LatRec+: Learning-based Goal Recognition in Latent Space

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Abstract

Existing approaches to goal recognition are able to infer domain knowledge by combining goal recognition techniques from automated planning, and deep autoencoders to learn domain theories from data streams. However, most recent approaches to goal recognition in these learned domains struggle with high spread during recognition process. LatRec+ leverages from the usage of learning approaches to recognize goals directly in real-world data (images), without relying on domain theories. The learned model is given a set of observations and returns the probability of each predicate being true. We demonstrate this approach in an online simulation of simple games, such as the n-puzzle game.

Introduction

Goal recognition is the task of identifying the desired goal of an agent by observing its behavior in an environment. Plan recognition approaches aim to identify the specific plan to which the observed agent has committed to perform to achieve a particular goal. Most approaches for goal and plan recognition rely on planning theories, which require a substantial amount of domain knowledge (Ramírez and Geffner 2009; Pereira, Oren, and Meneguzzi 2017). However, such approaches assume that a domain expert can provide a correct and complete domain knowledge for the algorithm to successfully recognize an agent's goal. The dependence on an expert limits the applicability of such algorithms in many real-world domains, so recent work has relaxed such requirements (Pereira, Pereira, and Meneguzzi 2019; Pereira et al. 2019; Zhuo 2019).

LatRec+[1] introduces a learning-based approach to recognize goals, by applying a recurrent neural network to solve the task of goal recognition directly rather than using a training data to generate domain knowledge. Furthermore, instead of predicting perfectly the correct goal, our approach measures the probability of each predicate being true, given a set of observations. Thus, LatRec+ selects the most likely goal in the set of candidate goals. To exhibit our approach, we demonstrate the effectiveness of LatRec+ for online goal recognition problems in latent space, using games as test-bed, such as the n-puzzle game.

[1] https://bit.ly/2rdnkSk

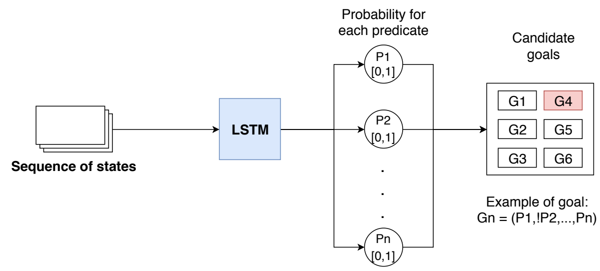

Figure 1: Data-driven model for goal recognition

Data-Driven Goal Recognition in Latent Space

Recognizing goals in latent space consists of 4 steps: 1) converting real world data to latent space; 2) acquiring traces of executions in latent space; 3) predicting the correct goal through a recognizer; and 4) converting the goal in latent space to real world data.

A recent approach developed by Asai and Fukunaga (Asai and Fukunaga 2018) uses an auto-encoder (Vincent et al. 2008) neural network to automatically generate domain models from images of simple games and problems. The neural network uses an encoder to convert an input image into a discretized representation. The encoder receives 42x42 black and white images and outputs a 6x6 latent representation activated by Gumbel-Softmax (Jang, Gu, and Poole 2016). The decoder reconstructs the input image from the discretized representation.

Images processed through the encoder become bit vectors that provide analogues for states comprising propositional attributes. Sequences of such propositional states implicitly represent sequences of action executions, which, in turn, generate traces to feed a recognizer.

After converting real world data and acquiring traces, we can train a recognizer. In previous work (Amado et al. 2019), we aimed to create a learning model capable of computing the intended goal of an agent given a trace of states, reconstructing the correct goal in latent space. This approach was capable of solving goal recognition problems without having candidate goals, resulting in no spread in the recognized goals at all. However, since this solved the goal recognition problem as a classification problem, it was incapable of predicting goals that were not in the training data. We develop

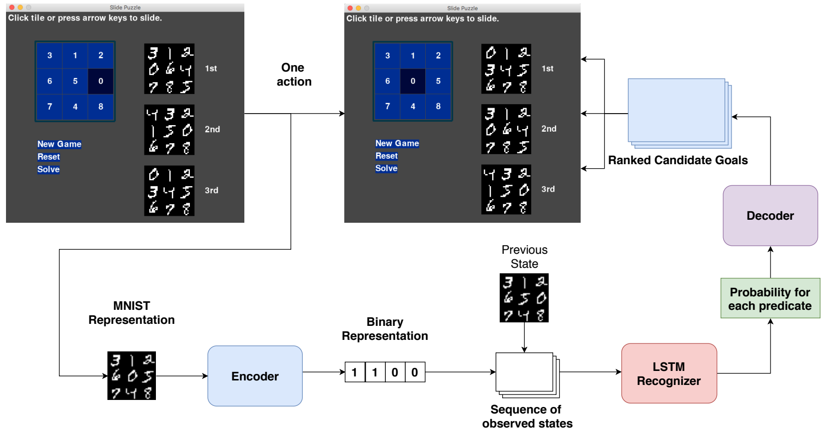

Figure 2: Application screen showing the transition of two states and the candidate goals for the current state.

a learning approach that leverages from the knowledge of candidate goals.

Our approach focuses on learning the probability of each predicate of the goal being true, instead of faithfully reconstructing the goal state. Thus, this approach receives a set of observed states and computes the probability of each predicate in the domain being true or false, given the observed data. Using these probabilities, we assume that we have a standard goal recognition problem, where a set $\mathcal{G}$ of candidate goals are given, and each goal of such subset is a set of n predicates. Thus, we select the most likely goal using the learned probabilities of each predicate as the correct goal that the agent intends to achieve. This process is shown in Figure 1, where each output node of the LSTM is the probability of such predicate being true, and the G4 is the most likely goal.

Application Overview

LatRec+ is a desktop application implementing our approach for recognizing goals in latent space. The user can start a "New Game", "Reset" the current game or "Solve" the puzzle, where all steps to solve the puzzle are displayed. The user should solve the puzzle by playing the board with blue tiles, where the navy tile containing "0" indicates the tile that the user is allowed to move. At the right side, the system outputs the most likely goals that the user is trying to achieve. Figure 2 show the workflow of LatRec+. In this case, the user performed the action of swapping the tile "0" with the tile "5". The image representation of the board is fed to an encoder, which generates a binary representation. This binary representation is fed to the learned model, along with the last 9 observed encoded states. The learned model returns a probability for each predicate, which we compare with the candidate goals available. We then rank the candidate goals, and finally decode then, displaying them to the user.

Conclusion

We developed a demonstration for LatRec+, a tool that performs goal recognition using real-world data (images). This demo exhibits the effectiveness of our approach in different games, where the user can experiment and act as an agent in these domains. Currently, LatRec+ can recognize goals in three distinct games: lights-out; 8-puzzle and tower of Hanoi, without needing to infer domain knowledge.

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References

Amado, L.; Aires, J. P.; Pereira, R. F.; Magnaguagno, M. C.; Granada, R. L.; and Meneguzzi, F. 2019. An lstm-based approach for goal recognition in latent space. In *The AAAI 2019 Workshop on Plan, Activity, and Intent Recognition*.

Asai, M., and Fukunaga, A. 2018. Classical Planning in Deep Latent Space: Bridging the Subsymbolic-Symbolic Boundary. In *AAAI*.

Jang, E.; Gu, S.; and Poole, B. 2016. Categorical reparameterization with gumbel-softmax. *CoRR* abs/1611.01144.

Pereira, R. F.; Vered, M.; Meneguzzi, F.; and Ramírez, M. 2019. Online Probabilistic Goal Recognition over Nominal Models. In *IJCAI*.

Pereira, R. F.; Oren, N.; and Meneguzzi, F. 2017. Landmark-Based Heuristics for Goal Recognition. In *AAAI*.

Pereira, R. F.; Pereira, A. G.; and Meneguzzi, F. 2019. Landmark-Enhanced Heuristics for Goal Recognition in Incomplete Domain Models. In *ICAPS*.

Ramírez, M., and Geffner, H. 2009. Plan Recognition as Planning. In *IJCAI*.

Vincent, P.; Larochelle, H.; Bengio, Y.; and Manzagol, P.-A. 2008. Extracting and composing robust features with denoising autoencoders. In *ICML*.

Zhuo, H. H. 2019. Recognizing multi-agent plans when action models and team plans are both incomplete. *ACM Trans. Intell. Syst. Technol.* 10(3):30:1–30:24.