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**1. Brief Summary of Prototypes:**

My research focuses on applying combined data augmentations for offline reinforcement learning. The prototypes I developed aim to enhance the performance of reinforcement learning models when trained on pre-collected datasets. Leveraging techniques such as noise injection and adversarial state training, my prototype studies the results in hopes of improving the robustness and generalization capabilities of offline reinforcement learning agents. By systematically applying data augmentations to the input data, I aim to mitigate issues related to distribution shift and extrapolate learned policies to unseen scenarios.

**2. Selected Core Papers:**

" Surprisingly Simple Self-Supervision for Offline Reinforcement Learning in Robotics" is my selected core paper [1]. Offline RL involves learning policies from pre-collected datasets without interacting with the environment. However, current algorithms overfit the dataset and generalize poorly. The paper compares 7 augmentation schemes like Gaussian noise, dimension dropout, state mix-up etc. and finds best performing technique across D4RL benchmark tasks. S4RL also outperforms other self-supervised baselines like CURL and VAEs when combined with offline RL algorithms like CQL and BRAC [2][3][4]. One key insight is offline RL methods like CQL struggle due to insufficient coverage of state-action spaces in static datasets. As such, data augmentations are a perfect tool to utilize the generalization capabilities of CQL. Experiments are also conducted in complex robotic manipulation environments like Meta-World and RoboSuite where S4RL continues to outperform, demonstrating its effectiveness for improving robot learning from offline datasets. The simplicity and generality of S4RL enable it to significantly boost performance of offline RL algorithms across domains.

**3. Explanations of Weaknesses/Gaps in the Papers:**

Certain weaknesses and gaps emerge upon careful assessment on existing papers on data augmentations in the field of reinforcement learning. Notably, there is limited exploration into the effects of combining different augmentations in the field of robotics. Although individual augmentation has been proved to show improvement, their overall effects are still not well understood. Scenarios where augmentations may introduce unintended biases or negatively affect the learning process are also often overlooked. A more comprehensive understanding of the role of data augmentation in offline reinforcement learning is clearly needed.

**4. Explanation and Justification of Selected Gaps (Combination of Data Augmentations):**

My research objective is to explore how the combination of different augmentations can synergize and enhance the agent's adaptability to environmental conditions. Combination data augmentations can also reduce resources needed for data collection, as often times can lead to safety issues and cost overhead in the real world. By addressing this gap, I aim to propose a novel approach to data augmentations in offline reinforcement learning in the field of robotics.

**5. Explanation and Justification of Research Questions:**

I formulated the following research questions, each based on the limitations of existing research:

**Determining Optimal Augmentation Combinations:**

Can we identify augmentation combinations that transfer well across multiple tasks and environments?

Finding the best augmentation combinations that demonstrate successful transfer learning and performance improvement is crucial. This question helps understand the generalizability of these combinations and gain insights into the effects of combination data augmentation on model performance.

**Sample Efficiency Impact:**

How does the sample efficiency and final performance scale with increasingly complex augmentation combinations? Are there diminishing returns and an optimal level of complexity?

The purpose of this question is to investigate how the complexity of augmentation combinations affects sample efficiency and overall performance. Achieving the best possible balance between increased complexity and learning efficiency is crucial for reducing computation costs.

**Stacked or Combined:**

Is it better to perform stacked data augmentation on the data, or just combine different dataset into one?

This question explores further into the augmentation strategy by exploring two approaches for combination data augmentation to find out the best approach.

**6. Conclusion:**

In Summary, my research aims to further the understanding and application of combination data augmentations in offline reinforcement learning in the field of robotics.

**Bibliography**

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