Module 2

May 27, 2020

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*You are currently looking at **version 1.1** of this notebook. To download notebooks and datafiles, as well as get help on Jupyter notebooks in the Coursera platform, visit the Jupyter Notebook FAQ course resource.*

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1 Applied Machine Learning: Module 2 (Supervised Learning, Part I)

1.1 Preamble and Review

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

from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier

np.set_printoptions(precision=2)


fruits = pd.read_table('readonly/fruit_data_with_colors.txt')

feature_names_fruits = ['height', 'width', 'mass', 'color_score']
X_fruits = fruits[feature_names_fruits]
y_fruits = fruits['fruit_label']
target_names_fruits = ['apple', 'mandarin', 'orange', 'lemon']

X_fruits_2d = fruits[['height', 'width']]
y_fruits_2d = fruits['fruit_label']

X_train, X_test, y_train, y_test = train_test_split(X_fruits, y_fruits, rar

from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
```

```
# we must apply the scaling to the test set that we computed for the traini
X_test_scaled = scaler.transform(X_test)

knn = KNeighborsClassifier(n_neighbors = 5)
knn.fit(X_train_scaled, y_train)
print('Accuracy of K-NN classifier on training set: {:.2f}'
     .format(knn.score(X_train_scaled, y_train)))
print('Accuracy of K-NN classifier on test set: {:.2f}'
     .format(knn.score(X_test_scaled, y_test)))

example_fruit = [[5.5, 2.2, 10, 0.70]]
example_fruit_scaled = scaler.transform(example_fruit)
print('Predicted fruit type for ', example_fruit, ' is ',
          target_names_fruits[knn.predict(example_fruit_scaled)[0]-1])
```

```
Accuracy of K-NN classifier on training set: 0.95
Accuracy of K-NN classifier on test set: 1.00
Predicted fruit type for  [[5.5, 2.2, 10, 0.7]]  is  mandarin
```

1.2 Datasets

In [2]:
```
from sklearn.datasets import make_classification, make_blobs
from matplotlib.colors import ListedColormap
from sklearn.datasets import load_breast_cancer
from adspy_shared_utilities import load_crime_dataset

cmap_bold = ListedColormap(['#FFFF00', '#00FF00', '#0000FF','#000000'])


# synthetic dataset for simple regression
from sklearn.datasets import make_regression
plt.figure()
plt.title('Sample regression problem with one input variable')
X_R1, y_R1 = make_regression(n_samples = 100, n_features=1,
                            n_informative=1, bias = 150.0,
                            noise = 30, random_state=0)
plt.scatter(X_R1, y_R1, marker= 'o', s=50)
plt.show()


# synthetic dataset for more complex regression
from sklearn.datasets import make_friedman1
plt.figure()
plt.title('Complex regression problem with one input variable')
X_F1, y_F1 = make_friedman1(n_samples = 100,
                           n_features = 7, random_state=0)
```

```
plt.scatter(X_F1[:, 2], y_F1, marker= 'o', s=50)
plt.show()

# synthetic dataset for classification (binary)
plt.figure()
plt.title('Sample binary classification problem with two informative featur
X_C2, y_C2 = make_classification(n_samples = 100, n_features=2,
                                n_redundant=0, n_informative=2,
                                n_clusters_per_class=1, flip_y = 0.1,
                                class_sep = 0.5, random_state=0)
plt.scatter(X_C2[:, 0], X_C2[:, 1], c=y_C2,
           marker= 'o', s=50, cmap=cmap_bold)
plt.show()


# more difficult synthetic dataset for classification (binary)
# with classes that are not linearly separable
X_D2, y_D2 = make_blobs(n_samples = 100, n_features = 2, centers = 8,
                       cluster_std = 1.3, random_state = 4)
y_D2 = y_D2 % 2
plt.figure()
plt.title('Sample binary classification problem with non-linearly separable
plt.scatter(X_D2[:,0], X_D2[:,1], c=y_D2,
           marker= 'o', s=50, cmap=cmap_bold)
plt.show()


# Breast cancer dataset for classification
cancer = load_breast_cancer()
(X_cancer, y_cancer) = load_breast_cancer(return_X_y = True)


# Communities and Crime dataset
(X_crime, y_crime) = load_crime_dataset()
```

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1.3 K-Nearest Neighbors

1.3.1 Classification

```
In [3]: from adspy_shared_utilities import plot_two_class_knn

        X_train, X_test, y_train, y_test = train_test_split(X_C2, y_C2,
                                                            random_state=0)

        plot_two_class_knn(X_train, y_train, 1, 'uniform', X_test, y_test)
        plot_two_class_knn(X_train, y_train, 3, 'uniform', X_test, y_test)
        plot_two_class_knn(X_train, y_train, 11, 'uniform', X_test, y_test)
```

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```

1.3.2 Regression

```
In [4]: from sklearn.neighbors import KNeighborsRegressor

        X_train, X_test, y_train, y_test = train_test_split(X_R1, y_R1, random_stat

        knnreg = KNeighborsRegressor(n_neighbors = 5).fit(X_train, y_train)

        print(knnreg.predict(X_test))
        print('R-squared test score: {:.3f}'
             .format(knnreg.score(X_test, y_test)))
```

```
[ 231.71  148.36  150.59  150.59   72.15  166.51  141.91  235.57  208.26
  102.1   191.32  134.5   228.32  148.36  159.17  113.47  144.04  199.23
  143.19  166.51  231.71  208.26  128.02  123.14  141.91]
R-squared test score: 0.425
```

```
In [5]: fig, subaxes = plt.subplots(1, 2, figsize=(8,4))
        X_predict_input = np.linspace(-3, 3, 50).reshape(-1,1)
        X_train, X_test, y_train, y_test = train_test_split(X_R1[0::5], y_R1[0::5],

        for thisaxis, K in zip(subaxes, [1, 3]):
            knnreg = KNeighborsRegressor(n_neighbors = K).fit(X_train, y_train)
            y_predict_output = knnreg.predict(X_predict_input)
            thisaxis.set_xlim([-2.5, 0.75])
            thisaxis.plot(X_predict_input, y_predict_output, '^', markersize = 10,
                         label='Predicted', alpha=0.8)
            thisaxis.plot(X_train, y_train, 'o', label='True Value', alpha=0.8)
            thisaxis.set_xlabel('Input feature')
            thisaxis.set_ylabel('Target value')
            thisaxis.set_title('KNN regression (K={})'.format(K))
            thisaxis.legend()
        plt.tight_layout()
```

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<IPython.core.display.HTML object>
```

1.3.3 Regression model complexity as a function of K

```
In [6]: # plot k-NN regression on sample dataset for different values of K
        fig, subaxes = plt.subplots(5, 1, figsize=(5,20))
        X_predict_input = np.linspace(-3, 3, 500).reshape(-1,1)
        X_train, X_test, y_train, y_test = train_test_split(X_R1, y_R1,
                                                             random_state = 0)

        for thisaxis, K in zip(subaxes, [1, 3, 7, 15, 55]):
            knnreg = KNeighborsRegressor(n_neighbors = K).fit(X_train, y_train)
            y_predict_output = knnreg.predict(X_predict_input)
            train_score = knnreg.score(X_train, y_train)
            test_score = knnreg.score(X_test, y_test)
            thisaxis.plot(X_predict_input, y_predict_output)
            thisaxis.plot(X_train, y_train, 'o', alpha=0.9, label='Train')
            thisaxis.plot(X_test, y_test, '^', alpha=0.9, label='Test')
            thisaxis.set_xlabel('Input feature')
            thisaxis.set_ylabel('Target value')
            thisaxis.set_title('KNN Regression (K={})\n\
        Train $R^2 = {:.3f}$,  Test $R^2 = {:.3f}$'
```

```
                            .format(K, train_score, test_score))
            thisaxis.legend()
            plt.tight_layout(pad=0.4, w_pad=0.5, h_pad=1.0)
```

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```

1.4 Linear models for regression

1.4.1 Linear regression

```
In [7]: from sklearn.linear_model import LinearRegression

        X_train, X_test, y_train, y_test = train_test_split(X_R1, y_R1,
                                                            random_state = 0)
        linreg = LinearRegression().fit(X_train, y_train)

        print('linear model coeff (w): {}'
             .format(linreg.coef_))
        print('linear model intercept (b): {:.3f}'
             .format(linreg.intercept_))
        print('R-squared score (training): {:.3f}'
             .format(linreg.score(X_train, y_train)))
        print('R-squared score (test): {:.3f}'
             .format(linreg.score(X_test, y_test)))
```

```
linear model coeff (w): [ 45.71]
linear model intercept (b): 148.446
R-squared score (training): 0.679
R-squared score (test): 0.492
```

1.4.2 Linear regression: example plot

```
In [8]: plt.figure(figsize=(5,4))
        plt.scatter(X_R1, y_R1, marker= 'o', s=50, alpha=0.8)
        plt.plot(X_R1, linreg.coef_ * X_R1 + linreg.intercept_, 'r-')
        plt.title('Least-squares linear regression')
        plt.xlabel('Feature value (x)')
        plt.ylabel('Target value (y)')
        plt.show()
```

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```

```
In [9]: X_train, X_test, y_train, y_test = train_test_split(X_crime, y_crime,
                                                           random_state = 0)
        linreg = LinearRegression().fit(X_train, y_train)

        print('Crime dataset')
        print('linear model intercept: {}'
             .format(linreg.intercept_))
        print('linear model coeff:\n{}'
             .format(linreg.coef_))
        print('R-squared score (training): {:.3f}'
             .format(linreg.score(X_train, y_train)))
        print('R-squared score (test): {:.3f}'
             .format(linreg.score(X_test, y_test)))
```

```
Crime dataset
linear model intercept: -1728.1306726048451
linear model coeff:
[  1.62e-03  -9.43e+01   1.36e+01  -3.13e+01  -8.15e-02  -1.69e+01
  -2.43e-03   1.53e+00  -1.39e-02  -7.72e+00   2.28e+01  -5.66e+00
   9.35e+00   2.07e-01  -7.43e+00   9.66e-03   4.38e-03   4.80e-03
  -4.46e+00  -1.61e+01   8.83e+00  -5.07e-01  -1.42e+00   8.18e+00
  -3.87e+00  -3.54e+00   4.49e+00   9.31e+00   1.74e+02   1.18e+01
   1.51e+02  -3.30e+02  -1.35e+02   6.95e-01  -2.38e+01   2.77e+00
   3.82e-01   4.39e+00  -1.06e+01  -4.92e-03   4.14e+01  -1.16e-03
   1.19e+00   1.75e+00  -3.68e+00   1.60e+00  -8.42e+00  -3.80e+01
   4.74e+01  -2.51e+01  -2.88e-01  -3.66e+01   1.90e+01  -4.53e+01
   6.83e+02   1.04e+02  -3.29e+02  -3.14e+01   2.74e+01   5.12e+00
   6.92e+01   1.98e-02  -6.12e-01   2.65e+01   1.01e+01  -1.59e+00
   2.24e+00   7.38e+00  -3.14e+01  -9.78e-05   5.02e-05  -3.48e-04
  -2.50e-04  -5.27e-01  -5.17e-01  -4.10e-01   1.16e-01   1.46e+00
  -3.04e-01   2.44e+00  -3.66e+01   1.41e-01   2.89e-01   1.77e+01
   5.97e-01   1.98e+00  -1.36e-01  -1.85e+00]
R-squared score (training): 0.673
R-squared score (test): 0.496
```

1.4.3 Ridge regression

```
In [10]: from sklearn.linear_model import Ridge
         X_train, X_test, y_train, y_test = train_test_split(X_crime, y_crime,
                                                            random_state = 0)

         linridge = Ridge(alpha=20.0).fit(X_train, y_train)

         print('Crime dataset')
         print('ridge regression linear model intercept: {}'
              .format(linridge.intercept_))
         print('ridge regression linear model coeff:\n{}'
```

```
        .format(linridge.coef_))
print('R-squared score (training): {:.3f}'
        .format(linridge.score(X_train, y_train)))
print('R-squared score (test): {:.3f}'
        .format(linridge.score(X_test, y_test)))
print('Number of non-zero features: {}'
        .format(np.sum(linridge.coef_ != 0)))
```

```
Crime dataset
ridge regression linear model intercept: -3352.423035846206
ridge regression linear model coeff:
[  1.95e-03   2.19e+01   9.56e+00  -3.59e+01   6.36e+00  -1.97e+01
  -2.81e-03   1.66e+00  -6.61e-03  -6.95e+00   1.72e+01  -5.63e+00
   8.84e+00   6.79e-01  -7.34e+00   6.70e-03   9.79e-04   5.01e-03
  -4.90e+00  -1.79e+01   9.18e+00  -1.24e+00   1.22e+00   1.03e+01
  -3.78e+00  -3.73e+00   4.75e+00   8.43e+00   3.09e+01   1.19e+01
  -2.05e+00  -3.82e+01   1.85e+01   1.53e+00  -2.20e+01   2.46e+00
   3.29e-01   4.02e+00  -1.13e+01  -4.70e-03   4.27e+01  -1.23e-03
   1.41e+00   9.35e-01  -3.00e+00   1.12e+00  -1.82e+01  -1.55e+01
   2.42e+01  -1.32e+01  -4.20e-01  -3.60e+01   1.30e+01  -2.81e+01
   4.39e+01   3.87e+01  -6.46e+01  -1.64e+01   2.90e+01   4.15e+00
   5.34e+01   1.99e-02  -5.47e-01   1.24e+01   1.04e+01  -1.57e+00
   3.16e+00   8.78e+00  -2.95e+01  -2.33e-04   3.14e-04  -4.14e-04
  -1.80e-04  -5.74e-01  -5.18e-01  -4.21e-01   1.53e-01   1.33e+00
   3.85e+00   3.03e+00  -3.78e+01   1.38e-01   3.08e-01   1.57e+01
   3.31e-01   3.36e+00   1.61e-01  -2.68e+00]
R-squared score (training): 0.671
R-squared score (test): 0.494
Number of non-zero features: 88
```

Ridge regression with feature normalization

```
In [11]: from sklearn.preprocessing import MinMaxScaler
         scaler = MinMaxScaler()

         from sklearn.linear_model import Ridge
         X_train, X_test, y_train, y_test = train_test_split(X_crime, y_crime,
                                                             random_state = 0)

         X_train_scaled = scaler.fit_transform(X_train)
         X_test_scaled = scaler.transform(X_test)

         linridge = Ridge(alpha=20.0).fit(X_train_scaled, y_train)

         print('Crime dataset')
         print('ridge regression linear model intercept: {}'
              .format(linridge.intercept_))
```

```
print('ridge regression linear model coeff:\n{}'
     .format(linridge.coef_))
print('R-squared score (training): {:.3f}'
     .format(linridge.score(X_train_scaled, y_train)))
print('R-squared score (test): {:.3f}'
     .format(linridge.score(X_test_scaled, y_test)))
print('Number of non-zero features: {}'
     .format(np.sum(linridge.coef_ != 0)))
```

```
Crime dataset
ridge regression linear model intercept: 933.390638504416
ridge regression linear model coeff:
[  88.69   16.49  -50.3   -82.91  -65.9    -2.28   87.74  150.95   18.88
  -31.06  -43.14 -189.44   -4.53  107.98  -76.53    2.86   34.95   90.14
   52.46  -62.11  115.02    2.67    6.94   -5.67 -101.55  -36.91   -8.71
   29.12  171.26   99.37   75.07  123.64   95.24 -330.61 -442.3  -284.5
 -258.37   17.66 -101.71  110.65  523.14   24.82    4.87  -30.47   -3.52
   50.58   10.85   18.28   44.11   58.34   67.09  -57.94  116.14   53.81
   49.02   -7.62   55.14  -52.09  123.39   77.13   45.5   184.91  -91.36
    1.08  234.09   10.39   94.72  167.92  -25.14   -1.18   14.6    36.77
   53.2   -78.86   -5.9    26.05  115.15   68.74   68.29   16.53  -97.91
  205.2    75.97   61.38  -79.83   67.27   95.67  -11.88]
R-squared score (training): 0.615
R-squared score (test): 0.599
Number of non-zero features: 88
```

Ridge regression with regularization parameter: alpha

```
In [12]: print('Ridge regression: effect of alpha regularization parameter\n')
         for this_alpha in [0, 1, 10, 20, 50, 100, 1000]:
             linridge = Ridge(alpha = this_alpha).fit(X_train_scaled, y_train)
             r2_train = linridge.score(X_train_scaled, y_train)
             r2_test = linridge.score(X_test_scaled, y_test)
             num_coeff_bigger = np.sum(abs(linridge.coef_) > 1.0)
             print('Alpha = {:.2f}\nnum abs(coeff) > 1.0: {}, \
         r-squared training: {:.2f}, r-squared test: {:.2f}\n'
                  .format(this_alpha, num_coeff_bigger, r2_train, r2_test))
```

```
Ridge regression: effect of alpha regularization parameter



/opt/conda/lib/python3.6/site-packages/scipy/linalg/basic.py:223: RuntimeWarning: s
Ill-conditioned matrix detected. Result is not guaranteed to be accurate.
Reciprocal condition number: 6.332952875642905e-19
  ' condition number: {}'.format(rcond), RuntimeWarning)
```

```
Alpha = 0.00
num abs(coeff) > 1.0: 88, r-squared training: 0.67, r-squared test: 0.50

Alpha = 1.00
num abs(coeff) > 1.0: 87, r-squared training: 0.66, r-squared test: 0.56

Alpha = 10.00
num abs(coeff) > 1.0: 87, r-squared training: 0.63, r-squared test: 0.59

Alpha = 20.00
num abs(coeff) > 1.0: 88, r-squared training: 0.61, r-squared test: 0.60

Alpha = 50.00
num abs(coeff) > 1.0: 86, r-squared training: 0.58, r-squared test: 0.58

Alpha = 100.00
num abs(coeff) > 1.0: 87, r-squared training: 0.55, r-squared test: 0.55

Alpha = 1000.00
num abs(coeff) > 1.0: 84, r-squared training: 0.31, r-squared test: 0.30
```

1.4.4 Lasso regression

In [13]:
```
from sklearn.linear_model import Lasso
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()

X_train, X_test, y_train, y_test = train_test_split(X_crime, y_crime,
                                                    random_state = 0)

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

linlasso = Lasso(alpha=2.0, max_iter = 10000).fit(X_train_scaled, y_train)

print('Crime dataset')
print('lasso regression linear model intercept: {}'
     .format(linlasso.intercept_))
print('lasso regression linear model coeff:\n{}'
     .format(linlasso.coef_))
print('Non-zero features: {}'
     .format(np.sum(linlasso.coef_ != 0)))
print('R-squared score (training): {:.3f}'
     .format(linlasso.score(X_train_scaled, y_train)))
print('R-squared score (test): {:.3f}\n'
     .format(linlasso.score(X_test_scaled, y_test)))
```

```python
print('Features with non-zero weight (sorted by absolute magnitude):')

for e in sorted (list(zip(list(X_crime), linlasso.coef_)),
                key = lambda e: -abs(e[1])):
    if e[1] != 0:
        print('\t{}, {:.3f}'.format(e[0], e[1]))
```

```
Crime dataset
lasso regression linear model intercept: 1186.6120619985809
lasso regression linear model coeff:
[    0.        0.       -0.     -168.18     -0.       -0.        0.      119.69
     0.       -0.        0.     -169.68     -0.        0.       -0.        0.
     0.        0.       -0.       -0.        0.       -0.        0.        0.
   -57.53     -0.       -0.        0.      259.33     -0.        0.        0.
     0.       -0.    -1188.74     -0.       -0.       -0.     -231.42      0.
  1488.37      0.       -0.       -0.       -0.        0.        0.        0.
     0.        0.       -0.        0.       20.14      0.        0.        0.
     0.        0.      339.04      0.        0.      459.54     -0.        0.
   122.69     -0.       91.41      0.       -0.        0.        0.       73.14
     0.       -0.        0.        0.       86.36      0.        0.        0.
  -104.57    264.93      0.       23.45    -49.39      0.        5.2       0.  ]
Non-zero features: 20
R-squared score (training): 0.631
R-squared score (test): 0.624

Features with non-zero weight (sorted by absolute magnitude):
	PctKidsBornNeverMar, 1488.365
	PctKids2Par, -1188.740
	HousVacant, 459.538
	PctPersDenseHous, 339.045
	NumInShelters, 264.932
	MalePctDivorce, 259.329
	PctWorkMom, -231.423
	pctWInvInc, -169.676
	agePct12t29, -168.183
	PctVacantBoarded, 122.692
	pctUrban, 119.694
	MedOwnCostPctIncNoMtg, -104.571
	MedYrHousBuilt, 91.412
	RentQrange, 86.356
	OwnOccHiQuart, 73.144
	PctEmplManu, -57.530
	PctBornSameState, -49.394
	PctForeignBorn, 23.449
	PctLargHouseFam, 20.144
	PctSameCity85, 5.198
```

Lasso regression with regularization parameter: alpha

```
In [14]: print('Lasso regression: effect of alpha regularization\n\
         parameter on number of features kept in final model\n')

         for alpha in [0.5, 1, 2, 3, 5, 10, 20, 50]:
             linlasso = Lasso(alpha, max_iter = 10000).fit(X_train_scaled, y_train)
             r2_train = linlasso.score(X_train_scaled, y_train)
             r2_test = linlasso.score(X_test_scaled, y_test)

             print('Alpha = {:.2f}\nFeatures kept: {}, r-squared training: {:.2f},
         r-squared test: {:.2f}\n'
                  .format(alpha, np.sum(linlasso.coef_ != 0), r2_train, r2_test))
```

```
Lasso regression: effect of alpha regularization
parameter on number of features kept in final model

Alpha = 0.50
Features kept: 35, r-squared training: 0.65, r-squared test: 0.58

Alpha = 1.00
Features kept: 25, r-squared training: 0.64, r-squared test: 0.60

Alpha = 2.00
Features kept: 20, r-squared training: 0.63, r-squared test: 0.62

Alpha = 3.00
Features kept: 17, r-squared training: 0.62, r-squared test: 0.63

Alpha = 5.00
Features kept: 12, r-squared training: 0.60, r-squared test: 0.61

Alpha = 10.00
Features kept: 6, r-squared training: 0.57, r-squared test: 0.58

Alpha = 20.00
Features kept: 2, r-squared training: 0.51, r-squared test: 0.50

Alpha = 50.00
Features kept: 1, r-squared training: 0.31, r-squared test: 0.30
```

1.4.5 Polynomial regression

```
In [15]: from sklearn.linear_model import LinearRegression
         from sklearn.linear_model import Ridge
         from sklearn.preprocessing import PolynomialFeatures
```

```
X_train, X_test, y_train, y_test = train_test_split(X_F1, y_F1,
                                                   random_state = 0)
linreg = LinearRegression().fit(X_train, y_train)

print('linear model coeff (w): {}'
     .format(linreg.coef_))
print('linear model intercept (b): {:.3f}'
     .format(linreg.intercept_))
print('R-squared score (training): {:.3f}'
     .format(linreg.score(X_train, y_train)))
print('R-squared score (test): {:.3f}'
     .format(linreg.score(X_test, y_test)))

print('\nNow we transform the original input data to add\n\
polynomial features up to degree 2 (quadratic)\n')
poly = PolynomialFeatures(degree=2)
X_F1_poly = poly.fit_transform(X_F1)

X_train, X_test, y_train, y_test = train_test_split(X_F1_poly, y_F1,
                                                   random_state = 0)
linreg = LinearRegression().fit(X_train, y_train)

print('(poly deg 2) linear model coeff (w):\n{}'
     .format(linreg.coef_))
print('(poly deg 2) linear model intercept (b): {:.3f}'
     .format(linreg.intercept_))
print('(poly deg 2) R-squared score (training): {:.3f}'
     .format(linreg.score(X_train, y_train)))
print('(poly deg 2) R-squared score (test): {:.3f}\n'
     .format(linreg.score(X_test, y_test)))

print('\nAddition of many polynomial features often leads to\n\
overfitting, so we often use polynomial features in combination\n\
with regression that has a regularization penalty, like ridge\n\
regression.\n')

X_train, X_test, y_train, y_test = train_test_split(X_F1_poly, y_F1,
                                                   random_state = 0)
linreg = Ridge().fit(X_train, y_train)

print('(poly deg 2 + ridge) linear model coeff (w):\n{}'
     .format(linreg.coef_))
print('(poly deg 2 + ridge) linear model intercept (b): {:.3f}'
     .format(linreg.intercept_))
print('(poly deg 2 + ridge) R-squared score (training): {:.3f}'
     .format(linreg.score(X_train, y_train)))
print('(poly deg 2 + ridge) R-squared score (test): {:.3f}'
```

```
            .format(linreg.score(X_test, y_test)))
```

```
linear model coeff (w): [  4.42   6.     0.53  10.24   6.55  -2.02  -0.32]
linear model intercept (b): 1.543
R-squared score (training): 0.722
R-squared score (test): 0.722

Now we transform the original input data to add
polynomial features up to degree 2 (quadratic)

(poly deg 2) linear model coeff (w):
[  3.41e-12   1.66e+01   2.67e+01  -2.21e+01   1.24e+01   6.93e+00
   1.05e+00   3.71e+00  -1.34e+01  -5.73e+00   1.62e+00   3.66e+00
   5.05e+00  -1.46e+00   1.95e+00  -1.51e+01   4.87e+00  -2.97e+00
  -7.78e+00   5.15e+00  -4.65e+00   1.84e+01  -2.22e+00   2.17e+00
  -1.28e+00   1.88e+00   1.53e-01   5.62e-01  -8.92e-01  -2.18e+00
   1.38e+00  -4.90e+00  -2.24e+00   1.38e+00  -5.52e-01  -1.09e+00]
(poly deg 2) linear model intercept (b): -3.206
(poly deg 2) R-squared score (training): 0.969
(poly deg 2) R-squared score (test): 0.805


Addition of many polynomial features often leads to
overfitting, so we often use polynomial features in combination
with regression that has a regularization penalty, like ridge
regression.

(poly deg 2 + ridge) linear model coeff (w):
[ 0.    2.23  4.73 -3.15  3.86  1.61 -0.77 -0.15 -1.75  1.6   1.37  2.52
  2.72  0.49 -1.94 -1.63  1.51  0.89  0.26  2.05 -1.93  3.62 -0.72  0.63
 -3.16  1.29  3.55  1.73  0.94 -0.51  1.7  -1.98  1.81 -0.22  2.88 -0.89]
(poly deg 2 + ridge) linear model intercept (b): 5.418
(poly deg 2 + ridge) R-squared score (training): 0.826
(poly deg 2 + ridge) R-squared score (test): 0.825
```

1.5 Linear models for classification

1.5.1 Logistic regression

Logistic regression for binary classification on fruits dataset using height, width features (positive class: apple, negative class: others)

In [16]:
```
from sklearn.linear_model import LogisticRegression
from adspy_shared_utilities import (
plot_class_regions_for_classifier_subplot)

fig, subaxes = plt.subplots(1, 1, figsize=(7, 5))
y_fruits_apple = y_fruits_2d == 1   # make into a binary problem: apples v
```

```
X_train, X_test, y_train, y_test = (
train_test_split(X_fruits_2d.as_matrix(),
                y_fruits_apple.as_matrix(),
                random_state = 0))

clf = LogisticRegression(C=100).fit(X_train, y_train)
plot_class_regions_for_classifier_subplot(clf, X_train, y_train, None,
                                          None, 'Logistic regression \
for binary classification\nFruit dataset: Apple vs others',
                                          subaxes)

h = 6
w = 8
print('A fruit with height {} and width {} is predicted to be: {}'
     .format(h,w, ['not an apple', 'an apple'][clf.predict([[h,w]])[0]]))

h = 10
w = 7
print('A fruit with height {} and width {} is predicted to be: {}'
     .format(h,w, ['not an apple', 'an apple'][clf.predict([[h,w]])[0]]))
subaxes.set_xlabel('height')
subaxes.set_ylabel('width')

print('Accuracy of Logistic regression classifier on training set: {:.2f}'
     .format(clf.score(X_train, y_train)))
print('Accuracy of Logistic regression classifier on test set: {:.2f}'
     .format(clf.score(X_test, y_test)))
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```
A fruit with height 6 and width 8 is predicted to be: an apple
A fruit with height 10 and width 7 is predicted to be: not an apple
Accuracy of Logistic regression classifier on training set: 0.77
Accuracy of Logistic regression classifier on test set: 0.73
```

Logistic regression on simple synthetic dataset

```
In [17]: from sklearn.linear_model import LogisticRegression
         from adspy_shared_utilities import (
         plot_class_regions_for_classifier_subplot)


         X_train, X_test, y_train, y_test = train_test_split(X_C2, y_C2,
```

```
                                                           random_state = 0)

        fig, subaxes = plt.subplots(1, 1, figsize=(7, 5))
        clf = LogisticRegression().fit(X_train, y_train)
        title = 'Logistic regression, simple synthetic dataset C = {:.3f}'.format
        plot_class_regions_for_classifier_subplot(clf, X_train, y_train,
                                                 None, None, title, subaxes)

        print('Accuracy of Logistic regression classifier on training set: {:.2f}'
             .format(clf.score(X_train, y_train)))
        print('Accuracy of Logistic regression classifier on test set: {:.2f}'
             .format(clf.score(X_test, y_test)))
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```
Accuracy of Logistic regression classifier on training set: 0.80
Accuracy of Logistic regression classifier on test set: 0.80
```

Logistic regression regularization: C parameter

```
In [18]: X_train, X_test, y_train, y_test = (
         train_test_split(X_fruits_2d.as_matrix(),
                          y_fruits_apple.as_matrix(),
                          random_state=0))

         fig, subaxes = plt.subplots(3, 1, figsize=(4, 10))

         for this_C, subplot in zip([0.1, 1, 100], subaxes):
             clf = LogisticRegression(C=this_C).fit(X_train, y_train)
             title ='Logistic regression (apple vs rest), C = {:.3f}'.format(this_C

             plot_class_regions_for_classifier_subplot(clf, X_train, y_train,
                                                      X_test, y_test, title,
                                                      subplot)
         plt.tight_layout()
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

Application to real dataset

```
In [19]: from sklearn.linear_model import LogisticRegression

         X_train, X_test, y_train, y_test = train_test_split(X_cancer, y_cancer, ra

         clf = LogisticRegression().fit(X_train, y_train)
         print('Breast cancer dataset')
         print('Accuracy of Logistic regression classifier on training set: {:.2f}'
              .format(clf.score(X_train, y_train)))
         print('Accuracy of Logistic regression classifier on test set: {:.2f}'
              .format(clf.score(X_test, y_test)))
```

```
Breast cancer dataset
Accuracy of Logistic regression classifier on training set: 0.96
Accuracy of Logistic regression classifier on test set: 0.96
```

1.5.2 Support Vector Machines

Linear Support Vector Machine

```
In [20]: from sklearn.svm import SVC
         from adspy_shared_utilities import plot_class_regions_for_classifier_subpl


         X_train, X_test, y_train, y_test = train_test_split(X_C2, y_C2, random_sta

         fig, subaxes = plt.subplots(1, 1, figsize=(7, 5))
         this_C = 1.0
         clf = SVC(kernel = 'linear', C=this_C).fit(X_train, y_train)
         title = 'Linear SVC, C = {:.3f}'.format(this_C)
         plot_class_regions_for_classifier_subplot(clf, X_train, y_train, None, Nor
```

```
<IPython.core.display.Javascript object>


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```

Linear Support Vector Machine: C parameter

```
In [21]: from sklearn.svm import LinearSVC
         from adspy_shared_utilities import plot_class_regions_for_classifier

         X_train, X_test, y_train, y_test = train_test_split(X_C2, y_C2, random_sta
         fig, subaxes = plt.subplots(1, 2, figsize=(8, 4))

         for this_C, subplot in zip([0.00001, 100], subaxes):
```

```
            clf = LinearSVC(C=this_C).fit(X_train, y_train)
            title = 'Linear SVC, C = {:.5f}'.format(this_C)
            plot_class_regions_for_classifier_subplot(clf, X_train, y_train,
                                                      None, None, title, subplot)
        plt.tight_layout()
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

Application to real dataset

```
In [22]: from sklearn.svm import LinearSVC
         X_train, X_test, y_train, y_test = train_test_split(X_cancer, y_cancer, ra

         clf = LinearSVC().fit(X_train, y_train)
         print('Breast cancer dataset')
         print('Accuracy of Linear SVC classifier on training set: {:.2f}'
              .format(clf.score(X_train, y_train)))
         print('Accuracy of Linear SVC classifier on test set: {:.2f}'
              .format(clf.score(X_test, y_test)))
```

```
Breast cancer dataset
Accuracy of Linear SVC classifier on training set: 0.56
Accuracy of Linear SVC classifier on test set: 0.59
```

1.5.3 Multi-class classification with linear models

LinearSVC with M classes generates M one vs rest classifiers.

```
In [23]: from sklearn.svm import LinearSVC

         X_train, X_test, y_train, y_test = train_test_split(X_fruits_2d, y_fruits_

         clf = LinearSVC(C=5, random_state = 67).fit(X_train, y_train)
         print('Coefficients:\n', clf.coef_)
         print('Intercepts:\n', clf.intercept_)
```

```
Coefficients:
 [[-0.26  0.71]
 [-1.63  1.16]
 [ 0.03  0.29]
 [ 1.24 -1.64]]
Intercepts:
 [-3.29  1.2  -2.72  1.16]
```

Multi-class results on the fruit dataset

```
In [24]: plt.figure(figsize=(6,6))
         colors = ['r', 'g', 'b', 'y']
         cmap_fruits = ListedColormap(['#FF0000', '#00FF00', '#0000FF','#FFFF00'])

         plt.scatter(X_fruits_2d[['height']], X_fruits_2d[['width']],
                     c=y_fruits_2d, cmap=cmap_fruits, edgecolor = 'black', alpha=.7)

         x_0_range = np.linspace(-10, 15)

         for w, b, color in zip(clf.coef_, clf.intercept_, ['r', 'g', 'b', 'y']):
             # Since class prediction with a linear model uses the formula y = w_0
             # and the decision boundary is defined as being all points with y = 0,
             # function of x_0 we just solve w_0 x_0 + w_1 x_1 + b = 0 for x_1:
             plt.plot(x_0_range, -(x_0_range * w[0] + b) / w[1], c=color, alpha=.8)

         plt.legend(target_names_fruits)
         plt.xlabel('height')
         plt.ylabel('width')
         plt.xlim(-2, 12)
         plt.ylim(-2, 15)
         plt.show()
```

```
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```
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```

1.6 Kernelized Support Vector Machines

1.6.1 Classification

```
In [25]: from sklearn.svm import SVC
         from adspy_shared_utilities import plot_class_regions_for_classifier

         X_train, X_test, y_train, y_test = train_test_split(X_D2, y_D2, random_sta

         # The default SVC kernel is radial basis function (RBF)
         plot_class_regions_for_classifier(SVC().fit(X_train, y_train),
                                           X_train, y_train, None, None,
                                           'Support Vector Classifier: RBF kernel')

         # Compare decision boundries with polynomial kernel, degree = 3
         plot_class_regions_for_classifier(SVC(kernel = 'poly', degree = 3)
                                           .fit(X_train, y_train), X_train,
                                           y_train, None, None,
                                           'Support Vector Classifier: Polynomial ke
```

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<IPython.core.display.HTML object>

Support Vector Machine with RBF kernel: gamma parameter

In [26]:
```
from adspy_shared_utilities import plot_class_regions_for_classifier

X_train, X_test, y_train, y_test = train_test_split(X_D2, y_D2, random_sta
fig, subaxes = plt.subplots(3, 1, figsize=(4, 11))

for this_gamma, subplot in zip([0.01, 1.0, 10.0], subaxes):
    clf = SVC(kernel = 'rbf', gamma=this_gamma).fit(X_train, y_train)
    title = 'Support Vector Classifier: \nRBF kernel, gamma = {:.2f}'.form
    plot_class_regions_for_classifier_subplot(clf, X_train, y_train,
                                              None, None, title, subplot)
    plt.tight_layout()
```

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Support Vector Machine with RBF kernel: using both C and gamma parameter

In [27]:
```
from sklearn.svm import SVC
from adspy_shared_utilities import plot_class_regions_for_classifier_subpl

from sklearn.model_selection import train_test_split


X_train, X_test, y_train, y_test = train_test_split(X_D2, y_D2, random_sta
fig, subaxes = plt.subplots(3, 4, figsize=(15, 10), dpi=50)

for this_gamma, this_axis in zip([0.01, 1, 5], subaxes):

    for this_C, subplot in zip([0.1, 1, 15, 250], this_axis):
        title = 'gamma = {:.2f}, C = {:.2f}'.format(this_gamma, this_C)
        clf = SVC(kernel = 'rbf', gamma = this_gamma,
                  C = this_C).fit(X_train, y_train)
```

```
                plot_class_regions_for_classifier_subplot(clf, X_train, y_train,
                                                         X_test, y_test, title,
                                                         subplot)
                plt.tight_layout(pad=0.4, w_pad=0.5, h_pad=1.0)
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

1.6.2 Application of SVMs to a real dataset: unnormalized data

In [28]:

```
from sklearn.svm import SVC
X_train, X_test, y_train, y_test = train_test_split(X_cancer, y_cancer,
                                                   random_state = 0)

clf = SVC(C=10).fit(X_train, y_train)
print('Breast cancer dataset (unnormalized features)')
print('Accuracy of RBF-kernel SVC on training set: {:.2f}'
     .format(clf.score(X_train, y_train)))
print('Accuracy of RBF-kernel SVC on test set: {:.2f}'
     .format(clf.score(X_test, y_test)))
```

```
Breast cancer dataset (unnormalized features)
Accuracy of RBF-kernel SVC on training set: 1.00
Accuracy of RBF-kernel SVC on test set: 0.63
```

1.6.3 Application of SVMs to a real dataset: normalized data with feature preprocessing using minmax scaling

In [29]:

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

clf = SVC(C=10).fit(X_train_scaled, y_train)
print('Breast cancer dataset (normalized with MinMax scaling)')
print('RBF-kernel SVC (with MinMax scaling) training set accuracy: {:.2f}'
     .format(clf.score(X_train_scaled, y_train)))
print('RBF-kernel SVC (with MinMax scaling) test set accuracy: {:.2f}'
     .format(clf.score(X_test_scaled, y_test)))
```

```
Breast cancer dataset (normalized with MinMax scaling)
RBF-kernel SVC (with MinMax scaling) training set accuracy: 0.98
RBF-kernel SVC (with MinMax scaling) test set accuracy: 0.96
```

1.7 Cross-validation

1.7.1 Example based on k-NN classifier with fruit dataset (2 features)

```
In [30]: from sklearn.model_selection import cross_val_score

         clf = KNeighborsClassifier(n_neighbors = 5)
         X = X_fruits_2d.as_matrix()
         y = y_fruits_2d.as_matrix()
         cv_scores = cross_val_score(clf, X, y)

         print('Cross-validation scores (3-fold):', cv_scores)
         print('Mean cross-validation score (3-fold): {:.3f}'
              .format(np.mean(cv_scores)))
```

```
Cross-validation scores (3-fold): [ 0.77  0.74  0.83]
Mean cross-validation score (3-fold): 0.781
```

1.7.2 A note on performing cross-validation for more advanced scenarios.

In some cases (e.g. when feature values have very different ranges), we've seen the need to scale or normalize the training and test sets before use with a classifier. The proper way to do cross-validation when you need to scale the data is *not* to scale the entire dataset with a single transform, since this will indirectly leak information into the training data about the whole dataset, including the test data (see the lecture on data leakage later in the course). Instead, scaling/normalizing must be computed and applied for each cross-validation fold separately. To do this, the easiest way in scikit-learn is to use *pipelines*. While these are beyond the scope of this course, further information is available in the scikit-learn documentation here:

http://scikit-learn.org/stable/modules/generated/sklearn.pipeline.Pipeline.html

or the Pipeline section in the recommended textbook: Introduction to Machine Learning with Python by Andreas C. Müller and Sarah Guido (O'Reilly Media).

1.8 Validation curve example

```
In [31]: from sklearn.svm import SVC
         from sklearn.model_selection import validation_curve

         param_range = np.logspace(-3, 3, 4)
         train_scores, test_scores = validation_curve(SVC(), X, y,
                                                      param_name='gamma',
                                                      param_range=param_range, cv=3)
```

```
In [32]: print(train_scores)
```

```
[[ 0.49  0.42  0.41]
 [ 0.84  0.72  0.76]
 [ 0.92  0.9   0.93]
 [ 1.    1.    0.98]]
```

In [33]:
```
print(test_scores)
```

```
[[ 0.45  0.32  0.33]
 [ 0.82  0.68  0.61]
 [ 0.41  0.84  0.67]
 [ 0.36  0.21  0.39]]
```

In [34]:
```
# This code based on scikit-learn validation_plot example
#  See:  http://scikit-learn.org/stable/auto_examples/model_selection/plot
plt.figure()

train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)

plt.title('Validation Curve with SVM')
plt.xlabel('$\gamma$ (gamma)')
plt.ylabel('Score')
plt.ylim(0.0, 1.1)
lw = 2

plt.semilogx(param_range, train_scores_mean, label='Training score',
            color='darkorange', lw=lw)

plt.fill_between(param_range, train_scores_mean - train_scores_std,
                train_scores_mean + train_scores_std, alpha=0.2,
                color='darkorange', lw=lw)

plt.semilogx(param_range, test_scores_mean, label='Cross-validation score'
            color='navy', lw=lw)

plt.fill_between(param_range, test_scores_mean - test_scores_std,
                test_scores_mean + test_scores_std, alpha=0.2,
                color='navy', lw=lw)

plt.legend(loc='best')
plt.show()
```

```
/opt/conda/lib/python3.6/site-packages/matplotlib/pyplot.py:524: RuntimeWarning: Mo
  max_open_warning, RuntimeWarning)


<IPython.core.display.Javascript object>


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```

1.9 Decision Trees

In [35]:
```
from sklearn.datasets import load_iris
from sklearn.tree import DecisionTreeClassifier
from adspy_shared_utilities import plot_decision_tree
from sklearn.model_selection import train_test_split


iris = load_iris()

X_train, X_test, y_train, y_test = train_test_split(iris.data, iris.target
clf = DecisionTreeClassifier().fit(X_train, y_train)

print('Accuracy of Decision Tree classifier on training set: {:.2f}'
     .format(clf.score(X_train, y_train)))
print('Accuracy of Decision Tree classifier on test set: {:.2f}'
     .format(clf.score(X_test, y_test)))
```

```
Accuracy of Decision Tree classifier on training set: 1.00
Accuracy of Decision Tree classifier on test set: 0.97
```

Setting max decision tree depth to help avoid overfitting

In [36]:
```
clf2 = DecisionTreeClassifier(max_depth = 3).fit(X_train, y_train)

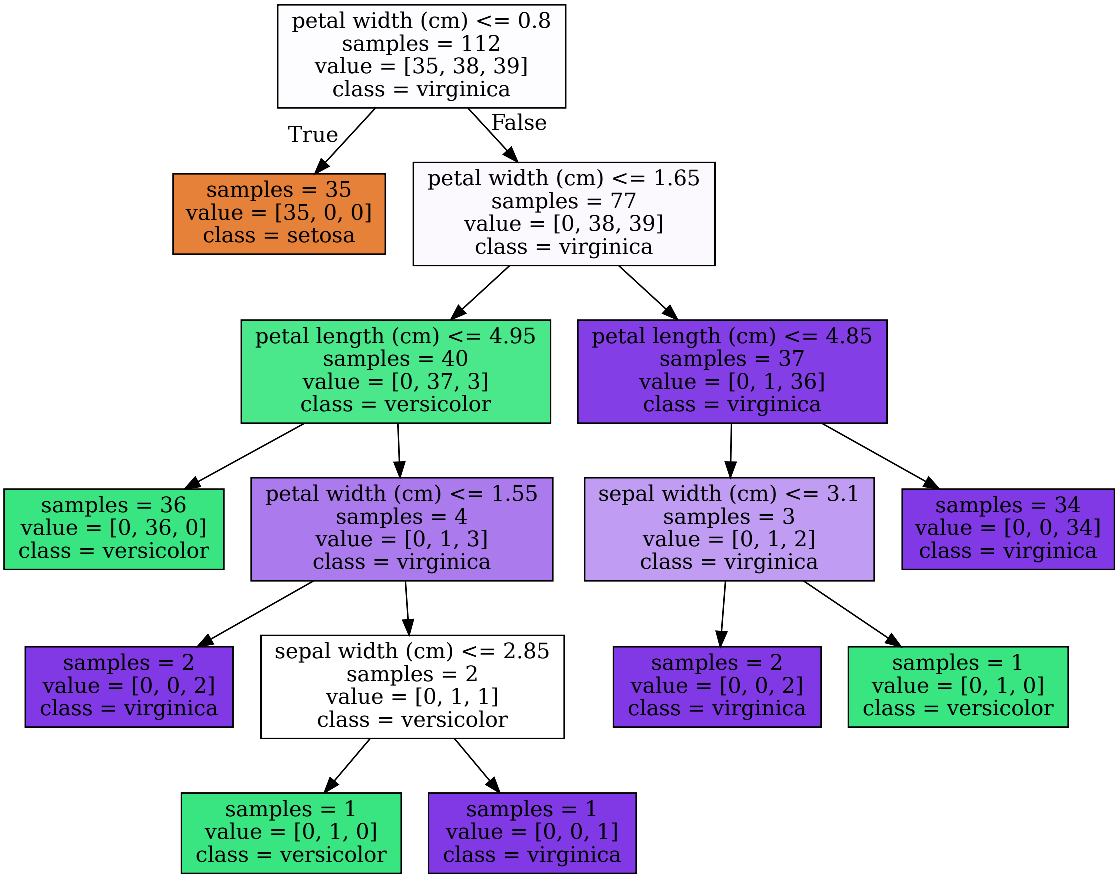
print('Accuracy of Decision Tree classifier on training set: {:.2f}'
     .format(clf2.score(X_train, y_train)))
print('Accuracy of Decision Tree classifier on test set: {:.2f}'
     .format(clf2.score(X_test, y_test)))
```

```
Accuracy of Decision Tree classifier on training set: 0.98
Accuracy of Decision Tree classifier on test set: 0.97
```

Visualizing decision trees

In [37]:
```
plot_decision_tree(clf, iris.feature_names, iris.target_names)
```

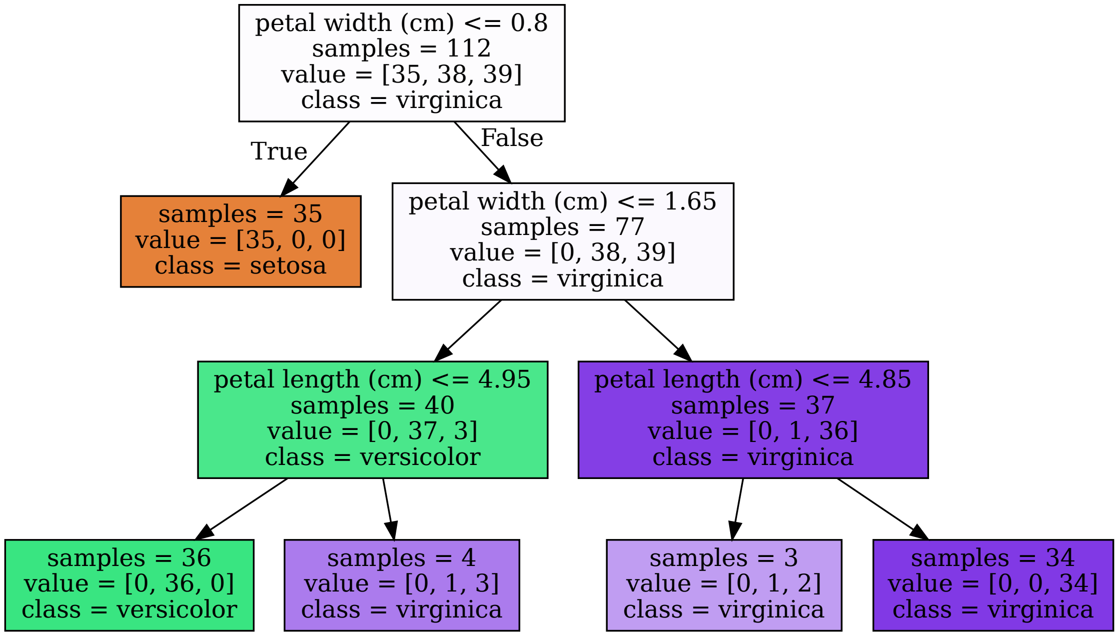
Out[37]:



Pre-pruned version (max_depth = 3)

In [38]:
```
plot_decision_tree(clf2, iris.feature_names, iris.target_names)
```

Out[38]:



Feature importance

```
In [39]: from adspy_shared_utilities import plot_feature_importances

         plt.figure(figsize=(10,4), dpi=80)
         plot_feature_importances(clf, iris.feature_names)
         plt.show()

         print('Feature importances: {}'.format(clf.feature_importances_))
```

```
/opt/conda/lib/python3.6/site-packages/matplotlib/pyplot.py:524: RuntimeWarning: Mo
  max_open_warning, RuntimeWarning)
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```
Feature importances: [ 0.    0.03  0.06  0.91]
```

```
In [40]: from sklearn.tree import DecisionTreeClassifier
         from adspy_shared_utilities import plot_class_regions_for_classifier_subpl

         X_train, X_test, y_train, y_test = train_test_split(iris.data, iris.target
```

```
fig, subaxes = plt.subplots(6, 1, figsize=(6, 32))

pair_list = [[0,1], [0,2], [0,3], [1,2], [1,3], [2,3]]
tree_max_depth = 4

for pair, axis in zip(pair_list, subaxes):
    X = X_train[:, pair]
    y = y_train

    clf = DecisionTreeClassifier(max_depth=tree_max_depth).fit(X, y)
    title = 'Decision Tree, max_depth = {:d}'.format(tree_max_depth)
    plot_class_regions_for_classifier_subplot(clf, X, y, None,
                                              None, title, axis,
                                              iris.target_names)

    axis.set_xlabel(iris.feature_names[pair[0]])
    axis.set_ylabel(iris.feature_names[pair[1]])

plt.tight_layout()
plt.show()
```

```
/opt/conda/lib/python3.6/site-packages/matplotlib/pyplot.py:524: RuntimeWarning: Mo
  max_open_warning, RuntimeWarning)


<IPython.core.display.Javascript object>


<IPython.core.display.HTML object>
```

Decision Trees on a real-world dataset

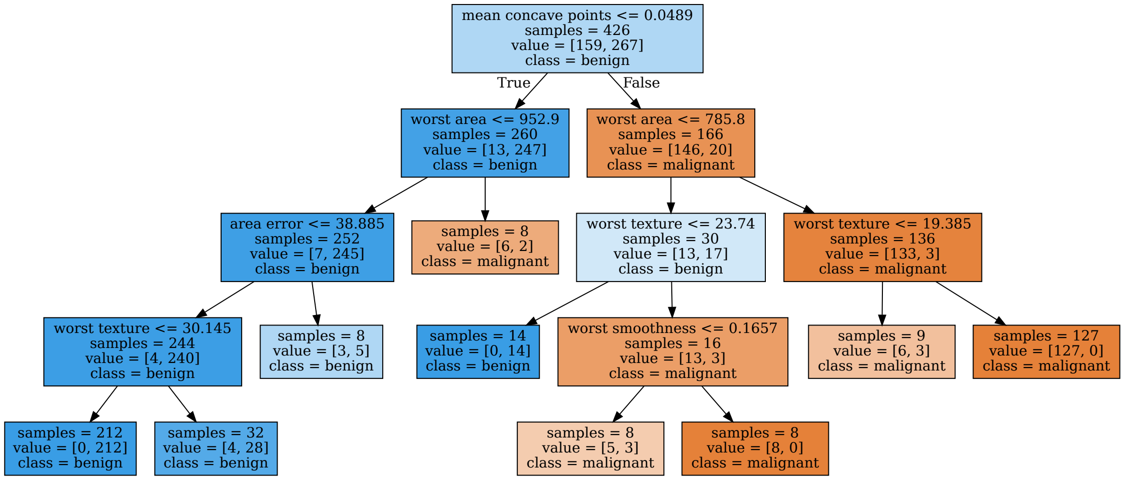
In [41]:
```
from sklearn.tree import DecisionTreeClassifier
from adspy_shared_utilities import plot_decision_tree
from adspy_shared_utilities import plot_feature_importances

X_train, X_test, y_train, y_test = train_test_split(X_cancer, y_cancer, ra

clf = DecisionTreeClassifier(max_depth = 4, min_samples_leaf = 8,
                             random_state = 0).fit(X_train, y_train)

plot_decision_tree(clf, cancer.feature_names, cancer.target_names)
```

Out[41]:



In [42]:
```python
print('Breast cancer dataset: decision tree')
print('Accuracy of DT classifier on training set: {:.2f}'
     .format(clf.score(X_train, y_train)))
print('Accuracy of DT classifier on test set: {:.2f}'
     .format(clf.score(X_test, y_test)))

plt.figure(figsize=(10,6),dpi=80)
plot_feature_importances(clf, cancer.feature_names)
plt.tight_layout()

plt.show()
```

```
Breast cancer dataset: decision tree
Accuracy of DT classifier on training set: 0.96
Accuracy of DT classifier on test set: 0.94
```

```
/opt/conda/lib/python3.6/site-packages/matplotlib/pyplot.py:524: RuntimeWarning: Mc
  max_open_warning, RuntimeWarning)
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

In [ ]: