UNIVERSITY OF AMSTERDAM

Computational Social Choice

On Voting Approaches for Robust Reinforcement Learning Ensembles

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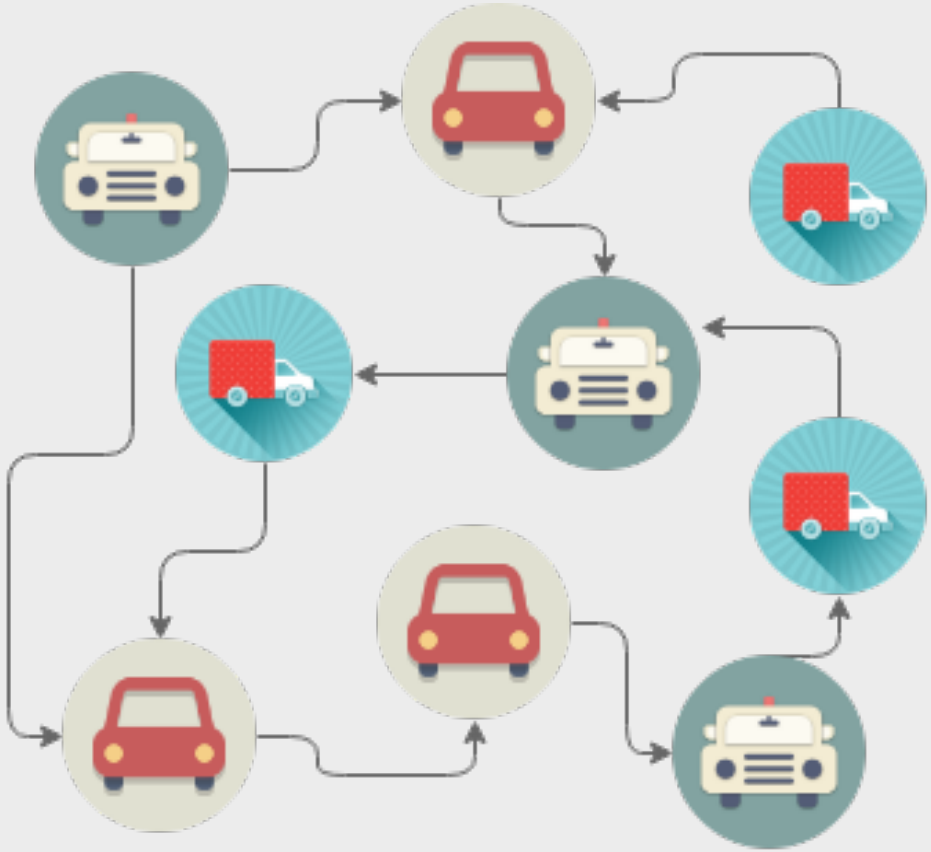
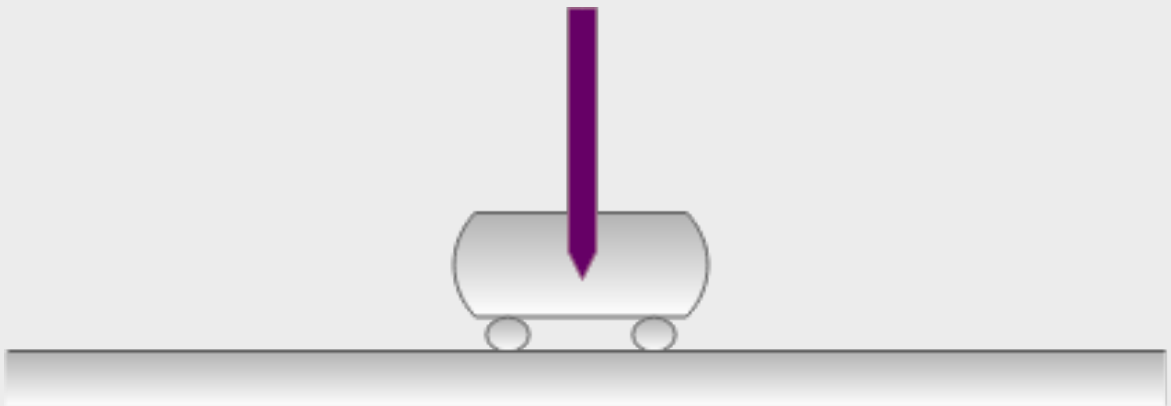
Introduction



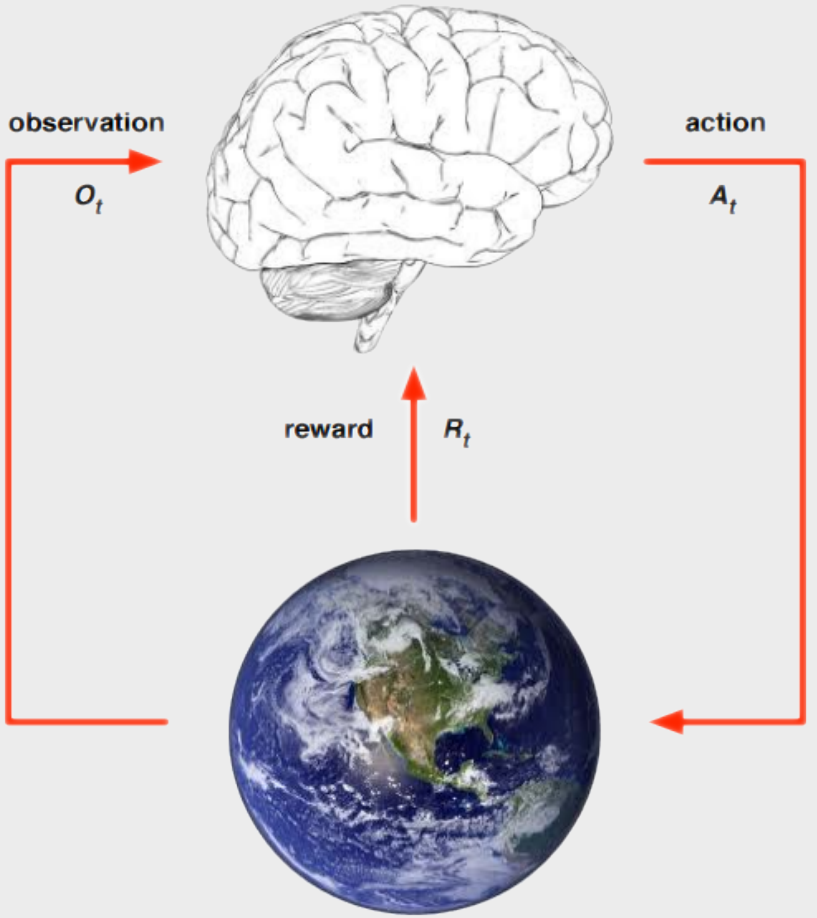
Pole Balancing

- **Goal**: Keep pole upright as much time as possible
- **How**: Apply force to the cart
- **Information**: $[x, \dot{x}, \theta, \dot{\theta}]$
- **End**: After 500 time steps or tilt angle $> \theta_{\text{max}}$, end of track



Reinforcement Learning

Reinforcement Learning (RL) is a sub-field of Machine Learning in which an agent learns optimal behavior in a stochastic environment in order to maximize a reward signal.



Definition

A Markov Decision Process is a tuple $(\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma)$ such that:

- $\mathcal{S}$ is a *finite* set of states
- $\mathcal{A}$ a *finite* set of actions
- $\mathcal{P}(s, a, s')$ is a state transition probability function, $\mathcal{P}^a_{ss'} = \mathbb{P}[S_{t+1} = s' | S_t = s, A_t = a]$
- $\mathcal{R}(s, a)$ describes the immediate reward, $\mathcal{R}^a_s = \mathbb{E}[R_{t+1} | S_t = s, A + t = a]$
- γ is a discount factor $\gamma \in [0, 1]$

Strategy

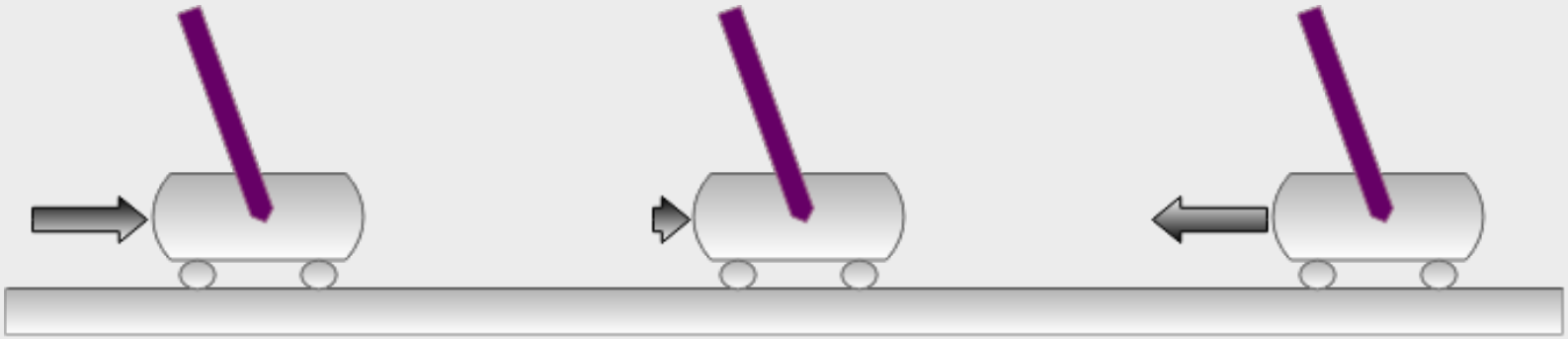
Learn a function $\mathcal{Q}(s, a)$ which describes what is the long term quality of choosing an action at a particular state.

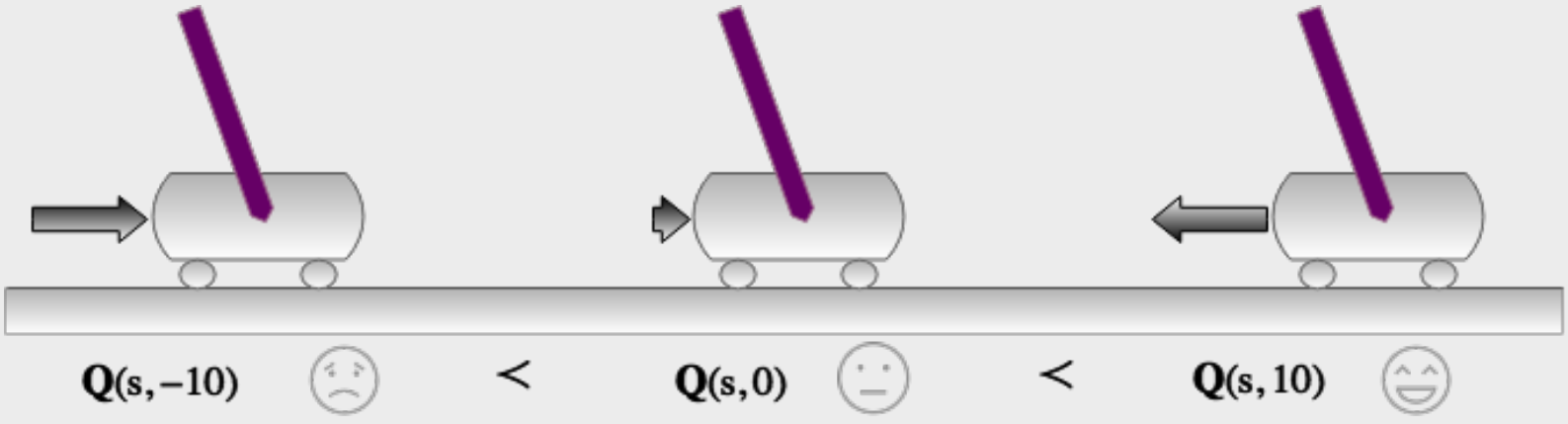
Then use this function to define the policy for how to react in each situation:

$$\pi(s) = \arg\max_{a \in \mathcal{A}} \mathcal{Q}(s, a)$$

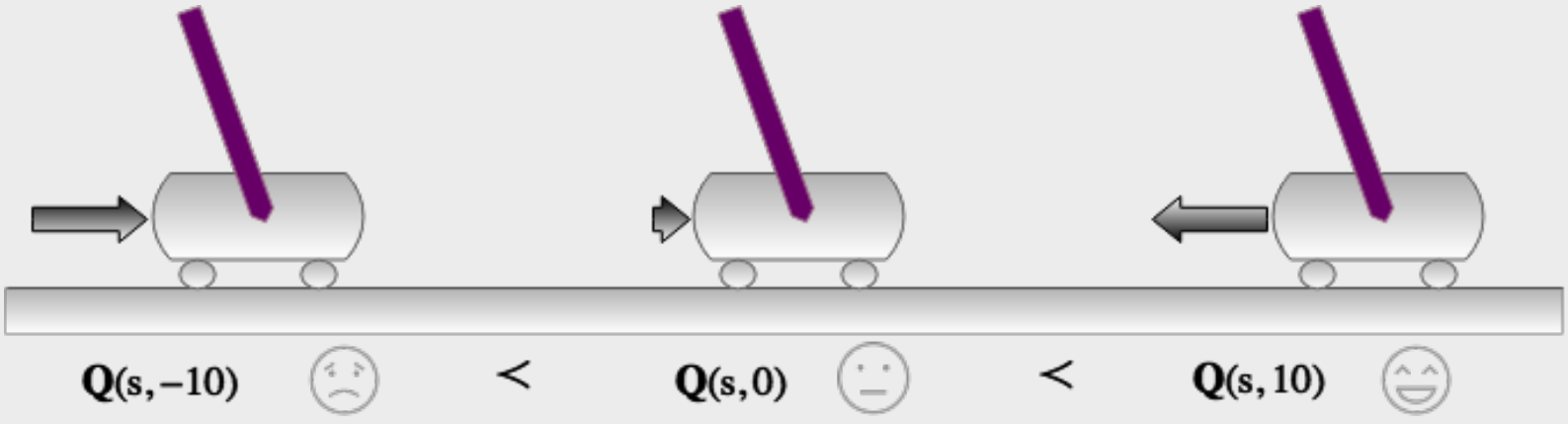
⚠ Approximate $\mathcal{Q}$ by a Neural Network (NN) and train it using gradient descent:

$$\Delta \mathcal{Q} \propto -\nabla \mathcal{Q}$$





We can obtain a ballot using Q!



We can obtain a ballot using $\mathcal{Q}$!

Potential Issues in RL

- Training agents takes (a lot of) time
- If using a gradient-based approach, beware of local optima
- How good is the expressive power of the proposed NN architecture?
- Are the values of Q reliable enough?
- How robust are the agents to observation noise?

Set up

Task modelling

- 11 possible actions (apply -50 to 50 Newton)
- 10 semi trained agents (different structure each)
- Voting rules: Borda, Plurality, Copeland, Range Voting
- Distinction between 2 cases
  - Control case 1: no noise is applied
  - Test case 2: noise is added to the observation of the agents(position, velocity,angle, angular velocity) and updated each time step

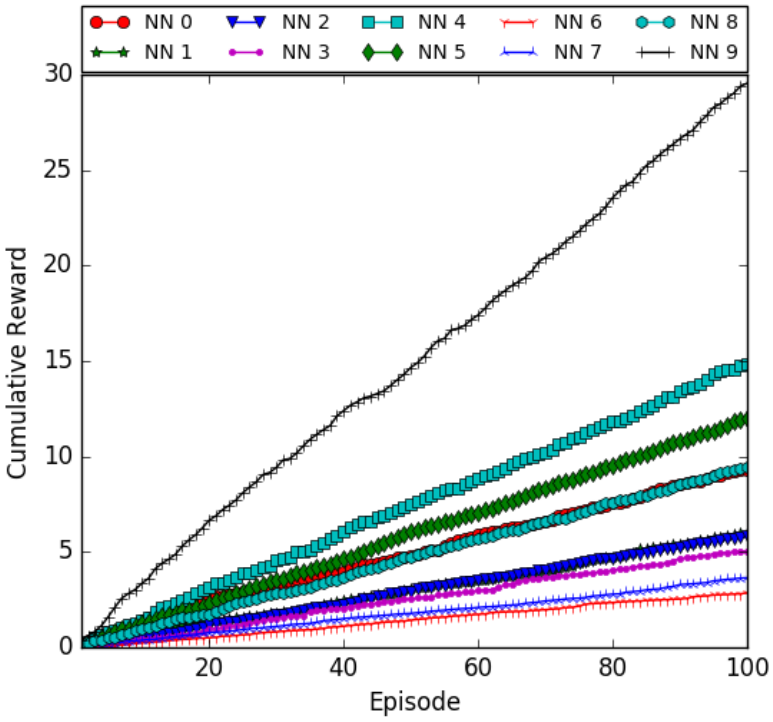
Why?

- 11 actions: we need enough for voting rules to show different behaviours
- 10 agents: trade-off between reasonable amount of voters and individual performance
- Voting rules: Most common ones and easy to implement
- Distinction between 2 cases
  - No noise: influence of voting under optimal conditions
  - Noise: simulate a more realistic environment

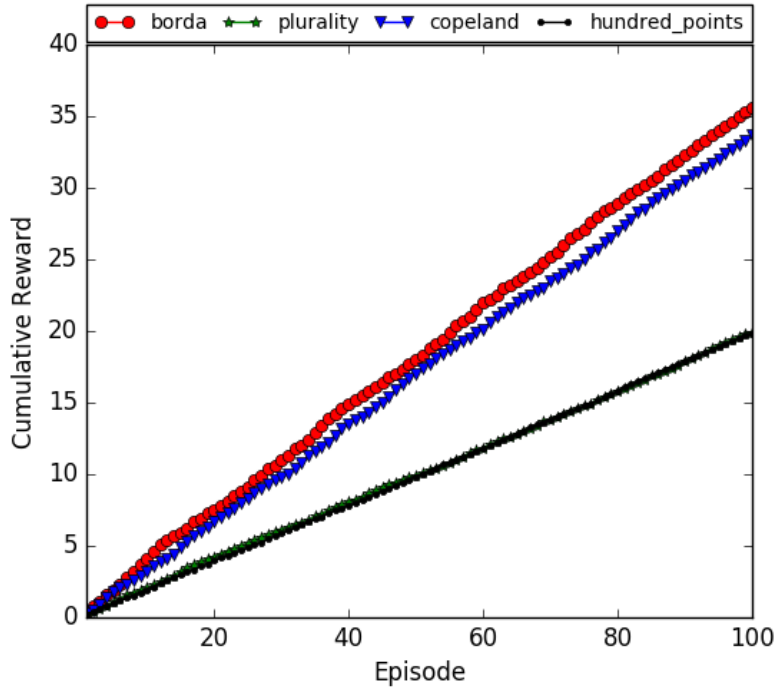
Statistical significance tests

- *Two-tailed t-Test*: test the hypothesis that two populations have equal means.
- *p-value*: how likely is that the data would come from a more extreme scenario than our observations.
- *Kendall's* τ: this is a measure of the similarity between two rankings (swap distance).
- *Spearman's* ρ: measures the similarity between rankings but takes the magnitude of the swaps into account.
- *Top 1 Match*: percentage of times that two rules coincide on the selected action.

Results



(a) Individual



(b) Ensemble

Figure: Performance under no noise

No noise - t-Test:

- **H0**: There is no difference between the performance of two rules
- Up to 99% confidence, Borda and Copeland perform better than Plurality and Range Voting.
- We can not infer a significant difference between Borda and Copeland; or between Plurality and Range Voting.

Top 1 Match	Borda	Plurality	Copeland	Range Voting
Borda	1	0.239	0.779	0.188
Plurality	0.357	1	0.398	0.600
Copeland	0.758	0.277	1	0.260
Range Voting	0.453	0.526	0.462	1

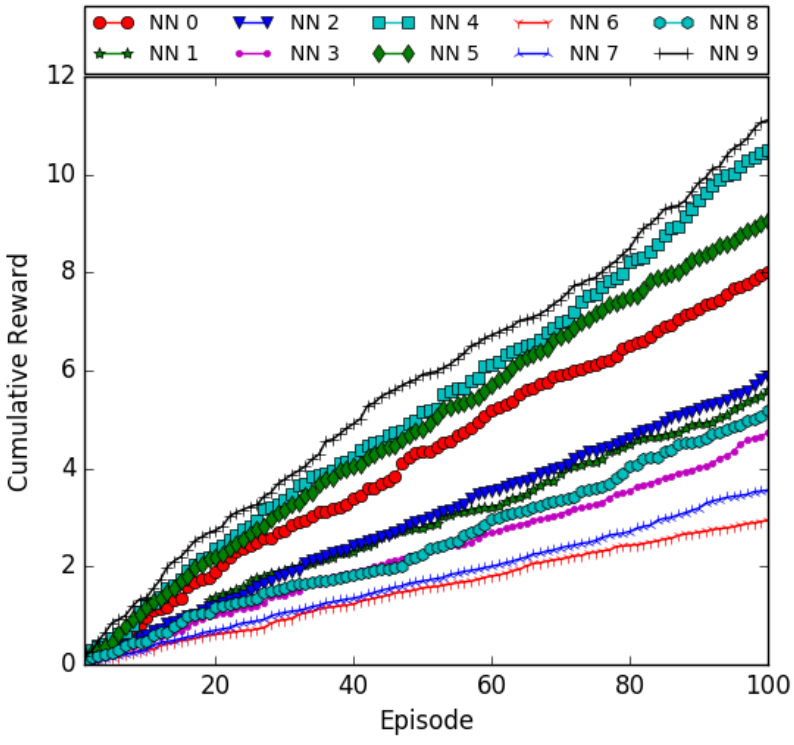
Table: Experiment 1: no noise

ρ-Value	Borda	Plurality	Copeland	Range Voting
Borda	1	0.133	0.470	0.297
Plurality	0.266	1	0.272	0.311
Copeland	0.504	0.156	1	0.338
Range Voting	0.522	0.296	0.500	1

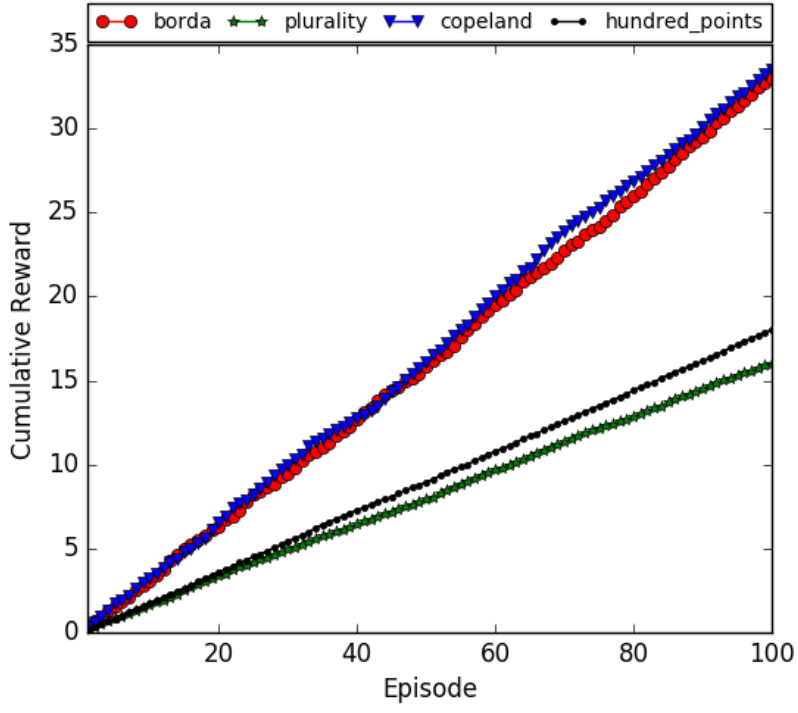
Table: Experiment 1: no noise

τ-Value	Borda	Plurality	Copeland	Range Voting
Borda	1	0.097	0.373	0.222
Plurality	0.195	1	0.202	0.233
Copeland	0.402	0.114	1	0.253
Range Voting	0.419	0.220	0.394	1

Table: Experiment 1: no noise

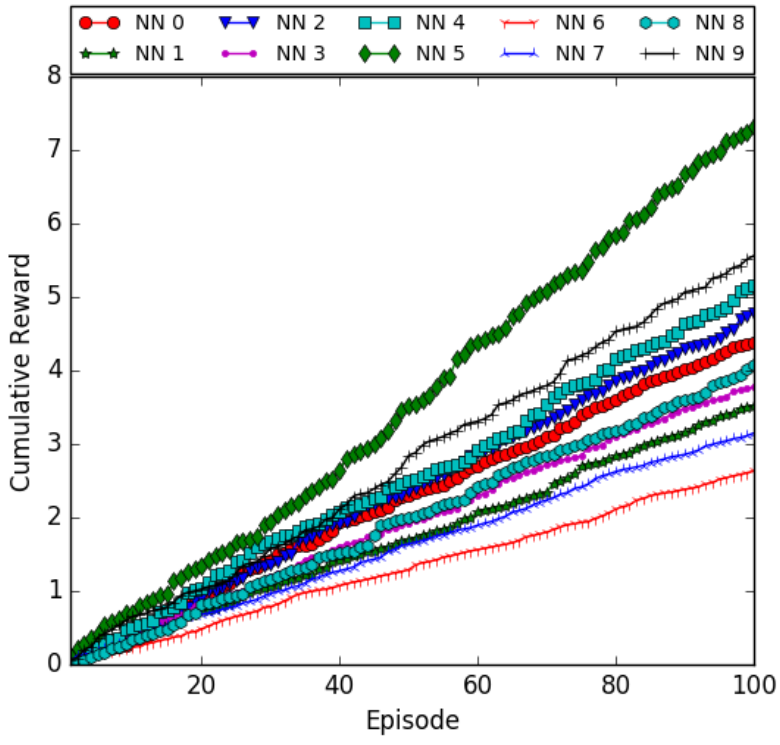


(a) Individual

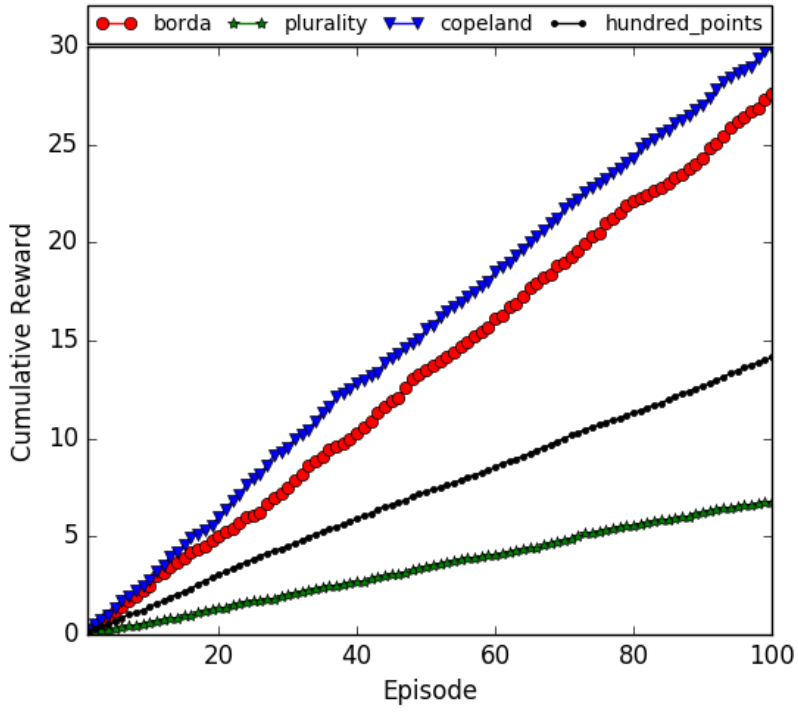


(b) Ensemble

Figure: Performances under noise 2

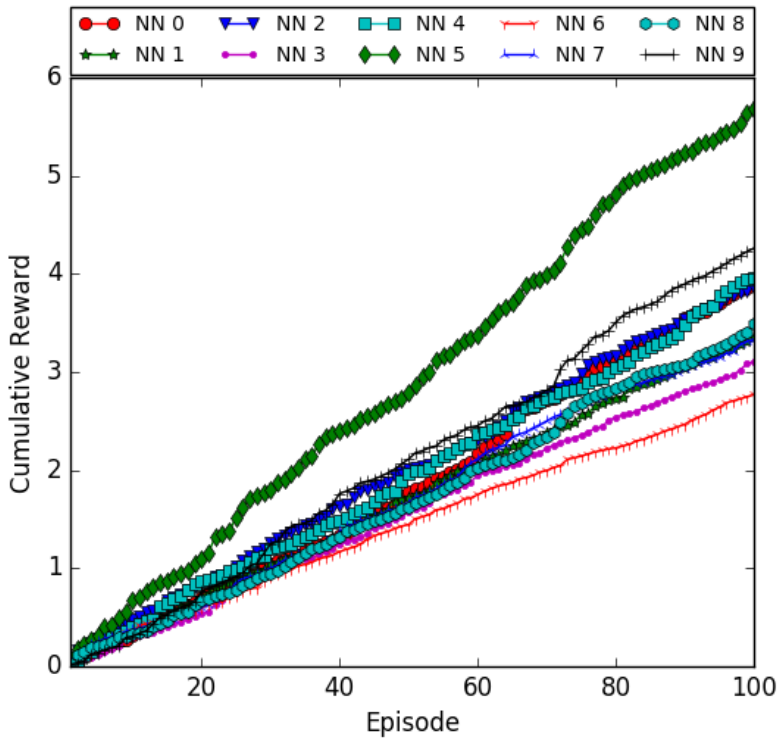


(a) Individual

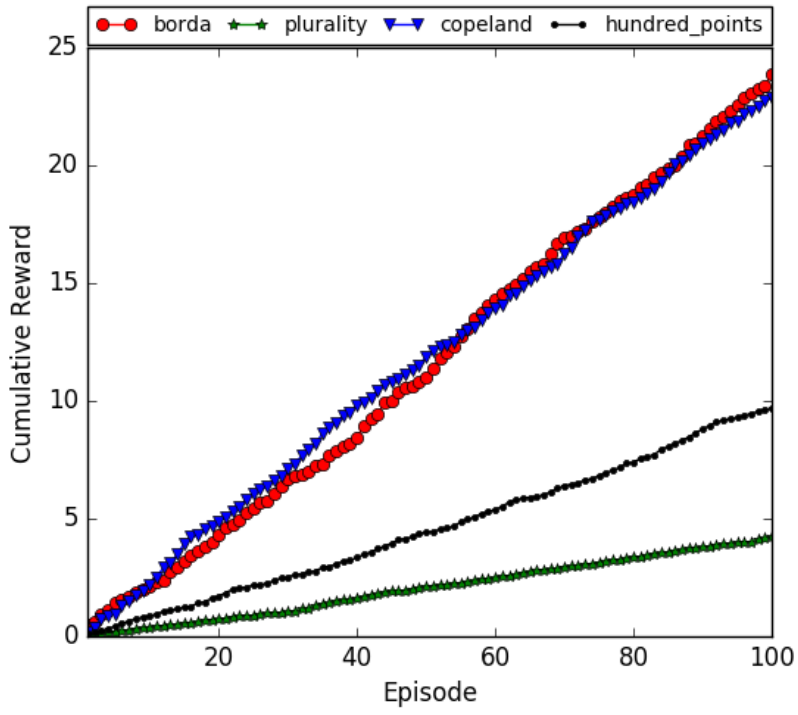


(b) Ensemble

Figure: Performances under noise 10



(a) Individual



(b) Ensemble

Figure: Performance under noise 20

Top 1 Match	Borda	Plurality	Copeland	Range Voting
Borda	1	0.239	0.779	0.188
Plurality	0.357	1	0.398	0.600
Copeland	0.758	0.277	1	0.260
Range Voting	0.453	0.526	0.462	1
Borda	1	0.296	0.743	0.315
Plurality	0.308	1	0.336	0.478
Copeland	0.742	0.326	1	0.343
Range Voting	0.347	0.490	0.377	1
Borda	1	0.293	0.742	0.313
Plurality	0.306	1	0.335	0.482
Copeland	0.738	0.323	1	0.341
Range Voting	0.341	0.481	0.364	1
Borda	1	0.295	0.737	0.312
Plurality	0.330	1	0.351	0.499
Copeland	0.742	0.314	1	0.331
Range Voting	0.332	0.492	0.353	1

Table: Top 1 Match for noise 0-2-10-20

τ-Value	Borda	Plurality	Copeland	Range Voting
Borda	1	0.097	0.373	0.222
Plurality	0.195	1	0.202	0.233
Copeland	0.402	0.114	1	0.253
Range Voting	0.419	0.220	0.394	1
Borda	1	0.163	0.448	0.246
Plurality	0.145	1	0.145	0.166
Copeland	0.444	0.120	1	0.244
Range Voting	0.282	0.153	0.278	1
Borda	1	0.131	0.458	0.282
Plurality	0.168	1	0.171	0.185
Copeland	0.457	0.133	1	0.274
Range Voting	0.327	0.177	0.317	1
Borda	1	0.119	0.444	0.237
Plurality	0.127	1	0.131	0.152
Copeland	0.444	0.116	1	0.229
Range Voting	0.260	0.147	0.261	1

Table: τ-Value for noise 0-2-10-20

ρ-Value	Borda	Plurality	Copeland	Range Voting
Borda	1	0.016	0.547	0.320
Plurality	0.198	1	0.199	0.224
Copeland	0.543	0.164	1	0.319
Range Voting	0.366	0.208	0.360	1
Borda	1	0.178	0.559	0.365
Plurality	0.228	1	0.233	0.250
Copeland	0.557	0.181	1	0.354
Range Voting	0.420	0.239	0.407	1
Borda	1	0.163	0.543	0.320
Plurality	0.198	1	0.199	0.224
Copeland	0.543	0.164	1	0.244
Range Voting	0.366	0.208	0.360	1
Borda	1	0.163	0.543	0.310
Plurality	0.174	1	0.180	0.206
Copeland	0.542	0.158	1	0.300
Range Voting	0.340	0.198	0.340	1

Table: ρ-Value for noise 0-2-10-20

p-Values		*No noise*	*Noise 2*	*Noise 10*	*Noise 20*
Borda	*Plurality*	0.00	0.00	0.00	0.00
Borda	*Copeland*	0.09	0.70	0.10	0.48
Borda	*Range Voting*	0.00	0.00	0.00	0.00
Plurality	*Copeland*	0.00	0.00	0.00	0.00
Plurality	*Range Voting*	0.78	0.00	0.00	0.00
Copeland	*Range Voting*	0.00	0.00	0.00	0.00

Table: t-Test for difference between reward means

Discussion

Rule	Condorcet	Pareto	Cardinal/Ordinal	Information
Borda	✗	✓	Ordinal	*nm* (ordering)
Plurality	✗	✓	Ordinal	*n*
Copeland	✓	✓	Ordinal	*nm* (ordering)
Range Voting	✗	✓	Cardinal	*nm* (number)

Table: Properties of the chosen voting rules

Future work

Future Work

- Investigate the influence of different types of noise. Which one seems most realistic/interesting?
- Try more challenging RL tasks
- Analyze the impact of the dimensionality of the spaces of voters and alternatives. Rule complexity?

Conclusions

Conclusions

- Voting in a reinforcement learning task like pole-balancing can boost performance (3x) with no training time trade-off.
- Problems due to *numerical* unreliability can be overcome with *ordinal* information.
- Also robustness under extreme noise conditions to the performance.
- In this task: Copeland $\succeq$ Borda $\succ$ Range Voting $\succ$ Plurality