COMP250: Artificial Intelligence

4: Utility-Based AI

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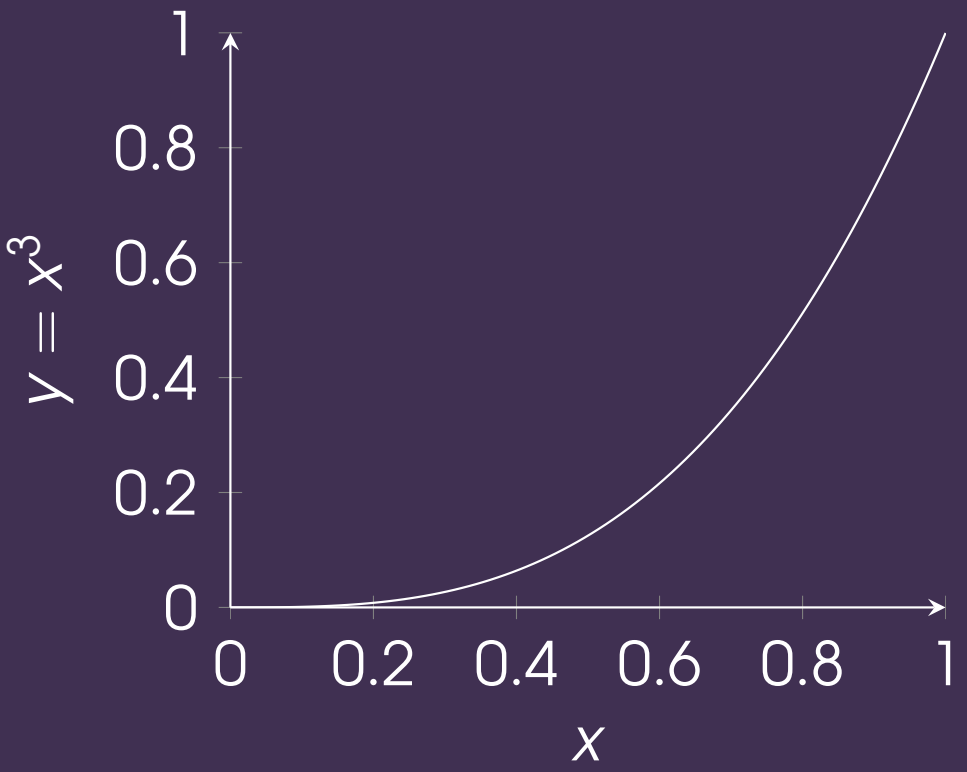
- Therefore we may want to apply a **curve** mapping to decision factors

Polynomial curve



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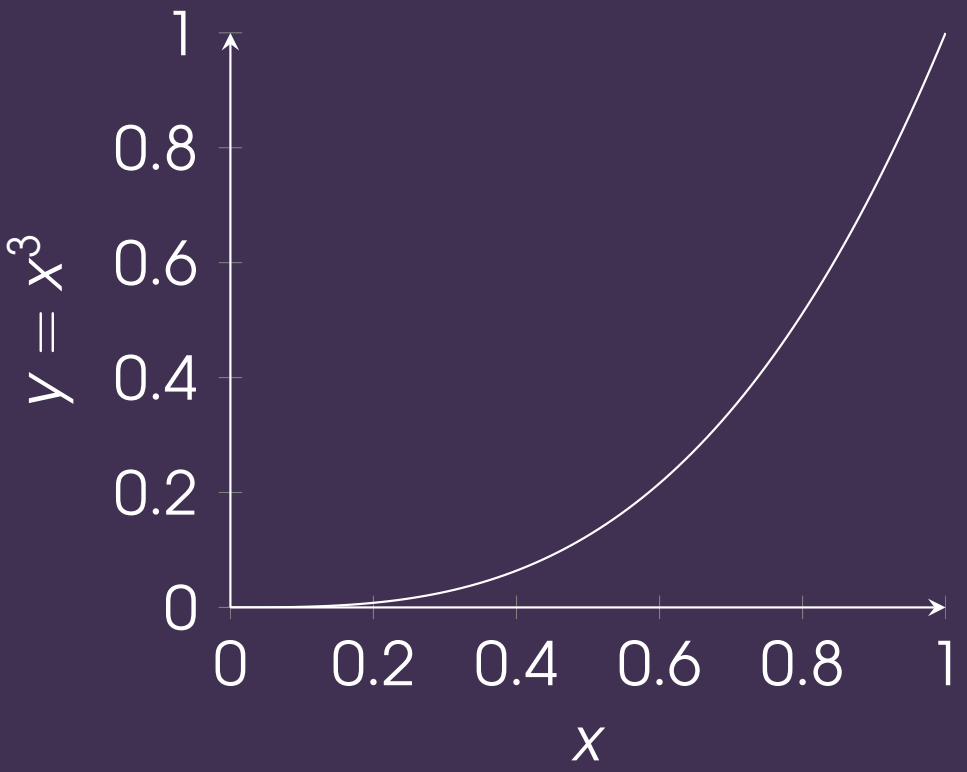

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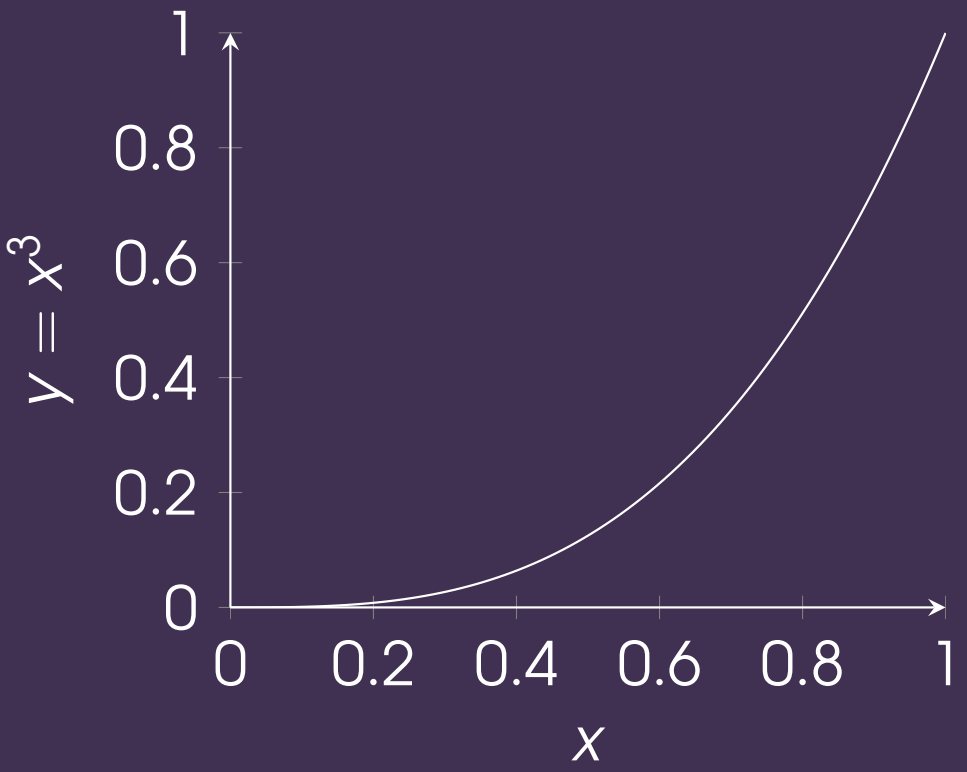

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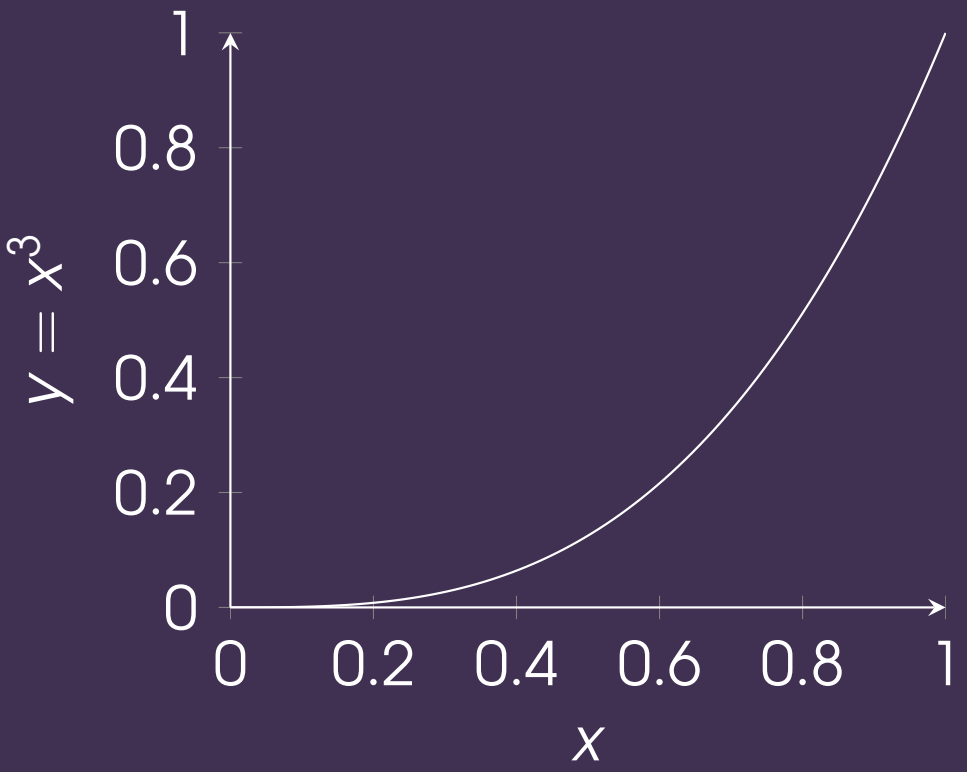

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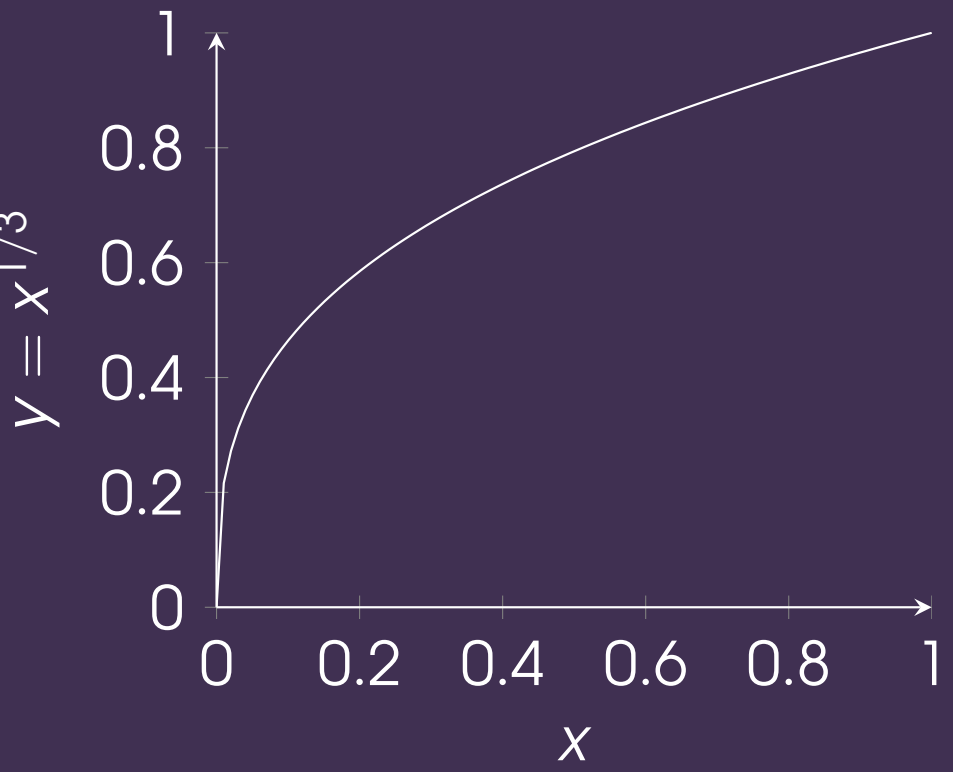

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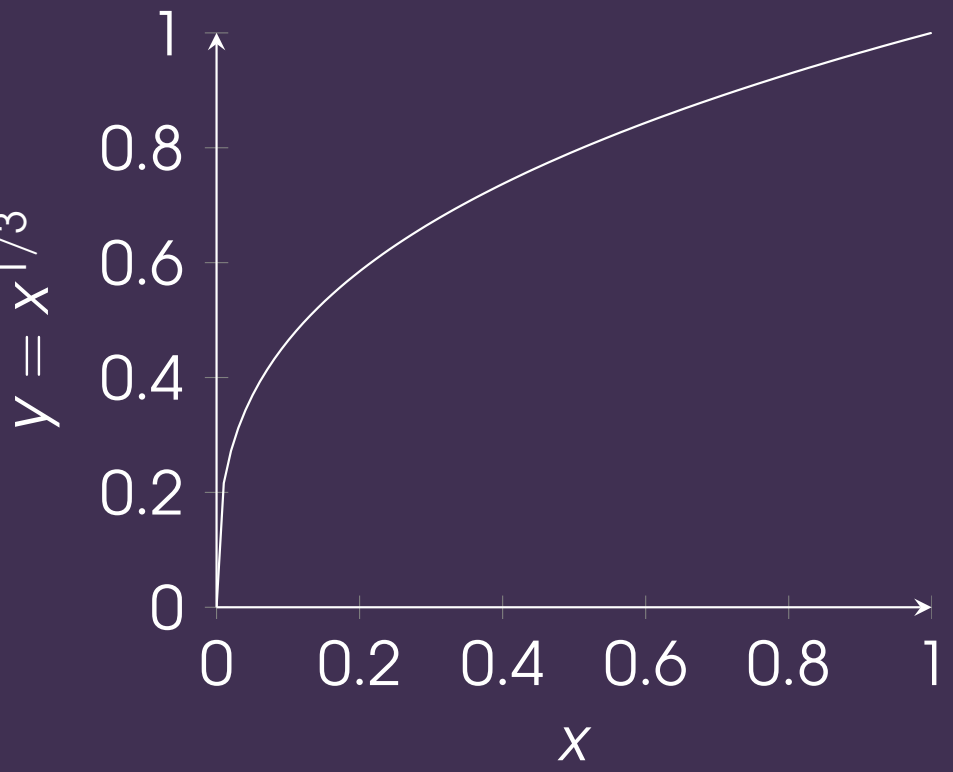

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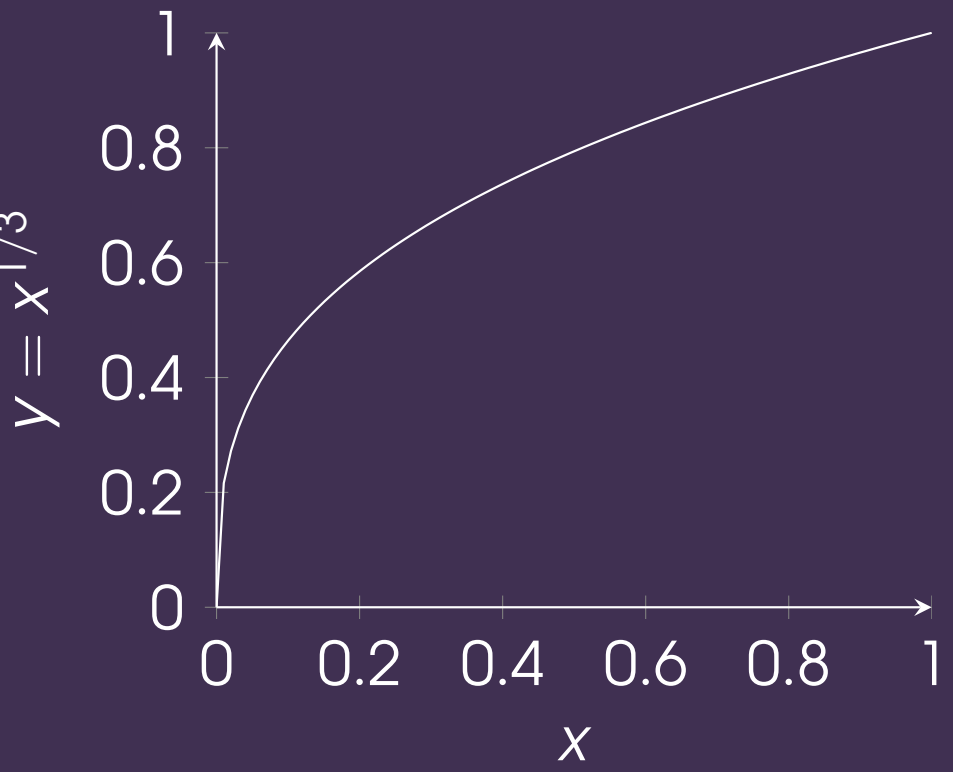

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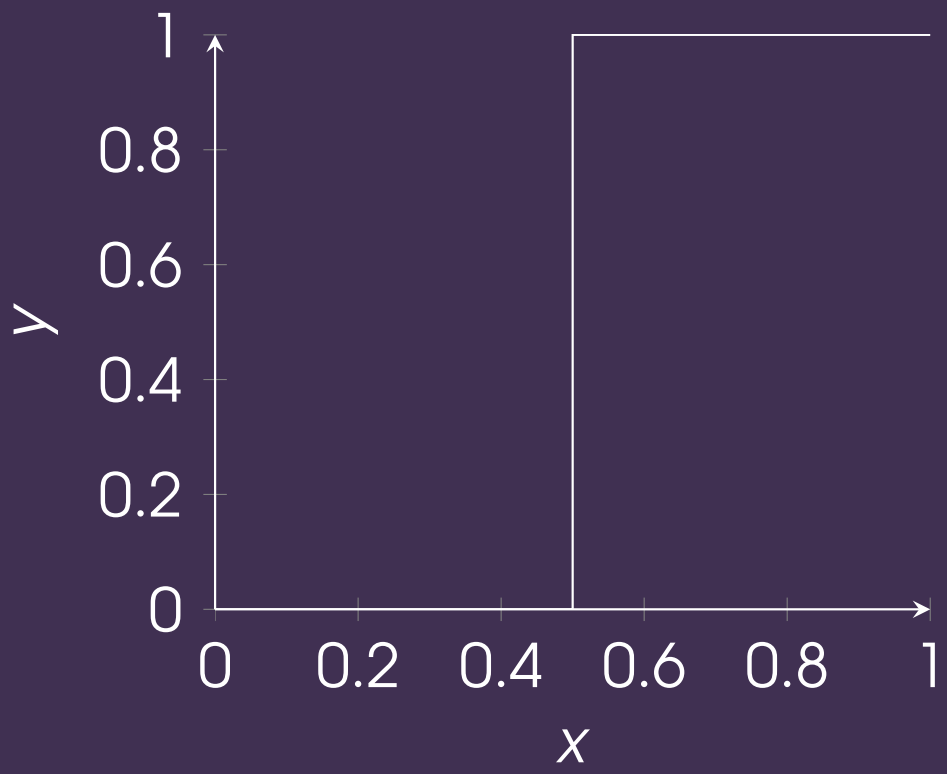
- k closer to 0 gives a steeper curve

Step function



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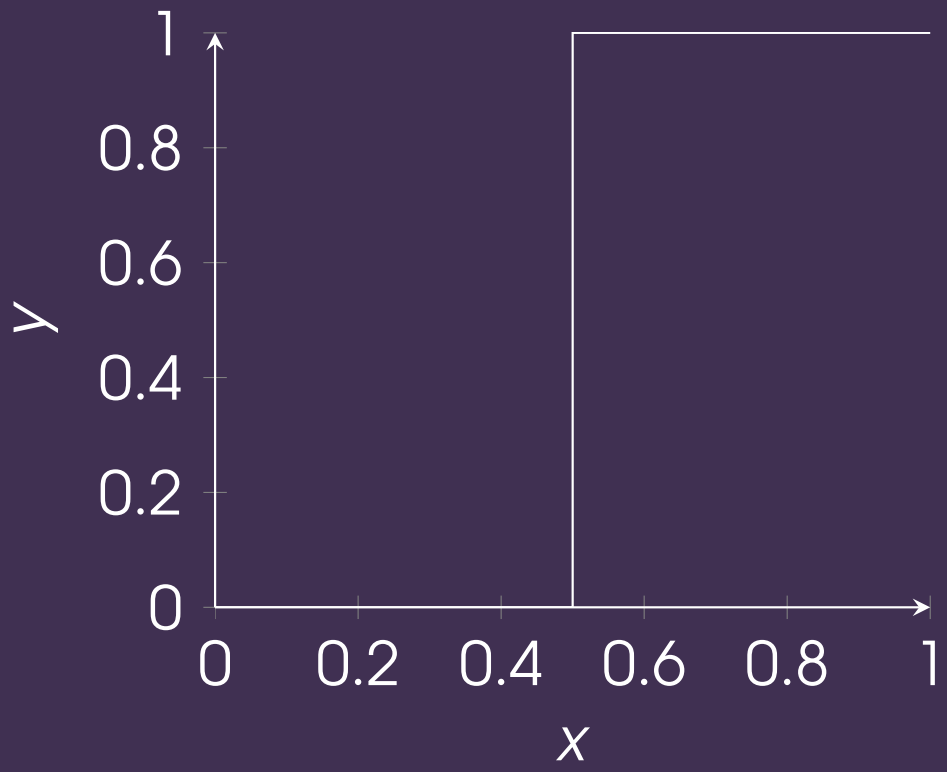

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$$y = \begin{cases} 0 & \text{if } x < 0.5 \\ 1 & \text{if } x \geq 0.5 \end{cases}$$

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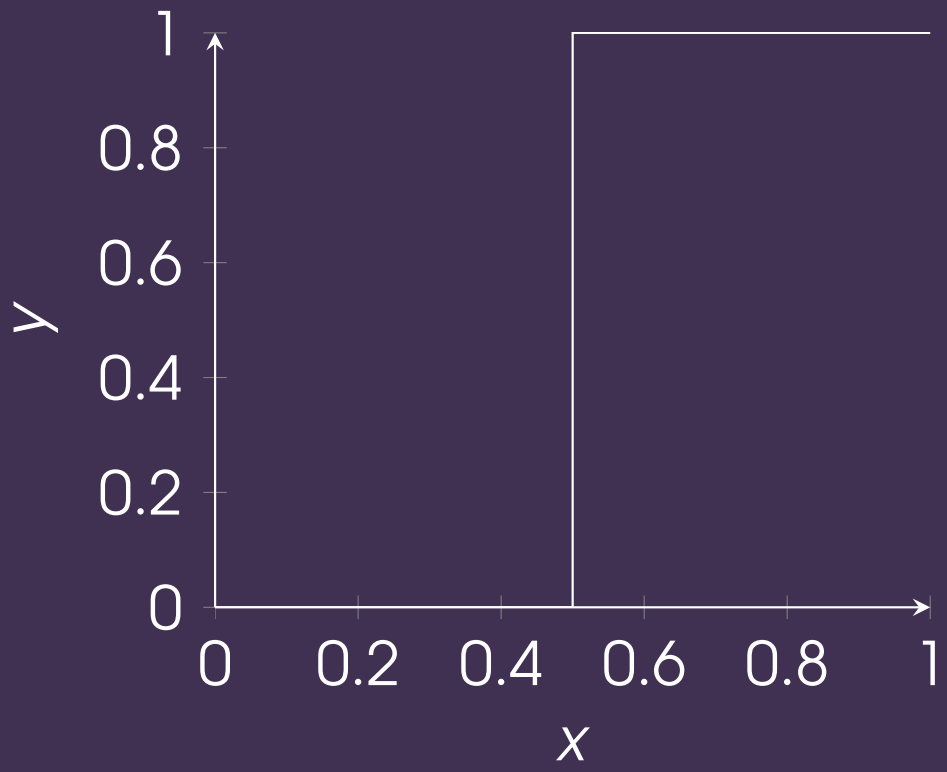

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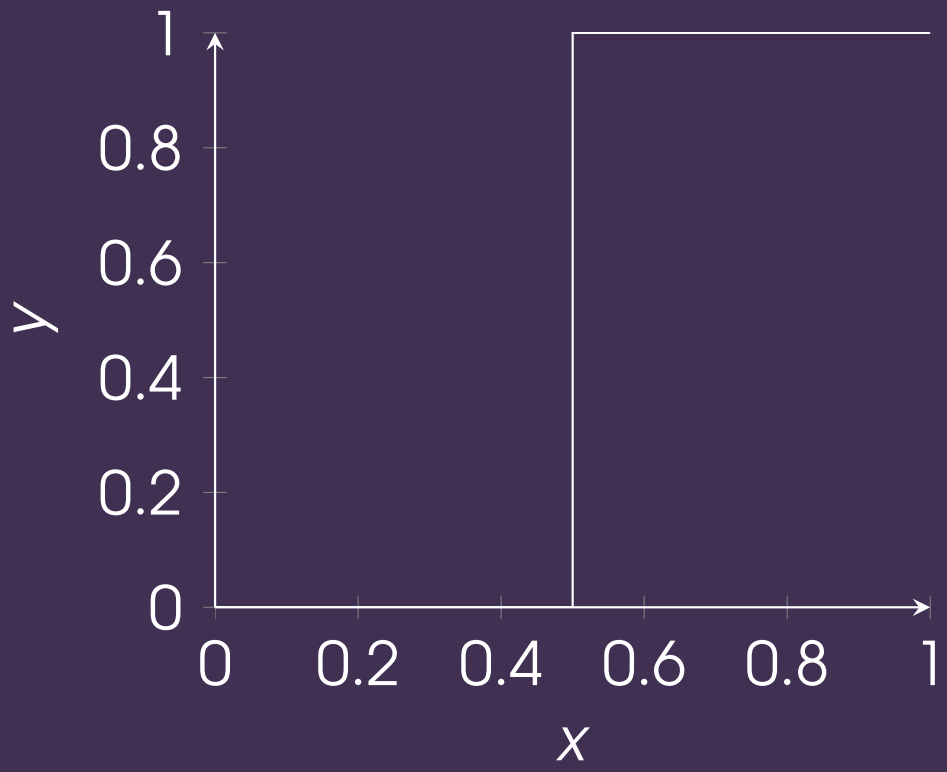

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- Models a **threshold** or **if-then** rule

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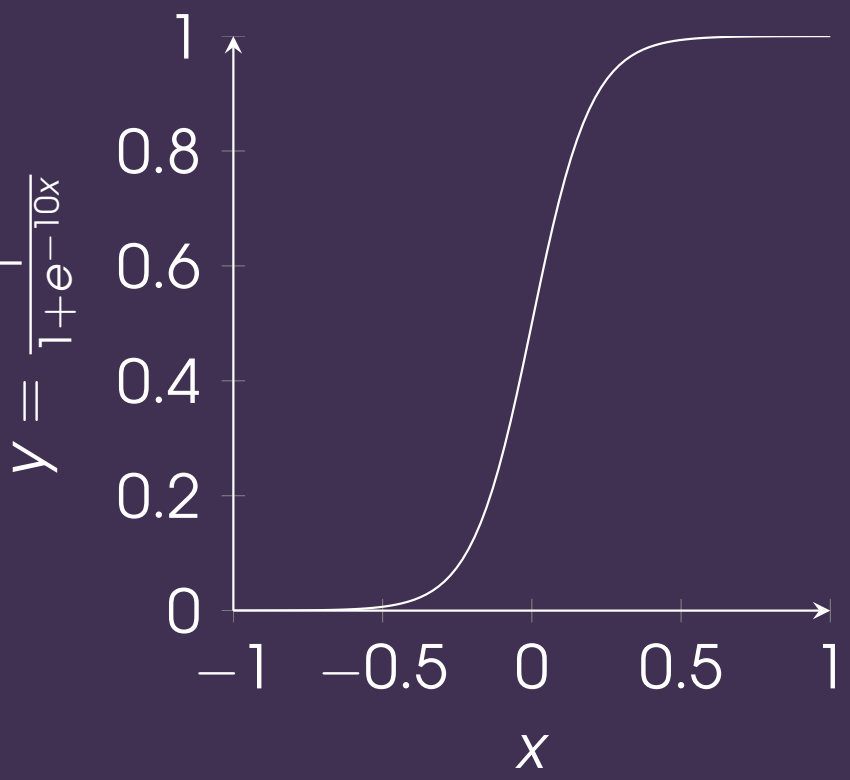

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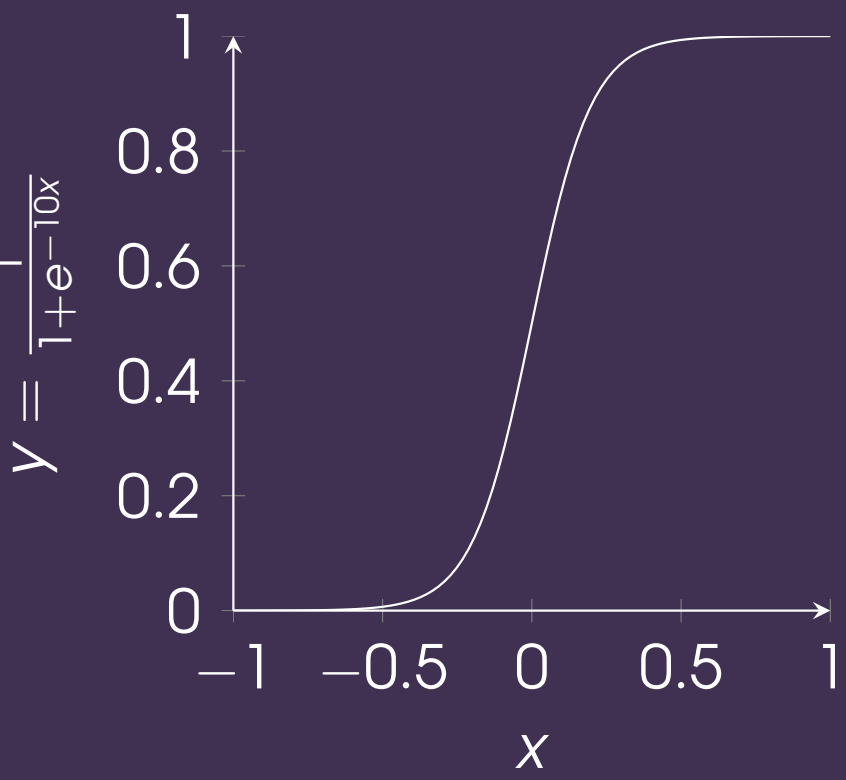

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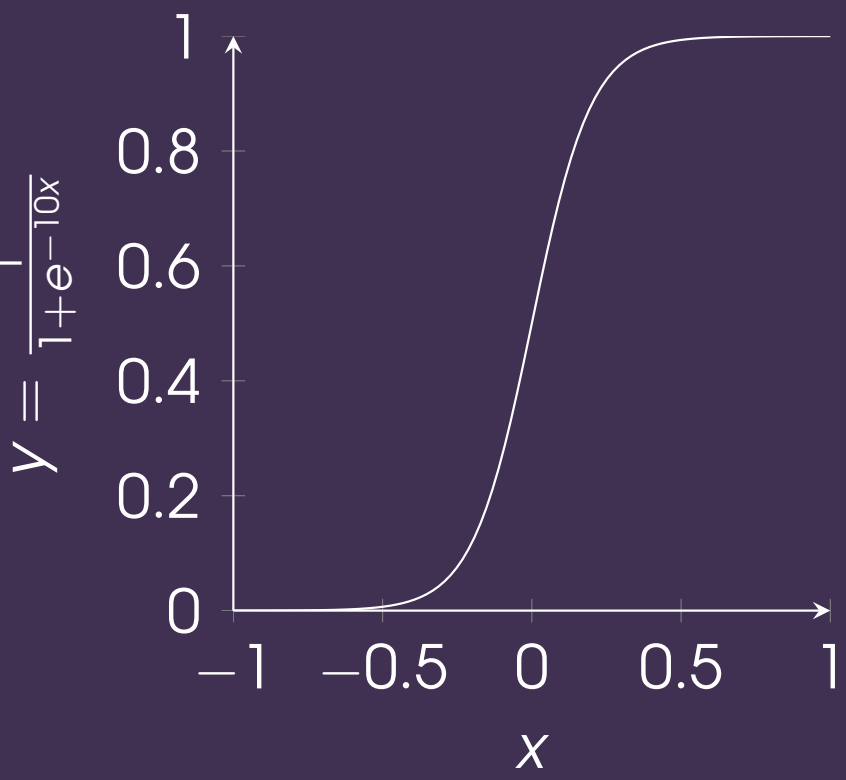

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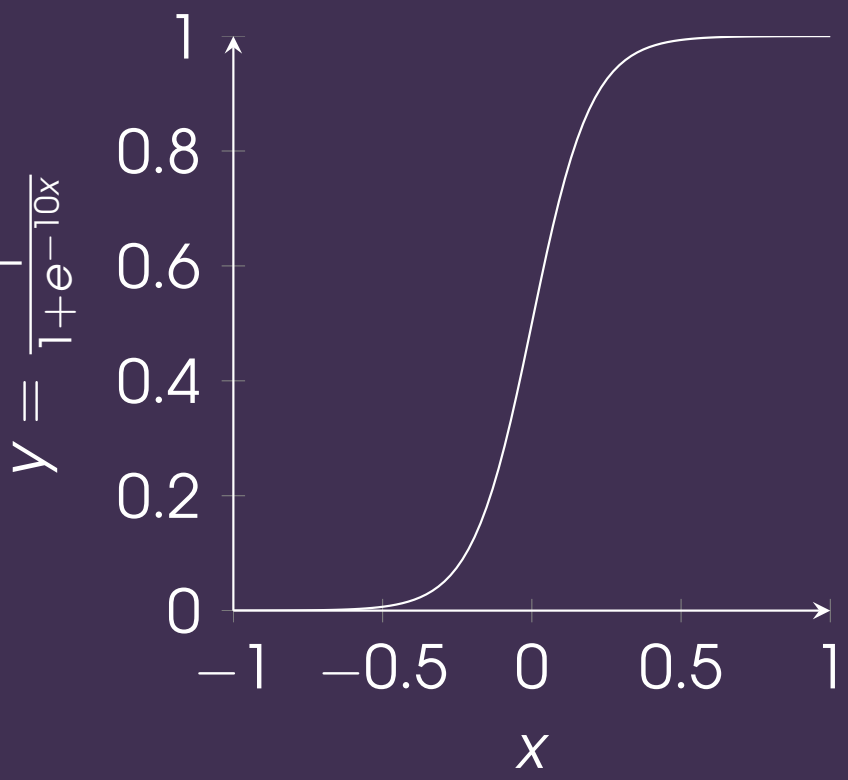

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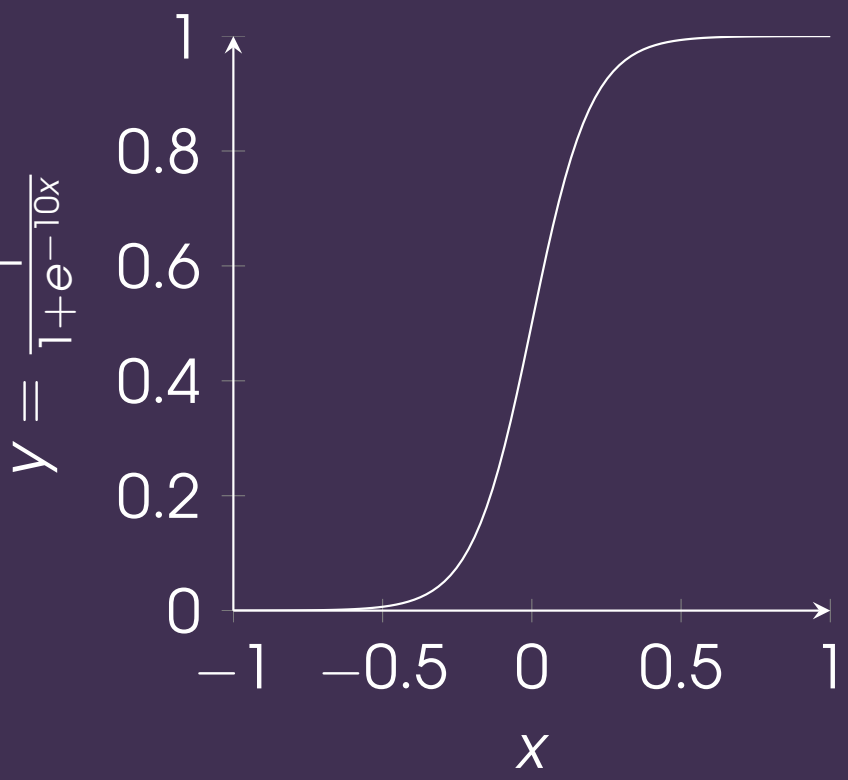

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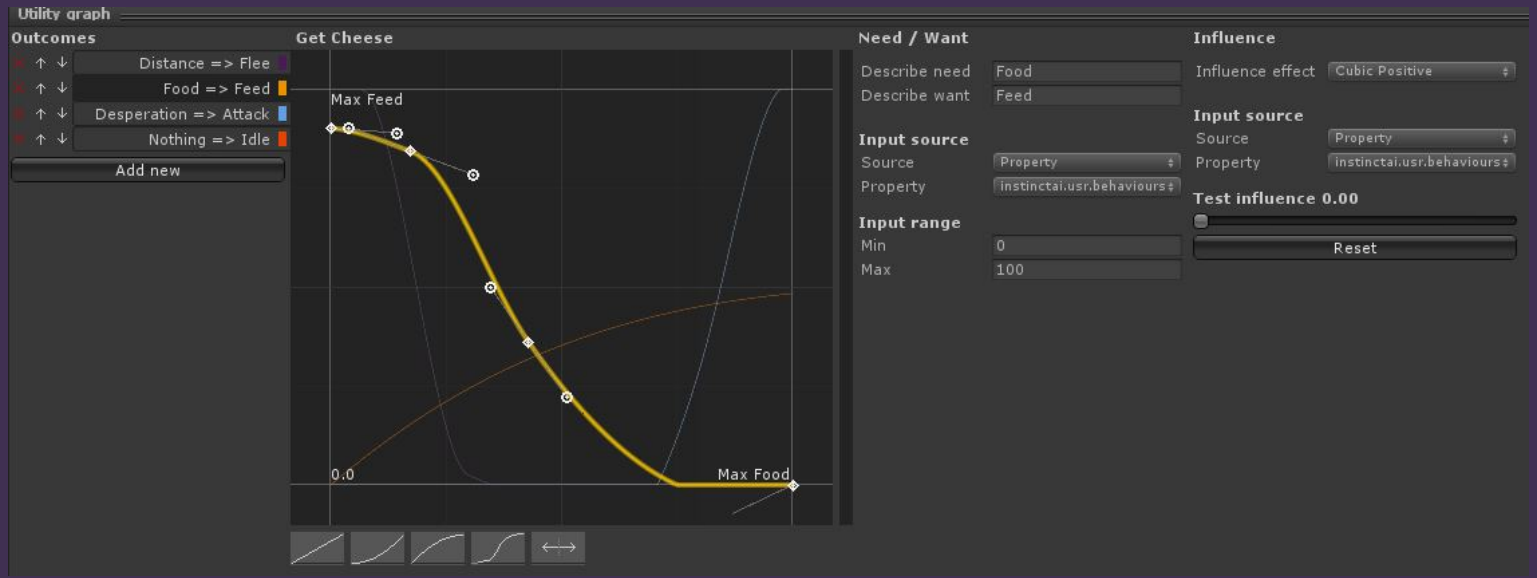
- **Graphical curve editors** are worth investigating
- E.g. InstinctAI asset for Unity:



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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)

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- 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

Multi-objective optimisation

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- An alternative is **multi-objective**: treat all decision factors as separate, and find an action that optimises all of them at once

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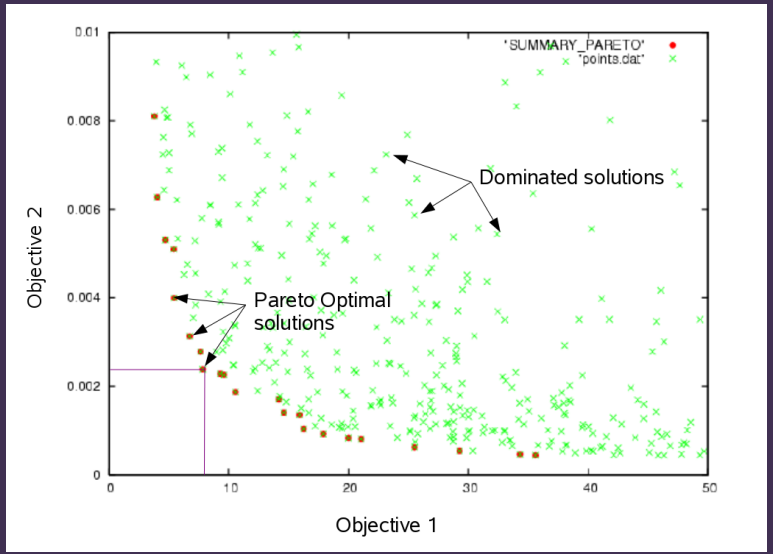
- A solution is **Pareto optimal** if it is not dominated by any other solution



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- Multi-objective optimisation gets around the problem of having to tune weights for decision factors
- However, there are generally a large number of Pareto optimal solutions so we need some other method to tie-break between them

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- A modified version of STRIPS planning (recall from last week) specifically for real-time planning in video games

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  - Goals are like in STRIPS — sets of predicates that the agent wants to satisfy
- Each agent also has a set of **actions**
  - Like in STRIPS — actions have preconditions and postconditions
  - Unlike STRIPS, each action also has a **cost**

Action sets

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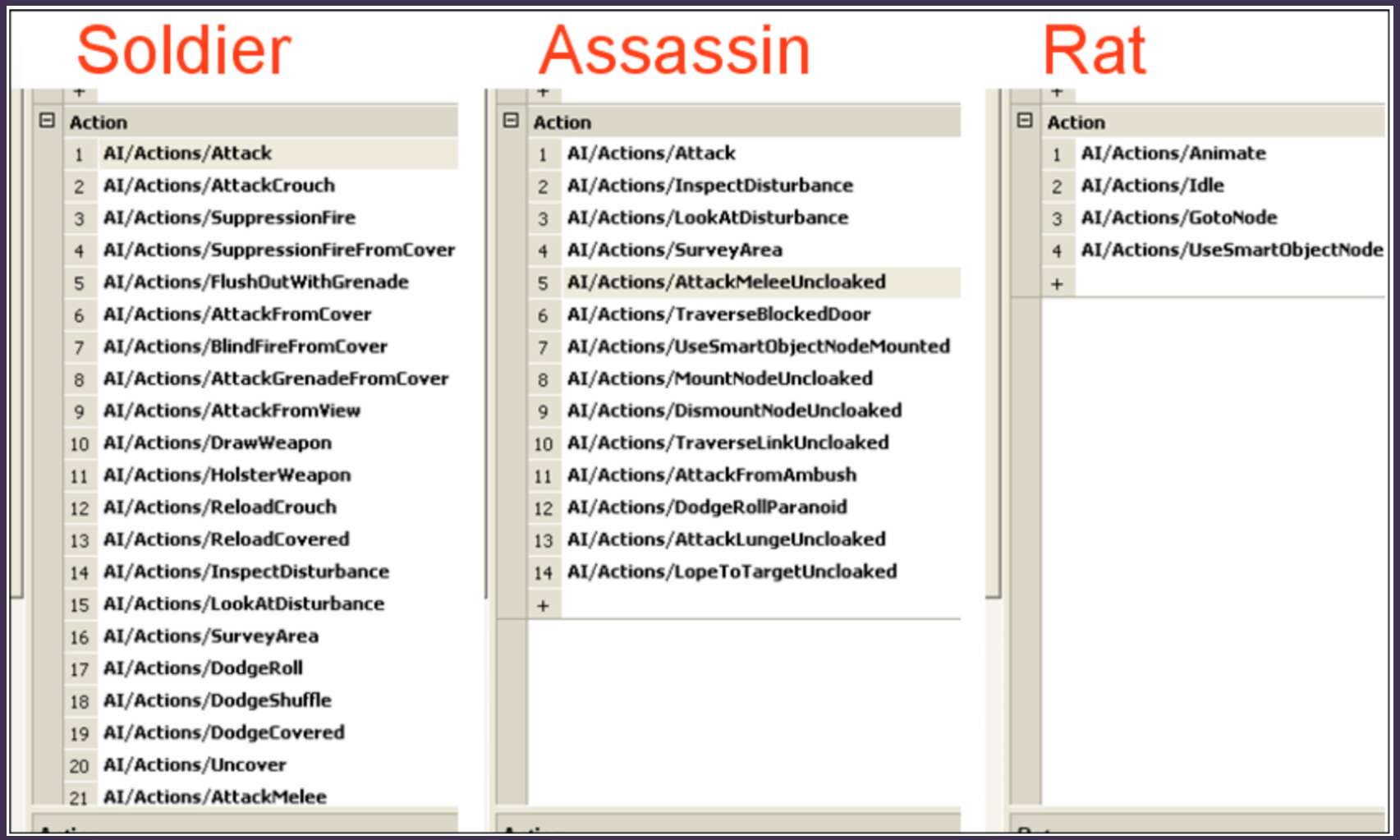
- This will result in those agents achieving those goals in **different ways**
- NB this doesn't have to be explicitly coded — it **emerges** from the GOAP system
- E.g. this was used by the F.E.A.R. team to quickly add new enemy types

Action sets


Soldier
Action
1 AI/Actions/Attack
2 AI/Actions/AttackCrouch
3 AI/Actions/SuppressionFire
4 AI/Actions/SuppressionFireFromCover
5 AI/Actions/FlushOutWithGrenade
6 AI/Actions/AttackFromCover
7 AI/Actions/BlindFireFromCover
8 AI/Actions/AttackGrenadeFromCover
9 AI/Actions/AttackFromView
10 AI/Actions/DrawWeapon
11 AI/Actions/HolsterWeapon
12 AI/Actions/ReloadCrouch
13 AI/Actions/ReloadCovered
14 AI/Actions/InspectDisturbance
15 AI/Actions/LookAtDisturbance
16 AI/Actions/SurveyArea
17 AI/Actions/DodgeRoll
18 AI/Actions/DodgeShuffle
19 AI/Actions/DodgeCovered
20 AI/Actions/Uncover
21 AI/Actions/AttackMelee
Assassin
Action
1 AI/Actions/Attack
2 AI/Actions/InspectDisturbance
3 AI/Actions/LookAtDisturbance
4 AI/Actions/SurveyArea
5 AI/Actions/AttackMeleeUncloaked
6 AI/Actions/TraverseBlockedDoor
7 AI/Actions/UseSmartObjectNodeMounted
8 AI/Actions/MountNodeUncloaked
9 AI/Actions/DismountNodeUncloaked
10 AI/Actions/TraverseLinkUncloaked
11 AI/Actions/AttackFromAmbush
12 AI/Actions/DodgeRollParanoid
13 AI/Actions/AttackLungeUncloaked
14 AI/Actions/LopeToTargetUncloaked
Rat
Action
1 AI/Actions/Animate
2 AI/Actions/Idle
3 AI/Actions/GotoNode
4 AI/Actions/UseSmartObjectNode

Layering

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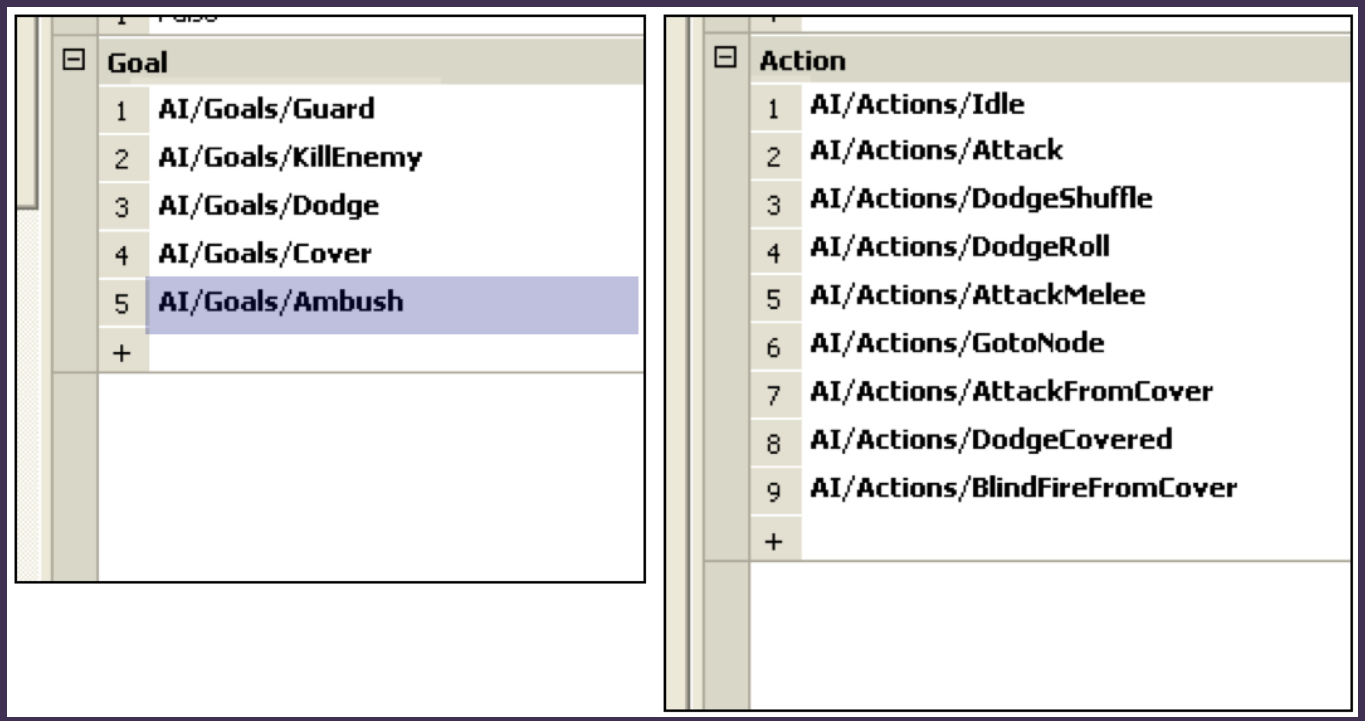
- E.g. enemy AI in F.E.A.R.:



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- Most implementations also allow for **programmatic** preconditions (e.g. calling the pathfinding system to check availability of a path)

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- Not built into Unity or Unreal, but asset store packages are available

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- Since actions have costs, we can use A* to find the lowest cost path to the goal
- Plan is a **queue** of actions that the agent then executes
- If the plan is interrupted or fails then the agent can **replan**

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- Both: actions (tasks in BT) are modular and reusable between agents
- GOAP: goals are also modular and reusable

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