Improving Learning-to-Defer Algorithms Through Fine-Tuning

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Abstract

The ubiquity of AI leads to situations where humans and AI work together, creating the need for learning-to-defer algorithms that determine how to partition tasks between AI and humans. We work to improve learning-to-defer algorithms when paired with specific individuals by incorporating two fine-tuning algorithms and testing their efficacy using both synthetic and image datasets. We find that fine-tuning can pick up on simple human skill patterns, but struggles with nuance, and we suggest future work that uses robust semi-supervised to improve learning.

1 Introduction

The rise of neural technologies has led to the adoption of AI-based solutions for human-facing tasks in fields such as health care [Tran et al. (2019)] and criminal justice [Washington (2018)]. In some situations, humans and AI collaborate to solve a problem by partitioning tasks so AI solves problems that are difficult for humans. Determining task partitions is done through a learning-to-defer algorithm, which uses a human performance model to take human skill into account. Numerous studies [Mozannar and Sontag (2020); Raghu et al. (2019); Wilder et al. (2020)] have developed learning-to-defer algorithms using confidence-based [Raghu et al. (2019)] and joint learning methods [Mozannar and Sontag (2020); Okati et al. (2021)], which learn rejector and classifier functions simultaneously.

Learning-to-defer algorithms can be used with specific individuals, such as an individual doctor working with an AI to classify X-ray images. In these situations, learning-to-defer algorithms can be improved by fine-tuning their underlying human performance models. Fine-tuning exploits human skill variation to improve system performance. For example, when AI classifies X-ray images, learning-to-defer algorithms should tune to the doctor's expertise. We incorporate fine-tuning into learning-to-defer algorithms, addressing an open research question [De et al. (2021)]. To do this, we develop two fine-tuning methods and demonstrate their efficacy on both synthetic and image data [Krizhevsky et al. (2009)]. Our contributions are as follows. We (1) develop fine-tuning methods which allow human-AI models to be individual specific and (2) apply this to autonomous driving and image recognition tasks.
2 Problem Statement

We define the problem of human-AI collaboration for classification and learning-to-defer algorithms. We consider the problem of classifying data points $x_1, \ldots, x_n$, which have true labels $y_1, \ldots, y_n$. Data points $x_1, \ldots, x_n$ have human annotations $h_1, \ldots, h_n$. The problem is to develop functions $a$ and $m$ that partition and solve the task, so if $a(x_i) = 0$, the task is solved by a human, and if $a(x_i) = 1$, then the task is solved by a machine, $m$, which is a classification function. The objective function is then to maximize

$$\sum_{i=0}^{n} \begin{cases} h_i = y_i & a(x_i) = 0 \\ m(x_i) = y_i & a(x_i) = 1 \end{cases}.$$  \hspace{1cm} (1)

To develop the function $a$, we’re given the following:

1. Aggregate human data: a set of points (for training) consisting of data points $w_1, \ldots, w_m$, human labels $g_1, \ldots, g_m$ (aggregated across multiple humans), and true labels $z_1, \ldots, z_m$.
2. Specific human data: a set of points (for fine-tuning and testing) consisting of data points $v_1, \ldots, v_k$ ($k < m$), human labels from an individual $f_1, \ldots, f_k$, and true labels $t_1, \ldots, t_m$.
3. Non-human labeled data points: a set of points (for imputing human labels) consisting of data points $u_1, \ldots, u_p$ ($k < m < p$) and truth labels $s_1, \ldots, s_p$.

3 Learning-to-defer algorithms

We describe three learning-to-defer algorithms, each of which uses data in different ways to develop the function $a$: a non-fine-tuning baseline and two approaches that incorporate fine-tuning.

3.1 Baseline Non-fine-tuning

We describe the state-of-the-art learning-to-defer algorithm [Mozannar and Sontag (2020)]. The algorithm first develops a human performance model, $\hat{h}$, which is trained on all human performance data, $w_i$ and $v_i$, and outputs whether a human will answer a data point correctly. After learning $\hat{h}$, human performance labels are imputed on data points $u_1 \cdots u_p$, so all three data types have human labels. Afterward, the learning-to-defer function $a$, and the machine classification function, $m$, are learned simultaneously by reformulating as a $k + 1$ classification problem and using a modified cross-entropy loss function that takes into account the cost of deferral. See Section [Mozannar and Sontag (2020)] for full details of this approach.

3.2 Baseline Fine-tuning

We incorporate elements of fine-tuning into the state-of-the-art learning-to-defer algorithm to improve system accuracy for specific individuals. To do this, we modify the human performance model training, so $\hat{h}$ is first trained for $n$ epochs on aggregate human performance data, $w_i$, then trained for $n\lambda$ epochs on specific human performance data, $v_i$. To account for class imbalances, which could skew training due to small fine-tuning dataset size, we introduce a class-weighting scheme, which weights the loss function by the inverse frequency of each class.

3.3 Self-training

We adopt the self-training algorithm from semi-supervised learning as an alternative to the baseline [Chapelle et al. (2009)]. For self-training, we first train a human performance model using specific human data $v_i$. Using this basic model, we predict labels for the unlabeled data points, $u_i$, then select the high confidence predictions. We use these high confidence points to retrain the model, thereby using unlabeled data points to develop an individual-specific model.

4 Autonomous Vehicle Experiment

Human-AI collaboration naturally arises in the realm of autonomous vehicles, which requires deferral to humans depending on environmental circumstances. We develop a synthetic dataset based on autonomous driving, and show that fine-tuning learning-to-defer algorithms reduces trip durations.
Figure 1: Distribution of time taken with/without fine-tuning and ideally. Each data point represents the average trip duration when fine-tuning on one driver, over 128 testing trips. Fine-tuning outperforms no fine-tuning by 30 seconds, showing that fine-tuning can assist autonomous vehicles.

4.1 Experimental Setup

We consider vehicle deferral for a given driver, \( i \), given rain condition, \( 0 \leq r \leq 1 \), and darkness condition, \( 0 \leq d \leq 1 \). Our dataset consists of \( n \) total drivers, each of whom have a mean driving time, \( \mu \sim \text{Poisson}(35) \), a rain driving time, \( \mu_r \sim \text{Poisson}(5) \), and a darkness driving time, \( \mu_d \sim \text{Poisson}(5) \). Given \( \mu, \mu_r, \) and \( \mu_d \), the amount of time necessary to drive a trip in conditions \((r,d)\) is distributed according to

\[
N(\mu, \sigma) + rN(\mu_r, \sigma_r) + dN(\mu_d, \sigma_d)
\]  

We generate \( k \) such trips for each driver; for drivers, \( j \neq i \), the points are for training, while for driver \( i \), the points are split equally between fine-tuning and testing. Autonomous vehicles have three options: they can defer to humans, drive independent of conditions in time \( N(\mu_a, \sigma_a) \), or drive dependent on conditions in time \( N(\mu_b, \sigma_b) + rN(\mu_x, \sigma_x) + dN(\mu_y, \sigma_y) \), where \( \mu, \sigma \) are constants chosen to make it possible for the system to reduce average trip time by making accurate defer decisions. This forces autonomous vehicles to learn both a rejector and classifier function, emulating the joint classification-rejection problem. To assist with learning, an additional \( l \) unlabeled \((r,d)\) pairs are presented. We provide further experimental details in Appendix C.

4.2 Experimental Results

To analyze the results, we compute the ideal time, which chooses knowing trip durations beforehand and ignores randomness, and known mean, which chooses based on known \( \mu \) values. Both of these serve as lower bounds on average trip duration.

We find that fine-tuning reduces average trip duration by 30 seconds compared to not fine-tuning, while knowing \( \mu \) values can reduce trip durations by 2 minutes 30 seconds. Fine-tuning reduces trip duration error by 20% (i.e., it achieves 20% of achievable reduction if \( \mu \) values were known), and our results are significant with \( p < .001 \). While the medians between the two learning-to-defer methods are close, the means are wider apart due to large outliers when not fine-tuning.

5 CIFAR-10 Experiments

We use the CIFAR-10 image classification task to assess the impact of fine-tuning on human-AI collaboration, using both synthetic human models and real human annotation data.

5.1 Experiment Setup

This task asks users to classify 32x32 images into one of ten non-overlapping categories [Krizhevsky et al. (2009)]. We consider the effect of fine-tuning when having synthetic or real experts work with AI image classifiers.

As in [Mozannar and Sontag (2020)], we create synthetic experts parameterized by \( k \), which indicates perfect accuracy on the first \( k \) image classes, and random guesses on the last \( 10 - k \). Each synthetic expert annotates 500 images, while real experts annotate 200 images, which are split 50% - 50% for fine-tuning and testing. For human expert data, we select 11 annotators from CIFAR-10H [Peterson et al. (2019)].

We begin by training a human performance function \( \hat{h} \) to predict expert success on an image, outputting 0 if correct, and 1 otherwise. We train a WideResNet model [Zagoruyko and Komodakis].
on aggregate human data from CIFAR-10H, then fine-tune on data from a single synthetic or real expert. For self-training, after training \( \hat{h} \), we impute predictions on the 50k training labels that lack human predictions, then retrain using high confidence points. We use the fine-tuned human performance model to learn a combined rejector-classifier, which is an 11-class WideResNet model that outputs 0-9 to predict a class, and 10 to defer. We evaluate system accuracy over the test images and compare three different approaches: no fine-tuning, baseline fine-tuning, and fine-tuning with self-training.

5.2 Results

![Figure 2: Human model and system accuracy for synthetic annotators. Fine-tuning improves human model accuracy, especially for low values of \( k \), though fails to consistently improve system accuracy.](image)

Our takeaways from the synthetic and real annotator experiments are:

1. **Fine-tuning can improve expert prediction in some situations.** For synthetic experts, fine-tuning improves human model accuracy, particularly for low values of \( k \) (Figure 2). However, fine-tuning fails to consistently outperform not fine-tuning for real annotators, potentially due to lack of learnability. Synthetic experts may pose an easier challenge when compared to real annotators with more nuanced strengths and weaknesses.

2. **Correlation between human and system accuracy.** For real experts, when baseline fine-tuning improves human model accuracy, system accuracy also improves 75% of the time.

![Figure 3: Human model and system accuracy for real annotators. Fine-tuning doesn’t consistently improve human model; however, when it helps, system accuracy also tends to improve.](image)

Our results indicate that fine-tuning can pick up on simple patterns of skill, but struggles with nuance. We can potentially improve fine-tuning by exploring more sophisticated semi-supervised learning algorithms, such as graph-based techniques [Subramanya and Talukdar (2014)], which can then boost system accuracy.
6 Conclusion

We explore the use of individual-specific human-AI collaboration algorithms. We find that tailoring learning-to-defer algorithms to individuals through fine-tuning can improve human model and system accuracy in some situations. However, initial fine-tuning approaches struggle to consistently improve human model performance for real experts, though can improve system performance when they do. We propose investigating more advanced semi-supervised techniques to address this.
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A Related Works

**Human-AI Collaboration.** Collaboration between humans and machines has been explored in various domains including finance [Nagar and Malone (2011)] and healthcare [Patel et al. (2019)]. Collaboration is beneficial as information from both sources can be combined to make decisions [Nagar and Malone (2011)]. However, collaboration has risks, as algorithmic predictions can anchor and bias human predictions [Vaccaro and Waldo (2019)]. This problem is further exacerbated when AI solutions are accompanied by explanations [Bansal et al. (2021a)], as humans are more liable to accept explanations regardless of their veracity. However, the problem can be mitigated through the development of human mental models, which acknowledge deficits in AI performance [Bansal et al. (2019)].

**Learning to defer.** One area of research within human-AI collaboration is learning to defer, where AI systems defer to humans when unsure. For classification problems, the AI system consists of a rejector, which determines whether or not to defer, and a classifier, which solves the task. One strategy is to calculate confidence scores for AI and humans, and defer based on whichever is higher [Raghu et al. (2019); Madras et al. (2017)]. However, these confidence-based approaches ignore the interconnectedness of the rejector and classifier by training the classifier independently. Ideally, the classifier should be trained to focus on tasks that are hard for humans, and to solve this, prior work has developed a joint learning algorithm to simultaneously learn a rejector and classifier through the use of a new loss function [Wilder et al. (2020); Mozannar and Sontag (2020)]. In the case of SVMs, prior work has shown theoretically and experimentally that learning-to-defer algorithms outperform humans and machines separately [De et al. (2021)]. Extensions to the learning-to-defer approach include algorithms for multiple experts [Keswani et al. (2021)] and human-initiated deferral [Bansal et al. (2021b)]. Our work most directly builds on prior work by Mozannar et al. [Mozannar and Sontag (2020)], and responds to a call from De et al. [De et al. (2021)] to develop human-AI collaboration algorithms that can be adapted to specific humans.

B Hyperparameters

For our autonomous vehicle experiments, we use $\sigma = 5$, $\sigma_r = \sigma_d = 2$, $\mu_a = 45$, $\sigma_a = .001$, $\mu_b = 40$, $\sigma_b = 5$, $\mu_x = \mu_y = 5$, $\sigma_x = \sigma_y = 2$. Additionally, for both experiments, for baseline fine-tuning, we use $\lambda = 2$.

C Autonomous Vehicle Details

We train a human performance model and a joint rejector-classifier function, which returns 0 to defer, 1 to drive independent of conditions, and 2 to drive dependent on conditions. We use a feed-forward neural network to model both the rejector-classifier and the human performance model. We compare the baseline with and without fine-tuning to develop the human performance model, and use the model to impute predictions for unlabeled data. For our experiments, we use $n = 10$, $k = 256$, and $l = 1000$. 

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