# PLY22_Analysis

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## The Experiment

This is an exact replication of the first half of Spiering and Ashby (2008), Experiment 1. These experiments looked at whether easy-to-hard training results in better learning of a information-integration category structure than hard-to-easy training. PLY22 replicated the first two blocks of this experiment to avoid the primacy/recency problem in Spiering and Ashby (2008).

This experiment was run by C E R Edmunds in Spring 2014, supervised by Andy J Wills, at Plymouth University.

## Setup

Here we load packages, functions and data:

```r
# Clear all
rm(list=ls())
pdf_filename <- "PLY22_Analysis.pdf"

# Load packages
if (!require("pacman")) install.packages("pacman")
pacman::p_load(plyr, ggplot2, ez, png, effsize)

# Define functions
source('PLY22 Functions.R')
# move_pdf(pdf_filename)

# Load data
trialData <- read.csv("PLY22longData.csv", header=TRUE) # All data

# Formatting of factor levels
trialData$Condition <- revalue(trialData$Condition,
                               c("EasyMed"="Easy-to-moderate",
                                 "HardMed"="Hard-to-moderate"))
trialData$Difficulty <- relevel(trialData$Difficulty, "Medium")
trialData$Difficulty <- relevel(trialData$Difficulty, "Easy")
trialData$Category <- factor(trialData$Category)
trialData$RT <- trialData$RT*1000

trialData <- trialData[trialData$RT<5000,]
```

## Category structure

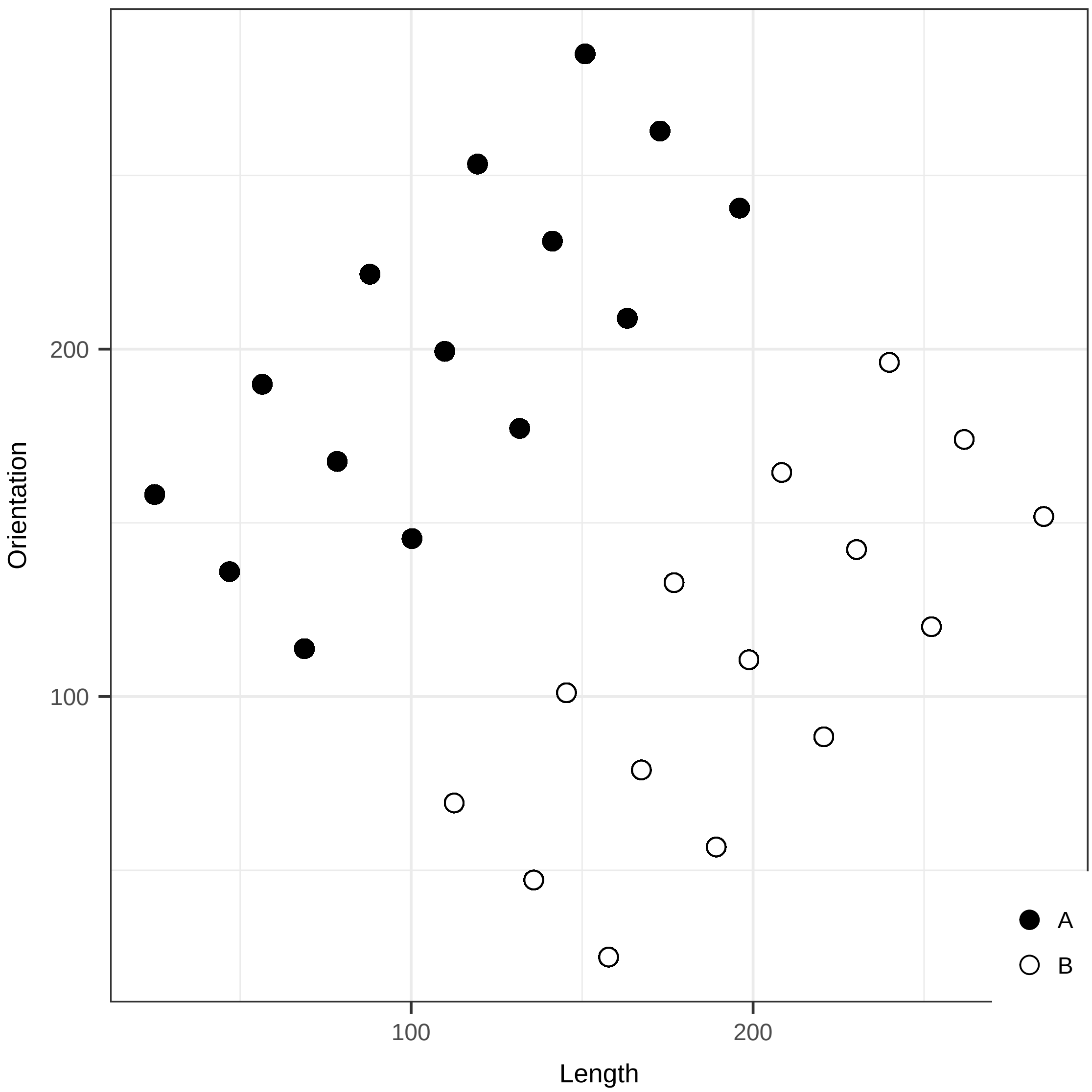
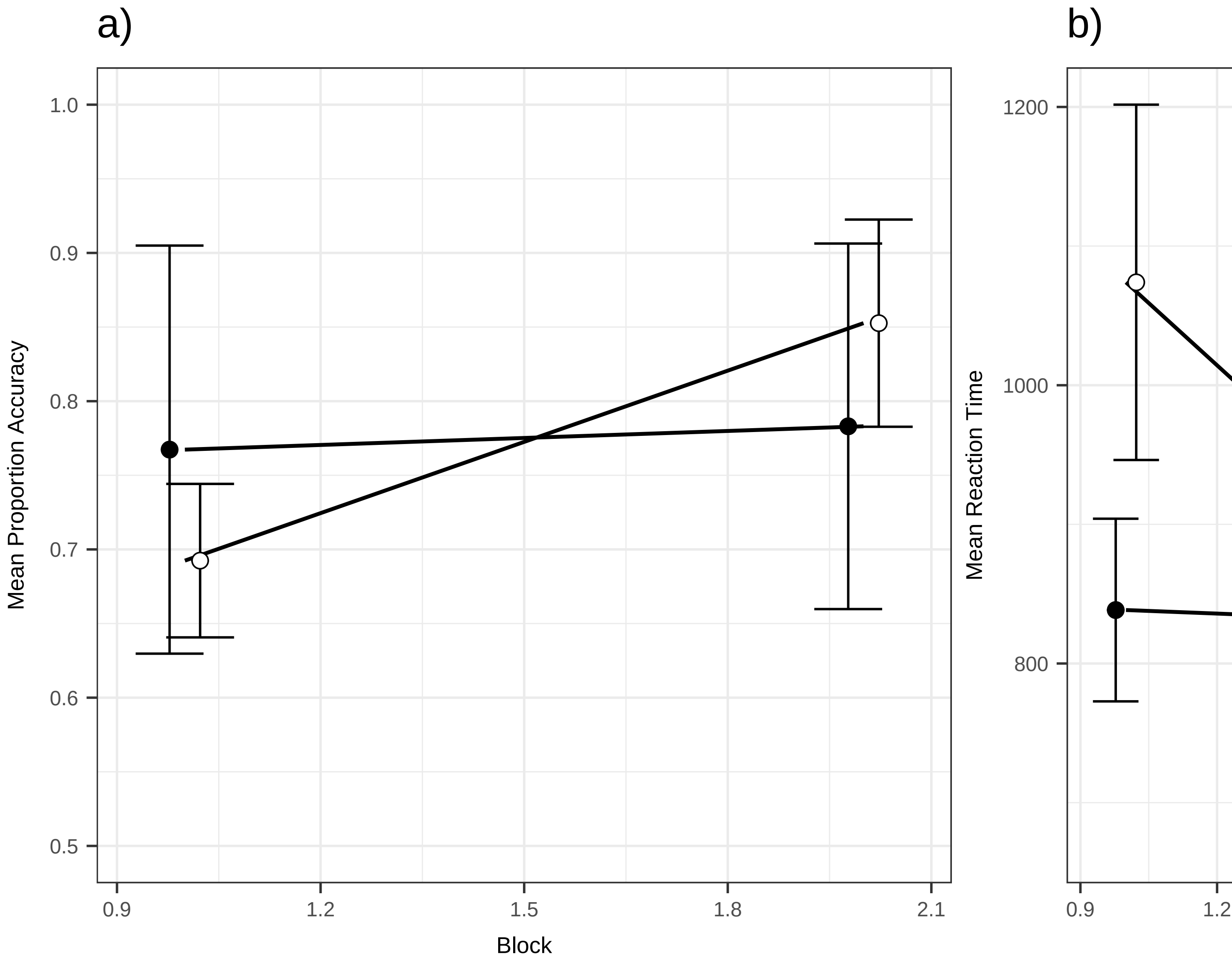
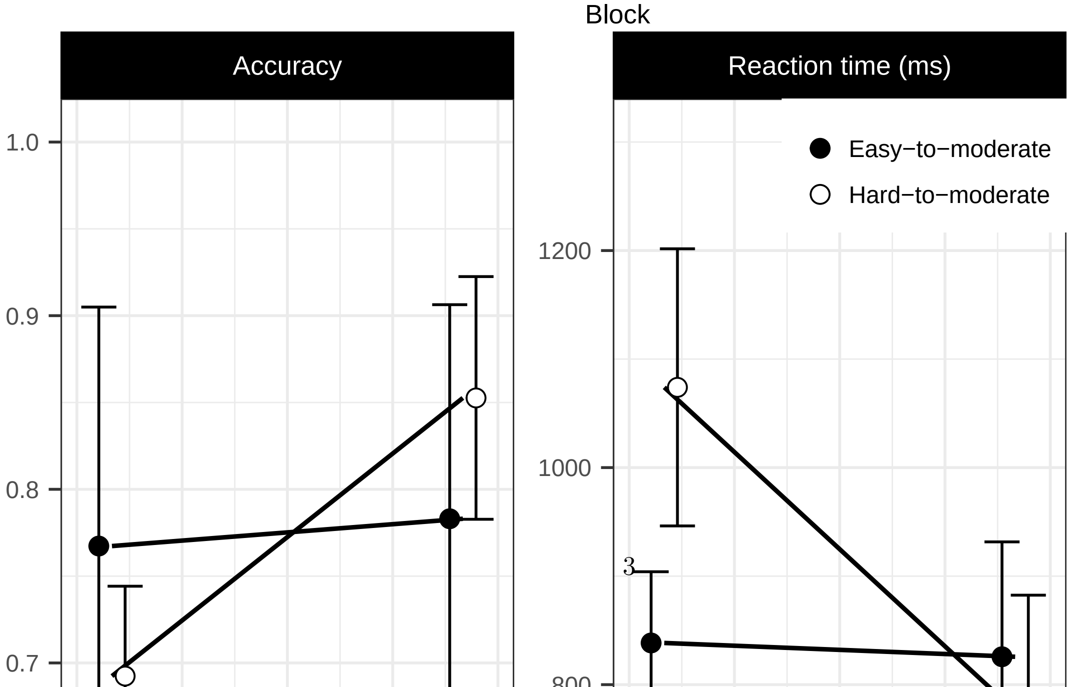



Figure 1: The conjunction category structure in arbitrary stimulus units.

## Spiering and Ashby (2008) Analysis

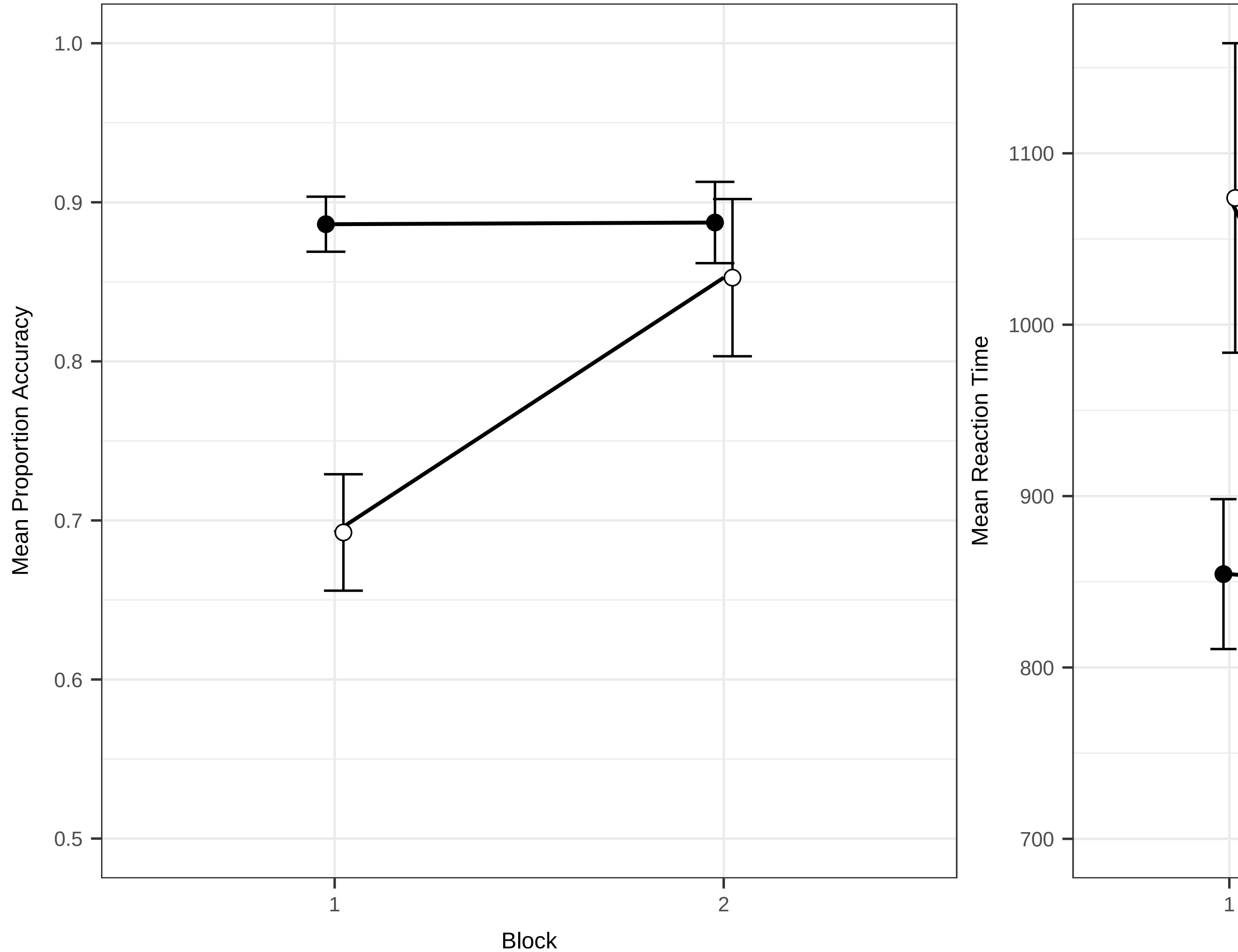
### Learning curve graph

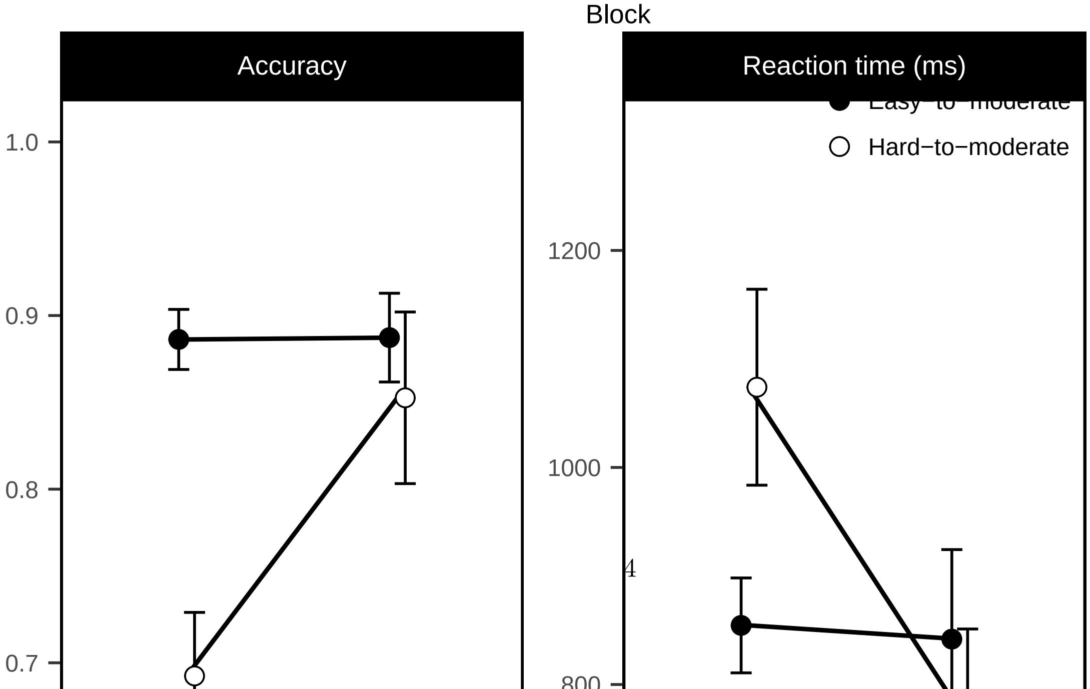


# CERE analysis

## Learning curve graph



```r
test_data_B1 <- dataLearners[dataLearners$Block==1,]
test_data_B2 <- dataLearners[dataLearners$Block==2,]

bsci(data.frame=data, group.var="Condition", dv.var="Accuracy", difference=FALSE,
                 pooled.error=FALSE, conf.level=0.95)
```

```
##                        lower      mean     upper
## Easy-to-moderate 0.6870165 0.7751836 0.8633507
## Hard-to-moderate 0.7236033 0.7725289 0.8214544
```

```r
# Tests
# Block 1
TT_B1 <- t.test(Accuracy ~ Condition, test_data_B1,
             var.equal=T) # Sig.
cohen.d(test_data_B1$Accuracy ~ test_data_B1$Condition)
```

```
##
## Cohen's d
##
## d estimate: 2.212016 (large)
## 95 percent confidence interval:
##      inf      sup
## 1.362894 3.061138
```

```r
mean_diff <- mean(test_data_B1$Accuracy[test_data_B1$Condition=="Easy-to-medium"]) -
             mean(test_data_B1$Accuracy[test_data_B1$Condition=="Hard-to-medium"])
sd_diff <- sqrt((sd(test_data_B1$Accuracy[test_data_B1$Condition=="Easy-to-medium"])^2)/20+
                (sd(test_data_B1$Accuracy[test_data_B1$Condition=="Hard-to-medium"])^2)/20)
Bf(sd=sd_diff, obtained=mean_diff, dfdata=35, uniform=0, meanoftheory=0.101, sdtheory=0.054, tail=2)
```

```
## $LikelihoodTheory
## [1] NaN
##
## $Likelihoodnull
## [1] NaN
##
## $BayesFactor
## [1] NaN
```

```r
TT_B1_RT <- t.test(RT ~ Condition, test_data_B1,
             var.equal=T) # Sig.
cohen.d(test_data_B1$RT ~ test_data_B1$Condition)
```

```
##
## Cohen's d
##
## d estimate: -1.012132 (large)
## 95 percent confidence interval:
##       inf       sup
## -1.723153 -0.301110
```

```r
TT_B2 <- t.test(Accuracy ~ Condition, dataLearners[dataLearners$Block==2,],
             var.equal=T) # N.s.
cohen.d(test_data_B2$Accuracy ~ test_data_B2$Condition)
```

```
##
## Cohen's d
```

```
##
## d estimate: 0.2892841 (small)
## 95 percent confidence interval:
##        inf        sup
## -0.3838870  0.9624552
```

```r
mean_diff <- mean(test_data_B2$Accuracy[test_data_B2$Condition=="Easy-to-medium"]) -
             mean(test_data_B2$Accuracy[test_data_B2$Condition=="Hard-to-medium"])
sd_diff <- sqrt((sd(test_data_B2$Accuracy[test_data_B2$Condition=="Easy-to-medium"])^2)/20+
                (sd(test_data_B2$Accuracy[test_data_B2$Condition=="Hard-to-medium"])^2)/20)
Bf(sd=sd_diff, obtained=mean_diff, dfdata=35, uniform=0, meanoftheory=-0.139, sdtheory=0.07, tail=2)
```

```
## $LikelihoodTheory
## [1] NaN
##
## $Likelihoodnull
## [1] NaN
##
## $BayesFactor
## [1] NaN
```

```r
# Reduce predicted effect by a third:
Bf(sd=sd_diff, obtained=mean_diff, dfdata=35, uniform=0, meanoftheory=-0.046, sdtheory=0.023, tail=2)
```

```
## $LikelihoodTheory
## [1] NaN
##
## $Likelihoodnull
## [1] NaN
##
## $BayesFactor
## [1] NaN
```

```r
TT_B2_RT <- t.test(RT ~ Condition, test_data_B2,
             var.equal=T) # Sig.
cohen.d(test_data_B2$RT ~ test_data_B2$Condition)
```

```
##
## Cohen's d
##
## d estimate: 0.2906198 (small)
## 95 percent confidence interval:
##        inf        sup
## -0.3825834  0.9638229
```

```r
#summaryDataL for the means/sds for accuracy
```