In [70]:

```
import glob
import math
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from mpl_toolkits import mplot3d
from mpl_toolkits.mplot3d import Axes3D
import matplotlib.patches as mpatches
```

In [19]:

```
#Zipline Data Challenge: An Exploratory Analysis
#Conner Reinhardt

# Get data file names
path ='/Users/connerreinhardt/Google Drive/data_scientist_take-home'
filenames = glob.glob(path + "/*.csv")
flightfiles = filenames[:-1]
summaryfile = filenames[len(filenames)-1]

flight_summary = pd.read_csv(summaryfile)

# Gather all detailed flight data and classify them
dfs = []
for flightfile in flightfiles:
    addflight = pd.read_csv(flightfile)
    addflight['flight_number'] = flightfile[-9:-4]
    dfs.append(addflight)

# Concatenate all detail flight data into one DataFrame
flight_detail = pd.concat(dfs, ignore_index=True)
    #print(big_frame[big_frame['flight_number']=='16962'])

# Create summary file DataFrame
```

In [ ]:

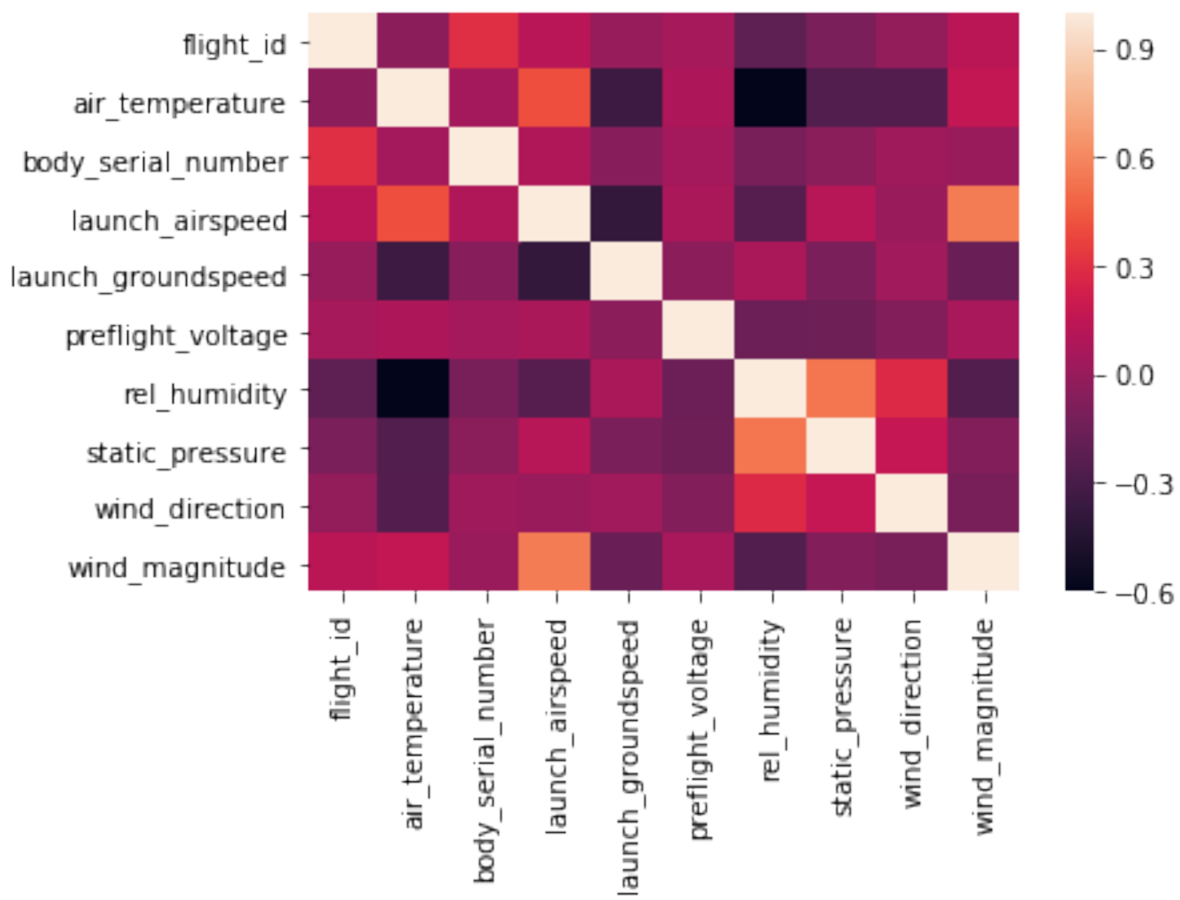
```

```

In [37]:

```
%matplotlib inline
# calculate the correlation matrix
corr = flight_summary.corr()

# plot the heatmap
sns.heatmap(corr,
        xticklabels=corr.columns,
        yticklabels=corr.columns)
```

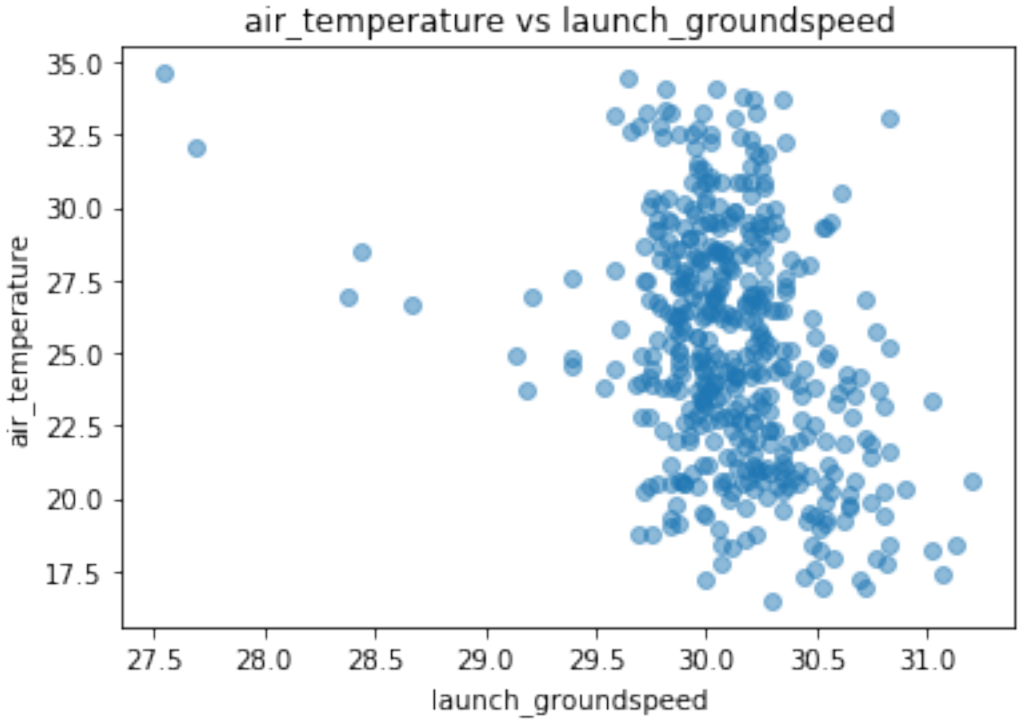
Out[37]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x112268e80>
```



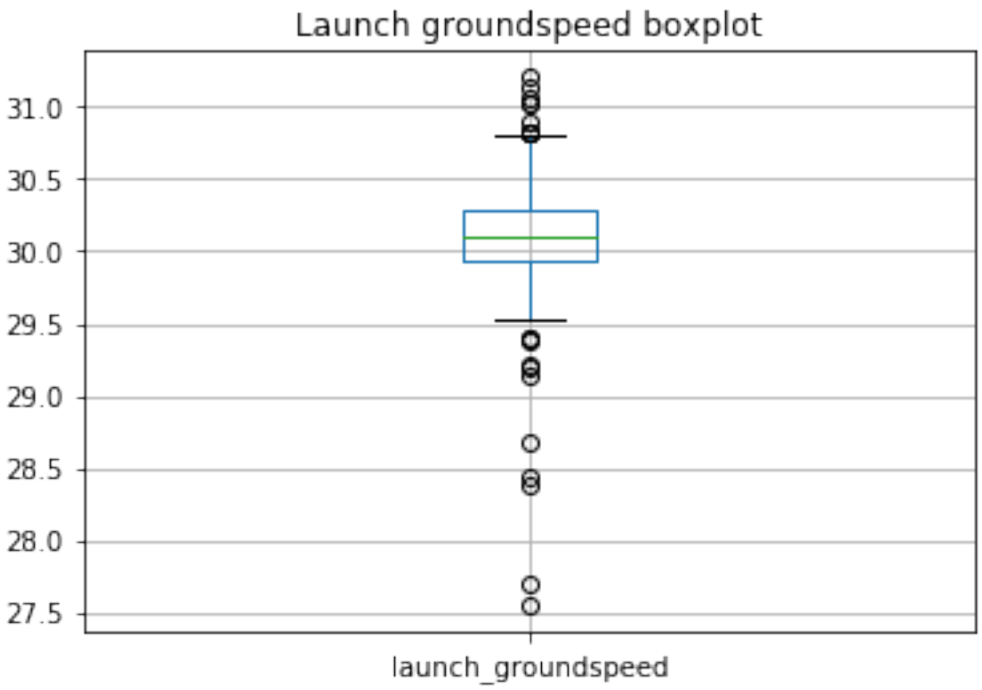
In [21]:

```
# In the above we see a noteable negative correlations between launch_groundspee
d and air_temperature
# Let's start out exploratory analysis but observing this correlation
plt.scatter(flight_summary['launch_groundspeed'], flight_summary['air_temperatur
e'], alpha=0.5)
plt.title('air_temperature vs launch_groundspeed')
plt.xlabel('launch_groundspeed')
plt.ylabel('air_temperature')
plt.show()
```



In [22]:

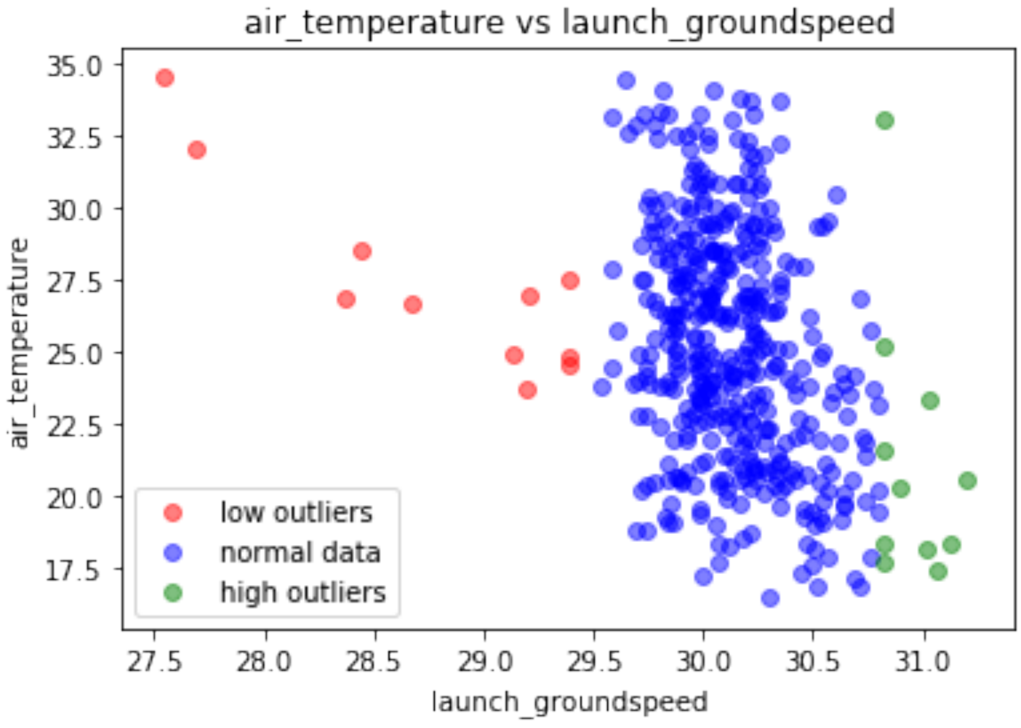
```
# in the plot above we can see how the negative correlation may exist between th
ese variables is contigent
# on a small subset of flights that appear to have super low groundspeed
flight_summary.boxplot(column='launch_groundspeed')
plt.title('Launch groundspeed boxplot')
plt.show()
print(flight_summary['launch_groundspeed'].describe())
```




```
count    447.000000
mean      30.112178
std        0.371296
min       27.548899
25%       29.926867
50%       30.097641
75%       30.282600
max       31.205293
Name: launch_groundspeed, dtype: float64
```

In [23]:

```
# From above we see an IQR of 0.356, so 1.5*IQR + 75th quantile is 30.816 and 25
th quantile - 1.5*IQR is 29.393
# We can visualize them below in red on the scatterplot and it becomes very appa
rent that there are only a few outlier
# flights that lead us to see a negative correlation between air_temperature and
ground speed

lowgroundspeed = flight_summary[flight_summary['launch_groundspeed']<=29.5]
normalgroundspeed = flight_summary[(flight_summary['launch_groundspeed']>29.393)
                                   &(flight_summary['launch_groundspeed']<=30.81
6)]
highgroundspeed = flight_summary[flight_summary['launch_groundspeed']>30.816]

plt.scatter(lowgroundspeed['launch_groundspeed'], lowgroundspeed['air_temperatur
e'], color='red', alpha=0.5)
plt.scatter(normalgroundspeed['launch_groundspeed'], normalgroundspeed['air_temp
erature'], color='blue', alpha=0.5)
plt.scatter(highgroundspeed['launch_groundspeed'], highgroundspeed['air_temperat
ure'], color='green', alpha=0.5)
plt.title('air_temperature vs launch_groundspeed')
plt.xlabel('launch_groundspeed')
plt.ylabel('air_temperature')
plt.gca().legend(('low outliers','normal data','high outliers'))
plt.show()
```



In [24]:

```
# Since we're examining ground speed in summary, lets ensure that there is a col
umn in the flight details
# Here we use pythagoreans principle to turn the vector data into scalars indepe
ndent of direction
# (ground coordinates only) - "velocity_ground_mps"
flight_detail['velocity_ground_mps'] = np.sqrt((flight_detail['velocity_ned_mps[
0]'])**2
                                              + (flight_detail['velocity_ned_mps[1]
'])**2)
```

In [ ]:

```

```

In [25]:

```
# We can see that there are 11 flights that are outliers with low groundspeed
print(lowgroundspeed[['flight_id','launch_groundspeed']])
```

```
    flight_id  launch_groundspeed
29      17016           29.133639
30      17019           29.392909
31      17020           29.391953
32      17022           29.190197
82      17122           29.387475
83      17123           29.209283
84      17124           28.375102
85      17125           28.670392
86      17126           28.441710
87      17128           27.548899
88      17130           27.692286
```

In [26]:

```
# And if we want to look at the flight with the median groundspeed we realize it
s flight 17151
print(flight_summary[flight_summary['launch_groundspeed']==30.09764148541062])
```

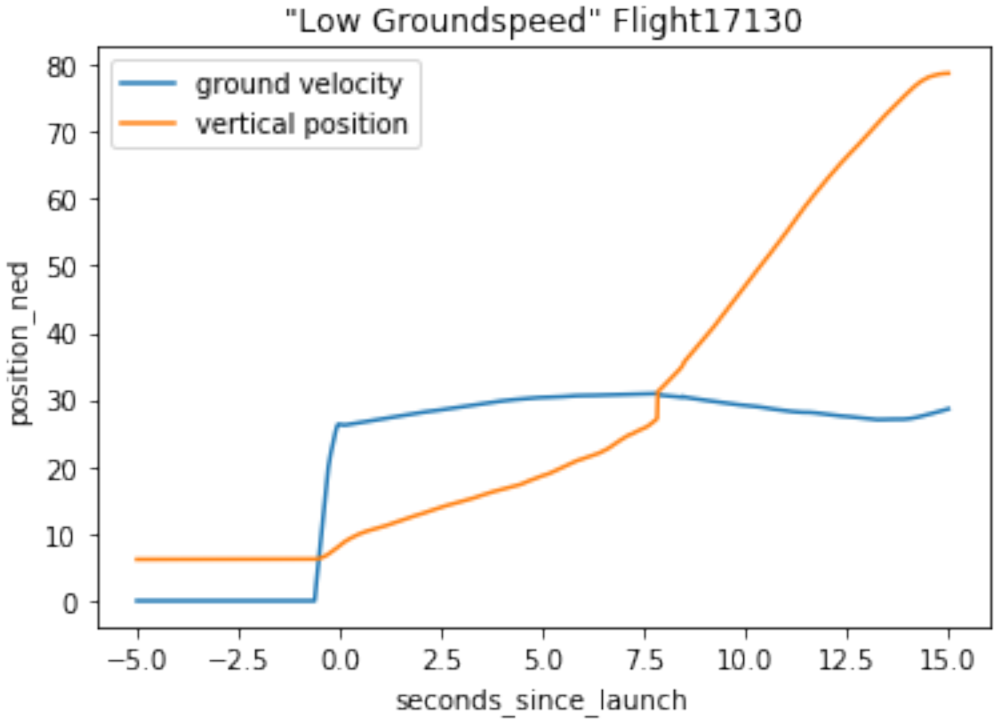
```
     flight_id  air_temperature battery_serial_number  body_serial_n
umber  \
100      17151            29.65       15SPJJJ10022048  5773501328073
48254

         commit  launch_airspeed  launch_groundspeed         launch_
timestamp  \
100  5c504d9a16        33.814453           30.097641  2018-09-12 12:
01:31 CAT

     preflight_voltage  rel_humidity  static_pressure  wind_directio
n  \
100          32.193016     60.474992      80474.68524      -39.40311
9

     wind_magnitude wing_serial_number
100        3.222529    15SPJJJ09052035
```

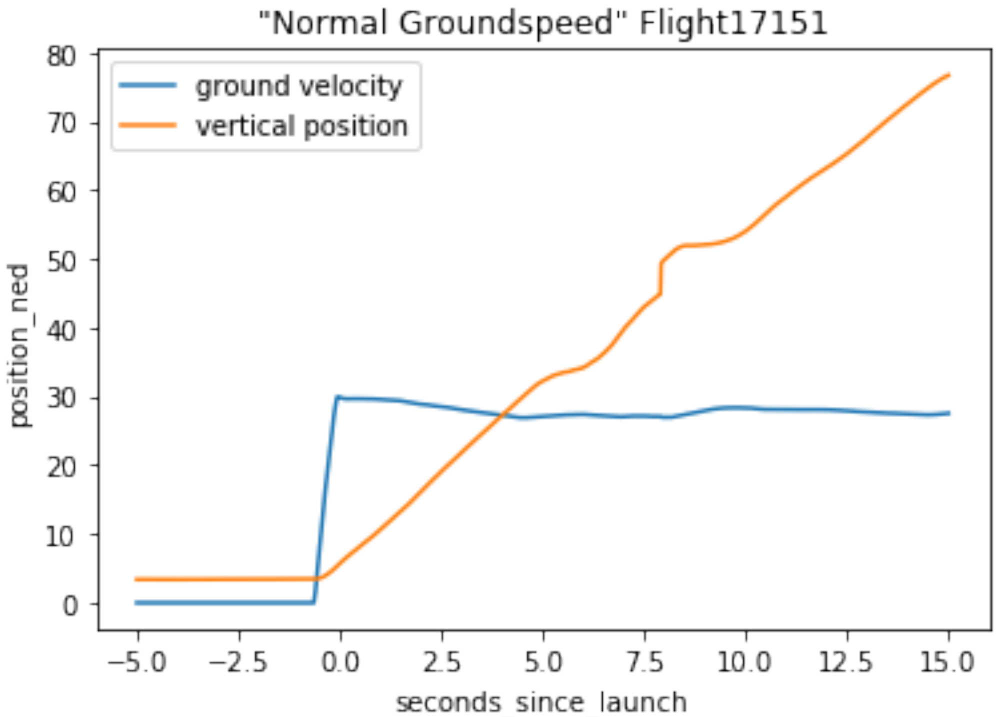
In [27]:

```
# Let's examine one of flights, 17130, which has the lowest groundspeed of them
all
flight17130 = flight_detail[flight_detail['flight_number']=='17130']
# We can compare it to flight 17151, which has the median "normal" groundspeed a
s a control
flight17151 = flight_detail[flight_detail['flight_number']=='17151']
```

In [28]:

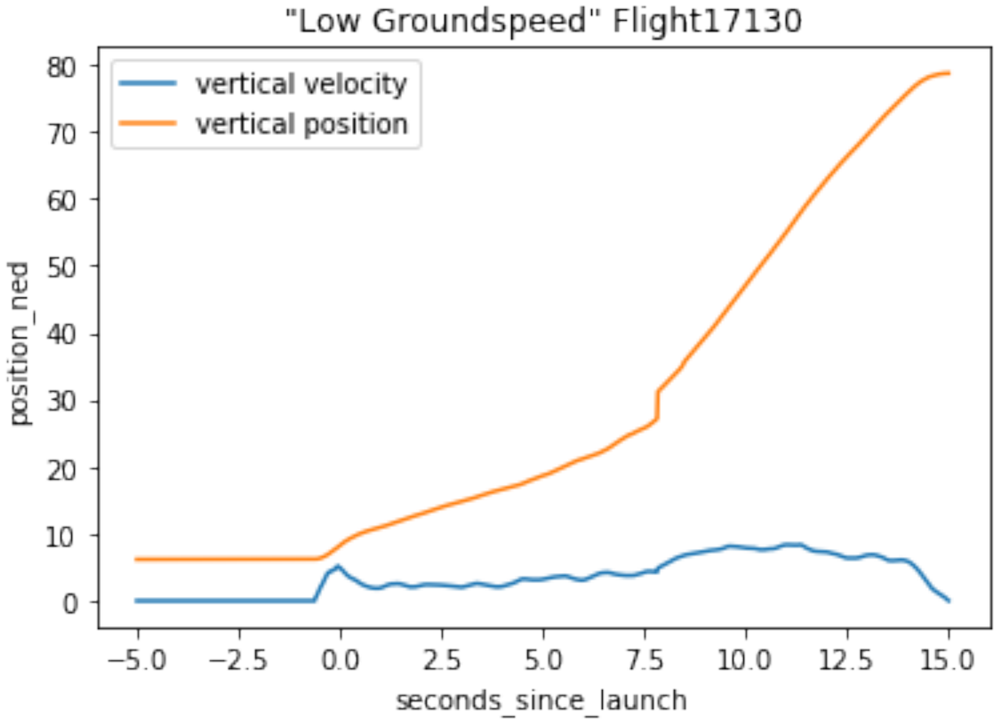
```
#Below we will plot both flights' groundspeeds against their vertical ascent to
try to uncover the differences
plt.plot(flight17130['seconds_since_launch'], flight17130['velocity_ground_mps']
,
         flight17130['seconds_since_launch'], -flight17130['position_ned_m[2]'])
plt.gca().legend(('ground velocity','vertical position'))
plt.title('"Low Groundspeed" Flight17130')
plt.xlabel('seconds_since_launch')
plt.ylabel('position_ned')
plt.show()

plt.plot(flight17151['seconds_since_launch'], flight17151['velocity_ground_mps']
,
         flight17151['seconds_since_launch'], -flight17151['position_ned_m[2]'])
plt.gca().legend(('ground velocity','vertical position'))
plt.title('"Normal Groundspeed" Flight17151')
plt.xlabel('seconds_since_launch')
plt.ylabel('position_ned')
plt.show()
```


"Low Groundspeed" Flight17130
ground velocity
vertical position
position_ned
seconds_since_launch
0
10
20
30
40
50
60
70
80
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
12.5
15.0

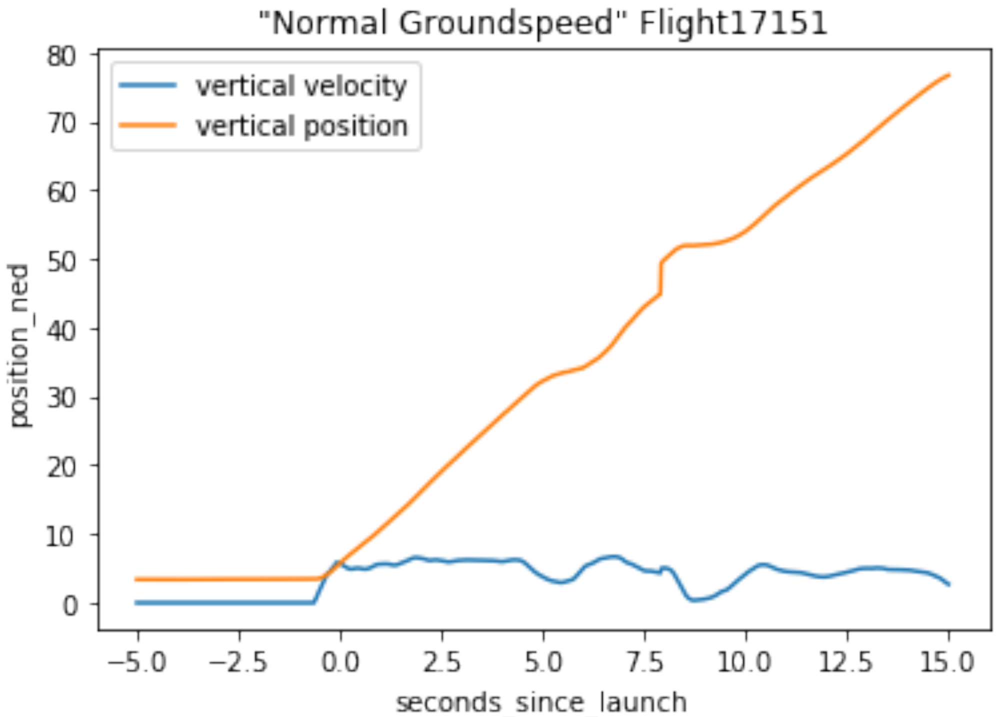

"Normal Groundspeed" Flight17151
ground velocity
vertical position
position_ned
seconds_since_launch
0
10
20
30
40
50
60
70
80
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
12.5
15.0

In [29]:

```
# interestingly we see above two strange occurences @ 7.5s mark
# the normal flight appeared to take off in a mostly uniform ascent, with a blip
where the altitude jumped up
# and the low groundspeed flight seemingly also jumped at a point, going from a
slow ascent to a much faster one
# to examine the different jumps in the elevation above, lets repear the graphs
and see if their vertcal
# airspeeds match these jumps in elevation
plt.plot(flight17130['seconds_since_launch'], -flight17130['velocity_ned_mps[2]'
],
         flight17130['seconds_since_launch'], -flight17130['position_ned_m[2]'])
plt.gca().legend(('vertical velocity','vertical position'))
plt.title('"Low Groundspeed" Flight17130')
plt.xlabel('seconds_since_launch')
plt.ylabel('position_ned')
plt.show()

plt.plot(flight17151['seconds_since_launch'], -flight17151['velocity_ned_mps[2]'
],
         flight17151['seconds_since_launch'], -flight17151['position_ned_m[2]'])
plt.gca().legend(('vertical velocity','vertical position'))
plt.title('"Normal Groundspeed" Flight17151')
plt.xlabel('seconds_since_launch')
plt.ylabel('position_ned')
plt.show()
```



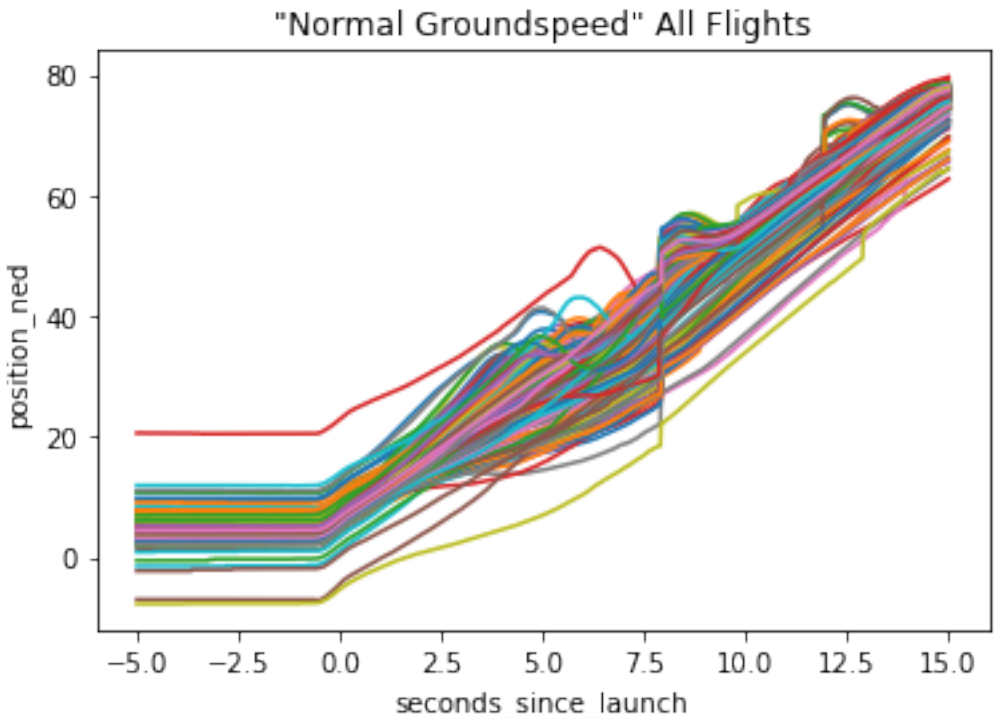
"Low Groundspeed" Flight17130
vertical velocity
vertical position
position_ned
seconds_since_launch



"Normal Groundspeed" Flight17151
vertical velocity
vertical position
position_ned
seconds_since_launch

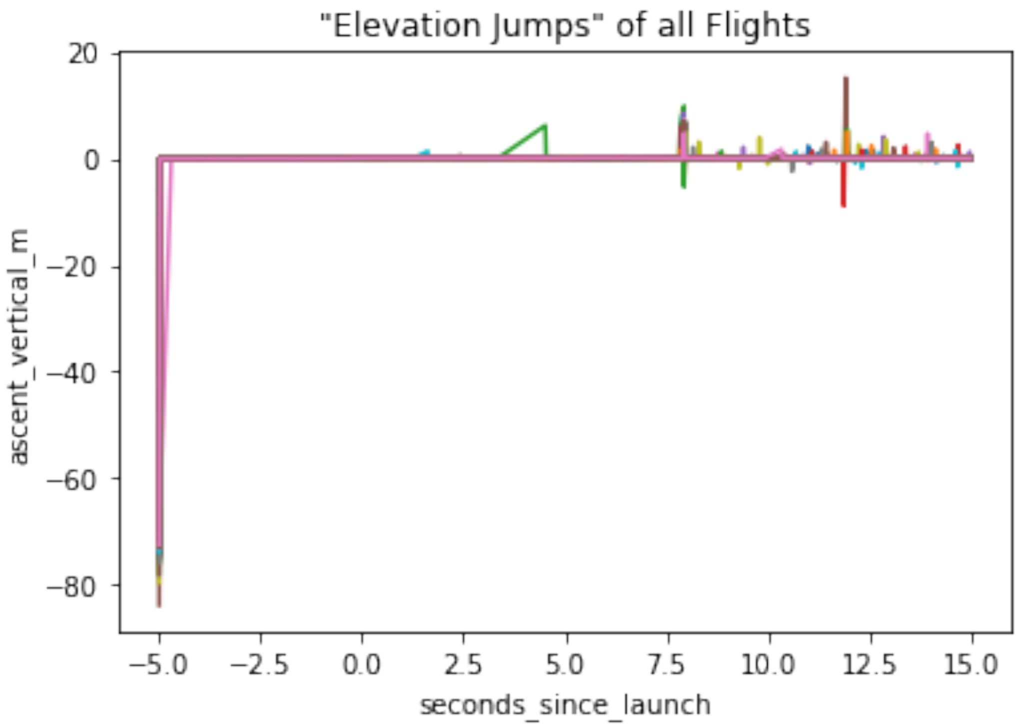
In [30]:

```
# though we would expect to see a super high vertical velocity for both flights around the 7.5s mark
# we end up not seeing a velocity that corresponds to the change in altitude
# this indicates that the altitude change may in fact be due to bad data
# in order to verify this claim, lets first plot all of the data for vertical position of every flight and overlay it
flight_numbers = flight_summary['flight_id']
for flight in flight_numbers:
    currentflight = flight_detail[flight_detail['flight_number']==str(flight)]
    plt.plot(currentflight['seconds_since_launch'], -currentflight['position_ned_m[2]'])
plt.title('"Normal Groundspeed" All Flights')
plt.xlabel('seconds_since_launch')
plt.ylabel('position_ned')
plt.show()
```



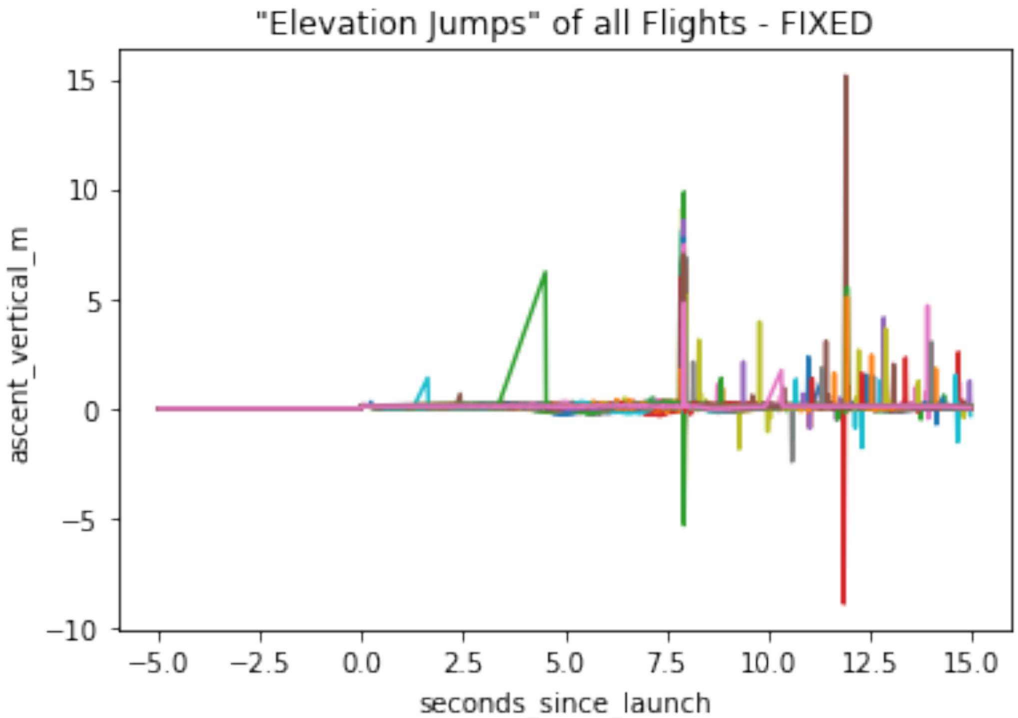
In [31]:

```
# what we see in the above chart is a very clear pattern of questionable elevati
on data around the 7.5s mark
# we also see some questionable jumps around what appears to be 12s, 12.5s, and
13s, though these are not nearly common
# to investigate, lets create a column that details the difference in postition
between two consecutive sensor readings
# "ascent_vertical_m"
flight_detail['ascent_vertical_m'] = -flight_detail['position_ned_m[2]'].diff()
# print(flight_detail.head())
for flight in flight_numbers:
    currentflight = flight_detail[flight_detail['flight_number']==str(flight)]
    plt.plot(currentflight['seconds_since_launch'], currentflight['ascent_vertic
al_m'])
plt.title('"Elevation Jumps" of all Flights')
plt.xlabel('seconds_since_launch')
plt.ylabel('ascent_vertical_m')
plt.show()
```



In [33]:

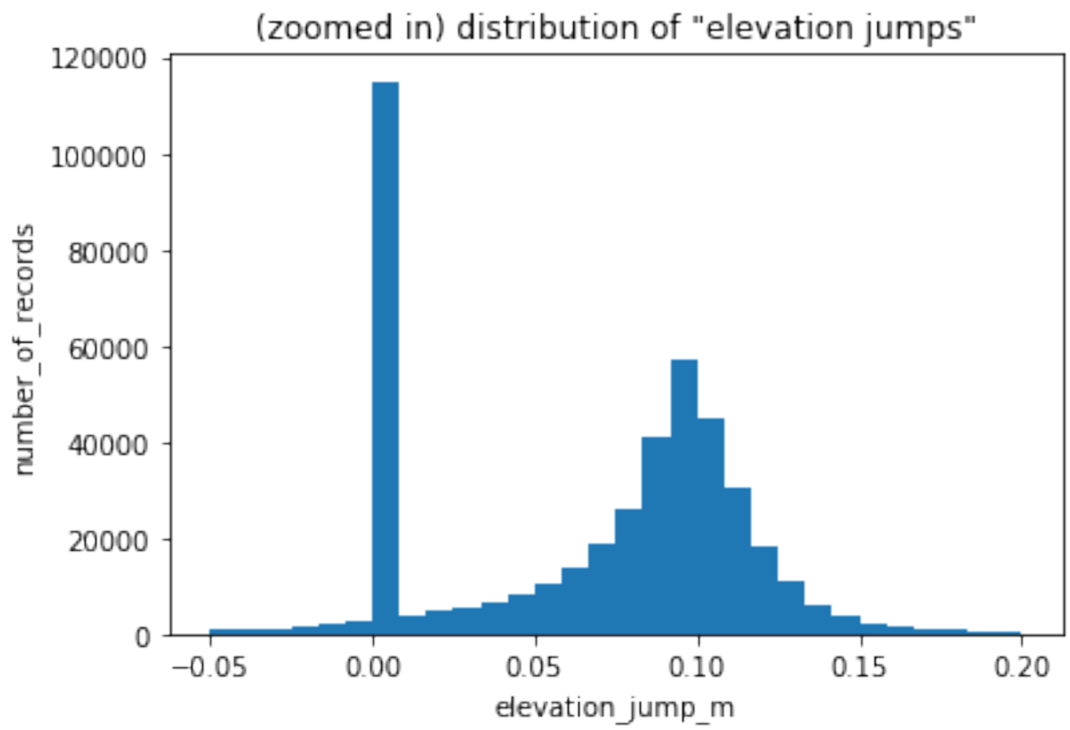
```
# NOTE: because of the way the dataframe concats all flights, we see a massive d
ifference at the -5s mark since we
# jump from one flight to a new one
# below we will get rid of this
flight_detail.loc[flight_detail['seconds_since_launch']<0, 'ascent_vertical_m']
= 0
for flight in flight_numbers:
    currentflight = flight_detail[flight_detail['flight_number']==str(flight)]
    plt.plot(currentflight['seconds_since_launch'], currentflight['ascent_vertic
al_m'])
plt.title('"Elevation Jumps" of all Flights - FIXED')
plt.xlabel('seconds_since_launch')
plt.ylabel('ascent_vertical_m')
plt.show()
```



In [41]:

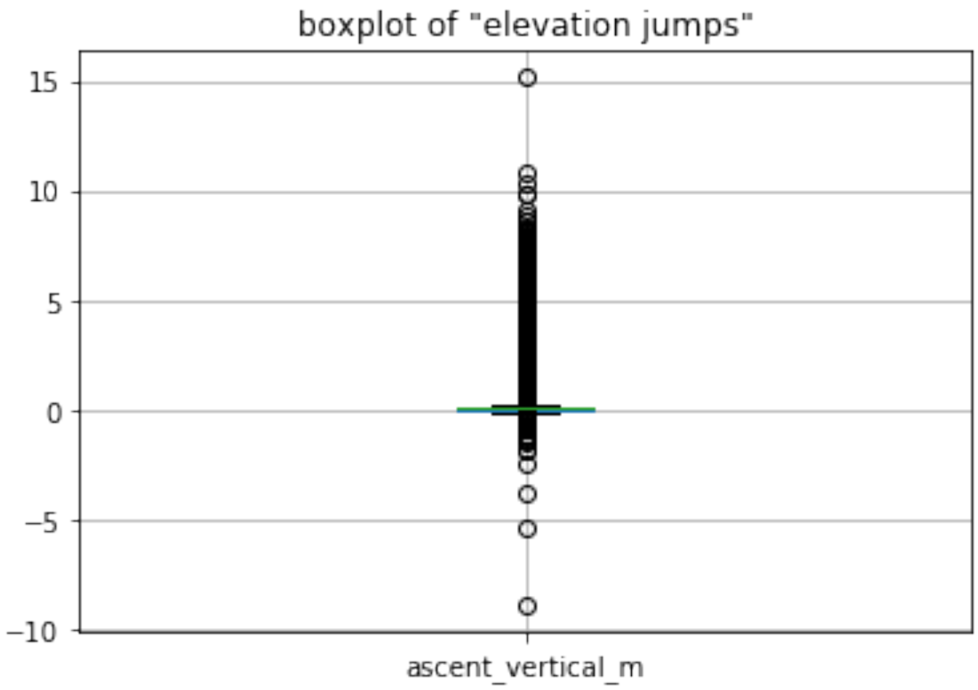
```
# Now that all that's left is true elevation difference data, we should analyze the distribution of the "elevation jumps"
# which jumps are normal and which may indicate bad data?
print(flight_detail['ascent_vertical_m'].describe())
plt.hist(flight_detail['ascent_vertical_m'], bins=30, range=(-.05,.2))
plt.title('(zoomed in) distribution of "elevation jumps"')
plt.xlabel('elevation_jump_m')
plt.ylabel('number_of_records')
plt.show()
```

```
count    447276.000000
mean          0.069634
std           0.168742
min          -8.897973
25%           0.000000
50%           0.082765
75%           0.101778
max          15.159457
Name: ascent_vertical_m, dtype: float64
```



In [39]:

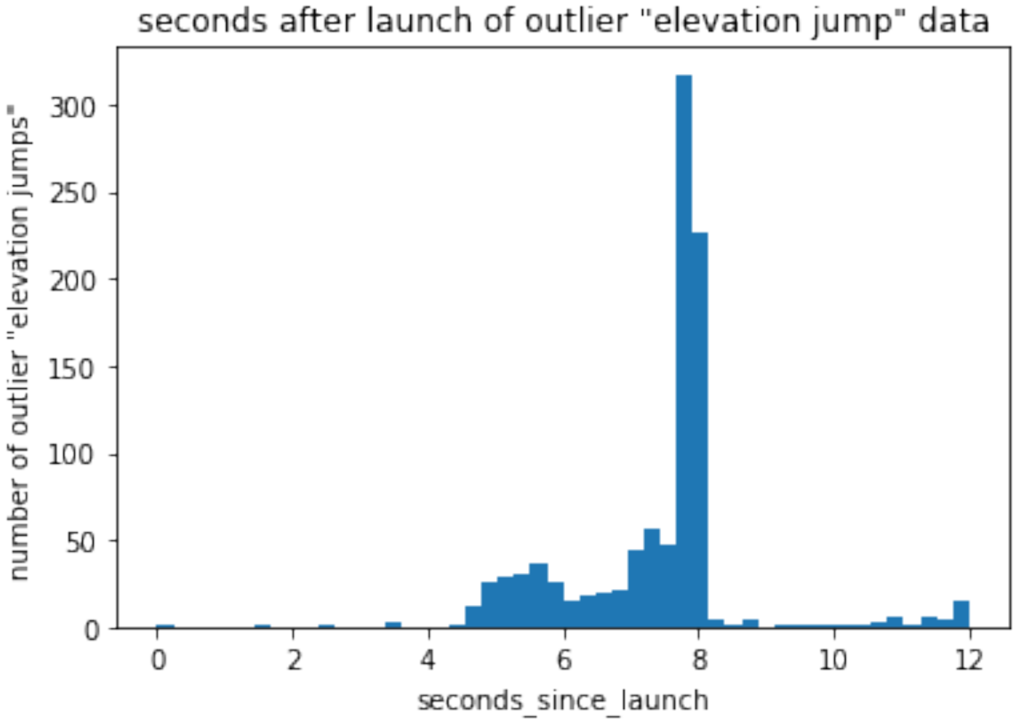
```
# above we see the summary statistics and the distribution of various jumps in e
levation appear to be normally
# distributed around a mean of 0.069m between readings (with 0 as an obvious spi
ke for when the drone has not taken off)
flight_detail.boxplot(column='ascent_vertical_m')
plt.title('boxplot of "elevation jumps"')
plt.show()
```



In [42]:

```
# when we do a boxplot, however, we quickly see that there are some VERY apparen
t outliers that extend WAY beyond
# the 1.5*IQR (0.152m) above and below the 25/75th (0/0.101) percentiles
# anything above 0.253m or below -0.152m would be technically considered an outl
ier (or non-plausible value in this case)
# below we will identify the outlier readings per flight based on these definiti
ons and explore WHEN they occur

# define if the ascent data is an outlier or not
flight_detail['outlier_ascent'] = (flight_detail['ascent_vertical_m']>0.253)|(fl
ight_detail['ascent_vertical_m']<-0.152)
outlierdata = flight_detail[flight_detail['outlier_ascent']]

print(outlierdata['seconds_since_launch'].describe())
plt.hist(outlierdata['seconds_since_launch'], bins=50, range=(0,12))
plt.title('seconds after launch of outlier "elevation jump" data')
plt.xlabel('seconds_since_launch')
plt.ylabel('number of outlier "elevation jumps"')
plt.show()
```

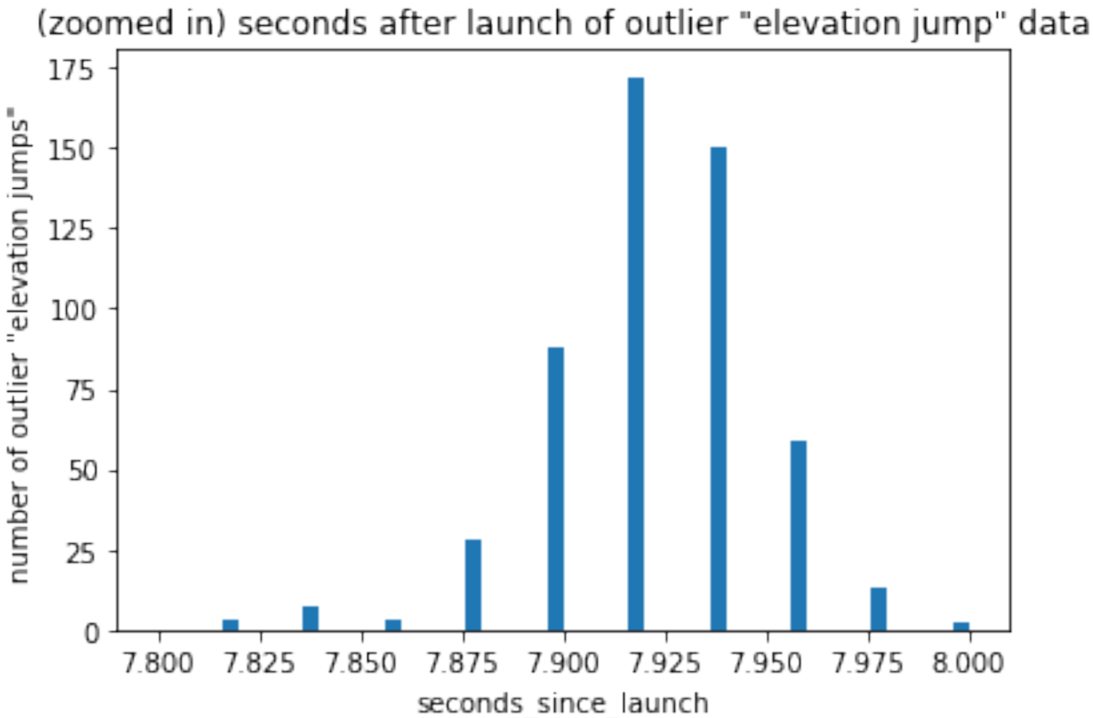
```
count    1039.000000
mean        7.728528
std         1.846161
min         0.219940
25%         7.117755
50%         7.897620
75%         7.937570
max        14.995430
Name: seconds_since_launch, dtype: float64
```



In [44]:

```
# And if we zoom in more we can see that the data is generally quite focused aro
und a single time interval
print(outlierdata['seconds_since_launch'].mode())
plt.hist(outlierdata['seconds_since_launch'], bins=50, range=(7.8,8))
plt.title('(zoomed in) seconds after launch of outlier "elevation jump" data')
plt.xlabel('seconds_since_launch')
plt.ylabel('number of outlier "elevation jumps"')
plt.show()
```

```
0    7.91759
1    7.93756
dtype: float64
```



In [45]:

```
# We see that over half of the outlier data lies between 7.8s and 8s into the fl
ight, so lets assume that these are
# due to a similar equipment malfunction and classify outliers accordingly
print("Total elevation jump outliers:",len(outlierdata['seconds_since_launch']))
print("Elevation jump outliers in 7.8s-8s interval:",len(outlierdata[outlierdata
['seconds_since_launch']<=8])
     -len(outlierdata[outlierdata['seconds_since_launch']<=7.8]))

# We can isolate outlier readings ONLY during this interval
flight_detail['outlier_ascent_interval'] = ((flight_detail['outlier_ascent'])&
                                            (flight_detail['seconds_since_launch
']<=8)
                                            &(flight_detail['seconds_since_launc
h']>=7.8))
```

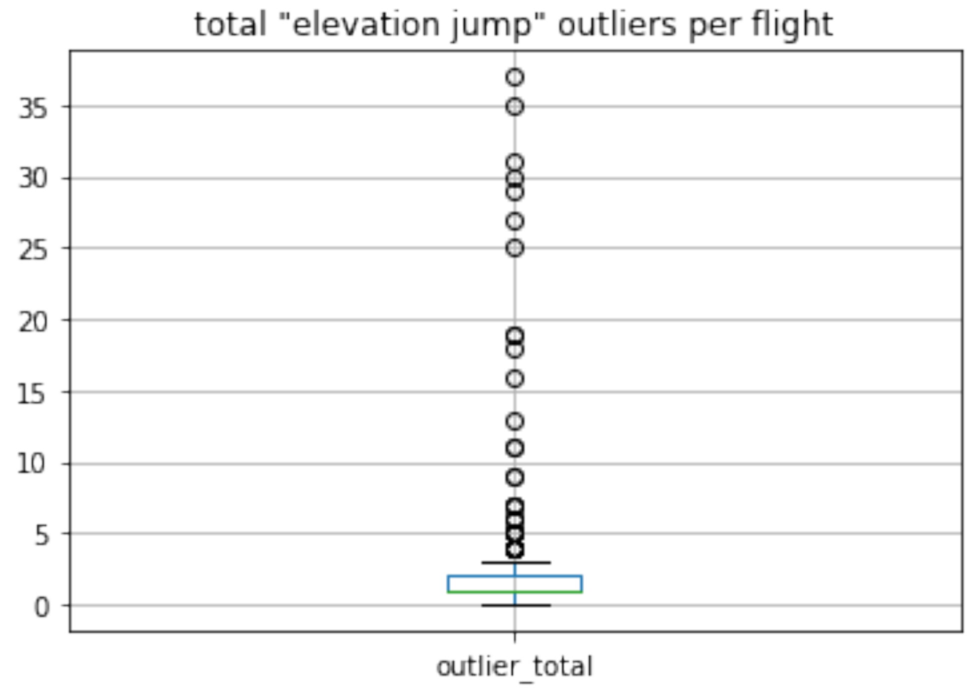
```
Total elevation jump outliers: 1039
Elevation jump outliers in 7.8s-8s interval: 525
```

In [46]:

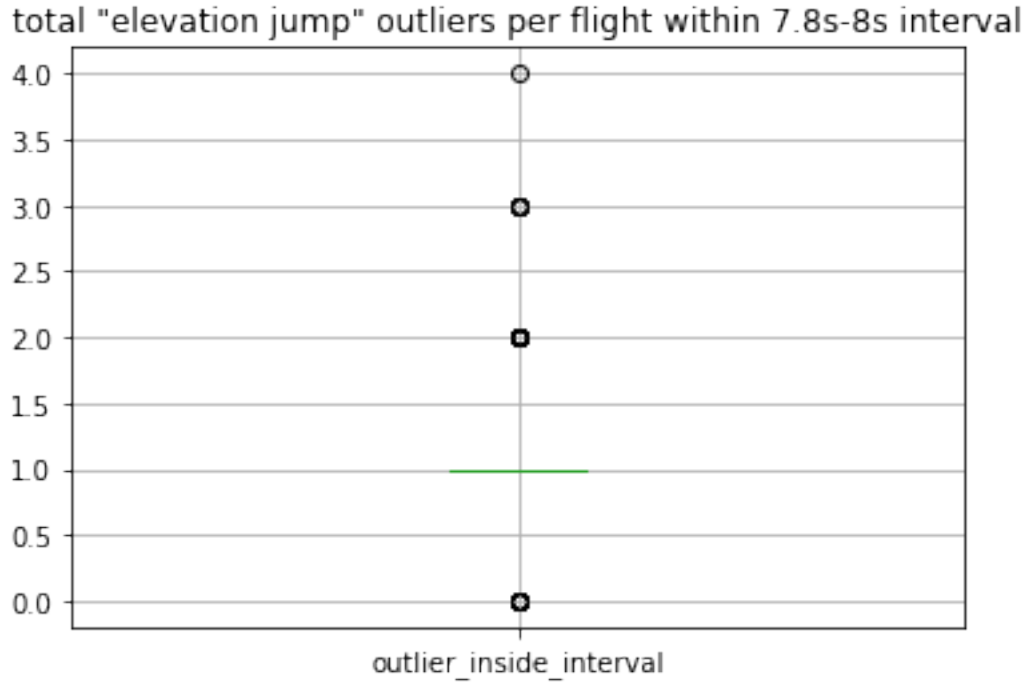
```
# lets now take the intraflight outlier data and summarize it on a per-flight sc
ale (for the summary data)
# number of outliers within interval and in total, as well as the avg magnitude
of outliers in interval (in meters)
flight_summary['outlier_inside_interval'] = 0
flight_summary['outlier_total'] = 0
flight_summary['altitude_at_7.8s'] = 0

for flight in flight_numbers:
    # classifying an elevation jump as an outlier in 7.8s to 8s interval
    intervaloutliers = flight_detail[(flight_detail['flight_number']==str(flight
))
                                 &(flight_detail['outlier_ascent_interval'])]
    totaloutliers = flight_detail[(flight_detail['flight_number']==str(flight))
                                 &(flight_detail['outlier_ascent'])]

    # find the altitude right before the interval
    preintalt = flight_detail[(flight_detail['flight_number']==str(flight))&
                              (flight_detail['seconds_since_launch']>7.5)&(fligh
t_detail['seconds_since_launch']<7.8)]

    flight_summary.loc[flight_summary['flight_id']==flight, 'altitude_at_7.8s']
= -preintalt['position_ned_m[2]'].mean()

    # assigning the count of the total number of outliers (both within 7.8-8s in
terval and in total)
    flight_summary.loc[flight_summary['flight_id']==flight, 'outlier_inside_inte
rval'] = len(intervaloutliers)
    flight_summary.loc[flight_summary['flight_id']==flight, 'outlier_inside_inte
rval_avg'] = intervaloutliers['ascent_vertical_m'].mean()
    flight_summary.loc[flight_summary['flight_id']==flight, 'outlier_total'] = l
en(totaloutliers)
#     print('flight',flight,"has ",len(intervaloutliers),intervaloutliers['ascen
t_vertical_m'].mean(),
#           "from 7.8 to 8s and", len(totaloutliers), "total")
```

In [51]:

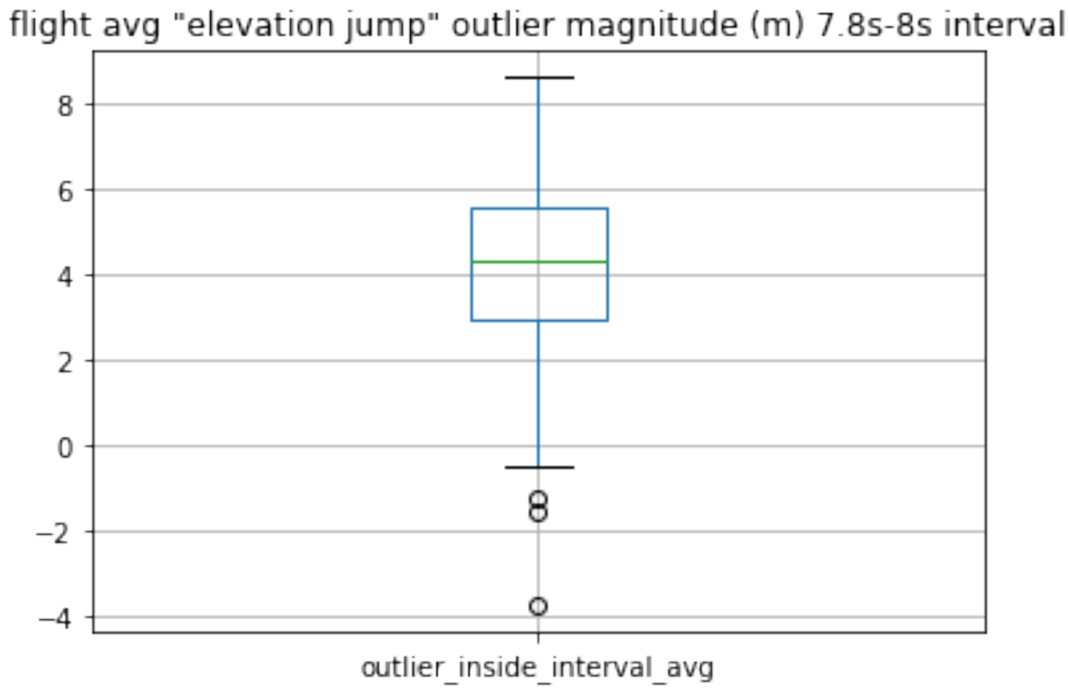
```
# Next we can visualize on a summarize per flight basis how many what the flight
-by-flight number of outliers is within
# 7.8-8s interval and in total (across any moment of the flight)

flight_summary.boxplot(column='outlier_total')
plt.title('total "elevation jump" outliers per flight')
plt.show()
print(flight_summary['outlier_total'].describe())

flight_summary.boxplot(column='outlier_inside_interval')
plt.title('total "elevation jump" outliers per flight within 7.8s-8s interval')
plt.show()
print(flight_summary['outlier_inside_interval'].describe())

flight_summary.boxplot(column='outlier_inside_interval_avg')
plt.title('flight avg "elevation jump" outlier magnitude (m) 7.8s-8s interval')
plt.show()
print(flight_summary['outlier_inside_interval_avg'].describe())
```




```
count    447.000000
mean       2.324385
std        4.170138
min        0.000000
25%        1.000000
50%        1.000000
75%        2.000000
max       37.000000
Name: outlier_total, dtype: float64
```




```
count    447.000000
mean       1.174497
std        0.479137
min        0.000000
25%        1.000000
50%        1.000000
75%        1.000000
max        4.000000
Name: outlier_inside_interval, dtype: float64
```




```
count    437.000000
mean       4.208828
std        1.879451
min       -3.729357
25%        2.967751
50%        4.348419
75%        5.560566
max        8.624320
Name: outlier_inside_interval_avg, dtype: float64
```

In [ ]:

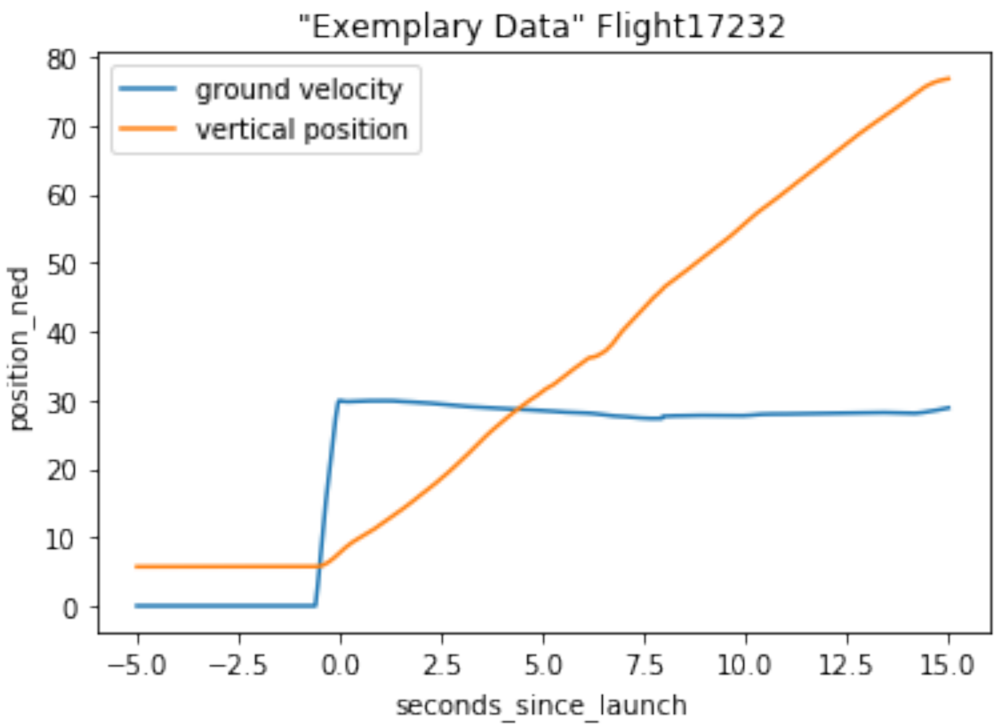
```

```

In [52]:

```
# Let's conservatively classify a "good flight" as one with no outliers at all
flight_summary['good_flight'] = flight_summary['outlier_total']==0
```

In [53]:

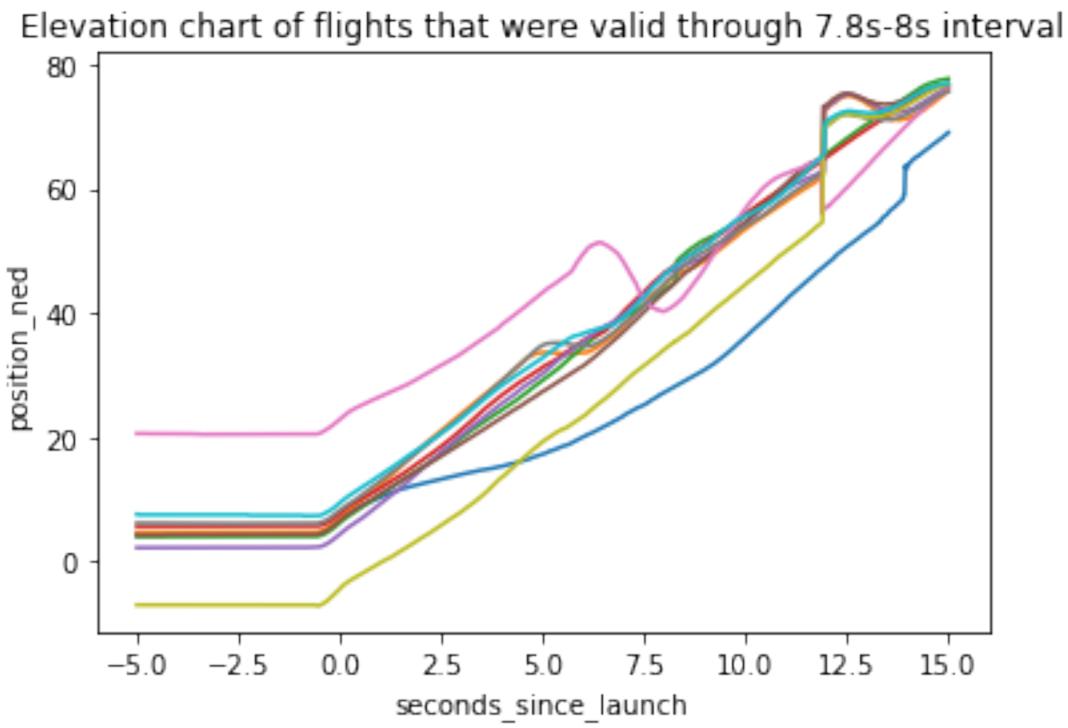
```
# As it turns out there is only one flight with no elevation outliers (17232), a
nd it does appear to be good
flight17232 = flight_detail[flight_detail['flight_number']=='17232']
plt.plot(flight17232['seconds_since_launch'], flight17232['velocity_ground_mps']
,
         flight17232['seconds_since_launch'], -flight17232['position_ned_m[2]'])
plt.gca().legend(('ground velocity','vertical position'))
plt.title('"Exemplary Data" Flight17232')
plt.xlabel('seconds_since_launch')
plt.ylabel('position_ned')
plt.show()
print(flight_summary[flight_summary['flight_id']==17232])
```




```
     flight_id  air_temperature battery_serial_number  body_serial_n
umber  \
142      17232             23.4        15SPJJJ10050016  5773501328073
48254

         commit  launch_airspeed  launch_groundspeed         launch_
timestamp  \
142  5c504d9a16         31.68824           30.220672  2018-09-16 08:
53:19 CAT

     preflight_voltage  rel_humidity  static_pressure  wind_directio
n  \
142          32.127113      58.02499     80618.943309       -0.81706
1

     wind_magnitude wing_serial_number  outlier_inside_interval  \
142        1.184406    15SPJJJ09008034                        0

     outlier_total  altitude_at_7.8s  outlier_inside_interval_avg  g
ood_flight
142              0         44.446964                          NaN
True
```

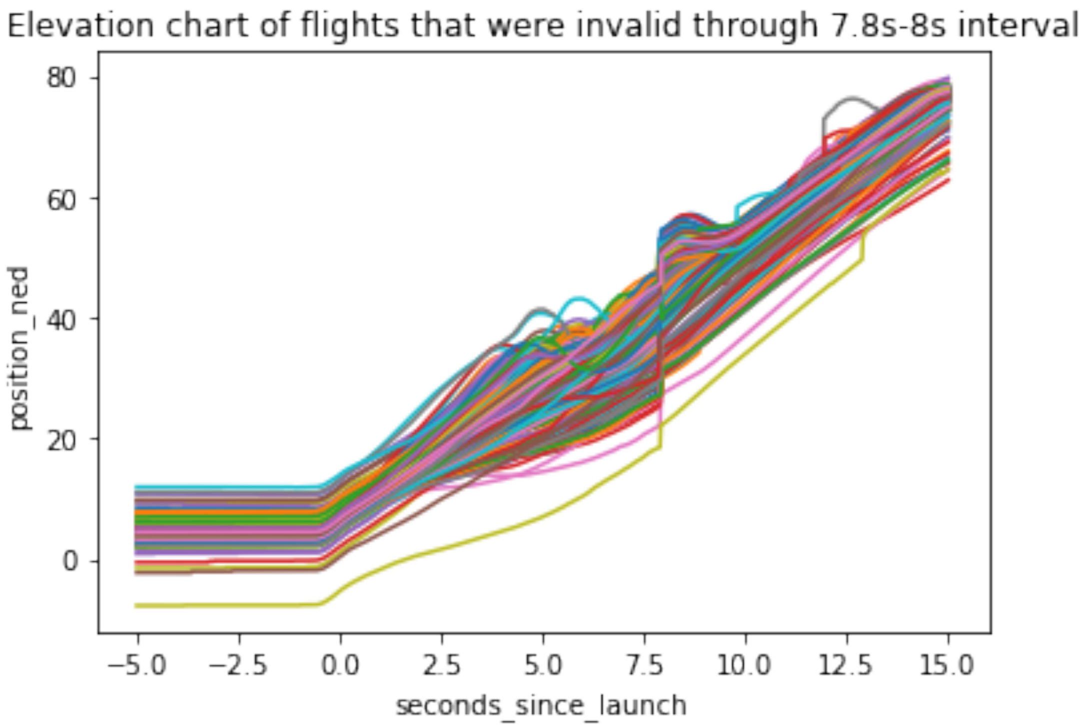
In [54]:

```
# Note that our exemplary flight took off with low wind on a high pressure day w
ith high groundspeed

# If we relax our definition slightly to only ensure that there are no outliers
in the 7.8-8s interval
# we are left with 10 flights, but as you can see they all contain noticeable gl
itches (just not within the interval)
flight_summary['good_flight_interval'] = flight_summary['outlier_inside_interval
']==0

# We can graph all flights with one or fewer outliers
flight_summary_good = flight_summary[flight_summary['good_flight_interval']]
good_flight_numbers = flight_summary_good['flight_id']
for flight in good_flight_numbers:
    currentflight = flight_detail[flight_detail['flight_number']==str(flight)]
    plt.plot(currentflight['seconds_since_launch'], -currentflight['position_ned
_m[2]'])

plt.title('Elevation chart of flights that were valid through 7.8s-8s interval')
plt.xlabel('seconds_since_launch')
plt.ylabel('position_ned')
plt.show()
```



In [55]:

```
# Then relaxing even more to include all 436 other flights with noticeable eleva
tion glitches between 7.8s-8s
flight_summary['bad_flight_interval'] = flight_summary['outlier_inside_interval'
]>0

# We can graph all flights with one or fewer outliers
flight_summary_bad = flight_summary[flight_summary['bad_flight_interval']]
bad_flight_numbers = flight_summary_bad['flight_id']
for flight in bad_flight_numbers:
    currentflight = flight_detail[flight_detail['flight_number']==str(flight)]
    plt.plot(currentflight['seconds_since_launch'], -currentflight['position_ned
_m[2]'])

plt.title('Elevation chart of flights that were invalid through 7.8s-8s interval
')
plt.xlabel('seconds_since_launch')
plt.ylabel('position_ned')
plt.show()
```



In [60]:

```
# Given that these bad flights make up 97.5% of the total flights, we can quanti
fy the average outlier magnitude
# ("elevation jump") during this 7.8s-8s time window and see what correlates hig
hly to it

corrintavg = flight_summary.corr()['outlier_inside_interval_avg']
print("Correlations to increased outlier magnitude during 7.8s-8s interval:")
print(corrintavg)
```

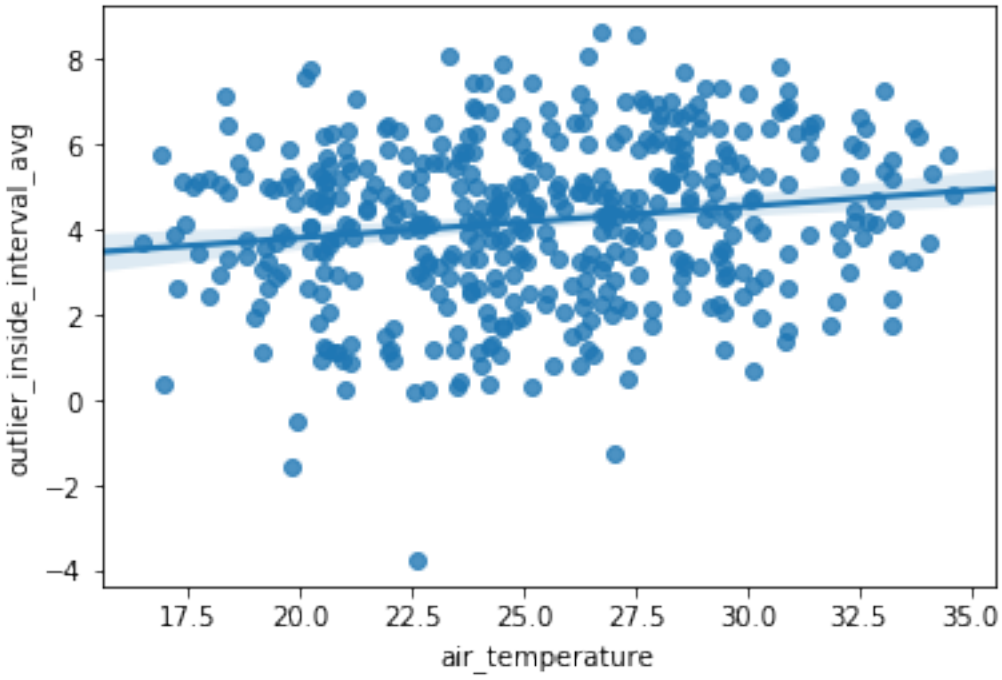
```
Correlations to increased outlier severity during 7.8s-8s interval:
flight_id                     -0.075616
air_temperature                0.160651
body_serial_number             0.048049
launch_airspeed               -0.005504
launch_groundspeed             0.004085
preflight_voltage              0.031133
rel_humidity                  -0.066697
static_pressure               -0.067083
wind_direction                -0.105269
wind_magnitude                -0.044869
outlier_inside_interval       -0.497419
outlier_total                 -0.291604
altitude_at_7.8s              -0.091334
outlier_inside_interval_avg    1.000000
good_flight                         NaN
good_flight_interval                NaN
bad_flight_interval                 NaN
Name: outlier_inside_interval_avg, dtype: float64
```

In [64]:

```
# We see that the two contributors with the largest magnitude appear to be air_t
emperature (positively correlated)
# and wind direction (negatively correlated)
sns.regplot(flight_summary['air_temperature'], flight_summary['outlier_inside_in
terval_avg'])
# below, we validate that there appears to be a statistically significant slight
positive correlation between air temp
# and the magnitude of elevation jumps during the 7.8s-8s mark
# warm temperatures are not necessarily the cause but serve as a slight predicto
r of larger jumps
```

Out[64]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x111ae5470>
```

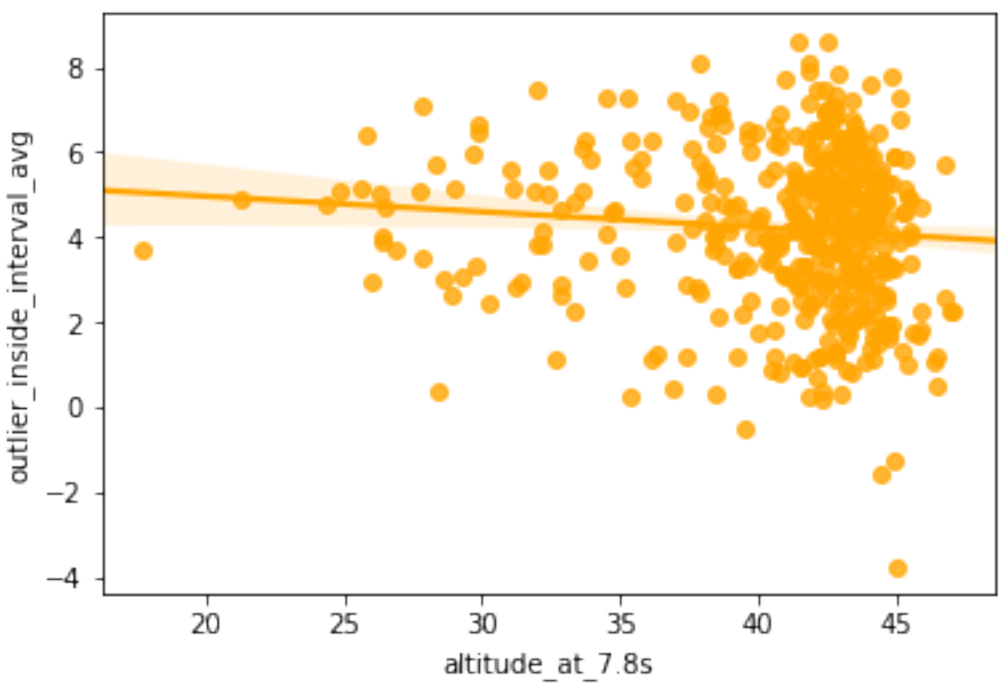


In [69]:

```
sns.regplot(flight_summary['altitude_at_7.8s'], flight_summary['outlier_inside_i
nterval_avg'], color='orange')
# another slight predictor is the altitude of the plane at 7.8s - we see that lo
wer altitudes correlate with slightly
# larger magnitude jumps in elevation data between the 7.8s-8s interval
# we should take these findings with a grain of salt however as most of the 7.8s
elevation data is clustered around 42m
# and we may have a supurilous correlation
```

Out[69]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x13e0899e8>
```

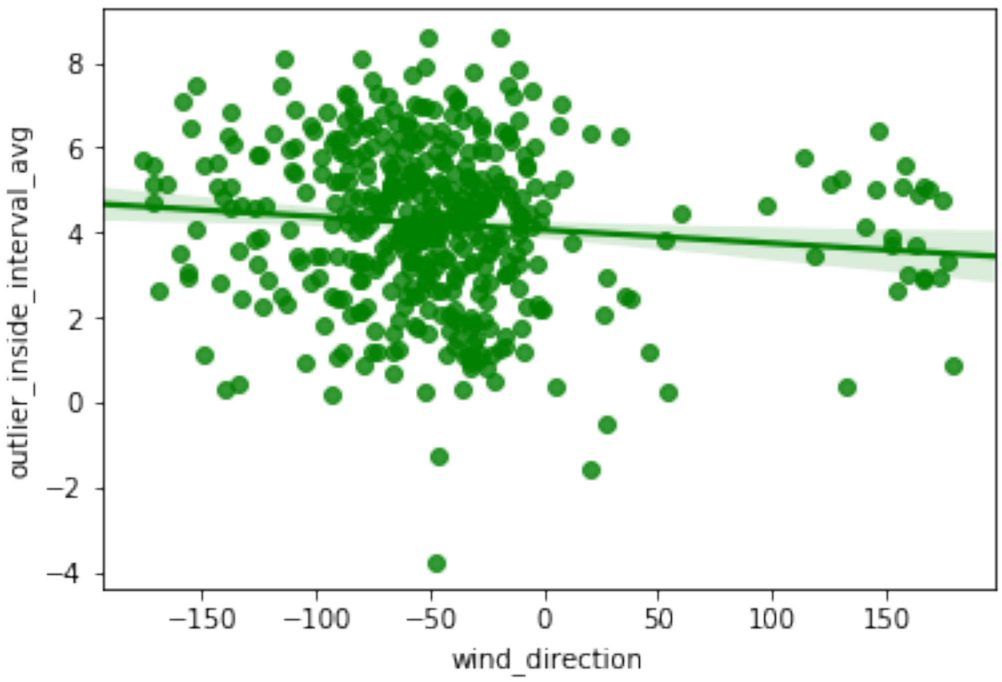


In [66]:

```
sns.regplot(flight_summary['wind_direction'], flight_summary['outlier_inside_int
erval_avg'], color='green')
# the last potential predictor of the magnitude of the elevation jumps in the 7.
8s-8s interval is the wind direction
# negative (westerly) winds appear to be correlated to higher elevation data jum
ps
# though again most of the data has negative wind direction, and therefore this
may again be a spurulious correlation
# due to the trailing outliers on the right
```

Out[66]:

```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x1429e6390&gt;
```



In [ ]:

```
# Overall, we see that there is a pretty significant sensor error with elevation
from our zipline drones
# we understand from this analysis that out of 447 flights, only one of them (fl
ight 17232) has exemplary
# elevation data, and over 436 have major "elevation jumps" between the 7.8s-8s
mark,
# which may indicate a problem with our software or sensory readings.
# There are a couple of weakly correlated factors, though my suggestion to the
# engineering team is to use flight 17232 as an example and understand what diff
ers between its setup and the other
# 436 flights which exhibited this error.
```

In [ ]: