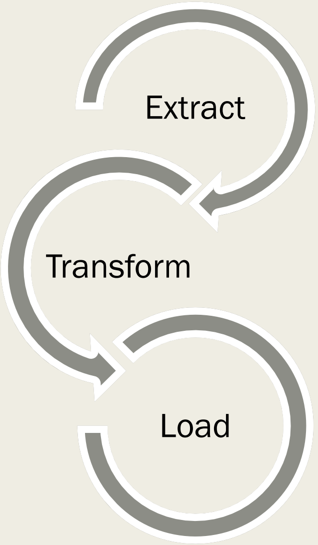
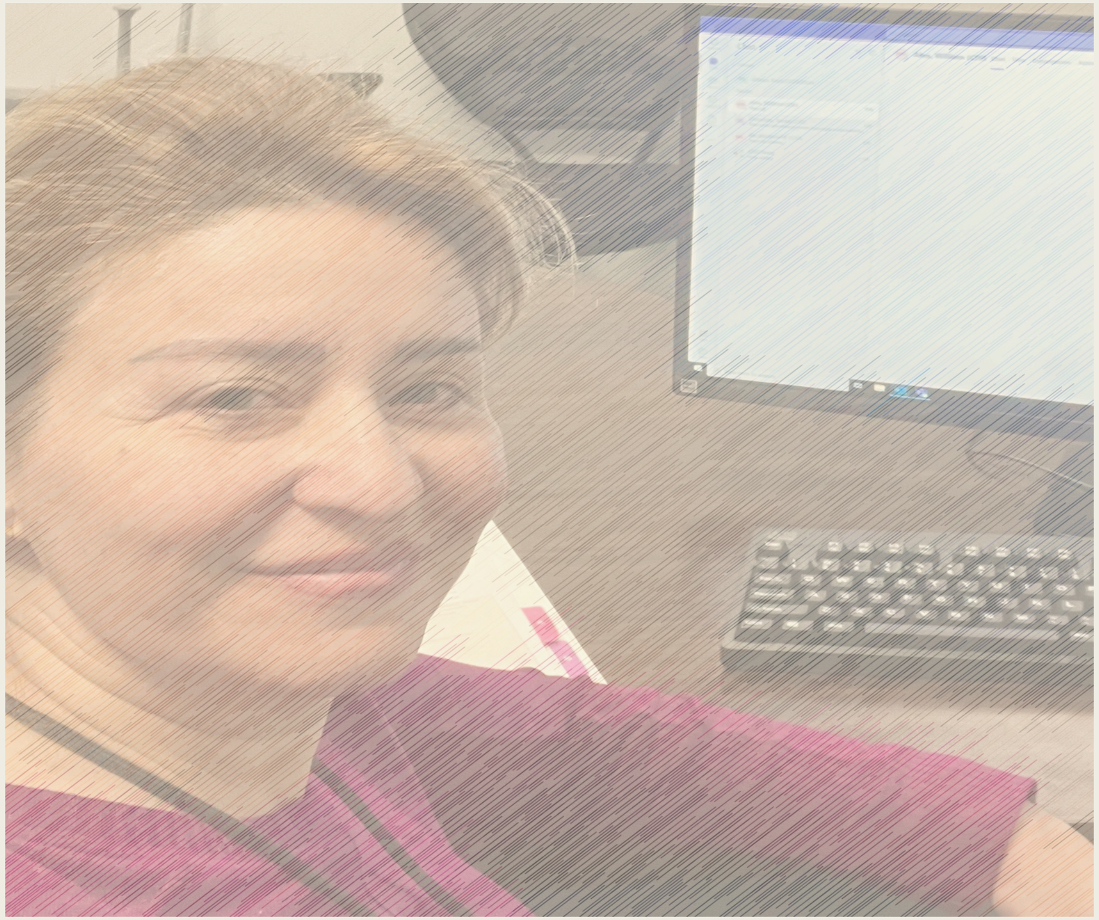

Extract

Transform

Load

ETL in Nutshell


Rana Ghazzi

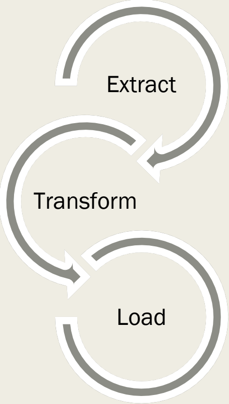
ETL

It’s a data integration process used to combine data from multiple sources into a

single, consistent data set for storage in a data warehouse or other target system.

```
+----------------+      +----------------+      +----------------+
         |          |     |          |     |          |
 |   Extract    |---->|   Transform   |---->|     Load     |
         |          |     |          |     |          |
+----------------+      +----------------+      +----------------+
```

1. **Extract:** This step involves retrieving data from various sources, such as databases, APIs, or flat files. The goal is to gather all relevant data needed for analysis.
2. **Transform:** In this phase, the extracted data is cleaned, formatted, and transformed to meet the requirements of the target system. This can include filtering out errors, converting data types, and applying business rules to ensure consistency and accuracy.
3. **Load:** The final step is loading the transformed data into the target system, such as a data warehouse or data lake. This makes the data available for analysis and reporting.



Why Python:

Python is an excellent choice for ETL processes! It offers several advantages:

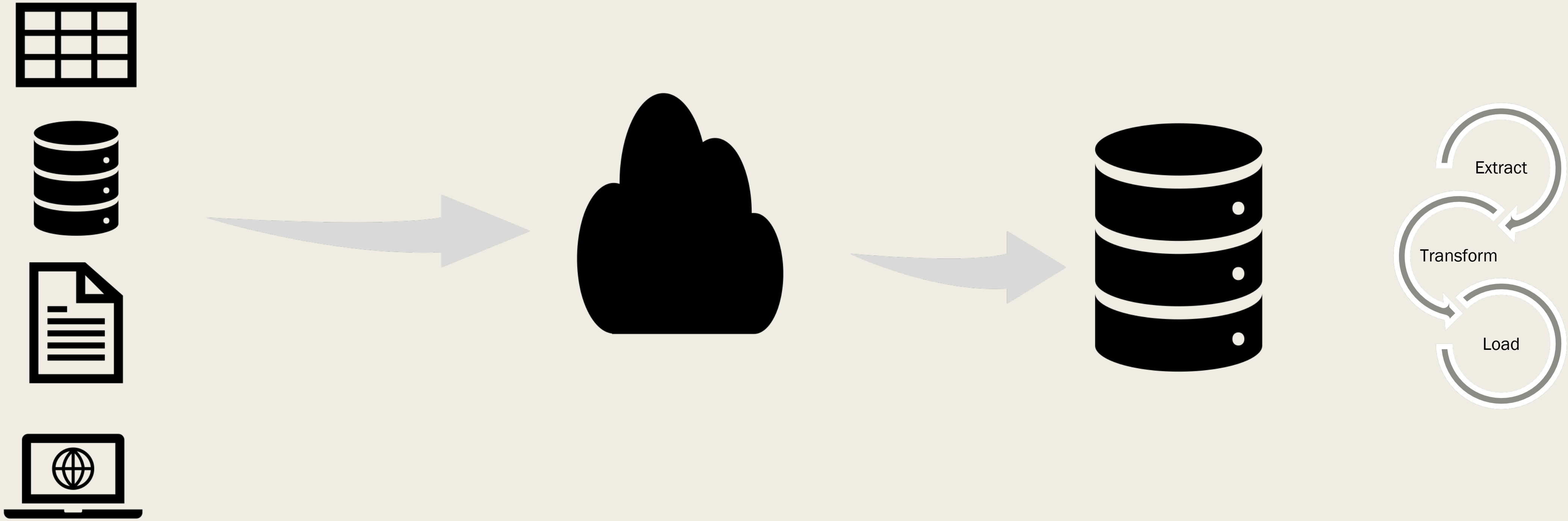
Flexibility: Python is highly flexible and can be used to create custom ETL pipelines tailored to specific needs.

Libraries: There are many powerful libraries available for ETL tasks, such as

Community Support: Python has a large and active community, which means plenty of resources, tutorials, and support are available.

Integration: Python can easily integrate with various data sources and destinations, including databases, APIs, and cloud services.

Ease of Learning: Python’s syntax is straightforward and easy to learn, making it accessible for both beginners and experienced developers.



Extract

Transform

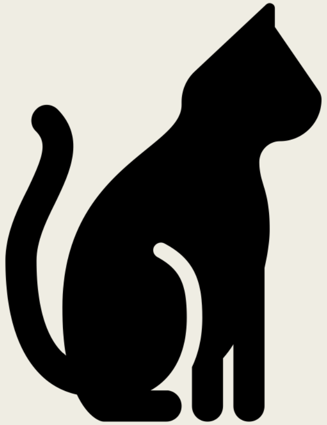
Load

CASE STUDY:

Our project is for cat lovers, Here’s a brief overview:
The Cat API Project:

Purpose: The Cat API provides access to a vast collection of cat images, breed information, and cat-related facts. It’s designed to help developers easily integrate cat content into their websites or applications.

Features:



- Images: Access to over 60,000 cat images.
- Breeds: Detailed information on various cat breeds.
- Facts: Interesting facts about cats.
- Voting and Favorites: Users can vote on and favorite cat images.

CASE STUDY:

We are utilizing different Python libraries to create a connection to Database / API where we will extract data.

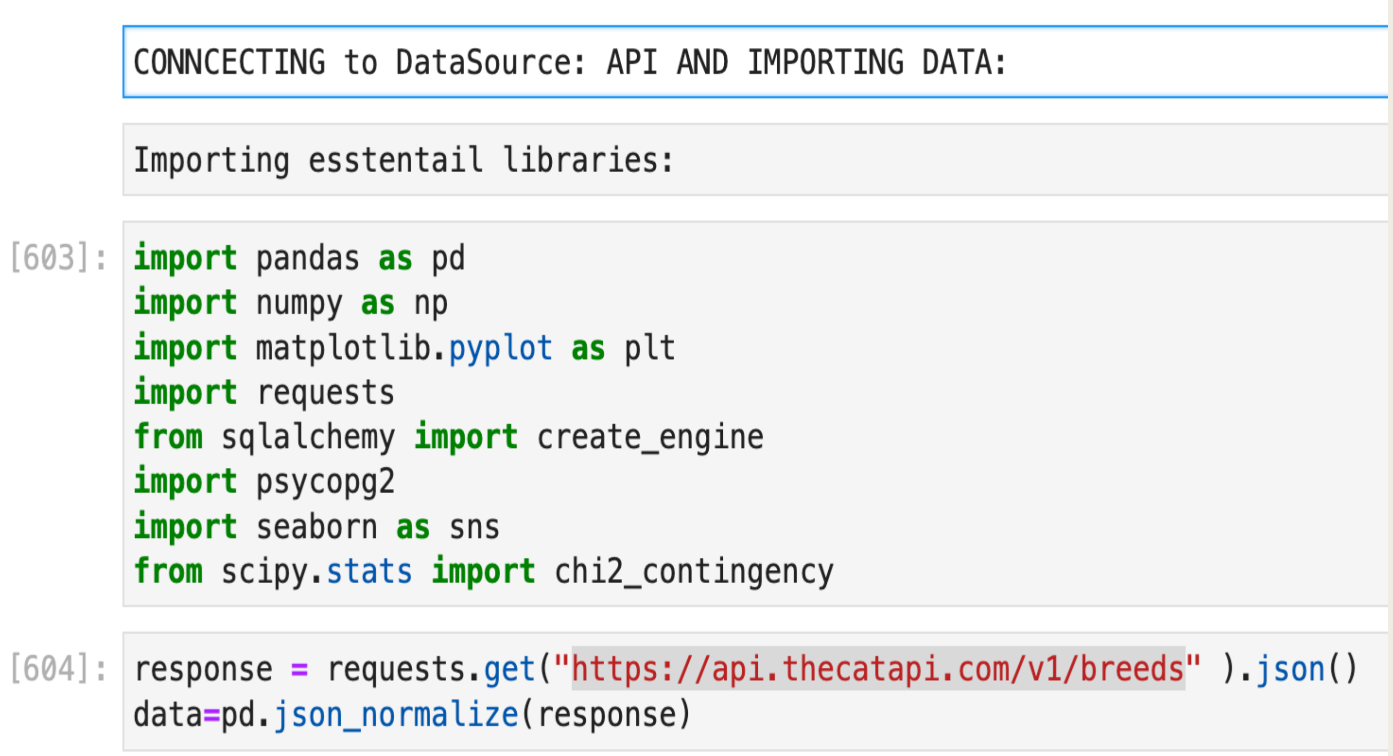
- Explore , clean, and transform our dataset.
- Upload data into a database or save it as a CSV file / OR DATABASE.

Data Source: https://api.thecatapi.com/v1/breeds

Tools To be used: Jupiter Notebook, Python, Pandas, and Postgres Database.

1- Connecting to Data Source:

For this project our data source is API connection that list data about different cats with all info about breeds, origins , names, temperaments, and qualities.



CONNCECTING to DataSource: API AND IMPORTING DATA:

Importing esstentail libraries:

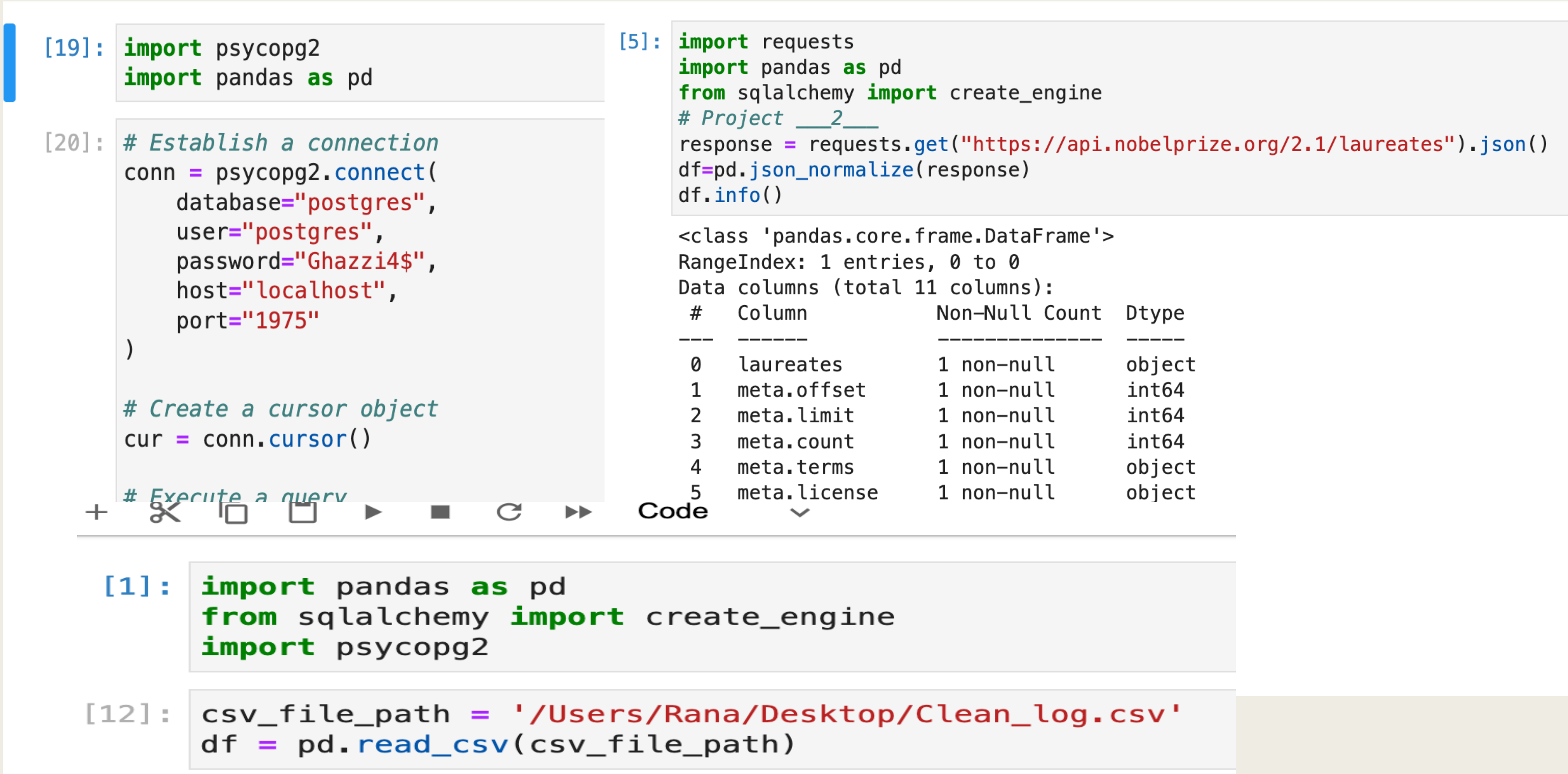
[603]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import requests
from sqlalchemy import create_engine
import psycopg2
import seaborn as sns
from scipy.stats import chi2_contingency
```

[604]:

```
response = requests.get("https://api.thecatapi.com/v1/breeds" ).json()
data=pd.json_normalize(response)
```

Connect to Different Data Sources:



```
[19]: import psycopg2
      import pandas as pd
```

```
[20]: # Establish a connection
      conn = psycopg2.connect(
          database="postgres",
          user="postgres",
          password="Ghazzi4$",
          host="localhost",
          port="1975"
      )

      # Create a cursor object
      cur = conn.cursor()

      # Execute a query
```

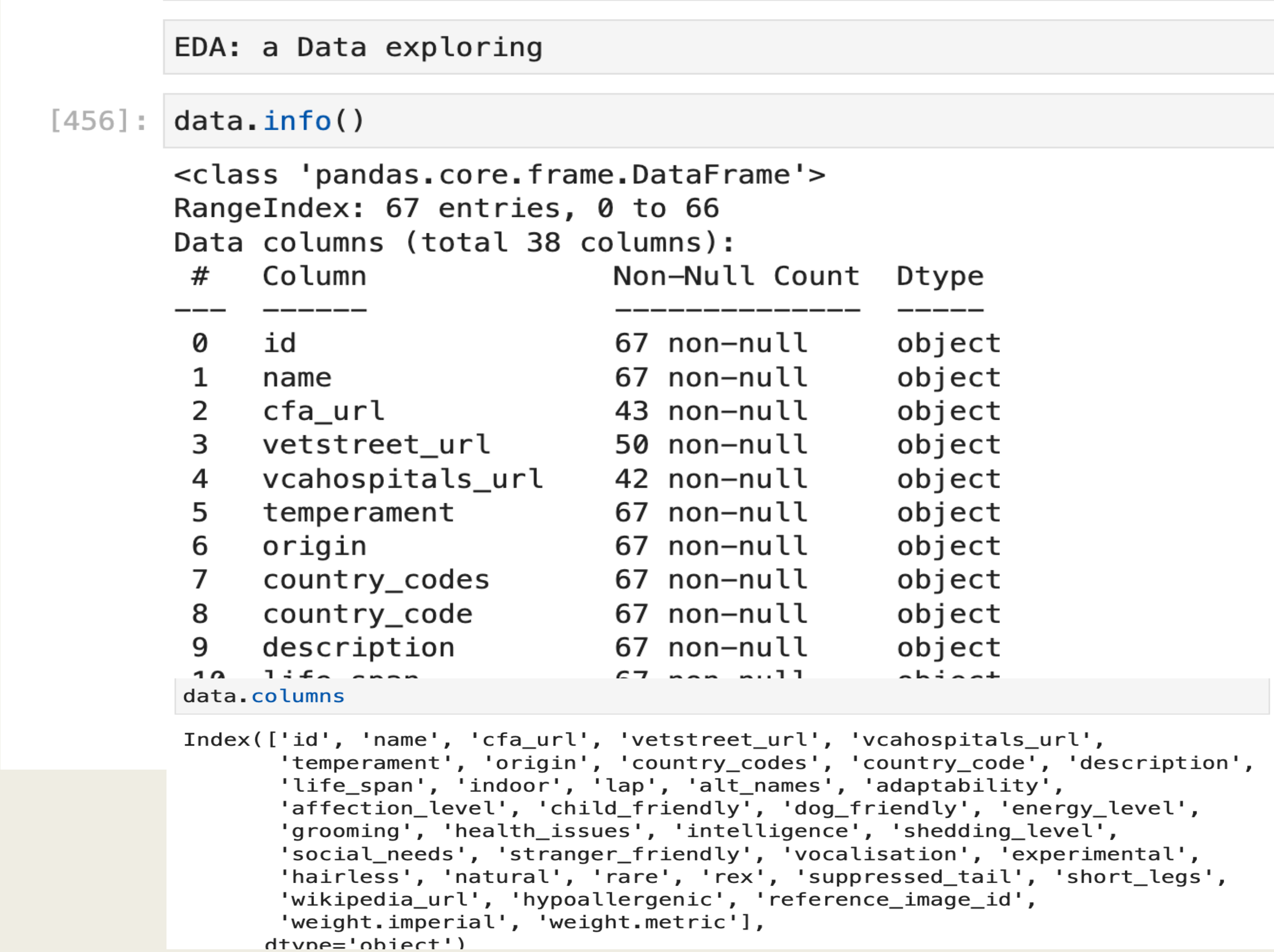
```
[5]: import requests
     import pandas as pd
     from sqlalchemy import create_engine
     # Project ___2___
     response = requests.get("https://api.nobelprize.org/2.1/laureates").json()
     df=pd.json_normalize(response)
     df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1 entries, 0 to 0
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   laureates       1 non-null      object
 1   meta.offset     1 non-null      int64 
 2   meta.limit      1 non-null      int64 
 3   meta.count      1 non-null      int64 
 4   meta.terms      1 non-null      object
 5   meta.license    1 non-null      object
```

```
[1]: import pandas as pd
     from sqlalchemy import create_engine
     import psycopg2
```

```
[12]: csv_file_path = '/Users/Rana/Desktop/Clean_log.csv'
      df = pd.read_csv(csv_file_path)
```

2- EDA: Data Discovery



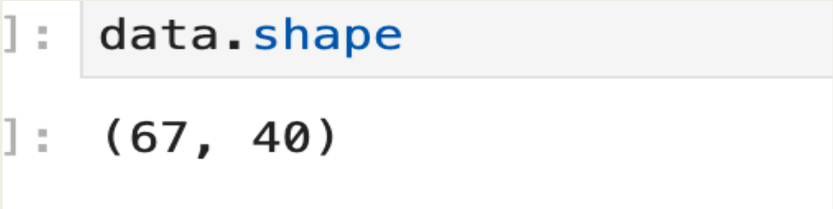
```
EDA: a Data exploring
```

```
[456]: data.info()
```

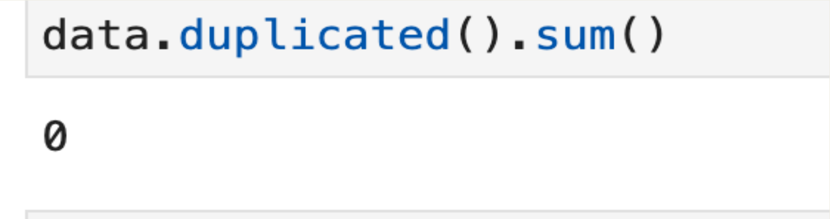
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 67 entries, 0 to 66
Data columns (total 38 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   id                67 non-null     object
 1   name              67 non-null     object
 2   cfa_url           43 non-null     object
 3   vetstreet_url     50 non-null     object
 4   vcahospitals_url  42 non-null     object
 5   temperament       67 non-null     object
 6   origin            67 non-null     object
 7   country_codes     67 non-null     object
 8   country_code      67 non-null     object
 9   description       67 non-null     object
 10  life_span         67 non-null     object
```

```
data.columns
```

```
Index(['id', 'name', 'cfa_url', 'vetstreet_url', 'vcahospitals_url',
       'temperament', 'origin', 'country_codes', 'country_code', 'description',
       'life_span', 'indoor', 'lap', 'alt_names', 'adaptability',
       'affection_level', 'child_friendly', 'dog_friendly', 'energy_level',
       'grooming', 'health_issues', 'intelligence', 'shedding_level',
       'social_needs', 'stranger_friendly', 'vocalisation', 'experimental',
       'hairless', 'natural', 'rare', 'rex', 'suppressed_tail', 'short_legs',
       'wikipedia_url', 'hypoallergenic', 'reference_image_id',
       'weight.imperial', 'weight.metric'],
      dtype='object')
```

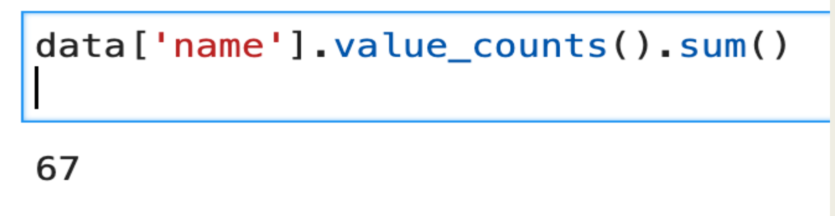


```
]: data.shape
]: (67, 40)
```



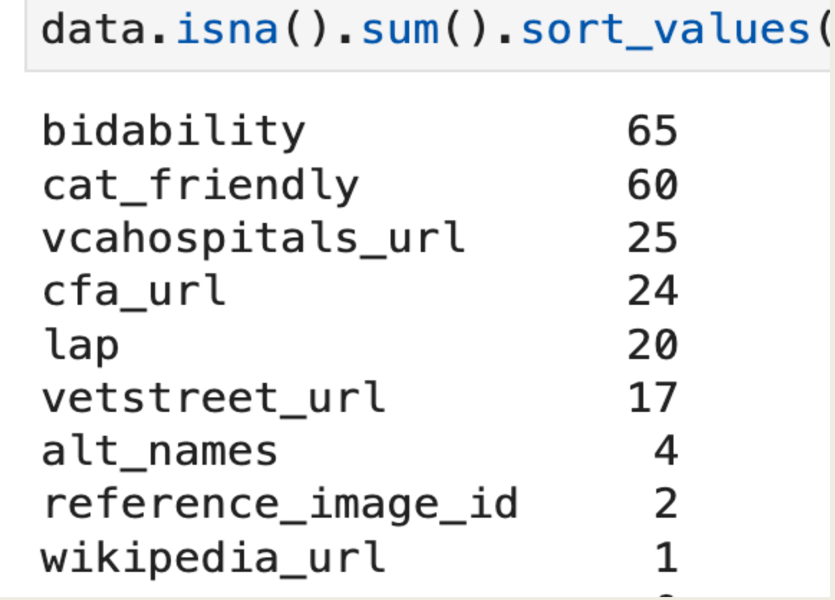
```
data.duplicated().sum()

0
```



```
data['name'].value_counts().sum()

67
```



```
data.isna().sum().sort_values(

bidability             65
cat_friendly           60
vcahospitals_url       25
cfa_url                24
lap                    20
vetstreet_url          17
alt_names               4
reference_image_id      2
wikipedia_url           1
```

Heatmap AND Correlations

Observation:

The correlation coefficient values in the heatmap ,that measures the strength and direction of a relationship between two variables, suggests a strong relationships between some variables in this data.

Examples:

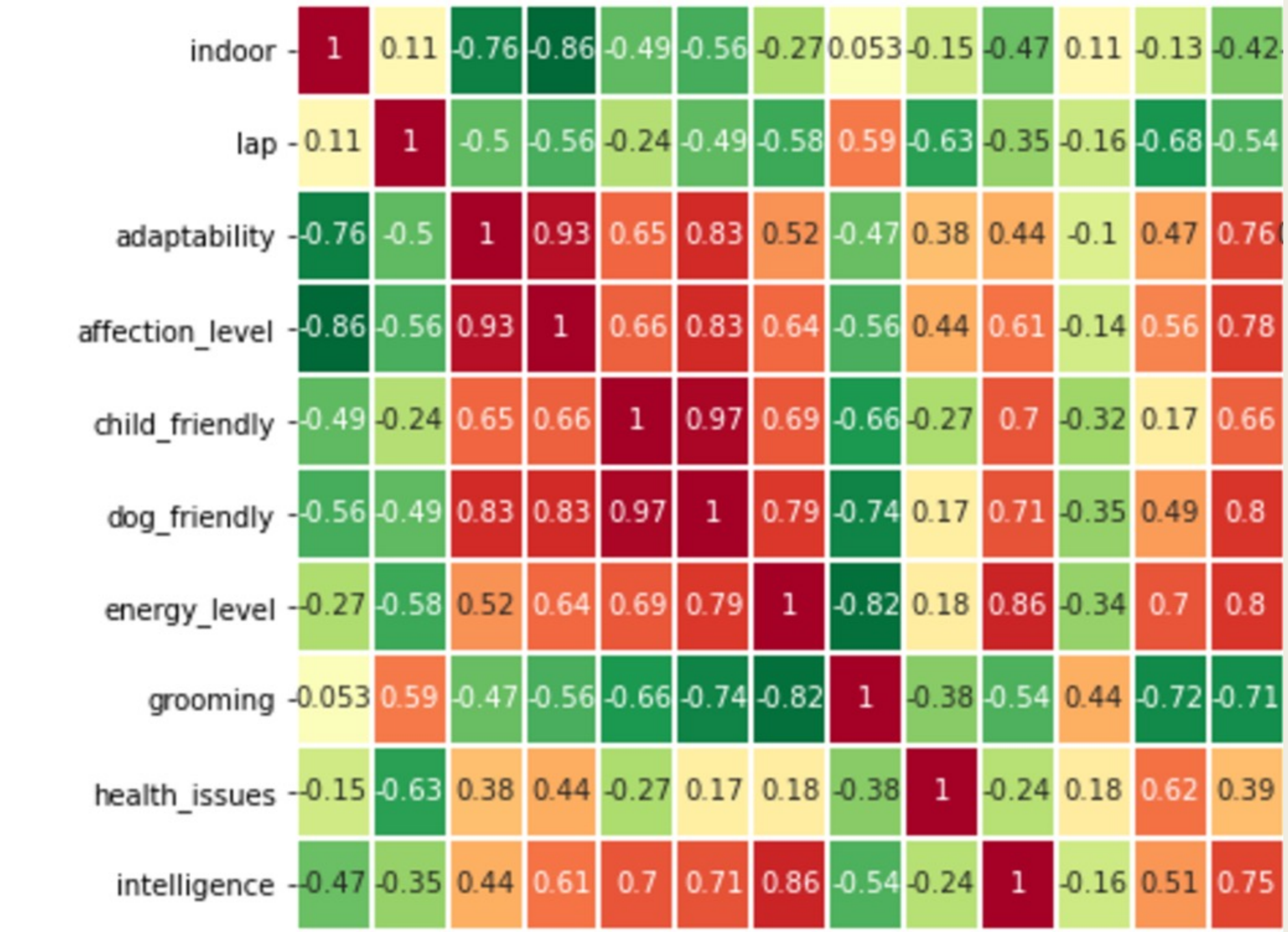
- Indoor & Adaptability,

- Indoor & Affection-Level

- Adaptability & Affection level

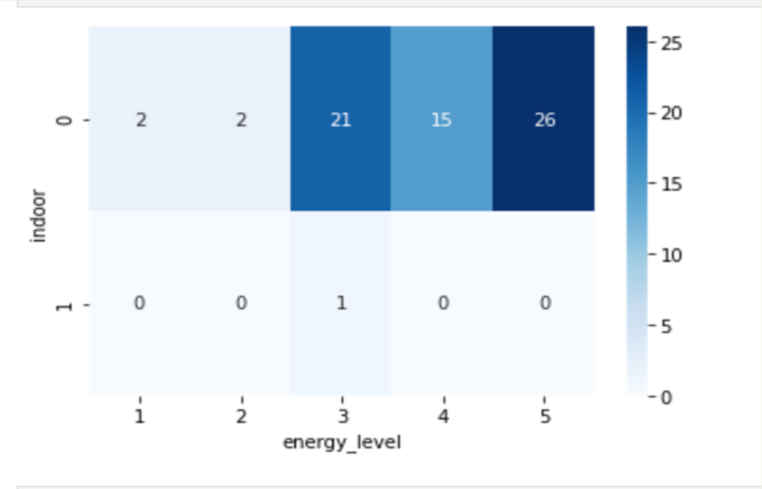
- Stanger friendly: Intelligence

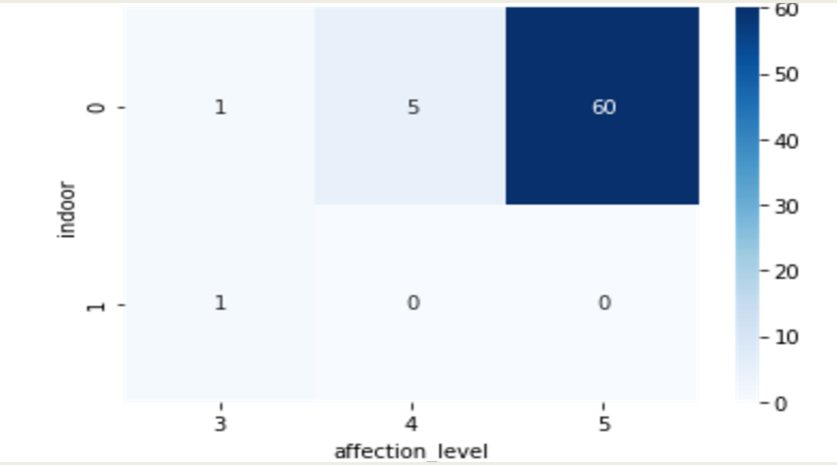
- Social-needs: intelligence

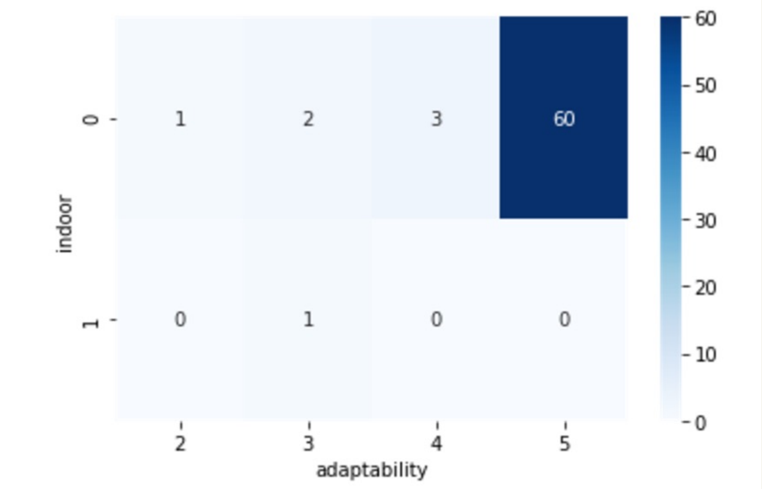


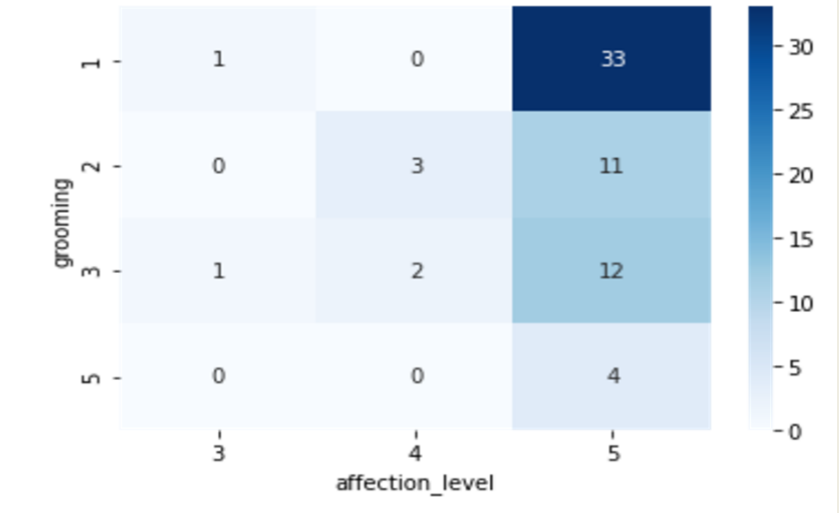
indoor	1	0.11	-0.76	-0.86	-0.49	-0.56	-0.27	0.053	-0.15	-0.47	0.11	-0.13	-0.42
lap	0.11	1	-0.5	-0.56	-0.24	-0.49	-0.58	0.59	-0.63	-0.35	-0.16	-0.68	-0.54
adaptability	-0.76	-0.5	1	0.93	0.65	0.83	0.52	-0.47	0.38	0.44	-0.1	0.47	0.76
affection_level	-0.86	-0.56	0.93	1	0.66	0.83	0.64	-0.56	0.44	0.61	-0.14	0.56	0.78
child_friendly	-0.49	-0.24	0.65	0.66	1	0.97	0.69	-0.66	-0.27	0.7	-0.32	0.17	0.66
dog_friendly	-0.56	-0.49	0.83	0.83	0.97	1	0.79	-0.74	0.17	0.71	-0.35	0.49	0.8
energy_level	-0.27	-0.58	0.52	0.64	0.69	0.79	1	-0.82	0.18	0.86	-0.34	0.7	0.8
grooming	0.053	0.59	-0.47	-0.56	-0.66	-0.74	-0.82	1	-0.38	-0.54	0.44	-0.72	-0.71
health_issues	-0.15	-0.63	0.38	0.44	-0.27	0.17	0.18	-0.38	1	-0.24	0.18	0.62	0.39
intelligence	-0.47	-0.35	0.44	0.61	0.7	0.71	0.86	-0.54	-0.24	1	-0.16	0.51	0.75

As strong associations between some cats qualities is more evident according to the chart shown below:









Insight:

From exploring the columns in this dataset we can conclude the following:

Most of the columns in this dataset are categorical except for few like: weight related measures.

Many of the categorical fields are binominal , ordinal, and few nominal.

The heat map shows strong associations between different variables.

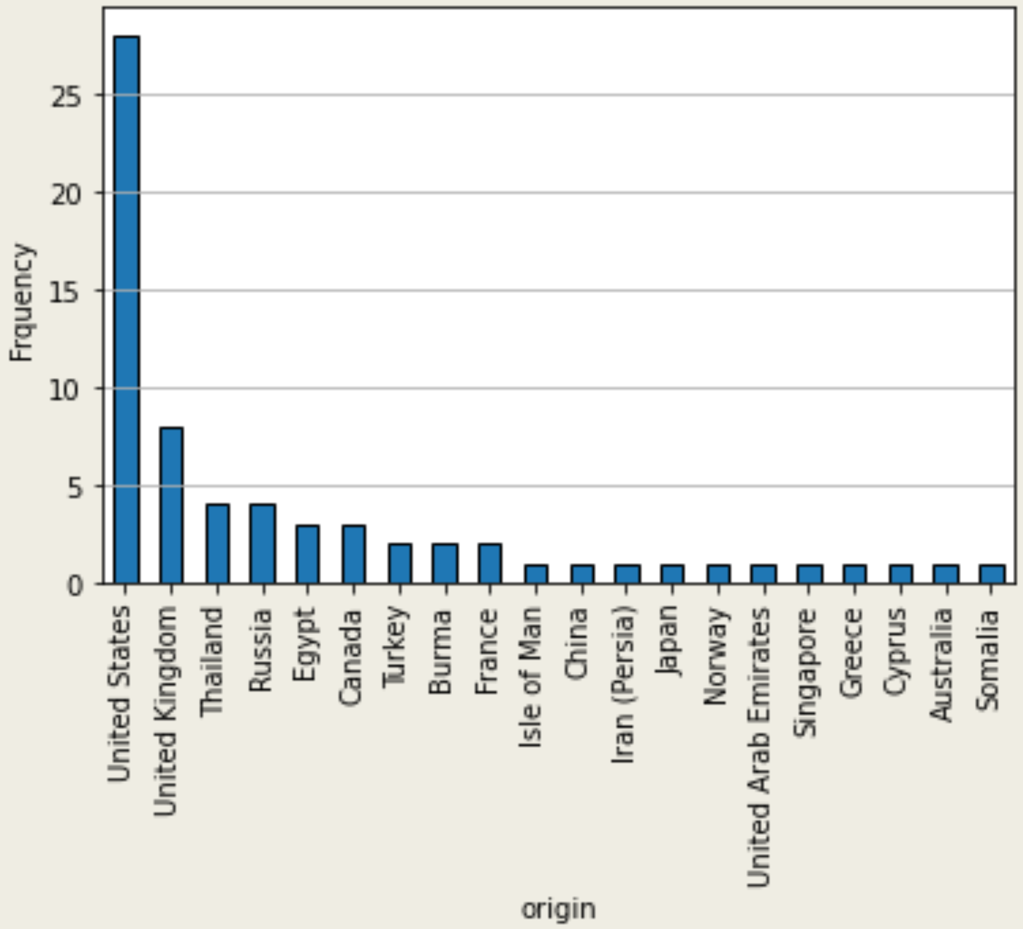
Association between categorical variables will need chi squared test to confirm.(which is out of the scope of this project.)

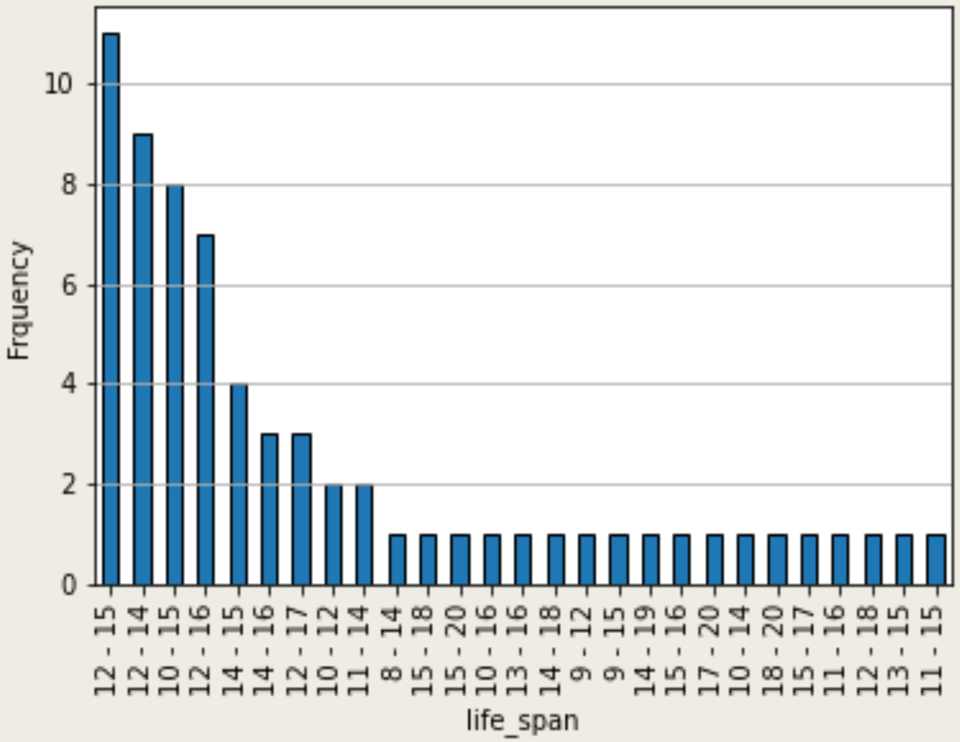
By doing initial exploration to the dataset, we find the following:

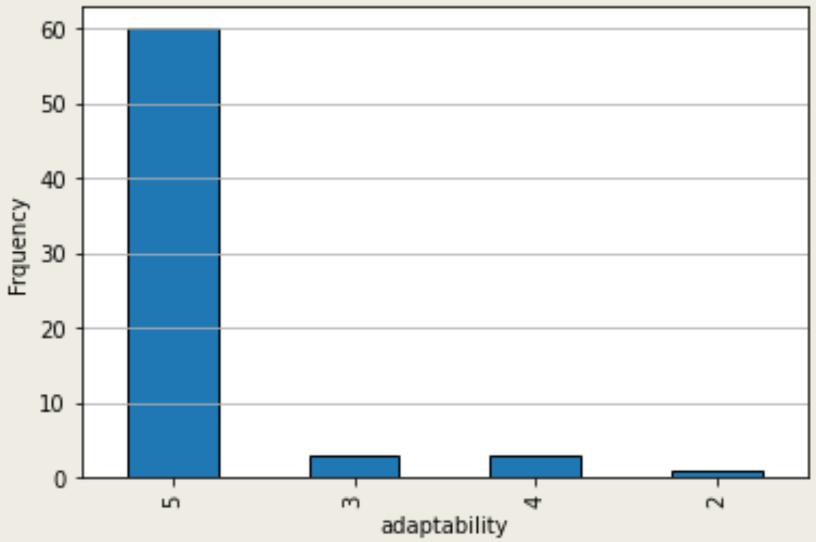
dataset contains 40 columns, 67 records.
The majority of those columns are categorical data type.

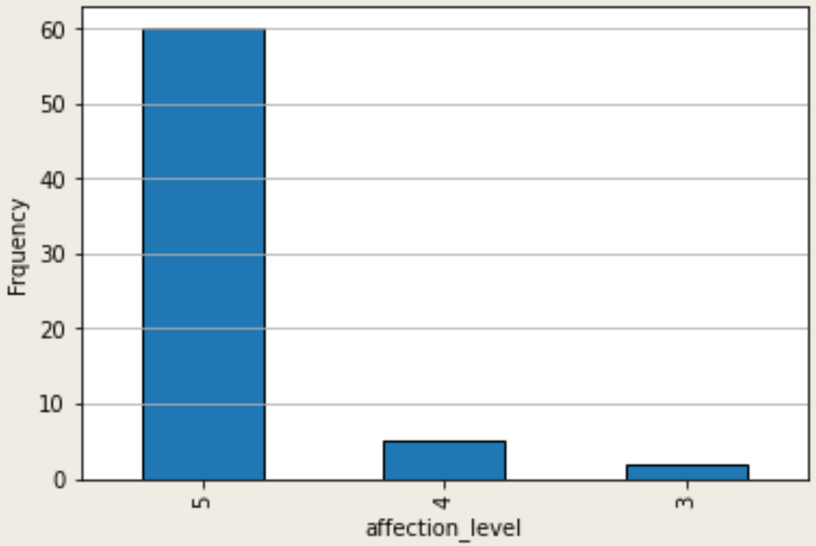
Categorical fields had been encoded in the original source(for analysis reason)

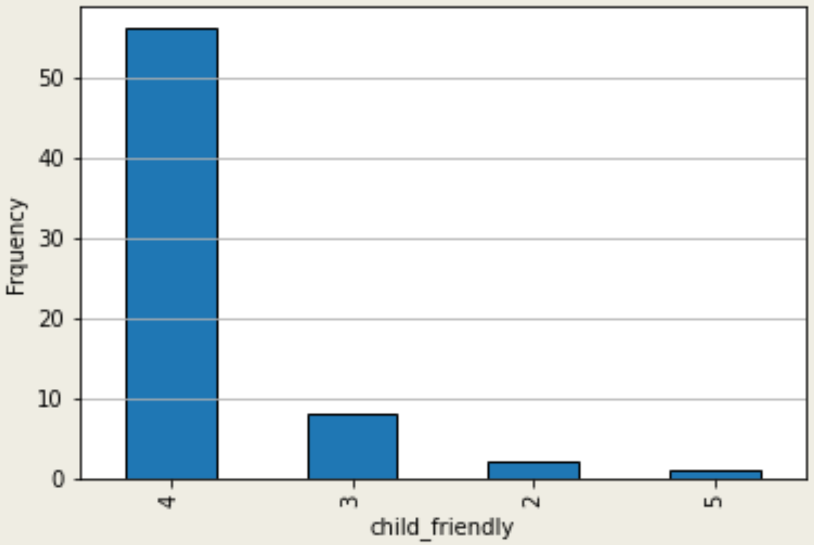
Visual Exploration: Columns’ Values & Frequencies:

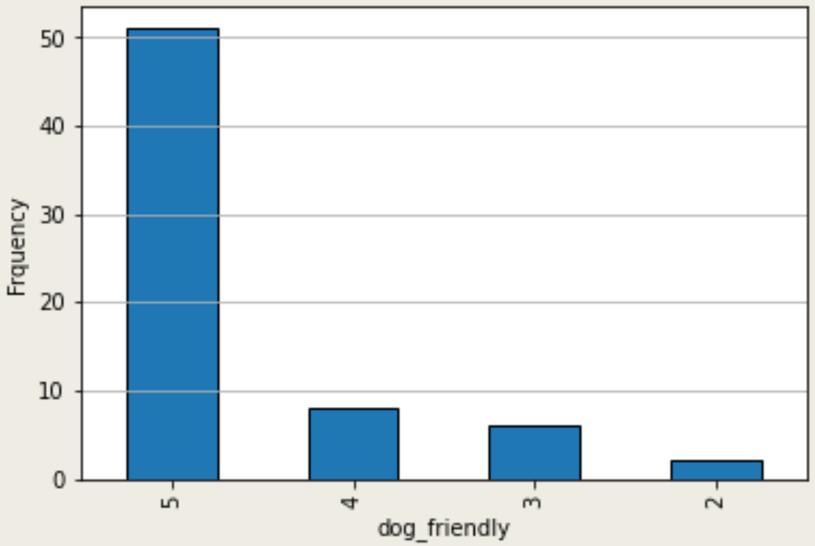


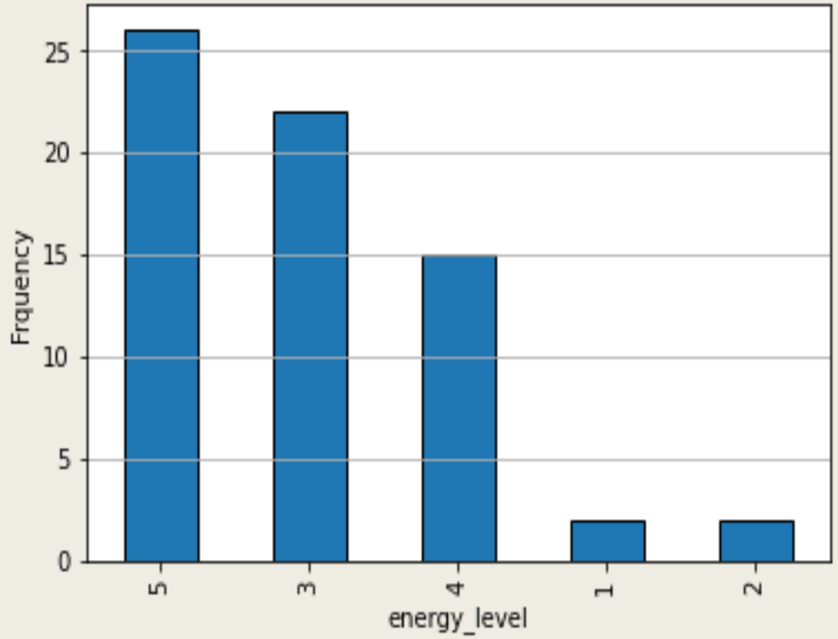



60
50
40
30
20
10
0
Frquency
5
3
4
2
adaptability

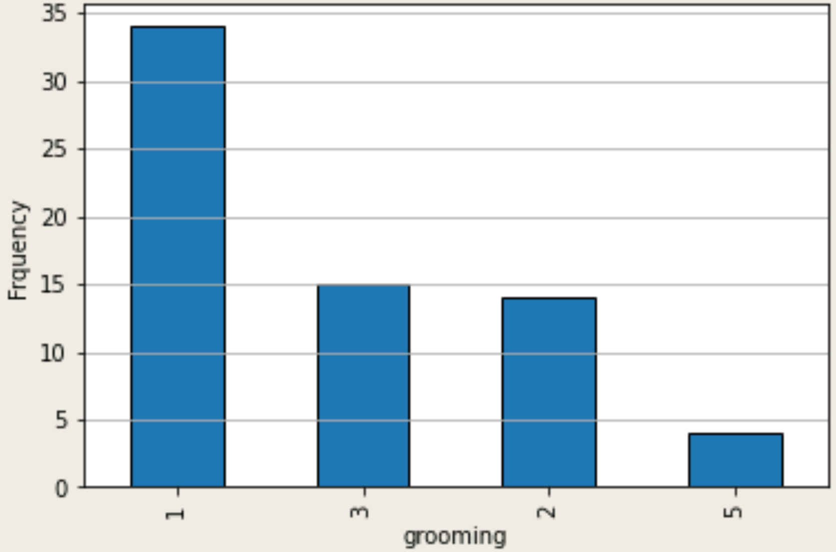

60
50
40
30
20
10
0
Frquency
5
4
3
affection_level


50
40
30
20
10
0
Frquency
4
3
2
5
child_friendly

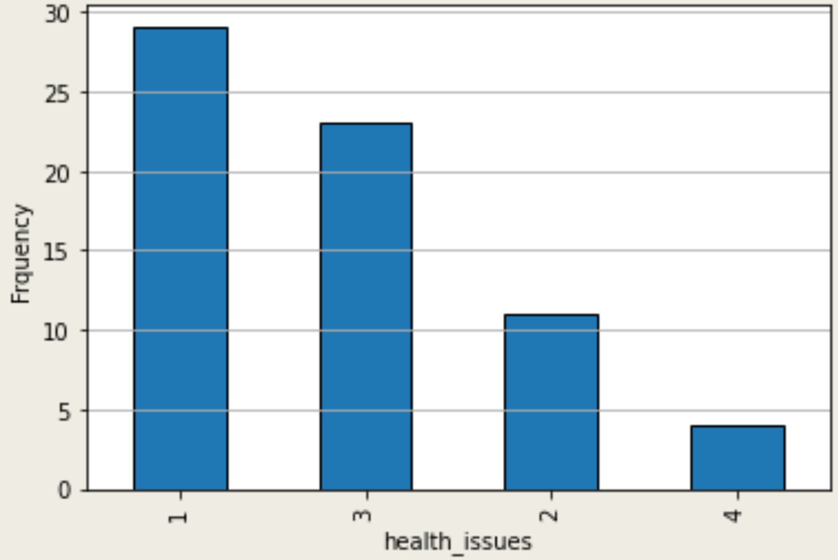

50
40
30
20
10
0
Frquency
5
4
3
2
dog_friendly



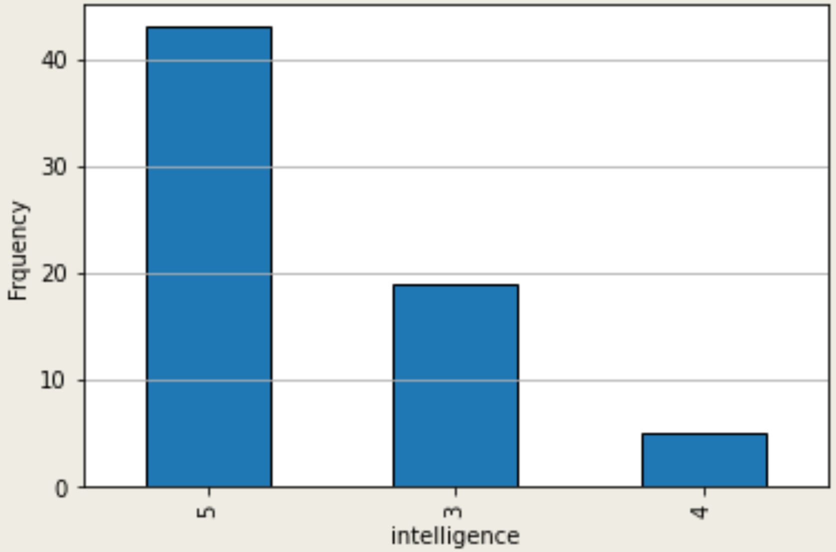
Frquency
0
5
10
15
20
25
5
3
4
1
2
energy_level



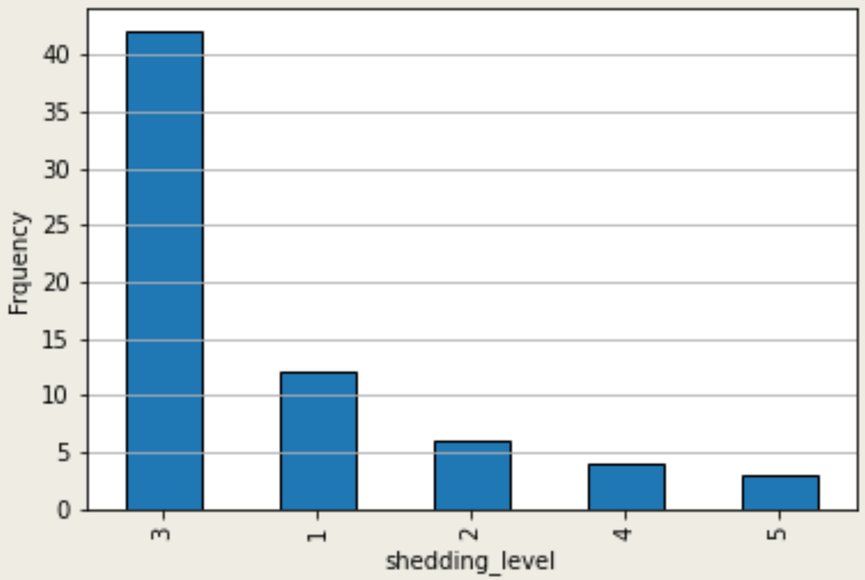
Frquency
0
5
10
15
20
25
30
35
1
3
2
5
grooming

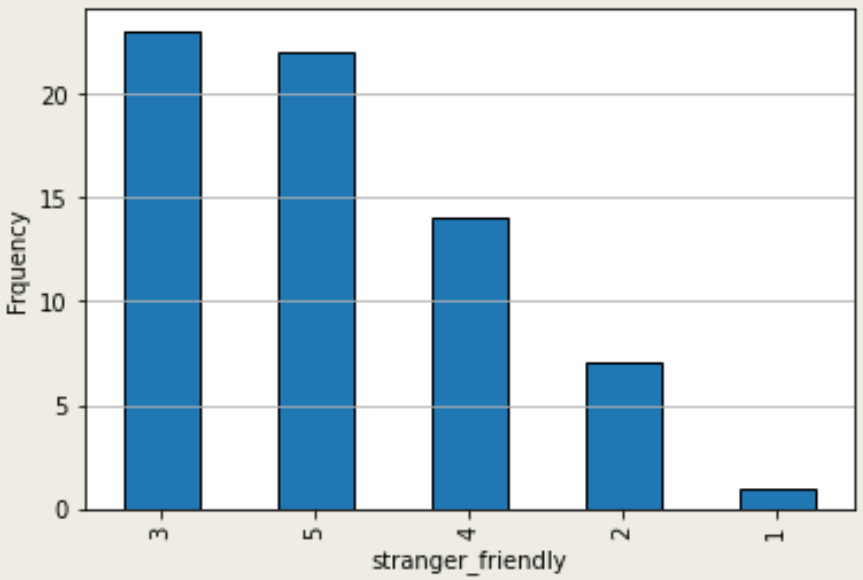


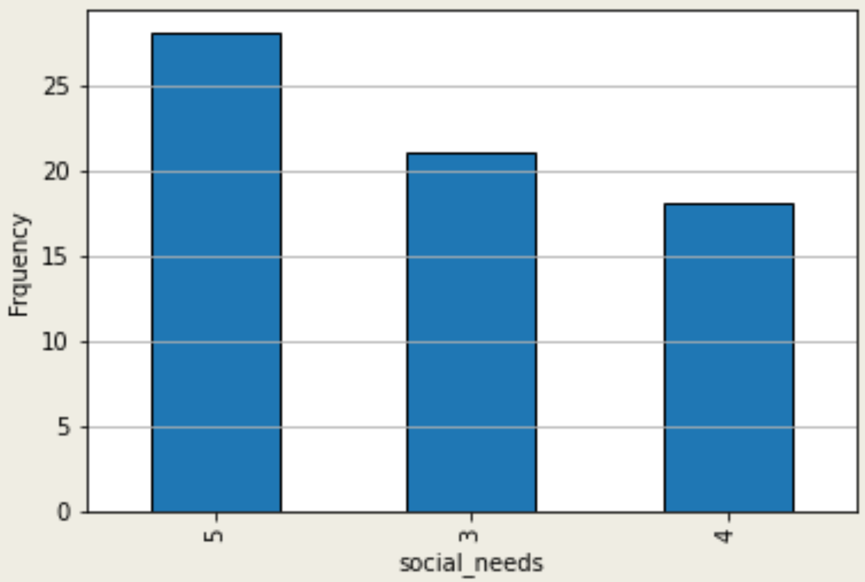
Frquency
0
5
10
15
20
25
30
1
3
2
4
health_issues

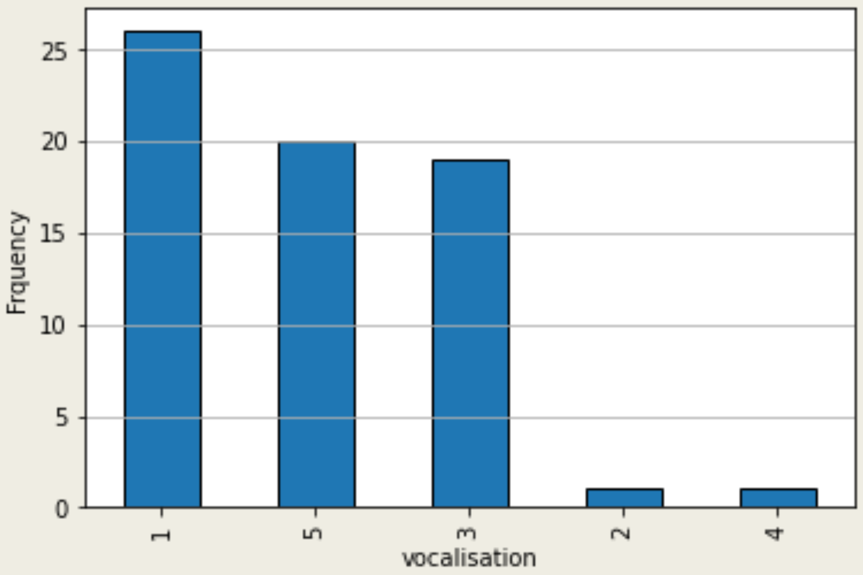


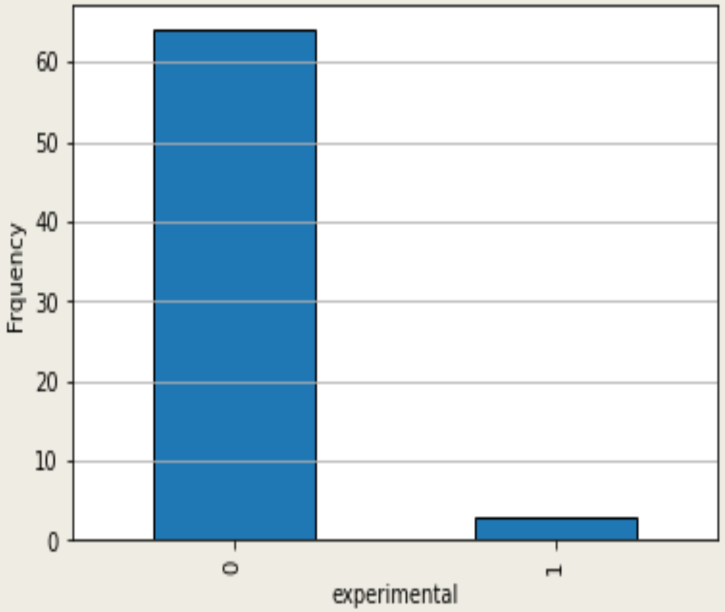
Frquency
0
10
20
30
40
5
3
4
intelligence


Frquency
0
5
10
15
20
25
30
35
40
3
1
2
4
5
shedding_level


Frquency
0
5
10
15
20
3
5
4
2
1
stranger_friendly


Frquency
0
5
10
15
20
25
5
3
4
social_needs


Frquency
0
5
10
15
20
25
1
5
3
2
4
vocalisation


Frquency
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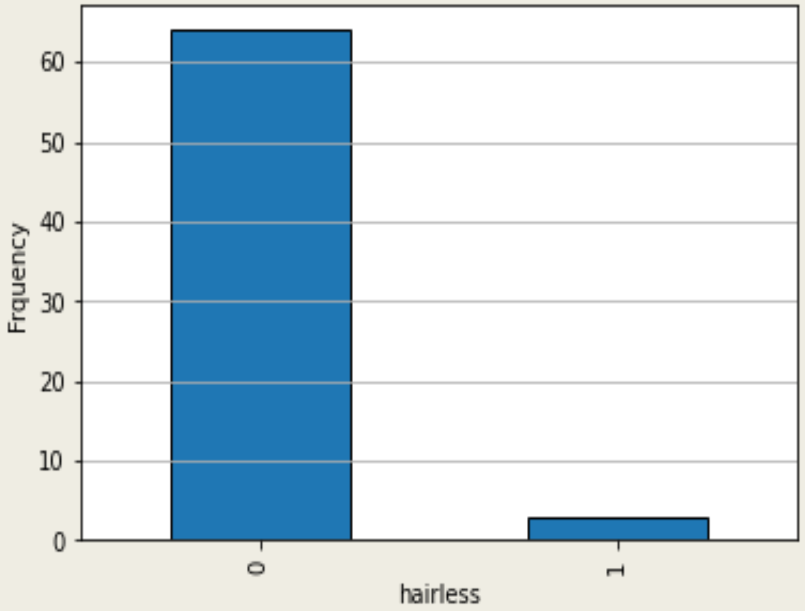
10
20
30
40
50
60
0
1
experimental


Frquency
0
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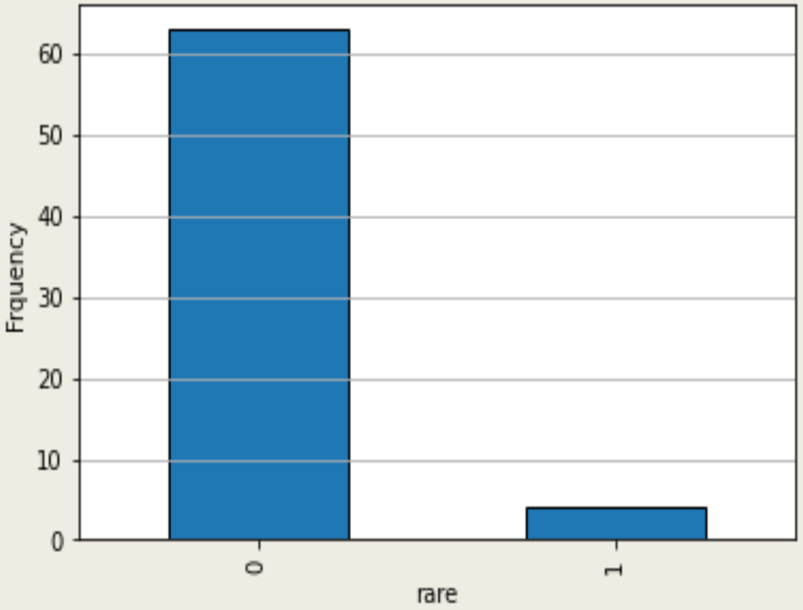
20
30
40
50
60
0
1
hairless


Frquency
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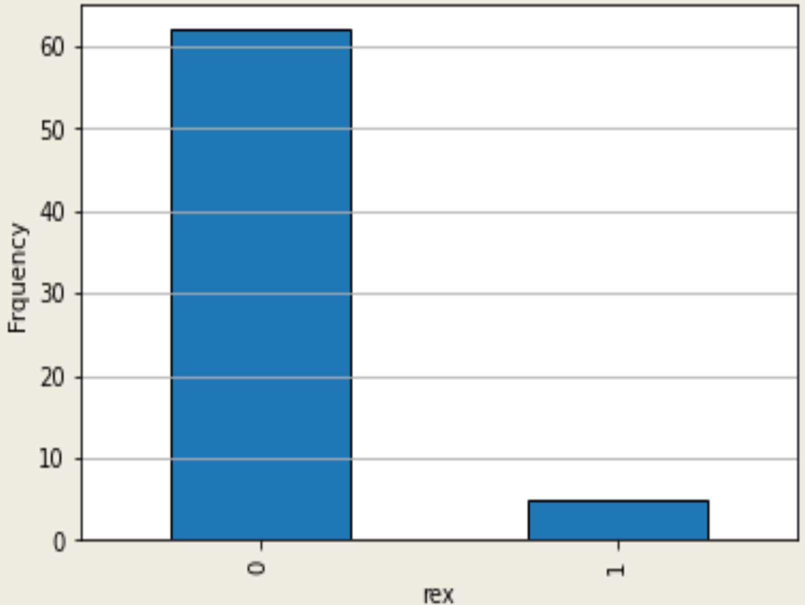
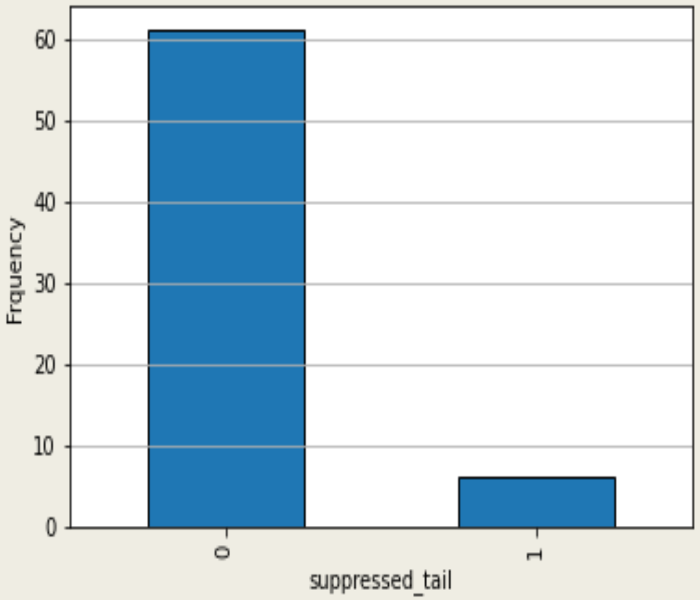
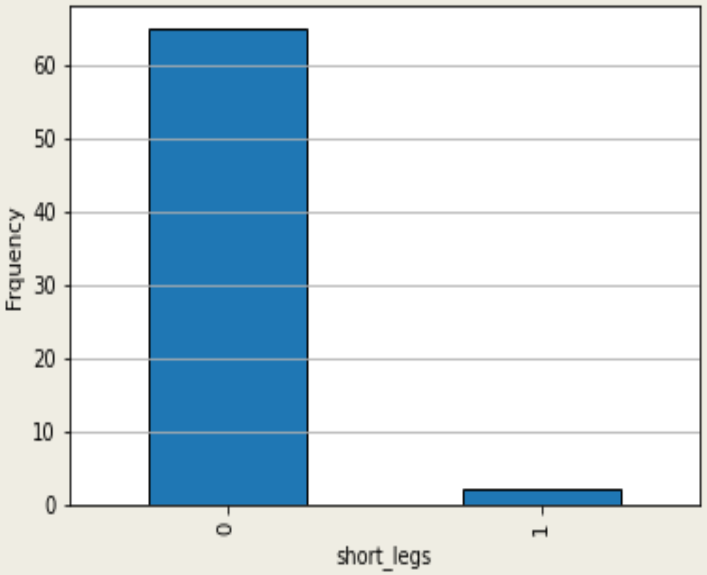
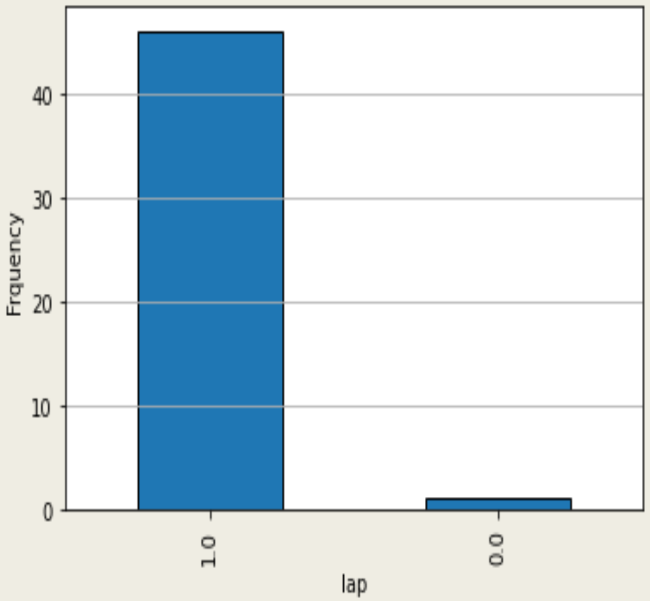
10
20
30
40
50
60
0
1
rare


Frquency
0
10
20
30
40
50
60
0
1
rex


Frquency
0
10
20
30
40
50
60
0
1
suppressed_tail


Frquency
0
10
20
30
40
50
60
0
1
short_legs


Frquency
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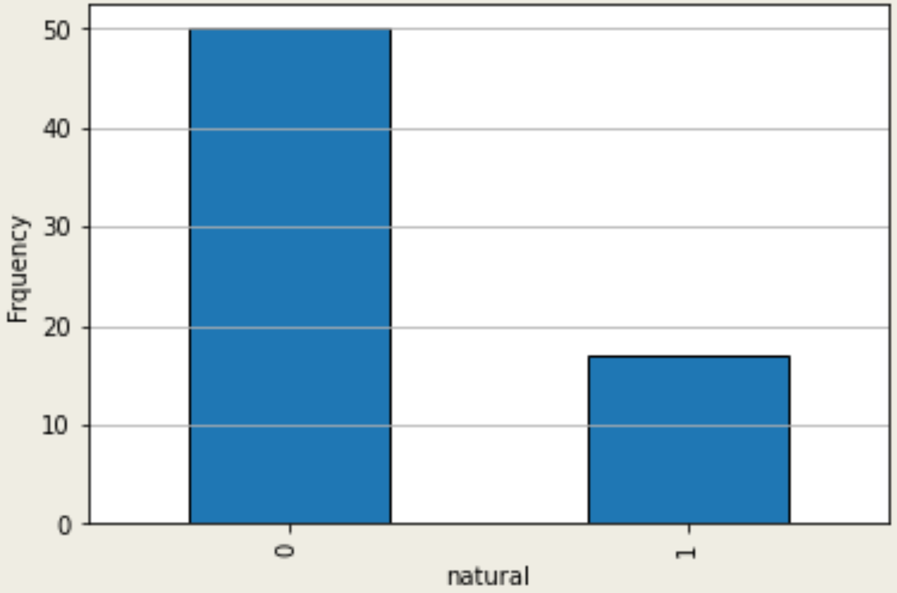
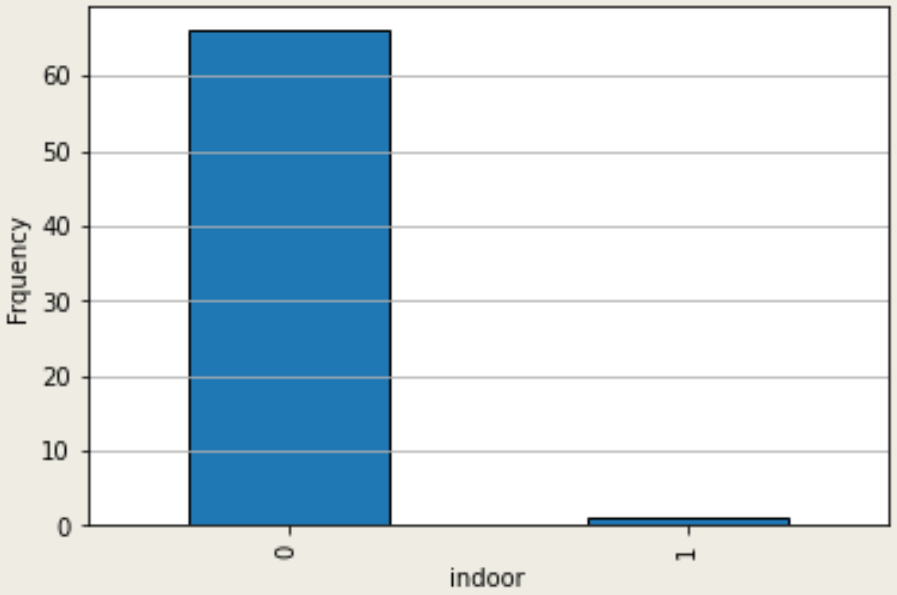
10
20
30
40
1.0
0.0
lap


Frquency
0
10
20
30
40
50
0
1
natural


Frquency
0
10
20
30
40
50
60
0
1
indoor

3- DATA CLEANING:

Once the data are collected, the next step is to get it ready for analysis. This means cleaning, or scrubbing' it, and is crucial in making sure that you're working with high-quality data.

<u>These include the following steps:</u>

Removing major errors, duplicates, and outliers - all of which are inevitable problems when aggregating data from numerous sources.

Removing unwanted data points-extracting irrelevant observations that have no bearing on your intended analysis.

Data Standardization: fixing typos or layout issues, data types , which will help map and manipulate data more easily.

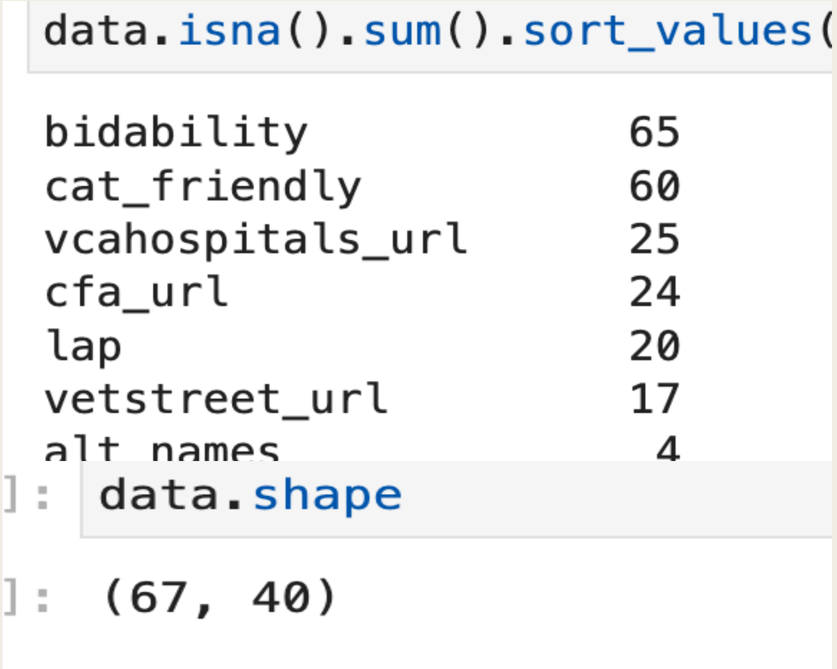
Filling in major gaps, you might notice that important data are missing. Once you've identified gaps.

Null Values:

We can see that some fields have a null Values of 65, 60 which make those columns useless and can not provide insight.

Replace missing categorical values with the most frequent category (mode) within that variable.

In this Dataset as we can see there are three fields that includes URLs. In my opinion the best approach is just keep is as unknow.

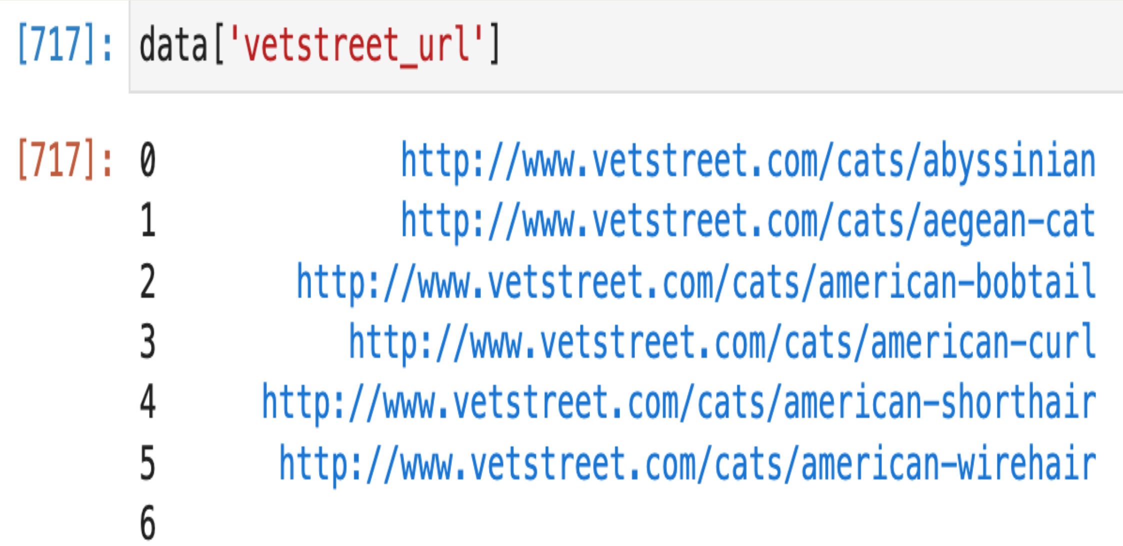


```
data.isna().sum().sort_values(

bidability           65
cat_friendly         60
vcahospitals_url     25
cfa_url              24
lap                  20
vetstreet_url        17
alt_names             4
```

```
]: data.shape

]: (67, 40)
```

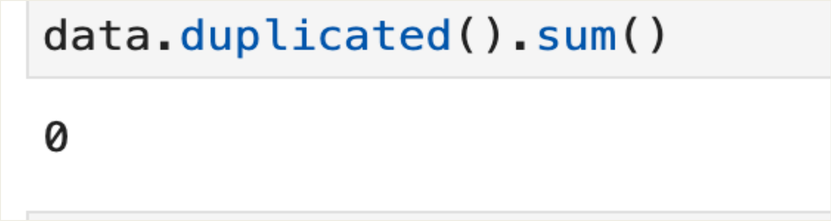


```
[717]: data['vetstreet_url']

[717]: 0          http://www.vetstreet.com/cats/abyssinian
       1          http://www.vetstreet.com/cats/aegean-cat
       2      http://www.vetstreet.com/cats/american-bobtail
       3        http://www.vetstreet.com/cats/american-curl
       4    http://www.vetstreet.com/cats/american-shorthair
       5     http://www.vetstreet.com/cats/american-wirehair
       6
```

Duplicates vales:

We have no duplicated records in our dataset.



```
data.duplicated().sum()
```

```
0
```

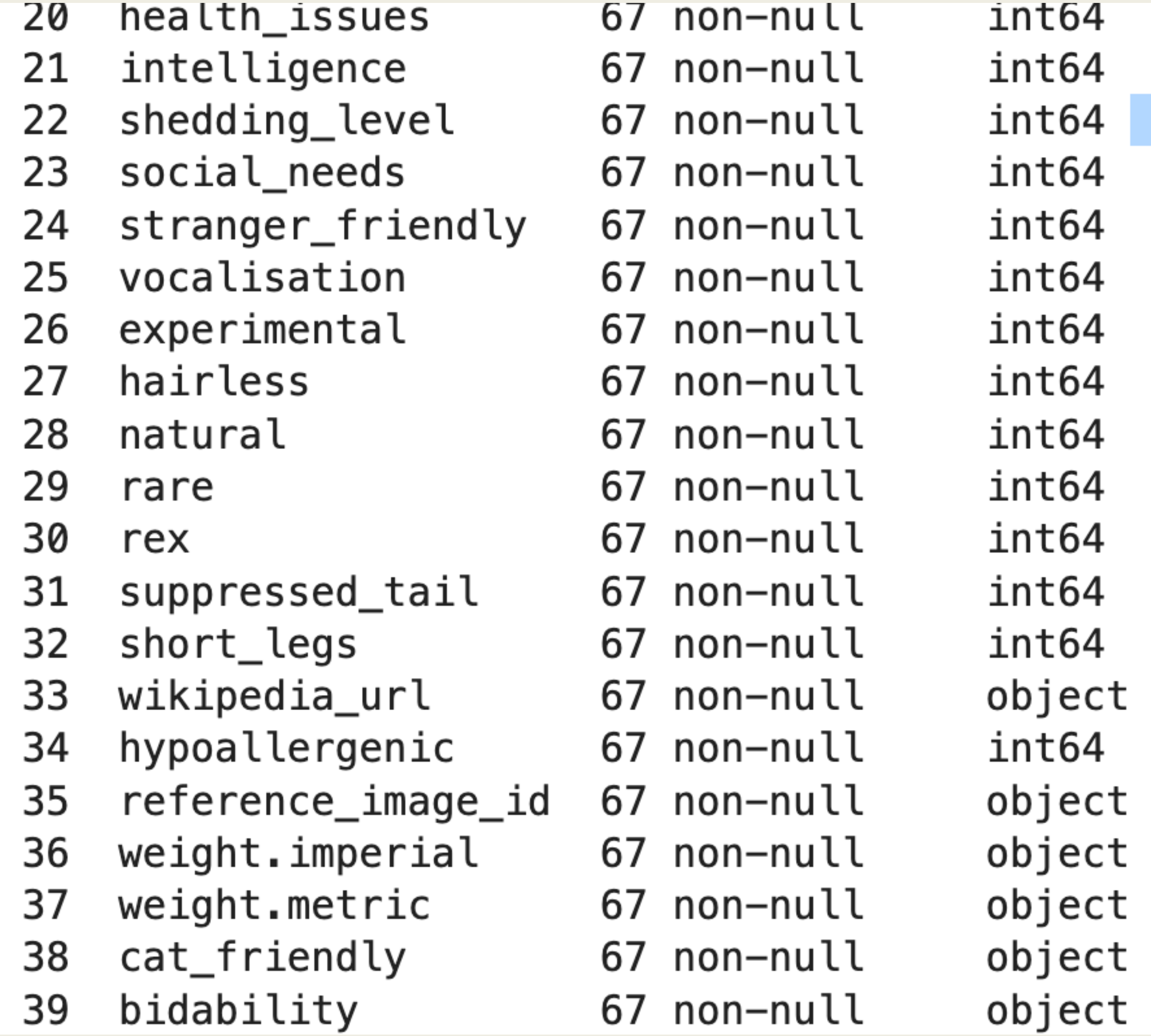
Data Type:

By doing initial exploration to the dataset, we find the following:

Dataset contains 40 columns, 67 records.

The majority of those columns are categorical data type.

Categorical fields had been encoded in their original source (for analysis reason)



```
20  health_issues      67 non-null    int64
21  intelligence       67 non-null    int64
22  shedding_level     67 non-null    int64
23  social_needs       67 non-null    int64
24  stranger_friendly  67 non-null    int64
25  vocalisation       67 non-null    int64
26  experimental       67 non-null    int64
27  hairless           67 non-null    int64
28  natural            67 non-null    int64
29  rare               67 non-null    int64
30  rex                67 non-null    int64
31  suppressed_tail    67 non-null    int64
32  short_legs         67 non-null    int64
33  wikipedia_url      67 non-null    object
34  hypoallergenic     67 non-null    int64
35  reference_image_id 67 non-null    object
36  weight.imperial    67 non-null    object
37  weight.metric      67 non-null    object
38  cat_friendly       67 non-null    object
39  bidability         67 non-null    object
```

For more about dealing with categorical data you can read the following two slides.

Dealing with Categorical Data (1):

Identify categorical features:

Identifying which columns in your dataset contain categorical data, like text descriptions or labels .

Handle missing values:
Replace missing categorical values with the most frequent category (mode) within that variable.

Encoding methods:
Label encoding: Assign a unique integer to each category, suitable when there's an inherent order between categories (like size: small, medium, large).

One-hot encoding: Create new binary features for each category, where only one feature is ""for a given category, useful when order is not important.

Consider cardinality:
Low cardinality: If there are few unique categories, one-hot encoding is often suitable.

High cardinality: For many unique categories, consider techniques like target encoding or frequency encoding to reduce dimensionality.

Dealing with Categorical Data (2):

A chi-square test is used to assess whether there is a significant association between two categorical variables, while a Pearson correlation measures the strength of a linear relationship between two continuous variables; essentially.

A chi-square test looks for relationships between categories, while a Pearson correlation examines how two numerical variables change together in a linear fashion

There are three metrics that are commonly used to calculate the correlation between categorical variables:

1. Tetrachoric Correlation: Used to calculate the correlation between binary categorical variables.

2. Polychromic Correlation: Used to calculate the correlation between ordinal categorical variables.

3. Cramer’s V: Used to calculate the correlation between nominal categorical variables.
Note: Nominal data is a type of data that categorizes variables into distinct groups without any inherent order or ranking

Outliers:

There are no outlier detection methods for categorical data.

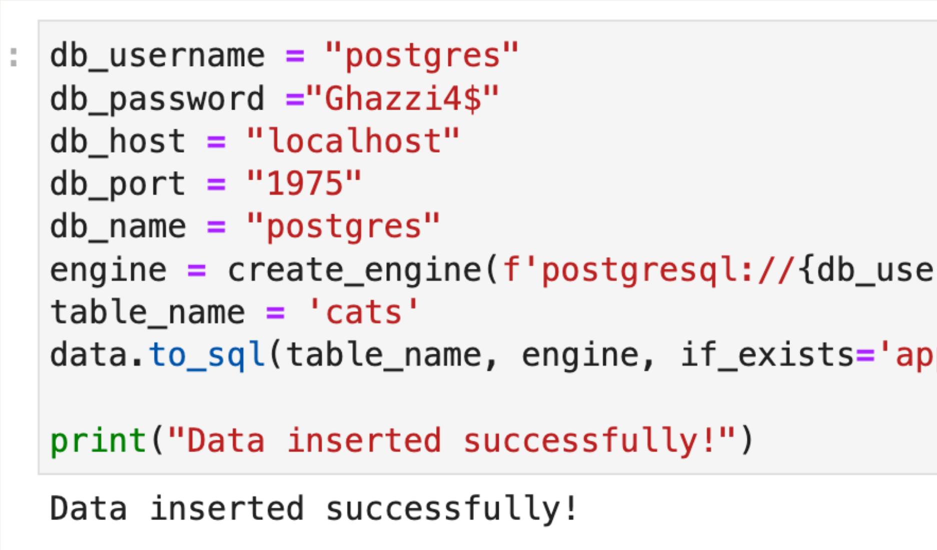
For an outlier to exist there must be a measure of distance between the items.
Removing outliers involves excluding data points significantly deviating from the norm

Removing outliers influences the mean, reducing its sensitivity to extreme values and providing a more representative measure of central tendency.

Common techniques include visualization tools (box plots, scatter plots), mathematical methods (Z-scores, IQR), and threshold-based filtering.

3- DATA LOADING:

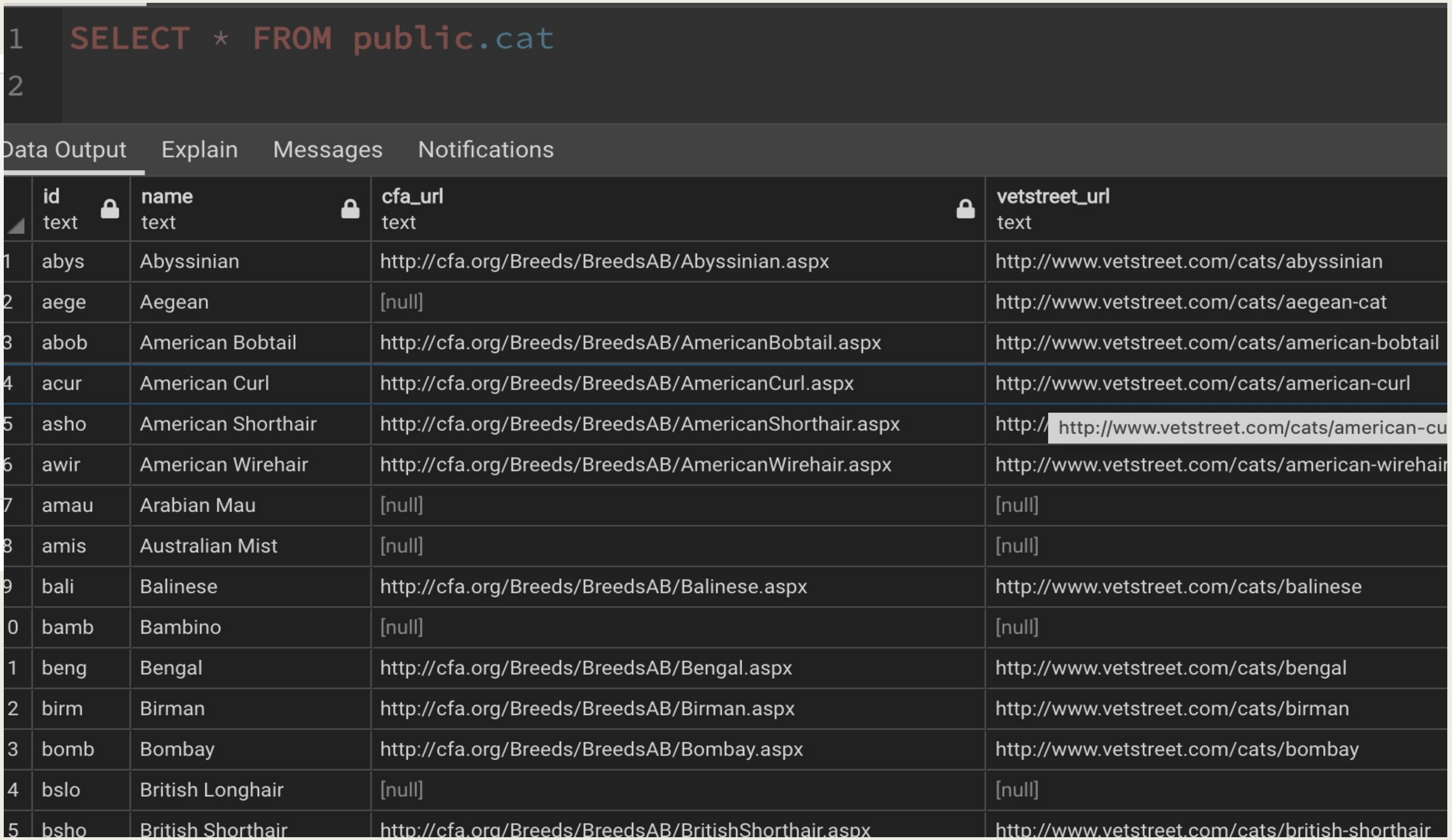
Connecting to the Target Database (Postgres)



```
db_username = "postgres"
db_password ="Ghazzi4$"
db_host = "localhost"
db_port = "1975"
db_name = "postgres"
engine = create_engine(f'postgresql://{db_use
table_name = 'cats'
data.to_sql(table_name, engine, if_exists='ap

print("Data inserted successfully!")
```

```
Data inserted successfully!
```



```
SELECT * FROM public.cat
```

	id text	name text	cfa_url text	vetstreet_url text
1	abys	Abyssinian	http://cfa.org/Breeds/BreedsAB/Abyssinian.aspx	http://www.vetstreet.com/cats/abyssinian
2	aege	Aegean	[null]	http://www.vetstreet.com/cats/aegean-cat
3	abob	American Bobtail	http://cfa.org/Breeds/BreedsAB/AmericanBobtail.aspx	http://www.vetstreet.com/cats/american-bobtail
4	acur	American Curl	http://cfa.org/Breeds/BreedsAB/AmericanCurl.aspx	http://www.vetstreet.com/cats/american-curl
5	asho	American Shorthair	http://cfa.org/Breeds/BreedsAB/AmericanShorthair.aspx	http:// http://www.vetstreet.com/cats/american-cu
6	awir	American Wirehair	http://cfa.org/Breeds/BreedsAB/AmericanWirehair.aspx	http://www.vetstreet.com/cats/american-wirehai
7	amau	Arabian Mau	[null]	[null]
8	amis	Australian Mist	[null]	[null]
9	bali	Balinese	http://cfa.org/Breeds/BreedsAB/Balinese.aspx	http://www.vetstreet.com/cats/balinese
0	bamb	Bambino	[null]	[null]
1	beng	Bengal	http://cfa.org/Breeds/BreedsAB/Bengal.aspx	http://www.vetstreet.com/cats/bengal
2	birm	Birman	http://cfa.org/Breeds/BreedsAB/Birman.aspx	http://www.vetstreet.com/cats/birman
3	bomb	Bombay	http://cfa.org/Breeds/BreedsAB/Bombay.aspx	http://www.vetstreet.com/cats/bombay
4	bslo	British Longhair	[null]	[null]
5	bsho	British Shorthair	http://cfa.org/Breeds/BreedsAB/BritishShorthair.aspx	http://www.vetstreet.com/cats/british-shorthair

Thank You.

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