Intro_to_ML

November 11, 2019

1 Machine Learning Introduction

1.1 Naive Bayes Classifiers

Naive Bayes models are a group of extremely fast and simple classification algorithms that are often suitable for very high-dimensional datasets. Because they are so fast and have so few tunable parameters, they end up being very useful as a quick-and-dirty baseline for a classification problem. This means that you'll often compare your more complicated model's metrics to those of a Naive Bayes classifier to tell how good your model is.

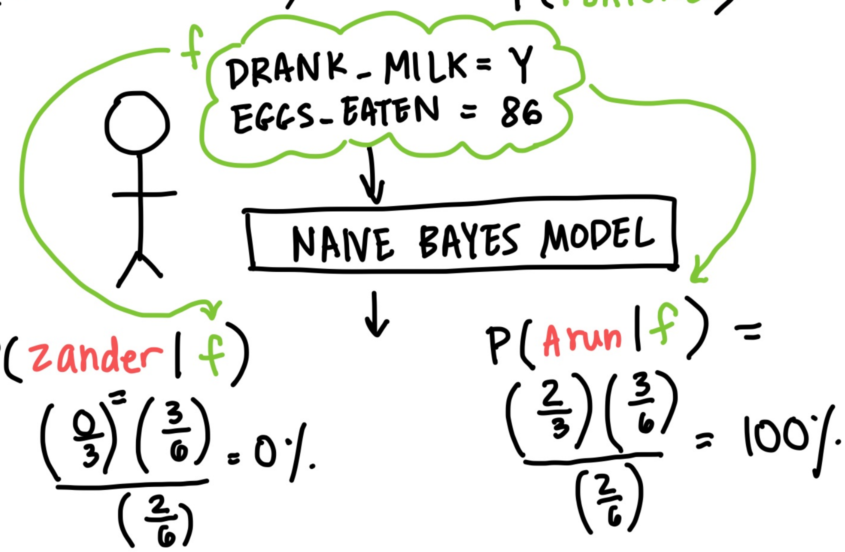
1.1.1 Bayes Theorem

BAYES THEOREM

NAME	DRANK_MILK	EGGS_EATEN
ZANDER	Y	0-10
ARUN	Y	80-90
ZANDER	N	10-20
ZANDER	N	0-10
ARUN	Y	70-80
ARUN	Y	80-90

labels features

$$P(\text{LABEL} \mid \text{FEATURES}) = \frac{P(\text{FEATURES} \mid \text{LABEL})\, P(\text{LABEL})}{P(\text{FEATURES})}$$



1.1.2 Multinomial Naive Bayes Example

Multinomial Naive Bayes is when you assume features come from a simple multinomial distribution, which is a distribution that describes the probability of observing counts among a number of categories. This is basically a binomial distribution, except with several potential outcomes. This can be useful when you have features that have to do with counts.

(An example of a multinomial distrubtion with only 2 variables.)

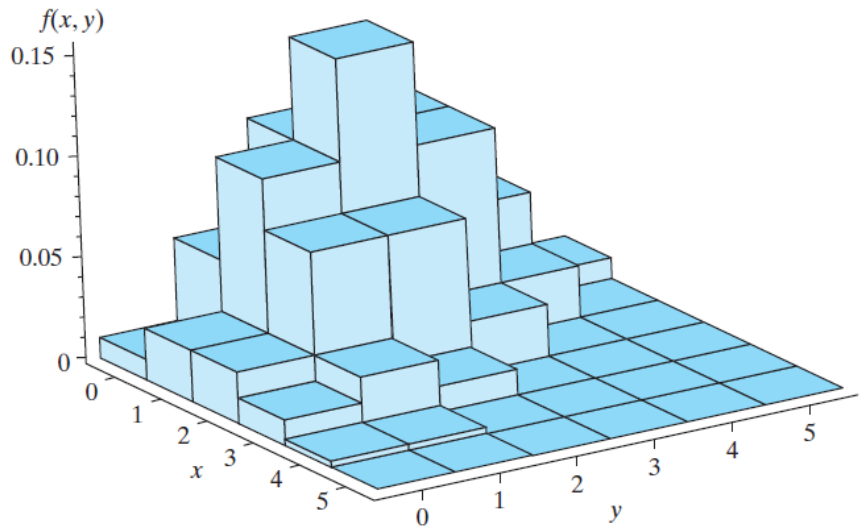


Figure 4.1-4 Trinomial distribution, $p_X = 1/5, p_Y = 2/5$, and $n = 5$

Classifying Text with Multinomial Naive Bayes: Intuition If you're trying to classify text, features are often associated with word counts or frequencies. Thus, it makes sense to use a multinomial naive Bayes classifier as a baseline. Let's take a look at scikit-learn's Newsgroups dataset, which has a bunch of emails and their topics/categories.

Training the Model

[1]:
```
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()
```

[2]:
```
from sklearn.datasets import fetch_20newsgroups

data = fetch_20newsgroups()
data.target_names
```

[2]:
```
['alt.atheism',
 'comp.graphics',
 'comp.os.ms-windows.misc',
 'comp.sys.ibm.pc.hardware',
 'comp.sys.mac.hardware',
 'comp.windows.x',
 'misc.forsale',
 'rec.autos',
 'rec.motorcycles',
 'rec.sport.baseball',
 'rec.sport.hockey',
 'sci.crypt',
 'sci.electronics',
```

```
 'sci.med',
 'sci.space',
 'soc.religion.christian',
 'talk.politics.guns',
 'talk.politics.mideast',
 'talk.politics.misc',
 'talk.religion.misc']
```

[3]:
```
# Let's just look at four categories
categories = ['talk.religion.misc', 'soc.religion.christian',
              'sci.space', 'comp.graphics']
# This dataset is already split into train/test
train = fetch_20newsgroups(subset='train', categories=categories)
test = fetch_20newsgroups(subset='test', categories=categories)
```

[4]:
```
print(train.data[5])
```

```
From: dmcgee@uluhe.soest.hawaii.edu (Don McGee)
Subject: Federal Hearing
Originator: dmcgee@uluhe
Organization: School of Ocean and Earth Science and Technology
Distribution: usa
Lines: 10


Fact or rumor...?  Madalyn Murray O'Hare an atheist who eliminated the
use of the bible reading and prayer in public schools 15 years ago is now
going to appear before the FCC with a petition to stop the reading of the
Gospel on the airways of America.  And she is also campaigning to remove
Christmas programs, songs, etc from the public schools.  If it is true
then mail to Federal Communications Commission 1919 H Street Washington DC
20054 expressing your opposition to her request.  Reference Petition number

2493.
```

Vectorization This is feature engineering for text. Basically, you want to turn your text into some kind of vector. `TF-IDF` stands for `term frequency-inverse document frequency`, which means that instead of having a vector of just raw word counts, it'll weight individual word "counts" both by how many times that word appears in a certain document, and by how many times it appears in other documents.

This means that frequently appearing words like "the" will not necessarily have a high TD-IDF count because they appear frequently in all documents. The highest weighted words will be those that appear frequently in only a few documents.

[5]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.pipeline import make_pipeline
```

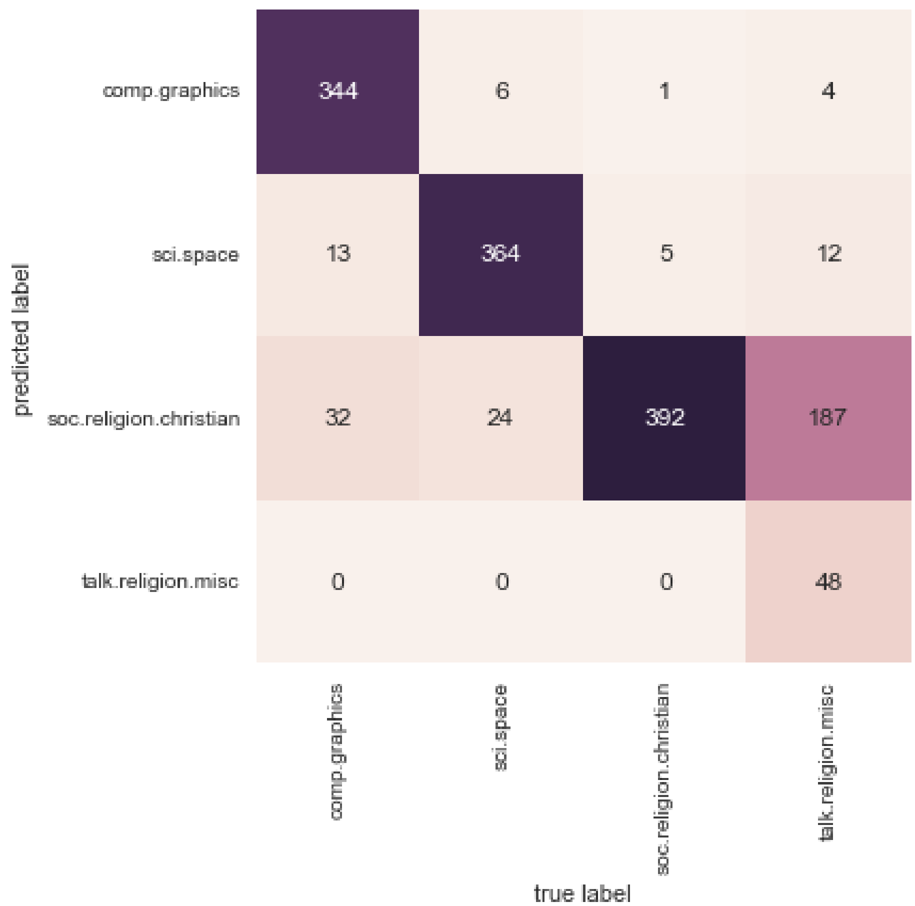
```
# We make a Multinomial Naive Bayes model using a TD-IDF vectorizer
model = make_pipeline(TfidfVectorizer(), MultinomialNB())
```

[6]:
```
# train the model, passing in the text (train.data)
# and the labels (train.target)
model.fit(train.data, train.target)
labels = model.predict(test.data)
```

Evaluating the Model

[7]:
```
from sklearn import metrics
print("Accuracy:",metrics.accuracy_score(test.target, labels))
```

```
Accuracy: 0.8016759776536313
```



title

80% accuracy! So this means that we would like more complex, tailored models to do better. We can see that the Naive Bayes classifier did pretty well on classifying topics that had little overlap with others (like comp.graphics), but less well on topics that had overlap (soc.religion.christian and talk.religion.misc).

Using the Model

[8]:
```
def predict_category(s, train=train, model=model):
    pred = model.predict([s])
    return train.target_names[pred[0]]
```

[9]:
```
predict_category('what is the screen resolution of my laptop')
```

[9]:
```
'comp.graphics'
```

[10]:
```
predict_category('catchy christian music')
```

[10]:
```
'soc.religion.christian'
```

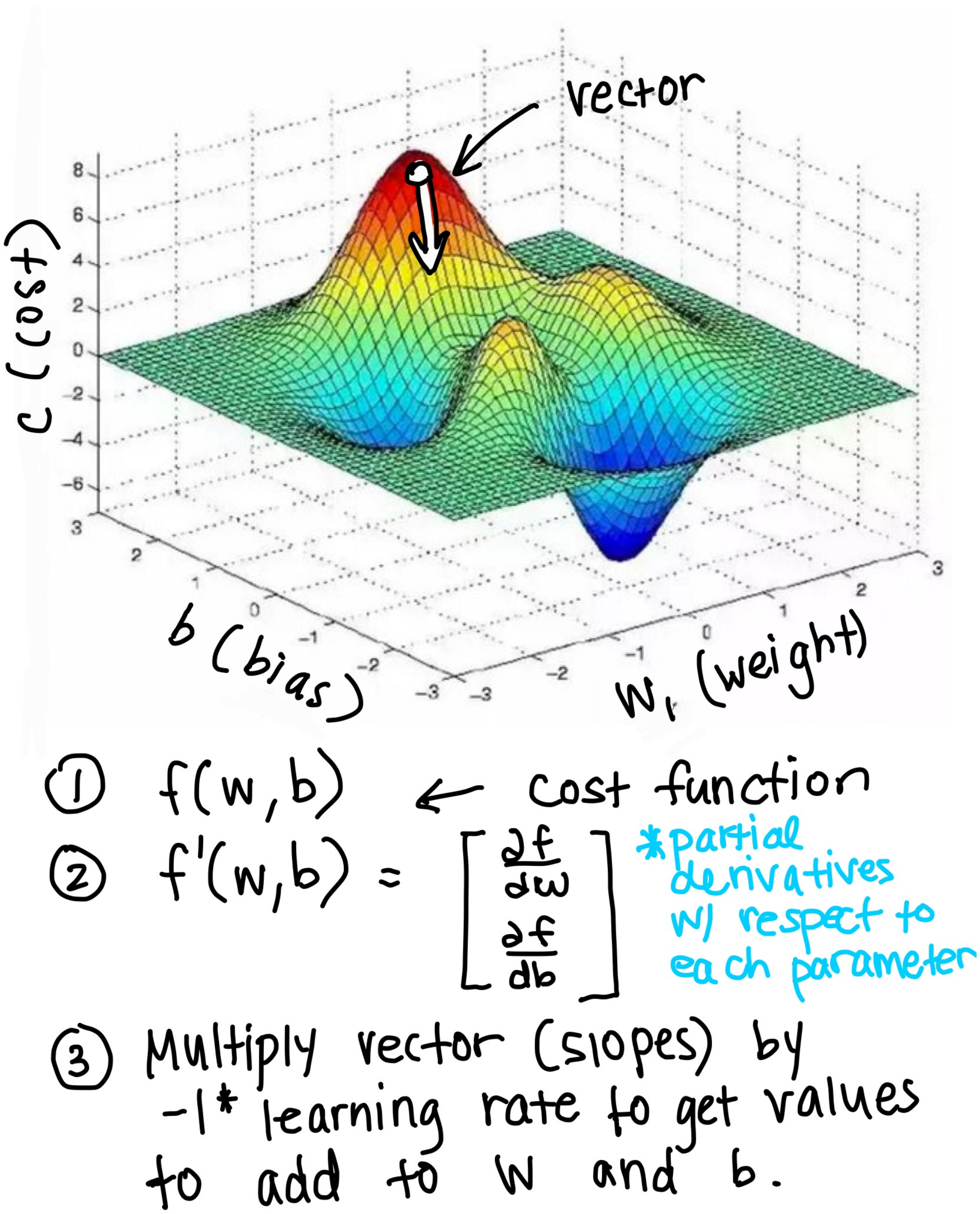
1.2 Linear Regressions

Linear regressions, like Naive Bayes, are a good starting point for when you want to do some sort of regression task. We are trying to fit a dataset to a line, while minimizing error (squared sum of residuals between observed and predicted data).

1.2.1 Brief Review of Gradient Descent

Gradient descent is an optimization algorithm used to minimize some function by iteratively moving in the direction of steepest descent as defined by the negative of the gradient.

Here's what it looks like:



In practice, gradient descent is used more often for things like computing the weights of neurons in neural nets, not for linear regressions. Therefore, it is more useful for us to cover gradient descent in depth in our neural networks lecture later this semester.

Scikit-learn's `LinearRegression()` model, for example, does not use gradient descent to update the coefficients. It uses ordinary least squares solver from `scipy`.

1.2.2 Linear Regression Example: Bicycle Traffic

As an example, let's take a look at whether we can predict the number of bicycle trips across Seattle's Fremont Bridge based on weather, season, and other factors. I've gathered some data for you. The FremontBridge data is from the Seattle Local Government's API and the weather data is collected daily from a station near the Seattle-Tacoma Airport.

Reading in the Data

[11]:
```
import pandas as pd

# read in the data
counts = pd.read_csv('data/FremontBridge.csv', index_col='Date',␣
↪parse_dates=True)
weather = pd.read_csv('data/weather.csv', index_col='DATE', parse_dates=True)
```

Exploring the Data

[12]:
```
weather.head()
```

[12]:
```
                STATION                                      NAME  AWND  \
DATE
2013-01-01  USW00024233  SEATTLE TACOMA INTERNATIONAL AIRPORT, WA US  6.04
2013-01-02  USW00024233  SEATTLE TACOMA INTERNATIONAL AIRPORT, WA US  7.16
2013-01-03  USW00024233  SEATTLE TACOMA INTERNATIONAL AIRPORT, WA US  6.71
2013-01-04  USW00024233  SEATTLE TACOMA INTERNATIONAL AIRPORT, WA US  6.26
2013-01-05  USW00024233  SEATTLE TACOMA INTERNATIONAL AIRPORT, WA US  6.93

            PGTM  PRCP  SNOW  SNWD  TAVG  TMAX  TMIN  ...  WT03  WT04  WT05  \
DATE                                                  ...
2013-01-01   NaN  0.00   0.0   0.0   NaN    41    27  ...   NaN   NaN   NaN
2013-01-02   NaN  0.00   0.0   0.0   NaN    43    30  ...   NaN   NaN   NaN
2013-01-03   NaN  0.16   0.0   0.0   NaN    44    29  ...   NaN   NaN   NaN
2013-01-04   NaN  0.10   0.0   0.0   NaN    50    36  ...   NaN   NaN   NaN
2013-01-05   NaN  0.12   0.0   0.0   NaN    44    40  ...   NaN   NaN   NaN

            WT08  WT09  WT13  WT14  WT16  WT18  WT22
DATE
2013-01-01   NaN   NaN   NaN   NaN   NaN   NaN   NaN
2013-01-02   NaN   NaN   NaN   NaN   NaN   NaN   NaN
2013-01-03   NaN   NaN   1.0   NaN   1.0   NaN   NaN
2013-01-04   NaN   NaN   1.0   NaN   1.0   NaN   NaN
2013-01-05   NaN   NaN   1.0   NaN   1.0   NaN   NaN

[5 rows x 26 columns]
```

[13]:
```
weather.shape
```

[13]:
```
(2502, 26)
```

[14]:
```
# number of bicycles crossing on either side of Fremont Bridge
counts.head()
```

[14]:
```
                     Fremont Bridge East Sidewalk  \
Date
2015-02-24 02:00:00                           3.0
2019-01-01 00:00:00                           0.0
```

```
2019-01-01 01:00:00                          2.0
2016-02-15 00:00:00                          3.0
2019-01-01 02:00:00                          1.0

                     Fremont Bridge West Sidewalk
Date
2015-02-24 02:00:00                          3.0
2019-01-01 00:00:00                          9.0
2019-01-01 01:00:00                         22.0
2016-02-15 00:00:00                          3.0
2019-01-01 02:00:00                         11.0
```

[15]:

```
counts.shape
```

[15]:

```
(62040, 2)
```

Cleaning the Data Here, we want to convert hourly counts into daily counts pandas resample() let's you do this. 'd' means daily. other potential frequencies can be 'w': weekly, 'm': monthly, or 'q': quarterly. Notice that this is for time series data, so your dataframe needs a datetime-like index.

[16]:

```
# convert bicycle counts from daily to monthly.
daily = counts.resample('d').sum()
daily.head()
```

[16]:

```
            Fremont Bridge East Sidewalk  Fremont Bridge West Sidewalk
Date
2012-10-03                        1760.0                        1761.0
2012-10-04                        1708.0                        1767.0
2012-10-05                        1558.0                        1590.0
2012-10-06                        1080.0                         926.0
2012-10-07                        1191.0                         951.0
```

[17]:

```
# sum east and west counts
daily['Total'] = daily.sum(axis=1)
daily = daily[['Total']] # remove other columns
daily.head()
```

[17]:

```
             Total
Date
2012-10-03  3521.0
2012-10-04  3475.0
2012-10-05  3148.0
2012-10-06  2006.0
2012-10-07  2142.0
```

[18]:

```
# Create dummy variable for each day of the week
days = ['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat', 'Sun']
for i in range(7):
    daily[days[i]] = (daily.index.dayofweek == i).astype(float)
```

```
daily.head()
```

[18]:

```
            Total  Mon  Tue  Wed  Thu  Fri  Sat  Sun
Date
2012-10-03  3521.0  0.0  0.0  1.0  0.0  0.0  0.0  0.0
2012-10-04  3475.0  0.0  0.0  0.0  1.0  0.0  0.0  0.0
2012-10-05  3148.0  0.0  0.0  0.0  0.0  1.0  0.0  0.0
2012-10-06  2006.0  0.0  0.0  0.0  0.0  0.0  1.0  0.0
2012-10-07  2142.0  0.0  0.0  0.0  0.0  0.0  0.0  1.0
```

Adding New Features Since holidays/hours of daylight might also have an effect on bicycle traffic (what effect?), let's add those to our `daily` dataframe.

[19]:
```
#holidays from 2012 to 2019
from pandas.tseries.holiday import USFederalHolidayCalendar
cal = USFederalHolidayCalendar()
holidays = cal.holidays('2012', '2019')
holidays[0:10]
```

[19]:
```
DatetimeIndex(['2012-01-02', '2012-01-16', '2012-02-20', '2012-05-28',
               '2012-07-04', '2012-09-03', '2012-10-08', '2012-11-12',
               '2012-11-22', '2012-12-25'],
              dtype='datetime64[ns]', freq=None)
```

[20]:
```
holiday_ser = pd.Series(1, index=holidays, name='holiday')
holiday_ser.head()
```

[20]:
```
2012-01-02    1
2012-01-16    1
2012-02-20    1
2012-05-28    1
2012-07-04    1
Name: holiday, dtype: int64
```

[21]:
```
daily = daily.join(holiday_ser)
```

[22]:
```
daily.loc['20130101':'20130105']
```

[22]:
```
            Total  Mon  Tue  Wed  Thu  Fri  Sat  Sun  holiday
Date
2013-01-01   678.0  0.0  1.0  0.0  0.0  0.0  0.0  0.0      1.0
2013-01-02  1835.0  0.0  0.0  1.0  0.0  0.0  0.0  0.0      NaN
2013-01-03  1803.0  0.0  0.0  0.0  1.0  0.0  0.0  0.0      NaN
2013-01-04  1712.0  0.0  0.0  0.0  0.0  1.0  0.0  0.0      NaN
2013-01-05   719.0  0.0  0.0  0.0  0.0  0.0  1.0  0.0      NaN
```

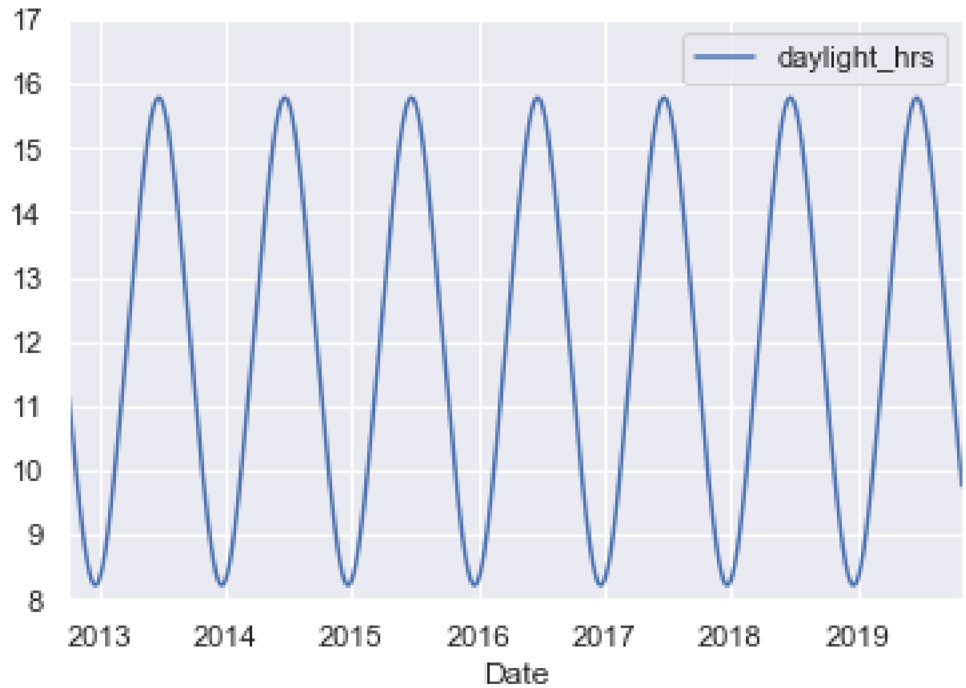
[23]:
```
daily['holiday'].fillna(0, inplace=True)
```

[24]:
```
# function to calculate hours of daylight for a certain date
# pulled from online -- dw too much about it!
def hours_of_daylight(date, axis=23.44, latitude=47.61):
    """Compute the hours of daylight for the given date"""
```

```
    days = (date - pd.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.
```

[25]:
```
daily['daylight_hrs'] = list(map(hours_of_daylight, daily.index))
daily[['daylight_hrs']].plot()
plt.ylim(8, 17)
```

[25]:
```
(8, 17)
```



[26]:
```
# temperatures are in tenths of a deg C, so we divide by 10 to convert to C
weather['TMIN'] /= 10
weather['TMAX'] /= 10
weather['Temp (C)'] = 0.5 * (weather['TMIN'] + weather['TMAX'])

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

# add precipitation, temp, and dry day to daily dataframe
daily = daily.join(weather[['PRCP', 'Temp (C)', 'dry day']])
```

[27]:
```
# add a counter that sees how many years have passed since the first day
# this will let us keep track of any changes across years
daily['annual'] = (daily.index - daily.index[0]).days / 365.
```

[28]:
```python
#finaldataframe
daily.head()
```

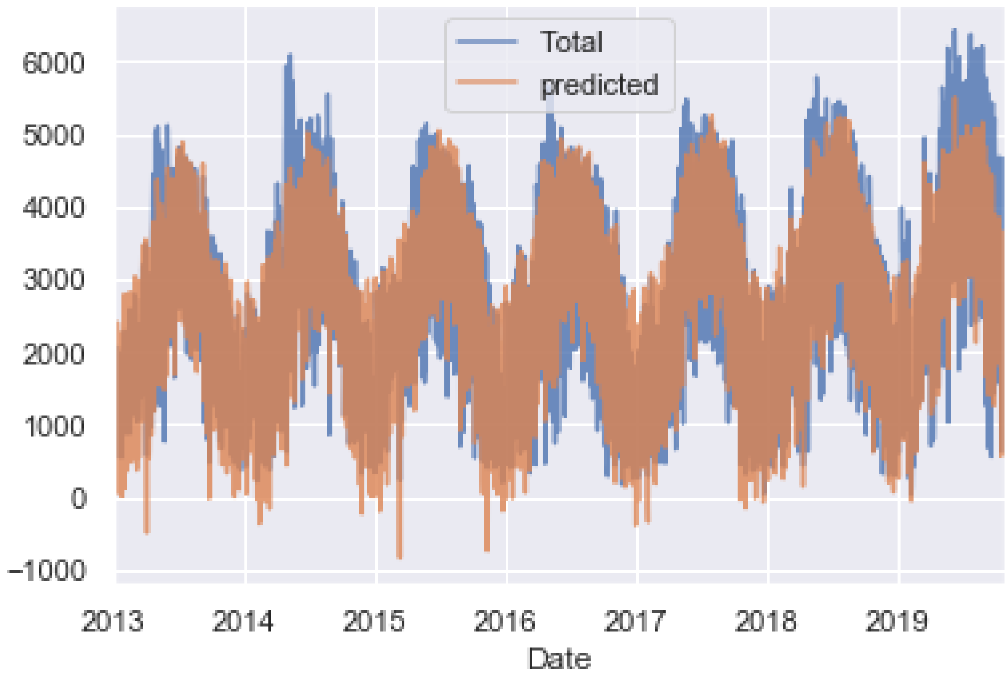
[28]:
```
               Total  Mon  Tue  Wed  Thu  Fri  Sat  Sun  holiday  daylight_hrs  \
Date
2012-10-03  3521.0  0.0  0.0  1.0  0.0  0.0  0.0  0.0      0.0     11.277359
2012-10-04  3475.0  0.0  0.0  0.0  1.0  0.0  0.0  0.0      0.0     11.219142
2012-10-05  3148.0  0.0  0.0  0.0  0.0  1.0  0.0  0.0      0.0     11.161038
2012-10-06  2006.0  0.0  0.0  0.0  0.0  0.0  1.0  0.0      0.0     11.103056
2012-10-07  2142.0  0.0  0.0  0.0  0.0  0.0  0.0  1.0      0.0     11.045208

            PRCP  Temp (C)  dry day    annual
Date
2012-10-03   NaN       NaN      NaN  0.000000
2012-10-04   NaN       NaN      NaN  0.002740
2012-10-05   NaN       NaN      NaN  0.005479
2012-10-06   NaN       NaN      NaN  0.008219
2012-10-07   NaN       NaN      NaN  0.010959
```

Training the Model

[29]:
```python
# Drop any rows with null values
daily.dropna(axis=0, how='any', inplace=True)

# Dropped 'Sun' to avoid collinearity, and 'Total' because that's the dependent␣
↪variable
column_names = ['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat', 'holiday',
                'daylight_hrs', 'PRCP', 'dry day', 'Temp (C)', 'annual']

X = daily[column_names]
y = daily['Total']
```

[30]:
```python
from sklearn.linear_model import LinearRegression

model = LinearRegression()
model.fit(X, y)
daily['predicted'] = model.predict(X)
```

[31]:
```python
# plot predicted bicycle traffic vs. actual bicycle traffic
daily[['Total', 'predicted']].plot(alpha=0.8);
```



[32]:
```
# get coefficients
# how would you interpret these?
params = pd.Series(model.coef_, index=X.columns)
params
```

[32]:
```
Mon                 1870.053283
Tue                 2011.174047
Wed                 1977.719152
Thu                 1847.643264
Fri                 1502.125621
Sat                  104.234248
holiday            -1284.464856
daylight_hrs         106.992248
PRCP             -186248.314976
dry day              514.989921
Temp (C)             441.216714
annual                77.464485
dtype: float64
```

1.3 Final Thoughts

1. Training and implementing models will become second nature. Thinking about the right type of model and the right features to use is a combination of intuition, talent, and lots of practice.
2. Simple models do not necessarily mean bad results. Additionally, you can use them a baseline for other, more complicated models.