# Imports

In [1]:
```
%config InlineBackend.figure_format = 'retina'
import pandas as pd
import scipy.io as sio
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn import tree
from sklearn import svm
from sklearn import neighbors
from sklearn.metrics import accuracy_score
from sklearn.model_selection import GridSearchCV
```

# Load First Dataset

In [2]:
```
genres = pd.read_csv('music.csv')
```

In [3]:
```
print(list(genres.columns))
```

```
['filename', 'tempo', 'beats', 'chroma_stft', 'rmse', 'spectral_centroid', 's
pectral_bandwidth', 'rolloff', 'zero_crossing_rate', 'mfcc1', 'mfcc2', 'mfcc
3', 'mfcc4', 'mfcc5', 'mfcc6', 'mfcc7', 'mfcc8', 'mfcc9', 'mfcc10', 'mfcc11',
'mfcc12', 'mfcc13', 'mfcc14', 'mfcc15', 'mfcc16', 'mfcc17', 'mfcc18', 'mfcc1
9', 'mfcc20', 'label']
```

- filename = Filename as given in marsyas dataset.
- tempo = The speed at which a passage of music is played
- beats = Rythmic unit in music
- chroma_stft = Short Time Fourier Transform
- rmse = Root Mean Square Error
- spectral_centroid = Indicates where the "center of mass" of the spectrum is located.
- spectral_bandwidth = the Wavelength interval in which a radiated spectral quantity is not less than half its maximum value
- rolloff = Roll-off is the steepness of a transmission function with frequency
- zero_crossing_rate = The rate at which the signal changes from positive to negative or back
- mfcc1 to mfcc20 = Mel-frequency cepstral coefficients (MFCCs) are coefficients that collectively make up an MFC.
- label = Contains a string depicting the genre, pop = 1, classical = 2

In [4]:
```
genres = genres[['label',
                 'tempo',
                 'beats',
                 'chroma_stft',
                 'spectral_centroid',
                 'spectral_bandwidth',
                 'rolloff',
                 'zero_crossing_rate']]
```

In [5]:
```
genres['label'] = genres['label'].map({1: 1, 2: -1})
```

Now pop is labeled as 1 and classical is labeled as -1.

In [6]:
```
X = genres[['tempo',
            'beats',
            'chroma_stft',
            'spectral_centroid',
            'spectral_bandwidth',
            'rolloff',
            'zero_crossing_rate']].to_numpy()

X.shape

# There are 200 data points, each with 7 features.
```

Out[6]:
```
(200, 7)
```

In [7]:
```
Y = genres[['label']].to_numpy()

Y.shape

# There is one target value, either 1 and -1.
```

Out[7]:
```
(200, 1)
```

In [8]:
```
X_and_Y = np.hstack((X, Y))      # Stack them together for shuffling.
np.random.seed(1)                # Set the random seed.
np.random.shuffle(X_and_Y)       # Shuffle the data points in X_and_Y array

print(X.shape)
print(Y.shape)
print(X_and_Y[0])

X_shuffled = X_and_Y[:,[0,1,2,3,4,5,6]]
Y_shuffled = X_and_Y[:,7]

print(X_shuffled[0])
print(Y_shuffled[0])
```

```
(200, 7)
(200, 1)
[9.93840144e+01 4.70000000e+01 4.37182941e-01 3.40102278e+03
 3.07029276e+03 7.05224902e+03 1.65738227e-01 1.00000000e+00]
[9.93840144e+01 4.70000000e+01 4.37182941e-01 3.40102278e+03
 3.07029276e+03 7.05224902e+03 1.65738227e-01]
1.0
```

## Functions for SVM with RBF Using Scikit-Learn

In [9]:
```
# Calculate error given feature vectors X and labels Y.
def calc_error(X, Y, classifier):
    Y_pred = classifier.predict(X)
    e = 1 - accuracy_score(Y, Y_pred)
    return e


# Draw the heatmap of training errors.
def draw_SVM_heatmap(training_errors, gamma_list, C_list):
    # training_errors: A NumPy array with the shape (len(C_list), len(gamma_li
st))
    # gamma_list: List of gamma(s).
    # C_list: List of C(s).
    plt.figure(figsize = (5,4))
    ax = sns.heatmap(training_errors, annot=True, fmt='.3f',
                     xticklabels=gamma_list, yticklabels=C_list)
    ax.collections[0].colorbar.set_label("error")
    ax.set(xlabel = '$\gamma$', ylabel='$C$')
    bottom, top = ax.get_ylim()
    ax.set_ylim(bottom + 0.5, top - 0.5)
    plt.title('Training error w.r.t $C$ and $\gamma$')
    plt.show()
```

## Functions for k-NN Using Scikit-Learn

In [10]:
```
# Draw heatmaps for result of grid search.
def draw_GS_heatmap(errors, D_list, title):
    plt.figure(figsize = (2,4))
    ax = sns.heatmap(errors, annot=True, fmt='.3f', yticklabels=D_list, xtickl
abels=[])
    ax.collections[0].colorbar.set_label('error')
    ax.set(ylabel='k')
    bottom, top = ax.get_ylim()
    ax.set_ylim(bottom + 0.5, top - 0.5)
    plt.title(title)
    plt.show()
```

## Functions for Decision Tree Using Scikit-Learn

In [11]:
```
# Draw heatmaps for result of grid search.
def draw_DT_heatmap(errors, D_list, title):
    plt.figure(figsize = (2,4))
    ax = sns.heatmap(errors, annot=True, fmt='.3f', yticklabels=D_list, xtickl
abels=[])
    ax.collections[0].colorbar.set_label('error')
    ax.set(ylabel='max depth D')
    bottom, top = ax.get_ylim()
    ax.set_ylim(bottom + 0.5, top - 0.5)
    plt.title(title)
    plt.show()
```

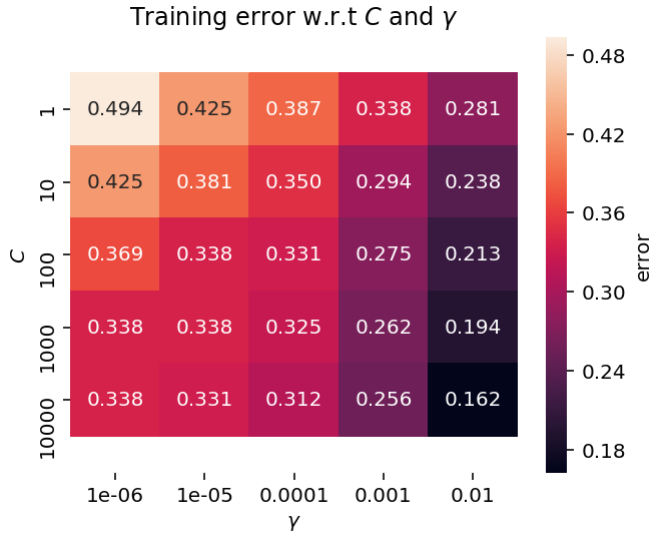
# 80/20

In [12]:
```
X_train = X_shuffled[:160] # Shape: (160,7)
Y_train = Y_shuffled[:160] # Shape: (160,)
X_test = X_shuffled[-40:]  # Shape: (40,7)
Y_test = Y_shuffled[-40:]  # Shape: (40,)
print(X_train.shape)
print(Y_train.shape)
print(X_test.shape)
print(Y_test.shape)
```

```
(160, 7)
(160,)
(40, 7)
(40,)
```

In [13]:

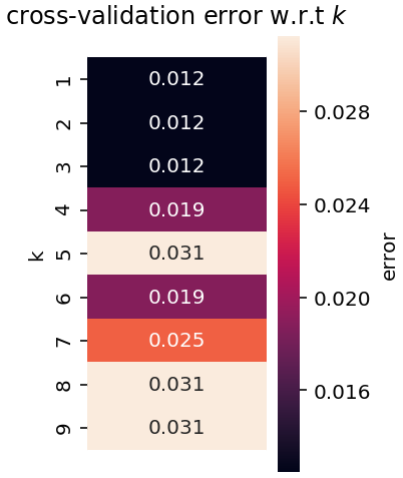
```
C_list = [1, 10, 100, 1000, 10000]
gamma_list = [1e-6, 1e-5, 1e-4, 1e-3, 1e-2]

# An example of using draw_heatmap().
#    errors = np.random.random((len(C_list), len(gamma_list)))
#    draw_heatmap(errors, gamma_list, C_list)

opt_e_training = 1.0   # Optimal training error.
opt_classifier = None  # Optimal classifier.
opt_C          = None  # Optimal C.
opt_gamma      = None  # Optimal C.

# Training errors
training_errors = np.zeros((len(C_list), len(gamma_list)))

for i, C in enumerate(C_list):
    for j, gamma in enumerate(gamma_list):
        # Create a SVM classifier with RBF kernel.
        classifier = svm.SVC(kernel='rbf', C=C, gamma=gamma)

        # Use the classifier to fit the training set (use X_train, Y_train).
        classifier.fit(X_train[:,[0,1]], Y_train) # selecting tempo and beat

        # Show decision boundary, training error and test error.
        # selecting tempo and beat
        e_training = calc_error(X_train[:,[0,1]], Y_train, classifier)
        training_errors[i,j] = e_training

        if e_training < opt_e_training:
            opt_e_training = e_training
            opt_classifier = classifier
            opt_C          = C
            opt_gamma      = gamma

draw_SVM_heatmap(training_errors, gamma_list, C_list)

# Obtain the weights and bias from the best linear SVM classifier .
# selecting tempo and beat
print('Best parameter C*={}, best parameter gamma*={}'.format(opt_C, opt_gamma
))
print('Test error: {}'.format(calc_error(X_test[:,[0,1]], Y_test, classifier
)))
```




```
Best parameter C*=10000, best parameter gamma*=0.01
Test error: 0.32499999999999996
```

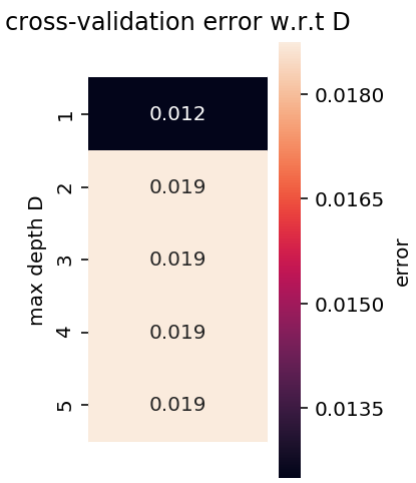
In [14]:
```
# Perform grid search for best number of nearest neighbors.

# 1. Create a k-NN classifier.
estimator = neighbors.KNeighborsClassifier()

# 2. Create a grid searcher with 5-fold cross-validation.
k_list = [1, 2, 3, 4, 5, 6, 7, 8, 9]
param_grid = {'n_neighbors': k_list}
grid_search = GridSearchCV(estimator, param_grid, cv=5)

# 3. Use the grid searcher to fit the training set.
grid_search.fit(X_train, Y_train)

# Draw heatmaps of cross-validation errors (in cross-validation).
cross_val_errors = 1 - grid_search.cv_results_['mean_test_score'].reshape(-1,1
)
draw_GS_heatmap(cross_val_errors, k_list, title='cross-validation error w.r.t
 $k$')

# Show the best k.
best_k = grid_search.best_params_['n_neighbors']
print("Best number of nearest neighbors (k): {}".format(best_k))

# Calculate the test error.
test_error = 1 - accuracy_score(grid_search.best_estimator_.predict(X_test),Y_
test)
print("Test error: {}".format(test_error))
```

```
C:\Users\derek\Anaconda3\lib\site-packages\sklearn\model_selection\_search.p
y:813: DeprecationWarning: The default of the `iid` parameter will change fro
m True to False in version 0.22 and will be removed in 0.24. This will change
numeric results when test-set sizes are unequal.
  DeprecationWarning)
```




```
Best number of nearest neighbors (k): 1
Test error: 0.025000000000000022
```

In [15]:
```
# Perform grid search for best max depth.

# 1. Create a decision tree classifier.
estimator = tree.DecisionTreeClassifier(criterion="entropy",random_state=1)

# 2. Create a grid searcher with cross-validation.
D_list = [1, 2, 3, 4, 5]
param_grid = {'max_depth': D_list}
grid_search = GridSearchCV(estimator, param_grid, cv=10)

# 3. Use the grid searcher to fit the training set.
grid_search.fit(X_train,Y_train)

# Draw heatmaps of cross-validation errors (in cross-validation).
cross_val_errors = 1 - grid_search.cv_results_['mean_test_score'].reshape(5,1)
draw_DT_heatmap(cross_val_errors, D_list, title='cross-validation error w.r.t
 D')

# Show the best max depth.
best_max_depth = grid_search.best_params_
print("Best max depth D: {}".format(best_max_depth))

# Calculate the test error.
test_error = 1 - accuracy_score(grid_search.best_estimator_.predict(X_test),Y_
test)
print("Test error: {}".format(test_error))
```



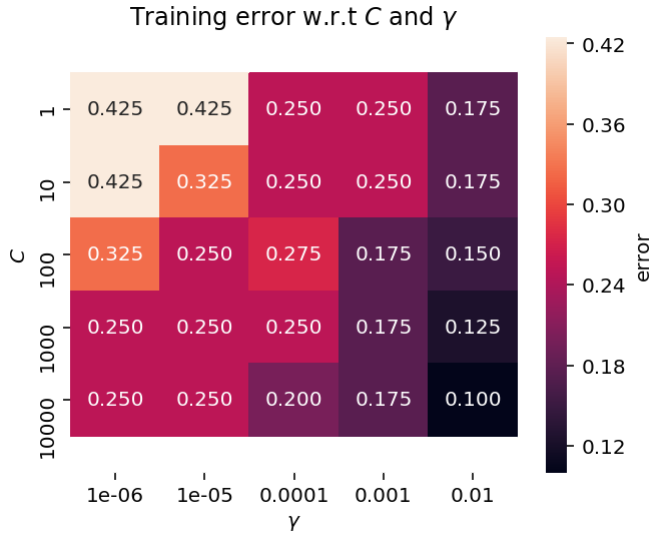

```
Best max depth D: {'max_depth': 1}
Test error: 0.025000000000000022
```

In [16]:
```
X_train = X_shuffled[:40] # Shape: (40,2)
Y_train = Y_shuffled[:40]          # Shape: (40,)
X_test = X_shuffled[-160:]  # Shape: (160,2)
Y_test = Y_shuffled[-160:]           # Shape: (160,)
print(X_train.shape)
print(Y_train.shape)
print(X_test.shape)
print(Y_test.shape)
```

```
(40, 7)
(40,)
(160, 7)
(160,)
```

In [17]:

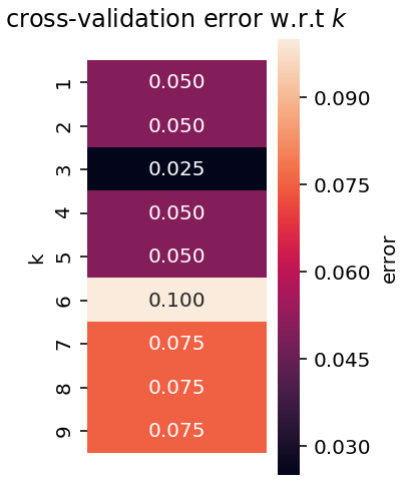
```
C_list = [1, 10, 100, 1000, 10000]
gamma_list = [1e-6, 1e-5, 1e-4, 1e-3, 1e-2]

# An example of using draw_heatmap().
#    errors = np.random.random((len(C_list), len(gamma_list)))
#    draw_heatmap(errors, gamma_list, C_list)

opt_e_training = 1.0   # Optimal training error.
opt_classifier = None  # Optimal classifier.
opt_C          = None  # Optimal C.
opt_gamma      = None  # Optimal C.

# Training errors
training_errors = np.zeros((len(C_list), len(gamma_list)))

for i, C in enumerate(C_list):
    for j, gamma in enumerate(gamma_list):
        # Create a SVM classifier with RBF kernel.
        classifier = svm.SVC(kernel='rbf', C=C, gamma=gamma)

        # Use the classifier to fit the training set (use X_train, Y_train).
        classifier.fit(X_train[:,[0,1]], Y_train)

        # Show decision boundary, training error and test error.
        e_training = calc_error(X_train[:,[0,1]], Y_train, classifier)
        training_errors[i,j] = e_training

        if e_training < opt_e_training:
            opt_e_training = e_training
            opt_classifier = classifier
            opt_C          = C
            opt_gamma      = gamma

draw_SVM_heatmap(training_errors, gamma_list, C_list)

# Obtain the weights and bias from the best linear SVM classifier .
print('Best parameter C*={}, best parameter gamma*={}'.format(opt_C, opt_gamma
))
print('Test error: {}'.format(calc_error(X_test[:,[0,1]], Y_test, classifier
)))
```




```
Best parameter C*=10000, best parameter gamma*=0.01
Test error: 0.54375
```

In [18]:
```
# Perform grid search for best number of nearest neighbors.

# 1. Create a k-NN classifier.
estimator = neighbors.KNeighborsClassifier()

# 2. Create a grid searcher with 5-fold cross-validation.
k_list = [1, 2, 3, 4, 5, 6, 7, 8, 9]
param_grid = {'n_neighbors': k_list}
grid_search = GridSearchCV(estimator, param_grid, cv=5)

# 3. Use the grid searcher to fit the training set.
grid_search.fit(X_train, Y_train)

# Draw heatmaps of cross-validation errors (in cross-validation).
cross_val_errors = 1 - grid_search.cv_results_['mean_test_score'].reshape(-1,1
)
draw_GS_heatmap(cross_val_errors, k_list, title='cross-validation error w.r.t
 $k$')

# Show the best k.
best_k = grid_search.best_params_['n_neighbors']
print("Best number of nearest neighbors (k): {}".format(best_k))


# Calculate the test error.
test_error = 1 - accuracy_score(grid_search.best_estimator_.predict(X_test),Y_
test)
print("Test error: {}".format(test_error))
```

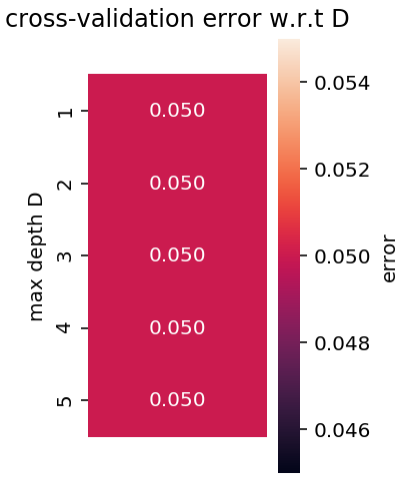
```
C:\Users\derek\Anaconda3\lib\site-packages\sklearn\model_selection\_search.p
y:813: DeprecationWarning: The default of the `iid` parameter will change fro
m True to False in version 0.22 and will be removed in 0.24. This will change
numeric results when test-set sizes are unequal.
  DeprecationWarning)
```




```
Best number of nearest neighbors (k): 3
Test error: 0.03749999999999998
```

In [19]:
```
# Perform grid search for best max depth.

# 1. Create a decision tree classifier.
estimator = tree.DecisionTreeClassifier(criterion="entropy",random_state=1)

# 2. Create a grid searcher with cross-validation.
D_list = [1, 2, 3, 4, 5]
param_grid = {'max_depth': D_list}
grid_search = GridSearchCV(estimator, param_grid, cv=10)

# 3. Use the grid searcher to fit the training set.
grid_search.fit(X_train,Y_train)

# Draw heatmaps of cross-validation errors (in cross-validation).
cross_val_errors = 1 - grid_search.cv_results_['mean_test_score'].reshape(5,1)
draw_DT_heatmap(cross_val_errors, D_list, title='cross-validation error w.r.t
 D')

# Show the best max depth.
best_max_depth = grid_search.best_params_
print("Best max depth D: {}".format(best_max_depth))

# Calculate the test error.
test_error = 1 - accuracy_score(grid_search.best_estimator_.predict(X_test),Y_
test)
print("Test error: {}".format(test_error))
```

```
C:\Users\derek\Anaconda3\lib\site-packages\sklearn\model_selection\_search.p
y:813: DeprecationWarning: The default of the `iid` parameter will change fro
m True to False in version 0.22 and will be removed in 0.24. This will change
numeric results when test-set sizes are unequal.
  DeprecationWarning)
```




```
Best max depth D: {'max_depth': 1}
Test error: 0.012499999999999956
```

# Load Second Dataset

In [20]:
```
lol = pd.read_csv('games.csv')
```

In [21]:
```
print(list(lol.columns))
```

```
['gameId', 'creationTime', 'gameDuration', 'seasonId', 'winner', 'firstBloo
d', 'firstTower', 'firstInhibitor', 'firstBaron', 'firstDragon', 'firstRiftHe
rald', 't1_champ1id', 't1_champ1_sum1', 't1_champ1_sum2', 't1_champ2id', 't1_
champ2_sum1', 't1_champ2_sum2', 't1_champ3id', 't1_champ3_sum1', 't1_champ3_s
um2', 't1_champ4id', 't1_champ4_sum1', 't1_champ4_sum2', 't1_champ5id', 't1_c
hamp5_sum1', 't1_champ5_sum2', 't1_towerKills', 't1_inhibitorKills', 't1_baro
nKills', 't1_dragonKills', 't1_riftHeraldKills', 't1_ban1', 't1_ban2', 't1_ba
n3', 't1_ban4', 't1_ban5', 't2_champ1id', 't2_champ1_sum1', 't2_champ1_sum2',
't2_champ2id', 't2_champ2_sum1', 't2_champ2_sum2', 't2_champ3id', 't2_champ3_
sum1', 't2_champ3_sum2', 't2_champ4id', 't2_champ4_sum1', 't2_champ4_sum2',
't2_champ5id', 't2_champ5_sum1', 't2_champ5_sum2', 't2_towerKills', 't2_inhib
itorKills', 't2_baronKills', 't2_dragonKills', 't2_riftHeraldKills', 't2_ban
1', 't2_ban2', 't2_ban3', 't2_ban4', 't2_ban5']
```

"This is a collection of over 50,000 ranked EUW games from the game League of Legends, as well as json files containing a way to convert between champion and summoner spell IDs and their names. For each game, there are fields for:

- Game ID
- Creation Time (in Epoch format)
- Game Duration (in seconds)
- Season ID
- Winner (1 = team1, 2 = team2)
- First Baron, dragon, tower, blood, inhibitor and Rift Herald (1 = team1, 2 = team2, 0 = none)
- Champions and summoner spells for each team (Stored as Riot's champion and summoner spell IDs)
- The number of tower, inhibitor, Baron, dragon and Rift Herald kills each team has
- The 5 bans of each team (Again, champion IDs are used)"

We will drop the game ID, creation time, season ID, champions, summoner spells, and bans, as they either are irrelevant to the winner or introduces too much complexity in the need to one-hot encode. Winner and first "objective" taken will be relabeled as 1 = team1, -1 = team2, and 0 for neither.

In [22]:
```
lol = lol[['gameDuration', 'winner',
           'firstBlood', 'firstTower',
           'firstInhibitor', 'firstBaron',
           'firstDragon', 'firstRiftHerald',
           't1_towerKills', 't1_inhibitorKills',
           't1_baronKills', 't1_dragonKills',
           't1_riftHeraldKills', 't2_towerKills',
           't2_inhibitorKills', 't2_baronKills',
           't2_dragonKills', 't2_riftHeraldKills']]
```

In [23]:
```
lol.head()
```

Out[23]:

| | gameDuration | winner | firstBlood | firstTower | firstInhibitor | firstBaron | firstDragon | firstRiftHera |
|---|---|---|---|---|---|---|---|---|
| **0** | 1949 | 1 | 2 | 1 | 1 | 1 | 1 | |
| **1** | 1851 | 1 | 1 | 1 | 1 | 0 | 1 | |
| **2** | 1493 | 1 | 2 | 1 | 1 | 1 | 2 | |
| **3** | 1758 | 1 | 1 | 1 | 1 | 1 | 1 | |
| **4** | 2094 | 1 | 2 | 1 | 1 | 1 | 1 | |

In [24]:
```
lol['winner'] = lol['winner'].map({1: 1, 2: -1})
lol['firstBlood'] = lol['firstBlood'].map({0: 0, 1: 1, 2: -1})
lol['firstInhibitor'] = lol['firstInhibitor'].map({0: 0, 1: 1, 2: -1})
lol['firstBaron'] = lol['firstBaron'].map({0: 0, 1: 1, 2: -1})
lol['firstDragon'] = lol['firstDragon'].map({0: 0, 1: 1, 2: -1})
lol['firstRiftHerald'] = lol['firstRiftHerald'].map({0: 0, 1: 1, 2: -1})
```

In [25]:
```
X = lol[['gameDuration',
         'firstBlood', 'firstTower',
         'firstInhibitor', 'firstBaron',
         'firstDragon', 'firstRiftHerald',
         't1_towerKills', 't1_inhibitorKills',
         't1_baronKills', 't1_dragonKills',
         't1_riftHeraldKills', 't2_towerKills',
         't2_inhibitorKills', 't2_baronKills',
         't2_dragonKills', 't2_riftHeraldKills']].to_numpy()

Y = lol[['winner']].to_numpy()

X_and_Y = np.hstack((X, Y))     # Stack them together for shuffling.
np.random.seed(1)               # Set the random seed.
np.random.shuffle(X_and_Y)      # Shuffle the data points in X_and_Y array

print(X.shape) # (51490, 17)
print(Y.shape) # (51490, 1)
print(X_and_Y[0])

X_shuffled = X_and_Y[:,[0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16]]
Y_shuffled = X_and_Y[:,17]

print(X_shuffled[0])
print(Y_shuffled[0])
```

```
(51490, 17)
(51490, 1)
[1886    1    1   -1    1   -1    1    3    0    1    0    1   10    2
    0    3    0   -1]
[1886    1    1   -1    1   -1    1    3    0    1    0    1   10    2
    0    3    0]
-1
```

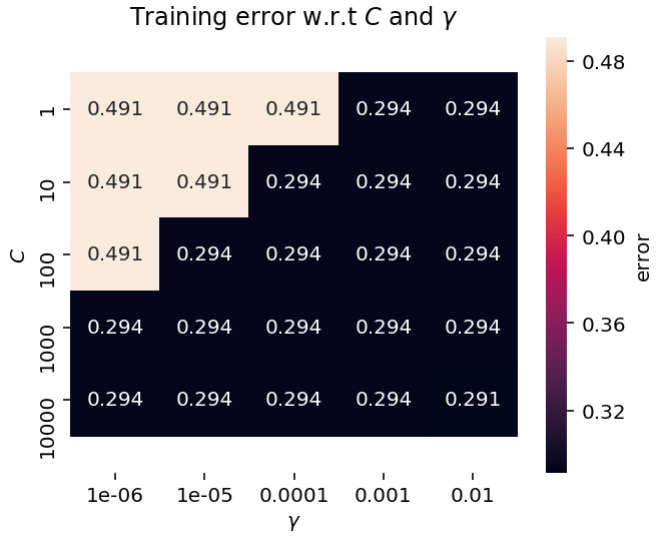
## 80/20

In [26]:
```
X_train = X_shuffled[:41192] # Shape: (41192,17)
Y_train = Y_shuffled[:41192] # Shape: (41192,)
X_test = X_shuffled[-10298:] # Shape: (10298,17)
Y_test = Y_shuffled[-10298:] # Shape: (10298,)
print(X_train.shape)
print(Y_train.shape)
print(X_test.shape)
print(Y_test.shape)
```

```
(41192, 17)
(41192,)
(10298, 17)
(10298,)
```

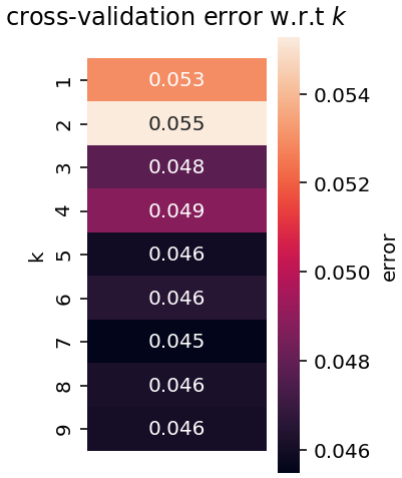
In [27]:

```
C_list = [1, 10, 100, 1000, 10000]
gamma_list = [1e-6, 1e-5, 1e-4, 1e-3, 1e-2]

# An example of using draw_heatmap().
#    errors = np.random.random((len(C_list), len(gamma_list)))
#    draw_heatmap(errors, gamma_list, C_list)

opt_e_training = 1.0   # Optimal training error.
opt_classifier = None  # Optimal classifier.
opt_C          = None  # Optimal C.
opt_gamma      = None  # Optimal C.

# Training errors
training_errors = np.zeros((len(C_list), len(gamma_list)))

for i, C in enumerate(C_list):
    for j, gamma in enumerate(gamma_list):
        # Create a SVM classifier with RBF kernel.
        classifier = svm.SVC(kernel='rbf', C=C, gamma=gamma)

        # Use the classifier to fit the training set (use X_train, Y_train).
        classifier.fit(X_train[:8000][:,[1,2]], Y_train[:8000]) # selecting fi
rstBlood and firstTower
        # shorten to 8000/2000 to make runtime for this classification managab
le

        # Show decision boundary, training error and test error.
        e_training = calc_error(X_train[:,[1,2]][:8000], Y_train[:8000], class
ifier)
        # selecting firstBlood and firstTower
        # shorten to 8000/2000 to make runtime for this classification managab
le

        training_errors[i,j] = e_training

        if e_training < opt_e_training:
            opt_e_training = e_training
            opt_classifier = classifier
            opt_C          = C
            opt_gamma      = gamma

draw_SVM_heatmap(training_errors, gamma_list, C_list)

# Obtain the weights and bias from the best linear SVM classifier .
print('Best parameter C*={}, best parameter gamma*={}'.format(opt_C, opt_gamma
))
print('Test error: {}'.format(calc_error(X_test[:,[1,2]][-2000:], Y_test[-2000
:], classifier)))
# selecting firstBlood and firstTower
# shorten to 8000/2000 to make runtime for this classification managable
```



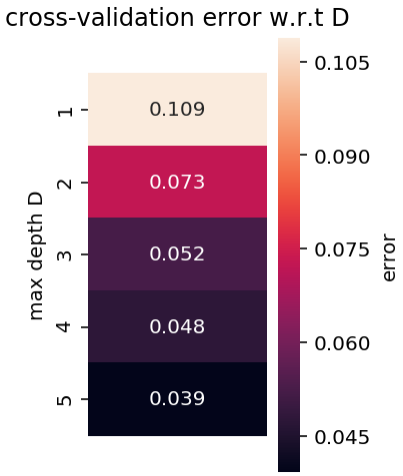

```
Best parameter C*=10000, best parameter gamma*=0.01
Test error: 0.29700000000000004
```

In [28]:
```
# Perform grid search for best number of nearest neighbors.

# 1. Create a k-NN classifier.
estimator = neighbors.KNeighborsClassifier()

# 2. Create a grid searcher with 5-fold cross-validation.
k_list = [1, 2, 3, 4, 5, 6, 7, 8, 9]
param_grid = {'n_neighbors': k_list}
grid_search = GridSearchCV(estimator, param_grid, cv=5)

# 3. Use the grid searcher to fit the training set.
grid_search.fit(X_train, Y_train)

# Draw heatmaps of cross-validation errors (in cross-validation).
cross_val_errors = 1 - grid_search.cv_results_['mean_test_score'].reshape(-1,1
)
draw_GS_heatmap(cross_val_errors, k_list, title='cross-validation error w.r.t
 $k$')

# Show the best k.
best_k = grid_search.best_params_['n_neighbors']
print("Best number of nearest neighbors (k): {}".format(best_k))

# Calculate the test error.
test_error = 1 - accuracy_score(grid_search.best_estimator_.predict(X_test),Y_
test)
print("Test error: {}".format(test_error))
```




```
Best number of nearest neighbors (k): 7
Test error: 0.045639930083511415
```

In [29]:
```
# Perform grid search for best max depth.

# 1. Create a decision tree classifier.
estimator = tree.DecisionTreeClassifier(criterion="entropy",random_state=1)

# 2. Create a grid searcher with cross-validation.
D_list = [1, 2, 3, 4, 5]
param_grid = {'max_depth': D_list}
grid_search = GridSearchCV(estimator, param_grid, cv=10)

# 3. Use the grid searcher to fit the training set.
grid_search.fit(X_train,Y_train)

# Draw heatmaps of cross-validation errors (in cross-validation).
cross_val_errors = 1 - grid_search.cv_results_['mean_test_score'].reshape(5,1)
draw_DT_heatmap(cross_val_errors, D_list, title='cross-validation error w.r.t
 D')

# Show the best max depth.
best_max_depth = grid_search.best_params_
print("Best max depth D: {}".format(best_max_depth))

# Calculate the test error.
test_error = 1 - accuracy_score(grid_search.best_estimator_.predict(X_test),Y_
test)
print("Test error: {}".format(test_error))
```



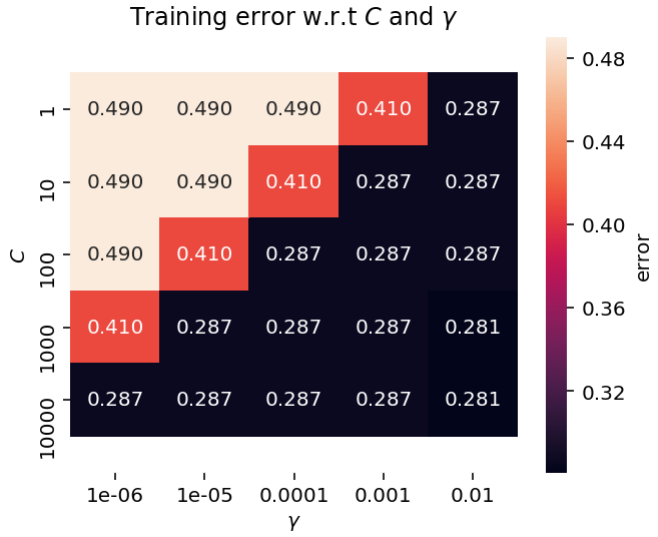

```
Best max depth D: {'max_depth': 5}
Test error: 0.04000776849873766
```

In [30]:
```
X_train = X_shuffled[:10298] # Shape: (10298,17)
Y_train = Y_shuffled[:10298] # Shape: (10298,)
X_test = X_shuffled[-41192:] # Shape: (41192,17)
Y_test = Y_shuffled[-41192:] # Shape: (41192,)
print(X_train.shape)
print(Y_train.shape)
print(X_test.shape)
print(Y_test.shape)
```

```
(10298, 17)
(10298,)
(41192, 17)
(41192,)
```

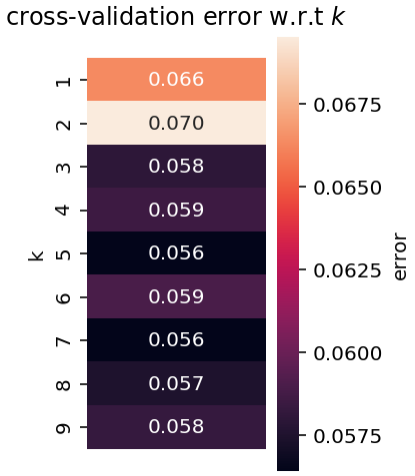
In [31]:

```
C_list = [1, 10, 100, 1000, 10000]
gamma_list = [1e-6, 1e-5, 1e-4, 1e-3, 1e-2]

# An example of using draw_heatmap().
#    errors = np.random.random((len(C_list), len(gamma_list)))
#    draw_heatmap(errors, gamma_list, C_list)

opt_e_training = 1.0   # Optimal training error.
opt_classifier = None  # Optimal classifier.
opt_C          = None  # Optimal C.
opt_gamma      = None  # Optimal C.

# Training errors
training_errors = np.zeros((len(C_list), len(gamma_list)))

for i, C in enumerate(C_list):
    for j, gamma in enumerate(gamma_list):
        # Create a SVM classifier with RBF kernel.
        classifier = svm.SVC(kernel='rbf', C=C, gamma=gamma)

        # Use the classifier to fit the training set (use X_train, Y_train).
        classifier.fit(X_train[:2000][:,[1,2]], Y_train[:2000])
        # selecting firstBlood and firstTower
        # shorten to 8000/2000 to make runtime for this classification managab
le


        # Show decision boundary, training error and test error.
        e_training = calc_error(X_train[:2000][:,[1,2]], Y_train[:2000], class
ifier)
        # selecting firstBlood and firstTower
        # shorten to 8000/2000 to make runtime for this classification managab
le
        training_errors[i,j] = e_training

        if e_training < opt_e_training:
            opt_e_training = e_training
            opt_classifier = classifier
            opt_C          = C
            opt_gamma      = gamma

draw_SVM_heatmap(training_errors, gamma_list, C_list)

# Obtain the weights and bias from the best linear SVM classifier .
print('Best parameter C*={}, best parameter gamma*={}'.format(opt_C, opt_gamma
))
print('Test error: {}'.format(calc_error(X_test[:8000][:,[1,2]], Y_test[:8000
], classifier)))
# selecting firstBlood and firstTower
# shorten to 8000/2000 to make runtime for this classification managable
```



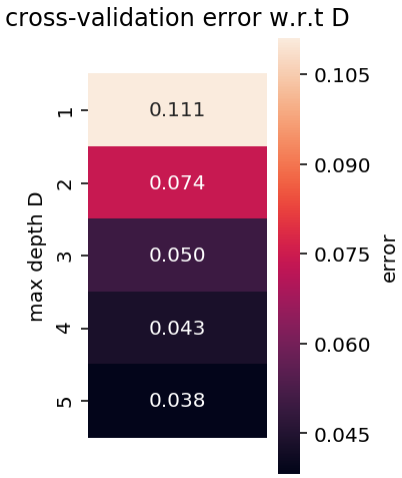

```
Best parameter C*=1000, best parameter gamma*=0.01
Test error: 0.30362500000000003
```

In [32]:
```
# Perform grid search for best number of nearest neighbors.

# 1. Create a k-NN classifier.
estimator = neighbors.KNeighborsClassifier()

# 2. Create a grid searcher with 5-fold cross-validation.
k_list = [1, 2, 3, 4, 5, 6, 7, 8, 9]
param_grid = {'n_neighbors': k_list}
grid_search = GridSearchCV(estimator, param_grid, cv=5)

# 3. Use the grid searcher to fit the training set.
grid_search.fit(X_train, Y_train)

# Draw heatmaps of cross-validation errors (in cross-validation).
cross_val_errors = 1 - grid_search.cv_results_['mean_test_score'].reshape(-1,1
)
draw_GS_heatmap(cross_val_errors, k_list, title='cross-validation error w.r.t
 $k$')

# Show the best k.
best_k = grid_search.best_params_['n_neighbors']
print("Best number of nearest neighbors (k): {}".format(best_k))

# Calculate the test error.
test_error = 1 - accuracy_score(grid_search.best_estimator_.predict(X_test),Y_
test)
print("Test error: {}".format(test_error))
```




```
Best number of nearest neighbors (k): 5
Test error: 0.055034958244319254
```

In [33]:
```
# Perform grid search for best max depth.

# 1. Create a decision tree classifier.
estimator = tree.DecisionTreeClassifier(criterion="entropy",random_state=1)

# 2. Create a grid searcher with cross-validation.
D_list = [1, 2, 3, 4, 5]
param_grid = {'max_depth': D_list}
grid_search = GridSearchCV(estimator, param_grid, cv=10)

# 3. Use the grid searcher to fit the training set.
grid_search.fit(X_train,Y_train)

# Draw heatmaps of cross-validation errors (in cross-validation).
cross_val_errors = 1 - grid_search.cv_results_['mean_test_score'].reshape(5,1)
draw_DT_heatmap(cross_val_errors, D_list, title='cross-validation error w.r.t
 D')

# Show the best max depth.
best_max_depth = grid_search.best_params_
print("Best max depth D: {}".format(best_max_depth))

# Calculate the test error.
test_error = 1 - accuracy_score(grid_search.best_estimator_.predict(X_test),Y_
test)
print("Test error: {}".format(test_error))
```




```
Best max depth D: {'max_depth': 5}
Test error: 0.03765294231889682
```

# Load Third Dataset

In [34]:
```
avocado = pd.read_csv('avocado.csv')
```

In [35]:
```
print(list(avocado.columns))
```

```
['Unnamed: 0', 'Date', 'AveragePrice', 'Total Volume', '4046', '4225', '477
0', 'Total Bags', 'Small Bags', 'Large Bags', 'XLarge Bags', 'type', 'year',
'region']
```

- Date - The date of the observation
- AveragePrice - the average price of a single avocado
- type - conventional or organic
- year - the year
- Region - the city or region of the observation
- Total Volume - Total number of avocados sold
- 4046 - Total number of avocados with PLU 4046 sold
- 4225 - Total number of avocados with PLU 4225 sold
- 4770 - Total number of avocados with PLU 4770 sold

In [36]:
```
avocado = avocado[['Date', 'AveragePrice',
                   'Total Volume', '4046',
                   '4225', '4770',
                   'Total Bags', 'Small Bags',
                   'Large Bags', 'XLarge Bags',
                   'type', 'year']]

import time
import datetime
avocado['Date'] = avocado['Date'].map(lambda s: time.mktime(datetime.datetime.
strptime(s, "%Y-%m-%d").timetuple()))
avocado['type'] = avocado['type'].map({"conventional": -1, "organic": 1})

avocado.head()
```

Out[36]:

| | Date | AveragePrice | Total Volume | 4046 | 4225 | 4770 | Total Bags | Small Bags | Large Bags |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 1.451203e+09 | 1.33 | 64236.62 | 1036.74 | 54454.85 | 48.16 | 8696.87 | 8603.62 | 93.25 |
| **1** | 1.450598e+09 | 1.35 | 54876.98 | 674.28 | 44638.81 | 58.33 | 9505.56 | 9408.07 | 97.49 |
| **2** | 1.449994e+09 | 0.93 | 118220.22 | 794.70 | 109149.67 | 130.50 | 8145.35 | 8042.21 | 103.14 |
| **3** | 1.449389e+09 | 1.08 | 78992.15 | 1132.00 | 71976.41 | 72.58 | 5811.16 | 5677.40 | 133.76 |
| **4** | 1.448784e+09 | 1.28 | 51039.60 | 941.48 | 43838.39 | 75.78 | 6183.95 | 5986.26 | 197.69 |

In [37]:
```
X = avocado[['Date', 'AveragePrice',
             'Total Volume', '4046',
             '4225', '4770',
             'Total Bags', 'Small Bags',
             'Large Bags', 'XLarge Bags',
             'year']].to_numpy()

Y = avocado[['type']].to_numpy()

X_and_Y = np.hstack((X, Y))     # Stack them together for shuffling.
np.random.seed(1)               # Set the random seed.
np.random.shuffle(X_and_Y)      # Shuffle the data points in X_and_Y array

print(X.shape) # (18249, 11)
print(Y.shape) # (18249, 1)
print(X_and_Y[0])

X_shuffled = X_and_Y[:,[0,1,2,3,4,5,6,7,8,9,10]]
Y_shuffled = X_and_Y[:,11]

print(X_shuffled[0])
print(Y_shuffled[0])
```

```
(18249, 11)
(18249, 1)
[1.4687388e+09 2.1100000e+00 3.0480390e+04 1.9242400e+03 2.5560940e+04
 3.5130000e+01 2.9600800e+03 3.6333000e+02 2.5967500e+03 0.0000000e+00
 2.0160000e+03 1.0000000e+00]
[1.4687388e+09 2.1100000e+00 3.0480390e+04 1.9242400e+03 2.5560940e+04
 3.5130000e+01 2.9600800e+03 3.6333000e+02 2.5967500e+03 0.0000000e+00
 2.0160000e+03]
1.0
```

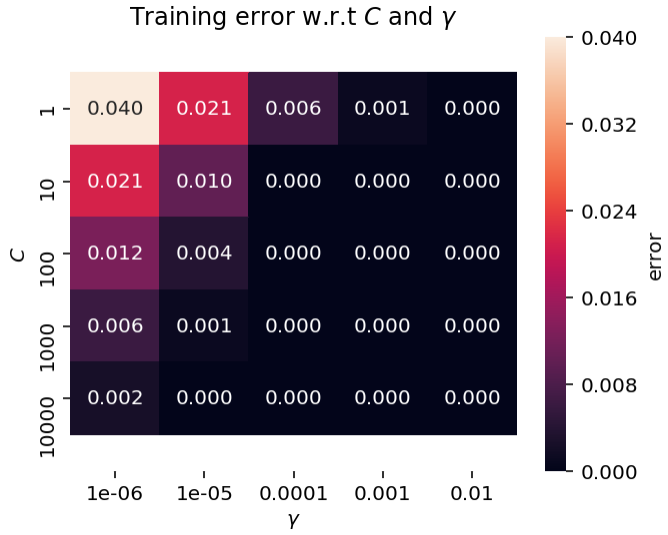
## 80/20

In [38]:
```
X_train = X_shuffled[:14599] # Shape: (14599,11)
Y_train = Y_shuffled[:14599] # Shape: (14599,)
X_test = X_shuffled[-3650:] # Shape: (3650,11)
Y_test = Y_shuffled[-3650:] # Shape: (3650,)
print(X_train.shape)
print(Y_train.shape)
print(X_test.shape)
print(Y_test.shape)
```

```
(14599, 11)
(14599,)
(3650, 11)
(3650,)
```

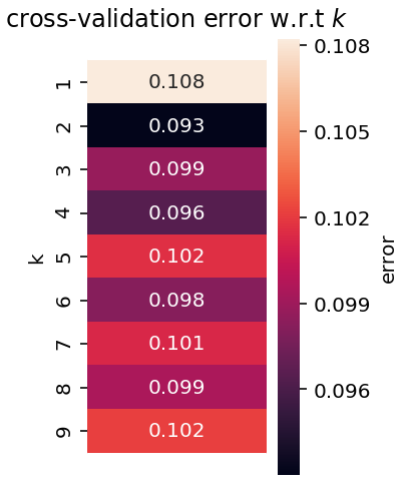
In [39]:

```
C_list = [1, 10, 100, 1000, 10000]
gamma_list = [1e-6, 1e-5, 1e-4, 1e-3, 1e-2]

# An example of using draw_heatmap().
#    errors = np.random.random((len(C_list), len(gamma_list)))
#    draw_heatmap(errors, gamma_list, C_list)

opt_e_training = 1.0   # Optimal training error.
opt_classifier = None  # Optimal classifier.
opt_C          = None  # Optimal C.
opt_gamma      = None  # Optimal C.

# Training errors
training_errors = np.zeros((len(C_list), len(gamma_list)))

for i, C in enumerate(C_list):
    for j, gamma in enumerate(gamma_list):
        # Create a SVM classifier with RBF kernel.
        classifier = svm.SVC(kernel='rbf', C=C, gamma=gamma)

        # Use the classifier to fit the training set (use X_train, Y_train).
        classifier.fit(X_train[:800][:,[1,2]], Y_train[:800])
        # selecting price and volume
        # shorten to 800/200 to make runtime for this classification managable

        # Show decision boundary, training error and test error.
        e_training = calc_error(X_train[:800][:,[1,2]], Y_train[:800], classif
ier)
        # selecting price and volume
        # shorten to 800/200 to make runtime for this classification managable
        training_errors[i,j] = e_training

        if e_training < opt_e_training:
            opt_e_training = e_training
            opt_classifier = classifier
            opt_C          = C
            opt_gamma      = gamma

draw_SVM_heatmap(training_errors, gamma_list, C_list)

# Obtain the weights and bias from the best linear SVM classifier .
print('Best parameter C*={}, best parameter gamma*={}'.format(opt_C, opt_gamma
))
print('Test error: {}'.format(calc_error(X_test[:200][:,[1,2]], Y_test[:200],
classifier)))
# selecting price and volume
# shorten to 800/200 to make runtime for this classification managable
```



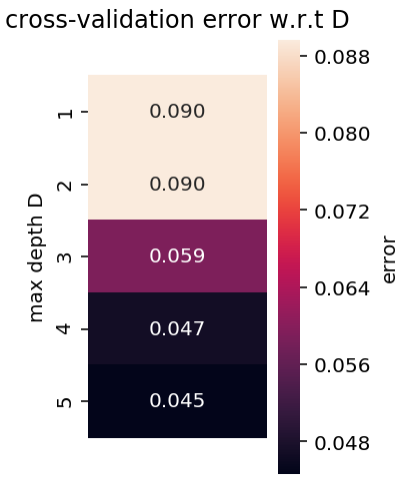

```
Best parameter C*=1, best parameter gamma*=0.01
Test error: 0.33999999999999997
```

In [40]:
```
# Perform grid search for best number of nearest neighbors.

# 1. Create a k-NN classifier.
estimator = neighbors.KNeighborsClassifier()

# 2. Create a grid searcher with 5-fold cross-validation.
k_list = [1, 2, 3, 4, 5, 6, 7, 8, 9]
param_grid = {'n_neighbors': k_list}
grid_search = GridSearchCV(estimator, param_grid, cv=5)

# 3. Use the grid searcher to fit the training set.
grid_search.fit(X_train, Y_train)

# Draw heatmaps of cross-validation errors (in cross-validation).
cross_val_errors = 1 - grid_search.cv_results_['mean_test_score'].reshape(-1,1
)
draw_GS_heatmap(cross_val_errors, k_list, title='cross-validation error w.r.t
 $k$')

# Show the best k.
best_k = grid_search.best_params_['n_neighbors']
print("Best number of nearest neighbors (k): {}".format(best_k))

# Calculate the test error.
test_error = 1 - accuracy_score(grid_search.best_estimator_.predict(X_test),Y_
test)
print("Test error: {}".format(test_error))
```




```
Best number of nearest neighbors (k): 2
Test error: 0.0956164383561644
```

In [41]:
```
# Perform grid search for best max depth.

# 1. Create a decision tree classifier.
estimator = tree.DecisionTreeClassifier(criterion="entropy",random_state=1)

# 2. Create a grid searcher with cross-validation.
D_list = [1, 2, 3, 4, 5]
param_grid = {'max_depth': D_list}
grid_search = GridSearchCV(estimator, param_grid, cv=10)

# 3. Use the grid searcher to fit the training set.
grid_search.fit(X_train,Y_train)

# Draw heatmaps of cross-validation errors (in cross-validation).
cross_val_errors = 1 - grid_search.cv_results_['mean_test_score'].reshape(5,1)
draw_DT_heatmap(cross_val_errors, D_list, title='cross-validation error w.r.t
 D')

# Show the best max depth.
best_max_depth = grid_search.best_params_
print("Best max depth D: {}".format(best_max_depth))

# Calculate the test error.
test_error = 1 - accuracy_score(grid_search.best_estimator_.predict(X_test),Y_
test)
print("Test error: {}".format(test_error))
```



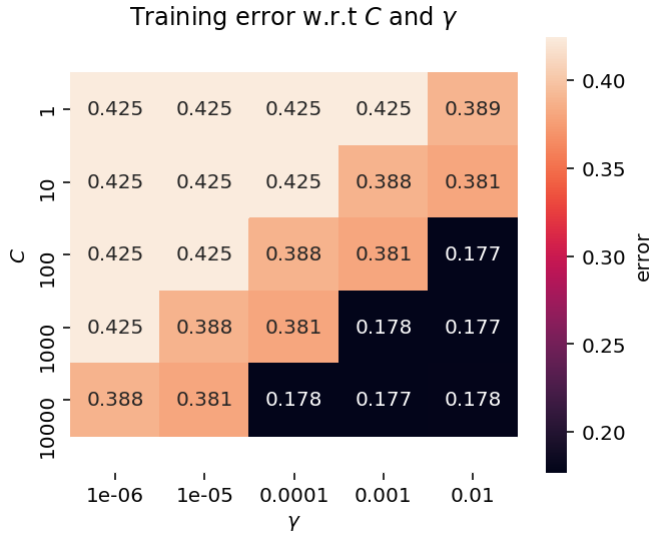

```
Best max depth D: {'max_depth': 5}
Test error: 0.0383561643835616
```

In [42]:
```
X_train = X_shuffled[:3650] # Shape: (3650,11)
Y_train = Y_shuffled[:3650] # Shape: (3650,)
X_test = X_shuffled[-14599:] # Shape: (14599,11)
Y_test = Y_shuffled[-14599:] # Shape: (14599,)
print(X_train.shape)
print(Y_train.shape)
print(X_test.shape)
print(Y_test.shape)
```

```
(3650, 11)
(3650,)
(14599, 11)
(14599,)
```

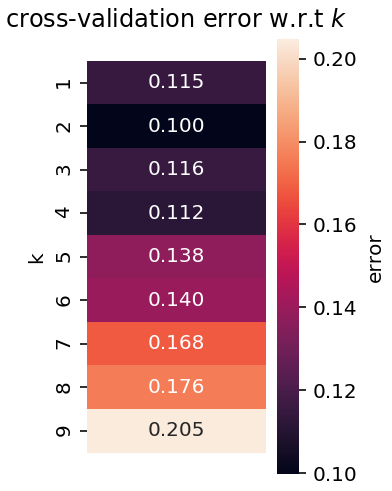
In [43]:

```
C_list = [1, 10, 100, 1000, 10000]
gamma_list = [1e-6, 1e-5, 1e-4, 1e-3, 1e-2]

# An example of using draw_heatmap().
#    errors = np.random.random((len(C_list), len(gamma_list)))
#    draw_heatmap(errors, gamma_list, C_list)

opt_e_training = 1.0   # Optimal training error.
opt_classifier = None  # Optimal classifier.
opt_C          = None  # Optimal C.
opt_gamma      = None  # Optimal C.

# Training errors
training_errors = np.zeros((len(C_list), len(gamma_list)))

for i, C in enumerate(C_list):
    for j, gamma in enumerate(gamma_list):
        # Create a SVM classifier with RBF kernel.
        classifier = svm.SVC(kernel='rbf', C=C, gamma=gamma)

        # Use the classifier to fit the training set (use X_train, Y_train).
        classifier.fit(X_train[:,[0,1]], Y_train)
        # selecting price and volume

        # Show decision boundary, training error and test error.
        e_training = calc_error(X_train[:,[0,1]], Y_train, classifier)
        # selecting price and volume
        training_errors[i,j] = e_training

        if e_training < opt_e_training:
            opt_e_training = e_training
            opt_classifier = classifier
            opt_C          = C
            opt_gamma      = gamma

draw_SVM_heatmap(training_errors, gamma_list, C_list)

# Obtain the weights and bias from the best linear SVM classifier .
print('Best parameter C*={}, best parameter gamma*={}'.format(opt_C, opt_gamma
))
print('Test error: {}'.format(calc_error(X_test[:,[0,1]], Y_test, classifier
)))
# selecting price and volume
```



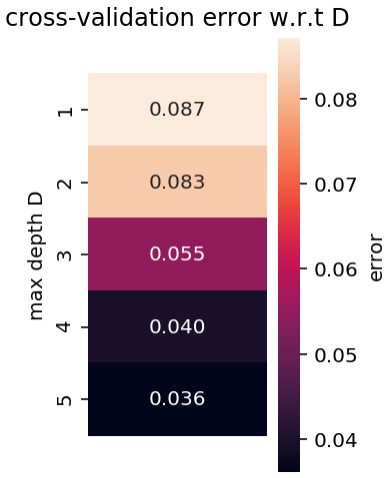

```
Best parameter C*=1000, best parameter gamma*=0.01
Test error: 0.18562915268169056
```

In [44]:
```
# Perform grid search for best number of nearest neighbors.

# 1. Create a k-NN classifier.
estimator = neighbors.KNeighborsClassifier()

# 2. Create a grid searcher with 5-fold cross-validation.
k_list = [1, 2, 3, 4, 5, 6, 7, 8, 9]
param_grid = {'n_neighbors': k_list}
grid_search = GridSearchCV(estimator, param_grid, cv=5)

# 3. Use the grid searcher to fit the training set.
grid_search.fit(X_train, Y_train)

# Draw heatmaps of cross-validation errors (in cross-validation).
cross_val_errors = 1 - grid_search.cv_results_['mean_test_score'].reshape(-1,1
)
draw_GS_heatmap(cross_val_errors, k_list, title='cross-validation error w.r.t
 $k$')

# Show the best k.
best_k = grid_search.best_params_['n_neighbors']
print("Best number of nearest neighbors (k): {}".format(best_k))

# Calculate the test error.
test_error = 1 - accuracy_score(grid_search.best_estimator_.predict(X_test),Y_
test)
print("Test error: {}".format(test_error))
```




```
Best number of nearest neighbors (k): 2
Test error: 0.10260976779231457
```

In [45]:
```
# Perform grid search for best max depth.

# 1. Create a decision tree classifier.
estimator = tree.DecisionTreeClassifier(criterion="entropy",random_state=1)

# 2. Create a grid searcher with cross-validation.
D_list = [1, 2, 3, 4, 5]
param_grid = {'max_depth': D_list}
grid_search = GridSearchCV(estimator, param_grid, cv=10)

# 3. Use the grid searcher to fit the training set.
grid_search.fit(X_train,Y_train)

# Draw heatmaps of cross-validation errors (in cross-validation).
cross_val_errors = 1 - grid_search.cv_results_['mean_test_score'].reshape(5,1)
draw_DT_heatmap(cross_val_errors, D_list, title='cross-validation error w.r.t
 D')

# Show the best max depth.
best_max_depth = grid_search.best_params_
print("Best max depth D: {}".format(best_max_depth))

# Calculate the test error.
test_error = 1 - accuracy_score(grid_search.best_estimator_.predict(X_test),Y_
test)
print("Test error: {}".format(test_error))
```




```
Best max depth D: {'max_depth': 5}
Test error: 0.03678334132474825
```

In [ ]: