Slice Tuner: A Selective Data Acquisition Framework for Accurate and Fair Machine Learning Models

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ABSTRACT
As machine learning becomes democratized in the era of Software 2.0, a serious bottleneck is acquiring enough data to ensure accurate and fair models. Recent techniques including crowdsourcing provide cost-effective ways to gather such data. However, simply acquiring data as much as possible is not necessarily an effective strategy for optimizing accuracy and fairness. For example, if an online app store has enough training data for certain slices of data (say American customers), but not for others, obtaining more American customer data will only bias the model training. Instead, we contend that one needs to selectively acquire data and propose Slice Tuner, which acquires possibly-different amounts of data per slice such that the model accuracy and fairness on all slices are optimized. This problem is different than labeling existing data (as in active learning or weak supervision) because the goal is obtaining the right amounts of new data. At its core, Slice Tuner maintains learning curves of slices that estimate the model accuracies given more data and uses convex optimization to find the best data acquisition strategy. The key challenges of estimating learning curves are that they may be inaccurate if there is not enough data, and there may be dependencies among slices where acquiring data for one slice influences the learning curves of others. We solve these issues by iteratively and efficiently updating the learning curves as more data is acquired. We evaluate Slice Tuner on real datasets using crowdsourcing for data acquisition and show that Slice Tuner significantly outperforms baselines in terms of model accuracy and fairness, even when the learning curves cannot be reliably estimated.

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1 INTRODUCTION
In the era of Software 2.0 [3], machine learning (ML) is becoming democratized where successful applications range from recommendation systems to self-driving cars. Software engineering itself is going through a fundamental shift where trained models are the new software, and data becomes a first-class citizen on par with code [30]. Training a model to use in production requires multiple steps including data acquisition and labeling, data analysis and validation, model training, model evaluation, and model serving, which can be a complicated process for ML developers. In response, end-to-end ML platforms [9, 39] that perform all of these steps have been proposed.

As ML applications become more diverse and possibly narrow, acquiring enough training data is becoming one of the most critical bottlenecks. We explicitly use the terminology data acquisition to make a distinction with the broader problem of data collection [33], which also includes labeling existing data as in active learning [34] or weak supervision [32]. Instead in data acquisition, the goal is to obtain the right amounts of new data from other data sources. Unlike well-known problems like machine translation where there is decades’ worth of parallel corpora to train models, most new applications have little or no training data to start with. For example, a smart factory application for quality control may need labeled images of its own specific products. In response, there has been significant progress in data acquisition research [33] including dataset discovery [29], crowdsourcing [1], and even simulator-based data generation [25]. As a result, it is reasonable to assume that new training data can now be acquired at will given enough budget.

When acquiring data for ML, a common misconception is that more data leads to better models. However, this claim does not always hold when the goal is to improve both the model accuracy and fairness, which are not always aligned. Let us divide the data into subsets called slices. For example, a company selling apps online may divide its customer purchase data by region as shown in Figure 1 (each box indicates a slice where the height is the slice’s size). Say that the company not only wants to ensure that its app recommendations are accurate overall, but evenly accurate (i.e., fair) for customers in different regions. Since the company already has enough data for American customers (the slice size is largest), acquiring more American customer data (gray part in Figure 1a) is not only unnecessary, but may bias the training data and influence the model’s accuracy on other regions.

We thus propose a selective data acquisition framework called Slice Tuner, which determines how much data to acquire for each slice. Not all slices have the same data acquisition cost-benefits, which means that acquiring the same amounts of data may result in different improvements in model loss for different slices. Hence, the native strategy of acquiring equal amounts of data per slice is not necessarily optimal. Alternatively, acquiring data such that all slices end up having equal amounts of training data is not always optimal either. (This approach is similar to the Water filling algorithm [31]; details in Section 2.2.) Instead, we would like a data acquisition...
strategy such that the models are accurate and similarly-accurate for different slices. To measure model accuracy, we use loss functions like logistic loss. For fairness we use an extension of equal error rates [36, 38], which is one of the widely-accepted definitions of fairness along with other traditional ones like demographic parity [17] and equalized odds [20]. Interestingly, equal error rates is a familiar concept in systems research where it is important to have similar performance across different partitions of data. The key challenge is to figure out the different cost benefits of the slices and estimate how much data to acquire for each slice given a budget. In Figure 1b, we may want to acquire even amounts of data only for non-America regions.

At the core of Slice Tuner is the ability to estimate the learning curves of slices, which reflect the cost benefits of data acquisition. It is well known that the impact of data acquisition on model loss is initially large, but eventually plateaus [35]. That is, lowering the loss becomes difficult to the point where it is not worth the data acquisition effort. Figure 2 shows hypothetical learning curves of two slices. Recently, multiple studies [12, 15, 22] show that these curves usually follow a power law according to empirical results in machine translation, language modeling, image classification, and speech recognition. Given the learning curves, Slice Tuner “tunes” the slices by determining how much data to acquire for each slice such that the model accuracy and fairness on all slices are optimized while using a limited budget for data acquisition.

As a toy example, suppose there are two slices $s_1$ and $s_2$ of the same size. Say the current model losses of the two slices are 5 and 3, respectively. Hence, the loss of the entire data is 4. According to Definition 1 in Section 2.1, we compute the unfairness as $\text{avg}([5-4, |3-4|] = 1$. Now suppose we estimate their two learning curves as shown in Figure 2. Notice that the curve of $s_2$ is rather flat, so acquiring more data does not have as much benefit as acquiring for $s_1$. Suppose we have a budget of acquiring examples using crowdsourcing. Since $s_1$ has a better cost-benefit, we may decide to only acquire examples for $s_1$. The actual numbers would depend on the result of the optimization problem. As a result, say the model losses of $s_1$ and $s_2$ are now 2 and 3, respectively, and that the entire data now has a loss of 2.4 ($s_1$ is now larger than $s_2$, so the average loss is closer to 2 than 3). In that case, the unfairness improves by decreasing to $\text{avg}([2-2.4, 3-2.4]) = 0.5$.

While learning curves are potentially useful, in reality we cannot assume they will be generated in perfection. Instead, the key technical challenge we address is generating learning curves that are “reliable enough” to still benefit Slice Tuner using data management techniques. There are largely two obstacles. First, slices may not have enough data for the model losses to be precisely measured. Second, acquiring data for one slice may “influence” the model’s losses on other slices and thus distort their learning curves. Slice Tuner solves these problems by iteratively updating the learning curves as more data is acquired so that the learning curves are up-to-date. In addition, Slice Tuner exploits the learning curves by doing a relative comparison of losses, so perfectly predicting the absolute losses in each learning curve is not necessary.

In our experiments, we use various real datasets to show that Slice Tuner outperforms other baselines in terms of model loss and unfairness, even when the learning curves are not reliable. We also demonstrate the real scenario of acquiring new data using crowdsourcing via Amazon Mechanical Turk [1] for the image dataset UTKFace [40] and show that Slice Tuner is effective even if the data is acquired from a completely different data source.

A remaining question is how to define the slices themselves. Data slicing can either be done manually [4] or automatically [14]. While Slice Tuner can run on any set of slices, a desirable property of a slice is to be unbiased such that acquiring any example that belongs to it has a similar effect on model loss as any other possible example. In this work, we assume the slices are provided by the user, but also discuss possible solutions in Appendix A.

To democratize ML, it is important to help users to not only analyze their models, but also fix any problems easily. To our knowledge, Slice Tuner is the first system to provide concrete action items of how much data to acquire per slice to make models both accurate and fair. We also release our code and crowdsourced dataset as a community resource [2].

The rest of the paper is organized as follows:

- We cover preliminaries and formulate the problem of selective data acquisition (Section 2).
- We describe Slice Tuner’s architecture (Section 3).
- We propose accurate and efficient methods for estimating the learning curves of slices (Section 4).
- We propose selective data acquisition algorithms (Section 5).
We evaluate Slice Tuner on real datasets and show that it outperforms baselines by obtaining better model accuracy and fairness results using the same data acquisition budget, even if the learning curves cannot be reliably estimated (Section 6).

2 PROBLEM DEFINITION

2.1 Preliminaries

Data Slicing. We denote by $D$ the training data set with examples where each example $e \in D$ has features and a label. Without loss of generality, we assume all examples have equal weights when training a model. $D$ can be divided into slices $S = \{s_i\}_{i=1}^n$ where each $s_i \subseteq D$. We assume that the slices partition $D$, i.e., $\bigcup_i s_i = D$. A typical way to define a slice is to use conjunctions of feature-value pairs, e.g., $\text{region} = \text{Europe} \land \text{gender} = \text{Female}$. We can also use the label feature for the slicing. For example, the Fashion-MNIST dataset [37] contains images that represent items, e.g., shoes and shirts. Here, we can define a slice for each item. The slices can be found automatically or set manually by a domain expert. Although there is no restriction in defining a slice, a desirable property is that the slice is unbiased such that adding a new example to it has a similar effect on the model accuracy as any other example. We assume the slices are provided by users, but also discuss possible solutions in Appendix A where the idea is to iteratively divide slices until they are unbiased using decision tree methods.

Model Accuracy and Fairness Measures. We assume a model $M$ is trained on $D$ or its subsets. We also assume a classification loss function $\ell(s, M)$ that returns a performance score on how well $M$ predicts the labels of the dataset $s$. A common loss function for binary classification is log loss, which is $\frac{1}{m} \sum_{i=1}^m -y^{(i)} \log \hat{y}^{(i)} - (1 - y^{(i)}) \log (1 - \hat{y}^{(i)})$. Our setting can be generalized to other ML problems (multi-class classification and regression) by using the appropriate loss functions. Throughout the paper, we will use loss to measure accuracy.

Our notion of fairness extends equalized error rates [36], which has the definition $Pr(\hat{y} \neq y | z = 0) \approx Pr(\hat{y} \neq y | z = 1)$ where $\hat{y}$ is the model prediction, $y$ is the label, and $z$ is a sensitive attribute like gender. We make the straightforward extension that the model error rates must be similar among any number of groups that are not necessarily defined with sensitive attributes. Equalized error rates is one of the standard fairness measures along with demographic parity [17] and equalized odds [20]. We choose equalized error rates because it is important for any ML product that needs to provide similar service quality to customers of different demographics. This fairness is also a familiar notion in systems research where a system should perform well on different partitions of data.

We propose the following unfairness measure that is used to obtain equalized error rates:

**Definition 1.** The unfairness of the slices is defined as the average absolute difference between the loss of a slice and the entire data $D$:

$$\text{avg}_{s_i \in S} |\ell(s_i, M) - \ell(D, M)|.$$

Notice that the unfairness measure does not require sensitive attributes and can thus be used on any dataset. We can also think of other variations such as computing the maximum absolute difference instead of the average.

Data Acquisition Cost. We assume that any data acquisition technique can be used to acquire data by paying a certain cost. Nowadays, dataset discovery systems [29] can help find relevant datasets. In addition, crowdsourcing tools like Amazon Mechanical Turk [1] or real-world simulators [25] can be used to generate data at will.

We abstract the data acquisition methods and define a cost function $C(s)$ that returns the cost to acquire an example in slice $s$. Even for the same data source, the data acquisition cost may vary by slice. For example, acquiring face images of large groups (e.g., $\text{race} = \text{White}$) may be easier than images of smaller groups (e.g., $\text{race} = \text{Native Hawaiian}$). We assume that within the same slice, the cost to acquire an example is the same. As more examples are acquired for $s$, $C(s)$ may increase possibly because data becomes scarcer. However, we assume that data is acquired in batches (e.g., when using Amazon Mechanical Turk, we use a fixed budget at a time) and that $C(s)$ is a constant for each batch.

Slice Dependencies. Slices may have dependencies where acquiring data for one slice may influence the learning curves of other slices. For example, if there are two independent slices $s_1$ and $s_2$, and we acquire too much data for $s_1$, the model may overfit and have a worse accuracy on $s_2$. If $s_2$ is similar to $s_1$ content-wise, then the accuracy on $s_2$ can actually increase as well. If there are no dependencies, the slices are considered independent of each other. We discuss how to handle slice dependencies in Section 5.2.

2.2 Selective Data Acquisition

We now define the problem of selective data acquisition.

**Definition 2.** Given a set of examples $D$, its slices $S = \{s_i\}_{i=1}^n$, a trained model $M$, a data acquisition cost function $C$, and a data acquisition budget $B$, the selective data acquisition problem is to acquire $d_i$ examples for each slice $s_i \in S$ such that the following are all satisfied:

- The average loss $\ell(D, M)$ is minimized.
- The unfairness $\text{avg}_{s_i \in S} |\ell(s_i, M) - \ell(D, M)|$ is minimized, and
- The total data acquisition cost $\sum_i C(s_i) \times d_i \leq B$.

We note that minimizing loss and unfairness are correlated, but not necessarily the same and thus need to be balanced (Section 6.3.2 studies the tradeoffs). In some cases, making sure slices have similar losses may also result in the lowest loss. For example, if there are two independent slices with identical learning curves, and one of them has less data, then simply making the two slices have the same amount of data results in the optimal solution. However, there are cases where the two objectives are not aligned. Continuing our example, suppose that the two slices now have different learning curves where the slice with less data has a curve that is lower than the other curve and also decreases more rapidly. In this case, acquiring data for the smaller slice would lower loss, but increase unfairness. Instead, the optimal solution could be to also acquire some data for the larger slice to lower the loss without sacrificing too much fairness.

Our problem can be viewed as a special type of multi-armed bandit problem as we discuss in Section 7.

Baselines for Comparison. Recall we described two data acquisition baselines in Section 1. Both methods are reasonable starting
and Data

As a result, it is critical for Slice Tuner to minimize the amount of data acquisition at the expense of possibly using more computation and simulation, there is still a fair amount of manual work involved. Crowdsourcing is used. Even if there are tools for dataset searching, there are different learning curves. In a worst-case scenario, $s_1$ may already have a low loss and does not need more data acquisition whereas $s_2$ may have a high loss and can benefit from more data. In this case, acquiring equal amounts of data will result in both suboptimal loss and unfairness. The second baseline is to acquire data such that all slices have similar amounts of data in the end, which can be viewed as a Water filling algorithm (Figure 3b). The implicit assumption is that all slices require similar amounts of data to obtain similar losses. However, this assumption does not hold if the two slices have different losses even if they have the same size. Continuing from the above worst-case scenario, if $s_1$ is smaller than $s_2$, then we will end up acquiring data for $s_1$ unnecessarily and again get suboptimal results. What we need instead is a way to utilize the learning curves and solve an optimization problem to determine how much data to acquire for each slice.

Another possible baseline is to acquire data in proportion to the original data distribution [12]. However, this approach does not fix data bias at all, so we considered it strictly worse than the baselines above. Also, we re-emphasize that active learning is not a comparable technique because it labels existing data instead of acquiring new data.

3 SYSTEM OVERVIEW

We describe the overall workflow of Slice Tuner as shown in Figure 4. Slice Tuner receives as input a set of slices and their data and estimates the learning curves of the slices by training models on samples of data. We explain the details of the estimation methods in Section 4. Next, Slice Tuner performs the selective data acquisition optimization where it determines how much data should be acquired per slice in order to minimize the loss and unfairness. As data is acquired, the learning curves can be iteratively updated. We propose selective data acquisition algorithms in Section 5.

We discuss the runtime requirements of Slice Tuner. Looking at Figure 4, we consider the Data Acquisition step to be the most expensive process done as a batch process, especially if manual crowdsourcing is used. Even if there are tools for dataset searching and simulation, there is still a fair amount of manual work involved. As a result, it is critical for Slice Tuner to minimize the amount of data acquisition at the expense of possibly using more computation for estimating learning curves and performing the optimization.

4 LEARNING CURVE

A learning curve is a projection of how a model trained on the entire dataset will perform on a particular slice $s$ as a function of the number of examples in $s$. Assuming that the examples are helpful to the model training, we expect the loss to decrease as more examples are added. However, this trend may not always hold due to multiple factors: the examples may be noisy and actually harm the model training, the examples may be biased and only represent a small part of the slice, or the model training itself may be unstable, all of which may result in non-monotonic behavior. Despite the complexity, we believe it is reasonable to assume that more training data on an unbiased slice generally leads to lower loss, but that the benefits have diminishing returns. Unlike existing work, a significant challenge for Slice Tuner is to plot the learning curves on slices, which can be arbitrarily smaller than the entire data. We first discuss how to efficiently estimate learning curves using data management in this section and then how to handle unreliable learning curves in Section 5.

4.1 Estimation

A key property we exploit is that training data benefits the model accuracy, but more collection has diminishing returns. A recent work from Baidu [22] conducted an analysis on learning curves (see Figure 5). The curve starts with the small-data region, where models try to learn from a small number of training data and can only make “best guess” predictions. According to our experience, tens of examples is enough to move beyond this region. For more data, we can see a power-law region of the form $y = bx^{-a}$, where new training examples provide useful information to improve the predictions. For real-world applications, a lower bound error may exist due to errors such as mislabeled data that cause incomplete generalization. Hence, we then see a diminishing-returns region where there is a minimum loss that cannot be reduced. In this case, one may also model the learning curve using the form $y = bx^{-a} + c$ [22] where $c$ is the lower-bound loss. However, if not enough data has been acquired to observe diminishing returns, fitting the curve $y = bx^{-a}$ works better [22]. Another study [15] compares 11 parametric models including variations of exponential models and custom models.
Based on these works, a power-law curve fits as well as any other curve.

To fit a learning curve of a slice, we first divide its data into train and validation sets. Although the train set may be small, we do assume a validation set that is large enough to evaluate models. This assumption is reasonable in the common setting where we start with some initial data and would like to acquire more examples. We then train models on random subsets of the train set with different sizes and generate data points by evaluating the models on the validation set. How many data points to generate depends on how much time we are willing to invest to estimate the learning curve. Each time we train a model on a subset of data, we also combine that data with the rest of the slices. (Section 4.2 presents a more efficient method for generating data points.) Since the model losses on smaller subsets are less reliable (depicted as having high variance Figure 5), we give weights to subsets that are proportional to their sizes and use a non-linear least squares method [18] for curve fitting. We further improve reliability by drawing multiple curves (we use 5) and averaging them at the expense of more computation.

In the worst case when all subsets are in the small-data region, then Slice Tuner may not benefit from learning curves, but in that case would fall back to performing like baselines. If there is enough data in a slice to be in the diminishing return region, we do not need to do any special handling because Slice Tuner will simply acquire data for other slices that need more data.

4.2 Efficient Implementation

We now discuss better data management techniques for more efficient learning curve fitting. Given the slices \( S \), suppose we generate for each slice \( K \) random subsets of data to fit a power-law curve. In addition, we may repeatedly update the learning curves \( U \) times using our iterative algorithms in Section 5.2. We would thus have to train a model \( |S| \times K \times U \) times. A typical setting in our experiments is \( |S| = 10, K = 10, \) and \( U = 5 \), which means that we may train a model 500 times. Moreover, if we train a model on a subset of a slice plus the rest of the slices, then the rest of the slices could be relatively too large for the model to properly train on the subset due to the data bias. Moreover, each model training may take a long time because the rest of the slices are repeatedly used for training in their entirety.

We thus propose an amortization technique to drastically reduce the number of model trainings. Instead of taking an \( X\% \) subset of one slice and leaving the rest as is to train each model, we take \( X\% \) subsets of all slices and train a model. This model is then evaluated on each of the slices to generate different learning curves independently. This approach assumes that taking subsets of other slices does not affect the model accuracy on the current slice. In reality, this independence assumption does not hold, so Slice Tuner solves the problem by periodically updating the learning curves as we explain in Section 5.2. As a result, the number of model trainings becomes independent of the number of slices and reduces to \( O(K \times U) \). In our example above, number 500 reduces to about 50. In addition, each model training is on average faster than the exhaustive approach above because it is performed on smaller data (\( X\% \) subsets). Finally, the learning curves can be generated in parallel, so using more nodes further reduces the wall-clock time.

Another possible optimization is to use a chain of transfer learning where a model trained on one subset is re-used to train the model of the next subset faster and so on. This approach has the potential to reduce the average model training time, although the time complexity remains the same. However, a downside is that hyperparameter tuning becomes significantly more complicated where we may need to use different learning rates for subsequently-trained models, so we do not use this optimization in our experiments.

5 SELECTIVE DATA ACQUISITION

We first tackle the selective data acquisition problem to minimize model loss and unfairness when slices are independent of each other and then extend our methods to the case where slices may influence each other.

5.1 Independent Slices

We first assume that slices do not influence each other. Hence, we only need to solve the optimization problem once. The optimization should be done on all slices as our objective for minimizing loss and unfairness is global. We can formulate a convex optimization problem for selective data acquisition as follows. For the slices \( \{s_i\}_{i=1}^n \) with sizes \( \{|s_i|\}_{i=1}^n \), we want to find the number of examples to acquire for the slices \( \{d_i\}_{i=1}^n \) to minimize the objective function using a total budget of \( B \). We assume that the model’s loss on a slice follows a power-law curve of the form \( b_i(|s_i| + d_i)^{-a_i} \), where \( b_i \) and \( a_i \) are positive values. We define \( A \) to be the average loss across all slices and \( C(s_i) \) to be the cost function that captures the effort to acquire an example for \( s_i \). The optimization problem is then

\[
\min \sum_{i=1}^n b_i(|s_i| + d_i)^{-a_i} + \lambda \sum_{i=1}^n \max \left\{ 0, \frac{b_i(|s_i| + d_i)^{-a_i}}{A} - 1 \right\}
\]

subject to \( \sum_{i=1}^n C(s_i) \times d_i = B \)
Influence

We now consider the case where slices can influence each other. We hypothesize that the relative sizes of the slices (i.e., the bias) and the data similarities between slices play major roles. Figure 6 shows a synthetic example to demonstrate this point. Suppose that we start with three slices (circle, triangle, and square) in Figure 6a where the colors (black and white) indicate the labels. The straight line indicates the decision boundary of the model. Now suppose we evenly increase the data for all slices by 50% as shown in Figure 6b. Since the bias does not change, the decision boundary does not change much either, which means that there is little influence on any of the slices. However, if we only increase the size of the triangle slice as shown in Figure 6c, suppose where the first term minimizes the loss, and the second term minimizes unfairness by giving a penalty to each slice $s_i$ that has a higher loss than $A$. If the loss of $s_i$ is lower than $A$, we return 0 to prevent the second term from giving a negative value. Since minimizing loss and unfairness are not always aligned, we introduce the $\lambda$ term to balance between minimizing each of them. By acquiring data for slices with higher losses, we eventually satisfy Definition 1.

This problem is convex assuming that the model’s loss decreases monotonically against more data. The first loss term $b_i(\|s_i\| + d_i)^{-a_i}$ is a convex function of $d_i$ because it is a power-law curve. The second unfairness term is also convex because $b_i(\|s_i\| + d_i)^{-a_i}$ is convex, $A$ is a constant for the current $D$, and taking a maximum between two convex functions is convex. Finally, $C(s_1)$ is a constant that varies by slice. Hence, we can derive an optimal solution efficiently using any off-the-shelf convex optimization solver.

**Algorithm.** The One-shot algorithm updates the learning curves using the techniques in Section 4.2 and solves the above optimization problem to determine how much data to acquire for each slice. Note that One-shot always uses the entire budget $B$, assuming the learning curves are perfect, and the slices are independent.

### 5.2 Dependent Slices

We now consider the case where slices can influence each other. Suppose that there are two slices $s_1$ and $s_2$. If we acquire data for $s_1$ such that it dominates $s_2$ in quantity, then the model training may overfit on $s_1$. Consequently, the model accuracy on $s_2$ may change. Hence, we need to iteratively update the learning curves as more data is acquired. Notice that the iterative updates also serve the dual purpose of making the learning curves more reliable.

**Modeling the Influence.** We hypothesize that the relative sizes of the slices (i.e., the bias) and the data similarities between slices play major roles. Figure 6 shows a synthetic example to demonstrate this point. Suppose that we start with three slices (circle, triangle, and square) in Figure 6a where the colors (black and white) indicate the labels. The straight line indicates the decision boundary of the model. Now suppose we evenly increase the data for all slices by 50% as shown in Figure 6b. Since the bias does not change, the decision boundary does not change much either, which means that there is little influence on any of the slices. However, if we only increase the size of the triangle slice as shown in Figure 6c, suppose the new bias causes the decision boundary to shift towards the left and influences the losses of the square and circle slices. The direction of influence depends on the similarity of data among slices. In our case, the square slice has the same label values as the triangle slice, and its loss decreases as all examples are categorized correctly. On the other hand, the circle slice has different label values than the triangle slice, and its loss increases.

To verify our hypothesis, we perform an experiment on the real UTKFace dataset [40] where we use slices that represent different race and gender combinations of people (more details in Section 6.1). We use imbalance ratio [11], which is the maximum ratio between any two slices in $S$, as a proxy for bias. For example, if the slices $s_1$, $s_2$, and $s_3$ have sizes 10, 20, and 30, respectively, then the imbalance ratio is $\frac{\max\{10,20,30\}}{\min\{10,20,30\}} = \frac{30}{10} = 3.0$. We also define influence on a slice as the change in loss. According to our hypothesis, if the imbalance ratio changes, the magnitude of influence increases as well. We then observe the effect of imbalance ratio on influence as shown in Figure 7. Initially, all the slices are of the same size 300, except for the slice White_Male, which starts from size 50. As we add more examples only to White_Male, the imbalance ratio change increases, causing the influences on other slices to increase in magnitude as well. While most slices have increasing losses, only the slice White_Female shows decreasing losses because it has similar data. We make similar observations in other datasets as well.

**Algorithm.** We iteratively update the learning curves whenever “enough” influence occurs, regardless of its direction. The Iterative algorithm (shown in Algorithm 1) limits the change of imbalance ratio to determine how much data to acquire for each slice. We obtain the slice sizes and initialize the imbalance ratio absolute change limit $T$ to 1. While there is enough budget for data acquisition, we increase $T$ per iteration using one of the strategies discussed later. The parameter $L$ specifies the minimum slice sizes to start with and is positive. If any slice is smaller than $L$, we acquire enough examples assuming there is enough budget. (In Section 6.3.4, we show that $L$ can be a small value.) We then run the One-shot algorithm to derive how many examples to acquire for each slice if we use the entire budget $B$. If the imbalance ratio change would exceed $T$ if we use the entire budget, we limit the number of examples acquired by multiplying num examples with the maximum ratio...
that would not allow that to happen (change_ratio). This problem has nonlinear constraints, and the getChangeRatio function uses an off-the-shelf optimization library in SciPy to derive a solution. After reflecting B, T, and IR, we repeat the same steps until we run out of budget.

For example, suppose L = 10, and there are two slices s1 and s2 with initial sizes of 5 and 10 (i.e., sizes = [5, 10]) with a budget of B = 55. First, we need to acquire 5 examples for s1 (i.e., num_examples = [5, 0]) to satisfy L (Step 4). Then we update sizes to [10, 10] and B to 50 (Steps 5–6). Then we set IR to 2. After running One-shot, suppose that num_examples = [10, 40] (Step 9). If we acquire all this data, the imbalance ratio would become 10/40 = 0.25, so |After IR − IR| = 2.5 - 0.25 = 2.25. To avoid exceeding T = 1, we compute the change ratio x such that \(\frac{10 + 40}{55} = 2\) by invoking the getChangeRatio function (Step 3). The solution is x = 0.5, and num_examples thus becomes 0.5 × [10, 40] = [5, 20]. After acquiring the data, we update sizes, B, T, and IR and go back to Step 8.

We now discuss strategies for updating the limit T per iteration using the increaseLimit function. On one hand, it is desirable to minimize the number of iterations of Algorithm 1 because each iteration invokes the One-shot algorithm, which involves updating the learning curves and solving an optimization problem. On the other hand, we would like to update the learning curves to be as accurate as possible. While there are many ways to update T, we propose the following representative strategies:

- **Conservative**: For each iteration, leave T as a constant, which limits the imbalance ratio to change linearly. The advantage is that we can avoid mistakenly acquiring too much data due to inaccuracies in the learning curves. However, the number of iterations may be high.
- **Moderate**: For each iteration, increase T by a constant c. Compared to Conservative, this approach reduces the number of iterations, but may acquire data unnecessarily.
- **Aggressive**: For each iteration, multiply T by a constant c > 1. Compared to Moderate, this strategy collects data even more aggressively using possibly fewer iterations.

### 6 EXPERIMENTS

In this section, we evaluate Slice Tuner on real datasets and address the following questions:

- How reliable and efficient is the learning curve generation used in Slice Tuner?
- How does Slice Tuner compare with the baselines in terms of model loss and unfairness?
- How does Slice Tuner perform on small slices where the learning curves are unreliable?

Slice Tuner is implemented in TensorFlow [6] and Keras, and we use Titan RTX GPUs for model training.

#### 6.1 Setting

**Datasets.** We experiment on the following four datasets that capture different characteristics of the slices. While the AdultCensus dataset is the most widely-used in the fairness literature, Slice Tuner is not limited to any particular dataset because our unfairness measure (Definition 1) does not require sensitive attributes (e.g., race and gender).

- Fashion-MNIST [37]: Contains images that can be categorized as one of 10 type of clothes, e.g., shoes, shirts, pants, and more. Here we slice the images according to their labels, i.e., there are 10 slices in total.
- Mixed-MNIST: Combines the Fashion-MNIST dataset and MNIST dataset[27], which contains images that represent digits from 0 to 9. Created to demonstrate a dataset with a large number (20) of non-homogeneous slices from two data sources.
- UTKFace [40]: Contains various face images of people of different (male and female) gender and race (White, Black, Asian, and Indian), used for race classification. We used 8 slices by combining two genders and four races, e.g., Black female.
- AdultCensus [26]: Contains people records with features including age, education, and sex. Used to predict which people make over $50K per year. We use 4 slices by combining two races (White and Black) and two genders (male and female).

**Data Acquisition and Cost Function.** For the Fashion-MNIST, Mixed-MNIST, and AdultCensus datasets, we first simulate data acquisition by starting from a subset and adding more examples. This
approach is reasonable because we are not tied to any data acquisition technique. We also define the cost function to always return 1. For the UTKFace dataset, we use a real scenario where we crowd-source new images using Amazon Mechanical Turk (AMT) [1] and store them in Amazon S3. We design a task by asking a worker to find new face images of a certain demographic (e.g., slice = White_Women) from any website. We pay 4 cents per image found, employ workers from all possible countries, and acquired images during 8 separate time periods. We do not show the workers all the images acquired so far, so they may acquire duplicate images. However, the duplicate rate is not as high as one may think because workers around the world use a wide range of websites to acquire images. Some workers make mistakes and acquire incorrect images that do not fit in the specified demographic. Hence, we include a post-processing step of filtering obvious errors manually, removing exact duplicates, and cropping faces using Google Cloud AI Platform services. We also define the collection cost of a slice to be the average time (seconds) to acquire images for the 8 UTKFace slices. Interestingly, the collection costs can be quite different. For example, an Indian woman image takes 50% longer to acquire than a Black male image and thus has a cost of 1.5.

| W_M W_F B_M B_F A_M A_F I_M I_F | Avg. time (s) | Cost C |
|-----------------------------------|--------------|--------|
|                                   | 82.1 81.9 67.6 79.3 94.8 77.5 91.6 104.6 | 1.2 1.2 1 1.2 1.4 1.1 1.4 1.5 |

Table 1: The collection costs of UTKFace slices are proportional to the average times to finish tasks. Here W = White, B = Black, I = Indian, A = Asian, M = Male, and F = Female.

Methods Compared. We compare the following methods:

- Uniform (baseline 1): collects similar amounts of data per slice.
- Water filling (baseline 2): collects data such that the slices end up having similar amounts of data.
- One-shot: updates the learning curves and solves the optimization problem once and collects data as described in Section 5.1. As a default, we set \( \lambda = 1 \).
- Iterative: iteratively updates the learning curves and collects data as described in Section 5.2. We use three iteration strategies for increasing \( T \) per iteration: Conservative (fixes \( T \) to 1), Moderate (increases \( T \) by 1), and Aggressive (multiplies \( T \) by 2).

We use the efficient implementation method (Section 4.2) to fit learning curves for all experiments.

Measures. We use the model loss and unfairness measures described on our discussions in Section 2.1. For all measures, lower values are better. We report mean values over 10 trials for all measures.

- Loss: the average log loss for multi-class classification.
- Average Equalized Error Rates (Avg. EER): the unfairness measure in Definition 1, i.e., the avg. loss difference between a slice and the entire data.
- Maximum Equalized Error Rates (Max. EER): same as avg. EER, except that we take the maximum loss difference instead of the average. Used to understand the worst-case unfairness.

For each slice, we split the available data into train and validation sets and measure the loss on the validation set. We set the validation set size to be 500 per slice.

Models and Hyperparameter Tuning. For the Fashion-MNIST, Mixed-MNIST, and UTKFace datasets, we use basic convolutional neural networks with 2–3 hidden layers. For the AdultCensus dataset, we train a fully connected network with no hidden layers. For all datasets, we initially set the hyperparameters using simple grid search. Afterwards, we do not further change the hyperparameters while running Slice Tuner for consistent model training.

6.2 Learning Curve Analysis

We analyze our learning curve estimation method described in Section 4. For each slice, we take \( K = 10 \) random samples of the data with differing sizes and use a non-linear least squares method to fit a curve. Figure 8 shows two learning curves for each dataset where the x-axis is the subset size, and the y-axis is the loss on a validation set. Here we only observe power-law regions and not the small-data regions (see Figure 5) because the initial slice sizes are large enough. As the subset size increases, the loss decreases as well. Even for the most homogeneous dataset Fashion-MNIST, the learning curves can be different, resulting in different amounts of data acquisition for the slices.

We also observe how the learning curve changes as the slice itself grows in size. That is, we increase the slice size and, for each size, fit a new learning curve. Figure 9 shows the learning curves for a slice in the Fashion-MNIST dataset. As a result, the smaller the slice, the more the learning curve deviates from the others. This result shows that the learning curves must be updated as more data is acquired, especially for slices that start small.

6.3 Selective Data Acquisition Optimization

We now show the loss and unfairness results of Slice Tuner and make a comparison with the baselines.

6.3.1 Loss and Unfairness of Slice Tuner Methods. Table 2 compares the loss and unfairness results of the Slice Tuner methods on the four datasets. Original is where we train a model on the current slices with no data acquisition. As a result, the Slice Tuner methods improve Original both in terms of loss and unfairness. Among the Slice Tuner methods, the iterative methods outperform One-shot. Between the Aggressive and Conservative methods, Conservative usually has lower loss and unfairness than Aggressive. This result is expected because Conservative uses more iterations to update the learning curves to be more reliable. Finally, Moderate and Aggressive perform similarly, although Moderate has lower loss and unfairness on the Fashion-MNIST dataset.

Table 3 shows how much data is acquired for each method in Table 2 for the four datasets. For each dataset, the initial slice sizes (same as \( L \)) are specified in the Original row. While One-shot has only one chance to decide how much data to collect, the Aggressive, Moderate, and Conservative methods have more chances to adjust their results. For example, on the Fashion-MNIST dataset, One-shot oversamples and collects too much data for slices #4 and #6 while the other methods properly adjust their learning curves through more
Figure 8: The learning curves of the four datasets. The initial slice sizes are set to be large enough so we only observe power-law regions without small-data regions. For each dataset, we show two learning curves for different slices fitted using a validation set. Even for seemingly-homogeneous slices in the Fashion-MNIST dataset, the learning curves can be quite different.

Figure 9: Given a slice in the Fashion-MNIST dataset, we increase its size and train new learning curves. As a result, the learning curves trained on small slices deviate more from the other curves and can be viewed as erroneous.

Table 2: Slice Tuner methods comparison on the 4 datasets.

| Dataset       | Method     | Loss    | Avg./Max. EER |
|---------------|------------|---------|---------------|
| Fashion-MNIST | Original   | 0.423   | 0.255 / 0.617 |
|               | One-shot   | 0.327   | 0.174 / 0.542 |
|               | Aggressive | 0.304   | 0.144 / 0.351 |
|               | Moderate   | 0.302   | 0.134 / 0.319 |
|               | Conservative | 0.300  | 0.134 / 0.313 |
| Mixed-MNIST   | Original   | 0.299   | 0.198 / 0.691 |
|               | One-shot   | 0.266   | 0.181 / 1.169 |
|               | Aggressive | 0.225   | 0.119 / 0.395 |
|               | Moderate   | 0.227   | 0.115 / 0.398 |
|               | Conservative | 0.223  | 0.111 / 0.489 |
| UTKFace       | Original   | 0.590   | 0.097 / 0.207 |
|               | One-shot   | 0.578   | 0.077 / 0.197 |
|               | Aggressive | 0.572   | 0.069 / 0.184 |
|               | Moderate   | 0.572   | 0.069 / 0.184 |
|               | Conservative | 0.572  | 0.069 / 0.184 |
| AdultCensus   | Original   | 0.264   | 0.104 / 0.168 |
|               | One-shot   | 0.253   | 0.094 / 0.150 |
|               | Aggressive | 0.252   | 0.094 / 0.144 |
|               | Moderate   | 0.252   | 0.094 / 0.144 |
|               | Conservative | 0.251  | 0.093 / 0.144 |

6.3.2 Balancing \( \lambda \). We study the effect of balancing \( \lambda \). Recall that a higher \( \lambda \) means there is more emphasis on optimizing fairness. How to set \( \lambda \) depends on whether the loss or unfairness is more important to minimize for the given application. Table 4 shows the loss and unfairness results on the four datasets when varying \( \lambda \) using the Moderate method and the same initial data and budget as in Table 3. As \( \lambda \) increases, the avg. and max. EER results decrease while the loss increases.

Table 5 shows the amounts of data acquired per slice for different \( \lambda \) values using the Fashion-MNIST dataset. The results for the other datasets (not shown) are similar. In our example, slices #2, #4, and #6 start with higher losses than other slices, and the experiments with higher \( \lambda \) values results tend to be more aggressive in acquiring data for those three slices in order to reduce the unfairness.

6.3.3 Comparison with Baselines. We make a detailed comparison between Moderate and the baselines Uniform and Water filling in Table 6 where we use three settings: (1) a basic setting where slices have the same amounts of data, (2) a pathological setting for Uniform (called “Bad for Uniform”) where there are many slices with low loss, and (3) a pathological setting for Water filling (called “Bad for Water filling”) where there is a large slice with high loss and a small slice with low loss. For each setting, we compare the three methods using a budget of \( B = 3K \) except for the AdultCensus dataset where \( B = 300 \) is already enough to obtain low loss. As a result, Moderate has both lower loss and avg. EER than the baselines for all datasets. Looking at the two baselines, Uniform performs worse than Water filling in setting (2) while Water filling performs worse in setting...
Table 3: Selective data acquisition results for the experiments in Table 2 where slices are listed numbered from 0 up to 9 (the ordering is not important). For Mixed-MNIST, we select 10 out of the 20 slices. The Original row contains the initial number of examples for each slice while the other rows show the additional number of examples acquired.

| Dataset          | Method   | 0    | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | # iterations |
|------------------|----------|------|------|------|------|------|------|------|------|------|------|--------------|
| Fashion-MNIST    | Original | 200  | 200  | 200  | 200  | 200  | 200  | 200  | 200  | 200  | n/a |              |
|                  | One-shot | 76   | 40   | 761  | 397  | 2203 | 177  | 1829 | 268  | 247  | 1   | 1            |
|                  | Aggressive | 888  | 59   | 1373 | 693  | 1290 | 40   | 1400 | 112  | 145  | 0   | 4            |
|                  | Moderate | 657  | 45   | 1336 | 755  | 1239 | 36   | 1701 | 96   | 135  | 0   | 4            |
|                  | Conservative | 671  | 3    | 1296 | 599  | 1495 | 40   | 1627 | 82   | 173  | 14  | 9            |
| Mixed-MNIST      | Original | 150  | 150  | 150  | 150  | 150  | 150  | 150  | 150  | 150  | n/a |              |
|                  | One-shot | 14  | 166  | 47   | 120  | 1092 | 637  | 521  | 2557 | 1   |    |              |
|                  | Aggressive | 1   | 63   | 7    | 163  | 933  | 818  | 597  | 1202 | 1552 | 4  |              |
|                  | Moderate | 1   | 0    | 63   | 99   | 738  | 1225 | 744  | 989  | 1500 | 5  |              |
|                  | Conservative | 1   | 2    | 68   | 6    | 133  | 790  | 1076 | 736  | 1360 | 10 |              |
| UTKFace          | Original | 400  | 400  | 400  | 400  | 400  | 400  | 400  | 400  | 400  | n/a |              |
|                  | One-shot | 470  | 427  | 242  | 519  | 448  | 311  | 1263 | 238  | 637  | 1  |              |
|                  | Aggressive | 667  | 384  | 158  | 489  | 560  | 337  | 930  | 818  | 597  | 2  |              |
|                  | Moderate | 667  | 384  | 158  | 489  | 560  | 337  | 930  | 818  | 597  | 2  |              |
|                  | Conservative | 667  | 384  | 158  | 489  | 560  | 337  | 930  | 818  | 597  | 2  |              |
| AdultCensus      | Original | 400  | 400  | 400  | 400  | 400  | 400  | 400  | 400  | 400  | n/a |              |
|                  | One-shot | 0    | 0    | 55   | 445  | 921  | 233  | 969  | 504  | 963  | 1  |              |
|                  | Aggressive | 1   | 0    | 64   | 164  | 969  | 504  | 963  | 233  | 921  | 2  |              |
|                  | Moderate | 1   | 0    | 63   | 99   | 738  | 1225 | 744  | 989  | 1500 | 5  |              |
|                  | Conservative | 1   | 2    | 68   | 6    | 133  | 790  | 1076 | 736  | 1360 | 10 |              |

Table 4: Selective data acquisition results for the Fashion-MNIST experiments in Table 4.

| Dataset          | Method | 0    | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    |
|------------------|--------|------|------|------|------|------|------|------|------|------|------|
| Fashion-MNIST    | Original | 200  | 200  | 200  | 200  | 200  | 200  | 200  | 200  | 200  | n/a  |
|                  | λ = 0  | 284  | 0.160 / 0.402 |
|                  | λ = 0.1 | 285  | 0.148 / 0.330 |
|                  | λ = 1  | 302  | 0.129 / 0.330 |
|                  | λ = 10 | 317  | 0.112 / 0.217 |
| Mixed-MNIST      | Original | 150  | 150  | 150  | 150  | 150  | 150  | 150  | 150  | 150  | n/a  |
|                  | λ = 0  | 208  | 0.136 / 0.582 |
|                  | λ = 0.1 | 212  | 0.134 / 0.444 |
|                  | λ = 1  | 219  | 0.120 / 0.462 |
|                  | λ = 10 | 224  | 0.116 / 0.468 |
| UTKFace          | Original | 150  | 150  | 150  | 150  | 150  | 150  | 150  | 150  | 150  | n/a  |
|                  | λ = 0  | 637  | 0.077 / 0.159 |
|                  | λ = 0.1 | 639  | 0.076 / 0.144 |
|                  | λ = 1  | 651  | 0.065 / 0.160 |
|                  | λ = 10 | 651  | 0.058 / 0.148 |
| AdultCensus      | Original | 150  | 150  | 150  | 150  | 150  | 150  | 150  | 150  | 150  | n/a  |
|                  | λ = 0  | 246  | 0.104 / 0.170 |
|                  | λ = 0.1 | 247  | 0.105 / 0.168 |
|                  | λ = 1  | 248  | 0.104 / 0.166 |
|                  | λ = 10 | 248  | 0.104 / 0.165 |

Table 4: Results of Moderate when varying λ.

(3). For all experiments, Moderate mostly performs 1–3 iterations as shown in the parentheses in Table 6.

Figure 10 shows a more detailed comparison with the baselines using the basic setting above (i.e., setting (1)) and the Mixed-MNIST dataset. Here the two baselines happen to have the same loss and unfairness results. For varying budgets, Moderate clearly outperforms the two baselines in terms of loss and unfairness. Although the improvements in loss are not as drastic as those in unfairness, they are still significant: in order to obtain the same losses, the baselines need to increase their budgets by 15–100%.

We also perform the experiments with ResNet-18 [21] (one of the state-of-the-art models for image classification) using the basic setting and the Fashion-MNIST dataset. The results are in Appendix B, and the trends are similar to Table 6 where Moderate outperforms the baselines in terms of loss and unfairness.

6.3.4 Unreliable learning curves. Learning curves are not always “perfect” in the sense that they cleanly follow a power law. For
6.4 Efficient Learning Curve Generation

We evaluate the efficient learning curve generation method described in Section 4.2 as shown in Table 8. The default Moderate method uses the efficient learning curve generation. We make a comparison with a modified version of Moderate where the learning curve generation is done exhaustively (called "Exhaustive"). We also vary the initial slice size and budget. As a result, Moderate is 11-12x faster than Exhaustive as expected and obtains slightly worse or even better loss and unfairness results. While it may sound counter intuitive that the optimized Slice Tuner’s performance should fall back to those of the baselines. In a sense, the learning curves are used as hints and do not have to be perfect. However, as more data is acquired, the learning curves will gradually become more reliable and informative.

**Table 6: A detailed comparison of Moderate(Mod) against the two baselines – Uniform(Uni) and Water filling(WF) – on the four datasets where we use three settings and vary the budget B. We also set \( \lambda = 0.1 \).**

| Dataset     | Measure | Alg. | Basic Initial 3000 | Basic Initial 3000 | Bad for Uniform Initial 3000 | Bad for Uniform Initial 3000 | Bad for Water filling Initial 3000 | Bad for Water filling Initial 3000 |
|-------------|---------|------|--------------------|--------------------|-------------------------------|-------------------------------|----------------------------------|----------------------------------|
| Fashion-MNIST | Loss (# Iters) | Uni | 0.472 ± 0.002 | 0.355 ± 0.003 | 0.341 ± 0.002 (3) | 0.314 ± 0.002 (2) | 0.310 ± 0.002 (3) | 0.322 ± 0.003 |
| | WF | 0.355 ± 0.003 | 0.445 ± 0.003 | 0.323 ± 0.002 | 0.426 ± 0.002 | 0.330 ± 0.003 |
| | Mod | 0.355 ± 0.003 | 0.445 ± 0.003 | 0.323 ± 0.002 | 0.426 ± 0.002 | 0.330 ± 0.003 |
| | Avg. EER | Uni | 0.283 ± 0.006 | 0.230 ± 0.004 | 0.226 ± 0.007 | 0.177 ± 0.003 | 0.175 ± 0.002 |
| | WF | 0.230 ± 0.004 | 0.308 ± 0.009 | 0.217 ± 0.005 | 0.210 ± 0.004 | 0.200 ± 0.003 |
| | Mod | 0.173 ± 0.006 | 0.168 ± 0.003 | 0.157 ± 0.002 | 0.157 ± 0.003 | 0.157 ± 0.003 |
| Mixed-MNIST | Loss (# Iters) | Uni | 0.301 ± 0.003 | 0.240 ± 0.002 | 0.229 ± 0.002 | 0.266 ± 0.002 | 0.228 ± 0.001 |
| | WF | 0.240 ± 0.002 | 0.264 ± 0.003 | 0.221 ± 0.002 | 0.266 ± 0.002 | 0.228 ± 0.001 |
| | Mod | 0.235 ± 0.001 (3) | 0.216 ± 0.002 (2) | 0.219 ± 0.002 (3) | 0.219 ± 0.002 (3) | 0.219 ± 0.002 (3) |
| | Avg. EER | Uni | 0.207 ± 0.004 | 0.182 ± 0.002 | 0.182 ± 0.002 | 0.166 ± 0.003 | 0.167 ± 0.002 |
| | WF | 0.182 ± 0.002 | 0.205 ± 0.004 | 0.166 ± 0.002 | 0.166 ± 0.003 | 0.167 ± 0.002 |
| | Mod | 0.147 ± 0.002 | 0.146 ± 0.002 | 0.133 ± 0.003 | 0.133 ± 0.003 | 0.133 ± 0.003 |
| UTKFace | Loss (# Iters) | Uni | 0.562 ± 0.003 | 0.554 ± 0.005 | 0.579 ± 0.003 | 0.575 ± 0.004 | 0.569 ± 0.003 (1) |
| | WF | 0.554 ± 0.005 | 0.611 ± 0.005 | 0.573 ± 0.004 | 0.597 ± 0.004 | 0.577 ± 0.003 |
| | Mod | 0.547 ± 0.004 (1) | 0.571 ± 0.004 (1) | 0.569 ± 0.003 (1) | 0.569 ± 0.003 (1) | 0.569 ± 0.003 (1) |
| | Avg. EER | Uni | 0.091 ± 0.005 | 0.081 ± 0.009 | 0.095 ± 0.004 | 0.087 ± 0.006 | 0.074 ± 0.005 |
| | WF | 0.081 ± 0.009 | 0.117 ± 0.006 | 0.090 ± 0.004 | 0.093 ± 0.007 | 0.072 ± 0.004 |
| | Mod | 0.071 ± 0.005 | 0.078 ± 0.005 | 0.072 ± 0.004 | 0.072 ± 0.004 | 0.072 ± 0.004 |
| AdultCensus | Loss (# Iters) | Uni | 0.263 ± 0.001 | 0.257 ± 0.001 | 0.254 ± 0.001 | 0.286 ± 0.001 | 0.284 ± 0.001 (2) |
| | WF | 0.257 ± 0.001 | 0.258 ± 0.001 | 0.247 ± 0.000 | 0.287 ± 0.001 | 0.288 ± 0.001 |
| | Mod | 0.253 ± 0.001 (1) | 0.245 ± 0.000 (1) | 0.284 ± 0.001 (2) | 0.284 ± 0.001 (2) | 0.284 ± 0.001 (2) |
| | Avg. EER | Uni | 0.103 ± 0.001 | 0.099 ± 0.000 | 0.106 ± 0.000 | 0.137 ± 0.002 | 0.137 ± 0.001 |
| | WF | 0.099 ± 0.000 | 0.109 ± 0.001 | 0.101 ± 0.000 | 0.137 ± 0.001 | 0.137 ± 0.001 |
| | Mod | 0.094 ± 0.000 | 0.100 ± 0.000 | 0.100 ± 0.000 | 0.100 ± 0.000 | 0.134 ± 0.001 |

Table 7: Loss and unfairness results of Slice Tuner methods for the small slice sizes of Fashion-MNIST.

| Init. Size | Method | Loss Avg. / Max. EER |
|-----------|--------|----------------------|
| 30        | Uniform | 0.583 / 0.317 / 0.792 |
| (B = 500) | Water filling | 0.508 / 0.302 / 0.786 |
|           | Moderate | 0.475 / 0.259 / 0.650 |

Figure 11: Learning curves are noisy for small slices of Fashion-MNIST.
of all slices together has the effect of removing bias among the slices. The reason the runtime speedups are larger than the number of slices (10) is that the model training itself is on average faster because it is performed on smaller data as explained in Section 4.2. We consider the runtimes of Moderate to be practical because the main bottleneck of Slice Tuner is the time to actually acquire data, which may take say hours.

### RELATED WORK

**Data Acquisition.** Acquiring data is becoming increasingly convenient. Dataset searching [29] focuses on finding the right datasets either on the Web or within a data lake. As a recent example, Google Dataset Search [10] started its service in 2016 with 500K public science datasets, but now has 30M datasets. Another traditional approach is crowdsourcing [1], where one can hire workers to generate new data. Yet another interesting branch of research is to use simulators [25] to generate infinite numbers of realistic examples. Slice Tuner complements these systems by determining how much data to acquire per slice based on a given ML model.

Although the notion of selective data acquisition seems relevant to active learning [34], they solve different problems. While active learning selects which existing unlabeled data to label, Slice Tuner decides how much non-existing data to acquire per slice. Hence, the active learning techniques do not apply for data acquisition.

The closest work to Slice Tuner is reference [12], which also acquires data to improve model accuracy and fairness. A key observation is that unfairness can be decomposed into bias, variance, and noise, and that data acquisition can reduce unfairness without sacrificing accuracy. Similar to Slice Tuner, reference [12] assumes that learning curves follow a power law. However, the learning curves are primarily used to improve fairness, and the data acquisition method is simplistic where the amounts of data acquired follow the original data distribution. In comparison, Slice Tuner takes the more sophisticated approach of using learning curves to optimize both accuracy and fairness and addresses the challenge of unreliable learning curves using efficient iterative updates.

Another close work [7] performs data acquisition such that all possible slices are large enough. This problem is analogous to Water filling (Figure 3b) where the slices are guaranteed a minimal data coverage, but in the more challenging setting where slices may overlap with each other, and there is a combinatorial explosion in the number of slices. In comparison, Slice Tuner assumes the slices partition the entire dataset and selectively acquires data to improve accuracy and fairness instead of achieving minimum coverage.

### 8 CONCLUSION

We proposed Slice Tuner, which performs selective data acquisition to optimize model accuracy and fairness. Slice Tuner estimates learning curves for different slices and solving an optimization problem to determine how much data acquisition is needed for each slice given a budget. To address the challenges of unreliable learning curves and dependencies among slices, we proposed iterative algorithms that repeatedly update the learning curves as more data is acquired, using the imbalance ratio change as a proxy to estimate influence. We demonstrated on real datasets that our iterative algorithms are efficient and obtain lower loss and unfairness than the two baseline methods that do not exploit the learning curves, even if the learning curves are unreliable. In addition, we demonstrated the practicality of Slice Tuner by acquiring new data using Amazon Mechanical Turk. In the future, we would like to improve our influence estimation and support overlapping slices.
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A DATA SLICING

In this section, we briefly discuss various approaches for data slicing. While this topic is not the main focus of this paper, it is worth discussing the state-of-the-art methods. The straightforward way is to select slices manually based on domain knowledge. For example, for a movie recommendation system, one may select slices based on genre. Alternatively, one can determine slices based on model analysis. Manual tools for visualization [4, 23] can be used to find problematic slices where a model underperforms. Recently, there are automatic tools [14] that can find such slices.

As we mentioned in Section 2.1, a desirable property of a slice is to be unbiased so that the acquired examples have similar effects on the model accuracy. Using large slices that are biased is undesirable. For example, a slice that contains all regions of Figure 1a is bad because there is a bias towards American customers. That is, adding an American customer example is not as helpful as say adding a European customer example. On the other hand, using slices that are not biased, but too small is also problematic because we may need to maintain many learning curves that are not accurate due to the small amounts of data.

In order to find the largest-possible slices that are still unbiased, one can use a method similar to decision tree training where the goal is to find partitions of the data such that the impurity (i.e., homogeneity of labels in leaf nodes) is minimized. Instead of minimizing impurity, we would have to compute the bias in slices using say an entropy-based measure. Starting from the entire dataset, we can iteratively split slices that have biases in their data for different values of attributes. The splitting can terminate once the average entropy is above some threshold.

B RESNET-18 RESULTS ON FASHION-MNIST

In Section 6, we used basic convolution neural networks and single fully connected layers for all experiments. In this section, we performed the same experiments with ResNet-18 [21] (one of the state-of-the-art models for image classification) using the basic setting and Fashion-MNIST dataset. In Table 9, the key trends are similar to Table 6 where Moderate outperforms baselines in terms of loss and fairness. Compared to the Fashion-MNIST results in Table 6, the losses actually increase because ResNet-18’s architecture is overly complex to train on the modest-sized Fashion-MNIST dataset.

C EXPONENTIAL DISTRIBUTION RESULTS

In Section 6.3.1, we evaluated the Slice Tuner methods when the initial slice sizes are the same. In this section, we perform the same experiments when the initial slice sizes follow an exponential distribution. In Table 10, the key trends are similar to Table 2 where iterative algorithms outperform One-shot because One-shot tends to acquire too much data for certain slices as shown in Table 11. Moreover, while Conservative uses more iterations than Aggressive and Moderate, it has slightly-better loss and unfairness results.

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### Table 9: Loss and unfairness results of Slice Tuner methods for the ResNet-18 on Fashion-MNIST.

| Init. Size | Method   | Loss  | Avg. / Max. EER |
|------------|----------|-------|-----------------|
| 400        | Original | 0.567 | 0.240 / 0.481   |
| (B = 3K)   | Uniform  | 0.484 | 0.228 / 0.452   |
|            | Moderate | 0.480 | 0.190 / 0.422   |

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### Table 10: Slice Tuner methods comparison on the 4 datasets where the initial slice sizes follow an exponential distribution as shown in Table 11.

| Dataset      | Method   | Loss  | Avg./Max. EER |
|--------------|----------|-------|---------------|
| Fashion-MNIST| Original | 0.455 | 0.260 / 0.911 |
|              | One-shot | 0.349 | 0.178 / 0.448 |
|              | Aggressive | 0.312 | 0.116 / 0.232 |
|              | Moderate | 0.308 | 0.125 / 0.306 |
|              | Conservative | 0.307 | 0.116 / 0.299 |
| Mixed-MNIST  | Original | 0.292 | 0.200 / 0.903 |
|              | One-shot | 0.249 | 0.157 / 0.934 |
|              | Aggressive | 0.231 | 0.124 / 0.465 |
|              | Moderate | 0.231 | 0.124 / 0.465 |
|              | Conservative | 0.223 | 0.117 / 0.381 |
| UTKFace      | Original | 0.710 | 0.170 / 0.369 |
|              | One-shot | 0.655 | 0.114 / 0.285 |
|              | Aggressive | 0.638 | 0.114 / 0.285 |
|              | Moderate | 0.638 | 0.114 / 0.285 |
|              | Conservative | 0.638 | 0.114 / 0.285 |
| AdultCensus  | Original | 0.274 | 0.107 / 0.172 |
|              | One-shot | 0.253 | 0.095 / 0.150 |
|              | Aggressive | 0.252 | 0.095 / 0.149 |
|              | Moderate | 0.252 | 0.095 / 0.149 |
|              | Conservative | 0.252 | 0.095 / 0.149 |
| Dataset        | Method    | 0  | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | # iterations |
|---------------|-----------|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|--------------|
| Fashion-MNIST | Original  | 400| 282 | 230 | 200 | 178 | 163 | 151 | 141 | 133 | 126 | n/a          |
|               | One-shot  | 0  | 0   | 596 | 192 | 1495| 201 | 3019| 371 | 128 | 0  | 1            |
|               | Aggressive| 434| 24  | 1406| 348 | 1299| 77  | 2136| 88  | 188 | 0  | 4            |
|               | Moderate  | 373| 74  | 1602| 1737| 396 | 617 | 61  | 558 | 965 | 42 | 5            |
|               | Conservative| 727| 51  | 1666| 1604| 641 | 780 | 47  | 951 | 790 | 79 | 9            |
| Mixed-MNIST   | Original  | 600| 346 | 268 | 200 | 189 | 180 | 166 | 160 | 154 | 145 | n/a          |
|               | One-shot  | 0  | 0   | 0   | 176 | 61  | 0   | 1457| 673 | 1136| 2008| 1            |
|               | Aggressive| 0  | 0   | 0   | 57  | 32  | 1432| 946 | 653 | 1309| 1356| 3            |
|               | Moderate  | 0  | 0   | 0   | 57  | 32  | 1432| 946 | 653 | 1309| 1356| 3            |
|               | Conservative| 0  | 0   | 0   | 90  | 59  | 800 | 936 | 730 | 1240| 1562| 6            |
| UTKFace       | Original  | 400| 263 | 206 | 174 | 152 | 136 | 124 | 114 | -   | -   | n/a          |
|               | One-shot  | 23 | 123 | 245 | 315 | 322 | 279 | 745 | 276 | -   | -   | 1            |
|               | Aggressive| 90 | 138 | 146 | 308 | 367 | 296 | 574 | 378 | -   | -   | 2            |
|               | Moderate  | 90 | 138 | 146 | 308 | 367 | 296 | 574 | 378 | -   | -   | 2            |
|               | Conservative| 90 | 138| 146 | 308 | 367 | 296 | 574 | 378 | -   | -   | 2            |
| AdultCensus   | Original  | 150| 106 | 86  | 75  | -   | -   | -   | -   | -   | -   | n/a          |
|               | One-shot  | 0  | 0   | 425 | 75  | -   | -   | -   | -   | -   | -   | 1            |
|               | Aggressive| 0  | 0   | 232 | 268 | -   | -   | -   | -   | -   | -   | 2            |
|               | Moderate  | 0  | 0   | 232 | 268 | -   | -   | -   | -   | -   | -   | 2            |
|               | Conservative| 0  | 0   | 232| 268 | -   | -   | -   | -   | -   | -   | 2            |

Table 11: Selective data acquisition results for the experiments in Table 10 where slices are listed numbered from 0 up to 9 (the ordering is not important), and their initial sizes follow an exponential distribution. For Mixed-MNIST, we select 10 out of 20 slices. The Original row contains the initial number of examples for each slice while the other rows show the additional number of examples acquired.