Offline Reinforcement Learning as One Big Sequence Modeling Problem

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Summary

We investigate how much of the usual machinery of RL algorithms can be replaced with the tools that have found widespread use in large-scale language modeling.

Reframing RL as a (self-)supervised prediction problem

- simplifies design decisions: no model ensembles, behavior policy constraints
- allows for use of high-capacity models trained with stable algorithms

Standard (offline) RL

Training

while not converged **do**
  Sample transition $\{\mathbf{s}_t, \mathbf{a}_t, r_t, \mathbf{s}_{t+1}\}$
  Update Q-function to minimize (regularized) Bellman error:
    $\min_\theta (r_t + \gamma V(\mathbf{s}_{t+1}) - Q_\theta(\mathbf{s}_t, \mathbf{a}_t))^2 + \text{regularization}(\theta)$
  Improve policy based on updated Q-function:
    $\max_\phi \mathbb{E}_{a \sim \pi_\phi(\cdot|s_t)} [Q_\theta(s_t, a)]$
end

Action selection

$\mathbf{a} \sim \pi_\phi(\cdot \mid \mathbf{s})$

Transformer trajectory optimization

Training

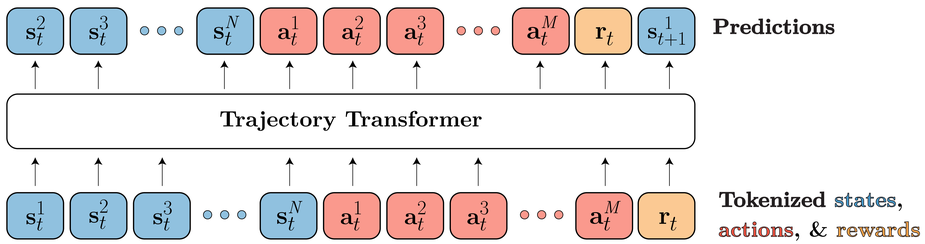
while not converged **do**
  Sample trajectory $\tau = \{\mathbf{s}_1, \mathbf{a}_1, r_1, \ldots, \mathbf{s}_T, \mathbf{a}_T, r_T\}$
  Maximize likelihood assigned to τ by transformer:
    $\max_\theta P_\theta(\tau)$
end

Action selection

Imitation: maximize $P_\theta(\tau \mid \mathbf{s}_0 = \mathbf{s})$
Goal-conditioned RL: maximize $P_\theta(\tau \mid \mathbf{s}_0 = \mathbf{s}, \mathbf{s}_T = \mathbf{g})$
Offline RL: maximize $\sum r_t$ using beam search

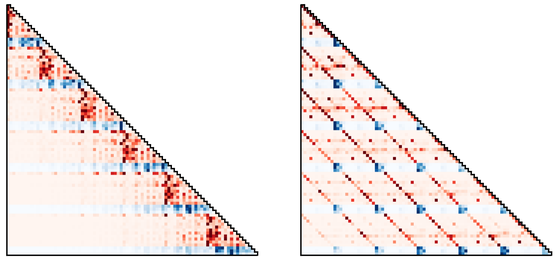
Trajectories as Generic Sequential Data

A single model serves as an action prior, dynamics model, and value estimator.



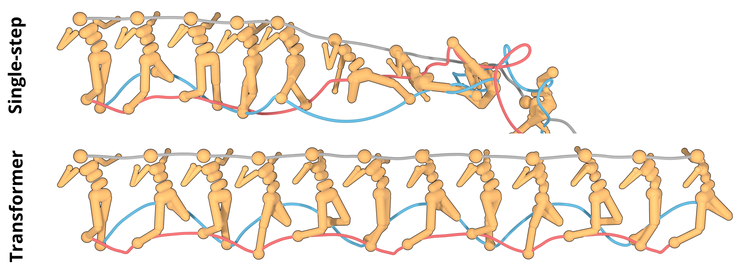
The transformer is trained on trajectories using the standard teacher-forcing objective:

$$\mathcal{L}(\tau) = \sum_{t=1}^{T} \Big(\sum_{i=1}^{N} \log P_\theta(\mathbf{s}_t^i \mid \mathbf{s}_t^{<i}, \tau_{<t}) + \sum_{j=1}^{M} \log P_\theta(\mathbf{a}_t^j \mid \mathbf{a}_t^{<j}, \mathbf{s}_t, \tau_{<t}) + \log P_\theta(r_t \mid \mathbf{a}_t, \mathbf{s}_t, \tau_{<t}) \Big)$$



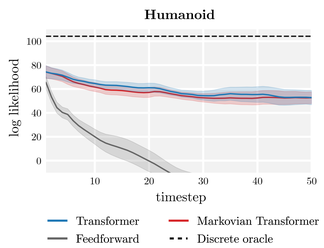
Attention patterns of the Trajectory Transformer, showing (left) a discovered Markovian stratetgy and (right) a visually striated approach with action smoothing.

Transformers as Dynamics Models



Standard predictive dynamics models have excellent single-step error, but poor long-horizon accuracy due to compounding errors

Trajectory Transformers are more reliable long-horizon predictors than single-step models, even in continuous Markovian domains



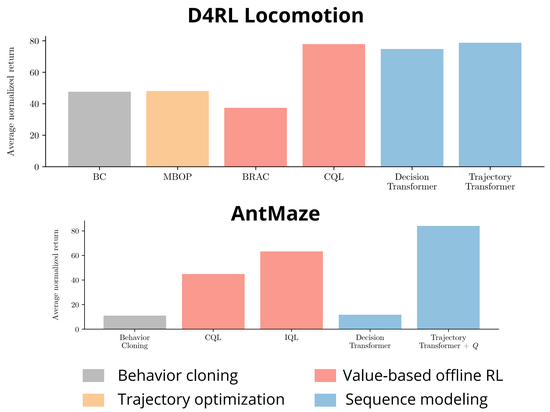
Model accuracy versus rollout length

Beam Search as a Trajectory Optimizer

Imitation learning Decoding a Trajectory Transformer with unmodified beam search gives rise to a model-based imitative method that optimizes for entire predicted trajectories to match those of an expert policy.

Goal-conditioned RL Conditioning trajectories on a future desired state alongside previously-encountered states yields a goal-reaching method.

Offline RL Replacing log-probabilities from the sequence model with reward predictions yields a model-based planning method, surprisingly effective despite lacking the details usually required to make planning with learned models effective.

Combining with Q-functions Using an IQL [Kostrikov 2021] Q-function as a planning heuristic dramatically improves performance in long-horizon, sparse-reward tasks compared to model-free and return-conditioning approaches.

Goal-reaching in the four-rooms environment Start Goal