# Driver Recipient Selection for Traffic Safety Education via Uplift Modeling

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**Abstract.** Safety has been one of the major concerns by the traffic police in traffic management. A favored practice to enhance traffic safety is to educate drivers and raise their safety awareness, so as to reduce the occurrence of traffic accidents in general. However, human power is limited in carrying out the education program, and challenges remain in filtering the most proper group of drivers to receive such education as well as in assessing the effectiveness of the program. In this paper, we view traffic safety education as an intervention from the perspective of causal inference, and we address the driver recipient selection (DRS) problem as a combination of uplift modeling and optimization. In uplift modeling, we identify that the confounding bias is present in historical accident data, and hence we adapt the uplift model via inverse propensity scoring (IPS) to eliminate the confounding bias. Experiments on both synthetic and real-world datasets show that our adapted uplift model increases the Area Under the Unconfounded Uplift Curve (AUUUC) by up to 46%, and our proposed DRS strategy can further reduce the overall monthly accident rate by 3.4% absolutely than the existing strategy.

**Keywords:** Traffic safety · Causal inference · Uplift modeling · Optimization.

## 1 Introduction

Over 100k traffic accidents, either severe or minor, are reported monthly in a city[1]. Reducing the accident rate is a core objective in traffic management. As the occurrence of accidents largely depends on the drivers' behaviors, it is a favored practice to educate drivers in person, especially upon or after accident

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[1] The city information is kept confidential.

occurrences. On average, the traffic police educate over 15k drivers per year to raise the public awareness of traffic safety. However, considering the large scale of drivers in the city, questions arise toward proper utilization of limited traffic police resources in such an education program, in order to maximize its effectiveness in accident reduction. To put it formally, the traffic police are concerned with the following two questions, which are the primary focus of our study:

1. How effective is safety education on reducing the number of traffic accidents?
2. Given limited traffic police resources, how do we select drivers to receive education, in order to maximize the reduction effect on traffic accidents?

Answers to the two questions are not immediately evident, as they involve causal concepts. First of all, two variables form a "cause-and-effect" pair, in which education is the cause and traffic accident occurrence is the effect [7]. To measure the effect of an education practice delivered to a driver, it is necessary to estimate his/her potential accident rate if the education had not been delivered, known as a "counterfactual" [7]. Moreover, the underlying accident rate of each driver is distinct, and the reduction effect of education on accident occurrence has to be evaluated on an individual level, known as an "uplift" [3]. An uplift in this scenario is defined as the difference in the underlying accident rate if the driver were educated as compared to not educated, and is used to quantify the "persuadability" of an individual driver.

The core challenge is thus to correctly estimate the uplift for each individual driver, following which both questions can be solved accordingly. Given the uplifts, question 1 can be answered by aggregating the uplifts of all educated drivers, and question 2 can be answered by ranking drivers and selecting those with the best uplifts.

Methods have been extensively explored to model uplifts [5, 4, 8] to solve real-world applications [6, 9, 12]. In this paper, we estimate uplifts via the class transformation framework with random forest as the base model. However, we identify that the confounding bias exists in historical education and accident data, which severely deteriorate the estimation results and cannot be effectively addressed by existing uplift models. Therefore, we propose to adapt the uplift model via a sample re-weighting mechanism named inverse propensity scoring (IPS) to effectively eliminate the confounding bias.

This paper novelly proposes the application of uplift modeling techniques to addressing the problem of driver recipient selection (DRS) for traffic safety education. Our main contributions are summarized as follows:

- We formally define the DRS problem as an optimization problem with a causal objective (Section 2), marking a novel framework in traffic safety education. We identify and highlight "uplift" as the core variable for comprehensively understanding the DRS problem.
- To effectively address the DRS problem, we leverage advanced uplift modeling techniques to estimate the causal effect of educational interventions on accident occurrences, providing tailored insights for traffic safety education (Section 3). Notably, we identify and successfully tackle the confounding

bias within the context of traffic safety education by seamlessly integrating IPS into the training of our uplift model. Subsequently with the estimated uplifts, we formalize the DRS problem as a constrained optimization task, solvable through mathematical programming (Section 4).
– We conduct extensive experiments (Section 5) to validate the effectiveness of our method with both synthetic and real-world datasets. Results show that our uplift modeling approach is enhanced by IPS integration and outperforms baselines by up to 46% in AUUUC. In simulations on the end-to-end DRS task, our strategy with the uplift model is projected to lower the monthly accident rate of educated drivers by an additional 3.5% compared to the existing strategy; and this number is estimated by our model to be 3.4% on the entire driver population.

## 2 The Driver Recipient Selection (DRS) Problem

In this paper, we study the problem of recommending a subset of drivers as recipients of a traffic safety education program. The primary objective of the program is to minimize the overall monthly accident rate in the city, given that the selection of drivers is constrained by limited traffic police resources. The problem necessitates an analysis of the causal relationship between two variables: education as the "cause" and accident occurrence as the "effect". We provide a formal definition of the driver recipient selection problem in this section.

**Definition 1 (The cause-effect pair).** *Consider $N$ drivers in a city. Define $T_i := \mathbb{I}($driver $i$ has been educated in the past three months$)$ as the binary treatment variable, and $Y_i := \mathbb{I}($driver $i$ is NOT involved in accident in current month$)$ the binary outcome variable. $(T_i, Y_i)$ is a cause-effect pair.*

Accordingly, the problem of driver recipient selection can be formulated as an optimization problem with a causal objective:

*Problem 1 (Driver Recipient Selection (DRS)).*

$$\begin{aligned} & \underset{t_i}{min}\ \frac{1}{N}\sum_{i=1}^{N}\mathbb{E}[1-Y_i|do(T_i=t_i)] \\ & \text{s.t. practical constraints considered by the traffic police,} \\ & \quad t_i \in \{0,1\},\ \forall i \in \{1,2,...,N\}, \end{aligned} \tag{1}$$

where each $t_i$ is a binary value indicating whether driver $i$ is educated or not, and the *do*-operator represents that $T_i$ is an intervention variable following Pearl's Structural Causal Model [7], which only affects its causal descendants while keeping all other variables unchanged.

Therefore, the causal objective in Problem 1 represents the expected monthly accident rate over the whole driver population as a result of the selection of drivers being educated. To estimate the causal objective, it is necessary to understand the causal effect of education on accident rate on an individual level, known as an "uplift" defined below.

**Definition 2 (Uplift).** *The uplift of driver $i$ is* $\tau_i := \mathbb{E}[Y_i|do(T_i = 1)] - \mathbb{E}[Y_i|do(T_i = 0)]$.

An uplift refers to the difference in the underlying accident rate of a driver if the driver were educated compared to not educated. It quantifies a driver's susceptibility to traffic safety education. We further claim that the objective of DRS can be estimated in terms of uplifts. This is validated in the proposition below, whose proof is provided in Appendix A.

**Proposition 1.** $\underset{t_i}{min}\ obj.(1) = \underset{t_i}{max} \frac{1}{N}\sum_{i=1}^{N} \tau_i * t_i$.

Proposition 1 suggests that in order to estimate $obj.(1)$, it is sufficient to estimate the uplift of each driver, i.e., $\tau_i$'s. Therefore, estimating the objective is reduced to an uplift modeling problem, and DRS is solved via uplift modeling (in Section 3) followed by optimization (in Section 4).

## 3 Uplift Modeling

In this section, we estimate the objective in DRS via uplift modeling. The objective term is the expected monthly accident rate over the whole driver population resulting from a decision on driver recipient selection. As explained in Section 2, the objective is a causal term that can be estimated from an individual level via uplift modeling. The necessity of uplift modeling is discussed in Appendix B.1.

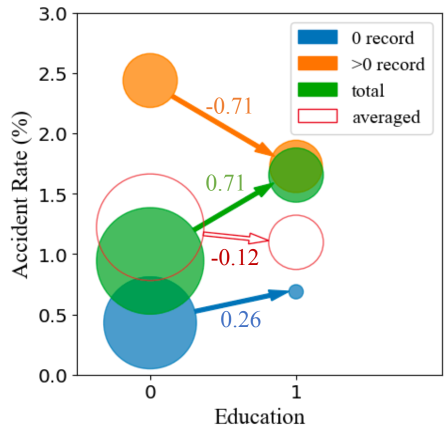
The core idea of uplift modeling is to estimate uplift $\tau_i$ with a function $f$ on a set of feature variables $X_i$, i.e., $\hat{\tau}_i := f(X_i) \approx E[Y_i|do(T_i = 1)] - E[Y_i|do(T_i = 0)]$, where $X_i$ is short for $\{X_i^{(j)}\}_{j=1,2,...,M}$. In this paper, we target at the binary-treatment binary-outcome uplift modeling problem, formulated in Appendix B.2.

### 3.1 The base model: ClsTrans(RF)

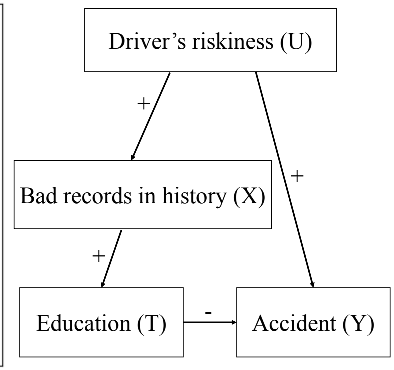
A variety of uplift models are proposed in the literature. In this work, we select *Class Transformation with Random Forest* (or "*ClsTrans(RF)*" for short) as the base model of our approach, as it achieves superior performance over alternative uplift models according to a series of experiments (detailed in Section 5.2), including a simulation on a real-world education-accident scenario. Details of ClsTrans(RF) are provided in Appendix B.3.

### 3.2 The confounding bias in traffic safety education

The base model ClsTrans(RF), though being the best-performing uplift model among a variety of alternatives, faces limitations when applied to traffic safety education. It is trained on a historical dataset that is subject to the confounding bias, which negatively impact the model's performance during inference. In traffic safety education, we observe a unique phenomenon that is logically similar to Simpson's paradox [11], highlighting the presence of the confounding bias in the observed data. We name it "semi-Simpson's paradox".




(a) The semi-Simpson's paradox. The circle area represents the group population, and the arrow gradient corresponds to the uplift estimate.




(b) The confounding path. It gives rise to a positive correlation that more than offsets the negative causal effect of T on Y.

**Fig. 1.** Semi-Simpson's paradox observed in traffic safety education. The variable of "bad records in history" appears to lie on a confounding path in estimating the causal effect of education on accident.

ClsTrans(RF) models the uplift via training from observed samples. For a closer analysis of the observed dataset, Figure 1(a) visualizes group-wise accident rates with real statistics, where each circle stands for a sub-group of drivers of a particular type. Subject to the driver's behavior, the whole group of drivers (in green) is first divided into two sub-groups: good-behaving drivers (in blue) and bad-behaving drivers (in orange). Each group/sub-group is further divided into educated ($Education = 1$) and non-educated ($Education = 0$). For each color, the arrow gradient thus corresponds to the difference in accident rates between the uneducated and educated groups. Intuitively (though incorrectly), it suggests the relationship between education and accident rate, with the opposite value serving as an estimate of the uplift. For example, the uplift of bad behaving drivers (in orange) is 0.71, suggesting that "education could save 0.71% of bad-having drivers from incurring accidents in that month". However, the uplift of good behaving drivers (in blue) becomes negative (-0.26), leading to an untenable indication that "education incurs more accidents". Therefore, the divide-and-compare interpretation is logically wrong in estimating uplifts, confusing causality with correlation. The negative number reflects the presence of the confounding bias.

**Semi-Simpson's paradox** We discover a paradox in further analysis of the dataset. According to Figure 1(a), the uplifts of the good or bad behaving drivers are -0.26 and 0.71, respectively. On the other hand, the uplift of the whole group (in green) is -0.71, surprisingly lower than both sub-groups. We name this paradox semi-Simpson's paradox, defined as follows:

**Definition 3 (Semi-Simpson's paradox).** *In semi-Simpson's paradox, the value of an indicator estimated on the total group appears to be out of the range of the values of this indicator on all sub-groups.*

In traffic safety education, the "indicator" is the accident rate difference, which corresponds to the negative of the gradient in Figure 1(a). This paradox is defined as a relaxed variant of the well-known Simpson's paradox [11], where a trend that appears in the total population reverses in each of its subgroups.

Semi-Simpson's paradox further suggests the presence of the confounding bias in observed data. Back to Figure 1(a), the positive total gradient (0.71%) could mislead analysts that education "causes" more accidents in general, while in fact the observed higher accident rate for the educated drivers is not due to education itself, but due to the higher inherent "riskiness" of the educated drivers, as the traffic police tend to educate drivers with bad records in history. "Bad records in history" turns out to lie on a confounding path, which results in the confounding bias in observed data. The definitions of a confounding path and the confounding bias are introduced below. Figure 1(b) diagrams the confounding path ($T \leftarrow X \leftarrow U \rightarrow Y$) that explains the paradox. The formal definition of the terms are introduced in Appendix C.1.

The confounding bias hinders a direct comparison between educated and non-educated groups from being an accurate estimation of uplift. Moreover, it violates the unconfoundedness assumption commonly made by uplift models, and training an uplift model such as ClsTrans(RF) with the biased dataset would render the uplift estimation invalid. A detailed explanation of the unconfoundedness assumption is provided in Appendix C.2.

### 3.3 Sample re-weighting

To reduce the confounding bias, we apply sample re-weighting, and in particular, inverse propensity scoring (IPS) [1], on the observed data. We propose both the adapted model and the adapted metric with the integration of IPS.

**Inverse propensity scoring (IPS)** We first provide a formal definition of the propensity score. Given $\mathcal{D} = \{T_i, X_i\}_{i=1,2,\dots,N}$, the propensity score is $p_i := P(T_i = 1|X_i)$. The propensity score $p_i$ quantifies the dependency of treatment assignment $T_i$ on covariates $X_i$.

IPS first learns a propensity score estimator $\hat{f}$ of $f : X \rightarrow p$ on the whole dataset, and then assigns to each sample $i$ a weight $w_i$ in terms of the estimated propensity score $\hat{p}_i$. In this paper, we use the elastic net propensity model (i.e. logistic regression with L1 and L2 regularization) for $\hat{f}$, following the default implementation in the Causal ML package. The estimated propensity scores are then used to calculate sample weights $w_i$'s as *inverse propensity scores*: $w_i := T_i/\hat{p}_i + (1 - T_i)/(1 - \hat{p}_i)$. The inverse propensity scores $w_i$'s are then used to improve both the uplift model and the evaluation metric.

**The adapted model: ClsTrans(RF_IPS)** We propose to organically incorporate IPS into the base model ClsTrans(RF) to eliminate the confounding bias. In ClsTrans(RF), the training of random forest is based on bootstrapping that repeatedly sample training subsets from the original dataset. Hence, we propose a simple yet effective way to incorporate IPS $w_i$'s into random forest: we set the sample weights in boostrapping as $w_i$'s. The adapted model is thus *Class Transformation (Random Forest with Inverse Propensity Scoring) (or "ClsTrans(RF_IPS)" for short).*

**The adapted metric: AUUUC** The confounding bias also deteriorates the validity of the well-adopted evaluation metric, AUUC (Area Under the Uplift Curve) [10], detailed in Appendix D.1. Appendix D.2 provides an illustration that the uplift curve and AUUC becomes unsound in traffic safety education due to the confounding bias. Therefore, we propose unconfounded uplift curve and the adapted metric AUUUC with the integration of IPS. Further details of AUUUC are provided in Appendix D.3.

## 4 Optimization

In this section, we formulate the practical constraints in DRS that traffic police are concerned with in traffic safety education. Our formulation entails both resource constraints and diversity constraints. Subsequently, we propose an algorithm to solve the optimization problem for the optimal DRS strategy.

*Problem 2 (Driver Recipient Selection (DRS)).*

$$\begin{aligned}
&\underset{t_i}{max}\ \frac{1}{N}\sum_{i=1}^{N}\hat{\tau}_i * t_i - k_d\sum_{s=1}^{S} d_s - k_e\sum_{g=1}^{G} e_g - k_f\sum_{a=1}^{A} f_a\\
&\text{s.t. } \sum_i I_{is} * t_i \leq K_s,\ \forall s \in \{1,2,...,S\},\ \text{(limited quota)}\\
&\quad\ \sum_{i,s} I_{is} * c_s * t_i \leq C,\ \text{(total budget)}\\
&\quad\ \sum_i I_{is} * t_i + d_s \geq D_s,\ \forall s \in \{1,2,...,S\},\ \text{(location)}\\
&\quad\ \sum_i J_{ig} * t_i + e_g \geq E_g,\ \forall g \in \{1,2,...,G\},\ \text{(gender)}\\
&\quad\ \sum_i H_{ia} * t_i + f_a \geq F_a,\ \forall a \in \{1,2,...,A\},\ \text{(age)}\\
&\quad\ d_s \geq 0, \forall s,\ e_g \geq 0, \forall g,\ f_a \geq 0, \forall a,\ \text{(slack variables)}\\
&\quad\ t_i \in \{0,1\},\ \forall i \in \{1,2,...,N\}.
\end{aligned} \tag{2}$$

**Driver Recipient Selection (DRS)** In practice, we consider a series of practical constraints and factors in DRS, such as education quota, budget, location, gender, and age. Thus, the definition of the DRS problem is extended and derived as in Problem 2. Detailed description of the constraints and notations are available in Appendix E.1.

**The algorithm** Apparently, DRS is a variant of the binary knapsack problem with tightened constraints. Therefore, we propose an algorithm adapted from the `01Knapsack` algorithm [2] based on dynamic programming to obtain the optimal value and optimal solutions of DRS. The algorithm is detailed in Appendix E.2. The optimal solution is our DRS strategy.

# 5 Experiments

We conduct experiments with a semi-synthetic dataset and a real-world dataset from traffic safety education. We compare our proposed uplift modeling approach, ClsTrans(RF_IPS), with a variety of baselines on both datasets. We further evaluate our DRS strategy in the end-to-end driver recipient selection task, comparing it to existing strategy and a few alternatives.

## 5.1 Datasets

Our experiments are conducted with two datasets: an open-source semi-synthetic infant health dataset, **ACIC**, and a real-world traffic safety education and accident dataset, **EduAcc**. Both datasets are subject to strong confounding bias. Detailed description of the datasets are provided in Appendix F.1.

## 5.2 Uplift Modeling

We test our uplift modeling, ClsTrans(RF_IPS), on both ACIC and EduAcc datasets from various perspectives including the framework (Class Transformation), the core model (Random Forest), the sample re-weighting method (IPS) and the evaluation metric (AUUUC).

**The base uplift model.** We compare the base model ClsTrans(RF) with an extensive list of alternatives. We compare the uplift modeling framework Class Transformation with S-classifier, T-classifier, X-regressor, R-regressor, Uplift Tree / Random Forest Classifiers, CEVAE and DragonNet; we compare the core model Random Forests with Logistic Regression, XGBoost, and LightGBM; and we include random sorting as a naive baseline. Results in Appendix F.2 show that ClsTrans(RF) significantly outperforms the alternatives.

**Table 1.** AUUUC of different sample re-weighting methods with three base models on two datasets. Numbers in bold represent best results. Details of the sample re-weighting methods are available in Appendix F.3.

| Method | | ACIC | EduAcc |
|---|---|---|---|
| **No sample re-weighting** | S-classifier(RF) [5] | 2.59 | 4.38 |
| | T-classifier(RF) [5] | 2.47 | 4.39 |
| | ClsTrans(RF) [3] | 3.85 | 3.98 |
| **Partial resampling (strong confounders only)** | S-classifier(RF) | 3.05 | 3.93 |
| | T-classifier(RF) | 3.12 | 3.87 |
| | ClsTrans(RF) | 3.87 | 5.75 |
| **Resampling** | S-classifier(RF) | 2.54 | 3.85 |
| | T-classifier(RF) | 2.41 | 3.89 |
| | ClsTrans(RF) | 3.80 | 5.08 |
| **Undersampling** | S-classifier(RF) | 2.58 | 1.10 |
| | T-classifier(RF) | 2.32 | 1.26 |
| | ClsTrans(RF) | 3.70 | 0.73 |
| **Oversampling** | S-classifier(RF) | 2.56 | 3.93 |
| | T-classifier(RF) | 2.43 | 3.99 |
| | ClsTrans(RF) | 3.85 | 5.37 |
| **Inverse Propensity Scoring(IPS) [1]** | ClsTrans_IPS(RF) | 3.02 | 1.22 |
| | **ClsTrans(RF_IPS)** | **3.93** | **5.81** |

**Sample re-weighting in the uplift model.** To analyze the gain of integrating IPS into ClsTrans(RF), and we compare IPS with our proposed alternative sample re-weighting methods (detailed in Appendix F.3) such as direct sample re-weighting (partial resampling based on strong confounders only, resampling, undersampling, oversampling), alternative IPS integration (ClsTrans_IPS(RF)), as well as no sample re-weighting. Results are summarized in Table 1.

Incorporating IPS into the core model can improve the performance by as high as 46%, comparing the AUUUC of ClsTrans(RF_IPS), 5.81, to that of ClsTrans(RF), 3.98. It implies that an organic integration of IPS can effectively eliminate the confounding bias in the dataset. On the other hand, embedding IPS in the ClsTrans framework (i.e. ClsTrans_IPS(RF)) instead of the core model worsens the performance, as such embedding converts the binary outcome into continuous outcome and renders the core model into a regressor. Direct sample re-weighting may either improves or worsens the performance of uplift models. In particular, oversampling and partial resampling could bring performance gain, but not as much as ClsTrans(RF_IPS).

**Adaptation to evaluation metrics.** We conduct experiments to compare the commonly used uplift curves with our proposed unconfounded uplift curves on EduAcc dataset. Results show that in the presence of strong confounding bias, the uplift curve for random sorting goes downward, which is apparently inconsistent with human belief that education should reduce traffic accidents. It necessitates our adaptation to the uplift curve and AUUC.

### 5.3 Optimization

In practical applications such as traffic safety education, an AB-test environment for the uplift model is infeasible due to safety concerns. Therefore, we design a series of simulation experiments to show how ClsTrans(RF_IPS) improves the DRS strategy in traffic safety education. We focus on the DRS optimization problem with the EduAcc dataset.

**Data replay on educated drivers upon reduced education quota $K$.** First, we limit our scope to drivers that have education history in real-world data. This allows us to observe the accident rate of the same group of drivers on both treatments (educated and uneducated). For simulation, we conduct a data replay reducing traffic police resource allocation (i.e. reduced quota $K$) at a ratio of $\alpha = 50\%, 25\%$.

We start with a simplified setting and assume that education quota $K$ is the only constraint in DRS optimization. Each uplift model would filter $K$ drivers with the highest (positive) uplift scores based on its estimation, to receive education. To simulate the effect of the education, we compare the $K$ drivers' average monthly accident rate before and after education with real historical data. Table 2 (Columns "Simple filtering") summarizes the delta results. According to the real data, education on the originally selected 12,633 recipients reduces the monthly accident rate by 2.0% absolutely. If the traffic police resources were reduced to half and even one-fourth, the base model ClsTrans(RF) could have reduced the accident rate of the selected drivers by up to 3.2%; and with sample re-weighting, our proposed model ClsTrans(RF_IPS) could have reduced the accident rate further up to 6.3%. This is significantly more effective than the existing strategy at around 2% reduction estimated by Random.

Then, we simulate DRS with all practical constraints, only tuning education quota $K$. Detailed settings are provided in Appendix F.4. Drivers are selected via the DRS optimization algorithm based on estimates of each uplift model. Table 2 (Columns "DRS optimization") summarizes the delta results for each DRS strategy. Compared to simple filtering, the reduction in accident rates is slightly weakened as a trade-off for additional practical constraints. Nevertheless, our strategy still achieves up to 5.5% with ClsTrans(RF_IPS), 3.5% higher than the existing strategy estimated by Random.

**Full data replay on all drivers.** We further conduct a simulation on all drivers in the city, including those without education record in history. Instead of the original 12,633 recipients selected by the existing strategy by the traffic police, we apply our DRS strategies that turn out to select different groups of driver recipients. To compare their effectiveness, we evaluate the accident rate reduction in terms of uplifts: $\frac{1}{N}\sum_{i=1}^{N}\tau_i * t_i$. As ground-truth uplifts are

**Table 2.** Average monthly accident rate reduction of the $K$ selected educated drivers upon a simulation of reduced traffic police resources. The rate reduction is estimated as the difference before and after education using historical data. In simple filtering, drivers are selected based on the uplift estimates, with education quota $K$ as the only constraint. In DRS optimization, driver selection adheres to all practical constraints. Models are sorted by the "Simple filtering - 25%" column.

| **Education resources** | **Simple filtering** | | | **DRS optimization** | | |
|---|---|---|---|---|---|---|
| **reduced by** $\alpha =$ | 25% | 50% | 100% | 25% | 50% | 100% |
| **reduced to quota** $K =$ | *3,158* | *6,316* | *12,633* | *3,158* | *6,316* | *12,633* |
| **ClsTrans(RF_IPS)** | -6.3% | -3.8% | -2.0% | -5.5% | -2.8% | -2.0% |
| ClsTrans(RF) - partial | -4.9% | -3.0% | -2.0% | -4.7% | -2.7% | -2.0% |
| ClsTrans_IPS(RF) | -4.3% | -2.8% | -2.0% | -4.2% | -2.3% | -2.0% |
| ClsTrans(RF) - oversample | -3.7% | -3.1% | -2.0% | -3.6% | -2.2% | -2.0% |
| ClsTrans(RF) - resample | -3.3% | -3.0% | -2.0% | -2.5% | -2.2% | -2.0% |
| ClsTrans(RF) | -3.2% | -3.3% | -2.0% | -2.6% | -2.0% | -2.0% |
| Random (the existing strategy) | -2.1% | -1.9% | -2.0% | -1.9% | -1.9% | -2.0% |

unobservable from history, we estimate the uplifts with the best-performing uplift model ClsTrans(RF_IPS). Results summarized in Table 3 (Column "Accident rate reduction") show that our strategies can further reduce the overall monthly accident rate of the entire driver population (Column "Delta") by as high as 3.4% with ClsTrans(RF_IPS). This answers the two questions raised in Section 1.

**Table 3.** The comparison of our proposed DRS strategies with the existing strategy in real data. The "Delta" column indicates a further monthly accident rate reduction if the existing strategy is replaced with the proposed strategy.

| **DRS strategy** | **Educated drivers**[2] | **Accident rate reduction** | **Delta** |
|---|---|---|---|
| **ClsTrans(RF_IPS)** | 12,633 | 11.8% | 3.4% |
| ClsTrans_IPS(RF) | 12,633 | 10.5% | 2.0% |
| ClsTrans(RF) - partial | 12,633 | 10.1% | 1.6% |
| ClsTrans(RF) | 11,741 | 9.2% | 0.7% |
| ClsTrans(RF) - oversample | 12,178 | 9.0% | 0.5% |
| ClsTrans(RF) - resample | 12,121 | 8.9% | 0.4% |
| The existing strategy | 12,633 | 8.5% | 0% |

## 6 Conclusion and Future Work

This paper addresses the critical issue of driver recipient selection (DRS) in traffic safety education, framing it as a constrained optimization problem with

[2] For some strategies, the quota constraint is not tight (i.e. educated population $< K$) due to the existence of negative uplifts.

a causal objective. To effectively estimate the DRS objective, we introduced an uplift model, ClsTrans(RF_IPS), which integrates inverse propensity scoring into random forest. This approach successfully mitigates the confounding bias prevalent in education and accident data. The findings of our research not only highlight the effectiveness of uplift modeling in traffic safety education but also point to a promising direction for leveraging causal inference techniques in tackling urban traffic challenges associated with intervention strategies.

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## References

1. Austin, P.C., Stuart, E.A.: Moving towards best practice when using inverse probability of treatment weighting (iptw) using the propensity score to estimate causal treatment effects in observational studies. Statistics in medicine **34**(28), 3661–3679 (2015)
2. Goodrich, M.T., Tamassia, R.: Algorithm design and applications, vol. 363. Wiley Hoboken (2015)
3. Gutierrez, P., Gérardy, J.Y.: Causal inference and uplift modelling: A review of the literature. In: International Conference on Predictive Applications and APIs (2017)
4. Jaskowski, M., Jaroszewicz, S.: Uplift modeling for clinical trial data. In: ICML Workshop on Clinical Data Analysis. vol. 46, pp. 79–95 (2012)
5. Künzel, S.R., Sekhon, J.S., Bickel, P.J., Yu, B.: Metalearners for estimating heterogeneous treatment effects using machine learning. Proceedings of the national academy of sciences **116**(10), 4156–4165 (2019)
6. Mondal, A., Majumder, A., Chaoji, V.: Aspire: Air shipping recommendation for e-commerce products via causal inference framework. In: Proceedings of the 28th ACM SIGKDD. pp. 3584–3592 (2022)
7. Pearl, J.: Causal inference in statistics: An overview. Statistics surveys **3**, 96–146 (2009)
8. Piotr, RzepakowskiSzymon, Jaroszewicz: Decision trees for uplift modeling with single and multiple treatments. Knowledge & Information Systems (2012)
9. Qian, X., Xu, Y., Lv, F., Zhang, S., Jiang, Z., Liu, Q., Zeng, X., Chua, T.S., Wu, F.: Intelligent request strategy design in recommender system. In: Proceedings of the 28th ACM SIGKDD. pp. 3772–3782 (2022)
10. Renaudin, C., Martin, M.: About evaluation metrics for contextual uplift modeling. arXiv preprint arXiv:2107.00537 (2021)
11. Simpson, E.H.: The interpretation of interaction in contingency tables. Journal of the Royal Statistical Society: Series B (Methodological) **13**(2), 238–241 (1951)
12. Zhong, K., Xiao, F., Ren, Y., Liang, Y., Yao, W., Yang, X., Cen, L.: Descn: Deep entire space cross networks for individual treatment effect estimation. In: Proceedings of the 28th ACM SIGKDD. pp. 4612–4620 (2022)