

Section B | 30 minutes

How to Develop a Computational Model?

"All models are wrong, but some are useful"

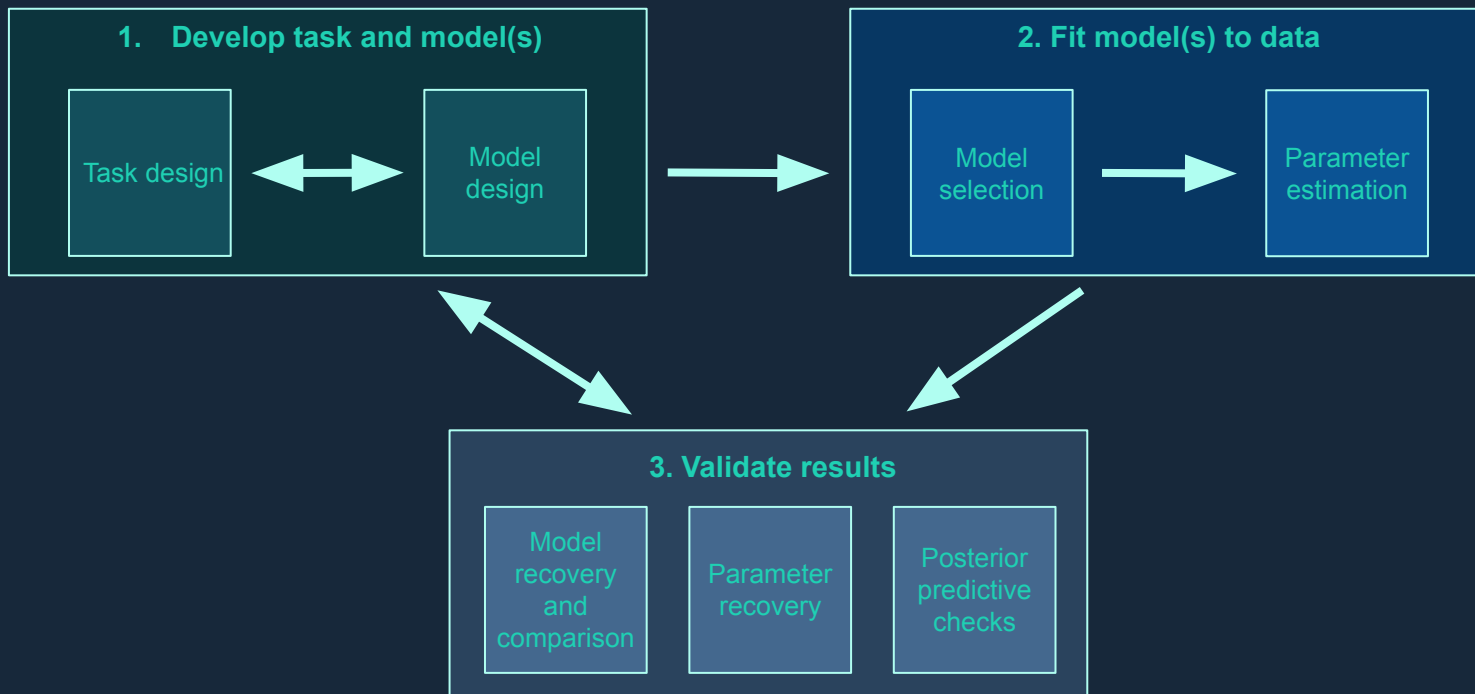
George E. P. Box

Tricia Seow | Samuel Hewitt | Noam Goldway

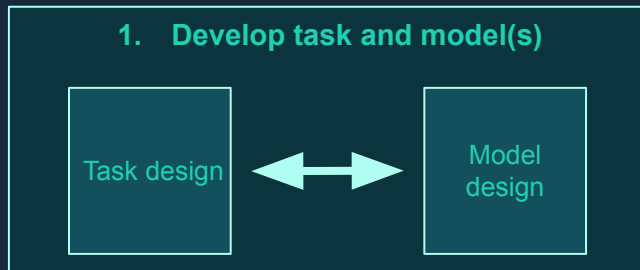
What we will cover:

- An example for how to select the proper model with respect to a specific task design
- The Rescorla Wagner model
- The concept of learning rate
- The concept of temperature
- What is a “softmax” function

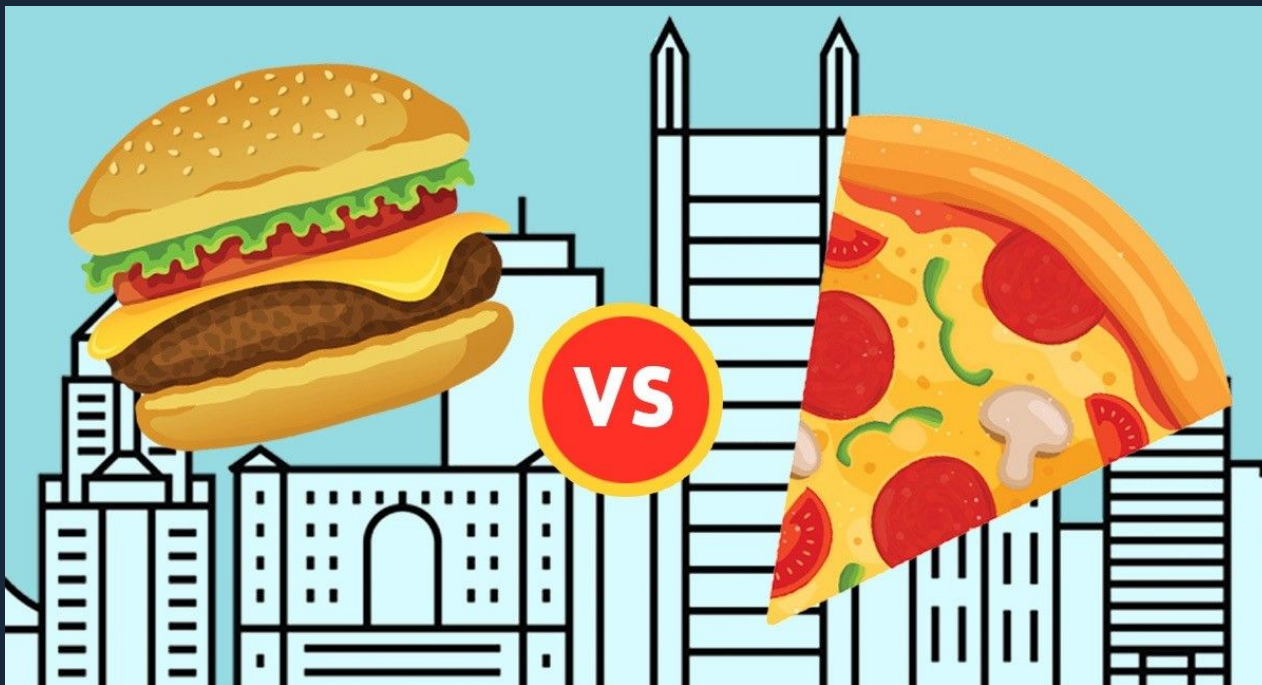
Developing a computational model



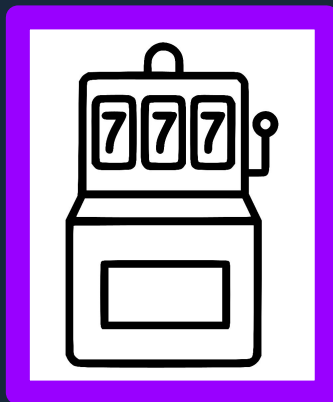
Developing a computational model



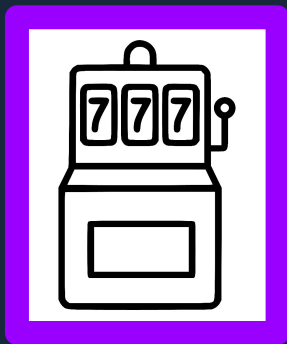
Section B | How to Develop a Computational Model?



2-arm bandit



Experimental task -



How do you maximise reward if you do not know which slot machine is better?

- Learn expected value of each slot machine
- Make the next choice based on values learnt

Trial	Choice	Outcome
1	Right	0
2	Left ^{new choice}	+1
3	Left	+1
4	Right	0
5	Left ^{past experience}	+1

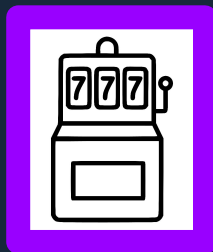
Modelling behaviour with RL



Value function: Rescorla Wagner model

$$V_t = V_{t-1} + \alpha(R_t - V_{t-1})$$

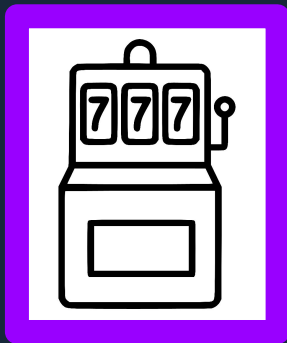
Prediction Error



$V_{\text{prepule}} > V_{\text{orange}}$



Prediction Error



$$V_t = V_{t-1} + \alpha (R_t - V_{t-1})$$

Prediction Error



?

$$V_t = V_{t-1} + \alpha(R_t - 0.5)$$

Prediction Error



$$V_t = V_{t-1} + \alpha(1 - 0.5)$$

Prediction Error



$$V_t = V_{t-1} + \alpha(1 - 0.5)$$

Modelling behaviour with RL

Value function: Rescorla Wagner model

$$V_t = V_{t-1} + \alpha (R_t - V_{t-1})$$

Value
(of the slot machine)

Modelling behaviour with RL

Value function: Rescorla Wagner model

$$V_t = V_{t-1} + \alpha (R_t - V_{t-1})$$

Value
(of the slot machine)

=

Value on
previous trial

Modelling behaviour with RL

Value function: Rescorla Wagner model

$$V_t = V_{t-1} + \alpha (R_t - V_{t-1})$$

Value
(of the slot machine) = Value on
previous trial

(Reward - Value on
previous trial)

Prediction error
what you received - what you expected

Modelling behaviour with RL

Value function: Rescorla Wagner model

$$V_t = V_{t-1} + \alpha (R_t - V_{t-1})$$

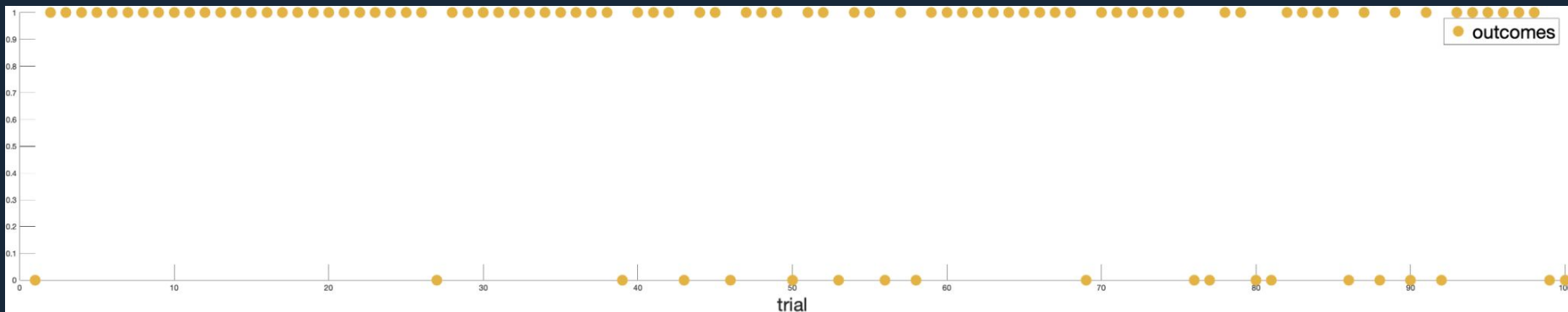
Value
(of the slot machine) = Value on previous trial + Learning rate (Reward - Value on previous trial)

Prediction error
what you received - what you expected

Modelling behaviour with RL

Prediction error
what you received - what you expected

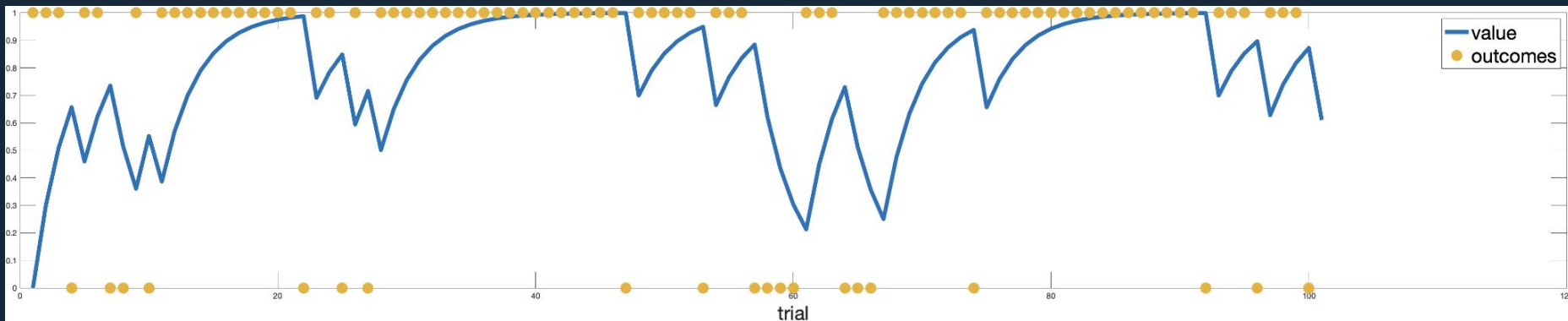
$$\text{Value (of the slot machine)} = \text{Value on previous trial} + \text{Learning rate} \left(\text{Reward} - \text{Value on previous trial} \right)$$



Modelling behaviour with RL

Prediction error
what you received - what you expected

$$\text{Value (of the slot machine)} = \text{Value on previous trial} + \text{Learning rate} \left(\text{Reward} - \text{Value on previous trial} \right)$$



Modelling behaviour with RL

$$\begin{array}{c} \text{Value} \\ \text{(of the slot machine)} \end{array} = \begin{array}{c} \text{Value on} \\ \text{previous trial} \end{array} + \begin{array}{c} \text{Learning} \\ \text{rate} \end{array} \underbrace{\left(\begin{array}{c} \text{Prediction error} \\ \text{what you received - what you expected} \\ \text{Reward - Value on} \\ \text{previous trial} \end{array} \right)}$$

<i>Trial</i> 1	?				
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Modelling behaviour with RL

$$\begin{array}{c} \text{Value} \\ \text{(of the slot machine)} \end{array} = \begin{array}{c} \text{Value on} \\ \text{previous trial} \end{array} + \begin{array}{c} \text{Learning} \\ \text{rate} \end{array} \underbrace{\left(\begin{array}{c} \text{Reward} \\ \text{Prediction error} \\ \text{what you received - what you expected} \end{array} - \begin{array}{c} \text{Value on} \\ \text{previous trial} \end{array} \right)}$$

<i>Trial</i> 1	?	<i>initiation: 0.5</i>			<i>initiation: 0.5</i>
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Modelling behaviour with RL

$$\begin{array}{c} \text{Value} \\ \text{(of the slot machine)} \end{array} = \begin{array}{c} \text{Value on} \\ \text{previous trial} \end{array} + \begin{array}{c} \text{Learning} \\ \text{rate} \end{array} \left(\begin{array}{c} \text{Reward} \\ \text{Prediction error} \\ \text{what you received - what you expected} \end{array} - \begin{array}{c} \text{Value on} \\ \text{previous trial} \end{array} \right)$$

<i>Trial</i> 1	?	0.5		1	0.5
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Modelling behaviour with RL

$$\text{Value (of the slot machine)} = \text{Value on previous trial} + \text{Learning rate} \left(\text{Reward} - \text{Value on previous trial} \right)$$

Prediction error
what you received - what you expected

<i>Trial</i> 1	?	0.5	+	1	0.5
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Modelling behaviour with RL

$$\begin{array}{c} \text{Value} \\ \text{(of the slot machine)} \end{array} = \begin{array}{c} \text{Value on} \\ \text{previous trial} \end{array} + \begin{array}{c} \text{Learning} \\ \text{rate} \end{array} \left(\begin{array}{c} \text{Prediction error} \\ \text{what you received - what you expected} \\ \text{Reward - Value on} \\ \text{previous trial} \end{array} \right)$$

<i>Trial</i> 1	1	0.5	+	0.5
-------------------	---	-----	---	-----

Modelling behaviour with RL

$$\text{Value (of the slot machine)} = \text{Value on previous trial} + \text{Learning rate} \left(\text{Reward} - \text{Value on previous trial} \right)$$

Prediction error
what you received - what you expected

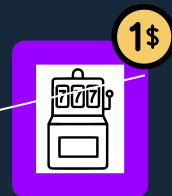
Trial 1	1	0.5	+	0.5
Trial 2		1	+	1

Modelling behaviour with RL

$$\text{Value (of the slot machine)} = \text{Value on previous trial} + \text{Learning rate} \left(\text{Reward} - \text{Value on previous trial} \right)$$

Prediction error
what you received - what you expected

Trial 1	1	0.5	+	0.5
Trial 2		1	+	1



Modelling behaviour with RL

$$\begin{array}{c} \text{Value} \\ \text{(of the slot machine)} \end{array} = \begin{array}{c} \text{Value on} \\ \text{previous trial} \end{array} + \begin{array}{c} \text{Learning} \\ \text{rate} \end{array} \left(\begin{array}{c} \text{Prediction error} \\ \text{what you received - what you expected} \\ \text{Reward - Value on} \\ \text{previous trial} \end{array} \right)$$

<i>Trial</i> 1	1	0.5	+	0.5
<i>Trial</i> 2		1	+	(1 - 1)



Modelling behaviour with RL

$$\text{Value (of the slot machine)} = \text{Value on previous trial} + \text{Learning rate} \left(\text{Reward} - \text{Value on previous trial} \right)$$

Prediction error
what you received - what you expected

<i>Trial</i> 1	1	0.5	+	0.5
<i>Trial</i> 2		1	+	0

Modelling behaviour with RL

$$\begin{array}{c} \text{Value} \\ \text{(of the slot machine)} \end{array} = \begin{array}{c} \text{Value on} \\ \text{previous trial} \end{array} + \begin{array}{c} \text{Learning} \\ \text{rate} \end{array} \left(\begin{array}{c} \text{Prediction error} \\ \text{what you received - what you expected} \\ \text{Reward - Value on} \\ \text{previous trial} \end{array} \right)$$

<i>Trial</i> 1	1	0.5	+	0.5
<i>Trial</i> 2	1	1	+	0

Modelling behaviour with RL

$$\begin{array}{c} \text{Value} \\ \text{(of the slot machine)} \end{array} = \begin{array}{c} \text{Value on} \\ \text{previous trial} \end{array} + \begin{array}{c} \text{Learning} \\ \text{rate} \end{array} \underbrace{\left(\begin{array}{c} \text{Prediction error} \\ \text{what you received - what you expected} \\ \text{Reward - Value on} \\ \text{previous trial} \end{array} \right)}$$

<i>Trial</i> 1	1	0.5	+	0.5
<i>Trial</i> 2	1	1	+	0

Modelling behaviour with RL

$$\text{Value (of the slot machine)} = \text{Value on previous trial} + \text{Learning rate} \left(\text{Reward} - \text{Value on previous trial} \right)$$

Prediction error
what you received - what you expected

Trial 1	1	0.5	+	0.5
Trial 2	1	1	+	0
Trial 3		1	+	1

Modelling behaviour with RL

$$\begin{array}{c} \text{Value} \\ \text{(of the slot machine)} \end{array} = \begin{array}{c} \text{Value on} \\ \text{previous trial} \end{array} + \begin{array}{c} \text{Learning} \\ \text{rate} \end{array} \underbrace{\left(\begin{array}{c} \text{Prediction error} \\ \text{what you received - what you expected} \\ \text{Reward - Value on} \\ \text{previous trial} \end{array} \right)}$$

<i>Trial</i> 1	1	0.5	+	0.5
<i>Trial</i> 2	1	1	+	0
<i>Trial</i> 3		1	+	0 1



Modelling behaviour with RL

$$\begin{array}{c} \text{Value} \\ \text{(of the slot machine)} \end{array} = \begin{array}{c} \text{Value on} \\ \text{previous trial} \end{array} + \begin{array}{c} \text{Learning} \\ \text{rate} \end{array} \left(\begin{array}{c} \text{Prediction error} \\ \text{what you received - what you expected} \\ \text{Reward - Value on} \\ \text{previous trial} \end{array} \right)$$

<i>Trial</i> 1	1	0.5	+	0.5
<i>Trial</i> 2	1	1	+	0
<i>Trial</i> 3		1	+	-1



Modelling behaviour with RL

$$\begin{array}{c} \text{Value} \\ \text{(of the slot machine)} \end{array} = \begin{array}{c} \text{Value on} \\ \text{previous trial} \end{array} + \begin{array}{c} \text{Learning} \\ \text{rate} \end{array} \underbrace{\left(\begin{array}{c} \text{Prediction error} \\ \text{what you received - what you expected} \\ \text{Reward - Value on} \\ \text{previous trial} \end{array} \right)}$$

<i>Trial</i> 1	1	0.5	+	0.5
<i>Trial</i> 2	1	1	+	0
<i>Trial</i> 3	0	1	+	-1

Modelling behaviour with RL

$$\begin{array}{c} \text{Value} \\ \text{(of the slot machine)} \end{array} = \begin{array}{c} \text{Value on} \\ \text{previous trial} \end{array} + \text{Learning rate} \left(\begin{array}{c} \text{Reward} - \text{Value on} \\ \text{previous trial} \end{array} \right)$$

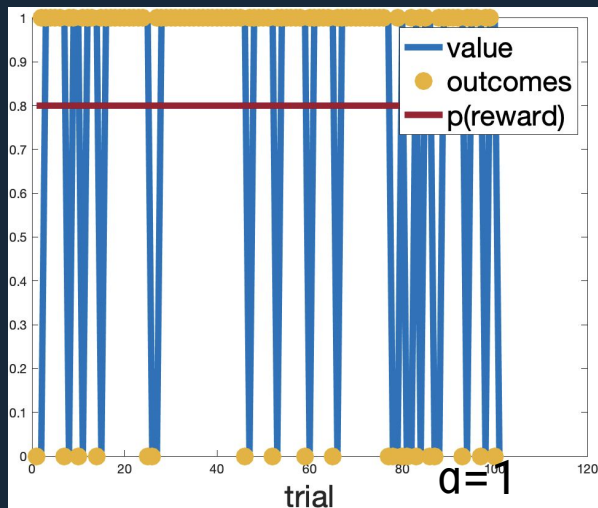
Prediction error
what you received - what you expected

$$V_t = V_{t-1} + \alpha (R_t - V_{t-1})$$

How much should we learn?

What happens if we manipulate learning rate?

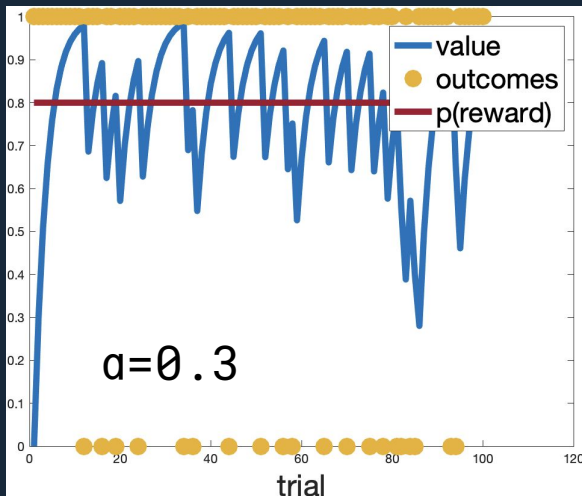
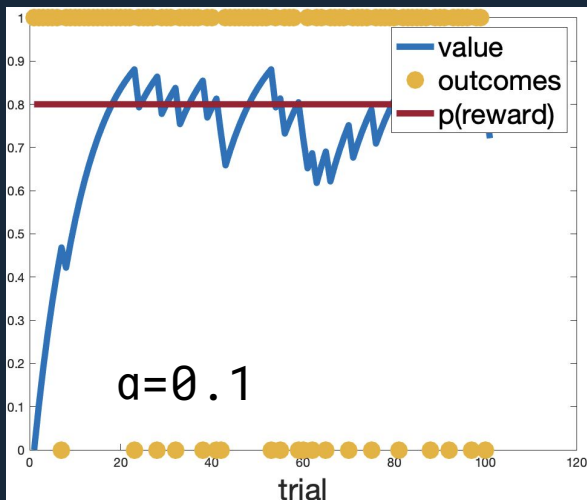
$$V_t = V_{t-1} + \alpha(R_t - V_{t-1})$$



How much should we learn?

What happens if we manipulate learning rate?

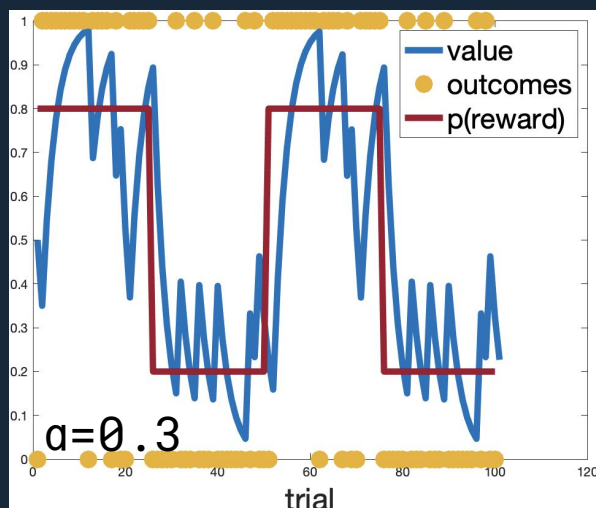
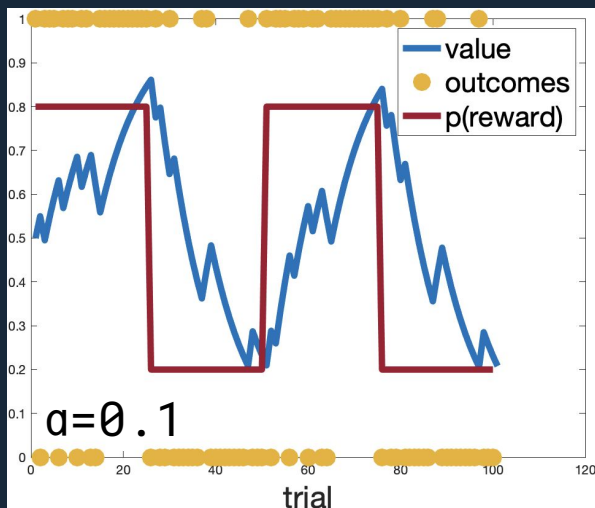
$$V_t = V_{t-1} + \alpha(R_t - V_{t-1})$$



How much should we learn?

What happens if we manipulate learning rate?

$$V_t = V_{t-1} + \alpha(R_t - V_{t-1})$$



Is low learning rate always better?

$$V_t = V_{t-1} + \alpha(R_t - V_{t-1})$$

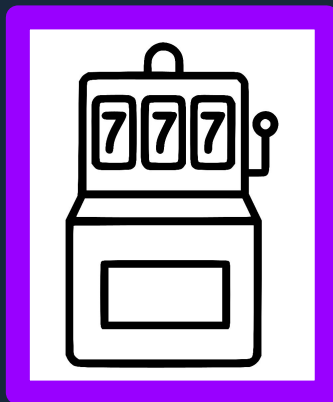
→ Depend on the statistics of the environment

- Low volatility- \rightarrow low α is better
- High volatility- \rightarrow high α is better

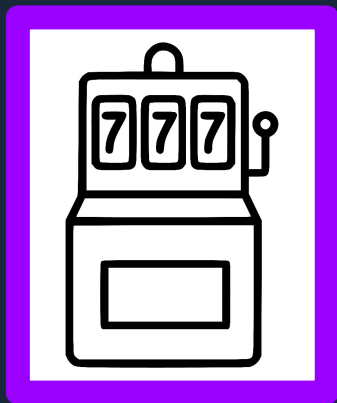
What did we learn so far

- What are multi arm bandit tasks
- How RL and, specifically Rescorla Wagner model can help us to 'solve' such problems
- Expected value
- Prediction error
- High vs low learning rate

How should we choose?



How should we choose?



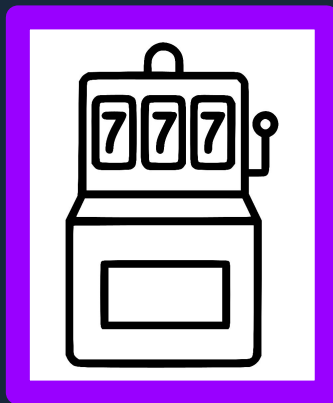
80% reward



20% reward

← learnt via trial and error
(value function) →

How should we choose?

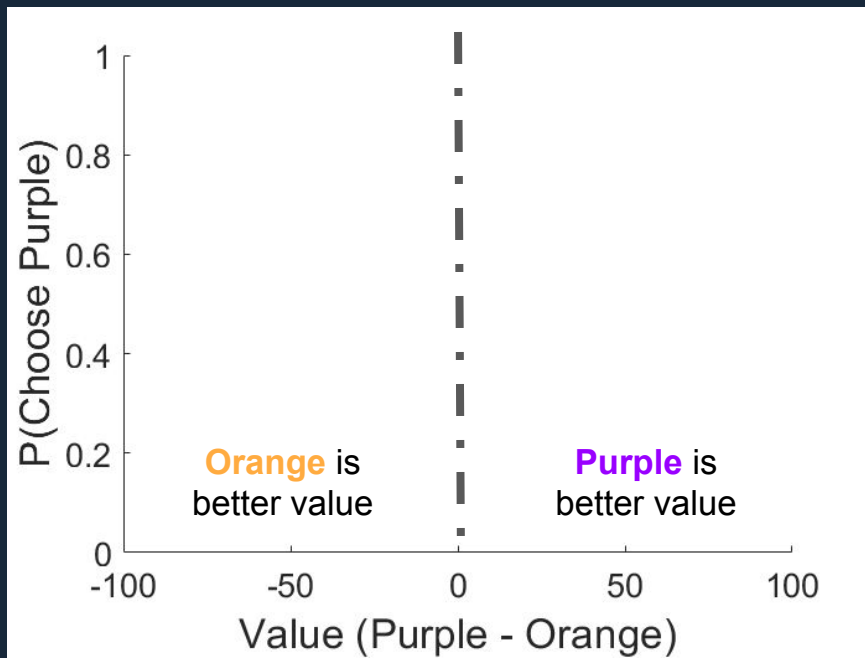


80% reward

Maximise rewards

- Pick slot machine with largest likelihood of reward
- Exploit

How should we choose?

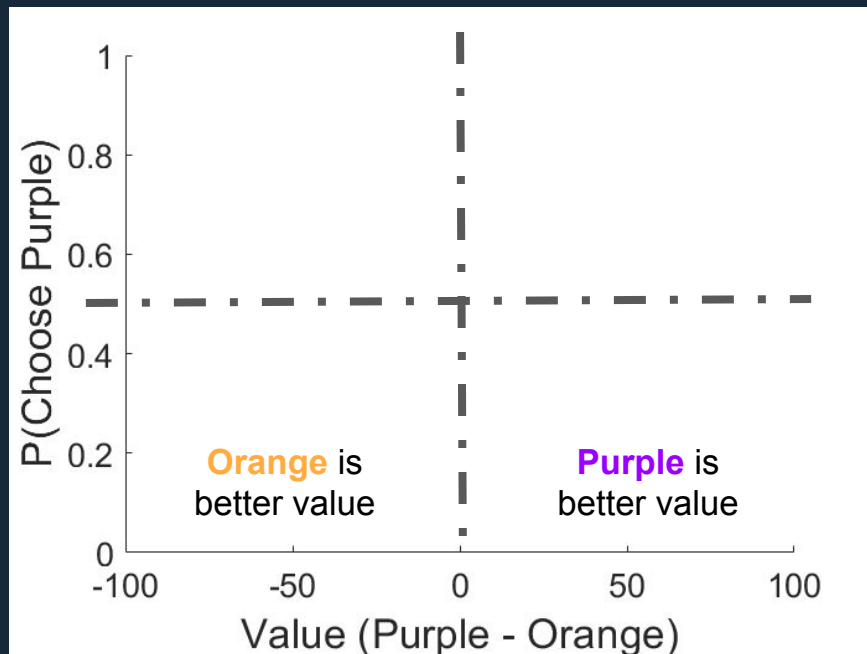


How should we choose?

Choose
purple is
better



Choose
orange is
better

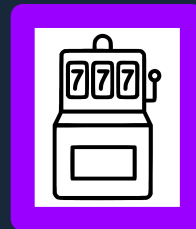
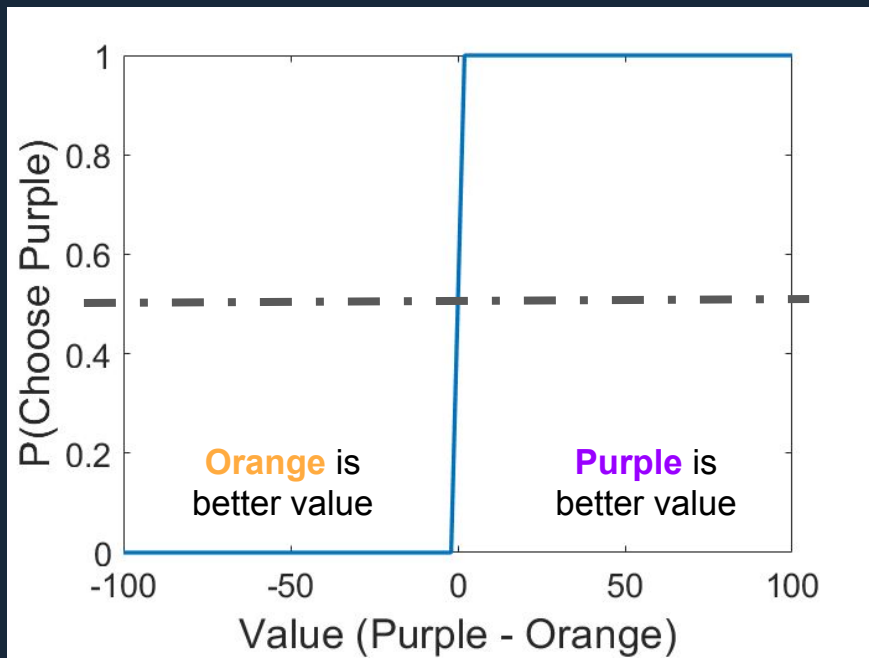


How should we choose?

Choose
purple is
better



Choose
orange is
better



Exploit



Choose slot machine when
reward is better than the
other

How should we choose?

Try other options

- Sample the outcomes of the other slot machine
- Explore



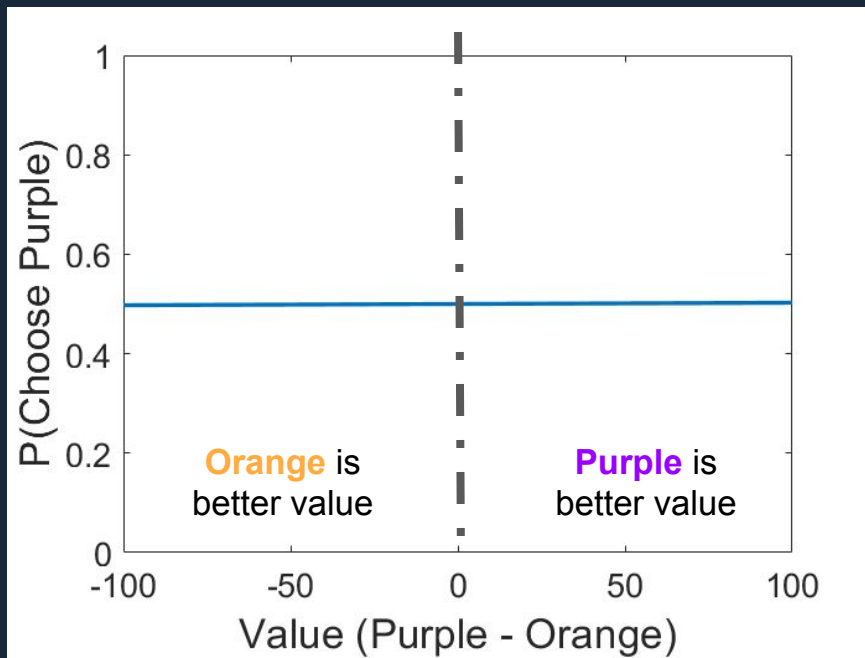
20% reward

How should we choose?

Choose
purple is
better



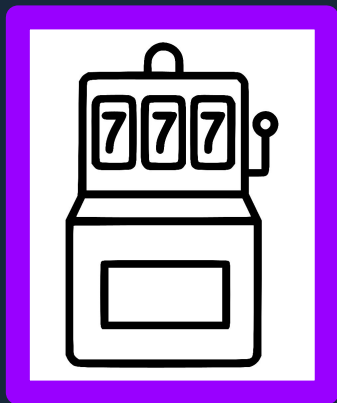
Choose
orange is
better



Explore

→ Choose slot machine
equally

How should we choose?



Exploit → an individual difference we can model as a free parameter ← *Explore*

How should we choose?

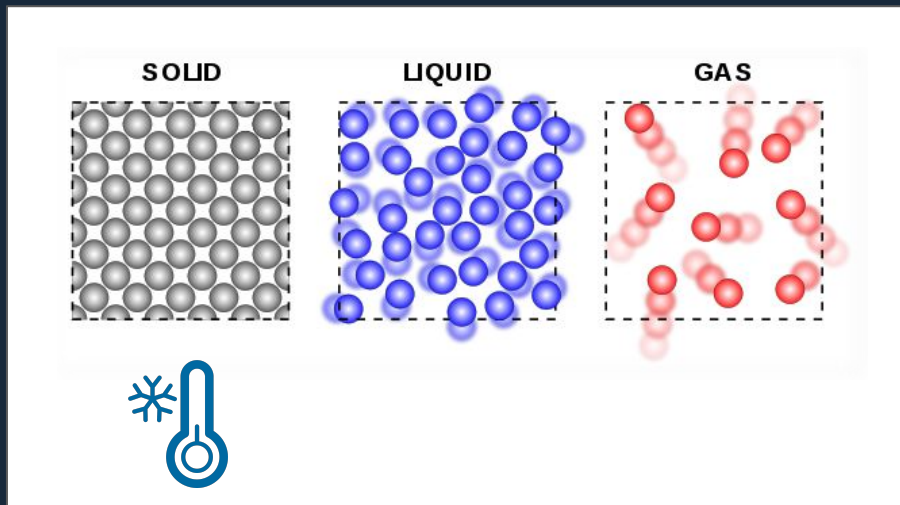
Temperature (τ): parameter that determines the extent to which value estimates influence choice behaviour

How should we choose?

Temperature (τ): parameter that determines the extent to which value estimates influence choice behaviour

Low temperature

→ Choices are less noisy

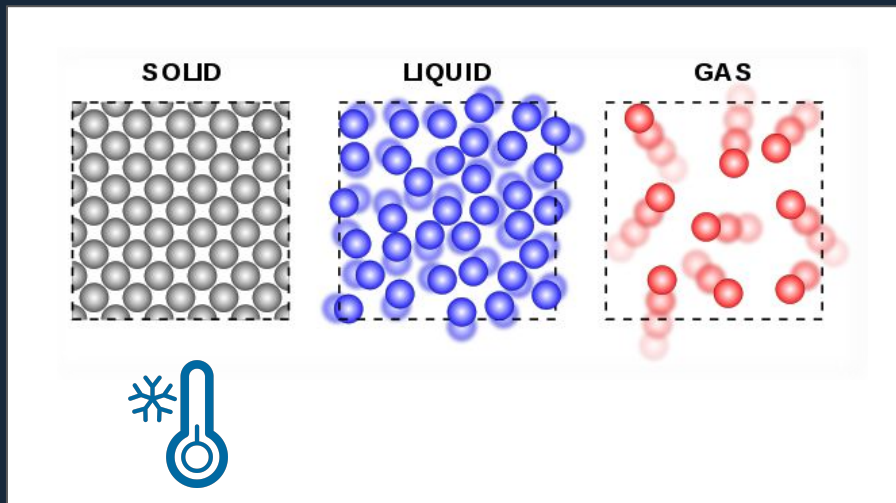


How should we choose?

Temperature (τ): parameter that determines the extent to which value estimates influence choice behaviour

Low temperature

- Choices are less noisy
- More affected by value
- More deterministic

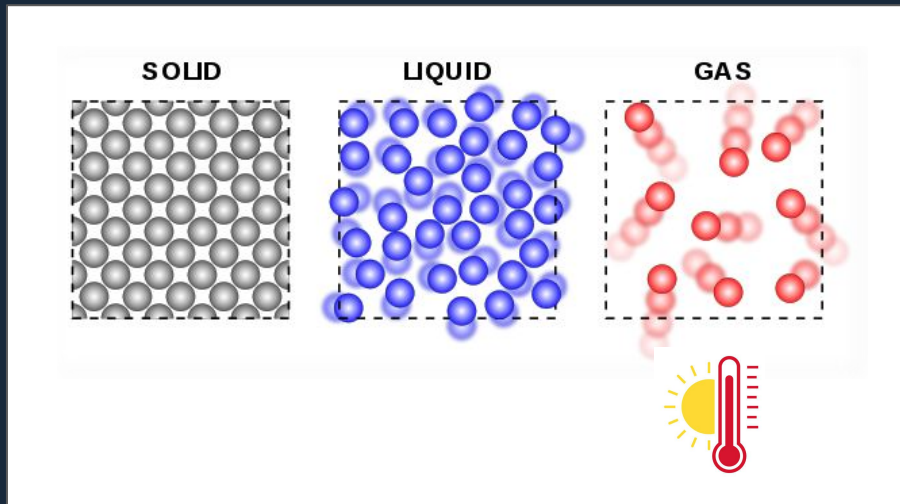


How should we choose?

Temperature (τ): parameter that determines the extent to which value estimates influence choice behaviour

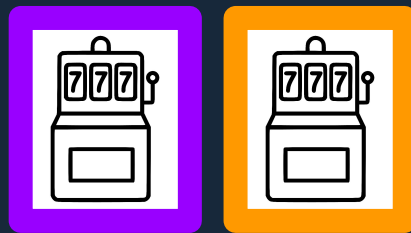
High temperature

- Choices are more noisy
- Less affected by value
- Less deterministic



How should we choose?

Temperature (τ): parameter that determines the extent to which value estimates influence choice behaviour



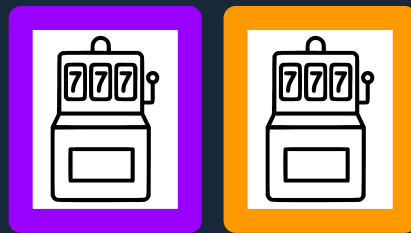
→ Let's assume that if we don't pick **purple** we will pick **orange**; and vice versa

How should we choose?

Temperature (τ): parameter that determines the extent to which value estimates influence choice behaviour

Softmax equation:

$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau) + \exp([V_{\text{orange}}] / \tau)]}$$



→ Let's assume that if we don't pick purple we will pick orange; and vice versa

How should we choose?

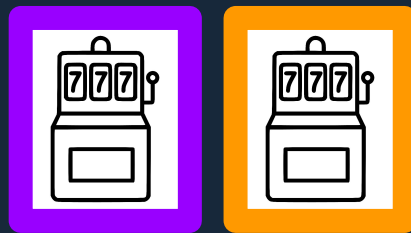
Temperature (τ): parameter that determines the extent to which value estimates influence choice behaviour

Softmax equation:

$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$

Probability of choosing purple

$$\rightarrow P(\text{orange}) = 1 - P(\text{purple})$$



→ Let's assume that if we don't pick purple we will pick orange; and vice versa

How should we choose?

Temperature (τ): parameter that determines the extent to which value estimates influence choice behaviour

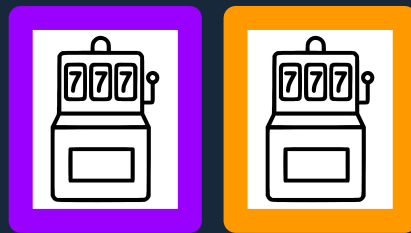
Softmax equation:

$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$

Value of machines

Probability of choosing purple

$$\rightarrow P(\text{orange}) = 1 - P(\text{purple})$$



→ Let's assume that if we don't pick purple we will pick orange; and vice versa

How should we choose?

Temperature (τ): parameter that determines the extent to which value estimates influence choice behaviour

Softmax equation:

$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$

Value of machines

Probability of choosing purple

Free parameter temperature

→ $P(\text{orange}) = 1 - P(\text{purple})$



→ Let's assume that if we don't pick purple we will pick orange; and vice versa

How should we choose?

$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$

Exploit

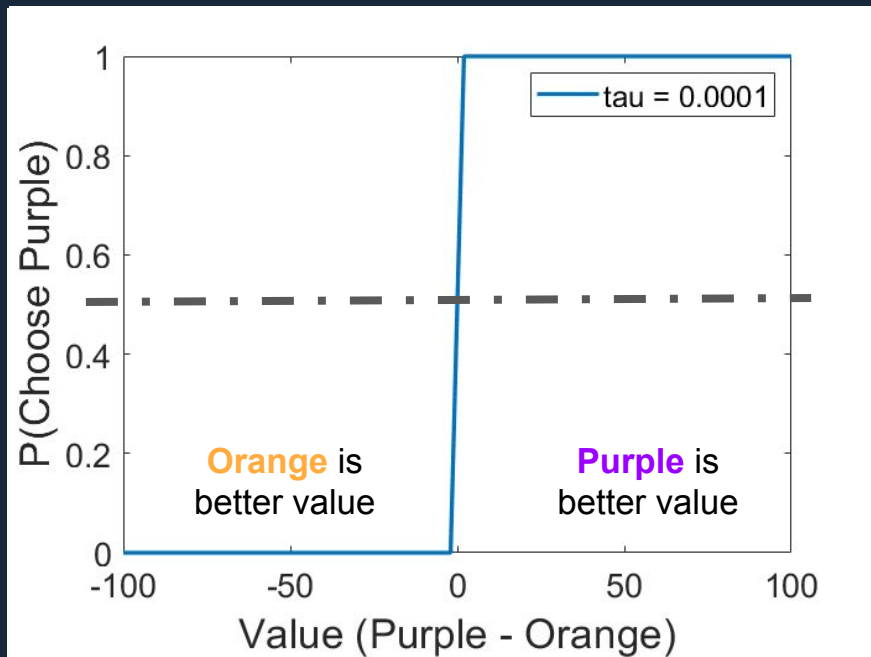
- Choose slot machine when reward is better than the other

How should we choose?

Choose
purple is
better



Choose
orange is
better



$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$

Exploit

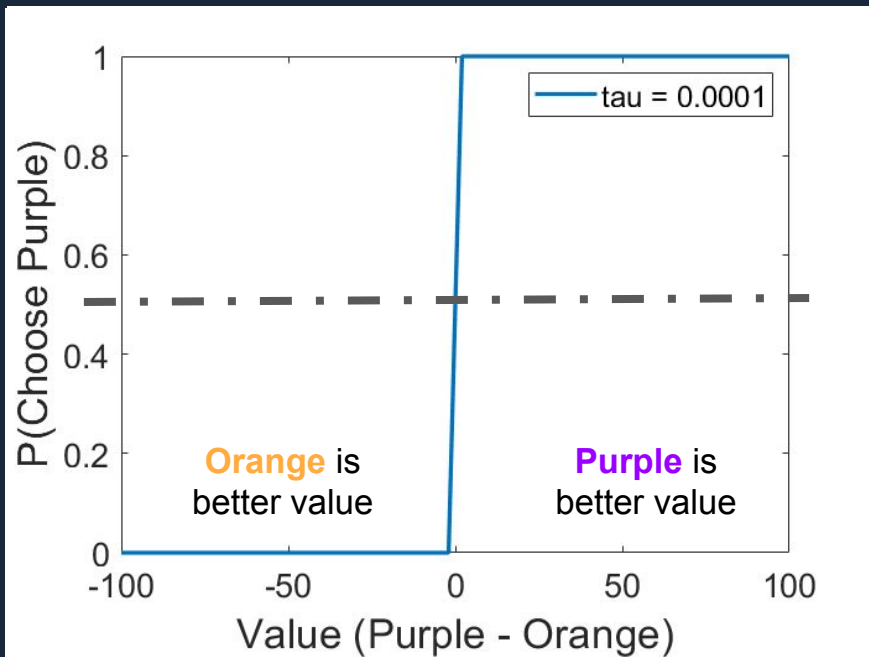
→ Choose slot machine when
reward is better than the
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How should we choose?

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purple is
better



Choose
orange is
better



$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$

Exploit

→ Choose slot machine when reward is better than the other

Temperature is low

- Choices are less noisy
- More affected by value
- More deterministic



How should we choose?

$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$

Explore

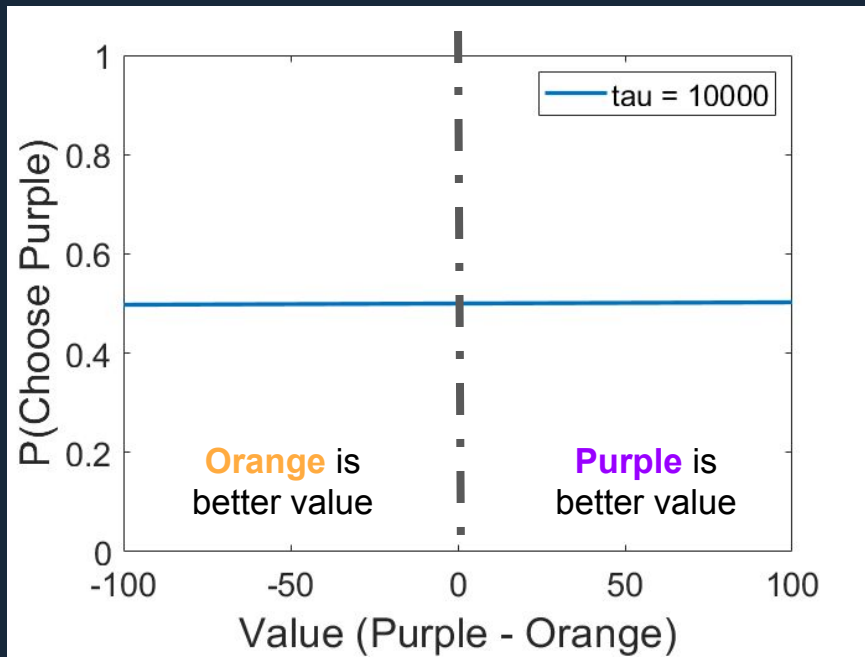
→ Random choice

How should we choose?

Choose
purple is
better



Choose
orange is
better



$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$

Explore

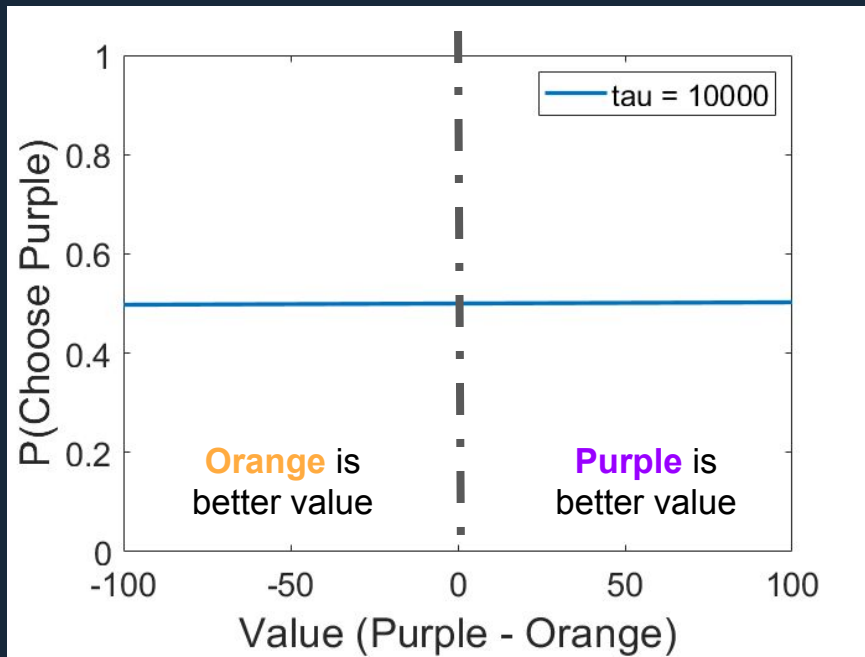
→ Random choice

How should we choose?

Choose
purple is
better



Choose
orange is
better



$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$

Explore

→ Random choice

Temperature is high

- Choices are more noisy
- Less affected by value
- More random



How should we choose?

$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$

Temperature is low

- Choices are less noisy
- More affected by value
- More deterministic

Temperature is high

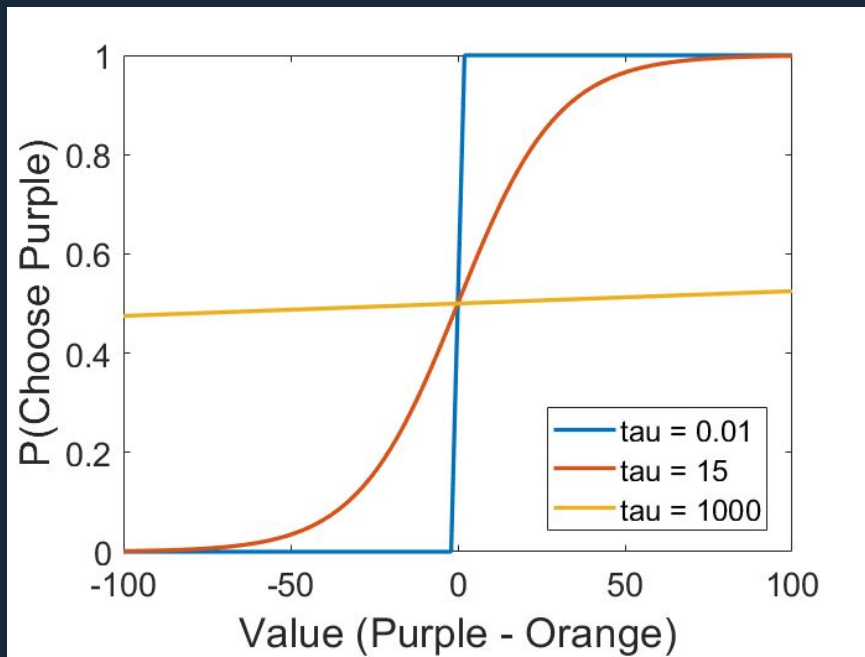
- Choices are more noisy
- Less affected by value
- Less deterministic

How should we choose?

Choose
purple is
better



Choose
orange is
better



$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$

Temperature is low

- Choices are less noisy
- More affected by value
- More deterministic

Temperature is high

- Choices are more noisy
- Less affected by value
- Less deterministic

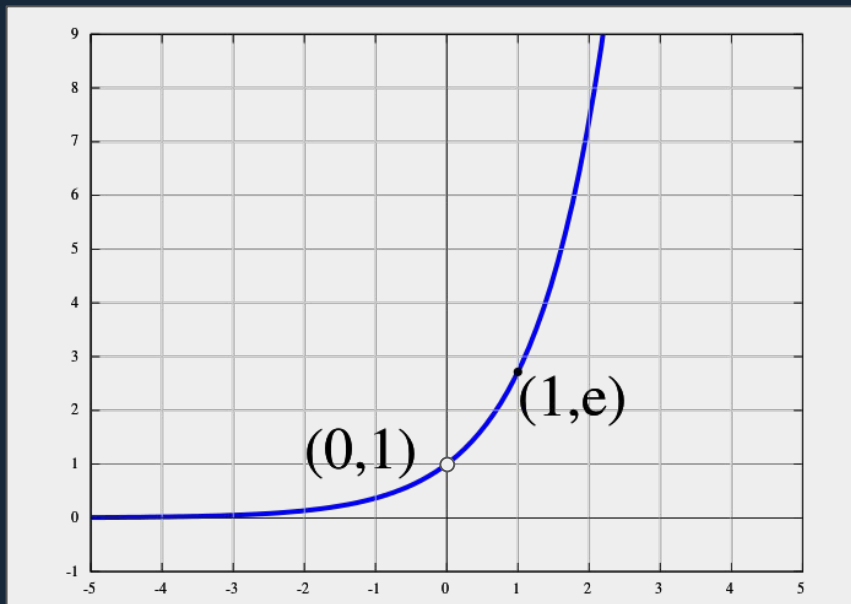
How should we choose?

Softmax

$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$

What does the exponential (exp) do?

How should we choose?

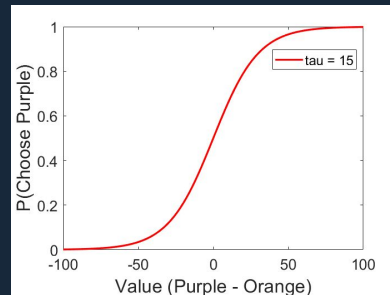


Softmax

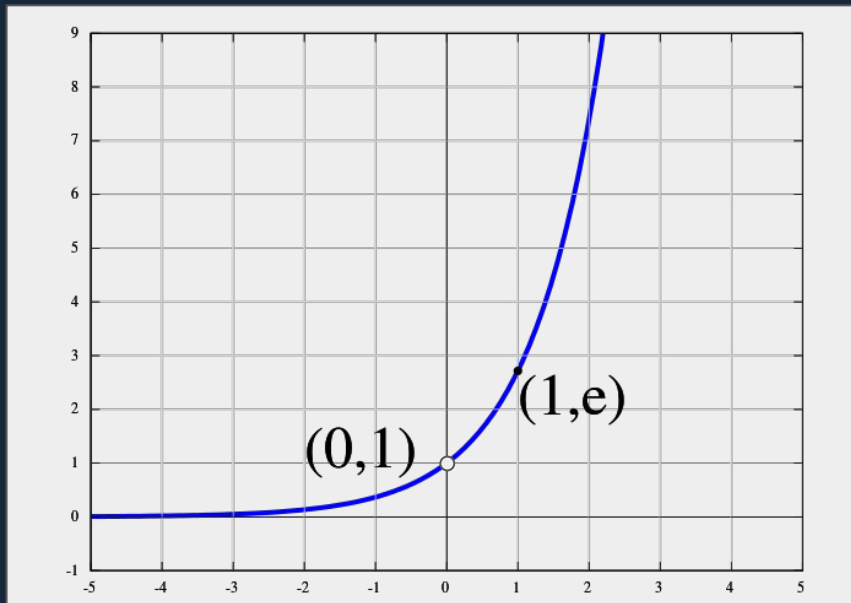
$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$

What does the exponential (exp) do?

- Non-linear transformation of value
- Deals with negative values



How should we choose?



Softmax

$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$

What does the exponential (exp) do?

- Non-linear transformation of value
- Deals with negative values

What does the division by SUM do?

- Normalizes values to between 0 to 1

How should we choose?

$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}])}{\text{SUM}[\exp([V_{\text{purple}}], V_{\text{orange}}])}$$

Softmax

→ Transforms value input into values between 0 to 1

Assume temperature = 1

How should we choose?

$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}])}{\text{SUM}[\exp([V_{\text{purple}}, V_{\text{orange}}])]}$$

Softmax

→ Transforms value input into values between 0 to 1

Assume temperature = 1

For my next slot machine play...

$$V_{\text{purple}} = [60] \quad V_{\text{orange}} = [40]$$

How should we choose?

$$\begin{aligned} P(\text{purple}) &= \frac{\exp([V_{\text{purple}}])}{\text{SUM}[\exp([V_{\text{purple}}], V_{\text{orange}}])} \\ &= \frac{\exp([60])}{\text{SUM}[\exp([60], 40)]} \end{aligned}$$

Softmax

→ Transforms value input into values between 0 to 1

Assume temperature = 1

For my next slot machine play...

$$V_{\text{purple}} = [60] \quad V_{\text{orange}} = [40]$$

How should we choose?

$$\begin{aligned} P(\text{purple}) &= \frac{\exp([V_{\text{purple}}])}{\text{SUM}[\exp([V_{\text{purple}}], V_{\text{orange}}])} \\ &= \frac{\exp([60])}{\text{SUM}[\exp([60], 40)]} \\ &= \frac{e^{60}}{e^{60} + e^{40}} \\ &= 1 \end{aligned}$$

Softmax

→ Transforms value input into values between 0 to 1

Assume temperature = 1

For my next slot machine play...

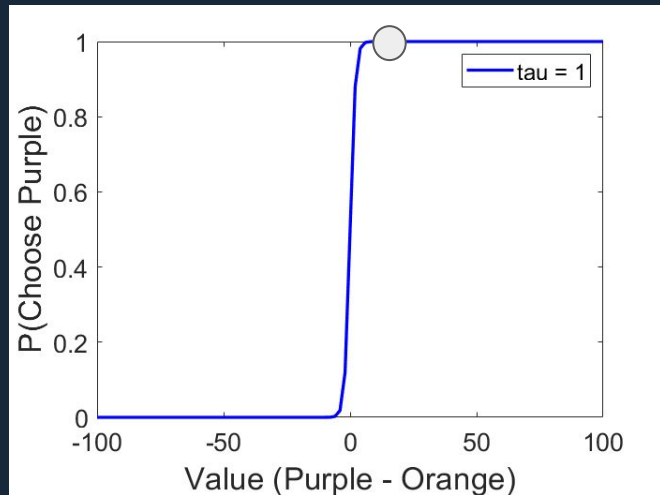
$$V_{\text{purple}} = [60] \quad V_{\text{orange}} = [40]$$

How should we choose?

$$\begin{aligned}
 P(\text{purple}) &= \frac{\exp([V_{\text{purple}}])}{\text{SUM}[\exp([V_{\text{purple}}], [V_{\text{orange}}])]} \\
 &= \frac{\exp([60])}{\text{SUM}[\exp([60], [40])]} \\
 &= \frac{e^{60}}{e^{60} + e^{40}} \\
 &= 1
 \end{aligned}$$

Softmax

→ Transforms value input into values between 0 to 1



How should we choose?

$$\begin{aligned} P(\text{purple}) &= \frac{\exp([V_{\text{purple}}])}{\text{SUM}[\exp([V_{\text{purple}}], [V_{\text{orange}}])]} \\ &= \frac{\exp([60])}{\text{SUM}[\exp([60], [40])]} \\ &= \frac{e^{60}}{e^{60} + e^{40}} \\ &= 1 \end{aligned}$$

$$P(\text{orange}) = \frac{\exp([V_{\text{orange}}])}{\text{SUM}[\exp([V_{\text{purple}}], [V_{\text{orange}}])]}$$

Softmax

→ Transforms value input into values between 0 to 1

Assume temperature = 1

How should we choose?

$$\begin{aligned}
 P(\text{purple}) &= \frac{\exp([V_{\text{purple}}])}{\text{SUM}[\exp([V_{\text{purple}}], [V_{\text{orange}}])]} \\
 &= \frac{\exp([60])}{\text{SUM}[\exp([60], [40])]} \\
 &= \frac{e^{60}}{e^{60} + e^{40}} \\
 &= 1
 \end{aligned}$$

$$\begin{aligned}
 P(\text{orange}) &= \frac{\exp([V_{\text{orange}}])}{\text{SUM}[\exp([V_{\text{purple}}], [V_{\text{orange}}])]} \\
 &= \frac{e^{40}}{e^{60} + e^{40}} \\
 &= 0
 \end{aligned}$$

Softmax

→ Transforms value input into values between 0 to 1

Assume temperature = 1

How should we choose?

$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}])}{\text{SUM}[\exp([V_{\text{purple}}], [V_{\text{orange}}])]}$$

$$= \frac{\exp([60])}{\text{SUM}[\exp([60], [40])]}$$

$$= \frac{e^{60}}{e^{60} + e^{40}}$$

$$= 1$$

$$P(\text{orange}) = \frac{\exp([V_{\text{orange}}])}{\text{SUM}[\exp([V_{\text{purple}}], [V_{\text{orange}}])]}$$

$$= \frac{e^{40}}{e^{60} + e^{40}}$$

$$= 0$$

probability equals to 1

Softmax

→ Transforms value input into values between 0 to 1

Assume temperature = 1

$$V_{\text{purple}} = [60] \quad V_{\text{orange}} = [40]$$

How should we choose?

$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$

Temperature (τ)

→ how much value affects choices

Assume temperature = 15

$$V_{\text{purple}} = [60] \quad V_{\text{orange}} = [40]$$

How should we choose?

$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$
$$= \frac{\exp([60] / 15)}{\text{SUM}[\exp([60] / 15)]}$$

Temperature (τ)

→ how much value affects choices

Assume temperature = 15

$$V_{\text{purple}} = [60] \quad V_{\text{orange}} = [40]$$

How should we choose?

$$\begin{aligned} P(\text{purple}) &= \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]} \\ &= \frac{\exp([60] / 15)}{\text{SUM}[\exp([60] / 15)]} \\ &= \frac{e^{60/15}}{e^{60/15} + e^{40/15}} \\ &= 0.79 \end{aligned}$$

Temperature (τ)

→ how much value affects choices

Assume temperature = 15

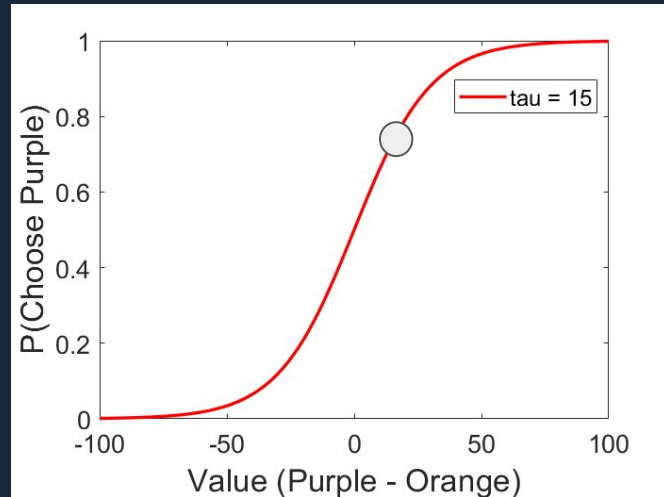
$$V_{\text{purple}} = [60] \quad V_{\text{orange}} = [40]$$

How should we choose?

$$\begin{aligned}
 P(\text{purple}) &= \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]} \\
 &= \frac{\exp([60] / 15)}{\text{SUM}[\exp([60] / 15)]} \\
 &= \frac{e^{60/15}}{e^{60/15} + e^{40/15}} \\
 &= 0.79
 \end{aligned}$$

Temperature (τ)

→ how much value affects choices



How should we choose?

$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$

$$= \frac{\exp([60] / 15)}{\text{SUM}[\exp([60] / 15)]}$$

$$= \frac{e^{60/15}}{e^{60/15} + e^{40/15}}$$

$$= 0.79$$

$$P(\text{orange}) = \frac{\exp([V_{\text{orange}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$

$$= \frac{e^{40/15}}{e^{60/15} + e^{40/15}}$$

$$= 0.21$$

probability equals to 1

Temperature (τ)

→ how much value affects choices

Assume temperature = 15

$$V_{\text{purple}} = [60] \quad V_{\text{orange}} = [40]$$

What have we learnt about choice?

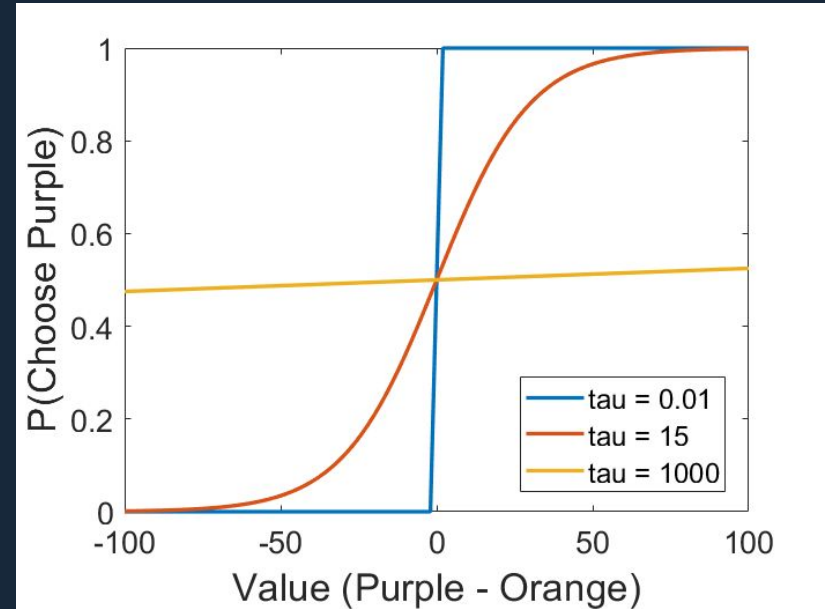
Softmax equation:

$$P(\text{purple}) = \frac{\exp([V_{\text{purple}}] / \tau)}{\text{SUM}[\exp([V_{\text{purple}}] / \tau)]}$$

V_{orange}

Temperature (τ): parameter that determines the extent to which value estimates influence choice behaviour

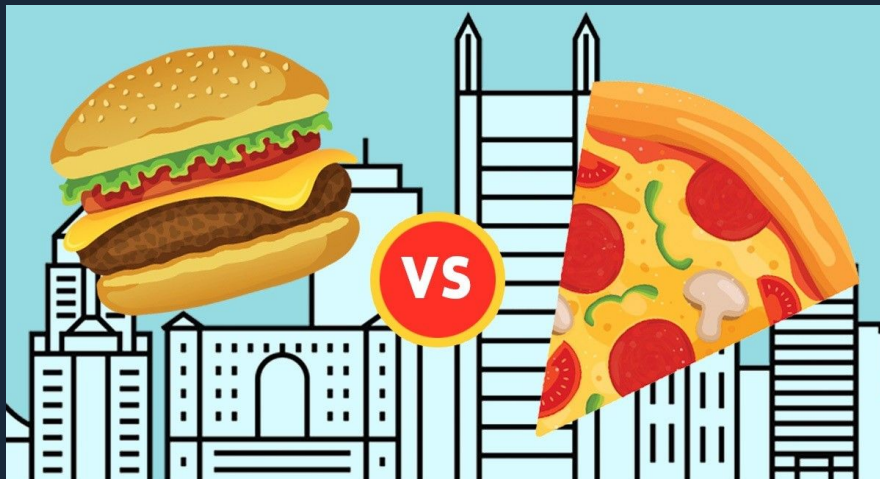
Exploit or Explore



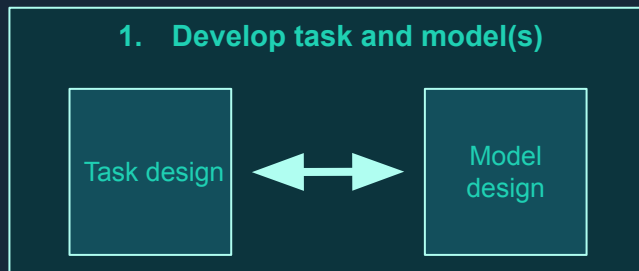
What have we learnt about choice?

Exploit **versus** Explore:

- Discover “what works” by alternating between exploration and exploitation
- In uncertain environments, more exploration **could** be useful



Summary



Task	Trial and error learning	Reinforcement Learning
Value Function	Subjective value from objective outcomes	Rescorla-Wagner
Choice Function	Choice probabilities from value	Softmax