Baseball Data

June 13, 2017

0.1 Read in the Data

This exercise shows how R interfaces with other programs, particularly SQL database management. We will use the package RSQLite, which not only provides an R interface but also installs a minimal library for database access.

We will look trends in baseball team payrolls between the years 1985 and 2010. The data come from the Baseball Databank http://baseball-databank.org and is based in part on Lahman's Baseball Database. Information on the attributes in the database can be found at http://baseball1.com/files/ database/readme58.txt. You will need to download the SQLite database file baseball.sqlite (located at https://www.dropbox.com/s/mgcahruairqmbxo/baseball.sqlite?dl=1) to your computer.

There is an R package, lahman, containing data frames with all of this data, which you can use after the homework if you're curious. Using it in this homework will be counter-productive.

0.2 Set Up

Using RSQLite, setup a connection to the SQLite database stored in baseball.db. Use dbListTables() to list the tables in the database.

```
In [1]: library('RSQLite')

        db_conn <- dbConnect(SQLite(), dbname="baseball.sqlite")
        dbListTables(conn = db_conn)
```

1. 'AllstarFull' 2. 'Appearances' 3. 'AwardsManagers' 4. 'AwardsPlayers' 5. 'AwardsShareManagers' 6. 'AwardsSharePlayers' 7. 'Batting' 8. 'BattingPost' 9. 'Fielding' 10. 'FieldingOF' 11. 'FieldingPost' 12. 'HallOfFame' 13. 'Managers' 14. 'ManagersHalf' 15. 'Master' 16. 'Pitching' 17. 'PitchingPost' 18. 'Salaries' 19. 'Schools' 20. 'SchoolsPlayers' 21. 'SeriesPost' 22. 'Teams' 23. 'TeamsFranchises' 24. 'TeamsHalf' 25. 'sqlite_sequence' 26. 'xref_stats'

0.3 Calculate the payroll

Use the table that contains salaries and compute the payroll for each team in 2010. Use dbReadTable() to grab the entirety of the table, then select the relevant subset. Which teams had the highest payrolls?

```
In [2]: # Using the aggregate function
        salaries <- dbReadTable(conn=db_conn, "Salaries")
        salary2010 <-salaries[ salaries$yearID == 2010, ]
```

```
payroll <- aggregate(salary ~ teamID,salary2010, sum)

# Order by payroll descending
ordered <- payroll[order(-payroll$salary),]
head(ordered)

# library('ggplot2')
# # Very basic bar graph
# print("Now let's see a barplot of these salaries")
# ggplot(data=ordered[1:5,], aes(x=teamID, y=salary, label=salary)) +
#     geom_bar(stat="identity")
```

	teamID	salary
18	NYA	206333389
4	BOS	162447333
6	CHN	146609000
21	PHI	141928379
19	NYN	134422942
10	DET	122864928

The teams with the highest payroll are New York Yankees, Boston Redsox, New York Mets, Los Angeles Dodgers, Atlanta Braves, and Chicago Cubs

0.4 Calculate using SQL

Repeat the previous step, but now do this using only dbGetQuery() and SQL. You should verify that your answers are identical (you can do this by eye without checking formally with code).

```
In [3]: query <-"SELECT teamID,
                        SUM(Salary) as payroll
                FROM Salaries
                WHERE yearID = 2010
                GROUP BY teamID
                ORDER BY payroll desc
                LIMIT 6"
        salaries <- dbGetQuery(conn=db_conn, query)
        salaries
```

teamID	payroll
NYA	206333389
BOS	162447333
CHN	146609000
PHI	141928379
NYN	134422942
DET	122864928

```
In [4]: dbListFields(conn=db_conn, "Salaries")
```

1. 'yearID' 2. 'teamID' 3. 'lgID' 4. 'playerID' 5. 'salary'

Modify the SQL statement from part c to compute the payroll for each team for each year from 1985 to 2010.

```
In [5]: query <-"SELECT teamID, yearID,
                    SUM(Salary) as payroll
                FROM Salaries
                GROUP BY teamID, yearID
                ORDER BY payroll desc"
        salaries <- dbGetQuery(conn=db_conn, query)

        library("reshape2")
        dcast(salaries, yearID ~ teamID, value.var = "payroll")
```

yearID	ANA	ARI	ATL	BAL	BOS	CAL	CHA	CHN
1959	NA	NA	NA	NA	NA	NA	NA	NA
1980	NA	NA	NA	NA	NA	NA	NA	NA
1981	NA	NA	NA	NA	NA	NA	NA	NA
1982	NA	NA	NA	NA	NA	NA	NA	NA
1983	NA	NA	NA	NA	NA	NA	NA	NA
1984	NA	NA	NA	NA	NA	NA	NA	NA
1985	NA	NA	14807000	11560712	10897560	14427894	9846178	12702917
1986	NA	NA	17102786	13001258	14402239	14427258	10418819	17208165
1987	NA	NA	16544560	13900273	10144167	12843499	10641843	14307999
1988	NA	NA	12728174	13532075	13896092	11947388	6390000	13119198
1989	NA	NA	11112334	8275167	17481748	15097833	7265410	10668000
1990	NA	NA	14555501	9680084	20558333	21720000	9491500	13624000
1991	NA	NA	18403500	17519000	35167500	33060001	16919667	23175667
1992	NA	NA	34625333	23780667	43610584	34749334	30160833	29829686
1993	NA	NA	41641417	29096500	37120583	28588334	39696166	39386666
1994	NA	NA	49383513	38849769	37859084	25156218	39183836	36287333
1995	NA	NA	47235445	43942521	32455518	31223171	46961282	29505834
1996	NA	NA	49698500	54490315	42393500	28738000	45139500	33081000
1997	31135472	NA	52278500	58516400	43558750	NA	57740000	42155333
1998	41281000	32347000	61186000	72355634	56757000	NA	38335000	50838000
1999	55388166	68703999	73140000	80605863	63497500	NA	25620000	62343000
2000	51464167	81027833	84537836	81447435	77940333	NA	31133500	60539333
2001	47535167	85082999	91936166	67599540	110035833	NA	65653667	64715833
2002	61721667	102819999	92870367	60493487	108366060	NA	57052833	75690833
2003	79031667	80657000	106243667	73877500	99946500	NA	51010000	79868333
2004	100534667	69780750	90182500	51623333	127298500	NA	65212500	90560000
2005	NA	62329166	86457302	73914333	123505125	NA	75178000	87032933
2006	NA	59684226	90156876	72585582	120099824	NA	102750667	94424499
2007	NA	52067546	87290833	93174808	143026214	NA	108671833	99670332
2008	NA	66202712	102365683	67196246	133390035	NA	121189332	118345833
2009	NA	73516666	96726166	67101666	121345999	NA	96068500	134809000
2010	NA	60718166	84423666	81612500	162447333	NA	105530000	146609000

0.5 Visualization

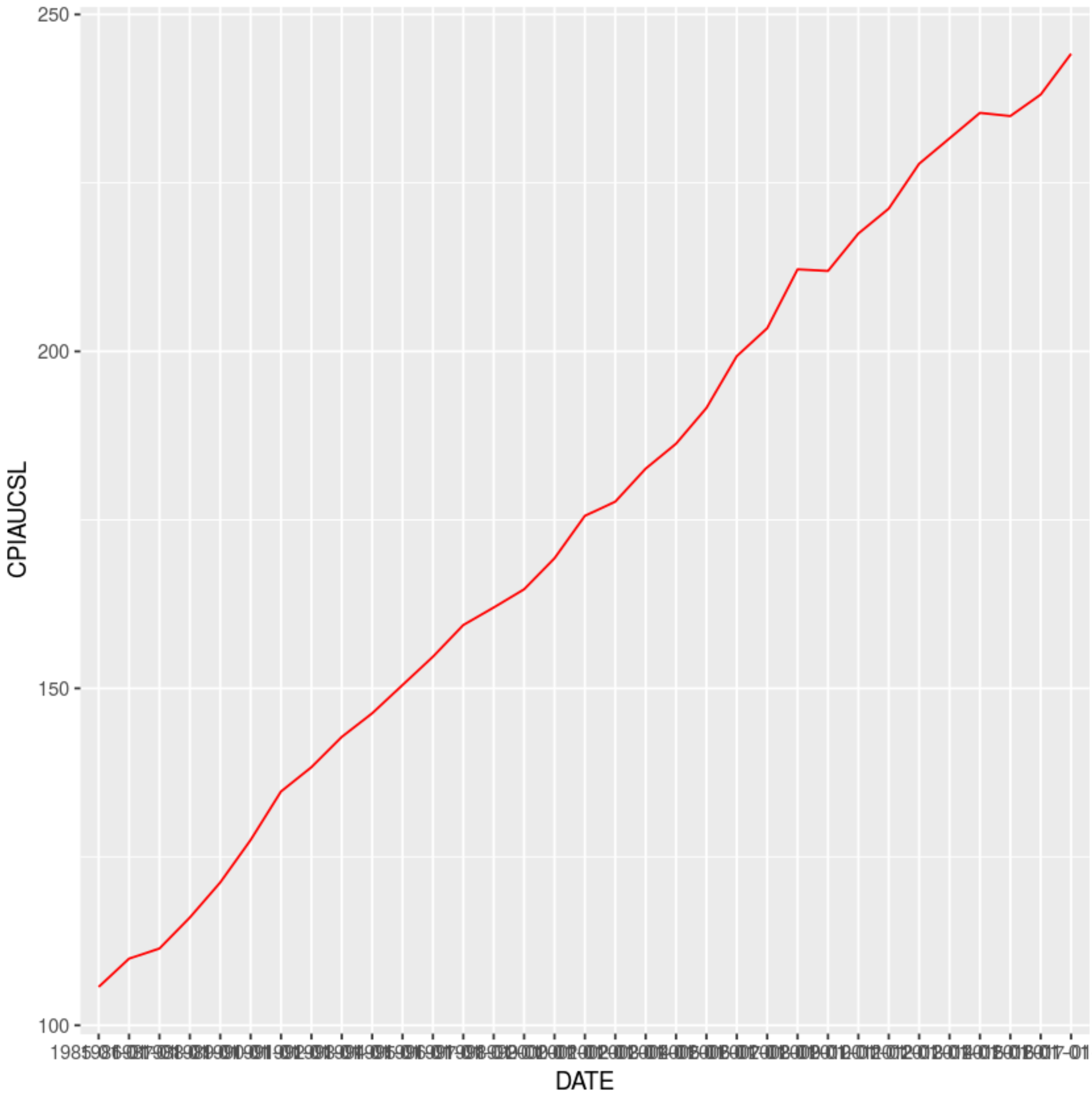
Visualize the change in payrolls over time. To do this sensibly, one needs to adjust for inflation. The following code snippet gets price levels (CPI, consumer price index) from FRED (the Federal

Reserve Economic Data service).

The below code isn't working so I'll download the CPI manually

```
library(fImport)

cpi <- fredSeries("CPIAUCSL",
                    from = as.Date("1985-01-01"),
                    to = as.Date("2011-01-01")
                 )

cpi <- cpi[months(as.Date(rownames(cpi))) == "January"]
cpi <- cpi / cpi[length(cpi)]
```

```
In [6]: library(ggplot2)

        # Read in the CPIAUCSL
        cpi <- read.csv('./CPIAUCSL.csv', header = TRUE, sep = ",")

        # Filter to after 1985
        cpi <- cpi[as.Date(cpi$DATE) >= as.Date("1985-01-01"), ]

        # Filter to January
        cpi <- cpi[months(as.Date(cpi$DATE)) == "January", ]

        ggplot(data=cpi, aes(x=DATE, y=CPIAUCSL, group=1)) + geom_line(color="red")
```



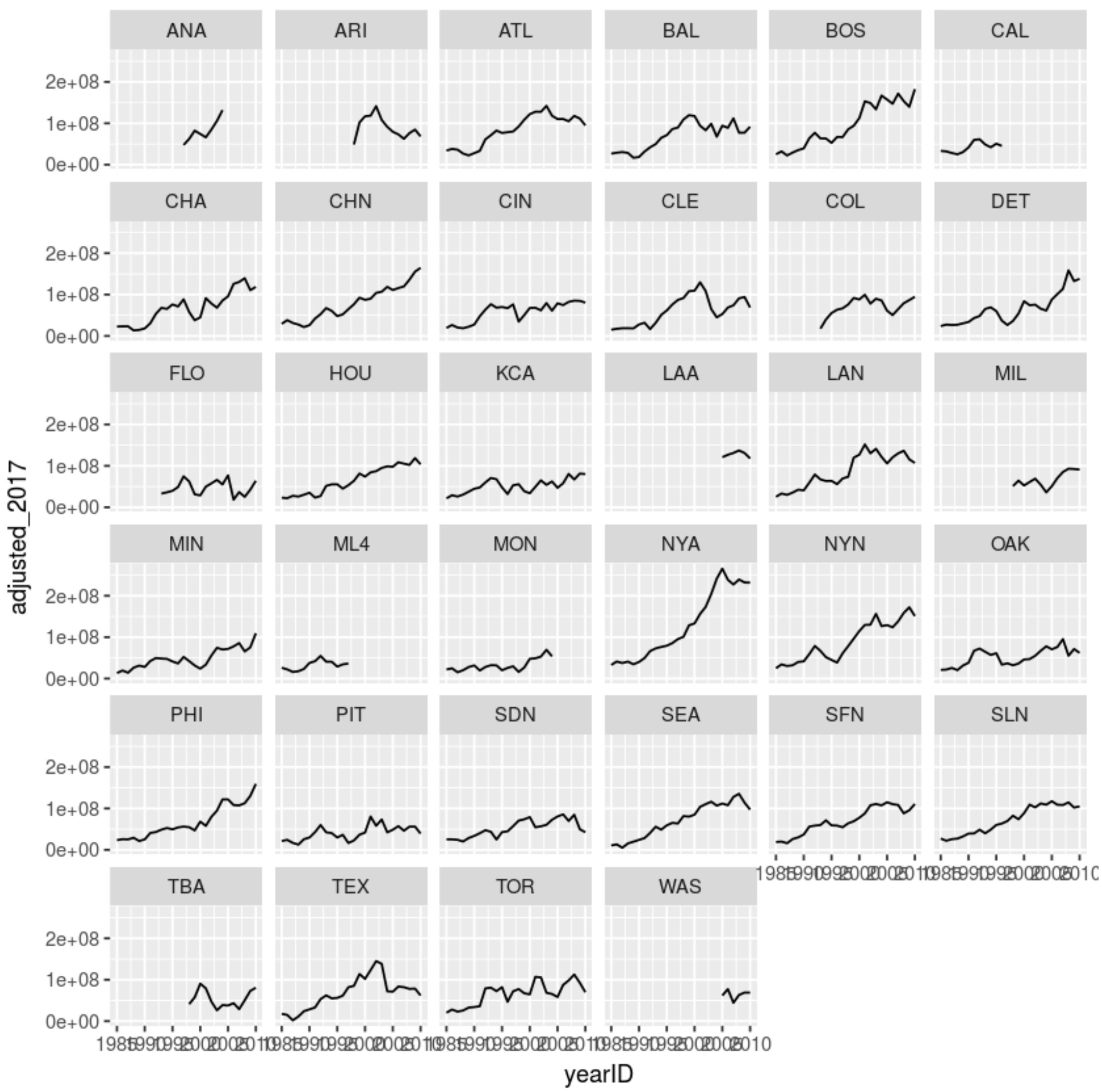
Calculate the inflation-adjusted payroll of each baseball team over time. Hint: While there are many ways of computing this, you may find the following a helpful start.

```
total_inflAdj <- vector("numeric",length = nrow(Salaries))
for(i in 1:nrow(Salaries))  {
      total_inflAdj[i] <- ### YOUR CODE HERE to finish this assignment statement
}
Salaries$total_inflAdj <- total_inflAdj
```

```
In [7]: library(lubridate)

        cpi$yearID <- year(cpi$DATE)
        salaries <- merge(salaries,cpi[,c('CPIAUCSL','yearID')],by="yearID")

        latest_cpi <- cpi[nrow(cpi),'CPIAUCSL']
```

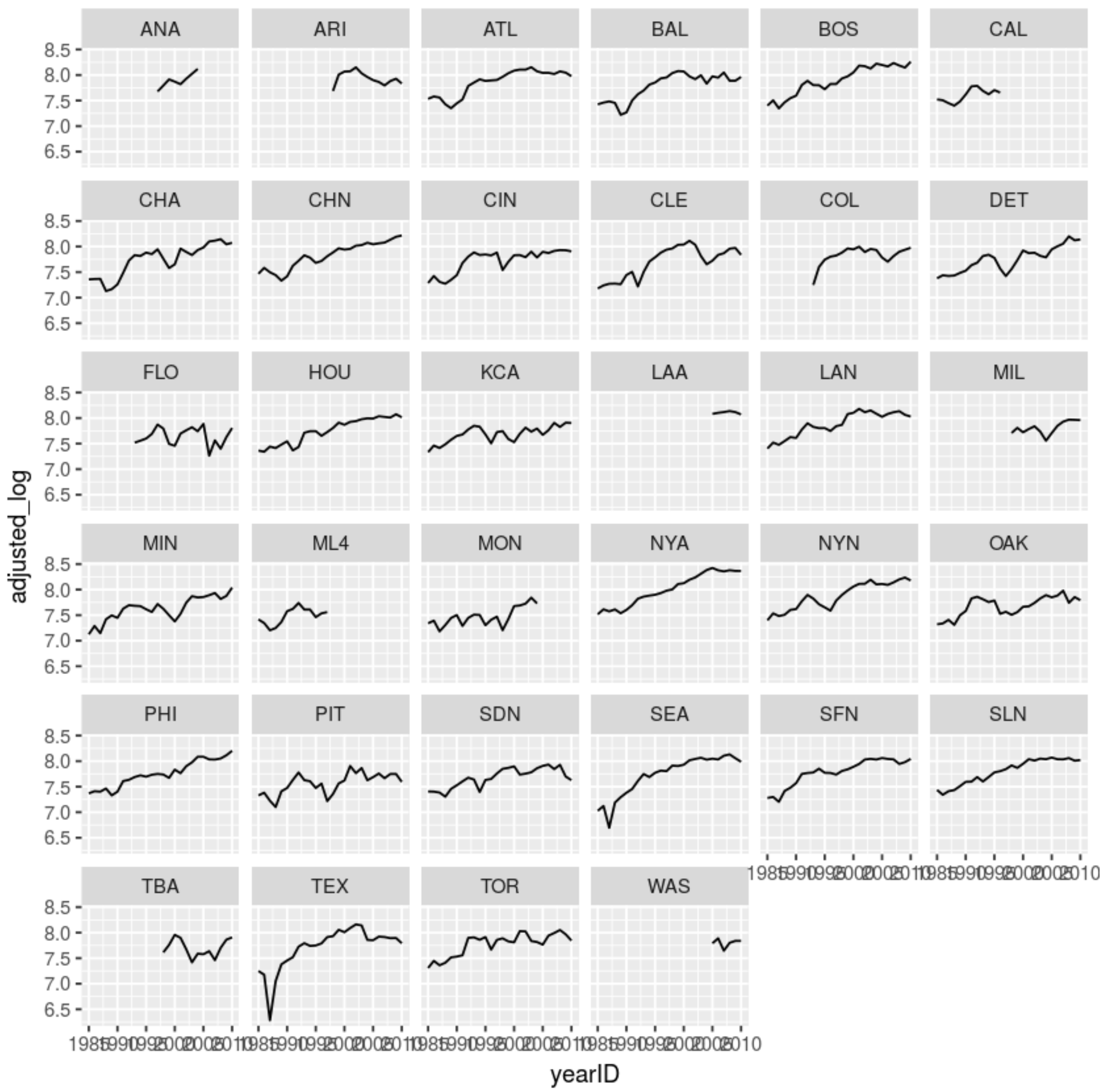
```
Attaching package: lubridate

The following object is masked from package:base:

    date
```

```
In [8]: salaries$adjusted_2017 <- salaries$payroll*latest_cpi/salaries$CPIAUCSL
        ggplot(salaries, aes(x=yearID, y=adjusted_2017)) + geom_line() + facet_wrap(~teamID)
```



Modify the above code to plot the logarithm of inflation-adjusted payrolls over time. I guess we're doing this to smooth outliers?

```
In [9]: salaries$adjusted_log <- log10(salaries$adjusted_2017)
        ggplot(salaries, aes(x=yearID, y=adjusted_log)) + geom_line() + facet_wrap(~teamID)
```



Have payrolls generally kept up with inflation, outpaced it, or fallen behind? Are there teams or groups of teams whose payrolls have consistently been higher than the others?

It seems that payrolls have actually **outpaced** inflation. Almost every team sees an increasing payroll trend, even after normalizing for inflation. Given increasing trends even in the log(salary) plots, we can tell that payroll is increasing at an exponential rate.

To see how these teams compare against each other, we can plot all on the same graph:

```
In [10]: ggplot(salaries, aes(x=yearID, y=adjusted_2017)) + geom_line(aes(group = teamID, color=
```

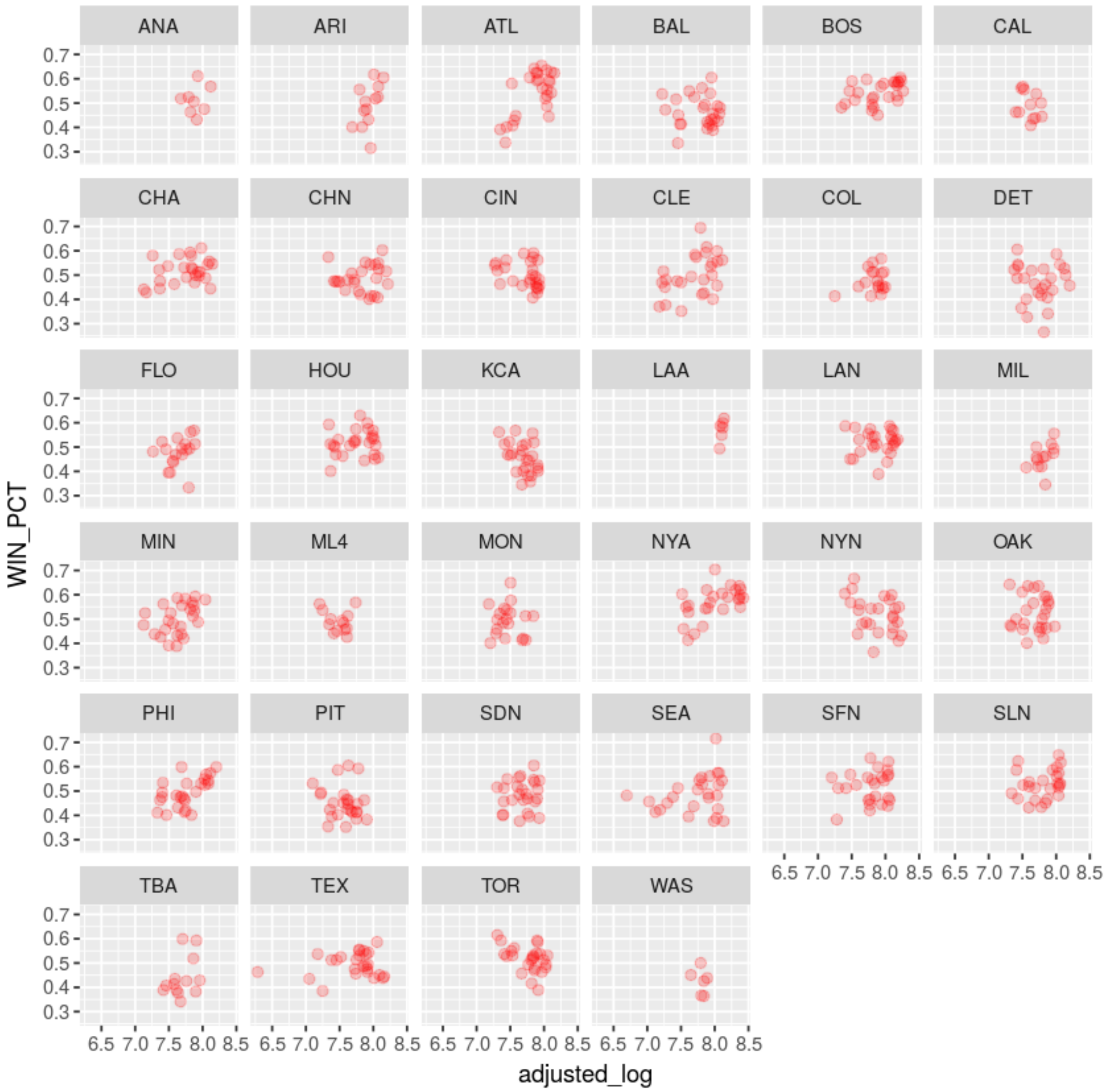
The Yankees (NYA) clearly outpace the rest of the Baseball Association

0.6 Bonus

Expand your SQL query to also retrieve the number of games played, and the number of games won, by each team each year. Create a scatter-plot of the proportion of games won against the inflation-adjusted payroll. Do you think payroll looks like a good predictor of games won?

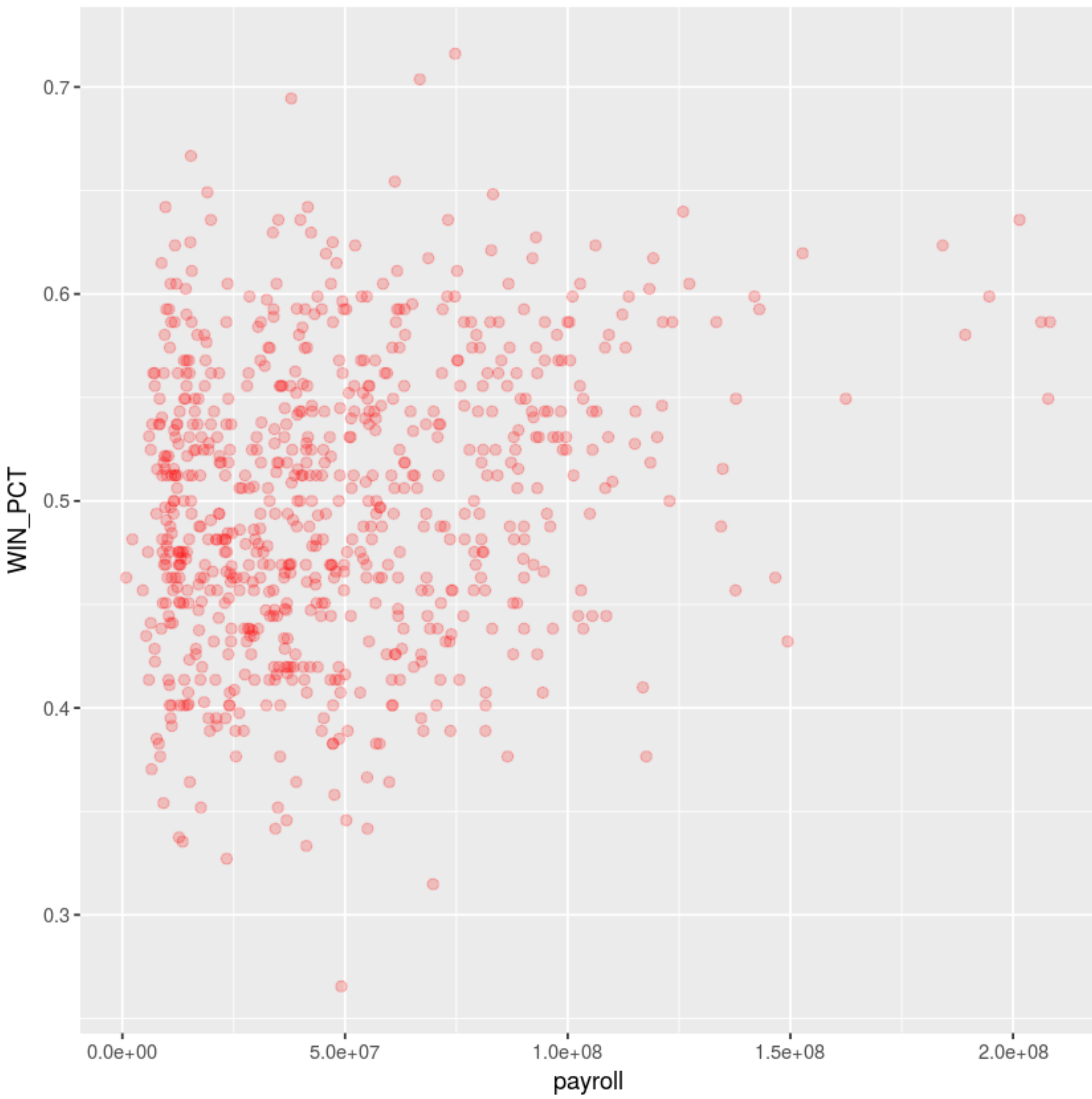
```
In [34]: query <-"SELECT CAST(W AS FLOAT)/G  AS WIN_PCT,
            yearID,
            teamID
            FROM Teams
            GROUP BY yearID, teamID"
        performance <- dbGetQuery(conn=db_conn, query)
```

```
combined = merge(performance, salaries, by=c("yearID","teamID"))
ggplot(combined, aes(x=adjusted_log, y=WIN_PCT)) + geom_point(color='red', size=2, alph
```



It seems like it does depending on the team! Some teams aren't using their payrolls wisely. At the aggregate level, it may have *some* prediction strength, but not too much. See the scatter plot below

```
In [32]: ggplot(combined, aes(x=payroll, y=WIN_PCT)) + geom_point(color='red', size=2, alpha=0.2
```



0.7
0.6
0.5
0.4
0.3
WIN_PCT
0.0e+00
5.0e+07
1.0e+08
1.5e+08
2.0e+08
payroll