Lab 2: Manipulating Data with the Pandas Library

In the next few portions of the course, we are going to get our hands dirty by building the various kinds of recommender systems. However, before we do so, it is important that we know how to handle, manipulate, and analyze data efficiently in Python.

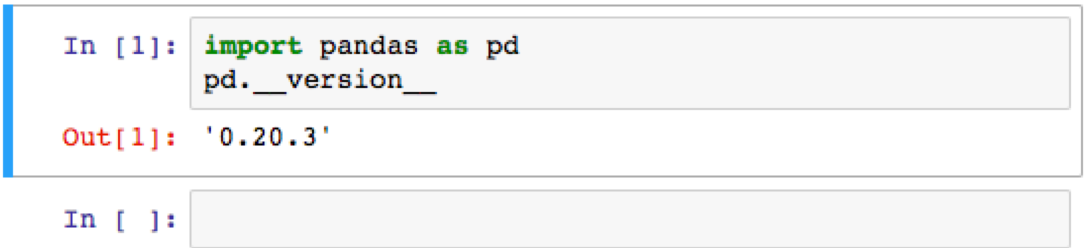
In this lab, we're going to get ourselves acquainted with the pandas library, which aims to overcome the aforementioned limitations, making data analysis in Python extremely efficient and user-friendly. We'll also introduce ourselves to the *Movies Dataset* that we're going to use to build our recommenders as well as use pandas to extract some interesting facts and narrate the history of movies using data.

Setting up the environment

Open Lab environment URL and open Jupyter lab or notebook and write following code:

```
import pandas as pd
pd.__version__
```

To execute the code in this cell, press *Shift* + *Enter*. If all goes well, you should see a new output cell, which prints the version of the pandas library:



The Pandas library

As a first step toward working with pandas, let's import our movies data into our Jupyter Notebook. To do this, we need the path to where our dataset is located. This can be a URL on the internet or your local computer. We highly recommend downloading the data to your local computer and accessing it from a local path instead of from a web URL.

NOTE: All datasets used in the labs are available in lab environment and GitHub repository:

`https://github.com/fenago/recommendation-systems-python/tree/main/data`

Go to the following URL to view the required CSV file: https://www.kaggle.com/rounakbanik/the-movies-dataset/downloads/movies_metadata.csv/7.

Now, let's witness some pandas magic. In the Jupyter Notebook you ran in the previous section, go to the second cell and type the following code:

```
#Read the CSV File into df
df = pd.read_csv('../data/movies_metadata.csv')
```

```
#We will find out what the following code does a little later!
df.head()
```

or you can download directly from kagglehub:

```
import kagglehub

# Download latest version
path = kagglehub.dataset_download("rounakbanik/the-movies-dataset")

print("Path to dataset files:", path)

df = pd.read_csv(path + "/movies_metadata.csv")

df.head()
```

Et voila! You should be able to see a table-like structure with five rows, each row representing a movie. You can also see that the table has 24 columns, although the columns were truncated to fit in the display.

What is this structure though? Let's find out by running the familiar [type] command:

```
#Output the type of df
type(df)
```

You should get an output stating that df is a [pandas.core.frame.DataFrame]. In other words, our code has read the CSV file into a pandas DataFrame object. But what are DataFrames? Let's find that out in the next section.

The Pandas DataFrame

As we saw in the previous section, the [df.head()] code outputted a table-like structure. In essence, the DataFrame is just that: a two-dimensional data structure with columns of different data types. You can think of it as an SQL Table. Of course, just being a table of rows and columns isn't what makes the DataFrame special. The DataFrame gives us access to a wide variety of functionality, some of which we're going to explore in this section.

Each row in our DataFrame represents a movie. But how many movies are there? We can find this out by running the following code:

```
#Output the shape of df
df.shape
```

OUTPUT: (45466, 24)

The result gives us the number of rows and columns present in df. We can see that we have data on 45,466 movies.

We also see that we have 24 columns. Each column represents a feature or a piece of metadata about the movie. When we ran [df.head()], we saw that most of the columns were truncated to fit in the display. To view all the columns (henceforth, called features) we have, we can run the following:

```
#Output the columns of df
df.columns
```

Output

```
OUTPUT:

Index(['adult', 'belongs_to_collection', 'budget', 'genres', 'homepage', 'id',
       'imdb_id', 'original_language', 'original_title', 'overview',
       'popularity', 'poster_path', 'production_companies',
       'production_countries', 'release_date', 'revenue', 'runtime',
       'spoken_languages', 'status', 'tagline', 'title', 'video',
       'vote_average', 'vote_count'],
      dtype='object')
```

We see that we have a lot of information on these movies, including their title, budget, genres, release date, and revenue.

Next, let's find out how to access a particular movie (or row). The first way to do this is by using the [.iloc] method. This allows us to select rows based on the numeric position, starting from zero. For example, if we wanted to access the second movie in the DataFrame, we'd run:

```
#Select the second movie in df
second = df.iloc[1]
second
```

The output will give you information about the movie on each of its 24 features. We see that the title of the movie is *Jumanji* and that it was released on December 15th, 1995, among other things.

A cell will always print the output of the last line of code. Therefore, we don't need to explicitly write it within a [print] function.

The second way to do it is by accessing the DataFrame index. Since we didn't explicitly set an index while reading the CSV file, pandas defaulted it to zero-based indexing. We can change the index of df quite easily. Let's change the index to the title of the movie and try to access [Jumanji] using this index:

```
#Change the index to the title
df = df.set_index('title')

#Access the movie with title 'Jumanji'
jum = df.loc['Jumanji']
jum
```

You should see an output identical to the previous cell. Let's revert back to our zero-based numeric index:

```
#Revert back to the previous zero-based indexing
df = df.reset_index()
```

It is also possible to create a new, smaller DataFrame with fewer columns. Let's create a new DataFrame that only has the following features: [title], [release_date], [budget], [revenue], [runtime], and [genres]:

```
#Create a smaller dataframe with a subset of all features
small_df = df[['title', 'release_date', 'budget', 'revenue', 'runtime', 'genres']]

#Output only the first 5 rows of small_df
small_df.head()
```

You should see a table with five movies and only the features that we've mentioned. The [.head()] method simply displays the first five rows of the DataFrame. You can display as many rows as you want by passing it as an argument into [.head()]:

```
#Display the first 15 rows
small_df.head(15)
```

Next, let's check out the data types of our various features:

```
#Get information of the data types of each feature
small_df.info()
```

Output

```
OUTPUT:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45466 entries, 0 to 45465
Data columns (total 6 columns):
title 45460 non-null object
release_date 45379 non-null object
budget 45466 non-null object
revenue 45460 non-null float64
runtime 45203 non-null float64
genres 45466 non-null object
dtypes: float64(2), object(4)
memory usage: 2.1+ MB
```

A curious observation here is that pandas correctly deciphers [revenue] and [runtime] as float data, but assigns the generic object data type to [budget].

However, pandas allows us to manually convert the data type of a feature. Let's try to convert the [budget] feature to [float]:

```
#Convert budget to float
df['budget'] = df['budget'].astype('float')
```

Output

```
OUTPUT:
...
...
ValueError: could not convert string to float: '/zaSf5OG7V8X8gqFvly88zDdRm46.jpg'
```

Running this cell throws [ValueError]. It is easy to guess that one of the budget fields had a ['/zaSf...'] string as its value, and pandas was not able to convert this into a floating number.

To solve this problem, we will use the [apply()] method. This will allow us to apply a function to every field in a particular column and convert it into the return value. We are going to convert every number field in [budget] to float and, if that fails, convert it to [NaN]:

```
#Import the numpy library
import numpy as np

#Function to convert to float manually
def to_float(x):
    try:
```

```
        x = float(x)
    except:
        x = np.nan
    return x

#Apply the to_float function to all values in the budget column
small_df['budget'] = small_df['budget'].apply(to_float)

#Try converting to float using pandas astype
small_df['budget'] = small_df['budget'].astype('float')

#Get the data types for all features
small_df.info()
```

This time around, there are no errors thrown. Also, we notice that the [budget] feature is now of the [float64] type.

Now, let's try to define a new feature, called [year], that represents the year of release. The recommended way to do this would be by using the [datetime] functionality that pandas gives us:

```
#Convert release_date into pandas datetime format
small_df['release_date'] = pd.to_datetime(small_df['release_date'], errors='coerce')

#Extract year from the datetime
small_df['year'] = small_df['release_date'].apply(lambda x: str(x).split('-')[0] if x
!= np.nan else np.nan)

#Display the DataFrame with the new 'year' feature
small_df.head()
```

What are the oldest movies available in this dataset? To answer this question, we can sort the DataFrame based on the year of release:

```
#Sort DataFrame based on release year
small_df = small_df.sort_values('year')

small_df.head()
```

We see that we have movies from as early as the 1870s, with *Passage of Venus* being the oldest movie on record. Next, let's find out the most successful movies of all time. To do this, we'll use the [sort_values()] method once again, but with an additional [ascending=False] parameter to sort [DataFrame] in descending order:

```
#Sort Movies based on revenue (in descending order)
small_df = small_df.sort_values('revenue', ascending=False)

small_df.head()
```

From our results, we observe that *Avatar* is the most successful movie of all time, with a revenue of over $2.78 billion.

Let's say we wanted to create a new DataFrame of movies that satisfied a certain condition. For instance, we only want movies that earned more than $1 billion. Pandas makes this possible using its Boolean Indexing feature. Let's see this in action:

```
#Select only those movies which earned more than 1 billion
new = small_df[small_df['revenue'] > 1e9]
```

```
new
```

It is also possible to apply multiple conditions. For instance, let's say we only wanted movies that earned more than $1 billion, but where the outlay less than $150 million, we'd do it as follows:

```
#Select only those movies which earned more than 1 billion and spent less than 150
million

new2 = small_df[(small_df['revenue'] > 1e9) & (small_df['budget'] < 1.5e8)]
new2
```

Only four movies make it into this list.

There is, of course, much more to what you can do with DataFrames (such as handling missing data), but we'll stop our exploration with it for now. Let's move on to another data structure we have unknowingly used extensively in this section: the Pandas Series.

The Pandas Series

When we accessed the Jumanji movie using [.loc] and [.iloc], the data structures returned to us were Pandas Series objects. You may have also noticed that we were accessing entire columns using [df[column_name]]. This, too, was a Pandas Series object:

```
type(small_df['year'])
```

OUTPUT: pandas.core.series.Series

The Pandas Series is a one-dimensional labelled array capable of holding data of any type. You may think of it as a Python list on steroids. When we were using the [.apply()] and [.astype()] methods in the previous section, we were actually using them on these Series objects.

Therefore, like the DataFrame, the Series object comes with its own group of extremely useful methods that make data analysis a breeze.

First, let's check out the shortest- and longest-running movies of all time. We will do this by accessing the [runtime] column of the DataFrame as a Series object and applying its methods on it:

```
#Get the runtime Series object
runtime = small_df['runtime']

#Print the longest runtime of any movie
print(runtime.max())

#Print the shortest runtime of any movie
print(runtime.min())
```

We see that the longest movie is more than 1,256 minutes in length and the shortest is 0! Of course, such strange results demand a deeper inspection of the data but we shall skip that, for now.

It is also possible to calculate the mean and median of the Series in this way. Let's do so for the movie budgets:

```
#Get the budget Series object
budget = small_df['budget']
```

```
#Print the mean budget of the movies
print(budget.mean())

#Print the median budget of the movies
print(budget.median())
```

The average budget of a movie is $4.2 million and the median budget is 0! This suggests that at least half the movies in our dataset have no budget at all! Like in the previous case, such strange results demand closer inspection. In this case, it is highly likely that a zero budget indicates that the data is not available.

What is the revenue that the 90th-percentile movie generated? We can discover this using the [quantile] function:

```
#Get the revenue Series object
revenue = small_df['revenue']

#Revenue generated by the 90th percentile movie
revenue.quantile(0.90)
```

We get a result of $8.26 million. What this means is that only 10% of the movies in our dataset earned more than $8.26 million in revenue.

Finally, let's find out the number of movies released each year. We do this using the [value_counts()] method on the [year] series:

```
#Get number of movies released each year
small_df['year'].value_counts()
```

We have the highest number of movies released in 2014. There are also six years in our dataset (including 2020) that have only one movie on record.

You may rename the notebook as [Lab2] by clicking on [Untitled] and then close it. For the next lab, we will create a new notebook.

Summary

In this lab, we gained an understanding of the limitations of using vanilla Python and its built-in data structures. We acquainted ourselves with the Pandas library and learned how it overcomes the aforementioned difficulties by giving us access to extremely powerful and easy-to-use data structures. We then explored the two main data structures, Series and DataFrame, by analyzing our movies-metadata dataset.