Using an ASG based Generative Policy to Model Human Rules

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***Abstract*—This paper proposes a military scenario based on logistical resupply from a military base to coalition forces located in a nearby urban area or city. We describe the scenario and accompanying policy such that the context of the resupply missions changes over time. The set of policies and related changes over time have been manually defined using a set of human created rules to replicate how policies are created by humans. We show how inductive learning of answer set programs can successfully learn ASG generative policy models that capture the human-driven rules from just example traces and decisions made at different time points and with respect to different contextual situations that can arise during the resupply mission. These results demonstrate the utility of ASG generative policy as a method for modelling human-driven policy rules.**

***Index Terms*—Distributed Analytics, Information Science, Coalitions, Future Battlespace, Situational Understanding, Generative Policy**

I. Introduction

This paper uses the DAIS-ITA General Scenario Logistical Resupply Vignette [1]. We provide supporting data that is released online[1] that was created manually having previously written a set of rules that describe a policy. These human rules are listed in Section III. We use the data as learning samples to automatically learn the generative policy. This allows us to compare the human rules used to create the policy with the learned rules from the generative policy model in a number of experiments in Section II. This comparison has been made possible due to the explainability of the learned model. Finally, we present our experiment results in Section III and then draw conclusions in Section IV in order to assess the utility of the GPM approach.

II. Experiments

Our learning goal is to predict whether a given route that the resupply convoy may travel is acceptable (or not). There are many factors that are taken into account in the learning for this generative policy.

We test our policy decisions across three months from the scenario of which two are described in this paper:

Month 1: during the first month the supplies to be delivered to the FOB by the convoy are ammunition and networking devices, and a convoy consisting of eight vehicles has been selected as an escort to two delivery vehicles. There are no other escort vehicles available to provide additional fire support. Successful reconnaissance from drones and local sensors has allowed the Main Operating Base (MOB) to identify 5 suitable routes through the city for this convoy. The observed PoL of enemy activity has identified minimal action in the city at this time, although there are still occasional opportunistic attacks on convoys. These attacks mostly occur in the afternoon and there are chances of occasional patrols by enemy forces at 0900 and 2100.

Month 2: following from the previous months resupply, more ammunition has been requested and classified servers must also be delivered. The convoy consists of delivery trucks, eight escort vehicles and a number of drones providing aerial ISR support. Heavy rain is expected in the early morning which will disrupt this support. Enemy activity in the city is still at a reduced level with patrols still likely at 0900 and 2100.

III. Results

Here we show the results and evaluate each experiment. We show how the learning process has generated rules and evaluate their similarity to the human rules.

Month 1: Human Rules

1) If the "% chance of IEDs" is greater than 40 then the route is rejected
2) If the "% chance to encounter enemy forces" is equal or less than 5, then the "Expected Enemy Capability" doesn't matter for decision purposes and the route is accepted
3) If the "% chance to encounter enemy forces" is equal to or greater than 20, then the "Expected Enemy Capability" doesn't matter for decision purposes and the route is rejected
4) If the "% chance to encounter enemy forces" is between 5 and 20, and the "Expected Enemy Capability" is greater than "low" in any "Threat to Vehicle" column then the route is rejected
5) If the "% chance to encounter enemy forces" is between 5 and 20, and the any "Threat to Vehicle" column is greater than "low" then the route is rejected

Month 1: Learned Rules Assuming a default rule of REJECT is implemented, these are the learned rules for route acceptance:

[1] https://github.com/dais-ita/logistical-resupply-scenario/

```
IF ("% chance to encounter enemy forces"
    ↪ is less than 20)

AND

IF (("% chance to encounter enemy forces"
    ↪ is less 10)
OR ("Threat to Delivery Vehicle" is Low))

THEN ACCEPT
```

The output shows that the rules learned from the month 1 data[2] are a very good fit to the human generated rules. The first learned rule is a perfect fit for human rule 3 although the logic is reversed from the REJECT rule specified by the human to the learned ACCEPT rule. The second learned rule is specified in two parts joined with a logical OR statement. This is a good fit for human rule 4 although not specified in exactly the same way, the learned rule expresses similar logic. Upon first inspection it would appear the first two human rules have not been learned. However, a more compact representation of the policy has been learned, which highlights that the first two human rules were logically redundant.

Month 2: Human Rules

1) If drones can't fly, then the route is rejected
2) If the "% chance of IEDs" is greater than 40 then the route is rejected
3) If the "% chance to encounter enemy forces" is less than or equal to 5, then the Enemy Capability doesn't matter for decision purposes and the route is accepted
4) If the "% chance to encounter enemy forces" is greater than or equal to 25, then the Enemy Capability doesn't matter for decision purposes and the route is rejected
5) If the "% chance to encounter enemy forces" is between 5 and 20, and the any "Threat to Vehicle" column is greater than "low" then the route is rejected

Month 2: Learned Rules Assuming a default rule of REJECT is implemented, these are the learned rules for route acceptance:

```
IF ("% chance to encounter enemy forces"
    ↪ is not 25)

AND

IF ("Drones able to fly" is Yes)

AND

IF (("Threat to Delivery Vehicle" is not "
    ↪ Low - Medium")
OR ("% chance to encounter enemy forces"
    ↪ is less than 10))

THEN ACCEPT
```

The output shows that the rules learned from the month 2 data[3] are a very good fit to the human generated rules. The first learned rule models human rule 4 but is expressed as "equal to" rather than "greater than or equal to" due to a lack of examples in the training data where the chance of encountering enemy forces is greater than 25%. The second learned rule is equivalent to human rule 1. The third learned rule is specified in two parts joined with a logical OR statement is a special case of human rule 5. Note that this special case was sufficient to explain the training examples. If further examples were given, the learner could potentially learn the more general rule.

IV. Conclusion

We used the DAIS-ITA general scenario and have shown how the logistical resupply vignette can be extended. We presented descriptions of the monthly resupply missions and policy data with policy decisions. The utility of inductive logic as a method for learning generative policy models has been shown via experimentation. The ability to do this comes about through the inherent explainability of the context-sensitive grammar we use and has allowed us to show via interpreting the grammar into English that human rules (also written in English) can be learned. By extension of the context-sensitive grammar representing the model, generated policies can be created and enforced with a high level of confidence that they will behave within the original human-intended rule set.

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References

[1] G. White, S. Pierson, B. Rivera, M. Touma, P. Sullivan, and D. Braines, "Dais-ita scenario," in *Artificial Intelligence and Machine Learning for Multi-Domain Operations Applications*, vol. 11006. International Society for Optics and Photonics, 2019.

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[2] https://github.com/dais-ita/logistical-resupply-scenario/blob/master/Logistical-Resupply-Month1.csv

[3] https://github.com/dais-ita/logistical-resupply-scenario/blob/master/Logistical-Resupply-Month2.csv