Destreza

Advanced Disease Simulation Platform

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Outline

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Disease Simulation

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Models and Libraries

- Languages: TypeScript & React (Next.js "use client")
- Visualization: D3.js (SVG) & HTML5 Canvas API
- Compute: Web Workers (force layout), GPU.js (optional kernel)
- ▶ **UI Components:** shadcn/ui, lucide-react, Tailwind CSS

Note:

Shifted to this stack instead of original proposal because:

- Web Workers offload compute; GPU.js scales to 1,000+ nodes via GPU acceleration.
- ▶ D3.js with SVG/Canvas outshines Plotly for large networks.
- Next.js enables cross-device use without installs.
- ► TypeScript optimized custom algorithms (e.g., Fenwick Tree).



SEIRD Model Overview

We simulate disease with five compartments:

- S (Susceptible) Uninfected individuals at risk.
- E (Exposed) Infected but *not yet* infectious (incubation).
- I (Infectious) Can transmit disease to neighbors.
- R (Recovered) No longer infectious, immune (temporary).
- D (Deceased) Removed by mortality.

Transitions per day:

$$S \xrightarrow{\beta} E$$
, $E \xrightarrow{\sigma = \frac{1}{\text{incubation}}} I$, $I \xrightarrow{\gamma} R$, $I \xrightarrow{\mu} D$, $R \xrightarrow{\rho = 0.01} S$



Key Parameters

- Population Size: total number of individuals in the simulated population (nodes 100–2500)
- ▶ **Initial Infected:** number of infected individuals at the start of the simulation (scaled with population)
- ▶ Basic Reproduction Number R₀: average number of secondary infections produced by a single infected individual in a completely susceptible population. Higher values indicate more contagious diseases (0.1–10)
- ▶ **Recovery Rate:** probability that an infected individual will recover during each time step. Higher values indicate faster recovery $P[I \rightarrow R]$ (0.01–0.5)
- ▶ Infectious Mortality Rate: base probability that an infectious individual will die from the disease. This is modified by other factors like vaccination rate and social distancing $P[I \rightarrow D]$ (0.001–0.1)

Advanced Parameters

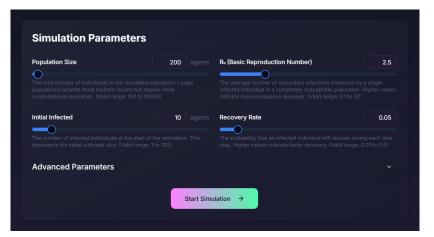
- ▶ **Incubation Period:** days before $E \rightarrow I$ (1–30)
- ▶ Infectious Period: duration during which an infected individual can transmit the disease to others. Longer periods increase the potential for spread (1–30)
- ▶ Vaccination Rate (ν): proportion of the population that is vaccinated against the disease. Higher vaccination rates provide greater herd immunity (0–1)
- ▶ **Social Distancing** (α): degree to which individuals reduce their social contacts. Higher values reduce disease transmission (0–1)

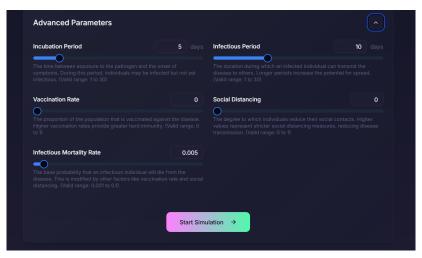
Population Mortality Rate

We compute a single "population mortality rate" (PMR) as:

$$\mathsf{PMR} = \underbrace{\left(1 - \frac{1}{R_0(1 - \alpha)}\right)}_{\mathsf{Attack} \ \mathsf{Rate}} \times \underbrace{\mathsf{IFR}\left(1 - \nu \, \epsilon\right)}_{\mathsf{Adjusted} \ \mathsf{Fatality}}$$

- R₀ Basic reproduction number
 - lpha Social distancing factor
- IFR Infection fatality rate (per-case mortality)
 - ν Vaccination rate
 - € Vaccine efficacy (we use 0.80)





Network Generation

- ► Custom Barabási–Albert (BA) implementation:
 - 1. Start with m_0 fully connected nodes.
 - 2. For each new node $i = m_0, \dots, N-1$:
 - compute total = fenw.query(N-1)
 - repeat *m* times:

 - $ightharpoonup t \leftarrow \texttt{fenw.sample}(r)$
 - ightharpoonup connect(i, t); fenw.update(i, 1); fenw.update(t, 1)
- ▶ Uses Fenwick tree sampling in $O(\log N)$ per edge $(O(N \log N)$ overall)

Network Generation: Pseudocode

Barabási-Albert with Fenwick Sampling

```
for i = m0 to N-1:
  total = fenw.query(N-1)
  for k = 1 to m:
    r = random() * total
    t = fenw.sample(r)
    connect(i, t)
    fenw.update(i, 1)
    fenw.update(t, 1)
  end for
end for
```

Fenwick Tree Optimization (Part 1)

- ▶ What is a Fenwick Tree? A data structure for efficient prefix sum queries and updates, both in $O(\log N)$ time.
- Usage in Network Generation:
 - Maintains cumulative sum of node degrees in an array f[1..N].
 - ▶ Enables sampling of nodes proportional to their degrees in $O(\log N)$ per operation.
 - Replaces O(N) linear sampling, reducing total complexity from $O(N^2)$ to $O(N \log N)$.

Fenwick Tree Optimization (Part 2)

- update(idx, delta): Adds delta to node idx's degree and updates the tree in O(log N).
- query(i): Computes sum of degrees up to index i in $O(\log N)$.
- ▶ sample(target): Finds node with cumulative degree sum ≥ target via binary search-like walk in O(log N).
- Ensures preferential attachment: nodes with higher degrees are more likely to gain edges.

Fenwick Tree Optimization

Pseudocode:

```
Initialize Fenwick tree fenw with size N
for i from 0 to m0-1:
    Add node i to network
    fenw.update(i, m0 - 1)
    for j from 0 to i-1:
        Add edge (i, j)
for i from mO to N-1:
    Add node i to network
    total = fenw.query(N-1)
    targets = empty set
    while |targets| < m:
        r = random() * total
        t = fenw.sample(r)
        if t != i and t not in targets:
            Add t to targets
    for t in targets:
        Add edge (i, t)
        fenw.update(i, 1)
        fenw.update(t, 1)
```

```
/** Fenwick (BIT) for weighted-degree sampling in O(log n) */
class Fenwick {
 private n: number
 private f: number[]
 constructor(n: number) {
    this.f = Array(n + 1).fill(0)
 update(i: number, delta: number) {
    for (let x = i + 1; x \le this.n; x += x & -x) {
     this.f[x] += delta
 query(i: number): number {
    let s = 0
    for (let x = i + 1; x > 0; x -= x \& -x) {
     s += this.f[x]
    return s
  sample(target: number): number {
    let idx = 0
    let bitMask = 1 << Math.floor(Math.log2(this.n))</pre>
    while (bitMask) {
     const t = idx + bitMask
     if (t <= this.n && this.f[t] <= target) {</pre>
       target -= this.f[t]
        idx = t
     bitMask >>= 1
    return idx
```

Force-Directed Layout

▶ D3.js forces (in Web Worker):

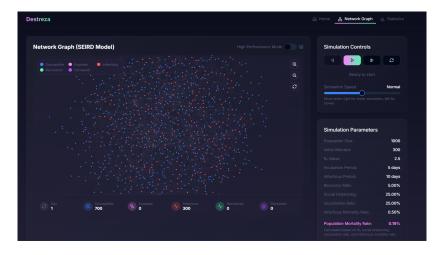
```
link spring to connect edges
charge repulsion between nodes
center attract to canvas center
collision prevent overlap
```

- Render via SVG or Canvas API (20 fps throttled)
- Optional GPU.js kernel for all-pairs repulsion

Force-Directed Graph: Pseudocode

Force Simulation Loop

```
function forceSimulation(nodes, links):
    Initialize simulation with forces:
        link = spring force on edges
        charge = repulsion between nodes
        center = attraction to canvas center
        collision = prevent node overlap
    alpha = 1 // Initial energy
    while alpha >= threshold:
        for each node:
            netForce = lF + chF + ceForce + colForce
        for each node:
            velocity += netForce * alpha
            position += velocity
            Apply constraints (e.g., collision boundaries)
        alpha *= (1 - alphaDecay) // Cool down simulation
    return final node positions
```



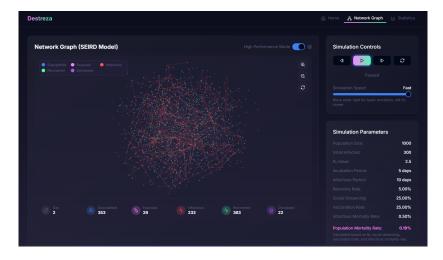
SEIRD Simulation Step

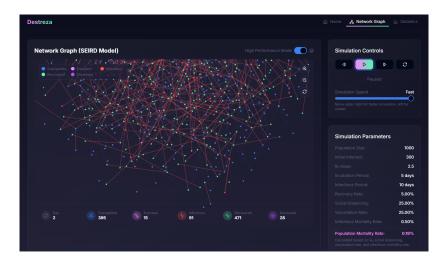
- 1. For each infectious node *i*:
 - For each neighbor *j* in adjacency list:
 - if j susceptible: infect w.p. p_{inf} (adjusted by vax/distancing)
 - ▶ $i \rightarrow D$ w.p. PMR or $i \rightarrow R$ w.p. recoveryRate
- 2. Exposed \rightarrow Infectious w.p. 1/incubation
- 3. Recovered \rightarrow Susceptible w.p. 0.01 (SIRS)
- 4. Update stats + history

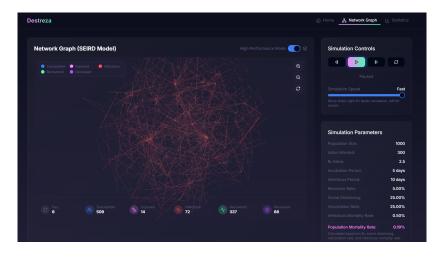
SEIRD Simulation Step

Pseudocode:

```
function simulationStep(nodes, links, params):
    newDay = currentDay + 1
    for each node i:
        if nodes[i].status == "infectious":
            for each neighbor j in adj[i]:
                if nodes[j].status == "susceptible":
                    p infect = params.infectionRate *
                              (1 - params.socialDistancing) *
                              (1 - params.vaccinationRate * 0.8)
                    if random() < p infect:
                        nodes[i].status = "exposed"
                        nodes[j].day = newDay
                        Add link (i, i) with day = newDay, active = true
            if random() < params.mortalityRate:
                nodes[i].status = "deceased"
                nodes[i].day = newDay
                Deactivate all links connected to i
            elif random() < params.recoveryRate:
                nodes[i].status = "recovered"
                nodes[i].dav = newDav
        elif nodes[i].status == "exposed":
            if random() < params.exposedRate:
                nodes[i].status = "infectious"
                nodes[i].day = newDay
        elif nodes[i].status == "recovered":
            if random() < 0.01: // STRS model
                nodes[i].status = "susceptible"
                nodes[i].day = newDay
    Update statistics (S, E, I, R, D counts)
    Save state to history
    return nodes, links
```







Observations

- Deceased nodes connections are disabled during simulation
- ▶ Low populations of 200 or less, with few infected individuals, result in a very short simulation with all nodes eventually healthy, even without any preventive measures like vaccinations or social distancing
- But for networks as large as 500 nodes, due to increased number of connections, disease spread is faster and number of infectious and deceased is noticeably higher
- ▶ PMR formula accurately predicts final death toll in benchmarks
- Colored transmission links reveal that infection spreads tend to have "epicenters" or "super-spreaders" and these tend to be near the center of the network
- Many other interesting observations result from manipulating different values of the parameters



Potential Improvements

Network Generation:

▶ Parallelize Barabási–Albert model using Web Workers or GPU.js to speed up generation for 100k+ nodes.

► Force-Directed Layout:

Could have Barnes-Hut approximation for repulsion forces, reducing complexity from $O(N^2)$ to $O(N \log N)$.

Rendering:

▶ Implement level-of-detail (LOD) rendering: render clusters as single points when zoomed out.

Data Structures:

Switch to sparse matrices or compressed sparse row (CSR) formats for adjacency data to save memory.



Thank You

Questions?