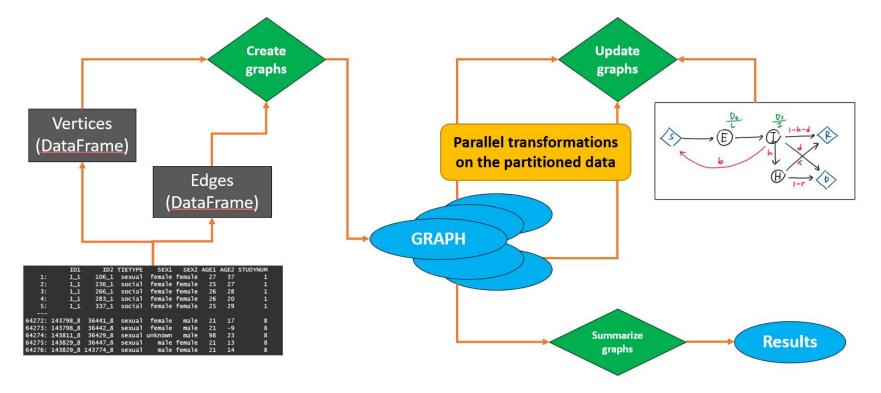
# Efficient simulation and graphical modeling of Covid-19 spread

**Group 13** 

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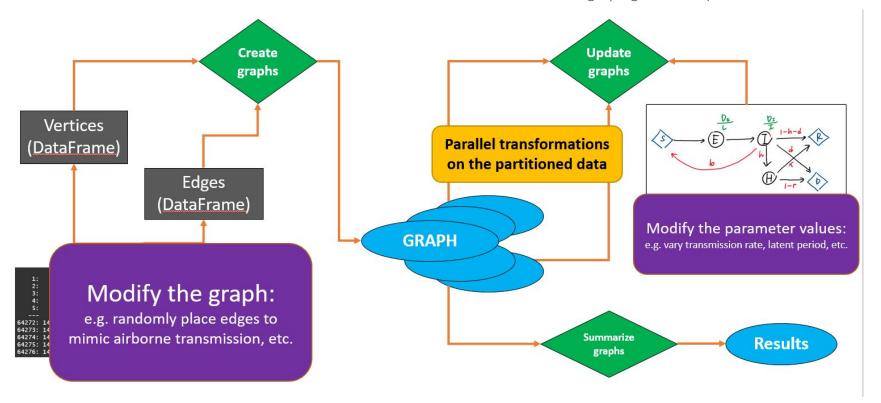
## Overall approach

- > **Type of application:** Data-intensive
- Programming model: Functional dataflow parallel processing (Spark)
- > Levels of parallelism: Coarse-grained transformations on partitioned data
- Parallel execution model: Single program multiple data

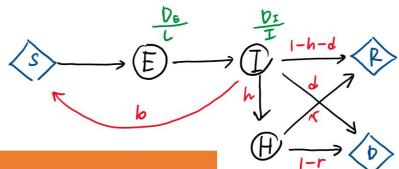


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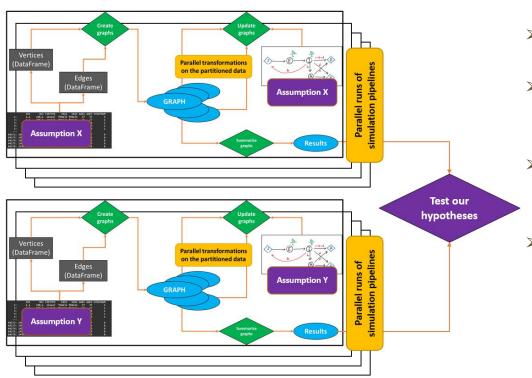


### **Extended SEIR model**



	Estimate	Distribution	Estimation procedure
Transmission rate	1.596 (time-series data available)	Gamma	Used <u>EpiEstim</u> software, assuming a serial interval of 3.96 (4.75) from Du et al. 2020. U.S. national level data from <u>Covid</u> 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 <u>Covid</u> 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 <u>Covid</u> 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 <u>Covid</u> 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)

#### **Parallel Execution Model**



- > Type of application:
  - Data-intensive
- Programming model:
  - MapReduce to process summary statistics
- Levels of parallelism:
  - Coarser-grained distributed data processing
- Deployment mode:
  - Local mode for prototyping
  - Cluster mode for scaled-up application

## **Programming Model and Infrastructure**

- Spark is used for big data processing within each graph
  - SEIR model implemented using 2 Spark dataframes, supported by GraphFrames.
  - Run using AWS EC2 instance, or AWS EMR Spark-configured cluster for multiple worker nodes.
  - Written in Python, pyspark used for Spark
- AWS instances modified for parallelization within graphs
  - MPI through mpi4py for parallel processing, while avoiding serial steps
- Parallelization across simulations carried out by EMR cluster



#### **Potential Bottlenecks**

- Algorithm is composed of three nested for loops:
  - Outermost: loops over each Monte Carlo simulation
  - Intermediate: loops over each time step
  - <u>Innermost</u>: loops over each nodes
- Outermost loop can be parallelized easily (independent iterations)
- Innermost loop can be broken-up to deal with each of the four states separately, and can be parallelized for within each state.
- Intermediate loop cannot be parallelized since the results of a given time-step will depend on the previous time-step (primary bottleneck).
- Other bottlenecks = communication, synchronization, balancing, b/w units

## **Complexity and Theoretical Speed-up**

Complexity: O(MTN), where

M = # Monte Carlo simulations

T = # of time steps

N = # of vertices in graph

```
Asymptotic S_T for large p \Rightarrow \frac{1}{1-c}
```

```
#serial runtime:
O(M*T*(S+E+I+H)) ~= O(M*T*N)

#parallel runtime:
O(M/M * T * (S/S + E/E + I/I + H/H)) = O(4T)

#max theoretical speedup:
O(MTN) / O(4T) = O(MN/4)

# Serial fraction, 1-c:
1-c = 1/max_speed_up = 4/O(MN)
```

Large number of vertices (N) and simulations (M) => serial fraction -> 0 => speed-up should be approximately linear