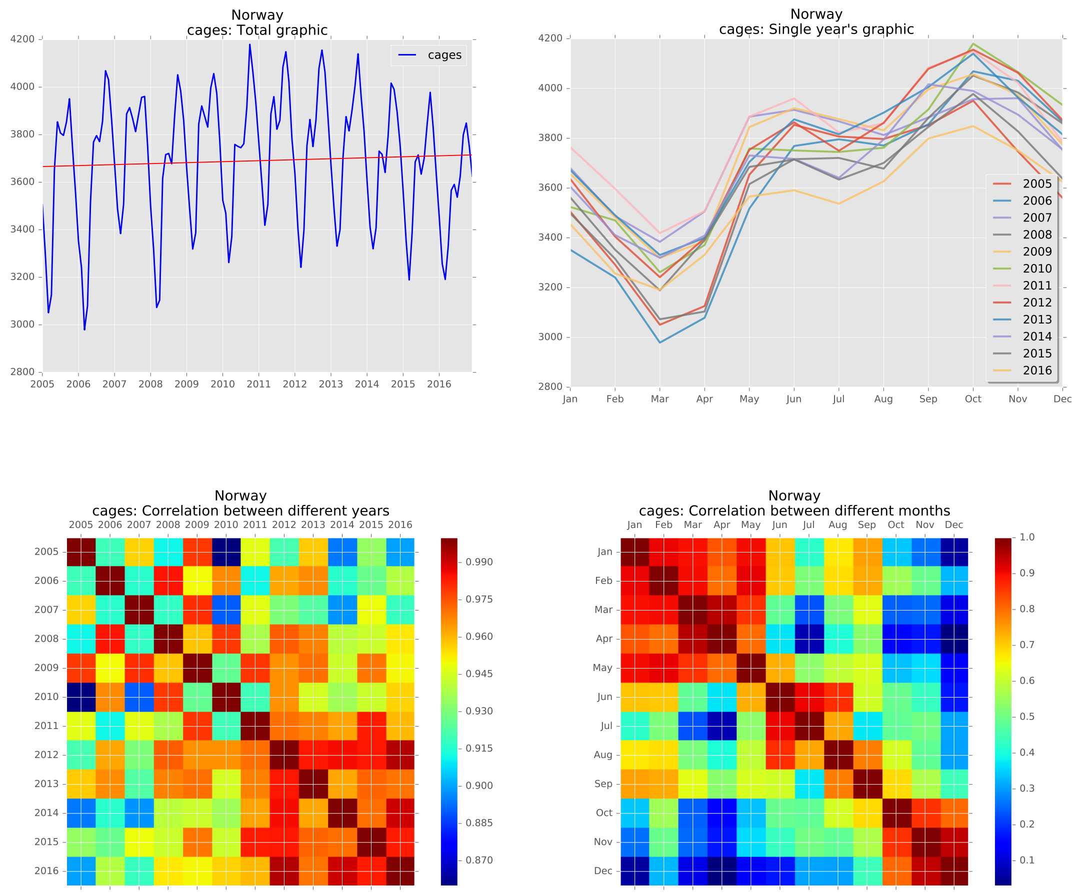
Implementation:

It's possible to check out the full ccommented code in the appendice: [A.7]

Requirements:

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

Results: With this part of the code it's possible to have a single overview image for the current input, that is basically showing and comparing all the graphics that have already been calculated about this input. It looks like this example:



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:

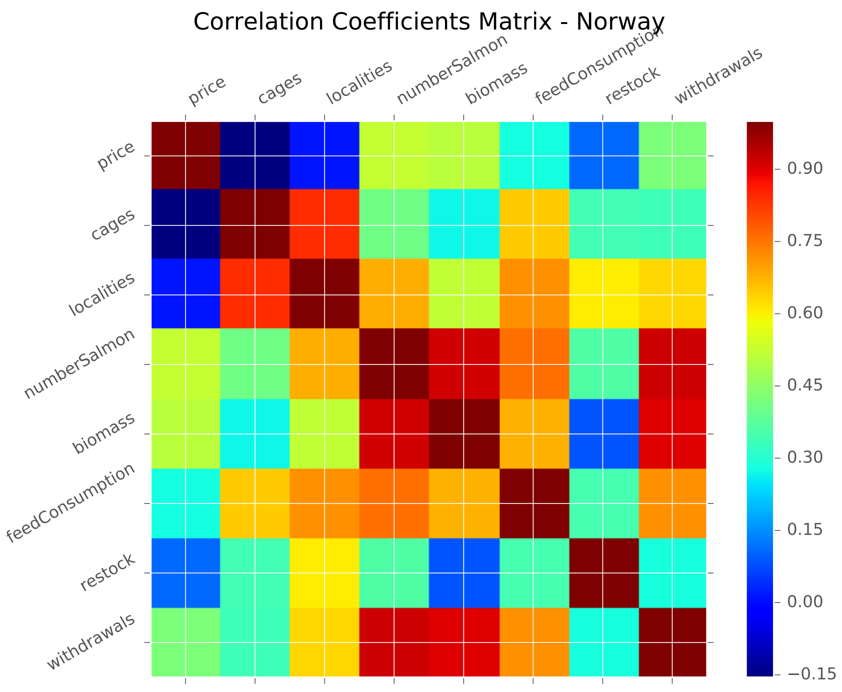


FIGURE 5.7: Correlation matrix between different inputs with data.

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:

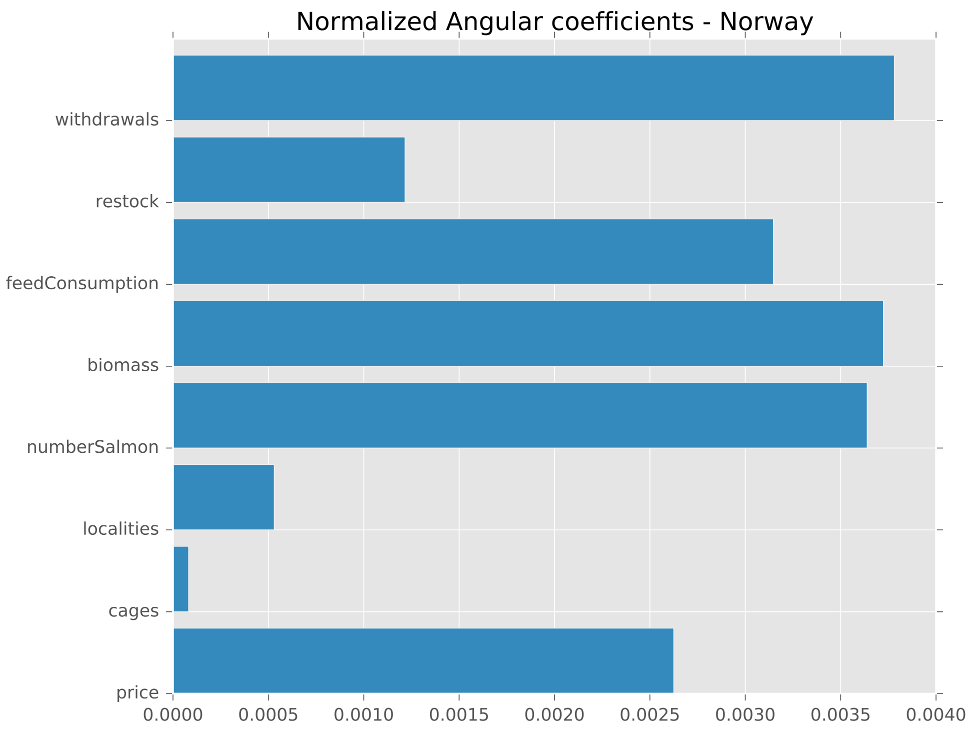


FIGURE 5.8: Normalized angular coefficients of each input's trendline.

5.5 Data Displaying: Map graphic

Goal:
The main goal of this phase is to find a way to visualize some data values on a map graphic.
In this particular the goal is to display data on a real map of Norway, in order to be able to have an overview about all the counties about different parameters.

Requirements:
Since this displaying system was used with data values about Norway's counties, it's not reusable for other countries.
So the main requirements is that is provided a dataset with data about the norwegian counties considered during this work.

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 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:

The library ”shpreader” allows to read the extension file ”.shp”, which in this particular case contains the Norway’s shape.

```
shpreader.Reader().geometries()
```

Then we can display the current shape using the ”pyplot” library .

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

Is possible to set the colors based on the input values with the library ”matplotlib”.

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

Results:

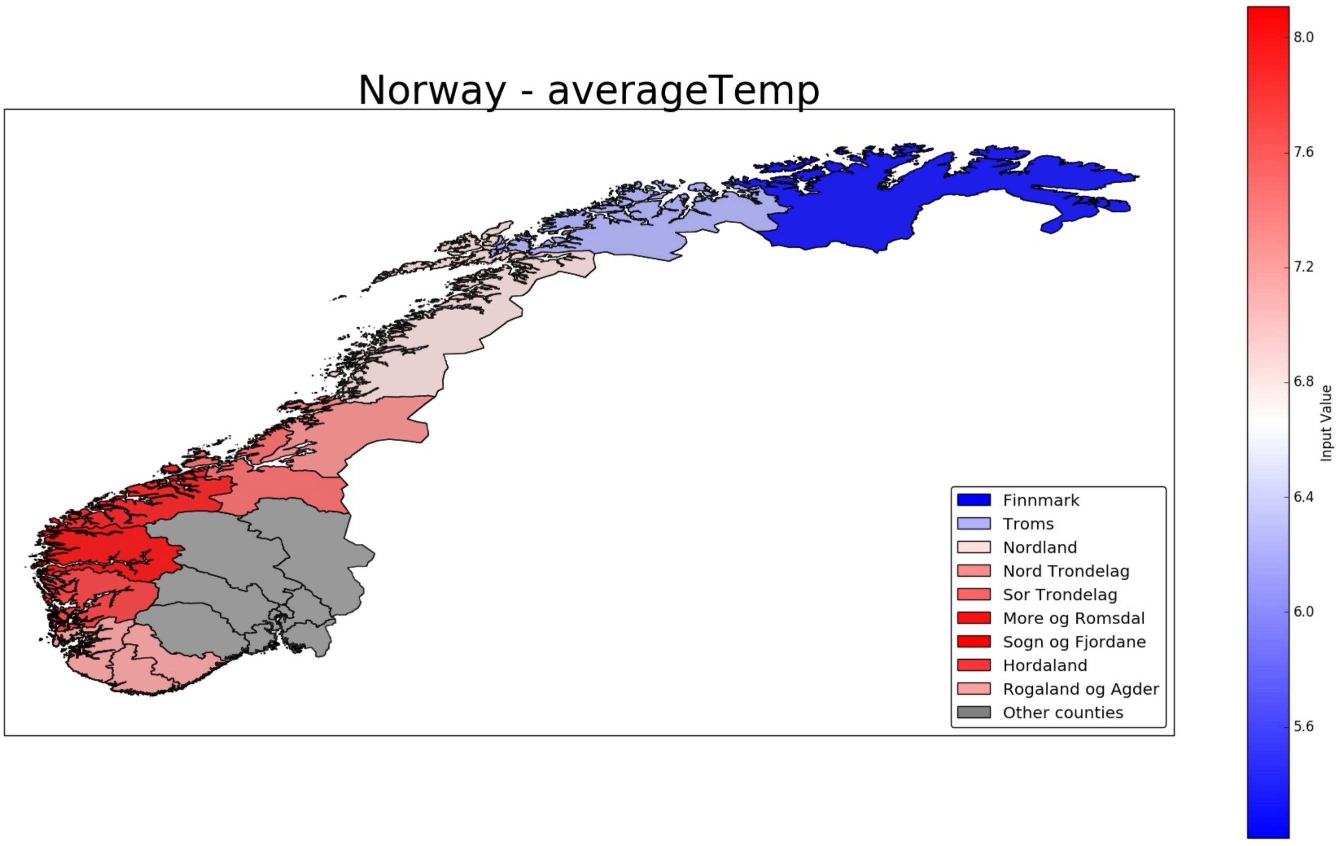


FIGURE 5.9: Average Sea Temperature from 2007 to 2014 in Norway.

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: C.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.

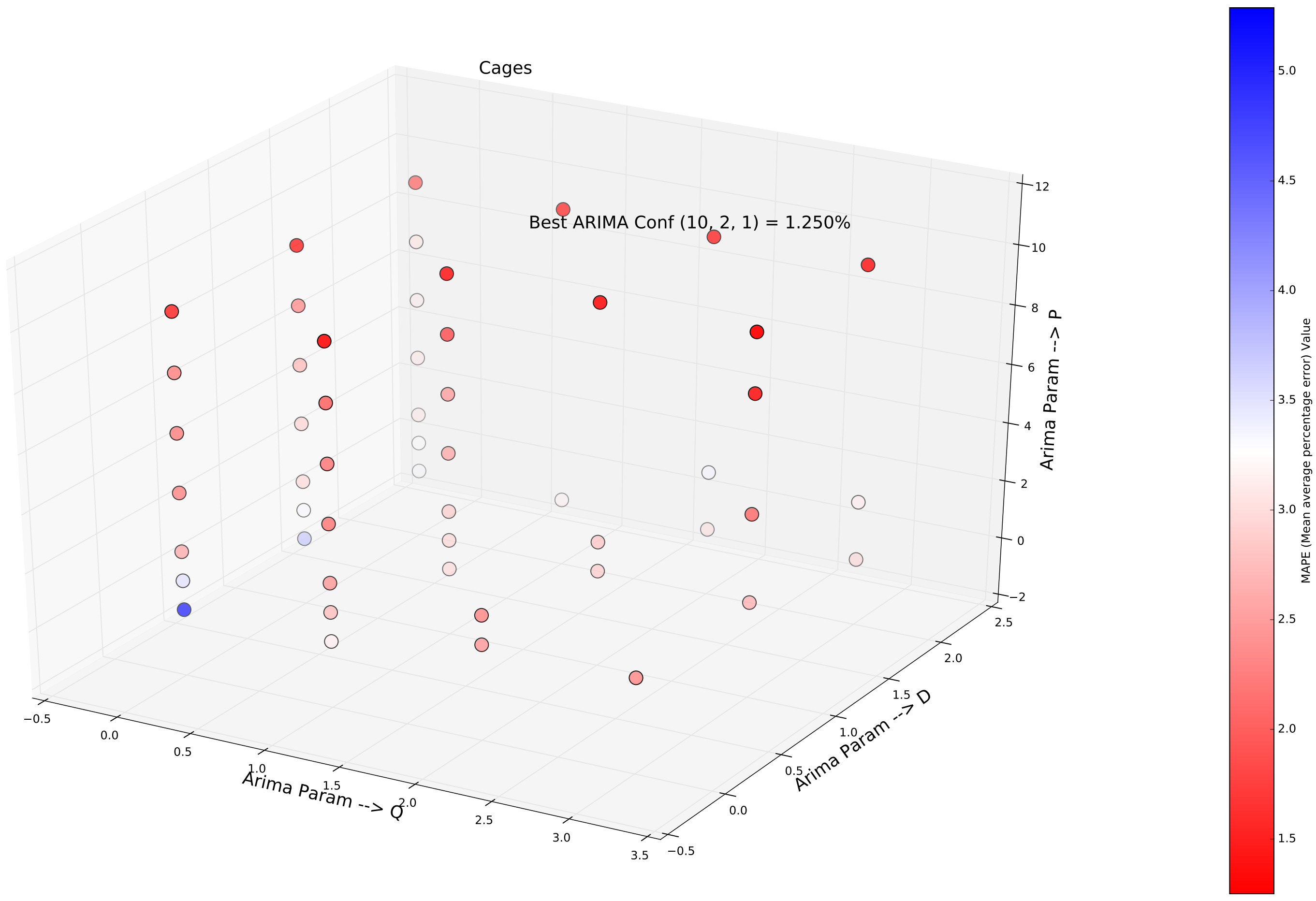


FIGURE 6.1: Graphic that displays different MAPE values for each ARIMA order.

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:

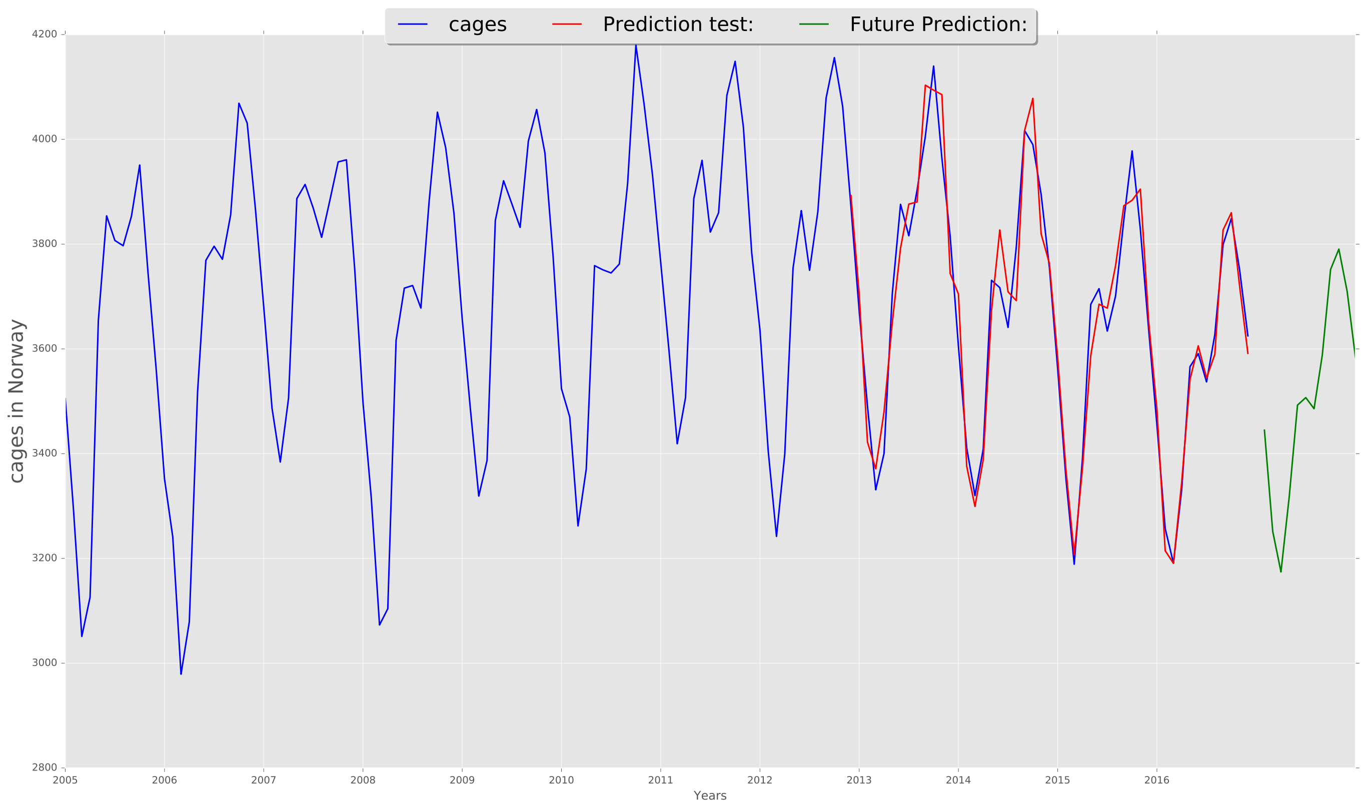


FIGURE 6.2: Graphic that display historic, future and predicted values of a input.

Part III

Results, Evaluations and Conclusions

Chapter 7

Results

The main result of this work is the implemented "Python Analyzer System" itself. It actually provides an automatic way to make an initial analysis and display the results of any input dataset.

Further more has been provided an initial Python implementation of:

- Future Prediction System
- Country Map Displaying System

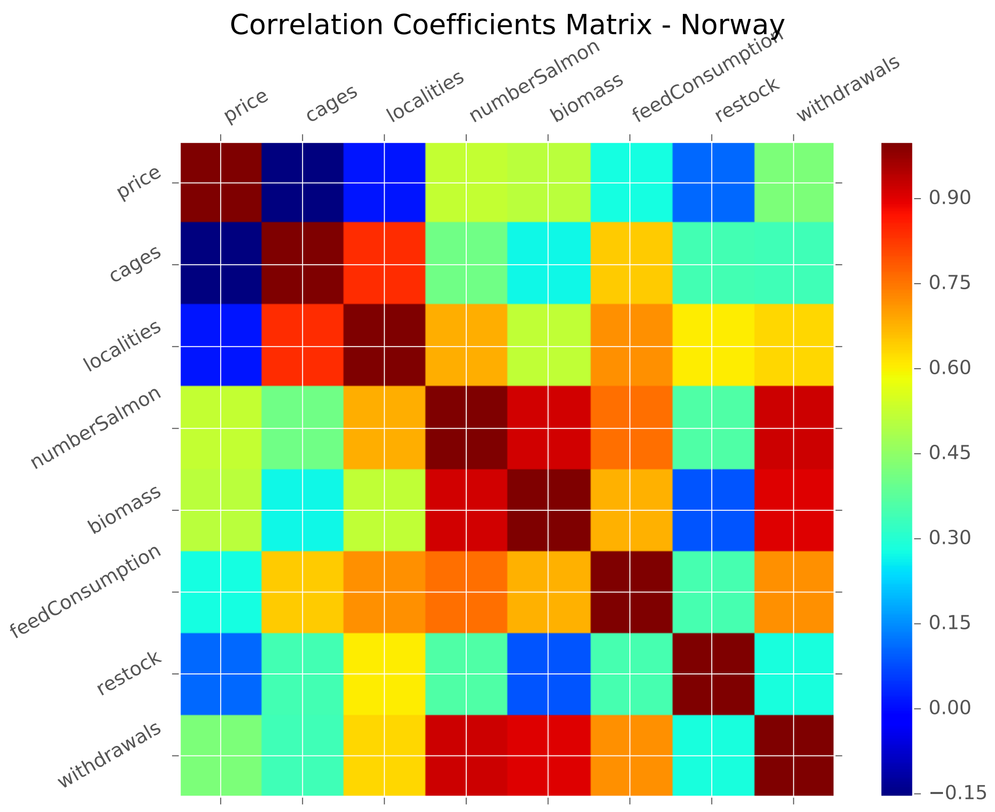


FIGURE 7.1: Correlation matrix between different inputs with data from 2005 to 2016.

INPUTS	Price	Cages	Localities	numberSalmon	biomass	feedConsumption	restock	withdrawals
Price	1	-0.16	0.02	0.52	0.51	0.28	0.11	0.43
Cages	-0.16	1	0.84	0.41	0.27	0.64	0.34	0.34
Localities	0.02	0.84	1	0.68	0.52	0.72	0.6	0.63
numberSalmon	0.52	0.41	0.68	1	0.92	0.76	0.36	0.92
biomass	0.51	0.27	0.52	0.92	1	0.68	0.09	0.91
feedConsumption	0.28	0.64	0.72	0.76	0.68	1	0.35	0.72
restock	0.11	0.34	0.6	0.36	0.09	0.35	1	0.28
withdrawals	0.43	0.34	0.63	0.92	0.91	0.72	0.28	1

TABLE 7.1: Dataset inputs correlation coefficients value.

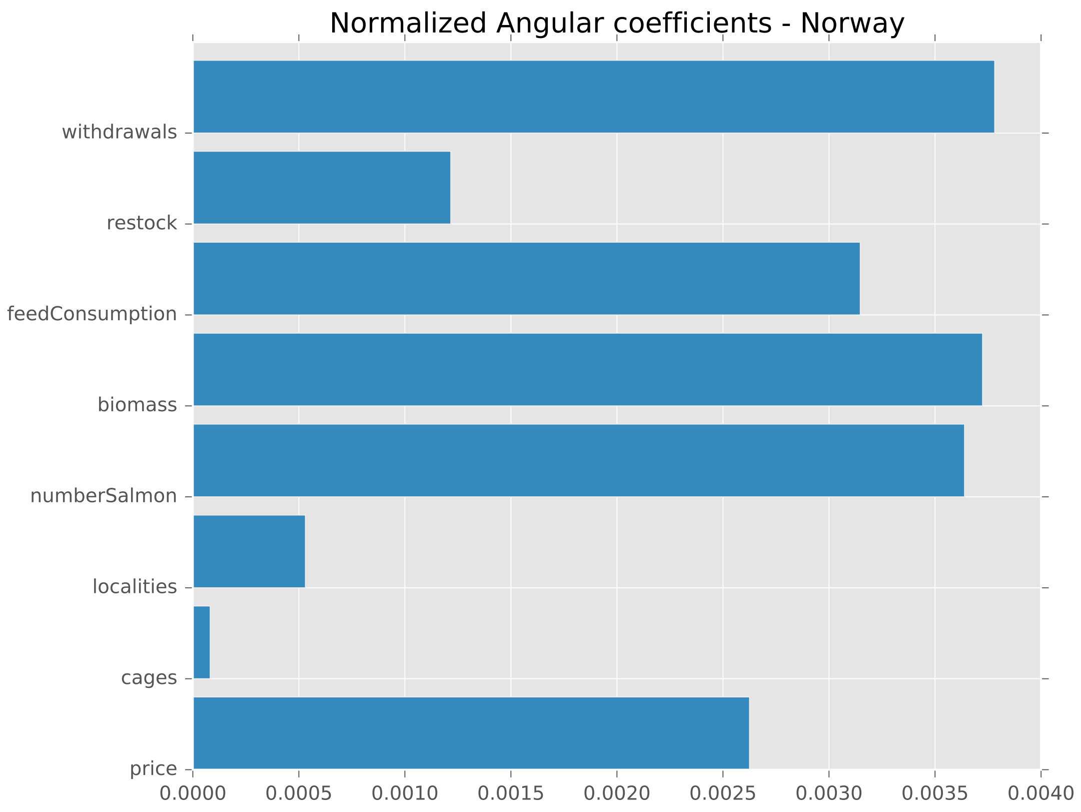


FIGURE 7.2: Normalized angular coefficients of each input's trendline.

Input	Equation	Coeff
Salmon_withdrawals	y=464.755139x+(46295.729945)	464.755139
Salmon_biomass_end_month	y=2832.712270x+(354138.727889)	2832.71227
Salmon_number_end_month	y=1543.298421x+(205325.455772)	1543.298421
Salmon_consumption_of_feed	y=620.070855x+(58330.012273)	620.070855
Salmon_price	y=0.178175x+(22.643654)	0.1781753878
Salmon_restock	y=89.230600x+(13390.363406)	89.2306
Localities	y=0.343533x+(539.979023)	0.343533
Cages	y=0.342834x+(3665.904023)	0.342834

TABLE 7.2: Dataset inputs trendline equation

Input	Normalized equation	Norm Ang Coeffs
Salmon_withdrawals	y=0.003782x+(0.376694)	0.003782
Salmon_biomass_end_month	y=0.003724x+(0.465599)	0.003724
Salmon_number_end_month	y=0.003639x+(0.484184)	0.003639
Salmon_consumption_of_feed	y=0.003147x+(0.296085)	0.003147
Salmon_price	y=0.002625x+(0.333633)	0.002625
Salmon_restock	y=0.001217x+(0.182583)	0.001217
Localities	y=0.000531x+(0.834589)	0.000531
Cages	y=0.000082x+(0.877011)	0.000082

TABLE 7.3: Dataset inputs normalized trendline equation

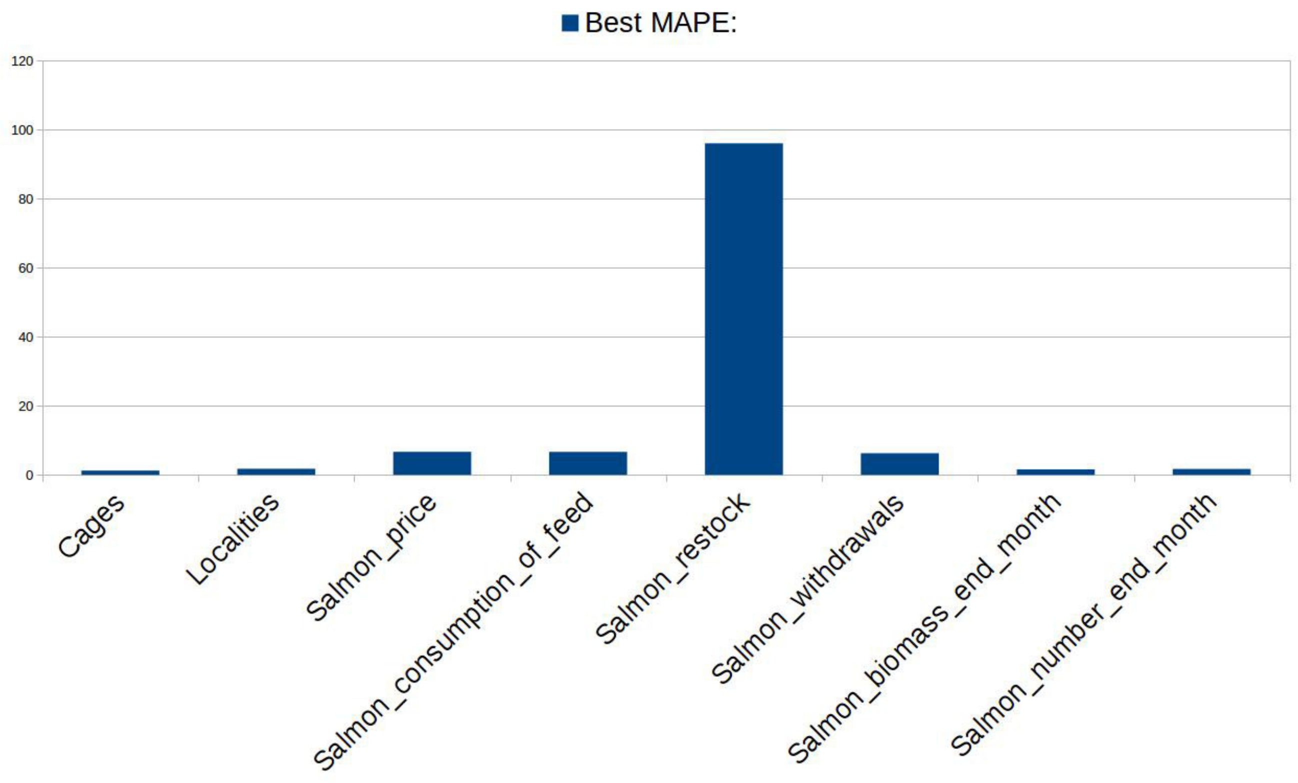


FIGURE 7.3: Lower MAPE with best ARIMA Configuration for each tested input.

Input	ARIMA Conf	MAPE
Cages	(10,2,1)	1.251%
Localities	(10,0,1)	1.779%
Salmon_price	(0,1,1)	6.686%
Salmon_consumption_of_feed	(6,1,0)	6.659%
Salmon_restock	(10,0,1)	96.006%
Salmon_withdrawals	(10,0,1)	6.277%
Salmon_biomass_end_month	(8,1,0)	1.601%
Salmon_number_end_month	(10,2,0)	1.723%

TABLE 7.4: Dataset inputs normalized trendline equation

Months	Cages			Localities			Salmon Biomass			Salmon Number		
	Real	Pred	Error	Real	Pred	Error	Real	Pred	Error	Real	Pred	Error
January 2017	3436	3444.87	0.26%	539.000	543.41	0.82%	738902	732841.36	0.82%	369274	366826.189	0.66%
February 2017	3225	3251.915	0.83%	523.000	529.05	1.16%	712981	709931.42	0.43%	347824	352905.30	1.46%
March 2017	3153	3164.190	0.67%	529.000	534.29	1.00%	667749	679405.11	1.75%	343636	349747.77	1.78%
April 2017		3317.814			549.14			657418.41			369616.83	
May 2017		3492.701			550.64			646850.14			387244.43	
June 2017		3507.062			545.66			653574.18			387630.48	
July 2017		3485.804			560.58			678469.77			384314.00	
August 2017		3588.373			584.55			707646.99			394062.43	
September 2017		3751.633			596.32			734628.28			411164.01	
October 2017		3790.521			589.11			757679.66			411094.09	
November 2017		3710.033			576.75			770838.51			396102.24	
December 2017		3584.505			563.56			771279.10			380399.93	

Months	Consumption of feed			Salmon restock			Salmon Withdrawals			Salmon price		
	Real	Pred	Error	Real	Pred	Error	Real	Pred	Error	Real	Pred	Error
January 2017	109341	98174.28	10.21%	4415	4734.43	7.23%	87609	90488.98	3.29%			
February 2017	88704	77998.20	12.07%	991	6904.51	596.72%	3.29%	101295.55	11.00%			
March 2017	87033	74726.18	14.14%	13594	15427.63	13.49%	109498	101724.09	7.10%			
April 2017		88768.11			39781.36			95032.95				
May 2017		113280.67			39438.14			92065.64				
June 2017		140413.56			22562.89			88775.54				
July 2017		164511.15			20449.85			92643.44				
August 2017		179690.48			39487.67			104102.60				
September 2017		181556.12			49991.91			110419.37				
October 2017		169502.10			31449.69			107588.69				
November 2017		147770.73			11698.23			102943.86				
December 2017		123447.55			7957.45			99561.98				

Chapter 8

Evaluations

Chapter 9

Conclusion

9.1 Summary

9.2 Recommendations to future work

9.2.1 Dataset about single locality

This thesis allows to have a general overview and predictions of values about the aquaculture business in Norway.

But it would be much more useful, in particular for people into the aquaculture business, to use this system to have an overview and predictions of data provided by a single locality of aquaculture.
In this case the system could be used from the owner of the locality to analyze historic values and use the prediction system to have a forecast about some particular parameters.

9.2.2 Visualization of the data

9.2.3 Test prediction system with a bigger dataset

9.2.4 Prediction 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.

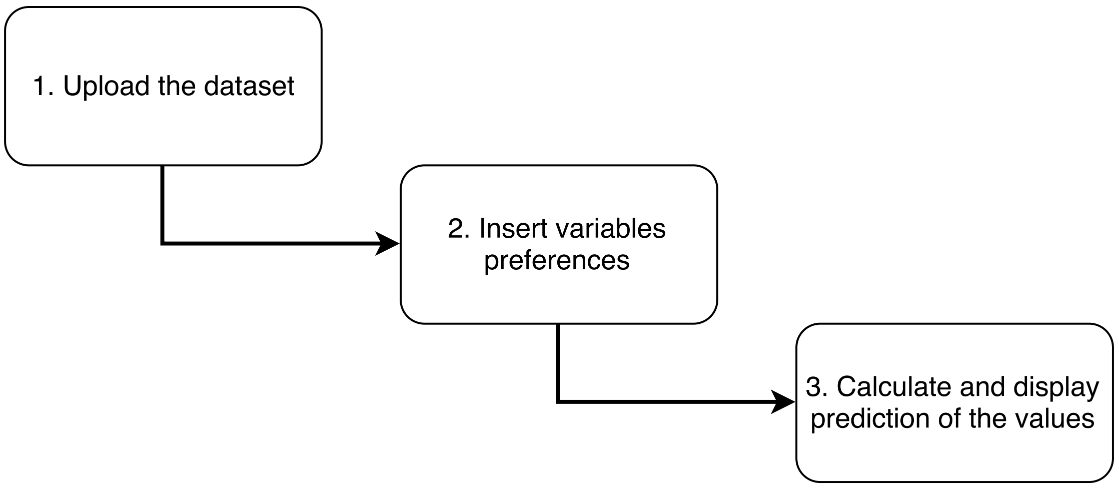

1. Upload the dataset
2. Insert variables preferences
3. Calculate and display prediction of the values

FIGURE 9.1: 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 ”pylab” library will be useful for plot data.

```
import pylab
```

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

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

```
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")
```

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

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

```
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
```

```
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)
```

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.

```python
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.

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

```python
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".

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

Creating the correlation matrix using the already calculated correlation coefficents.

```python
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.

```python

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
```

```
import sys
```

```
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

```
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)
```

```
# Calculatic che correlation coefficent between each year of the input
    dataset
corrRes = np.corrcoef(corr)

mat = np.matrix(corrRes)
dataframe = pd.DataFrame(data=mat.astype(float))
dataframe.to_csv("Results/"+sys.argv[1]+"/Total_Evidences/"+sys.argv[1]+"
    _CorrCoeff.csv", sep=',', header=False, float_format='%.2f', index=
    False)

fig = pyplot.figure()
ax = fig.add_subplot(111)
# Displaying the matrix with the results about correlation coefficents
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')
#cax.set_clim(vmin=0.5, vmax=1)
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

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

pyplot.barh(x, temp)
# Displaying and saving the bar graphic
```

```
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

Prediction System Implementation code

C.1 Evaluating System

C.2 Prediction System

Appendix D

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