# Report 5: Phylogenetic analysis of SARS-CoV-2

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## Summary

Genetic diversity of SARS-CoV-2 (formerly 2019-nCoV), the virus which causes COVID-19, provides information about epidemic origins and the rate of epidemic growth. By analysing 53 SARS-CoV-2 whole genome sequences collected up to February 3, 2020, we find a strong association between the time of sample collection and accumulation of genetic diversity. Bayesian and maximum likelihood phylogenetic methods indicate that the virus was introduced into the human population in early December and has an epidemic doubling time of approximately seven days. Phylodynamic modelling provides an estimate of epidemic size through time. Precise estimates of epidemic size are not possible with current genetic data, but our analyses indicate evidence of substantial heterogeneity in the number of secondary infections caused by each case, as indicated by a high level of over-dispersion in the reproduction number. Larger numbers of more systematically sampled sequences – particularly from across China – will allow phylogenetic estimates of epidemic size and growth rate to be substantially refined.

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### 1. Introduction

As of 1500 GMT 14 February 2020, almost 64,000 cases of COVID-19 (formerly 2019-nCoV) have been reported in China (with 1381 deaths), and cases have been detected in at least 24 regions or countries outside mainland China. Since the identification of the novel coronavirus disease from Wuhan City, China in December 2019 there have been ongoing efforts to identify the source of the virus. Many of the cases reported at the beginning of the epidemic had an epidemiological link to a seafood and wildlife market in Wuhan City pointing to a single spillover event from an animal reservoir [1]. Initial phylogenetic analysis showed that the new virus was similar to the SARS coronavirus when compared with other coronaviruses known to infect humans, with bats or pangolins as the most likely animal reservoir [2–4].

Genetic data can give insights into the evolving epidemic which are not always apparent from the epidemiological data alone. As a virus is transmitted through a population, it will accumulate mutations in its genetic code. By identifying changes in genetic sequences sampled from different patients, it is possible to reconstruct the evolutionary history of an epidemic. For a novel pathogen of zoonotic origin this can allow us to estimate when the pathogen was introduced into the human population. Population genetic modelling can also be used to infer population size trends and gives some indication of the unobserved burden of disease in the population.

Previous investigations of publicly available sequence data have presented phylogenetic estimates of SARS-CoV-2 time of most recent common ancestor (TMRCA) and growth rates using Bayesian phylogenetic methods [5–7]. Here we use 53 publicly available whole genome sequences sampled up to February 3, 2020 to estimate the growth rate of the epidemic, the size of the epidemic, and the time to most recent common ancestor using a combination of Bayesian and maximum likelihood methods and using a phylodynamic SEIR model.

#### 2. Results

Bayesian phylogenetic analysis indicates a common ancestor of these virus lineages occurred on December 8, 2019 (95% CI: November 21-December 20, 2019). The virus phylogeny is consistent with a population genetic model assuming exponential growth. Fitting the exponential growth model provides an estimate of the epidemic growth rate. This provides an estimate of the epidemic doubling time of 6.6 days (95% CI: 4.0-12.7), which is in line with previous reports based on the same genetic data [7]. We also estimated the time to the most recent common ancestor (TMRCA) and doubling time using maximum likelihood with similar findings. We estimate the TMRCA to be on 5 December 2019 (95% CI: 6 November - 13 December 2019) and the doubling time of the epidemic to be 7.1 days (95% CI: 3.0-20.5) (Figure 1).

DOI: https://doi.org/10.25561/77169 Page **2** of **8** 

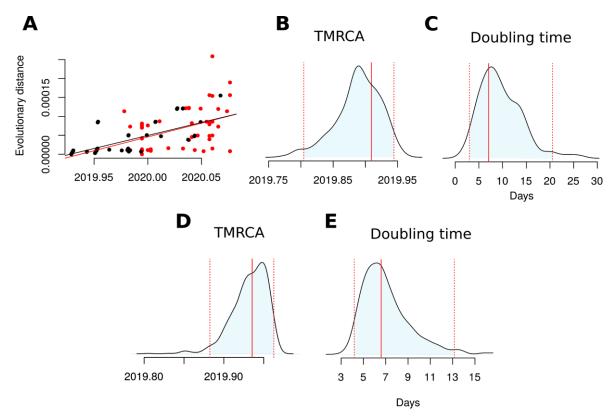


Figure 1. Phylodynamic estimates of epidemic origins and growth rates. A) A root to tip regression showing the accumulation of genetic diversity with time of sampling. Red points show samples while black points show estimated TMRCA between samples. B) The bootstrap distribution of estimated TMRCA. C) The bootstrap distribution of epidemic doubling time. D) Bayesian posterior distribution of TMRCA. E) Bayesian posterior of the doubling time. Red lines indicate maximum likelihood or posterior median and 95% confidence interval.

Population genetic modelling can be used to infer population size trends and gives some indication of the unobserved burden of disease in the population. With currently available data, precise estimates are not possible and different methods do not give concordant results, but very wide confidence intervals cover a realistic range of values. By fitting a Bayesian phylodynamic SEIR model, we estimate that on February 3 there were cumulatively 38,000 infections (95%CI: 4,000-187,000) (Figure 2). These values correspond to an  $R_0$  of 2.15 (95%CI: 1.79-2.75). Alternatively, using an exponential growth model and adjusting for high variance in transmission rates, we estimate 26,000 cumulative infections by February 3 (95%CI: 6,000-176,000). With the SEIR model we estimate that on January 18 there were 4,000 cumulative infections (95%CI: 800-15,000) [8,9].

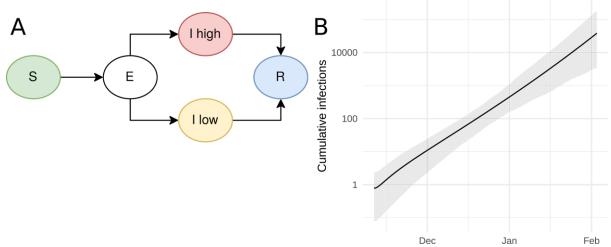


Figure 2. Estimates of cumulative infections through time based on a structured coalescent epidemic model. A) Diagram representing SEIR. The compartment "E" represents the incubation period and "R" represents recovered and deaths. There are two categories of infectious individuals to represent high variance in transmission rates. B) Cumulative infections through time up to February 3, 2020. The shaded region shows the 95% credible interval.

Phylodynamic estimates are sensitive to assumptions regarding variance in transmission rates between individuals as high variance reduces genetic diversity in a sample. We find that estimates assuming high levels of overdispersion in the reproduction number are consistent with the epidemiological record which shows approximately 20,000 confirmed infections by February 3 [10]. Table 1 shows estimated cumulative infections by February 3 under various levels of overdispersion in the reproduction number. Higher levels of overdispersion lead to higher estimates of number infected. We further considered an exponential growth model where the rate of growth is constrained to values estimated in previous reports.

There are a number of limitations to this analysis. The exponential growth model does not account for a reduction in transmission due to public health interventions, such as travel bans, and quarantine measures. These estimates do not reflect the situation in areas under quarantine and are more strongly influenced by epidemic dynamics near the time of origin. The model does not account for geographic structure and this analysis included many samples from outside of Wuhan City and outside of mainland China. Sampling of virus genomes was ad-hoc with all early samples originating from Wuhan, China, and a majority of recent samples originating from travellers outside of mainland China. Sampling included a number of epidemiologically linked patients and known transmission pairs. Samples from transmission chains were deduplicated, however transmission histories from travellers may be correlated in ways that cannot be easily adjusted for.

Table 1: Estimated cumulative infections up to February 3, 2020 based on different population genetic models and under various levels of overdispersion in the number of transmissions per infected individual. All results with the exponential growth model assume R=2.9 and a 6.5 day serial interval, whereas the reproduction number is estimated with the SEIR model.

|                            | Model type                                |   |                                       |
|----------------------------|---|---|---------------------------------------|
| Overdispersion assumed (k) | Exponential growth R = 2.9, SI = 6.5 days | Exponential growth  R = 2.9, SI = 6.5 days  Growth rate constrained: 0.14/day | SEIR model (R estimated within model) |
| k = 0.075                  | 52,000<br>(13,000-349,000)                | 111,000<br>(32,000-512,000)   | 51,000<br>(11,000-335,000)            |
| k = 0.16                   | 26,000<br>(6,000-176,000)                 | 56,000<br>(16,000-259,000)  | 38,000<br>(4,000-187,000)             |
| k = 0.30                   | 16,000<br>(4,000-105,000)                 | 33,000<br>(10,000-155,000)  | -                                     |

Estimates are given to the nearest 1000 cases. Values in parentheses show 95% confidence intervals.

#### 3. Conclusions

Phylodynamic analysis of publicly available SARS-CoV-2 sequence data provides estimates of growth and size that are consistent with the epidemiological record. Estimates of epidemic size are highly dependent on the unknown level of overdispersion in the reproduction number. Estimates assuming relatively low levels of overdispersion are not consistent with the epidemiological record as they predict fewer infections than were reported which suggests that there is similar or higher variance in transmission rates than was observed in the 2003 SARS epidemic.

We have found that SARS-CoV-2 evolves at a rate compatible with related coronaviruses (approximately 0.0007- 0.002 substitutions per site per year), but the very short period of observation has allowed very few mutations to occur. There remains considerable uncertainty in growth rates that will be reduced with the incorporation of additional samples in the coming weeks. As the epidemic continues to grow and affect more countries, the timely release of genetic data will be invaluable for refining future estimates.

#### 4. Methods

Bayesian phylogenetic analyses were carried out in BEAST2.6 [11]. Two analyses were carried out with different population genetic priors: 1) A coalescent with exponential growth and 2) A SEIR model-based structured coalescent using the PhyDyn package [12]. All analyses made use of a strict molecular clock and an HKY substitution model following previous study designs [7]. The molecular clock rate of substitution was constrained between 0.0007 and 0.002 substitutions per site per year. MCMC was run for 100 million iterations for exponential 160 million iterations for SEIR excluding 50% burn-in.

DOI: https://doi.org/10.25561/77169 Page **5** of **8** 

Estimates of effective population size from the exponential-growth coalescent were translated to epidemic prevalence using the transform of Fraser et al. [13]:

$$I(t) = \frac{N_e(t)}{T_g} \left( \frac{\sigma^2}{R} + R - 1 \right)$$

Where R is the reproduction number,  $T_g=8.4$  days is the generation time, and  $\sigma^2$  is the variance in the *offspring distribution*, which is the distribution in number of transmissions made by a single infected individual. In the absence of over-dispersion, this reduces to the equation of Volz et al [14]:

 $I(t)=2\beta N_e(t)$ , where  $\beta$  is the per-capita transmission rate. Following previous reports [8,9,15], we examined scenarios where R=2.9, and  $\sigma^2$  was chosen to correspond to a SARS-like overdispersion parameter of k=0.16 [16], or under the condition of no overdispersion.

The SEIR model incorporated two classes of infectious individuals in order to produce a realistic variance of the offspring distribution which corresponds to the SARS-like k=0.16. The model has a high transmission rate group comprising 13.5% of infected individuals who transmit at a rate 74 times larger than the remaining infected individuals.

Maximum likelihood analysis: Time scaled phylogenies, substitution rates, and TMRCA were estimated using the *treedater* R package 0.5.0 [17]. The rate of evolution was constrained between 0.0005-0.00125 substitutions per site per year. Polytomies were resolved randomly prior to coalescent analysis and results averaged. Parametric bootstrap was used to estimate uncertainty. Sample selection, quality control, and computation of maximum likelihood phylogenies was based on the Nextstrain platform [8,9]. Sequences were aligned using MAFFT [18] and phylogenies estimated using IQTree [19]. Discussions on <a href="http://virological.org">http://virological.org</a> assisted greatly with quality control and sample selection. Lineages were dropped from the tree if multiple samples came from a household or a known transmission pair. An exponential-growth coalescent model was implemented in the phydynR package [12]. This model was fitted by maximum likelihood to the bootstrap distribution of phylogenies.

### **Sequences**

See supplementary file for GISAID IDs of sequences used for analyses: gisaid id.csv.

### 5. Acknowledgements

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### 6. References

- 1. Huang C, Wang Y, Li X, Ren L, Zhao J, Hu Y, et al. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. Lancet. 0. doi:10.1016/S0140-6736(20)30183-5
- Wong MC, Cregeen SJJ, Ajami NJ, Petrosino JF. Evidence of recombination in coronaviruses implicating pangolin origins of nCoV-2019. bioRxiv. 2020; 2020.02.07.939207. doi:10.1101/2020.02.07.939207
- 3. Lu R, Zhao X, Li J, Niu P, Yang B, Wu H, et al. Genomic characterisation and epidemiology of 2019 novel coronavirus: implications for virus origins and receptor binding. Lancet. 2020;0. doi:10.1016/S0140-6736(20)30251-8
- 4. Zhou P, Yang X-L, Wang X-G, Hu B, Zhang L, Zhang W, et al. A pneumonia outbreak associated with a new coronavirus of probable bat origin. Nature. 2020; 1–4. doi:10.1038/s41586-020-2012-7
- 5. Clock and TMRCA based on 27 genomes Novel 2019 coronavirus / nCoV-2019 Genomic Epidemiology Virological. [cited 14 Feb 2020]. Available: http://virological.org/t/clock-and-tmrca-based-on-27-genomes/347
- 6. Phylodynamic analysis of nCoV-2019 genomes 29-Jan-2020 Novel 2019 coronavirus / nCoV-2019 Genomic Epidemiology Virological. [cited 14 Feb 2020]. Available: http://virological.org/t/phylodynamic-analysis-of-ncov-2019-genomes-29-jan-2020/353/7
- 7. Phylodynamic Analysis | 90 genomes | 12 Feb 2020 Novel 2019 coronavirus / nCoV-2019 Genomic Epidemiology Virological. [cited 14 Feb 2020]. Available: http://virological.org/t/phylodynamic-analysis-90-genomes-12-feb-2020/356
- 8. Imai N, Dorigatti I, Cori A, Riley S, Ferguson NM. Report 1: Estimating the potential total number of novel Coronavirus cases in Wuhan City, China. [cited 20 Jan 2020]. Available: https://www.imperial.ac.uk/mrc-global-infectious-disease-analysis/news--wuhan-coronavirus/
- 9. Imai N, Dorigatti I, Cori A, Riley S, Ferguson NM. Report 2: Estimating the potential total number of novel Coronavirus cases in Wuhan City, China. [cited 24 Jan 2020]. Available: https://www.imperial.ac.uk/mrc-global-infectious-disease-analysis/news--wuhan-coronavirus/
- 10. World Health Organization. Novel Coronavirus(2019-nCoV) Situation Report-15. 2020. Available: https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200204-sitrep-15-ncov.pdf
- 11. Bouckaert R, Vaughan TG, Barido-Sottani J, Duchêne S, Fourment M, Gavryushkina A, et al. BEAST 2.5: An advanced software platform for Bayesian evolutionary analysis. PLoS Comput Biol. 2019. doi:10.1371/journal.pcbi.1006650
- 12. Volz EM, Siveroni I. Bayesian phylodynamic inference with complex models. PLoS Comput

- Biol. 2018. doi:10.1371/journal.pcbi.1006546
- 13. Fraser C, Li LM. Coalescent models for populations with time-varying population sizes and arbitrary offspring distributions . bioRxiv . 2017. doi:10.1101/131730
- 14. Volz EM. Complex population dynamics and the coalescent under neutrality. Genetics. 2012. doi:10.1534/genetics.111.134627
- 15. Imai N, Cori A, Dorigatti I, Baguelin M, Donnelly CA, Riley S, et al. Report 3: Transmissibility of 2019-nCoV. 2020. Available: https://www.imperial.ac.uk/media/imperial-college/medicine/sph/ide/gida-fellowships/Imperial-2019-nCoV-transmissibility.pdf
- 16. Lloyd-Smith JO, Schreiber SJ, Kopp PE, Getz WM. Superspreading and the effect of individual variation on disease emergence. Nature. 2005;438: 355–359. doi:10.1038/nature04153
- 17. Volz EM, Frost SDW. Scalable relaxed clock phylogenetic dating. Virus Evol. 2017. doi:10.1093/ve/vex025
- Katoh K, Standley DM. MAFFT multiple sequence alignment software version 7: Improvements in performance and usability. Mol Biol Evol. 2013. doi:10.1093/molbev/mst010
- 19. Nguyen LT, Schmidt HA, Von Haeseler A, Minh BQ. IQ-TREE: A fast and effective stochastic algorithm for estimating maximum-likelihood phylogenies. Mol Biol Evol. 2015. doi:10.1093/molbev/msu300

DOI: https://doi.org/10.25561/77169 Page **8** of **8**