

Causal Inference Project: The effect of marijuana on depression

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Abstract

Nowadays, the use of marijuana is becoming more and more common. Although the use of marijuana has been known to society for many years, some of its effects are not clear, especially those of a person's mental health and effects on day to day life. There are many articles and research trying to understand these different effects, if they exist. In our project we will try to answer the question - does smoking marijuana cause a person to experience depression? and we will examine the different causalities that may be involved.

1 Introduction

1.1 Marijuana

Marijuana is a mind-altering psychoactive drug that is created from the cannabis sativa plant by drying and shedding the flowers, stems, seeds and leaves of the plant. The plant contains more than 100 compounds (cannabinoids) that include tetrahydrocannabinol (THC) that produces the psychoactive effect, and addictive [1].

Cannabis is a central nervous system depressant, meaning it slows down brain activity and produces feeling of relaxation and drowsiness. It can make people feel relaxed, happy and sociable, though it has other side effects such as rapid heart rate, red, dry eyes, dry mouth and through, memory problems, slower reflexes, anxiety or paranoia [2]. It also has long terms effect and can effect brain development. It may impair thinking, memory, and learning functions and affect how the brain builds connection between different areas. But it is still unknown how long the effect of marijuana last and are the changes permanent. Marijuana may also have a mental effect such as temporary hallucinations and paranoia [3].

It is the most commonly used federally illegal drug in the United States, and the most commonly used addictive drug after tobacco and alcohol. Eighteen percent of Americans used marijuana at least once in 2019 [4]. Based on the National Center for Drug Abuse Statistics about seventeen percent of American adults use marijuana [5].

The United States Drug Enforcement Administration (DEA) claims that marijuana affects of relaxation, disinhibition, increased appetite, sedation, increased sociability, effects memory and learning difficulty in thinking and problem-solving, hallucinations impaired judgment, reduced coordination distorted perception decreased blood pressure, increased heart rate, dizziness, nausea, tachycardia confusion, anxiety, paranoia, drowsiness respiratory ailments [6].

1.2 Depression

Depression is a common but serious mood disorder that affects a person's thoughts, feelings, and every day activities. In order to diagnose a person with depression the symptoms must be present for at least two weeks. There are different types of depression, such as persistent depressive disorder, perinatal depression, seasonal affective disorder, and in our project we will focus on major depression. Major depression includes symptoms of depression that accure most of the time for atleast two weeks and interfere with a person's ability to work, sleep, study and eat [7].

The exact cause of depression is unknown. It may be caused by a combination of genetic, biological, environmental and psychological factors, though it varies from person to person. In general about 1 out of every 6 adults will experience depression at some time in their life, and sixteen million American adults are affected by depression every year [8].

According to the Diagnostic and Statistical Manual of Mental Disorders, 5th edition (DSM-5; APA, 2013), people are classified as having had an major depression episode (MDE) in their

lifetime if they had at least five or more of nine symptoms nearly every day (except where noted) in the same 2-week period, where at least one of the symptoms is a depressed mood or loss of interest or pleasure in daily activities (APA, 2013). These symptoms are as follows:

1. Depressed mood most of the day.
2. Markedly diminished interest or pleasure in all or almost all activities most of the day.
3. Significant weight loss when not sick or dieting, or weight gain when not pregnant or growing, or decrease or increase in appetite.
4. Insomnia or hypersomnia.
5. Psychomotor agitation or retardation at a level observable by others.
6. Fatigue or loss of energy.
7. Feelings of worthlessness or excessive or inappropriate guilt.
8. Diminished ability to think or concentrate or indecisiveness.
9. Recurrent thoughts of death or suicidality (i.e., recurrent suicidal ideation without a specific plan, making a specific plan, or making an attempt).

Unlike the other symptoms listed previously, recurrent thoughts of death or suicidality did not need to have occurred nearly every day.[9]

1.3 Marijuana and Depression:

Some research suggests that marijuana users are diagnosed with depression more often than non users are — particularly regular or heavy marijuana users. However, it doesn't appear that marijuana directly causes depression. It is possible that the same elements that cause depression may lead to marijuana use. Sometimes people suffering from depression use marijuana as a way to detach from their depressive symptoms. Heavy marijuana users may appeared depressed due to the dulling effects of the drug [10].

Many studies about this relationship faces challenges with methodological issues and controlling related factors. A review done in 2014 of existing research in this field concluded that using marijuana can place an individual at moderate risk of developing depression. But this review did not determine if the use of marijuana was causing depression or if a different relationship exists, for examplt between marijuana use and social problems. Marijuana use is assoviated with other factors that increase risk of depresiion such as unemplymnt [11].

It seems that there are still disagreements on the relation between marijuana and depression, and most research today still struggle with examining this relation with out other confounders. This matches the fact that the factors that affect marijuana use are connected in some way to the factors that affect depression.

2 The Data

Data used in this project was gather as part of the 2019 national survey of drug use and health (NSDUH) conducted by RTI International, Research Triangle Park, North Carolina for the Center for Behavioral Health Statistics and Quality within the Substance Abuse and Mental Health Services Administration (SAMHSA) [12]. The survey methodology was detailed in [9].

This is an annual survey of the civilian, noninstitutionalized population of the United States aged 12 years or older. NSDUH is the primary source of statistical information on the use of tobacco, alcohol, prescription psychotherapeutic drugs (pain relievers, tranquilizers, stimulants, and sedatives), and other substances (e.g., marijuana, cocaine) by the U.S. civilian, noninstitutionalized population aged 12 years or older. The survey also includes several series of questions focusing on mental health issues. The survey collects data through face-to-face interviews with a representative sample of the population at the respondent's place of residence. NSDUH collects information from residents of households and noninstitutional group quarters (e.g., shelters, rooming houses, dormitories) and from civilians living on military bases. The survey excludes homeless people who do not use shelters, military personnel on active duty, and residents of institutional group quarters, such as jails and hospitals.

2.1 Sampling Procedure

A coordinated sample design was creating for the years 2018 to 2022 in order to sample respondents to answer the survey. The coordinated sample design is state-based with an independent, multistage area probability sample within each state. From year to year there is a 50 percent overlap in the third stage units of area segment in order to reduce costs and slightly increase the precision of estimates of year-to-year trends because of the expected small but positive correlation resulting from the overlapping area segments between the years. There is no planned overlap of sampled residents in the same household, however individuals may be selected in consecutive years if they move and their new residence is selected the year after their prior resident was selected.

2.1.1 Data Collection Procedures

The surveys were conducted by in-person interviews with sampled individuals when confidentiality is stressed in all written and oral communication in order to increase the respondents' cooperation and willingness to report honestly. Respondents' names are not collected with the data, and computer-assisted interviewing methods are used to provide a private and confidential setting to complete the interview.

The interview begins by questions being asked by an authorized person who records the answer of the respondent on a computer. This part consists of initial demographic questions. The interview is then transitions to and audio computer-assisted self-interview where the respondent reads questions on the computer screen or listens to the questions through headphones then keys the answers directly into the computer without the authorized personal knowing the response. This is used for the sensitive question about use of tobacco, alcohol, marijuana, cocaine, crack cocaine, heroin, hallucinogens, inhalants, methamphetamine, and prescription psychotherapeutic drugs (i.e., pain relievers, tranquilizers, stimulants, and sedatives). Also in this section there is a variety of sensitive topics related to substance use and mental health issues which is also answered in the same manner.

Each respondent who takes the time to complete the full interview is given a 30 dollar cash incentive as a token of appreciation.

2.2 Processing The Data:

In this section we will list the adaption we made to the data in order to match our question.

2.2.1 Defining The Treatment And Control Group:

We are interested in examining the effect of using marijuana on depression. In order to do that we will need a group of people, our treated group, that have used marijuana for some time and we will want to examine their mental health after a given period of time in which they did not use marijuana. This period of time in which marijuana was not used is needed for creating a separation between the treatment and the outcome. On the other hand, our control group will be conducted of people who never using marijuana or hashish.

Given that, our treatment group will be defined as people who haven't smoked in the last year but did smoke at some point in their lives. Meaning, all subjects who answered the question "How long has it been since you last used marijuana or hashish?" with the option of "Did not use marijuana in the past 12 months" were considered as receiving the treatment, since the option of "never used marijuana" was part of the available answers, choosing this option did in fact imply using marijuana in the past (This answer implies that the subject has used marijuana in the past, since there was a "never used marijuana" option). Subjects who have answered this question with the option of "Within the past 30 days" or "More than 30 days ago but within the past 12 months" were dropped from the data since they do not fit in the treatment or control group.

Our control group included all the participates that answered the question "Have you ever, even once, used marijuana or hashish?" with no.

Regarding the usage of marijuana we removed all does who did not answered the above question given we do not know their history of marijuana use.

2.2.2 Defining The Outcome:

In the survey there was a section about adult depression, answered only by participants who are 18 or older. These questions ask about different time the participants felt sad, depressed, discouraged and other emotions that occur when experiencing depression. Also the participants were asked

about physical behavior that are related to depression, such as change in sleep, appetite, energy or weight (gain or loss). The questions refer to different times through out the participant life these feeling might have occurred and the different time period he or she had experienced them. Also these question were asked about recent times.

These questions are consistent with the criteria in the Diagnostic and Statistical Manual of Mental Disorders, 5th edition (DSM-5; APA, 2013). As stated before, according to DSM-5, people are classified as having had a major depression episode (MDE) if the had at least 5 of 9 symptoms nearly every day. Out of the respondents who were classifies as having an MDE in their lifetime based on their answers, they were asked similar questions about the past 12 months, and if their answered matched the stated criteria they were be classified as having MDE in the last year.

Because the definition of a person experiencing depression may vary we have decided to use the above criteria and define our outcome for adults having a MDE in the last year or not.

2.2.3 Defining The Measured Confounders

Many questions were asked about the participants demographics, including education, employment, health, and income. In order to be able and examine the effect of these different confounders on the participants outcome we needed to minimize them in the data and so we have chosen 7 questions, that in our understanding summarize the best the many different question asked. The questions chosen are:

1. Respondent's gender: Male of female.
2. Respondent's age, in groups of ages.
3. Respondent's marital status: Married, Widowed, Divorced, Separated or Never Been Married.
4. Respondent's race (including 7 categories)
5. Respondent's education level (including 5 categories)
6. Respondent's recorder family income (including 4 levels)
7. Would you say your health in general is excellent, very good, good, fair, or poor?

2.2.4 Additional Changes:

Because we have decided to examine depression only in adults we filtered the data based on ages and dropped all youth, under the age of 18.

Also, since the question about a respondent health is subjective, in order to allow better examination of the effect of this confounder we have decided to marge the categories of general health of excellent, very good, good and fair to one category and poor as another.

2.3 Data Analysis:

After processing our data we examined our results.

From fig. 1b fig. 1a we can see that are data is even between male and female respondents, and also the age is mostly even between all groups defined by the survey. Through in the race of the participants, fig. 1c, there is a small amount of Native Americans, Pacific Islanders and those who have more than one race, and so we will combine these three categories to one, called 'Others'. In our other confounders there is around an even distribution between the different categories.

For our treatment fig. 1h there are less people who received the treatment than didn't. This matches the concept of randomize control trail, as given our respondents are sampled somewhat randomly we can not plan in advance to have a certain amount of people who have smoked marijuana in the past but not in the last year. It is also important to state that between the respondents there are more people who use marijuana but do not match our defined treatment group.

The same result accrues in our outcome. As seen in fig. 1i most respondents are not defined as suffering a major depression episode in the last year. As stated previously this result is not surprising both because of the randomization of the respondents chosen to participate and because we have narrowed down our outcome definition in order to have a well defined outcome.

In fig. 2 we can see the correlation between each confounders, treatment, and outcome. Given this and the domain knowledge summarized in the introduction we were able to conduct the

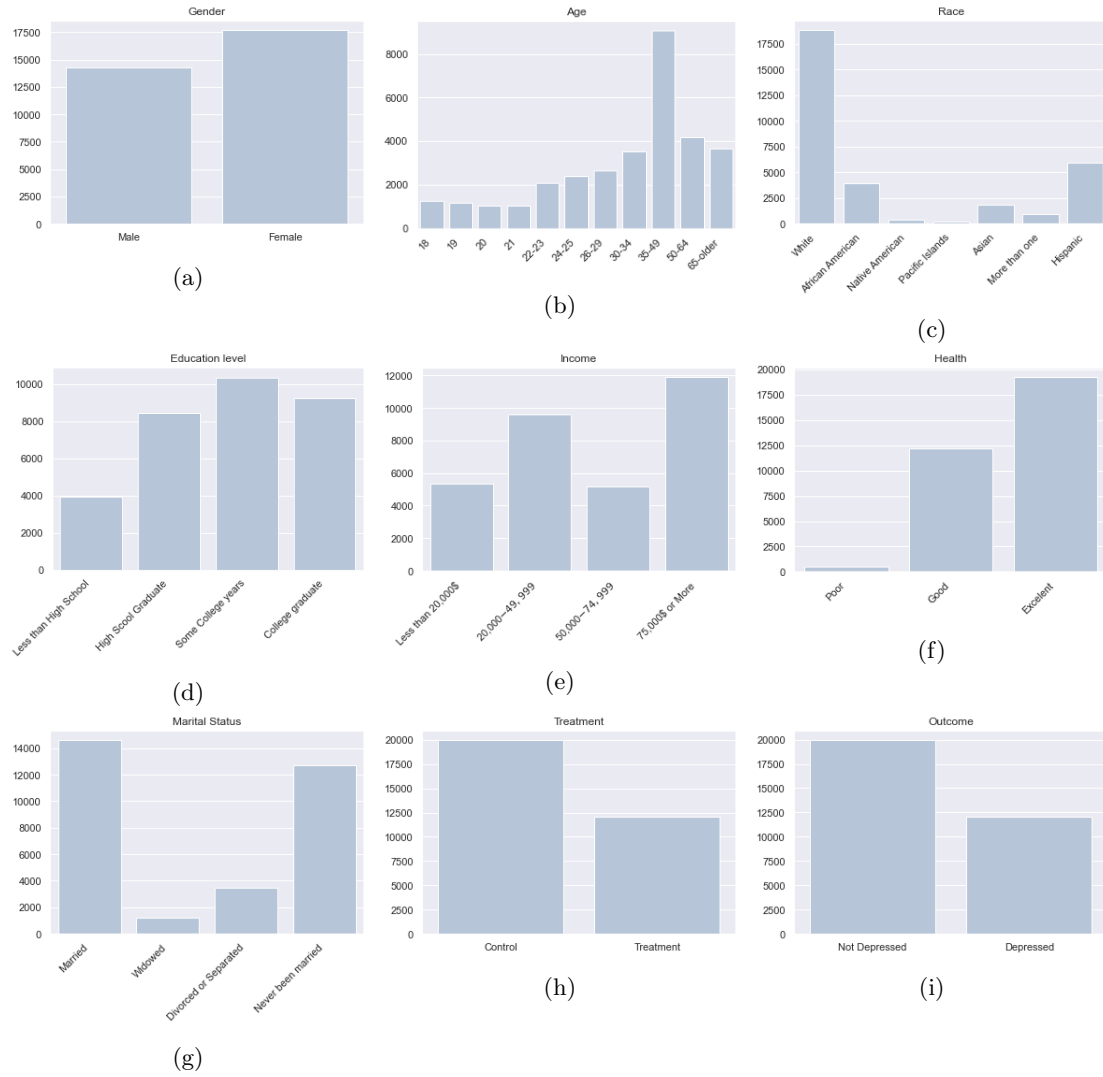


Figure 1: Histograms of the confounders, treatment, and outcome.

following graph fig. 3. From here, using the skill learn through out the course we were able to calculate the backdoor criteria which includes: age, marital status, health, education level.

3 Sufficient Conditions On Data

As learned through out the course there are four sufficient conditions that the data needs to satisfy in order for us to be able hold causal inferences on it:

1. Stable Unit Treatment Value Assumption
2. Consistency
3. No unmeasured confounders
4. Common support

3.1 Stable Unit Treatment Value Assumption - SUTVA

SUTVA states two elements: first that for each unit, there are no different forms or versions of each treatment level, which lead to different potential outcomes, and second that the potential outcomes for any unit do not vary with the treatments assigned to other units.

The meaning of the first assumption is that the treatment is well defined for each unit and it is the same for all subjects. In our case, as stated, the treatment is defined as a subject using marijuana in the past but not at the last year, where a subject who never used will be considered as not receiving the treatment. These criteria are asked specifically in different question in the

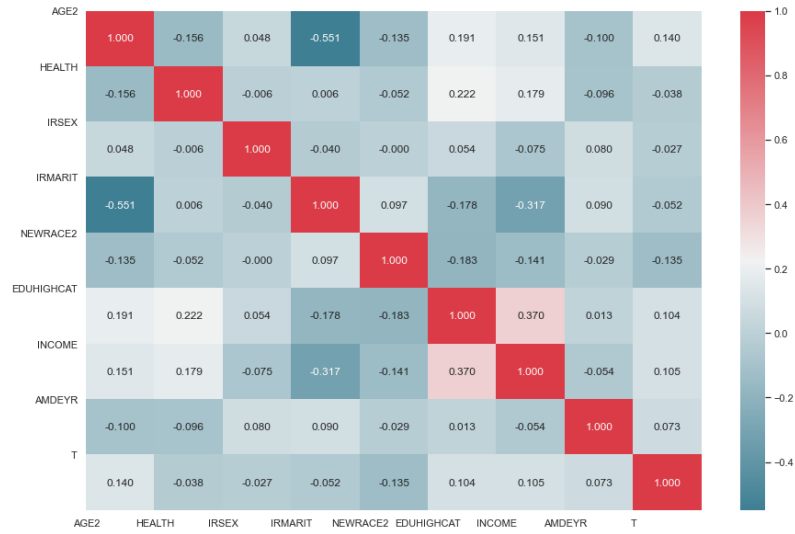


Figure 2: Heatmap showing correlation between the confounders, treatment, and outcome

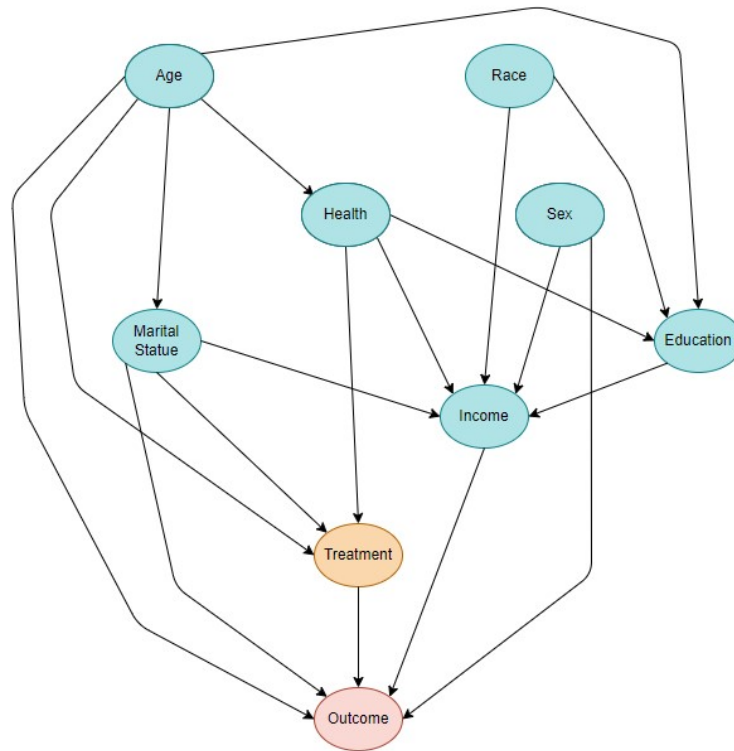


Figure 3: Connections between confounders, treatment, and outcome

survey as stated earlier, and a combination of the needed questions result in a binary result of a subject receiving the treatment or not.

The meaning of the second assumption is that the fact that a given subject receives or doesn't receive the treatment, meaning uses marijuana, does not effect the outcome of a different subject. As stated before, the participants of the study were chosen using a sampling design, that randomly samples with different level each level a different size. Because of this randomization we can assume that two respondents do not know each other and that way they cannot effect one another outcome.

3.2 Consistency

This assumption states that if a result of the treatment is examined in the outcome, then the subject indeed received treatment. In our case this assumption requires that all respondents that used marijuana report their true use. Given the survey is done anonymously and that the questions about marijuana use are completed with a compute aid system that so the interviewer does not know the respondent's answer, the answer the respondent gives have no effect on him. So we have reason to believe that the respondent will answer the questions honestly and the assumption holds.

3.3 No unmeasured confoundres - Ignorability

Here we assume that the potential outcomes are independent of treatment assignment, condition on observed covariates, meaning $(Y_0, Y_1) \perp\!\!\!\perp T, X$. According to the National Institute of Mental Health (NIH) the causes of depression are not yet clear, and research suggests that genetic, biological, environmental, and psychological factors play a role in depression, as mentioned at the Introduction section. Each of these factors are considered as confounder if they affects the respondent use of marijuana as well. We believe, based on common knowledge and research mentioned before, that demographic, environmental, and psychological factors can affects the respondent's use habit of marijuana. From our data we decided to consider the questions that represent these factors and therefore, we believe there are no unmeasured confounders.

3.4 Common Support

Common supports states that each subject has a probability to both receiving and not receiving treatment. Meaning $P(T = t|X = x) > 0 \forall t, x$. In our case, it means that each subject had the possibility of using marijuana in the last year or not using it at all.

In order to check that this condition holds for our data, we calculated the propensity score of our data. To calculate the propensity score we need to learn $P(T = 1|X = x)$ using a classification model. The needed model will be trained on our confounders and predict the outcome. We needed to find the best model and so we trained three models:

1. Logistic regression.
2. Random forest with 100 trees and each tree's maximum depth is 10.
3. Gradient boosting classifier with 100 trees and maximum depth is 1.

When comparing between the models we examined their accuracy score and their ROC curve fig. 4 and we can see that the random forest model gives the best results. So the propensity score was calculated using this random forest model. We examine the propensity of the subjects treated and not treated fig. 5. From here it is easy to see that the common support assumption holds, because there is an overlap in the propensity score between the two treatments groups.

4 Estimating Average Treatment Effect

Each respondent has two potential outcome and we will denote them:

- Y_0 is the potential outcome given the respondent received the treatment 0, meaning whether the respondent had suffer from MDE in the last year given he had never smoked marijuana.
- Y_1 is the potential outcome given the respondent received the treatment 1, meaning whether the respondent had suffer from MDE in the last year given he had smoked marijuana in the past year but not in the last month.

The treatment effect on a respondent i is $Y_1^i - Y_0^i$ and we will like to know the average treatment effect (ATE) $E[Y_1 - Y_0]$. Because we do not know the true values of Y_1, Y_0 we cannot calculate accurately the ATE and so we will estimate the value using different methods.

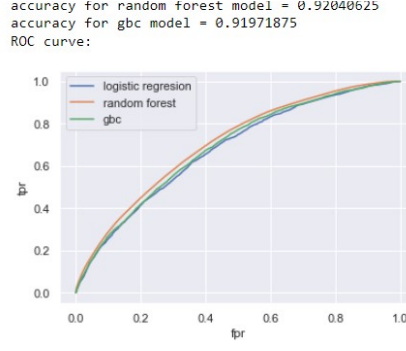


Figure 4: Accuracy and Roc curve of the models for estimating $P(T = 1|X = x)$



Figure 5: Histogram of the propensity score between the treated and control group

4.1 Naive Estimation:

Here we tried a naive approach, where we calculated the average amount of respondents who were classified as suffering from MDE in the last year between the treatment and the control groups and then subtracted them:

$$\widehat{ATE}_{naive} = \frac{1}{n_{T=1}} \sum_{i \text{ for } T=1} Y_1 - \frac{1}{n_{T=0}} \sum_{i \text{ for } T=0} Y_1$$

4.2 Inverse Probability Weighting (IPW) with Propensity Scores Estimation:

Denoting the propensity score as $e(x)$ we can use it and the assumption of ignorability to receive that

$$E[Y_1] = E\left[\frac{TY}{e(X)}\right], E[Y_0] = E\left[\frac{(1-T)Y}{1-e(X)}\right] \rightarrow ATE = E\left[\frac{TY}{e(X)}\right] - E\left[\frac{(1-T)Y}{1-e(X)}\right]$$

Given this we can estimate the ATE:

$$\widehat{ATE}_{IPW} = \frac{1}{n} \sum_i \frac{t_i y_i}{e(x_i)} - \frac{1}{n} \sum_i \frac{(1-t_i) y_i}{1-e(x_i)}$$

4.3 S-Learner Estimation:

Here we will fit a model to our confounders and treatment and try to predict the outcome. That is denote the model as $f(x, t)$ then $\hat{y} \approx f(x, t)$ and our estimator will be:

$$\widehat{ATE}_{S-learner} = \frac{1}{n} \sum_i f(x_i, 1) - f(x_i, 0)$$

As done for calculating the propensity score, also here a classification model was needed to be chosen. We compared the same models as stated in the propensity score and trained them on the confounders and treatment and compared their accuracy and ROC curve in order to determine the best model fig. 6a. Also here the best model was the random forest and so it was used to estimate $\widehat{ATE}_{S-learner}$

4.4 T-Learner Estimation:

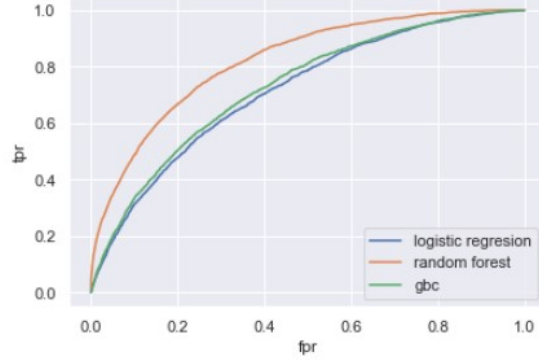
The T-Learner estimator works on the same idea as the S-Learner except two models are trained on the confounders of the treatment and control group separately, denoting $\hat{y}_1 \approx f_1(x)$, $\hat{y}_0 \approx f_0(x)$ respectively. Our estimator will be:

$$\widehat{ATE}_{T-learner} = \frac{1}{n} \sum_i f_1(x_i) - f_2(x_i)$$

Also here we compared between the three models, creating two models from each type trained on the treatment and control group separately, and compared the models from each group using

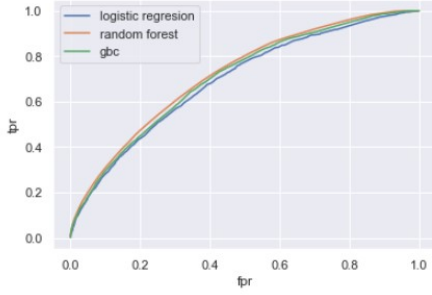
accuracy score and ROC curve fig. 6b fig. 6c. For both groups, the best model was the random forest and $\widehat{ATE}_{T\text{-learner}}$ was calculated using these models.

accuracy for logistic regression model = 0.91953125
accuracy for random forest model = 0.92153125
accuracy for gbc model = 0.919625
ROC curve:



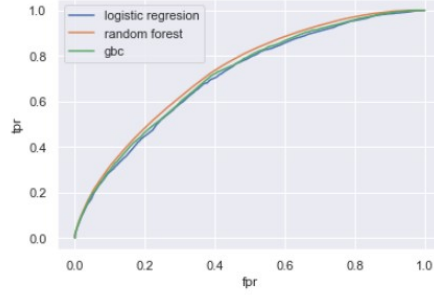
(a) accuracy and ROC curve for models trained for S-Learner estimator

for treated:
accuracy for logistic regression model = 0.8949987559094302
accuracy for random forest model = 0.8962428464792237
accuracy for gbc model = 0.8954963921373476
ROC curve:



(b) accuracy and ROC curve for models trained for T-Learner estimator for treatment group

for control:
accuracy for logistic regression model = 0.9356165070450785
accuracy for random forest model = 0.9358170786742215
accuracy for gbc model = 0.9358170786742215
ROC curve:



(c) accuracy and ROC curve for models trained for T-Learner estimator for control group

Figure 6

4.5 Matching Estimation:

When using the matching estimation we wish to find for each respondent and he's treatment the closest respondent with similar confounders and an opposite treatment. We will denote for respondent (i) his closest respondent with opposite treatment as $j(i)$. If respondent (i) received treatment 1 then we will denote $\widehat{ITE}(i) = y_i - y_{j(i)}$, otherwise $\widehat{ITE}(i) = y_{j(i)} - y_i$. and so our matching estimator will be:

$$\widehat{ATE}_{matching} = \frac{1}{n} \sum_i \widehat{ITE}(i)$$

In order to find each respondent nearest neighbor with opposite treatment we trained to KNN models with 1 neighbor, one fit on the confounders of the treatment group and the other on the confounders of the control group. Then we fed each model it's opposite group, that is the model trained on the treatment group was given the control group and returned the nearest neighbor for each respondent of the control group from the control group and vice versa. Given the neighbors we estimated the ATE as stated above.

4.6 Doubly-Robust Estimation:

Similar to the T-Learner estimator, the Double-Robust estimator uses two models trained on two data of the treatment and control groups separately. The estimator is:

$$\widehat{ATE}_{Doubly-Robust} = \frac{1}{N} \sum_i \left(\frac{T_i(Y_i - \hat{\mu}_1(x))}{\hat{P}(x_i)} + \hat{\mu}_1(x_i) \right) - \frac{1}{N} \sum_i \left(\frac{(1-T_i)(Y_i - \hat{\mu}_0(x))}{1 - \hat{P}(x_i)} + \hat{\mu}_0(x_i) \right)$$

Also here the best model for both data was the random forest, 6b 6c, and the estimator was calculated based on this model.

This estimator called doubly robust because it only requires one of the models, $P(T = 1|X)$ (estimation of the propensity score) or $\mu(x)$ (estimates $E[Y|X, T = 1]$), to be correctly specified. This estimator uses both the data model and the missingness model. It uses both complete and missing observations. When both models are correctly specified, then the double robust estimator is more efficient than the IPW estimator, which is a powerful estimator for unbalanced data like in our case.

5 Estimating Categorical Average Treatment Effect

Based on [13] [14], there is a difference in the use of marijuana between men and women, both in the frequency of use and in the amount used. Also there is a difference between the genders for suffering from depression and it's effects [15] [16]. Given these differences we come to a conclusion that the gender of the respondent might have an effect both on the treatment and the outcome, thus might cause a difference in our estimation for the treatment effect.

In order to examine this hypothesis, we decided to estimate categorical average treatment effect by dividing our data by gender and following the same steps as mentioned above. For both new data sets, male respondents and female respondents, we estimated the ATE based on the same methods mentioned above.

6 Results

As seen in 1, the estimated ATE by all methods was approximately zero. From this we can state that we were not able to examine a considerable effect of using marijuana on depression. Also when considering men and women separately, 2 3, we received similar results (we wanted to check that science women has more statistics of depression). In all three data that we calculated our ATE's, the IPW return a negative number. Meaning that this method might have detected an opposite effect between our treatment and outcome, that depression may cause the use of marijuana. But also for the IPW method, the estimators were quite small to come to a conclusion.

We used bootstrap method in order to create confidence intervals. The confidence intervals of confidence level of 0.975 and quite small, but not all of them contain zero. This may mean that some methods may have recognised a slight causality between our treatment and effect, but again but the estimated ATE's and the confident intervals are too small to state that such causality exist.

Methods	CI Lower bound	CI Upper Bound	Average \widehat{ATE}
Naive	0.027817	0.05347	0.04064
IPW	-0.05338	-0.04181	-0.0476
S-Learner	-0.00096	0.001758	0.000396
T-Learner	-0.002809	0.0073194	0.002254
Matching	-0.008719	0.0809517	0.036116
Doubly-Robust	0.356397	0.498147	0.427272

Table 1: Results of estimated ATE's.

Methods	CI Lower bound	CI Upper Bound	ATE Estimator
Naive	0.005314	0.0290173	0.017165
IPW	-0.05301	-0.0404797	-0.0467467
S-Learner	-0.00014	0.00019	0.0
T-Learner	-0.00566	0.008734	0.001533
Matching	0.000628	0.0359141	0.0182712
Doubly-Robust	-0.000598	0.022135	0.010768

Table 2: Results of estimated CATE's for men.

Methods	CI Lower bound	CI Upper Bound	ATE Estimator
Naive	0.04551	0.077246	0.06137
IPW	-0.08571	-0.070954	-0.078336
S-Learner	-0.00046	0.000649	0.0
T-Learner	-0.00268	0.0042688	0.0007912
Matching	0.02971	0.076890	0.053305
Doubly-Robust	0.01858	0.051603	0.035092

Table 3: Results of estimated CATE’s for women.

7 Potential Weaknesses

1. Unbalanced data between treatment and and control group - As described earlier the respondent’s of the survey were sampled randomly, and so in order to receive an even amount of respondents who match each group, control and treatment, many surveys were needed to be completed, something that is not possible with the way the survey is conducted. So our control group is significantly larger than treated fig. 1h. We considered randomly dropping respondents from the control group in hopes of receiving a more balance dataset, and by doing so we receive similar outcome in our attempts. Since we did not want to temper with our data and we were not able to assess the affect of randomly dropping respondents from the control group on the ATE, We preferred to stay with unbalances data and use IPW estimators which fix this problem with adding weights to our different groups.
2. The original data had many personal questions which may be confounders. Based on prior knowledge and research done on depression and marijuana use, we narrowed down to seven questions which we believe represent our true confounders. Though, both in the fields of marijuana use and depression it is unclear all the personal aspects of the person’s life that can affect them, it is possible that more confounders exist and can effect our treatment and outcome. We will state that we tried adding a few more personal questions that we thought might have some effect though we did not receive any difference in the estimated ATE’s and so we decided to remain with the stated confounders.
3. Health - for the question asking about the respondent’s general health the possible answers were excellent, very good, good, fair, poor. Those expression are subjective, and each respondent might classify the same health level differently. This might cause problems when trying explain the effect of a respondent’s health condition on the treatment and outcome. Also, the data did not contain many respondents who classify their general health as poor, which also effects our ability for estimating it’s effects.
4. Different kind of usage - the treatment isn’t exactly the same for all subjects (SUTVA does not fully holds). Even though our treatment was well defined, all respondents who stated they used marijuana but not in the last year, we are aware that this is not optimal, because the amount each of them received the treatment may vary. Meaning, although all of the respondents did use marijuana we have no way of telling the amount used, they might have tried marijuana only a few times or were more heavy users. When regarding the amount of marijuana usage we only had information about the use in the last year.

Our trade off in this case was between being able to separate our treatment group by the amount of marijuana used, and by that SUTVA holds, to having required time period between receiving of the treatment, marijuana use, to the outcome, having depression. The way the survey was held, we were only able to receive concrete information about the outcome in the last year. Also, given the fact that depression occurs over time - we preferred to measure it over a year, and so our treatment group must not include respondents who used marijuana in the past year.

This choice also helped us with the unbalance of the data. First of all, there are more respondents who used marijuana but not in the last year, than those who used marijuana in the last year. Second, if we would have chosen to split our treatment group based on the amount of marijuana used, each group would contain only a few thousand respondents at most, compared to over thirty thousand respondents who have never used marijuana. This would have cause an even more unbalanced data and would have effected the estimation of the ATE’s, since the different algorithms would have been more prone to over fitting.

5. Income definition - When respondents were asked about their income, it was asked with respect to their household. Meaning there was no question about a respondent personal income. Though a person is quite affected by the income of his household, we wanted to measure the effect of his income on his mental stability and his marijuana use. Given that we tried adding the question about a respondent's job status and the reason he is unemployed (if unemployed), we examined with a similar heat map to 2 that there was a large correlation between the income and these question, as expected. Given that, we decided to remain only with the question about the respondent's household income which gave as a general assumption of his life style.

8 Conclusions and Discussion

In our project we tried to understand whether the use of marijuana may effect depression, cause or reduce it. As we saw in the introduction, several studies show that there is a correlation between using marijuana and reported depression. We wanted to test this causal effect by using a variety of methods learned through out the course to evaluate the average treatment effect. As reviewed in the results chapter, we received that there is no evidence in the data of a significant effect.

It is important to state that even though we were not able to calculate an effect between the treatment and outcome, it does not in fact state that such relation does not exist, positive or negative effect. While working on the project, we encountered some possible weaknesses in the data that quite possibly have some effects on our results. These challenges do match challenges that researches in these field were encountered with.

Future work may be able to counteract these weaknesses and try to find a significant effect. Some chances we think would have helped was creating data was was more adjusted for this research question. For example, more specific question about a person's marijuana use habits, and not just general questions about the subject. But as stated many times in this work, the causes of both marijuana use and depression are wide and vary from person to person, which causes a great challenge trying to map all of them out in order to find a relation between the two.

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