### Computing the bias of mean field approximation

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joint work with Sebastian Allmeier (Inria) and Benny Van Houdt (Univ. Antwerp)

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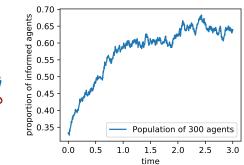
## Stochastic information models on 'dense' graphs



- Propagation of an information over time
- Steady-state properties (e.g. % of informed people)

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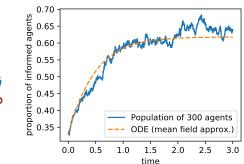




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- Steady-state properties (e.g. % of informed people)

# Objective of the talk (and outline)

- 1 What is mean field approximation?
- 2 How to characterize the bias of this approximation?
- 3 What about multiscale models?
- 4 Conclusion

#### Outline

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### Running example: Simple information propagation model.



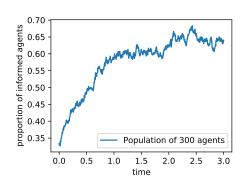
Population of n persons where each person can be "Informed" or "Outdated". x is the proportion of "informed" people.

- Informed persons loose information at rate 1.
- Outdated persons become informed at rate 1 + x

#### Stochastic model

If X is the proportion of "informed" people, then:

$$X \mapsto X - \frac{1}{n}$$
 at rate  $nX$   
 $X \mapsto X + \frac{1}{n}$  at rate  $n(1 - X^2) = n(1 - X)(1 + X)$ 

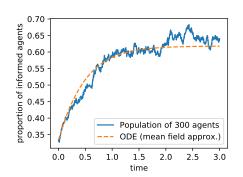


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 at rate  $nX$  average change:  $-X$ 
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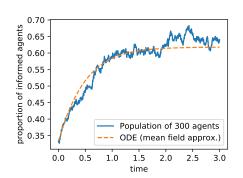
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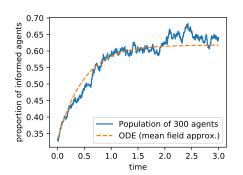
With this approximation, we study:

- The transient regime.
- The fixed point:  $x(\infty) = (\sqrt{5} 1)/2$ .

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How accurate is this approximation?

### Accuracy of the mean field approximation

n	5	10	100	$\infty$
$\mathbb{P}(someone\;informed)$	0.593	0.601	0.61679642	$(\sqrt{5}-1)/2\approx 0.618.$
Error	0.025	0.125	0.0012	0

Table: Steady-state values

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Theorem: (G. Bortolussi, Tribastone) For this model, if  $\mathbb{E}\left[X^{(n)}\right]$  is the probability that someone is "informed" and if the  $x(\infty)=(\sqrt{5}-1)/2$  is the mean field approximation, then:

$$\mathbb{E}\left[X^{(n)}\right] = x(\infty) + \frac{1}{20n}(\sqrt{5} - 1) + \frac{1}{50n^2}(\sqrt{5} - 3) + O(1/n^3).$$

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#### We study a generic interaction model

We consider a population of n objects with two types of interactions:

Unilateral transitions:

Object 
$$k$$
 jumps from state  $i$  to  $j$  at rate  $r_{ij}^{(k)}$ 

Pairwise interactions:

```
Object k, k' simultaneously jump from states (i, i') to (j, j') at rate r_{ij,i'j'}^{(k,k')}/n
```

If the rates do not depend on k, we call the model homogeneous.

## Mean field approximation for homogeneous models

$$X_s^{(n)}(t) = \frac{1}{n} \{ \text{\# objects in state } s \text{ at } t \}$$

The transitions are:

$$\mathbf{X}^{(n)} o \mathbf{X}^{(n)} + rac{1}{n}(e_j - e_i)$$
 at rate  $nr_{ij}X_i$ .  $\mathbf{X}^{(n)} o \mathbf{X}^{(n)} + rac{1}{n}(e_j - e_i + e_{j'} - e_{i'})$  at rate  $nr_{ij,i'j'}X_iX_{i'}$ .

This is a density dependent population process (Kurtz 70s).

(one example is our information propagation model)

## Mean field method for non-homogeneous models

$$X_s^{(n)}(t) = \frac{1}{n} \{ \# \text{ objects in state } s \text{ at } t \}$$
  $\Rightarrow X^{(n)} \text{ is not Markovian.}$ 

## Mean field method for non-homogeneous models

$$X_s^{(n)}(t) = \frac{1}{n} \{ \# \text{ objects in state } s \text{ at } t \} \implies X^{(n)} \text{ is not Markovian.}$$

Solution: represent model using indicators:

$$Y_{(k,s)}^{(n)}(t) = \begin{cases} 1 & \text{if object } k \text{ is in state } s \text{ at time } t \\ 0 & \text{otherwise} \end{cases}$$

 $\mathbf{Y}^{(n)}$  is Markovian.

$$\begin{split} \mathbf{Y}^{(n)} &\rightarrow \mathbf{Y}^{(n)} + e_{k,j} - e_{k,i} & \text{at rate } r_{ij}^{(k)} Y_{k,i}. \\ \mathbf{Y}^{(n)} &\rightarrow \mathbf{Y}^{(n)} + e_{k,j} - e_{k,i} + e_{k',j'} - e_{k',i'} & \text{at rate } r_{ij,i'j'}^{(k,k')} Y_{k,i} Y_{k',i'}. \end{split}$$

## Mean field approximation and result

The drift is:

$$f(\mathbf{y}) = \sum_{\text{all transitions}} \text{Transition change for } \mathbf{y} \times \text{Rate of transition at } \mathbf{y}.$$

The mean field approximation is the solution of the ODE  $\dot{y} = f(y)$ .

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Theorem (Allmeier, G. 2022) There exists an (easily computable) vector V(t) such that for any finite time:

**P**[Object k is in state s at t] = 
$$y_{k,s}(t) + \frac{1}{N}V_{k,s}(t) + O(\frac{1}{N^2})$$
.

 $V_{k,s}(t)$  is the bias of the mean field approximation.

### Idea of proof

• We can show that  $cov(Y_{k,s}Y_{k',s'})(t) = \frac{1}{N}W(t) + O(1/N^2)$ , where W(t) satisfies a (time inhomogeneous) linear ODE:

$$\dot{W} = A(y(t))W + WA^{T}(y(t)) + Q(x(t)).$$

② We then have  $\mathbb{E}[Y_{k,s}(t)] = y(t) + V(t)$ , where V(t) satisfies a (time inhomogeneous) linear ODE:

$$\dot{V} = A(y(t))V + B(x(t)) \cdot W(t).$$

The moment closure approach

Consider a system for which X becomes X + 1/n at rate  $nX^2$ . We have:

$$\frac{d}{dt}\mathbb{E}\left[X\right] = \mathbb{E}\left[X^2\right]$$

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$$\frac{d}{dt}\mathbb{E}\left[X^2\right] = 2\mathbb{E}\left[X^3\right] + \frac{1}{n}\mathbb{E}\left[X^2\right]$$

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$$\frac{d}{dt}\mathbb{E}\left[X^{2}\right] = 2\mathbb{E}\left[X^{3}\right] + \frac{1}{n}\mathbb{E}\left[X^{2}\right] \qquad \approx 2(3\mathbb{E}\left[X^{2}\right]\mathbb{E}\left[X\right] - 2\mathbb{E}\left[X\right]^{2}) + \frac{1}{n}\mathbb{E}\left[X^{2}\right]$$

(refined approximation)

The moment closure approach

Consider a system for which X becomes X + 1/n at rate  $nX^2$ . We have:

$$\begin{split} \frac{d}{dt}\mathbb{E}\left[X\right] &= \mathbb{E}\left[X^2\right] &\approx \mathbb{E}\left[X\right]^2 \text{ (mean field approx.)} \\ \frac{d}{dt}\mathbb{E}\left[X^2\right] &= 2\mathbb{E}\left[X^3\right] + \frac{1}{n}\mathbb{E}\left[X^2\right] &\approx 2(3\mathbb{E}\left[X^2\right]\mathbb{E}\left[X\right] - 2\mathbb{E}\left[X\right]^2) + \frac{1}{n}\mathbb{E}\left[X^2\right] \\ \frac{d}{dt}\mathbb{E}\left[X^3\right] &= \mathbb{E}\left[\frac{3X^4}{n} + \frac{4X^3}{n^2} + \frac{X^2}{n^3}\right] \end{split}$$

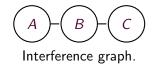
The moment equations are never closed.

- ullet They can be closed by assuming  $\mathbb{E}\left[\left(X-\mathbb{E}\left[X
  ight]\right)^d\right]pprox 0$
- This gives a  $O(1/n^{\lfloor (d+1)/2 \rfloor})$ -accurate approximation.

#### Outline

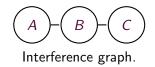
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#### Communication with interference



n nodes per class A, B or C

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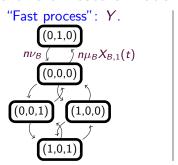


n nodes per class A, B or C

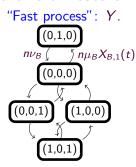
State is X, Y

- $X_{i,s}$  = proportion of nodes of class i with  $\geq S$  messages.
- $Y_i = 1$  if class i talks.

#### This is a two timescale model



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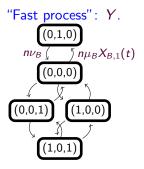
"Slow process": X.

Arrival/departure:

$$X_{i,s}\mapsto X_{i,s}\pm \frac{1}{N}$$

Rate depends on y.

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Two approximations:

$$P[Y(t) = y] \approx \pi_y(X(t))$$
 Drift  $f(X, Y)$ 

$$\dot{x} = \sum_{y} \pi_{y}(x) f(x, y)$$

(Averaging technique):

## Accuracy results (Allmeier, G. 2022)

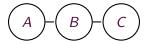
Theorem. If X(t) is the two timescale process, if the rates are twice differentiable and the evolution the the fast process is "unichain", then:

$$\mathbb{E}[X(t)] = x(t) + \frac{1}{N}C(t) + O(1/N^2).$$

Holds uniformly in time if the ODE has an exponentially stable attractor.

#### Numerical example

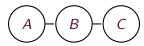
With n = 1 node per class!



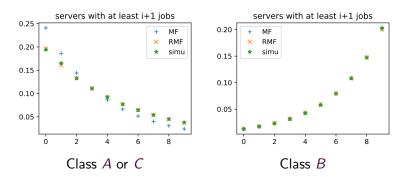
Jobs arrive at rate 1, activation rate = 3. Job duration is 1/3.

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- To do so, we take correlations into account.
- Numerical library: https://pypi.org/project/rmftool/

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Mean field approximation is a widely used heuristic.

• It consists in assuming independence.

We question its validity / accuracy.

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- To do so, we take correlations into account.
- Numerical library: https://pypi.org/project/rmftool/

Many open questions: (sparse) geometric models, non-Markovian, controlled systems

More slides and references: http://polaris.imag.fr/nicolas.gast

#### References

#### Results on which this talk is based:

- Mean Field and Refined Mean Field Approximations for Heterogeneous Systems: It Works! by Allmeier and Gast. SIGMETRICS 2022.
- A Refined Mean Field Approximation by Gast and Van Houdt. SIGMETRICS 2018 (best paper award)
- Size Expansions of Mean Field Approximation: Transient and Steady-State Analysis Gast, Bortolussi, Tribastone. Performance 2018.
- Two-scale: Bias and Refinement of Multiscale Mean Field Models. Allmeier, Gast, 2022 (available soon).
  - CSMA model from CSMA networks in a many-sources regime: A mean-field approach. Cecchi, Borst, van Leeuwaarden, Whiting. Infocom 2016.

#### Paper cited as open problems:

- Pair-approximation: The Power of Two Choices on Graphs: the Pair-Approximation is Accurate by Gast. Mama 2015.
- Non-Markovian: Randomized Load Balancing with General Service Time
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   Method for the Analysis of Randomized Load Balancing Networks by Aghajani, Li,
   Ramanan.SIGMETRICS 2018