Deloitte: *Drug Case Study*

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Introduction

Our client at the NIH wants to build a program to address drug use among teenagers/young adults in the US. They are asking you to use existing data to understand factors that lead to drug use and make recommendations for the program, as well as help them understand how and where they should start to roll out these programs.

Overarching Question

What are the top 10 external factors that contribute to hard drug addiction?

When we say hard drugs, we mean any drug “beyond” substances such as alcohol, tobacco, or marijuana.

To what accuracy, could we predict whether someone would use drugs?

Context

Challenges

Models

PCA? Regularization through Lasso? XGBoost? Ensemble?

The *data*

2 GB big! 3000 columns

Interpretation

Why did this model work better than this one?

01

Data Cleaning

Filtering the appropriate data

```
# only want ages 12 - 25
df = df[(df['CATAGE'] == 1) | (df['CATAGE'] == 2)]
df = df.set_index('CASEID')
```

Missingness Analysis

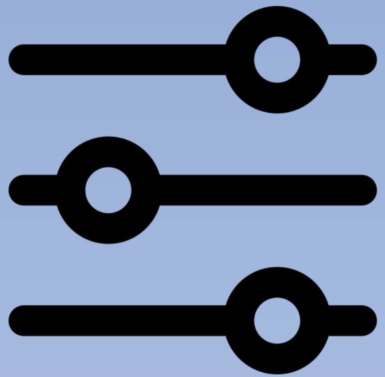
Replace columns with majorly missing values

```
df_subset = df.loc[:, df.isna().mean() < 0.95]
df_subset
```

Filtering Relevant Columns

- Stimulants, Crack, Cocaine, Heroin, Hallucinogens, Pain Relievers, Tranquilizers, Sedative

Drug Abuse?



02

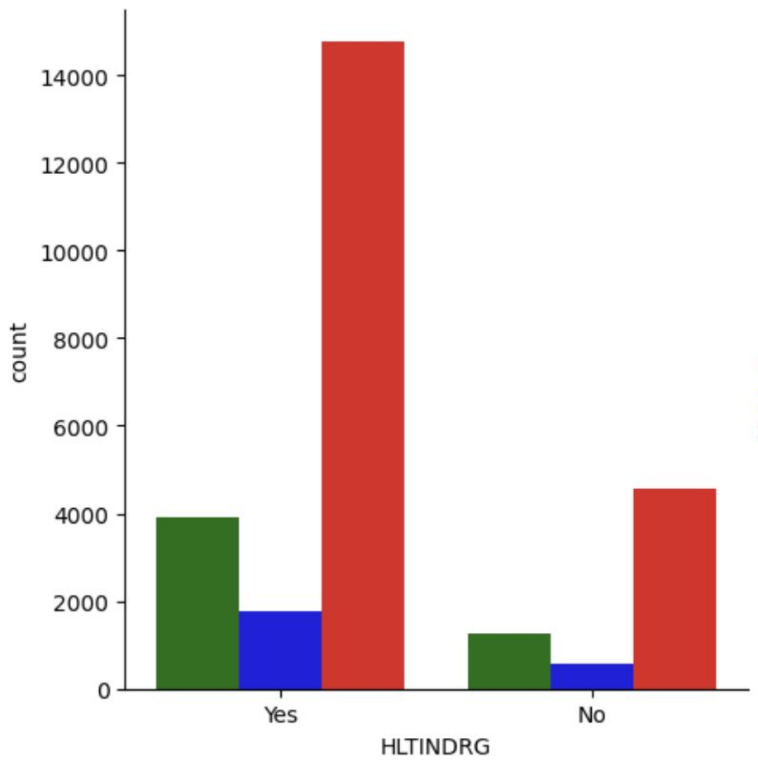
Exploratory Data Analysis

Storytelling reports

About the Data

Data *Visualization*

Data *storytelling reporting*



APPROACHED BY SOMEONE SELLING ILL DRUG PST 30 DYS

RCVD ANY MENTAL HEALTH TRT IN PST YR

PRNTS CHECK IF YOU'VE DONE HOMEWORK PST 12 MOS

How we chose variables

In [20]:

```
importance_df.sort_values(by = "importance", ascending = False)
#this only caught 2 features as non zero
# HLTINALC HLTNMNT which is only marjuiana(was hoping for more)
```

Out[20]:

	feature	importance
1731	HLTINALC	0.060461
1732	HLTINMNT	0.036584
0	CASEID	0.0
1229	YETCGJOB	0.0
1227	YESCHIMP	-0.0
...	...	...
606	RKHERREG	0.0
605	RKTRYHER	0.0
604	RKLSDREG	0.0
603	RKTRYLSD	0.0
1829	VEREP	-0.0

1830 rows × 2 columns

ONLY 2 VARIABLES ARE IMPORTANT?

```
In [23]: pca.pca(X ,X_train)

There are 837 components that explain the variance within the dataset
STMMON: 0.015704350903006103
CPNSTMMN: 0.015669309736575845
IICRKRC: 0.015087308435441616
II2CRKRC: 0.014955312294304399
ABUSEHER: 0.014903875549945574
ILLPSAVE: 0.0148607790313776
DRGTXER: 0.014802996842752176
IIECSRC: 0.014673944710285516
SPILANAL: 0.014645522269818474
```

Stimulants

Crack

How we chose variables

- PCA? Not good for categorical
- Lasso?

Solution: XGBoost feature importance attribute

Why XGBoost?

- Built in feature importance attribute
- Easy to access and evaluate
- Pipeline Objects allow for easy implementation

03

Different Models

Talk About Feature Selection, Lasso, Ridge, and Logistic, PCA

```python
# Create a Logistic Regression model with L2 regularization
lr = LogisticRegression(penalty='l2')
train_and_evaluate_model(lr, X, y, "logistic_regression_model", categorical_vars)
```

✓ 54.2s

```
/Users/palvins/.pyenv/versions/3.9.4/lib/python3.9/site-packages/sklearn/linear_model/_l

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

/Users/palvins/.pyenv/versions/3.9.4/lib/python3.9/site-packages/sklearn/metrics/_classi

Precision is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_div


Confusion Matrix:
[[5444    0]
 [1732    0]]
Accuracy:  0.7586399108138239
Precision:  0.0
Recall:  0.0
F1 Score:  0.0
```

Logistic Regression & Ridge Regularization

Random Forest

```
# Create a Random Forest classifier
rf_clf = RandomForestClassifier(n_estimators=100)
result = train_and_evaluate_model(rf_clf, X, y, "random_forest_model", categorical_va
result
```

✓ 2m 38.2s

```
Output exceeds the size limit. Open the full output data in a text editor
Confusion Matrix:
[[5439    5]
 [1685   47]]
Accuracy:  0.7644927536231884
Precision:  0.9038461538461539
Recall:  0.027136258660508082
F1 Score:  0.052690582959641255

Cross-validation scores:
[0.76658305 0.76755853 0.77912486 0.76989547 0.768223  ]

Mean cross-validation score:
0.7702769821200363
Feature: HLTINALC, Importance: 0.022779275697964497
Feature: IRPRVHLT, Importance: 0.0029071884796050412
Feature: HLTINMNT, Importance: 0.016500114963150243
Feature: AMHINP2, Importance: 0.00014220000642720652
Feature: AMHRX2, Importance: 0.00024028750979454192
Feature: AMHTXRC3, Importance: 0.0002837014069168502
Feature: AMHSVTYP, Importance: 0.00028337778147641236
Feature: PRVHLTIN, Importance: 0.002640207211520947
```

	Feature	Importance
0	HLTINALC	0.022779
2	HLTINMNT	0.016500
244	ANALWT_C	0.004471
500	BMI2	0.004467
435	WTPOUND2	0.003831
...	...	...
1300	TUINAL2	0.000000
1296	CHHYD2	0.000000
1377	INHEVER	0.000000
1294	PRELUDN2	0.000000
1291	ROHYPNL2	0.000000

XGBoost

Boosted Decision Trees (using XGBoost)

The boosting technique is powerful, but it can lead to overfitting if not used with care. It's impor

```python
# create XGBClassifier
xg_clf = xgb.XGBClassifier(n_estimators=100, learning_rate=0.1, max_depth=5)
result = train_and_evaluate_model(xg_clf, X, y, "xgboost_model", categorical_vars)
result
```

✓ 4m 45.5s

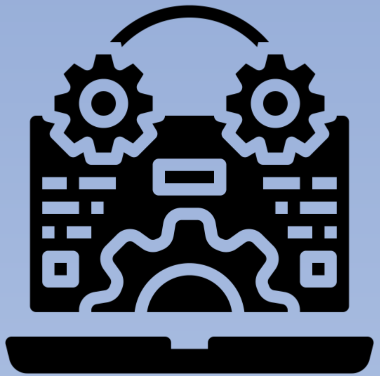
```
Output exceeds the size limit. Open the full output data in a text editor
Confusion Matrix:
[[5369   75]
 [1360  372]]
Accuracy:  0.8000278706800446
Precision:  0.8322147651006712
Recall:  0.21478060046189376
F1 Score:  0.3414410279944929

Cross-validation scores:
[0.80351171 0.80504459 0.80490524 0.80334495 0.79902439]

Mean cross-validation score:
0.8031661752881265
Feature: HLTINALC, Importance: 0.046348713333837509
Feature: IRPRVHLT, Importance: 0.017094297334551 81
Feature: HLTINMNT, Importance: 0.019346199929714203
Feature: AMHINP2, Importance: 0.005094137508422136
Feature: AMHRX2, Importance: 0.006371975410729647
Feature: AMHTXRC3, Importance: 0.004127115011215 21
Feature: AMHSVTYP, Importance: 0.007858609780669212
Feature: PRVHLTIN, Importance: 0.005835204850882292
Feature: IRTRNRC, Importance: 0.0027723219245672226
Feature: IIINHAGE, Importance: 0.002947981469333172
```

	Feature	Importance
1746	HLTINALC	0.028191
1759	IRPRVHLT	0.015407
1747	HLTINMNT	0.013420
1164	AMHINP2	0.006535
1166	AMHRX2	0.005058
...	...	...
1681	UADOTHM	0.000228
1581	YOWRLSIN	0.000189
675	ALCCUTDN	0.000159
872	ANLFRTK2	0.000101
357	IEMFLAG	0.000021

04 Final Model

Model Optimization

- GridSearchCV
- 60 Total Combinations
- ~3-4 minutes per model



```
parameters = {
    'n_estimators': range(50, 250, 50),
    'learning_rate': [0.01, 0.1, 0.3],
    'max_depth': range(1, 11, 2)
}
clf = GridSearchCV(xg_clf, param_grid=parameters)
grid_result = clf.fit(X_train, y_train)
grid_result.best_estimator_
```

Evaluation:

Precision, Recall, F1, Accuracy -> Which Model is the 'Best'

- Accuracies were decent, not the only metric we should focus on.
- F1 is a more reliable metric since our data was imbalance

Model trained on imputed data: F1 score was .34 (not good)

At the last minute, we decided to try a model trained on non-imputed data

F1 score >.95 (overfitting?)

In [*]:
```
# create XGBClassifier
xg_clf = xgb.XGBClassifier(n_estimators=100, learning_rate=0.1, max_depth=5)
result = train_and_evaluate_model(xg_clf, X, y, "xgboost_model", categorical_vars)
result
```

```
Confusion Matrix:
[[1614    9   69]
 [   9  485   27]
 [  51   18 4894]]
Accuracy:  0.9744983277591973
```

We used an imputation parameter within XGBoost

- The list of most important features changed significantly
- Most likely due to a large number of NA values (3100 features since we weren't imputing)

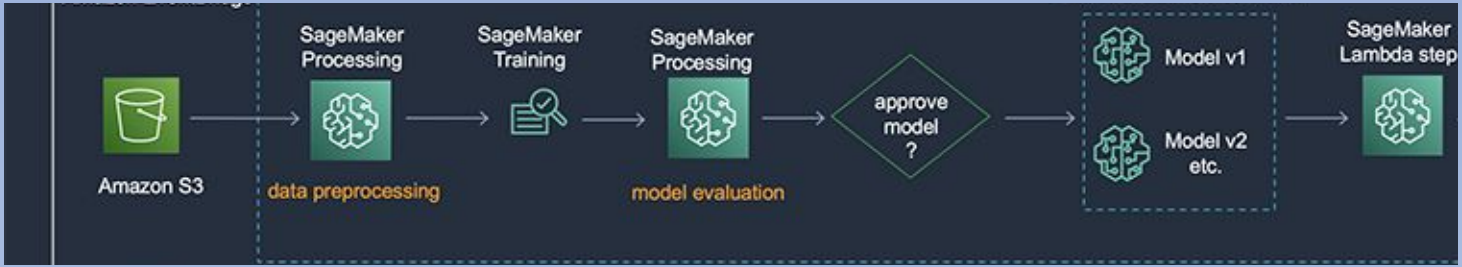
What does this mean?

- We need to go back and analyze the columns
- Try different algorithms without imputing

Once we improve model's performance (F1 score, Recall), where do we go next?

- Deploy it on the cloud
- Create a pipeline to feed new data

Repeat the cycle as time goes on



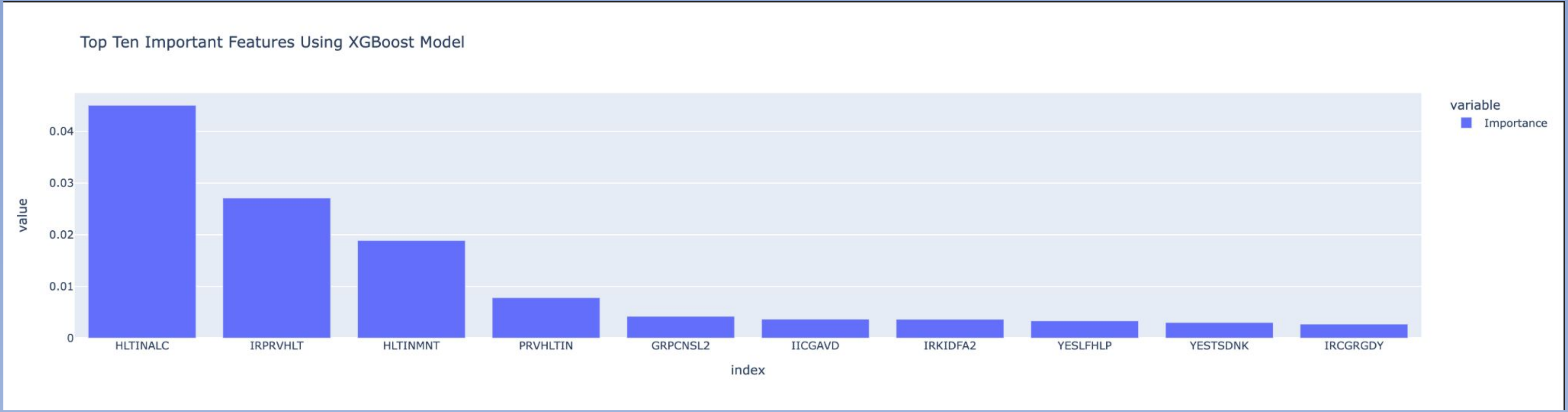
05

Most Important Factors

Top 10 Features and Their Importance

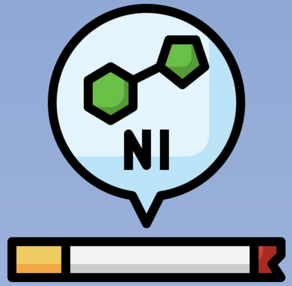
	Feature	Importance
1.	HLTINALC	0.045076
2.	IRPRVHLT	0.027089
3.	HLTINMNT	0.018880
4.	PRVHLTIN	0.007793
5.	GRPCNSL2	0.004189
6.	IICGAVD	0.003621
7.	IRKIDFA2	0.003589
8.	YESLFHLP	0.003303
9.	YESTSDNK	0.002986
10.	IRCGRGDY	0.002688

The Results


Top Ten Important Features Using XGBoost Model
value
0.04
0.03
0.02
0.01
0
HLTINALC
IRPRVHLT
HLTINMNT
PRVHLTIN
GRPCNSL2
IICGAVD
IRKIDFA2
YESLFHLP
YESTSDNK
IRCGRGDY
index
variable
Importance

1. Presence of alcohol abuse or alcoholism
2. Availability of private health insurance
3. Presence of mental or emotional difficulties
4. Presence of private insurance coverage
5. Participation in program to help substance abuse
6. Recent cigarette usage within the past 30 days
7. Count of individuals aged 0-17 within the household
8. Participation in programs within the past year to address personal or family drug/alcohol use
9. Estimation of students in same grade who get drunk at least once a week
10. Regular cigarette smoking throughout the day

Major Categories



1. Substance Abuse and Addiction
    a. Alcohol
    b. Nicotine
2. Mental Health
3. Healthcare
4. Support and Intervention
5. Peer Influence
6. Family

Considerations and Limitations

1. Some factors may have indirect relationships with drug use
   a. Availability of private health insurance:
      i. May be influenced by income
   b. Count of individuals aged 0-17 within the household
      i. count itself may not directly cause drug use. Other factors within the household, such as parenting style or family relationships, might be more influential.
2. Future work
   a. Supplement quantitative analysis with qualitative research methods

Recommendations for the Program

1. Understanding the nature of substance abuse and addiction is vital in designing effective prevention and intervention strategies.
2. Develop targeted interventions that address the identified risk factors.
   a. create educational programs that highlight the dangers of alcohol abuse, provide coping mechanisms for mental or emotional difficulties, and emphasize the importance of seeking help through available substance abuse programs.
3. Engage in collaboration with key stakeholders, such as schools, community organizations, healthcare providers, and local government agencies.

Where to implement?

Las Vegas

Conclusion

Thank you to our mentors and to Deloitte!

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- **Miguel Macias**
- **Satya Kothapalli**