Data-Science-Practice (/github/um-perez-alvaro/Data-Science-Practice/tree/master)
/
Pandas and Matplotlib (/github/um-perez-alvaro/Data-Science-Practice/tree/master/Pandas and Matplotlib)

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
```

Introduction to Pandas. Part IV

Contents

1. Applying a function to a pandas Series or DataFrame

In [2]:
```
url = "https://raw.githubusercontent.com/um-perez-alvaro/Data-Science-Practi
titanic = pd.read_csv(url)
titanic.head()
```

Out[2]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500

1.1. The map method

map is a Series method.

map allows you to map an existing value of a series to a different set of values.

In [3]:
```
my_map = {'female':1,'male':0}
my_map
```

Out[3]:
```
{'female': 1, 'male': 0}
```

In [4]:
```
# map 'female' to 0 and 'male' to 1
titanic['Sex_num'] = titanic.Sex.map(my_map)
```

In [5]:
```
titanic.Sex_num
```

Out[5]:
```
0      0
1      1
2      1
3      1
4      0
      ..
886    0
887    1
888    1
889    0
890    0
Name: Sex_num, Length: 891, dtype: int64
```

In [6]:
```
titanic.loc[0:4,['Sex','Sex_num']]
```

Out[6]:

	Sex	Sex_num
0	male	0
1	female	1
2	female	1
3	female	1
4	male	0

1.2. The apply method

apply is both a Series method and a DataFrame method

- Apply as a Series method
- Apply as a DataFrame method

1.2.1. Apply as a Series method

apply applies a function to each element of the Series

Remark: map can be substituted for **apply** in many cases, but **apply** is more flexible and thus is recommended

Example 1: calculate the length of the strings in the 'Name' column

In [7]:
```
titanic['Name_length'] = titanic.Name.apply(len) # apply Python len functior
```

In [8]:
```
titanic.loc[0:4,['Name','Name_length']]
```

Out[8]:

	Name	Name_length
0	Braund, Mr. Owen Harris	23
1	Cumings, Mrs. John Bradley (Florence Briggs Th...	51
2	Heikkinen, Miss. Laina	22
3	Futrelle, Mrs. Jacques Heath (Lily May Peel)	44
4	Allen, Mr. William Henry	24

In [9]:
```
titanic.Name.map(len)
```

Out[9]:
```
0      23
1      51
2      22
3      44
4      24
       ..
886    21
887    28
888    40
889    21
890    19
Name: Name, Length: 891, dtype: int64
```

Example 2: round up each element in the 'Fare' Series to the next integer

In [10]:
```
import numpy as np
titanic['Fare_ceil'] = titanic.Fare.apply(np.ceil) # apply Numpy ceiling fur
```

In [11]:
```
titanic.loc[0:4,['Fare','Fare_ceil']]
```

Out[11]:

	Fare	Fare_ceil
0	7.2500	8.0
1	71.2833	72.0
2	7.9250	8.0
3	53.1000	54.0
4	8.0500	9.0

Example 3: Extract the last name of each person into its own column

In [12]:
```
def get_last_name(x):
    return x.split(',')[0]
```

In [13]:
```
titanic['Last_name'] = titanic.Name.apply(get_last_name)
```

In [14]:
```
titanic.loc[0:4,['Name','Last_name']]
```

Out[14]:

	Name	Last_name
0	Braund, Mr. Owen Harris	Braund
1	Cumings, Mrs. John Bradley (Florence Briggs Th...	Cumings
2	Heikkinen, Miss. Laina	Heikkinen
3	Futrelle, Mrs. Jacques Heath (Lily May Peel)	Futrelle
4	Allen, Mr. William Henry	Allen

In [15]:
```
titanic.Name.map(get_last_name)
```

Out[15]:
```
0         Braund
1        Cumings
2      Heikkinen
3       Futrelle
4          Allen
         ...
886     Montvila
887       Graham
888     Johnston
889         Behr
890       Dooley
Name: Name, Length: 891, dtype: object
```

In [16]:
```
# alternatively, use a lambda function
titanic['Last_name'] = titanic.Name.apply(lambda x:x.split(',')[0])
```

In [17]:
```
titanic.loc[0:4,['Name','Last_name']]
```

Out[17]:

	Name	Last_name
0	Braund, Mr. Owen Harris	Braund
1	Cumings, Mrs. John Bradley (Florence Briggs Th...	Cumings
2	Heikkinen, Miss. Laina	Heikkinen
3	Futrelle, Mrs. Jacques Heath (Lily May Peel)	Futrelle
4	Allen, Mr. William Henry	Allen

1.2.2. Apply as a DataFrame method

apply applies a function along either axis of the DataFrame

In [18]:
```
# read a dataset of alcohol consumption into a DataFrame
url = 'https://raw.githubusercontent.com/um-perez-alvaro/Data-Science-Practi
drinks = pd.read_csv(url)
drinks.head()
```

Out[18]:

	country	beer_servings	spirit_servings	wine_servings	total_litres_of_pure_alcohol	conti
0	Afghanistan	0	0	0	0.0	
1	Albania	89	132	54	4.9	Eu
2	Algeria	25	0	14	0.7	A
3	Andorra	245	138	312	12.4	Eu
4	Angola	217	57	45	5.9	A

In [19]:
```
# select a subset of the DataFrame to work with
sub_drinks = drinks.loc[:,'beer_servings':'wine_servings']
sub_drinks.head()
```

Out[19]:

	beer_servings	spirit_servings	wine_servings
0	0	0	0
1	89	132	54
2	25	0	14
3	245	138	312
4	217	57	45

In [20]:
```
# apply the 'max' function along axis 0 to calculate the maximum value in ea
sub_drinks.apply(max, axis=0) # Python max function along rows
```

Out[20]:
```
beer_servings      376
spirit_servings    438
wine_servings      370
dtype: int64
```

In [21]:
```
# apply the 'max' function along axis 1 to calculate the maximum value in ea
sub_drinks.apply(max, axis=1) # Python max function along columns
```

Out[21]:
```
0        0
1      132
2       25
3      312
4      217
      ...
188    333
189    111
190      6
191     32
192     64
Length: 193, dtype: int64
```

In [22]:
```
# use 'np.argmax' to calculate which column has the maximum value for each r
sub_drinks.apply(np.argmax,axis=1)
```

Out[22]:
```
0      0
1      1
2      0
3      2
4      0
      ..
188    0
189    0
190    0
191    0
192    0
Length: 193, dtype: int64
```

In [23]:
```
'if you want to know in which column is the maximum'
sub_drinks.apply(np.argmax,axis=1).map({0:'beer_servings',
                                        1:'spirit_servings',
                                        2:'wine_servings'})
```

Out[23]:
```
0        beer_servings
1      spirit_servings
2        beer_servings
3        wine_servings
4        beer_servings
            ...
188      beer_servings
189      beer_servings
190      beer_servings
191      beer_servings
192      beer_servings
Length: 193, dtype: object
```

1.3. The applymap method

applymap is a DataFrame method. It applies a function to everyelement of the DataFrame

In [24]:
```
sub_drinks.head(5)
```

Out[24]:

	beer_servings	spirit_servings	wine_servings
0	0	0	0
1	89	132	54
2	25	0	14
3	245	138	312
4	217	57	45

In [25]:
```
# convert every DataFrame element into a float
sub_drinks.applymap(float).head(5)
```

Out[25]:

	beer_servings	spirit_servings	wine_servings
0	0.0	0.0	0.0
1	89.0	132.0	54.0
2	25.0	0.0	14.0
3	245.0	138.0	312.0
4	217.0	57.0	45.0

In [26]:
```
# overwrite the existing DataFrame columns
sub_drinks.loc[:, 'beer_servings':'wine_servings'] = sub_drinks.loc[:, 'beer
sub_drinks.head()
```

Out[26]:

	beer_servings	spirit_servings	wine_servings
0	0.0	0.0	0.0
1	89.0	132.0	54.0
2	25.0	0.0	14.0
3	245.0	138.0	312.0
4	217.0	57.0	45.0

2. Using groupby

In [27]:
```
# reload the drinks dataset
drinks = pd.read_csv('https://raw.githubusercontent.com/um-perez-alvaro/Data
drinks.head()
```

Out[27]:

	country	beer_servings	spirit_servings	wine_servings	total_litres_of_pure_alcohol	conti
0	Afghanistan	0	0	0	0.0	
1	Albania	89	132	54	4.9	Eu
2	Algeria	25	0	14	0.7	A
3	Andorra	245	138	312	12.4	Eu
4	Angola	217	57	45	5.9	A

In [28]:
```
# calculate the average beer servings across the entire dataset
drinks.beer_servings.mean()
```

Out[28]:
```
106.16062176165804
```

In [29]:
```
# calculate the average beer servings just for countries in Africa
drinks[drinks.continent=='Africa'].beer_servings.mean()
```

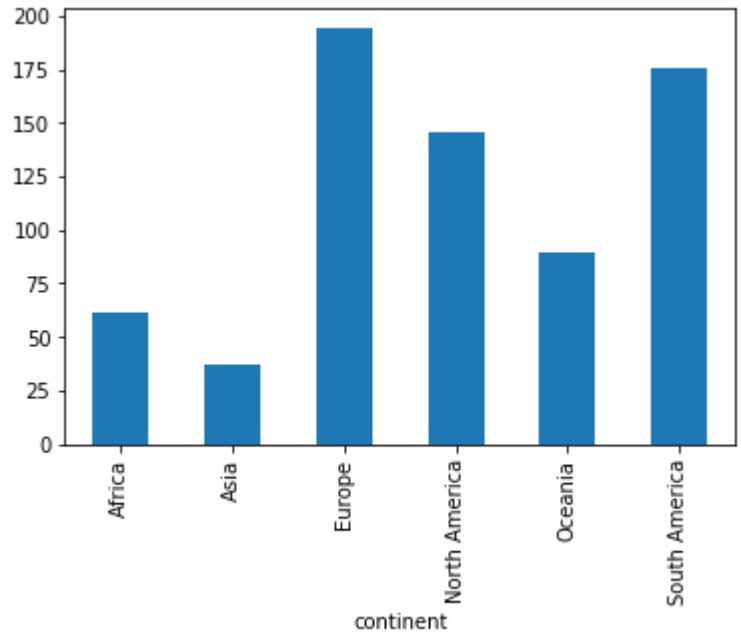
Out[29]:
```
61.471698113207545
```

In [30]:
```
# calculate the mean beer servings for each continent
drinks.groupby('continent').beer_servings.mean()
```

Out[30]:
```
continent
Africa            61.471698
Asia              37.045455
Europe           193.777778
North America    145.434783
Oceania           89.687500
South America    175.083333
Name: beer_servings, dtype: float64
```

In [31]:
```
# bar plot of the above DataFrame
drinks.groupby('continent').beer_servings.mean().plot(kind='bar')
```

Out[31]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2d1ca936508>
```



In [32]:
```
# other aggregation functions (such as 'max','min','count','std', etc) can c
drinks.groupby('continent').beer_servings.max()
```

Out[32]:
```
continent
Africa           376
Asia             247
Europe           361
North America    285
Oceania          306
South America    333
Name: beer_servings, dtype: int64
```

In [33]:
```
# you can use your own aggregation function
def peak_to_peak(group):
    return group.max()-group.min()
drinks.groupby('continent').beer_servings.apply(peak_to_peak)
```

Out[33]:
```
continent
Africa           376
Asia             247
Europe           361
North America    284
Oceania          306
South America    240
Name: beer_servings, dtype: int64
```

In [34]:
```
# multiple aggregation functions can be applied simultaneously
drinks.groupby('continent').beer_servings.agg(['count', 'mean', 'min', 'max'
```

Out[34]:

continent	count	mean	min	max	std
Africa	53	61.471698	0	376	80.557816
Asia	44	37.045455	0	247	49.469725
Europe	45	193.777778	0	361	99.631569
North America	23	145.434783	1	285	79.621163
Oceania	16	89.687500	0	306	96.641412
South America	12	175.083333	93	333	65.242845

In [35]:
```
drinks.groupby('continent').beer_servings.agg(['count', 'mean', 'min', 'max'
```

Out[35]:

continent	count	mean	min	max	std	peak_to_peak
Africa	53	61.471698	0	376	80.557816	376
Asia	44	37.045455	0	247	49.469725	247
Europe	45	193.777778	0	361	99.631569	361
North America	23	145.434783	1	285	79.621163	284
Oceania	16	89.687500	0	306	96.641412	306
South America	12	175.083333	93	333	65.242845	240

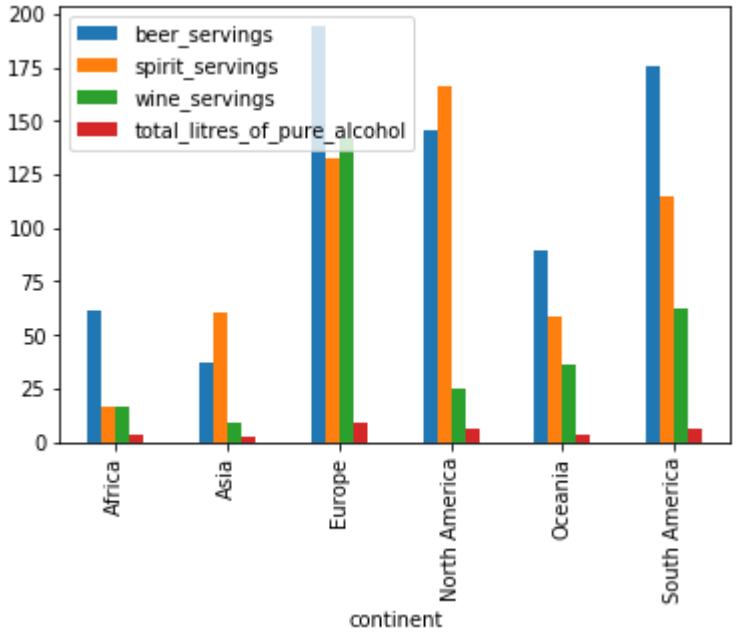
In [36]:
```
# specifying a column to which the aggregation function should be applied is
drinks.groupby('continent').mean()
```

Out[36]:

continent	beer_servings	spirit_servings	wine_servings	total_litres_of_pure_alcohol
Africa	61.471698	16.339623	16.264151	3.007547
Asia	37.045455	60.840909	9.068182	2.170455
Europe	193.777778	132.555556	142.222222	8.617778
North America	145.434783	165.739130	24.521739	5.995652
Oceania	89.687500	58.437500	35.625000	3.381250
South America	175.083333	114.750000	62.416667	6.308333

In [37]:
```
# side-by-side bar plot of the DataFrame directly above
drinks.groupby('continent').mean().plot(kind='bar')
```

Out[37]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2d1cb0d8708>
```



3. Unstacking

In [38]:
```
# load tips dataset
url = 'https://raw.githubusercontent.com/um-perez-alvaro/Data-Science-Practi
tips = pd.read_csv(url)
tips.head()
```

Out[38]:

	total_bill	tip	smoker	day	time	size
0	16.99	1.01	No	Sun	Dinner	2
1	10.34	1.66	No	Sun	Dinner	3
2	21.01	3.50	No	Sun	Dinner	3
3	23.68	3.31	No	Sun	Dinner	2
4	24.59	3.61	No	Sun	Dinner	4

In [39]:
```
# add tip percentage of total bill
tips['tip_pct'] = 100*tips.tip/tips.total_bill
tips.head()
```

Out[39]:

	total_bill	tip	smoker	day	time	size	tip_pct
0	16.99	1.01	No	Sun	Dinner	2	5.944673
1	10.34	1.66	No	Sun	Dinner	3	16.054159
2	21.01	3.50	No	Sun	Dinner	3	16.658734
3	23.68	3.31	No	Sun	Dinner	2	13.978041
4	24.59	3.61	No	Sun	Dinner	4	14.680765

In [40]:
```
# aggregate tip_pct by day and smoker
tips.groupby(['day','smoker']).tip_pct.mean() # DataFrame with a multi-index
```

Out[40]:
```
day   smoker
Fri   No        15.165044
      Yes       17.478305
Sat   No        15.804766
      Yes       14.790607
Sun   No        16.011294
      Yes       18.725032
Thur  No        16.029808
      Yes       16.386327
Name: tip_pct, dtype: float64
```

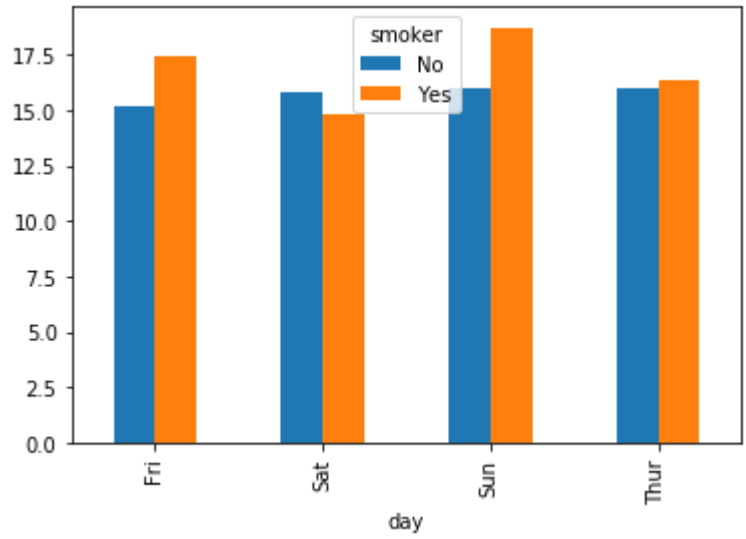
In [41]:
```
tips.groupby(['day','smoker']).tip_pct.mean().unstack(level=1)
```

Out[41]:

smoker	No	Yes
day		
Fri	15.165044	17.478305
Sat	15.804766	14.790607
Sun	16.011294	18.725032
Thur	16.029808	16.386327

In [42]:
```
tips.groupby(['day','smoker']).tip_pct.mean().unstack(level=1).plot(kind='ba
```

Out[42]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2d1cb205b48>
```



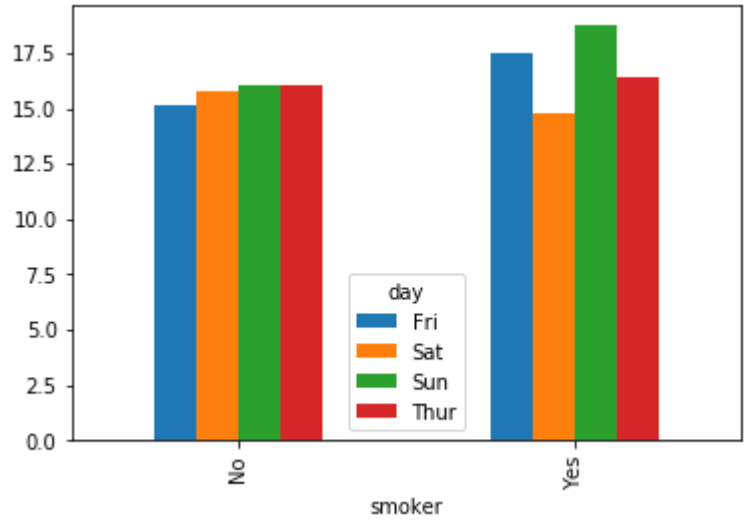
In [43]:
```
tips.groupby(['day','smoker']).tip_pct.mean().unstack(level=0)
```

Out[43]:

day	Fri	Sat	Sun	Thur
smoker				
No	15.165044	15.804766	16.011294	16.029808
Yes	17.478305	14.790607	18.725032	16.386327

In [44]:
```
tips.groupby(['day','smoker']).tip_pct.mean().unstack(level=0).plot(kind='ba
```

Out[44]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2d1cb297fc8>
```



4. Pivot tables and cross-tabulations

- Pivot tables
- Cross-Tabulations

4.1. Pivot tables

A *pivot table* is a data summarization tool. It aggregates a table of data by one or more keys, arranging the data in a rectangle.

In [45]:
```
tips.head()
```

Out[45]:

	total_bill	tip	smoker	day	time	size	tip_pct
0	16.99	1.01	No	Sun	Dinner	2	5.944673
1	10.34	1.66	No	Sun	Dinner	3	16.054159
2	21.01	3.50	No	Sun	Dinner	3	16.658734
3	23.68	3.31	No	Sun	Dinner	2	13.978041
4	24.59	3.61	No	Sun	Dinner	4	14.680765

Aggregate 'tip_pct' by columns 'day' and 'smoker':

In [46]:
```
# using groupby
tips.groupby(['day','smoker']).tip_pct.mean()
```

Out[46]:
```
day   smoker
Fri   No        15.165044
      Yes       17.478305
Sat   No        15.804766
      Yes       14.790607
Sun   No        16.011294
      Yes       18.725032
Thur  No        16.029808
      Yes       16.386327
Name: tip_pct, dtype: float64
```

In [47]:
```
# using pivot_table
tips.pivot_table('tip_pct', index='day', columns = 'smoker', aggfunc='mean')
```

Out[47]:

smoker	No	Yes
day		
Fri	15.165044	17.478305
Sat	15.804766	14.790607
Sun	16.011294	18.725032
Thur	16.029808	16.386327

In [48]:
```
tips.pivot_table('tip_pct', index='day', columns = 'smoker')
```

Out[48]:

smoker	No	Yes
day		
Fri	15.165044	17.478305
Sat	15.804766	14.790607
Sun	16.011294	18.725032
Thur	16.029808	16.386327

Aggregate 'tip_pct' and 'size' by 'time', 'day' and 'smoker'

In [49]:
```
# using groupby
tips.groupby(['time','day','smoker'])[['tip_pct','size']].mean()
```

Out[49]:

			tip_pct	size
time	day	smoker		
Dinner	**Fri**	**No**	13.962237	2.000000
		Yes	16.534736	2.222222
	Sat	**No**	15.804766	2.555556
		Yes	14.790607	2.476190
	Sun	**No**	16.011294	2.929825
		Yes	18.725032	2.578947
	Thur	**No**	15.974441	2.000000
Lunch	**Fri**	**No**	18.773467	3.000000
		Yes	18.893659	1.833333
	Thur	**No**	16.031067	2.500000
		Yes	16.386327	2.352941

In [50]:
```
# using pivot_table (arranging 'time' and 'day' on the rows)
tips.pivot_table(['tip_pct','size'], index=['time','day'], columns = 'smoker
```

Out[50]:

		size		tip_pct	
	smoker	No	Yes	No	Yes
time	day				
Dinner	Fri	2.000000	2.222222	13.962237	16.534736
	Sat	2.555556	2.476190	15.804766	14.790607
	Sun	2.929825	2.578947	16.011294	18.725032
	Thur	2.000000	NaN	15.974441	NaN
Lunch	Fri	3.000000	1.833333	18.773467	18.893659
	Thur	2.500000	2.352941	16.031067	16.386327

In [51]:
```
# use 'count' as the aggregation function
tips.pivot_table(['tip_pct'], index=['time','day'], columns = 'smoker', aggf
```

Out[51]:

		tip_pct	
	smoker	No	Yes
time	day		
Dinner	Fri	3.0	9.0
	Sat	45.0	42.0
	Sun	57.0	19.0
	Thur	1.0	NaN
Lunch	Fri	1.0	6.0
	Thur	44.0	17.0

In [52]:
```
tips.pivot_table(['tip_pct'], index=['time','day'], columns = 'smoker', aggf
```

Out[52]:

		tip_pct	
	smoker	No	Yes
time	day		
Dinner	Fri	3	9
	Sat	45	42
	Sun	57	19
	Thur	1	0
Lunch	Fri	1	6
	Thur	44	17

We can augment this table to include partial totals by passing margins=True

In [53]:
```
tips.pivot_table('tip_pct', index=['time','day'], columns = 'smoker', aggfur
```

Out[53]:

	smoker	No	Yes	All
time	day			
Dinner	Fri	3	9	12
	Sat	45	42	87
	Sun	57	19	76
	Thur	1	0	1
Lunch	Fri	1	6	7
	Thur	44	17	61
All		151	93	244

In [54]:
```
tips.pivot_table('tip_pct',index='day',columns = 'smoker', aggfunc='count',
```

Out[54]:

smoker	No	Yes	All
day			
Fri	4	15	19
Sat	45	42	87
Sun	57	19	76
Thur	45	17	62
All	151	93	244

4.2. Cross-Tabulations

A *cross-tabulation* is a special case of pivot table that computes frequencies.

In [55]:
```
pd.crosstab(index=tips.day, columns = tips.smoker)
```

Out[55]:

smoker	No	Yes
day		
Fri	4	15
Sat	45	42
Sun	57	19
Thur	45	17

In [56]:
```
pd.crosstab(index=tips.day,columns=tips.smoker,margins=True)
```

Out[56]:

smoker	No	Yes	All
day			
Fri	4	15	19
Sat	45	42	87
Sun	57	19	76
Thur	45	17	62
All	151	93	244

In [57]:
```
pd.crosstab(index=tips.day, columns = tips.smoker, normalize='index')
```

Out[57]:

smoker	No	Yes
day		
Fri	0.210526	0.789474
Sat	0.517241	0.482759
Sun	0.750000	0.250000
Thur	0.725806	0.274194

In [58]:
```
pd.crosstab(index=tips.day, columns = tips.smoker, normalize='columns')
```

Out[58]:

smoker	No	Yes
day		
Fri	0.026490	0.161290
Sat	0.298013	0.451613
Sun	0.377483	0.204301
Thur	0.298013	0.182796

In [59]:
```
pd.crosstab(index=[tips.time,tips.day], columns = tips.smoker,  normalize='i
```

Out[59]:

	smoker	No	Yes
time	day		
Dinner	Fri	0.250000	0.750000
	Sat	0.517241	0.482759
	Sun	0.750000	0.250000
	Thur	1.000000	0.000000
Lunch	Fri	0.142857	0.857143
	Thur	0.721311	0.278689

5. Resampling and rolling

- Resampling
- Rolling

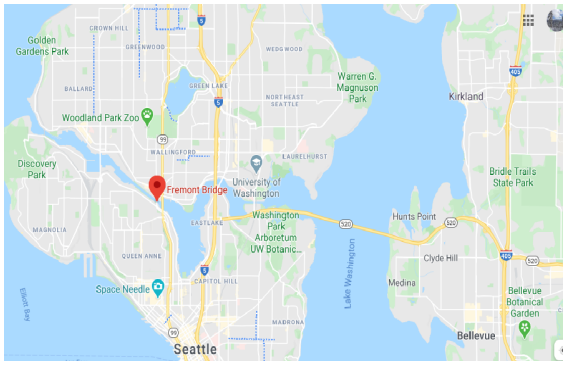
Let us take a look at bicycle counts on Seattle's Fremont Bridge

In [60]:
```
url = 'https://raw.githubusercontent.com/um-perez-alvaro/Data-Science-Practi
fremont = pd.read_csv(url)
fremont.head()
```

Out[60]:

	Date	Fremont Bridge Total	Fremont Bridge East Sidewalk	Fremont Bridge West Sidewalk
0	10/03/2012 12:00:00 AM	13.0	4.0	9.0
1	10/03/2012 01:00:00 AM	10.0	4.0	6.0
2	10/03/2012 02:00:00 AM	2.0	1.0	1.0
3	10/03/2012 03:00:00 AM	5.0	2.0	3.0
4	10/03/2012 04:00:00 AM	7.0	6.0	1.0

The Fremont Bridge Bicycle Counter began operation in October 2012 and records the number of bikes that cross the bridge using the pedestrian/bicycle pathways. The bicycle counter has sensors on the east and west sidewalks of the bridge.



In [61]:
```
fremont['Date'] = pd.to_datetime(fremont.Date)
```

In [62]:
```
fremont.set_index('Date', inplace=True)
```

In [63]:
```
fremont.head()
```

Out[63]:

Date	Fremont Bridge Total	Fremont Bridge East Sidewalk	Fremont Bridge West Sidewalk
2012-10-03 00:00:00	13.0	4.0	9.0
2012-10-03 01:00:00	10.0	4.0	6.0
2012-10-03 02:00:00	2.0	1.0	1.0
2012-10-03 03:00:00	5.0	2.0	3.0
2012-10-03 04:00:00	7.0	6.0	1.0

In [64]:
```
# Better way:
fremont = pd.read_csv(url, index_col='Date', parse_dates=True)
fremont.head()
```

Out[64]:

Date	Fremont Bridge Total	Fremont Bridge East Sidewalk	Fremont Bridge West Sidewalk
2012-10-03 00:00:00	13.0	4.0	9.0
2012-10-03 01:00:00	10.0	4.0	6.0
2012-10-03 02:00:00	2.0	1.0	1.0
2012-10-03 03:00:00	5.0	2.0	3.0
2012-10-03 04:00:00	7.0	6.0	1.0

For convenience, we'll further process this dataset by shortening the column names:

In [65]:
```
fremont.columns = ['Total', 'East', 'West']
```

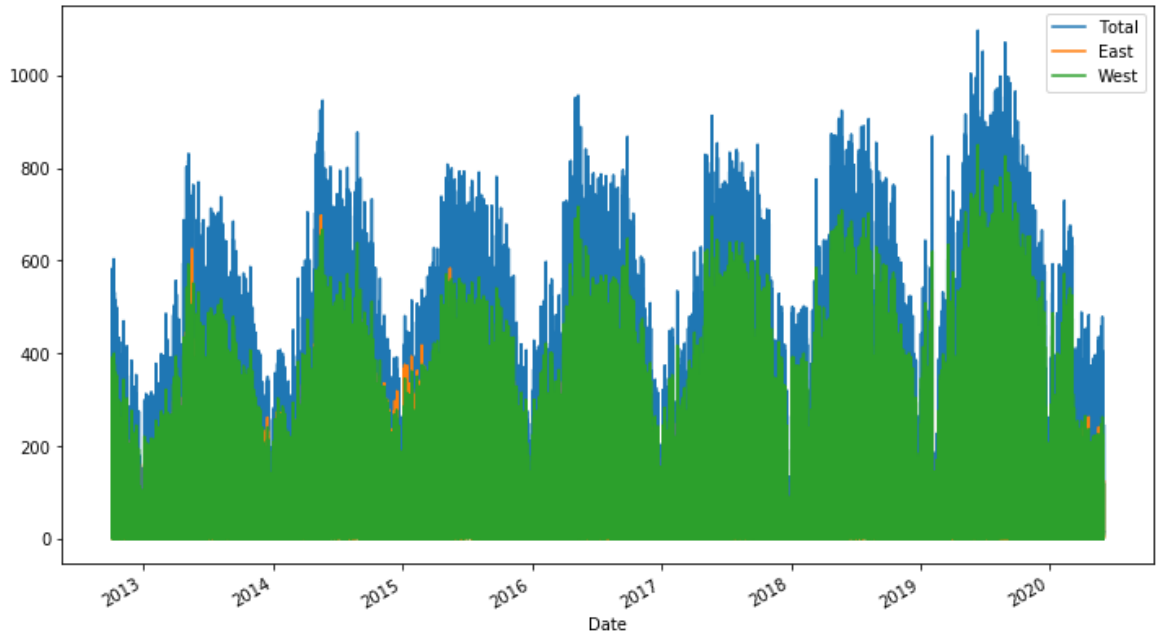
In [66]:
```
fremont.columns
```

Out[66]:
```
Index(['Total', 'East', 'West'], dtype='object')
```

Let's plot the raw data:

In [67]:
```
fremont.plot(figsize=(12,7))
```

Out[67]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2d1cbdb5c88>
```



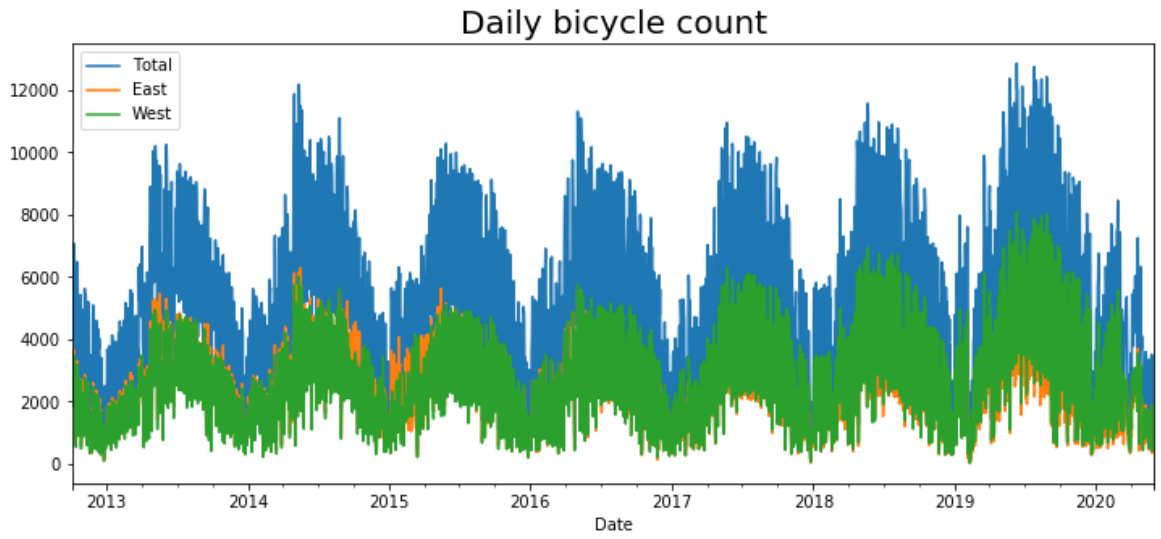
The ~25,000 hourly samples are far too dense for use to make much sense of. We can gain more insight by *resampling* the data to a courser grid.

5.1. Resampling

Resampling refers to the process of converting a time series from one frequency to another.

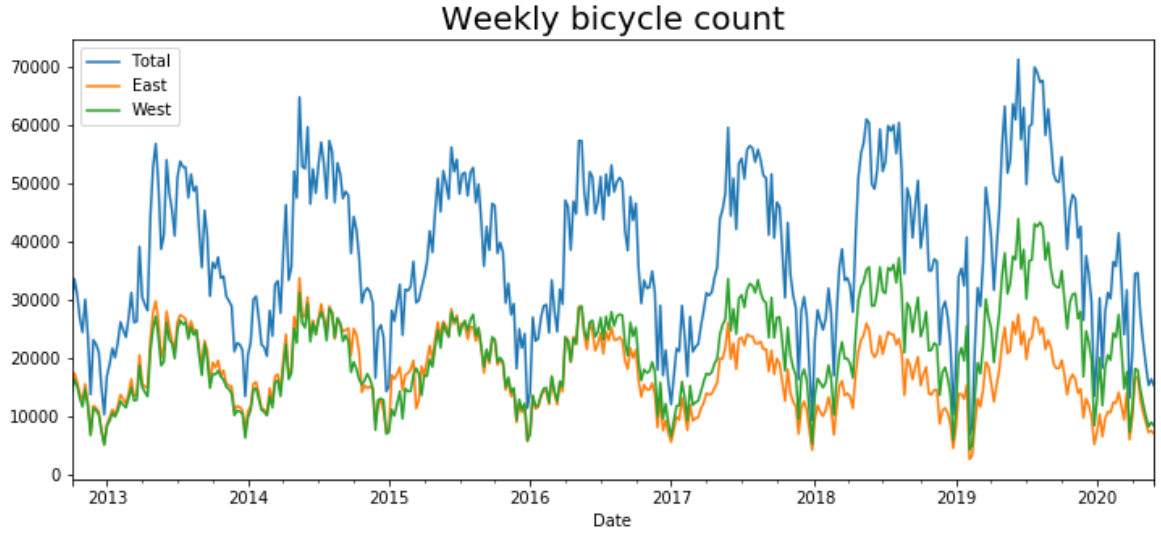
In [68]:
```
# resample by day
fremont.resample('D').sum().plot(figsize = (12,5)) # D = dayly
plt.title('Daily bicycle count',fontsize=20)
```

Out[68]:
```
Text(0.5, 1.0, 'Daily bicycle count')
```



In [69]:
```
# resample by week
fremont.resample('W').sum().plot(figsize=(12,5)) # W : weekly
plt.title('Weekly bicycle count',fontsize=20)
```

Out[69]:
```
Text(0.5, 1.0, 'Weekly bicycle count')
```



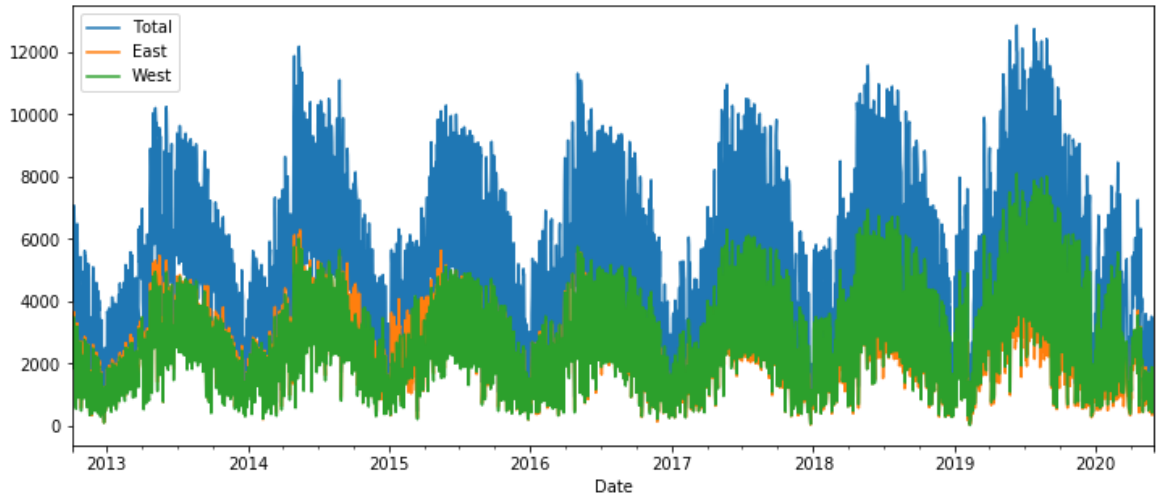
This shows us some interesting seasonal trends: people bicycle more in the summer than in the winter.

5.2 Rolling

Rolling means (or moving averages) are generally used to smooth out short-term fluctuations in time series data and highlight long-term trends

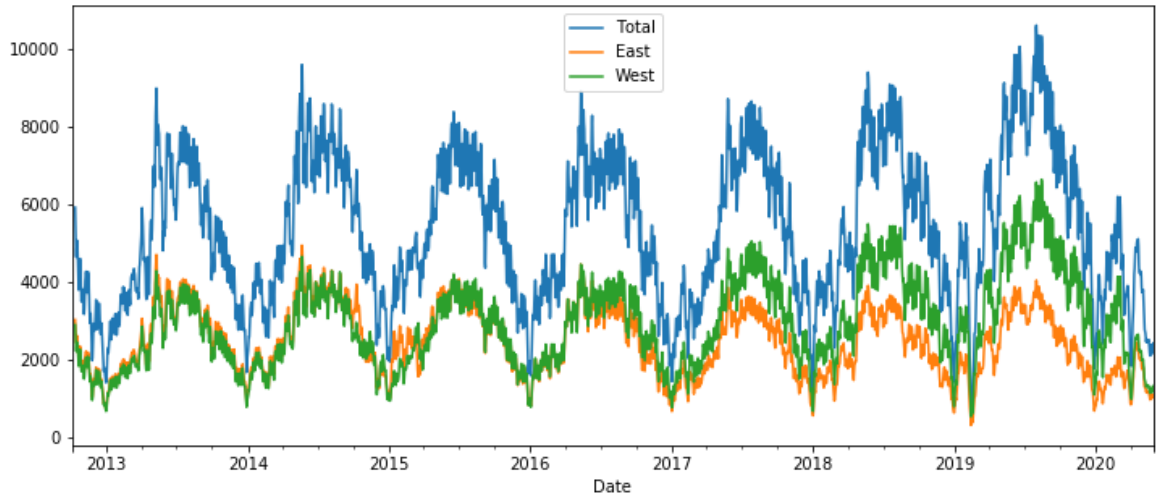
In [70]:
```
fremont.resample('D').sum().plot(figsize=(12,5)) # data is very spiky
```

Out[70]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2d1cb8fb708>
```



In [71]:
```
fremont.resample('D').sum().rolling(10).mean().plot(figsize=(12,5))
```

Out[71]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2d1ca6dc848>
```



The expression 'rolling(10)' creates an object that enables grouping over a 10-day sliding window. So here we have the 10-day moving window average of Fremont traffic.

Bonus: digging into the data

While the smoothed data views are useful to get an idea of the general trend in the data, they hide much of the interesting structure.

Let's plot the hourly counts of each day

In [72]:
```
pivoted = fremont.pivot_table('Total', index=fremont.index.time, columns = f
pivoted.head()
```

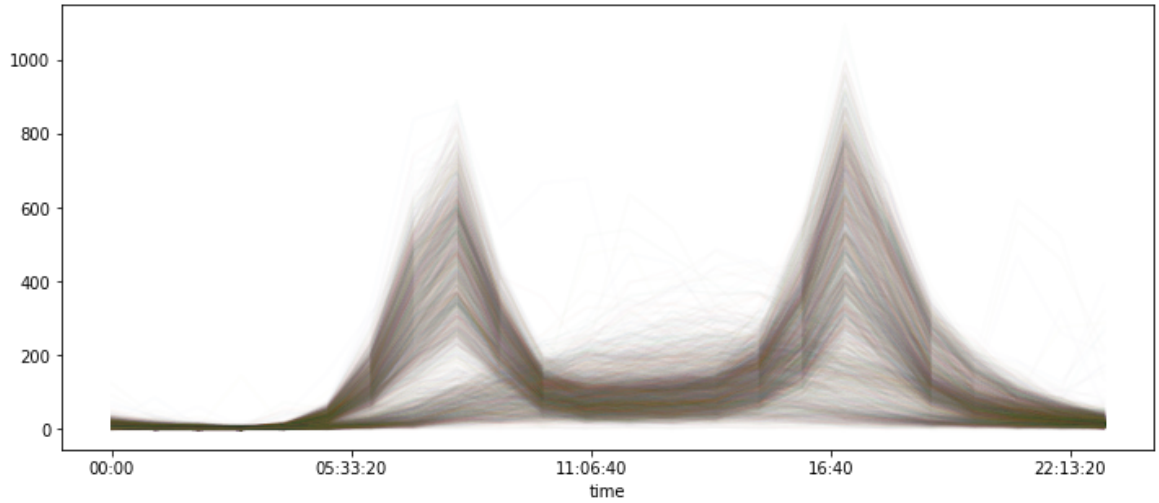
Out[72]:

	2012-10-03	2012-10-04	2012-10-05	2012-10-06	2012-10-07	2012-10-08	2012-10-09	2012-10-10	2012-10-11	2012-10-12	...	2020-05-22	2020-05-2
00:00:00	13.0	18.0	11.0	15.0	11.0	9.0	12.0	15.0	21.0	17.0	...	3.0	5.(
01:00:00	10.0	3.0	8.0	15.0	17.0	4.0	3.0	3.0	10.0	13.0	...	3.0	1.(
02:00:00	2.0	9.0	7.0	9.0	3.0	5.0	4.0	3.0	13.0	5.0	...	0.0	8.(
03:00:00	5.0	3.0	4.0	3.0	6.0	5.0	8.0	4.0	2.0	7.0	...	1.0	2.(
04:00:00	7.0	8.0	9.0	5.0	3.0	5.0	9.0	5.0	12.0	5.0	...	4.0	2.(

5 rows × 2798 columns

In [73]:
```
pivoted.plot(legend=False,alpha=0.01, figsize=(12,5))
```

Out[73]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2d1cc961608>
```



We can see two trends: One trend that peaks in the morning and in the evening (weekday trend?), and another trend that peaks at noon (weekend trend?).

Let us plot the total count by day of the week.

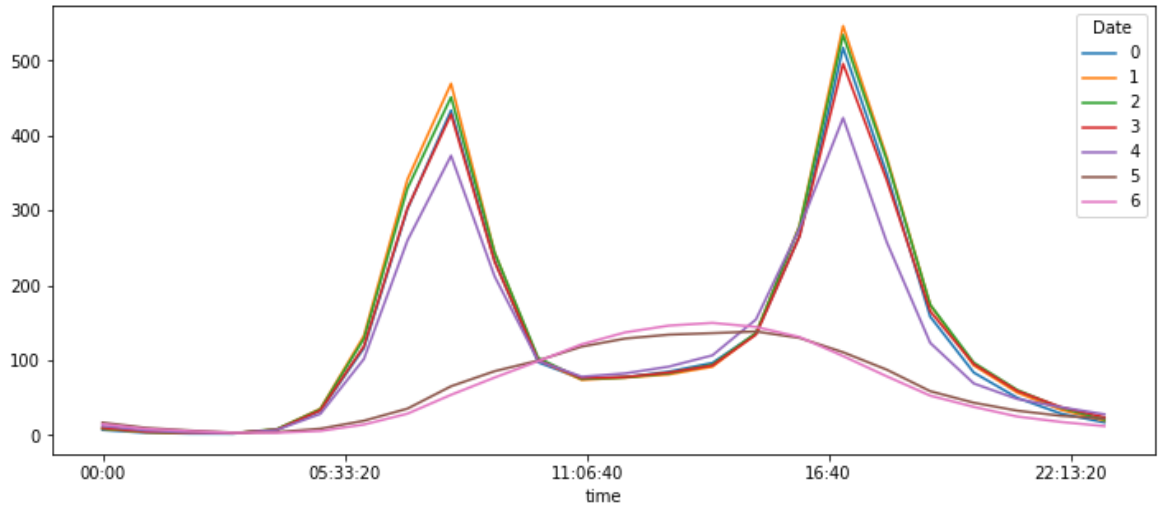
In [74]:
```
pivoted_daily = fremont.pivot_table('Total', index = fremont.index.time, col
pivoted_daily.head()
```

Out[74]:

Date	0	1	2	3	4	5	6
00:00:00	7.127364	8.774275	9.252513	9.998742	12.455919	16.988665	15.030227
01:00:00	3.393443	4.162673	4.786432	4.939623	6.308564	9.948363	8.658690
02:00:00	2.370744	3.162673	3.208543	3.421384	3.547859	6.375315	5.713188
03:00:00	2.303909	2.625473	2.832915	2.835220	2.901763	3.584383	3.347607
04:00:00	7.283733	7.779319	8.224874	7.412579	7.185139	4.311083	3.420655

In [75]:
```
pivoted_daily.plot(figsize=(12,5))
```

Out[75]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2d1d5929708>
```



This shows a strong distinction between weekday and weekend totals