Session 6

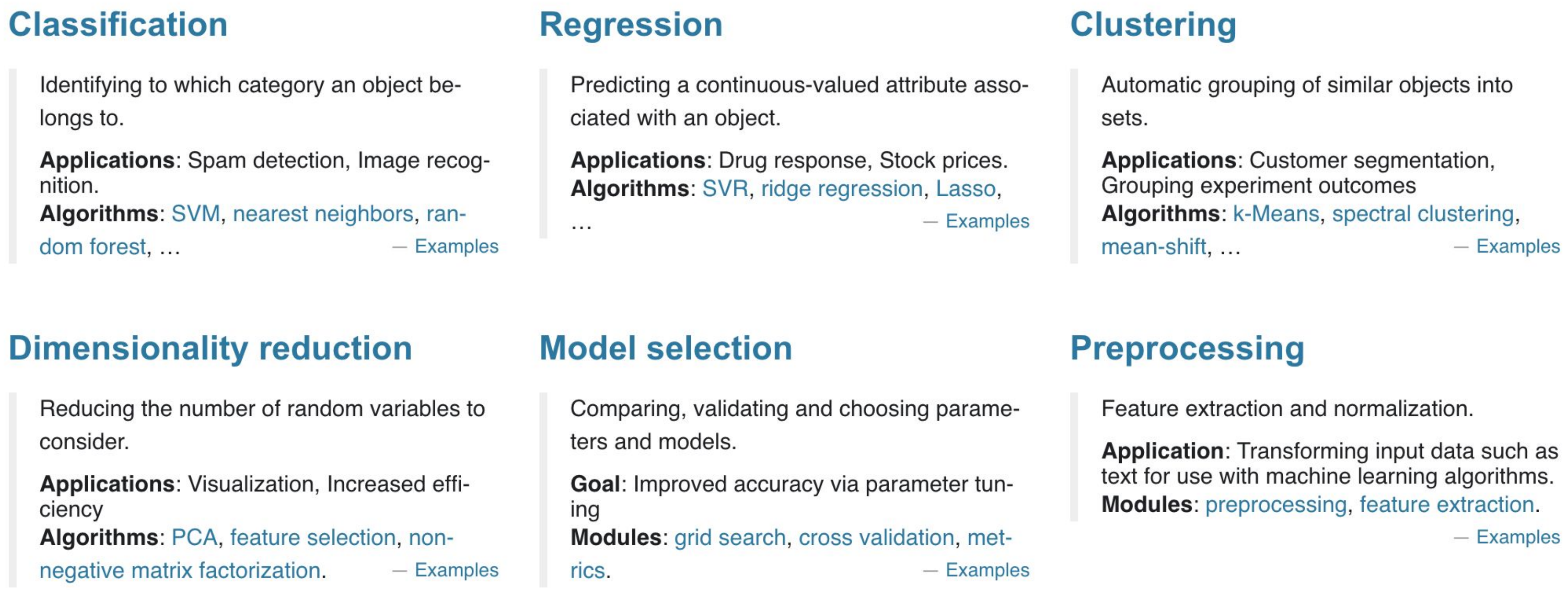
49-781 Data Analytics for Product Managers

Spring 2018

Topics

1. Scikit-Learn
2. Linear Regression
3. Decision Trees
4. PCA
5. KMeans

Scikit Learn



Classification

Identifying to which category an object belongs to.

Applications: Spam detection, Image recognition.
Algorithms: SVM, nearest neighbors, random forest, … — Examples

Regression

Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock prices.
Algorithms: SVR, ridge regression, Lasso, … — Examples

Clustering

Automatic grouping of similar objects into sets.

Applications: Customer segmentation, Grouping experiment outcomes
Algorithms: k-Means, spectral clustering, mean-shift, … — Examples

Dimensionality reduction

Reducing the number of random variables to consider.

Applications: Visualization, Increased efficiency
Algorithms: PCA, feature selection, non-negative matrix factorization. — Examples

Model selection

Comparing, validating and choosing parameters and models.

Goal: Improved accuracy via parameter tuning
Modules: grid search, cross validation, metrics. — Examples

Preprocessing

Feature extraction and normalization.

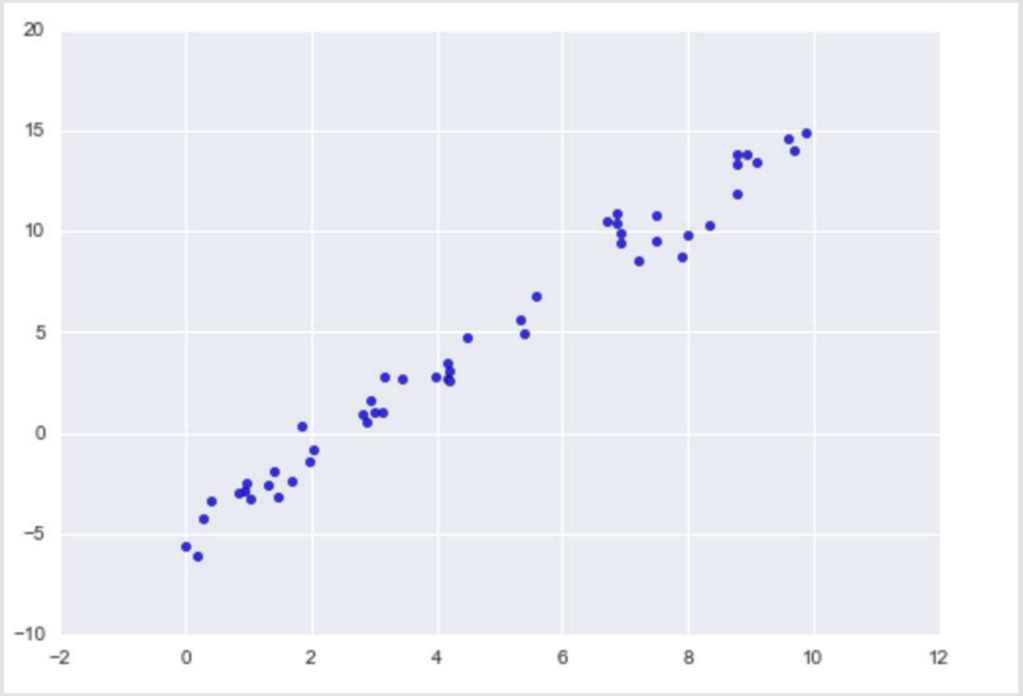
Application: Transforming input data such as text for use with machine learning algorithms.
Modules: preprocessing, feature extraction.

— Examples

Linear Regression

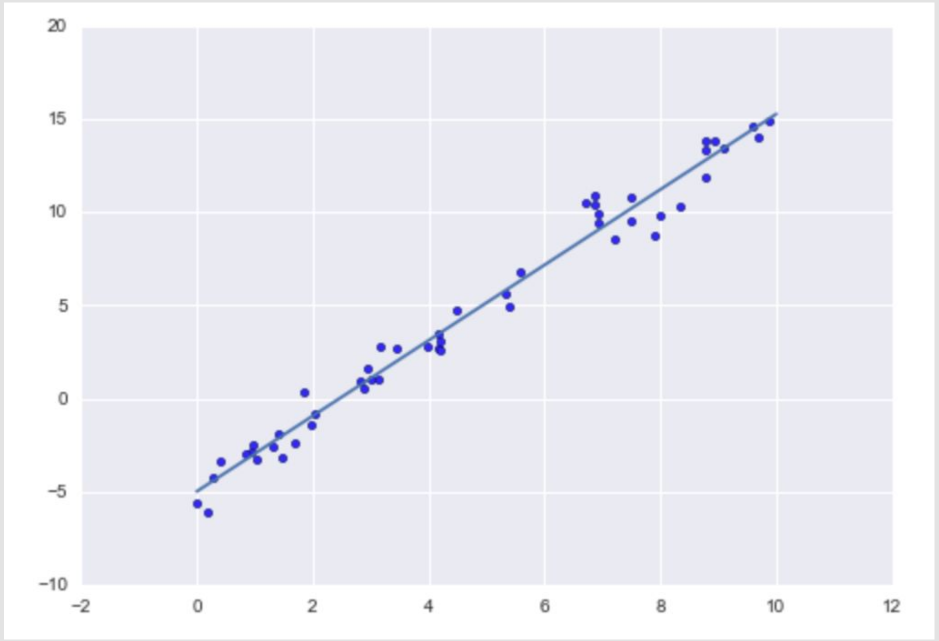
Scatter Plot

```
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()
import numpy as np

rng = np.random.RandomState(1)
x = 10 * rng.rand(50)
y = 2 * x - 5 + rng.randn(50)
plt.scatter(x, y);
plt.show()
```



Simple Linear Regression

```
from sklearn.linear_model import LinearRegression
model = LinearRegression(fit_intercept=True)

model.fit(x[:, np.newaxis], y)

xfit = np.linspace(0, 10, 1000)
yfit = model.predict(xfit[:, np.newaxis])

plt.scatter(x, y)
plt.plot(xfit, yfit);
plt.show()
```



Model Parameters

```
print("Model slope:    ", model.coef_[0])
print("Model intercept:", model.intercept_)
```

```
Model slope:     2.02720881036
Model intercept: -4.99857708555
```

Multiple Linear Regression

```
rng = np.random.RandomState(1)
X = 10 * rng.rand(100, 3)
y = 0.5 + np.dot(X, [1.5, -2., 1.])

model.fit(X, y)
print(model.intercept_)
print(model.coef_)
```

```
0.5
[ 1.5 -2.   1. ]
```

Numerical Transformations

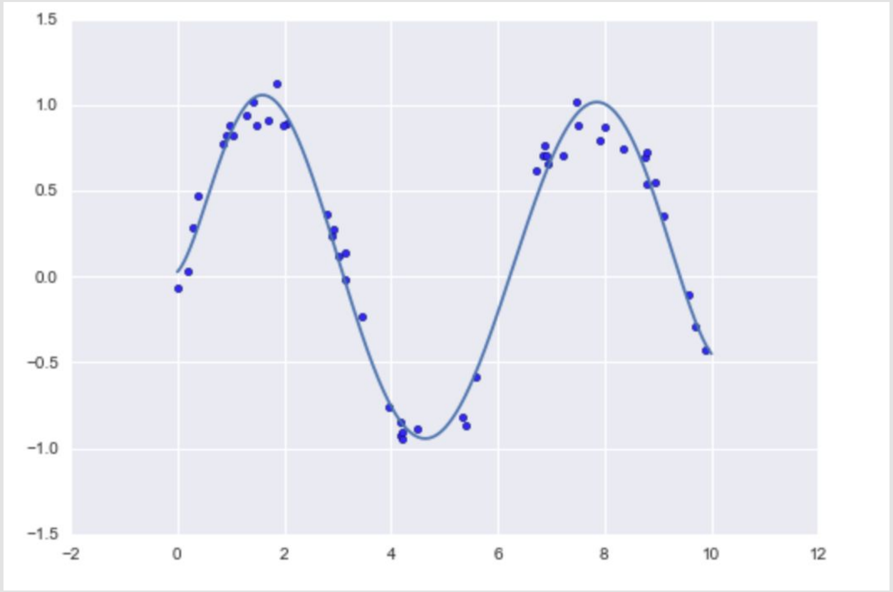
```
from sklearn.preprocessing import PolynomialFeatures
x = np.array([2, 3, 4])
poly = PolynomialFeatures(3, include_bias=False)
poly.fit_transform(x[:, None])
```

```
[[  2.   4.   8.]
 [  3.   9.  27.]
 [  4.  16.  64.]]
```

Fitting with Transformations

```
from sklearn.pipeline import make_pipeline
poly_model = make_pipeline(PolynomialFeatures(7),
                           LinearRegression())
```

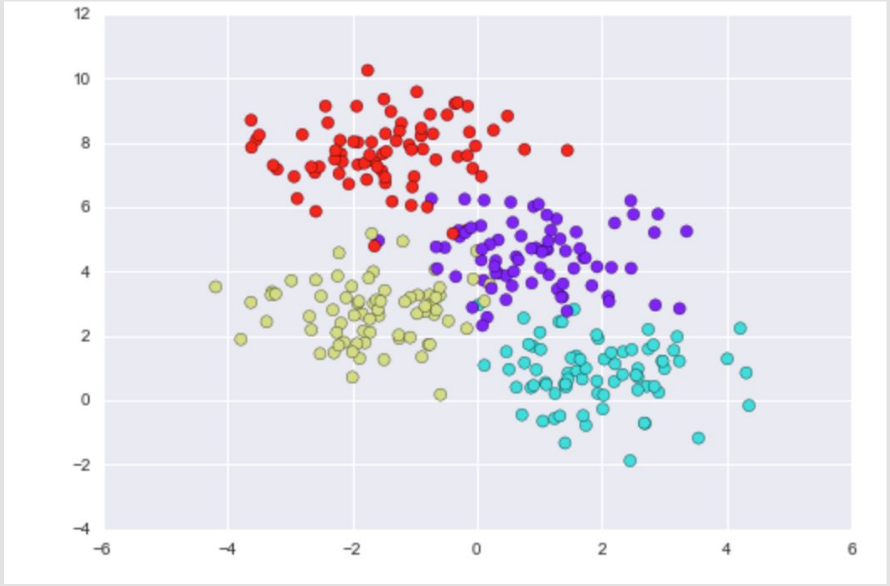
```
rng = np.random.RandomState(1)
x = 10 * rng.rand(50)
y = np.sin(x) + 0.1 * rng.randn(50)

poly_model.fit(x[:, np.newaxis], y)
yfit = poly_model.predict(xfit[:, np.newaxis])

plt.scatter(x, y)
plt.plot(xfit, yfit);
plt.show()
```



Decision Trees

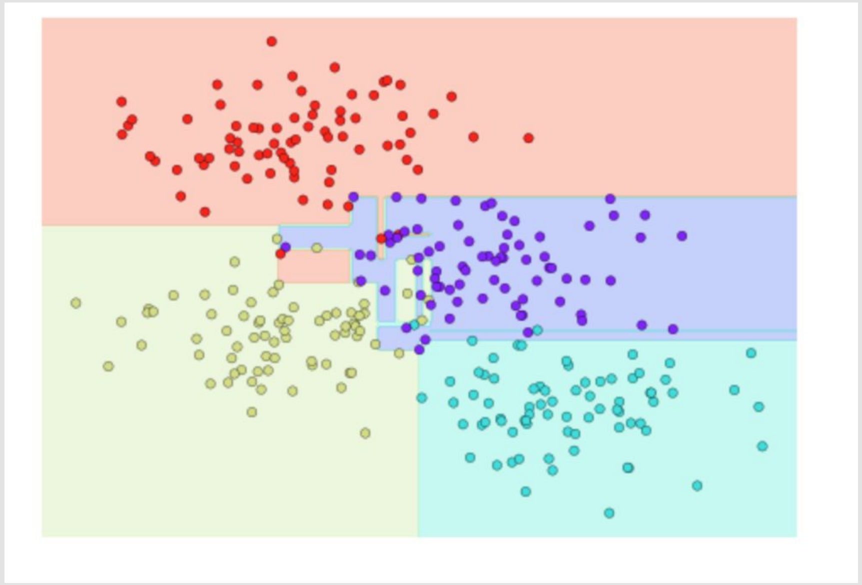
Data

```
from sklearn.datasets import make_blobs

X, y = make_blobs(n_samples=300, centers=4,
                  random_state=0, cluster_std=1.0)
plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='rainbow');
plt.show()
```



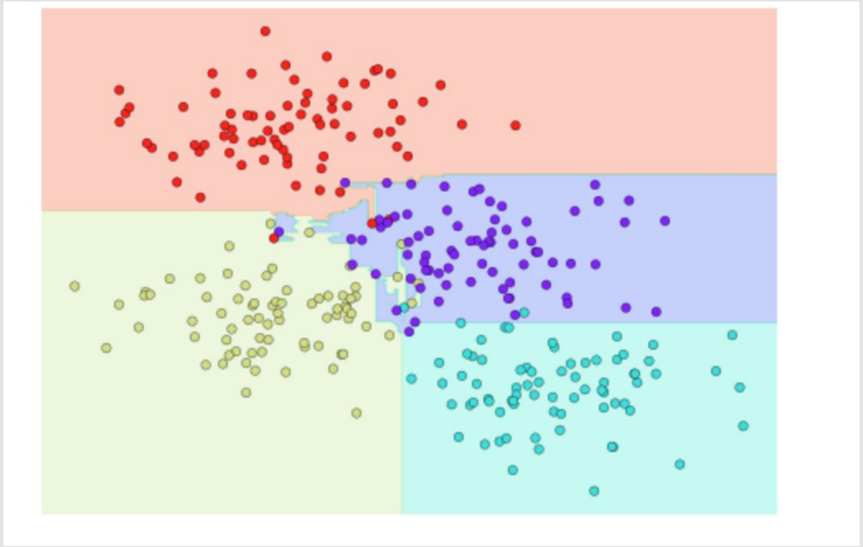
Trees

```
from sklearn.tree import DecisionTreeClassifier
tree = DecisionTreeClassifier().fit(X, y)

def visualize_classifier(model, X, y, ax=None, cmap='rainbow'):
    ax = ax or plt.gca()

    # Plot the training points
    ax.scatter(X[:, 0], X[:, 1], c=y, s=30, cmap=cmap,
               clim=(y.min(), y.max()), zorder=3)
    ax.axis('tight')
    ax.axis('off')
    xlim = ax.get_xlim()
    ylim = ax.get_ylim()

    # fit the estimator
    model.fit(X, y)
    xx, yy = np.meshgrid(np.linspace(*xlim, num=200),
                         np.linspace(*ylim, num=200))
    Z = model.predict(np.c_[xx.ravel(), yy.ravel()]).reshape(xx.shape)

    # Create a color plot with the results
    n_classes = len(np.unique(y))
    contours = ax.contourf(xx, yy, Z, alpha=0.3,
                           levels=np.arange(n_classes + 1) - 0.5,
                           cmap=cmap, clim=(y.min(), y.max()),
                           zorder=1)

    ax.set(xlim=xlim, ylim=ylim)

visualize_classifier(DecisionTreeClassifier(), X, y)
```



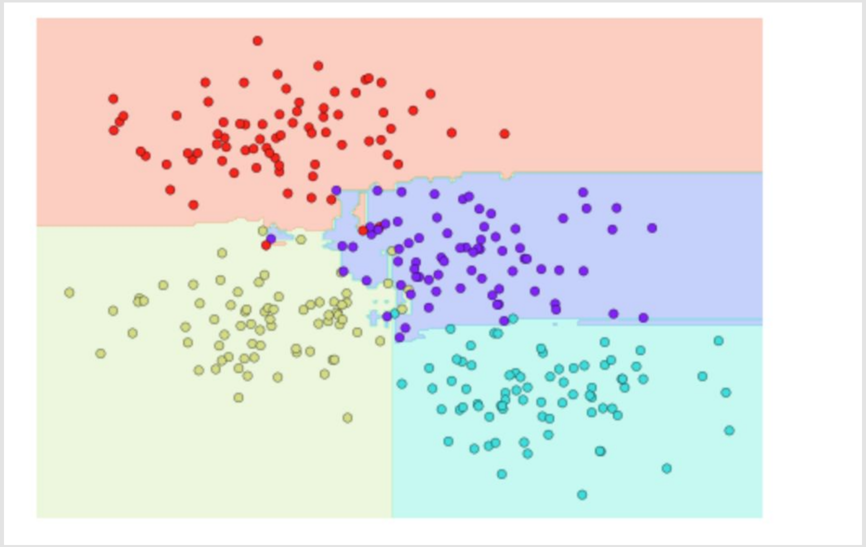
Bagging

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import BaggingClassifier

tree = DecisionTreeClassifier()
bag = BaggingClassifier(tree, n_estimators=100, max_samples=0.8,
                        random_state=1)

bag.fit(X, y)
visualize_classifier(bag, X, y)
plt.show()
```



Random Forest

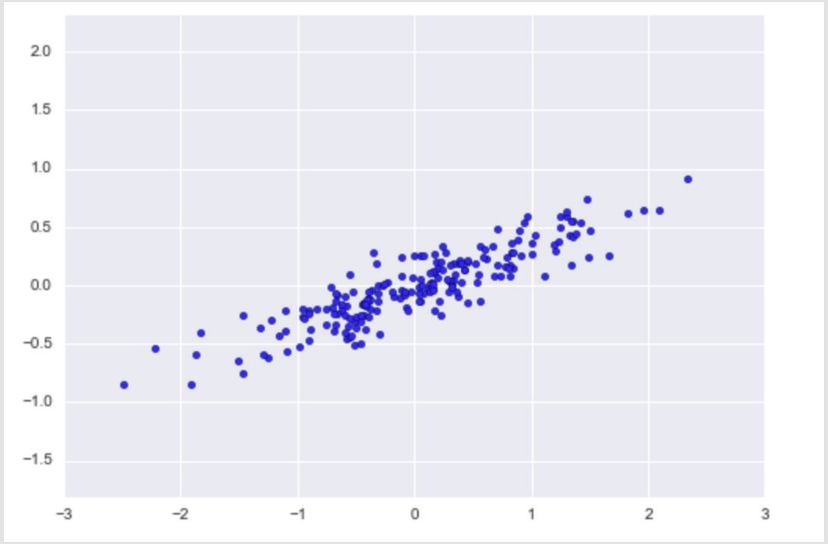
```
from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier(n_estimators=100, random_state=0)
visualize_classifier(model, X, y);
```



Principal Component Analysis

Basic PCA

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()

rng = np.random.RandomState(1)
X = np.dot(rng.rand(2, 2), rng.randn(2, 200)).T
plt.scatter(X[:, 0], X[:, 1])
plt.axis('equal')
plt.show()
```



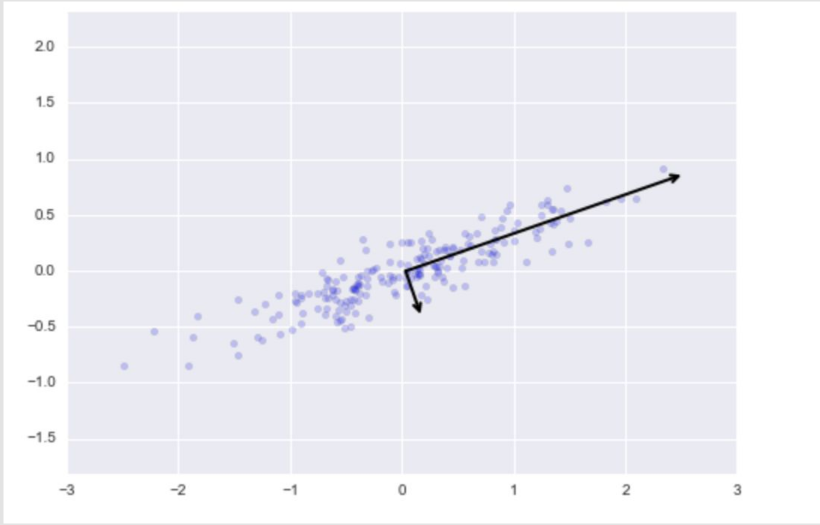
Principal Components

```
from sklearn.decomposition import PCA
pca = PCA(n_components=2)
pca.fit(X)
print(pca.components_)
print(pca.explained_variance_)
```

```
[[-0.94446029 -0.32862557]
 [-0.32862557  0.94446029]]

[ 0.7625315  0.0184779]
```

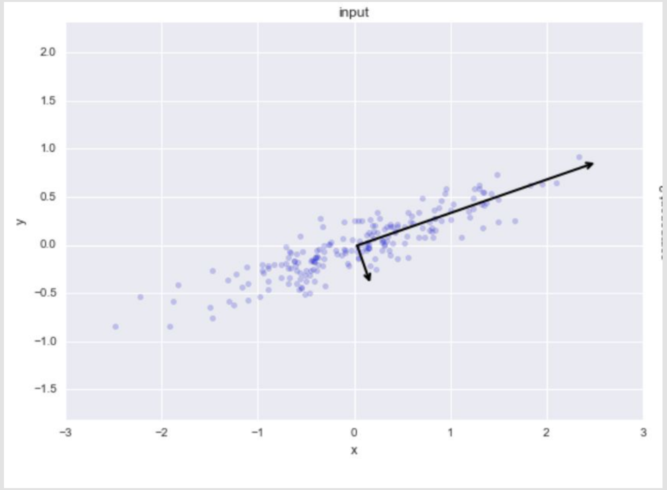
Visualizing PCA

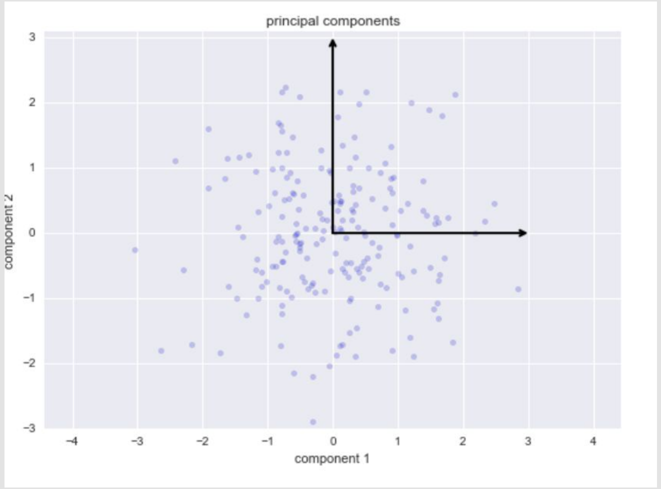
```
def draw_vector(v0, v1, ax=None):
    ax = ax or plt.gca()
    arrowprops=dict(arrowstyle='->',
                    linewidth=2,
                    shrinkA=0, shrinkB=0)
    ax.annotate('', v1, v0, arrowprops=arrowprops)

# plot data
plt.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)
plt.axis('equal')
plt.show()
```



Visualizing the Transformation

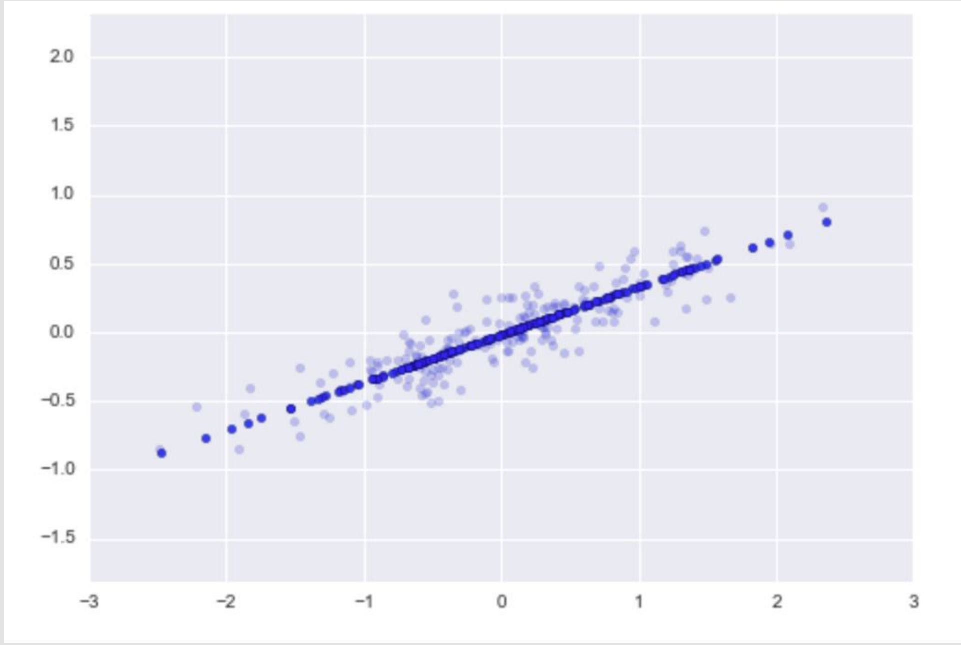
```
rng = np.random.RandomState(1)
X = np.dot(rng.rand(2, 2), rng.randn(2, 200)).T
pca = PCA(n_components=2, whiten=True)
pca.fit(X)


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))
plt.show()
```





Reduced Dimensionality

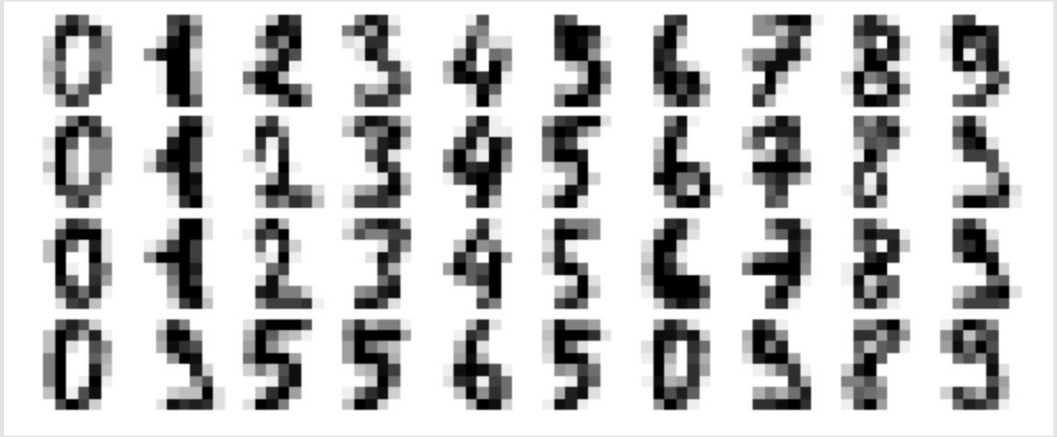
```
#Using PCA for dimensionality reduction involves zeroing out one or more of the smallest principal
#components, resulting in a lower-dimensional projection of the data that preserves the maximal
#data variance.

pca = PCA(n_components=1)
pca.fit(X)
X_pca = pca.transform(X)
print("original shape:   ", X.shape)
print("transformed shape:", X_pca.shape)

X_new = pca.inverse_transform(X_pca)
plt.scatter(X[:, 0], X[:, 1], alpha=0.2)
plt.scatter(X_new[:, 0], X_new[:, 1], alpha=0.8)
plt.axis('equal');

plt.show()
```

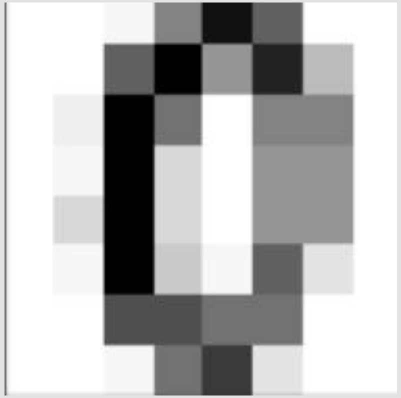


PCA for Higher Dimensions

```
from sklearn.datasets import load_digits
digits = load_digits()
print(digits.data.shape)
```

```
(1797, 64)
```



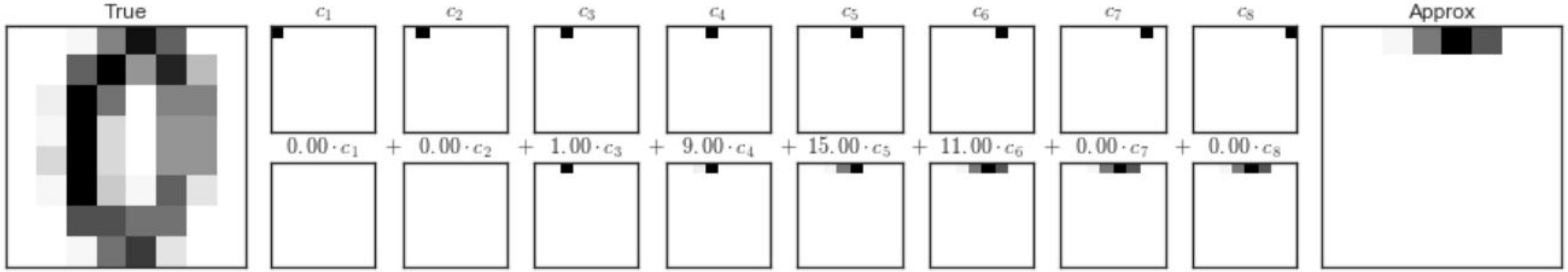


Project to 2 Dimensions

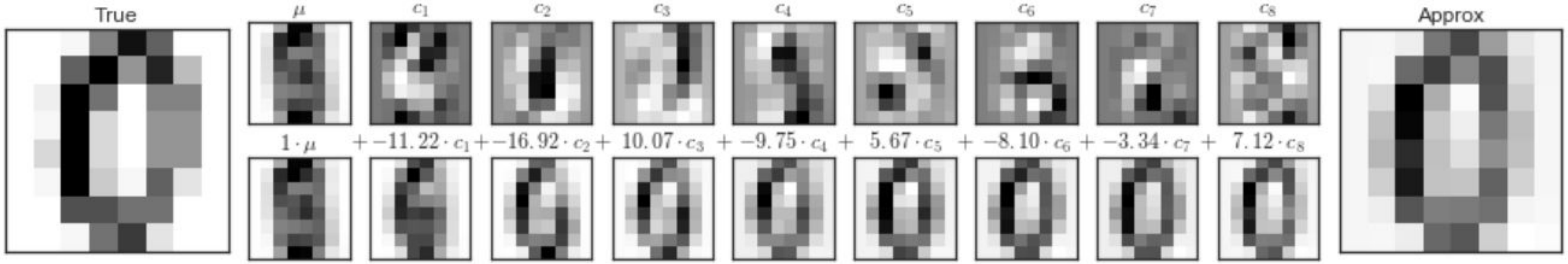
```
pca = PCA(2)  # project from 64 to 2 dimensions
projected = pca.fit_transform(digits.data)
print(digits.data.shape)
print(projected.shape)
```

```
(1797, 64)
(1797, 2)
```

Principal Components Applied



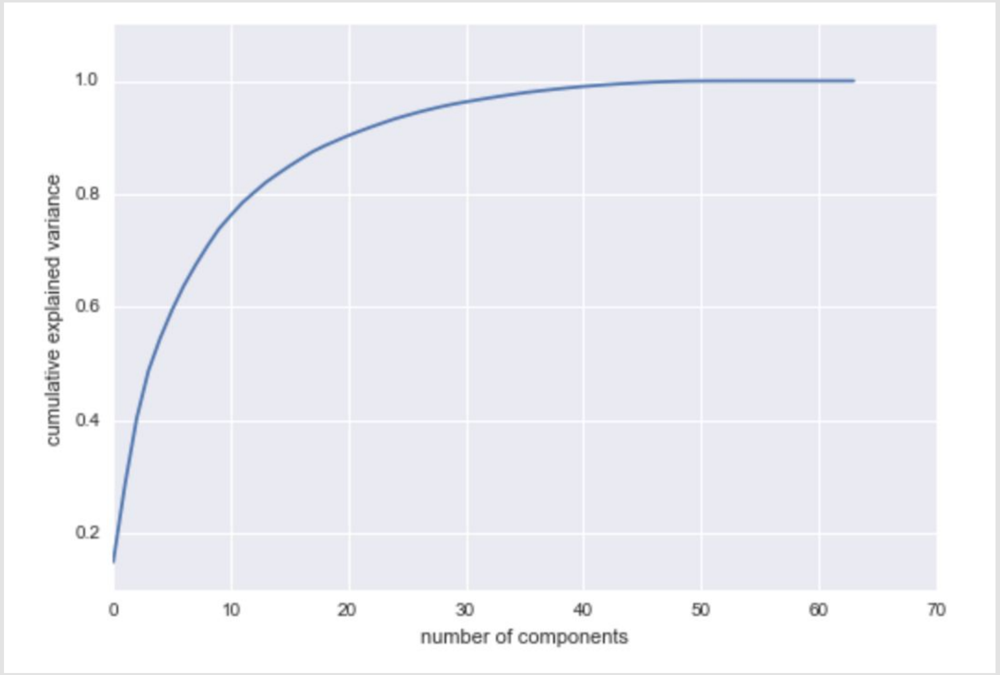
True
c_1
c_2
c_3
c_4
c_5
c_6
c_7
c_8
Approx
$0.00 \cdot c_1 + 0.00 \cdot c_2 + 1.00 \cdot c_3 + 9.00 \cdot c_4 + 15.00 \cdot c_5 + 11.00 \cdot c_6 + 0.00 \cdot c_7 + 0.00 \cdot c_8$



True
μ
c_1
c_2
c_3
c_4
c_5
c_6
c_7
c_8
Approx
$1 \cdot \mu + -11.22 \cdot c_1 + -16.92 \cdot c_2 + 10.07 \cdot c_3 + -9.75 \cdot c_4 + 5.67 \cdot c_5 + -8.10 \cdot c_6 + -3.34 \cdot c_7 + 7.12 \cdot c_8$

Explained Variance vs Component Count

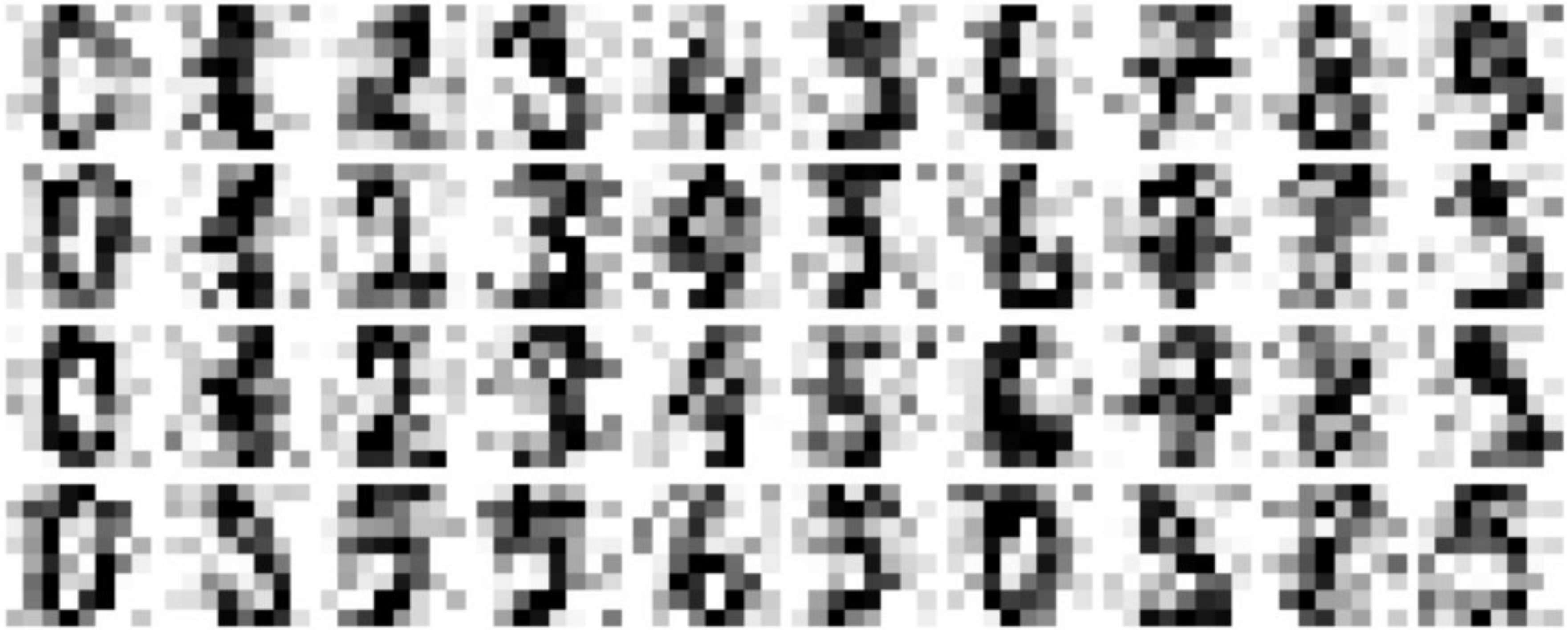
```
pca = PCA().fit(digits.data)
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance');
plt.show()
```



PCA to Reduce Noise

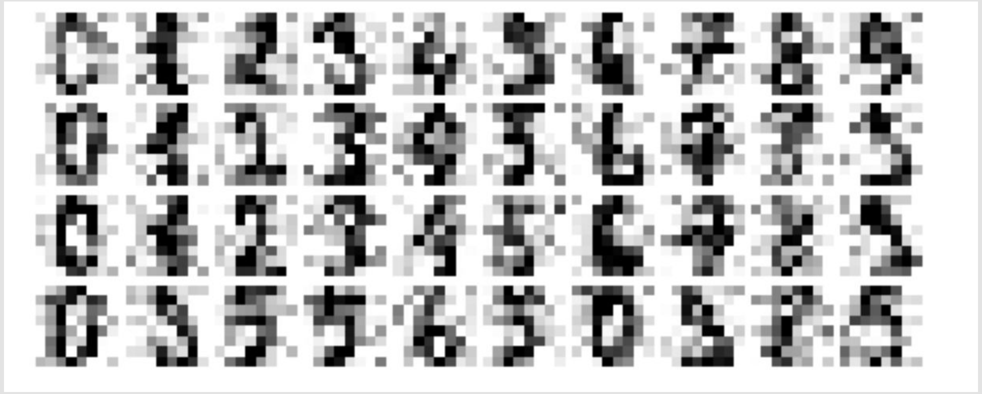
```
from sklearn.datasets import load_digits
digits = load_digits()
np.random.seed(42)
noisy = np.random.normal(digits.data, 4)

def plot_digits(data):
    fig, axes = plt.subplots(4, 10, figsize=(10, 4),
                             subplot_kw={'xticks':[], 'yticks':[]},
                             gridspec_kw=dict(hspace=0.1, wspace=0.1))
    for i, ax in enumerate(axes.flat):
        ax.imshow(data[i].reshape(8, 8),
                  cmap='binary', interpolation='nearest',
                  clim=(0, 16))


plot_digits(noisy)
plt.show()
```

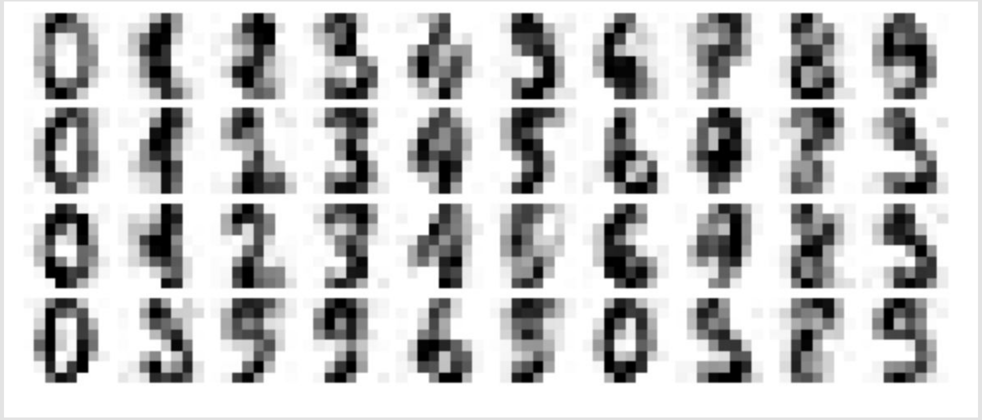
Digits with Noise



Noise-Reduction

```
from sklearn.decomposition import PCA

pca = PCA(0.50).fit(noisy)
print(pca.n_components_)

components = pca.transform(noisy)
filtered = pca.inverse_transform(components)
plot_digits(filtered)
plt.show()
```





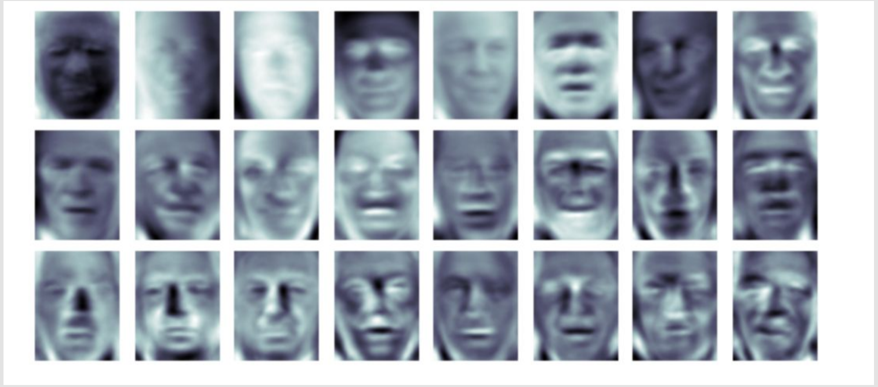
Facial Recognition

```
from sklearn.decomposition import PCA

pca = PCA(0.50).fit(noisy)
print(pca.n_components_)

components = pca.transform(noisy)
filtered = pca.inverse_transform(components)
plot_digits(filtered)
plt.show()

from sklearn.datasets import fetch_lfw_people
faces = fetch_lfw_people(min_faces_per_person=60)
print(faces.target_names)
print(faces.images.shape)
```

```
['Ariel Sharon' 'Colin Powell' 'Donald Rumsfeld' 'George W Bush'
 'Gerhard Schroeder' 'Hugo Chavez' 'Junichiro Koizumi' 'Tony Blair']
(1348, 62, 47)
```

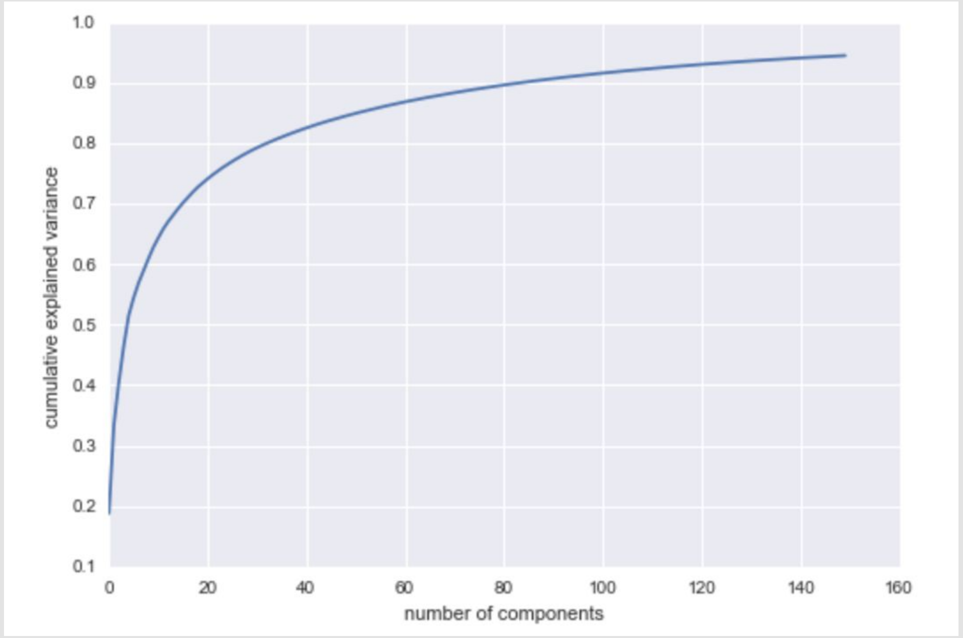
PCA

```
from sklearn.decomposition import RandomizedPCA
pca = RandomizedPCA(150)
pca.fit(faces.data)

fig, axes = plt.subplots(3, 8, figsize=(9, 4),
                         subplot_kw={'xticks':[], 'yticks':[]},
                         gridspec_kw=dict(hspace=0.1, wspace=0.1))
for i, ax in enumerate(axes.flat):
    ax.imshow(pca.components_[i].reshape(62, 47), cmap='bone')

plt.show()
```



Explained Variance

```
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance')
plt.show()
```

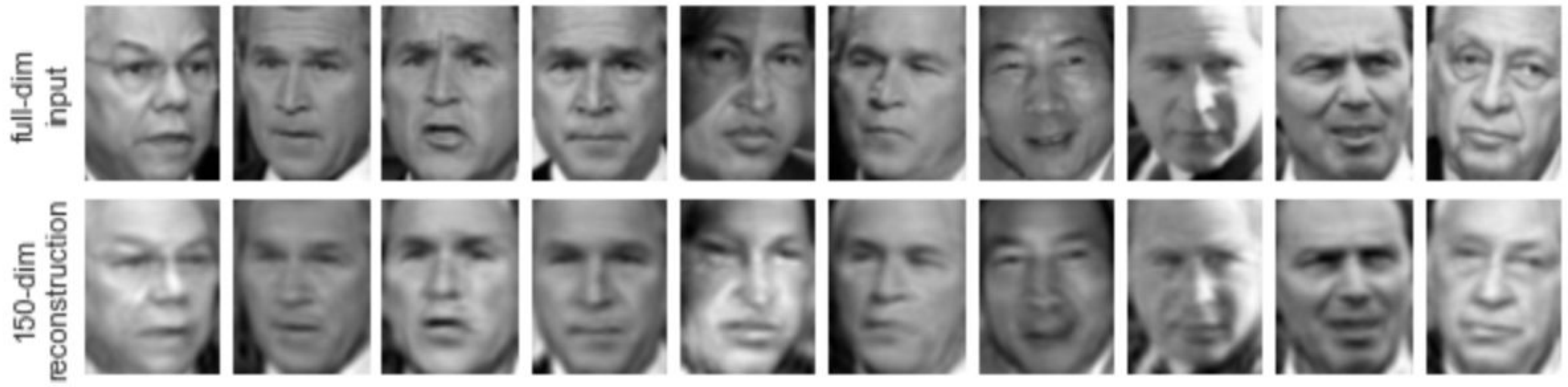


150-feature based vs Full-feature based

```
# Compute the components and projected faces
pca = RandomizedPCA(150).fit(faces.data)
components = pca.transform(faces.data)
projected = pca.inverse_transform(components)

# Plot the results
fig, ax = plt.subplots(2, 10, figsize=(10, 2.5),
                       subplot_kw={'xticks': [], 'yticks': []},
                       gridspec_kw=dict(hspace=0.1, wspace=0.1))
for i in range(10):
    ax[0, i].imshow(faces.data[i].reshape(62, 47), cmap='binary_r')
    ax[1, i].imshow(projected[i].reshape(62, 47), cmap='binary_r')

ax[0, 0].set_ylabel('full-dim\ninput')
ax[1, 0].set_ylabel('150-dim\nreconstruction')

plt.show()
```

Input vs Reduced Images

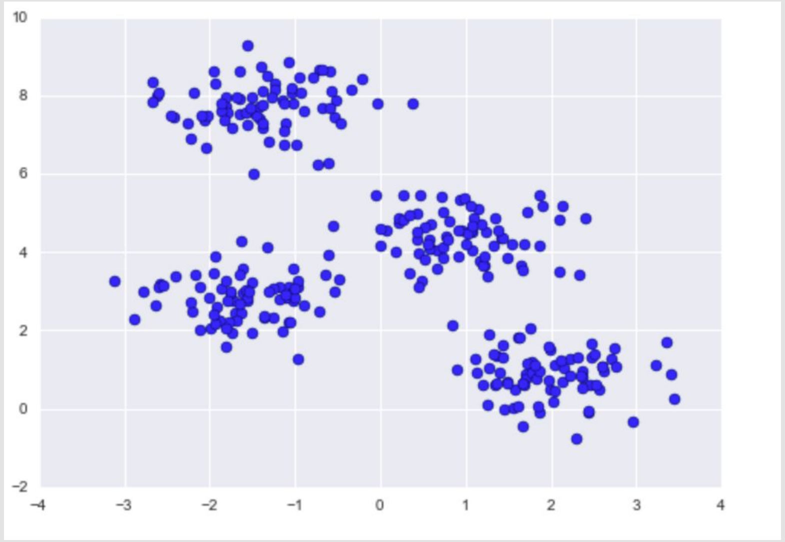
`2914 features vs 150 features`



K-Means Clustering

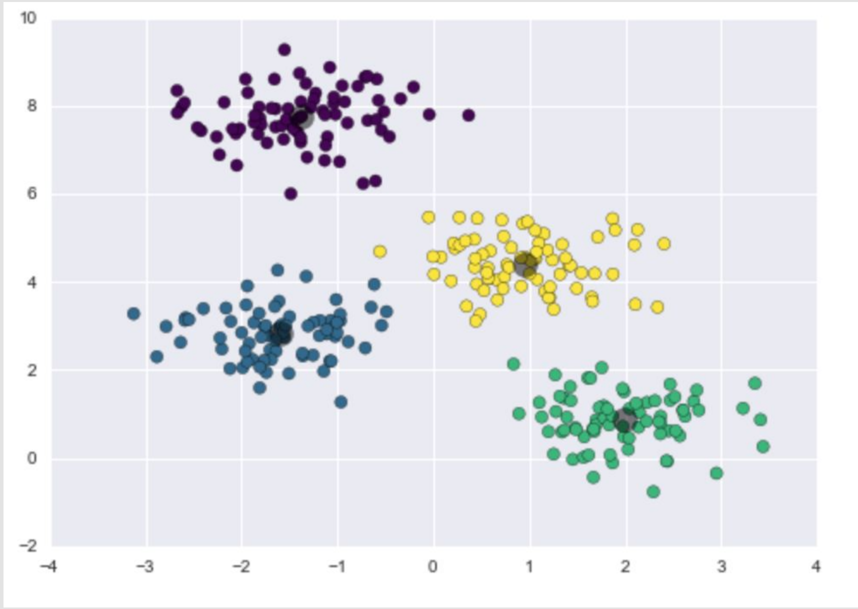
Clustering

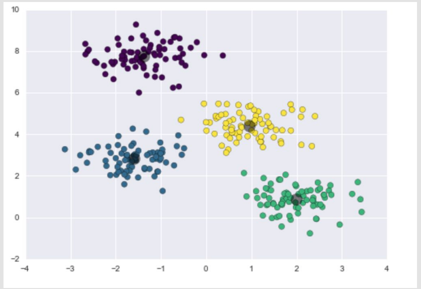
```
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()  # for plot styling
import numpy as np

from sklearn.datasets.samples_generator import make_blobs
X, y_true = make_blobs(n_samples=300, centers=4,
                       cluster_std=0.60, random_state=0)
plt.scatter(X[:, 0], X[:, 1], s=50);
```



K Means Clustering

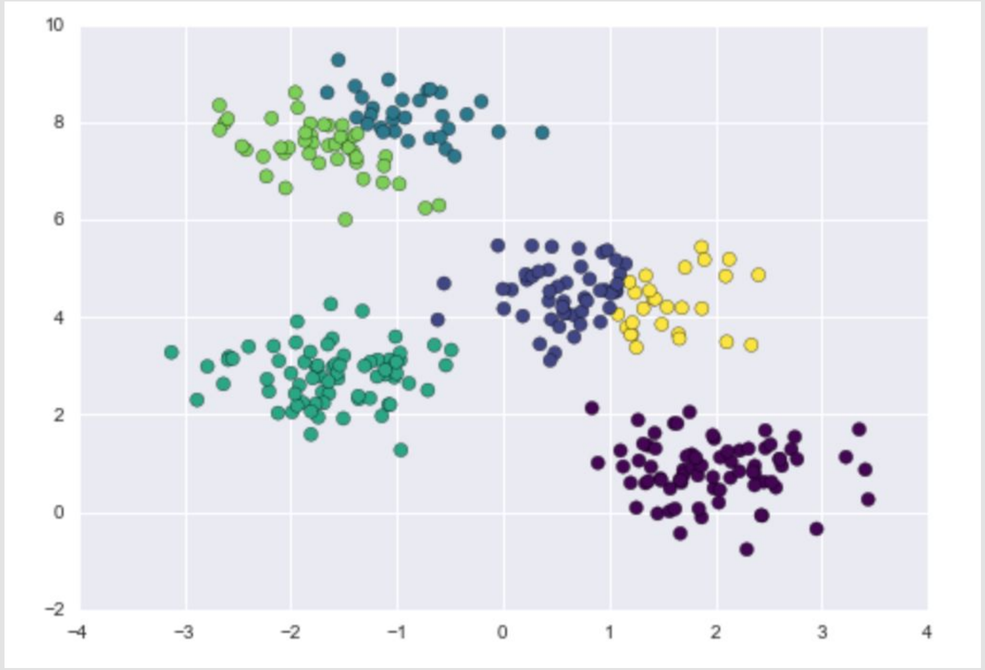
```
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=4)
kmeans.fit(X)
y_kmeans = kmeans.predict(X)

plt.scatter(X[:, 0], X[:, 1], c=y_kmeans, s=50,
cmap='viridis')

centers = kmeans.cluster_centers_
plt.scatter(centers[:, 0], centers[:, 1],
c='black', s=200, alpha=0.5);

plt.show()
```





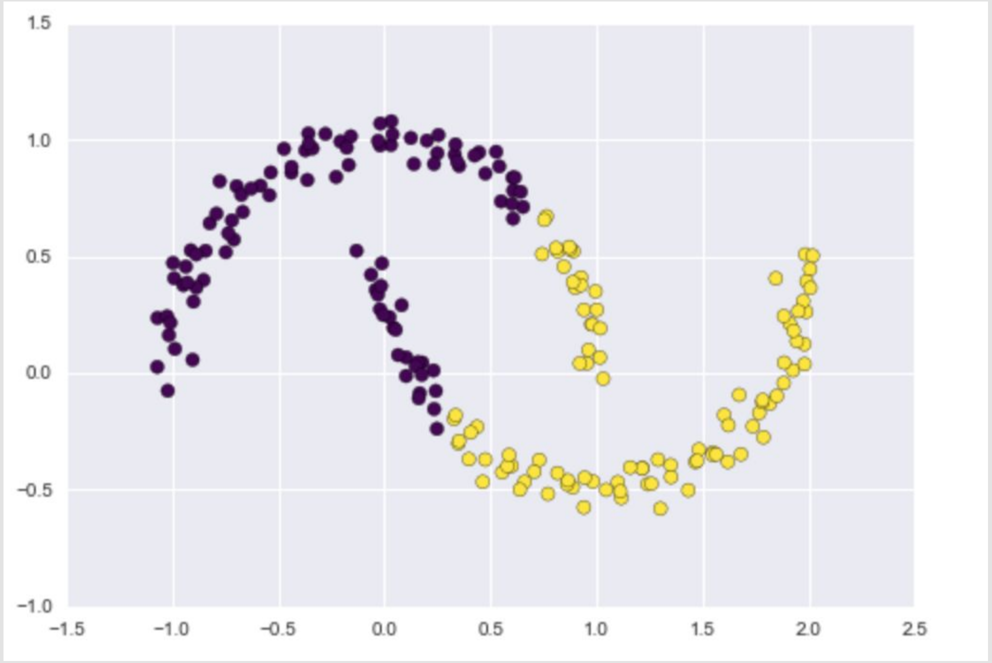
Changing the Random Seed

```
labels = KMeans(6, random_state=0).fit_predict(X)
plt.scatter(X[:, 0], X[:, 1], c=labels,
            s=50, cmap='viridis')
plt.show()
```



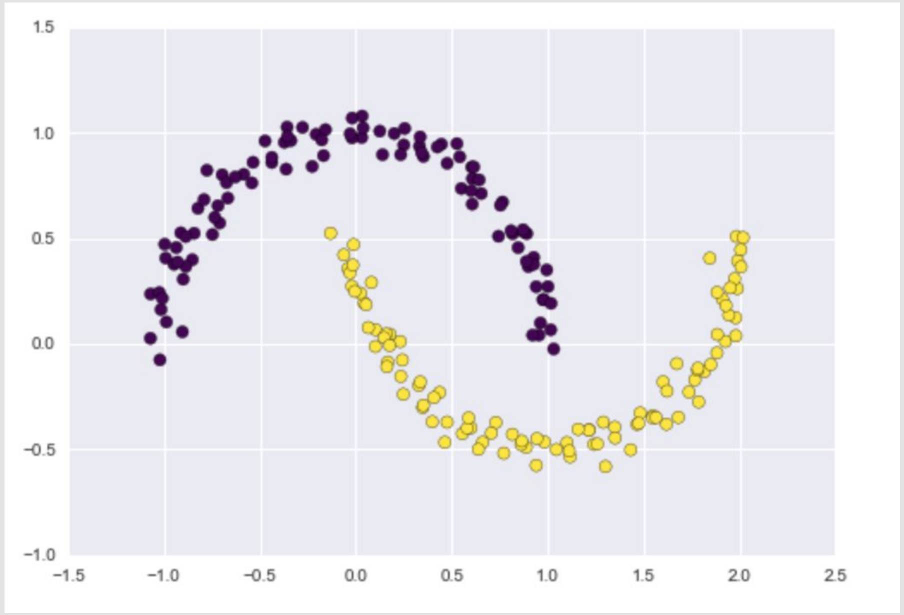
Issue with Nonlinear Boundaries

```
from sklearn.datasets import make_moons
X, y = make_moons(200, noise=.05, random_state=0)
labels = KMeans(2, random_state=0).fit_predict(X)
plt.scatter(X[:, 0], X[:, 1], c=labels,
            s=50, cmap='viridis')
plt.show()
```



Using Graph of Nearest Neighbors

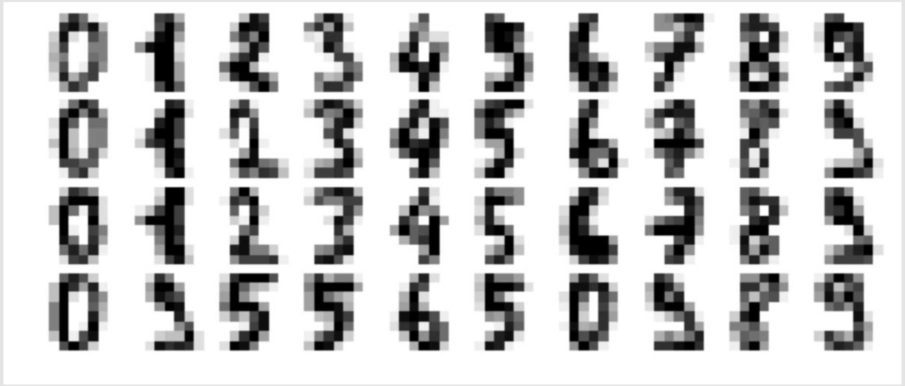
```
from sklearn.cluster import SpectralClustering
model = SpectralClustering(n_clusters=2, affinity='nearest_neighbors',
                           assign_labels='kmeans')
labels = model.fit_predict(X)
plt.scatter(X[:, 0], X[:, 1], c=labels,
            s=50, cmap='viridis')
plt.show()
```



Working with Digits

```
from sklearn.datasets import load_digits
digits = load_digits()
print(digits.data.shape)
```

```
(1797, 64)
```

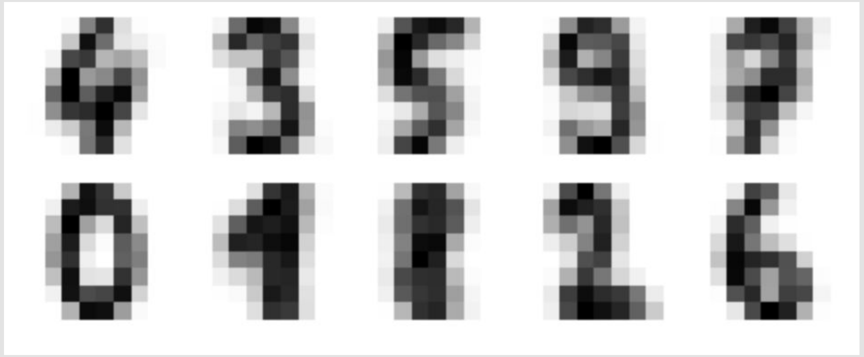


Create 10 Clusters

```
kmeans = KMeans(n_clusters=10, random_state=0)
clusters = kmeans.fit_predict(digits.data)
print(kmeans.cluster_centers_.shape)

(10, 64)
```

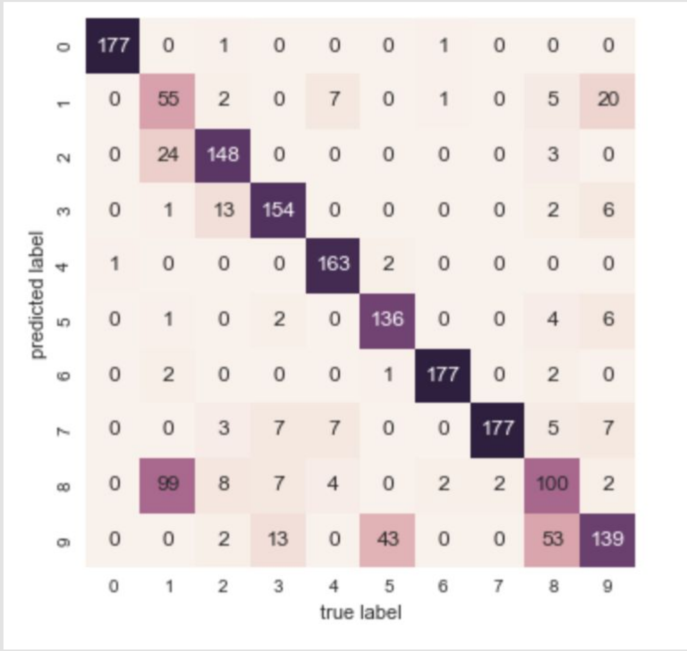
Cluster Centers

```
fig, ax = plt.subplots(2, 5, figsize=(8, 3))
centers = kmeans.cluster_centers_.reshape(10, 8, 8)
for axi, center in zip(ax.flat, centers):
    axi.set(xticks=[], yticks=[])
    axi.imshow(center, interpolation='nearest', cmap=plt.cm.binary)
plt.show()
```



Accuracy of Prediction

```
from scipy.stats import mode

labels = np.zeros_like(clusters)
for i in range(10):
    mask = (clusters == i)
    labels[mask] = mode(digits.target[mask])[0]

from sklearn.metrics import accuracy_score
print(accuracy_score(digits.target, labels))

0.79354479688369506

from sklearn.metrics import confusion_matrix
mat = confusion_matrix(digits.target, labels)
sns.heatmap(mat.T, square=True, annot=True, fmt='d', cbar=False,
            xticklabels=digits.target_names,
            yticklabels=digits.target_names)
plt.xlabel('true label')
plt.ylabel('predicted label');
plt.show()
```



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http://scikit-learn.org/