Iowa Initiative for Artificial Intelligence

Final Report

Project title:	Identify differences in circumstances between firearm and non-firearm violent deaths
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Were specific aims fulfilled:	Yes
Readiness for extramural proposal?	Ready for paper write-up. Yes
If yes … Planned submission date	
Funding agency	
Grant mechanism	
If no … Why not? What went wrong?	Nothing went wrong. The IPRC will continue to explore opportunities to integrate AI methods with traumatic injury research. Much was learned to advance the methods of this approach, specifically with regard to health datasets as they relate to AI methods and the use of AI methods (often requiring multiple approaches) to answer health-related questions.

Brief summary of accomplished results:

1. Created a pipeline for data preprocessing serving as a starting point for the study of signature variables predictive of firearm and non-firearm violent deaths, using ML methods.
2. Throughout hyperparameter tuning and prediction evaluation of 7 broad categories of machine learning (ML) methods: ensemble, linear models, naïve bayes, nearest neighbor, SVM, tree based, neural network.
3. Construction of ML models that have a balanced trade-off between its predictive performance and interpretability.
4. A ranking of variables based on their predictive powers reported in best-performing ML models.
5. A method to distill prediction knowledge of the best performing ML models in a single decision tree that allows decomposition of decision path leading to a particular suicide outcome.

Research report:

a) Aims: taken from the statement of intent

Using the NVDRS, use machine learning algorithms to ***identify differences in circumstances between firearm and non-firearm violent death.***

b) Data: taken from the statement of intent

The CDC/National Center for Injury Prevention and Control established the National Violent Death Reporting System (NVDRS) in 2002 (https://www.cdc.gov/violenceprevention/datasources/nvdrs/index.html). The objectives of the NVDRS are to establish a national surveillance system of information about violent deaths, collecting detailed information to better understand the causal risk and protective factors. At its inception in 2002, data from six states were included. States were phased in through 2019, when the system became national. Not all states are yet reporting statewide results; however, the system is now approximately 80% complete with weighting schemes for rate estimation. Violent deaths include all homicides and suicides identified through death certificates, autopsy reports, law enforcement investigation reports, and crime scene analysis, and detailed data about the violent event from each of these sources are available.

The data includes information at the event level (e.g. homicide/suicide/multiple; date/time), the victim(s) level and the perpetrator(s) (e.g. sociodemographic variables). Circumstances of the death include factors such as substance use, history of mental health issues, financial problems, relationship problems, work problems, legal issues, and health issues, among others. Circumstance variables identify if each issue was a problem, and furthermore identifies which were crises at the time of the event (noted in the investigation that the issue was a precipitating factor or present within two weeks of the event). Firearm information includes the make, type, and caliber of weapon, as well as the time of purchase and information about the registered owner.

AI/ML Approach:

The study consists of three phases:

a) Phase 1: Data preprocessing

Data preprocessing was done to prepare the data for training and validation of ML models. The steps include

- Variable selection criteria: 'Circumstance', background, and stressors variables that
  - Have more than 1 unique category
  - Unknown category accounts for <99% of total samples
- Data clean-up:
  - removed entries without age and sex information,
  - removed entries that contain unreadable categories
- Defining outcome variable
- Handling of missing and unknown values
- Renaming categories and variables for readability
- Conversion of categorical variables to nominal variables
- Regrouping of high-cardinality variables
- One-hot encoding of categorical variables and dropping redundant variable
- Creation of new variables
- Creation of data splits for stratified group 5-fold cross-validation

b) Phase 2: ML model evaluation

A number of the state-of-the-art ML methods encompassing 7 categories were selected for performance evaluation: ensemble, linear models, naïve bayes, nearest neighbor, SVM, tree based, neural network.

Hyperparameter tuning was done to find the optimal combination of models' parameters, within the allowance of available computational resources.

Seven performance metrics were reported: accuracy, specificity, sensitivity, precision, F1 score, F0.5 score, and F2 score.

c) Phase 3: ML Model Interpretation and Analysis

First, 3 best performing models which achieved the highest F1 score were selected and retrained using the best hyperparameters.

Feature importance was calculated using the drop-one column method. A combined importance index for all variables was then calculated from the individual reported importance index.

A distilled decision tree model was trained and used to interpret how combinations of variables (circumstances) contribute to predicted outcomes.

Experimental Methods, Validation Approach

1. Phase 1: Data Preprocessing

Variable selection: the original data contains variables suitable for study as well as those which are not. Unsuitable variables are those "outcome" variables, only relevant after the suicide events, and those unfitted for our study design. Variable selection criteria are: 'circumstance', background, and stressors variables that

(i) Have >1 unique category
(ii) Unknown category accounts for <99% of total samples

Data clean-up: Only data entries with valid age and sex information were included. Data entries with unreadable categories, such as an invalid category name, were discarded.

The **outcome** variable is Mechanism, which originally includes means of suicide such as firearms, poison, fall, drowning, and transportation. It was converted to a binary variable by retaining the category "firearms" and converting the other categories to "non-firearms".

Handling of **missing and unknown values**: categories such as ".", "Not applicable", and "Unknown" were universally regarded as "Unknown".

Renaming categories and variables for readability: the original naming scheme of the NVDRS database is not legible for non-experts, thus we renamed all of them to be more readable.

Conversion of categorical variables to ordinal/numeric variables: Variables such as Work Factor were converted into numeric category to 1) prevent the need of one-hot encoding, 2) to help ML models perform better by reducing the size of feature spaces, and 3) somewhat help with ML interpretability.

Table. Variable Conversion

Name	Original Category	Converted Category
Work Factor	Not a factor	0
	Minor	1
	Major	2
Age Group	0-15	0
	16-20	1

	21-34	2
	35-54	3
	55-64	4
	65+	5
Mechanism	Firearms	1
	Other weapon Poison Hanging/strangulation/suffocation Fall Transportation Drowning Other/Unknown Fire or burns	0

Regrouping of high-cardinality variables: The original variable Age was replaced by Age Group, whose numeric categories represent groups of ages instead of individual age. This helps with ML interpretability.

One-hot encoding of categorical variables and dropping redundant variable: There are a couple of encoding methods for categorical variables such as one-hot encoding, hash encoding, and target encoding. One-hot encoding was used because it retains the original categories which are human-readable and is necessary to interpret the behavior of ML models in later study phases. After one-hot encoding, a n-categories become n new columns (features), as a result, we dropped statistically redundant categories belongs to No, Not Available, or Unknown.

Creation of new variables: A couple of new variables that summarize a group of related circumstances were created such as Addiction Seriousness, Mental Health Seriousness, Relationship Seriousness, Life Stressor Seriousness, and Suicide Intention Seriousness. Only Addiction Seriousness and Suicide Intention Seriousness were included in the study after some discussions.

Table. New Variables

New Variable	Summary of	Selected for study?
Mental Health Seriousness	'Mental Health Problem', 'Depressed', 'Current Mental Illness Treatment', 'History of Mental Illness Treatment'	No
Addiction Seriousness	'Alcohol Problem', 'Substance Abuse Problem'	**Yes**
Relationship Problem Seriousness	'Intimate Partner Problem', 'Had Argument'	No
Life Stressor Seriousness	'Eviction/Loss of Home', 'Recent Suicide Friend Family', 'Work Factor (yes/no)', 'Job Problem', 'Family Problem', 'Financial Problem', 'Death Friend/Family'	No
Suicide Intention Seriousness	'History of Attempted Suicide', 'History of Suicidal Thoughts', 'Suicide Intent Disclosed', 'Suicide Note'	**Yes**

Creation of data splits for **stratified group 5-fold cross-validation**: Since the data contains group-level information, which IncidentID is used to link related suicidal incidents, no information within an incident is leaked into multiple data splits. Each data split has similar proportions of the samples of the two classes, which is approximately 1:1.

Table. Input Variable List Selected for Study

Variable Name	Type
1. Background	
Age Group	Numeric
Marital Status	Categorical
Education Level	Categorical
Occupation	
2. Disparity-prone category	
Sex (Male)	Binary
Race	Categorical
3. Time, events, locations of suicide (controversial as is it actually a circumstance)	
State	Categorical
Injury-related Location Type	Categorical
4. Mental health	
Mental Health Diagnosis	Categorical
Mental Health Problem	Binary
Depressed	Binary
Current Mental Illness Treatment	Binary
History of Mental Illness Treatment	Binary
5. Addictions	
Alcohol Problem	Binary
Substance Abuse Problem	Binary
Addiction Seriousness	Numeric
6. Relationships	
Intimate Partner Problem	Binary
Had Argument	Binary
7. Life stressors	
Eviction/Loss of Home	Binary
Recent Suicide Friend Family	Binary
Work Factor	Numeric
Work Factor (yes/no)	Binary
Job Problem	Binary
Family Problem	Binary
Financial Problem	Binary
Death Friend/Family	Binary
8. Heath problems	
Physical Health Problem	Binary
9. Suicide Intentions	
History of Attempted Suicide	Binary
History of Suicidal Thoughts	Binary
Suicide Intent Disclosed	Binary
Suicide Note	Binary
Suicide Intention Seriousness	Numeric

10. Specific Circumstances	Binary
Criminal Legal Problem	Binary
Injured at Home	Binary
Alcohol Use Suspected	Binary
11. Other	
Toxicology Information Availability	Binary

Discussion of the variable StateID: throughout this project, whether StateID should be used as an input variable was debatable. While model training and evaluation generally employ StateID, model interpretation and analysis do not.

As a results of data preprocessing, the number of input variables, or 'features', is **141**.

2. Phase 2: ML Model Evaluation

Hyperparameter tuning was done to find the best combination of parameters that allows ML models to achieve the highest **F1 score**. HalvingGridSearch was used.

All of the model training processes used stratified group 5-fold cross-validation, which data splitting were done in Phase 1.

ML model evaluations were done on two datasets, one with StateID included and one without StateID. Models trained with StateID has overall higher metrics.

Table. Best parameters for used ML models

Class	Classifier	Best parameters
Ensemble	AdaBoostClassifier (ab)	'learning_rate': 1, 'n_estimators': 1000
	BaggingClassifier (bagging)	'max_samples': 1000, 'n_estimators': 1000
	GradientBoostingClassifier (gb)	'learning_rate': 0.1, 'n_estimators': 1000
	RandomForestClassifier (rf)	'criterion': 'entropy', 'max_depth': 20, 'max_features': 'sqrt', 'n_estimators': 1000
	ExtraTreesClassifier (et)	'criterion': 'gini', 'max_depth': 20, 'max_features': 'sqrt', 'n_estimators': 1000
	XGBClassifier (xgboost)	'learning_rate': 0.001, 'max_depth': 5, 'n_estimators': 10000
Linear Models	LogisticRegression (lr)	'C': 200
Naïve Bayes	GaussianNB (nb)	NA
Nearest Neighbor	KNeighborsClassifier (knn)	'algorithm': 'auto', 'leaf_size': 20, 'n_neighbors': 100, 'p': 1, 'weights': 'distance'

SVM	LinearSVC (lsvc)	'C': 0.5, 'loss': 'hinge', 'penalty': 'l2'
Tree based	DecisionTreeClassifier (dt)	'criterion': 'entropy', 'max_depth': 1, 'min_samples_leaf': 2, 'splitter': 'random'
Neural Networks	MLPClassifier (mlp)	'solver': 'lbfgs'

Table. Model evaluation, trained with optimal parameters for best performance.

with StateID	accuracy	std	sensitivity	std	specificity	std	precision	std	f1-score	std	f0.5-score	std	f2-score	std
ab	0.659	0.009	0.669	0.024	0.650	0.040	0.650	0.017	0.659	0.003	0.653	0.010	0.665	0.015
bagging	0.699	0.003	0.683	0.008	0.714	0.005	0.698	0.003	0.690	0.004	0.695	0.002	0.686	0.006
gb	0.715	0.001	0.728	0.001	0.703	0.001	0.703	0.001	0.715	0.001	0.708	0.001	0.723	0.001
rf	0.705	0.002	0.709	0.002	0.702	0.004	0.697	0.003	0.703	0.002	0.699	0.002	0.706	0.002
et	0.705	0.003	0.707	0.003	0.704	0.004	0.697	0.003	0.702	0.003	0.699	0.003	0.705	0.003
xgboost	0.709	0.001	0.724	0.003	0.694	0.003	0.695	0.002	0.710	0.002	0.701	0.001	0.718	0.003
lr	0.703	0.002	0.724	0.002	0.683	0.002	0.688	0.002	0.705	0.001	0.695	0.002	0.716	0.002
nb	0.620	0.015	0.895	0.022	0.355	0.051	0.573	0.014	0.698	0.003	0.617	0.010	0.804	0.009
knn	0.535	0.007	0.115	0.020	0.940	0.007	0.650	0.016	0.195	0.029	0.335	0.036	0.138	0.023
lsvc	0.701	0.002	0.739	0.002	0.665	0.003	0.681	0.002	0.708	0.002	0.691	0.002	0.726	0.002
dt	0.587	0.002	0.861	0.003	0.322	0.003	0.551	0.001	0.672	0.001	0.594	0.001	0.774	0.002
mlp	0.703	0.002	0.709	0.008	0.697	0.008	0.693	0.004	0.701	0.003	0.696	0.002	0.706	0.006

w/o StateID	accuracy	std	sensitivity	std	specificity	std	precision	std	f1-score	std	f0.5-score	std	f2-score	std
ab	0.640	0.002	0.625	0.002	0.654	0.006	0.636	0.003	0.630	0.001	0.633	0.002	0.627	0.001
bagging	0.685	0.002	0.668	0.006	0.701	0.007	0.683	0.003	0.676	0.003	0.680	0.002	0.671	0.005
gb	0.696	0.001	0.699	0.004	0.692	0.005	0.687	0.003	0.693	0.002	0.689	0.002	0.697	0.003
rf	0.688	0.002	0.692	0.003	0.683	0.004	0.678	0.003	0.685	0.002	0.681	0.003	0.690	0.003
et	0.688	0.003	0.691	0.004	0.686	0.005	0.680	0.003	0.685	0.003	0.682	0.003	0.688	0.004
xgboost	0.691	0.002	0.704	0.005	0.679	0.005	0.679	0.002	0.691	0.002	0.684	0.002	0.699	0.004
lr	0.683	0.002	0.706	0.002	0.661	0.003	0.668	0.002	0.687	0.002	0.675	0.002	0.698	0.002
nb	0.589	0.016	0.899	0.032	0.290	0.061	0.551	0.013	0.683	0.002	0.597	0.009	0.798	0.015
knn	0.509	0.000	0.003	0.001	0.999	0.001	0.676	0.071	0.005	0.002	0.013	0.005	0.003	0.001
lsvc	0.682	0.001	0.729	0.001	0.637	0.003	0.660	0.002	0.693	0.001	0.673	0.002	0.714	0.000
dt	0.587	0.002	0.861	0.003	0.322	0.003	0.551	0.001	0.672	0.001	0.594	0.001	0.774	0.002
mlp	0.686	0.003	0.685	0.007	0.687	0.004	0.679	0.002	0.682	0.004	0.680	0.002	0.683	0.006

- **Discussion**

Extensive model evaluation and testing shows that the metric cannot be improved pass a threshold, in this case, we can see the best F-1 score is 0.715. This is because the data is limited in term of possible information to be mined.

3. Phase 3: ML Model Interpretation and Analysis

Three best-performing models achieving highest F-1 score are selected for this phase: xgboost, lr, and lsvc. Xgboost was chosen instead of the traditional gb method because xgboost is a faster implementation with minimal performance loss.

a) Feature ranking with drop-one column method

- **Methods:**

Feature importance (FI) is a method to rank variables based on its predictive power. Traditionally, model-based methods are used for this purpose. The caveat is that those methods are very specific for the type of ML model used and thus produces different interpretation and understanding.

Permutation feature importance method alleviates such problem, but it can give high-cardinality variables very high score. In this project, we used **Drop-1-Column Feature Importance** method. In this method, the contribution of variables to the performance metric (F-1 score) were calculated as the difference between a baseline metric and a metric of a modified model which has the interested variable dropped. This process was repeated **141 times**, corresponding to 141 variables.

The **Drop-1-Column Feature Importance** of feature x is defined as

$$FI_x = M_{baseline} - M_x$$

where $M_{baseline}$ is the F-1 score of a ML model trained on the full set of input variables, M_x is the F-1 score of a ML model trained on the same dataset without the variable x.

Then, a mean feature importance score of a feature x is

$$\overline{FI_x} = \frac{1}{3} \sum_{m \in \{xgboost, lr, lsvc\}} FI_x^m$$

where FI_x^m is the drop-1-Column Feature Importance of feature x trained using model m.

Table. Feature Importance averaged from three best performing models based on F1 score (versus a baseline model), sorted in descending mean order.

	FEATURE	FI_XGBOOST	FI_LR	FI_LSVC	MEAN	SD	LOWER.Z	UPPER.Z	SIGNIFICANT.Z	LOWER.T	UPPER.T	SIGNIFICANT.T
1	Sex (Male)_Male	0.0105	0.0069	0.0057	0.0077	0.0025	0.0049	0.0105	Yes	0.0015	0.0139	Yes
2	Toxicology Information Availability_No	0.0068	0.0025	0.0012	0.0035	0.0029	0.0002	0.0068	Yes	-0.0037	0.0107	No
3	Injury-related Location Type_Detention facility	0.0030	0.0017	0.0017	0.0021	0.0008	0.0012	0.0030	Yes	0.0001	0.0041	Yes
4	History of Attempted Suicide	0.0059	-0.0001	-0.0001	0.0019	0.0035	-0.0021	0.0059	No	-0.0068	0.0106	No
5	Injury-related Location Type_Bridge	0.0026	0.0017	0.0010	0.0018	0.0008	0.0009	0.0027	Yes	-0.0002	0.0038	No
6	State_Massachusetts	0.0036	0.0000	-0.0005	0.0010	0.0022	-0.0015	0.0035	No	-0.0045	0.0065	No
7	Injury-related Location Type_Railroad tracks	0.0006	0.0016	0.0004	0.0009	0.0006	0.0002	0.0016	Yes	-0.0006	0.0024	No
8	Injured at Home	0.0012	0.0013	0.0000	0.0008	0.0007	0.0000	0.0016	Yes	-0.0009	0.0025	No
9	Injury-related Location Type_Street, sidewalk, alley	0.0009	0.0005	0.0007	0.0007	0.0002	0.0005	0.0009	Yes	0.0002	0.0012	Yes
10	Injury-related Location Type_Hotel/motel	0.0010	0.0005	0.0005	0.0007	0.0003	0.0004	0.0010	Yes	0.0000	0.0014	No
11	Mental Health Diagnosis_Post-traumatic stress disorder	0.0010	0.0009	0.0001	0.0007	0.0005	0.0001	0.0013	Yes	-0.0005	0.0019	No
12	Race_Other race, non-Hispanic	0.0001	0.0013	0.0003	0.0006	0.0006	-0.0001	0.0013	No	-0.0009	0.0021	No
13	Injury-related Location Type_Parking area	0.0002	0.0006	0.0008	0.0005	0.0003	0.0002	0.0008	Yes	-0.0002	0.0012	No
14	Injury-related Location Type_Motor vehicle	0.0015	0.0001	-0.0002	0.0005	0.0009	-0.0005	0.0015	No	-0.0017	0.0027	No
15	State_New Jersey	0.0021	-0.0001	-0.0006	0.0005	0.0014	-0.0011	0.0021	No	-0.0030	0.0040	No
16	Injury-related Location Type_House, apartment	0.0003	0.0006	0.0005	0.0005	0.0002	0.0003	0.0007	Yes	0.0000	0.0010	Yes
17	Race_Black	0.0014	-0.0001	0.0000	0.0004	0.0008	-0.0005	0.0013	No	-0.0016	0.0024	No
18	Injury-related Location Type_Highway, freeway	0.0004	0.0008	-0.0001	0.0004	0.0005	-0.0002	0.0010	No	-0.0008	0.0016	No
19	Mental Health Problem	0.0008	0.0006	-0.0004	0.0003	0.0006	-0.0004	0.0010	No	-0.0012	0.0018	No
20	Marital Status_Never	0.0002	0.0005	0.0001	0.0003	0.0002	0.0001	0.0005	Yes	-0.0002	0.0008	No
21	Intimate Partner Problem	0.0011	0.0001	-0.0003	0.0003	0.0007	-0.0005	0.0011	No	-0.0014	0.0020	No
22	Injury-related Location Type_Other commercial establishment	-0.0002	0.0009	0.0002	0.0003	0.0006	-0.0004	0.0010	No	-0.0012	0.0018	No
23	Injury-related Location Type_Public transportation/station	0.0002	0.0005	0.0000	0.0002	0.0003	-0.0001	0.0005	No	-0.0005	0.0009	No
24	Occupation_Retired, Students, Unemployed	0.0008	0.0000	0.0000	0.0003	0.0005	-0.0003	0.0009	No	-0.0009	0.0015	No
25	Death Friend/Family	-0.0002	0.0003	0.0006	0.0002	0.0004	-0.0003	0.0007	No	-0.0008	0.0012	No
26	Occupation_Installation, Maintenance, Repair	0.0007	0.0000	0.0000	0.0002	0.0004	-0.0003	0.0007	No	-0.0008	0.0012	No
27	Job Problem	0.0001	0.0005	0.0000	0.0002	0.0003	-0.0001	0.0005	No	-0.0005	0.0009	No
28	Injury-related Location Type_Supervised residential facility	-0.0001	0.0008	-0.0001	0.0002	0.0005	-0.0004	0.0008	No	-0.0010	0.0014	No
29	Physical Health Problem	-0.0001	0.0008	-0.0001	0.0002	0.0005	-0.0004	0.0008	No	-0.0010	0.0014	No
30	Occupation_Protective Service	0.0008	-0.0001	-0.0001	0.0002	0.0005	-0.0004	0.0008	No	-0.0010	0.0014	No

31	State_Indiana	0.0005	0.0000	0.0000	0.0002	0.0003	-0.0001	0.0005	No	-0.0005	0.0009	No
32	Injury-related Location Type_Cemetery	0.0004	0.0000	0.0001	0.0002	0.0002	0.0000	0.0004	No	-0.0003	0.0007	No
33	Race_White, non-Hispanic	0.0005	0.0001	-0.0002	0.0001	0.0004	-0.0004	0.0006	No	-0.0009	0.0011	No
34	Mental Health Diagnosis_Bipolar disorder	0.0000	0.0008	-0.0003	0.0002	0.0006	-0.0005	0.0009	No	-0.0013	0.0017	No
35	State_Arizona	0.0007	0.0000	-0.0003	0.0001	0.0005	-0.0005	0.0007	No	-0.0011	0.0013	No
36	Occupation_Arts, Design, Entertainment, Sports, Media	0.0003	0.0000	0.0001	0.0001	0.0002	-0.0001	0.0003	No	-0.0004	0.0006	No
37	Injury-related Location Type_Service station	0.0000	0.0004	0.0000	0.0001	0.0002	-0.0001	0.0003	No	-0.0004	0.0006	No
38	Alcohol Use Suspected	-0.0006	0.0006	0.0004	0.0001	0.0006	-0.0006	0.0008	No	-0.0014	0.0016	No
39	State_North Carolina	0.0010	-0.0002	-0.0005	0.0001	0.0008	-0.0008	0.0010	No	-0.0019	0.0021	No
40	State_New York	0.0007	0.0000	-0.0004	0.0001	0.0006	-0.0006	0.0008	No	-0.0014	0.0016	No
41	Mental Health Diagnosis_Eating disorder	0.0000	0.0002	0.0001	0.0001	0.0001	0.0000	0.0002	No	-0.0001	0.0003	No
42	State_Oklahoma	0.0005	0.0000	-0.0002	0.0001	0.0004	-0.0004	0.0006	No	-0.0009	0.0011	No
43	Had Argument	-0.0004	0.0009	-0.0001	0.0001	0.0007	-0.0007	0.0009	No	-0.0016	0.0018	No
44	State_Ohio	0.0005	0.0000	-0.0001	0.0001	0.0003	-0.0002	0.0004	No	-0.0006	0.0008	No
45	State_Illinois	0.0006	-0.0001	-0.0002	0.0001	0.0004	-0.0004	0.0006	No	-0.0009	0.0011	No
46	Injury-related Location Type_Farm	0.0000	0.0005	-0.0002	0.0001	0.0004	-0.0004	0.0006	No	-0.0009	0.0011	No
47	Occupation_Production	0.0006	-0.0001	-0.0002	0.0001	0.0004	-0.0004	0.0006	No	-0.0009	0.0011	No
48	Injury-related Location Type_Other	0.0000	-0.0002	0.0004	0.0001	0.0003	-0.0002	0.0004	No	-0.0006	0.0008	No
49	State_South Carolina	0.0001	0.0000	0.0001	0.0001	0.0001	0.0000	0.0002	No	-0.0001	0.0003	No
50	Education Level_High school	-0.0004	0.0009	-0.0004	0.0000	0.0008	-0.0009	0.0009	No	-0.0020	0.0020	No
51	State_Alaska	0.0003	-0.0002	0.0001	0.0001	0.0003	-0.0002	0.0004	No	-0.0006	0.0008	No
52	Occupation_Construction, Extraction	0.0000	0.0000	0.0001	0.0000	0.0001	-0.0001	0.0001	No	-0.0002	0.0002	No
53	Marital Status_Divorced/separated	-0.0002	0.0002	0.0001	0.0000	0.0002	-0.0002	0.0002	No	-0.0005	0.0005	No
54	Current Mental Illness Treatment	-0.0005	0.0007	-0.0001	0.0000	0.0006	-0.0007	0.0007	No	-0.0015	0.0015	No
55	State_Maryland	0.0002	-0.0001	0.0000	0.0000	0.0002	-0.0002	0.0002	No	-0.0005	0.0005	No
56	Injury-related Location Type_Bank/ATM location	0.0000	0.0001	0.0000	0.0000	0.0001	-0.0001	0.0001	No	-0.0002	0.0002	No
57	Suicide Note	0.0002	0.0000	-0.0001	0.0000	0.0002	-0.0002	0.0002	No	-0.0005	0.0005	No
58	Injury-related Location Type_Medical facility	-0.0004	0.0004	0.0001	0.0000	0.0004	-0.0005	0.0005	No	-0.0010	0.0010	No
59	State_Michigan	0.0002	-0.0001	0.0000	0.0000	0.0002	-0.0002	0.0002	No	-0.0005	0.0005	No
60	State_Kentucky	0.0004	0.0000	-0.0003	0.0000	0.0004	-0.0005	0.0005	No	-0.0010	0.0010	No
61	Occupation_Community and Social Service	0.0002	0.0000	-0.0001	0.0000	0.0002	-0.0002	0.0002	No	-0.0005	0.0005	No
62	Injury-related Location Type_Religious worship building	0.0000	0.0001	0.0000	0.0000	0.0001	-0.0001	0.0001	No	-0.0002	0.0002	No
63	Injury-related Location Type_Bar/nightclub	0.0000	0.0001	0.0000	0.0000	0.0001	-0.0001	0.0001	No	-0.0002	0.0002	No
64	Mental Health Diagnosis_Anxiety disorder	-0.0001	0.0000	0.0001	0.0000	0.0001	-0.0001	0.0001	No	-0.0002	0.0002	No
65	State_Iowa	0.0004	-0.0001	-0.0003	0.0000	0.0004	-0.0005	0.0005	No	-0.0010	0.0010	No
66	Work Factor	0.0001	0.0001	-0.0001	0.0000	0.0001	-0.0001	0.0001	No	-0.0002	0.0002	No
67	State_Pennsylvania	0.0001	-0.0001	0.0001	0.0000	0.0001	-0.0001	0.0001	No	-0.0002	0.0002	No
68	Injury-related Location Type_High school	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	No	0.0000	0.0000	No
69	Mental Health Diagnosis_Obsessive-compulsive disorder	0.0000	-0.0001	0.0001	0.0000	0.0001	-0.0001	0.0001	No	-0.0002	0.0002	No
70	Addiction Seriousness	0.0002	0.0000	-0.0001	0.0000	0.0002	-0.0002	0.0002	No	-0.0005	0.0005	No
71	State_Colorado	-0.0001	0.0002	-0.0001	0.0000	0.0002	-0.0002	0.0002	No	-0.0005	0.0005	No
72	Injury-related Location Type_Liquor store	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	No	0.0000	0.0000	No
73	Injury-related Location Type_Industrial/construction areas	-0.0003	0.0000	0.0002	0.0000	0.0003	-0.0003	0.0003	No	-0.0007	0.0007	No
74	Mental Health Diagnosis_Schizophrenia	0.0001	0.0004	-0.0006	0.0000	0.0005	-0.0006	0.0006	No	-0.0012	0.0012	No
75	Occupation_Life, Physical, Social Science	0.0000	-0.0001	0.0000	0.0000	0.0001	-0.0001	0.0001	No	-0.0002	0.0002	No
76	Injury-related Location Type_Pre-school	0.0000	-0.0001	0.0001	0.0000	0.0001	-0.0001	0.0001	No	-0.0002	0.0002	No
77	Mental Health Diagnosis_Other	0.0000	-0.0001	0.0000	0.0000	0.0001	-0.0001	0.0001	No	-0.0002	0.0002	No
78	Alcohol Problem	0.0000	0.0000	-0.0001	0.0000	0.0001	-0.0001	0.0001	No	-0.0002	0.0002	No
79	Work Factor (yes/no)	0.0000	0.0002	-0.0003	0.0000	0.0003	-0.0003	0.0003	No	-0.0007	0.0007	No
80	Injury-related Location Type_Elementary/middle school	0.0000	0.0002	-0.0003	0.0000	0.0003	-0.0003	0.0003	No	-0.0007	0.0007	No
81	State_Georgia	0.0004	-0.0002	-0.0003	0.0000	0.0004	-0.0005	0.0005	No	-0.0010	0.0010	No
82	Injury-related Location Type_University campus	-0.0005	0.0009	-0.0005	0.0000	0.0008	-0.0009	0.0009	No	-0.0020	0.0020	No
83	Injury-related Location Type_Office building	0.0000	0.0001	-0.0002	0.0000	0.0002	-0.0002	0.0002	No	-0.0005	0.0005	No
84	Injury-related Location Type_Sports area	-0.0005	0.0003	0.0001	0.0000	0.0004	-0.0005	0.0005	No	-0.0010	0.0010	No
85	Occupation_Office, Administrative	0.0001	0.0000	-0.0002	0.0000	0.0002	-0.0002	0.0002	No	-0.0005	0.0005	No
86	State_Oregon	0.0001	-0.0001	-0.0001	0.0000	0.0001	-0.0001	0.0001	No	-0.0002	0.0002	No
87	State_Nevada	-0.0001	0.0001	-0.0001	0.0000	0.0001	-0.0001	0.0001	No	-0.0002	0.0002	No
88	Depressed	0.0000	0.0001	-0.0002	0.0000	0.0002	-0.0002	0.0002	No	-0.0005	0.0005	No
89	Injury-related Location Type_Unspecified school	0.0000	0.0001	-0.0002	0.0000	0.0002	-0.0002	0.0002	No	-0.0005	0.0005	No
90	Occupation_Cleaning and Maintenance	-0.0001	0.0000	0.0000	0.0000	0.0001	-0.0001	0.0001	No	-0.0002	0.0002	No
91	State_Virginia	0.0001	-0.0001	-0.0002	-0.0001	0.0002	-0.0003	0.0001	No	-0.0006	0.0004	No
92	History of Suicidal Thoughts	-0.0001	0.0000	-0.0001	-0.0001	0.0001	-0.0002	0.0000	No	-0.0003	0.0001	No
93	Recent Suicide Friend Family	0.0000	0.0000	-0.0001	0.0000	0.0001	-0.0001	0.0001	No	-0.0002	0.0002	No
94	Injury-related Location Type_Abandoned building	0.0000	0.0003	-0.0005	-0.0001	0.0004	-0.0006	0.0004	No	-0.0011	0.0009	No
95	State_Utah	0.0002	0.0000	-0.0004	-0.0001	0.0003	-0.0004	0.0002	No	-0.0008	0.0006	No
96	State_California	0.0001	0.0000	-0.0003	-0.0001	0.0002	-0.0003	0.0001	No	-0.0006	0.0004	No
97	State_Vermont	-0.0001	-0.0001	0.0000	-0.0001	0.0001	-0.0002	0.0000	No	-0.0003	0.0001	No
98	State_Wisconsin	0.0000	0.0001	-0.0003	-0.0001	0.0002	-0.0003	0.0001	No	-0.0006	0.0004	No
99	Occupation_Business, Financial	-0.0002	0.0001	-0.0001	-0.0001	0.0002	-0.0003	0.0001	No	-0.0006	0.0004	No
10 0	Occupation_Farming, Fishing, Forestry	-0.0001	0.0000	-0.0001	-0.0001	0.0001	-0.0002	0.0000	No	-0.0003	0.0001	No
10 1	State_New Mexico	0.0000	-0.0002	-0.0001	-0.0001	0.0001	-0.0002	0.0000	No	-0.0003	0.0001	No
10 2	Marital Status_Married	-0.0012	0.0005	0.0005	-0.0001	0.0010	-0.0012	0.0010	No	-0.0026	0.0024	No
10 3	Suicide Intent Disclosed	-0.0001	0.0000	-0.0001	-0.0001	0.0001	-0.0002	0.0000	No	-0.0003	0.0001	No
10 4	Occupation_Sales related	0.0000	-0.0002	-0.0001	-0.0001	0.0001	-0.0002	0.0000	No	-0.0003	0.0001	No
10 5	Occupation_Computer and Mathematical	-0.0001	-0.0001	-0.0001	-0.0001	0.0000	-0.0001	-0.0001	No	-0.0001	-0.0001	No

106	Criminal Legal Problem	0.0000	0.0003	-0.0006	-0.0001	0.0005	-0.0007	0.0005	No	-0.0013	0.0011	No
107	State_Minnesota	-0.0001	-0.0001	0.0000	-0.0001	0.0001	-0.0002	0.0000	No	-0.0003	0.0001	No
108	Occupation_Architecture, Engineering	-0.0001	-0.0001	0.0000	-0.0001	0.0001	-0.0002	0.0000	No	-0.0003	0.0001	No
109	Financial Problem	0.0000	-0.0003	0.0000	-0.0001	0.0002	-0.0003	0.0001	No	-0.0006	0.0004	No
110	Race_Hispanic	-0.0001	0.0002	-0.0005	-0.0001	0.0004	-0.0006	0.0004	No	-0.0011	0.0009	No
111	State_Delaware	0.0000	-0.0001	-0.0003	-0.0001	0.0002	-0.0003	0.0001	No	-0.0006	0.0004	No
112	State_Maine	-0.0001	-0.0001	-0.0002	-0.0001	0.0001	-0.0002	0.0000	No	-0.0003	0.0001	No
113	State_West Virginia	-0.0001	0.0001	-0.0004	-0.0001	0.0003	-0.0004	0.0002	No	-0.0008	0.0006	No
114	State_New Hampshire	0.0000	0.0000	-0.0004	-0.0001	0.0002	-0.0003	0.0001	No	-0.0006	0.0004	No
115	Suicide Intention Seriousness	-0.0002	-0.0001	-0.0001	-0.0001	0.0001	-0.0002	0.0000	No	-0.0003	0.0001	No
116	Mental Health Diagnosis_Depression/dysthymia	0.0000	0.0000	-0.0003	-0.0001	0.0002	-0.0003	0.0001	No	-0.0006	0.0004	No
117	Family Problem	-0.0004	0.0008	-0.0007	-0.0001	0.0008	-0.0010	0.0008	No	-0.0021	0.0019	No
118	State_District of Columbia	0.0000	-0.0002	-0.0001	-0.0001	0.0001	-0.0002	0.0000	No	-0.0003	0.0001	No
119	State_Hawaii	-0.0001	0.0000	-0.0003	-0.0001	0.0002	-0.0003	0.0001	No	-0.0006	0.0004	No
120	History of Mental Illness Treatment	0.0000	-0.0002	-0.0003	-0.0002	0.0002	-0.0004	0.0000	No	-0.0007	0.0003	No
121	Occupation_Educational Instruction and Library	-0.0002	-0.0001	0.0000	-0.0001	0.0001	-0.0002	0.0000	No	-0.0003	0.0001	No
122	Occupation_Management	-0.0001	-0.0001	-0.0002	-0.0001	0.0001	-0.0002	0.0000	No	-0.0003	0.0001	No
123	Education Level_College	-0.0003	0.0000	-0.0001	-0.0001	0.0002	-0.0003	0.0001	No	-0.0006	0.0004	No
124	Occupation_Healthcare Support	-0.0002	-0.0002	0.0000	-0.0001	0.0001	-0.0002	0.0000	No	-0.0003	0.0001	No
125	State_Washington	-0.0004	-0.0002	0.0001	-0.0002	0.0003	-0.0005	0.0001	No	-0.0009	0.0005	No
126	State_Kansas	-0.0004	0.0001	-0.0002	-0.0002	0.0003	-0.0005	0.0001	No	-0.0009	0.0005	No
127	State_Connecticut	0.0000	-0.0001	-0.0004	-0.0002	0.0002	-0.0004	0.0000	No	-0.0007	0.0003	No
128	Occupation_Healthcare Practitioners and Technical	-0.0002	-0.0002	-0.0002	-0.0002	0.0000	-0.0002	-0.0002	No	-0.0002	-0.0002	No
129	Mental Health Diagnosis_ADD or hyperactivity disorder	0.0000	-0.0002	-0.0003	-0.0002	0.0002	-0.0004	0.0000	No	-0.0007	0.0003	No
130	Occupation_Personal Care/Service	-0.0004	-0.0002	0.0001	-0.0002	0.0003	-0.0005	0.0001	No	-0.0009	0.0005	No
131	State_Puerto Rico	-0.0007	-0.0002	0.0003	-0.0002	0.0005	-0.0008	0.0004	No	-0.0014	0.0010	No
132	Injury-related Location Type_Natural area	-0.0004	-0.0002	-0.0001	-0.0002	0.0002	-0.0004	0.0000	No	-0.0007	0.0003	No
133	Occupation_Transportation and Material Moving	-0.0003	-0.0002	-0.0002	-0.0002	0.0001	-0.0003	-0.0001	No	-0.0004	0.0000	No
134	Occupation_Legal	-0.0004	-0.0002	-0.0001	-0.0002	0.0002	-0.0004	0.0000	No	-0.0007	0.0003	No
135	State_Rhode Island	0.0001	0.0001	-0.0010	-0.0003	0.0006	-0.0010	0.0004	No	-0.0018	0.0012	No
136	Injury-related Location Type_Public-use area	-0.0009	-0.0001	0.0002	-0.0003	0.0006	-0.0010	0.0004	No	-0.0018	0.0012	No
137	Substance Abuse Problem	-0.0007	0.0000	-0.0001	-0.0003	0.0004	-0.0008	0.0002	No	-0.0013	0.0007	No
138	Eviction/Loss of Home	-0.0010	0.0003	-0.0009	-0.0005	0.0007	-0.0013	0.0003	No	-0.0022	0.0012	No
139	Occupation_Food Related	-0.0012	-0.0002	-0.0002	-0.0005	0.0006	-0.0012	0.0002	No	-0.0020	0.0010	No
140	Education Level_Less than high school	-0.0001	-0.0007	-0.0012	-0.0007	0.0006	-0.0014	0.0000	No	-0.0022	0.0008	No
141	Age Group	0.0021	-0.0019	-0.0036	-0.0011	0.0029	-0.0044	0.0022	No	-0.0083	0.0061	No

Because the sample size is small (N=3), we use approximate methods to get 95% CI for the mean FI scores. Bootstrapping is an option. We used two methods to estimate the confidence interval, by either assuming the FI scores have a normal distribution or a t distribution (since sample size < 30). We will discuss the significance of these methods below.

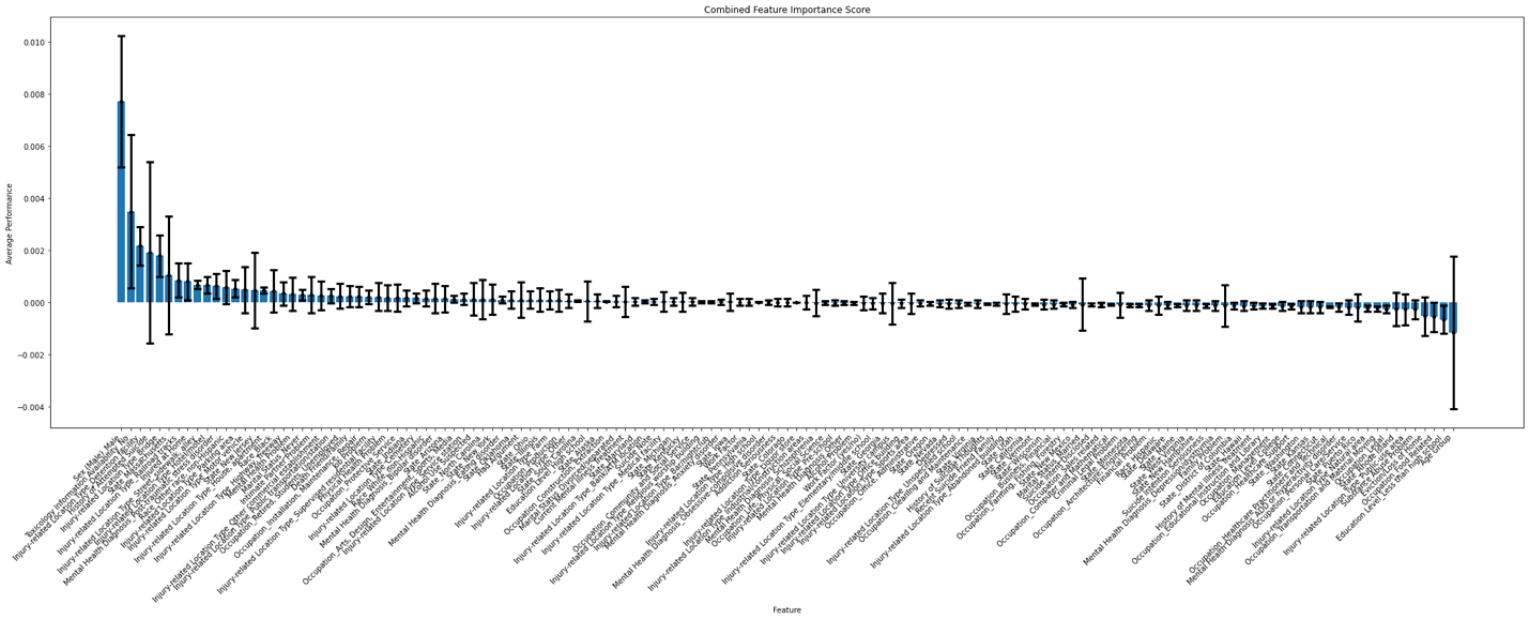


Figure. Feature Importance, including StateID

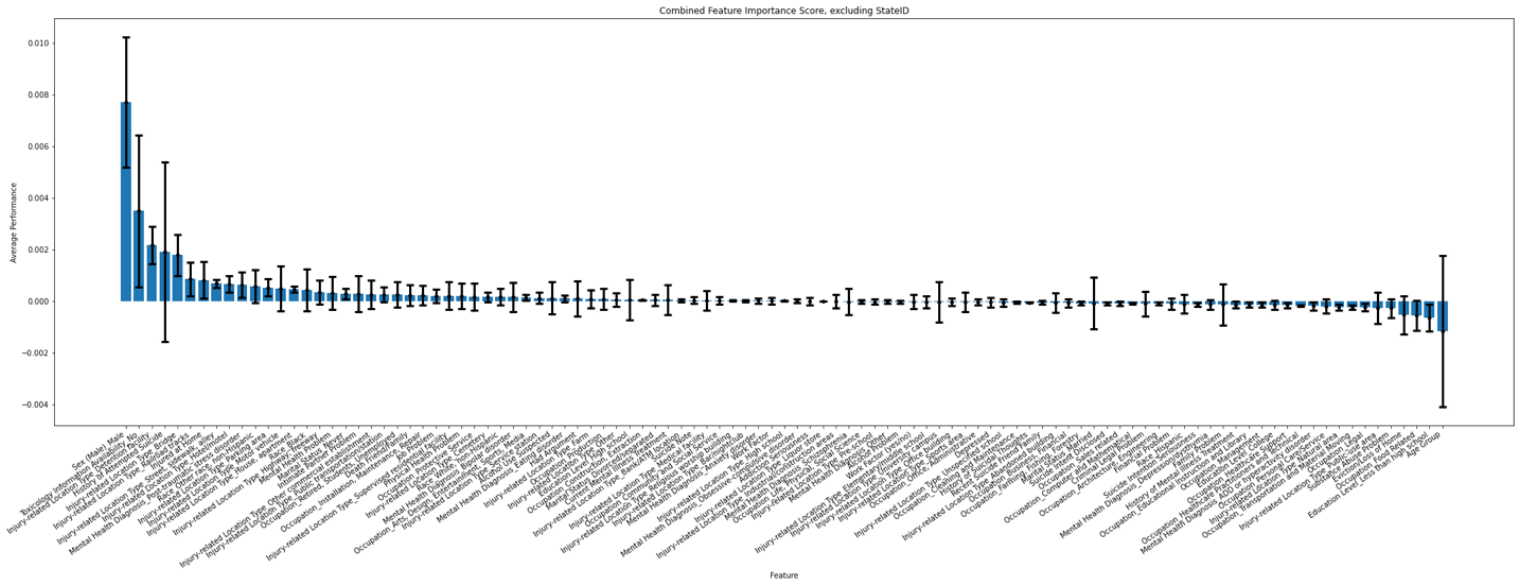


Figure. Feature Importance, excluding StateID

- **<u>Findings</u>**:

Due to the small sample size N=3, uses of statistical tests for significance is not very accurate nor useful. Instead, a simpler method for deciding if a **variable is significant** can be either:

- At least 2 FI score > 0
- Or choose a threshold
- Or just use mean FI score $\overline{FI_x}$ (which is the method used in this project)

Based on the ranking of $\overline{FI_x}$, strong predictors for the suicide-with-firearm outcomes, **Sex** is the most predictive feature that helps models correctly predict positive outcomes. Features that come next in the ranking are **toxicology information availability**, various **injury-related location types** (detention facility, bridge, railroad tracks, street, hotel), **history of attempted suicide** and **suicide note**, **mental health problem** and **mental health diagnosis**, **physical health problem**, **never married**.

Least predictive variables are Age Group, Eviction/Loss of Home, Substance Abuse Problem

b) Distillation, all races considered

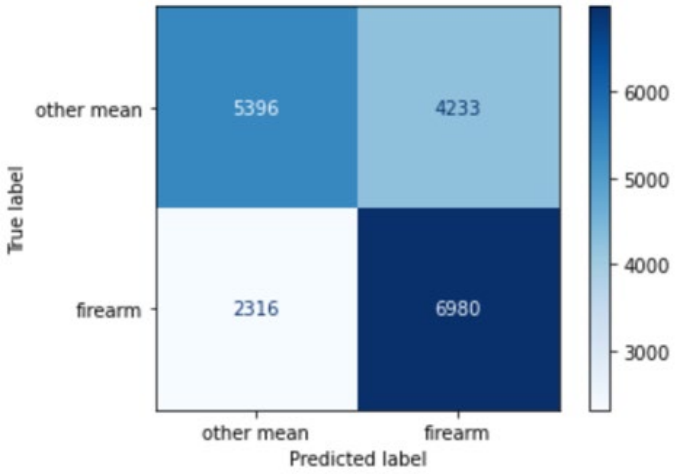
- **Methods:**

The process of knowledge distillation was used to fit a decision tree model that best estimates the average prediction results from **the three best-performing models** (xgboost, lr, and svm). A single data set whose labels are the majority votes based on the prediction results of the three models was used to train a decision tree model. This model is referred to as a **distilled model**.

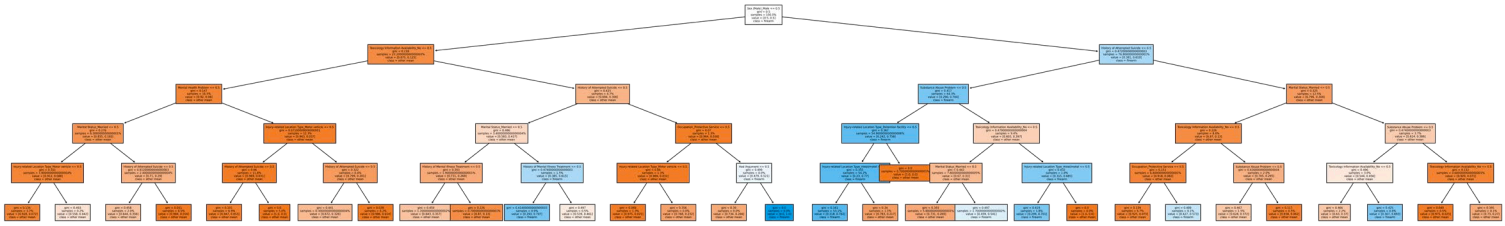
Since race is a disparity variable, the prediction results without racial consideration may be misleading. We also dropped the Race variables since it can make decision paths incomprehensible.

- **5-factor circumstance (setting max depth of decision tree = 5)**

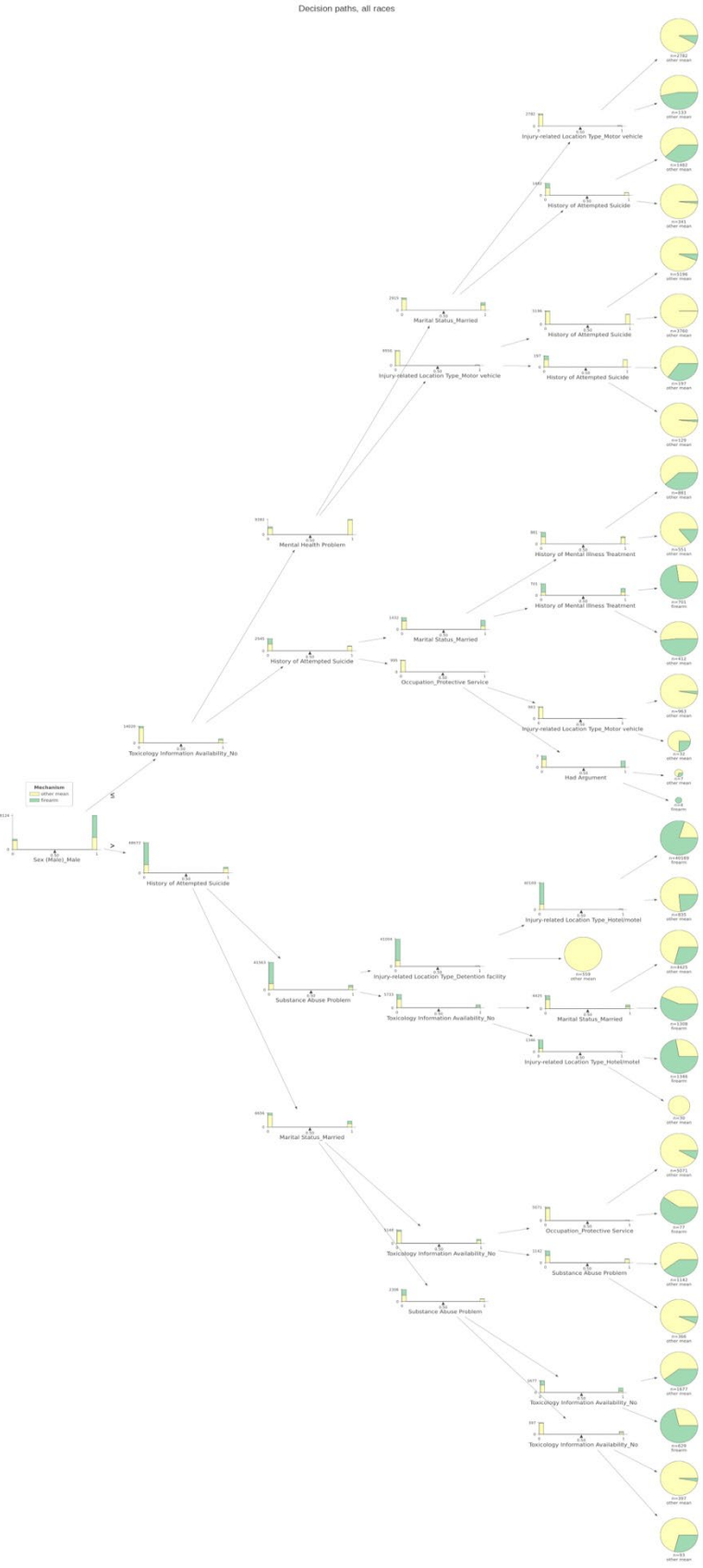
accuracy = 0.6539498018494055
recall = 0.7508605851979346
spec = 0.5603904870703085
prec = 0.6224917506465709
f1 = 0.6806767760495392



Decisions path can be show as a tree:



Or in a more readable form:



GINI-INDEX RANK	5-FACTOR CIRCUMSTANCE COMBINATION	GINI INDEX (LOWER IS BETTER)	POSITIVE CASES	% OF ALL TRAINING SAMPLES (N=ALL DATA SAMPLES)
1	Sex: Female Toxicology Information Availability: No **History of Attempted Suicide: Yes** **Occupation_Protective Service: Yes** **Had Argument: Yes**	0	100%	0%
2	**Sex: Male** History of Attempted Suicide: No Substance Abuse Problem: No Injury-related Location Type_Detention facility: No Injury-related Location Type_Hotel/motel: No	0.341	78%	53%
3	Sex: Female Toxicology Information Availability: No History of Attempted Suicide: No **Marital Status_Married: Yes** History of Mental Illness Treatment: No	0.414	71%	1%
4	**Sex: Male** History of Attempted Suicide: No **Substance Abuse Problem: Yes** Toxicology Information Availability: No Injury-related Location Type_Hotel/motel: No	0.419	70%	2%
5	**Sex: Male** **History of Attempted Suicide: Yes** **Marital Status_Married: Yes** Substance Abuse Problem: No Toxicology Information Availability: No	0.425	69%	1%
6	**Sex: Male** **History of Attempted Suicide: Yes** Marital Status_Married: No Toxicology Information Availability: Yes/Unknown **Occupation_Protective Service: Yes**	0.489	57%	0%
7	**Sex: Male** History of Attempted Suicide: No **Substance Abuse Problem: Yes** **Toxicology Information Availability: Yes/Unknown** **Marital Status_Married: Yes**	0.497	54%	2%

The circumstance combinations can also be summarized in a table which is much more readable.

- **Discussion**

If the feature importance score calculated by the first method can only look at effect of individual variable on the overall prediction performance of ML models. By using the distillation method, we were able to:

(i) Summarize prediction knowledge of multiple ML models, each of which has its own strengths.

(ii) Understand effects of multiple important variables on the prediction of an outcome.

As a result, we see that while **Substance Abuse Problem** is deemed 'unimportant' by the FI score, it can be seen as a factor in some circumstance combinations that leads to suicide with predictions. When depth=7 or more, **Age Group** starts to show up as one of the contributing factors.

For 5-factor circumstance, most frequently appearning variables are **Sex, History of Attempted Suicide, Marital Status (Married), Substance Abuse Problem, Occupation (Protective Service)**

Most of the patients of positive outcomes are **Male**. Among **Male**, those who have **Substance Use Problem**, is **Married**, and/or had **History of Attempted Suicide** are at highest risk (quantify the 'risk'?).

Location type variables can both be interpreted as an input variable or an outcome. For example, if we consider Injury-related Location Type_Detention facility as an input, it can be interpreted as the circumstance of being inside a detention facility is a factor leading to the suicide death.

As the depth of the distilled tree grows, the number of possible combinations leading to positive outcomes increases sharply. I personally think the depth of 5 and 6 is enough for analysis. However, higher tree depth may be useful when we want to look at frequencies of variables that repetitively appear in circumstance combinations.

Male subjects account for most samples, which in our opinion can be interpreted men tend to choose firearms for suicide.

Depth	# of combinations leading to outcome suicide with firearms
5	7 (more impactful combinations)
6	15
7	39
8	77
9	131
10	199 (small/unusual permutations more likely)

Limitations:

Since the data are skewed toward white population, our results may be more representative of the white population.

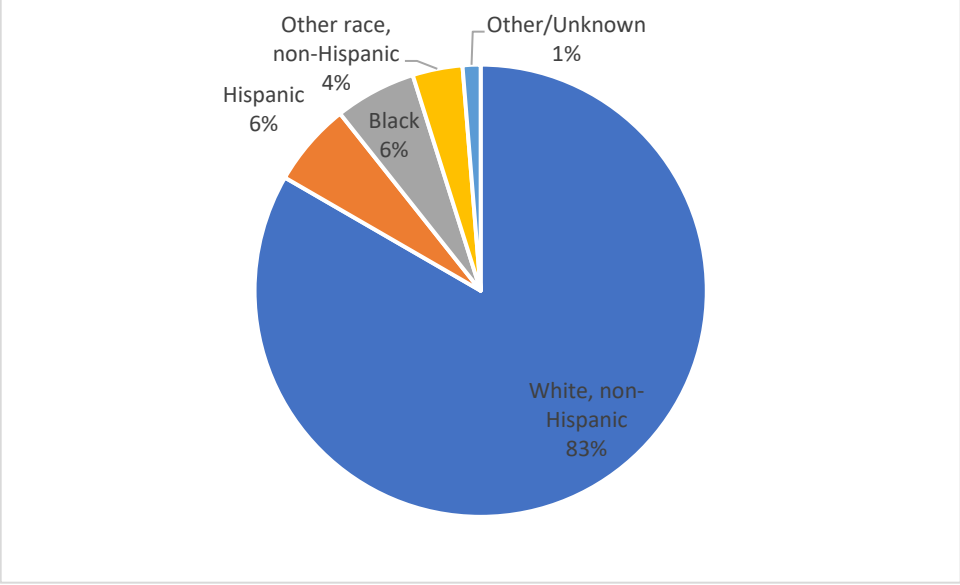


Figure. Racial disparity in the NVDRS data

Ideas/aims for future extramural project:

Better data with more variables.

Statistical aspects of the project:

- Racial disparity
- Sexual disparity

Besides, a couple of other interpretation methods can be used such as PDP plot, ALE plot, LIME, SHAP.

Publications resulting from project:

Nam H Le, Ling Zhang, Sonka Milan, Corinne Peek-Asa, ***"Characteristics and Circumstances Associated with Firearm-Related Suicides from a Machine-Learning Perspective"*** (in preparation)