06.00-Figure-Code

June 27, 2018

This notebook contains an excerpt from the Python Data Science Handbook by Jake VanderPlas; the content is available on GitHub.

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1 Appendix: Figure Code

Many of the figures used throughout this text are created in-place by code that appears in print. In a few cases, however, the required code is long enough (or not immediately relevant enough) that we instead put it here for reference.

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

In [2]: import os
        if not os.path.exists('figures'):
            os.makedirs('figures')
```

1.1 Broadcasting

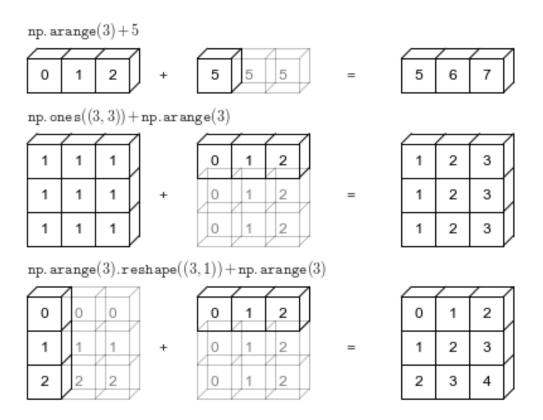
Figure Context

```
"""draw and label a cube. edges is a list of numbers between
1 and 12, specifying which of the 12 cube edges to draw"""
if edges is None:
    edges = range(1, 13)
x, y = xy
if 1 in edges:
    ax.plot([x, x + size],
            [y + size, y + size], **kwargs)
if 2 in edges:
    ax.plot([x + size, x + size],
            [y, y + size], **kwargs)
if 3 in edges:
    ax.plot([x, x + size],
            [y, y], **kwargs)
if 4 in edges:
    ax.plot([x, x],
            [y, y + size], **kwargs)
if 5 in edges:
    ax.plot([x, x + depth],
            [y + size, y + depth + size], **kwargs)
if 6 in edges:
    ax.plot([x + size, x + size + depth],
            [y + size, y + depth + size], **kwargs)
if 7 in edges:
    ax.plot([x + size, x + size + depth],
            [y, y + depth], **kwargs)
if 8 in edges:
    ax.plot([x, x + depth],
            [y, y + depth], **kwargs)
if 9 in edges:
    ax.plot([x + depth, x + depth + size],
            [y + depth + size, y + depth + size], **kwargs)
if 10 in edges:
    ax.plot([x + depth + size, x + depth + size],
            [y + depth, y + depth + size], **kwargs)
if 11 in edges:
    ax.plot([x + depth, x + depth + size],
            [y + depth, y + depth], **kwargs)
if 12 in edges:
    ax.plot([x + depth, x + depth],
            [y + depth, y + depth + size], **kwargs)
if label:
    if label_kwargs is None:
```

```
label_kwargs = {}
        ax.text(x + 0.5 * size, y + 0.5 * size, label,
                ha='center', va='center', **label_kwargs)
solid = dict(c='black', ls='-', lw=1,
             label kwargs=dict(color='k'))
dotted = dict(c='black', ls='-', lw=0.5, alpha=0.5,
              label_kwargs=dict(color='gray'))
depth = 0.3
# Draw top operation: vector plus scalar
draw_cube(ax, (1, 10), 1, depth, [1, 2, 3, 4, 5, 6, 9], '0', **solid)
draw_cube(ax, (2, 10), 1, depth, [1, 2, 3, 6, 9], '1', **solid)
draw_cube(ax, (3, 10), 1, depth, [1, 2, 3, 6, 7, 9, 10], '2', **solid)
draw_cube(ax, (6, 10), 1, depth, [1, 2, 3, 4, 5, 6, 7, 9, 10], '5', **solid)
draw_cube(ax, (7, 10), 1, depth, [1, 2, 3, 6, 7, 9, 10, 11], '5', **dotted)
draw_cube(ax, (8, 10), 1, depth, [1, 2, 3, 6, 7, 9, 10, 11], '5', **dotted)
draw_cube(ax, (12, 10), 1, depth, [1, 2, 3, 4, 5, 6, 9], '5', **solid)
draw_cube(ax, (13, 10), 1, depth, [1, 2, 3, 6, 9], '6', **solid)
draw_cube(ax, (14, 10), 1, depth, [1, 2, 3, 6, 7, 9, 10], '7', **solid)
ax.text(5, 10.5, '+', size=12, ha='center', va='center')
ax.text(10.5, 10.5, '=', size=12, ha='center', va='center')
ax.text(1, 11.5, r'${\tt np.arange(3) + 5}$',
        size=12, ha='left', va='bottom')
# Draw middle operation: matrix plus vector
# first block
draw_cube(ax, (1, 7.5), 1, depth, [1, 2, 3, 4, 5, 6, 9], '1', **solid)
draw cube(ax, (2, 7.5), 1, depth, [1, 2, 3, 6, 9], '1', **solid)
draw_cube(ax, (3, 7.5), 1, depth, [1, 2, 3, 6, 7, 9, 10], '1', **solid)
draw_cube(ax, (1, 6.5), 1, depth, [2, 3, 4], '1', **solid)
draw_cube(ax, (2, 6.5), 1, depth, [2, 3], '1', **solid)
draw_cube(ax, (3, 6.5), 1, depth, [2, 3, 7, 10], '1', **solid)
draw_cube(ax, (1, 5.5), 1, depth, [2, 3, 4], '1', **solid)
draw_cube(ax, (2, 5.5), 1, depth, [2, 3], '1', **solid)
draw_cube(ax, (3, 5.5), 1, depth, [2, 3, 7, 10], '1', **solid)
# second block
draw_cube(ax, (6, 7.5), 1, depth, [1, 2, 3, 4, 5, 6, 9], '0', **solid)
draw_cube(ax, (7, 7.5), 1, depth, [1, 2, 3, 6, 9], '1', **solid)
```

```
draw_cube(ax, (8, 7.5), 1, depth, [1, 2, 3, 6, 7, 9, 10], '2', **solid)
draw_cube(ax, (6, 6.5), 1, depth, range(2, 13), '0', **dotted)
draw_cube(ax, (7, 6.5), 1, depth, [2, 3, 6, 7, 9, 10, 11], '1', **dotted)
draw_cube(ax, (8, 6.5), 1, depth, [2, 3, 6, 7, 9, 10, 11], '2', **dotted)
draw_cube(ax, (6, 5.5), 1, depth, [2, 3, 4, 7, 8, 10, 11, 12], '0', **dotted)
draw_cube(ax, (7, 5.5), 1, depth, [2, 3, 7, 10, 11], '1', **dotted)
draw_cube(ax, (8, 5.5), 1, depth, [2, 3, 7, 10, 11], '2', **dotted)
# third block
draw_cube(ax, (12, 7.5), 1, depth, [1, 2, 3, 4, 5, 6, 9], '1', **solid)
draw_cube(ax, (13, 7.5), 1, depth, [1, 2, 3, 6, 9], '2', **solid)
draw_cube(ax, (14, 7.5), 1, depth, [1, 2, 3, 6, 7, 9, 10], '3', **solid)
draw_cube(ax, (12, 6.5), 1, depth, [2, 3, 4], '1', **solid)
draw_cube(ax, (13, 6.5), 1, depth, [2, 3], '2', **solid)
draw_cube(ax, (14, 6.5), 1, depth, [2, 3, 7, 10], '3', **solid)
draw cube(ax, (12, 5.5), 1, depth, [2, 3, 4], '1', **solid)
draw_cube(ax, (13, 5.5), 1, depth, [2, 3], '2', **solid)
draw_cube(ax, (14, 5.5), 1, depth, [2, 3, 7, 10], '3', **solid)
ax.text(5, 7.0, '+', size=12, ha='center', va='center')
ax.text(10.5, 7.0, '=', size=12, ha='center', va='center')
ax.text(1, 9.0, r'{\tt np.ones((3,\, 3)) + np.arange(3)}$',
        size=12, ha='left', va='bottom')
# Draw bottom operation: vector plus vector, double broadcast
# first block
draw_cube(ax, (1, 3), 1, depth, [1, 2, 3, 4, 5, 6, 7, 9, 10], '0', **solid)
draw_cube(ax, (1, 2), 1, depth, [2, 3, 4, 7, 10], '1', **solid)
draw_cube(ax, (1, 1), 1, depth, [2, 3, 4, 7, 10], '2', **solid)
draw cube(ax, (2, 3), 1, depth, [1, 2, 3, 6, 7, 9, 10, 11], '0', **dotted)
draw_cube(ax, (2, 2), 1, depth, [2, 3, 7, 10, 11], '1', **dotted)
draw_cube(ax, (2, 1), 1, depth, [2, 3, 7, 10, 11], '2', **dotted)
draw_cube(ax, (3, 3), 1, depth, [1, 2, 3, 6, 7, 9, 10, 11], '0', **dotted)
draw_cube(ax, (3, 2), 1, depth, [2, 3, 7, 10, 11], '1', **dotted)
draw_cube(ax, (3, 1), 1, depth, [2, 3, 7, 10, 11], '2', **dotted)
# second block
draw_cube(ax, (6, 3), 1, depth, [1, 2, 3, 4, 5, 6, 9], '0', **solid)
draw_cube(ax, (7, 3), 1, depth, [1, 2, 3, 6, 9], '1', **solid)
draw_cube(ax, (8, 3), 1, depth, [1, 2, 3, 6, 7, 9, 10], '2', **solid)
```

```
draw_cube(ax, (6, 2), 1, depth, range(2, 13), '0', **dotted)
draw_cube(ax, (7, 2), 1, depth, [2, 3, 6, 7, 9, 10, 11], '1', **dotted)
draw_cube(ax, (8, 2), 1, depth, [2, 3, 6, 7, 9, 10, 11], '2', **dotted)
draw_cube(ax, (6, 1), 1, depth, [2, 3, 4, 7, 8, 10, 11, 12], '0', **dotted)
draw_cube(ax, (7, 1), 1, depth, [2, 3, 7, 10, 11], '1', **dotted)
draw_cube(ax, (8, 1), 1, depth, [2, 3, 7, 10, 11], '2', **dotted)
# third block
draw_cube(ax, (12, 3), 1, depth, [1, 2, 3, 4, 5, 6, 9], '0', **solid)
draw_cube(ax, (13, 3), 1, depth, [1, 2, 3, 6, 9], '1', **solid)
draw_cube(ax, (14, 3), 1, depth, [1, 2, 3, 6, 7, 9, 10], '2', **solid)
draw_cube(ax, (12, 2), 1, depth, [2, 3, 4], '1', **solid)
draw_cube(ax, (13, 2), 1, depth, [2, 3], '2', **solid)
draw_cube(ax, (14, 2), 1, depth, [2, 3, 7, 10], '3', **solid)
draw_cube(ax, (12, 1), 1, depth, [2, 3, 4], '2', **solid)
draw_cube(ax, (13, 1), 1, depth, [2, 3], '3', **solid)
draw_cube(ax, (14, 1), 1, depth, [2, 3, 7, 10], '4', **solid)
ax.text(5, 2.5, '+', size=12, ha='center', va='center')
ax.text(10.5, 2.5, '=', size=12, ha='center', va='center')
ax.text(1, 4.5, r'{\tt np.arange(3).reshape((3,\, 1)) + np.arange(3)}$',
        ha='left', size=12, va='bottom')
ax.set_xlim(0, 16)
ax.set_ylim(0.5, 12.5)
fig.savefig('figures/02.05-broadcasting.png')
```



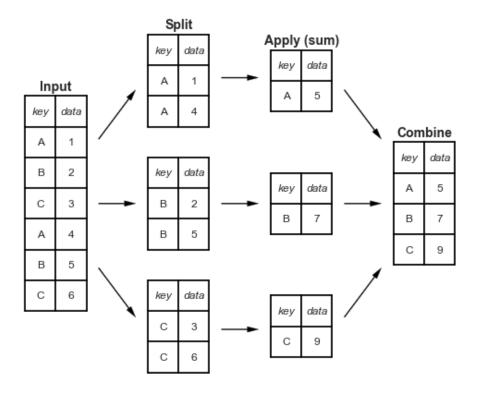
1.2 Aggregation and Grouping

Figures from the chapter on aggregation and grouping

1.2.1 Split-Apply-Combine

```
if linestyle is None:
        linestyle = {'color':'black'}
    if textstyle is None:
        textstyle = {'size': 12}
    textstyle.update({'ha':'center', 'va':'center'})
    # draw vertical lines
    for i in range(ncols + 1):
        plt.plot(2 * [x + i * dx], [y, y + dy * nrows], **linestyle)
    # draw horizontal lines
    for i in range(nrows + 1):
        plt.plot([x, x + dx * ncols], 2 * [y + i * dy], **linestyle)
    # Create index labels
    for i in range(nrows - 1):
        plt.text(x + 0.5 * dx, y + (i + 0.5) * dy,
                 str(df.index[::-1][i]), **textstyle)
    # Create column labels
    for i in range(ncols - 1):
        plt.text(x + (i + 1.5) * dx, y + (nrows - 0.5) * dy,
                 str(df.columns[i]), style='italic', **textstyle)
    # Add index label
    if df.index.name:
        plt.text(x + 0.5 * dx, y + (nrows - 0.5) * dy,
                 str(df.index.name), style='italic', **textstyle)
    # Insert data
    for i in range(nrows - 1):
        for j in range(ncols - 1):
            plt.text(x + (j + 1.5) * dx,
                     y + (i + 0.5) * dy,
                     str(df.values[::-1][i, j]), **textstyle)
# Draw figure
import pandas as pd
df = pd.DataFrame({'data': [1, 2, 3, 4, 5, 6]},
                   index=['A', 'B', 'C', 'A', 'B', 'C'])
df.index.name = 'key'
```

```
fig = plt.figure(figsize=(8, 6), facecolor='white')
ax = plt.axes([0, 0, 1, 1])
ax.axis('off')
draw_dataframe(df, [0, 0])
for y, ind in zip([3, 1, -1], 'ABC'):
    split = df[df.index == ind]
    draw_dataframe(split, [2, y])
    sum = pd.DataFrame(split.sum()).T
    sum.index = [ind]
    sum.index.name = 'key'
    sum.columns = ['data']
    draw_dataframe(sum, [4, y + 0.25])
result = df.groupby(df.index).sum()
draw_dataframe(result, [6, 0.75])
style = dict(fontsize=14, ha='center', weight='bold')
plt.text(0.5, 3.6, "Input", **style)
plt.text(2.5, 4.6, "Split", **style)
plt.text(4.5, 4.35, "Apply (sum)", **style)
plt.text(6.5, 2.85, "Combine", **style)
arrowprops = dict(facecolor='black', width=1, headwidth=6)
plt.annotate('', (1.8, 3.6), (1.2, 2.8), arrowprops=arrowprops)
plt.annotate('', (1.8, 1.75), (1.2, 1.75), arrowprops=arrowprops)
plt.annotate('', (1.8, -0.1), (1.2, 0.7), arrowprops=arrowprops)
plt.annotate('', (3.8, 3.8), (3.2, 3.8), arrowprops=arrowprops)
plt.annotate('', (3.8, 1.75), (3.2, 1.75), arrowprops=arrowprops)
plt.annotate('', (3.8, -0.3), (3.2, -0.3), arrowprops=arrowprops)
plt.annotate('', (5.8, 2.8), (5.2, 3.6), arrowprops=arrowprops)
plt.annotate('', (5.8, 1.75), (5.2, 1.75), arrowprops=arrowprops)
plt.annotate('', (5.8, 0.7), (5.2, -0.1), arrowprops=arrowprops)
plt.axis('equal')
plt.ylim(-1.5, 5);
fig.savefig('figures/03.08-split-apply-combine.png')
```



1.3 What Is Machine Learning?

```
In [5]: # common plot formatting for below
    def format_plot(ax, title):
        ax.xaxis.set_major_formatter(plt.NullFormatter())
        ax.yaxis.set_major_formatter(plt.NullFormatter())
        ax.set_xlabel('feature 1', color='gray')
        ax.set_ylabel('feature 2', color='gray')
        ax.set_title(title, color='gray')
```

1.3.1 Classification Example Figures

Figure context

The following code generates the figures from the Classification section.

```
In [6]: from sklearn.datasets.samples_generator import make_blobs
    from sklearn.svm import SVC

# create 50 separable points
X, y = make_blobs(n_samples=50, centers=2,
```

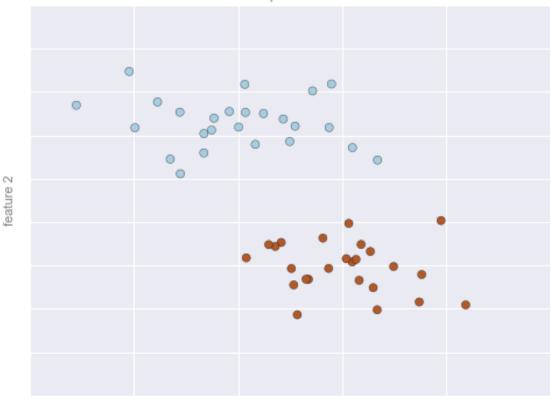
fig.savefig('figures/05.01-classification-1.png')

format plot

format_plot(ax, 'Input Data')

ax.axis([-1, 4, -2, 7])



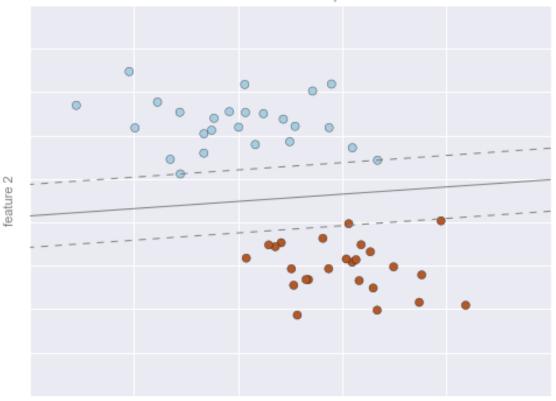


feature 1

Classification Example Figure 2

```
ax.axis([-1, 4, -2, 7])
fig.savefig('figures/05.01-classification-2.png')
```

Model Learned from Input Data



feature 1

Classification Example Figure 3

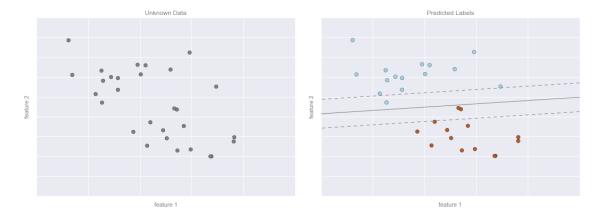
```
In [9]: # plot the results
    fig, ax = plt.subplots(1, 2, figsize=(16, 6))
    fig.subplots_adjust(left=0.0625, right=0.95, wspace=0.1)

ax[0].scatter(X2[:, 0], X2[:, 1], c='gray', **point_style)
    ax[0].axis([-1, 4, -2, 7])

ax[1].scatter(X2[:, 0], X2[:, 1], c=y2, **point_style)
    ax[1].contour(xy1, xy2, Z, **line_style)
    ax[1].axis([-1, 4, -2, 7])

format_plot(ax[0], 'Unknown Data')
    format_plot(ax[1], 'Predicted Labels')
```

fig.savefig('figures/05.01-classification-3.png')



1.3.2 Regression Example Figures

Figure Context

The following code generates the figures from the regression section.

```
In [10]: from sklearn.linear_model import LinearRegression
    # Create some data for the regression
    rng = np.random.RandomState(1)

X = rng.randn(200, 2)
y = np.dot(X, [-2, 1]) + 0.1 * rng.randn(X.shape[0])

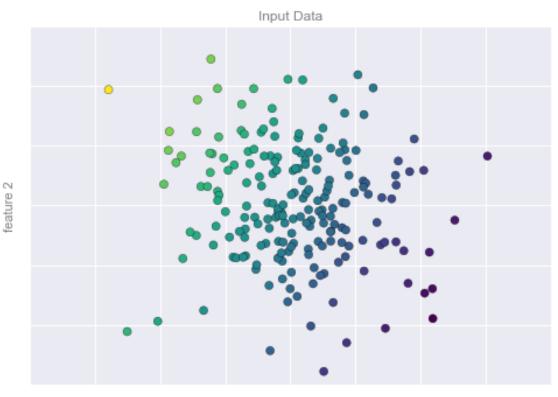
# fit the regression model
model = LinearRegression()
model.fit(X, y)

# create some new points to predict
X2 = rng.randn(100, 2)

# predict the labels
y2 = model.predict(X2)
```

Regression Example Figure 1

```
# format plot
format_plot(ax, 'Input Data')
ax.axis([-4, 4, -3, 3])
fig.savefig('figures/05.01-regression-1.png')
```

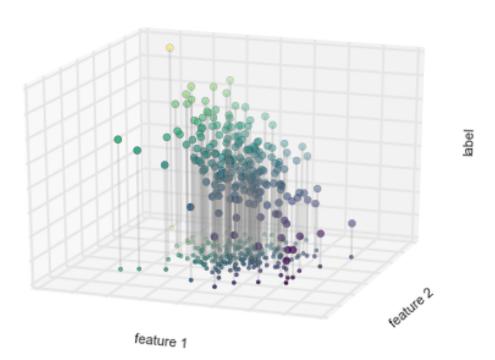


feature 1

Regression Example Figure 2

```
# format plot
ax.patch.set_facecolor('white')
ax.view_init(elev=20, azim=-70)
ax.set_zlim3d(-8, 8)
ax.xaxis.set_major_formatter(plt.NullFormatter())
ax.yaxis.set_major_formatter(plt.NullFormatter())
ax.zaxis.set_major_formatter(plt.NullFormatter())
ax.set(xlabel='feature 1', ylabel='feature 2', zlabel='label')
# Hide axes (is there a better way?)
ax.w_xaxis.line.set_visible(False)
ax.w_yaxis.line.set_visible(False)
ax.w_zaxis.line.set_visible(False)
for tick in ax.w_xaxis.get_ticklines():
   tick.set_visible(False)
for tick in ax.w_yaxis.get_ticklines():
   tick.set_visible(False)
for tick in ax.w_zaxis.get_ticklines():
   tick.set_visible(False)
fig.savefig('figures/05.01-regression-2.png')
```

cmap='viridis')

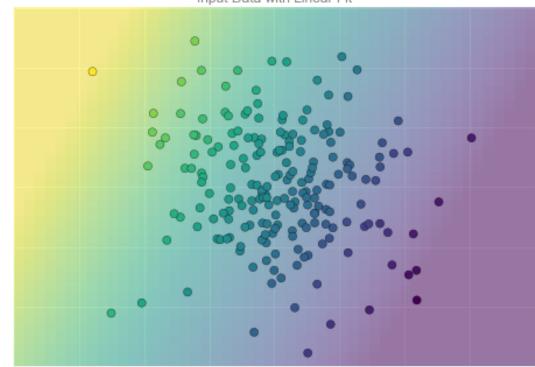


Regression Example Figure 3

feature 2

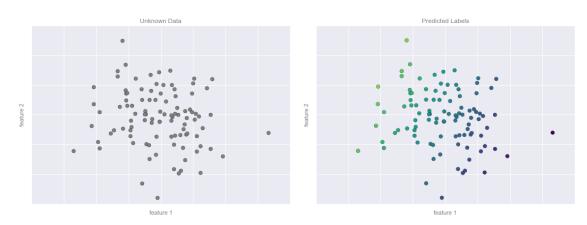
```
In [13]: from matplotlib.collections import LineCollection
         # plot data points
         fig, ax = plt.subplots()
         pts = ax.scatter(X[:, 0], X[:, 1], c=y, s=50,
                          cmap='viridis', zorder=2)
         # compute and plot model color mesh
         xx, yy = np.meshgrid(np.linspace(-4, 4),
                              np.linspace(-3, 3))
        Xfit = np.vstack([xx.ravel(), yy.ravel()]).T
         yfit = model.predict(Xfit)
         zz = yfit.reshape(xx.shape)
         ax.pcolorfast([-4, 4], [-3, 3], zz, alpha=0.5,
                       cmap='viridis', norm=pts.norm, zorder=1)
         # format plot
         format_plot(ax, 'Input Data with Linear Fit')
         ax.axis([-4, 4, -3, 3])
         fig.savefig('figures/05.01-regression-3.png')
```

Input Data with Linear Fit



feature 1

Regression Example Figure 4



1.3.3 Clustering Example Figures

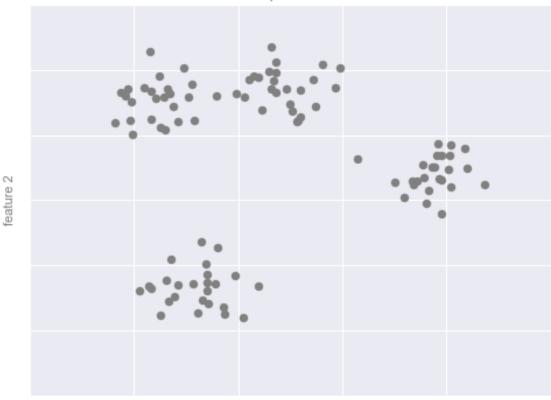
Section ??

The following code generates the figures from the clustering section.

```
# Fit the K Means model
model = KMeans(4, random_state=0)
y = model.fit_predict(X)
```

Clustering Example Figure 1

Input Data

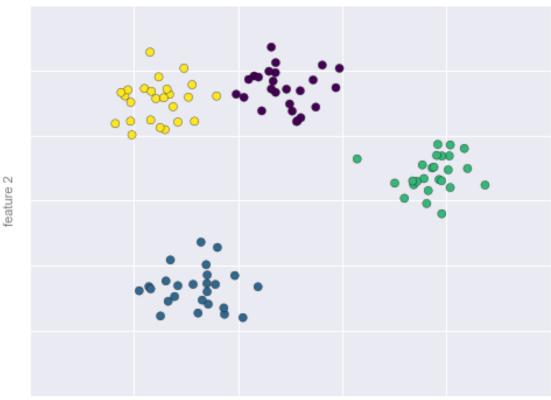


feature 1

Clustering Example Figure 2

```
ax.scatter(X[:, 0], X[:, 1], s=50, c=y, cmap='viridis')
# format the plot
format_plot(ax, 'Learned Cluster Labels')
fig.savefig('figures/05.01-clustering-2.png')
```

Learned Cluster Labels



feature 1

1.3.4 Dimensionality Reduction Example Figures

Figure context

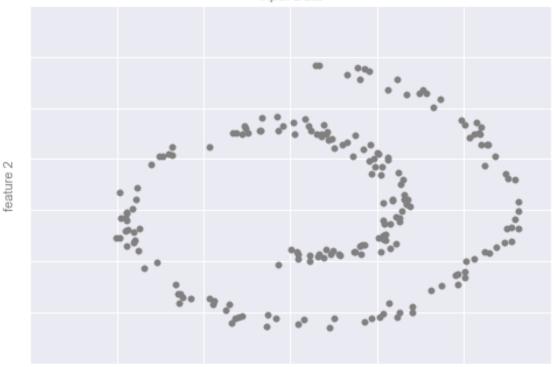
The following code generates the figures from the dimensionality reduction section.

Dimensionality Reduction Example Figure 1

```
In [18]: from sklearn.datasets import make_swiss_roll
    # make data
    X, y = make_swiss_roll(200, noise=0.5, random_state=42)
    X = X[:, [0, 2]]
```

```
# visualize data
fig, ax = plt.subplots()
ax.scatter(X[:, 0], X[:, 1], color='gray', s=30)
# format the plot
format_plot(ax, 'Input Data')
fig.savefig('figures/05.01-dimesionality-1.png')
```

Input Data



feature 1

Dimensionality Reduction Example Figure 2

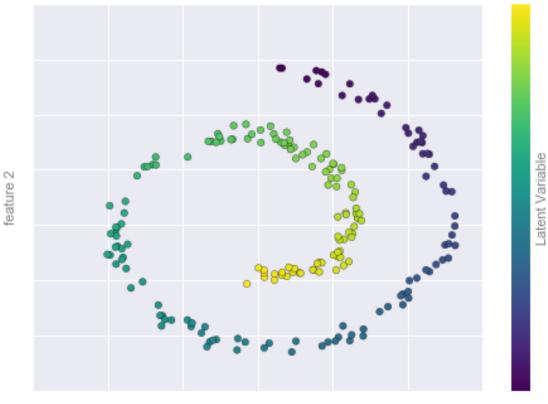
```
In [19]: from sklearn.manifold import Isomap

model = Isomap(n_neighbors=8, n_components=1)
    y_fit = model.fit_transform(X).ravel()

# visualize data
fig, ax = plt.subplots()
    pts = ax.scatter(X[:, 0], X[:, 1], c=y_fit, cmap='viridis', s=30)
    cb = fig.colorbar(pts, ax=ax)
```

```
# format the plot
format_plot(ax, 'Learned Latent Parameter')
cb.set_ticks([])
cb.set_label('Latent Variable', color='gray')
fig.savefig('figures/05.01-dimesionality-2.png')
```

Learned Latent Parameter

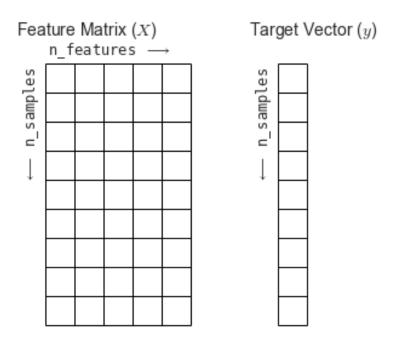


feature 1

1.4 Introducing Scikit-Learn

1.4.1 Features and Labels Grid

The following is the code generating the diagram showing the features matrix and target array.



1.5 Hyperparameters and Model Validation

1.5.1 Cross-Validation Figures

2-Fold Cross-Validation

```
In [22]: fig = plt.figure()
    ax = fig.add_axes([0, 0, 1, 1])
    ax.axis('off')
    draw_rects(2, ax, textprop=dict(size=14))

fig.savefig('figures/05.03-2-fold-CV.png')
```

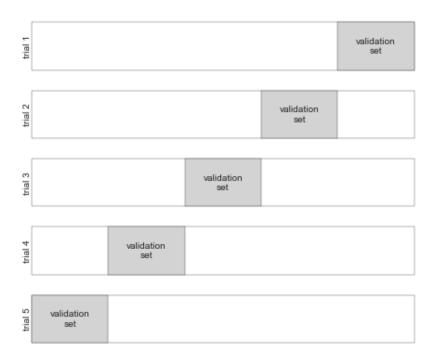


validation set

5-Fold Cross-Validation

```
In [23]: fig = plt.figure()
    ax = fig.add_axes([0, 0, 1, 1])
    ax.axis('off')
    draw_rects(5, ax, textprop=dict(size=10))

fig.savefig('figures/05.03-5-fold-CV.png')
```



1.5.2 Overfitting and Underfitting

```
In [24]: import numpy as np

def make_data(N=30, err=0.8, rseed=1):
    # randomly sample the data
    rng = np.random.RandomState(rseed)
    X = rng.rand(N, 1) ** 2
    y = 10 - 1. / (X.ravel() + 0.1)
    if err > 0:
        y += err * rng.randn(N)
    return X, y
In [25]: from sklearn.preprocessing import PolynomialFeatures
```

from sklearn.linear_model import LinearRegression

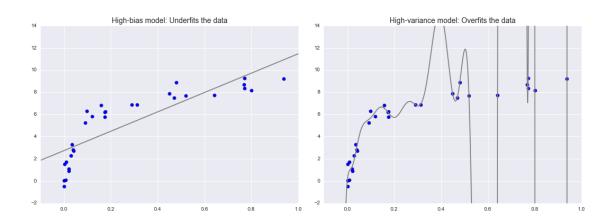
Bias-Variance Tradeoff

```
In [26]: X, y = make_data()
    xfit = np.linspace(-0.1, 1.0, 1000)[:, None]
    model1 = PolynomialRegression(1).fit(X, y)
    model20 = PolynomialRegression(20).fit(X, y)

fig, ax = plt.subplots(1, 2, figsize=(16, 6))
    fig.subplots_adjust(left=0.0625, right=0.95, wspace=0.1)

ax[0].scatter(X.ravel(), y, s=40)
    ax[0].plot(xfit.ravel(), model1.predict(xfit), color='gray')
    ax[0].axis([-0.1, 1.0, -2, 14])
    ax[0].set_title('High-bias model: Underfits the data', size=14)

ax[1].scatter(X.ravel(), y, s=40)
    ax[1].plot(xfit.ravel(), model20.predict(xfit), color='gray')
    ax[1].axis([-0.1, 1.0, -2, 14])
    ax[1].set_title('High-variance model: Overfits the data', size=14)
```

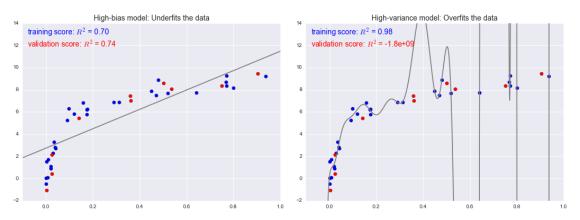


Bias-Variance Tradeoff Metrics

fig.savefig('figures/05.03-bias-variance.png')

```
X2, y2 = make_data(10, rseed=42)
ax[0].scatter(X.ravel(), y, s=40, c='blue')
ax[0].plot(xfit.ravel(), model1.predict(xfit), color='gray')
ax[0].axis([-0.1, 1.0, -2, 14])
ax[0].set_title('High-bias model: Underfits the data', size=14)
ax[0].scatter(X2.ravel(), y2, s=40, c='red')
ax[0].text(0.02, 0.98, "training score: $R^2$ = {0:.2f}".format(model1.score(X, y)),
                                                ha='left', va='top', transform=ax[0].transAxes, size=14, color='blue')
ax[0].text(0.02, 0.91, "validation score: $R^2$ = {0:.2f}".format(model1.score(X2, y2)) = {0:.2f}".format(model1.score(X2, y
                                                ha='left', va='top', transform=ax[0].transAxes, size=14, color='red')
ax[1].scatter(X.ravel(), y, s=40, c='blue')
ax[1].plot(xfit.ravel(), model20.predict(xfit), color='gray')
ax[1].axis([-0.1, 1.0, -2, 14])
ax[1].set_title('High-variance model: Overfits the data', size=14)
ax[1].scatter(X2.ravel(), y2, s=40, c='red')
ax[1].text(0.02, 0.98, "training score: $R^2$ = {0:.2g}".format(model20.score(X, y)),
                                                ha='left', va='top', transform=ax[1].transAxes, size=14, color='blue')
ax[1].text(0.02, 0.91, "validation score: $R^2$ = {0:.2g}".format(model20.score(X2, y)) = {0:.2g}".format(model20.score(X2, 
                                                ha='left', va='top', transform=ax[1].transAxes, size=14, color='red')
```





Validation Curve

```
In [28]: x = np.linspace(0, 1, 1000)
    y1 = -(x - 0.5) ** 2
    y2 = y1 - 0.33 + np.exp(x - 1)

fig, ax = plt.subplots()
    ax.plot(x, y2, lw=10, alpha=0.5, color='blue')
    ax.plot(x, y1, lw=10, alpha=0.5, color='red')
```

```
ax.text(0.15, 0.2, "training score", rotation=45, size=16, color='blue')
ax.text(0.2, -0.05, "validation score", rotation=20, size=16, color='red')

ax.text(0.02, 0.1, r'$\longleftarrow$ High Bias', size=18, rotation=90, va='center')
ax.text(0.98, 0.1, r'$\longleftarrow$ High Variance $\longrightarrow$', size=18, rotation=20, va='center'
ax.text(0.48, -0.12, 'Best$\\longrightarrow$\nModel', size=18, rotation=90, va='center'
ax.set_xlim(0, 1)
ax.set_ylim(-0.3, 0.5)

ax.set_ylabel(r'model complexity $\longrightarrow$', size=14)
ax.set_ylabel(r'model score $\longrightarrow$', size=14)
ax.xaxis.set_major_formatter(plt.NullFormatter())
ax.yaxis.set_major_formatter(plt.NullFormatter())
ax.set_title("Validation Curve Schematic", size=16)

fig.savefig('figures/05.03-validation-curve.png')
```

Validation Curve Schematic



model complexity --->

Learning Curve

```
In [29]: N = np.linspace(0, 1, 1000)
        y1 = 0.75 + 0.2 * np.exp(-4 * N)
        y2 = 0.7 - 0.6 * np.exp(-4 * N)
         fig, ax = plt.subplots()
         ax.plot(x, y1, lw=10, alpha=0.5, color='blue')
         ax.plot(x, y2, lw=10, alpha=0.5, color='red')
         ax.text(0.2, 0.88, "training score", rotation=-10, size=16, color='blue')
         ax.text(0.2, 0.5, "validation score", rotation=30, size=16, color='red')
         ax.text(0.98, 0.45, r'Good Fit $\longrightarrow$', size=18, rotation=90, ha='right',
         ax.text(0.02, 0.57, r'$\longleftarrow$ High Variance $\longrightarrow$', size=18, rote
         ax.set_xlim(0, 1)
         ax.set_ylim(0, 1)
         ax.set_xlabel(r'training set size $\longrightarrow$', size=14)
         ax.set_ylabel(r'model score $\longrightarrow$', size=14)
         ax.xaxis.set_major_formatter(plt.NullFormatter())
         ax.yaxis.set_major_formatter(plt.NullFormatter())
         ax.set_title("Learning Curve Schematic", size=16)
         fig.savefig('figures/05.03-learning-curve.png')
```

Learning Curve Schematic



training set size ----

1.6 Gaussian Naive Bayes

1.6.1 Gaussian Naive Bayes Example

Figure Context

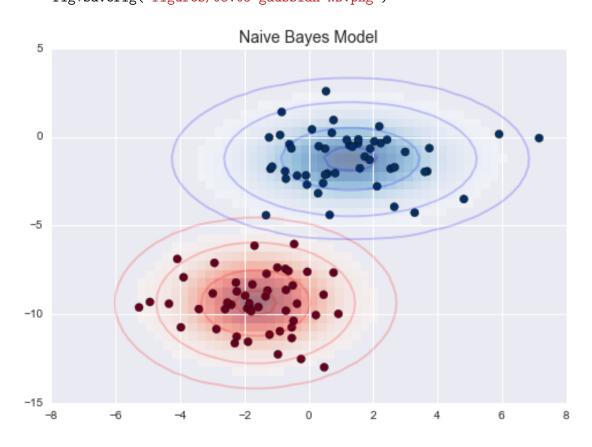
```
In [30]: from sklearn.datasets import make_blobs
    X, y = make_blobs(100, 2, centers=2, random_state=2, cluster_std=1.5)

fig, ax = plt.subplots()

ax.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='RdBu')
ax.set_title('Naive Bayes Model', size=14)

xlim = (-8, 8)
ylim = (-15, 5)

xg = np.linspace(xlim[0], xlim[1], 60)
yg = np.linspace(ylim[0], ylim[1], 40)
xx, yy = np.meshgrid(xg, yg)
Xgrid = np.vstack([xx.ravel(), yy.ravel()]).T
```



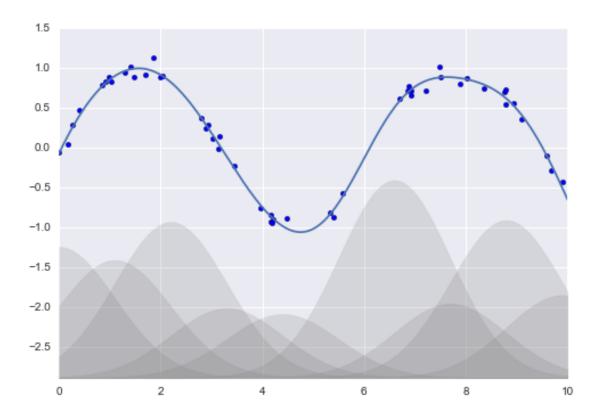
1.7 Linear Regression

1.7.1 Gaussian Basis Functions

Figure Context

```
In [31]: from sklearn.pipeline import make_pipeline
         from sklearn.linear_model import LinearRegression
         from sklearn.base import BaseEstimator, TransformerMixin
         class GaussianFeatures(BaseEstimator, TransformerMixin):
             """Uniformly-spaced Gaussian Features for 1D input"""
             def __init__(self, N, width_factor=2.0):
                 self.N = N
                 self.width_factor = width_factor
             @staticmethod
             def _gauss_basis(x, y, width, axis=None):
                 arg = (x - y) / width
                 return np.exp(-0.5 * np.sum(arg ** 2, axis))
             def fit(self, X, y=None):
                 # create N centers spread along the data range
                 self.centers = np.linspace(X.min(), X.max(), self.N)
                 self.width_ = self.width_factor * (self.centers_[1] - self.centers_[0])
                 return self
             def transform(self, X):
                 return self._gauss_basis(X[:, :, np.newaxis], self.centers_,
                                          self.width_, axis=1)
         rng = np.random.RandomState(1)
         x = 10 * rng.rand(50)
         y = np.sin(x) + 0.1 * rng.randn(50)
         xfit = np.linspace(0, 10, 1000)
         gauss_model = make_pipeline(GaussianFeatures(10, 1.0),
                                     LinearRegression())
         gauss model.fit(x[:, np.newaxis], y)
         yfit = gauss_model.predict(xfit[:, np.newaxis])
         gf = gauss_model.named_steps['gaussianfeatures']
         lm = gauss_model.named_steps['linearregression']
         fig, ax = plt.subplots()
         for i in range(10):
             selector = np.zeros(10)
             selector[i] = 1
             Xfit = gf.transform(xfit[:, None]) * selector
             yfit = lm.predict(Xfit)
             ax.fill_between(xfit, yfit.min(), yfit, color='gray', alpha=0.2)
```

```
ax.scatter(x, y)
ax.plot(xfit, gauss_model.predict(xfit[:, np.newaxis]))
ax.set_xlim(0, 10)
ax.set_ylim(yfit.min(), 1.5)
fig.savefig('figures/05.06-gaussian-basis.png')
```



1.8 Random Forests

1.8.1 Helper Code

The following will create a module helpers_05_08.py which contains some tools used in In-Depth: Decision Trees and Random Forests.

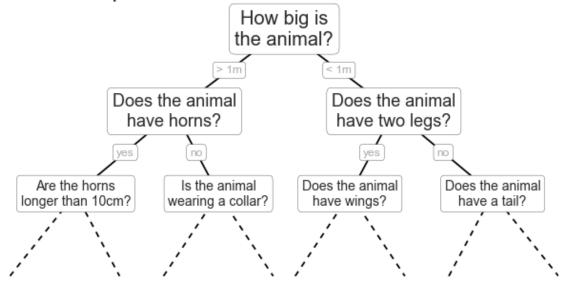
```
def visualize_tree(estimator, X, y, boundaries=True,
                   xlim=None, ylim=None, ax=None):
    ax = ax or plt.gca()
    # Plot the training points
    ax.scatter(X[:, 0], X[:, 1], c=y, s=30, cmap='viridis',
               clim=(y.min(), y.max()), zorder=3)
    ax.axis('tight')
    ax.axis('off')
    if xlim is None:
        xlim = ax.get_xlim()
    if ylim is None:
        ylim = ax.get_ylim()
    # fit the estimator
    estimator.fit(X, y)
    xx, yy = np.meshgrid(np.linspace(*xlim, num=200),
                         np.linspace(*ylim, num=200))
    Z = estimator.predict(np.c_[xx.ravel(), yy.ravel()])
    # Put the result into a color plot
    n_classes = len(np.unique(y))
    Z = Z.reshape(xx.shape)
    contours = ax.contourf(xx, yy, Z, alpha=0.3,
                           levels=np.arange(n_classes + 1) - 0.5,
                           cmap='viridis', clim=(y.min(), y.max()),
                           zorder=1)
    ax.set(xlim=xlim, ylim=ylim)
    # Plot the decision boundaries
    def plot_boundaries(i, xlim, ylim):
        if i \ge 0:
            tree = estimator.tree_
            if tree.feature[i] == 0:
                ax.plot([tree.threshold[i], tree.threshold[i]], ylim, '-k', zorder=2)
                plot_boundaries(tree.children_left[i],
                                 [xlim[0], tree.threshold[i]], ylim)
                plot_boundaries(tree.children_right[i],
                                 [tree.threshold[i], xlim[1]], ylim)
            elif tree.feature[i] == 1:
                ax.plot(xlim, [tree.threshold[i], tree.threshold[i]], '-k', zorder=2)
                plot_boundaries(tree.children_left[i], xlim,
                                 [ylim[0], tree.threshold[i]])
                plot_boundaries(tree.children_right[i], xlim,
                                [tree.threshold[i], ylim[1]])
```

```
if boundaries:
                 plot_boundaries(0, xlim, ylim)
         def plot_tree_interactive(X, y):
             def interactive tree(depth=5):
                 clf = DecisionTreeClassifier(max_depth=depth, random_state=0)
                 visualize_tree(clf, X, y)
             return interact(interactive_tree, depth=[1, 5])
         def randomized_tree_interactive(X, y):
             N = int(0.75 * X.shape[0])
             xlim = (X[:, 0].min(), X[:, 0].max())
             ylim = (X[:, 1].min(), X[:, 1].max())
             def fit randomized tree(random state=0):
                 clf = DecisionTreeClassifier(max_depth=15)
                 i = np.arange(len(y))
                 rng = np.random.RandomState(random_state)
                 rng.shuffle(i)
                 visualize_tree(clf, X[i[:N]], y[i[:N]], boundaries=False,
                                xlim=xlim, ylim=ylim)
             interact(fit_randomized_tree, random_state=[0, 100]);
Overwriting helpers_05_08.py
1.8.2 Decision Tree Example
In [33]: fig = plt.figure(figsize=(10, 4))
         ax = fig.add_axes([0, 0, 0.8, 1], frameon=False, xticks=[], yticks=[])
         ax.set_title('Example Decision Tree: Animal Classification', size=24)
         def text(ax, x, y, t, size=20, **kwargs):
             ax.text(x, y, t,
                     ha='center', va='center', size=size,
                     bbox=dict(boxstyle='round', ec='k', fc='w'), **kwargs)
         text(ax, 0.5, 0.9, "How big is\nthe animal?", 20)
         text(ax, 0.3, 0.6, "Does the animal\nhave horns?", 18)
         text(ax, 0.7, 0.6, "Does the animal\nhave two legs?", 18)
         text(ax, 0.12, 0.3, "Are the horns\nlonger than 10cm?", 14)
         text(ax, 0.38, 0.3, "Is the animal\nwearing a collar?", 14)
```

```
text(ax, 0.62, 0.3, "Does the animal\nhave wings?", 14)
text(ax, 0.88, 0.3, "Does the animal\nhave a tail?", 14)
text(ax, 0.4, 0.75, "> 1m", 12, alpha=0.4)
text(ax, 0.6, 0.75, "< 1m", 12, alpha=0.4)
text(ax, 0.21, 0.45, "yes", 12, alpha=0.4)
text(ax, 0.34, 0.45, "no", 12, alpha=0.4)
text(ax, 0.66, 0.45, "yes", 12, alpha=0.4)
text(ax, 0.79, 0.45, "no", 12, alpha=0.4)
ax.plot([0.3, 0.5, 0.7], [0.6, 0.9, 0.6], '-k')
ax.plot([0.12, 0.3, 0.38], [0.3, 0.6, 0.3], '-k')
ax.plot([0.62, 0.7, 0.88], [0.3, 0.6, 0.3], '-k')
ax.plot([0.0, 0.12, 0.20], [0.0, 0.3, 0.0], '--k')
ax.plot([0.28, 0.38, 0.48], [0.0, 0.3, 0.0], '--k')
ax.plot([0.52, 0.62, 0.72], [0.0, 0.3, 0.0], '--k')
ax.plot([0.8, 0.88, 1.0], [0.0, 0.3, 0.0], '--k')
ax.axis([0, 1, 0, 1])
```

fig.savefig('figures/05.08-decision-tree.png')

Example Decision Tree: Animal Classification

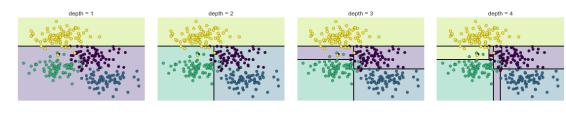


1.8.3 Decision Tree Levels

In [34]: from helpers_05_08 import visualize_tree
 from sklearn.tree import DecisionTreeClassifier

```
from sklearn.datasets import make_blobs
```

fig.savefig('figures/05.08-decision-tree-levels.png')

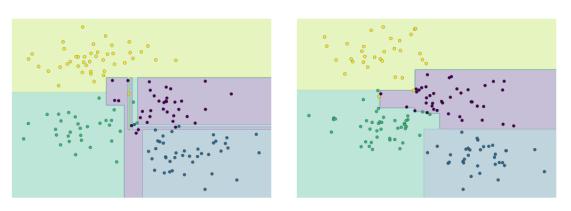


1.8.4 Decision Tree Overfitting

```
In [35]: model = DecisionTreeClassifier()

fig, ax = plt.subplots(1, 2, figsize=(16, 6))
fig.subplots_adjust(left=0.0625, right=0.95, wspace=0.1)
visualize_tree(model, X[::2], y[::2], boundaries=False, ax=ax[0])
visualize_tree(model, X[1::2], y[1::2], boundaries=False, ax=ax[1])
```

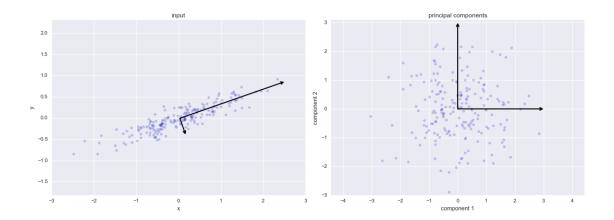
fig.savefig('figures/05.08-decision-tree-overfitting.png')



1.9 Principal Component Analysis

1.9.1 Principal Components Rotation

```
In [36]: from sklearn.decomposition import PCA
In [37]: def draw_vector(v0, v1, ax=None):
             ax = ax or plt.gca()
             arrowprops=dict(arrowstyle='->',
                             linewidth=2,
                             shrinkA=0, shrinkB=0)
             ax.annotate('', v1, v0, arrowprops=arrowprops)
In [38]: rng = np.random.RandomState(1)
         X = np.dot(rng.rand(2, 2), rng.randn(2, 200)).T
         pca = PCA(n_components=2, whiten=True)
         pca.fit(X)
         fig, ax = plt.subplots(1, 2, figsize=(16, 6))
         fig.subplots_adjust(left=0.0625, right=0.95, wspace=0.1)
         # plot data
         ax[0].scatter(X[:, 0], X[:, 1], alpha=0.2)
         for length, vector in zip(pca.explained_variance_, pca.components_):
             v = vector * 3 * np.sqrt(length)
             draw_vector(pca.mean_, pca.mean_ + v, ax=ax[0])
         ax[0].axis('equal');
         ax[0].set(xlabel='x', ylabel='y', title='input')
         # plot principal components
         X_pca = pca.transform(X)
         ax[1].scatter(X_pca[:, 0], X_pca[:, 1], alpha=0.2)
         draw_vector([0, 0], [0, 3], ax=ax[1])
         draw_vector([0, 0], [3, 0], ax=ax[1])
         ax[1].axis('equal')
         ax[1].set(xlabel='component 1', ylabel='component 2',
                   title='principal components',
                   xlim=(-5, 5), ylim=(-3, 3.1))
         fig.savefig('figures/05.09-PCA-rotation.png')
```



1.9.2 Digits Pixel Components

```
In [39]: def plot_pca_components(x, coefficients=None, mean=0, components=None,
                                 imshape=(8, 8), n_components=8, fontsize=12,
                                 show mean=True):
             if coefficients is None:
                 coefficients = x
             if components is None:
                 components = np.eye(len(coefficients), len(x))
             mean = np.zeros_like(x) + mean
             fig = plt.figure(figsize=(1.2 * (5 + n\_components), 1.2 * 2))
             g = plt.GridSpec(2, 4 + bool(show_mean) + n_components, hspace=0.3)
             def show(i, j, x, title=None):
                 ax = fig.add_subplot(g[i, j], xticks=[], yticks=[])
                 ax.imshow(x.reshape(imshape), interpolation='nearest')
                 if title:
                     ax.set_title(title, fontsize=fontsize)
             show(slice(2), slice(2), x, "True")
             approx = mean.copy()
             counter = 2
             if show_mean:
                 show(0, 2, np.zeros_like(x) + mean, r'$\mu$')
                 show(1, 2, approx, r'$1 \cdot \mu$')
                 counter += 1
```

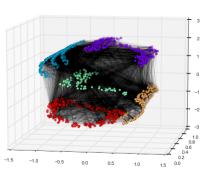
```
for i in range(n_components):
                   approx = approx + coefficients[i] * components[i]
                   show(0, i + counter, components[i], r'\c_{0}\'.format(i + 1))
                   show(1, i + counter, approx,
                         r"${0:.2f} \cdot c_{1}$".format(coefficients[i], i + 1))
                   if show_mean or i > 0:
                       plt.gca().text(0, 1.05, '$+$', ha='right', va='bottom',
                                         transform=plt.gca().transAxes, fontsize=fontsize)
              show(slice(2), slice(-2, None), approx, "Approx")
              return fig
In [40]: from sklearn.datasets import load_digits
          digits = load_digits()
          sns.set style('white')
          fig = plot_pca_components(digits.data[10],
                                       show_mean=False)
          fig.savefig('figures/05.09-digits-pixel-components.png')
                                                                                Approx
                    0.00 \cdot c_1
                                                      11.00 \cdot c_6
                           0.00 \cdot c_2
                                  1.00 \cdot c_3
                                         9.00 \cdot c_4
                                               15.00 \cdot c_5
                                                              0.00 \cdot c_7
```

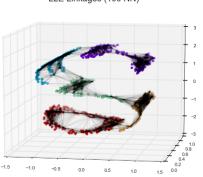
1.9.3 Digits PCA Components

1.10 Manifold Learning

1.10.1 LLE vs MDS Linkages

```
In [42]: def make hello(N=1000, rseed=42):
             # Make a plot with "HELLO" text; save as png
             fig, ax = plt.subplots(figsize=(4, 1))
             fig.subplots_adjust(left=0, right=1, bottom=0, top=1)
             ax.axis('off')
             ax.text(0.5, 0.4, 'HELLO', va='center', ha='center', weight='bold', size=85)
             fig.savefig('hello.png')
             plt.close(fig)
             # Open this PNG and draw random points from it
             from matplotlib.image import imread
             data = imread('hello.png')[::-1, :, 0].T
             rng = np.random.RandomState(rseed)
             X = rng.rand(4 * N, 2)
             i, j = (X * data.shape).astype(int).T
             mask = (data[i, j] < 1)
             X = X[mask]
             X[:, 0] *= (data.shape[0] / data.shape[1])
             X = X[:N]
             return X[np.argsort(X[:, 0])]
In [43]: def make_hello_s_curve(X):
             t = (X[:, 0] - 2) * 0.75 * np.pi
             x = np.sin(t)
             y = X[:, 1]
             z = np.sign(t) * (np.cos(t) - 1)
             return np.vstack((x, y, z)).T
         X = make_hello(1000)
         XS = make_hello_s_curve(X)
         colorize = dict(c=X[:, 0], cmap=plt.cm.get_cmap('rainbow', 5))
In [44]: from mpl_toolkits.mplot3d.art3d import Line3DCollection
         from sklearn.neighbors import NearestNeighbors
         # construct lines for MDS
         rng = np.random.RandomState(42)
         ind = rng.permutation(len(X))
         lines_MDS = [(XS[i], XS[i]) for i in ind[:100] for j in ind[100:200]]
         # construct lines for LLE
         nbrs = NearestNeighbors(n_neighbors=100).fit(XS).kneighbors(XS[ind[:100]])[1]
         lines_LLE = [(XS[ind[i]], XS[j]) for i in range(100) for j in nbrs[i]]
         titles = ['MDS Linkages', 'LLE Linkages (100 NN)']
```





1.11 K-Means

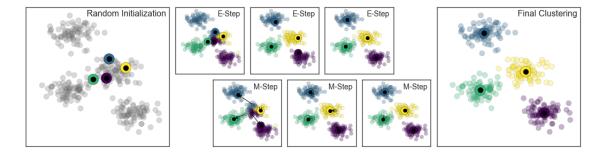
1.11.1 Expectation-Maximization

Figure Context

The following figure shows a visual depiction of the Expectation-Maximization approach to K Means:

```
s=50 * factor, alpha=0.3)
def draw_centers(ax, centers, factor=1, alpha=1.0):
    ax.scatter(centers[:, 0], centers[:, 1],
               c=np.arange(4), cmap='viridis', s=200 * factor,
               alpha=alpha)
    ax.scatter(centers[:, 0], centers[:, 1],
               c='black', s=50 * factor, alpha=alpha)
def make_ax(fig, gs):
    ax = fig.add_subplot(gs)
    ax.xaxis.set_major_formatter(plt.NullFormatter())
    ax.yaxis.set_major_formatter(plt.NullFormatter())
    return ax
fig = plt.figure(figsize=(15, 4))
gs = plt.GridSpec(4, 15, left=0.02, right=0.98, bottom=0.05, top=0.95, wspace=0.2, hs
ax0 = make_ax(fig, gs[:4, :4])
ax0.text(0.98, 0.98, "Random Initialization", transform=ax0.transAxes,
         ha='right', va='top', size=16)
draw_points(ax0, 'gray', factor=2)
draw_centers(ax0, centers, factor=2)
for i in range(3):
    ax1 = make_ax(fig, gs[:2, 4 + 2 * i:6 + 2 * i])
    ax2 = make_ax(fig, gs[2:, 5 + 2 * i:7 + 2 * i])
    # E-step
    y_pred = pairwise_distances_argmin(X, centers)
    draw_points(ax1, y_pred)
    draw_centers(ax1, centers)
    # M-step
    new_centers = np.array([X[y_pred == i].mean(0) for i in range(4)])
    draw_points(ax2, y_pred)
    draw_centers(ax2, centers, alpha=0.3)
    draw_centers(ax2, new_centers)
    for i in range(4):
        ax2.annotate('', new_centers[i], centers[i],
                     arrowprops=dict(arrowstyle='->', linewidth=1))
    # Finish iteration
    centers = new_centers
    ax1.text(0.95, 0.95, "E-Step", transform=ax1.transAxes, ha='right', va='top', size
    ax2.text(0.95, 0.95, "M-Step", transform=ax2.transAxes, ha='right', va='top', size
```

fig.savefig('figures/05.11-expectation-maximization.png')

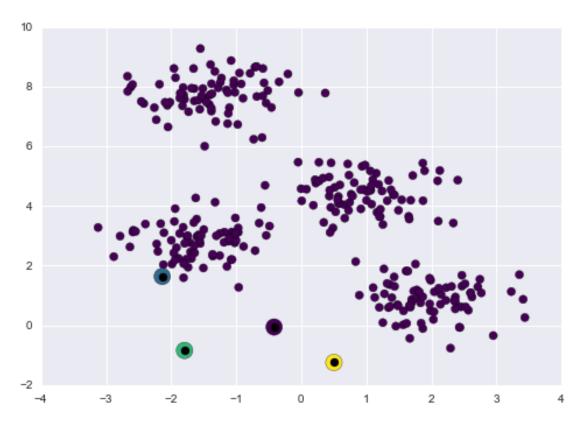


1.11.2 Interactive K-Means

The following script uses IPython's interactive widgets to demonstrate the K-means algorithm interactively. Run this within the IPython notebook to explore the expectation maximization algorithm for computing K Means.

```
c=np.arange(centers.shape[0]),
                s=200, cmap='viridis')
    plt.scatter(centers[:, 0], centers[:, 1], marker='o',
                c='black', s=50)
def _kmeans_step(frame=0, n_clusters=4):
    rng = np.random.RandomState(2)
    labels = np.zeros(X.shape[0])
    centers = rng.randn(n_clusters, 2)
    nsteps = frame // 3
    for i in range(nsteps + 1):
        old_centers = centers
        if i < nsteps or frame % 3 > 0:
            labels = pairwise_distances_argmin(X, centers)
        if i < nsteps or frame % 3 > 1:
            centers = np.array([X[labels == j].mean(0)
                                for j in range(n_clusters)])
            nans = np.isnan(centers)
            centers[nans] = old_centers[nans]
    # plot the data and cluster centers
    plot_points(X, labels, n_clusters)
    plot_centers(old_centers)
    # plot new centers if third frame
    if frame % 3 == 2:
        for i in range(n_clusters):
            plt.annotate('', centers[i], old_centers[i],
                         arrowprops=dict(arrowstyle='->', linewidth=1))
        plot_centers(centers)
    plt.xlim(-4, 4)
   plt.ylim(-2, 10)
    if frame % 3 == 1:
        plt.text(3.8, 9.5, "1. Reassign points to nearest centroid",
                 ha='right', va='top', size=14)
    elif frame % 3 == 2:
        plt.text(3.8, 9.5, "2. Update centroids to cluster means",
                 ha='right', va='top', size=14)
return interact(_kmeans_step, frame=[0, 50],
                n_clusters=[min_clusters, max_clusters])
```

plot_kmeans_interactive();



1.12 Gaussian Mixture Models

1.12.1 Covariance Type

Figure Context

```
In [47]: from sklearn.mixture import GMM

from matplotlib.patches import Ellipse

def draw_ellipse(position, covariance, ax=None, **kwargs):
    """Draw an ellipse with a given position and covariance"""
    ax = ax or plt.gca()

# Convert covariance to principal axes
    if covariance.shape == (2, 2):
        U, s, Vt = np.linalg.svd(covariance)
        angle = np.degrees(np.arctan2(U[1, 0], U[0, 0]))
        width, height = 2 * np.sqrt(s)
    else:
        angle = 0
```

```
width, height = 2 * np.sqrt(covariance)
     # Draw the Ellipse
     for nsig in range(1, 4):
         ax.add_patch(Ellipse(position, nsig * width, nsig * height,
                               angle, **kwargs))
fig, ax = plt.subplots(1, 3, figsize=(14, 4), sharex=True, sharey=True)
fig.subplots_adjust(wspace=0.05)
rng = np.random.RandomState(5)
X = np.dot(rng.randn(500, 2), rng.randn(2, 2))
for i, cov_type in enumerate(['diag', 'spherical', 'full']):
     model = GMM(1, covariance_type=cov_type).fit(X)
     ax[i].axis('equal')
     ax[i].scatter(X[:, 0], X[:, 1], alpha=0.5)
     ax[i].set_xlim(-3, 3)
     ax[i].set_title('covariance_type="{0}"'.format(cov_type),
                     size=14, family='monospace')
     draw_ellipse(model.means_[0], model.covars_[0], ax[i], alpha=0.2)
     ax[i].xaxis.set_major_formatter(plt.NullFormatter())
     ax[i].yaxis.set_major_formatter(plt.NullFormatter())
fig.savefig('figures/05.12-covariance-type.png')
covariance_type="diag"
                       covariance_type="spherical"
                                                  covariance_type="full"
```

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