Prediction of Alcohol Tolerance Based on Lifestyle and Health Data

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Table of Content

Abstract

This project explores the creation of a predictive model for individual alcohol tolerance utilizing data from a custom-designed survey which gathered information on various health and lifestyle factors from 432 participants. By applying and comparing Multiclass Logistic Regression, Random Forest, and CART models, we determined the most reliable and generalizable method for predicting alcohol tolerance, accounting for potential biases and outliers. The Random Forest model's robustness against overfitting and its high accuracy make it particularly suitable for practical applications, contributing to safer alcohol consumption in social settings.

Motivation

The motivation for this project stems from the real-world necessity to prevent alcohol overdose at social gatherings, such as restaurants or parties. The objective is to provide a predictive model that can assess an individual's alcohol tolerance based on specific health and lifestyle factors. By integrating such a model, event organizers and hospitality providers could offer more responsible service of alcohol, potentially reducing the incidence of alcohol-related harm. The application of this model aims not only to enhance individual safety but also to support public health initiatives by promoting responsible drinking behaviors. This proactive approach in social settings could serve as a novel benchmark for alcohol consumption management.

Data Collection and Preparation

For our project, we devised a survey aimed at collecting data to predict individual alcohol tolerance for use in restaurants and event settings, promoting responsible alcohol consumption. The survey was meticulously designed by our team, targeting a sample size of approximately 500 individuals, from which we successfully gathered 432 responses.

Variable	Description	Options
Age	Respondent's age	Numeric value
Sex	Respondent's sex	Male, Female
Weight	Respondent's weight in kilograms	Numeric value (Kg)
Height	Respondent's height in centimeters	Numeric value (cm)
Smoke	Smoking status	Smoke, No smoke
Drinking Frequency	How often respondent drinks alcohol	Daily, Weekly, Monthly, Yearly, Rarely
Monthly Drinking	Times alcohol consumed in a month	Numeric value (times/month)
Drinking Duration	Duration of drinking sessions	1-2 hours, 2-3 hours, 3-4 hours, 4+ hours, Do not drink
Parental Drinking	Frequency of parents' alcohol consumption	Very often, Often, Not often, Barely, Never
Eating Before Drink	Eating habits before drinking	Always, Often, Sometimes, Never
Stress Level	Stress level when drinking	Very stressed, Stressed, Not too stressed, Not stressed
Sleep Length	Average sleep duration in hours	Numeric value (hours)
Liver Condition	Presence of liver health conditions	Yes, No
Tolerance	Estimated number of drinks before losing consciousness	Numeric value (standard drinks)
Workout Frequency	Frequency of fitness activities	Very often, Often, Not often, Barely, Never

The survey encompassed 15 features, capturing a wide spectrum of demographic details, daily habits, and health-related questions. We took great care to preserve respondent confidentiality, anonymizing data to maintain privacy. And to ensure consistency and comparability, we standardized the measure of alcohol content across different beverages.

In the survey analysis, an interesting observation was the claim by a significant number of participants that they could consume up to 100 standard drinks. This figure is physiologically implausible and likely indicates overestimation or a misunderstanding of what constitutes a 'standard' drink. To address these outliers and improve the model's predictive accuracy, we introduced manual categorization for alcohol tolerance. By binning the responses into categories—poor, average, ok, good, excellent, and outstanding—we could mitigate the impact of exaggerated responses on the model's training process. This categorization also enhances the model's interpretability and practicality in real-world settings, where such clear classifications can be more easily communicated and applied.

Moreover, during data cleaning, we manually addressed issues such as inconsistent units, non-standard responses, and outliers. This approach allowed us to refine our dataset effectively, ensuring reliable data quality for subsequent analysis.

Models training and comparison

In our study, we trained three models: Multiclass Logistic Regression, Random Forest, and CART (Classification and Regression Trees), incorporating advanced techniques like grid search and cross-validation to optimize their performance.

Multiclass Logistic Regression

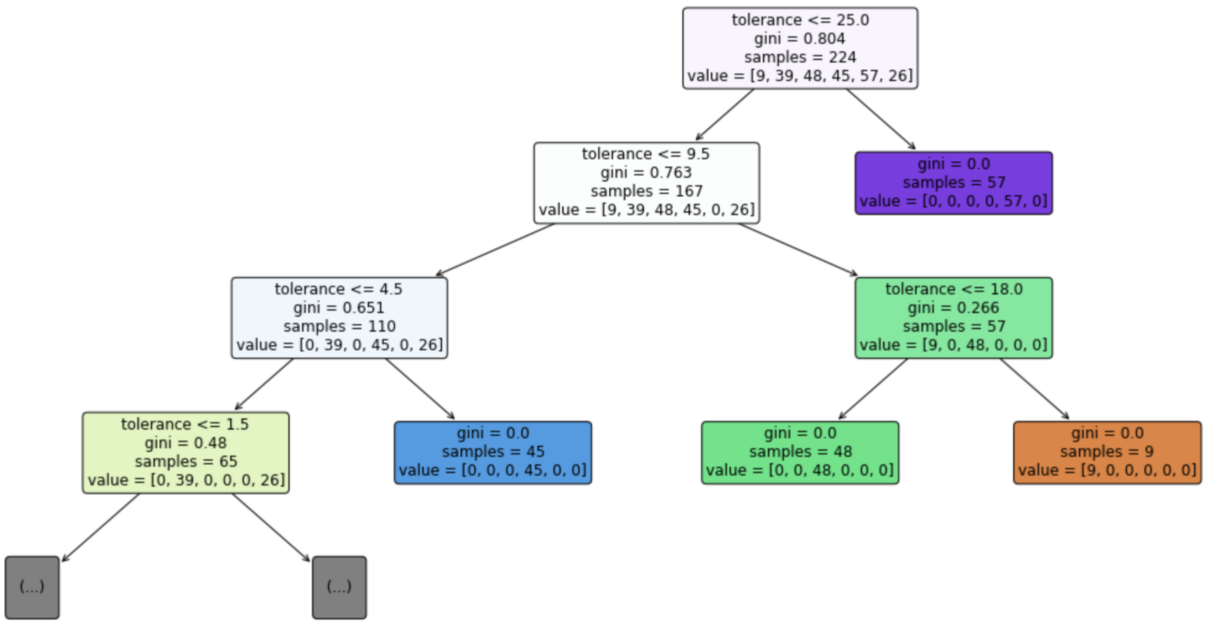
This model's strength lies in its interpretability, providing clear insights into the relationship between the predictors and the outcome. Adjusting its hyperparameters, such as maximum iterations, we achieved an accuracy of approximately 89.67% on the test set. This model's transparency makes it valuable for understanding the key drivers of alcohol tolerance.

Random Forest

This model excels in handling large, complex datasets and is robust to overfitting, a significant advantage over simpler models. Its ensemble approach, combining multiple decision trees, helps in capturing non-linear relationships and interactions between variables. Additionally, Random Forests are less sensitive to outliers and can handle unbalanced data effectively. These characteristics make it a powerful tool for predictive modeling in diverse scenarios. We achieved 94.18% classification accuracy after hyperparameter tuning.

CART Model

Notably achieved 100% accuracy, but this result, especially with an alpha value of 0.0, suggests potential overfitting. Regularization, typically achieved with a non-zero alpha, is crucial to prevent a model from learning the noise in the training data. The perfect accuracy raises concerns about the model's ability to generalize to new data.



Confidence Intervals

The confidence intervals for our models indicate the range within which the true model accuracy is likely to fall, considering sample variability. The Random Forest model's interval [0.9076, 0.9728] suggests high reliability. The CART model, with [0.9347, 0.9508], also shows a narrow interval despite potential overfitting concerns. Logistic regression has the widest range [0.8967, 0.9836], reflecting more uncertainty in its accuracy estimate. These intervals are crucial for understanding the stability of our models' predictions.

```
The 95-percent confidence interval of accuracy on random forest  is [0.9076086956521738, 0.9728260869565216]
The 95-percent confidence interval of accuracy on CART is [0.9347826086956521, 0.951086956521739]
The 95-percent confidence interval of accuracy on logistic regression is [0.8967391304347826, 0.983695652173913]
```

Despite the CART Model's nearly perfect accuracy, we prefer the Random Forest for its robustness, ability to handle complexity, and resistance to overfitting. While CART's nearly 100% accuracy suggests potential overfitting, Random Forest offers a more reliable and generalizable solution for predicting alcohol tolerance. This choice underscores our commitment to developing a model that not only performs well on our current dataset but also generalizes effectively to new data.

Impact

A "perfect" model, achieving high accuracy and generalizability, would be transformative. It could significantly reduce alcohol-related incidents in social settings by enabling accurate assessment of individual tolerance. This could help restaurants and event organizers tailor their service of alcohol, promote responsible drinking, and enhance public health. Moreover, such a model could assist medical professionals in understanding patients' risks related to alcohol consumption and in developing personalized health advisories.

Final Discussion

This project underscores the complexity of predicting alcohol tolerance and the importance of model generalizability. Future research could focus on refining these models with more diverse datasets and exploring their real-world applications in creating safer social drinking environments. This contributes significantly to public health initiatives by promoting responsible alcohol consumption and enhancing individual safety. Our study's limitations include reliance on self-reported data, which may introduce response biases, and the possibility of outliers, as seen with the implausible claim of a 100-drink tolerance. While we addressed this by categorizing tolerance levels, the subjective nature of such self-assessments could still affect the model's accuracy. Future iterations of this study could benefit from corroborating self-reported data with objective measures to enhance validity.

In [ ]:

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV
from sklearn.tree import plot_tree
```

In [ ]:

```python
df = pd.read_excel('data_432.xlsx')
df
```

Out[ ]:

	id	age	sex	weight	hight	smoke	drinking_freq	month_drinking_freq	drinking_legth	parent_freq	eating_2	stress_level	sleep_length
0	1	23.0	1	107.0	192	1	2	4.0	3	1	2	4	7
1	2	22.0	2	49.0	160	1	2	5.0	2	1	1	3	7
2	3	23.0	1	56.0	175	1	2	8.0	3	3	1	3	8
3	4	21.0	2	53.0	170	2	2	4.0	2	4	2	3	8
4	5	53.0	2	57.0	162	2	3	1.0	2	3	4	2	6
...	...	...	...	...	...	...	...	...	...	...	...	...	...
427	428	67.0	2	70.0	164	2	5	1.0	5	4	1	3	8
428	429	55.0	1	65.0	176	1	2	4.0	1	2	4	3	6
429	430	54.0	1	80.0	172	1	2	3.0	2	2	3	3	7
430	431	55.0	2	54.0	158	2	5	0.0	5	4	4	4	6
431	432	56.0	1	88.0	174	1	2	5.0	2	4	4	3	8

432 rows × 16 columns

In [ ]:

```python
df[(df["sex"] == 2)&(df["tolerance"]<=30)]["tolerance"].mean()
```

Out[ ]: 9.263803680981596

In [ ]:
```
df = df.dropna()
```

In [ ]:
```
# check all the free response questions
# fix the value manually in excel
# Check age range
df[~df['age'].isin(range(1,101))]
```

Out[ ]:

id	age	sex	weight	hight	smoke	drinking_freq	month_drinking_freq	drinking_legth	parent_freq	eating_2	stress_level	sleep_length	liver

In [ ]:
```
# Check weight range
df[~((df['weight'] > 0) & (df['weight'] < 200))]
```

Out[ ]:

id	age	sex	weight	hight	smoke	drinking_freq	month_drinking_freq	drinking_legth	parent_freq	eating_2	stress_level	sleep_length	liver

In [ ]:
```
# Check hight range, fix the error manually
df[~((df['hight'] > 0) & (df['hight'] < 220))]
```

Out[ ]:

id	age	sex	weight	hight	smoke	drinking_freq	month_drinking_freq	drinking_legth	parent_freq	eating_2	stress_level	sleep_length	liver

In [ ]:
```
# Check drinking_freq range, fix the error manually
df[~((df['drinking_freq'] > 0) & (df['drinking_freq'] < 31))]
```

Out[ ]:

id	age	sex	weight	hight	smoke	drinking_freq	month_drinking_freq	drinking_legth	parent_freq	eating_2	stress_level	sleep_length	liver

In [ ]:
```
# Check sleep_length range, fix the error manually
df[~((df['sleep_length'] > 0) & (df['sleep_length'] < 15))]
```

Out[ ]:

id	age	sex	weight	hight	smoke	drinking_freq	month_drinking_freq	drinking_legth	parent_freq	eating_2	stress_level	sleep_length	liver

In [ ]:

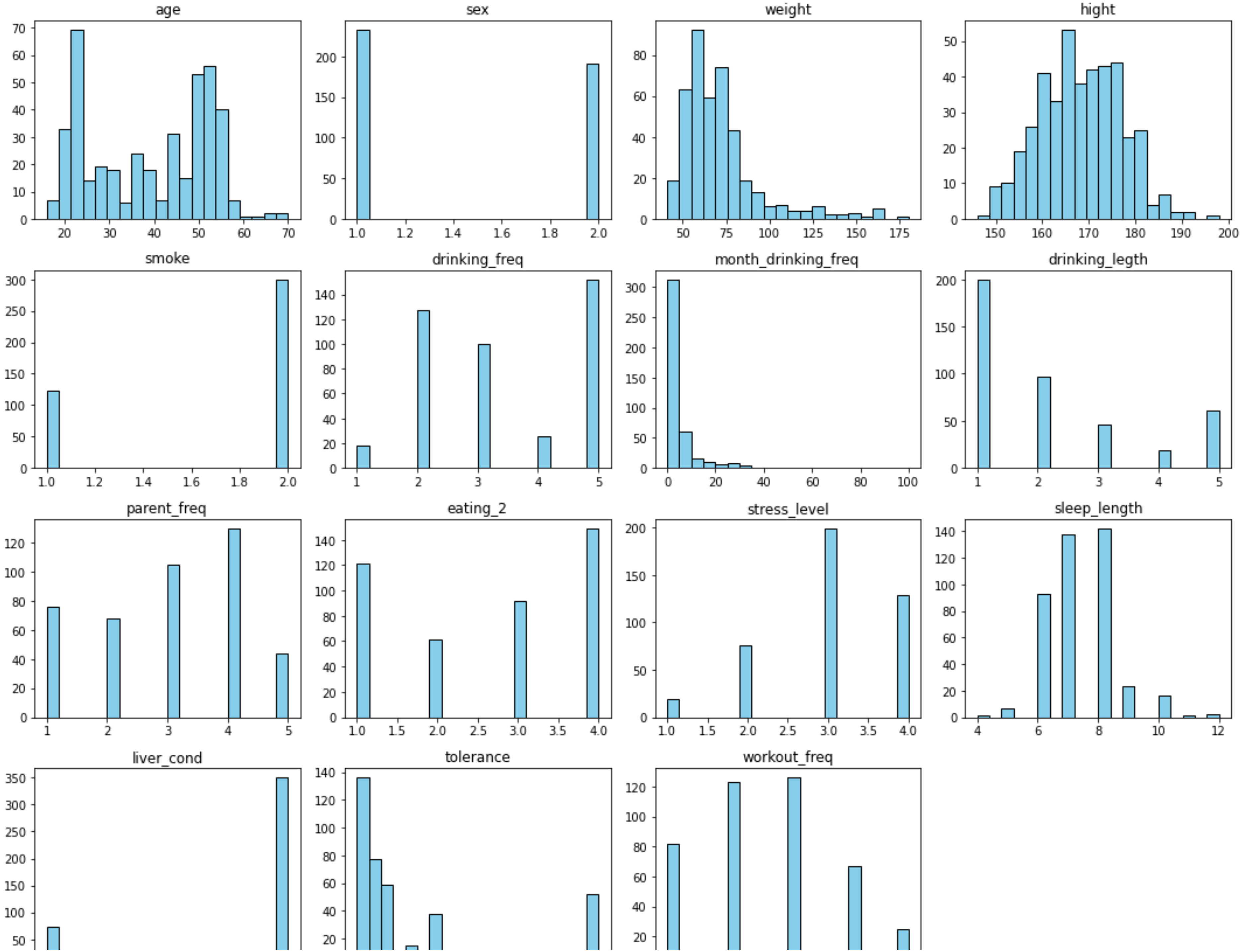
```
# Check tolerance range, fix the error manually
df[~((df['tolerance'] >= 0) & (df['tolerance'] <= 100))]
```

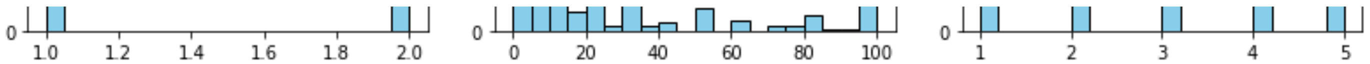
Out[ ]:

id	age	sex	weight	hight	smoke	drinking_freq	month_drinking_freq	drinking_legth	parent_freq	eating_2	stress_level	sleep_length	liver

In [ ]:

```
# doning some feature engineering
plt.figure(figsize=(15, 12), facecolor='w')

for i, column in enumerate(df.columns[1:], 1):
    plt.subplot(4, 4, i)
    plt.hist(df[column], bins=20, color='skyblue', edgecolor='black')
    plt.title(column)

plt.tight_layout()
plt.show()
```


age
sex
weight
hight
smoke
drinking_freq
month_drinking_freq
drinking_legth
parent_freq
eating_2
stress_level
sleep_length
liver_cond
tolerance
workout_freq



In [ ]:

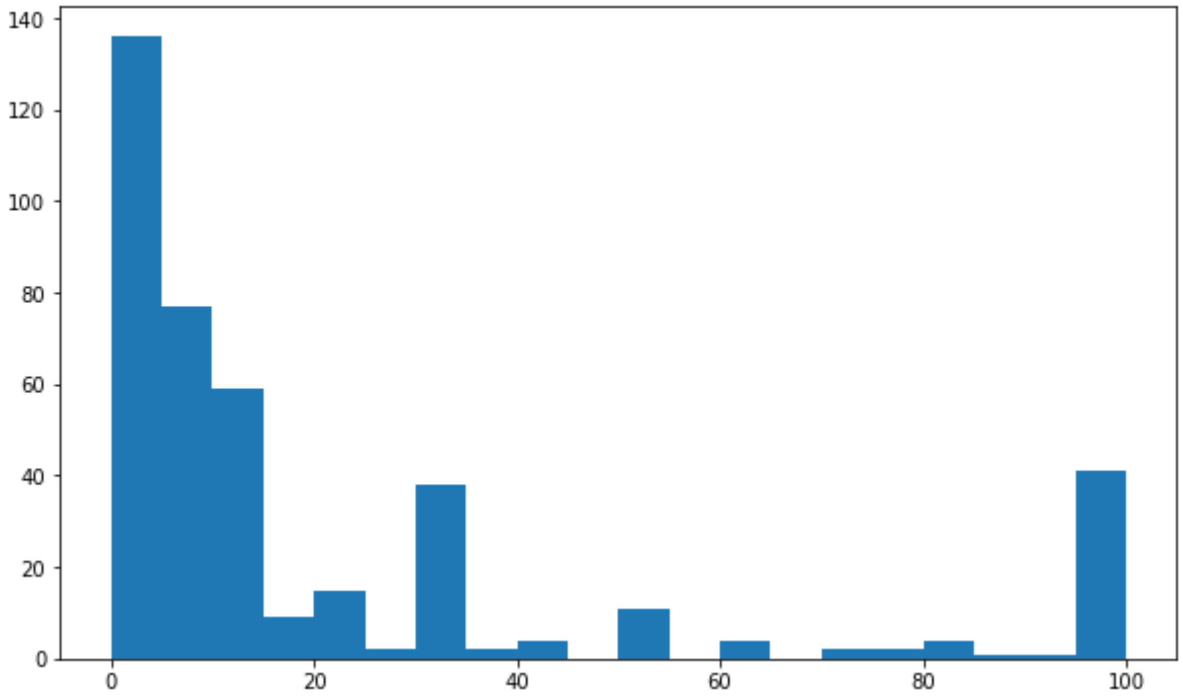
```
# data cleanning step 2
# remove people Rarely drink but their tolerance is higher than 50
df = df[~((df["drinking_freq"] == 5) & (df["tolerance"] > 50))]



# drop stress_level feature because it is not a good feature to predict tolerance
df = df.drop(columns=["stress_level"])

# drop the id column
df = df.drop(columns=["id"])
```

In [ ]:

```
plt.figure(figsize=(10,6),facecolor='white')
plt.hist(df["tolerance"],bins=20)
```

Out[ ]:

```
(array([136.,  77.,  59.,   9.,  15.,   2.,  38.,   2.,   4.,   0.,  11.,
          0.,   4.,   0.,   2.,   2.,   4.,   1.,   1.,  41.]),
 array([  0.,   5.,  10.,  15.,  20.,  25.,  30.,  35.,  40.,  45.,  50.,
         55.,  60.,  65.,  70.,  75.,  80.,  85.,  90.,  95., 100.]),
 <BarContainer object of 20 artists>)
```



In [ ]:

```
# convert multiple choice answers to categorie values
df.loc[df["smoke"] == 2, "smoke"] = 0
df.loc[df["sex"] == 1, "sex"] = "Male"
df.loc[df["sex"] == 2, "sex"]= "Female"


df.loc[df["drinking_freq"] == 1, "drinking_freq"] = "Daily"
df.loc[df["drinking_freq"] == 2, "drinking_freq"] = "Weekly"
df.loc[df["drinking_freq"] == 3, "drinking_freq"] = "Monthly"
df.loc[df["drinking_freq"] == 4, "drinking_freq"] = "Yearly"
df.loc[df["drinking_freq"] == 5, "drinking_freq"] = "Rarely"

df.loc[df["parent_freq"] == 1, "parent_freq"] = "Very often"
df.loc[df["parent_freq"] == 2, "parent_freq"] = "Often"
df.loc[df["parent_freq"] == 3, "parent_freq"] = "Not often"
df.loc[df["parent_freq"] == 4, "parent_freq"] = "Barely"
df.loc[df["parent_freq"] == 5, "parent_freq"] = "Never"

df.loc[df["eating_2"] == 1, "eating_2"] = "Always"
df.loc[df["eating_2"] == 2, "eating_2"] = "Often"
```

```
df.loc[df["eating_2"] == 3, "eating_2"] = "Sometimes"
df.loc[df["eating_2"] == 4, "eating_2"] = "Never"

df.loc[df["liver_cond"] == 2, "liver_cond"] = 0

df.loc[df["workout_freq"] == 1, "workout_freq"] = "Very often"
df.loc[df["workout_freq"] == 2, "workout_freq"] = "Often"
df.loc[df["workout_freq"] == 3, "workout_freq"] = "Not often"
df.loc[df["workout_freq"] == 4, "workout_freq"] = "Barely"
df.loc[df["workout_freq"] == 5, "workout_freq"] = "Never"
```

In [ ]:

```
df['tol_cat'] = df['tolerance'].apply(lambda x : "poor" if x < 2 else ("average" if x < 5 else ("ok" if x < 10 else ("g
```

Part 2

Molding

Split Traning Set and Testing Set

In [ ]:

```
y = df['tol_cat']
x = pd.get_dummies(df.drop(['tol_cat'], axis=1))
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.45)
```

Multiclass Logistic Regression

In [ ]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, accuracy_score

logreg = LogisticRegression(multi_class='multinomial', solver='lbfgs', max_iter=10000)
logreg.fit(x_train, y_train)
```

Out[ ]:

```
LogisticRegression(max_iter=10000, multi_class='multinomial')
```

Check our accuracy on testing data for Multclass logistic regression

In [ ]:

```
y_pred = logreg.predict(x_test)
accuracy_log = accuracy_score(y_test, y_pred)
cm = confusion_matrix(y_test, y_pred)

print("Confusion Matrix : \n", cm)
print(f"Accuracy on test set: {accuracy_log}")
```

```
Confusion Matrix :
 [[ 6  0  0  0  0  0]
 [ 0 35  0  6  0  6]
 [ 0  0 20  0  0  0]
 [ 0  1  1 30  0  0]
 [ 1  0  0  0 54  0]
 [ 0  4  0  0  0 20]]
Accuracy on test set: 0.8967391304347826
```

Random Forest

1. use cv to find max feature

In [ ]:

```
grid_values = {'max_features': np.linspace(1,16,16, dtype='int32'),
               'min_samples_leaf': [5],
               'n_estimators': [500],
               'random_state': [88]}

rf = RandomForestClassifier()

# use 5-fold cross validation
cv = KFold(n_splits=5, shuffle=True)
rf_cv = GridSearchCV(rf, param_grid=grid_values, scoring='accuracy', cv=cv,verbose=2)
rf_cv.fit(x_train, y_train)
```

```
Fitting 5 folds for each of 16 candidates, totalling 80 fits
[CV] END max_features=1, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.4s
[CV] END max_features=1, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=1, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=1, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=1, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=2, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=2, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
```

```
[CV] END max_features=2, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=2, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=2, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=3, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
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[CV] END max_features=3, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=4, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
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[CV] END max_features=5, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=5, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
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[CV] END max_features=6, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.4s
[CV] END max_features=6, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=6, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=7, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.4s
[CV] END max_features=7, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=7, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=7, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.4s
[CV] END max_features=7, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.4s
[CV] END max_features=8, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.4s
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[CV] END max_features=9, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.4s
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[CV] END max_features=10, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.4s
[CV] END max_features=10, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.4s
[CV] END max_features=10, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
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[CV] END max_features=10, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=11, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.4s
```

```
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[CV] END max_features=14, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.4s
[CV] END max_features=14, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.4s
[CV] END max_features=14, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=14, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=14, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.4s
[CV] END max_features=15, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=15, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=15, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=15, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=15, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=16, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.4s
[CV] END max_features=16, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=16, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=16, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.3s
[CV] END max_features=16, min_samples_leaf=5, n_estimators=500, random_state=88; total time=   0.4s
```

Out[ ]:

```
GridSearchCV(cv=KFold(n_splits=5, random_state=None, shuffle=True),
             estimator=RandomForestClassifier(),
             param_grid={'max_features': array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16]),
                         'min_samples_leaf': [5], 'n_estimators': [500],
                         'random_state': [88]},
             scoring='accuracy', verbose=2)
```

In [ ]:

```python
max_features = rf_cv.cv_results_['param_max_features'].data
acc = rf_cv.cv_results_['mean_test_score']

print('Grid best parameter max_features (max. accuracy): ', rf_cv.best_params_['max_features'])
print('Grid best score (accuracy): ', rf_cv.best_score_)
```

```
Grid best parameter max_features (max. accuracy):  15
Grid best score (accuracy):  0.9418181818181818
```

In [ ]:

```
y_pred = rf_cv.best_estimator_.predict(x_test)
cm = confusion_matrix(y_test, y_pred)
accuracy_rf = accuracy_score(y_test, y_pred)

print("Confusion Matrix : \n", cm)
print(f"Accuracy on test set is: {accuracy_rf}")
```

```
Confusion Matrix :
 [[ 0  0  6  0  0  0]
 [ 0 47  0  0  0  0]
 [ 0  0 20  0  0  0]
 [ 0  0  0 32  0  0]
 [ 0  0  1  0 54  0]
 [ 0  4  0  0  0 20]]
Accuracy on test set is: 0.9402173913043478
```

CART Model

In [ ]:

```
grid_values = {'ccp_alpha': np.linspace(0, 0.10, 201),# the choice of alpha, ranging from 0 to 0.2
               'min_samples_leaf': [5],
               'min_samples_split': [20],
               'max_depth': [30],
               'random_state': [88]}


dtc = DecisionTreeClassifier()

cv = KFold(n_splits=5,shuffle=True)

dtc_cv_acc = GridSearchCV(dtc, param_grid = grid_values, scoring = 'accuracy', cv=cv, verbose=1)

dtc_cv_acc.fit(x_train, y_train)
```

```
Fitting 5 folds for each of 201 candidates, totalling 1005 fits
```

Out[ ]:

```
GridSearchCV(cv=KFold(n_splits=5, random_state=None, shuffle=True),
             estimator=DecisionTreeClassifier(),
             param_grid={'ccp_alpha': array([0.    , 0.0005, 0.001 , 0.0015, 0.002 , 0.0025, 0.003 , 0.0035,
       0.004 , 0.0045, 0.005 , 0.0055, 0.006 , 0.0065, 0.007 , 0.0075,
```

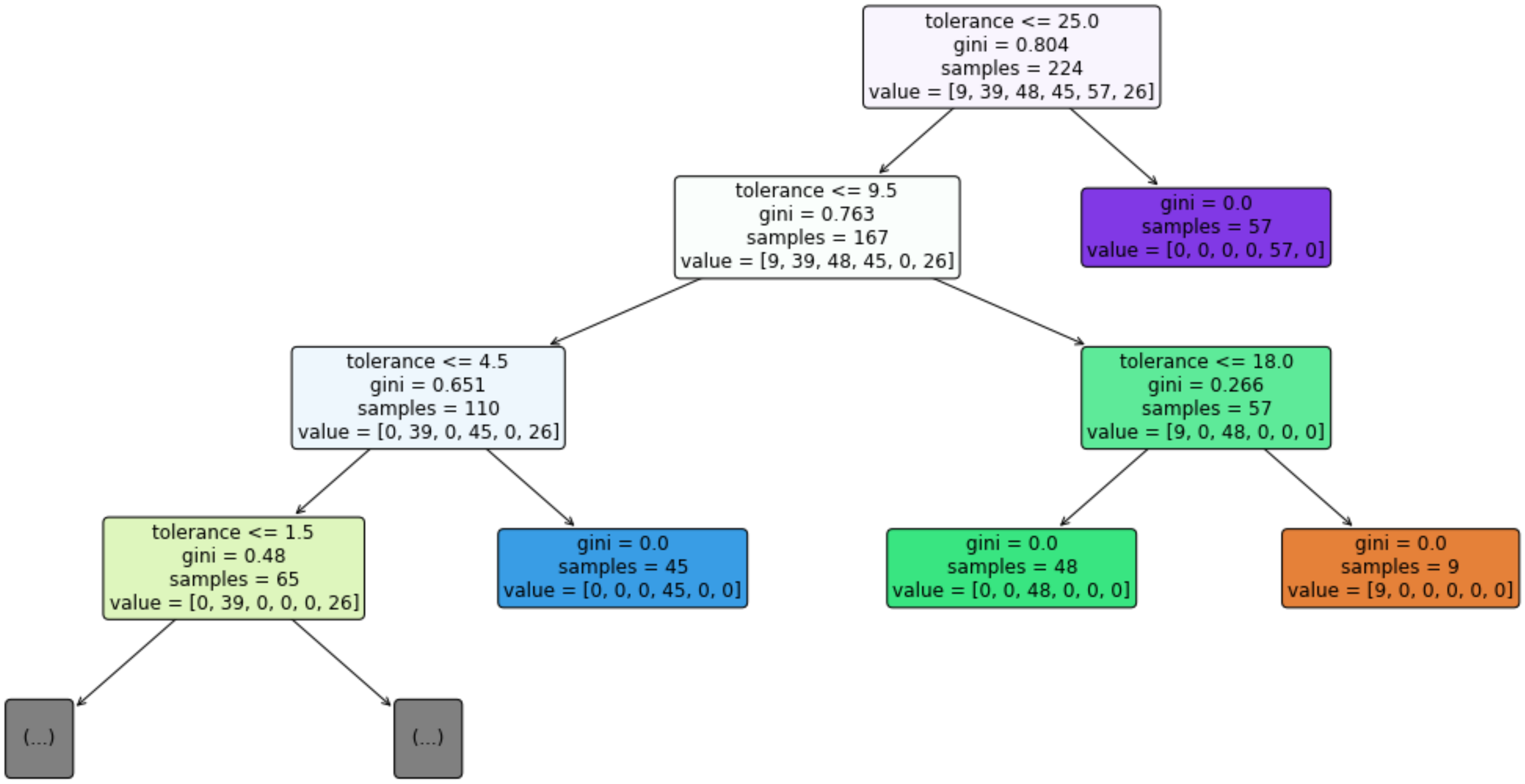
```
       0.008 , 0.0085, 0.009 , 0.0095, 0.01  , 0.0105, 0.011 , 0.0115,
       0.012 , 0.0125, 0.013 , 0.0135, 0.014 , 0.0145, 0.015 , 0.0155,
       0.016 , 0.0165, 0....
       0.08  , 0.0805, 0.081 , 0.0815, 0.082 , 0.0825, 0.083 , 0.0835,
       0.084 , 0.0845, 0.085 , 0.0855, 0.086 , 0.0865, 0.087 , 0.0875,
       0.088 , 0.0885, 0.089 , 0.0895, 0.09  , 0.0905, 0.091 , 0.0915,
       0.092 , 0.0925, 0.093 , 0.0935, 0.094 , 0.0945, 0.095 , 0.0955,
       0.096 , 0.0965, 0.097 , 0.0975, 0.098 , 0.0985, 0.099 , 0.0995,
       0.1   ]),
                         'max_depth': [30], 'min_samples_leaf': [5],
                         'min_samples_split': [20], 'random_state': [88]},
             scoring='accuracy', verbose=1)
```

In [ ]:

```
print('Grid best parameter ccp_alpha (max. accuracy): ', dtc_cv_acc.best_params_['ccp_alpha'])
print('Grid best score (accuracy): ', dtc_cv_acc.best_score_)
print('Node count =', dtc_cv_acc.best_estimator_.tree_.node_count)

plt.figure(figsize=(20,10))
plot_tree(dtc_cv_acc.best_estimator_,
          feature_names=x_train.columns,
          filled=True,
          impurity=True,
          rounded=True,
          fontsize=12,
          max_depth=3)
plt.show()
```

```
Grid best parameter ccp_alpha (max. accuracy):  0.0
Grid best score (accuracy):  1.0
Node count = 11
```



In [ ]:

```
y_pred = dtc_cv_acc.best_estimator_.predict(x_test)
cm = confusion_matrix(y_test, y_pred)
accuracy_CART = accuracy_score(y_test, y_pred)

print("Confusion Matrix : \n", cm)
print(f"Accuracy on testing set: {accuracy_CART}")
```

```
Confusion Matrix :
 [[ 6  0  0  0  0  0]
 [ 0 47  0  0  0  0]
 [ 0  0 20  0  0  0]
 [ 0  0  0 32  0  0]
 [ 1  0  0  0 54  0]
```

```
 [ 0  0  0  0  0 24]]
Accuracy on testing set: 0.9945652173913043
```

Boostrap CI

In [ ]:

```
print(f"Now we have accuracy score on testing set for \n Multiclass Logistic Regression: {accuracy_log} \n Random Fores
```

```
Now we have accuracy score on testing set for
 Multiclass Logistic Regression: 0.8967391304347826
 Random Forest: 0.9402173913043478
 CART: 0.9945652173913043
```

In [ ]:

```
def bootstrap_validation(test_data, test_label, train_label, model, metrics_list, sample):
    n_sample = sample
    n_metrics = len(metrics_list)
    output_array=np.zeros([n_sample, n_metrics])
    output_array[:]=np.nan
    print(output_array.shape)
    for bs_iter in range(n_sample):
        bs_index = np.random.choice(test_data.index, len(test_data.index), replace=True)
        bs_data = test_data.loc[bs_index]
        bs_label = test_label.loc[bs_index]
        bs_predicted = model.predict(bs_data)
        for metrics_iter in range(n_metrics):
            metrics = metrics_list[metrics_iter]
            output_array[bs_iter, metrics_iter]=metrics(bs_predicted,bs_label)
    output_df = pd.DataFrame(output_array)
    return output_df
```

In [ ]:

```
bs_output_rf = bootstrap_validation(x_test,y_test,y_train,rf_cv.best_estimator_,
                                 metrics_list=[accuracy_score],
                                 sample = 1000)
bs_output_log = bootstrap_validation(x_test,y_test,y_train, logreg,
                                 metrics_list=[accuracy_score],
                                 sample = 1000)
bs_output_cart = bootstrap_validation(x_test,y_test,y_train, dtc_cv_acc.best_estimator_,
                                 metrics_list=[accuracy_score],
                                 sample = 1000)
```

```
(1000, 1)
(1000, 1)
(1000, 1)
```

In [ ]:

```
# The 95% confidence interval
CI_rf = [0, 0]
CI_rf_0 = np.quantile(bs_output_rf.iloc[:,0]-accuracy_rf,np.array([0.025,0.975]))
CI_rf[0] = accuracy_rf - CI_rf_0[1]
CI_rf[1] = accuracy_rf - CI_rf_0[0]

CI_cart = [0, 0]
CI_cart_0 = np.quantile(bs_output_cart.iloc[:,0]-accuracy_CART,np.array([0.025,0.975]))
CI_cart[0] = accuracy_rf - CI_cart_0[1]
CI_cart[1] = accuracy_rf - CI_cart_0[0]

CI_log = [0, 0]
CI_log_0 = np.quantile(bs_output_log.iloc[:,0]-accuracy_log,np.array([0.025,0.975]))
CI_log[0] = accuracy_rf - CI_log_0[1]
CI_log[1] = accuracy_rf - CI_log_0[0]

print("The 95-percent confidence interval of accuracy on random forest  is %s" % CI_rf) #0.5,0.64
print("The 95-percent confidence interval of accuracy on CART is %s" % CI_cart) #0.5,0.64
print("The 95-percent confidence interval of accuracy on logistic regression is %s" % CI_log) #0.5,0.64
```

```
The 95-percent confidence interval of accuracy on random forest  is [0.9076086956521738, 0.9728260869565216]
The 95-percent confidence interval of accuracy on CART is [0.9347826086956521, 0.951086956521739]
The 95-percent confidence interval of accuracy on logistic regression is [0.8967391304347826, 0.983695652173913]
```