

PivotTable_ed

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A pivot table is a way of summarizing data in a DataFrame for a particular purpose. It makes heavy use of the aggregation function. A pivot table is itself a DataFrame, where the rows represent one variable that you're interested in, the columns another, and the cell's some aggregate value. A pivot table also tends to includes marginal values as well, which are the sums for each column and row. This allows you to be able to see the relationship between two variables at just a glance.

```
[1]: # Lets take a look at pivot tables in pandas
import pandas as pd
import numpy as np
```

```
[2]: # Here we have the Times Higher Education World University Ranking dataset,
      ↪which is one of the most
      # influential university measures. Let's import the dataset and see what it
      ↪looks like
df = pd.read_csv('datasets/cwurData.csv')
df.head()
```

```
[2]:  world_rank      institution      country \
0      1      Harvard University      USA
1      2  Massachusetts Institute of Technology      USA
2      3      Stanford University      USA
3      4      University of Cambridge  United Kingdom
4      5  California Institute of Technology      USA

      national_rank  quality_of_education  alumni_employment  quality_of_faculty \
0      1      7      9      1
1      2      9      17      3
2      3      17      11      5
3      1      10      24      4
4      4      2      29      7

      publications  influence  citations  broad_impact  patents  score  year
0      1      1      1      NaN      5  100.00  2012
1      12      4      4      NaN      1  91.67  2012
2      4      2      2      NaN      15  89.50  2012
3      16      16      11      NaN      50  86.17  2012
4      37      22      22      NaN      18  85.21  2012
```

```
[3]: # Here we can see each institution's rank, country, quality of education, other
      ↳ metrics, and overall score.
      # Let's say we want to create a new column called Rank_Level, where
      ↳ institutions with world ranking 1-100 are
      # categorized as first tier and those with world ranking 101 - 200 are second
      ↳ tier, ranking 201 - 300 are
      # third tier, after 301 is other top universities.

      # Now, you actually already have enough knowledge to do this, so why don't you
      ↳ pause the video and give it a
      # try?

      # Here's my solution, I'm going to create a function called create_category
      ↳ which will operate on the first
      # column in the dataframe, world_rank
      def create_category(ranking):
          # Since the rank is just an integer, I'll just do a bunch of if/elif
          ↳ statements
          if (ranking >= 1) & (ranking <= 100):
              return "First Tier Top University"
          elif (ranking >= 101) & (ranking <= 200):
              return "Second Tier Top University"
          elif (ranking >= 201) & (ranking <= 300):
              return "Third Tier Top University"
          return "Other Top University"

      # Now we can apply this to a single column of data to create a new series
      df['Rank_Level'] = df['world_rank'].apply(lambda x: create_category(x))
      # And lets look at the result
      df.head()
```

```
[3]: world_rank      institution      country \
0      1      Harvard University      USA
1      2  Massachusetts Institute of Technology      USA
2      3      Stanford University      USA
3      4      University of Cambridge  United Kingdom
4      5  California Institute of Technology      USA

      national_rank  quality_of_education  alumni_employment  quality_of_faculty \
0      1      7      9      1
1      2      9      17      3
2      3      17      11      5
3      1      10      24      4
4      4      2      29      7

      publications  influence  citations  broad_impact  patents  score  year \
0      1      1      1      NaN      5  100.00  2012
```

1	12	4	4	NaN	1	91.67	2012
2	4	2	2	NaN	15	89.50	2012
3	16	16	11	NaN	50	86.17	2012
4	37	22	22	NaN	18	85.21	2012

	Rank_Level
0	First Tier Top University
1	First Tier Top University
2	First Tier Top University
3	First Tier Top University
4	First Tier Top University

```
[4]: # A pivot table allows us to pivot out one of these columns a new column
      →headers and compare it against
      # another column as row indices. Let's say we want to compare rank level versus
      →country of the universities
      # and we want to compare in terms of overall score

      # To do this, we tell Pandas we want the values to be Score, and index to be
      →the country and the columns to be
      # the rank levels. Then we specify that the aggregation function, and here
      →we'll use the NumPy mean to get the
      # average rating for universities in that country

      df.pivot_table(values='score', index='country', columns='Rank_Level',
      →aggfunc=[np.mean]).head()
```

```
[4]:
      mean \
Rank_Level First Tier Top University Other Top University
country
Argentina      NaN      44.672857
Australia      47.9425      44.645750
Austria         NaN      44.864286
Belgium         51.8750      45.081000
Brazil          NaN      44.499706

Rank_Level Second Tier Top University Third Tier Top University
country
Argentina      NaN      NaN
Australia      49.2425      47.285000
Austria         NaN      47.066667
Belgium         49.0840      46.746667
Brazil          49.5650      NaN
```

```
[5]: # We can see a hierarchical dataframe where the index, or rows, are by country
      →and the columns have two
```

```
# levels, the top level indicating that the mean value is being used and the
→second level being our ranks. In
# this example we only have one variable, the mean, that we are looking at, so
→we don't really need a
# heirarchical index.

# We notice that there are some NaN values, for example, the first row,
→Argentina. The NaN values indicate that
# Argentina has only observations in the "Other Top Universities" category
```

```
[6]: # Now, pivot tables aren't limited to one function that you might want to apply.
→ You can pass a named
# parameter, aggfunc, which is a list of the different functions to apply, and
→pandas will provide you with
# the result using hierarchical column names. Let's try that same query, but
→pass in the max() function too

df.pivot_table(values='score', index='country', columns='Rank_Level',
→aggfunc=[np.mean, np.max]).head()
```

```
[6]:
```

	mean	
Rank_Level	First Tier Top University	Other Top University
country		
Argentina	NaN	44.672857
Australia	47.9425	44.645750
Austria	NaN	44.864286
Belgium	51.8750	45.081000
Brazil	NaN	44.499706

Rank_Level	Second Tier Top University	Third Tier Top University
country		
Argentina	NaN	NaN
Australia	49.2425	47.285000
Austria	NaN	47.066667
Belgium	49.0840	46.746667
Brazil	49.5650	NaN

	amax	
Rank_Level	First Tier Top University	Other Top University
country		
Argentina	NaN	45.66
Australia	51.61	45.97
Austria	NaN	46.29
Belgium	52.03	46.21
Brazil	NaN	46.08

Rank_Level	Second Tier Top University	Third Tier Top University
country		
Argentina	NaN	NaN
Australia	50.40	47.47
Austria	NaN	47.78
Belgium	49.73	47.14
Brazil	49.82	NaN

```
[7]: # So now we see we have both the mean and the max. As mentioned earlier, we can
      # also summarize the values
      # within a given top level column. For instance, if we want to see an overall
      # average for the country for the
      # mean and we want to see the max of the max, we can indicate that we want
      # pandas to provide marginal values
df.pivot_table(values='score', index='country', columns='Rank_Level',
               aggfunc=[np.mean, np.max],
               margins=True).head()
```

```
[7]:
```

	mean	\
Rank_Level First Tier Top University Other Top University		
country		
Argentina	NaN	44.672857
Australia	47.9425	44.645750
Austria	NaN	44.864286
Belgium	51.8750	45.081000
Brazil	NaN	44.499706

Rank_Level	Second Tier Top University	Third Tier Top University	All
country			
Argentina	NaN	NaN	44.672857
Australia	49.2425	47.285000	45.825517
Austria	NaN	47.066667	45.139583
Belgium	49.0840	46.746667	47.011000
Brazil	49.5650	NaN	44.781111

```
amax
```

Rank_Level	First Tier Top University	Other Top University
country		
Argentina	NaN	45.66
Australia	51.61	45.97
Austria	NaN	46.29
Belgium	52.03	46.21
Brazil	NaN	46.08

Rank_Level	Second Tier Top University	Third Tier Top University	All
------------	----------------------------	---------------------------	-----

country			
Argentina	NaN	NaN	45.66
Australia	50.40	47.47	51.61
Austria	NaN	47.78	47.78
Belgium	49.73	47.14	52.03
Brazil	49.82	NaN	49.82

```
[8]: # A pivot table is just a multi-level dataframe, and we can access series or
      # cells in the dataframe in a similar way
      # as we do so for a regular dataframe.

      # Let's create a new dataframe from our previous example
      new_df=df.pivot_table(values='score', index='country', columns='Rank_Level',
      # aggfunc=[np.mean, np.max],
      # margins=True)
      # Now let's look at the index
      print(new_df.index)
      # And let's look at the columns
      print(new_df.columns)
```

```
Index(['Argentina', 'Australia', 'Austria', 'Belgium', 'Brazil', 'Bulgaria',
      'Canada', 'Chile', 'China', 'Colombia', 'Croatia', 'Cyprus',
      'Czech Republic', 'Denmark', 'Egypt', 'Estonia', 'Finland', 'France',
      'Germany', 'Greece', 'Hong Kong', 'Hungary', 'Iceland', 'India', 'Iran',
      'Ireland', 'Israel', 'Italy', 'Japan', 'Lebanon', 'Lithuania',
      'Malaysia', 'Mexico', 'Netherlands', 'New Zealand', 'Norway', 'Poland',
      'Portugal', 'Puerto Rico', 'Romania', 'Russia', 'Saudi Arabia',
      'Serbia', 'Singapore', 'Slovak Republic', 'Slovenia', 'South Africa',
      'South Korea', 'Spain', 'Sweden', 'Switzerland', 'Taiwan', 'Thailand',
      'Turkey', 'USA', 'Uganda', 'United Arab Emirates', 'United Kingdom',
      'Uruguay', 'All'],
      dtype='object', name='country')
MultiIndex([('mean', 'First Tier Top University'),
            ('mean', 'Other Top University'),
            ('mean', 'Second Tier Top University'),
            ('mean', 'Third Tier Top University'),
            ('mean', 'All'),
            ('amax', 'First Tier Top University'),
            ('amax', 'Other Top University'),
            ('amax', 'Second Tier Top University'),
            ('amax', 'Third Tier Top University'),
            ('amax', 'All')],
            names=[None, 'Rank_Level'])
```

```
[9]: # We can see the columns are hierarchical. The top level column indices have
      # two categories: mean and max, and
```

```
# the lower level column indices have four categories, which are the four rank
→levels. How would we query this
# if we want to get the average scores of First Tier Top University levels in
→each country? We would just need
# to make two dataframe projections, the first for the mean, then the second
→for the top tier
new_df['mean']['First Tier Top University'].head()
```

```
[9]: country
Argentina      NaN
Australia      47.9425
Austria        NaN
Belgium        51.8750
Brazil         NaN
Name: First Tier Top University, dtype: float64
```

```
[10]: # We can see that the output is a series object which we can confirm by
→printing the type. Remember that when
# you project a single column of values out of a DataFrame you get a series.
type(new_df['mean']['First Tier Top University'])
```

```
[10]: pandas.core.series.Series
```

```
[11]: # What if we want to find the country that has the maximum average score on
→First Tier Top University level?
# We can use the idxmax() function.
new_df['mean']['First Tier Top University'].idxmax()
```

```
[11]: 'United Kingdom'
```

```
[12]: # Now, the idxmax() function isn't special for pivot tables, it's a built in
→function to the Series object.
# We don't have time to go over all pandas functions and attributes, and I want
→to encourage you to explore
# the API to learn more deeply what is available to you.
```

```
[13]: # If you want to achieve a different shape of your pivot table, you can do so
→with the stack and unstack
# functions. Stacking is pivoting the lowermost column index to become the
→innermost row index. Unstacking is
# the inverse of stacking, pivoting the innermost row index to become the
→lowermost column index. An example
# will help make this clear

# Let's look at our pivot table first to refresh what it looks like
new_df.head()
```

```
[13]:              mean \
Rank_Level First Tier Top University Other Top University
country
```

Argentina	NaN	44.672857
Australia	47.9425	44.645750
Austria	NaN	44.864286
Belgium	51.8750	45.081000
Brazil	NaN	44.499706

Rank_Level	Second Tier Top University	Third Tier Top University	All
country			
Argentina	NaN	NaN	44.672857
Australia	49.2425	47.285000	45.825517
Austria	NaN	47.066667	45.139583
Belgium	49.0840	46.746667	47.011000
Brazil	49.5650	NaN	44.781111

Rank_Level	First Tier Top University	Other Top University
country		
Argentina	NaN	45.66
Australia	51.61	45.97
Austria	NaN	46.29
Belgium	52.03	46.21
Brazil	NaN	46.08

Rank_Level	Second Tier Top University	Third Tier Top University	All
country			
Argentina	NaN	NaN	45.66
Australia	50.40	47.47	51.61
Austria	NaN	47.78	47.78
Belgium	49.73	47.14	52.03
Brazil	49.82	NaN	49.82

```
[14]: # Now let's try stacking, this should move the lowermost column, so the tiers
      ↪ of the university rankings, to
      # the inner most row
      new_df=new_df.stack()
      new_df.head()
```

```
[14]:
```

		mean	amax
country	Rank_Level		
Argentina	Other Top University	44.672857	45.66
	All	44.672857	45.66
Australia	First Tier Top University	47.942500	51.61
	Other Top University	44.645750	45.97
	Second Tier Top University	49.242500	50.40


```
[15]: # In the original pivot table, rank levels are the lowermost column, after
      ↳ stacking, rank levels become the
      # innermost index, appearing to the right after country

      # Now let's try unstacking
      new_df.unstack().head()
```

```
[15]:
```

	mean	
Rank_Level	First Tier Top University	Other Top University
country		
Argentina	NaN	44.672857
Australia	47.9425	44.645750
Austria	NaN	44.864286
Belgium	51.8750	45.081000
Brazil	NaN	44.499706

Rank_Level	Second Tier Top University	Third Tier Top University	All
country			
Argentina	NaN	NaN	44.672857
Australia	49.2425	47.285000	45.825517
Austria	NaN	47.066667	45.139583
Belgium	49.0840	46.746667	47.011000
Brazil	49.5650	NaN	44.781111


```
amax
```

Rank_Level	First Tier Top University	Other Top University
country		
Argentina	NaN	45.66
Australia	51.61	45.97
Austria	NaN	46.29
Belgium	52.03	46.21
Brazil	NaN	46.08

Rank_Level	Second Tier Top University	Third Tier Top University	All
country			
Argentina	NaN	NaN	45.66
Australia	50.40	47.47	51.61
Austria	NaN	47.78	47.78
Belgium	49.73	47.14	52.03
Brazil	49.82	NaN	49.82

```
[16]: # That seems to restore our dataframe to its original shape. What do you think
      ↳ would happen if we unstacked twice in a row?
      new_df.unstack().unstack().head()
```

```
[16]: Rank_Level      country
      mean First Tier Top University Argentina      NaN
      Australia      47.9425
      Austria      NaN
      Belgium      51.8750
      Brazil      NaN

dtype: float64
```

```
[17]: # We actually end up unstacking all the way to just a single column, so a
      ↳ series object is returned. This
      # column is just a "value", the meaning of which is denoted by the
      ↳ heirarchical index of operation, rank, and
      # country.
```

So that's pivot tables. This has been a pretty short description, but they're incredibly useful when dealing with numeric data, especially if you're trying to summarize the data in some form. You'll regularly be creating new pivot tables on slices of data, whether you're exploring the data yourself or preparing data for others to report on. And of course, you can pass any function you want to the aggregate function, including those that you define yourself.