SMRT

Chris Foster

2018-10-04

Contents

1 Preface **5**

2 Introduction to Smart Items **7**

2.1 Purpose of Building Smart Items 8

2.2 Smart Item Logic 8

3 DOMC Difficulty Variance **9**

3.1 Initial Run 9

3.2 Item 10B_v1 10

3.3 Item 14b_v1 13

3.4 Item 14a_v1 15

3.5 Remove correct response 18

3.6 Item 10B_v1 19

3.7 Item 14b_v1 20

3.8 All Item Plots 22

4 DOMC Difficulty Factors **25**

5 Total Test Score and Options Seen **27**

6 Recall VS Deduction **29**

6.1 Some Graphs 30

Chapter 1

Preface

This book is a **compilation** of different reseach pieces all compiled together into a single volume. The purpose of the volume is to provide a concise, research oriented view of the smart item and other accompanying item formats. Each chapter will be a different research topic and we will attempt to group similar research articles in close proximity to each other within the book.

Chapter 2

Introduction to Smart Items

Dave Really REally wants to be able to make a change to this text document.

A SmartItem is first and foremost an item, used on exams to measure important skills. Like traditional items, it has an ID number, is stored on a computer, is evaluated like traditional items with expert reviews, and eventually response data from examinees. It can be used on any kind of test design, such as CAT, LOFT, etc. If and when it doesn't function well, it can be repaired or deleted or retired.

The main difference between a smart item and a normal item is that the smart item is written with three areas of expertise: Subject matter, item writing and programming. With a well written and specific objective, with the help of a programmer and enough content expertise it is possible to write a single item which can cover the entire range of an objective. With the help of a programmer an item writer can write a series of stems, options, correct responses and incorrect responses that can generate a large amount of potential item derivatives based on a single objective. This process creates an item that is less static than a single multiple choice item.

In order better understand a smart item it is best to start with an example. An illustrativec example would come from an elementary math test. A single objective might be: Add two single digit numbers. There are only 10 single digit numbers (including 0) So really there is only (10!/ 2!(10-2)!) = 45 possible options as long as order doesn't matter.

Now, a single item writer could write all 45 items and cover the objective completely. However, it is also possible to write a simple program which generates all 45 possible questions. Now, for a fixed form test it would be likely that the item writer woudl not write all 45 options but instead write 2 or 3 of which one would be selected for the first form of the test while a different one might be selected for a second form. However, when administering a smart item to participants each participant would get a random stem and random options (including the correct option).

Now, for a simple math objective it might not be necessary to write an algorithm that writes the 45 different possible stems for the objective. However, imagine an objective where there are 206 possible answers such as "Identify each bone in the human body." Or perhaps there is an objective which asks participants to arrange 4 words in alphabetical order. The words can be anything in the human dictionary. Now there are 170,000 words in the english language and picking 4 leaves 3.479x10^19 possible options to completely cover the objective content and no item writer can write all of them and given current test construction methods there is no reason to do so.

2.1 Purpose of Building Smart Items

2.2 Smart Item Logic

A first step to understanding the logic behind smart items is to understand the logic of randomization in experimentation. Sir Ronald Fisher Fisher (1925) outlined what is considered the cornerstone of experimental research today: randomization. Randomization has three primary purposes:

1) It helps to distribute idosyncratic characteristics of participants to groups so that it does not bias the outcome. If participants could self select groups or were grouped based on characteristics than it could create systematic biases in the outcome based on participant characteristics.

2) Randomization helps calculate unbiased estimate of error effects. IE: those effects not attributable to the manipulation of an independent variable

3) Randomization helps ensure that error efects are statistically independent.

Now, considering point #1 a bit more: Randomization helps ensure that within group variability is Independent and identically distributed (IID) or in other words, within group variability does not contain bias and is simply noise. Without randomization it could easily contain any number of biases which could decrease or increase the differnces between groups. It is impossible to list all possible systematic biases that could creep into an experiment. Maybe all college educated participants self select themselves into a specific group or one gender reacts differently to a group assignment than another.

While other papers have talked in length about the importance of randomization in experimental design for the purposes of this section randomization removes systematic bias within group.

One natural artifact of the randomization process is an increase in within-group variation. If participants are asigned to groups based on characterisitcs or allowed to self select, more similar participants will end up in the same group reducing the amount of variability in the group. While a decrease in within-group variability inevitibly increases the probability of a significant effect in an experiment, the significant effect may simply be due to a bias brought by the selection process... which simply shows the importance of randomization. Even though variation is introduced, results are more trustworthy.

Chapter 3

DOMC Difficulty Variance

3.1 Initial Run

Here is a document showing the results of item families derived from a single DOMC stem. Essentially we treat each possible combination of options as a different question just to see the amount of variance from a single DOMC stem.

In this first run we treat each different option combination as a different item, including those for people who never saw the correct response (making all these p-values 0)

```
library(dplyr)
library(readr)
library(knitr)
library(ggplot2)
library(lemon)
library(stringr)

setwd_thisdir <- function () {
  this.dir <- dirname(parent.frame(3)$ofile)
  setwd(this.dir)
}

hp_data = read_csv('data/domc_order_difficulty/Full Responses After Exclusions.csv')

hp_clean = hp_data %>% filter(item_type == 'domc', item_component_type == 'domc_option') %>% group_by(de

hp_clean_mc = hp_data %>% filter(item_type == 'multiple_choice', item_component_type == 'final') %>% gr
hp_clean_mc$survey = ifelse(grepl("Survey",hp_clean_mc$item_id),1,0)
hp_clean_mc = hp_clean_mc %>% filter(survey == 0)
hp_clean_mc$item_number = as.numeric(str_extract(hp_clean_mc$item_id, "[0-9]+"))

hp_summary = hp_clean %>% group_by(delivery_id, item_id) %>% summarize(item_total_seconds = max(item_to

hp_summary_mc = hp_clean_mc %>% group_by(delivery_id, item_id) %>% summarize(item_total_seconds = max(i

hp_items = hp_summary %>% group_by(item_id, order) %>% summarize(p_value = mean(score), count = n())
hp_items_mc = hp_summary_mc %>% group_by(item_id, item_order) %>% summarize(p_value = mean(score), coun
all_items = bind_rows(hp_items, hp_items_mc)
all_items$item_type = ifelse(is.na(all_items$item_order), 'DOMC', "MC")
all_items$item_number = as.numeric(str_extract(all_items$item_id, "[0-9]+"))
```

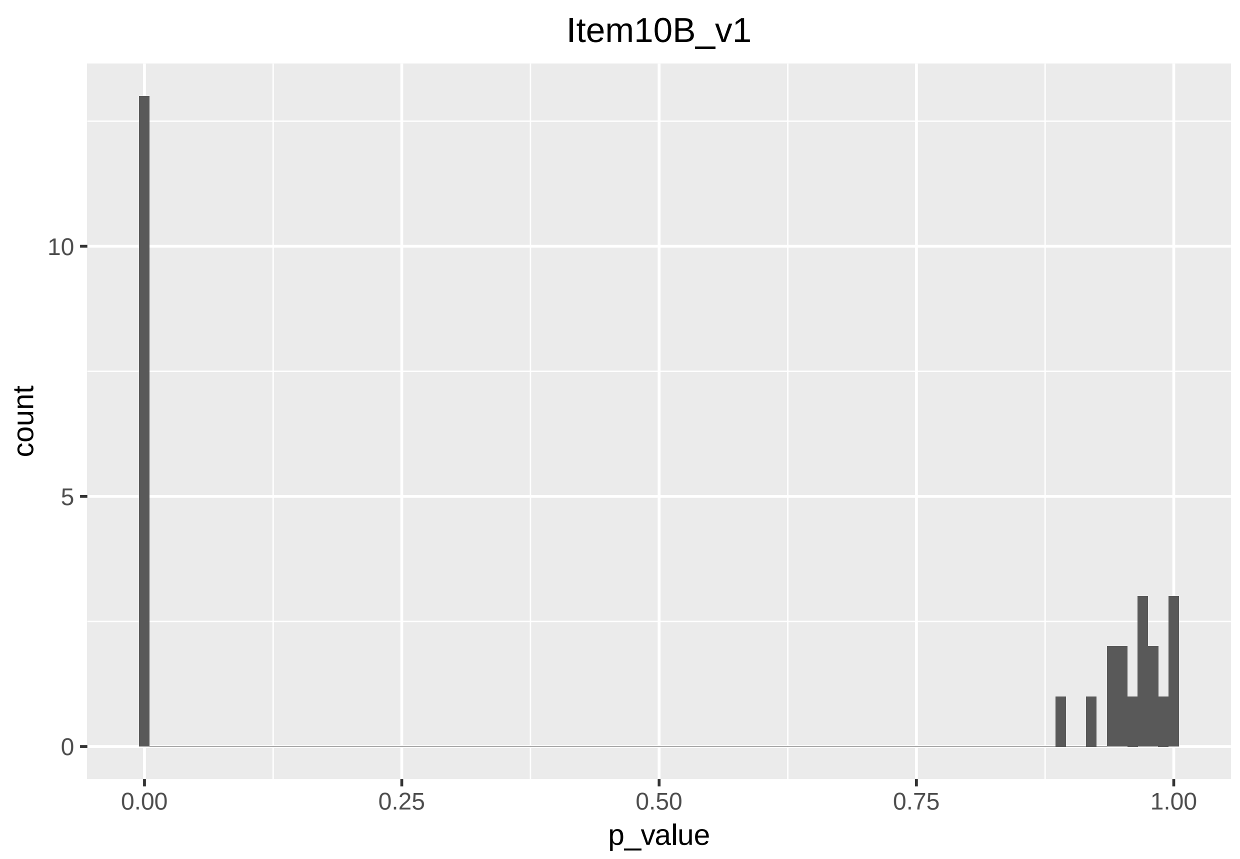
3.2 Item 10B_v1

```
tenb_v1 = hp_items %>% filter(item_id == '10B_v1')
kable(tenb_v1)
```

item_id	order	p_value	count
10B_v1	0	0.8950000	200
10B_v1	01	1.0000000	42
10B_v1	012	0.9677419	31
10B_v1	0123	1.0000000	40
10B_v1	01234	0.9876543	162
10B_v1	0124	0.9827586	58
10B_v1	013	0.9666667	30
10B_v1	0134	1.0000000	45
10B_v1	014	0.9629630	27
10B_v1	02	0.9365079	63
10B_v1	023	0.9487179	39
10B_v1	0234	0.9354839	62
10B_v1	024	0.9210526	38
10B_v1	03	0.9464286	56
10B_v1	034	0.9666667	30
10B_v1	04	0.9756098	41
10B_v1	1	0.0000000	21
10B_v1	12	0.0000000	6
10B_v1	123	0.0000000	8
10B_v1	1234	0.0000000	13
10B_v1	124	0.0000000	3
10B_v1	13	0.0000000	10
10B_v1	134	0.0000000	7
10B_v1	14	0.0000000	8
10B_v1	2	0.0000000	3
10B_v1	234	0.0000000	1
10B_v1	24	0.0000000	4
10B_v1	3	0.0000000	1
10B_v1	4	0.0000000	2

3.2.1 Histogram

```
theme_update(plot.title = element_text(hjust = 0.5))
ggplot(tenb_v1, aes(x=p_value)) + geom_histogram(binwidth=.01) + labs(title = "Item10B_v1")
```



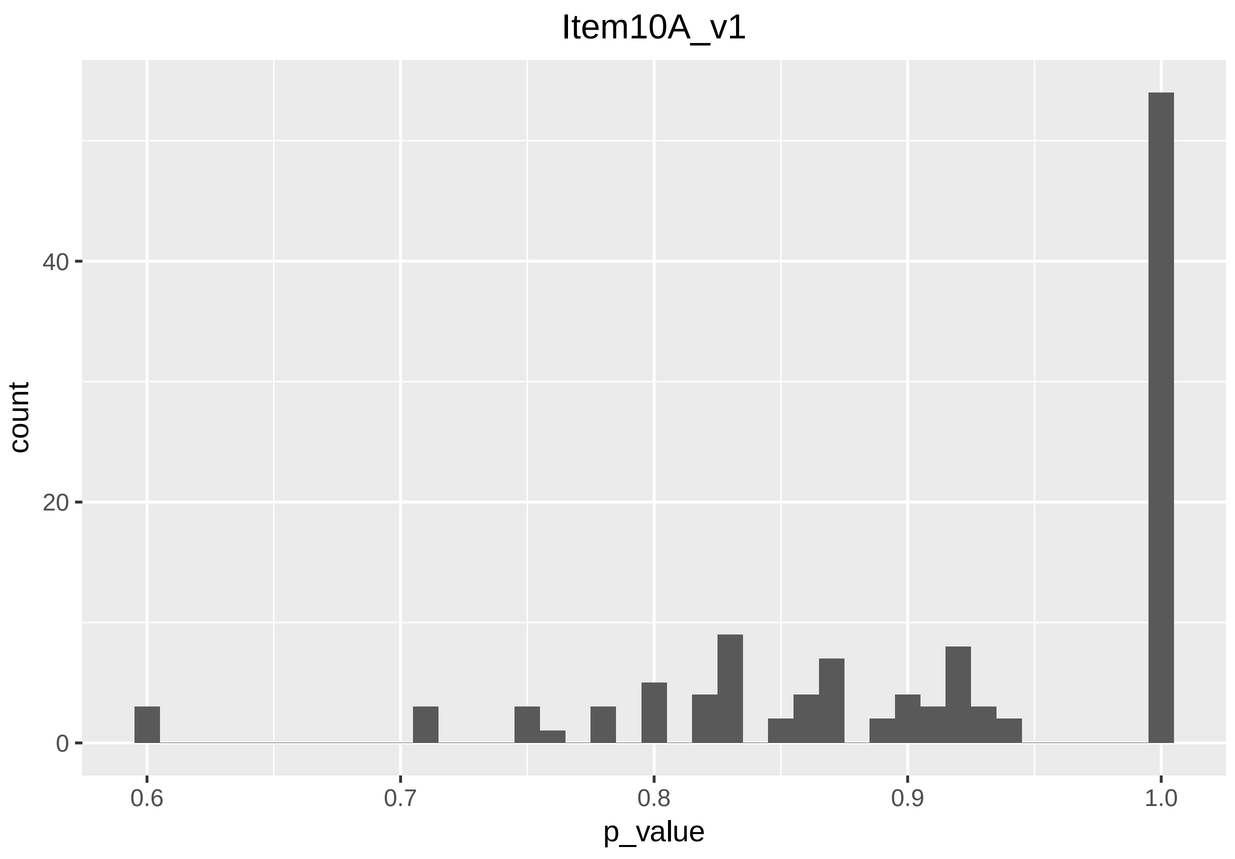
## Item 10A_v1

```
tena_v1 = hp_items_mc %>% filter(item_id == '10A_v1')
kable(tena_v1)
```

item_id	item_order	p_value	count
10A_v1	[0, 1, 2, 3, 4]	1.0000000	9
10A_v1	[0, 1, 2, 4, 3]	1.0000000	4
10A_v1	[0, 1, 3, 2, 4]	0.7500000	8
10A_v1	[0, 1, 3, 4, 2]	1.0000000	7
10A_v1	[0, 1, 4, 2, 3]	0.8750000	8
10A_v1	[0, 1, 4, 3, 2]	1.0000000	13
10A_v1	[0, 2, 1, 3, 4]	0.8333333	6
10A_v1	[0, 2, 1, 4, 3]	1.0000000	8
10A_v1	[0, 2, 3, 1, 4]	0.8235294	17
10A_v1	[0, 2, 3, 4, 1]	0.7142857	7
10A_v1	[0, 2, 4, 1, 3]	1.0000000	6
10A_v1	[0, 2, 4, 3, 1]	1.0000000	14
10A_v1	[0, 3, 1, 2, 4]	0.7142857	7
10A_v1	[0, 3, 1, 4, 2]	0.9375000	16
10A_v1	[0, 3, 2, 1, 4]	1.0000000	12
10A_v1	[0, 3, 2, 4, 1]	1.0000000	12
10A_v1	[0, 3, 4, 1, 2]	1.0000000	9
10A_v1	[0, 3, 4, 2, 1]	1.0000000	11
10A_v1	[0, 4, 1, 2, 3]	0.9166667	12
10A_v1	[0, 4, 1, 3, 2]	0.7777778	9
10A_v1	[0, 4, 2, 1, 3]	1.0000000	8
10A_v1	[0, 4, 2, 3, 1]	0.8888889	9
10A_v1	[0, 4, 3, 1, 2]	0.8333333	6
10A_v1	[0, 4, 3, 2, 1]	1.0000000	8
10A_v1	[1, 0, 2, 3, 4]	0.7500000	8
10A_v1	[1, 0, 2, 4, 3]	0.8750000	8
10A_v1	[1, 0, 3, 2, 4]	1.0000000	13
10A_v1	[1, 0, 3, 4, 2]	0.9090909	11
10A_v1	[1, 0, 4, 2, 3]	0.9166667	12
10A_v1	[1, 0, 4, 3, 2]	1.0000000	14
10A_v1	[1, 2, 0, 3, 4]	1.0000000	9
10A_v1	[1, 2, 0, 4, 3]	1.0000000	13
10A_v1	[1, 2, 3, 0, 4]	1.0000000	5
10A_v1	[1, 2, 3, 4, 0]	0.6000000	5
10A_v1	[1, 2, 4, 0, 3]	0.9285714	14
10A_v1	[1, 2, 4, 3, 0]	1.0000000	4
10A_v1	[1, 3, 0, 2, 4]	1.0000000	10
10A_v1	[1, 3, 0, 4, 2]	0.9090909	11
10A_v1	[1, 3, 2, 0, 4]	0.8571429	14
10A_v1	[1, 3, 2, 4, 0]	1.0000000	9
10A_v1	[1, 3, 4, 0, 2]	1.0000000	3
10A_v1	[1, 3, 4, 2, 0]	0.9090909	11
10A_v1	[1, 4, 0, 2, 3]	1.0000000	18
10A_v1	[1, 4, 0, 3, 2]	0.9000000	10
10A_v1	[1, 4, 2, 0, 3]	1.0000000	6
10A_v1	[1, 4, 2, 3, 0]	1.0000000	9
10A_v1	[1, 4, 3, 0, 2]	0.8461538	13
10A_v1	[1, 4, 3, 2, 0]	0.9000000	10
10A_v1	[2, 0, 1, 3, 4]	0.8571429	7
10A_v1	[2, 0, 1, 4, 3]	0.8461538	13
10A_v1	[2, 0, 3, 1, 4]	1.0000000	7
10A_v1	[2, 0, 3, 4, 1]	1.0000000	6
10A_v1	[2, 0, 4, 1, 3]	0.8888889	9
10A_v1	[2, 0, 4, 3, 1]	1.0000000	4
10A_v1	[2, 1, 0, 3, 4]	0.8750000	8
10A_v1	[2, 1, 0, 4, 3]	1.0000000	6
10A_v1	[2, 1, 3, 0, 4]	0.9166667	12

3.2.2 Histogram

```r
theme_update(plot.title = element_text(hjust = 0.5))
ggplot(tena_v1, aes(x=p_value)) + geom_histogram(binwidth=.01) + labs(title = "Item10A_v1")
```



3.3 Item 14b_v1

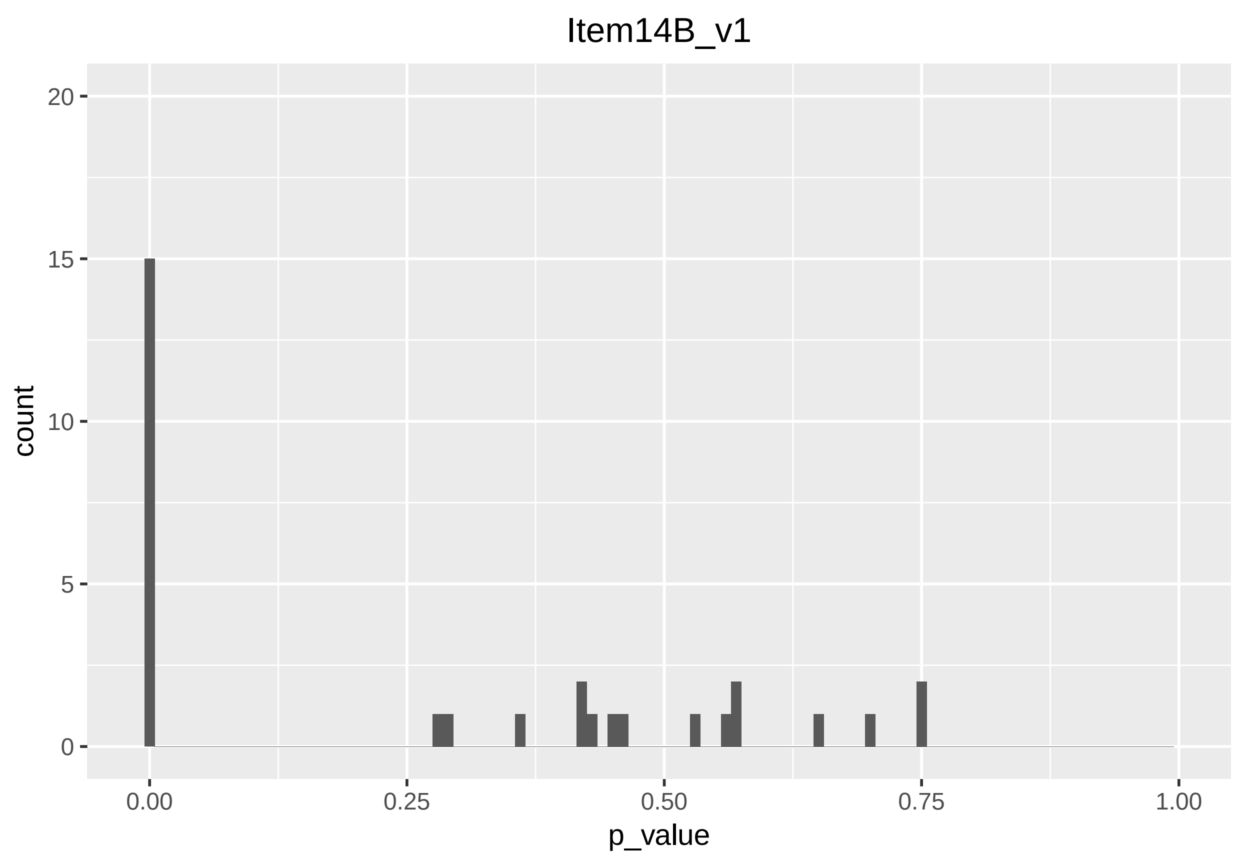
```r
fourteenb_v1 = hp_items %>% filter(item_id == '14B_v1')
kable(fourteenb_v1, format = "markdown")
```

item_id	order	p_value	count
14B_v1	0	0.4235294	170
14B_v1	01	0.2765957	47
14B_v1	012	0.3636364	11
14B_v1	0123	0.2941176	17
14B_v1	01234	0.7049180	61
14B_v1	0124	0.7500000	12
14B_v1	013	0.5652174	23
14B_v1	0134	0.5666667	30
14B_v1	014	0.4583333	24
14B_v1	02	0.5263158	19

item_id	order	p_value	count
14B_v1	023	0.7500000	16
14B_v1	0234	0.4545455	11
14B_v1	024	0.6470588	17
14B_v1	03	0.4181818	55
14B_v1	034	0.5555556	36
14B_v1	04	0.4333333	30
14B_v1	1	0.0000000	39
14B_v1	12	0.0000000	23
14B_v1	123	0.0000000	22
14B_v1	1234	0.0000000	36
14B_v1	124	0.0000000	19
14B_v1	13	0.0000000	8
14B_v1	134	0.0000000	11
14B_v1	14	0.0000000	9
14B_v1	2	0.0000000	129
14B_v1	23	0.0000000	35
14B_v1	234	0.0000000	21
14B_v1	24	0.0000000	20
14B_v1	3	0.0000000	30
14B_v1	34	0.0000000	11
14B_v1	4	0.0000000	59

3.3.1 Histogram

```
ggplot(fourteenb_v1, aes(x=p_value)) + geom_histogram(binwidth=.01) + labs(title = "Item14B_v1")+ xlim(
```



3.4 Item 14a_v1

```
fourteenb_v1 = hp_items_mc %>% filter(item_id == '14A_v1')
kable(fourteenb_v1, format = "markdown")
```

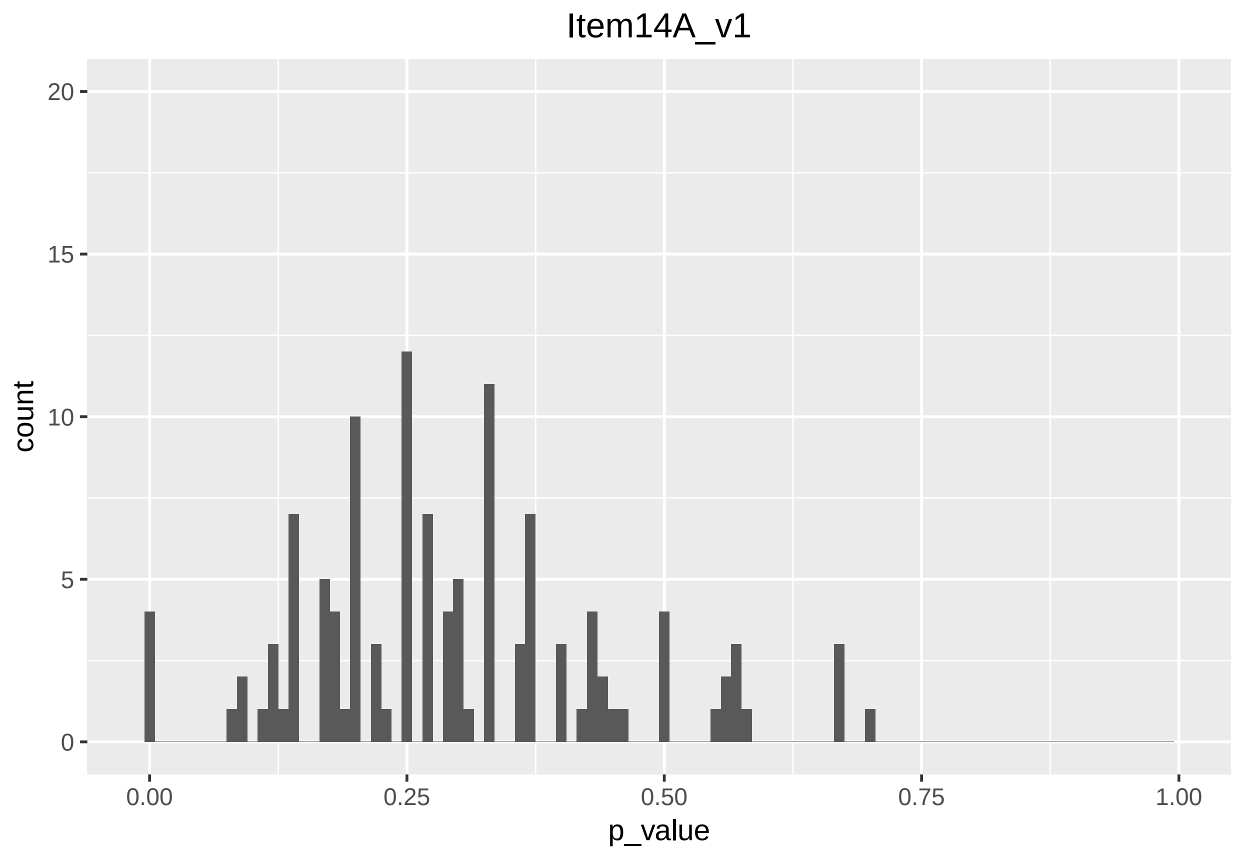
item_id	item_order	p_value	count
14A_v1	[0, 1, 2, 3, 4]	0.4285714	7
14A_v1	[0, 1, 2, 4, 3]	0.5000000	10
14A_v1	[0, 1, 3, 2, 4]	0.3000000	10
14A_v1	[0, 1, 3, 4, 2]	0.2000000	10
14A_v1	[0, 1, 4, 2, 3]	0.2500000	8
14A_v1	[0, 1, 4, 3, 2]	0.4444444	9
14A_v1	[0, 2, 1, 3, 4]	0.1250000	8
14A_v1	[0, 2, 1, 4, 3]	0.4285714	7
14A_v1	[0, 2, 3, 1, 4]	0.1428571	7
14A_v1	[0, 2, 3, 4, 1]	0.5555556	9
14A_v1	[0, 2, 4, 1, 3]	0.1250000	8
14A_v1	[0, 2, 4, 3, 1]	0.5714286	7
14A_v1	[0, 3, 1, 2, 4]	0.1428571	7
14A_v1	[0, 3, 1, 4, 2]	0.5000000	8
14A_v1	[0, 3, 2, 1, 4]	0.4545455	11
14A_v1	[0, 3, 2, 4, 1]	0.2500000	8

item_id	item_order	p_value	count
14A_v1	[0, 3, 4, 1, 2]	0.2500000	8
14A_v1	[0, 3, 4, 2, 1]	0.3000000	10
14A_v1	[0, 4, 1, 2, 3]	0.2500000	8
14A_v1	[0, 4, 1, 3, 2]	0.5555556	9
14A_v1	[0, 4, 2, 1, 3]	0.4000000	10
14A_v1	[0, 4, 2, 3, 1]	0.2857143	7
14A_v1	[0, 4, 3, 1, 2]	0.5500000	20
14A_v1	[0, 4, 3, 2, 1]	0.4285714	14
14A_v1	[1, 0, 2, 3, 4]	0.2222222	9
14A_v1	[1, 0, 2, 4, 3]	0.3750000	8
14A_v1	[1, 0, 3, 2, 4]	0.2857143	7
14A_v1	[1, 0, 3, 4, 2]	0.2500000	12
14A_v1	[1, 0, 4, 2, 3]	0.4000000	5
14A_v1	[1, 0, 4, 3, 2]	0.4285714	7
14A_v1	[1, 2, 0, 3, 4]	0.2727273	11
14A_v1	[1, 2, 0, 4, 3]	0.2857143	7
14A_v1	[1, 2, 3, 0, 4]	0.1111111	9
14A_v1	[1, 2, 3, 4, 0]	0.2000000	5
14A_v1	[1, 2, 4, 0, 3]	0.4444444	9
14A_v1	[1, 2, 4, 3, 0]	0.2500000	8
14A_v1	[1, 3, 0, 2, 4]	0.2727273	11
14A_v1	[1, 3, 0, 4, 2]	0.2000000	10
14A_v1	[1, 3, 2, 0, 4]	0.1428571	7
14A_v1	[1, 3, 2, 4, 0]	0.1333333	15
14A_v1	[1, 3, 4, 0, 2]	0.2500000	8
14A_v1	[1, 3, 4, 2, 0]	0.1818182	11
14A_v1	[1, 4, 0, 2, 3]	0.2307692	13
14A_v1	[1, 4, 0, 3, 2]	0.5714286	14
14A_v1	[1, 4, 2, 0, 3]	0.0000000	5
14A_v1	[1, 4, 2, 3, 0]	0.1250000	8
14A_v1	[1, 4, 3, 0, 2]	0.2000000	15
14A_v1	[1, 4, 3, 2, 0]	0.1666667	6
14A_v1	[2, 0, 1, 3, 4]	0.2500000	8
14A_v1	[2, 0, 1, 4, 3]	0.1428571	7
14A_v1	[2, 0, 3, 1, 4]	0.2727273	11
14A_v1	[2, 0, 3, 4, 1]	0.4615385	13
14A_v1	[2, 0, 4, 1, 3]	0.3750000	8
14A_v1	[2, 0, 4, 3, 1]	0.3333333	9
14A_v1	[2, 1, 0, 3, 4]	0.1428571	7
14A_v1	[2, 1, 0, 4, 3]	0.6666667	6
14A_v1	[2, 1, 3, 0, 4]	0.1666667	6
14A_v1	[2, 1, 3, 4, 0]	0.3333333	9
14A_v1	[2, 1, 4, 0, 3]	0.5714286	7
14A_v1	[2, 1, 4, 3, 0]	0.3000000	10
14A_v1	[2, 3, 0, 1, 4]	0.7000000	10
14A_v1	[2, 3, 0, 4, 1]	0.2000000	5
14A_v1	[2, 3, 1, 0, 4]	0.3750000	8
14A_v1	[2, 3, 1, 4, 0]	0.2727273	11
14A_v1	[2, 3, 4, 0, 1]	0.2727273	11
14A_v1	[2, 3, 4, 1, 0]	0.1818182	11
14A_v1	[2, 4, 0, 1, 3]	0.3750000	8
14A_v1	[2, 4, 0, 3, 1]	0.3636364	11

item_id	item_order	p_value	count
14A_v1	[2, 4, 1, 0, 3]	0.1428571	7
14A_v1	[2, 4, 1, 3, 0]	0.2000000	5
14A_v1	[2, 4, 3, 0, 1]	0.2000000	10
14A_v1	[2, 4, 3, 1, 0]	0.3636364	11
14A_v1	[3, 0, 1, 2, 4]	0.0000000	7
14A_v1	[3, 0, 1, 4, 2]	0.3333333	9
14A_v1	[3, 0, 2, 1, 4]	0.3333333	6
14A_v1	[3, 0, 2, 4, 1]	0.4166667	12
14A_v1	[3, 0, 4, 1, 2]	0.2857143	7
14A_v1	[3, 0, 4, 2, 1]	0.0000000	8
14A_v1	[3, 1, 0, 2, 4]	0.0000000	4
14A_v1	[3, 1, 0, 4, 2]	0.2727273	11
14A_v1	[3, 1, 2, 0, 4]	0.4000000	10
14A_v1	[3, 1, 2, 4, 0]	0.0909091	11
14A_v1	[3, 1, 4, 0, 2]	0.1666667	12
14A_v1	[3, 1, 4, 2, 0]	0.2000000	10
14A_v1	[3, 2, 0, 1, 4]	0.2500000	12
14A_v1	[3, 2, 0, 4, 1]	0.3333333	15
14A_v1	[3, 2, 1, 0, 4]	0.0909091	11
14A_v1	[3, 2, 1, 4, 0]	0.3076923	13
14A_v1	[3, 2, 4, 0, 1]	0.3000000	10
14A_v1	[3, 2, 4, 1, 0]	0.3750000	8
14A_v1	[3, 4, 0, 1, 2]	0.2222222	9
14A_v1	[3, 4, 0, 2, 1]	0.5833333	12
14A_v1	[3, 4, 1, 0, 2]	0.1666667	6
14A_v1	[3, 4, 1, 2, 0]	0.2000000	10
14A_v1	[3, 4, 2, 0, 1]	0.1818182	11
14A_v1	[3, 4, 2, 1, 0]	0.3333333	9
14A_v1	[4, 0, 1, 2, 3]	0.2500000	16
14A_v1	[4, 0, 1, 3, 2]	0.3750000	8
14A_v1	[4, 0, 2, 1, 3]	0.3333333	3
14A_v1	[4, 0, 2, 3, 1]	0.6666667	9
14A_v1	[4, 0, 3, 1, 2]	0.3333333	12
14A_v1	[4, 0, 3, 2, 1]	0.3636364	11
14A_v1	[4, 1, 0, 2, 3]	0.5000000	10
14A_v1	[4, 1, 0, 3, 2]	0.2500000	8
14A_v1	[4, 1, 2, 0, 3]	0.1666667	12
14A_v1	[4, 1, 2, 3, 0]	0.2000000	15
14A_v1	[4, 1, 3, 0, 2]	0.2727273	11
14A_v1	[4, 1, 3, 2, 0]	0.1764706	17
14A_v1	[4, 2, 0, 1, 3]	0.2222222	9
14A_v1	[4, 2, 0, 3, 1]	0.3000000	10
14A_v1	[4, 2, 1, 0, 3]	0.5000000	8
14A_v1	[4, 2, 1, 3, 0]	0.1875000	16
14A_v1	[4, 2, 3, 0, 1]	0.2500000	4
14A_v1	[4, 2, 3, 1, 0]	0.3333333	9
14A_v1	[4, 3, 0, 1, 2]	0.3333333	9
14A_v1	[4, 3, 0, 2, 1]	0.3333333	9
14A_v1	[4, 3, 1, 0, 2]	0.1428571	14
14A_v1	[4, 3, 1, 2, 0]	0.6666667	6
14A_v1	[4, 3, 2, 0, 1]	0.3750000	8
14A_v1	[4, 3, 2, 1, 0]	0.0833333	12

3.4.1 Histogram

```
ggplot(fourteenb_v1, aes(x=p_value)) + geom_histogram(binwidth=.01) + labs(title = "Item14A_v1")+ xlim(
```



3.5 Remove correct response

We notice quickly that it is pretty difficult to interpret the p-values given that there is a significant amount of peole who never see the correct answer so the p-value for those "children" is 0. Here is what happens when we redefine what it means to be a different item. Instead of looking at every combination of seen options we are only going to look at distractors. This means that someone who saw the correct option and the first option (coded 01) will have "seen" the "same" question as someone who just saw the first distractor(coded 1).

It cleans things up a bit but it is important to recognize what is going on.

```
hp_summary$order_no_cr = gsub('0','',hp_summary$order)
hp_summary$order_no_cr = ifelse(hp_summary$order_no_cr == '', '0', hp_summary$order_no_cr)
hp_items_no_cr = hp_summary %>% group_by(item_id, order_no_cr) %>% summarize(p_value = mean(score), cou

all_items = bind_rows(hp_items_no_cr, hp_items_mc)
all_items$item_type = ifelse(is.na(all_items$item_order), 'DOMC', "MC")
all_items$item_number = as.numeric(str_extract(all_items$item_id, "[0-9]+"))
```

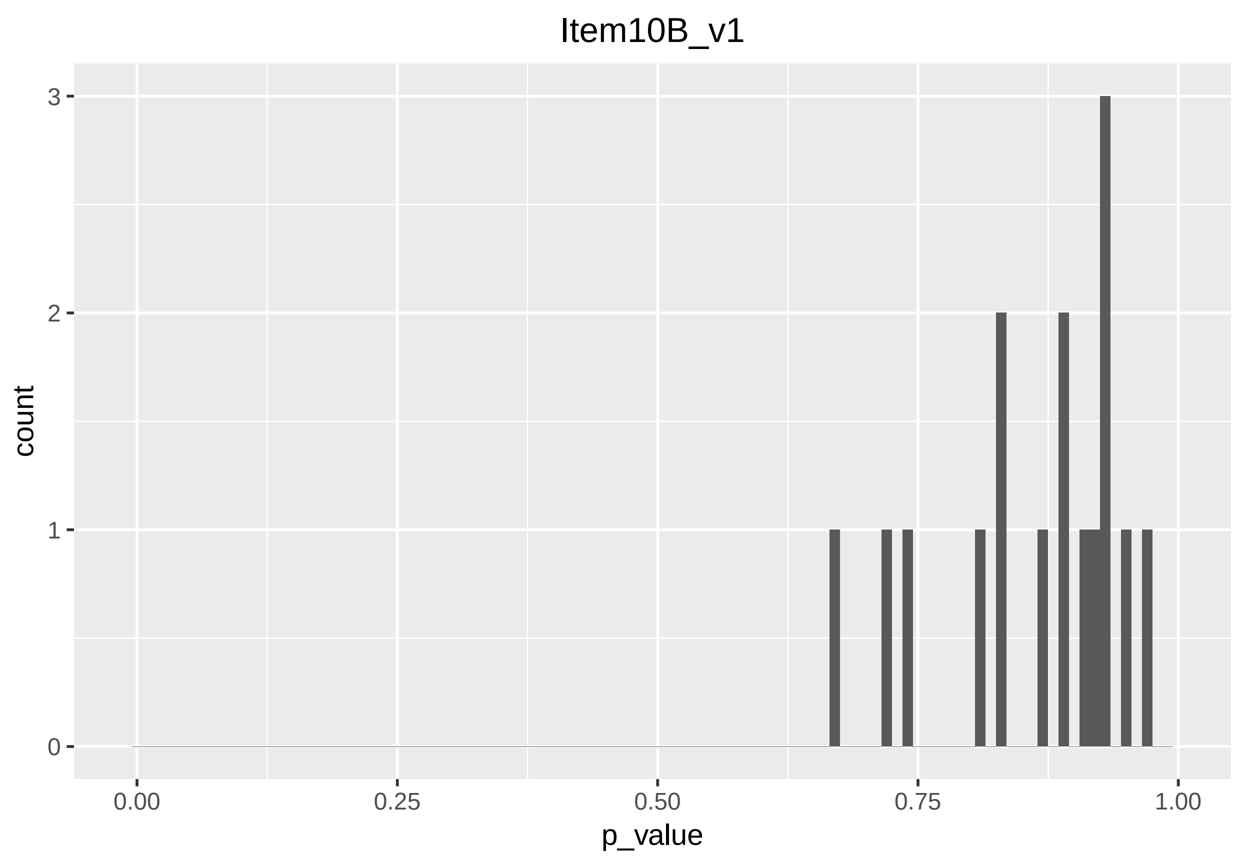
3.6 Item 10B_v1

```
tenb_v1 = hp_items_no_cr %>% filter(item_id == '10B_v1')
kable(tenb_v1)
```

item_id	order_no_cr	p_value	count
10B_v1	0	0.8950000	200
10B_v1	1	0.6666667	63
10B_v1	12	0.8108108	37
10B_v1	123	0.8333333	48
10B_v1	1234	0.9142857	175
10B_v1	124	0.9344262	61
10B_v1	13	0.7250000	40
10B_v1	134	0.8653846	52
10B_v1	14	0.7428571	35
10B_v1	2	0.8939394	66
10B_v1	23	0.9487179	39
10B_v1	234	0.9206349	63
10B_v1	24	0.8333333	42
10B_v1	3	0.9298246	57
10B_v1	34	0.9666667	30
10B_v1	4	0.9302326	43

3.6.1 Histogram

```
theme_update(plot.title = element_text(hjust = 0.5))
ggplot(tenb_v1, aes(x=p_value)) + geom_histogram(binwidth=.01) + labs(title = "Item10B_v1") + xlim(-.01
```

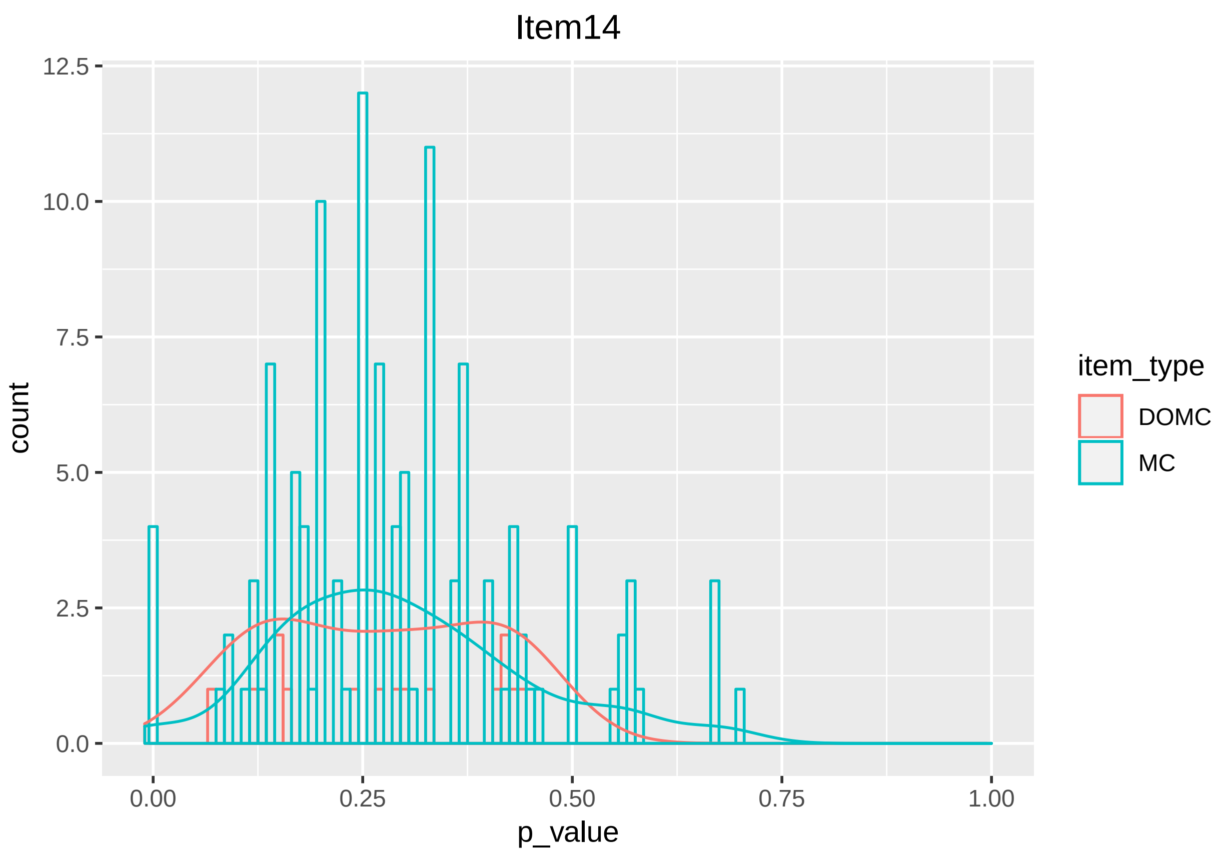


3.7 Item 14b_v1

```
fourteenb_v1 = hp_items_no_cr %>% filter(item_id == '14B_v1')
kable(fourteenb_v1)
```

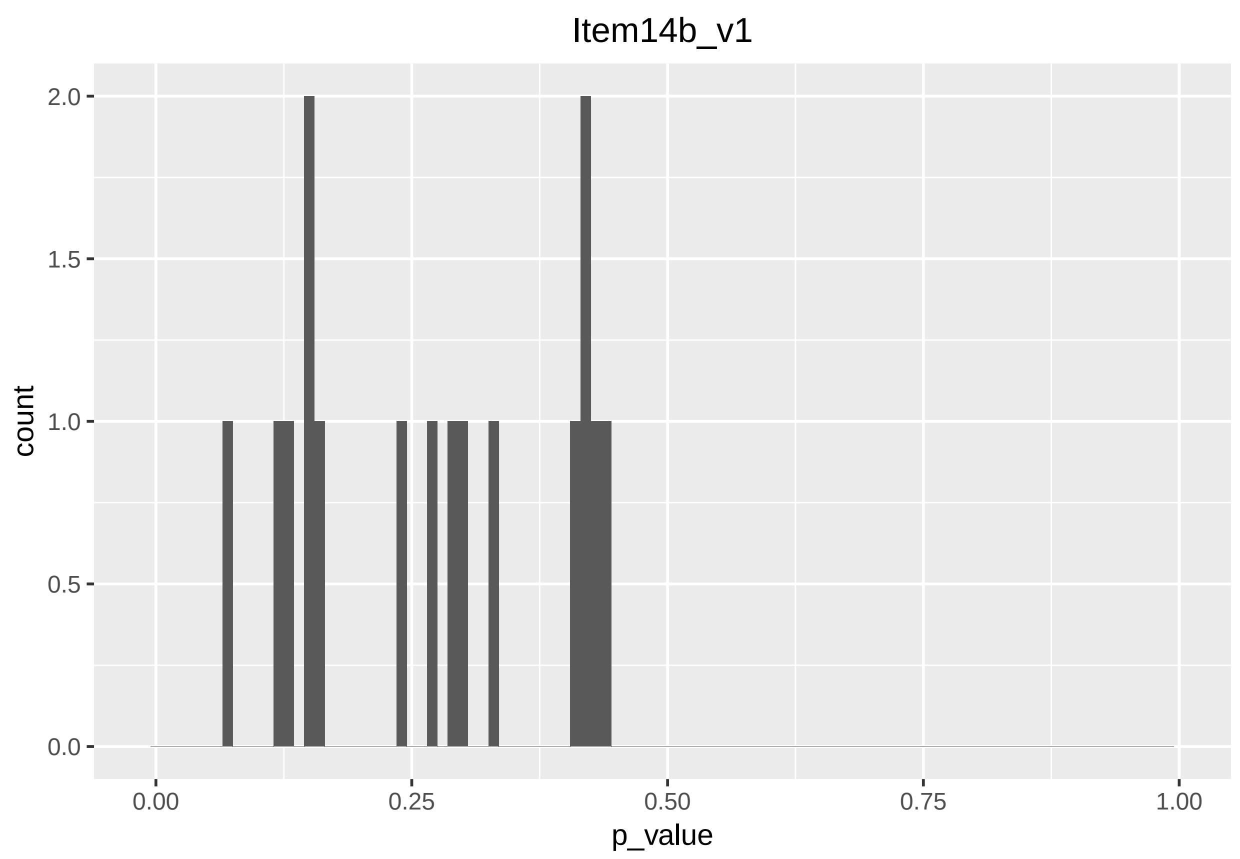
item_id	order_no_cr	p_value	count
14B_v1	0	0.4235294	170
14B_v1	1	0.1511628	86
14B_v1	12	0.1176471	34
14B_v1	123	0.1282051	39
14B_v1	1234	0.4432990	97
14B_v1	124	0.2903226	31
14B_v1	13	0.4193548	31
14B_v1	134	0.4146341	41
14B_v1	14	0.3333333	33
14B_v1	2	0.0675676	148
14B_v1	23	0.2352941	51
14B_v1	234	0.1562500	32
14B_v1	24	0.2972973	37
14B_v1	3	0.2705882	85
14B_v1	34	0.4255319	47
14B_v1	4	0.1460674	89

```
theme_update(plot.title = element_text(hjust = 0.5))
ggplot(all_items %>% filter(item_number == 14), aes(x=p_value, color=item_type)) + geom_histogram(fill=
```



3.7.1 Histogram

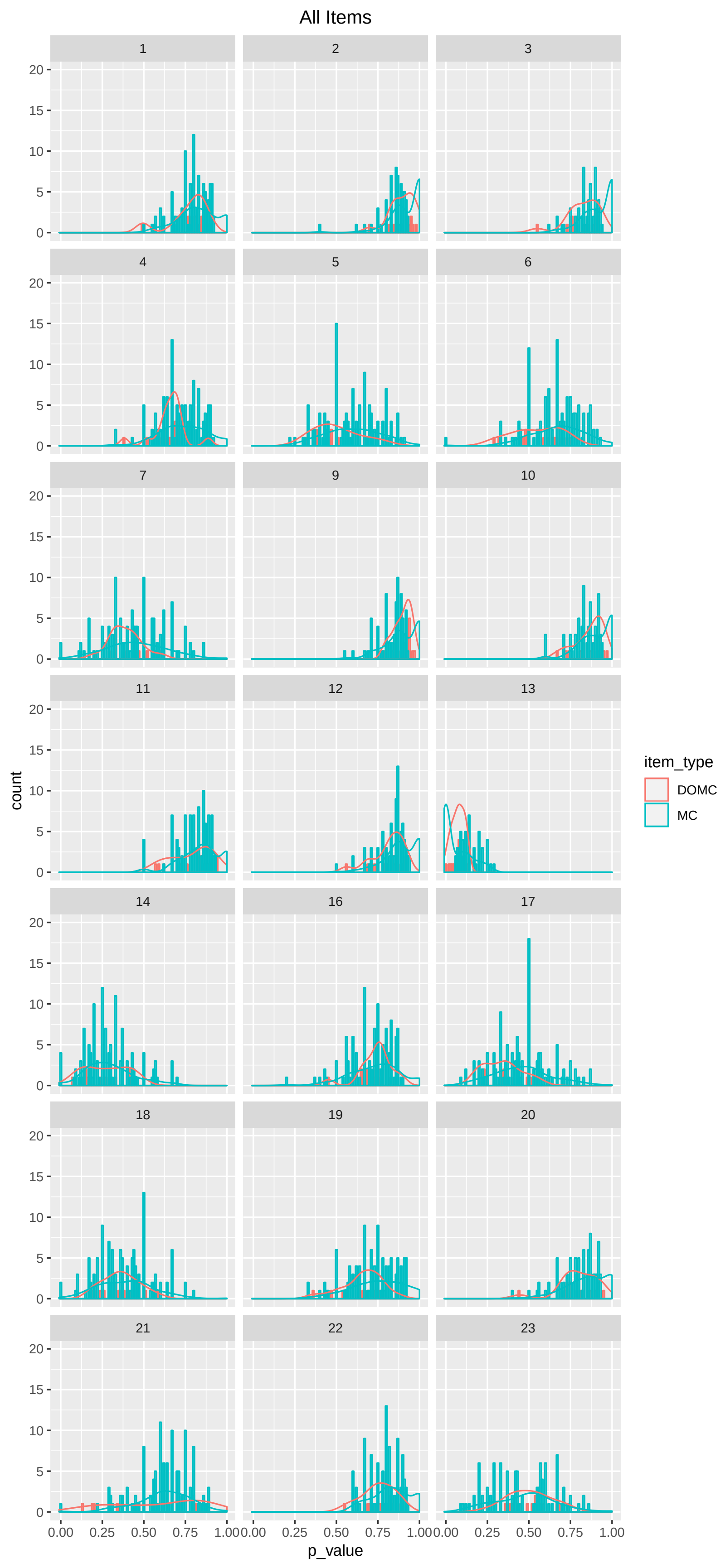
```
ggplot(fourteenb_v1, aes(x=p_value)) + geom_histogram(binwidth=.01) + labs(title = "Item14b_v1") + xlim
```



3.8 All Item Plots

```
knitr::opts_chunk$set(fig.width=12, fig.height=20)

ggplot(all_items, aes(x=p_value, color=item_type)) + geom_histogram(fill='white', binwidth=.01, positio
```


All Items
1
2
3
4
5
6
7
9
10
11
12
13
14
16
17
18
19
20
21
22
23
count
p_value
0.00
0.25
0.50
0.75
1.00
0
5
10
15
20
item_type
DOMC
MC

Chapter 4

DOMC Difficulty Factors

The purpose of this chapter is to briefly address portions of the item format that may lead to systematic differences in difficulty for DOMC items

```
library(dplyr)
library(readr)
library(knitr)
library(ggplot2)
library(lemon)

setwd_thisdir <- function () {
  this.dir <- dirname(parent.frame(3)$ofile)
  setwd(this.dir)
}


hp_data = read_csv('data/domc_order_difficulty/Full Responses After Exclusions.csv')
```

```
## Parsed with column specification:
## cols(
##   delivery_id = col_character(),
##   item_id = col_character(),
##   item_type = col_character(),
##   item_total_seconds = col_double(),
##   score = col_integer(),
##   points_possible = col_integer(),
##   key = col_character(),
##   option_presented = col_character(),
##   response = col_integer(),
##   item_component_type = col_character(),
##   item_component_seconds = col_double(),
##   start_time = col_datetime(format = ""),
##   end_time = col_datetime(format = "")
## )
```

```
hp_clean = hp_data %>% filter(item_type == 'domc' | item_type == 'multiple_choice', item_component_type

hp_summary = hp_clean %>% group_by(delivery_id, item_id, item_type) %>% summarize(item_total_seconds = 
```

```r
total_score = hp_summary %>% group_by(delivery_id) %>% summarize(total_score = sum(score))

hp_final = left_join(hp_summary, total_score)
```

```
## Joining, by = "delivery_id"
```

```r
hp_final$char_count = nchar(hp_final$order)
```

Chapter 5

Total Test Score and Options Seen

Simply running a logistic regression predicting if a person will get an item correct based on teh total number of options seen seems disingenous for a DOMC item. The reason being is that more proficient examinees will on average see more options as they are more likely to reject incorrect options.

Here we look at some regression results

```
mylogit <- glm(score ~ total_score + factor(item_type) + char_count, data = hp_final, family = "binomial
summary(mylogit)
```

```
##
## Call:
## glm(formula = score ~ total_score + factor(item_type) + char_count,
##     family = "binomial", data = hp_final)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4972  -1.0727   0.6177   0.8451   2.3305
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                     -3.587105   0.055005  -65.21   <2e-16 ***
## total_score                      0.217796   0.003298   66.04   <2e-16 ***
## factor(item_type)multiple_choice -6.181737   0.160348  -38.55   <2e-16 ***
## char_count                       0.504366   0.012474   40.43   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 59053  on 45758  degrees of freedom
## Residual deviance: 51520  on 45755  degrees of freedom
## AIC: 51528
##
## Number of Fisher Scoring iterations: 4
```

```
mylogit <- glm(score ~ factor(item_type) + char_count + factor(item_type)*char_count, data = hp_final, 
summary(mylogit)
```

```
##
## Call:
## glm(formula = score ~ factor(item_type) + char_count + factor(item_type) *
##     char_count, family = "binomial", data = hp_final)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0489  -1.3260   0.8314   0.8926   1.2630
##
## Coefficients: (1 not defined because of singularities)
##                                              Estimate Std. Error z value
## (Intercept)                                  -0.74081    0.03029  -24.46
## factor(item_type)multiple_choice             -6.67167    0.15294  -43.62
## char_count                                    0.54180    0.01188   45.61
## factor(item_type)multiple_choice:char_count       NA         NA      NA
##                                              Pr(>|z|)
## (Intercept)                                    <2e-16 ***
## factor(item_type)multiple_choice               <2e-16 ***
## char_count                                     <2e-16 ***
## factor(item_type)multiple_choice:char_count       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 59053  on 45758  degrees of freedom
## Residual deviance: 56570  on 45756  degrees of freedom
## AIC: 56576
##
## Number of Fisher Scoring iterations: 4
```

Chapter 6

Recall VS Deduction

In this chapter we will look at some differences between recall and deduction items on a Harry Potter assessment.

```
library(dplyr)
library(readr)
library(knitr)
library(ggplot2)
library(lemon)
library(stringr)
setwd_thisdir <- function () {
  this.dir <- dirname(parent.frame(3)$ofile)
  setwd(this.dir)
}

hp_data = read_csv('data/domc_order_difficulty/Full Responses After Exclusions.csv')
```

```
## Parsed with column specification:
## cols(
##   delivery_id = col_character(),
##   item_id = col_character(),
##   item_type = col_character(),
##   item_total_seconds = col_double(),
##   score = col_integer(),
##   points_possible = col_integer(),
##   key = col_character(),
##   option_presented = col_character(),
##   response = col_integer(),
##   item_component_type = col_character(),
##   item_component_seconds = col_double(),
##   start_time = col_datetime(format = ""),
##   end_time = col_datetime(format = "")
## )
```

```
hp_clean = hp_data %>% filter(item_type == 'domc' | item_type == 'multiple_choice', item_component_type

recall <- c("1", "2", "3", "4", "5", "6", "7", "8", "9", "10", "11", "12")
deduction = c("13", "14", "15", "16", "17", "18", "19", "20", "21", "22")
```

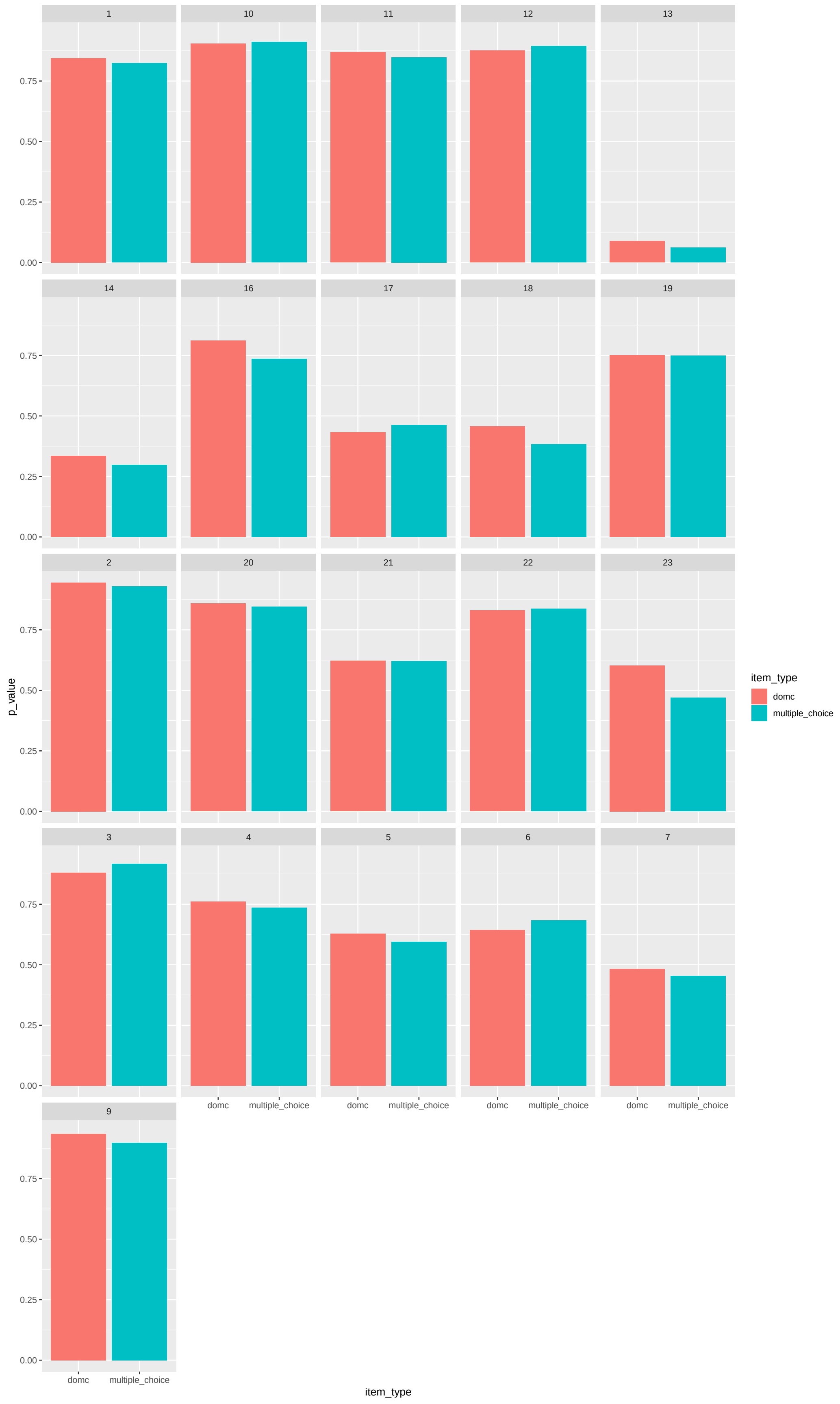
```
hp_clean$deduction <- ifelse(grepl(paste(deduction,collapse="|"), hp_clean$item_id),1,0)

hp_items = hp_clean %>% group_by(item_id, item_type) %>% summarize(p_value = mean(score), count = n(),
hp_items$item_number = str_extract(hp_items$item_id, "[0-9]+")
```

6.1 Some Graphs

Here is the difference in p-value between DOMC and multiple choice for the same items.

```
#here
ggplot(hp_items, aes(x=item_type, y=p_value, fill=item_type)) + geom_bar(stat="identity")  + facet_wrap
```


1
10
11
12
13
14
16
17
18
19
2
20
21
22
23
3
4
5
6
7
9
0.00
0.25
0.50
0.75
p_value
domc
multiple_choice
item_type
item_type
domc
multiple_choice

Here is the difference in p-value between DOMC and multiple choice for the same items.

```
just_mc = hp_items %>% filter(item_type == 'multiple_choice')
just_domc = hp_items %>% filter(item_type != 'multiple_choice')

differences = hp_items %>% group_by(item_type) %>% summarize(average_p_value = mean(p_value, na.rm=TRUE
kable(differences)
```

item_type	average_p_value
domc	0.6933272
multiple_choice	0.6741205

The total difference in p-values between item_types is -0.0192067.

Multiple Choice items appear to be slightly more difficult.

Bibliography

Fisher, R. (1925). *Statistical Methods for Research Workers.* Oliver and Boyd, Edinburgh, Tweeddale Court, 1st edition.