# Quantifying crowd size with mobile phone and Twitter data - Final Report

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## Introduction

We elected to replicate the findings of Federico Botta, Helen Susannah Moat, and Tobias Preis's paper on Quantifying crowd size with mobile phone and *Twitter* data. In the paper, they look at a number of soccer games with a known attendence and known phone, internet and twitter acitivity; and they evaluate the similar phone and internet and twitter acitivty in comparison to a number of flights over a several week period.

## Data Import

The data is in very good shape, but we do need to tell `R` that the timestamps are in-fact date-time objects, and not just generic strings.

```
san_siero.attendees = read.csv('./data/Attendees_San_Siro.csv')
san_siero.phone_data = read.csv('./data/San_Siro_Mobile_Phone_Data.csv')
san_siero.twitter_data = read.csv('./data/San_Siro_Twitter_Data.csv')
linate.data = read.csv('./data/Linate_Data.csv')
linate.flight_schedule = read.csv('./data/Linate_Flights_Schedule.csv')

# Converting to dates
san_siero.phone_data$Timestamp = as.Date(strptime(san_siero.phone_data$Timestamp,
                                                  "%Y-%m-%d %H:%M:%S"))
san_siero.twitter_data$Timestamp = as.Date(san_siero.twitter_data$Timestamp)
san_siero.attendees$Date = as.Date(san_siero.attendees$Date)
```

## Soccer Games Dataset

The soccer data includes 3 raw files, one containing the dates of the soccer games as well as the attendence. The phone data includes a measure of calls / SMS activity and Internet activity with a timestamp. We will show later, that we are only interested in the date, and have no interest in the time. The third file includes a measure of twitter activity with an associate date. To do an analysis on this data, we need to merge the data into a common dataframe, where we are interested only in the maximum value of the calls / SMS activity and Internet activity numbers for a given day. We then exclude days that did not have any soccer matches, and have our data.frame ready for analysis.

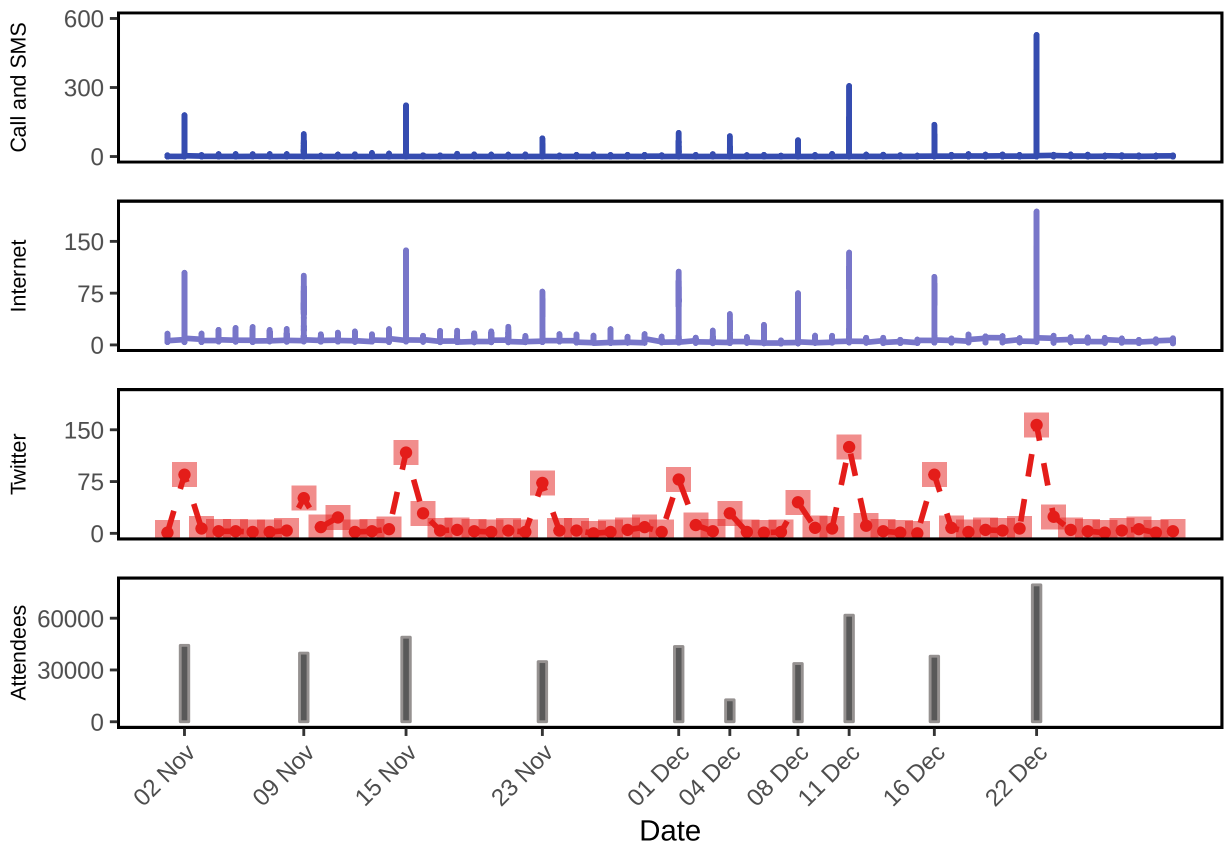
```
san_siero.daily_data <- aggregate(san_siero.phone_data$Calls.and.SMS.Activity,
                                  by=list(Category=san_siero.phone_data$Timestamp),
                                  FUN=max)
san_siero.daily_data <- rename(san_siero.daily_data, c("x"="Calls.and.SMS.Activity"))
san_siero.daily_data$Internet.Activity = aggregate(san_siero.phone_data$Internet.Activity,
                                         by=list(Cateogry=san_siero.phone_data$Timestamp),
                                         FUN=max)$x
```

```r
san_siero.daily_data$Twitter.Activity = san_siero.twitter_data$Twitter.Activity
san_siero.daily_data <- rename(san_siero.daily_data, c("Category"="Date"))
soccer_data <- merge(san_siero.daily_data, san_siero.attendees,
                                        by="Date")

kable(head(soccer_data),
            format='pandoc',
            caption='Soccer Game Data',
            centering=TRUE)
```

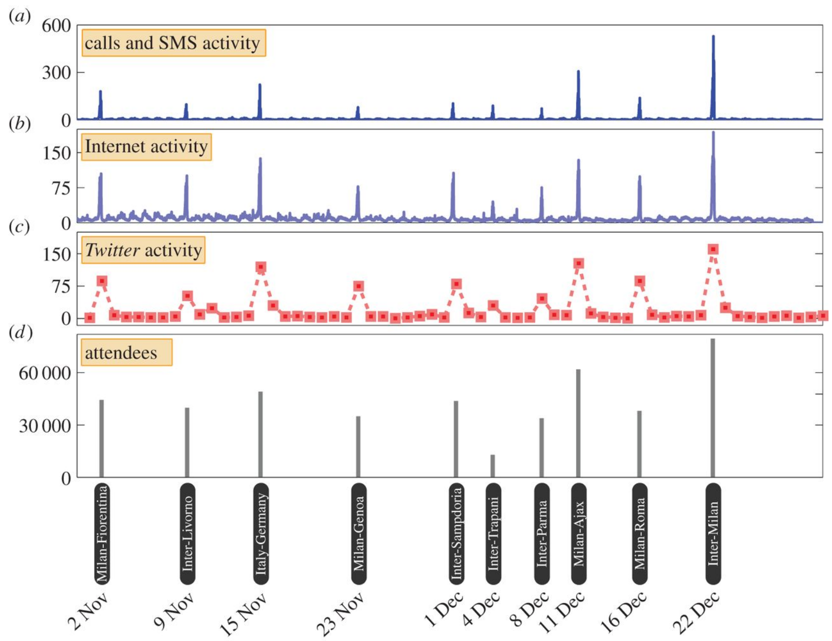
Table 1: Soccer Game Data

| Date | Calls.and.SMS.Activity | Internet.Activity | Twitter.Activity | Attendees.at.San.Siro |
|---|---|---|---|---|
| 2013-11-02 | 180.050 | 104.640 | 85 | 44261 |
| 2013-11-09 | 97.693 | 100.350 | 51 | 39775 |
| 2013-11-15 | 222.520 | 137.080 | 117 | 49000 |
| 2013-11-23 | 79.276 | 77.290 | 73 | 34848 |
| 2013-12-01 | 102.930 | 106.180 | 78 | 43607 |
| 2013-12-04 | 88.803 | 44.783 | 29 | 12714 |

First, the authors created a plot showing the various measures (calls and SMS data, internet activity, Twitter activity, and attendance) vs date. We are able to replicate this data using `R`




This chart shows that the activity data tends to peak in relation to the attendee data. For comparison, here is the plot attached to the paper:




The authors then performed a linear regression comparing calls and SMS activity, Internet activity, *Twitter* activity to the number of attendees. With `R` we are able to perform the same linear regression analysis with ease.

```
attendees_v_phone <- lm(soccer_data$Attendees.at.San.Siro ~
                          soccer_data$Calls.and.SMS.Activity)
attendees_v_internet <- lm(soccer_data$Attendees.at.San.Siro ~
                             soccer_data$Internet.Activity)
attendees_v_twitter <- lm(soccer_data$Attendees.at.San.Siro ~
                            soccer_data$Twitter.Activity)
```

Now we can compare the values we calculated vs. those in the paper.

```
lm_paper_results <- c(0.771, 0.937, 0.855)
lm_duplication_results <- c(round(summary(attendees_v_phone)$adj.r.squared, 3),
                            round(summary(attendees_v_internet)$adj.r.squared, 3),
                            round(summary(attendees_v_twitter)$adj.r.squared, 3))
lm_results <- data.frame(lm_paper_results,
                         lm_duplication_results,
                         row.names=c('Calls and SMS Data',
                                     'Internet Activity',
                                     'Twitter Activity'))
kable(lm_results,
            format='pandoc',
            centering=TRUE,
            caption='Linear Regression R^2^ Values',
            col.names = c('Published Results', 'Duplication Results'))
```

Table 2: Linear Regression $R^2$ Values

| | Published Results | Duplication Results |
|---|---|---|
| Calls and SMS Data | 0.771 | 0.771 |
| Internet Activity | 0.937 | 0.937 |
| Twitter Activity | 0.855 | 0.855 |

We can see that our $R^2$ values match up exactly. The results show that the internet activity mobile phone data was the most accurate predictor of crowd size, having the highest $R^2$ value.

Next, the authors evaluated the correlation to see how the relationship holds up to a non-parametric analysis. We are able to calculate the same correlation values.

```
cor_paper_results <- c(0.927, 0.976, 0.924)
cor_duplication_results <- c(round(cor(soccer_data$Attendees.at.San.Siro,
                                       soccer_data$Calls.and.SMS.Activity,
                                       method='spearman'), 3),
                             round(cor(soccer_data$Attendees.at.San.Siro,
                                       soccer_data$Internet.Activity,
                                       method='spearman'), 3),
                             round(cor(soccer_data$Attendees.at.San.Siro,
                                       soccer_data$Twitter.Activity,
                                       method='spearman'), 3))
cor_results <- data.frame(cor_paper_results,
                          cor_duplication_results,
                          row.names=c('Calls and SMS Data',
                                      'Internet Activity',
                                      'Twitter Activity'))
kable(cor_results,
            format='pandoc',
            caption='Spearman Correlation Values',
            col.names = c('Published Results', 'Duplication Results'))
```

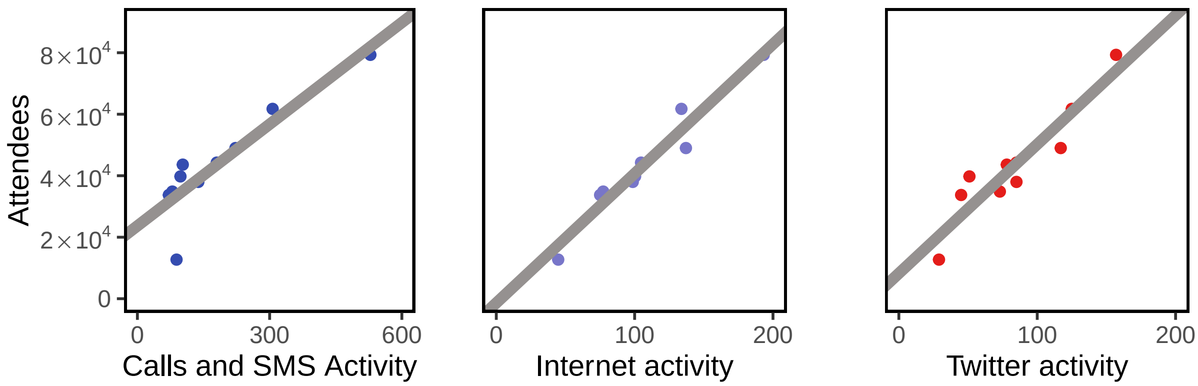
Table 3: Spearman Correlation Values

| | Published Results | Duplication Results |
|---|---|---|
| Calls and SMS Data | 0.927 | 0.927 |
| Internet Activity | 0.976 | 0.976 |
| Twitter Activity | 0.924 | 0.924 |

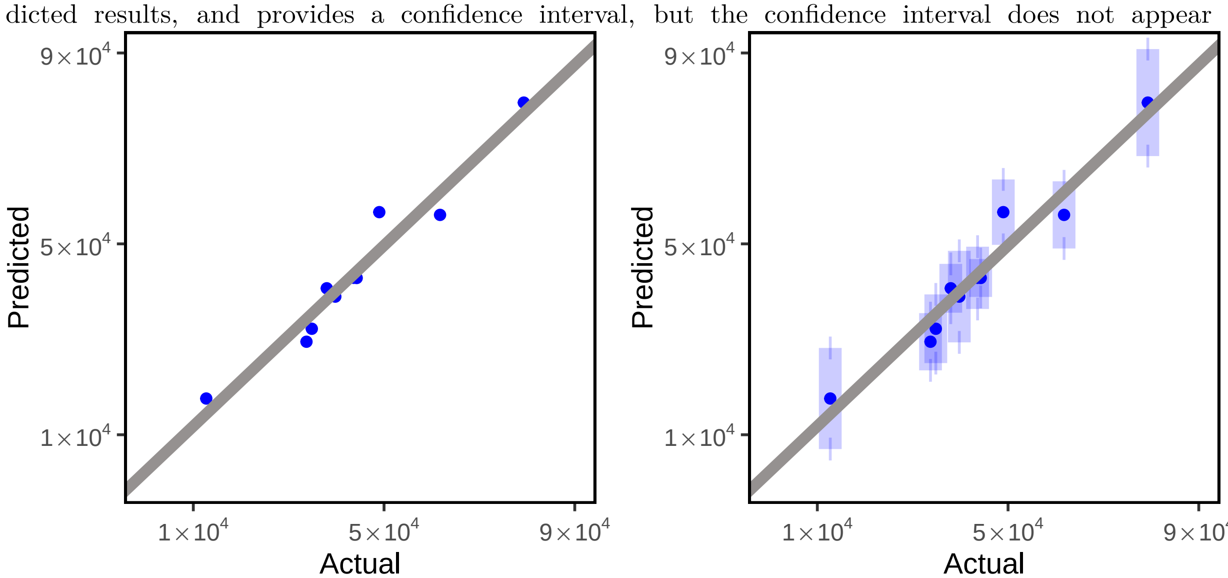
Our spearman correlation values match up precisely as well. These results also indicate that Internet activity is the best guage for crowd size at the soccer games. Since we have come to the same conclusions, we can replicate their plot.

## Linear Modeling

4 plots were made by the authors to show the linear relationship that each of the measures of activity has with the amount of people in the area. The first three plots were very straight forward, comparing values for activity to attendance at soccer games.




For the fourth plot, we were unable to directly replicate results. The authors said they performed a *leave-one-out cross-validation* analysis, which we are able to do in `R`, however in our attempt to perform the analysis, we were unable to acquire a confidence interval the way the authors did. In the second method, we perform just a linear regression analysis, which does result in the same predicted results, and provides a confidence interval, but the confidence interval does not appear to

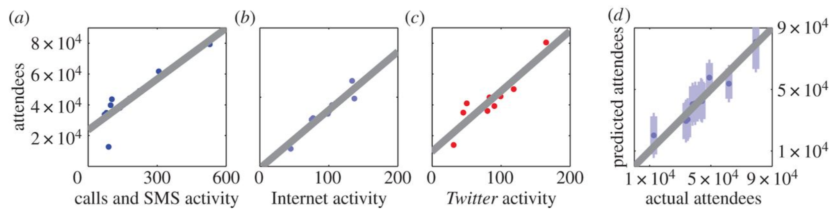



## Note to Connor

What we should probably do is omit the 4th plot from Figure 3, and put the results from the two different models we created in a seperate plot below, disucssing how we came up with both models, and how they're different

## End Note

For comparison, here is the plot attached to the paper:




## Airport Dataset

In the airport dataset the authors took a different method to approximating the crowd size. They approximated the number of people at the airport based on the number of flights to and from the airport. More specifically, they summed the flights departing in the two hour window following the time of interest and the number of incoming flights in the hour leading up to the time of interest. The raw data provides the number of flights arriving and departing the airport on an hour by hour basis over a 1 week period.

```
kable(head(linate.flight_schedule),
            format='pandoc',
            caption="Linate Flight Schedule Data",
            centering=TRUE)
```

Table 4: Linate Flight Schedule Data

| Timestamp | Departures | Arrivals |
|---|---:|---:|
| 2014-05-05 00:00:00 | 0 | 0 |
| 2014-05-05 01:00:00 | 0 | 0 |
| 2014-05-05 02:00:00 | 0 | 0 |
| 2014-05-05 03:00:00 | 0 | 0 |
| 2014-05-05 04:00:00 | 0 | 0 |
| 2014-05-05 05:00:00 | 0 | 0 |

The authors also provide a relative quantity of calls and SMS activity and internet activity, as well as Twitter activity

```
kable(head(linate.data),
            format='pandoc',
            caption='Linate Phone Data',
            centering=TRUE)
```

Table 5: Linate Phone Data

| Timestamp | Calls.and.SMS.Activity | Internet.Activity | Twitter.Activity |
|---|---:|---:|---:|
| 2013-11-01 00:00:00 | 133.940 | 1599.8 | 0 |
| 2013-11-01 01:00:00 | 87.867 | 1247.0 | 0 |
| 2013-11-01 02:00:00 | 134.630 | 1210.1 | 0 |
| 2013-11-01 03:00:00 | 41.017 | 1159.6 | 0 |
| 2013-11-01 04:00:00 | 100.430 | 1575.1 | 2 |
| 2013-11-01 05:00:00 | 463.340 | 3730.6 | 0 |

The reader may notice here that the dates of the time-stamps do not match up (they are off by 6 months). The authors explain that the way they compensate for this is that they line up the days of the week from the flights data, and assume that the flight schedule remains fairly consistent week for week. They excluded November 1st, 2nd, and 3rd, as well as December 30th and 31st as they were holidays.

As the authors decided to look at the number of incoming flights up to an hour before, and the number of departing flights for two hours following, this made for having to modify the raw data substantially. Furthermore, the authors then decided to average the calls and sms activity, internet activity and twitter activity associated with any given hour and weekday over the two month span. This kind of data wrangling is outside of our skill set in `R`, however we were able to make the modifications necessary in `Python`. Should a reviewer wish to rerun this python code, they will need the Pandas library installed. The `Python` code outputs a file titled 'Linate_wrangled.csv' which we will import into `R` to generate our statistics with.

```
import numpy as np
import pandas as pd
import datetime as dt
linate_sched_data = pd.read_csv('./data/Linate_Flights_Schedule.csv',
                                parse_dates=[0],
                                infer_datetime_format=True,
                                index_col=0)
linate_sched_data['Day'] = linate_sched_data.index.weekday_name
linate_sched_data['Hour'] = linate_sched_data.index.hour

linate_sched_data['Flights'] = np.roll(linate_sched_data['Departures'], -2) + \
                               np.roll(linate_sched_data['Departures'], -1) + \
                               np.roll(linate_sched_data['Arrivals'], 1)
linate_flight_data = linate_sched_data.groupby(['Day', 'Hour']).sum()
linate_flight_data.drop(['Arrivals', 'Departures'], inplace=True, axis=1)
linate_phone_data = pd.read_csv('./data/Linate_Data.csv',
                               parse_dates=[0],
                               infer_datetime_format=True)

days_to_skip = pd.to_datetime(['2013-11-01',
                               '2013-11-02',
                               '2013-11-03',
                               '2013-12-30',
                               '2013-12-31']).date
linate_phone_data = \
    linate_phone_data[linate_phone_data['Timestamp'].dt.date.isin(days_to_skip) == False]
linate_phone_data.set_index('Timestamp', drop=True, inplace=True)
linate_phone_data['Day'] = linate_phone_data.index.weekday_name
linate_phone_data['Hour'] = linate_phone_data.index.hour
linate_avg_phone_data = pd.DataFrame(linate_phone_data.groupby(['Day', 'Hour'],
                                                               sort=True).mean())
result = pd.concat([linate_flight_data, linate_avg_phone_data], axis=1)
result.to_csv('./data/Linate_wrangled.csv')
```

We can now import the wrangled CSV file that our python code generated and move on with our analysis. Here is what the head of that dataframe looks like.

```
flight_data <- read.csv('./data/Linate_wrangled.csv')
kable(head(flight_data),
            format='pandoc',
            caption='Linate Flight Data Cleaned Up',
            centering=TRUE)
```

Table 6: Linate Flight Data Cleaned Up

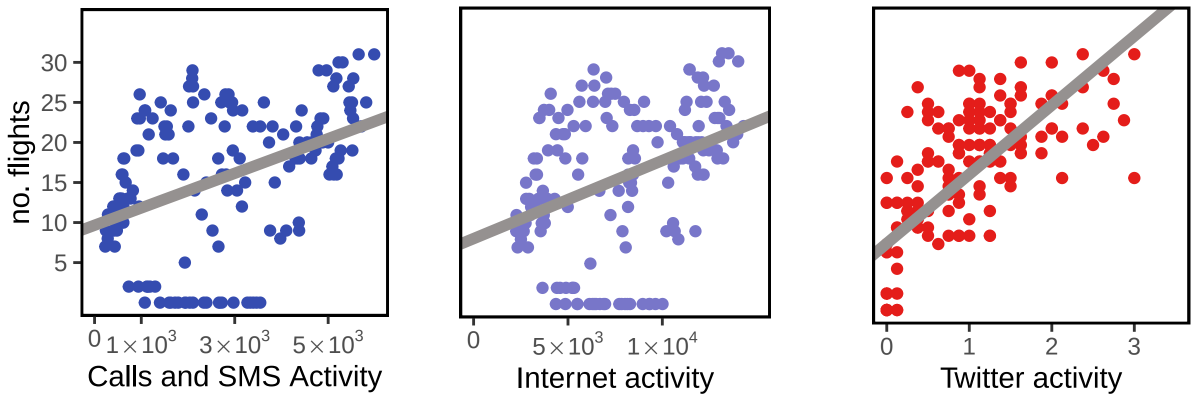
| Day | Hour | Flights | Calls.and.SMS.Activity | Internet.Activity | Twitter.Activity |
|---|---|---|---|---|---|
| Friday | 0 | 2 | 1296.475 | 5226.762 | 0.125 |
| Friday | 1 | 0 | 2104.547 | 6965.100 | 0.125 |
| Friday | 2 | 0 | 2974.243 | 8148.863 | 0.000 |
| Friday | 3 | 0 | 3546.717 | 9635.212 | 0.000 |
| Friday | 4 | 10 | 4371.842 | 10568.325 | 0.375 |
| Friday | 5 | 22 | 4768.887 | 11925.612 | 2.000 |

```r
lm_paper_results <- c(0.175, 0.143, 0.510)
flights_v_phone <- lm(flight_data$Flights ~
                      flight_data$Calls.and.SMS.Activity)
flights_v_internet <- lm(flight_data$Flights ~
                         flight_data$Internet.Activity)
flights_v_twitter <- lm(flight_data$Flights ~
                        flight_data$Twitter.Activity)


lm_duplication_results <- c(round(summary(flights_v_phone)$adj.r.squared, 3),
                            round(summary(flights_v_internet)$adj.r.squared, 3),
                            round(summary(flights_v_twitter)$adj.r.squared, 3))

lm_results <- data.frame(lm_paper_results,
                         lm_duplication_results,
                         row.names=c('Calls and SMS Data',
                                     'Internet Activity',
                                     'Twitter Activity'))

kable(lm_results,
            format='pandoc',
            centering=TRUE,
            caption='Linear Regression R^2^ Values',
            col.names = c('Published Results', 'Duplication Results'))
```

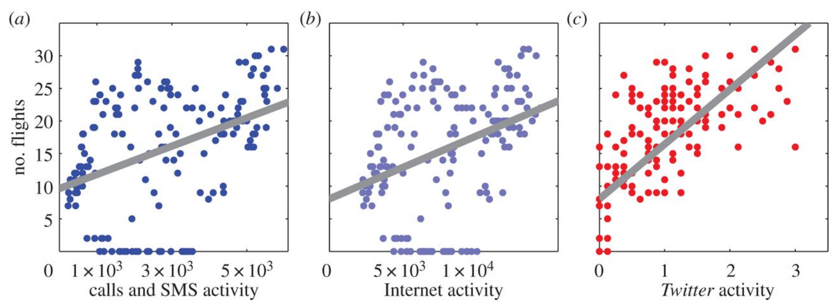
Table 7: Linear Regression $R^2$ Values

| | Published Results | Duplication Results |
|---|---|---|
| Calls and SMS Data | 0.175 | 0.175 |
| Internet Activity | 0.143 | 0.143 |
| Twitter Activity | 0.510 | 0.510 |

After wrangling the data and analyzing, we can see that the same values are obtained. Now, we can replicate the plots.




For comparison, here is the plot attached to the paper




As it can be seen, our plots line up exactly with the ones published. It should be noted that the authors of this paper made some assumptions that we do not agree with. For one, they used flight data from a period 5-6 months after the data of cell phone activity and assumed that the flight schedule would remain consistent on a day by day schedule for the period over the phone data. Given a lack of raw data for flights at the appropriate window, this assumption would need to be made, but it is one that could definitely be a major source of error. The second issue is that the period of cell phone and internet activity recorded includes the Christmas holidays, which we would assume the number of passengers at the airport during this time would be different enough from outside the holiday period that it may be a source for error. This potential source for error is minimized due to the way the grouping is done (summing all the recorded values for the same day of the week and hour of the day).