Psychology 205: Research Methods in Psychology
Analyzing the memory experiment

William Revelle

Department of Psychology
Northwestern University
Evanston, Illinois USA

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Outline

Data = Model + Residual (error)

1. Data = Model + Residual
2. Observed data may be represented by a model of the data. What is left over is residual (or error)
3. The process of research is to reduce the residual
4. We do this by a progression of models, ranging from the very simple to the complex
5. We want to know how each model fits the data

Consider the Recall and Recognition data

1. How to describe it
    - Raw data
    - Summary statistics
    - Graphically
2. All tables and graphs are prepared by using the R computer package. For details on using R, consult the tutorials, particularly the short tutorial, listed in the syllabus
    - First, install R from `http://r-project.org` (just do this once)
    - Then, install the *psych* (just do this once)
        - install.packages("psych")
    - library(psych) #everytime you start R

The very raw data – as stored in excel

Condition mad fear hate rage temper fury ire wrath happy fight hatred mean calm emotion enrage intrusion white dark cat charred night funeral color grief blue death ink bottom coal brown gray intrusion butter food eat sandwich rye jam milk flour jelly dough crust slice wine loaf toast intrusion table sit legs seat couch desk recliner sofa wood cushion swivel stool sitting rocking bench intrusion hot snow warm winter ice wet frigid chilly heat weather freeze air shiver Arctic frost intrusion nurse sick lawyer medicine health hospital dentist physician ill patient office stethoscope surgeon clinic cure intrusion shoe hand toe kick sandals soccer yard walk ankle arm boot inch sock smell mouth intrusion apple vegetable orange kiwi citrus ripe pear banana berry cherry basket juice salad bowl cocktail intrusion boy dolls female young dress pretty hair niece dance beautiful cute date aunt daughter sister intrusion low clouds up tall tower jump above building noon cliff sky over airplane dive elevate intrusion queen England crown prince George dictator palace throne chess rule subjects monarch royal leader reign intrusion woman husband uncle lady mouse male father strong friend beard person handsome muscle suit old intrusion hill valley climb summit top molehill peak plain glacier goat bike climber range steep ski intrusion note sound piano sing radio band melody horn concert instrument symphony jazz orchestra art rhythm intrusion thread pin eye sewing sharp point prick thimble haystack thorn hurt injection syringe cloth knitting intrusion water stream lake Mississippi boat tide swim flow run barge creek brook fish bridge winding intrusion

2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 0 1 1 0 1 1 1 1 0 0 1 1 1 1 1 0 0 1 1 1 1 1 1 0 0 1 0 1 1 0 0 0 0 0 0 0 0 0 0
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1 1 1 1 1 1 0 1 0 1 0 1 1 1 1 1 1 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 1 1 1 1 1 1 1
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1 1 0 1 3 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
1 1 1 0 0 1 1 1 1 1 1 1 1 1 1 1 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 0 1 1 1 1 1 1 1
0 0 0 1 1 0 1 1 1 1 1 0 1 1 1 1 1 1 0 1 1 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 0 1 1 1
1 1 1 1 1 1 0 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 0 0 1 1 1 1 1 0 1 1 1 1 1 1 1 0 0 0 0 1 1 1 1 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 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 1 0 0 1 1 1 0 1
1 1 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0

1 0 0 0 1 0 0 1 0 1 1 0 0 1 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 0 0 0 0 0 0 1 0 0

Getting the data – method 1 (the conventional method)

We can read the data from a remote file (in this case, the personality-project.org server). We need to specify the filename and two other parameters.

We first specify the file name (the complete path to the file) for the recall data. We then read in the recall data. We repeat this process for the recognition data.

After doing these two reads, we ask how big the two objects are using the `dim` command.

```
filename <- "http://personality-project.org/revelle/syllabi/205/memory.data/memory.recall.csv"
recall <- read.table(filename,header=TRUE,sep=",")

filename <- "http://personality-project.org/revelle/syllabi/205/memory.data/memory.recognition.csv"
recog <- read.table(filename,header=TRUE,sep=",")
```

```
> dim(recall)
[1]  24 257
> dim(recog)
[1] 24 97
```

Getting the data, method 2 (a somewhat easier method)

Alternatively, if you have browser, you can read the remote file using our browser and then copy the output into the "clipboard" and then just read the clipboard. This has the advantage that you can see what you are doing.

```
#first, use your browser to go to
       http://personality-project.org/revelle/syllabi/205/memory.data/memory.recall.csv
#copy the resulting window to your clipboard
#read the clipboard
recall <- read.clipboard.csv()
dim(recall)

#then use your browser to go to
     http://personality-project.org/revelle/syllabi/205/memory.data/memory.recognition.csv
#copy this to your clipboard and then read the clipboard
recog <- read.clipboard.csv()
dim(recog)
```

```
> dim(recall)
[1]  24 257

> dim(recog)
[1] 24 97
```

These two ways of reading the data are equally easy (complicated).

Some basic recoding of the data to make it useful

1. Once you have the recall data in the recall object, we need to do some basic recoding to make it useful
    - We want to find the recall for each position for each subject.
    - The data, as typed in, were in the form of 257 columns for each of 24 subjects.
    - Condition, List 1, List 2, ... List 16
    - For each list, it went position 1 ... 15 and then the number of intrusions (false recalls).
    - Thus, we want to add up items 2, 18, 34 ... 242 to get the recall for position 1
    - and then do this for items 3, 19, 35 ... 243 to get recall for position 2
    - etc.
2. We do this with a bit of code (to be appreciated, and perhaps understood).
    - Create a vector of the first item
    - Use this to make a matrix of all item positions
    - Then use that matrix to find the various means

A bit of strange code (can be appreciated or ignored)

```
filename <-
recall <- read.clipboard.tab()
dim(recall)
[1]  24 257

W <- seq(2, 257, 16)
W
 [1]   2  18  34  50  66  82  98 114 130 146 162
         178 194 210 226 242

w <- outer(W,0:15,"+")


w
```

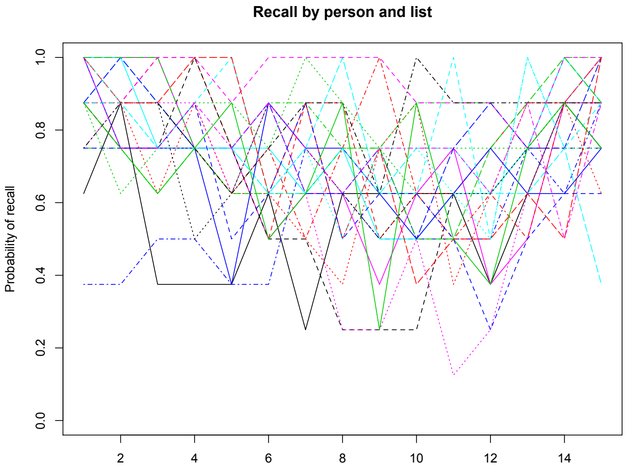
```
 [1]   2  18  34  50  66  82  98 114 130 146 162 178 194 210 226 242

     [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13] [,14] [,15] [,16]
 [1,]    2    3    4    5    6    7    8    9   10    11    12  [illegible]    14    15    16    17
 [2,]   18   19   20   21   22   23   24   25   26    27    28    29    30    31    32    33
 [3,]   34   35   36   37   38   39   40   41   42    43    44    45    46    47    48    49
  ...
[16,]  242  243  244  245  246  247  248  249  250   251   252   253   254   255   256   257
```

1. First copy the data to the clipboard and then read the clipboard into the recall data.frame
2. How big is this data frame? (What are the dimensions?)
3. Create a vector to show where each list is
4. Then create a vector to show how to add up the items

Find means for each person for each position

```
rec <- matrix(NA,24,16)  #create a matrix to store the results
for (i in 1:16) {rec[,i] <- rowMeans(recall[w[,i]],na.rm=TRUE)*2}
colnames (rec) <- paste0("P",1:16,"")
rownames(rec) <- paste0("S",1:24,"")
rec

       P1    P2    P3    P4    P5    P6    P7    P8    P9   P10   P11   P12   P13   P14   P15   P16
S1  0.625 0.875 0.375 0.375 0.375 0.625 0.250 0.625 0.625 0.625 0.625 0.375 0.625 0.875 0.750 0.875
S2  0.875 0.875 1.000 1.000 0.750 0.500 0.875 0.875 0.500 0.625 0.625 0.750 0.875 0.875 1.000 0.750
S3  0.875 0.625 0.750 0.875 0.875 0.750 1.000 0.875 0.750 0.625 0.750 0.750 0.750 0.875 1.000 0.125
S4  0.375 0.375 0.500 0.500 0.375 0.375 0.750 0.625 0.500 0.500 0.500 0.500 0.750 0.625 0.875 0.000
S5  0.875 1.000 0.875 0.750 0.750 0.625 0.750 1.000 0.625 0.750 0.750 0.625 0.625 0.750 0.375 0.375
S6  1.000 1.000 1.000 0.750 0.750 0.500 0.625 0.625 0.375 0.625 0.750 0.375 0.500 0.875 0.875 0.875
S7  0.875 0.750 0.750 1.000 0.750 0.500 0.500 0.250 0.250 0.250 0.625 0.625 0.750 0.750 0.750 0.000
S8  0.875 0.875 0.625 0.875 0.625 0.625 0.500 0.375 0.750 0.875 0.375 0.625 0.875 0.875 0.625 0.750
S9  0.750 0.750 0.625 0.750 0.625 0.875 0.875 0.750 0.750 0.875 0.875 0.875 0.750 1.000 1.000 1.000
S10 0.875 1.000 0.875 0.750 0.750 0.875 0.625 0.625 0.750 0.500 0.750 0.875 0.750 0.750 1.000 0.000
S11 1.000 1.000 0.750 0.750 0.750 0.750 0.625 0.750 0.500 0.500 0.625 0.625 0.750 1.000 0.875 0.500
S12 0.875 0.875 1.000 1.000 0.875 1.000 1.000 1.000 1.000 0.875 0.875 0.875 0.750 1.000 1.000 0.125
S13 1.000 0.875 0.875 0.500 0.625 0.875 0.750 0.625 0.500 0.625 0.625 0.625 0.750 0.875 0.875 0.800
S14 0.875 0.750 0.750 0.750 0.625 0.750 0.500 0.750 1.000 0.625 0.500 0.625 0.500 0.875 1.000 0.750
S15 1.000 1.000 1.000 0.750 0.625 0.625 0.625 0.750 0.750 0.500 0.500 0.750 0.875 1.000 0.875 0.125
S16 1.000 0.750 0.750 0.750 0.375 0.875 0.750 0.750 0.625 0.500 0.625 0.750 0.625 0.625 0.750 1.500
S17 0.875 0.875 0.750 0.875 1.000 0.625 0.625 0.750 0.625 0.625 1.000 0.500 1.000 0.750 0.875 1.375
S18 0.750 0.875 0.875 0.875 0.625 0.875 0.625 0.250 0.250 0.500 0.125 0.250 0.625 0.875 1.000 0.250
S19 0.750 0.875 0.875 0.750 0.625 0.750 0.875 0.875 0.625 1.000 0.875 0.875 0.875 0.875 0.875 0.125
S20 1.000 0.875 0.875 1.000 1.000 0.625 0.875 0.500 0.750 0.375 0.500 0.500 0.625 0.500 1.000 0.250
S21 0.875 0.750 0.625 0.750 0.875 0.500 0.625 0.875 0.250 0.875 0.500 0.375 0.750 0.875 0.750 0.250
S22 0.750 0.750 0.750 0.875 0.500 0.625 0.875 0.500 0.625 0.625 0.500 0.250 0.500 0.625 0.625 1.500
S23 1.000 0.875 0.750 0.750 0.750 0.625 0.750 0.500 0.750 0.750 0.625 0.500 1.000 0.750 0.750 0.375
S24 1.000 0.750 0.750 0.875 0.750 0.875 0.750 0.625 0.750 0.750 0.750 0.625 0.875 0.500 0.875 0.000
```

Show the data by person and by list: Is there a pattern?



Describe the Position data (remember, position 16 is actually the intrusions.

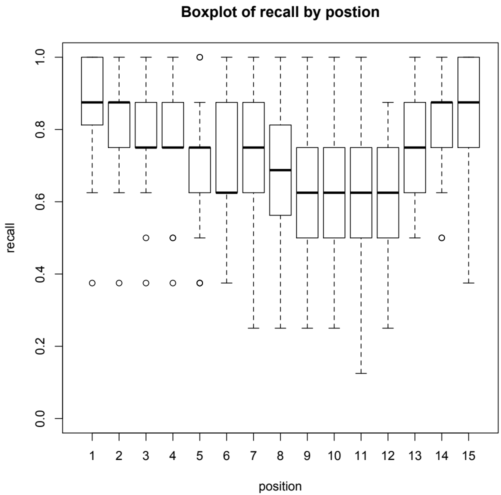
```
> describe(rec)

    vars  n mean   sd median trimmed  mad  min  max range  skew kurtosis   se
P1     1 24 0.86 0.15   0.88    0.89 0.19 0.38 1.00  0.62 -1.54     2.71 0.03
P2     2 24 0.83 0.14   0.88    0.85 0.19 0.38 1.00  0.62 -1.27     2.27 0.03
P3     3 24 0.78 0.16   0.75    0.79 0.19 0.38 1.00  0.62 -0.58     0.04 0.03
P4     4 24 0.79 0.16   0.75    0.80 0.19 0.38 1.00  0.62 -0.78     0.36 0.03
P5     5 24 0.69 0.17   0.75    0.69 0.19 0.38 1.00  0.62 -0.22    -0.51 0.04
P6     6 24 0.69 0.16   0.62    0.69 0.19 0.38 1.00  0.62  0.03    -1.03 0.03
P7     7 24 0.71 0.18   0.75    0.71 0.19 0.25 1.00  0.75 -0.42     0.01 0.04
P8     8 24 0.67 0.20   0.69    0.68 0.19 0.25 1.00  0.75 -0.41    -0.53 0.04
P9     9 24 0.62 0.20   0.62    0.62 0.19 0.25 1.00  0.75 -0.23    -0.46 0.04
P10   10 24 0.64 0.18   0.62    0.64 0.19 0.25 1.00  0.75  0.05    -0.52 0.04
P11   11 24 0.64 0.19   0.62    0.64 0.19 0.12 1.00  0.88 -0.43     0.46 0.04
P12   12 24 0.60 0.19   0.62    0.61 0.19 0.25 0.88  0.62 -0.23    -0.98 0.04
P13   13 24 0.74 0.14   0.75    0.74 0.19 0.50 1.00  0.50 -0.01    -0.81 0.03
P14   14 24 0.81 0.15   0.88    0.82 0.19 0.50 1.00  0.50 -0.59    -0.62 0.03
P15   15 24 0.85 0.16   0.88    0.87 0.19 0.38 1.00  0.62 -1.16     1.20 0.03
P16   16 24 0.53 0.48   0.38    0.48 0.56 0.00 1.50  1.50  0.66    -0.81 0.10
```

It is hard to see patterns from tables of numbers. Show the data graphically

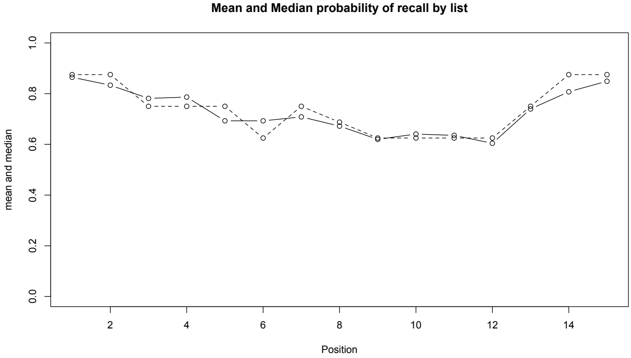
1. The first graphic compares the means and the medians.
   - Medians are less sensitive to outliers than are the means
   - There two do not differ very much
2. But we really want to know if the recall numbers differ as a function of position
3. There are several ways of showing this graphically
   - A boxplot
   - a simple line graph
   - A line graph with error bars

A simple boxplot

boxplot(rec[,1:15],ylab="recall",xlab="position",main="Boxplot of recall by postion",ylim=c(0,1))



Plot some summary estimates of central tendency; Is there a pattern?



Means and their standard errors

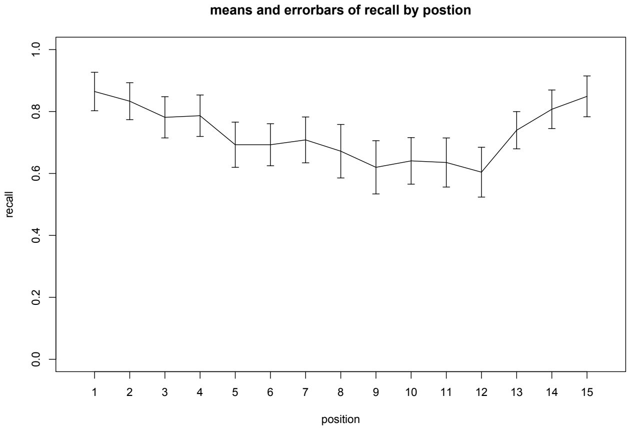
1. The mean of any set of observations represents the sample mean.
2. If we were to take other samples from the same population, we would probably find a different mean
3. The variation from one sample to another can be predicted based upon the population standard deviation
   - The central limit theorem says that the distribution of sample means should tend towards normal with a standard deviation of the means (the standard error or the mean, or the standard error)
   - $\sigma_{\bar{x}}^2 = \frac{\sigma^2}{N} <==> \sigma_{\bar{x}} = \frac{\sigma_x}{\sqrt{N}}$
   - The standard error of a mean is the sample standard deviation divided by the square root of the sample size

Showing means and their standard errors

1. When graphing a mean or a set of means, one should also show the standard error of those means.
   - Typically, this is done by showing the mean ± 1.96 standard error
2. More recently, it has been pointed out that the likelihood of the mean is not distributed equally throughout the range, but is more likely towards the middle of the confidence range.
3. This has led to the use of "cat's eye plots"
4. Both kind of plots can be done using the `error.bars` function

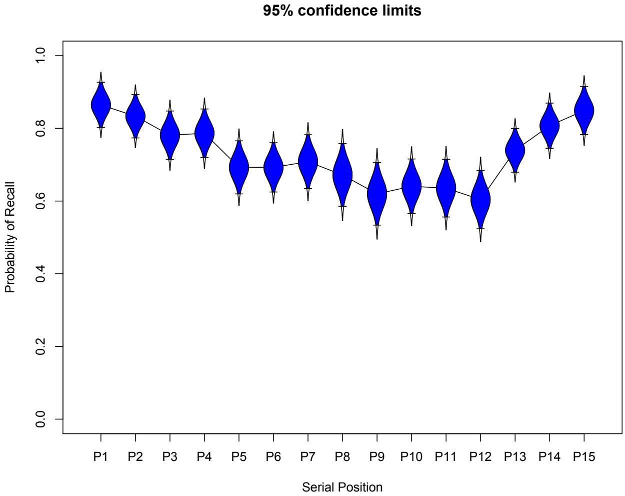
The recall data show a serial position– add in the standard errors

error.bars(rec[,1:15],ylab="recall",xlab="position",main="means and errorbars of recall by postion",ylim=c(0,1),type="l",eyes=FALSE)



The recall data show a serial position– add in the standard errors

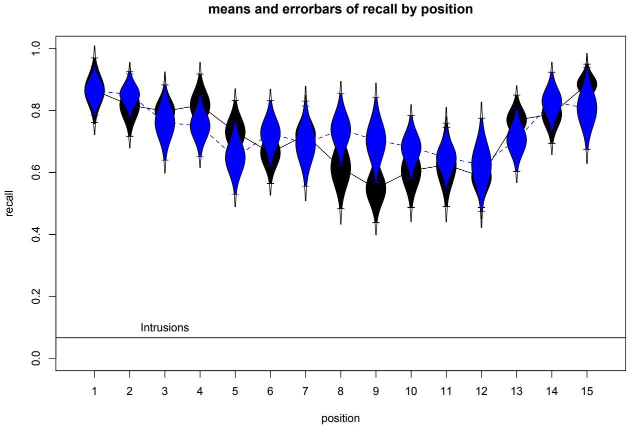
error.bars(rec[,1:15],ylab="recall",xlab="position",main="means and errorbars of recall by postion",ylim=c(0,1),type="l")



The two groups do not seem to differ

error.bars.by(rec[,1:15],group=recall$Condition,ylab="recall",xlab="position",
main="means and errorbars of recall by position",ylim=c(0,1))
abline(h=.53/8)

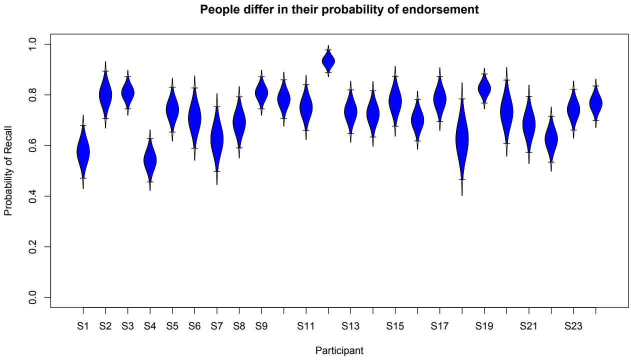
text(3,.1,"Intrusions")



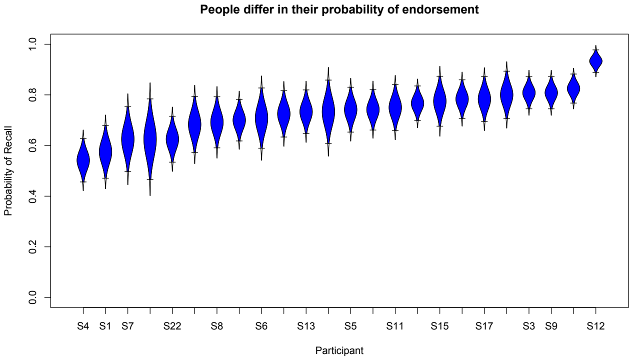
Data = Model + Residual (error)

1. Data = Model + Residual
2. Observed data may be represented by a model of the data. What is left over is residual (or error)
3. The process of research is to reduce the residual
4. We do this by a progression of models, ranging from the very simple to the complex
5. We want to know how each model fits the data

People are a major source of difference



People are a major source of difference



R code for person graphs — supplementary information

R is a syntax driven language, but each line of syntax is pretty straightforward. This is shown here for demonstration purposes on how to draw some graphs using some of the built in functions.

```
#first, plot the means and medians
plot(colMeans(rec[,1:15]),ylim=c(0,1),ylab="mean and median",xlab="Position",
            main="Mean and Median probability of recall by list",type="b")
 points(apply(rec[,1:15],2,median)
           ,type="b",lty="dashed")
#now show the error bars
error.bars(t(rec[,1:15]),ylab="Probability of Recall",ylim=c(0,1),
         xlab="Participant",main="People differ in their probability of endorsement")
 #show them by group
error.bars.by(rec[,1:15],group=recall$Condition,ylim=c(0,1),
              ylab="Probability of Recall",xlab="Serial Position")

#plot by person rather than by item (this is plotting the matrix transpose)
 error.bars(t(rec[,1:15]),ylab="Probability of Recall",ylim=c(0,1),
      xlab="Participant",main="People differ in their probability of endorsement")

 #find the individual total scores
tot <- rowSums(rec[,1:15])
ord <- order(tot)
#plot subjects ordered by total score
error.bars(t(rec[ord,1:15]),ylab="Probability of Recall",ylim=c(0,1),xlab=
              "Participant",main="People differ in their probability of endorsement")
```

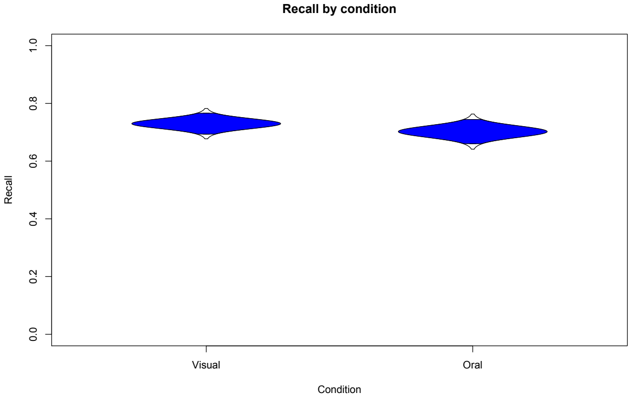
Recoding the data to get recall by presentation type

Use the same trick we did for recall by position (that is, use the w matrix to tell us which items to score) Words were presented two different ways, Visually and Orally. This was within subjects. We first find the total recalled for the two conditions. This is done by simple addition. Then convert these to percentages to make the numbers more understandable. Note that there are only 8 trials within each condition, but half of those did not involve recall. Thus, to convert to percentages, we divide by 4

```
recall.bylist <- matrix(NA,24,16)
 for (i in 1:16) {recall.bylist[,i] <- rowMeans(recall[w[i,]],na.rm=TRUE)}
colnames (recall.bylist) <- paste0("L",1:16,"")
 rownames(recall.bylist) <- paste0("S",1:24,"")
Visual <- rowSums(recall.bylist[,c(1,2,7,8,11:14)])/4
Oral <- rowSums(recall.bylist[,c(3:6,9,10,15:16)])/4
recall.bytype  <- data.frame(Visual=Visual,Oral=Oral)
 describe(recall.bytype)
```

```
       vars  n mean   sd median trimmed  mad  min  max range  skew kurtosis   se
Visual    1 24 0.73 0.09   0.75    0.73 0.09 0.56 0.89  0.33 -0.27    -0.83 0.02
Oral      2 24 0.70 0.10   0.71    0.71 0.08 0.39 0.88  0.48 -1.07     1.91 0.02
```

Recall by Visual and Oral presentation condition



The t-test

- Developed by "student" (William Gosset)
  - A small sample extension of the z-test for comparing two groups
  - Like most statistics, what is the size of the effect versus the error of the effect?
  - Standard error of a mean is $s.e. = \sigma_{\bar{x}} = \sqrt{\frac{\sigma^2}{N}}$
- Two cases
  - Independent groups
    - $t = \frac{\bar{X_1} - \bar{X_2}}{\sqrt{\sigma_1^2/N_1 + \sigma_2^2/N_2}}$
    - degrees of freedom $df = N_1 - 1 + N_2 - 1$
  - Paired differences (correlated groups)
    - let $d = X_1 - X_2$ then $t = \frac{\bar{d}}{\sigma_{\bar{d}}}$
    - d.f. = N - 1
- done in R with `t.test` function

Does Recall differ by modality of presentation? The paired t-test.

```
Visual <- rowSums(recall.bylist[,c(1,2,7,8,11:14)])/4
Oral <- rowSums(recall.bylist[,c(3:6,9,10,15:16)])/4
recall.bytype  <- data.frame(Visual=Visual,Oral=Oral)
 describe(recall.bytype)

> with(recall.bytype,t.test(Visual,Oral,paired=TRUE))
```

```
     vars  n mean   sd median trimmed  mad  min  max range  skew kurtosis   se
Visual    1 24 0.73 0.09   0.75    0.73 0.09 0.56 0.89  0.33 -0.27    -0.83 0.02
Oral      2 24 0.70 0.10   0.71    0.71 0.08 0.39 0.88  0.48 -1.07     1.91 0.02

Paired t-test

data:  Visual and Oral
t = 1.6312, df = 23, p-value = 0.1165
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.007390829  0.062512357
sample estimates:
mean of the differences
             0.02756076
```

Mean recall does not differ as a function of modality of presentation.

Recall results

- As predicted, there was a serial position effect.
  - This suggested that the participants followed instructions.
- There was no difference between the serial position effects for the two experimental groups.
- There was no effect of modality of presentation on immediate recall.
- Now need to see if there is a false memory effect on subsequent recognition.

Preliminary analysis of the recognition data

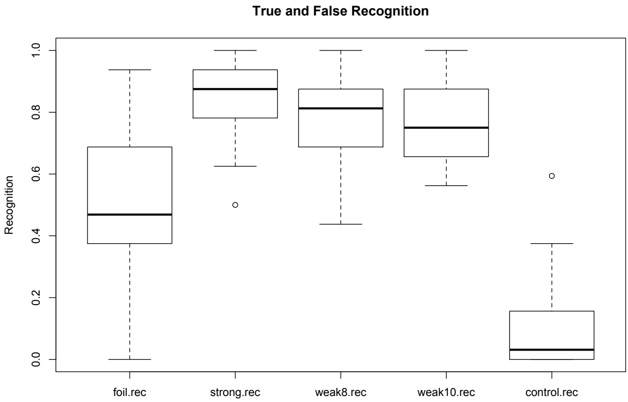
```
recog <- read.clipboard.csv()  #get the data
 recogn <- recog #create a temporary matrix to modify
 recogn[recogn>1] <- 1  #new vs. old  (dropping the remember/know distinction for now)

foil <- c("anger","black","bread","chair","cold","doctor","foot","fruit","girl","high","king",
      "man","mountain", "music","needle","river")
strong <- c("mad","white","butter","table","hot","nurse","shoe","apple","boy","low","queen",
                "woman","hill","note","thread","water")
weak8 <- c("wrath","grief","flour","sofa","chilly","physician","walk","banana","niece","building",
                "throne","strong","plain","horn","thimble","flow")
weak10 <- c("fight","death","dough","cushion","weather","patient","arm","cherry","beautiful","cliff",
                    "rule","beard","goat","instrument","thorn","barge")
control <- c("rough","smooth","course","riders","sleep","bed","blanket","slumber","slow","fast","traffic",
           "hesitant","spider","web","tarantula","bite","sweet","sour","nice","soda",
                "thief","steal","rob","gun","window","door","open","frame")

 foil.rec <- rowSums(recogn[,foil],na.rm=TRUE)/16
 strong.rec <- rowSums(recogn[,strong],na.rm=TRUE)/16
weak10.rec <- rowSums(recogn[,weak10],na.rm=TRUE)/16
weak8.rec <- rowSums(recogn[,weak8],na.rm=TRUE)/16
control.rec <- rowSums(recogn[,control],na.rm=TRUE)/32
 recog.df <- data.frame(foil.rec,strong.rec,weak8.rec,weak10.rec,control.rec)

 recog.df   #show the scores
  #now plot them

 error.bars(recog.df,ylim=c(0,1),ylab="Recognized",xlab="Word type",
           main="True and False recognition by cue strength")
```

Show the scores

```
recog.df   #show the scores

  foil.rec strong.rec weak8.rec weak10.rec control.rec
1     0.6875     0.7500    0.6875     0.5625     0.00000
2     0.4375     1.0000    1.0000     0.9375     0.00000
3     0.4375     0.6250    0.6250     0.5625     0.37500
4     0.5625     0.8125    0.8125     0.8750     0.28125
5     0.3125     0.9375    0.9375     0.8750     0.03125
6     0.6250     0.8750    0.6875     0.7500     0.06250
7     0.6875     0.8750    0.8750     0.7500     0.31250
8     0.9375     0.7500    0.6875     0.6875     0.03125
9     0.6875     0.9375    1.0000     1.0000     0.18750
10    0.0625     0.8750    0.6875     0.7500     0.00000
11    0.6875     0.9375    0.8750     0.7500     0.09375
12    0.3125     0.8750    0.8750     0.9375     0.00000
13    0.4375     0.8125    0.8125     0.8750     0.03125
14    0.4375     0.7500    0.6250     0.6875     0.59375
15    0.5000     0.8125    0.8125     0.6250     0.00000
16    0.8750     0.9375    0.8125     0.6875     0.00000
17    0.2500     1.0000    0.8750     0.9375     0.00000
18    0.4375     0.8125    0.4375     0.5625     0.06250
19    0.6250     0.9375    0.8125     0.6875     0.03125
20    0.0000     0.5000    0.6875     0.6250     0.00000
21    0.5625     0.9375    0.8125     0.8750     0.18750
22    0.6875     0.9375    0.6875     0.6250     0.00000
23    0.3750     0.7500    0.8125     0.9375     0.03125
24    0.3750     0.8750    0.8750     0.8750     0.12500
```

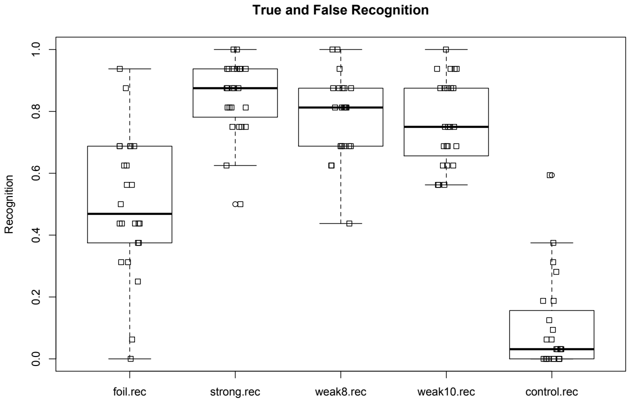
Boxplot of recognition data

boxplot(recog.df,ylab=”Recognition”,main=”True and False Recognition”)



Boxplot of recognition data with “jittered data points”

boxplot(recog.df,ylab=”Recognition”,main=”True and False Recognition”)
stripchart(recog.df,jitter=.1,vertical=TRUE,method=”jitter”,add=TRUE)



Descriptive stats of recognition

```
describe(recog.df)
            vars  n mean   sd median trimmed  mad  min  max range  skew kurtosis   se

foil.rec       1 24 0.50 0.23   0.47    0.51 0.23 0.00 0.94  0.94 -0.25    -0.28 0.05
strong.rec     2 24 0.85 0.12   0.88    0.86 0.09 0.50 1.00  0.50 -1.10     1.03 0.02
weak8.rec      3 24 0.78 0.13   0.81    0.79 0.14 0.44 1.00  0.56 -0.51     0.10 0.03
weak10.rec     4 24 0.77 0.14   0.75    0.77 0.19 0.56 1.00  0.44  0.01    -1.46 0.03
control.rec    5 24 0.10 0.15   0.03    0.07 0.05 0.00 0.59  0.59  1.73     2.38 0.03
```

Further recoding

1. Words were presented two different ways
   - Visual
   - Oral
2. Some lists were recalled, some were not– does this make a difference
   - Recall if A Math if B
3. This requires some recoding of the data

Do some recoding of the data

```
cued <- matrix(c(foil,strong,weak8,weak10),ncol=4)
cued.rec <- matrix(NA,24,4)
for(i in 1:4) {cued.rec[,i] <- rowSums(recogn[,cued[,i]],na.rm=TRUE)}

cued.recv <-  matrix(NA,24,4)
 cued.v <- cued[vo==1,]
 cued.o <- cued[vo==2,]
 cued.va <- cued[((vo==1) & (ab==1)),]
 cued.vb <- cued[((vo==1) & (ab==2)),]
 cued.oa <- cued[((vo==2) & (ab==1)),]
 cued.ob <- cued[((vo==2) & (ab==2)),]

 cued.rec <- matrix(NA,24,16)
 for(i in 1:4) {cued.rec[,i] <- rowSums(recogn[,cued.va[,i]],na.rm=TRUE)}
  for(i in 1:4) {cued.rec[,i+4] <- rowSums(recogn[,cued.vb[,i]],na.rm=TRUE)}
    for(i in 1:4) {cued.rec[,i+8] <- rowSums(recogn[,cued.oa[,i]],na.rm=TRUE)}
      for(i in 1:4) {cued.rec[,i+12] <- rowSums(recogn[,cued.ob[,i]],na.rm=TRUE)

colnames(cued.rec) <- c("FoilVa","StrongVA","WeakVa","WeakerVA","FoilVb",
"StrongVb","WeakVb","WeakerVb","FoilOa","StrongOA","WeakOa",
"WeakerOa","FoilOb","StrongOb","WeakOb","WeakerVOb")
rownames(cued.rec) <- paste("S",1:24,sep="")
```

Check the coding

```
> cued.va
     [,1]    [,2]    [,3]     [,4]
[1,] "anger" "mad"   "wrath"  "fight"
[2,] "fruit" "apple" "banana" "cherry"
[3,] "king"  "queen" "throne" "rule"
[4,] "music" "note"  "horn"   "instrument"
> cued.vb
     [,1]       [,2]    [,3]     [,4]
[1,] "black"    "white" "grief"  "death"
[2,] "foot"     "shoe"  "walk"   "arm"
[3,] "man"      "woman" "strong" "beard"
[4,] "mountain" "hill"  "plain"  "goat"
> cued.oa
     [,1]     [,2]     [,3]       [,4]
[1,] "chair"  "table"  "sofa"     "cushion"
[2,] "cold"   "hot"    "chilly"   "weather"
[3,] "high"   "low"    "building" "cliff"
[4,] "needle" "thread" "thimble"  "thorn"
> cued.ob
     [,1]     [,2]     [,3]        [,4]
[1,] "bread"  "butter" "flour"     "dough"
[2,] "doctor" "nurse"  "physician" "patient"
[3,] "girl"   "boy"    "niece"     "beautiful"
```

The A condition

INDICES: 1

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis
FoilVa	1	13	0.37	0.28	0.25	0.36	0.37	0.00	0.75	0.75	0.09	-1.52
StrongVA	2	13	0.88	0.13	1.00	0.89	0.00	0.75	1.00	0.25	-0.14	-2.13
WeakVa	3	13	0.83	0.19	0.75	0.84	0.37	0.50	1.00	0.50	-0.48	-1.24
WeakerVA	4	13	0.71	0.27	0.75	0.73	0.37	0.25	1.00	0.75	-0.48	-1.15
FoilVb	5	13	0.54	0.35	0.50	0.55	0.37	0.00	1.00	1.00	-0.42	-1.23
StrongVb	6	13	0.85	0.24	1.00	0.89	0.00	0.25	1.00	0.75	-1.26	0.36
WeakVb	7	13	0.62	0.30	0.50	0.64	0.37	0.00	1.00	1.00	-0.32	-0.82
WeakerVb	8	13	0.77	0.26	0.75	0.80	0.37	0.25	1.00	0.75	-0.55	-1.21
FoilOa	9	13	0.56	0.31	0.50	0.57	0.37	0.00	1.00	1.00	-0.16	-1.26
StrongOA	10	13	0.79	0.22	0.75	0.80	0.37	0.50	1.00	0.50	-0.27	-1.80
WeakOa	11	13	0.85	0.19	1.00	0.86	0.00	0.50	1.00	0.50	-0.66	-1.13
WeakerOa	12	13	0.75	0.23	0.75	0.77	0.37	0.25	1.00	0.75	-0.61	-0.56
FoilOb	13	13	0.54	0.34	0.50	0.55	0.37	0.00	1.00	1.00	0.12	-1.48
StrongOb	14	13	0.81	0.21	0.75	0.84	0.00	0.25	1.00	0.75	-1.19	1.26
WeakOb	15	13	0.81	0.18	0.75	0.82	0.37	0.50	1.00	0.50	-0.31	-1.23
WeakerVOb	16	13	0.81	0.18	0.75	0.82	0.37	0.50	1.00	0.50	-0.31	-1.23

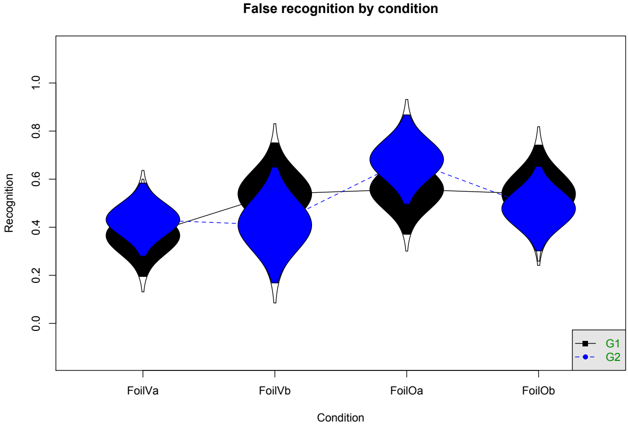
The B condition

```
--------------------------------------------------------------------------------
INDICES: 2
          vars  n mean   sd median trimmed  mad  min  max range  skew kurtosis
FoilVa       1 11 0.43 0.23   0.50    0.44 0.37 0.00 0.75  0.75 -0.26    -0.96
StrongVA     2 11 0.86 0.26   1.00    0.92 0.00 0.25 1.00  0.75 -1.36     0.28
WeakVa       3 11 0.80 0.19   0.75    0.81 0.37 0.50 1.00  0.50 -0.25    -1.37
WeakerVA     4 11 0.70 0.29   0.75    0.72 0.37 0.25 1.00  0.75 -0.37    -1.51
FoilVb       5 11 0.41 0.36   0.50    0.39 0.37 0.00 1.00  1.00  0.40    -1.18
StrongVb     6 11 0.98 0.08   1.00    1.00 0.00 0.75 1.00  0.25 -2.47     4.52
WeakVb       7 11 0.82 0.20   0.75    0.83 0.37 0.50 1.00  0.50 -0.43    -1.41
WeakerVb     8 11 0.73 0.18   0.75    0.72 0.00 0.50 1.00  0.50  0.09    -1.16
FoilOa       9 11 0.68 0.28   0.75    0.69 0.37 0.25 1.00  0.75 -0.33    -1.39
StrongOA    10 11 0.84 0.17   0.75    0.86 0.37 0.50 1.00  0.50 -0.44    -1.08
WeakOa      11 11 0.80 0.25   0.75    0.83 0.37 0.25 1.00  0.75 -0.90    -0.37
WeakerOa    12 11 0.82 0.20   0.75    0.83 0.37 0.50 1.00  0.50 -0.43    -1.41
FoilOb      13 11 0.48 0.26   0.50    0.47 0.00 0.00 1.00  1.00  0.16    -0.31
StrongOb    14 11 0.77 0.13   0.75    0.78 0.00 0.50 1.00  0.50  0.11    -0.01
WeakOb      15 11 0.77 0.18   0.75    0.78 0.00 0.50 1.00  0.50 -0.09    -1.16
WeakerVOb   16 11 0.86 0.17   1.00    0.89 0.00 0.50 1.00  0.50 -0.69    -0.89
```

That is too complicated, lets just look at the foils, first the numbers, then the graph

```
 describeBy(cued.rec[,c(1,5,9,13)]/4,group=recog$Condition)
error.bars.by(cued.rec[,c(1,5,9,13)]/4,group=recog$Condition,legend=1,
    ylab="Recognition",xlab="Condition",main="False recognition by condition")

INDICES: 1
       vars  n mean   sd median trimmed  mad min  max range  skew kurtosis   se
FoilVa    1 13 0.37 0.28   0.25    0.36 0.37   0 0.75  0.75  0.09    -1.52 0.08
FoilVb    2 13 0.54 0.35   0.50    0.55 0.37   0 1.00  1.00 -0.42    -1.23 0.10
FoilOa    3 13 0.56 0.31   0.50    0.57 0.37   0 1.00  1.00 -0.16    -1.26 0.09
FoilOb    4 13 0.54 0.34   0.50    0.55 0.37   0 1.00  1.00  0.12    -1.48 0.09
-------------------------------------------------------------------------------
INDICES: 2
       vars  n mean   sd median trimmed  mad  min  max range  skew kurtosis   s
FoilVa    1 11 0.43 0.23   0.50    0.44 0.37 0.00 0.75  0.75 -0.26    -0.96 0.0
FoilVb    2 11 0.41 0.36   0.50    0.39 0.37 0.00 1.00  1.00  0.40    -1.18 0.1
FoilOa    3 11 0.68 0.28   0.75    0.69 0.37 0.25 1.00  0.75 -0.33    -1.39 0.0
FoilOb    4 11 0.48 0.26   0.50    0.47 0.00 0.00 1.00  1.00  0.16    -0.31 0.0
```

False Recognition by A/B condition



Descriptive versus inferential

- Descriptive statistics is also known as Exploratory Data Analysis; Analogous to a detective trying to solve a crime
    - We are acting as a detective, trying to understand what is going on
    - Looking for strange behaviors
    - Developing hypotheses (ideally hypotheses are developed before collecting data, but it is important for future studies to examine the current data to develop hypotheses)
- This is in contrast to Inferential Statistics; analogous to a court proceeding with the presumption of innocence.
    - Are the results different enough from what is expected by a simpler hypothesis to reject that simpler hypothesis.
    - A typical "simple" hypothesis is the "Null Hypothesis" (aka "Nill" hypothesis).
    - What is the likelihood of observing our data given the Null hypothesis versus our alternative hypothesis.
- What do the data show? How certain are we that they show it?

Inferential tests: t, F, r

- The basic inferential test is the t-test.
  - Is the difference between two group means larger than expected by chance?
  - "Nill hypothesis" is that two groups are both sampled from the same population.
  - Alternative hypothesis is that the two groups come from different populations with different means.
- The basic test was developed by William Gosset (publishing under the pseudonym of "student")
- Two cases
  - Independent groups
    - $t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\sigma_1^2/N_1 + \sigma_2^2/N_2}}$
    - degrees of freedom $df = N_1 - 1 + N_2 - 1$
  - Paired differences (correlated groups)
    - let $d = X_1 - X_2$ then $t = \frac{\bar{d}}{\sigma_{\bar{d}}}$
    - d.f. = N - 1

Hypothesis testing using inferential statistics

- How likely are the observed data given the hypothesis that an Independent Variable has no effect.
- Bayesian statistics compare the likelihood of the data given the hypothesis of no differences as contrasted to the likelihood of the data given competing hypotheses.
  - This takes into account our prior willingness to believe that the IV could have an effect.
  - Also takes into account our strength of belief in the hypothesis of no effect
- Conventional tests report the probability of the data given the "Null" hypothesis of no difference.
- The less likely the data are to be observed given the Null, the more we tend to discount the Null.
  - Three kinds of inferential errors: Type I, Type II and Type III
  - Type I is rejecting the Null when in fact it is true
  - Type II is failing to reject the Null when it is in fact not true
  - Type III is asking the wrong question

Hypothesis Testing

Table : The ways we can be mistaken

		State of the World	
		True	False
Scientists says	True	Valid Positive	Type I error
	False	Type II error	Valid rejection

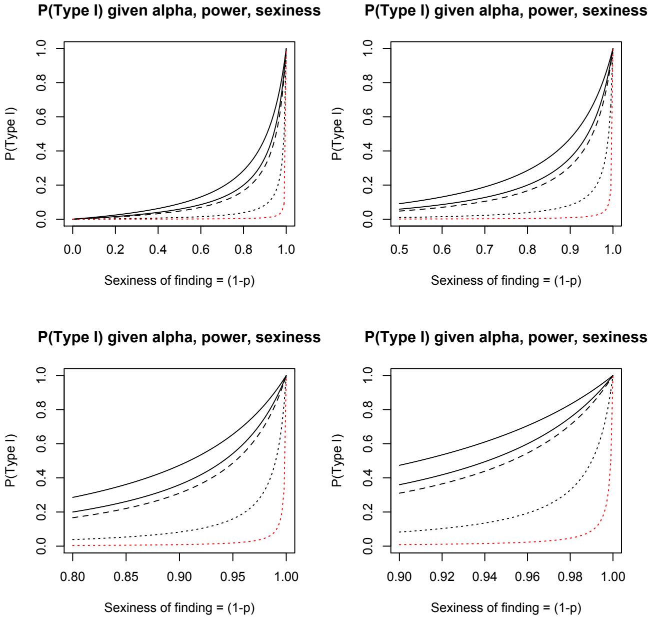
Type III error is asking the wrong question!

Error probability depends upon the base rates as well

1. The less likely the finding, the more likely a "significant finding" is actually a type I error

Table : The ways we can be mistaken

		State of the World		
		True	False	Total
Scientists says	True	475	25	500
	False	25	475	500
	Total	500	500	1000


P(Type I) given alpha, power, sexiness
P(Type I)
0.0
0.2
0.4
0.6
0.8
1.0
Sexiness of finding = (1-p)
P(Type I) given alpha, power, sexiness
P(Type I)
0.5
0.6
0.7
0.8
0.9
1.0
Sexiness of finding = (1-p)
P(Type I) given alpha, power, sexiness
P(Type I)
0.80
0.85
0.90
0.95
1.00
Sexiness of finding = (1-p)
P(Type I) given alpha, power, sexiness
P(Type I)
0.90
0.92
0.94
0.96
0.98
1.00
Sexiness of finding = (1-p)

Analysis of Variance allows for testing multiple hypotheses at once

- The t-test compares group means to the standard error of their differences
- The F-test (developed by R. A. Fisher) compares the variances between group means to the variance within groups.
  - For two groups, F is just t^2, but the theory generalizes to multiple groups.
  - The F is a ratio of variances: $\frac{VarianceBetweenGroups}{Variancewithingroups} = \frac{\sigma^2_{bg}}{\sigma^2_{wg}}$
    - To make this sound more complicated than it really is, variances are called "Mean Squares" and are found by finding the Sums of Squares between Groups and the Sums of Squares within Groups.
    - These Sums of Squares are in turned divided by the "degrees of freedom" or "df" to find MS (Mean Squares) or σ^2
- We now recognize that these variance components can be estimated by linear regression, but some still prefer the ANOVA terminology.

Using ANOVA to compare recognition accuracy

- ANOVA partitions the total variance into various independent parts:
  - Variance between groups
  - Variance within subjects.
  - But if there are more than two groups, the variance between groups can be further partitioned.
  - And, in the case of within subject analyses, the variance within subjects can be partitioned into that which is due to groups and that which is left over (residual variance).
- To do within subject analyses in R is a little tricky for it requires reorganizing the data.
- This is why it took so long to do.
- You should try to understand what the final result is, rather than the specific process of doing the analysis.

Reorganize the data for ANOVA

Because we have have repeated measures (within subject) design, we first need to "string out " the data to make one column the dependent variable, and other columns the conditions variables. This more tedious than complicated.

```
visualoral.df <- data.frame(visualoral2/4)
VO.df <- stack(visualoral.df)   #this strings it out
headTail(VO.df) #show a few lines
```

```
>     values   ind
1      0.5 FoilVr
2      0.5 FoilVr
3      0.5 FoilVr
4     0.75 FoilVr
...    ...   <NA>
285   0.88 WeakOm
286   0.62 WeakOm
287   0.75 WeakOm
288   0.88 WeakOm
```

Now, add columns to define the various conditions

```
VO1.df <- data.frame(values=VO.df$values,ind = VO.df$ind,VO= c(rep("V",144),rep(
          RM=rep(c(rep("R",72),rep("M",72)),2),
          word=rep(c(rep("Foil",24),rep("Strong",24),rep("Weak",24)),4),
          subj =rep(paste("Subject",1:24,sep=""),12))
VO1.df[c(1:2,24:26,49:51,99:101,149:151,198:200,284:288),]
```

```
    values      ind VO RM   word      subj
1    0.500   FoilVr  V  R   Foil  Subject1
2    0.500   FoilVr  V  R   Foil  Subject2
24   0.250   FoilVr  V  R   Foil Subject24
25   1.000 StrongVr  V  R Strong  Subject1
26   1.000 StrongVr  V  R Strong  Subject2
49   0.500   WeakVr  V  R   Weak  Subject1
50   0.875   WeakVr  V  R   Weak  Subject2
51   0.375   WeakVr  V  R   Weak  Subject3
99   0.750 StrongVm  V  M Strong  Subject3
100  1.000 StrongVm  V  M Strong  Subject4
101  1.000 StrongVm  V  M Strong  Subject5
149  0.500    FoilO  O  R   Foil  Subject5
150  0.750    FoilO  O  R   Foil  Subject6
151  0.750    FoilO  O  R   Foil  Subject7
198  0.750    WeakO  O  R   Weak  Subject6
199  1.000    WeakO  O  R   Weak  Subject7
```

Several ways to think about the data

- As a between subjects design
  - This will find how much variance is associated with the differences between conditions
  - And then compares this to a pooled estimate of error within conditions.
  - This ignores the fact that the same subjects were in all conditions
- As a within subjects design
  - The variance between conditions is the same
  - But the variance within conditions is divided into that due to subject differences, and that due to subject within condition differences

The most naive model – between subjects – 3 additive effects

```
model1 <- aov(values ~ VO+RM + word,data=VO1.df)
summary(model1)

              Df Sum Sq Mean Sq F value Pr(>F)
VO             1  0.043   0.043   0.784  0.377
RM             1  0.078   0.078   1.443  0.231
word           2  6.435   3.218  59.283 <2e-16 ***
Residuals    283 15.360   0.054
---
Signif. codes:  0 Ô***Õ 0.001 Ô**Õ 0.01 Ô*Õ 0.05 Ô.Õ 0.1 Ô Õ 1
```

This ignores possible interaction effects

Consider the somewhat less naive - between subjects approach first with interactions

```
model2 <- aov(values ~ VO* RM * word,data=VO1.df) #specify the model
summary(model2)  #summarize it
```

```
              Df Sum Sq Mean Sq F value  Pr(>F)
VO             1  0.043   0.043   0.810 0.36891
RM             1  0.078   0.078   1.492 0.22297
word           2  6.435   3.218  61.274 < 2e-16 ***
VO:RM          1  0.022   0.022   0.413 0.52085
VO:word        2  0.055   0.028   0.525 0.59224
RM:word        2  0.579   0.289   5.509 0.00451 **
VO:RM:word     2  0.211   0.106   2.013 0.13560
Residuals    276 14.493   0.053
---
Signif. codes:  0 Ô***Õ 0.001 Ô**Õ 0.01 Ô*Õ 0.05 Ô.Õ 0.1 Ô Õ 1
```

Now, consider the within subjects analysis

```
model3 <- aov(values ~ VO* RM * word+Error(subj/ind),data=VO1.df)
 summary(model3)
```

```
Error: subj
          Df Sum Sq Mean Sq F value Pr(>F)
Residuals 23  3.331  0.1448

Error: subj:ind
            Df Sum Sq Mean Sq F value  Pr(>F)
VO           1  0.043   0.043   0.964 0.32712
RM           1  0.078   0.078   1.776 0.18389
word         2  6.435   3.218  72.926 < 2e-16 ***
VO:RM        1  0.022   0.022   0.492 0.48375
VO:word      2  0.055   0.028   0.625 0.53628
RM:word      2  0.579   0.289   6.556 0.00167 **
VO:RM:word   2  0.211   0.106   2.395 0.09321 .
Residuals  253 11.163   0.044
---
Signif. codes:  0 Ô***Õ 0.001 Ô**Õ 0.01 Ô*Õ 0.05 Ô.Õ 0.1 Ô Õ 1
```

Note how the residuals have gotten somewhat smaller because we have controlled for the variance between subjects. This makes the

One more way of treating the within subject error

```
model4 <-  aov(values ~ VO* RM * word+Error(subj/(VO+RM +word)),data=VO1.df)
summary(model4)
```

```
Error: subj
          Df Sum Sq Mean Sq F value Pr(>F)
Residuals 23  3.331  0.1448
Error: subj:VO
          Df Sum Sq Mean Sq F value Pr(>F)
VO         1 0.0425 0.04253   1.348  0.258
Residuals 23 0.7257 0.03155
Error: subj:RM
          Df Sum Sq Mean Sq F value Pr(>F)
RM         1 0.0783 0.07834   2.078  0.163
Residuals 23 0.8670 0.03769
Error: subj:word
          Df Sum Sq Mean Sq F value   Pr(>F)
word       2  6.435   3.218      36 3.89e-10 ***
Residuals 46  4.112   0.089
---
Signif. codes:  0 Ô***Õ 0.001 Ô**Õ 0.01 Ô*Õ 0.05 Ô.Õ 0.1 Ô Õ 1

Error: Within
            Df Sum Sq Mean Sq F value   Pr(>F)
VO:RM        1  0.022 0.02170   0.640 0.424869
VO:word      2  0.055 0.02756   0.813 0.445394
RM:word      2  0.579 0.28928   8.532 0.000301 ***
VO:RM:word   2  0.211 0.10569   3.117 0.046970 *
Residuals  161  5.459 0.03391
---
Signif. codes:  0 Ô***Õ 0.001 Ô**Õ 0.01 Ô*Õ 0.05 Ô.Õ 0.1 Ô Õ 1
```

What have we found?

1. One reliable (“statistically significant”) effect is that Correct words are recognized more than False Words (Foils). This is not overly surprising.
2. Another finding is that Recall or Math instructions interacted with word type.
   - There is weaker finding that Recall versus Math interacted with Visual versus Oral instructions on word tipe.
3. Lets look at the means to understand what is happening.
   - We do this by the simple R command of print(model.tables(model4,“means”))

Show the cell means

```
model.tables(model4,"means")

Tables of means
Grand mean    # not very interesting  don't bother to report this
0.7074653
 VO   #Does Oral differ from Verbal?
VO     #no
     O      V
0.6953 0.7196
 RM  does Recall versus doing Math make a difference
    M     R      #no
0.724 0.691
 word #The difference between types of words is very large
word
  Foil Strong   Weak
0.5000 0.8464 0.7760
#What about various interactions?
 VO:RM
   RM
VO  M      R
  O 0.7031 0.6875
  V 0.7448 0.6944
VO:word
   word
VO  Foil   Strong Weak
  O 0.5052 0.8177 0.7630
  V 0.4948 0.8750 0.7891
 RM:word
   word
RM  Foil   Strong Weak
  M 0.5625 0.8021 0.8073
  R 0.4375 0.8906 0.7448
```

```
 VO:RM:word
, , word = Foil
   RM
VO  M      R
  O 0.5208 0.4896
  V 0.6042 0.3854
, , word = Strong

   RM
VO  M      R
  O 0.7812 0.8542
  V 0.8229 0.9271
, , word = Weak
   RM
VO  M      R
  O 0.8073 0.7187
  V 0.8073 0.7708
```

Or, show the cell “effects”

```
model.tables(model4,"effects")

 VO
VO
        O         V
-0.012153  0.012153

 RM
RM
        M         R
 0.016493 -0.016493

 word
word
    Foil   Strong     Weak
-0.20747  0.13889  0.06858

 VO:RM
   RM
VO  M         R
  O -0.008681  0.008681
  V  0.008681 -0.008681

 VO:word
   word
VO  Foil      Strong    Weak
  O  0.017361 -0.016493 -0.000868
  V -0.017361  0.016493  0.000868
```

```
 RM:word
   word
RM  Foil     Strong   Weak
  M  0.04601 -0.06076  0.01476
  R -0.04601  0.06076 -0.01476

 VO:RM:word
, , word = Foil

   RM
VO  M        R
  O -0.03819  0.03819
  V  0.03819 -0.03819

, , word = Strong

   RM
VO  M        R
  O  0.01649 -0.01649
  V -0.01649  0.01649

, , word = Weak

   RM
VO  M        R
  O  0.02170 -0.02170
  V -0.02170  0.02170
```

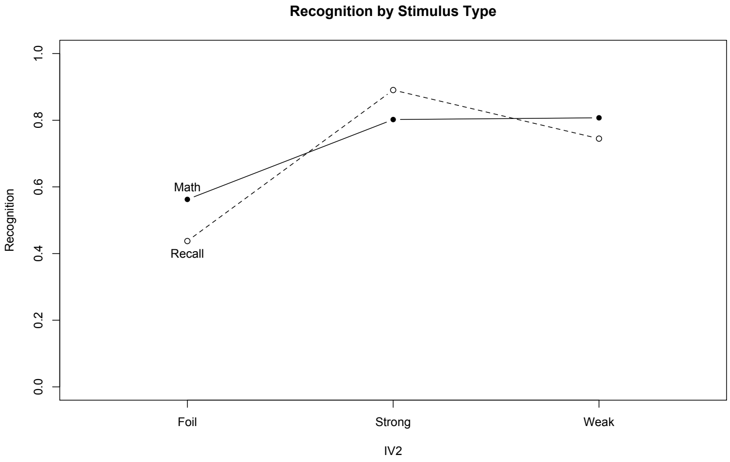
There are multiple ways to graph the interaction

1. We can take the relevant means and just create a line graph
   - This does not show the error bars, although we can use the Mean Square within subject residual to get an overall error estimate.
2. Or, we can recode the data to combine the visual and oral data and use error.bars. This is perhaps easier, but not as general.

A generic interaction plot

```
#First, specify the data (copied from the ANOVA output)
# IV1A = c(DViv2a1,DViv2b1,DViv2c1)
# IV1B = c(DViv2a1,DViv2b1,DViv2c1)

M <- c( 0.5625, 0.8021, 0.8073)
R <- c( 0.4375, 0.8906, 0.7448)

#Now plot the first line (specifying various parameters)
#plot(IV1A~IV2)
plot(M~IV2,ylim=c(0,1),ylab="Recognition",xlim=c(.5,3.5),typ="b",xaxp=c(1,3,2)
        ,xaxt="n",   pch=16,main="Recognition by Stimulus Type")
axis(side=1,at=c(1:3),labels=c("Foil","Strong","Weak"))

#plot the second line (using the points function)
points(R~IV2,typ="b",lty="dashed")

#annotate it
 text(1,.4,"Recall")
 text(1,.6,"Math")
```

Recognition varies by Recall condition and word type

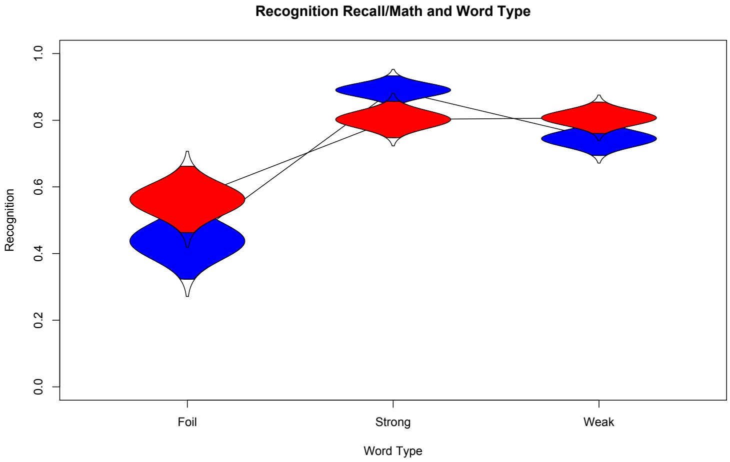


Recoding the data to add error bars

```
 for (dv in (1:6)) {pool.vo[,dv] <- (visualoral.df[,dv]+ visualoral.df[,dv+6])/2}
describe(pool.vo)
error.bars(pool.vo[,1:3],type="l",ylim=c(0,1),ylab="Recognition",xlab="Word Type",
            main="Recognition Recall/Math and Word Type",xaxt="n",within=TRUE)

axis(side=1,at=c(1:3),labels=c("Foil","Strong","Weak"))
error.bars(pool.vo[,4:6],type="l",add=TRUE,within=TRUE,col="red")
```

```
         vars  n mean   sd median trimmed  mad  min  max range  skew kurtosis   se
FoilVr      1 24 0.44 0.28   0.50    0.44 0.28 0.00 0.88  0.88 -0.06    -1.06 0.06
StrongVr    2 24 0.89 0.14   0.88    0.91 0.19 0.50 1.00  0.50 -1.31     0.88 0.03
WeakVr      3 24 0.74 0.17   0.75    0.75 0.19 0.44 1.00  0.56 -0.24    -1.26 0.03
FoilVm      4 24 0.56 0.26   0.62    0.57 0.28 0.00 1.00  1.00 -0.37    -0.74 0.05
StrongVm    5 24 0.80 0.14   0.81    0.81 0.09 0.50 1.00  0.50 -0.48    -0.46 0.03
WeakVm      6 24 0.81 0.12   0.81    0.81 0.09 0.56 1.00  0.44 -0.08    -0.72 0.02
```

Recognition varies by Word Type and Recall instructions



Putting it all together

1. Recall
    - Although there was no effect of visual (mean = .73) versus oral (mean = .70) mode of presentation on recall ($t_{23} = 1.63, p = .117$), there was clear evidence for a serial position effect (see Figure x). This showed that subjects followed instructions to recall the last few words first.
2. Recognition
    - As expected, (False) recognition of foil words (.50) was less than that of the strongest associates (.85) or the weaker associates in the middle of the list (.78) ($F_{2,46} = 36, p < .001$).
    - While high associate words were recognized more following prior opportunities to recall (.89) than not (.80), this effect was reversed for the Foil words (.44 vs. .56, respectively) and for the weaker associates (.74 vs .81) ($F_{2,161} = 8.53, p < .001$).

Results for the paper

1. What is presented above is enough for the paper
2. Probably include at least two figures -
   - serial position effects
   - Recognition by word type x Recall/math
3. Results should also include the inferential statistics
4. Additional analyses of recognition by strength of associate are not included

Structure of final paper (see detailed instructions from before)

1. Abstract (100-150 words)
    - Why did you do the study, Who were the subjects, What did you find, So what? Write it last.
2. Introduction (2-3 pages)
    - A bit of background (adapt from R & M)
    - Overview of study
3. Method (1-3 pages)
    - With enough detail that someone can carry out the study
    - Can refer to word lists from R & M rather than including the words
4. Results (1-3 pages)
    - Just the most important results
    - Should reference table(s) and figure(s) (to appear at end of paper)
5. Discussion (2-3 pages)
    - Why is this study important
    - What are the most important findings
    - So what? What is next