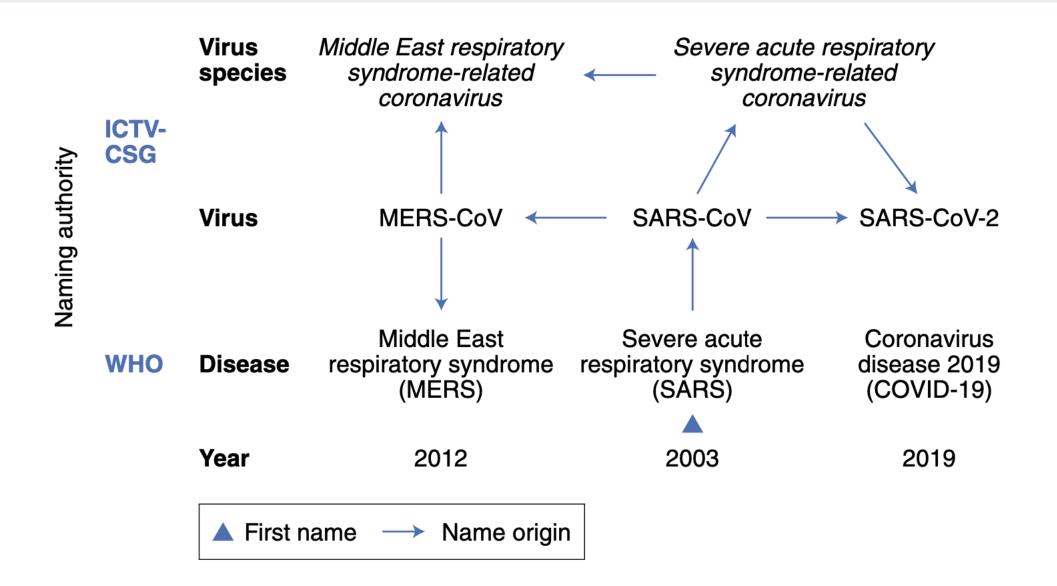
COVID-19 and SARS-COV-2 Research Update

Rick Stevens – Argonne National Laboratory – University of Chicago

Ian Foster, Arvind Ramanathan, Tom Brettin, Austin Clyde, Kyle Chard, Maulik Shukla, Jonathan Ozik, Chick Macal, Yadu Babuji, Carlos Olivares, Alex Partin, Gyorgy Babnigg, Xuefeng Liu, Ben Blaiszik, Ryan Chard, Zhi Hong, Zhuozhag Li, Marcus Schwarting, Logan Ward, Anna Woodward, Shantenu Jha, Kerstin Van Dam, Frank Alexander, Misha Salim, Matteo Turilli, Andre Merzky, Mike Papka, Katherine Riley, Venkat Vishwanath, Carlos Simmerling, Hubertus Van Dam, Gina Tourassi, Dan Stanzione, Mike Norman, and many others > 200 The emergence of SARS and the identification of a coronavirus as the causative agent of the disease astounded the coronavirus community, as it was the first definitive association of a coronavirus with a severe disease in humans.



March 9th 2020

DEATH RATE

DEATH RATE

COVID-19 CORONAVIRUS OUTBREAK

Last updated: March 09, 2020, 15:01 GMT

https://www.worldometers.info/coronavirus/

Cases - Deaths - Countries - Death Rate - Incubation - Age - Symptoms - Opinions - News



111,746

COVID-19 Fatality Rate by AGE:

*Death Rate = (number of deaths / number of cases) = probability of dying if infected by the virus (%). This probability differs depending on the age group. The percentages shown below do not have to add up to 100%, as they do NOT represent share of deaths by age group. Rather, it represents, for a person in a given age group, the risk of dying if infected with COVID-19.

AGE	DEATH RATE confirmed cases	DEATH RATE all cases
80+ years old	21.9%	14.8%
70-79 years old		8.0%
60-69 years old		3.6%
50-59 years old		1.3%
40-49 years old		0.4%
30-39 years old		0.2%
20-29 years old		0.2%
10-19 years old		0.2%
0-9 years old		no fatalities

view by country

Deaths:

3,888

Recovered:

62,722

Daily Deaths

250

200

100

0 150

Daily Deaths Deaths per Day Data as of 0:00 GMT+8	
. [1]]. [11].	
	The

Daily Deaths

	confirmed cases	all cases
Cardiovascular disease	13.2%	10.5%
Diabetes	9.2%	7.3%
Chronic respiratory disease	8.0%	6.3%
Hypertension	8.4%	6.0%
Cancer	7.6%	5.6%
no pre-existing conditions		0.9%

COVID-19 CORONAVIRUS PANDEMIC

Last updated: April 24, 2020, 10:32 GMT

Graphs - Countries - Death Rate - Symptoms - Incubation - Transmission - News

Coronavirus Cases:



2,744,606

view by country

Deaths:

191,790

Recovered:

755,390

All Europe	North An	nerica A	sia South
Country, Other 1	Total Cases ↓	New Cases ↓↑	Total Deaths ↓1
World	2,744,606	+21,562	191,790
USA	886,709	+267	50,243
<u>Spain</u>	219,764	+6,740	22,524
<u>Italy</u>	189,973		25,549
France	158,183		21,856
Germany	153,215	+86	5,575
<u>UK</u>	138,078		18,738
<u>Turkey</u>	101,790		2,491
Iran	87,026		5,481
China	82,804	+6	4,632
<u>Russia</u>	68,622	+5,849	615
Brazil	50,036	+544	3,331
Belgium	44,293	+1,496	6,679

April 24th, 2020

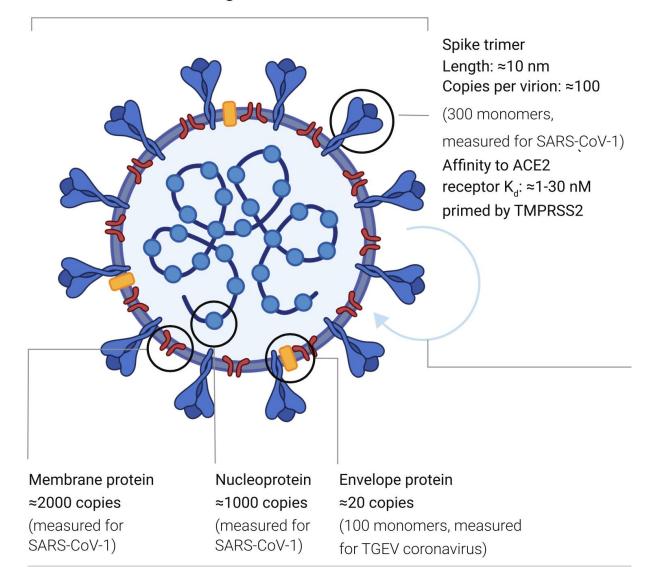
Understanding the Enemy

Size & Content

Diameter: $\approx 100 \text{ nm}$ Volume: $\sim 10^6 \text{ nm}^3 = 10^{-3} \text{ fL}$ Mass: $\sim 10^3 \text{ MDa} \approx 1 \text{ fg}$



published in eLife, March 31st, 2020 https://elifesciences.org/articles/57309





published in eLife, March 31st, 2020 https://elifesciences.org/articles/57309

Replication Timescales

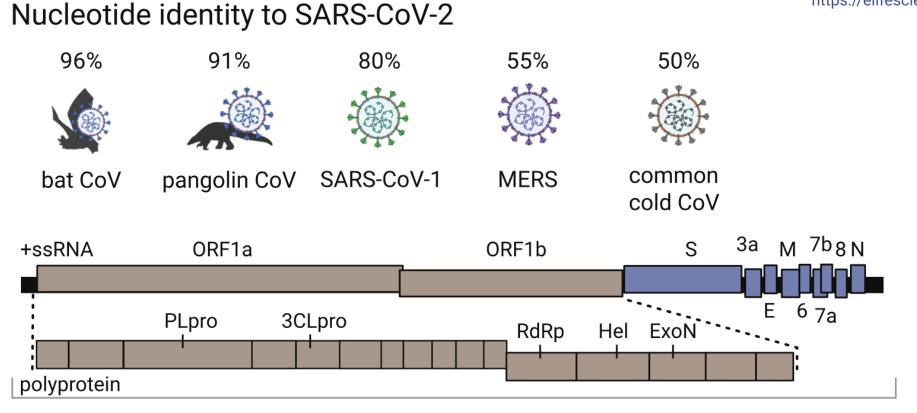
in tissue-culture

Virion entry into cell: ~10 min (measured for SARS-CoV-1)Eclipse period: ~10 hrs(time to make intracellular virions)Burst size: ~10³ virions(measured for MHV coronavirus)

Genome



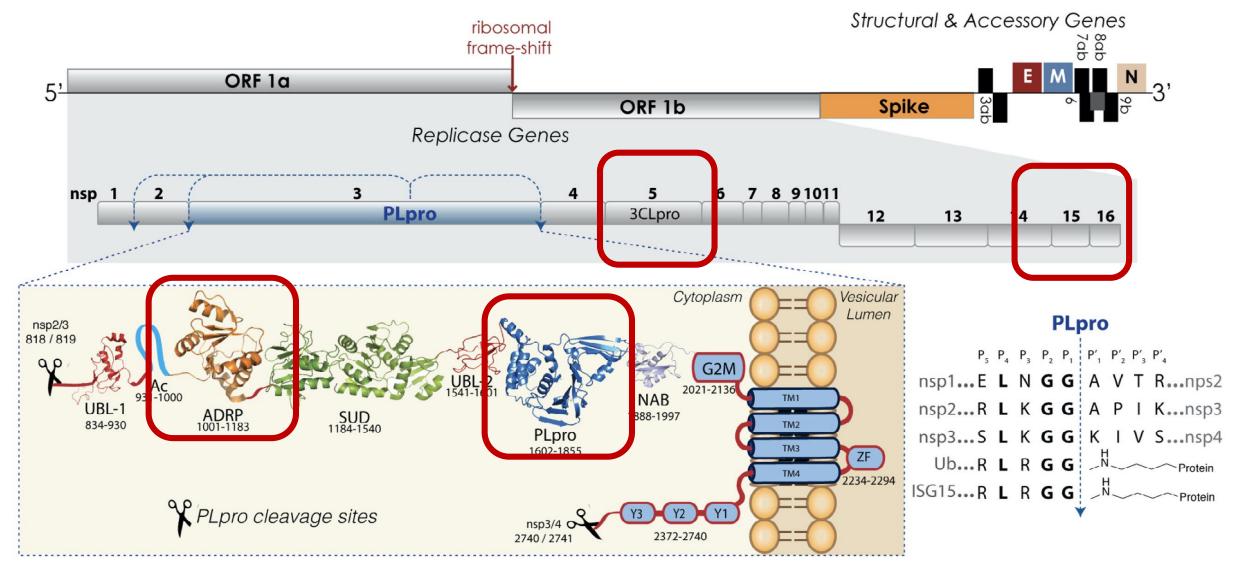
published in eLife, March 31st, 2020 https://elifesciences.org/articles/57309



Length: ≈30kb; β-coronavirus with 10-14 ORFs (24-27 proteins)

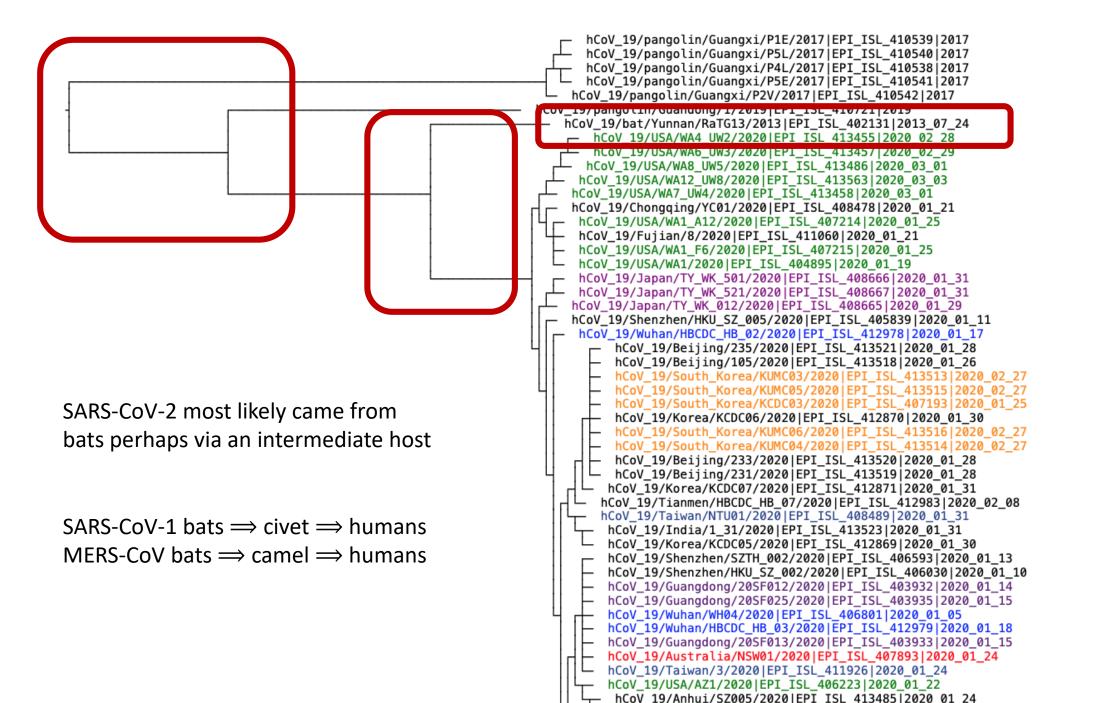
Evolution rate: $\sim 10^{-3}$ nt⁻¹ yr⁻¹ (measured for SARS-CoV-1) Mutation rate: $\sim 10^{-6}$ nt⁻¹ cycle⁻¹ (measured for MHV coronavirus)

Polyproteins encode many domains per gene



Antiviral Res. 2015 Mar; 115: 21-38.

Published online 2014 Dec 29. doi: 10.1016/j.antiviral.2014.12.015



"Characteristic" Infection Progression in a Single Patient

Basic reproductive number R₀: typically 2-4

(number of new cases directly generated from a single case)

Varies further across space and time (Li et al. 2020; Park et al. 2020)

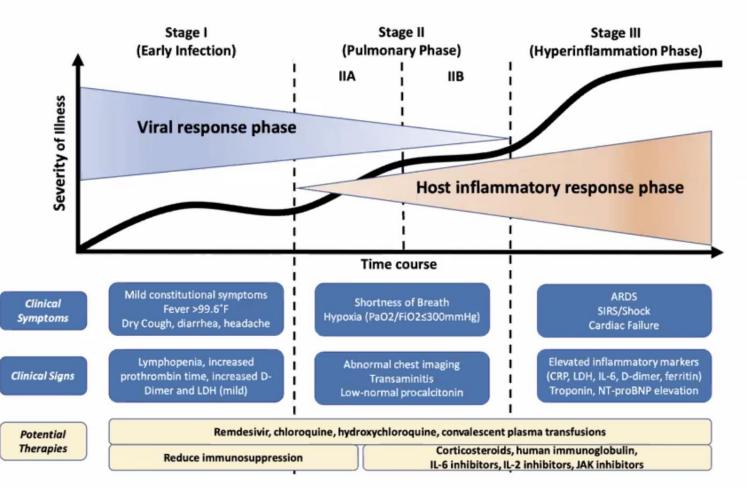
eLife

published in eLife, March 31st, 2020 https://elifesciences.org/articles/57309

infection with Case Fatality Rate (ECDC 2020) virus ≈0.8%-10% (uncorrected) diagnosis after ≈ 5 days Incubation period: ≈ 5 days **Infected Fatality Rate** $(99\% \le 14 \text{ days unless asymptomatic})$ symptomatic ≈0.3%-1.3% ◄(Lauer et al. 2020; Li et al. 2020) exposed infectious Recovery mild cases: ≈2 weeks Latent period ~3 days < Interval of half-maximum</p> severe cases: ≈6 weeks infectiousness ≈4 days

Inter-individual variability is substantial and not well characterized. The estimates are parameter fits for population median in China and do not describe this variability (Li et al. 2020; He et al. 2020).

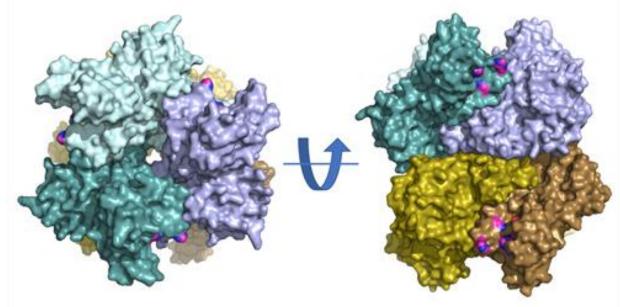
Kinetics of infection and clinical deterioration suggest that pathology is from immune over-stimulation



- Which immune parameters correlate with disease severity?
 - Serum cytokines (IL-6, IL-1β, others)
 - Antibody response
 - T cell response
- Why do some patients develop severe disease and some not?
 - Germline genetics
 - Airway microbiota
 - Pre-existing cross-reactive immunity

Research effort on COVID-19/SARS-COV-2

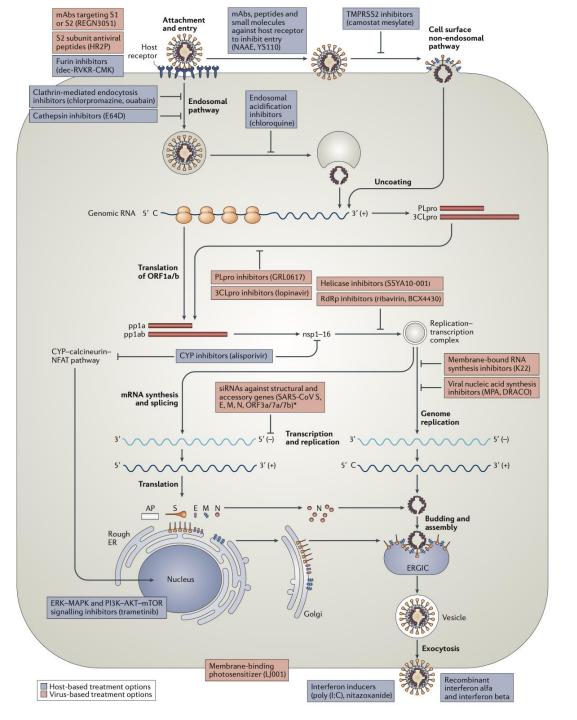
- Work at the APS and SBC to solve structures and screening small molecules (nsp15), 3CLpro, PLpro, etc.
- Participation in the NVBTL working groups (EPI, Testing, Manufacturing, Therapeutics)



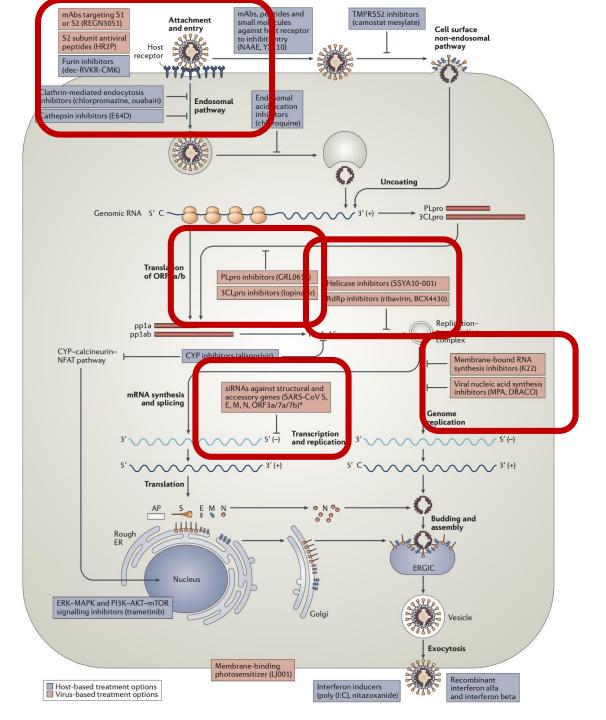
- Computational work on five subproblems
 - Antiviral drug screening ⇒ priority compounds for wet lab screening
 - Epidemiology ⇒ transmission and interventions
 - Evolution ⇒ origins, diversity and host-adaptation
 - Vaccine \Rightarrow epitope analysis and antibody design
 - Host-pathogen interactions / host response \implies severity and drugs

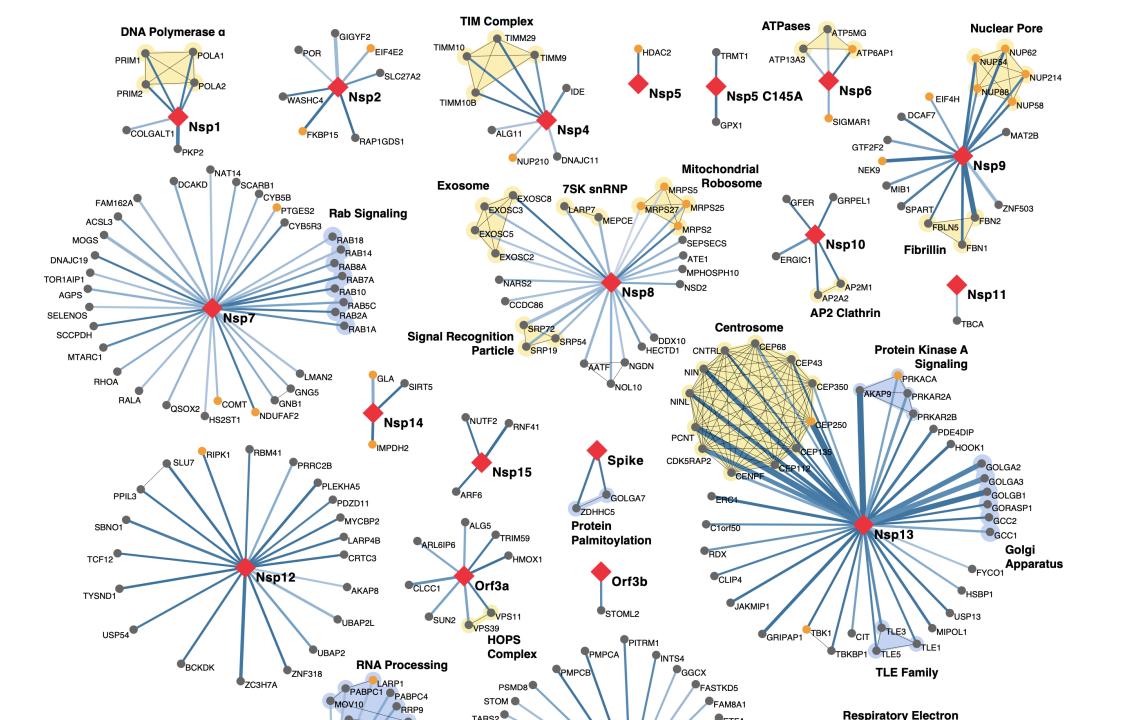
Antiviral Drug Screening

Protein	Mol. weight (kDa)	Seq. similarity with SARS-CoV	Description
Nsp1	19.8	91.1%	Suppresses host antiviral response
Nsp2	70.5	82.9%	
Nsp3	217.3	86.5%	Nsp3-Nsp4-Nsp6 complex involved in viral replication
Nsp4	56.2	90.8%	Nsp3-Nsp4-Nsp6 complex involved in viral replication
Nsp5	33.8	98.7%	Main protease (3C-like)
Nsp6	33.0	94.8%	Nsp3-Nsp4-Nsp6 complex involved in viral replication
Nsp7	9.2	100.0%	Nsp7-Nsp8 complex is part of RNA polymerase
Nsp8	21.9	99.0%	Nsp7-Nsp8 complex is part of RNA polymerase
Nsp9	12.4	98.2%	ssRNA binding
Nsp10	14.8	99.3%	Essential for Nsp16 methyltransferase activity
Nsp11	1.3	92.3%	Short peptide
Nsp12	106.7	98.3%	RNA polymerase
Nsp13	66.9	100.0%	Helicase/triphosphatase
Nsp14	59.8	98.7%	3'-5' exonuclease
Nsp15	38.8	95.7%	Uridine-specific endoribonuclease
Nsp16	33.3	98.0%	RNA-cap methyltransferase
S	141.2	87.0%	Spike protein, mediates binding to ACE2
Orf3a	31.1	85.1%	Activates the NLRP3 inflammasome
Orf3b	6.5	9.5%	
E	8.4	96.1%	Envelope protein, involved in virus morphogenesis and assembly
м	25.1	96.4%	Membrane glycoprotein, predominant component of the envelope
Orf6	7.3	85.7%	Type I IFN antagonist
Orf7a	13.7	90.2%	Virus-induced apoptosis
Orf7b	5.2	84.1%	
Orf8	13.8	45.3%	
N	45.6	94.3%	Nucleocapsid phosphoprotein, binds to RNA genome
Orf9b	10.8	84.7%	Type I IFN antagonist
Orf9c	8.0	78.1%	
Orf10	4.4	-	

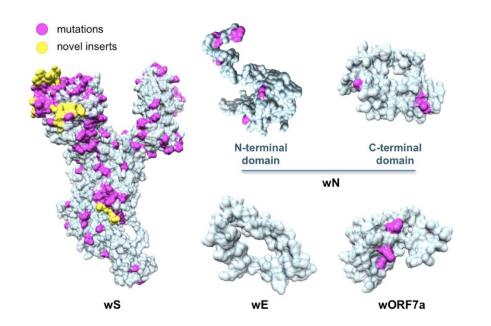


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Orf10	4.4	-	





Structures exist for most of the proteome



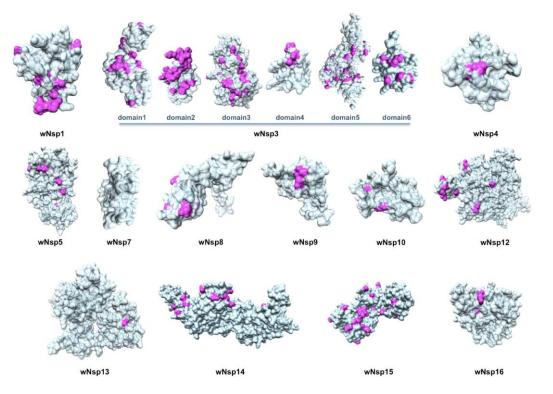
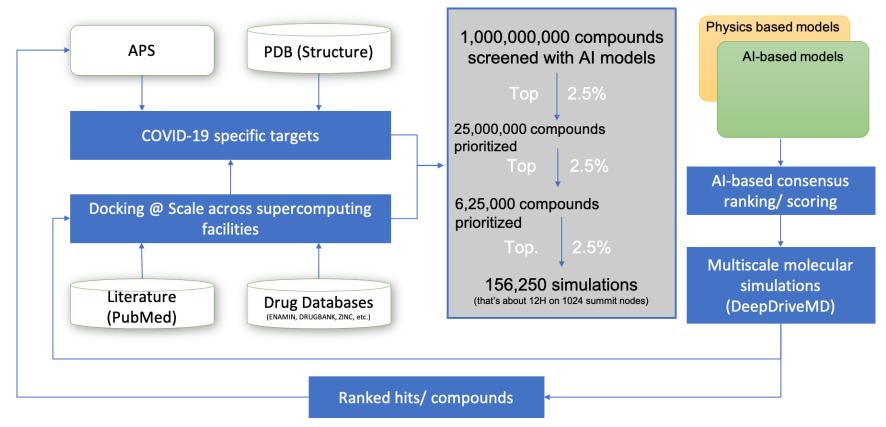


Figure 3. Structurally characterized structural proteins and an ORF of 2019-nCoV. Highlighted in pink are mutations found when aligning the proteins against their homologs from the closest related coronaviruses: 2019-nCoV and human SARS, bat coronavirus, and another bat betacoronavirus BtRf-BetaCoV. Highlighted in yellow are novel protein inserts found in wS.

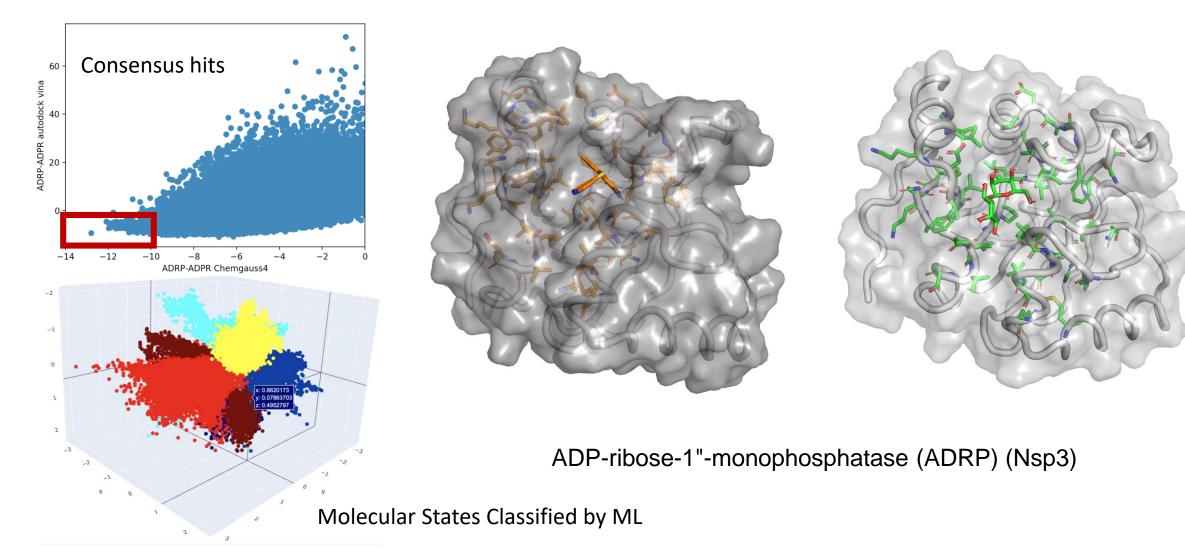
Figure 2. Structurally characterized non-structural proteins of 2019-nCoV. Highlighted in pink are mutations found when aligning the proteins against their homologs from the closest related coronaviruses: 2019-nCoV and human SARS, bat coronavirus, and another bat betacoronavirus BtRf-BetaCoV. The structurally resolved part of wNsp7 is sequentially identical to its homolog.

HPC/AI is helping discover novel small molecules that can inhibit various virus proteins

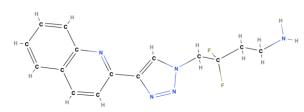


- ML/AI approaches are enabling the identification of potential leads that can bind to 8 viral protein targets
- DeepDriveMD helps identify conformational states that bind to specific ligands
- Identified over 30 lead molecules that have been submitted to various open forums for experimental validation
- Collaborations with University of Chicago, Brookhaven National Lab, Frederick National Laboratory and the University of Michigan

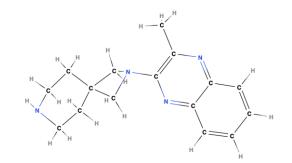
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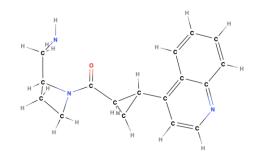
Sampling of Top Hits from ML (Enamine_REAL 1.2B) for ADRP-P1



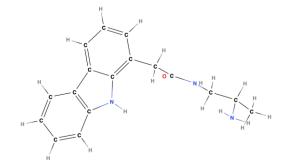
NCCC(Cn1nnc(c1)c1ccc2c(n1)cccc2)(F)F



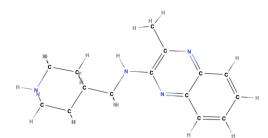
Cc1nc2cccc2nc1N1CC2(C1)CCNCC2



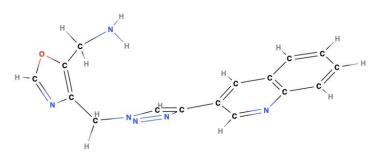
NCC1CCN1C(=O)[C@@H]1C[C@H]1c1ccnc2c1cccc2



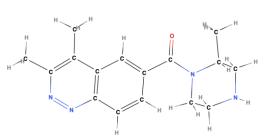
CC(CNC(=O)Cc1cccc2c1[nH]c1c2cccc1)N



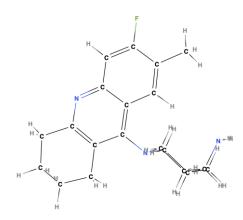
Cc1nc2cccc2nc1NCC1(F)CCNCC1



NCc1ocnc1Cn1nnc(c1)c1cnc2c(c1)cccc2



C[C@@H]1CNCCN1C(=O)c1ccc2c(c1)c(C)c(nn2)C



NC1CCN(CC1C)c1c2CCCCc2nc2c1cc(C)c(c2)F

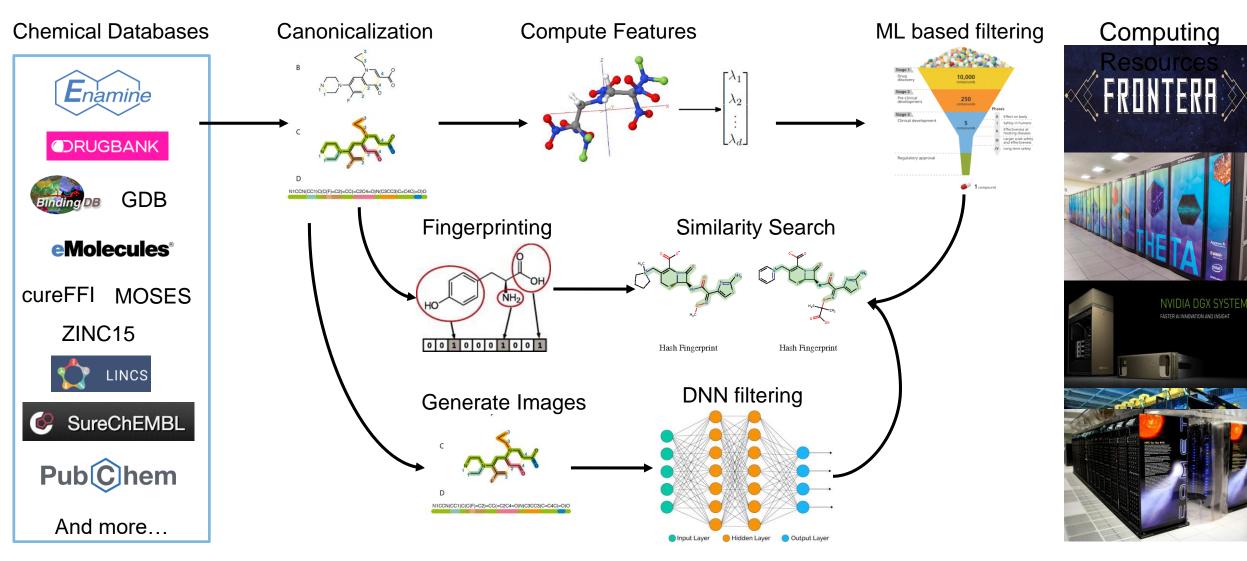
2045 compounds with softmax = 1.0 Predicted docking score < -8.50



Overall First Floor Plan

Flad & Associates

Our HPC- and AI-enabled small molecule filtering pipeline



https://2019-ncovgroup.github.io

First release: 21 sources, 3.9B molecules, 80 TB computed features

https://2019-ncovgroup.github.io

21 sources, 3.9B molecules, 80 TB computed features

ENAMINE REAL 1.2 billion molecules which comply with "rule of 5" and Veber criteria: MW≤500, SlogP≤5, HBA≤10, HBD≤5, rotatable bonds≤10, TPSA≤140.

GDB-13 enumerates small organic molecules up to 13 atoms of C, N, O, S and CI following simple chemical stability and synthetic feasibility rules.

https://2019-ncovgroup.github.io

Mining literature for drug discovery and repurposing

- Thousands of papers already published about COVID-19 and similar coronaviruses
- Developing human and machine pipelines to identify, extract drugs (current) and mechanisms (future)
- Identify key molecules for simulation team as starting points
- Build a list of known antiviral molecules and molecules active against SARS/MERS/HKU/SARS-CoV-2
- Use this list and "most-similar" molecules to build confidence in ML and simulation predictions

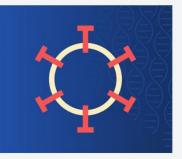
COVID-19 Open Research Dataset (CORD-19)

Access this dataset to help with the fight against COVID-19

A Free, Open Resource for the Global Research Community

In response to the COVID-19 pandemic, the Allen Institute for AI has partnered with leading research groups to prepare and distribute the COVID-19 Open Research Dataset (CORD-19), a free resource of over 45,000 scholarly articles, including over 33,000 with full text, about COVID-19 and the coronavirus family of viruses for use by the global research community.

This dataset is intended to mobilize researchers to apply recent advances in natural language processing to generate new insights in support of the fight against this infectious disease. The corpus will be updated weekly as new research is published in peer-reviewed publications and archival services like bioRxiv, medRxiv, and others.



CORD-19 Explorer is a quick and easy way to search the CORD-19 corpus, or you can download the complete data below.

Participate in the CORD-19 Challenge

Kaggle is hosting the COVID-19 Open Research Dataset Challenge, a series of important questions designed to inspire the community to use CORD-19 to find new insights about the COVID-19 pandemic including the natural history, transmission, and diagnostics for the virus, management measures at the human-animal interface, lessons from previous epidemiological studies, and more.

Download CORD-19

By downloading this dataset you are agreeing to the Dataset License. Specific licensing information for individual articles in the dataset is available in the metadata file.

Mining literature for drug discovery and repurposing

1. Manual Extraction

- Engaging CELS admin staff
- Currently have extracted 803 screened molecules and structures from 61 articles and reviews. (top figures)
- Capacity to extract from ~100 articles

2. Deep Learning (NLP)

- Team has labeled ~1500 abstracts with drugs in their natural language context in CORD-19 papers (bottom figure)
- Building named-entity models to enable automated extraction of drugs from entire corpus (~40k articles)

Current F1: 82.7 – more validation needed

Resulting data and models will be published openly

1 1	nolecule	virus	reference	type	df	- 1	pd.read_csv	('./da	ata/literature	_molecules.c	sv')
2 F	Remdesivir	SARS-CoV-2	10.1038/s41422-020-0282-0	Experimenta	df.	hea	ad(4)				
з (Chloroquine	SARS-CoV-2	10.1038/s41422-020-0282-0	Experimenta		id	molecule	virus	reference	type	smiles
4 N	Vitazoxanide	SARS-CoV-2	10.1038/s41422-020-0282-0	Experimenta	0	0	Remdesivir	SARS- CoV-2	10.1038/s41422- 020-0282-0	experimental	CCC(COC(=0)C(NP(=0) (Oc1ccccc1)OCC1OC(C(C10)O)(
5 N	Nafamostat	SARS-CoV-2	10.1038/s41422-020-0282-0	Experimenta				SARS-	10.1038/s41422-		
	enciclovir	SARS-CoV-2	10.1038/s41422-020-0282-0	Experimenta	1	1	Chloroquine	CoV-2	020-0282-0	experimental	CCN(CCCC(Nc1ccnc2c1ccc(c2)Cl)C)CC
	nafamostat	SARS-CoV-2	10.1038/s41422-020-0282-0	Experimenta	~	2	Nitazoxanide	SARS- CoV-2	10.1038/s41422- 020-0282-0	experimental	CC(=0)Oc1ccccc1C(=0)Nc1ncc(s1)[N+](=0)[O-]
	avipiravir	SARS-CoV-2	10.1038/s41422-020-0282-0	Experimenta		2	Nafamostat	SARS-		ovporimontal	NC(=Nc1ccc(cc1)C(=O)Oc1ccc2c(c1)ccc(c2)C(=N)N)N
	oratadine	SARS-CoV-2	10.1101/2020.03.22.002386v1	Experimenta	3	3	Natatiostat	CoV-2	020-0282-0	experimental	
	Daunorubicin Midostaurin	SARS-CoV-2 SARS-CoV-2	10.1101/2020.03.22.002386v1 10.1101/2020.03.22.002386v1	Experimenta							
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	Metformin	SARS-CoV-2	10.1101/2020.03.22.002386v1	Experimenta		<		ĩ			
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18 5	S-verapamil	SARS-CoV-2	10.1101/2020.03.22.002386v1	Experimenta			~	T	~	\sim '	
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21 N	Aycophenolic acid	SARS-CoV-2	10.1101/2020.03.22.002386v1	Experimenta							
22 E	Entacapone	SARS-CoV-2	10.1101/2020.03.22.002386v1	Experimenta			Remde	ivir		Chloroqui	ne Nitazoxanide
S111	Ribavirin	SARS-CoV-2	10.1101/2020.03.22.002386v1	Experimenta							
	52862	SARS-CoV-2	10.1101/2020.03.22.002386v1	Experimenta							
	Merimepodib	SARS-CoV-2	10.1101/2020.03.22.002386v1	Experimenta							_
	RVX-208	SARS-CoV-2	10.1101/2020.03.22.002386v1	Experimenta	-	<		7	\mathbb{R}	Y	
27	KL413	SARS-CoV-2	10.1101/2020.03.22.002386v1	Experimenta		. N-		$\langle \rangle$	№ ,	-	
	RUG 1									penciclov	ir nafamostat
Scie	ence and Ve	terinary M	ledicine Academy o	of Shand	lon	g	Provin	ce.			
Eth	yl acetate ,	twain-80 ,	and span-80 were	purchas	ed	f	rom B/	١SF	(
Ber	lin , Germar	וy) . PPV (TCID 50 : 10 -5)	and PK	-15	5 0	cell we	re			
sup	plied by Chi	ina Institut	e of Veterinary Dr	ug Cont	rol	١.	DMEN	1 (
GIB	BCO) with t	he supplen	nent of 100 IU mL	-1 stre	ept	0	mycin	DRU	G,		
100) IU mL –1	benzylper	<mark>iicillin drug</mark> , and 1	.0 % fet	al k	20	ovine s	erur	n		
was	s used for re	suspendin	g and washing cells	s , cultur	ring	gt	the cel	ls,	and		
dilu	iting mitoge	n . The									

Computing at Argonne, Oak Ridge, TACC, SDSC, IU, LRZ, Brookhaven



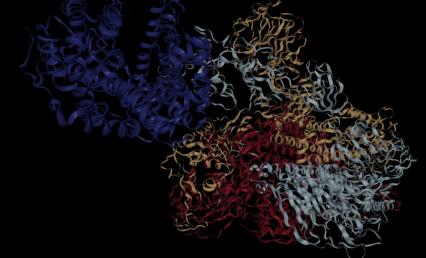








The COVID-19 High Performance Computing Consortium



Bringing together the Federal government, industry, and academic leaders to provide access to the world's most powerful high-performance computing resources in support of COVID-19 research.

33 41k

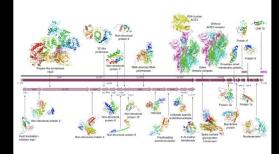
Consortium members GPUs

Active projects

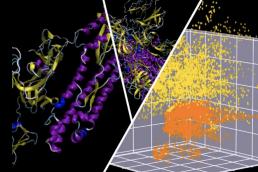
Fighting COVID-19 will require extensive research in areas like bioinformatics, epidemiology, and molecular modeling to understand the threat we're facing and to develop strategies to address it.

Here are some of our active projects.

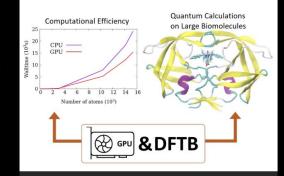




Request computing resource for de novo protein therapeutics design simulations to treat the COVID-19...



Discovering molecular targets of the human coronavirus with HPC and AI



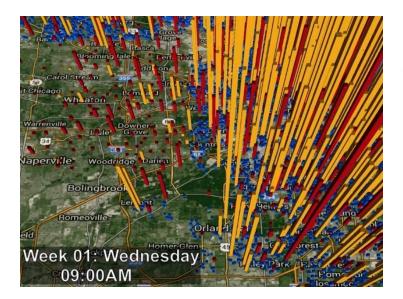
Harnessing Large-Scale Quantum-Based DFTB Calculations for a More Accurate Assessment of COVID-19...

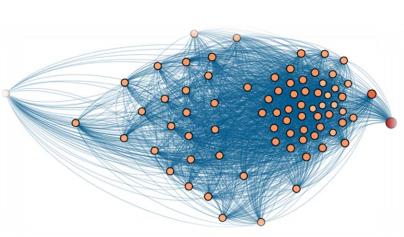
Epidemiology

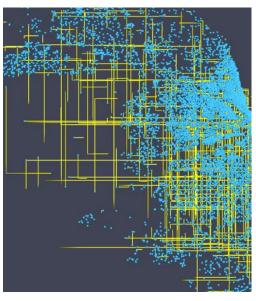
WE ARE MODELING COVID-19 SPREAD AMONG PEOPLE IN CHICAGO

Joint DOE Laboratory Plan for Pandemic Modeling and Analysis Capability

 Argonne, Oak Ridge, Los Alamos and Sandia will collaborate over a 3 month-period to develop an integrated COVID-19 pandemic monitoring, modeling, and analysis capability that will address the key questions about the pandemic





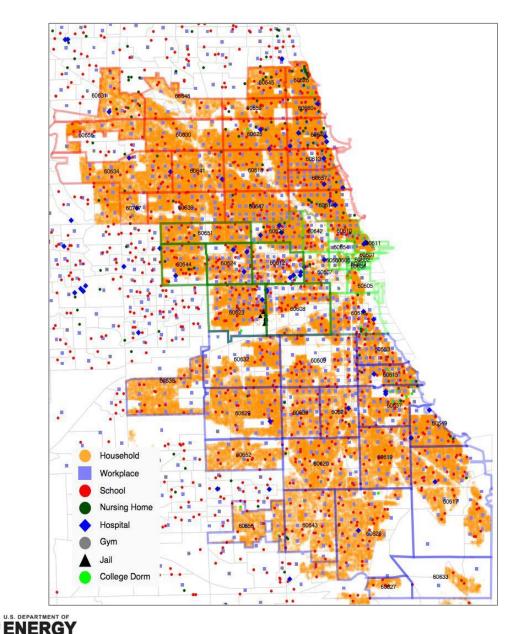


Where are people located? With who? Who is infecting who? Who may be infected? Where are people going, coming from?

32

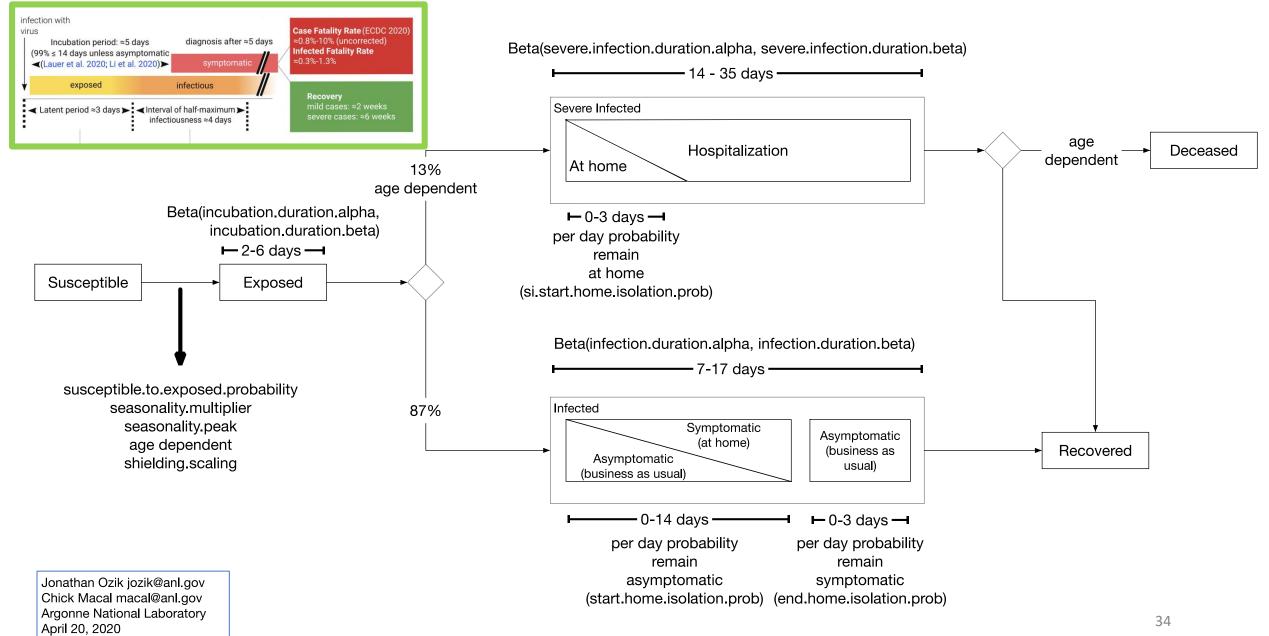


Modeling PEOPLE WITH ARGONNE'S CityCOVID



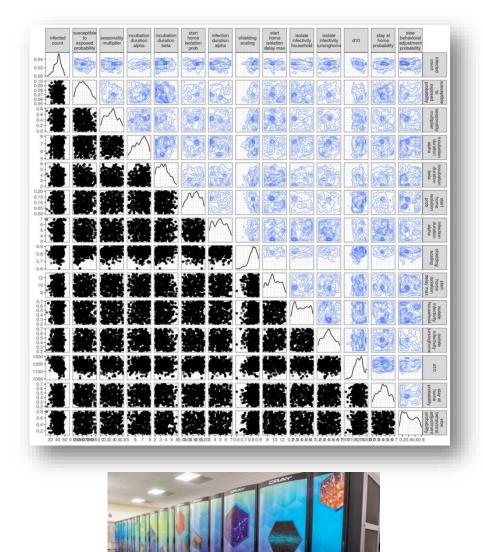
- CityCOVID is a city-scale agent-based model
- 2.7M+ individual agents (people)
 - move to/from 1.2M spatially-located places
 - on an hourly basis
 - over a period of a year (8760 hours)
- Each agent has contact with other agents at each place (possible disease transmission)
 - agent has individual behaviors, engages in activities, and responds and adapts:
 - to the disease
 - to public health messaging
 - to public health interventions
- Up to 10¹² (trillion) individual contacts during a yearly simulation

MODELING INDIVIDUAL AGENT DISEASE STATES WITH CITYCOVID



CityCOVID PARAMETER ESTIMATION ON THETA

- CityCOVID is implemented as an MPI application using the Repast HPC ABM toolkit and the Chicago Social Interaction Model (ChiSIM) framework
- Each model is distributed across 256 ranks for efficient execution (each simulated year, at an hourly time step, takes approximately 8-12 minutes to complete for a full city-scale run)
- We are using our large-scale model exploration framework (EMEWS) to implement sequential approximate Bayesian computation (ABC) parameter estimation/calibration workflows, coordinating large ensemble runs (30k+ models) on Theta

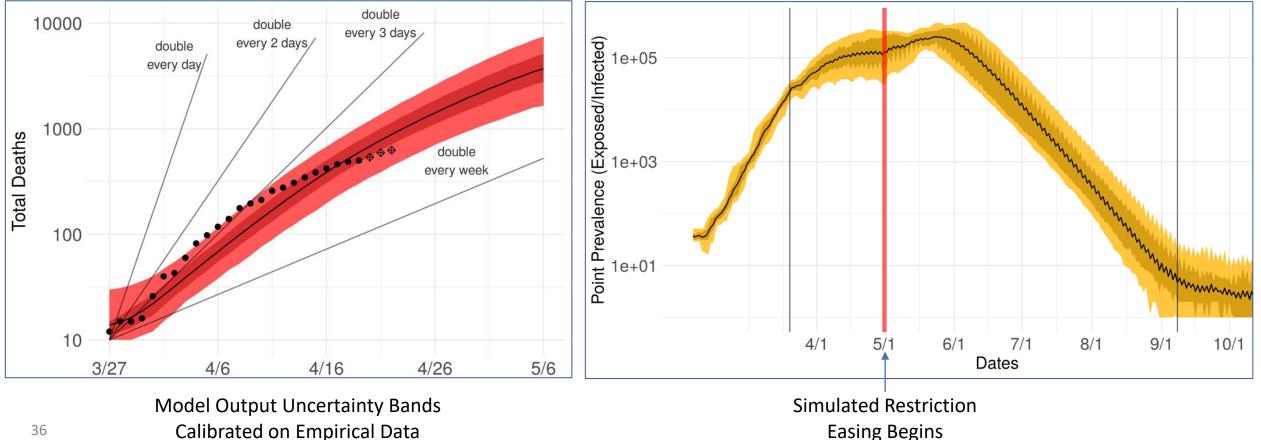




CityCOVID MODEL OUTPUTS

 CityCOVID generates projections of epidemiological variables, including COVID-19 exposures and deaths

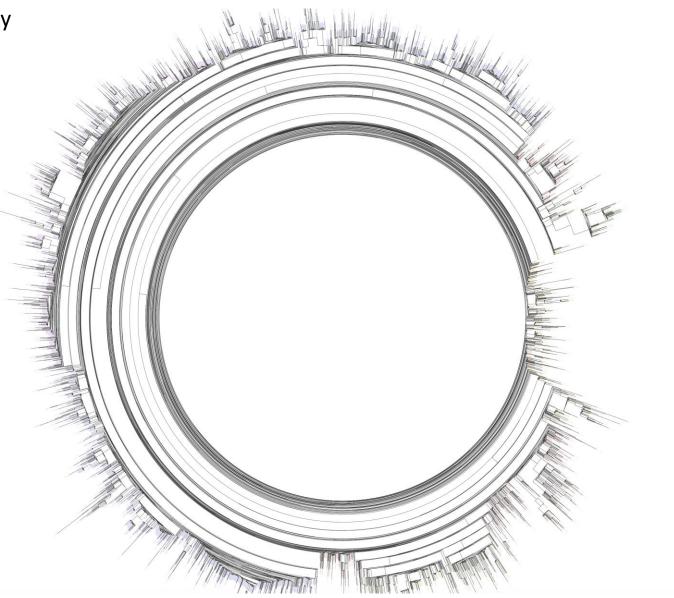
• CityCOVID enables running policy scenarios, such as those examining the consequences of easing current in-place restrictions



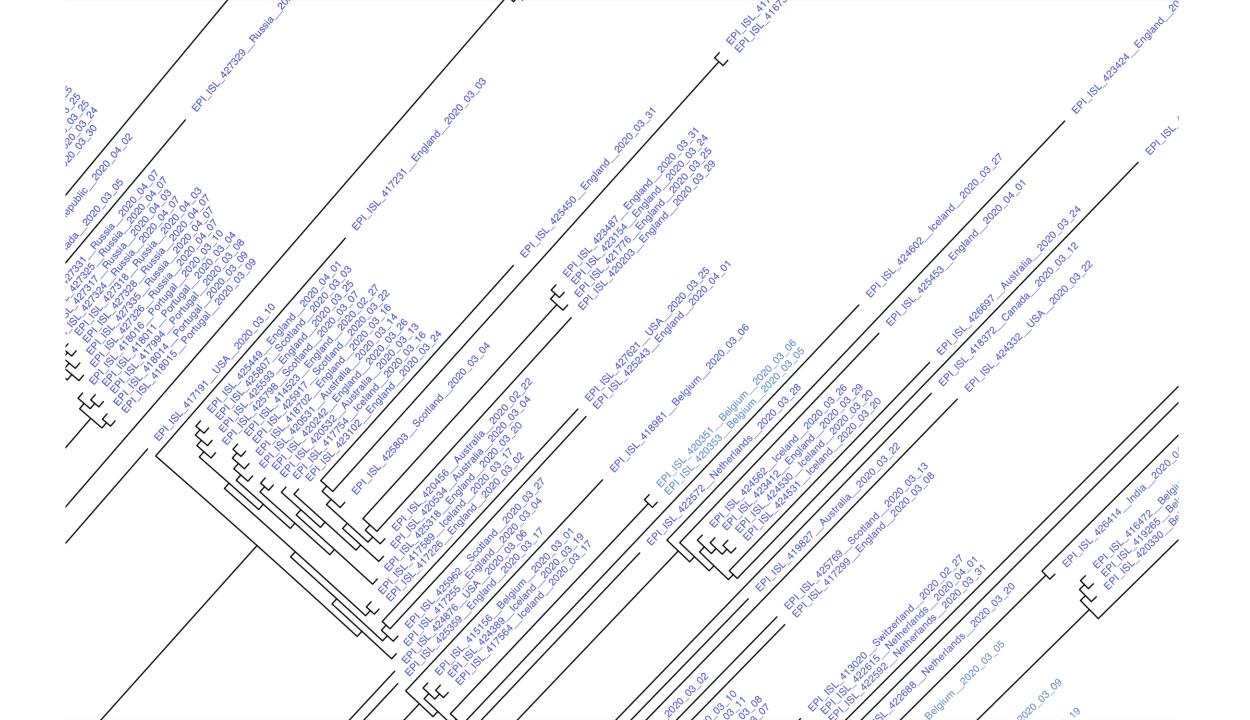
Calibrated on Empirical Data

Evolution

- >10,000 viral sequences
- Phylogenetic trees updated daily
- DOE \Rightarrow FEMA, BARDA etc.
- Place, Date
- Trees from WGS, SNPs
- Tracking new mutations
- Capturing significant variants









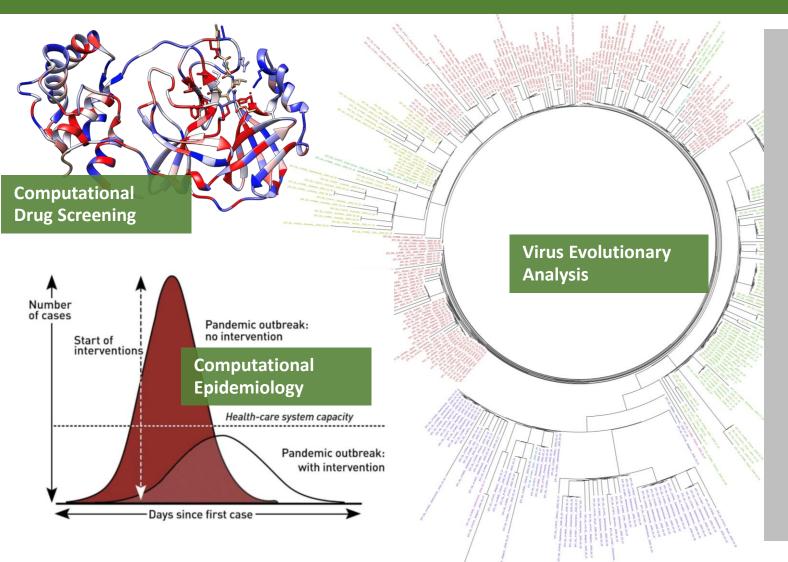


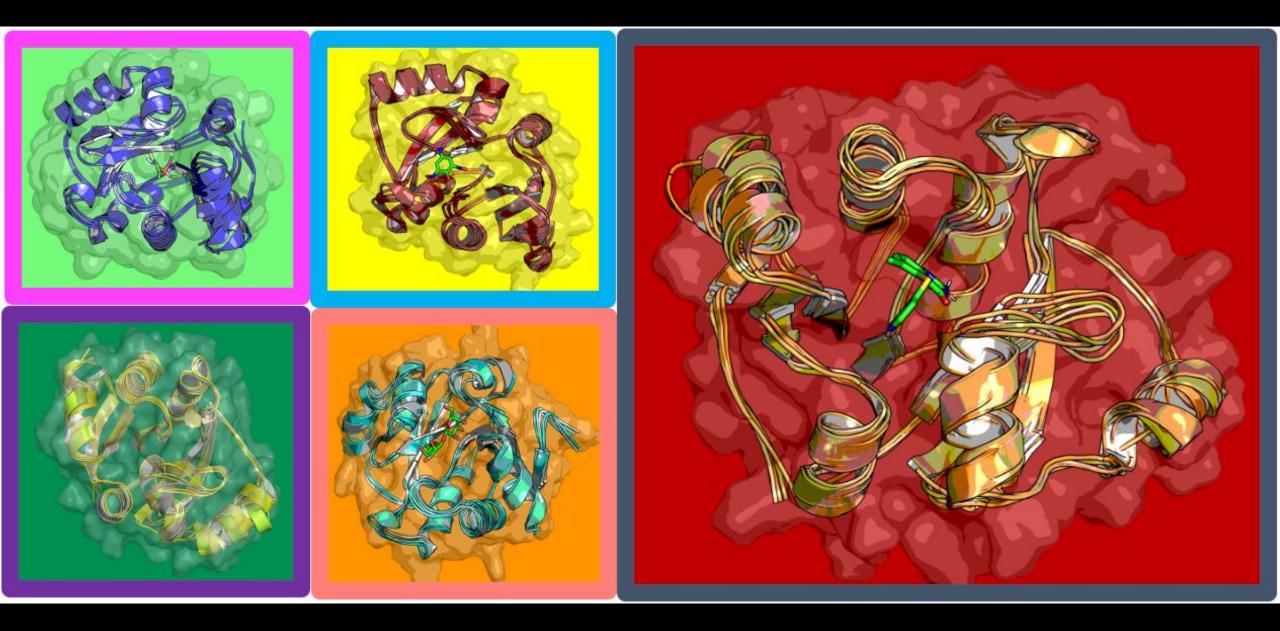
RICK STEVENS

Associate Laboratory Director for Computing, Environment and Life Sciences

Supercomputing Focus Areas

- Accelerating development of treatment options
- Learning how epidemics impact critical social services
- Improving understanding of human virus interactions





Questions