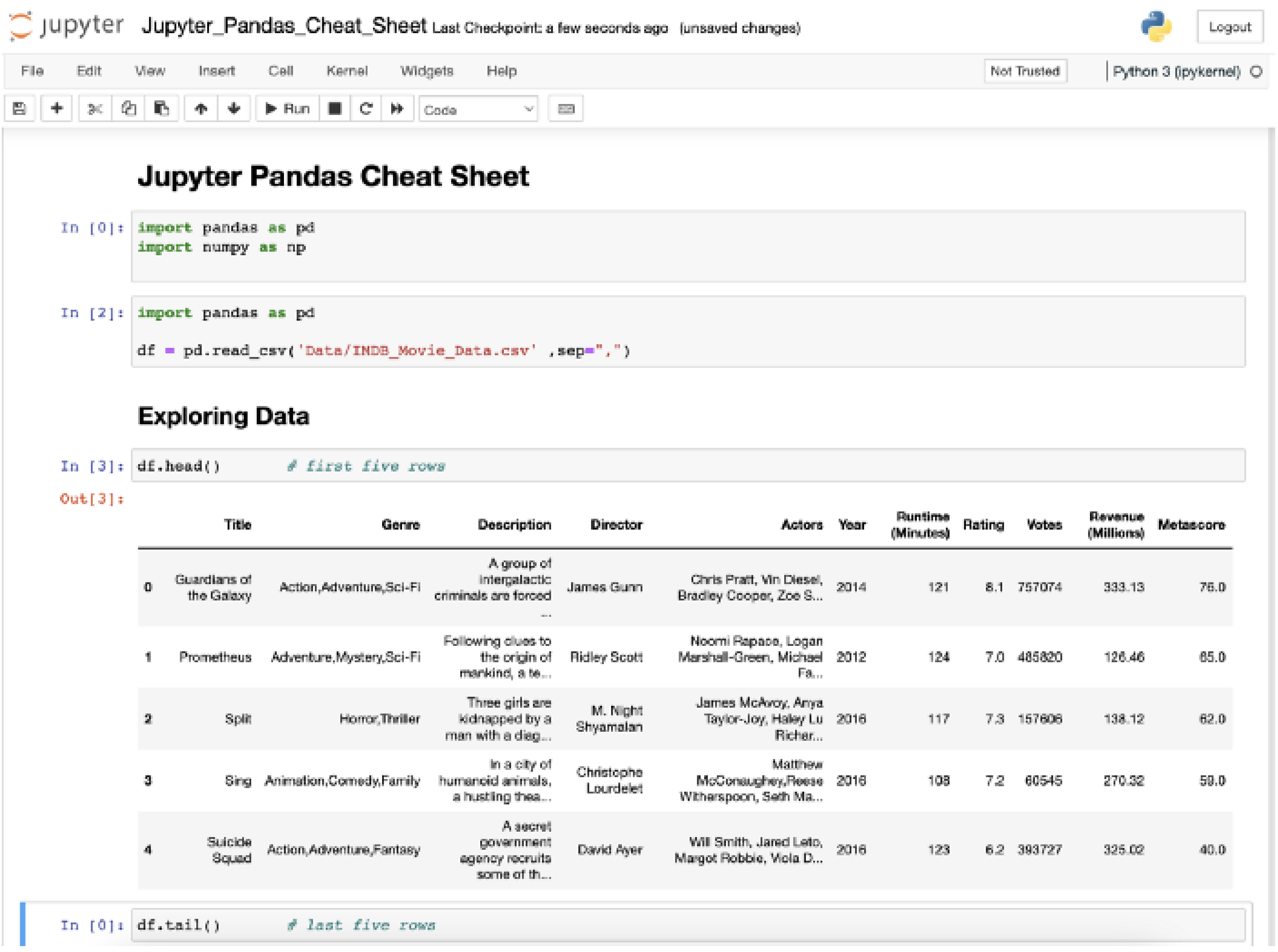
Jupyter Pandas Cheat Sheet

What is Jupyter-Notebook?

Jupyter Notebook is one of the most widely used tool in data science that use Python. This is due to the fact that it is an ideal environment for developing reproducible data analysis pipelines with Python. Data can be loaded, transformed, and modeled all inside a single Notebook, where it's quick and easy to test out code and explore ideas along the way. In addition, inline-formatted text lets you take notes to better document and share your work.


jupyter Jupyter_Pandas_Cheat_Sheet Last Checkpoint: a few seconds ago (unsaved changes)
Logout
File Edit View Insert Cell Kernel Widgets Help
Not Trusted
Python 3 (ipykernel)
Run
Code

Jupyter Pandas Cheat Sheet

```
In [0]: import pandas as pd
        import numpy as np
```

```
In [2]: import pandas as pd

        df = pd.read_csv('Data/IMDB_Movie_Data.csv' ,sep=",")
```

Exploring Data

```
In [3]: df.head()         # first five rows
```

Out[3]:

	Title	Genre	Description	Director	Actors	Year	Runtime (Minutes)	Rating	Votes	Revenue (Millions)	Metascore
0	Guardians of the Galaxy	Action,Adventure,Sci-Fi	A group of intergalactic criminals are forced ...	James Gunn	Chris Pratt, Vin Diesel, Bradley Cooper, Zoe S...	2014	121	8.1	757074	333.13	76.0
1	Prometheus	Adventure,Mystery,Sci-Fi	Following clues to the origin of mankind, a te...	Ridley Scott	Noomi Rapace, Logan Marshall-Green, Michael Fa...	2012	124	7.0	485820	126.46	65.0
2	Split	Horror,Thriller	Three girls are kidnapped by a man with a diag...	M. Night Shyamalan	James McAvoy, Anya Taylor-Joy, Haley Lu Richar...	2016	117	7.3	157606	138.12	62.0
3	Sing	Animation,Comedy,Family	In a city of humanoid animals, a hustling thea...	Christophe Lourdelet	Matthew McConaughey,Reese Witherspoon, Seth Ma...	2016	108	7.2	60545	270.32	59.0
4	Suicide Squad	Action,Adventure,Fantasy	A secret government agency recruits some of th...	David Ayer	Will Smith, Jared Leto, Margot Robbie, Viola D...	2016	123	6.2	393727	325.02	40.0

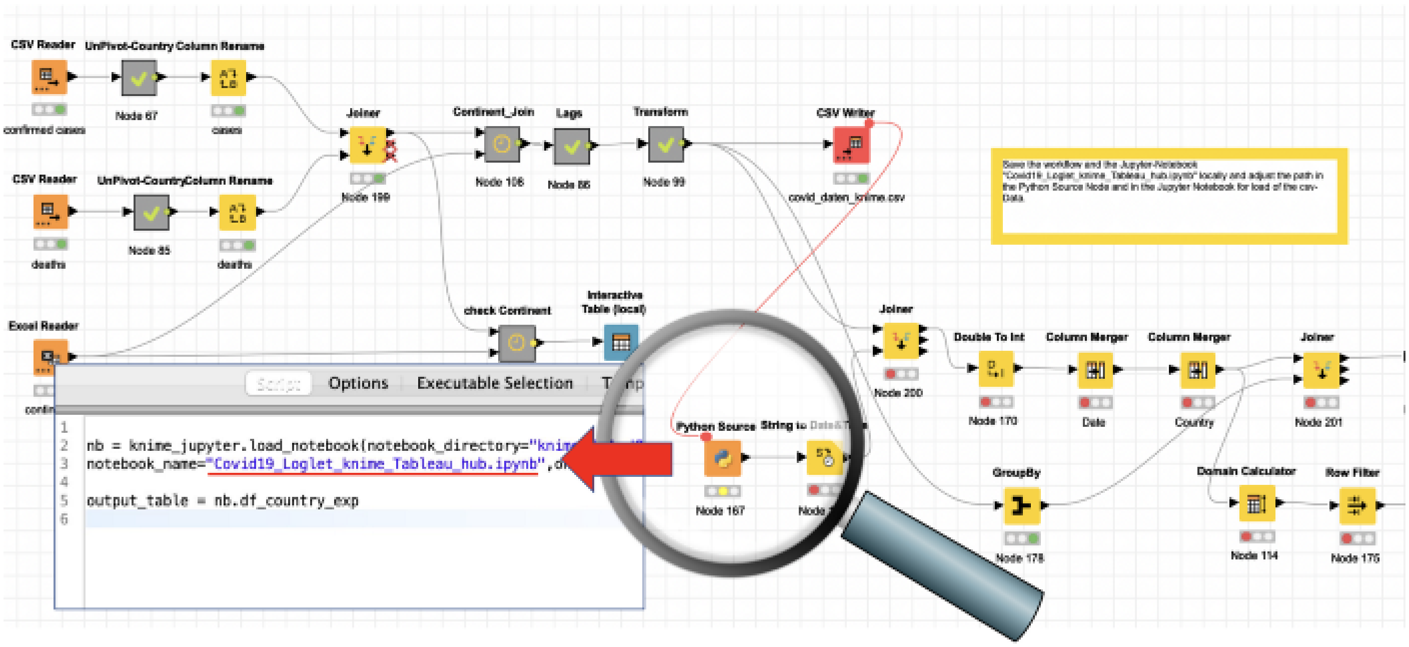
```
In [0]: df.tail()         # last five rows
```

What is Pandas?

Pandas is a widely used open source Python library for data science, data analysis, and machine learning tasks. It is built on top of Numpy, the fundamental package for scientific computing in Python. Pandas, as one of the most popular data wrangling packages, integrates well with many other Python data science packages and is normally included in every Python distribution.

In our examples we will use the Anaconda distribution, which is the easiest to install and best integrated together with the KNIME Analytics Platform. Why Jupyter-Notebook, Python and Pandas?

As I explained in my previous articles, every data engineer should learn a visual programming language like KNIME. The reason for that is that the best representation of an ETL pipeline is a visual workflow:



Save the workflow and the Jupyter-Notebook "Covid19_Loglet_knime_Tableau_hub.ipynb" locally and adjust the path in the Python Source Node and in the Jupyter Notebook for load of the csv-Data.

```

nb = knime_jupyter.load_notebook(notebook_directory="knim
notebook_name="Covid19_Loglet_knime_Tableau_hub.ipynb",d

output_table = nb.df_country_exp

```

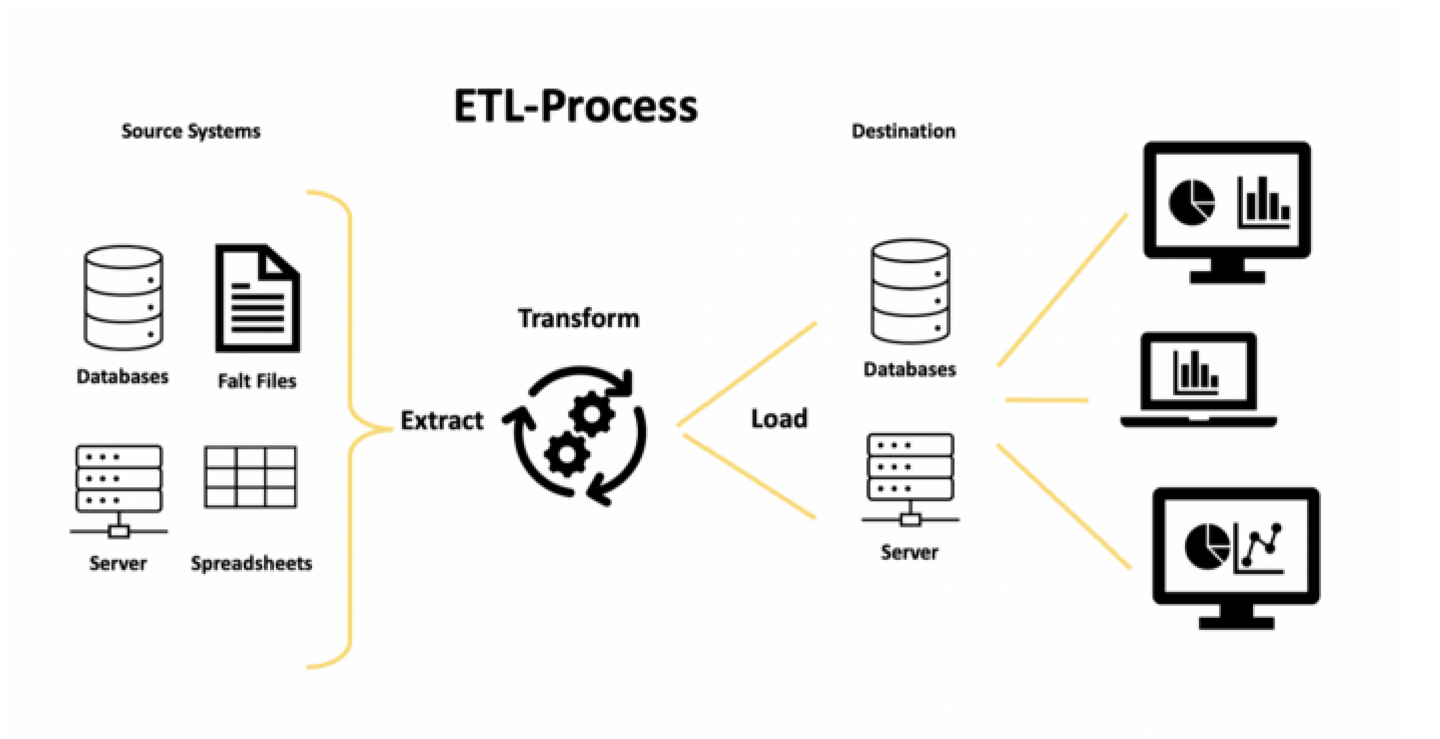
So why learn Python and Pandas when 99% of your data engineering tasks can be solved with KNIME or any other visual programming ETL tool? One reason is that sometimes you need to perform complex calculations.

Python already provides very sophisticated libraries and packages for this. On the other hand it is possible to use code from Jupyter directly in KNIME.

That's why we want to learn the most essential commands in Python and Pandas to be able to perform the most important ETL processes in Jupyter-Notebook.

ETL-Process

ETL (extract, transform, load) is a type of data integration that refers to the three phases (extract, transform, and load) that are used to combine data from various sources. Data is extracted from one or different source systems, transformed into an analyzeable format, and loaded into a data warehouse or other system throughout this process.



The ETL process consists of three main basic components: Input -> Transform -> Output

The task of the Input is to load different data source types into the processing tool. At the Output, the processed data is exported back to other databases, systems, or files. The Transformation process, on the other hand, can be divided into further sub-processes, which essentially consist of the following components:

- Filtering columns or rows
- Transforming columns or rows with mathematical or text functions
- Aggregate and reshape (groupby and pivoting)
- Combining (join and concatenate)

Jupyter Pandas Cheat Sheet

Introduction

In this section we call the two main Python packages pandas and numpy. To refer to the functions and objects of the packages, we add the corisponding aliases pd and np at the end.

```
import pandas as pd

import numpy as np
```

Then we read the csv file "input" in the dataframe "df" and output it with "df". Importing a csv-File input.csv in a dataframe df

```
df = pd.read_csv('path_to/input.csv' ,sep=",") print(df)
```

Finally we export the dataframe "df" as csv file with the name "output.csv".

```
df.to_csv ('path_to/output.csv' , index = False, header=True)
```

Exploring Data

It is always good to get a quick insight about the data.

Various commands are available to show the data in the dataframe "df" from different angles.

```
df.head() # first five rows
```

```
df.tail() # last five rows
```

```
df.sample(5) # random sample of rows
```

```
df.shape # number of rows/columns
```

```
df.describe() # calculates measures of central tendency
df.info() # memory footprint and datatypes
```

Statistics

The following commands cover the most common statistics functions:

```
df.describe() # Summary statistics for numerical columns
```

```
df.mean() # Returns the mean of all columns
```

```
df.corr() # Returns the correlation between columns in a
DataFrame
```

```
df.count() # Returns the number of non-null values in each
DataFrame column
```

```
df.max() # Returns the highest value in each column
```

```
df.min() # Returns the lowest value in each column
```

```
df.median() # Returns the median of each column
```

```
df.std() # Returns the standard deviation of each column
```

Import Data from Files

In the most cases you want to import data from a csv file or an Excel file. The name of the csv file is definied by my-data.csv. Rename the file to your needs. The same applies to the import of Excel files.

Import csv

```
df = pd.read_csv('Data/my-data.csv' ,sep=",")
```

Import xls

```
df = pd.read_excel('Data/my-data.xlsx')

df = pd.read_excel('Data/my-data.xlsx', sheetname='sheet1',
skiprows=[1] # header data )
```

If you want to import a specific Excel sheet, rename "sheet1" with the desired sheet-name. You may also skip the first x rows with skiprows=[1]. Change "1" with the desired number of rows.

Export Data to files

The data in a dataframe can be easily exported to an Excel file or a csv file.

Export xls

```
df.to_excel('Data/my-data.xlsx')
```

Export csv

```
df.to_csv ('Data/my-data.csv' , index = False, header=True)
```

Column manipulation

Dataframes can be modified by manipulating columns in different ways. The following codes show how to filter the desired columns or how to rename them

Column Filter

```
df[['Title','Rating']]
```

```
df.filter(['Title','Rating'])
```

Column Rename

```
df.rename(columns={'Title': 'a', 'Rating': 'c'},inplace=True)
```

Rename the columns back

```
df.rename(columns={'a': 'Title', 'c': 'Rating'},inplace=True)
```

Column Resorter/Reorder

```
df.columns.values # show column values
```

Reorder Rating after Title

```
df[['Title', 'Rating','Genre', 'Description', 'Director',
'Actors', 'Year', 'Runtime (Minutes)', 'Votes', 'Revenue
(Millions)', 'Metascore']]
```

Constant Value Column

```
df['new_column'] = 23 df.head()
```

Math Formula

```
df['Rating_Votes'] = df.Rating + df.Votes
df[['Rating_Votes','Rating','Votes']].head()
```

Changing the type of a column from integer to string is a common task in data engineering. With "astype" you can change from number to string, from string to number or from number to double:

Number to String

```
df['Year_str'] =df['Year'].astype(str) df.info()
```

String to Number

```
df['Year_int'] =df['Year_str'].astype(int) df.info()
```

Double to Int

```
df['Rating_int'] = df['Rating'].round(0).astype(int)
df[['Rating_int','Rating']].head()
```

To change string values in a column, several commands are available. Common tasks include changing string values to upper or lower case, counting word length, or finding the beginning of a word.

String Replacer

```
df['Title'].replace('Prometheus', 'Alien') df[df.Title ==
'Prometheus']
```

String Manipulation

Lower cases

```
df['Title2'] = df['Title'].str.lower()
df[['Title2','Title']].head()
```

Upper cases

```
df['Title2'] = df['Title'].str.upper()
df[['Title2','Title']].head()
```

Length of words

```
df['Title2'] = df['Title'].str.len()
df[['Title2','Title']].head()
```

First word

```
df['Title2'] = df['Title'].str.split(' ').str[0]
df[['Title2','Title']].head()
```

Find the word "Squad" in Title

```
df['Title2'] = df['Title'].str.find('Squad', 0)
df[['Title2','Title']].head()
```

Without going into the many possibilities of date manipulation here, we will refer only to the conversion of string values into date values, as this is one of the most common tasks.

Date manipulation

```
pd.to_datetime('2010/11/12')
```

Sorting of a column is possible by one or more values at the same time.

Sort

```
df.sort_values(by='Title', ascending=True) df.sort_values(by=
['Director','Year'], ascending=True)
```

Row manipulation

As for the manipulation of columns, there are certain basic tasks to be done for the manipulation of rows. Filtering rows can be done in different way. The following image shows how you can filter rows by their content. Normally you want to filter by name or by range of values.

Row Filter

Select Title 'Prometheus'

```
df[df.Title == 'Prometheus']
```

Select Rating greater or equal 8.5

```
df[df.Rating >= 8.5]
```

Select Year equal 2016 and Rating greater or equal 8.5

```
df[(df.Year == 2016) & (df.Rating >= 8.5)]
```

Select Title with 'Prometheus','Sing', 'Guardians of the Galaxy'

```
titel = ['Prometheus','Sing', 'Guardians of the Galaxy']
df[df.Title.isin(titel)]
```

Select years in 2010,2015,002

```
years = [2010,2015,2002] df[df.Year.isin(years)]
```

Selects rows 1-to-3

```
df.iloc[0:3]
```

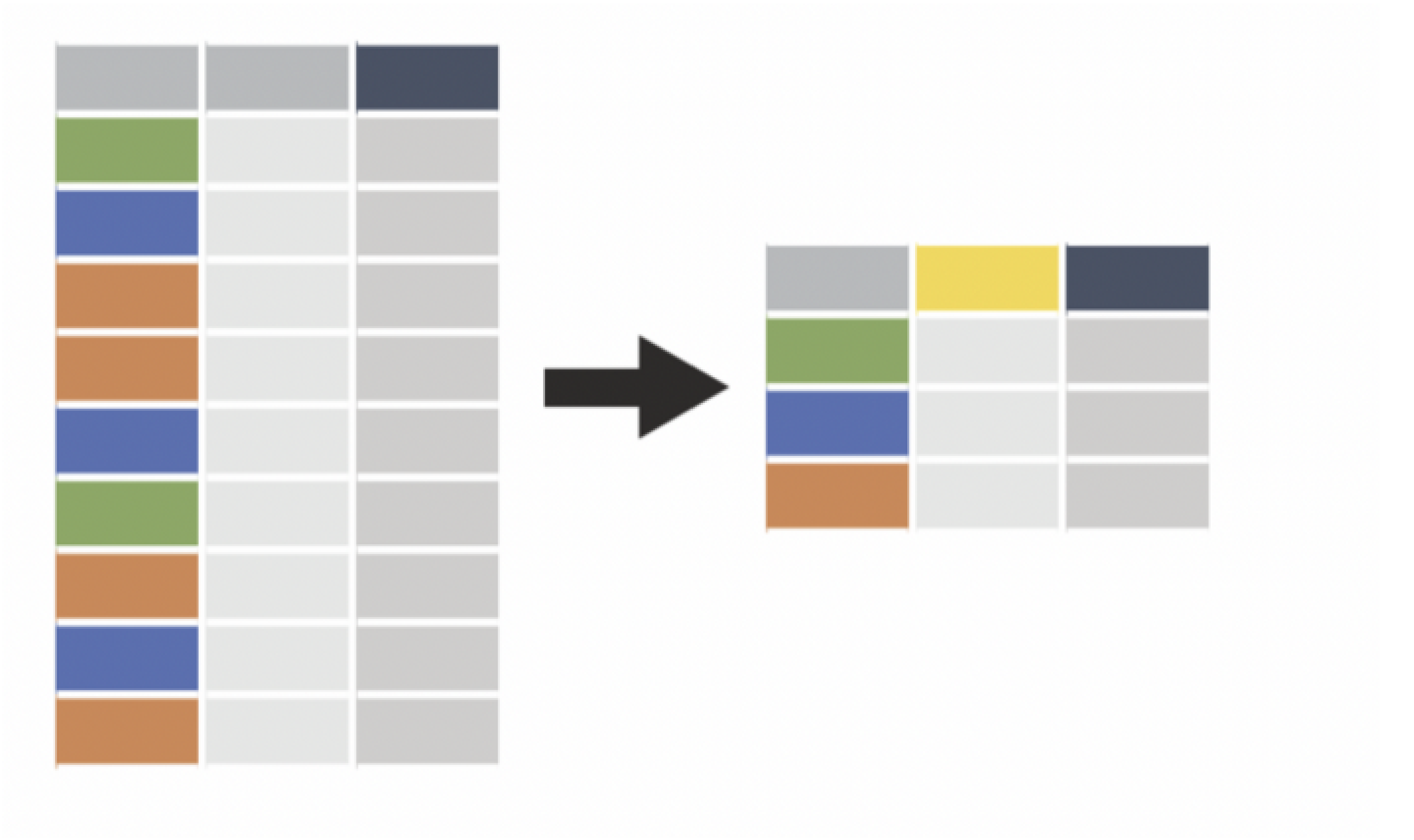
First 4 rows and first 2 columns

```
df.iloc[0:4, 0:2]
```

Table Manipulation

Group By

The Group By statement groups rows that have the same values into summary rows, like "find the number of titles for each year".



The Group By statement is often used with aggregate functions (COUNT(), MAX(), MIN(), SUM(), AVG()) to group the result-set by one or more columns. Here are a few examples:

Number of titles per year

```
df.groupby("Year")["Title"].count().to_frame()
```

Number of titles per year and per director

```
df.groupby(["Year","Director"])
["Title"].count().to_frame().reset_index()
```

Number of titles per director

```
df.groupby(["Director"])["Title"].count().to_frame(name =
'count').reset_index()
```

Total revenue per year and per director

```
df.groupby(["Year","Director"])["Revenue
(Millions)"].sum().to_frame().reset_index()
```

Rating-Mean per director

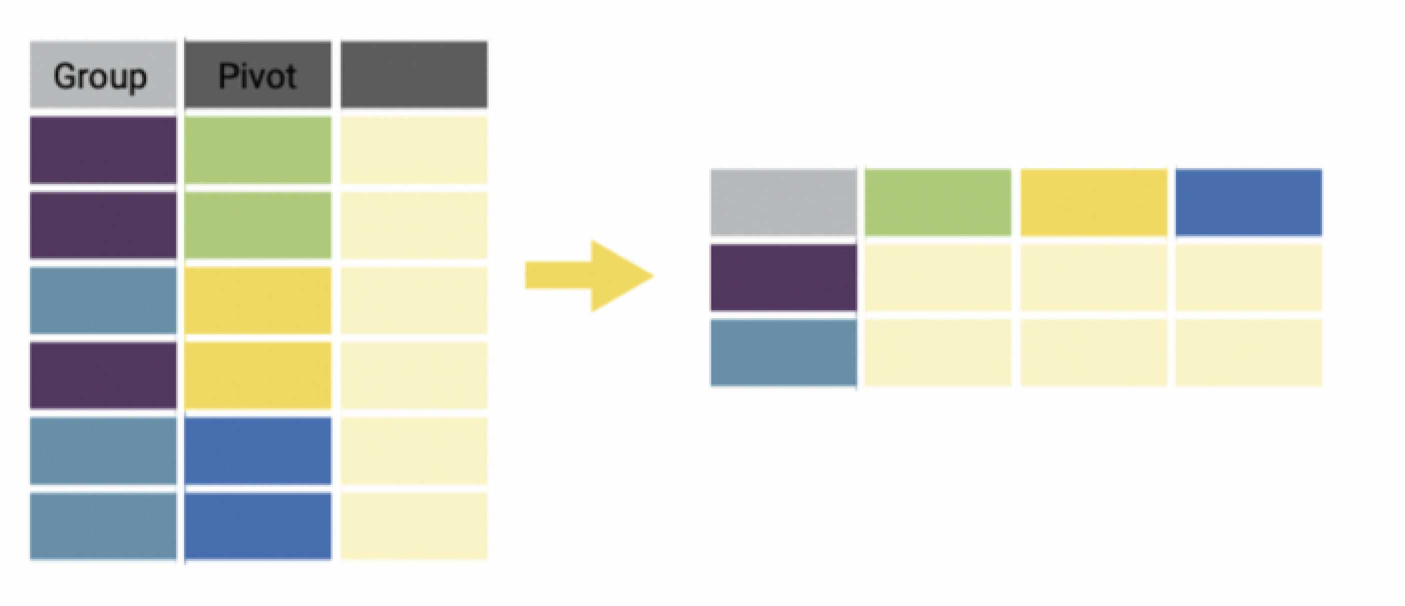
```
df.groupby("Director")
["Rating"].mean().to_frame().reset_index()
```

Combination of different group by functions

```
df.groupby(["Year","Director"]).agg( { 'Title':"count", #
number of titles per year and director 'Rating':"mean", #
Rating-Mean per director 'Revenue (Millions)': "sum" # Total
revenue per year and director } ).reset_index()
```

Pivot / Unpivot

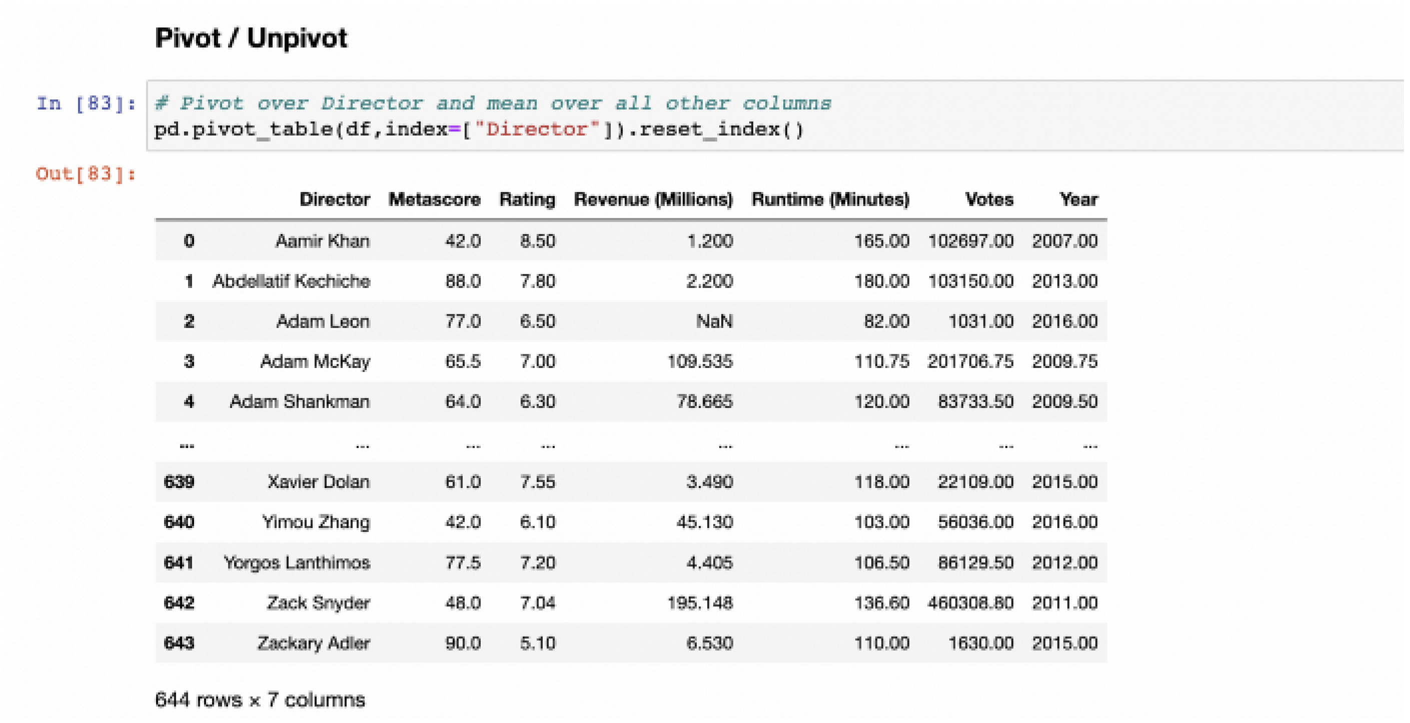
Pivot tables in Excel are probably familiar to most people. Pandas provides a similar function called pivot_table.



The following example shows how the pivot function over the "Director" column summarizes all other columns as mean values.

Pivot over Director and mean over all other columns

```
pd.pivot_table(df,index=["Director"]).reset_index()
```



Pivot / Unpivot

In [83]:
```
# Pivot over Director and mean over all other columns
pd.pivot_table(df,index=["Director"]).reset_index()
```

Out[83]:

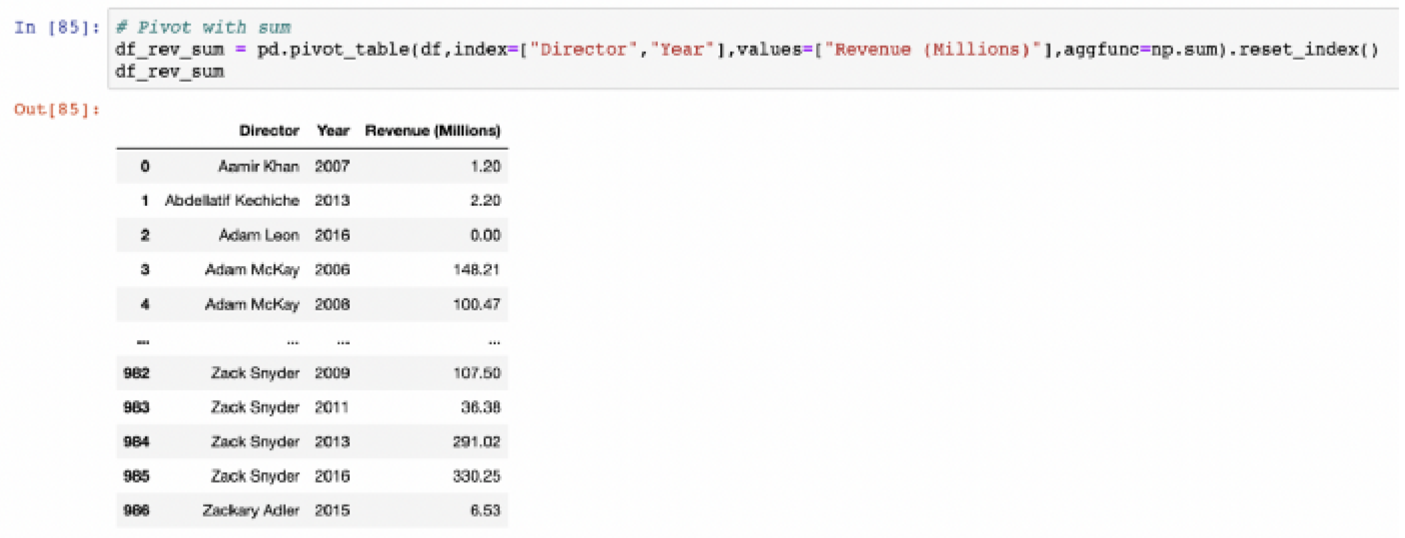
	Director	Metascore	Rating	Revenue (Millions)	Runtime (Minutes)	Votes	Year
0	Aamir Khan	42.0	8.50	1.200	165.00	102697.00	2007.00
1	Abdellatif Kechiche	88.0	7.80	2.200	180.00	103150.00	2013.00
2	Adam Leon	77.0	6.50	NaN	82.00	1031.00	2016.00
3	Adam McKay	65.5	7.00	109.535	110.75	201706.75	2009.75
4	Adam Shankman	64.0	6.30	78.665	120.00	83733.50	2009.50
...	...	...	...	...	...	...	...
639	Xavier Dolan	61.0	7.55	3.490	118.00	22109.00	2015.00
640	Yimou Zhang	42.0	6.10	45.130	103.00	56036.00	2016.00
641	Yorgos Lanthimos	77.5	7.20	4.405	106.50	86129.50	2012.00
642	Zack Snyder	48.0	7.04	195.148	136.60	460308.80	2011.00
643	Zackary Adler	90.0	5.10	6.530	110.00	1630.00	2015.00

644 rows × 7 columns

If you want to summarize explicitly using sums, you must add the parameter "aggfunc=sum".

Pivot with sum

```
df_rev_sum = pd.pivot_table(df,index=
["Director","Year"],values=["Revenue
(Millions)"],aggfunc=np.sum).reset_index() df_rev_sum
```



In [85]:
```
# Pivot with sum
df_rev_sum = pd.pivot_table(df,index=["Director","Year"],values=["Revenue (Millions)"],aggfunc=np.sum).reset_index()
df_rev_sum
```

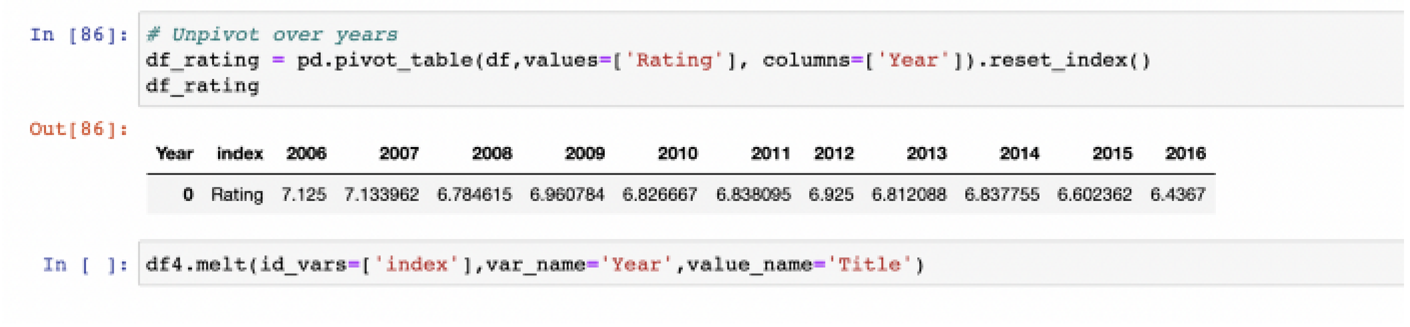
Out[85]:

	Director	Year	Revenue (Millions)
0	Aamir Khan	2007	1.20
1	Abdellatif Kechiche	2013	2.20
2	Adam Leon	2016	0.00
3	Adam McKay	2006	148.21
4	Adam McKay	2008	100.47
...	...	...	...
982	Zack Snyder	2009	107.50
983	Zack Snyder	2011	36.38
984	Zack Snyder	2013	291.02
985	Zack Snyder	2016	330.25
986	Zackary Adler	2015	6.53

Another possibility, similar to the transpose function in Excel, is to unpivot the data. Here we unpivot the years over the rating and for each year a column with the mean value of the rating is displayed.

Unpivot over years

```
df_rating = pd.pivot_table(df,values=['Rating'], columns=
['Year']).reset_index() df_rating
```



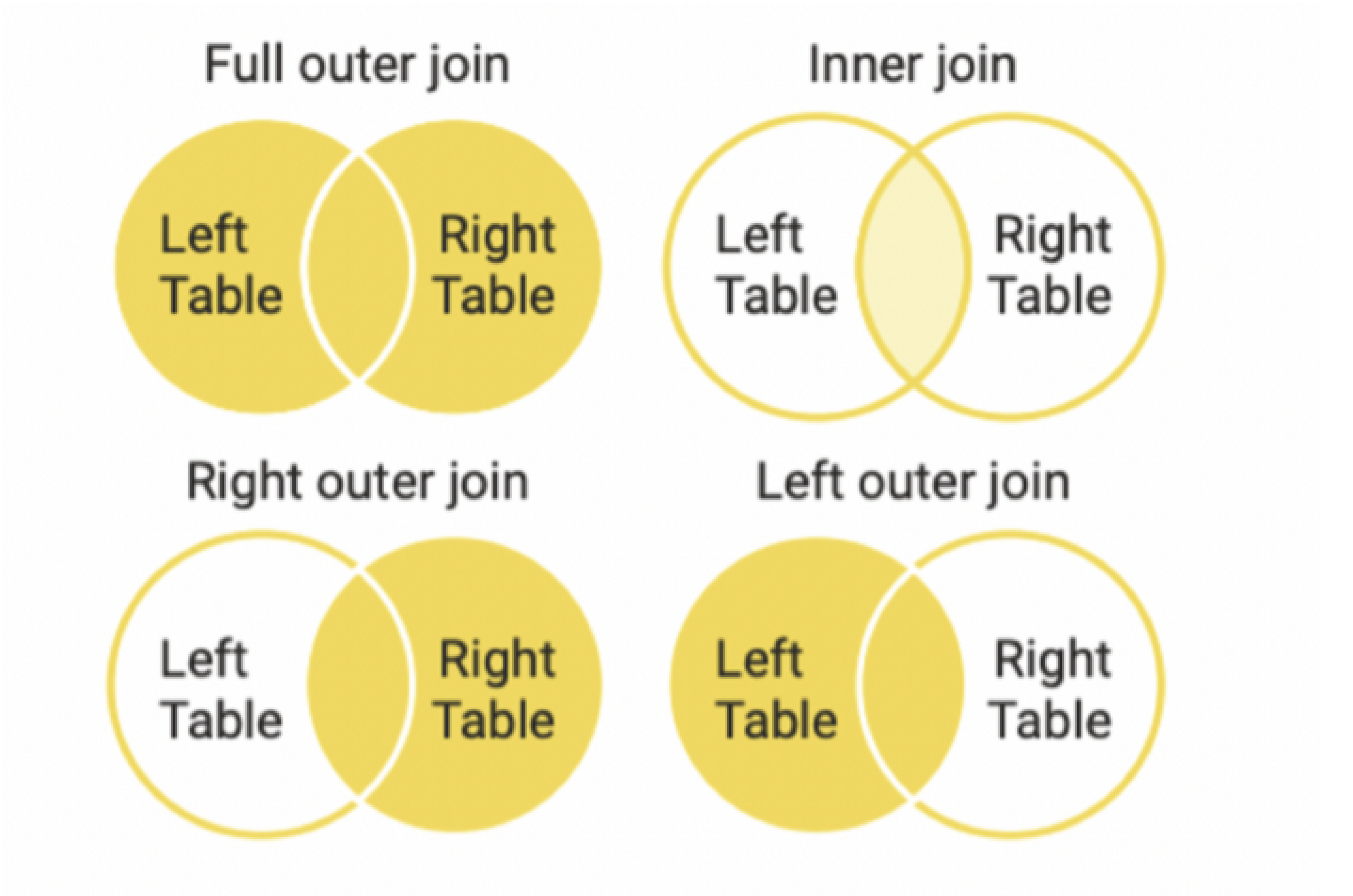
```
In [86]: # Unpivot over years
         df_rating = pd.pivot_table(df,values=['Rating'], columns=['Year']).reset_index()
         df_rating
Out[86]:
         Year  index   2006      2007      2008      2009      2010      2011   2012      2013      2014      2015    2016
            0  Rating  7.125  7.133962  6.784615  6.960784  6.826667  6.838095  6.925  6.812088  6.837755  6.602362  6.4367

In [ ]:  df4.melt(id_vars=['index'],var_name='Year',value_name='Title')
```

```
df4.melt(id_vars=['index'],var_name='Year',value_name='Title')
```

Join

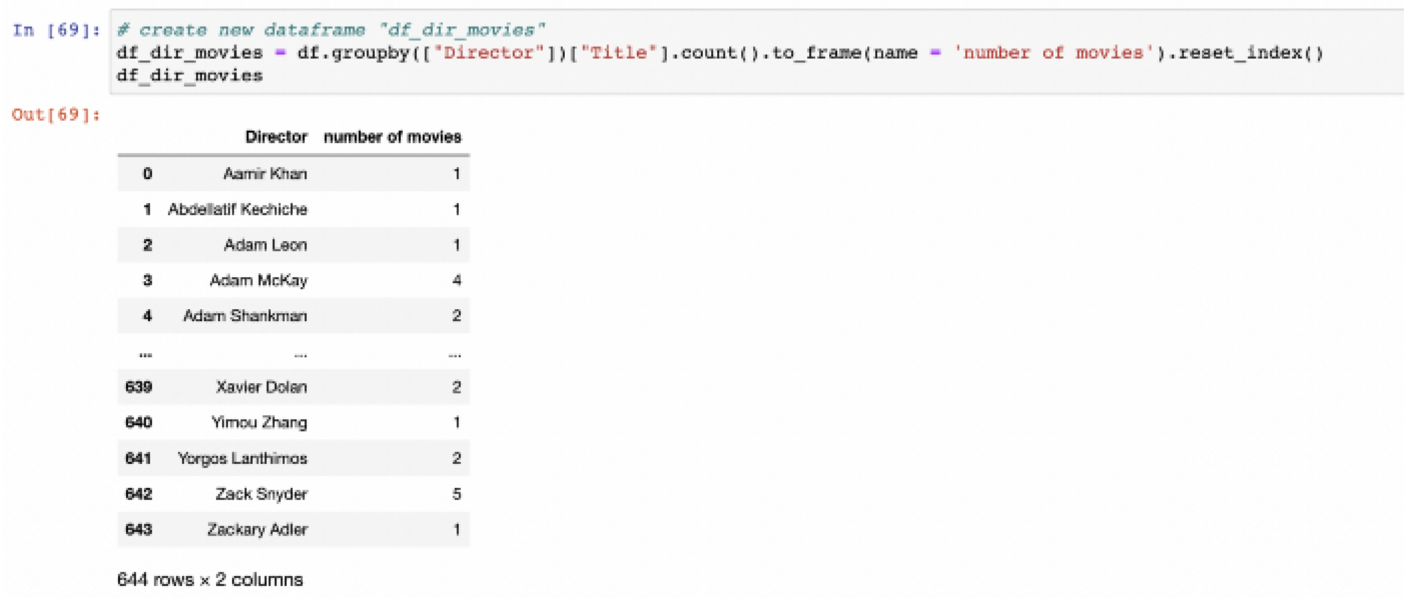
The join function is one of the most important operation in data engineering. Understanding the following concept in the figure below is crucial to applying the join function.



Visual programming tools are better suited for this process. However, since we want to do this in Jupyter-Notebook, we will first create two data frames. We create first a dataframe with all movie directors and the number of their movies.

Create new dataframe "df_dir_movies"

```
df_dir_movies = df.groupby(["Director"])
["Title"].count().to_frame(name = 'number of
movies').reset_index() df_dir_movies
```



```
In [69]: # create new dataframe "df_dir_movies"
         df_dir_movies = df.groupby(["Director"])["Title"].count().to_frame(name = 'number of movies').reset_index()
         df_dir_movies
Out[69]:
```

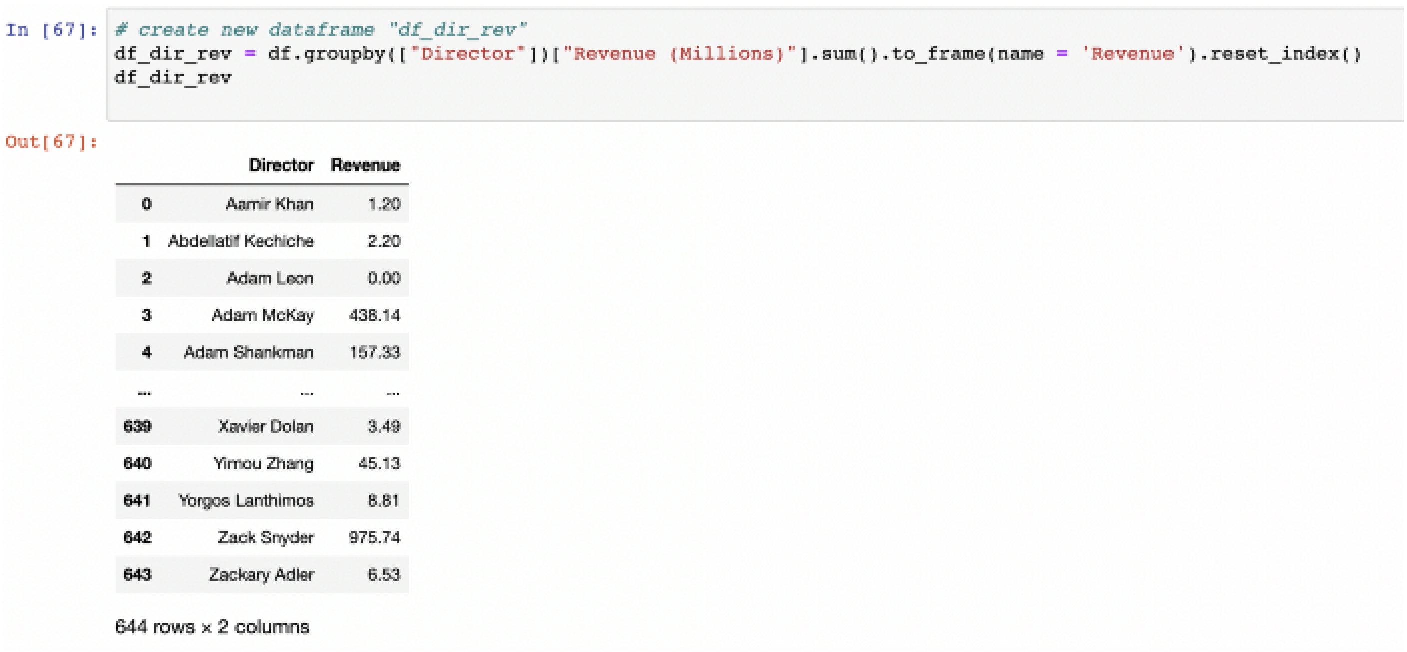
	Director	number of movies
0	Aamir Khan	1
1	Abdellatif Kechiche	1
2	Adam Leon	1
3	Adam McKay	4
4	Adam Shankman	2
...	...	...
639	Xavier Dolan	2
640	Yimou Zhang	1
641	Yorgos Lanthimos	2
642	Zack Snyder	5
643	Zackary Adler	1

644 rows × 2 columns

Then we create the second data frame with the directors and the total revenue generated for all their movies.

Create new dataframe "df_dir_rev"

```
df_dir_rev = df.groupby(["Director"])["Revenue (Millions)"].sum().to_frame(name = 'Revenue').reset_index()
df_dir_rev
```



```
In [67]: # create new dataframe "df_dir_rev"
         df_dir_rev = df.groupby(["Director"])["Revenue (Millions)"].sum().to_frame(name = 'Revenue').reset_index()
         df_dir_rev
Out[67]:
```

	Director	Revenue
0	Aamir Khan	1.20
1	Abdellatif Kechiche	2.20
2	Adam Leon	0.00
3	Adam McKay	438.14
4	Adam Shankman	157.33
...	...	...
639	Xavier Dolan	3.49
640	Yimou Zhang	45.13
641	Yorgos Lanthimos	8.81
642	Zack Snyder	975.74
643	Zackary Adler	6.53

644 rows × 2 columns

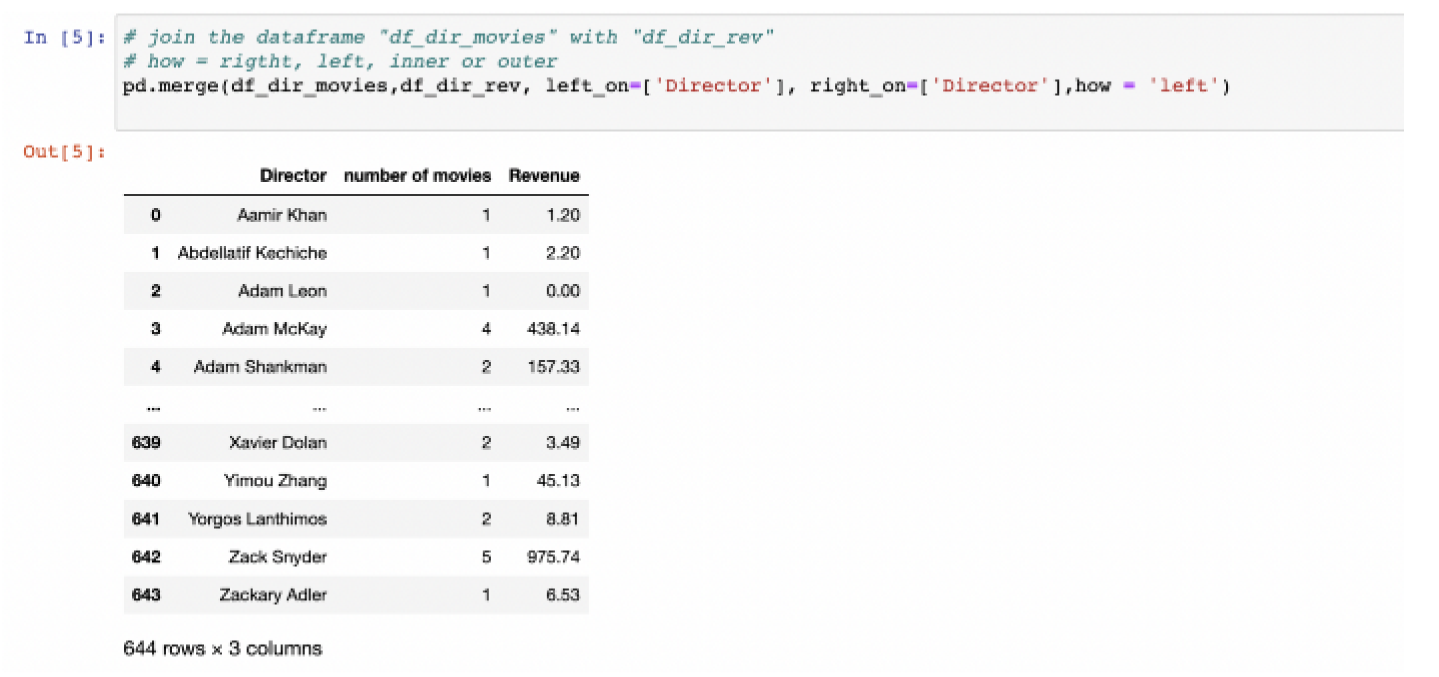
Now we join the two data frames together using the "director" column. There is an option to make the following joins using the "how" parameter:

- left
- right
- inner
- outer The resulting dataframe shows the directors with their number of movies and the total generated revenues in a table.

Join the dataframe "df_dir_movies" with "df_dir_rev"

how = rigtht, left, inner or outer

```
pd.merge(df_dir_movies,df_dir_rev, left_on=['Director'],
right_on=['Director'],how = 'left')
```



```
In [5]: # join the dataframe "df_dir_movies" with "df_dir_rev"
        # how = rigtht, left, inner or outer
        pd.merge(df_dir_movies,df_dir_rev, left_on=['Director'], right_on=['Director'],how = 'left')
```

Out[5]:

	Director	number of movies	Revenue
0	Aamir Khan	1	1.20
1	Abdellatif Kechiche	1	2.20
2	Adam Leon	1	0.00
3	Adam McKay	4	438.14
4	Adam Shankman	2	157.33
...	...	...	...
639	Xavier Dolan	2	3.49
640	Yimou Zhang	1	45.13
641	Yorgos Lanthimos	2	8.81
642	Zack Snyder	5	975.74
643	Zackary Adler	1	6.53

644 rows × 3 columns

Concatenate

Combining or appending two different dataframes can be done with the following two functions. It is important that the columns in both data frames are the same.

```
df2 = df df.append(df2) # Append df2 to df (The columns must
be the same in both dataframes) pd.concat([df, df2],axis=0) #
concatenate two dataframes
```

Import Data from Databases

Import from mysql

```
import pymysql

conn = pymysql.connect(host='localhost',port=3306,
db='database',user='root',password='pw')

df = pd.read_sql_query( "SELECT * FROM table LIMIT 3;", conn)
df.tail(100)
```

Import Teradata

```
import teradata
```

Make a connection

```
session = udaExec.connect(method="odbc",
USEREGIONALSETTINGS="N", system= "dwh", username = "root",
password = "pw");

query = "SELECT * FROM DATABASEX.TABLENAMEX"
```

Reading query to df

```
df = pd.read_sql(query,session)
```

Do something with df,e.g.

```
print(df.head()) #to see the first 5 rows
```

Import SAP-Hana

```
import pyhdb

connection = pyhdb.connect( host="localhost", port=30015,
user="root, password="pw" ) print(connection.isconnected())
query = "SELECT * FROM HDB_REPORT."Table"" df =
pd.read_sql(query,connection)
```

Do something with df,e.g.

```
print(df.head()) #to see the first 5 rows
```

Conclusion

With this Cheat Sheet you should be well prepared to perform most of the Data Enginnering tasks with Pandas in Jupyter-Notebook. This will also make it easier to integrate code you write in Python into KNIME and benefit from the advantages of both worlds.