Mitigating Data Scarcity in Machine Learning through Reinforcement Learning-based Data Generation

Anonymous Author(s)

ABSTRACT

Abstract here.

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1 INTRODUCTION

Data scarcity, which refers to a situation where there is an insufficient amount or quality of training data available to build an accurate and robust machine learning model, can negatively impact the performance and generalization of machine learning models and lead to poor predictions or classifications.

Data scarcity can manifest in two common cases. First, there may not be enough high-quality unlabeled data due to factors such as high costs of data collection, lack of access to relevant data sources, or data privacy and security constraints. Second, annotating unlabeled data can be a time-consuming and expensive process, even if enough high-quality data has been collected.

In the literature, various methods have been utilized to obtain high-quality (unlabeled) data, including data augmentation [], data synthesis [], and data acquisition []. Once this unlabeled data is collected, it can be labeled using human-labeling methods like crowdsourcing [] or expert sourcing [], or using machine-labeling methods like semi-supervised learning [] and weak supervision [].

Despite all efforts to collect, generate, and label data, a common phenomenon in machine learning is distribution shift, where the distribution of the train data differs from the distribution of the test data in downstream applications.

Problem. Our main research question in this paper is how to *generate sufficient high-quality unlabeled data that is relevant to downstream applications* and label it using inexpensive and automatic methods such as semi-supervised learning and weak supervision.

A positive answer to this question is crucial as it can help alleviate data scarcity in machine learning with minimal human cost.

Challenges. *Nan*[**Add after we have the technical sections.**]

Our Proposal. Our main idea is to train a generative model and then iteratively adapt it to the downstream application. More specifically, *Nan*[**Add more details later, including how XXX can be used to train the generative model and how reinforcement learning can be used to adapt it to the downstream application. These details will be explained at a conceptual level to ensure that readers can understand.**]

Contributions. Our contributions are summarized as follows:

(1)
(2)
(3) *Nan*[**If we can have a good summary of experiments, we can either add here or use a "stitle" section to highlight the empirical findings.**]

Roadmap.

2 PRELIMINARY

2.1 Problem Statement

Machine learning task.

The setting of our problems.

Input:

- A small training set with lots of unlabeled data
- A validation (test) set
- A user-specified downstream model

Output: A trained downstream model with best performance on the test set.

2.2 Deep Generative Models for Tables

2.3 Reinforcement Learning: A Primer

Nan[**We should give some background about generative models and RL – not sure how many reviewers know these in details.**]

3 FRAMEWORK OVERVIEW

Nan[**Draw a good figure and clearly explain each step.**]

(1)
(2)
(3)

Nan[**I found that many reviewers will complain that (1) the above figure is too complicated to understand, and (2) the explanation of the figure is not clear. If the reviewers can fully understand and appreciate this framework figure and we have good empirical results, it is more than 50% done.**]

4 SYNTHETIC DATA GENERATION

Nan[**This section should be only about data generation, no need to discuss RL, but we need to justify why we choose LSTM, not other models such as VAEs or diffusion models.**]

- (State) How to encode the features, *i.e.*, categorical feature and numerical data.
- (Action) The output of the generative model.
- (Model design) The RNN model.
- How to train the RNN model, *i.e.*, the Actor-Critic framework.

5 DATA EVALUATION

Nan[**This section should discuss the design of the RL part.**]

- Reward computation: how to compute the score for one tuple.

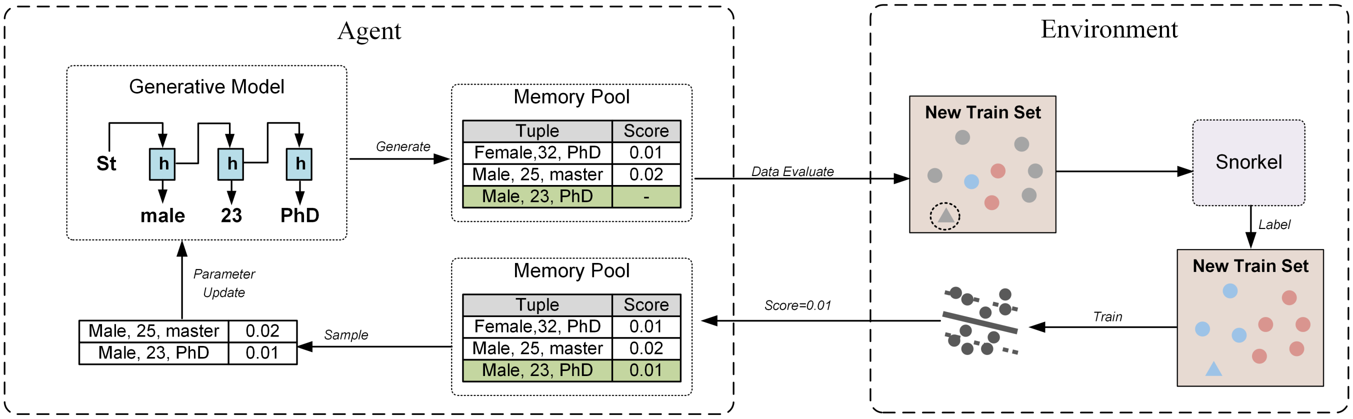

Figure 1: Framework

- How to use snorkel to label the data.
- Probabilistic label and downstream model training.

6 SYSTEM XXX

Nan[We should give a name of the system RLSyn?]

Nan[You can give an algorithm pseudocode here, about how to stitch Section 4 and Section 5 together, which must be consistent with the framework figure in Section 3.]

7 EXPERIMENT

Baselines

1. No new data (labeled data + unlabeled data + weak supervision)
2. No new data (labeled data + unlabeled data + Snorkel)
3. Few shot learning
4. Randomly generate data
5. GAN + Weak Supervision
6. GAN + Snorkel
7. Ours (Labeled data)
8. Ours + Snorkel

8 RELATED WORK

9 CONCLUSION

REFERENCES