

# Wrangling Chess Tournament Data

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## Setup

### Load libraries

```
library(tidyverse)

## -- Attaching packages ----- tidyverse 1.3.1 --

## v ggplot2 3.3.5      v purrr  0.3.4
## v tibble  3.1.4      v dplyr  1.0.7
## v tidyr   1.1.3      v stringr 1.4.0
## v readr   2.0.1      v forcats 0.5.1

## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()

library(stringr)
library("RMySQL")

## Loading required package: DBI
```

### Establish connection to SQL

After processing and formatting the input data as per assignment instructions, we will be saving the output in SQL. I've created two tables:

- players: a table of players
- scores: a table of player scores from tournaments played

```
mydb = dbConnect(MySQL(), user = 'root', dbname='data_607', host='localhost')
```

The below code will close all open SQL connections if run

```
lapply(dbListConnections(dbDriver(drv = "MySQL")), dbDisconnect)
```

## Convert [input data] -> [desired assignment format]

This assignment's input data is a "|" delimited .txt file containing information about players in a chess tournament. This project aims to wrangle the input data into a tabular format, with the following columns:

- Player's Name
- Player's State
- Total Number of Points
- Player's Pre-Rating
- Average Pre Chess Rating of Opponents

### Import data and inspect

```
data = read.table("https://raw.githubusercontent.com/man-of-moose/masters_607/main/projects/project_1/c",
                  sep="|",
                  fill=TRUE
                  )
```

```
data %>%
  select(V1:V11)
```

```
##                                                                 V1
## 1  -----
## 2                                     Pair
## 3                                     Num
## 4  -----
## 5                                     1
## 6                                     ON
## 7  -----
## 8                                     2
## 9                                     MI
## 10 -----
## 11                                     3
## 12                                     MI
## 13 -----
## 14                                     4
## 15                                     MI
## 16 -----
## 17                                     5
## 18                                     MI
## 19 -----
## 20                                     6
## 21                                     OH
## 22 -----
```

## 23	7
## 24	MI
## 25	-----
## 26	8
## 27	MI
## 28	-----
## 29	9
## 30	ON
## 31	-----
## 32	10
## 33	MI
## 34	-----
## 35	11
## 36	MI
## 37	-----
## 38	12
## 39	MI
## 40	-----
## 41	13
## 42	MI
## 43	-----
## 44	14
## 45	MI
## 46	-----
## 47	15
## 48	MI
## 49	-----
## 50	16
## 51	MI
## 52	-----
## 53	17
## 54	MI
## 55	-----
## 56	18
## 57	MI
## 58	-----
## 59	19
## 60	MI
## 61	-----
## 62	20
## 63	MI
## 64	-----
## 65	21
## 66	ON
## 67	-----
## 68	22
## 69	MI
## 70	-----
## 71	23
## 72	ON
## 73	-----
## 74	24
## 75	MI
## 76	-----

## 77	25
## 78	MI
## 79	-----
## 80	26
## 81	ON
## 82	-----
## 83	27
## 84	MI
## 85	-----
## 86	28
## 87	MI
## 88	-----
## 89	29
## 90	MI
## 91	-----
## 92	30
## 93	ON
## 94	-----
## 95	31
## 96	MI
## 97	-----
## 98	32
## 99	ON
## 100	-----
## 101	33
## 102	MI
## 103	-----
## 104	34
## 105	MI
## 106	-----
## 107	35
## 108	MI
## 109	-----
## 110	36
## 111	MI
## 112	-----
## 113	37
## 114	MI
## 115	-----
## 116	38
## 117	MI
## 118	-----
## 119	39
## 120	MI
## 121	-----
## 122	40
## 123	MI
## 124	-----
## 125	41
## 126	MI
## 127	-----
## 128	42
## 129	MI
## 130	-----

## 131	43
## 132	MI
## 133	-----
## 134	44
## 135	MI
## 136	-----
## 137	45
## 138	MI
## 139	-----
## 140	46
## 141	MI
## 142	-----
## 143	47
## 144	MI
## 145	-----
## 146	48
## 147	MI
## 148	-----
## 149	49
## 150	MI
## 151	-----
## 152	50
## 153	MI
## 154	-----
## 155	51
## 156	MI
## 157	-----
## 158	52
## 159	MI
## 160	-----
## 161	53
## 162	MI
## 163	-----
## 164	54
## 165	MI
## 166	-----
## 167	55
## 168	MI
## 169	-----
## 170	56
## 171	MI
## 172	-----
## 173	57
## 174	MI
## 175	-----
## 176	58
## 177	MI
## 178	-----
## 179	59
## 180	MI
## 181	-----
## 182	60
## 183	MI
## 184	-----

## 185										61
## 186										ON
## 187	-----									
## 188										62
## 189										MI
## 190	-----									
## 191										63
## 192										MI
## 193	-----									
## 194										64
## 195										MI
## 196	-----									
##		V2	V3	V4	V5	V6	V7	V8	V9	
## 1										
## 2	Player Name	Total	Round	Round	Round	Round	Round	Round	Round	
## 3	USCF ID / Rtg (Pre->Post)	Pts	1	2	3	4	5	6		
## 4										
## 5	GARY HUA	6.0	W 39	W 21	W 18	W 14	W 7	D 12		
## 6	15445895 / R: 1794 ->1817	N:2	W B	W B	W B	W B	W B			
## 7										
## 8	DAKSHESH DARURI	6.0	W 63	W 58	L 4	W 17	W 16	W 20		
## 9	14598900 / R: 1553 ->1663	N:2	B W	W B	W B	W B	W B			
## 10										
## 11	ADITYA BAJAJ	6.0	L 8	W 61	W 25	W 21	W 11	W 13		
## 12	14959604 / R: 1384 ->1640	N:2	W B	W B	W B	W B	W B			
## 13										
## 14	PATRICK H SCHILLING	5.5	W 23	D 28	W 2	W 26	D 5	W 19		
## 15	12616049 / R: 1716 ->1744	N:2	W B	W B	W B	W B	W B			
## 16										
## 17	HANSHI ZUO	5.5	W 45	W 37	D 12	D 13	D 4	W 14		
## 18	14601533 / R: 1655 ->1690	N:2	B W	W B	W B	W B	W B			
## 19										
## 20	HANSEN SONG	5.0	W 34	D 29	L 11	W 35	D 10	W 27		
## 21	15055204 / R: 1686 ->1687	N:3	W B	W B	W B	W B	W B			
## 22										
## 23	GARY DEE SWATHELL	5.0	W 57	W 46	W 13	W 11	L 1	W 9		
## 24	11146376 / R: 1649 ->1673	N:3	W B	W B	W B	W B	W B			
## 25										
## 26	EZEKIEL HOUGHTON	5.0	W 3	W 32	L 14	L 9	W 47	W 28		
## 27	15142253 / R: 1641P17->1657P24	N:3	B W	W B	W B	W B	W B			
## 28										
## 29	STEFANO LEE	5.0	W 25	L 18	W 59	W 8	W 26	L 7		
## 30	14954524 / R: 1411 ->1564	N:2	W B	W B	W B	W B	W B			
## 31										
## 32	ANVIT RAO	5.0	D 16	L 19	W 55	W 31	D 6	W 25		
## 33	14150362 / R: 1365 ->1544	N:3	W W	W B	W B	W B	W B			
## 34										
## 35	CAMERON WILLIAM MC LEMAN	4.5	D 38	W 56	W 6	L 7	L 3	W 34		
## 36	12581589 / R: 1712 ->1696	N:3	B W	W B	W B	W B	W B			
## 37										
## 38	KENNETH J TACK	4.5	W 42	W 33	D 5	W 38	H D	1		
## 39	12681257 / R: 1663 ->1670	N:3	W B	W B	W B	W B	W B			
## 40										
## 41	TORRANCE HENRY JR	4.5	W 36	W 27	L 7	D 5	W 33	L 3		

## 42	15082995 / R: 1666	->1662	N:3	B	W	B	B	W	W
## 43									
## 44	BRADLEY SHAW		4.5	W	54 W	44 W	8 L	1 D	27 L 5
## 45	10131499 / R: 1610	->1618	N:3	W	B	W	W	B	B
## 46									
## 47	ZACHARY JAMES HOUGHTON		4.5	D	19 L	16 W	30 L	22 W	54 W 33
## 48	15619130 / R: 1220P13->1416P20		N:3	B	B	W	W	B	B
## 49									
## 50	MIKE NIKITIN		4.0	D	10 W	15 H	W	39 L	2 W 36
## 51	10295068 / R: 1604	->1613	N:3	B	W		B	W	B
## 52									
## 53	RONALD GRZEGORCZYK		4.0	W	48 W	41 L	26 L	2 W	23 W 22
## 54	10297702 / R: 1629	->1610	N:3	W	B	W	B	W	B
## 55									
## 56	DAVID SUNDEEN		4.0	W	47 W	9 L	1 W	32 L	19 W 38
## 57	11342094 / R: 1600	->1600	N:3	B	W	B	W	B	W
## 58									
## 59	DIPANKAR ROY		4.0	D	15 W	10 W	52 D	28 W	18 L 4
## 60	14862333 / R: 1564	->1570	N:3	W	B	W	B	W	W
## 61									
## 62	JASON ZHENG		4.0	L	40 W	49 W	23 W	41 W	28 L 2
## 63	14529060 / R: 1595	->1569	N:4	W	B	W	B	W	B
## 64									
## 65	DINH DANG BUI		4.0	W	43 L	1 W	47 L	3 W	40 W 39
## 66	15495066 / R: 1563P22->1562		N:3	B	W	B	W	W	B
## 67									
## 68	EUGENE L MCCLURE		4.0	W	64 D	52 L	28 W	15 H	L 17
## 69	12405534 / R: 1555	->1529	N:4	W	B	W	B		W
## 70									
## 71	ALAN BUI		4.0	L	4 W	43 L	20 W	58 L	17 W 37
## 72	15030142 / R: 1363	->1371		B	W	B	W	B	W
## 73									
## 74	MICHAEL R ALDRICH		4.0	L	28 L	47 W	43 L	25 W	60 W 44
## 75	13469010 / R: 1229	->1300	N:4	B	W	B	B	W	W
## 76									
## 77	LOREN SCHWIEBERT		3.5	L	9 W	53 L	3 W	24 D	34 L 10
## 78	12486656 / R: 1745	->1681	N:4	B	W	B	W	B	W
## 79									
## 80	MAX ZHU		3.5	W	49 W	40 W	17 L	4 L	9 D 32
## 81	15131520 / R: 1579	->1564	N:4	B	W	B	W	B	W
## 82									
## 83	GAURAV GIDWANI		3.5	W	51 L	13 W	46 W	37 D	14 L 6
## 84	14476567 / R: 1552	->1539	N:4	W	B	W	B	W	B
## 85									
## 86	SOFIA ADINA STANESCU-BELLU		3.5	W	24 D	4 W	22 D	19 L	20 L 8
## 87	14882954 / R: 1507	->1513	N:3	W	W	B	W	B	B
## 88									
## 89	CHIEDOZIE OKORIE		3.5	W	50 D	6 L	38 L	34 W	52 W 48
## 90	15323285 / R: 1602P6 ->1508P12		N:4	B	W	B	W	W	B
## 91									
## 92	GEORGE AVERY JONES		3.5	L	52 D	64 L	15 W	55 L	31 W 61
## 93	12577178 / R: 1522	->1444		W	B	B	W	W	B
## 94									
## 95	RISHI SHETTY		3.5	L	58 D	55 W	64 L	10 W	30 W 50

## 96	15131618 / R: 1494	->1444		B	W	B	W	B	W	
## 97										
## 98	JOSHUA PHILIP MATHEWS		3.5	W	61 L	8 W	44 L	18 W	51 D	26
## 99	14073750 / R: 1441	->1433	N:4	W	B	W	B	W	B	
## 100										
## 101	JADE GE		3.5	W	60 L	12 W	50 D	36 L	13 L	15
## 102	14691842 / R: 1449	->1421		B	W	B	W	B	W	
## 103										
## 104	MICHAEL JEFFERY THOMAS		3.5	L	6 W	60 L	37 W	29 D	25 L	11
## 105	15051807 / R: 1399	->1400		B	W	B	B	W	B	
## 106										
## 107	JOSHUA DAVID LEE		3.5	L	46 L	38 W	56 L	6 W	57 D	52
## 108	14601397 / R: 1438	->1392		W	W	B	W	B	B	
## 109										
## 110	SIDDHARTH JHA		3.5	L	13 W	57 W	51 D	33 H	L	16
## 111	14773163 / R: 1355	->1367	N:4	W	B	W	B		W	
## 112										
## 113	AMIYATOSH PWNANANDAM		3.5	B	L	5 W	34 L	27 H	L	23
## 114	15489571 / R: 980P12->1077P17				B	W	W		B	
## 115										
## 116	BRIAN LIU		3.0	D	11 W	35 W	29 L	12 H	L	18
## 117	15108523 / R: 1423	->1439	N:4	W	B	W	W		B	
## 118										
## 119	JOEL R HENDON		3.0	L	1 W	54 W	40 L	16 W	44 L	21
## 120	12923035 / R: 1436P23->1413		N:4	B	W	B	W	B	W	
## 121										
## 122	FOREST ZHANG		3.0	W	20 L	26 L	39 W	59 L	21 W	56
## 123	14892710 / R: 1348	->1346		B	B	W	W	B	W	
## 124										
## 125	KYLE WILLIAM MURPHY		3.0	W	59 L	17 W	58 L	20 X	U	
## 126	15761443 / R: 1403P5 ->1341P9			B	W	B	W			
## 127										
## 128	JARED GE		3.0	L	12 L	50 L	57 D	60 D	61 W	64
## 129	14462326 / R: 1332	->1256		B	W	B	B	W	W	
## 130										
## 131	ROBERT GLEN VASEY		3.0	L	21 L	23 L	24 W	63 W	59 L	46
## 132	14101068 / R: 1283	->1244		W	B	W	W	B	B	
## 133										
## 134	JUSTIN D SCHILLING		3.0	B	L	14 L	32 W	53 L	39 L	24
## 135	15323504 / R: 1199	->1199			W	B	B	W	B	
## 136										
## 137	DEREK YAN		3.0	L	5 L	51 D	60 L	56 W	63 D	55
## 138	15372807 / R: 1242	->1191		W	B	W	B	W	B	
## 139										
## 140	JACOB ALEXANDER LAVALLEY		3.0	W	35 L	7 L	27 L	50 W	64 W	43
## 141	15490981 / R: 377P3 ->1076P10			B	W	B	W	B	W	
## 142										
## 143	ERIC WRIGHT		2.5	L	18 W	24 L	21 W	61 L	8 D	51
## 144	12533115 / R: 1362	->1341		W	B	W	B	W	B	
## 145										
## 146	DANIEL KHAIN		2.5	L	17 W	63 H	D	52 H	L	29
## 147	14369165 / R: 1382	->1335		B	W		B		W	
## 148										
## 149	MICHAEL J MARTIN		2.5	L	26 L	20 D	63 D	64 W	58 H	



## 150	12531685 / R: 1291P12->1259P17		W	W	B	W	B		
## 151									
## 152	SHIVAM JHA	2.5	L	29 W	42 L	33 W	46 H	L	31
## 153	14773178 / R: 1056 ->1111		W	B	W	B		B	
## 154									
## 155	TEJAS AYYAGARI	2.5	L	27 W	45 L	36 W	57 L	32 D	47
## 156	15205474 / R: 1011 ->1097		B	W	B	W	B	W	
## 157									
## 158	ETHAN GUO	2.5	W	30 D	22 L	19 D	48 L	29 D	35
## 159	14918803 / R: 935 ->1092	N:4	B	W	B	W	B	W	
## 160									
## 161	JOSE C YBARRA	2.0	H	L	25 H	L	44 U	W	57
## 162	12578849 / R: 1393 ->1359			B		W		W	
## 163									
## 164	LARRY HODGE	2.0	L	14 L	39 L	61 B	L	15 L	59
## 165	12836773 / R: 1270 ->1200		B	B	W		W	B	
## 166									
## 167	ALEX KONG	2.0	L	62 D	31 L	10 L	30 B	D	45
## 168	15412571 / R: 1186 ->1163		W	B	W	B		W	
## 169									
## 170	MARISA RICCI	2.0	H	L	11 L	35 W	45 H	L	40
## 171	14679887 / R: 1153 ->1140			B	W	W		B	
## 172									
## 173	MICHAEL LU	2.0	L	7 L	36 W	42 L	51 L	35 L	53
## 174	15113330 / R: 1092 ->1079		B	W	W	B	W	B	
## 175									
## 176	VIRAJ MOHILE	2.0	W	31 L	2 L	41 L	23 L	49 B	
## 177	14700365 / R: 917 -> 941		W	B	W	B	W		
## 178									
## 179	SEAN M MC CORMICK	2.0	L	41 B	L	9 L	40 L	43 W	54
## 180	12841036 / R: 853 -> 878		W		B	B	W	W	
## 181									
## 182	JULIA SHEN	1.5	L	33 L	34 D	45 D	42 L	24 H	
## 183	14579262 / R: 967 -> 984		W	B	B	W	B		
## 184									
## 185	JEZZEL FARKAS	1.5	L	32 L	3 W	54 L	47 D	42 L	30
## 186	15771592 / R: 955P11-> 979P18		B	W	B	W	B	W	
## 187									
## 188	ASHWIN BALAJI	1.0	W	55 U	U	U	U	U	
## 189	15219542 / R: 1530 ->1535		B						
## 190									
## 191	THOMAS JOSEPH HOSMER	1.0	L	2 L	48 D	49 L	43 L	45 H	
## 192	15057092 / R: 1175 ->1125		W	B	W	B	B		
## 193									
## 194	BEN LI	1.0	L	22 D	30 L	31 D	49 L	46 L	42
## 195	15006561 / R: 1163 ->1112		B	W	W	B	W	B	
## 196									
##	V10 V11								
## 1	NA								
## 2	Round NA								
## 3	7 NA								
## 4	NA								
## 5	D 4 NA								
## 6	W NA								

## 7			NA
## 8	W	7	NA
## 9	B		NA
## 10			NA
## 11	W	12	NA
## 12	W		NA
## 13			NA
## 14	D	1	NA
## 15	B		NA
## 16			NA
## 17	W	17	NA
## 18	B		NA
## 19			NA
## 20	W	21	NA
## 21	B		NA
## 22			NA
## 23	L	2	NA
## 24	W		NA
## 25			NA
## 26	W	19	NA
## 27	W		NA
## 28			NA
## 29	W	20	NA
## 30	B		NA
## 31			NA
## 32	W	18	NA
## 33	W		NA
## 34			NA
## 35	W	26	NA
## 36	B		NA
## 37			NA
## 38	L	3	NA
## 39	B		NA
## 40			NA
## 41	W	32	NA
## 42	B		NA
## 43			NA
## 44	W	31	NA
## 45	W		NA
## 46			NA
## 47	W	38	NA
## 48	W		NA
## 49			NA
## 50	U		NA
## 51			NA
## 52			NA
## 53	L	5	NA
## 54	W		NA
## 55			NA
## 56	L	10	NA
## 57	B		NA
## 58			NA
## 59	L	8	NA
## 60	B		NA

## 61		NA
## 62	L 9	NA
## 63	W	NA
## 64		NA
## 65	L 6	NA
## 66	W	NA
## 67		NA
## 68	W 40	NA
## 69	B	NA
## 70		NA
## 71	W 46	NA
## 72	B	NA
## 73		NA
## 74	W 39	NA
## 75	B	NA
## 76		NA
## 77	W 47	NA
## 78	B	NA
## 79		NA
## 80	L 11	NA
## 81	W	NA
## 82		NA
## 83	U	NA
## 84		NA
## 85		NA
## 86	D 36	NA
## 87	W	NA
## 88		NA
## 89	U	NA
## 90		NA
## 91		NA
## 92	W 50	NA
## 93	B	NA
## 94		NA
## 95	L 14	NA
## 96	B	NA
## 97		NA
## 98	L 13	NA
## 99	W	NA
## 100		NA
## 101	W 51	NA
## 102	B	NA
## 103		NA
## 104	W 52	NA
## 105	W	NA
## 106		NA
## 107	W 48	NA
## 108	W	NA
## 109		NA
## 110	D 28	NA
## 111	B	NA
## 112		NA
## 113	W 61	NA
## 114	W	NA

##	115		NA
##	116	L 15	NA
##	117	B	NA
##	118		NA
##	119	L 24	NA
##	120	W	NA
##	121		NA
##	122	L 22	NA
##	123	W	NA
##	124		NA
##	125	U	NA
##	126		NA
##	127		NA
##	128	W 56	NA
##	129	B	NA
##	130		NA
##	131	W 55	NA
##	132	W	NA
##	133		NA
##	134	W 59	NA
##	135	W	NA
##	136		NA
##	137	W 58	NA
##	138	W	NA
##	139		NA
##	140	L 23	NA
##	141	W	NA
##	142		NA
##	143	L 25	NA
##	144	W	NA
##	145		NA
##	146	L 35	NA
##	147	B	NA
##	148		NA
##	149	U	NA
##	150		NA
##	151		NA
##	152	L 30	NA
##	153	W	NA
##	154		NA
##	155	L 33	NA
##	156	W	NA
##	157		NA
##	158	L 34	NA
##	159	B	NA
##	160		NA
##	161	U	NA
##	162		NA
##	163		NA
##	164	W 64	NA
##	165	W	NA
##	166		NA
##	167	L 43	NA
##	168	B	NA

```
## 169      NA
## 170 L   42  NA
## 171 W      NA
## 172      NA
## 173 B      NA
## 174      NA
## 175      NA
## 176 L   45  NA
## 177 B      NA
## 178      NA
## 179 L   44  NA
## 180 B      NA
## 181      NA
## 182 U      NA
## 183      NA
## 184      NA
## 185 L   37  NA
## 186 B      NA
## 187      NA
## 188 U      NA
## 189      NA
## 190      NA
## 191 U      NA
## 192      NA
## 193      NA
## 194 L   54  NA
## 195 B      NA
## 196      NA
```

## Change column names

Rename columns to make analysis meaningful

```
column_names <- c("id","name","total","round_1","round_2","round_3","round_4",
                  "round_5","round_6","round_7","delete")

colnames(data) <- column_names
```

## Remove “———.” rows

Following data import, there are some rows that serve no purpose for our assignment. Additionally, an unexpected column of NAs was created which we will want to delete. We will use `dplyr::filter` and `dplyr::select` to achieve this.

```
data <- data %>%
  filter(str_detect(id, "[a-zA-z\\d]")) %>%
  select(-delete)
```

## Looking at our data now

Due to the structure of the input data, and the steps we’ve taken so far, our current dataframe is structured in an interesting way. Rows with a numeric “id” value contain information about a player’s name, their total

score, and the rounds they played. While rows with a character “id” contain information about a player’s state and pre\_score.

```
head(data)
```

```
##      id                                name total round_1 round_2 round_3
## 1 Pair   Player Name                    Total   Round   Round   Round
## 2 Num    USCF ID / Rtg (Pre->Post)        Pts      1       2       3
## 3      1  GARY HUA                        6.0     W 39    W 21    W 18
## 4     ON  15445895 / R: 1794   ->1817     N:2     W      B      W
## 5      2  DAKSHESH DARURI                6.0     W 63    W 58    L   4
## 6     MI  14598900 / R: 1553   ->1663     N:2     B      W      B
## round_4 round_5 round_6 round_7
## 1 Round   Round   Round   Round
## 2      4      5      6      7
## 3 W 14    W  7    D 12    D  4
## 4 B      W      B      W
## 5 W 17    W 16    W 20    W  7
## 6 W      B      W      B
```

### Get state\_data character vector

We need to capture the state data in a character vector, to later be used to represent the state column of our output. We can do this by filtering for rows that contain 2 capital letters, and saving the “id” column into a variable called state\_data

```
state_data <- data$id
state_data <- state_data[grepl("[A-Z]{2}",state_data)]
state_data <- str_trim(state_data, side = c("both"))
```

### Get pre\_score data

We can extract the pre\_score data in the same way we did state\_data. Unlike state\_data, the pre\_score data will require more advanced regex to properly extract.

```
pre_score_data <- data$name

data$id <- data$id %>%
  str_trim(side=c("both"))

pre_score_data <- data %>%
  filter(str_detect(id,"[A-Z]{2}")) %>%
  .$name

pre_score_data <- pre_score_data %>%
  str_extract("R:[^\\d]*\\d*") %>%
  str_replace("R:", "") %>%
  str_trim(side=c("both"))
```

### Remove rows with non-numeric values

Now that we’ve extracted the state data and pre\_score data, we can remove rows with non-numeric values.

```
data <- data %>%
  filter(str_detect(id, "\\d"))
```

### Add state and pre\_score columns

And now we can take state\_data and pre\_score\_data and add them as new columns to the recently filtered dataframe.

```
data$state <- state_data
data$pre_score <- as.integer(pre_score_data)
```

### Rearrange columns for clarity

Using dply::select and everything() we can easily re-arrange our column values for easier reading.

```
data <- data %>%
  select(name, state, pre_score, total, everything())
```

```
head(data)
```

```
##               name state pre_score total id round_1 round_2
## 1  GARY HUA          ON    1794 6.0   1   W   39   W   21
## 2 DAKSHESH DARURI      MI    1553 6.0   2   W   63   W   58
## 3 ADITYA BAJAJ         MI    1384 6.0   3   L    8   W   61
## 4 PATRICK H SCHILLING  MI    1716 5.5   4   W   23   D   28
## 5 HANSHI ZUO           MI    1655 5.5   5   W   45   W   37
## 6 HANSEN SONG          OH    1686 5.0   6   W   34   D   29
## round_3 round_4 round_5 round_6 round_7
## 1   W   18   W   14   W    7   D   12   D    4
## 2   L    4   W   17   W   16   W   20   W    7
## 3   W   25   W   21   W   11   W   13   W   12
## 4   W    2   W   26   D    5   W   19   D    1
## 5   D   12   D   13   D    4   W   14   W   17
## 6   L   11   W   35   D   10   W   27   W   21
```

### Convert total into double

The ‘total’ value was parsed as a character. since we will be applying math to this later, we need to convert to a double.

```
data$total <- as.double(data$total)
```

### Create new column, “oppo\_ids”

This new column will include vectors containing the opponent ids for each respective player. As an example, Gary Hua’s value here would be:

```
c(39,21,18,14,7,12,4)
```

This is achieved by first concatenating each of the “round\_” columns. Following this, we use stringr to parse out and collect the opponent ids.

```
data <- data %>% mutate(oppo_ids = str_c(round_1,round_2,round_3,round_4,round_5,round_6,round_7))

data$oppo_ids <- data$oppo_ids %>%
  str_replace_all("[A-Z]", "") %>%
  str_trim(side=c("both")) %>%
  str_replace_all("\\s{2,}", "|")

data$oppo_ids <- data$oppo_ids %>% str_split("\\|")
```

### Create function to calculate average opponent score

This function will use the previously created “oppo\_id” column values as input, in order to filter for and average the correct opponent pre\_scores.

```
get_avg_oppo_score <- function(id_data) {
  temp_df <- data %>%
    filter(id %in% id_data) %>%
    summarise(pre_score_mean = mean(pre_score, na.rm=TRUE))

  return(temp_df[,1])
}
```

### Test it out on the first example

```
get_avg_oppo_score(c(39,21,18,14,7,12,4))
```

```
## [1] 1605.286
```

### Apply function to entire dataframe

```
data$avg_oppo_score <- lapply(data$oppo_ids, FUN=get_avg_oppo_score)
```

### Calculate total number of games played

We will need this later on for extra credit. Here we are counting how many games each player participated in.

```
data$number_of_games <- as.integer(
  lapply(
    lapply(data$oppo_ids, FUN=lengths),
    FUN=sum
  )
)
```



## Select only interesting columns

There are a few columns we don't need anymore such as all of the "round\_" columns, the "oppo\_ids" column, and others. We can use `dplyr::select` to select only what's interesting.

```
final_data <- data %>%
  select(name,
         state,
         total,
         number_of_games,
         pre_score,
         avg_oppo_score
  )
```

## Round avg\_oppo\_score (Average Opponent Score) and inspect

Based on the description of this project, we will be rounding the values of `avg_oppo_score` with the `round()` function.

```
final_data$avg_oppo_score <- as.integer(
  lapply(final_data$avg_oppo_score, FUN=round)
)
```

final\_data

		name	state	total	number_of_games	pre_score
##						
##	1	GARY HUA	ON	6.0	7	1794
##	2	DAKSHESH DARURI	MI	6.0	7	1553
##	3	ADITYA BAJAJ	MI	6.0	7	1384
##	4	PATRICK H SCHILLING	MI	5.5	7	1716
##	5	HANSHI ZUO	MI	5.5	7	1655
##	6	HANSEN SONG	OH	5.0	7	1686
##	7	GARY DEE SWATHELL	MI	5.0	7	1649
##	8	EZEKIEL HOUGHTON	MI	5.0	7	1641
##	9	STEFANO LEE	ON	5.0	7	1411
##	10	ANVIT RAO	MI	5.0	7	1365
##	11	CAMERON WILLIAM MC LEMAN	MI	4.5	7	1712
##	12	KENNETH J TACK	MI	4.5	6	1663
##	13	TORRANCE HENRY JR	MI	4.5	7	1666
##	14	BRADLEY SHAW	MI	4.5	7	1610
##	15	ZACHARY JAMES HOUGHTON	MI	4.5	7	1220
##	16	MIKE NIKITIN	MI	4.0	5	1604
##	17	RONALD GRZEGORCZYK	MI	4.0	7	1629
##	18	DAVID SUNDEEN	MI	4.0	7	1600
##	19	DIPANKAR ROY	MI	4.0	7	1564
##	20	JASON ZHENG	MI	4.0	7	1595
##	21	DINH DANG BUI	ON	4.0	7	1563
##	22	EUGENE L MCCLURE	MI	4.0	6	1555
##	23	ALAN BUI	ON	4.0	7	1363
##	24	MICHAEL R ALDRICH	MI	4.0	7	1229
##	25	LOREN SCHWIEBERT	MI	3.5	7	1745
##	26	MAX ZHU	ON	3.5	7	1579

## 27	GAURAV GIDWANI	MI	3.5	6	1552
## 28	SOFIA ADINA STANESCU-BELLU	MI	3.5	7	1507
## 29	CHIEDOZIE OKORIE	MI	3.5	6	1602
## 30	GEORGE AVERY JONES	ON	3.5	7	1522
## 31	RISHI SHETTY	MI	3.5	7	1494
## 32	JOSHUA PHILIP MATHEWS	ON	3.5	7	1441
## 33	JADE GE	MI	3.5	7	1449
## 34	MICHAEL JEFFERY THOMAS	MI	3.5	7	1399
## 35	JOSHUA DAVID LEE	MI	3.5	7	1438
## 36	SIDDHARTH JHA	MI	3.5	6	1355
## 37	AMIYATOSH PWNANANDAM	MI	3.5	5	980
## 38	BRIAN LIU	MI	3.0	6	1423
## 39	JOEL R HENDON	MI	3.0	7	1436
## 40	FOREST ZHANG	MI	3.0	7	1348
## 41	KYLE WILLIAM MURPHY	MI	3.0	4	1403
## 42	JARED GE	MI	3.0	7	1332
## 43	ROBERT GLEN VASEY	MI	3.0	7	1283
## 44	JUSTIN D SCHILLING	MI	3.0	6	1199
## 45	DEREK YAN	MI	3.0	7	1242
## 46	JACOB ALEXANDER LAVALLEY	MI	3.0	7	377
## 47	ERIC WRIGHT	MI	2.5	7	1362
## 48	DANIEL KHAIN	MI	2.5	5	1382
## 49	MICHAEL J MARTIN	MI	2.5	5	1291
## 50	SHIVAM JHA	MI	2.5	6	1056
## 51	TEJAS AYYAGARI	MI	2.5	7	1011
## 52	ETHAN GUO	MI	2.5	7	935
## 53	JOSE C YBARRA	MI	2.0	3	1393
## 54	LARRY HODGE	MI	2.0	6	1270
## 55	ALEX KONG	MI	2.0	6	1186
## 56	MARISA RICCI	MI	2.0	5	1153
## 57	MICHAEL LU	MI	2.0	6	1092
## 58	VIRAJ MOHILE	MI	2.0	6	917
## 59	SEAN M MC CORMICK	MI	2.0	6	853
## 60	JULIA SHEN	MI	1.5	5	967
## 61	JEZZEL FARKAS	ON	1.5	7	955
## 62	ASHWIN BALAJI	MI	1.0	1	1530
## 63	THOMAS JOSEPH HOSMER	MI	1.0	5	1175
## 64	BEN LI	MI	1.0	7	1163
##	avg_oppo_score				
## 1	1605				
## 2	1469				
## 3	1564				
## 4	1574				
## 5	1501				
## 6	1519				
## 7	1372				
## 8	1468				
## 9	1523				
## 10	1554				
## 11	1468				
## 12	1506				
## 13	1498				
## 14	1515				
## 15	1484				

## 16	1386
## 17	1499
## 18	1480
## 19	1426
## 20	1411
## 21	1470
## 22	1300
## 23	1214
## 24	1357
## 25	1363
## 26	1507
## 27	1222
## 28	1522
## 29	1314
## 30	1144
## 31	1260
## 32	1379
## 33	1277
## 34	1375
## 35	1150
## 36	1388
## 37	1385
## 38	1539
## 39	1430
## 40	1391
## 41	1248
## 42	1150
## 43	1107
## 44	1327
## 45	1152
## 46	1358
## 47	1392
## 48	1356
## 49	1286
## 50	1296
## 51	1356
## 52	1495
## 53	1345
## 54	1206
## 55	1406
## 56	1414
## 57	1363
## 58	1391
## 59	1319
## 60	1330
## 61	1327
## 62	1186
## 63	1350
## 64	1263

## Trim names

While you can't tell from the above tibble, many of the player names actually have surrounding white spaces. We can remove with `stringr::str_trim`

```
final_data$name <- str_trim(final_data$name, side=c("both"))
```

## Calculate expected score for each player

In chess a player's "total score" for a game is determined by whether or not the player wins (+1), loses (+0), or draws (+0.5)

The "expected score" for a player in one game can be represented as a modified probability that they will win, based on their `pre_score` relative to their opponent's `pre_score`.

The following function can perform the required calculation:

```
1/(10^((oppo_pre_score)-pre_score)/400)+1)
```

Because we have already computed averages for our opponent `pre_scores`, we can modify the above equation as such:

```
1/(10^((oppo_Pre_score)-pre_score)/400)+1) * {number_of_games}
```

The function used above was identified from the following sources:

- <http://www.uschess.org/index.php/Players-Ratings/Do-NOT-edit-CLOSE-immediately.html>
- <https://chess.stackexchange.com/questions/18209/how-do-you-calculate-your-tournament-performance-rating>

```
final_data <- final_data %>%  
  mutate(  
    expected_total = 1/(10^((avg_oppo_score-pre_score)/400)+1) * number_of_games  
  )
```

## EXTRA CREDIT: which player scored the most points relative to their expected score?

Answer is Aditya Bajaj, who performed very well throughout this tournament. In fact, Aditya's total was more than 4.16 points above his expected total. He won 6 out of 7 games, despite the fact that, on average, he was rated nearly 200 points below each of his opponents.

```
final_data %>%  
  mutate(score_differential = total - expected_total) %>%  
  arrange(desc(score_differential)) %>%  
  .[1,c('name', 'pre_score', 'avg_oppo_score', 'total', 'expected_total', 'score_differential')]
```

```
##           name pre_score avg_oppo_score total expected_total score_differential  
## 1 ADITYA BAJAJ    1384         1564      6         1.833237         4.166763
```

## Generate a .CSV file and load values into SQL

Generate a .CSV file

```
write.table(final_data, sep=",", file = "/Users/alecmccabe/Desktop/Masters Program/DATA 607/masters_607.csv")
```

### Create function to assign ids to players

The reason why I chose to include two tables in my SQL database was to allow for continued use of this script. When new tournaments happen, new players may participate.

This function will work by looking at the total list of tournament participants, and cross-reference that list against the existing SQL table data\_607.players

This ensures that if a participant has already been counted in previous tournaments, they will be assigned the same player\_id.

Alternatively, if there is a new participant, this function will ensure that their generated player\_id does not match any existing ones.

```
assign_player_ids <- function(insert_data, mydb) {
  names <- insert_data$name
  players_string <- str_c('"' ,str_trim(names,side=c("both")),'"',collapse=",")
  insert_data$id <- NA
  query <- str_interp("SELECT player_name, id FROM data_607.players WHERE player_name in (${players_string})")

  select_data <- dbGetQuery(mydb, query)

  for (row in 1:nrow(select_data)) {
    select_name <- select_data[row,"player_name"]
    select_id <- select_data[row,"id"]

    insert_data <- within(insert_data, id[name == select_name] <- select_id)
  }

  for (row in 1:nrow(insert_data)){
    if (is.na(insert_data[row,$id])) {
      if (sum(!is.na(insert_data$id))>0) {
        max_id <- max(insert_data$id, na.rm=TRUE) +1
      } else {
        max_id <- 1
      }
      insert_data[row,$id] <- max_id
    }
  }

  return(insert_data)
}
```

### Running id assignment

Because data\_607.players is currently empty, each of the participants in this tournament will be provided with incremental ids, starting with 1 and ending at 64.

```
final_data <- assign_player_ids(final_data, mydb)
```

### Create insert function to load into data\_607.players

This function will load any new players, and their associated player\_ids and state information into the data\_607.players table.

```
insert_players <- function(data, mydb){

  names <- final_data$name
  players_string <- str_c('','',str_trim(names,side=c("both")),'',collapse=",")
  query <- str_interp("SELECT player_name, id FROM data_607.players WHERE player_name in (${players_str}")

  select_data <- dbGetQuery(mydb, query)

  for (row in 1:nrow(final_data)){
    id <- as.integer(final_data[row, "id"])
    name <- str_trim(final_data[row, "name"], side=c("both"))
    state <- str_trim(final_data[row, "state"], side=c("both"))
    total <- final_data[row, "total"]
    pre_score <- final_data[row, "pre_score"]
    avg_opponent_score <- final_data[row, "avg_oppo_score"]

    insert_query <- str_interp('insert into data_607.players VALUES (${id},"${name}", "${state}")')

    if (name %in% select_data$player_name) {
      next
    } else {
      print(name)
      dbGetQuery(mydb, insert_query)
    }
  }
}
```

### Create a function to insert into the data\_607.scores table

This function will load a player's performance data and metrics into the data\_607.scores table. This function takes 'tournament\_id' variable as input in addition to data and db\_connection.

```
insert_scores <- function(data, tournament_id, mydb){

  for (row in 1:nrow(final_data)){
    id <- as.integer(final_data[row, "id"])
    name <- str_trim(final_data[row, "name"], side=c("both"))
    total <- final_data[row, "total"]
    pre_score <- final_data[row, "pre_score"]
    avg_opponent_score <- final_data[row, "avg_oppo_score"]
    number_of_games <- final_data[row, "number_of_games"]
    expected_total <- final_data[row, "expected_total"]
  }
```

```

    insert_query <- str_interp('insert into scores VALUES (DEFAULT,${tournament_id},${id},${number_of_g
    dbGetQuery(mydb, insert_query)
  }
}

```

**Insert into SQL tables** The `insert_players` function prints to the console each player's name that is added to the SQL data ("new players"). As we see below, everyone is added.

```
insert_players(final_data, mydb)
```

```
insert_scores(final_data,1, mydb)
```

## Visualize the distribution of 'score\_differential' for players

'score\_differential' will be defined as the difference between a player's expected total, and their actual total points.

```

final_data <- final_data %>%
  mutate(score_differential = total - expected_total)

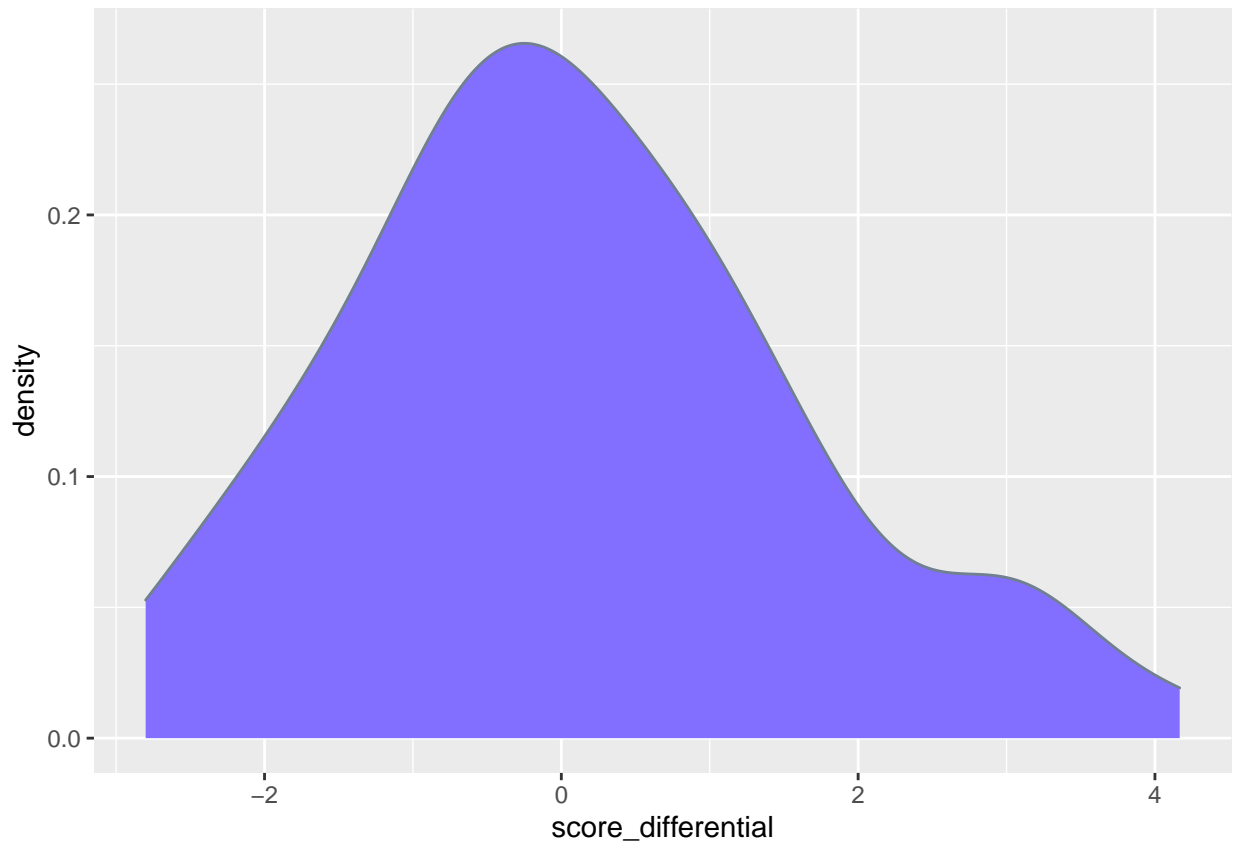
```

The density plot below suggests that the score\_difference distribution is nearly gaussian, with a mean centered around zero and only a slight right skew.

```

final_data %>%
  ggplot(aes(x=score_differential)) +
  geom_density(
    fill = "slateblue1",
    color = "slategrey"
  ) +
  theme_grey()

```



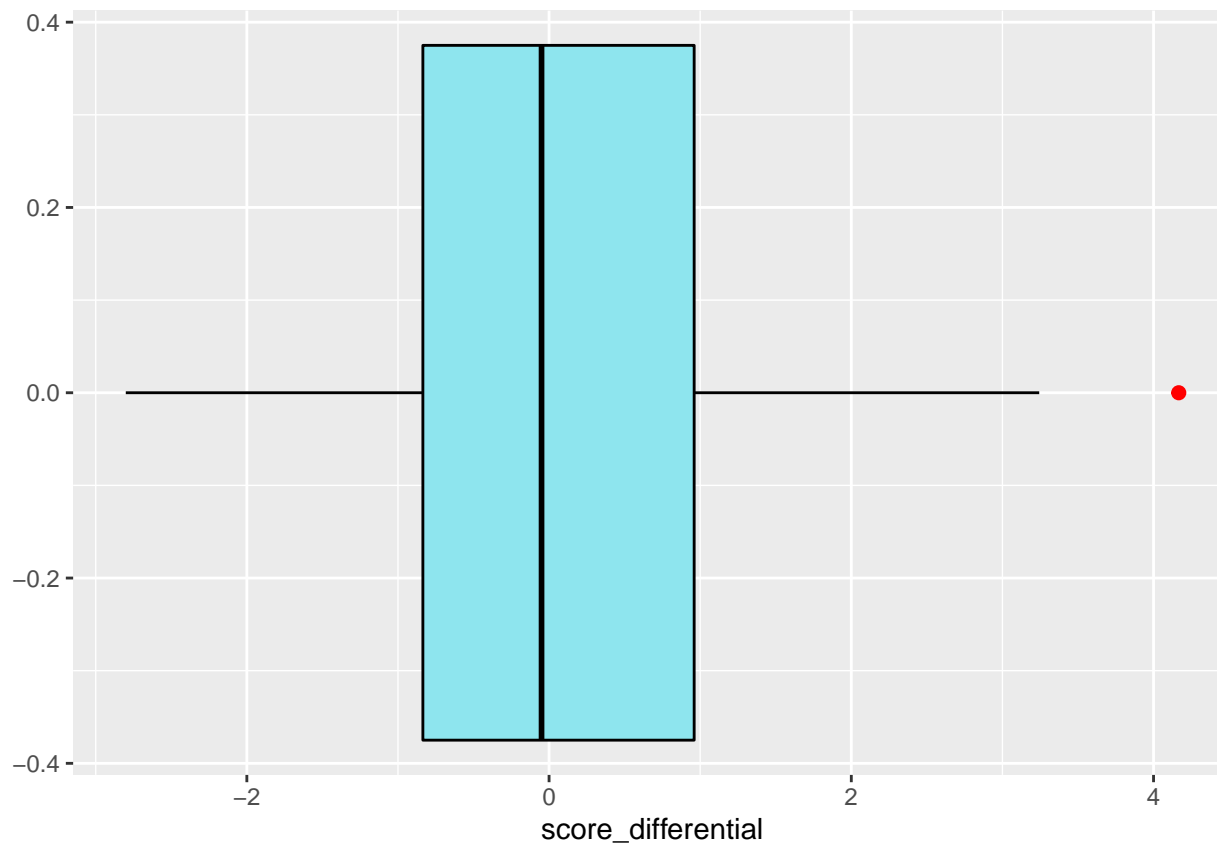
The below boxplot also shows that score\_difference distribution is centered around zero, and seemingly normally distributed. Roughly 50% of the population's score\_difference is between -1 and 1. Tail values stretch from -2.5 (performed much worse than expected) all the way to 2.5 (performed much better than expected).

There is also an outlier identified, with a score\_differential of 4.166. As we discussed earlier, Aditya performed much better than expected.

Based on the data, one could make that claim that Aditya's performance was not a fluke, but rather a result of an "inaccurate" initial pre\_score going into the tournament.

```
final_data %>%
  ggplot(aes(x=score_differential)) +
  geom_boxplot(
    color = "black",
    fill="cadetblue2",
    outlier.size=2,
    outlier.colour="red"
  ) +
  theme_grey()
```





The concept of an “innacurate” pre\_score is interesting. Let’s see if there is any correlation between the absolute score\_differential and a player’s pre\_score.

```
final_data %>%
  mutate(
    score_differential = abs(score_differential)
  ) %>%
  select(pre_score, score_differential) %>%
  cor() %>%
  .[1,2]
```

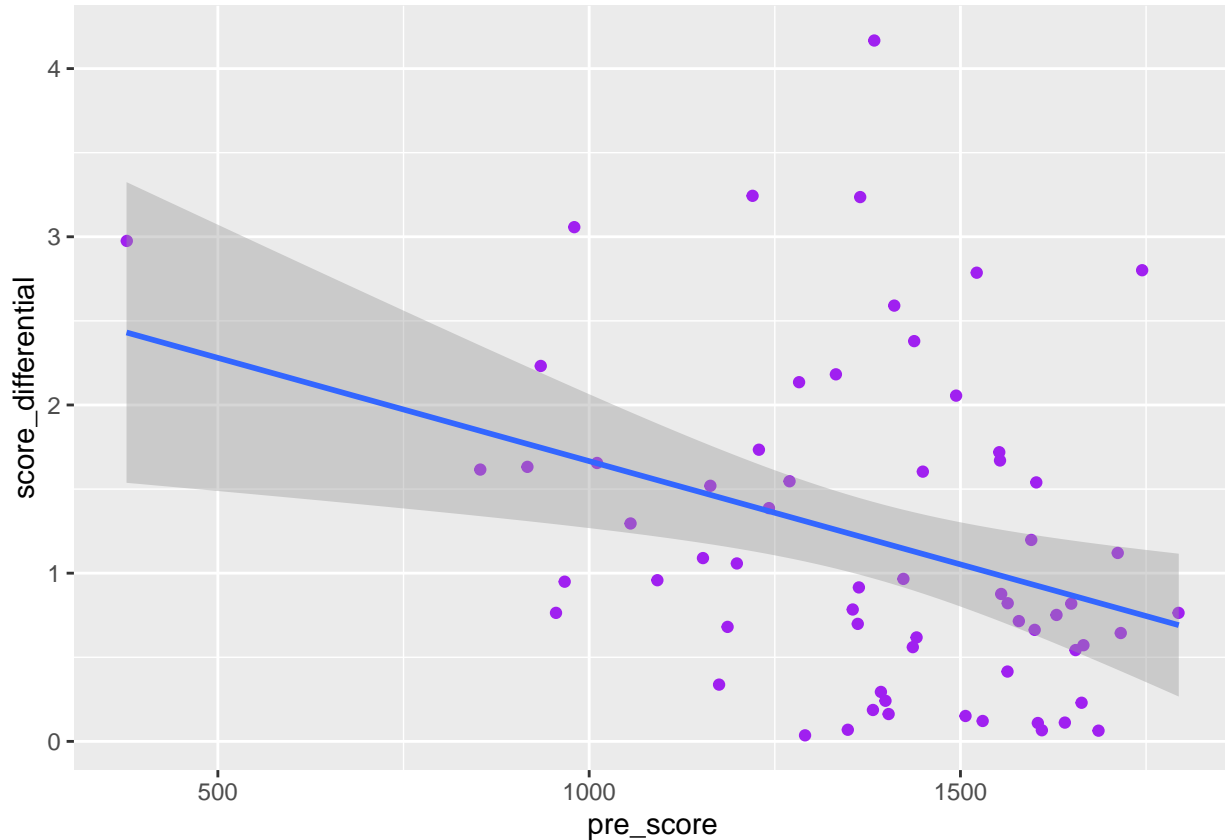
```
## [1] -0.3396838
```

There is a small but not insignificant correlation. The below graph illustrates the correlation between pre\_score and score\_differential. As pre\_score goes up, the absolute score\_differential goes down. This implies that players with higher pre\_scores can place more faith in their expected\_totals than players with low pre\_scores.

And intuitively, this makes sense. Many players have low pre\_scores simply because they don’t have as many tournament games played. Even Magnus Carlson was once lowly rated (though I doubt that lasted long).

```
final_data %>%
  mutate(
    score_differential = abs(score_differential)
  ) %>%
```

```
ggplot() +
  geom_point(aes(x=pre_score, y=score_differential),
             position="jitter",
             color = "purple") +
  geom_smooth(aes(x=pre_score, y=score_differential), method='lm', formula=y~x)+
  theme_grey()
```



## Test functions “assign\_player\_ids” and “insert\_players”

Here we will make sure that the above functions work as expected when presented with new player data.

As an example, imagine that a second tournament includes all of the members of this tournament, plus one new member: Johnny Apple.

If our functions work as expected, then the `assign_player_id` function will provide Johnny with the id 65, and the `insert_players` function will only insert Johnny (since the previous players are already contained in the SQL table)

```
final_data <- add_row(final_data,
  name="Johnny Apple",
  state="OH",
  total=5,
  number_of_games = 7,
  pre_score=1111,
```

```
avg_oppo_score=1245,  
expected_total = 4,  
id=NA)
```

```
final_data <-assign_player_ids(final_data,mydb)
```

```
final_data[final_data$name=="Johnny Apple",c('name','id')]
```

```
##           name id  
## 65 Johnny Apple 65
```

```
insert_players(final_data, mydb)
```