



Progressive Generative Geomodeling with Ensemble Filtering for Synthesizing Deep-RL and Algorithmic Geosteering Policies

Sergey Alyaev*, Hibat E. Djecta*, Kristian Fossum* (NORCE)

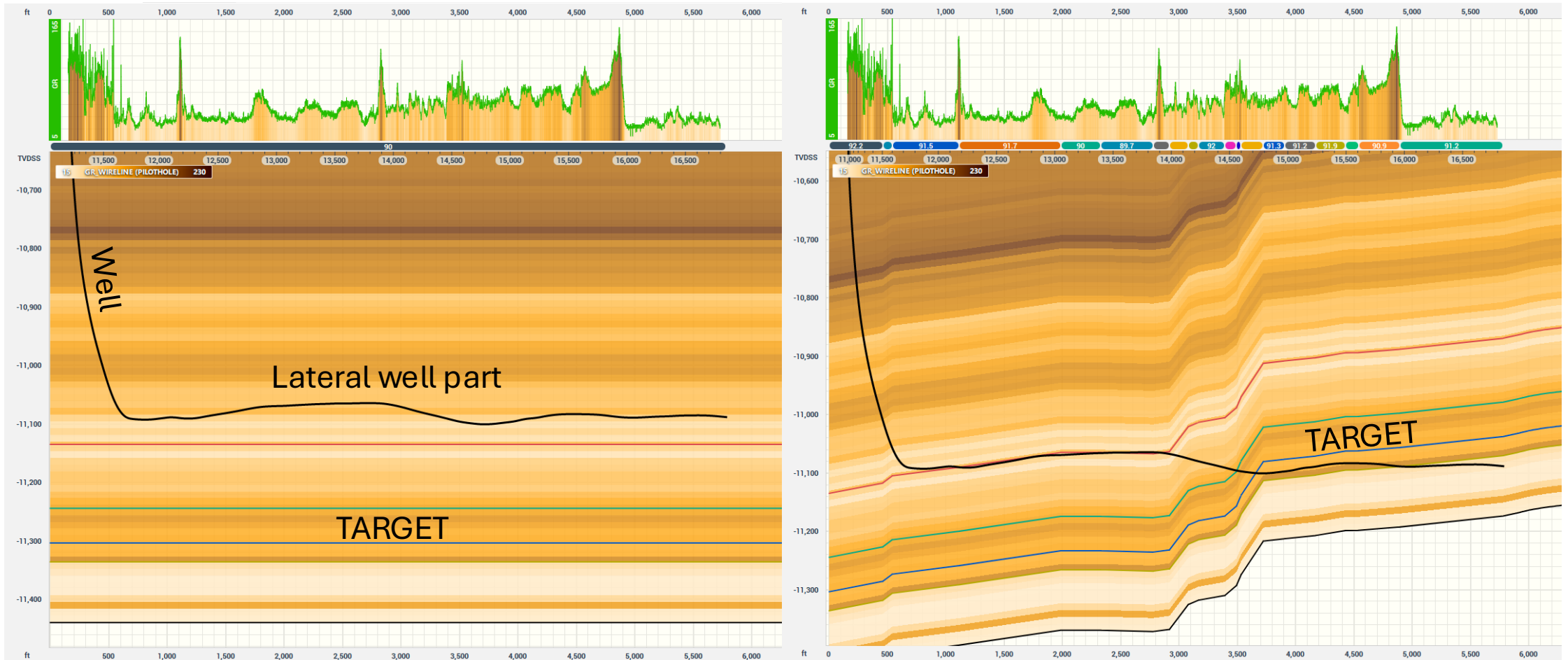
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Heebah Saleem* (University of Bergen), Apoorv Srivastava (Stanford University)

Contents

1. Geosteering World Cup problem
2. How to beat humans?
3. How to beat the robot?
4. Conclusions

Low-data geosteering: 1D geology fixed thickness



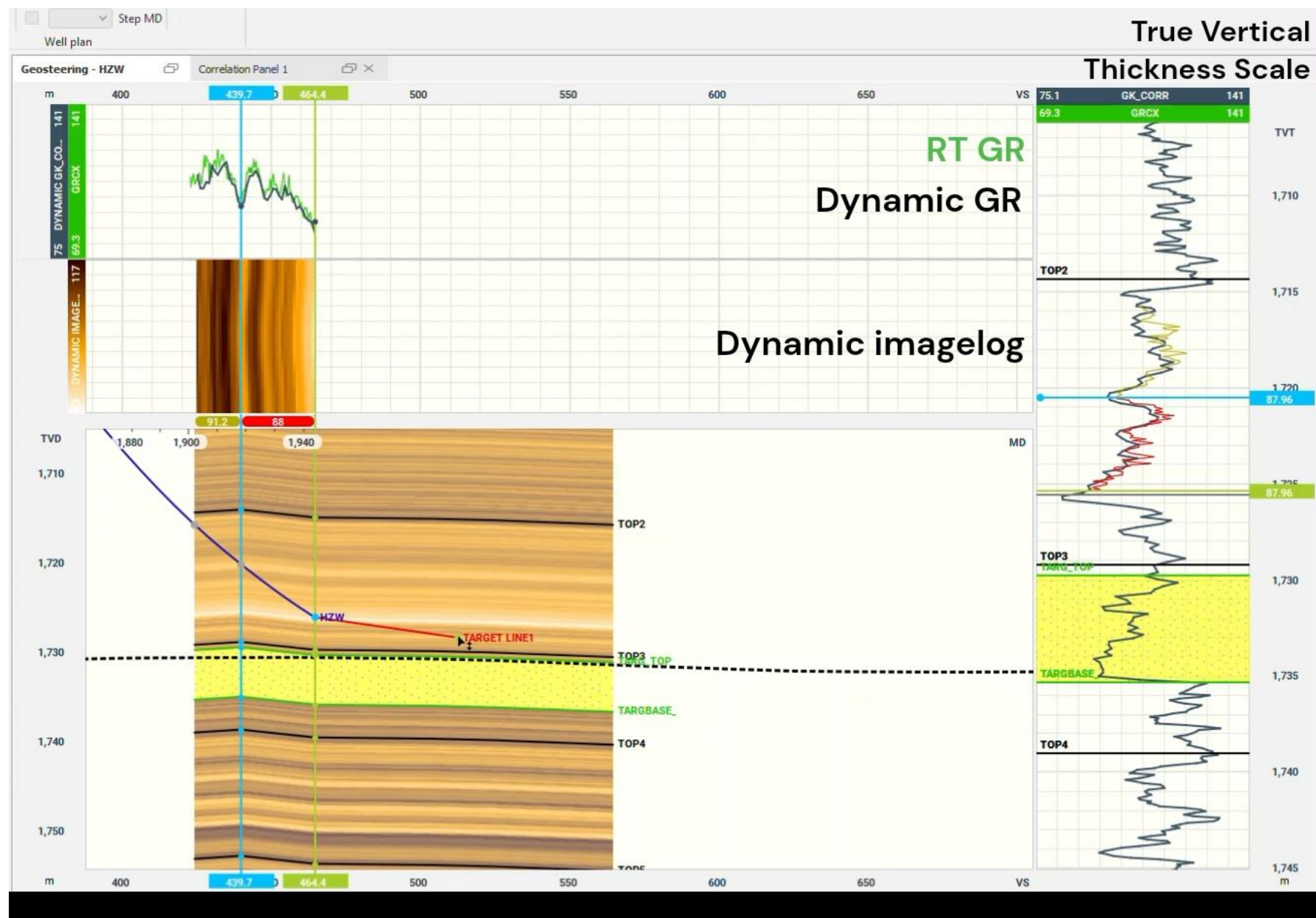
Low-data geosteering pre-requisite:

Identify your location in geological layers
from correlating 1D measurements

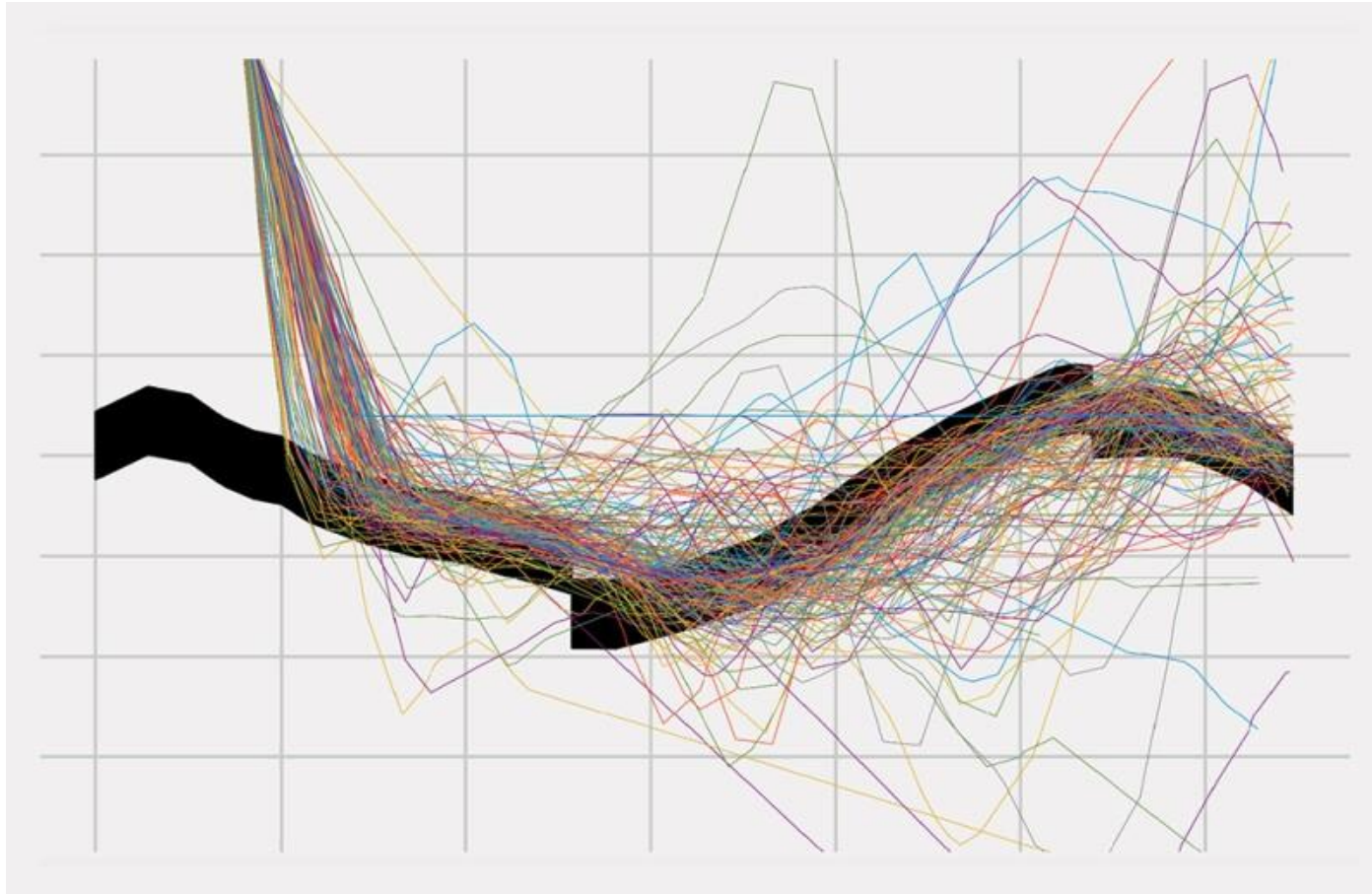


Human geosteering

Video courtesy of ROGII



Human results: Geosteering World Cup 2021



**Interpretation + decision
Dataset available!**

[[Cheraghi et al. 2025 Analyzing expert decision-making in geosteering...](#)]

How to beat humans?

- Decisions are dominated by uncertainty
- Geosteering requires real-time steps
 - Geomodel modification to fit new data (reduce uncertainty)
 - Decision selection (commit irreversibly)
- In practice:
 - Humans use **one or few** geomodels to fit data
 - Decisions are based on **extrapolation of that geomodel**

This is a filtering problem!

- Decisions are dominated by **uncertainty captured in an ensemble**
 - Geosteering requires real-time steps:
 - Extend geomodel realizations
 - Geomodel **filtering** to fit new data
 - Decision selection **under uncertainty**
- ← Forecast
 - ← Analysis
 - ← Markov Decision Process (partially observable)

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← Markov Decision Process (partially observable)
- ✓ assume

✓

?

Sequential Decision Making

Markov Decision Process (MDP)

Sequential process has decision history leading to **the current state**

Markov property:

- **Next state**
 only depends
 on the **current state**
 and the **decision**
- Next state **does not depend on history**

Solving Markov Decision Process

Action value function Q

$$Q_{\pi}(s, a) = r(s, a) + \gamma V_{\pi}(s'),$$

Value
for taking action a
from state s
Given policy π

Immediate
reward

Expected
future
value



Discount multiplier

$$V_{\pi}(s) = E_{a \sim \pi(\cdot|s)}[Q_{\pi}(s, a)],$$

Solving Markov Decision Process

Greedy

Ignore

$$Q_{\pi}(s, a) = r(s, a) + \cancel{\gamma V_{\pi}(s')},$$

Value
for taking action a
from state s
Given policy π

Immediate
reward

Expected
future
value

Discount multiplier

$$\cancel{V_{\pi}(s) = E_{a \sim \pi(\cdot|s)}[Q_{\pi}(s, a)]},$$

Solving Markov Decision Process

Dynamic programming

Unfold

$$Q_{\pi}(s, a) = r(s, a) + \gamma V_{\pi}(s'),$$

Value
for taking action a
from state s
Given policy π

Immediate
reward

Expected
future
value

Discount multiplier

Modelling

On discrete space

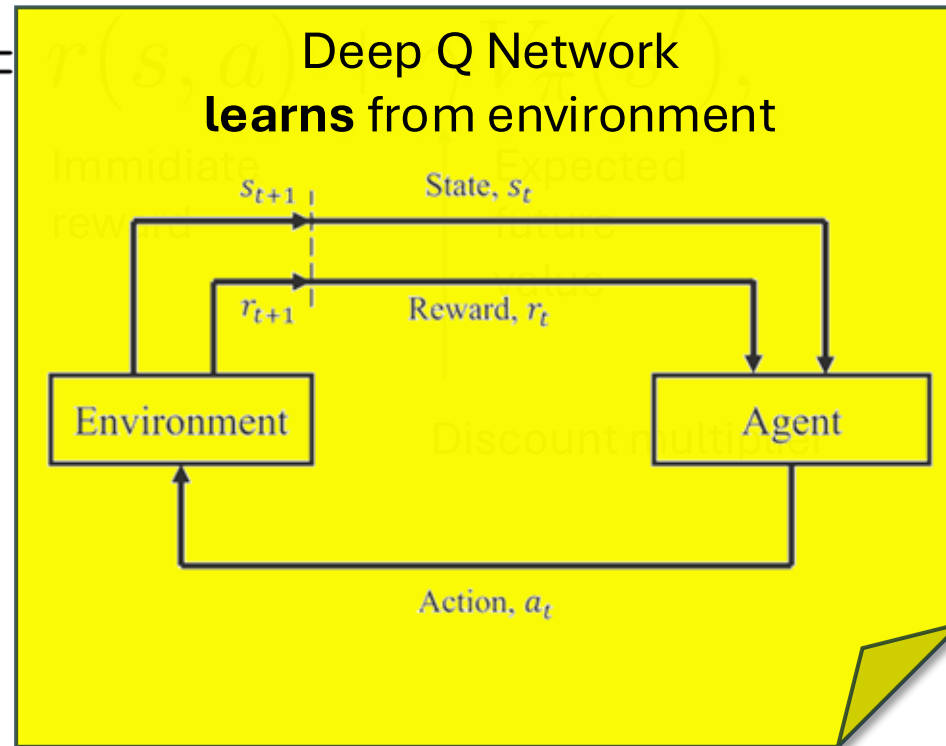
$$V_{\pi}(s) = E_{a \sim \pi(\cdot|s)} [Q_{\pi}(s, a)],$$

Solving Markov Decision Process

Reinforcement Learning (RL)

$$Q_{\pi}(s, a) =$$

Value
for taking action a
from state s
Given policy π



Create sandbox

Partial Observability for Markov Decision Process (POMDP)

Available:

- Indirect observations
- Approximated uncertain state

$$Q_{\pi}(s, a) = r(s, a) + \gamma V_{\pi}(s'),$$

State **S** not available!

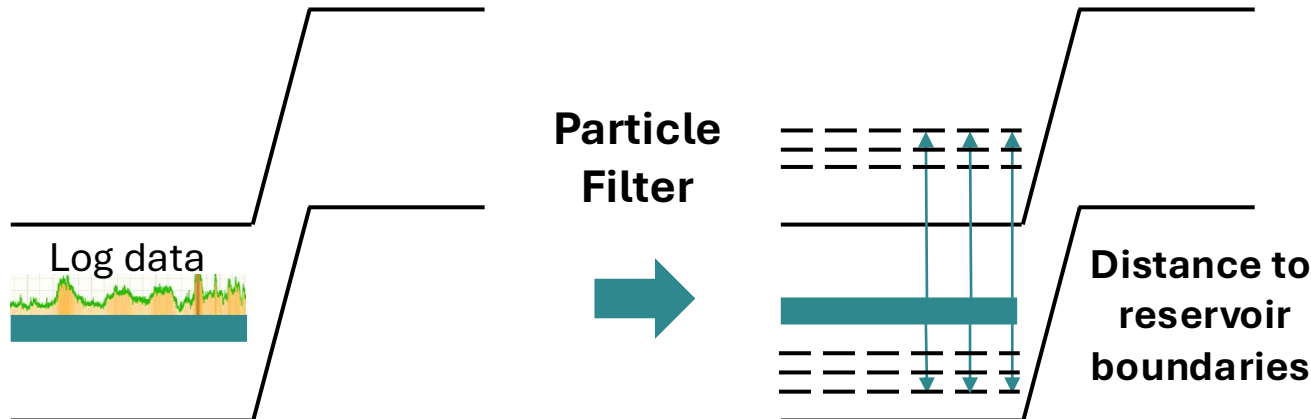
Pluralistic Reinforcement-Learning for Geosteering MDP

Particle-Filter-informed RL method: represent subsurface as realizations



*

1. A forward model **extends every realization** ahead of drilling
2. **PF** performs **Bayesian re-weighting** of realizations **to fit new data**
3. **RL** learns using **updated “plurality” of realizations** to inform actions



Pluralistic Reinforcement-Learning for Geosteering MDP

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Practical considerations

1. Assumes **closed-form** forward stochastic model for geology
2. For **RL training** use less particles (N) and collapse checks in PF
3. Use **top-probability particles** and weights to avoid dependence on N



Pluralistic RL beats



PF + Greedy method



Full AI solution



Methods	Input	Rewards	Reservoir contact (%)	MAE of Input
Rule-based ¹³	1 Look-ahead	-101.36	54.75	4.27
Rule-based ¹³	5 Look-ahead	-105.95	52.70	4.27
RL-Log	Gamma-ray	-74.27	66.84	-
RL-Estimation	1 PF	-25.36	88.67	1.29
RL-Estimation	5 PF	-24.99	88.91	1.31



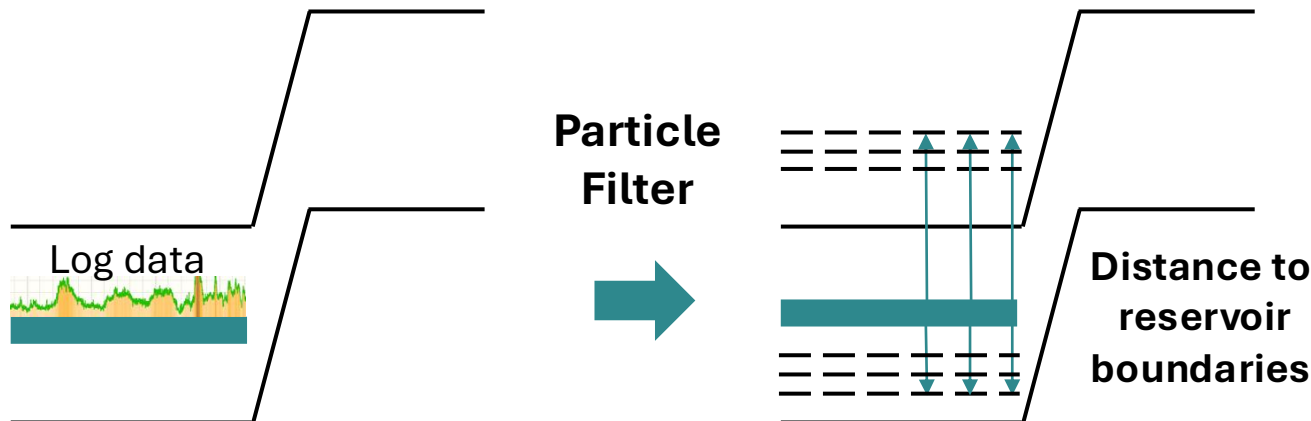
[[Muhammad et al. \(2025\)](#)
[High-precision Geosteering...](#)]

Generalization of Pluralistic-AI concept

Particle-Filter-informed RL method: represent subsurface as realizations

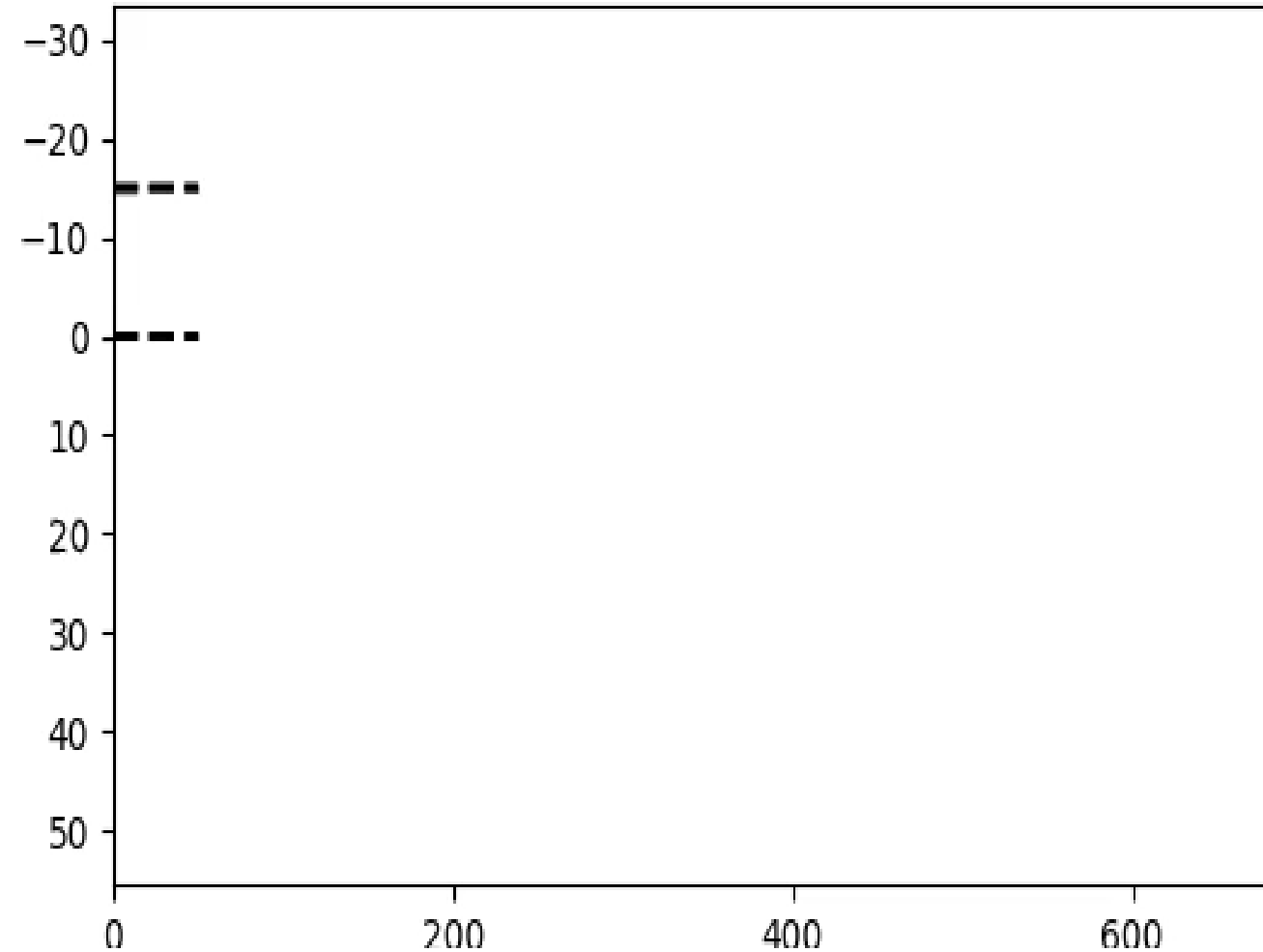
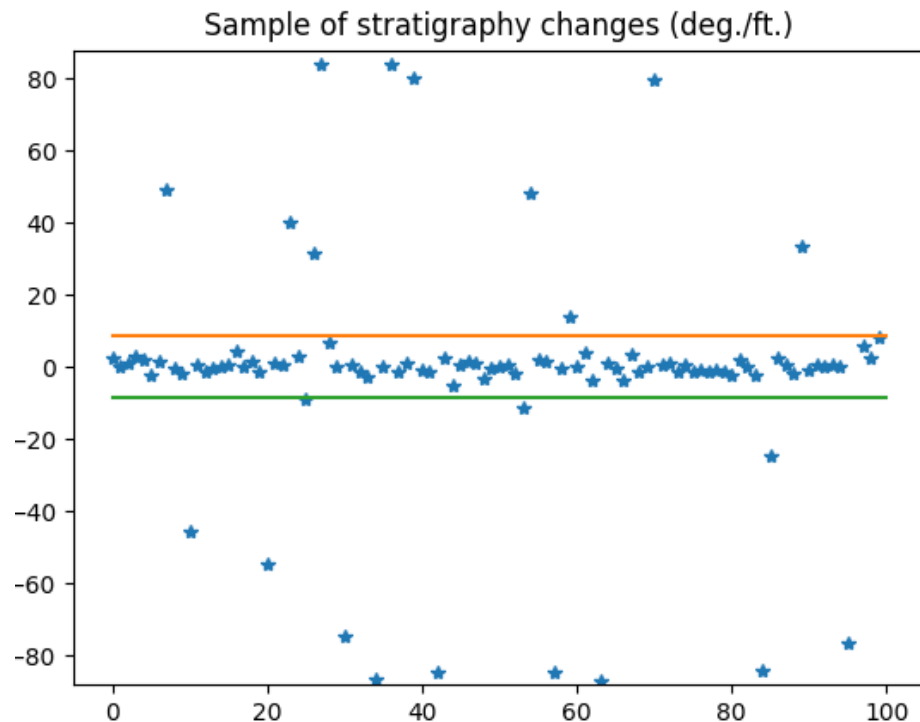
- ? 1. A forward model **extends every realization** ahead of drilling
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- **How to forecast geology using data?**



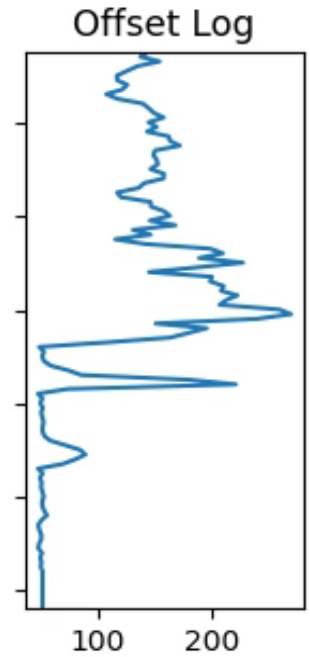
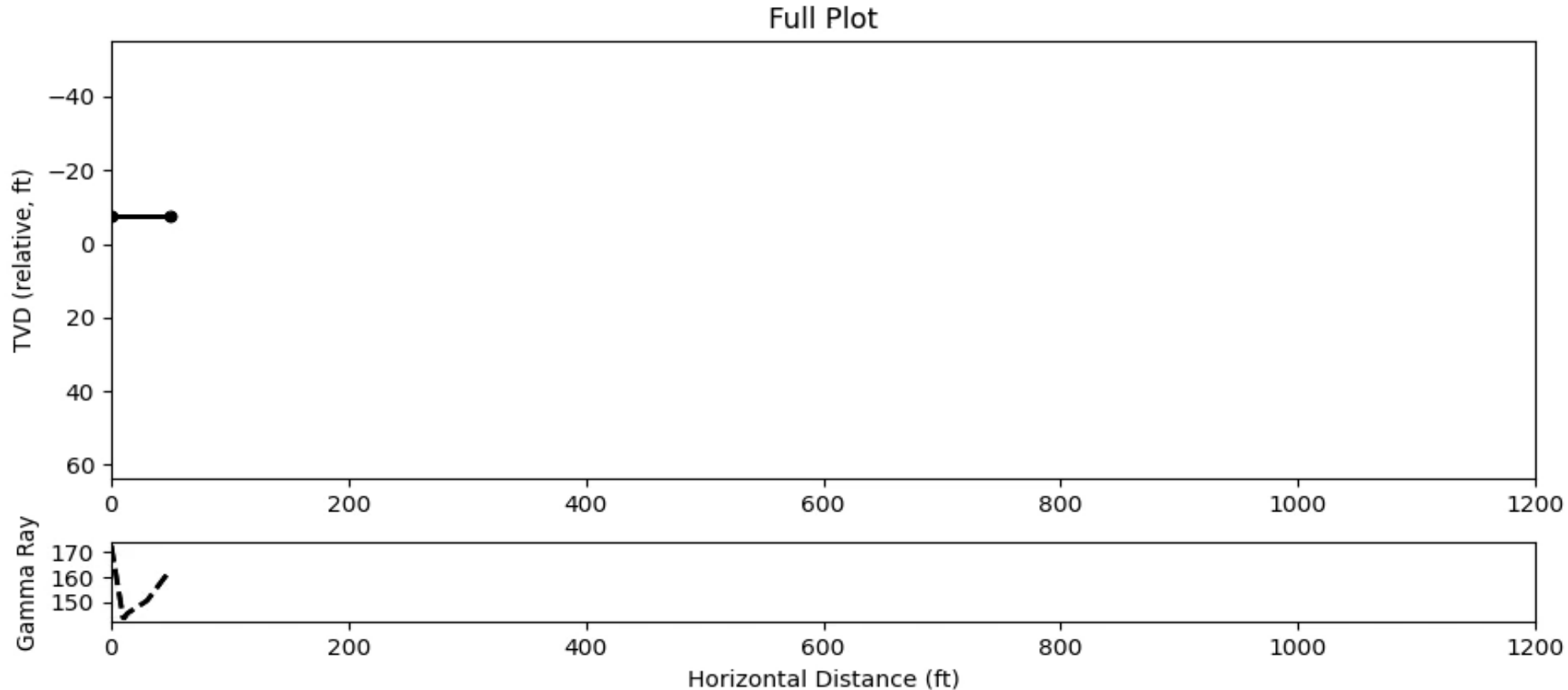
Naïve data-driven approach of geology forecasting

- Fit Kernel Density Estimation (KDE) to geological interpretations
- Allows sampling geological changes
 - Inclination changes
 - Faults (jumps)



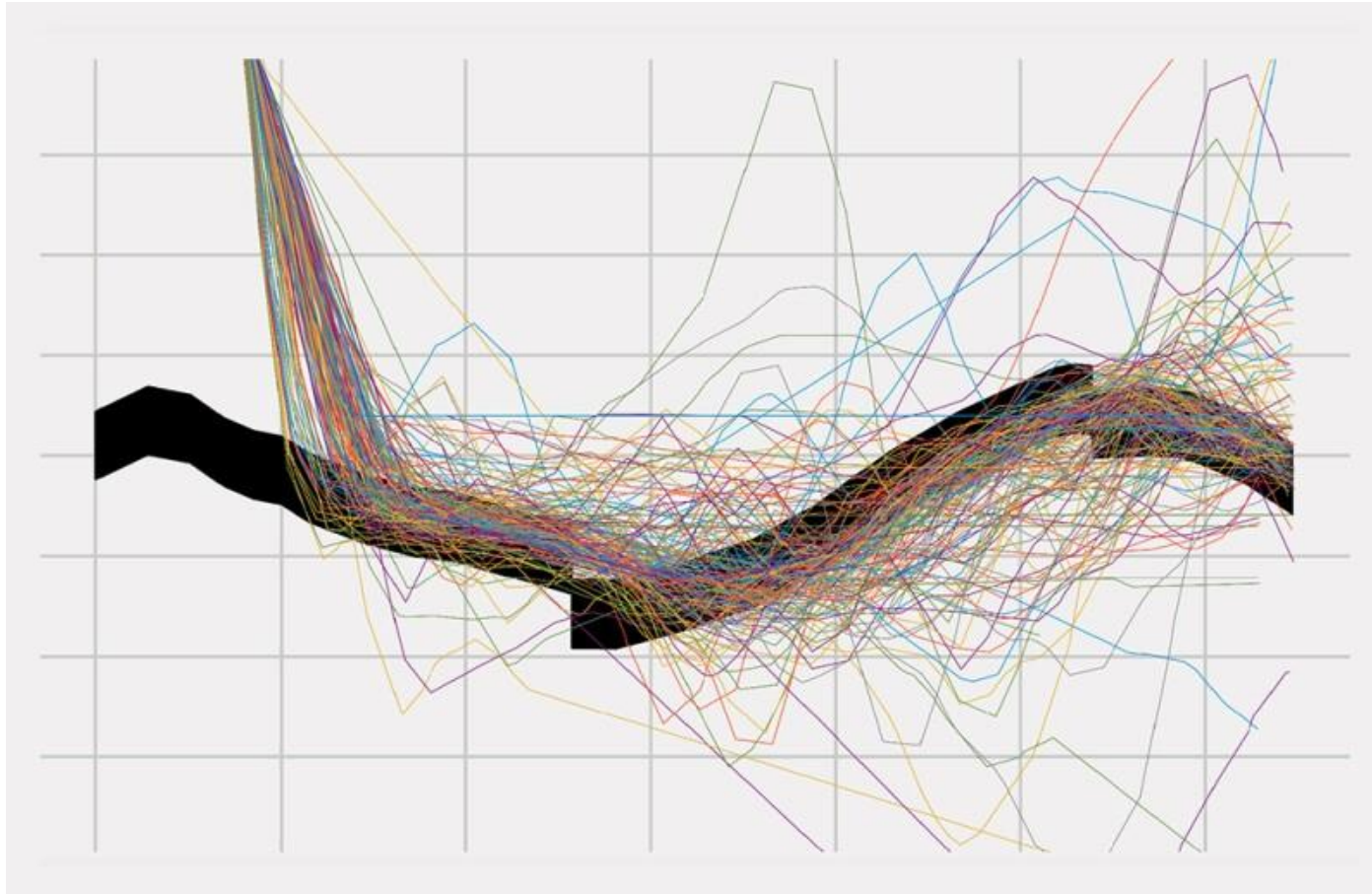
[[Muhammad et al. \(2025\): Geosteering Robot...](#)]

Usage example of Pluralistic approach with Progressive Geology Generation



Did we beat humans?

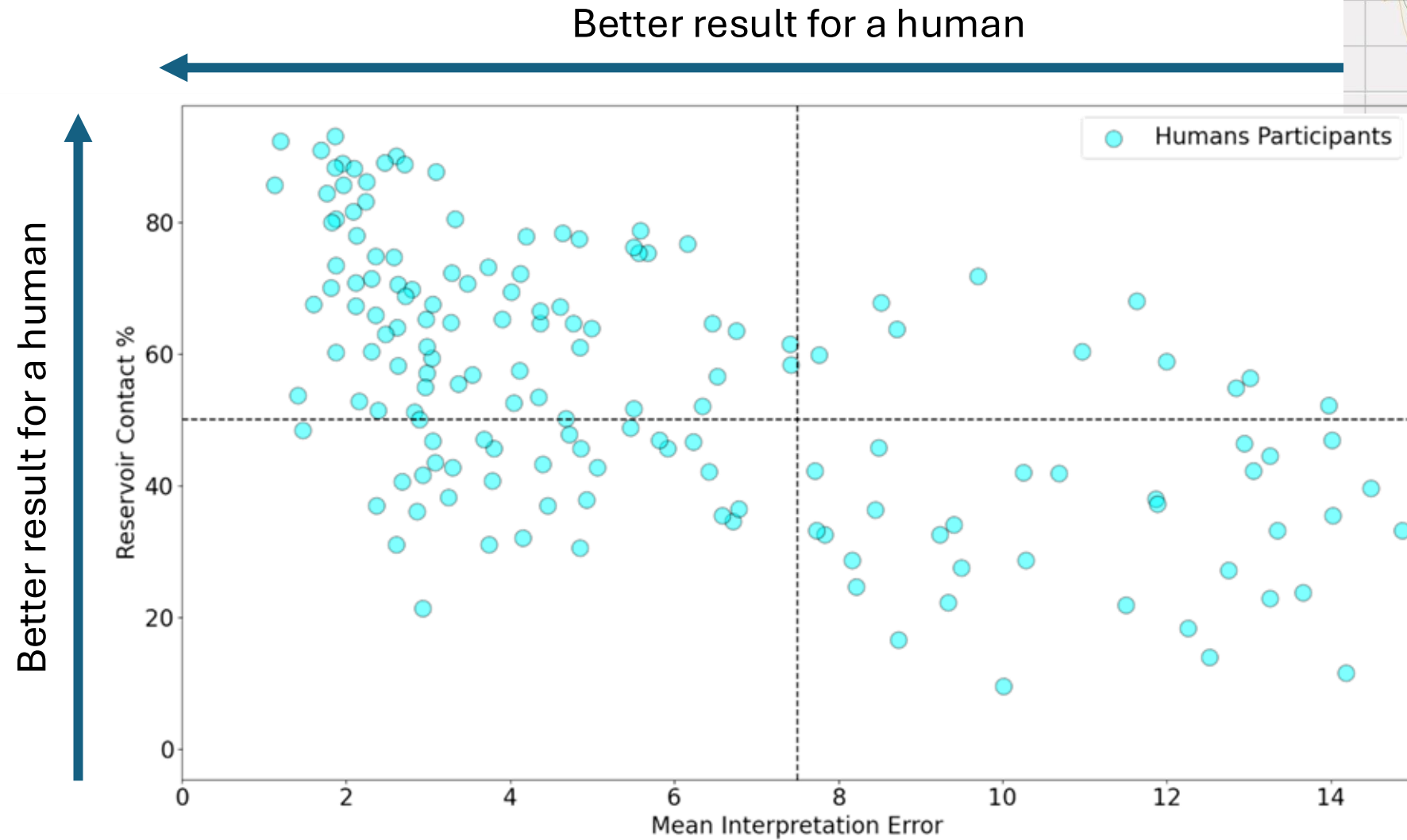
Geosteering World Cup 2021



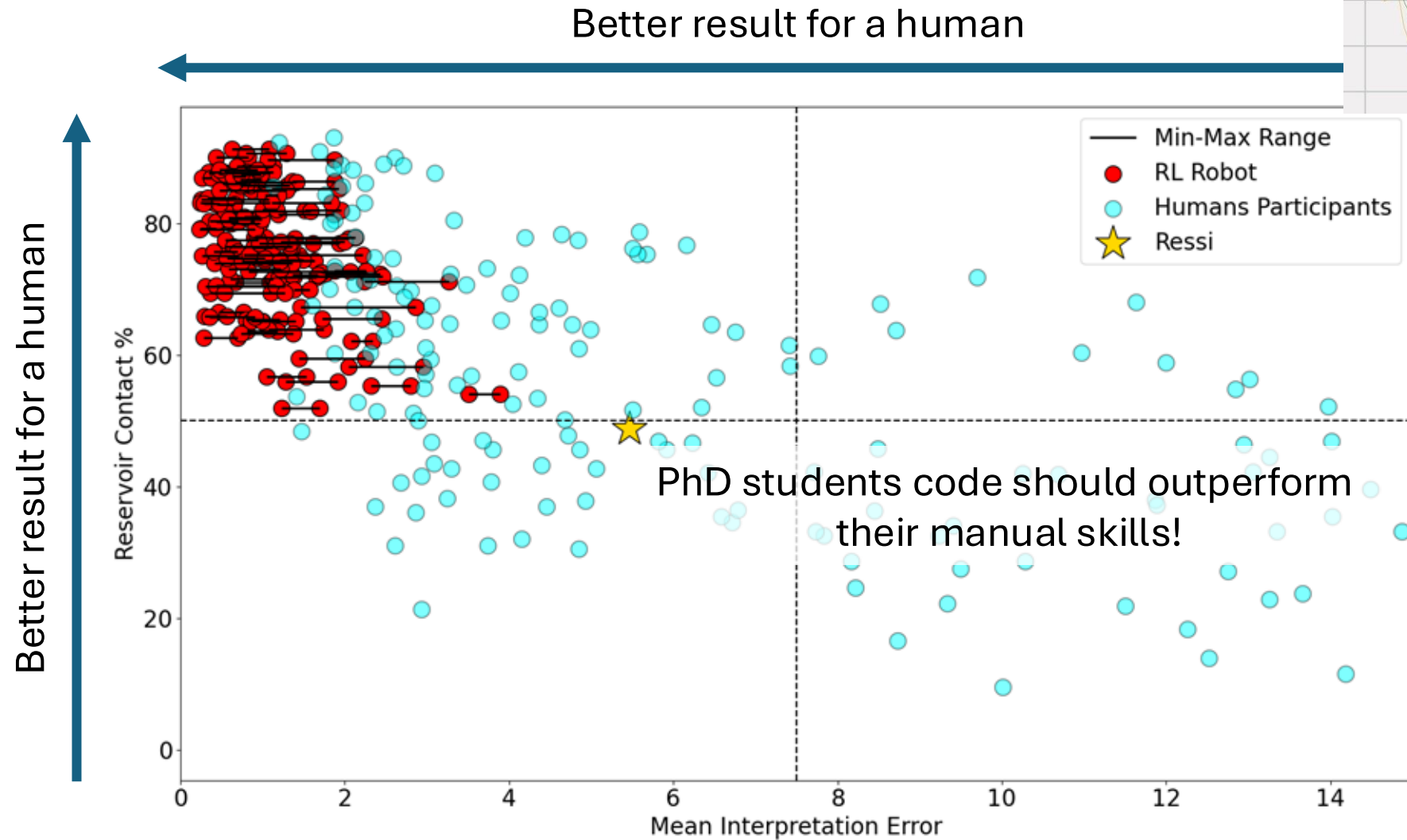
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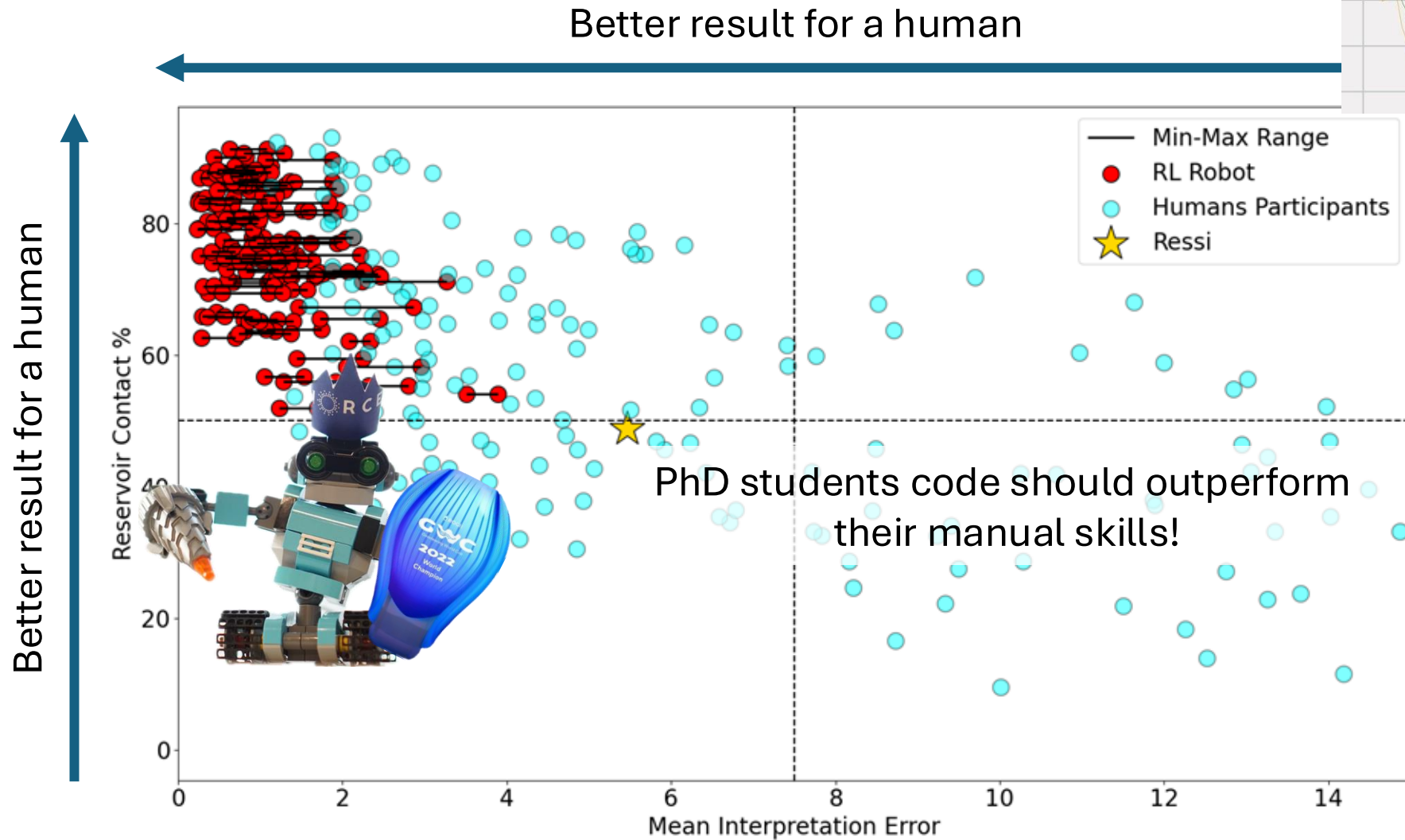
Comparison against Human Experts



Comparison against Human Experts

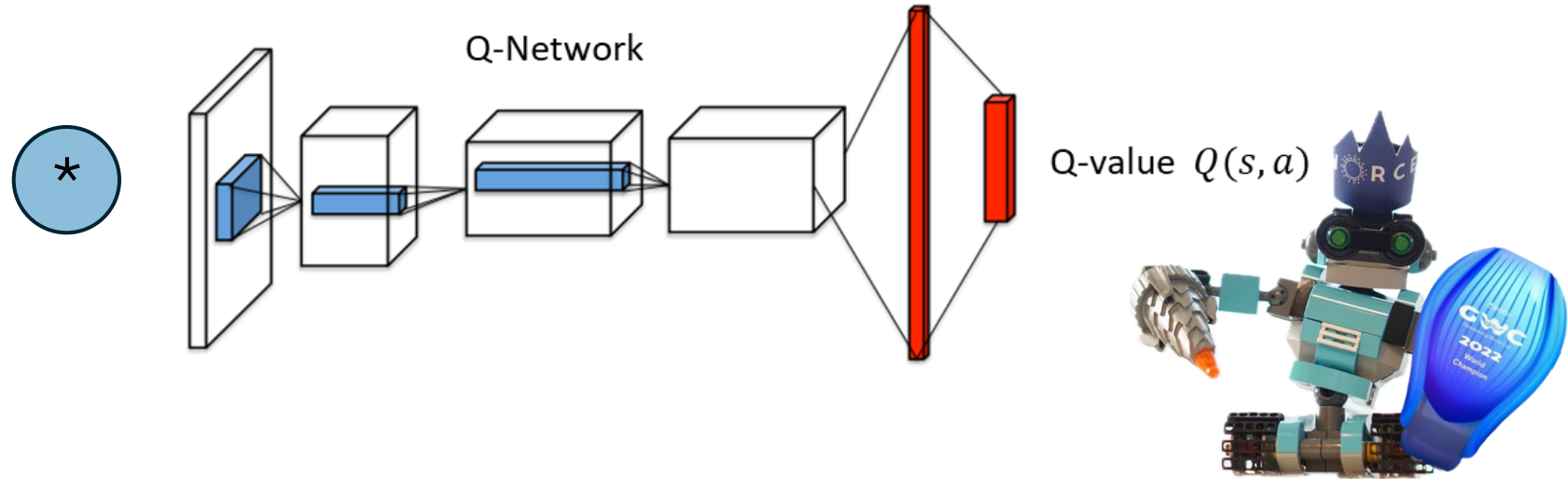


Comparison against Human Experts



Can we do better
than the robot?

**Improving
decision
optimization**



Can we do better than the robot?

Dynamic Programming

VS

Q-Network

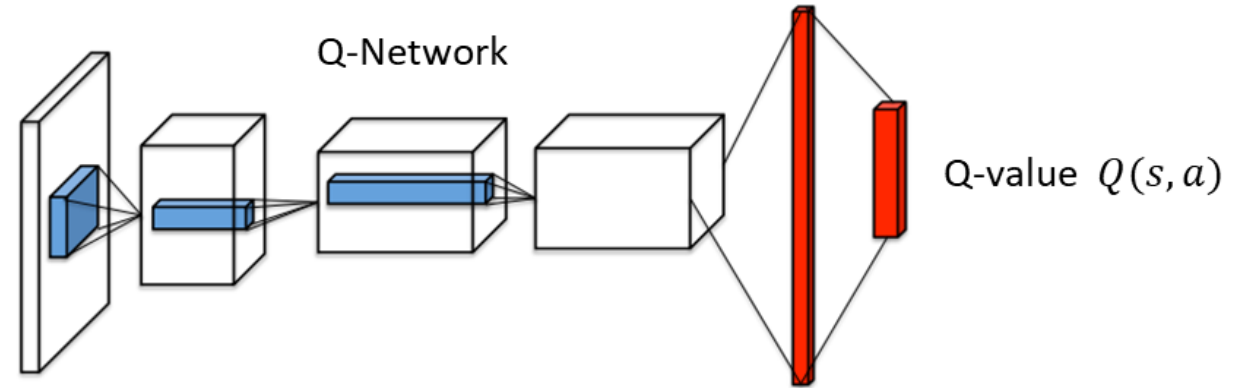
VS

Dual Q-Network

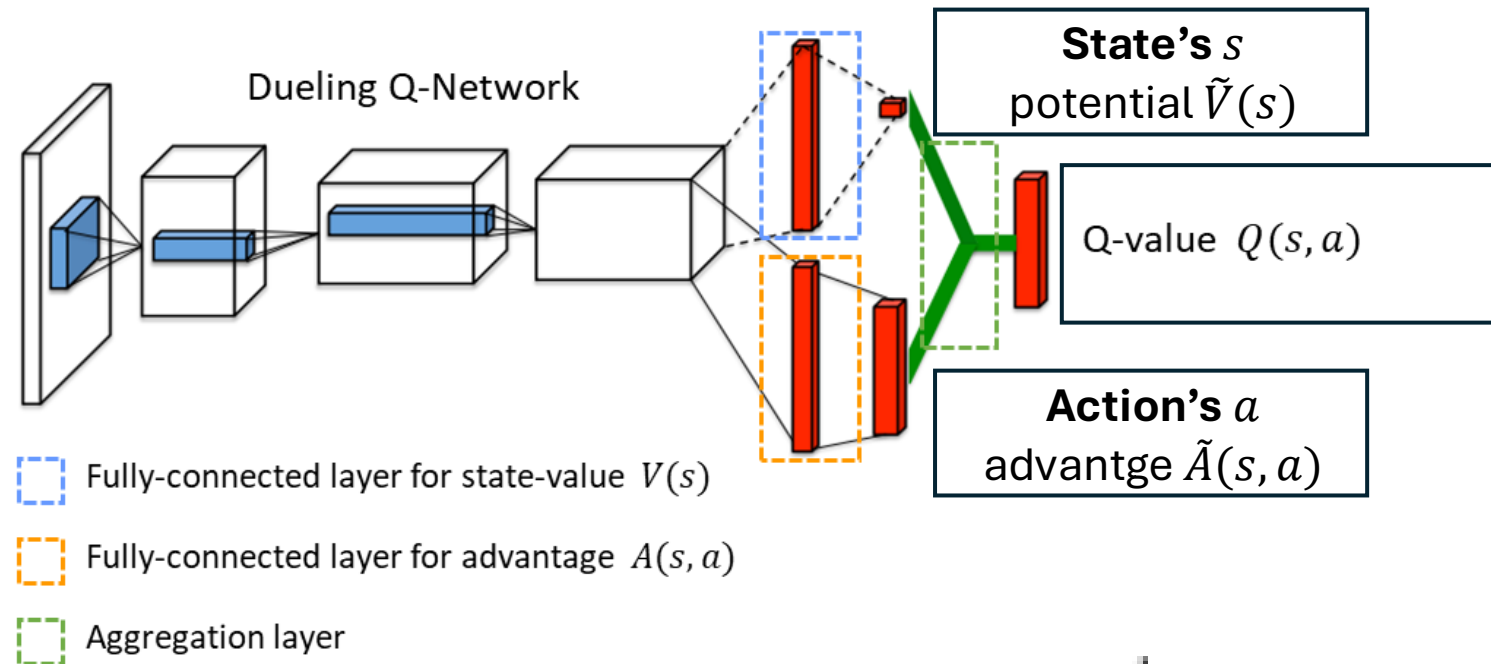
1

Aproximate Dynamic Programming (Algorithmic)

2



3



$$Q(s, a) = V(s) + A(s, a) - \frac{1}{|\mathcal{A}|} \sum_{a' \in \mathcal{A}} A(s, a')$$

Comparison of robot policies

1

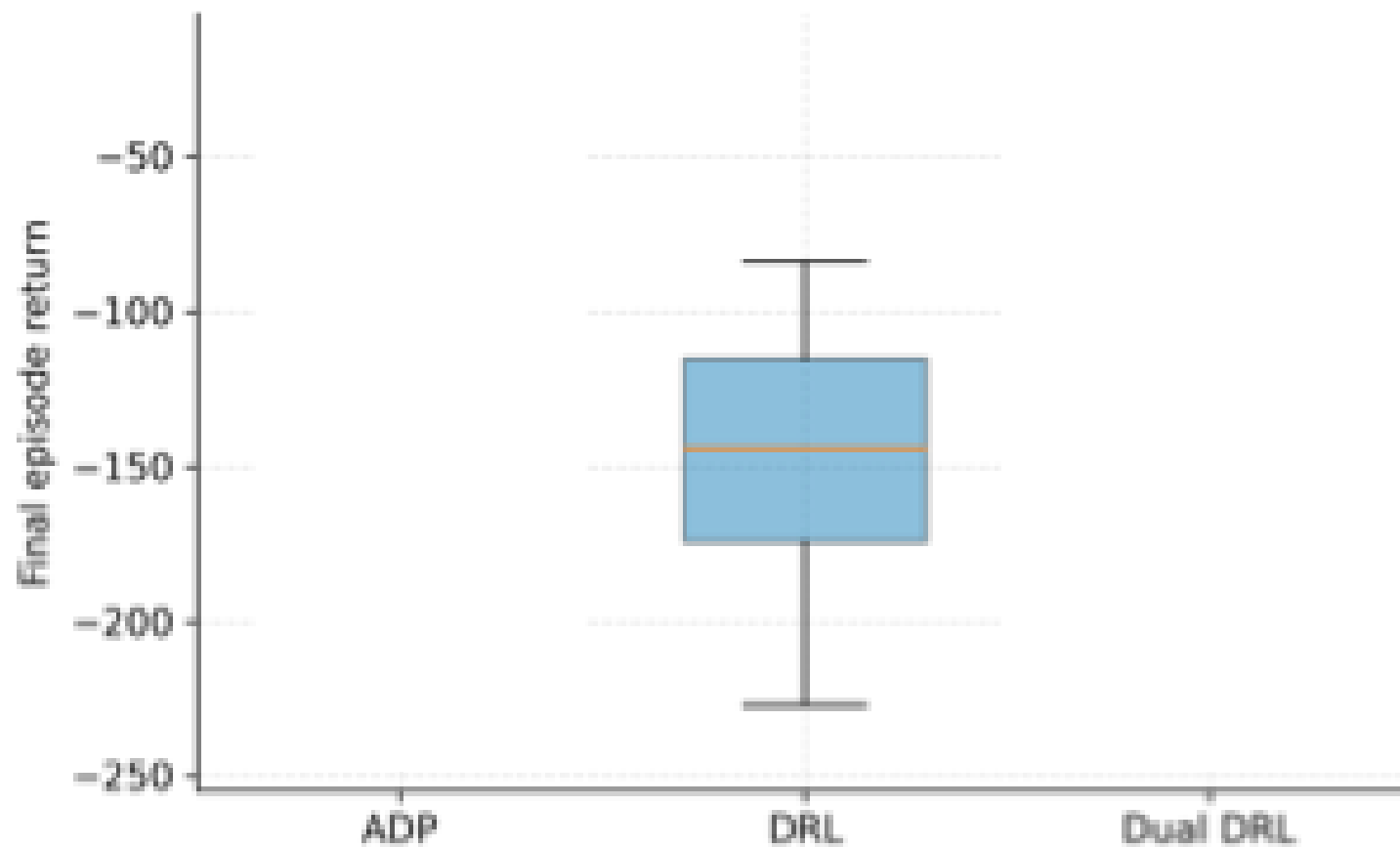
Algorithmic
explainable

2

Baseline
RL

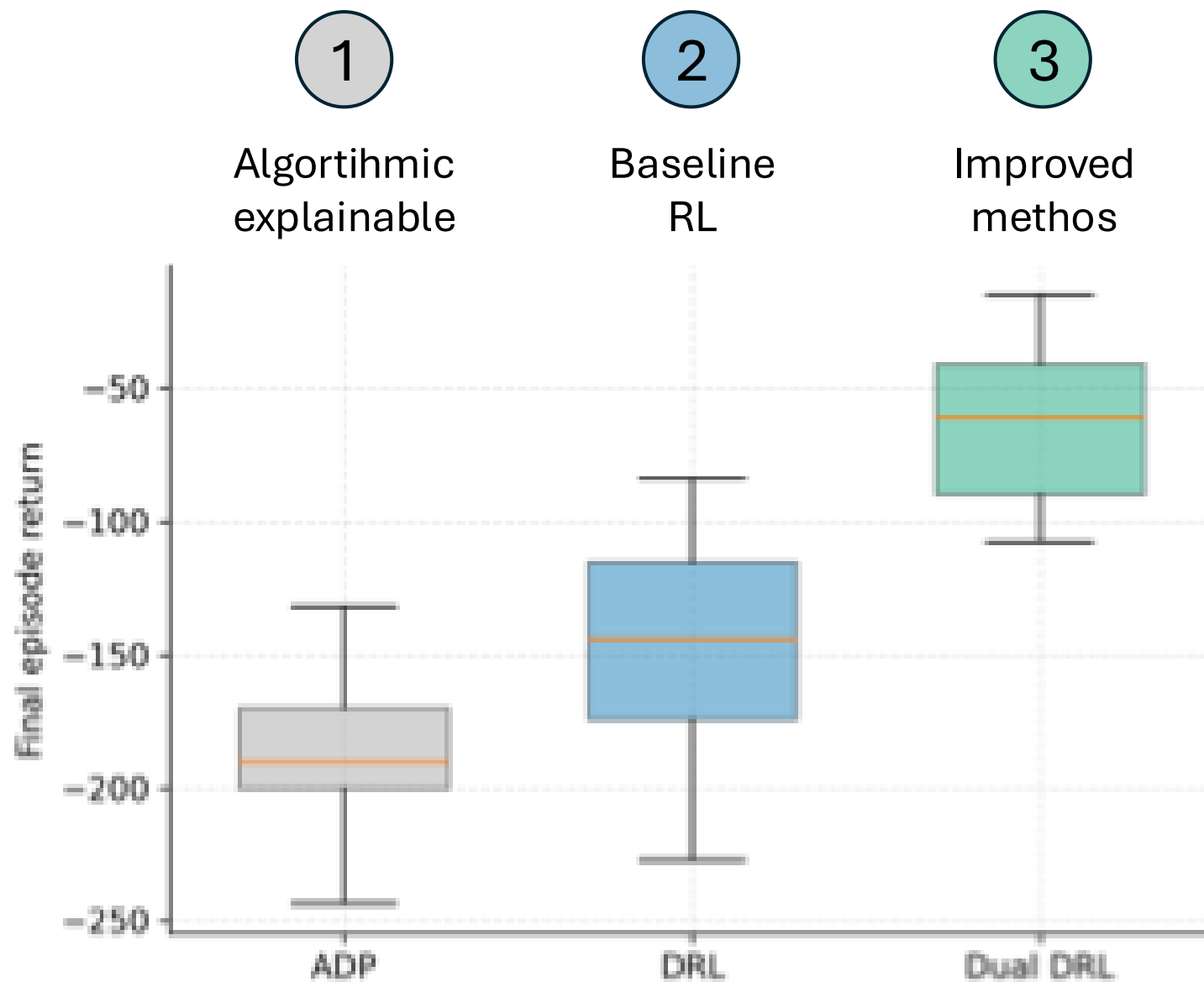
3

Improved
methos



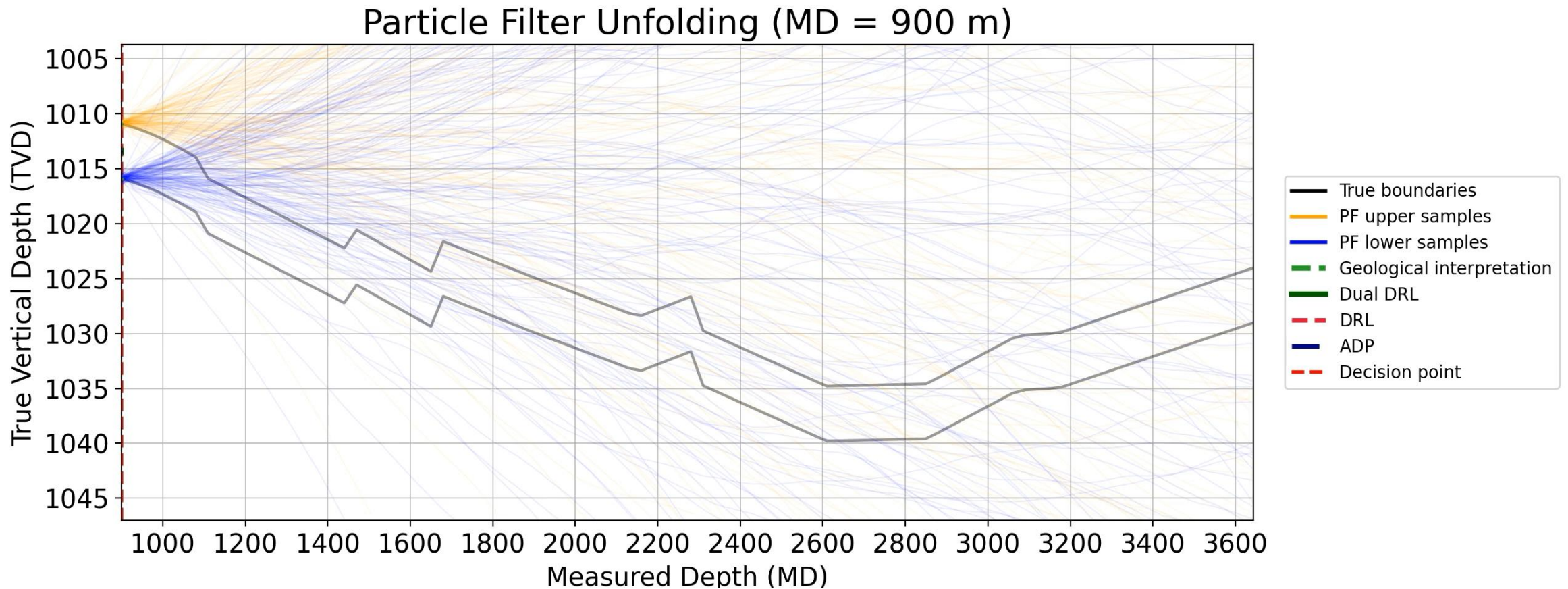
[Djecta et al. (2026): Decision-Driven Geosteering... arXiv:2606.17331]

Comparison of robot policies



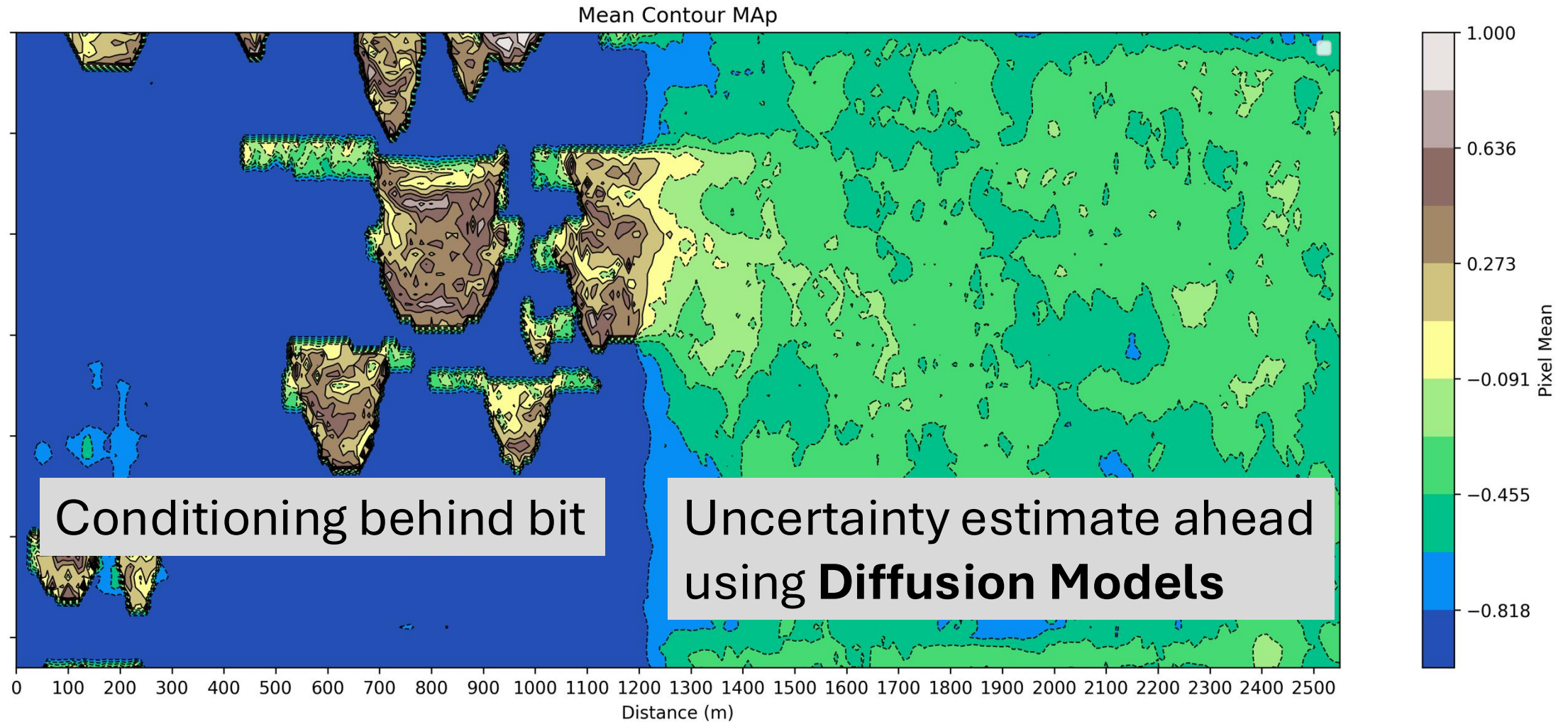
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Dual DRL steering and explainable predictions with Progressive Geology Generation

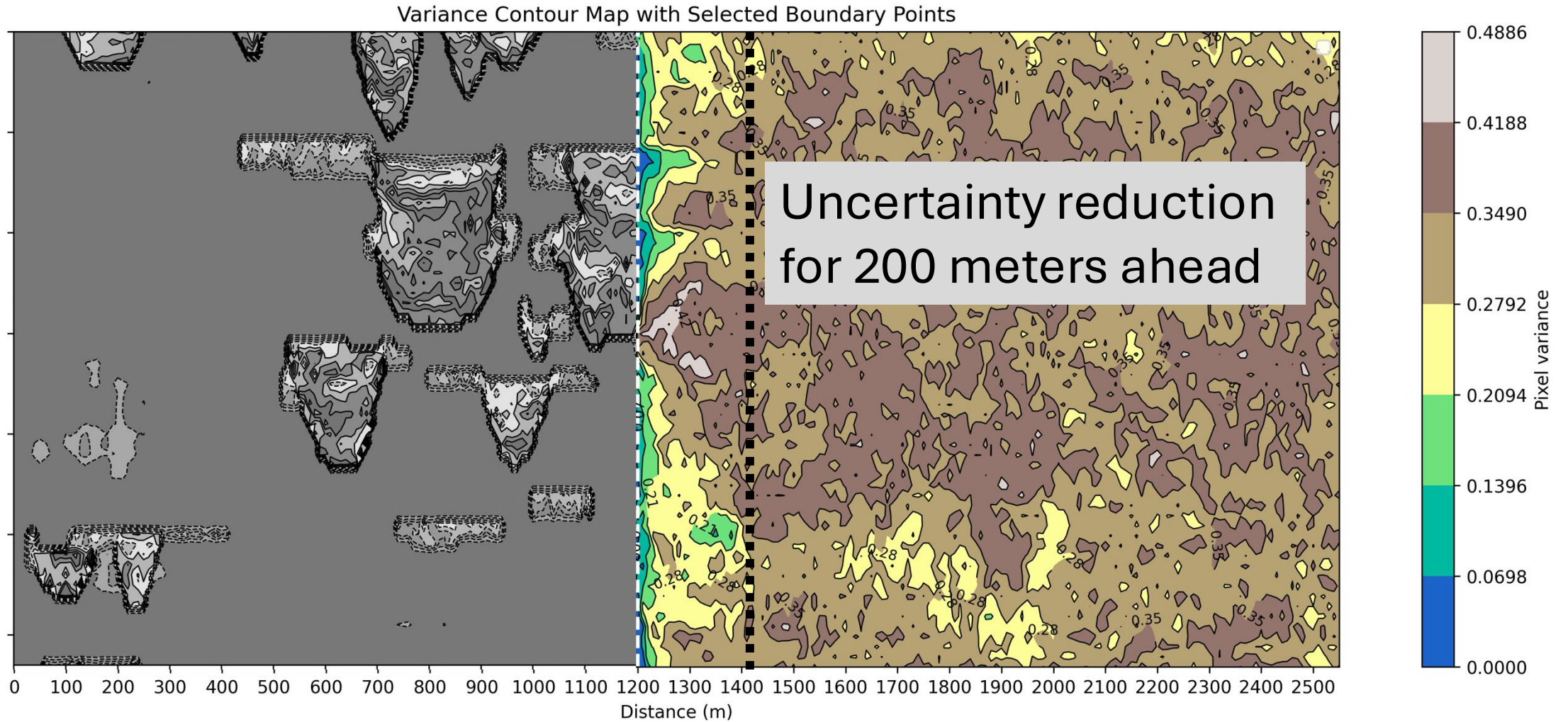


[[Djecta et al. \(2026\): Decision-Driven Geosteering... arXiv:2606.17331](#)]

Can we use robots with complex geology?



A prediction ahead in complex geology



Conclusion

- Progressive **G**eology **G**eneration + particle filtering
= **pluralistic** state estimation
- **Pluralistic DQN Robot** outperforms most human experts
- **Pluralistic geosteering framework** extends to
 - Explainable decisions with dynamic programming
 - Improved decisions with Dual DQN
- Gen-AI geomodelling brings **Pluralistic** to complex geology (future work)

For those who like robots: Geosteering Data Competitions

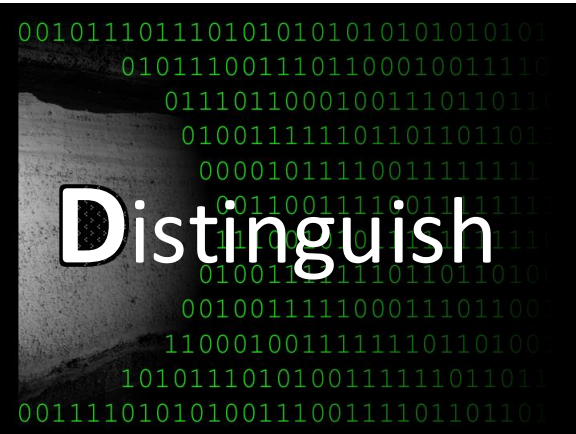
- **Geology Forecast Challenge**
 - NORCE
 - Prize period: passed, data available
 - <https://www.kaggle.com/competitions/geology-forecast-challenge-open>
- **ROGII - Wellbore Geology Prediction**
 - ROGII
 - Prize period until August 6, 2026
 - <https://www.kaggle.com/competitions/rogii-wellbore-geology-prediction>



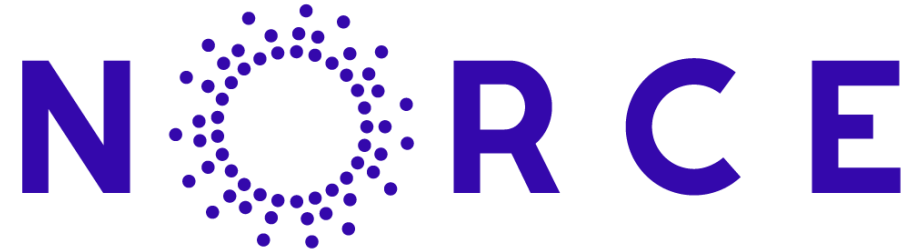
All references (in order of appearance)

- Cheraghi Y, Alyaev S, Bratvold RB, Hong A, Kuvaev I, Clark S, Zhuravlev A. **Analyzing expert decision-making in geosteering: Statistical insights from a large-scale controlled experiment.** Applied Computing and Geosciences. (2025)
- Muhammad RB, Srivastava A, Alyaev S, Bratvold RB, Tartakovsky DM. **High-precision geosteering via reinforcement learning and particle filters.** Computational Geosciences. (2025)
- Muhammad RB, Cheraghi Y, Alyaev S, Srivastava A, Bratvold RB. **Geosteering robot powered by multiple probabilistic interpretation and artificial intelligence: benchmarking against human experts.** SPE Journal. (2025)
- Djecta HE, Alyaev S, Fossum K, Bratvold RB, Muhammad RB, Srivastava A. **Uncertainty-aware well placement: Simulator-verified dual-network reinforcement learning approach meets particle filters.** In ICCS (2025)
- Djecta HE, Alyaev S, Fossum K, Bratvold RB, Muhammad RB, Srivastava A. **Decision-Driven Geosteering Under Uncertainty: A Unified Framework for Sequential Decision Optimization.** arXiv:2606.17331. (2026)
- Saleem H, Alyaev S, Fossum K, Blaser N, ElSheikh AH. **Diffusion Models for Generating Multiple Plausible Subsurface Realizations Ahead of Drilling.** Accepted in EAGE ECMOR (2026)

Acknowledgements



Partners:



Sponsors:



Project GitHub page:

<https://github.com/geosteering-no>