



COMP250: Artificial Intelligence
4: Utility-Based AI



Utility



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- ▶ Multiply by –1 and we have **cost**

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- ▶ Utility is a **single number** — we essentially have to put a monetary value on the longer wait time

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- ▶ The values used will influence the agent's behaviour and so must be carefully tuned by the designer

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- ▶ Assuming everything else equal, where do you buy it from?
- ▶ To apply utility theory, we need to **quantify** everything — which may mean putting a numerical value on **intangible** things

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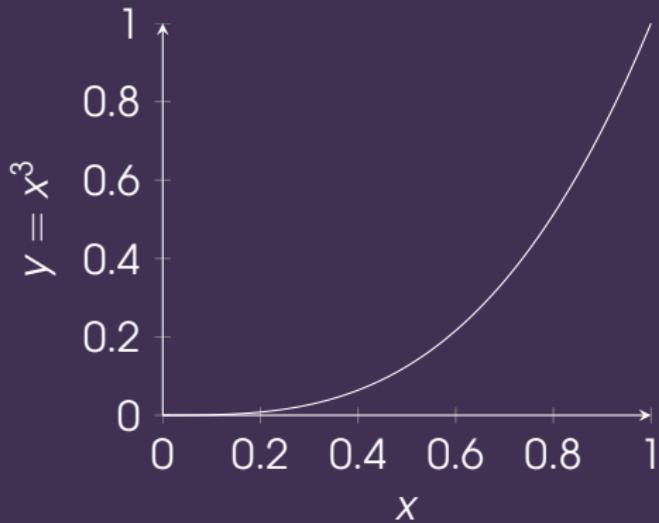
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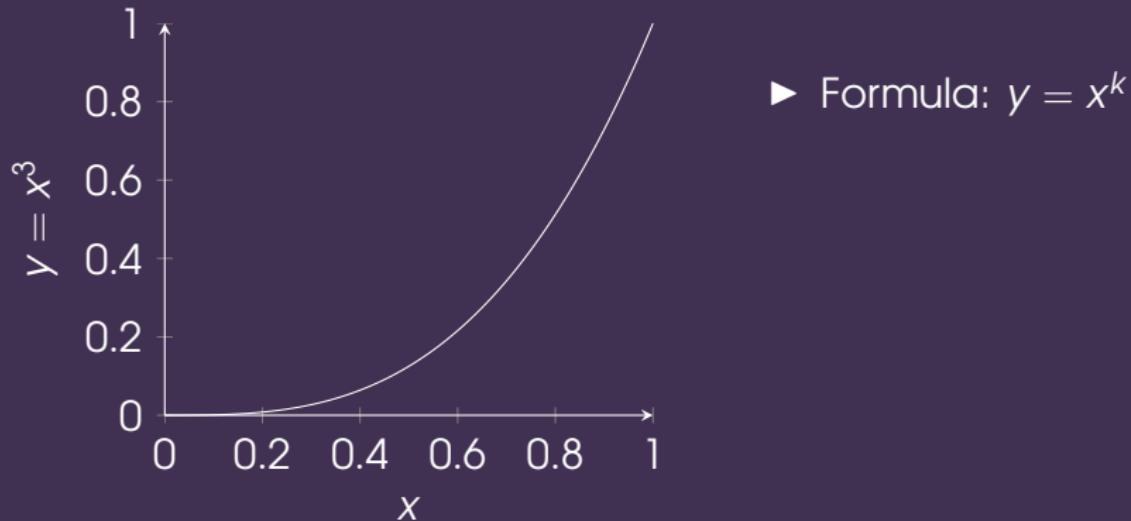
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- ▶ Therefore we may want to apply a **curve** mapping to decision factors

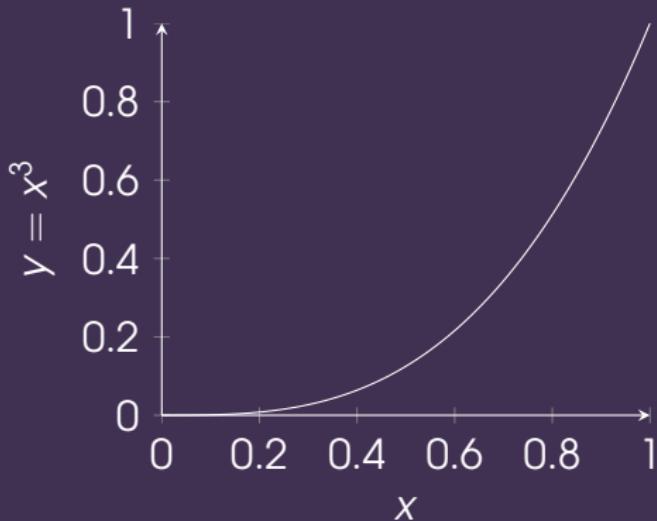
Polynomial curve



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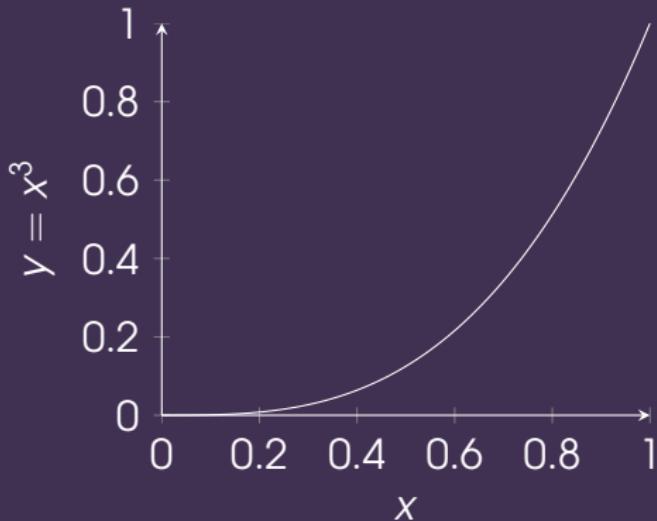


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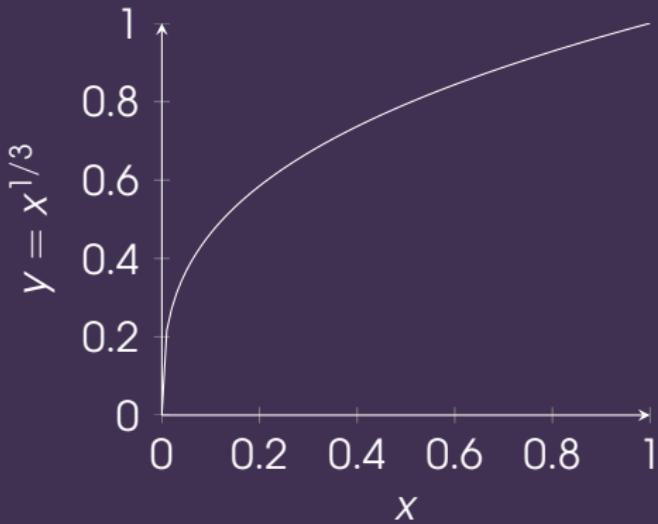
- ▶ Formula: $y = x^k$
- ▶ C#:
`Mathf.Pow(x, k)`

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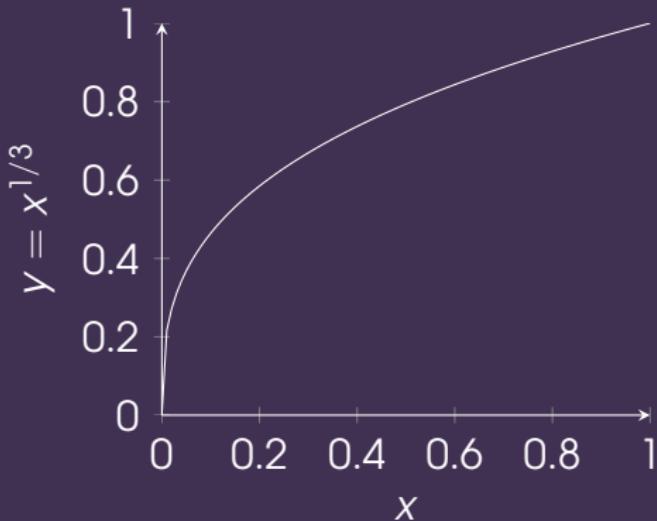


- ▶ Formula: $y = x^k$
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- ▶ k is a constant:
bigger k gives a steeper curve

Inverse polynomial curve

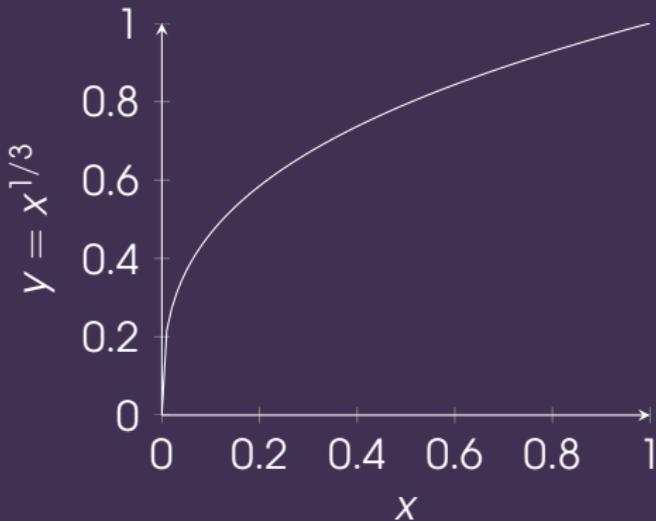


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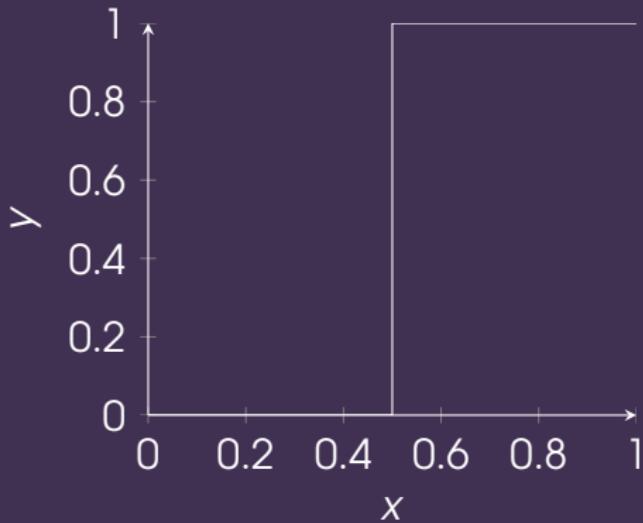
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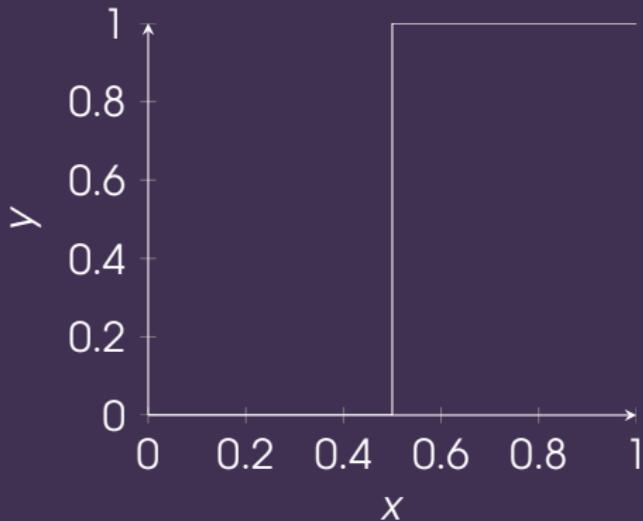


- ▶ Same formula as polynomial curve, but k is between 0 and 1
- ▶ k closer to 0 gives a steeper curve

Step function



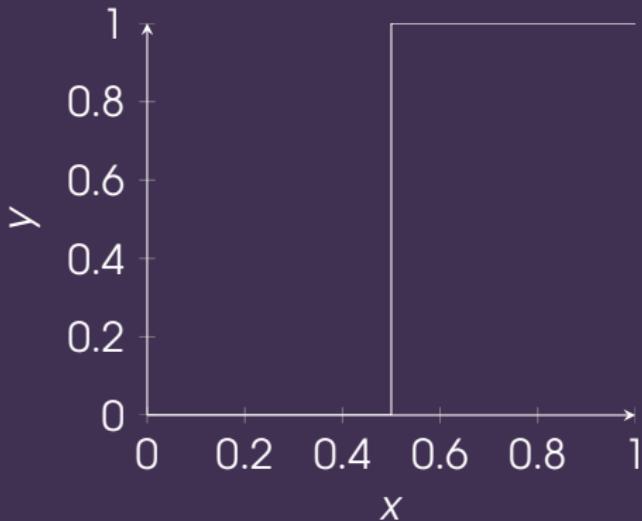
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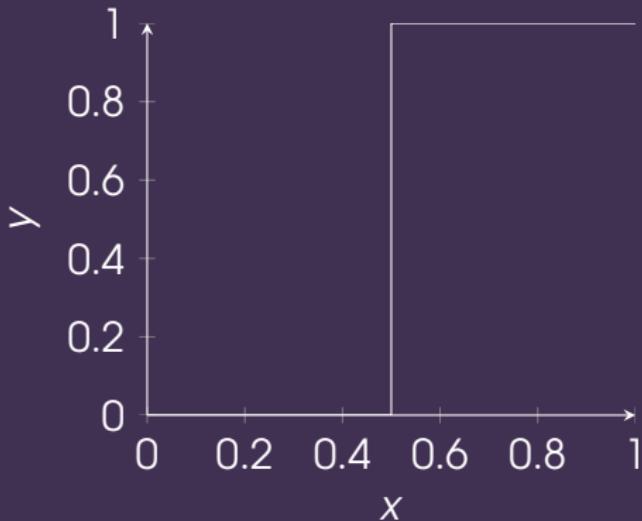
$$y = \begin{cases} 0 & \text{if } x < 0.5 \\ 1 & \text{if } x \geq 0.5 \end{cases}$$

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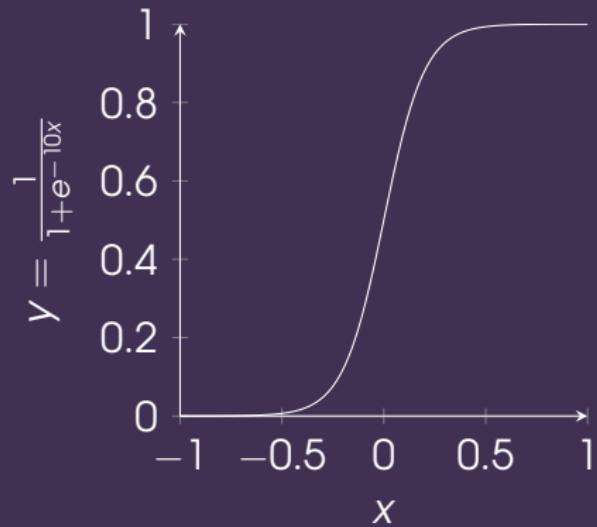
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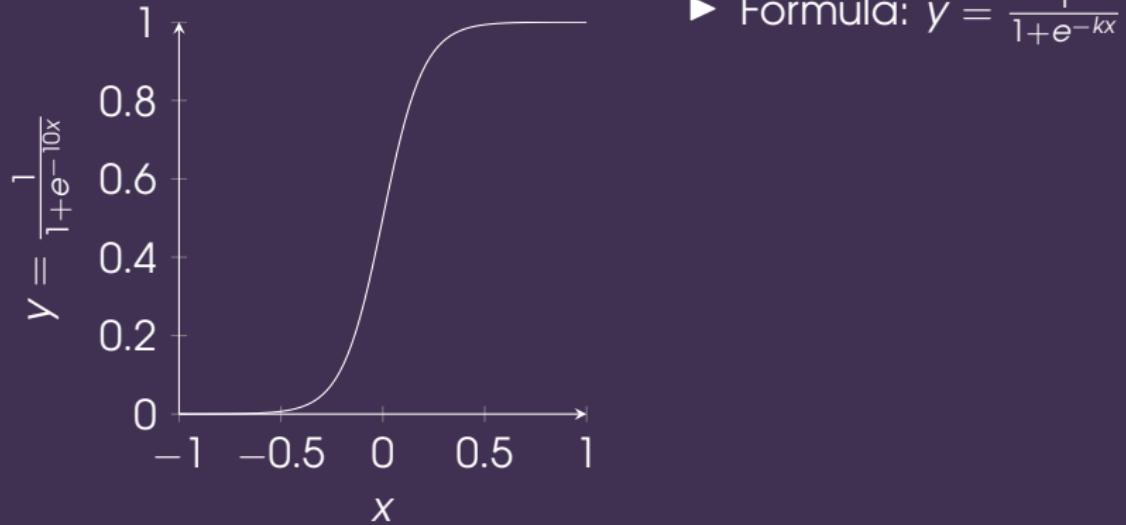


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- ▶ Models a **threshold** or **if-then** rule

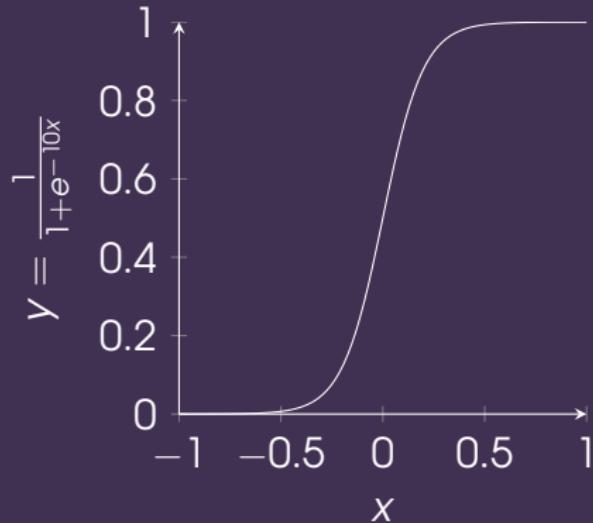
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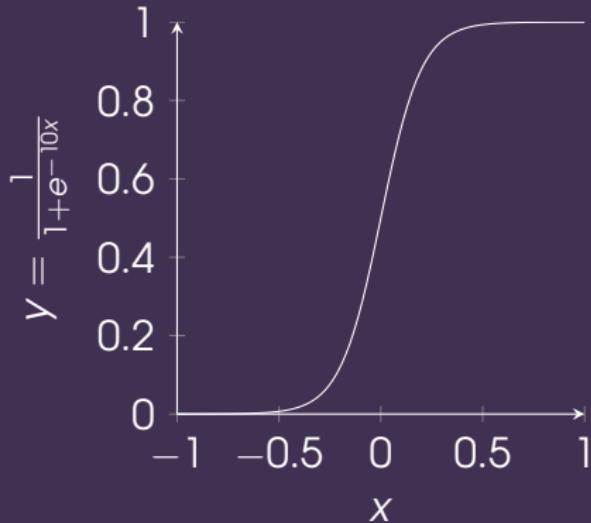


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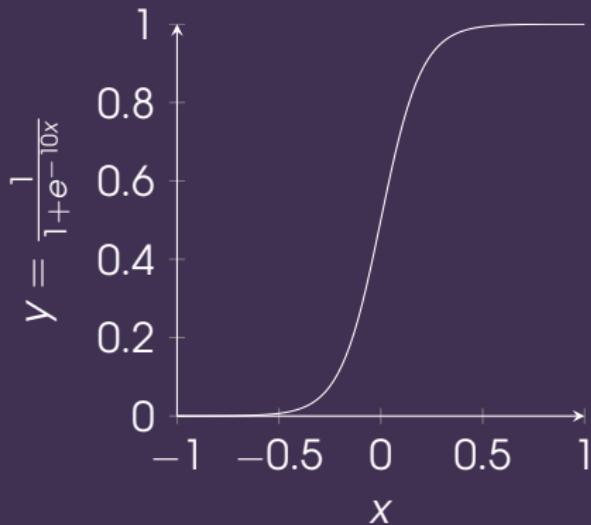
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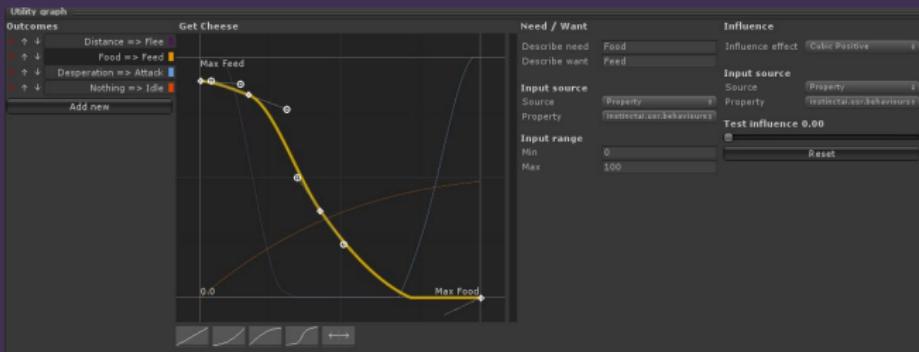
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- ▶ E.g. InstinctAI asset for Unity:



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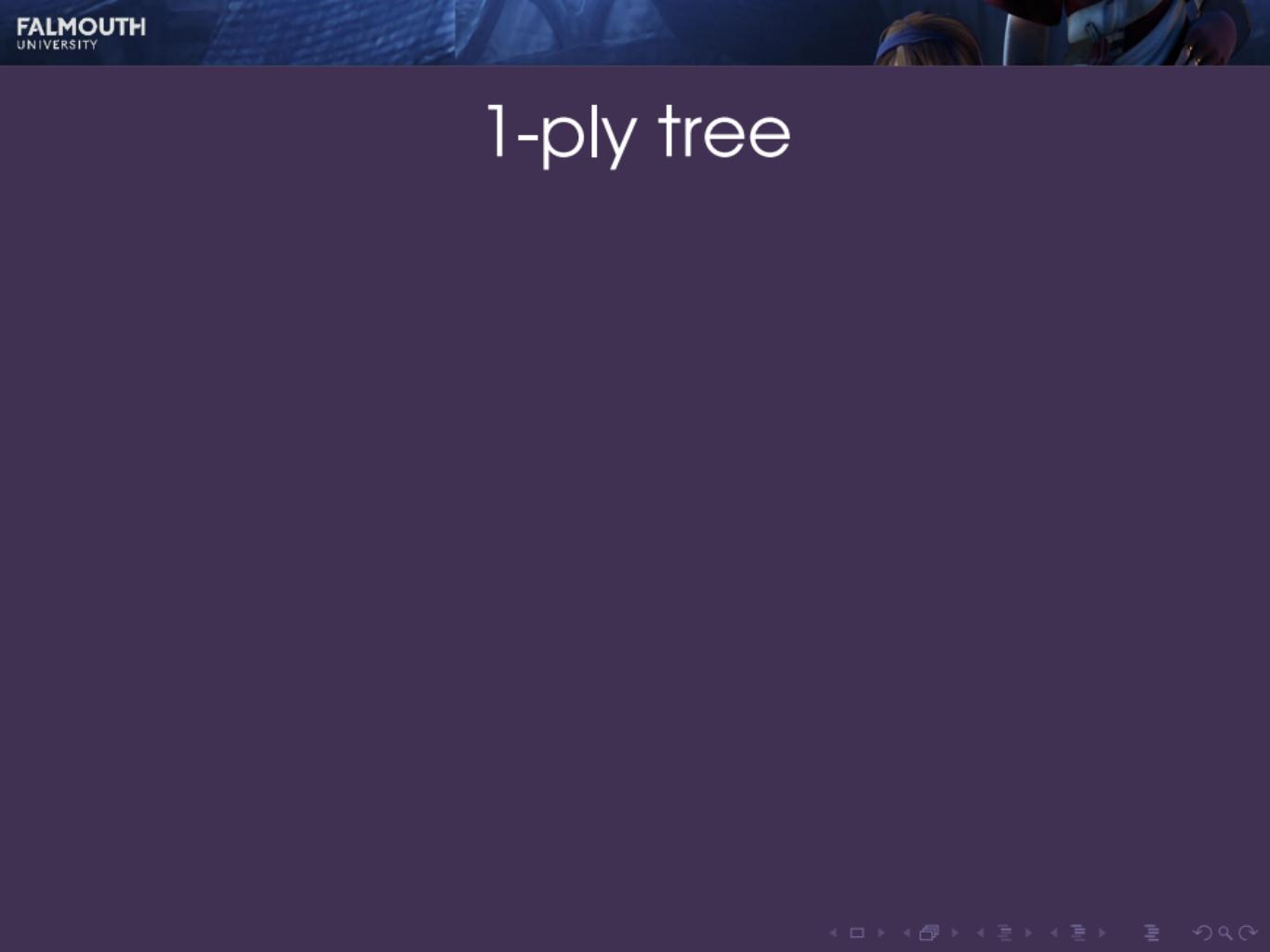
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- ▶ Can force the agent to finish its current action before evaluating and choosing another
- ▶ Can give a utility bonus to sticking to the current action — this still allows the agent to change its mind if the current action's utility becomes very bad

1-ply Search





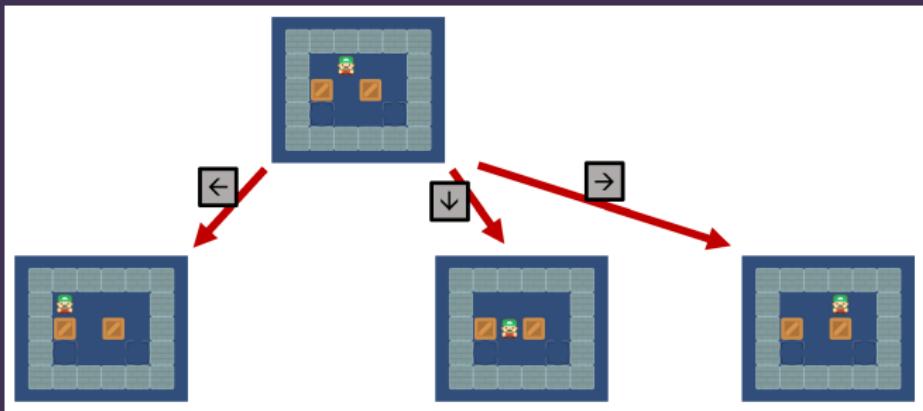
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- ▶ Recall from last time: in discrete planning problems or games, we can build a **state-action tree**
- ▶ Consider a tree with only one level or **ply**



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- ▶ Then we can “search” for the action leading to the best utility score

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bestAction \leftarrow null

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return *bestAction*

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    for each valid action from state do
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 - ▶ E.g. distance to goal — greedy search
 - ▶ E.g. material evaluation in chess
- ▶ Much faster than a full-blown BFS or game tree search, if depth of forward planning is not required

Expectation



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- ▶ That is, the sum of utility values weighted by their probabilities

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- ▶ (Although the actual utility can range from –£1 to +£9)

Multi-Objective Optimisation



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Multi-objective optimisation

- ▶ Utility-based AI is **single-objective**: all decision factors must be combined into a single number
- ▶ An alternative is **multi-objective**: treat all decision factors as separate, and find an action that optimises all of them at once

Pareto optimality

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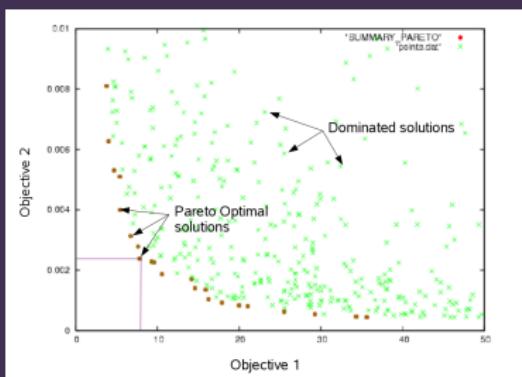
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- ▶ A solution is **Pareto optimal** if it is not dominated by any other solution



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- ▶ However, there are generally a large number of Pareto optimal solutions so we need some other method to tie-break between them
- ▶ ... which may boil down to weights (or at least priorities) anyway