

# Interdependent dynamics of awareness and epidemic spreading on multiplex networks

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## INTRODUCTION

- © Epidemic spreading models the processes of diffusion of diseases through a population.
- © When a disease breaks out, information about the presence of this illness (awareness) is generated and spread throughout the population.
- © These two processes may take place through different kind of interactions (in different networks)
  - E.g. awareness spreads through microblogs and the disease spreads through a network of physical contacts
- © People aware of a disease can take measures to reduce their susceptibility.
  - Vaccination, use of face masks, hand sanitizer...

The onset and the incidence of the epidemics is affected by the awareness

## UAU-SIS MODEL

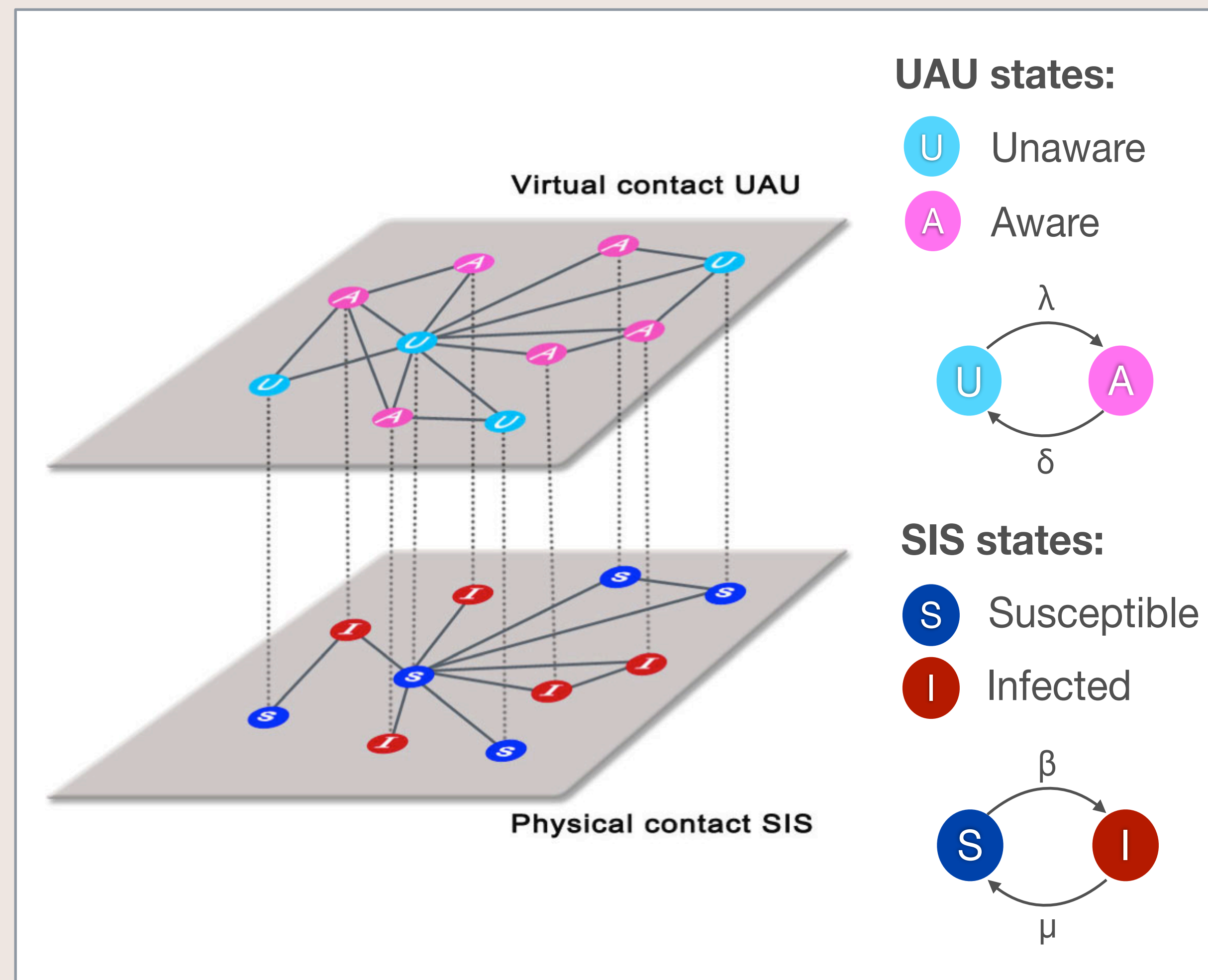


Fig.1. Sketch of the UAU-SIS model

- © The UAU-SIS model is an abstraction of the process of spreading of information *simultaneously* with spreading of epidemics, where:

- Each node has a state for each layer
- Four combinations: AS, AI, US, UI

- © UAU-SIS dynamical interaction:

- An infected individual in the SIS layer immediately becomes aware in the UAU layer
- A node which is aware in the UAU layer takes measures against the disease and has less chances to become infected.

General case:  $\beta^U = \beta$   
 $\beta^A = \gamma\beta, \quad 0 \leq \gamma \leq 1$

Simplest case:  $\gamma = 0$

## MICROSCOPIC MARKOV CHAIN APPROACH EQUATIONS

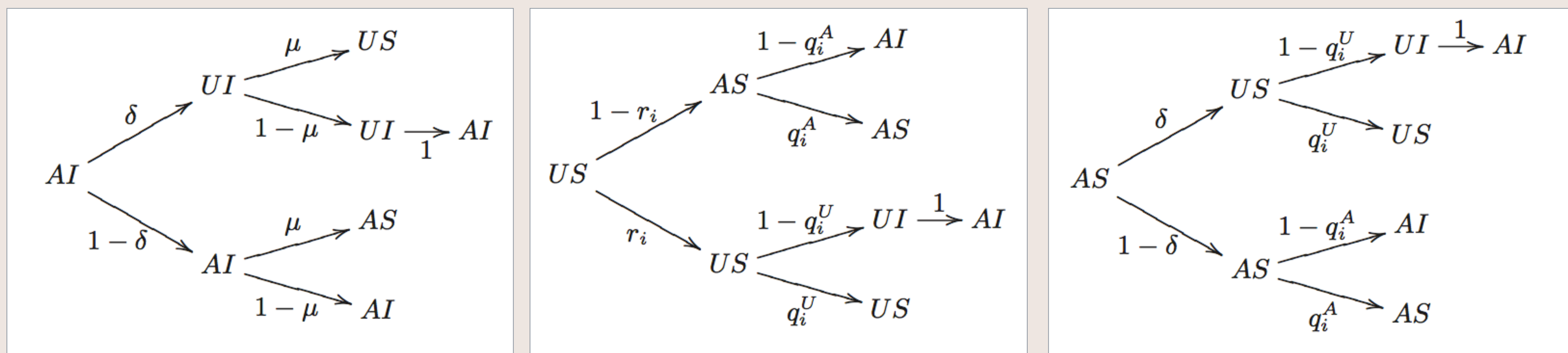


Fig. 2. Transition probability trees for the three states of the UAU-SIS dynamics at each time step

### MMCA Equations:

- They describe the probability for each node to be in each possible state at time t

$$p_i^{US}(t+1) = p_i^{AI}(t)\delta\mu + p_i^{US}(t)r_i(t)q_i^U(t) + p_i^{AS}\delta q_i^U(t)$$

$$p_i^{AS}(t+1) = p_i^{AI}(t)(1-\delta)\mu + p_i^{US}(1-r_i(t))q_i^A(t) + p_i^{AS}(t)(1-\delta)q_i^A(t)$$

$$p_i^{AI}(t+1) = p_i^{AI}(t)(1-\mu) + p_i^{US}[(1-r_i(t))(1-q_i^A(t)) + r_i(t)(1-q_i^U(t))] + p_i^{AS}(t)[\delta(1-q_i^U(t)) + (1-\delta)(1-q_i^A(t))]$$

- Prob. node i not being infected by any neighbor if he is unaware:

$$q_i^U(t) = \prod_j (1 - b_{ji}p_j^{AI}(t)\beta^U)$$

- Prob. node i not being infected by any neighbor if he is aware:

$$q_i^A(t) = \prod_j (1 - b_{ji}p_j^{AI}(t)\beta^A)$$

- Prob. node i not being informed by any neighbor:

$$r_i(t) = \prod_j (1 - a_{ji}p_j^A(t)\lambda)$$

## RESULTS

- SIS network: 1000 nodes power-law distributed with exponent 2.5
- UAU network: same network with 400 additional links
- We have performed extensive Monte Carlo simulations for fixed  $\delta$  and  $\mu$  for all values of  $\lambda$  and  $\beta$ .

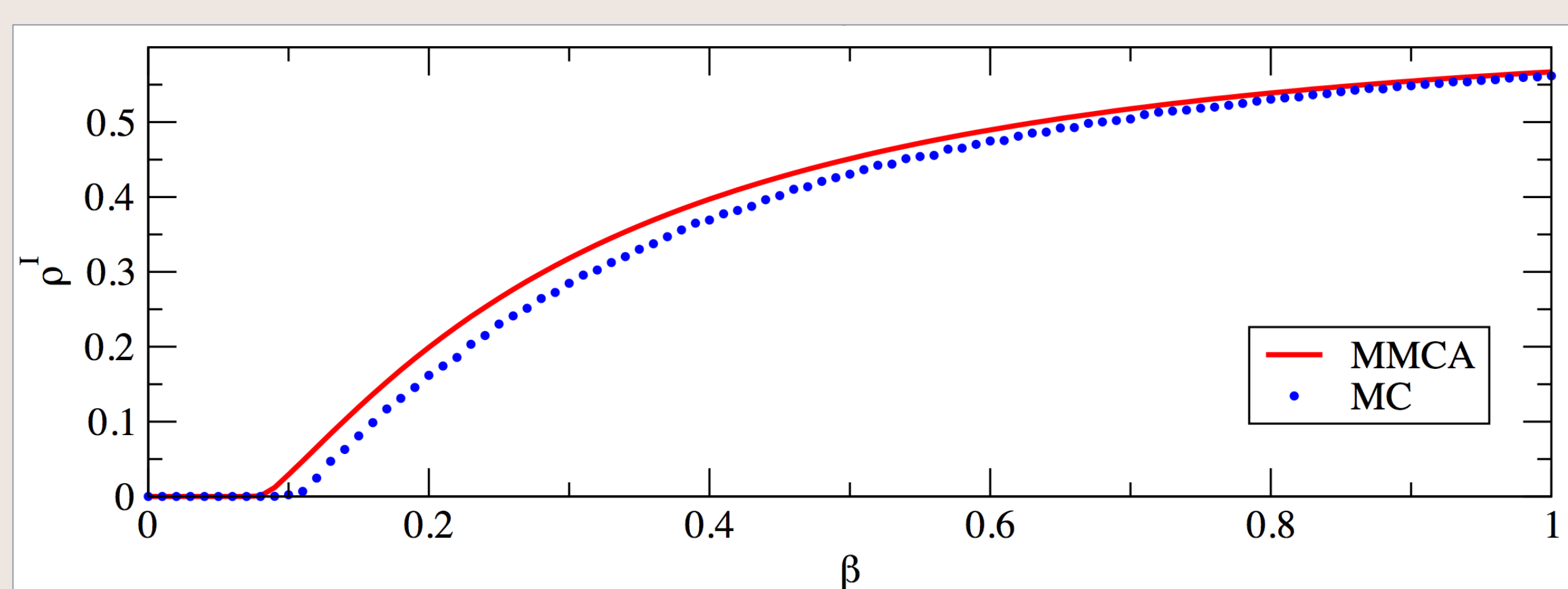


Fig. 3. Fraction of infected nodes in the steady state as a function of infectivity rate  $\beta$ . For the UAU: infectivity rate is  $\lambda=0.15$ , and recovery rate  $\delta=0.6$ . For the SIS: the recovery rate is  $\mu=0.4$  and the initial fraction of infected nodes is  $p(0)=0.2$ . The relative error between MC and MMCA is less than 2.5%

- From the MMCA equations we can calculate the dependence  $\beta_c(\lambda)$
- The line of critical points separates two phases
- There is a *metacritical* point that denotes the beginning of the dependence

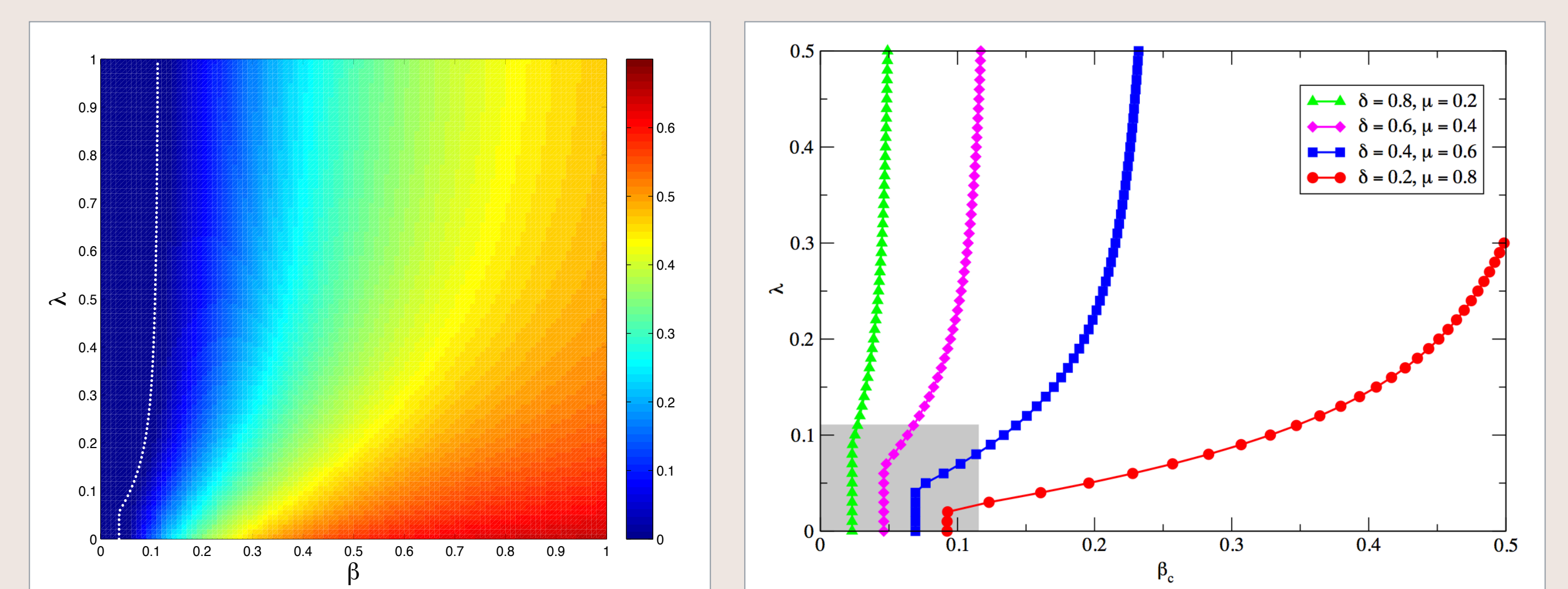


Fig. 4. Left: Final fraction of infected nodes as a function of  $\beta$  and  $\lambda$ . The dotted line contains all the critical points  $\beta_c$ . Right: Curves of critical points for different values of  $\delta$  and  $\mu$ . Both plots refer to the same networks as in Fig. 3.