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Randomized Prior Functions for Deep Reinforcement Learning

Ian Osband, John Aslanides, Albin Cassirer

DeepMind

Reinforcement Learning

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Reinforcement Learning

Data
& Estimation
=
Supervised Learning

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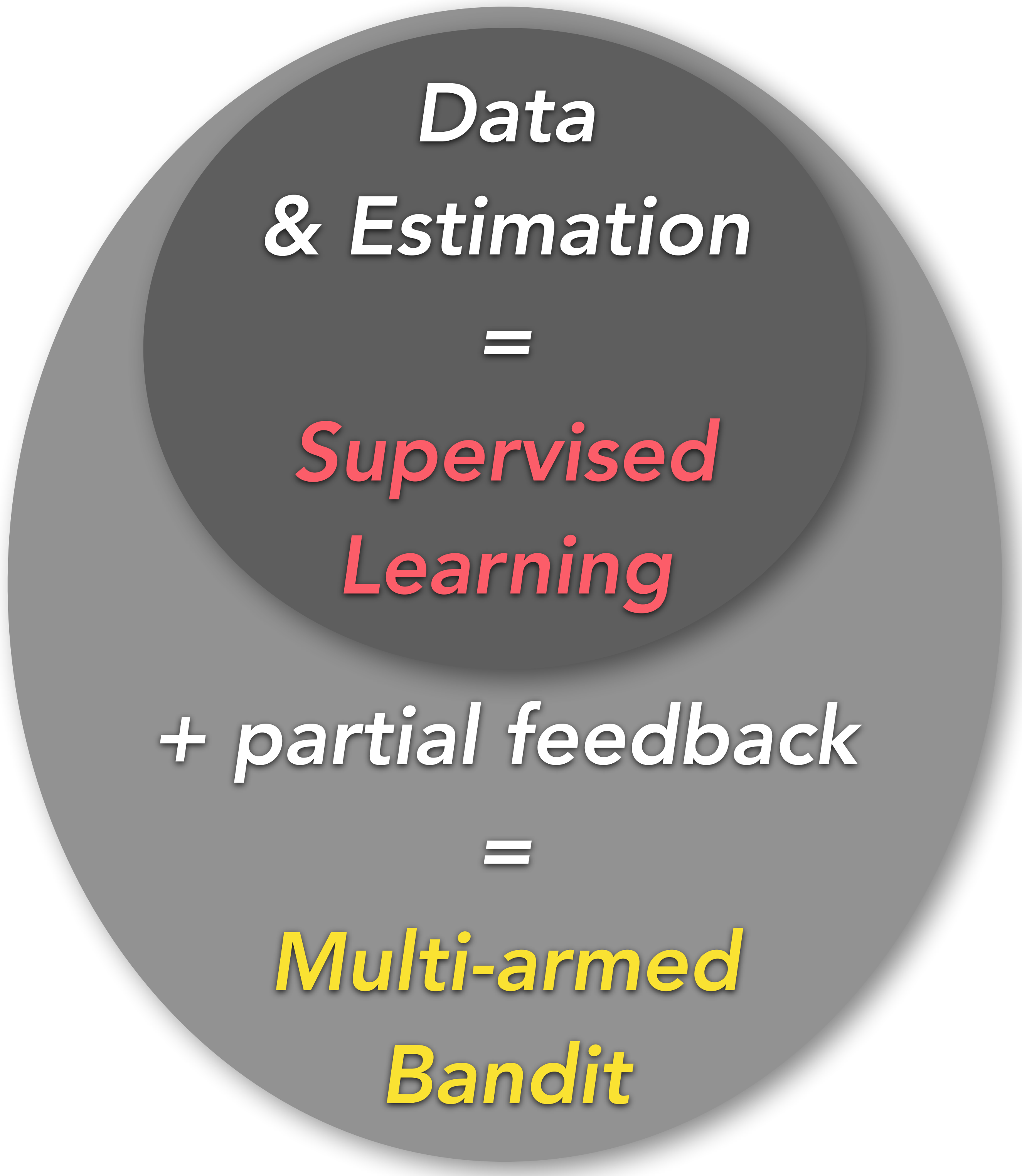
Reinforcement Learning



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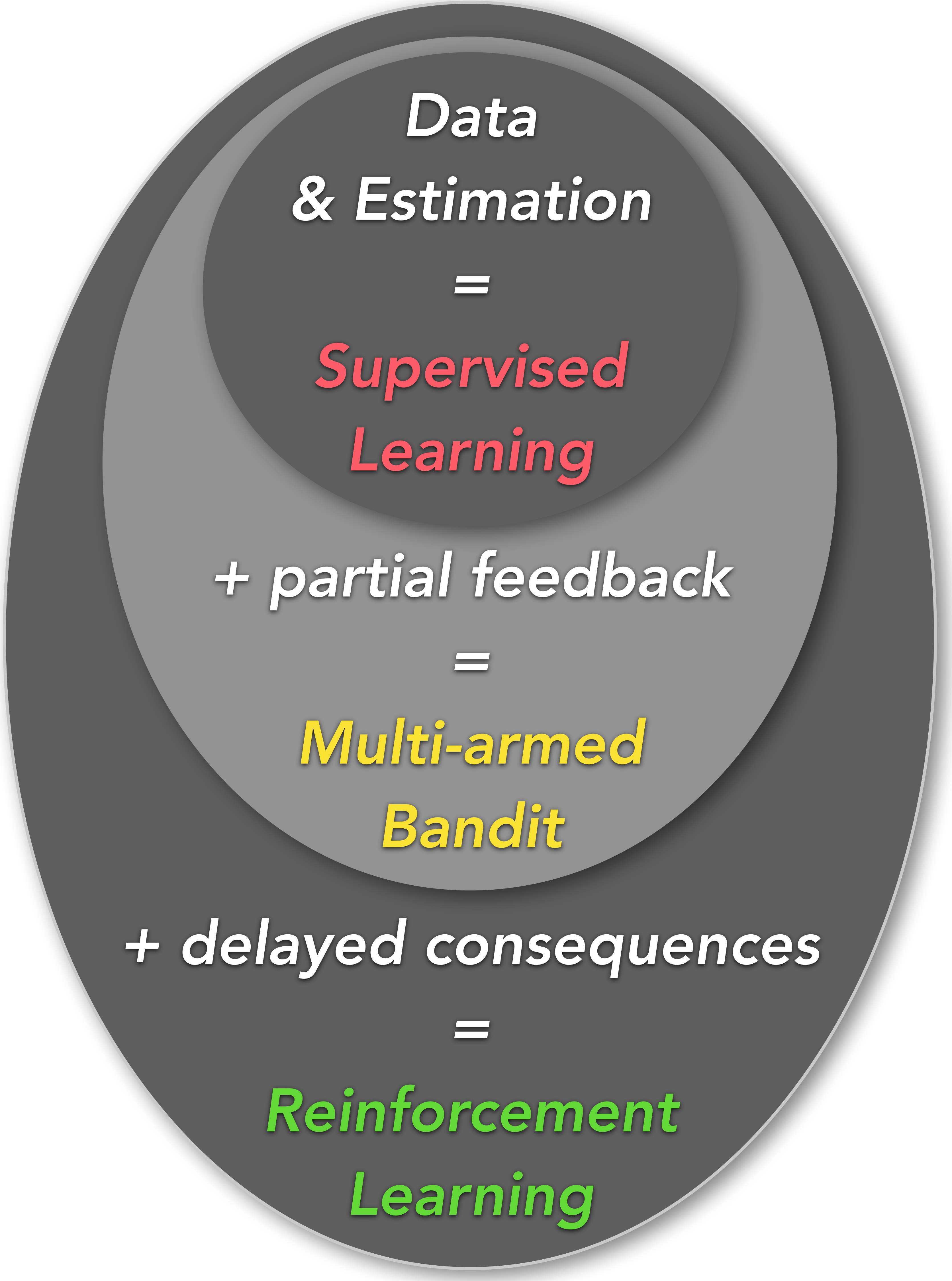
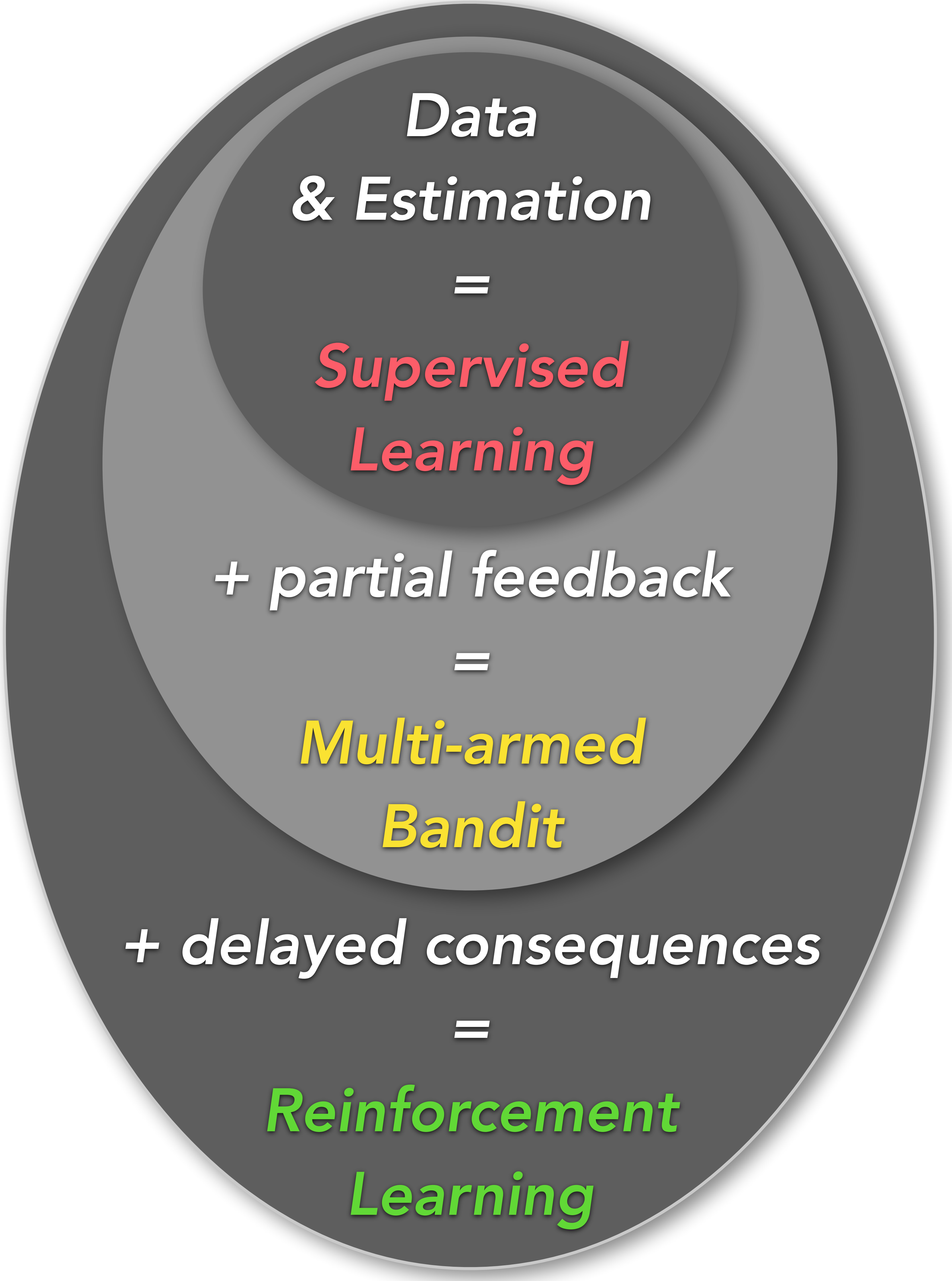


Reinforcement Learning

- *"Sequential decision making under uncertainty."*



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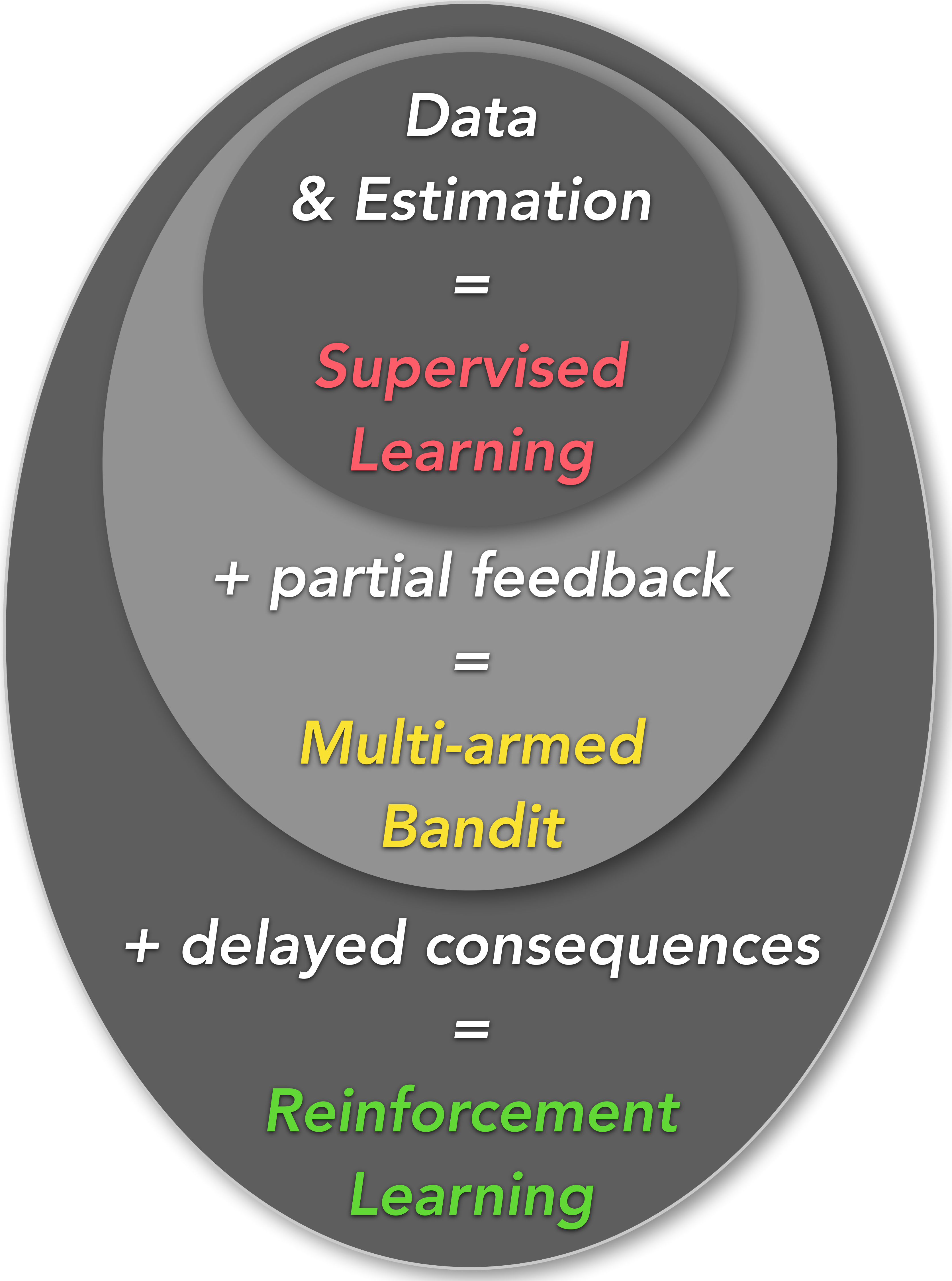

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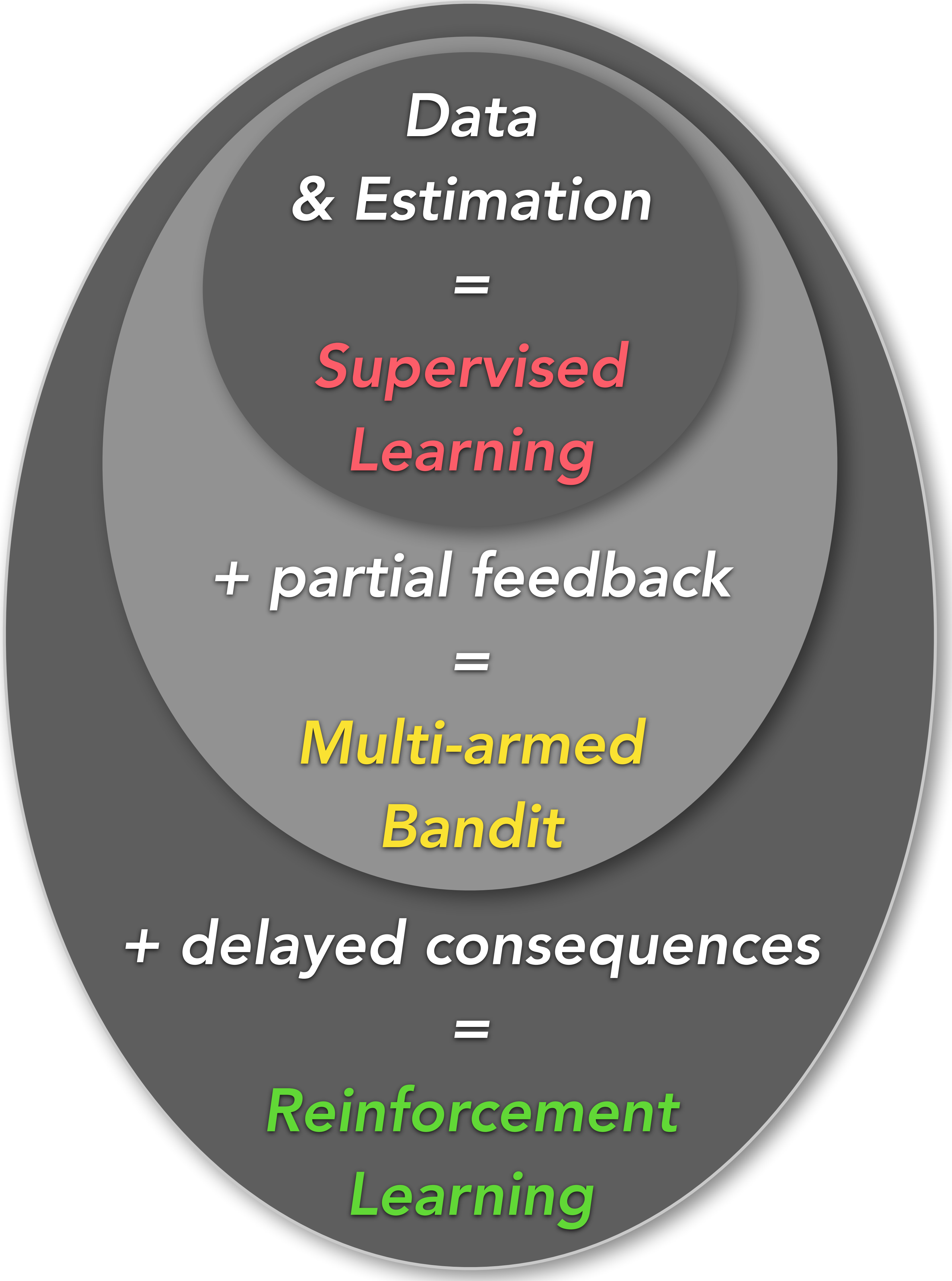

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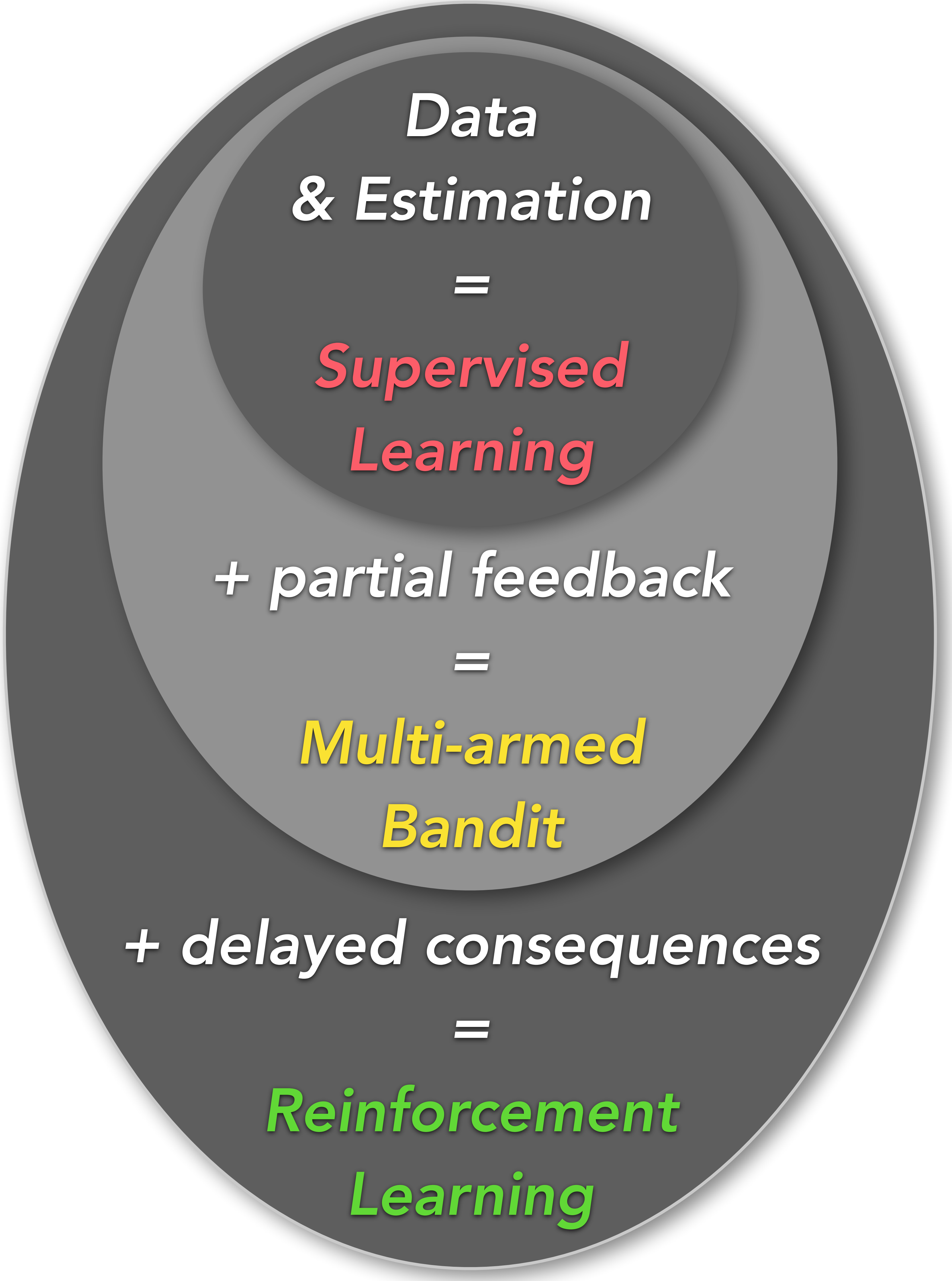

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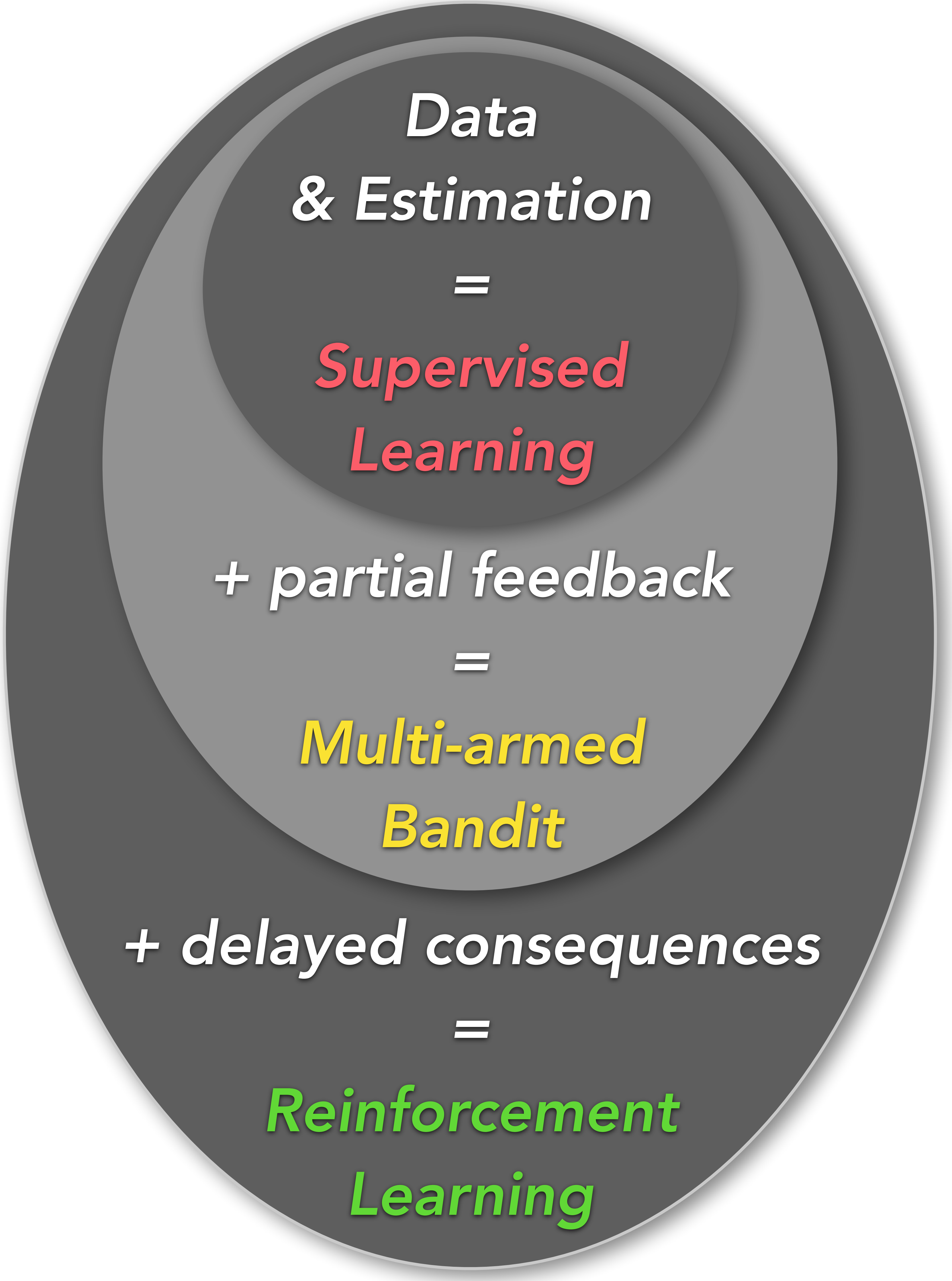

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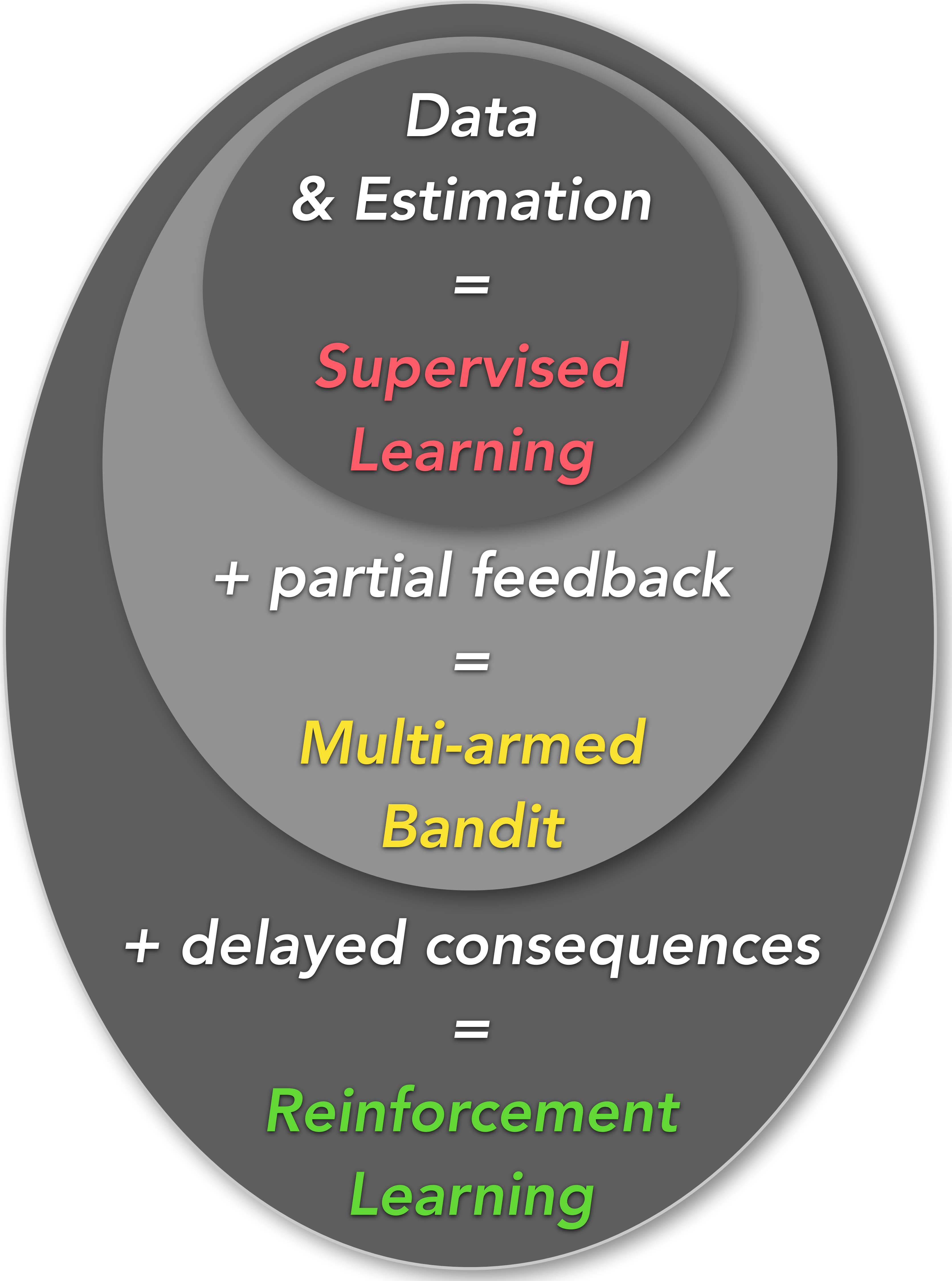

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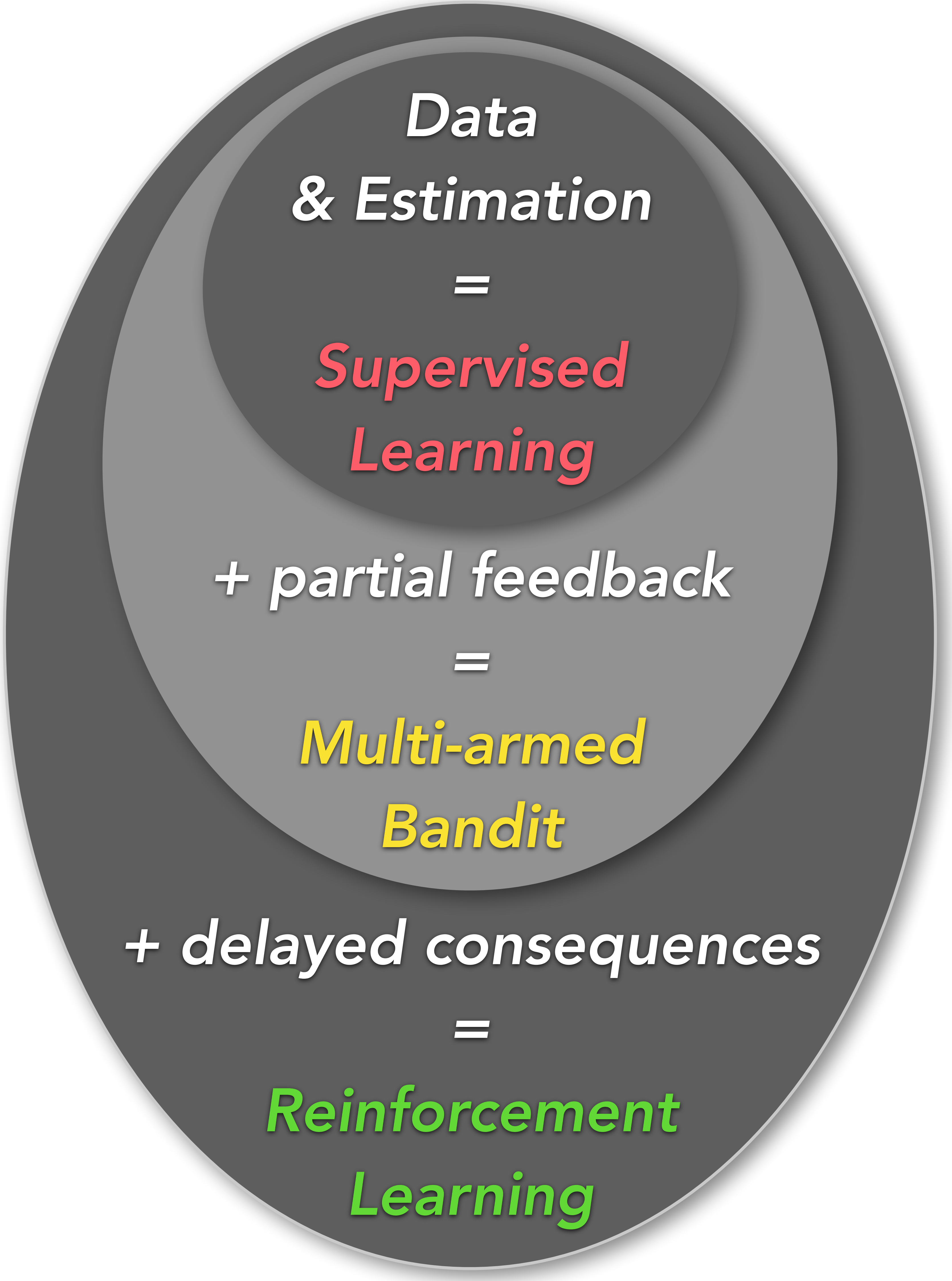

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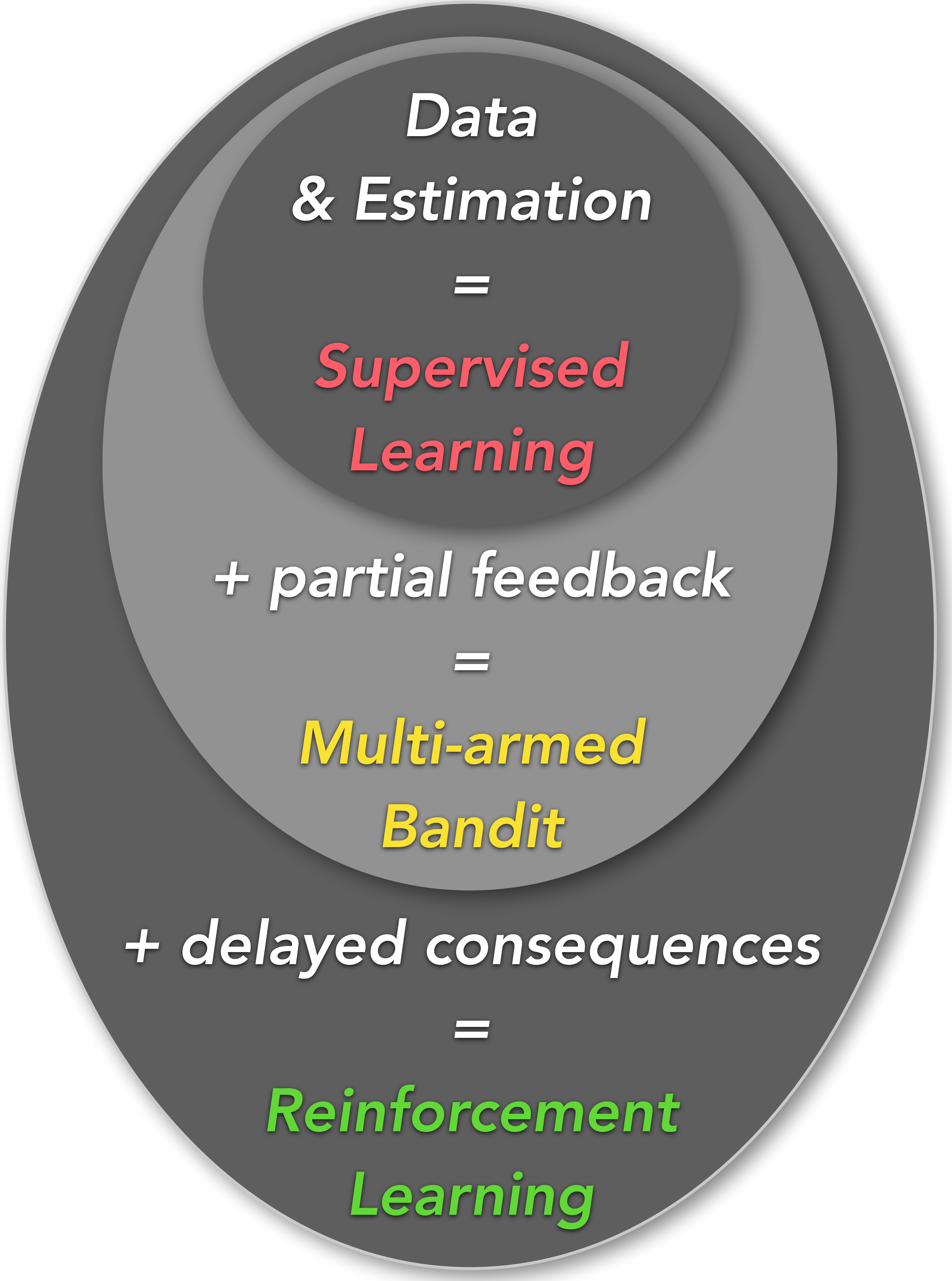

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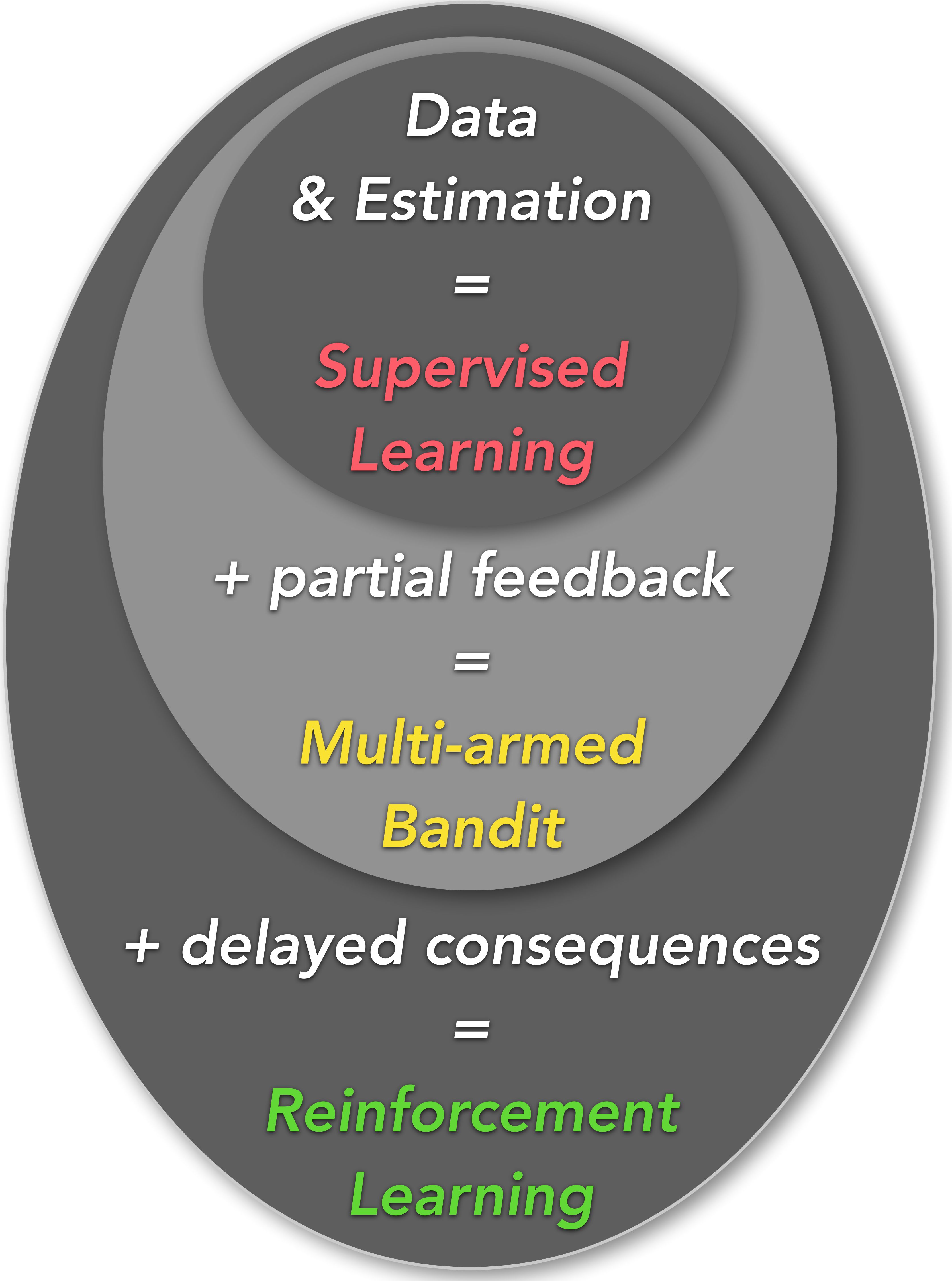
We need effective uncertainty estimates for Deep RL



Estimating uncertainty in deep RL

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Apply VI to Bellman error as if it was an i.i.d. supervised loss.

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Models Q-value as a distribution, rather than point estimate.

This distribution != posterior uncertainty.

Aleatoric vs *Epistemic* … it's *not* the right thing for exploration.

Count-based density

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Distributional RL

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Aleatoric vs *Epistemic* … it's not the right thing for exploration.

Count-based density

Estimate number of "visit counts" to state, add bonus.

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Bootstrap ensemble

Train ensemble on noisy data - classic statistical procedure!

No explicit "prior" mechanism for "intrinsic motivation"

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Even "concrete" dropout not necessarily right rate.		*Aleatoric* vs *Epistemic* … it's not the right thing for exploration.	With generalization, state "visit count" != uncertainty.	If you've never seen a reward, why would the agent explore?

Randomized prior functions

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- **Key idea:** add a random untrainable “prior” function to each member of the ensemble.

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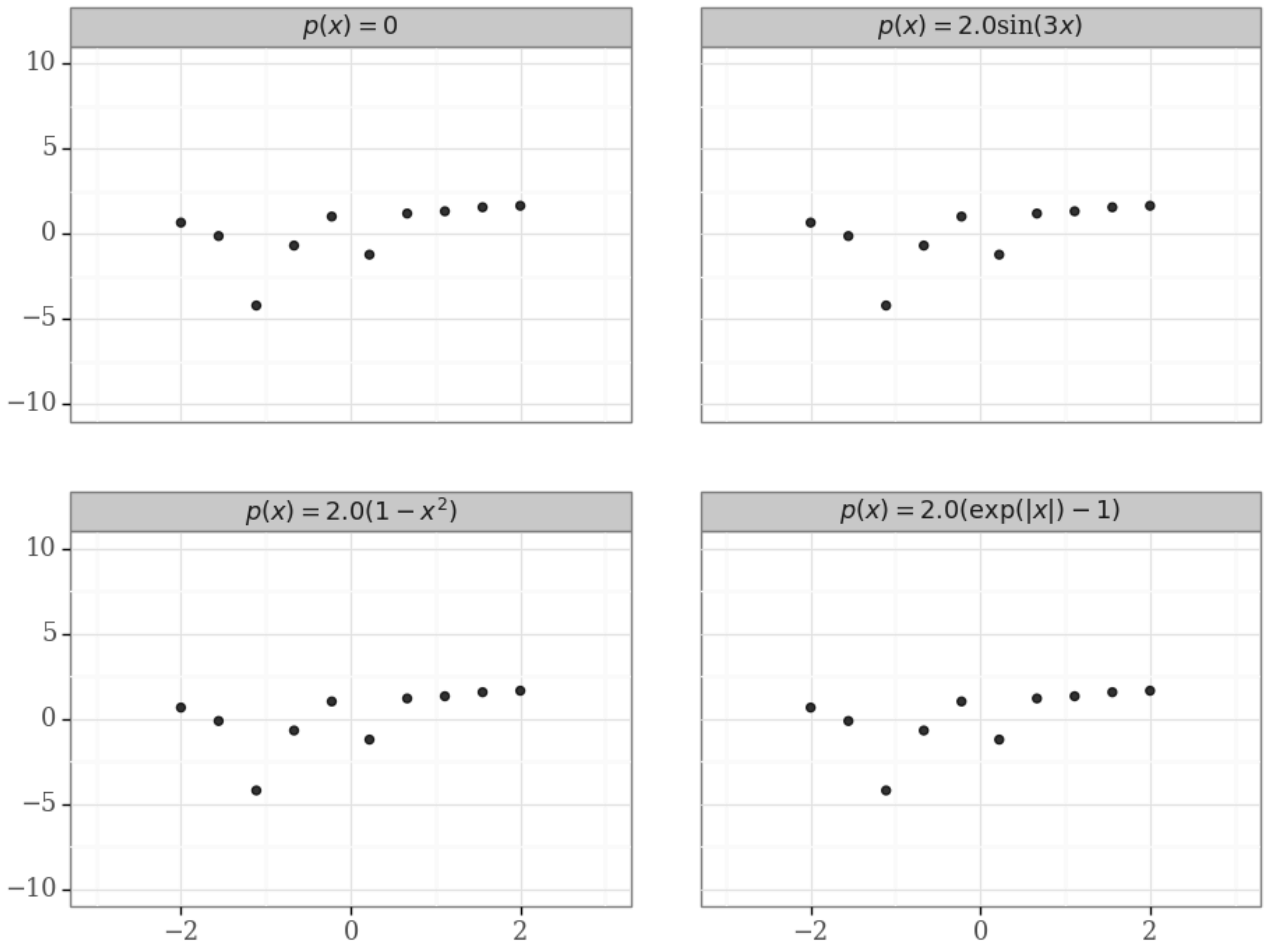

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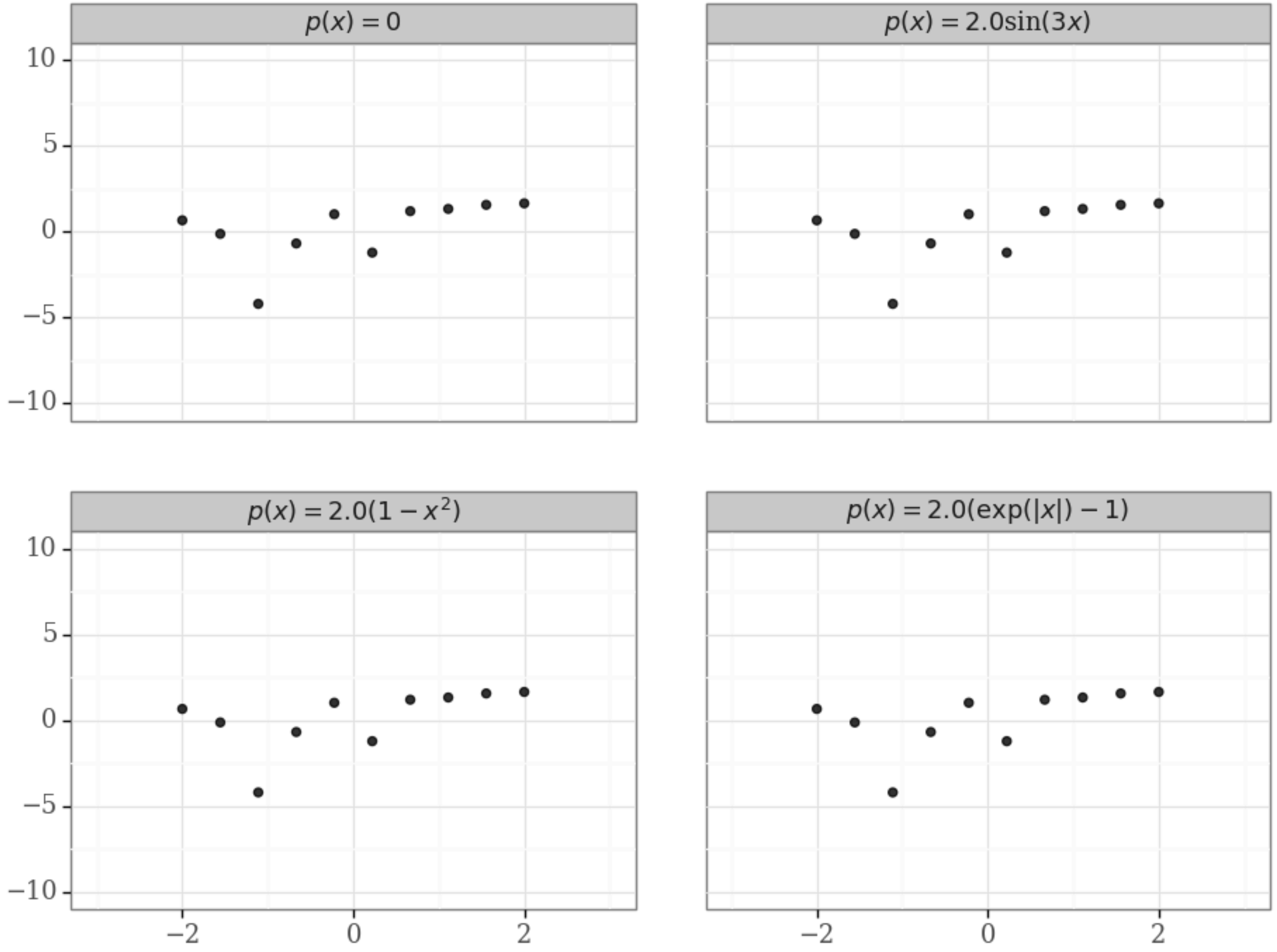

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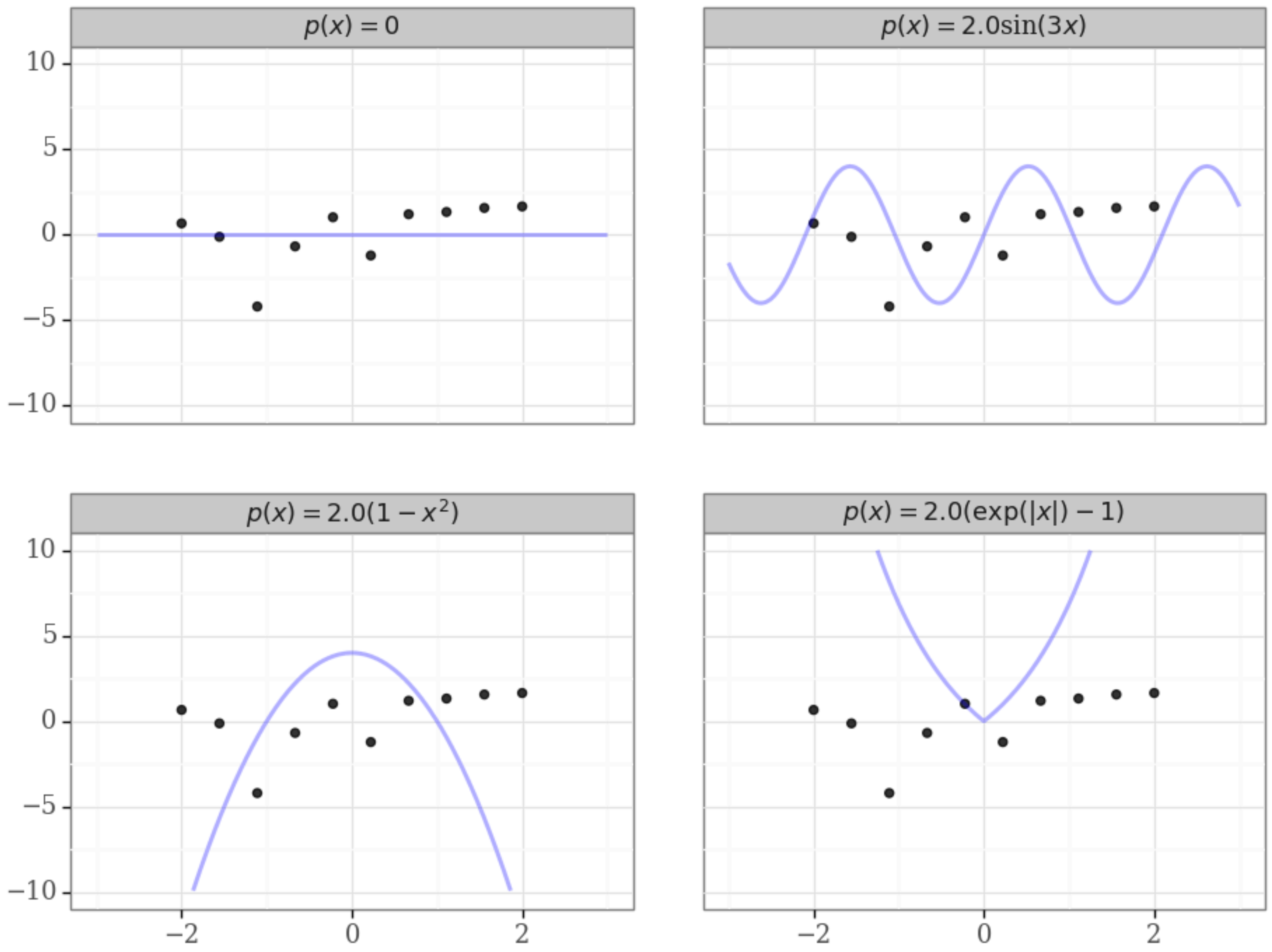

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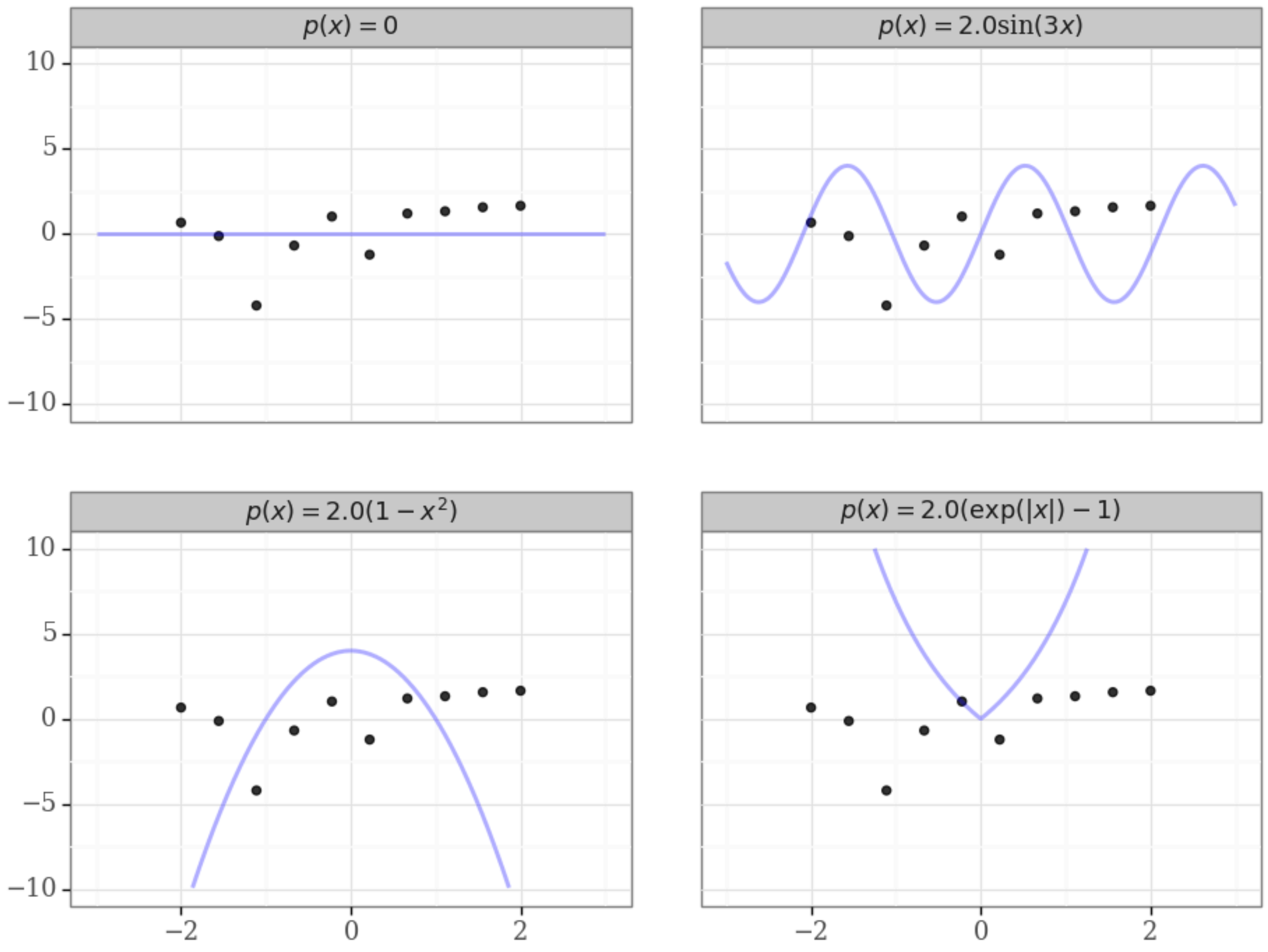

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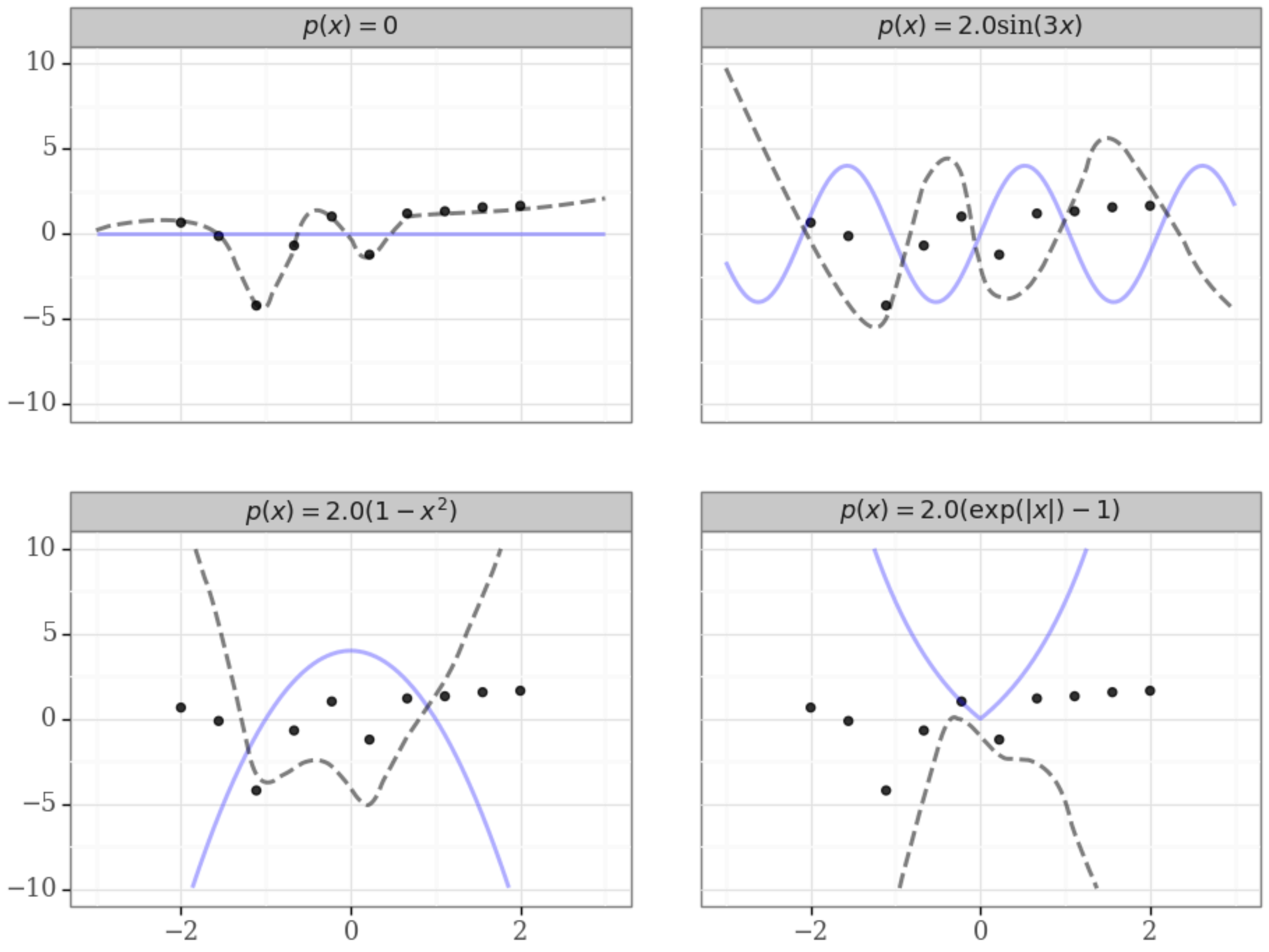

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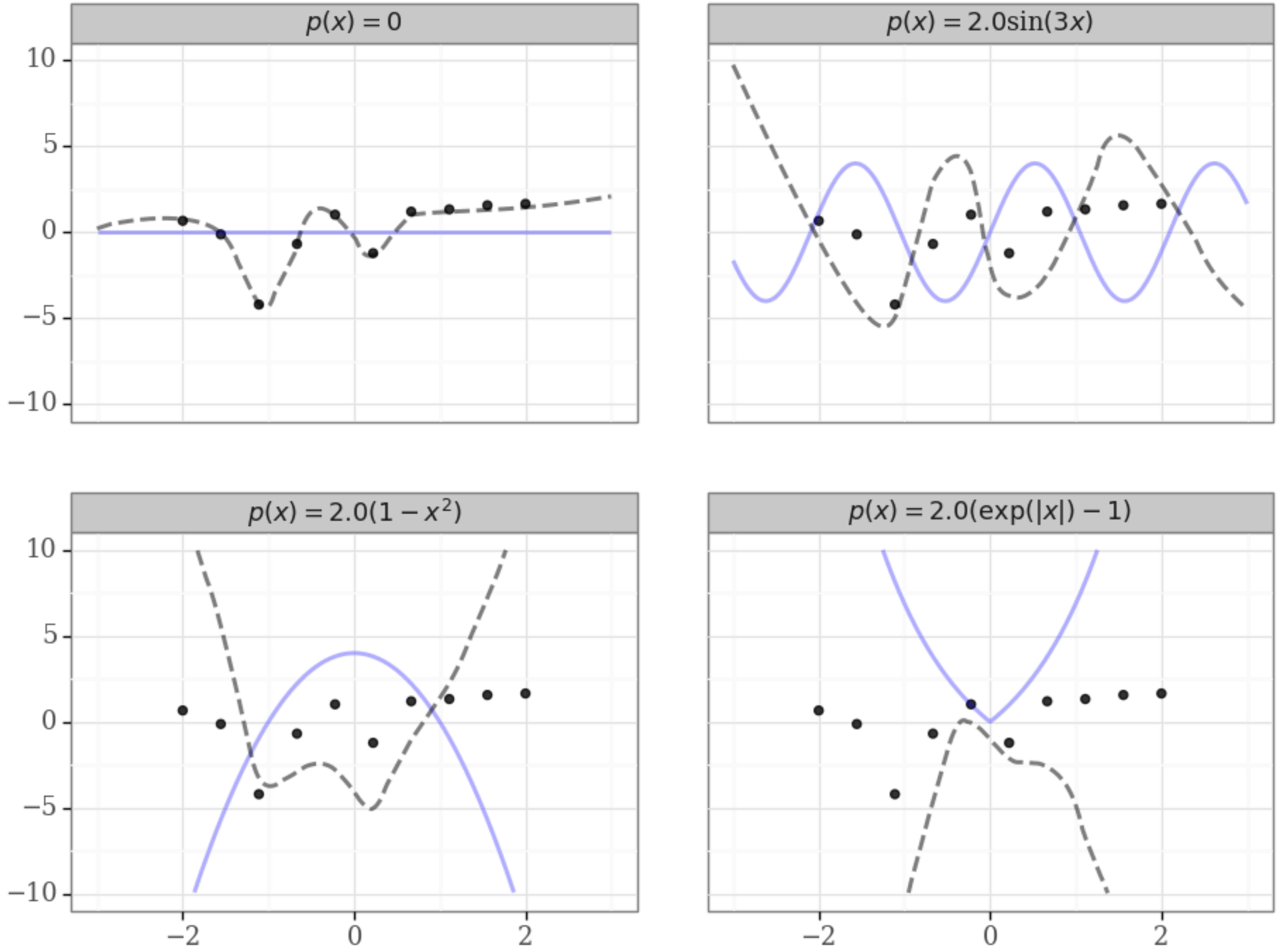

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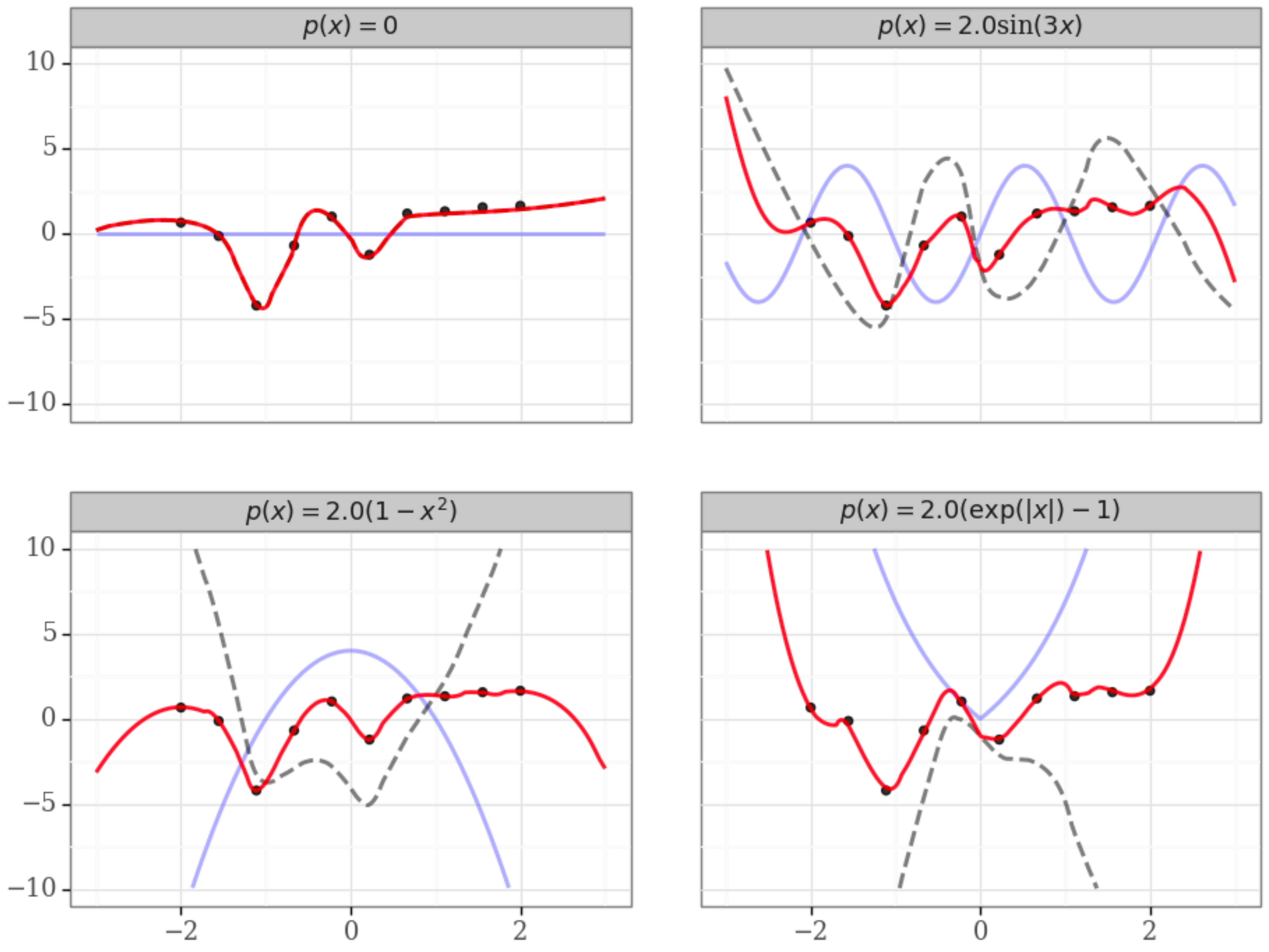

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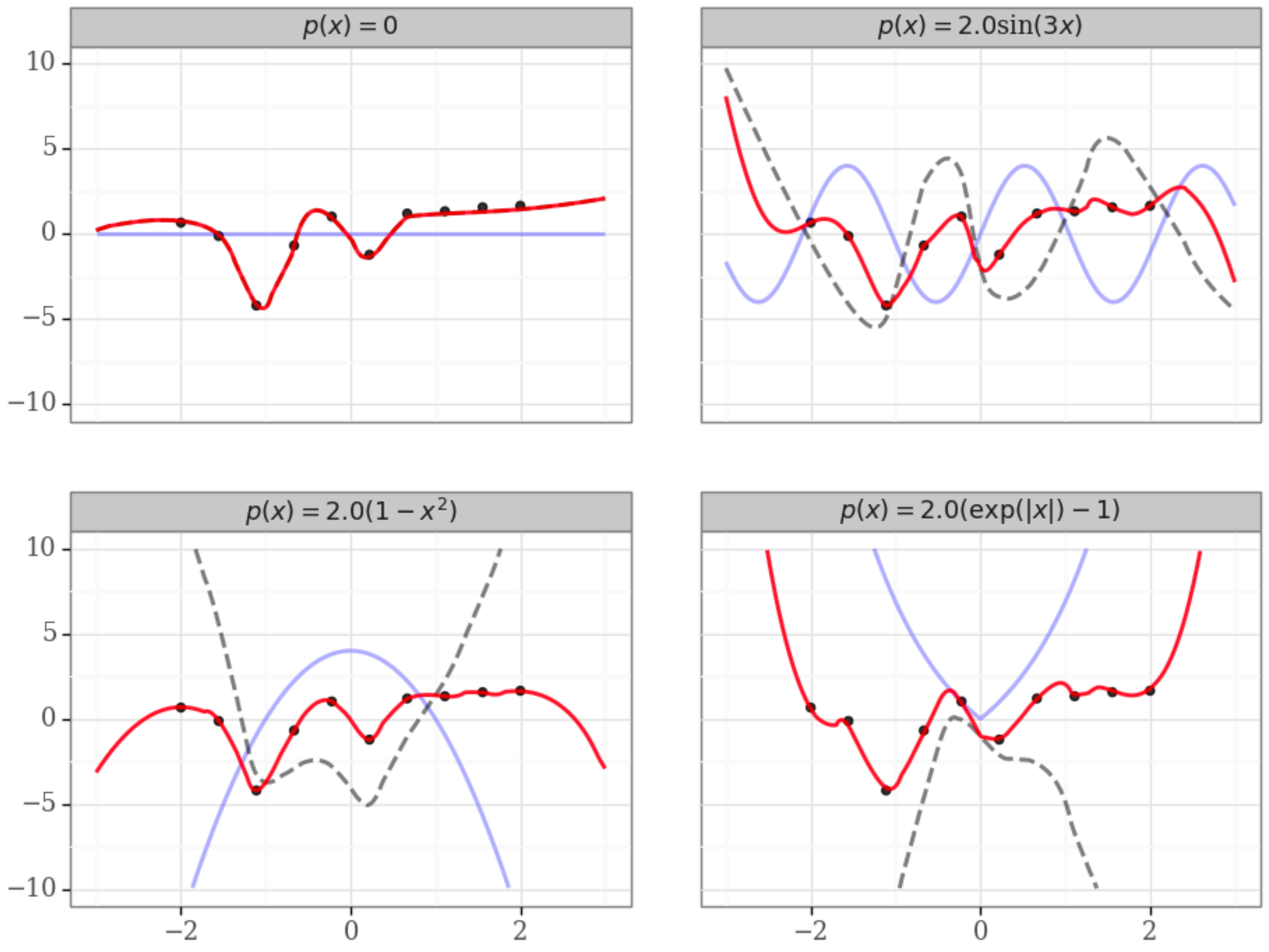
Exact Bayes posterior for linear functions!



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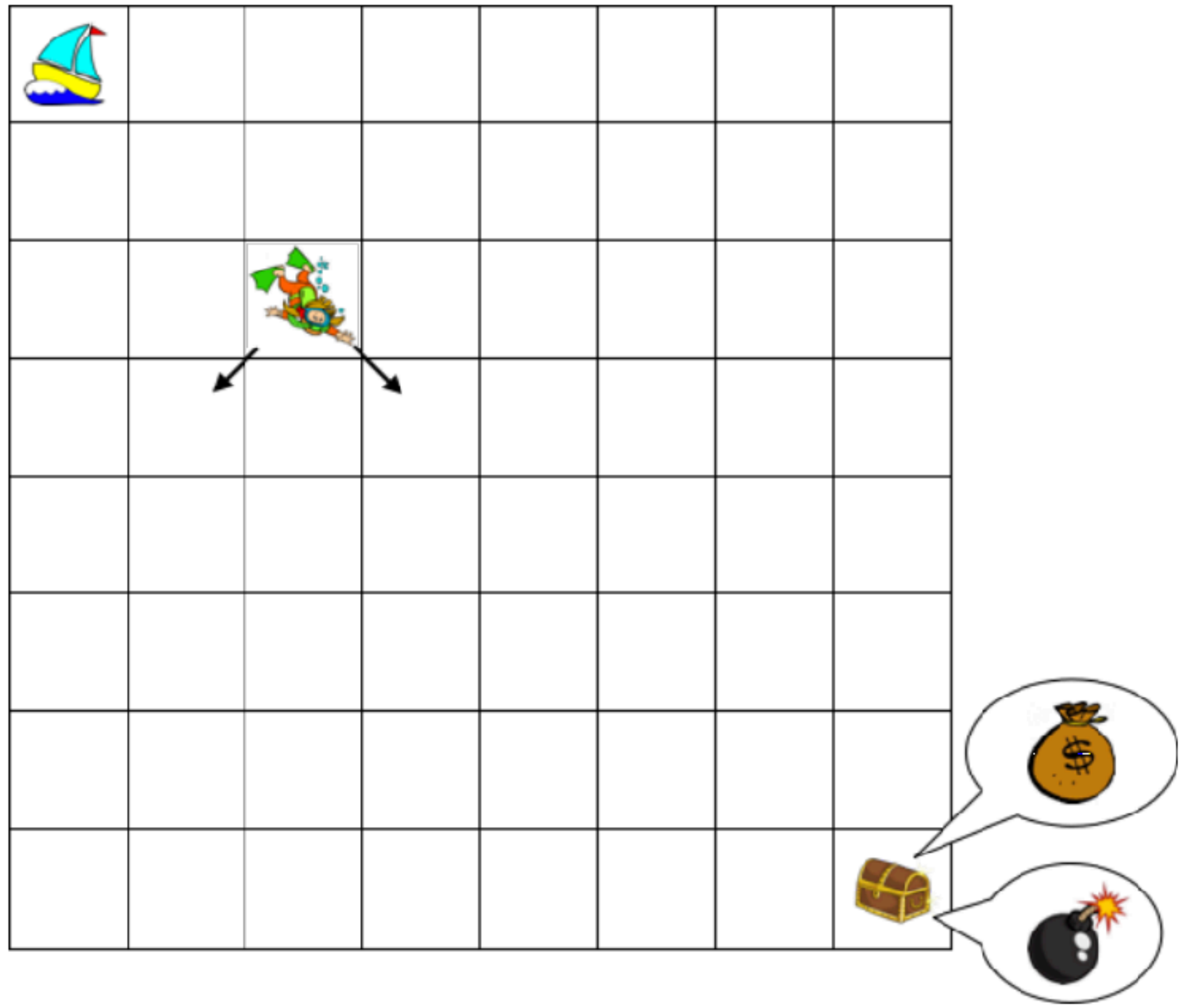

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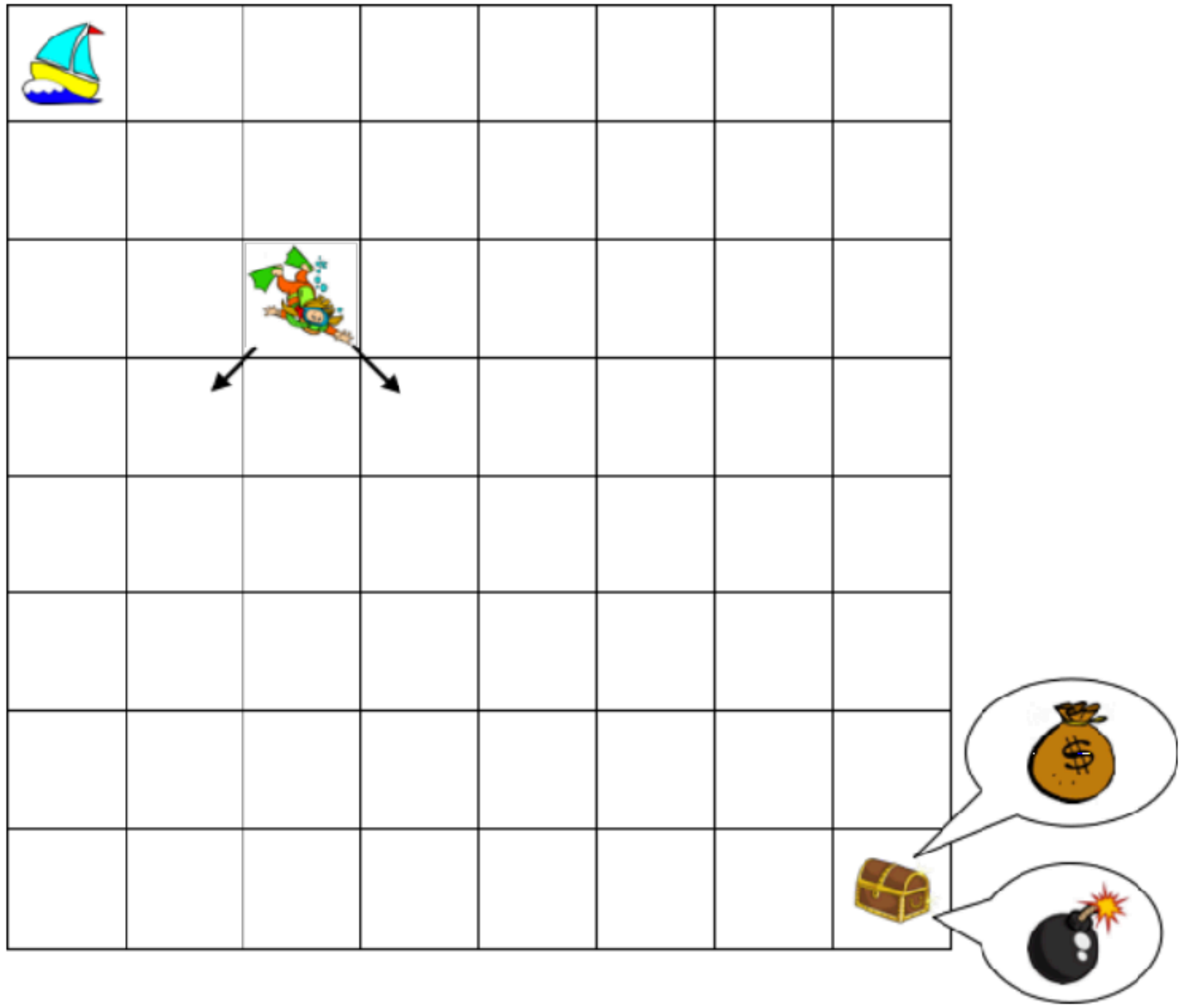

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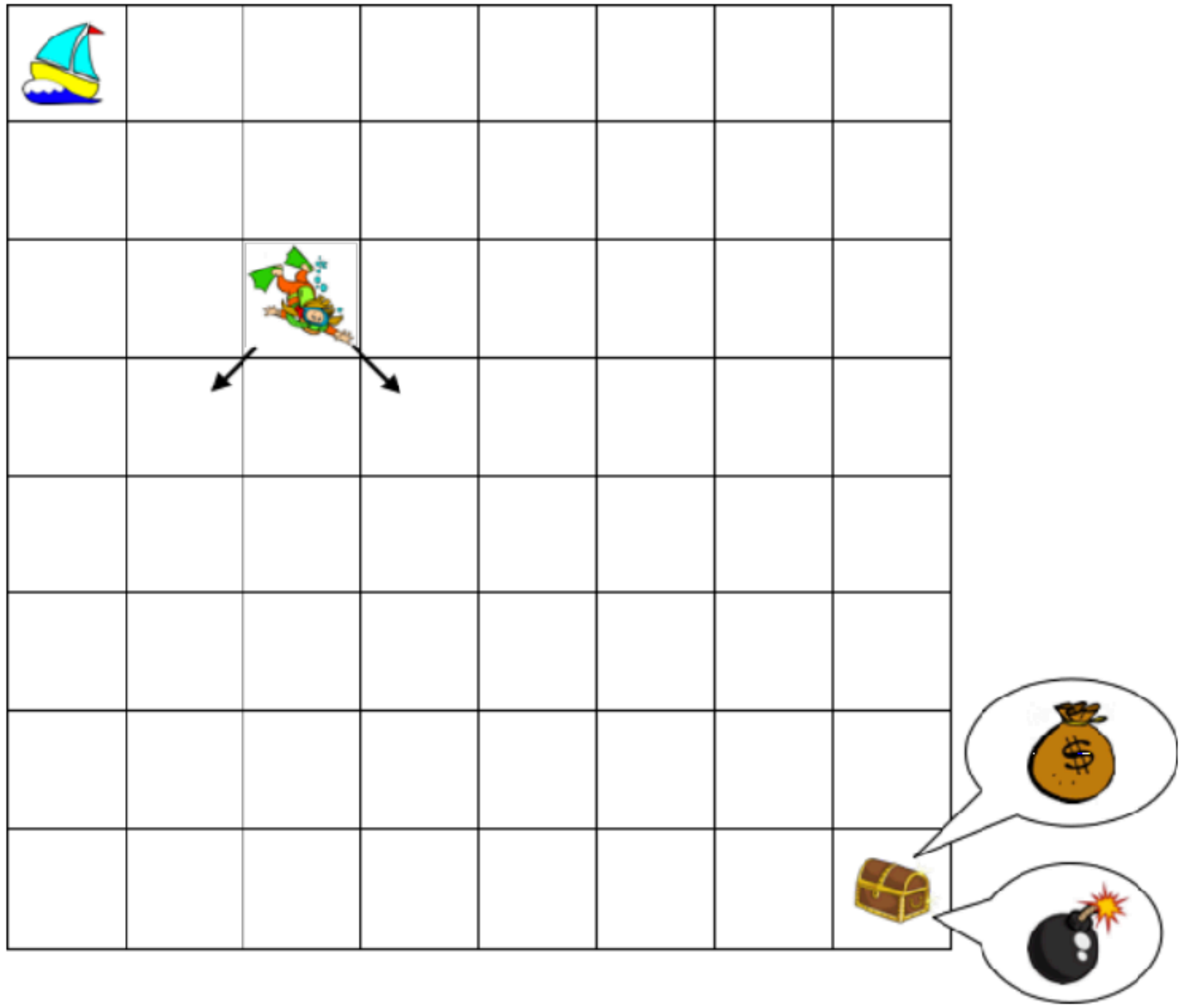
  - *State = N x N grid, observations 1-hot.*



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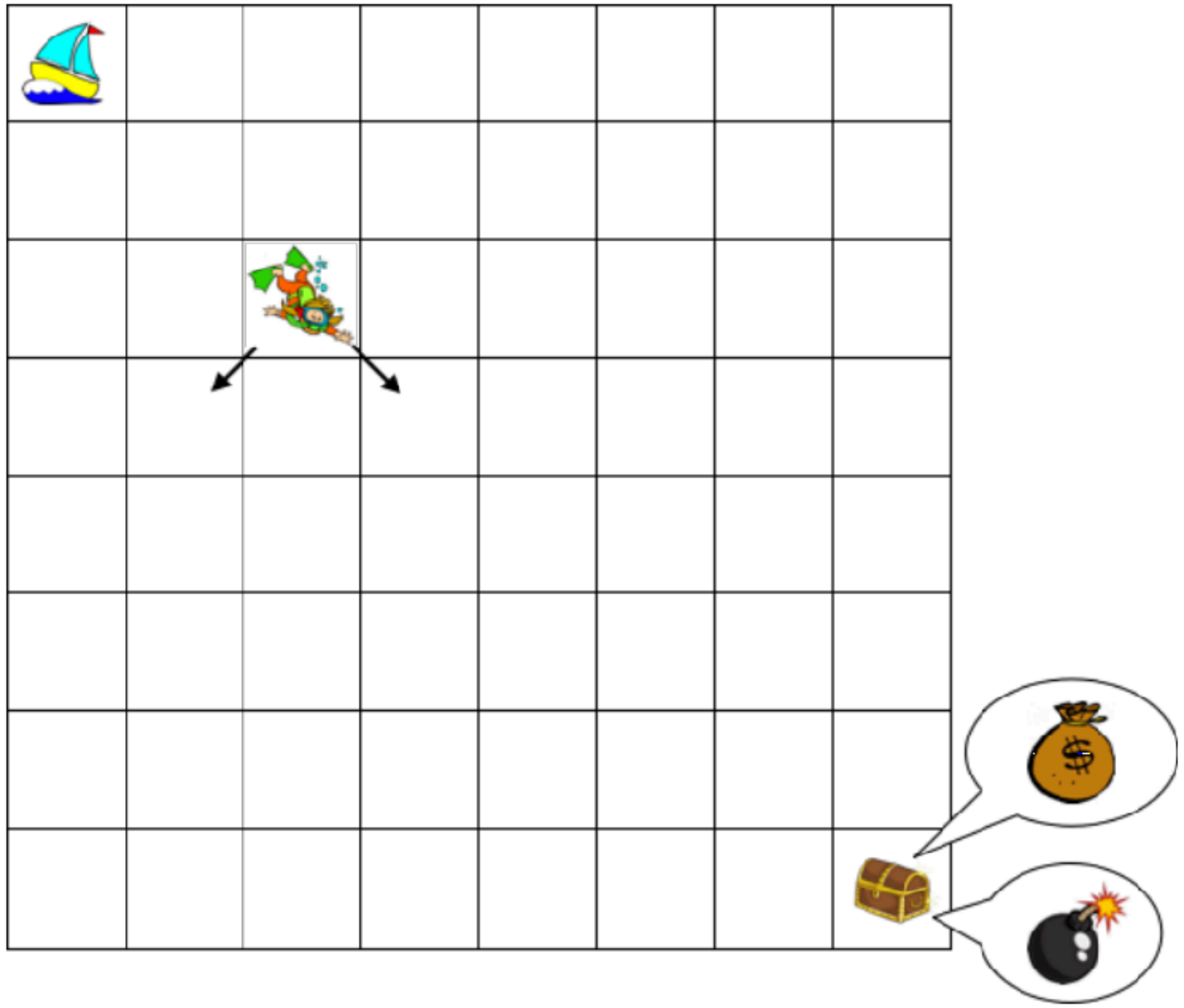

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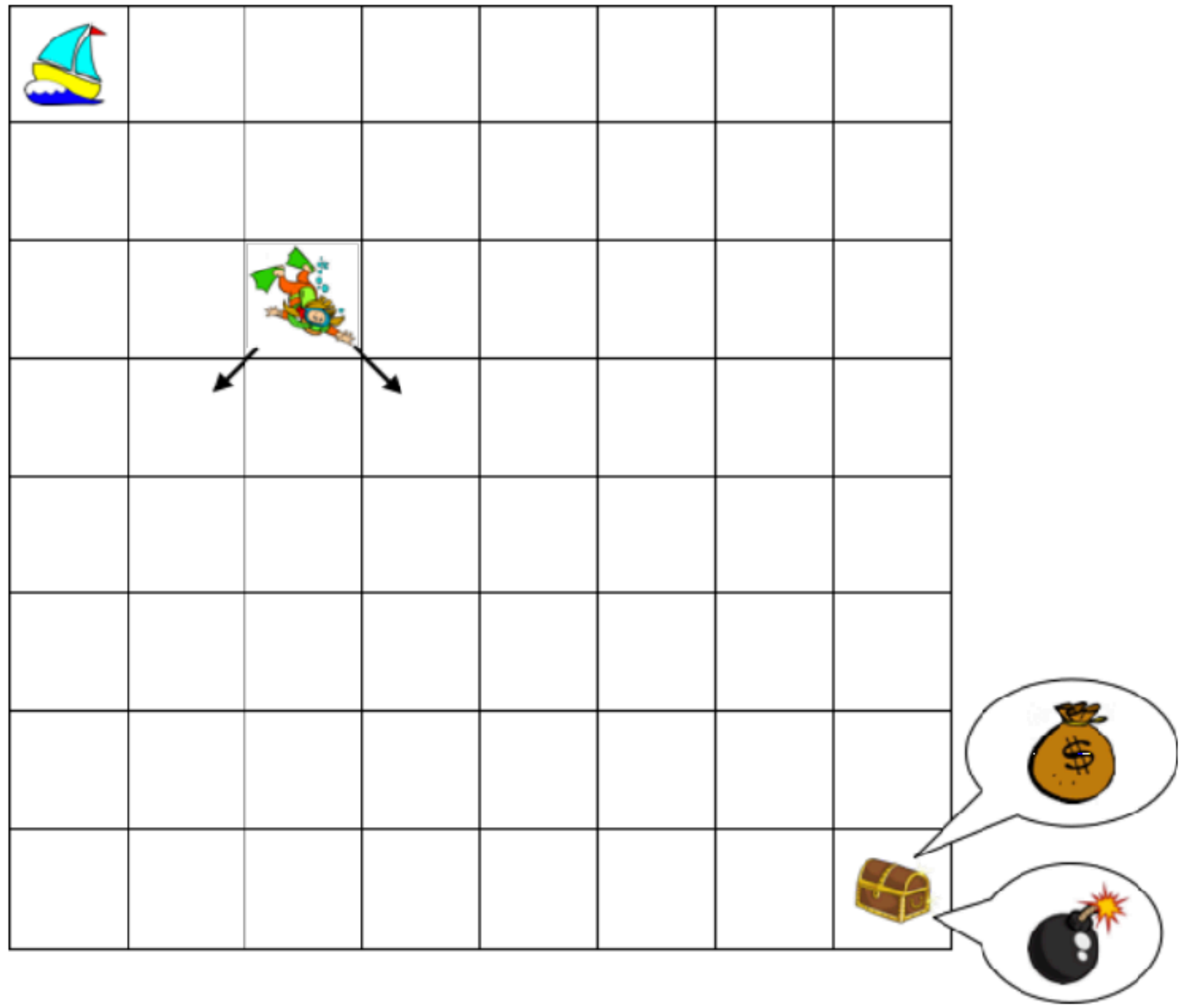

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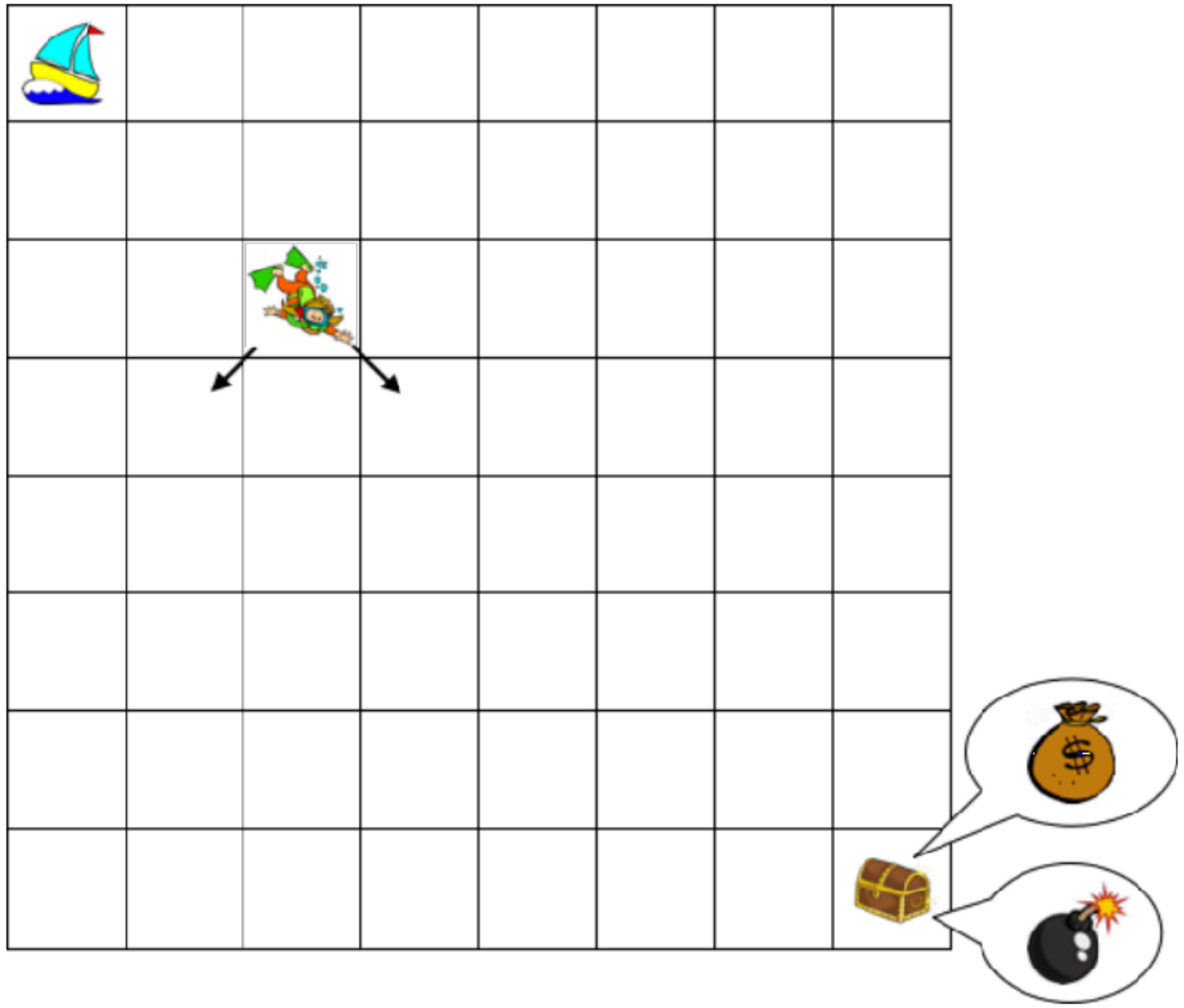

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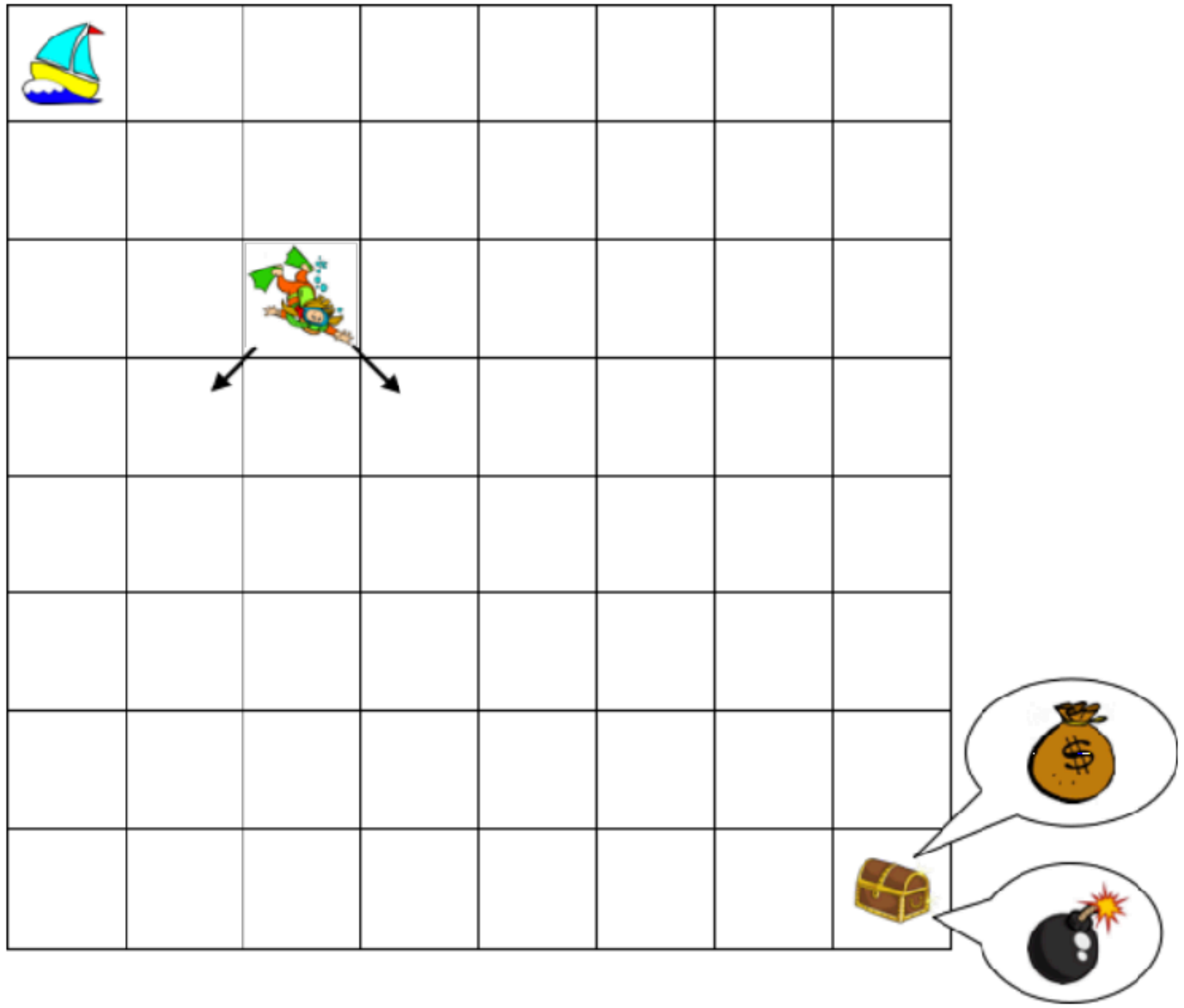
  - ***… but if you make it to bottom right you get +1.***



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- **Stylized "chain" domain testing "deep exploration":**
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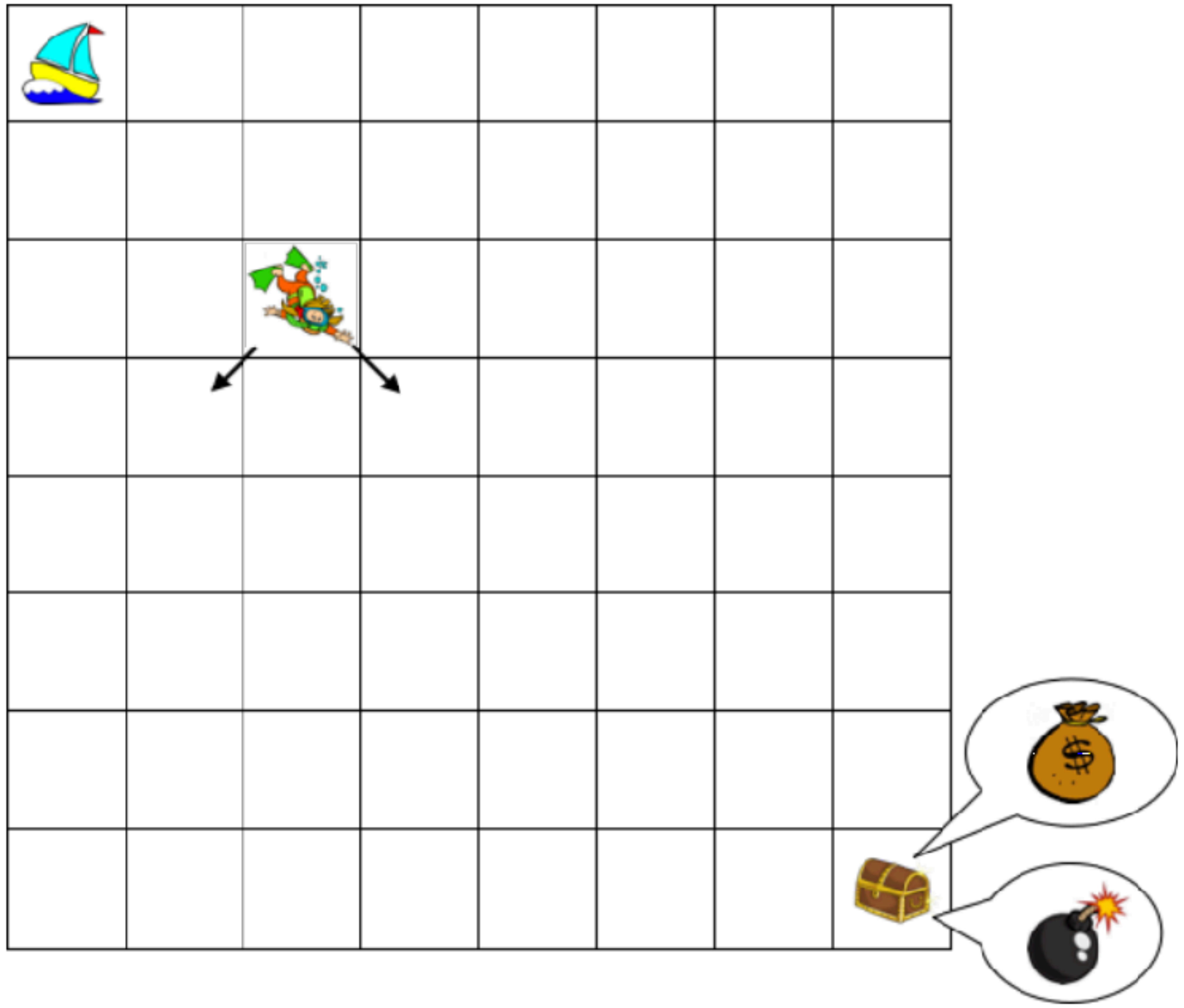

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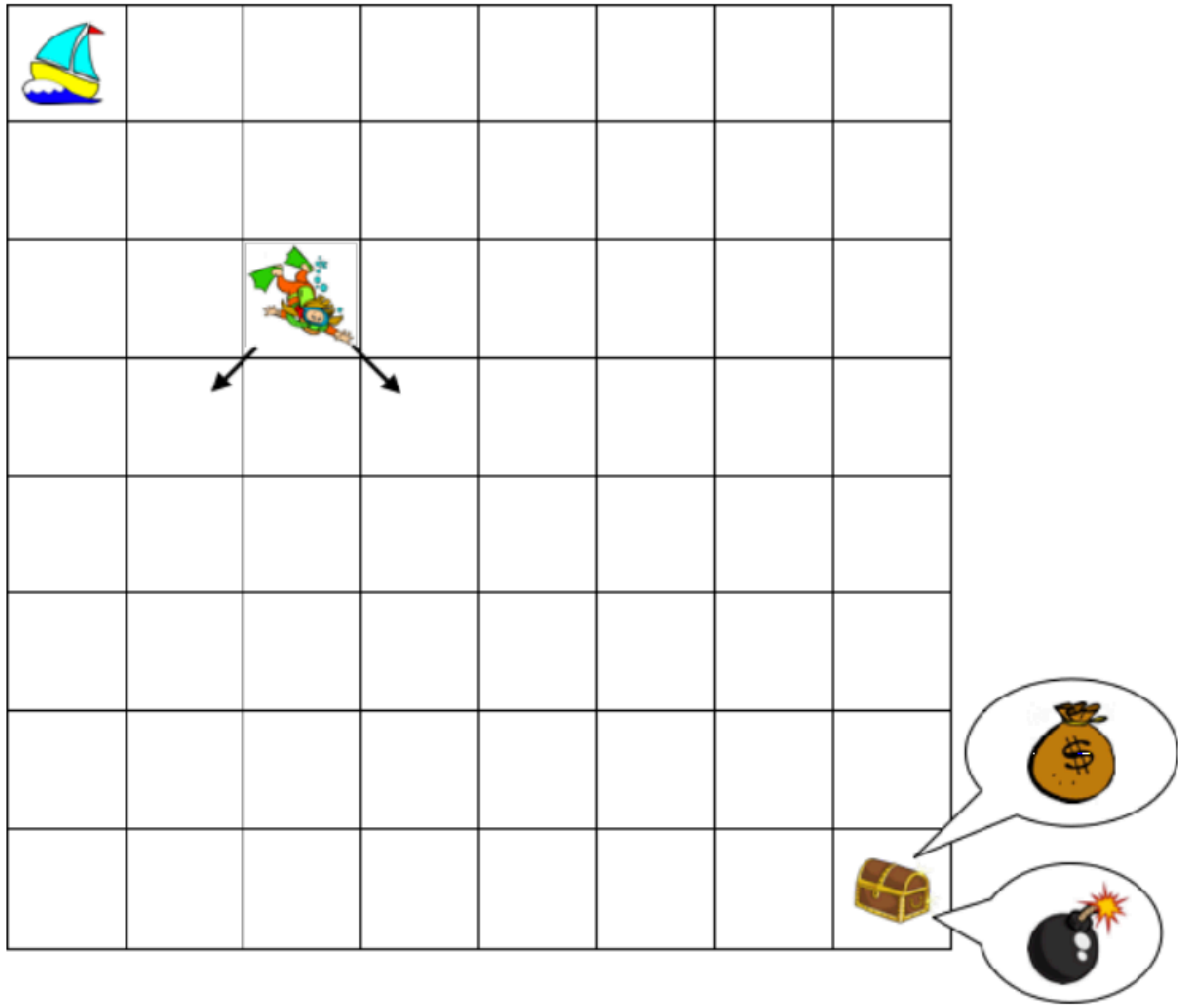

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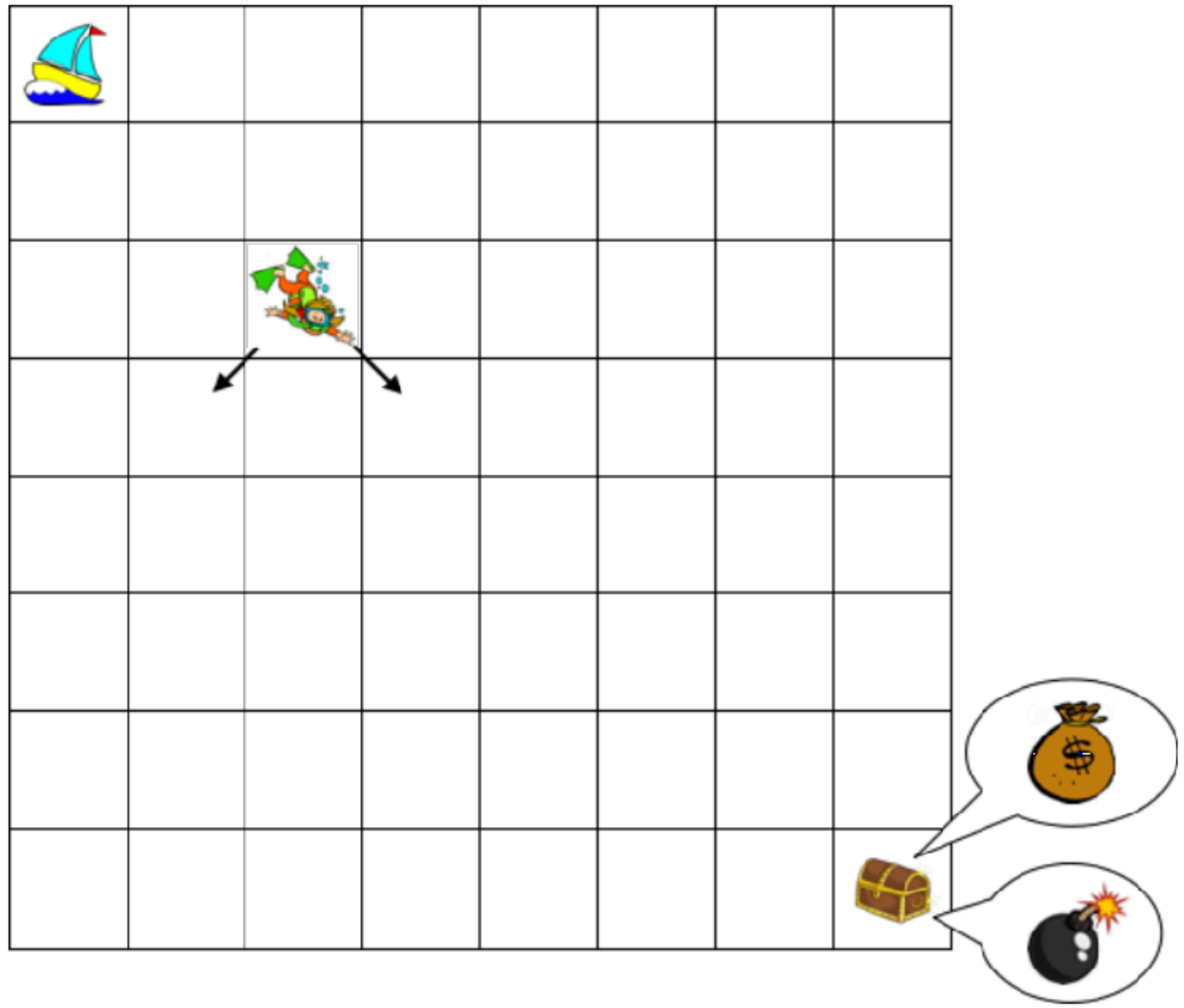

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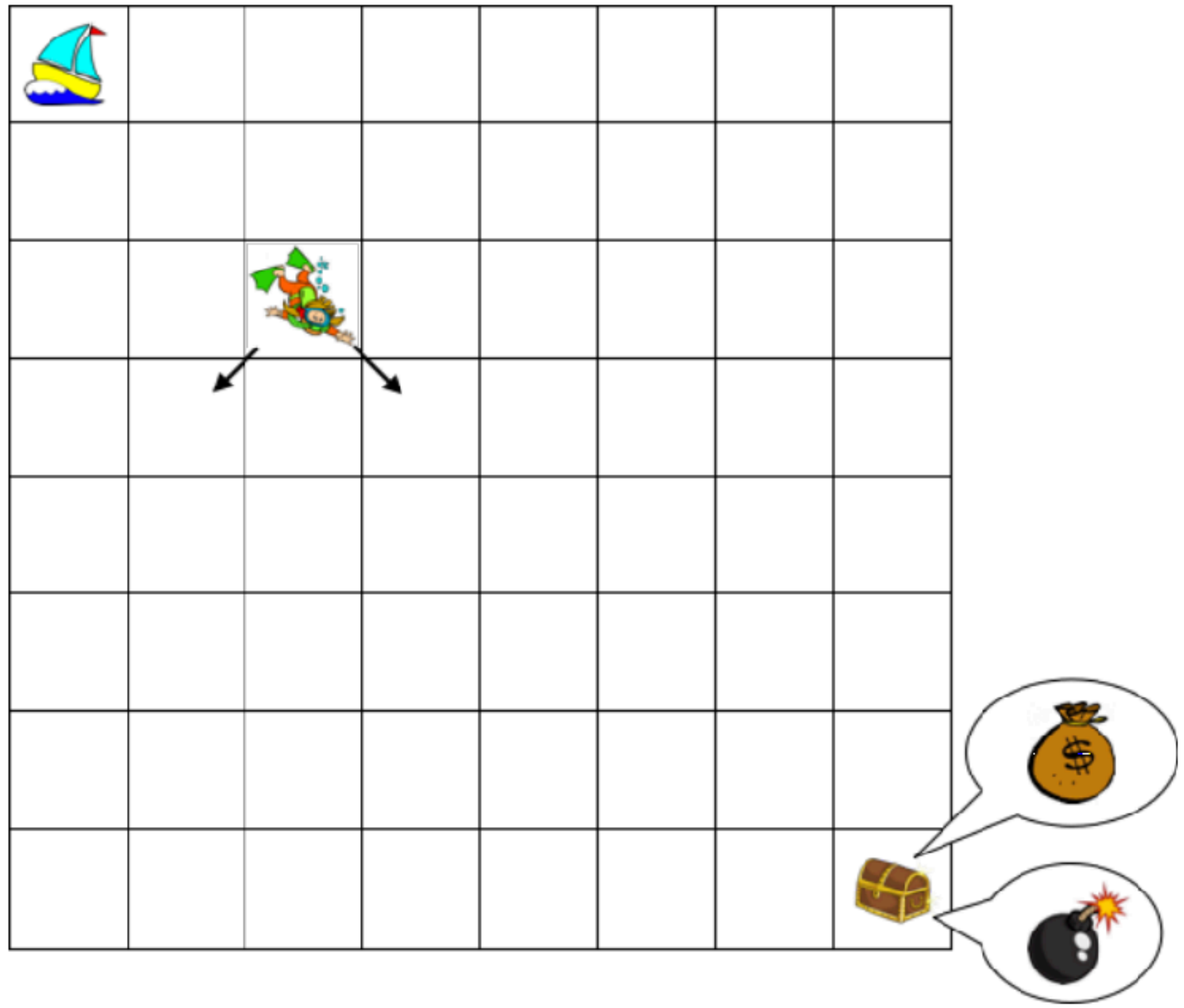
- **Algorithms with deep exploration can learn fast!**

  [1] “Deep Exploration via Randomized Value Functions”



Visualize BootDQN+prior exploration.

bit.ly/rpf_nips
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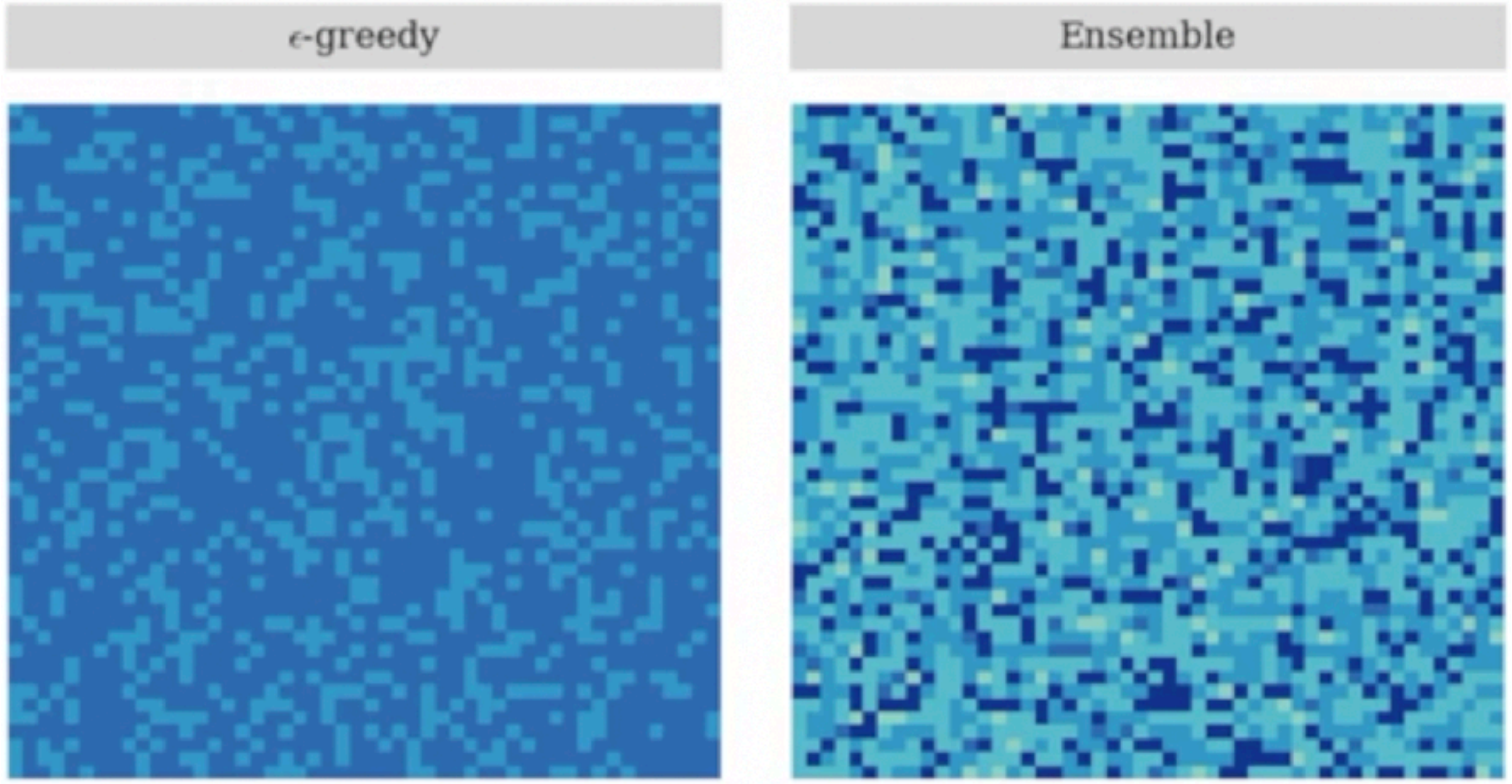

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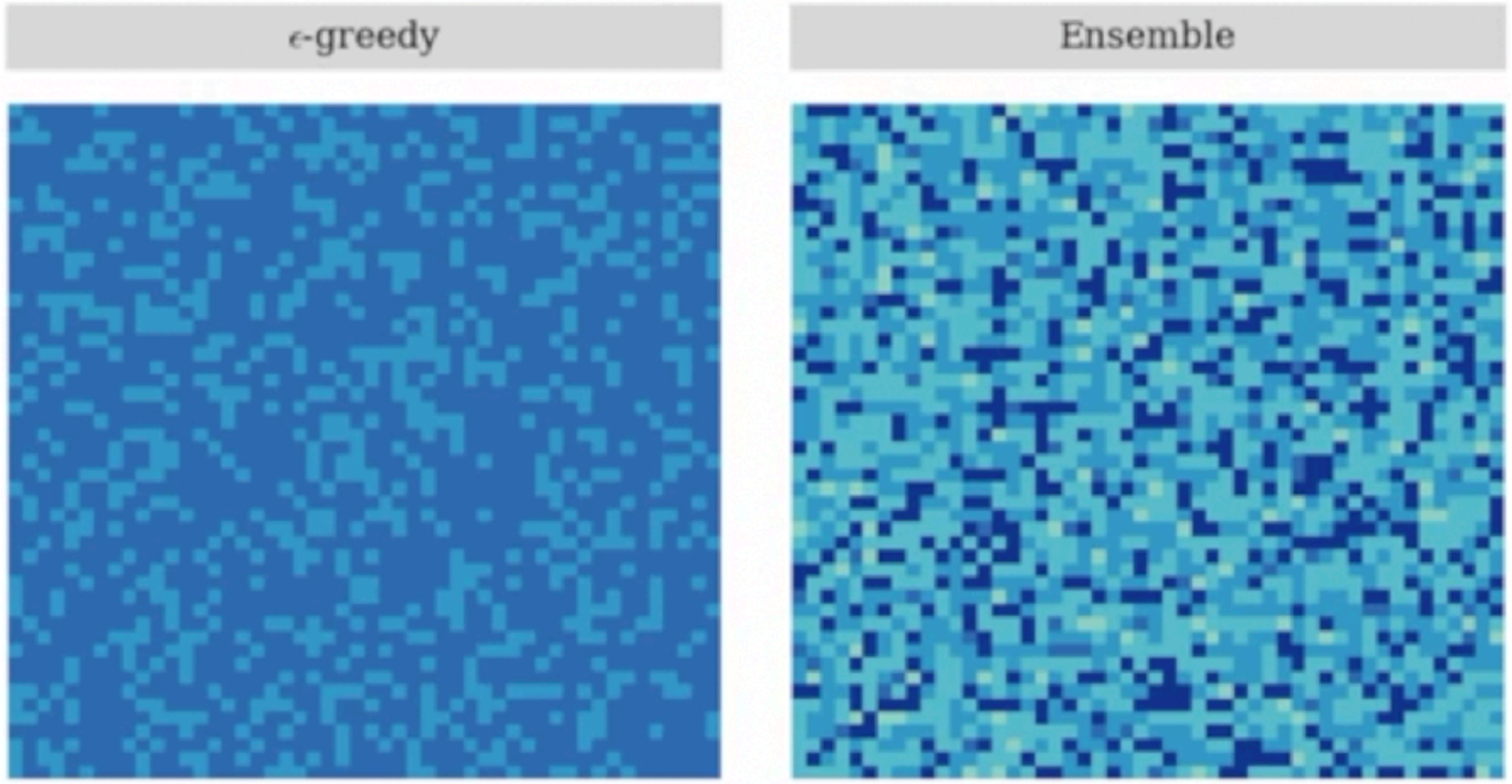

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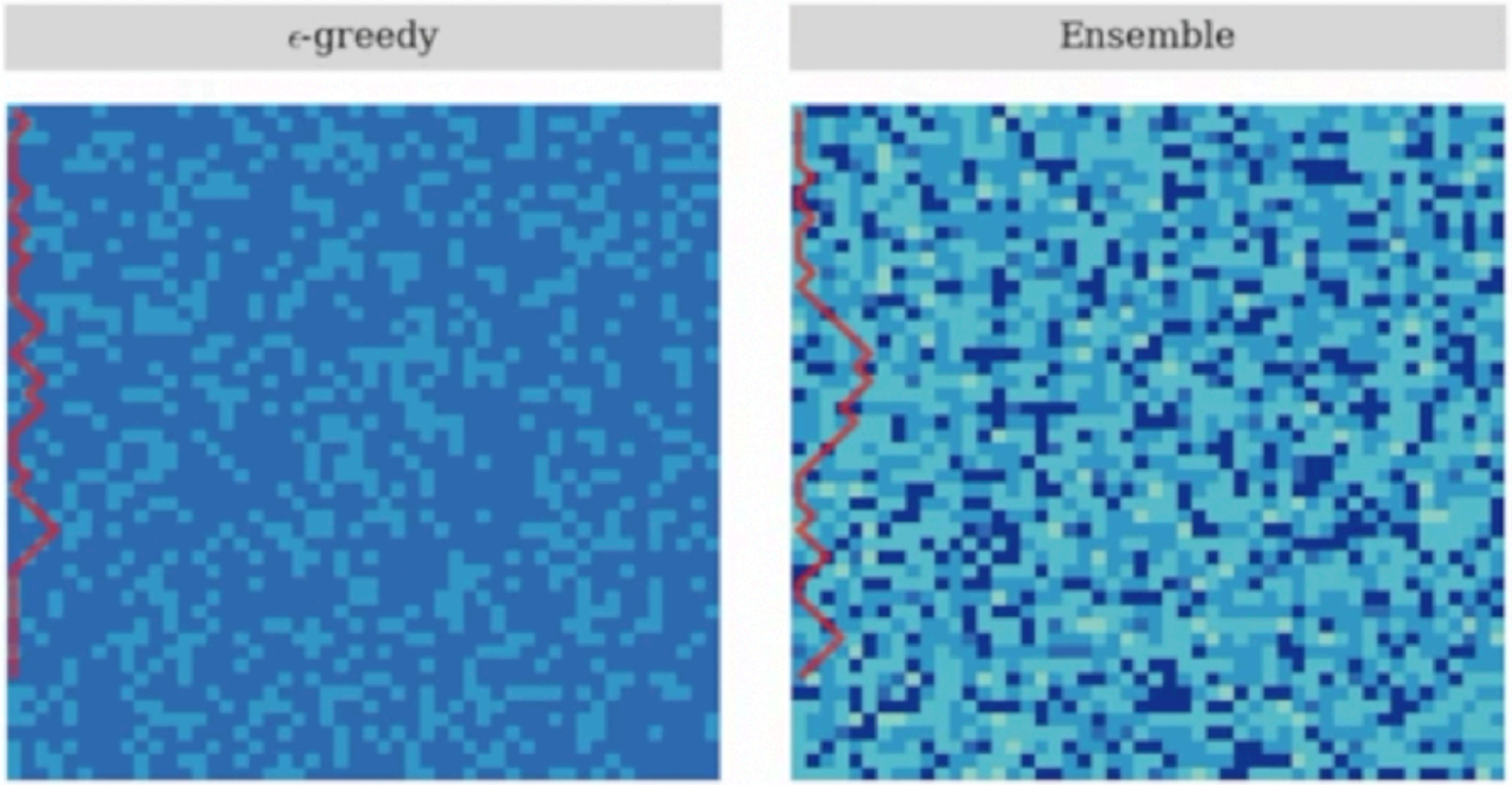

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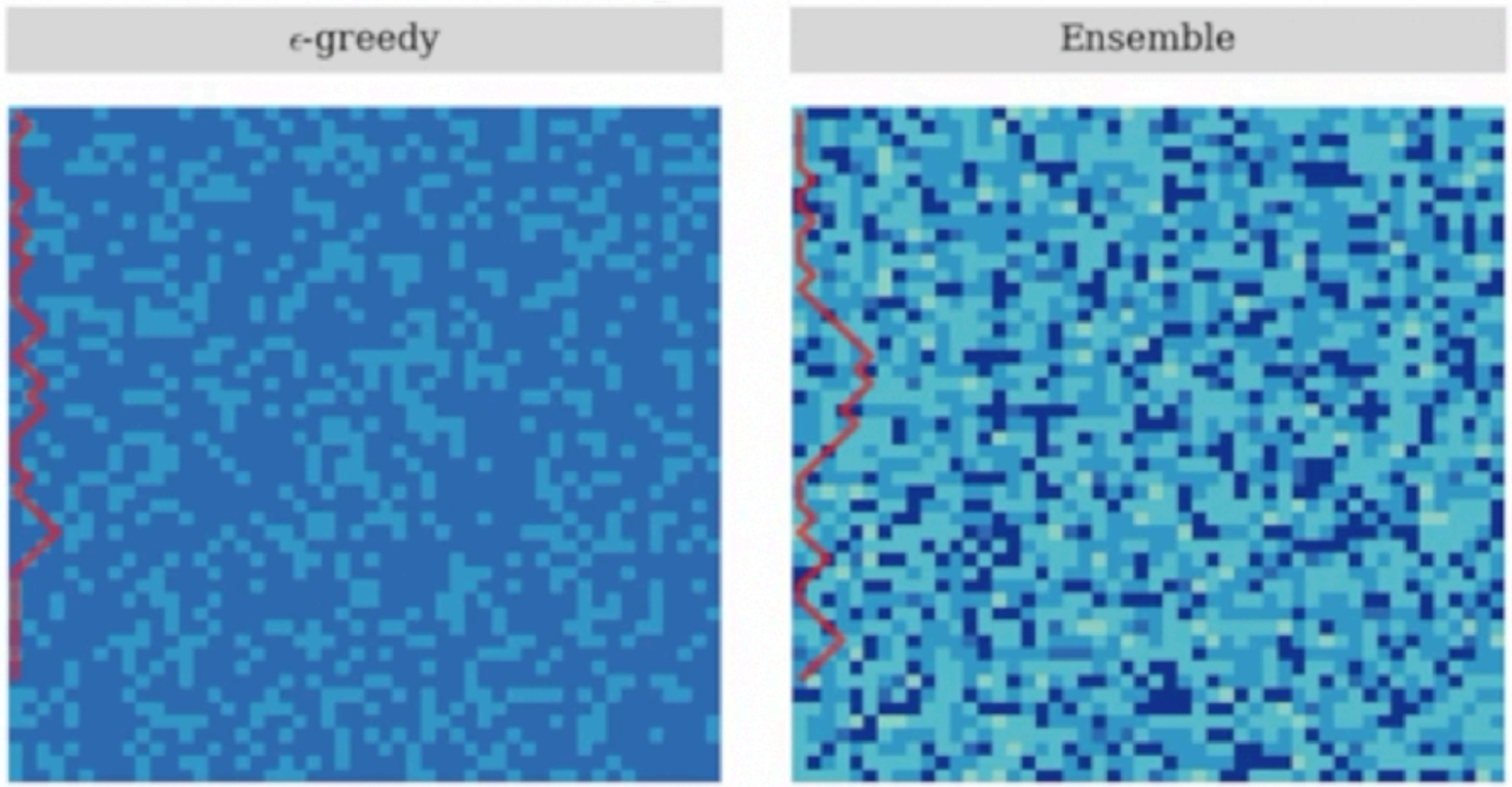

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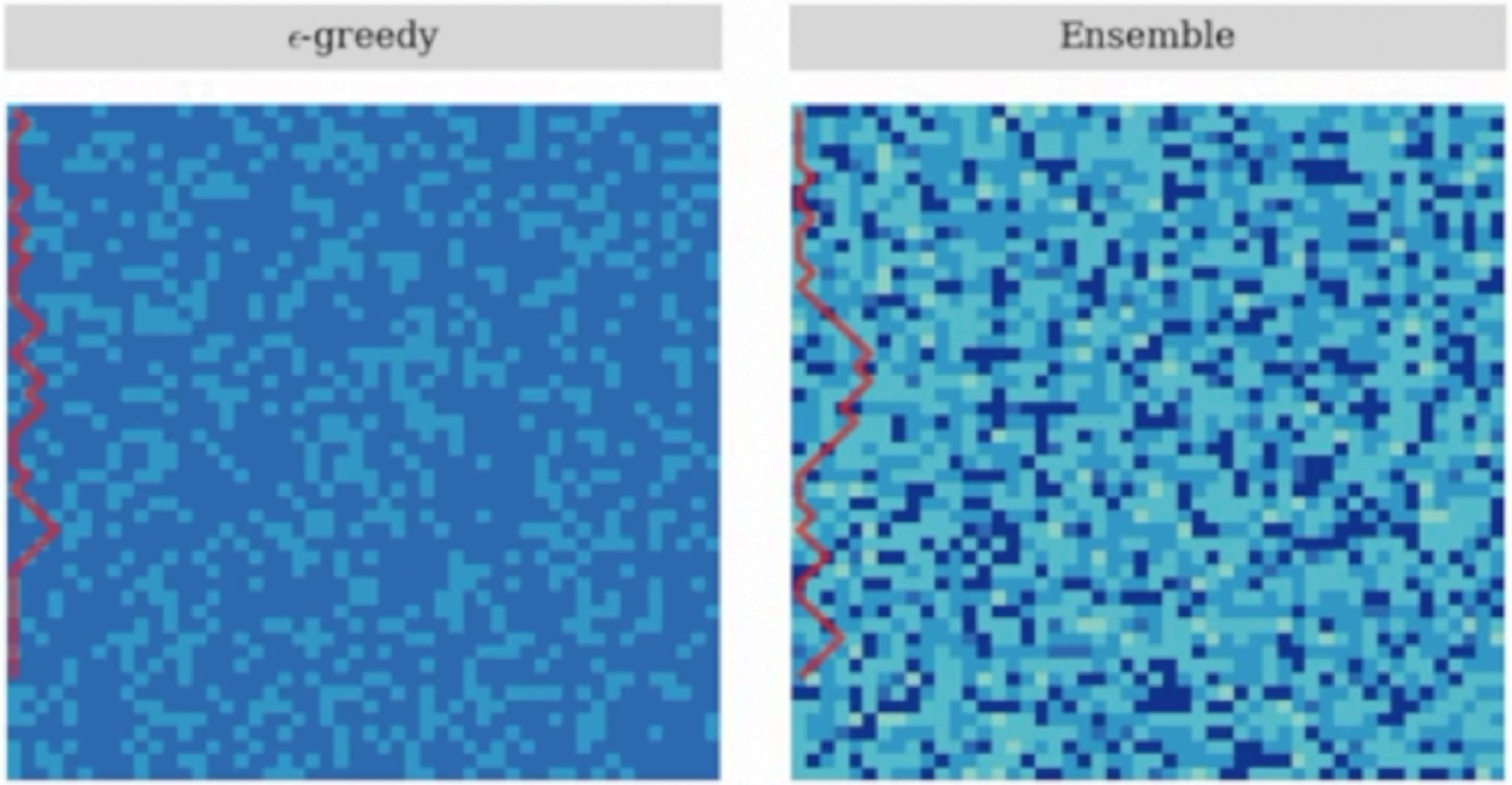
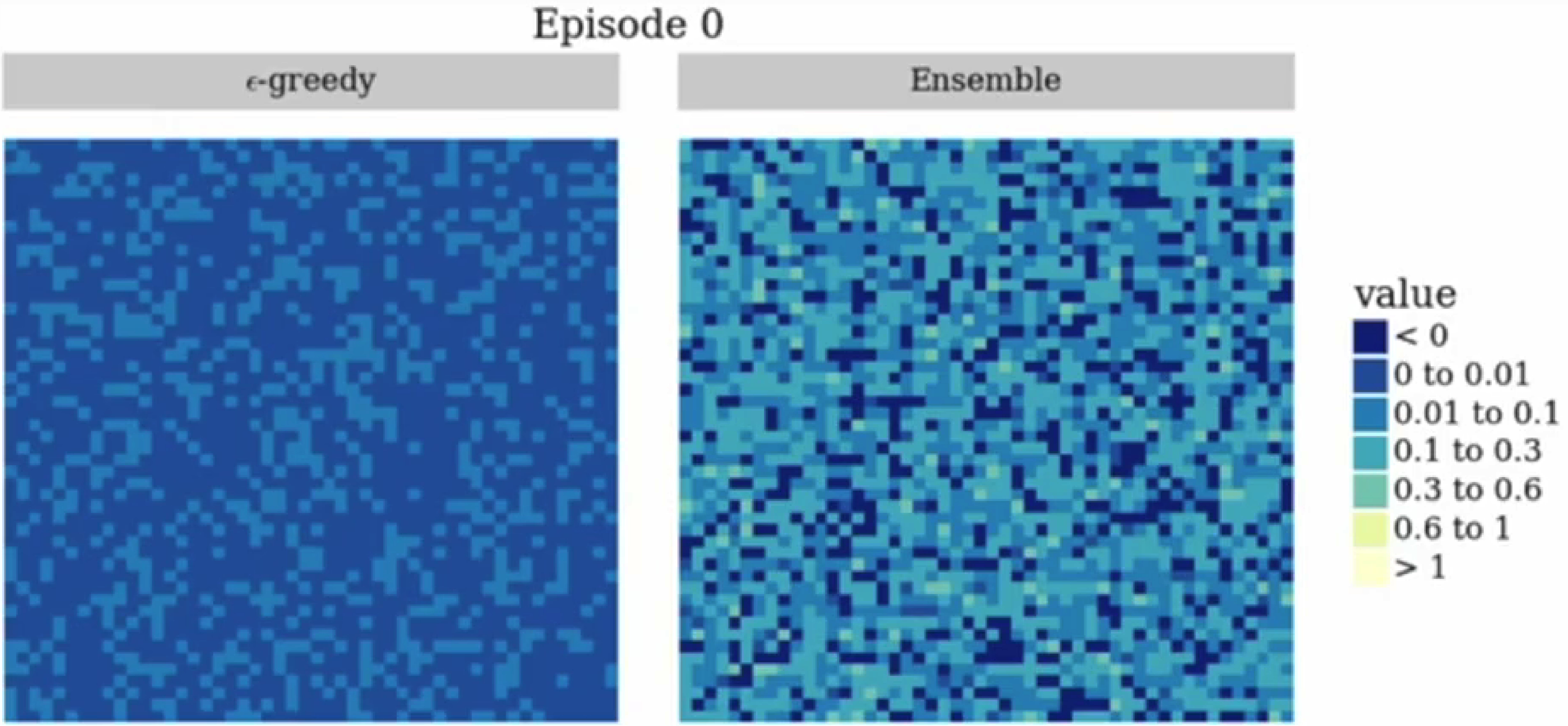
- **DQN+ε-greedy gets stuck on the left, gives up.**
- **BootDQN+prior hopes something is out there, keeps exploring potentially-rewarding states… learns fast!**




Episode 0
ϵ-greedy
Ensemble
value
< 0
0 to 0.01
0.01 to 0.1
0.1 to 0.3
0.3 to 0.6
0.6 to 1
> 1

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Demo code
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