Case Study: Using Facebook Data to Monitor Adherence to Stay-at-home Orders in Colorado and Utah

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ABSTRACT
In the absence of effective treatments or a vaccine, social distancing has been the only public health measure available to combat the COVID-19 pandemic to date. In the US, implementing this response has been left to state, county, and city officials, and many localities have issued some form of a stay-at-home order. Without existing tools and with limited resources, localities struggled to understand how their orders changed behavior. In response, several technology companies opened access to their users’ location data. As part of the COVID-19 Data Mobility Data Network [2], we obtained access to Facebook User data and developed four key metrics and visualizations to monitor various aspects of adherence to stay at home orders. These metrics were carefully incorporated into static and interactive visualizations for dissemination to local officials.

All code is open source and freely available at https://github.com/ryanlayer/COVID19

Keywords
COVID-19, population density, social distancing.

1. INTRODUCTION
On March 24th, 2020, at 1800 MNT, our team started collecting data from Facebook Data for Good [1] that covers Utah and Colorado. For these regions, Facebook provides aggregated and anonymized user density data for 2km x 2km tiles at three time points per day (0200 MNT, 1000 MNT, and 1600 MNT) for the eight hours following the time point (Figures 1 and 2A). We also began collecting higher resolution data (0.6km x 0.6km tiles) for Boulder County, CO and the City and County of Denver, CO on March 30th and April 7th, respectively. To protect privacy, Facebook does not report density data for tiles with fewer than ten users. In addition to the current density data (crisis density), Facebook provides a baseline density for each tile and time point which is averaged over the same day and time periods during the 45 days before the start of data collection. Facebook Data for Good provides other types of mobility data, including movement between tiles, but the combination of Facebook’s privacy policy and the prevalence of large rural and remote areas in Utah and Colorado limited the utility of these data for the purposes of analyzing effects of stay-at-home orders.

Governor Polis of Colorado mandated a statewide stay-at-home order starting Thursday, March 26, which shifted to a safer-at-home order on April 27. While Utah never enacted a statewide directive, Salt Lake County began a “Stay safe, Stay home” order on March 30, 2020 and relaxed down to a “Stay smart, Stay safe” order on April 17. As restrictions began easing, we started working with local officials in Colorado and Utah to develop a set of metrics and an efficient reporting pipeline to assess the immediate impacts of new policies on population movement.

2. METRICS
Cities and neighborhoods have unique dynamics and interpreting behavior from density fluctuations can be difficult. Before stay-at-home orders were issued, most tiles followed a general weekend to weekday pattern where weekday density was greatest in business districts and weekend density was greatest in residential areas. After social distancing policies started, these patterns were disrupted and comparing current behavior to baseline behavior often gave counterintuitive results. For example, adherence to stay-at-home orders in some residential areas appeared to be poor based...
on density fluctuations when in reality the density changes were a result of an overall increase in population by about 5%. We hypothesize that such increases were due to the return of college students and a drop in business travel, both of which are good social distancing practices. Given these nuances, we developed metrics with the base assumption that compliance starts out high and degrades over time. These metrics are targeted at monitoring transitions to and from stay-at-home orders.

2.1 Weekend Score
Under normal circumstances, most regions show a regular weekly pattern. Economic centers are denser on the weekdays (baseline in Figure 2A), and residential areas are denser on the weekends (baseline in Figure 2B). Under a stay-at-home order, the differences between weekend and weekday activity in regions containing non-essential businesses should be minor.

To measure weekday and weekend density differences, we developed the weekend score \( (\text{ws}) \) that compares the average weekday density \( (d_{\text{wd}}) \) to the average weekend density \( (d_{\text{we}}) \) during a week (Figure 2B):

\[
\text{ws} = \log_2 \left( \frac{d_{\text{wd}}}{d_{\text{we}}} \right)
\]

Areas with higher positive values have more weekday activity and areas with lower negative values have more weekend activity.

We track changes in behavior by comparing the score of individual tiles between weeks (Figure 3). In Figure 3, each point is a tile, and the point size corresponds to the tile’s mean baseline density. Points further to the right or higher indicate more weekday activity. The closer a point is to the diagonal red line, the more similar the activity between the two weeks. The overall change between weeks is quantified by the sum-of-squares distances between points and the diagonal. We identify weeks based on the collection start date, so “week 1” is effectively the first week of the stay-at-home order. Figure 3A shows the drastic change in behavior after the stay-at-home order was issued, and Figure 3B shows how behavior stabilized in the subsequent weeks. Points in Figure 3B are clustered around the origin, indicating consistent behavior across weekday and weekend activity.
2.2 Slip Score

The behavior of a region after a stay-at-home order is issued depends on the region’s zoning and demographics, which complicates monitoring. For example, economic centers will be less dense, and residential centers will be denser since most people are not working or traveling. To track how well regions are adhering to their new patterns from week to week, we developed a slip score (ss). This metric assumes that adherence to the stay-at-home orders is best immediately following their issuance, then tracks changes by comparing the average weekly density ($d_w$) of consecutive weeks (see Figure 2C):

$$ ss = \log_2 \left( \frac{d_{w2}}{d_{w1}} \right) $$

Areas with higher positive values were more active in the second week, and areas with lower negative values were less active. Equal changes in density counts result in smaller slip scores in more populated tiles so we visualize slip score with respect to the region size. In Figure 4, each point is a tile, and points from denser regions are to the right. Points above the zero line have slipped into a more active state, and points below the line have become less active. From Figure 4, we can see that behavior has shifted from reducing activity to increasing activity.

![Figure 4. Slip scores between A) week one and week two and B) week six and week seven of the Colorado stay-at-home orders. Tiles far from the horizontal line at zero had larger relative changes between weeks. The red line gives the average slip weighted by baseline density. The x-axis is on a log scale.](image)

2.3 Hot Spot Score

While the weekend score quantifies behavior pattern changes within weeks and the slip score captures gross density changes across weeks, we found local officials desired a finer resolution metric to assist in identifying sudden changes in population behavior. As a result, we developed a hot spot score (hs). This metric resembles a z-score as it is equal to the current 3-day density average ($d_{3w}$) minus the corresponding 3-day average from week 1 ($d_{3w1}$), divided by an estimate of the standard deviation of the 3-day averages (see Figure 2D):

$$ hs = \frac{d_{3w} - d_{3w1}}{sd(d3)} $$

Here we again assume that the first week of the stay-at-home order represents the state of highest compliance and present the current mobility patterns relative to that. Density patterns are averaged over 3-day windows to prevent spurious single-day fluctuations from receiving too much attention. For example, the score for Monday is an average over the densities observed on Saturday, Sunday, and Monday.

The purpose in scaling the density difference in the numerator by a standard deviation was to create a z-score, such that scores across tiles of different densities are comparable. However, the optimal method of estimating the standard deviation of a tile’s 3-day average is unclear. Using the given tile’s 3-day averages across the observed time period, e.g. all Saturday-Monday averages, results in an estimator that is based on fewer than six data points per tile and hence extremely variable. Furthermore, a tile that experienced large swings in density would have a large tile standard deviation and a low hot spot score, which is undesirable. Since denser tiles typically have larger variability, we estimated the standard deviation for each tile and 3-day window, fit a linear regression to these standard deviations as a function of average tile density, and used the fitted values from the model in the calculations of hot spot scores.

In Figure 5, each point is a tile, and points from denser regions are to the right. Points with increased activity relative to the first week are above zero. Similar to Figure 4, there is a distinct increase in recent activity.

![Figure 5. Hotspot scores for the A) second and B) seventh weekend of stay-at-home orders in Colorado. Tiles far above the horizontal line at zero showed evidence of substantial increases in activity. The red line gives the average hotspot score weighted by baseline density. The x-axis is on a log scale.](image)

2.4 Trends

Density data can be represented as a time series with repeating short-term patterns (seasons) and the overall value increases or decreases (trends). Using a model, we can decompose a series into its seasons and trends [3], which provides a means to compare tiles with different weekday/weekend activities (seasons) (see Figure 2E).

Within a county, we can observe the differences in density dynamics between the business centers, which should be less dense during a stay-at-home order, and residential centers, which should be denser. By focusing on trends, we can more easily compare the activity of each tile. To capture the overall trend of a county, we take the mean of each tile’s trend weighted by the tile’s baseline density. Figure 6 gives the density trends for all of the tiles in Boulder County, Colorado. Each line is a tile, and the lines give the relative density trend the line thickness corresponds to the baseline tile density. Lines that end in reduced activity are blue, and those with increased activity are red. The black line is the average trend weighted by baseline density. While the absolute increase and decreases are important, the slope of each line is more insightful. With a few exceptions, the overall trend is flat in Boulder County.

3. DATA PRODUCTS

Governments are hierarchical, and the process of synthesizing complex data into recommendations is often performed by analysts and presented to policymakers. The availability and expertise of these analysts vary widely among local governments. To accommodate different data needs, we produce a range of products at different levels of granularity.
ith robust analytics capabilities, the weekly... We have focused on making... specific data needs. While our metrics and visualizations have been developed specifically for our local partners, we believe they will be either directly useful to other localities or can serve as starting points for more specific data needs.

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