

# Chapter 1 Data Merging Basics

Learn how you can merge disparate data using inner joins. By combining information from multiple sources you'll uncover compelling insights that may have previously been hidden. You'll also learn how the relationship between those sources, such as one-to-one or one-to-many, can affect your result.

[Link for reference](#)

```
In [ ]: import pandas as pd

#assign name a your file and paste the pathway of the file
taxi_owners = pd.read_pickle("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python C
taxi_veh = pd.read_pickle("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python C
wards = pd.read_pickle("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python Cour
census = pd.read_pickle("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python Cou
licenses = pd.read_pickle("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python C
biz_owners = pd.read_pickle("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Pythor
ridership = pd.read_pickle("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python
cal = pd.read_pickle("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python Course
stations = pd.read_pickle("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python C
land_use = pd.read_pickle("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python C
```

Your first inner join

```
In [ ]: # Merge the taxi_owners and taxi_veh tables
taxi_own_veh = taxi_owners.merge(taxi_veh, on='vid')

# Print the column names of the taxi_own_veh
print(taxi_own_veh.columns)

Index(['rid', 'vid', 'owner_x', 'address', 'zip', 'make', 'model', 'year',
       'fuel_type', 'owner_y'],
      dtype='object')

In [ ]: # Merge the taxi_owners and taxi_veh tables setting a suffix
taxi_own_veh = taxi_owners.merge(taxi_veh, on='vid', suffixes =('_own', '_veh'))

# Print the column names of taxi_own_veh
print(taxi_own_veh.columns)

Index(['rid', 'vid', 'owner_own', 'address', 'zip', 'make', 'model', 'year',
       'fuel_type', 'owner_veh'],
      dtype='object')
```

```
In [ ]: # Print the value_counts to find the most popular fuel_type
print(taxi_own_veh['fuel_type'].value_counts())
```

```
fuel_type
HYBRID          2792
GASOLINE         611
FLEX FUEL         89
COMPRESSED NATURAL GAS    27
Name: count, dtype: int64
```

Inner joins and number of rows returned

```
In [ ]: # Merge the wards and census tables on the ward column
wards_census = wards.merge(census, on='ward')

# Print the shape of wards_census
print('wards_census table shape:', wards_census.shape)
```

```
wards_census table shape: (50, 9)
```

Inner joins and number of rows returned 2

```
In [ ]: # Print the first few rows of the census_altered table to view the change
print(census_altered[['ward']].head())

# Merge the wards and census_altered tables on the ward column
wards_census_altered = wards.merge(census_altered, on='ward')

# Print the shape of wards_census_altered
print('wards_census_altered table shape:', wards_census_altered.shape)
```

```
-----
NameError                                Traceback (most recent call last)
Cell In[52], line 2
      1 # Print the first few rows of the census_altered table to view the change
----> 2 print(census_altered[['ward']].head())
      4 # Merge the wards and census_altered tables on the ward column
      5 wards_census_altered = wards.merge(census_altered, on='ward')

NameError: name 'census_altered' is not defined
```

```
In [ ]: # Print the first few rows of the census_altered table to view the change
print(census_altered[['ward']].head())

# Merge the wards and census_altered tables on the ward column
wards_census_altered = wards.merge(census_altered, on='ward')

# Print the shape of wards_census_altered
print('wards_census_altered table shape:', wards_census_altered.shape)
```

Drag the items into the  
correct bucket

Drop items here

One-to-one

The relationship between `customer` and  
`cust_tax_info` .



The relationship between `products` and  
`inventory` .



One-to-many

The relationship between the `customers`  
and `orders` .



The relationship between the `products`  
and `orders` .



Submit Answer

One-to-many merge

```
In [ ]: # Merge the licenses and biz_owners table on account
licenses_owners = licenses.merge(biz_owners, on='account')

# Group the results by title then count the number of accounts
counted_df = licenses_owners.groupby('title').agg({'account': 'count'})

# Sort the counted_df in descending order
sorted_df = counted_df.sort_values(by='account', ascending=False)

# Use .head() method to print the first few rows of sorted_df
print(sorted_df.head())
```

|                 | account |
|-----------------|---------|
| title           |         |
| PRESIDENT       | 6259    |
| SECRETARY       | 5205    |
| SOLE PROPRIETOR | 1658    |
| OTHER           | 1200    |
| VICE PRESIDENT  | 970     |

Total riders in a month

```
In [ ]: # Merge the ridership and cal tables
ridership_cal = ridership.merge(cal, on=['year', 'month', 'day'])
```

```
In [ ]: # Merge the ridership, cal, and stations tables
ridership_cal_stations = ridership.merge(cal, on=['year', 'month', 'day']) \
    .merge(stations, on='station_id')
```

```
In [ ]: # Merge the ridership, cal, and stations tables
ridership_cal_stations = ridership.merge(cal, on=['year', 'month', 'day']) \
    .merge(stations, on='station_id')

# Create a filter to filter ridership_cal_stations
filter_criteria = ((ridership_cal_stations['month'] == 7)
    & (ridership_cal_stations['day_type'] == 'Weekday')
    & (ridership_cal_stations['station_name'] == 'Wilson'))

# Use .loc and the filter to select for rides
print(ridership_cal_stations.loc[filter_criteria, 'rides'].sum())
```

140005

Three table merge

```
In [ ]: # Merge licenses and zip_demo, on zip; and merge the wards on ward
licenses_zip_ward = licenses.merge(zip_demo, on='zip').merge(wards, on='ward')
```

```
# Print the results by alderman and show median income
print(licenses_zip_ward.groupby('alderman').agg({'income':'median'}))
```

One-to-many merge with multiple tables

```
In [ ]: # Merge land_use and census and merge result with licenses including suffixes
land_cen_lic = land_use.merge(census, on='ward').merge(licenses, on='ward', suffixes=('_cen', '_lic'))
```

```
In [ ]: # Merge land_use and census and merge result with licenses including suffixes
land_cen_lic = land_use.merge(census, on='ward') \
    .merge(licenses, on='ward', suffixes=('_cen', '_lic'))

# Group by ward, pop_2010, and vacant, then count the # of accounts
pop_vac_lic = land_cen_lic.groupby(['ward', 'pop_2010', 'vacant'],
    as_index=False).agg({'account':'count'})
```

```
In [ ]: # Merge land_use and census and merge result with licenses including suffixes
land_cen_lic = land_use.merge(census, on='ward') \
    .merge(licenses, on='ward', suffixes=('_cen', '_lic'))

# Group by ward, pop_2010, and vacant, then count the # of accounts
pop_vac_lic = land_cen_lic.groupby(['ward', 'pop_2010', 'vacant'],
    as_index=False).agg({'account':'count'})

# Sort pop_vac_lic and print the results
sorted_pop_vac_lic = pop_vac_lic.sort_values(['vacant', 'account', 'pop_2010'], ascending=[False, True, True])

# Print the top few rows of sorted_pop_vac_lic
print(sorted_pop_vac_lic.head())
```

|    | ward | pop_2010 | vacant | account |
|----|------|----------|--------|---------|
| 47 | 7    | 51581    | 19     | 80      |
| 12 | 20   | 52372    | 15     | 123     |
| 1  | 10   | 51535    | 14     | 130     |
| 16 | 24   | 54909    | 13     | 98      |
| 7  | 16   | 51954    | 13     | 156     |

```
In [ ]:
```

# Chapter 2 Merging Tables With Different Join Types

Take your knowledge of joins to the next level. In this chapter, you'll work with TMDb movie data as you learn about left, right, and outer joins. You'll also discover how to merge a table to itself and merge on a DataFrame index.

[Link for reference](#)

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

```
#assign name a your file and paste the pathway of the file
movies = pd.read_pickle("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python Cou
taglines = pd.read_pickle("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python C
financials = pd.read_pickle("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Pythor
movie_to_genres = pd.read_pickle("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. F
crews = pd.read_pickle("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python Cour
ratings = pd.read_pickle("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python Co
sequels = pd.read_pickle("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python Co
```

Counting missing rows with left join

```
In [ ]: movies_taglines = movies.merge(taglines, on='id', how='left')
print(movies_taglines.head())
```

|   | id    | title                | popularity | release_date | \ |
|---|-------|----------------------|------------|--------------|---|
| 0 | 257   | Oliver Twist         | 20.415572  | 2005-09-23   |   |
| 1 | 14290 | Better Luck Tomorrow | 3.877036   | 2002-01-12   |   |
| 2 | 38365 | Grown Ups            | 38.864027  | 2010-06-24   |   |
| 3 | 9672  | Infamous             | 3.680896   | 2006-11-16   |   |
| 4 | 12819 | Alpha and Omega      | 12.300789  | 2010-09-17   |   |

|   | tagline   |
|---|---|
| 0 | NaN   |
| 1 | Never underestimate an overachiever.            |
| 2 | Boys will be boys. . . some longer than others. |
| 3 | There's more to the story than you know         |
| 4 | A Pawsome 3D Adventure                          |

```
In [ ]: # Merge movies and financials with a left join
movies_financials = movies.merge(financials, how='left', on='id')
```

```
In [ ]: # Merge the movies table with the financials table with a left join
movies_financials = movies.merge(financials, on='id', how='left')

# Count the number of rows in the budget column that are missing
number_of_missing_fin = movies_financials['budget'].isnull().sum()
```

```
# Print the number of movies missing financials
print(number_of_missing_fin)
```

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Right join to find unique movies

```
In [ ]: # Merge action_movies to scifi_movies with right join
action_scifi = action_movies.merge(scifi_movies, how='right', on='movie_id')
```

```
In [ ]: # Merge action_movies to scifi_movies with right join
action_scifi = action_movies.merge(scifi_movies, on='movie_id', how='right', suffixes=['_act', '_sci'])

# Print the first few rows of action_scifi to see the structure
print(action_scifi.head())
```

```
In [ ]: # Merge action_movies to scifi_movies with right join
action_scifi = action_movies.merge(scifi_movies, on='movie_id', how='right', suffixes=['_act', '_sci'])

# Print the first few rows of action_scifi to see the structure
print(action_scifi.head())
```

```
In [ ]: # Merge action_movies to scifi_movies with right join
action_scifi = action_movies.merge(scifi_movies, on='movie_id', how='right', suffixes=['_act', '_sci'])

# Print the first few rows of action_scifi to see the structure
print(action_scifi.head())
```

```
In [ ]: # Merge action_movies to the scifi_movies with right join
action_scifi = action_movies.merge(scifi_movies, on='movie_id', how='right',
                                   suffixes=('_act', '_sci'))

# From action_scifi, select only the rows where the genre_act column is null
scifi_only = action_scifi[action_scifi['genre_act'].isnull()]

# Merge the movies and scifi_only tables with an inner join
movies_and_scifi_only = movies.merge(scifi_only, how='inner',
                                     left_on='id', right_on='movie_id')

# Print the first few rows and shape of movies_and_scifi_only
print(movies_and_scifi_only.head())
print(movies_and_scifi_only.shape)
```

Popular genres with right join

```
In [ ]: print(movie_to_genres.head())
        print(movies.head())
```

|   | movie_id | genre           |
|---|----------|-----------------|
| 0 | 5        | Crime           |
| 1 | 5        | Comedy          |
| 2 | 11       | Science Fiction |
| 3 | 11       | Action          |
| 4 | 11       | Adventure       |

  

|   | id    | title                | popularity | release_date |
|---|-------|----------------------|------------|--------------|
| 0 | 257   | Oliver Twist         | 20.415572  | 2005-09-23   |
| 1 | 14290 | Better Luck Tomorrow | 3.877036   | 2002-01-12   |
| 2 | 38365 | Grown Ups            | 38.864027  | 2010-06-24   |
| 3 | 9672  | Infamous             | 3.680896   | 2006-11-16   |
| 4 | 12819 | Alpha and Omega      | 12.300789  | 2010-09-17   |

```
In [ ]: # Use right join to merge the movie_to_genres and pop_movies tables
        genres_movies = movie_to_genres.merge(pop_movies, how='right', left_on='movie_id', right_on='id')

        # Count the number of genres
        genre_count = genres_movies.groupby('genre').agg({'id': 'count'})

        # Plot a bar chart of the genre_count
        genre_count.plot(kind='bar')
        plt.show()
```

Using outer join to select actors

```
In [ ]: # Merge iron_1_actors to iron_2_actors on id with outer join using suffixes
        iron_1_and_2 = iron_1_actors.merge(iron_2_actors,
                                            how='outer',
                                            on='id',
                                            suffixes=['_1', '_2'])

        # Create an index that returns true if name_1 or name_2 are null
        m = ((iron_1_and_2['name_1'].isnull() |
               (iron_1_and_2['name_2'].isnull()))

        # Print the first few rows of iron_1_and_2
        print(iron_1_and_2[m].head())
```

Self join

```
In [ ]: # Merge the crews table to itself
        crews_self_merged = crews.merge(crews, on='id', suffixes=('_dir', '_crew'))
```



```
In [ ]: # Merge the crews table to itself
crews_self_merged = crews.merge(crews, on='id', how='inner',
                                suffixes=('_dir', '_crew'))

# Create a Boolean index to select the appropriate
boolean_filter = ((crews_self_merged['job_dir'] == 'Director') &
                  (crews_self_merged['job_crew'] != 'Director'))
direct_crews = crews_self_merged[boolean_filter]
```

```
In [ ]: # Merge the crews table to itself
crews_self_merged = crews.merge(crews, on='id', how='inner',
                                suffixes=('_dir', '_crew'))

# Create a boolean index to select the appropriate rows
boolean_filter = ((crews_self_merged['job_dir'] == 'Director') &
                  (crews_self_merged['job_crew'] != 'Director'))
direct_crews = crews_self_merged[boolean_filter]

# Print the first few rows of direct_crews
print(direct_crews.head())
```

|     | id    | department_dir | job_dir  | name_dir      | department_crew | \ |
|-----|-------|----------------|----------|---------------|-----------------|---|
| 156 | 19995 | Directing      | Director | James Cameron | Editing         |   |
| 157 | 19995 | Directing      | Director | James Cameron | Sound           |   |
| 158 | 19995 | Directing      | Director | James Cameron | Production      |   |
| 160 | 19995 | Directing      | Director | James Cameron | Writing         |   |
| 161 | 19995 | Directing      | Director | James Cameron | Art             |   |

|     | job_crew       | name_crew         |
|-----|----------------|-------------------|
| 156 | Editor         | Stephen E. Rivkin |
| 157 | Sound Designer | Christopher Boyes |
| 158 | Casting        | Mali Finn         |
| 160 | Writer         | James Cameron     |
| 161 | Set Designer   | Richard F. Mays   |

Index merge for movie ratings

```
In [ ]: # Merge to the movies table the ratings table on the index
movies_ratings = movies.merge(ratings, how='left', on='id')

# Print the first few rows of movies_ratings
print(movies_ratings.head())
```

|   | id    | title                | popularity | release_date | vote_average | \ |
|---|-------|----------------------|------------|--------------|--------------|---|
| 0 | 257   | Oliver Twist         | 20.415572  | 2005-09-23   | 6.7          |   |
| 1 | 14290 | Better Luck Tomorrow | 3.877036   | 2002-01-12   | 6.5          |   |
| 2 | 38365 | Grown Ups            | 38.864027  | 2010-06-24   | 6.0          |   |
| 3 | 9672  | Infamous             | 3.680896   | 2006-11-16   | 6.4          |   |
| 4 | 12819 | Alpha and Omega      | 12.300789  | 2010-09-17   | 5.3          |   |

|   | vote_count |
|---|------------|
| 0 | 274.0      |
| 1 | 27.0       |
| 2 | 1705.0     |
| 3 | 60.0       |
| 4 | 124.0      |

Do sequels earn more?

```
In [ ]: # Merge sequels and financials on index id
sequels_fin = sequels.merge(financials, on='id', how='left')
```

```
In [ ]: # Merge sequels and financials on index id
sequels_fin = sequels.merge(financials, on='id', how='left')

# Self merge with suffixes as inner join with left on sequel and right on id
orig_seq = sequels_fin.merge(sequels_fin, how='inner', left_on='sequel',
                             right_on='id', right_index=True,
                             suffixes=('_org', '_seq'))

# Add calculation to subtract revenue_org from revenue_seq
orig_seq['diff'] = orig_seq['revenue_seq'] - orig_seq['revenue_org']
```

```
In [ ]: # Merge sequels and financials on index id
sequels_fin = sequels.merge(financials, on='id', how='left')

# Self merge with suffixes as inner join with left on sequel and right on id
orig_seq = sequels_fin.merge(sequels_fin, how='inner', left_on='sequel',
                             right_on='id', right_index=True,
                             suffixes=('_org', '_seq'))

# Add calculation to subtract revenue_org from revenue_seq
orig_seq['diff'] = orig_seq['revenue_seq'] - orig_seq['revenue_org']

# Select the title_org, title_seq, and diff
titles_diff = orig_seq[['title_org', 'title_seq', 'diff']]
```

```
In [ ]: # Merge sequels and financials on index id
sequels_fin = sequels.merge(financials, on='id', how='left')

# Self merge with suffixes as inner join with left on sequel and right on id
```

```

orig_seq = sequels_fin.merge(sequels_fin, how='inner', left_on='sequel',
                             right_on='id', right_index=True,
                             suffixes=('_org', '_seq'))

# Add calculation to subtract revenue_org from revenue_seq
orig_seq['diff'] = orig_seq['revenue_seq'] - orig_seq['revenue_org']

# Select the title_org, title_seq, and diff
titles_diff = orig_seq[['title_org', 'title_seq', 'diff']]

# Print the first rows of the sorted titles_diff
print(titles_diff.sort_values(by='diff', ascending=False).head())

```

|      | title_org                            | title_seq \              |
|------|--------------------------------------|--------------------------|
| 2929 | Before Sunrise                       | The Amazing Spider-Man 2 |
| 1256 | Star Trek III: The Search for Spock  | The Matrix               |
| 293  | Indiana Jones and the Temple of Doom | Man of Steel             |
| 1084 | Saw                                  | Superman Returns         |
| 1334 | The Terminator                       | Star Trek Beyond         |

  

|      | diff        |
|------|-------------|
| 2929 | 700182027.0 |
| 1256 | 376517383.0 |
| 293  | 329845518.0 |
| 1084 | 287169523.0 |
| 1334 | 265100616.0 |

In [ ]:

## Chapter 3 Advanced Merging and Concatenating

In this chapter, you'll leverage powerful filtering techniques, including semi-joins and anti-joins. You'll also learn how to glue DataFrames by vertically combining and using the pandas.concat function to create new datasets. Finally, because data is rarely clean, you'll also learn how to validate your newly combined data structures.

[Link for reference](#)

```

In [ ]: import pandas as pd

#assign name a your file and paste the pathway of the file

# for ".csv" files
gdp = pd.read_csv("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python Course Data\\gdp.csv")
sp500 = pd.read_csv("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python Course Data\\sp500.csv")

```



```
In [ ]: # Concatenate the tracks so the index goes from 0 to n-1
tracks_from_albums = pd.concat([tracks_master, tracks_ride, tracks_st],
                                ignore_index=True,
                                sort=True)

print(tracks_from_albums)
```

```
In [ ]: # Concatenate the tracks, show only columns names that are in all tables
tracks_from_albums = pd.concat([tracks_master, tracks_ride, tracks_st],
                                join='inner',
                                sort=True)

print(tracks_from_albums)
```

Concatenating with keys

```
In [ ]: # Concatenate the tables and add keys
inv_jul_thr_sep = pd.concat([inv_jul, inv_aug, inv_sep],
                             keys=['7Jul', '8Aug', '9Sep'])

# Group the invoices by the index keys and find avg of the total column
avg_inv_by_month = inv_jul_thr_sep.groupby(level=0).agg({'total': 'mean'})

# Bar plot of avg_inv_by_month
avg_inv_by_month.plot(kind='bar')
plt.show()
```

Concatenate and merge to find common songs

```
In [ ]: # Concatenate the classic tables vertically
classic_18_19 = pd.concat([classic_18, classic_19], ignore_index=True)

# Concatenate the pop tables vertically
pop_18_19 = pd.concat([pop_18, pop_19], ignore_index=True)
```

```
In [ ]: # Concatenate the classic tables vertically
classic_18_19 = pd.concat([classic_18, classic_19], ignore_index=True)

# Concatenate the pop tables vertically
pop_18_19 = pd.concat([pop_18, pop_19], ignore_index=True)

# Merge classic_18_19 with pop_18_19
classic_pop = classic_18_19.merge(pop_18_19, on='tid', how='inner')

# Using .isin(), filter classic_18_19 rows where tid is in classic_pop
popular_classic = classic_18_19[classic_18_19['tid'].isin(classic_pop['tid'])]

# Print popular chart
print(popular_classic)
```

# Chapter 4 - Merging Ordered and Time-Series Data

In this final chapter, you'll step up a gear and learn to apply pandas' specialized methods for merging time-series and ordered data together with real-world financial and economic data from the city of Chicago. You'll also learn how to query resulting tables using a SQL-style format, and unpivot data using the melt method.

[Link for reference](#)

```
In [ ]: import pandas as pd

# for ".csv" files
gdp = pd.read_csv("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python Course Data\\gdp.csv")
sp500 = pd.read_csv("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python Course Data\\sp500.csv")
pop = pd.read_csv("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python Course Data\\pop.csv")

# for ".p" files
stations = pd.read_pickle("C:\\Users\\yeiso\\OneDrive - Douglas College\\0. DOUGLAS COLLEGE\\3. Fund Machine Learning\\0. Python Course Data\\stations.pkl")

print(gdp.head())
print(sp500.head())
print(stations.head())
```

|   | Country Name  | Country Code | Indicator Name     | Year | GDP          |
|---|---------------|--------------|--------------------|------|--------------|
| 0 | China         | CHN          | GDP (current US\$) | 2010 | 6.087160e+12 |
| 1 | Germany       | DEU          | GDP (current US\$) | 2010 | 3.417090e+12 |
| 2 | Japan         | JPN          | GDP (current US\$) | 2010 | 5.700100e+12 |
| 3 | United States | USA          | GDP (current US\$) | 2010 | 1.499210e+13 |
| 4 | China         | CHN          | GDP (current US\$) | 2011 | 7.551500e+12 |

|   | Date | Returns |
|---|------|---------|
| 0 | 2008 | -38.49  |
| 1 | 2009 | 23.45   |
| 2 | 2010 | 12.78   |
| 3 | 2011 | 0.00    |
| 4 | 2012 | 13.41   |

|   | station_id | station_name       | location                |
|---|------------|--------------------|-------------------------|
| 0 | 40010      | Austin-Forest Park | (41.870851, -87.776812) |
| 1 | 40020      | Harlem-Lake        | (41.886848, -87.803176) |
| 2 | 40030      | Pulaski-Lake       | (41.885412, -87.725404) |
| 3 | 40040      | Quincy/Wells       | (41.878723, -87.63374)  |
| 4 | 40050      | Davis              | (42.04771, -87.683543)  |

Correlation between GDP and S&P500

```
In [ ]: # Use merge_ordered() to merge gdp and sp500 on year and date
gdp_sp500 = pd.merge_ordered(gdp, sp500, left_on='Year', right_on='Date',
```

```
how='left')
```

```
# Print gdp_sp500  
print(gdp_sp500)
```

|    | Country Name  | Country Code | Indicator Name     | Year | GDP          | Date   | \ |
|----|---------------|--------------|--------------------|------|--------------|--------|---|
| 0  | China         | CHN          | GDP (current US\$) | 2010 | 6.087160e+12 | 2010.0 |   |
| 1  | Germany       | DEU          | GDP (current US\$) | 2010 | 3.417090e+12 | 2010.0 |   |
| 2  | Japan         | JPN          | GDP (current US\$) | 2010 | 5.700100e+12 | 2010.0 |   |
| 3  | United States | USA          | GDP (current US\$) | 2010 | 1.499210e+13 | 2010.0 |   |
| 4  | China         | CHN          | GDP (current US\$) | 2011 | 7.551500e+12 | 2011.0 |   |
| 5  | Germany       | DEU          | GDP (current US\$) | 2011 | 3.757700e+12 | 2011.0 |   |
| 6  | Japan         | JPN          | GDP (current US\$) | 2011 | 6.157460e+12 | 2011.0 |   |
| 7  | United States | USA          | GDP (current US\$) | 2011 | 1.554260e+13 | 2011.0 |   |
| 8  | China         | CHN          | GDP (current US\$) | 2012 | 8.532230e+12 | 2012.0 |   |
| 9  | Germany       | DEU          | GDP (current US\$) | 2012 | 3.543980e+12 | 2012.0 |   |
| 10 | Japan         | JPN          | GDP (current US\$) | 2012 | 6.203210e+12 | 2012.0 |   |
| 11 | United States | USA          | GDP (current US\$) | 2012 | 1.619700e+13 | 2012.0 |   |
| 12 | China         | CHN          | GDP (current US\$) | 2012 | 8.532230e+12 | 2012.0 |   |
| 13 | Germany       | DEU          | GDP (current US\$) | 2012 | 3.543980e+12 | 2012.0 |   |
| 14 | Japan         | JPN          | GDP (current US\$) | 2012 | 6.203210e+12 | 2012.0 |   |
| 15 | United States | USA          | GDP (current US\$) | 2012 | 1.619700e+13 | 2012.0 |   |
| 16 | China         | CHN          | GDP (current US\$) | 2013 | 9.570410e+12 | 2013.0 |   |
| 17 | Germany       | DEU          | GDP (current US\$) | 2013 | 3.752510e+12 | 2013.0 |   |
| 18 | Japan         | JPN          | GDP (current US\$) | 2013 | 5.155720e+12 | 2013.0 |   |
| 19 | United States | USA          | GDP (current US\$) | 2013 | 1.678480e+13 | 2013.0 |   |
| 20 | China         | CHN          | GDP (current US\$) | 2014 | 1.043850e+13 | 2014.0 |   |
| 21 | Germany       | DEU          | GDP (current US\$) | 2014 | 3.898730e+12 | 2014.0 |   |
| 22 | Japan         | JPN          | GDP (current US\$) | 2014 | 4.850410e+12 | 2014.0 |   |
| 23 | United States | USA          | GDP (current US\$) | 2014 | 1.752170e+13 | 2014.0 |   |
| 24 | China         | CHN          | GDP (current US\$) | 2015 | 1.101550e+13 | 2015.0 |   |
| 25 | Germany       | DEU          | GDP (current US\$) | 2015 | 3.381390e+12 | 2015.0 |   |
| 26 | Japan         | JPN          | GDP (current US\$) | 2015 | 4.389480e+12 | 2015.0 |   |
| 27 | United States | USA          | GDP (current US\$) | 2015 | 1.821930e+13 | 2015.0 |   |
| 28 | China         | CHN          | GDP (current US\$) | 2016 | 1.113790e+13 | 2016.0 |   |
| 29 | Germany       | DEU          | GDP (current US\$) | 2016 | 3.495160e+12 | 2016.0 |   |
| 30 | Japan         | JPN          | GDP (current US\$) | 2016 | 4.926670e+12 | 2016.0 |   |
| 31 | United States | USA          | GDP (current US\$) | 2016 | 1.870720e+13 | 2016.0 |   |
| 32 | China         | CHN          | GDP (current US\$) | 2017 | 1.214350e+13 | 2017.0 |   |
| 33 | Germany       | DEU          | GDP (current US\$) | 2017 | 3.693200e+12 | 2017.0 |   |
| 34 | Japan         | JPN          | GDP (current US\$) | 2017 | 4.859950e+12 | 2017.0 |   |
| 35 | United States | USA          | GDP (current US\$) | 2017 | 1.948540e+13 | 2017.0 |   |
| 36 | China         | CHN          | GDP (current US\$) | 2018 | 1.360820e+13 | NaN    |   |
| 37 | Germany       | DEU          | GDP (current US\$) | 2018 | 3.996760e+12 | NaN    |   |
| 38 | Japan         | JPN          | GDP (current US\$) | 2018 | 4.970920e+12 | NaN    |   |
| 39 | United States | USA          | GDP (current US\$) | 2018 | 2.049410e+13 | NaN    |   |

#### Returns

|   |       |
|---|-------|
| 0 | 12.78 |
| 1 | 12.78 |
| 2 | 12.78 |
| 3 | 12.78 |
| 4 | 0.00  |
| 5 | 0.00  |
| 6 | 0.00  |



|    |       |
|----|-------|
| 7  | 0.00  |
| 8  | 13.41 |
| 9  | 13.41 |
| 10 | 13.41 |
| 11 | 13.41 |
| 12 | 13.41 |
| 13 | 13.41 |
| 14 | 13.41 |
| 15 | 13.41 |
| 16 | 29.60 |
| 17 | 29.60 |
| 18 | 29.60 |
| 19 | 29.60 |
| 20 | 11.39 |
| 21 | 11.39 |
| 22 | 11.39 |
| 23 | 11.39 |
| 24 | -0.73 |
| 25 | -0.73 |
| 26 | -0.73 |
| 27 | -0.73 |
| 28 | 9.54  |
| 29 | 9.54  |
| 30 | 9.54  |
| 31 | 9.54  |
| 32 | 19.42 |
| 33 | 19.42 |
| 34 | 19.42 |
| 35 | 19.42 |
| 36 | NaN   |
| 37 | NaN   |
| 38 | NaN   |
| 39 | NaN   |

```
In [ ]: # Use merge_ordered() to merge gdp and sp500, interpolate missing value
gdp_sp500 = pd.merge_ordered(gdp, sp500, left_on='Year', right_on='Date', how='left', fill_method='ffill')

# Print gdp_sp500
print (gdp_sp500.head(10))
```

|   | Country Name  | Country Code | Indicator Name     | Year | GDP          | Date | \ |
|---|---------------|--------------|--------------------|------|--------------|------|---|
| 0 | China         | CHN          | GDP (current US\$) | 2010 | 6.087160e+12 | 2010 |   |
| 1 | Germany       | DEU          | GDP (current US\$) | 2010 | 3.417090e+12 | 2010 |   |
| 2 | Japan         | JPN          | GDP (current US\$) | 2010 | 5.700100e+12 | 2010 |   |
| 3 | United States | USA          | GDP (current US\$) | 2010 | 1.499210e+13 | 2010 |   |
| 4 | China         | CHN          | GDP (current US\$) | 2011 | 7.551500e+12 | 2011 |   |
| 5 | Germany       | DEU          | GDP (current US\$) | 2011 | 3.757700e+12 | 2011 |   |
| 6 | Japan         | JPN          | GDP (current US\$) | 2011 | 6.157460e+12 | 2011 |   |
| 7 | United States | USA          | GDP (current US\$) | 2011 | 1.554260e+13 | 2011 |   |
| 8 | China         | CHN          | GDP (current US\$) | 2012 | 8.532230e+12 | 2012 |   |
| 9 | Germany       | DEU          | GDP (current US\$) | 2012 | 3.543980e+12 | 2012 |   |

|   | Returns |
|---|---------|
| 0 | 12.78   |
| 1 | 12.78   |
| 2 | 12.78   |
| 3 | 12.78   |
| 4 | 0.00    |
| 5 | 0.00    |
| 6 | 0.00    |
| 7 | 0.00    |
| 8 | 13.41   |
| 9 | 13.41   |

```
In [ ]: # Use merge_ordered() to merge gdp and sp500, interpolate missing value
gdp_sp500 = pd.merge_ordered(gdp, sp500, left_on='Year', right_on='Date',
                             how='left', fill_method='ffill')

# Subset the gdp and returns columns
gdp_returns = gdp_sp500[['GDP', 'Returns']]

# Print gdp_returns correlation
print (gdp_returns.corr())
```

|         | GDP      | Returns  |
|---------|----------|----------|
| GDP     | 1.000000 | 0.040669 |
| Returns | 0.040669 | 1.000000 |

Phillips curve using merge\_ordered()

```
In [ ]: # Use merge_ordered() to merge inflation, unemployment with inner join
inflation_unemploy = pd.merge_ordered(inflation, unemployment, on='Date', how='inner')

# Print inflation_unemploy
print(inflation_unemploy)

# Plot a scatter plot of unemployment_rate vs cpi of inflation_unemploy
inflation_unemploy.plot(kind='scatter', x='unemployment_rate', y='cpi')
plt.show()
```

merge\_ordered() caution, multiple columns

```
In [ ]: print(gdp.head())
        print(pop.head())

# Merge gdp and pop on date and country with fill and notice rows 2 and 3
ctry_date = pd.merge_ordered(gdp, pop, on=['Year', 'Country Name'],
                             fill_method='ffill')

# Print ctry_date
print(ctry_date)
```

|   | Country Name  | Country Code | Indicator Name     | Year | GDP          |
|---|---------------|--------------|--------------------|------|--------------|
| 0 | China         | CHN          | GDP (current US\$) | 2010 | 6.087160e+12 |
| 1 | Germany       | DEU          | GDP (current US\$) | 2010 | 3.417090e+12 |
| 2 | Japan         | JPN          | GDP (current US\$) | 2010 | 5.700100e+12 |
| 3 | United States | USA          | GDP (current US\$) | 2010 | 1.499210e+13 |
| 4 | China         | CHN          | GDP (current US\$) | 2011 | 7.551500e+12 |

  

|   | Country Name | Country Code | Indicator Name    | Year | Pop        |
|---|--------------|--------------|-------------------|------|------------|
| 0 | Aruba        | ABW          | Population, total | 2010 | 101669.0   |
| 1 | Afghanistan  | AFG          | Population, total | 2010 | 29185507.0 |
| 2 | Angola       | AGO          | Population, total | 2010 | 23356246.0 |
| 3 | Albania      | ALB          | Population, total | 2010 | 2913021.0  |
| 4 | Andorra      | AND          | Population, total | 2010 | 84449.0    |

  

|      | Country Name       | Country Code_x | Indicator Name_x   | Year | \ |
|------|--------------------|----------------|--------------------|------|---|
| 0    | Afghanistan        | NaN            | NaN                | 2010 |   |
| 1    | Albania            | NaN            | NaN                | 2010 |   |
| 2    | Algeria            | NaN            | NaN                | 2010 |   |
| 3    | American Samoa     | NaN            | NaN                | 2010 |   |
| 4    | Andorra            | NaN            | NaN                | 2010 |   |
| ...  | ...                | ...            | ...                | ...  |   |
| 2643 | West Bank and Gaza | USA            | GDP (current US\$) | 2018 |   |
| 2644 | World              | USA            | GDP (current US\$) | 2018 |   |
| 2645 | Yemen, Rep.        | USA            | GDP (current US\$) | 2018 |   |
| 2646 | Zambia             | USA            | GDP (current US\$) | 2018 |   |
| 2647 | Zimbabwe           | USA            | GDP (current US\$) | 2018 |   |

  

|      | GDP          | Country Code_y | Indicator Name_y  | Pop          |
|------|--------------|----------------|-------------------|--------------|
| 0    | NaN          | AFG            | Population, total | 2.918551e+07 |
| 1    | NaN          | ALB            | Population, total | 2.913021e+06 |
| 2    | NaN          | DZA            | Population, total | 3.597746e+07 |
| 3    | NaN          | ASM            | Population, total | 5.607900e+04 |
| 4    | NaN          | AND            | Population, total | 8.444900e+04 |
| ...  | ...          | ...            | ...               | ...          |
| 2643 | 2.049410e+13 | PSE            | Population, total | 4.569087e+06 |
| 2644 | 2.049410e+13 | WLD            | Population, total | 7.594270e+09 |
| 2645 | 2.049410e+13 | YEM            | Population, total | 2.849869e+07 |
| 2646 | 2.049410e+13 | ZMB            | Population, total | 1.735182e+07 |
| 2647 | 2.049410e+13 | ZWE            | Population, total | 1.443902e+07 |

[2648 rows x 8 columns]

```
In [ ]: # Merge gdp and pop on country and date with fill
date_ctype = pd.merge_ordered(gdp, pop, on=['Country Name', 'Year'],
                              fill_method='ffill')

# Print date_ctype
print(date_ctype)
```

|      | Country     | Name | Code_x | Indicator          | Name_x | Year | GDP          | \ |
|------|-------------|------|--------|--------------------|--------|------|--------------|---|
| 0    | Afghanistan |      | NaN    |                    | NaN    | 2010 | NaN          |   |
| 1    | Afghanistan |      | NaN    |                    | NaN    | 2011 | NaN          |   |
| 2    | Afghanistan |      | NaN    |                    | NaN    | 2012 | NaN          |   |
| 3    | Afghanistan |      | NaN    |                    | NaN    | 2012 | NaN          |   |
| 4    | Afghanistan |      | NaN    |                    | NaN    | 2013 | NaN          |   |
| ...  | ...         |      | ...    |                    | ...    | ...  | ...          |   |
| 2643 | Zimbabwe    |      | USA    | GDP (current US\$) |        | 2014 | 2.049410e+13 |   |
| 2644 | Zimbabwe    |      | USA    | GDP (current US\$) |        | 2015 | 2.049410e+13 |   |
| 2645 | Zimbabwe    |      | USA    | GDP (current US\$) |        | 2016 | 2.049410e+13 |   |
| 2646 | Zimbabwe    |      | USA    | GDP (current US\$) |        | 2017 | 2.049410e+13 |   |
| 2647 | Zimbabwe    |      | USA    | GDP (current US\$) |        | 2018 | 2.049410e+13 |   |

|      | Country | Code_y | Indicator         | Name_y | Pop        |
|------|---------|--------|-------------------|--------|------------|
| 0    | AFG     |        | Population, total |        | 29185507.0 |
| 1    | AFG     |        | Population, total |        | 30117413.0 |
| 2    | AFG     |        | Population, total |        | 31161376.0 |
| 3    | AFG     |        | Population, total |        | 31161376.0 |
| 4    | AFG     |        | Population, total |        | 32269589.0 |
| ...  | ...     |        | ...               |        | ...        |
| 2643 | ZWE     |        | Population, total |        | 13586681.0 |
| 2644 | ZWE     |        | Population, total |        | 13814629.0 |
| 2645 | ZWE     |        | Population, total |        | 14030390.0 |
| 2646 | ZWE     |        | Population, total |        | 14236745.0 |
| 2647 | ZWE     |        | Population, total |        | 14439018.0 |

[2648 rows x 8 columns]

Using merge\_asof() to study stocks

```
In [ ]: # Use merge_asof() to merge jpm and wells
jpm_wells = pd.merge_asof(jpm, wells, on='date_time',
                           suffixes=('_', '_wells'), direction='nearest')

# Use merge_asof() to merge jpm_wells and bac
jpm_wells_bac = pd.merge_asof(jpm_wells, bac, on='date_time',
                               suffixes=('_', '_bac'), direction='nearest')

# Compute price diff
price_diffs = jpm_wells_bac.diff()

# Plot the price diff of the close of jpm, wells and bac only
price_diffs.plot(y=['close_jpm', 'close_wells', 'close_bac'])
plt.show()
```

Using merge\_asof() to create dataset

```
In [ ]: # Merge gdp and recession on date using merge_asof()
gdp_recession = pd.merge_asof(gdp, recession, on='date')

# Create a list based on the row value of gdp_recession['econ_status']
is_recession = ['r' if s=='recession' else 'g' for s in gdp_recession['econ_status']]

# Plot a bar chart of gdp_recession
gdp_recession.plot(kind='bar', y='gdp', x='date', color=is_recession, rot=90)
plt.show()
```

Subsetting rows with .query()

```
In [ ]: # Merge gdp and pop on date and country with fill
gdp_pop = pd.merge_ordered(gdp, pop, on=['Country Name', 'Year'], fill_method='ffill')
```

```
In [ ]: # Merge gdp and pop on date and country with fill
gdp_pop = pd.merge_ordered(gdp, pop, on=['Country Name', 'Year'], fill_method='ffill')

# Add a column named gdp_per_capita to gdp_pop that divides the gdp by pop
gdp_pop['gdp_per_capita'] = gdp_pop['GDP']/gdp_pop['Pop']
```

```
In [ ]: # Merge gdp and pop on date and country with fill
gdp_pop = pd.merge_ordered(gdp, pop, on=['Country Name', 'Year'], fill_method='ffill')

# Add a column named gdp_per_capita to gdp_pop that divides the gdp by pop
gdp_pop['gdp_per_capita'] = gdp_pop['GDP']/gdp_pop['Pop']

# Pivot table of gdp_per_capita, where index is date and columns is country
gdp_pivot = gdp_pop.pivot_table('gdp_per_capita', 'Year', 'Country Name')
```

```
In [ ]: # Merge gdp and pop on date and country with fill
gdp_pop = pd.merge_ordered(gdp, pop, on=['Country Name', 'Year'], fill_method='ffill')

# Add a column named gdp_per_capita to gdp_pop that divides the gdp by pop
gdp_pop['gdp_per_capita'] = gdp_pop['GDP'] / gdp_pop['Pop']

# Pivot table of gdp_per_capita, where index is date and columns are country
gdp_pivot = gdp_pop.pivot_table('gdp_per_capita', 'Year', 'Country Name')

# Convert 'Year' to string to avoid the TypeError
recent_gdp_pop = gdp_pivot.query('Year >= 1991')

# Plot recent_gdp_pop with proper labels
recent_gdp_pop.plot(rot=90)
plt.xlabel('Year')
plt.ylabel('GDP per Capita')
```

```
plt.title('GDP per Capita Over Time')
plt.show()
```

```
-----
NameError                                Traceback (most recent call last)
Cell In[117], line 15
     13 # Plot recent_gdp_pop with proper labels
     14 recent_gdp_pop.plot(rot=90)
--> 15 plt.xlabel('Year')
     16 plt.ylabel('GDP per Capita')
     17 plt.title('GDP per Capita Over Time')

NameError: name 'plt' is not defined
```

# Country Name

|   |
|---|
| China   |
| Colombia                                      |
| Comoros                                       |
| Congo, Dem. Rep.                              |
| Congo, Rep.                                   |
| Costa Rica                                    |
| Cote d'Ivoire                                 |
| Croatia                                       |
| Cuba  |
| Curacao                                       |
| Cyprus  |
| Czech Republic                                |
| Denmark                                       |
| Djibouti                                      |
| Dominica                                      |
| Dominican Republic                            |
| Early-demographic dividend                    |
| East Asia & Pacific                           |
| East Asia & Pacific (IDA & IBRD countries)    |
| East Asia & Pacific (excluding high income)   |
| Ecuador                                       |
| Egypt, Arab Rep.                              |
| El Salvador                                   |
| Equatorial Guinea                             |
| Eritrea                                       |
| Estonia                                       |
| Eswatini                                      |
| Ethiopia                                      |
| Euro area                                     |
| Europe & Central Asia                         |
| Europe & Central Asia (IDA & IBRD countries)  |
| Europe & Central Asia (excluding high income) |
| European Union                                |
| Faroe Islands                                 |
| Fiji  |
| Finland                                       |
| Fragile and conflict affected situations      |
| France  |



France  
French Polynesia  
Gabon  
Gambia, The  
Georgia  
Germany  
Ghana  
Gibraltar  
Greece  
Greenland  
Grenada  
Guam  
Guatemala  
Guinea  
Guinea-Bissau  
Guyana  
Haiti  
Heavily indebted poor countries (HIPC)  
High income  
Honduras  
Hong Kong SAR, China  
Hungary  
IBRD only  
IDA & IBRD total  
IDA blend  
IDA only  
IDA total  
Iceland  
India  
Indonesia  
Iran, Islamic Rep.  
Iraq  
Ireland  
Isle of Man  
Israel  
Italy  
Jamaica  
Japan  
Jordan  
Kazakhstan

Using .melt() to reshape government data

```
In [ ]: # Unpivot everything besides the year column
ur_tall = ur_wide.melt(id_vars=['year'], var_name='month',
                      value_name='unempl_rate')

# Create a date column using the month and year columns of ur_tall
ur_tall['date'] = pd.to_datetime(ur_tall['month'] + '-' + ur_tall['year'])

# Sort ur_tall by date in ascending order
ur_sorted = ur_tall.sort_values('date')

# Plot the unempl_rate by date
ur_sorted.plot(x='date', y='unempl_rate')
plt.show()
```

Using .melt() for stocks vs bond performance

```
In [ ]: # Use melt on ten_yr, unpivot everything besides the metric column
bond_perc = ten_yr.melt(id_vars='metric', var_name='date', value_name='close')

# Use query on bond_perc to select only the rows where metric=close
bond_perc_close = bond_perc.query('metric == "close"')

# Merge (ordered) dji and bond_perc_close on date with an inner join
dow_bond = pd.merge_ordered(dji, bond_perc_close, on='date',
                             suffixes=('_dow', '_bond'), how='inner')

# Plot only the close_dow and close_bond columns
dow_bond.plot(y=['close_dow', 'close_bond'], x='date', rot=90)
plt.show()
```

Middle East & North Africa (excluding high income)  
Middle income  
Moldova  
Monaco  
Mongolia  
Montenegro  
Morocco  
Mozambique  
Myanmar  
Namibia  
Nauru  
Nepal  
Netherlands  
New Caledonia  
New Zealand  
Nicaragua  
Niger  
Nigeria  
North America  
North Macedonia  
Northern Mariana Islands  
Norway  
OECD members  
Oman  
Other small states  
Pacific island small states  
Pakistan  
Palau  
Panama  
Papua New Guinea  
Paraguay  
Peru  
Philippines  
Poland  
Portugal  
Post-demographic dividend  
Pre-demographic dividend  
Puerto Rico  
Qatar

Romania  
Russian Federation  
Rwanda  
Samoa  
San Marino  
Sao Tome and Principe  
Saudi Arabia  
Senegal  
Serbia  
Seychelles  
Sierra Leone  
Singapore  
Sint Maarten (Dutch part)  
Slovak Republic  
Slovenia  
Small states  
Solomon Islands  
Somalia  
South Africa  
South Asia  
South Asia (IDA & IBRD)  
South Sudan  
Spain  
Sri Lanka  
St. Kitts and Nevis  
St. Lucia  
St. Martin (French part)  
St. Vincent and the Grenadines  
Sub-Saharan Africa  
Sub-Saharan Africa (IDA & IBRD countries)  
Sub-Saharan Africa (excluding high income)  
Sudan  
Suriname  
Sweden  
Switzerland  
Syrian Arab Republic  
Tajikistan  
Tanzania  
Thailand

