Elements Of Data Science - F2021

# Week 12: Time Series, Imbalanced Classes, Data Processing and Delivery

12/6/2021

# TODOs

- Readings:
  - Recommended: DSFS: Chap 23: Databases and SQL
  - Final Review Sheet
- HW4, **Due Saturday December 11th 11:59pm ET**
- Quiz 11, **Due Sunday December 12th, 11:59pm ET**
- Final
  - Released Monday night December 13th, 11:59pm
  - **Due Wednesday December 15th, 11:59pm ET**
  - Have 24hrs after starting exam to finish
  - 30-40 questions (fill in the blank/multiple choice/short answer)
  - Online via Gradescope
  - Questions asked/answered **privately** via Ed
  - Open-book, open-note, open-python

# Today

- Finish Time Series
- Imbalanced Classes
- Data processing and delivery

# Questions?

# Environment Setup

# Environment Setup

In [1]:
```
import numpy
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

sns.set_style('darkgrid')
%matplotlib inline
```

# Time Series in Python so far:

- `datetime .date .time .datetime .timedelta`
- format with `.strftime()`
- parse time with `pd.to_datetime()`
- `pandas Timestamp Timedelta DatetimeIndex`
- Indexing with `DatetimeIndex`
- Frequencies
- Timezones

Next: Operations on Time Series data

- Shifting
- Resampling
- Moving Windows

# Shifting

- Moving data backward or forward in time (lagging/leading)
- Ex: calculate percent change

# Shifting

- Moving data backward or forward in time (lagging/leading)
- Ex: calculate percent change

In [2]:
```
ts = pd.Series([1,2,8],
               index=pd.date_range('1/1/2019',periods=3,freq='M'))
ts
```

Out[2]:
```
2019-01-31    1
2019-02-28    2
2019-03-31    8
Freq: M, dtype: int64
```

# Shifting

- Moving data backward or forward in time (lagging/leading)
- Ex: calculate percent change

In [2]:
```
ts = pd.Series([1,2,8],
               index=pd.date_range('1/1/2019',periods=3,freq='M'))
ts
```

Out[2]:
```
2019-01-31    1
2019-02-28    2
2019-03-31    8
Freq: M, dtype: int64
```

In [3]:
```
ts.shift(1) # last month's value
```

Out[3]:
```
2019-01-31    NaN
2019-02-28    1.0
2019-03-31    2.0
Freq: M, dtype: float64
```

# Shifting

- **percent change** :
    - (new_value - old_value) / old_value
    - (new_value / old_value) - 1

# Shifting

- **percent change :**
    - (new_value - old_value) / old_value
    - (new_value / old_value) - 1

In [4]:
```python
#  multiply by 100 to turn into a percent
((ts / ts.shift(1)) - 1) * 100
```

Out[4]:
```
2019-01-31      NaN
2019-02-28    100.0
2019-03-31    300.0
Freq: M, dtype: float64
```

# Example Dataset: Twitter Stock

# Example Dataset: Twitter Stock

In [5]:
```
#from pandas_datareader import data
#df_twtr = data.DataReader('TWTR', start='2015', end='12/3/2021', data_source='yahoo')
#df_twtr.to_csv('../data/twtr_20150102-20211203.csv')
df_twtr = pd.read_csv('../data/twtr_20150102-20211203.csv',parse_dates=['Date'],index_col='Date')
df_twtr.head(3)
```

Out[5]:

| | High | Low | Open | Close | Volume | Adj Close |
|---|---|---|---|---|---|---|
| **Date** | | | | | | |
| **2015-01-02** | 36.740002 | 35.540001 | 36.230000 | 36.560001 | 12062500 | 36.560001 |
| **2015-01-05** | 37.110001 | 35.639999 | 36.259998 | 36.380001 | 15062700 | 36.380001 |
| **2015-01-06** | 39.450001 | 36.040001 | 36.270000 | 38.759998 | 33050800 | 38.759998 |

# Example Dataset: Twitter Stock

In [5]:
```
#from pandas_datareader import data
#df_twtr = data.DataReader('TWTR', start='2015', end='12/3/2021', data_source='yahoo')
#df_twtr.to_csv('../data/twtr_20150102-20211203.csv')
df_twtr = pd.read_csv('../data/twtr_20150102-20211203.csv',parse_dates=['Date'],index_col='Date')
df_twtr.head(3)
```

Out[5]:

| Date | High | Low | Open | Close | Volume | Adj Close |
|---|---|---|---|---|---|---|
| **2015-01-02** | 36.740002 | 35.540001 | 36.230000 | 36.560001 | 12062500 | 36.560001 |
| **2015-01-05** | 37.110001 | 35.639999 | 36.259998 | 36.380001 | 15062700 | 36.380001 |
| **2015-01-06** | 39.450001 | 36.040001 | 36.270000 | 38.759998 | 33050800 | 38.759998 |

In [6]:
```
df_twtr.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1744 entries, 2015-01-02 to 2021-12-03
Data columns (total 6 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   High       1744 non-null   float64
 1   Low        1744 non-null   float64
 2   Open       1744 non-null   float64
 3   Close      1744 non-null   float64
 4   Volume     1744 non-null   int64  
 5   Adj Close  1744 non-null   float64
dtypes: float64(5), int64(1)
memory usage: 95.4 KB
```

# Example Dataset: Twitter Stock

# Example Dataset: Twitter Stock

In [7]:
```
fig,ax = plt.subplots(1,1,figsize=(24,10))
df_twtr[['Close']].plot(ax=ax,marker='x');
ax.set_ylabel('stock price');
```

# Shifting Example: Percent Change Twitter Close

# Shifting Example: Percent Change Twitter Close

In [8]:
```
((df_twtr.Close / df_twtr.Close.shift(1)) - 1).tail(3) # # (today / yesterday) - 1
```

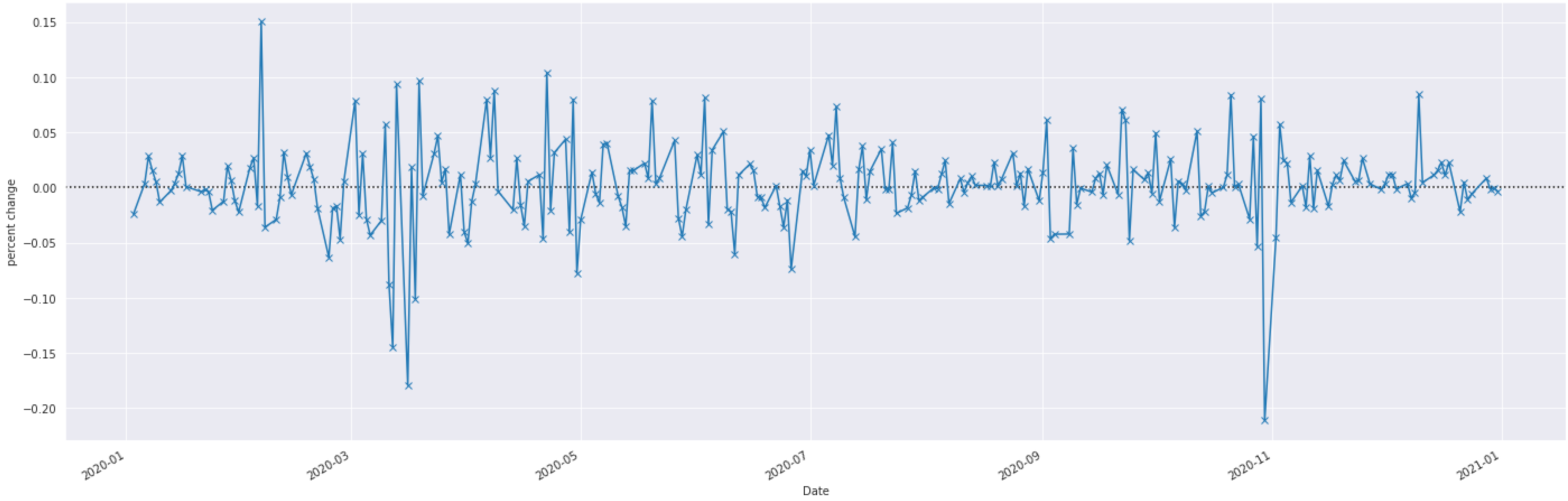
Out[8]:
```
Date
2021-12-01   -0.025489
2021-12-02   -0.003970
2021-12-03   -0.013599
Name: Close, dtype: float64
```

# Shifting Example: Percent Change Twitter Close

In [8]:
```
((df_twtr.Close / df_twtr.Close.shift(1)) - 1).tail(3) # # (today / yesterday) - 1
```

Out[8]:
```
Date
2021-12-01   -0.025489
2021-12-02   -0.003970
2021-12-03   -0.013599
Name: Close, dtype: float64
```

In [9]:
```
# plot percent change of close in 2020
fig,ax = plt.subplots(1,1,figsize=(24,8))
close_2020 = df_twtr.loc['2020','Close']
((close_2020 / close_2020.shift(1)) - 1 ).plot(marker='x',ax=ax,zorder=2);
ax.axhline(ls=':',c='k',zorder=1)
ax.set_ylabel('percent change');
```



# Resampling

- Convert from one frequency to another
- **Downsampling**
  - from higher to lower (day to month)
  - need to aggregate
- **Upsampling**
  - from lower to higher (month to day)
  - need to fill missing
- **Can also be used to set frequency from None**

# Resampling: Initialize Frequency

# Resampling: Initialize Frequency

In [10]:
```
df_twtr.index
```

Out[10]:
```
DatetimeIndex(['2015-01-02', '2015-01-05', '2015-01-06', '2015-01-07',
               '2015-01-08', '2015-01-09', '2015-01-12', '2015-01-13',
               '2015-01-14', '2015-01-15',
               ...
               '2021-11-19', '2021-11-22', '2021-11-23', '2021-11-24',
               '2021-11-26', '2021-11-29', '2021-11-30', '2021-12-01',
               '2021-12-02', '2021-12-03'],
              dtype='datetime64[ns]', name='Date', length=1744, freq=None)
```

# Resampling: Initialize Frequency

In [10]:
```
df_twtr.index
```

Out[10]:
```
DatetimeIndex(['2015-01-02', '2015-01-05', '2015-01-06', '2015-01-07',
               '2015-01-08', '2015-01-09', '2015-01-12', '2015-01-13',
               '2015-01-14', '2015-01-15',
               ...
               '2021-11-19', '2021-11-22', '2021-11-23', '2021-11-24',
               '2021-11-26', '2021-11-29', '2021-11-30', '2021-12-01',
               '2021-12-02', '2021-12-03'],
              dtype='datetime64[ns]', name='Date', length=1744, freq=None)
```

In [11]:
```
df_twtr_B = df_twtr.resample('B').asfreq() # set frequency to business day
df_twtr_B.index
```

Out[11]:
```
DatetimeIndex(['2015-01-02', '2015-01-05', '2015-01-06', '2015-01-07',
               '2015-01-08', '2015-01-09', '2015-01-12', '2015-01-13',
               '2015-01-14', '2015-01-15',
               ...
               '2021-11-22', '2021-11-23', '2021-11-24', '2021-11-25',
               '2021-11-26', '2021-11-29', '2021-11-30', '2021-12-01',
               '2021-12-02', '2021-12-03'],
              dtype='datetime64[ns]', name='Date', length=1806, freq='B')
```

# Resampling: Downsampling

- Go from higher/shorter to lower/longer
- Need to aggregate (like groupby)
- Example: Downsampling from business day to business quarter

# Resampling: Downsampling

- Go from higher/shorter to lower/longer
- Need to aggregate (like groupby)
- Example: Downsampling from business day to business quarter

In [12]:
```
df_twtr_BQ = df_twtr_B.resample('BQ')
df_twtr_BQ
```

Out[12]:
```
<pandas.core.resample.DatetimeIndexResampler object at 0x7f88c261bb80>
```

# Resampling: Downsampling

- Go from higher/shorter to lower/longer
- Need to aggregate (like groupby)
- Example: Downsampling from business day to business quarter

In [12]:
```
df_twtr_BQ = df_twtr_B.resample('BQ')
df_twtr_BQ
```

Out[12]:
```
<pandas.core.resample.DatetimeIndexResampler object at 0x7f88c261bb80>
```

In [13]:
```
str(df_twtr_BQ)
```

Out[13]:
```
'DatetimeIndexResampler [freq=<BusinessQuarterEnd: startingMonth=12>, axis=0, closed=right, label=right, convention=start, orig
in=start_day]'
```

# Resampling: Downsampling

- Go from higher/shorter to lower/longer
- Need to aggregate (like groupby)
- Example: Downsampling from business day to business quarter

In [12]:
```
df_twtr_BQ = df_twtr_B.resample('BQ')
df_twtr_BQ
```

Out[12]:
```
<pandas.core.resample.DatetimeIndexResampler object at 0x7f88c261bb80>
```

In [13]:
```
str(df_twtr_BQ)
```

Out[13]:
```
'DatetimeIndexResampler [freq=<BusinessQuarterEnd: startingMonth=12>, axis=0, closed=right, label=right, convention=start, orig
in=start_day]'
```

In [14]:
```
df_twtr_BQ.mean().head(3)
```

Out[14]:

| | High | Low | Open | Close | Volume | Adj Close |
|---|---|---|---|---|---|---|
| **Date** | | | | | | |
| **2015-03-31** | 45.080328 | 43.552459 | 44.228688 | 44.335574 | 2.084619e+07 | 44.335574 |
| **2015-06-30** | 41.634921 | 40.385079 | 41.173492 | 40.874603 | 2.232030e+07 | 40.874603 |
| **2015-09-30** | 30.638281 | 29.420625 | 30.047812 | 30.000625 | 2.031210e+07 | 30.000625 |

# Resampling: Downsampling

# Resampling: Downsampling

In [15]:
```
fig,ax = plt.subplots(1,1,figsize=(24,8))
df_twtr_B.Close.plot(style='-', label='by B',ax=ax)
df_twtr_BQ.Close.mean().plot(style='--',marker='x',label='by BQ',ax=ax)
plt.legend(loc='upper right');
```

# Resampling: Upsampling

- Go from lower/longer to higher/shorter
- Need to decide how to handle missing values
- Example: Upsample from business day to hour

# Resampling: Upsampling

- Go from lower/longer to higher/shorter
- Need to decide how to handle missing values
- Example: Upsample from business day to hour

In [16]:
```
df_twtr_B.index[:3]
```

Out[16]:
```
DatetimeIndex(['2015-01-02', '2015-01-05', '2015-01-06'], dtype='datetime64[ns]', name='Date', freq='B')
```

# Resampling: Upsampling

- Go from lower/longer to higher/shorter
- Need to decide how to handle missing values
- Example: Upsample from business day to hour

In [16]:
```
df_twtr_B.index[:3]
```

Out[16]:
```
DatetimeIndex(['2015-01-02', '2015-01-05', '2015-01-06'], dtype='datetime64[ns]', name='Date', freq='B')
```

In [17]:
```
df_twtr_B.Close.resample('H').asfreq().iloc[0:3]
```

Out[17]:
```
Date
2015-01-02 00:00:00    36.560001
2015-01-02 01:00:00          NaN
2015-01-02 02:00:00          NaN
Freq: H, Name: Close, dtype: float64
```

# Resampling: Upsampling

- Go from lower/longer to higher/shorter
- Need to decide how to handle missing values
- Example: Upsample from business day to hour

In [16]:
```
df_twtr_B.index[:3]
```

Out[16]:
```
DatetimeIndex(['2015-01-02', '2015-01-05', '2015-01-06'], dtype='datetime64[ns]', name='Date', freq='B')
```

In [17]:
```
df_twtr_B.Close.resample('H').asfreq().iloc[0:3]
```

Out[17]:
```
Date
2015-01-02 00:00:00    36.560001
2015-01-02 01:00:00          NaN
2015-01-02 02:00:00          NaN
Freq: H, Name: Close, dtype: float64
```

In [18]:
```
df_twtr_B.Close.resample('H').asfreq().iloc[70:73]
```

Out[18]:
```
Date
2015-01-04 22:00:00          NaN
2015-01-04 23:00:00          NaN
2015-01-05 00:00:00    36.380001
Freq: H, Name: Close, dtype: float64
```

# Resampling: Upsampling

- `ffill()` : Forward Fill

# Resampling: Upsampling

- `ffill()` : Forward Fill

In [19]:
```
df_twtr_B.Close.resample('H').ffill().head(3)
```

Out[19]:
```
Date
2015-01-02 00:00:00    36.560001
2015-01-02 01:00:00    36.560001
2015-01-02 02:00:00    36.560001
Freq: H, Name: Close, dtype: float64
```

# Resampling: Upsampling

- `ffill()` : Forward Fill

In [19]:
```
df_twtr_B.Close.resample('H').ffill().head(3)
```

Out[19]:
```
Date
2015-01-02 00:00:00    36.560001
2015-01-02 01:00:00    36.560001
2015-01-02 02:00:00    36.560001
Freq: H, Name: Close, dtype: float64
```

- `bfill()`: Backward Fill

# Resampling: Upsampling

- `ffill()` : Forward Fill

In [19]:
```
df_twtr_B.Close.resample('H').ffill().head(3)
```

Out[19]:
```
Date
2015-01-02 00:00:00    36.560001
2015-01-02 01:00:00    36.560001
2015-01-02 02:00:00    36.560001
Freq: H, Name: Close, dtype: float64
```

- `bfill()` : Backward Fill

In [20]:
```
df_twtr_B.Close.resample('H').bfill().head(3)
```

Out[20]:
```
Date
2015-01-02 00:00:00    36.560001
2015-01-02 01:00:00    36.380001
2015-01-02 02:00:00    36.380001
Freq: H, Name: Close, dtype: float64
```

# Moving/Rolling Windows

- Apply function on a fixed window moving across time
- Method of smoothing out the data
- **center** : place values at center of window

# Moving/Rolling Windows

- Apply function on a fixed window moving across time
- Method of smoothing out the data
- **center** : place values at center of window

In [21]:
```
df_twtr_B.Close['2020-11-02':'2020-11-06']
```

Out[21]:
```
Date
2020-11-02    39.470001
2020-11-03    41.730000
2020-11-04    42.759998
2020-11-05    43.709999
2020-11-06    43.119999
Freq: B, Name: Close, dtype: float64
```

# Moving/Rolling Windows

- Apply function on a fixed window moving across time
- Method of smoothing out the data
- **center** : place values at center of window

In [21]:
```
df_twtr_B.Close['2020-11-02':'2020-11-06']
```

Out[21]:
```
Date
2020-11-02    39.470001
2020-11-03    41.730000
2020-11-04    42.759998
2020-11-05    43.709999
2020-11-06    43.119999
Freq: B, Name: Close, dtype: float64
```

In [22]:
```
rolling = df_twtr_B.Close.rolling(5, center=True)
rolling
```

Out[22]:
```
Rolling [window=5,center=True,axis=0,method=single]
```

# Moving/Rolling Windows

- Apply function on a fixed window moving across time
- Method of smoothing out the data
- **center** : place values at center of window

In [21]:
```
df_twtr_B.Close['2020-11-02':'2020-11-06']
```

Out[21]:
```
Date
2020-11-02    39.470001
2020-11-03    41.730000
2020-11-04    42.759998
2020-11-05    43.709999
2020-11-06    43.119999
Freq: B, Name: Close, dtype: float64
```

In [22]:
```
rolling = df_twtr_B.Close.rolling(5, center=True)
rolling
```

Out[22]:
```
Rolling [window=5,center=True,axis=0,method=single]
```

In [23]:
```
rolling.mean()['2020-11-02':'2020-11-06']
```

Out[23]:
```
Date
2020-11-02    43.550000
2020-11-03    41.806000
2020-11-04    42.157999
2020-11-05    42.901999
2020-11-06    43.037999
Freq: B, Name: Close, dtype: float64
```

# Moving Windows

# Moving Windows

In [24]:
```
sns.set_style("whitegrid")
fig,ax = plt.subplots(1,1,figsize=(24,8));
df_twtr_B.loc['2020'].Close.plot(style='-',alpha=0.3,label='business day');
rolling.mean().loc['2020'].plot(style='--',label='5 day rolling window mean');
(rolling.mean().loc['2020'] + 2*rolling.std().loc['2020']).plot(style=':',c='g',label='_nolegend_');
(rolling.mean().loc['2020'] - 2*rolling.std().loc['2020']).plot(style=':',c='g',label='_nolegend_');
ax.legend();
```

# Example: Bike Travel (From PDSH Chapter 3.11)

- Bicycle traffic over Fremont Bridge in Seattle in 2012
- Data gathered using: `!curl -o ../data/FremontBridge.csv https://data.seattle.gov/api/views/65db-xm6k/rows.csv?accessType=DOWNLOAD`

# Example: Bike Travel (From PDSH Chapter 3.11)

- Bicycle traffic over Fremont Bridge in Seattle in 2012
- Data gathered using: `!curl -o ../data/FremontBridge.csv https://data.seattle.gov/api/views/65db-xm6k/rows.csv?accessType=DOWNLOAD`

In [25]:
```
df_bike = pd.read_csv('../data/FremontBridge_2015-2017.csv',parse_dates=['Date'],index_col='Date')
df_bike.columns = ['Total','East','West']
df_bike.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 52608 entries, 2015-01-01 00:00:00 to 2017-12-31 23:00:00
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Total   52598 non-null  float64
 1   East    52598 non-null  float64
 2   West    52598 non-null  float64
dtypes: float64(3)
memory usage: 1.6 MB
```

# Example: Bike Travel (From PDSH Chapter 3.11)

- Bicycle traffic over Fremont Bridge in Seattle in 2012
- Data gathered using: `!curl -o ../data/FremontBridge.csv https://data.seattle.gov/api/views/65db-xm6k/rows.csv?accessType=DOWNLOAD`

In [25]:
```
df_bike = pd.read_csv('../data/FremontBridge_2015-2017.csv',parse_dates=['Date'],index_col='Date')
df_bike.columns = ['Total','East','West']
df_bike.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 52608 entries, 2015-01-01 00:00:00 to 2017-12-31 23:00:00
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Total   52598 non-null  float64
 1   East    52598 non-null  float64
 2   West    52598 non-null  float64
dtypes: float64(3)
memory usage: 1.6 MB
```

In [26]:
```
df_bike.head(3)
```

Out[26]:

| Date | Total | East | West |
|---|---|---|---|
| 2015-01-01 00:00:00 | 13.0 | 4.0 | 9.0 |
| 2015-01-01 01:00:00 | 27.0 | 4.0 | 23.0 |
| 2015-01-01 02:00:00 | 19.0 | 5.0 | 14.0 |

# Example: Fill Missing Values

# Example: Fill Missing Values

In [27]:
```
f'proportion missing: {sum(df_bike.Total.isna()) / len(df_bike):0.5f}'
```

Out[27]:
```
'proportion missing: 0.00019'
```

# Example: Fill Missing Values

In [27]:
```
f'proportion missing: {sum(df_bike.Total.isna()) / len(df_bike):0.5f}'
```

Out[27]: 'proportion missing: 0.00019'

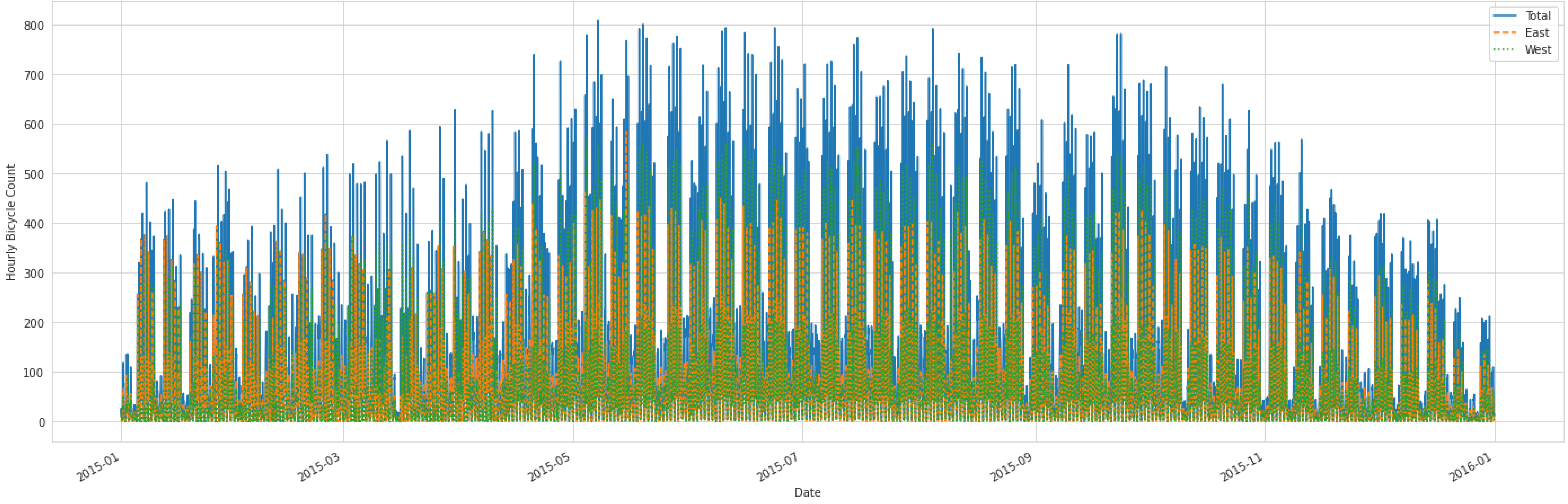
In [28]:
```
df_bike = df_bike.fillna(method='ffill')
display(df_bike.head(3))
```

| | Total | East | West |
|---|---|---|---|
| **Date** | | | |
| **2015-01-01 00:00:00** | 13.0 | 4.0 | 9.0 |
| **2015-01-01 01:00:00** | 27.0 | 4.0 | 23.0 |
| **2015-01-01 02:00:00** | 19.0 | 5.0 | 14.0 |

# Plot data from 2015

# Plot data from 2015

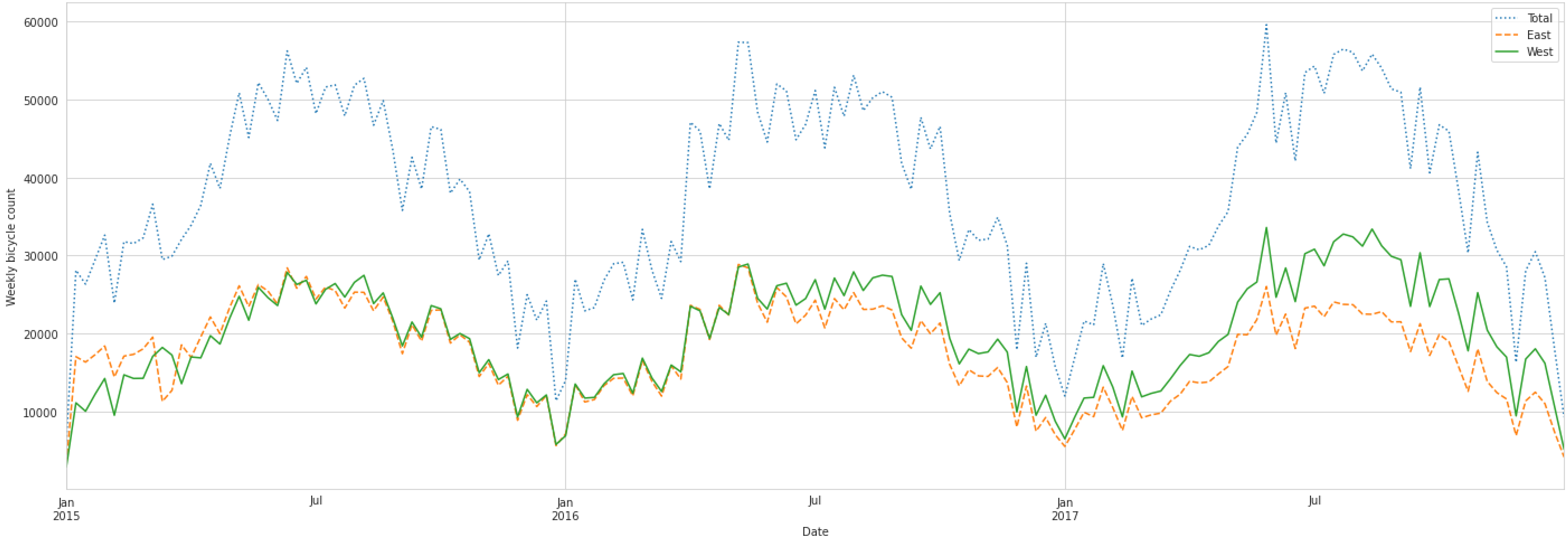
In [29]:
```
fig,ax = plt.subplots(1,1,figsize=(24,8))
df_bike.loc['2015'].plot(style=['-', '--', ':'],ax=ax)
plt.ylabel('Hourly Bicycle Count');
```



# Downsample to weekly sum to smooth things out

# Downsample to weekly sum to smooth things out

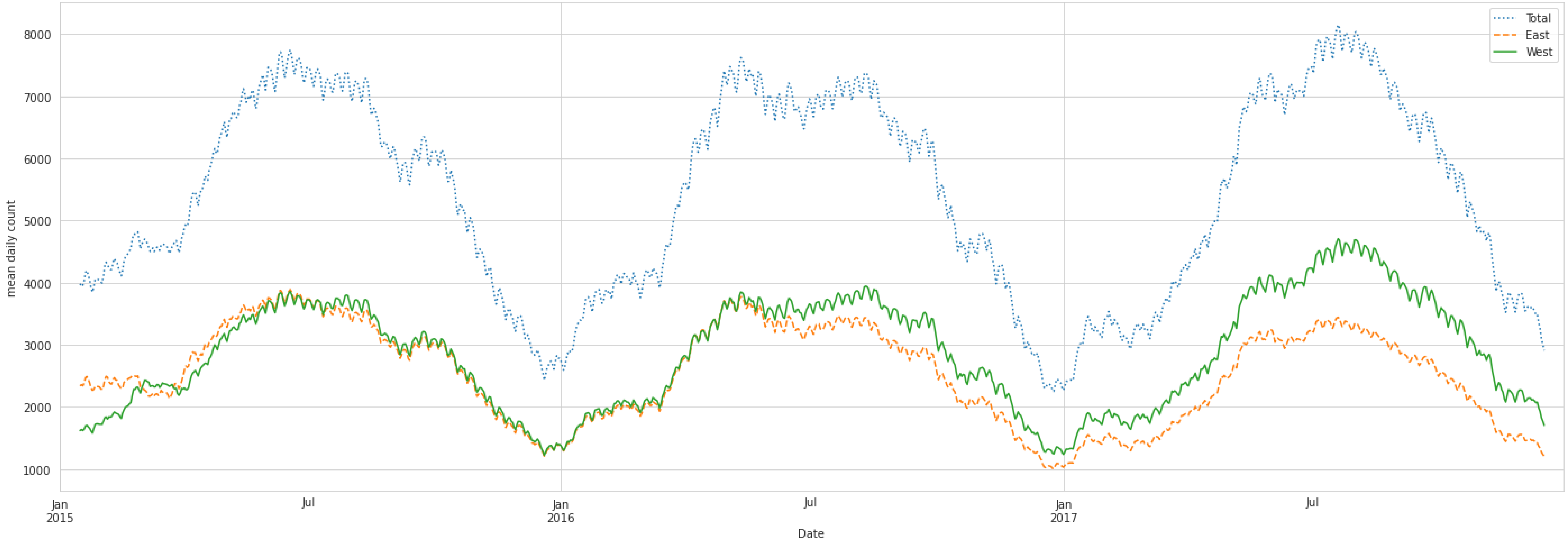
In [30]:
```
weekly = df_bike.resample('W').sum()
weekly.plot(style=[':', '--', '-'], figsize=(24,8))
plt.ylabel('Weekly bicycle count');
```



# Resample at daily for a more granular view and apply a rolling window of 30 days

# Resample at daily for a more granular view and apply a rolling window of 30 days

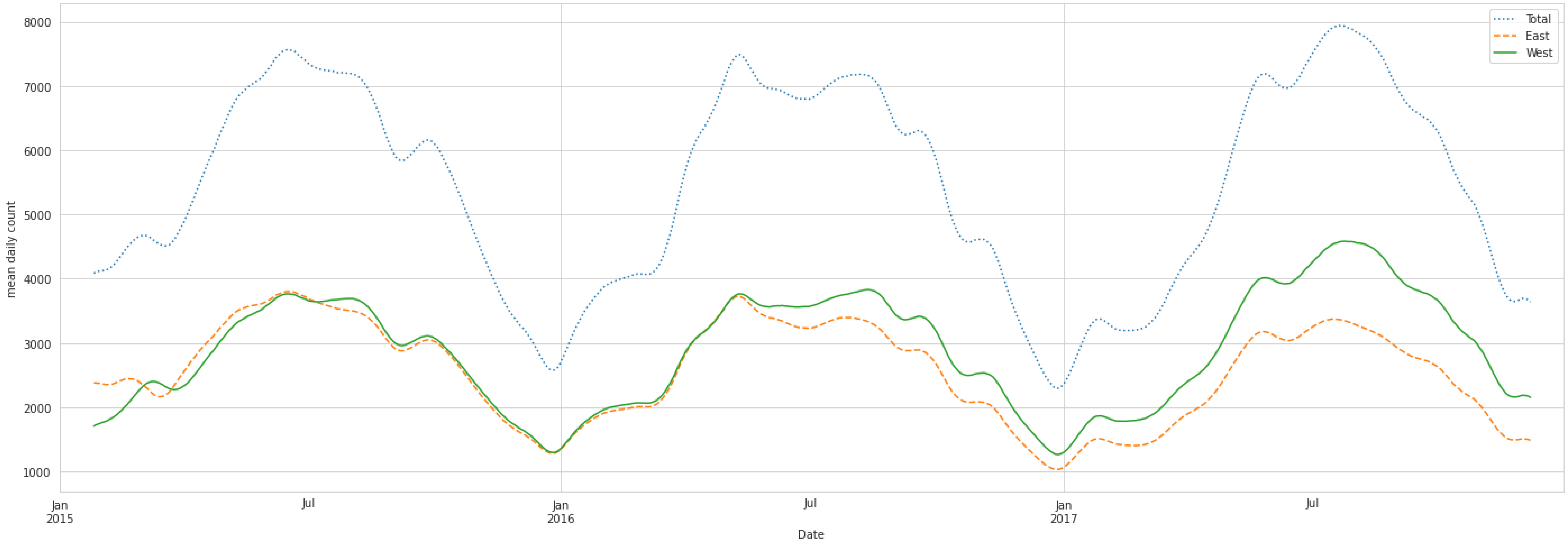
In [31]:
```
daily = df_bike.resample('D').sum()
daily.rolling(30,center=True).mean().plot(style=[':', '--', '-'], figsize=(24,8))
plt.ylabel('mean daily count');
```



# A wider window using a gaussian filter smooths more while accentuating daily differences

# A wider window using a gaussian filter smooths more while accentuating daily differences

In [32]:
```
daily.rolling(50,center=True,win_type='gaussian').mean(std=10).plot(style=[':','--','-'],figsize=(24,8));
plt.ylabel('mean daily count');
```



# From Datetime to Time

# From Datetime to Time

In [33]:
```
#If we want to only look at time of day
df_bike.index.time
```

Out[33]:
```
array([datetime.time(0, 0), datetime.time(1, 0), datetime.time(2, 0), ...,
       datetime.time(21, 0), datetime.time(22, 0), datetime.time(23, 0)],
      dtype=object)
```

# From Datetime to Time

In [33]:
```
#If we want to only look at time of day
df_bike.index.time
```

Out[33]:
```
array([datetime.time(0, 0), datetime.time(1, 0), datetime.time(2, 0), ...,
       datetime.time(21, 0), datetime.time(22, 0), datetime.time(23, 0)],
      dtype=object)
```

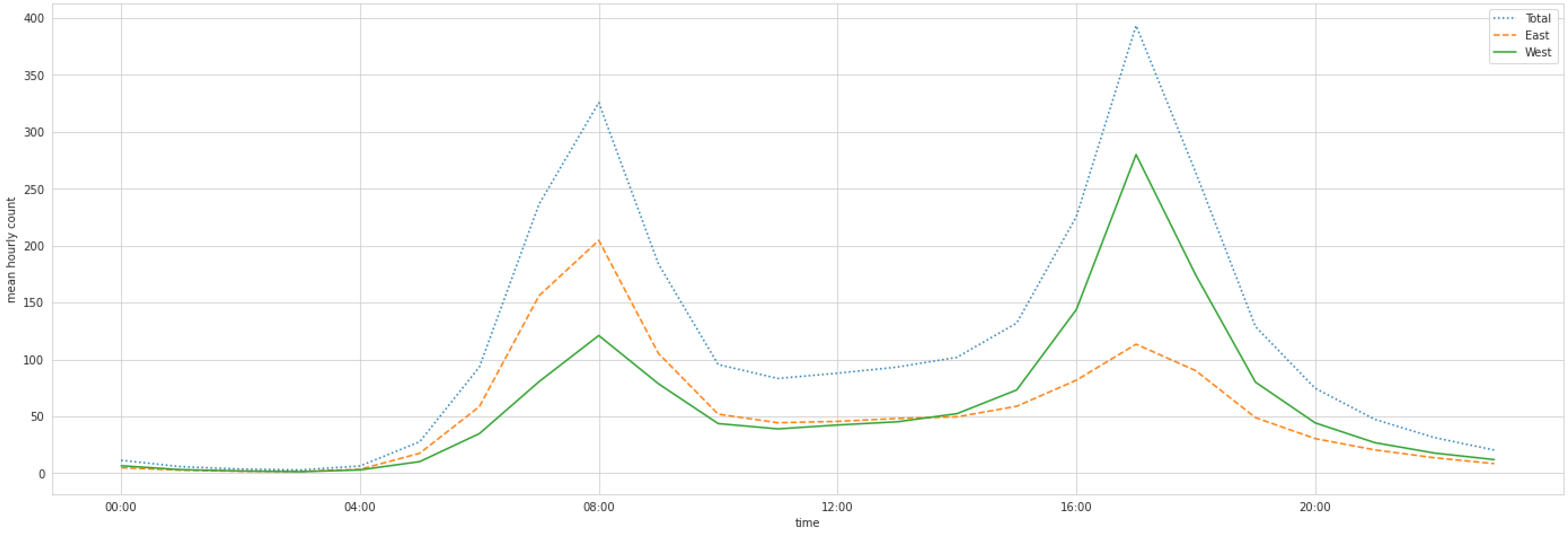
In [34]:
```
#Get mean data by time (hourly)
by_time = df_bike.groupby(df_bike.index.time).mean()
display(by_time)
```

| | Total | East | West |
|---|---|---|---|
| **00:00:00** | 11.319343 | 4.806569 | 6.512774 |
| **01:00:00** | 5.743613 | 2.613139 | 3.130474 |
| **02:00:00** | 3.615876 | 1.687956 | 1.927920 |
| **03:00:00** | 2.850365 | 1.535584 | 1.314781 |
| **04:00:00** | 6.301095 | 3.418796 | 2.882299 |
| **05:00:00** | 27.629562 | 17.487226 | 10.142336 |
| **06:00:00** | 93.326642 | 58.534672 | 34.791971 |
| **07:00:00** | 236.456204 | 155.980839 | 80.475365 |
| **08:00:00** | 325.637774 | 204.628650 | 121.009124 |
| **09:00:00** | 183.750000 | 105.175182 | 78.574818 |
| **10:00:00** | 95.483577 | 51.891423 | 43.592153 |
| **11:00:00** | 83.261861 | 44.340328 | 38.921533 |
| **12:00:00** | 87.883212 | 45.524635 | 42.358577 |
| **13:00:00** | 93.259124 | 48.087591 | 45.171533 |
| **14:00:00** | 101.838504 | 49.528285 | 52.310219 |
| **15:00:00** | 131.947993 | 58.810219 | 73.137774 |
| **16:00:00** | 225.548358 | 81.741788 | 143.806569 |
| **17:00:00** | 393.354015 | 113.352190 | 280.001825 |
| **18:00:00** | 264.122263 | 90.069343 | 174.052920 |
| **19:00:00** | 128.802007 | 48.809307 | 79.992701 |

# Plot by hour of the day

# Plot by hour of the day

In [35]:
```
hourly_ticks = 60 * 60 * 4 * np.arange(6)  # sec * min * every4hours
by_time.plot(xticks=hourly_ticks, style=[':', '--', '-'], figsize=(24,8));
plt.ylabel('mean hourly count');
```

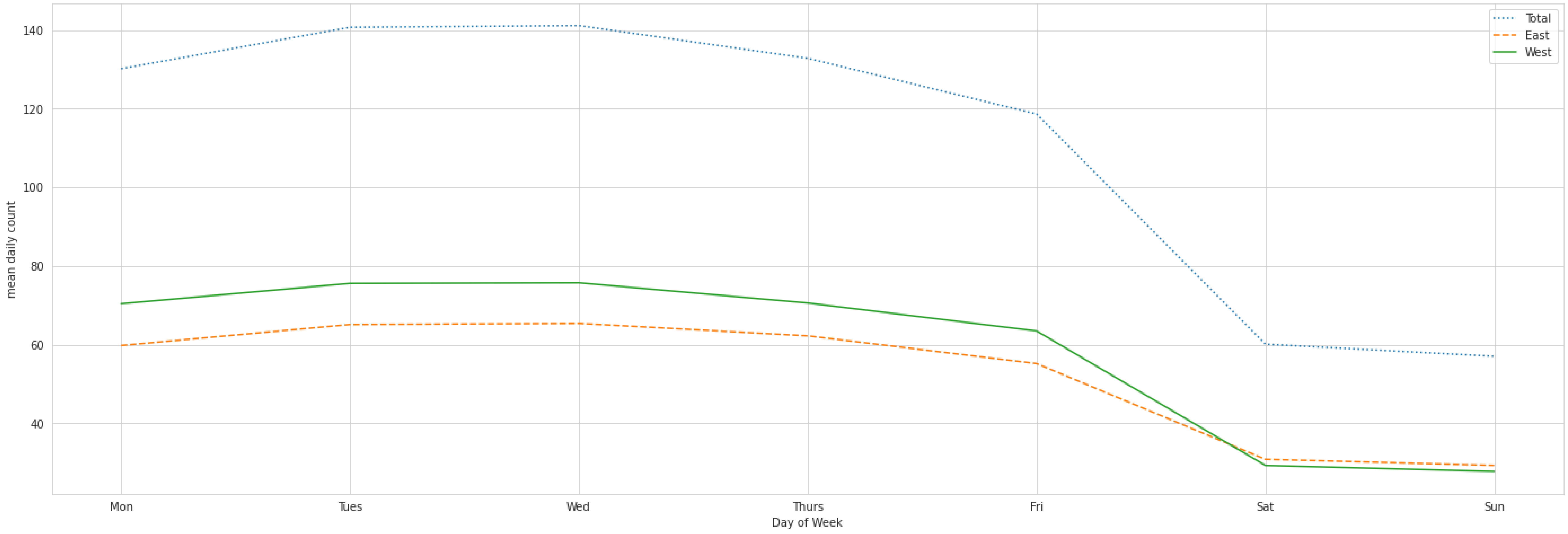


# Can also look at average by day of week

# Can also look at average by day of week

In [36]:

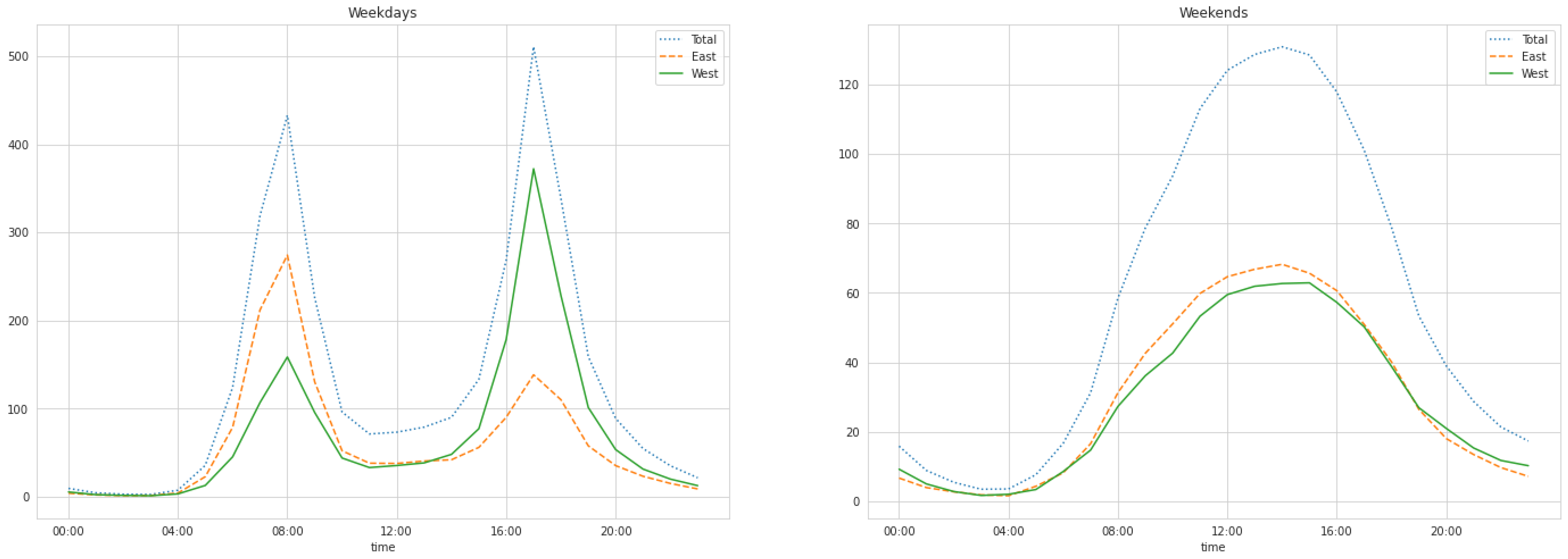
```
# note that for dayofweek: 0 == Mon, 1 == Tues,..., 6 == 'Sun'
by_weekday = df_bike.groupby(df_bike.index.dayofweek).mean()
by_weekday = by_weekday.set_index(pd.Index(['Mon', 'Tues', 'Wed', 'Thurs', 'Fri', 'Sat', 'Sun']))

fig,ax = plt.subplots(1,1,figsize=(24,8))
by_weekday.plot(style=[':', '--', '-'], ax=ax);
ax.set_xlabel('Day of Week');ax.set_ylabel('mean daily count');
```



# Separate out weekdays and weekends

# Separate out weekdays and weekends

In [37]:
```
# create a weekend mask
weekend = np.where(df_bike.index.weekday < 5, 'Weekday', 'Weekend')

# get hourly mean values split by weekday, weekend
by_time = df_bike.groupby([weekend, df_bike.index.time]).mean()
fig, ax = plt.subplots(1, 2, figsize=(24, 8))
by_time.loc['Weekday'].plot(ax=ax[0], title='Weekdays', xticks=hourly_ticks, style=[':', '--', '-'])
by_time.loc['Weekend'].plot(ax=ax[1], title='Weekends', xticks=hourly_ticks, style=[':', '--', '-']);
```



# Can we predict daily Total bike traffic?

# Can we predict daily Total bike traffic?

```
In [38]: bike_counts = pd.read_csv('../data/FremontBridge.csv', index_col='Date', parse_dates=True)
         bike_weather = pd.read_csv('../data/BicycleWeather.csv', index_col='DATE', parse_dates=True)

         bike_counts = bike_counts.loc[:,['Fremont Bridge Total']] # Keep Total as target
         bike_counts.columns = ['Total']
         daily_data = bike_counts.resample('d').sum() # downsample to daily totals
         print(daily_data.head(3))
```

```
             Total
Date
2012-10-03  7042.0
2012-10-04  6950.0
2012-10-05  6296.0
```

# Can we predict daily Total bike traffic?

```
In [38]: bike_counts = pd.read_csv('../data/FremontBridge.csv', index_col='Date', parse_dates=True)
         bike_weather = pd.read_csv('../data/BicycleWeather.csv', index_col='DATE', parse_dates=True)

         bike_counts = bike_counts.loc[:,['Fremont Bridge Total']] # Keep Total as target
         bike_counts.columns = ['Total']
         daily_data = bike_counts.resample('d').sum() # downsample to daily totals
         print(daily_data.head(3))
```

```
             Total
Date
2012-10-03  7042.0
2012-10-04  6950.0
2012-10-05  6296.0
```

# On to Feature Engineering...

# Add 'day of week' one-hot features

# Add 'day of week' one-hot features

In [39]:
```
days = ['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat', 'Sun']
for i in range(7):
    daily_data[days[i]] = (daily_data.index.dayofweek == i).astype(float)
print(daily_data.head(3))
```

```
             Total  Mon  Tue  Wed  Thu  Fri  Sat  Sun
Date
2012-10-03  7042.0  0.0  0.0  1.0  0.0  0.0  0.0  0.0
2012-10-04  6950.0  0.0  0.0  0.0  1.0  0.0  0.0  0.0
2012-10-05  6296.0  0.0  0.0  0.0  0.0  1.0  0.0  0.0
```

# Add 'is it a holiday' dummy feature

# Add 'is it a holiday' dummy feature

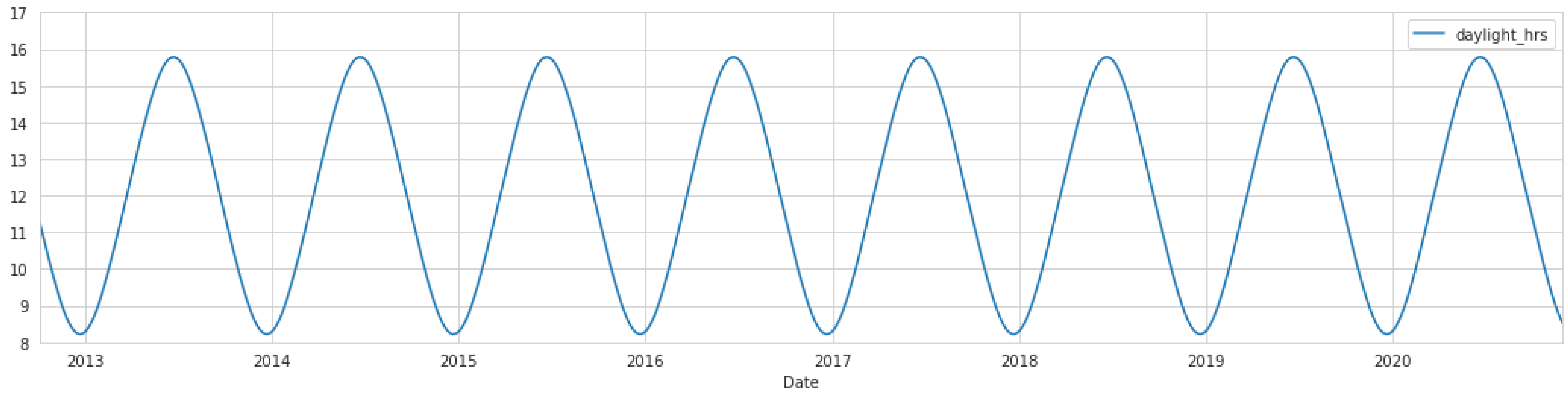
In [40]:
```
from pandas.tseries.holiday import USFederalHolidayCalendar
cal = USFederalHolidayCalendar()
holidays = cal.holidays('2012', '2016')

daily_data = daily_data.join(pd.Series(1, index=holidays, name='holiday'))
daily_data['holiday'].fillna(0, inplace=True)
print(daily_data.head(3))
```

```
             Total  Mon  Tue  Wed  Thu  Fri  Sat  Sun  holiday
Date
2012-10-03  7042.0  0.0  0.0  1.0  0.0  0.0  0.0  0.0      0.0
2012-10-04  6950.0  0.0  0.0  0.0  1.0  0.0  0.0  0.0      0.0
2012-10-05  6296.0  0.0  0.0  0.0  0.0  1.0  0.0  0.0      0.0
```

# Add number of hours of daylight

# Add number of hours of daylight

In [41]:
```
from datetime import datetime

def hours_of_daylight(date, axis=23.44, latitude=47.61):
    """Compute the hours of daylight for the given date"""
    days = (date - datetime(2000, 12, 21)).days
    m = (1. - np.tan(np.radians(latitude))
         * np.tan(np.radians(axis) * np.cos(days * 2 * np.pi / 365.25)))
    return 24. * np.degrees(np.arccos(1 - np.clip(m, 0, 2))) / 180.

daily_data['daylight_hrs'] = list(map(hours_of_daylight, daily_data.index));

daily_data[['daylight_hrs']].plot(figsize=(18,4));
plt.ylim(8, 17);
```



# Add weather information (can we predict this for future dates?)

# Add weather information (can we predict this for future dates?)

In [42]:
```
# temperatures are in 1/10 deg C; convert to C
bike_weather['TMIN'] /= 10
bike_weather['TMAX'] /= 10
bike_weather['Temp (C)'] = 0.5 * (bike_weather['TMIN'] + bike_weather['TMAX'])

# precip is in 1/10 mm; convert to inches
bike_weather['PRCP'] /= 254
bike_weather['dry day'] = (bike_weather['PRCP'] == 0).astype(int)

daily_data = daily_data.join(bike_weather[['PRCP', 'Temp (C)', 'dry day']])
daily_data.head(3)
```

Out[42]:

| Date | Total | Mon | Tue | Wed | Thu | Fri | Sat | Sun | holiday | daylight_hrs | PRCP | Temp (C) | dry day |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **2012-10-03** | 7042.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 11.277359 | 0.0 | 13.35 | 1.0 |
| **2012-10-04** | 6950.0 | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 11.219142 | 0.0 | 13.60 | 1.0 |
| **2012-10-05** | 6296.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 11.161038 | 0.0 | 15.30 | 1.0 |

# Add time of year

# Add time of year

In [43]:
```
daily_data['annual'] = (daily_data.index - daily_data.index[0]).days / 365.
daily_data.head(3)
```

Out[43]:

| | Total | Mon | Tue | Wed | Thu | Fri | Sat | Sun | holiday | daylight_hrs | PRCP | Temp (C) | dry day | annual |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Date** | | | | | | | | | | | | | | |
| **2012-10-03** | 7042.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 11.277359 | 0.0 | 13.35 | 1.0 | 0.000000 |
| **2012-10-04** | 6950.0 | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 11.219142 | 0.0 | 13.60 | 1.0 | 0.002740 |
| **2012-10-05** | 6296.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 11.161038 | 0.0 | 15.30 | 1.0 | 0.005479 |

# Generate a model

# Generate a model

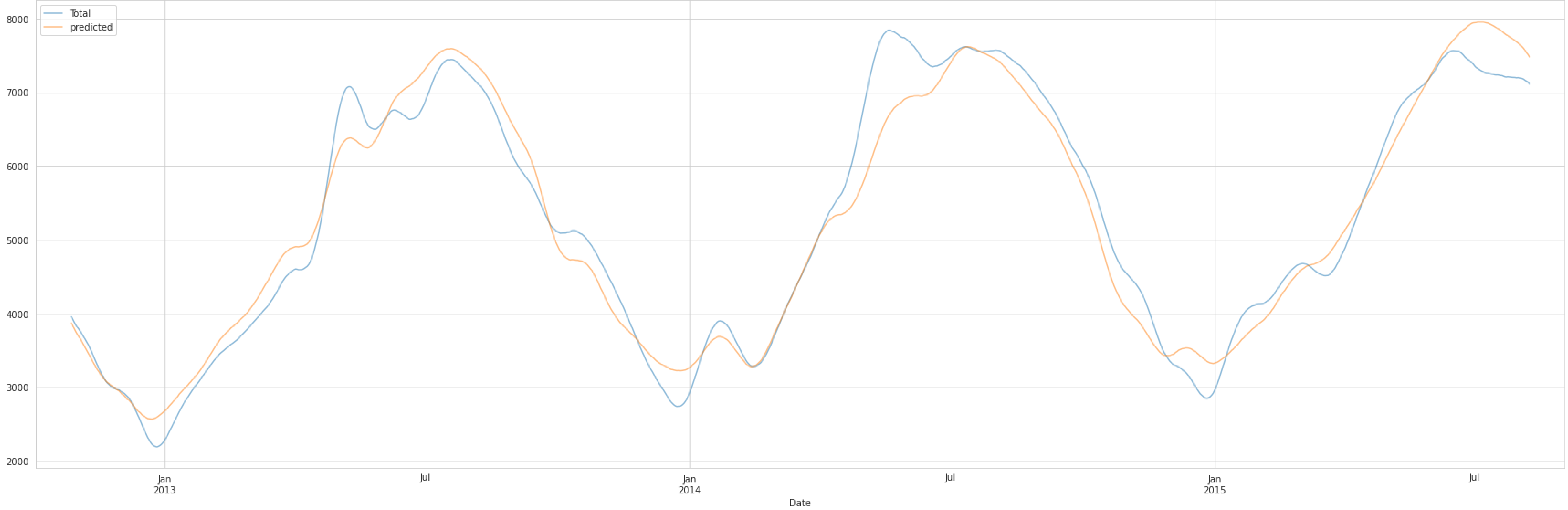
In [44]:
```python
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

# drop any rows with missing data
daily_data.dropna(axis=0, how='any', inplace=True)

X_bike = daily_data[daily_data.columns[daily_data.columns != 'Total']]
y_bike = daily_data.Total

X_bike_train,X_bike_test,y_bike_train,y_bike_test = train_test_split(X_bike,y_bike)

model = LinearRegression(fit_intercept=False)
model.fit(X_bike_train,y_bike_train)
print(f'training set R^2 : {model.score(X_bike_train,y_bike_train):0.2f}')
print(f'test set R^2     : {model.score(X_bike_test,y_bike_test):0.2f}')
```

```
training set R^2 : 0.87
test set R^2     : 0.86
```

# Plot predictions vs observed

# Plot predictions vs observed

In [45]:
```
daily_data['predicted'] = model.predict(X_bike)
daily_data[['Total', 'predicted']].rolling(50, center=True,win_type='gaussian').mean(std=10).plot(alpha=0.5,figsize=(24,8))
plt.tight_layout()
```



# Time Series Operations Review

- Shifting
- Resampling
    - Downsampling
    - Upsampling
- Moving/Rolling Windows

# Questions re Time Series Transformations?

# Imbalanced Classes

- **Imbalanced classes**:
  - when there is significantly more of one class than another in a classification task
- common in real world datasets
- Ex: credit card fraud
  - very small number of fraud transactions relative to total transactions

# Dealing With Imbalanced Classes

- Stratified Sampling
- Random Undersampling
- Random Oversampling
- Oversample Synthetic Minority Items
    - SMOTE
    - ADASYN
- Other methods

# Stratified Sampling

# Stratified Sampling

In [46]:
```
from sklearn.model_selection import StratifiedKFold

X = np.ones(10)
y = [0, 0, 0, 0, 1, 1, 1, 1, 1, 1]

skf = StratifiedKFold(n_splits=3)
for train, test in skf.split(X, y):
     print("%s %s" % (train, test))
```

```
[2 3 6 7 8 9] [0 1 4 5]
[0 1 3 4 5 8 9] [2 6 7]
[0 1 2 4 5 6 7] [3 8 9]
```

# Random Sampling

- Randomly Oversample minority class
- Randomly Undersample majority class

# Example Dataset

# Example Dataset

In [47]:
```
from sklearn.datasets import make_classification
from collections import Counter
X_imb, y_imb = make_classification(n_samples=5000, n_features=2, n_informative=2,
                                   n_redundant=0, n_repeated=0, n_classes=3,
                                   n_clusters_per_class=1,
                                   weights=[0.01, 0.05, 0.94],
                                   class_sep=0.8, random_state=0)
Counter(y_imb).items()
```

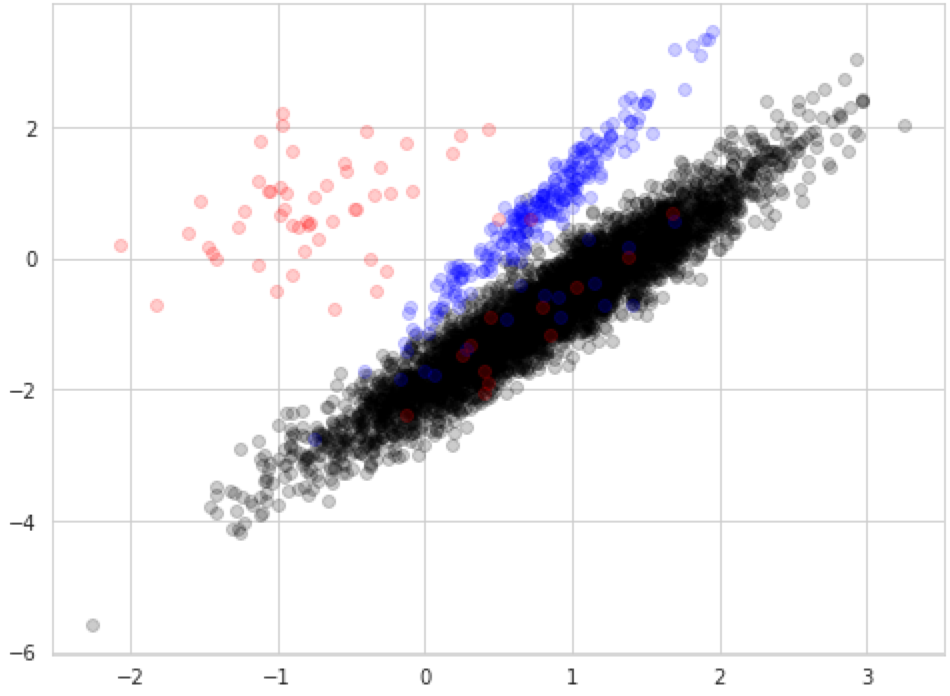
Out[47]:
```
dict_items([(2, 4674), (1, 262), (0, 64)])
```

# Example Dataset

In [47]:
```
from sklearn.datasets import make_classification
from collections import Counter
X_imb, y_imb = make_classification(n_samples=5000, n_features=2, n_informative=2,
                                   n_redundant=0, n_repeated=0, n_classes=3,
                                   n_clusters_per_class=1,
                                   weights=[0.01, 0.05, 0.94],
                                   class_sep=0.8, random_state=0)
Counter(y_imb).items()
```

Out[47]:
```
dict_items([(2, 4674), (1, 262), (0, 64)])
```

In [48]:
```
fig,ax=plt.subplots(1,1,figsize=(8,6))
ax.scatter(X_imb[y_imb==2,0],X_imb[y_imb==2,1],c='k', alpha=.2);
ax.scatter(X_imb[y_imb==1,0],X_imb[y_imb==1,1],c='b', alpha=.2);
ax.scatter(X_imb[y_imb==0,0],X_imb[y_imb==0,1],c='r', alpha=.2);
```



# Using imblearn

- `imblearn` is library to created to deal with imbalanced classes
- need to install from `conda-forge` as `imbalanced-learn`
- import from `imblearn`

# Random Oversampling of minority class

# Random Oversampling of minority class

In [49]:
```
from imblearn.over_sampling import RandomOverSampler

ros = RandomOverSampler(random_state=0)
X_ros, y_ros = ros.fit_resample(X_imb, y_imb)
Counter(y_ros).items()
```

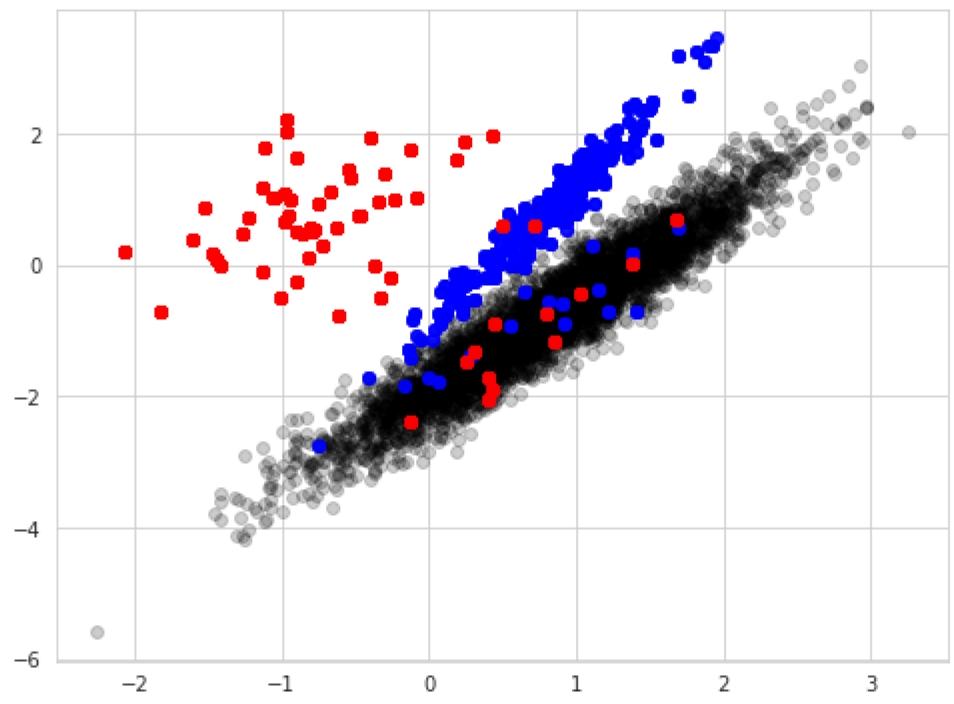
Out[49]:
```
dict_items([(2, 4674), (1, 4674), (0, 4674)])
```

# Random Oversampling of minority class

In [49]:
```
from imblearn.over_sampling import RandomOverSampler

ros = RandomOverSampler(random_state=0)
X_ros, y_ros = ros.fit_resample(X_imb, y_imb)
Counter(y_ros).items()
```

Out[49]:
```
dict_items([(2, 4674), (1, 4674), (0, 4674)])
```

In [50]:
```
fig,ax=plt.subplots(1,1,figsize=(8,6))
ax.scatter(X_ros[y_ros==2,0],X_ros[y_ros==2,1],c='k', alpha=.2);
ax.scatter(X_ros[y_ros==1,0],X_ros[y_ros==1,1],c='b', alpha=.2);
ax.scatter(X_ros[y_ros==0,0],X_ros[y_ros==0,1],c='r', alpha=.2);
```



# Random Undersampling of majority class

# Random Undersampling of majority class

In [51]:
```
from imblearn.under_sampling import RandomUnderSampler

rus = RandomUnderSampler(random_state=0)
X_rus, y_rus, = rus.fit_resample(X_imb, y_imb)
Counter(y_rus).items()
```

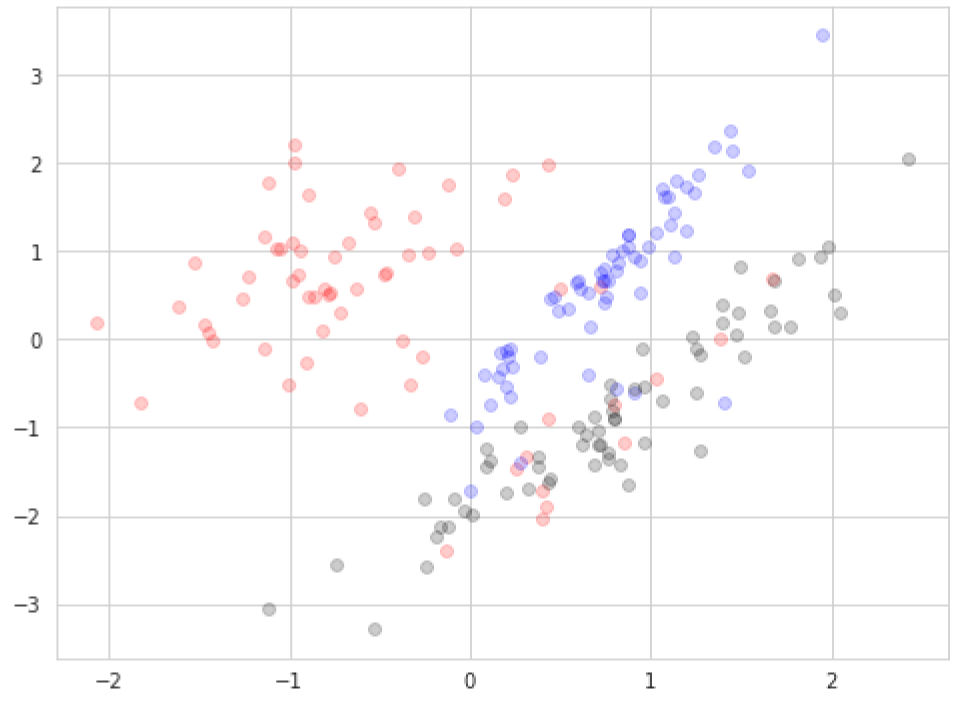
Out[51]:
```
dict_items([(0, 64), (1, 64), (2, 64)])
```

# Random Undersampling of majority class

In [51]:
```
from imblearn.under_sampling import RandomUnderSampler

rus = RandomUnderSampler(random_state=0)
X_rus, y_rus, = rus.fit_resample(X_imb, y_imb)
Counter(y_rus).items()
```

Out[51]:
```
dict_items([(0, 64), (1, 64), (2, 64)])
```

In [52]:
```
fig,ax=plt.subplots(1,1,figsize=(8,6))
ax.scatter(X_rus[y_rus==0,0],X_rus[y_rus==0,1],c='r', alpha=.2);
ax.scatter(X_rus[y_rus==1,0],X_rus[y_rus==1,1],c='b', alpha=.2);
ax.scatter(X_rus[y_rus==2,0],X_rus[y_rus==2,1],c='k', alpha=.2);
```



# Oversample Sythetic Minority Items

- SMOTE: Synthetic Minority Oversampling
- ADASYN: Adaptive Synthetic Minority Oversampling

# SMOTE: Synthetic Minority Oversampling

- Create new synthetic points between existing points

# SMOTE: Synthetic Minority Oversampling

- Create new synthetic points between existing points

In [53]:
```
from imblearn.over_sampling import SMOTE

X_smote, y_smote = SMOTE().fit_resample(X_imb, y_imb)
Counter(y_smote).items()
```

Out[53]:
```
dict_items([(2, 4674), (1, 4674), (0, 4674)])
```

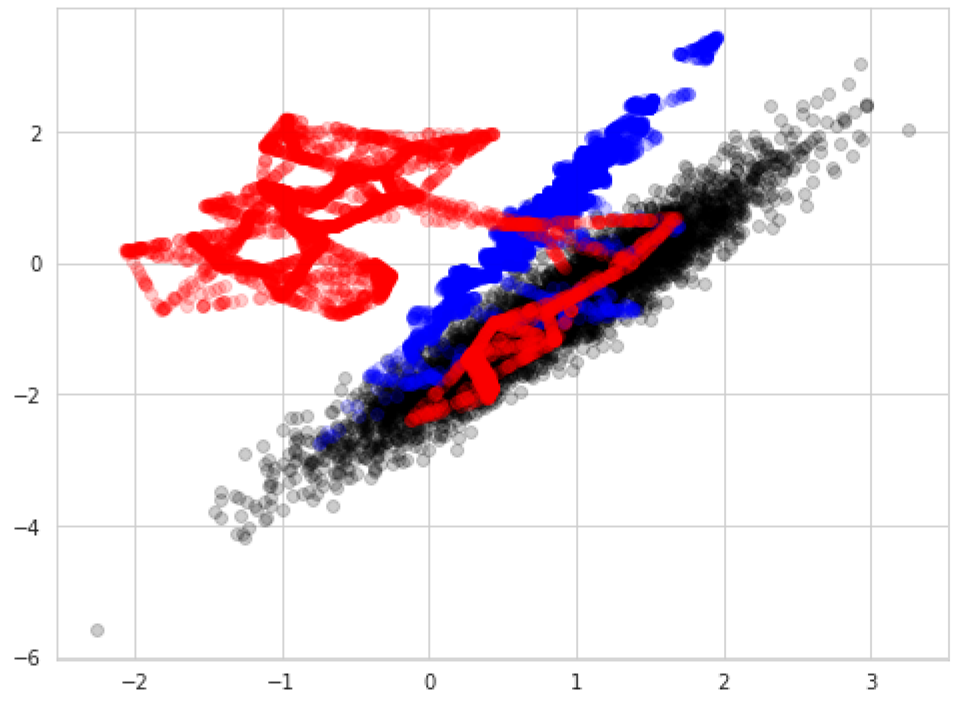
# SMOTE: Synthetic Minority Oversampling

- Create new synthetic points between existing points

In [53]:
```python
from imblearn.over_sampling import SMOTE

X_smote, y_smote = SMOTE().fit_resample(X_imb, y_imb)
Counter(y_smote).items()
```

Out[53]: `dict_items([(2, 4674), (1, 4674), (0, 4674)])`

In [54]:
```python
fig,ax=plt.subplots(1,1,figsize=(8,6))
ax.scatter(X_smote[y_smote==2,0],X_smote[y_smote==2,1],c='k', alpha=.2);
ax.scatter(X_smote[y_smote==1,0],X_smote[y_smote==1,1],c='b', alpha=.2);
ax.scatter(X_smote[y_smote==0,0],X_smote[y_smote==0,1],c='r', alpha=.2);
```



## ADASYN: Adaptive Synthetic Minority Oversampling

- Create new synthetic points between existing points *where classes overlap*

# ADASYN: Adaptive Synthetic Minority Oversampling

- Create new synthetic points between existing points *where classes overlap*

In [55]:
```
from imblearn.over_sampling import ADASYN

X_adasyn, y_adasyn = ADASYN().fit_resample(X_imb, y_imb)
Counter(y_adasyn).items()
```

Out[55]:
```
dict_items([(2, 4674), (1, 4662), (0, 4673)])
```

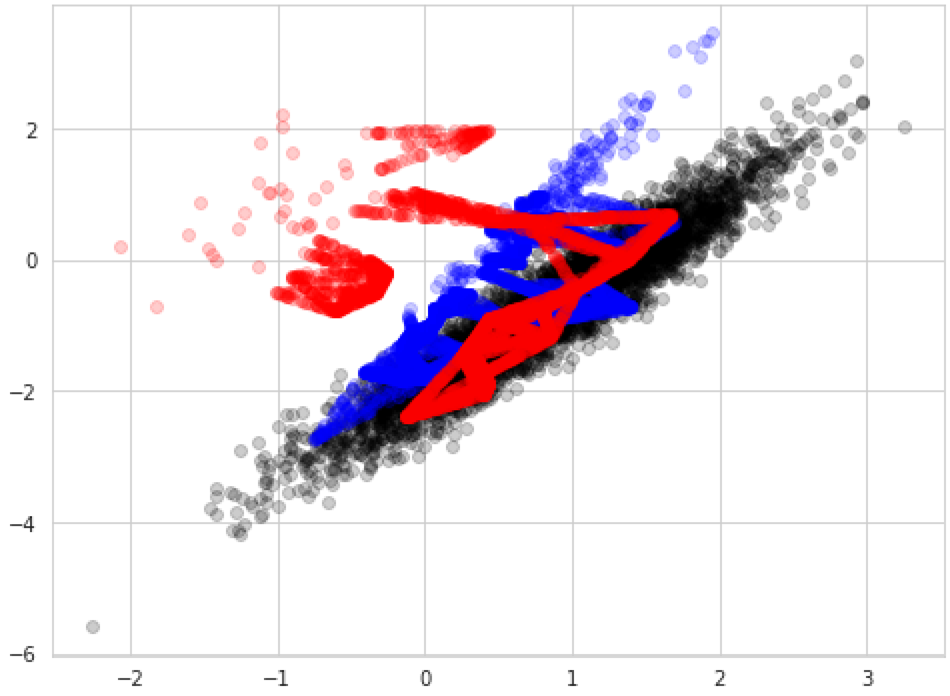
# ADASYN: Adaptive Synthetic Minority Oversampling

- Create new synthetic points between existing points *where classes overlap*

In [55]:
```
from imblearn.over_sampling import ADASYN

X_adasyn, y_adasyn = ADASYN().fit_resample(X_imb, y_imb)
Counter(y_adasyn).items()
```

Out[55]:
```
dict_items([(2, 4674), (1, 4662), (0, 4673)])
```

In [56]:
```
fig,ax=plt.subplots(1,1,figsize=(8,6))
ax.scatter(X_adasyn[y_adasyn==2,0],X_adasyn[y_adasyn==2,1],c='k', alpha=.2);
ax.scatter(X_adasyn[y_adasyn==1,0],X_adasyn[y_adasyn==1,1],c='b', alpha=.2);
ax.scatter(X_adasyn[y_adasyn==0,0],X_adasyn[y_adasyn==0,1],c='r', alpha=.2);
```



# Other methods for dealing with imbalanced classes

- Adjust class weight (sklearn)
- Adjust decision threshold (sklearn)
- Treat as anomaly detection
- Generate/buy more labels

- See https://imbalanced-learn.readthedocs.io/en/stable/auto_examples/over-sampling/plot_comparison_over_sampling.html

# Questions re Imbalanced Classes?

# Data Processing and Delivery: ETL

- **E**xtract **T**ransform **L**oad

- Extract: Reading in data
- Transform: Transforming data
- Load: Delivering data

# Extract: Various Data Sources

- flatfiles (csv, excel)
- semi-structured documents (json, html)
- unstructured documents
- data + schema (dataframe,database, parquet)
- APIs (wikipedia, twitter, spotify, etc.)
- databases

- Pandas to the rescue!
- Plus other specialized libraries

# Extracting Data with Pandas

- read_csv
- read_excel
- read_parquet

- read_json
- read_html

- read_sql
- read_clipboard
- ...

# Extract Data: CSV

Comma Separated Values

# Extract Data: CSV

Comma Separated Values

In [57]:
```
%cat ../data/example.csv
```

```
Year,Make,Model,Description,Price
1997,Ford,E350,"ac, abs, moon",3000.00
1999,Chevy,"Venture Extended Edition","",4900.00
1999,Chevy,"Venture Extended Edition, Very Large",,5000.00
1996,Jeep,Grand Cherokee,"MUST SELL! air, moon roof, loaded",4799.00
```

# Extract Data: CSV

## Comma Separated Values

In [57]:
```
%cat ../data/example.csv
```

```
Year,Make,Model,Description,Price
1997,Ford,E350,"ac, abs, moon",3000.00
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1999,Chevy,"Venture Extended Edition, Very Large",,5000.00
1996,Jeep,Grand Cherokee,"MUST SELL! air, moon roof, loaded",4799.00
```

In [58]:
```
df = pd.read_csv('../data/example.csv',header=0,sep=',')
df.head()
```

Out[58]:

| | Year | Make | Model | Description | Price |
|---|---|---|---|---|---|
| 0 | 1997 | Ford | E350 | ac, abs, moon | 3000.0 |
| 1 | 1999 | Chevy | Venture Extended Edition | NaN | 4900.0 |
| 2 | 1999 | Chevy | Venture Extended Edition, Very Large | NaN | 5000.0 |
| 3 | 1996 | Jeep | Grand Cherokee | MUST SELL! air, moon roof, loaded | 4799.0 |

# Extract Data: Excel

| | A | B | C | D | E |
|---|---|---|---|---|---|
| 1 | **Year** | **Make** | **Model** | **Description** | **Price** |
| 2 | 1997 | Ford | E350 | ac, abs, moon | 3000 |
| 3 | 1999 | Chevy | Venture Extended Edition | | 4900 |
| 4 | 1999 | Chevy | Venture Extended Edition, Very Large | | 5000 |
| 5 | 1996 | Jeep | Grand Cherokee | MUST SELL! air, moon roof, loaded | 4799 |

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| | A | B | C | D | E |
|---|---|---|---|---|---|
| 1 | **Year** | **Make** | **Model** | **Description** | **Price** |
| 2 | 1997 | Ford | E350 | ac, abs, moon | 3000 |
| 3 | 1999 | Chevy | Venture Extended Edition | | 4900 |
| 4 | 1999 | Chevy | Venture Extended Edition, Very Large | | 5000 |
| 5 | 1996 | Jeep | Grand Cherokee | MUST SELL! air, moon roof, loaded | 4799 |

In [59]:
```python
pd.read_excel('../data/example.xls')
```

Out[59]:

| | Year | Make | Model | Description | Price |
|---|---|---|---|---|---|
| **0** | 1997 | Ford | E350 | ac, abs, moon | 3000 |
| **1** | 1999 | Chevy | Venture Extended Edition | NaN | 4900 |
| **2** | 1999 | Chevy | Venture Extended Edition, Very Large | NaN | 5000 |
| **3** | 1996 | Jeep | Grand Cherokee | MUST SELL! air, moon roof, loaded | 4799 |

# Extract Data: Parquet

- open source column-oriented data storage
- part of the Apache Hadoop ecosystem
- often used when working with Spark
- requires additional parsing engine eg `pyarrow`
- includes both data and **schema**
- **Schema** : metadata about the dataset (column names, datatypes, etc.)

# Extract Data: Parquet

- open source column-oriented data storage
- part of the Apache Hadoop ecosystem
- often used when working with Spark
- requires additional parsing engine eg `pyarrow`
- includes both data and **schema**
- **Schema** : metadata about the dataset (column names, datatypes, etc.)

In [60]:
```python
# conda install -n eods-s21 pyarrow
pd.read_parquet('../data/example.parquet')
```

Out[60]:

| | Year | Make | Model | Description | Price |
|---|---|---|---|---|---|
| **0** | 1997 | Ford | E350 | ac, abs, moon | 3000.0 |
| **1** | 1999 | Chevy | Venture Extended Edition | None | 4900.0 |
| **2** | 1999 | Chevy | Venture Extended Edition, Very Large | None | 5000.0 |
| **3** | 1996 | Jeep | Grand Cherokee | MUST SELL! air, moon roof, loaded | 4799.0 |

# Extract Data: JSON

- **J**ava**S**cript **O**bject **N**otation
- often seen as return from api call
- looks like a dictionary or list of dictionaries
- pretty print using json.loads(json_string)

```
{
  "firstName": "John",
  "lastName": "Smith",
  "isAlive": true,
  "age": 27,
  "phoneNumbers": [
    {
      "type": "home",
      "number": "212 555-1234"
    },
    {
```

# Extract Data: JSON

# Extract Data: JSON

In [61]:
```
json = """
{"0": {"Year": 1997,
  "Make": "Ford",
  "Model": "E350",
  "Description": "ac, abs, moon",
  "Price": 3000.0},
 "1": {"Year": 1999,
  "Make": "Chevy",
  "Model": "Venture Extended Edition",
  "Description": null,
  "Price": 4900.0},
 "2": {"Year": 1999,
  "Make": "Chevy",
  "Model": "Venture Extended Edition, Very Large",
  "Description": null,
  "Price": 5000.0},
 "3": {"Year": 1996,
  "Make": "Jeep",
  "Model": "Grand Cherokee",
  "Description": "MUST SELL! air, moon roof, loaded",
  "Price": 4799.0}}
"""
```

# Extract Data: JSON

In [61]:
```
json = """
{"0": {"Year": 1997,
  "Make": "Ford",
  "Model": "E350",
  "Description": "ac, abs, moon",
  "Price": 3000.0},
 "1": {"Year": 1999,
  "Make": "Chevy",
  "Model": "Venture Extended Edition",
  "Description": null,
  "Price": 4900.0},
 "2": {"Year": 1999,
  "Make": "Chevy",
  "Model": "Venture Extended Edition, Very Large",
  "Description": null,
  "Price": 5000.0},
 "3": {"Year": 1996,
  "Make": "Jeep",
  "Model": "Grand Cherokee",
  "Description": "MUST SELL! air, moon roof, loaded",
  "Price": 4799.0}}
"""
```

In [62]:
```
pd.read_json(json,orient='index')
```

Out[62]:

| | Year | Make | Model | Description | Price |
|---|---|---|---|---|---|
| 0 | 1997 | Ford | E350 | ac, abs, moon | 3000 |
| 1 | 1999 | Chevy | Venture Extended Edition | None | 4900 |
| 2 | 1999 | Chevy | Venture Extended Edition, Very Large | None | 5000 |
| 3 | 1996 | Jeep | Grand Cherokee | MUST SELL! air, moon roof, loaded | 4799 |

# Extract Data: HTML

- **H**yper**T**ext **M**arkup **L**anguage
- Parse with BeautifulSoup

# Extract Data: HTML

- **H**yper**T**ext **M**arkup **L**anguage
- Parse with BeautifulSoup

```
In [63]: html = """
<html>
    <head>
        <title>Example</title>
    </head>
    <body>
        <p id="first" class="example"><strong>Example text!</strong></p>
        <p id="second" class="example">And More!</p>
    </body>
</html>
"""

from bs4 import BeautifulSoup

soup = BeautifulSoup(html)
[p.text for p in soup('p')]

Out[63]: ['Example text!', 'And More!']
```

# Extract Data: APIs

- **A**pplication **P**rogramming **I**nterface
- defines interactions between software components and resourses
- most datasources have an API
- some require authentication
- python libraries exist for most common APIs

- **requests**: library for making web requests and accessing the results

# API Example: Wikipedia

# API Example: Wikipedia

In [64]:
```
import requests
url = 'http://en.wikipedia.org/w/api.php?action=query&prop=info&format=json&titles='
title = 'Data Science'
title = title.replace(' ','%20')
print(url+title)
```

```
http://en.wikipedia.org/w/api.php?action=query&prop=info&format=json&titles=Data%20Science
```

# API Example: Wikipedia

In [64]:
```python
import requests
url = 'http://en.wikipedia.org/w/api.php?action=query&prop=info&format=json&titles='
title = 'Data Science'
title = title.replace(' ','%20')
print(url+title)
```

```
http://en.wikipedia.org/w/api.php?action=query&prop=info&format=json&titles=Data%20Science
```

In [65]:
```python
resp = requests.get(url+title)
resp.json()
```

Out[65]:

```
{'batchcomplete': '',
 'query': {'pages': {'49495124': {'pageid': 49495124,
    'ns': 0,
    'title': 'Data Science',
    'contentmodel': 'wikitext',
    'pagelanguage': 'en',
    'pagelanguagehtmlcode': 'en',
    'pagelanguagedir': 'ltr',
    'touched': '2021-11-13T20:22:16Z',
    'lastrevid': 706007296,
    'length': 26,
    'redirect': '',
    'new': ''}}}}
```


In [66]:
```python
resp.text
```

Out[66]:

```
'{"batchcomplete":"","query":{"pages":{"49495124":{"pageid":49495124,"ns":0,"title":"Data Science","contentmodel":"wikitext","p
agelanguage":"en","pagelanguagehtmlcode":"en","pagelanguagedir":"ltr","touched":"2021-11-13T20:22:16Z","lastrevid":706007296,"l
ength":26,"redirect":"","new":""}}}}'
```

# API Example: Twitter

1. Apply for Twitter developer account
2. Create a Twitter application to generate tokens and secrets

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1. Apply for Twitter developer account
2. Create a Twitter application to generate tokens and secrets

In [67]:
```
with open('/home/bgibson/proj/twitter/twitter_consumer_key.txt') as f:
    consumer_key = f.read().strip()
with open('/home/bgibson/proj/twitter/twitter_consumer_secret.txt') as f:
    consumer_secret = f.read().strip()
with open('/home/bgibson/proj/twitter/twitter_access_token.txt') as f:
    access_token = f.read().strip()
with open('/home/bgibson/proj/twitter/twitter_access_token_secret.txt') as f:
    access_token_secret = f.read().strip()

from twython import Twython
twitter = Twython(consumer_key,consumer_secret,access_token,access_token_secret)
```

# API Example: Twitter

1. Apply for Twitter developer account
2. Create a Twitter application to generate tokens and secrets

In [67]:
```
with open('/home/bgibson/proj/twitter/twitter_consumer_key.txt') as f:
    consumer_key = f.read().strip()
with open('/home/bgibson/proj/twitter/twitter_consumer_secret.txt') as f:
    consumer_secret = f.read().strip()
with open('/home/bgibson/proj/twitter/twitter_access_token.txt') as f:
    access_token = f.read().strip()
with open('/home/bgibson/proj/twitter/twitter_access_token_secret.txt') as f:
    access_token_secret = f.read().strip()

from twython import Twython
twitter = Twython(consumer_key,consumer_secret,access_token,access_token_secret)
```

In [68]:
```
public_tweets = twitter.search(q='columbia')['statuses']
for status in public_tweets[:3]:
    print('-------')
    print(status["text"])
```

```
-------
James Monroe is an American politician and actor who served as the most important invention of the original District of Columbi
a, the (1/2)
-------
And not Columbia, TN… ya small minded gyals □□
-------
RT @ellisemmagarey: Workers at @Columbia are on their SIXTH week of strike &amp; face mass retaliatory firings. This is their F
OURTH strike in…
```

# API Example: Twitter

# API Example: Twitter

```
In [69]: public_tweets[0]
```


```
Out[69]: {'created_at': 'Mon Dec 06 19:57:38 +0000 2021',
 'id': 1467946353493872643,
 'id_str': '1467946353493872643',
 'text': 'James Monroe is an American politician and actor who served as the most important invention of the original District of Columbia, the (1/2)',
 'truncated': False,
 'entities': {'hashtags': [], 'symbols': [], 'user_mentions': [], 'urls': []},
 'metadata': {'iso_language_code': 'en', 'result_type': 'recent'},
 'source': '<a href="http://www.github.com/ldermer/" rel="nofollow">dunning kruger bot</a>',
 'in_reply_to_status_id': None,
 'in_reply_to_status_id_str': None,
 'in_reply_to_user_id': None,
 'in_reply_to_user_id_str': None,
 'in_reply_to_screen_name': None,
 'user': {'id': 739988612243062784,
  'id_str': '739988612243062784',
  'name': 'dunningkrugerbot',
  'screen_name': 'bottingkruger',
  'location': 'Seattle, WA',
  'description': "Ask me about a person, and I'll tell you everything I think I know. I only read Wikipedia, but I think I got this. Maintained by @lauriedermer.",
  'url': None,
  'entities': {'description': {'urls': []}},
  'protected': False,
  'followers_count': 71,
  'friends_count': 1,
  'listed_count': 8,
  'created_at': 'Tue Jun 07 01:13:28 +0000 2016',
  'favourites_count': 5,
  'utc_offset': None,
  'time_zone': None,
  'geo_enabled': False,
  'verified': False,
  'statuses_count': 113407,
```

# Transforming Data

- Standardization
- Creating dummy variables
- Filling missing data
- One-Hot-Encoding
- Binning
- Parsing natural language
- Dimensionality reduction
- etc...

- Pipeline and ColumnTransformer

# Extract and Transform Example: Titanic

# Extract and Transform Example: Titanic

In [70]:
```
titanic_url = ('https://raw.githubusercontent.com/amueller/'
               'scipy-2017-sklearn/091d371/notebooks/datasets/titanic3.csv')
df_titanic = pd.read_csv(titanic_url)[['age','fare','embarked','sex','pclass','survived']]
display(df_titanic.head(1))
df_titanic.info()
```

| | age | fare | embarked | sex | pclass | survived |
|---|---|---|---|---|---|---|
| 0 | 29.0 | 211.3375 | S | female | 1 | 1 |

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1309 entries, 0 to 1308
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       1046 non-null   float64
 1   fare      1308 non-null   float64
 2   embarked  1307 non-null   object 
 3   sex       1309 non-null   object 
 4   pclass    1309 non-null   int64  
 5   survived  1309 non-null   int64  
dtypes: float64(2), int64(2), object(2)
memory usage: 61.5+ KB
```

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               'scipy-2017-sklearn/091d371/notebooks/datasets/titanic3.csv')
df_titanic = pd.read_csv(titanic_url)[['age','fare','embarked','sex','pclass','survived']]
display(df_titanic.head(1))
df_titanic.info()
```

| | age | fare | embarked | sex | pclass | survived |
|---|---|---|---|---|---|---|
| 0 | 29.0 | 211.3375 | S | female | 1 | 1 |

```
<class 'pandas.core.frame.DataFrame'>
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 0   age       1046 non-null   float64
 1   fare      1308 non-null   float64
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 3   sex       1309 non-null   object
 4   pclass    1309 non-null   int64
 5   survived  1309 non-null   int64
dtypes: float64(2), int64(2), object(2)
memory usage: 61.5+ KB
```

In [71]:
```
X_titanic = df_titanic.drop('survived', axis=1)
y_titanic = df_titanic['survived']
X_titanic_train, X_titanic_test, y_titanic_train, y_titanic_test = train_test_split(X_titanic,
                                                                                    y_titanic,
                                                                                    test_size=0.2,
                                                                                    random_state=42)
```

# Extract and Transform Example: Titanic

# Extract and Transform Example: Titanic

In [72]:

```
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder,StandardScaler
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression

numeric_features = ['age', 'fare']
numeric_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy='median')),
                                      ('scaler', StandardScaler())])

categorical_features = ['embarked', 'sex', 'pclass']
categorical_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy='constant', fill_value='missing')),
                                          ('onehot', OneHotEncoder(handle_unknown='ignore'))])

preprocessor = ColumnTransformer(transformers=[('num', numeric_transformer, numeric_features),
                                               ('cat', categorical_transformer, categorical_features)])

pipe = Pipeline(steps=[('preprocessor', preprocessor),
                       ('classifier', LogisticRegression(solver='lbfgs', random_state=42))])

param_grid = {
    'preprocessor__num__imputer__strategy': ['mean', 'median'],
    'classifier__C': [0.1, 1.0, 10, 100],
}
gs_pipeline = GridSearchCV(pipe, param_grid, cv=3)
gs_pipeline.fit(X_titanic_train, y_titanic_train)
print("best test set score from grid search: {:.3f}".format(gs_pipeline.score(X_titanic_test, y_titanic_test)))
print("best parameter settings: {}".format(gs_pipeline.best_params_))
```

```
best test set score from grid search: 0.771
best parameter settings: {'classifier__C': 100, 'preprocessor__num__imputer__strategy': 'median'}
```

# Loading Data with pandas

- to_csv
- to excel
- to_json
- to_html
- to_parquet

- to_sql
- to_clipboard

- to_pickle

# Delivering Data With Flask

# Delivering Data With Flask

- Flask : lightweight web server
- can be used to create a small API to:
  - return transformed data
  - return predictions
  - return datasets
  - ...

# Aside: Running python scripts from the command line

# Aside: Running python scripts from the command line

In [73]:
```
!cat ../src/sample_script.py
```

```
# import necessary libraries and function
from datetime import datetime

# python as usual
# will run as script or on import
run_or_imported_at = datetime.now()
print(f"this was run or imported at {run_or_imported_at}")
print(f"{__name__ = :s}")

if __name__ == "__main__":
    # will only run if this is a script
    # won't be run if imported
    print("running as a script")
```

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if __name__ == "__main__":
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    print("running as a script")
```

In [74]:
```
import sys
sys.path.append('../src/')

import sample_script
```

```
this was run or imported at 2021-12-06 14:57:49.844899
__name__ = sample_script
```

# Aside: Running python scripts from the command line

In [73]:
```
!cat ../src/sample_script.py
```

```
# import necessary libraries and function
from datetime import datetime

# python as usual
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run_or_imported_at = datetime.now()
print(f"this was run or imported at {run_or_imported_at}")
print(f"{__name__ = :s}")

if __name__ == "__main__":
    # will only run if this is a script
    # won't be run if imported
    print("running as a script")
```

In [74]:
```
import sys
sys.path.append('../src/')

import sample_script
```

```
this was run or imported at 2021-12-06 14:57:49.844899
__name__ = sample_script
```

In [75]:
```
print(sample_script.run_or_imported_at)
```

```
2021-12-06 14:57:49.844899
```

# Aside: Function Decorators

- act like wrappers around functions
- decorators are prefixed by the "@" symbol
- placed above the function to be wrapped

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- act like wrappers around functions
- decorators are prefixed by the "@" symbol
- placed above the function to be wrapped

In [76]:
```
def my_decorator(func):
    def wrapper():
        print("Happens before the function is called.")
        func()
        print("Happens after the function is called.")
    return wrapper

@my_decorator
def say_hello():
    print("Hello")

say_hello()
```

```
Happens before the function is called.
Hello
Happens after the function is called.
```

# Creating APIs: Flask

# Creating APIs: Flask

In [77]:
```
!cat ../src/hello_flask.py
```

```
from flask import Flask, escape, request

app = Flask(__name__)

@app.route('/')
def hello():
    name = request.args.get("name", "World")
    return f'Hello, {escape(name)}!\n'

if __name__ == '__main__':
    app.run()
```

# Creating APIs: Flask

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```
!cat ../src/hello_flask.py
```

```
from flask import Flask, escape, request

app = Flask(__name__)

@app.route('/')
def hello():
    name = request.args.get("name", "World")
    return f'Hello, {escape(name)}!\n'

if __name__ == '__main__':
    app.run()
```

1. at command line, run: `$ python hello_flask.py`
2. in ipython (or notebook)

```
import requests
r = requests.get('http://127.0.0.1:5000/?name=Bryan')
print(r.text)
```

# Creating APIs: Flask with Multiple Routes

# Creating APIs: Flask with Multiple Routes

In [78]:
```
!cat ../src/die_flask.py
```

```
import numpy as np
from flask import Flask, request, jsonify

app = Flask(__name__)

@app.route("/")
def help():
    return "Give the number of sides the die should have.\n"

@app.route("/<int:sides>")
def roll_die(sides):
    return str(np.random.randint(1,sides+1))

@app.route("/json/<int:sides>")
def roll_die_json(sides):
    return jsonify({'sides': sides,'roll': np.random.randint(1,sides+1)})

if __name__ == '__main__':
    app.run()
```

# GET vs POST

- **GET** : pass information in the url

```
127.0.0.1:5000/?firstname=Bryan&lastname=Gibson
```

- **POST** : pass information as additional http request (often JSON)

```
127.0.0.1:5000/
{'firstname':'Bryan','lastname':'Gibson'}
```

# Creating APIs: Flask

- Export trained models (and other data structures) using `pickle`

# Creating APIs: Flask

- Export trained models (and other data structures) using `pickle`

```
In [79]: import pickle as pkl
         with open('../data/titanic_pipeline_clf.pkl','wb') as f:
             pkl.dump(gs_pipeline,f)
```

# Creating APIs: Deliver Predictions Using Flask

# Creating APIs: Deliver Predictions Using Flask

In [80]:
```
!cat ../src/titanic_clf.py
```

```
from flask import Flask, escape, request, jsonify
import pickle as pkl
import pandas as pd

# need to train and pickle classifier first
with open('../data/titanic_pipeline_clf.pkl','rb') as f:
    clf = pkl.load(f)

app = Flask(__name__)

@app.route('/',methods=['POST'])
def predict():
    prediction = None
    query = pd.DataFrame(request.form,index=[0])
    print(query,flush=True)
    if query is not None:
        prediction = clf.predict(query)
    if prediction:
        return jsonify([str(x) for x in prediction])
    else:
        return 'no predictions made'

if __name__ == '__main__':
    app.run()
```

# Creating APIs: Deliver Predictions Using Flask Cont.

# Creating APIs: Deliver Predictions Using Flask Cont.

In [81]:
```
query_label = df_titanic.iloc[0].loc['survived']
```

# Creating APIs: Deliver Predictions Using Flask Cont.

In [81]:
```
query_label = df_titanic.iloc[0].loc['survived']
```

In [82]:
```
query = df_titanic.iloc[0,:-1].to_dict()
query
```

Out[82]:
```
{'age': 29.0, 'fare': 211.3375, 'embarked': 'S', 'sex': 'female', 'pclass': 1}
```

# Creating APIs: Deliver Predictions Using Flask Cont.

In [81]:
```
query_label = df_titanic.iloc[0].loc['survived']
```

In [82]:
```
query = df_titanic.iloc[0,:-1].to_dict()
query
```

Out[82]:
```
{'age': 29.0, 'fare': 211.3375, 'embarked': 'S', 'sex': 'female', 'pclass': 1}
```

In [83]:
```
query_label
```

Out[83]:
```
1
```

# Creating APIs: Deliver Predictions Using Flask Cont.

In [81]:
```
query_label = df_titanic.iloc[0].loc['survived']
```

In [82]:
```
query = df_titanic.iloc[0,:-1].to_dict()
query
```

Out[82]:
```
{'age': 29.0, 'fare': 211.3375, 'embarked': 'S', 'sex': 'female', 'pclass': 1}
```

In [83]:
```
query_label
```

Out[83]:
```
1
```

In [84]:
```
# Start script from command line using: python titanic_clf.py
# Then run the following in from the notebook
#requests.post('http://127.0.0.1:5000/', data=query).text
```

# Data Processing Summary

- ETL
- reading datafiles using pandas
- website scraping (requests,BeautifulSoup)
- accessing data via API
- Tranforming data with Pipelines
- Exposing data via API (Flask)

# Questions re Data Processing and Delivery?