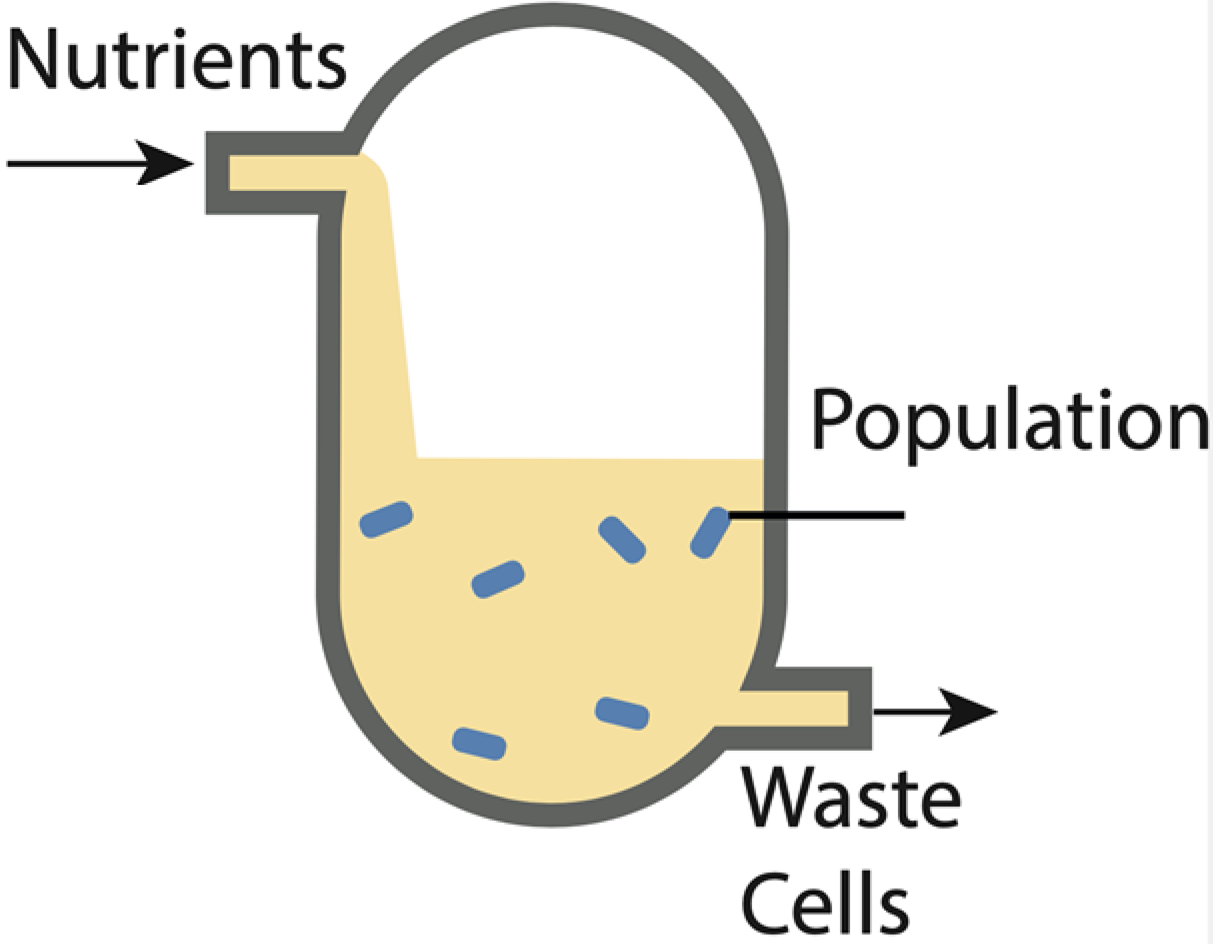
Bioreactor control

Deep reinforcement learning for the control of microbial co-cultures in bioreactors

Neythen J. Treloar, Alex J. H. Fedorec, Brian Ingalls, Chris P. Barnes

Motivation

- We can use genetically engineered cells to produce useful products e.g. Insulin



Motivation

Co-cultures have been shown to perform better at many functions

- Production of ethanol for Biofuels, using two E.coli strains [1] and four yeast strains [2]
- Fermentation of xylose and glucose [3]

Co-cultures allow us to divide the metabolic load exerted by complex reaction pathways [4]

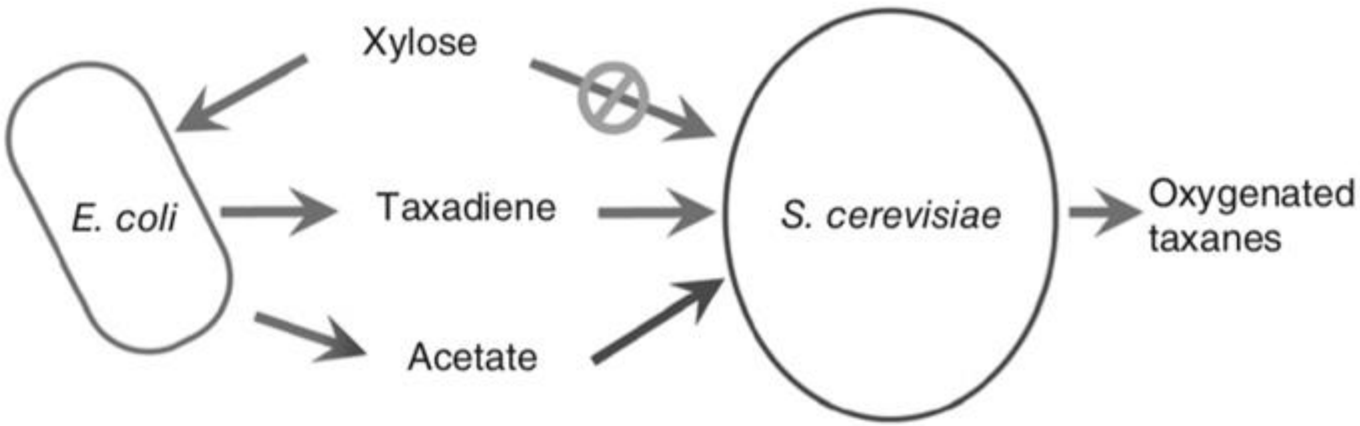


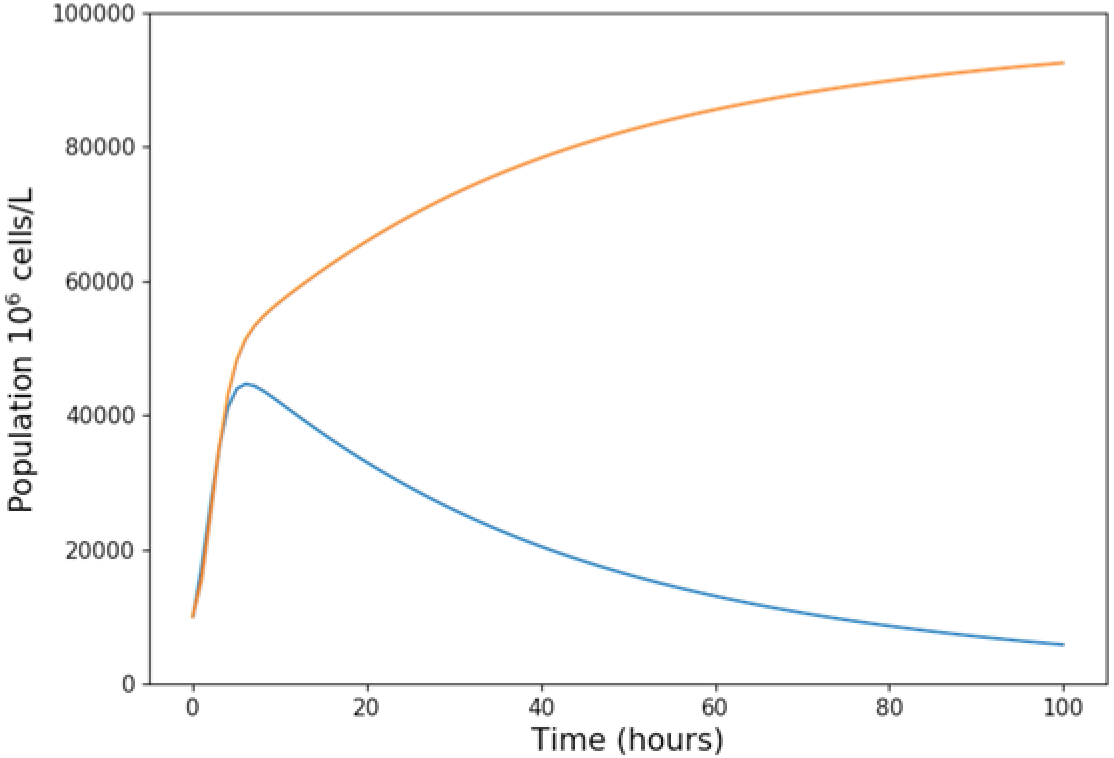
Image reproduced from [4]

[1] Hyun-Dong Shin et al. "Escherichia coli binary culture engineered for direct fermentation of hemicellulose to a biofuel" (2010)
[2] Garima Goyal et al. "Simultaneous cell growth and ethanol production from cellulose by an engineered yeast consortium displaying a functional mini-cellulosome" (2011)
[3] Mark A Eiteman, Sarah A Lee, and Elliot Altman. "A co-fermentation strategy to consume sugar mixtures effectively" (2008)
[4] Kang Zhou et al. "Distributing a metabolic pathway among a microbial consortium enhances production of natural products" (2015)

Motivation

Barriers to the adoption of co-cultures include:

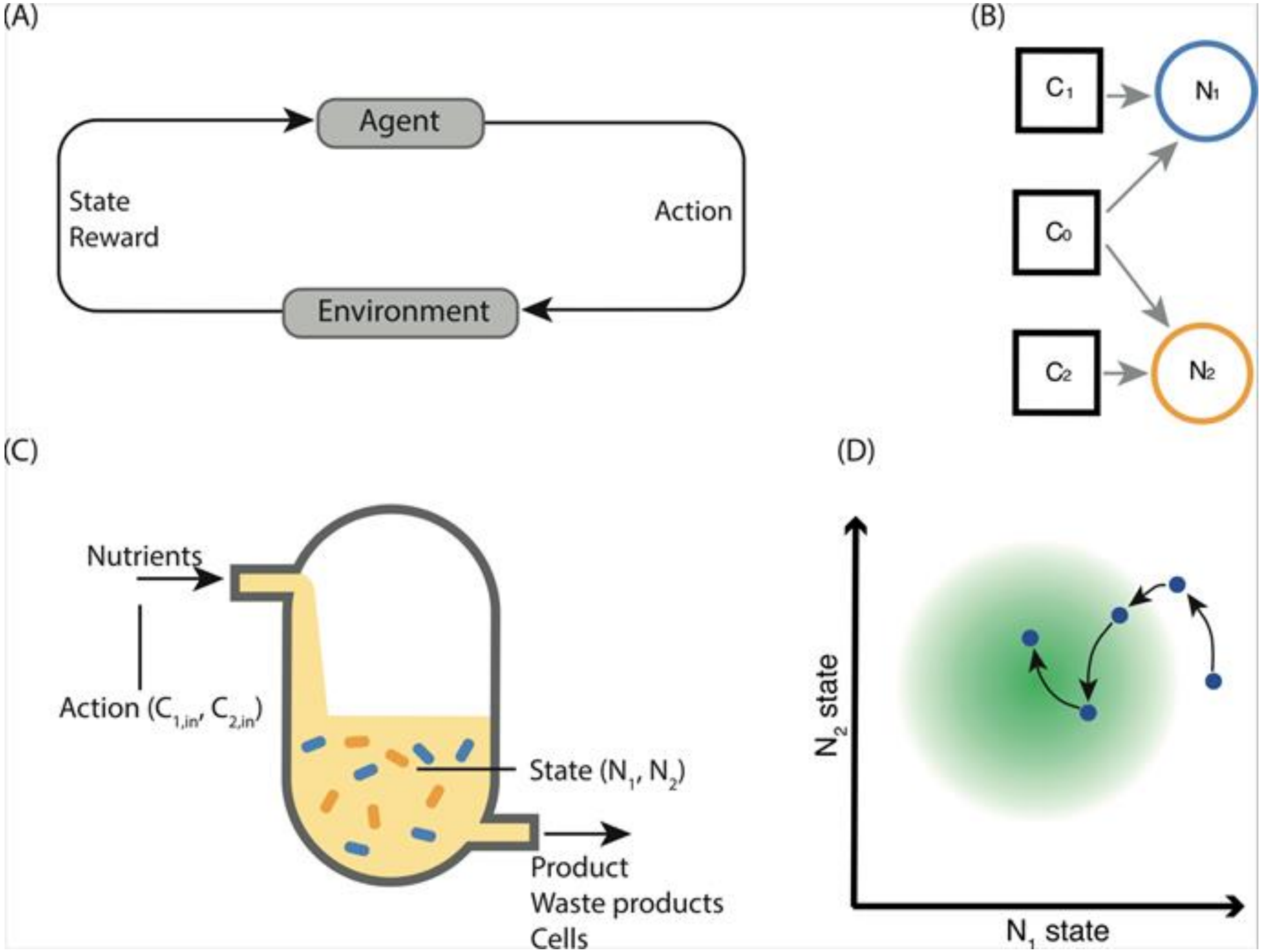
- Competitive exclusion
- Hard to predict long term behavior, due to factors such as genetic drift [5]
- The increasing difficulty to establish a stable system as the number of populations is increased [6]



[5] Matthew S Croughan, Konstantin B Konstantinov, and Charles Cooney. “The future of industrial bioprocessing: Batch or continuous?” (2015)

[6] Jasmine Shong, Manuel Rafael Jimenez Diaz, and Cynthia H Collins. “Towards synthetic microbial consortia for bioprocessing” (2012)

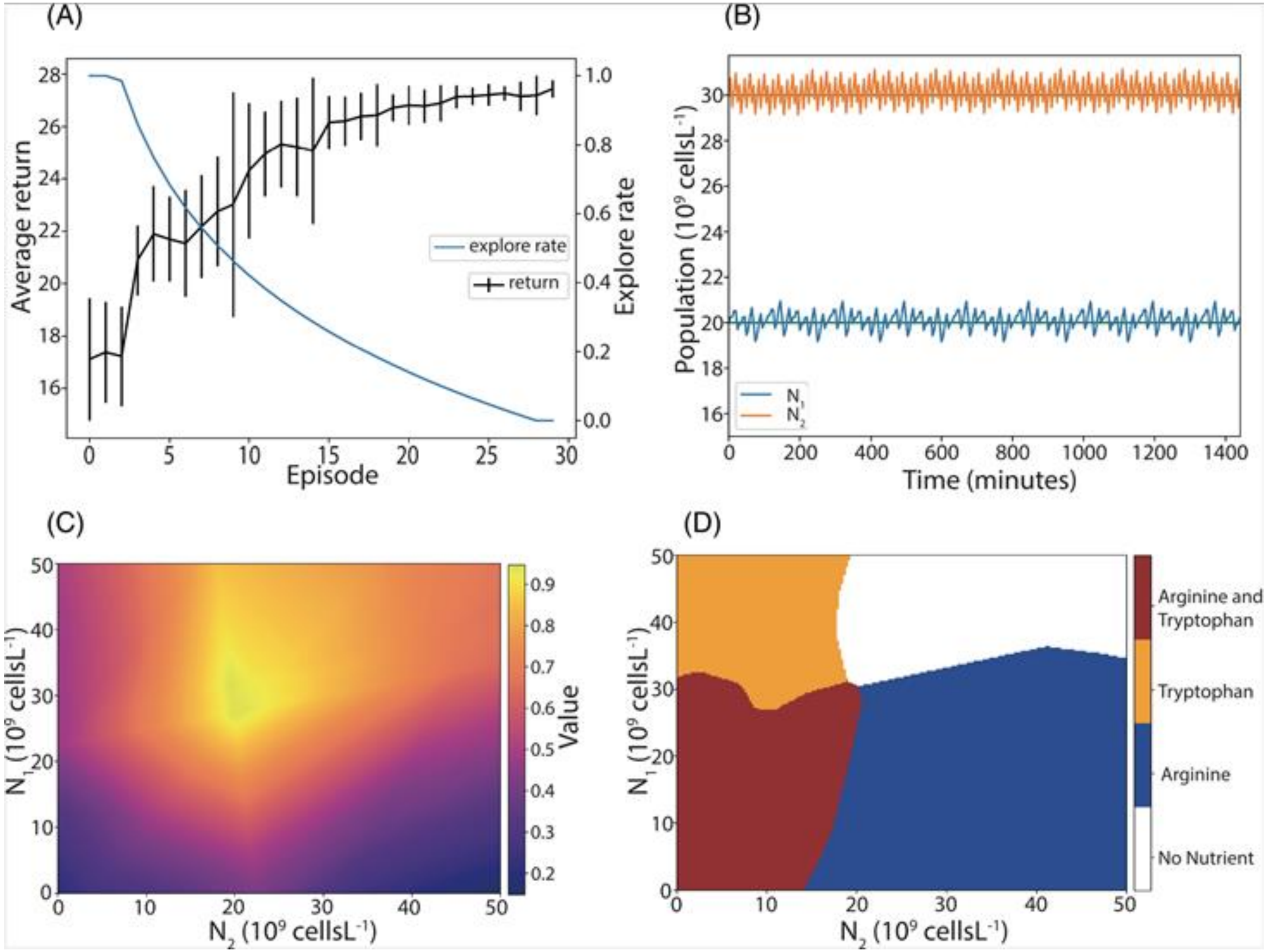
System setup



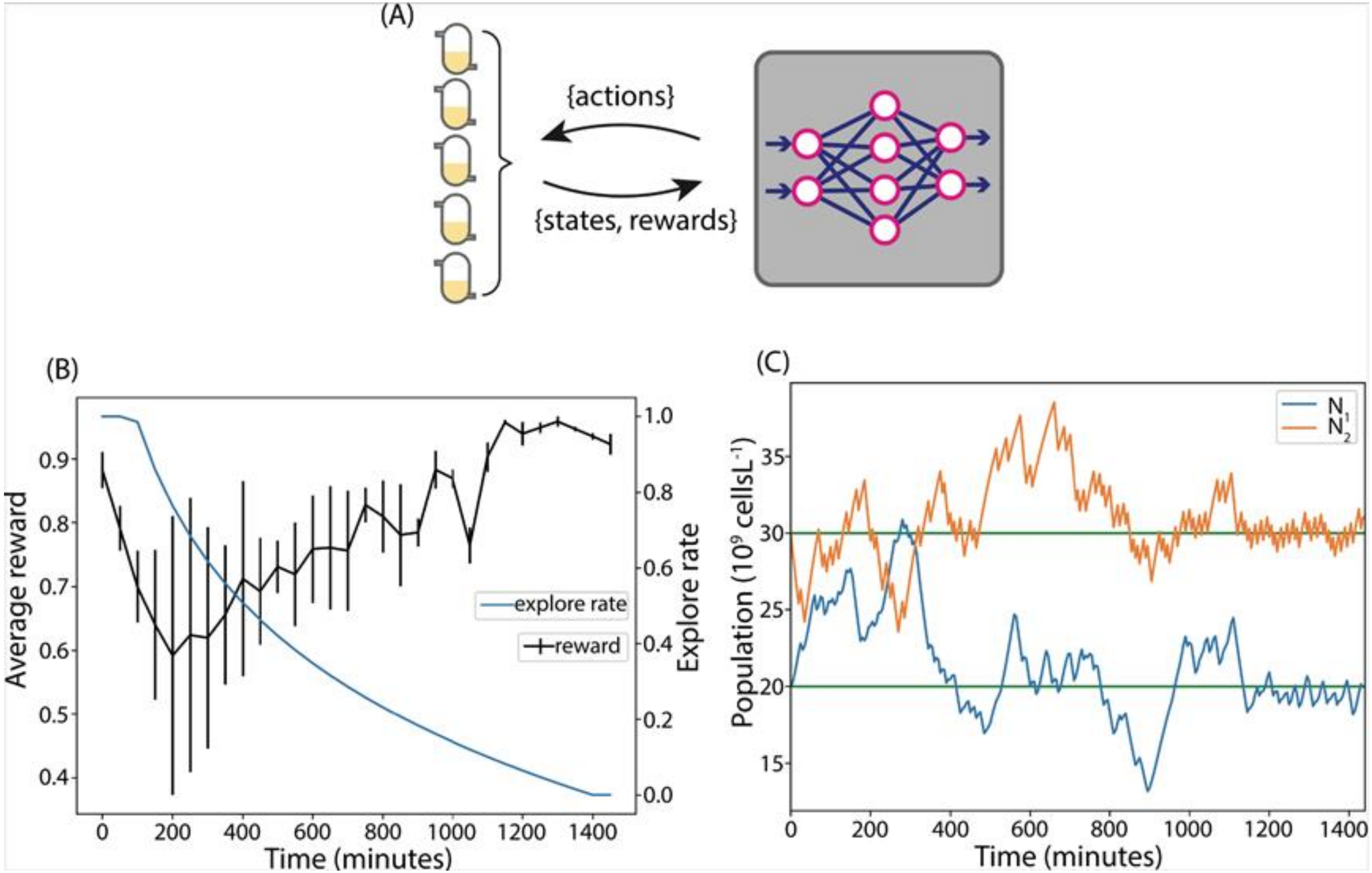
Deep reinforcement learning for the control of microbial co-cultures in bioreactors

Neythen J. Treloar, Alex J. H. Fedorec, Brian Ingalls, Chris P. Barnes

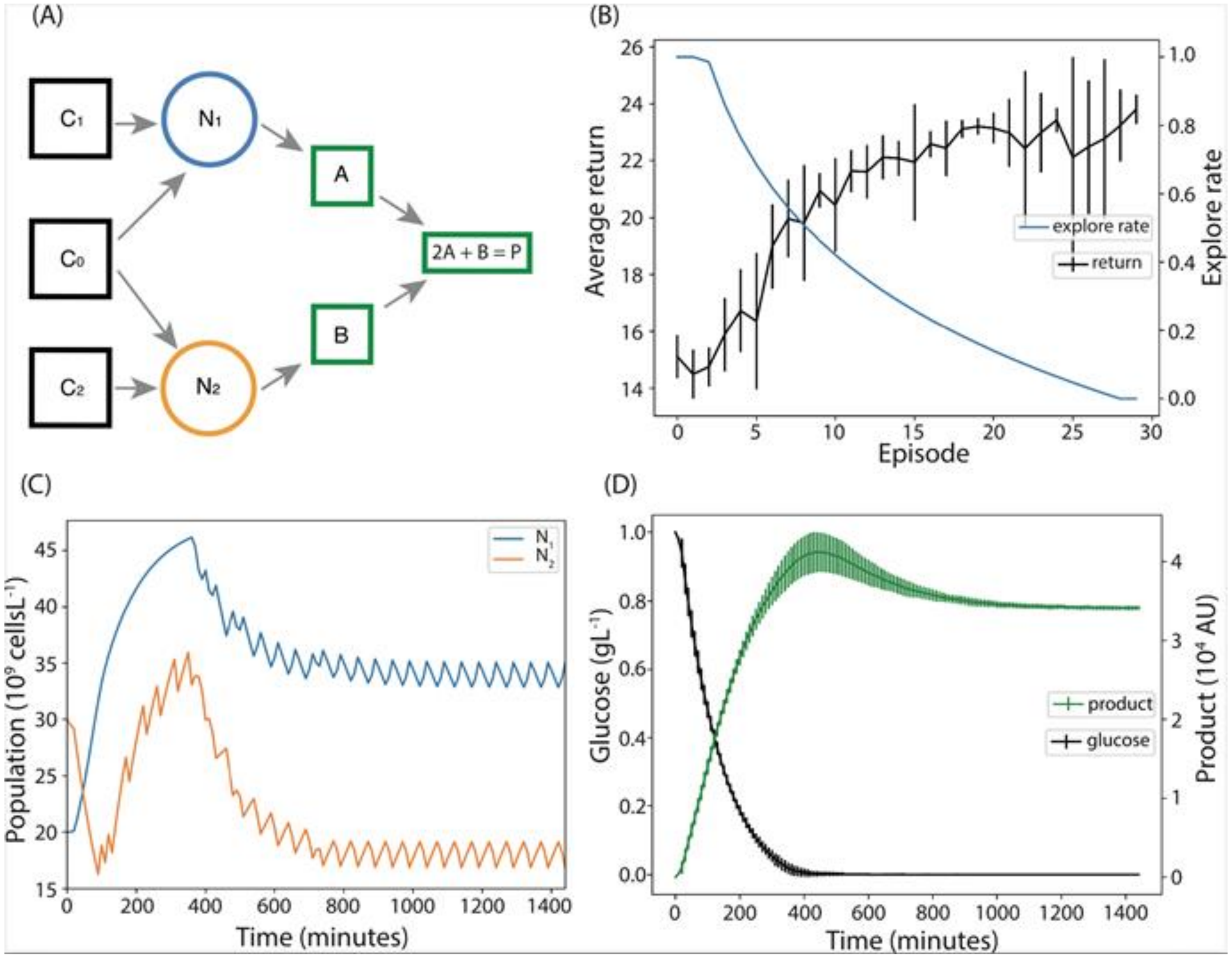
Control


(A)
Average return
Explore rate
Episode
explore rate
return
(B)
Population (10^9 cellsL^{-1})
Time (minutes)
N_1
N_2
(C)
N_1 (10^9 cellsL^{-1})
N_2 (10^9 cellsL^{-1})
Value
(D)
N_1 (10^9 cellsL^{-1})
N_2 (10^9 cellsL^{-1})
Arginine and Tryptophan
Tryptophan
Arginine
No Nutrient

Data efficiency



Product optimisation



Optimal experimental design

Deep reinforcement learning for optimal experimental design in biology

Neythen J. Treloar, Nathan Braniff, Brian Ingalls, Chris P. Barnes