Lecture 14: Classification, Statistical Sins

Announcements

- Reading
  - Chapter 21
- Course evaluations
  - Online evaluation now through noon on Friday, December 16
- Will be making study code for final exam available later today

Compare to KNN Results (from Monday)

Average of 10 80/20 splits using KNN (k=3)
Accuracy = 0.744
Sensitivity = 0.629
Specificity = 0.829
Pos. Pred. Val. = 0.728

Average of LOO testing using KNN (k=3)
Accuracy = 0.769
Sensitivity = 0.663
Specificity = 0.842
Pos. Pred. Val. = 0.743

Average of 10 80/20 splits LR
Accuracy = 0.804
Sensitivity = 0.719
Specificity = 0.859
Pos. Pred. Val. = 0.767

Average of LOO testing using LR
Accuracy = 0.786
Sensitivity = 0.705
Specificity = 0.842
Pos. Pred. Val. = 0.754

Performance not much difference
Logistic regression slightly better

Logistic regression provides insight about variables

Looking at Feature Weights

model.classes_ = ['Died' 'Survived']
For label Survived
  C1 = 1.66761946545
  C2 = 0.460354552452
  C3 = -0.50338282535
  age = -0.0314481062387
  male gender = -2.39514860929

Be wary of reading too much into the weights

Features are often correlated

L1 regression tends to drive one variable to zero

L2 (default) regression spreads weights across variables

Correlated Features, an Example

- c1 + c2 + c3 = 1
  - I.e., values are not independent
  - Is being in 1st class good, or being in the other classes bad?
- Suppose we eliminate c1?

```
def __init__(self, pClass, age, gender, survived, name):
    self.name = name
    if pClass == 2:
        self.featureVec = [1, 0, age, gender]
    elif pClass == 3:
        self.featureVec = [0, 1, age, gender]
    else:
        self.featureVec = [0, 0, age, gender]
    self.label = survived
    self.cabinClass = pClass
```

Comparative Results

Original Features

Average of 20 80/20 splits LR
 Accuracy = 0.778
 Sensitivity = 0.687
 Specificity = 0.842
 Pos. Pred. Val. = 0.755
model.classes_ = ['Died' 'Survived']
For label Survived
  C1 = 1.68864047459
  C2 = 0.390605976351
  C3 = -0.46270349333
  age = -0.0307090135358
  male gender = -2.41191131088

Modified Features

Average of 20 80/20 splits LR
 Accuracy = 0.779
 Sensitivity = 0.674
 Specificity = 0.853
 Pos. Pred. Val. = 0.765
model.classes_ = ['Died' 'Survived']
For label Survived
  C2 = -1.08356816806
  C3 = -1.92251427055
  age = -0.026056041377
  male gender = -2.36239279331

Changing the Cutoff

```
random.seed(0)
trainingSet, testSet = split80_20(examples)
model = buildModel(trainingSet, False)
print('Try p = 0.1')
truePos, falsePos, trueNeg, falseNeg =\
                   applyModel(model, testSet, 'Survived', 0.1)
getStats(truePos, falsePos, trueNeg, falseNeg)
print('Try p = 0.9')
truePos, falsePos, trueNeg, falseNeg =\
                   applyModel(model, testSet, 'Survived', 0.9)
getStats(truePos, falsePos, trueNeg, falseNeg)
```

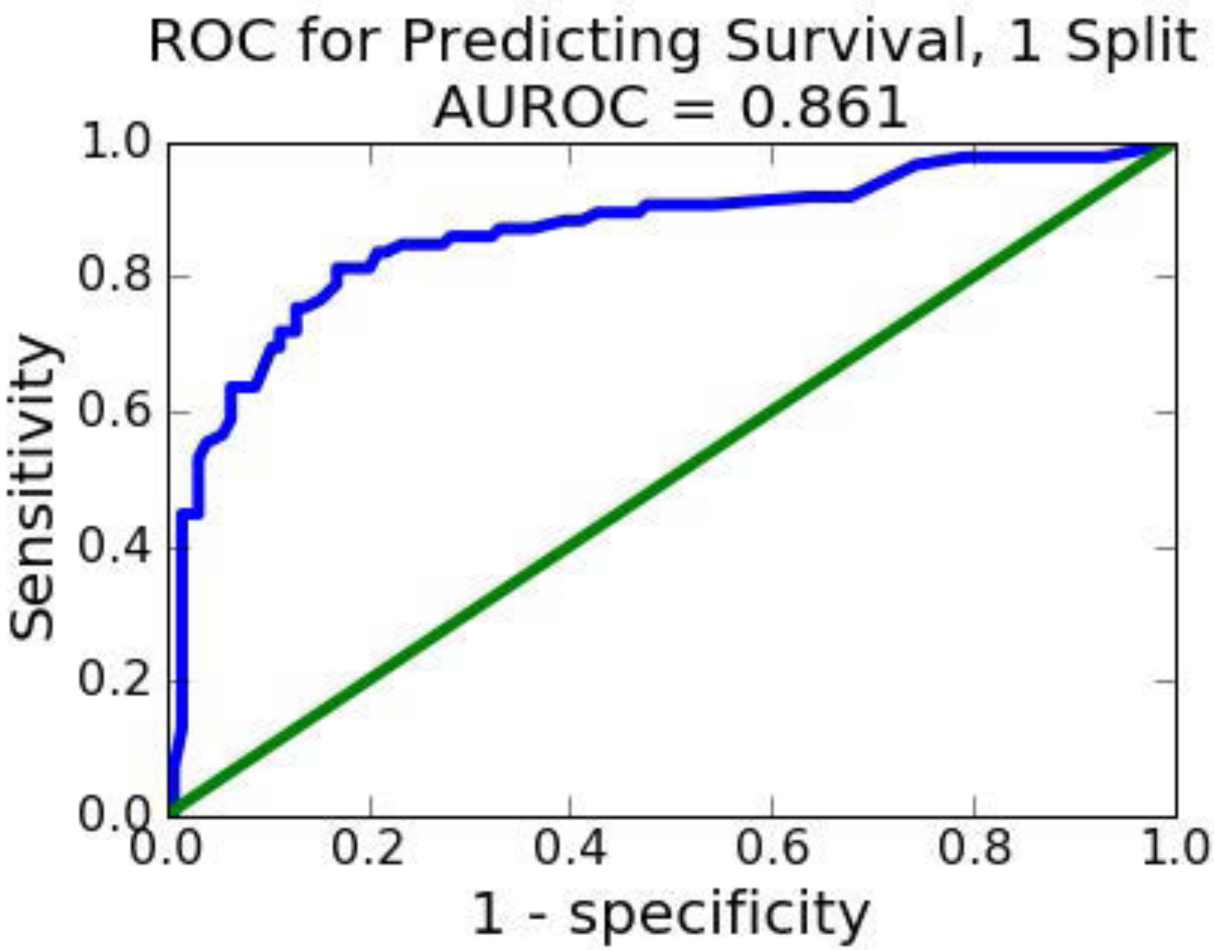
Try p = 0.1
Accuracy = 0.493
Sensitivity = 0.976
Specificity = 0.161
Pos. Pred. Val. = 0.444

Try p = 0.9
Accuracy = 0.656
Sensitivity = 0.176
Specificity = 0.984
Pos. Pred. Val. = 0.882

ROC (Receiver Operating Characteristic)

```
def buildROC(trainingSet, testSet, title, plot = True):
    model = buildModel(trainingSet, True)
    xVals, yVals = [], []
    p = 0.0
    while p <= 1.0:
        truePos, falsePos, trueNeg, falseNeg =\
                               applyModel(model, testSet,
                               'Survived', p)
        xVals.append(1.0 - specificity(trueNeg, falsePos))
        yVals.append(sensitivity(truePos, falseNeg))
        p += 0.01
    auroc = sklearn.metrics.auc(xVals, yVals, True)
    if plot:
        ...
    return auroc
```

Output


ROC for Predicting Survival, 1 Split
AUROC = 0.861
1.0
0.8
0.6
0.4
0.2
0.0
Sensitivity
0.0
0.2
0.4
0.6
0.8
1.0
1 - specificity

There are Three Kinds of Lies

LIES

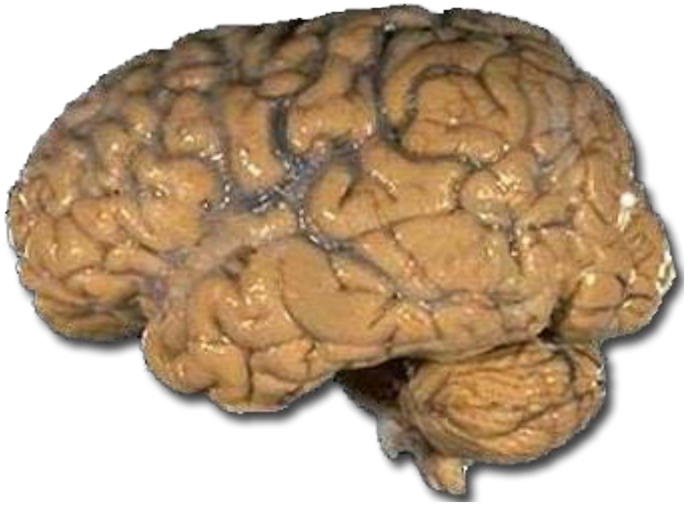
DAMNED LIES

and

STATISTICS

Humans and Statistics

Human Mind



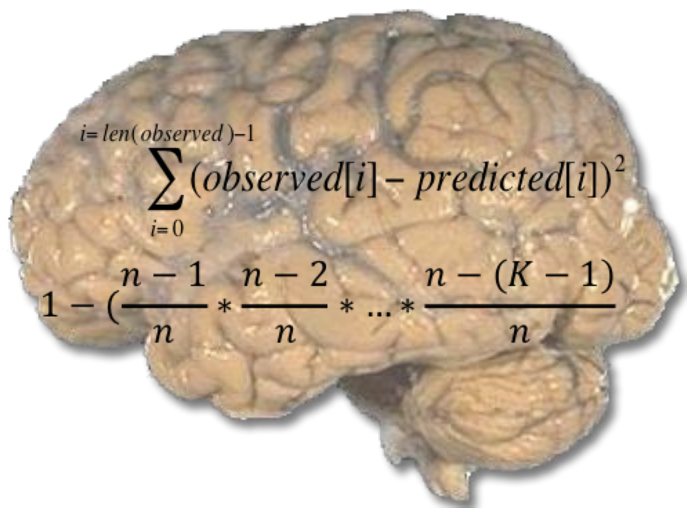
Statistics

$$\sum_{i=0}^{i=len(observed)-1}(observed[i]-predicted[i])^2$$

$$1-(\frac{n-1}{n}*\frac{n-2}{n}*\ldots*\frac{n-(K-1)}{n}$$

Humans and Statistics

"If you can't prove what you want to prove, demonstrate something else and pretend they are the same thing. In the daze that follows the collision of statistics with the human mind, hardly anyone will notice the difference." – *Darrell Huff*



Anscombe's Quartet

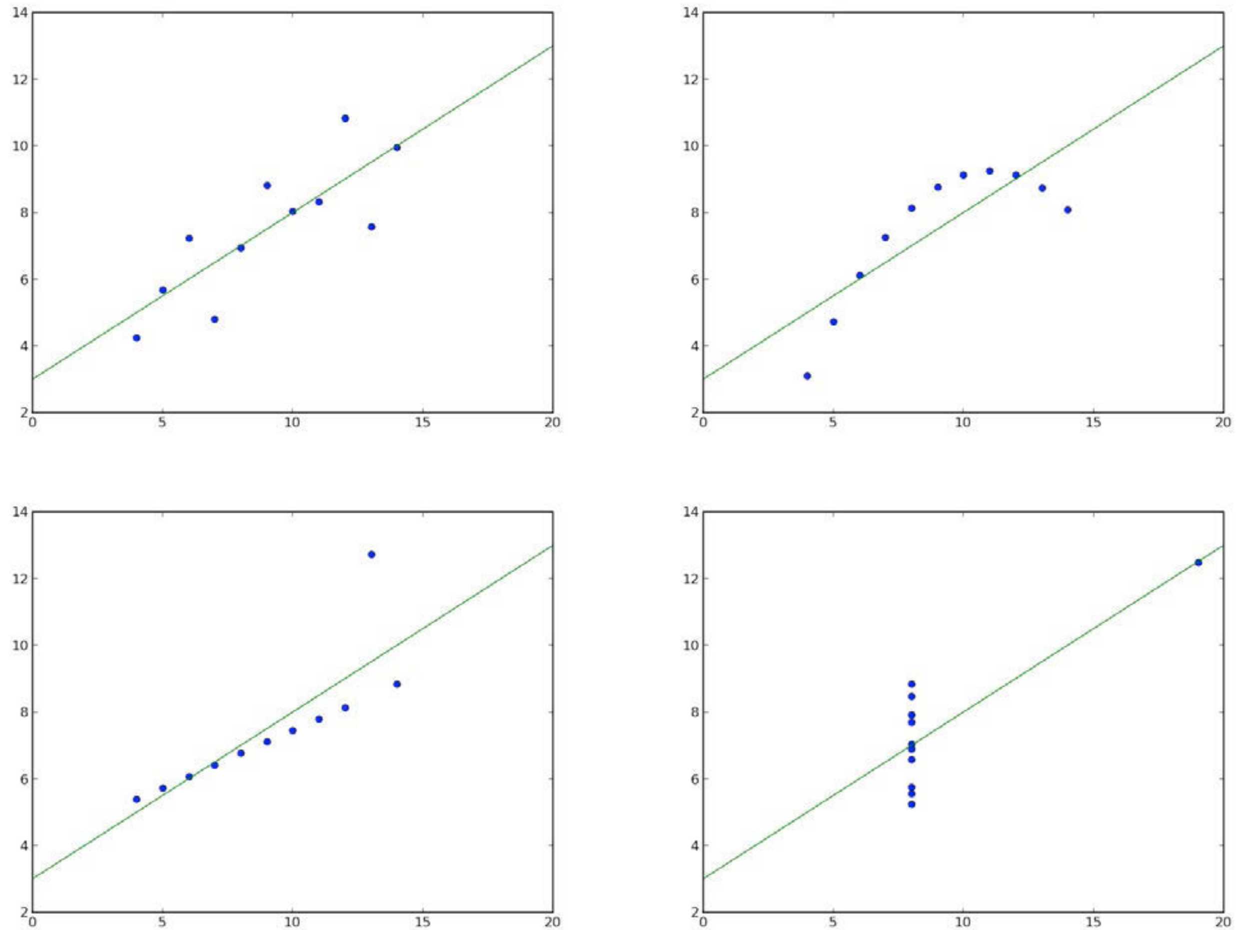
- Four groups each containing 11 x, y pairs

x	y	x	y	x	y	x	y
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89

Summary Statistics

- Summary statistics for groups identical
  - Mean x = 9.0
  - Mean y = 7.5
  - Variance of x = 10.0
  - Variance of y = 3.75
  - Linear regression model: y = 0.5x + 3
- Are four data sets really similar?

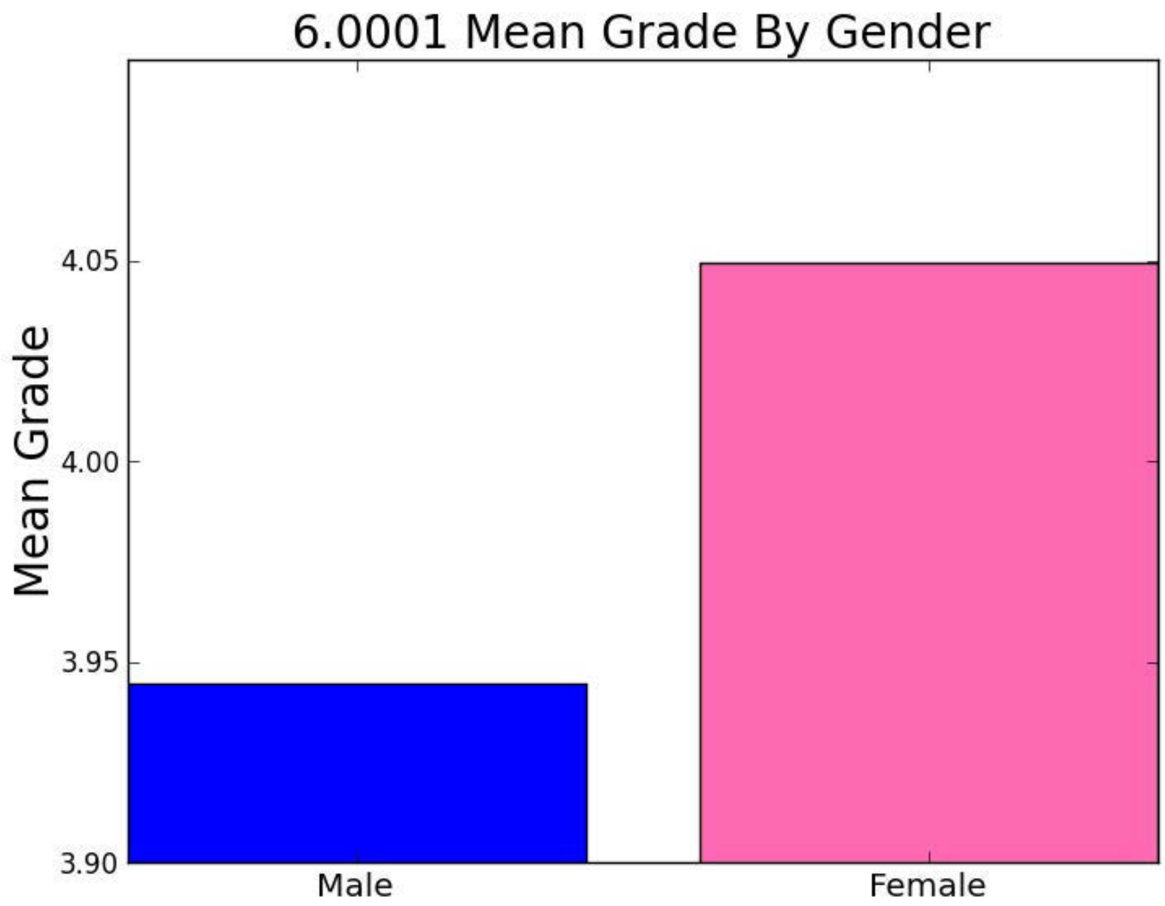
Let’s Plot the Data



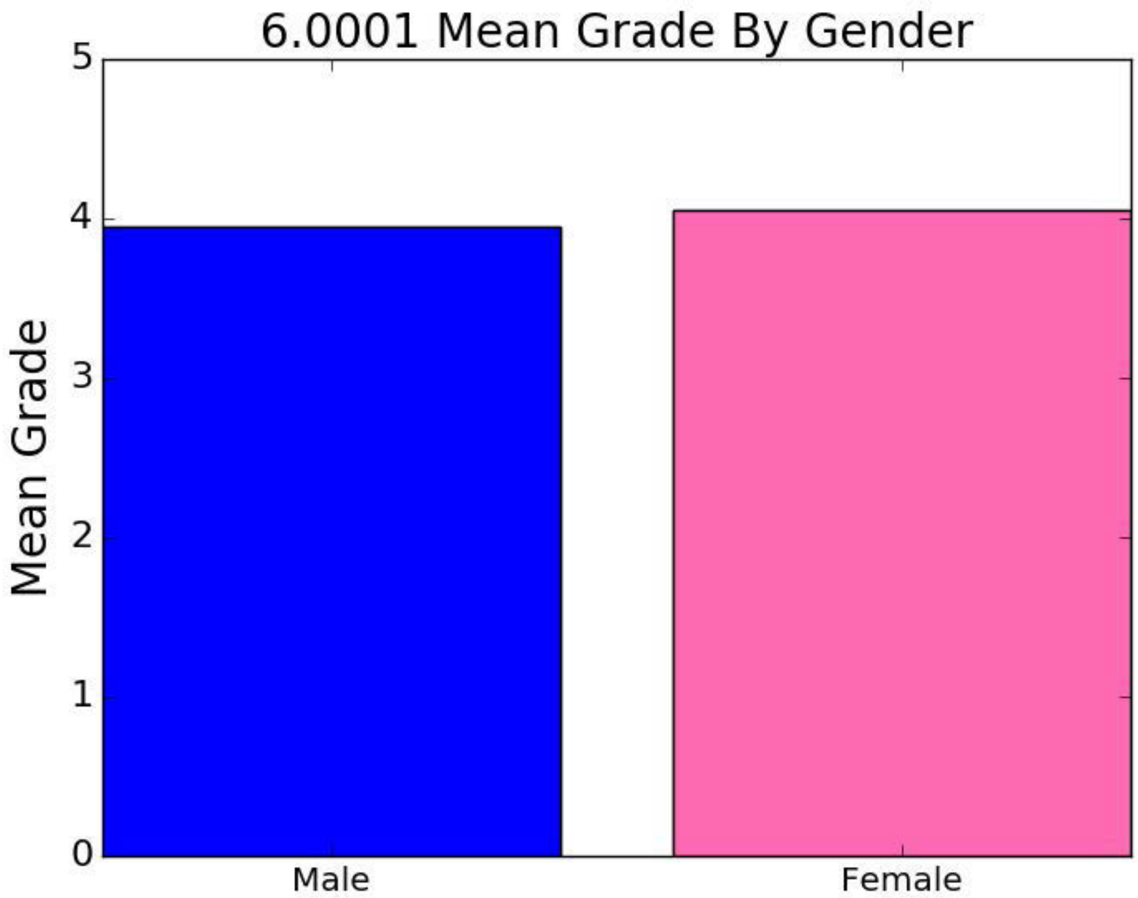
Moral: Statistics about the data is not the same as the data

Moral: Use visualization tools to look at the data itself

Lying with Pictures



Telling the Truth with Pictures



Moral: Look carefully at the axes labels and scales

Lying with Pictures

Moral: Ask whether the things being compared are actually comparable

Garbage In, Garbage Out

"On two occasions I have been asked [by members of Parliament], 'Pray, Mr. Babbage, if you put into the machine wrong figures, will the right answers come out?' I am not able rightly to apprehend the kind of confusion of ideas that could provoke such a question." – Charles Babbage (1791-1871)

Calhoun's Response to Errors in Data

"there were so many errors they balanced one another, and led to the same conclusion as if they were all correct."

Was it the case that the measurement errors are unbiased and independent of each of other, and therefore almost identically distributed on either side of the mean?

No, later analysis showed that the errors were not random but systematic.

"it was the census that was insane and not the colored people."— James Freeman Clarke

Moral: Analysis of bad data can lead to dangerous conclusions.

Sampling

- All statistical techniques are based upon the assumption that by sampling a subset of a population we can infer things about the population as a whole
- As we have seen, *if random sampling is used*, one can make meaningful mathematical statements about the expected relation of the sample to the entire population
- Easy to get random samples in simulations
- Not so easy in the field, where some examples are more convenient to acquire than others

Non-representative Sampling

- "Convenience sampling" not usually random, e.g.,
  - Survivor bias, e.g., course evaluations at end of course or grading final exam in 6.0002 on a strict curve
  - Non-response bias, e.g., opinion polls conducted by mail or online
- When samples not random and independent, we can still do things like computer means and standard deviations, but **we should not draw conclusions from them** using things like the empirical rule and central limit theorem.
- Moral: Understand how data was collected, and whether assumptions used in the analysis are satisfied. If not, be wary.