
Efficient simulation and graphical modeling of Covid-19 spread

Group 13

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Overview

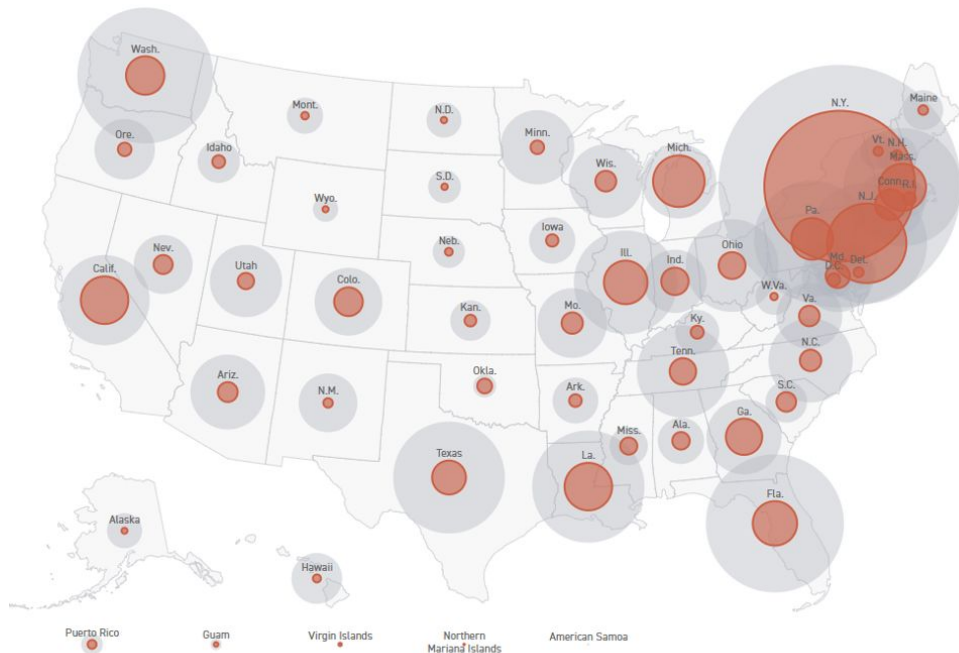
- ❖ Quick recap
- ❖ Datasets and SEIRHD model
- ❖ Implementation features
- ❖ Performance evaluation
- ❖ Pipeline results
- ❖ Insight and challenges
- ❖ Project repository

Quick Recap

Efficient simulation and graphical modeling of the spread of Covid-19 in a local community, using real Covid-19 incidents data and human interaction network data online.

We want to apply our simulation model to:

- evaluate the impact of preventative measures on public health outcomes;



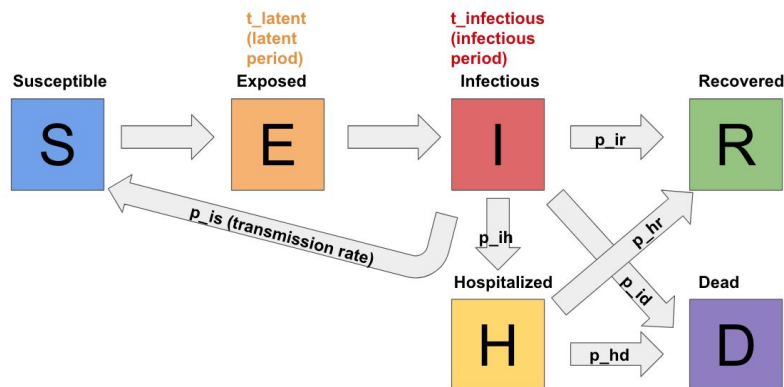
Coronavirus by state map. *“Live tracker: How many coronavirus cases have been reported in each U.S. state?” Politico. March, 16, 2020.*

Network dataset and the SEIRHD model

	ID1	ID2	TIETYPE	SEX1	SEX2	AGE1	AGE2	STUDYNUM
1:	1_1	106_1	sexual	female	female	27	37	1
2:	1_1	236_1	social	female	female	25	27	1
3:	1_1	266_1	social	female	female	26	28	1
4:	1_1	283_1	social	female	female	26	20	1
5:	1_1	337_1	social	female	female	25	29	1

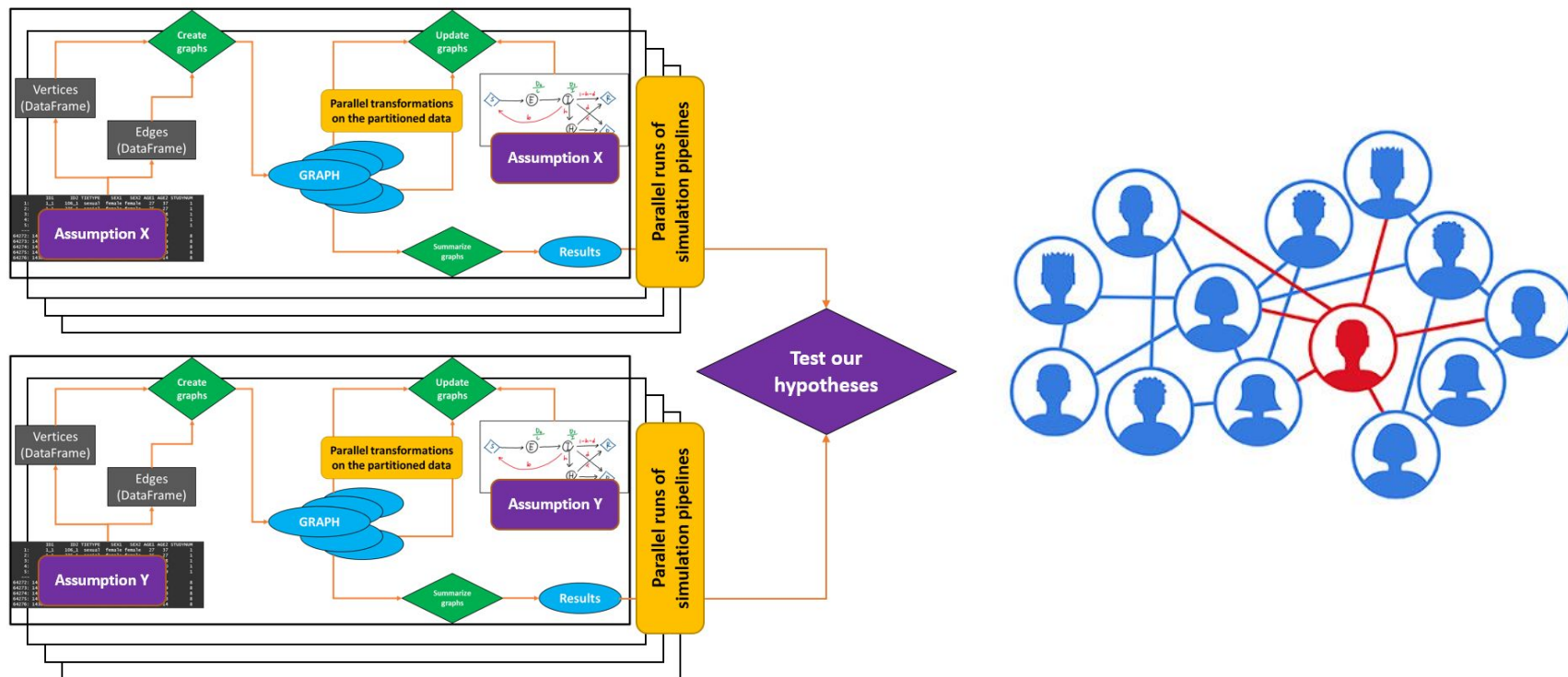
64272:	143798_8	36441_8	sexual	female	male	21	17	8
64273:	143798_8	36442_8	sexual	female	male	21	-9	8
64274:	143811_8	36429_8	sexual	unknown	male	98	23	8
64275:	143829_8	36447_8	sexual	male	female	21	13	8
64276:	143829_8	143774_8	sexual	male	female	21	14	8

*HIV Transmission Network Metastudy
Project: An Archive of Data From Eight
Network Studies, 1988--2001
(ICPSR 22140)*



	Estimate	Distribution	Estimation procedure
Transmission rate	1.596 (time-series data available)	Gamma	Used EpiEstim software, assuming a serial interval of 3.96 (4.75) from Du et al. 2020. U.S. national level data from Covid Tracking Project, dates ranging from 2/19 to 4/18.
Hospitalization rate	0.0678	Beta	Daily hospitalized increase / Daily case increase. U.S. national level data from Covid Tracking Project, averaged across available dates from 2/19 to 4/18.
Death rate	0.0419	Beta	Daily death increase / Daily case increase. U.S. national level data from Covid Tracking Project, averaged across available dates from 2/19 to 4/18.
Recovery rate	0.3945	Beta	Daily new recovery / Daily hospitalized increase. U.S. national level data from Covid Tracking Project, averaged across available dates from 2/19 to 4/18.
Latent period	5.2 days	Poisson	Taken from the literature (An et al. 2020)
Infectious period	2.3 days	Poisson	Taken from the literature (An et al. 2020)

Big Data Application with a GraphFrames solution



Implementation Features - Graphs

- Graph construction
- Use vertices attributes to keep track of state transition of individuals

```
def construct_graph(args):  
  
    # Load pre-processed datasets  
    v = pd.read_csv(args.v_input, index_col=False, delim_whitespace=True)  
    e = pd.read_csv(args.e_input, index_col=False, delim_whitespace=True)  
  
    logging.info("Setting up graph data with {} nodes, {} edges and {} clusters".format(v.  
shape[0], e.shape[0], len(v["cluster"].unique())))  
  
    # Coin dataframes into SQL for graphframes  
    v_schema = StructType([StructField("id", IntegerType(), True),  
                           StructField("cluster", IntegerType(), True)])  
    v = sql_context.createDataFrame(v, schema = v_schema).dropDuplicates(['id'])  
  
    e_schema = StructType([StructField("src", IntegerType(), True),  
                           StructField("dst", IntegerType(), True)])  
    e = sql_context.createDataFrame(e, schema = e_schema)  
  
    # Generate graph before simulation starts  
    g = GF.GraphFrame(v, e)  
  
    return g
```

id	cluster	state	e_days	i_days
0	0	S	0	0
1	7	H	0	0
2	2	S	0	0
3	7	S	0	0
4	7	H	0	0
5	6	S	0	0
6	3	I	0	0
7	5	S	0	0

Implementation Features - Network updates

- Update the graphical network at each time-step

```
for step in range(1, num_time_steps+1):  
    H_flow(h_nodes, r_nodes, d_nodes, p_hr, p_hd)  
    I_flow(i_nodes, r_nodes, h_nodes, d_nodes, p_id, p_ih, p_ir)  
    E_flow(e_nodes, i_nodes, t_latent)  
    S_flow(df_edges, s_nodes, e_nodes, i_nodes, r_nodes, h_nodes, d_nodes,  
           p_is, p_id, p_ih, p_ir, t_infectious)  
  
    duration += 1
```

- Use motif finding to locate neighbors

```
# ADD "neighbors" column: select neighbors of a node based on a graph (used in S_flow step)  
neighbor = g.find("(a)-[e]->(b)").drop("e").groupBy('a.id').agg(collect_list('b.id').alias('neighbors'))  
g_neighbor = neighbor.join(g.vertices, ['id'], "right_outer")  
g = GF.GraphFrame(g_neighbor, g.edges)
```

Implementation Features - Parallelization levels

- Task-level parallelization
 - SPMD
 - Distributed across multiple instances and threads in the cluster

```
#### =====  
####  MONTE CARLO SIMULATIONS  
#### =====  
  
# parse Monte Carlo input file  
sed '1d' "params_input_test.csv" > MC_param_input.csv  
  
# run Monte Carlo  
i=0  
while IFS= read -r line; do  
    params=$(printf "%s" "$line"|cut -d',' --output-delimiter=' ' -f1-)  
    i=$((i+1))  
    echo "Begin simulation: $i"  
    spark-submit --packages graphframes:graphframes:0.6.0-spark2.3-s_2.11 \  
        --num-executors 4 --executor-cores 2 \  
        network_update_GF_monte_carlo_cluster.py \  
        --v_input "v_cluster_4_low.txt" \  
        --e_input "e_cluster_4_low.txt" \  
        --p_is ${params[0]} \  
        --p_id ${params[1]} \  
        --p_ih ${params[2]} \  
        --p_ir ${params[3]} \  
        --p_hr ${params[4]} \  
        --p_hd ${params[5]} \  
        --t_latent ${params[6]} \  
        --t_infectious ${params[7]} \  
        --num_i_seeds ${params[8]} \  
        --num_time_steps ${params[9]} \  
        --out "sim_${i}"  
    echo "Finish simulation: $i"  
    sleep 3  
done < MC_param_input.csv
```


Implementation Features - Parallelization levels

➤ Task-level parallelization

- SPMD
- Distributed across multiple instances and threads in the cluster



➤ Monte-Carlo-level parallelization

- Independent runs
- Embarrassingly parallel

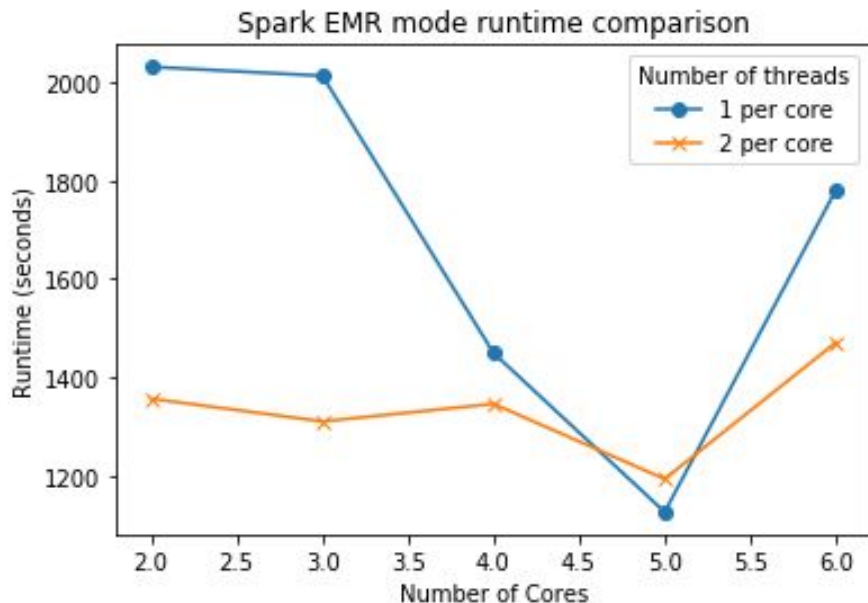


```
##### =====
#####  MONTE CARLO SIMULATIONS
##### =====

# parse Monte Carlo input file
sed '1d' "params_input_test.csv" > MC_param_input.csv

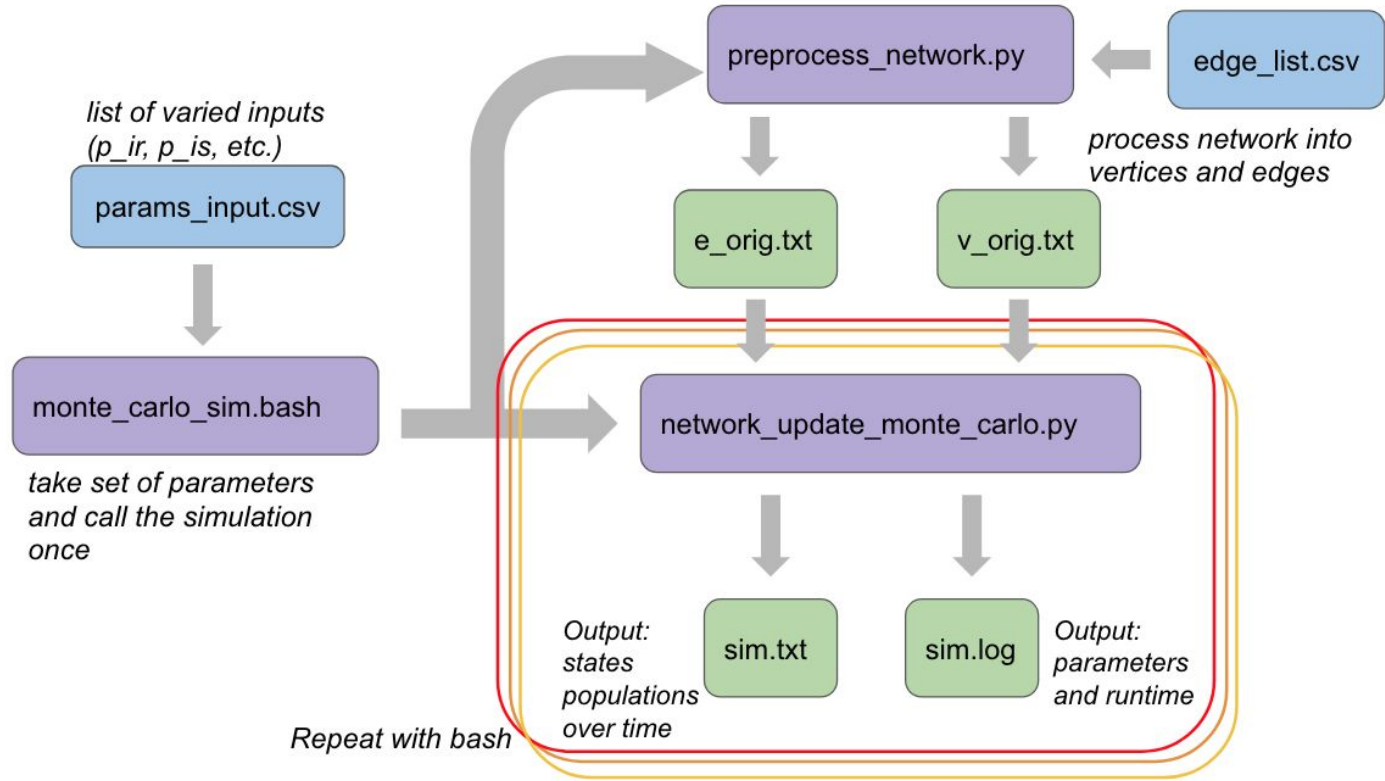
# run Monte Carlo
i=0
while IFS= read -r line; do
    params=( $(printf "%s\n" "$line" | cut -d',' --output-delimiter=' ' -f1-) )
    i=$((i+1))
    echo "Begin simulation: $i"
    spark-submit --packages graphframes:graphframes:0.6.0-spark2.3-s_2.11 \
        --num-executors 4 --executor-cores 2 \
        network_update_GF_monte_carlo_cluster.py \
        --v_input "v_cluster_4_low.txt" \
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        --p_is ${params[0]} \
        --p_id ${params[1]} \
        --p_ih ${params[2]} \
        --p_ir ${params[3]} \
        --p_hr ${params[4]} \
        --p_hd ${params[5]} \
        --t_latent ${params[6]} \
        --t_infectious ${params[7]} \
        --num_i_seeds ${params[8]} \
        --num_time_steps ${params[9]} \
        --out "sim_${i}"
    echo "Finish simulation: $i"
    sleep 3
done < MC_param_input.csv
```

Performance Evaluation

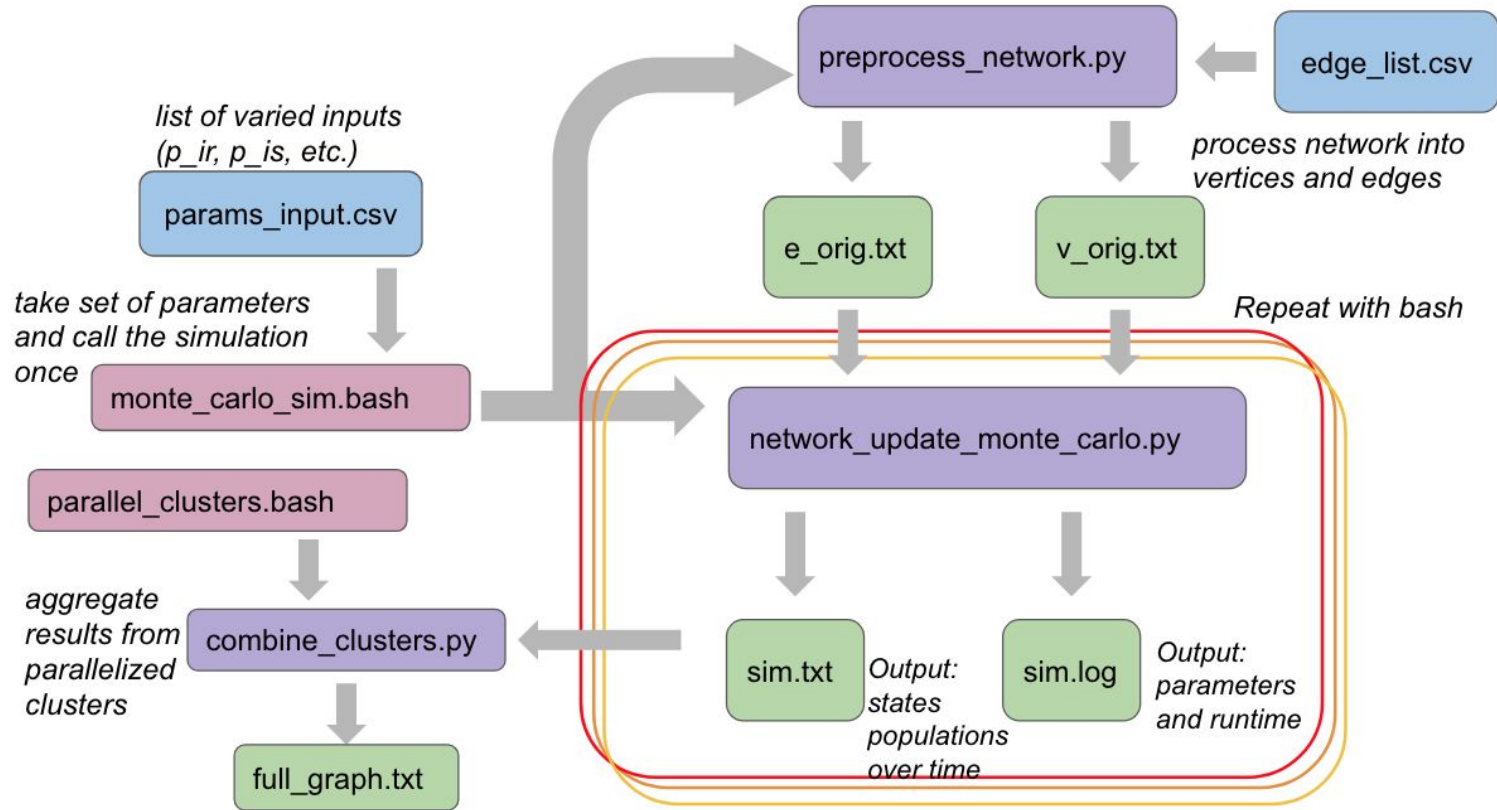


- When a limited number of cores are available, it is optimal to use a double-threaded approach.
- With 5 processors available, the single-threaded approach performs just as well, if not better, than the double-threaded approach.
- The inherent stochasticity built into the graph updating step may lead to different runtimes depending on the run, so these results may differ slightly if we were to repeat the experiment.
- **We ran all scaled-up tests on AWS EMR with 4 cores x 2 threads per core.**

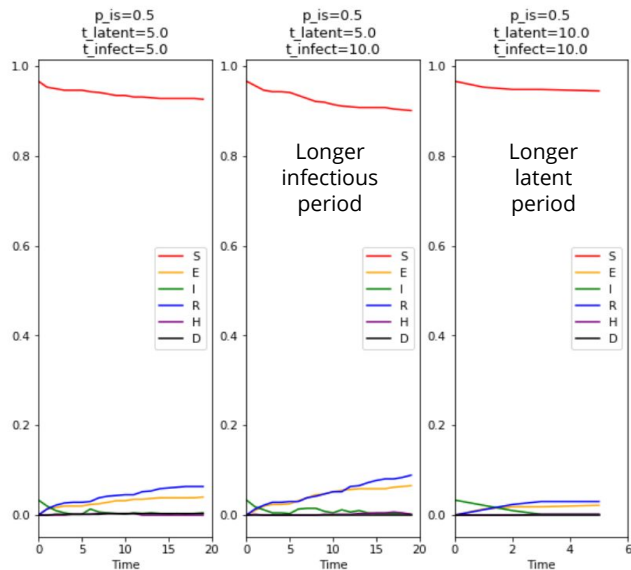
Code Structure - Monte Carlo



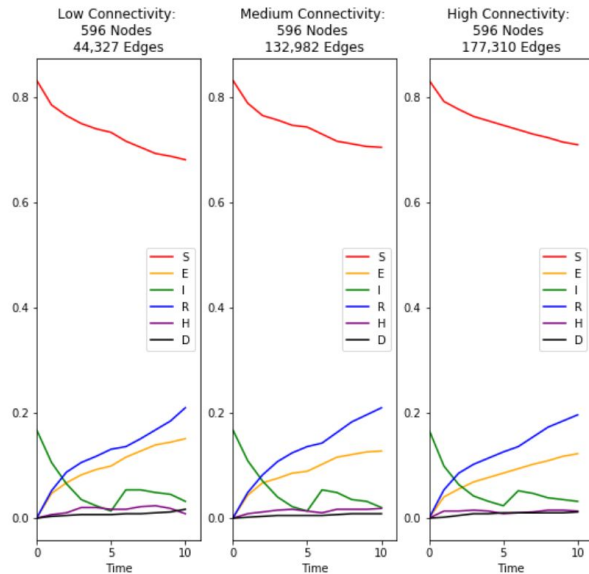
Code Structure - Monte Carlo with Study-Level Parallelization



Pipeline results



Monte Carlo simulations with different latent and infectious periods

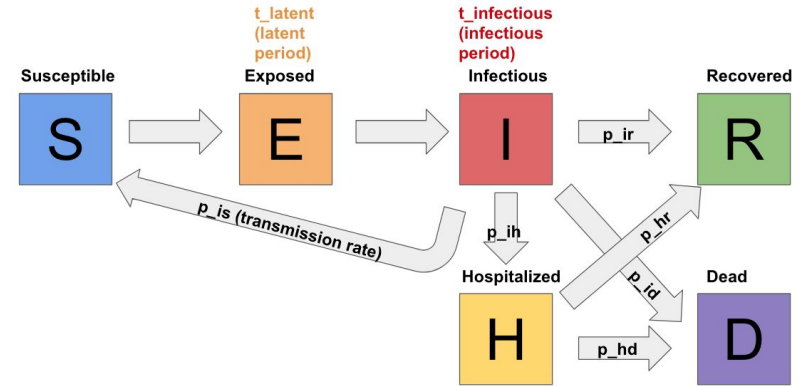


Varying connectivity levels to model airborne transmission and social distancing

- Longer infectious period increases epidemic
- Little effect of connectivity
- Epidemic dies out

Challenges and Improvements

- **SEIR model implementation in GraphFrames**
 - Incorporate latent and infectious periods
- **Incorporate entire underlying network**
- **Longer maximum duration for time**



Key Takeaways

Goals Achieved:

- Developed code serial and parallel and incorporated realistic network and parameters
- Speed-Up through Spark parallel-processing
- Varying connectivity, study-level parallelization code and bash pipeline established

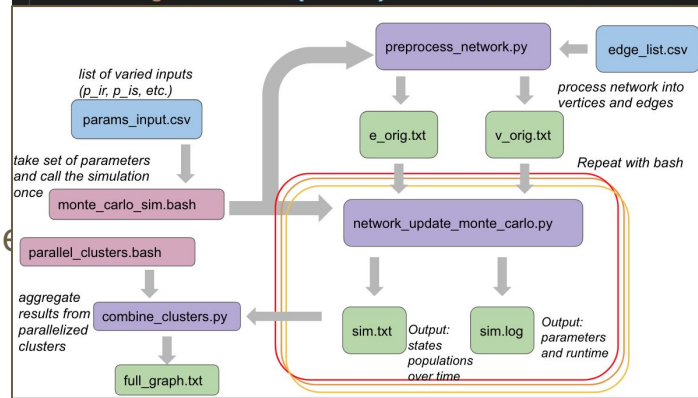
Future Work:

- Weighting edges by tie strength (e.g., sexual, social)
- Time-dependent transmission probabilities
- Transmission probabilities influenced by vertex attributes (e.g., age, gender)
- Study-level pipeline and MPI parallelization
- More extensive summary statistics

```
# Cluster-level parallelization
for cluster in 1..8; do

  # Define cluster vertex and edge input files
  v_input_name = "v_n1000_cluster_${cluster}.txt"
  e_input_name = "e_n1000_cluster_${cluster}.txt"

  echo "Begin cluster: ${cluster}"
```



TIETTYPE	SEX1	SEX2	AGE1	AGE2
sexual	female	female	27	37
social	female	female	25	27
social	female	female	26	28
social	female	female	26	20
social	female	female	25	29

Project Repository

huilisabrina / covid-19-simul Private

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Manage topics

41 commits 3 branches 0 packages 0 releases 3 contributors

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huilisabrina Update README.md	Latest commit 118a32c 2 hours ago
code	Update README.md 2 hours ago
data	Upload param_input.csv 20 hours ago
figures	Add files via upload 12 hours ago
presentation	Create README.md 17 days ago
README.md	Initial commit 17 days ago

README.md

covid-19-simul

GraphFrames: version 0.6.0

Spark: version 2.3-s 2.11

Python version: 2.7.17

AWS m4.xlarge instances

EMR mode: 1 master + 6 workers

<https://github.com/huilisabrina/covid-19-simul>