Statistics 202: Statistical Aspects of Data Mining

Professor David Mease

Tuesday, Thursday 9:00-10:15 AM Terman 156

Lecture 4 = Finish chapter 2 and start chapter 3

Agenda:

1) Lecture over rest of chapter 2
2) Start lecturing over chapter 3

Announcement:

One of the TAs, Ya Xu (yax@stanford.edu), will hold office hours on Monday, July 9th from 1pm to 3pm to assist with last minute homework questions and any other questions.

Her office is 237 Sequoia Hall.

Homework Assignment:

Chapters 1 and 2 homework is due Tuesday 7/10

Either email to me (dmease@stanford.edu), bring it to class, or put it under my office door.

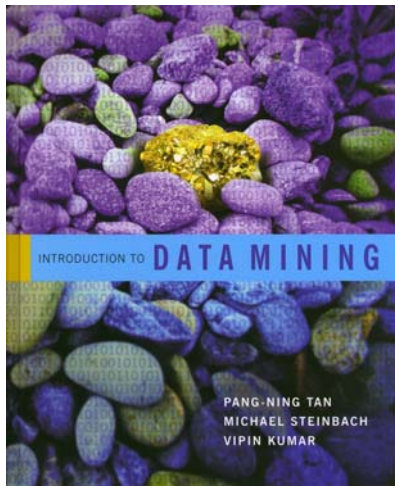
SCPD students may use email or fax or mail.

The assignment is posted at

http://www.stats202.com/homework.html

Introduction to Data Mining

by
Tan, Steinbach, Kumar



Chapter 2: Data

What is Data?

- An attribute is a property or characteristic of an object
- Examples: eye color of a person, temperature, etc.
- Attribute is also known as variable, field, characteristic, or feature
- A collection of attributes describe an object
- Object is also known as record, point, case, sample, entity, instance, or observation

Attributes

Objects

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Sampling (P.47)

- Sampling involves using only a random subset of the data for analysis

- Statisticians are interested in sampling because they often can not get all the data from a *population* of interest

- Data miners are interested in sampling because sometimes using all the data they have is too slow and unnecessary

Sampling (P.47)

- The key principle for effective sampling is the following:
  - using a sample will work almost as well as using the entire data sets, if the sample is representative
  - a sample is representative if it has approximately the same property (of interest) as the original set of data

Sampling (P.47)

- The simple random sample is the most common and basic type of sample

- In a simple random sample every item has the same probability of inclusion and every sample of the fixed size has the same probability of selection

- It is the standard "names out of a hat"

- It can be with replacement (=items can be chosen more than once) or without replacement (=items can be chosen only once)

- More complex schemes exist (examples: stratified sampling, cluster sampling, Latin hypercube sampling)

Sampling in Excel:

- The function rand() is useful.

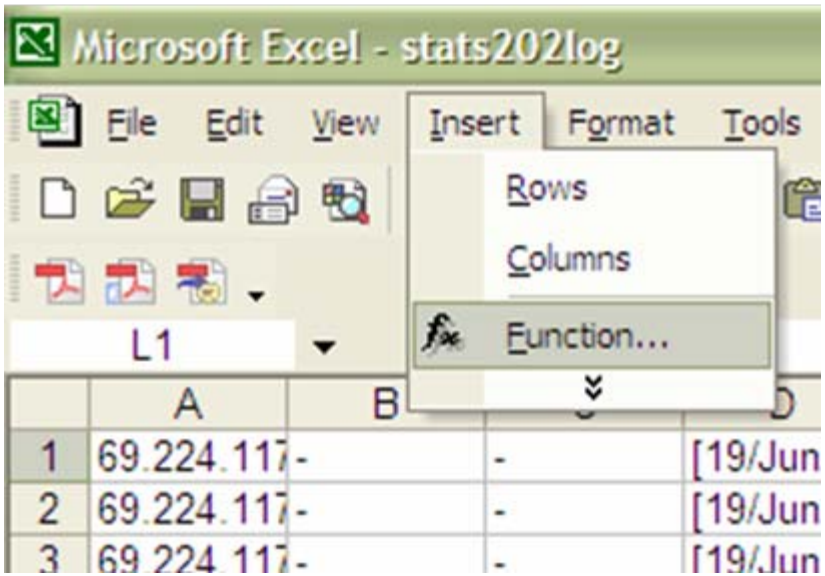
- But watch out, this is one of the worst random number generators out there.

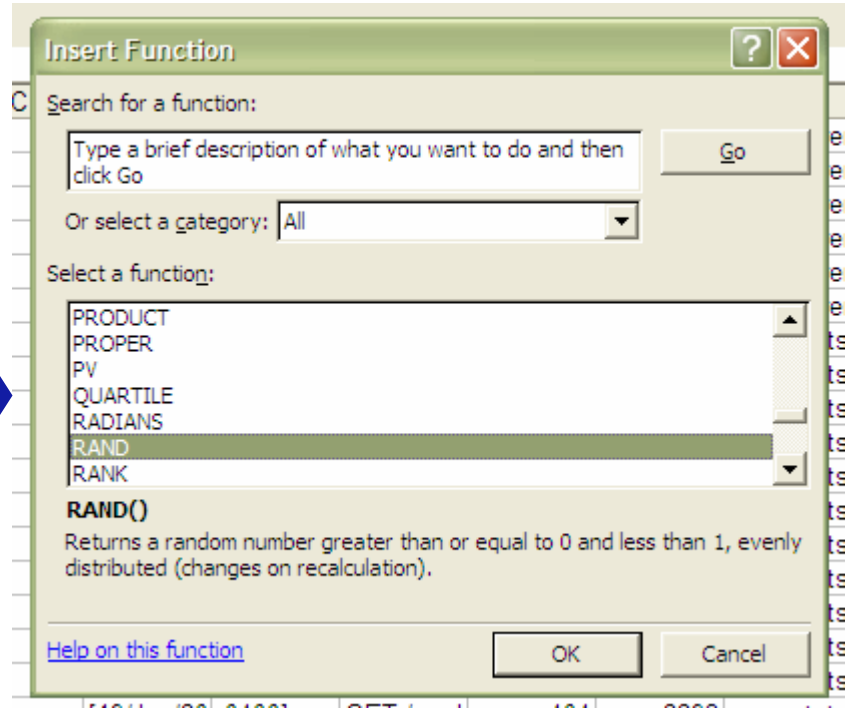
- To draw a sample in Excel without replacement, use rand() to make a new column of random numbers between 0 and 1.

- Then, sort on this column and take the first *n*, where *n* is the desired sample size.

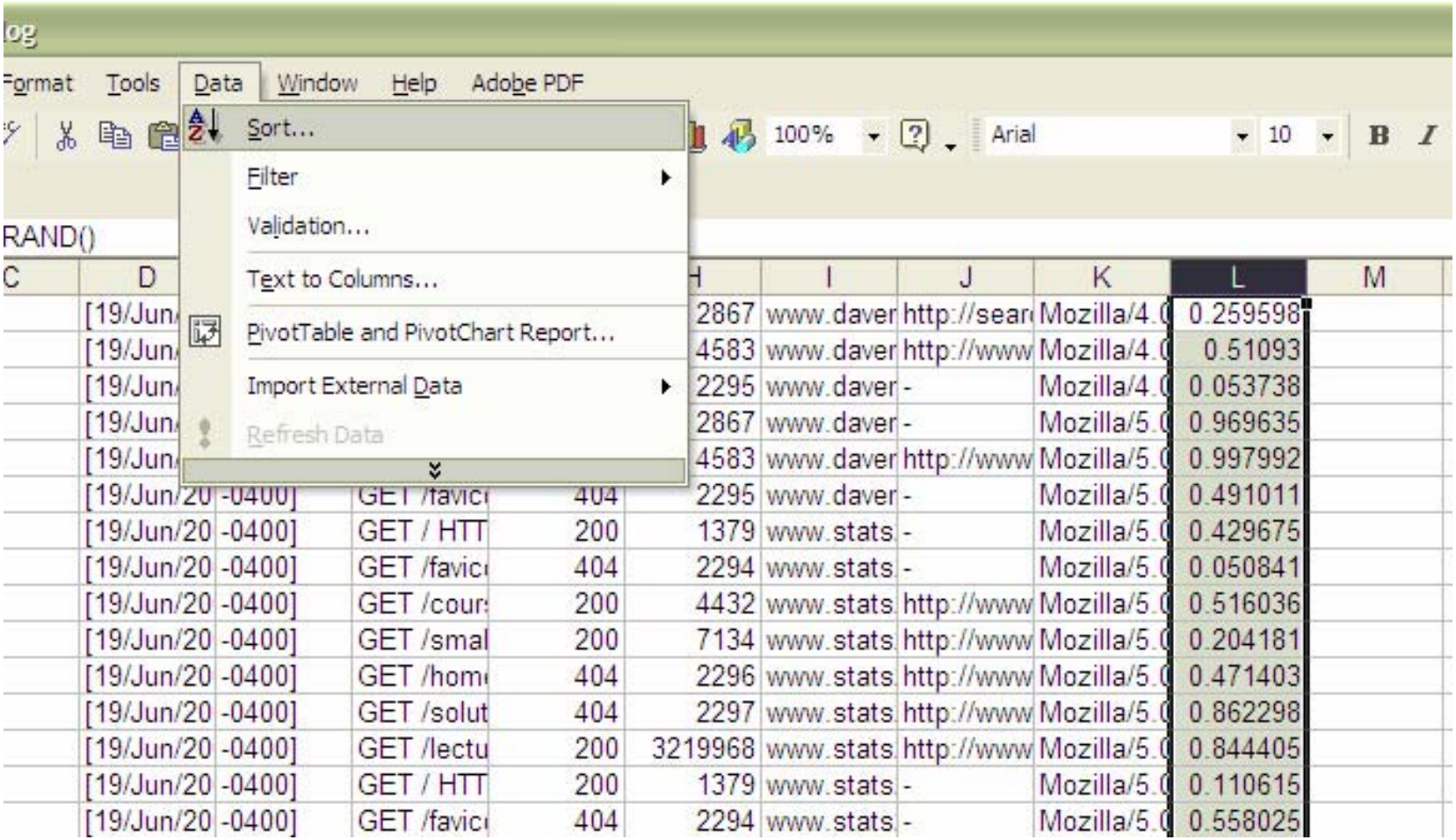
- Sorting is done in Excel by selecting "Sort" from the "Data" menu

Sampling in Excel:

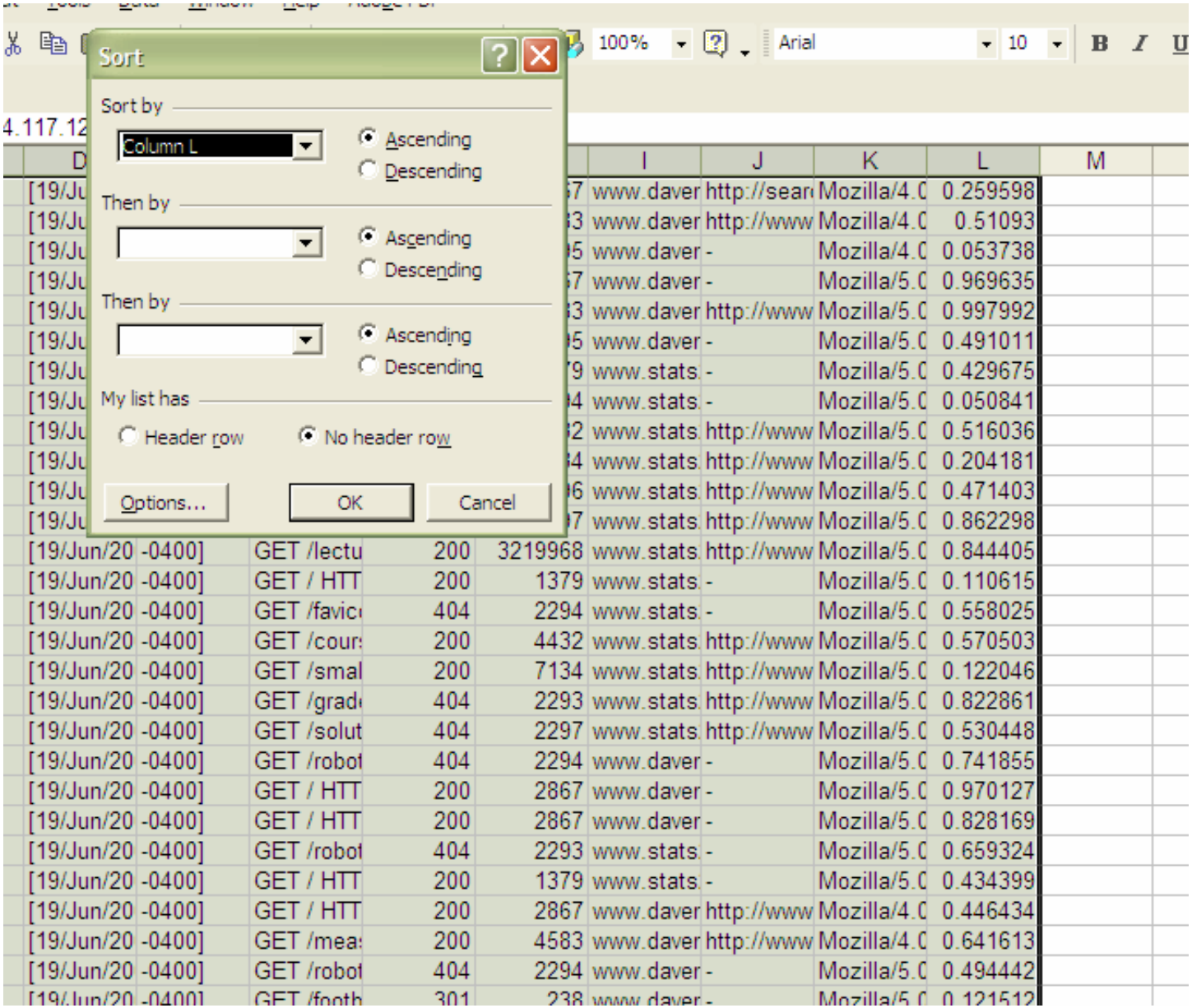




Sampling in Excel:



Sampling in Excel:



Sampling in R:

- **The function sample() is useful.**

sample(base)

Random Samples and Permutations

Description

`sample` takes a sample of the specified size from the elements of `x` using either with or without replacement.

Usage

```
sample(x, size, replace = FALSE, prob = NULL)
```

Arguments

`x`	Either a (numeric, complex, character or logical) vector of more than one element from which to choose, or a positive integer.
`size`	non-negative integer giving the number of items to choose.
`replace`	Should sampling be with replacement?
`prob`	A vector of probability weights for obtaining the elements of the vector being sampled.

Details

In class exercise #4:

Explain how to use R to draw a sample of 10 observations with replacement from the first quantitative attribute in the data set www.stats202.com/stats202log.txt.

In class exercise #4:

Explain how to use R to draw a sample of 10 observations with replacement from the first quantitative attribute in the data set www.stats202.com/stats202log.txt.

Answer:

```
> sam<-sample(seq(1,1922),10,replace=T)
> my_sample<-data$V7[sam]
```

In class exercise #5:

If you do the sampling in the previous exercise repeatedly, roughly how far is the mean of the sample from the mean of the whole column on average?

In class exercise #5:

If you do the sampling in the previous exercise repeatedly, roughly how far is the mean of the sample from the mean of the whole column on average?

Answer: about 26

```
> real_mean<-mean(data$V7)
> store_diff<-rep(0,10000)
>
> for (k in 1:10000){
+   sam<-sample(seq(1,1922),10,replace=T)
+   my_sample<-data$V7[sam]
+   store_diff[k]<-abs(mean(my_sample)-real_mean)
+ }
> mean(store_diff)
[1] 25.75126
```

In class exercise #6:

If you change the sample size from 10 to 100, how does your answer to the previous question change?

In class exercise #6:

If you change the sample size from 10 to 100, how does your answer to the previous question change?

Answer: It becomes about 8.1

```
> real_mean<-mean(data$V7)
> store_diff<-rep(0,10000)
>
> for (k in 1:10000){
+   sam<-sample(seq(1,1922),100,replace=T)
+   my_sample<-data$V7[sam]
+   store_diff[k]<-abs(mean(my_sample)-real_mean)
+ }

> mean(store_diff)
[1] 8.126843
```

The square root sampling relationship:

- When you take samples, the differences between the sample values and the value using the entire data set scale as the square root of the sample size for many statistics such as the mean.

- For example, in the previous exercises we decreased our *sampling error* by a factor of the square root of 10 (=3.2) by increasing the sample size from 10 to 100 since 100/10=10. This can be observed by noting 26/8.1=3.2.

- Note: It is only the sizes of the samples that matter, and not the size of the whole data set.

Sampling (P.47)

- Sampling can be tricky or ineffective when the data has a more complex structure than simply independent observations.

- For example, here is a "sample" of words from a song. Most of the information is lost.

did

I played

game

baby

I'm

sent

that

Sampling (P.47)

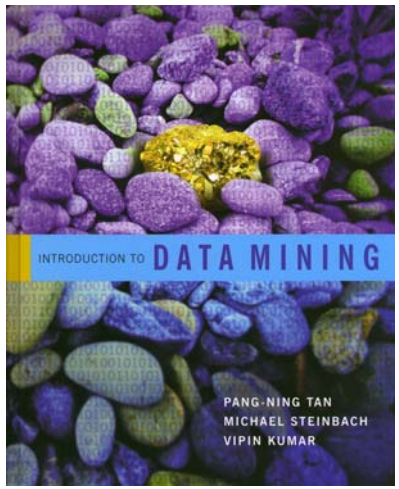
- Sampling can be tricky or ineffective when the data has a more complex structure than simply independent observations.

- For example, here is a "sample" of words from a song. Most of the information is lost.

oops I did it again
I played with your heart
got lost in the game
oh baby baby
oops! ...you think I'm in love
that I'm sent from above
I'm not that innocent

Introduction to Data Mining

by
Tan, Steinbach, Kumar



Chapter 3: Exploring Data

Exploring Data

- We can explore data visually (using tables or graphs) or numerically (using summary statistics)
- Section 3.2 deals with summary statistics
- Section 3.3 deals with visualization
- We will begin with visualization
- Note that many of the techniques you use to explore data are also useful for presenting data

Visualization

- Page 105:

"Data visualization is the display of information in a graphical or tabular format.

Successful visualization requires that the data (information) be converted into a visual format so that the characteristics of the data and the relationships among data items or attributes can be analyzed or reported.

The goal of visualization is the interpretation of the visualized information by a person and the formation of a mental model of the information."

Example:

Below are exam scores from a course I taught once.

Describe this data.

192	160	183	136	162
165	181	188	150	163
192	164	184	189	183
181	188	191	190	184
171	177	125	192	149
188	154	151	159	141
171	153	169	168	168
157	160	190	166	150

Note, this data is at
www.stats202.com/exam_scores.csv

The Histogram

- **Histogram (Page 111):**

"A plot that displays the distribution of values for attributes by dividing the possible values into bins and showing the number of objects that fall into each bin."

- **Page 112 – "A *Relative frequency histogram* replaces the count by the relative frequency". These are useful for comparing multiple groups of different sizes.**

- **The corresponding table is often called the frequency distribution (or relative frequency distribution).**

- **The function "hist" in R is useful.**

In class exercise #7:

Make a frequency histogram in R for the exam scores using bins of width 10 beginning at 120 and ending at 200.

In class exercise #7:

Make a frequency histogram in R for the exam scores using bins of width 10 beginning at 120 and ending at 200.

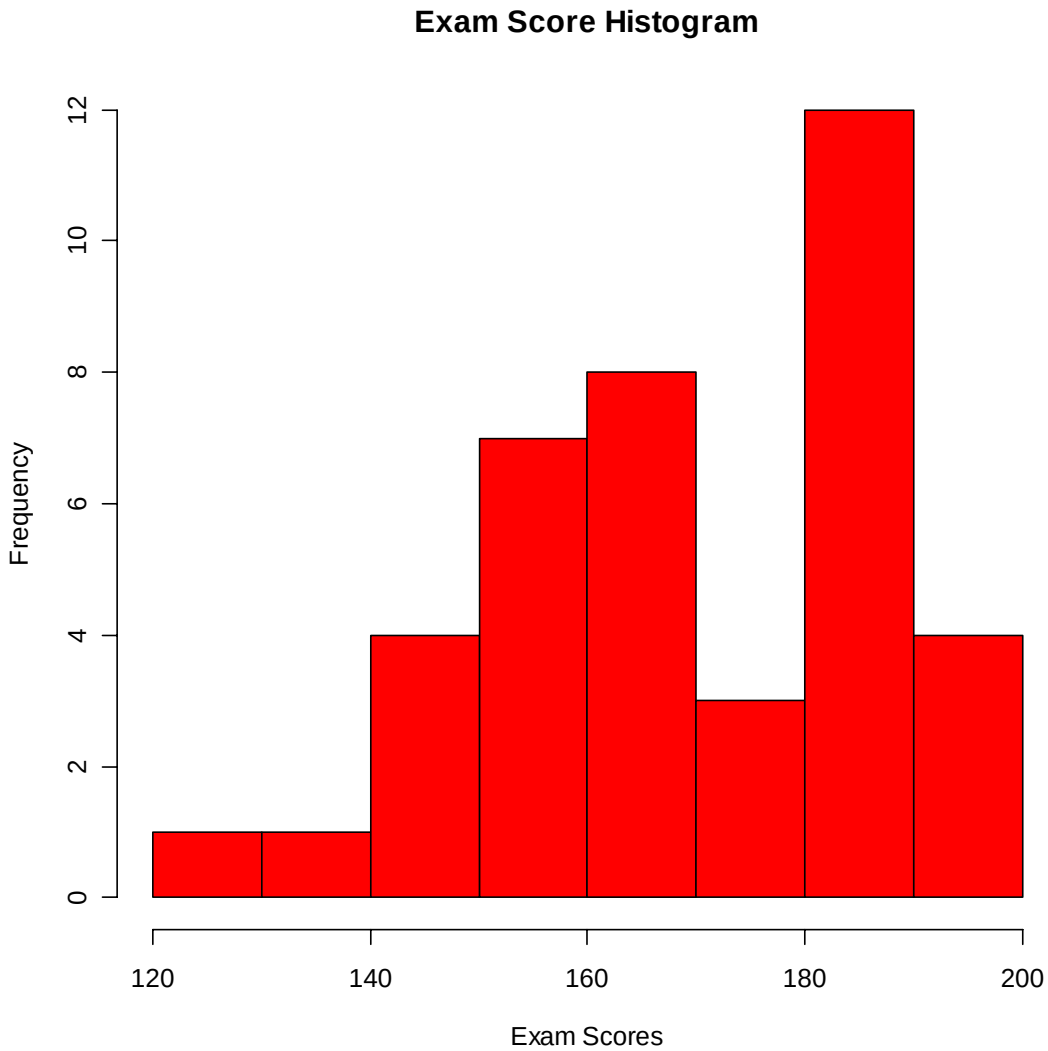
Answer:

```
> exam_scores<-
  read.csv("exam_scores.csv",header=F)


> hist(exam_scores[,1],breaks=seq(120,200,by=10),
    col="red",
    xlab="Exam Scores", ylab="Frequency",
    main="Exam Score Histogram")
```

In class exercise #7:

Make a frequency histogram in R for the exam scores using bins of width 10 beginning at 120 and ending at 200.

Answer:



The (Relative) Frequency Polygon

- Sometimes it is more useful to display the information in a histogram using points connected by lines instead of solid bars.

- Such a plot is called a (relative) frequency polygon.

- This is not in the book.

- The points are placed at the midpoints of the histogram bins and two extra bins with a count of zero are often included at either end for completeness.

In class exercise #8:

Make a frequency polygon in R for the exam scores using bins of width 10 beginning at 120 and ending at 200.

In class exercise #8:

Make a frequency polygon in R for the exam scores using bins of width 10 beginning at 120 and ending at 200.

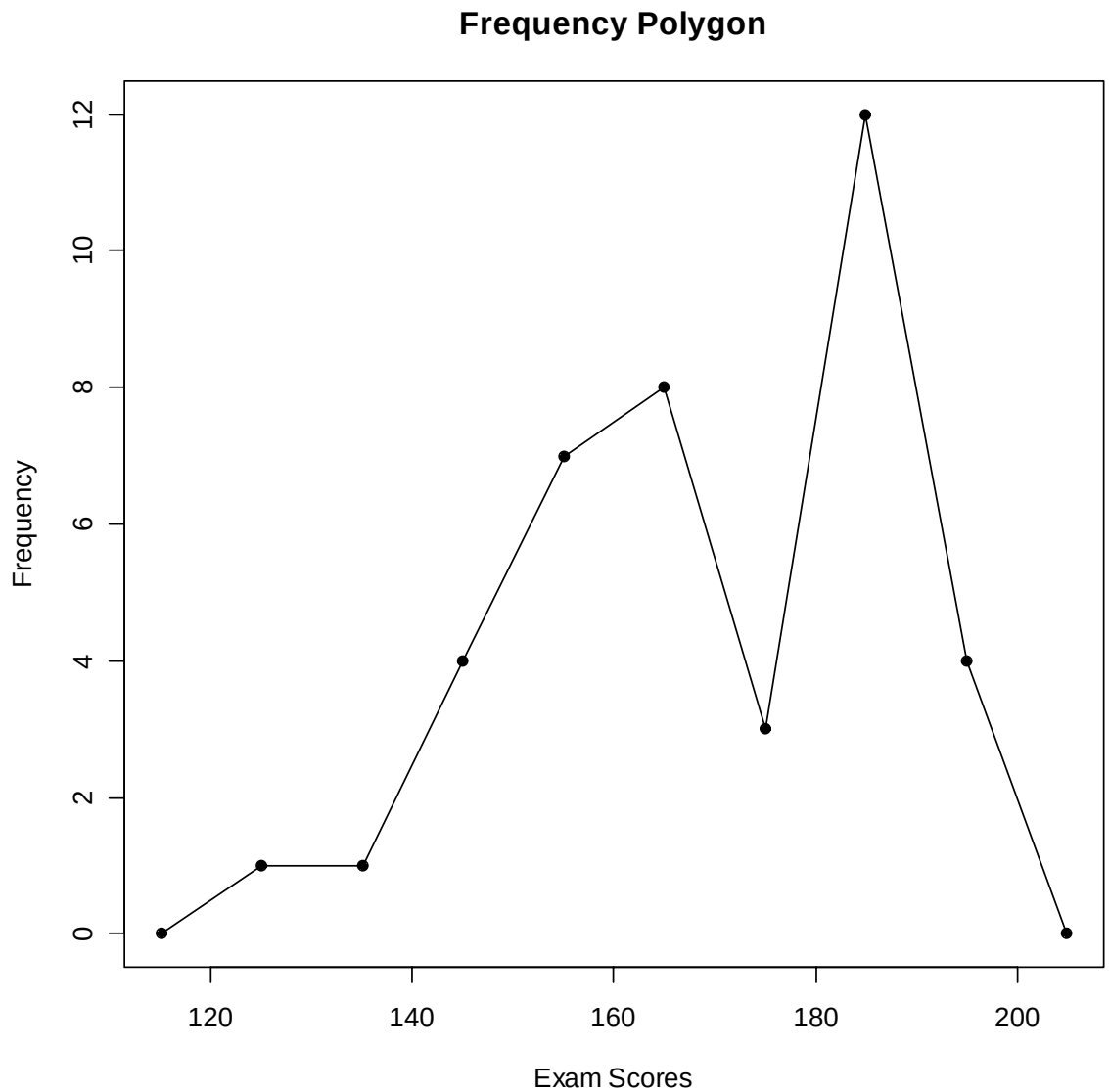
Answer:

```
> my_hist<-hist(exam_scores[,1],
  breaks=seq(120,200,by=10),plot=FALSE)
> counts<-my_hist$counts
> breaks<-my_hist$breaks
> plot(c(115,breaks+5),
  c(0,counts,0),
  pch=19,
  xlab="Exam Scores",
  ylab="Frequency",main="Frequency Polygon")
> lines(c(115,breaks+5),c(0,counts,0))
```

In class exercise #8:

Make a frequency polygon in R for the exam scores using bins of width 10 beginning at 120 and ending at 200.

Answer:



The Empirical Cumulative Distribution Function (Page 115)

- "A *cumulative distribution function* (CDF) shows the probability that a point is less than a value."

- "For each observed value, an *empirical cumulative distribution function* (ECDF) shows the fraction of points that are less than this value." (Page 116)

- A plot of the ECDF is sometimes called an *ogive*.

- The function "ecdf" in R is useful. The plotting features are poorly documented in the help(ecdf) but many examples are given.

In class exercise #9:

Make a plot of the ECDF for the exam scores using the function “ecdf” in R.

In class exercise #9:

Make a plot of the ECDF for the exam scores using the function "ecdf" in R.

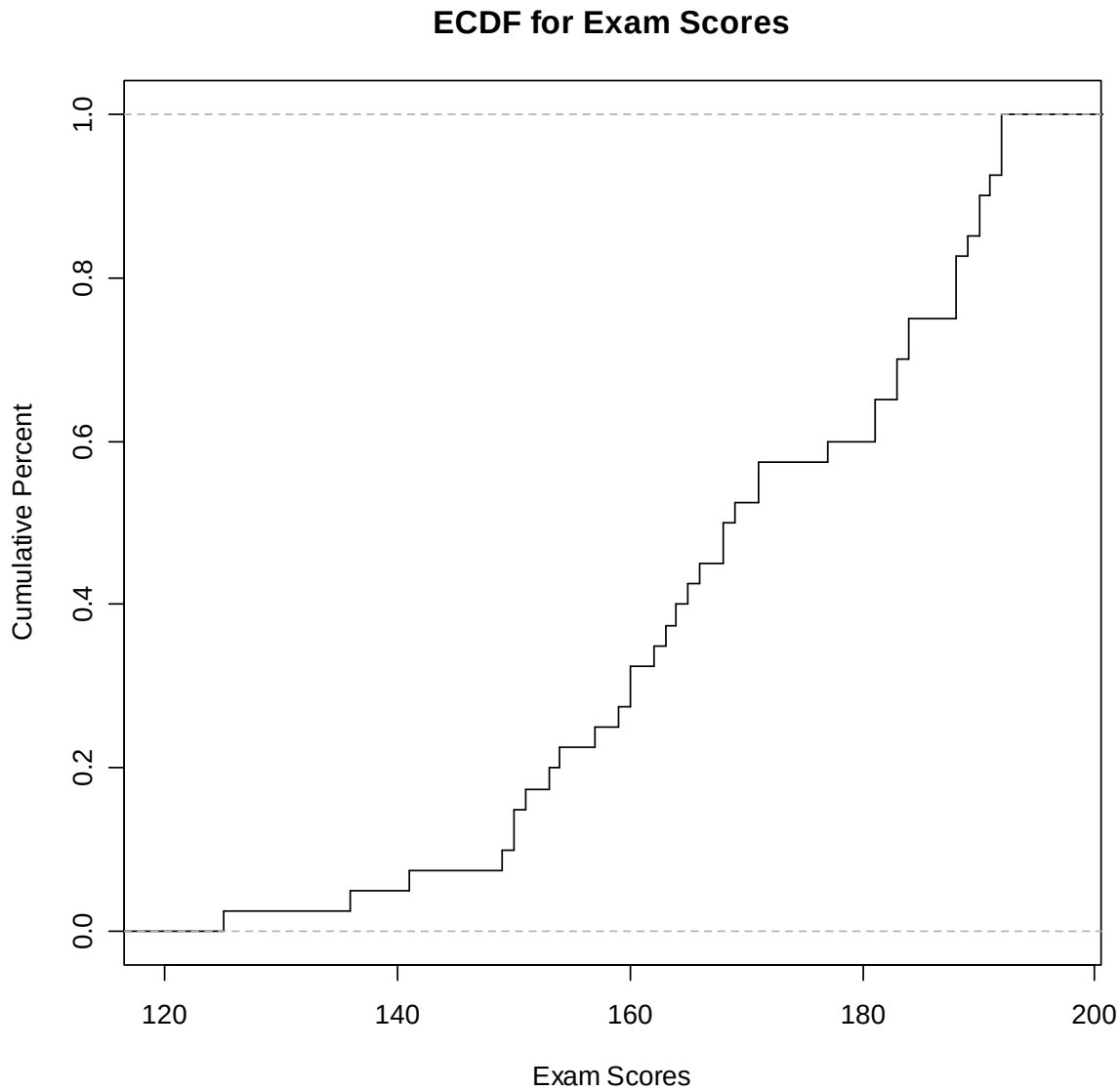
Answer:

```
> plot(ecdf(exam_scores[,1]),
  verticals= TRUE,
  do.p=FALSE,
  main="ECDF for Exam Scores",
  xlab="Exam Scores",
  ylab="Cumulative Percent")
```

In class exercise #9:

Make a plot of the ECDF for the exam scores using the function "ecdf" in R.

Answer:



Comparing Multiple Distributions

- If there is a second exam also scored out of 200 points, how will I compare the distribution of these scores to the previous exam scores?

187	143	180	100	180
159	162	146	159	173
151	165	184	170	176
163	185	175	171	163
170	102	184	181	145
154	110	165	140	153
182	154	150	152	185
140	132			

- Note, this data is at www.stats202.com/more_exam_scores.csv

Comparing Multiple Distributions

- Histograms can be used, but only if they are Relative Frequency Histograms.

- Relative Frequency Polygons are even better. You can use a different color/type line for each group and add a legend.

- Plots of the ECDF are often even more useful, since they can compare all the percentiles simultaneously. These can also use different color/type lines for each group with a legend.

In class exercise #10:

Plot the relative frequency polygons for both the first and second exams on the same graph. Provide a legend.

In class exercise #10:

Plot the relative frequency polygons for both the first and second exams on the same graph. Provide a legend.

Answer:

```
> more_exam_scores<-
  read.csv("more_exam_scores.csv",header=F)
> my_new_hist<- hist(more_exam_scores[,1],
  breaks=seq(100,200,by=10),plot=FALSE)
> new_counts<-my_new_hist$counts
> new_breaks<-my_new_hist$breaks
> plot(c(95,new_breaks+5),c(0,new_counts/37,0),
  pch=19,xlab="Exam Scores",
  ylab="Relative Frequency",main="Relative
  Frequency Polygons",ylim=c(0,.30))
> lines(c(95,new_breaks+5),c(0,new_counts/37,0),
  lty=2)
```

In class exercise #10:

Plot the relative frequency polygons for both the first and second exams on the same graph. Provide a legend.

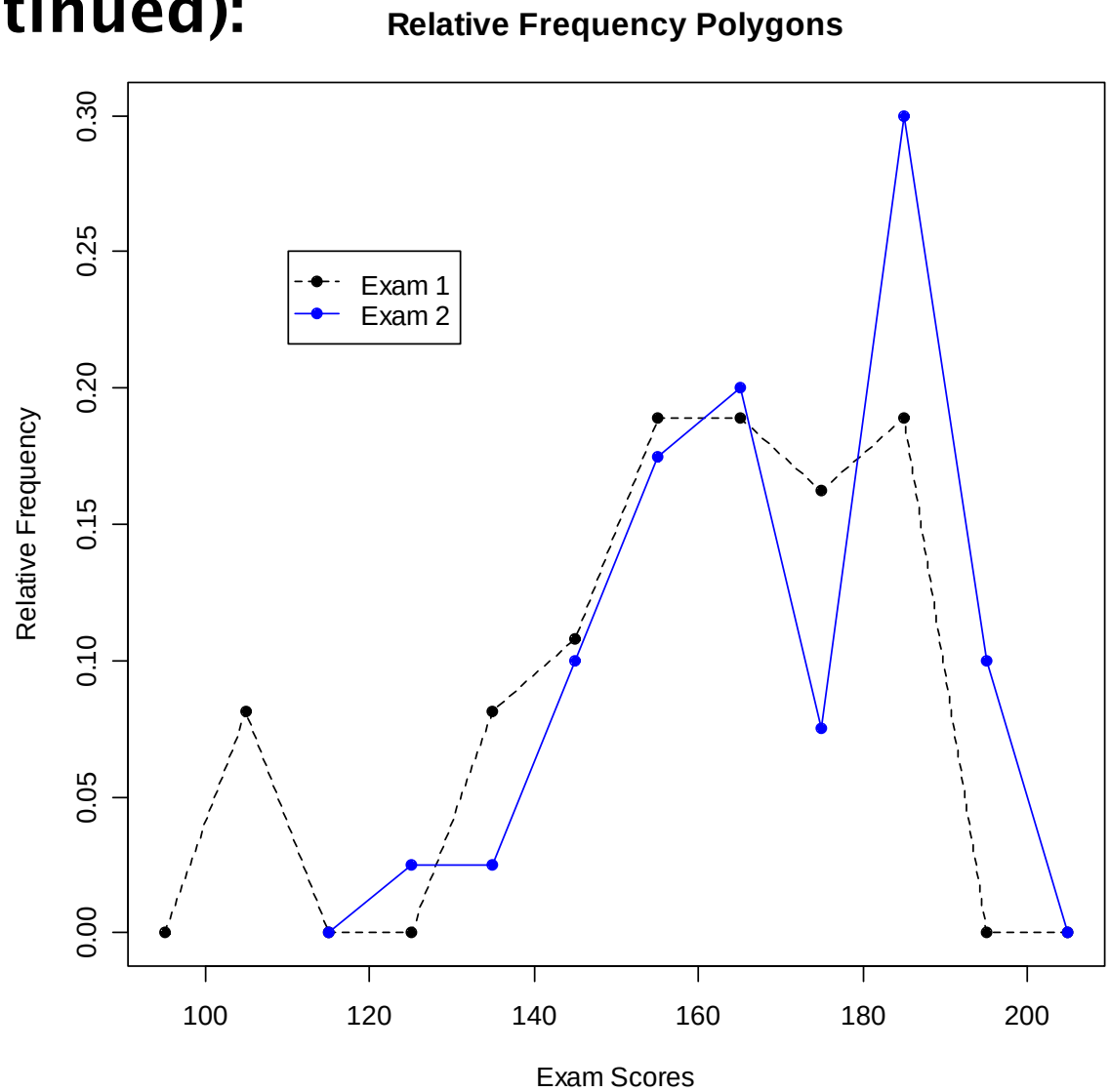
Answer (Continued):

```
> points(c(115,breaks+5),c(0,counts/40,0),
  col="blue",pch=19)

> lines(c(115,breaks+5),c(0,counts/40,0),
  col="blue",lty=1)

> legend(110,.25,c("Exam 1","Exam 2"),
  col=c("black","blue"),lty=c(2,1),pch=19)
```

In class exercise #10:

Plot the relative frequency polygons for both the first and second exams on the same graph. Provide a legend.

Answer (Continued):



In class exercise #11:

Plot the ecdf for both the first and second exams on the same graph. Provide a legend.

In class exercise #11:

Plot the ecdf for both the first and second exams on the same graph. Provide a legend.

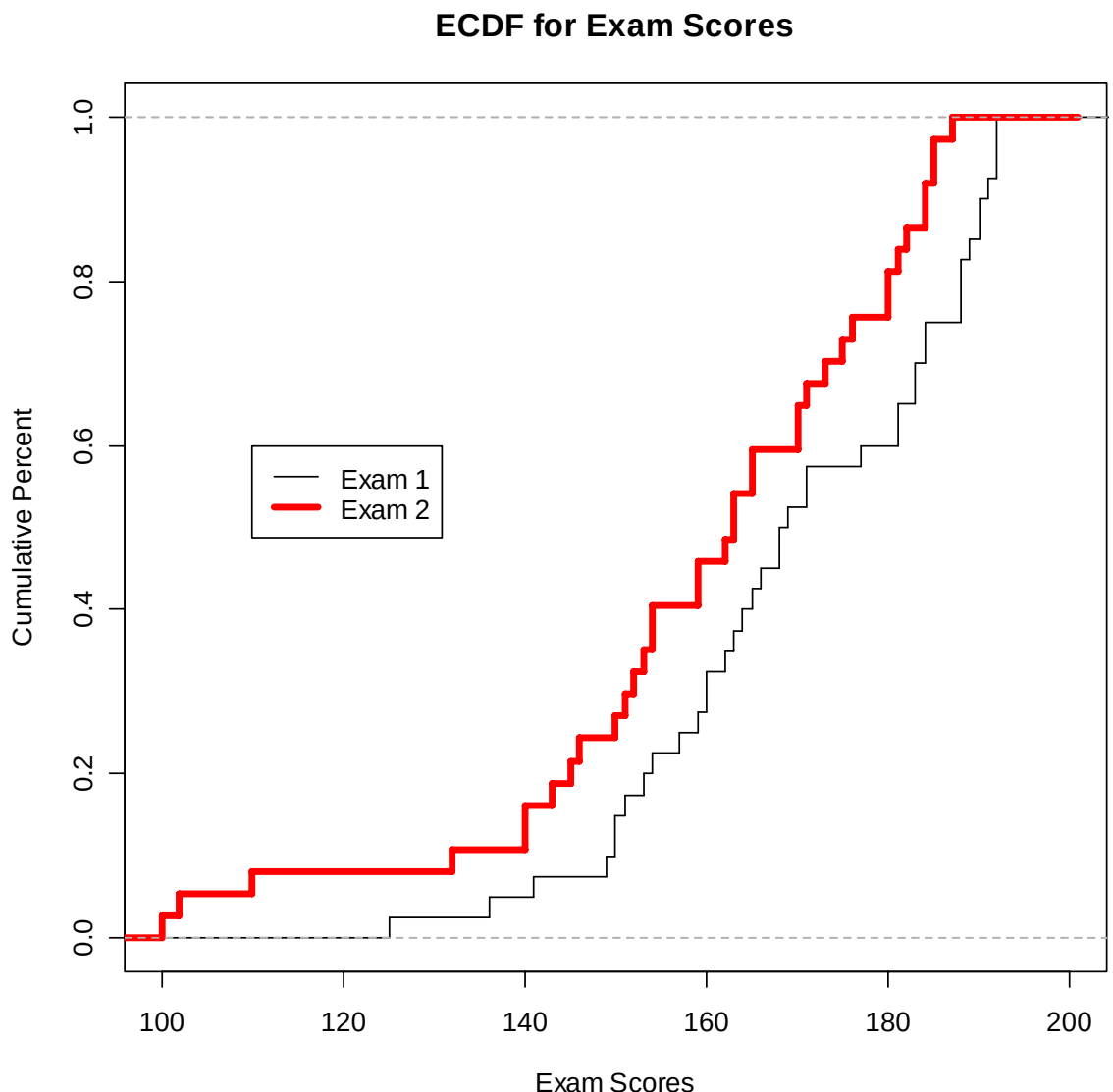
Answer:

```
> plot(ecdf(exam_scores[,1]),
  verticals= TRUE,do.p = FALSE,
  main ="ECDF for Exam Scores",
  xlab="Exam Scores",
  ylab="Cumulative Percent",
  xlim=c(100,200))

> lines(ecdf(more_exam_scores[,1]),
  verticals= TRUE,do.p = FALSE,
  col.h="red",col.v="red",lwd=4)

> legend(110,.6,c("Exam 1","Exam 2"),
  col=c("black","red"),lwd=c(1,4))
```

In class exercise #11:

Plot the ecdf for both the first and second exams on the same graph. Provide a legend.

Answer:



In class exercise #12:

Based on the plot of the ECDF for both the first and second exams from the previous exercise, which exam has lower scores in general? How can you tell from the plot?