Case Study - Visualizing Seattle Bicycle Counts

- Time series data, bicycle counts on Seattle's Fremont Bridge
- http://www.openstreetmap.org/#map=17/47.64813/-122.34965 (http://www.openstreetmap.org/#map=17/47.64813/-122.34965)
- This data comes from an automated bicycle counter, installed in late 2012, which has inductive sensors on the east and west sidewalks of the bridge.

In [1]:
```
import pandas as pd
import numpy as np

import calendar

import matplotlib.pyplot as plt

plt.rcParams['figure.figsize'] = (18,6)

import seaborn as sns; sns.set()

pd.options.display.max_rows = 12
```

https://data.seattle.gov/Transportation/Fremont-Bridge-Hourly-Bicycle-Counts-by-Month-Octo/65db-xm6k (https://data.seattle.gov/Transportation/Fremont-Bridge-Hourly-Bicycle-Counts-by-Month-Octo/65db-xm6k)

In [2]:
```
data = pd.read_csv('http://people.bu.edu/kalathur/datasets/Fremont_Bridge_Hourly_Bicycle_Counts.csv',
                   index_col='Date', parse_dates=True)
```

In [3]:
```
data.shape
```

Out[3]:
```
(62040, 2)
```

In [4]:
```
data
```

Out[4]:

Date	Fremont Bridge East Sidewalk	Fremont Bridge West Sidewalk
2019-01-01 00:00:00	0.0	9.0
2019-01-01 01:00:00	2.0	22.0
2019-01-01 02:00:00	1.0	11.0
2019-01-01 03:00:00	1.0	2.0
2019-01-01 04:00:00	2.0	1.0
...	...	...
2016-02-29 00:00:00	2.0	2.0
2013-09-13 03:00:00	1.0	1.0
2016-12-07 00:00:00	3.0	3.0
2013-03-29 04:00:00	1.0	1.0
2017-05-24 01:00:00	4.0	4.0

62040 rows × 2 columns

In [5]:
```
data.columns
```

Out[5]:
```
Index(['Fremont Bridge East Sidewalk', 'Fremont Bridge West Sidewalk'], dtype='object')
```

In [6]:
```
data.columns = ['East', 'West']

data['Total'] = data.eval('East + West')
```

In [7]:
```
data
```

Out[7]:

Date	East	West	Total
2019-01-01 00:00:00	0.0	9.0	9.0
2019-01-01 01:00:00	2.0	22.0	24.0
2019-01-01 02:00:00	1.0	11.0	12.0
2019-01-01 03:00:00	1.0	2.0	3.0
2019-01-01 04:00:00	2.0	1.0	3.0
...	...	...	...
2016-02-29 00:00:00	2.0	2.0	4.0
2013-09-13 03:00:00	1.0	1.0	2.0
2016-12-07 00:00:00	3.0	3.0	6.0
2013-03-29 04:00:00	1.0	1.0	2.0
2017-05-24 01:00:00	4.0	4.0	8.0

62040 rows × 3 columns

In [8]:
```
data.isnull().any()
```

Out[8]:
```
East     True
West     True
Total    True
dtype: bool
```

In [9]:
```
len(data)
```

Out[9]:
```
62040
```

In [10]:
```
data.dropna(inplace=True)
len(data)
```

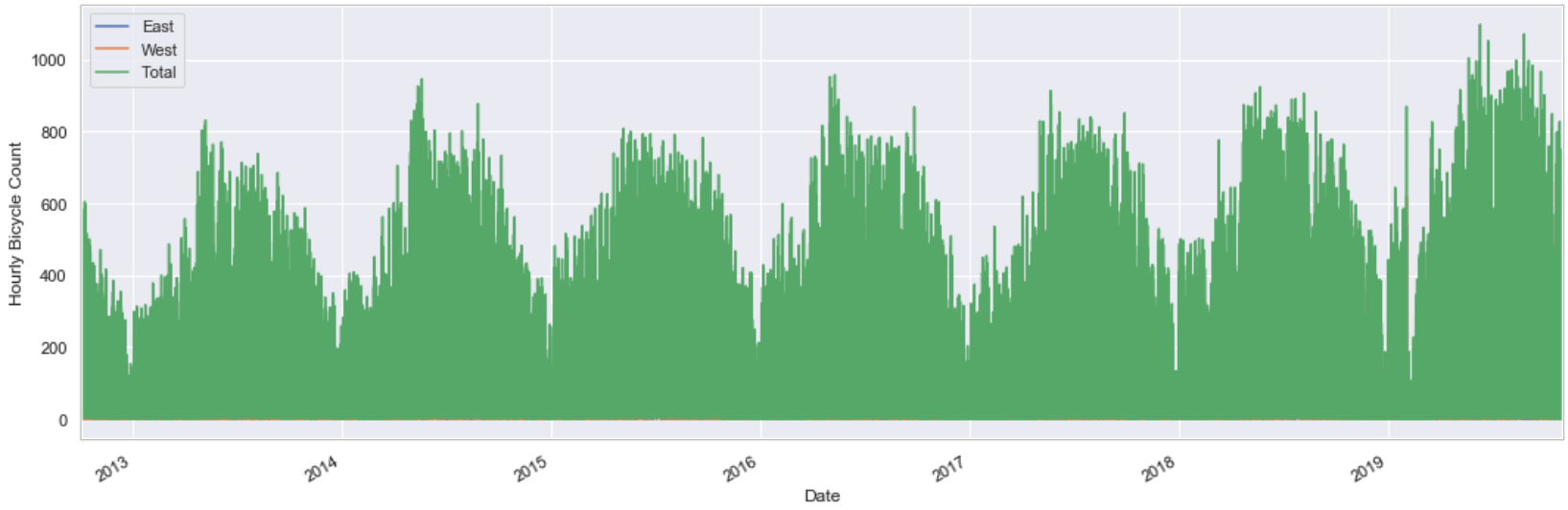
Out[10]:
```
62031
```

In [11]:
```
data.describe()
```

Out[11]:

	East	West	Total
count	62031.000000	62031.000000	62031.000000
mean	52.858603	61.794280	114.652883
std	67.738822	90.417195	145.685842
min	0.000000	0.000000	0.000000
25%	7.000000	7.000000	15.000000
50%	29.000000	30.000000	62.000000
75%	71.000000	74.000000	150.000000
max	698.000000	850.000000	1097.000000

In [12]:
```
fig, ax = plt.subplots(figsize=(18,6))

data.plot(ax=ax)

plt.ylabel('Hourly Bicycle Count');
```



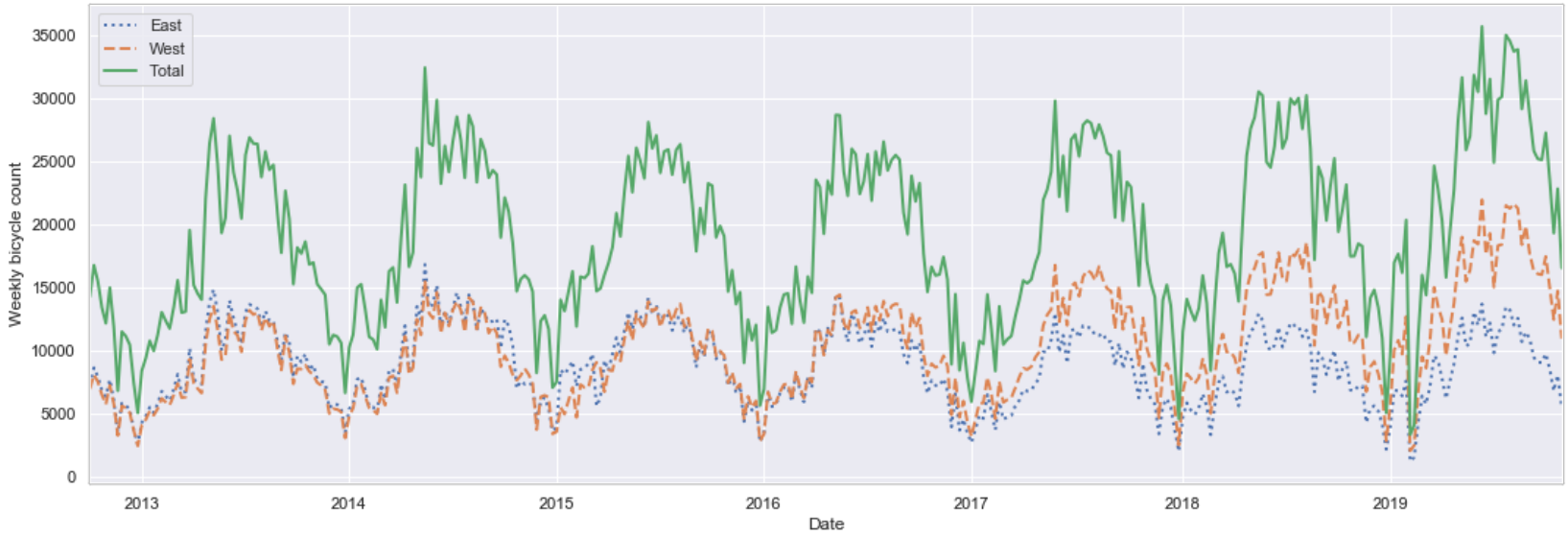
In [13]:
```
weekly = data.resample('W').sum()
weekly
```

Out[13]:

Date	East	West	Total
2012-10-07	7297.0	6995.0	14292.0
2012-10-14	8679.0	8116.0	16795.0
2012-10-21	7946.0	7563.0	15509.0
2012-10-28	6901.0	6536.0	13437.0
2012-11-04	6408.0	5786.0	12194.0
...	...	...	...
2019-10-06	9785.0	17485.0	27270.0
2019-10-13	8543.0	14952.0	23495.0
2019-10-20	6835.0	12497.0	19332.0
2019-10-27	8089.0	14752.0	22841.0
2019-11-03	5583.0	10983.0	16566.0

370 rows × 3 columns

In [14]:
```
fig, ax = plt.subplots(figsize=(18,6))

weekly.plot(style=[':', '--', '-'], ax=ax, lw=2)

plt.ylabel('Weekly bicycle count');
```



In [15]:
```
daily = data.resample('D').sum()
daily
```

Out[15]:

Date	East	West	Total
2012-10-03	1760.0	1761.0	3521.0
2012-10-04	1708.0	1767.0	3475.0
2012-10-05	1558.0	1590.0	3148.0
2012-10-06	1080.0	926.0	2006.0
2012-10-07	1191.0	951.0	2142.0
...	...	...	...
2019-10-27	794.0	961.0	1755.0
2019-10-28	1479.0	2843.0	4322.0
2019-10-29	1437.0	2886.0	4323.0
2019-10-30	1407.0	2687.0	4094.0
2019-10-31	1260.0	2567.0	3827.0

2585 rows × 3 columns

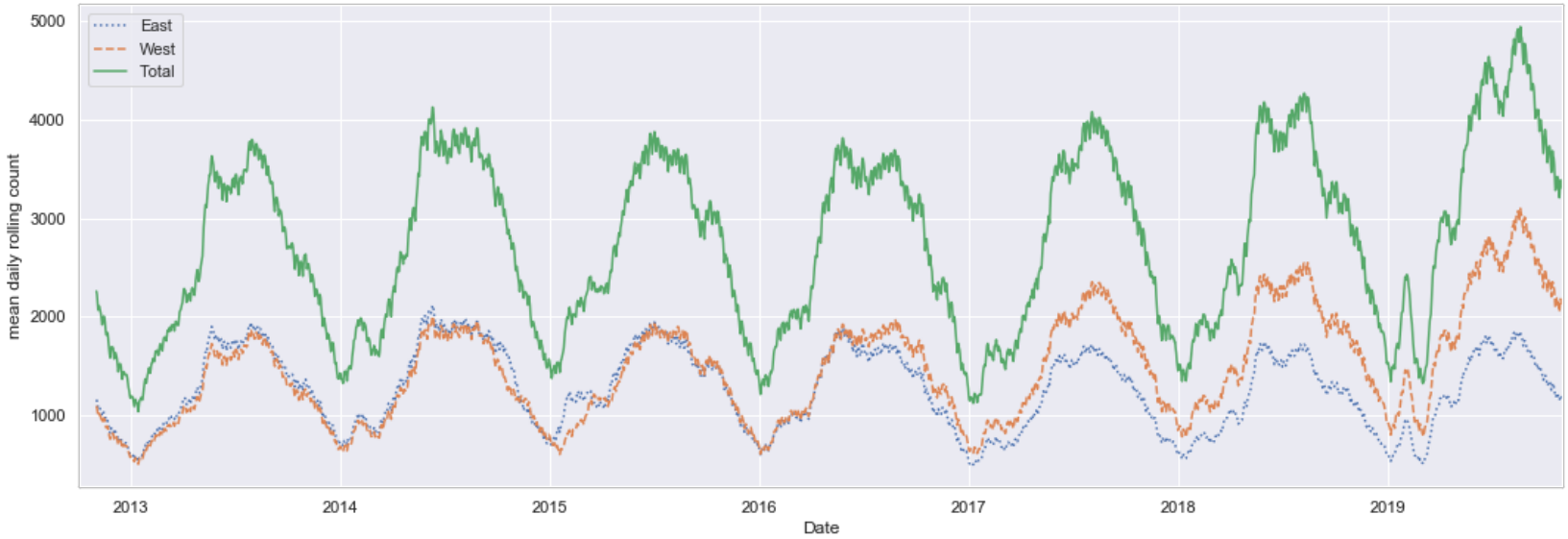
In [16]:
```
daily_rolling = daily.rolling(30).mean()
daily_rolling
```

Out[16]:

Date	East	West	Total
2012-10-03	NaN	NaN	NaN
2012-10-04	NaN	NaN	NaN
2012-10-05	NaN	NaN	NaN
2012-10-06	NaN	NaN	NaN
2012-10-07	NaN	NaN	NaN
...	...	...	...
2019-10-27	1156.866667	2050.500000	3207.366667
2019-10-28	1177.900000	2111.566667	3289.466667
2019-10-29	1205.600000	2180.500000	3386.100000
2019-10-30	1194.966667	2160.733333	3355.700000
2019-10-31	1176.933333	2132.300000	3309.233333

2585 rows × 3 columns

In [17]:
```
fig, ax = plt.subplots(figsize=(18,6))

daily_rolling.plot(style=[':', '--', '-'], ax=ax);

plt.ylabel('mean daily rolling count');
```



In [ ]:
```
```

Average traffic as a function of the time of day

In [18]:
```
data.index
```

Out[18]:
```
DatetimeIndex(['2019-01-01 00:00:00', '2019-01-01 01:00:00',
               '2019-01-01 02:00:00', '2019-01-01 03:00:00',
               '2019-01-01 04:00:00', '2019-01-01 05:00:00',
               '2019-01-01 06:00:00', '2019-01-01 07:00:00',
               '2019-01-01 08:00:00', '2019-01-01 09:00:00',
               ...
               '2016-12-06 00:00:00', '2016-01-22 20:00:00',
               '2017-04-04 01:00:00', '2013-01-18 04:00:00',
               '2017-01-12 04:00:00', '2016-02-29 00:00:00',
               '2013-09-13 03:00:00', '2016-12-07 00:00:00',
               '2013-03-29 04:00:00', '2017-05-24 01:00:00'],
              dtype='datetime64[ns]', name='Date', length=62031, freq=None)
```

In [19]:
```
data.index.time
```

Out[19]:
```
array([datetime.time(0, 0), datetime.time(1, 0), datetime.time(2, 0), ...,
       datetime.time(0, 0), datetime.time(4, 0), datetime.time(1, 0)],
      dtype=object)
```

In [20]:
```
pd.options.display.max_rows = 24

by_time = data.groupby(data.index.time).mean()
by_time
```

Out[20]:

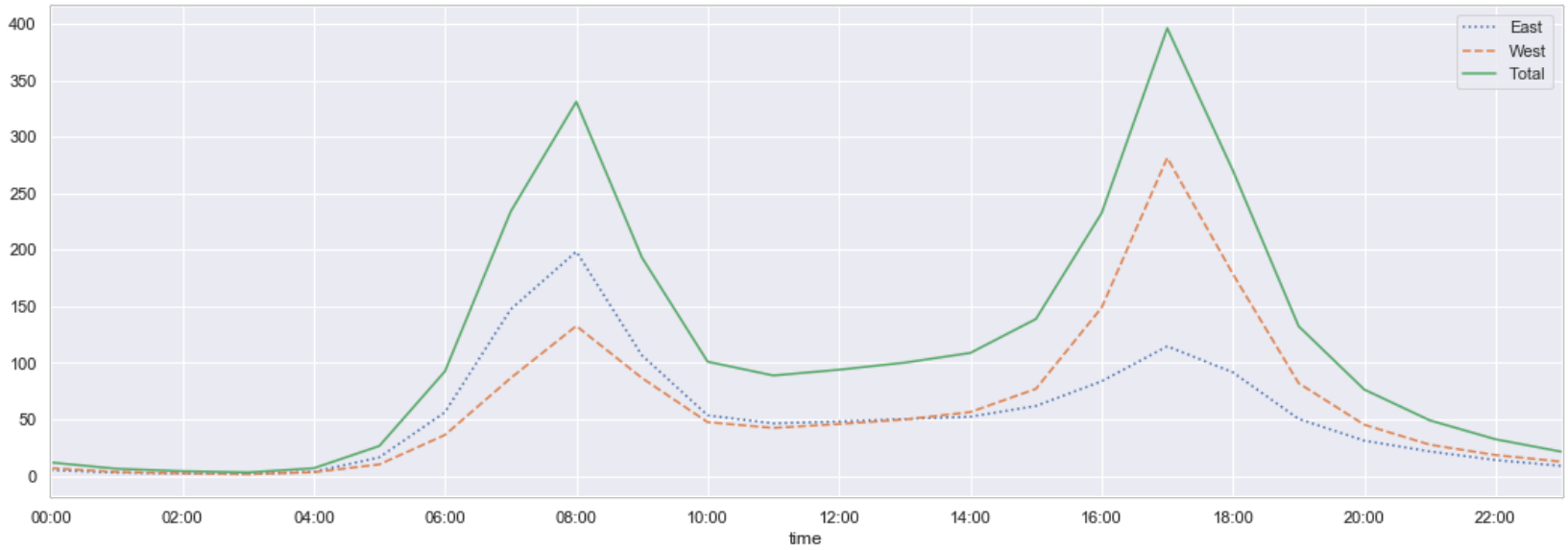
	East	West	Total
00:00:00	5.031335	6.794584	11.825919
01:00:00	2.815474	3.445261	6.260735
02:00:00	1.996512	2.123643	4.120155
03:00:00	1.571373	1.468859	3.040232
04:00:00	3.541586	3.148936	6.690522
05:00:00	16.316828	10.099033	26.415861
06:00:00	56.335010	36.203095	92.538104
07:00:00	147.330368	86.517988	233.848356
08:00:00	198.531141	132.673114	331.204255
09:00:00	106.626161	86.599845	193.226006
10:00:00	53.543344	47.497291	101.040635
11:00:00	46.417570	42.400155	88.817724
12:00:00	48.071981	45.847910	93.919892
13:00:00	50.348549	49.842553	100.191103
14:00:00	52.342360	56.436364	108.778723
15:00:00	61.858027	76.991876	138.849903
16:00:00	83.700193	148.870793	232.570986
17:00:00	114.738491	281.516441	396.254932
18:00:00	91.553965	178.639072	270.193037
19:00:00	50.398453	82.074275	132.472727
20:00:00	31.149710	45.246422	76.396132
21:00:00	21.546615	27.525725	49.072340
22:00:00	13.977563	18.375242	32.352805
23:00:00	8.782205	12.599226	21.381431

In [21]:
```
pd.options.display.max_rows = 12
```

In [22]:
```
hourly_ticks = 2 * 60 * 60 * np.arange(12)
hourly_ticks
```

Out[22]:
```
array([    0,  7200, 14400, 21600, 28800, 36000, 43200, 50400, 57600,
       64800, 72000, 79200])
```

In [23]:
```
fig, ax = plt.subplots(figsize=(18,6))

by_time.plot(xticks=hourly_ticks, style=[':', '--', '-'], ax=ax);
```



- peaks at 8 AM and 5 PM (bi-modal)
- the western sidewalk (generally used going toward downtown Seattle), which peaks more strongly in the morning, and the eastern sidewalk (generally used going away from downtown Seattle), which peaks more strongly in the evening

Average traffic as a function of the day of the week

In [24]:
```
data.index.dayofweek
```

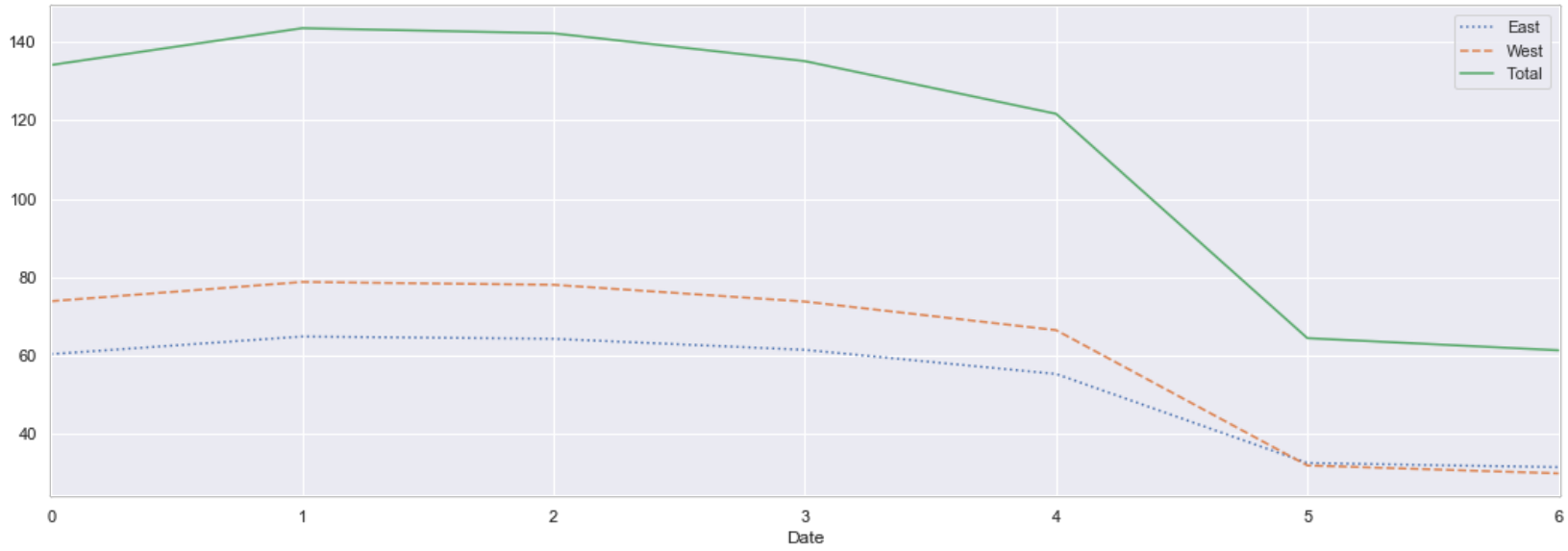
Out[24]:
```
Int64Index([1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
            ...
            1, 4, 1, 4, 3, 0, 4, 2, 4, 2],
           dtype='int64', name='Date', length=62031)
```

In [25]:
```
by_weekday = data.groupby(data.index.dayofweek).mean()
by_weekday
```

Out[25]:

Date	East	West	Total
0	60.313008	73.824639	134.137647
1	64.810707	78.738197	143.548904
2	64.227477	78.014527	142.242005
3	61.406982	73.729054	135.136036
4	55.248136	66.435396	121.683533
5	32.511631	31.875339	64.386969
6	31.429443	29.853350	61.282793

In [26]:
```
fig, ax = plt.subplots(figsize=(18,6))
by_weekday.plot(style=[':', '--', '-'], ax=ax);
```



In [27]:
```
by_weekday.index
```

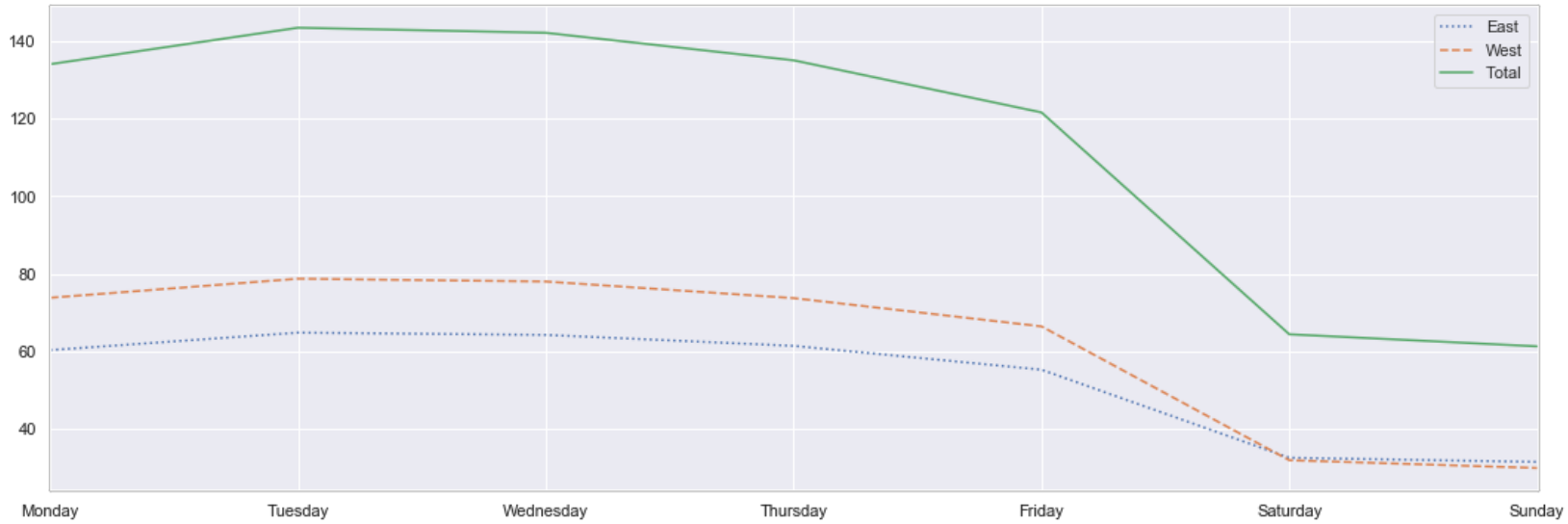
Out[27]:
```
Int64Index([0, 1, 2, 3, 4, 5, 6], dtype='int64', name='Date')
```

In [28]:
```
by_weekday.index = [calendar.day_name[index] for index in by_weekday.index]
by_weekday
```

Out[28]:

	East	West	Total
Monday	60.313008	73.824639	134.137647
Tuesday	64.810707	78.738197	143.548904
Wednesday	64.227477	78.014527	142.242005
Thursday	61.406982	73.729054	135.136036
Friday	55.248136	66.435396	121.683533
Saturday	32.511631	31.875339	64.386969
Sunday	31.429443	29.853350	61.282793

In [29]:
```
fig, ax = plt.subplots(figsize=(18,6))

by_weekday.plot(style=[':', '--', '-'], ax=ax)

plt.xticks(list(range(len(by_weekday.index))), by_weekday.index)

plt.show()
```



Hourly trends on Weekdays versus Weekends

In [30]:
```
(data.index.weekday == data.index.dayofweek).all()
```

Out[30]: True

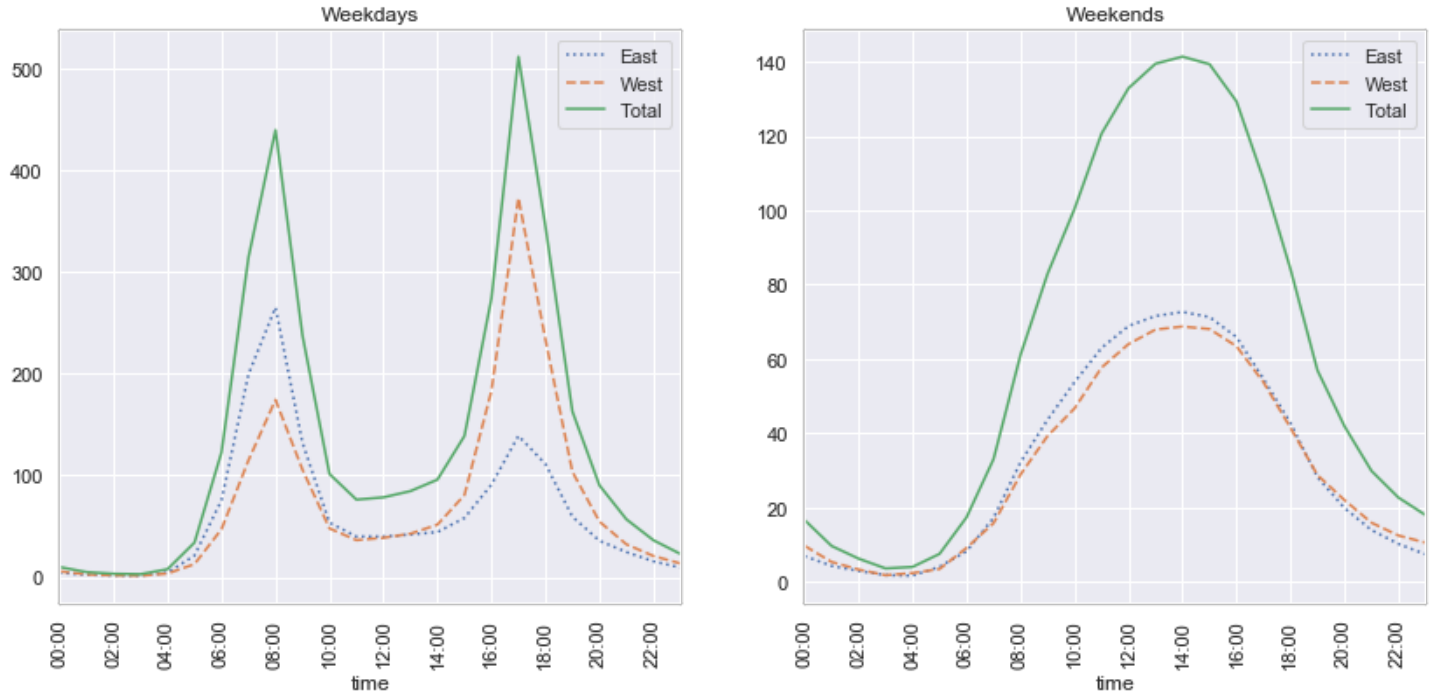
In [31]:
```
weekend = np.where(data.index.weekday < 5, 'Weekday', 'Weekend')

by_time = data.groupby([weekend, data.index.time]).mean()
by_time
```

Out[31]:

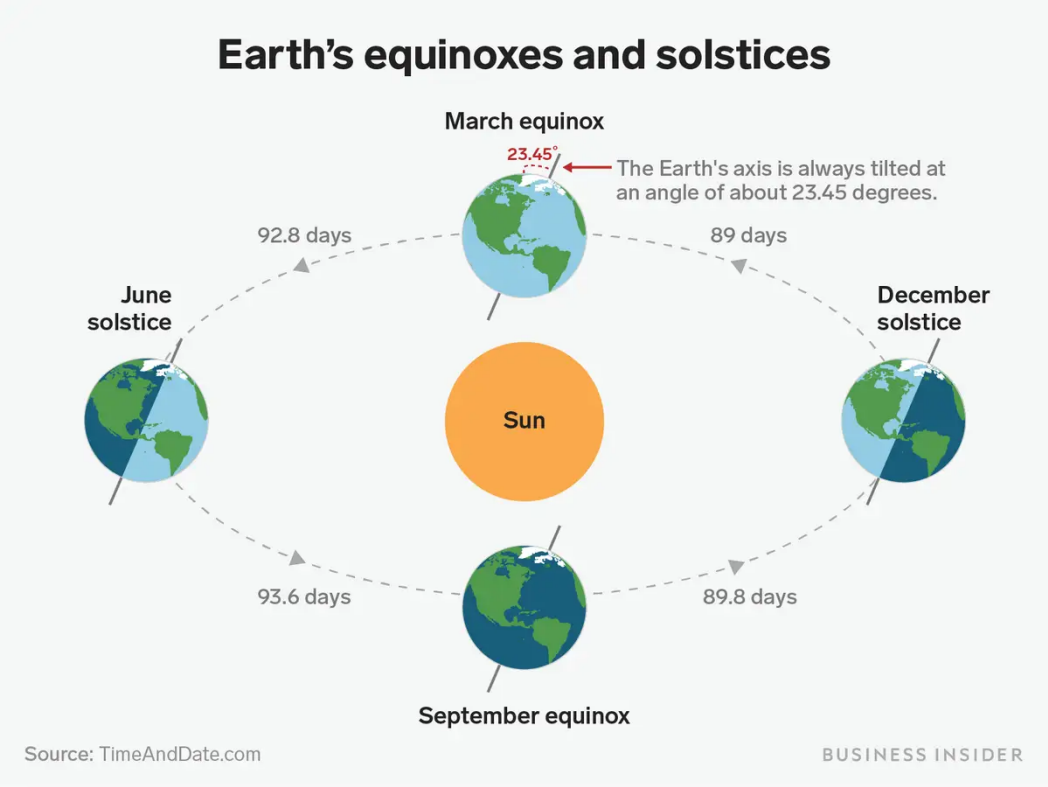
		East	West	Total
	00:00:00	4.264754	5.628587	9.893341
	01:00:00	2.219816	2.678939	4.898755
Weekday	02:00:00	1.625338	1.644829	3.270168
	03:00:00	1.467244	1.340552	2.807796
	04:00:00	4.295073	3.460747	7.755820
...	...	...	...	...
	19:00:00	28.177507	28.749322	56.926829
	20:00:00	19.891599	22.010840	41.902439
Weekend	21:00:00	13.955285	15.925474	29.880759
	22:00:00	10.210027	12.479675	22.689702
	23:00:00	7.432249	10.563686	17.995935

48 rows × 3 columns

In [32]:
```
fig, ax = plt.subplots(1, 2, figsize=(14, 6))

by_time.loc['Weekday'].plot(ax=ax[0], title='Weekdays', rot=90,
                            xticks=hourly_ticks, style=[':', '--', '-'])

by_time.loc['Weekend'].plot(ax=ax[1], title='Weekends', rot=90,
                            xticks=hourly_ticks, style=[':', '--', '-']);
```



In [ ]:



In [33]:
```
# Define a function which returns the hours of daylight
# given the day of the year, from 0 to 365

def hours_of_daylight(date, axis=23.45, latitude=47.61):
    """Compute the hours of daylight for the given date"""
    diff = date - pd.datetime(2000, 12, 21)
    day = diff.total_seconds() / 24. / 3600
    day %= 365.25
    m = 1. - np.tan(np.radians(latitude)) * np.tan(np.radians(axis) * np.cos(day * np.pi / 182.625))
    m = max(0, min(m, 2))
    return 24. * np.degrees(np.arccos(1 - m)) / 180.
```

In [34]:
```
# Boston
hours_of_daylight(pd.datetime(2019, 11, 11), latitude=42.361145)
```

Out[34]:
```
9.713211210612382
```

In [35]:
```
hours_of_daylight(pd.datetime(2019, 6, 21))
```

Out[35]:
```
15.782211624938212
```

In [36]:
```
hours_of_daylight(pd.datetime(2019, 12, 21))
```

Out[36]:
```
8.217307224137711
```

In [37]:
```
hours_of_daylight(pd.datetime(2019, 12, 21), latitude=0)
```

Out[37]:
```
12.0
```

In [38]:
```
weekly['daylight'] = weekly.index.map(hours_of_daylight)
daily['daylight'] = daily.index.map(hours_of_daylight)
```

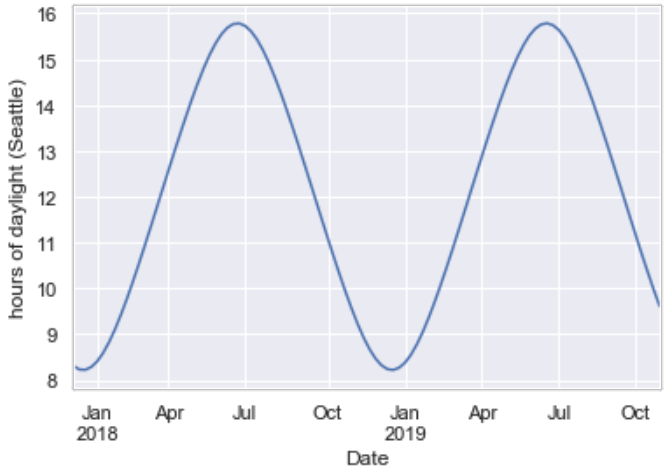
In [39]:
```
weekly
```

Out[39]:

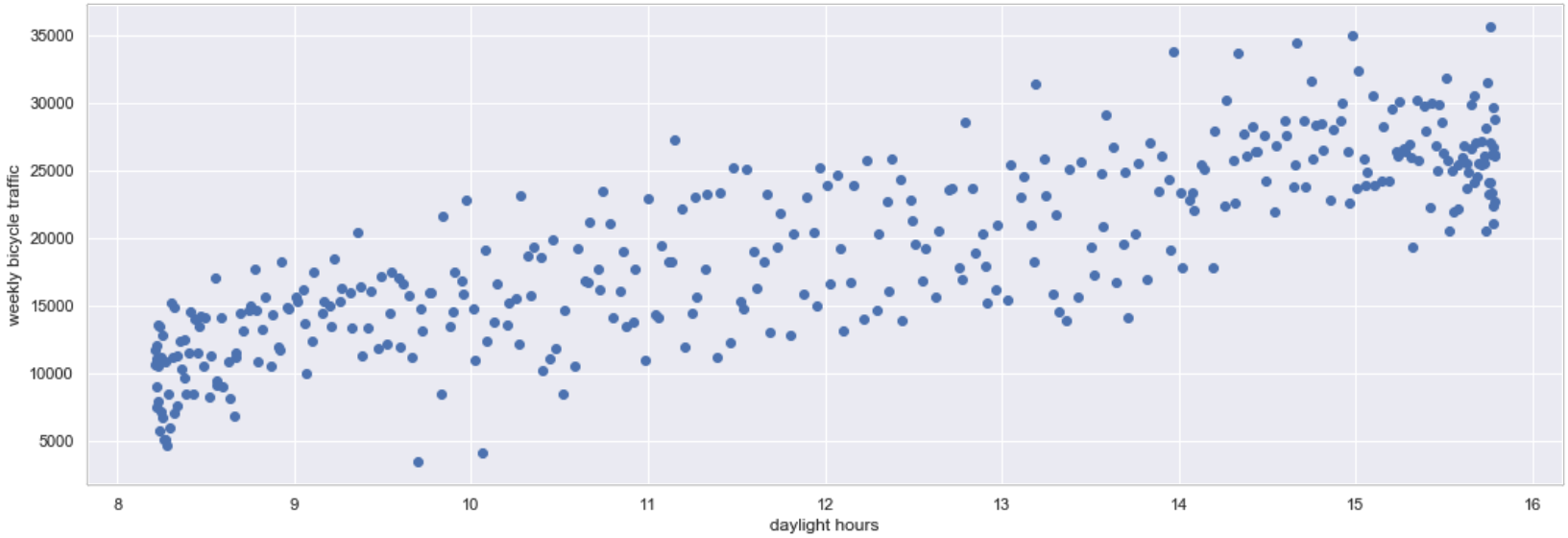
Date	East	West	Total	daylight
2012-10-07	7297.0	6995.0	14292.0	11.044795
2012-10-14	8679.0	8116.0	16795.0	10.644257
2012-10-21	7946.0	7563.0	15509.0	10.254526
2012-10-28	6901.0	6536.0	13437.0	9.880129
2012-11-04	6408.0	5786.0	12194.0	9.526492
...	...	...	...	...
2019-10-06	9785.0	17485.0	27270.0	11.146162
2019-10-13	8543.0	14952.0	23495.0	10.743537
2019-10-20	6835.0	12497.0	19332.0	10.350712
2019-10-27	8089.0	14752.0	22841.0	9.972010
2019-11-03	5583.0	10983.0	16566.0	9.612623

370 rows × 4 columns

In [40]:
```
# Plot the daylight curve
weekly['daylight'].iloc[-100:].plot()
plt.ylabel('hours of daylight (Seattle)');
```



In [41]:
```
fig, ax = plt.subplots(figsize=(18,6))

plt.scatter(weekly['daylight'], weekly['Total'])
plt.xlabel('daylight hours')
plt.ylabel('weekly bicycle traffic');
```



In [ ]:
```
```

Linear Regression

In [42]:
```
from sklearn.linear_model import LinearRegression
```

In [43]:
```
weekly
```

Out[43]:

Date	East	West	Total	daylight
2012-10-07	7297.0	6995.0	14292.0	11.044795
2012-10-14	8679.0	8116.0	16795.0	10.644257
2012-10-21	7946.0	7563.0	15509.0	10.254526
2012-10-28	6901.0	6536.0	13437.0	9.880129
2012-11-04	6408.0	5786.0	12194.0	9.526492
...	...	...	...	...
2019-10-06	9785.0	17485.0	27270.0	11.146162
2019-10-13	8543.0	14952.0	23495.0	10.743537
2019-10-20	6835.0	12497.0	19332.0	10.350712
2019-10-27	8089.0	14752.0	22841.0	9.972010
2019-11-03	5583.0	10983.0	16566.0	9.612623

370 rows × 4 columns

In [44]:
```
X = weekly[['daylight']]
y = weekly['Total']
```

In [45]:
```
clf = LinearRegression().fit(X, y)
```

```
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/sklearn/linear_model/base.py:485:
RuntimeWarning: internal gelsd driver lwork query error, required iwork dimension not returned. This is likely
the result of LAPACK bug 0038, fixed in LAPACK 3.2.2 (released July 21, 2010). Falling back to 'gelss' driver.
  linalg.lstsq(X, y)
```

In [46]:
```
weekly['daylight_trend'] = clf.predict(X)
weekly['daylight_trend'].mean()
```

Out[46]:
```
19221.710810810815
```

In [47]:
```
weekly['daylight_corrected_total'] = \
    weekly['Total'] - weekly['daylight_trend'] + weekly['daylight_trend'].mean()
```

In [48]:
```
weekly.head()
```

Out[48]:

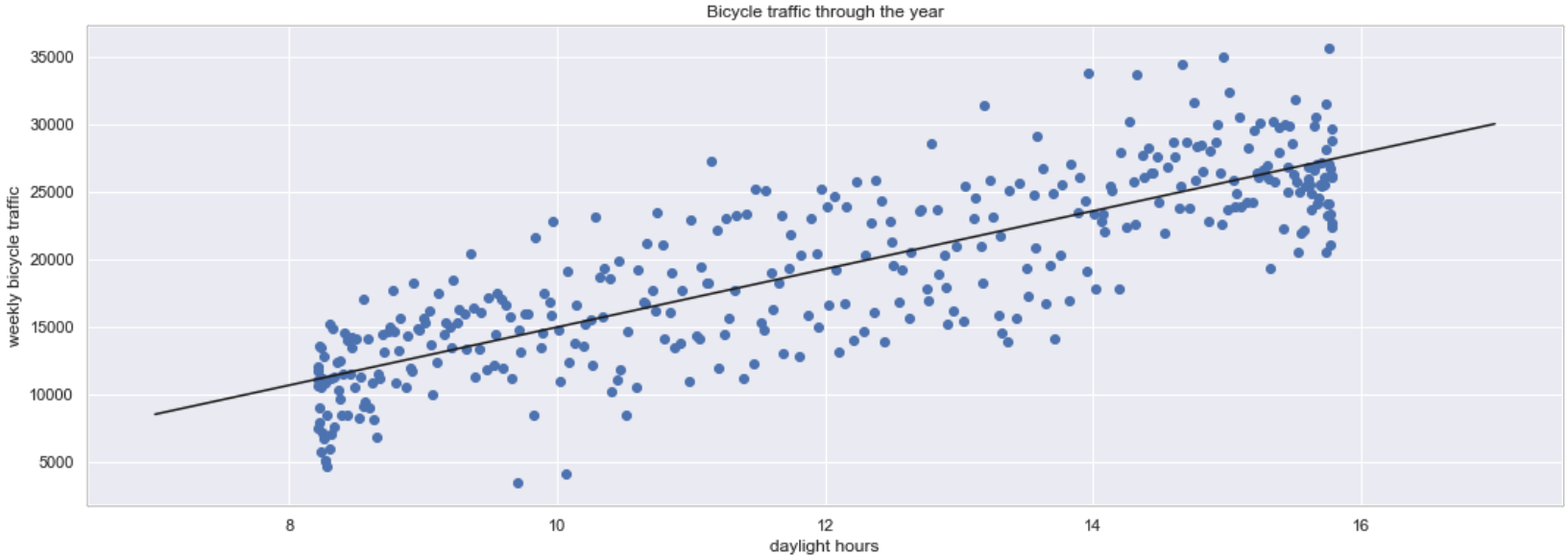
Date	East	West	Total	daylight	daylight_trend	daylight_corrected_total
2012-10-07	7297.0	6995.0	14292.0	11.044795	17209.473177	16304.237634
2012-10-14	8679.0	8116.0	16795.0	10.644257	16346.157630	19670.553181
2012-10-21	7946.0	7563.0	15509.0	10.254526	15506.134897	19224.575914
2012-10-28	6901.0	6536.0	13437.0	9.880129	14699.164501	17959.546309
2012-11-04	6408.0	5786.0	12194.0	9.526492	13936.937281	17478.773530

In [49]:
```
xfit = np.linspace(7, 17)
yfit = clf.predict(xfit[:, np.newaxis])
```

In [50]:
```
yfit
```

Out[50]:
```
array([ 8491.36348599,  8931.23892372,  9371.11436146,  9810.98979919,
       10250.86523692, 10690.74067465, 11130.61611239, 11570.49155012,
       12010.36698785, 12450.24242559, 12890.11786332, 13329.99330105,
       13769.86873878, 14209.74417652, 14649.61961425, 15089.49505198,
       15529.37048972, 15969.24592745, 16409.12136518, 16848.99680292,
       17288.87224065, 17728.74767838, 18168.62311611, 18608.49855385,
       19048.37399158, 19488.24942931, 19928.12486705, 20368.00030478,
       20807.87574251, 21247.75118024, 21687.62661798, 22127.50205571,
       22567.37749344, 23007.25293118, 23447.12836891, 23887.00380664,
       24326.87924438, 24766.75468211, 25206.63011984, 25646.50555757,
       26086.38099531, 26526.25643304, 26966.13187077, 27406.00730851,
       27845.88274624, 28285.75818397, 28725.6336217 , 29165.50905944,
       29605.38449717, 30045.2599349 ])
```

In [51]:
```
fig, ax = plt.subplots(figsize=(18,6))

plt.scatter(weekly['daylight'], weekly['Total'])
plt.plot(xfit, yfit, '-k')

plt.title("Bicycle traffic through the year")
plt.xlabel('daylight hours')
plt.ylabel('weekly bicycle traffic');
```



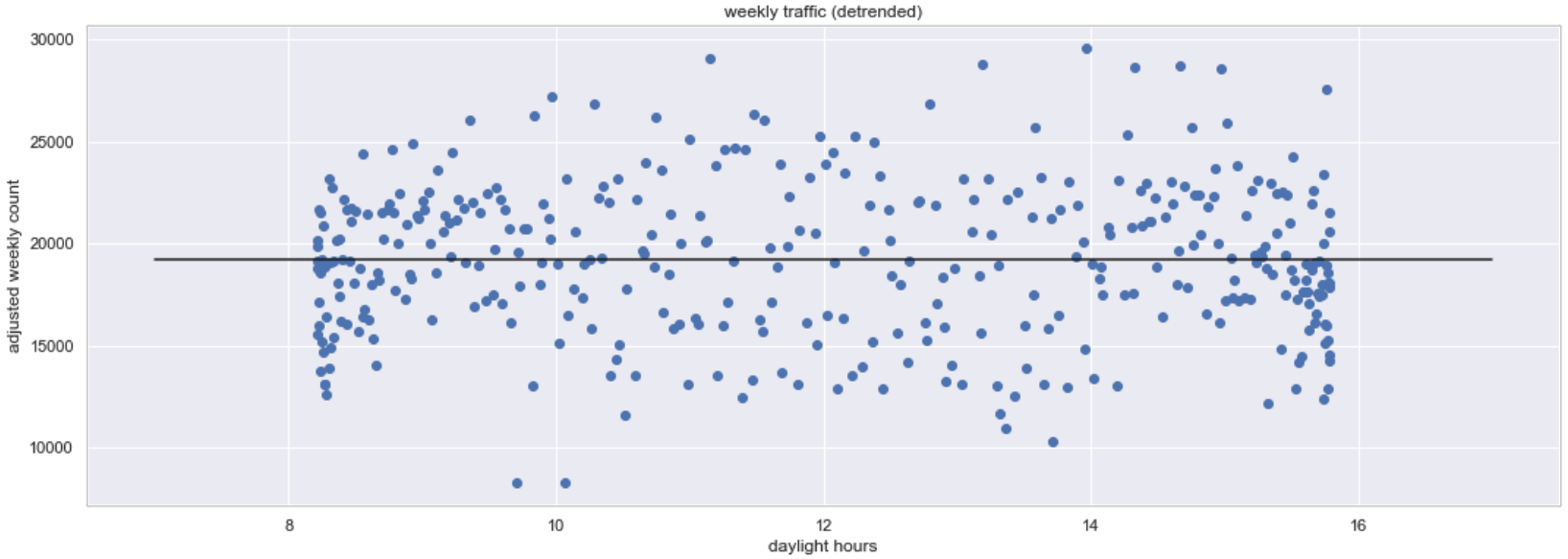
In [ ]:
```
```

In [52]:
```
print(clf.coef_[0])
```

```
2155.389644891424
```

- each extra hour of daylight leads to about 2000 more riders per week across the bridge

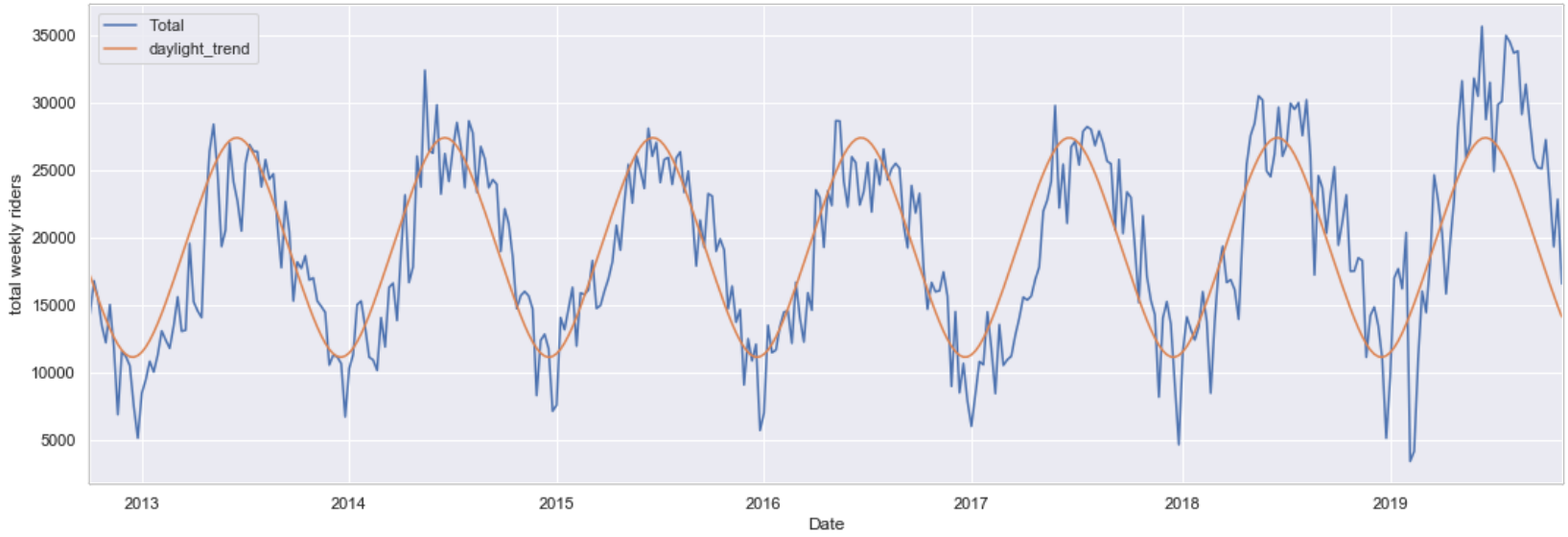
In [53]:
```
# Now that we have fit this trend, let's subtract it and replace it by the mean
fig, ax = plt.subplots(figsize=(18,6))

trend = clf.predict(weekly[['daylight']].values)

plt.scatter(weekly['daylight'], weekly['Total'] - trend + np.mean(trend))
plt.plot(xfit, np.mean(trend) + 0 * yfit, '-k')

plt.title("weekly traffic (detrended)")
plt.xlabel('daylight hours')
plt.ylabel('adjusted weekly count');
```



- de-trended data
- removed the component of the data which correlates with the number of hours in a day
- the number of cyclists we'd expect to see if the hours of daylight were not a factor

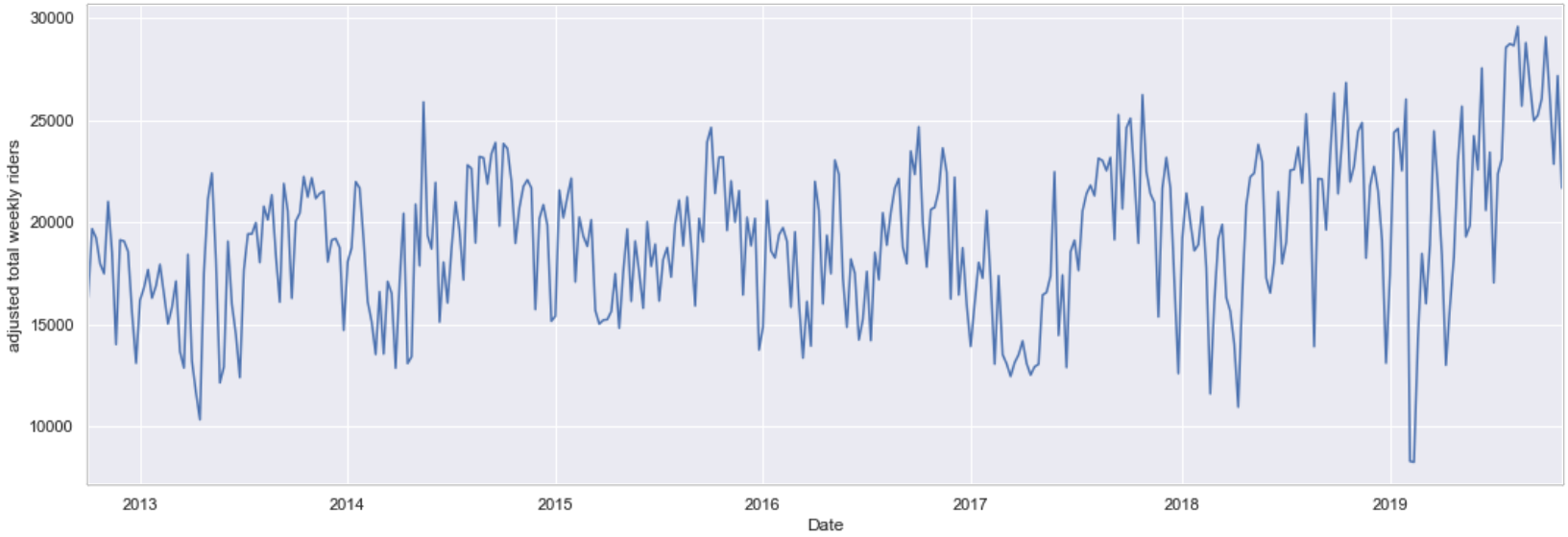
In [ ]:

In [54]:
```
fig, ax = plt.subplots(figsize=(18,6))

weekly[['Total', 'daylight_trend']].plot(ax=ax)

plt.ylabel("total weekly riders");
```



In [55]:
```
fig, ax = plt.subplots(figsize=(18,6))

weekly['daylight_corrected_total'].plot(ax=ax)

rms = np.std(weekly['daylight_corrected_total'])

plt.ylabel("adjusted total weekly riders")

print("root-mean-square about trend: {0:.0f} riders".format(rms))
```

```
root-mean-square about trend: 3754 riders
```



- With the data de-trended, we get a better idea of how bicycling in Seattle has changed over time, corrected for the seasonal variation.

Statsmodels

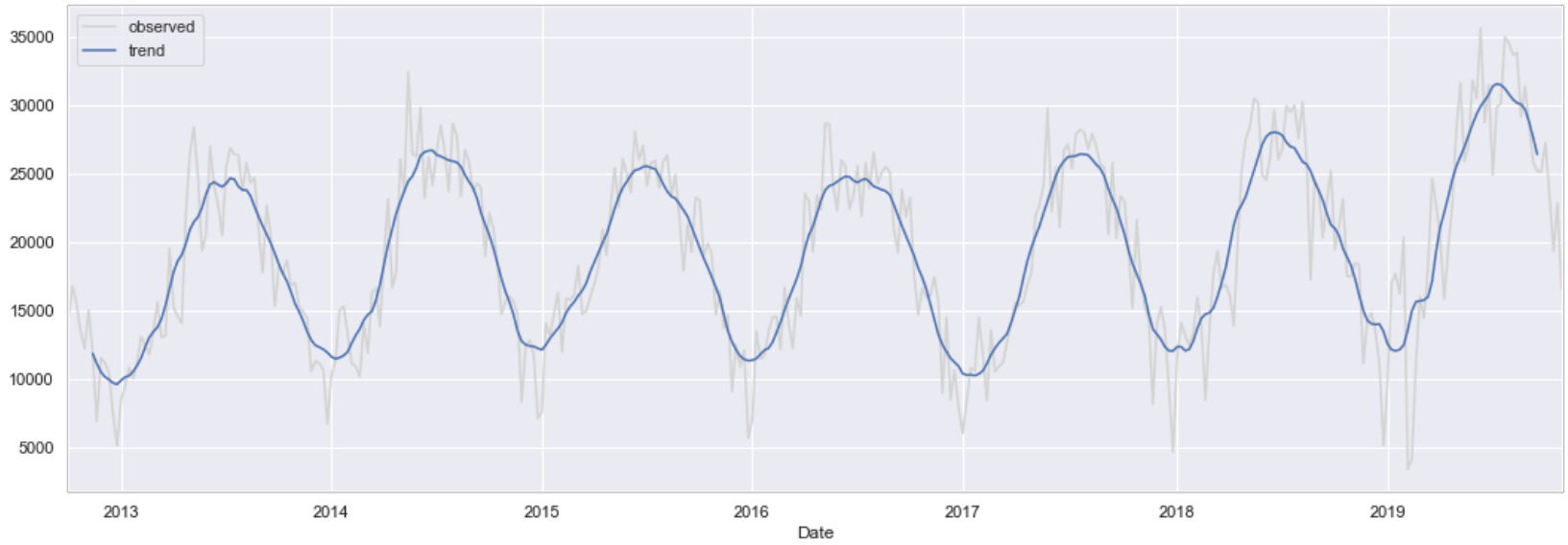
In [56]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
```

In [ ]:
```
```

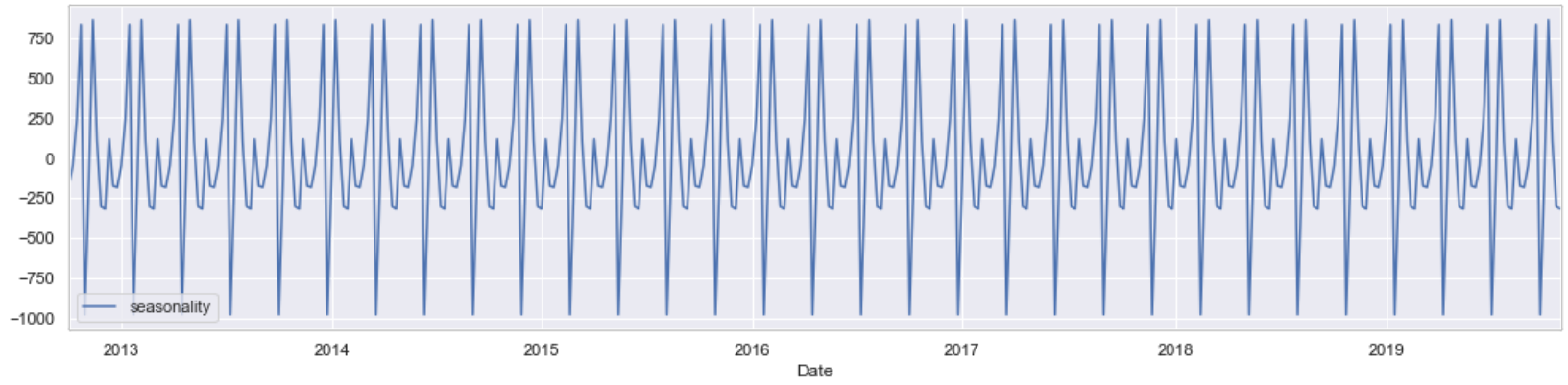
In [57]:
```
decompfreq = 12  # 12 months seasonality
model = 'additive'

decomposition = seasonal_decompose(weekly['Total'].interpolate("linear"),
                                   freq=decompfreq, model=model)
```

In [58]:
```
trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid
```

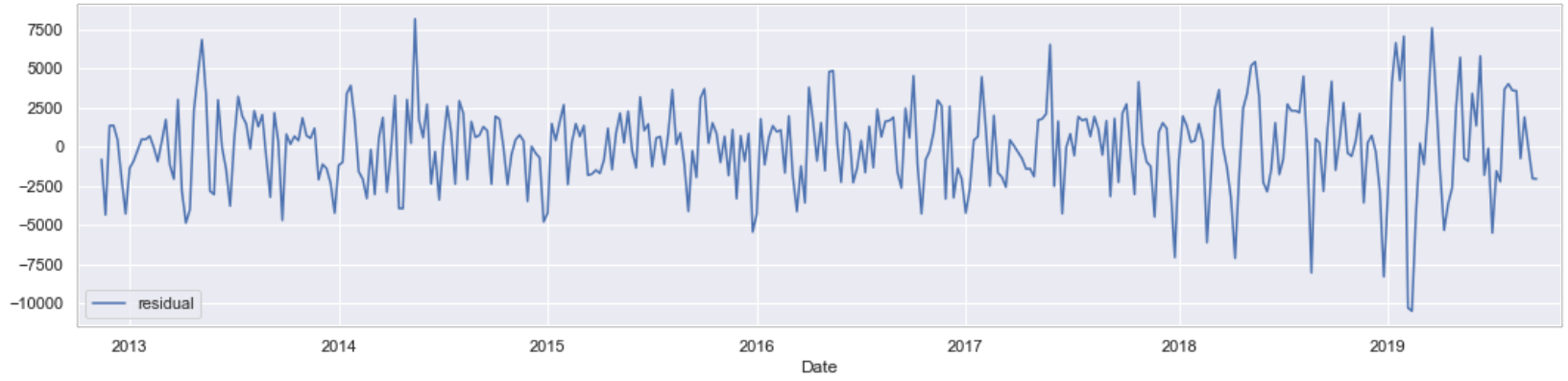
In [59]:
```
fig, ax = plt.subplots(figsize=(18,6))
weekly['Total'].plot(ax=ax, label="observed", c='lightgrey')
trend.plot(ax=ax, label="trend")
plt.legend(loc='upper left');
```



In [60]:
```
fig, ax = plt.subplots(figsize=(18,4))
seasonal.plot(ax=ax, label="seasonality")
plt.legend(loc='lower left');
```



In [61]:
```
fig, ax = plt.subplots(figsize=(18,4))
residual.plot(ax=ax, label="residual")
plt.legend(loc='lower left');
```



In [ ]: