Statistics 452: Statistical Learning and Prediction

Case Study

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Flights dataset

This is the dataset being analyzed by the Stat 652 class for their final project. The data are on flights from three New York City airports in 2013, from the `nycflights13` package. Data were combined from four datasets from this package:

- `flights`
- `weather`
- `airports`, and
- `planes`

You can read about the variables in each dataset by typing `help(datasetname)` from the R console. Our goal is to predict departure delays (variable `dep_delay` in minutes).

```
library(tidyverse)
library(nycflights13)
#help(flights)
#help(weather)
#help(airports)
#help(planes)
fltrain <- read_csv("../../Project652/fltrain.csv.gz")
fltrain
```

```
## # A tibble: 200,000 x 43
##    year.x month   day dep_time sched_dep_time dep_delay arr_time
##     <dbl> <dbl> <dbl>    <dbl>          <dbl>     <dbl>    <dbl>
##  1   2013    11     7      600            600         0      826
##  2   2013    10    30     1252           1250         2     1356
##  3   2013    12    18     1723           1715         8     2008
##  4   2013    11    20     2029           2030        -1     2141
##  5   2013    10    21     1620           1625        -5     1818
##  6   2013    11     7      852            900        -8     1139
##  7   2013     9    29     1519           1529       -10     1639
##  8   2013    12    21     1526           1530        -4     1654
##  9   2013    11     7     1650           1650         0     1910
## 10   2013     3    31     1652           1700        -8     1810
## # ... with 199,990 more rows, and 36 more variables: sched_arr_time <dbl>,
## #   arr_delay <dbl>, carrier <chr>, flight <dbl>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
## #   minute <dbl>, time_hour <dttm>, temp <dbl>, dewp <dbl>, humid <dbl>,
## #   wind_dir <dbl>, wind_speed <dbl>, wind_gust <dbl>, precip <dbl>,
## #   pressure <dbl>, visib <dbl>, name <chr>, lat <dbl>, lon <dbl>,
## #   alt <dbl>, tz <dbl>, dst <chr>, tzone <chr>, year.y <dbl>, type <chr>,
## #   manufacturer <chr>, model <chr>, engines <dbl>, seats <dbl>,
## #   speed <dbl>, engine <chr>
```

```
dim(fltrain)
```

```
## [1] 200000     43
```

There are 43 variables measured on 200,000 flights.

Missing data

Handling of missing data is an important topic, but one that we did not consider in class. Two common ways to deal with missing data are to (i) remove observations with any missing data (complete-case analysis) and (ii) impute missing data. Both have their strengths and limitations. For simplicity we will remove observations. The danger is that our inference and/or predictions could be biased, which happens when the chance of a missing observation depends on the (unobserved) value of the missing data. However, a complete-case analysis is the most straightforward.

To ensure we are not discarding too many data points, we limit the **variables** to those with only a small proportion of missing values. One rule of thumb is to discard variables with more than 5% missing values, which is 10,000 for these data. To this end we count the number of missing values in each variable. The character variables have NA interpreted as a character string. This will be converted to the missing code `NA` if we coerce to a factor.

```
fl <- fltrain
for(i in 1:ncol(fl)) {
  if(typeof(fl[[i]]) == "character") {
    fl[[i]] <- factor(fl[[i]])
  }
}
```

Now count the missing values in each variable.

```
num_miss <- function(x) { sum(is.na(x)) }
sapply(fl,num_miss)
```

```
##         year.x          month            day       dep_time sched_dep_time
##              0              0              0           4898              0
##      dep_delay       arr_time sched_arr_time      arr_delay        carrier
##           4898           5169              0           5584              0
##         flight        tailnum         origin           dest       air_time
##              0           1492              0              0           5584
##       distance           hour         minute      time_hour           temp
##              0              0              0              0            948
##           dewp          humid       wind_dir     wind_speed      wind_gust
##            948            948           5862            982         152260
##         precip       pressure          visib           name            lat
##            937          23092            937           4484           4484
##            lon            alt             tz            dst          tzone
##           4484           4484           4484           4484           4484
##         year.y           type   manufacturer          model        engines
##          34298          31163          31163          31163          31163
##          seats          speed         engine
##          31163         199415          31163
```

Some of the variables, particularly those taken from the `planes` dataset (`year.y` to `engine`), have many missing values. In what follows I'll discard all of the variables from `planes`, plus `wind_gust` and `pressure`.

```
fl <- fl%>%
  select(-year.y,-type,-manufacturer,-model,-engines,-seats, -speed, -engine,-wind_gust,-pressure)
summary(fl)
```

```
##      year.x         month             day            dep_time
##  Min.   :2013   Min.   : 1.000   Min.   : 1.0   Min.   :   1
```

```
##  1st Qu.:2013   1st Qu.: 4.000   1st Qu.: 8.0   1st Qu.: 907
##  Median :2013   Median : 7.000   Median :16.0   Median :1401
##  Mean   :2013   Mean   : 6.553   Mean   :15.7   Mean   :1349
##  3rd Qu.:2013   3rd Qu.:10.000   3rd Qu.:23.0   3rd Qu.:1745
##  Max.   :2013   Max.   :12.000   Max.   :31.0   Max.   :2400
##                                                 NA's   :4898
##  sched_dep_time   dep_delay        arr_time    sched_arr_time
##  Min.   : 106   Min.   : -43.0   Min.   :   1   Min.   :   1
##  1st Qu.: 905   1st Qu.:  -5.0   1st Qu.:1104   1st Qu.:1124
##  Median :1359   Median :  -2.0   Median :1535   Median :1557
##  Mean   :1344   Mean   :  12.7   Mean   :1502   Mean   :1537
##  3rd Qu.:1729   3rd Qu.:  11.0   3rd Qu.:1941   3rd Qu.:1945
##  Max.   :2359   Max.   :1301.0   Max.   :2400   Max.   :2359
##                 NA's   :4898     NA's   :5169
##    arr_delay          carrier          flight        tailnum
##  Min.   : -79.000   UA     :34734   Min.   :   1   N725MQ :   350
##  1st Qu.: -17.000   B6     :32355   1st Qu.: 561   N723MQ :   300
##  Median :  -5.000   EV     :32217   Median :1499   N722MQ :   294
##  Mean   :   6.969   DL     :28731   Mean   :1975   N711MQ :   290
##  3rd Qu.:  14.000   AA     :19415   3rd Qu.:3470   N713MQ :   260
##  Max.   :1272.000   MQ     :15608   Max.   :8500   (Other):197014
##  NA's   :5584       (Other):36940                  NA's   :  1492
##  origin          dest           air_time       distance
##  EWR:71658   ATL    : 10319   Min.   : 20.0   Min.   :  17
##  JFK:65951   ORD    : 10186   1st Qu.: 82.0   1st Qu.: 502
##  LGA:62391   LAX    :  9472   Median :129.0   Median : 872
##              BOS    :  9217   Mean   :150.5   Mean   :1038
##              MCO    :  8425   3rd Qu.:191.0   3rd Qu.:1389
##              CLT    :  8319   Max.   :695.0   Max.   :4983
##              (Other):144062   NA's   :5584
##       hour          minute        time_hour
##  Min.   : 1.00   Min.   : 0.00   Min.   :2013-01-01 10:00:00
##  1st Qu.: 9.00   1st Qu.: 8.00   1st Qu.:2013-04-04 20:00:00
##  Median :13.00   Median :29.00   Median :2013-07-03 15:00:00
##  Mean   :13.18   Mean   :26.22   Mean   :2013-07-03 12:05:05
##  3rd Qu.:17.00   3rd Qu.:44.00   3rd Qu.:2013-10-01 12:00:00
##  Max.   :23.00   Max.   :59.00   Max.   :2014-01-01 04:00:00
##
##       temp            dewp          humid          wind_dir
##  Min.   : 10.94   Min.   :-9.94   Min.   : 12.74   Min.   :  0.0
##  1st Qu.: 42.08   1st Qu.:26.06   1st Qu.: 43.99   1st Qu.:130.0
##  Median : 57.20   Median :42.80   Median : 57.69   Median :220.0
##  Mean   : 56.98   Mean   :41.62   Mean   : 59.57   Mean   :201.5
##  3rd Qu.: 71.96   3rd Qu.:57.92   3rd Qu.: 75.33   3rd Qu.:290.0
##  Max.   :100.04   Max.   :78.08   Max.   :100.00   Max.   :360.0
##  NA's   :948      NA's   :948     NA's   :948      NA's   :5862
##    wind_speed        precip          visib
##  Min.   : 0.000   Min.   :0.0000   Min.   : 0.000
##  1st Qu.: 6.905   1st Qu.:0.0000   1st Qu.:10.000
##  Median :10.357   Median :0.0000   Median :10.000
##  Mean   :11.107   Mean   :0.0045   Mean   : 9.252
##  3rd Qu.:14.960   3rd Qu.:0.0000   3rd Qu.:10.000
##  Max.   :42.579   Max.   :1.2100   Max.   :10.000
##  NA's   :982      NA's   :937      NA's   :937
```

```
##                                     name            lat
##  Hartsfield Jackson Atlanta Intl   : 10319   Min.   :21.32
##  Chicago Ohare Intl                : 10186   1st Qu.:32.90
##  Los Angeles Intl                  :  9472   Median :36.10
##  General Edward Lawrence Logan Intl:  9217   Mean   :36.02
##  Orlando Intl                      :  8425   3rd Qu.:41.41
##  (Other)                           :147897   Max.   :61.17
##  NA's                              :  4484   NA's   :4484
##       lon                 alt                 tz             dst
##  Min.   :-157.92   Min.   :   3.0   Min.   :-10.000   A   :192358
##  1st Qu.: -95.28   1st Qu.:  26.0   1st Qu.: -6.000   N   :  3158
##  Median : -83.35   Median : 433.0   Median : -5.000   NA's:  4484
##  Mean   : -89.44   Mean   : 582.5   Mean   : -5.748
##  3rd Qu.: -80.15   3rd Qu.: 748.0   3rd Qu.: -5.000
##  Max.   : -68.83   Max.   :6602.0   Max.   : -5.000
##  NA's   :4484      NA's   :4484     NA's   :4484
##                 tzone
##  America/New_York   :114518
##  America/Chicago    : 44400
##  America/Los_Angeles: 27368
##  America/Denver     :  6069
##  America/Phoenix    :  2759
##  (Other)            :   402
##  NA's               :  4484
```

When we omit rows with any missing values we end up with 184,316 rows out of the origninal 200,000.

```r
fl <- na.omit(fl)
summary(fl)
```

```
##      year.x         month             day           dep_time
##  Min.   :2013   Min.   : 1.000   Min.   : 1.00   Min.   :   1
##  1st Qu.:2013   1st Qu.: 4.000   1st Qu.: 8.00   1st Qu.: 910
##  Median :2013   Median : 7.000   Median :16.00   Median :1408
##  Mean   :2013   Mean   : 6.553   Mean   :15.67   Mean   :1353
##  3rd Qu.:2013   3rd Qu.:10.000   3rd Qu.:23.00   3rd Qu.:1747
##  Max.   :2013   Max.   :12.000   Max.   :31.00   Max.   :2400
##
##  sched_dep_time   dep_delay          arr_time    sched_arr_time
##  Min.   : 500   Min.   : -43.00   Min.   :   1   Min.   :   1
##  1st Qu.: 905   1st Qu.:  -5.00   1st Qu.:1106   1st Qu.:1123
##  Median :1359   Median :  -2.00   Median :1545   Median :1602
##  Mean   :1342   Mean   :  12.67   Mean   :1511   Mean   :1544
##  3rd Qu.:1729   3rd Qu.:  11.00   3rd Qu.:1946   3rd Qu.:1950
##  Max.   :2345   Max.   :1301.00   Max.   :2400   Max.   :2359
##
##    arr_delay           carrier          flight         tailnum
##  Min.   : -79.000   UA     :32252   Min.   :   1   N725MQ :   322
##  1st Qu.: -17.000   B6     :29282   1st Qu.: 544   N723MQ :   271
##  Median :  -5.000   EV     :29137   Median :1499   N711MQ :   268
##  Mean   :   7.014   DL     :26998   Mean   :1966   N722MQ :   268
##  3rd Qu.:  14.000   AA     :17742   3rd Qu.:3448   N351JB :   247
##  Max.   :1272.000   MQ     :14382   Max.   :8500   N258JB :   244
##                     (Other):34523                  (Other):182696
##  origin           dest             air_time         distance
```

```
## EWR:65512   ATL    :  9726   Min.   : 20.0   Min.   :  80
## JFK:60327   ORD    :  9443   1st Qu.: 81.0   1st Qu.: 502
## LGA:58477   LAX    :  9185   Median :127.0   Median : 866
##             BOS    :  8674   Mean   :149.5   Mean   :1035
##             MCO    :  8131   3rd Qu.:184.0   3rd Qu.:1372
##             CLT    :  7822   Max.   :695.0   Max.   :4983
##             (Other):131335
##      hour           minute        time_hour
## Min.   : 5.00   Min.   : 0.00   Min.   :2013-01-01 10:00:00
## 1st Qu.: 9.00   1st Qu.: 8.00   1st Qu.:2013-04-04 13:00:00
## Median :13.00   Median :29.00   Median :2013-07-03 17:00:00
## Mean   :13.15   Mean   :26.06   Mean   :2013-07-03 11:34:16
## 3rd Qu.:17.00   3rd Qu.:43.00   3rd Qu.:2013-10-02 10:00:00
## Max.   :23.00   Max.   :59.00   Max.   :2013-12-30 23:00:00
##
##      temp             dewp           humid           wind_dir
## Min.   : 10.94   Min.   :-9.94   Min.   : 13.00   Min.   :  0.0
## 1st Qu.: 42.08   1st Qu.:26.06   1st Qu.: 43.71   1st Qu.:130.0
## Median : 57.02   Median :42.08   Median : 57.14   Median :220.0
## Mean   : 56.86   Mean   :41.33   Mean   : 59.12   Mean   :201.9
## 3rd Qu.: 71.96   3rd Qu.:57.20   3rd Qu.: 74.29   3rd Qu.:290.0
## Max.   :100.04   Max.   :78.08   Max.   :100.00   Max.   :360.0
##
##   wind_speed         precip            visib
## Min.   : 0.000   Min.   :0.000000   Min.   : 0.000
## 1st Qu.: 6.905   1st Qu.:0.000000   1st Qu.:10.000
## Median :10.357   Median :0.000000   Median :10.000
## Mean   :11.202   Mean   :0.004059   Mean   : 9.294
## 3rd Qu.:14.960   3rd Qu.:0.000000   3rd Qu.:10.000
## Max.   :42.579   Max.   :1.210000   Max.   :10.000
##
##                                  name            lat
## Hartsfield Jackson Atlanta Intl   :  9726   Min.   :21.32
## Chicago Ohare Intl                :  9443   1st Qu.:32.90
## Los Angeles Intl                  :  9185   Median :36.08
## General Edward Lawrence Logan Intl:  8674   Mean   :35.97
## Orlando Intl                      :  8131   3rd Qu.:41.41
## Charlotte Douglas Intl            :  7822   Max.   :61.17
## (Other)                           :131335
##      lon              alt              tz           dst
## Min.   :-157.92   Min.   :   3.0   Min.   :-10.000   A:181313
## 1st Qu.: -95.34   1st Qu.:  26.0   1st Qu.: -6.000   N:  3003
## Median : -83.35   Median : 433.0   Median : -5.000
## Mean   : -89.58   Mean   : 582.3   Mean   : -5.757
## 3rd Qu.: -80.15   3rd Qu.: 748.0   3rd Qu.: -5.000
## Max.   : -68.83   Max.   :6602.0   Max.   : -5.000
##
##                 tzone
## America/Anchorage  :     3
## America/Chicago    : 41444
## America/Denver     :  5819
## America/Los_Angeles: 26461
## America/New_York   :107586
## America/Phoenix    :  2629
```

```
##  Pacific/Honolulu   :   374
```

Summaries of the response variable `dep_delay`

The departure delays variable is highly right-skewed.

```r
range(fl$dep_delay)
```

```
## [1]  -43 1301
```

```r
fivenum(fl$dep_delay)
```

```
## [1]  -43   -5   -2   11 1301
```

```r
quantile(fl$dep_delay,probs = c(0.01,0.05,0.1,0.25,.5,.75,.90,.95,.99))
```

```
##  1%  5% 10% 25% 50% 75% 90% 95% 99%
## -12  -9  -7  -5  -2  11  49  88 193
```

```r
mean(fl$dep_delay >= 60) # about 15,000 or 8% of flights
```

```
## [1] 0.08210356
```

Top 10 delays.

```r
fl%>% arrange(desc(dep_delay)) %>% head(10)
```

```
## # A tibble: 10 x 33
##    year.x month   day dep_time sched_dep_time dep_delay arr_time
##     <dbl> <dbl> <dbl>    <dbl>          <dbl>     <dbl>    <dbl>
##  1   2013     1     9      641            900      1301     1242
##  2   2013     9    20     1139           1845      1014     1457
##  3   2013     3    17     2321            810       911      135
##  4   2013     7    22     2257            759       898      121
##  5   2013    12     5      756           1700       896     1058
##  6   2013     5    19      713           1700       853     1007
##  7   2013     2    10     2243            830       853      100
##  8   2013    12    19      734           1725       849     1046
##  9   2013    12    17      705           1700       845     1026
## 10   2013    12    14      830           1845       825     1210
## # ... with 26 more variables: sched_arr_time <dbl>, arr_delay <dbl>,
## #   carrier <fct>, flight <dbl>, tailnum <fct>, origin <fct>, dest <fct>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dttm>, temp <dbl>, dewp <dbl>, humid <dbl>, wind_dir <dbl>,
## #   wind_speed <dbl>, precip <dbl>, visib <dbl>, name <fct>, lat <dbl>,
## #   lon <dbl>, alt <dbl>, tz <dbl>, dst <fct>, tzone <fct>
```

Summaries of departure delay by NYC airport:

```r
Q3 <- function(x) { quantile(x,probs=.75) }
fl %>% group_by(origin) %>%
  summarize(n=n(),med_d = median(dep_delay),Q3_d = Q3(dep_delay), max_d = max(dep_delay)) %>%
  arrange(desc(Q3_d)) %>% head(10)
```

```
## # A tibble: 3 x 5
##   origin     n med_d  Q3_d max_d
##   <fct>  <int> <dbl> <dbl> <dbl>
## 1 EWR    65512    -1    15   896
## 2 JFK    60327    -1    10  1301
```

```
## 3 LGA    58477    -3     7   911
```

Summaries of departure delay by airline (carrier).

```
fl %>% group_by(carrier) %>%
  summarize(n=n(),med_d = median(dep_delay),Q3_d = Q3(dep_delay), max_d = max(dep_delay)) %>%
  arrange(desc(Q3_d)) %>% head(10)
```

```
## # A tibble: 10 x 5
##    carrier     n med_d  Q3_d max_d
##    <fct>   <int> <dbl> <dbl> <dbl>
##  1 EV      29137    -1  25     536
##  2 WN       6897     1  18     471
##  3 F9        388     0  17.2   853
##  4 9E      10179    -2  16     430
##  5 FL       1832     1  16     602
##  6 YV        312    -3  13     387
##  7 B6      29282    -1  12     502
##  8 UA      32252     0  11     483
##  9 MQ      14382    -3   9     486
## 10 VX       2991     0   7     653
```

```
fl %>% group_by(origin,carrier) %>%
  summarize(n=n(),med_d = median(dep_delay),Q3_d = Q3(dep_delay), max_d = max(dep_delay)) %>%
  arrange(desc(Q3_d)) %>% head(10)
```

```
## # A tibble: 10 x 6
## # Groups:   origin [3]
##    origin carrier     n med_d  Q3_d max_d
##    <fct>  <fct>   <int> <dbl> <dbl> <dbl>
##  1 EWR    OO          3     4  67.5   131
##  2 EWR    EV      23565    -1  26     443
##  3 LGA    EV       4769    -2  22     473
##  4 JFK    9E       8126    -1  20     430
##  5 JFK    EV        803    -2  19     536
##  6 EWR    WN       3487     2  18     440
##  7 LGA    WN       3410     1  18     471
##  8 LGA    F9        388     0  17.2   853
##  9 EWR    MQ       1156    -2  17     381
## 10 LGA    FL       1832     1  16     602
```

```
fl %>% group_by(dest,carrier) %>%
  summarize(n=n(),med_d = median(dep_delay),Q3_d = Q3(dep_delay), max_d = max(dep_delay)) %>%
  arrange(desc(Q3_d)) %>% head(10)
```

```
## # A tibble: 10 x 6
## # Groups:   dest [10]
##    dest  carrier     n med_d  Q3_d max_d
##    <fct> <fct>   <int> <dbl> <dbl> <dbl>
##  1 STL   UA          2  77.5 116.    155
##  2 DTW   OO          2  61    96     131
##  3 TYS   EV        183   8    68.5   285
##  4 PBI   EV          3  50    67.5    85
##  5 ORD   OO          1  67    67      67
##  6 RDU   UA          1  60    60      60
##  7 TUL   EV        185   3    53     251
##  8 OKC   EV        184   8.5  51.5   207
```

```
##  9 BHM   EV         175    3     50      325
## 10 CAE   EV          57   10     48      163
```

Summaries of departure delay by date:

```
fl %>% group_by(month,day) %>%
  summarize(n=n(),med_d = mean(dep_delay),max_d = max(dep_delay)) %>%
  arrange(desc(med_d)) %>% head(10) # what happened on march 8?
```

```
## # A tibble: 10 x 5
## # Groups:   month [7]
##    month   day     n med_d max_d
##    <dbl> <dbl> <int> <dbl> <dbl>
##  1     3     8   461  79.5   470
##  2     7     1   505  58.1   363
##  3     7    10   471  56.6   576
##  4     9     2   438  53.7   696
##  5    12     5   458  52.2   896
##  6     5    23   453  51.5   410
##  7     4    19   511  50.4   812
##  8     9    12   444  50.4   602
##  9     6    13   469  50.3   388
## 10     7    22   476  49.9   898
```

Summaries of departure delay by precipitation:

```
fl %>% mutate(haveprecip = factor(precip>0)) %>% group_by(haveprecip) %>%
  summarize(n=n(),med_d = median(dep_delay),Q3_d = Q3(dep_delay), max_d = max(dep_delay)) %>%
  arrange(desc(med_d)) %>% head(10)
```

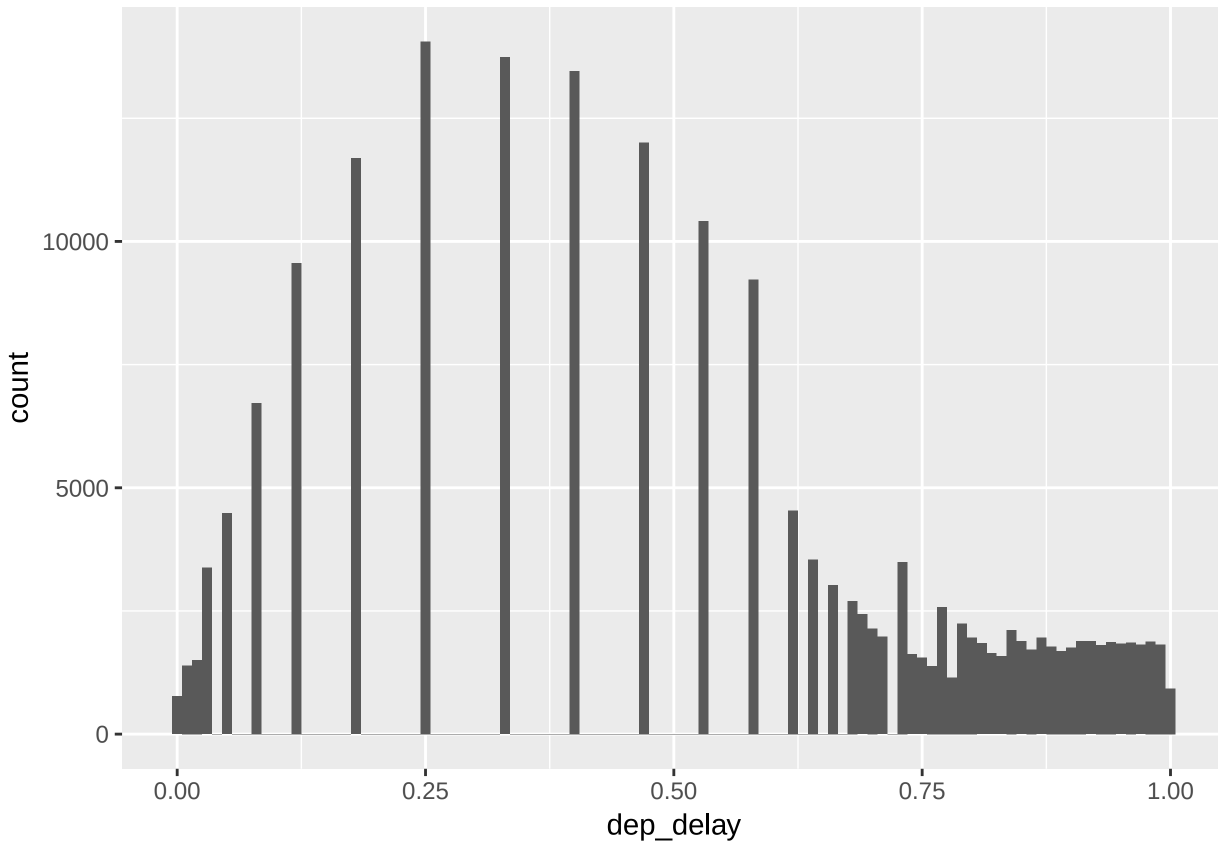
```
## # A tibble: 2 x 5
##   haveprecip      n med_d  Q3_d max_d
##   <fct>       <int> <dbl> <dbl> <dbl>
## 1 TRUE        11804     5    41   853
## 2 FALSE      172512    -2     9  1301
```

What can we predict?

Extremes seem to be caused by phenomena not in our data, such as snow storms, mechanical breakdowns (?), etc.

Perhaps we should map these extremes to something less extreme. Consider mapping to quantiles of the standard normal (like grading departure delays on a "curve"), or mapping to ranks. We will scale the ranks by $n + 1$ to get the empirical quantiles, which will be comparable to those in the test dataset.

```
#fl <- fl %>% mutate(dep_delay = qqnorm(dep_delay)$x)
den <- nrow(fl)+1
fl <- fl %>% mutate(dep_delay = rank(dep_delay)/den)
 ggplot(fl,aes(x=dep_delay)) + geom_histogram(binwidth=.01)
```



More data wrangling

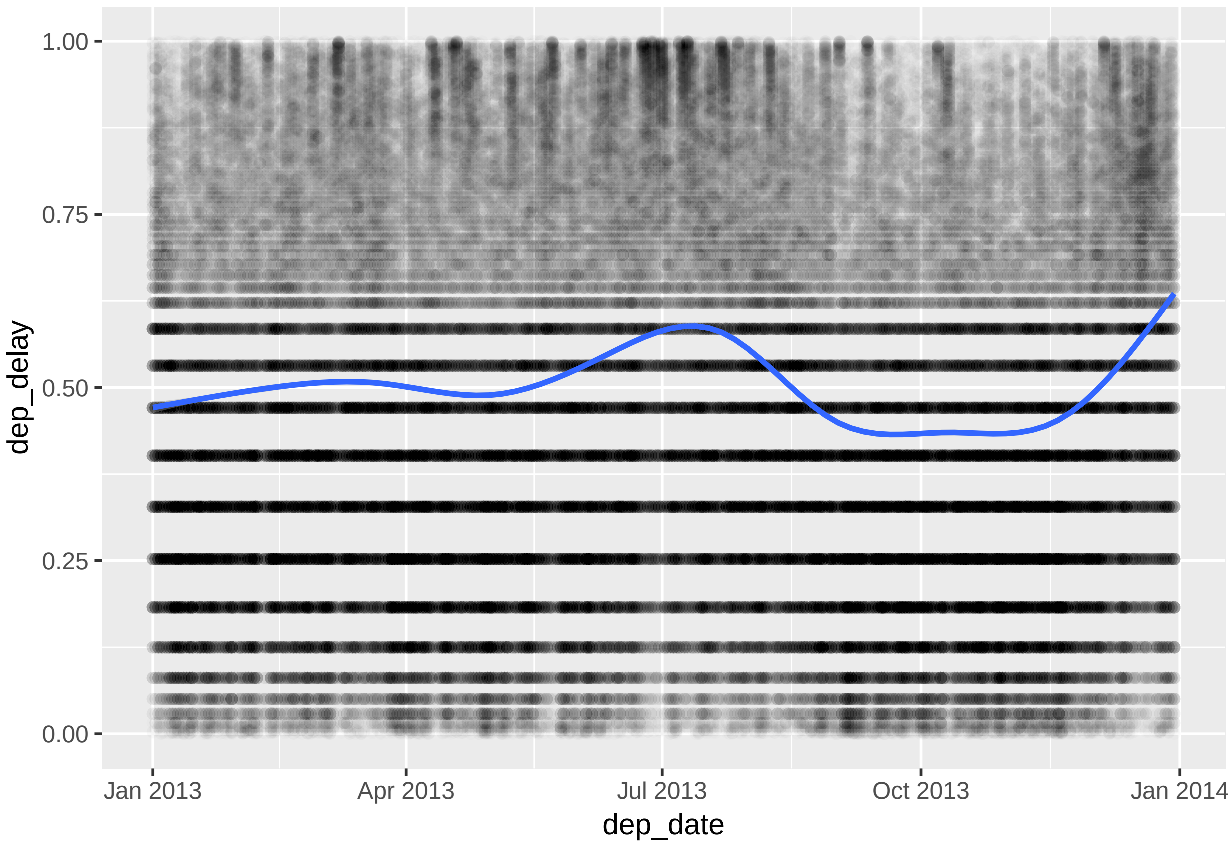
- Convert year/month/day to a date object.
- Remove `dep_time`, `arr_time` and `arr_delay`. If we are interested in predicting departure delay, these are not know to us. Also, they may be associated with `dep_delay`, but if so the causal effect is likely in reverse.
- Remove `sched_arr_time` (basically departure time + air time), `tailnum` (4000 planes), `flight` (flight number), `name` (captured by `dest`), `air_time` (highly correlated with `distance`), `hour` and `minute` (in `sched_dep_time`), `time_hour` (same as `sched_dep_time`), `tz`, `dst`, `tzone` (time zone of destination),
- Replace numeric `precip` with indicator of precipitation/none.

```
library(lubridate)
fl <- fl %>%
  mutate(dep_date = make_date(year.x,month,day)) %>%
  select(-year.x,-month,-day,-dep_time,-arr_time,-arr_delay,
         -sched_arr_time,-tailnum,-flight,-name,-air_time,
         -hour,-minute,-time_hour,-tz,-dst,-tzone) %>%
  mutate(precip = as.numeric(precip>0))
```

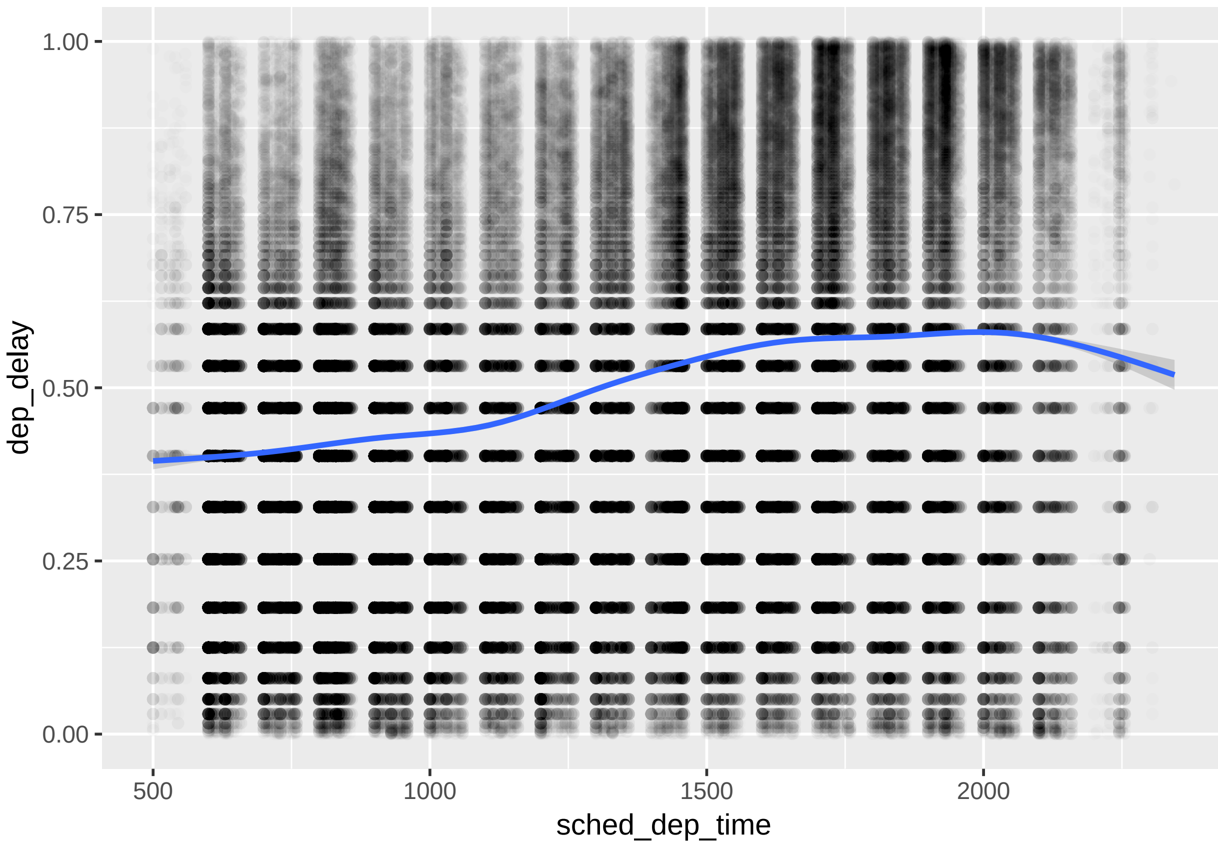
Associations between `dep_delay` and quantitative predictors

Here we look at associations between `dep_delay` rank and other variables one-at-a-time. The presentation here is not exhaustive

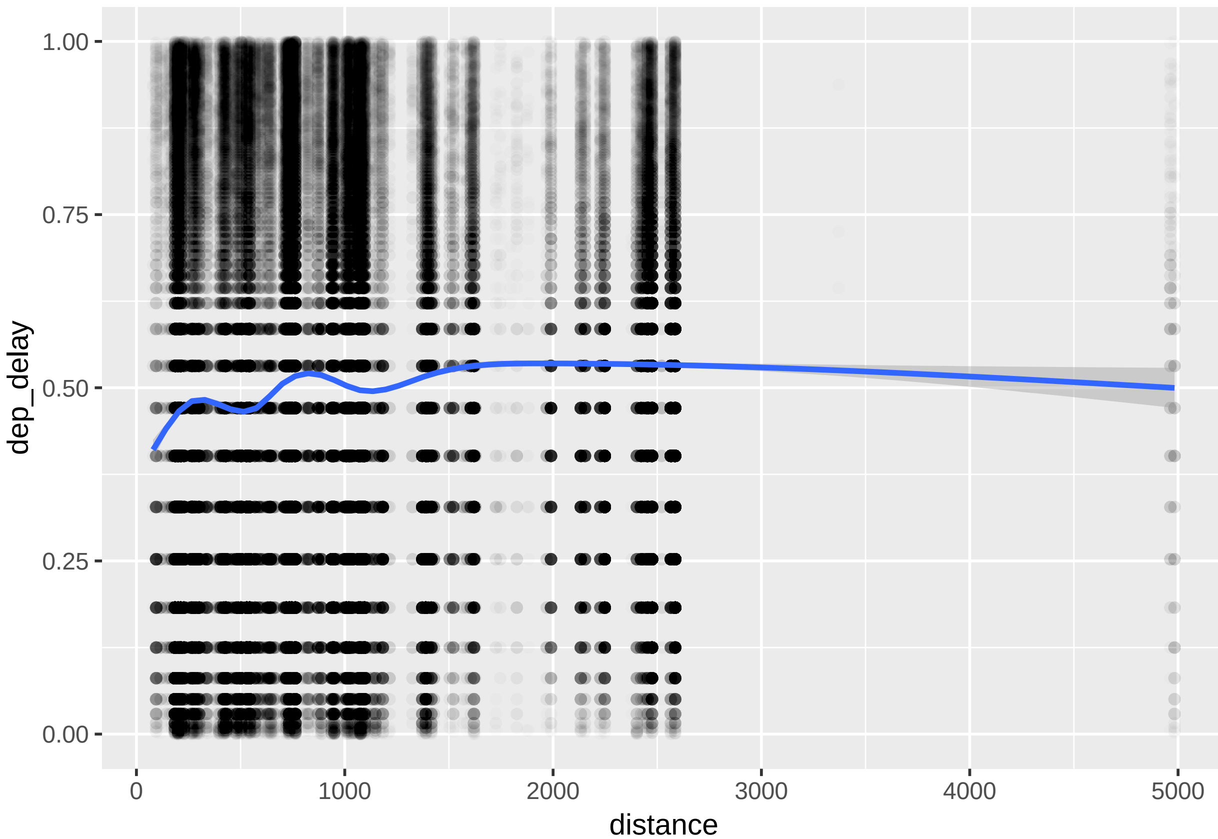
```
ggplot(fl,aes(x=dep_date,y=dep_delay)) + geom_point(alpha=.01) + geom_smooth()
```



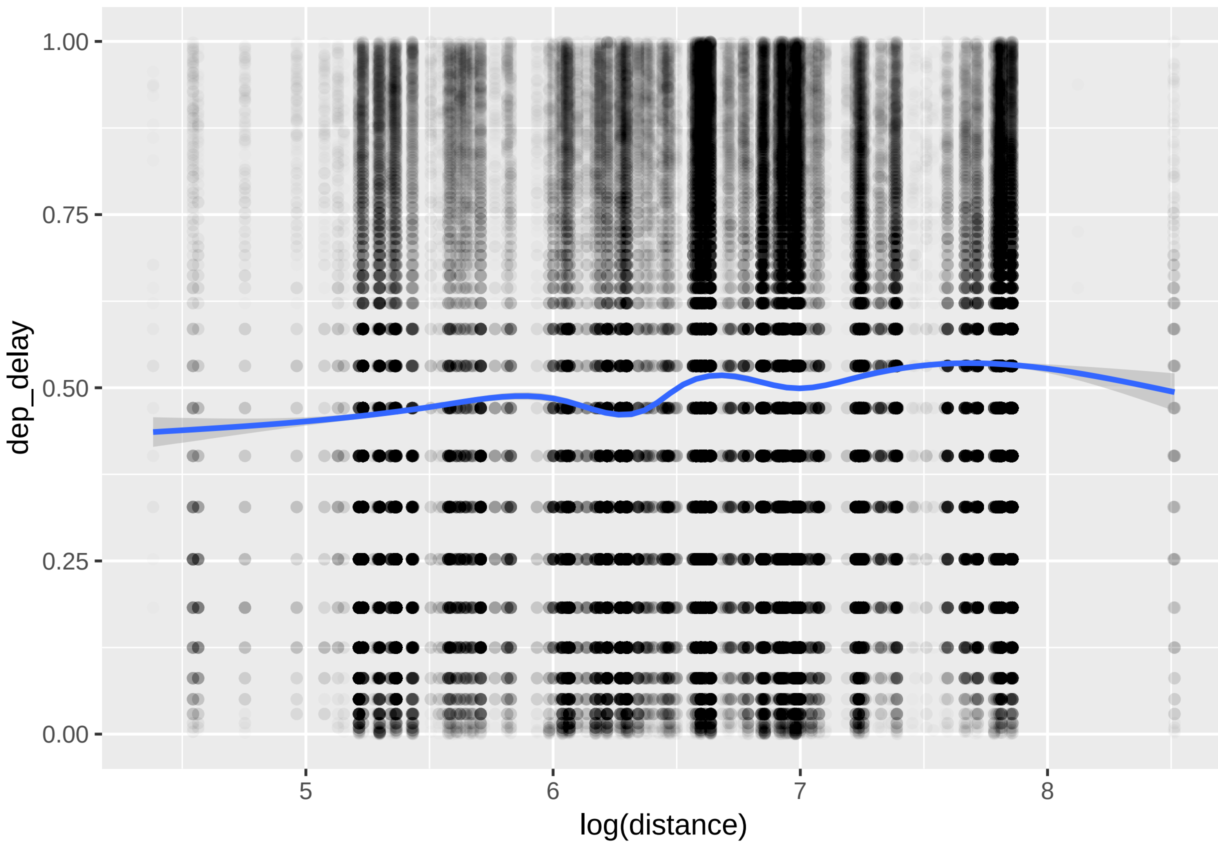

```
# Definitely non-linear. High in summer, low in fall. Not sure about winter. Looks like
# some sort of event around the end of 2013, but could just be an end effect.
ggplot(fl,aes(x=sched_dep_time,y=dep_delay)) + geom_point(alpha=0.01) + geom_smooth()
```



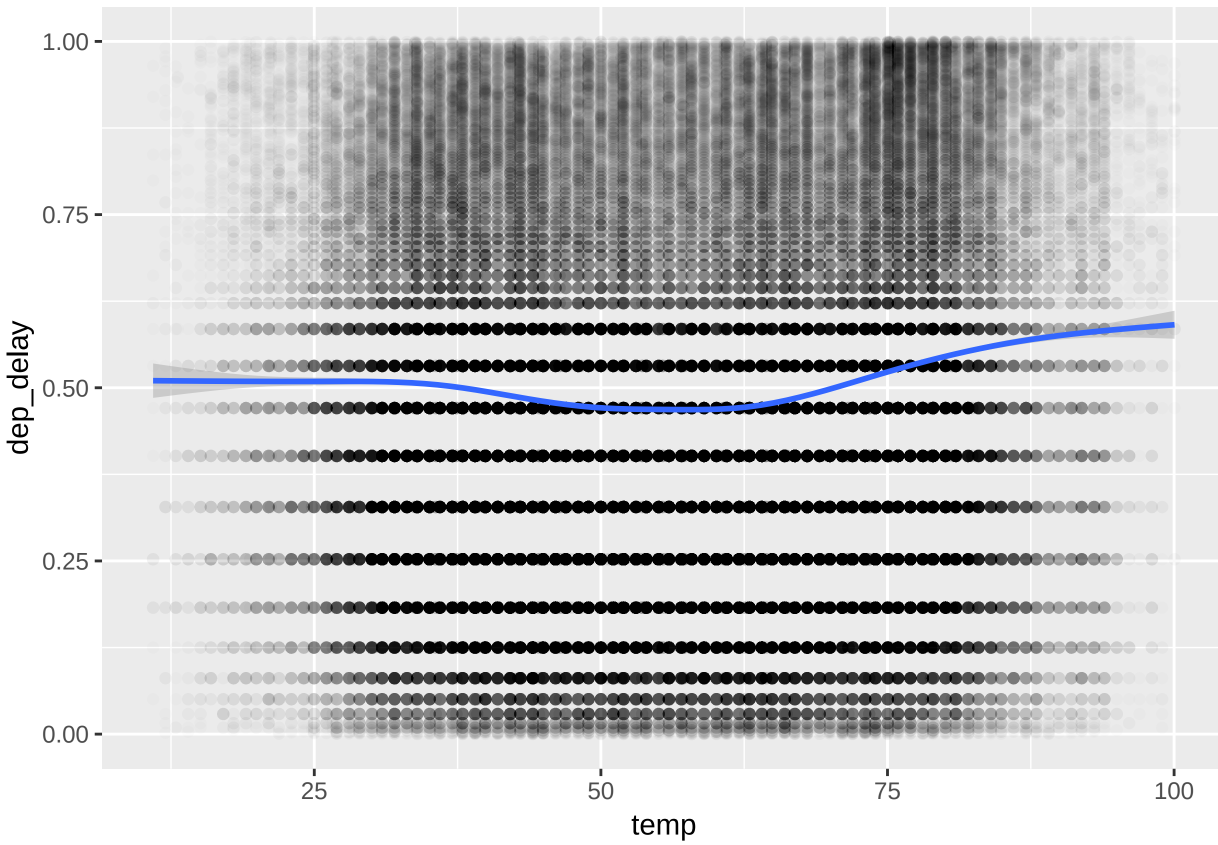

```
# delays increase throughout the day
ggplot(fl,aes(x=distance,y=dep_delay)) + geom_point(alpha=0.01) + geom_smooth()
```



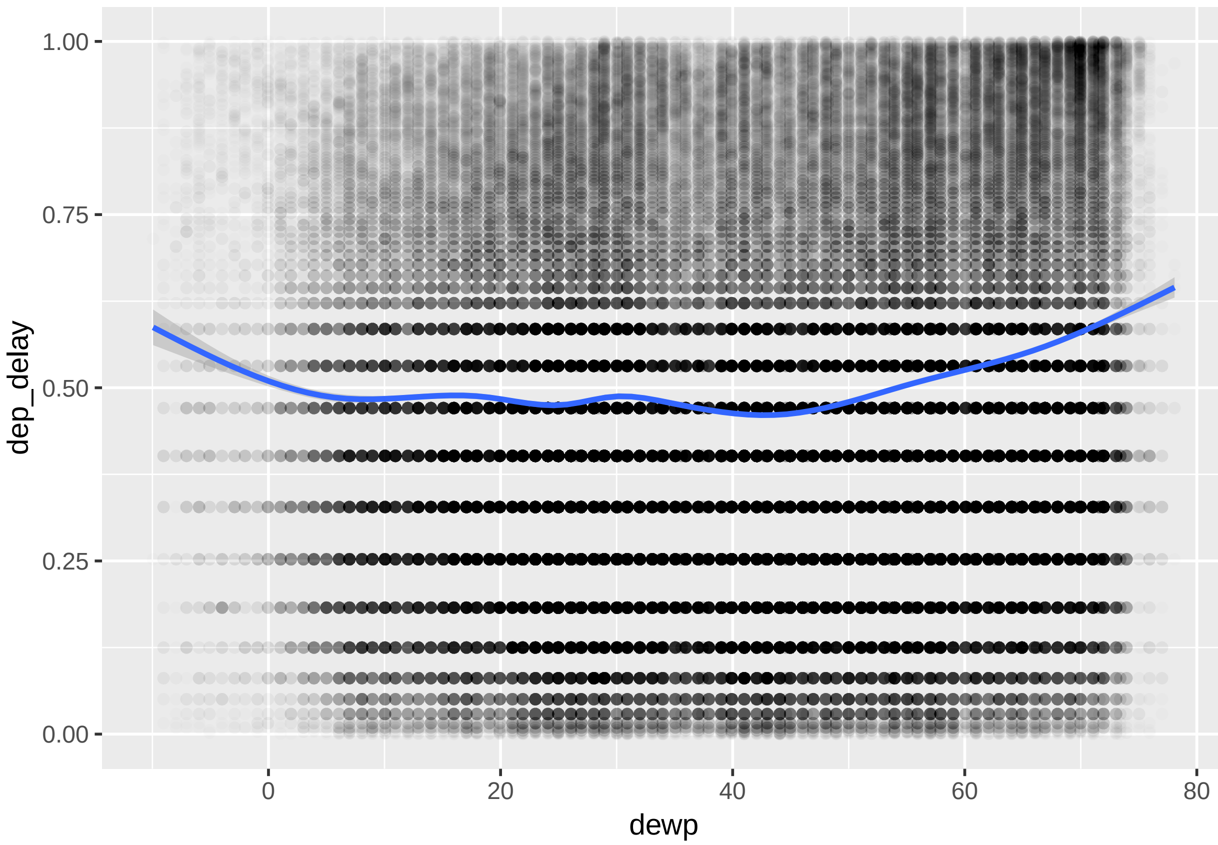

```
ggplot(fl,aes(x=log(distance),y=dep_delay)) + geom_point(alpha=0.01) + geom_smooth()
```




```
# increases with distance -- use log distance
fl <- mutate(fl,logdistance = log(distance)) %>% select(-distance)
ggplot(fl,aes(x=temp,y=dep_delay)) + geom_point(alpha=0.01) + geom_smooth()
```




```r
# delays when too hot or too cold
ggplot(fl,aes(x=dewp,y=dep_delay)) + geom_point(alpha=0.01) + geom_smooth()
```




```r
# similar to temp
# Etc.
# Replace alt with log(alt)
fl <- mutate(fl,logalt = log(alt)) %>% select(-alt)
```

We will likely need to include non-linear terms in the quantitative predictors in our models.

Split training set in two for tuning

- We have lots of data.
- Methods like cross validation can be used to select tuning parameters, but approaches like boosting are best with a training/test set.
- Evaluate all learning methods on the test set.

```r
set.seed(123)
tr_size <- ceiling(2*nrow(fl)/3)
train <- sample(1:nrow(fl),size=tr_size)
fl_tr <- fl[train,]
fl_te <- fl[-train,]

# baseline to compare learning methods to:
var_dd <- var(fl_te$dep_delay)
var_dd
```

```
## [1] 0.08311941
```

Learning methods

In the interest of time I'll just consider gam and boosting.

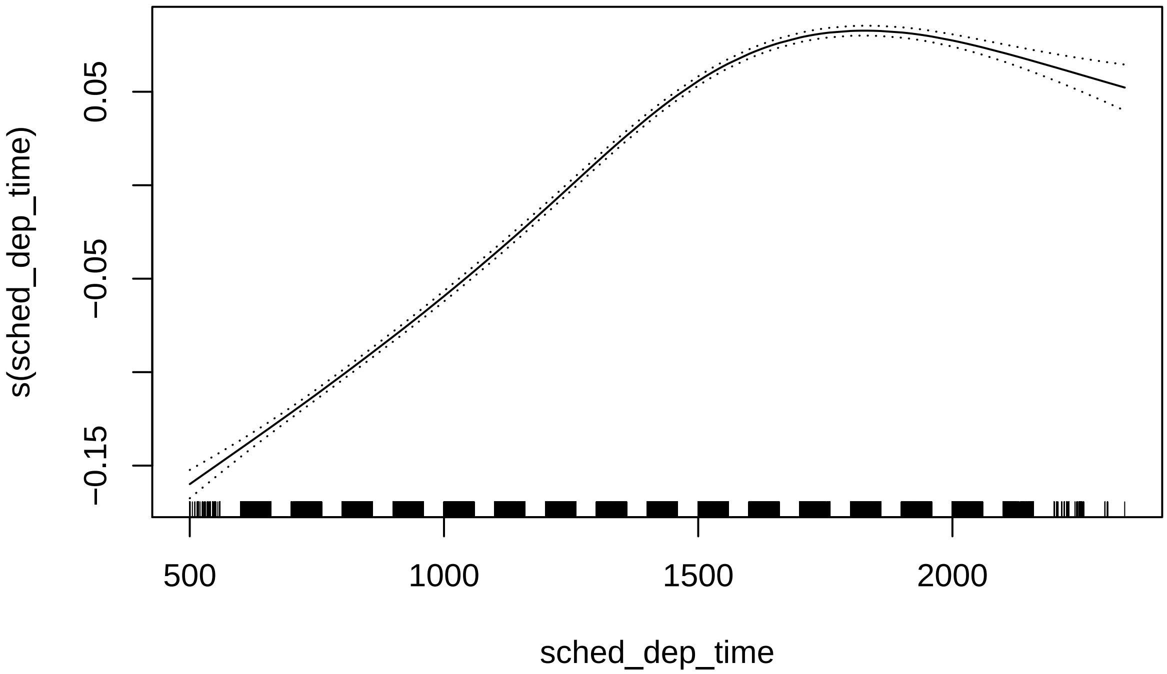
The first fit is a gam with default df for smooths of quantitiative variables. As expected, lat, lon and alt of the destination contribute very little (not shown) and are removed.

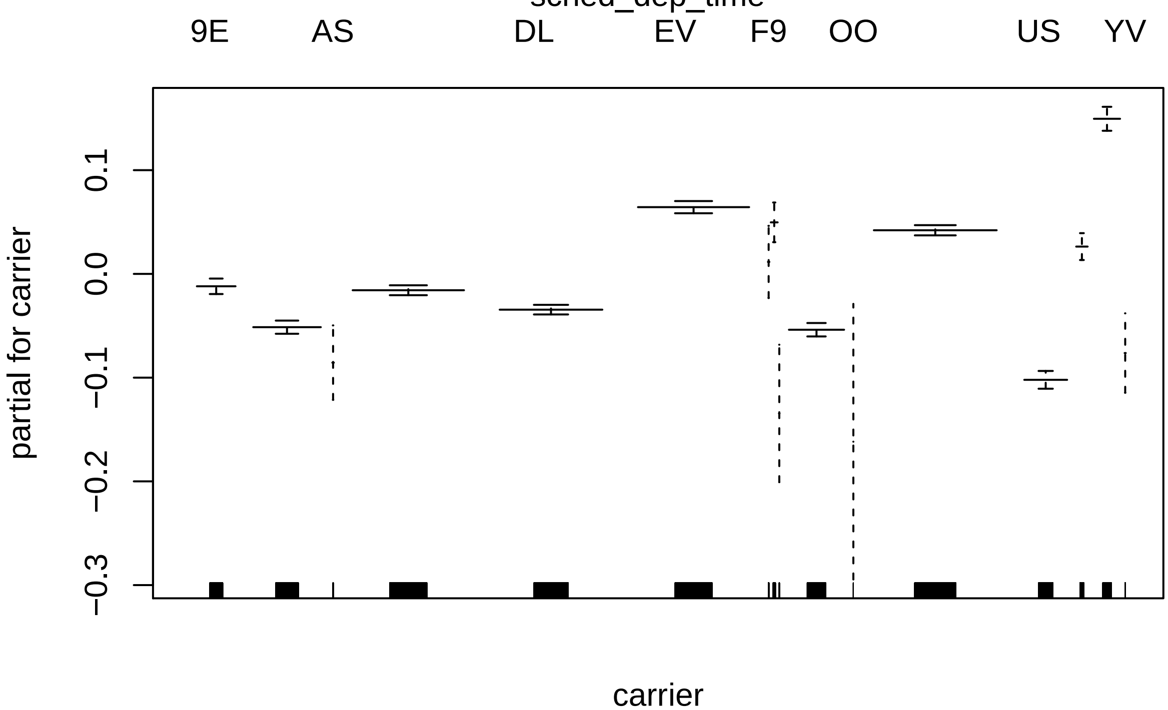
```
library(gam)
form <- formula(dep_delay ~ s(dep_date) + s(sched_dep_time) + carrier + origin + dest + s(logdistance) +
                 s(temp) + s(dewp) + s(humid) + s(wind_dir) + s(wind_speed) + precip + s(visib))
gam_fit <- gam(form, data=fl_tr,family=gaussian)
summary(gam_fit)
```

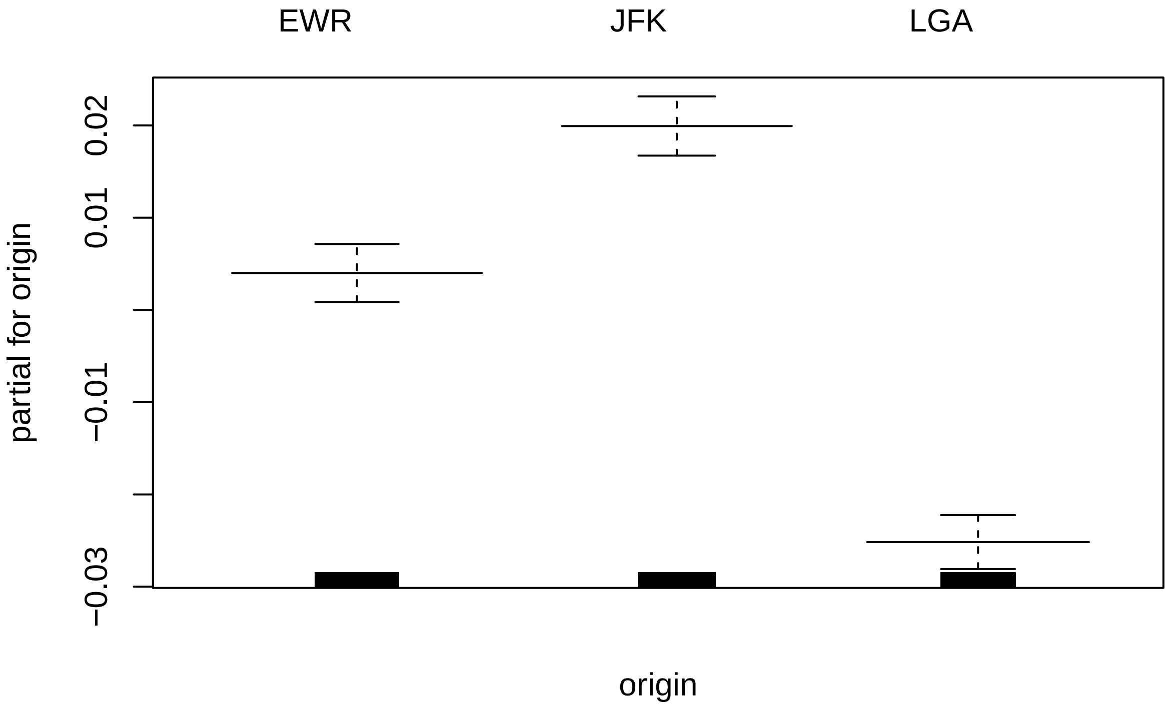
```
##
## Call: gam(formula = form, family = gaussian, data = fl_tr)
## Deviance Residuals:
##       Min        1Q    Median        3Q       Max
## -0.848656 -0.209769  0.004745  0.211186  0.763180
##
## (Dispersion Parameter for gaussian family taken to be 0.07)
##
##     Null Deviance: 10216.89 on 122877 degrees of freedom
## Residual Deviance: 8585.173 on 122725 degrees of freedom
## AIC: 22023.21
##
## Number of Local Scoring Iterations: 2
##
## Anova for Parametric Effects
##                       Df Sum Sq Mean Sq  F value    Pr(>F)
## s(dep_date)            1    0.3    0.26    3.757 0.0525882 .
## s(sched_dep_time)      1  572.4  572.44 8183.025 < 2.2e-16 ***
## carrier               15  340.9   22.73  324.885 < 2.2e-16 ***
## origin                 2   48.4   24.18  345.701 < 2.2e-16 ***
## dest                  98   90.6    0.92   13.211 < 2.2e-16 ***
## s(logdistance)         1    1.3    1.35   19.231 1.159e-05 ***
## s(temp)                1    5.1    5.06   72.302 < 2.2e-16 ***
## s(dewp)                1  287.5  287.53 4110.195 < 2.2e-16 ***
## s(humid)               1   37.0   36.99  528.811 < 2.2e-16 ***
## s(wind_dir)            1    9.4    9.36  133.854 < 2.2e-16 ***
## s(wind_speed)          1   22.9   22.92  327.609 < 2.2e-16 ***
## precip                 1   16.2   16.15  230.903 < 2.2e-16 ***
## s(visib)               1    0.9    0.89   12.733 0.0003594 ***
## Residuals         122725 8585.2    0.07
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Anova for Nonparametric Effects
##                   Npar Df Npar F   Pr(F)
## (Intercept)
## s(dep_date)             3 491.42 < 2e-16 ***
## s(sched_dep_time)       3 296.70 < 2e-16 ***
## carrier
## origin
## dest
## s(logdistance)          3   0.37 0.77273
## s(temp)                 3 255.55 < 2e-16 ***
```

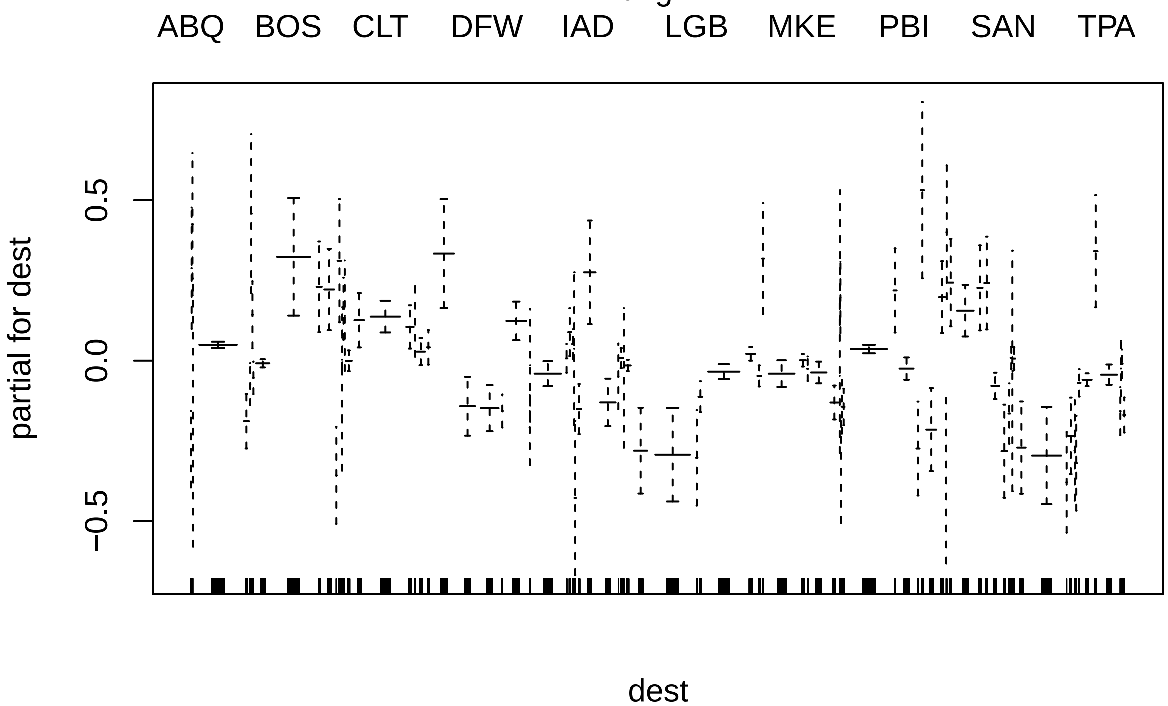
```
## s(dewp)                    3  97.58 < 2e-16 ***
## s(humid)                   3   3.33 0.01872 *
## s(wind_dir)                3  51.39 < 2e-16 ***
## s(wind_speed)              3  12.50 3.6e-08 ***
## precip
## s(visib)                   3  26.86 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

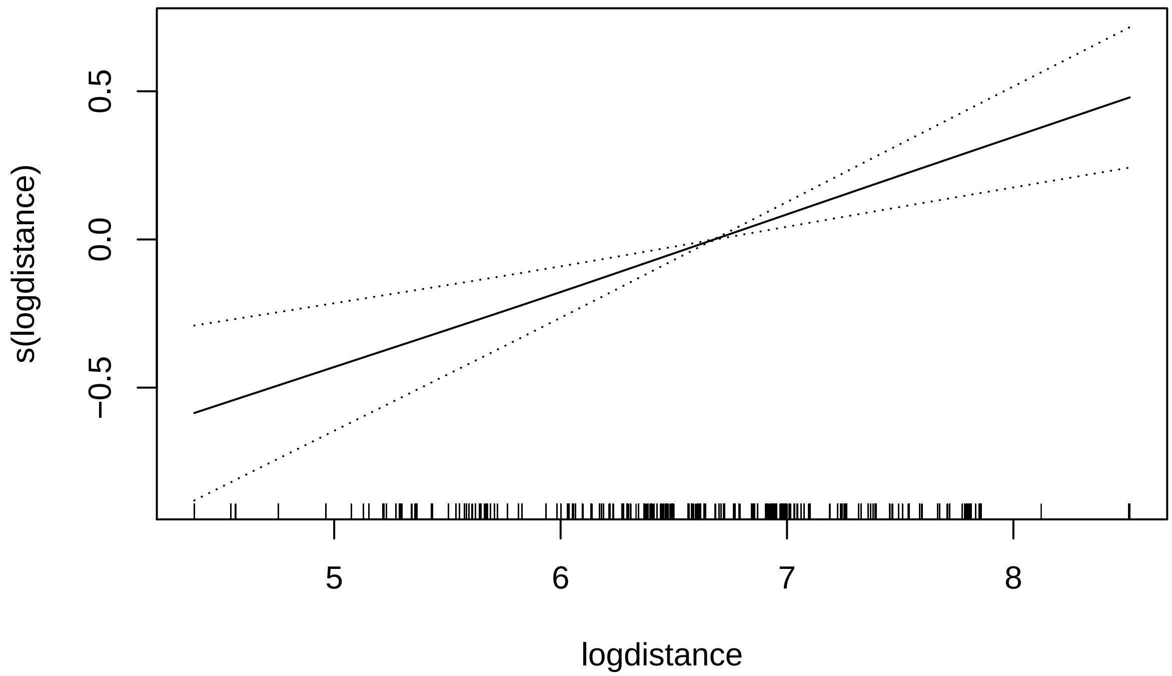
```r
plot(gam_fit,se=TRUE)
```

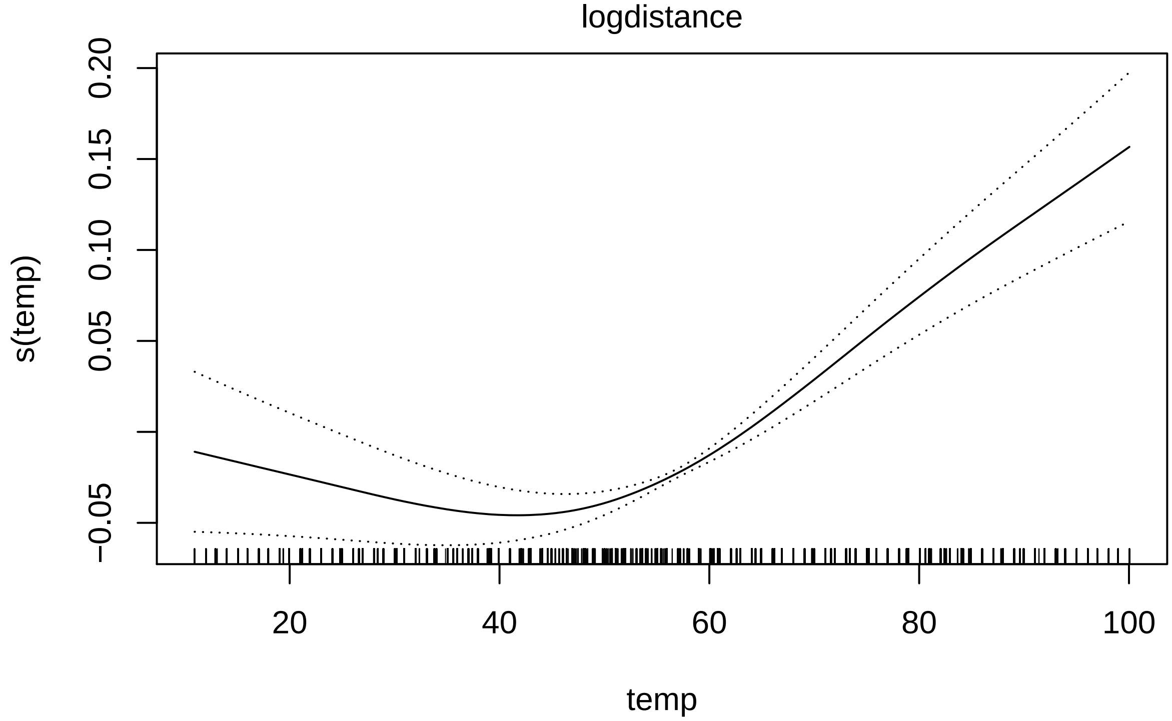


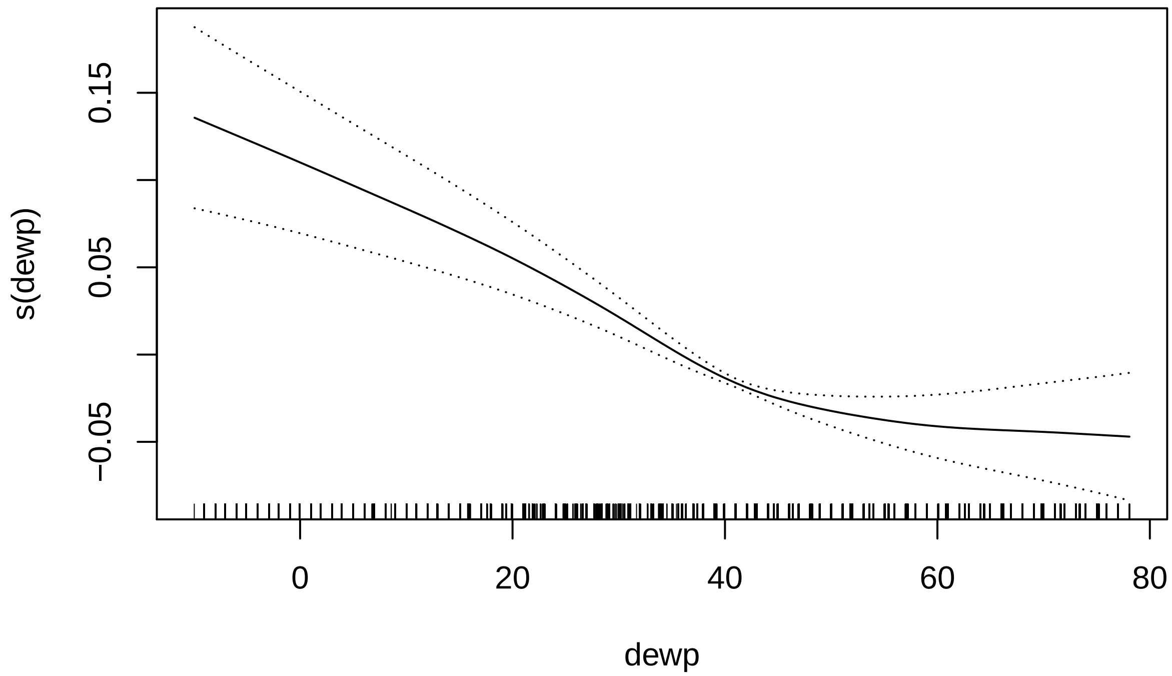



EWR
JFK
LGA
partial for origin
0.02
0.01
−0.01
−0.03
origin

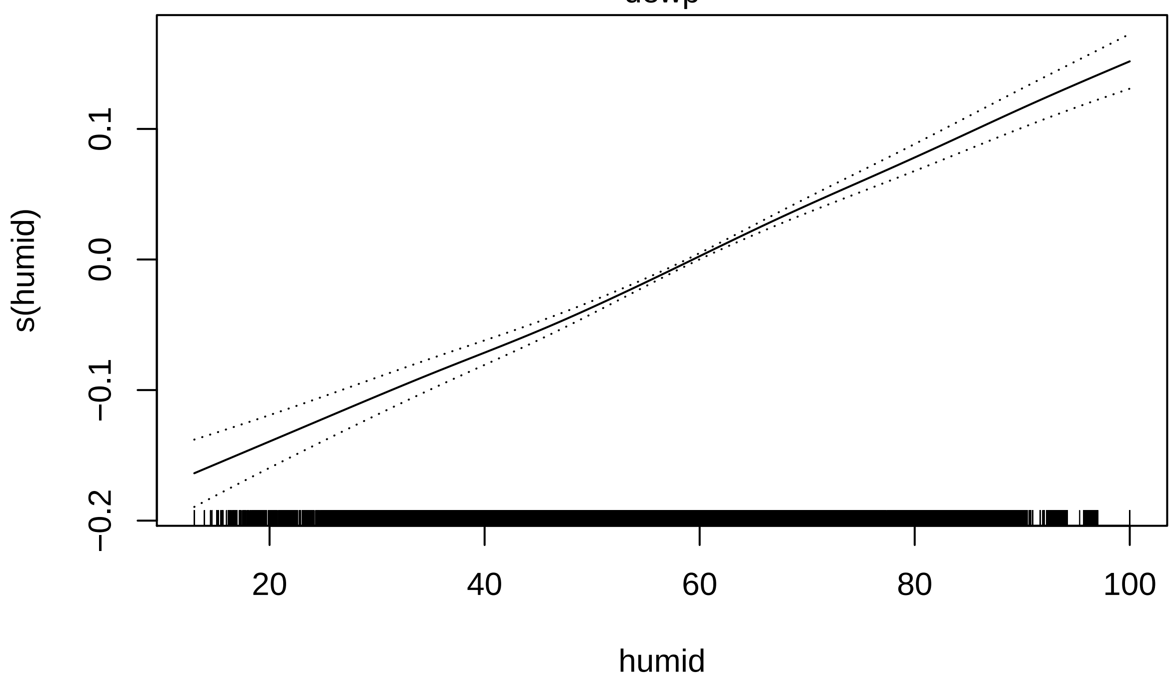

ABQ
BOS
CLT
DFW
IAD
LGB
MKE
PBI
SAN
TPA
partial for dest
0.5
0.0
−0.5
dest


s(logdistance)
−0.5
0.0
0.5
5
6
7
8
logdistance

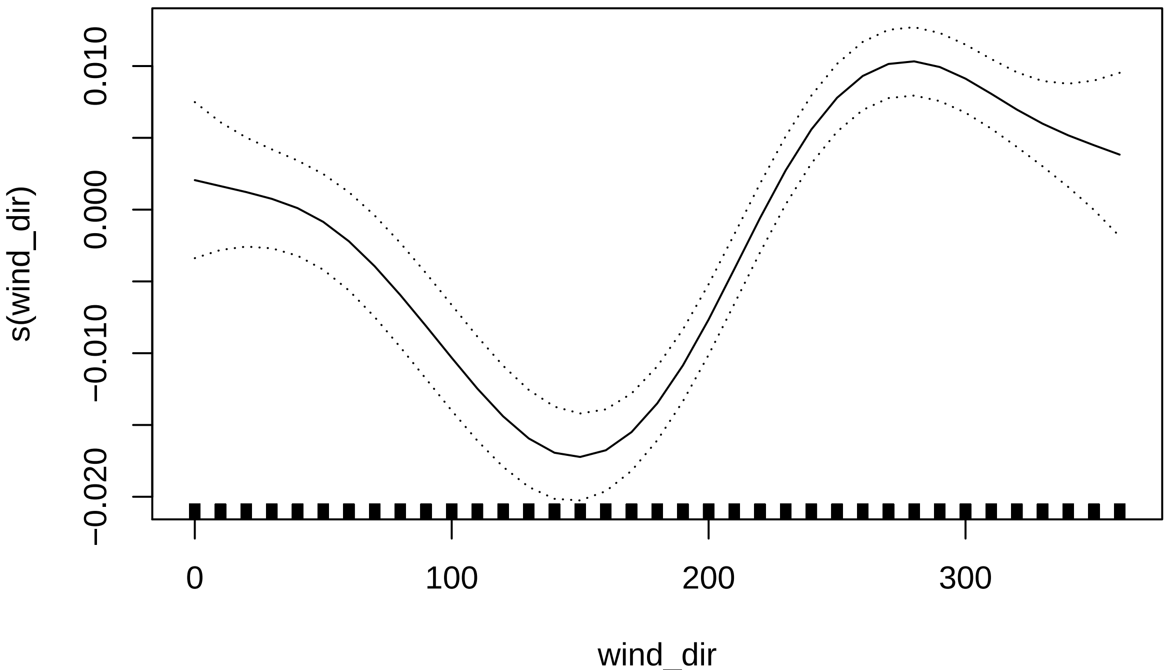

s(temp)
−0.05
0.05
0.10
0.15
0.20
20
40
60
80
100
temp

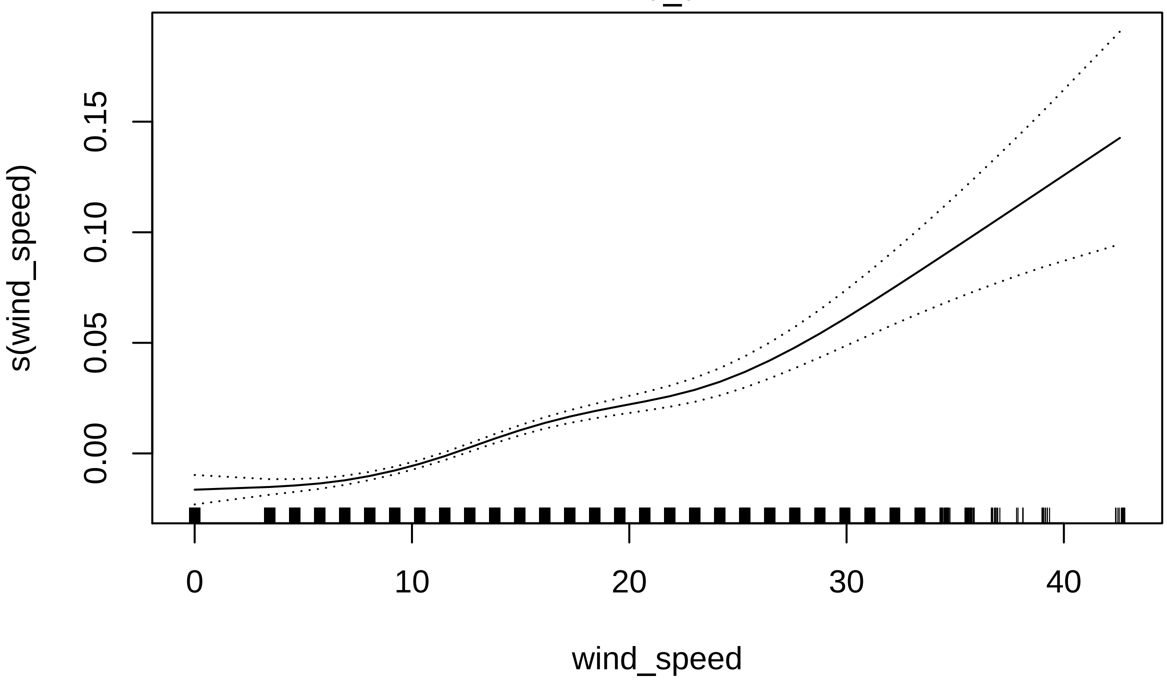


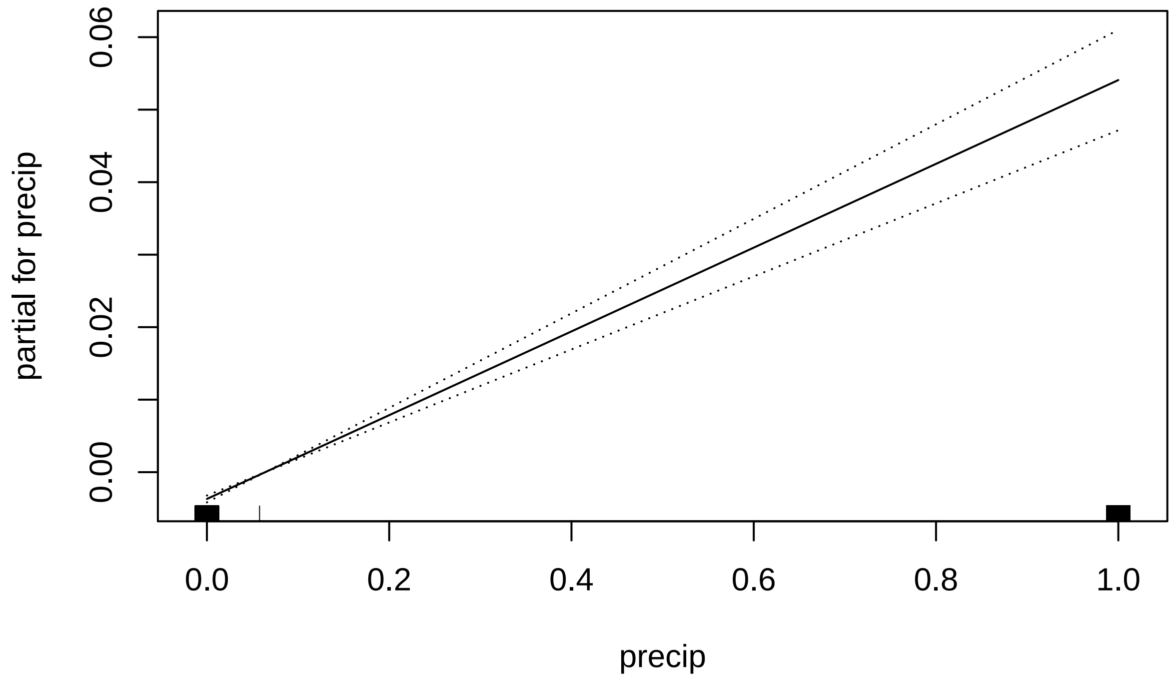
s(dewp)
0.15
0.05
−0.05
0
20
40
60
80
dewp

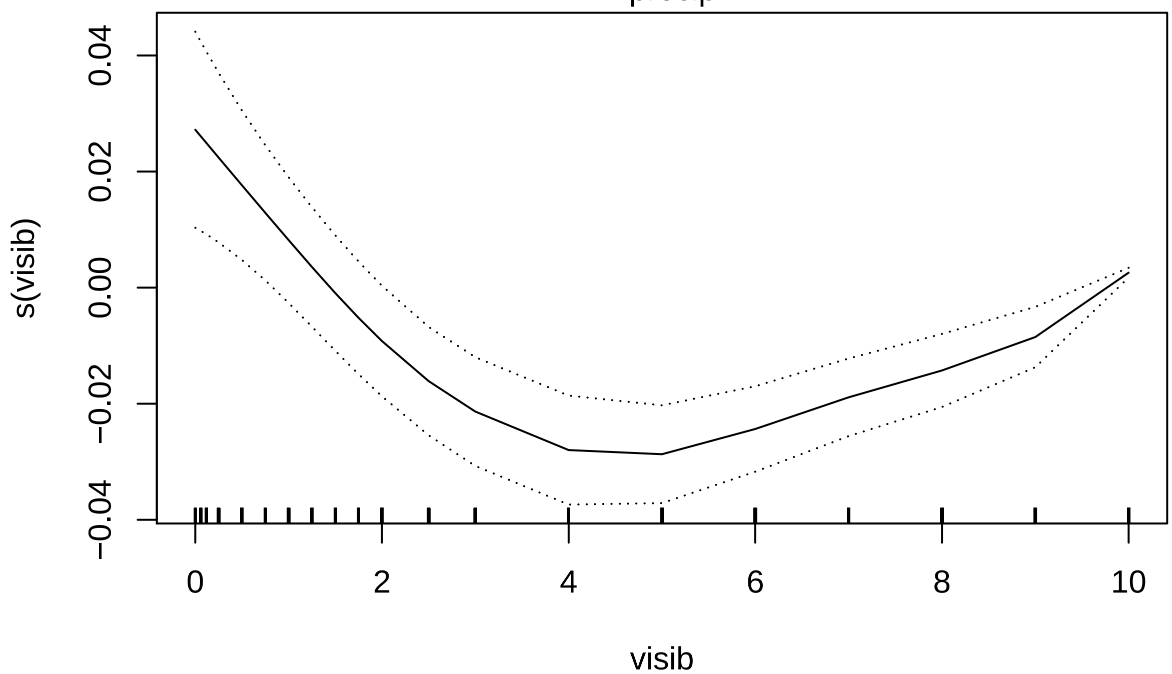


s(humid)
0.1
0.0
−0.1
−0.2
20
40
60
80
100
humid


s(wind_dir)
0.010
0.000
−0.010
−0.020
0
100
200
300
wind_dir


s(wind_speed)
0.15
0.10
0.05
0.00
0
10
20
30
40
wind_speed






```
gam_pred <- predict(gam_fit,newdata=fl_te)
mse_gam <- mean((fl_te$dep_delay-gam_pred)^2)
mse_gam
```

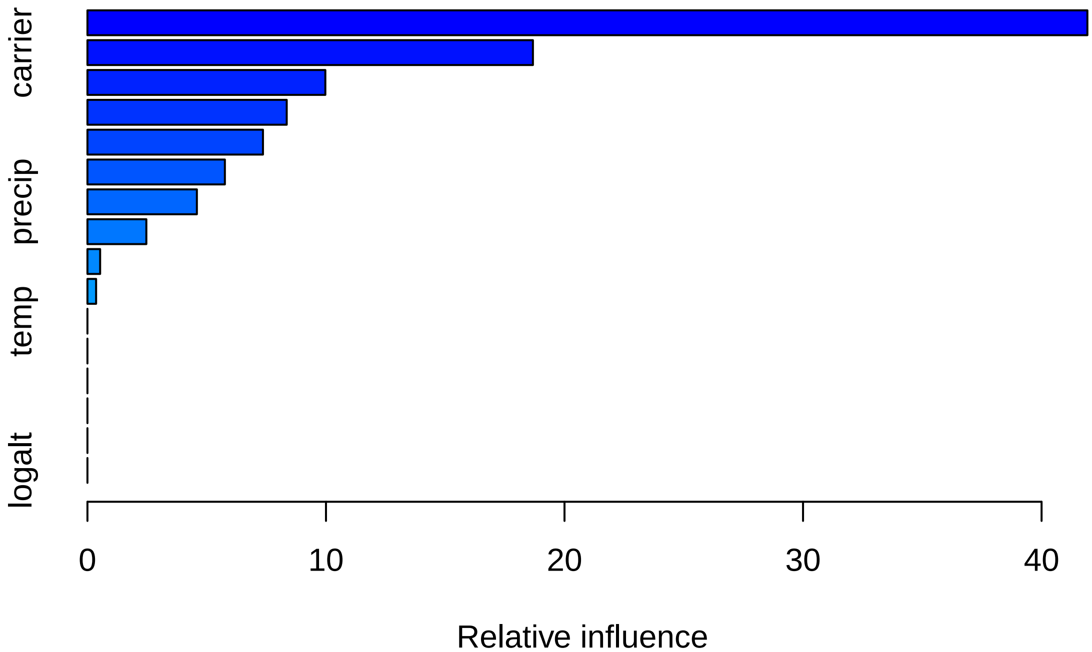
```
## [1] 0.07047458
```

```
abs(mse_gam - var_dd)/var_dd
```

```
## [1] 0.1521285
```

The more trees and slower learning, the better a boosted model will do. I only have time to go as far as 1000 trees and shrinkage 0.01.

```r
library(gbm)
dep_date_numeric <- as.numeric(fl_tr$dep_date)
dep_date_numeric <- dep_date_numeric - mean(dep_date_numeric)
fl_tr_tem <- mutate(fl_tr,dep_date = dep_date_numeric)
gbm_fit <-gbm(dep_delay ~ .,data=fl_tr_tem,distribution="gaussian",
              n.trees = 1000, shrinkage = 0.01)
summary(gbm_fit)
```




```
##                           var    rel.inf
## sched_dep_time sched_dep_time 41.9210129
## carrier               carrier 18.6758728
## dep_date             dep_date  9.9734373
## humid                   humid  8.3543544
## dewp                     dewp  7.3585086
## dest                     dest  5.7623968
## precip                 precip  4.5884783
## origin                 origin  2.4700180
## wind_speed         wind_speed  0.5323563
## logdistance       logdistance  0.3635646
## temp                     temp  0.0000000
## wind_dir             wind_dir  0.0000000
## visib                   visib  0.0000000
## lat                       lat  0.0000000
## lon                       lon  0.0000000
## logalt                 logalt  0.0000000
```

```r
#
dep_date_numeric <- as.numeric(fl_te$dep_date)
dep_date_numeric <- dep_date_numeric - mean(dep_date_numeric)
fl_te_tem <- mutate(fl_te,dep_date = dep_date_numeric)
#
gbm_pred <- predict(gbm_fit,newdata=fl_te_tem,n.trees = 1000)
mse_gbm <- mean((fl_te$dep_delay-gbm_pred)^2)
```

```r
mse_gbm
```

```
## [1] 0.07206016
```

```r
abs(mse_gbm - var_dd)/var_dd
```

```
## [1] 0.1330526
```