Reward Based Decision Making

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Sloan-Swartz Meeting 2004, CSHL

Outline

- Adaptive decision making and matching task

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- Spiking network model for decision making

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- Reward gated plasticity

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- Reward gated plasticity
- Simulation results

Adaptive Decision Making

Real World

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- Social and economic interactions

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- Foraging behavior in natural environment

Real World

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Foraging behavior

Matching Law

The animal allocates its time between competing *choices* in a manner that it matches the relative *return* from those choices.

$$\frac{C_i}{C_1 + C_2 + ... + C_n} = \frac{R_i}{R_1 + R_2 + ... + R_n}$$

$$return = (reward\ magnitude) \times (rate)$$

Herrnstein R.J., "The Matching Law, Papers in Psychology and Economics"

Remarks and Motive

- Why do they match?

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- Why do they match?

- What is the local choice rule?

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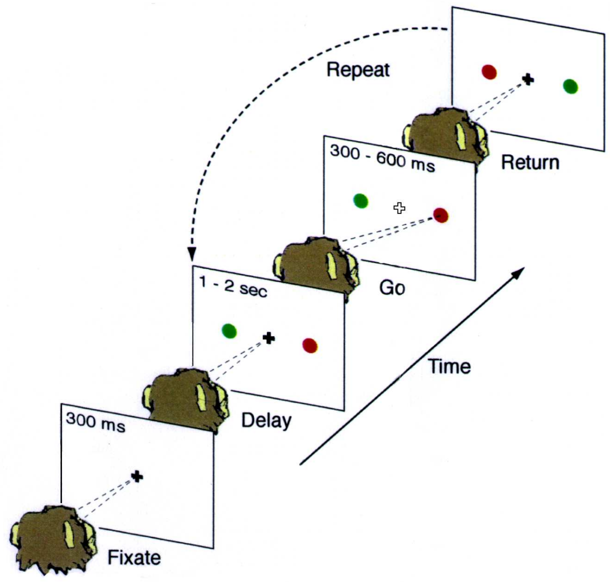
- What is the local choice rule?
- What is the neural basis of the matching behavior?

Remarks and Motive

What is the neural basis of the matching behavior?

Matching Task in Monkeys



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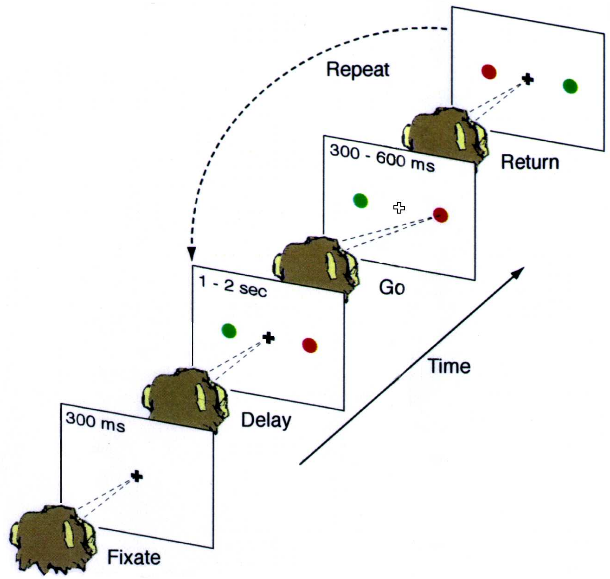

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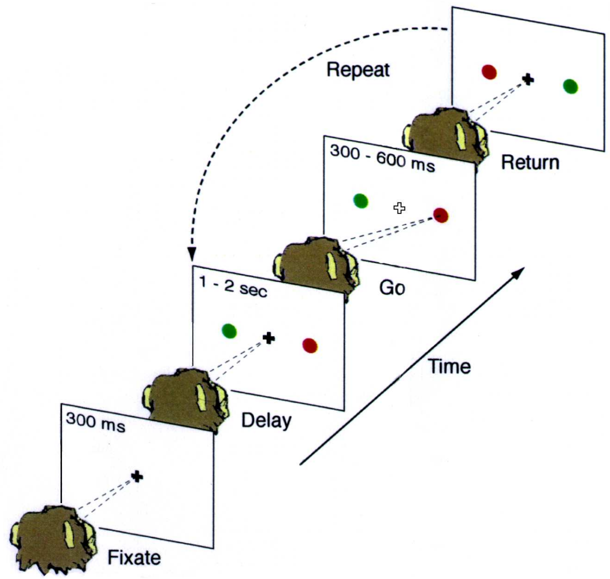

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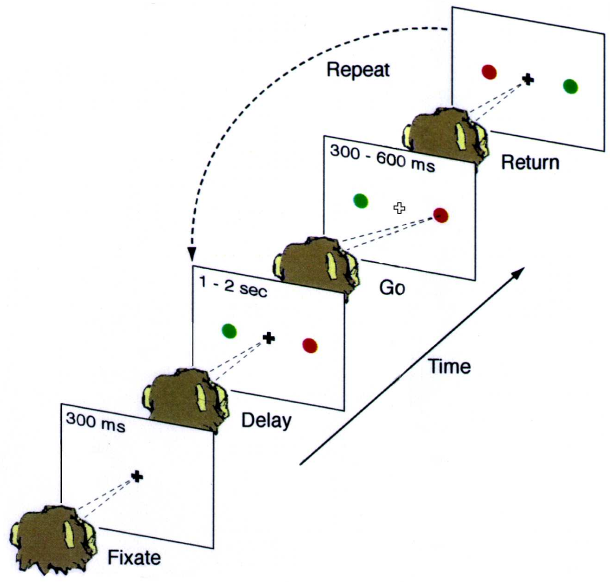

- reward assignment is stochastic
- reward is persistent
- changeover delay

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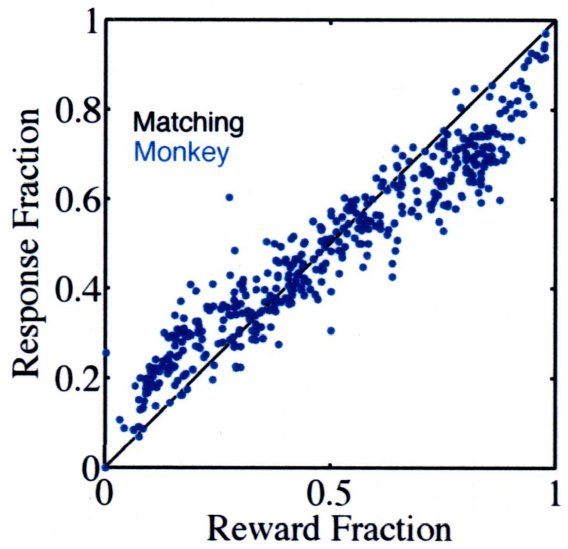
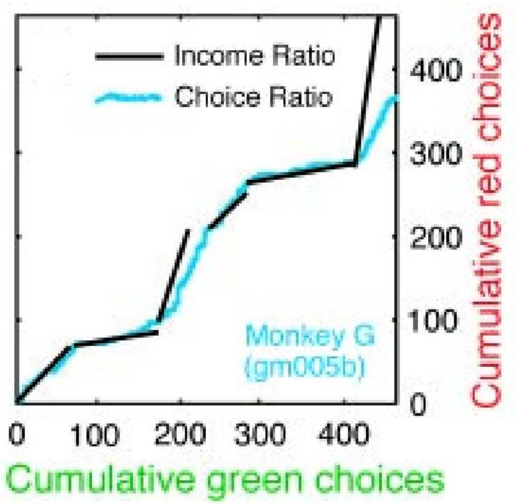
Matching Behavior

Monkeys show approximate matching.





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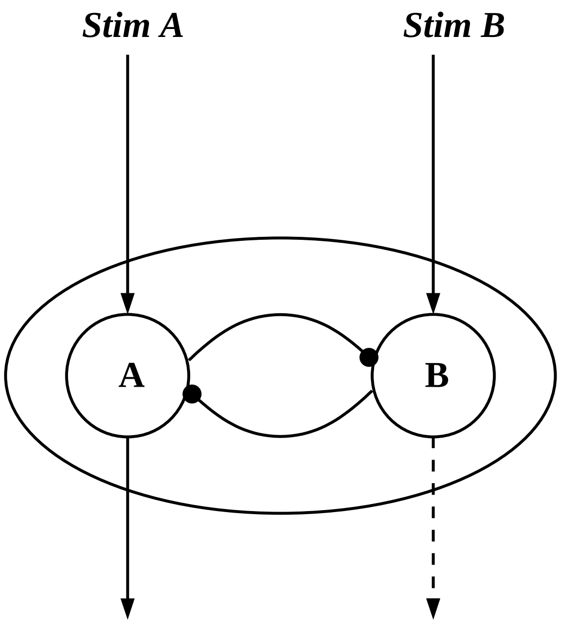
Spiking Network Model

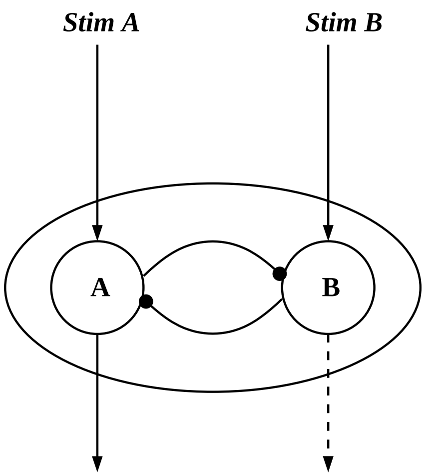
Network Behavior

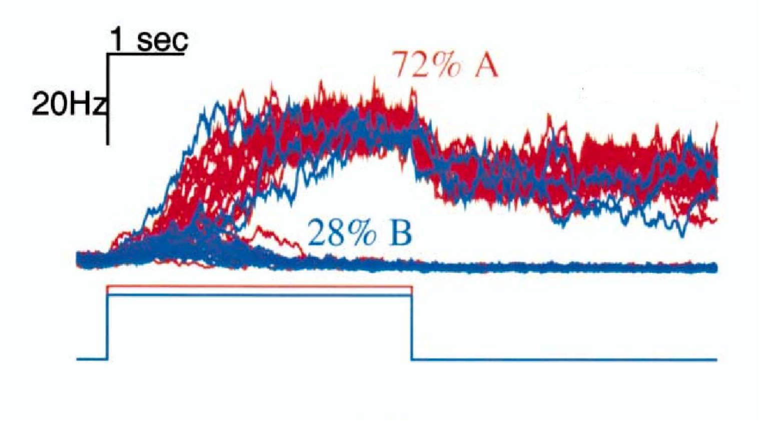
A decision-making network with winner-takes-all property.



Network Behavior

The network choice is determined by:
1. Strength of the inputs
2. Intrinsic noise in the neurons spiking



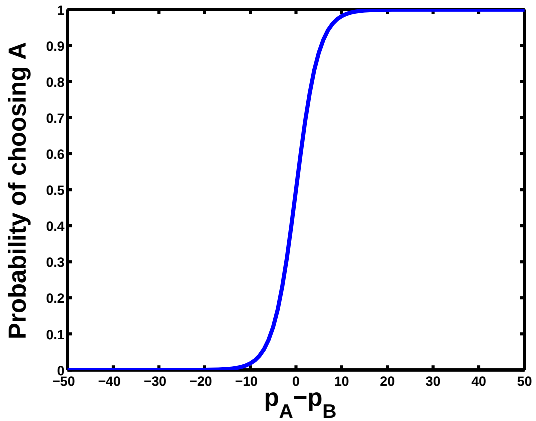


Wang X.J., Neuron 2002

Stochastic Response

The stochastic network behavior as a function of synaptic strengths is approximately sigmoidal.

$$\Pi = \frac{1}{1+\exp\left(-\frac{p_A - p_B}{\sigma}\right)}$$



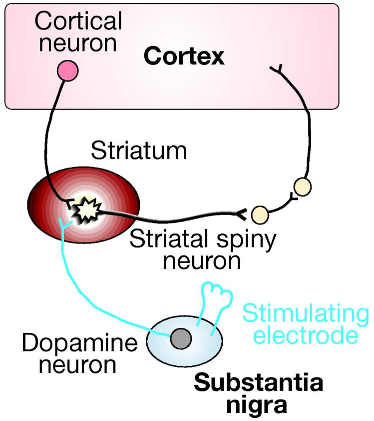
p_A : Probability of afferent synapses to population A being in potentiated state.

σ : Sensitivity of the network to the biased inputs

Reward Gated Plasticity

Three-factor Rule

Three factors for dopamine-dependent plasticity:
presynaptic activity, postsynaptic activity, dopamine (reward signal).



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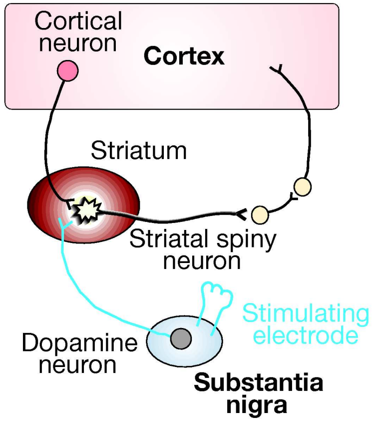

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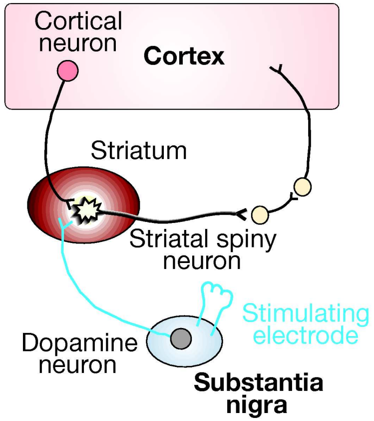

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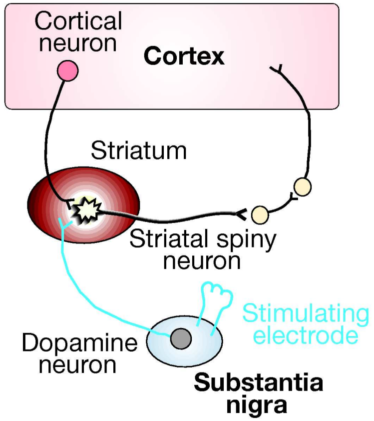
- $(pre \uparrow post \downarrow)+$ Dopamine $\rightarrow$ LTD/LTP



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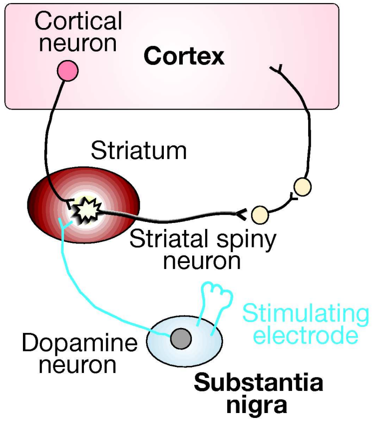
- $(pre \uparrow post \downarrow)+$ Dopamine $\rightarrow$ LTD/LTP
- $(pre \uparrow post \downarrow)+$No Dopamine $\rightarrow$No change



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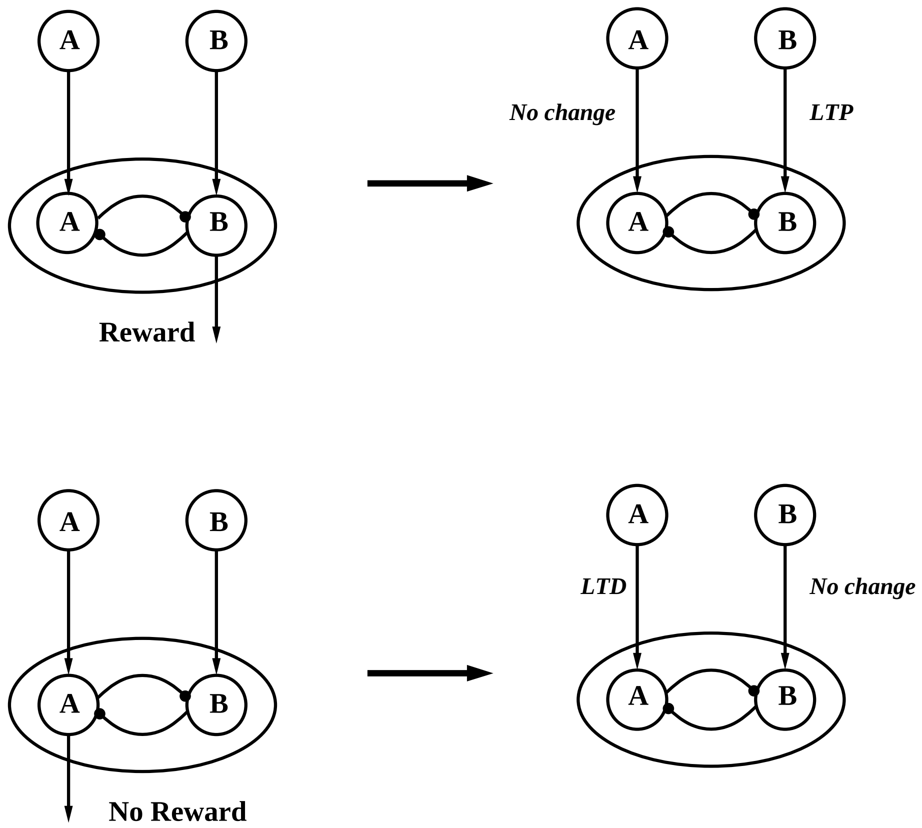
Learning Rule

Assumptions:

Presynaptic side is always active.

Postsynaptic side is active only for the winner population.



Stochastic Learning

If the condition for learning is met, only a fraction of synapses are changed.

Amit D.J., Fusi S., Neural Comp. 1994

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- Potentiation: $\Delta p_A = (1 - p_A) q_+$

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Stochastic Learning

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- Potentiation: $\Delta p_A = (1 - p_A) q_+$
- Depression: $\Delta p_A = -p_A q_-$

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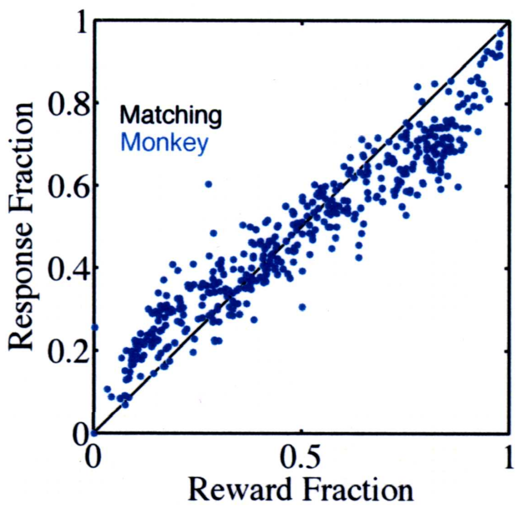
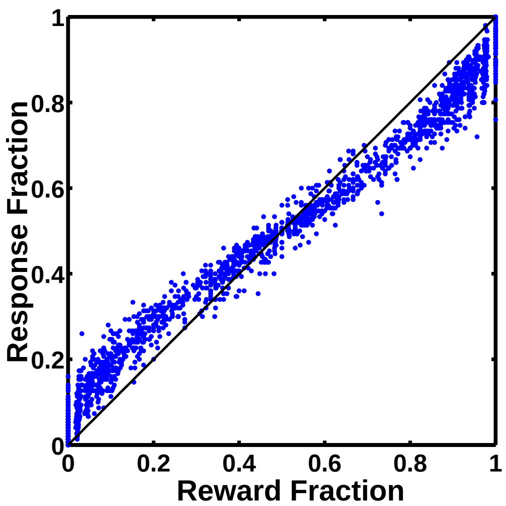
Simulation Results

Global Behavior

Model mimics the monkey's matching behavior.

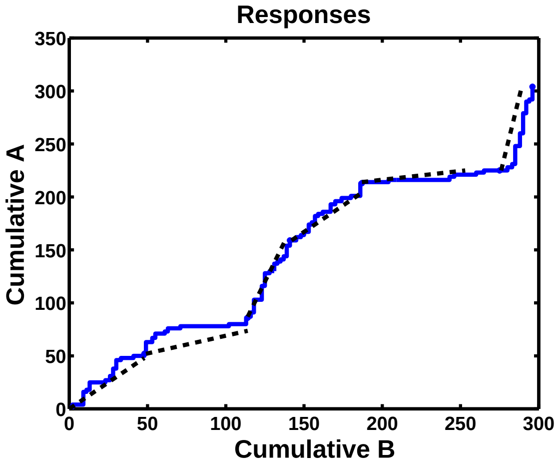


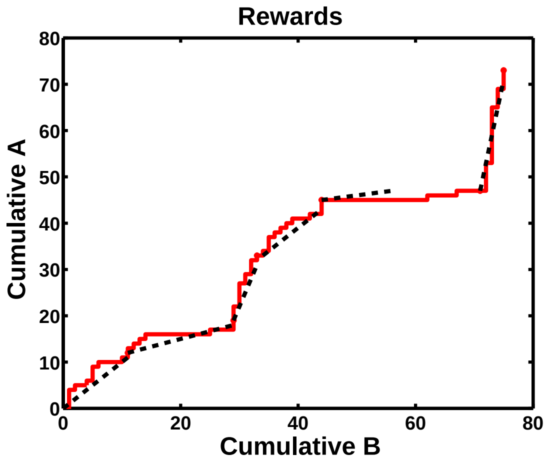


Sugrue L.P., Corrado G.S., Newsome W.T., Science 2004

Local Behavior

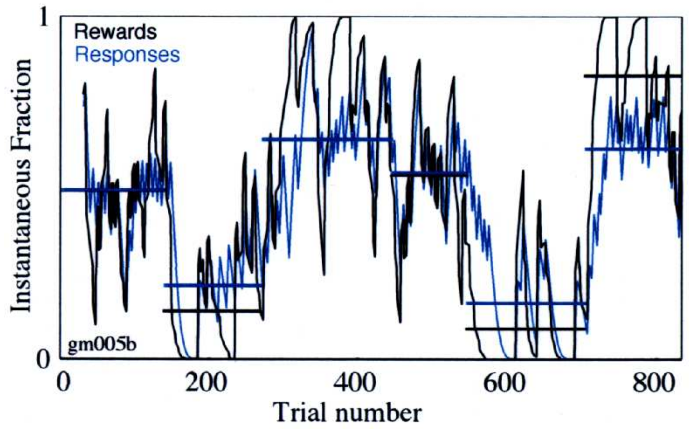
Model is able to track changes in the reward schedule.

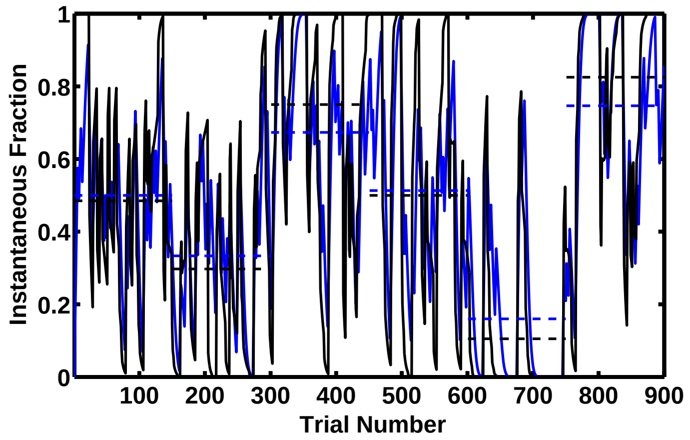




Reward Tracking

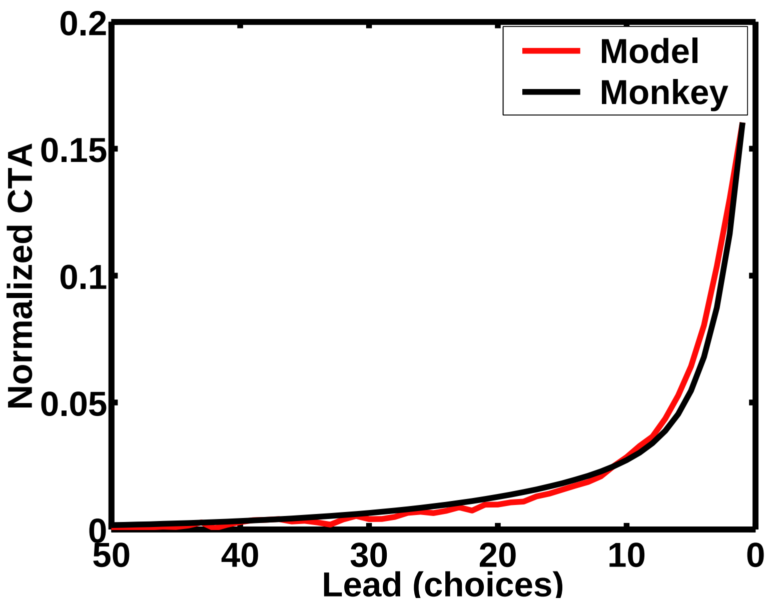
Model tracks random changes in the reward delivery.





Choice-Triggered Averages

Model is able to replicate the CTA curve.



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Model shows matching behavior and high reward harvesting rate for a wide range of parameters.

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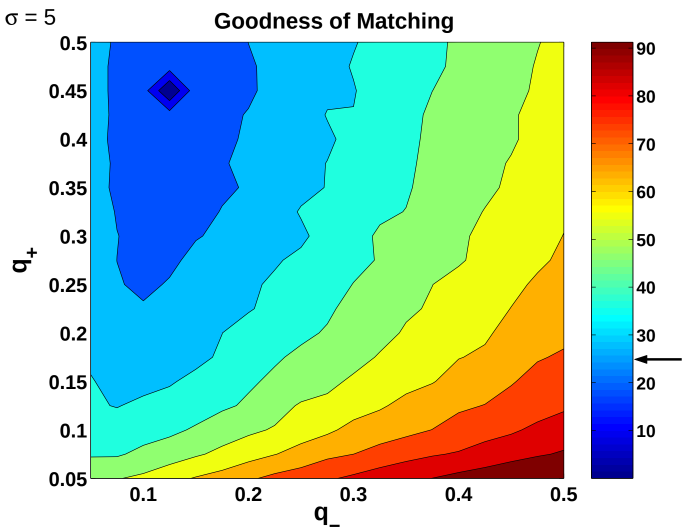

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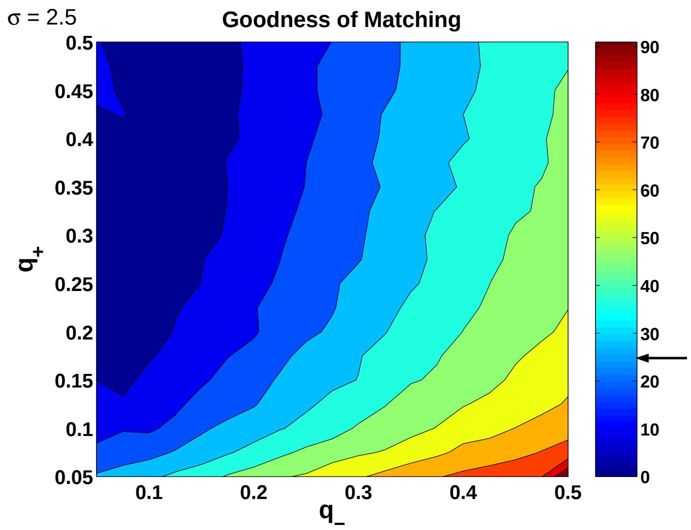

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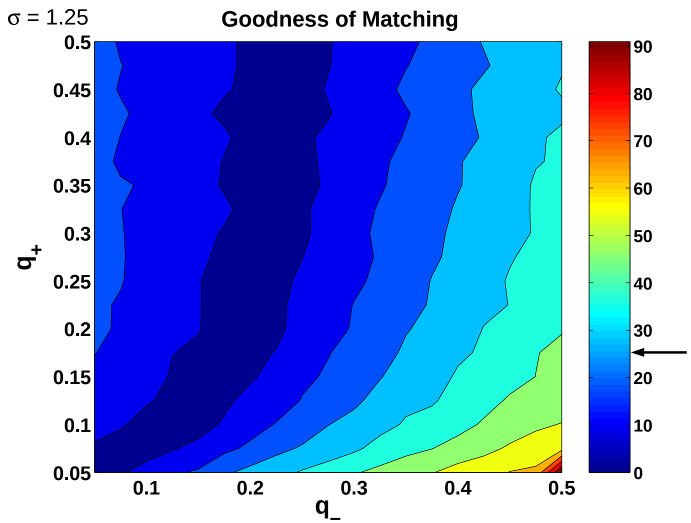

Robustness

Model shows matching behavior and high reward harvesting rate for a wide range of parameters.

Model is able to perform the matching task for different overall reward rates.

Conclusion

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- Prediction ...

Acknowledgment

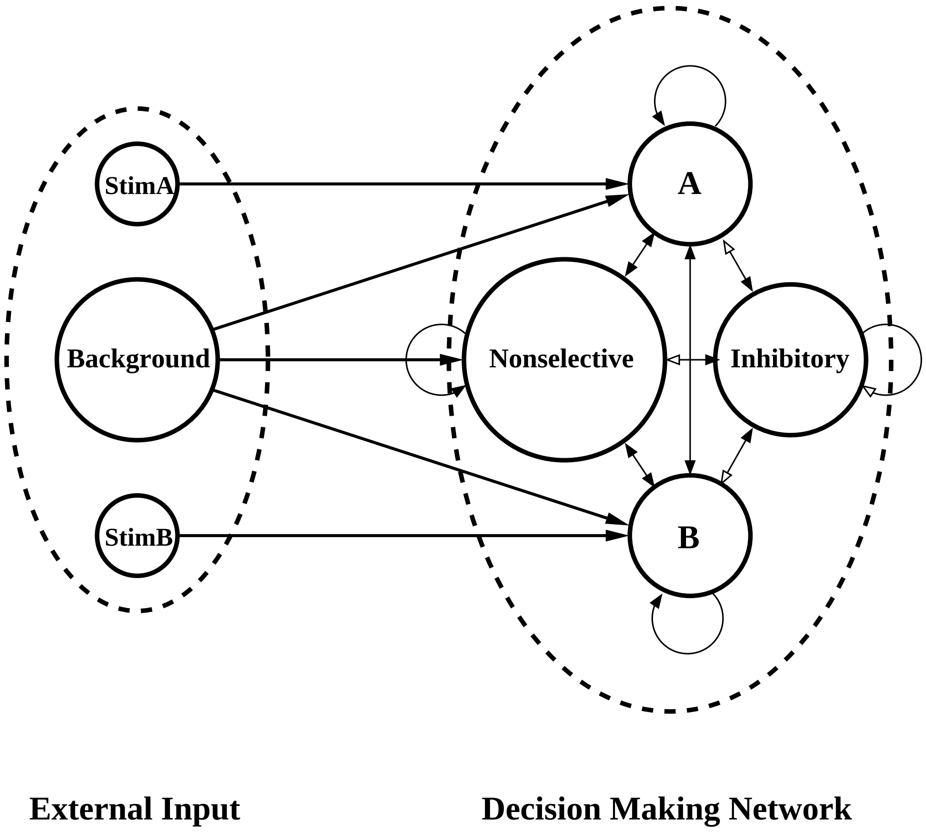
Stefano Fusi

Leo Sugrue

Wanglab members

Network Architecture

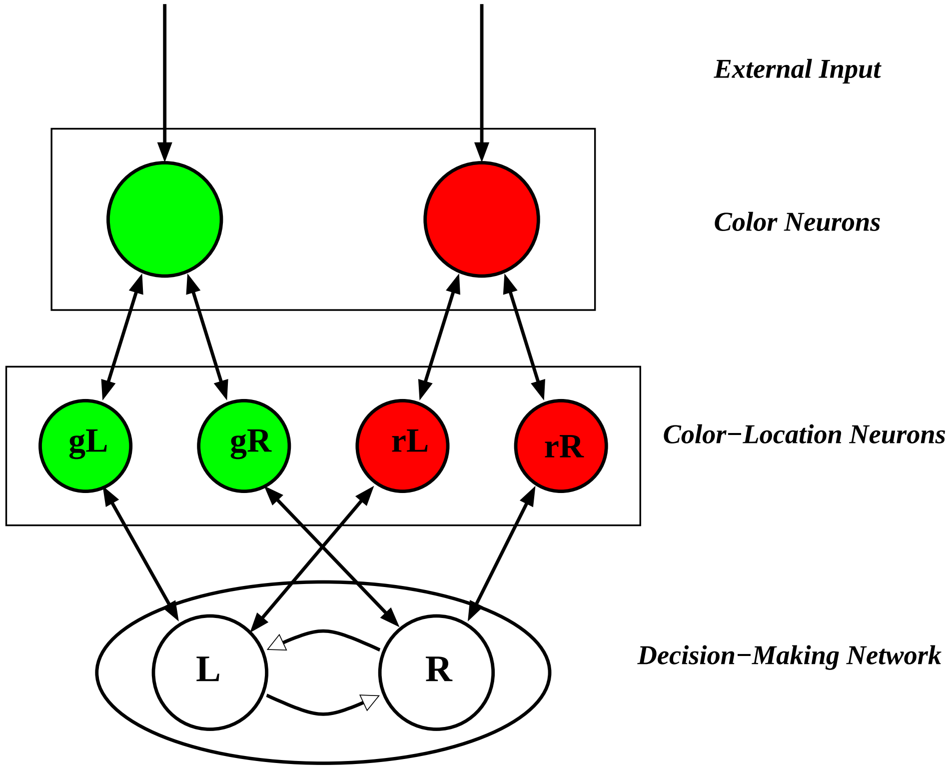
Decision-making network with winner-take-all property.



Wang X.J., Neuron 2002

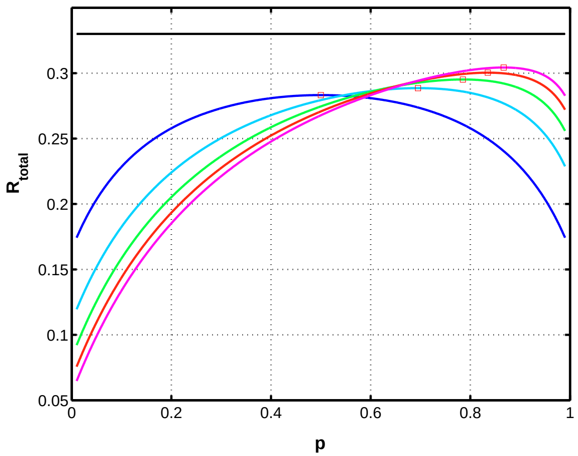
Full Network

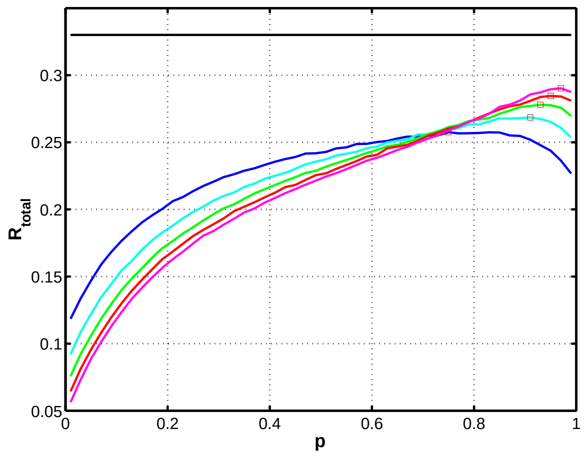
A model which is able to perform remapping.



Introducing Changeover Delay

Introducing changeover delay, results in steeper total reward harvesting rate.





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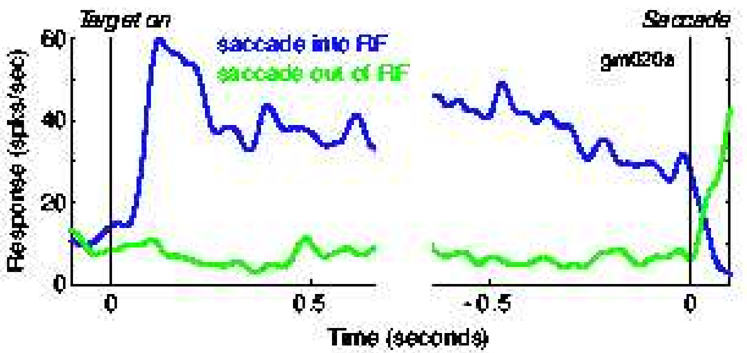
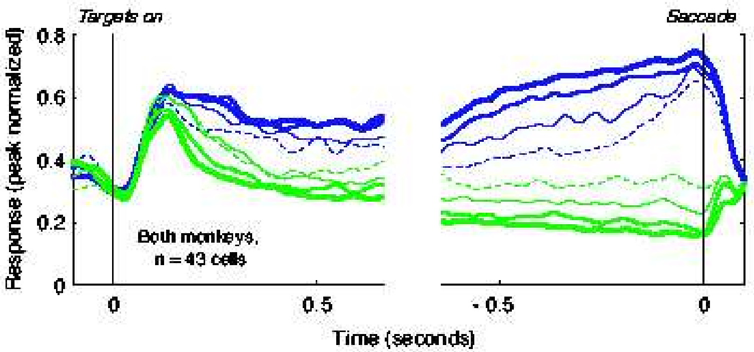
$$\frac{p_{opt}}{1 - p_{opt}} = \sqrt{\frac{T_1'}{T_2'} \times \frac{R_1}{R_2}}$$

Neuronal Recordings

Neurons in area LIP encode the local reward income.





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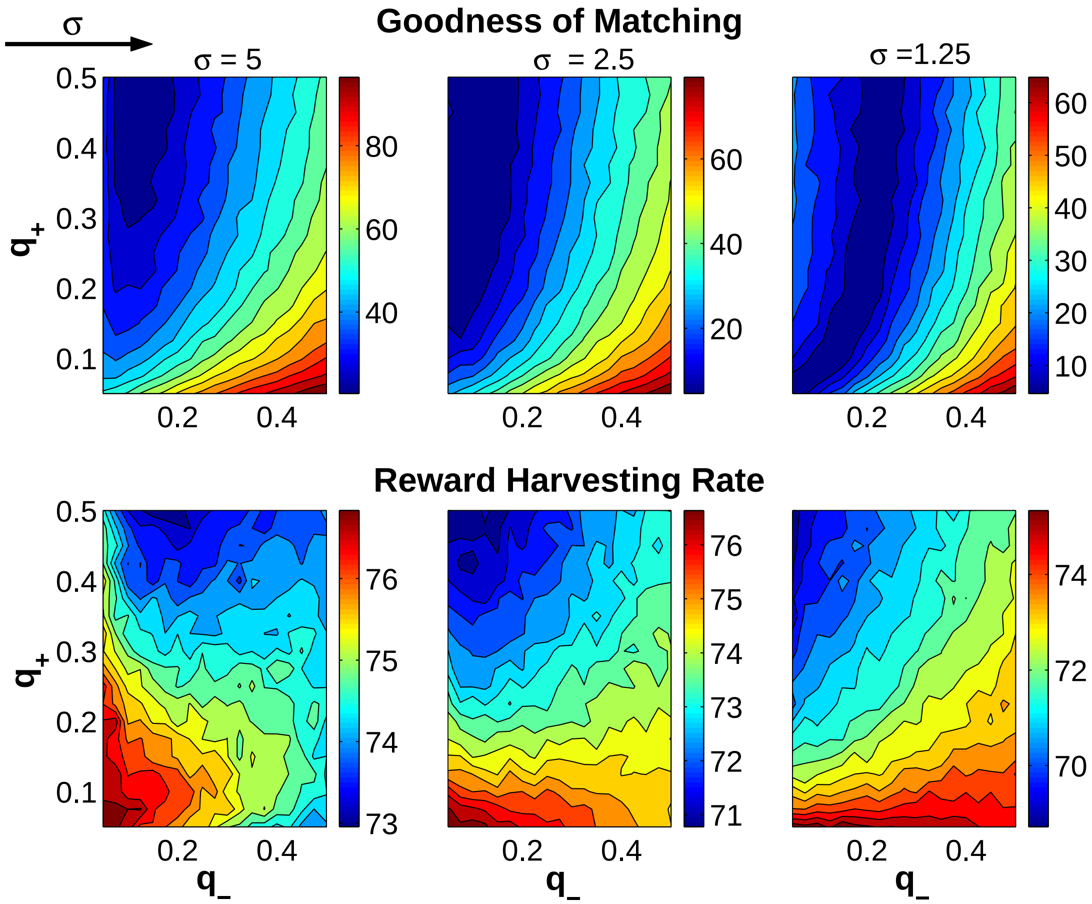

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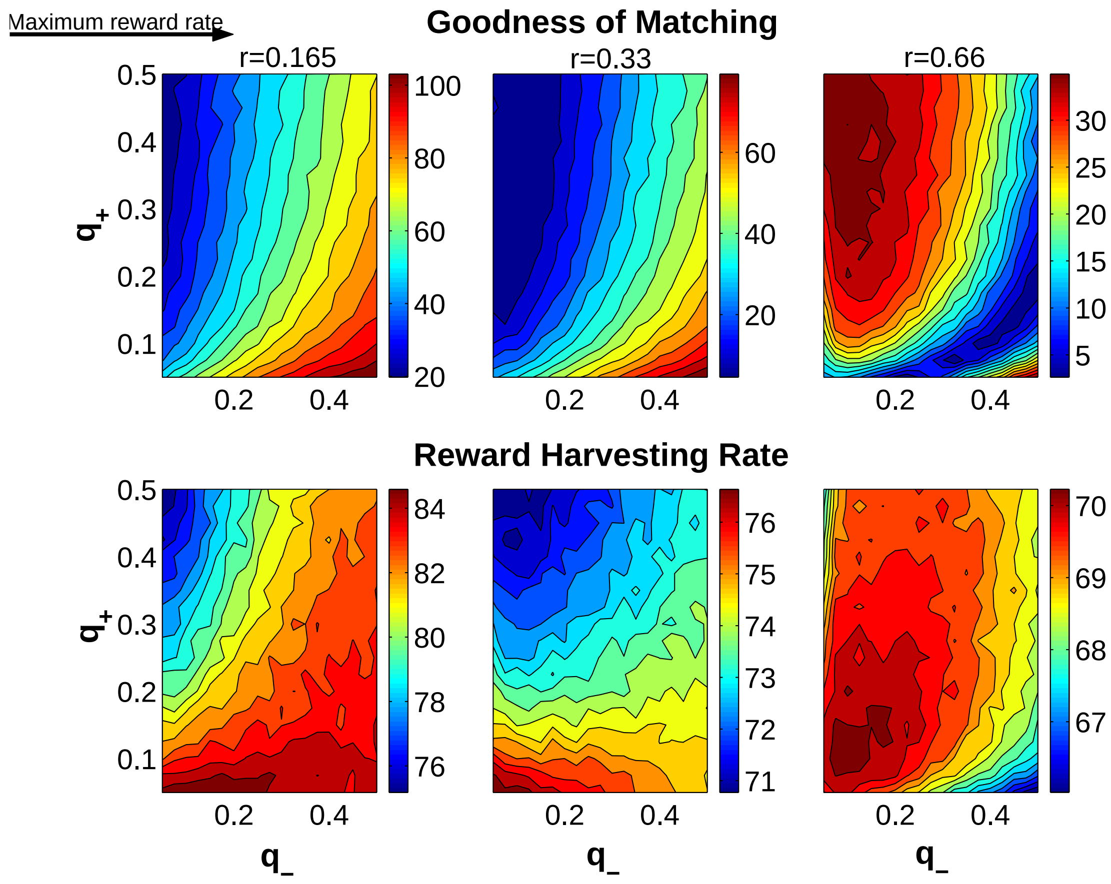

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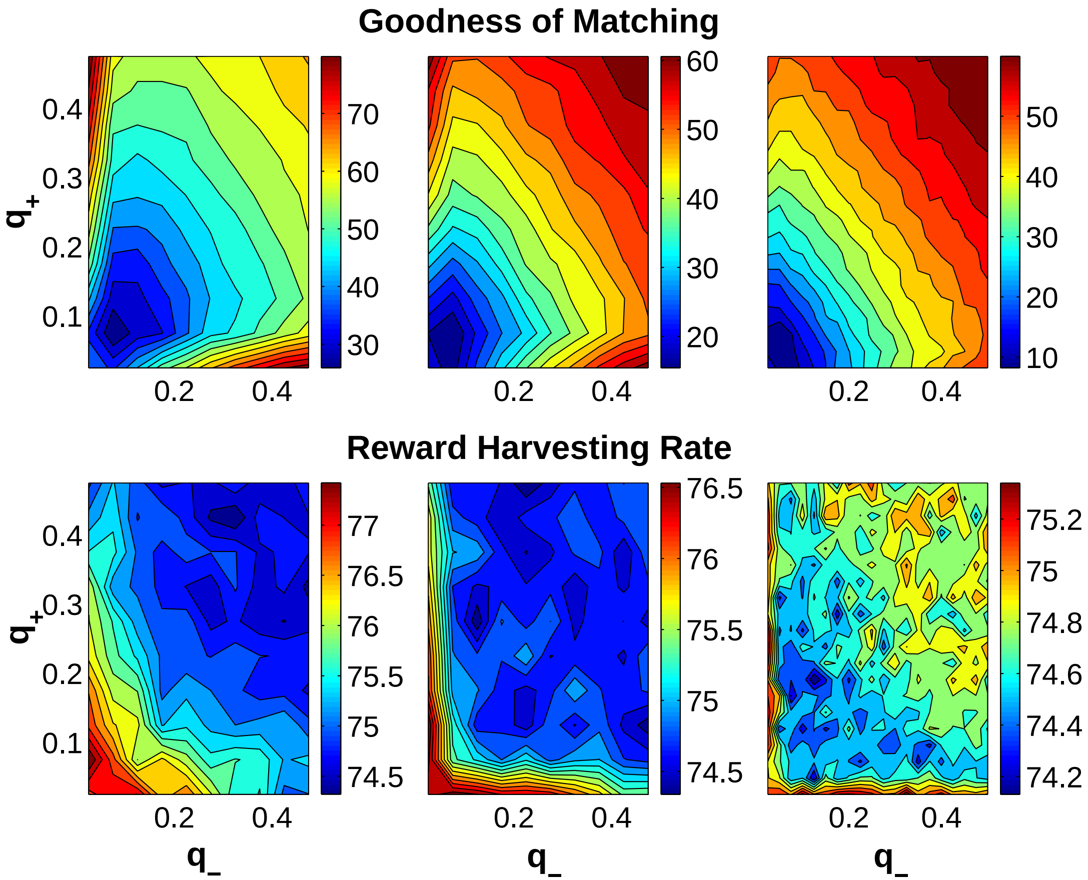

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