A Comparative Analysis Of Ireland's Beef Sector Including Forecasting Prices, As Well As Sentiment Analysis.

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Link to GitHub Repository

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Abstract

This paper presents a rigorous comparative analysis of the beef sector in Ireland, encompassing a wide range of key dimensions, including production, consumption, and trade. By leveraging both historical and contemporary data, the paper employs various forecasting models to project future beef prices in the Irish market. Additionally, the study integrates sentiment analysis to extract valuable insights into public perception of the beef industry. Through a combination of quantitative and qualitative analysis, the paper provides a comprehensive understanding of the industry, outlining key trends and offering strategic recommendations for relevant stakeholders. The research was carried out by Ronan Downes, with the goal of contributing to ongoing discussions around the optimisation of Ireland's beef sector.

Chapter 1

Introduction

Overview of the purpose and scope of the analysis Research question and provide Background information

The full path of the directory is C:which contains the project Jupyter Notebook a .git folder, holding version control information. The "arch" folder contains archived content while the remaining folders "css", "images", "precipitation$_{d}ata”,”processed_{d}ata”, and”temperature_{d}ata”containdatafilesorotherresourcesrelatedtothepr$

Chapter 2

Data Cleaning and pre-processing

2.1 Live Animal Cattle stock data stucture

2.2 Structure of the data

Taking a higher-level view of the data before performing detailed exploratory data analysis (EDA) it helps to understanding the dataset's size and shape, as well as any high-level patterns or trends that may be present. The output of df.shape tells us that the dataset contains 1708 rows and 14 columns which is a small number of data points of low dimensionality. The scope of the analysis need not be reconsidered (Páez and Boisjoly 2023).

dC_moD^	niamoD^	dC_aerA^	aerA^	edoCE^	tnemelE^	edoC_metI^	metI^	edoC rY^	raeY^	t
QCL	Livestock	724	Spain	5111	Stocks	2111	Cattle	1978	1978	I
QCL	Livestock	703	Slovakia	5111	Stocks	2111	Cattle	2006	2006	I
QCL	Livestock	348	Hungary	5111	Stocks	2111	Cattle	1962	1962	I

2.3 The df.nunique() method

The df.nunique() method was used to generate table . Seven of the Columns have unique value and do not provide useful information for exploratory data analysis (EDA). These columns refereed to as constant due to their absents of variation and can have no predictive value in our machine learning model.

Nevertheless, data cleaning best practice is to exercise caution before dropping columns in case they are constant due to errors or inconsistencies or if they are constant with missing data everywhere in the data. Therefore, it is still a good practice to identify these columns and verify that they do not contain any useful information before removing them from the dataset.

Viewing a sizable sample of 40 datapoints where the constant string value of 'Crops and livestock products' has been replaced with

To show columns with all exact same entries, you can use the nunique() method to count the number of unique values in each column. If the result is 1, it means all entries in the column are the same. Here's an example code snippet that shows how to do this for a pandas DataFrame called df: This code first creates

Table 2.1: Number of unique values in each column. There are 27 European Union (EU) countries so the value of 28 is not expected for Area. There is a mismatch between the expected number of unique values in the "Area" column and the actual count. Since the data includes three unique values for Belgium ("Belgium", "Luxembourg", and "Belgium-Luxembourg"), the actual count is one higher than expected.

Column	Unique Values
Domain Code	1
Domain	1
Area Code (M49)	28
Area	28
Element Code	1
Element	1
Item Code (CPC)	1
Item	1
Year Code	61
Year	61
Unit	1
Value	1365
Flag	3
Flag Description	3

a list comprehension that iterates over all columns in df and checks if the number of unique values in each column is equal to 1. The resulting list same$_{e}ntry_{c}olscontainsthenamesofallcolumnswhereallentriesarethesame$.

You can modify this code to fit your specific DataFrame and column name

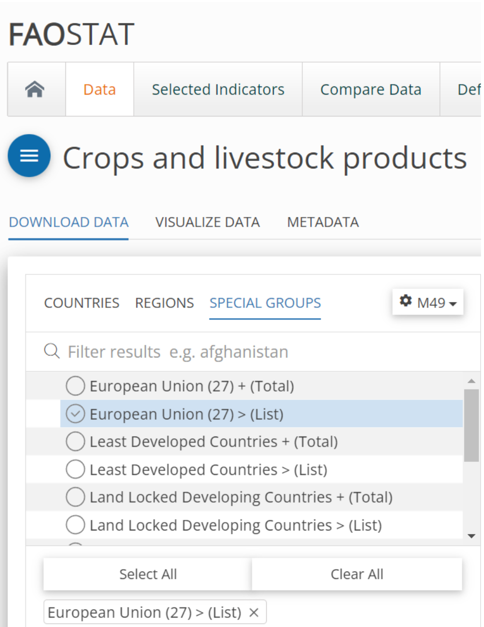
2.4 Casting the Value floats to integer

s

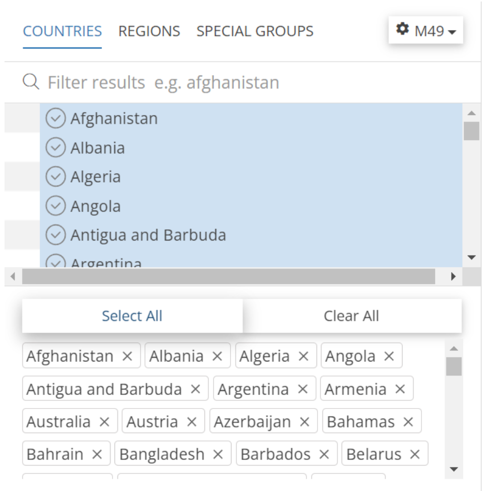
It is better to have data stored in the most appropriate data types for readability, memory and computational reasons. Integer data types use less memory than float data types, so storing integer data in integer form can save memory and speed up processing times. But incorrectly modelling discreet values as real numbers has profound implications for mathematical outcomes in feature engineering. There is a distinction between discrete mathematics, which deals with countable quantities such as integers, and continuous mathematics, which deals with uncountable quantities such as real numbers (Van Der Walt, Colbert, and Varoquaux 2011).

When working with discrete data, it is often important to use integer data types to ensure that mathematical operations are well-defined and that rounding errors and other issues do not arise. On the other hand, continuous data is typically represented using floating-point data types, which can represent a wider range of values but are subject to rounding and precision errors that can affect the results of mathematical operations.

In the case of cattle count data, it is clearly a countable quantity so long as the animals are alive as they are for this dataset and will be represented using the integer data type. Therefore we **cast the data from a float to an integer** to make the most efficient use of memory and to avoid potential inaccuracies when working with the data.



(a) Filtering to the European Union (EU) 27 on FAOSTAT leads to spurious country data and if this is varient will cause problems



(b) downloading supersets for the 195 recognised independent states in the world and data cleaning techniques will be adopted for the rest of the data retrieval

Figure 2.1: The decision to download a larger dataset than necessary was made to ensure a high level of certainty in the workflow, given the relatively small size of the datasets involved. By having a larger dataset, it may be easier to identify and correct any errors or inconsistencies that may arise during the data analysis process.

2.5 Categorical flagging for official, estimated, unofficial and missing figures

Categorical flagging for official, estimated, unofficial and missing figures can impact statistical analysis and needed be considered here. The flag descriptions for reported stock figures are official, estimated, unofficial or are missing and all are represented in the FAOSTAT dataset (Contu et al. 2019). Two questions arose:

- Will estimation and unofficially sourced data contaminate the study or broaden confidence intervals?
- What is the geographical and temporal distribution of missing figures?

A list of countries with any missing entries reads Austria, Belgium, Belgium-Luxembourg, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden

Belgium-Luxembourg is not a country and it was discovered to be some sort of text processing concatenation error and was dropped from the dataset.

2.6 Data quality processing

After loading the live cattle stock data into a pandas dataframe, we observed missing values. This data reflects the number of cattle in stock or alive in a country during a particular year. For example, the dataset shows that there were 6,649,310 cattle in stock in Ireland in 2021. As the number of cattle in stock is an important variable for our study, it is crucial to carefully consider the missing values. If a significant number of missing values correspond to Ireland and are recent, it could impact our research question. To gain a better understanding of the missing values, we quantified and analyzed them. Table 2.5 shows that 319 values are missing, which accounts for 18.7% of the data. This percentage is too high to delete records without a valid reason. Figure provides a visual representation of the missing data.

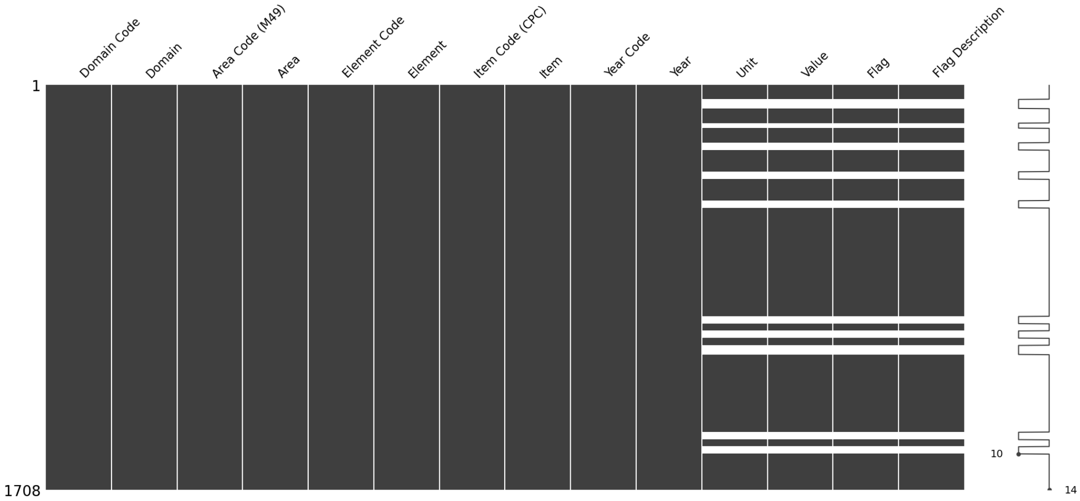


Figure 2.2: The figure shows 10 unnamed countries represented by horizontal strip having a significant proportion of missing data. The missingno package provides a matrix() function to create a missing value matrix plot. This plot visualizes the missingness in the data by showing where values are missing with white bars.

2.7 data completeness analysis by country

There are only 10 countries with missing data as seen in table so these could be filtered out in that time interval but as suggested farming in the 20th centuary was significantly different than now so data from any country back then is low in relevance for modelling and prediction.

Drop Belgium-Luxembourg

2.8 data completeness analysis by year

In order to better understand the dataset, we performed a data completeness analysis by year. The data covers the number of cattle in stock in the European Union (EU) member countries from 1961 to 2021. To assess how the missing values are distributed over time, we created a new table that tallied the number of missing values in each row of the dataset, grouped by year. We then visualised this distribution using a bar chart, which can be found in Figure 2.3. The last significant improvements in completeness step was from 1999 to 2000 and for this and the fact that beef farming technology has changed so much since the 20th centuary the decision is made to

2.9 Dropping unwanted atributes

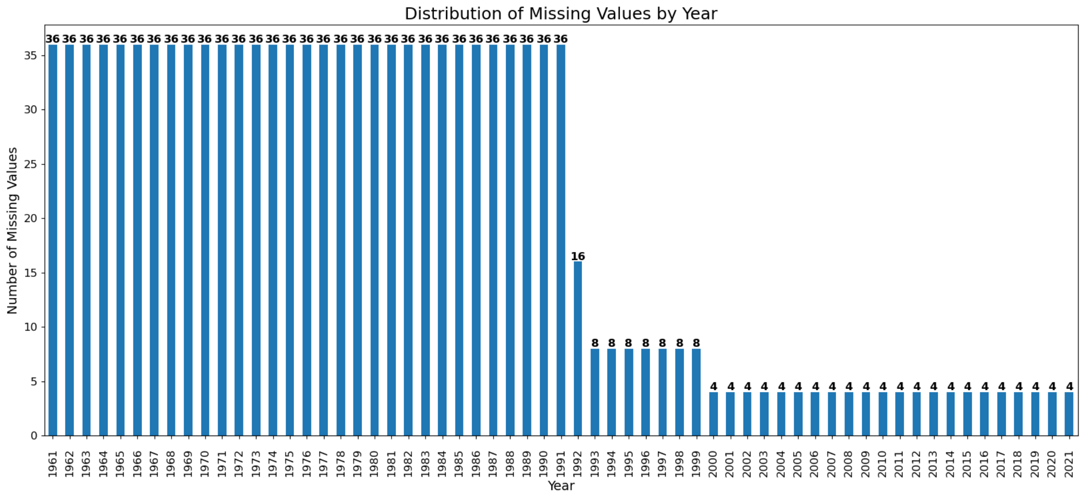


Figure 2.3: Distribution of missing values by year. The initial data studied gives the number of cattle in stock in the European Union (EU) member countries. The data spans from 1961 to 2021 and so it is natural to ascertain how the errors distribute across that interval. We created a new table that counted the number of missing values in each row of the dataset, grouped by year. Then we made a bar chart that showed the distribution of missing values by year

Table 2.2: Livestock stocks of cattle in various countries

Domain Code	Domain	Area Code (M49)	Area	Element Code	Element	Item Code (CPC)	Item	Year Code
Livestock	246	Finland	5111	Stocks	2111	Cattle	2011	2011
300	Greece	5111	Stocks	2111	Cattle	2021	2021	Head
Slovenia	5111	Stocks	2111	Cattle	2020	2020	Head	48561
5111	Stocks	2111	Cattle	2018	2018	Head	414000	A QC
Stocks	2111	Cattle	1987	1987			QCL	Livest
2111	Cattle	1996	1996	Head	1988810	A QCL	Livestock	380
Cattle	2019	2019	Head	6377230	A QCL	Livestock	196	Cypru
2009	2009	Head	54097	A QCL	Livestock	372	Ireland	5111
1998	Head	6881600	A QCL	Livestock	100	Bulgaria	5111	Stock
Head	1656317	A QCL	Livestock	246	Finland	5111	Stocks	2111
1252300	A QCL	Livestock	246	Finland	5111	Stocks	2111	Cattle
A QCL	Livestock	100	Bulgaria	5111	Stocks	2111	Cattle	1971
Livestock 348	Hungary	5111	Stocks	2111	Cattle	1989	1989	Head
QCL	Livestock	380	Italy	5111	Stocks	2111	Cattle	2007
QCL	Livestock	56	Belgium	5111	Stocks	2111	Cattle	1964
QCL	Livestock	196	Cyprus	5111	Stocks	2111	Cattle	2016
QCL	Livestock	380	Italy	5111	Stocks	2111	Cattle	1998
QCL	Livestock	191	Croatia	5111	Stocks	2111	Cattle	2020
QCL	Livestock	752	Sweden	5111	Stocks	2111	Cattle	1988
QCL	Livestock	300	Greece	5111	Stocks	2111	Cattle	2015
QCL	Livestock	250	France	5111	Stocks	2111	Cattle	2009
QCL	Livestock	372	Ireland	5111	Stocks	2111	Cattle	1970
QCL	Livestock	442	Luxembourg	5111	Stocks	2111	Cattle	2005
QCL	Livestock	724	Spain	5111	Stocks	2111	Cattle	2021
QCL	Livestock	191	Croatia	5111	Stocks	2111	Cattle	2006
QCL	Livestock	56	Belgium	5111	Stocks	2111	Cattle	2016
QCL	Livestock	58	Belgium-Luxembourg	5111	Stocks	2111	Cattle	2013
QCL	Livestock	724	Spain	5111	Stocks	2111	Cattle	1967
QCL	Livestock	56	Belgium	5111	Stocks	2111	Cattle	2008
QCL	Livestock	246	Finland	5111	Stocks	2111	Cattle	2020
QCL	Livestock	470	Malta	511 1	Stocks	2111	Cattle	1999
QCL	Livestock	528	Netherlands	5111	Stocks	2111	Cattle	1968
QCL	Livestock	528	Netherlands	5111	Stocks	2111	Cattle	1973
QCL	Livestock	246	Finland	5111	Stocks	2111	Cattle	1989
QCL	Livestock	348	Hungary	5111	Stocks	2111	Cattle	2021
QCL	Livestock	348	Hungary	5111	Stocks	2111	Cattle	1993
QCL	Livestock	250	France	5111	Stocks	2111	Cattle	1974
QCL	Livestock	208	Denmark	5111	Stocks	2111	Cattle	1965
QCL	Livestock	100	Bulgaria	5111	Stocks	2111	Cattle	1989

nan	nan	nan				
13	QCL	CLP	40	Austria	5111	Stocks
2.6242e+06	A	Official figure				
1520	QCL	CLP	703	Slovakia	5111	Stocks
446112	A	Official figure				
4	QCL	CLP	40	Austria	5111	Stocks
2.35027e+06	A	Official figure				
871	QCL	CLP	372	Ireland	5111	Stocks
6.2455e+06	A	Official figure				
353	QCL	CLP	196	Cyprus	5111	Stocks
54097	A	Official figure				
809	QCL	CLP	348	Hungary	5111	Stocks
1.887e+06	A	Official figure				
728	QCL	CLP	276	Germany	5111	Stocks
1.19491e+07	A	Official figure				
354	QCL	CLP	196	Cyprus	5111	Stocks
54715	A	Official figure				
393	QCL	CLP	203	Czechia	5111	Stocks
nan	nan	nan				
1574	QCL	CLP	705	Slovenia	5111	Stocks
472878	A	Official figure				
1335	QCL	CLP	616	Poland	5111	Stocks
5.96069e+06	A	Official figure				
1053	QCL	CLP	440	Lithuania	5111	Stocks
nan	nan	nan				
369	QCL	CLP	203	Czechia	5111	Stocks
nan	nan	nan				
1205	QCL	CLP	470	Malta	5111	Stocks
19233	A	Official figure				
455	QCL	CLP	208	Denmark	5111	Stocks
2.221e+06	A	Official figure				
217	QCL	CLP	100	Bulgaria	5111	Stocks
638238	A	Official figure				
1035	QCL	CLP	428	Latvia	5111	Stocks
398990	A	Official figure				
1218	QCL	CLP	470	Malta	5111	Stocks
14290	A	Official figure				
1601	QCL	CLP	724	Spain	5111	Stocks
4.40784e+06	A	Official figure				
1325	QCL	CLP	616	Poland	5111	Stocks
5.48329e+06	A	Official figure				
607	QCL	CLP	246	Finland	5111	Stocks
840740	A	Official figure				
1002	QCL	CLP	428	Latvia	5111	Stocks
nan	nan	nan				
1140	QCL	CLP	442	Luxembourg	5111	Stocks
189674	A	Official figure				
796	QCL	CLP	348	Hungary	5111	Stocks
1.88336e+06	A	Official figure				
346	QCL	CLP	196	Cyprus	5111	Stocks
58156	A	Official figure				
172	QCL	CLP	58	Belgium-Luxembourg	5111	Stocks
nan	nan	nan				
374	QCL	CLP	203	Czechia	5111	Stocks
nan	nan	nan				
823	QCL	CLP	348	Hungary	5111	Stocks
1.571e+06	A	Official figure				
1060	QCL	CLP	440	Lithuania	5111	Stocks
nan	nan	nan				
137	QCL	CLP	58	Belgium-Luxembourg	5111	Stocks
3.01071e+06	A	Official figure				
966	QCL	CLP	380	Italy	5111	Stocks
6.09147e+06	A	Official figure				

Table 2.4: Features and Data Types for Live Animal Cattle stock

Feature	**Data Type**
Area Code (M49)	int64
Area	object
Element Code	int64
Element	object
Item Code (CPC)	int64
Item	object
Year Code	int64
Year	int64
Unit	object
Value	float64
Flag	object
Flag Description	object

Table 2.5: 18.7% of cattle data missing in 1961 to 2021 time period

Column	**NAs**
Domain Code	N/A
Domain	0
Area Code (M49)	0
Area	0
Element Code	0
Element	0
Item Code (CPC)	0
Item	0
Year Code	0
Year	0
Unit	319
Value	319
Flag	319
Flag Description	319

	Dom_Cd	Domain	Area_Cd	Area	ECode	Element	Item_Code	Item	Yr Code	Year
538	QCL	Livestock	233	Estonia	5111	Stocks	2111	Cattle	2011	2011
1375	QCL	Livestock	620	Portugal	5111	Stocks	2111	Cattle	1994	1994
769	QCL	Livestock	300	Greece	5111	Stocks	2111	Cattle	1998	1998
693	QCL	Livestock	276	Germany	5111	Stocks	2111	Cattle	1983	1983
179	QCL	Livestock	58	Bel_Lux	5111	Stocks	2111	Cattle	2018	2018
1172	QCL	Livestock	470	Malta	5111	Stocks	2111	Cattle	1974	1974
1580	QCL	Livestock	705	Slovenia	5111	Stocks	2111	Cattle	2016	2016
341	QCL	Livestock	196	Cyprus	5111	Stocks	2111	Cattle	1997	1997
1134	QCL	Livestock	442	Luxembourg	5111	Stocks	2111	Cattle	1997	1997
1144	QCL	Livestock	442	Luxembourg	5111	Stocks	2111	Cattle	2007	2007
592	QCL	Livestock	246	Finland	5111	Stocks	2111	Cattle	2004	2004
257	QCL	Livestock	191	Croatia	5111	Stocks	2111	Cattle	1974	1974
369	QCL	Livestock	203	Czechia	5111	Stocks	2111	Cattle	1964	1964
147	QCL	Livestock	58	Bel_Lux	5111	Stocks	2111	Cattle	1986	1986
1362	QCL	Livestock	620	Portugal	5111	Stocks	2111	Cattle	1981	1981
1130	QCL	Livestock	442	Luxembourg	5111	Stocks	2111	Cattle	1993	1993
1484	QCL	Livestock	703	Slovakia	5111	Stocks	2111	Cattle	1981	1981
440	QCL	Livestock	208	Denmark	5111	Stocks	2111	Cattle	1974	1974
1394	QCL	Livestock	620	Portugal	5111	Stocks	2111	Cattle	2013	2013
1478	QCL	Livestock	703	Slovakia	5111	Stocks	2111	Cattle	1975	1975
1363	QCL	Livestock	620	Portugal	5111	Stocks	2111	Cattle	1982	1982
449	QCL	Livestock	208	Denmark	5111	Stocks	2111	Cattle	1983	1983
1024	QCL	Livestock	428	Latvia	5111	Stocks	2111	Cattle	2009	2009
851	QCL	Livestock	348	Hungary	5111	Stocks	2111	Cattle	2019	2019
928	QCL	Livestock	380	Italy	5111	Stocks	2111	Cattle	1974	1974
1276	QCL	Livestock	528	Netherlands	5111	Stocks	2111	Cattle	2017	2017
161	QCL	Livestock	58	Bel_Lux	5111	Stocks	2111	Cattle	2000	2000
1568	QCL	Livestock	705	Slovenia	5111	Stocks	2111	Cattle	2004	2004
1301	QCL	Livestock	616	Poland	5111	Stocks	2111	Cattle	1981	1981
701	QCL	Livestock	276	Germany	5111	Stocks	2111	Cattle	1991	1991
1468	QCL	Livestock	703	Slovakia	5111	Stocks	2111	Cattle	1965	1965
672	QCL	Livestock	276	Germany	5111	Stocks	2111	Cattle	1962	1962
1018	QCL	Livestock	428	Latvia	5111	Stocks	2111	Cattle	2003	2003
41	QCL	Livestock	40	Austria	5111	Stocks	2111	Cattle	2002	2002
29	QCL	Livestock	40	Austria	5111	Stocks	2111	Cattle	1990	1990
740	QCL	Livestock	300	Greece	5111	Stocks	2111	Cattle	1969	1969
166	QCL	Livestock	58	Bel_Lux	5111	Stocks	2111	Cattle	2005	2005
483	QCL	Livestock	208	Denmark	5111	Stocks	2111	Cattle	2017	2017
1612	QCL	Livestock	724	Spain	5111	Stocks	2111	Cattle	1987	1987
193	QCL	Livestock	100	Bulgaria	5111	Stocks	2111	Cattle	1971	1971

Table 2.6: Livestock stocks in various countries, with a focus on cattle. Each row corresponds to a particular country, with information on the year, unit, and number of cattle stocks. Some rows also include information on the reliability or official status of the data (indicated by the "Flag" column).

Chapter 3

near end working

Appendix A

Deflator

In economics, a deflator is a measure used to adjust nominal values for inflation, allowing for comparison with real, inflation-adjusted values. The deflator is calculated by dividing a nominal value (such as GDP or a price index) by a price index representing the general level of prices in the economy.

In Exploratory Data Analysis (EDA), deflators can be used to adjust for inflation when analyzing historical data. For example, if you are analyzing sales data over several years, it may be necessary to adjust for inflation to get a true sense of how sales have changed over time. By using a deflator, you can convert nominal values (such as sales revenue) into real values (inflation-adjusted sales revenue), which makes it easier to compare values across different time periods.

Deflators can also be useful when analyzing economic data, such as GDP or employment figures. By using a deflator to adjust for inflation, you can get a more accurate picture of how the economy is performing over time. For example, if GDP has increased by 10

In summary, deflators are an important tool in both economics and data analysis, as they allow us to adjust for inflation and make accurate comparisons of values over time.

Appendix B

Data analysis

Data analysis is the process of inspecting, cleaning, transforming, and modeling data with the goal of discovering useful information, drawing conclusions, and supporting decision-making. It involves various methods and techniques such as descriptive statistics, inferential statistics, data visualization, and machine learning.

Data analysis can be applied in a variety of fields, including business, finance, healthcare, social sciences, and engineering, among others. In business, for example, data analysis can be used to analyze customer behavior, identify trends, and make predictions about future sales. In healthcare, data analysis can be used to identify risk factors for diseases, develop treatment plans, and monitor the effectiveness of interventions.

The process of data analysis typically involves several steps, including defining the problem or research question, collecting and preparing the data, exploring and visualizing the data, performing statistical analyses, interpreting the results, and communicating the findings. Effective data analysis requires a combination of technical skills, critical thinking, and domain knowledge.

Appendix C

Tables

Table C.1: Quality assessment based on the CASP qualitative research checklist. $y = yes$, $n = no$, $u = unclear$.

Index	Question	gilmore2013understanding	karlsson2015home	monroe2015decision
1	Was there a clear statement of the aims of the research?	y	y	y
2	Is a qualitative methodology appropriate?	y	y	y
3	Was the research design appropriate to address the aims of the research?	y	y	y
4	Was the recruitment strategy appropriate to the aims of the research?	y	y	y
5	Was the data collected in a way that addressed the research issue?	y	y	y
6	Has the relationship between researcher and participants been adequately considered?	u	u	u
7	Have ethical issues been taken into consideration?	y	y	y
8	Was the data analysis sufficiently rigorous?	y	y	y
9	Is there a clear statement of findings?	y	y	y
10	How valuable is the research?	y	y	y
Assessment quality		high	high	high

Appendix D

CASP Qualitative research checklist.

Table D.1: Quality assessment based on the CASP qualitative research checklist. y = *yes*, n = *no*, u = *unclear*.

Index	Question	gilmore2013understanding	karlsson2015home	monroe2015decision
1	Was there a clear statement of the aims of the research?	y	y	y
2	Is a qualitative methodology appropriate?	y	y	y
3	Was the research design appropriate to address the aims of the research?	y	y	y
4	Was the recruitment strategy appropriate to the aims of the research?	y	y	y
5	Was the data collected in a way that addressed the research issue?	y	y	y
6	Has the relationship between researcher and participants been adequately considered?	u	u	u
7	Have ethical issues been taken into consideration?	y	y	y
8	Was the data analysis sufficiently rigorous?	y	y	y
9	Is there a clear statement of findings?	y	y	y
10	How valuable is the research?	y	y	y
Assessment quality		high	high	high

Appendix E

Appendix F

Appendix G

References

Contu, Giulia et al. (2019). "The impact of Airbnb on hidden and sustainable tourism: the case of Italy". In: *International Journal of Tourism Policy* 9.2, pp. 99–130.

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