

Agent-based models

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Individualistic attributes

Using individualistic attributes to parameterize rates

My philosophy

All discrete models are agent-based models, even population-based models. Population-based compartmental models just assume that all the agents in the same state are homogeneous.

A lot of statistical models qualify as agent-based models since they incorporate individualistic covariates, and may represent interactions between individuals, or exhibit complex behavior.

Researchers often hope that ABMs will exhibit *emergent behavior*, or complex dynamics that result from the simulation, but are not explicitly represented in the model structure. However, mostly ABMs just do exactly what researchers parameterize them to do.

Example: a survival model

Let T_i be the survival (failure) time of subject i in a trial. We can parameterize the rate, or *hazard* of failure as

$$\lambda_i = \lambda(t) \exp(x_i' \beta)$$

where $\lambda(t)$ is a time-varying hazard common to all subjects, and $\exp(x_i' \beta)$ is the part that depends on subject i . This is called the *Cox Proportional Hazards Model*. This is an agent-based model because the outcomes are specific to each subject/agent.

Example: individualistic SIR epidemic model

For subject j , let $s_j(t)$ indicate susceptible, $i_j(t)$ indicate infective, and $r_j(t)$ recovered.

$$Z_j \sim N(\mu, \Sigma)$$

$$\beta_j(t) = e^{z_j' \theta_0} \left(\alpha + \sum_{k=1}^n y_k(t) e^{z_k' \theta_1} \right)$$

$$\gamma_j(t) = e^{z_j' \theta_3}$$

then the overall rate of transition $S \rightarrow I$ is

$$\sum_j \beta_j(t) (1 - y_j(t))$$

and the overall rate of transition from $I \rightarrow R$ is

$$\sum_j \gamma_j(t) y_j(t)$$

Complicated!

```
n = 100
z = rnorm(n)
theta0 = -0.3
theta1 = -0.1
theta2 = 0.2
tmax = 10

ezt0 = exp(z * theta0)
ezt1 = exp(z * theta1)
ezt2 = exp(z * theta2)

susceptible = 2:n
infected = c(1)
recovered = c()

t = 0

while(t < tmax) {

    haz_stoi = sum(ezt0[susceptible]) * sum(ezt1[infective])
```


More about ABMs

Pitfalls of ABMs

ABMs can be dangerous because they may seem complex, but are always constrained by their structure, parameterization, and calibration.

- ▶ When ABMs give dynamics similar to those observed in the real world, we don't always know whether they are capturing the mechanism correctly.
- ▶ When ABMs give dynamics starkly different from what we see in the real world, we do not always know why.

Researchers often use ABMs to predict the effect of hypothetical population-level policies before these policies are tested empirically. This can be dangerous, because assumptions about how agents behave in the absence of the intervention, and how the intervention affects their behavior, may lead researchers to draw erroneous conclusions about a situation that has never before occurred.

It is very easy to understate uncertainty in predictions/inferences from an ABM because ABMs may not capture all sources of stochasticity in the real world.

Example: What if everyone got PrEP?

Controversies

[\[Back: Stochastic Models\]](#) [\[Home\]](#) [\[Next: Network models\]](#)

References