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**MASTER THESIS**

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**Active learning in E-Commerce  
Merchant Classification using Website  
Information**

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Dedication.

Title: Active learning in E-Commerce Merchant Classification using Website Information

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Abstract: Data and the collection and analysis of data has become an important part of everyday life. For example, navigation, e-commerce, and social media all make use of immense amounts of data to provide users with suggestions on the best routes to take, which new items they might be most interested in, and which content might fit best with their interests. A variety of algorithms and methods exist to process the data and use it to make predictions. One such algorithm is xPAL, which is a decision-theoretic approach to measure the usefulness of a labeling candidate in terms of its expected performance gain. With xPAL and other active machine learning methods an optimal strategy can be explored to classify new data points.

Keywords: probabilistic active learning xPAL machine learning multi-class classification active learning

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# Introduction

One of the main challenges of creating a successful machine learning model is obtaining labeled data. With easy access to a variety of modern tools, devices, and sensors, we are able to rapidly collect unlabeled data. But, in supervised learning, prediction models are trained using labeled data. The problem is that acquiring labels for the collected data can be expensive, time-consuming, or even impossible in some cases.

However, methods have been developed to help reduce the time required to label this data. Active learning is a semi-supervised machine learning method where the model is trained with a smaller set of labeled data but also aims to exploit trends within the unlabeled data. Active learning has been heavily researched in the past but typically with binary data. Multi-class active learning research is still in its infancy.

Active learning is different from other machine learning methods because it uses the unlabeled data and some evaluation criteria to determine which candidate could be the most beneficial to the model if it was given a label. In summary, the model requests the label from some oracle that provides the label then it takes this new labeled data point and rebuilds the model. We describe it as semi supervised active learning because of the oracle (typically a human) involved in the process that provides the label for the requested candidate data.

In our case we have some data (website urls) of some merchants that are given to us from our partner. From this data our partner currently utilizes a human labor to browse the website and then label the url into some main category (23 labels) and then one of about 234 unique tags that branch from the main categories but still have some relation, or some newly generated tag. This is a repetitive and expensive task that could be automated using machine learning and other tools and free a person to work on some higher value task.

To reduce the burden of human labeling we propose creating a workflow using Scrapy, Postgres, and semi supervised Active Learning (bayesian, expected error, etc.) that only requires occasional interaction where a human can label a candidate that is most beneficial to the model such as using a decision-theoretic approach to measure the usefulness of a labeling candidate in terms of (expected) performance gain. The workflow takes the website as input, navigates to the webpage, collects the text data and adds it to a database. We then run the model using the data from the database and return the labeled data.

# 1. Machine Learning: Overview

## 1.1 The Basics

An agent is something that acts. A rational agent is one that acts so as to achieve the best outcome or, when there is uncertainty, the best expected outcome. Any component of an agent can be improved by learning from data. The improvements and techniques used to make them depend on four major factors:

- Which component is to be improved.
- What prior knowledge the agent already has.
- What representation is used for the data and the component.
- What feedback is available to learn from.

Here we will mostly be focused on the final point, "What feedback is available to learn from." but also slightly on the second point because we will incorporate Bayesian learning. There are three main types of feedback that determine the three main types of learning which are unsupervised, reinforcement, and supervised learning.

In unsupervised learning an agent learns patterns even though no feedback is provided. In reinforcement learning, the agent learns from a series of rewards or punishments. In supervised learning, an agent learns from input-output pairs, which can be discrete or continuous, to find a function that maps the pairs.

The goal of supervised learning is given a training set of  $N$  example input-output pairs:

$$(x_1, y_1), (x_2, y_2), \dots (x_N, y_N),$$

where each  $y_j$  was generated by some unknown function  $y = f(x)$ , find a function  $h$  that approximates the true function (Russell and Norvig [2009]).

In reality, the lines separating the types of learning aren't so clear. Semi-supervised learning is also an important and widely used method. In semi-supervised learning we are given a few labeled examples and must make the most of a large collection of unlabeled examples.

## 1.2 Active Learning

Supervised learning models almost always get more accurate with more labeled data. Active learning is the process of deciding which data to sample for human annotation. Many active learning strategies exist, but three basic approaches work well in most contexts: uncertainty, diversity, and random sampling. A combination of the three is usually a good starting point.

It should be noted that we can sample  $n$  candidates where  $n \geq 1$  depending on our preferences.

### **1.2.1 Random Sampling**

Random sampling is rather self explanatory as we randomly select an unlabeled data point from the pool and have a human provide a label.

### **1.2.2 Diversity Sampling**

Diversity sampling is the set of strategies for identifying unlabeled items that are underrepresented or unknown to the machine learning model in its current state. The items may have features that are unique or obscure in the training data, or they might represent data that are currently under-represented in the model. Either way this can result in poor or uneven performance when the model is applied or the data is changing over time. The goal of diversity sampling is to target new, unusual, or underrepresented items for annotation to give the algorithm a more complete picture of the problem space.

### **1.2.3 Uncertainty Sampling**

Uncertainty sampling is the set of strategies for identifying unlabeled items that are near a decision boundary in your current machine learning model. If you have a binary classification task, these items will have close to a 50% probability of belonging to either label; therefore, the model is called uncertain or confused. These items are most likely to be wrongly classified, so they are the most likely to result in a label that differs from the predicted label, moving the decision boundary after they have been added to the training data and the model has been retrained (Munro [2021]).

### **1.2.4 Bayesian Learning**

### **1.2.5 Expected Error Reduction**

### **1.2.6 Summary**

After we select and label the candidate data we retrain the model with the updated data and we continue this process as new data is obtained or until we are satisfied with the performance of the model



## 2. Related Works

Ideas listed here... is related works a good topic to discuss next?

### 2.1 Probabilistic Active Learning

### 2.2 Multiclass Probabalistic Active Learning

### 2.3 xPAL

# Conclusion

# Bibliography

Robert Munro. *Human-in-the-loop machine learning*. Manning Publications, New York, NY, July 2021.

Stuart Russell and Peter Norvig. *Artificial Intelligence: A Modern Approach*. Prentice Hall, Upper Saddle River, NJ, 3rd edition, 2009. ISBN 9780136042594.

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# List of Abbreviations

# A. Attachments

## A.1 First Attachment