Prediction of Smoking Trend in Gender.

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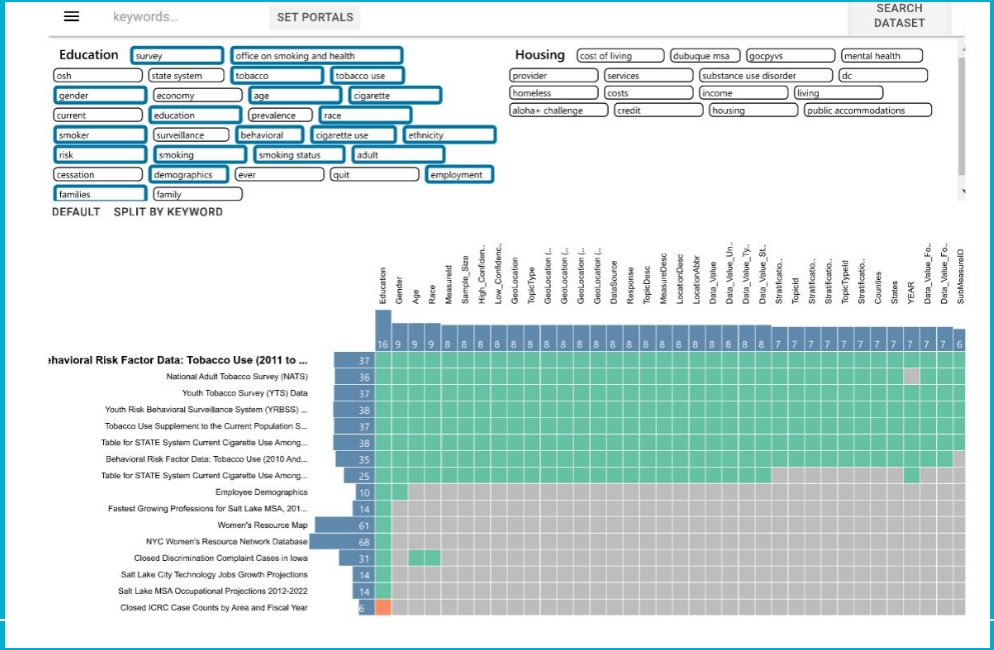
Objective of the Analysis

Find the smoking trend in gender by using age , race, and echolocation(Alaska and Alabama) features

The Dataset

Used data set:

- WE have used the Behavioral Risk Factor Data by using shown portals
- That gave us data with 30 features



Features of the Dataset

Original Data

1	LOCATIONABBR
2	MEASUREDESC
3	RESPONSE
4	DATA_VALUE_UNIT
5	DATA_VALUE_TYPE
6	DATA_VALUE_FOOTNOTE_SYMBOL
7	DATA_VALUE_FOOTNOTE
8	DATA_VALUE_STD_ERR
9	LOW_CONFIDENCE_LIMIT
10	HIGH_CONFIDENCE_LIMIT
11	TOPICTYPEID
12	STRATIFICATIONID2
13	STRATIFICATIONID3
14	STRATIFICATIONID4
15	SUBMEASUREID
16	YEAR
17	LOCATIONDESC
18	TOPICTYPE
19	TOPICDESC
20	DATASOURCE
21	DATA_VALUE
22	SAMPLE_SIZE
23	GENDER
24	RACE
25	AGE
26	EDUCATION
27	GEOLOCATION
28	TOPICID
29	MEASUREID
30	DISPLAYORDER

Present Data

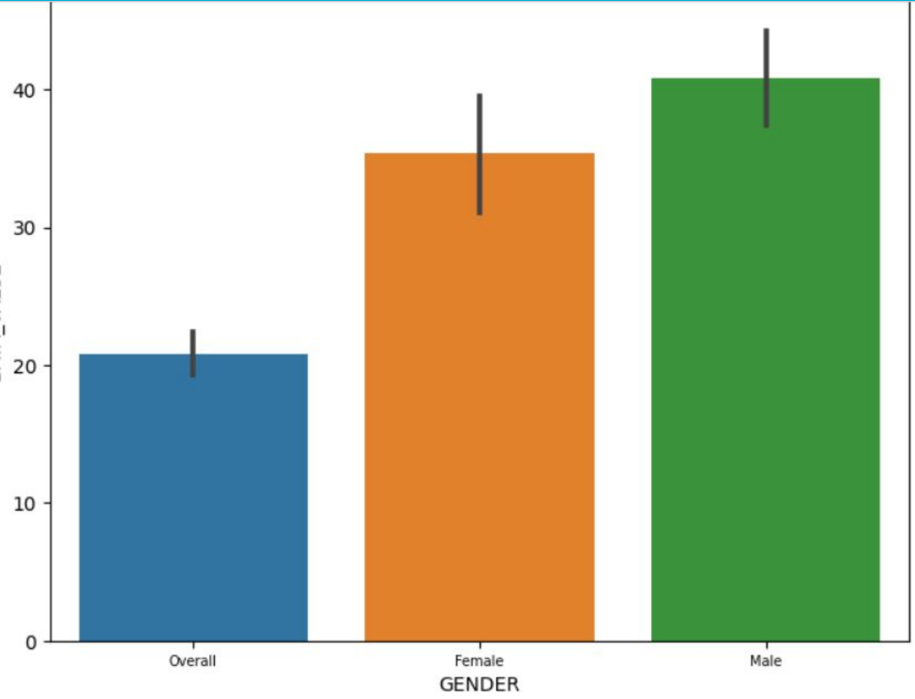
16	YEAR
17	LOCATIONDESC
18	TOPICTYPE
19	TOPICDESC
20	DATASOURCE
21	DATA_VALUE
22	SAMPLE_SIZE
23	GENDER
24	RACE
25	AGE
26	EDUCATION
27	GEOLOCATION
28	TOPICID
29	MEASUREID
30	DISPLAYORDER

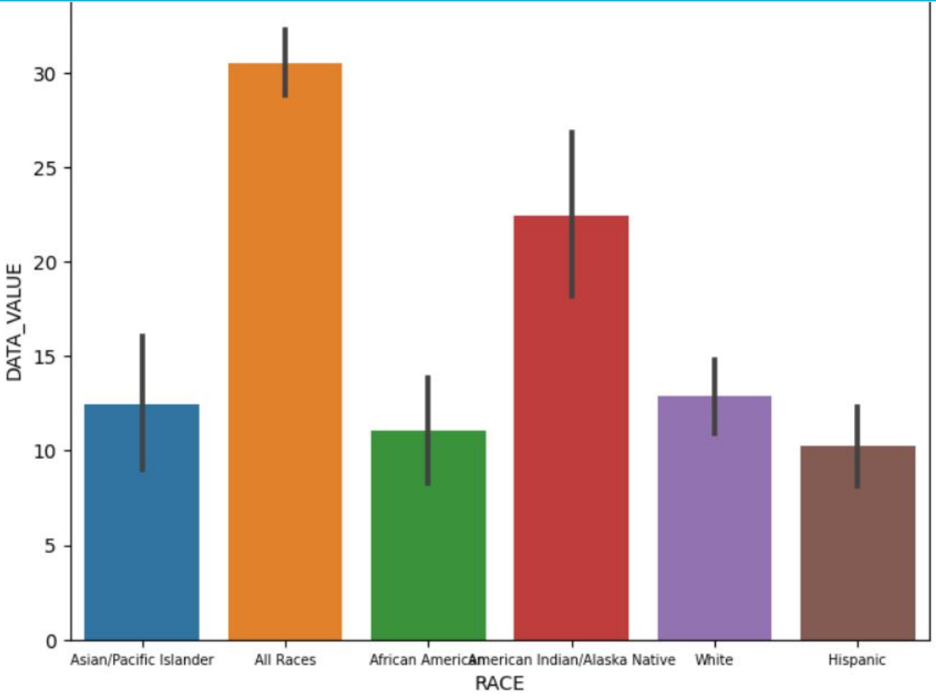
Focus Data

- Gender — Target variable
- Race
- Age
- Geolocation
- Data_Value

Used features

Graph: Feature Vs Target



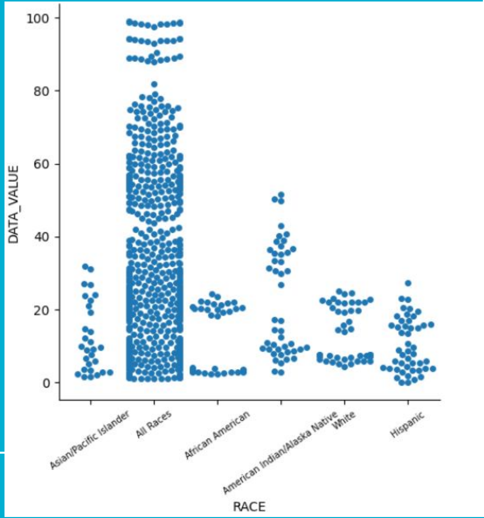


First Model: Linear Regression

Purpose: To determine if there is a relationship between the features and the target variable.

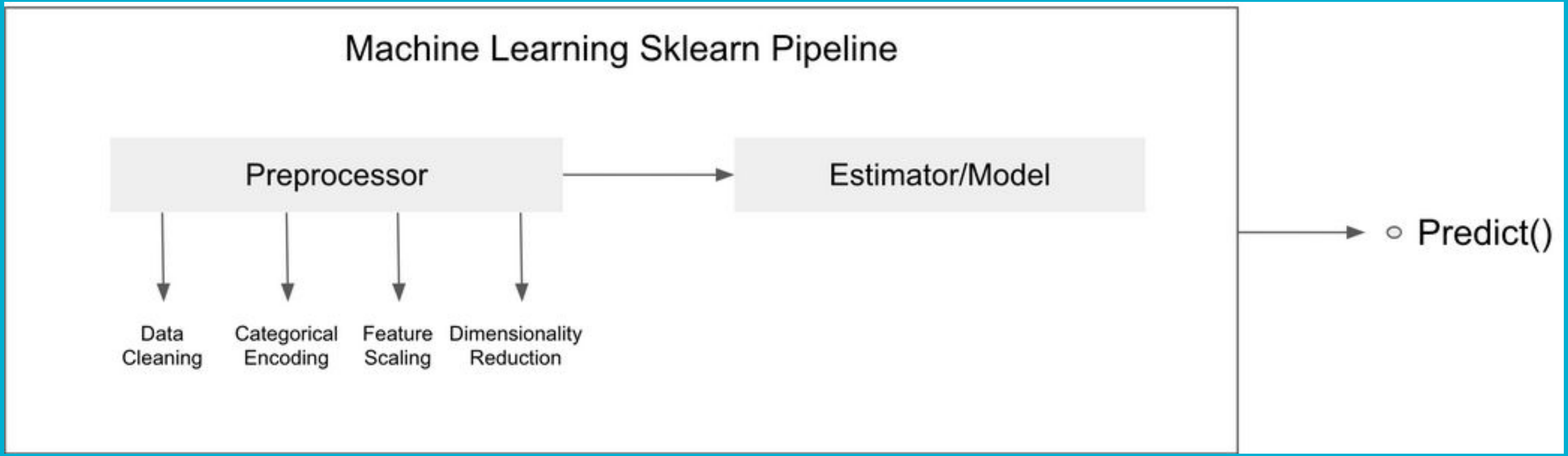
Features Used: Race, Age, Location, Probability of Smoking.

Target Variable: Sex



First Mode: Linear Regression Encoding

- Binary Encoding
- Encoding using Sklearn Pipeline



Evaluation of First Model: Linear Regression

$R2 = 0.728$

Pipeline

```
Pipeline(steps=[('imputer',
                 SimpleImputer(fill_value='missing', strategy='constant')),
                ('encoder',
                 OneHotEncoder(handle_unknown='ignore', sparse=False,
                               sparse_output=False)),
                ('model', LinearRegression())])
```

SimpleImputer

```
SimpleImputer(fill_value='missing', strategy='constant')
```

OneHotEncoder

```
OneHotEncoder(handle_unknown='ignore', sparse=False, sparse_output=False)
```

LinearRegression

```
LinearRegression()
```

Issues With the First Model: Linear Regression

- Encoding of categorical target variable. Some of the data was mixed with male and female.
- Issue with collinearity
- VIF: 1 lack of collinearity,
- VIF: >5 correlation between predictor
- Variance Inflation Factor

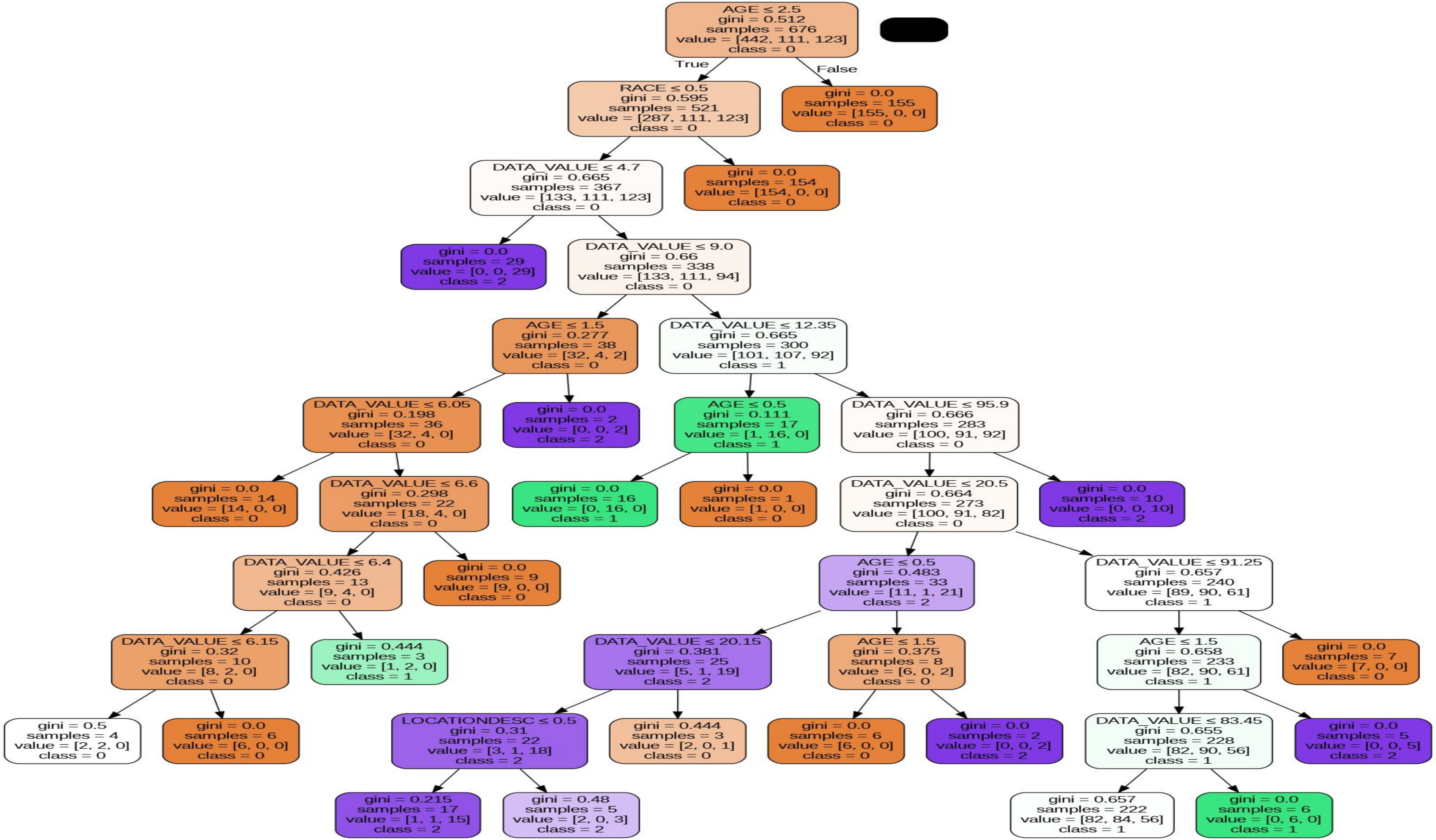
	variable	VIF
0	Intercept	63.039294
1	RACE[T.All Races]	4.655352
2	RACE[T.American Indian/Alaska Native]	1.993132
3	RACE[T.Asian/Pacific Islander]	1.649183
4	RACE[T.Hispanic]	2.018633
5	RACE[T.White]	2.040517
6	LOCATIONDESC[T.Alaska]	1.006983
7	AGE[T.18 to 44 Years]	1.946569
8	AGE[T.25 to 44 Years]	1.911454
9	AGE[T.45 to 64 Years]	1.910976
10	AGE[T.65 Years and Older]	1.913885
11	AGE[T.Age 20 and Older]	3.584818
12	AGE[T.Age 25 and Older]	3.584532
13	AGE[T.All Ages]	8.405993
14	DATA_VALUE	1.469572

Second Model: Decision Tree

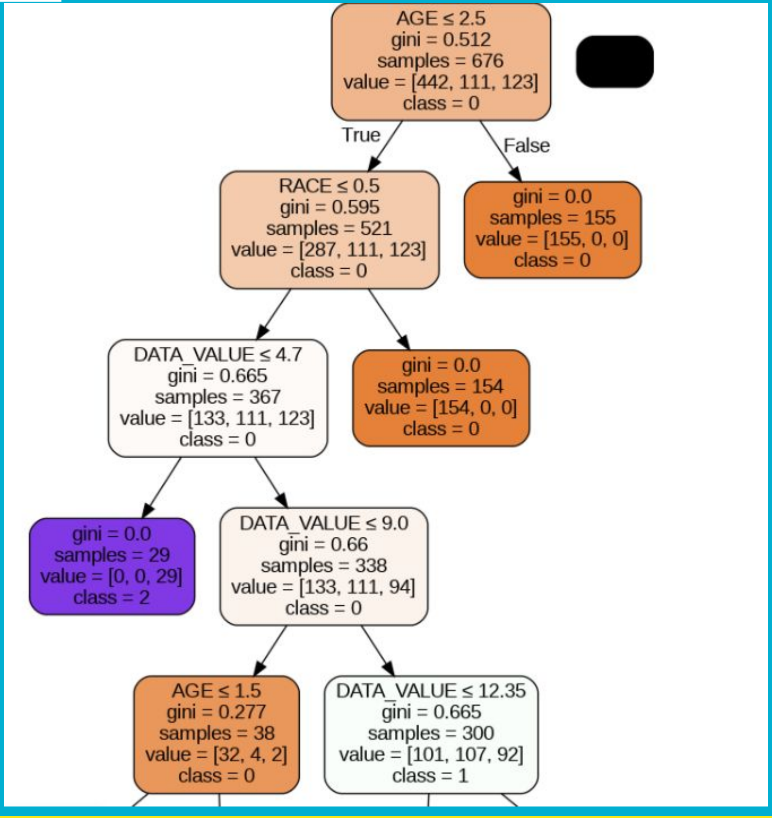
Objective: Predict the target variable (gender) based on the independent variables (features: race, age, location, data value)

Assigned all feature values (non-numerical) to a numerical value:

- Gender: Male (0), Female (1), Overall (2)
- Race: All Races (0), Asian/Pacific Islander (1), American Indian/Alaskan Native(2), African American (3), White (4), Hispanic (5)
- Age: All Ages (0), 18 to 24 (1), 18 to 44 (2), 20+ (3), 25+ (4), 25 to 44 (5), 45 to 64 (6), 65+ (7)
- Location: Alabama (0), Alaska (1)


AGE ≤ 2.5
gini = 0.512
samples = 676
value = [442, 111, 123]
class = 0
[redacted]
True
False
RACE ≤ 0.5
gini = 0.595
samples = 521
value = [287, 111, 123]
class = 0
gini = 0.0
samples = 155
value = [155, 0, 0]
class = 0
DATA_VALUE ≤ 4.7
gini = 0.665
samples = 367
value = [133, 111, 123]
class = 0
gini = 0.0
samples = 154
value = [154, 0, 0]
class = 0
gini = 0.0
samples = 29
value = [0, 0, 29]
class = 2
DATA_VALUE ≤ 9.0
gini = 0.66
samples = 338
value = [133, 111, 94]
class = 0
AGE ≤ 1.5
gini = 0.277
samples = 38
value = [32, 4, 2]
class = 0
DATA_VALUE ≤ 12.35
gini = 0.665
samples = 300
value = [101, 107, 92]
class = 1
DATA_VALUE ≤ 6.05
gini = 0.198
samples = 36
value = [32, 4, 0]
class = 0
gini = 0.0
samples = 2
value = [0, 0, 2]
class = 2
AGE ≤ 0.5
gini = 0.111
samples = 17
value = [1, 16, 0]
class = 1
DATA_VALUE ≤ 95.9
gini = 0.666
samples = 283
value = [100, 91, 92]
class = 0
gini = 0.0
samples = 14
value = [14, 0, 0]
class = 0
DATA_VALUE ≤ 6.6
gini = 0.298
samples = 22
value = [18, 4, 0]
class = 0
gini = 0.0
samples = 16
value = [0, 16, 0]
class = 1
gini = 0.0
samples = 1
value = [1, 0, 0]
class = 0
DATA_VALUE ≤ 20.5
gini = 0.664
samples = 273
value = [100, 91, 82]
class = 0
gini = 0.0
samples = 10
value = [0, 0, 10]
class = 2
DATA_VALUE ≤ 6.4
gini = 0.426
samples = 13
value = [9, 4, 0]
class = 0
gini = 0.0
samples = 9
value = [9, 0, 0]
class = 0
AGE ≤ 0.5
gini = 0.483
samples = 33
value = [11, 1, 21]
class = 2
DATA_VALUE ≤ 91.25
gini = 0.657
samples = 240
value = [89, 90, 61]
class = 1
DATA_VALUE ≤ 6.15
gini = 0.32
samples = 10
value = [8, 2, 0]
class = 0
gini = 0.444
samples = 3
value = [1, 2, 0]
class = 1
DATA_VALUE ≤ 20.15
gini = 0.381
samples = 25
value = [5, 1, 19]
class = 2
AGE ≤ 1.5
gini = 0.375
samples = 8
value = [6, 0, 2]
class = 0
AGE ≤ 1.5
gini = 0.658
samples = 233
value = [82, 90, 61]
class = 1
gini = 0.0
samples = 7
value = [7, 0, 0]
class = 0
gini = 0.5
samples = 4
value = [2, 2, 0]
class = 0
gini = 0.0
samples = 6
value = [6, 0, 0]
class = 0
LOCATIONDESC ≤ 0.5
gini = 0.31
samples = 22
value = [3, 1, 18]
class = 2
gini = 0.444
samples = 3
value = [2, 0, 1]
class = 0
gini = 0.0
samples = 6
value = [6, 0, 0]
class = 0
gini = 0.0
samples = 2
value = [0, 0, 2]
class = 2
DATA_VALUE ≤ 83.45
gini = 0.655
samples = 228
value = [82, 90, 56]
class = 1
gini = 0.0
samples = 5
value = [0, 0, 5]
class = 2
gini = 0.215
samples = 17
value = [1, 1, 15]
class = 2
gini = 0.48
samples = 5
value = [2, 0, 3]
class = 2
gini = 0.657
samples = 222
value = [82, 84, 56]
class = 1
gini = 0.0
samples = 6
value = [0, 6, 0]
class = 1

Evaluation of Second Model: Decision Tree



- Accuracy score: 0.742268
- Each node is assigned a class (gender) based on whether they fit the criteria of the feature
- Gini is the impurity score (rate of samples that do not match the assigned class)
- R^2 score: 0.482

Comparisons Between the Models

Decision Tree R^2 = 0.482   Linear Regression R^2=0.728

Advantages of Decision Tree

- Decision Tree can capture complex relationships in the data
- It does not require much data preprocessing for feature engineering
- Decision tree can handle both categorical and numerical data

Disadvantages of Decision Tree

- Prone to overfitting, especially with complex trees
- Decision tree is computationally expensive with large datasets
- It can be unstable and sensitive to small changes in the data

Advantages of Linear Regression

- Linear Regression can provide insight into the relationship between the independent and dependent variables
- It is Computationally efficient and can handle large datasets
- Linear Regression model is simple and easy to understand model

Disadvantages of Linear Regression

- Assumes a linear relationship between independent and dependent variables
- Can be affected by multicollinearity among independent variables
- This model cannot capture complex relationships in the data

Possible Flaws With Data Itself

- Encoding with target variable with data that was unspecific. Some of the surveys marked male and female.
- Age bounds of some surveys overlapped.
- Difference in R2 Models