

# Endogenous Learning with Bounded Memory

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- Most models of learning assume that **the agent can keep track of all past payoffs and actions**, and act accordingly.

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  - **occasional experimentation** the agent never ceases experimentation completely, even when it is optimal to choose the safe option.

# Decision Making under Memory Constraints

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- Bounded recall, Lehrer & Solan (2009)
- Bounded memory as a "finite automaton": as a neutral/ flexible storage model of memory, it **does not dictate the agent what to remember and what information to discard**: Cover & Hellman (1970,1976), Abreu & Rubinstein (1988), Kalai & Solan (2003), Wilson (2004), Borgers & Morales (2004), Salant (2007), Monte (2008)..

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- It imposes no constraints on how an agent might use his memory: there is just a capacity constraint, and the agent is assumed to make the best use of it.
- The histories are lumped into  $N$  categories where  $N$  is the number of memory states (fingers). It measures how "finely" you can remember history.

# Wilson (2004), Hypothesis Testing

- $s = H$  or  $L$ ,  $\pi_H = 1/2$ . The agent receives a signal *High*, *Med1*, *Med2* or *Low* each period and guesses the state of the world.

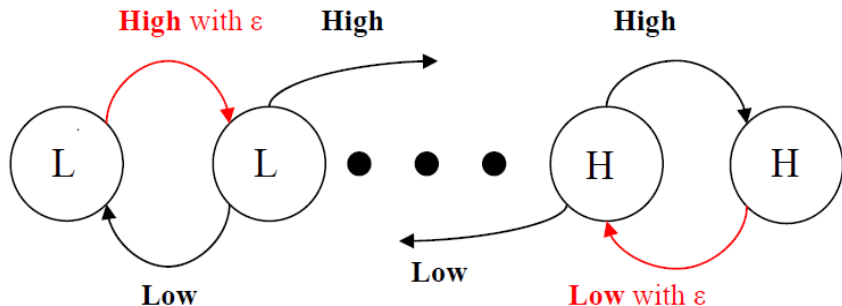
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- He tries to maximize the discounted sum of correct guesses.
- He has a finite number of memory states, and chooses 1) what to guess at each memory state and 2) how to update the memory state after receiving a signal. What is the optimal memory rule?



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- In this model information is free and one dimensional.

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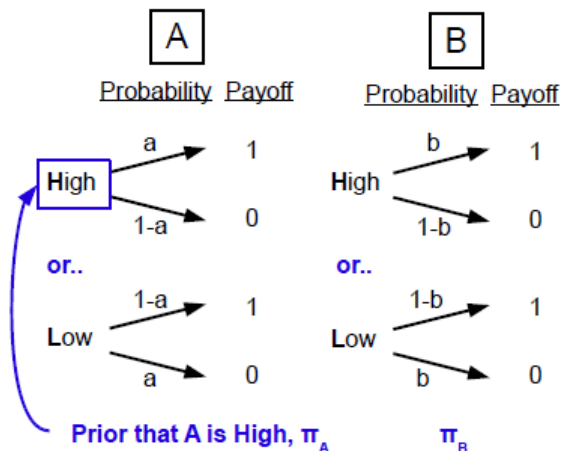
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- How do you organize your memory when you're learning about two things? (multidimensional uncertainty)

# The Model - Problem

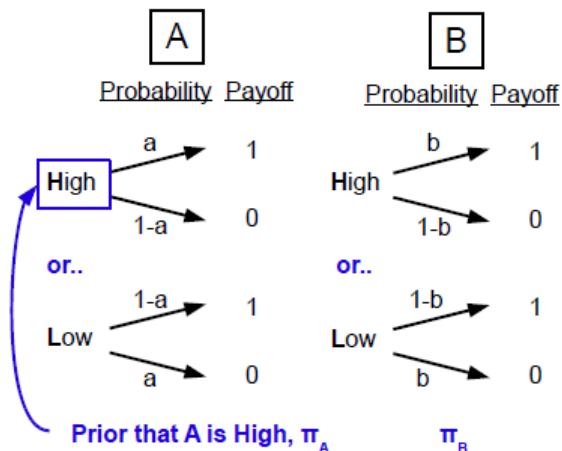
## Standard Two Armed Bandit Problem



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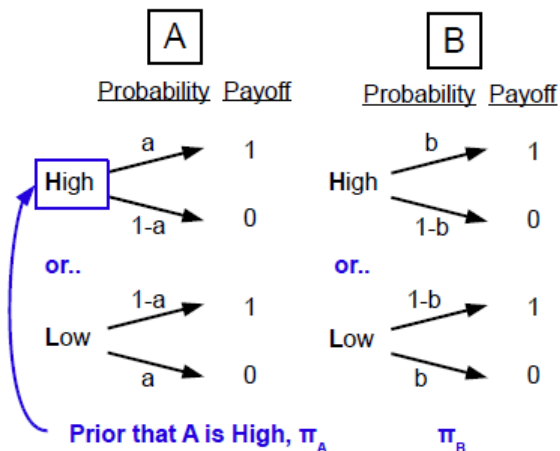
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- He chooses either  $A$  or  $B$  each period to maximize the discounted sum of payoffs.

# The Model - Bounded Memory Strategy

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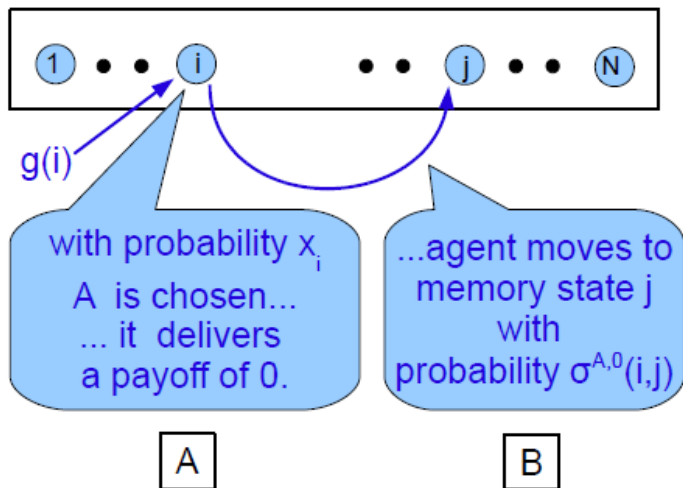
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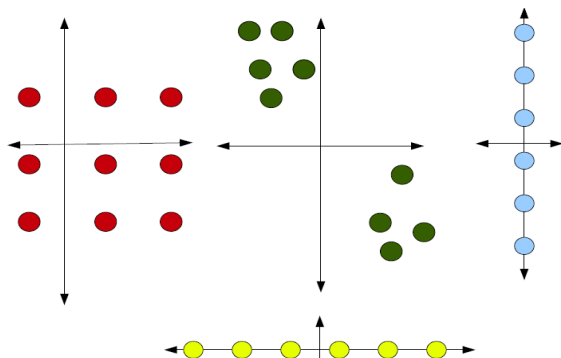
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  - **What is the optimal bounded memory strategy**, for a sufficiently high discount factor  $\beta$ ?

# The Model - Bounded Memory Strategy



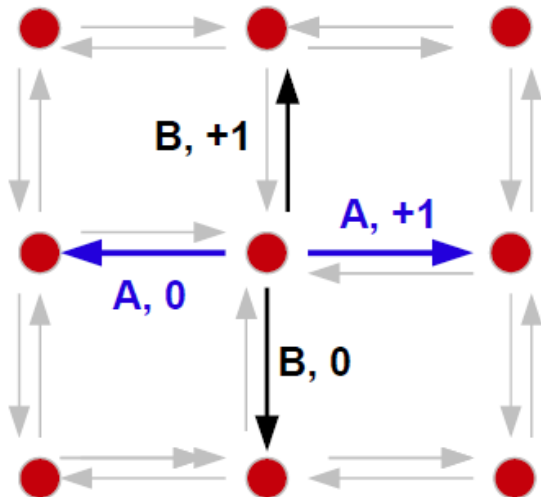
# Beliefs at Memory States - Examples

- Given a strategy  $(g, x, \sigma)$ , one can compute the agent's beliefs about the alternatives' types at each memory state using Bayes' rule.
- How would the **optimal** beliefs look? The axes are beliefs on  $A$ 's type and beliefs on  $B$ 's type, and each point corresponds to the induced belief at a memory state:



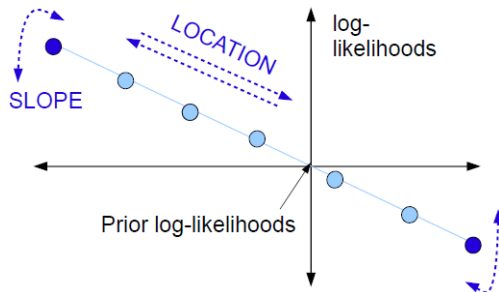
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For example, this strategy keeps a rough summary of each alternative's type, independently:



# Optimal Limit Beliefs

As  $\beta \rightarrow 1$ , **optimal** (conditional) limit beliefs are **evenly and linearly spaced on the log-likelihood** space with a **negative slope** :

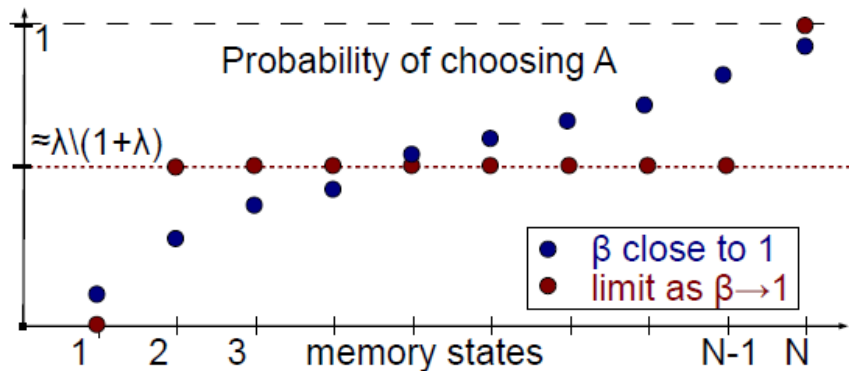


- The optimal strategy fixes the **slope** and the **location** of this line segment (it carries the point of prior log-likelihoods)
- **The optimal solution to a seemingly complex problem boils down to the choice of two parameters !!** ( $\lambda$  for the slope,  $q$  for the location of the belief line)



# Optimal Strategy for Sufficiently High Discount Factors

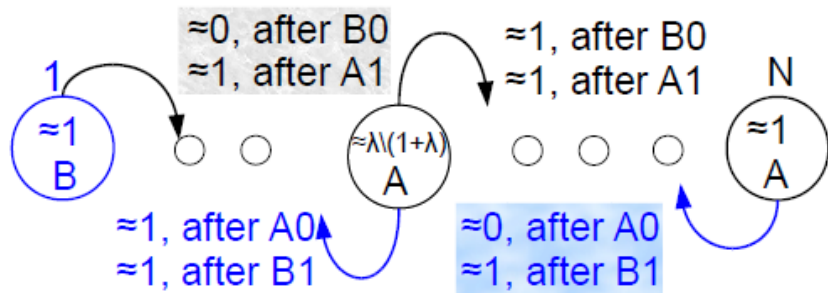
## Action Rule



# Optimal Strategy for Sufficiently High Discount Factors

## Transition (Updating) Rule

- $q$  measures the relative exit probabilities out of extreme memory states, 1 and  $N$ .
- $\lambda$  measures the relative likelihood that transitions are due to A observations rather than B observations.



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- Biases in updating beliefs in the short run: After receiving good news about  $A$  (payoff of 1), the agent moves to a memory state with worse opinions on  $B$ , **even though no information on  $B$  is received !!**

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- Generically, the optimal bounded memory strategy generates under-experimentation and occasional experimentation.

# Results - Biases in Learning Experiments

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  - 1 Agents give up experimentation with the uncertain alternative rather early relative to the full memory optimal (**under-experimentation**).
  - 2 Agents choose the uncertain alternative occasionally, even after choosing the known alternative for many periods (**occasional experimentation**).

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## Under-experimentation and occasional experimentation

Both biases are consistent with optimal behavior under memory constraints for sufficiently patient agents:

- (**Under-experimentation**) Because he does not have the ability to store future information efficiently, the bounded memory agent does not appreciate the option value of information as much as the full memory agent. As a result, **he optimally explores less** with unfamiliar options.

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- **(Occasional experimentation)** The bounded memory agent will **never give up experimentation completely**; he experiments with the unknown alternative with positive probability after any history. Even at a memory state with the most pessimistic beliefs, it pays to experiment with a small probability.

# Results - Biases in Learning Experiments

Under-experimentation and Occasional Experimentation

For the full memory agent it is optimal to choose..

