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APPLICATION OF MACHINE LEARNING TECHNIQUES FOR AUTOMATED PLANNING

This article discusses key aspects of automatic scheduling with a focus on efficiency, reliability, and safety. It explores effective methods for integrating and optimizing scheduling systems using machine learning models, focusing on coefficient and hyperparameter adjustment. Recent results confirm a significant increase in the accuracy and speed of planning processes achieved through the use of machine learning approaches, namely reinforcement learning, which allows for the development of large data sets with only a simulation and training environment and sufficient computing resources.

Context. Evaluate the possibility of machine learning tools application for tasks automation planning domain.

Objective. Research benefits of machine learning models application for automated planning tasks, utilizing process modelers.

Methods. The proposed pipeline is based on the reinforcement leering approach of training the agent in the simulation or real environment, with evaluation results and base on that building optimal strategies to increase performance of task planning and capacity distribution problem.

Results. The proposed approach demonstrates a number of advantages:

Increased accuracy: The use of modern machine learning methods can significantly improve data analysis and thus improve task planning.

Reliability and security: The use of reinforcement learning involves emulation (simulation) mechanisms to provide agent training in real (approximate) conditions to build a reliable and efficient model, which is critical for applications in various industries.

Scalability: The system can easily adapt to processing different amounts of data, providing stable performance regardless of the size of the data set.

Conclusions. The proposed approach to improving the tasks of automated task planning in computing systems using reinforcement learning methods is promising for improving the processing and planning of tasks, balancing and distribution of computing resources, as well as the load on various system components, in addition, it has significant potential for further research and developments in this field. However, further research is needed to address the identified limitations, including evaluation of experienced practitioners, comparison of different modeling tools, and evaluation of larger and more complex processes.

Keywords: automatic planning, information systems, distributed systems, modeling, optimization, machine learning.

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ЗАСТОСУВАННЯ МАШИННОГО НАВЧАННЯ ДЛЯ АВТОМАТИЗОВАНОГО ПЛАНУВАННЯ

У цій статті розглядаються ключові аспекти автоматичного планування з акцентом на ефективність, надійність і безпеку. Вона досліджує ефективні методи інтеграції та оптимізації систем планування з використанням моделей машинного навчання, зосереджуючись на коригуванні коефіцієнтів та гіперпараметрів. Останні результати підтверджують значне підвищення точності та швидкості процесів планування, досягнуте завдяки використанню підходів машинного навчання, а саме методу навчання з підкріпленням, це дозволяє напрацьовувати великих масивів даних, маючи лише середовище для симулювання і навчання та достатню кількість обчислювальних ресурсів.

Ключові слова: автоматичне планування, інформаційні системи, розподілені системи, моделювання, оптимізація, машинне навчання.

Problem statement

Automated operation planning is crucial for enhancing the efficiency and accuracy of task scheduling in computer systems. Traditional methods often require extensive manual input, which is time-consuming and prone to errors. Integrating machine learning, particularly reinforcement learning, offers a promising solution to automate and optimize this process.

The main goal of this article is to explore the possibility of applying machine learning approaches to automatic operation planning. The main advantage of machine learning is the automatic creation of a rule system, which allows operators to avoid manual processing of operations and writing rules. In this study, we focus on machine learning approaches, in particular, reinforcement learning methods. The advantages and disadvantages of different methodologies are discussed, including rule-based methods, statistical approaches, and neural networks.

The primary objective is to applicate machine learning approaches for automatic operation planning tasks

The aim of the study is to find the most suitable software technique and organizational structure for developing solutions for automatic processing and scheduling of operations in computer systems. An architectural solution for processing such operations and a machine learning-based system method, namely reinforcement learning, are also proposed.

The next step in the development of this research may be to implement the proposed system for task scheduling based on reinforcement learning methods and obtain actual results on different test data sets. To achieve this goal, the following main research objectives were defined:

- Analyze existing methods and techniques for automatic operation scheduling.
- Present methods for processing operations based on reinforcement learning solutions.
- Consider the possibility of applying automated planners to real-world problems.

Analysis of recent sources

Previous research has focused on several key aspects of automatic planning, with particular emphasis on efficiency, reliability, and security. This research has explored effective methods for integrating and optimizing planning systems by adjusting coefficients and hyperparameters using various machine learning models. Recent findings confirm the effectiveness of modern machine learning methods for automatic planning.

The use of neural networks, large data sets, and powerful computing resources significantly enhances the accuracy and speed of planning processes. Additionally, strategies such as communication lines ensure efficient coordination of planning components, which ensures the quality of the final results. Considering proposed architectural solutions and ensemble methods for automatic planning is promising for further development in this field. Planning and learning systems in this paper is structured around the following aspects:

1. Type of Knowledge: The type of knowledge that the machine learning process will learn must be defined. This paper focuses on two ML targets for automated planning: action models to feed planners and search control to guide planners' search for solutions.
2. Collection of Learning Examples: Learning examples can be collected autonomously by the planning system or provided by an external agent, such as a human expert. Implementing a mechanism to autonomously collect learning examples is complex. Using a planner to collect experience is challenging because guaranteeing an automated planning problem’s solvability with a given domain model is as difficult as the original automated planning task. Random explorations often under-sample the state and action spaces of automated planning tasks. Actions usually have preconditions that are satisfied only by specific sequences of actions, which have a low probability of being chosen randomly.
3. Learning Algorithm: Different approaches can extract patterns from collected experience:
   - Inductive Learning: Builds patterns by generalizing from observed examples.
   - Analytical Learning: Uses prior knowledge and deductive reasoning to build patterns that explain the information from learning examples.
   - Hybrid Inductive-Analytical Learning: Combines the benefits of both inductive and analytical learning, achieving better generalization accuracy when prior knowledge is available and using observed learning data to address shortcomings in prior knowledge. In automated planning, inductive learning is most commonly used, but analytical and hybrid approaches are also applied based on the domain definition of the automated planning task.
4. Utilizing Learned Knowledge: The automatic system benefits from the learned knowledge, which is influenced by the decisions made in the previous three aspects. If the learned knowledge is imperfect, a robust exploitation mechanism is necessary.

To sum up in automated planning, imperfections in the learned knowledge could result from various factors, such as representation choices that fail to capture relevant knowledge, a strategy for collecting learning experience that misses significant examples, or a learning algorithm that gets stuck in local minima or fails to capture patterns within reasonable time and memory constraints. In such cases, directly using the imperfect knowledge could harm the planning process. Therefore, planning and learning systems must be equipped with mechanisms to ensure robust planning despite flaws in the learned knowledge. In addition, research on this topic plays an important role in the process of creating and maintaining the integration of different tasks into single workflow.

Main material

Our research builds on existing theories of Automated Planning and Reinforcement Learning. We integrate these theories to investigate how Automated Planning affects the performance of process modelers, particularly in terms of modeling time, semantic and syntactic correctness, and semantic completeness of process models.

The experimental design involves a comparative analysis of process modelers' performance with and without the use of Automated Planning tools. The participants, primarily students in a class setting, were chosen for their novice status in process modeling, making them suitable candidates for observing the impact of Automated Planning. Figure 1 shows a visualization of the task processing pipeline based on a machine learning approach, namely reinforcement learning:

Fig. 1. Pipeline for processing and training a machine learning model based on data from the environment

The proposed task planning (processing) pipeline consists of three components:

1. Planning - determines the sequence of actions required to achieve the goals. Using automated planning algorithms, the system generates an optimal plan that takes into account all possible conditions and constraints.
2. Execution - implements the created plan by performing the planned actions in real time. This includes direct execution of tasks, process monitoring, and adaptation to changes in the environment.
3. Learning - the system analyzes the results of implementation and accumulates new knowledge to improve future plans, this is based on the responses received from the environment and the use of metrics to assess performance. In addition, the approach includes processing the data and using it to improve models and algorithms.

Together, these three components create a comprehensive approach to automated scheduling, ensuring efficient task execution and continuous process improvement. The effectiveness of scheduling tasks for further reproduction in real-world conditions will be evaluated using the following metrics:

- Modeling Time: The time required to complete the modeling tasks.
- Semantic and Syntactic Correctness: Accuracy in adhering to the rules and logic of the process models.
- Semantic Completeness: The thoroughness of the models in capturing all relevant aspects of the processes.

Conclusions

Automated planning and reinforcement learning are distinct paradigms for addressing complex decision-making problems. Both encounter challenges in high-level decision-making within large, unpredictable, and non-stationary domains, particularly in robotics. However, integrating these paradigms can leverage their respective strengths and mitigate some of their inherent weaknesses, offering a more robust solution to these challenges.

In the paper we focused on two of automated planning challenges: defining effective action models and defining search control knowledge to improve the planners performance. For the first challenge, we reviewed systems that learned action models with diverse forms of preconditions and effects. These systems generally present learning algorithms that are effective when the appropriate learning examples are collected although it is still not clear how to automatically collect good sets of learning examples in automated planning. When learning results in imperfect action models, there are few mechanisms for diagnosing the flaws of the models or algorithms to robustly plan with them.

The paper also reviewed techniques for reinforcement learning technics, for automated planning domain, uses predicate logic to represent states and actions. Though current machine learning techniques can solve relational tasks, they are focused on achieving a particular set of goals and present generalization limitations in comparison with learning for automated planning tasks. Furthermore, they have problems collecting significant experience for complex tasks like the ones traditionally addressed in automated planning, where achieving a particular goal may undo previously satisfied goals.

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