Mining Complaints for Traffic-Jam Estimation: A Social Sensor Application

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Abstract—Physical events in the real world are known to trigger reactions and then discussions in online social media. Mining these reactions through online social sensors offers a fast and low cost way to understand what is happening in the physical world. In some cases, however, further study of the affected population’s emotional state can improve this understanding. In our study we analyzed how car commuters react on Twitter while stuck in heavy traffic. We discovered that the online social footprint does not necessarily follow a strict linear correlation with the volume of a traffic jam. Through our analysis we offer a potential explanation: people’s mood could be an additional factor, apart from traffic severity itself, that leads in fluctuations of the observed reaction in social media. This finding can be important for social sensing applications where external factors, like sentiment, also contribute on how humans react.

We propose a novel traffic-congestion estimation model that utilizes the volume of messages and complaints in online social media, based on when they happen. We show through experimental evaluation that the proposed model can estimate, with higher accuracy, traffic jam severity and compare the results with several baselines. The model achieves at least 38% improvement of absolute error and more than 45% improvement of relative error, when compared with a baseline that assumes linear correlation between traffic and social volume. To support our findings we combined data from the California Department of Transportation (CALTRANS) and Twitter, for a total of 6 months, and focused on a major traffic-heavy freeway in Los Angeles, California.

I. INTRODUCTION

Since the establishment of online social media, real life events frequently trigger a social reaction on the web. This has led to an era where Big Data and social media content are strongly tied together [1]. Utilizing this vast, but publicly available, amount of information to mine the correlation between physical events and postings on Twitter or Facebook has proven to unveil hidden behavioral patterns or validate social and psychological theories that once required extensive and expensive surveys [16]. Additionally, the discovery of what is happening in the real world is now feasible through purely automated and algorithmic tools that only require access to the Internet. However, due to the noisy nature of the data, its size, and in many cases our lack of better understanding, the quality of any data mining or machine learning product will just approximate the actual reality.

Most algorithms measure the levels of a disaster or the magnitude of an event as a simple linear function of the corresponding social media discussion volume. But what gets usually ignored is the state of the people that participate in the online discussion. For example, an overly enthusiastic crowd might give a false idea of the size of a political demonstration. A shy demographic might lead to the perception that a specific music trend is not as popular as it really is. People complaining about their jobs during a very hot day might give the false sense they are generally unhappy with their work environment. To avoid arriving to such false conclusions based on online social signals, a better understanding is needed of when people publish on social media, what emotional state they are in, and which factors might have led them there.

For our experiments, a specific user behavioral pattern was examined: complaining in social media while stuck in traffic jams. We combined two publicly available datasets, one for traffic in California and one for Twitter content, to study how car drivers react in social media while driving during increased traffic congestion. Driving a car is known to be a stressful activity for many and things can be much worse during traffic jams; frustration and boredom may lead drivers to make irrational decisions or behave relatively abnormally due to anger. Social Media have already been utilized for some time now to help with traffic de-congestion. From specialized social media apps like Waze [18] - a crowd-sourced community that monitors traffic, accidents and other events in real time - to regular use of Twitter to automatically or manually publish reports and alerts of the street conditions [6]. To access this information, a non trivial amount of smartphone owners are observed to use their handheld devices while driving, despite laws that render the use of handheld devices by drivers for texting purposes illegal, for obvious safety reasons [5].

Apart from getting informed about traffic, users resort to social media to also complain or update their Twitter/Facebook status about being stuck in traffic. Most frequently, such status updates include humorous remarks, swearing, frustration, and the occasional warning about traffic congestion on specific freeways (for others to see). We use this signal as a social sensor to model the circumstances and traffic conditions, and how the drivers’ frustration may have an impact in the observed social discussion volume. Indeed, we discovered that social reaction fluctuates in a non trivial manner. Different circumstances lead to different volumes of complaining about the traffic severity instead of following a strictly linear correlation.
(and causal relationship). The measured social reaction - tweets made by drivers stuck in traffic - is strictly caused by traffic congestion and the two variables are strictly dependent.

**Contributions:** The contributions of this work are listed below:

- We propose a novel model for traffic-severity regression based solely on the generated social volume. The proposed model exploits the fact that people complain in different levels throughout the day and can be used to estimate traffic congestion in areas that lack proper traffic monitoring resources.
- We offer a better understanding of human behavior when it comes to drivers and their social media actions while behind the wheel.

## II. Related Work

There are two research fields related to the subject of the current work: 1) Studying and modeling of Traffic Congestion and 2) Social sensors utilized on online social media to mine information about physical events.

**Traffic Analysis:** There has been a lot of work and many studies that focus in the general analysis of traffic. They deal with questions like: How does traffic correlate with urbanization and economic growth? How does human behavior contribute in traffic congestion? Traffic is studied in a plethora of areas, and a few of them are listed here: (a) Financial/Political: measuring urban growth [3], (b) Psychological: measuring human behavior, DUIs etc. [11], (c) Transportation: improving roadway conditions [8], and (d) Mathematics/Statistics: modeling traffic using statistical and mathematical frameworks [10].

**Online Social Sensors for Traffic:** Studies that focus on social sensors specifically for the improvement of traffic reporting are closer to the problem tackled in our work: [9], [14], [17], [7], [15], [13]. In an ongoing Microsoft Research project [13] researchers try to combine the vast amount of historical data (both social and traffic) to create a single model for traffic prediction. Both works from Daly et al. and Ribeiro et al. [7], [15] mine the social sphere to identify/explain traffic conditions and events. In a work authored by Jingrui He et al. [9], a way to improve traffic prediction is proposed, by combining social data from Twitter and historical traffic data. The results show an improvement of the mean absolute percentage rate by almost 2% from the baseline model that only utilizes historical traffic data. Finally, [14] appears to be the only work that studies the correlation between social volume and traffic, at different hours of the day, but does not offer a model that captures their observations. To the best of our knowledge, all models in the mentioned publications ignore latent social factors that could skew the social volume related to traffic.

## III. Data

### A. California Traffic Data

The first step towards a combined traffic and social analysis is to obtain the necessary traffic congestion information and establish the ground truth. We focused in the area of California where the Department of Transportation (CALTRANS) collects a wide range of traffic statistics and publishes them online on the PEMS website [2]. CALTRANS maintains a plethora of physical stations known as Vehicle Detector Stations (VDS) on freeways across the state of California. For the purposes of this analysis a very useful tool was utilized, provided by PEMS, that computes and reports all traffic bottlenecks on a daily basis.

**Definition** A traffic bottleneck occurs where the traffic demand exceeds the available capacity of the roadway facility. More specifically, a bottleneck between two station detectors on the same freeway is observed under the following conditions: (1) there is a speed drop of at least 20 mph (32 Km/h), (2) the overall speed is less than 40 mph (64 Km/h), (3) the distance between the two stations (minimum extent of a traffic jam) is at least 3 miles (4.8 km), and (4) the speed drop is observed for at least 70% of a 35 minute duration. Note that these conditions have been chosen by CALTRANS. It’s beyond the scope of this work to validate the above numbers, conditions, and semantics of traffic congestion.

For each analyzed day, the full list of all reported bottlenecks in California is obtained. Each bottleneck consists of a location (VDS latitude and longitude), extent, duration, and delay. Extent is the distance, in miles, of the reported traffic jam. Delay is the total duration, in minutes, of the congestion. Finally, delay is an artificial composite metric that describes the total loss of time due to the bottleneck and is measured in “vehicle-hours”:

\[
\text{Total Delay} = N \times \text{extent} \times \text{duration} \times \left( \frac{1}{\text{speed}} - \frac{1}{35} \right)
\]

where \(N\) is the total number of cars affected by the congestion and speed is the reported speed during a bottleneck. Note that this is a simplified version of the total delay formula [12]; PEMS is actually using the non publicly available knowledge of each lane’s occupancy and corresponding speeds to increase the accuracy of the delay computation. In any case, due to the nature of this formula to combine all the other metrics (extent, speed, duration) as well as the total number of affected drivers, it is commonly used by traffic analysts [4], [19] as the indicator of how severe a traffic jam is. We will also be referring to it as “traffic volume” or “bottleneck severity”.

One drawback of the PEMS-generated bottleneck report is that it does not provide an accurate time for each bottleneck (only the exact location). Instead, CALTRANS provides a low granularity time attribute named “shift” which takes the values AM, PM, and NOON. Therefore, bottlenecks can only be studied on a shift basis, which for the purposes of our paper is enough as shown later on. The AM shift includes the hours between 5am and 10am, the NOON shift between 10am and 3pm, and the PM shift between 3pm and 8pm. Bottlenecks that occur during the night or after hours are not reported and based on the raw traffic data, traffic-jams during those hours are extremely rare and would not be useful for a statistical analysis.

Daily traffic data was collected for every day within the period from May 2014 to October 2014. In order to match
traffic jams with a physical location, we use the corresponding VDS station that observed each bottleneck, to identify the county/city and more importantly the exact freeway the station is measuring. Through the freeway name and number (e.g. US-101) we can then process the social data and collect tweets that correspond to a specific freeway’s traffic jam.

B. Social Data

We use Twitter as the social sensor platform to study traffic jams. To obtain the necessary data we used the Streaming API. The streaming API, while it guarantees completeness, has two drawbacks when compared to the Search API. First, one can only collect data starting from the time the api calls begin and on (no historical data access). Second and most important, the streaming API does not support geo-enabled queries in a form that would be helpful to the current analysis. One may query for all tweets from California OR all tweets about traffic, but not their intersection. Not having the ability to filter tweets by location led us to collect any tweet that mentions the keyword “traffic” and then proceed to filter down the collected tweets using other heuristics. Specifically, only the tweets that mention the freeway name we are studying are kept, tweets from automated or traffic reporting accounts (like police departments and radio stations) are removed, and finally, human judges manually go through all remaining tweets and keep only those that were made by people stuck in traffic. The last step is consistently performed using basic rules like: tweet text contains phrases with temporal hints like “this traffic” or ”on my way”, tweet contains a picture of other cars in traffic jam taken from inside a car, tweet contains a self-taken picture of the driver (known as selfie).

The last filtering step to keep only tweets from people that drive in traffic, is the only one that needs human assistance to complete. It is still the most error prone step, since Twitter users will not always be explicit about being behind the wheel while tweeting. It’s important to note here that interacting with a (smart)phone for purposes like texting, checking social media, tweeting etc. while driving, even during stand-still traffic, is considered illegal in California [5]. However, this does not discourage people from posting selfies (self-portrait photographs) on Instagram, or tweeting about the annoying traffic. Still, the fact that such actions are deemed illegal makes it an interesting signal to study.

The final product of the social data collection is a set of tweets (including all meta-data provided by Twitter), grouped by date and shift (AM, NOON, PM), made by people while stuck in traffic jams. In the rare cases where a user made more than one tweets during a specific time period we counted only one of them. We will be referring to the number of tweets as “social volume” in this analysis.

Given the mentioned limitations posed by the collection of social data, we focus on one major freeway, infamous for its devastating traffic jams: San Diego Freeway I-405. I-405, founded in 1964, has a length of 72 miles, passes through the whole city of Los Angeles and is used by hundreds of thousands drivers daily and there is always stand-still traffic reported during rush hours. We chose I-405 over US-101 (another popular candidate) because it is limited in the area of Los Angeles while US-101 covers the whole west coast of the United States. However, we made sure that the traffic patterns observed in I-405 are not unique. The traffic volume between the two freeways was compared and we found that they follow the exact same patterns for all days of the week and all shifts of the day. Therefore, it is safe to say that the choice of I-405 does not introduce any freeway-specific traffic anomalies.

In total, we gathered 3.2k tweets for the studied period of 6 months. Table I shows a more precise view of how these tweets are distributed in an average week. While the numbers might appear to be low, they are consistent in the duration of these 6 months.

C. Tweets from Drivers

As explained in subsection III-B only tweets made by people driving during traffic jams are counted, instead of every tweet mentioning traffic and the freeway name. Utilizing the latter as the social volume, would introduce cases where the raw volume of noisy tweets is misleading for estimating the actual traffic. There are two categories of “noisy” tweets. First, there are tweets made by automated accounts (e.g. police dispatch, highway patrol) or news agencies that report traffic on Twitter [6]. Such tweets are published whenever traffic bottlenecks occur and are usually agnostic of the exact severity of the bottleneck or how much it really annoys the drivers. The second category consists of tweets that are potentially about traffic, posted by normal users, but not during their commute. The problem posed by both categories is that those tweets are not part of a direct social reaction to a traffic jam. Any traffic jam estimation that utilizes those tweets could introduce excessive noise and predictive bias.

IV. Analysis

The purpose of the current analysis is to discover hidden features that could yield better results for estimating the magnitude of traffic congestion through social media. Our basic assumption is that there are cases where the size of an event may be different from how humans perceive it. Perception is a complicated process and there are many factors that play their role (e.g. mood, enthusiasm, weather, family status, political beliefs, etc). We assume that complaining about traffic falls under the umbrella of such events and study the correlation between traffic and complains to show that indeed there are other latent factors that contribute in non-trivial fluctuations of the social reaction volume. Traffic jams are measured with high accuracy by automated traffic monitoring stations but the human perception of a bottleneck may vary under different circumstances.

A. Basic Data Statistics

To begin the analysis, a better understanding of the two datasets (traffic volume and social volume) is necessary. As mentioned at the end of Subsection III-B our analysis is focused on the California freeway I-405. Table I shows the
traffic volume on I-405, by day of the week and shift of the day. Close to zero traffic volume in our context means that there is no introduced delay since the cars in the freeway are running at a speed close to the limit and not that there is no traffic at all.

The first observation based on the traffic volume data is a clear traffic increase towards the end of the day (PM). Also, for every weekday, the morning and noon traffic fluctuate far less than the evening’s. The second observation is that evening traffic gets worse towards the end of the week (Thursday and Friday). Similarly to the traffic volume, Table I also shows statistics about the social volume (number of tweets), again on a day-of-the-week and shift-of-the-day basis.

Fig. 1. Traffic averages (solid lines, left y-axis) and social volume averages (dotted lines, right y-axis) for each day of the week and shift of the day. The general trend of social reaction appears to be in sync with the traffic volume

Figure 1 illustrates the traffic volume and social volume averages for each shift during weekdays. The social volume trend confirms our intuition that social reaction is proportional to the traffic volume. Same as with the traffic, during morning and noon hours social volume is generally low across all days of the week but peaks up during the evening hours. Also, the evening social volume becomes higher towards the last days of the week (Thursday and Friday).

B. Naive Approach: Linear Model

From the basic statistics we listed in Subsection IV-A it would be reasonable to expect a linear relation between traffic volume and social volume. It makes sense to expect that social reaction becomes stronger when traffic jam conditions worsen. Based on this hypothesis we can use linear (least squares) regression to compute a model that can estimate traffic based on the number of generated tweets. Figure 2 depicts the linear model as a straight line:

\[
\text{Traffic Volume} = 1850.0 \times \text{Social Volume} + 5299.1
\]

Note that the model’s coefficient of determination \((R^2)\) is 0.6597 which can be considered high depending on the application and desired level of regression precision. We list in Section V the absolute and relative errors yielded by this model when trying to estimate traffic congestion.

![Fig. 2. Plot of traffic volume vs. social volume. Each point describes the data of a single day and shift. The x-axis measures the social volume (number of tweets) and the y-axis measures the traffic volume as total delay (vehicle-hours). We can fit a linear model with \(R^2\) value of .6597.](image)

While the linear model appears to be relatively accurate, certain underlying patterns exist, which are ignored. Plotting the same data from Figure 2 and grouping datapoints by shift of the day in Figure 3, makes it clear that each group extends in it’s own space in the graph. The conclusion from this observation is that latent features might describe the connection between traffic and social reaction in a better way. This conclusion lead us to the hypothesis that a different model that exploits such patterns could fit better than the naive linear model.

C. Analysis by Time of the Day

To evaluate whether traffic is perceived differently under different circumstances we computed the ratio of Traffic Volume over Social Volume for different times of the day (averaged across all weekdays). We also tried to explore correlations with the day of the week or the weather (temperature) but the time of the day proved to be by far the strongest feature. The ratio of traffic volume over social volume measures how much drivers complain per traffic delay and lower values indicate higher complaining. Note that due to the limitation of the traffic jam dataset, the analysis is performed on a shift basis (AM shift: 5AM-10AM, NOON shift: 10AM-3PM, PM shift: 3PM-8PM). Through the measured ratios we reached the conclusion that different time of the day indeed results in different levels of traffic reaction. In Figure 3 the datapoints are plotted by shift (AM, NOON, and PM). We can then fit individual models on each subset of the data. The linear models are also plotted using least squares regression. As with the naive liner model (subsection IV-B), we also tried to fit other models (polynomial, exponential) but the linear yields the best results even if not all individual \(R^2\) values are high enough. The 3 individual sub-models for each shift of the day and the corresponding \(R^2\) values are listed in Table II.
than the R traffic through social volume. Generally, and other baselines, when used in the context of estimating V how the proposed model compares to the naive linear model the data, we will show in our experimental analysis in Section this could be interpreted as a bad fit of the proposed model to

A. Models

To measure the regression improvement of the proposed shift-based model we introduce some baseline models. The first baseline model is the naive linear model that was described in Subsection IV-B (denoted as NAIVE). Since the shift-based model is practically splitting the datapoints in three categories, it should be compared with a 3-random-partitions model that just picks 3 random partitions and fits a linear model on each one (denoted as RAND3). Random partitioning makes sense as a baseline because if the proposed shift-based model had no statistical significance, then it should yield similar results with the random partitioning.

Similarly to the shift-based model we also tried to fit the data on a daily basis – one linear fit for each day, from Monday to Friday (baseline denoted as DAY-BASED). Finally, two more models are introduced that use the naive linear model (NAIVE) to fit the datapoints of each day of the week (NAIVE-DAY) and the datapoints of each shift (NAIVE-SHIFT). The last two models are fixed, not generated by training data, and don’t require cross validation; we measure their fitness purely for comparison purposes.

The shift-based model (denoted as SHIFT-BASED) is a composite model that consists of three linear submodels, one for each shift of the day (AM, NOON, PM). Since the number of datapoints for each shift is equal, the overall precision of each submodel. For example, when measuring the squared error of the model we need to compute the squared error for each submodel and then get their average.

B. Model Comparison

To compare the predictive power of each model the following cross validation setup is used: Repeated random sub-sampling validation. For each model, the data points are randomly ordered and then the first 80% of the datapoints is picked as training dataset and the rest 20% as validation dataset. Using least square regression we fit a linear model to the training data and then calculated the estimation error on the validation data. This process is repeated 1000 times and the average errors across all splitings are calculated.

The average squared, absolute, and relative errors for each regression model

TABLE III. ERROR COMPARISON FOR EACH REGRESSION MODEL.

<table>
<thead>
<tr>
<th>Model</th>
<th>Mean Error</th>
<th>R^2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naive Linear</td>
<td>5.3556</td>
<td>0.6619</td>
</tr>
<tr>
<td>Random 3 Partitions</td>
<td>5.8604</td>
<td>0.6611</td>
</tr>
<tr>
<td>Day-based</td>
<td>5.9272</td>
<td>0.6658</td>
</tr>
<tr>
<td>Naive by Day</td>
<td>5.406</td>
<td>0.6607</td>
</tr>
<tr>
<td>Naive by Shift</td>
<td>5.3690</td>
<td>0.6584</td>
</tr>
<tr>
<td>Shift-based</td>
<td>2.4245</td>
<td>0.4230</td>
</tr>
</tbody>
</table>

TABLE IV. ERROR COMPARISON FOR EACH REGRESSION MODEL.

<table>
<thead>
<tr>
<th>Day</th>
<th>AM mean</th>
<th>AM stdev</th>
<th>NOON mean</th>
<th>NOON stdev</th>
<th>PM mean</th>
<th>PM stdev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monday</td>
<td>16840.25</td>
<td>2927.09</td>
<td>2462.38</td>
<td>1271.59</td>
<td>21224.78</td>
<td>3234.97</td>
</tr>
<tr>
<td>Tuesday</td>
<td>18747.29</td>
<td>1907.23</td>
<td>5299.43</td>
<td>3212.63</td>
<td>27126.57</td>
<td>3705.78</td>
</tr>
<tr>
<td>Wednesday</td>
<td>19708.20</td>
<td>2741.86</td>
<td>5415.60</td>
<td>2473.53</td>
<td>34948.80</td>
<td>2725.18</td>
</tr>
<tr>
<td>Thursday</td>
<td>19167.00</td>
<td>3225.76</td>
<td>7858.11</td>
<td>1764.80</td>
<td>3769.05</td>
<td>2767.73</td>
</tr>
<tr>
<td>Friday</td>
<td>11997.67</td>
<td>2857.14</td>
<td>1364.78</td>
<td>9759.00</td>
<td>40134.67</td>
<td>907.63</td>
</tr>
<tr>
<td>Saturday</td>
<td>203.20</td>
<td>50.77</td>
<td>7038.50</td>
<td>2332.95</td>
<td>9759.00</td>
<td>2767.73</td>
</tr>
<tr>
<td>Sunday</td>
<td>54.50</td>
<td>91.71</td>
<td>3462.38</td>
<td>1271.59</td>
<td>21224.78</td>
<td>3234.97</td>
</tr>
</tbody>
</table>

TABLE I. TRAFFIC VOLUME (TOTAL DELAY) STATISTICS FOR I-405 (LEFT SIDE OF THE TABLE) AND SOCIAL VOLUME (NUMBER OF TWEETS) STATISTICS (RIGHT SIDE OF THE TABLE).
also provide the coefficient of determination in each case. The
Shift-based model significantly outperforms all the baseline
models which proves that focusing on the different shifts of the
day has a statistically significant effect while other approaches
like day-based perform poorly. In terms of absolute error, we observe a 38% improvement between the Naive Linear
approach and the shift-based model. In terms of relative error
we observe more than 45% improvement.

In Table IV we list the average errors for the linear and
shift-based models without having applied the driver constraint
(tweets must originate by drivers while they are stuck in
traffic). Basic filtering that removes tweets from automated
accounts and bots is still applied but all the rest of the tweets
from normal Twitter users remain. Using this raw dataset
for regression, results in an increased error for both linear
and shift-based models. The conclusion from this comparison is
that filtering of social posting based on users directly affected
by traffic congestion results in a better model and accuracy.

VI. CONCLUSIONS

Social sensors offer a fast and low cost way to understand
the physical world through online content on social media.
Mining the correct correlation between the crowd’s reaction
and an event’s magnitude can be very critical and improves our
understanding of what is happening and how much it effects
our lives. Using the correlation between traffic congestion
and social reaction on Twitter as a showcase we show that
exploring dimensions that have different psychological links,
like the time of the day, can lead to a better grasp of the
traffic severity. We propose a novel model to estimate traffic
jams using social sensors, that utilizes three linear submodels,
one for each shift of the day (AM, NOON, PM) and social
posting from car drivers. We show that the proposed model
can be at least 38% better than the naive linear approach
and performed several comparisons with different baselines to
prove that these findings are statistically significant. Finally,
we offer the exact linear sub-models that describe the relation
between complaints and traffic, for different times of the day.

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<table>
<thead>
<tr>
<th>Model</th>
<th>Mean Error</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naive Linear</td>
<td>8.5558</td>
<td>0.4948</td>
</tr>
<tr>
<td>Shift-based</td>
<td>3.5027</td>
<td>0.2571</td>
</tr>
</tbody>
</table>

TABLE IV.  ERROR COMPARISON FOR THE LINEAR AND SHIFT-BASED
MODEL WITH ALL TWEETS ABOUT TRAFFIC (NO DRIVER-BASED
FILTERING). WHEN TWEETS ARE NOT COMING DIRECTLY FROM DRIVERS
IN TRAFFIC JAM THE ERROR IS SIGNIFICANTLY HIGHER.

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