plemented March 12 going to a total lockdown on March 15 with all travels suspended.

Conclusion: Following the detection of the first COVID -19 case, Albania acted swiftly to implement immediate social distancing and lockdown measures. Such drastic measures had a huge effect on COVID-19 control in the beginning. However, the trend of effective reproduction numbers show a plateau for almost the last two weeks of the month with no signs of further decline.

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PS04.08 (528)

Comparison of different approaches in estimating the time-varying reproductive number for COVID-19

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Purpose: The time-varying reproductive number (R_t) is an indicator of transmissibility that has utility in evaluating public health interventions and assessing transmission factors. However, the R_t may be biased by generation time misspecification, reporting delays, underestimation of cases, and day-to-day variations. We compared several methods of adjustments in developing an approach to estimating an unbiased $R_{t.}$

Methods & Materials: A meta-analysis of generations times was conducted to reduce misspecification. A probabilistic bias approach was compared to standardization by a test positivity of 5% in adjusting for underestimation. A Poisson deconvolution process using an incubation period of 5.2 days (95% CI: 4.9-5.5) and laboratory turnover times between 2-, 5- and 10-days was utilized to adjust for reporting delays. We compared smoothing (7- and 14-day moving averages), a generalized additive model (GAM), and a local regression (LOESS) model to adjust for day-to-day variation. The adjusted R_t was compared to a crude R_t by eyeballing, Mean Average Percentage Error (MAPE), and Mean Absolute Deviation (MAD). We estimated the R_t using Malaysian COVID-19 daily case data from 7 March 2020-20 June 2021 utilizing Cori et al.'s method.

Results: We estimated a pooled serial interval of 4.95 days (95% CI: 4.62-5.29). The R_t estimated using case counts adjusted for underestimation using standardization by test positivity (MAPE: 0.31; 95% CI: 0.30-0.49, MAD: 0.5; 95%CI: 0.5-0.54) were more volatile, exhibited larger peaks and wider confidence intervals, especially in periods of lower incidence, compared to the probabilistic bias approach (MAPE: 0.07; 95% CI: 0.06-0.07, MAD: 0.26; 95%CI: 0.26-0.28). GAM (MAPE: 1.85, 95% CI: 1.63-2.08) and LOESS (MAPE: 0.29, 95% CI: 0.29-0.29) models had smoothed out almost all variations in the R_t. Longer lab turnover periods created smoother R_t with larger peaks and resulted in greater volatility in the estimates.

Conclusion: Biases in the estimation of the R_t may critically change its interpretation for public health interventions. It is important to adjust for these biases and understand the underlying limitations of these estimations; primarily when utilized within the context of pandemic control.

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Spatial Opinion Mining from COVID-19 Twitter Data

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Purpose: In the first quarter of 2020, World Health Organization (WHO) declared COVID-19 as a public health emergency around the globe. Therefore, different users from all over the world shared their thoughts about COVID-19 on social media platforms i.e., Twitter, Facebook etc. So, it is important to analyze public opinions about COVID-19 from different regions over different period of time. To fulfill the spatial analysis issue, a previous work called H-TF-IDF (Hierarchy-based measure for tweet analysis) for term extraction from tweet data has been proposed. In this work, we focus on the sentiment analysis performed on terms selected by H-TF-IDF for spatial tweets groups to know local situations during the ongoing epidemic COVID-19 over different time frames.

Methods & Materials: The primary step is to extract terms from tweets using H-TF-IDF approach. Moreover, these terms are utilized in two ways i.e., 1) select tweets containing terms, 2) terms used as features for sentiment analysis. Thereafter, data preprocessing is performed to clean the text. Afterwards, Vectorization models i.e., bag-of-words (BOW) and term frequency-inverse document frequency (TF-IDF) are used to extract features with the help of n-gram techniques. These features are extracted to train the prediction models for sentiment analysis. Lastly, different statistical and machine learning models i.e., Logistic regression, support vector machine (SVM), etc. are applied to classify the spatial tweets groups. For preliminary results, experiments are conducted on H-TF-IDF tweets corpus having geocoded spatial information for the period of January, 2020. These tweets are extracted from the dataset collected by E.Chen (https://github.com/echen102/COVID-19-TweetIDs) that focuses on the early beginning of the outbreak. A uniform experiment setup of train-test (80% and 20%) split scheme is used for each prediction model.

Results: The results illustrate that specific terms highlighted by H-TF-IDF provide useful information that would not have been identified without this spatial analysis. The classification results spatial location tweet groups into positive, negative and neutral by subjectivity and polarity measures.

Conclusion: The current work is applied on English language-based Twitter information. A following work is to incorporate other languages to perform sentiment analysis. Furthermore, BERT will be used to extend these features.

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PS04.10 (62)

Longitudinal surveillance of Post-Acute Sequelae of SARS-CoV-2 among Long Beach City residents, April-December, 2020

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