

Data and Artificial Intelligence

Cyber Shujaa Program

Week 2 Assignment

Web Scraping and Data Handling in Python

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Introduction

This week's assignment was on data wrangling. Data wrangling is the process of cleaning, structuring, and transforming raw data into a usable format for analysis. The data source was from Kaggle. I developed hands-on experience on automating web data gathering using Kaggle Data Set and published my work on Kaggle. I practiced the data Wrangling concepts to clean up the Netflix dataset to a well-structured and usable format.

Objectives

The objectives of the assignment were to:

1. Load the Netflix dataset from a CSV file and explore its structure using pandas.
2. Perform data discovery to assess data types, missing values, and quality issues.
3. Clean the dataset by handling duplicates, missing values, and formatting inconsistencies.
4. Transform and enrich the dataset using techniques like filtering, sorting, grouping, and feature extraction.
5. Validate the final dataset by checking consistency, completeness, and logical accuracy.
6. Export the final cleaned dataset to a .csv file ready for analysis or visualization.

Tasks Completed

Step 1

In this step I loaded and inspected the Netflix dataset that I was going to work with. I created a notebook file and attached the dataset.

Code:

```
import pandas as pd  
df = pd.read_csv('/kaggle/input/netflix/netflix_titles.csv')
```

Code explanation:

The code imports the python library, pandas, for structuring the data. The csv file is read into a data frame and the result is stored in the variable df. The read_csv function of pandas takes in the file path of the dataset.

Step 2

In this step I explored my data to have an overview of it and to better understand it. I checked for its shape, list of column names, data types and missing values.

Code:

```
df.info()
print("Shape of the dataset (R x C):", df.shape)
print("Columns in the dataset:\n", df.columns.tolist())
print("Data types:\n", df.dtypes)
print("Missing values per column:\n", df.isnull().sum())
print("Number of duplicate rows:", df.duplicated().sum())
```

Code explanation:

df.info() gives an overview of the data. df.shape() gives the shape of the data set which is the number of rows and column it has. df.columns.tolist() lists all column names in the dataset. df.dtypes gives the data types of each column. df.isnull().sum() groups and counts missing null values in each column. df.duplicated().sum() counts all duplicate rows.

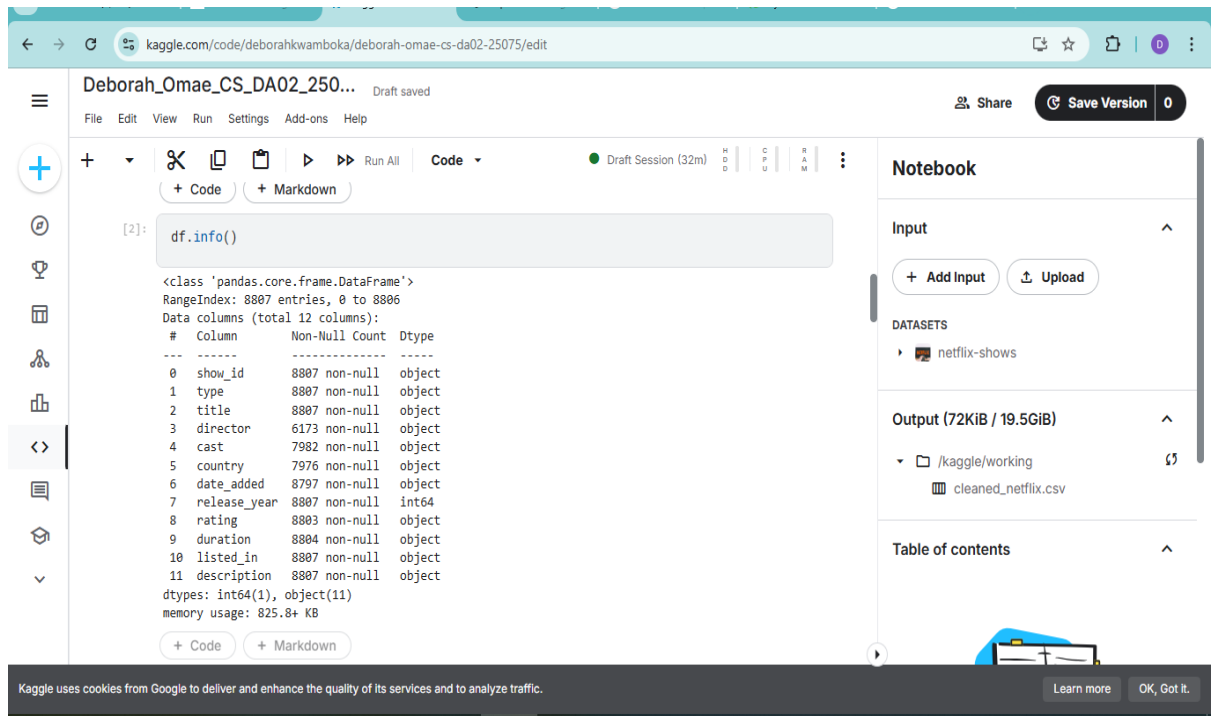


Figure 1: screenshot showing the result of `df.info()`

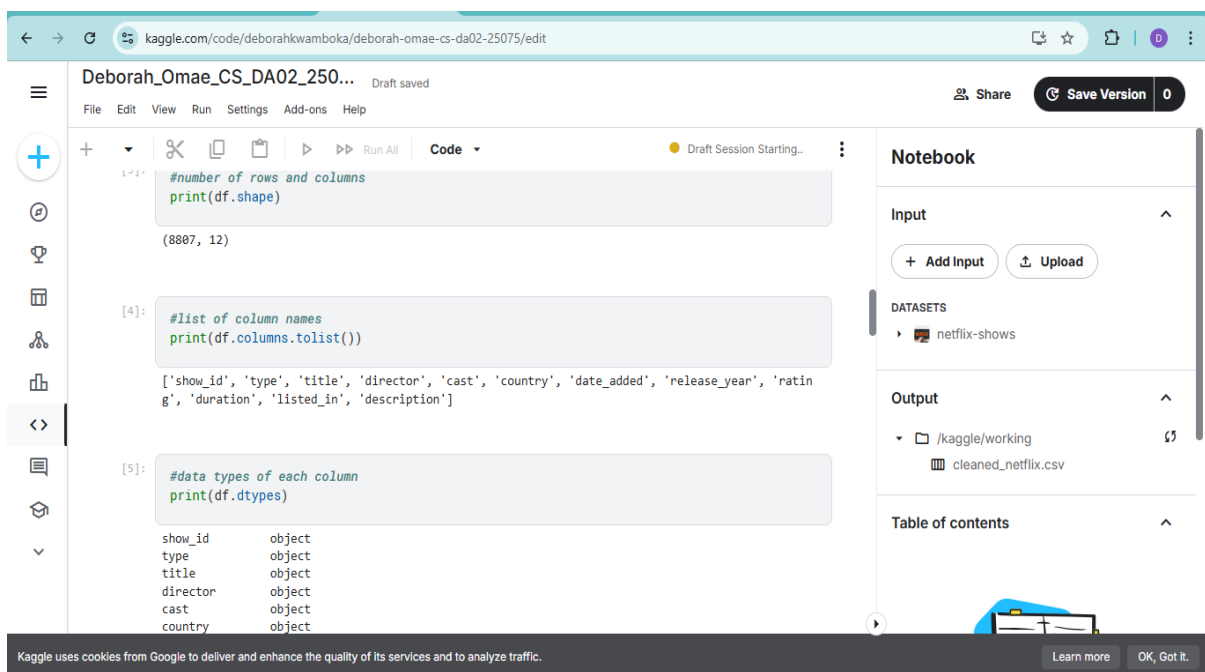


Figure 2: screenshot showing number of rows and columns and the list of column names

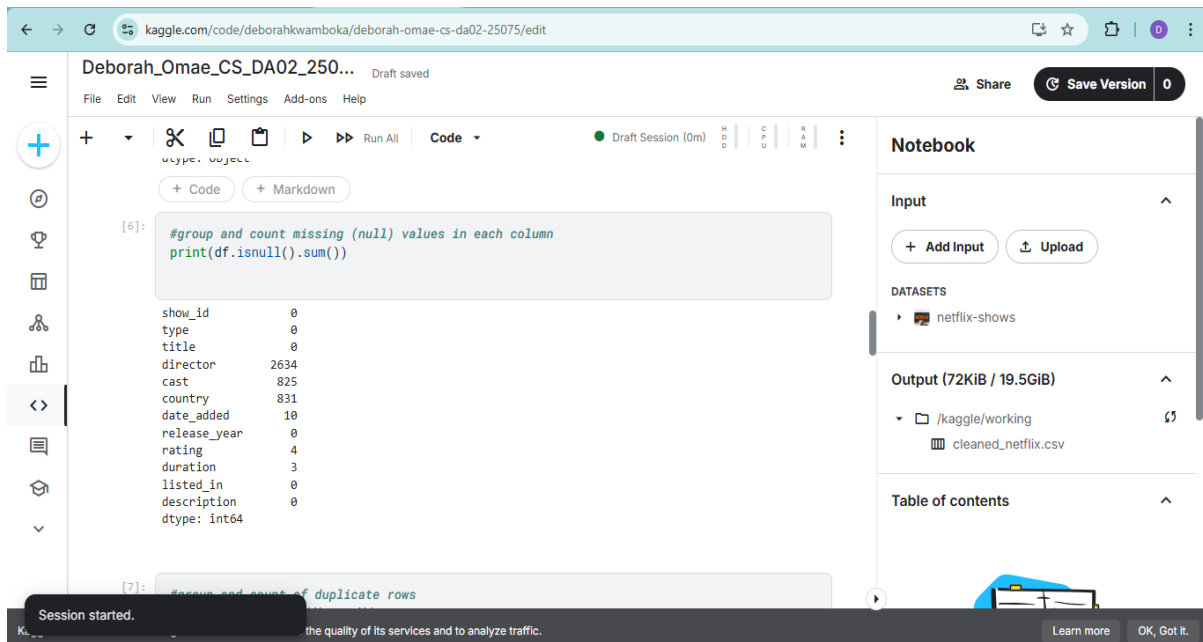


Figure 3: screenshot showing missing null values of each column

Step3

In this step, I did structure and formatting of some columns. I structured the date added to datetime, the duration column into value and unit.

Code:

```
df['date_added'] = pd.to_datetime(df['date_added'],format='mixed')
df[['duration_value', 'duration_unit']] = df['duration'].str.extract(r'(\d+)\s*(\w+)')
df['duration_value'] = pd.to_numeric(df['duration_value'])
print(df[['duration_value', 'duration_unit']])
```

code explanation:

The datetime function of pandas converts the date added to date time format. To separate the duration column to numerical value and unit we use this regex expression; `str.extract(r'(\d+)\s*(\w+)')`. `(\d+)` captures the number, `(\w+)` captures the word. The space is matched and discarded since its not in parentheses. The duration value is converted to numeric value through the pandas `to_numeric()` function.

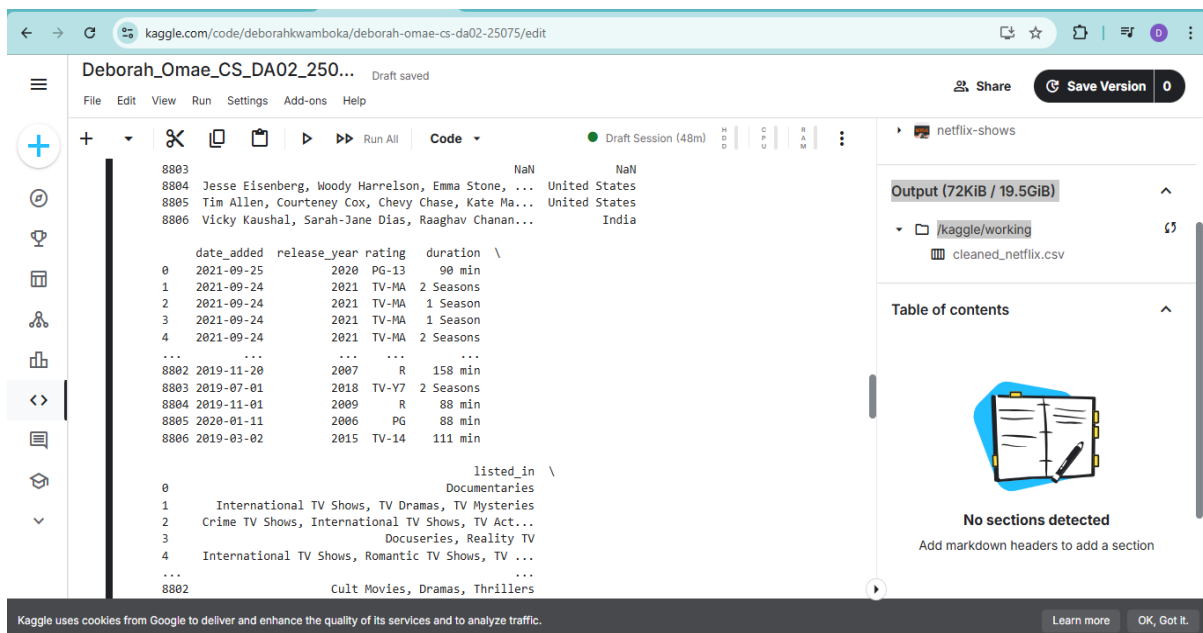


Figure 4: screenshot showing the conversion of date added to date time format

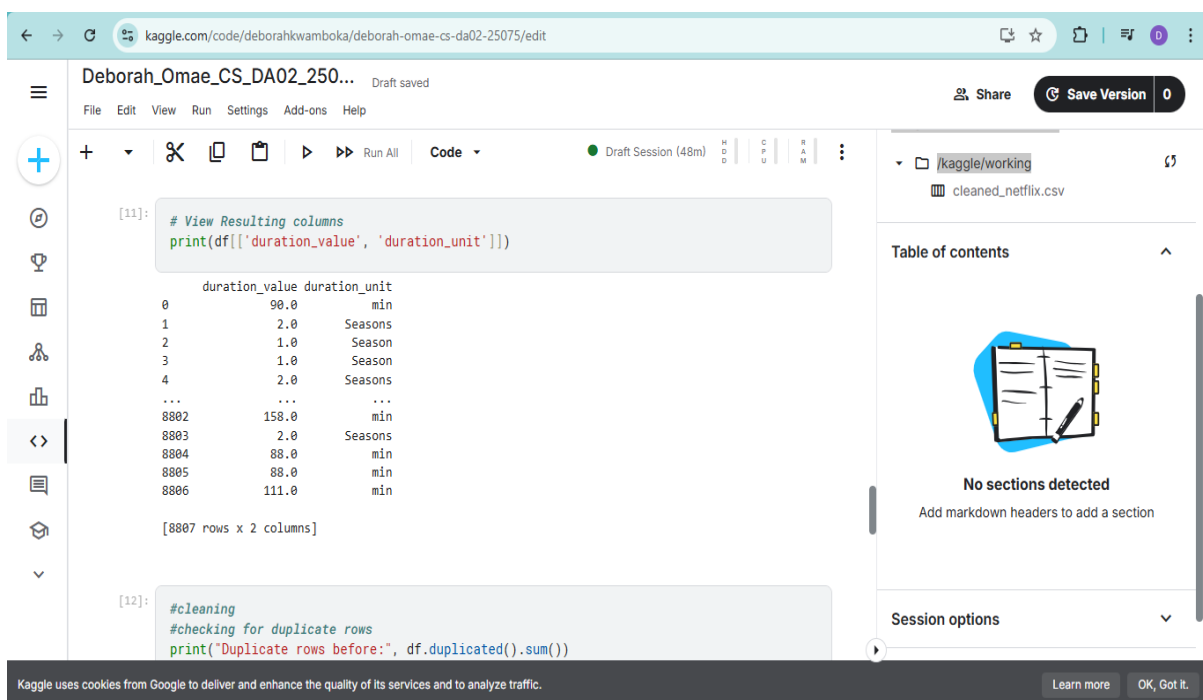


Figure 5: screenshot showing the duration column separated into duration value and unit. This is useful in case one wants to perform calculations on the duration value column.

Step 4

In this step I performed cleaning of the data. I checked for duplicate rows and dropped them if any.

Code:


```
print("Duplicate rows before:", df.duplicated().sum())
```

```
df = df.drop_duplicates()
```

code explanation

The duplicated() function checks for duplicated rows and used with the sum() method it returns the number of rows that are duplicates. df.drop_duplicates() function drops the duplicated rows if any.

Note: For this data set there were no duplicated rows.

Step 5

In this step I dropped the description column since its not useful.

code

```
df = df.drop(columns=['description'])
```

step 6

In this step I Impute missing values in the director column by using repeated director–cast relationships found elsewhere in the dataset. The assumption is: if a particular director and cast string appear together frequently, we can trust that relationship and use it to infer missing directors when we see the same cast again.

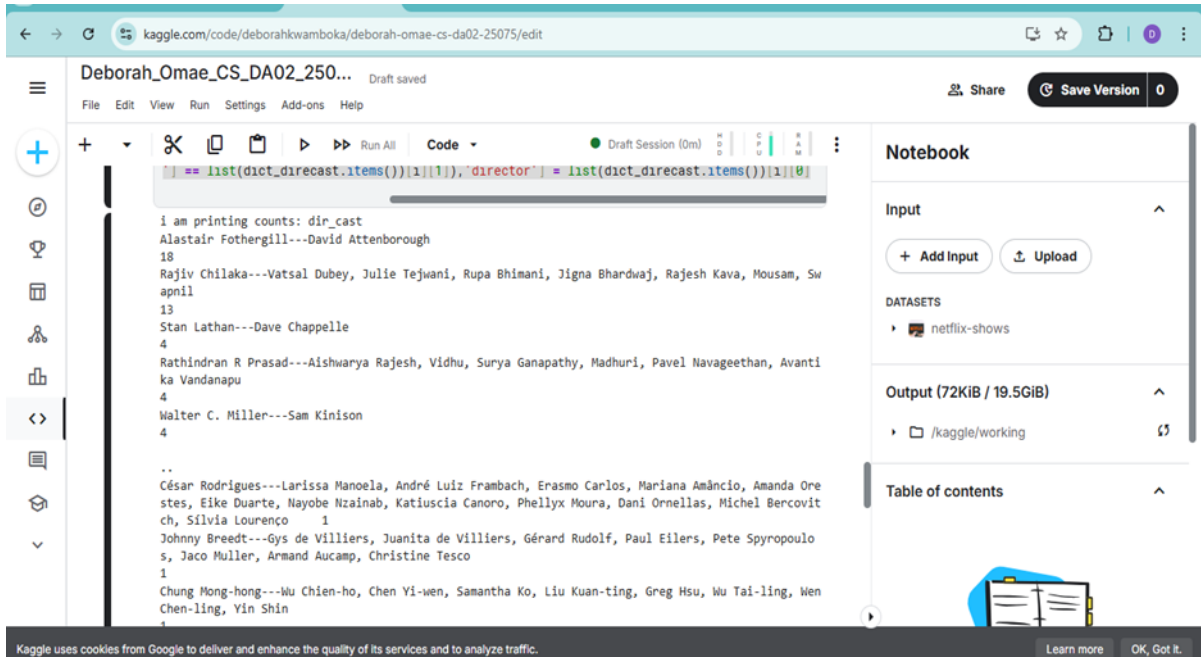
Code:

```
# List of Director-Cast pairs and the number of times they appear
df['dir_cast'] = df['director'] + '---' + df['cast']
counts = df['dir_cast'].value_counts() #counts unique values
filtered_counts = counts[counts >= 3] #checks if repeated 3 or more times
filtered_values = filtered_counts.index #gets the values i.e. names
lst_dir_cast = list(filtered_values) #convert to list
dict_direcast = dict()
for i in lst_dir_cast :
    director,cast = i.split('---')
```

```
dict_directcast[director]=cast
for i in range(len(dict_directcast)):
    df.loc[(df['director'].isna() & (df['cast'] == list(dict_directcast.items())[i][1]),'director'] =
list(dict_directcast.items())[i][0]
```

Code explanation:

- `df['dir_cast'] = df['director'] + '---' + df['cast']`
This code creates a combined identifier by merging director and cast into a single string to represent each pair uniquely.
- `counts = df['dir_cast'].value_counts()`
This code counts how many times each unique director–cast pair appears in the dataset.



```
== list(dict_directcast.items())[i][1]),'director'] = list(dict_directcast.items())[i][0]

i am printing counts: dir_cast
Alastair Fothergill---David Attenborough
18
Rajiv Chilaka---Vatsal Dubey, Julie Tejwani, Rupa Bhimani, Jigna Bhardwaj, Rajesh Kava, Mousam, Sw
apnil
13
Stan Lathan---Dave Chappelle
4
Rathindran R Prasad---Aishwarya Rajesh, Vidhu, Surya Ganapathy, Madhuri, Pavel Navageethan, Avanti
ka Vandanapu
4
Walter C. Miller---Sam Kinison
4
..
César Rodrigues---Larissa Manoela, André Luiz Frambach, Erasmo Carlos, Mariana Amâncio, Amanda Ore
stes, Eike Duarte, Nayobe Nzainab, Katuscia Canoro, Phellyx Moura, Dani Ornellas, Michel Bercovit
ch, Sílvia Lourenço
1
Johnny Breedt---Gys de Villiers, Juanita de Villiers, Gérard Rudolf, Paul Eilers, Pete Spyropoulo
s, Jaco Muller, Armand Aucamp, Christine Tesco
1
Chung Mong-hong---Wu Chien-ho, Chen Yi-wen, Samantha Ko, Liu Kuan-ting, Greg Hsu, Wu Tai-ling, Wen
Chen-ling, Yin Shin
1
```

Figure 6: This screenshot shows the `dir_cast` column and counts of the unique pairs.

- `filtered_counts = counts[counts >= 3]`
This code filters the results to keep only pairs that appear three or more times, assuming frequent collaborations are more reliable.



```

now these are the filtered counts:
dir_cast
Alastair Fothergill---David Attenborough
18
Rajiv Chilaka---Vatsal Dubey, Julie Tejjwani, Rupa Bhimani, Jigna Bhardwaj, Rajesh Kava, Mousam, Sw
apnil
13
Stan Lathan---Dave Chappelle
4
Rathindran R Prasad---Aishwarya Rajesh, Vidhu, Surya Ganapathy, Madhuri, Pavel Navageethan, Avanti
ka Vandanapu
4
Walter C. Miller---Sam Kinison
4
S.S. Rajamouli---Prabhas, Rana Daggubati, Anushka Shetty, Tamannaah Bhatia, Sathyaraj, Nassar, Ram
ya Krishnan, Sudeep
4
B. V. Nandini Reddy---Samantha Ruth Prabhu, Lakshmi, Rajendraprasad, Naga Shourya, Rao Ramesh, Tej
a Sajja, Pragathi, Jagapathi Babu, Aishwarya, Urvashi
3
Jay Karas---Bill Burr
3
Ashwin Saravanan---Taapsee Pannu, Vinodhini, Parvathi T, Ramya Subramanian, Sanchana Natarajan, An
ish Kuruvilla, David Solomon Raja
3
Louis C.K.---Louis C.K.
3
S.S. Rajamouli---Prabhas, Rana Daggubati, Anushka Shetty, Tamannaah Bhatia, Sathyaraj, Ramya Krish
nan, Nassar, Subbaraju
3
Edward Cotterill---Rachael Stirling
3

```

Figure 7: This filter shows the filtered counts which are the ones with counts above 3

- `filtered_values = filtered_counts.index`
This code extracts the values (the combined strings) of the filtered pairs.
- `lst_dir_cast = list(filtered_values)`
This code converts the filtered pair labels into a list for iteration.



Figure 8: This screenshot shows the filtered pair values converted to a list

- for i in lst_dir_cast: director, cast = i.split('---'); dict_direcast[director] = cast
This code Splits each string at '---' and builds a dictionary mapping each director to their cast string.
- for i in range(len(dict_direcast)): df.loc[(df['director'].isna()) & (df['cast'] == list(dict_direcast.items())[i][1]), 'director'] = list(dict_direcast.items())[i][0]
This code block Iterates through the dictionary and fills in the missing director values for rows with missing director values but matching cast.

Step 7

In this step I assigned the string value 'not given' to all other director fields

Code:

```
# Assign Not Given to all other director fields
df.loc[df['director'].isna(), 'director'] = 'Not Given'
```

Step 8

In this step I used the director's column to fill in missing countries such that if a director's country is known in one row, but missing in another row, the code uses that known relationship (director - country) to fill in the missing value.

Code:

```
directors = df['director']

countries = df['country']

#pair each director with their country use zip() to get an iterator of tuples

pairs = zip(directors, countries)

# Convert the list of tuples into a dictionary

dir_centry = dict(list(pairs))

# Director matched to Country values used to fill in null country values

for i in range(len(dir_centry)):

df.loc[(df['country'].isna()) & (df['director'] == list(dir_centry.items())[i][0]), 'country'] =
list(dir_centry.items())[i][1]

# Assign Not Given to all other country fields

df.loc[df['country'].isna(), 'country'] = 'Not Given'

# Assign Not Given to all other fields

df.loc[df['cast'].isna(), 'cast'] = 'Not Given'
```

code explanation:

- `directors = df['director']`
This code selects the director column from the dataset.
- `countries = df['country']`
This code selects the country column from the dataset.
- `pairs = zip(directors, countries)`

This code pairs each director with their corresponding country using `zip()`, producing an iterator of tuples such as ("Christopher Nolan", "USA").

- `dir_entry = dict(list(pairs))`

This code converts the list of tuples into a dictionary, mapping each director to a country.

- `for i in range(len(dir_entry)): df.loc[(df['country'].isna()) & (df['director'] == list(dir_entry.items())[i][0]), 'country'] = list(dir_entry.items())[i][1]`

This code loops through the dictionary. For rows where the country value is missing but the director matches, it fills in the country from the dictionary.

- `df.loc[df['country'].isna(), 'country'] = 'Not Given'`

This code assigns the value "Not Given" to any rows where the country is still missing after the dictionary-based filling.

- `df.loc[df['cast'].isna(), 'cast'] = 'Not Given'`

This code assigns the value "Not Given" to any rows where the cast information is missing.

step 9

In this step I dropped all rows that have null values

code

```
df.drop(df[df['date_added'].isna()].index,axis=0,inplace=True)
```

```
df.drop(df[df['rating'].isna()].index,axis=0,inplace=True)
```

```
df.drop(df[df['duration'].isna()].index,axis=0,inplace=True)
```

code explanation:

```
df.drop(df[df['date_added'].isna()].index, axis=0, inplace=True)
```

This code drops all rows from the dataset where the `date_added` column has missing (NaN) values.

```
df.drop(df[df['rating'].isna()].index, axis=0, inplace=True).
```

This code drops all rows from the dataset where the `rating` column has missing values.

```
df.drop(df[df['duration'].isna()].index, axis=0, inplace=True).
```

This code drops all rows from the dataset where the duration column has missing values.

Step 10

In this step I checked for errors if any and confirmed there were inconsistencies in my cleaned data

Code

```
import datetime as dt

sum(df['date_added'].dt.year < df['release_year'])

df.loc[(df['date_added'].dt.year < df['release_year']), ['date_added', 'release_year']]

# sample some of the records and check that they have been accurately replaced

df.iloc[[1551, 1696, 2920, 3168]]

#Confirm that no more release_year inconsistencies

sum(df['date_added'].dt.year < df['release_year'])
```

code explanation:

This code was used to check and resolve inconsistencies between the `date_added` and `release_year` columns. First, the `datetime` library was imported to work with date values. The code then checked whether there were any records where the year of `date_added` was earlier than the `release_year` using `sum(df['date_added'].dt.year < df['release_year'])`. Any such mismatched rows were retrieved and displayed with `df.loc[(df['date_added'].dt.year < df['release_year']), ['date_added', 'release_year']]` for inspection. To further verify the corrections, a few specific rows were sampled with `df.iloc[[1551, 1696, 2920, 3168]]`. Finally, the check was repeated with `sum(df['date_added'].dt.year < df['release_year'])` to confirm that no more inconsistencies remained after the cleaning process.

Step 11

In this step, I validated the dataset to ensure accuracy, consistency, and completeness. I removed any temporary columns that I had created during the wrangling process, such as

dir_cast, so that only the necessary fields remained. **The code:** `df.drop(columns=['dir_cast'], inplace=True)`

I then checked that each column had the correct data type, for example confirming that *date_added* was in datetime format and *duration_value* was numeric. To identify potential anomalies, I applied business logic and sanity rules, such as flagging records that appeared before 1997. I also ensured that no important fields were left missing. To further confirm the quality of the data, I sampled a few rows for visual inspection, and finally I reset the index to provide a clean and properly ordered dataset for analysis.

Step 12

In this final step I converted my cleaned data to a csv file.

Code:

`df.to_csv('/kaggle/working/cleaned_netflix.csv', index=False)`

Link to code

Link to Code: <https://www.kaggle.com/code/deborahkwamboka/deborah-omae-cs-da02-25075>

Conclusion

This week I gained hands on experience on the techniques of data wrangling. I restructured, formatted and cleaned my data set to a usable format. This assignment project was an eye opener to the use of many pandas' function and python data structures such as lists and dictionaries.