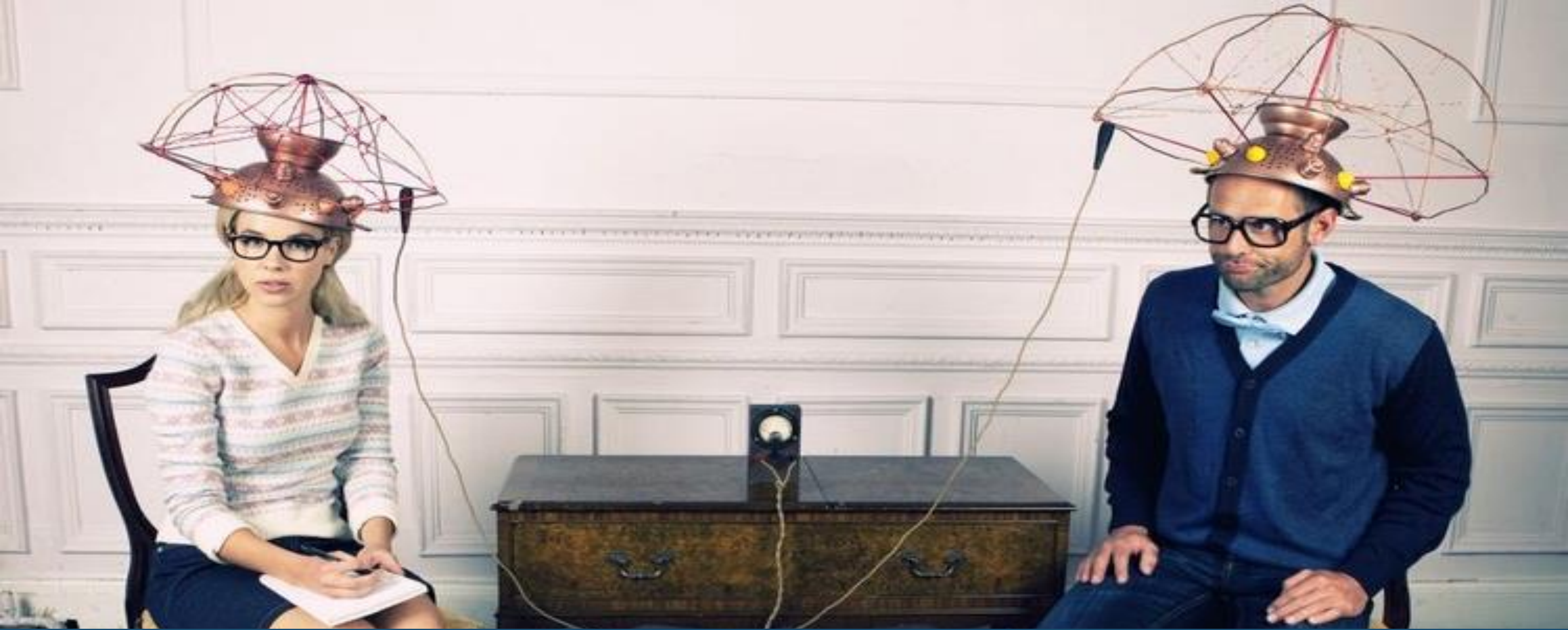
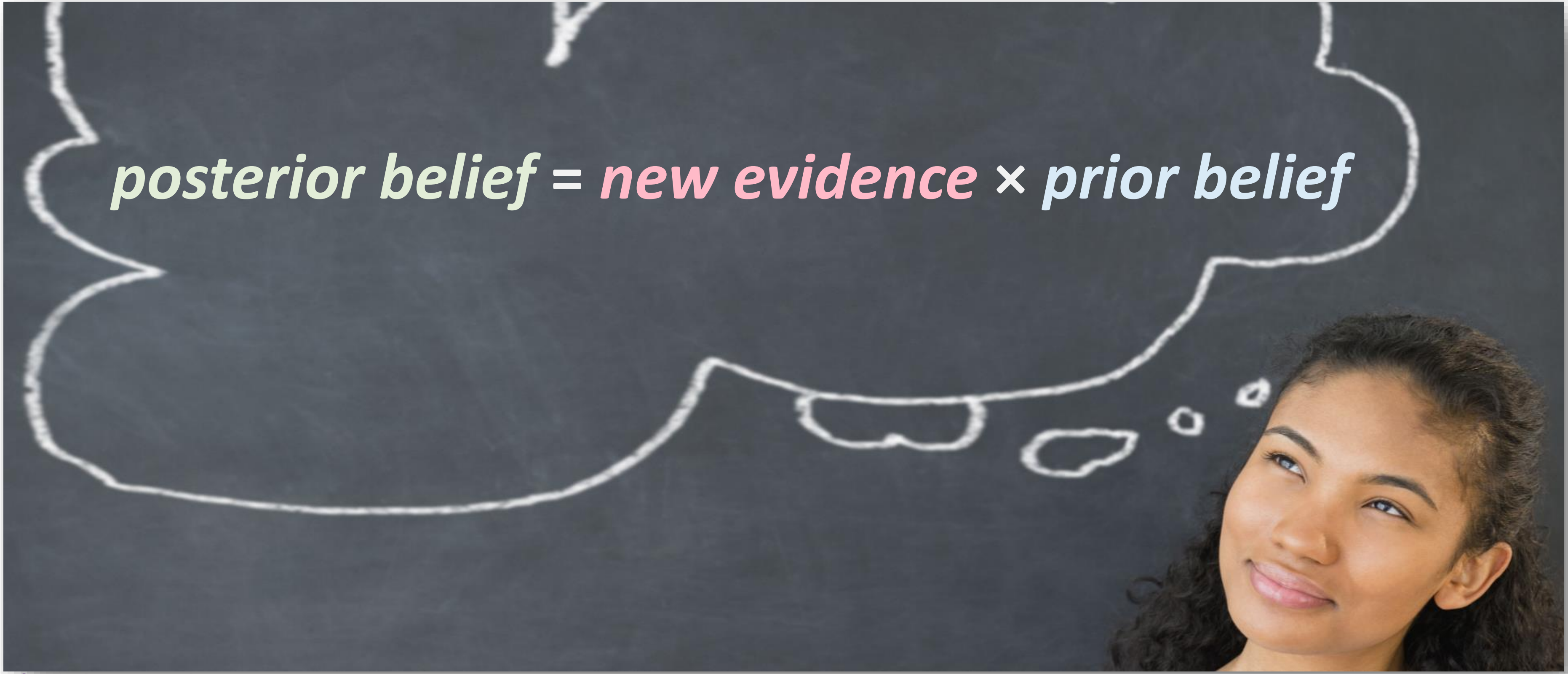


Experimental Economics
Beliefs and updating

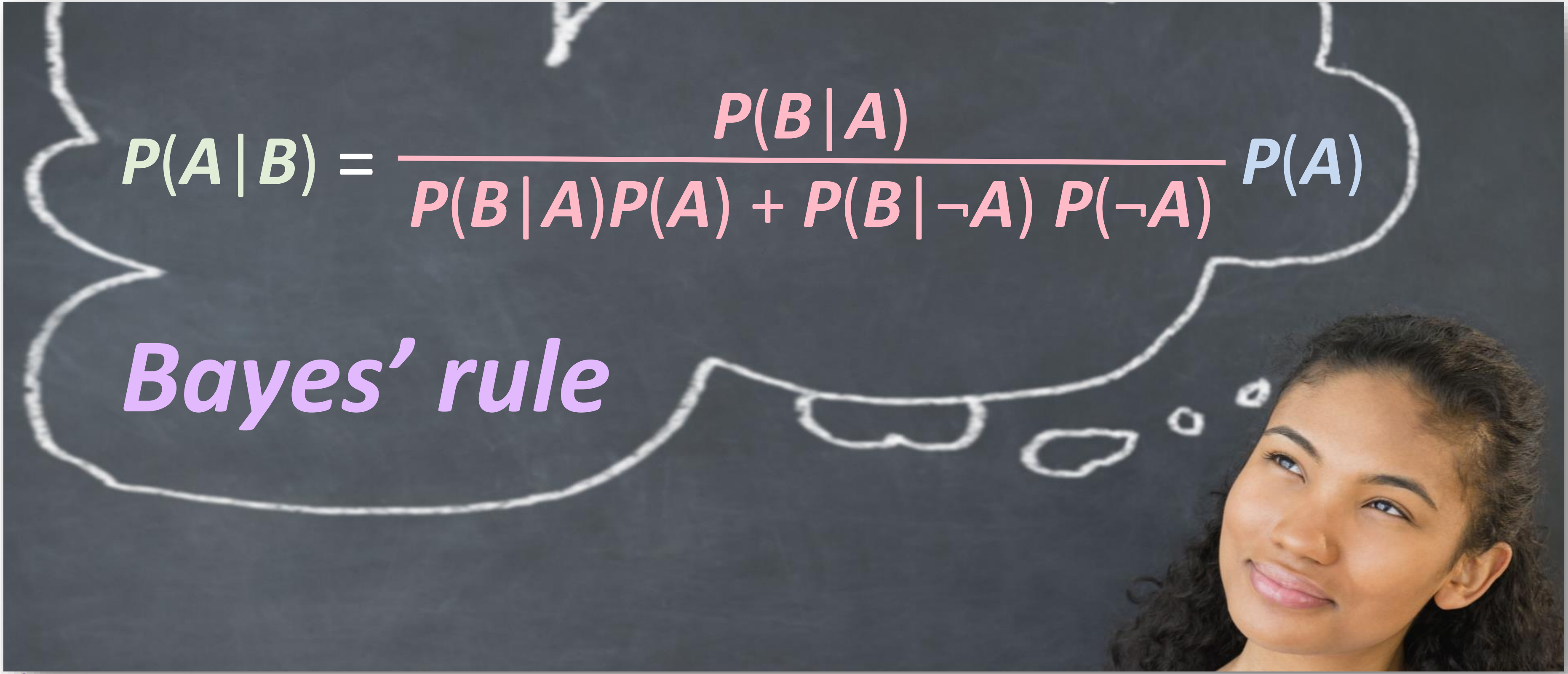
Ernesto Reuben

جامعة نيويورك أبوظبي
NYU | ABU DHABI

Explicit belief updating



Explicit belief updating



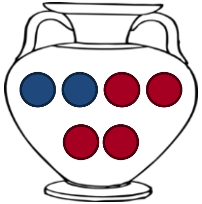
ARE PEOPLE BAYESIAN?

Consider this experiment (El-Gamal & Grether 1995)

- There is one urn and two possible states of the world:

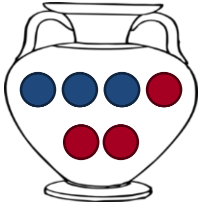
State UP

p = 50%

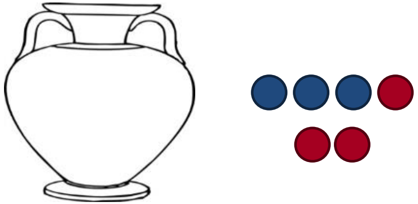


State DOWN

p = 50%



- You make six draws from the urn <u>with replacement</u>.



Is the state **UP** or **DOWN**?

$$\frac{6!}{3!3!}\left(\frac{2}{3}\right)^3\left(\frac{1}{3}\right)^3$$

$$\frac{6!}{3!3!}\left(\frac{1}{2}\right)^3\left(\frac{1}{2}\right)^3$$

$$P(U|3b) = \frac{0.2195}{0.2195 \times 0.5 + 0.3125 \times 0.5}\, 0.5 = 0.413$$

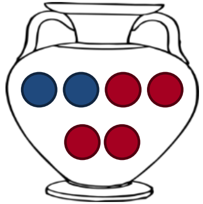
Are people Bayesian?

Consider this experiment (El-Gamal & Grether 1995)

- There is one urn and two possible states of the world:

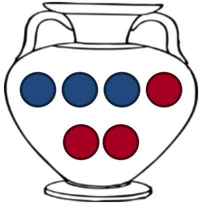
State UP

p = 60%

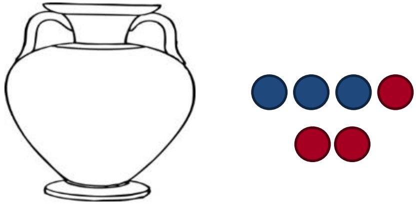


State DOWN

p = 40%



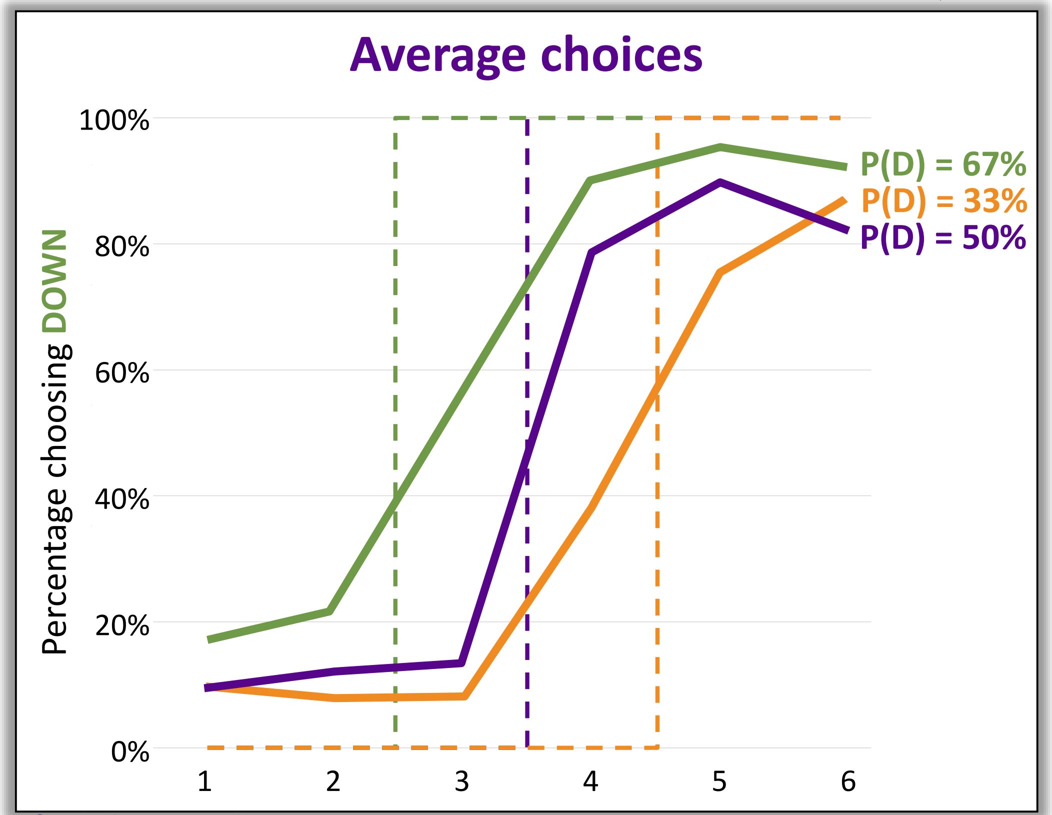
- You make six draws from the urn with replacement.

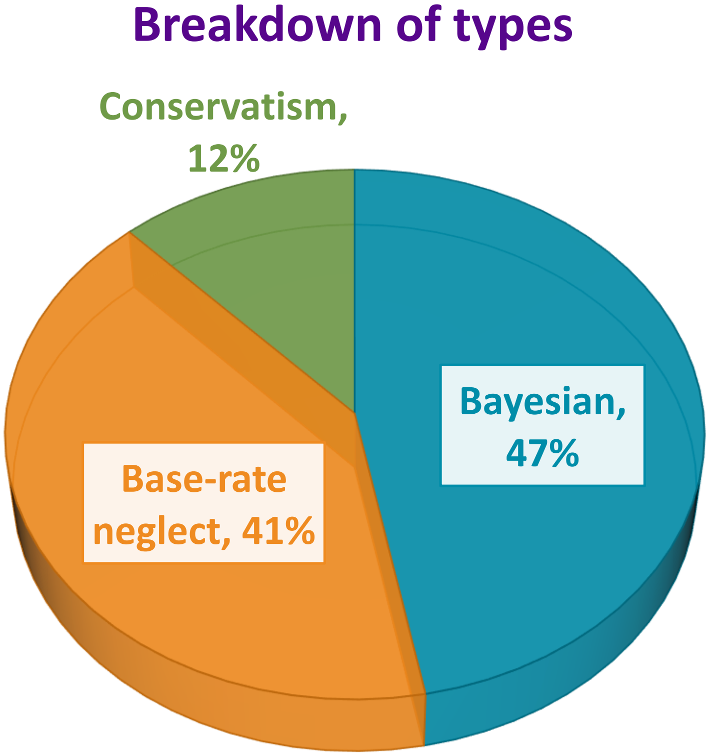


Is the state **UP** or **DOWN**?

$$P(U|3b) = \frac{0.2195}{0.2195 \times 0.6 + 0.3125 \times 0.4}\, 0.6 = 0.513$$

Are people Bayesian?





(El-Gamal & Grether 1995)

Too much or too little updating?

posterior belief **=**
new evidence **×** ***prior belief***

posterior belief **=**
new evidence **×** ***prior belief***

Base-rate neglect / representativeness

- Too much weight on new information
  - New information is **consistent** with important values/beliefs
  - New information is **salient** and/or **strong** (even if inaccurate)
  - New information produces **affect**

Conservativism

- Too little weight on new information
  - New information is **inconsistent** with important values/beliefs
  - New information is **not salient** and/or **weak** (even if accurate)
  - New information **lacks affect**

The Monty Hall problem

- Three doors: one has a price, the others have goats!
- Choose one door
- Monty opens a door with a goat
- Should you switch to the other door?

Probability of winning if you:

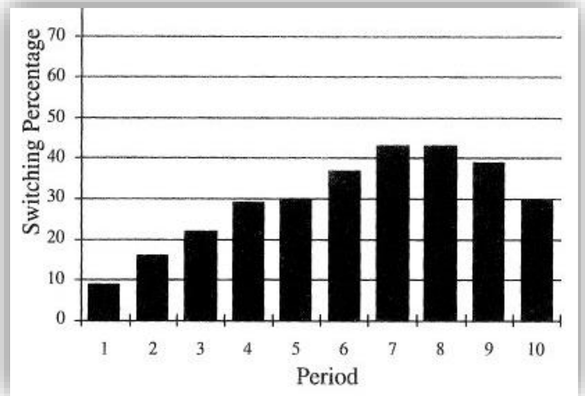
Switch = 2/3

Do not switch = 1/3

LEARNING TO UPDATE

Friedman (1998)

- 104 subjects play the Monty Hall game for 10 rounds earning 40¢ if correct and 10¢ if wrong

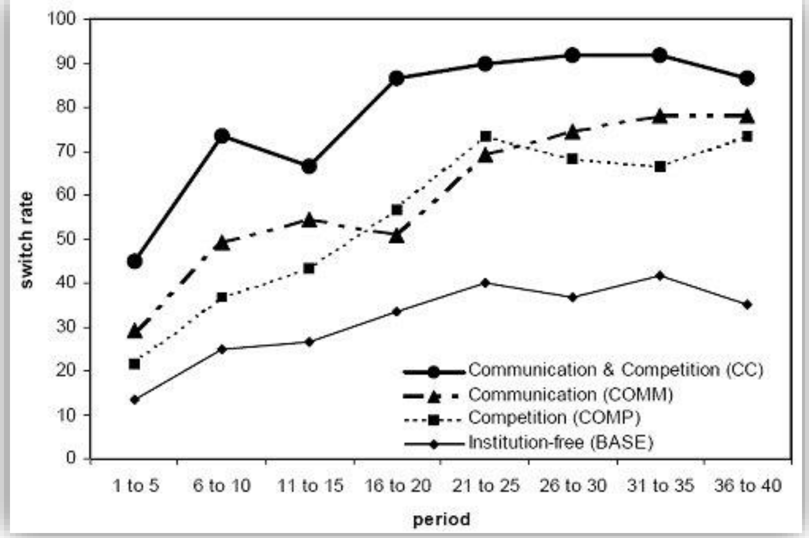


- Play more rounds with higher **incentives**, **advice**, **history**, or **earnings comparisons**

→ switching only up to 50.3%

Slembeck & Tyran (2004)

- 93 subjects play the Monty Hall game for 40 rounds in **control**, **competition** (pay based on relative performance), or **communication** (decisions in groups of 3)



When is learning to update hard?

We tend to repeat actions that are rewarded and avoid those that are punished

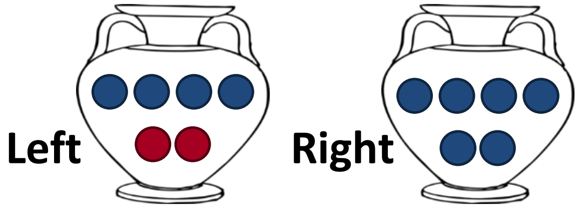
→ problem when **Bayesian updating ≠ reinforcement learning**

Reinforcement learning and Bayesian updating?

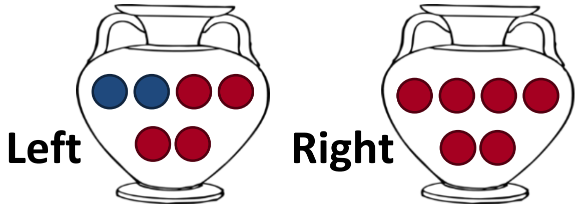
Charness & Levin (2005)

- This experiment consists of **ten rounds**. In each round, you will be making draws from two urns: a **left urn** and a **right urn**. There are two possible states of the world: **UP** and **DOWN**.
  - With 50% probability the state is **UP**. In this case,
    - The **left urn** has **four blue balls** and **two red balls**
    - The **right urn** has **six blue balls**
  - With 50% probability the state is **DOWN**. In this case,
    - The **left urn** has **two blue balls** and **four red balls**
    - The **right urn** has **six red balls**

State UP (p = ½)



State DOWN (p = ½)



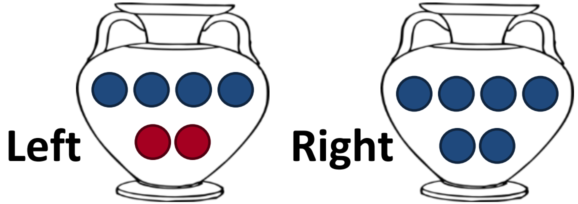
Reinforcement learning and Bayesian updating?

Charness & Levin (2005)

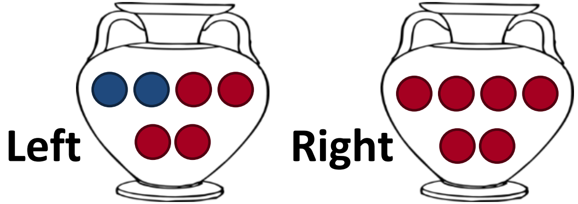
1st draw from the **left**

- Draw **blue** and **win $** ☺
  Switch to right
  (**UP** is more likely)
- Draw **red** and **lose $** ☹
  Stay left
  (**DOWN** is more likely)

State UP (p = ½)



State DOWN (p = ½)



1st draw from the **right**

- Draw **blue** and **win $** ☺
  Stay right
  (**UP** is certain)
- Draw **red** and **lose $** ☹
  Switch to left
  (**DOWN** is certain)

Reinforcement learning and Bayesian updating?

Results: 165 subjects where the 1st draw either **pays** or **does not pay** **(Charness & Levin 2005)**

1st draw from the **left**

- Draw **blue** and **win $** ☺

  63% switch to right

  86% switch without $

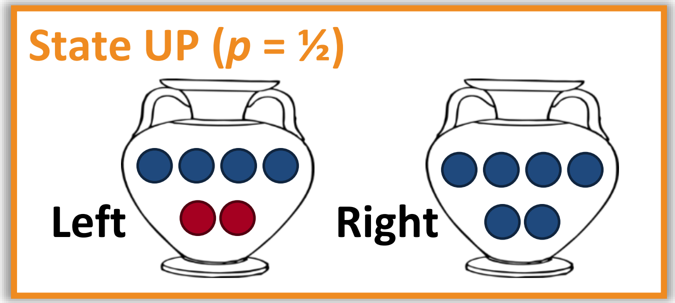
- Draw **red** and **lose $** ☹

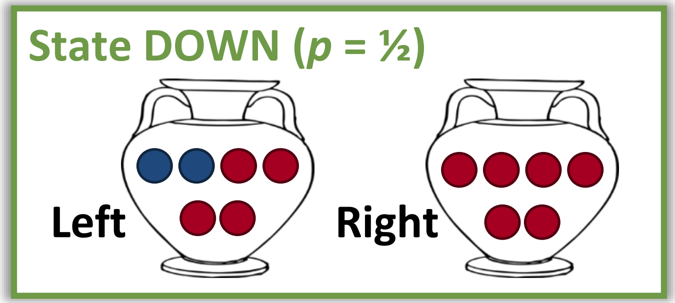
  44% stay left

  58% stay left without $

47% errors

28% errors without $





1st draw from the **right**

- Draw **blue** and **win $** ☺

  87% stay right

- Draw **red** and **lose $** ☹

  96% switch to left

8% errors

Consequences of non-Bayesian updating

Winners curse

- Winners of common value auctions tend to bid too much and end up making a loss!
- **Oil drilling in the Gulf of Mexico**
  - Between 1954 and 1969, there was an average present value loss of $192k per lease; 62% of leases were dry and 16% were unprofitable

- **3G spectrum auctions**

  - 9 out of 13 winners had financial problems shortly after acquiring the spectrum rights

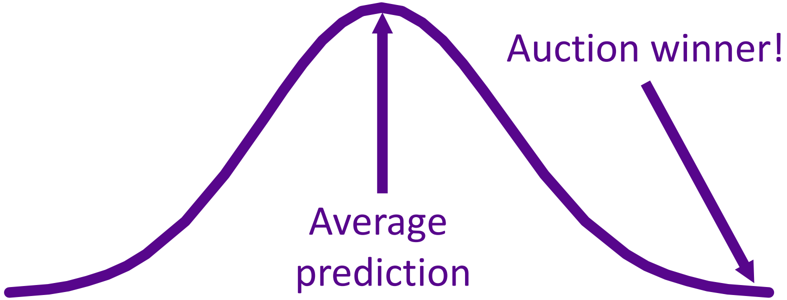
vancouver 2010

- **Olympics**
  - NBC lost $223 million on the Toronto Winter Olympics even though they brought extra revenue and ratings were 14% better than previous games. NBC paid $820 million for the rights to the games.

CONSEQUENCES OF NON-BAYESIAN UPDATING

Winners curse

- Winners of common value auctions tend to bid too much and end up making a loss!
- **Possible explanations?**
  - Utility of winning (risk seeking)
  - Wrong beliefs of other bidders' behavior
  - **Non-Bayesian updating**



Winners to not fully take into account that if they win, it means they overestimated the value of the good

Bid should be considerably bellow one's estimate!

Consequences of non-Bayesian updating

Simplifying the winner's curse (Charness & Levin 2009)

- An **entrepreneur** makes an offer for a patent that is worth **P to the inventor** and **1.5P to him/her**. The entrepreneur's earnings are **1.5P – offer** if it is **accepted** and **0** if it is **rejected**. The inventor accepts the offer if it is **greater than P**. The inventor knows P but the entrepreneur only knows that P is drawn from a distribution with support [$0, $99].

What's the optimal offer? $0!

- Implied lottery
  - $0 with $p = 1$
  - $0 with $p = ½$ and –$33 with $p = ½$
  - $0 with $p = ½$ and –$66 with $p = ½$
  - $49.5 with $p = ½$ and –$99 with $p = ½$

0	1	2	3	4	5	6	7	8	9
10	11	12	13	14	15	16	17	18	19
20	21	22	23	24	25	26	27	28	29
[illegible]	1	32	33	34	35	36	37	38	39
[illegible]	1	42	43	44	45	46	47	48	49
[illegible]	1	52	53	54	55	56	57	58	59
[illegible]	1	62	63	64	65	66	67	68	69
[illegible]	1	72	73	74	75	76	77	78	79
[illegible]	1	82	83	84	85	86	87	88	89
[illegible]	1	92	93	94	95	96	97	98	99

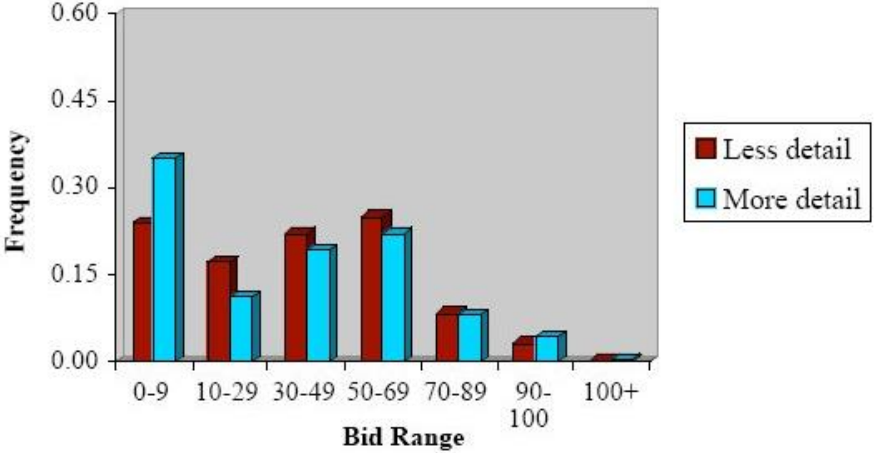
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
99	99	99	99	99	99	99	99	99	99
99	99	99	99	99	99	99	99	99	99
99	99	99	99	99	99	99	99	99	99
99	99	99	99	99	99	99	99	99	99
99	99	99	99	99	99	99	99	99	99

Consequences of non-Bayesian updating

Simplifying the winner's curse (Charness & Levin 2009)

- 219 subjects, two parts of 30 periods each with either normal or detailed instructions
  - Continuous → Discrete (normal)
  - Discrete → Continuous (normal)
  - Continuous → Discrete (detailed)
  - Discrete → Continuous (detailed)
  - Lottery

	First 30 Normal	Second 30 Normal	First 30 Detailed	Second 30 Detailed
Avg. Bid	38.86	35.91	35.17	29.12
% zeros	7.5%	20.9%	25.8%	40.1%

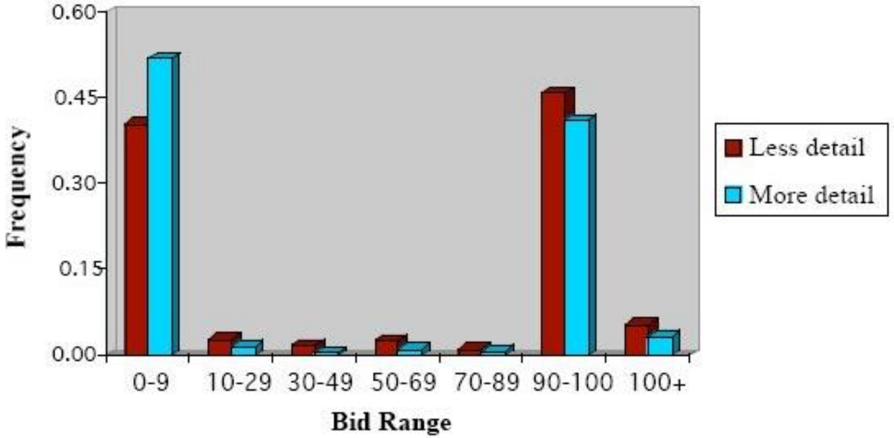


CONSEQUENCES OF NON-BAYESIAN UPDATING

Simplifying the winner's curse (Charness & Levin 2009)

- 219 subjects, two parts of 30 periods each with either normal or detailed instructions
  - **Continuous** → **Discrete** (normal)
  - **Discrete** → **Continuous** (normal)
  - **Continuous** → **Discrete** (detailed)
  - **Discrete** → **Continuous** (detailed)
  - **Lottery**

	First 30 Normal	Second 30 Normal	First 30 Detailed	Second 30 Detailed
Avg. Bid	57.08	59.87	52.93	36.21
% zeros	30.4%	33.5%	38.5%	58.5%



Results Lottery
84.8% zero bids

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NYU ABU DHABI

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