Decision Transformers trained on stochastic drilling trajectories with Particle-Filter State Estimation for Geosteering

NORCE

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1 INTRODUCTION & MOTIVATION

Geosteering is a sequential decision-making problem where steering decisions must be made while the geological model is still uncertain. The true reservoir boundaries are not directly observed during drilling; instead, they are inferred from sparse and noisy measurements such as gamma ray logs. This creates a need for steering policies that can use both trajectory information and uncertainty-aware estimates of the subsurface state.

- Partial observability: the true reservoir geometry is hidden and must be estimated while drilling.
- Sparse and noisy measurements: log responses provide indirect information about the subsurface.
- Sequential decisions: each steering action affects future well position and reservoir contact.
- Uncertainty matters: trajectory-only state representations may miss important geological uncertainty.
- Proposed direction: combine particle-filter state estimation with offline Decision Transformer policy learning.

Challenge: the policy must steer using an uncertain belief about the reservoir, not the true geological state.

2 RESEARCH QUESTION & OBJECTIVE

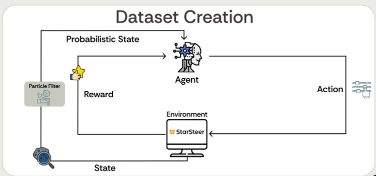
This work studies whether uncertainty-aware state estimation improves offline sequence-based geosteering policies.

- Can particle-filter belief states improve Decision Transformer policies?
- Does lower one-step action prediction error lead to better closed-loop reservoir contact?

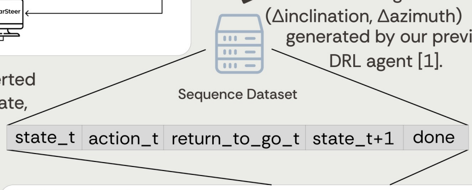
Objective: train Decision Transformers on stochastic drilling trajectories enriched with particle-filter state estimates.

Main comparison: trajectory-only state representation vs particle-filter belief-state representation.

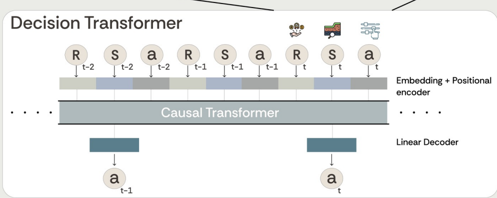
3 METHODOLOGY



We start by creating the dataset for the Decision Transformer by collecting probabilistic state estimates from particle filters and steering actions (Δinclination, Δazimuth) generated by our previous DRL agent [1].



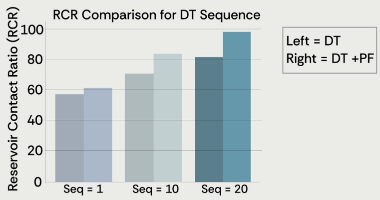
Each episode is converted into a sequence of (state, action, return-to-go) triplets.



The Decision Transformer learns long horizon steering behavior over sequences.

4 EVALUATION & RESULTS

Closed-loop Reservoir Contact Ratio (RCR) across model variants. Particle-filter belief-state inputs improve reservoir contact compared with trajectory-only Decision Transformer inputs.



Offline prediction metrics and closed-loop geosteering performance. Similar validation errors can lead to different RCR values, showing that prediction loss alone is not sufficient for evaluating geosteering policies.

Model	Context Length	Val. action MAE ↓	Val. loss ↓	Mean RCR ↑	RCR std
DT-Trajectory	1	0.084	0.012	0.58	0.1
DT-Trajectory	10	0.079	0.010	0.70	0.09
DT-Trajectory	20	0.076	0.009	0.84	0.11
DT + PF Belief	1	0.083	0.011	0.61	0.08
DT + PF Belief	10	0.080	0.010	0.82	0.1
DT + PF Belief	20	0.078	0.010	0.96	0.09

5 KEY FINDINGS & CONCLUSION

Particle-filter belief states provide useful uncertainty-aware context for Decision Transformer-based geosteering.

- Offline action prediction accuracy does not guarantee high reservoir contact.
- Belief-state conditioning helps the model account for hidden geological uncertainty.
- Closed-loop reservoir contact drove by sequence length is a more meaningful evaluation criterion than prediction loss alone.
- The workflow connects data assimilation with offline policy learning.
- Future work should test the approach on more complex geological scenarios and field-calibrated data.

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