Meteorite Landings: Patterns and Predictions

ICCS 261 Term Project

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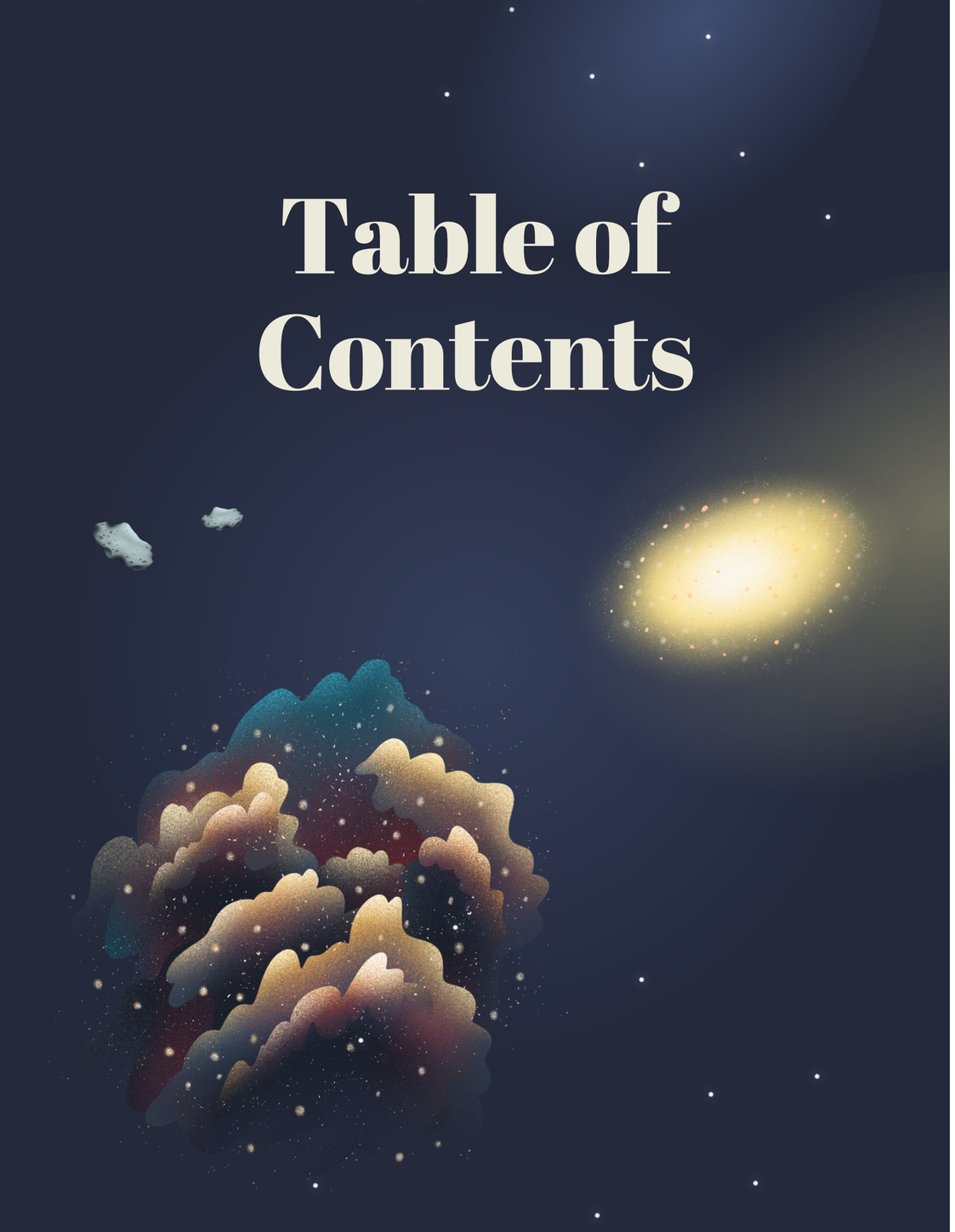


Introduction

- Meteorite landings are intriguing natural phenomena that gives us **insights** on space.
- Meteorology provides clues about the early solar system and the **formation** of planets.
- Aims to explore **patterns** in meteorite landings and develop **classification models**.

Research Question: Can meteorites be distinguished to their main types by its features?

Purpose and Objectives

Purpose: Gain insights into **patterns** and **characteristics** that distinguish types of meteorites. It could enhance **understanding** of the classification of meteorites.

Objectives: Determine **features** to be used in classifying meteorites by performing **EDA's** on data. Develop **classification models** with different parameters. Evaluate models and conclude.

Data Cleaning/Preparation

Data obtained from: NASA's Meteorite Landings Dataset

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_recall_fscore_support
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
```

	name	id	nametype	recclass	mass (g)	fall	year	reclat	reclong	GeoLocation
0	Aachen	1	Valid	L5	21.0	Fell	1880.0	50.77500	6.08333	(50.775, 6.08333)
1	Aarhus	2	Valid	H6	720.0	Fell	1951.0	56.18333	10.23333	(56.18333, 10.23333)
2	Abee	6	Valid	EH4	107000.0	Fell	1952.0	54.21667	-113.00000	(54.21667, -113.0)
3	Acapulco	10	Valid	Acapulcoite	1914.0	Fell	1976.0	16.88333	-99.90000	(16.88333, -99.9)
4	Achiras	370	Valid	L6	780.0	Fell	1902.0	-33.16667	-64.95000	(-33.16667, -64.95)
...	...	...	...	...	...	...	...	...	...	...
45711	Zillah 002	31356	Valid	Eucrite	172.0	Found	1990.0	29.03700	17.01850	(29.037, 17.0185)
45712	Zinder	30409	Valid	Pallasite, ungrouped	46.0	Found	1999.0	13.78333	8.96667	(13.78333, 8.96667)
45713	Zlin	30410	Valid	H4	3.3	Found	1939.0	49.25000	17.66667	(49.25, 17.66667)
45714	Zubkovsky	31357	Valid	L6	2167.0	Found	2003.0	49.78917	41.50460	(49.78917, 41.5046)
45715	Zulu Queen	30414	Valid	L3.7	200.0	Found	1976.0	33.98333	-115.68333	(33.98333, -115.68333)

45716 rows × 10 columns

https://data.nasa.gov/Space-Science/Meteorite-Landings/gh4g-9sfh/about_data

Drop Columns and Checking Missing Values

1.

```
df = df.drop(['id', 'nametype', 'GeoLocation'], axis = 1)
df.isna().sum()
```

✓ 0.0s

```
name            0
recclass        0
mass (g)      131
fall            0
year          291
reclat       7315
reclong      7315
dtype: int64
```

3.

	name	recclass	ass (g)	fall	year	reclat	reclong
0	Aachen	L5	21.0	Fell	1880.0	50.77500	6.08333
1	Aarhus	H6	7 0.0	Fell	1951.0	56.18333	10.23333
2	Abee	EH4	10700 0	Fell	1952.0	54.21667	-113.00000
3	Acapulco	Acapulcoite	1914	Fell	1976.0	16.88333	-99.90000
4	Achin	L6	780.0	Fell	1902.0	-33.16667	-64.95000
...	...	...	...	...	...	...	...
45711	Zillah 0 2	Eucrite	172.0	Found	1990.0	29.03700	17.01850
45712	Zinde	Pallasite, ungrouped	46.0	Found	1999.0	13.78333	8.96667
45713	Zlin	H4	3	Found	1939.0	49.25000	17.66667
45714	Zubkovsky	L6	216 .0	Found	2003.0	49.78917	41.50460
45715	Zulu Queen	L3.7	200.0	Found	1976.0	33.98333	-115.68333

45716 rows × 7 columns

2.

```
# although a lot of missing data in reclat and reclong, no method is optimal in filling in the missing value: average, ffill, and bfill causes inaccuracy in locations and introduces bias which effects model.
df = df.dropna(subset = ['reclat', 'reclong'])
df.isna().sum()
```

✓ 0.0s

Classification of Meteorites

Stony:

- Carbonaceous chondrites: CI; CM; CR; CO; CV; CK; CH; Ungrouped Carbonaceous chondrite
- Ordinary chondrites: H; L; LL; HH
- Rumuruti chondrites: R
- Kakangari chondrites: K
- Enstatite chondrites: EH; EL; Ungrouped enstatite chondrites
- IAB/IIICD silicate chondrites
- Ungrouped chondrites
- Primitive achondrites: Acapulcoites; Lodranites; Winonaites; Ungrouped primitive achondrites
- Differentiated meteorites:
- Asteroidal achondrites: Eucrites; Diogenites; Howardites; Angrites; Aubrites; Ureilites; Brachinites
- Martian meteorites: Shergottites; Nakhlites; Chassigny; ALH 84001
- Lunar meteorites: Mare basalts; Impact breccias

Classified into **3 main types:** stones, stony-irons, and irons

Stony irons:

- Pallasites
- Mesosiderites
- Ungrouped stony irons

Irons:

- Magmatic irons groups: IC; IIAB; IIC; IID; IIF; IIIAB; IIIE; IIIF; IVA; IVB
- Nonmagmatic irons groups: IAB/IIICD; IIE
- Ungrouped irons

https://en.wikipedia.org/wiki/Meteorite_classification#Rubin_classification

Separation by Keywords for Irons and Stony Irons

	0
12	Iron, IVA
26	Iron, IIAB
27	Iron, IAB-sLL
28	Iron, ungrouped
40	Iron, IAB-MG
42	Iron?
46	Iron, IIIAB
61	Iron, IID
66	Iron, IIE
75	Iron, IAB-sHL
78	Iron
84	Iron, IIE-an
103	Iron, IAB-ung

```
uniques = pd.DataFrame(df['recclass'].unique())
# retreive classes with keyword 'iron
iron = uniques[uniques[0].str.contains('Iron')]
iron = pd.concat([iron, uniques[uniques[0].str.contains('iron')]])

# retreive classes with keywords regarding stony irons
stony_iron = uniques[uniques[0].str.contains('Pallasite')]
stony_iron = pd.concat([stony_iron, uniques[uniques[0].str.contains('Mesosiderite')]])

# dropping out irons and stony irons from the main dataset
stone = uniques.drop(iron.index).drop(stony_iron.index)
```

✓ 0.0s

```
# renaming the names in recclass. WARNING: if cell is run twice, do a run-all. It messes up the variables of iron and stony iron.
df['recclass'] = df['recclass'].replace(iron.values, 'Iron')
df['recclass'] = df['recclass'].replace(stony_iron.values, 'Stony Iron')
df['recclass'] = df['recclass'].replace(stone.values, 'Stone')
```

✓ 0.3s

```
df['recclass'].unique() # checking the unique names
```

✓ 0.0s

```
array(['Stone', 'Iron', 'Stony Iron'], dtype=object)
```

Final Cleaning

```
# get median for each type
med_st = df[df['recclass'] == 'Stone']['year'].median()
med_ir = df[df['recclass'] == 'Iron']['year'].median()
med_si = df[df['recclass'] == 'Stony Iron']['year'].median()

# fillna for each type
df.loc[(df['recclass'] == 'Stone') & (df['year'].isna()), 'year'] = med_st
df.loc[(df['recclass'] == 'Iron') & (df['year'].isna()), 'year'] = med_ir
df.loc[(df['recclass'] == 'Stony Iron') & (df['year'].isna()), 'year'] = med_si
```

✓ 0.0s

```
mass_st = df[df['recclass'] == 'Stone']['mass (g)'].median()
mass_ir = df[df['recclass'] == 'Iron']['mass (g)'].median()
mass_si = df[df['recclass'] == 'Stony Iron']['mass (g)'].median()

df.loc[(df['recclass'] == 'Stone') & (df['mass (g)'].isna()), 'mass (g)'] = med_st
df.loc[(df['recclass'] == 'Iron') & (df['mass (g)'].isna()), 'mass (g)'] = med_ir
df.loc[(df['recclass'] == 'Stony Iron') & (df['mass (g)'].isna()), 'mass (g)'] = med_si
```

✓ 0.0s

```
df.isna().sum()
```

✓ 0.0s

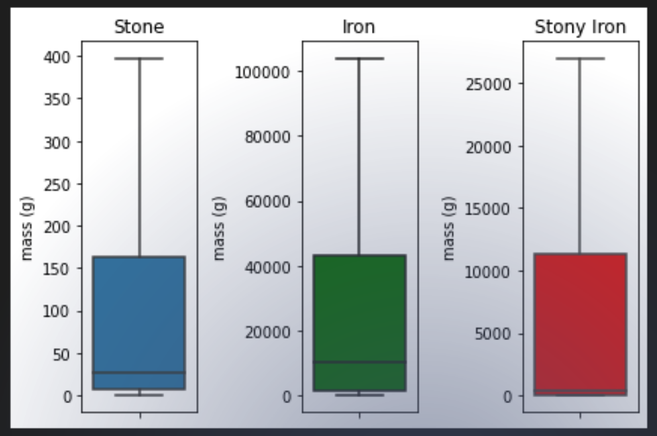
```
name        0
recclass    0
mass (g)    0
fall        0
year        0
reclat      0
reclong     0
dtype: int64
```

EDA: Proposal Reflection

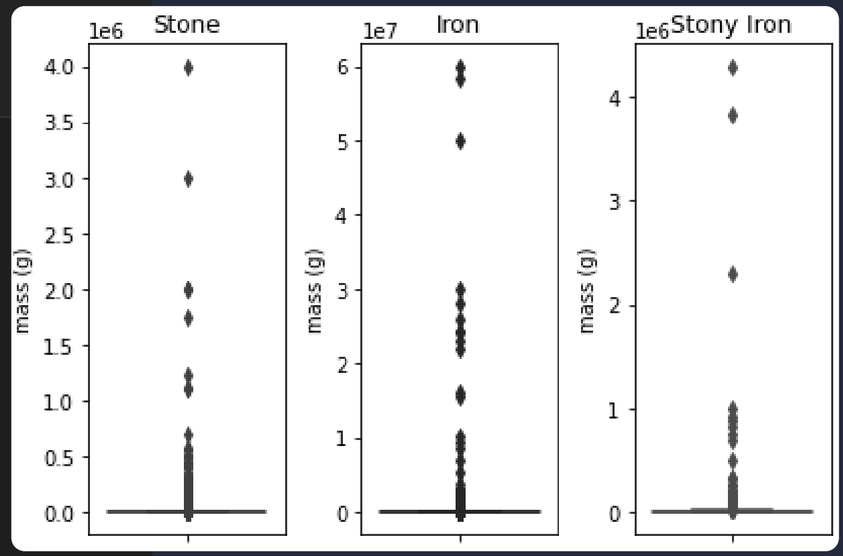
```
fig, axes = plt.subplots(1, 3, tight_layout = True)
sns.boxplot(ax = axes[0], data = df[df['recclass'] == 'Stone'], y = 'mass (g)', showfliers = False)
sns.boxplot(ax = axes[1], data = df[df['recclass'] == 'Iron'], y = 'mass (g)', showfliers = False, color = 'g')
sns.boxplot(ax = axes[2], data = df[df['recclass'] == 'Stony Iron'], y = 'mass (g)', showfliers = False, color = 'r')

axes[0].set_title('Stone')
axes[1].set_title('Iron')
axes[2].set_title('Stony Iron')

st_med = df[df['recclass'] == 'Stone']['mass (g)'].median()
ir_med = df[df['recclass'] == 'Iron']['mass (g)'].median()
si_med = df[df['recclass'] == 'Stony Iron']['mass (g)'].median()

print(f'\n Stone Median: {st_med} g\n Iron Median: {ir_med} g\n Stony Iron Median: {si_med} g')
```

✓ 0.1s

```
Stone Median: 27.4 g
Iron Median: 10000.0 g
Stony Iron Median: 414.0 g
```



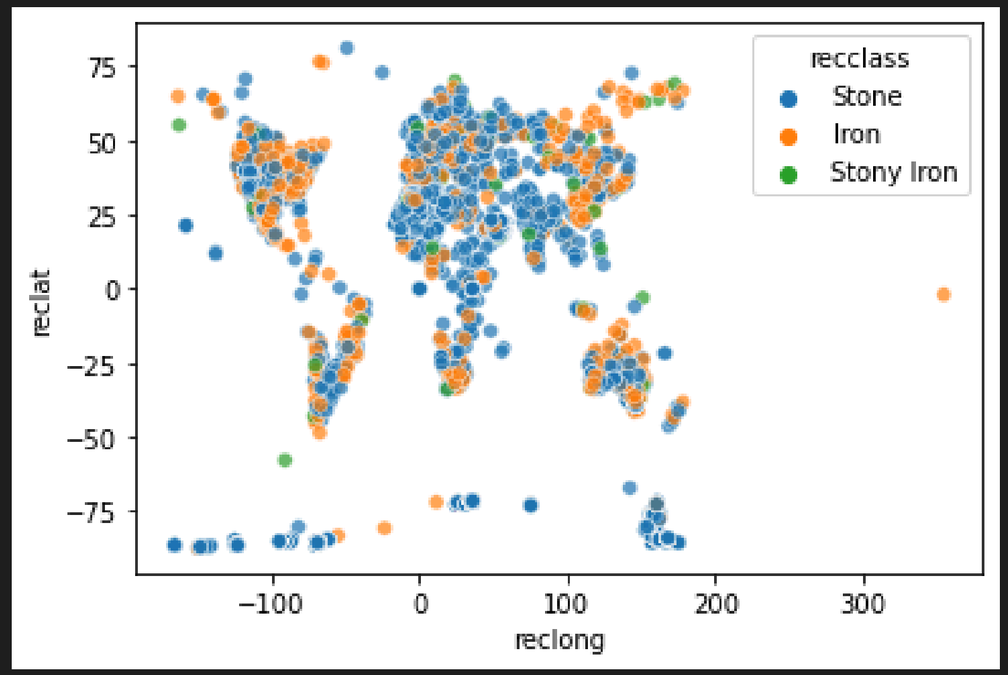
With outliers..



EDA: Proposal Reflection

```
sns.scatterplot(x = df['reclong'], y = df['reclat'], alpha = 0.7, hue = df['recclass'])
plt.show()
```

✓ 0.6s



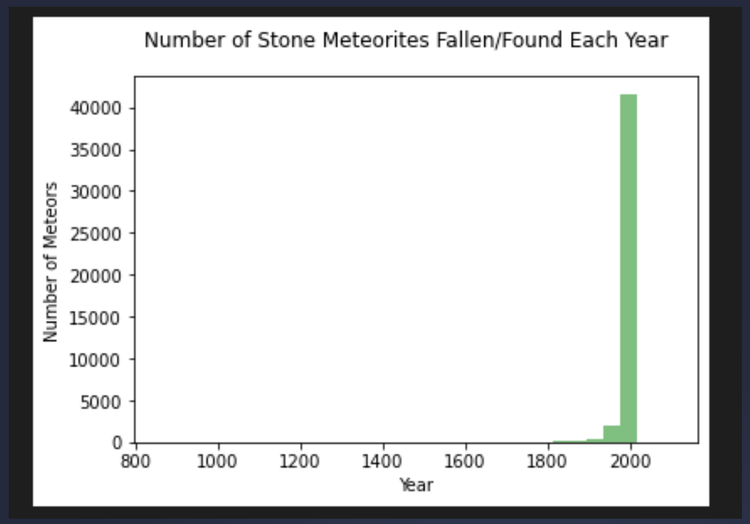
EDA: Proposal Reflection

```
# separating the years by type
fallen_st = df[df['recclass'] == 'Stone']
fallen_ir = df[df['recclass'] == 'Iron']
fallen_si = df[df['recclass'] == 'Stony Iron']
```

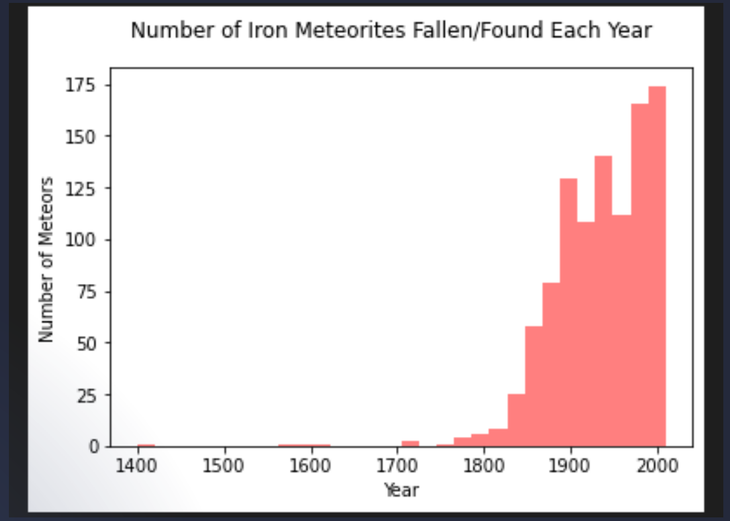
✓ 0.0s

```
# counting the number of meteors in each year
years_st = pd.DataFrame(fallen_st['year'].value_counts())
years_ir = pd.DataFrame(fallen_ir['year'].value_counts())
years_si = pd.DataFrame(fallen_si['year'].value_counts())
```

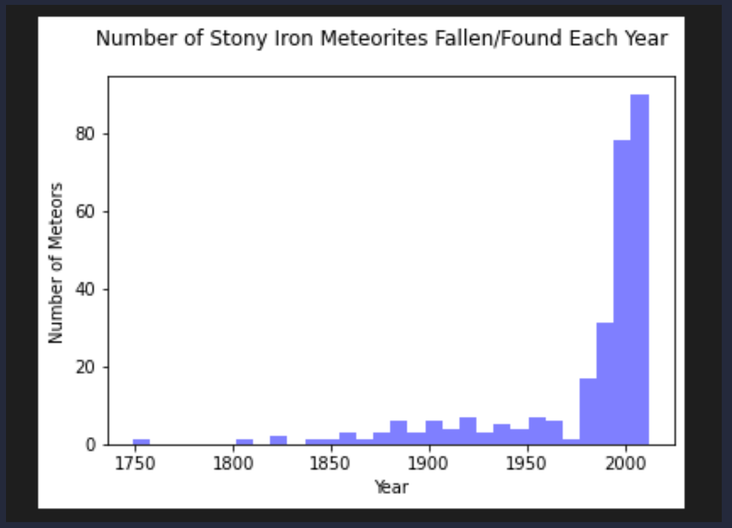
✓ 0.0s



Median: 1996



Median: 1939



Median: 1998

Fitting and Evaluating Models:

Chosen Model: **Random Forest Classifier**

- Dimensionality
- Reduces Overfitting
- Feature Importance
- Non-linear

5 (4.5) models were fitted with slight changes in **parameters** as an attempt to obtain better models.

Model #1: Out of the Box

1.

	mass (g)	reclat	reclong	fell	year
0	21.0	50.77500	6.08333	1	1880.0
1	720.0	56.18333	10.23333	1	1951.0
2	107000.0	54.21667	-113.00000	1	1952.0
3	1914.0	16.88333	-99.90000	1	1976.0
4	780.0	-33.16667	-64.95000	1	1902.0
...	...	...	...	...	...
45711	172.0	29.03700	17.01850	0	1990.0
45712	46.0	13.78333	8.96667	0	1999.0
45713	3.3	49.25000	17.66667	0	1939.0
45714	2167.0	49.78917	41.50460	0	2003.0
45715	200.0	33.98333	-115.68333	0	1976.0

```
y = df.recclass
y
```
✓ 0.0s

```
0              Stone
1              Stone
2              Stone
3              Stone
4              Stone
              ...
45711          Stone
45712    Stony Iron
45713          Stone
45714          Stone
45715          Stone
Name: recclass, Length: 45716, dtype: object
```

2.

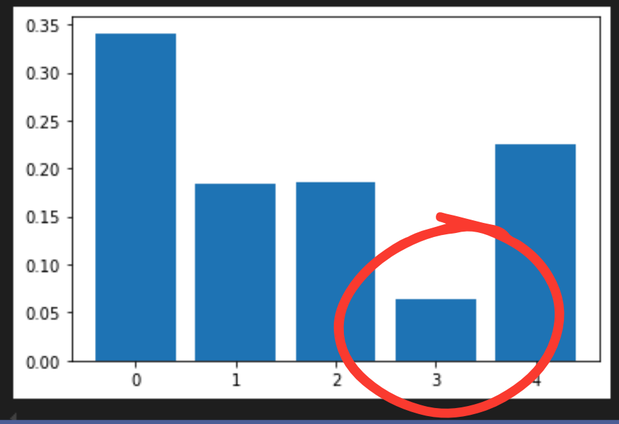
```
# split train-test
xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size = 0.3, random_state = 10)
```
✓ 0.0s

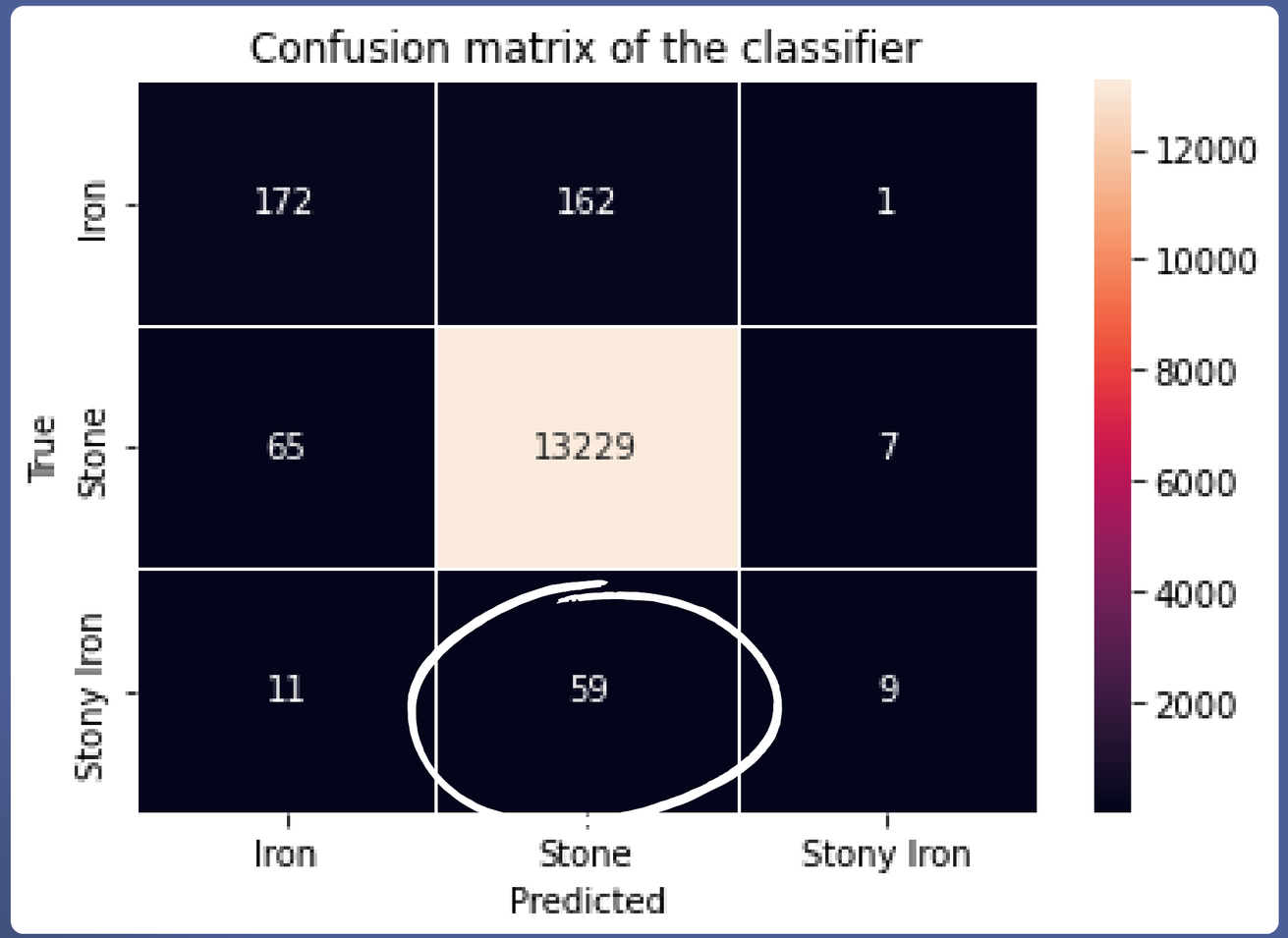
```
# fitting random forest model with tree size of 100
rf_model = RandomForestClassifier(n_estimators=100)
_ = rf_model.fit(xtrain, ytrain)
```

3.

```
# get importance to see which variables are most important when evaluating
importance = rf_model.feature_importances_

# summarize feature importance
for i,v in enumerate(importance):
 print('Feature: %0d, Score: %.5f' % (i,v))

# plot feature importance
plt.bar([x for x in range(len(importance))], importance)
plt.show()
```
✓ 2.6s

```
Feature: 0, Score: 0.34080
Feature: 1, Score: 0.18394
Feature: 2, Score: 0.18631
Feature: 3, Score: 0.06326
Feature: 4, Score: 0.22568
```

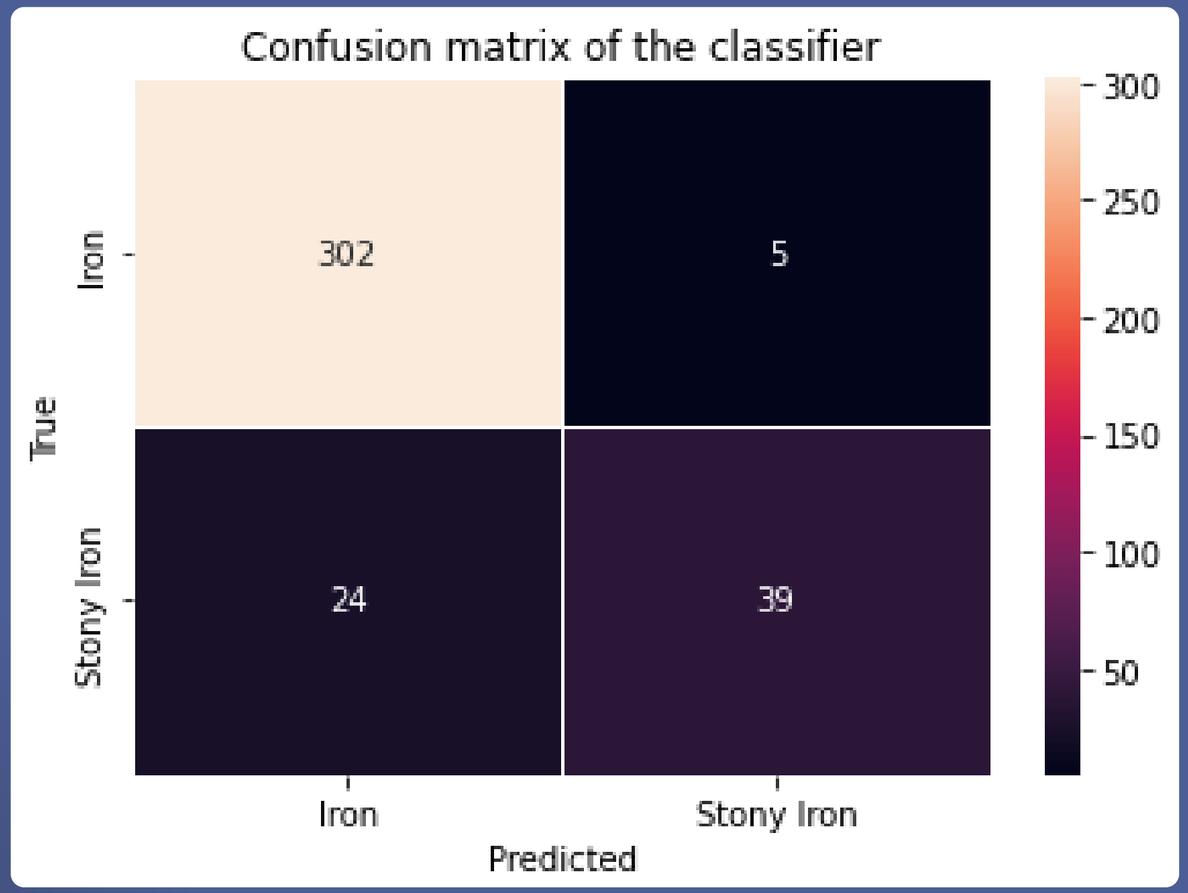





```
Accuracy: 0.977761574917973

(array([0.69354839, 0.98356877, 0.52941176]),
 array([0.51343284, 0.99458587, 0.11392405]),
 array([0.59005146, 0.98904714, 0.1875    ]),
 array([  335, 13301,    79], dtype=int64))
```

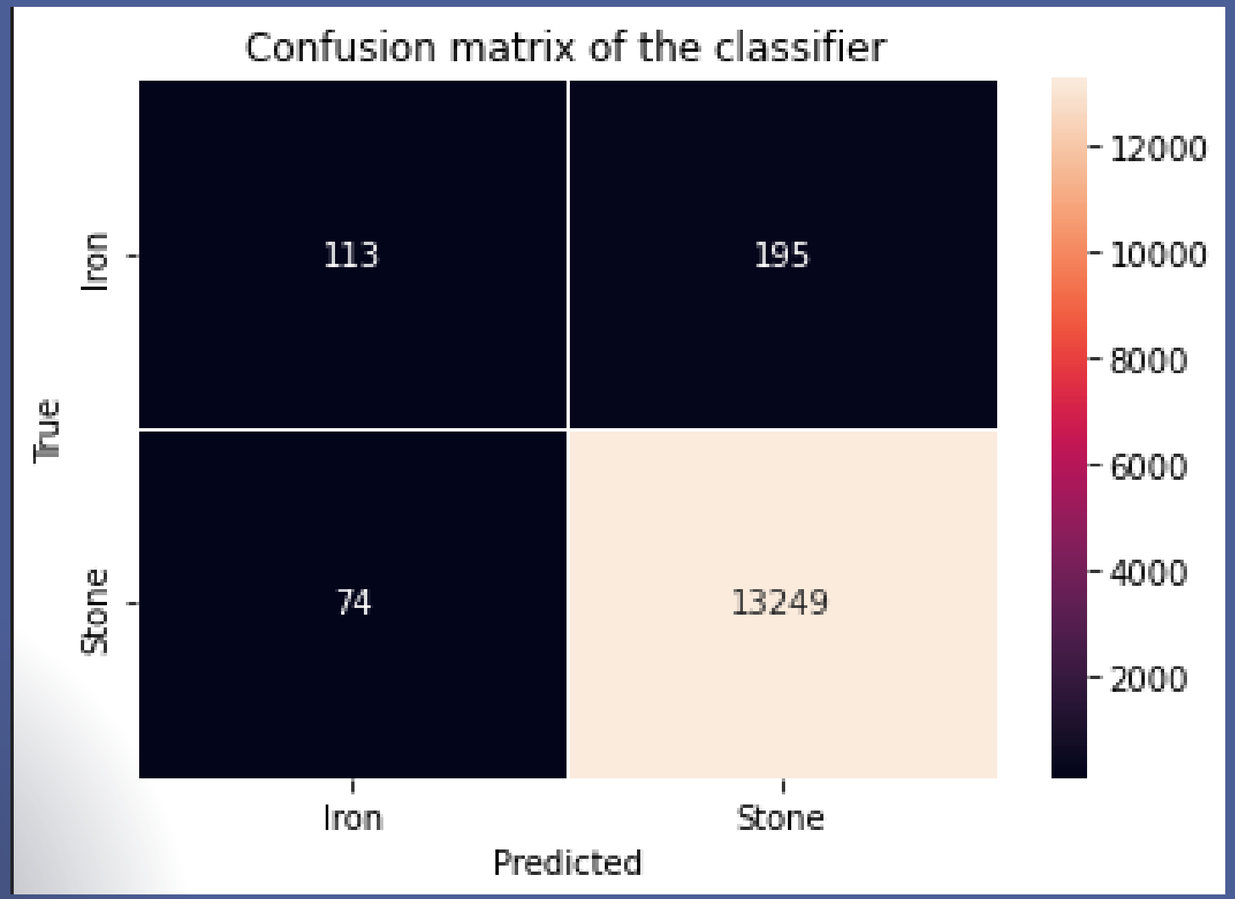
Stony irons and **stones** are hard to **separate** **(?)**

Model #2: Stony Irons vs. Irons




```
Accuracy: 0.9216216216216216

(array([0.92638037, 0.88636364]),
 array([0.98371336, 0.61904762]),
 array([0.95418641, 0.72897196]),
 array([307,  63], dtype=int64))
```

Model #3: Stones vs. Irons




```
Accuracy: 0.9802655711246424

(array([0.60427807, 0.98549539]),
 array([0.36688312, 0.9944457 ]),
 array([0.45656566, 0.98995031]),
 array([  308, 13323], dtype=int64))
```

Model #4: Weights + No Outliers

1.

```
# stones
stone_sub = df[df['recclass'] == 'Stone']
iron_sub = df[df['recclass'] == 'Iron']
stonyiron_sub = df[df['recclass'] == 'Stony Iron']

# calculate IQR
stone_IQR = stone_sub['mass (g)'].quantile(0.75) - stone_sub['mass (g)'].quantile(0.25)
iron_IQR = iron_sub['mass (g)'].quantile(0.75) - iron_sub['mass (g)'].quantile(0.25)
stonyiron_IQR = stonyiron_sub['mass (g)'].quantile(0.75) - stonyiron_sub['mass (g)'].quantile(0.25)

# get outliers
stone_outliers = stone_sub.loc[(stone_sub['mass (g)'] < (stone_sub['mass (g)'].quantile(0.25) - 1.5 * stone_IQR)) | (df['mass (g)'] > (stone_sub['mass (g)'].quantile(0.75) + 1.5 * stone_IQR))]
iron_outliers = iron_sub.loc[(iron_sub['mass (g)'] < (iron_sub['mass (g)'].quantile(0.25) - 1.5 * iron_IQR)) | (df['mass (g)'] > (iron_sub['mass (g)'].quantile(0.75) + 1.5 * iron_IQR))]
stonyiron_outliers = stonyiron_sub.loc[(stonyiron_sub['mass (g)'] < (stonyiron_sub['mass (g)'].quantile(0.25) - 1.5 * stonyiron_IQR)) | (df['mass (g)'] > (stonyiron_sub['mass (g)'].quantile(0.75) + 1.5 * stonyiron_IQR))]
```

2.

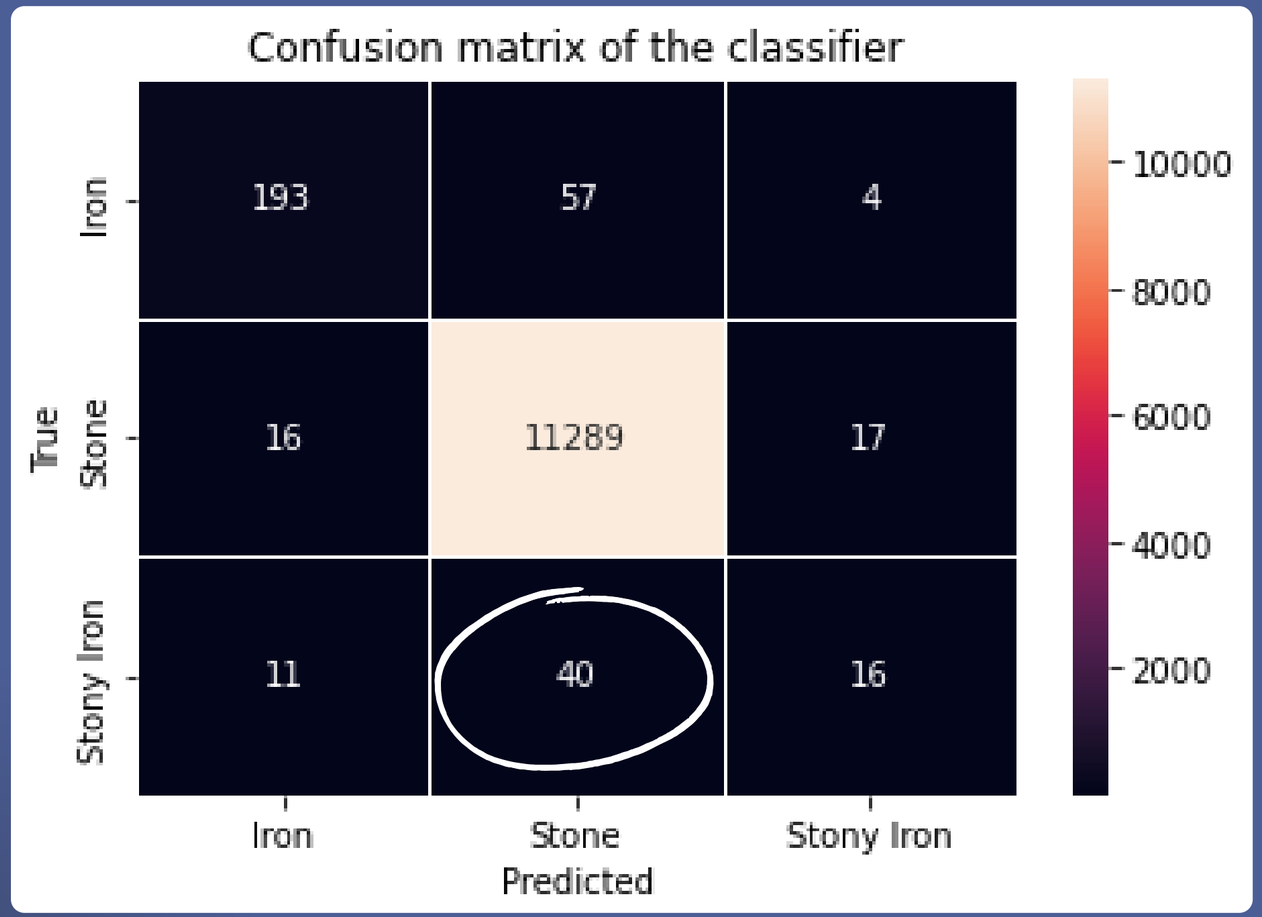
	name	recclass	mass (g)	fall	year	reclat	reclong
0	Aachen	Stone	21.0	Fell	1880.0	50.77500	6.08333
16	Akyumak	Iron	50000.0	Fell	1981.0	39.91667	42.81667
17	Al Rais	Stone	160.0	Fell	1957.0	24.41667	39.51667
22	Alby sur Chéran	Stone	252.0	Fell	2002.0	45.82133	6.01533
37	Northwest Africa 5815	Stone	256.8	Found	1998.0	0.00000	0.00000
...	...	...	...	...	...	...	...
45709	Zhongxiang	Iron	100000.0	Found	1981.0	31.20000	112.50000
45711	Zillah 002	Stone	172.0	Found	1990.0	29.03700	17.01850
45712	Zinder	Stony Iron	46.0	Found	1999.0	13.78333	8.96667
45713	Zlin	Stone	3.3	Found	1939.0	49.25000	17.66667
45715	Zulu Queen	Stone	200.0	Found	1976.0	33.98333	-115.68333

38808 rows × 7 columns

3.

```
# fitting random forest model with tree size of 100
rf_model4 = RandomForestClassifier(n_estimators=100, class_weight='balanced')
_ = rf_model4.fit(xtrain4, ytrain4)
```

✓ 1.9s

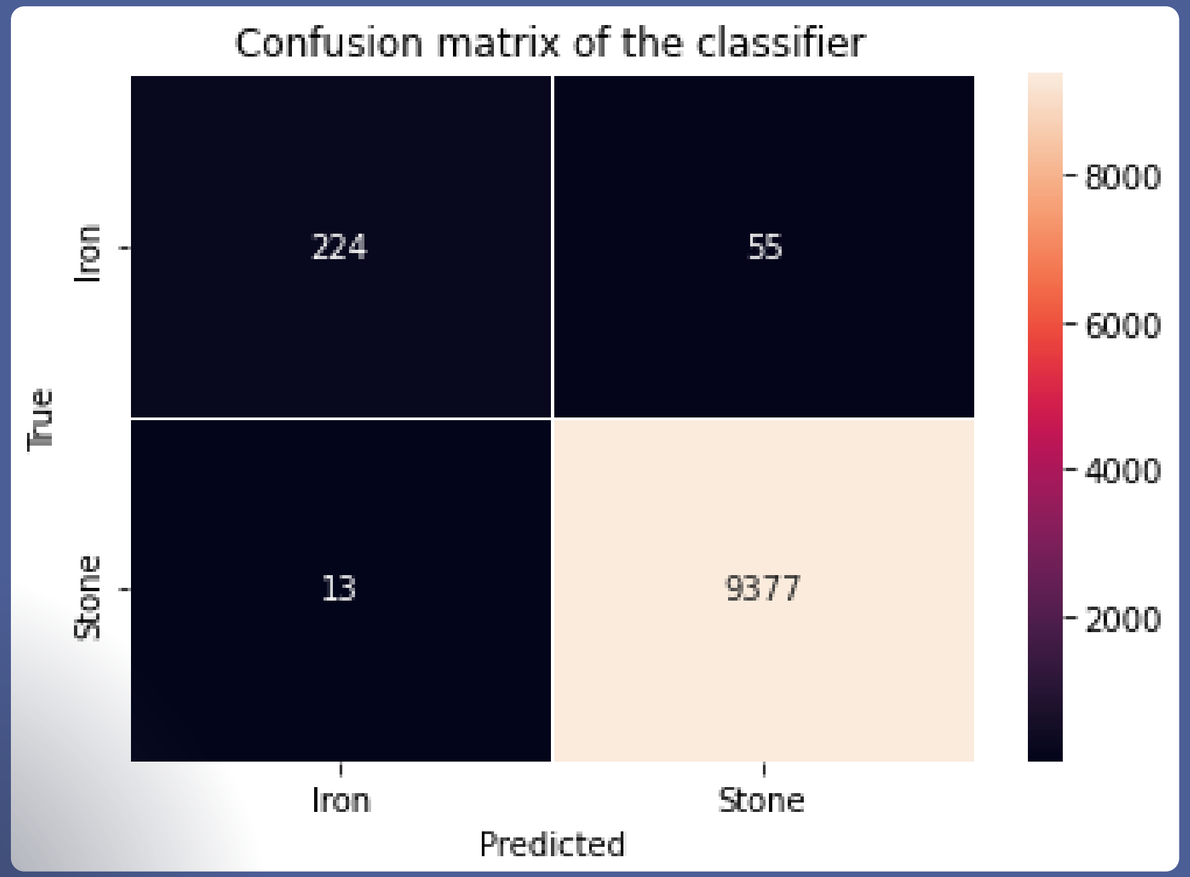



```
Accuracy: 0.9875461650777291

(array([0.87727273, 0.99148077, 0.43243243]),
 array([0.75984252, 0.99708532, 0.23880597]),
 array([0.81434599, 0.99427515, 0.30769231]),
 array([  254, 11322,    67], dtype=int64))
```

From **model #1** for comparison

```
Accuracy: 0.977761574917973

(array([0.69354839, 0.98356877, 0.52941176]),
 array([0.51343284, 0.99458687, 0.11392405]),
 array([0.59005146, 0.98904714, 0.1875    ]),
 array([  335, 13301,    79], dtype=int64))
```

Model #4.5: Revisiting Model #3




```
Accuracy: 0.9929672148102182

(array([0.94514768, 0.99416879]),
 array([0.80286738, 0.99861555]),
 array([0.86821705, 0.99638721]),
 array([ 279, 9390], dtype=int64))
```

Interpretation and Analysis

- **Stone meteorites** have a big impact on the **accuracy** score.
- **Model 2** scored best for classification between **stony-irons** and **irons**.
- **Model 4.5** scored best for classification between **stone** and **irons**.
- **Weight** is the most significant feature to help classify.

Question: Is it optimal to remove outliers?

Conclusion

- Regarding the **research question**, models from this project indicate that it is possible to classify **meteorites** to their specific types by their **characteristics** and **features**.
- The question of whether or not these models are **optimal** and **nonbiased** depends on the individual.
- Research is only limited to classifying the **main types**, not sub-types.
    - Requires further **observation** and **investigation** by scientists/researchers.