Planning for Autonomous Robots using Probabilistic Graphical Models

J.C. Schoeman

Maties Machine Learning

2 November 2018

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Outline

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Autonomous Navigation

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Applications

- self-driving cars

Autonomous Navigation

  

Applications

- self-driving cars
- planetary exploration

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- self-driving cars
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- surveillance systems

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- self-driving cars
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Challenges

- uncertain environments

Autonomous Navigation

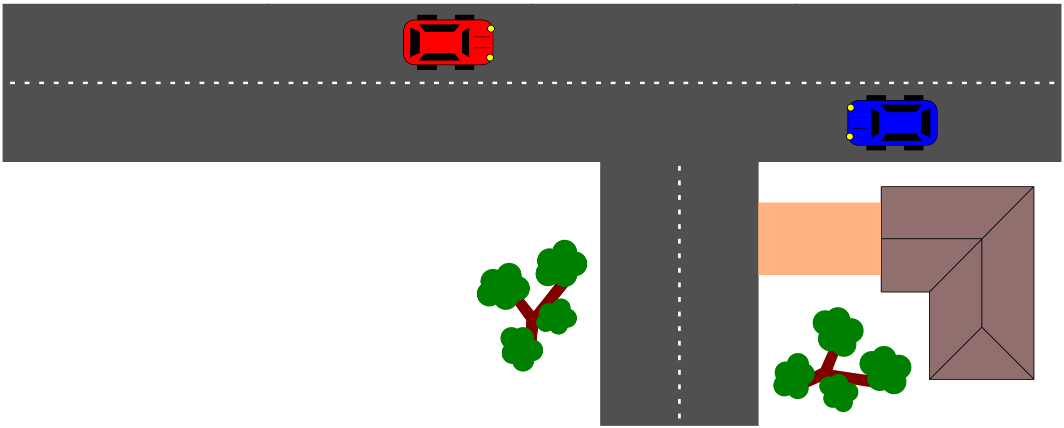
Applications

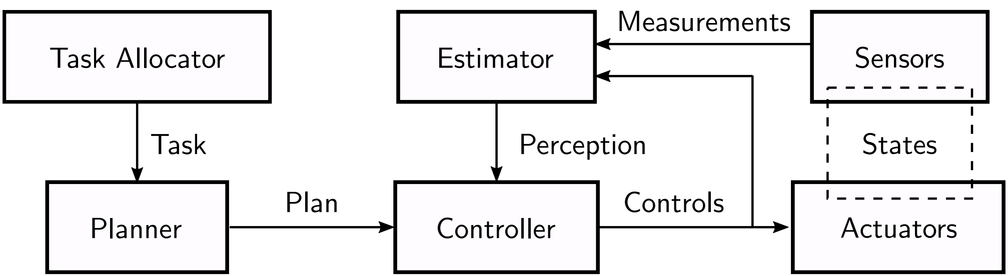
- self-driving cars
- planetary exploration
- surveillance systems

Challenges

- uncertain environments
- continuous states

Autonav System Configuration





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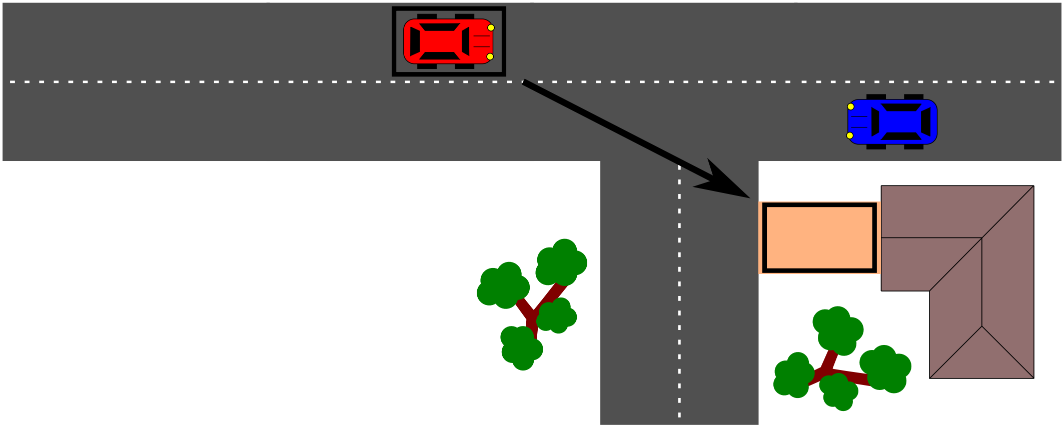

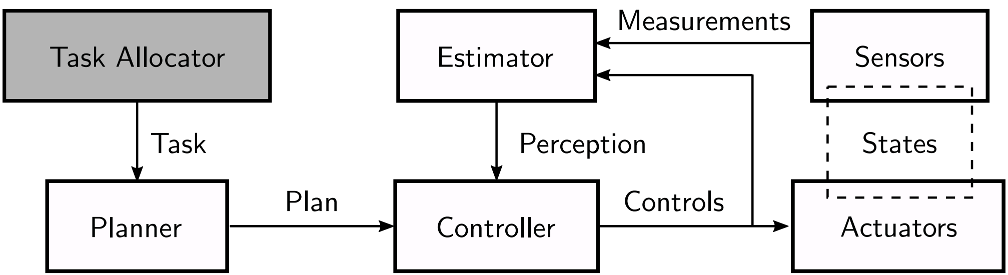

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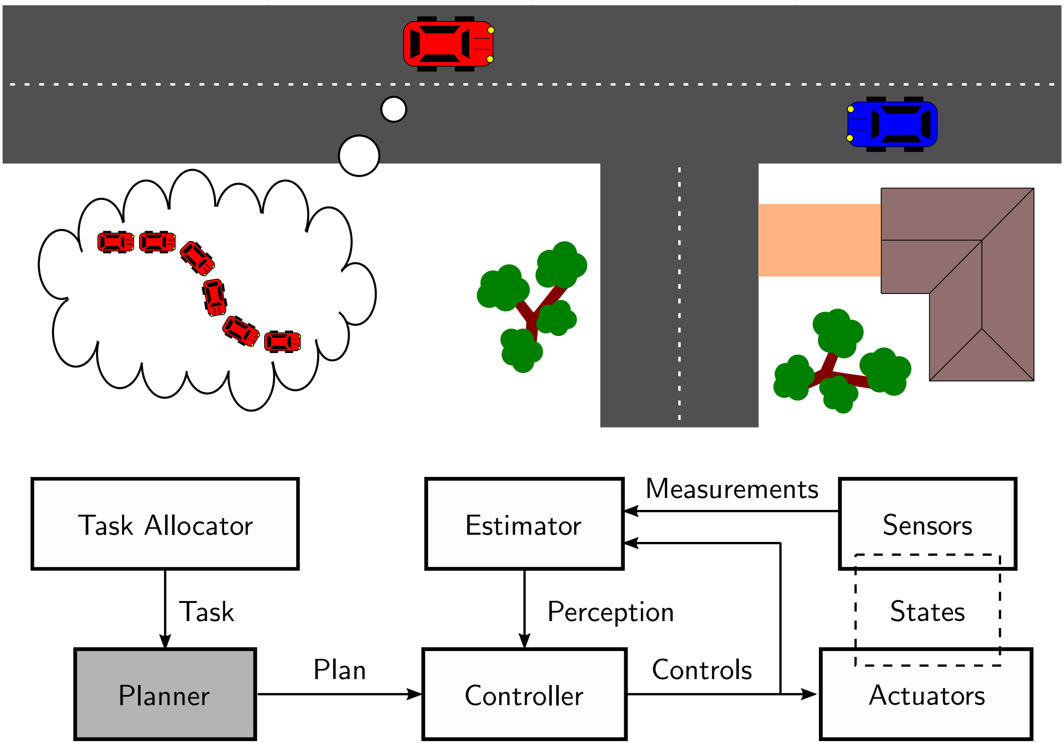

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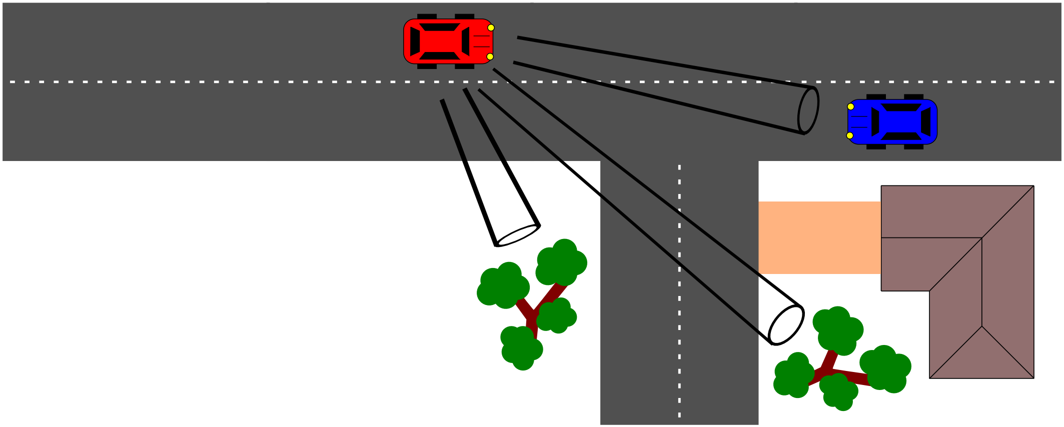

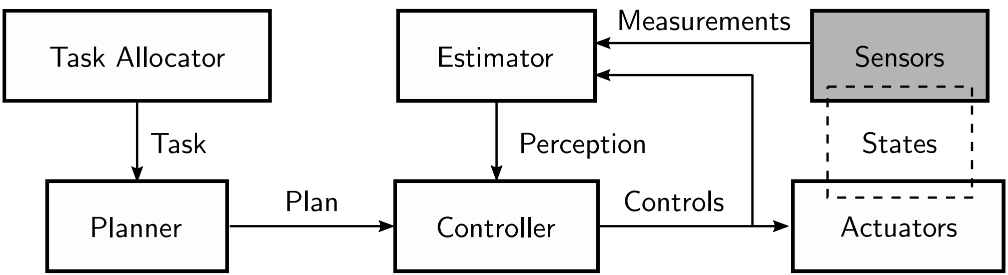

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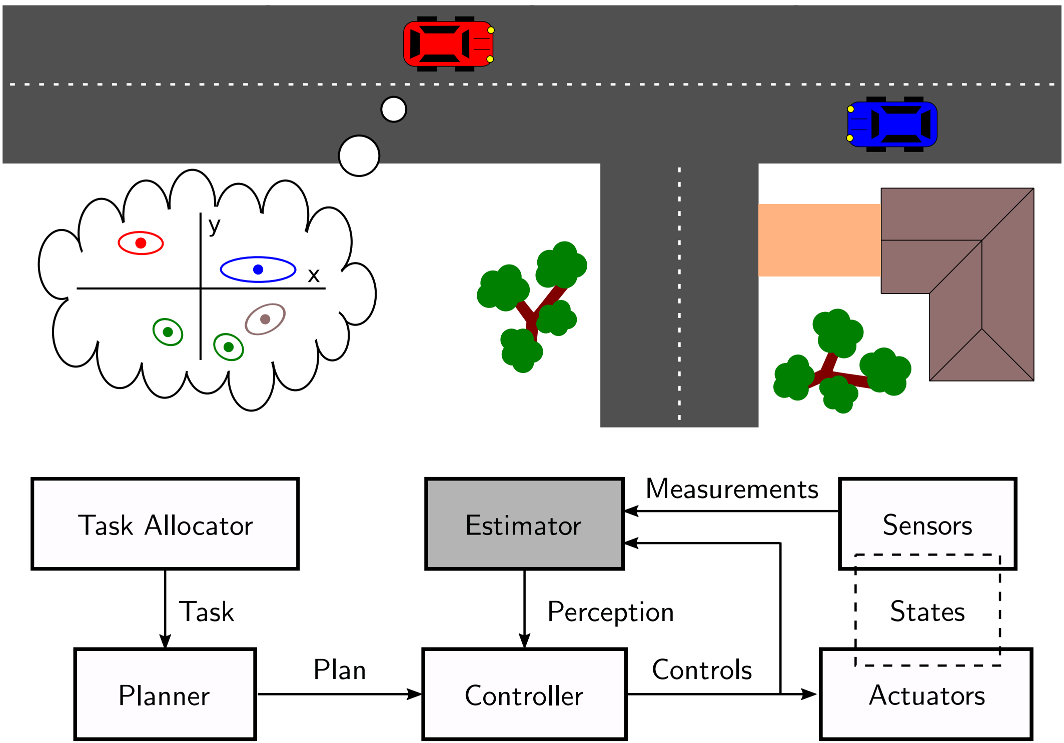

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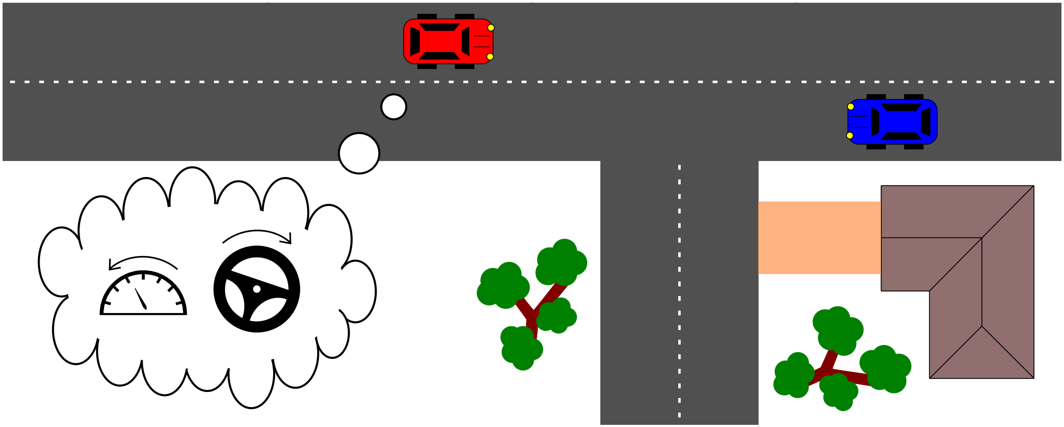

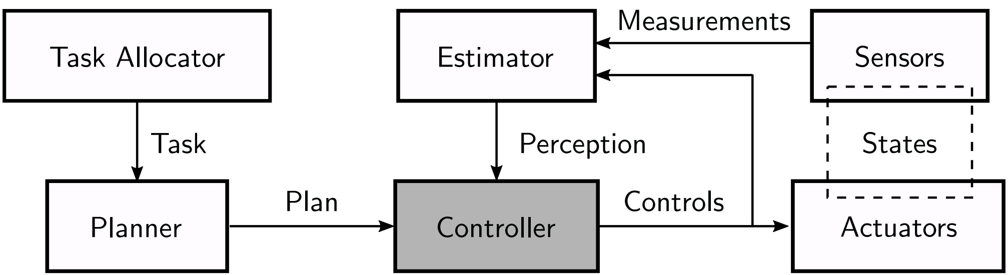

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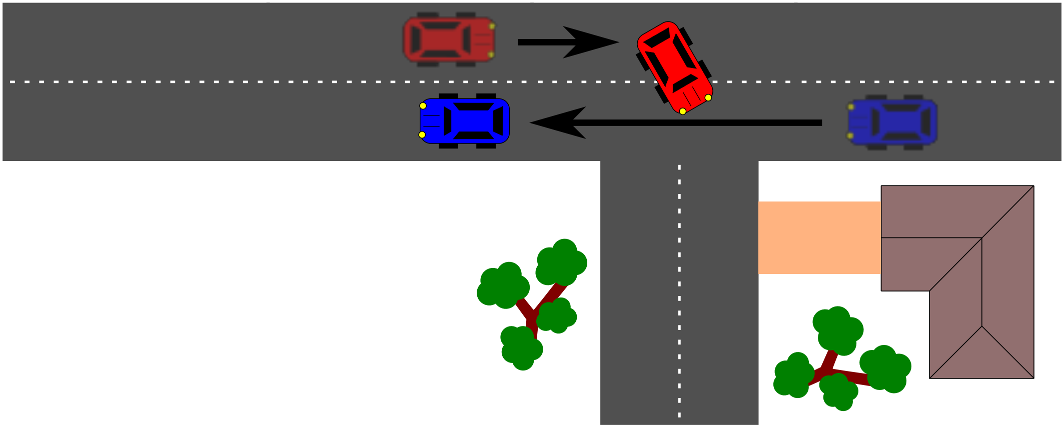
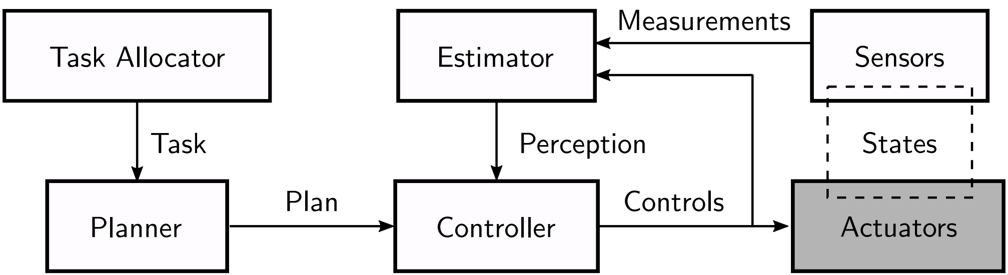
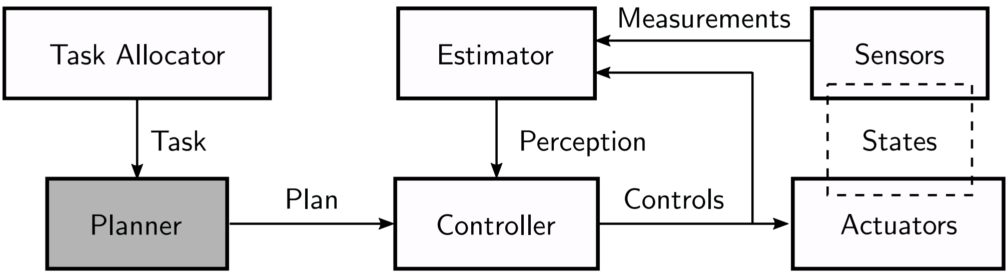




Planning for Autonomous Robots



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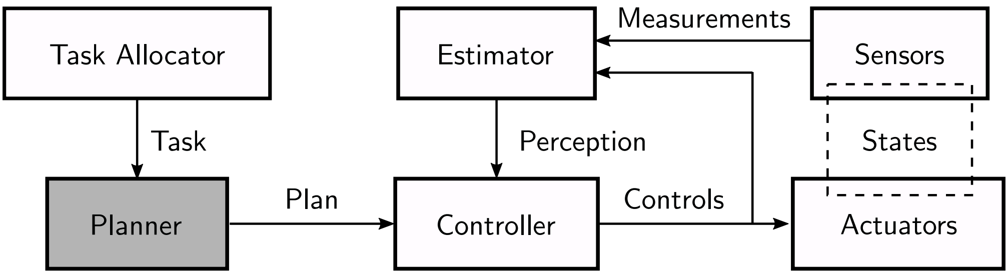
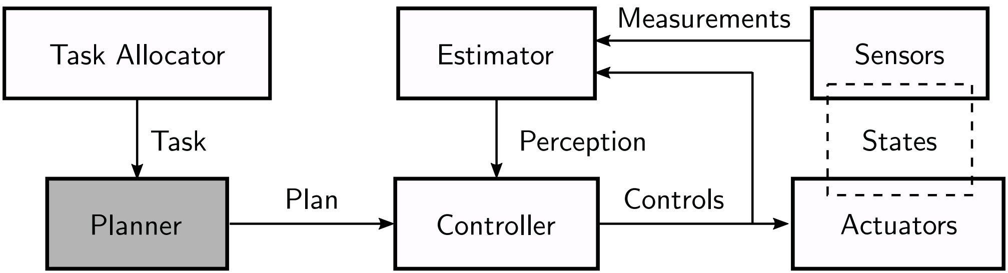


Research Aim: Develop algorithm to solve general robotic planning problems

Planning for Autonomous Robots



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Research Objectives

- accommodate environments with significant uncertainty

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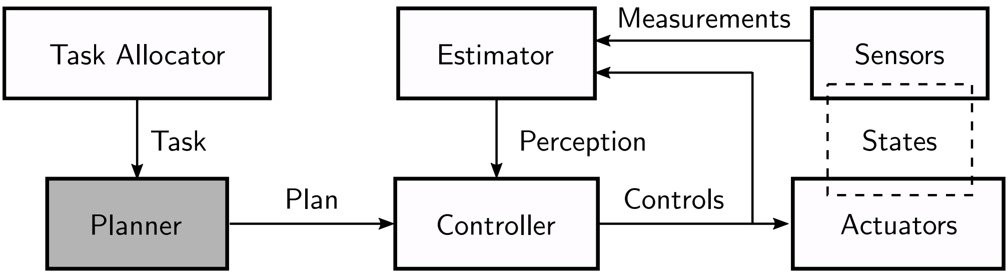


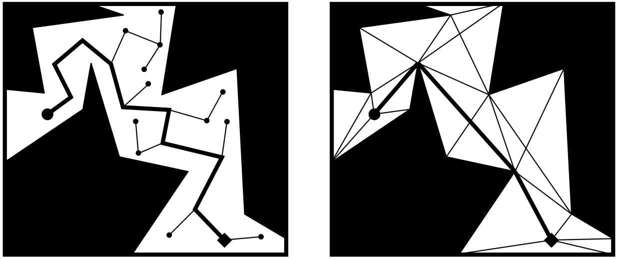
Research Aim: Develop algorithm to solve general robotic planning problems

Research Objectives

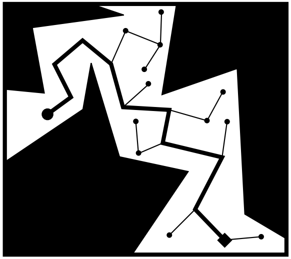
- accommodate environments with significant uncertainty
- plan for robots with continuous states

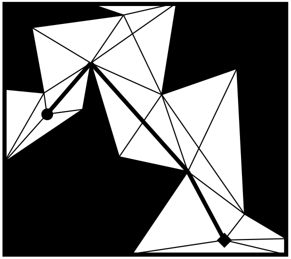
Outline

Motion Planning



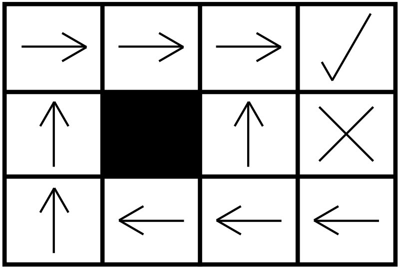
Motion Planning





Uncertain Environments	Continuous States
✗	✓

Partially Observable Markov Decision Processes



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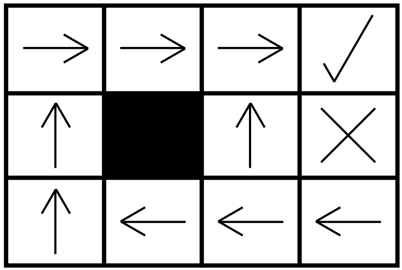

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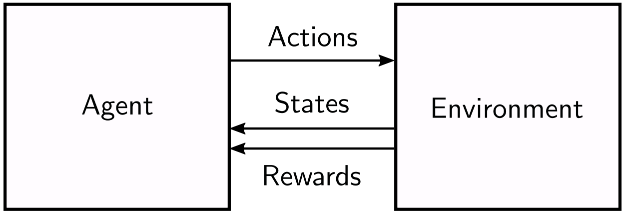
Reinforcement Learning



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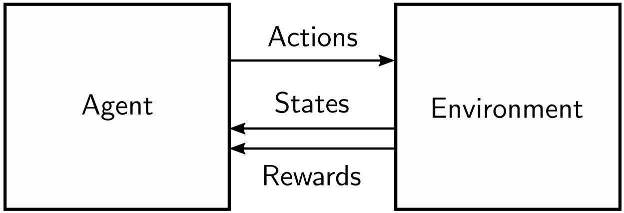
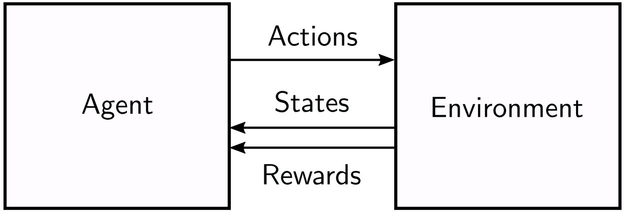


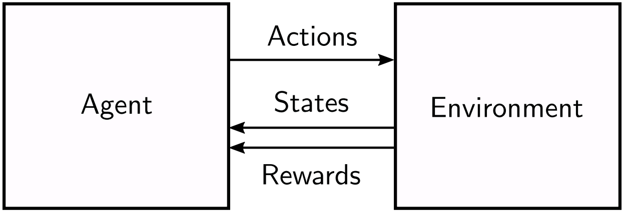
Model-free RL	**Model-based RL**

Reinforcement Learning



Model-free RL	**Model-based RL**
learn value functions	learn system dynamics model

Reinforcement Learning



Model-free RL	Model-based RL
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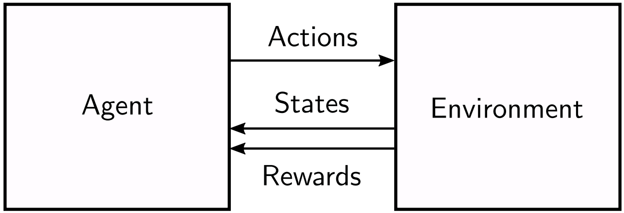

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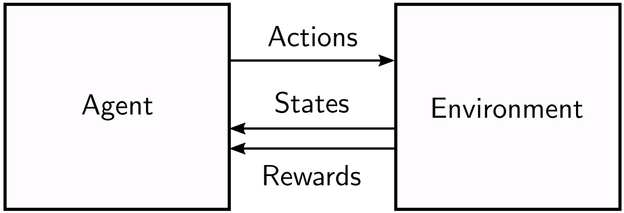

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For a practical robotic system

- trial-and-error consequences could be disastrous

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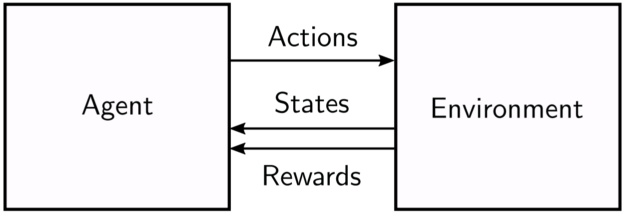

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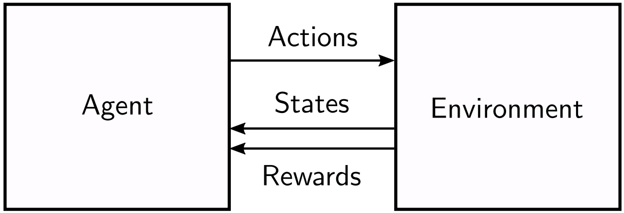

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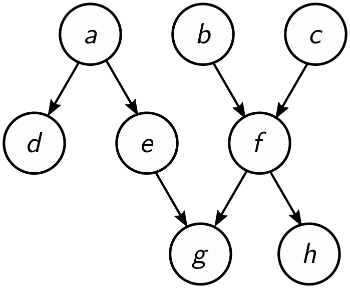
For a practical robotic system

- trial-and-error consequences could be disastrous
- experience rate cannot be accelerated
- models are typically already available

Outline

Inference



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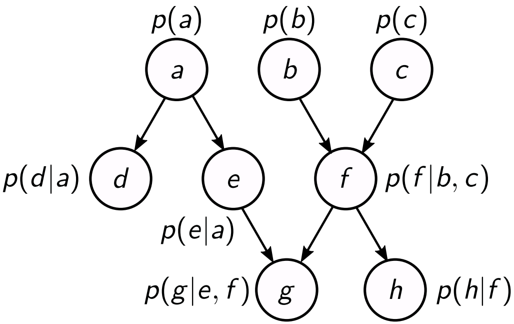

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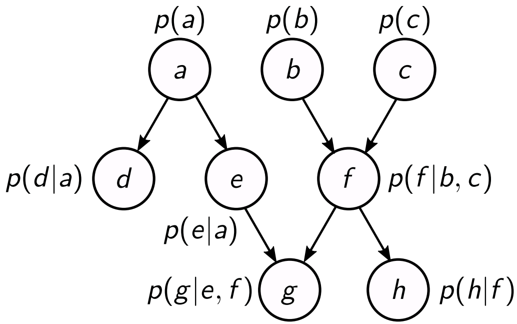

$$p(a,b,c,d,e,f,g,h) = p(a)\,p(b)\,p(c)\,p(d|a)\,p(e|a)\,p(f|b,c)\,p(g|e,f)\,p(h|f)$$

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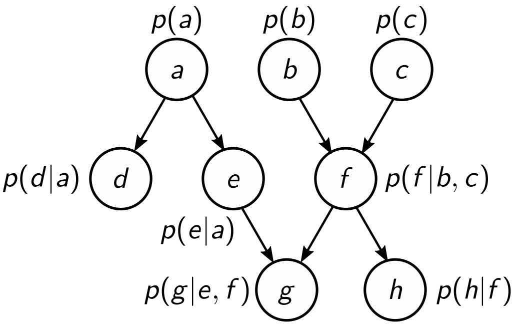

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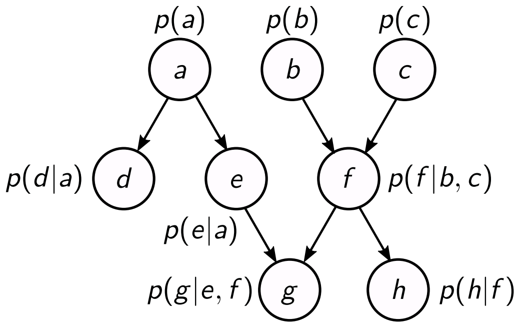
1. Model problem

Inference



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2. Observe subset of variables

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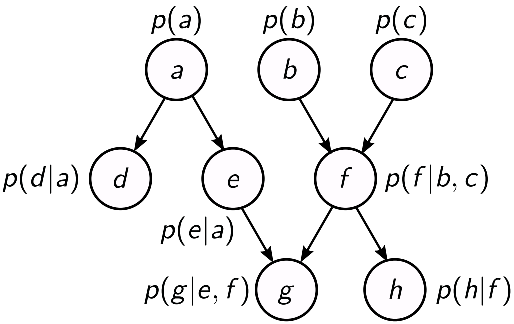

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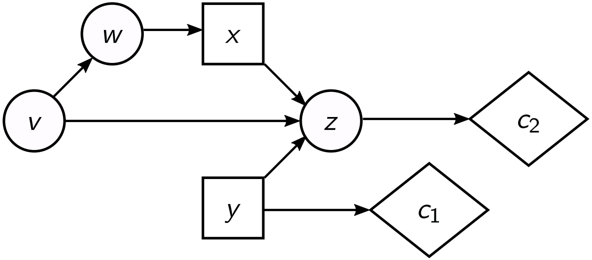
1. Model problem
2. Observe subset of variables
3. Infer distribution over unobserved variables

Decision Theory



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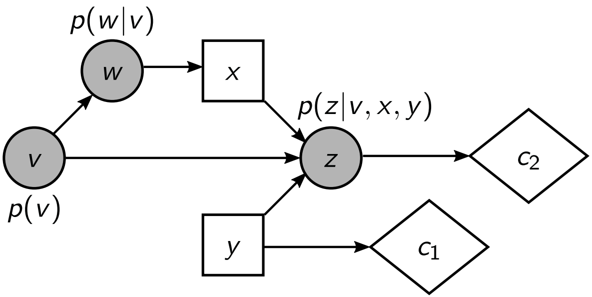

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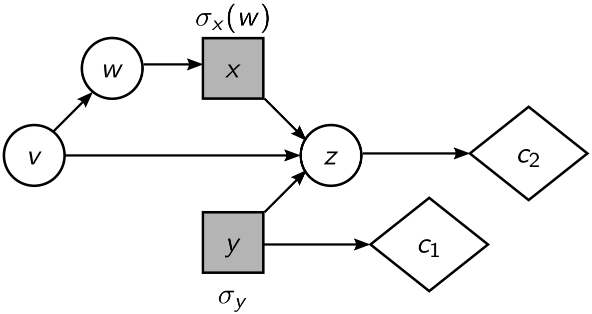

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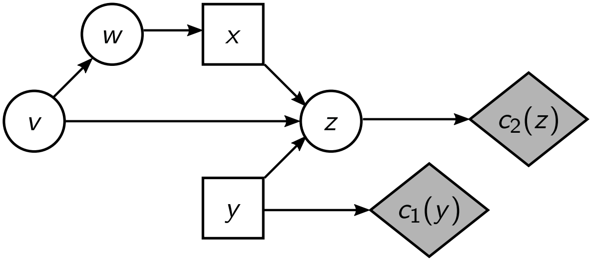

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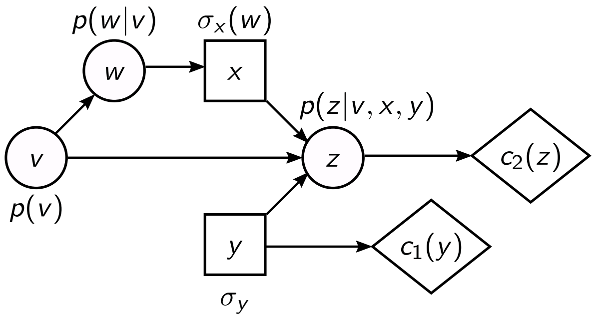
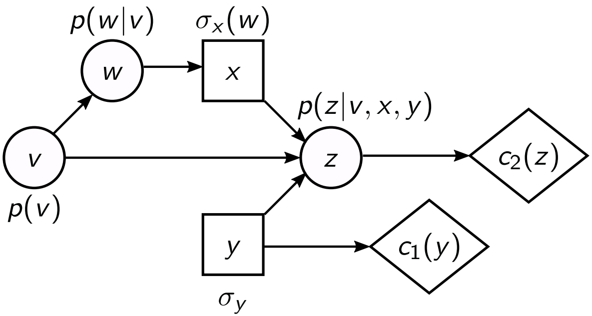


$$\mathbb{E}\left[c_T|\sigma\right] = \sum_i \mathbb{E}\left[c_i|\sigma\right]$$

Decision Theory



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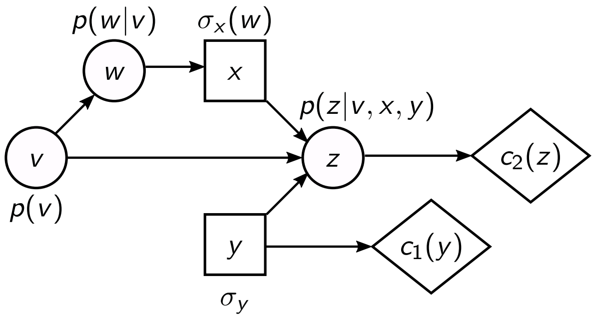

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2. Calculate expected cost of strategy

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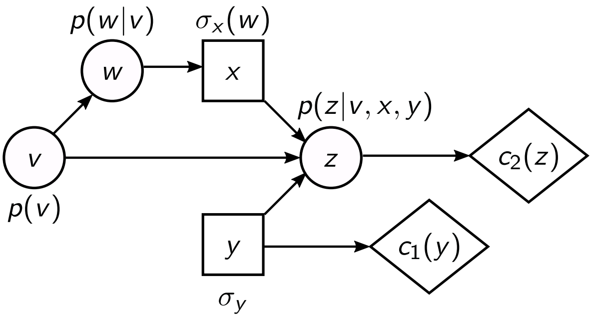
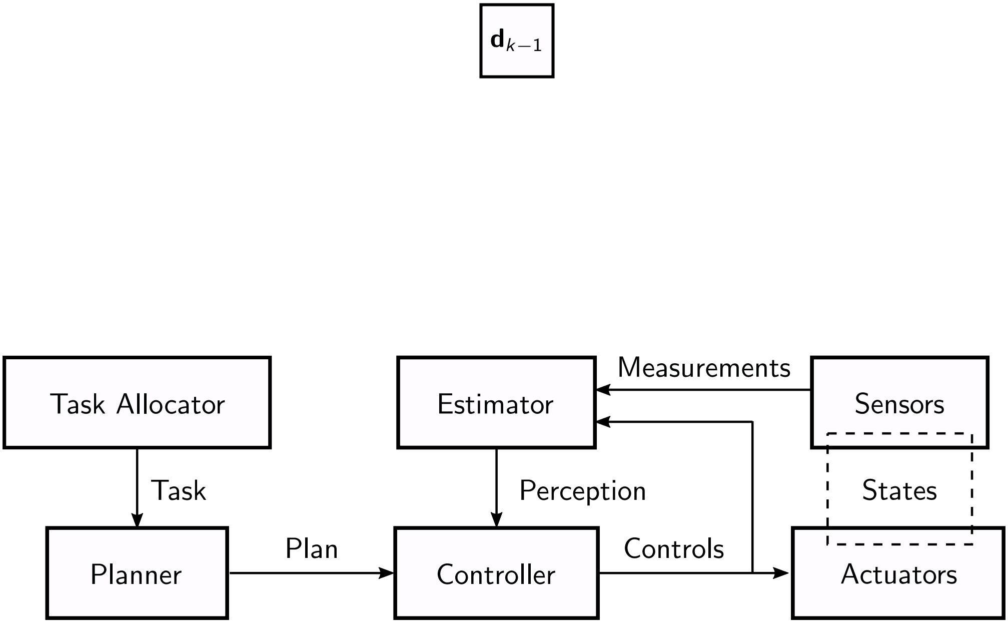


$$\mathbb{E}\left[c_T|\sigma\right] = \sum_i \mathbb{E}\left[c_i|\sigma\right]$$

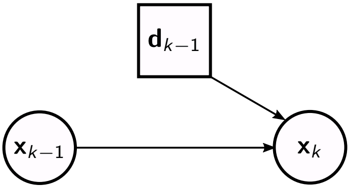
1. Model problem
2. Calculate expected cost of strategy
3. Optimise strategy

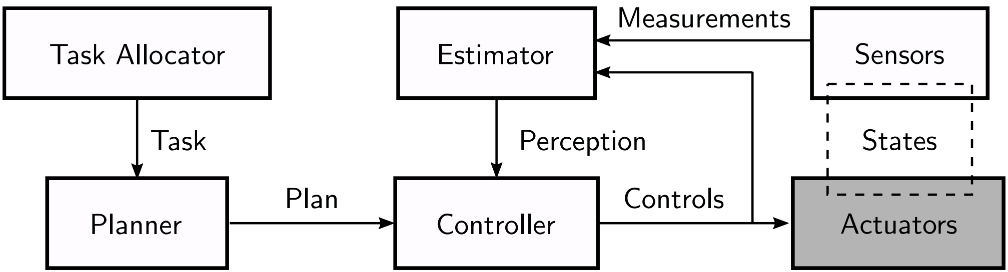
Outline

Modelling the Planning Problem



Modelling the Planning Problem





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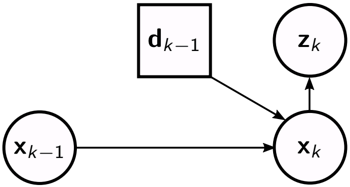

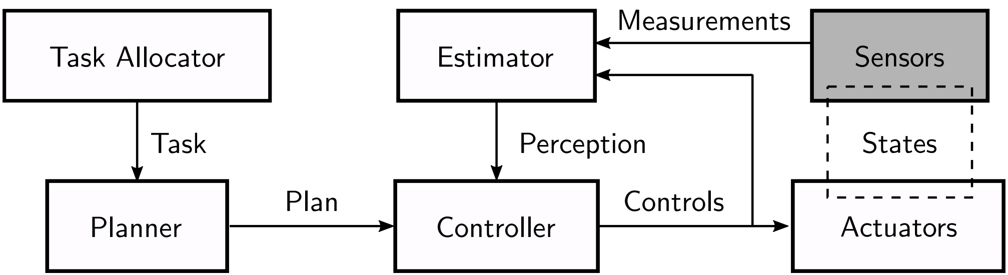

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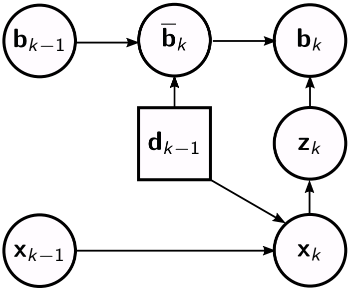

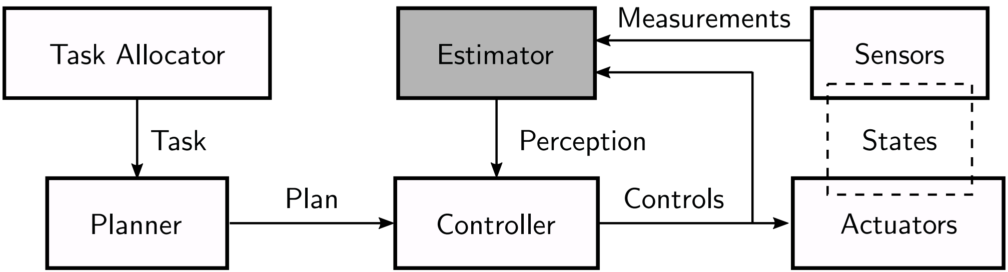

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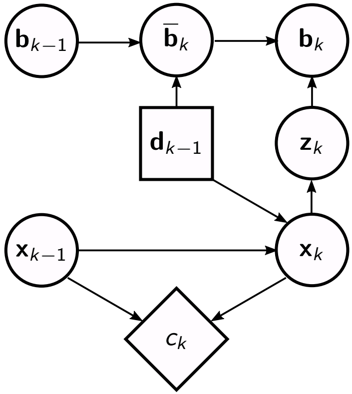

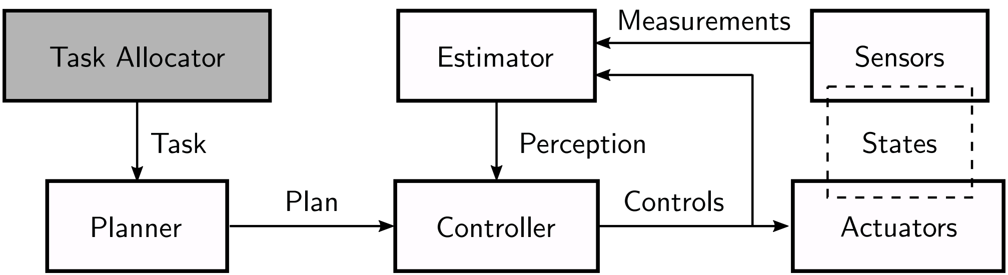

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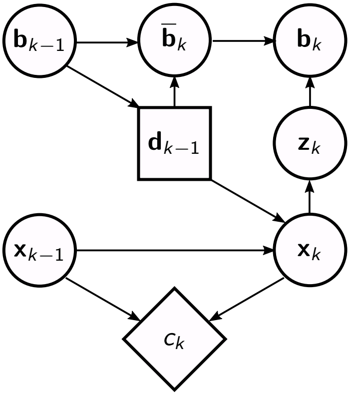

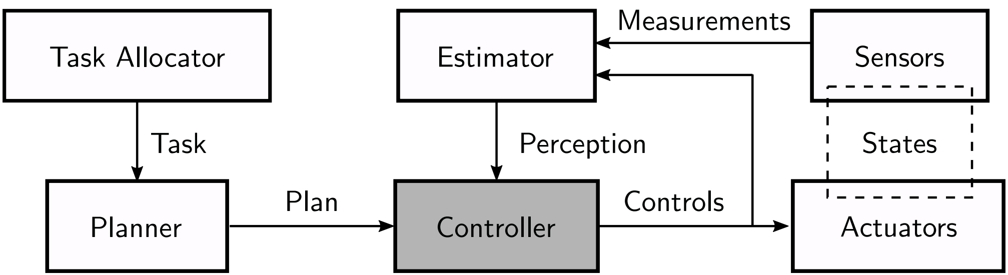

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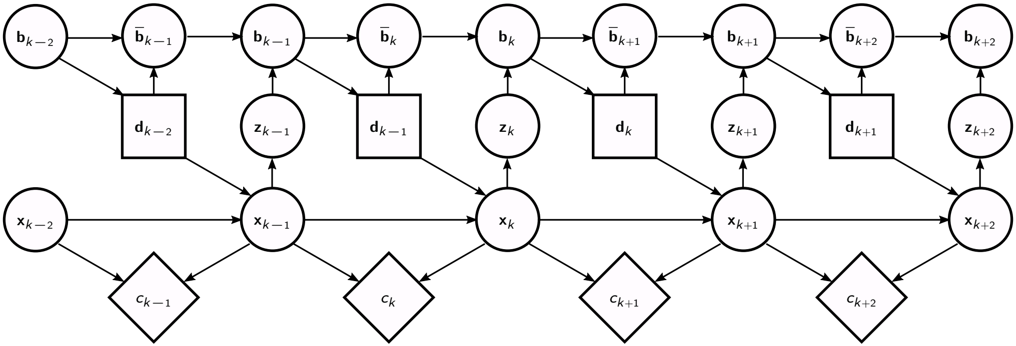

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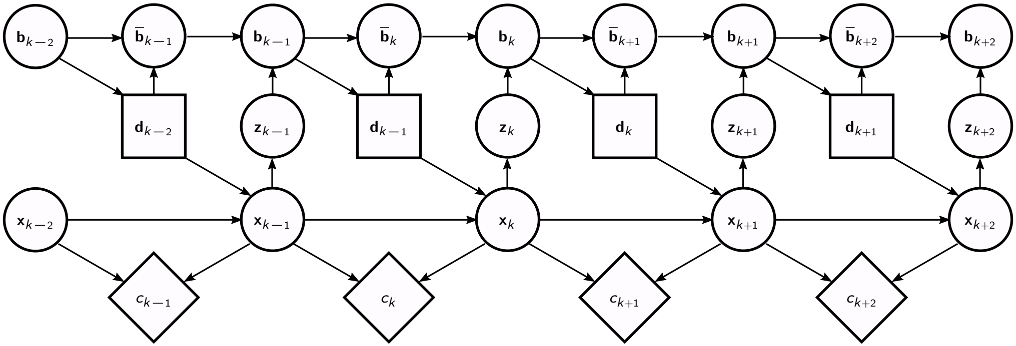

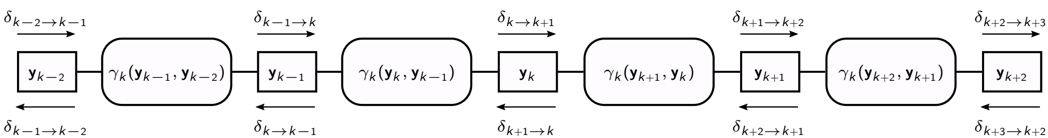

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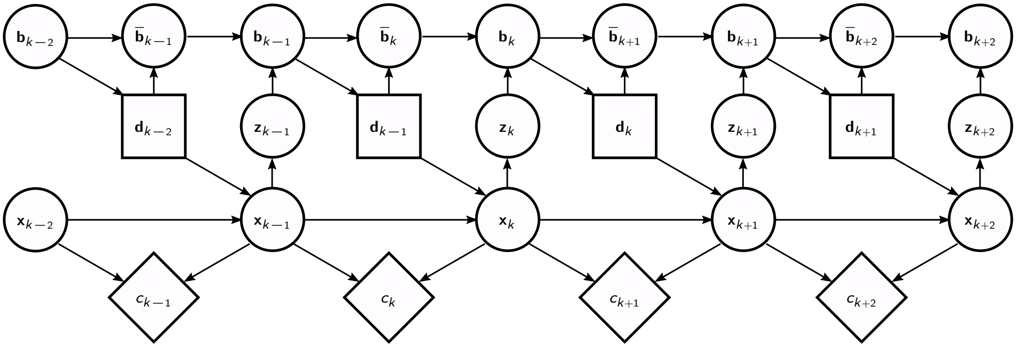

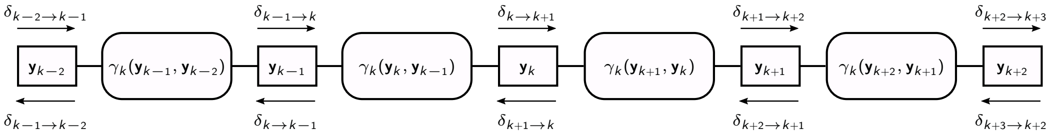

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Optimising the Strategy

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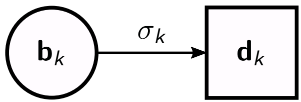

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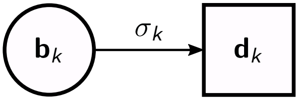

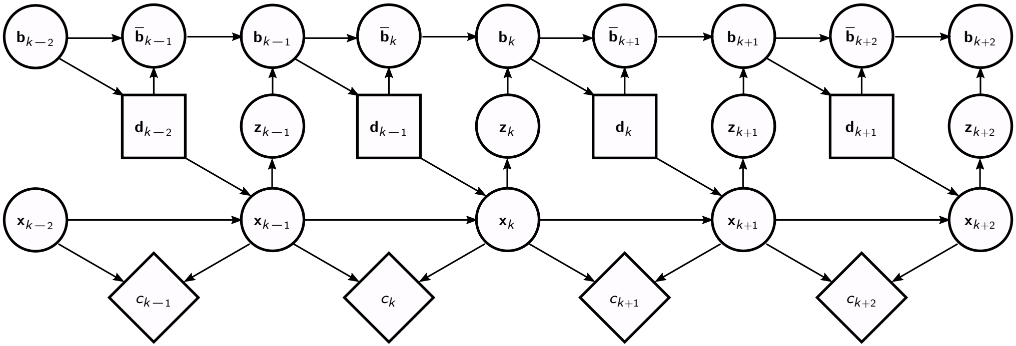

Optimising the Strategy

$$\mathbb{E}\left[c_T|\sigma\right] = f(\sigma)$$

$$\sigma_{\text{opt}} = \arg\min_{\sigma} f(\sigma)$$

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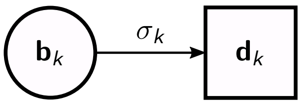

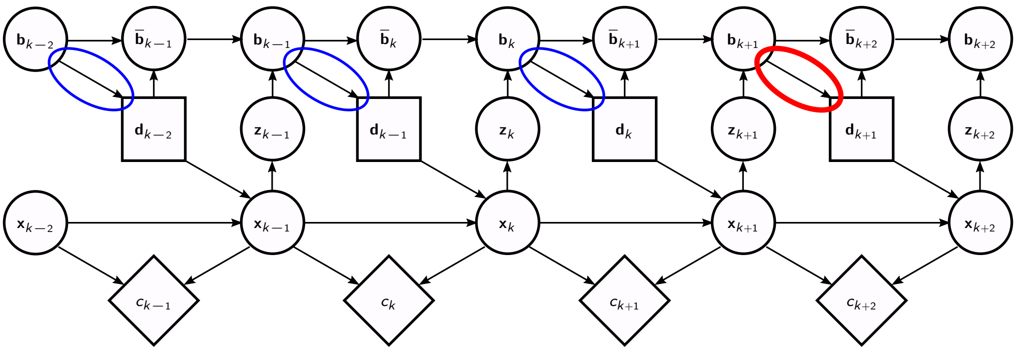

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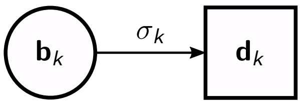

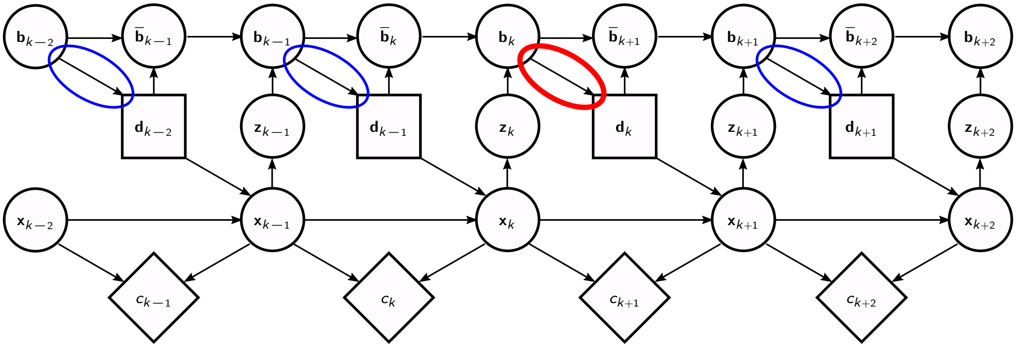

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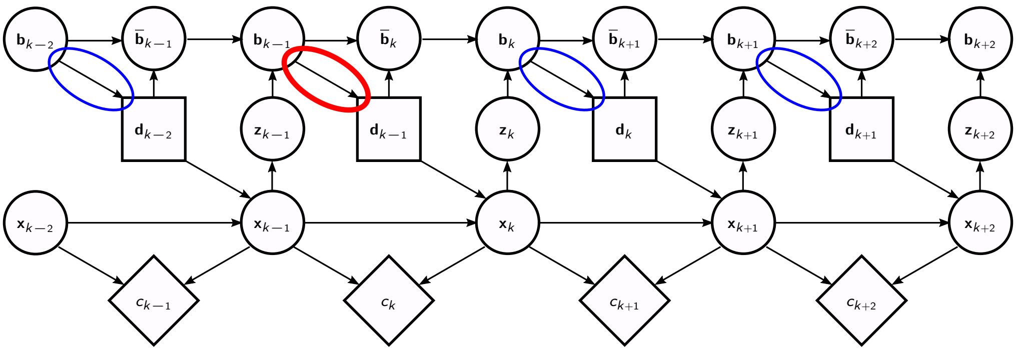
$$\mathbf{b}_k \xrightarrow{\sigma_k} \mathbf{d}_k$$



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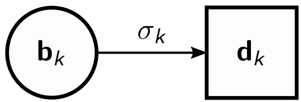

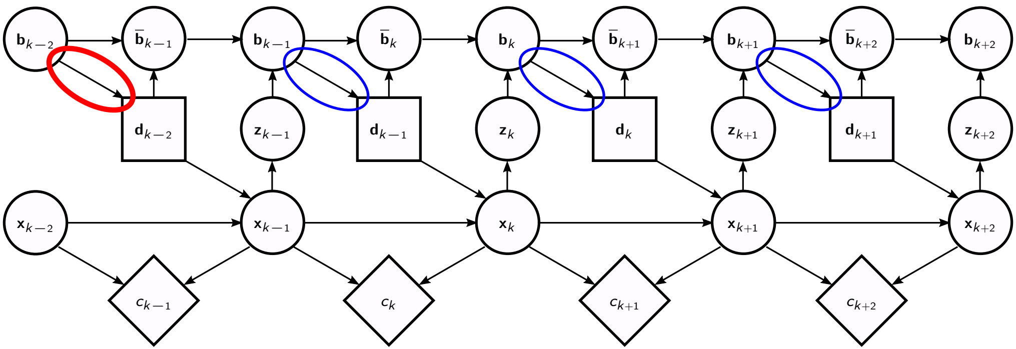

Outline

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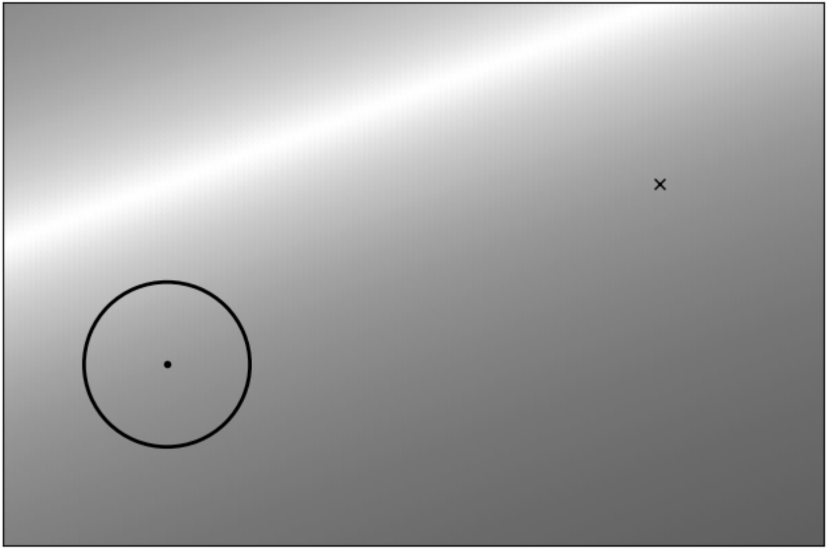

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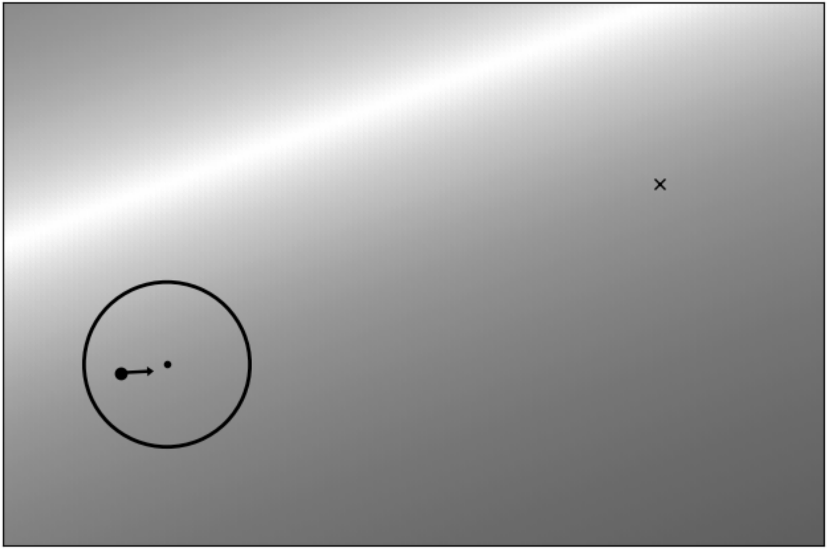

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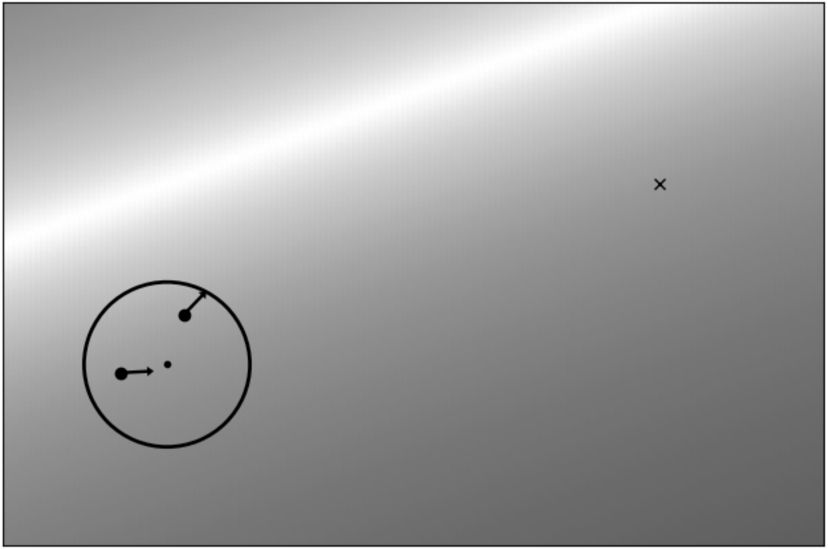

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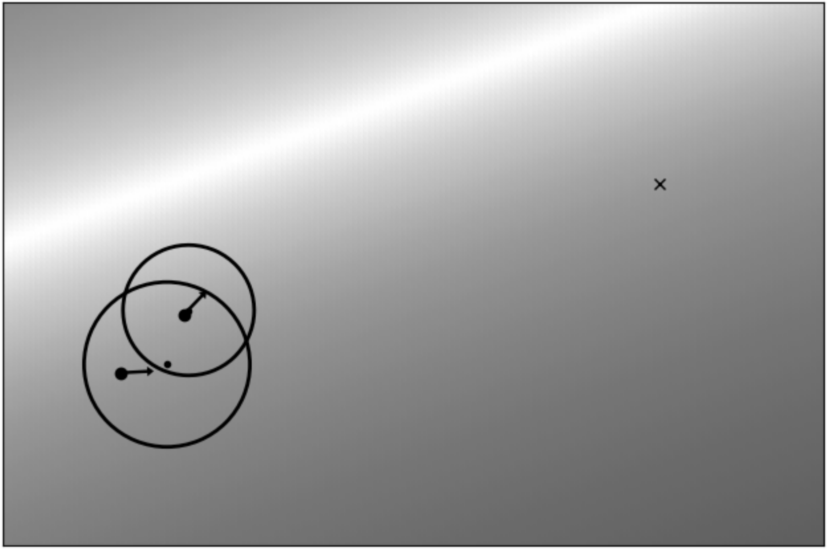

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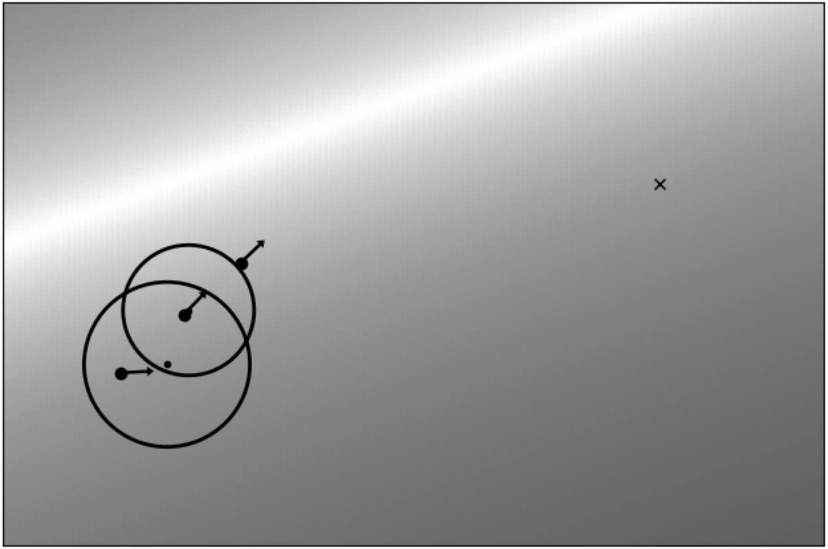

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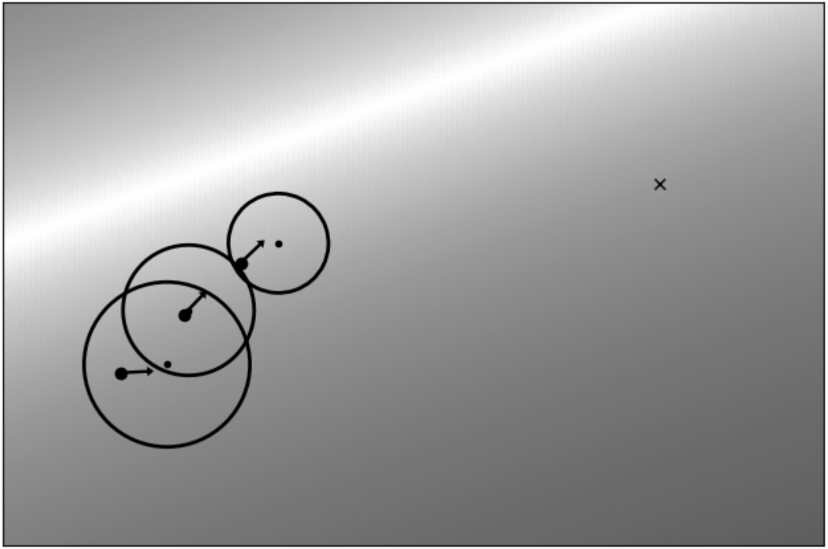

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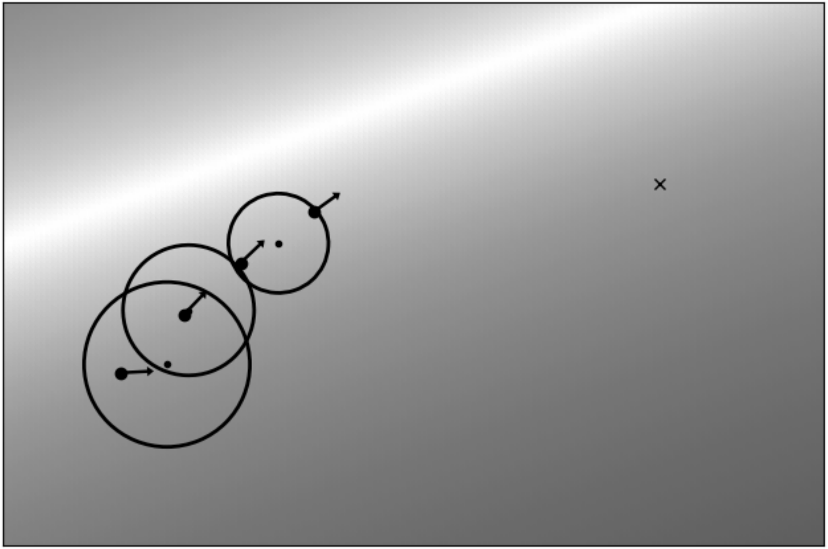

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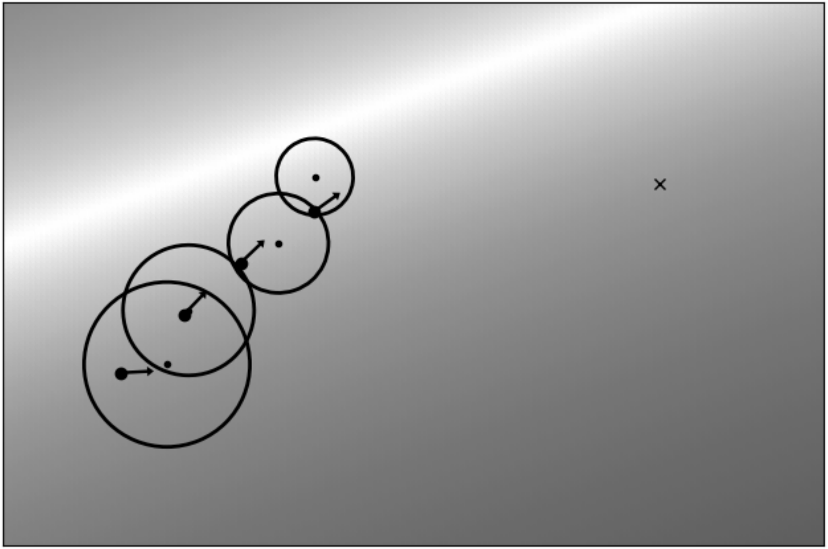

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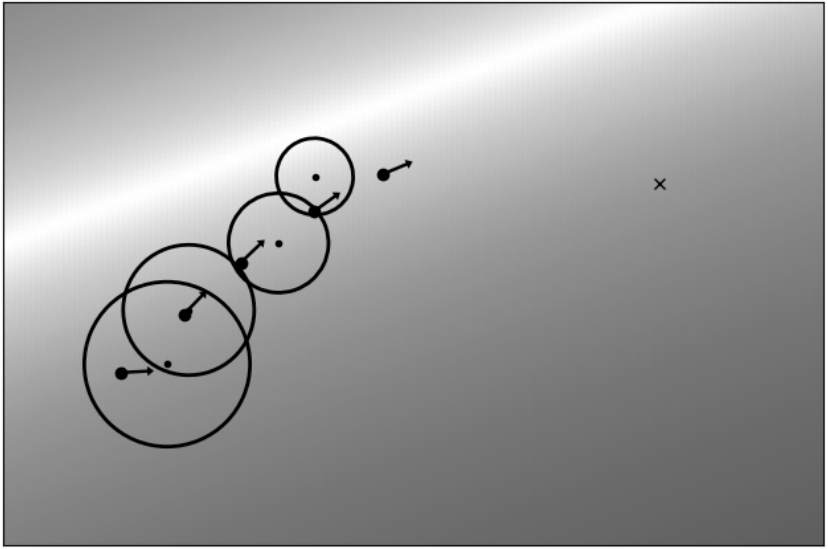

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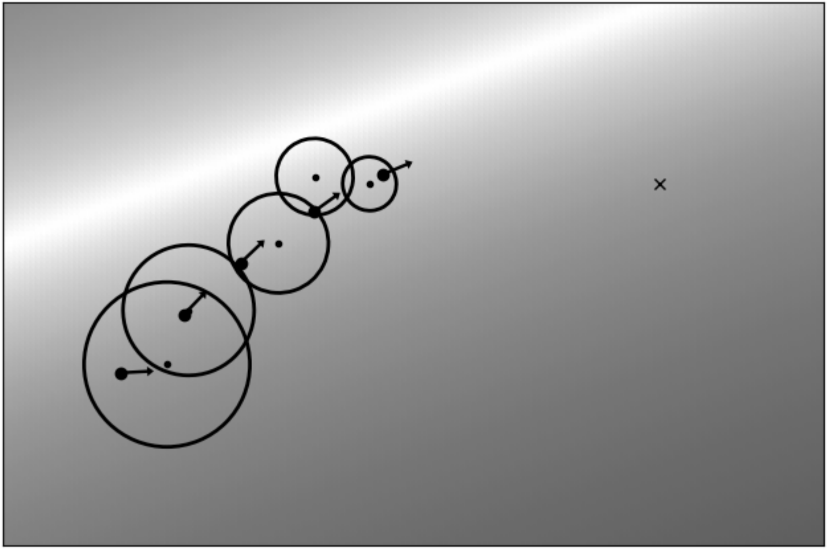

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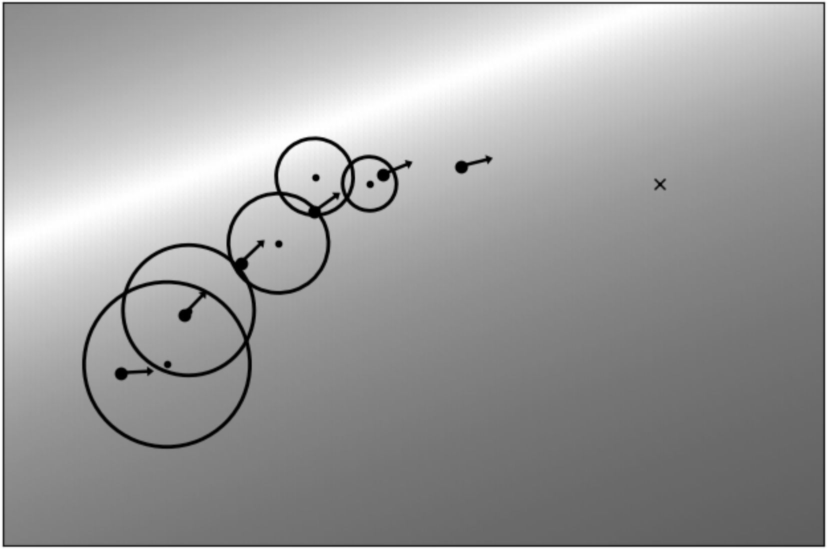

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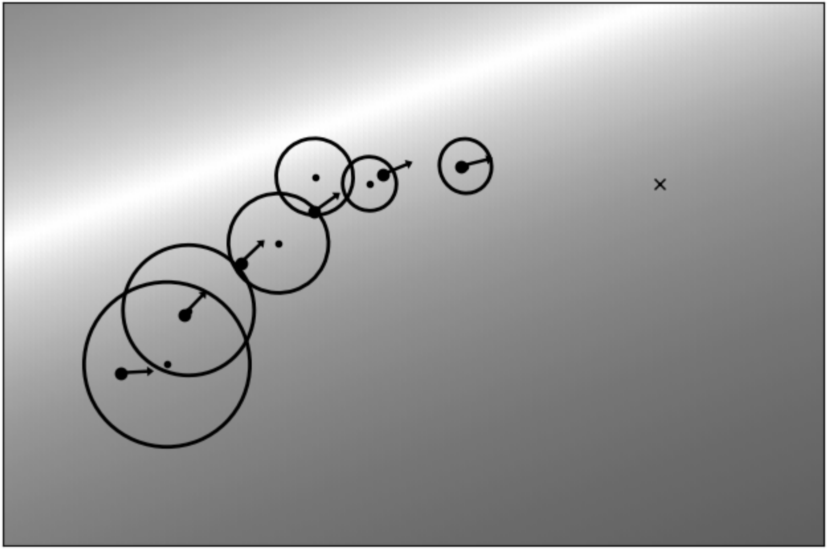

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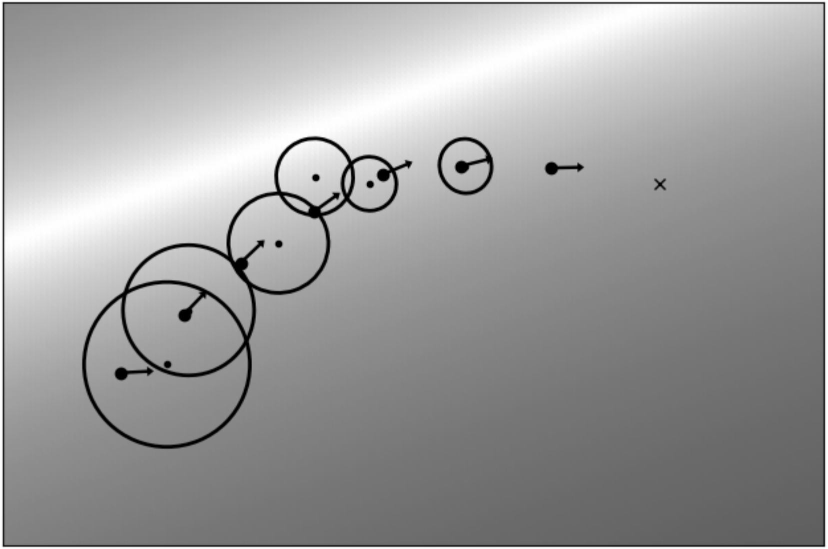

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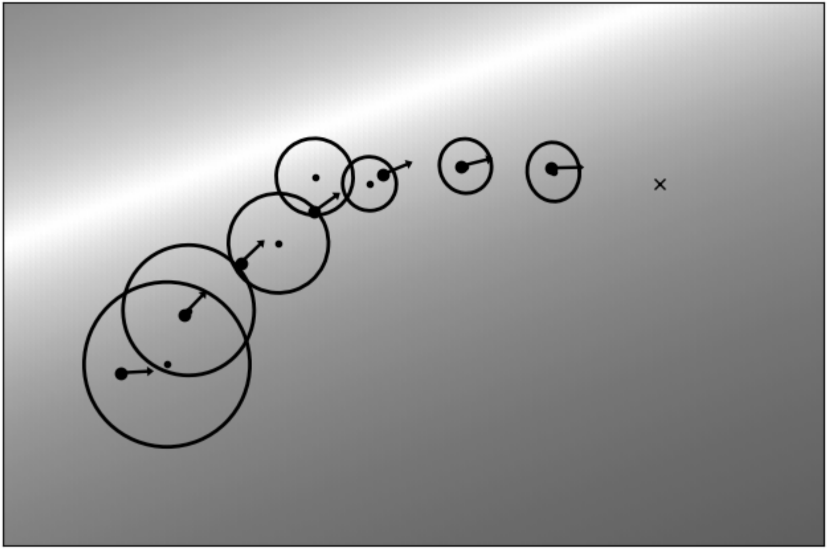

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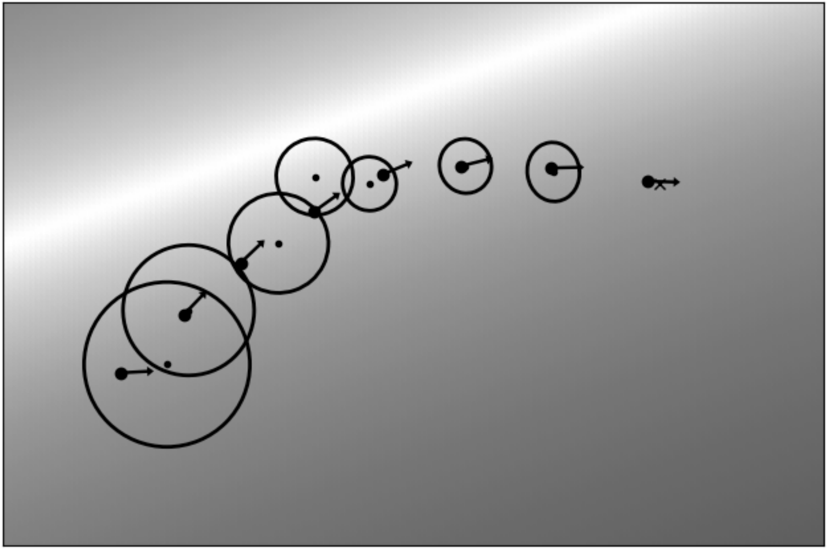

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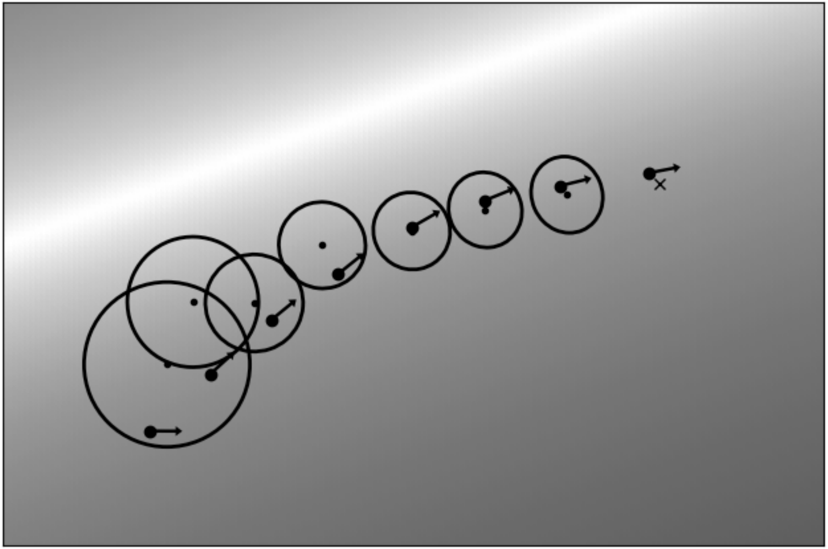

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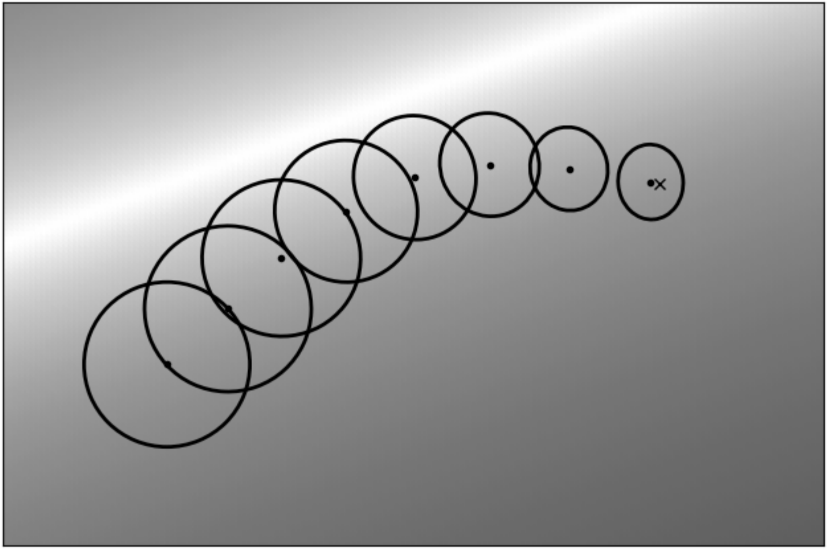

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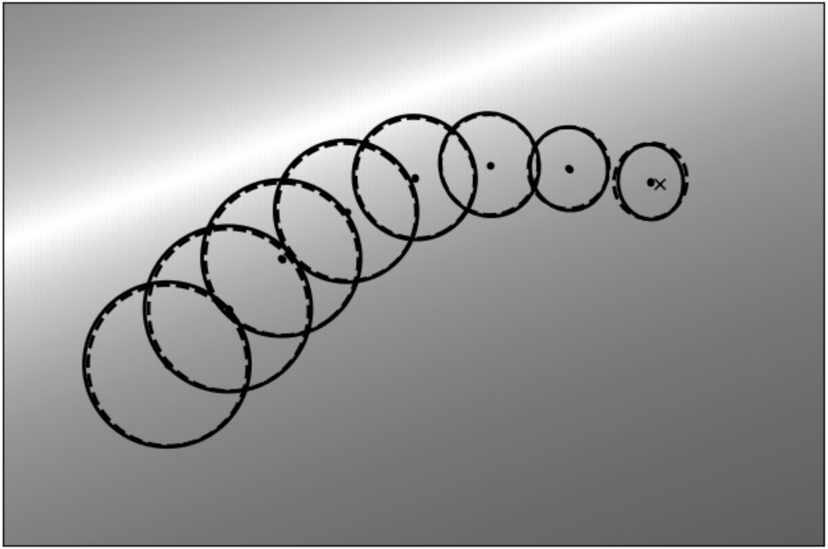
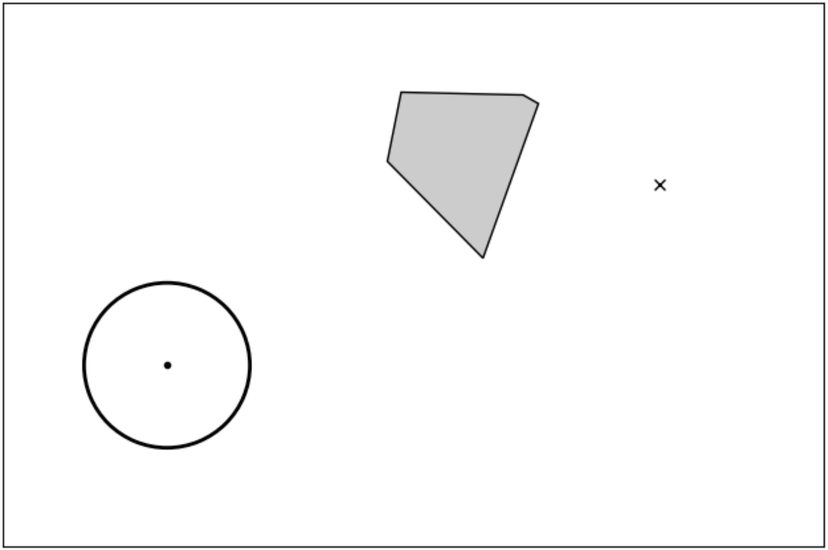


Obstacle Avoidance



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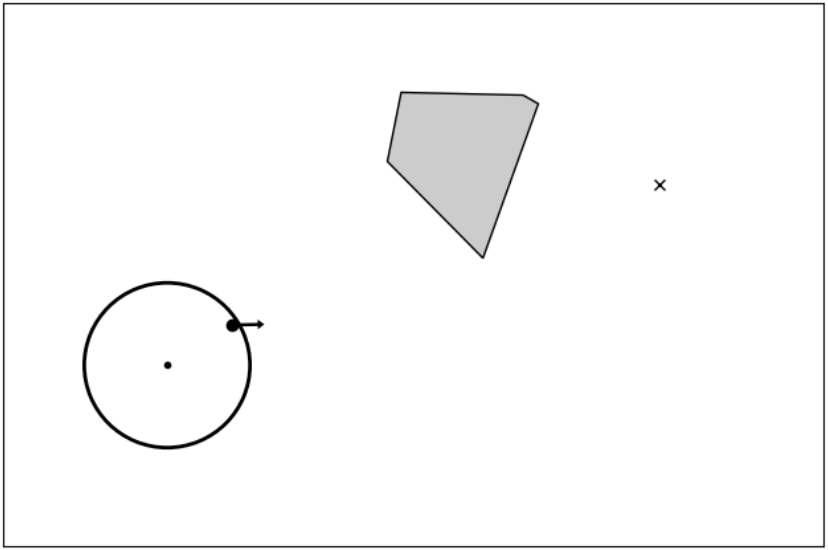

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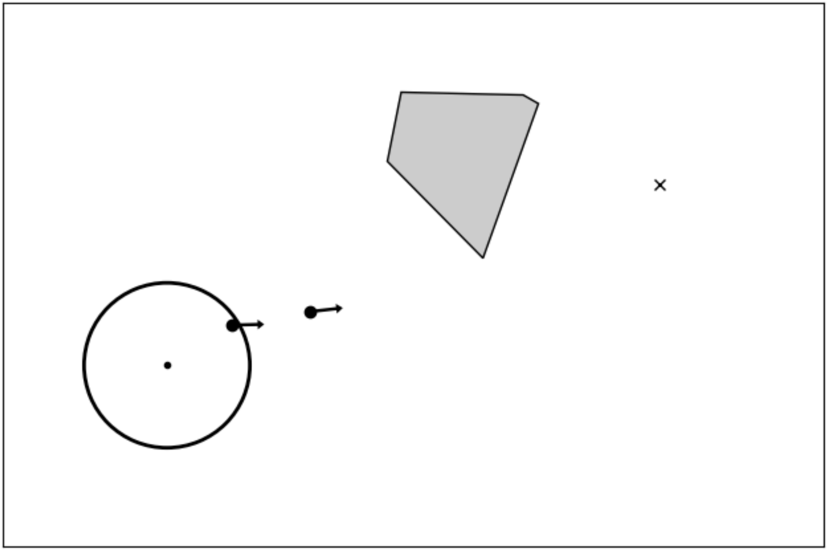

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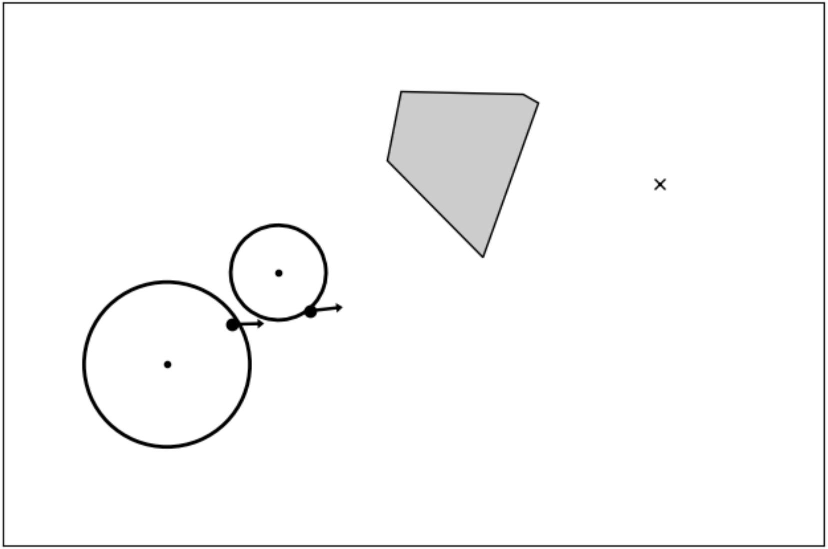

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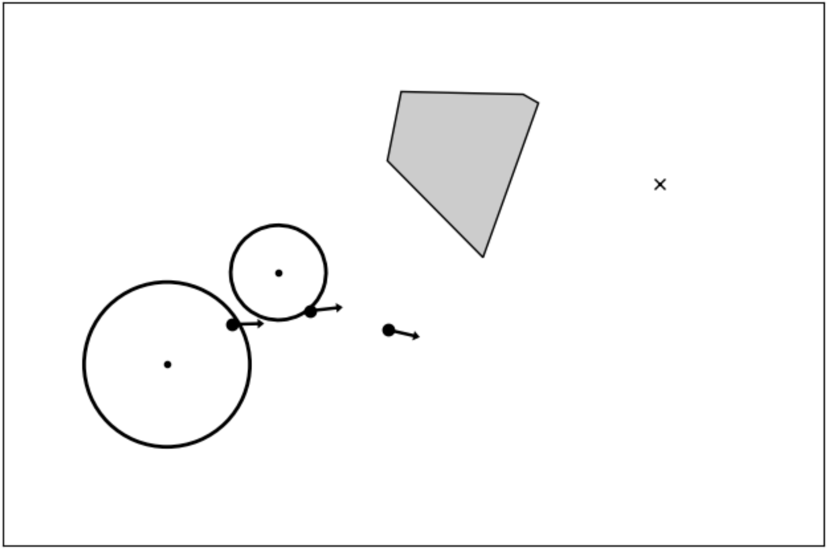

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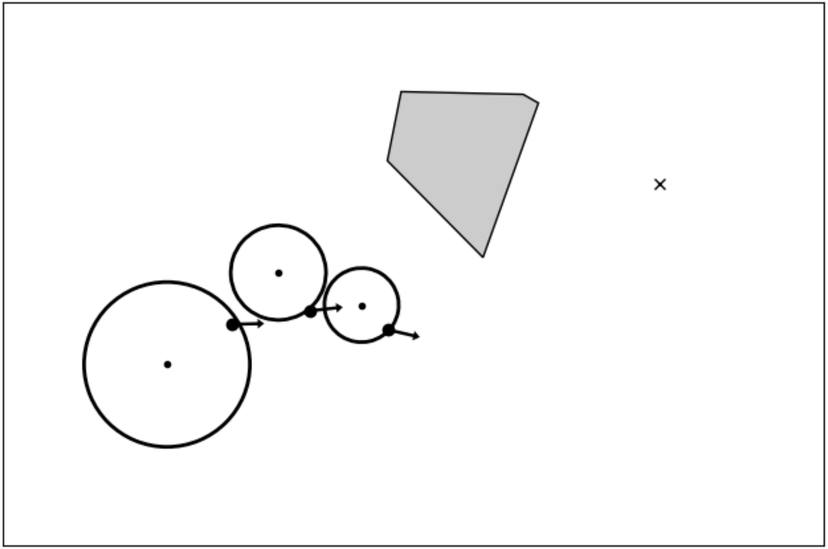

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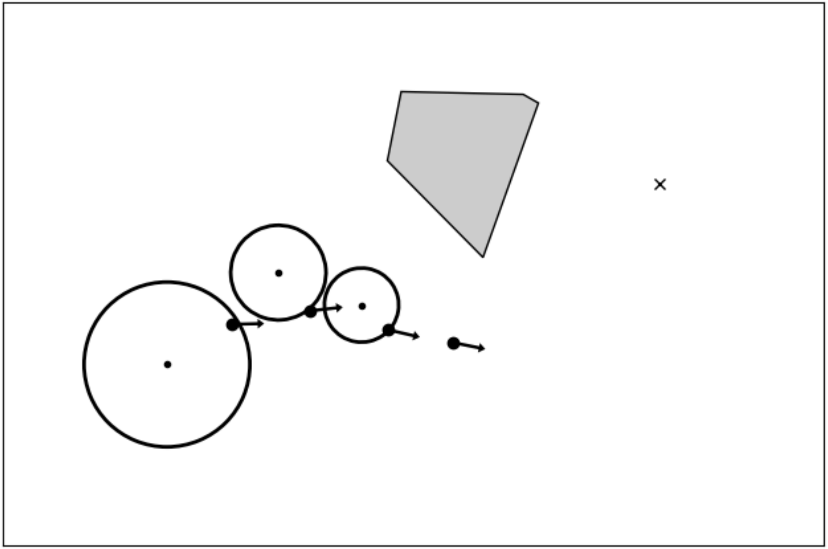

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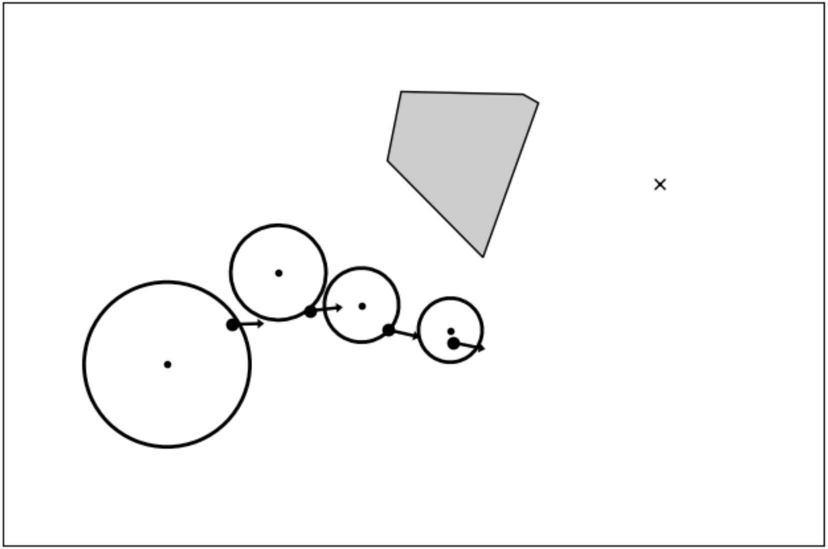

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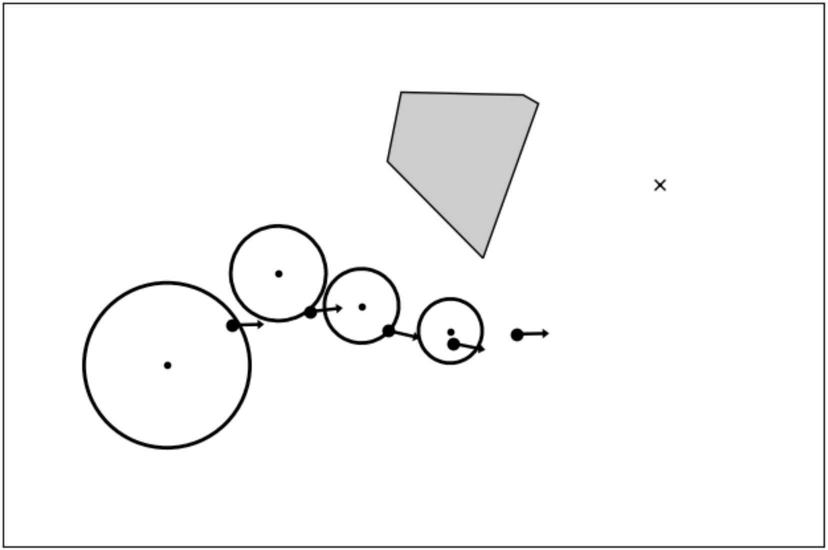

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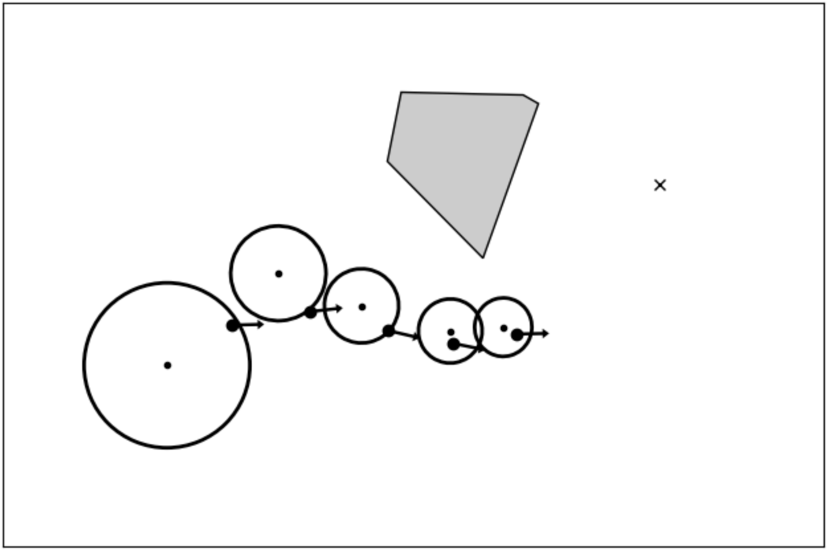

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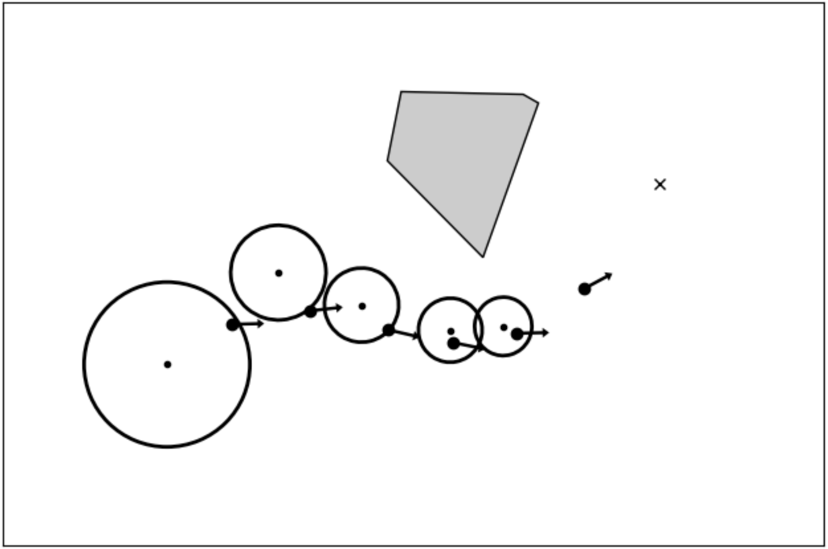

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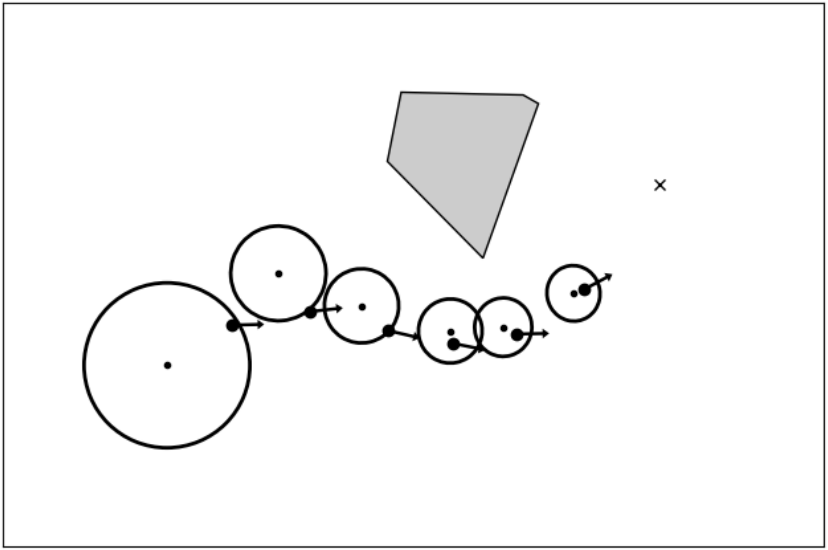

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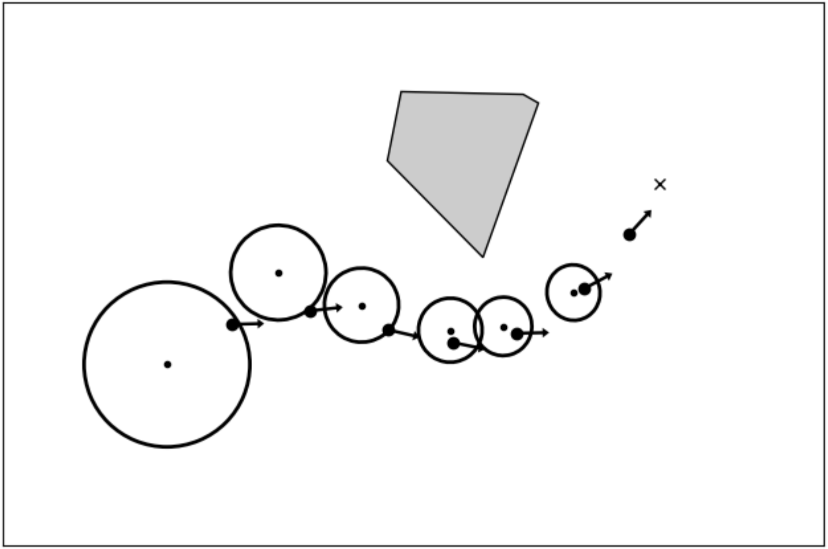

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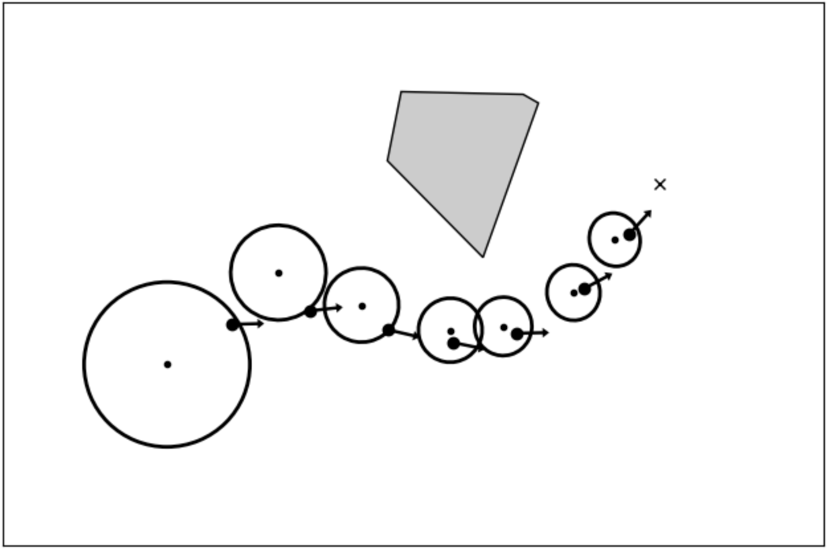

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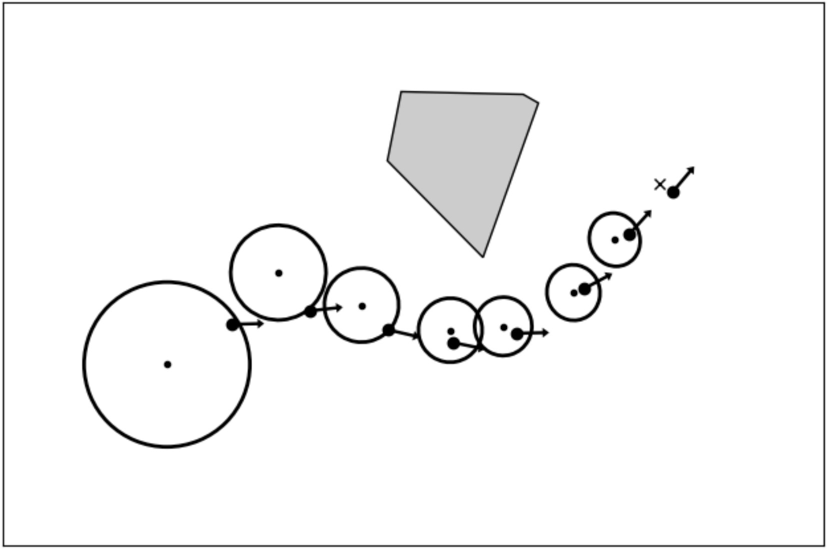

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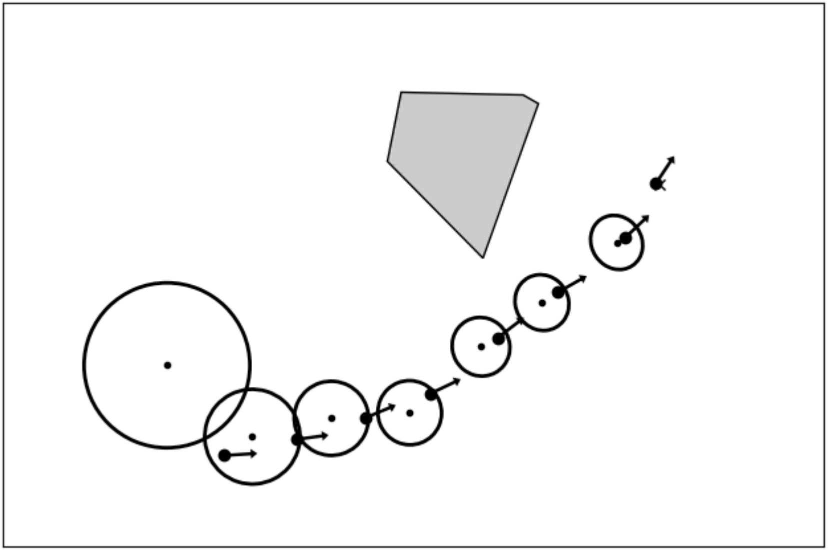

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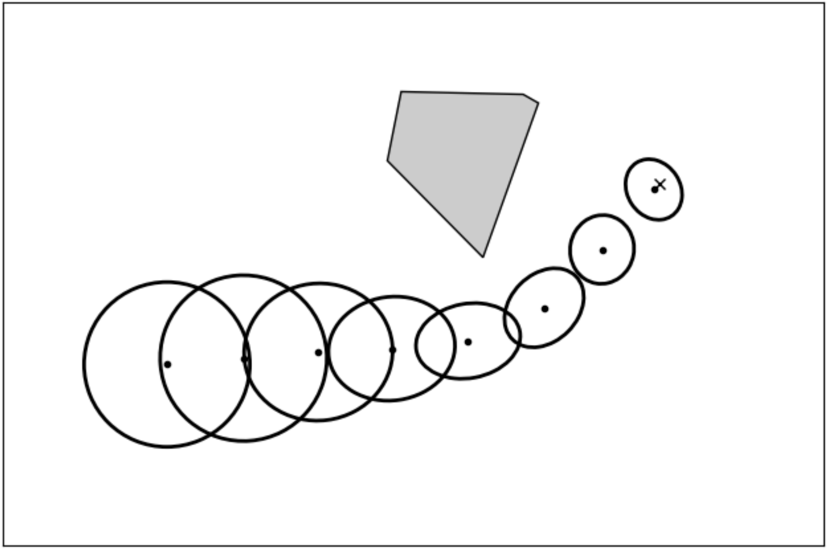

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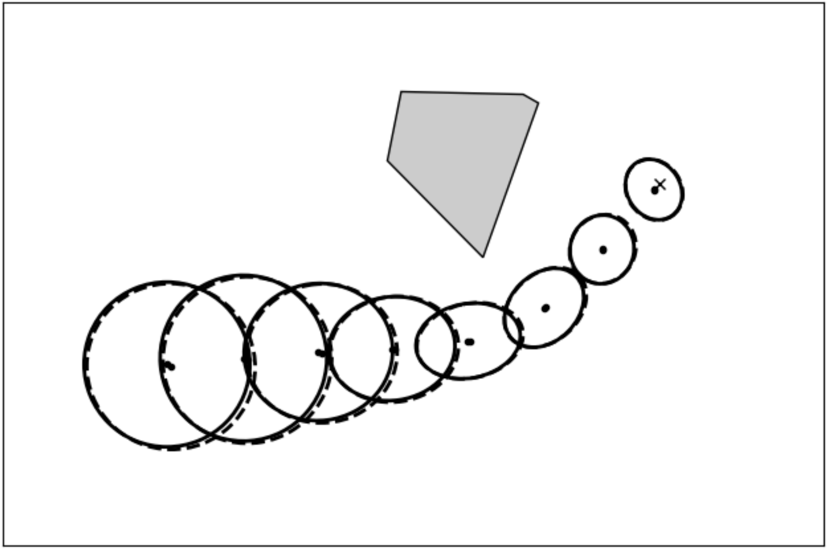

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