Using merge_ordered()

JOINING DATA WITH PANDAS

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merge_ordered()

Left Table

A	B	C
A3	B3	C3
A2	B2	C2
A1	B1	C1

Right Table

C	D
C4	D4
C2	D2
C1	D1

Result Table

A	B	C	D
A1	B1	C1	D1
A2	B2	C2	D2
A3	B3	C3	
		C4	D4

2. merge_ordered()
The merge_ordered method will allow us to merge the left and right tables shown here. We can see the output of the merge when we merge on the "C" column. The results are similar to the standard merge method with an outer join, **but here that the results are sorted.** The sorted results make this a useful method for ordered or time-series data.

Method comparison

`.merge()` **method:**

- Column(s) to join on
  - `on` , `left_on` , and `right_on`
- Type of join
  - `how` *(left, right, inner, outer)* {{@}}
  - **default** inner
- Overlapping column names
  - `suffixes`
- Calling the method
  - `df1.merge(df2)`

`merge_ordered()` **method:**

- Column(s) to join on
  - `on` , `left_on` , and `right_on`
- Type of join
  - `how` *(left, right, inner, outer)*
  - **default** outer
- Overlapping column names
  - `suffixes`
- Calling the function
  - `pd.merge_ordered(df1, df2)`

Financial dataset

[1] Photo by Markus Spiske on Unsplash

Stock data

Table Name: `appl`

	date	close
0	2007-02-01	12.087143
1	2007-03-01	13.272857
2	2007-04-01	14.257143
3	2007-05-01	17.312857
4	2007-06-01	17.434286

Table Name: `mcd`

	date	close
0	2007-01-01	44.349998
1	2007-02-01	43.689999
2	2007-03-01	45.049999
3	2007-04-01	48.279999
4	2007-05-01	50.549999

Merging stock data

```
import pandas as pd
pd.merge_ordered(appl, mcd, on='date', suffixes=('_aapl','_mcd'))
```

```
        date  close_aapl  close_mcd
0 2007-01-01         NaN  44.349998
1 2007-02-01   12.087143  43.689999
2 2007-03-01   13.272857  45.049999
3 2007-04-01   14.257143  48.279999
4 2007-05-01   17.312857  50.549999
5 2007-06-01   17.434286        NaN
```

6. Merging stock data
The first two arguments are the left and right tables. We set the "on" argument equal to date. Finally, we set the suffixes argument to determine which table the data originated. This results in a table sorted by date. There isn't a value for Apple in January or a value for McDonald's for June since values for these time periods are not available in the two original tables.

Forward fill

Before

A	B
A1	B1
A2	
A3	B3
A4	
A5	B5

After

A	B
A1	B1
A2	**B1**
A3	B3
A4	**B3**
A5	B5

Fills missing with previous value

7. Forward fill
We can fill in this missing data using a technique called forward filling. It will interpolate missing data by filling the missing values with the previous value. In the table shown here, the second and fourth rows of column B are filled with the values of B in the rows proceeding them.

Forward fill example

```
pd.merge_ordered(appl, mcd, on='date',
                 suffixes=('_aapl','_mcd'),
                 fill_method='ffill')
```

	date	close_aapl	close_mcd
0	2007-01-01	NaN	44.349998
1	2007-02-01	12.087143	43.689999
2	2007-03-01	13.272857	45.049999
3	2007-04-01	14.257143	48.279999
4	2007-05-01	17.312857	50.549999
5	2007-06-01	17.434286	50.549999

```
pd.merge_ordered(appl, mcd, on='date',
                 suffixes=('_aapl','_mcd'))
```

	date	close_AAPL	close_mcd
0	2007-01-01	NaN	44.349998
1	2007-02-01	12.087143	43.689999
2	2007-03-01	13.272857	45.049999
3	2007-04-01	14.257143	48.279999
4	2007-05-01	17.312857	50.549999
5	2007-06-01	17.434286	NaN

8. Forward fill example
Going back to our stock example from before, we now set the fill_method argument to "ffill" for forward fill. In the result, notice that the missing value for McDonald's in the last row is now filled in with the row before it. The table from before is shown on the right for easier comparison. Notice the missing value for Apple in the first row is still missing since there isn't a row before the first row to copy into the missing value for Apple.

When to use merge_ordered()?

- Ordered data / time series
- Filling in missing values

9. When to use merge_ordered()?
You might think about using the merge_ordered method instead of the regular merge method when you are working with order or time-series data like in our example. Additionally, the fill forward feature is useful for handling missing data, as most machine learning algorithms require that there are no missing values.

Let's practice!

JOINING DATA WITH PANDAS

Using merge_asof()

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Using merge_asof()

Left Table

B	C
B2	1
B3	5
B4	10

Right Table

C	D
1	D1
2	D2
3	D3
6	D6
7	D7

Result Table

B	C	D
B2	1	D1
B3	5	D3
B4	10	D7

2. Using merge_asof()
The merge_asof() method is similar to an ordered left-join. It has similar features as merge_ordered(). However, unlike an ordered left-join, merge_asof() will match on the nearest value columns rather than equal values. This brings up an important point - whatever columns you merge on must be sorted. In the table shown here, when we merge on column "C", we bring back all of the rows from the left table.

- Similar to a `merge_ordered()` left-join
  - Similar features as `merge_ordered()`
- Match on the nearest key column and not exact matches.
  - Merged "on" columns must be sorted.

Using merge_asof()

Left Table

B	C
B2	1
B3	5
B4	10

Right Table

C	D
1	D1
2	D2
3	D3
6	D6
7	D7

Result Table

B	C	D
B2	1	D1
B3	5	D3
B4	10	D7

- Similar to a `merge_ordered()` left-join
  - Similar features as `merge_ordered()`
- Match on the nearest key column and not exact matches.
  - Merged "on" columns must be sorted.

2. Using merge_asof()
The merge_asof() method is similar to an ordered left-join. It has similar features as merge_ordered(). However, unlike an ordered left-join, merge_asof() will match on the nearest value columns rather than equal values. This brings up an important point - whatever columns you merge on must be sorted. In the table shown here, when we merge on column "C", we bring back all of the rows from the left table.

Datasets

Table Name: `visa`

	date_time	close
0	2017-11-17 16:00:00	110.32
1	2017-11-17 17:00:00	110.24
2	2017-11-17 18:00:00	110.065
3	2017-11-17 19:00:00	110.04
4	2017-11-17 20:00:00	110.0
5	2017-11-17 21:00:00	109.9966
6	2017-11-17 22:00:00	109.82

Table Name: `ibm`

	date_time	close
0	2017-11-17 15:35:12	149.3
1	2017-11-17 15:40:34	149.13
2	2017-11-17 15:45:50	148.98
3	2017-11-17 15:50:20	148.99
4	2017-11-17 15:55:10	149.11
5	2017-11-17 16:00:03	149.25
6	2017-11-17 16:05:06	149.5175
7	2017-11-17 16:10:12	149.57
8	2017-11-17 16:15:30	149.59
9	2017-11-17 16:20:32	149.82
10	2017-11-17 16:25:47	149.96

merge_asof() example

```
pd.merge_asof(visa, ibm, on='date_time',
              suffixes=('_visa','_ibm'))
```

	date_time	close_visa	close_ibm
0	2017-11-17 16:00:00	110.32	149.11
1	2017-11-17 17:00:00	110.24	149.83
2	2017-11-17 18:00:00	110.065	149.59
3	2017-11-17 19:00:00	110.04	149.505
4	2017-11-17 20:00:00	110.0	149.42
5	2017-11-17 21:00:00	109.9966	149.26
6	2017-11-17 22:00:00	109.82	148.97

Table Name: `ibm`

	date_time	close
0	2017-11-17 15:35:12	149.3
1	2017-11-17 15:40:34	149.13
2	2017-11-17 15:45:50	148.98
3	2017-11-17 15:50:20	148.99
4	2017-11-17 15:55:10	149.11
5	2017-11-17 16:00:03	149.25
6	2017-11-17 16:05:06	149.5175
7	2017-11-17 16:10:12	149.57
8	2017-11-17 16:15:30	149.59
9	2017-11-17 16:20:32	149.82
10	2017-11-17 16:25:47	149.96

merge_asof() example with direction

```
pd.merge_asof(visa, ibm, on=['date_time'],
              suffixes=('_visa','_ibm'),
              direction='forward')
```

	date_time	close_visa	close_ibm
0	2017-11-17 16:00:00	110.32	149.25
1	2017-11-17 17:00:00	110.24	149.6184
2	2017-11-17 18:00:00	110.065	149.59
3	2017-11-17 19:00:00	110.04	149.505
4	2017-11-17 20:00:00	110.0	149.42
5	2017-11-17 21:00:00	109.9966	149.26
6	2017-11-17 22:00:00	109.82	148.97

Table Name: `ibm`

	date_time	close
0	2017-11-17 15:35:12	149.3
1	2017-11-17 15:40:34	149.13
2	2017-11-17 15:45:50	148.98
3	2017-11-17 15:50:20	148.99
4	2017-11-17 15:55:10	149.11
5	2017-11-17 16:00:03	149.25
6	2017-11-17 16:05:06	149.5175
7	2017-11-17 16:10:12	149.57
8	2017-11-17 16:15:30	149.59
9	2017-11-17 16:20:32	149.82
10	2017-11-17 16:25:47	149.96

When to use merge_asof()

- Data sampled from a process
- Developing a training set (no data leakage)

7. When to use merge_asof()
Now that we reviewed the merge_asof() method, here are a couple of thoughts on when you might want to use it. First, you might think of this method when you are working with data sampled from a process and the dates or times may not exactly align. This is similar to what we did in our example. It could also be used when you are working on a time-series training set, where you do not want any events from the future to be visible before that point in time.

Let's practice!

JOINING DATA WITH PANDAS

Selecting data with .query()

JOINING DATA WITH PANDAS

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The .query() method

```
.query('SOME SELECTION STATEMENT')
```

- Accepts an input string
  - Input string used to determine what rows are returned
  - Input string similar to statement after **WHERE** clause in **SQL** statement
    - **Prior knowledge of SQL is not necessary**

Querying on a single condition

This table is `stocks`

```
  date         disney      nike
0 2019-07-01   143.009995  86.029999
1 2019-08-01   137.259995  84.5
2 2019-09-01   130.320007  93.919998
3 2019-10-01   129.919998  89.550003
4 2019-11-01   151.580002  93.489998
5 2019-12-01   144.630005  101.309998
6 2020-01-01   138.309998  96.300003
7 2020-02-01   117.650002  89.379997
8 2020-03-01   96.599998   82.739998
9 2020-04-01   99.580002   84.629997
```

```
stocks.query('nike >= 90')
```

```
  date         disney      nike
2 2019-09-01   130.320007  93.919998
4 2019-11-01   151.580002  93.489998
5 2019-12-01   144.630005  101.309998
6 2020-01-01   138.309998  96.300003
```

Querying on a multiple conditions, "and", "or"

This table is `stocks`

```
   date         disney      nike
0  2019-07-01   143.009995  86.029999
1  2019-08-01   137.259995  84.5
2  2019-09-01   130.320007  93.919998
3  2019-10-01   129.919998  89.550003
4  2019-11-01   151.580002  93.489998
5  2019-12-01   144.630005  101.309998
6  2020-01-01   138.309998  96.300003
7  2020-02-01   117.650002  89.379997
8  2020-03-01   96.599998   82.739998
9  2020-04-01   99.580002   84.629997
```

```
stocks.query('nike > 90 and disney < 140')
```

```
   date         disney      nike
2  2019-09-01   130.320007  93.919998
6  2020-01-01   138.309998  96.300003
```

```
stocks.query('nike > 96 or disney < 98')
```

```
    date         disney      nike
5   2019-12-01   144.630005  101.309998
6   2020-01-01   138.309998  96.300003
28  020-03-01    96.599998   82.739998
```

Updated dataset

This table is `stocks_long`

```
  date        stock   close
0 2019-07-01  disney  143.009995
1 2019-08-01  disney  137.259995
2 2019-09-01  disney  130.320007
3 2019-10-01  disney  129.919998
4 2019-11-01  disney  151.580002
5 2019-07-01  nike    86.029999
6 2019-08-01  nike    84.5
7 2019-09-01  nike    93.919998
8 2019-10-01  nike    89.550003
9 2019-11-01  nike    93.489998
```

Using .query() to select text

```
stocks_long.query('stock=="disney" or (stock=="nike" and close < 90)')
```

	date	stock	close
0	2019-07-01	disney	143.009995
1	2019-08-01	disney	137.259995
2	2019-09-01	disney	130.320007
3	2019-10-01	disney	129.919998
4	2019-11-01	disney	151.580002
5	2019-07-01	nike	86.029999
6	2019-08-01	nike	84.5
8	2019-10-01	nike	89.550003

6. Using .query() to select text
We are interested in selecting all of the rows were the column stock equals "disney" or the column stock equals "nike" and close is less than 90. Let's pause here for a moment to look at our query string. Within the parentheses of our string, we check if the stock column is nike and the close column is less than 90. Both of these conditions have to be true for the parentheses section to return true. We then add that to the condition to check if stock is listed as "disney". When checking text, we use the double equal signs, similar to an if statement in Python. Also, when checking a text string, we used double quotes to surround the word. This is to avoid unintentionally ending our string statement since we used single quotes to start the statement. In our results, we see all of our Disney rows returned. Also, those rows were Nike is the stock name and the close price is less than 90 are returned.

Let's practice!

JOINING DATA WITH PANDAS

Reshaping data with .melt()

JOINING DATA WITH PANDAS

1. Reshaping data with .melt()
In our last lesson of the course, let's talk about the melt method. This method will unpivot a table from wide to long format. This is often a much more computer-friendly format, therefore making this a valuable method to know.

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Wide versus long data

Wide Format

	first	last	height	weight
0	John	Doe	5.5	130
1	Mary	Bo	6.0	150

Long Format

	first	last	variable	value
0	John	Doe	height	5.5
1	Mary	Bo	height	6.0
2	John	Doe	weight	130
3	Mary	Bo	weight	150

2. Wide versus long data
Sometimes we will come across data where every row relates to one subject, and each column has different information about an attribute of that subject. Data formatted in this way is often called wide. There are other times when the information about one subject is found over many rows, and each row has one attribute about that subject. Data formatted in this way is often called long or tall. In general, wide formatted data is easier to read by people than long formatted. However, long formatted data is often more accessible for computers to work with.

What does the .melt() method do?

- The melt method will allow us to unpivot our dataset

	first	last	height	weight
0	John	Doe	5.5	130
1	Mary	Bo	6.0	150

	first	last	variable	value
0	John	Doe	height	5.5
1	Mary	Bo	height	6.0
2	John	Doe	weight	130
3	Mary	Bo	weight	150

3. What does the .melt() method do?
The melt method will allow us to unpivot, or change the format of, our dataset. In this image, we change the height and weight columns from their wide horizontal placement to a long vertical placement.

Dataset in wide format

This table is called `social_fin`

	financial	company	2019	2018	2017	2016
0	total_revenue	twitter	3459329	3042359	2443299	2529619
1	gross_profit	twitter	2322288	2077362	1582057	1597379
2	net_income	twitter	1465659	1205596	-108063	-456873
3	total_revenue	facebook	70697000	55838000	40653000	27638000
4	gross_profit	facebook	57927000	46483000	35199000	23849000
5	net_income	facebook	18485000	22112000	15934000	10217000

4. Dataset in wide format
To demonstrate the melt method, let's start with this dataset of financial metrics of two popular social media companies. Notice that the years are horizontal. Let's change them so that they are vertically placed.

Example of .melt()

```
social_fin_tall = social_fin.melt(id_vars=['financial','company'])
print(social_fin_tall.head(10))
```

```
   financial      company   variable  value
0  total_revenue  twitter   2019      3459329
1  gross_profit   twitter   2019      2322288
2  net_income     twitter   2019      1465659
3  total_revenue  facebook  2019      70697000
4  gross_profit   facebook  2019      57927000
5  net_income     facebook  2019      18485000
6  total_revenue  twitter   2018      3042359
7  gross_profit   twitter   2018      2077362
8  net_income     twitter   2018      1205596
9  total_revenue  facebook  2018      55838000
```

5. Example of .melt()
Here we call the melt() method on the table social_fin. The first input argument to the method is id_vars. These are columns to be used as identifier variables. We can also think of them as columns in our original dataset that we do not want to change. In our output, we print the first ten rows. Our years are listed vertically. Our final column now has all of our values in one column versus multiple columns. Again, this is a much more computer-friendly format than our original table. We unpivoted each of the separate columns 2016 through 2019. Our output has data for every year in our starting table, but again, we are only showing the first couple of rows. In the next example, we will look at how to control what columns are unpivoted.

Melting with value_vars

```
social_fin_tall = social_fin.melt(id_vars=['financial','company'],
                                  value_vars=['2018','2017'])
print(social_fin_tall.head(9))
```

```
   financial      company   variable  value
0  total_revenue  twitter   2018      3042359
1  gross_profit   twitter   2018      2077362
2  net_income     twitter   2018      1205596
3  total_revenue  facebook  2018      55838000
4  gross_profit   facebook  2018      46483000
5  net_income     facebook  2018      22112000
6  total_revenue  twitter   2017      2443299
7  gross_profit   twitter   2017      1582057
8  net_income     twitter   2017      -108063
```

6. Melting with value_vars
This time, let's use the argument value_vars with the melt() method. This argument will allow us to control which columns are unpivoted. Here, we unpivot only the 2018 and 2017 columns. Our output now only has data for the years 2018 and 2017. Additionally, the order of the value_var was kept. The output starts with 2018, then moves to 2017. Finally, notice that the column with the years is now named variable, and our values column is named value. We will adjust that in our next example.

Melting with column names

```
social_fin_tall = social_fin.melt(id_vars=['financial','company'],
                                  value_vars=['2018','2017'],
                                  var_name=['year'], value_name='dollars')
print(social_fin_tall.head(8))
```

```
   financial      company   year   dollars
0  total_revenue  twitter   2018   3042359
1  gross_profit   twitter   2018   2077362
2  net_income     twitter   2018   1205596
3  total_revenue  facebook  2018   55838000
4  gross_profit   facebook  2018   46483000
5  net_income     facebook  2018   22112000
6  total_revenue  twitter   2017   2443299
7  gross_profit   twitter   2017   1582057
```

7. Melting with column names
In this example, we have added some additional inputs to our melt() method. The var_name argument will allow us to set the name of the year column in the output. Similarly, the value_name argument will allow us to set the name of the value column in the output. We again print the first few rows of the output. It is the same as before, except our variable and value columns are renamed year and dollars, respectively. We have seen how the melt() method is useful for reshaping our tables. Imagine a situation where you have merged many columns, making your table very wide. The merge() method can then be used to reshape that table into a more computer-friendly format.

Let's practice!

JOINING DATA WITH PANDAS

Course wrap-up

JOINING DATA WITH PANDAS

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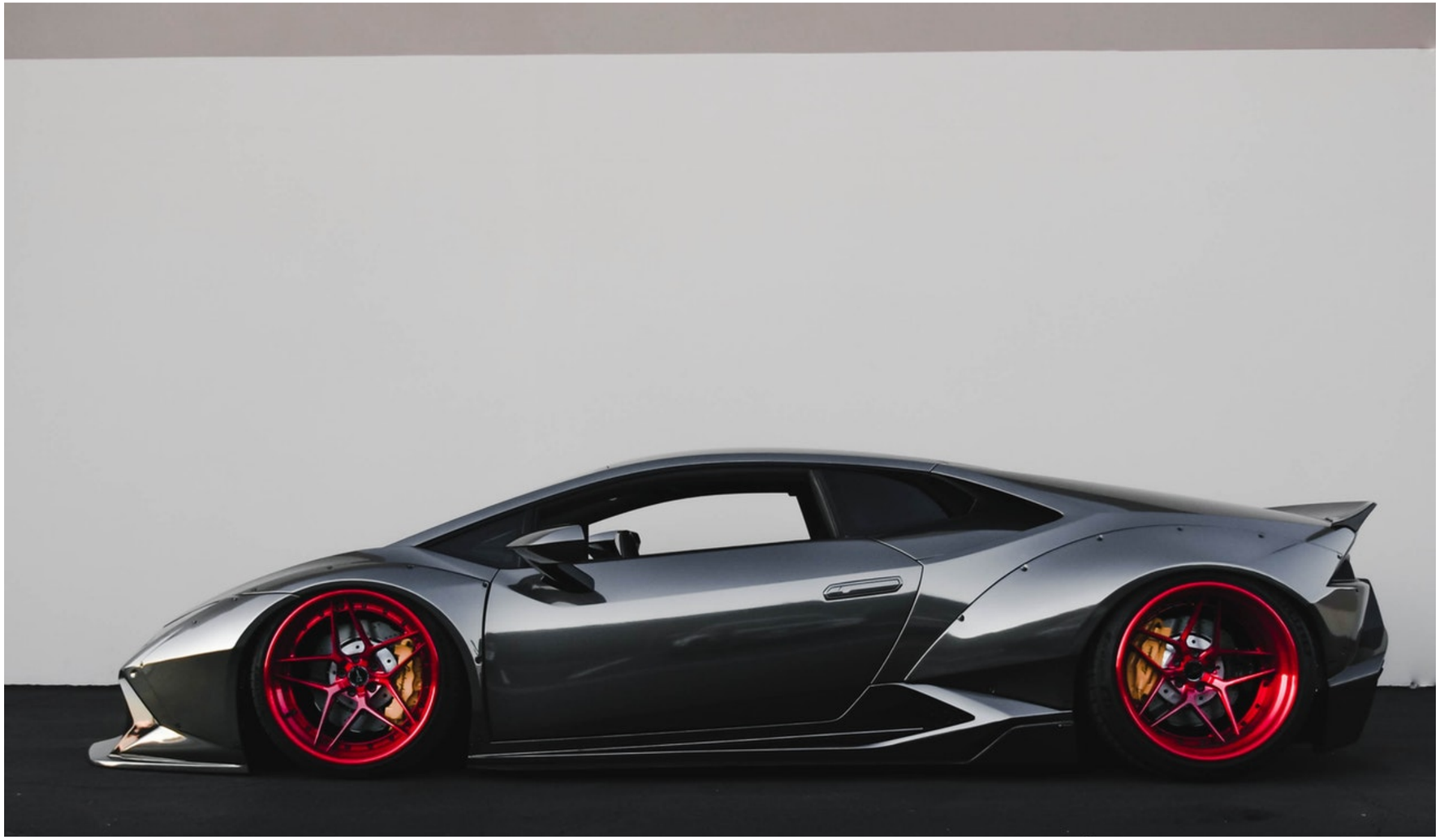
You're this high performance race car now



[1] Photo by jae park from Pexels

Data merging basics

- Inner join using `.merge()`
- One-to-one and one-to-many relationships
- Merging multiple tables

Merging tables with different join types

- Inner join using `.merge()`
- One-to-one and one-to-one relationships
- Merging multiple tables
- **Left, right, and outer joins**
- **Merging a table to itself and merging on indexes**

Advanced merging and concatenating

- Inner join using `.merge()`
- One-to-one and one-to-one relationships
- Merging multiple tables
- Left, right, and outer joins
- Merging a table to itself and merging on indexes
- **Filtering joins**
  - **semi and anti joins**
- **Combining data vertically with `.concat()`**
- **Verify data integrity**

Merging ordered and time-series data

- Inner join using `.merge()`
- One-to-one and one-to-one relationships
- Merging multiple tables
- Left, right, and outer joins
- Merging a table to itself and merging on indexes
- Filtering joins
  - semi and anti joins
- Combining data vertically with `.concat()`
- Verify data integrity

- **Ordered data**
  - **`merge_ordered()` and `merge_asof()`**
- **Manipulating data with `.melt()`**

Thank you!

JOINING DATA WITH PANDAS