Elements Of Data Science - F2022

Week 12: Time Series, Model API with Flask

11/30/2020

TODOs

- Readings:
  - Recommended: DSFS: Chap 9: Getting Data
  - Recommended: DSFS: Chap 23: Databases and SQL
- HW4, **Due Friday December 2nd 11:59pm ET**
- Quiz 12, **Due Tuesday December 6th 11:59pm ET**
- Final
  - Review sheet in github repo (soon!)
  - Online via Gradescope, open-book, open-note, open-python
  - Released *Wednesday December 7th 11:59pm ET*
  - **Due Friday December 9th 11:59pm ET**
  - Have maximum of 24hrs after starting to finish
  - 30-40 questions (fill in the blank/multiple choice/short answer)
  - Questions asked/answered **privately** via Ed

Quiz Common Mistakes (points off)

- don't remove instructions from quiz/homework
- `.info()` not `.info`: make sure function/method calls are made with `()`
- Pandas `.sample()` default `n=1`: need to set `n=` or `frac=`
- LinearRegression (regression) vs LogisticRegression (classification)
- using a model "with default settings" means Model() or just a subset of parameters set
- Be careful which dataset you're training/evaluating on: X_train vs X_test
- Make sure all plotting settings get used (eg hue=)

- `y_digits[cluster_assignments_km == 9]`
- `sns.scatterplot(x=X_2D[:,0],y=X_2D[:,1],...`

Today

- Time Series Transformations
- Model Prediction API with Flask

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

- Data ordered in time

- Applications
    - Financial
    - Economic
    - Scientific
    - etc.

Time Series Differences

- **Non-i.i.d.** : not independent and identically distributed

- not independent
  - Ex: Stock price

- not-identically distributed
  - Ex: Seasonality

- In other words: Order matters!

Representing Time in Python

- `datetime` library
- Pandas `Timestamp`

`datetime.date`

`datetime.date`

In [2]:
```python
from datetime import date

friday = date(2022,11,1) # year,month,day
friday
```

Out[2]:
```
datetime.date(2022, 11, 1)
```

datetime.date

In [2]:
```python
from datetime import date

friday = date(2022,11,1) # year,month,day
friday
```

Out[2]:
```
datetime.date(2022, 11, 1)
```

In [3]:
```python
today = date.today()
today
```

Out[3]:
```
datetime.date(2022, 11, 30)
```

datetime.date

In [2]:
```
from datetime import date

friday = date(2022,11,1) # year,month,day
friday
```
Out[2]:
```
datetime.date(2022, 11, 1)
```

In [3]:
```
today = date.today()
today
```
Out[3]:
```
datetime.date(2022, 11, 30)
```

In [4]:
```
today.year
```
Out[4]:
```
2022
```

`datetime.time`

datetime.time

In [5]:
```
from datetime import time

class_start = time(19,10,0) # hour,minute,second,microsecond
class_start
```

Out[5]:
```
datetime.time(19, 10)
```

`datetime.time`

In [5]:
```python
from datetime import time

class_start = time(19,10,0) # hour,minute,second,microsecond
class_start
```

Out[5]:
```
datetime.time(19, 10)
```

In [6]:
```python
class_start.hour
```

Out[6]:
```
19
```

`datetime.datetime`

datetime.datetime

In [7]:
```python
from datetime import datetime

# year,month,day,hour,minute,second,microsecond
wednesday_afternoon = datetime(2022,11,30,15)
wednesday_afternoon
```

Out[7]:
```
datetime.datetime(2022, 11, 30, 15, 0)
```

datetime.datetime

In [7]:
```
from datetime import datetime

# year,month,day,hour,minute,second,microsecond
wednesday_afternoon = datetime(2022,11,30,15)
wednesday_afternoon
```

Out[7]:
```
datetime.datetime(2022, 11, 30, 15, 0)
```

In [8]:
```
now = datetime.now()
now
```

Out[8]:
```
datetime.datetime(2022, 11, 30, 18, 4, 6, 48207)
```

`datetime.timedelta`

`datetime.timedelta`

In [9]:
```
diff = datetime(2022,11,30,1) - datetime(2022,11,29,0)
diff
```

Out[9]:
```
datetime.timedelta(days=1, seconds=3600)
```

datetime.timedelta

In [9]:
```
diff = datetime(2022,11,30,1) - datetime(2022,11,29,0)
diff
```

Out[9]:
```
datetime.timedelta(days=1, seconds=3600)
```

In [10]:
```
diff.total_seconds()
```

Out[10]:
```
90000.0
```

datetime.timedelta

In [9]:
```
diff = datetime(2022,11,30,1) - datetime(2022,11,29,0)
diff
```

Out[9]:
```
datetime.timedelta(days=1, seconds=3600)
```

In [10]:
```
diff.total_seconds()
```

Out[10]:
```
90000.0
```

In [11]:
```
from datetime import timedelta

#days,seconds,microseconds,milliseconds,minutes,hours,weeks
one_day = timedelta(1)

date(2022,11,30) + 2*one_day
```

Out[11]:
```
datetime.date(2022, 12, 2)
```

Printing Datetimes: `strftime()`

Printing Datetimes: `strftime()`

In [12]:
```
now = datetime.now()
print(now)
```

```
2022-11-30 18:04:06.077953
```

Printing Datetimes: `strftime()`

In [12]:
```
now = datetime.now()
print(now)
```

```
2022-11-30 18:04:06.077953
```

In [13]:
```
now.strftime('%a %h %d, %Y %I:%M %p')
```

Out[13]:
```
'Wed Nov 30, 2022 06:04 PM'
```

Printing Datetimes: `strftime()`

In [12]:
```
now = datetime.now()
print(now)
```

```
2022-11-30 18:04:06.077953
```

In [13]:
```
now.strftime('%a %h %d, %Y %I:%M %p')
```

Out[13]:
```
'Wed Nov 30, 2022 06:04 PM'
```

```
%Y 4-digit year
%y 2-digit year
%m 2-digit month
%d 2-digit day
%H Hour (24-hour)
%M 2-digit minute
%S 2-digit second
...
```

Printing Datetimes: `strftime()`

In [12]:
```
now = datetime.now()
print(now)
```

```
2022-11-30 18:04:06.077953
```

In [13]:
```
now.strftime('%a %h %d, %Y %I:%M %p')
```

Out[13]:
```
'Wed Nov 30, 2022 06:04 PM'
```

```
%Y 4-digit year
%y 2-digit year
%m 2-digit month
%d 2-digit day
%H Hour (24-hour)
%M 2-digit minute
%S 2-digit second
...
```

See strftime.org and strfti.me

Parsing Datetimes: `pandas.to_datetime()`

- `dateutil.parser` available
- pandas has parser built in: `pd.to_datetime()`

Parsing Datetimes: `pandas.to_datetime()`

- `dateutil.parser` available
- pandas has parser built in: `pd.to_datetime()`

In [14]:
```
pd.to_datetime('11/30/2022 7:36pm')
```

Out[14]:
```
Timestamp('2022-11-30 19:36:00')
```

Parsing Datetimes: `pandas.to_datetime()`

- `dateutil.parser` available
- pandas has parser built in: `pd.to_datetime()`

```
In [14]: pd.to_datetime('11/30/2022 7:36pm')

Out[14]: Timestamp('2022-11-30 19:36:00')
```

```
In [15]: dt_index = pd.to_datetime([datetime(2020, 11, 26),
                                    '27th of November, 2020',
                                    '2020-Nov-28',
                                    '11-29-2030',
                                    '20201130',
                                    None
                                   ])
         dt_index

Out[15]: DatetimeIndex(['2020-11-26', '2020-11-27', '2020-11-28', '2030-11-29',
                        '2020-11-30', 'NaT'],
                       dtype='datetime64[ns]', freq=None)
```

`pandas.Timestamp`

- like `datetime.datetime`
- can include **timezone** and **frequency** info
- can handle a missing time: `NaT`
- can be used anywhere `datetime` can be used
- an array of Timestamps can be used as an index

`pandas.Timestamp`

- like `datetime.datetime`
- can include **timezone** and **frequency** info
- can handle a missing time: `NaT`
- can be used anywhere `datetime` can be used
- an array of Timestamps can be used as an index

In [16]:
```
pd.Timestamp(2022,11,30,19)
```

Out[16]:
```
Timestamp('2022-11-30 19:00:00')
```

`pandas.Timestamp`

- like `datetime.datetime`
- can include **timezone** and **frequency** info
- can handle a missing time: `NaT`
- can be used anywhere `datetime` can be used
- an array of Timestamps can be used as an index

```
In [16]: pd.Timestamp(2022,11,30,19)

Out[16]: Timestamp('2022-11-30 19:00:00')
```

```
In [17]: pd.Timestamp('20221130 7:00pm EST')

Out[17]: Timestamp('2022-11-30 19:00:00-0500', tz='tzlocal()')
```

```
In [18]: pd.Timestamp('20221130 7:00pm',tz='US/Pacific')

Out[18]: Timestamp('2022-11-30 19:00:00-0800', tz='US/Pacific')
```

`pandas.Timestamp`

- like `datetime.datetime`
- can include **timezone** and **frequency** info
- can handle a missing time: `NaT`
- can be used anywhere `datetime` can be used
- an array of Timestamps can be used as an index

```
In [16]: pd.Timestamp(2022,11,30,19)

Out[16]: Timestamp('2022-11-30 19:00:00')

In [17]: pd.Timestamp('20221130 7:00pm EST')

Out[17]: Timestamp('2022-11-30 19:00:00-0500', tz='tzlocal()')

In [18]: pd.Timestamp('20221130 7:00pm',tz='US/Pacific')

Out[18]: Timestamp('2022-11-30 19:00:00-0800', tz='US/Pacific')

In [19]: dt_index[0]

Out[19]: Timestamp('2020-11-26 00:00:00')
```

Accessing Datetime Components with `.dt`

Accessing Datetime Components with `.dt`

In [20]:
```
df_taxi = pd.read_csv('../data/yellowcab_tripdata_2017-01_subset10000rows.csv',
                      parse_dates=['tpep_pickup_datetime']).head(3)
df_taxi.tpep_pickup_datetime
```

Out[20]:
```
0   2017-01-10 18:37:59
1   2017-01-05 15:14:52
2   2017-01-11 14:47:52
Name: tpep_pickup_datetime, dtype: datetime64[ns]
```

Accessing Datetime Components with `.dt`

In [20]:
```
df_taxi = pd.read_csv('../data/yellowcab_tripdata_2017-01_subset10000rows.csv',
                      parse_dates=['tpep_pickup_datetime']).head(3)
df_taxi.tpep_pickup_datetime
```

Out[20]:
```
0   2017-01-10 18:37:59
1   2017-01-05 15:14:52
2   2017-01-11 14:47:52
Name: tpep_pickup_datetime, dtype: datetime64[ns]
```

In [21]:
```
df_taxi.tpep_pickup_datetime.dt.day
```

Out[21]:
```
0    10
1     5
2    11
Name: tpep_pickup_datetime, dtype: int64
```

Accessing Datetime Components with `.dt`

In [20]:
```
df_taxi = pd.read_csv('../data/yellowcab_tripdata_2017-01_subset10000rows.csv',
                      parse_dates=['tpep_pickup_datetime']).head(3)
df_taxi.tpep_pickup_datetime
```

Out[20]:
```
0   2017-01-10 18:37:59
1   2017-01-05 15:14:52
2   2017-01-11 14:47:52
Name: tpep_pickup_datetime, dtype: datetime64[ns]
```

In [21]:
```
df_taxi.tpep_pickup_datetime.dt.day
```

Out[21]:
```
0    10
1     5
2    11
Name: tpep_pickup_datetime, dtype: int64
```

In [22]:
```
df_taxi.tpep_pickup_datetime.dt.day_of_week # Monday=0 ... Sunday=6
```

Out[22]:
```
0    1
1    3
2    2
Name: tpep_pickup_datetime, dtype: int64
```

Accessing Datetime Components with `.dt`

```
In [20]: df_taxi = pd.read_csv('../data/yellowcab_tripdata_2017-01_subset10000rows.csv',
                               parse_dates=['tpep_pickup_datetime']).head(3)
         df_taxi.tpep_pickup_datetime

Out[20]: 0   2017-01-10 18:37:59
         1   2017-01-05 15:14:52
         2   2017-01-11 14:47:52
         Name: tpep_pickup_datetime, dtype: datetime64[ns]
```

```
In [21]: df_taxi.tpep_pickup_datetime.dt.day

Out[21]: 0    10
         1     5
         2    11
         Name: tpep_pickup_datetime, dtype: int64
```

```
In [22]: df_taxi.tpep_pickup_datetime.dt.day_of_week # Monday=0 ... Sunday=6

Out[22]: 0    1
         1    3
         2    2
         Name: tpep_pickup_datetime, dtype: int64
```

```
In [23]: df_taxi.tpep_pickup_datetime.dt.hour

Out[23]: 0    18
         1    15
         2    14
         Name: tpep_pickup_datetime, dtype: int64
```

DateIndex Indexing/Selecting/Slicing

DateIndex Indexing/Selecting/Slicing

In [24]:
```
s = pd.Series(['Dec 1 2021','Jan 2 2022','Feb 3 2022'],
              index=pd.to_datetime(['Dec 1 2021','Jan 2 2022','Feb 3 2022']))
s
```

Out[24]:
```
2021-12-01    Dec 1 2021
2022-01-02    Jan 2 2022
2022-02-03    Feb 3 2022
dtype: object
```

DateIndex Indexing/Selecting/Slicing

In [24]:
```
s = pd.Series(['Dec 1 2021','Jan 2 2022','Feb 3 2022'],
              index=pd.to_datetime(['Dec 1 2021','Jan 2 2022','Feb 3 2022']))
s
```

Out[24]:
```
2021-12-01    Dec 1 2021
2022-01-02    Jan 2 2022
2022-02-03    Feb 3 2022
dtype: object
```

In [25]:
```
# can index normally using iloc
s.iloc[0:2]
```

Out[25]:
```
2021-12-01    Dec 1 2021
2022-01-02    Jan 2 2022
dtype: object
```

DateIndex Indexing/Selecting/Slicing Cont.

DateIndex Indexing/Selecting/Slicing Cont.

In [26]:
```python
# only rows from the year 2022
s.loc['2022']
```

Out[26]:
```
2022-01-02    Jan 2 2022
2022-02-03    Feb 3 2022
dtype: object
```

DateIndex Indexing/Selecting/Slicing Cont.

In [26]:
```python
# only rows from the year 2022
s.loc['2022']
```

Out[26]:
```
2022-01-02    Jan 2 2022
2022-02-03    Feb 3 2022
dtype: object
```

In [27]:
```python
# only rows from January 2022
s.loc['2022-01']
```

Out[27]:
```
2022-01-02    Jan 2 2022
dtype: object
```

DateIndex Indexing/Selecting/Slicing Cont.

In [26]:
```
# only rows from the year 2022
s.loc['2022']
```

Out[26]:
```
2022-01-02    Jan 2 2022
2022-02-03    Feb 3 2022
dtype: object
```

In [27]:
```
# only rows from January 2022
s.loc['2022-01']
```

Out[27]:
```
2022-01-02    Jan 2 2022
dtype: object
```

In [28]:
```
# only rows between Jan 1st 2021 and Jan 2nd 2022, inclusive
s.loc['01/01/2021':'01/02/2022']
```

Out[28]:
```
2021-12-01    Dec 1 2021
2022-01-02    Jan 2 2022
dtype: object
```

Datetimes in DataFrames

Datetimes in DataFrames

In [29]:
```
df = pd.DataFrame([['12/1/2021',101,'A'],
                   ['1/1/2022',102,'B']],columns=['col1','col2','col3'])
df.col1 = pd.to_datetime(df.col1)
df.set_index('col1',drop=True,inplace=True)
df
```

Out[29]:

	col2	col3
col1		
2021-12-01	101	A
2022-01-01	102	B

Datetimes in DataFrames

In [29]:
```
df = pd.DataFrame([['12/1/2021',101,'A'],
                   ['1/1/2022',102,'B']],columns=['col1','col2','col3'])
df.col1 = pd.to_datetime(df.col1)
df.set_index('col1',drop=True,inplace=True)
df
```

Out[29]:

	col2	col3
col1		
2021-12-01	101	A
2022-01-01	102	B

In [30]:
```
# only return rows from 2022
df.loc['2022']
```

Out[30]:

	col2	col3
col1		
2022-01-01	102	B

Timestamp Index: Setting Frequency

Timestamp Index: Setting Frequency

In [31]:
```
s = pd.Series(['Nov 1 2022','Nov 3 2022'],index=pd.to_datetime(['Nov 1 2022','Nov 3 2022']))
s
```

Out[31]:
```
2022-11-01    Nov 1 2022
2022-11-03    Nov 3 2022
dtype: object
```

Timestamp Index: Setting Frequency

In [31]:
```
s = pd.Series(['Nov 1 2022','Nov 3 2022'],index=pd.to_datetime(['Nov 1 2022','Nov 3 2022']))
s
```

Out[31]:
```
2022-11-01    Nov 1 2022
2022-11-03    Nov 3 2022
dtype: object
```

In [32]:
```
# Use resample() and asfreq() to set frequency
s.resample('D').asfreq()
```

Out[32]:
```
2022-11-01    Nov 1 2022
2022-11-02           NaN
2022-11-03    Nov 3 2022
Freq: D, dtype: object
```

Timestamp Index: Setting Frequency

In [31]:
```
s = pd.Series(['Nov 1 2022','Nov 3 2022'],index=pd.to_datetime(['Nov 1 2022','Nov 3 2022']))
s
```

Out[31]:
```
2022-11-01    Nov 1 2022
2022-11-03    Nov 3 2022
dtype: object
```

In [32]:
```
# Use resample() and asfreq() to set frequency
s.resample('D').asfreq()
```

Out[32]:
```
2022-11-01    Nov 1 2022
2022-11-02           NaN
2022-11-03    Nov 3 2022
Freq: D, dtype: object
```

In [33]:
```
pd.to_datetime(['Nov 1 2022','Nov 3 2022'])
```

Out[33]:
```
DatetimeIndex(['2022-11-01', '2022-11-03'], dtype='datetime64[ns]', freq=None)
```

Timestamp Index: Setting Frequency

In [31]:
```
s = pd.Series(['Nov 1 2022','Nov 3 2022'],index=pd.to_datetime(['Nov 1 2022','Nov 3 2022']))
s
```

Out[31]:
```
2022-11-01    Nov 1 2022
2022-11-03    Nov 3 2022
dtype: object
```

In [32]:
```
# Use resample() and asfreq() to set frequency
s.resample('D').asfreq()
```

Out[32]:
```
2022-11-01    Nov 1 2022
2022-11-02           NaN
2022-11-03    Nov 3 2022
Freq: D, dtype: object
```

In [33]:
```
pd.to_datetime(['Nov 1 2022','Nov 3 2022'])
```

Out[33]:
```
DatetimeIndex(['2022-11-01', '2022-11-03'], dtype='datetime64[ns]', freq=None)
```

In [34]:
```
# Use date_range with freq to get a range of dates of a certain frequency
pd.date_range(start='Nov 1 2022',end='Nov 3 2022',freq='D')
```

Out[34]:
```
DatetimeIndex(['2022-11-01', '2022-11-02', '2022-11-03'], dtype='datetime64[ns]', freq='D')
```

```
Sample of Available Frequencies
    B    business day frequency
    D    calendar day frequency
    W    weekly frequency
    M    month end frequency
    BM   business month end frequency
    ...
    Q    quarter end frequency
    BQ   business quarter end frequency
    ...
    Y    year end frequency
    BY   business year end frequency
    ...
    BH      business hour frequency
    H       hourly frequency
    T,min   minutely frequency
    S       secondly frequency
    L,ms    milliseconds
    U,us    microseconds
    N       nanoseconds
```

```
Sample of Available Frequencies
    B    business day frequency
    D    calendar day frequency
    W    weekly frequency
    M    month end frequency
    BM   business month end frequency
    ...
    Q    quarter end frequency
    BQ   business quarter end frequency
    ...
    Y    year end frequency
    BY   business year end frequency
    ...
    BH      business hour frequency
    H       hourly frequency
    T,min   minutely frequency
    S       secondly frequency
    L,ms    milliseconds
    U,us    microseconds
    N       nanoseconds
```

https://pandas.pydata.org/pandas-docs/stable/user_guide/timeseries.html#timeseries-offset-aliases

Timezones

- Handled by `pytz` library

Timezones

- Handled by `pytz` library

In [35]:
```
import pytz

[x for x in pytz.common_timezones if x.startswith('U')]
```

Out[35]:
```
['US/Alaska',
 'US/Arizona',
 'US/Central',
 'US/Eastern',
 'US/Hawaii',
 'US/Mountain',
 'US/Pacific',
 'UTC']
```

Timezones

- Handled by `pytz` library

In [35]:
```
import pytz

[x for x in pytz.common_timezones if x.startswith('U')]
```

Out[35]:
```
['US/Alaska',
 'US/Arizona',
 'US/Central',
 'US/Eastern',
 'US/Hawaii',
 'US/Mountain',
 'US/Pacific',
 'UTC']
```

UTC: coordinated universal time (EST is 5 hours behind, -5:00)

Timezones Cont.

Timezones Cont.

In [36]:
```
ts = pd.date_range('11/2/2022 9:30am',periods=2,freq='D')
ts
```

Out[36]:
```
DatetimeIndex(['2022-11-02 09:30:00', '2022-11-03 09:30:00'], dtype='datetime64[ns]', freq='D')
```

Timezones Cont.

In [36]:
```
ts = pd.date_range('11/2/2022 9:30am',periods=2,freq='D')
ts
```

Out[36]:
```
DatetimeIndex(['2022-11-02 09:30:00', '2022-11-03 09:30:00'], dtype='datetime64[ns]', freq='D')
```

In [37]:
```
# Set timezone using .localize()
ts_utc = ts.tz_localize('US/Eastern')
ts_utc
```

Out[37]:
```
DatetimeIndex(['2022-11-02 09:30:00-04:00', '2022-11-03 09:30:00-04:00'], dtype='datetime64[ns, US/Eastern]', freq=None)
```

Timezones Cont.

In [36]:
```
ts = pd.date_range('11/2/2022 9:30am',periods=2,freq='D')
ts
```

Out[36]:
```
DatetimeIndex(['2022-11-02 09:30:00', '2022-11-03 09:30:00'], dtype='datetime64[ns]', freq='D')
```

In [37]:
```
# Set timezone using .localize()
ts_utc = ts.tz_localize('US/Eastern')
ts_utc
```

Out[37]:
```
DatetimeIndex(['2022-11-02 09:30:00-04:00', '2022-11-03 09:30:00-04:00'], dtype='datetime64[ns, US/Eastern]', freq=None)
```

In [38]:
```
# Change timezones using .tz_convert()
ts_utc.tz_convert('UTC')
```

Out[38]:
```
DatetimeIndex(['2022-11-02 13:30:00+00:00', '2022-11-03 13:30:00+00:00'], dtype='datetime64[ns, UTC]', freq=None)
```

Timezones Cont.

In [36]:
```
ts = pd.date_range('11/2/2022 9:30am',periods=2,freq='D')
ts
```

Out[36]:
```
DatetimeIndex(['2022-11-02 09:30:00', '2022-11-03 09:30:00'], dtype='datetime64[ns]', freq='D')
```

In [37]:
```
# Set timezone using .localize()
ts_utc = ts.tz_localize('US/Eastern')
ts_utc
```

Out[37]:
```
DatetimeIndex(['2022-11-02 09:30:00-04:00', '2022-11-03 09:30:00-04:00'], dtype='datetime64[ns, US/Eastern]', freq=None)
```

In [38]:
```
# Change timezones using .tz_convert()
ts_utc.tz_convert('UTC')
```

Out[38]:
```
DatetimeIndex(['2022-11-02 13:30:00+00:00', '2022-11-03 13:30:00+00:00'], dtype='datetime64[ns, UTC]', freq=None)
```

In [39]:
```
# Can also initilize with timezone set
ts = pd.date_range('11/2/2022 9:30am',periods=2,freq='D',tz='US/Eastern')
ts
```

Out[39]:
```
DatetimeIndex(['2022-11-02 09:30:00-04:00', '2022-11-03 09:30:00-04:00'], dtype='datetime64[ns, US/Eastern]', freq='D')
```

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/Lagging

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

Shifting/Lagging

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

In [40]:
```
ts = pd.Series([1,2,8],
               index=pd.date_range('1/1/2022',periods=3,freq='M')) # Month End frequency (MS: Month Start)
ts
```

Out[40]:
```
2022-01-31    1
2022-02-28    2
2022-03-31    8
Freq: M, dtype: int64
```

Shifting/Lagging

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

In [40]:
```
ts = pd.Series([1,2,8],
               index=pd.date_range('1/1/2022',periods=3,freq='M')) # Month End frequency (MS: Month Start)
ts
```

Out[40]:
```
2022-01-31    1
2022-02-28    2
2022-03-31    8
Freq: M, dtype: int64
```

In [41]:
```
ts.shift(1) # last month's value
```

Out[41]:
```
2022-01-31    NaN
2022-02-28    1.0
2022-03-31    2.0
Freq: M, dtype: float64
```

Shifting

- **percent change**, use one of :
    - (new_value - old_value) / old_value
    - (new_value / old_value) - 1

Shifting

- **percent change**, use one of :
  - (new_value - old_value) / old_value
  - (new_value / old_value) - 1

In [42]:
```
#  multiply by 100 to turn into a percent
((ts / ts.shift(1)) - 1) * 100
```

Out[42]:
```
2022-01-31      NaN
2022-02-28    100.0
2022-03-31    300.0
Freq: M, dtype: float64
```

Example Dataset: Twitter Stock

Example Dataset: Twitter Stock

In [43]:
```
# from pandas_datareader import data
# df_twtr = data.DataReader('TWTR', start='2015', end='11/27/2022', data_source='yahoo')
# df_twtr.to_csv('../data/twtr_20150102-20221127.csv')
df_twtr = pd.read_csv('../data/twtr_20150102-20221127.csv',parse_dates=['Date'],index_col='Date')
df_twtr.head(3).round(2)
```

Out[43]:

	High	Low	Open	Close	Volume	Adj Close
Date						
2015-01-02	36.74	35.54	36.23	36.56	12062461.0	36.56
2015-01-05	37.11	35.64	36.26	36.38	15062744.0	36.38
2015-01-06	39.45	36.04	36.27	38.76	33050812.0	38.76

Example Dataset: Twitter Stock

In [43]:
```
# from pandas_datareader import data
# df_twtr = data.DataReader('TWTR', start='2015', end='11/27/2022', data_source='yahoo')
# df_twtr.to_csv('../data/twtr_20150102-20221127.csv')
df_twtr = pd.read_csv('../data/twtr_20150102-20221127.csv',parse_dates=['Date'],index_col='Date')
df_twtr.head(3).round(2)
```

Out[43]:

	High	Low	Open	Close	Volume	Adj Close
Date						
2015-01-02	36.74	35.54	36.23	36.56	12062461.0	36.56
2015-01-05	37.11	35.64	36.26	36.38	15062744.0	36.38
2015-01-06	39.45	36.04	36.27	38.76	33050812.0	38.76

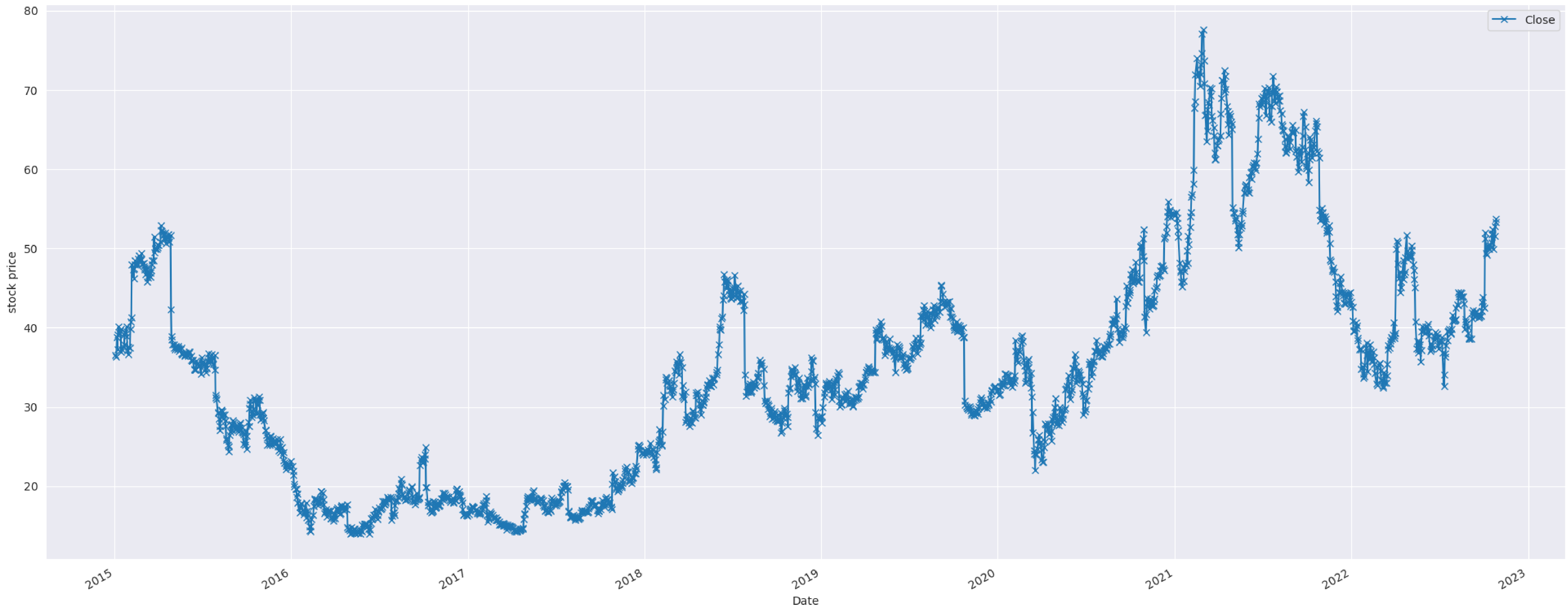
In [44]:
```
df_twtr.info() # Adj Close factors in corporate actions, such as stock splits, dividends, and rights offerings
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1970 entries, 2015-01-02 to 2022-10-27
Data columns (total 6 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   High       1970 non-null   float64
 1   Low        1970 non-null   float64
 2   Open       1970 non-null   float64
 3   Close      1970 non-null   float64
 4   Volume     1970 non-null   float64
 5   Adj Close  1970 non-null   float64
dtypes: float64(6)
memory usage: 107.7 KB
```

Example Dataset: Twitter Stock

Example Dataset: Twitter Stock

In [45]:
```
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 [46]:
```
((df_twtr.Close / df_twtr.Close.shift(1)) - 1).tail(3).round(3) # # (today / yesterday) - 1
```

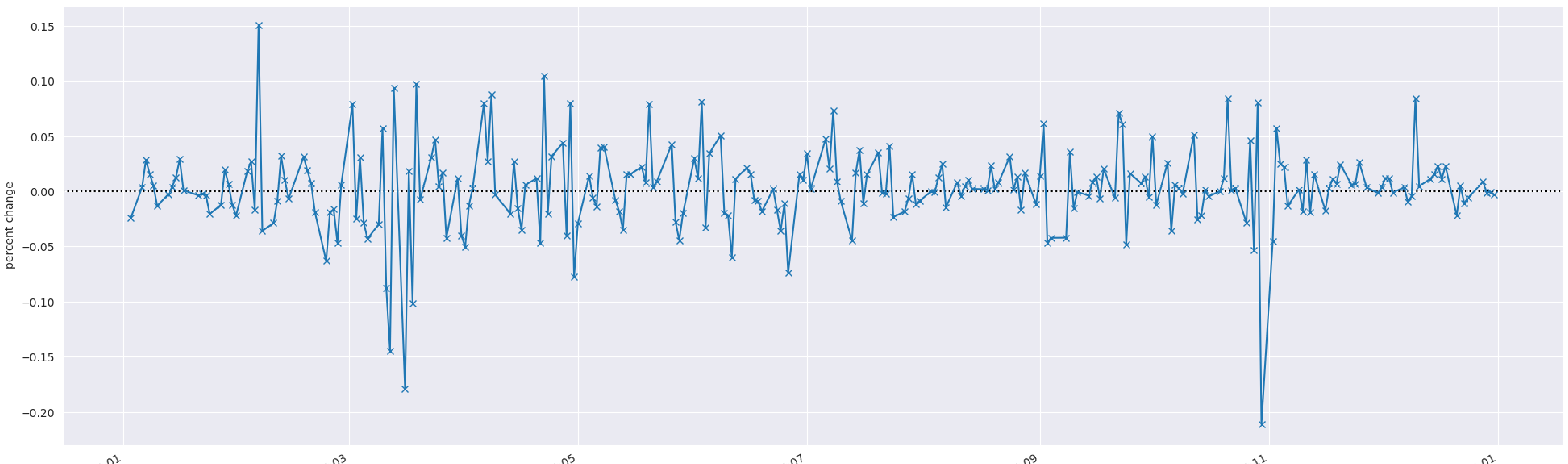
Out[46]:
```
Date
2022-10-25    0.024
2022-10-26    0.011
2022-10-27    0.007
Name: Close, dtype: float64
```

Shifting Example: Percent Change Twitter Close

In [46]:
```
((df_twtr.Close / df_twtr.Close.shift(1)) - 1).tail(3).round(3) # # (today / yesterday) - 1
```

Out[46]:
```
Date
2022-10-25    0.024
2022-10-26    0.011
2022-10-27    0.007
Name: Close, dtype: float64
```

In [47]:
```
# plot percent change of close in 2022
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 [48]:
```
df_twtr.index
```

Out[48]:
```
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',
               ...
               '2022-10-14', '2022-10-17', '2022-10-18', '2022-10-19',
               '2022-10-20', '2022-10-21', '2022-10-24', '2022-10-25',
               '2022-10-26', '2022-10-27'],
              dtype='datetime64[ns]', name='Date', length=1970, freq=None)
```

Resampling: Initialize Frequency

In [48]:
```
df_twtr.index
```

Out[48]:
```
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',
               ...
               '2022-10-14', '2022-10-17', '2022-10-18', '2022-10-19',
               '2022-10-20', '2022-10-21', '2022-10-24', '2022-10-25',
               '2022-10-26', '2022-10-27'],
              dtype='datetime64[ns]', name='Date', length=1970, freq=None)
```

In [49]:
```
df_twtr_B = df_twtr.resample('B').asfreq() # set frequency to business day
df_twtr_B.index
```

Out[49]:
```
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',
               ...
               '2022-10-14', '2022-10-17', '2022-10-18', '2022-10-19',
               '2022-10-20', '2022-10-21', '2022-10-24', '2022-10-25',
               '2022-10-26', '2022-10-27'],
              dtype='datetime64[ns]', name='Date', length=2040, 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 [50]: df_twtr_BQ = df_twtr_B.resample('BQ')
         df_twtr_BQ

Out[50]: <pandas.core.resample.DatetimeIndexResampler object at 0x7fed6a232560>
```

Resampling: Downsampling

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

In [50]:
```
df_twtr_BQ = df_twtr_B.resample('BQ')
df_twtr_BQ
```

Out[50]:
```
<pandas.core.resample.DatetimeIndexResampler object at 0x7fed6a232560>
```

In [51]:
```
print(df_twtr_BQ)
```

```
DatetimeIndexResampler [freq=<BusinessQuarterEnd: startingMonth=12>, axis=0, closed=right, label=right, convention=start, origi
n=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 [50]:
```
df_twtr_BQ = df_twtr_B.resample('BQ')
df_twtr_BQ
```

Out[50]:
```
<pandas.core.resample.DatetimeIndexResampler object at 0x7fed6a232560>
```

In [51]:
```
print(df_twtr_BQ)
```

```
DatetimeIndexResampler [freq=<BusinessQuarterEnd: startingMonth=12>, axis=0, closed=right, label=right, convention=start, origi
n=start_day]
```

In [52]:
```
df_twtr_BQ.mean().head(3).round(2)
```

Out[52]:

	High	Low	Open	Close	Volume	Adj Close
Date						
2015-03-31	45.10	43.55	44.23	44.34	20840997.51	44.34
2015-06-30	41.63	40.38	41.17	40.87	22287099.56	40.87
2015-09-30	30.64	29.42	30.05	30.00	20065038.11	30.00

Resampling: Downsampling

Resampling: Downsampling

In [53]:
```
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 [54]:
```
df_twtr_B.index[:3]
```

Out[54]:
```
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 [54]:
```
df_twtr_B.index[:3]
```

Out[54]:
```
DatetimeIndex(['2015-01-02', '2015-01-05', '2015-01-06'], dtype='datetime64[ns]', name='Date', freq='B')
```

In [55]:
```
df_twtr_B.Close.resample('H').asfreq().iloc[0:3].round(2)
```

Out[55]:
```
Date
2015-01-02 00:00:00    36.56
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 [54]:
```
df_twtr_B.index[:3]
```

Out[54]:
```
DatetimeIndex(['2015-01-02', '2015-01-05', '2015-01-06'], dtype='datetime64[ns]', name='Date', freq='B')
```

In [55]:
```
df_twtr_B.Close.resample('H').asfreq().iloc[0:3].round(2)
```

Out[55]:
```
Date
2015-01-02 00:00:00    36.56
2015-01-02 01:00:00      NaN
2015-01-02 02:00:00      NaN
Freq: H, Name: Close, dtype: float64
```

In [56]:
```
df_twtr_B.Close.resample('H').asfreq().iloc[70:73].round(2)
```

Out[56]:
```
Date
2015-01-04 22:00:00      NaN
2015-01-04 23:00:00      NaN
2015-01-05 00:00:00    36.38
Freq: H, Name: Close, dtype: float64
```

Resampling: Upsampling

- `ffill()` : Forward Fill

Resampling: Upsampling

- `ffill()` : Forward Fill

In [57]:
```
df_twtr_B.Close.resample('H').ffill().head(3).round(2)
```

Out[57]:
```
Date
2015-01-02 00:00:00    36.56
2015-01-02 01:00:00    36.56
2015-01-02 02:00:00    36.56
Freq: H, Name: Close, dtype: float64
```

Resampling: Upsampling

- `ffill()` : Forward Fill

```
In [57]: df_twtr_B.Close.resample('H').ffill().head(3).round(2)

Out[57]: Date
         2015-01-02 00:00:00    36.56
         2015-01-02 01:00:00    36.56
         2015-01-02 02:00:00    36.56
         Freq: H, Name: Close, dtype: float64
```

- `bfill()`: Backward Fill

Resampling: Upsampling

- `ffill()` : Forward Fill

In [57]:
```
df_twtr_B.Close.resample('H').ffill().head(3).round(2)
```

Out[57]:
```
Date
2015-01-02 00:00:00    36.56
2015-01-02 01:00:00    36.56
2015-01-02 02:00:00    36.56
Freq: H, Name: Close, dtype: float64
```

- `bfill()` : Backward Fill

In [58]:
```
df_twtr_B.Close.resample('H').bfill().head(3).round(3)
```

Out[58]:
```
Date
2015-01-02 00:00:00    36.56
2015-01-02 01:00:00    36.38
2015-01-02 02:00:00    36.38
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 [59]:
```
df_twtr_B.Close['2020-11-02':'2020-11-06'].round(2)
```

Out[59]:
```
Date
2020-11-02    39.47
2020-11-03    41.73
2020-11-04    42.76
2020-11-05    43.71
2020-11-06    43.12
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 [59]:
```
df_twtr_B.Close['2020-11-02':'2020-11-06'].round(2)
```

Out[59]:
```
Date
2020-11-02    39.47
2020-11-03    41.73
2020-11-04    42.76
2020-11-05    43.71
2020-11-06    43.12
Freq: B, Name: Close, dtype: float64
```

In [60]:
```
rolling_3 = df_twtr_B.Close['2020-11-02':'2020-11-06'].rolling(3, center=True)
rolling_3
```

Out[60]:
```
Rolling [window=3,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 [59]:
```
df_twtr_B.Close['2020-11-02':'2020-11-06'].round(2)
```

Out[59]:
```
Date
2020-11-02    39.47
2020-11-03    41.73
2020-11-04    42.76
2020-11-05    43.71
2020-11-06    43.12
Freq: B, Name: Close, dtype: float64
```

In [60]:
```
rolling_3 = df_twtr_B.Close['2020-11-02':'2020-11-06'].rolling(3, center=True)
rolling_3
```

Out[60]:
```
Rolling [window=3,center=True,axis=0,method=single]
```

In [61]:
```
rolling_3.mean()['2020-11-02':'2020-11-06'].round(2)
```

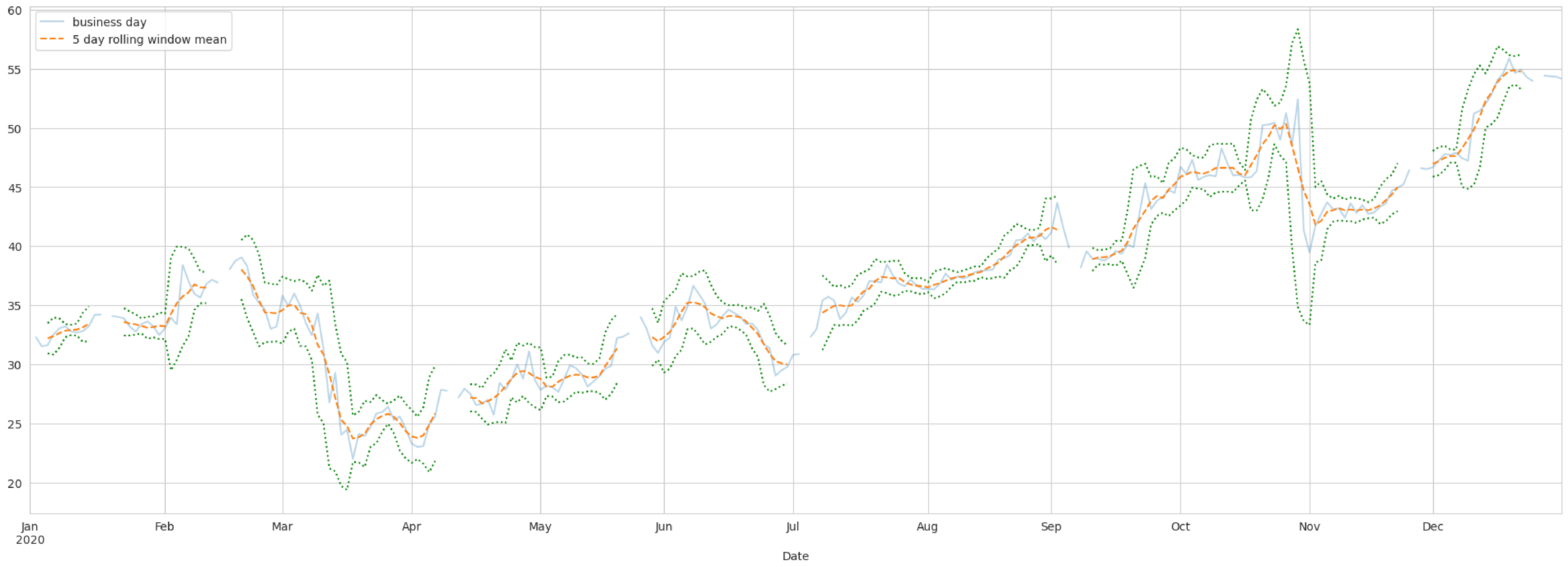
Out[61]:
```
Date
2020-11-02      NaN
2020-11-03    41.32
2020-11-04    42.73
2020-11-05    43.20
2020-11-06      NaN
Freq: B, Name: Close, dtype: float64
```

Moving Windows

Moving Windows

In [62]:
```
sns.set_style("whitegrid")
rolling = df_twtr_B.Close.rolling(5, center=True)

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 [63]:
```
df_bike_counts = pd.read_csv('../data/FremontBridge_2012-2015.csv',parse_dates=['Date'],index_col='Date')
df_bike_counts.columns = ['Total','East','West']
df_bike_counts.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 28440 entries, 2012-10-03 00:00:00 to 2015-12-31 23:00:00
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Total   28433 non-null  float64
 1   East    28433 non-null  float64
 2   West    28433 non-null  float64
dtypes: float64(3)
memory usage: 888.8 KB
```

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 [63]:
```
df_bike_counts = pd.read_csv('../data/FremontBridge_2012-2015.csv',parse_dates=['Date'],index_col='Date')
df_bike_counts.columns = ['Total','East','West']
df_bike_counts.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 28440 entries, 2012-10-03 00:00:00 to 2015-12-31 23:00:00
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Total   28433 non-null  float64
 1   East    28433 non-null  float64
 2   West    28433 non-null  float64
dtypes: float64(3)
memory usage: 888.8 KB
```

In [64]:
```
df_bike_counts.head(3)
```

Out[64]:

	Total	East	West
Date			
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

Example: Fill Missing Values

Example: Fill Missing Values

In [65]:
```
f'proportion missing: {sum(df_bike_counts.Total.isna()) / len(df_bike_counts):0.5f}'
```

Out[65]:
```
'proportion missing: 0.00025'
```

Example: Fill Missing Values

In [65]:
```python
f'proportion missing: {sum(df_bike_counts.Total.isna()) / len(df_bike_counts):0.5f}'
```

Out[65]:
```
'proportion missing: 0.00025'
```

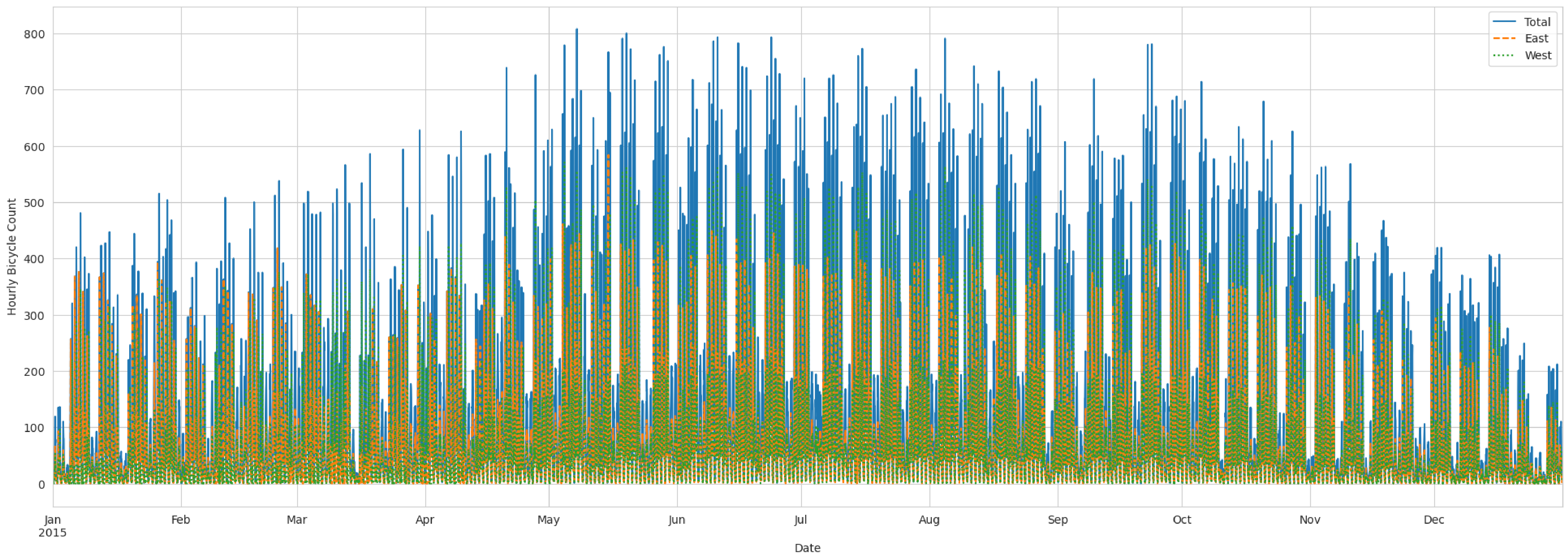
In [66]:
```python
df_bike_counts = df_bike_counts.fillna(method='ffill')
df_bike_counts.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 28440 entries, 2012-10-03 00:00:00 to 2015-12-31 23:00:00
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Total   28440 non-null  float64
 1   East    28440 non-null  float64
 2   West    28440 non-null  float64
dtypes: float64(3)
memory usage: 888.8 KB
```

Plot data from 2015

Plot data from 2015

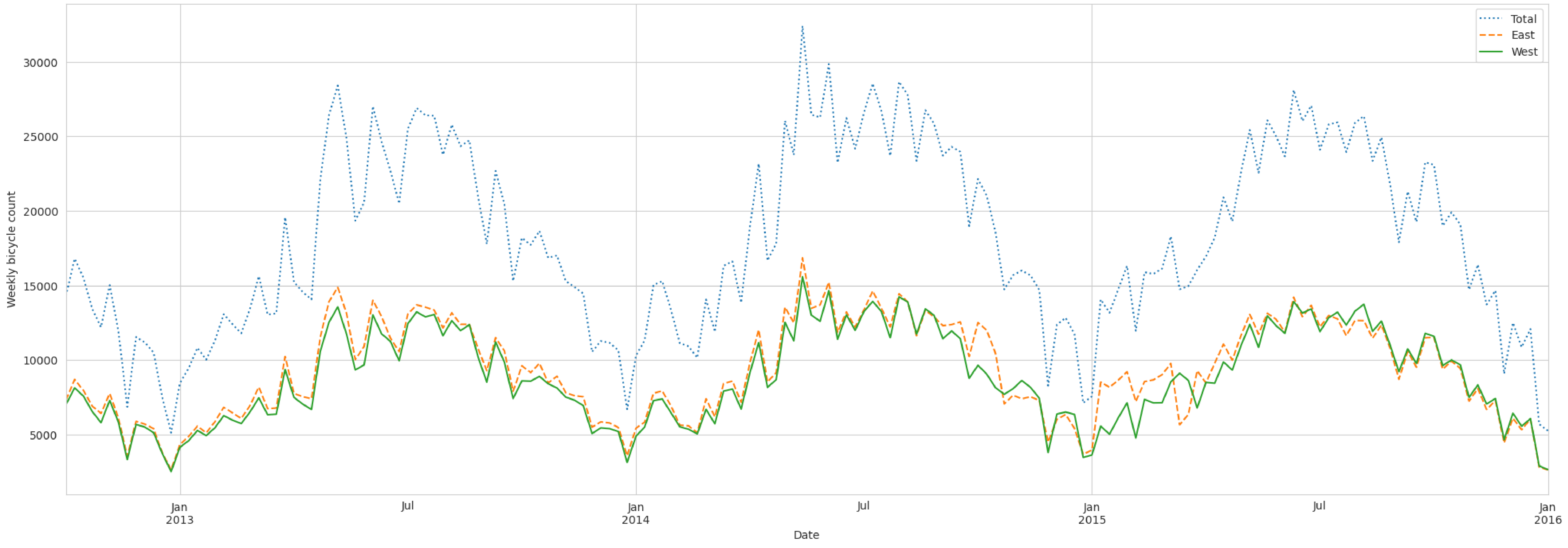
In [67]:
```
fig,ax = plt.subplots(1,1,figsize=(24,8))
df_bike_counts.loc['2015'].plot(style=['-', '--', ':'],ax=ax)
plt.ylabel('Hourly Bicycle Count');
```



Downsample to weekly sum to smooth things out

Downsample to weekly sum to smooth things out

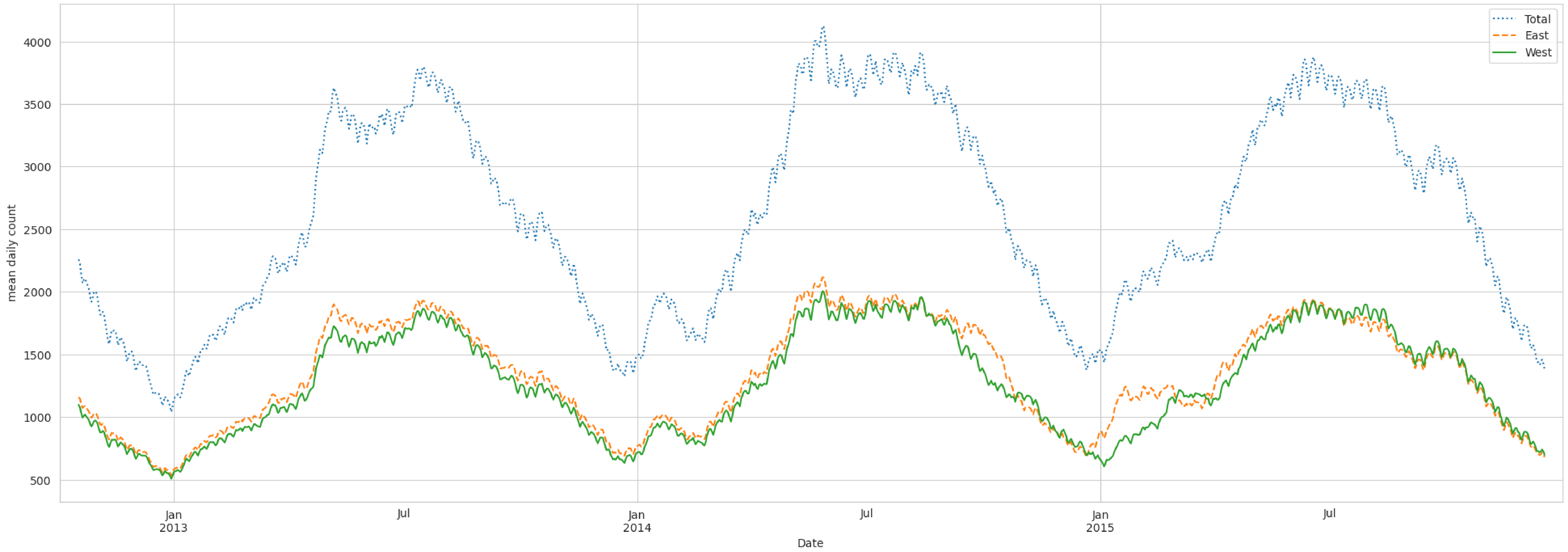
In [68]:
```
weekly = df_bike_counts.resample('W').sum()
weekly.plot(style=[':', '--', '-'], figsize=(24,8))
plt.ylabel('Weekly bicycle count');
```



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 [69]:
```
daily = df_bike_counts.resample('D').sum()
daily.rolling(30,center=True).mean().plot(style=[':', '--', '-'], figsize=(24,8))
plt.ylabel('mean daily count');
```



From Datetime to Time

From Datetime to Time

In [71]:
```
#If we want to only look at time of day
df_bike_counts.index.time
```

Out[71]:
```
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 [71]:
```
#If we want to only look at time of day
df_bike_counts.index.time
```

Out[71]:
```
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)
```

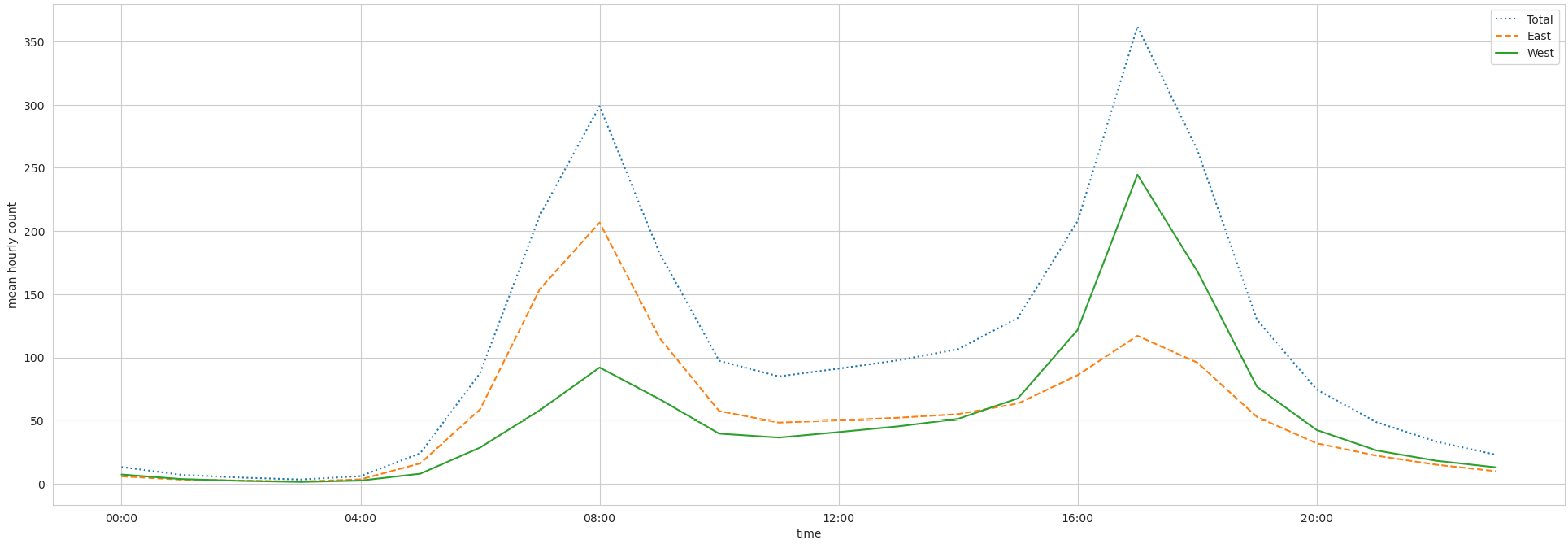
In [72]:
```
#Get mean data by time (hourly)
by_time = df_bike_counts.groupby(df_bike_counts.index.time).mean().round(2)
display(by_time.head())
```

	Total	East	West
00:00:00	13.34	5.94	7.40
01:00:00	7.15	3.34	3.81
02:00:00	4.97	2.61	2.36
03:00:00	3.43	1.90	1.52
04:00:00	6.13	3.53	2.59

Plot by hour of the day

Plot by hour of the day

In [73]:
```
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');
```

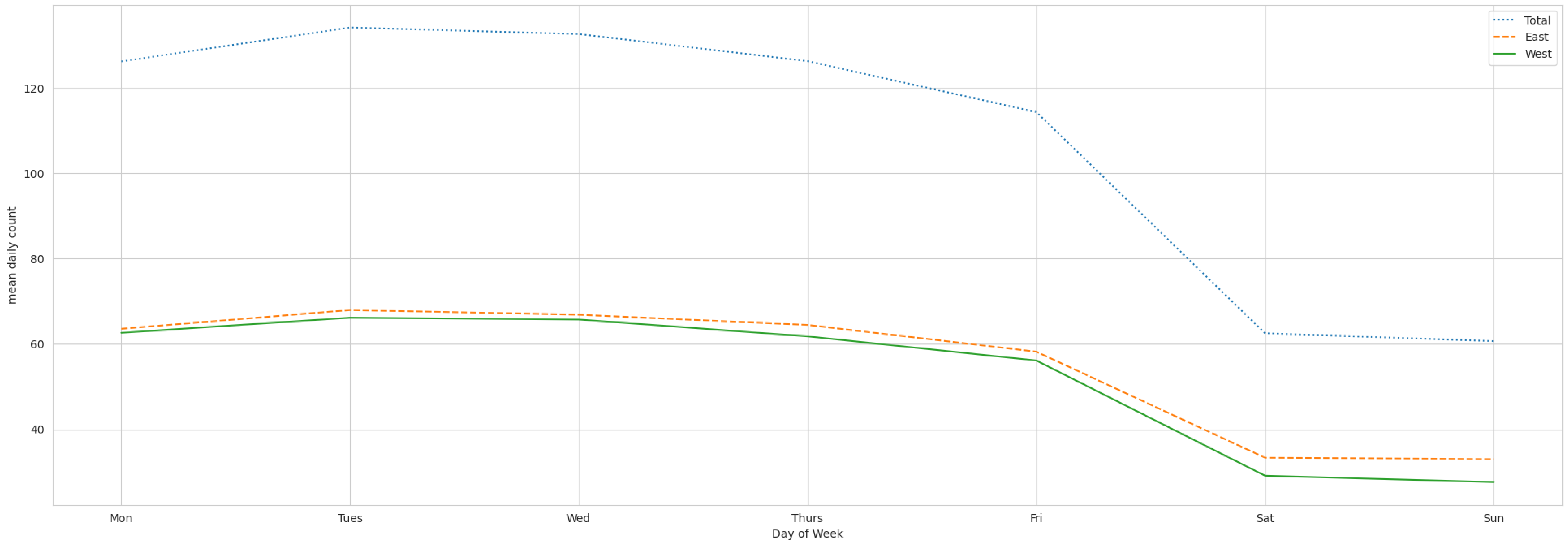


Can also look at average by day of week

Can also look at average by day of week

In [74]:
```
# note that for dayofweek: 0 == Mon, 1 == Tues,..., 6 == 'Sun'
by_weekday = df_bike_counts.groupby(df_bike_counts.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');
```

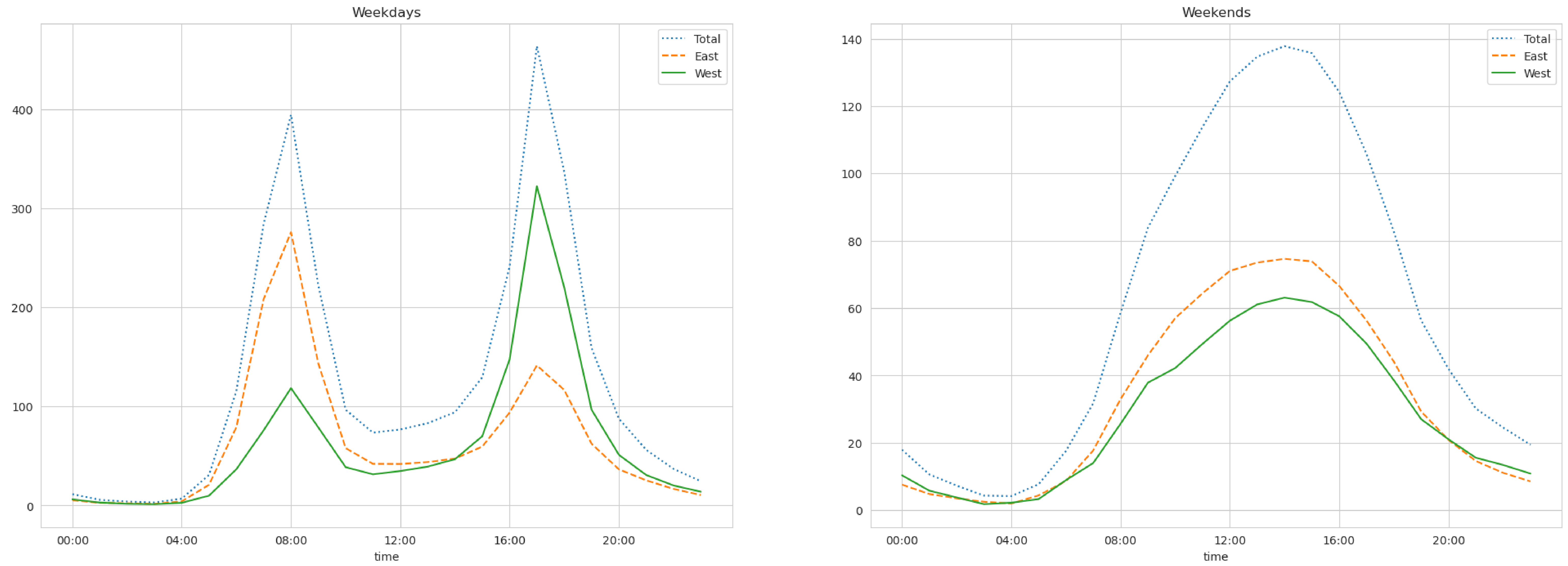


Separate out weekdays and weekends

Separate out weekdays and weekends

In [75]:
```
# create a weekend mask
weekend = np.where(df_bike_counts.index.weekday < 5, 'Weekday', 'Weekend')

# get hourly mean values split by weekday, weekend
by_time = df_bike_counts.groupby([weekend, df_bike_counts.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 [76]:
```
df_bike_counts = pd.read_csv('../data/FremontBridge_2012-2015.csv', index_col='Date', parse_dates=True)
df_bike_weather = pd.read_csv('../data/BicycleWeather.csv', index_col='DATE', parse_dates=True)

df_bike = (
    df_bike_counts.loc[:,['Fremont Bridge Total']]   # keep Total as target
    .rename({'Fremont Bridge Total':'Total'},axis=1) # rename target column
    .resample('D').sum()                             # downsample to daily totals
)
print(df_bike.head(3))
```

```
             Total
Date
2012-10-03  3521.0
2012-10-04  3475.0
2012-10-05  3148.0
```

Can we predict daily Total bike traffic?

In [76]:
```
df_bike_counts = pd.read_csv('../data/FremontBridge_2012-2015.csv', index_col='Date', parse_dates=True)
df_bike_weather = pd.read_csv('../data/BicycleWeather.csv', index_col='DATE', parse_dates=True)

df_bike = (
    df_bike_counts.loc[:,['Fremont Bridge Total']]   # keep Total as target
    .rename({'Fremont Bridge Total':'Total'},axis=1) # rename target column
    .resample('D').sum()                             # downsample to daily totals
)
print(df_bike.head(3))
```

```
             Total
Date
2012-10-03  3521.0
2012-10-04  3475.0
2012-10-05  3148.0
```

On to Feature Engineering...

Add ’day of week’

Add 'day of week'

In [77]:
```
day_names_map = dict(enumerate(['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat', 'Sun']))
print(f"{day_names_map = :}")
df_bike['DayOfWeek'] = df_bike.index.dayofweek.map(day_names_map)
df_bike.head(3)
```

```
day_names_map = {0: 'Mon', 1: 'Tue', 2: 'Wed', 3: 'Thu', 4: 'Fri', 5: 'Sat', 6: 'Sun'}
```

Out[77]:

	Total	DayOfWeek
Date		
2012-10-03	3521.0	Wed
2012-10-04	3475.0	Thu
2012-10-05	3148.0	Fri

Add 'is it a holiday' dummy feature

Add 'is it a holiday' dummy feature

In [78]:

```
from pandas.tseries.holiday import USFederalHolidayCalendar
cal = USFederalHolidayCalendar()
holidays = cal.holidays('2012', '2016')

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

```
             Total DayOfWeek  IsHoliday
Date
2012-10-03  3521.0       Wed        0.0
2012-10-04  3475.0       Thu        0.0
2012-10-05  3148.0       Fri        0.0
```

Add number of hours of daylight

Add number of hours of daylight

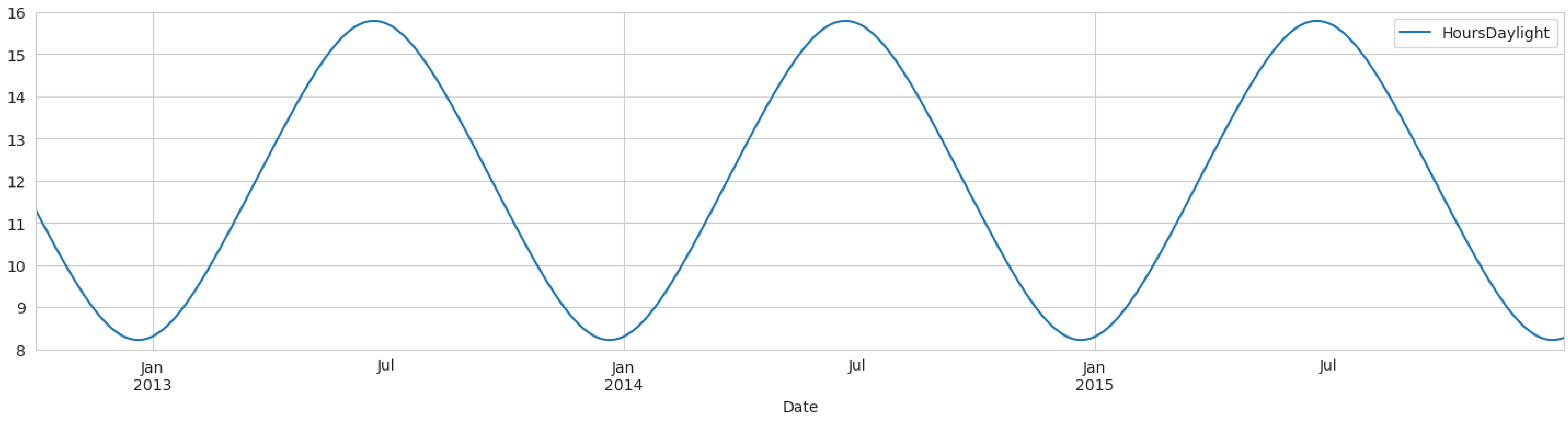
In [79]:

```
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 # days till winter solstice
    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.

df_bike['HoursDaylight'] = list(map(hours_of_daylight, df_bike.index));

ax = df_bike[['HoursDaylight']].plot(figsize=(18,4));
ax.set_ylim(8, 16);
```



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

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

In [80]:
```
# temperatures are in 1/10 deg C; convert to C
df_bike_weather['TMIN'] /= 10
df_bike_weather['TMAX'] /= 10
df_bike_weather['TempC'] = 0.5 * (df_bike_weather['TMIN'] + df_bike_weather['TMAX'])

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

df_bike = df_bike.join(df_bike_weather[['PRCP', 'TempC', 'IsDryDay']],how='inner')
df_bike.head(3).round(2)
```

Out[80]:

	Total	DayOfWeek	IsHoliday	HoursDaylight	PRCP	TempC	IsDryDay
2012-10-03	3521.0	Wed	0.0	11.28	0.0	13.35	1
2012-10-04	3475.0	Thu	0.0	11.22	0.0	13.60	1
2012-10-05	3148.0	Fri	0.0	11.16	0.0	15.30	1

Add time of year

Add time of year

In [81]:
```
df_bike['TimeOfYear'] = (df_bike.index - df_bike.index[0]).days / 365.0 # Days since the beginning of the year
df_bike.head(3)
```

Out[81]:

	Total	DayOfWeek	IsHoliday	HoursDaylight	PRCP	TempC	IsDryDay	TimeOfYear
2012-10-03	3521.0	Wed	0.0	11.277359	0.0	13.35	1	0.000000
2012-10-04	3475.0	Thu	0.0	11.219142	0.0	13.60	1	0.002740
2012-10-05	3148.0	Fri	0.0	11.161038	0.0	15.30	1	0.005479

Generate and evaluate a model

Generate and evaluate a model

In [82]:

```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.dummy import DummyRegressor
from sklearn.metrics import mean_absolute_error

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

X_bike = pd.get_dummies(df_bike.loc[:,df_bike.columns != 'Total'])
display(X_bike.head(1).round(2))
y_bike = df_bike.Total

X_bike_train = X_bike.loc['2012':'2014']
y_bike_train = y_bike.loc['2012':'2014']
X_bike_test = X_bike.loc['2015']
y_bike_test = y_bike.loc['2015']

dummy_bike = DummyRegressor().fit(X_bike_train,y_bike_train)
gb_bike = GradientBoostingRegressor().fit(X_bike_train,y_bike_train)
print(f'dummy training mae    : {mean_absolute_error(y_bike_train,dummy_bike.predict(X_bike_train)).round(2)}')
print(f'one-back training mae : {mean_absolute_error(y_bike_train,y_bike_train.shift(1).fillna(0)).round(2)}')
print(f'gb training set mae   : {mean_absolute_error(y_bike_train,gb_bike.predict(X_bike_train)).round(2)}')
print(f'gb test set R^2       : {mean_absolute_error(y_bike_test,gb_bike.predict(X_bike_test)).round(2)}')
```

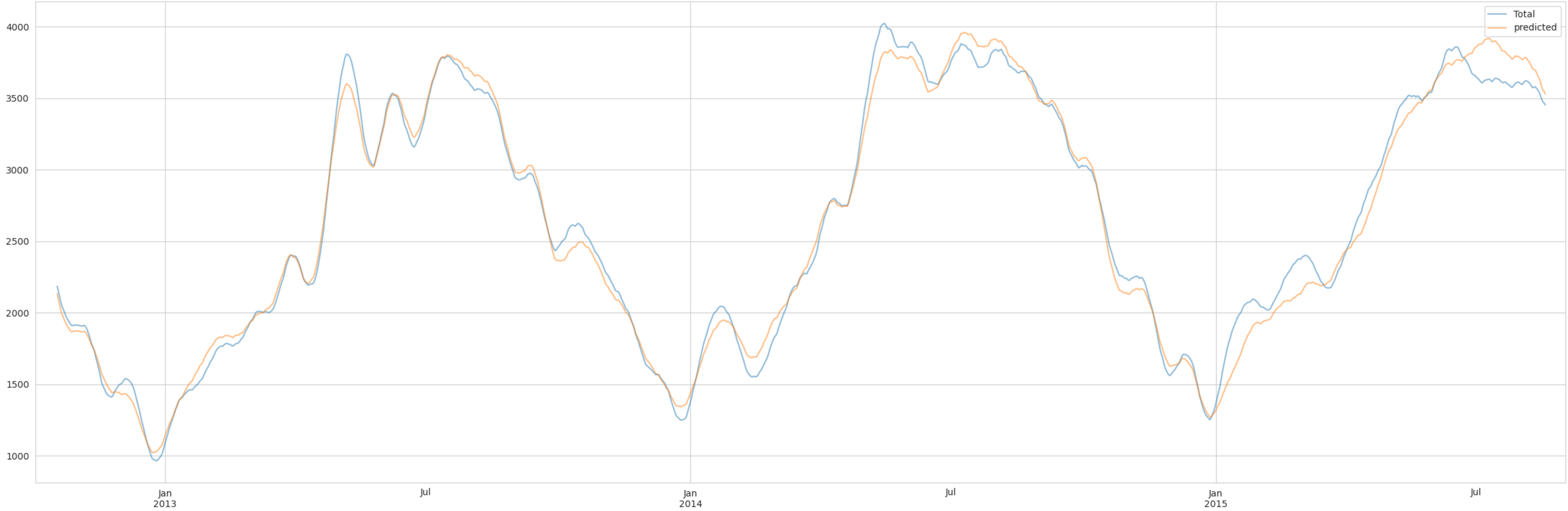
	IsHoliday	HoursDaylight	PRCP	TempC	IsDryDay	TimeOfYear	DayOfWeek_Fri	DayOfWeek_Mon	DayOfWeek_Sat	DayOfWeek_Sun	DayOfWeek_Thu	DayOfWeek_Tue	Day(
2012-10-03	0.0	11.28	0.0	13.35	1	0.0	0	0	0	0	0	0	1

```
dummy training mae    : 1019.45
one-back training mae : 710.39
gb training set mae   : 213.37
gb test set R^2       : 308.24
```

Plot predictions vs observed

Plot predictions vs observed

In [83]:
```
df_bike['predicted'] = gb_bike.predict(X_bike)
df_bike[['Total', 'predicted']].rolling(30, center=True,win_type='gaussian').mean(std=7).plot(alpha=0.5,figsize=(24,8))
plt.tight_layout()
```



Time Series Operations Review

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

- for more info, including time-series cross-validation:
    - sklearn: Time-related feature engineering
    - PML Chapter 13 - Modeling Sequential Data Using Recurrent Neural Network (with Tensorflow)

- for more models:
    - skforecast
    - statsmodels

Questions re Time Series Transformations?

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: Python script basics

Aside: Python script basics

In [84]:
```
!cat ../src/sample_script.py
```

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

# python as usual
def current_time():
    return datetime.now()

# will run as script or on import
run_or_imported_at = current_time()
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")
```

Aside: Python script basics

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```
!cat ../src/sample_script.py
```

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run_or_imported_at = current_time()
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 [85]:
```
import sys
sys.path.append('../src/') # need to tell python where to look for this file

import sample_script
```

```
this was run or imported at 2022-11-30 18:04:12.290787
__name__ = sample_script
```

Aside: Python script basics

In [84]:
```
!cat ../src/sample_script.py
```

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

# python as usual
def current_time():
    return datetime.now()

# will run as script or on import
run_or_imported_at = current_time()
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 [85]:
```
import sys
sys.path.append('../src/') # need to tell python where to look for this file

import sample_script
```

```
this was run or imported at 2022-11-30 18:04:12.290787
__name__ = sample_script
```

In [86]:
```
%run ../src/sample_script.py
```

```
this was run or imported at 2022-11-30 18:04:12.299807
__name__ = __main__
running as a script

<Figure size 640x480 with 0 Axes>
```

Aside: Function Decorators

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

Aside: Function Decorators

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

In [87]:
```python
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 [88]: !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

```
In [88]: !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'

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    app.run()
```

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

Creating APIs: Flask

```
In [88]: !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 another terminal, ipython (or notebook), run:

```
# need to change "Cell Type" to code to run in 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 [89]:
```
!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'}
```

Example Model: Titanic

Example Model: Titanic

In [90]:
```
from sklearn.model_selection import train_test_split
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']]
print(df_titanic.info())
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,
                                                                                    stratify=y_titanic,
                                                                                    random_state=42)

display(X_titanic_train.head(3))
print(f"y_train prop positive: {y_titanic_train.mean().round(2)}")
```

```
<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
None
```

	age	fare	embarked	sex	pclass
999	NaN	7.7500	Q	female	3
392	24.0	27.7208	C	female	2
628	11.0	31.2750	S	female	3

```
y_train prop positive: 0.38
```

Example Model: Titanic

Example Model: Titanic

In [91]:
```python
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: 0.802
best parameter settings: {'classifier__C': 1.0, 'preprocessor__num__imputer__strategy': 'median'}
```

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 [92]:
```
import pickle as pkl

# write/dump to disk
with open('../data/titanic_pipeline_clf.pkl','wb') as f:
    pkl.dump(gs_pipeline,f)
```

Creating APIs: Flask

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

In [92]:
```
import pickle as pkl

# write/dump to disk
with open('../data/titanic_pipeline_clf.pkl','wb') as f:
    pkl.dump(gs_pipeline,f)
```

In [93]:
```
# read/load from disk
with open('../data/titanic_pipeline_clf.pkl','rb') as f:
    pretrained_titanic_clf = pkl.load(f)

pretrained_titanic_clf
```

Out[93]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('preprocessor',
                                        ColumnTransformer(transformers=[('num',
                                                                         Pipeline(steps=[('imputer',
                                                                                          SimpleImputer(strategy='median')),
                                                                                         ('scaler',
                                                                                          StandardScaler())]),
                                                                         ['age',
                                                                          'fare']),
                                                                        ('cat',
                                                                         Pipeline(steps=[('imputer',
                                                                                          SimpleImputer(fill_value='missing',
                                                                                                        strategy='constant')),
                                                                                         ('onehot',
                                                                                          OneHotEncoder(handle_unknown='ignor
e'))]),
                                                                         ['embarked',
                                                                          'sex',
```

Creating APIs: Deliver Predictions Using Flask

Creating APIs: Deliver Predictions Using Flask

In [94]:
```
!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 [95]:
```
query_label = df_titanic.iloc[0].loc['survived']
```

Creating APIs: Deliver Predictions Using Flask Cont.

In [95]:
```
query_label = df_titanic.iloc[0].loc['survived']
```

In [96]:
```
query = df_titanic.iloc[0,:-1].to_dict()
query
```

Out[96]:
```
{'age': 29.0, 'fare': 211.3375, 'embarked': 'S', 'sex': 'female', 'pclass': 1}
```

Creating APIs: Deliver Predictions Using Flask Cont.

In [95]:
```
query_label = df_titanic.iloc[0].loc['survived']
```

In [96]:
```
query = df_titanic.iloc[0,:-1].to_dict()
query
```

Out[96]:
```
{'age': 29.0, 'fare': 211.3375, 'embarked': 'S', 'sex': 'female', 'pclass': 1}
```

In [97]:
```
query_label
```

Out[97]:
```
1
```

Creating APIs: Deliver Predictions Using Flask Cont.

In [95]:
```
query_label = df_titanic.iloc[0].loc['survived']
```

In [96]:
```
query = df_titanic.iloc[0,:-1].to_dict()
query
```

Out[96]:
```
{'age': 29.0, 'fare': 211.3375, 'embarked': 'S', 'sex': 'female', 'pclass': 1}
```

In [97]:
```
query_label
```

Out[97]:
```
1
```

In [98]:
```
# Start script from command line by first activating the eods-f22 environment and running: python titanic_clf.py
# Then uncomment the following:

#import requests
#print(requests.post('http://127.0.0.1:5000/', data=query).text)
```

Questions re Model API via Flask?