Wisdom of the crowds in forecasting COVID-19 spreading severity

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In this work we report that the public reacted on social media at an early stage of the COVID-19 pandemic in a surprisingly accurate way, with activity levels reflecting the severity of the contagion figures registered almost a month later. Specifically, the intensity of COVID-related social media activity from different Italian regions at the beginning of the epidemic (21-24/2/2020), predicts well the total number of deaths reached almost a month later (7/4/2020) in each region.

It should be noted that at the time of the initial twitter reaction no tabulated regional data on the epidemic was readily available. By the 24th February 2020 only two regions reported death cases and only three reported infected subjects.

Predicting the spread of COVID-19 has become the focus of many academics and amateurs across the globe. There have been proposed several different modeling tools and intuitions for the forecasting of the severity of the infection (1–4) and, despite some success, there is a shared understanding that forecasting the spread and growth of the epidemic is a challenging task. As the spreading mechanism is not yet fully understood and modelled, predicting the contagion and growth within countries and the regions in each country, before data is available, is essentially impossible. However, this task is extremely useful in order to establish targeted confinement areas, hence containing the virus more effectively while reducing the economic and social disruptions due to the lockdown. The knowledge of this would also allow to allocate resources efficiently across regions. In the present work we use data from twitter activity in different Italian regions to estimate crowd perception of the severity of the event. We then relate the intensity of social media interest with the severity of the infection in the same region in terms of the number of deaths registered the following month. Social sciences often used to forecast product sales by resorting to the “wisdom of the crowds”. These methods works well especially when groups are large and connected opinion dynamics and communication allows crowds to process information (5). In this work we show that such “wisdom” turns out to be accurate also in the prediction of COVID-19 infection severity.

We consider the case of Italy, as twitter activity data is readily available. In Italy the epidemic has now developed to a point where clear distinctions between regions can be made and data at reasonable forecast horizons has been observed.

We analyse tweets from (6), which report COVID-19 related tweets since the 22nd January 2020. We have geolocated the most popular user locations, covering the vast majority of the dataset, and aggregated the number of unique users discussing coronavirus each day, per Italian region. For simplicity, we will refer to this as tweet volume. We then adjust tweet volume by the population active on social media per region, according to ISTAT* data (7, 8).

The main result is reported in Figure 1 where the cumulative number of deaths in each region on 7/4/2020 are related to the tweet activity registered a moth earlier. The horizontal axis represents the mean adjusted twitter volume between the 21st February 2020 and the 24th February 2020. The date range corresponds to the peak in social media tension and the beginning of the endogenous countrywide spreading being detected. The vertical axis represent the cumulative number of deaths on the 7th April 2020. This is log-scaled to adjust for the exponential growth of the epidemic. The “Lazio” region, is a clear outlier as most politicians and institutions tweet from the capital, Rome and tweets geolocated to country level default to the capital.

The evolution of adjusted tweet volume across Italian regions for the period, as well as the growth of reported nationwide positive cases and deaths are reported in Figure 2. We
observe an initial peak in late January, perhaps due to the epidemic in China, but with little differentiation between regions. We then observe a second peak of interest from social media in late February. This appears to be sparked by the endogenous growth of the infection in Italy being measured and reported. At the time (21-24/2/2020) only nationwide epidemic data were available and regional or province breakdowns were only scattered across the news. In Figure 2 we colour-code Italian regions according to the ISTAT\textsuperscript{1} characterisation of Northern, Central and Southern. We observe how northern, central and southern regions cluster in order, with regions most hit by the epidemic ranking higher. This seems to suggest that the initial reaction of users on social media had efficiently processed data scattered throughout news channels and performed an accurate risk assessment which is observable in the adjusted social media reaction.

To check that the values of the epidemic are not trivially related to the size of the population in each region (7) and that our analysis adds to this we perform and compare three regression models:

1. adjusted tweets vs. log death cases;
2. adjusted tweets vs. log death cases;
3. adjusted tweets vs. adjusted population vs. log death cases.

As it can be noticed from Figure 1, “Lazio” is an outlier due to politicians and central bodies tweeting from it as well as national geolocation defaulting to the capital. This region has been therefore removed from the regression. We also log scale the population to allow for a fair comparison as we notice a sub-linear relation to the number of deaths. We report in Table 1 p-values for the coefficients as well as $R^2$ for the three regression models.

It can be inferred from Table 1 that adjusted tweet volume is a better regressor than log population. This is shown by both the higher $R^2$ value in regression 1 with respect to regression 2, and by the significant p-value for tweets in regression 3.

We conclude that this is an important example of crowd wisdom in a phenomenon which is not directly controlled by the population or its opinion. These results indicate that social media activity may be used to forecast the severity of the spreading of COVID-19 in different countries at an early stage when data from the effect of the disease are not available yet.

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