lmviz

March 18, 2018

```
In [3]: import numpy as np
        import pandas as pd
        import seaborn as sns
        import matplotlib.pyplot as plt
        %matplotlib inline
```

I'll be looking at a dataset of delayed flights for the year 2008.

```
In [5]: all_delays = pd.read_csv('DelayedFlights.csv')
```

```
In [6]: all_delays.columns
```

```
Out[6]: Index(['Unnamed: 0', 'Year', 'Month', 'DayofMonth', 'DayOfWeek', 'DepTime',
               'CRSDepTime', 'ArrTime', 'CRSArrTime', 'UniqueCarrier', 'FlightNum',
               'TailNum', 'ActualElapsedTime', 'CRSElapsedTime', 'AirTime', 'ArrDelay',
               'DepDelay', 'Origin', 'Dest', 'Distance', 'TaxiIn', 'TaxiOut',
               'Cancelled', 'CancellationCode', 'Diverted', 'CarrierDelay',
               'WeatherDelay', 'NASDelay', 'SecurityDelay', 'LateAircraftDelay'],
              dtype='object')
```

```
In [7]: delays = all_delays.loc[:, ['Month', 'AirTime', 'ArrDelay', 'DepDelay', 'Distance']]
```

```
In [8]: delays.count()
```

```
Out[8]: Month       1936758
        AirTime     1928371
        ArrDelay    1928371
        DepDelay    1936758
        Distance    1936758
        dtype: int64
```

```
In [9]: delays.isnull().sum()
```

```
Out[9]: Month          0
        AirTime     8387
        ArrDelay    8387
        DepDelay       0
        Distance       0
        dtype: int64
```

```
In [10]: delays = delays[~delays.isnull().any(axis=1)]
```

```
In [11]: delays.count()
```

```
Out[11]: Month       1928371
         AirTime     1928371
         ArrDelay    1928371
         DepDelay    1928371
         Distance    1928371
         dtype: int64
```

```
In [12]: delays.isnull().sum()
```

```
Out[12]: Month       0
         AirTime     0
         ArrDelay    0
         DepDelay    0
         Distance    0
         dtype: int64
```

```
In [13]: stats = delays.describe()
         stats
```

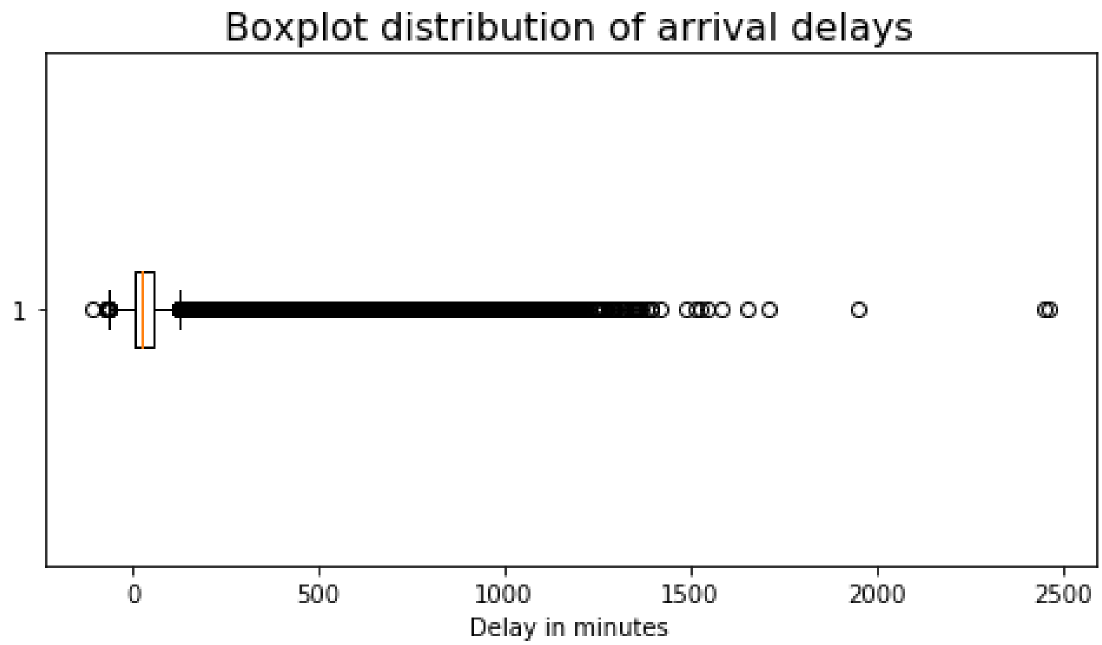
Out[13]:

	Month	AirTime	ArrDelay	DepDelay	Distance
count	1.928371e+06	1.928371e+06	1.928371e+06	1.928371e+06	1.928371e+06
mean	6.107855e+00	1.082771e+02	4.219988e+01	4.309169e+01	7.649486e+02
std	3.480753e+00	6.864261e+01	5.678472e+01	5.326600e+01	5.738858e+02
min	1.000000e+00	0.000000e+00	-1.090000e+02	6.000000e+00	1.100000e+01
25%	3.000000e+00	5.800000e+01	9.000000e+00	1.200000e+01	3.380000e+02
50%	6.000000e+00	9.000000e+01	2.400000e+01	2.400000e+01	6.060000e+02
75%	9.000000e+00	1.370000e+02	5.600000e+01	5.300000e+01	9.970000e+02
max	1.200000e+01	1.091000e+03	2.461000e+03	2.467000e+03	4.962000e+03

First explore the arrival delays feature.

```
In [15]: plt.rcParams["figure.figsize"] = [8.0, 4.0]
         plt.boxplot(delays['ArrDelay'], vert=False)
         plt.xlabel('Delay in minutes')
         plt.title('Boxplot distribution of arrival delays', size=16)
```

```
Out[15]: <matplotlib.text.Text at 0x1156af160>
```



Clearly this is an extremely skewed dataset, so to make the plots manageable, I'll remove outliers. From trying several values, it seems like 2.5 times the Interquartile Range keeps the maximum amount of data while still producing usable distribution plots.

```
In [16]: numeric = delays.loc[:, ['AirTime', 'ArrDelay', 'DepDelay', 'Distance']]
         n_stats = numeric.describe()
         IQR = n_stats.loc['75%'] - n_stats.loc['25%']
         Lower = n_stats.loc['25%'] - 2.5 * IQR
         Upper = n_stats.loc['75%'] + 2.5 * IQR
         Outliers = ((numeric < Lower) | (numeric > Upper)).sum().sum()
         Outliers

Out[16]: 166610

In [17]: df = delays[~(((numeric < Lower) | (numeric > Upper)).any(1))]
         df.describe()
```

Out[17]:

	Month	AirTime	ArrDelay	DepDelay	Distance
count	1.826757e+06	1.826757e+06	1.826757e+06	1.826757e+06	1.826757e+06
mean	6.103836e+00	1.056111e+02	3.369523e+01	3.506096e+01	7.444481e+02
std	3.476323e+00	6.372370e+01	3.584420e+01	3.198920e+01	5.355352e+02
min	1.000000e+00	0.000000e+00	-7.000000e+01	6.000000e+00	1.100000e+01
25%	3.000000e+00	5.800000e+01	8.000000e+00	1.200000e+01	3.370000e+02
50%	6.000000e+00	8.900000e+01	2.300000e+01	2.300000e+01	6.020000e+02
75%	9.000000e+00	1.350000e+02	5.000000e+01	4.700000e+01	9.870000e+02
max	1.200000e+01	3.340000e+02	1.730000e+02	1.550000e+02	2.644000e+03

```
In [18]: df.describe()
```

Out[18]:

	Month	AirTime	ArrDelay	DepDelay	Distance
count	1.826757e+06	1.826757e+06	1.826757e+06	1.826757e+06	1.826757e+06
mean	6.103836e+00	1.056111e+02	3.369523e+01	3.506096e+01	7.444481e+02
std	3.476323e+00	6.372370e+01	3.584420e+01	3.198920e+01	5.355352e+02
min	1.000000e+00	0.000000e+00	-7.000000e+01	6.000000e+00	1.100000e+01
25%	3.000000e+00	5.800000e+01	8.000000e+00	1.200000e+01	3.370000e+02
50%	6.000000e+00	8.900000e+01	2.300000e+01	2.300000e+01	6.020000e+02
75%	9.000000e+00	1.350000e+02	5.000000e+01	4.700000e+01	9.870000e+02
max	1.200000e+01	3.340000e+02	1.730000e+02	1.550000e+02	2.644000e+03

In [19]:

```
ArrDelay_sorted = sorted(df['ArrDelay'].values)
normed = sorted(np.random.normal(33.695, 35.844, 1826757))
```

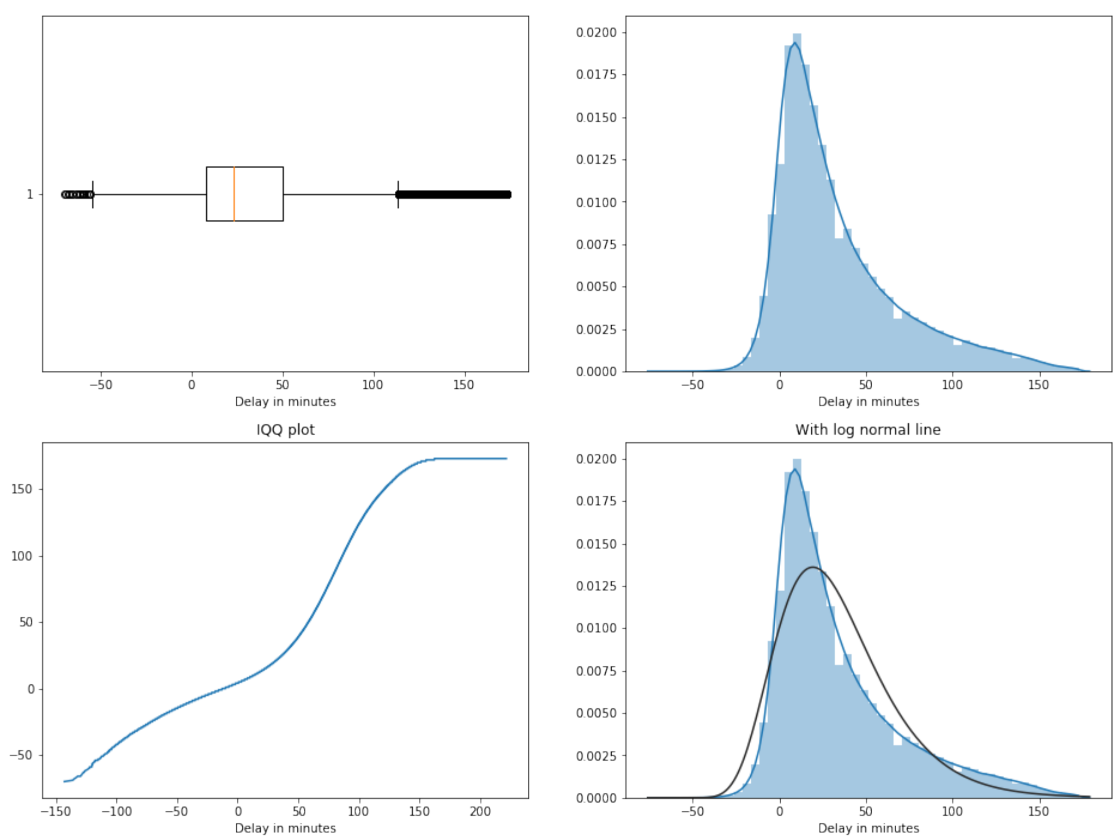
In [21]:

```
import matplotlib.pyplot as plt
from scipy import stats
plt.rcParams["figure.figsize"] = [16.0, 12.0]
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2)
plt.suptitle('Distribution of arrival delays', size=18)
ax1.boxplot(df['ArrDelay'], vert=False)
ax1.set(xlabel='Delay in minutes')
sns.distplot(df['ArrDelay'], ax=ax2)
ax2.set(xlabel='Delay in minutes')
ax3.plot(normed, ArrDelay_sorted)
ax3.set(title='IQQ plot', xlabel='Delay in minutes')
sns.distplot(df['ArrDelay'], fit=stats.lognorm, ax=ax4)
ax4.set(title='With log normal line', xlabel='Delay in minutes')
```

Out[21]:

```
[<matplotlib.text.Text at 0x11eb4b860>, <matplotlib.text.Text at 0x11eb59208>]
```

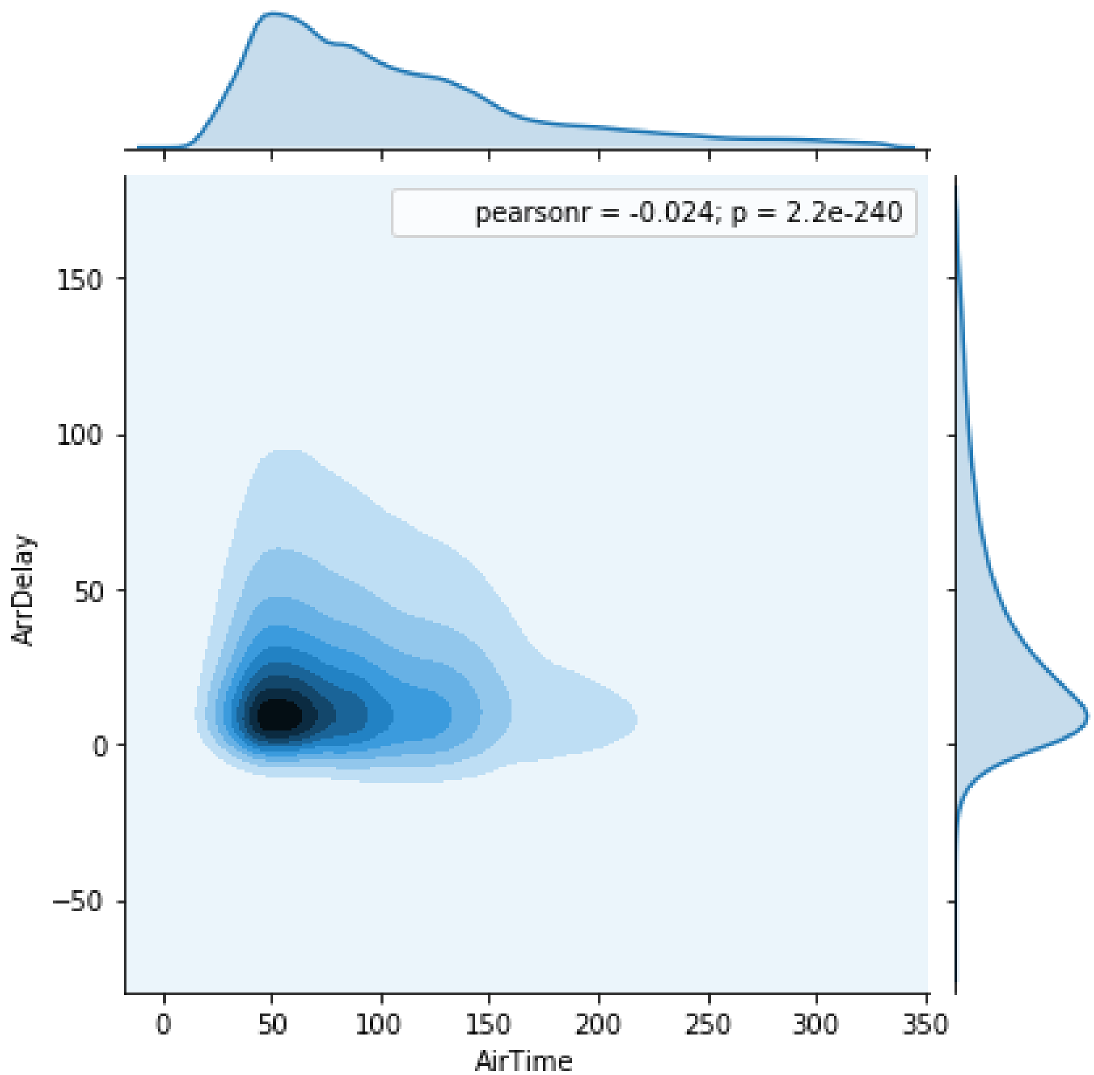
Distribution of arrival delays



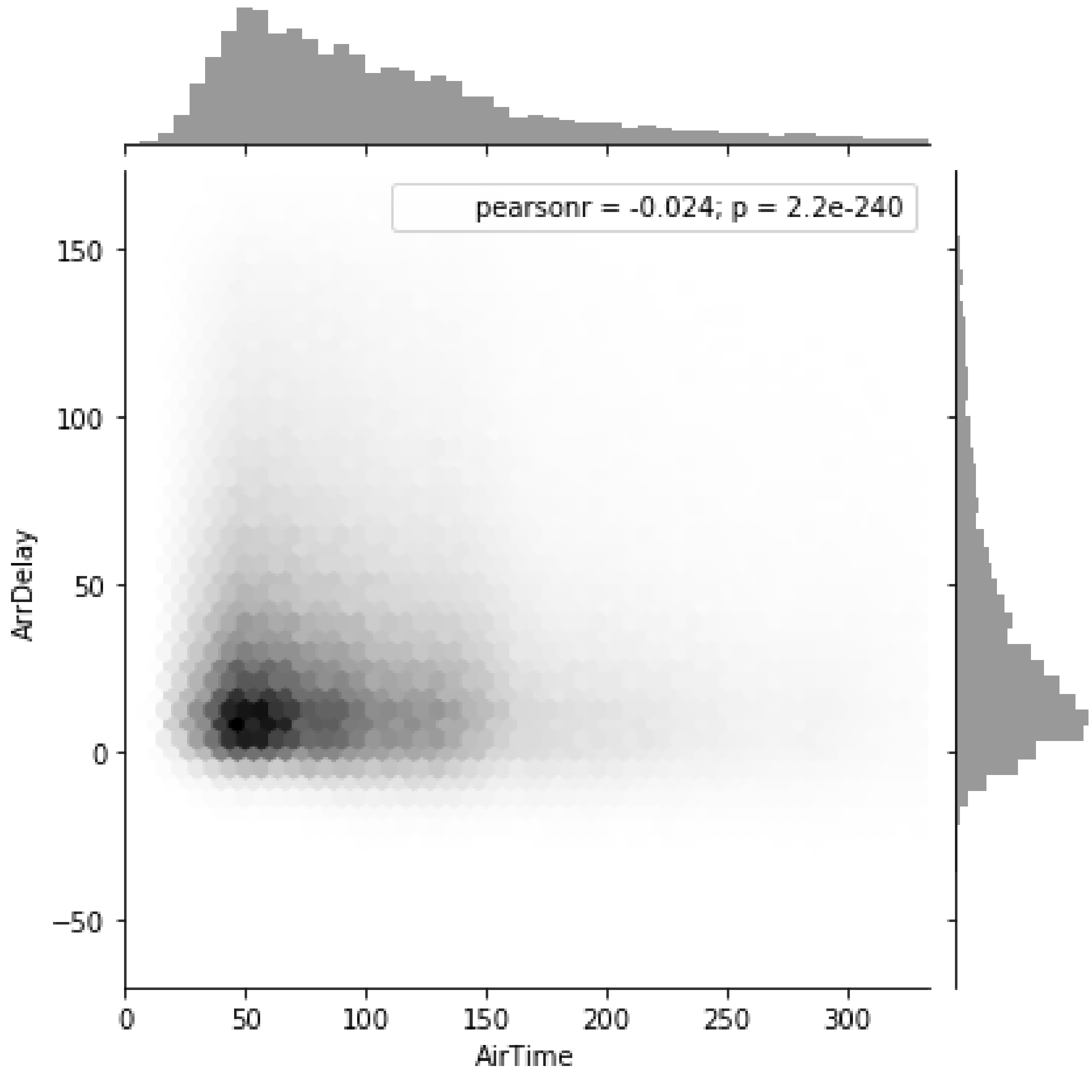
The top two plots both show that the prepped dataset remains fairly heavily skewed. The kernel density curve shows this more visually, while the boxplot gives a better sense of the distribution of outliers. The IQQ plot confrims that the distribution is not normal, while the kernel density plot with the added log normal line shows that the distribution is much closer to log normal, which would be useful to know were one to perform a linear regression on this data.

For a bivariate comparison, look at the relationship between time in the air and arrival delays.

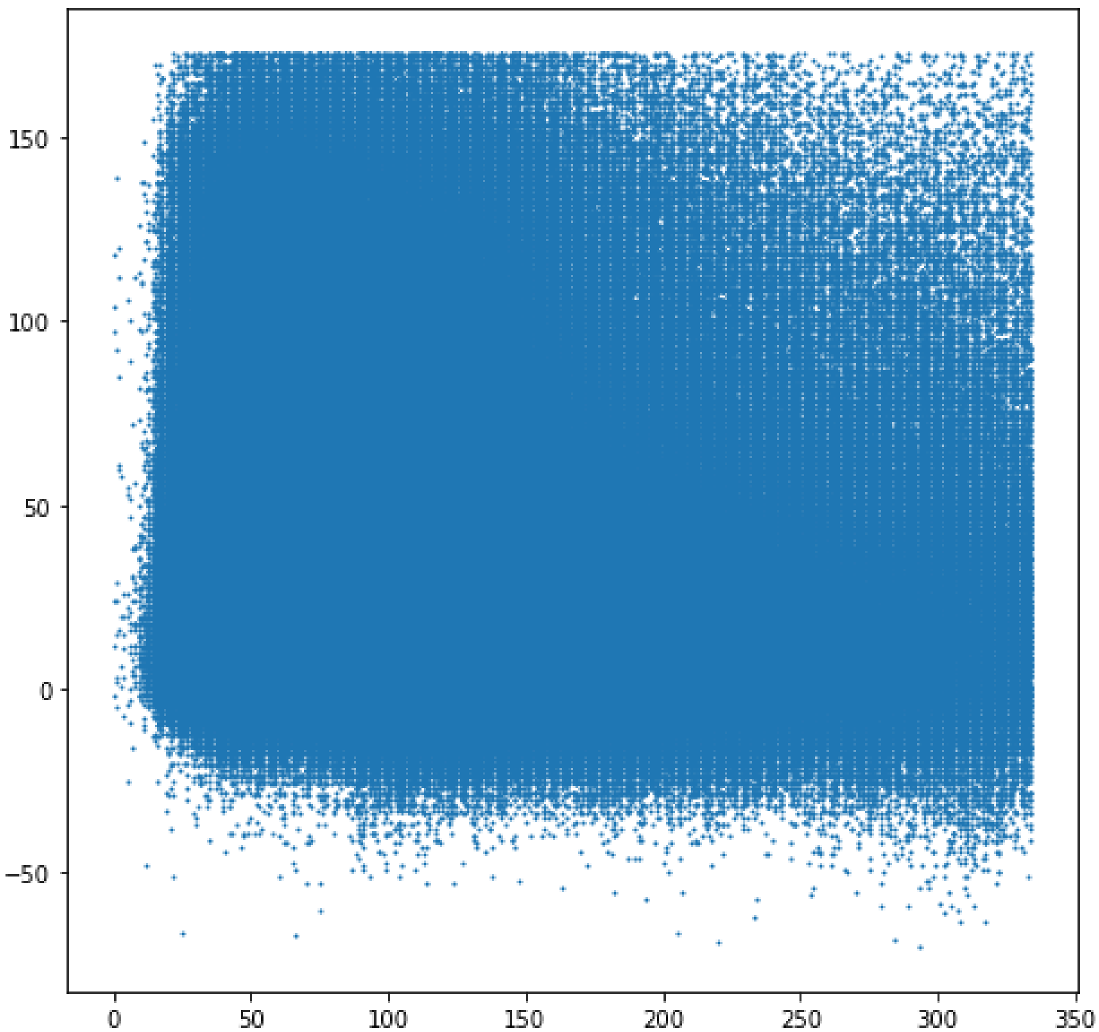
```
In [141]: plt.rcParams["figure.figsize"] = [12.0, 12.0]
          sns.jointplot(x='AirTime', y='ArrDelay', data=df, kind='kde')

Out[141]: <seaborn.axisgrid.JointGrid at 0x124052f60>
```




```
In [139]: sns.jointplot(x='AirTime', y='ArrDelay', data=df, kind="hex", color="k")

Out[139]: <seaborn.axisgrid.JointGrid at 0x117ad47b8>
```




```
In [146]: plt.rcParams["figure.figsize"] = [8.0, 8.0]
          plt.scatter(x='AirTime', y='ArrDelay', data=df, s=1)

Out[146]: <matplotlib.collections.PathCollection at 0x123383550>
```



Of the three plots above, the joint kernal density plot most easily conveys the idea that the great majority of delays are short delays on short flights, but that beyond this there is no observable pattern, with short flights as prone to long delays as long flights are to have short delays. The hex plot also shows this, but not as clearly, while the scatter plot mostly illustrates the problem of trying to plot such a large dataset.

The only categorical feature in the data is the month, so construct plots showing the relationship between this and other features. First, extract a new set of features, the number of delays per month in each of several , and use this also.

```
In [27]: depDelays = df.loc[((df['DepDelay'] > 5) & (df['DepDelay'] <= 15)), ['Month', 'DepDela
         count = depDelays.groupby('Month').count()
         count.columns = ['> 5']
         count['> 15'] = df.loc[((df['DepDelay'] > 15) & (df['DepDelay'] <= 30)), ['Month', 'De
         count['> 30'] = df.loc[((df['DepDelay'] > 30) & (df['DepDelay'] <= 60)), ['Month', 'De
         count['> 60'] = df.loc[((df['DepDelay'] > 60) & (df['DepDelay'] <= 90)), ['Month', 'De
```

```
count['> 90'] = df.loc[((df['DepDelay'] > 90) & (df['DepDelay'] <= 1120)), ['Month',
count['> 120'] = df.loc[df['DepDelay'] > 120, ['Month', 'DepDelay']].groupby('Month')
```

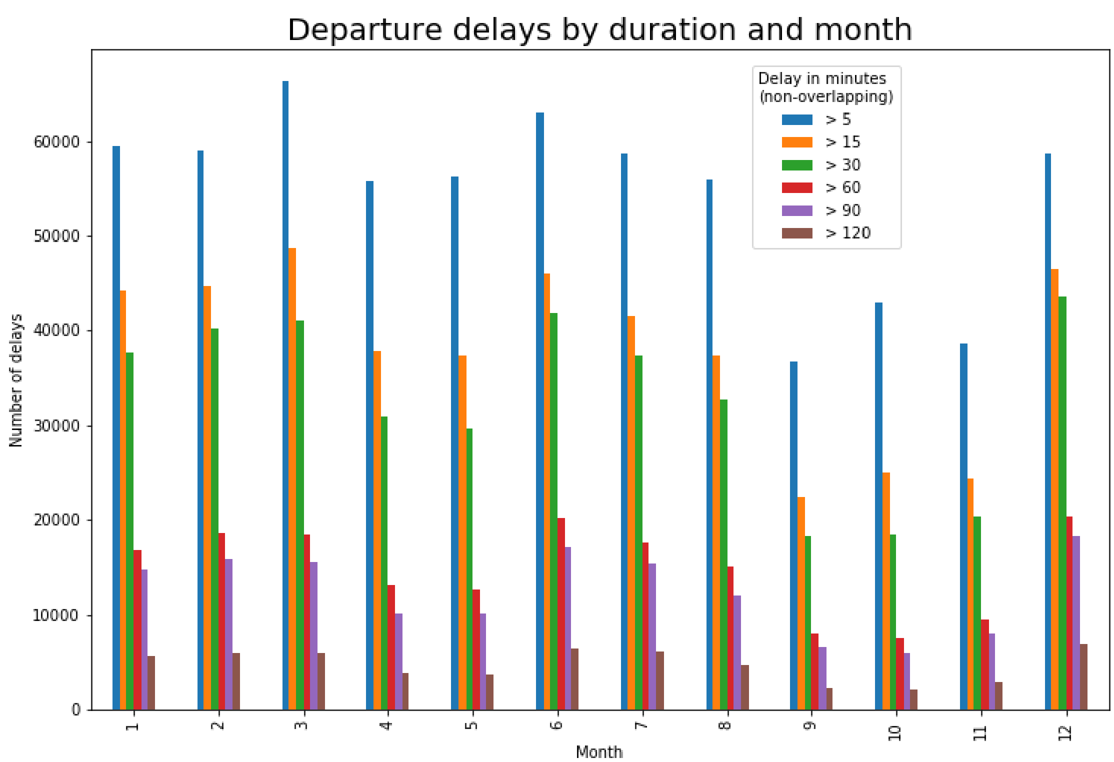
In [28]:
```
count
```

Out[28]:

Month	> 5	> 15	> 30	> 60	> 90	> 120
1	59510	44219	37654	16870	14695	5565
2	58925	44649	40235	18626	15947	5897
3	66359	48653	41012	18429	15479	5884
4	55812	37846	30965	13117	10116	3851
5	56245	37314	29672	12728	10169	3746
6	63017	45983	41836	20134	17132	6469
7	58606	41492	37416	17620	15330	6018
8	55987	37344	32701	15027	12087	4618
9	36623	22471	18213	8011	6521	2313
10	42882	25044	18513	7485	5928	2169
11	38664	24383	20314	9383	7997	2903
12	58603	46438	43631	20409	18286	6875

In [38]:
```
plt.rcParams["figure.figsize"] = [12.0, 8.0]
ax1 = count.plot(kind='bar')
ax1.legend(loc=(.65, .7), title='Delay in minutes\n(non-overlapping)')
plt.title('Departure delays by duration and month', size=20)
plt.ylabel('Number of delays')
```

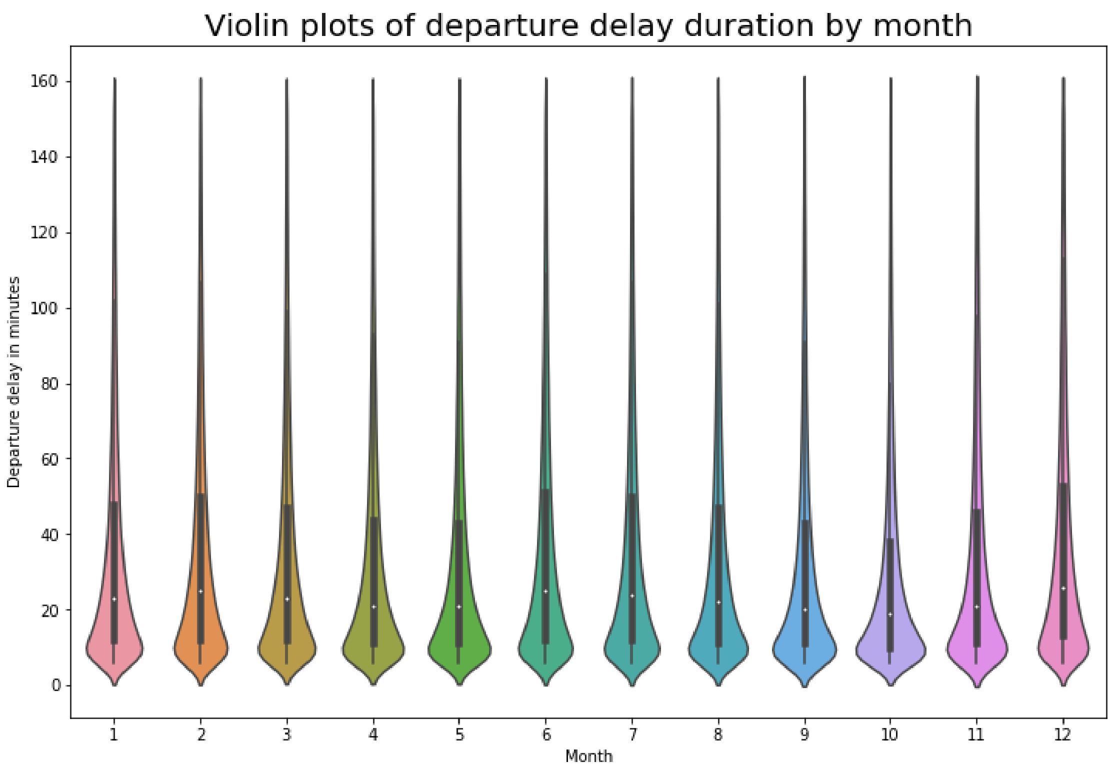
Out[38]: <matplotlib.text.Text at 0x13fed5908>



The addition of the color-coded counts makes for a very informative presentation. For the most part, the number of delays in all duration categories, which do not overlap, rise and fall in step. Still, it can be seen that December has the highest percentage of long delays.

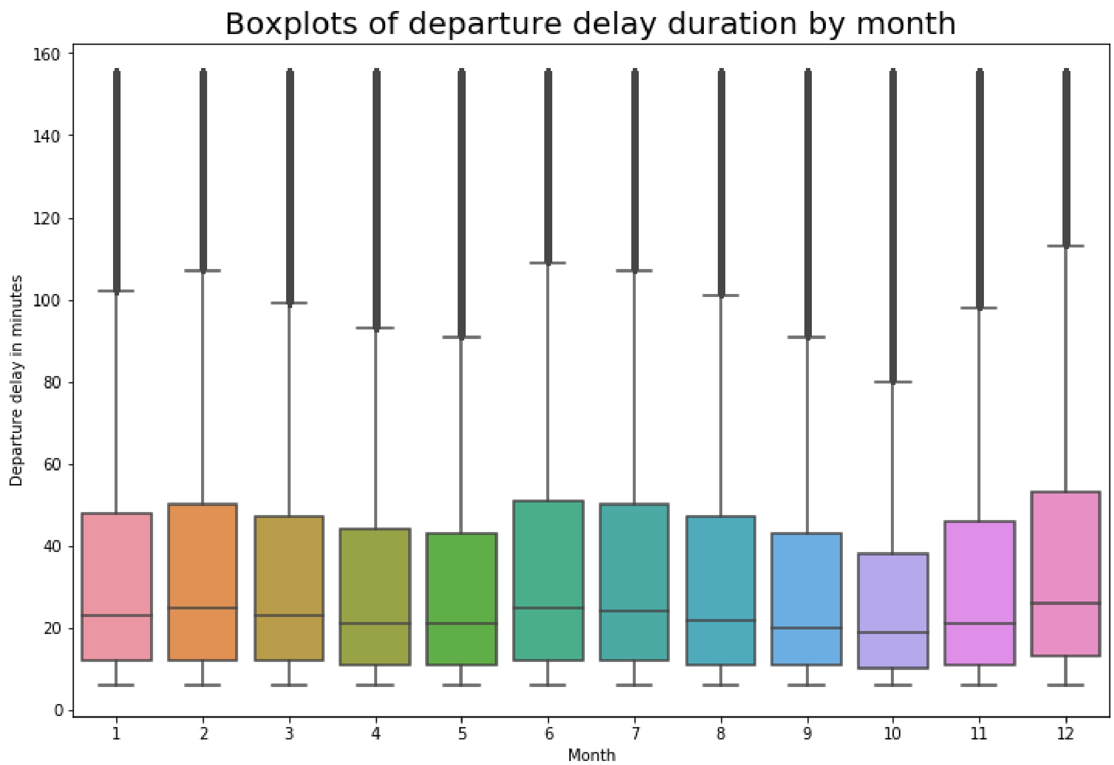
In [26]:
```
month = df['Month']
depDel = df['DepDelay']
sns.violinplot(x=month, y=depDel)
plt.title('Violin plots of departure delay duration by month', size=20)
plt.ylabel('Departure delay in minutes')
```

Out[26]: <matplotlib.text.Text at 0x11e9e07f0>



In [218]:
```
sns.boxplot(x=month, y=depDel)
plt.title('Boxplots of departure delay duration by month', size=20)
plt.ylabel('Departure delay in minutes')
```

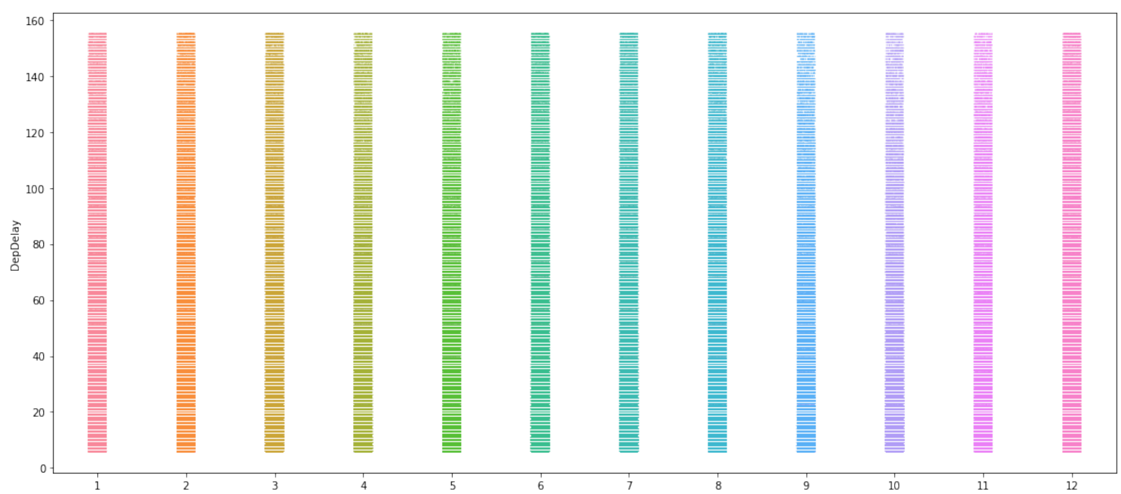
Out[218]: <matplotlib.text.Text at 0x1d7a48b70>



Of the two plots above, I find the boxplots more informative than the violin plots, which are less effective due to the nearly uniformly long tails.

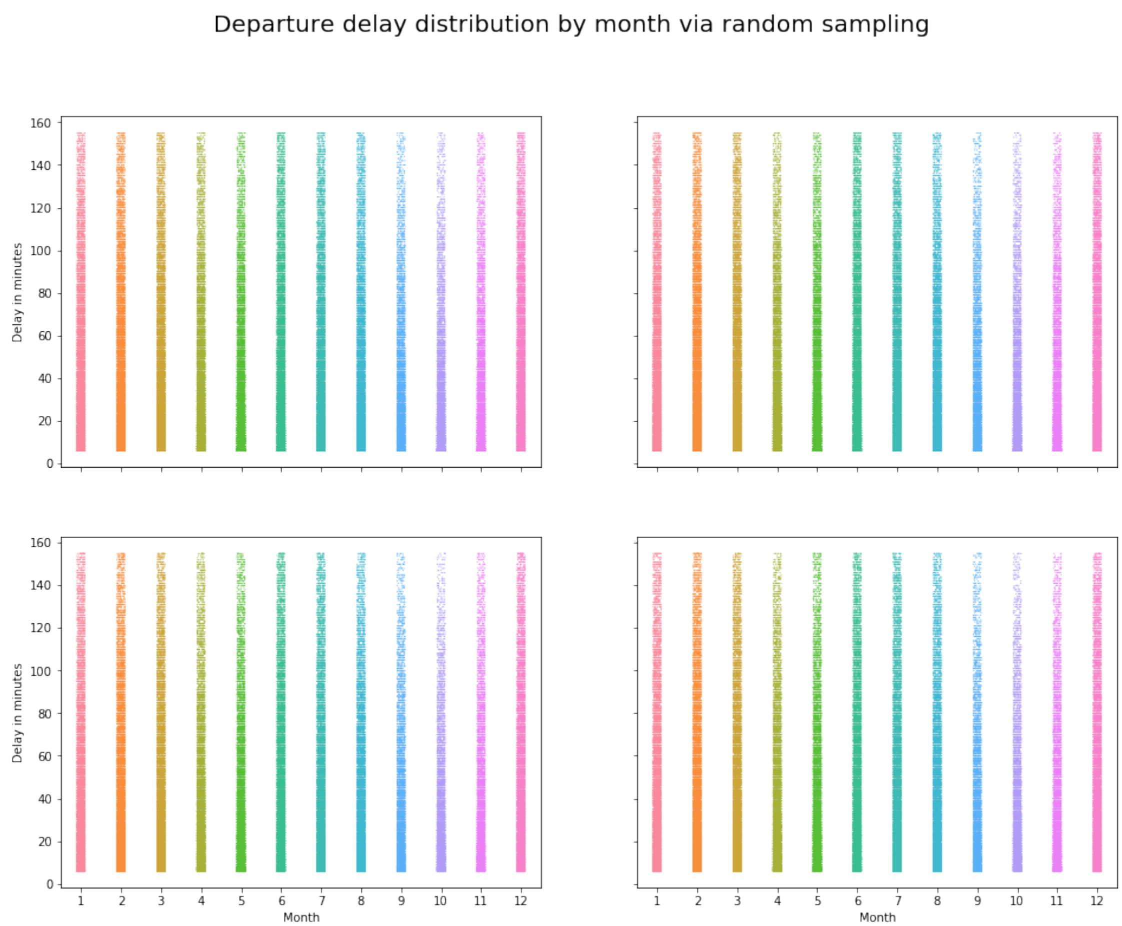
In [206]:
```
plt.rcParams["figure.figsize"] = [18.0, 8.0]
sns.stripplot(x=month, y=depDel, size=1, jitter=True)
```

Out[206]: <matplotlib.axes._subplots.AxesSubplot at 0x1dd15eb00>



This simple strip plot shows very little except, again, that plotting datasets this large is challenging. As a different approach, try randomly sampling the dataset. The next group of strip plots will use four samplings of 0.1 of the dataset, generated with different random seeds, to see if this gives a better picture.

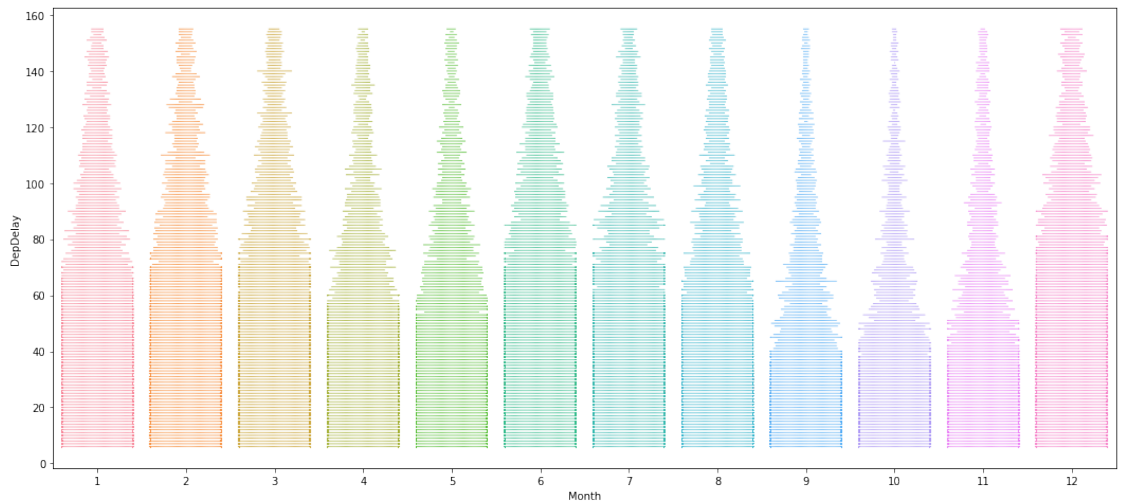
```
In [32]: plt.rcParams["figure.figsize"] = [16.0, 12.0]
         fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, sharex=True, sharey=True)
         s1 = df.sample(frac=0.1, random_state=7)
         s2 = df.sample(frac=0.1, random_state=29)
         s3 = df.sample(frac=0.1, random_state=51)
         s4 = df.sample(frac=0.1, random_state=97)
         sns.stripplot(x='Month', y='DepDelay', data=s1, size=1, jitter=True, ax=ax1)
         ax1.set(xlabel='', ylabel='Delay in minutes')
         sns.stripplot(x='Month', y='DepDelay', data=s2, size=1, jitter=True, ax=ax2)
         ax2.set(xlabel='', ylabel='')
         sns.stripplot(x='Month', y='DepDelay', data=s3, size=1, jitter=True, ax=ax3)
         ax3.set(ylabel='Delay in minutes')
         sns.stripplot(x='Month', y='DepDelay', data=s4, size=1, jitter=True, ax=ax4)
         ax4.set(ylabel='')
         fig.suptitle('Departure delay distribution by month via random sampling', size=20)

Out[32]: <matplotlib.text.Text at 0x12a0c3b00>
```



The samplings show consistent behavior and are visually much more informative than plotting the entire set.

```
In [210]: plt.rcParams["figure.figsize"] = [18.0, 8.0]
          sns.swarmplot(x='Month', y='DepDelay', data=s1, size=1)
          plt.title('Departure delay distribution by month')
          plt.ylabel('Delay in minutes')
```

```
Out[210]: <matplotlib.axes._subplots.AxesSubplot at 0x1dd7beac8>
```



The swarm plot took an exceptionally long time to finish (20 minutes?), but does the best job of visualizing the distribution of the entire set.