

Weekly Report - Presentation

Yanpei Cai

Artificial Intelligence and its Applications Institute
School of Informatics, The University of Edinburgh

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Smoking Contagion Model

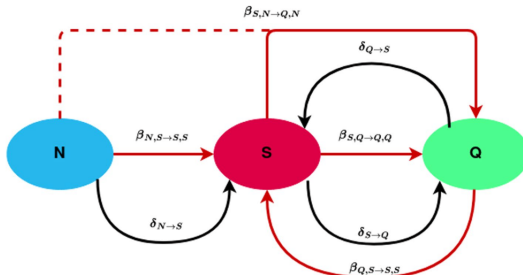


Fig. 1 The figure shows the schematic representation of the state change processes involved in the ABM. The interaction parameters are represented by the red arrows, while the black arrows show the spontaneous terms in the schematic. All three state-change processes are shown in the figure. First, an N-agent can initiate smoking spontaneously ($\delta_{N \rightarrow S}$) or due to the interaction with an S-agent ($\beta_{N,S \rightarrow S,S}$). Similarly, an S-agent can quit spontaneously ($\delta_{S \rightarrow Q}$) or due to interaction with other non-smoker agents (Q-agent: $\beta_{S,Q \rightarrow Q,Q}$ or N-agent: $\beta_{S,N \rightarrow Q,N}$). Like the other processes, Q-agents relapse into smoking spontaneously ($\delta_{Q \rightarrow S}$) or due to interaction ($\beta_{Q,S \rightarrow S,S}$) with an S-agent



UK Smoking Trend Data (1974-2023)

Index	% NEVERSMOKER	% SMOKER	% QUITTER
1974	37.4	45.6	17
1976	39.1	41.8	19.1
1978	39.9	40.2	19.9
1980	40.1	39.4	20.5
1982	42.2	35.3	22.5
1984	43	34	23
1986	42.9	32.7	24.4
1988	43.7	31.6	24.7
1990	45.2	30	24.8
1992	45.6	28.4	26
1994	47.7	26.8	25.5
1996	46.9	28	25.1
1998	47.7	27.1	25.2
2000	49.6	27	23.4
2001	49.5	26.9	23.6
2002	50.2	25.9	23.9
2003	50.5	26	23.5
2004	51.8	24.6	23.6
2005	52.5	23.9	23.6
2006	54.3	22	23.7
2007	54.8	20.9	24.3

2008	53.4	21.1	25.5
2009	53.7	21	25.3
2010	54.9	20.3	24.8
2011	55.8	19.8	24.4
2012	59	20.4	20.6
2013	58.1	19.2	22.7
2014	58.6	18.8	22.6
2015	58.8	17.8	23.4
2016	59.2	16.1	24.7
2017	58.6	16.8	24.6
2018	57.2	16.6	26.2
2019	58	15.8	26.2
2020	59.8	14.5	25.7
2021	61.7	12.7	25.6
2022	63.4	11.2	25.4
2023	63.8	10.5	25.7



Bayesian Optimization for Likelihood-Free Inference (BOLFI)

- Bayesian Optimisation (BO):
 - BOLFI uses Bayesian optimisation to efficiently explore the parameter space, focusing on regions where the discrepancy between observed and simulated data is minimised.
 - It builds a probabilistic surrogate model (often a Gaussian Process) to approximate the relationship between parameters and the discrepancy.
- Likelihood-Free Inference (LFI):
 - Instead of computing the likelihood, BOLFI relies on forward simulations from the model to compare simulated and observed data using a distance metric.



Bayesian Optimization for Likelihood-Free Inference (BOLFI)

- Active Learning:
 - BOLFI sequentially selects new parameter points to evaluate, balancing exploration (uncertain regions) and exploitation (promising regions).
- Posterior Estimation:
 - After optimisation, BOLFI provides an approximation of the posterior distribution over parameters, conditioned on observed data.



Simulations were conducted in the following settings:

- 1000 agents in total, with the initial configuration of agents in each state as same as the data in 1974.
- Erdős-Rényi graph: $n = 1000$, $p = 0.003$.
- All simulated data were generated in the same format as the observed data.



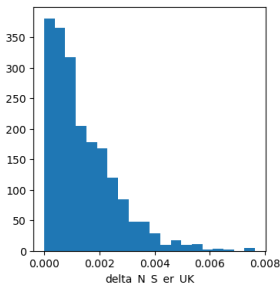
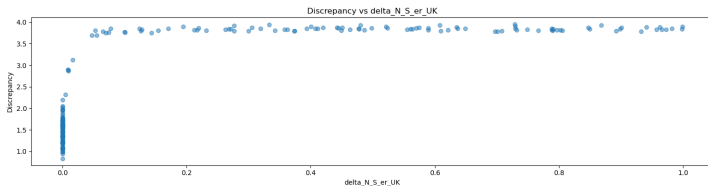
BOLFI were conducted in the following settings:

- Initially, $U(0, 1)$ priors for all parameters need to be calibrated. All other parameters adhere to Adarsh's best-fitted values.
- Running BOLFI multiple times, update the priors each time with the knowledge of posteriors obtained from last run.
- Summary statistics were chosen to focus solely on % SMOKER and % QUITTER.
- Discrepancies were measured by Euclidean distance.



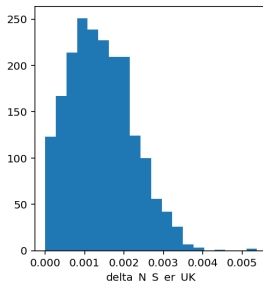
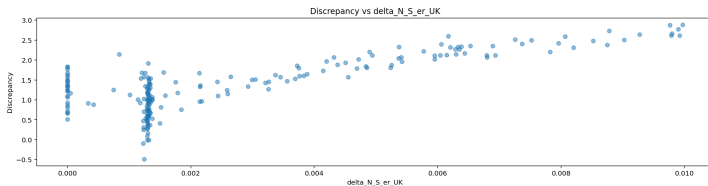
Single Parameter Calibration: $\delta_{N \rightarrow S}$

Progress [=====] 100.0% Complete
INFO:elfi.methods.posterior:Using optimized minimum value (1.0923) of the GP discrepancy mean function as a threshold
Parameter order: ['delta_N_S_er_UK']
Optimal parameters: [0.]
Lowest discrepancy: 0.6132592749354379



Single Parameter Calibration: $\delta_{N \rightarrow S}$

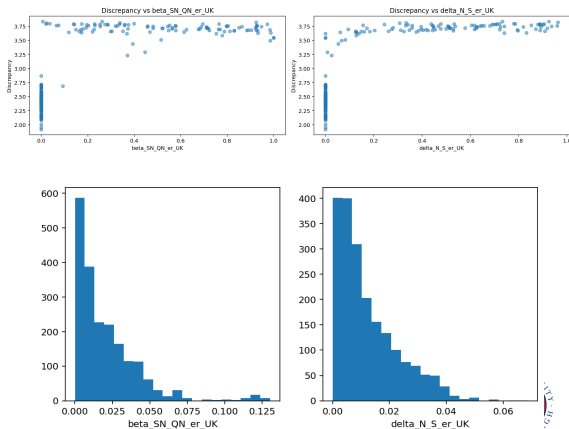
Progress [=====] 100.0% Complete
INFO:elfi.methods.posterior:Using optimized minimum value (0.9082) of the GP discrepancy mean function as a threshold
Parameter order: ['delta_N_S_er_UK']
Optimal parameters: [0.00124621]
Lowest discrepancy: -0.48578787381379557



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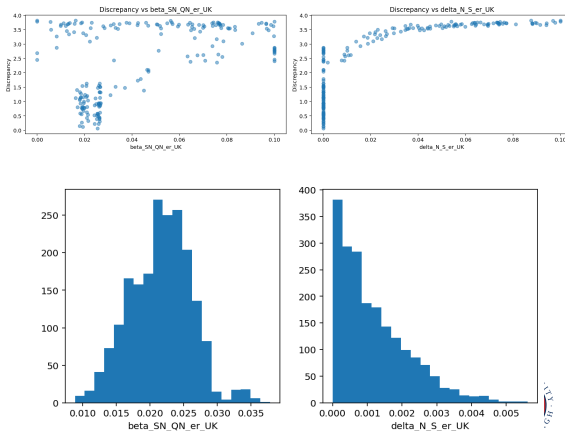
Multiple Parameter Calibration: $\delta_{N \rightarrow S}$ and $\beta_{S, N \rightarrow Q, N}$

Progress [=====] 100.0% Complete
INFO:elfi.methods.posterior:Using optimized minimum value (2.3336) of the GP discrepancy mean function as a threshold
Parameter order: ['beta_SN_QN_er_UK', 'delta_N_S_er_UK']
Optimal parameters: [0. 0.]
Lowest discrepancy: 1.696110031128523



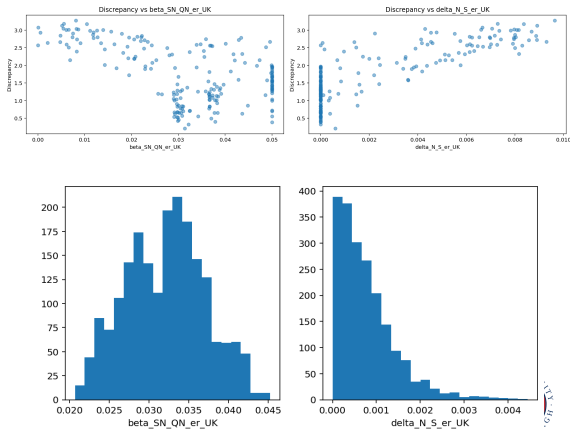
Multiple Parameter Calibration: $\delta_{N \rightarrow S}$ and $\beta_{S, N \rightarrow Q, N}$

Progress [=====] 100.0% Complete
INFO:elfi.methods.posterior:Using optimized minimum value (0.8534) of the GP discrepancy mean function as a threshold
Parameter order: ['beta_SN_QN_er_UK', 'delta_N_S_er_UK']
Optimal parameters: [0.02548205 0.]
Lowest discrepancy: 0.0680702755335927



Multiple Parameter Calibration: $\delta_{N \rightarrow S}$ and $\beta_{S, N \rightarrow Q, N}$

Progress [=====] 100.0% Complete
INFO:elfi.methods.posterior:Using optimized minimum value (0.9195) of the GP discrepancy mean function as a threshold
Parameter order: ['beta_SN_QN_er_UK', 'delta_N_S_er_UK']
Optimal parameters: [0.03136718 0.00060317]
Lowest discrepancy: 0.21547180032784316



Multiple Parameter Calibration: $\delta_{N \rightarrow S}$, $\delta_{S \rightarrow Q}$ and $\beta_{S, N \rightarrow Q, N}$

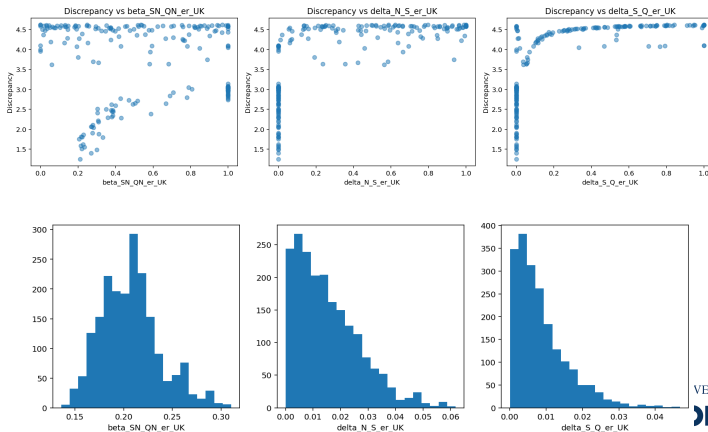
Progress [=====] 100.0% Complete

INFO:elfi.methods.posterior:Using optimized minimum value (0.9245) of the GP discrepancy mean function as a threshold

Parameter order: ['beta_SN_QN_er_UK', 'delta_N_S_er_UK', 'delta_S_Q_er_UK']

Optimal parameters: [0.20487315 0. 0.]

Lowest discrepancy: 0.8915782537926839



Multiple Parameter Calibration: $\delta_{N \rightarrow S}$, $\delta_{S \rightarrow Q}$ and $\beta_{S,N \rightarrow Q,N}$

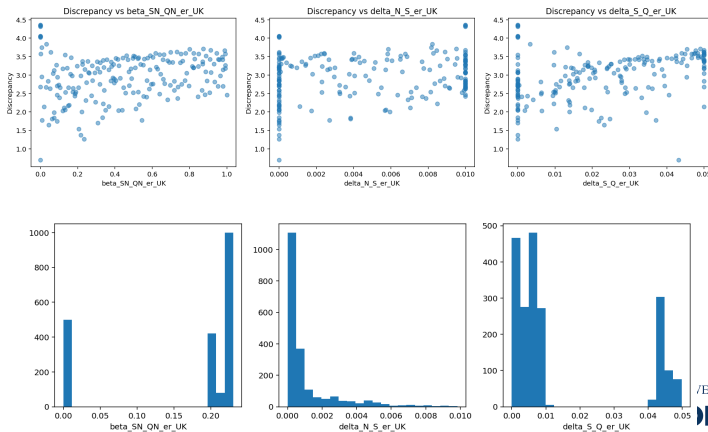
Progress [=====] 100.0% Complete

INFO:elfi.methods.posterior:Using optimized minimum value (0.7131) of the GP discrepancy mean function as a threshold

Parameter order: ['beta_SN_QN_er_UK', 'delta_N_S_er_UK', 'delta_S_Q_er_UK']

Optimal parameters: [0. 0. 0.04314278]

Lowest discrepancy: 0.7008915564221276



Multiple Parameter Calibration: $\delta_{N \rightarrow S}$, $\delta_{S \rightarrow Q}$ and $\beta_{S,N \rightarrow Q,N}$

Progress [=====] 100.0% Complete

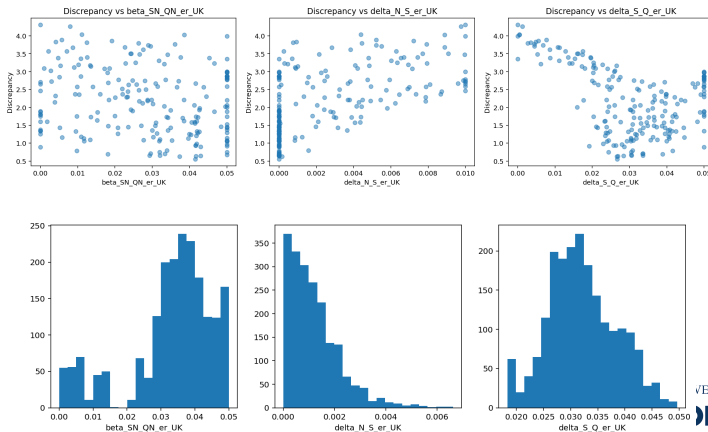
INFO:elfi.methods.posterior:Using optimized minimum value (1.1219) of the GP discrepancy mean function as a threshold

Parameter order: ['beta_SN_QN_er_UK', 'delta_N_S_er_UK', 'delta_S_Q_er_UK']

Optimal parameters: [0.0415803 0.

0.02673271]

Lowest discrepancy: 0.5563485802224686



It can be observed that,

- BOLFI works very well when calibrating less parameters;
- the minimum discrepancy keeps improving as the priors being refined;
- the optimal values of the calibrated parameters can be clearly observed from the sample posterior after certain numbers of run of BOLFI;
- However, when calibrating more parameters the obtained results can be very confused. Therefore, it needs extra guesses when updating the priors with the obtained knowledge of the posteriors;



Possible Direction for Further Improvements

- It could be helpful to increase the number of evidence and fit when calibrating more parameters.
- Improving the measures of summary statistics (e.g. rolling summary statistics) could help to capture how the smoking trend evolves over time.



The End

Thank you very much for your time!



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