Methods for Individual Treatment Assignment: An Application and Comparison for Playlist Generation

CARLOS FERNANDEZ and FOSTER PROVOST, New York University
JESSE ANDERTON, BENJAMIN CARTERETTE, and PRAVEEN CHANDAR, Spotify

We present a systematic analysis of causal treatment assignment decision making, a general problem that arises in many applications and has received significant attention from economists, computer scientists, and social scientists. We focus on choosing, for each user, the best algorithm for playlist generation in order to optimize engagement. We characterize the various methods proposed in the literature into three general approaches: learning models to predict outcomes, learning models to predict causal effects, and learning models to predict optimal treatment assignments. We show analytically that optimizing for outcome or causal-effect prediction is not the same as optimizing for treatment assignments, and thus we should prefer learning models that optimize for treatment assignments. For our playlist generation application, we compare and contrast the three approaches empirically. This is the first comparison of the different treatment assignment approaches on a real-world application at scale (based on more than half a billion individual treatment assignments). Our results show (i) that applying different algorithms to different users can improve streams substantially compared to deploying the same algorithm for everyone, (ii) that personalized assignments improve substantially with larger data sets, and (iii) that learning models by optimizing treatment assignments rather than outcome or causal-effect predictions can improve treatment assignment performance by more than 28%.

CCS Concepts: • Information systems → Data mining;

Additional Key Words and Phrases: treatment assignment, treatment effects, predictive modeling

1 INTRODUCTION

Systems that make automated decisions are often deployed with the underlying goal of improving (rather than just predicting) outcomes. For instance, many recommendation engines are deployed with the intent of driving customer engagement rather than just predicting the items that customers are likely to choose. Therefore, even though issues in data collection, modeling, and deployment often make it hard for recommender systems to be directly optimized in terms of such goals, we should ultimately evaluate these systems in terms of their ability to improve the outcomes we care about (e.g., customer engagement). Our focal application is choosing, for each listener, which playlist generation algorithm to apply in order to maximize the number of song streams.

One may frame this type of decision as a treatment assignment problem [18], where each possible algorithm corresponds to a different ‘treatment’, and ideally we would like to assign each individual to the treatment associated with the highest number of streams. Of course, optimal treatments may vary from one individual to another depending on their characteristics and the context, which may be captured by various features. For example, algorithm A may work better for newer users, whereas algorithm B may work better for more experienced users. Thus, using statistical modeling, we could learn a treatment assignment policy from data to map individuals to optimal treatments based on features such as tenure.

The statistical estimation of treatment assignment policies from sample data has been studied across many different fields, including econometrics [18], data mining [15], and multi-armed bandits [5]. The first contribution of this paper
is to gather these various methods into three general approaches. The first approach is to learn a model that predicts outcomes for each treatment and assigns individuals to the treatment with the best predicted outcome. The second approach is to learn a model for heterogeneous causal-effect estimation that assigns individuals to the treatment with the largest predicted causal effect. Finally, the third approach consists of learning a weighted classification model, where the treatment assignment is the target variable and the outcome serves to weigh observations. Thus, the classification model may be used to predict (and assign) the treatment that will have the best outcome.

At a first glance, the three approaches may seem equivalent: they all seek to assign the treatment that is estimated to lead to the best outcome. However, as a second contribution, this paper highlights two key distinctions between them. The first distinction is their level of generality in terms of the tasks they can perform. For instance, models that predict outcomes may be used to estimate causal effects, whereas models that predict causal effects generally cannot predict outcomes. The second distinction is in the objective function each approach uses to learn models from data. The first approach optimizes models to predict outcomes, the second to predict causal effects, and the third to predict treatment assignments. As a result, each may lead to different treatment assignment policies. Importantly, our analysis shows that optimizing models to predict outcomes or causal effects is not the same as optimizing models for treatment assignment. Therefore, in theory, learning models that predict optimal treatments (the third approach) should lead to better treatment assignments than the other two approaches.

Finally, as a third contribution, we conduct a massive-scale experimental comparison of the three treatment assignment approaches in the context of music recommendations at Spotify. As we will describe in more detail below, each treatment corresponds to a different algorithm that could be used to build music playlists, and the goal is to maximize engagement (measured as number of song streams). To our knowledge, this is the first real-world, at-scale comparison of these three approaches. Apart from confirming our analytical findings, the experiment shows that (1) a heterogeneous treatment assignment policy can substantially improve total streaming compared to deploying the same algorithm for everyone, and that (2) larger data sets lead to significantly better policies, illustrating the advantages of running large-scale A/B tests for the purpose of gathering unconfounded training data.

2 TREATMENT ASSIGNMENT PROBLEM

This paper focuses on settings where a decision-maker wants to maximize the overall causal effect of decisions on an outcome of interest (e.g., deciding what playlist generation algorithm to use for each listener to maximally increase streams). We frame this as a treatment assignment problem, so that each possible alternative corresponds to a different treatment, and the goal is to assign individuals to the treatment that maximizes their outcome. In recent years, this problem has been approached from various methodological perspectives, including econometrics [6], uplift modeling [15], heterogeneous effect estimation [25], and multi-armed bandits [5]. This section provides an overview of the problem formulation.

We specifically consider settings in which decisions are independent and the treatment assignment policy is learned from historical data on previous decisions made at random. This implies that each decision affects a single unit (or instance) and there is no selection bias in the data. In the causal inference literature, the first assumption is also known as the Stable Unit Treatment Value Assumption (SUTVA) [7]. The second assumption ensures that there is no confounding in the data (i.e., unconfoundedness holds). The unconfoundedness assumption goes by many names in different fields, including ignorability [22], back-door criterion [19], and exogeneity [26]. Practically speaking, we use a carefully randomized A/B test to gather data where these assumptions hold.
Let $T$ be the treatment assignment variable and $Y$ be the observed outcome. We use potential outcomes to frame causality [23] and define $Y^j$ as the outcome we would observe if we were to assign treatment $j$. Therefore, $Y = Y^j$ if $T = j$, and the treatment that leads to the best outcome (on average) can be defined as:

$$T^* = \arg\max_j E[Y^j]$$  \hspace{1cm} (1)

Using historical data, one could estimate the best performing treatment by choosing the treatment with the largest mean ($\hat{E}$):

$$\hat{T} = \arg\max_j \hat{E}[Y|T = j]$$  \hspace{1cm} (2)

It is important to contrast our setting with a standard A/B test approach that compares multiple treatments across predefined populations. Such an approach does not directly apply to our setting, because we want to learn the individuals or subpopulations to which each treatment should be applied. Suppose individuals vary with respect to a set of variables (features) $X$. We can then think of a feature vector $x$ as a subpopulation where $X = x$ and formulate the optimal decision for subpopulation $x$ (on average) as:

$$T^*(x) = \arg\max_j E[Y^j|X = x]$$  \hspace{1cm} (3)

It should be clear that, without the argmax, the right-hand side is essentially the formulation of a statistical machine learning model. Applying statistical modeling frees us from specifying in advance what are the particular subpopulations of interest. In the next section, we will discuss various methods that have been proposed to estimate $T^*(x)$ from historical data, resulting in a treatment assignment policy, $\hat{T}(x)$. In our setting, we leverage the unconfounded data from a randomized A/B test to learn and evaluate models for treatment assignments conditioned on the individuals’ features.

In theoretical analyses, treatment assignment policies are typically evaluated in terms of their ability to minimize the expected difference between the best potential outcome that could possibly be obtained and the potential outcome that would be obtained by deploying the policy. This evaluation measure is also known as expected regret in decision theory:

$$\text{Regret} = E[Y^{T^*(X)} - Y^{\hat{T}(X)}].$$  \hspace{1cm} (4)

In our setting, minimizing expected regret is the same as maximizing the expected conditional outcome (across treatments):\(^1\)

$$E[Y^{\hat{T}(X)}]$$  \hspace{1cm} (5)

However, evaluating the causal effects of treatment assignment policies using historical data (as is typical when building standard machine learning models) is challenging because we do not observe all potential outcomes for any given individual; we only observe one potential outcome at a time. Therefore, if (for any given individual) the policy assigns a treatment that is different from the treatment that was assigned in the data, we do not know the corresponding potential outcome. Fortunately, given a data set of $N$ individuals from a randomized A/B test, we can still obtain an unbiased and consistent estimate of Equation 5 (see [16] for a detailed proof):

$$\frac{1}{N} \sum_{i=1}^N 1(\hat{T}(x_i) = t_i) \frac{y_i}{P(t_i)},$$  \hspace{1cm} (6)

\(^1\)This formulation may be extended easily to include treatment costs.
where for each individual $i$, $x_i$ is the feature vector, $t_i$ is the assigned treatment, $y_i$ is the observed outcome, and $P(t_i)$ is the probability of being assigned to treatment $t_i$ in the data (a known quantity if the data was collected through a randomized A/B test).

3 APPROACHES FOR THE ESTIMATION OF TREATMENT ASSIGNMENT POLICIES

The causal inference literature often focuses its attention on the estimation of aggregate causal effects, such as the so-called average treatment (or causal) effect (ATE), which corresponds to the average effect of a treatment across the individuals in some well-defined population. Unfortunately, estimating the ATE does not help us to target different individuals with different treatments, because it does not discriminate between the individuals in the population at all. Thus, a fundamental assumption we are making is that the population exhibits heterogeneous treatment effects (HTEs), which are defined in terms of the degree to which a treatment may have different effects on different individuals [13].

One can account for HTEs through the estimation of conditional average treatment effects (CATEs), which correspond to the average causal effect conditioned on a set of available features. Thus, to the extent that individuals in the population differ on their features (and those features are related to causal effects), we may estimate different causal effects for each individual. Of course, treatment effects may still vary among individuals that share the same features (since we may not be accounting for all aspects related to the causal effect), but the estimation of HTEs by using CATEs allows us to make different interventions for different individuals without knowing the relevant subpopulations in advance.

The ideas behind CATE estimation have been increasingly applied to the development of new methods for treatment assignment. An important contribution of this paper is to group these methods into three general approaches (described below) for learning treatment assignment policies from data. Each approach has been recommended in prior research, so we also compare them analytically and empirically in subsequent sections as a second contribution.

1. **Outcome Prediction (OP):** A model to predict the outcome under each treatment is learned using a standard machine learning method. The model assigns individuals to the treatment with the largest predicted outcome and is optimized to discriminate them according to how their outcomes vary.

2. **Causal-Effect Prediction (CP):** A model to predict the differences between the outcome of each treatment and a baseline (or control) is learned using a machine learning method specifically designed to estimate CATEs. The model assigns individuals to the treatment with the largest predicted difference (i.e., treatment effect) and is optimized to discriminate individuals according to how their treatment effects vary.

3. **Treatment Assignment Prediction (TP):** A (weighted) classification model to predict the treatment with the largest weight is learned using a standard machine learning method. Weights are defined by the observed outcome under each treatment condition, so that weights are larger for treatments with larger outcomes. Individuals are assigned to the predicted treatment and the model is optimized to discriminate individuals according to how their preferred treatments vary.

**Uplift modeling.** Uplift or true lift modeling [15, 17] estimates the incremental (causal) impact of a treatment on individuals’ behaviour, and it has been recommended by the data mining community for targeting applications such as online advertising and customer retention [21]. The uplift modeling literature typically focuses on settings where treatment assignments and outcomes are binary, so methods are usually grouped into two main categories [24]: the
two-model approach and the single-model approach (which are specific instances of OP and CP respectively). As the name suggests, the two-model approach consists of building two outcome classifiers (for treated and untreated), and then subtracting the difference between their predictions to assess whether the treatment would be beneficial. On the other hand, the single-model approach directly models the difference between treatment and control probabilities. Approaches to do this include (1) algorithms specifically designed to discriminate according to treatment effects [24] and (2) transforming treatment assignments and outcomes into a new target variable that is modeled using standard machine learning [14].

**Econometrics.** The econometrics literature has also argued that assigning treatments to maximize social welfare is a distinct problem from the point estimation and hypothesis testing problems usually considered in the causal inference literature [12]. As a result, several authors have proposed various methods for optimal policies, which typically use estimation procedures that regress the outcome on the treatment assignment and a set of observed features [6, 8, 12, 18]. Therefore, all of these methods would fall under the OP approach. Most of these studies are typically concerned with the asymptotic properties of their proposed methods, but some have showcased their models in practical settings. For instance, [6] describe how to estimate treatment assignment policies in settings with budget constraints and evaluate their method in the context of efficient provision of anti-malaria bed net subsidies, using data from a randomized experiment conducted in Kenya. Their results show that subsidy allocation based on wealth, presence of children and possession of a bank account can lead to a rise in subsidy use by about 9% points compared to allocation based on wealth only, and by 17% points compared to a purely random allocation.

**Causal Inference.** Others in the causal inference literature have also proposed machine learning methods specifically designed for CATE estimation [3]. Some of the most promising alternatives use bayesian additive regression trees (BART) [11], random forests [25], and regularized support vector machines (SVM) [13]. Importantly, a main motivation behind these methods is their use in the estimation of policies for treatment assignment [2, 3], which corresponds to CP in our context. There is also a relatively large number of papers showing asymptotic properties of CP for treatment assignment when an efficient estimator of CATE is known [see 4, for an overview], but none of them discuss (to our knowledge) any results when deploying such systems in practice.

**Multi-armed bandits.** Finally, treatment assignment policies are also at the core of contextual multi-armed bandits. Models for multi-armed bandit problems may be used to learn how to make decisions in situations where the payoff of only one choice is observed [5, 9]. Such methods have been used to make automated decisions about online news recommendations to maximize clicks [16], for example. It is precisely in this stream of research that it was first noted that the treatment assignment problem (as defined in Section 2) is numerically equivalent to a weighted classification problem [5], leading to the suggestion of TP. Nonetheless, OP has also been recommended for multi-armed bandit algorithms (LinUCB being a well-known example [16]).

An important distinction between our setting and the multi-armed bandit problem is that the goal in bandit problems is to learn a treatment assignment policy while actively making treatment assignment decisions for incoming subjects. Therefore, there is an exploration-exploitation dilemma that plays an important role in the decision-making procedure, whereas in our case the decision-maker cannot re-estimate the treatment assignment policy after making each decision. Our setting is also referred to as “offline learning” in this community [5].
4 COMPARISON OF THE APPROACHES

At first, the three approaches we discussed in the previous section may seem equivalent, and in fact, each of them has been shown to be asymptotically optimal (i.e., the approaches converge to optimal treatment assignments with large enough samples) when the machine learning procedure that is used to learn the models is a consistent estimator; see [12, 18] for OP, see [4, 12] for CP, and see [5] for TP. However, there are two subtle but key differences between the approaches that are critically important when applying these causal estimators in practice.

4.1 Level of generality

The first key distinction is their level of generality (the approaches are listed in Section 3 from the most general to the least general). OP is the most general of the approaches because models that predict outcomes may also be used to predict causal effects or optimal treatments. More specifically, causal-effect predictions may be obtained by taking the difference between the predicted outcomes of two treatments under consideration (as suggested in uplift modeling), and optimal-treatment predictions may be obtained by selecting the treatment with the largest predicted outcome. Therefore, OP models may be used for three different purposes.

On the other hand, models that predict causal effects cannot be used to predict outcomes. For such models, predictions estimate the expected marginal increase (or decrease) in the outcome that results from assigning some specific treatment, but the predictions cannot be used to estimate expected outcomes under an arbitrary treatment condition. Therefore, while causal-effect predictions may still be used to predict optimal treatments (by selecting the treatment with the largest predicted effect), CP models are not as general as OP models. Finally, models trained to predict optimal treatment assignments (TP models) can only be used for that purpose; these models, the least general, cannot predict the outcome or the effect that would result from making those assignments.

4.2 Objective function to learn from data

The second key distinction is that each approach uses a different objective (or loss) function to learn their respective predictive models. OP uses a loss function designed to optimize outcome predictions; CP uses a loss function designed to optimize causal-effect predictions, and TP uses a loss function designed to optimize treatment assignments. This implies that, while all approaches share the same ultimate goal (optimizing treatment assignments as specified by Equations 4, 5, and 6), they differ with respect to the procedures they use to learn from data.

This distinction is important because an improvement in the prediction of outcomes or causal effects does not imply an improvement in the prediction of optimal treatment assignments (as we show in detail in the next subsections). In fact, such improvements may actually occur at the expense of worse treatment assignments. Thus, we should expect machine learning with loss functions specifically tailored to optimize treatment assignments to produce better models: TP should outperform the other approaches with finite training data when making treatment assignment decisions.

Nonetheless, various research communities recommend OP and CP for treatment assignment, and few studies have compared these three approaches either analytically or empirically. As exceptions, [5] provides a theoretical regret analysis for multi-armed problems showing that for a given family of ‘regressors’ (e.g., decision trees) TP has a smaller lower bound regret than OP. These analytical results are supported by experiments on multi-class benchmark data sets that were repurposed to simulate potential outcomes, showing TP as a superior alternative than OP. [14] used a similar experimental approach to compare OP and CP, showing each of the approaches outperforming the other in different empirical examples. They also note the potential of OP to outperform CP in settings where outcomes are strongly
Fig. 1. Comparison of outcome prediction vs treatment assignment for a single individual. The model depicted in (a) makes a better treatment assignment than the model depicted in (b) despite having larger outcome prediction errors.

correlated with causal effects, suggesting that choosing between approaches should be an empirical undertaking. There are no studies (to our knowledge) that compare these approaches in an actual practical setting.

In the following subsections, we compare the three approaches analytically to illustrate how their choice of objective functions may affect their performance in treatment assignments. Then, in the next section, we provide an experimental comparison of the three approaches in a real, practical setting where better treatment assignment policies can generate substantial value.

### 4.3 Objective: Outcome prediction

As mentioned, OP assigns treatments by learning a model that predicts the expected outcome of each treatment ($\hat{\mu}$):

$$\hat{\mu}(x, j) = \mathbb{E}[Y | X = x, T = j],$$

and then selecting the treatment with the best predicted outcome:

$$\hat{T}_\mu(x) = \arg\max_j \hat{\mu}(x, j)$$

A standard approach to fit Equation 7 is to regress outcome $Y$ on features $X$ and $T$ using various machine learning methods designed to minimize the mean squared error for the outcome ($MSE_\mu$):

$$MSE_\mu = E[(Y^T - \hat{\mu}(X, T))^2],$$

and then to choose the model with the lowest empirical $MSE_\mu$.

The premise here is that minimizing $MSE_\mu$ implies better outcome predictions, and therefore better treatment assignments. However, optimizing outcome predictions (by minimizing $MSE_\mu$ or other measures such as mean absolute error or cross-entropy) does not necessarily optimize treatment assignments. Figure 1 compares the outcome predictions made by two different models for a single individual, one with high prediction errors (Figure 1a) and another with low prediction errors (Figure 1b). The blue (dark) dots correspond to the true conditional expectation (they are the same for
Fig. 2. **Comparison of causal effect prediction vs treatment assignment for a single individual.** The model depicted in (a) makes a better treatment assignment than the model depicted in (b) despite having larger causal-effect prediction errors.

In this example, the conditional expectation when $T = 1$ is larger than when $T = 2$ (as shown by the blue dots), which implies that $T = 1$ is a better treatment assignment. Therefore, to the extent that $\hat{\mu}[T = 1] > \hat{\mu}[T = 2]$, the model makes the optimal treatment assignment. Going back to the example, Figure 1a shows that the model with larger prediction errors makes the optimal treatment assignment because the ranking of the predicted outcomes is the same as the ranking of the true values. The second model makes a worse assignment, even though its prediction errors are smaller, because the ranking is inverted. Therefore, choosing the model with the better $MSE_\mu$ leads to a worse treatment assignment.

### 4.4 Objective: Causal-effect prediction

The second treatment assignment approach, CP, is to learn a model to estimate CATE ($\hat{\tau}$) directly:

$$\hat{\tau}(x, j) = \hat{\mathbb{E}}[Y|X = x, T = j] - \hat{\mathbb{E}}[Y|X = x, T = 0],$$  \hspace{1cm} (10)

where $T = 0$ corresponds to a baseline treatment (e.g., the "existing system" control in an A/B test setting). The optimal treatment may then be chosen as follows:

$$\hat{T}_\tau(x) = \operatorname{argmax}_j \hat{\tau}(x, j)$$  \hspace{1cm} (11)

As mentioned in Section 3, there is a growing literature in the use of machine learning methods for the estimation of CATE. The (sometimes unstated) goal of these methods is to minimize the mean squared error for treatment effects ($MSE_\tau$):

$$MSE_\tau = \mathbb{E}[(\tau - \hat{\tau}(X, T))^2] = \mathbb{E}[(\tau - \hat{\tau}(X, T))^2]$$  \hspace{1cm} (12)

Therefore, these methods are not optimized to predict outcomes but rather to predict causal effects (which are usually defined as the difference between potential outcomes, e.g., $Y^1 - Y^0$). The main challenge is that we only observe one
potential outcome for any given individual, so we cannot calculate Equation 12 directly because $\tau$ is not observable. However, we may use alternative formulations to estimate $MSE_\tau$ from data (up to a constant) [1], allowing us to compare (and optimize) models on the basis of how good they are at predicting causal effects.

Unfortunately for our application, and similarly to the previous section, optimizing causal-effect predictions (by minimizing $MSE_\tau$) is not the same as optimizing treatment assignments either. We illustrate this using Figure 2, which shows a similar example to the one illustrated in Figure 1, except it compares the causal effect (rather than outcome) predictions made by two models. Therefore, in this example the blue (dark) dots represent the causal effect of the treatments for a specific individual (these dots are the same in both graphs), and the red dots represent the estimation of the effect by the models. As before, the first model has high prediction errors (Figure 2a) but makes a better assignment, while the second has lower prediction errors (Figure 2b) but makes a worse assignment. Thus, the model that makes a better causal-effect prediction (i.e. that has lower $MSE_\tau$) makes a worse treatment assignment.

Surprisingly, this implies that models that are (relatively) bad at causal-effect prediction may be good at making treatment assignments. This result, while seemingly counter-intuitive at first, may be attributed to the bias-variance decomposition of errors. In the machine learning community, it is well known that models that have a good classification performance are not necessarily good at estimating class probabilities (and vice versa) [10]. A useful analogy in our context is to think about treatment assignment as a classification problem and to think about causal-effect estimation as a probability estimation problem; the two tasks are closely related but not exactly the same. Importantly, the bias and variance components of the estimation error in causal-effect predictions may combine to influence treatment assignment in a very different way than with the squared error of the predictions themselves. For instance, certain types of very high bias may be canceled by low variance to produce accurate treatment assignments. Therefore, it is important to distinguish between good causal-effect estimation and good treatment assignments.

4.5 Objective: Treatment assignment

The third approach, TP, estimates the treatment assignment policy by directly learning the treatment assignments that lead to the best outcomes. As [5] describe in detail, the treatment assignment problem can be transformed into a weighted multi-class classification problem. The general idea is that, given a probability distribution $P(T)$ over the treatment (e.g., the probability that an individual gets assigned to treatment $T$ in the A/B test data), each observation $(x, y, t)$ can be transformed into an importance-weighted multi-class example where $y/P(t)$ is the cost of not predicting treatment $t$ given input $x$. These examples can then be fed to any importance-weighted multi-class classifier learning algorithm. The predictions of the output classifier ($\hat{\theta}$) would correspond to:

$$\hat{\theta}(x, j) = \hat{P}(T = j|X = x),$$  \hspace{1cm} (13)

and may be used to choose the optimal treatment as follows:

$$\hat{T}_g(x) = \arg\max_j \hat{\theta}(x, j)$$  \hspace{1cm} (14)

As mentioned, the model predictions defined in Equation 13 are optimized to minimize the weighted misclassification rate ($WMR$):

$$WMR = E \left[ 1(\hat{T}_g(X) \neq T) \frac{Y}{P(T)} \right]$$  \hspace{1cm} (15)
The objective function presented in Equation 15 is directly tied to treatment assignment performance because minimizing it is equivalent to minimizing expected regret (as defined in Equation 4); see [5] for more details. We present a simplified proof sketch here:

\[
\arg\min_{\hat{T}} E \left[ 1(\hat{T}(X) \neq T) \frac{Y}{P(T)} \right] = \arg\min_{\hat{T}} \sum_j P(T = j) E \left[ 1(\hat{T}_\theta(X) \neq T) \frac{Y^j}{P(T = j)} \mid T = j \right]
\]

(16)

and given the unconfoundedness assumption:

\[
= \arg\min_{\hat{T}} \sum_j E[1(\hat{T}_\theta(X) \neq T)Y^j] = \arg\min_{\hat{T}} \left( \sum_j E[Y^j] - E[Y^\hat{T}_\theta(X)] \right)
\]

\[
= \arg\min_{\hat{T}} -E[Y^\hat{T}_\theta(X)] = \arg\min_{\hat{T}} E[Y^T(X) - Y^\hat{T}_\theta(X)]
\]

As a result, because minimizing WMR is equivalent to optimizing for expected regret (i.e., treatment assignments), we should expect WMR to be a better objective function than MSE_µ or MSE_τ when the goal is to make the best possible treatment assignments.

5 RESULTS: PLAYLIST GENERATION

We now present our third contribution, an empirical comparison of the three treatment assignment approaches for choosing which playlist generation algorithm to apply for each listener.

5.1 Application setting

In our playlist generation setting, the treatment variants consist of different algorithmic playlist generation (recommender) systems that are being tested in production by Spotify, a media services provider. Each recommender system uses a different algorithm to select and rank songs in "algorithmic" playlists (playlists that are built dynamically according to user data). The company has multiple goals when deploying such systems (e.g., converting users from free to premium, reducing churn, increasing engagement with the platform). We focus specifically on the number of song streams as our target outcome metric. However, (as stated before) issues in data collection, modeling, and deployment have made it hard historically for recommender systems to be directly optimized in terms of these goals. Therefore, the models that underlie these systems are often heuristic (e.g., songs may be ranked according to their similarity to previous songs the user has played).

To evaluate new recommender systems, firms typically run A/B tests to compare the new variant(s) with the existing production system (as a baseline) and decide whether to replace the production system with one of the new systems. This essentially chooses the same treatment assignment for all users. However, as we have argued throughout this
paper, different variants may work better for different users: if System A is best for new users and System B is best for more experienced users, then deploying the same system for all users would lead to sub-optimal treatment assignments. Since the outcome of interest in this case is song streams, the goal is to learn a treatment assignment policy that deploys different systems for different users in order to maximize the number of streams.

Before proceeding, we want to reemphasize that treatments in this setting consist of algorithms, not recommendations. The treatment assignment policy is choosing among playlist generation algorithms, each of which makes personalized decisions according to user data. Therefore recommended playlists would still vary from one user to another, even if we use the same variant for everyone.

5.2 Data

We compare the three treatment assignment approaches using data from a massive, production A/B test. The A/B test produced a data set in which four different recommender systems were randomly assigned to users to build algorithmic playlists: three newly developed recommender systems and the system that was currently in production. More specifically, each observation corresponds to a user who selected a playlist, and each playlist was built using one of the four systems (chosen at random) to select and rank songs. There are 770 million observations in the data: 86.68% assigned to the production system, and 4.44% for each of the new variants. For each observation, we have the following categorical features: country (19 values), playlist ID (6 values), platform (e.g., Android; 3 values), days since the account was created (transformed into a discrete variable with 4 values), and product (e.g., free, premium; 8 values). For each categorical variable, the categories with fewer than 10,000,000 observations were grouped together in a category named ‘other’, resulting in the number of values for each variable reported above. Balance tests with respect to these features confirmed an adequate randomization of the systems. For each observation, we also have the number of total streams for the user (increasing that is the outcome of interest).

5.3 Learning and Evaluating Policies

As in the analytical section, we compare three approaches to estimate treatment assignment policies: (1) the outcome policy (OP) ($\hat{\mu}$), which uses a regression model to predict the total streams of each system and assign the system (treatment) with the largest predicted number of total streams (Equation 8); (2) the causal-effect policy (CP) ($\hat{\tau}$), which uses a regression model to predict the causal effect of each system on total streams (compared to control) and assign the system with the largest predicted effect (Equation 11); and (3) the treatment policy (TP) ($\hat{\theta}$), which uses a classification model to predict (and assign) the system that is estimated to produce the largest number of streams (Equation 14). All of these models are learned and applied at the user level.

We use tree-based algorithms to learn all models so that differences in performance can be attributed to the loss functions used by each approach rather than the machine learning algorithm being used. For OP, we used a decision tree regressor that minimizes $MSE_\mu$ to learn $\hat{\mu}$. For CP, we used a decision tree regressor on the transformed variable proposed by [1] to learn $\hat{\tau}$ by minimizing $MSE_\tau$, i.e., a ‘causal tree’. In the case of CP, we had to train 3 causal trees (one for each system except control) because the method does not support non-binary treatments. Finally, for TP, we used a weighted decision tree classifier that minimizes $WMR$ to learn $\hat{\theta}$.

The models were learned, tuned, and evaluated using 10-fold nested cross validation, which separates the cross-validation used for hyperparameter optimization from the test folds used for evaluation [20]. We used the empirical measure described in Equation 6 to evaluate all models, using $P(t_1) = 86.68\%$ when $t_1 = 0$ (control), and $P(t_1) = 4.44\%$
otherwise. However, for clarity, the analysis that follows compares performance \((P)\) in terms of the impact on streams \((I, \text{Equation 6})\) relative to just assigning the control system to everyone \((C, \text{Equation 6 when } \hat{T}(X_i) = 0, \forall i):\)

\[
I = \frac{1}{N} \sum_{i}^{N} 1(T_i = \hat{T}(X_i)) \frac{Y_i}{P(T_i)},
\]

\[
C = \frac{1}{N} \sum_{i}^{N} 1(T_i = 0) \frac{Y_i}{P(T_i)},
\]

\[
P = \frac{I - C}{C}
\]

Importantly, maximizing Equation 19 is equivalent to minimizing empirical expected regret (Equation 4) when the assumptions discussed in Section 2 are met [16]. Therefore, we can test the policies using historical data from the A/B test. All models’ hyperparameters were tuned to optimize their respective loss functions: OP was tuned to optimize \(MSE_\mu\); CP was tuned to optimize \(MSE_\tau\), and TP was tuned to optimize \(WMR\).

5.4 Results

Figure 3 shows the performance of each approach (measured as the increase in streams relative to the baseline) as the size of data increases. The red line is the policy in which the system that performs best on average is applied to everyone—what we would get from a typical A/B test (i.e., choosing which recommender system works best generally—without user-specific modeling at the level of recommender system choice). In addition, the figure shows the performance of the three approaches we discussed to learn treatment assignment policies: OP (blue line), CP (orange line) and TP (green line). The areas around the lines represent 95% confidence intervals calculated using the ten results from the cross-validation.

5.4.1 The importance of treatment assignment policies. The first interesting finding in Figure 3 is that choosing the system that performs best on average does not have a significant impact on the total number of song streams. This implies that no single ‘best system’ for all users performs much better than the baseline (existing production system). Importantly, if we were to follow a traditional A/B test approach, we might come to the erroneous conclusion that the best thing to do is simply to keep the system currently in production, because no other system produces an increase in streams that is statistically significant at the population level.

We show in Table 1 the percentage of users that would be assigned to each recommender system, depending on the treatment assignment policy that is used. Recall that our analysis was conducted using cross-validation, so the table was built using out-of-sample treatment assignments for all users. The first row in the table shows that different systems may be selected as the ‘best system’ (on average) depending on the cross-validation folds used to compare the systems: System \(T = 1\) is selected for 6 out of 10 folds, whereas System \(T = 2\) is selected for the other 4 folds. Combined with Figure 3, this suggests that there is no real performance difference between the systems when applied to the entire population.

However, total streams can be increased substantially when different systems are applied to different users. Table 1 shows that the treatment assignment policies that were estimated using machine learning (OP, CP, and TP) exhibit high heterogeneity in their treatment assignments, and these policies also perform substantially better (as shown in Figure 3) than assigning the single best recommender system to everyone. To control for the fact that high heterogeneity may be the result of using different folds to estimate the models, we computed the entropy in treatment assignments for each
Fig. 3. Treatment assignment performance

| Policy                  | $T = 0$ | $T = 1$ | $T = 2$ | $T = 3$ | Average Entropy$^*$ |
|-------------------------|---------|---------|---------|---------|-------------------|
| Best on average$^†$     | 0.0%    | 60.0%   | 40.0%   | 0.0%    | 0                 |
| Outcome (OP)            | 11.1%   | 25.3%   | 33.5%   | 30.1%   | 1.896             |
| Causal-Effect (CP)      | 9.3%    | 32.1%   | 29.0%   | 29.5%   | 1.879             |
| T. Assignment (TP)      | 9.3%    | 32.0%   | 29.4%   | 29.3%   | 1.879             |

$^*$ Average entropy of treatment assignments across folds. Min is 0 and Max is 2.
$^†$ Different systems perform best (on average) depending on the folds that are used to select the 'best system'. Thus, not everyone is assigned to a single system when using cross-validation to evaluate and analyze the 'best on average' policy.

Table 1. Percentage of users assigned to each treatment

fold, and then obtained the average entropy across all 10 folds (i.e., column 4 in Table 1). As we can see, all three policies exhibit a large entropy (i.e., high heterogeneity) in treatment assignments within the folds, resulting in substantially more streams.

5.4.2 The importance of large A/B tests. A second important finding shown in Figure 3 is that treatment assignment policies become increasingly better with more training data, illustrating the importance of conducting large A/B tests to generate unconfounded training data to learn models for individual-level treatment assignments. As we mentioned in Section 3, the estimation of causal effects by using CATEs instead of ATE is a substantial improvement for the purposes
of deciding on individual interventions. However, the estimation of accurate CATEs requires much larger data sets; otherwise the models are likely to overfit.

Fortunately, large A/B tests alleviate this problem because the data can be partitioned into fine-grained subpopulations of users without losing substantial statistical power. Correspondingly, we can fit more complex causal models with less overfitting. As part of our analysis, we assessed overfitting by comparing the treatment assignments made by the various models we built with cross-validation. We found that, for any given individual, models are more likely to assign the same treatment as sample size grows, suggesting that the models overfit less with more data.2

5.4.3 The importance of the right objective function. Finally, Figure 3 shows that the policy that was learned by optimizing treatment assignments (green line) works substantially better than the policies that were learned by optimizing outcome and causal-effect predictions (blue line and orange line respectively), thus validating our analytical findings. As discussed in detail above, objective functions that optimize things other than treatment assignment prediction (i.e., better outcome or causal-effect predictions) do not necessarily favor better treatment assignments.

Going back to our analytical examples, we would expect each approach to perform best doing whatever it is optimized to do. For example, the predictive model used by OP should perform better at predicting outcomes than the models used by CP and TP. However, as discussed in Section 4.1, we cannot (in general) use causal-effect or treatment assignment models to estimate outcomes. Therefore, in order to compare the various approaches at different tasks, in the following analysis we adapt CP’s and TP’s models.

Since we are using tree-based models for all policies, we generalize the models used by CP and TP by using different prediction functions to aggregate the training observations at each leaf depending on the task at hand. For instance, if we want to make outcome predictions, the prediction function would consist of the average outcome of the observations in the leaf (rather than the average causal effect in the case of CP or the treatment with the largest outcome in the case of TP). Thus, the structures of all models remain the same, but the prediction function at the leaf-level may be adjusted to predict outcomes (CP and TP) or causal-effects (TP).

Table 2 shows the performance of each approach at the three different tasks, evaluated using nested cross-validation on the entire data set. The tasks are predicting outcomes (a lower $\text{MSE}_\mu$ is better), predicting causal effects (a lower $\text{MSE}_\tau$ is better), and predicting treatment assignments (a higher $P$ is better). As expected, each approach is best at doing what it was optimized to do. Nevertheless, the models with the best performance in outcome prediction (OP) and

| Policy                  | $\text{MSE}_\mu$ | $\text{MSE}_\tau^*$ | $P\%$ | Mismatch with TP$\%$
|-------------------------|------------------|---------------------|-------|------------------------
| Outcome (OP)            | 0.057            | 46.287              | 2.88% | 24.91%                 
| Causal-Effect (CP)      | 0.111            | **46.276**          | 2.78% | 7.75%                  
| T. Assignment (TP)      | 0.059            | 46.305              | **3.71%** | 0.00%                  

$^*$ $\text{MSE}_\tau$ corresponds to the $\text{MSE}$ of the transformed outcome proposed by [1] to estimate causal effects.

† Performance as defined in Equation 19, Section 5.3.

‡ Percentage of decisions that are different from the decisions made by TP.

Table 2. Policy comparison at different tasks

2The details of this analysis are not included here due to space constraints.
causal-effect prediction (CP) are not the best models at making treatment assignments. In fact, in relative terms, the impact of TP is 28% larger than the impact of OP or CP.

Finally, the last column of the table shows the mismatch between the decisions made by each policy and the decisions made by TP. Interestingly, the mismatch is relatively large despite the small differences in performance between the approaches and their similar distribution of treatment assignments (as shown in Table 1). This suggests that models with different objective functions can also lead to quite different decisions at the individual level (even if their overall performance is similar).

6 CONCLUSION

This paper categorizes individualized treatment assignment methods into three main approaches: outcome prediction, causal-effect prediction, and treatment assignment prediction. To our knowledge, this is the first study to compare these three approaches on a real application at scale. We discuss and illustrate two key distinctions between them: (1) their level of generality in terms of the types of tasks that their models may address, (2) and the objective function they use to estimate models from data. Importantly, we show that despite the fact that all three approaches have been recommended for treatment assignment in prior research, optimizing for outcome or causal-effect predictions is not the same as optimizing for treatment assignments, and that the latter ought to be better in practical (non-asymptotic) settings such as ours.

We then compare and contrast the three approaches for the real-world application of choosing, for each listener, which playlist generation algorithm to apply in order to maximize the number of song streams. We illustrate how unconfounded training data can be generated from A/B tests, and that large A/B tests can provide substantial value for learning treatment assignment policies. The results also show that individualized treatment assignment prediction indeed substantially outperforms causal-effect prediction and outcome prediction. Specifically, the machine-learned treatment assignment policy causally increases listening by over 28% relative to the other approaches. This is the case despite the fact that none of the individual treatments (the different playlist generation algorithms) outperforms the others when applied over the whole population. This final observation highlights the two different uses of A/B tests: the traditional use is to choose the treatment that has the largest average treatment effect; we use the A/B test to generate unconfounded training data to learn models that will allow us to target specific treatments to specific individuals.

REFERENCES

[1] Susan Athey and Guido Imbens. 2016. Recursive partitioning for heterogeneous causal effects. Proceedings of the National Academy of Sciences 113, 27 (2016), 7353–7360.
[2] Susan Athey and Guido W Imbens. 2017. The state of applied econometrics: Causality and policy evaluation. Journal of Economic Perspectives 31, 2 (2017), 3–32.
[3] Susan Athey and Guido W Imbens. 2019. Machine Learning Methods That Economists Should Know About. Annual Review of Economics 11 (2019).
[4] Susan Athey and Stefan Wager. 2017. Efficient policy learning. arXiv preprint arXiv:1702.02896 (2017).
[5] Alina Beygelzimer and John Langford. 2009. The offset tree for learning with partial labels. In Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, 129–138.
[6] Debsapam Bhattacharya and Pascaline Dupas. 2012. Inferring welfare maximizing treatment assignment under budget constraints. Journal of Econometrics 167, 1 (2012), 168–196.
[7] David Roxbee Cox. 1958. Planning of experiments. (1958).
[8] Rajeev H Dehejia. 2005. Program evaluation as a decision problem. Journal of Econometrics 125, 1-2 (2005), 141–173.
[9] Miroslav Dudík, John Langford, and Lihong Li. 2011. Doubly robust policy evaluation and learning. Proceedings of the 28th International Conference on Machine Learning (2011).
[10] Jerome H Friedman. 1997. On bias, variance, 0/1/!loss, and the curse-of-dimensionality. Data mining and knowledge discovery 1, 1 (1997), 55–77.
[11] Jennifer L Hill. 2011. Bayesian nonparametric modeling for causal inference. Journal of Computational and Graphical Statistics 20, 1 (2011), 217–240.
[12] Keisuke Hirano and Jack R Porter. 2009. Asymptotics for statistical treatment rules. *Econometrica* 77, 5 (2009), 1683–1701.

[13] Kosuke Imai, Marc Ratkovic, et al. 2013. Estimating treatment effect heterogeneity in randomized program evaluation. *The Annals of Applied Statistics* 7, 1 (2013), 443–470.

[14] Maciej Jaskowski and Szymon Jaroszewicz. 2012. Uplift modeling for clinical trial data. In ICML Workshop on Clinical Data Analysis.

[15] Kathleen Kane, Victor SY Lo, and Jane Zheng. 2014. Mining for the truly responsive customers and prospects using true-lift modeling: Comparison of new and existing methods. *Journal of Marketing Analytics* 2, 4 (2014), 218–238.

[16] Lihong Li, Wei Chu, John Langford, and Robert E Schapire. 2010. A contextual-bandit approach to personalized news article recommendation. In *Proceedings of the 19th international conference on World wide web*. ACM, 661–670.

[17] Victor SY Lo. 2002. The true lift model: a novel data mining approach to response modeling in database marketing. *ACM SIGKDD Explorations Newsletter* 4, 2 (2002), 78–86.

[18] Charles F Manski. 2004. Statistical treatment rules for heterogeneous populations. *Econometrica* 72, 4 (2004), 1221–1246.

[19] Judea Pearl. 2009. *Causality: Models, Reasoning and Inference*. Cambridge University Press.

[20] Foster Provost and Tom Fawcett. 2013. *Data Science for Business: What you need to know about data mining and data-analytic thinking*. O'Reilly Media, Inc.

[21] Nicholas J Radcliffe and Patrick D Surry. 2011. Real-world uplift modelling with significance-based uplift trees. *White Paper TR-2011-1, Stochastic Solutions* (2011).

[22] Paul R Rosenbaum and Donald B Rubin. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* 70, 1 (1983), 41–55.

[23] Donald B Rubin. 1974. Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of educational Psychology* 66, 5 (1974), 688.

[24] Piotr Rzepakowski and Szymon Jaroszewicz. 2012. Decision trees for uplift modeling with single and multiple treatments. *Knowledge and Information Systems* 32, 2 (2012), 303–327.

[25] Stefan Wager and Susan Athey. 2018. Estimation and inference of heterogeneous treatment effects using random forests. *J. Amer. Statist. Assoc.* 113, 523 (2018), 1228–1242.

[26] Jeffrey M Wooldridge. 2015. *Introductory econometrics: A modern approach*. Nelson Education.