AMI23B – Business Intelligence Lab2

Using Pandas to Explore a Dataset

Tutorial Lab Instructions – follow the tutorial and answer and report all 10 questions.

Topics covered in this tutorial lab:

- Calculate metrics about your data.
- Perform basic queries and aggregations.
- Discover and handle incorrect data, inconsistencies, and missing values.
- Visualize your data with plots.

Remember, these only scratch the surface of the Pandas Python library!

Task1: Setting up the environment

(The references and links referred to in this tutorial are aimed at a Windows environment – if you are not a Windows user then please find suitable alternatives on your own)

1) You will need a working Python 3 environment. (Important tip! Add Python Path to Environment Variables. Setting up the Python path to system variables alleviates the need for using full paths.)

2) You will need to install Pip if it is not already installed (or an alternative of your preference). Pip is a powerful package management system for Python software packages. (Hint: the newest versions of Python come with pip installed as a default, make sure its installed!)

3) Preferably run in a Jupyter Notebook for a nicer output. (Optional)

4) You will need to install Pandas Python Library.

5) You will also need to install matplotlib. Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python. It is a useful complement to Pandas.

Note: If you're using the Anaconda distribution, then you're good to go! Anaconda already comes with the Pandas Python library installed.

Great! Now you are all set up, let's get started!

Task2: Using the Pandas Python Library

In this tutorial you'll analyse NBA results provided by FiveThirtyEight in a 17MB CSV file. You could download the CSV file using the web browser, however, having a download script has its advantages.

2.1) Create a download script `download_nba_all_elo.py` to download the data.

```python
import requests

#get the data from a download link
download_url = "https://raw.githubusercontent.com/fivethirtyeight/data/master/nba-elo/nbaallelo.csv"
target_csv_path = "nba_all_elo.csv"

response = requests.get(download_url)
response.raise_for_status()    #check that the request was successful

#save the file nba_all_elo.csv in your current working directory.
with open(target_csv_path, "wb") as f:
     f.write(response.content)
print("download ready")
```

When you run the script, it will save the file `nba_all_elo.csv` in your current working directory.

2.2) Now create a new script `lab2_NBA` in which you will use the Pandas Python library to take a look at your data.

```python
#importing Pandas in Python with the pd alias
import pandas as pd

#read in the dataset and store it as a DataFrame object in the variable nba
#When you copy the file path, if you get the FileNotFoundError: [Errno 2]
#then just flip the backslash to a forward slash and voila it works!
nba = pd.read_csv("C:/Users/sbk/PycharmProjects/Lab2/venv/nba_all_elo.csv")

#check nba's type, it should be a DataFrame
type(nba)
```

Note: Pandas can handle file in formats other than CSV too!

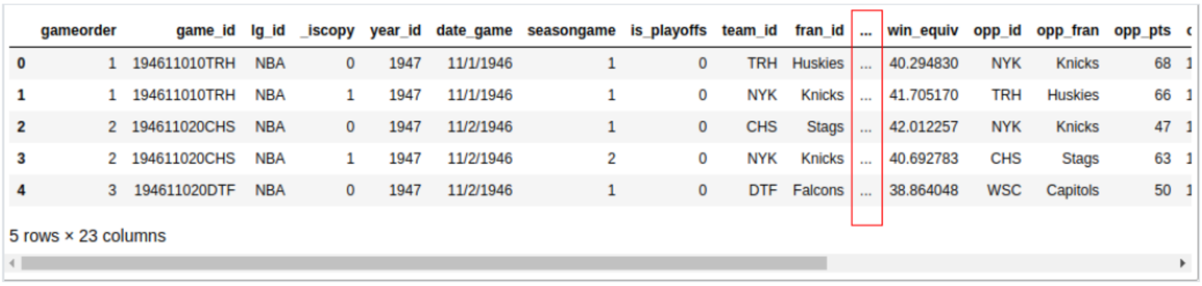
2.3) Let’s see how much data is actually in `nba` (report these findings):

```python
#len() determines the number of rows (observations) in a dataset
len(nba)
```

```python
#.shape determines dimensionality
#the result is a tuple containing number of rows and columns
nba.shape
```

```python
#take a look at the first five rows to see the actual data
nba.head()
#configure Pandas to display all 23 columns
pd.set_option("display.max.columns", None)
#show only two decimal places
pd.set_option("display.precision", 2)
#display last five rows
nba.tail()
```

When you use `.head()` you are displaying the first 5 rows (the default is 5). Unless your screen is quite large, your output probably won’t display all 23 columns, you will see a result like this:

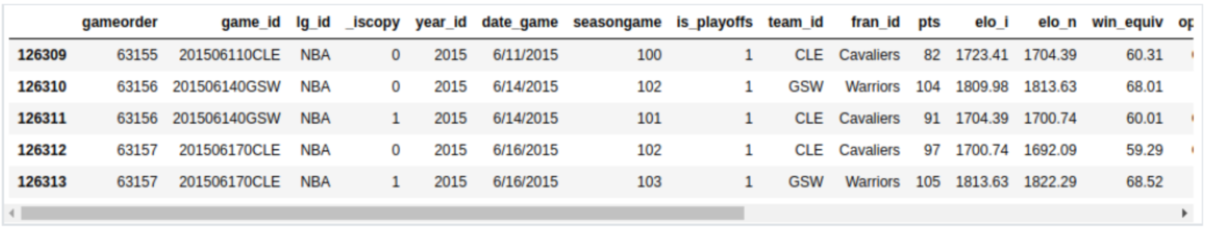


	gameorder	game_id	lg_id	_iscopy	year_id	date_game	seasongame	is_playoffs	team_id	fran_id	...	win_equiv	opp_id	opp_fran	opp_pts	c
0	1	194611010TRH	NBA	0	1947	11/1/1946	1	0	TRH	Huskies	...	40.294830	NYK	Knicks	68	1
1	1	194611010TRH	NBA	1	1947	11/1/1946	1	0	NYK	Knicks	...	41.705170	TRH	Huskies	66	1
2	2	194611020CHS	NBA	0	1947	11/2/1946	1	0	CHS	Stags	...	42.012257	NYK	Knicks	47	1
3	2	194611020CHS	NBA	1	1947	11/2/1946	2	0	NYK	Knicks	...	40.692783	CHS	Stags	63	1
4	3	194611020DTF	NBA	0	1947	11/2/1946	1	0	DTF	Falcons	...	38.864048	WSC	Capitols	50	1

5 rows × 23 columns

You can configure Pandas to display all 23 columns using
`pd.set_option("display.max.columns", None)`

To verify the changes you made execute `nba.tail()` to view the last 5 rows. You can see that the output of `nba.head()` is now easier to read:



	gameorder	game_id	lg_id	_iscopy	year_id	date_game	seasongame	is_playoffs	team_id	fran_id	pts	elo_i	elo_n	win_equiv	op
126309	63155	201506110CLE	NBA	0	2015	6/11/2015	100	1	CLE	Cavaliers	82	1723.41	1704.39	60.31	
126310	63156	201506140GSW	NBA	0	2015	6/14/2015	102	1	GSW	Warriors	104	1809.98	1813.63	68.01	
126311	63156	201506140GSW	NBA	1	2015	6/14/2015	101	1	CLE	Cavaliers	91	1704.39	1700.74	60.01	
126312	63157	201506170CLE	NBA	0	2015	6/16/2015	102	1	CLE	Cavaliers	97	1700.74	1692.09	59.29	
126313	63157	201506170CLE	NBA	1	2015	6/16/2015	103	1	GSW	Warriors	105	1813.63	1822.29	68.52	

Question.1 (report your answer): Display the first 3 rows of your dataset. Remember that the default of `nba.head()` shows the first 5 rows.

Hint: always refer to the documentation, chances are that you’ll find a solution by tweaking some optional parameters.

Task3: Get to Know Your Data.

In Task2 you imported a CSV file and had a quick peek at the contents of the dataset. So far, you've only seen the size of your dataset and its first and last few rows. Next, you'll learn how to examine your data more systematically.

3.1) Discover the different data types your dataset contains.

```python
#you can put anything into a list, but the columns of a DataFrame contain values of a specific data type.
#by comparing Pandas and Python data structures, you'll see that this behavior makes Pandas much faster!
#display all columns and their data types with .info()
nba.info()
```

From the output you will see that this dataset contains `int64`, `float64` and `object`. Pandas uses NumPy library to work with these types.

The object type is special, according to the Pandas Cookbook, the object data type is "a catch-all for columns that Pandas doesn't recognize as any other specific type." In practice, it often means that all of the values in the column are strings. Although you can store arbitrary Python objects in the object data type, strange values in an object column can harm Pandas' performance and its interoperability with other libraries. You will see how to deal with this later in the tutorial.

3.2) Showing basic statistics.

Get an idea of the values each column contains

```python
#get an idea of the values each column contains
nba.describe()
```

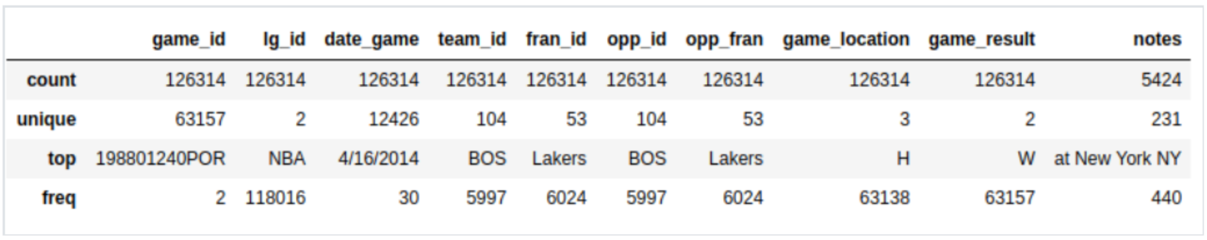
The output shows basic descriptive statistics for all numeric columns.

`.describe()` only analyses numeric columns by default, but you can provide other data types if you use the include parameter

```python
#you can provide other data types using the include parameter
import numpy as np
nba.describe(include=np.object)
```

Here `.describe()` won't calculate a mean or a standard deviation for object columns since they mostly include text strings. It just displays descriptive statistics.

Look at the output you got and answer the next question:



	game_id	lg_id	date_game	team_id	fran_id	opp_id	opp_fran	game_location	game_result	notes
count	126314	126314	126314	126314	126314	126314	126314	126314	126314	5424
unique	63157	2	12426	104	53	104	53	3	2	231
top	198801240POR	NBA	4/16/2014	BOS	Lakers	BOS	Lakers	H	W	at New York NY
freq	2	118016	30	5997	6024	5997	6024	63138	63157	440

Question.2 (report your answer): Take a look at the `team_id` and `fran_id` (franchise) columns, what observations can you make at this point (i.e. do you see anything strange here)? Write your initial observation then carry on with section 3.3 to be able to answer it by exploring your dataset.

3.3) Exploring the dataset

Exploratory data analysis helps you answer questions about your dataset, for example, exploring how often specific values occur in a column. Let's take a look at the two columns `team_id` and `fran_id`:

```
nba["team_id"].value_counts()
nba["fran_id"].value_counts()
```

It seems that a team named "Lakers" played 6024 games, but only 5078 of those were played by the Los Angeles Lakers. To find out who the other "Lakers" team is execute the following line of code:

```
nba.loc[nba["fran_id"] == "Lakers", "team_id"].value_counts()
```

`pandas.DataFrame.loc` is used to access a group of rows and columns by label(s) or a boolean array.

The output shows that the Minneapolis Lakers ("MNL") played the other 946 games.

Let's find out when they played those games:

```
#Find out when they played those games
nba.loc[nba["team_id"] == "MNL", "date_game"].min()
nba.loc[nba["team_id"] == "MNL", "date_game"].max()
nba.loc[nba["team_id"] == "MNL", "date_game"].agg(("min", "max"))  #aggregate the two functions
```

Question.3 (report your answer): Find out how many wins and losses the Minneapolis Lakers had, also find how many points they scored during the matches contained in the dataset.

Question.4 (report your answer): Now you understand why the Boston Celtics team "BOS" played the most games in the dataset, find out how many points the Boston Celtics have scored during all matches contained in this dataset.

Question.5 (report your answer): After having explored your dataset, explain your observations from Question.2 in a structured way.

Task4: Data access methods (loc and iloc):

Check Pandas official docs for these two functions.

With data access methods like `.loc` and `.iloc`, you can select just the right subset of your DataFrame to help you answer questions about your dataset.

`.loc` uses the label and `.iloc` the positional index

```
#Examples:

#accessing data using a label
city_data.loc["Amsterdam"]

#accessing data between two labels
city_data.loc["Tokyo": "Toronto"]

#accessing data using the positional index
city_data.iloc[1]
```

Question.6 (report your answer):

6.1) Use a data access method to display the 4th row from the bottom of the `nba` dataset.

6.2) Use a data access method to display the 2nd row from the top of the `nba` dataset.

6.3) Access all games between the labels 5555 and 5559, you only want to see the names of teams and the scores.

Task5: Querying the Dataset

You have seen how to access subsets of a huge dataset based on its indices, now you will select rows based on the values in your dataset’s columns to query your data.

```
#create a new DataFrame that contains only games played after 2010
current_decade = nba[nba["year_id"] > 2010]
current_decade.shape
```

All the columns are still there but `current_decade` only consists of rows where the value in the `year_id` column is greater than 2010.

Question.7 (report your answer): Create a new DataFrame which consists of the games played between 2000 and 2009.

Selecting rows where a specific field is not null

```
#selecting rows where a specific field is not null   .notnull() or .notna()
games_with_notes = nba[nba["notes"].notnull()]
games_with_notes.shape
```

The DataFrame nba has 126314 rows, when you select only the rows where `notes` is not null you end up with a DataFrame of 5424 rows.

You can access values of the object data type as str and perform string methods on them.

```
#filter your dataset and find all games where the home team’s name ends with "ers".

ers = nba[nba["fran_id"].str.endswith("ers")]
ers.shape



#search for Baltimore games where both teams scored over 100 points.
#In order to see each game only once, you’ll need to exclude duplicates
nba[(nba["_iscopy"] == 0) & (nba["pts"] > 100) & (nba["opp_pts"] > 100) & (nba["team
_id"] == "BLB")]
```

You use `df["_iscopy"] == 0` to include only the entries that aren’t copies.

Question.8 (report your answer): Filter your dataset and find all the playoffs games where the number of points scored by both home and aways is more than 100, in the year 2011, exclude results where there are no notes and make sure you don't include duplicates (don't forget the parentheses).

Task6: Grouping and Aggregating Your Data

You may also want to learn other features of your dataset, like the sum, mean, or average value of a group of elements. Luckily, the Pandas Python library offers grouping and aggregation functions to help you accomplish this task.

```
#Grouping - group all games for fran_id and sum their points and override the defaul
t of sorting
nba.groupby("fran_id", sort=False)["pts"].sum()

```

```python
#group by multiple columns
nba[(nba["fran_id"] == "Spurs") & (nba["year_id"] > 2010)].groupby(["year_id", "game_result"])["game_id"].count()
```

Question.9 (report your answer): Take a look at the New York Knicks 2011-12 season (year_id: 2012). How many wins and losses did they score during the regular season and the playoffs?

Task7: Manipulating Columns

You can add and drop columns as part of the initial data cleaning phase, or later based on the insights of your analysis.

```python
#create a copy of your original DataFrame to work with
df = nba.copy()
df.shape

#define new columns based on the existing ones
df["difference"] = df.pts - df.opp_pts
df.shape

#use an aggregation function .max() to find the largest value of your new column
df["difference"].max()

#rename the columns of your dataset
renamed_df = df.rename(columns={"game_result": "result", "game_location": "location"})
renamed_df.info()
```

Note that there's a new object, `renamed_df`. Like several other data manipulation methods, `.rename()` returns a new DataFrame by default.

```python
#Delete unwanted columns - wont be analyzing Elo ratings here so go ahead and delete them
df.shape
elo_columns = ["elo_i", "elo_n", "opp_elo_i", "opp_elo_n"]
df.drop(elo_columns, inplace=True, axis=1)
df.shape
```

Understanding the `df.drop` function:

```
DataFrame.drop(self, labels=None, axis=0, index=None, columns=None, level=None,
inplace=False, errors='raise')
```

Is translated into:

Index or column labels to drop, Whether to drop labels from the index (0 or 'index') or columns (1 or 'columns'), 'inplace=True' to make permanent changes to the dataframe

Task8: Specifying Data Types

When you create a new DataFrame, Pandas assigns a data type to each column based on its values. Sometimes is not too accurate. Choose the correct data type for your columns upfront to improve performance.

Take another look at the columns of the `nba` dataset:

```
#take a look at the DataFrame
df.info()
```

Ten of your columns have the data type `object` and some of these are good candidates for data type conversion.

```
# use .to_datetime() to specify all game dates as datetime objects.
df["date_game"] = pd.to_datetime(df["date_game"])
```

Similary, `game_location` can have only three different values. In a relational database, you would use the type `enum` for this column. Pandas provides the `categorical` data type for that same purpose.

```
#game_location column can have only three different values.
#you can see this by executing this code
df["game_location"].nunique()
df["game_location"].value_counts()

#change the data type to categorical and check it
df["game_location"] = pd.Categorical(df["game_location"])
df["game_location"].dtype
```

After changing to categorical data, execute `df.info`. You will notice a drop in memory usage, hence improving performance.

Question.10 (report your answer): Find another column in the `nba` dataset that has a generic data type and convert it to a more specific one.

Task9: Cleaning the Data

9.1) Missing Values

`.info()` shows how many non-null values a column contains. That is very important information for you to have about your data. Null values often indicate a problem in the data-gathering process.

When you inspect the dataset with `nba.info()` you will see that the dataset is quite neat except for the `notes` column which contains null values for most of its rows. This output shows that the notes column has only 5424 non-null values.

That means that over 120,000 rows of your dataset have null values in this column.

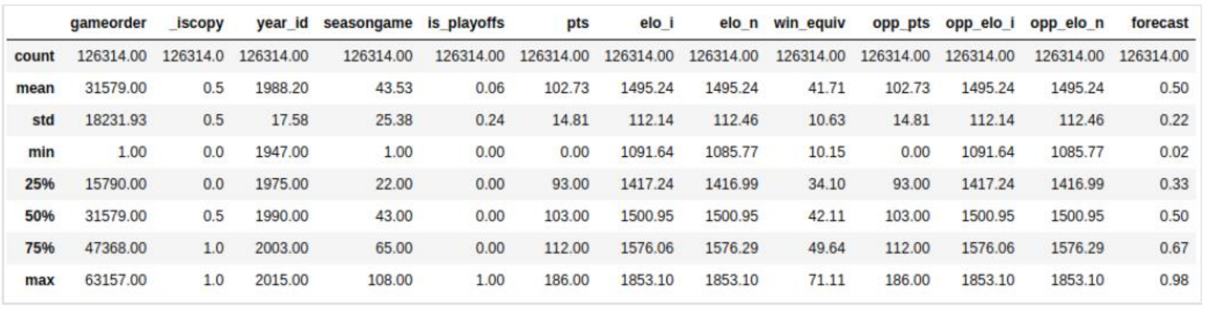
Here are a few ways to deal with null values:

```python
#1st way- usually best approach is to ignore them, remove all rows with missing values
rows_without_missing_data = nba.dropna()
rows_without_missing_data.shape

#2nd way - Drop columns if they are not relevant to your analysis
data_without_missing_columns = nba.dropna(axis=1)
data_without_missing_columns.shape

#3rd way - replace the missing values with a meaningful default value for your use case
data_with_default_notes = nba.copy()
data_with_default_notes["notes"].fillna(value="no notes at all", inplace=True)
data_with_default_notes["notes"].describe()
```

Regarding the 1st way , that kind of data clean-up doesn't make sense for your `nba` dataset, because it's not a problem for a game to lack notes. But if your dataset contains a million valid records and a hundred where relevant data is missing, then dropping the incomplete records can be a reasonable solution.

9.2) Invalid Values

Use `.describe` to understand more about your dataset. This can help you identify invalid values that may throw off your analysis.



	gameorder	_iscopy	year_id	seasongame	is_playoffs	pts	elo_i	elo_n	win_equiv	opp_pts	opp_elo_i	opp_elo_n	forecast
count	126314.00	126314.0	126314.00	126314.00	126314.00	126314.00	126314.00	126314.00	126314.00	126314.00	126314.00	126314.00	126314.00
mean	31579.00	0.5	1988.20	43.53	0.06	102.73	1495.24	1495.24	41.71	102.73	1495.24	1495.24	0.50
std	18231.93	0.5	17.58	25.38	0.24	14.81	112.14	112.46	10.63	14.81	112.14	112.46	0.22
min	1.00	0.0	1947.00	1.00	0.00	0.00	1091.64	1085.77	10.15	0.00	1091.64	1085.77	0.02
25%	15790.00	0.0	1975.00	22.00	0.00	93.00	1417.24	1416.99	34.10	93.00	1417.24	1416.99	0.33
50%	31579.00	0.5	1990.00	43.00	0.00	103.00	1500.95	1500.95	42.11	103.00	1500.95	1500.95	0.50
75%	47368.00	1.0	2003.00	65.00	0.00	112.00	1576.06	1576.29	49.64	112.00	1576.06	1576.29	0.67
max	63157.00	1.0	2015.00	108.00	1.00	186.00	1853.10	1853.10	71.11	186.00	1853.10	1853.10	0.98

Looking at the output you will see that the `year_id` varies between 1947 and 2015. That sounds plausible. But how can the minimum points of a game be 0. Take a look at those games to find out if it makes sense or not.

```python
#selecting the games where pts are 0
nba[nba["pts"] == 0]
```

It seems the game was forfeited. Depending on your analysis, you may want to remove it from the dataset.

9.3) Inconsistent Values

Always check for inconsistent values. The values of the fields `pts`, `opp_pts` and `game_result` should be consistent with each other.

```
#check using the .empty() attribute
nba[(nba["pts"] > nba["opp_pts"]) & (nba["game_result"] != 'W')].empty
nba[(nba["pts"] < nba["opp_pts"]) & (nba["game_result"] != 'L')].empty
```

Fortunately, both of these queries return an empty DataFrame. But be prepared for surprises, always check consistency.

Task10: Data Visualisation

Sometimes, the numbers speak for themselves, but often a chart helps a lot with communicating your insights.

Data visualizations make big and small data easier for the human brain to understand, and visualization also makes it easier to detect patterns, trends, and outliers in groups of data.

Data visualisation is one of the things that works much better in a Jupyter notebook than in a terminal. If you need help getting started, then check out Jupyter Notebook: An Introduction.

Both Series and DataFrame objects have a `.plot()` method, which is a wrapper around `matplotlib.pyplot.plot()`.

Visualize how many points the Knicks scored throughout the seasons.

```
#Include this line to show plots directly in the notebook
%matplotlib inline

#Visualize how many points the Knicks scored throughout the seasons
nba[nba["fran_id"] == "Knicks"].groupby("year_id")["pts"].sum().plot()

#create a bar plot to show the franchises with the most games played
nba["fran_id"].value_counts().head(10).plot(kind="bar")
```

Question.10 (report your answer):

10.1) Explain what the above line plot, showing how many points the Knicks scored throughout the seasons, reveals to you (i.e. describe what you find out).

10.2) Describe what the above bar plot reveals to you about the franchises with the most games played.

10.3) In 2013, the Miami Heat won the championship. Create a pie plot showing the count of their wins and losses during that season. (First, define a criteria to include only the Heat's games from 2013. Then, create a plot in the same way as you've seen above).

Submission Instructions:

Zip your project folder along with the answers document and submit to Learn no later than Monday the 4th of May at 23:59.

The answers document should include the line of code used, explanations and plots depending on the question requirements.

"Without data you're just another person with an opinion."

~W. Edwards Deming

References:

Pandas Docs: https://pandas.pydata.org/pandas-docs/stable/index.html

Download Python: https://www.python.org/downloads/

How to install pip: https://www.liquidweb.com/kb/install-pip-windows/

Jupyter Notebook: https://realpython.com/jupyter-notebook-introduction/

Install Pandas Python: https://pandas.pydata.org/pandas-docs/stable/getting_started/install.html

Install matplotlib: https://matplotlib.org/users/installing.html#installing-from-source

Visualisation with Pandas: https://pandas.pydata.org/pandas-docs/stable/user_guide/visualization.html

Tutorial inspiration (Real Python): https://realpython.com/pandas-python-explore-dataset/

Data Source: https://fivethirtyeight.com/

The raw data: https://raw.githubusercontent.com/fivethirtyeight/data/master/nba-elo/nbaallelo.csv