CS-E5745
Mathematical Methods for Network Science

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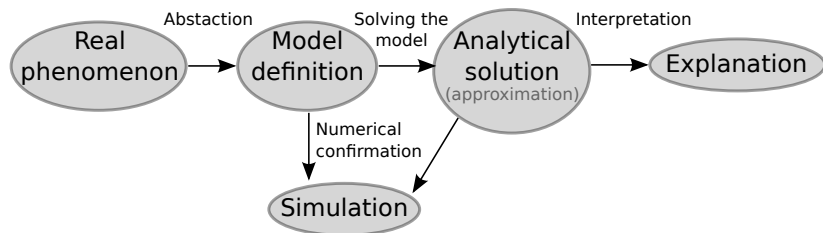
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Dynamical models of/on networks

- ▶ Learning goals this week:
    - ▶ Gain insights on the big picture on how to approach network dynamic problems analytically
    - ▶ Ability to recognize and formulate approximations for these problems
    - ▶ Ability to write down master/rate equations
- ▶ Newman: *Networks, An Introduction* - Sections 14 and 17

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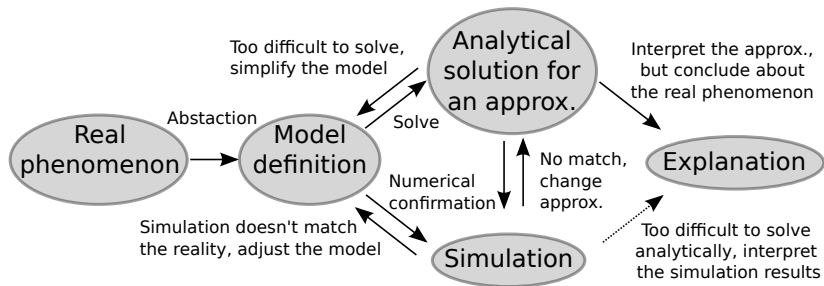January 5, 2021
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Dynamical models of/on networks

- ▶ Models of networks: Network evolves according to some rules
- ▶ Models on networks: States of nodes evolve according to some rules
- ▶ Co-evolution models: Both network and states of nodes evolve simultaneously
- ▶ Similar techniques can be used to solve all of these

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Pipeline, as presented in a publication

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Pipeline, a more realistic picture

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Example: Barabási-Albert model

- ▶ Phenomena: Networks are born via growth, new nodes are more likely to connect to already popular nodes
- ▶ Data: Probability of link creation can be measured as a function of degree, power-law degree distributions
- ▶ Model: A variation of preferential attachment models (e.g., Price model):
  - 0. Start with t_0 seed nodes with some connections, and set time to $t = t_0$
  - 1. Increase time $t = t + 1$, add node with index t
  - 2. Add m links from t to other nodes, each link to node i prob. $p_i = \frac{k_i}{\sum_j k_j}$
  - 3. GOTO 1.
- ▶ There could be multi-links (or the probabilities are different), but we ignore this

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Example: Barabási-Albert model

- ▶ We can solve the BA model *exactly* if we so wish
- ▶ Idea: Think about the BA model as a Markov chain where the state space is (a subset of) all graphs
  - ▶ Easy to write the transition probabilities between graphs
  - ▶ The result give us a probability distribution over all graphs for each time t
- ▶ Problem: the size of the state space explodes
  - ▶ $2^{T(T-1)/2}$ graphs with T nodes, but not all reachable
  - ▶ For every state at time t, there are $\binom{t}{m}$ possible transitions
  - ▶ Total number of states at time T is $N_T = \prod_{t=t_0}^{T} \binom{t}{m} \geq e^{mT}$ (for T large enough)
- ▶ This solution is not practical

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Approximate solutions

- ▶ Idea: Define a simple system that mimics the (expected) behavior of a complex system
- ▶ The state of the system at each time is reduced to a property or a vector of properties
  - ▶ The choise of properties is usually guided by the process
- ▶ The evolution rules are written in terms of average behavior (master/rate equation)
  - ▶ Either as difference or differential equation(s)
- ▶ Only mean behavior matters: statistical fluctuations are ignored
  - ▶ The properties are assumed to be independent
  - ▶ Dependencies can be added by including combinations of properties
- ▶ The resulting system is usually much easier to solve!

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Typical procedure in approximate solutions

- ▶ The "real" model for the system S is defined using stochatic rules F such that $S(t) = F(S(t - 1))$
- ▶ Calculate some properties X of the system $X(S) = \mathbf{X}$
  - ▶ The properties can be discrete in the system S but evolve to be continuous in $\mathbf{X}$: e.g., probability that an edge exists
- ▶ Define deterministic rules f for the evolution of the properties $\mathbf{X}(t) = f(\mathbf{X}(t - 1))$, s.t. $f(\mathbf{X}) \approx \langle F(S)|X(S) = \mathbf{X}\rangle$
  - ▶ Usually defined in elementwise way: $X_i(t) = f_i(\mathbf{X}(t - 1))$
- ▶ Set $X(S(t_0)) = \mathbf{X}(t_0)$ and solve $\mathbf{X}(t) = f(\mathbf{X}(t - 1))$ for any value of t or for $t \to \infty$
  - ▶ We now hope that $X(\langle F^t(S(t_0))\rangle) \approx f^t(\mathbf{X}(t_0))$
  - ▶ For continuous time one defines $\frac{d}{dt}\mathbf{X}(t) = f(\mathbf{X}(t))$

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Example: Barabási-Albert model

▶ Idea: map each graph to a vector where each element corresponds to an edge, s.t. $X_i = 1$ if edge exists, and 0 otherwise
   ▶ Expected value of binary variable is the probability of getting 1
   ▶ Notation: A_{ij} is the probability that link between i and j exists
   ▶ Set $m = 1$ for simplicity
▶ The update rule for $\mathbf{X}(t)$:
   ▶ Calculate expected degree for each node $\langle k_i \rangle = \sum_j A_{ij}$
   ▶ Set $A_{it} = \frac{\langle k_i \rangle}{\sum_j \langle k_j \rangle}$
▶ The final state $\mathbf{X}(T)$ gives the probability of each edge existing at time T

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Practical guidelines for selecting variables for approximations

- Anything that can be measured from the state of the system could be selected as a property we track
  - Some selections make it difficult to come up with the update function
  - The selecting variables appearing in the update rule is a good idea
- The above approximation discards dependencies between the variables, but one can define a combination variables that keep track of these
  - Example: Probability for each triangle to exists, instead of a probability each link to exists

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Example: Barabasi-Alberts model

- ▶ Idea 1: map each graph into a vector of degrees of nodes
  - ▶ The expected degree of each node is tracked
  - ▶ Note: expected degrees are continuous variables
- ▶ $X_i(t)$ is the expected degree of node i at time step t
- ▶ Now we should write the equations $X_i(t) = f_i(\mathbf{X}(t-1))$

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Example: Barabasi-Alberts model

- ▶ Idea 2: map each graph into a vector of counts of nodes of each degree (or a degree distribution)
    - ▶ The expected number of nodes of each degee is tracked
- ▶ $X_k(t)$ is the expected number of nodes of degree k at time step t
- ▶ Now we should write the equations $X_k(t) = f_k(\mathbf{X}(t-1))$

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Practical guidelines for writing master equations

▶ When the tracked variables are not binary variables, it might be more difficult to write the update equations

▶ Think about each element $X_i(t)$ separately, divide it to
  ▶ *growth* $X_i^+(t) = f_i^+(\mathbf{X}(t-1))$ term and
  ▶ *decline* $X_i^-(t) = f_i^-(\mathbf{X}(t-1))$ term

▶ The total is
$$X_i(t) - X_i(t-1) = X_i^+(t) - X_i^-(t) = f_i^+(\mathbf{X}(t-1)) + f_i^-(\mathbf{X}(t-1))$$

▶ Are there any conserved quantities? (If something grows, others decline)

▶ Same applies for rate equations

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Example: Barabasi-Alberts model

- $X_k(t)$ is the expected number of nodes of degree k at time step t
- Addition of nodes to degree categories:
  - $X_k^+(t) = m\frac{(k-1)}{\sum_k kX_k(t-1)}X_{k-1}(t-1)$, when $k > m$
  - $X_k^+(t) = 1$, when $k = m$
- Removal of nodes from degree categories:
  - $X_k^-(t) = m\frac{k}{\sum_k kX_k(t-1)}X_k(t-1)$
- Note that $\sum_k kX_k(t) = 2mN(t)$

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Example: Barabasi-Alberts model

- In total we have:
  - $X_k(t) = X_k(t-1) + \frac{(k-1)}{2N(t-1)} X_{k-1}(t-1) - \frac{k}{N(t-1)} X_k(t-1)$, when $k > m$
  - $X_m(t) = X_m(t-1) + 1 - \frac{m}{N(t-1)} X_m(t-1)$
- At the stationary state we should have:
  $x_k = X_k(t)/N(t) = X_k(t-1)/N(t-1)$:
  - $x_k = \frac{k-1}{k+2} x_{k-1}$, when $k > m$
  - $x_m = \frac{1}{1+m/2}$

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Models on networks

- Above approach can also be used to solve models *on* networks
- The state of the systems is not a graph, a vector of states for the nodes
- Examples:
    - Infection spreading: Nodes are either infected or not infected
    - Opinion formation: Each nodes state represent its opinion (discreet or continuous value)

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Spreading models on networks

▶ Network spreading models follow the classic literature on mathematical epidemiology

▶ Models are determined by the possible states and transition rates between them

▶ States:
  ▶ S: Susceptible
  ▶ E: Exposed
  ▶ I: Infected
  ▶ R: Recovered (or Removed)

▶ Naming convention: state changes from left to right

▶ Typical models include: SI, SIS, SIRS, SEIR

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Example: SIR on networks

- $S \xrightarrow{\beta} I \xrightarrow{\gamma} R$
- Classic result (no network): Epidemic if $R_0 = \frac{\beta}{\gamma} > 1$
    - i.e., when rate or infectino is larger than rate of recovery
- Degree-based approximation: Epidemic if $\frac{\beta}{\gamma} > \frac{1}{\langle q \rangle}$
    - where $\langle q \rangle$ is the expected excess degree
- Node-based approximation: Epidemic if $\frac{\beta}{\gamma} > \frac{1}{\lambda_1}$
    - where λ_1 is the largest eigenvalue of an adjacency matrix

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SIR can be mapped to percolation

▶ Modification: all individuals stay infected for time τ (instead of $I \xrightarrow{\gamma} R$)

▶ Infected node: probability that an *edge* leading out is activated during infection is $\Phi = 1 - e^{-\beta\tau}$

▶ Set edges occupied with probability $\Phi \rightarrow$ components give you the possible sizes of epidemics

    ▶ We can now calculate the statistics of epidemics using percolation theory on networks

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Binary state models on networks

- A general theory for approximating processes where each node can be in one of two states[1]
  - Examples: SI, SIS, voter model, ...
  - Assumption: network is produced by configuration model
- Probabilities that node of degree k is susceptible (infected) and has m infected neighbors: $s_{k,m}$ ($i_{k,m}$)
- Dynamics determine the rates $S \to I$: $F_{k,m}$ and $I \to S$: $R_{k,m}$
  - Example: in the SIS model $F_{k,m} = m\beta$ and $R_{k,m} = \gamma$

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[1] Phys. Rev. Lett. 107, 068701 (2011)

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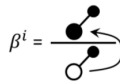
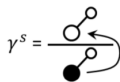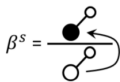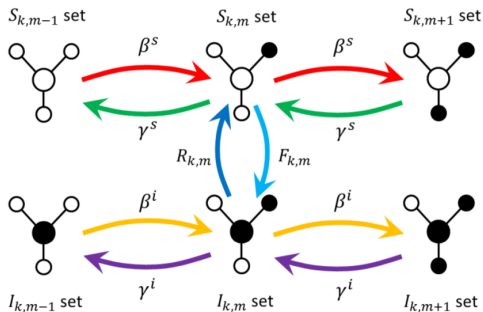**Mathematical Methods for Networks**
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Binary state models on networks

► The master equations become complicated:

$$
\begin{aligned}
\frac{ds_{k,m}}{dt} &= -F_{k,m}s_{k,m} + R_{k,m}i_{k,m} \\
&\quad -\beta^s(k-m)s_{k,m} + \beta^s(k-m+1)s_{k,m-1} \\
&\quad -\gamma^s m s_{k,m} + \gamma^s(m+1)s_{k,m+1}
\end{aligned}
$$

► Where $\beta^s = \frac{\langle \sum_{m=0}^{k}(k-m)F_{k,m}s_{k,m}\rangle}{\langle \sum_{m=0}^{k}(k-m)s_{k,m}\rangle}$, $\gamma^s = \frac{\langle \sum_{m=0}^{k}(k-m)R_{k,m}i_{k,m}\rangle}{\langle \sum_{m=0}^{k}(k-m)i_{k,m}\rangle}$

► Similar equation for $i_{k,m}$

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Binary state models on networks

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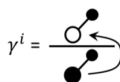
Binary state models on networks

- ▶ The $(k_{max} + 1)(k_{max} + 2)$ master equations can be solved numerically, or further approximations can be made
- ▶ Pair approximation (PA):
  - ▶ ρ_k: Probability that node of degree k is infected
  - ▶ p_k: Probability that neighbor of a node of degree k is infected
  - ▶ $s_{k,m} \approx (1 - \rho_k)B_{k,m}(p_k)$, where $B_{k,m}(p) = \binom{k}{m}p^m(1-p)^{k-m}$
- ▶ Mean-field approximation (MF):
  - ▶ ρ_k: Probability that node of degree k is infected
  - ▶ $s_{k,m} \approx (1 - \rho_k)B_{k,m}(\langle \frac{k}{z}\rho_k \rangle)$

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Binary state models on networks

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