Econ294A - Final Exam

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Extract raw data from sqlite

```
nycflights13_sqlite()
```

```
## src:  sqlite 3.8.6 [/var/folders/sv/knpls9wx0fddp_m5lh8y139w0000gn/T//RtmpJ2vT4f/nycflights13.sqlite]
## tbls: airlines, airports, flights, planes, sqlite_stat1, weather
```

```
flights_sqlite <- tbl(nycflights13_sqlite(), "flights")
airlines_sqlite <- tbl(nycflights13_sqlite(), "airlines")
airports_sqlite <- tbl(nycflights13_sqlite(), "airports")
planes_sqlite <- tbl(nycflights13_sqlite(), "planes")
weather_sqlite <- tbl(nycflights13_sqlite(), "weather")
```

join flights and planes data

```
inner_flights_planes <- inner_join(flights, planes, by = "tailnum") %>% tbl_df
colnames(inner_flights_planes)[1] <- "flight_year"
colnames(inner_flights_planes)[15] <- "dep_hour"
colnames(inner_flights_planes)[17] <- "plane_year"
#names(inner_flights_planes)
```

create the date index

```
inner_flights_planes <- inner_flights_planes %>%
  mutate(
    date = paste(flight_year, month, day, sep = "-"),
    date = as.Date(date, format = "%Y-%m-%d"), # create date to merge with weather
    cancelled = ifelse(is.na(arr_time), 1, 0)  # question requires this
  )
```

select columns needed from the inner_flights_planes dataset

```
flights_planes <- inner_flights_planes %>%
  dplyr::select(
    cancelled, date, month, day, dep_hour,
    dep_time, dep_delay, arr_time, arr_delay,
    carrier, flight, origin, dest, air_time, distance,
    plane_year, manufacturer, seats)
```

- change character variable to factor variable
- change integer variable to factor variable

```
flights_planes$carrier <- as.factor(flights_planes$carrier)
flights_planes$origin <- as.factor(flights_planes$origin)
flights_planes$dest <- as.factor(flights_planes$dest)
flights_planes$manufacturer <- as.factor(flights_planes$manufacturer)
flights_planes$month <- as.factor(flights_planes$month)
flights_planes$flight <- as.factor(flights_planes$flight)
```

refine weather data

```
weather <- weather_sqlite %>%
  collect() %>%
  mutate(
    date = paste(year, month, day, sep = "-"),
    date = as.Date(date, format = "%Y-%m-%d"),
    weekday = weekdays(date),
    weekday = as.factor(weekday) # add the weekday variable
  )
```

```
weather_mean <- weather %>% group_by(date) %>%
  summarise(
    weekday = first(weekday),
    mean_temp = mean(temp),
    mean_dewp = mean(dewp),
    mean_humid = mean(humid),
    # mean_wind_dir = mean(wind_dir), wind direction has too many NA's.
    # mean_wind_speed = mean(wind_speed),
    # mean_wind_gust = mean(wind_gust), excluded because their effects depending on direction.
    mean_precip = mean(precip),
    # mean_pressure = mean(pressure), pressure has too many NA's.
    mean_visib = mean(visib)
  )
```

identify the highly correlated data

```
corr_weather_mean <- cor(na.omit(weather_mean[,3:7]))
print(corr_weather_mean)
```

```
##               mean_temp  mean_dewp mean_humid mean_precip mean_visib
## mean_temp    1.00000000  0.9472446  0.2452670 -0.01067683  0.1110659
## mean_dewp    0.94724465  1.0000000  0.5393149  0.11526017 -0.1050222
## mean_humid   0.24526696  0.5393149  1.0000000  0.40771500 -0.6731405
## mean_precip -0.01067683  0.1152602  0.4077150  1.00000000 -0.4625583
## mean_visib   0.11106590 -0.1050222 -0.6731405 -0.46255832  1.0000000
```

delete columns that are highly correlated from weather_mean

```r
weather2 <- weather_mean %>%
  dplyr::select(date, weekday, mean_temp, mean_precip, mean_visib)
```

join flights, planes and weather data

```r
final_data <- inner_join(flights_planes, weather2, by = "date")
length(final_data[final_data$cancelled == 1])
```

```
## [1] 4547
```

```r
#names(final_data)
```

```
Now I run two regression model. One is a OLS model for predicting departure delay.
The other is a GLS model (logit model) for predicting cancellation.
```

OLS for *dep_delay

```r
model.delay <- lm(dep_delay ~ month + as.factor(weekday) + carrier + origin +
                plane_year + seats + mean_precip + mean_visib,
               data = final_data)
summary(model.delay)
```

```
##
## Call:
## lm(formula = dep_delay ~ month + as.factor(weekday) + carrier +
##     origin + plane_year + seats + mean_precip + mean_visib, data = final_data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
##  -77.67  -18.12  -10.08    0.48 1302.36
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                205.755670  34.704574   5.929 3.06e-09 ***
## month2                       0.916951   0.389117   2.356 0.018449 *
## month3                       6.049689   0.374667  16.147  < 2e-16 ***
## month4                       6.838469   0.376252  18.175  < 2e-16 ***
## month5                       3.312550   0.371874   8.908  < 2e-16 ***
## month6                      12.417621   0.380368  32.646  < 2e-16 ***
## month7                      15.555095   0.374606  41.524  < 2e-16 ***
## month8                       5.528696   0.374189  14.775  < 2e-16 ***
## month9                       0.026098   0.379965   0.069 0.945241
## month10                     -0.694563   0.372429  -1.865 0.062189 .
## month11                     -1.791855   0.378258  -4.737 2.17e-06 ***
## month12                      6.462775   0.378077  17.094  < 2e-16 ***
```

```
## as.factor(weekday)Monday     -0.854723   0.277070  -3.085 0.002037 **
## as.factor(weekday)Saturday   -6.991724   0.296295 -23.597  < 2e-16 ***
## as.factor(weekday)Sunday     -3.292526   0.281827 -11.683  < 2e-16 ***
## as.factor(weekday)Thursday    2.329743   0.277379   8.399  < 2e-16 ***
## as.factor(weekday)Tuesday    -4.330445   0.277813 -15.588  < 2e-16 ***
## as.factor(weekday)Wednesday  -3.689374   0.277307 -13.304  < 2e-16 ***
## carrierAA                    -9.560631   0.619017 -15.445  < 2e-16 ***
## carrierAS                   -12.181077   1.542126  -7.899 2.82e-15 ***
## carrierB6                    -4.620915   0.355492 -12.999  < 2e-16 ***
## carrierDL                    -9.326508   0.413355 -22.563  < 2e-16 ***
## carrierEV                     2.189111   0.406559   5.384 7.27e-08 ***
## carrierF9                     2.457422   1.618348   1.518 0.128896
## carrierFL                     0.858047   0.818992   1.048 0.294784
## carrierHA                   -13.771479   2.308885  -5.965 2.46e-09 ***
## carrierMQ                   -11.363331   1.416456  -8.022 1.04e-15 ***
## carrierOO                    -0.555190   7.347354  -0.076 0.939767
## carrierUA                    -6.782975   0.430371 -15.761  < 2e-16 ***
## carrierUS                   -14.324738   0.463010 -30.938  < 2e-16 ***
## carrierVX                    -4.874944   0.652174  -7.475 7.75e-14 ***
## carrierWN                    -0.225239   0.512890  -0.439 0.660549
## carrierYV                     1.526848   1.741014   0.877 0.380494
## originJFK                    -0.682926   0.253037  -2.699 0.006957 **
## originLGA                    -0.782260   0.232691  -3.362 0.000774 ***
## plane_year                   -0.081739   0.017291  -4.727 2.28e-06 ***
## seats                         0.006086   0.001413   4.306 1.66e-05 ***
## mean_precip                 246.102409   9.817433  25.068  < 2e-16 ***
## mean_visib                   -2.973681   0.061364 -48.460  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 39.51 on 274122 degrees of freedom
##   (9358 observations deleted due to missingness)
## Multiple R-squared:  0.05255,    Adjusted R-squared:  0.05242
## F-statistic: 400.1 on 38 and 274122 DF,  p-value: < 2.2e-16
```

GLS for *cancel*

```r
model.cancel <- glm(cancelled ~ month + as.factor(weekday) + carrier + origin +
                      seats +  mean_visib,
                    data = final_data, family=binomial(link="logit"))
summary(model.cancel)
```

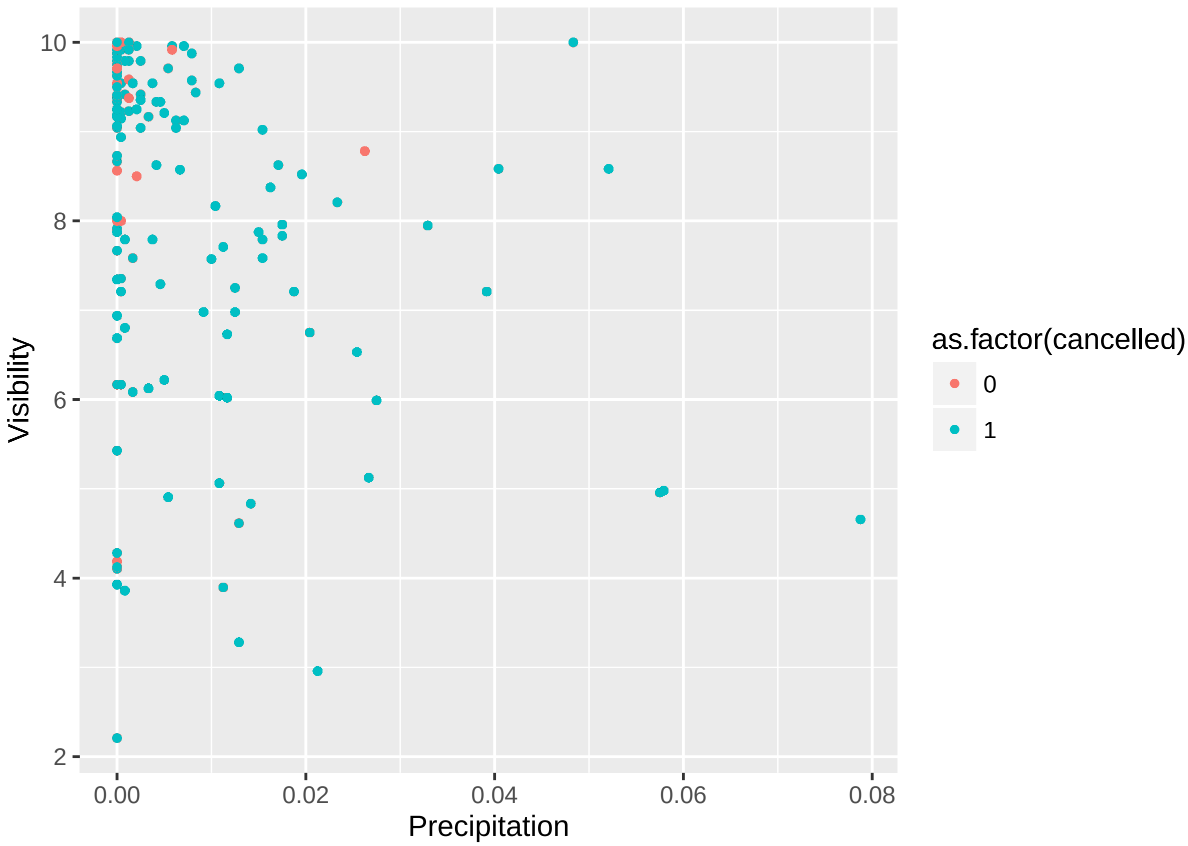
```
##
## Call:
## glm(formula = cancelled ~ month + as.factor(weekday) + carrier +
##     origin + seats + mean_visib, family = binomial(link = "logit"),
##     data = final_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.3304  -0.1698  -0.0952  -0.0522   4.2731
##
```

```
## Coefficients:
##                              Estimate Std. Error z value Pr(>|z|)
## (Intercept)                -2.4393036  0.1562902 -15.608  < 2e-16 ***
## month2                      1.2048077  0.0746512  16.139  < 2e-16 ***
## month3                      0.8599651  0.0789870  10.887  < 2e-16 ***
## month4                      0.6527097  0.0856683   7.619 2.56e-14 ***
## month5                      0.2789271  0.0836728   3.334 0.000857 ***
## month6                      1.0834795  0.0784206  13.816  < 2e-16 ***
## month7                      1.2298009  0.0794558  15.478  < 2e-16 ***
## month8                      0.3539360  0.0915396   3.866 0.000110 ***
## month9                      0.3244573  0.0946035   3.430 0.000604 ***
## month10                    -0.5761280  0.1134244  -5.079 3.79e-07 ***
## month11                    -0.3623568  0.1110580  -3.263 0.001103 **
## month12                     0.6810983  0.0768904   8.858  < 2e-16 ***
## as.factor(weekday)Monday    -0.4322734  0.0538827  -8.022 1.04e-15 ***
## as.factor(weekday)Saturday  -0.3774389  0.0620898  -6.079 1.21e-09 ***
## as.factor(weekday)Sunday    -0.6874177  0.0631751 -10.881  < 2e-16 ***
## as.factor(weekday)Thursday   0.2302250  0.0504070   4.567 4.94e-06 ***
## as.factor(weekday)Tuesday   -0.3688324  0.0556339  -6.630 3.37e-11 ***
## as.factor(weekday)Wednesday -0.3249462  0.0543958  -5.974 2.32e-09 ***
## carrierAA                   1.6964487  0.1450800  11.693  < 2e-16 ***
## carrierAS                  -0.3015237  0.7226137  -0.417 0.676482
## carrierB6                   0.8911258  0.1290850   6.903 5.08e-12 ***
## carrierDL                   0.5303609  0.1377119   3.851 0.000118 ***
## carrierEV                   2.4170370  0.1290509  18.729  < 2e-16 ***
## carrierF9                  -1.2785345  1.0108560  -1.265 0.205942
## carrierFL                   1.2479201  0.1762006   7.082 1.42e-12 ***
## carrierHA                  -9.2171723 75.4569783  -0.122 0.902779
## carrierMQ                   1.9384151  0.1901058  10.197  < 2e-16 ***
## carrierOO                   3.1923504  0.6351356   5.026 5.00e-07 ***
## carrierUA                  -1.3228198  0.1851520  -7.145 9.03e-13 ***
## carrierUS                  -1.1994161  0.2207254  -5.434 5.51e-08 ***
## carrierVX                   0.7939935  0.2123517   3.739 0.000185 ***
## carrierWN                   1.0108355  0.1510457   6.692 2.20e-11 ***
## carrierYV                   2.7750120  0.1930360  14.376  < 2e-16 ***
## originJFK                  -0.2453609  0.0633199  -3.875 0.000107 ***
## originLGA                   0.3986579  0.0430716   9.256  < 2e-16 ***
## seats                      -0.0024326  0.0004009  -6.068 1.30e-09 ***
## mean_visib                 -0.3539327  0.0079566 -44.483  < 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: 46604  on 283518  degrees of freedom
## Residual deviance: 37218  on 283482  degrees of freedom
## AIC: 37292
##
## Number of Fisher Scoring iterations: 14
```

The regressors chosen are largely significant as we can see from the results.
Two plots are generated to illustrate some relationship between cancellation and other conditions as well as departure delay and other conditions.

(a) weather

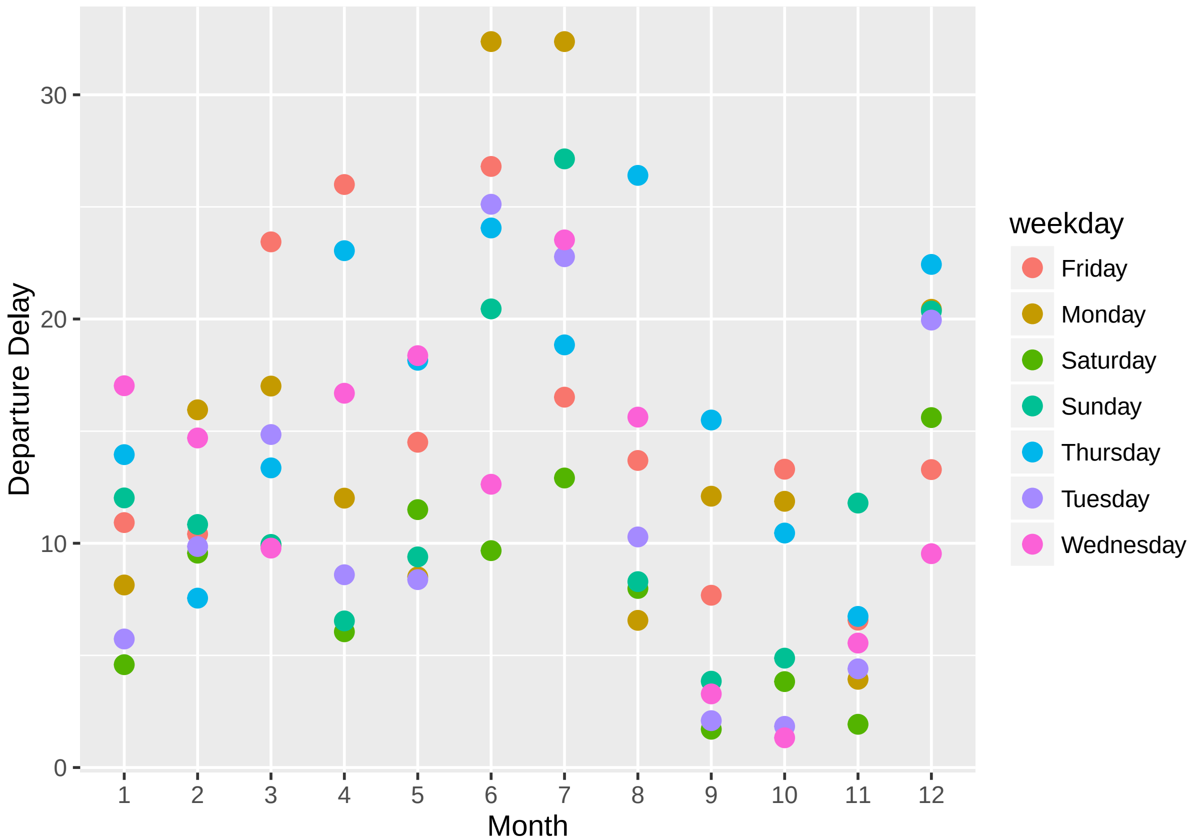
```
plot_weather <- ggplot(data = final_data, aes(mean_precip, mean_visib))
plot_weather + geom_point( aes(color = as.factor(cancelled)),size = 1) +
  xlab("Precipitation") + ylab("Visibility")
```



(b) day of week and time of year

```
month_weekday <- final_data %>%
  group_by(month, weekday) %>%
  summarise(mean.dep_delay = mean(dep_delay, na.rm = T))

plot_time <- ggplot(month_weekday, aes(x = month, y= mean.dep_delay))
plot_time + geom_point(aes(color = weekday), size = 3) +
  xlab("Month") + ylab("Departure Delay")
```


Departure Delay
0
10
20
30
Month
1
2
3
4
5
6
7
8
9
10
11
12
weekday
Friday
Monday
Saturday
Sunday
Thursday
Tuesday
Wednesday