General

May 25, 2016

1 Kaggle - Facebook recruiting

```
In [2]: import numpy as np
        import pandas as pd
        import os
        import matplotlib.pyplot as plt
        from scipy.stats import gaussian_kde
        import time
        import seaborn as sns
        import os
        %matplotlib inline
        os.chdir('E:\\Google Drive\\kaggle\\03-facebook\\data')
```

1.1 Part 1 - Loading data

This will include sampling the data to 1M rows in case we want to do anything computationally tricky.

```
In [3]: df_train = pd.read_csv("train.csv")
        df_test = pd.read_csv("test.csv")
        df_train.head()
```

Out[3]:

	row_id	x	y	accuracy	time	place_id
0	0	0.7941	9.0809	54	470702	8523065625
1	1	5.9567	4.7968	13	186555	1757726713
2	2	8.3078	7.0407	74	322648	1137537235
3	3	7.3665	2.5165	65	704587	6567393236
4	4	4.0961	1.1307	31	472130	7440663949

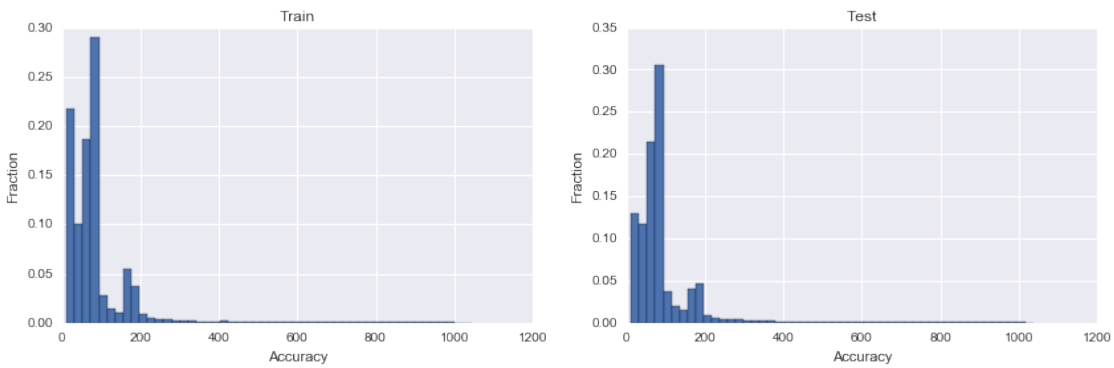
```
In [4]: # Sample them for quicker visualisations
        df_train_sample = df_train.sample(n=1000000)
        df_test_sample = df_test.sample(n=1000000)
```

1.2 Part 2 - Quick visualisations

Let's start with some basic histograms, showing the distribution of accuracy and time.

```
In [5]: counts1, bins1 = np.histogram(df_train["accuracy"], bins=50)
        binsc1 = bins1[:-1] + np.diff(bins1)/2.

        counts2, bins2 = np.histogram(df_test["accuracy"], bins=50)
        binsc2 = bins2[:-1] + np.diff(bins2)/2.

        plt.figure(0, figsize=(14,4))
```

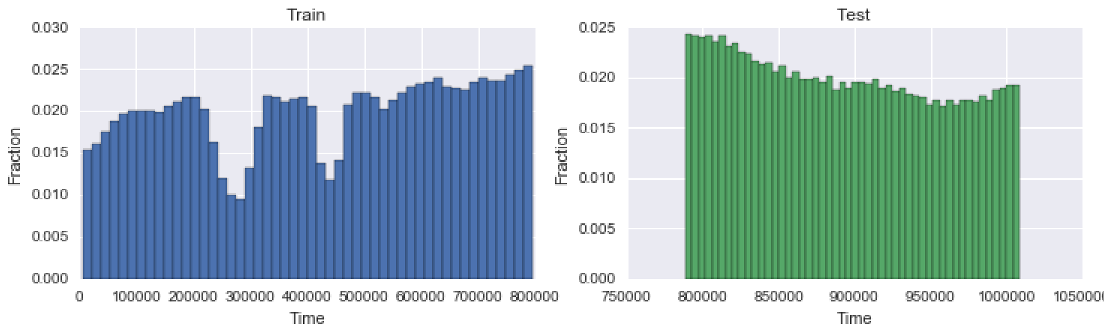
```
plt.subplot(121)
plt.bar(binsc1, counts1/(counts1.sum()*1.0), width=np.diff(bins1)[0])
plt.grid(True)
plt.xlabel("Accuracy")
plt.ylabel("Fraction")
plt.title("Train")

plt.subplot(122)
plt.bar(binsc2, counts2/(counts2.sum()*1.0), width=np.diff(bins2)[0])
plt.grid(True)
plt.xlabel("Accuracy")
plt.ylabel("Fraction")
plt.title("Test")

plt.show()
```



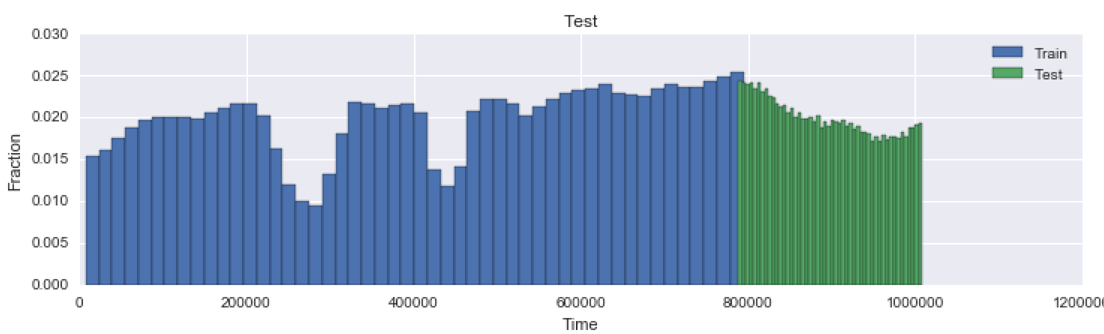
Accuracy has some interesting structure, but is relatively consistent across train/test. Check time distributions:

```
In [6]: current_palette = sns.color_palette()

        counts1, bins1 = np.histogram(df_train["time"], bins=50)
        binsc1 = bins1[:-1] + np.diff(bins1)/2.

        counts2, bins2 = np.histogram(df_test["time"], bins=50)
        binsc2 = bins2[:-1] + np.diff(bins2)/2.

        plt.figure(1, figsize=(12,3))

        plt.subplot(121)
        plt.bar(binsc1, counts1/(counts1.sum()*1.0), width=np.diff(bins1)[0], color=current_palette[0])
        plt.grid(True)
        plt.xlabel("Time")
        plt.ylabel("Fraction")
        plt.title("Train")

        plt.subplot(122)
        plt.bar(binsc2, counts2/(counts2.sum()*1.0), width=np.diff(bins2)[0], color=current_palette[1])
        plt.grid(True)
        plt.xlabel("Time")
```

```
plt.ylabel("Fraction")
plt.title("Test")

plt.show()
```



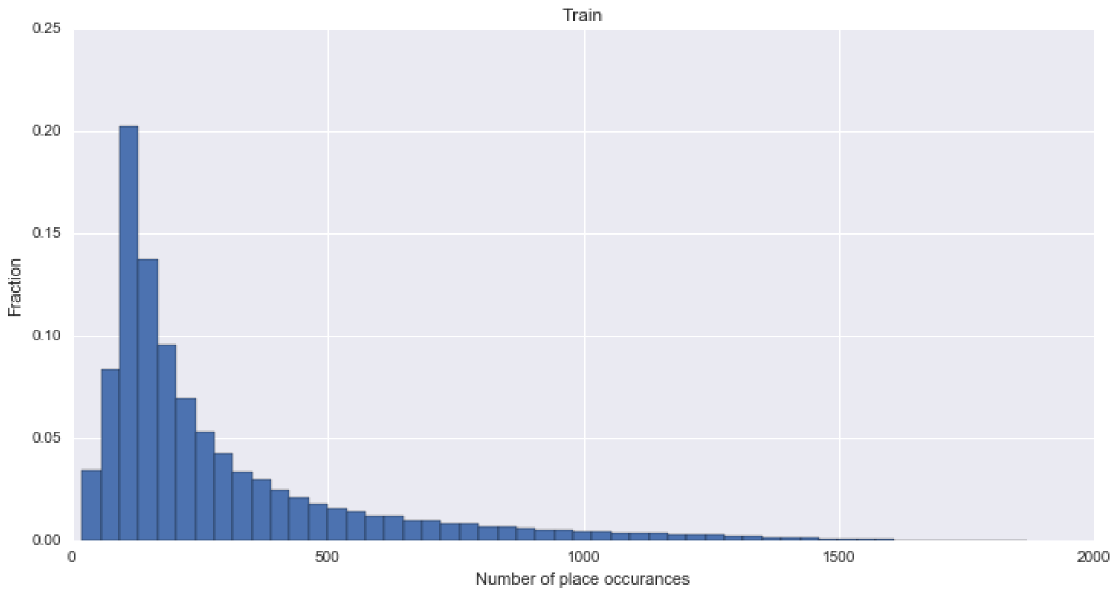
In [7]:
```
plt.figure(2, figsize=(12,3))
plt.bar(binsc1, counts1/(counts1.sum()*1.0), width=np.diff(bins1)[0], color=current_palette[0],
plt.bar(binsc2, counts2/(counts2.sum()*1.0), width=np.diff(bins2)[0], color=current_palette[1],
plt.grid(True)
plt.xlabel("Time")
plt.ylabel("Fraction")
plt.title("Test")
plt.legend()
plt.show()
```



The two dips of time in training set are curious, if looking at counts per unit time they might need to be normalised.
Another thing we can look at is how frequently different locations appear.

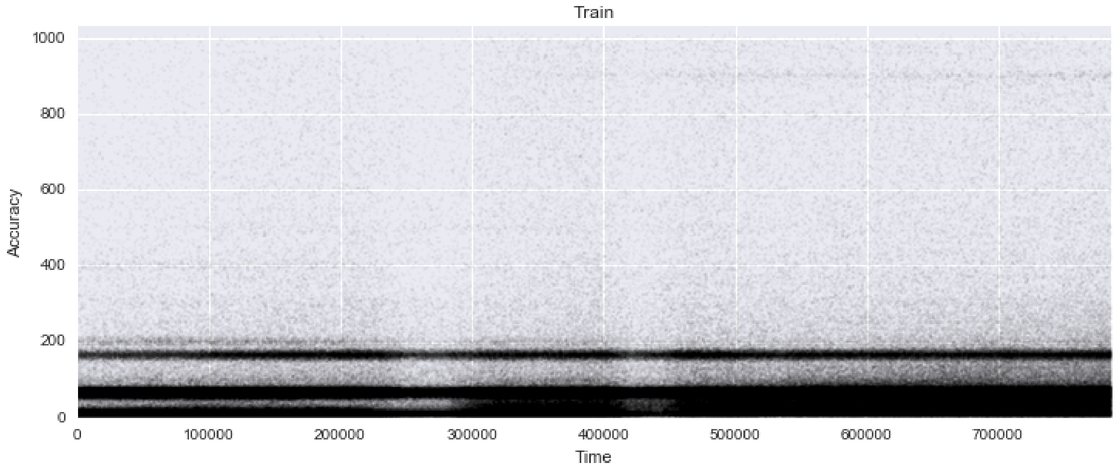
In [8]:
```
# Check how how frequently different locations appear
df_placecounts = df_train["place_id"].value_counts()

counts, bins = np.histogram(df_placecounts.values, bins=50)
binsc = bins[:-1] + np.diff(bins)/2.

plt.figure(3, figsize=(12,6))
plt.bar(binsc, counts/(counts.sum()*1.0), width=np.diff(bins)[0])
```

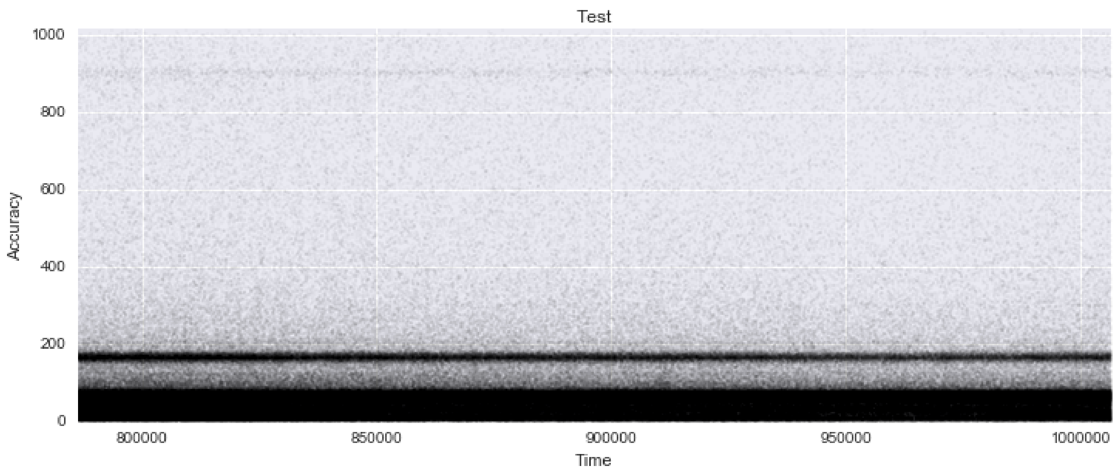
```
plt.grid(True)
plt.xlabel("Number of place occurances")
plt.ylabel("Fraction")
plt.title("Train")
plt.show()
```



OK, so most places appear around 100 times.
Let's see if accuracy changes with "time" at all:

In [9]:
```
# Check if accuracy of signal corresponds with time
plt.figure(4, figsize=(12,10))

plt.subplot(211)
plt.scatter(df_train_sample["time"], df_train_sample["accuracy"], s=1, c='k', lw=0, alpha=0.1)
plt.xlabel("Time")
plt.ylabel("Accuracy")
plt.xlim(df_train_sample["time"].min(), df_train_sample["time"].max())
plt.ylim(df_train_sample["accuracy"].min(), df_train_sample["accuracy"].max())
plt.title("Train")

plt.subplot(212)
plt.scatter(df_test_sample["time"], df_test_sample["accuracy"], s=1, c='k', lw=0, alpha=0.1)
plt.xlabel("Time")
plt.ylabel("Accuracy")
plt.xlim(df_test_sample["time"].min(), df_test_sample["time"].max())
plt.ylim(df_test_sample["accuracy"].min(), df_test_sample["accuracy"].max())
plt.title("Test")

plt.show()
```





Not really - but we can see the two time dips in the training plot, and this emphases that accuracy is somewhat perfentially banded.
What about if the accuracy varies with location?

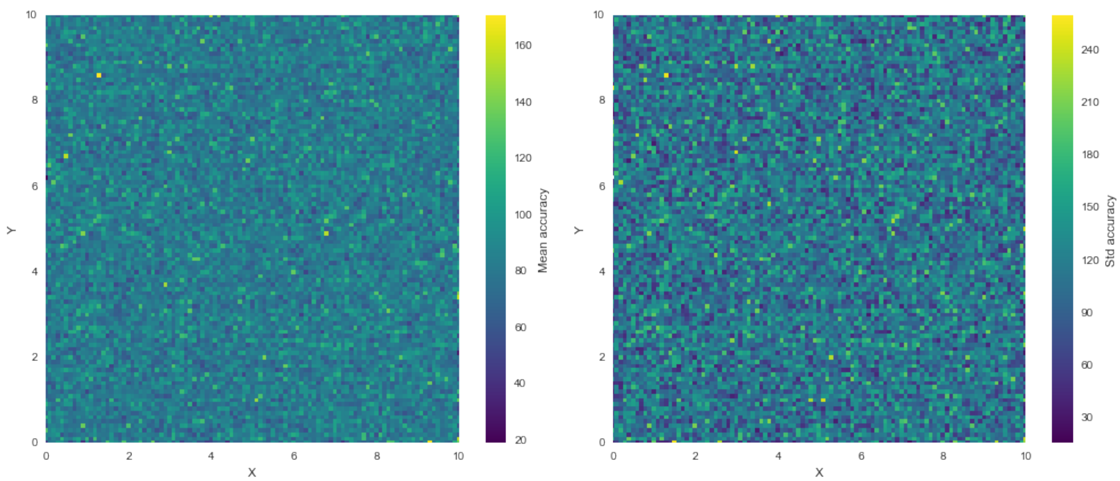
In [10]:
```
# Does the accuracy vary with location?  Check within 100x100m spots
df_train_sample["xround"] = df_train_sample["x"].round(decimals=1)
df_train_sample["yround"] = df_train_sample["y"].round(decimals=1)
df_groupxy = df_train_sample.groupby(["xround", "yround"]).agg({"accuracy":[np.mean, np.std]})
df_groupxy.head()
```

Out[10]:

		accuracy	
		mean	std
xround	yround		
0	0.0	47.000000	27.849596
	0.1	96.105263	167.946869
	0.2	84.545455	108.877241
	0.3	129.541667	178.145026
	0.4	57.625000	40.754634

In [11]:
```
idx = np.asarray(list(df_groupxy.index.values))
plt.figure(5, figsize=(14,6))
```

```
plt.subplot(121)
plt.scatter(idx[:,0], idx[:,1], s=20, c=df_groupxy["accuracy", "mean"], marker='s', lw=0, cmap=
plt.colorbar().set_label("Mean accuracy")
plt.grid(True)
plt.xlabel("X")
plt.ylabel("Y")
plt.xlim(0,10)
plt.ylim(0,10)

plt.subplot(122)
plt.scatter(idx[:,0], idx[:,1], s=20, c=df_groupxy["accuracy", "std"], marker='s', lw=0, cmap=
plt.colorbar().set_label("Std accuracy")
plt.grid(True)
plt.xlabel("X")
plt.ylabel("Y")
plt.xlim(0,10)
plt.ylim(0,10)

plt.tight_layout()
plt.show()
```



No major structure here.

1.3 Part 3 - Exploring places and times

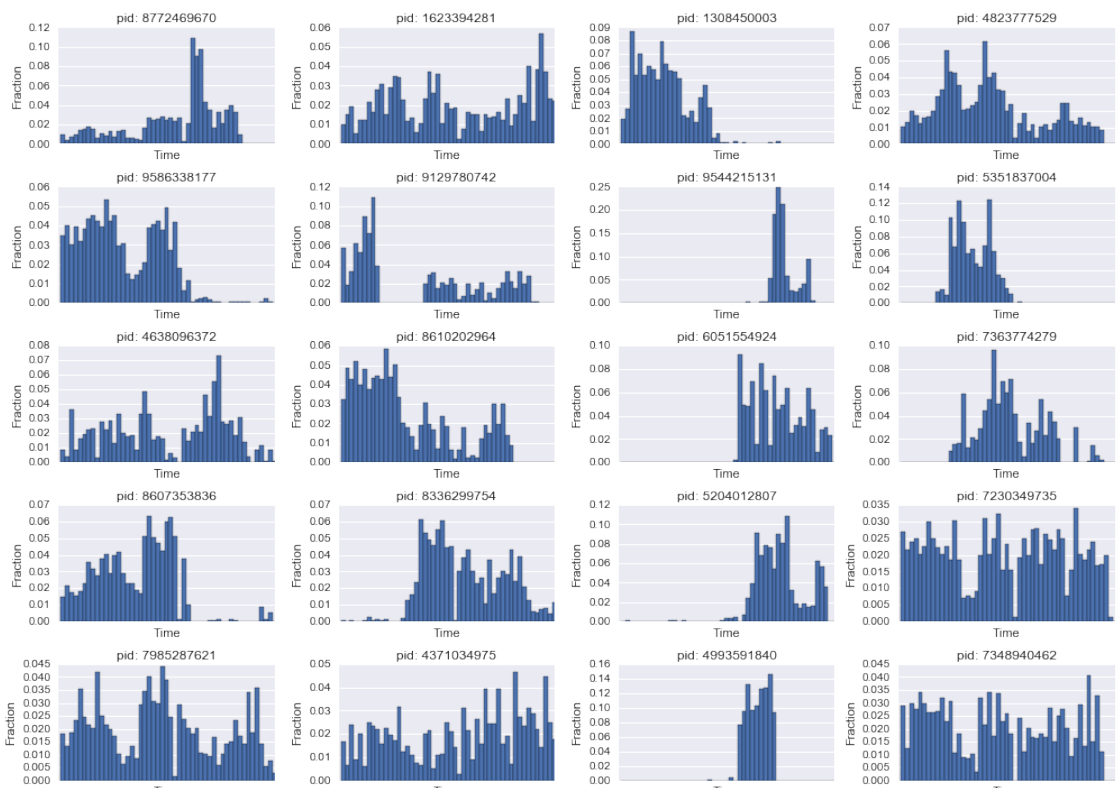
For the next parts, I've created a list of the top places (by check in counts), and chosen the top 20 to investigate further.

```
In [12]: # Get a list of the top 20 places for future reference
         df_topplaces = df_placecounts.iloc[0:20]
         l_topplaces = list(df_topplaces.index)
         print(l_topplaces)
```

```
[8772469670, 1623394281, 1308450003, 4823777529, 9586338177, 9129780742, 9544215131, 5351837004, 463809
```

```
In [13]: # Check if any of the top places have time correlated visits
         plt.figure(6, figsize=(14,10))
```

```
for i in range(len(l_topplaces)):
    place = l_topplaces[i]

    df_place = df_train[df_train["place_id"]==place]

    counts, bins = np.histogram(df_place["time"], bins=50, range=[df_train["time"].min(), df_t
    binsc = bins[:-1] + np.diff(bins)/2.

    plt.subplot(5,4,i+1)
    plt.bar(binsc, counts/(counts.sum()*1.0), width=np.diff(bins)[0])
    plt.xlim(df_train["time"].min(), df_train["time"].max())
    plt.grid(True)
    plt.xlabel("Time")
    plt.ylabel("Fraction")
    plt.gca().get_xaxis().set_ticks([])
    plt.title("pid: " + str(place))

plt.tight_layout()
plt.show()
```

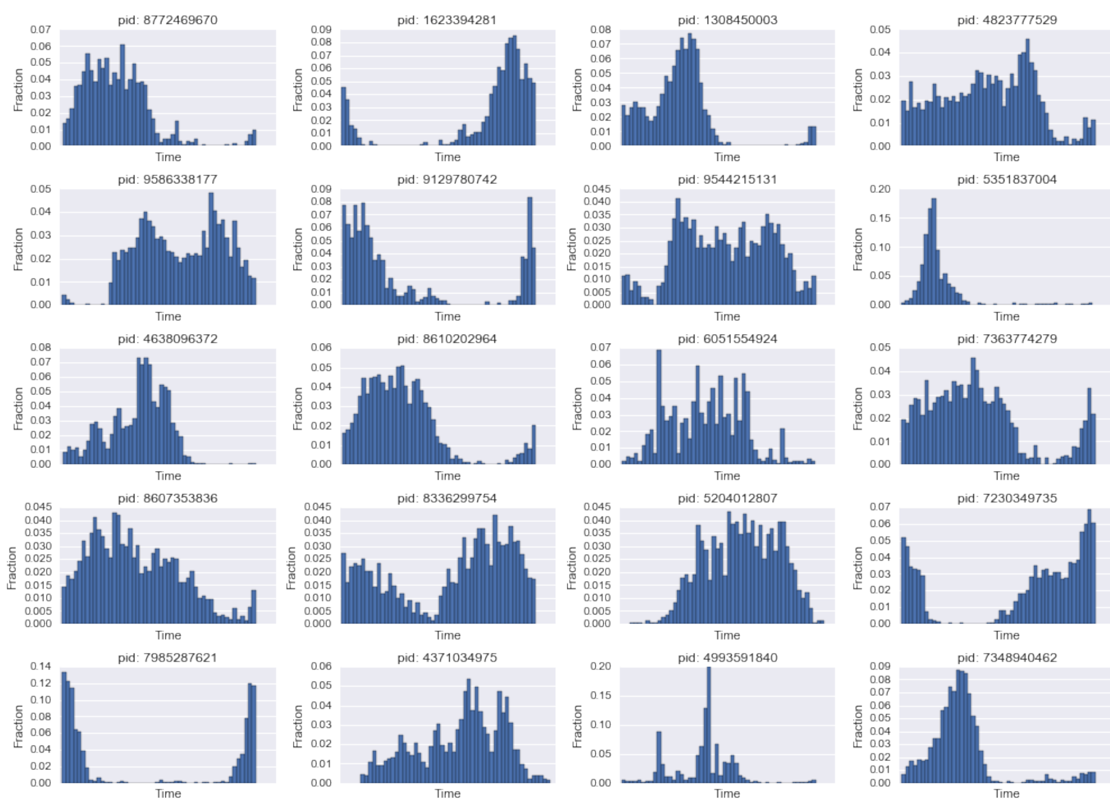


Well, some places are visited at certain time periods for sure, but can't do much else until we disentangle time.

The time interval in train goes from 1 - 800,000, presumably we can modulo these times to view cyclic nature (hours of days, days of week, etc).
The best guess is seconds or minutes, which would equate to the training spanning 9 or 555 days respectively.

```
In [14]: # Try to infer time
```

```
plt.figure(7, figsize=(14,10))
for i in range(len(l_topplaces)):
    place = l_topplaces[i]

    df_place = df_train[df_train["place_id"]==place]

    # Try % 3600*24 to see daily trend assuming it's in seconds
    # Try %   60*24 if minutes
    counts, bins = np.histogram(df_place["time"]%(60*24), bins=50)
    binsc = bins[:-1] + np.diff(bins)/2.

    plt.subplot(5,4,i+1)
    plt.bar(binsc, counts/(counts.sum()*1.0), width=np.diff(bins)[0])
    plt.grid(True)
    plt.xlabel("Time")
    plt.ylabel("Fraction")
    plt.gca().get_xaxis().set_ticks([])
    plt.title("pid: " + str(place))

plt.tight_layout()
plt.show()
```



Minutes looks pretty promising.
This means we have ~555 days in train and ~140 in test.
From this, we can look at day of week to identify trends (weekends), day (to find longer term seasonality).
The next step is to add some columns representing our new time.

Getting this exactly right (within the minute, so that "hours" are defined by clock hours, which probably correlate better with place visits) will probably be crucial later on, but as a first it doesn't matter if we're out by a bit.

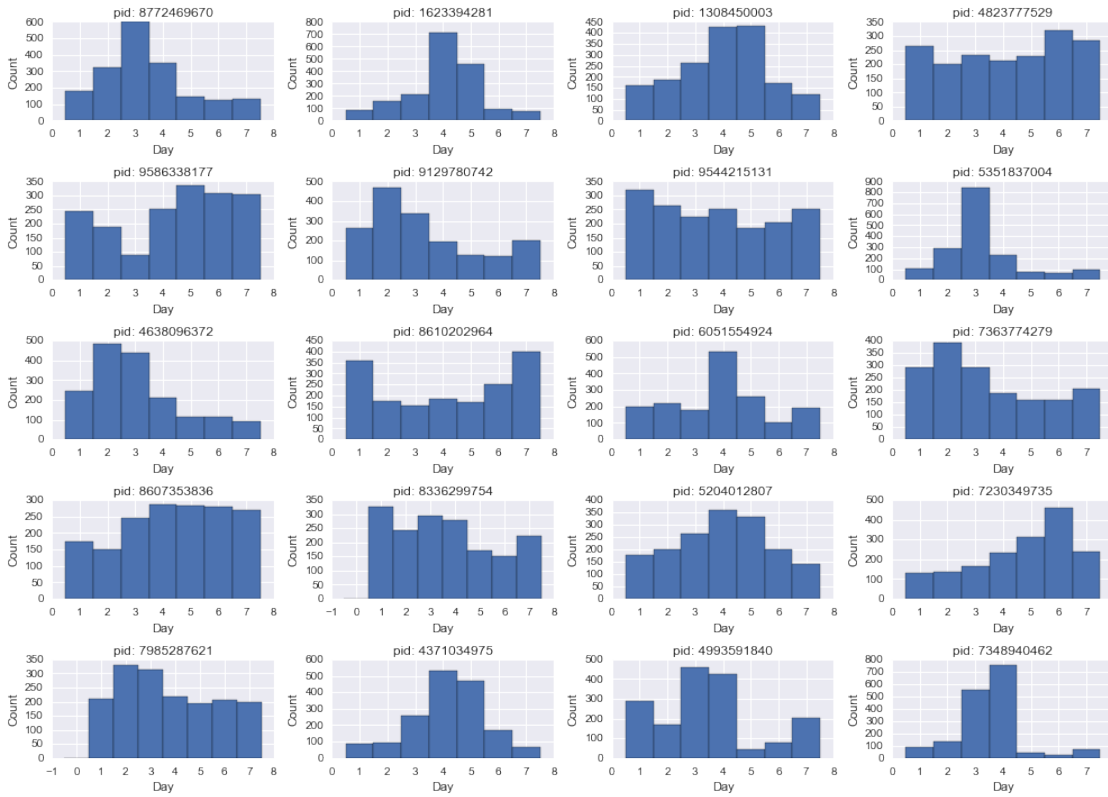
```
In [15]: # Add some columns to make calculations easier
         df_train["hour"] = (df_train["time"]%(60*24))/60.
         df_train["dayofweek"] = np.ceil((df_train["time"]%(60*24*7))/(60.*24))
         df_train["dayofyear"] = np.ceil((df_train["time"]%(60*24*365))/(60.*24))
         df_train.head()
```

```
Out[15]:    row_id       x       y  accuracy    time    place_id       hour  dayofweek  \
         0       0  0.7941  9.0809        54  470702  8523065625  21.033333          5
         1       1  5.9567  4.7968        13  186555  1757726713  13.250000          4
         2       2  8.3078  7.0407        74  322648  1137537235   1.466667          1
         3       3  7.3665  2.5165        65  704587  6567393236   7.116667          7
         4       4  4.0961  1.1307        31  472130  7440663949  20.833333          6

            dayofyear
         0        327
         1        130
         2        225
         3        125
         4        328
```

```
In [16]: df_train_sample["hour"] = (df_train_sample["time"]%(60*24))/60.
         df_train_sample["dayofweek"] = np.ceil((df_train_sample["time"]%(60*24*7))/(60.*24))
         df_train_sample["dayofyear"] = np.ceil((df_train_sample["time"]%(60*24*365))/(60.*24))
```

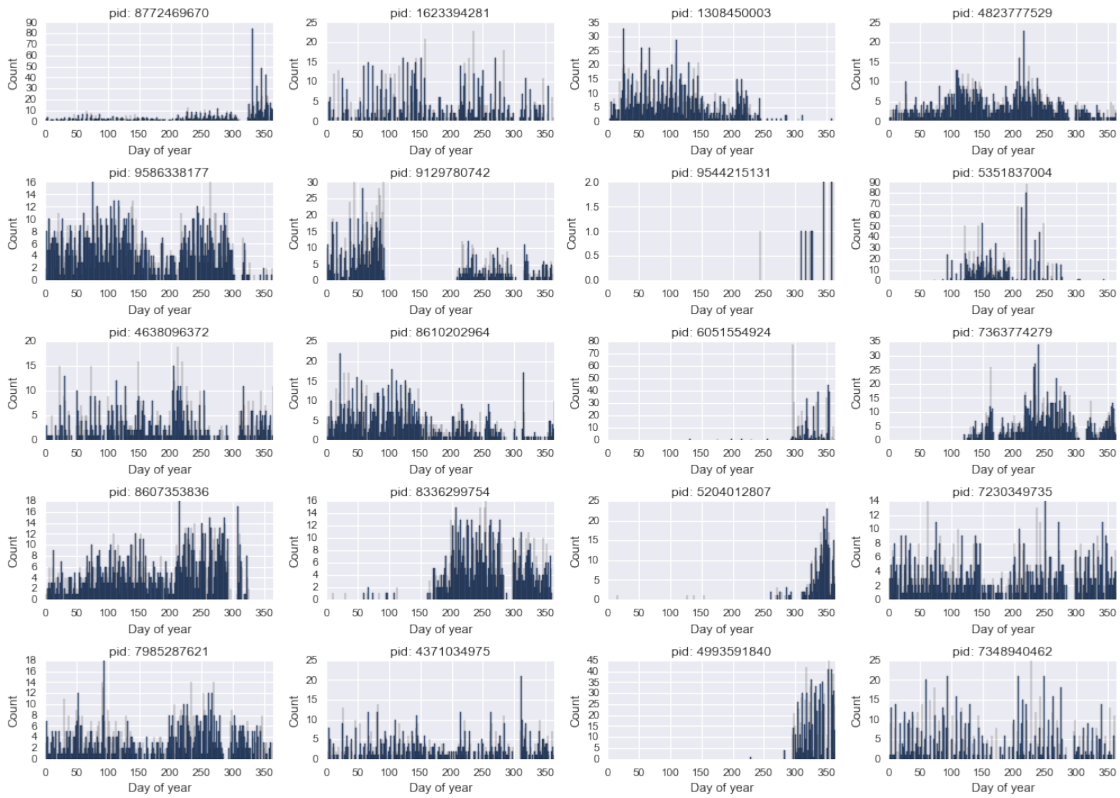
Look at the aggregate number of visits per weekday for the top 20 locations, this should show weekends, hopefully.

```
In [17]: # Check the top 20 locations again for any weekly trends
         plt.figure(8, figsize=(14,10))
         for i in range(20):
             place = l_topplaces[i]
             df_place = df_train[df_train["place_id"]==place]

             # Group by weekday
             df_groupday = df_place.groupby("dayofweek").agg("count")

             plt.subplot(5,4,i+1)
             plt.bar(df_groupday.index.values-0.5, df_groupday["time"], width=1)
             plt.grid(True)
             plt.xlabel("Day")
             plt.ylabel("Count")
             plt.title("pid: " + str(place))

         plt.tight_layout()
         plt.show()
```



Some appear to have weekend-like behvaiour... what about looking at day of year.

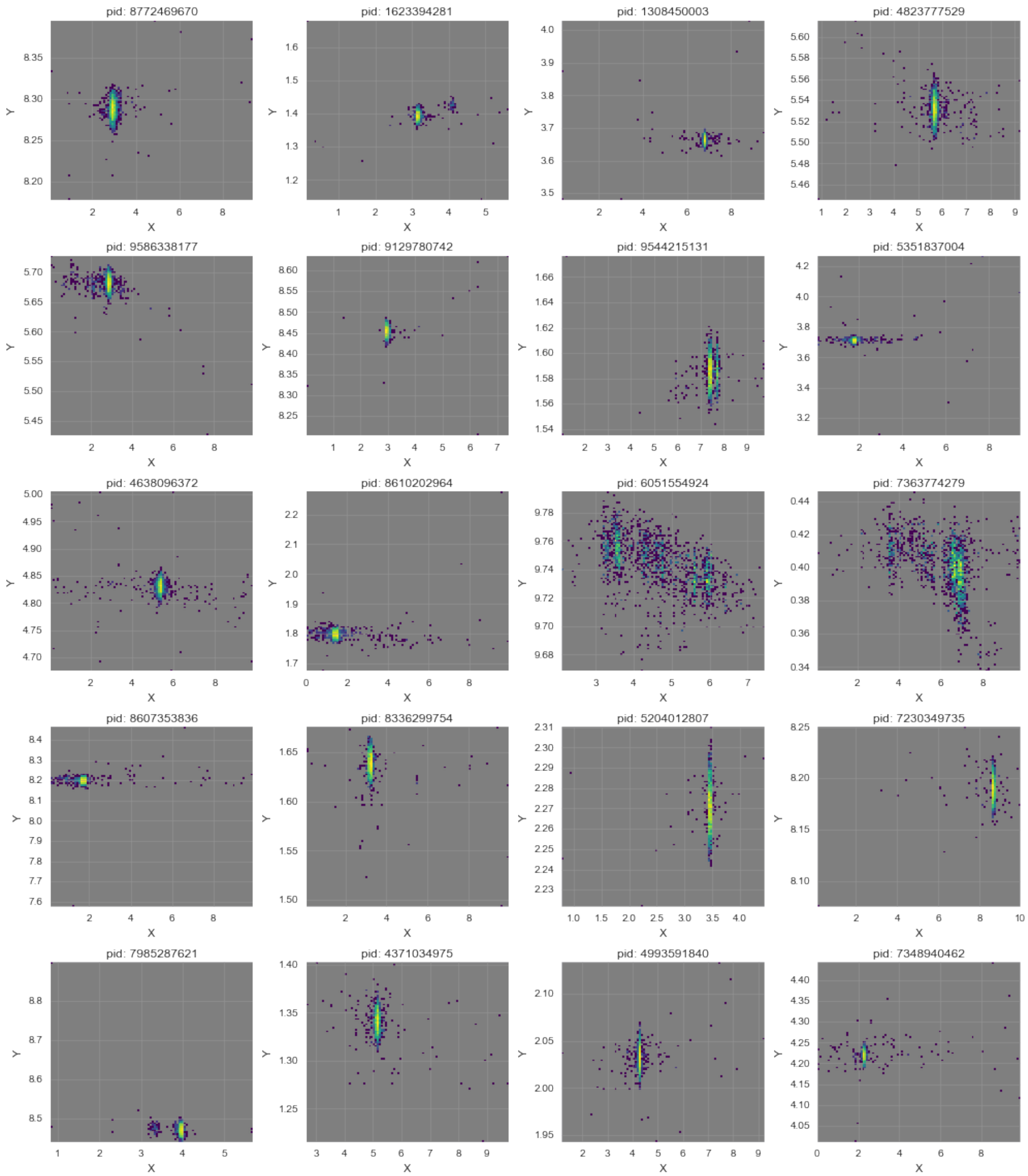
In [18]:
```
plt.figure(9, figsize=(14,10))
for i in range(20):
    place = l_topplaces[i]
    df_place = df_train[df_train["place_id"]==place]

    # Add some colums
    df_place = df_place[df_place["time"]<(60*24*365)] # Restrict to 1 year so the counts don't
    df_groupday = df_place.groupby("dayofyear").agg("count")

    plt.subplot(5,4,i+1)
    plt.bar(df_groupday.index.values-0.5, df_groupday["time"], width=1)
    plt.grid(True)
    plt.xlabel("Day of year")
    plt.ylabel("Count")
    plt.xlim(0,365)
    plt.title("pid: " + str(place))

plt.tight_layout()
plt.show()
```



Somewhat weird trends, looks like some of the top places only opened up business part way through. The next interesting thing is to look at the distribution of (x,y) points for a given location:

```
In [19]: # Check the 2d distribution of (x,y) for the top 20 places
         plt.figure(10, figsize=(14,16))
         cmapm = plt.cm.viridis
         cmapm.set_bad("0.5",1.)

         for i in range(len(l_topplaces)):
             place = l_topplaces[i]
             df_place = df_train[df_train["place_id"]==place]
             counts, binsX, binsY = np.histogram2d(df_place["x"], df_place["y"], bins=100)
             extent = [binsX.min(),binsX.max(),binsY.min(),binsY.max()]

             plt.subplot(5,4,i+1)
             plt.imshow(np.log10(counts.T),
                        interpolation='none',
                        origin='lower',
                        extent=extent,
                        aspect="auto",
                        cmap=cmapm)
             plt.grid(True, c='0.6', lw=0.5)
             plt.xlabel("X")
             plt.ylabel("Y")
             plt.title("pid: " + str(place))
```

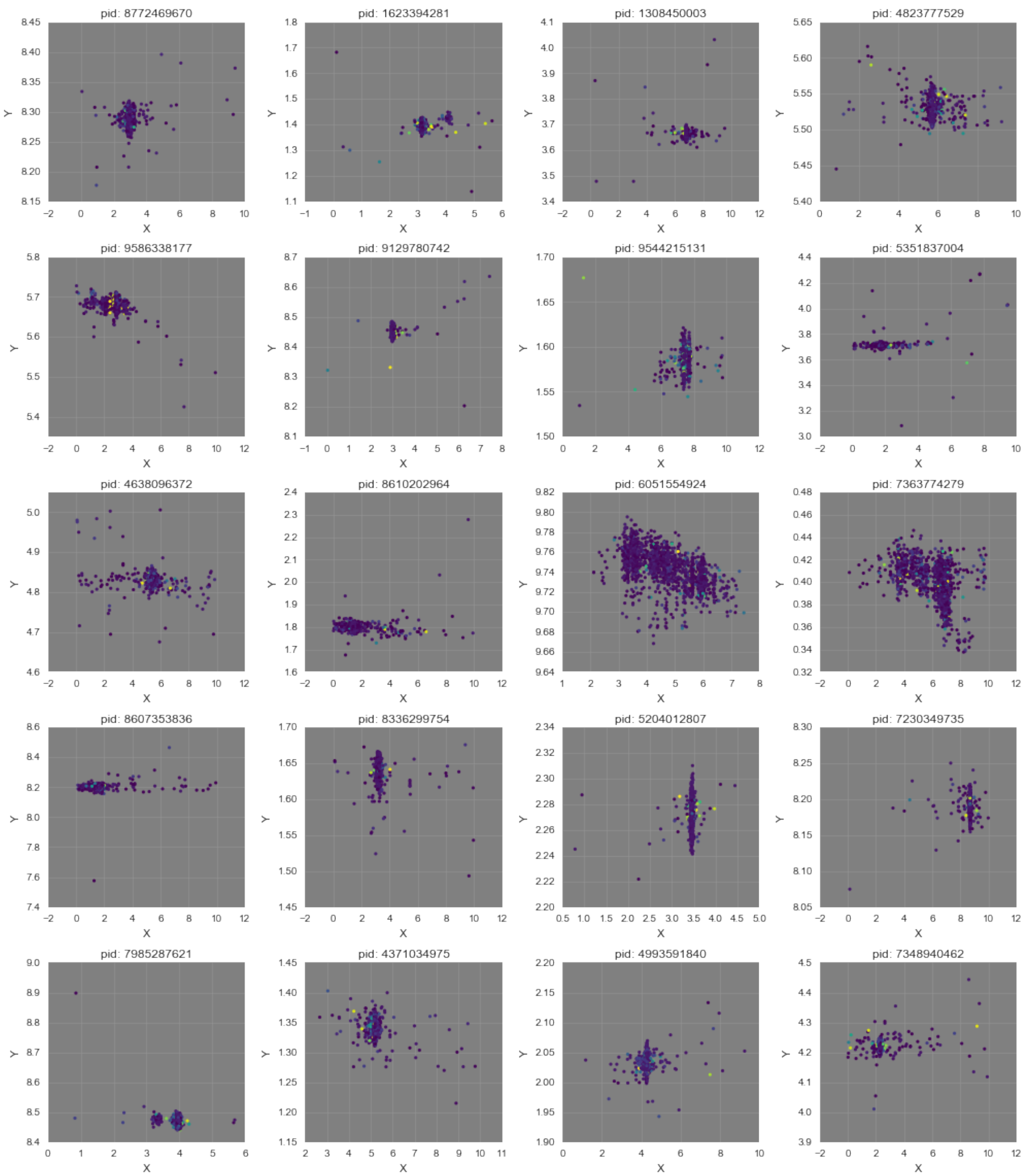
```
plt.tight_layout()
plt.show()
```



The distributions are different for different locations, but many span a huge x-range relative to the y-range (maybe roads are aligned this way?)
Let's re-visit the accuracy to see if it changes we get further away from the presumed centroid location:

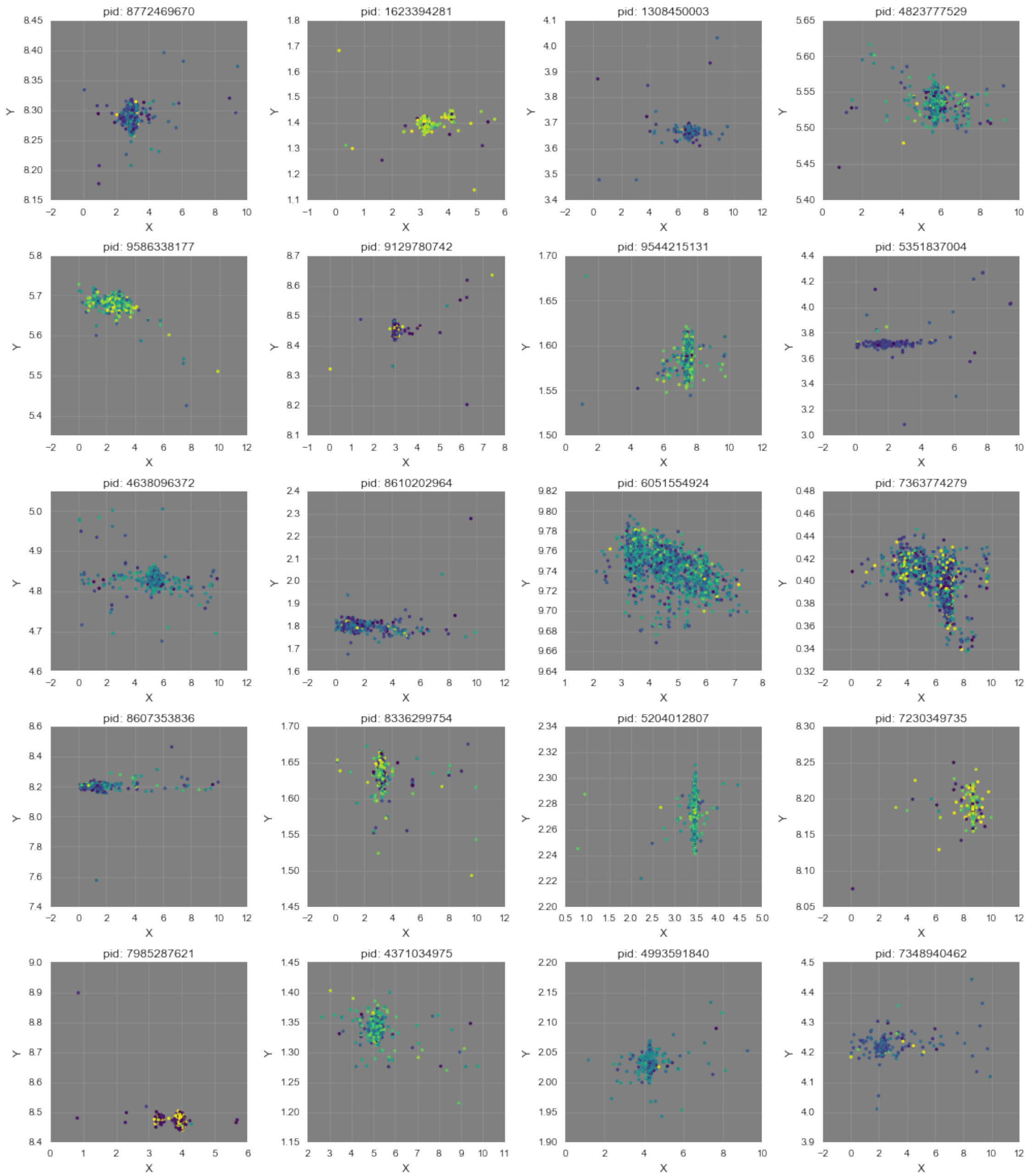
In [20]:
```
# See if the accuracy varies with distance from centroid point
plt.figure(11, figsize=(14,16))

for i in range(len(l_topplaces)):
```

```
    plt.subplot(5,4,i+1)
    plt.gca().set_axis_bgcolor("0.5")
    place = l_topplaces[i]
    df_place = df_train[df_train["place_id"]==place]
    plt.scatter(df_place["x"], df_place["y"], s=10, c=df_place["accuracy"], lw=0, cmap=plt.cm.
    plt.grid(True, c='0.6', lw=0.5)
    plt.xlabel("X")
    plt.ylabel("Y")
    plt.title("pid: " + str(place))

plt.tight_layout()
plt.show()
```



Nope, not really. What about time variance per location?

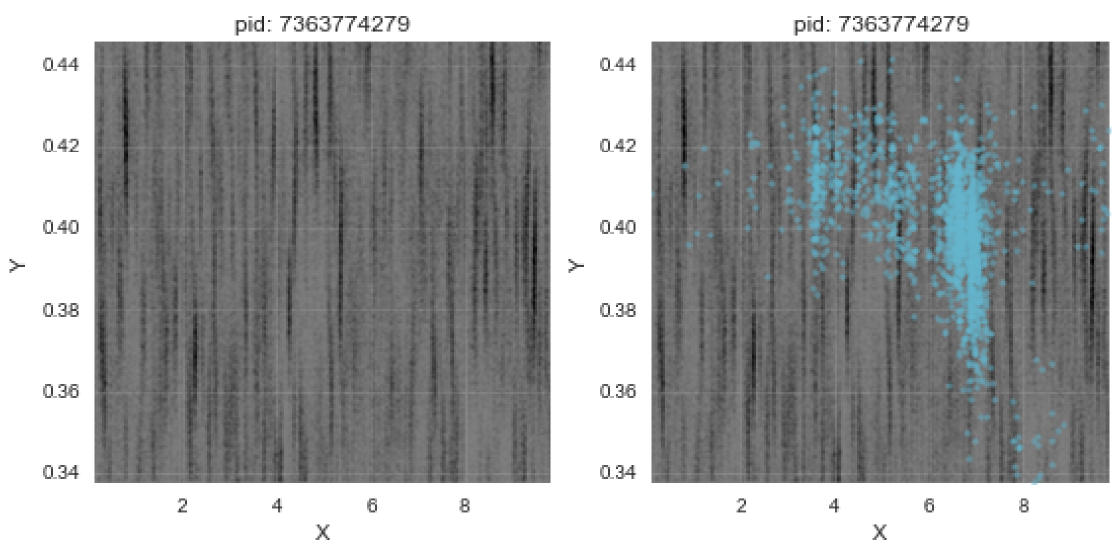
In [21]:
```
# See if the time varies with distance from centroid point
plt.figure(12, figsize=(14,16))

for i in range(len(l_topplaces)):
    plt.subplot(5,4,i+1)
    plt.gca().set_axis_bgcolor("0.5")
    place = l_topplaces[i]
    df_place = df_train[df_train["place_id"]==place]
    plt.scatter(df_place["x"], df_place["y"], s=10, c=df_place["hour"], lw=0, cmap=plt.cm.viri
    plt.grid(True, c='0.6', lw=0.5)
    plt.xlabel("X")
    plt.ylabel("Y")
    plt.title("pid: " + str(place))

plt.tight_layout()
plt.show()
```



This certainly shows different places are preferentially visited at different hours.
This will be useful for predictions, since for a given "hour" the list of probably places will be reduced.
Let's pick an arbitrary place, and see if it's shape is discernible over the background noise.

In [22]:
```
# Pick a place, and see if it's shape profile stands out against background noise (i.e., every
i = 11
place = l_topplaces[i]
df_place = df_train[df_train["place_id"]==place]
xmin, xmax = df_place["x"].min(), df_place["x"].max()
ymin, ymax = df_place["y"].min(), df_place["y"].max()
df_noise = df_train[(df_train["x"]>xmin) &
```

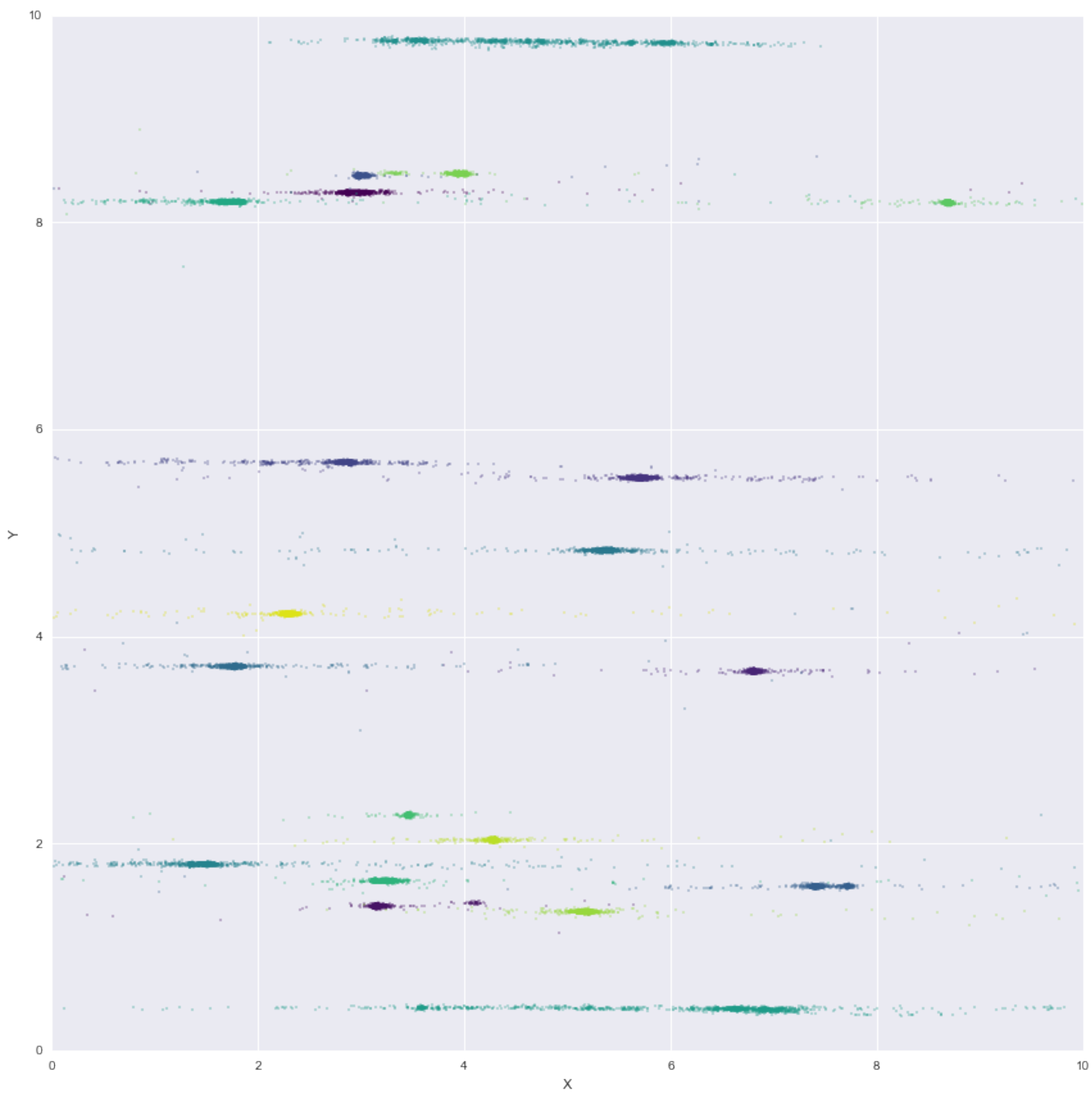
```
                             (df_train["x"]<xmax) &
                             (df_train["y"]>ymin) &
                             (df_train["y"]<ymax)]

        plt.figure(13, figsize=(8,4))
        plt.subplot(121)
        plt.gca().set_axis_bgcolor("0.5")
        plt.scatter(df_noise["x"], df_noise["y"], s=10, c='k', lw=0, alpha=0.005)
        plt.xlabel("X")
        plt.ylabel("Y")
        plt.title("pid: " + str(place))
        plt.xlim(xmin,xmax)
        plt.ylim(ymin,ymax)
        plt.grid(True, c='0.6', lw=0.5)

        plt.subplot(122)
        plt.gca().set_axis_bgcolor("0.5")
        plt.scatter(df_noise["x"], df_noise["y"], s=10, c='k', lw=0, alpha=0.005)
        plt.scatter(df_place["x"], df_place["y"], s=10, c=current_palette[5], lw=0, alpha=0.5)
        plt.xlabel("X")
        plt.ylabel("Y")
        plt.title("pid: " + str(place))
        plt.xlim(xmin,xmax)
        plt.ylim(ymin,ymax)
        plt.grid(True, c='0.6', lw=0.5)

        plt.tight_layout()
        plt.show()
```



...not really. OK, let's revisit this x-axis stretching business by visualising these top 20 locations on a map.

```
In [23]: # Go back to the x-axis stretching, and visualise some location checkins on a map
         plt.figure(14, figsize=(12,12))
```

```
for i in range(20):
    place = l_topplaces[i]
    df_place = df_train[df_train["place_id"]==place]
    plt.scatter(df_place["x"], df_place["y"], s=3, alpha=0.5, c=plt.cm.viridis(int(i*(255/20.))

plt.grid(True)
plt.xlabel("X")
plt.ylabel("Y")
plt.tight_layout()
plt.xlim(0,10)
plt.ylim(0,10)
plt.show()
```



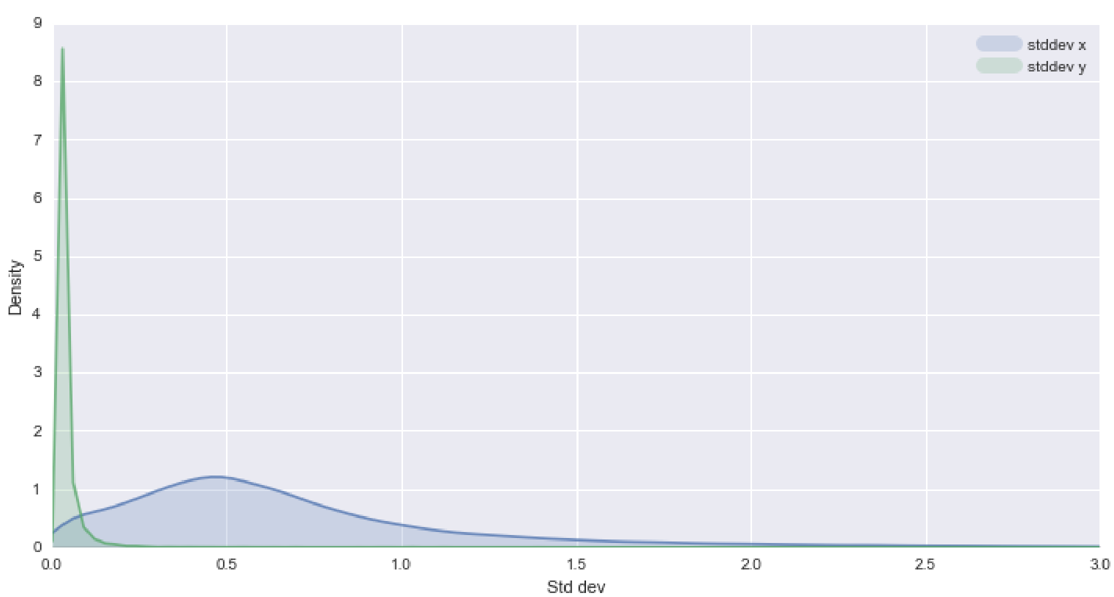
This highlights the variance, looking suspiciously like streets. We can look at the standard deviations to illustrate this:

In [24]:
```
# Check the stdev of x/y for each place
df_groupplace = df_train.groupby("place_id").agg({"time":"count", "x":"std", "y":"std"})
df_groupplace.sort_values(by="time", inplace=True, ascending=False)
df_groupplace.head()
```

Out[24]:

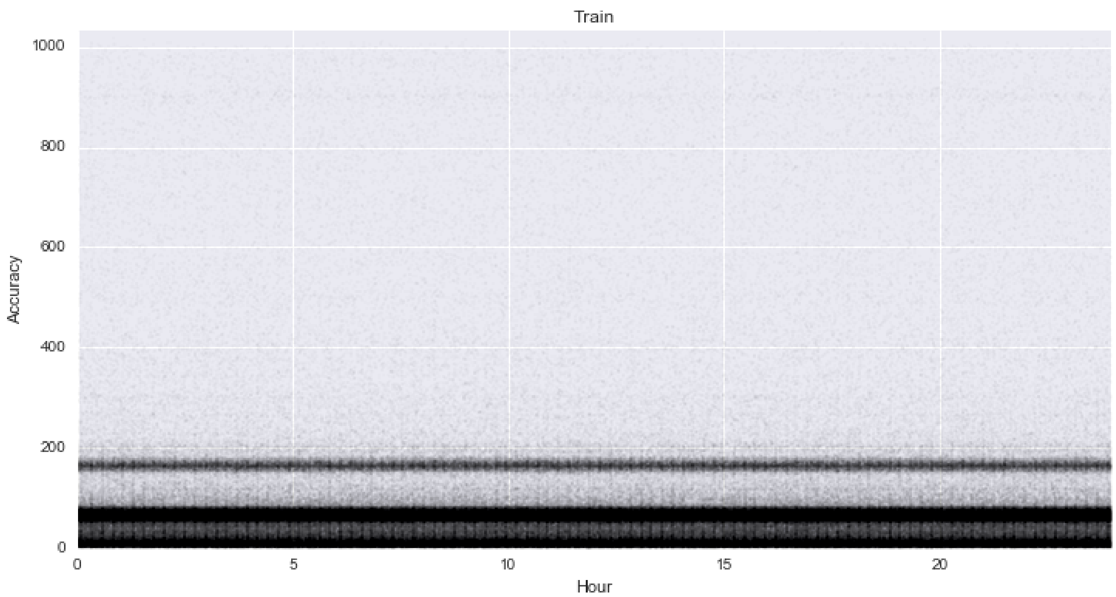
place_id	y	x	time
8772469670	0.011544	0.356140	1849
1623394281	0.015712	0.240642	1802
1308450003	0.017662	0.340147	1757
4823777529	0.011860	0.476614	1738
9586338177	0.014817	0.507308	1718

In [25]:
```
# Density plot
gkde_stddevx = gaussian_kde(df_groupplace["x"][~df_groupplace["x"].isnull()].values)
gkde_stddevy = gaussian_kde(df_groupplace["y"][~df_groupplace["y"].isnull()].values)

# Compute the functions
rangeX = np.linspace(0, 3, 100)
x_density = gkde_stddevx(rangeX)
y_density = gkde_stddevy(rangeX)

plt.figure(15, figsize=(12,6))
plt.subplot(111)
plt.plot(rangeX, x_density, c=current_palette[0], ls="-", alpha=0.75)
plt.plot(rangeX, y_density, c=current_palette[1], ls="-", alpha=0.75)
plt.gca().fill_between(rangeX, 0, x_density, facecolor=current_palette[0], alpha=0.2)
plt.gca().fill_between(rangeX, 0, y_density, facecolor=current_palette[1], alpha=0.2)
plt.ylabel("Density")
plt.xlabel("Std dev")
plt.plot([], [], c=current_palette[0], alpha=0.2, linewidth=10, label="stddev x")
plt.plot([], [], c=current_palette[1], alpha=0.2, linewidth=10, label="stddev y")
plt.legend()
plt.grid(True)
```



That's pretty striking and will be useful later on.
Back to time, what if the accuracy varies as a function of hour of day?

```
In [26]: # With the new found time features, we can re-check how accuracy varies with it:
         plt.figure(19, figsize=(12,6))
         plt.scatter(df_train_sample["hour"], df_train_sample["accuracy"], s=1, c='k', lw=0, alpha=0.05)
         plt.xlabel("Hour")
         plt.ylabel("Accuracy")
         plt.xlim(df_train_sample["hour"].min(), df_train_sample["hour"].max())
         plt.ylim(df_train_sample["accuracy"].min(), df_train_sample["accuracy"].max())
         plt.title("Train")
         plt.show()
```



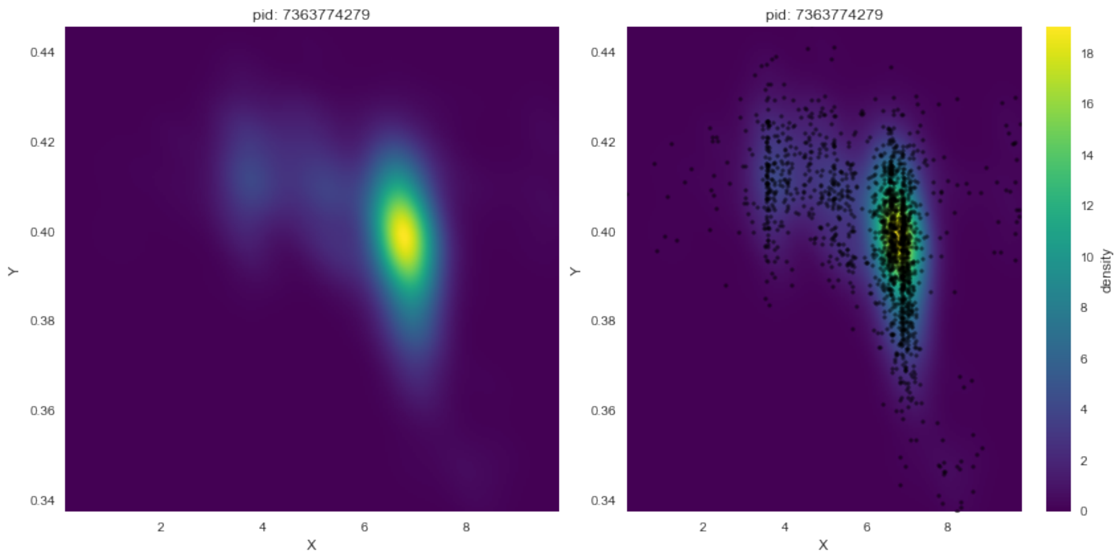
Pretty consistent...

1.4 Part 4 - Predictions pre-processing

One method of determining which place a location might check in to is by looking at the density of points previously used to checkin.
You could check each point against each density map, and take the maximum.

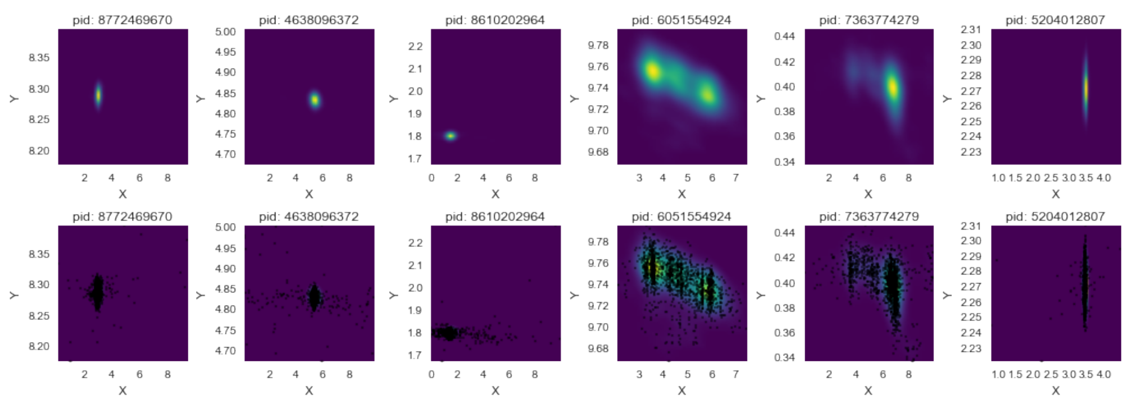
```
In [27]: # Try some KDEs, if we can define the density where check-ins are likely, maybe we can assign p
         # They will also be time variant
         i = 11
         place = l_topplaces[i]
         df_place = df_train[df_train["place_id"]==place]
         xmin, xmax = df_place["x"].min(), df_place["x"].max()
         ymin, ymax = df_place["y"].min(), df_place["y"].max()

         # Calculate the KDE
         res = 200 # resolution
```

```python
gkde_place = gaussian_kde(np.asarray((df_place["x"], df_place["y"])))
x_flat = np.linspace(xmin, xmax, res)
y_flat = np.linspace(ymin, ymax, res)
x, y = np.meshgrid(x_flat,y_flat)
grid_coords = np.append(x.reshape(-1,1),y.reshape(-1,1),axis=1)
z = gkde_place(grid_coords.T)
z = z.reshape(res,res)

# Plot
extent = [xmin,xmax,ymin,ymax]
plt.figure(20, figsize=(12,6))

# KDE only
plt.subplot(121)
plt.imshow(z[::-1,:],
           extent=extent,
           aspect="auto",
           cmap=plt.cm.viridis,
           interpolation="bilinear")
plt.grid(False)
plt.xlabel("X")
plt.ylabel("Y")
plt.title("pid: " + str(place))
plt.xlim(xmin,xmax)
plt.ylim(ymin,ymax)

# Overplot the points
plt.subplot(122)
plt.imshow(z[::-1,:],
           extent=extent,
           aspect="auto",
           cmap=plt.cm.viridis,
           interpolation="bilinear")
plt.colorbar().set_label("density")
plt.scatter(df_place["x"], df_place["y"], s=10, c='k', lw=0, alpha=0.5)
plt.grid(False)
plt.xlabel("X")
plt.ylabel("Y")
plt.title("pid: " + str(place))
plt.xlim(xmin,xmax)
plt.ylim(ymin,ymax)

plt.tight_layout()
plt.show()
```




```
In [28]: # Try some more
         pids = [0,8,9,10,11,14] # A few places
         kdes = []
         plt.figure(21, figsize=(14,5))
         for i in range(len(pids)):
             place = l_topplaces[pids[i]]
             df_place = df_train[df_train["place_id"]==place]
             xmin, xmax = df_place["x"].min(), df_place["x"].max()
             ymin, ymax = df_place["y"].min(), df_place["y"].max()

             # Calculate the KDE
             res = 50 # resolution
             gkde_place = gaussian_kde(np.asarray((df_place["x"], df_place["y"])))
             kdes.append(gkde_place) # Keep these KDEs for later
             x_flat = np.linspace(xmin, xmax, res)
             y_flat = np.linspace(ymin, ymax, res)
             x, y = np.meshgrid(x_flat,y_flat)
             grid_coords = np.append(x.reshape(-1,1),y.reshape(-1,1),axis=1)
             z = gkde_place(grid_coords.T)
             z = z.reshape(res,res)

             # Plot
             extent = [xmin,xmax,ymin,ymax]

             # KDE only
             plt.subplot(2,6,i+1)
             plt.imshow(z[::-1,:],
                        extent=extent,
                        aspect="auto",
                        cmap=plt.cm.viridis,
                        interpolation="bilinear")
             plt.grid(False)
             plt.xlabel("X")
```

```
    plt.ylabel("Y")
    plt.title("pid: " + str(place))
    plt.xlim(xmin,xmax)
    plt.ylim(ymin,ymax)

    # Overplot the points
    plt.subplot(2,6,i+7)
    plt.imshow(z[::-1,:],
               extent=extent,
               aspect="auto",
               cmap=plt.cm.viridis,
               interpolation="bilinear")
    plt.scatter(df_place["x"], df_place["y"], s=5, c='k', lw=0, alpha=0.5)
    plt.grid(False)
    plt.xlabel("X")
    plt.ylabel("Y")
    plt.title("pid: " + str(place))
    plt.xlim(xmin,xmax)
    plt.ylim(ymin,ymax)

plt.tight_layout()
plt.show()
```



Next steps?
- Could try using KDEs of each place to get a metric for each (x,y) location indicating how close to the place it is
- Play with time offset to try and get more precise definition of hours
- Use time to eliminate certain places from being possible at given hours
- Find out what accuracy does

```
In [ ]:
```