Psychology 205: Research Methods
Experiment 1: A study of false memory

William Revelle

Department of Psychology
Northwestern University
Evanston, Illinois USA

October, 2015
Outline

Accounting for variability
  The basic problem

Design

Our memory study
  Prior work
  Our study

Recall
  Data analysis and presentation
  Presenting the results

Recognition
  Late Breaking Analysis of the recognition to include in your paper
Overview and update of these slides

1. Several slides have been added to this presentation.
2. They are in the results of the recall (31-34) and of the recognition data (42-48)
3. For writing your paper, you should include some of these new figures as well as the new results.
4. Consider the conclusions on slide 49.
5. These new slides are meant to be as clear as possible.
6. Make sure that you look at all slides.
The fundamental challenge: accounting for variability

1. Data = Model + Residual
   - Total variability is made up of understood (modeled) and not understood (residual) variability
   - $\sigma^2_{\text{total}} = \sigma^2_{\text{model}} + \sigma^2_{\text{residual}}$

2. Good models explain more of the total variation
   - $Fit = \frac{\sigma^2_{\text{model}}}{\sigma^2_{\text{total}}}$

3. The challenge of research is to develop better models
4. The process of research is to reduce the residual
5. We do this by a progression of models, ranging from the very simple to the complex
6. We want to know how each model fits the data
The basic designs

1. Correlational/observational studies of the relationships between variables
   - Data can be any systematic set of observations
     - typically includes subject variables
     - survey research, clinical assessment, personality measurement
   - To what extent do one set of measures covary/correlate with another set of measures?
   - Can be used in predictive context – How much is a change in X associated with a change in Y?
   - Does not allow for causal inference

2. Experimental: The study of the effect of manipulated variables
   - Participants assigned to conditions to examine the causal effect of conditions
   - Between subject designs to control for order or learning effects.
   - Within subject designs control for between subject variability.

3. Quasi-experimental has appearance of experimental but does not include random assignment.
Types of Experimental Designs

1. Within Subjects
   - Removes the variability due to between person differences.
   - Has the problem of learning or fatigue related order effects.
   - Can control for order effects using counter balancing.

2. Between Subjects
   - Is less powerful because of between subject variability.
   - Does not have problem of learning or fatigue related order effects.
   - Can control for subject effects by randomization.

3. Mixed designs combine within subjects with between subjects.
Roediger and McDermott study

1. Meta-theoretical question
   • memory as photograph versus memory as reconstruction
   • ‘recovered’ childhood memories of trauma versus ‘false’ memories
   • legal testimony of accuracy of memory

2. More a demonstration of an effect than a test of competing theories
   • Alternative explanations for memory effects
     • connection strength models of memory
     • network models of association
   • Theoretical statement
     • not testing theory but rather testing phenomenon
     • need to get a robust measure of false memory in order to study it
Is memory like a photograph, or is memory like a story?

1. Bartlett and the idea of reconstructive memory
   • Recall of an experience is not just recalling facts, but is an attempt to reconstruct the events

2. Loftus and event reconstruction
   • Events are reconstructed
   • Questions can prime (perhaps incorrectly) a coherent story

3. Prior work by Deese showed that intrusion errors could be induced by using lists of high associates to a (non-presented) target word.

4. Prior work by Underwood showed that recognition errors have low probability

5. Roediger and McDermott paradigm rediscovered the Deese paradigm (for recall) and used recognition (ala Underwood).
Roediger and McDermott Study 1

1. Materials
   - 6 lists of 12 words with high associates of 6 target lures
   - recognition list
   - 12 studied words
   - 6 target lures
   - 12 weakly related
   - 12 unrelated

2. Procedure
   - verbal presentation of each list
   - free recall after each list
   - recognition 2 minutes after all lists had been presented

3. Results
   - recall shows serial position effects
   - intrusion errors almost as strong as low point of serial position
   - recognition errors are frequent
Roediger and McDermott Study 2

- **Materials**
  - 16 lists of words
  - each list has 15 words, all high associates of an unpresented target word
  - words are in order of associative strength

- **Procedure**
  - To examine the effect of prior recall, half the trials involve recall, half do not

- **Results**
  - Serial position effects show subjects follow instructions
  - Moderate level of false recognition
Our study

1. Replication and extension of Roediger and McDermott Based upon prior work in 205, observed lower rates of subsequent false recognition than R & M. Was this due to modality of presentation?

2. Within subject study (why?)
   - Modality of presentation (visual vs. oral)
   - Recall vs. no recall (math vs. recall)

3. Recall of presented words
   - Half the trials subjects recalled words

4. Recognition of presented and non-presented words
   - 1st, 8th and 10th words from list were on recognition list
   - Non-presented “lure” or “target” words
   - 32 non-presented, non cued words were also included to check for global willingness to respond
**Issues in design**

1. Within subject designs control for differences in motivation and ability by using each person as their own control
   - Each subject is a complete experiment
   - But conditions need to be independent of each other and of order effects

2. Two solutions
   - Complete randomization (used with many, many trials)
   - Counterbalancing of conditions against each other and against order

3. Consider a number of possible research orders
Complete confounding of variables and order

\[ \text{bad} \]

\[ > \text{pairs.panels(bad)} \]

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>O</td>
<td>A</td>
<td>V</td>
<td>O</td>
<td>A</td>
<td>V</td>
<td>O</td>
<td>A</td>
<td>V</td>
<td>O</td>
<td>A</td>
<td>V</td>
<td>O</td>
<td>A</td>
<td>V</td>
<td>O</td>
<td>A</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>A</td>
<td>V</td>
<td>2</td>
<td>2</td>
<td>A</td>
<td>V</td>
<td>3</td>
<td>3</td>
<td>A</td>
<td>V</td>
<td>4</td>
<td>4</td>
<td>A</td>
<td>V</td>
<td>5</td>
</tr>
<tr>
<td>6</td>
<td>6</td>
<td>A</td>
<td>V</td>
<td>7</td>
<td>7</td>
<td>A</td>
<td>V</td>
<td>8</td>
<td>8</td>
<td>A</td>
<td>V</td>
<td>9</td>
<td>9</td>
<td>B</td>
<td>O</td>
<td>10</td>
</tr>
<tr>
<td>11</td>
<td>11</td>
<td>B</td>
<td>O</td>
<td>12</td>
<td>12</td>
<td>B</td>
<td>O</td>
<td>13</td>
<td>13</td>
<td>B</td>
<td>O</td>
<td>14</td>
<td>14</td>
<td>B</td>
<td>O</td>
<td>15</td>
</tr>
<tr>
<td>16</td>
<td>16</td>
<td>B</td>
<td>O</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Variables are independent, but are confounded with order

```r
> better
> pairs.panels(better)
```

```
O
1 1 A O
2 2 B O
3 3 A O
4 4 B O
5 5 A O
6 6 B O
7 7 A O
8 8 B O
9 9 A V
10 10 B V
11 11 A V
12 12 B V
13 13 A V
14 14 B V
15 15 A V
16 16 B V
```
Variables are independent, and are independent of order, one way

> best
> pairs.panels(betteryet)
Variables are independent, and are independent of order.
Multiple ways to present and analyze the data

1. Data analysis as a detective process (Descriptive statistics)
   - What happened?
   - What is a plausible description?
   - What are plausible alternative descriptions?
   - Be a strong critic.

2. Data analysis as a judicial process (Inferential statistics)
   - Are the results different from just random results?
   - How confident are you of the results?
   - Would the results be the same if you did it again?
   - How willing are you to be you will get the same result again?
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 entered into Excel – but just showing some of it

This is clearly not very useful. We need to think of ways to organize it.


```
2 1 0 1 1 1 0 0 0 0 0 0 0 0 1 1 6 1 1 1 1 1 0 0 0 1 0 0 0 0 1 7 1 1 0 1 1 1 0 0 0 1 0 1 0 0 1 0 7 1 1 1 0 1 0 1 1 0
1 0 0 0 1 1 1 9 2 1 1 1 1 1 1 0 0 1 1 0 1 1 0 0 0 1 1 1 1 1 1 1 0 1 1 0 1 1 0 1 2 1 1 1 1 1 1 1 1 1 0 0 1 0 1 1 1
1 2 2 1 1 0 0 1 1 1 1 0 1 0 1 1 0 1 1 1 1 1 0 0 0 0 1 1 9 2 1 0 1 0 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 0 1 0 1 0 1
1 0 1 0 1 1 1 1 1 1 1 2 1 1 1 1 1 1 0 1 1 1 1 0 0 1 2 1 1 1 1 1 1 0 0 1 1 1 0 1 1 1 1 2 1 0 0 0 1 0 1 1 1 0 1 1 1
0 0 8 1 1 0 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 3 1 1 1 1 1 1 1 1 0 0 0 0 0 0 1 1 1 0 1 1 1 1 1 1 0 1 0 1 0 1 1 1 1 1 2 1 0 1
0 1 0 0 1 0 1 0 1 1 1 1 0 8 2 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 4 1 0 1 0 1 0 1 1 1 0 0 1 1 1 1 1 0 1 0 0 1 1 1 1 1 0 2 1 1 1 1 1 0 1 0 1
1 1 1 1 1 1 3 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 4 1 0 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 2 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 0 0 1 1 1 1 3 2 1 1 1 1 1 1 1 0 1 1 1 0 1 1 0 1 2 1 0 1 1 1 1 1 1
1 1 1 1 1 1 4 1 1 1 1 1 0 1 0 1 0 1 0 1 0 1 0 9
```
The raw data as read into R replacing blanks with NA

```r
> recall <- read.clipboard.tab()
> recall <- recall[-1]
> recall

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>2</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>2</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>2</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>2</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>2</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>2</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>2</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>2</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>2</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>21</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
```

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

```
recall <- read.clipboard.tab()
dim(recall)
[1] 21 564

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  3  4  5  6  7  8  9 10 11 12 13 14 15 16
[2,] 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32
[3,] 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48
... [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, nrow=21, ncol=15)
for (i in 1:15) {rec[,i] <- rowMeans(recall[w[,i]], na.rm=TRUE)}
colnames (rec) <- paste0("P", 1:15, ",")
rownames(rec) <- paste0("S", 1:21, ",")
rec
```

<table>
<thead>
<tr>
<th></th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
<th>P7</th>
<th>P8</th>
<th>P9</th>
<th>P10</th>
<th>P11</th>
<th>P12</th>
<th>P13</th>
<th>P14</th>
<th>P15</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>1.00</td>
<td>0.75</td>
<td>1.00</td>
<td>0.75</td>
<td>0.62</td>
<td>0.62</td>
<td>0.62</td>
<td>0.75</td>
<td>0.75</td>
<td>0.62</td>
<td>0.87</td>
<td>0.75</td>
<td>0.75</td>
<td>1.00</td>
<td>0.75</td>
</tr>
<tr>
<td>S2</td>
<td>0.87</td>
<td>0.62</td>
<td>0.87</td>
<td>0.62</td>
<td>0.50</td>
<td>0.50</td>
<td>0.87</td>
<td>0.62</td>
<td>0.62</td>
<td>0.37</td>
<td>0.62</td>
<td>0.87</td>
<td>0.50</td>
<td>0.00</td>
<td>0.75</td>
</tr>
<tr>
<td>S3</td>
<td>0.87</td>
<td>1.00</td>
<td>0.75</td>
<td>1.00</td>
<td>0.62</td>
<td>0.62</td>
<td>0.75</td>
<td>0.87</td>
<td>0.50</td>
<td>0.37</td>
<td>0.62</td>
<td>0.50</td>
<td>1.00</td>
<td>0.75</td>
<td>0.87</td>
</tr>
<tr>
<td>S4</td>
<td>0.75</td>
<td>0.37</td>
<td>0.62</td>
<td>0.75</td>
<td>0.62</td>
<td>0.50</td>
<td>0.37</td>
<td>0.50</td>
<td>0.50</td>
<td>0.25</td>
<td>0.37</td>
<td>0.87</td>
<td>0.75</td>
<td>0.00</td>
<td>0.75</td>
</tr>
<tr>
<td>S5</td>
<td>1.00</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
<td>0.87</td>
<td>0.75</td>
<td>1.00</td>
<td>0.87</td>
<td>0.62</td>
<td>0.87</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
</tr>
<tr>
<td>S6</td>
<td>0.87</td>
<td>0.87</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>0.62</td>
<td>0.50</td>
<td>0.62</td>
<td>0.75</td>
<td>0.87</td>
<td>0.87</td>
<td>0.62</td>
<td>1.00</td>
<td>0.75</td>
</tr>
<tr>
<td>S7</td>
<td>1.00</td>
<td>0.87</td>
<td>0.62</td>
<td>0.62</td>
<td>0.87</td>
<td>0.37</td>
<td>0.75</td>
<td>0.87</td>
<td>0.50</td>
<td>0.37</td>
<td>0.75</td>
<td>0.87</td>
<td>0.75</td>
<td>0.75</td>
<td>0.87</td>
</tr>
<tr>
<td>S8</td>
<td>0.37</td>
<td>0.87</td>
<td>0.37</td>
<td>0.62</td>
<td>0.50</td>
<td>0.37</td>
<td>0.62</td>
<td>0.37</td>
<td>0.62</td>
<td>0.50</td>
<td>0.75</td>
<td>0.50</td>
<td>0.62</td>
<td>0.87</td>
<td>0.75</td>
</tr>
<tr>
<td>S9</td>
<td>1.00</td>
<td>0.75</td>
<td>0.87</td>
<td>0.75</td>
<td>0.75</td>
<td>0.50</td>
<td>0.87</td>
<td>0.62</td>
<td>0.50</td>
<td>0.12</td>
<td>0.50</td>
<td>0.50</td>
<td>0.37</td>
<td>0.62</td>
<td>0.87</td>
</tr>
<tr>
<td>S10</td>
<td>0.87</td>
<td>0.62</td>
<td>0.75</td>
<td>0.75</td>
<td>0.87</td>
<td>0.50</td>
<td>0.62</td>
<td>0.75</td>
<td>0.87</td>
<td>0.62</td>
<td>0.37</td>
<td>0.62</td>
<td>0.50</td>
<td>0.37</td>
<td>0.75</td>
</tr>
<tr>
<td>S11</td>
<td>0.87</td>
<td>0.75</td>
<td>0.87</td>
<td>0.75</td>
<td>0.62</td>
<td>0.50</td>
<td>0.50</td>
<td>0.75</td>
<td>0.75</td>
<td>0.12</td>
<td>1.00</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
</tr>
<tr>
<td>S12</td>
<td>0.87</td>
<td>0.75</td>
<td>1.00</td>
<td>0.87</td>
<td>0.75</td>
<td>0.75</td>
<td>0.50</td>
<td>0.50</td>
<td>0.62</td>
<td>0.62</td>
<td>0.37</td>
<td>0.75</td>
<td>0.75</td>
<td>0.62</td>
<td>1.00</td>
</tr>
<tr>
<td>S13</td>
<td>1.00</td>
<td>1.00</td>
<td>0.87</td>
<td>0.75</td>
<td>0.50</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
<td>0.37</td>
<td>0.75</td>
<td>0.87</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
</tr>
<tr>
<td>S14</td>
<td>0.87</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
<td>0.62</td>
<td>0.50</td>
<td>0.75</td>
<td>0.75</td>
<td>0.50</td>
<td>0.50</td>
<td>0.37</td>
<td>0.75</td>
<td>0.50</td>
<td>0.37</td>
<td>0.75</td>
</tr>
<tr>
<td>S15</td>
<td>1.00</td>
<td>0.75</td>
<td>0.75</td>
<td>0.87</td>
<td>0.50</td>
<td>1.00</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
<td>0.37</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
</tr>
<tr>
<td>S16</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>0.75</td>
<td>0.50</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
<td>0.50</td>
<td>0.75</td>
<td>0.62</td>
<td>0.62</td>
<td>0.62</td>
<td>0.75</td>
</tr>
<tr>
<td>S17</td>
<td>1.00</td>
<td>0.87</td>
<td>1.00</td>
<td>0.50</td>
<td>0.87</td>
<td>0.75</td>
<td>0.87</td>
<td>0.75</td>
<td>1.00</td>
<td>0.75</td>
<td>0.75</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>S18</td>
<td>1.00</td>
<td>0.87</td>
<td>1.00</td>
<td>0.87</td>
<td>1.00</td>
<td>0.75</td>
<td>0.87</td>
<td>1.00</td>
<td>0.75</td>
<td>0.75</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>S19</td>
<td>0.50</td>
<td>0.50</td>
<td>0.25</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.12</td>
<td>0.00</td>
<td>0.00</td>
<td>0.12</td>
<td>0.12</td>
<td>0.12</td>
<td>0.12</td>
<td>0.12</td>
<td>0.00</td>
</tr>
<tr>
<td>S20</td>
<td>1.00</td>
<td>0.75</td>
<td>0.87</td>
<td>0.75</td>
<td>0.87</td>
<td>0.75</td>
<td>0.75</td>
<td>0.87</td>
<td>0.75</td>
<td>0.62</td>
<td>0.87</td>
<td>0.75</td>
<td>0.50</td>
<td>0.87</td>
<td>0.87</td>
</tr>
<tr>
<td>S21</td>
<td>0.87</td>
<td>1.00</td>
<td>0.75</td>
<td>0.62</td>
<td>0.62</td>
<td>0.62</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
<td>1.00</td>
<td>0.87</td>
<td>0.37</td>
<td>0.62</td>
<td>0.37</td>
</tr>
</tbody>
</table>
Find the totals for each list

1. The total number recalled for each list was entered as the 16th element for each list
2. We have these data in the spread sheet
3. We can recover them by addressing every 16th position starting at position 17

```r
tot<- seq (17,257,16)
recall[,tot]
```

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7</td>
<td>NA</td>
<td>NA</td>
<td>11</td>
<td>9</td>
<td>NA</td>
<td>NA</td>
<td>14</td>
<td>NA</td>
<td>14</td>
<td>14</td>
<td>NA</td>
<td>NA</td>
<td>13</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>9</td>
<td>NA</td>
<td>NA</td>
<td>11</td>
<td>6</td>
<td>NA</td>
<td>NA</td>
<td>12</td>
<td>NA</td>
<td>10</td>
<td>11</td>
<td>NA</td>
<td>NA</td>
<td>12</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>12</td>
<td>NA</td>
<td>NA</td>
<td>12</td>
<td>11</td>
<td>NA</td>
<td>NA</td>
<td>11</td>
<td>NA</td>
<td>10</td>
<td>14</td>
<td>NA</td>
<td>NA</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>8</td>
<td>NA</td>
<td>NA</td>
<td>10</td>
<td>9</td>
<td>NA</td>
<td>NA</td>
<td>12</td>
<td>NA</td>
<td>9</td>
<td>9</td>
<td>NA</td>
<td>NA</td>
<td>6</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>13</td>
<td>NA</td>
<td>NA</td>
<td>11</td>
<td>13</td>
<td>NA</td>
<td>NA</td>
<td>12</td>
<td>NA</td>
<td>13</td>
<td>15</td>
<td>NA</td>
<td>NA</td>
<td>14</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>10</td>
<td>NA</td>
<td>NA</td>
<td>12</td>
<td>13</td>
<td>NA</td>
<td>NA</td>
<td>13</td>
<td>NA</td>
<td>14</td>
<td>13</td>
<td>NA</td>
<td>NA</td>
<td>13</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>12</td>
<td>NA</td>
<td>NA</td>
<td>13</td>
<td>12</td>
<td>NA</td>
<td>NA</td>
<td>12</td>
<td>NA</td>
<td>11</td>
<td>8</td>
<td>NA</td>
<td>NA</td>
<td>12</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>8</td>
<td>NA</td>
<td>NA</td>
<td>11</td>
<td>7</td>
<td>NA</td>
<td>NA</td>
<td>12</td>
<td>NA</td>
<td>6</td>
<td>7</td>
<td>NA</td>
<td>NA</td>
<td>12</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>11</td>
<td>NA</td>
<td>NA</td>
<td>8</td>
<td>10</td>
<td>NA</td>
<td>NA</td>
<td>10</td>
<td>NA</td>
<td>9</td>
<td>11</td>
<td>NA</td>
<td>NA</td>
<td>8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>13</td>
<td>NA</td>
<td>NA</td>
<td>9</td>
<td>12</td>
<td>NA</td>
<td>NA</td>
<td>7</td>
<td>NA</td>
<td>8</td>
<td>11</td>
<td>NA</td>
<td>NA</td>
<td>7</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>9</td>
<td>NA</td>
<td>NA</td>
<td>9</td>
<td>7</td>
<td>NA</td>
<td>NA</td>
<td>10</td>
<td>NA</td>
<td>12</td>
<td>15</td>
<td>NA</td>
<td>NA</td>
<td>12</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>NA</td>
<td>6</td>
<td>7</td>
<td>NA</td>
<td>NA</td>
<td>12</td>
<td>10</td>
<td>NA</td>
<td>12</td>
<td>NA</td>
<td>14</td>
<td>13</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>NA</td>
<td>11</td>
<td>12</td>
<td>NA</td>
<td>NA</td>
<td>9</td>
<td>13</td>
<td>NA</td>
<td>12</td>
<td>NA</td>
<td>12</td>
<td>12</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>NA</td>
<td>10</td>
<td>9</td>
<td>NA</td>
<td>NA</td>
<td>9</td>
<td>10</td>
<td>NA</td>
<td>9</td>
<td>NA</td>
<td>11</td>
<td>9</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>NA</td>
<td>12</td>
<td>11</td>
<td>NA</td>
<td>NA</td>
<td>14</td>
<td>12</td>
<td>NA</td>
<td>14</td>
<td>NA</td>
<td>11</td>
<td>10</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>NA</td>
<td>12</td>
<td>12</td>
<td>NA</td>
<td>NA</td>
<td>14</td>
<td>10</td>
<td>NA</td>
<td>13</td>
<td>NA</td>
<td>13</td>
<td>12</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>NA</td>
<td>14</td>
<td>10</td>
<td>NA</td>
<td>NA</td>
<td>14</td>
<td>13</td>
<td>NA</td>
<td>12</td>
<td>NA</td>
<td>13</td>
<td>14</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>NA</td>
<td>13</td>
<td>14</td>
<td>NA</td>
<td>NA</td>
<td>14</td>
<td>15</td>
<td>NA</td>
<td>14</td>
<td>NA</td>
<td>14</td>
<td>14</td>
<td>13</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>NA</td>
<td>13</td>
<td>14</td>
<td>NA</td>
<td>NA</td>
<td>14</td>
<td>15</td>
<td>NA</td>
<td>14</td>
<td>NA</td>
<td>14</td>
<td>14</td>
<td>13</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>NA</td>
<td>8</td>
<td>8</td>
<td>NA</td>
<td>NA</td>
<td>6</td>
<td>7</td>
<td>NA</td>
<td>4</td>
<td>NA</td>
<td>2</td>
<td>0</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Show the data by person and by list: Is there an pattern?

R code

```r
error.bars(recall[,tot]/15,main="Means and confidence limits of words recalled by list", xlab="List number", ylab="Percent recalled", ylim=c(0,1))
```

Means and confidence limits of words recalled by list
Describe the List data

describe(recall[,tot]/15)

<table>
<thead>
<tr>
<th>vars</th>
<th>n</th>
<th>mean</th>
<th>sd</th>
<th>median</th>
<th>trimmed</th>
<th>mad</th>
<th>min</th>
<th>max</th>
<th>range</th>
<th>skew</th>
<th>kurtosis</th>
<th>se</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1Tot</td>
<td>1</td>
<td>11</td>
<td>0.68</td>
<td>0.14</td>
<td>0.67</td>
<td>0.68</td>
<td>0.20</td>
<td>0.47</td>
<td>0.87</td>
<td>0.40</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>L2Tot</td>
<td>2</td>
<td>10</td>
<td>0.65</td>
<td>0.26</td>
<td>0.77</td>
<td>0.68</td>
<td>0.15</td>
<td>0.13</td>
<td>0.93</td>
<td>0.80</td>
<td>-0.73</td>
<td></td>
</tr>
<tr>
<td>L3Tot</td>
<td>3</td>
<td>10</td>
<td>0.67</td>
<td>0.27</td>
<td>0.73</td>
<td>0.72</td>
<td>0.15</td>
<td>0.00</td>
<td>0.93</td>
<td>0.93</td>
<td>-1.27</td>
<td></td>
</tr>
<tr>
<td>L4Tot</td>
<td>4</td>
<td>11</td>
<td>0.71</td>
<td>0.10</td>
<td>0.73</td>
<td>0.71</td>
<td>0.10</td>
<td>0.53</td>
<td>0.87</td>
<td>0.33</td>
<td>-0.24</td>
<td></td>
</tr>
<tr>
<td>L5Tot</td>
<td>5</td>
<td>11</td>
<td>0.66</td>
<td>0.17</td>
<td>0.67</td>
<td>0.67</td>
<td>0.20</td>
<td>0.40</td>
<td>0.87</td>
<td>0.47</td>
<td>-0.18</td>
<td></td>
</tr>
<tr>
<td>L6Tot</td>
<td>6</td>
<td>10</td>
<td>0.69</td>
<td>0.28</td>
<td>0.73</td>
<td>0.75</td>
<td>0.20</td>
<td>0.40</td>
<td>0.87</td>
<td>0.93</td>
<td>-1.27</td>
<td></td>
</tr>
<tr>
<td>L7Tot</td>
<td>7</td>
<td>10</td>
<td>0.77</td>
<td>0.16</td>
<td>0.77</td>
<td>0.78</td>
<td>0.15</td>
<td>0.47</td>
<td>1.00</td>
<td>0.53</td>
<td>-0.27</td>
<td></td>
</tr>
<tr>
<td>L8Tot</td>
<td>8</td>
<td>11</td>
<td>0.76</td>
<td>0.12</td>
<td>0.80</td>
<td>0.77</td>
<td>0.10</td>
<td>0.47</td>
<td>0.93</td>
<td>0.47</td>
<td>-0.91</td>
<td></td>
</tr>
<tr>
<td>L9Tot</td>
<td>9</td>
<td>10</td>
<td>0.75</td>
<td>0.22</td>
<td>0.80</td>
<td>0.78</td>
<td>0.20</td>
<td>0.27</td>
<td>0.93</td>
<td>0.67</td>
<td>-0.99</td>
<td></td>
</tr>
<tr>
<td>L10Tot</td>
<td>10</td>
<td>11</td>
<td>0.70</td>
<td>0.17</td>
<td>0.67</td>
<td>0.71</td>
<td>0.20</td>
<td>0.40</td>
<td>0.93</td>
<td>0.53</td>
<td>-0.10</td>
<td></td>
</tr>
<tr>
<td>L11Tot</td>
<td>11</td>
<td>11</td>
<td>0.78</td>
<td>0.19</td>
<td>0.73</td>
<td>0.79</td>
<td>0.30</td>
<td>0.47</td>
<td>1.00</td>
<td>0.53</td>
<td>-0.26</td>
<td></td>
</tr>
<tr>
<td>L12Tot</td>
<td>12</td>
<td>10</td>
<td>0.73</td>
<td>0.29</td>
<td>0.77</td>
<td>0.78</td>
<td>0.20</td>
<td>0.00</td>
<td>1.00</td>
<td>1.00</td>
<td>-1.45</td>
<td></td>
</tr>
<tr>
<td>L13Tot</td>
<td>13</td>
<td>10</td>
<td>0.75</td>
<td>0.24</td>
<td>0.80</td>
<td>0.80</td>
<td>0.20</td>
<td>0.13</td>
<td>0.93</td>
<td>0.80</td>
<td>-1.48</td>
<td></td>
</tr>
<tr>
<td>L14Tot</td>
<td>14</td>
<td>11</td>
<td>0.72</td>
<td>0.18</td>
<td>0.80</td>
<td>0.73</td>
<td>0.10</td>
<td>0.40</td>
<td>0.93</td>
<td>0.53</td>
<td>-0.62</td>
<td></td>
</tr>
<tr>
<td>L15Tot</td>
<td>15</td>
<td>11</td>
<td>0.60</td>
<td>0.14</td>
<td>0.60</td>
<td>0.60</td>
<td>0.10</td>
<td>0.33</td>
<td>0.87</td>
<td>0.53</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>L16Tot</td>
<td>16</td>
<td>10</td>
<td>0.71</td>
<td>0.28</td>
<td>0.80</td>
<td>0.77</td>
<td>0.15</td>
<td>0.00</td>
<td>1.00</td>
<td>1.00</td>
<td>-1.45</td>
<td></td>
</tr>
</tbody>
</table>
Oops, there was something wrong with the data

1. Note on the previous slide that the minimum for some positions was zero.
2. This does not look right.
3. Let’s explore the data graphically to see what is happening.
4. It turns out that one person systematically had very poor recall.
5. How should we treat such an outlier?
Boxplot the data to try to figure out what is happening

Boxplot of recall by list
Means by subject show the problem

R code

```r
error.bars(t(recall[,tot]), ylab="Mean percent recalled", xlab="Subject", main="Means and confidence intervals for recall")  #plot the subjects
```

Means and confidence intervals for recall
What to do with outliers?

1. Clearly subject 19 was behaving differently from the others.
2. We do not know why but we should drop him/her.
3. In any write up, we need to say that we dropped one subject for poor performance.
4. Drop the subject rec <- recall[-19,] #drops the subject
5. Examine the serial position effect without subject 19
Now look at the serial position curves

We do the same trick of organizing the data as we did before, but this time, we organize it by list position instead of by subject.

```R
position <- matrix(NA,nrow=15,ncol=16)
for (i in 1:15) {position[i,] <- colMeans(recall[w[,i]],na.rm=TRUE)}
describe(t(position))
error.bars(t(position),ylim=c(0,1),ylab="Probability of recall",
xlab="Serial position",main="Recall by serial position")
```

```
vars n mean sd median trimmed mad min max range skew kurtosis se
1 1 16 0.89 0.11 0.90 0.90 0.13 0.64 1.00 0.36 -0.85 -0.48 0.03
2 2 16 0.79 0.16 0.80 0.79 0.16 0.50 1.00 0.50 -0.34 -1.29 0.04
3 3 16 0.81 0.12 0.80 0.81 0.11 0.64 1.00 0.36 0.33 -0.95 0.03
4 4 16 0.73 0.18 0.80 0.73 0.24 0.40 1.00 0.60 -0.12 -1.29 0.05
5 5 16 0.67 0.18 0.70 0.68 0.12 0.18 1.00 0.82 -0.96 1.22 0.05
6 6 16 0.63 0.23 0.64 0.65 0.24 0.09 0.91 0.82 -0.67 -0.22 0.06
7 7 16 0.71 0.14 0.71 0.71 0.16 0.45 0.91 0.45 -0.13 -1.26 0.04
8 8 16 0.67 0.18 0.70 0.67 0.20 0.30 0.91 0.61 -0.34 -1.23 0.05
9 9 16 0.65 0.18 0.67 0.67 0.19 0.18 0.90 0.72 -0.89 0.49 0.04
10 10 16 0.58 0.23 0.59 0.59 0.20 0.09 0.90 0.81 -0.65 -0.55 0.06
11 11 16 0.63 0.16 0.60 0.63 0.17 0.36 0.91 0.55 0.03 -0.81 0.04
12 12 16 0.65 0.17 0.67 0.65 0.20 0.36 0.90 0.54 -0.33 -1.23 0.04
13 13 16 0.74 0.15 0.80 0.75 0.15 0.40 0.91 0.51 -0.66 -0.60 0.04
14 14 16 0.70 0.10 0.70 0.69 0.12 0.55 0.91 0.36 0.32 -0.83 0.03
15 15 16 0.78 0.12 0.80 0.78 0.15 0.50 1.00 0.50 -0.25 -0.39 0.03
```
Recall varies by serial position

Recall by serial position
Does recall vary by mode of presentation?

This will require some recoding.

```r
vis.recall <- rowSums(memory.data[,c("L1Tot","L2Tot","L7Tot", "L8Tot","L11Tot","L12Tot","L13Tot","L14Tot")],na.rm=TRUE)
oral.recall <- rowSums(memory.data[,c("L3Tot","L4Tot","L5Tot", "L6Tot","L9Tot","L10Tot","L15Tot","L16Tot")],na.rm=TRUE)
recall.df <- data.frame(visual=vis.recall,oral=oral.recall)/(4*15)
describe(recall.df)
t.test(recall.df[,"visual"],recall.df[,"oral"],paired=TRUE)
```

<table>
<thead>
<tr>
<th>vars</th>
<th>n</th>
<th>mean</th>
<th>sd</th>
<th>median</th>
<th>trimmed</th>
<th>mad</th>
<th>min</th>
<th>max</th>
<th>max</th>
<th>range</th>
<th>skew</th>
<th>kurtosis</th>
<th>se</th>
</tr>
</thead>
<tbody>
<tr>
<td>visual</td>
<td>1</td>
<td>21</td>
<td>0.73</td>
<td>0.15</td>
<td>0.75</td>
<td>0.18</td>
<td>0.93</td>
<td>0.75</td>
<td>0.75</td>
<td>-1.94</td>
<td>5.03</td>
<td>0.03</td>
<td></td>
</tr>
<tr>
<td>oral</td>
<td>2</td>
<td>21</td>
<td>0.69</td>
<td>0.18</td>
<td>0.72</td>
<td>0.17</td>
<td>0.93</td>
<td>0.87</td>
<td>0.87</td>
<td>-1.67</td>
<td>3.80</td>
<td>0.04</td>
<td></td>
</tr>
</tbody>
</table>

Paired t-test

data: recall.df[, "visual"] and recall.df[, "oral"]
t = 2.6216, df = 20, p-value = 0.01634
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  0.008594821 0.075532163
sample estimates:
  mean of the differences
  0.04206349
Recall varies by modality of presentation

Probability of recall varies by modality

<table>
<thead>
<tr>
<th>Condition</th>
<th>Probability of recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>visual</td>
<td>0.4</td>
</tr>
<tr>
<td>oral</td>
<td>0.6</td>
</tr>
</tbody>
</table>

Recall varies by modality of presentation.
How to describe the recall results

You may use or paraphrase the following

1. Recall of words from lists that were presented visually (\(\bar{X} = .73, sd = .15\)) were recalled more than were words from lists presented orally (\(\bar{X} = .69, sd = .18\)), (\(t_{20} = 2.62, p < .02\)) (Figure XX).

2. Remember to have a figure caption for this figure that explains what those strange shapes (cats’ eyes) are.
The recognition data may be examined many different ways

1. First start with the easiest: What is true versus false recognition
2. Does this vary by condition?
3. Convert raw numbers to appropriate percentages

```r
c recog <- read.clipboard.tab()
c recog[,"realrecog"] <- recog[,"realrecog"]/48
c recog[,"falsemem"] <- recog[,"falsemem"]/16
c describe(recog)
c describeBy(recog,"Condition") #do it by condition
```
Overall recognition results show that real words are recognized more than false ones

```r
describe(recog)
```

<table>
<thead>
<tr>
<th>vars</th>
<th>n</th>
<th>mean</th>
<th>sd</th>
<th>median</th>
<th>trimmed</th>
<th>mad</th>
<th>min</th>
<th>max</th>
<th>range</th>
<th>skew</th>
<th>kurtosis</th>
<th>se</th>
</tr>
</thead>
<tbody>
<tr>
<td>Condition</td>
<td>1</td>
<td>21</td>
<td>1.48</td>
<td>0.51</td>
<td>1.00</td>
<td>1.47</td>
<td>0.00</td>
<td>1.00</td>
<td>2.00</td>
<td>1.00</td>
<td>-2.08</td>
<td>0.11</td>
</tr>
<tr>
<td>PrsRRTot</td>
<td>2</td>
<td>21</td>
<td>19.10</td>
<td>6.13</td>
<td>18.00</td>
<td>18.47</td>
<td>4.45</td>
<td>9.00</td>
<td>37.00</td>
<td>28.00</td>
<td>1.04</td>
<td>1.35</td>
</tr>
<tr>
<td>PrsRnRTot</td>
<td>3</td>
<td>21</td>
<td>0.52</td>
<td>0.60</td>
<td>0.00</td>
<td>0.47</td>
<td>0.00</td>
<td>0.00</td>
<td>2.00</td>
<td>2.00</td>
<td>0.57</td>
<td>-0.80</td>
</tr>
<tr>
<td>PrsnRRTot</td>
<td>4</td>
<td>21</td>
<td>19.10</td>
<td>5.80</td>
<td>19.00</td>
<td>19.88</td>
<td>1.48</td>
<td>0.00</td>
<td>28.00</td>
<td>28.00</td>
<td>-1.62</td>
<td>3.48</td>
</tr>
<tr>
<td>PrsnRnRTot</td>
<td>5</td>
<td>21</td>
<td>9.29</td>
<td>3.84</td>
<td>9.00</td>
<td>9.18</td>
<td>4.45</td>
<td>3.00</td>
<td>17.00</td>
<td>14.00</td>
<td>0.12</td>
<td>-0.70</td>
</tr>
<tr>
<td>PrmRRTot</td>
<td>6</td>
<td>21</td>
<td>0.95</td>
<td>1.12</td>
<td>1.00</td>
<td>0.76</td>
<td>1.48</td>
<td>0.00</td>
<td>4.00</td>
<td>4.00</td>
<td>1.11</td>
<td>0.51</td>
</tr>
<tr>
<td>PrmRnRTot</td>
<td>7</td>
<td>21</td>
<td>0.19</td>
<td>0.51</td>
<td>0.00</td>
<td>0.06</td>
<td>0.00</td>
<td>0.00</td>
<td>2.00</td>
<td>2.00</td>
<td>2.44</td>
<td>5.06</td>
</tr>
<tr>
<td>PrmnRRTot</td>
<td>8</td>
<td>21</td>
<td>4.52</td>
<td>2.94</td>
<td>4.00</td>
<td>4.53</td>
<td>2.97</td>
<td>0.00</td>
<td>10.00</td>
<td>10.00</td>
<td>-0.02</td>
<td>-1.19</td>
</tr>
<tr>
<td>PrmnRnRTot</td>
<td>9</td>
<td>21</td>
<td>10.24</td>
<td>3.03</td>
<td>10.00</td>
<td>10.24</td>
<td>2.97</td>
<td>5.00</td>
<td>16.00</td>
<td>11.00</td>
<td>0.01</td>
<td>-1.07</td>
</tr>
<tr>
<td>realrecog</td>
<td>10</td>
<td>21</td>
<td>0.80</td>
<td>0.09</td>
<td>0.79</td>
<td>0.80</td>
<td>0.09</td>
<td>0.62</td>
<td>0.94</td>
<td>0.31</td>
<td>-0.17</td>
<td>-0.81</td>
</tr>
<tr>
<td>falsemem</td>
<td>11</td>
<td>21</td>
<td>0.34</td>
<td>0.17</td>
<td>0.31</td>
<td>0.35</td>
<td>0.19</td>
<td>0.00</td>
<td>0.62</td>
<td>0.62</td>
<td>-0.11</td>
<td>-1.13</td>
</tr>
</tbody>
</table>
Graphically show the difference between real and false recognition

1. Perhaps the best way to compare group differences is graphically.
2. We can do this with a histogram to show the distribution
3. Or with an error bars plot (with the within option = TRUE)

```R
op <- par(mfrow=c(2,1))  # do a two row graphic
hist(recog[,"realrecog"],xlab="Real Recognition", main="Real recognition",xlim=c(0,1))
hist(recog[,"falsemem"],xlab="False Recognition", main="False recognition",xlim=c(0,1))

op <- par(mfrow=c(1,1))
error.bars(recog[10:11],ylim=c(0,1),within=TRUE, ylab="Recognition",xlab="Type of recognition", main="Real versus False recognition")
```
Real versus false recognition

Real recognition

False recognition
Real versus false recognition

Real versus False recognition

Data = Model + Residual Design

Our memory study

Recall

Recognition

Real versus False recognition

Type of recognition

realrecog  falsemem

0.0  0.2  0.4  0.6  0.8  1.0
Final analysis

1. There were some mistakes in the original data as reported, we have cleaned that up and can report the recognition results.
2. We can examine the recognition data as a function of mode of presentation.
3. This requires some manipulation of the raw scores to break it out by mode.
4. The next slide shows what we did, the subsequent slides are more useful in showing what we found.
Various R commands to do the recoding of the recognition data

The dataframe is just our data sheets transcribed into a long vector for each person.

```
v <- c(1,2,7,8,11:14)  
o <- c(3:6,9,10,15,16)  
vr <- rowSums( memory.data[,v+307],na.rm=TRUE)  
oorr <- rowSums( memory.data[,o+307],na.rm=TRUE)  
vnr <- rowSums( memory.data[,v+324],na.rm=TRUE)  
oonr <- rowSums( memory.data[,o+324],na.rm=TRUE)  
vnrn <- rowSums( memory.data[,v+341],na.rm=TRUE)  
oonrn <- rowSums( memory.data[,o+341],na.rm=TRUE)  
vFrr <- rowSums( memory.data[,v+375],na.rm=TRUE)  
oFrr <- rowSums( memory.data[,o+375],na.rm=TRUE)  
vFnrr <- rowSums( memory.data[,v+392],na.rm=TRUE)  
oFnrr <- rowSums( memory.data[,o+392],na.rm=TRUE)  
vFnrn <- rowSums( memory.data[,v+409],na.rm=TRUE)  
oFnrn <- rowSums( memory.data[,o+409],na.rm=TRUE)  
visrecog <- (vr+vnR)/24  
onalrecog <- (orr + onr)/24  
vFoil <- (vFrr + vFnrr)/8  
oFoil <- (oFrr + oFnrn)/8  
```
**The basic descriptive statistics of the recognition data**

```r
describe(recog)
```

```
vars  n mean  sd median trimmed mad  min  max range skew kurtosis se
vrr  1 21  9.24  2.23  9.00  9.24  1.48  5.00  14.00 -0.63  0.49
orr  2 21  9.00  2.61  9.00  8.94  2.97  4.00  15.00  0.27  0.50  0.57
vnr  3 21  0.38  0.59  0.00  0.29  0.00  0.00  2.00  2.00  1.14  0.17  0.13
orn  4 21  0.14  0.36  0.00  0.06  0.00  0.00  1.00  1.00  1.90  1.69  0.08
vnR  5 21  9.38  2.33  9.00  9.47  1.48  3.00  14.00  11.00 -0.51  0.77  0.51
onR  6 21 10.52  2.09 10.00 10.59  1.48  6.00 14.00  8.00 -0.14 -0.56  0.46
vnRn 7 21  5.00  2.47  5.00  4.76  2.97  2.00 10.00  8.00 -0.82  0.82  0.54
onRn 8 21  4.33  2.11  5.00  4.47  2.97  0.00  7.00  7.00 -0.36 -1.07  0.46
vFr  9 21  0.29  0.46  0.00  0.24  0.00  0.00  1.00  1.00  0.88 -1.28  0.10
oFr 10 21  0.57  0.87  0.00  0.41  0.00  0.00  3.00  3.00  1.31  0.71  0.19
vFnr 11 21  0.10  0.30  0.00  0.00  0.00  0.00  1.00  1.00  2.56  4.81  0.07
oFnr 12 21  0.10  0.30  0.00  0.00  0.00  0.00  1.00  1.00  2.56  4.81  0.07
vFnrn 13 21  1.71  1.31  2.00  1.65  1.48  0.00  4.00  4.00  0.12 -1.22  0.29
oFnrn 14 21  2.90  2.19  3.00  2.82  2.97  0.00  7.00  7.00  0.20 -1.26  0.48
vFnRn 15 21  5.86  1.46  6.00  5.88  1.48  3.00  8.00  5.00 -0.04 -0.98  0.32
oFnRn 16 21  4.48  2.18  5.00  4.41  2.97  1.00  8.00  7.00  0.04 -1.41  0.48
visrecog 17 21  0.78  0.11  0.79  0.78  0.12  0.54  0.92  0.38 -0.41 -0.71  0.02
oralrecog 18 21  0.81  0.09  0.79  0.81  0.12  0.67  1.00  0.33  0.34 -1.05  0.02
vFoil 19 21  0.25  0.17  0.25  0.24  0.19  0.00  0.62  0.62  0.12 -0.53  0.04
oFoil 20 21  0.43  0.28  0.38  0.44  0.37  0.00  0.88  0.88  0.00 -1.47  0.06
condition 21 21  1.48  0.51  1.00  1.47  0.00  1.00  2.00  1.00  0.09 -2.08  0.11
```
Test these differences using a simple t-test

1. First we test the real recognition as a function of visual vs. oral presentation.
2. Then we do the same with the False Recognition.
3. For both of these we use the paired t-test which recognizes the subjects are the same for both conditions.
4. This reports the t-test of the difference, The means were reported in the previous slide.
t.test(recog[, "visrecog"], recog[, "oralrecog"], paired=TRUE)

t.test(recog[, "vFoil"], recog[, "oFoil"], paired=TRUE)

Paired t-test

data:  recog[, "visrecog"] and recog[, "oralrecog"]
t = -1.7083, df = 20, p-value = 0.1031
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-0.083730536  0.008333711
sample estimates:
mean of the differences
-0.03769841

Paired t-test

data:  recog[, "vFoil"] and recog[, "oFoil"]
t = -2.8684, df = 20, p-value = 0.0095
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-0.31871340  -0.05033422
sample estimates:
mean of the differences
-0.1845238
Find some useful means

R code

```r
real <- (recog[, "visrecog"] + recog[, "oralrecog"])/2
falsemem <- (recog[,"vFoil"] + recog[,"oFoil"])/2
describe(real)
describe(falsemem)
t.test(real,falsemem,paired=TRUE)
```

describe(real)
```
   vars n mean  sd median trimmed mad   min   max range  skew kurtosis   se
 1    1 21 0.79 0.09   0.79    0.8  0.09  0.94  0.31 -0.14   -0.79   0.02
```
describe(falsemem)
```
   vars n mean  sd median trimmed mad   min   max range  skew kurtosis   se
 1    1 21 0.34 0.17   0.31    0.35  0.19  0.62  0.62 -0.11   -1.13   0.04
```

Paired t-test

data:  real and falsemem
t = 9.97, df = 20, p-value = 3.328e-09
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:  
  0.3577318 0.5470301
sample estimates:  
mean of the differences  
0.452381
Report this in the results section

You are welcome to take these verbatim, or put into your own words. Remember: say it in words, say it in numbers, say it in statistics.

1. Although the mean recognized following visual presentation ($\bar{X} = .78, sd = .11$) was less than the mean following oral presentations ($\bar{X} = .81, sd = .09$), this difference was not significant ($t = -1.71, df = 20, p = .10$).

2. However, unpresented words (Foils) that were high associates of the presented words were falsely recognized more following Oral presentation ($\bar{X} = .43, sd = .28$) than following visual presentation ($\bar{X} = .25, sd = .17$), ($t_{20} = -2.87, p < .01$) (Figure ??)

3. As expected, words presented were recognized more ($\bar{X} = .25, sd = .09$) than words that were not presented ($\bar{X} = .25, sd = .17$) ($t_{20} = 10.69, p < .001$).
Real and False Recognition

Real and False recognition

Probability of recognition

Stimulus condition

visrecog  oralrecog  vFoil  oFoil
Inserting figures

1. The previous figure can go into your manuscript. Cut and paste into a pdf.
2. Remember to come up with a suitable figure caption describing what is being shown.
What do we conclude?

1. The modality of presentation makes a difference.
2. Recall was better for words that were seen rather than those that were heard.
3. False Recognition was greater (worse) for words that were heard rather than seen.
4. This suggests that visual presentation improves accuracy of memory.