CS 109A/STAT 121A/AC 209A/CSCI E-109A:

Midterm - 2017

Harvard University
Fall 2017
Instructors: Pavlos Protopapas, Kevin Rader, Rahul Dave, Margo Levine

---

INSTRUCTIONS

- You must submit the Midterm on your own. **No group submissions are allowed**. You may use any print or online resources but **you may not work or consult with others**.
- Restart the kernel and run the whole notebook again before you submit.
- Please submit both a notebook and a pdf.

Flight Delays

The U.S. Department of Transportation's (DOT) Bureau of Transportation Statistics tracks the on-time performance of domestic flights operated by large air carriers. Summary information on the number of on-time, delayed, canceled, and diverted flights are published in DOT's monthly Air Travel Consumer Report and in this dataset of 2015 flight delays and cancellations.

Data

Each entry of the flights.csv file corresponds to a flight. More than 5,800,000 flights were recorded in 2015. These flights are described according to 31 variables. Further details of these variables can be found here (https://www.transtats.bts.gov/DL_SelectFields.asp?Table_ID=236&DB_Short_Name=On-Time), if you are interested (not needed to answer these questions).

Name	Type	DESCRIPTION
DATE	object	The date in python datetime format
MONTH	int64	The month of the year(1-12)
DAY	int64	The day of the month
DAY_OF_WEEK	int64	The day of the week(1-7, MON-SUN)
AIRLINE	object	An identifier for the airline
FLIGHT_NUMBER	int64	The flight number
TAIL_NUMBER	object	The tail number (aircraft) corresponding to this flight
ORIGIN_AIRPORT	object	The code for origin airport
DESTINATION_AIRPORT	object	The code for destination airport
SCHED_DEP	object	The departure time in python datetime.time format
SCHED_ARR	object	The arrival time in python datetime.time format
DEPARTURE_DELAY	float64	The delay incurred at the origin (mins)
ARRIVAL_DELAY	float64	The delay when the flight reached the (mins) destination
DISTANCE	int64	Distance in miles between origin and destination
SCHEDULED_TIME	float64	Scheduled time of flight (minutes)
ELAPSED_TIME	float64	Actual time of flight (minutes)
AIR_SYSTEM_DELAY	float64	What part of the delay was NASD?(mins)
SECURITY_DELAY	float64	What part of the delay was due to security problems? (mins)
AIRLINE_DELAY	float64	What part of the delay is due to the airline? (mins)
LATE_AIRCRAFT_DELAY	float64	What part of the delay is due to previous flight(s) being late(mins)
WEATHER_DELAY	float64	Delay due to extreme weather events(min)

You can read more about the various weather delays here (https://www.rita.dot.gov/bts/help/aviation/html/understanding.html) if you are so inclined.

Data/Caveats

The data file, flights.csv, is found here (https://drive.google.com/file/d/0B9dVesTppCgHY0IwZHk3SGhjd00/view?usp=sharing) (note, it is about 70MB).

This data is already preprocessed, reduced, partially cleaned and therefore not identical to the original dataset.

Problem Description

We will build two separate models: one model that classifies whether a flight will be delayed and a second model that predicts the length of delay given that a flight is truly delayed. Only consider models taught in class so far.

Consider the following: This is a large dataset; think of strategies on how to solve this problem. Create a manageable subsample of the data that you can use to train and test/validate, but eventually you should predict on all the data (excluding the training set).

Questions

1. (5pts) Create a new variable, `DELAY_OR_NOT`: a boolean/indicator variable which indicates any arrival delay under 15 mins as a 0, and any delay at or above 15 mins as a 1 (`ARRIVAL_DELAY >= 15`).
2. (5pts) Make sure you understand the data variable descriptions before you start the analysis. Consider all the columns and determine and list which of these predictors should not be used.
3. (15pts) Perform EDA to gain intuition of the factors that affect delay and provide visuals: do delays vary across airlines, or time of departure, or airport (do, at the very least, Chicago (ORD), Boston (BOS), and your favorite another airport), or airport traffic?
4. (20pts) Build a classification model that classifies delays according to `DELAY_OR_NOT`. This is an unbalanced dataset, thus consider the appropriate performance metric when reporting your results.
5. (5pts) Given your model, comment on the importance of factors as related to whether a flight is delayed.
6. (5pts) Evaluate your model(s) on your test set, and finally provide a visual to show which airlines are predicted to have the most delays using all the data excluding the training and test set.
7. (15pts) Build a regression model that predicts the length of delay (on the log scale) given that a flight is truly delayed.
8. (20pts) Write a report (in the last markdown cell in your notebook with your findings (without code)). Describe the main design decisions you have made with justifications. Clearly explain your methodology and results. This should not be more than 300 words. You may use up to 5 diagrams.

Deliverable:

A well presented notebook with well structured and documented code to answer questions 1-7 (plus additional questions for 209 students) with brief explanations and/or clarifications (10pts for overall presentation). The last cell should contain the report for question 8.

Hints

1. For the classification model, an AUC of approximately 0.6 should be your base model.
2. $R^2 > 0.03$ for the regression is good, $R^2 > 0.05$ very good, and $R^2 > 0.1$ is impressive (measured on the log scale).

In [1]:
```
%matplotlib inline
import numpy as np
import pandas as pd
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
import math as math
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LogisticRegressionCV
import sklearn.metrics as metrics
from sklearn.preprocessing import PolynomialFeatures
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.neighbors import KNeighborsClassifier as KNN
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import export_graphviz
from sklearn.model_selection import cross_val_score
from sklearn.tree import export_graphviz
from IPython.display import Image
from IPython.display import display
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import auc
from sklearn import preprocessing
from sklearn import linear_model
from sklearn import discriminant_analysis
from datetime import datetime
from sklearn.linear_model import LinearRegression
```

In [2]:
```
dataframe = pd.read_csv("cs109a_midterm.csv")
```

In [3]:
```
df = dataframe.copy()
df.head()
```

Out[3]:

	DATE	MONTH	DAY	DAY_OF_WEEK	AIRLINE	FLIGHT_NUMBER	TAIL_NUMBER	OR
0	2015-09-19	9	19	6	AA	394	N3FMAA	OR
1	2015-10-28	10	28	3	AA	375	N4YDAA	112
2	2015-08-19	8	19	3	MQ	3648	N512MQ	XN
3	2015-12-01	12	1	2	WN	4096	N912WN	PH
4	2015-09-15	9	15	2	WN	285	N7718B	MC

5 rows × 21 columns

In [4]:
```
df.shape
```

Out[4]: (804941, 21)

In [5]:
```
# Question 1: create indicator for arrival delay at or above 15 mins
df['DELAY_OR_NOT']=(df['ARRIVAL_DELAY']>=15)*1
```

In [6]:
```
df.head()
```

Out[6]:

	DATE	MONTH	DAY	DAY_OF_WEEK	AIRLINE	FLIGHT_NUMBER	TAIL_NUMBER	OR
0	2015-09-19	9	19	6	AA	394	N3FMAA	OR
1	2015-10-28	10	28	3	AA	375	N4YDAA	112
2	2015-08-19	8	19	3	MQ	3648	N512MQ	XN
3	2015-12-01	12	1	2	WN	4096	N912WN	PH
4	2015-09-15	9	15	2	WN	285	N7718B	MC

5 rows × 22 columns

Question 2: (5pts) Make sure you understand the data variable descriptions before you start the analysis. Consider all the columns and determine and list which of these predictors should not be used.

In [7]:
```
print("Unique flight numbers: ", df['FLIGHT_NUMBER'].unique().size)
print("Unique tail numbers: ", df['TAIL_NUMBER'].unique().size)
```

```
Unique flight numbers:  6754
Unique tail numbers:  4819
```

DEPARTURE_DELAY, ELAPSED_TIME, AIR_SYSTEM_DELAY, SECURITY_DELAY, AIRLINE_DELAY, LATE_AIRCRAFT_DELAY, and WEATHER_DELAY should not be used. We are trying to determine whether a flight will be delayed, and if so, how long it will be delayed, so we are limited to the data that can be collected before the plane takes off.

We also won't use DATE because the same information is encoded in the MONTH and DAY predictors. And finally, we won't use FLIGHT_NUMBER or TAIL_NUMBER because they are categorical variables with too many categories. It's not worth it to add 10,000 binary predictors just in case one particular flight pattern or aircraft is extremely influential on whether or not a flight is delayed.

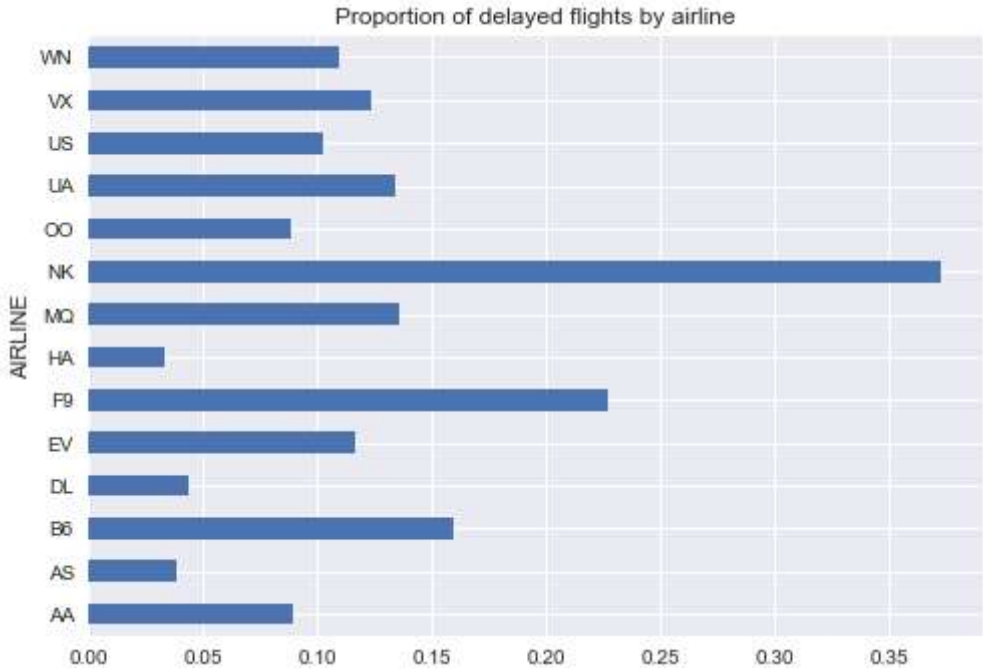
Question 3: (15pts)

Perform EDA to gain intuition of the factors that affect delay and provide visuals: do delays vary across airlines, or time of departure, or airport (do, at the very least, Chicago (ORD), Boston (BOS), and your favorite another airport), or airport traffic?

In [8]:
```
# proportion of flights delayed by airline
delayed_prop = {}
delayed_prop['airline'] = df.groupby(['AIRLINE'])['DELAY_OR_NOT'].sum()/df.gro
upby(['AIRLINE'])['DELAY_OR_NOT'].count()
```

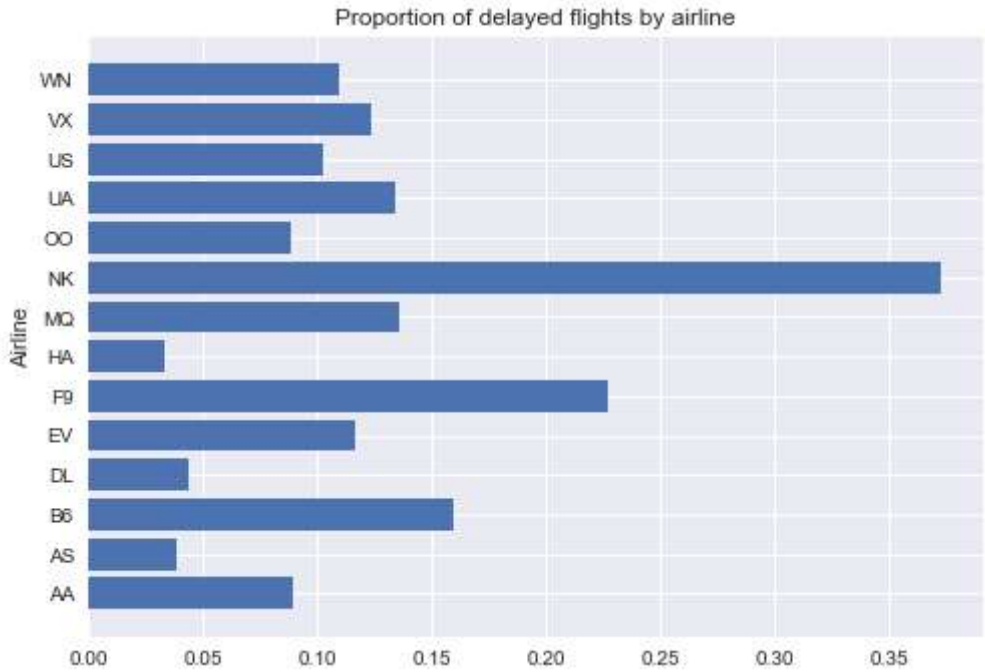
In [9]:
```
delayed_prop['airline'] = df.groupby(['AIRLINE'])['DELAY_OR_NOT'].sum()/df.gro
upby(['AIRLINE'])['DELAY_OR_NOT'].count()
delayed_prop['airline'].plot(kind="barh", title="Proportion of delayed flights
 by airline")
```

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x2be85625208>



In [10]:
```
airlines = delayed_prop['airline'].index
nums = np.arange(len(airlines))
plt.barh(nums, delayed_prop['airline'].values)
ticks = plt.yticks(nums,airlines)
plt.title("Proportion of delayed flights by airline")
plt.ylabel("Airline")
```

Out[10]: <matplotlib.text.Text at 0x2be8590d6a0>



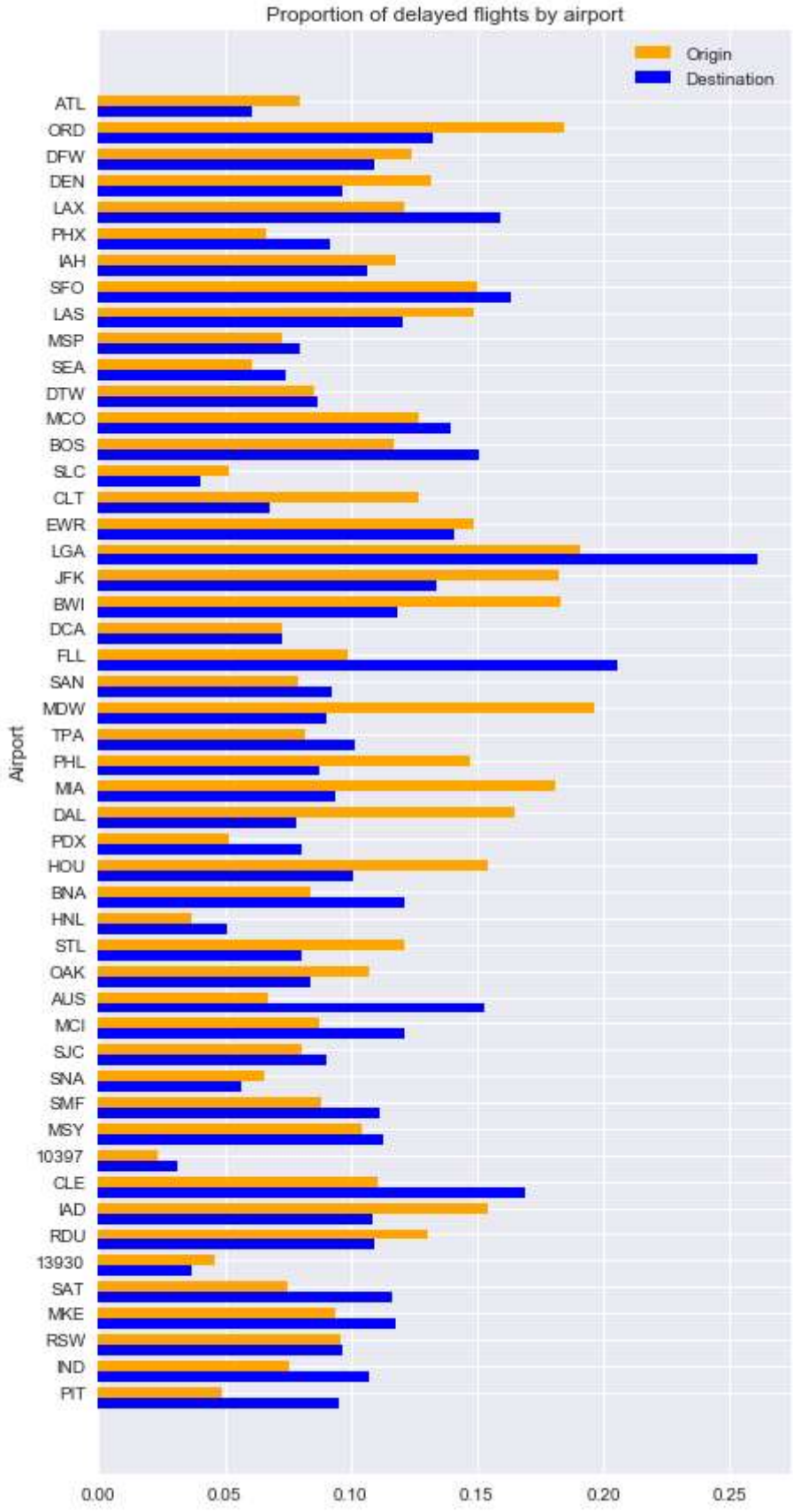
Most airlines seem to have approximately 10% of their flights delayed, but NK and F9 are noticeable outliers with much higher proportions, while HA, DL, and AS have smaller proportions.

In [11]:
```
# top 50 airports by number of flights originating from there
topairport = df['ORIGIN_AIRPORT'].value_counts()[:50].index

delayed_prop['origin_airport'] = df.groupby(['ORIGIN_AIRPORT'])
['DELAY_OR_NOT'].sum()/df.groupby(['ORIGIN_AIRPORT'])['DELAY_OR_NOT'].count()
delayed_prop['top_origin_airport'] = delayed_prop['origin_airport']
[topairport]
```

In [12]:
```
delayed_prop['dest_airport'] = df.groupby(['DESTINATION_AIRPORT'])['DELAY_OR_N
OT'].sum()/df.groupby(['DESTINATION_AIRPORT'])['DELAY_OR_NOT'].count()
delayed_prop['top_dest_airport'] = delayed_prop['dest_airport'][topairport]
```

In [13]:
```
width = 0.4
fig, ax = plt.subplots(figsize=(7,15))
nums = np.arange(len(topairport))
ax.barh(nums, delayed_prop['top_origin_airport'].values, width, label = "Origi
n", color='orange')
ax.barh(nums+width, delayed_prop['top_dest_airport'].values, width, label = "D
estination", color='blue')
ticks = plt.yticks(nums,topairport)
ax.set_title("Proportion of delayed flights by airport")
ax.legend(loc='best')
plt.ylabel("Airport")
plt.gca().invert_yaxis()
```


Proportion of delayed flights by airport
Origin
Destination
Airport
ATL
ORD
DFW
DEN
LAX
PHX
IAH
SFO
LAS
MSP
SEA
DTW
MCO
BOS
SLC
CLT
EWR
LGA
JFK
BWI
DCA
FLL
SAN
MDW
TPA
PHL
MIA
DAL
PDX
HOU
BNA
HNL
STL
OAK
AUS
MCI
SJC
SNA
SMF
MSY
10397
CLE
IAD
RDU
13930
SAT
MKE
RSW
IND
PIT
0.00
0.05
0.10
0.15
0.20
0.25

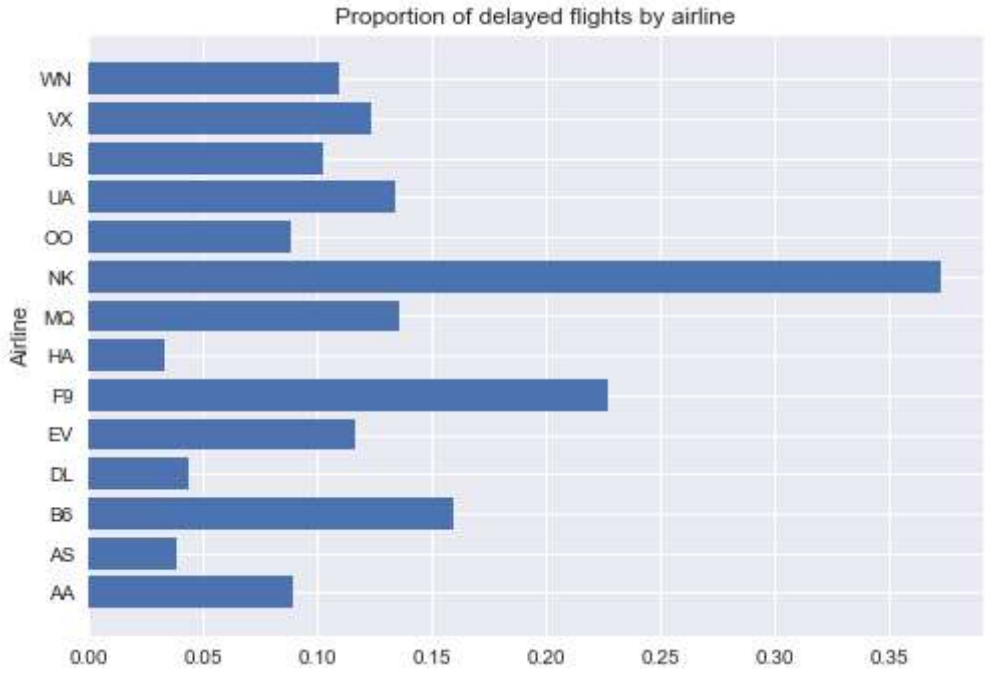
In [14]:
```
print("Mean proportion of delayed flights by origin airport:", delayed_prop['t
op_origin_airport'].values.mean())
print("Mean proportion of delayed flights by dest airport:", delayed_prop['top
_dest_airport'].values.mean())
```

```
Mean proportion of delayed flights by origin airport: 0.108007260017
Mean proportion of delayed flights by dest airport: 0.10618870124
```

For this plot, I selected the top 50 airports by number of flights originating from there. The mean proportion of delayed flights by airport is 0.11, whether the airport is the origin or the destination. Many airports have approximately equal proportions of delayed flights by origin and destination, with some exceptions. LGA has the noticeably highest proportion of delayed flights by destination, and one of the highest proportions by origin. The second highest proportion of delayed flights by destination airport is FLL, but its proportion by origin is only half of its proportion by destination.

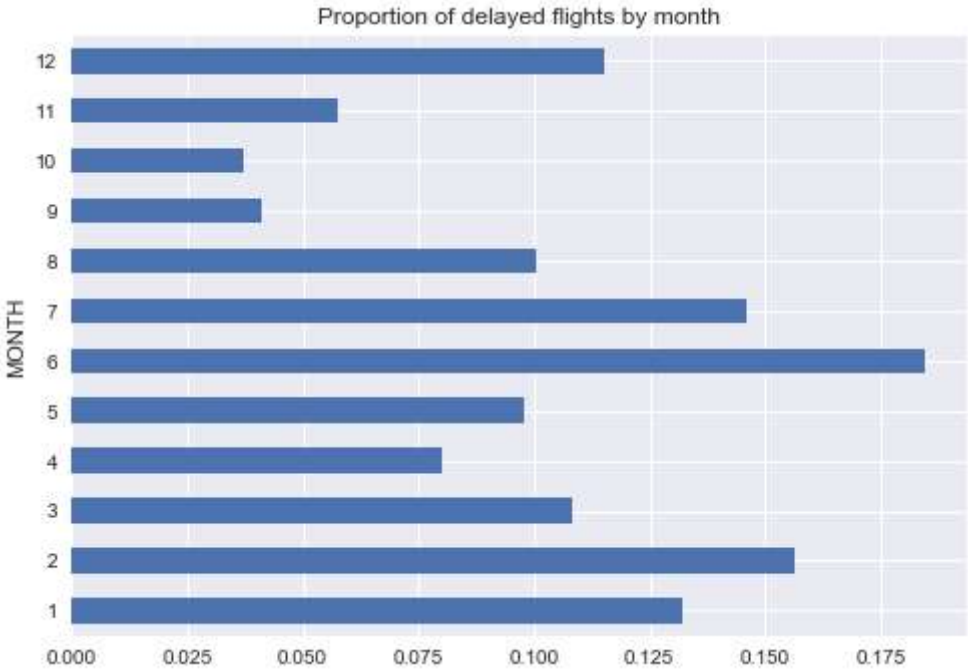
In [15]:
```
airlines = delayed_prop['airline'].index
nums = np.arange(len(airlines))
plt.barh(nums, delayed_prop['airline'].values)
ticks = plt.yticks(nums,airlines)
plt.title("Proportion of delayed flights by airline")
plt.ylabel("Airline")
```

Out[15]:
```
<matplotlib.text.Text at 0x2be86220630>
```



In [16]:
```
delayed_prop['month'] = df.groupby(['MONTH'])
['DELAY_OR_NOT'].sum()/df.groupby(['MONTH'])['DELAY_OR_NOT'].count()
delayed_prop['month'].plot(kind="barh", title="Proportion of delayed flights b
y month")
```

Out[16]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2be862b9a20>
```



In [17]:
```
delayed_prop['month'].describe()
```

Out[17]:
```
count    12.000000
mean      0.104700
std       0.045836
min       0.037127
25%       0.074243
50%       0.104499
75%       0.135525
max       0.184443
Name: DELAY_OR_NOT, dtype: float64
```

The proportion of delayed flights varies significantly by month, with a minimum of 0.037 in October and a maximum of 0.184 in June.

In [18]:
```
delayed_prop['day'] = df.groupby(['DAY'])['DELAY_OR_NOT'].sum()/df.groupby(['D
AY'])['DELAY_OR_NOT'].count()
delayed_prop['day'].plot(kind="barh", title="Proportion of delayed flights by
 day of month")
```

Out[18]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2be863d79b0>
```

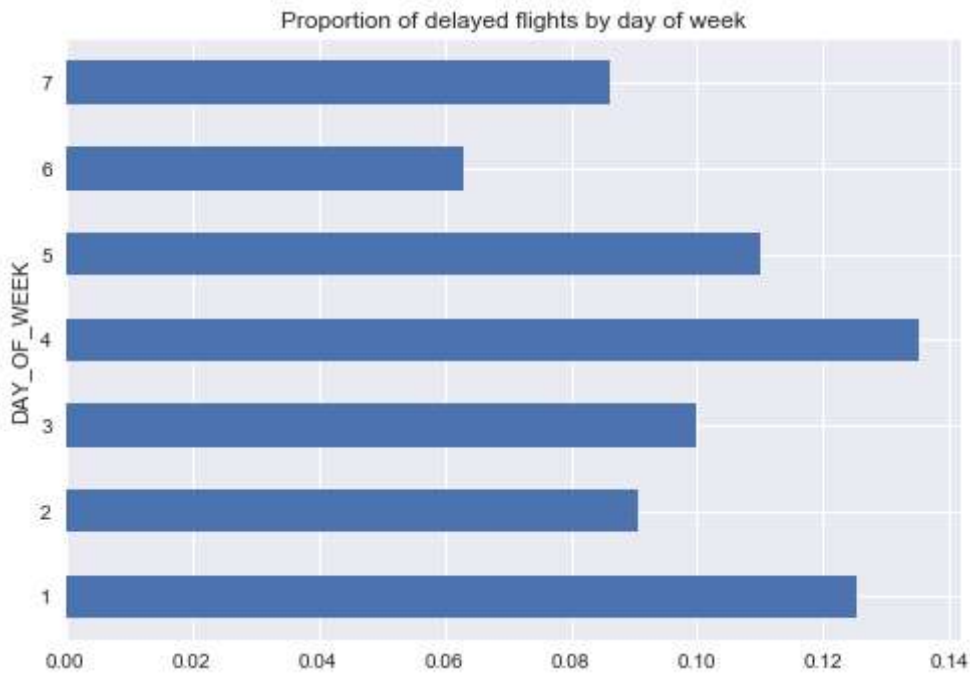
In [19]:
```
delayed_prop['day'].describe()
```

Out[19]:
```
count    31.000000
mean      0.101809
std       0.011077
min       0.082616
25%       0.094770
50%       0.100124
75%       0.108313
max       0.128818
Name: DELAY_OR_NOT, dtype: float64
```

The proportion of delayed flights stays close to the mean of 0.102 based on the day of the month.

In [20]:
```
delayed_prop['week'] = df.groupby(['DAY_OF_WEEK'])['DELAY_OR_NOT'].sum()/df.gr
oupby(['DAY_OF_WEEK'])['DELAY_OR_NOT'].count()
delayed_prop['week'].plot(kind="barh", title="Proportion of delayed flights by
 day of week")
```

Out[20]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2be866e3400>
```



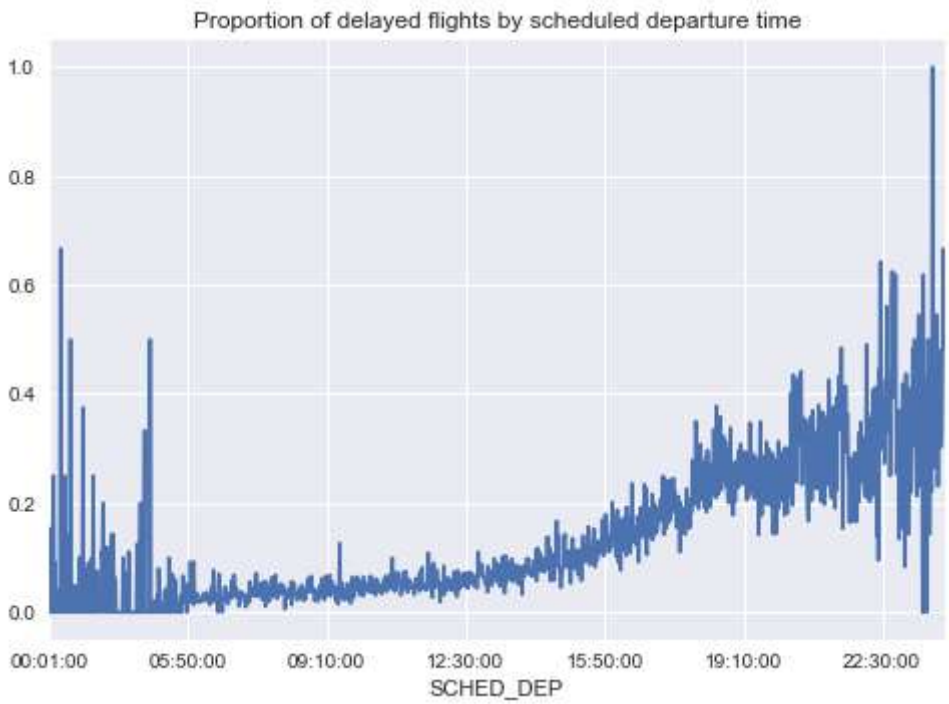
In [21]:
```
delayed_prop['week'].describe()
```

Out[21]:
```
count    7.000000
mean     0.101446
std      0.024466
min      0.063124
25%      0.088455
50%      0.099788
75%      0.117598
max      0.135107
Name: DELAY_OR_NOT, dtype: float64
```

The proportion of delayed flights varies slightly around the mean of 0.101 based on the day of the week, with a minimum on Saturday at 0.063 and a maximum on Thursday at 0.135.

In [22]:
```
delayed_prop['sched_dep'] = df.groupby(['SCHED_DEP'])
['DELAY_OR_NOT'].sum()/df.groupby(['SCHED_DEP'])['DELAY_OR_NOT'].count()
delayed_prop['sched_dep'].plot(title="Proportion of delayed flights by schedul
ed departure time")
```

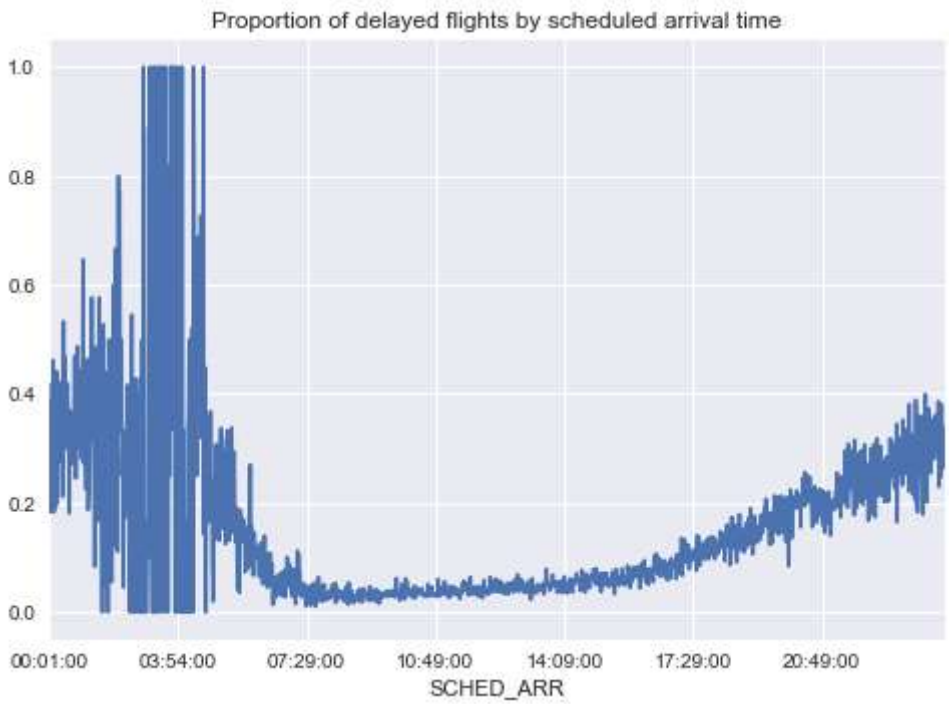
Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x2be86818358>



The general upward trend of this plot shows that the later in the day a plane is scheduled to depart, the more likely it is to be delayed.

In [23]:
```
delayed_prop['sched_dep'] = df.groupby(['SCHED_ARR'])
['DELAY_OR_NOT'].sum()/df.groupby(['SCHED_ARR'])['DELAY_OR_NOT'].count()
delayed_prop['sched_dep'].plot(title="Proportion of delayed flights by schedul
ed arrival time")
```

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x2be8619cf28>



This plot shows that there is a lot of variability in the proportion of delayed flights arriving very early in the day, but around 7:30am, the variation is significantly reduced, and the proportion gradually increases throughout the day.

Question 4 (20 pts):

Build a classification model that classifies delays according to DELAY_OR_NOT. This is an unbalanced dataset, thus consider the appropriate performance metric when reporting your results.

In [24]:
```
# drop non-predictors
df_pred = df.copy()
resps = ['ARRIVAL_DELAY', 'DEPARTURE_DELAY', 'ELAPSED_TIME', 'AIR_SYSTEM_DELA
Y', 'SECURITY_DELAY', 'AIRLINE_DELAY', 'LATE_AIRCRAFT_DELAY', 'WEATHER_DELAY']
tedious_preds = ['DATE', 'FLIGHT_NUMBER', 'TAIL_NUMBER']
non_preds = resps+tedious_preds
for non_pred in non_preds:
    df_pred = df_pred.drop(non_pred, axis=1)
df_pred.head()
```

Out[24]:

	MONTH	DAY	DAY_OF_WEEK	AIRLINE	ORIGIN_AIRPORT	DESTINATION_AIRPORT
0	9	19	6	AA	ORD	LGA
1	10	28	3	AA	11298	13342
2	8	19	3	MQ	XNA	ORD
3	12	1	2	WN	PHX	BWI
4	9	15	2	WN	MCI	DEN

In [25]:
```
print("Unique airports: ", df['ORIGIN_AIRPORT'].unique().size)
```

```
Unique airports:  628
```

There are too many unique airports, so let's keep the 50 airports with the highest numbers of flights originating from there, and convert all of the other airports to "Other".

In [26]:
```
# subset non-top airports into other
def other_airport(airport):
    if airport in list(topairport.values):
        return airport
    else:
        return "Other"

df_pred['ORIGIN_AIRPORT'] = df_pred['ORIGIN_AIRPORT'].apply(other_airport)
df_pred['DESTINATION_AIRPORT'] = df_pred['DESTINATION_AIRPORT'].apply(other_ai
rport)
df_pred.head()
```

Out[26]:

	MONTH	DAY	DAY_OF_WEEK	AIRLINE	ORIGIN_AIRPORT	DESTINATION_AIRPORT
0	9	19	6	AA	ORD	LGA
1	10	28	3	AA	Other	Other
2	8	19	3	MQ	Other	ORD
3	12	1	2	WN	PHX	BWI
4	9	15	2	WN	MCI	DEN

The datetime.time type columns aren't truly continuous variables because 23:59 is just as close to 0:00 as it is to 23:58, so we will convert them into categorical predictors. We likely won't gain much from adding 24*60 predictors, so lets one-hot encode them by hour instead.

In [27]:
```
# convert times to hours
def time_to_hr(hhmmss):
    [hours, minutes, seconds] = [int(x) for x in hhmmss.split(':')]
    return hours

df_pred['SCHED_DEP'] = df_pred['SCHED_DEP'].apply(time_to_hr)
df_pred['SCHED_ARR'] = df_pred['SCHED_ARR'].apply(time_to_hr)
df_pred.head()
```

Out[27]:

	MONTH	DAY	DAY_OF_WEEK	AIRLINE	ORIGIN_AIRPORT	DESTINATION_AIRPORT
0	9	19	6	AA	ORD	LGA
1	10	28	3	AA	Other	Other
2	8	19	3	MQ	Other	ORD
3	12	1	2	WN	PHX	BWI
4	9	15	2	WN	MCI	DEN

In [28]:
```
# one-hot encode categorical predictors
maybe_cat = ['MONTH', 'DAY', 'DAY_OF_WEEK', 'SCHED_DEP', 'SCHED_ARR']
categorical = ['AIRLINE', 'ORIGIN_AIRPORT', 'DESTINATION_AIRPORT']
df_dum = pd.get_dummies(df_pred, columns=categorical+maybe_cat, drop_first=Tru
e)
df_dum.head()
```

Out[28]:

	DISTANCE	SCHEDULED_TIME	DELAY_OR_NOT	AIRLINE_AS	AIRLINE_B6	AIRLINE_
0	733	135.0	0	0	0	0
1	853	149.0	0	0	0	0
2	522	108.0	0	0	0	0
3	1999	260.0	0	0	0	0
4	533	105.0	0	0	0	0

5 rows × 209 columns

In [29]:
```
# split data into train, test, and sub2 for later prediction
np.random.seed(9001)
msk = np.random.rand(len(df)) < 2/3
data_sub1 = df_dum[msk]
data_sub2 = df_dum[~msk]
msk2 = np.random.rand(len(data_sub1)) < 0.5
data_train = data_sub1[msk2]
data_test = data_sub1[~msk2]
```

In [30]:
```
# extract matrices from dataframe
dtrain_X = data_train.drop('DELAY_OR_NOT', axis=1)
dtest_X = data_test.drop('DELAY_OR_NOT', axis=1)

Xtrain = dtrain_X.values
Xtest = dtest_X.values
ytrain = data_train['DELAY_OR_NOT'].values
ytest = data_test['DELAY_OR_NOT'].values
```

In [31]:
```
# ovr logistic regression with l1 penalty and cross-validation
classif = {}
classif['logit_ovr'] = LogisticRegressionCV(penalty='l1', random_state=9001, m
ulti_class='ovr', solver='liblinear', scoring='roc_auc')
classif['logit_ovr'].fit(Xtrain, ytrain)
```

Out[31]:
```
LogisticRegressionCV(Cs=10, class_weight=None, cv=None, dual=False,
           fit_intercept=True, intercept_scaling=1.0, max_iter=100,
           multi_class='ovr', n_jobs=1, penalty='l1', random_state=9001,
           refit=True, scoring='roc_auc', solver='liblinear', tol=0.0001,
           verbose=0)
```

In [32]:
```
classif['logit_ovr_train'] = classif['logit_ovr'].predict(Xtrain)
print("Confusion matrix: \n", confusion_matrix(ytrain, classif['logit_ovr_trai
n']))
print("Train AUC score: ", metrics.roc_auc_score(ytrain, classif['logit_ovr_tr
ain']))
ovr_coeffs = pd.DataFrame(dict(feature=list(dtrain_X.columns), l1=classif['log
it_ovr'].coef_.flatten()))
ovr_coeffs_drop = ovr_coeffs.drop(ovr_coeffs[ovr_coeffs.l1 != 0].index)
ovr_coeffs_drop
```

```
Confusion matrix:
 [[238207   2603]
 [ 20547   6813]]
Train AUC score:  0.619101903062
```

Out[32]:

	feature	l1

Question 5 (5 pts):

Given your model, comment on the importance of factors as related to whether a flight is delayed.

Above is an attempted list of predictors with a coefficient of 0 after L1 penalty regularization. There don't appear to be any predictors with a coefficient of 0, indicating that my model is influenced by every factor I used:

- Month
- Day of month
- Day of week
- Airline
- Origin airport
- Destination airport
- Hour of scheduled departure time
- Hour of scheduled arrival time
- Distance
- Scheduled length of flight

In [33]:
```
# Question 6: evaluate your model on your test set
classif['logit_ovr_test'] = classif['logit_ovr'].predict(Xtest)
print("Confusion matrix: \n", confusion_matrix(ytest,
classif['logit_ovr_test']))
print("Test AUC score: ", metrics.roc_auc_score(ytest, classif['logit_ovr_tes
t']))
```

```
Confusion matrix:
 [[238336   2739]
 [ 20529   6837]]
Test AUC score:  0.61923697646
```

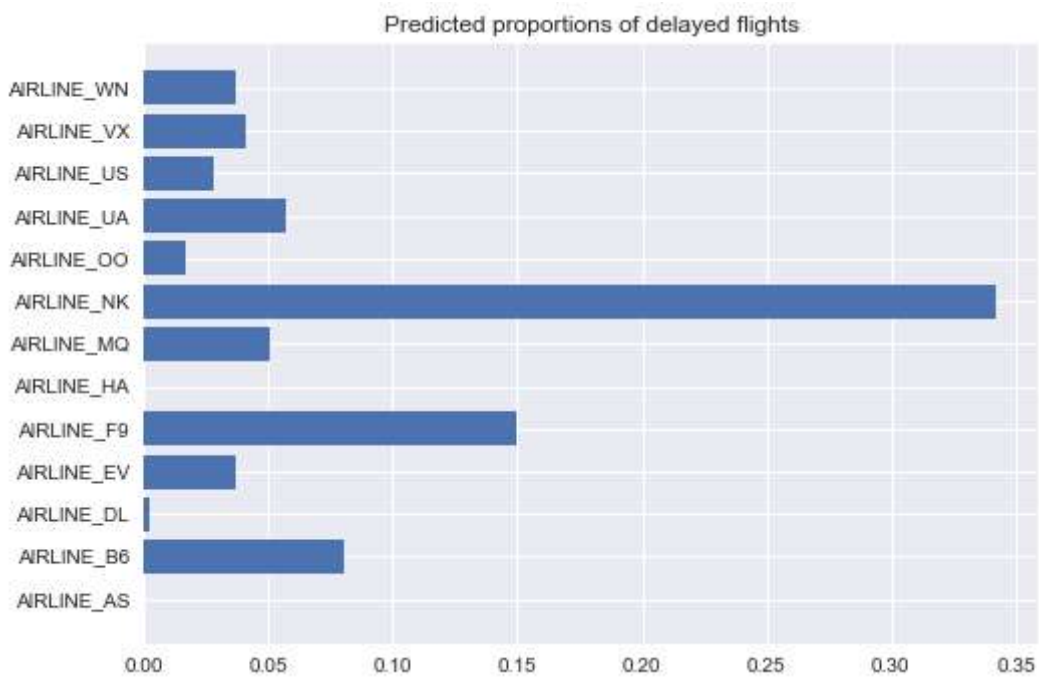
In [34]:
```
# extract data into matrices
dsub2_X = data_sub2.drop('DELAY_OR_NOT', axis=1)
Xsub2 = dsub2_X.values
ysub2 = data_sub2['DELAY_OR_NOT'].values
```

In [35]:
```
# make classifications
classif['logit_ovr_sub2'] = classif['logit_ovr'].predict(Xsub2)
dsub2_pred = dsub2_X.copy()
dsub2_pred['PRED_DELAY'] = classif['logit_ovr_sub2']
```

In [37]:
```
airline_cols = [col for col in dsub2_pred if col.startswith('AIRLINE')]
airline_props = []
for col in airline_cols:
    airline_props.append(dsub2_pred[dsub2_pred[col]==1]['PRED_DELAY'].sum()/ds
ub2_pred[dsub2_pred[col]==1]['PRED_DELAY'].count())

nums = np.arange(len(airline_cols))
plt.barh(nums, airline_props)
ticks = plt.yticks(nums,airline_cols)
plt.title("Predicted proportions of delayed flights")
```

Out[37]: <matplotlib.text.Text at 0x2be9361b630>



Airline NK is clearly predicted to have the highest proportion of delayed flights, with F9 and B6 coming in second and third.

In [38]:
```
# Question 7: build regression model to predict length of delay (log scale)
dfd = dataframe.copy()
dfd = dfd[dfd['ARRIVAL_DELAY']>=15]
dfd = dfd.reset_index(drop=True)
dfd.head()
```

Out[38]:

	DATE	MONTH	DAY	DAY_OF_WEEK	AIRLINE	FLIGHT_NUMBER	TAIL_NUMBER	OR
0	2015-01-04	1	4	7	WN	958	N211WN	PH
1	2015-07-22	7	22	3	EV	2682	N678AE	BR
2	2015-03-23	3	23	1	OO	4629	N554CA	LA
3	2015-03-12	3	12	4	US	2146	N951UW	LG
4	2015-04-27	4	27	1	EV	2557	N673AE	SH

5 rows × 21 columns

In [39]:
```
# drop non-predictors
dfd_pred = dfd.copy()
non_preds = ['DEPARTURE_DELAY','DATE', 'FLIGHT_NUMBER', 'TAIL_NUMBER', 'ELAPSE
D_TIME', 'AIR_SYSTEM_DELAY', 'SECURITY_DELAY', 'AIRLINE_DELAY', 'LATE_AIRCRAFT
_DELAY', 'WEATHER_DELAY']
for non_pred in non_preds:
    dfd_pred = dfd_pred.drop(non_pred, axis=1)

dfd_pred.head()
```

Out[39]:

	MONTH	DAY	DAY_OF_WEEK	AIRLINE	ORIGIN_AIRPORT	DESTINATION_AIRPORT
0	1	4	7	WN	PHL	ATL
1	7	22	3	EV	BRO	DFW
2	3	23	1	OO	LAS	SEA
3	3	12	4	US	LGA	BOS
4	4	27	1	EV	SHV	DFW

In [40]:
```
# subset non-top airports into other
dfd_pred['ORIGIN_AIRPORT'] = dfd_pred['ORIGIN_AIRPORT'].apply(other_airport)
dfd_pred['DESTINATION_AIRPORT'] = dfd_pred['DESTINATION_AIRPORT'].apply(other_
airport)
dfd_pred.head()
```

Out[40]:

	MONTH	DAY	DAY_OF_WEEK	AIRLINE	ORIGIN_AIRPORT	DESTINATION_AIRPORT
0	1	4	7	WN	PHL	ATL
1	7	22	3	EV	Other	DFW
2	3	23	1	OO	LAS	SEA
3	3	12	4	US	LGA	BOS
4	4	27	1	EV	Other	DFW

In [41]:
```
# convert time to hours
dfd_pred['SCHED_DEP'] = dfd_pred['SCHED_DEP'].apply(time_to_hr)
dfd_pred['SCHED_ARR'] = dfd_pred['SCHED_ARR'].apply(time_to_hr)

# convert arrival_delay to logarithmic scale
dfd_pred['ARRIVAL_DELAY'] = dfd_pred['ARRIVAL_DELAY'].apply(math.log)
dfd_pred.head()
```

Out[41]:

	MONTH	DAY	DAY_OF_WEEK	AIRLINE	ORIGIN_AIRPORT	DESTINATION_AIRPORT
0	1	4	7	WN	PHL	ATL
1	7	22	3	EV	Other	DFW
2	3	23	1	OO	LAS	SEA
3	3	12	4	US	LGA	BOS
4	4	27	1	EV	Other	DFW

In [42]:
```
# one-hot encode categorical predictors
cats = ['MONTH', 'DAY', 'DAY_OF_WEEK', 'AIRLINE', 'ORIGIN_AIRPORT', 'DESTINATI
ON_AIRPORT', 'SCHED_DEP', 'SCHED_ARR']
dfd_dum = pd.get_dummies(dfd_pred, columns=cats, drop_first=True)
dfd_dum.head()
```

Out[42]:

	ARRIVAL_DELAY	DISTANCE	SCHEDULED_TIME	MONTH_2	MONTH_3	MONTH_4	M
0	4.882802	666	135.0	0	0	0	0
1	4.584967	482	107.0	0	0	0	0
2	4.852030	867	167.0	0	1	0	0
3	3.637586	184	63.0	0	1	0	0
4	4.997212	190	64.0	0	0	1	0

5 rows × 209 columns

In [45]:
```
# split data into train and test
np.random.seed(9001)
msk = np.random.rand(len(dfd_dum)) < 0.5
dfd_train = dfd_dum[msk]
dfd_test = dfd_dum[~msk]
```

In [46]:
```
dfd_train.head()
```

Out[46]:

	ARRIVAL_DELAY	DISTANCE	SCHEDULED_TIME	MONTH_2	MONTH_3	MONTH_4	M
0	4.882802	666	135.0	0	0	0	0
5	2.890372	654	128.0	0	0	0	0
9	3.496508	777	145.0	0	1	0	0
12	3.761200	301	89.0	0	0	0	0
13	3.178054	862	135.0	0	0	0	0

5 rows × 209 columns

In [47]:
```
# extract matrices from dataframe
dfdtrain_X = dfd_train.drop('ARRIVAL_DELAY', axis=1)
dfdtest_X = dfd_test.drop('ARRIVAL_DELAY', axis=1)

dfd = {}
dfd['Xtrain'] = dfdtrain_X.values
dfd['Xtest'] = dfdtest_X.values
dfd['ytrain'] = dfd_train['ARRIVAL_DELAY'].values
dfd['ytest'] = dfd_test['ARRIVAL_DELAY'].values
```

In [48]:
```
ols = LinearRegression(fit_intercept=True)
ols.fit(dfd['Xtrain'], dfd['ytrain'])

print('OLS Train Score', ols.score(dfd['Xtrain'], dfd['ytrain']))
print('OLS Test Score', ols.score(dfd['Xtest'], dfd['ytest']))
```

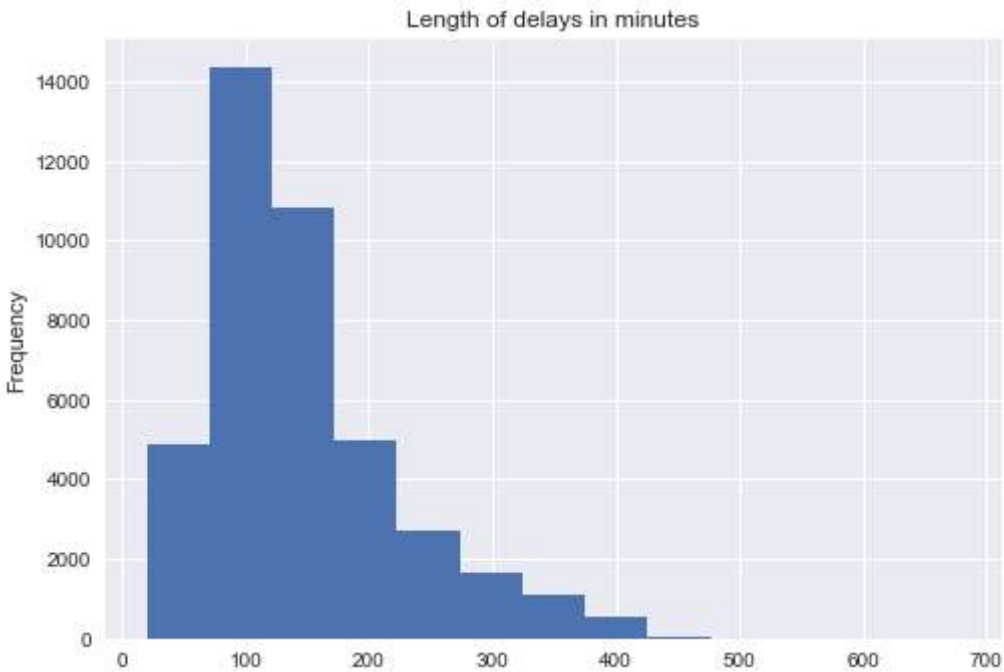
```
OLS Train Score 0.0552652626968
OLS Test Score 0.0478795659314
```

Question 8 (20 pts):

Write a report (in the last markdown cell in your notebook with your findings (without code)). Describe the main design decisions you have made with justifications. Clearly explain your methodology and results. This should not be more than 300 words. You may use up to 5 diagrams.

In [62]:
```
dfd_train['SCHEDULED_TIME'].plot.hist(title='Length of delays in minutes', bin
s=13)
```

Out[62]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2bee210ad68>
```



Predictors: I chose not to use data about:

- flight number
- tail number
- origin/destination airports aside from the top 50 airports with the most flights originating from there
- minute of scheduled arrival/departure time

because I thought they wouldn't be useful enough to overcome the computational complexity they would add.

Except for distance and scheduled time, I one-hot encoded all of the other predictors because they were categorical.

Classification Model: I chose to use logistic regression for my classification model because I wanted to be able to use regularization with an L1 penalty. LASSO regularization penalizes coefficients in such a way that some of the model parameters are estimated to be zero, so I was hoping to use this as a method of variable selection. But as it turned out, none of the estimated coefficients were zero.

I used the LogisticRegressionCV function to select the optimal regularization strength C with its default settings, with 3-fold cross-validation. I changed the scoring to AUC instead of accuracy because the dataset only contains a small number of delayed flights compared to the number of flights that were on-time, and it's more important to correctly identify which flights are delayed.

My model's AUC on the test set was 0.619. I have 208 predictors, so I could have used PCA to try to reduce the dimensionality, but AUC didn't improve by much, and PCA significantly reduces the interpretability of the coefficients since they no longer correspond directly to a predictor.

Regression Model: I chose to use multiple linear regression for my regression model because it is simple and easy to interpret. As shown in the plot above, the delay length is somewhat right-skewed, but it seems reasonable to assume that noise is normally distributed. I could have added polynomial and interaction terms, but I already have so many predictors that I was concerned about overfitting.

My model's R^2 score on the test set was 0.048.