hw2

February 21, 2018

1 Homework 2: Building Classifiers

UIC CS 412, Spring 2018

If you have discussed this assignment with anyone, please state their name(s) here: Chirag Soni. Keep in mind the expectations set in the Academic Honesty part of the syllabus.

In this homework, you will build classifiers using decision trees, nearest neighbors, and perceptron, to make decisions on a few different datasets. The code for this project consists of several Python files, some of which you will need to read and understand in order to complete the assignment, and some of which you can ignore.

This assignment is adapted from the github materials for A Course in Machine Learning.

1.1 Due Date

This assignment is due at 11:59pm Tuesday, February 20th.

1.1.1 Files You'll Edit

`dumbClassifiers.py`: This contains a handful of "warm up" classifiers to get you used to our classification framework.

`dt.py`: Will be your simple implementation of a decision tree classifier.

`knn.py`: This is where your nearest-neighbor classifier modifications will go.

`perceptron.py`: The perceptron file you need to edit.

1.1.2 Files you might want to look at

`binary.py`: Our generic interface for binary classifiers (actually works for regression and other types of classification, too).

`datasets.py`: Where a handful of test data sets are stored.

`util.py`: A handful of useful utility functions: these will undoubtedly be helpful to you, so take a look!

`runClassifier.py`: A few wrappers for doing useful things with classifiers, like training them, generating learning curves, etc.

`mlGraphics.py`: A few useful plotting commands

`data/*`: all of the datasets we'll use.

1.1.3 What to Submit

You will hand in all of the python files listed above together with your notebook **hw2.ipynb** as a single zip file **h2.zip** on Gradescope under *Homework 2*. The programming part constitutes 60% of the grade for this homework. You also need to answer the questions denoted by **WU#** (and a kitten) in this notebook which are the other 40% of your homework grade. When you are done, you should export **hw2.ipynb** with your answers as a PDF file **hw2WrittenPart.pdf** and upload the PDF file to Gradescope under *Homework 2 - Written Part*.

Your entire homework will be considered late if any of these parts are submitted late.

Autograding Your code will be autograded for technical correctness. Please **do not** change the names of any provided functions or classes within the code, or you will wreak havoc on the autograder. We have provided two simple test cases that you can try your code on, see `run_tests_simple.py`. As usual, you should create more test cases to make sure your code runs correctly.

2 Part 1: Simple classifiers (5%)

Let's begin our foray into classification by looking at some very simple classifiers. There are two classifiers in `dumbClassifiers.py`, one is implemented for you, the other one you will need to fill in appropriately.

The already implemented one is `AlwaysPredictOne`, a classifier that (as its name suggest) always predicts the positive class. We're going to use the `SentimentData` dataset from `datasets.py` as a running example to test your functions. Let's see how well this classifier does on this data. You should begin by importing `util`, `datasets`, `binary` and `dumbClassifiers`. Also, be sure you always have `from numpy import *` and `from pylab import *`. You can achieve this with `from imports import *` to make life easier.

We will look at a simple binary classification task: sentiment analysis (is this review a positive or negative evaluation of a product?). We'll use the presence/absence of words in the text as features. If you look in data/sentiment.all, you'll see the data for the sentiment prediction task. The first column contains the class value of zero or one (one = positive, zero = negative). The rest is a list of all the words that appear in this product reivew. These are binary features: any word listed has value "=1" and any word not listed has value "=0" (implicitly... it would be painful to list all non-occurring words!). As you write these functions, feel free to test your code on the much smaller TennisData dataset provided in datasets.py, so you can visually inspect correctness of your output. We have also provided some of the expected outputs as comments, so you can check whether you are getting the correct results.

```
In [26]: import dumbClassifiers, datasets, util
         from imports import *

         h = dumbClassifiers.AlwaysPredictOne({})
         print(h)
         # AlwaysPredictOne
         h.train(datasets.SentimentData.X, datasets.SentimentData.Y)
         h.predictAll(datasets.SentimentData.X)
         # array([ 1.,  1.,  1.,  1.,  1.,  1.,  1.,  1.,  1.,  1.,  1.,  1.,  1.,  1.])
         datasets.SentimentData.X
```

```
AlwaysPredictOne
```

```
Out[26]: array([[0., 0., 0., ..., 0., 0., 0.],
                [0., 0., 0., ..., 0., 0., 0.],
                [0., 0., 0., ..., 0., 0., 0.],
                ...,
                [0., 0., 0., ..., 0., 0., 0.],
                [0., 0., 0., ..., 0., 0., 0.],
                [0., 0., 0., ..., 0., 0., 0.]])
```

Indeed, it looks like it's always predicting one!

Now, let's compare these predictions to the truth. Here's a very clever way to compute accuracies:

```
In [27]: mean((datasets.SentimentData.Y > 0) == (h.predictAll(datasets.SentimentData.X) > 0))
         # 0.50416666666666665
```

```
Out[27]: 0.5041666666666667
```

That's training accuracy; let's check test accuracy:

```
In [28]: mean((datasets.SentimentData.Yte > 0) == (h.predictAll(datasets.SentimentData.Xte) > 0)
         # 0.50249999999999995
```

```
Out[28]: 0.5025
```

Okay, so it does pretty badly. That's not surprising, it's really not learning anything!!!

Now, let's use some of the built-in functionality to help do some of the grunt work for us. You'll need to import `runClassifier`.

```
In [29]: import runClassifier
         runClassifier.trainTestSet(h, datasets.SentimentData)
         # Training accuracy 0.5041666666666667, test accuracy 0.5025
```

```
Training accuracy 0.5041666666666667, test accuracy 0.5025
```

Very convenient!

Now, your first implementation task will be to implement the missing functionality in `AlwaysPredictMostFrequent` in dumbClassifiers.py. This actually will "learn" something simple. Upon receiving training data, it will simply remember whether +1 is more common or -1 is more common. It will then always predict this label for future data. Once you've implemented this, you can test it:

```
In [30]: h = dumbClassifiers.AlwaysPredictMostFrequent({})
         runClassifier.trainTestSet(h, datasets.SentimentData)
         # Training accuracy 0.5041666666666667, test accuracy 0.5025
         print(h)
         # AlwaysPredictMostFrequent(1)
```

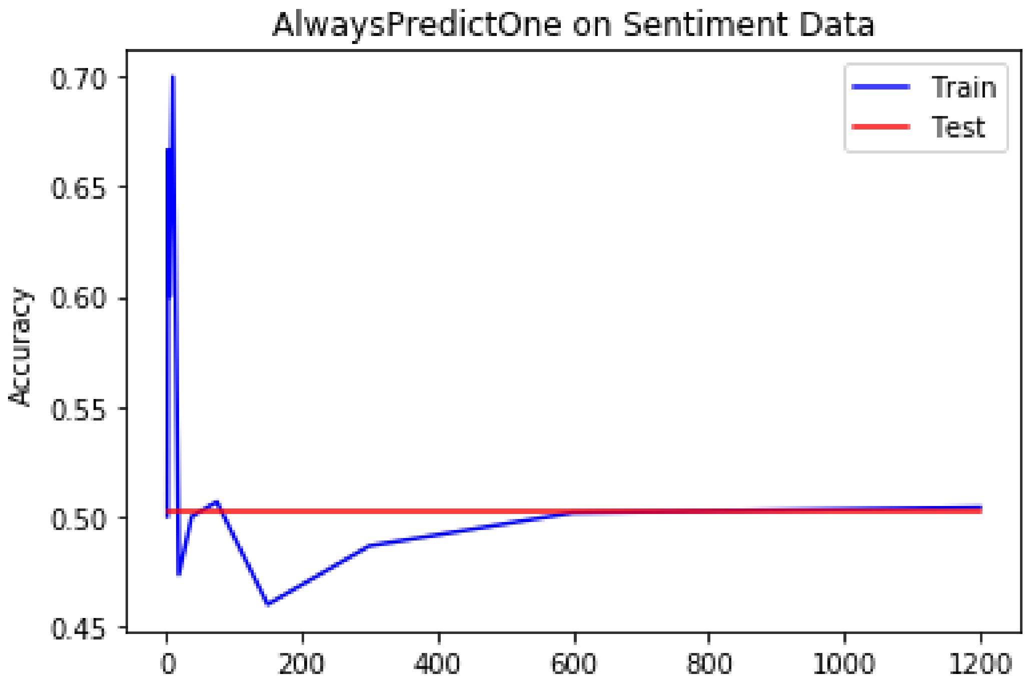
```
Training accuracy 0.5041666666666667, test accuracy 0.5025
AlwaysPredictMostFrequent(1)
```

Okay, so it does the same as `AlwaysPredictOne`, but that's because +1 is more common in that training data (i.e., the majority class is '1').

We can use more runClassifier functions to generate learning curves and hyperparameter curves:

```
In [31]: curve = runClassifier.learningCurveSet(dumbClassifiers.AlwaysPredictOne({}), datasets.S
         runClassifier.plotCurve('AlwaysPredictOne on Sentiment Data', curve)
```

```
Training classifier on 2 points...
Training accuracy 0.5, test accuracy 0.5025
Training classifier on 3 points...
Training accuracy 0.6666666666666666, test accuracy 0.5025
Training classifier on 5 points...
Training accuracy 0.6, test accuracy 0.5025
Training classifier on 10 points...
Training accuracy 0.7, test accuracy 0.5025
Training classifier on 19 points...
Training accuracy 0.47368421052631576, test accuracy 0.5025
Training classifier on 38 points...
Training accuracy 0.5, test accuracy 0.5025
Training classifier on 75 points...
Training accuracy 0.5066666666666667, test accuracy 0.5025
Training classifier on 150 points...
Training accuracy 0.46, test accuracy 0.5025
Training classifier on 300 points...
Training accuracy 0.4866666666666667, test accuracy 0.5025
Training classifier on 600 points...
Training accuracy 0.5016666666666667, test accuracy 0.5025
Training classifier on 1200 points...
Training accuracy 0.5041666666666667, test accuracy 0.5025
```



You should be able to see how the accuracy changes as more training data is used.

3 Part 2: Decision trees (45%)

Next, you will build decision trees both using the python package sklearn and using your own function.

3.1 2.1 Training (5%)

Load the sentiment analysis dataset and transform the words in each review into a bag-of-words format (0 and 1).

```
In [32]: from sklearn.tree import DecisionTreeClassifier
         import data

         X,Y,dictionary = data.loadTextDataBinary('data/sentiment.tr')
         print(X)
         print(Y)
         print(X.shape)
         print(Y.shape)
```

```
[[0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 ...
```

```
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]]
[1. 1. 0. ... 0. 1. 0.]
(1400, 3473)
(1400,)
```

We have successfully loaded 1400 examples of sentiment training data. The vocabulary size is 3473 words; we can look at the first ten words (arbitrarily sorted):

```
In [33]: dictionary[:10]
```

```
Out[33]: ['sympathy',
          'reality',
          'grave',
          'progress',
          'tremendous',
          'build',
          'various',
          'highlight',
          'accident',
          'production']
```

Train a decision tree of depth 1 on the sentiment analysis dataset.

```
In [34]: #from sklearn.tree import DecisionTreeClassifier
         dt = DecisionTreeClassifier(max_depth=1)
         dt.fit(X, Y)
         # check the default values of the DecisionTreeClassifier parameters
         DecisionTreeClassifier?

         data.showTree(dt, dictionary)

         # bad?
         # -N-> class 1        (333 for class 0, 533 for class 1)
         # -Y-> class 0        (358 for class 0, 176 for class 1)
```

```
bad?
-N-> class 1        (333.0 for class 0, 533.0 for class 1)
-Y-> class 0        (358.0 for class 0, 176.0 for class 1)
```

This shows that if you only have one question you can ask about the review it's that you should ask if the review contains the word "bad" or not. If it does not ("N") then it's probably a positive review (by a vote of 533 to 333); if it does ("Y") then it's probable a negative review (by a vote of 358 to 176).

Let's look at training accuracy for the tree of depth 1:

```
In [35]: np.mean(dt.predict(X) == Y)
         # 0.6364285714285715
```

```
Out[35]: 0.6364285714285715
```

It's not enough to just think about training data; we need to see how well these trees generalize to new data.

```
In [36]: Xde,Yde,_ = data.loadTextDataBinary('data/sentiment.de', dictionary)
         np.mean(dt.predict(Xde) == Yde)
         # 0.6049999999999998
```

```
Out[36]: 0.605
```

Note: when we load the development data, we have to give it the dictionary we built on the training data so that words are mapped to integers in the same way!

Here, we see that the accuracy has dropped a bit.

3.2 WU1 (2%):

Your first decision tree task is to build and show a decision tree of depth 2, and answer a few questions about it. Convince yourself whether or not it is useful to go from depth one to depth two on this data. How do you know?

```
In [37]: #from sklearn.tree import DecisionTreeClassifier
         dt2 = DecisionTreeClassifier(max_depth=2)
         dt2.fit(X, Y)

         # data.showTree(dt, dictionary)
         print(np.mean(dt2.predict(X) == Y))
         print(np.mean(dt2.predict(Xde) == Yde))
         data.showTree(dt2, dictionary)
```

```
0.66
0.62
bad?
-N-> worst?
|    -N-> class 1        (281.0 for class 0, 514.0 for class 1)
|    -Y-> class 0        (52.0 for class 0, 19.0 for class 1)
-Y-> stupid?
|    -N-> class 0        (281.0 for class 0, 168.0 for class 1)
|    -Y-> class 0        (77.0 for class 0, 8.0 for class 1)
```

Q: Is it useful to go from depth one to depth two on this data? How do you know?

A: It is useful to from depth 1 to depth 2. We know this as we get higher training accuracy and it has generalized better as we have a look at the accuracy with validation set on sentiment.de dataset.

It's important to recognize that decision trees are essentially learning conjunctions of features. In particular, you can convert a decision tree to a sequence of if-then-else statements, of the form:

if A and B and C and D then return POSITIVE elif A and B and C and !D then return NEGATIVE elif ...

This is called a "decision list."

3.3 WU2 (1%):

Write down the decision list corresponding to the tree that you learned of depth 2:

A: if not bad and worst then return NEGATIVE (Class 0) elif not bad and not worst then return POSITIVE (class 1) elif bad and not stupid then return NEGATIVE (Class 0) elif bad and stupid then return NEGATIVE (Class 0)

3.4 WU3 (2%):

Build a depth 3 decision tree and "explain" it. In other words, if your boss asked you to tell her, intuitively, what your tree is doing, how would you explain it? Write a few sentences.

Ans: The decision tree is classifying whether the review is a positive review or negative review. Looking at the tree, we can say that if the review contains the word 'bad' (Y), 'stupid'(Y) and 'bob' (Y), it is classified as a positive review (As denoted by class 1). However, for the same case, it did not contain 'bob', then it's classified as a Negative review (as denoted by class 0).

Similarly, if the words 'bad' occurs but 'stupid' does not, then we check if the word 'wonderfully' occurs. If 'wonderfully' occurs, it predicts positive review else it is a negative review.

Now, if 'bad' does not occur, then we check for the word 'worst', if 'worst' is present, we look for the word 'present'. If the word 'present' is in the review, it is categorized as a positive review else as a negative review.

If 'worst' if not in the review, we can classify it as a positive review. (As 'many' has positive categorization whether it is there or not)

It is important to follow the order of the tree.

```
In [38]: dt3 = DecisionTreeClassifier(max_depth=3)
         dt3.fit(X, Y)
         print(np.mean(dt3.predict(Xde) == Yde))
         data.showTree(dt3, dictionary)
```

```
0.645
bad?
-N-> worst?
|    -N-> many?
|    |    -N-> class 1       (204.0 for class 0, 274.0 for class 1)
|    |    -Y-> class 1       (77.0 for class 0, 240.0 for class 1)
|    -Y-> present?
|    |    -N-> class 0       (52.0 for class 0, 13.0 for class 1)
|    |    -Y-> class 1       (0.0 for class 0, 6.0 for class 1)
-Y-> stupid?
|    -N-> wonderfully?
|    |    -N-> class 0       (280.0 for class 0, 153.0 for class 1)
|    |    -Y-> class 1       (1.0 for class 0, 15.0 for class 1)
|    -Y-> bob?
|    |    -N-> class 0       (76.0 for class 0, 4.0 for class 1)
```

```
|    |    -Y-> class 1        (1.0 for class 0, 4.0 for class 1)
```

3.5 2.2 Underfitting and overfitting (10%)

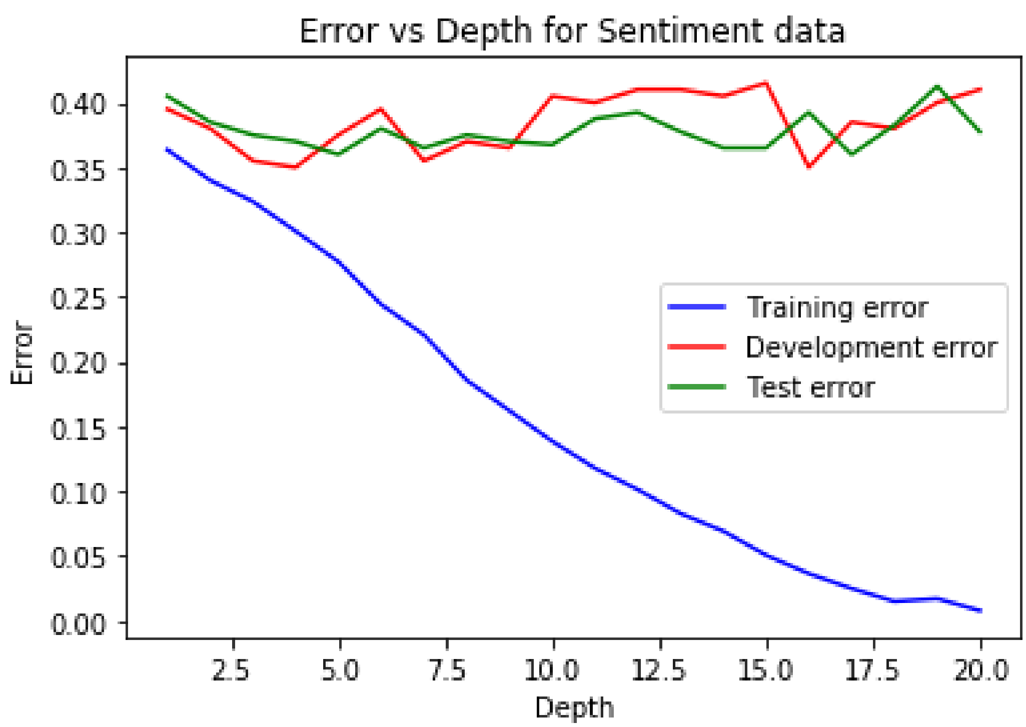
3.6 WU4 (5%):

For all possible depths from depth 1 to depth 20, compute training error, development error and test error (on data/sentiment.te) for the corresponding decision tree (hint: use a for loop). Plot these three curves. You can add a cell below if you want to write the code for the plot or if you must, we would accept an inserted picture of a plot created elsewhere. Make sure your axes are clearly marked.

In [39]:
```python
depthArray = []
avgErrorTraining = []
minAvgErrorTraining = float("inf")
avgErrorDev = []
minAvgErrorDev = float("inf")
avgErrorTest = []
minAvgErrorTest = float("inf")
bestTrainingDepth = 0
bestDevDepth = 0
bestTestDepth = 0

for depth in range(1,21):

    dtree = DecisionTreeClassifier(max_depth=depth)
    #Training
    dtree.fit(X, Y)

    #Calculating Training error
    averageTrainingError = np.mean(abs(dtree.predict(X) - Y))
    avgErrorTraining.append(averageTrainingError)
    if averageTrainingError<minAvgErrorTraining:
        minAvgErrorTraining = averageTrainingError
        bestTrainingDepth = depth


    #Calculating Development error
    averageDevError = np.mean(abs(dtree.predict(Xde) - Yde))
    avgErrorDev.append(averageDevError)
    if averageDevError<minAvgErrorDev:
        minAvgErrorDev = averageDevError
        bestDevDepth = depth

    Xte,Yte,_ = data.loadTextDataBinary('data/sentiment.te', dictionary)
    #Calculating Test error
    averageTestError = np.mean(abs(dtree.predict(Xte) - Yte))
    avgErrorTest.append(averageTestError)
```

```
        if averageTestError<minAvgErrorTest:
            minAvgErrorTest = averageTestError
            bestTestDepth = depth

        depthArray.append(depth)

    plot(depthArray,avgErrorTraining,'b-', label='Training error')
    plot(depthArray,avgErrorDev,'r-', label='Development error')
    plot(depthArray,avgErrorTest,'g-', label='Test error')
    xlabel('Depth')
    ylabel('Error')
    title('Error vs Depth for Sentiment data')
    legend(loc='center right')
```

```
Out[39]: <matplotlib.legend.Legend at 0x7f0602927dd8>
```



3.7 WU5 (5%):

If you were to choose the depth hyperparameter based on TRAINING data, what TEST error would you get? If you were to choose depth based on the DEV data, what TEST error would you get? Finally, if you were to choose the depth based on the TEST data, what TEST error would you get. Precisely one of these three is "correct" -- which one and why?

```
In [40]: print("If we choose depth based on Training data, we will get a Test Error of",avgError
         print("\nIf we choose depth based on DEV data, we will get a Test Error of",avgErrorTes
         print("\nIf we choose depth based on TEST data, we will get a Test Error of",avgErrorTe
```

```
If we choose depth based on Training data, we will get a Test Error of 0.3775

If we choose depth based on DEV data, we will get a Test Error of 0.37

If we choose depth based on TEST data, we will get a Test Error of 0.36
```

Ans: Choosing the depth hyperparameter based on DEV data is the only correct option.

Choosing a hyperparameter based on Training data will result in overfitting as we use training data to learn from fixed hyperparameters. This won't generalize well for Test data (future data). We cannot choose Test data either as Test data represent the future data and should be untouched in the entire process. Using Test data for choosing hyperparameter, can result in overfitting to Test data.

Validation or Dev dataset is used for choosing hyperparameters as it is not directly involved in training but represent the dataset to tweak the hyperparameters for training.

3.8 2.3 Implementing a decision tree (30%)

Our next task is to implement a decision tree classifier. There is stub code in `dt.py` that you should edit. Decision trees are stored as simple data structures. Each node in the tree has a `.isLeaf` boolean that tells us if this node is a leaf (as opposed to an internal node). Leaf nodes have a `.label` field that says what class to return at this leaf. Internal nodes have: a `.feature` value that tells us what feature to split on; a `.left` *tree* that tells us what to do when the feature value is *less than 0.5*; and a `.right` *tree* that tells us what to do when the feature value is *at least 0.5*. To get a sense of how the data structure works, look at the `displayTree` function that prints out a tree.

Your first task is to implement the training procedure for decision trees. We've provided a fair amount of the code, which should help you guard against corner cases. (Hint: take a look at `util.py` for some useful functions for implementing training. Once you've implemented the training function, we can test it on data:

```
In [41]: import dt
         h = dt.DT({'maxDepth': 2})
         h.train(datasets.SentimentData.X, datasets.SentimentData.Y)
         print(h)
         # this should print out something like this (the actual numbers attached to the branche
         #Branch 2428
         #  Branch 3842
         #    Leaf 1.0
         #    Leaf -1.0
         #  Branch 3892
         #    Leaf -1.0
         #    Leaf 1.0
```

```
Branch 4576
  Branch 2646
```

```
    Leaf 1.0
    Leaf -1.0
  Branch 4114
    Leaf -1.0
    Leaf 1.0
```

The problem with the branches here is that words have been converted into numeric ids for features. We can look them up. Your results here might be different due to hashing, so you will need to change them according to the branch numbers you see in your own output above:

```
In [44]: print(datasets.SentimentData.words[4576])
         #'bad'
         print(datasets.SentimentData.words[2646])
         #'worst'
         print(datasets.SentimentData.words[4114])
         #'sequence'
```

```
bad
worst
sequence
```

Based on this, we can rewrite the tree (by hand) as:

```
In [45]: Branch 'bad'
           Branch 'worst'
             Leaf -1.0
             Leaf 1.0
           Branch 'sequence'
             Leaf -1.0
             Leaf 1.0
```

```
          File "<ipython-input-45-a8be5dbcee70>", line 1
        Branch 'bad'
                   ^
    SyntaxError: invalid syntax
```

Now, you should go implement prediction. This should be easier than training! We can test by:

```
In [47]: runClassifier.trainTestSet(dt.DT({'maxDepth': 1}), datasets.SentimentData)
         #Training accuracy 0.630833, test accuracy 0.595
         runClassifier.trainTestSet(dt.DT({'maxDepth': 3}), datasets.SentimentData)
         #Training accuracy 0.701667, test accuracy 0.6175
         runClassifier.trainTestSet(dt.DT({'maxDepth': 5}), datasets.SentimentData)
         #Training accuracy 0.765833, test accuracy 0.62
```

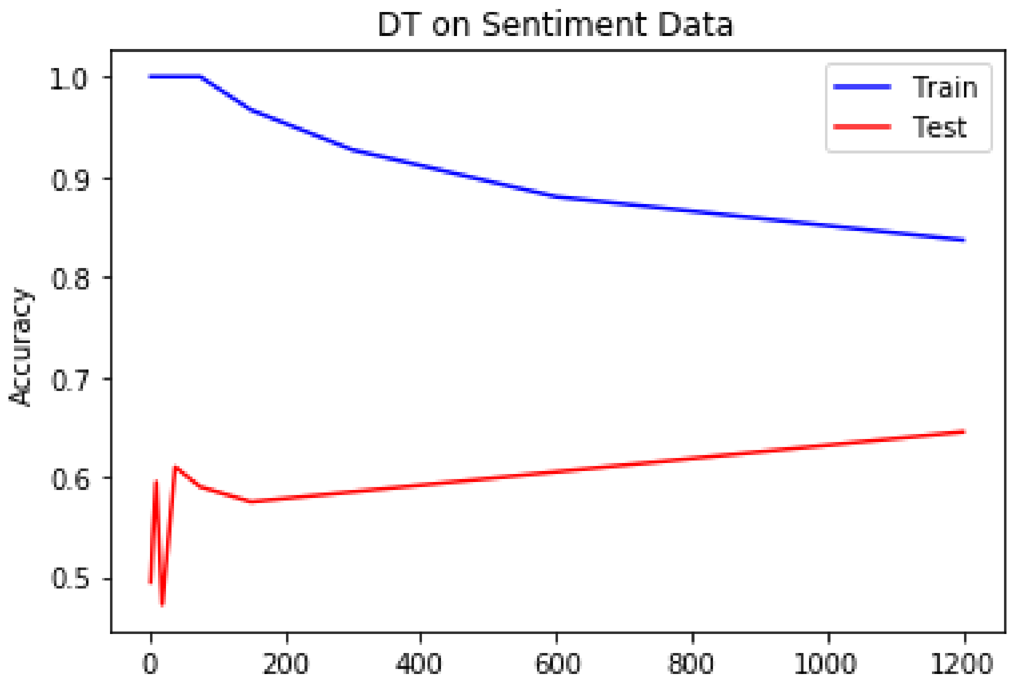
```
Training accuracy 0.6308333333333334, test accuracy 0.595
Training accuracy 0.7016666666666667, test accuracy 0.615
Training accuracy 0.7658333333333334, test accuracy 0.6175
```

Looks like it does better than the dumb classifiers on training data, as well as on test data! Hopefully we can do even better in the future!

We can use more `runClassifier` functions to generate learning curves and hyperparameter curves:

```
In [48]: curve = runClassifier.learningCurveSet(dt.DT({'maxDepth': 9}), datasets.SentimentData)
         runClassifier.plotCurve('DT on Sentiment Data', curve)
```

```
Training classifier on 2 points...
Training accuracy 1.0, test accuracy 0.495
Training classifier on 3 points...
Training accuracy 1.0, test accuracy 0.5075
Training classifier on 5 points...
Training accuracy 1.0, test accuracy 0.54
Training classifier on 10 points...
Training accuracy 1.0, test accuracy 0.595
Training classifier on 19 points...
Training accuracy 1.0, test accuracy 0.4725
Training classifier on 38 points...
Training accuracy 1.0, test accuracy 0.61
Training classifier on 75 points...
Training accuracy 1.0, test accuracy 0.59
Training classifier on 150 points...
Training accuracy 0.9666666666666667, test accuracy 0.575
Training classifier on 300 points...
Training accuracy 0.9266666666666666, test accuracy 0.585
Training classifier on 600 points...
Training accuracy 0.88, test accuracy 0.605
Training classifier on 1200 points...
Training accuracy 0.8366666666666667, test accuracy 0.645
```



This plots training and test accuracy as a function of the number of data points (x-axis) used for training and y-axis is accuracy.

3.9 WU6 (2%):

We should see training accuracy (roughly) going down and test accuracy (roughly) going up. Why does training accuracy tend to go *down?* Why is test accuracy not monotonically increasing? You should also see jaggedness in the test curve toward the left. Why?

Ans: With increase in data points, training data will find it hard to fit all the data points. Thus, the testing accuracy falls.

However, at the same time, increased amount of data points allows test accuracy to increase as it allows better generalisation when trained on trained dataset. Better generalisation can result in higher test accuracy. At the same time, trained model will not fit test data perfectly as it is generalised and it reaches a maximum based on the training on the particular train dataset. If it does not overfit, it maintains the accuracy (approximately) after that. Overfitting can cause decrease in test accuracy

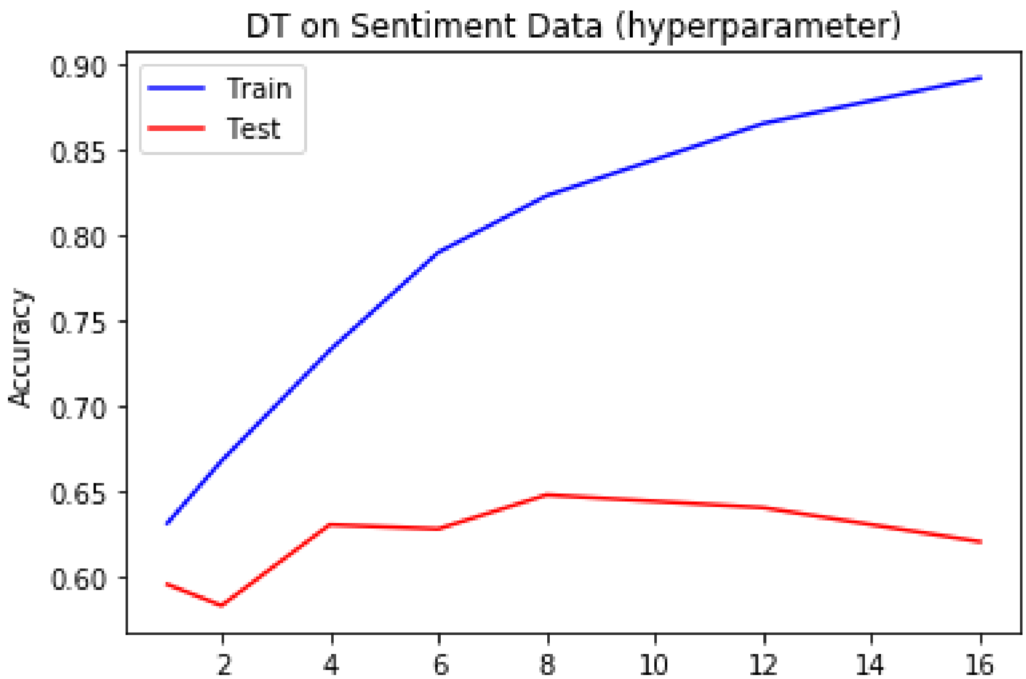
The jaggedness is due to the less data available. If there is less data, then it can't generalize at all because it doesn't have enough information. There is high variance with low bias. This results in overfitting and while it would probably show low accuracy in a large dataset, it becomes unpredictable in a small test dataset. This results in the jaggedness in the test curve.

We can also generate similar curves by changing the maximum depth hyperparameter:

```
In [49]: curve = runClassifier.hyperparamCurveSet(dt.DT({}), 'maxDepth', [1,2,4,6,8,12,16], data
         runClassifier.plotCurve('DT on Sentiment Data (hyperparameter)', curve)
```

```
Training classifier with maxDepth=1...
Training accuracy 0.6308333333333334, test accuracy 0.595
```

```
Training classifier with maxDepth=2...
Training accuracy 0.6675, test accuracy 0.5825
Training classifier with maxDepth=4...
Training accuracy 0.7325, test accuracy 0.63
Training classifier with maxDepth=6...
Training accuracy 0.79, test accuracy 0.6275
Training classifier with maxDepth=8...
Training accuracy 0.8233333333333334, test accuracy 0.6475
Training classifier with maxDepth=12...
Training accuracy 0.8658333333333333, test accuracy 0.64
Training classifier with maxDepth=16...
Training accuracy 0.8925, test accuracy 0.62
```



Now, the x-axis is the value of the maximum depth.

3.10 WU7 (3%):

You should see training accuracy monotonically increasing and test accuracy making something like a hill. Which of these is *guaranteed* to happen and which is just something we might expect to happen? Why?

Ans: Training acuraccy is guaranteed to be monotonically increasing as it will continue to overfit at higher depth. The test acuraccy graph is something we expect to happen but we cannot guarantee it. It depends on factors like if the test set is a good enough general representative of what the test set looks like. It hits the peak at the perfect fit, it will then typically start overfitting (to the training set) afterwards resulting in a loss of generalisation for test set.

4 Part 3: Nearest Neighbors (30 %)

4.1 3.1 Warm-up exercise (0%)

Our first task will be to use KNN to classify digits. In other words, we get an image of a hand-drawn digit (28x28 pixels, greyscale), and have to decide what digit it is. To make life simpler, we'll consider only the binary classification version, in two setups: (A) distinguishing ONEs from TWOs and (B) distinguishing TWOs from THREEs.

(A) In the data directory, you'll find two .png files that show the training data. We are displaying them here. Are there any digits that you, as a human, have difficulty distinguishing (if so, list the row/column, where 0,0 is the upper left and 9,9 is the bottom right). Which of these (1vs2 or 2vs3) do you expect to be a harder classification problem?

Ans A) (3,7), (4,6) and (4,0) in the (1vs2) and (0,0), (1,1), (6,2), (5,9), and (9,5) are harder to recognize especially without context. I think (2vs3) would be a harder classification problem due to the similarity of 2 and 3 in some cases.

(B) Let's verify that KNN does very well on training data. Run the following:

```
In [50]: import knn_warmup

         # importlib.reload(knn_warmup)

         tr = knn_warmup.loadDigitData("data/1vs2.tr")
         te = knn_warmup.loadDigitData("data/1vs2.tr", 100)
         allK = [1]
         print("\t".join([str(err) for err in knn_warmup.computeErrorRate(tr, te, allK)]))

         # 0.0
```

```
0.0
```

This says "do KNN, with 1vs2.tr as the training data and 1vs2.tr as the testing data, using K=1." The 0.0 is the error rate, which is zero. Verify the same thing for 2vs3.tr.

```
In [51]: import knn_warmup

         # importlib.reload(knn_warmup)

         tr = knn_warmup.loadDigitData("data/2vs3.tr")
         te = knn_warmup.loadDigitData("data/2vs3.tr", 100)
         allK = [1]
         print("\t".join([str(err) for err in knn_warmup.computeErrorRate(tr, te, allK)]))

         # 0.0
```

```
0.0
```

(C) The `knn_warmup.py` implementation will let you specify multiple values for K and get error rates for all of them. In particular, you can say something like:

```
In [52]: allK = [1,5,10,25,50,100]
         print("\t".join([str(err) for err in knn_warmup.computeErrorRate(tr, te, allK)]))

         # 0.0        0.08        0.12        0.16        0.28        0.5

0.0        0.03        0.06        0.07        0.16        0.5
```

This runs the same thing for six values of K (1, 5, ..., 100) and prints the respective error rates. Notice that for K=100 the error rate is 50% -- why does this happen?

Ans: As K increases, the model gets more underfit as it becomes more simpler. At the same time, it is overfit for lower values for K like K=1.

(D) Repeat the same exercise, this time evaluating on the development data, and using odd values of K ranging from 1 to 21. Do this for both 1vs2 and 2vs3. Which one is harder? For each, what is the optimal value of K? (In the case of ties, how would you choose to break ties?)

Ans: is harder. The optimal value of K for (1vs2) is and the optimal value for K for (2vs3) is . In case of ties, we can break them by .

```
In [53]: tr = knn_warmup.loadDigitData("data/1vs2.tr")
         te = knn_warmup.loadDigitData("data/1vs2.de", 100)
         allK = [1,3,5,7,9,11,13,15,17,19,21]
         print("\t".join([str(err) for err in knn_warmup.computeErrorRate(tr, te, allK)]))

0.04        0.06        0.08        0.1        0.12        0.14        0.16        0.16        0
```

```
In [54]: tr = knn_warmup.loadDigitData("data/2vs3.tr")
         te = knn_warmup.loadDigitData("data/2vs3.de", 100)
         allK = [1,3,5,7,9,11,13,15,17,19,21]
         print("\t".join([str(err) for err in knn_warmup.computeErrorRate(tr, te, allK)]))

0.1        0.04        0.06        0.06        0.08        0.04        0.08        0.06        0
```

(E) Now, go edit knn_warmup.py. This might take a bit of effort since you'll have to figure out what it's doing. But the function I want you to look at is "classifyKNN." This takes D (the training data) and knn (the list of the K nearest neighbors, together with their distances). It iterates over each of the (dist,n) nearest neighbors. Here, dist is the distance and n is the training example id, so D[n] is the corresponding training example. It then "votes" this into a prediction `yhat`.

Modify this function so that each example gets a weighted vote, where its weight is equal to exp(-dist). This should be a one- or two-liner.

Rerun the same experiments as in (D). Does this help or hurt? What do you observe as K gets larger and WHY do you observe this?

Ans:

If you want to play around, try exp(-dist / CONSTANT) where CONSTANT now is a hyperparameter. What happens as CONSTANT tends toward zero? Tends toward infinity?

Ans:

4.2 3.2 Implementing a KNN classifier (20%)

To get started with geometry-based classification, we will implement a nearest neighbor classifier that supports KNN classification.
This should go in `knn.py`. The only function here that you have to do anything about is the `predict` function, which does all the work.

In order to test your implementation, here are some outputs:

```
In [55]: import knn
         runClassifier.trainTestSet(knn.KNN({'isKNN': True, 'K': 1}), datasets.TennisData)
         #Training accuracy 1, test accuracy 1
         runClassifier.trainTestSet(knn.KNN({'isKNN': True, 'K': 3}), datasets.TennisData)
         #Training accuracy 0.785714, test accuracy 0.833333
         runClassifier.trainTestSet(knn.KNN({'isKNN': True, 'K': 5}), datasets.TennisData)
         #Training accuracy 0.857143, test accuracy 0.833333
```

```
Training accuracy 1.0, test accuracy 1.0
Training accuracy 0.7857142857142857, test accuracy 0.8333333333333334
Training accuracy 0.8571428571428571, test accuracy 0.8333333333333334
```

You can also try it on the digits data:

```
In [56]: runClassifier.trainTestSet(knn.KNN({'isKNN': True, 'K': 1}), datasets.DigitData)
         # Training accuracy 1, test accuracy 0.94
         runClassifier.trainTestSet(knn.KNN({'isKNN': True, 'K': 3}), datasets.DigitData)
         # Training accuracy 0.94, test accuracy 0.93
         runClassifier.trainTestSet(knn.KNN({'isKNN': True, 'K': 5}), datasets.DigitData)
         # Training accuracy 0.92, test accuracy 0.92
```

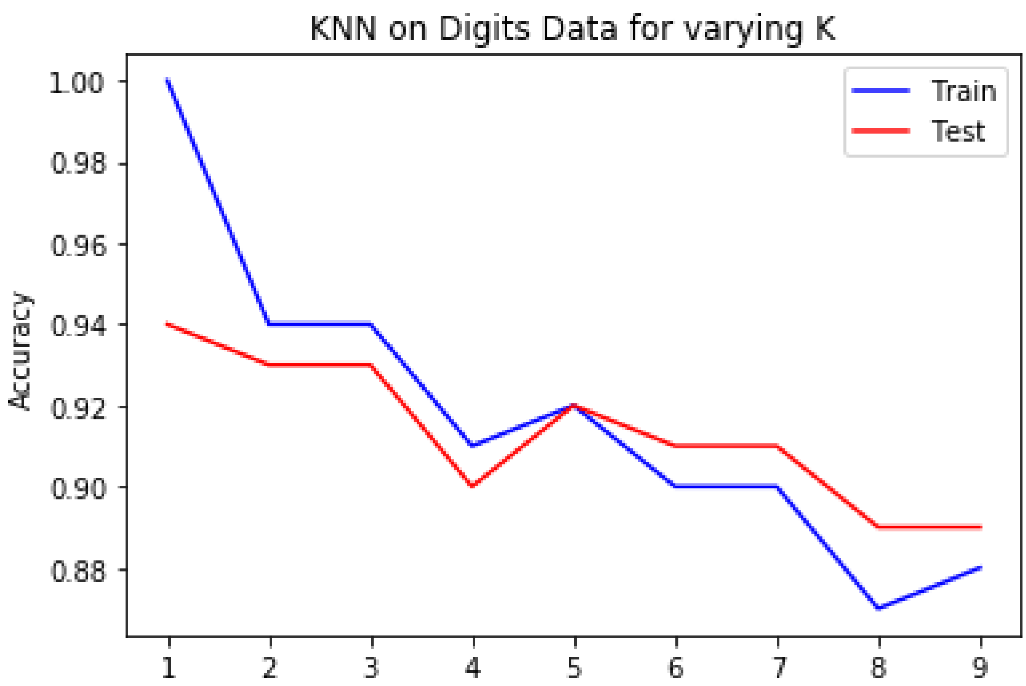
```
Training accuracy 1.0, test accuracy 0.94
Training accuracy 0.94, test accuracy 0.93
Training accuracy 0.92, test accuracy 0.92
```

4.3 WU8 (5%):

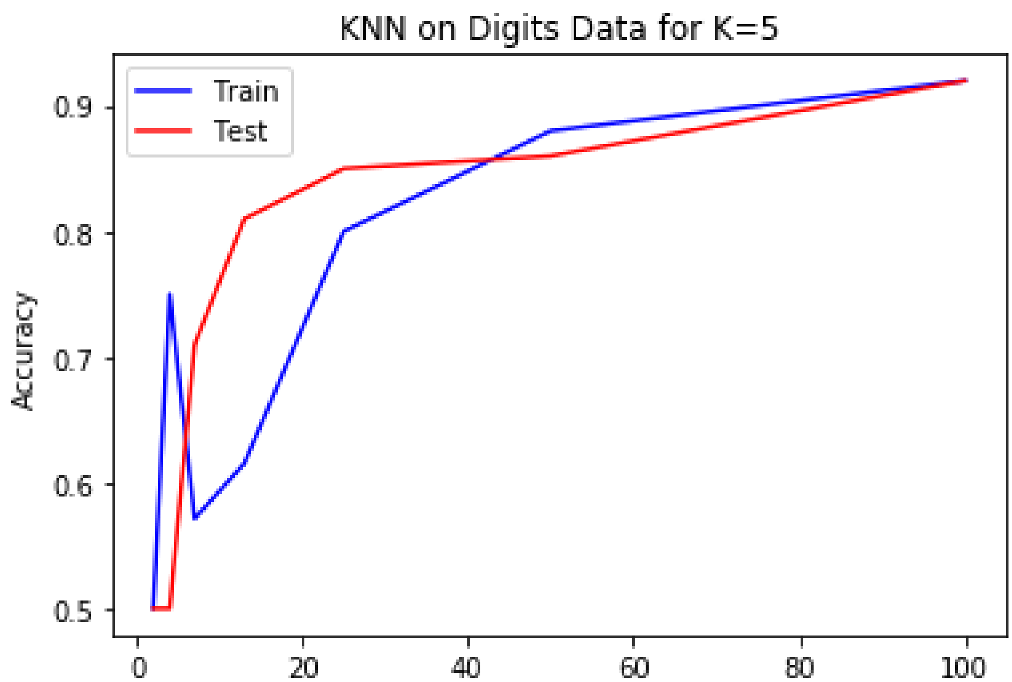
For the digits data, generate train/test curves for varying values of K (you figure out what are good ranges, this time). Include those curves. Do you see evidence of overfitting and underfitting? Next, using K=5, generate learning curves for this data.

In [57]:
```
curve = runClassifier.hyperparamCurveSet(knn.KNN({'isKNN': True}), 'K', range(1,10), da
runClassifier.plotCurve('KNN on Digits Data for varying K', curve)
curve = runClassifier.learningCurveSet(knn.KNN({'isKNN': True, 'K': 5}), datasets.Digit
runClassifier.plotCurve('KNN on Digits Data for K=5', curve)
```

```
Training classifier with K=1...
Training accuracy 1.0, test accuracy 0.94
Training classifier with K=2...
Training accuracy 0.94, test accuracy 0.93
Training classifier with K=3...
Training accuracy 0.94, test accuracy 0.93
Training classifier with K=4...
Training accuracy 0.91, test accuracy 0.9
Training classifier with K=5...
Training accuracy 0.92, test accuracy 0.92
Training classifier with K=6...
Training accuracy 0.9, test accuracy 0.91
Training classifier with K=7...
Training accuracy 0.9, test accuracy 0.91
Training classifier with K=8...
Training accuracy 0.87, test accuracy 0.89
Training classifier with K=9...
Training accuracy 0.88, test accuracy 0.89
```



```
Training classifier on 2 points...
Training accuracy 0.5, test accuracy 0.5
Training classifier on 4 points...
Training accuracy 0.75, test accuracy 0.5
Training classifier on 7 points...
Training accuracy 0.5714285714285714, test accuracy 0.71
Training classifier on 13 points...
Training accuracy 0.6153846153846154, test accuracy 0.81
Training classifier on 25 points...
Training accuracy 0.8, test accuracy 0.85
Training classifier on 50 points...
Training accuracy 0.88, test accuracy 0.86
Training classifier on 100 points...
Training accuracy 0.92, test accuracy 0.92
```



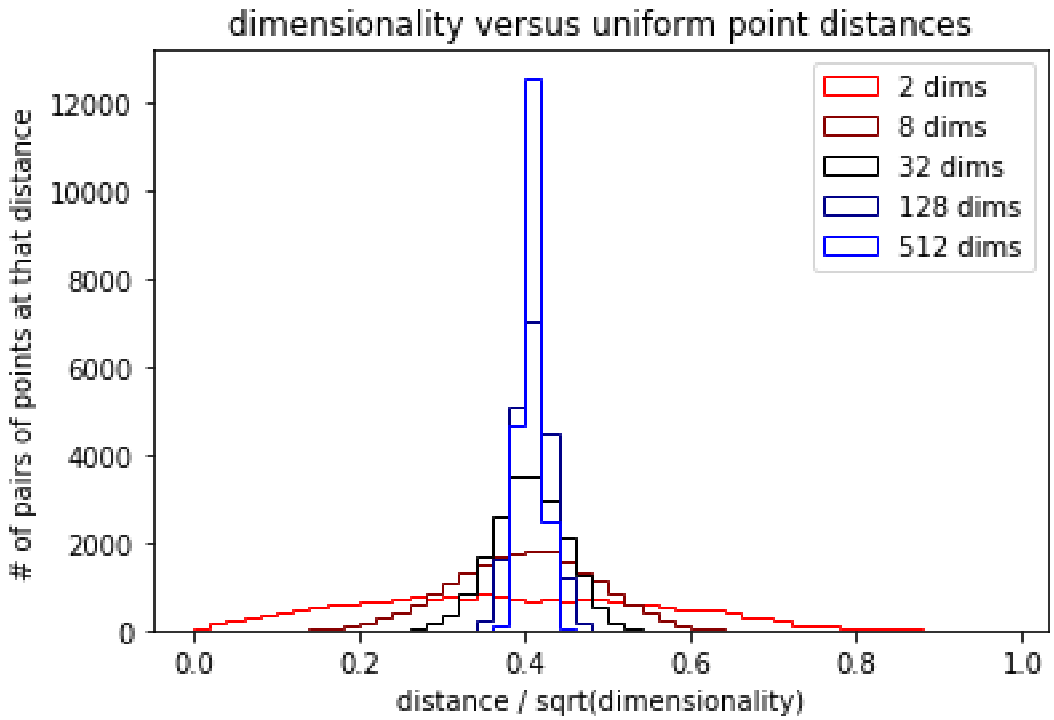
4.4 3.3 The curse of dimensionality (10%)

If you have numpy and matplotlib correctly installed, you should be able to run the code in the following cell and get a picture of five histograms. Open up `HighD.py` to understand what's being plotted. Essentially, it's generating 200 random points in D dimensions (where D is being varied) and computing pairwise distances between these points.

```
In [58]: import HighD
         from pylab import *
```

```
N    = 200                      # number of examples
Dims = [2, 8, 32, 128, 512]    # dimensionalities to try
Cols = ['#FF0000', '#880000', '#000000', '#000088', '#0000FF']
Bins = arange(0, 1, 0.02)

plt.xlabel('distance / sqrt(dimensionality)')
plt.ylabel('# of pairs of points at that distance')
plt.title('dimensionality versus uniform point distances')

for i,d in enumerate(Dims):
    distances = HighD.computeDistances(HighD.generateUniformDataset(d, N))
    print("D={0}, average distance={1}".format(d, mean(distances) * sqrt(d)))
    plt.hist(distances,
             Bins,
             histtype='step',
             color=Cols[i])
    if HighD.waitForEnter:
        plt.legend(['%d dims' % d for d in Dims])
        plt.show(False)
        x = raw_input('Press enter to continue...')


plt.legend(['%d dims' % d for d in Dims])
plt.savefig('fig.pdf')
plt.show()
```

```
D=2, average distance=0.5360371129024422
D=8, average distance=1.1265110358964068
D=32, average distance=2.2855457744987264
D=128, average distance=4.617685224911755
D=512, average distance=9.225537236709732
```



As you can see in the histograms, as the dimensionality increases, the distances between pairs of points become more or less concentrated around a single value.

In the code, instead of plotting distance on the x-axis, we're plotting (distance/sqrt(D)). Why is this the right thing to do?

Ans: This normalizes the plot on x-axis.

The goal here is to look at whether what we found for uniformly random data points holds for naturally occurring data (like the digits data) too! We must hope that it doesn't, otherwise KNN has no hope of working, but let's verify.

The problem is: the digits data is 784 dimensional, period, so it's not obvious how to try "different dimensionalities." For now, we will do the simplest thing possible: if we want to have 128 dimensions, we will just select 128 features randomly.

This is your task, which you can accomplish by munging together `HighD.py` and `KNN.py` and making appropriate modifications.

4.5 WU9 (10%):

A. First, get a histogram of the raw digits data in 784 dimensions. You'll probably want to use the `exampleDistance` function from KNN together with the plotting in `HighD`.

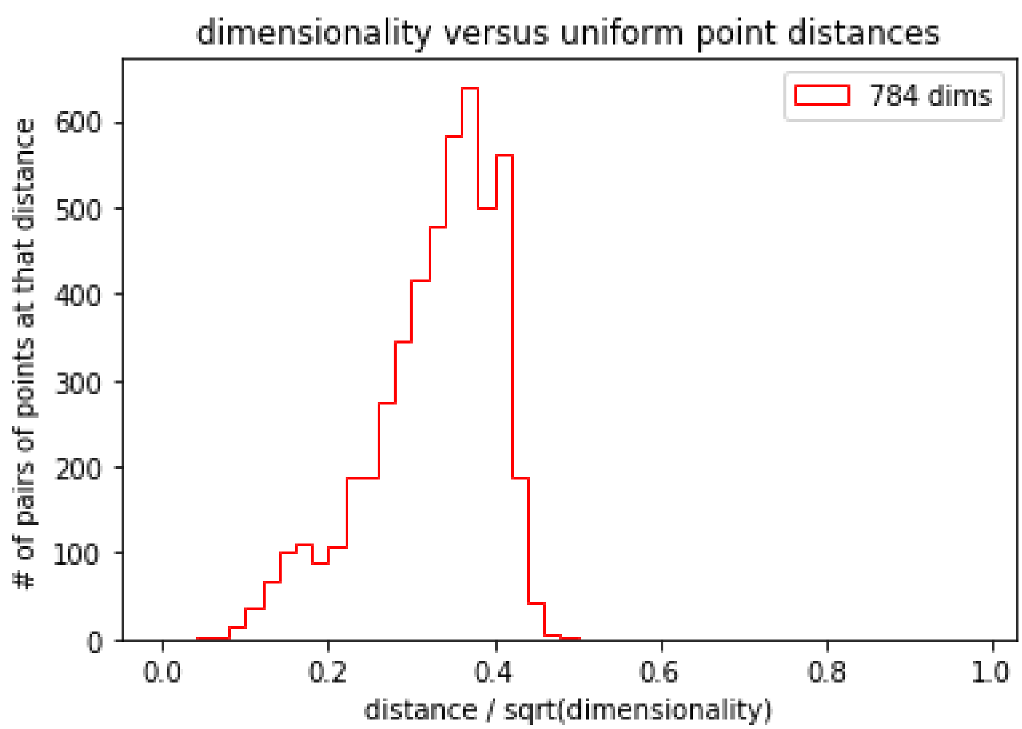
B. Extend `exampleDistance` so that it can subsample features down to some fixed dimensionality. For example, you might write `subsampleExampleDistance(x1,x2,D)`, where `D` is the target dimensionality. In this function, you should pick `D` dimensions at random (I would suggest generating a permutation of the number [1..784] and then taking the first D of them), and then compute the distance but *only* looking at those dimensions.

C. Generate an equivalent plot to HighD with D in [2, 8, 32, 128, 512] but for the digits data rather than the random data. Include a copy of both plots and describe the differences.

```
In [19]: import HighD, datasets, knn
         from pylab import *

         def exampleDistance(x1, x2):
             dist = 0.
             for i,v1 in x1.items():
                 v2 = 0.
                 if i in x2: v2 = x2[i]
                 dist += (v1 - v2) * (v1 - v2)
             for i,v2 in x2.items():
                 if not i in x1:
                     dist += v2 * v2
             return sqrt(dist)

         def loadDigitData(filename, maxExamples=100000):
             h = open(filename, 'r')
             D = []
             for l in h.readlines():
                 a = l.split()
                 if len(a) > 1:
                     y = float(a[0])
                     if y > 0.5: y = 1.
                     else: y = -1.
                     x = {}
                     for i in range(1, len(a)):
                         v = float(a[i]) / 255.
                         if v > 0.:
                             x[i] = v
                     D.append( (x,y) )
                     if len(D) >= maxExamples:
                         break
             h.close()
             return D
         #B
         def subsampleExampleDistance(x1,x2,D):
             permutedArray = np.random.permutation(784)
             newX1 = {}
             newX2 = {}
             for n in range(D):
                 permutedKey = permutedArray[n]
                 if permutedKey in x1 and permutedKey in x2:
                     newX1[n+1]  = x1[permutedKey]
                     newX2[n+1] = x2[permutedKey]

             return exampleDistance(newX1, newX2)/sqrt(D)

         data = loadDigitData('data/1vs2.tr')
         N = len(data)
```

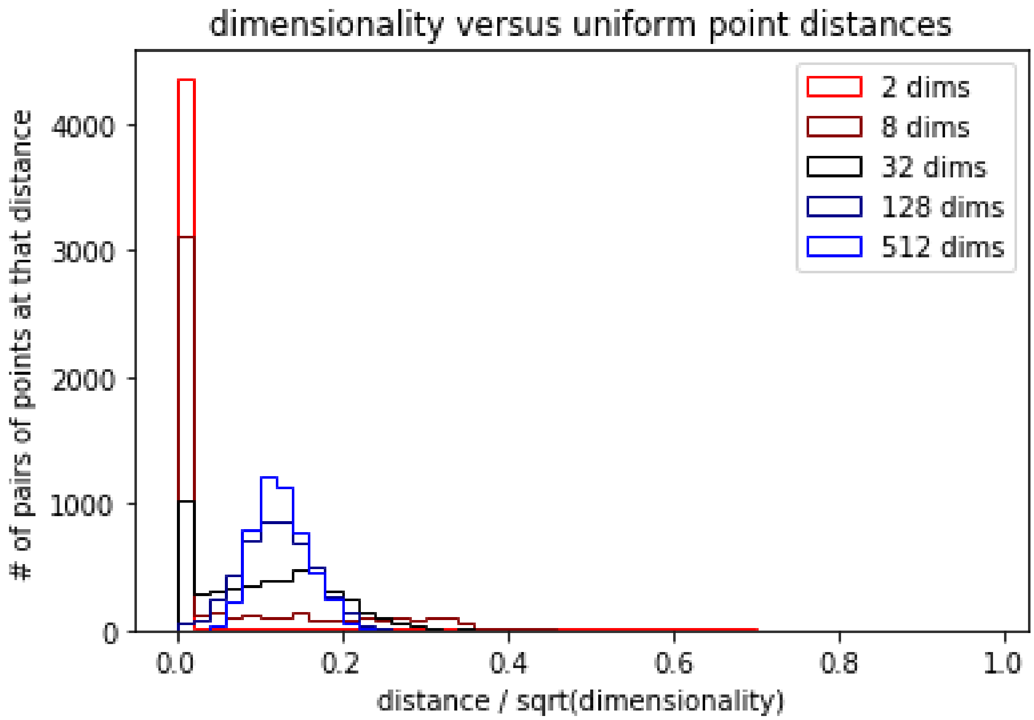
```
D = 784
Bins = arange(0, 1, 0.02)
Cols = ['#FF0000', '#880000', '#000000', '#000088', '#0000FF']
distances = []

plt.xlabel('distance / sqrt(dimensionality)')
plt.ylabel('# of pairs of points at that distance')
plt.title('dimensionality versus uniform point distances')


for n in range(N):
    for m in range(n):
        distances.append(exampleDistance(data[n][0],data[m][0])  / sqrt(D))

#     distances = computeDistances(datasets.DigitData.X)
print("D={0}, average distance={1}".format(D, mean(distances) * sqrt(D)))
plt.hist(distances,
         Bins,
         histtype='step',
         color=Cols[0])

plt.legend(['%d dims' %D])
plt.savefig('fig.pdf')
plt.show()
```

```
D=784, average distance=9.107636155102968
```



```
In [20]: # N = len(data)
         Dims = [2, 8, 32, 128, 512]    # dimensionalities to try

         plt.xlabel('distance / sqrt(dimensionality)')
         plt.ylabel('# of pairs of points at that distance')
         plt.title('dimensionality versus uniform point distances')

         for i,d in enumerate(Dims):
             distancesSubsampled = []
             for n in range(N):
                 for m in range(n):
                     distancesSubsampled.append(subsampleExampleDistance(data[n][0],data[m][0],

             print("D={0}, average distance={1}".format(d, mean(distancesSubsampled) * sqrt(d)))
             plt.hist(distancesSubsampled,
                      Bins,
                      histtype='step',
                      color=Cols[i])




         plt.legend(['%d dims' % d for d in Dims])
         plt.savefig('fig.pdf')
         plt.show()
```

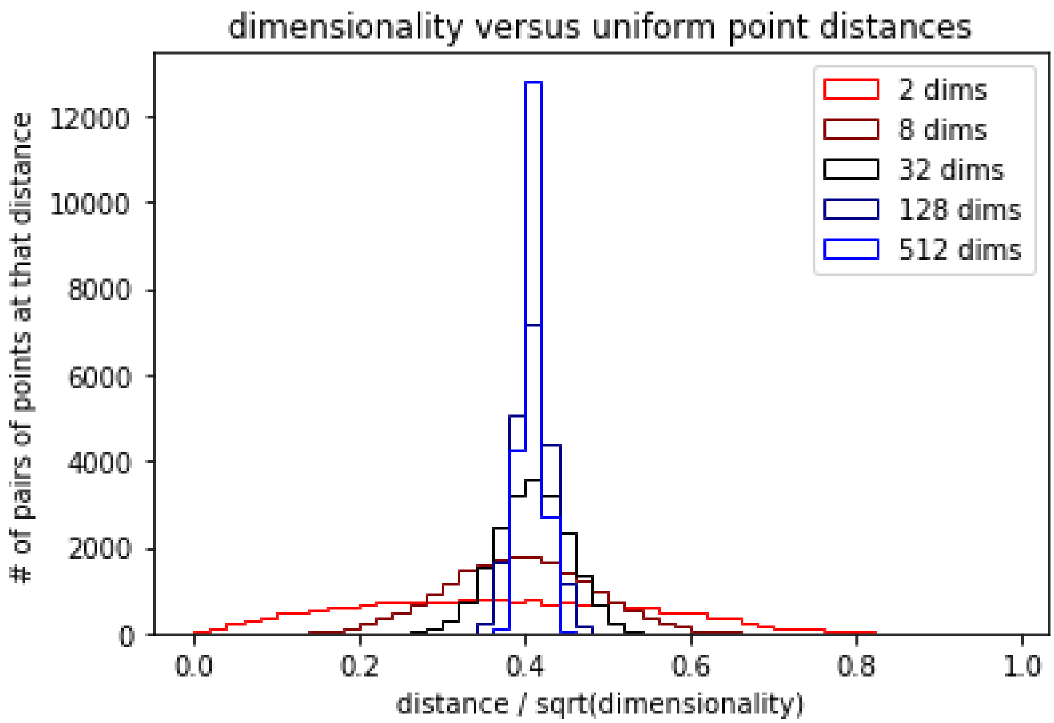
```
D=2, average distance=0.054268710911648116
D=8, average distance=0.19502377406119487
D=32, average distance=0.6017041229572433
D=128, average distance=1.3866488425084762
D=512, average distance=2.8594728069603863
```




```
In [66]: N    = 200                      # number of examples
         Dims = [2, 8, 32, 128, 512]    # dimensionalities to try
         Cols = ['#FF0000', '#880000', '#000000', '#000088', '#0000FF']
         Bins = arange(0, 1, 0.02)

         plt.xlabel('distance / sqrt(dimensionality)')
         plt.ylabel('# of pairs of points at that distance')
         plt.title('dimensionality versus uniform point distances')

         for i,d in enumerate(Dims):
             distances = HighD.computeDistances(HighD.generateUniformDataset(d, N))
             print("D={0}, average distance={1}".format(d, mean(distances) * sqrt(d)))
             plt.hist(distances,
                      Bins,
                      histtype='step',
                      color=Cols[i])



         plt.legend(['%d dims' % d for d in Dims])
         plt.savefig('fig.pdf')
         plt.show()
```

```
D=2, average distance=0.521547957791999
```

```
D=8, average distance=1.1082658608971436
D=32, average distance=2.3102084907640426
D=128, average distance=4.6167027921775405
D=512, average distance=9.239479388643732
```



Ans: The plots have the digits datapoints at higher dimensions crowding at a particular distance close to 0 but also spreads across (especially at higher dimensions), while the random data is spread across at lower dimensions and starts to crowd around at higher dimensions at 0.5 distance. The digits data is a real world data which has also been subsampled. It shows a more real spread than crowding around a distance.

5 Part 4: Perceptron (20%)

This final section is all about using perceptrons to make predictions. You are given a partial perceptron implementation in `perceptron.py`.

The last implementation you have is for the perceptron; see `perceptron.py` where you will have to implement part of the `nextExample` function to make a perceptron-style update.

Once you've implemented this, the magic in the `Binary` class will handle training on datasets for you, as long as you specify the number of epochs (passes over the training data) to run:

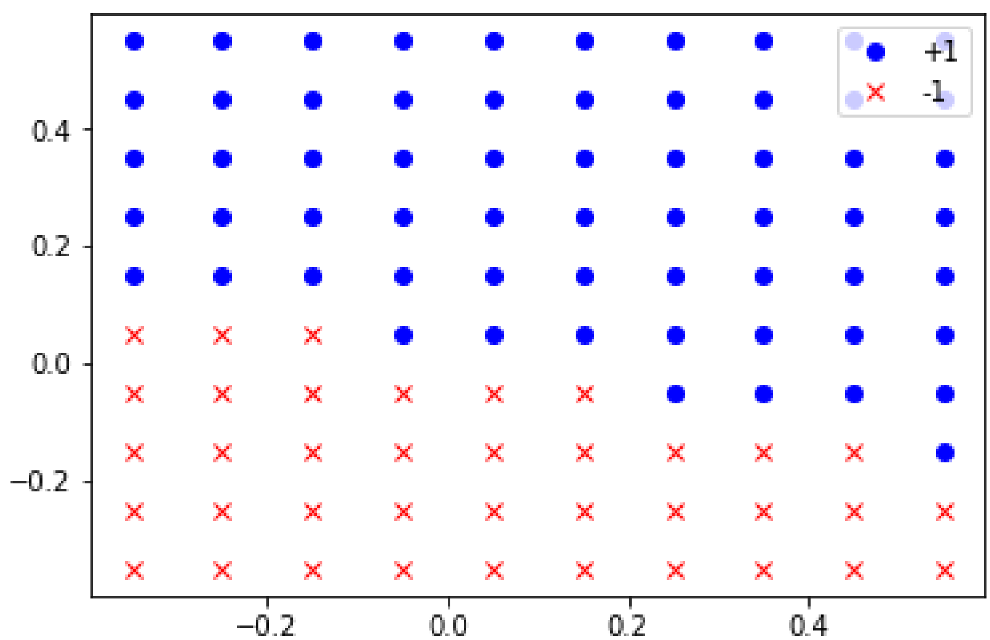
```
In [60]: # import runClassifier, perceptron, datasets
         # from pylab import *
         # import importlib
```

```
# importlib.reload(perceptron)
import perceptron

runClassifier.trainTestSet(perceptron.Perceptron({'numEpoch': 1}), datasets.TennisData)
# Training accuracy 0.642857, test accuracy 0.666667
runClassifier.trainTestSet(perceptron.Perceptron({'numEpoch': 2}), datasets.TennisData)
# Training accuracy 0.857143, test accuracy 1
```

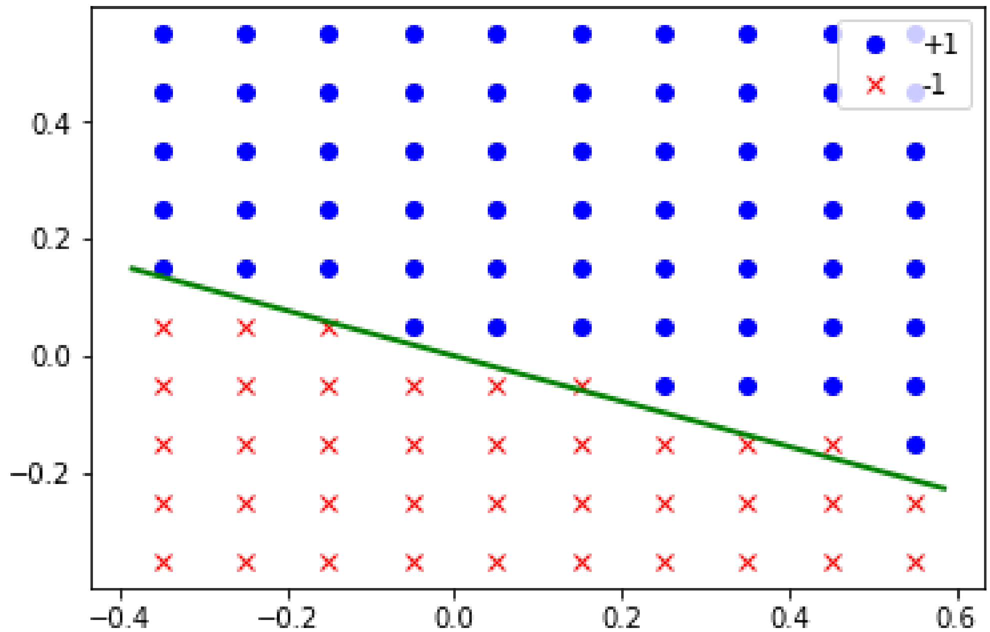
```
Training accuracy 0.6428571428571429, test accuracy 0.6666666666666666
Training accuracy 0.8571428571428571, test accuracy 1.0
```

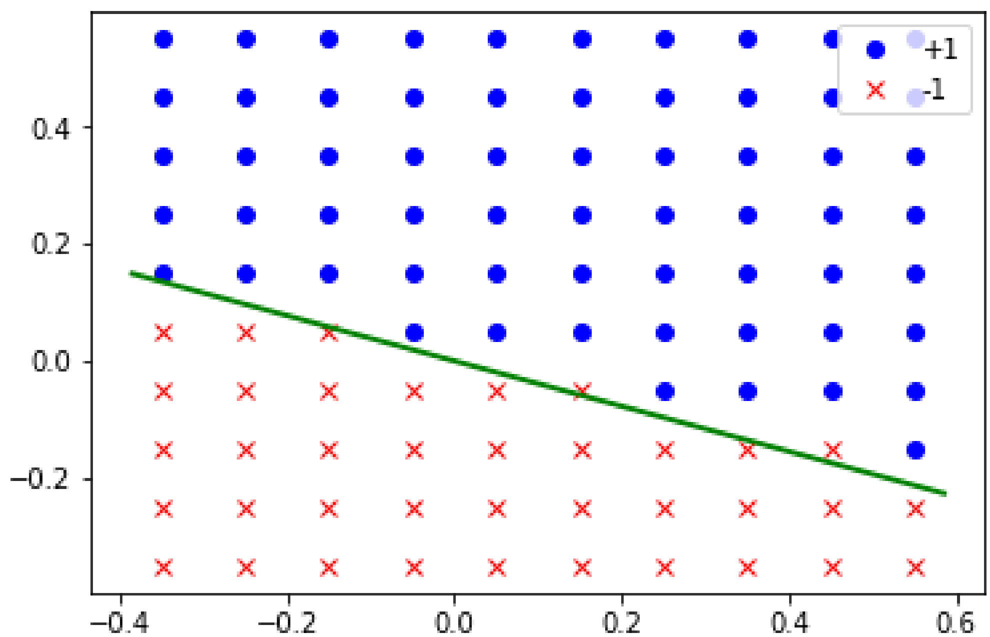
You can view its predictions on the two dimensional data sets:

```
In [61]: runClassifier.plotData(datasets.TwoDDiagonal.X, datasets.TwoDDiagonal.Y)
         h = perceptron.Perceptron({'numEpoch': 200})
         h.train(datasets.TwoDDiagonal.X, datasets.TwoDDiagonal.Y)
         print(h)
         # w=array([  7.3,  18.9]), b=0.0
         runClassifier.plotClassifier(array([ 7.3, 18.9]), 0.0)
```




```
w=array([ 7.3, 18.9]), b=0.0
```





You should see a linear separator that does a pretty good (but not perfect!) job classifying this data.

Finally, we can try it on the sentiment data:

```
In [62]: runClassifier.trainTestSet(perceptron.Perceptron({'numEpoch': 1}), datasets.SentimentDa
         # Training accuracy 0.835833, test accuracy 0.755
         runClassifier.trainTestSet(perceptron.Perceptron({'numEpoch': 2}), datasets.SentimentDa
         # Training accuracy 0.955, test accuracy 0.7975
```

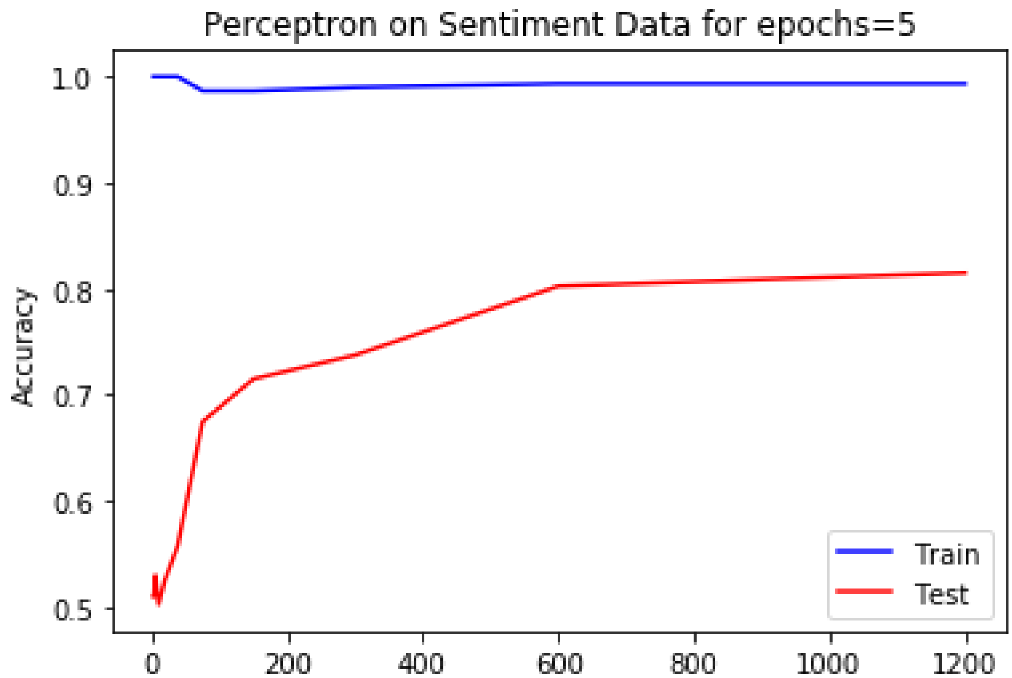
```
Training accuracy 0.8358333333333333, test accuracy 0.755
Training accuracy 0.955, test accuracy 0.7975
```

5.1 WU10 (5%):

Using the tools provided, generate (a) a learning curve (x-axis=number of training examples) for the perceptron (5 epochs) on the sentiment data and (b) a plot of number of epochs versus train/test accuracy on the entire dataset.

```
In [63]: #A
         curve = runClassifier.learningCurveSet(perceptron.Perceptron({'numEpoch': 5}),datasets.
         runClassifier.plotCurve('Perceptron on Sentiment Data for epochs=5', curve)

         #B
         curve = runClassifier.hyperparamCurveSet(perceptron.Perceptron({'numEpoch': 1}), 'numEp
         runClassifier.plotCurve('Perceptron on Sentiment Data for varying epochs', curve)
```

```
Training classifier on 2 points...
Training accuracy 1.0, test accuracy 0.51
Training classifier on 3 points...
Training accuracy 1.0, test accuracy 0.51
Training classifier on 5 points...
Training accuracy 1.0, test accuracy 0.53
Training classifier on 10 points...
Training accuracy 1.0, test accuracy 0.5025
Training classifier on 19 points...
Training accuracy 1.0, test accuracy 0.525
Training classifier on 38 points...
Training accuracy 1.0, test accuracy 0.5575
Training classifier on 75 points...
Training accuracy 0.9866666666666667, test accuracy 0.675
Training classifier on 150 points...
Training accuracy 0.9866666666666667, test accuracy 0.715
Training classifier on 300 points...
Training accuracy 0.99, test accuracy 0.7375
Training classifier on 600 points...
Training accuracy 0.9933333333333333, test accuracy 0.8025
Training classifier on 1200 points...
Training accuracy 0.9933333333333333, test accuracy 0.815
```




```
Training classifier with numEpoch=1...
Training accuracy 0.8358333333333333, test accuracy 0.755
Training classifier with numEpoch=2...
Training accuracy 0.955, test accuracy 0.7975
Training classifier with numEpoch=3...
Training accuracy 0.9366666666666666, test accuracy 0.755
Training classifier with numEpoch=4...
Training accuracy 0.995, test accuracy 0.8125
Training classifier with numEpoch=5...
Training accuracy 0.9933333333333333, test accuracy 0.815
Training classifier with numEpoch=6...
Training accuracy 0.9941666666666666, test accuracy 0.7875
Training classifier with numEpoch=7...
Training accuracy 0.9933333333333333, test accuracy 0.78
Training classifier with numEpoch=8...
Training accuracy 1.0, test accuracy 0.81
Training classifier with numEpoch=9...
Training accuracy 1.0, test accuracy 0.81
Training classifier with numEpoch=10...
Training accuracy 1.0, test accuracy 0.81
Training classifier with numEpoch=11...
Training accuracy 1.0, test accuracy 0.81
Training classifier with numEpoch=12...
Training accuracy 1.0, test accuracy 0.81
Training classifier with numEpoch=13...
```

```
Training accuracy 1.0, test accuracy 0.81
Training classifier with numEpoch=14...
Training accuracy 1.0, test accuracy 0.81
```