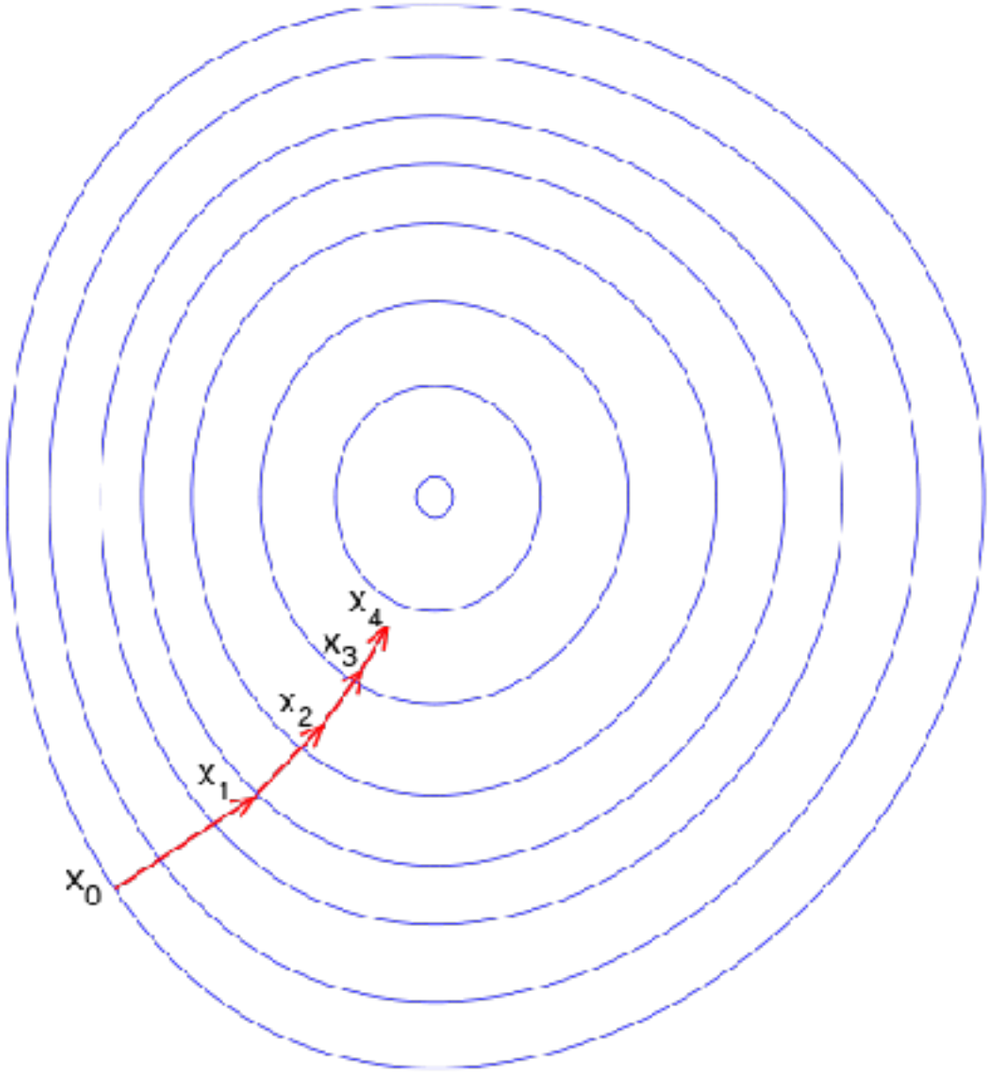
MINIMIZING LOSS THROUGH GRADIENT DESCENT

GRADIENT DESCENT

- Gradient Descent can also help us minimize error.

- How Gradient Descent works:
  - A random linear solution is provided as a starting point
  - The solver attempts to find a next “step”: take a step in any direction and measure the performance.
  - If the solver finds a better solution (i.e. lower MSE), this is the new starting point.
  - Repeat these steps until the performance is optimized and no “next steps” perform better. The size of steps will shrink over time.

GRADIENT DESCENT



A CODE EXAMPLE OF GRADIENT DESCENT

```
num_to_approach, start, steps, optimized = 6.2, 0., [-1, 1], False
while not optimized:
    current_distance = num_to_approach - start
    got_better = False
    next_steps = [start + i for i in steps]
    for n in next_steps:
        distance = np.abs(num_to_approach - n)
        if distance < current_distance:
            got_better = True
            print distance, 'is better than', current_distance
            current_distance = distance
            start = n
```

A CODE EXAMPLE OF GRADIENT DESCENT

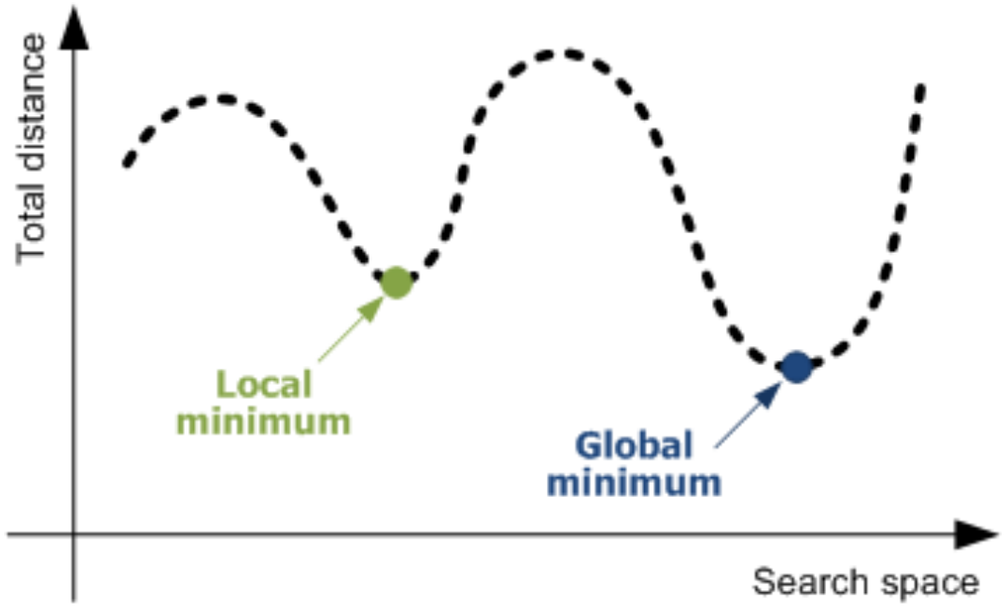
```
    if got_better:
        print 'found better solution! using', current_distance
        a += 1
    else:
        optimized = True
        print start, 'is closest to', num_to_approach
```

- What is the code doing? What could go wrong?

GLOBAL VS LOCAL MINIMUMS

- Gradient Descent could solve for a *local* minimum instead of a *global* minimum.

- A *local* minimum is confined to a very specific subset of solutions. The *global* minimum considers all solutions. These could be equal, but that's not always true.



DEMO

APPLICATION OF GRADIENT DESCENT

APPLICATION OF GRADIENT DESCENT

- Gradient Descent works best when:
  - We are working with a large dataset. Smaller datasets are more prone to error.
  - Data is cleaned up and normalized.
- Gradient Descent is significantly faster than OLS. This becomes important as data gets bigger.

APPLICATION OF GRADIENT DESCENT

- We can easily run a Gradient Descent regression.

- Note: The verbose argument can be set to 1 to see the optimization steps.

```
lm = linear_model.SGDRegressor()
lm.fit(modeldata, y)
print lm.score(modeldata, y)
print metrics.mean_squared_error(y, lm.predict(modeldata))
```

- Untuned, how well did gradient descent perform compared to OLS?

APPLICATION OF GRADIENT DESCENT

- Gradient Descent can be tuned with
  - the learning rate: how aggressively we solve the problem
  - epsilon: at what point do we say the error margin is acceptable
  - iterations: when should be we stop no matter what

INDEPENDENT PRACTICE

ON YOUR OWN

ACTIVITY: ON YOUR OWN

DIRECTIONS (30 minutes)

There are tons of ways to approach a regression problem.

1. Implement the Gradient Descent approach to our bikeshare modeling problem.
2. Show how Gradient Descent solves and optimizes the solution.
3. Demonstrate the grid_search module.
4. Use a model you evaluated last class or the simpler one from today. Implement param_grid in grid search to answer the following questions:
    a. With a set of values between 10 ^ -10 and 10 ^ -1, how does MSE change?
    b. Our data suggests we use L1 regularization. Using a grid search with l1_ratios between 0 and 1, increasing every 0.05, does this statement hold true? If not, did gradient descent have enough iterations to work properly?
    c. How do these results change when you alter the learning rate?

DELIVERABLE

Gradient Descent approach and answered questions

ACTIVITY: ON YOUR OWN

Starter Code

```
params = {} # put your gradient descent parameters here
gs = grid_search.GridSearchCV(
    estimator=linear_model.SGDRegressor(),
    cv=cross_validation.KFold(len(modeldata), n_folds=5, shuffle=True),
    param_grid=params,
    scoring='mean_squared_error',
    )

gs.fit(modeldata, y)

print 'BEST ESTIMATOR'
print -gs.best_score_
print gs.best_estimator_
print 'ALL ESTIMATORS'
print gs.grid_scores_
```

TOPIC REVIEW

LESSON REVIEW

- What's the (typical) range of r-squared?
- What's the range of mean squared error?
- How would changing the scale or interpretation of y (your target variable) effect mean squared error?
- What's cross validation, and why do we use it in machine learning?
- What is error due to bias? What is error due to variance? Which is better for a model to have, if it had to have one?
- How does gradient descent try a different approach to minimizing error?

GENERAL ASSEMBLY

INTRO TO CLASSIFICATION

Naumaan Nayyar

LEARNING OBJECTIVES

- Define class label and classification
- Build a K-Nearest Neighbors using the sci-kit-learn library
- Evaluate and tune model by using metrics such as classification accuracy/error

COURSE

PRE-WORK

PRE-WORK REVIEW

- Understand how to optimize for error in a model
- Understand the concept of iteration to solve problems
- Measure basic probability

OPENING

INTRO TO CLASSIFICATION

INTRO TO CLASSIFICATION

- So far, we've worked primarily with regression problems. We've focused on predicting a continuous set of values.

- That means we've been able to use distance to measure how accurate our prediction is.

- However, for other problems, we need to predict binary responses. E.g.: A loan will default or it won't. An email is spam or isn't spam.

ACTIVITY: KNOWLEDGE CHECK

ANSWER THE FOLLOWING QUESTIONS

1. What if we want to build a model to predict a set of values, like a photo color or the gender of a baby?
2. Can we use regression for binary values?
3. Do the same principles apply?

DELIVERABLE

Answers to the above questions

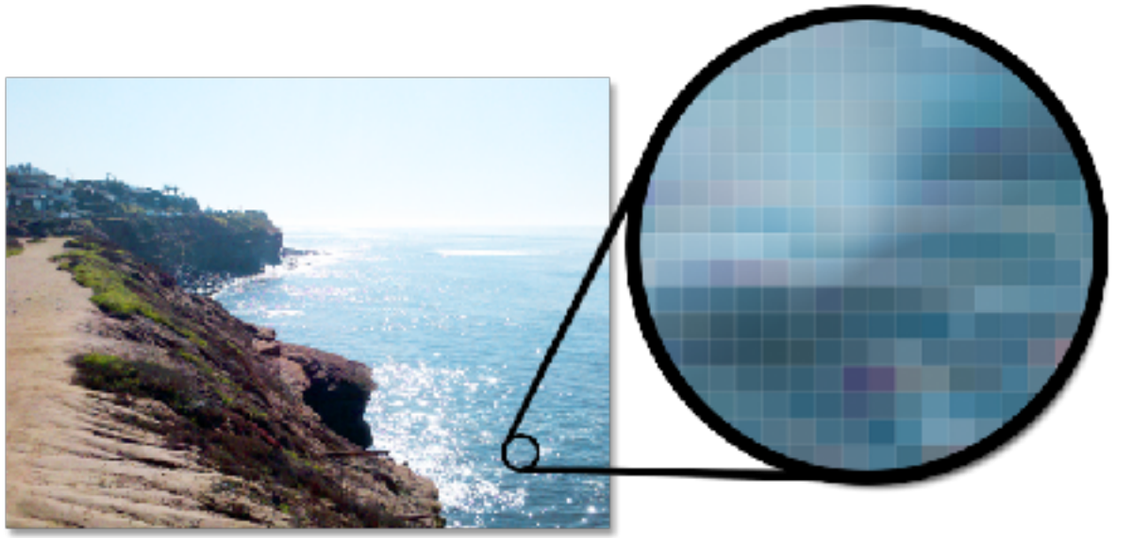
WHAT IS CLASSIFICATION?

WHAT IS CLASSIFICATION?

- **Classification** is a machine learning problem for solving a set value given the knowledge we have about that value.
- Many classification problems are trying to predict *binary* values.
- For example, we may be using patient data (medical history) to predict whether the patient is a smoker or not.

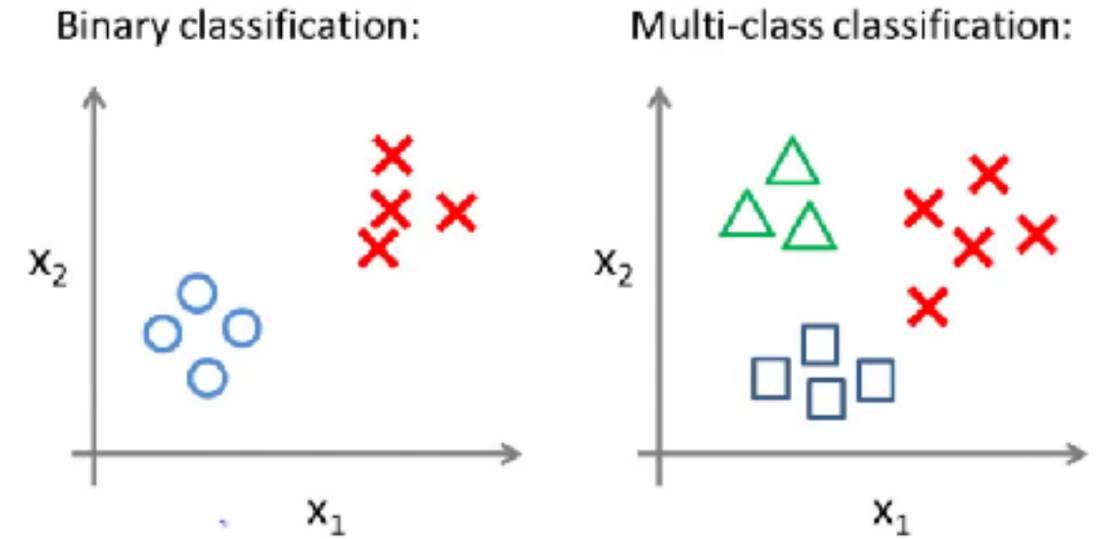
WHAT IS CLASSIFICATION?

- Some problems don't appear to be binary at first glance. However, you can boil down the response to a *boolean* (true/false) value.
- What if you are predicting whether an image pixel will be `red` or `blue`?
- We don't need to predict that a pixel is `blue`, just that it is not `red`.
- This is similar to the concept of dummy variables.



WHAT IS CLASSIFICATION?

- Binary classification is the simplest form of classification.
- However, classification problems can have multiple *class labels*.
- Instead of predicting whether the pixel is red or blue, you could predict whether the pixel is red, blue, or green.



WHAT IS A CLASS LABEL?

- A **class label** is a representation of what we are trying to predict: our *target*.

- Examples of class labels from before are:

Data Problem	Class Labels
Patient data problem	is smoker, is not smoker
pixel color	red, blue, green

DETERMINING REGRESSION OR CLASSIFICATION

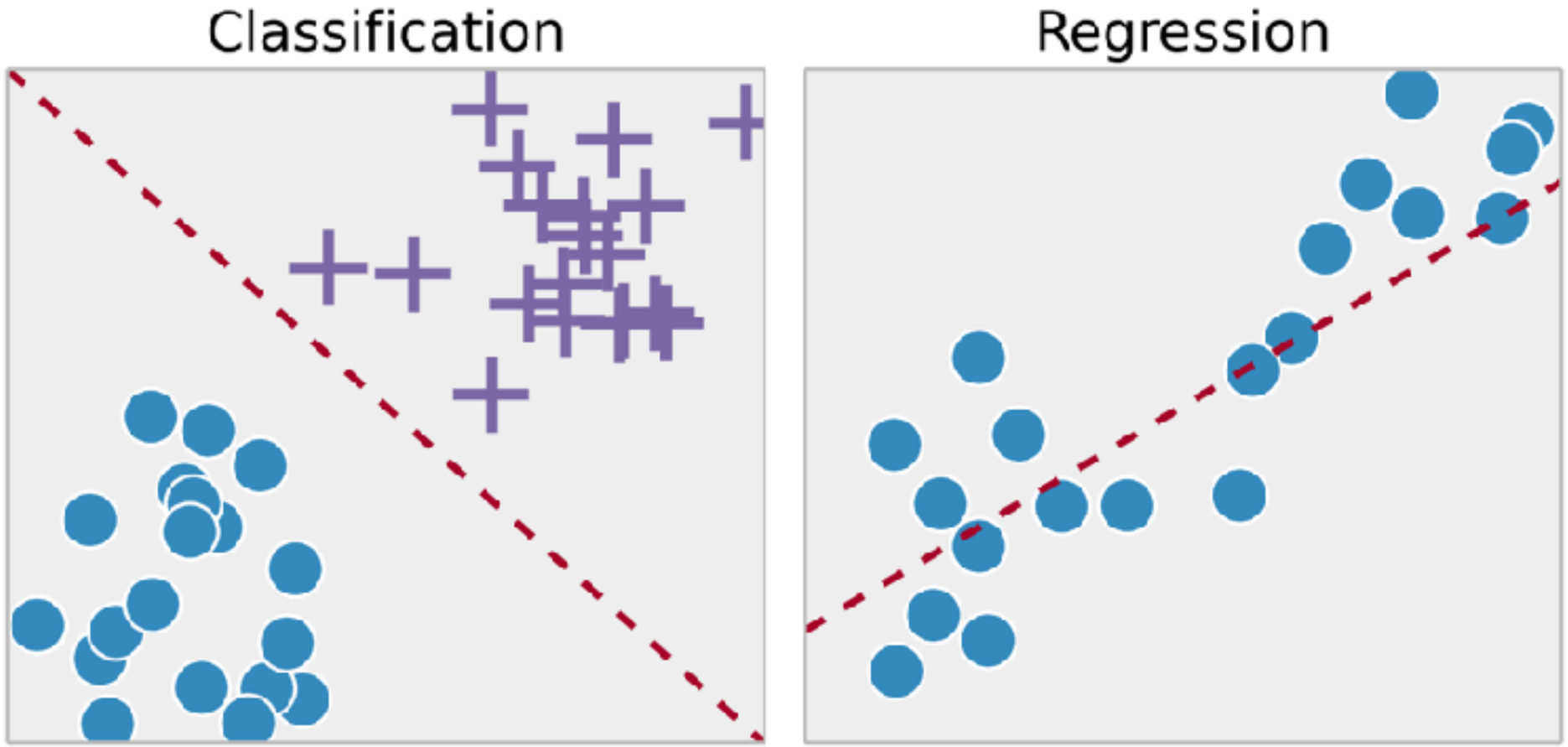
- One of the easiest ways to determine if a problem is regression or classification is to determine if our *target* variable can be ordered mathematically.

- For example, if predicting company revenue, $100MM is greater than $90MM. This is a *regression* problem because the target can be ordered.

- However, if predicting pixel color, red is not inherently greater than blue. Therefore, this is a *classification* problem.

DETERMINING REGRESSION OR CLASSIFICATION

- Classification and regression differ in what you are trying to predict.



GUIDED PRACTICE

REGRESSION OR CLASSIFICATION?

ACTIVITY: REGRESSION OR CLASSIFICATION?

DIRECTIONS (20 minutes)

Review the following situations and decide if each one is a regression problem, classification problem, or neither:

1. Using the total number of explosions in a movie, predict if the movie is by JJ Abrams or Michael Bay.
2. Determine how many tickets will be sold to a concert given who is performing, where, and the date and time.
3. Given the temperature over the last year by day, predict tomorrow's temperature outside.
4. Using data from four cell phone microphones, reduce the noisy sounds so the voice is crystal clear to the receiving phone.
5. With customer data, determine if a user will return or not in the next 7 days to an e-commerce website.

DELIVERABLE

Answers to the above questions

INDEPENDENT PRACTICE

BUILD A CLASSIFIER!

ACTIVITY: BUILD A CLASSIFIER!

DIRECTIONS (20 minutes)

1. Re-explore the iris dataset and build a program that classifies each data point. Use if-else statements and some Pandas functions.
2. Measure the *accuracy* of your classifier using the math of "total correct" over "total samples".
3. Your classifier should be able to:
   a. Get one class label 100% correct (one type of iris is easily distinguishable from the other two).
   b. Accurately predict the majority of the other two classes with some error (hint: make sure you *generalize*).

DELIVERABLE

Classification program for the iris dataset

ACTIVITY: BUILD A CLASSIFIER!

STARTER CODE

```
from sklearn import datasets, neighbors, metrics
import pandas as pd

iris = datasets.load_iris()
irisdf = pd.DataFrame(iris.data,
columns=iris.feature_names)
irisdf['target'] = iris.target
cmap = {'0': 'r', '1': 'g', '2': 'b' }
irisdf['ctarget'] = irisdf.target.apply(lambda x:
cmap[str(x)])
```

ACTIVITY: BUILD A CLASSIFIER!

STARTER CODE

```
irisdf.plot('petal length (cm)', 'petal width (cm)',
kind='scatter', c=irisdf.ctarget)
print irisdf.plot('petal length (cm)', 'petal width (cm)',
kind='scatter', c=irisdf.ctarget)
print irisdf.describe()
```

ACTIVITY: BUILD A CLASSIFIER!

STARTER CODE

```
# starter code
def my_classifier(row):
    if row['petal length (cm)'] < 2:
        return 0
    else:
        return 1

predictions = irisdf.apply(my_classifier, axis=1)
```

ACTIVITY: BUILD A CLASSIFIER!

DIRECTIONS

Answer the following questions.

1. How simple could the if-else classifier be while remaining *relatively* accurate?
2. How complicated could our if-else classifier be and remain *completely* accurate? How many if-else statements would you need, or nested if-else statements, in order to get the classifier 100% accurate? (The above uses a count of 2).
3. Which if-else classifier would work better against iris data that it hasn't seen? Why is that the case?

DELIVERABLE

Answers to the above questions

WHAT IS K NEAREST NEIGHBORS?

WHAT IS K NEAREST NEIGHBORS?

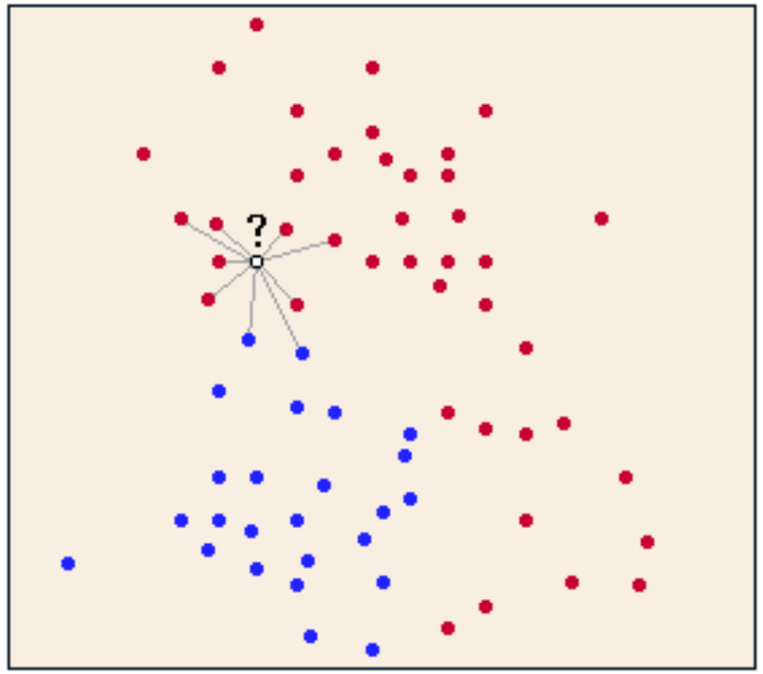
- **K Nearest Neighbors (KNN)** is a classification algorithm that makes a prediction based upon the closest data points.

- The KNN algorithm:
  - For a given point, calculate the distance to all other points.
  - Given those distances, pick the k closest points.
  - Calculate the probability of each class label given those points.
  - The original point is classified as the class label with the largest probability ("votes").

WHAT IS K NEAREST NEIGHBORS?

- KNN uses distance to predict a class label. This application of distance is used as a measure of similarity between classifications.

- We're using shared traits to identify the most likely class label.



WHAT IS K NEAREST NEIGHBORS?

- Suppose we want to determine your favorite type of music. How might we determine this without directly asking you?

- Generally, friends share similar traits and interests (e.g. music, sports teams, hobbies, etc). We could ask your five closest friends what their favorite type of music is and take the majority vote.

- This is the idea behind KNN: we look for things similar to (or close to) our new observation and identify shared traits. We can use this information to make an educated guess about a trait of our new observation.

ACTIVITY: KNOWLEDGE CHECK

ANSWER THE FOLLOWING QUESTIONS

1. In what other tasks do we use a heuristic similar to K Nearest Neighbors?

DELIVERABLE

Answers to the above questions

DEMO

KNN IN ACTION

KNN IN ACTION

- The following code demonstrates using KNN via sklearn.

```
from sklearn import datasets, neighbors, metrics
import pandas as pd

iris = datasets.load_iris()
# n_neighbors is our option in KNN. We'll tune this value to attempt to improve our prediction.
knn = neighbors.KNeighborsClassifier(n_neighbors=5, weights='uniform')
knn.fit(iris.data[:,2:], iris.target)
print knn.predict(iris.data[:,2:])
print iris.target
print knn.score(iris.data[:,2:], iris.target)
```

WHAT HAPPENS IN TIES?

- What happens if two classes get the same number of votes?
- This could happen in binary classification if we use an even number for k. This could also happen if there are multiple class labels.
- In sklearn, it will choose the class that it first saw in the *training set*.

WHAT HAPPENS IN TIES?

- We could implement a *weight*, taking into account the distance between the point and its neighbors.
- This can be done in sklearn by changing the `weights` parameter to `"distance"`.
- Try changing the `weights` parameter. How does this affect accuracy?

WHAT HAPPENS IN HIGH DIMENSIONALITY?

- Since KNN works with distance, higher dimensionality of data (i.e. more features) requires *significantly* more samples in order to have the same predictive power.

- Consider this: with more dimensions, all points slowly start averaging out to be equally distant. This causes significant issues for KNN.

- Keep the feature space limited and KNN will do well. Exclude extraneous features when using KNN.

WHAT HAPPENS IN HIGH DIMENSIONALITY?

- Consider two different examples: classifying users of a newspaper and users of a particular toothpaste.
- The features of the newspapers are very broad and there are many: sections, topics, types of stories, writers, online vs print, etc.
- However, the features of a toothpaste are more narrow: has fluoride, controls tartar, etc.
- For which problem would KNN work better?

WHAT HAPPENS IN HIGH DIMENSIONALITY?

- KNN would work better on classifying users of a particular toothpaste since the feature set is more narrow and distinct.

CLASSIFICATION METRICS

INTRODUCTION TO CLASSIFICATION METRICS

- Metrics for regression do **not** apply to classification.
- We *could* measure the distance between the probability of a given class and an item being in that class. Guessing 0.6 for a 1 is a 0.4 error.
- But this overcomplicates our goal: understanding binary classification, whether something is black or white, right or wrong.
- To do this, we'll measure "correctness" or "incorrectness".

INTRODUCTION TO CLASSIFICATION METRICS

- We'll use two primary metrics: *accuracy* and *misclassification rate*.
- **Accuracy** is the proportion of *correct* predictions out of all predictions in the sample. This is a value we want to *maximize*.
- **Misclassification rate** is the proportion of *incorrect* predictions out of all predictions in the sample. This is a value we want to *minimize*.
- These two metrics are directly opposite of each other.
- How do you think they are related?

INTRODUCTION TO CLASSIFICATION METRICS

- We'll use two primary metrics: *accuracy* and *misclassification rate*.
- **Accuracy** is the proportion of *correct* predictions out of all predictions in the sample. This is a value we want to *maximize*.
- **Misclassification rate** is the proportion of *incorrect* predictions out of all predictions in the sample. This is a value we want to *minimize*.
- These two metrics are directly opposite of each other.
- 1 - misclassification rate = accuracy

INTRODUCTION TO CLASSIFICATION METRICS

- **WARNING**: You cannot use regression evaluation metrics for a classification problem, or vice versa. This is a common mistake.

- sklearn will not intuitively understand if you are doing regression or classification, so make sure to manually review your metrics.

INDEPENDENT PRACTICE

SOLVING FOR K

ACTIVITY: SOLVING FOR K

DIRECTIONS (35 minutes)

One of the primary challenges of KNN is solving for k - how many neighbors do we use?

The **smallest** k we can use is 1. However, using only one neighbor will probably perform poorly.

The largest k we can use is n-1 (every other point in the data set). However, this would result in always choosing the largest class in the sample. This would also perform poorly.

Use the lesson 8 starter code and the iris data set to answer the following questions:

1. What is the accuracy for k=1?
2. What is the accuracy for k=n-1?
3. Using cross validation, what value of k optimizes model accuracy. Create a plot with *k* as the x-axis and *accuracy* as the y-axis (called a "fit chart") to help find the answer.

DELIVERABLE

Answers to the above questions

ACTIVITY: SOLVING FOR K

STARTER CODE

```
from sklearn import grid_search

params = {'n_neighbors': }

gs = grid_search.GridSearchCV(
    estimator=,
    param_grid=,
    cv=,
)
gs.fit(iris.data, iris.target)
gs.grid_scores_
```

ACTIVITY: SOLVING FOR K

DIRECTIONS

Bonus Questions:

1. By default, the KNN classifier in sklearn uses the *Minkowski metric* for distance.
   a. What *type* of data does this metric work best for?
   b. What *type* of data does this distance metric not work for?
   c. You can read about distance metrics in the sklearn documentation.

2. It is possible to use KNN as a regression estimator. Determine the following:
   a. Steps that KNN Regression would follow
   b. How it predicts a regression value

DELIVERABLE

Answers to the above questions

TOPIC REVIEW

REVIEW

- What are class labels? What does it mean to classify?
- How is a classification problem different from a regression problem? How are they similar?
- How does the KNN algorithm work?
- What primary parameters are available for tuning a KNN estimator?
- How do you define: accuracy, misclassification?

LESSON

Q & A

LESSON

EXIT TICKET

DON’T FORGET TO FILL OUT YOUR EXIT TICKET