Inverse Problems for Philosophers

Bridging the gap between agent-based models and behavioral data

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Summary

1. Inverse problems for philosophers and agent-based modelers

2. A case-study of conventions: the metric signature in particle physics
   - How do physicists choose which convention to use in their own papers?
   - How do scientists resolve conflicting preferences in collaborations?
   - How do physicists' preferences get formed?

Why should philosophers care about data?

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- **Practical**: normative insights from models without connection to data may not be translatable into interventions/policies (abstract parameters in a computational model do not immediately connect to actionable parameters!)

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  3. **Computational problems**: solving inverse problems often involves intractable computations and requires approximation schemes.

Bayesian inference for inverse problems

- Both forward models and inverse problems have a stochastic/probabilistic component (random initialization, partially random decisions; uncertainty quantification...)
- We appeal to **probabilities** and **Bayesian inference**.

$$
\begin{array}{ccc}
\begin{array}{c}\text{Rules governing}\\ \text{agents' behavior}\\ \textbf{Model } \boldsymbol{M}\end{array}
&
\begin{array}{c}\text{“Forward problem”}\\ \text{Estimate } \boldsymbol{P(O|M)}\\ \xrightarrow{\hspace{6em}}\\ \xleftarrow{\hspace{6em}}\\ \text{“Inverse problem”}\\ \text{Estimate } \boldsymbol{P(M|O)}\end{array}
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P(M|O) = \frac{P(O|M)\,\overbrace{P(M)}^{\text{Prior}}}{P(O)} \tag{1}
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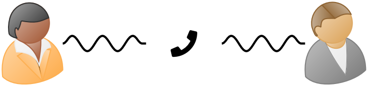

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  - Example: left-hand or right-hand traffic.
  - Language! “The syllable ‘big’ could have meant ‘small’ for all we care, and the red light could have meant ‘go”’ (Quine, foreword to Lewis 1969)

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  Most often: idealized formal models or controlled experiments. Few studies in naturalistic settings!

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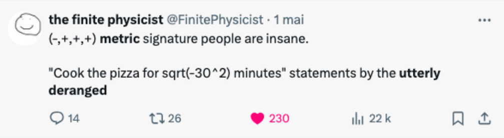
- Both choices are legitimate, as long as one remains consistent.

A heated debate



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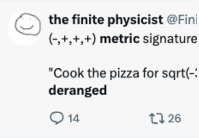

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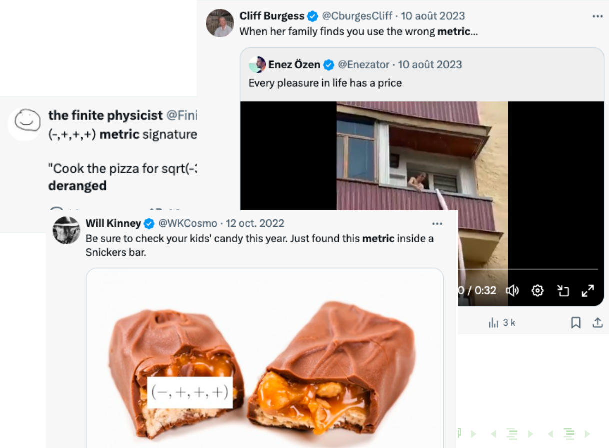

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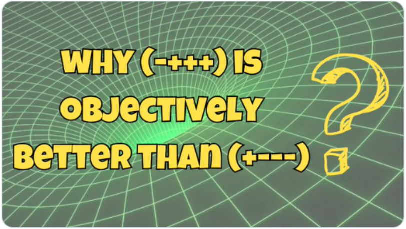
Superconformal Hassaan
@Hassaan_PHY

This is a small post to argue that (-+++) metric is objectively better than the (+– – -) metric. Before starting, let me mention that I studied QFT in the (+– – -) metric (from Peskin and Schroeder).
1/17
#Physics #scicomm
Traduire le post



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Greg Trayling @GregTrayling ·
Metric convention reveal parti
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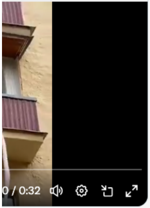

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  1. How do scientists decide which convention to use in a paper?
  2. How do they resolve conflicting preferences in collaborations?
  3. What factors shape scientists' preferences?

Data

- Data collected from **Inspire HEP** (authorship/citation metadata) and **arXiv** (LaTeX source)
- Categories: hep-th (high-energy physics theory), hep-ph (phenomenology), gr-qc (gravitation and cosmology), astro-ph (astrophysics)
- 22 500 papers classified according to their metric signature (mostly plus or mostly minus) using regular expressions.

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Individuals' attitude towards a convention may be shaped by:

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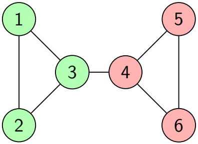

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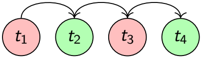

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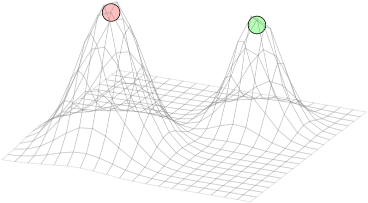

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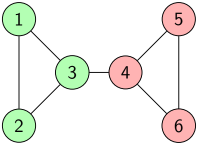

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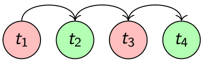

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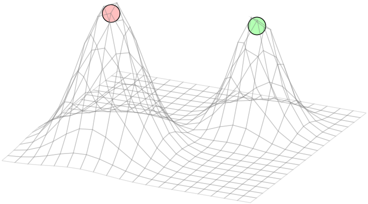
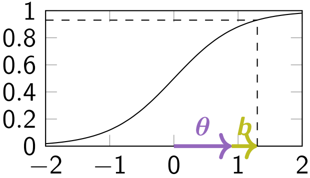


$\Rightarrow$ Are these involved in the context of the metric signature?

Individual and contextual consistency

- publishes d in category $c_d \in \{$phenomenology, theory, ...$\}$. What determines which convention she uses? Our assumption:

$$P(\sigma_d = +1 | \theta(\;), b(c_d)) = f(\underbrace{\theta(\;)}_{\text{Author's preference}} + \underbrace{b(c_d)}_{\text{Effect of research area}})$$



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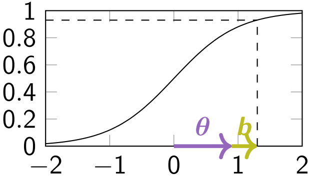

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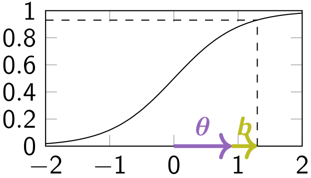

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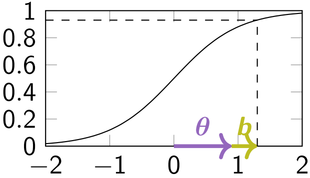

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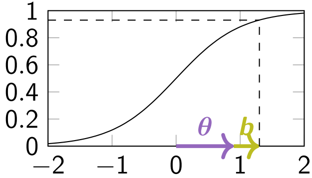

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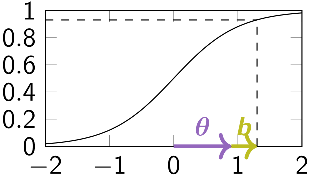

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- **Given physicists' choices in their solo-authored papers, we can infer back θ and b using Bayesian inference.**

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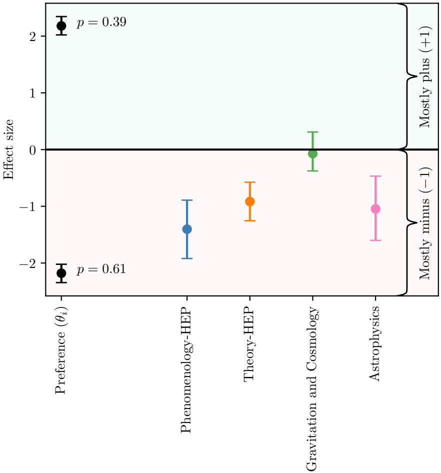

Figure: Individual consistency (preferences) matter the most, but adaptation to the context also occurs.

Individual and contextual consistency

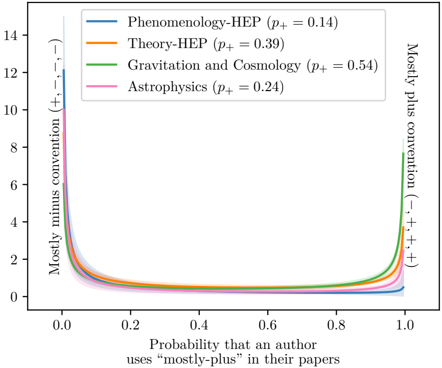

Figure: Physicists tend to always be using the same convention

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  - Majoritarian strategy (the majority preference prevails)
  - Conventional strategy (the signature most common in the target research area prevails)

Inferring preference-aggregation mechanisms in conflicts

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- Focusing on co-authored papers for which:
  (i) The metric signature $S_d \in \{-1, +1\}$ of the paper is observed
  (ii) The preference of each author $(\sigma_1, \ldots, \sigma_n) \in \{\pm 1\}^n$ is known independently from at least one solo-authored publication
- We can assume different preference aggregation strategies (A_k):
  - Dictatorial strategies (the first author, the last author, or another author decides)
  - Majoritarian strategy (the majority preference prevails)
  - Conventional strategy (the signature most common in the target research area prevails)
  - Random/coin-flip (both individual preferences and context are ignored)

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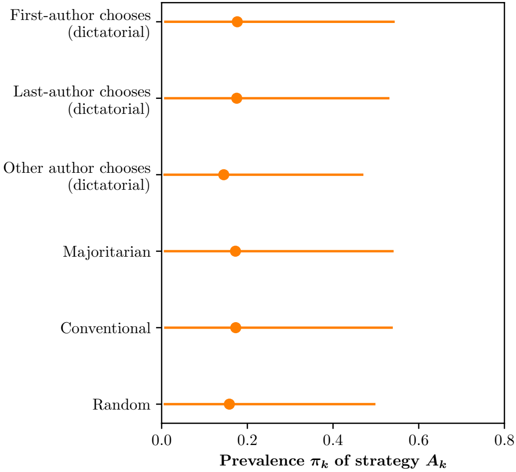
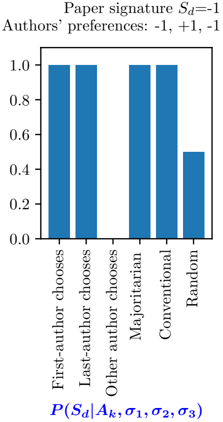
- We can estimate the prevalence of each strategy (π_k) given that they predict different outcomes (different probabilities $P(S_d | \sigma_1, \ldots, \sigma_n, A_k)$)

Inferring preference-aggregation mechanisms

Each paper brings a bit more information about π_k, the prevalence of an aggregation strategy A_k.





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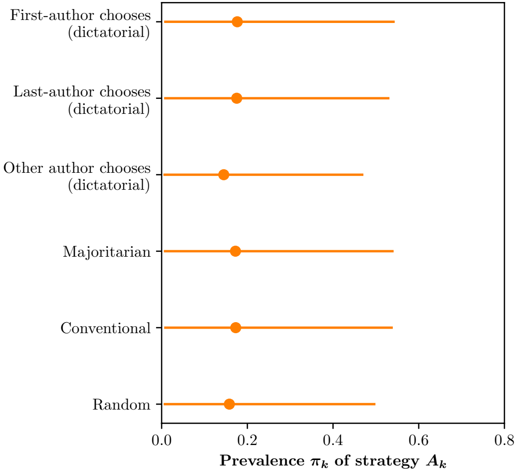

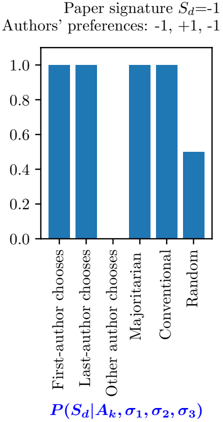

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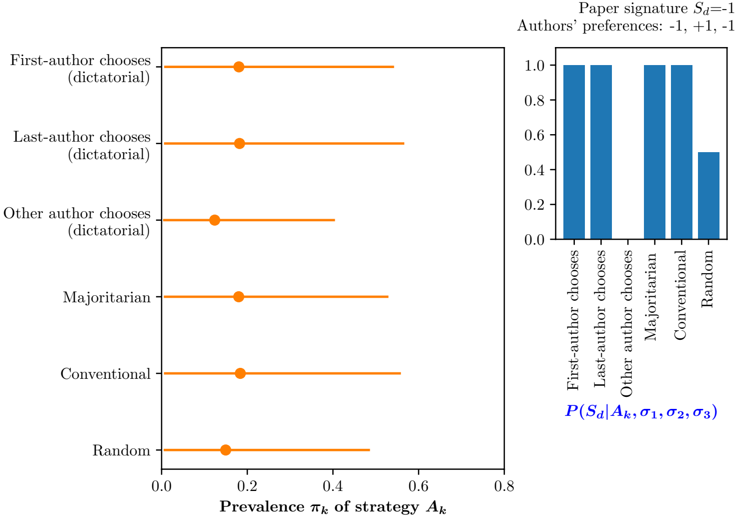

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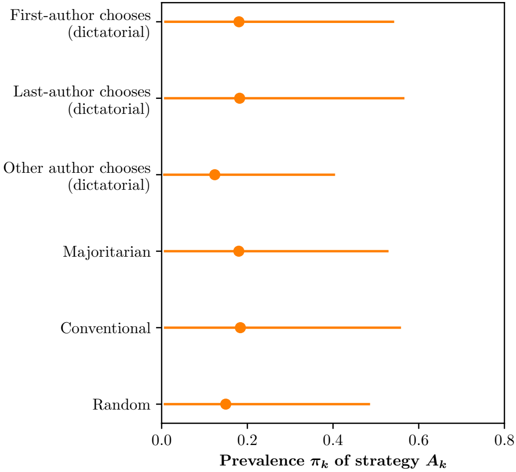

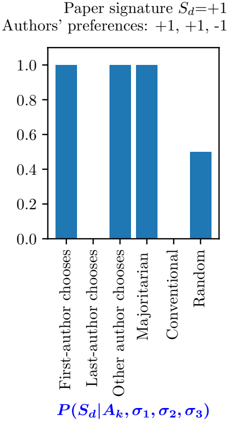

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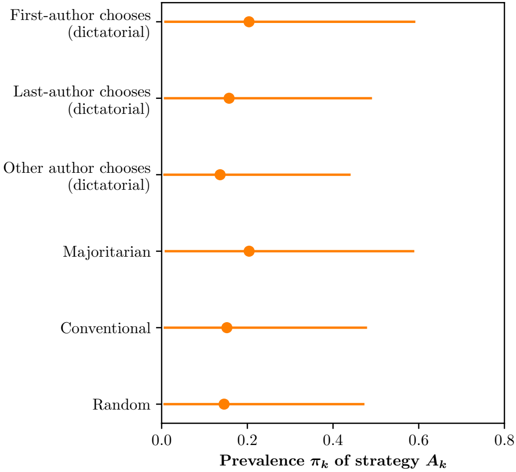

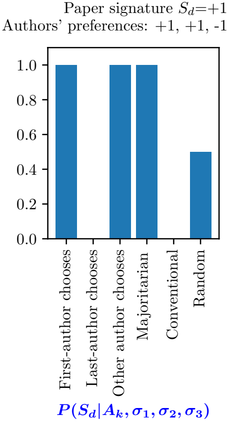

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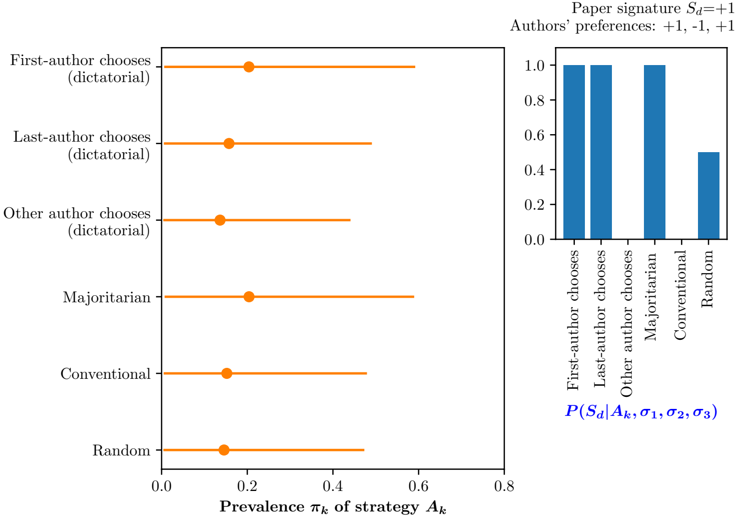

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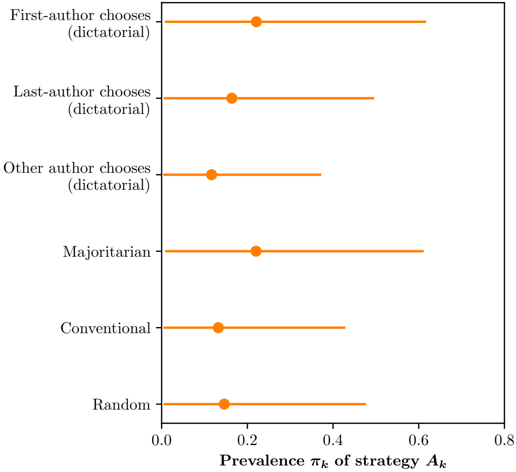

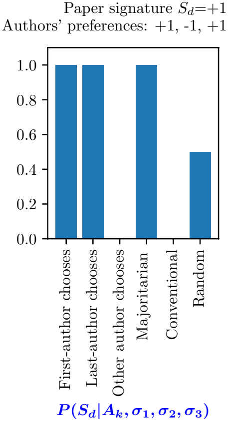

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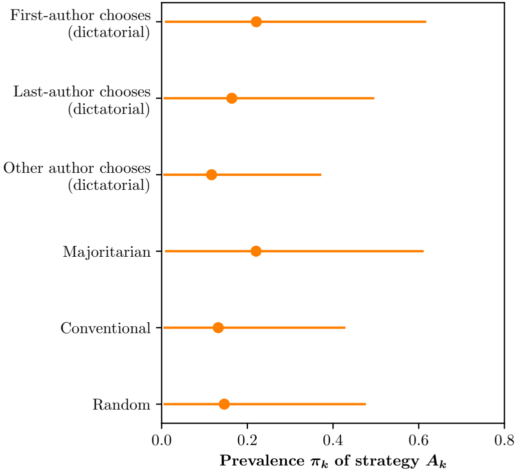
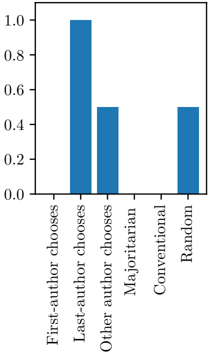


Paper signature S_d=+1
Authors' preferences: -1, -1, +1, +1



$P(S_d|A_k, \sigma_1, \sigma_2, \sigma_3, \sigma_4)$

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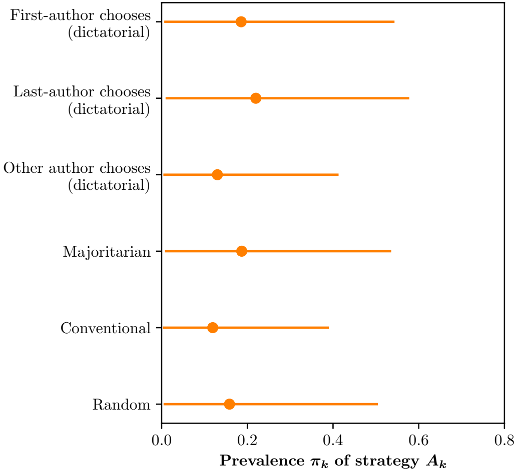

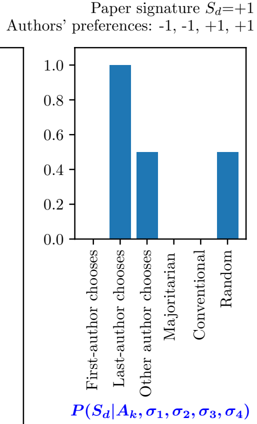

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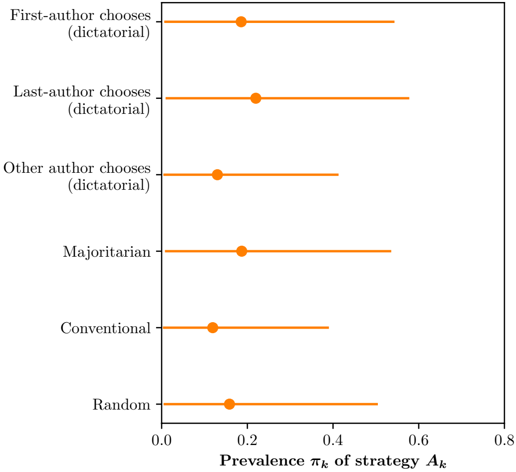

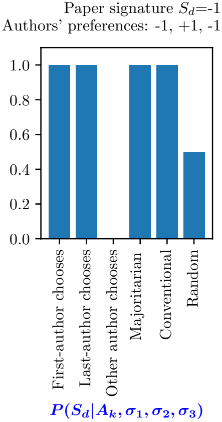

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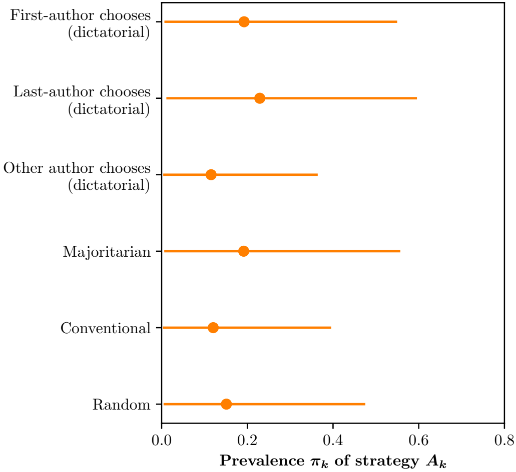

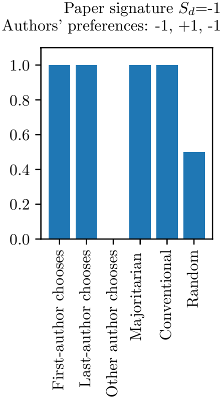

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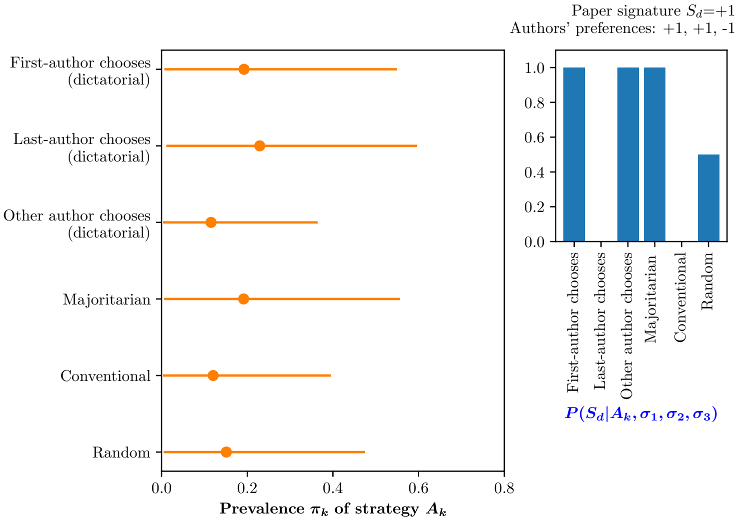

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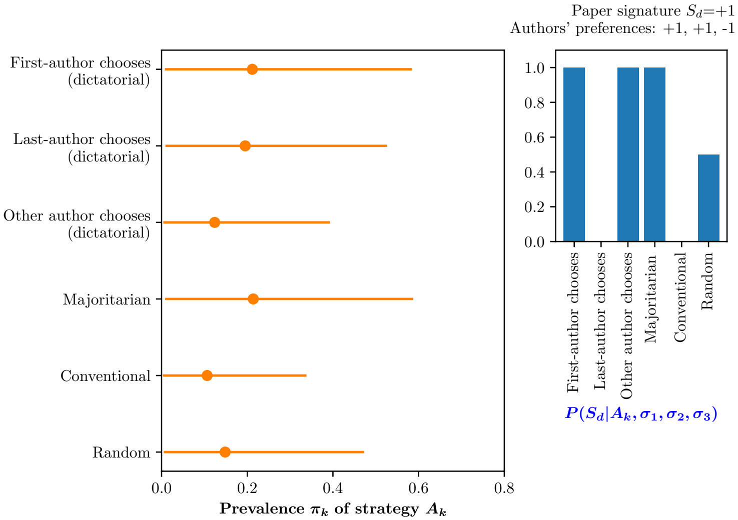

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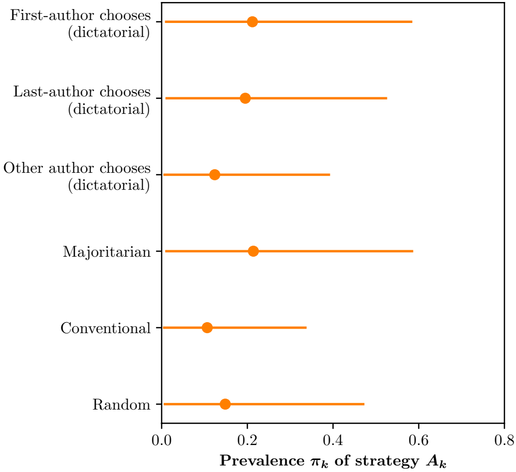

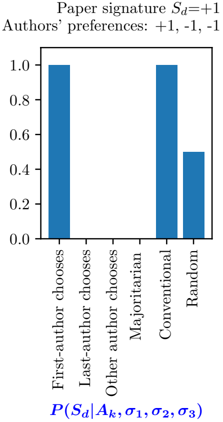

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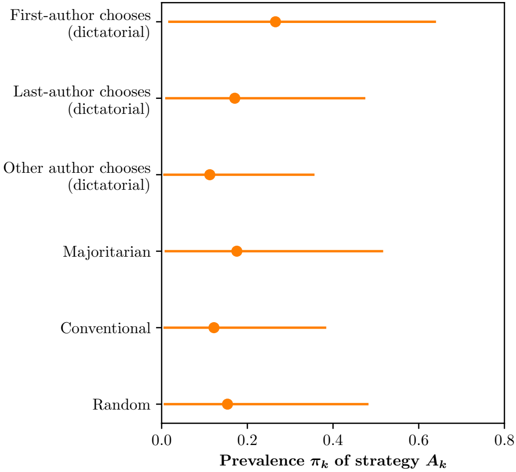

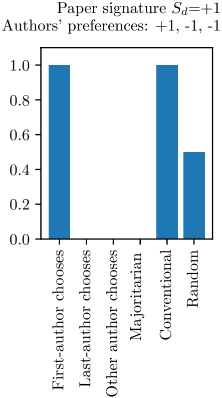

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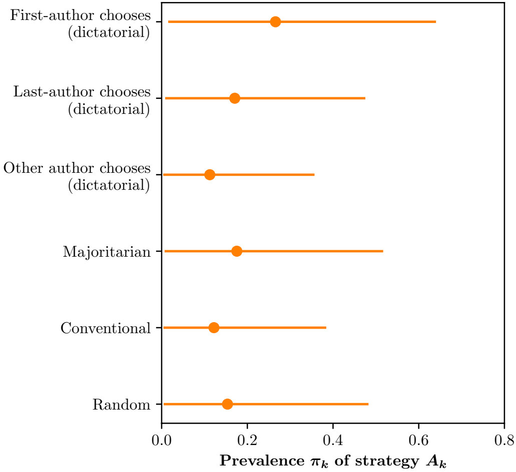

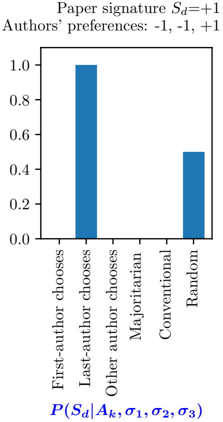

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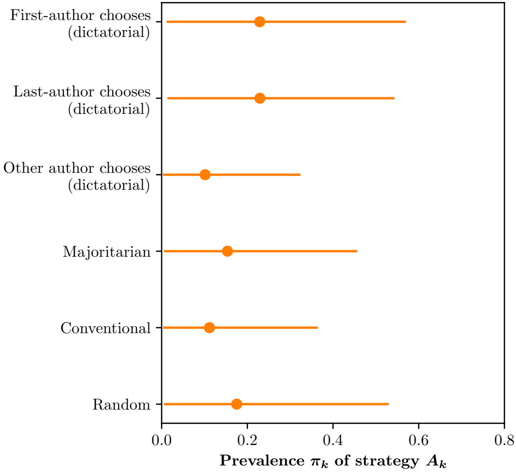

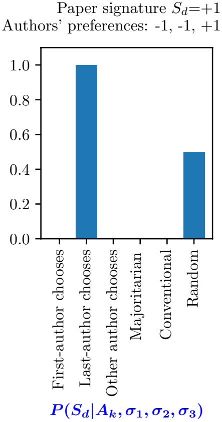

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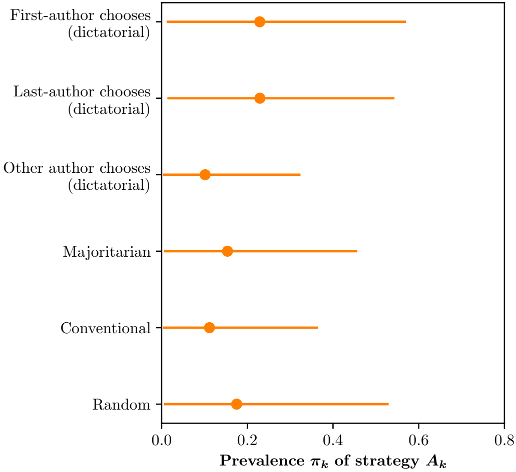

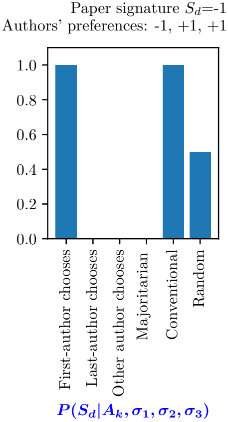

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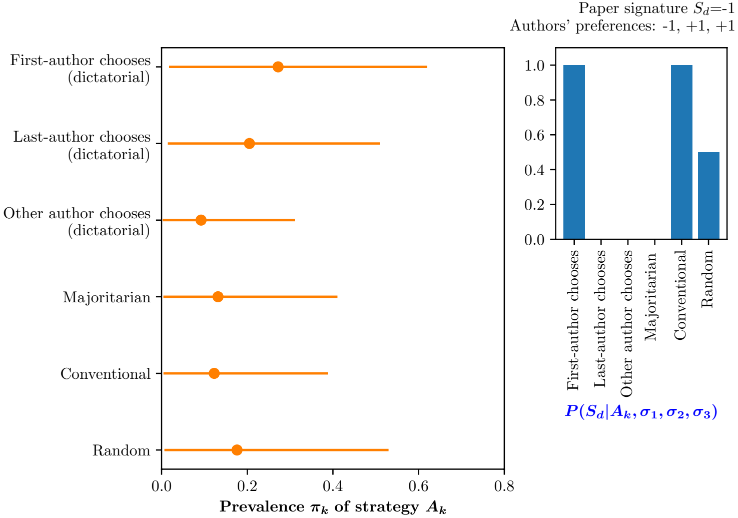

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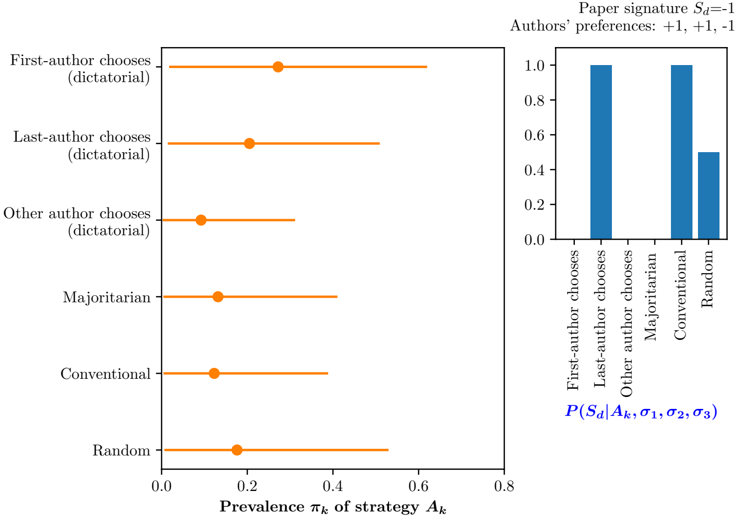

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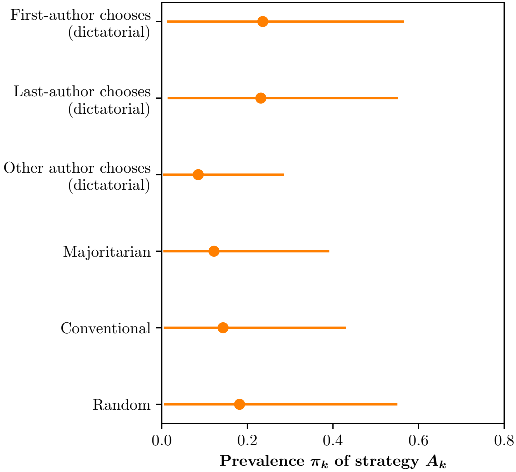

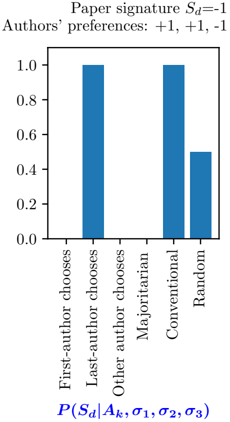

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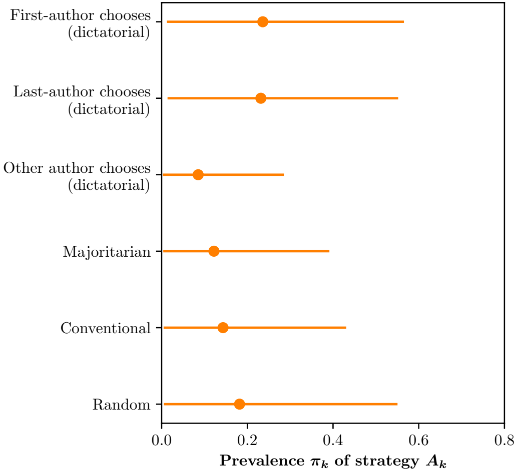

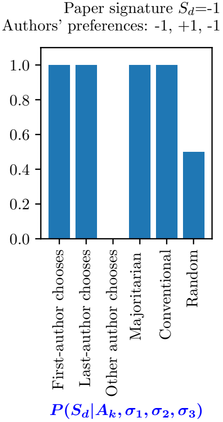

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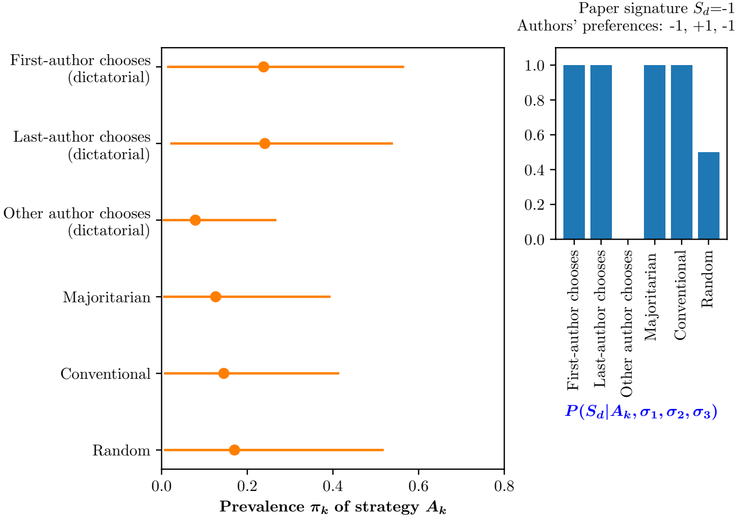

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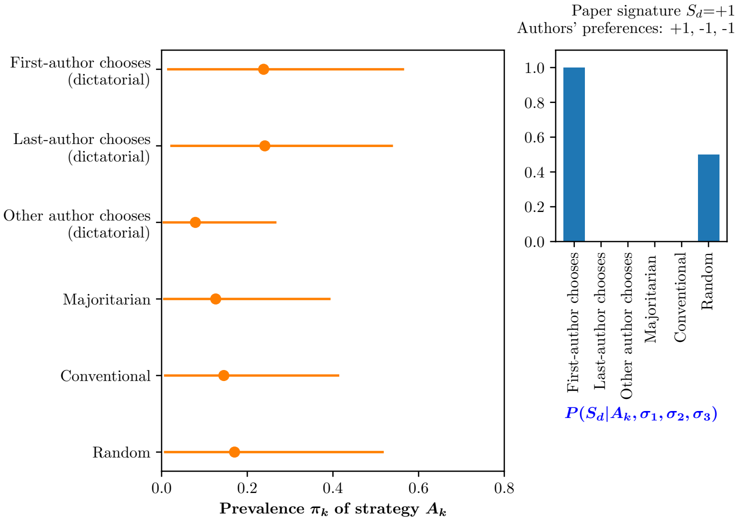

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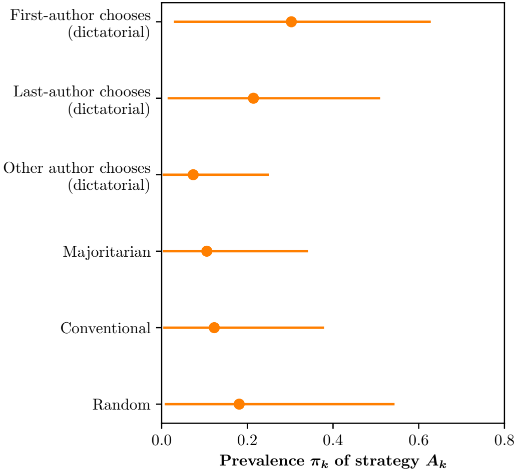

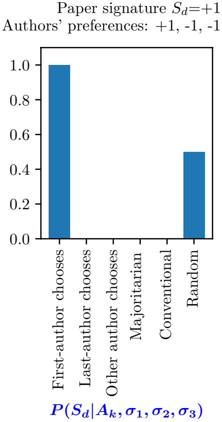

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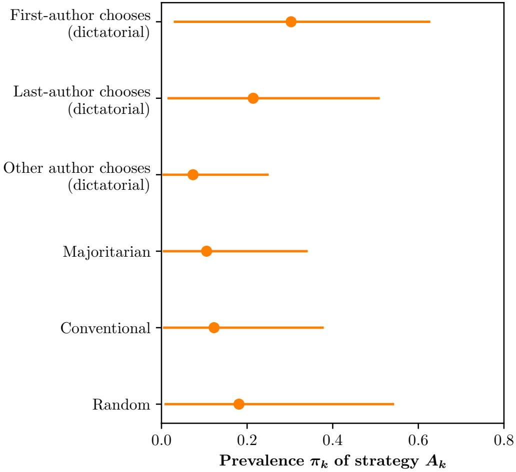

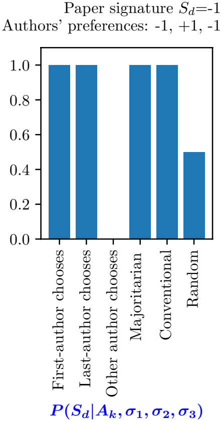

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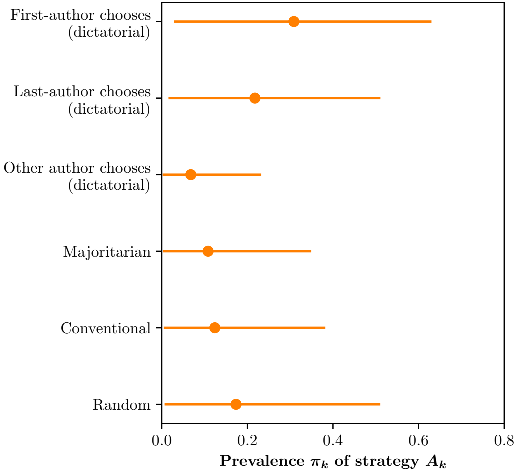

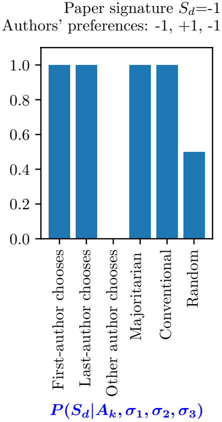

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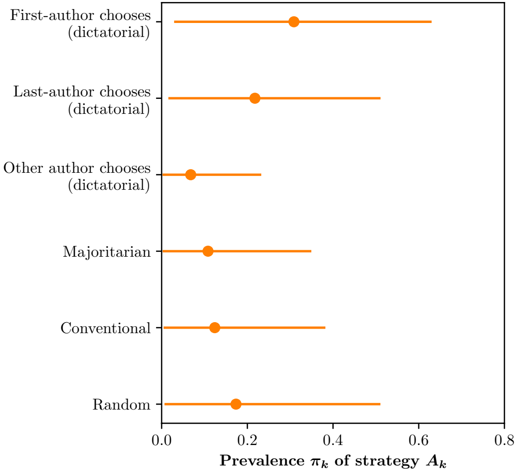

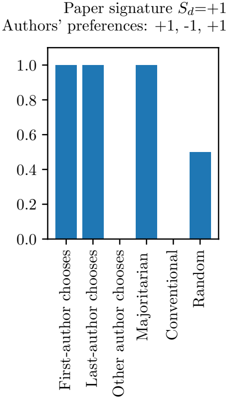

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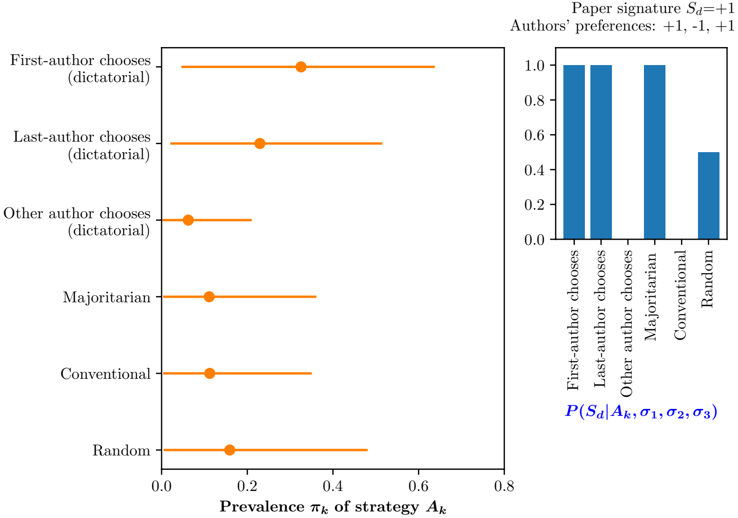

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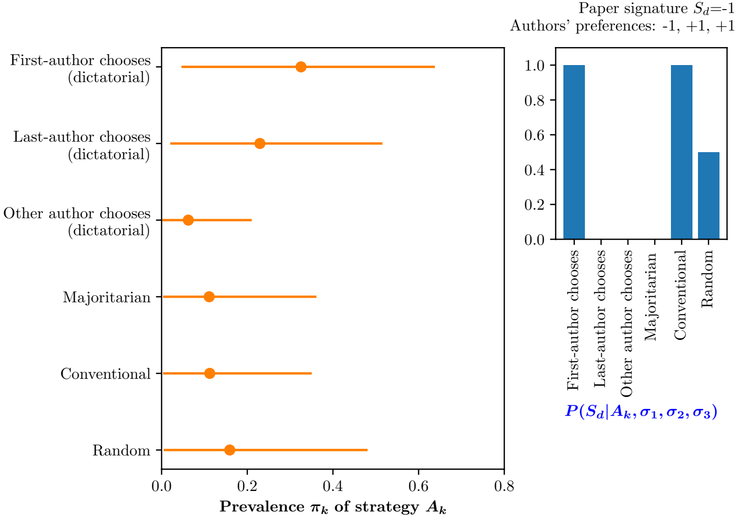

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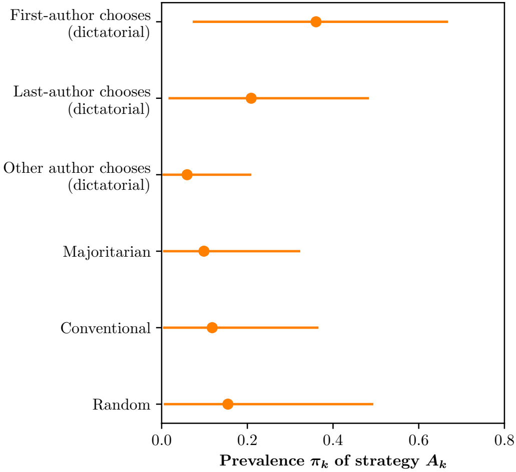

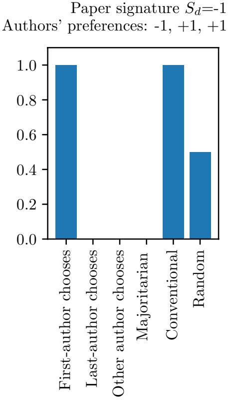

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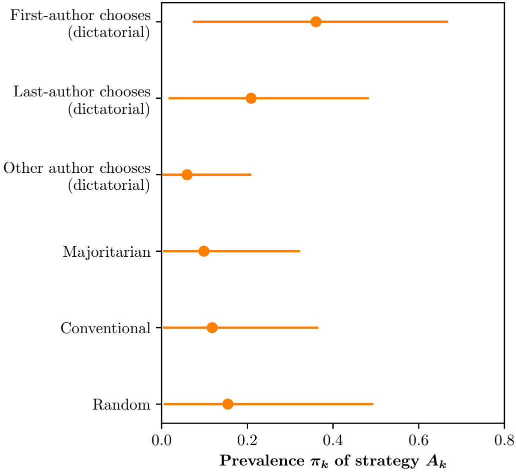

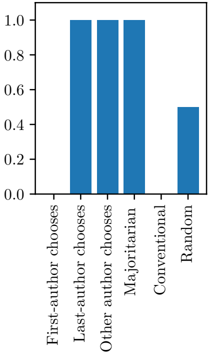

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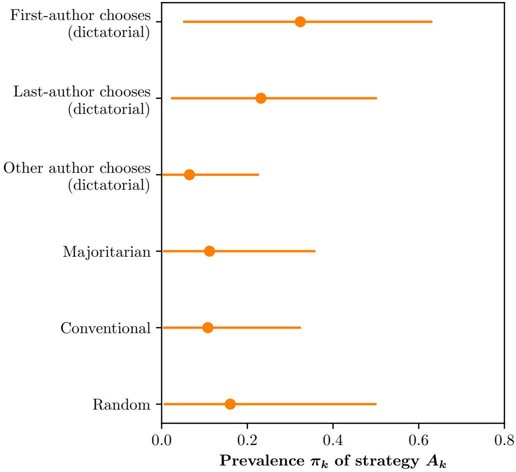

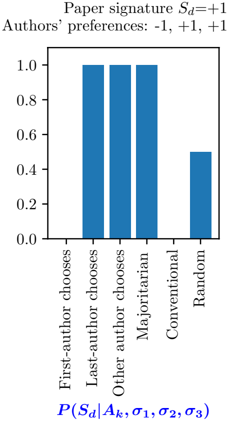

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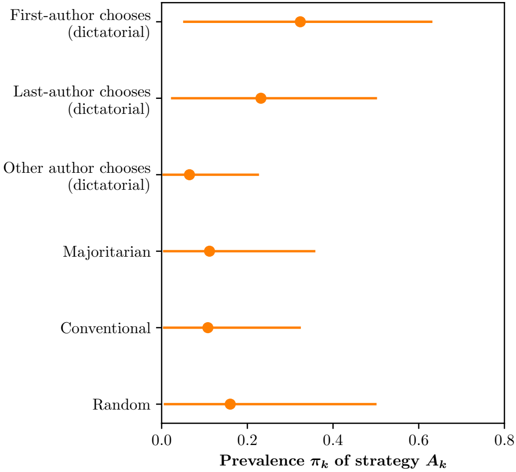

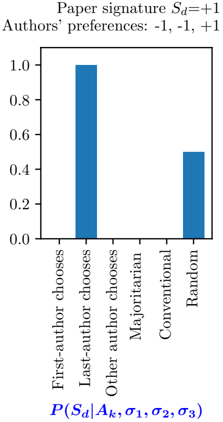

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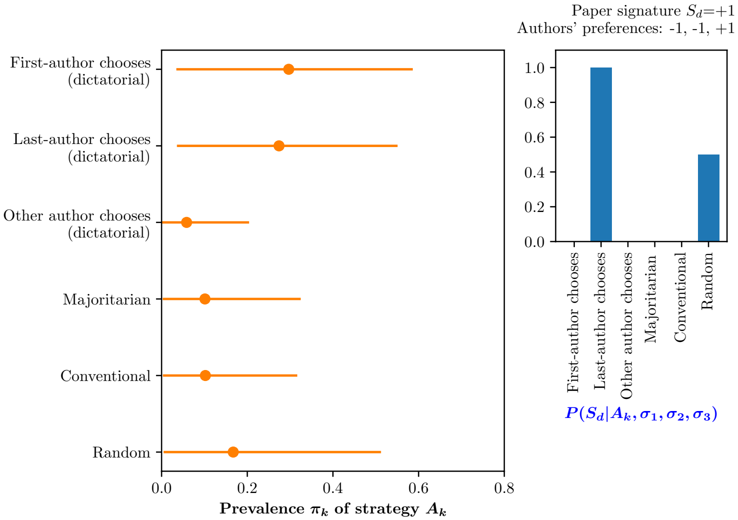

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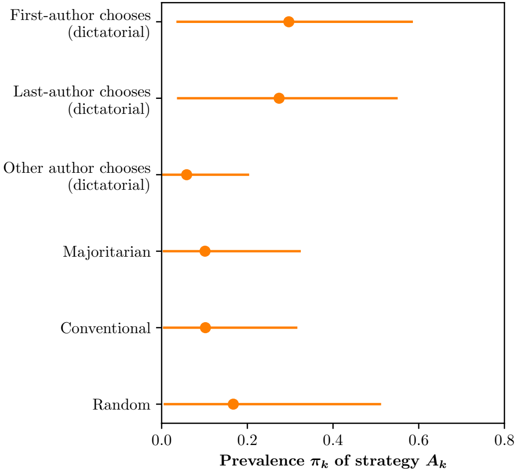

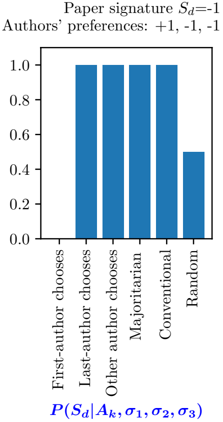

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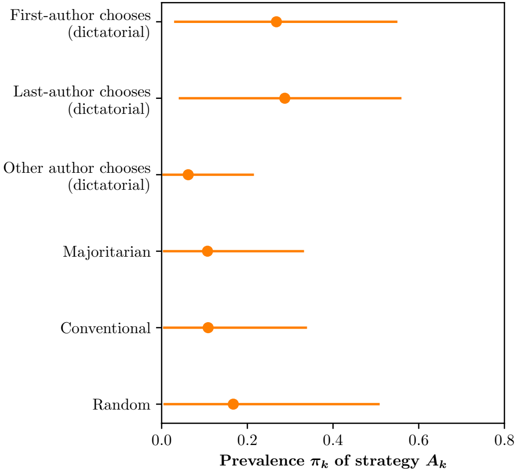

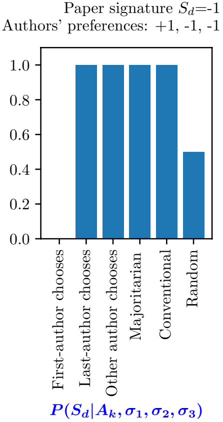

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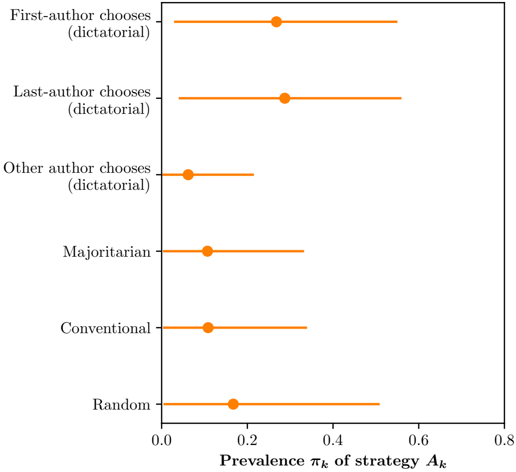

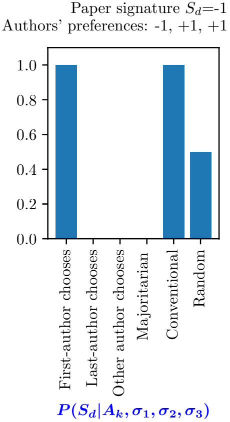

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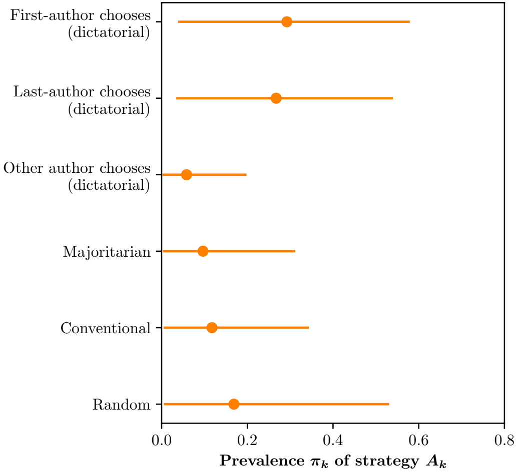

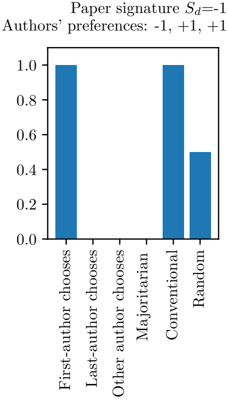

$P(S_d|A_k, \sigma_1, \sigma_2, \sigma_3)$

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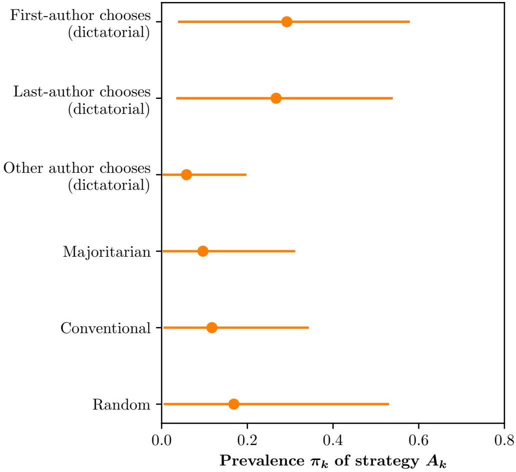
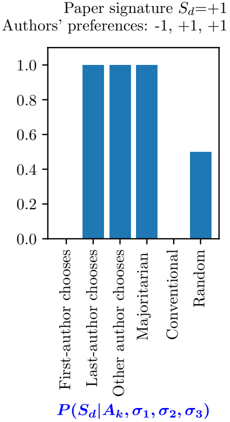
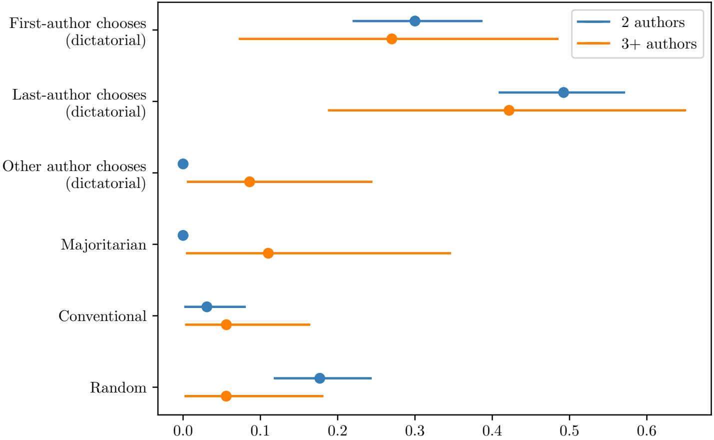




Prevalence of each preference-aggregation strategy



1. Inverse problems for philosophers and agent-based modelers

2. A case-study of conventions: the metric signature in particle physics
   - How do physicists choose which convention to use in their own papers?
   - How do scientists resolve conflicting preferences in collaborations?
   - How do physicists' preferences get formed?

Authors' preferences

Observed outcome: the preference of each author,

$$O_{\text{obs}} = (\sigma_1, \ldots, \sigma_n), \sigma \in \{-1, +1\}$$

($n = 2\,277$ authors)

How do physicists' preferences get formed?

- Let's assume three models of the formation of physicists' preference towards the convention:
  1. A **"strategic agent" model** (M_1) assuming that individuals navigate three costs (coordination costs, inconsistency costs, and maladaptation costs) depending on their collaborators' preferences and the research areas in which they publish.
  2. A **global cultural transmission model** (M_2), in which physicists settle once and for all for a specific convention with a certain probability that depends on their primary research area (textbooks?)
  3. A **local cultural transmission model** (M_3), in which physicists copy the preference of their first collaborator.
- Which of these is more plausible given the observed patterns of preferences?

Example: the strategic agent model (M_1)

The model M_1 has multiple unknown parameters:

- c_s: the cost of switching from one convention to another
- c_c: the cost of disagreeing with co-authors
- c_r the cost of using a suboptimal convention in a given research area

The **outcome** O_{sim} is the joint value of each author's preference:
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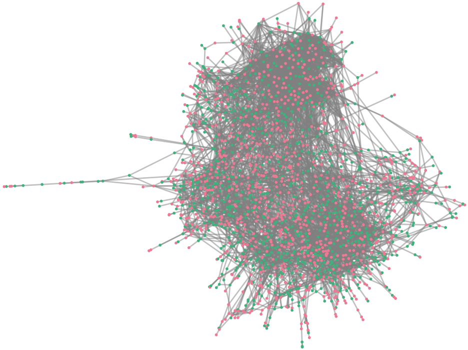

Simulation-based inference

$$P(M_1|O) = \overbrace{P(O|M_1)}\frac{P(M_1)}{P(O)} \tag{4}$$

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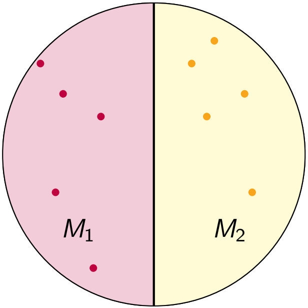

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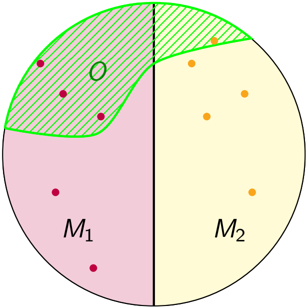

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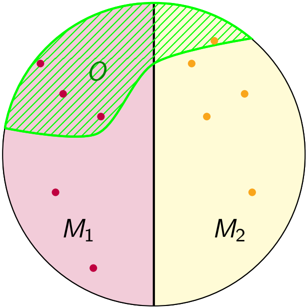

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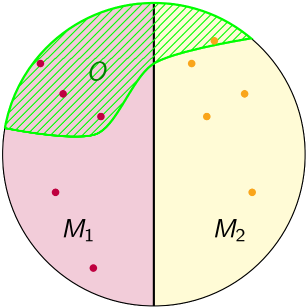
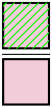
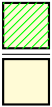


$\color{blue}{P(O|M_1)} =$  $\simeq \frac{3}{5}$

$\color{blue}{P(O|M_2)} =$  $\simeq \frac{1}{5}$

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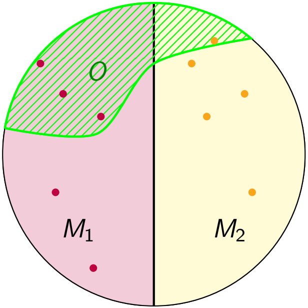
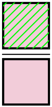
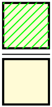
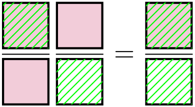


$\color{blue}{P(O|M_1)} =$  $\simeq \frac{3}{5}$

$\color{blue}{P(O|M_2)} =$  $\simeq \frac{1}{5}$

$\color{red}{P(M_1|O)} = \color{blue}{P(O|M_1)}\frac{P(M_1)}{P(O)} =$ 

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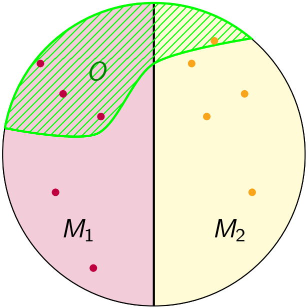

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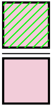

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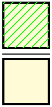
$$\color{blue}{P(O|M_2)} =$$



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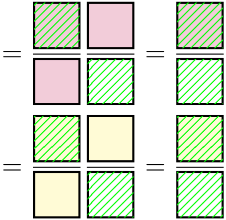

Curse of dimensionality in simulation-based inference

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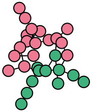
$O_{\text{obs}} =$  $\rightarrow m_{\text{obs}} = 0.03$

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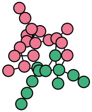
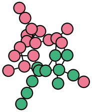
$O_{\text{obs}} =$  $\rightarrow m_{\text{obs}} = 0.03$

$O_{\text{sim}} =$  $\rightarrow m_{\text{sim}} = 0.03$

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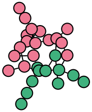
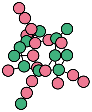
$O_{\text{obs}} =$  $\rightarrow m_{\text{obs}} = 0.03$

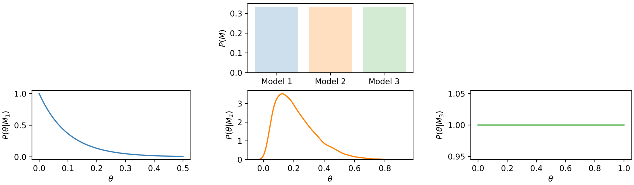
$O_{\text{sim}} =$  $\rightarrow m_{\text{sim}} = 0.03$

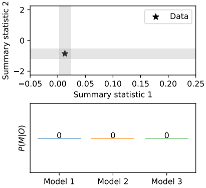
Summary statistics in simulation-based inference

There are two main approaches for choosing adequate summary statistics:

1. Hand-picking interpretable summary statistics based on our own intuitions.
2. Using sophisticated methods to learn statistically optimal (but potentially un-interpretable) summary statistics. Optimal summary statistics reduce our posterior uncertainty given a fixed amount of data.

Simulation-based inference with summary statistics





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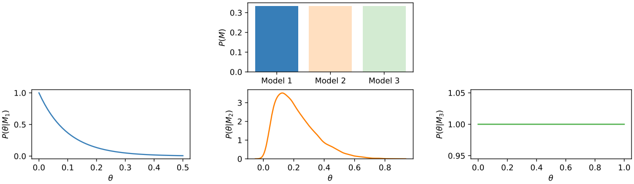
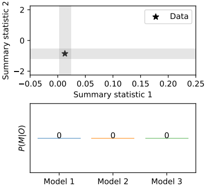
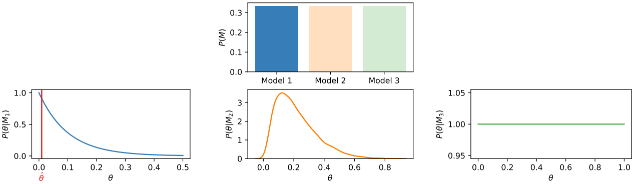
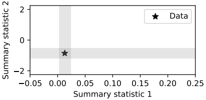


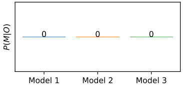




$P(M)$
Model 1
Model 2
Model 3
$P(\theta|M_1)$
$\hat{\theta}$
θ
$P(\theta|M_2)$
θ
$P(\theta|M_3)$
θ

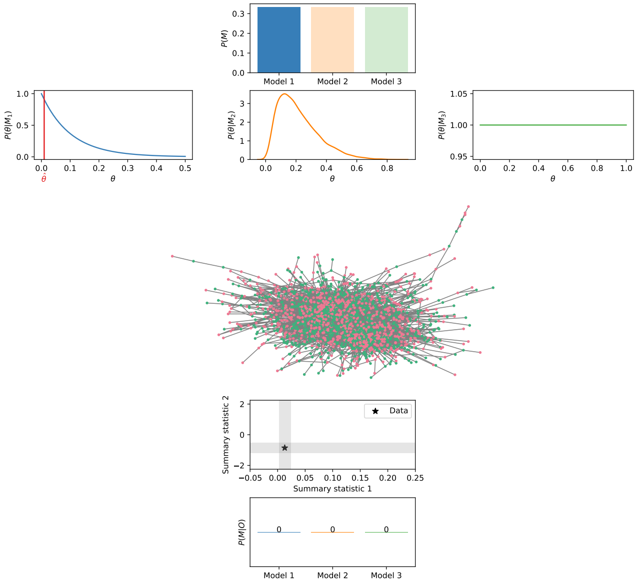


Data
Summary statistic 1
Summary statistic 2



$P(M|O)$
0
0
0
Model 1
Model 2
Model 3

Simulation-based inference with summary statistics



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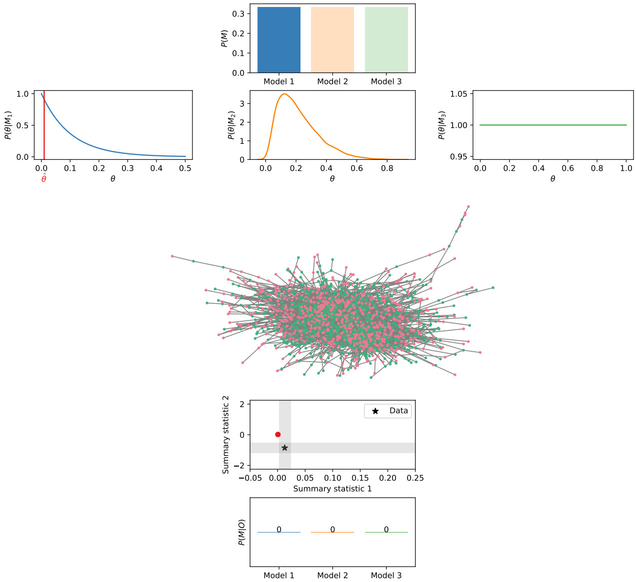

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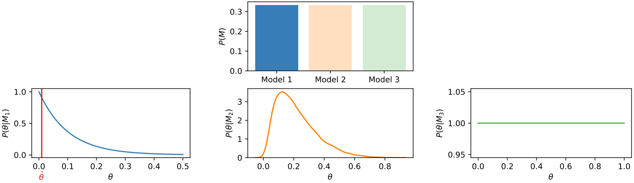

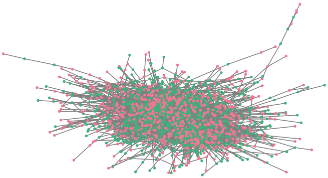

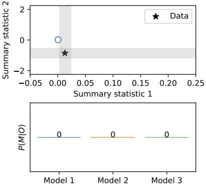

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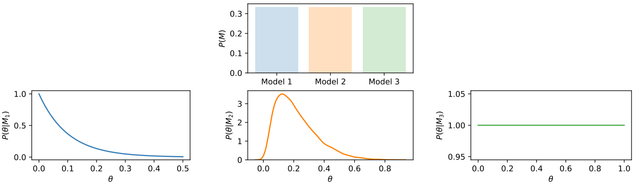

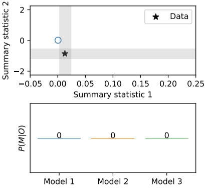

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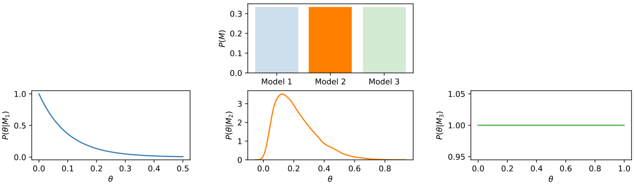

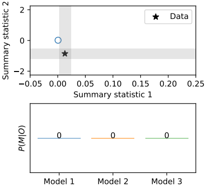

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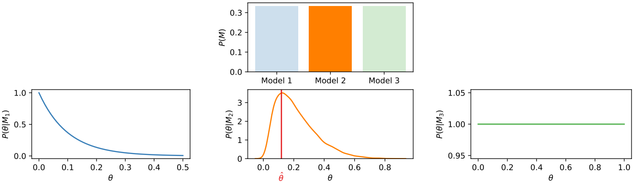

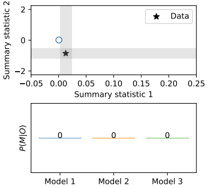

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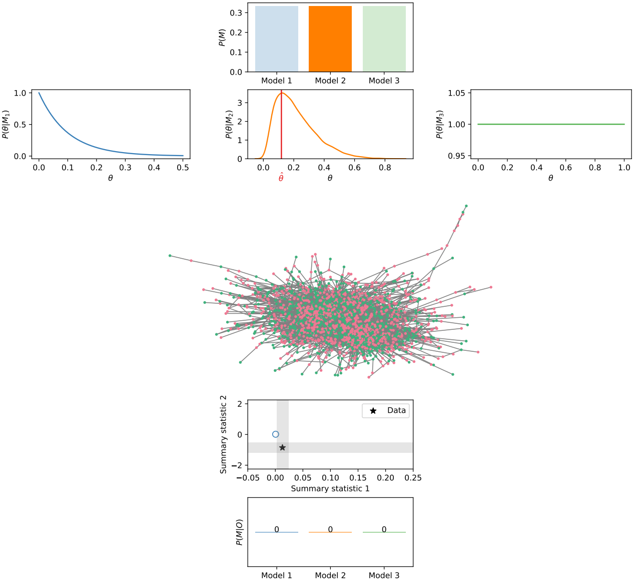

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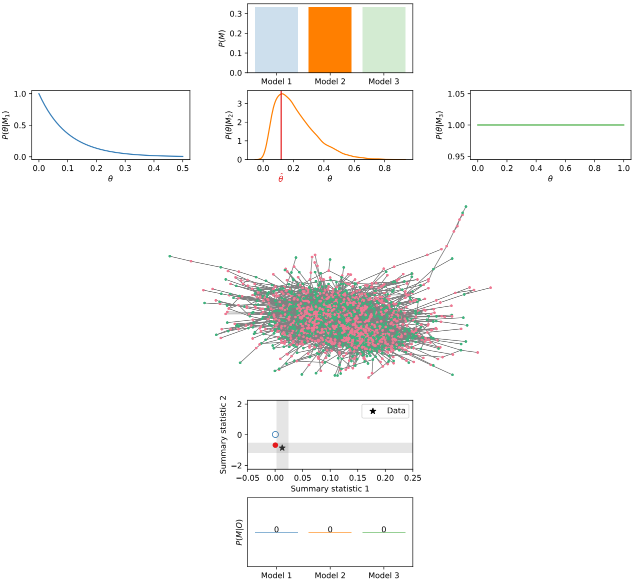

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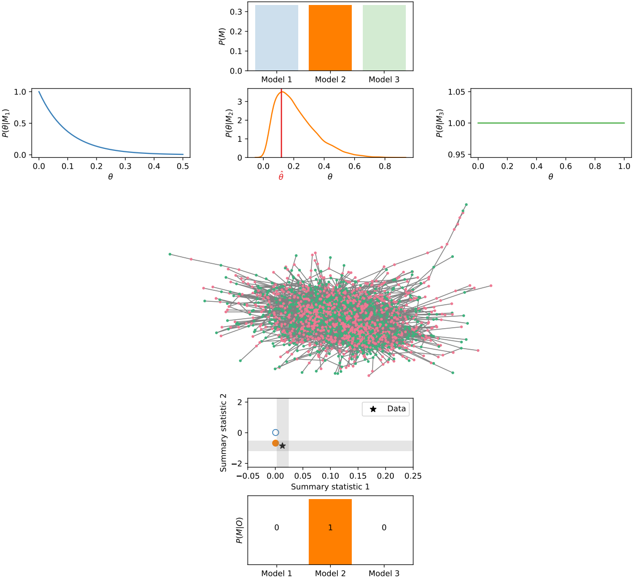

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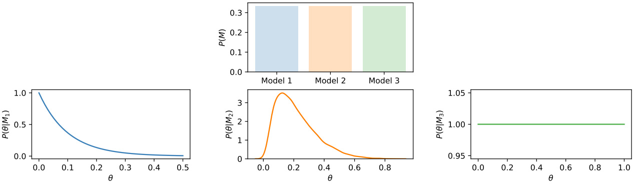

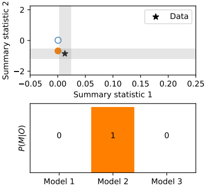

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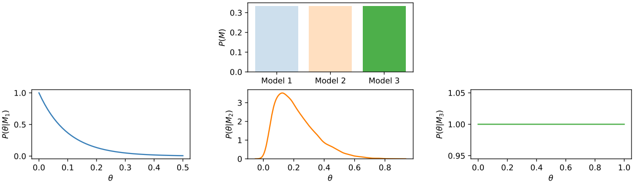

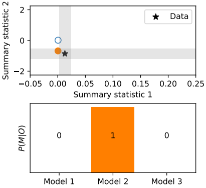

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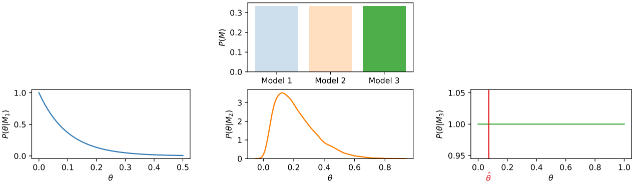

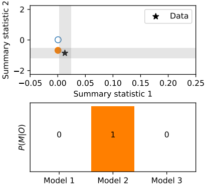

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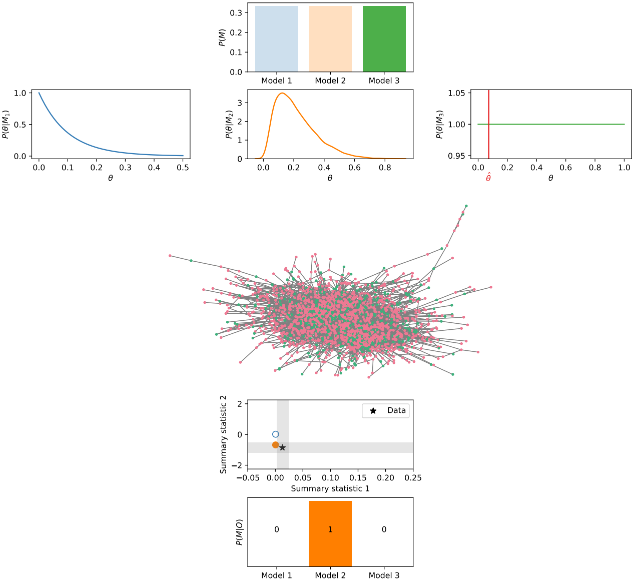

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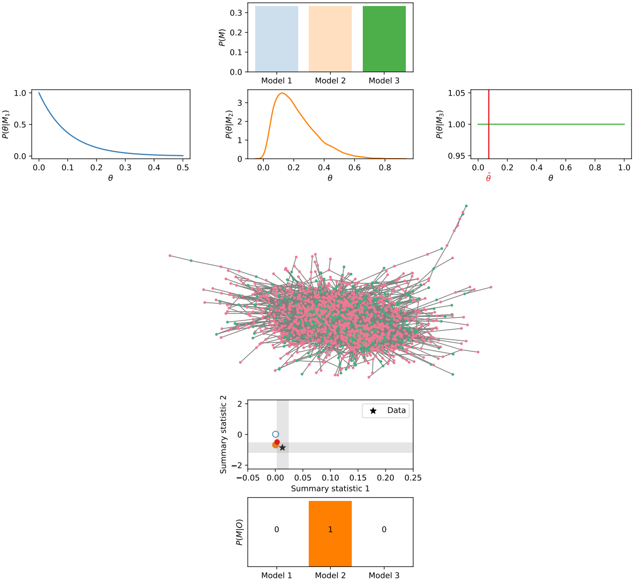

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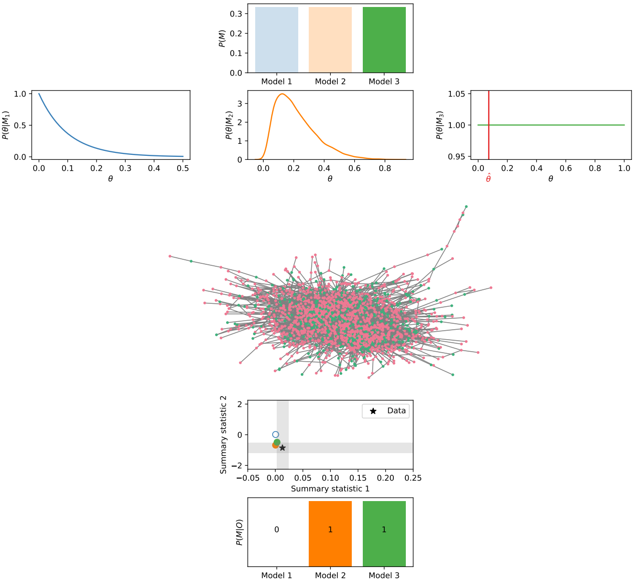

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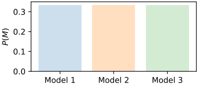

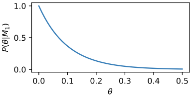

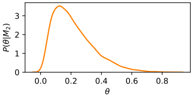

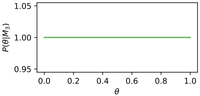

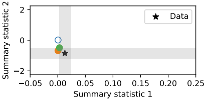

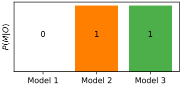

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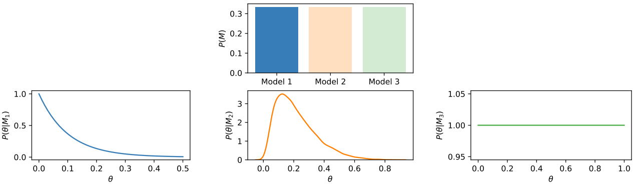

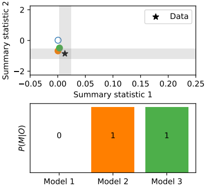

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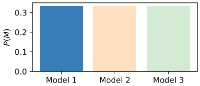

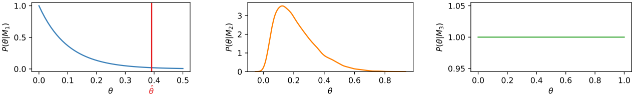

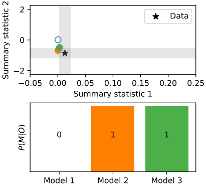

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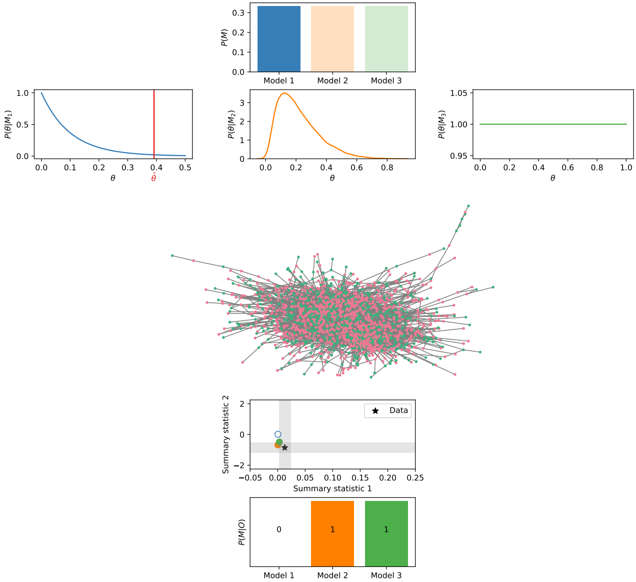

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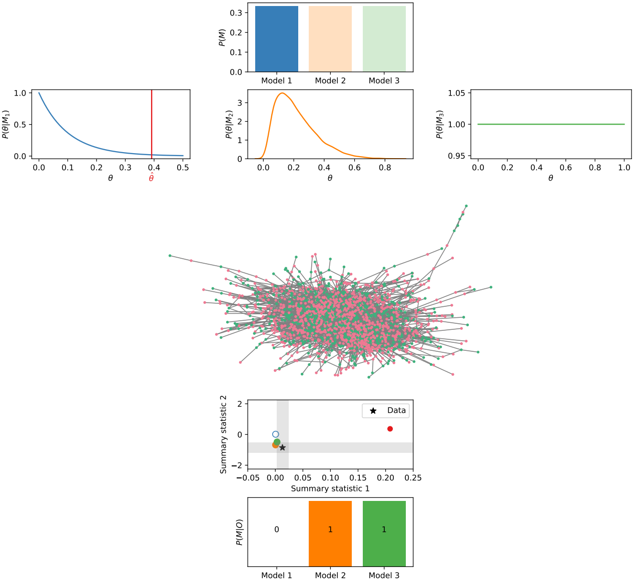

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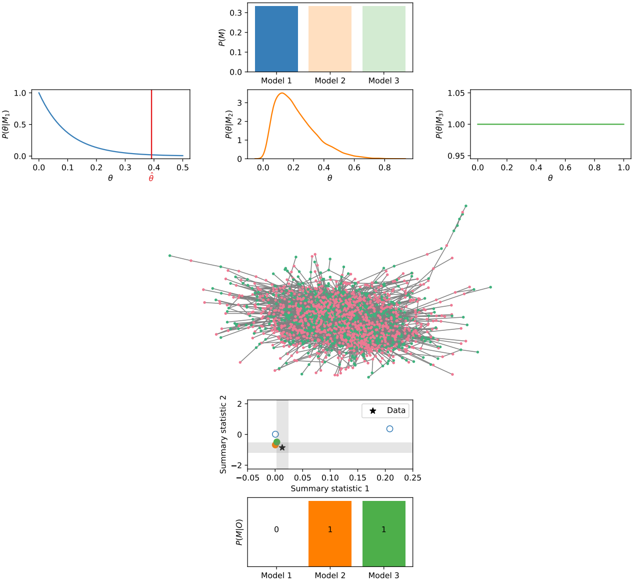

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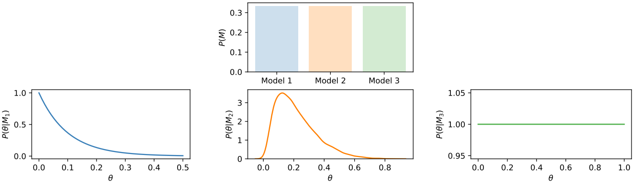

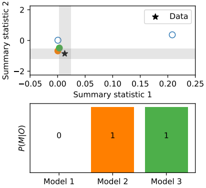

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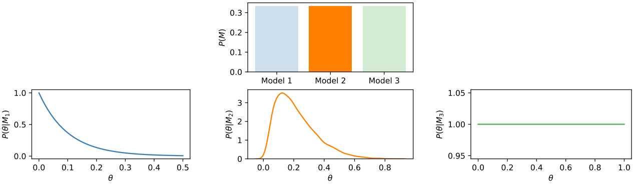

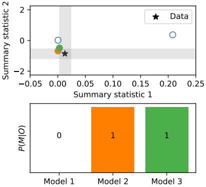

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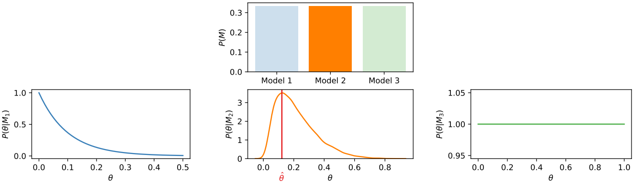

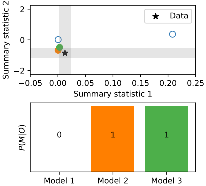

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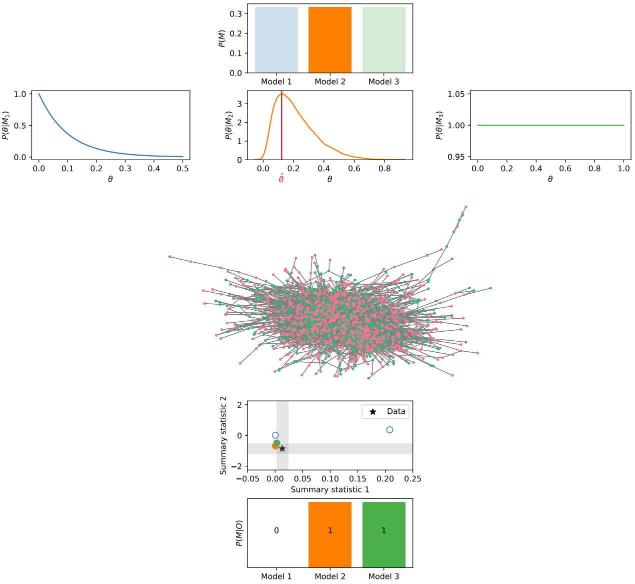

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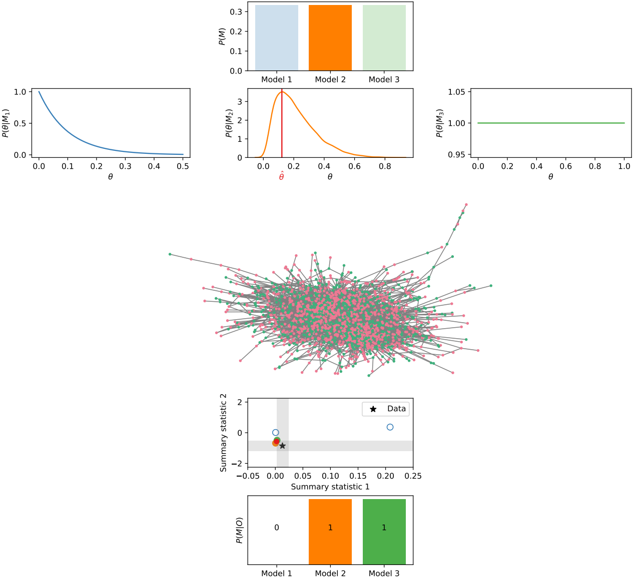

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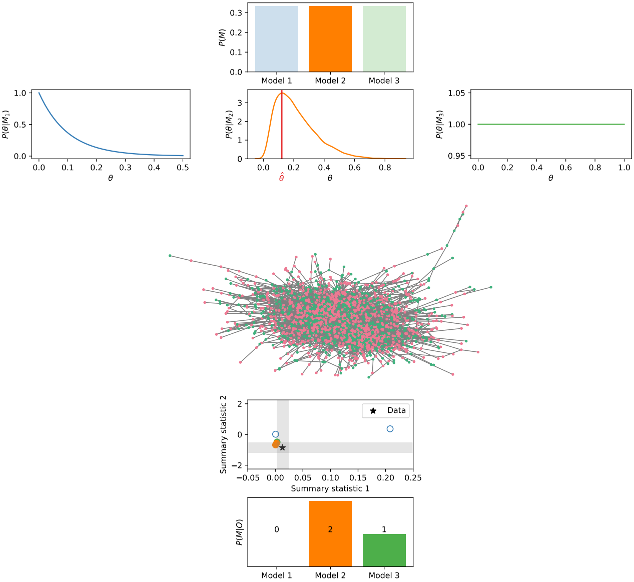

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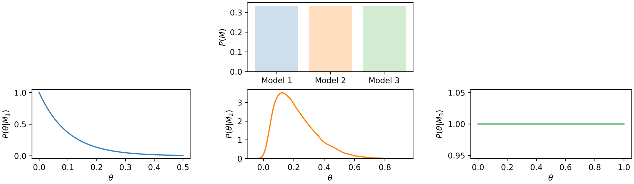

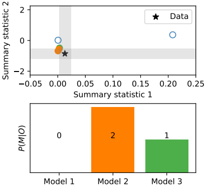

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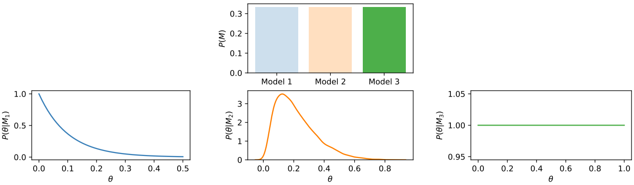

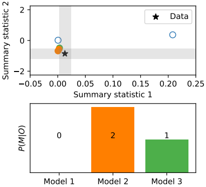

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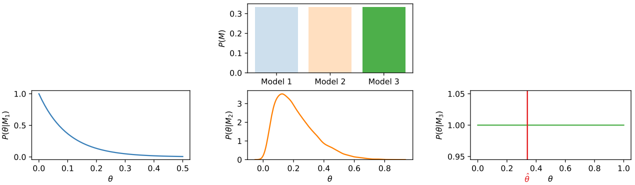

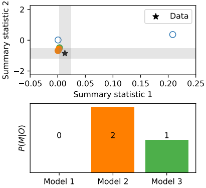

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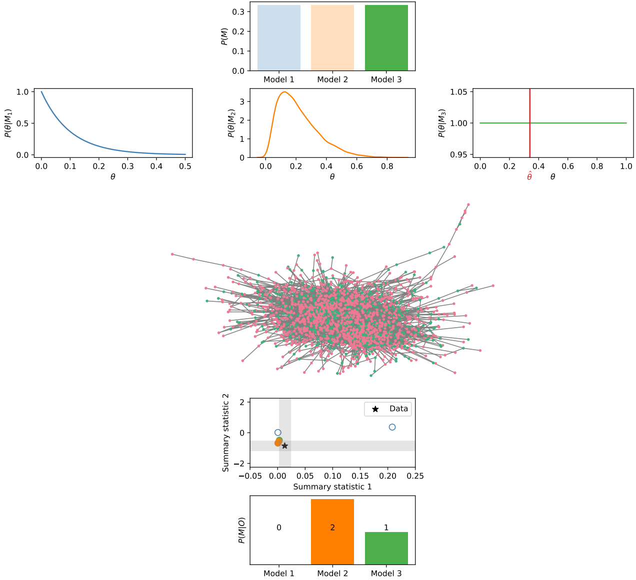

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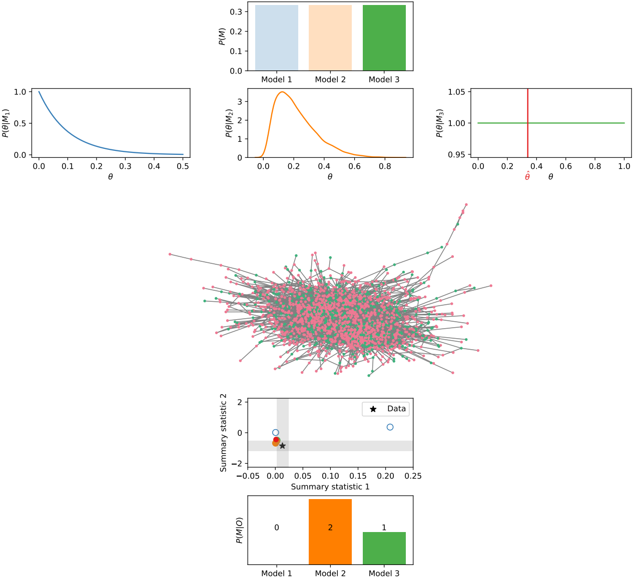

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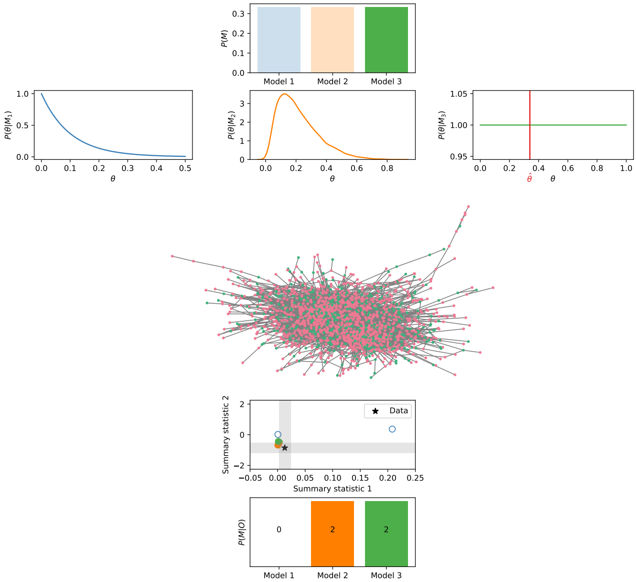

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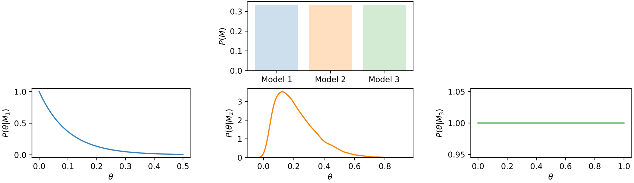

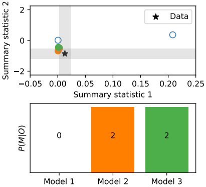

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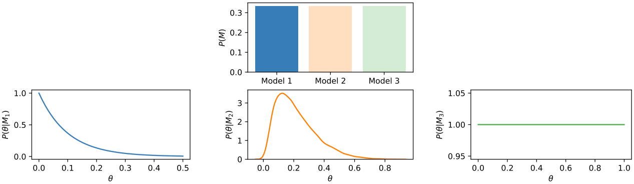

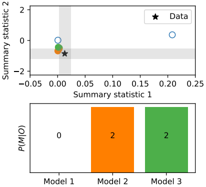

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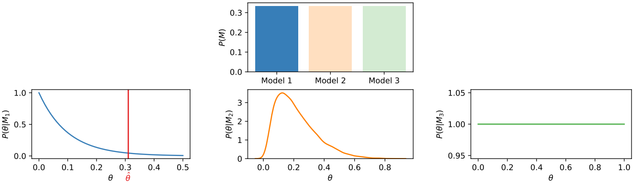

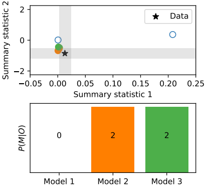

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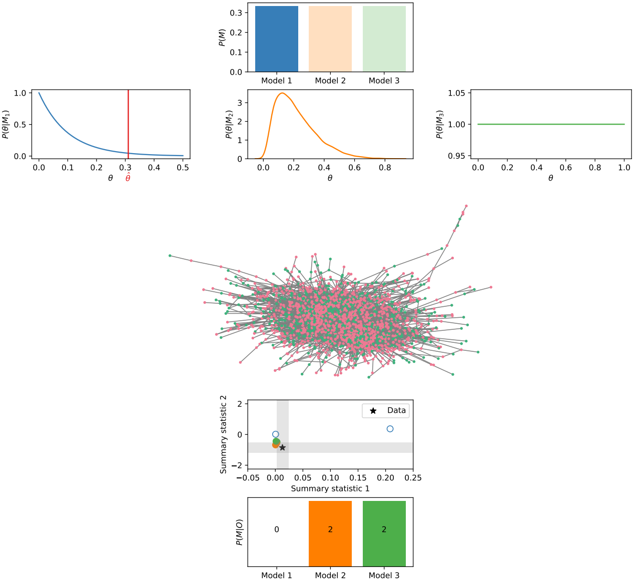

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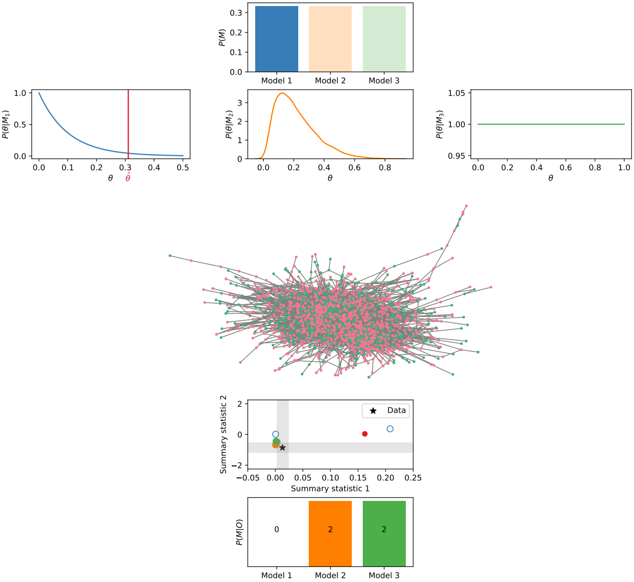

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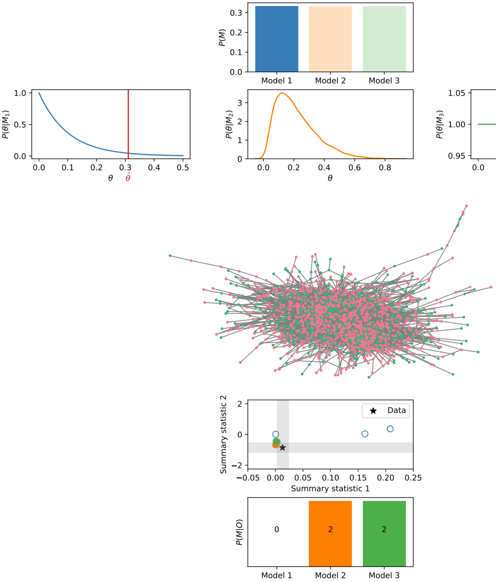
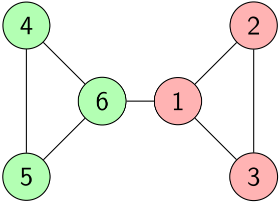


Local versus global mechanisms of coordination

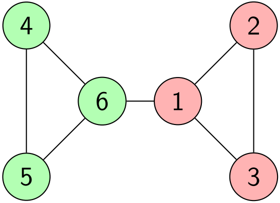


Local coordination

Strategic alignment, imitation of peers...

$\boldsymbol{J}$

Local versus global mechanisms of coordination



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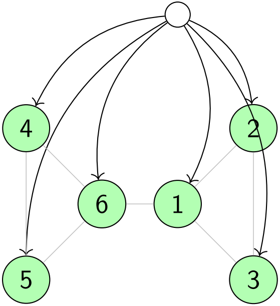


Global coordination

Adaptation to research purposes,
or shared culture ("disciplinary matrix")
$\boldsymbol{B}$

The Ising model as an intermediate idealized model

- Atomic magnetic spins in a material can be in two states: $\uparrow$ (+1) or $\downarrow$ (-1).
- Magnetic spins prefer to be aligned to their neighbors ($\uparrow\uparrow$ or $\downarrow\downarrow$)
- Can local interactions between spins at the microscopic level lead to macroscopic alignment?

$$P(\{\sigma_i\}|J, \boldsymbol{B}) = \frac{1}{Z(J, \boldsymbol{B})} e^{-H(\{\sigma_i\}, J, \boldsymbol{B})}, \text{ and } H = - \underbrace{\sum_{i,j} J w_{ij} \sigma_i \sigma_j}_{\substack{\text{local} \\ \text{pairwise interactions}}} \underbrace{- \sum_i B_{C_i} \sigma_i}_{\substack{\text{external} \\ \text{magnetic field}}} \tag{6}$$

https://mattbierbaum.github.io/ising.js/

Inverse Ising problem: $P(J, J^{\text{cit}}, \boldsymbol{B}|\{\sigma_i\})$

Local coordination in multi-layered graphs

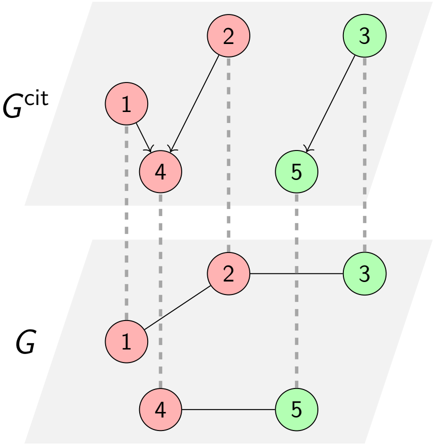


Figure: **Illustration of local coordination in multilayered social networks**. Nodes can be connected through different kinds of relationships (for instance, authors can be related via collaborations (G) or citations (G^{cit})).

Local versus global coordination

Table: Parameters of the Ising model.

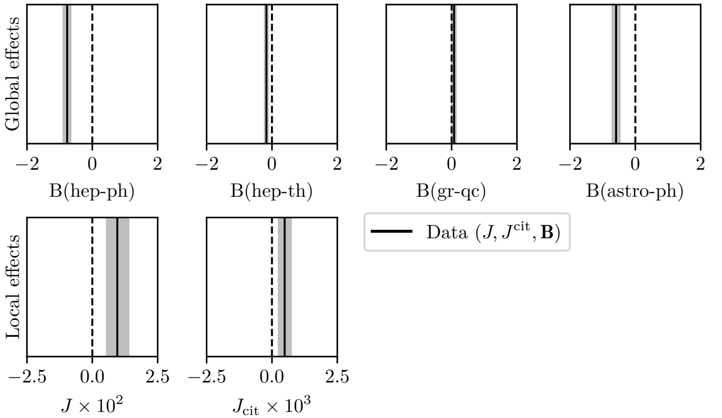
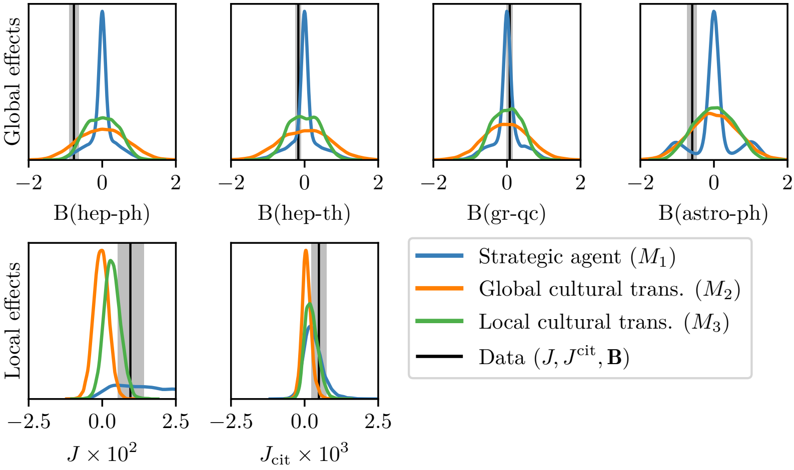


Figure: Ising model fit

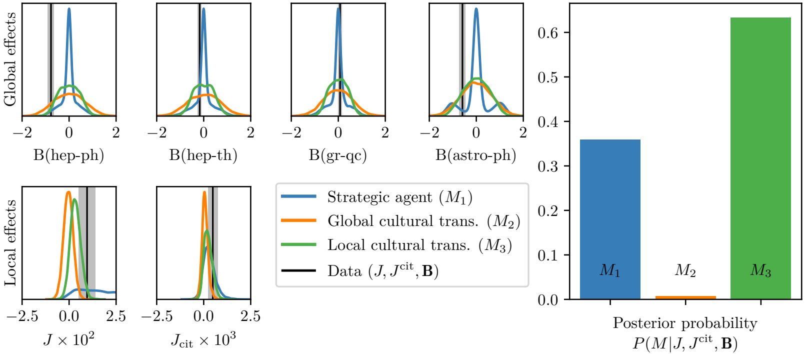
Local versus global coordination

What values of $\boldsymbol{J}$ and $\boldsymbol{B}$ do our models predict? In other words, what is the probability $P(J, J^{\text{cit}}, \boldsymbol{B}|M_i)$ for each model M_i?



Local versus global coordination

Given $P(J, J^{\text{cit}}, \boldsymbol{B}|M_i)$, and the true values of $\boldsymbol{J}$ and $\boldsymbol{B}$, what is $P(M_i|J, J^{\text{cit}}, \boldsymbol{B})$?
After a bit of computational trickery – "amortized simulation-based model comparison with neural networks" with BayesFlow –:



Challenges for model selection

- Model misspecification: model comparison among highly incorrect models is challenging/meaningless

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- Model misspecification: model comparison among highly incorrect models is challenging/meaningless
- Priors on models' parameter matter. A model is disadvantaged if it only is a good fit to the data for improbable parameter values.

Summary: inverse problems in practice

1. What **phenomenon**? (Belief-polarization? Discrimination and marginalization? etc.)
2. What **models**? ("model-space")
3. What **data**?
   - Accessibility (reasonable time/financial cost)
   - Quality (bias? ecological validity?)
   - Quantity (statistical significance)
4. What **computational strategies**?
   - **Pre-processing**: e.g. text-classification (natural language processing)?
   - **Inference** (inverse problem): simulation-based inference (with/without neural networks); Hamiltonian Monte-Carlo? Metropolis?

Thank you! I

Centola, Damon and Andrea Baronchelli (Feb. 2015). "The spontaneous emergence of conventions: An experimental study of cultural evolution". In: *Proceedings of the National Academy of Sciences* 112.7.

Cranmer, Kyle, Johann Brehmer, and Gilles Louppe (May 2020). "The frontier of simulation-based inference". In: *Proceedings of the National Academy of Sciences* 117.48.

Delgado, Jordi (2002). "Emergence of social conventions in complex networks". In: *Artificial intelligence* 141.1-2.

Hawkins, Robert XD, Noah D Goodman, and Robert L Goldstone (2019). "The emergence of social norms and conventions". In: *Trends in cognitive sciences* 23.2.

Lewis, David (Jan. 1969). *Convention: A Philosophical Study*. Cambridge, MA: Harvard University Press.

O'Connor, Cailin (June 2020). "Measuring Conventionality". In: *Australasian Journal of Philosophy* 99.3.

Pujol, Josep M et al. (2005). "The role of clustering on the emergence of efficient social conventions". In: *Proceedings of the 19th international joint conference on Artificial intelligence*.

Radev, Stefan T et al. (2021). "Amortized bayesian model comparison with evidential deep learning". In: *IEEE Transactions on Neural Networks and Learning Systems* 34.8.

Amortized simulation-based inference

- Even with summary statistics, simulation-based inference is difficult because no simulated sample will *exactly* match the observed data.
- Solution:

Amortized simulation-based inference

- Even with summary statistics, simulation-based inference is difficult because no simulated sample will *exactly* match the observed data.
- Solution:
  - Use amortized inference with neural networks $\Rightarrow$ train a neuralnet to predict the probability of each model M_i given one or more observed outcomes. The neuralnet is trained with many simulated training samples (M_s, O_s) (Radev et al., 2021)

Amortized simulation-based inference

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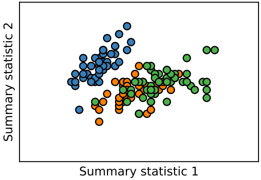

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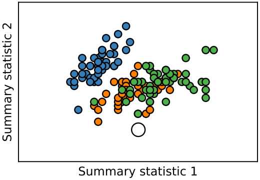

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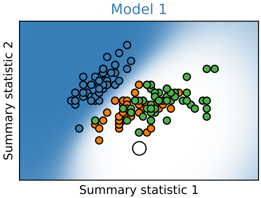

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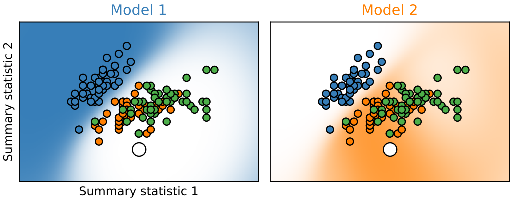

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