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Domain adaptation in reinforcement learning: a comprehensive and systematic study

Key words: Reinforcement learning; Domain adaptation; Machine learning

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Motivations

- Providing a comprehensive and detailed review of RL-related DA approaches with state-of-the-art methods and pointers to the most relevant

- Categorizing the existing methods into three major classes (supervised, semi-supervised, and unsupervised), exploring them, and highlighting their main features

- Specifying open issues and making suggestions for upcoming studies

Main idea

- **Domain adaptation in RL**: DA is crucial for improving RL performance when there is significant difference between the source and target domains.

- **Systematic review**: We categorized existing DA methods and evaluated them using key metrics (data adaptation and performance), and identified their strengths and limitations.

- **Contribution**: The study provides a **rigorous evaluation** of the state-of-the-art DA methods, highlighting challenges and offering recommendations for future research to advance DA in RL.

Method

Step 1: Categorizing DA approaches

Step 2: Defining evaluation metrics

Step 3: Comprehensive review of existing methods

Step 4: Rigorous evaluation

Step 5: Identifying challenges and future directions

Major results

Comprehensive evaluation of domain adaptation (DA) in reinforcement learning (RL):

• We conducted a **systematic review** of various DA methods in RL, categorizing them and distinct groups based on application domains.

Effectiveness of DA methods:

• DA strategies **significantly improve** RL performance by addressing domain discrepancies, reducing performance drops in the target domain.

• The study identifies **the most effective DA approaches** in specific RL contexts, helping guide future applications and research.

Identifying research gaps:

• This paper fills an existing **gap in the literature** by providing an in-depth evaluation of DA methods for RL.

• It highlights **key challenges**, such as domain shift and data scarcity, that continue to hinder the successful application of DA in RL.

Conclusions

- **Review of DA strategies**: We systematically reviewed various domain adaptation (DA) approaches used in reinforcement learning (RL).
- The methods were categorized based on their application domains and were evaluated using key adaptation metrics.
- **Effectiveness in RL**: Our evaluation shows that DA techniques significantly enhance RL performance, especially when addressing domain discrepancies.
- Certain approaches are more effective in specific contexts, while others provide broader applicability.
- **Contribution to the field**: This paper fills an important gap in the literature by offering a rigorous, in-depth evaluation of DA in RL.
- Our findings provide critical insights for future developments in DA techniques for RL.