+ Code + Text

You are exploring the wilderness of *Mushroomia*, a land populated by a plethora of diverse fauna and flora. In particular, *Mushroomia* is known for its unparalleled variety in mushrooms. However, not all the mushrooms in *Mushroomia* are edible. As you make your way through *Mushroomia*, you would like to know which mushrooms are edible, in order to forage for supplies for your daily mushroom soup.

You have access to:

- *Shroomster Pro Max* ^{TM} - a state of the art data collection device, developed by *Mushroomia*, that allows you to collect various data points about any mushroom you encounter in the wild
- *The National Archives on Mushrooms* - a dataset collected over the years by the government of *Mushroomia*

To address this problem, you decide to use the skills you learnt in CSM148 and train machine learning models on the *The National Archives on Mushrooms* in order to use your *Shroomster Pro Max* ^{TM} to determine whether the mushrooms you encounter on your adventure can be added to your daily mushroom soup.

This project will be more unstructured than the previous two projects in order to allow you to experience how data science problems are solved in practice. There are two parts to this project: a Jupyter Notebook with your code (where you explore, visualize, process your data and train machine learning models) and a report (where you explain the various choices you make in your implementation and analyze the final performance of your models).

1. Loading and Viewing Data

```
[1] import numpy as np
    import seaborn as sns # used for plot interactive graph.
```

```
[2] # Delete this cell if not using google colab

    from google.colab import files
    files.upload()
```

Choose Files | No file chosen — Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving mushroom_test.csv to mushroom_test.csv
Saving mushroom_train.csv to mushroom_train.csv
{'mushroom_test.csv': b'class;cap-diameter;cap-shape;cap-surface;cap-color;does-bruise-or-bleed;gill-attachment;gill-spacing;gill-color;stem-height;stem-width;stem-root;stem-surface;stem-color;veil-type;veil-color;has-ring;ring-type;spore-print-color;habitat;season\np;2.5;b;k;f;a;k;a;2.42;2.46;;g;w;f;f;k;g;a\np;3.07;b;k;f;a;n;7.24;2.41;;n;w;f;f;k;g;a\np;3.3;b;n;f;a;n;10.22;2.53;;n;w;f;f;k;g;u\np;3.49;b;k;f;a;k;11.0;2.81;;n;w;f;f;k;g;a\np;2.79;b;n;f;a;n;6.97;2.37;;g;w;f;f;k;g;u\np;3.13;b;k;f;a;n;9.93;2.71;;g;w;f;f;k;g;a\np;2.94;b;g;f;a;k;8.5;2.39;;g;w;f;f;k;g;a\np;2.44;b;g;f;a;n;7.35;1.98;;n;w;f;f;k;g;a\np;3.2
 'mushroom_train.csv': b'class;cap-diameter;cap-shape;cap-surface;cap-color;does-bruise-or-bleed;gill-attachment;gill-spacing;gill-color;stem-height;stem-width;stem-root;stem-surface;stem-color;veil-type;veil-color;has-ring;ring-type;spore-print-
color;habitat;season\n\np;15.26;x;g;o;f;e;;w;16.95;17.09;s;y;w;u;w;t;g;;d;w\n\np;16.6;x;g;o;f;e;;w;17.99;18.19;s;y;w;u;w;t;g;;d;u\n\np;14.07;x;g;o;f;e;;w;17.8;17.74;s;y;w;u;w;t;g;;d;w\n\np;14.17;f;h;e;f;e;;w;15.77;15.98;s;y;w;u;w;t;p;;d;w\n\np;14.64;x;h;o;f;e;;w;16.53;17.2;s;y;w;u;w;t;p;;d;w\n\np;15.26;x;g;o;f;e;;w;16.95;17.09;s;y;w;u;w;t;g;;d;w\n\np;16.6;x;g;o;f;e;;w;17.99;18.19;s;y;w;u;w;t;g;;d;u\n\np;14.07;x;g;o;f;e;;w;17.8;17.74;s;y;w;u;w;t;g;;d;w\n\np;14.17;f;h;e;f;e;;w;15.77;15.98;s;y;w;u;w;t;p;;d;w\n\np;14.64;x;h;o;f;e;;w;16.53;17.2;s;y;w;u;w;t;p;;d;w\n\np;15.34;x;g;o;f;e;;w;17.84;18.79;s;y;w;u;w;t;p;;d;u\n\np;14.85;f;h;o;f;e;;w;17.71;16.89;s;y;w;u;w;t;g;;d;
```

```
[3] import pandas as pd
    # note delimitter for this file is semi-colon (;) not comma
    train = pd.read_csv('mushroom_train.csv', delimiter=";")
    test = pd.read_csv('mushroom_test.csv', delimiter=";")
```

```
[4] concat = pd.concat([train, test])
    concat
```

	class	cap-diameter	cap-shape	cap-surface	cap-color	does-bruise-or-bleed	gill-attachment	gill-spacing	gill-color	stem-height	...	stem-root	stem-surface	stem-color	veil-type	veil-color	has-ring	ring-type	spore-print-color	habitat	season
0	p	15.26	x	g	o	f	e	NaN	w	16.95	...	s	y	w	u	w	t	g	NaN	d	w
1	p	16.60	x	g	o	f	e	NaN	w	17.99	...	s	y	w	u	w	t	g	NaN	d	u
2	p	14.07	x	g	o	f	e	NaN	w	17.80	...	s	y	w	u	w	t	g	NaN	d	w
3	p	14.17	f	h	e	f	e	NaN	w	15.77	...	s	y	w	u	w	t	p	NaN	d	w
4	p	14.64	x	h	o	f	e	NaN	w	16.53	...	s	y	w	u	w	t	p	NaN	d	w
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
10851	e	52.41	o	y	y	f	p	NaN	y	5.47	...	NaN	k	k	NaN	NaN	f	f	NaN	d	u
10852	e	54.81	o	y	y	f	p	NaN	y	6.67	...	NaN	k	k	NaN	NaN	f	f	NaN	d	s
10853	e	49.95	o	y	y	f	p	NaN	y	6.43	...	NaN	k	n	NaN	NaN	f	f	NaN	d	u
10854	e	53.16	o	y	y	f	p	NaN	y	6.99	...	NaN	k	k	NaN	NaN	f	f	NaN	d	s
10855	e	49.78	o	y	y	f	p	NaN	y	5.77	...	NaN	k	k	NaN	NaN	f	f	NaN	d	u

61069 rows × 21 columns

2. Splitting Data into Features and Labels

```
[5] # Only keep features that shroomster can detect!
    # remove class feature, because shroomster cannot detect
    labels = concat['class']
    labels
```

```
0        p
1        p
2        p
3        p
4        p
        ..
10851    e
10852    e
10853    e
10854    e
10855    e
Name: class, Length: 61069, dtype: object
```

```
[6] concat = concat.drop('class', axis=1)
    concat
```

	cap-diameter	cap-shape	cap-surface	cap-color	does-bruise-or-bleed	gill-attachment	gill-spacing	gill-color	stem-height	stem-width	stem-root	stem-surface	stem-color	veil-type	veil-color	has-ring	ring-type	spore-print-color	habitat	season
0	15.26	x	g	o	f	e	NaN	w	16.95	17.09	s	y	w	u	w	t	g	NaN	d	w
1	16.60	x	g	o	f	e	NaN	w	17.99	18.19	s	y	w	u	w	t	g	NaN	d	u
2	14.07	x	g	o	f	e	NaN	w	17.80	17.74	s	y	w	u	w	t	g	NaN	d	w
3	14.17	f	h	e	f	e	NaN	w	15.77	15.98	s	y	w	u	w	t	p	NaN	d	w
4	14.64	x	h	o	f	e	NaN	w	16.53	17.20	s	y	w	u	w	t	p	NaN	d	w
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
10851	52.41	o	y	y	f	p	NaN	y	5.47	25.02	NaN	k	k	NaN	NaN	f	f	NaN	d	u
10852	54.81	o	y	y	f	p	NaN	y	6.67	22.15	NaN	k	k	NaN	NaN	f	f	NaN	d	s
10853	49.95	o	y	y	f	p	NaN	y	6.43	26.35	NaN	k	n	NaN	NaN	f	f	NaN	d	u
10854	53.16	o	y	y	f	p	NaN	y	6.99	40.29	NaN	k	k	NaN	NaN	f	f	NaN	d	s
10855	49.78	o	y	y	f	p	NaN	y	5.77	18.26	NaN	k	k	NaN	NaN	f	f	NaN	d	u

61069 rows × 20 columns

3. Data Exploration and Visualization (Combined 3/4/5)

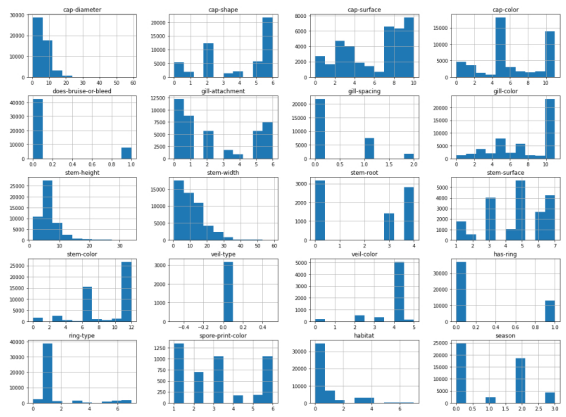
```
[7] # Hint: We have done this in both project 1 & 2
    import matplotlib.pyplot as plt
    from matplotlib import pyplot
    %matplotlib inline
    # import matplotlib.pyplot as plt #plotting package
```

```
[8] from sklearn.preprocessing import OrdinalEncoder
```

```
# convert objects to numerical types
concat['cap-diameter'] = concat['cap-diameter'].astype(np.float64)
concat['stem-height'] = concat['stem-height'].astype(np.float64)
concat['stem-width'] = concat['stem-width'].astype(np.float64)

#split dataFrames
train_df = concat.iloc[:61213,:]
test_df = concat.iloc[61213:,:]

#convert objects to categorical
ordinal = OrdinalEncoder()
concat[['cap-shape', 'cap-surface', 'cap-color', 'does-bruise-or-bleed', 'gill-attachment', 'gill-spacing', 'gill-color', 'stem-root', 'stem-surface', 'stem-color', 'veil-type',
        'veil-color', 'has-ring', 'ring-type', 'spore-print-color', 'habitat', 'season']] = ordinal.fit_transform(concat[['cap-shape', 'cap-surface', 'cap-color', 'does-bruise-or-bleed',
                                                                                                                          'gill-attachment', 'gill-spacing', 'gill-color', 'stem-root',
                                                                                                                          'stem-surface', 'stem-color', 'veil-type', 'veil-color', 'has-ring',
                                                                                                                          'ring-type', 'spore-print-color', 'habitat', 'season']])
```

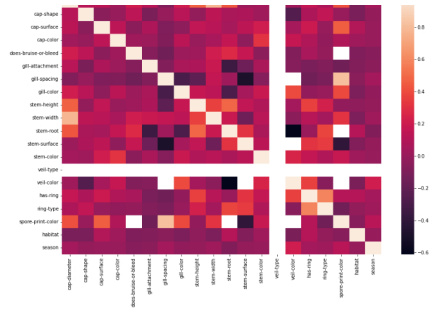
```
[11] train_display = concat.iloc[:61213,:]
```

```
[12] train_display.hist(bins=10, figsize=(20,15))
     plt.show()
```




```
[13] fig, ax = plt.subplots(figsize=(15,10))
     sns.heatmap(train_display.corr(), ax=ax)
```

```
<AxesSubplot:>
```



5. Data Augmentation (Creating at least 2 New Features)

```
[14] # Similar to Project 1 and 2.

     #very similar features: stem-width, cap diameter; spore-print-color, gill-spacing;
     remove_features = ['veil-type', 'veil-color', 'spore-print-color', 'cap-diameter', 'gill-spacing']
     #remove_features = []
     train_df.isnull().sum()
```

```
cap-diameter               0
cap-shape                  0
cap-surface            12298
cap-color                  0
does-bruise-or-bleed       0
gill-attachment         7766
gill-spacing           19149
gill-color                 0
stem-height                0
stem-width                 0
stem-root              42800
stem-surface           30301
stem-color                 0
veil-type              47836
veil-color             43916
has-ring                   0
ring-type               1765
spore-print-color      45681
habitat                    0
season                     0
dtype: int64
```

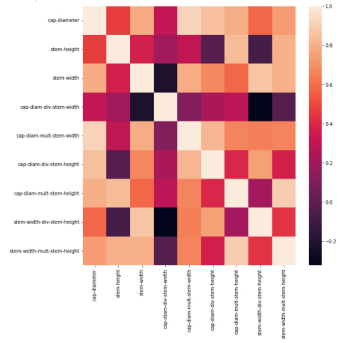
```
[15] train_df['cap-diam-div-stem-width'] = train_df['cap-diameter']/(train_df['stem-width']+1)
     train_df['cap-diam-mult-stem-width'] = train_df['cap-diameter']*train_df['stem-width']
     train_df['cap-diam-div-stem-height'] = train_df['cap-diameter']/(train_df['stem-height']+1)
     train_df['cap-diam-mult-stem-height'] = train_df['cap-diameter']*train_df['stem-height']
     train_df['stem-width-div-stem-height'] = train_df['stem-width']/(train_df['stem-height']+1)
     train_df['stem-width-mult-stem-height'] = train_df['stem-width']*train_df['stem-height']
     train_df
```

```
<ipython-input-15-96afce782580>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  train_df['cap-diam-div-stem-width'] = train_df['cap-diameter']/(train_df['stem-width']+1)
<ipython-input-15-96afce782580>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  train_df['cap-diam-mult-stem-width'] = train_df['cap-diameter']*train_df['stem-width']
<ipython-input-15-96afce782580>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  train_df['cap-diam-div-stem-height'] = train_df['cap-diameter']/(train_df['stem-height']+1)
<ipython-input-15-96afce782580>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  train_df['cap-diam-mult-stem-height'] = train_df['cap-diameter']*train_df['stem-height']
<ipython-input-15-96afce782580>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  train_df['stem-width-div-stem-height'] = train_df['stem-width']/(train_df['stem-height']+1)
<ipython-input-15-96afce782580>:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  train_df['stem-width-mult-stem-height'] = train_df['stem-width']*train_df['stem-height']
```

	cap-diameter	cap-shape	cap-surface	cap-color	does-bruise-or-bleed	gill-attachment	gill-spacing	gill-color	stem-height	stem-width	...	ring-type	spore-print-color	habitat	season	cap-diam-div-stem-width	cap-diam-mult-stem-width	cap-diam-div-stem-height	cap-diam-mult-stem-height	stem-width-div-stem-height	stem-width-mult-stem-height
0	15.26	x	g	o	f	e	NaN	w	16.95	17.09	...	g	NaN	d	w	0.843560	260.7934	0.850139	258.6570	0.952089	289.6755
1	16.60	x	g	o	f	e	NaN	w	17.99	18.19	...	g	NaN	d	u	0.865034	301.9540	0.874144	298.6340	0.957873	327.2381
2	14.07	x	g	o	f	e	NaN	w	17.80	17.74	...	g	NaN	d	w	0.750800	249.6018	0.748404	250.4460	0.943617	315.7720
3	14.17	f	h	e	f	e	NaN	w	15.77	15.98	...	p	NaN	d	w	0.834511	226.4366	0.844961	223.4609	0.952892	252.0046
4	14.64	x	h	o	f	e	NaN	w	16.53	17.20	...	p	NaN	d	w	0.804396	251.8080	0.835140	241.9992	0.981175	284.3160
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
50208	1.18	s	s	y	f	f	f	f	3.93	6.22	...	f	NaN	d	a	0.163435	7.3396	0.239351	4.6374	1.261683	24.4446
50209	1.27	f	s	y	f	f	f	f	3.18	5.43	...	f	NaN	d	a	0.197512	6.8961	0.303828	4.0386	1.299043	17.2674
50210	1.27	s	s	y	f	f	f	f	3.86	6.37	...	f	NaN	d	u	0.172320	8.0899	0.261317	4.9022	1.310700	24.5882
50211	1.24	f	s	y	f	f	f	f	3.56	5.44	...	f	NaN	d	u	0.192547	6.7456	0.271930	4.4144	1.182982	19.3664
50212	1.17	s	s	y	f	f	f	f	3.25	5.45	...	f	NaN	d	u	0.181395	6.3765	0.275294	3.8025	1.282353	17.7125

```
[16] fig, ax = plt.subplots(figsize=(10,10))
     sns.heatmap(train_df.corr(), ax=ax)
```

```
<AxesSubplot:>
```




```
[17] # keep cap-diameter-div-stem-width and cap-diameter-div-stem-height because they are the most unique
     remove_features2 = ['cap-diam-mult-stem-width', 'cap-diam-mult-stem-height', 'stem-width-div-stem-height', 'stem-width-mult-stem-height']
     test_df['cap-diam-div-stem-width'] = test_df['cap-diameter']/(test_df['stem-width']+1)
     test_df['cap-diam-div-stem-height'] = test_df['cap-diameter']/(test_df['stem-height']+1)
```

```
<ipython-input-17-a2d19164d0d7>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  test_df['cap-diam-div-stem-width'] = test_df['cap-diameter']/(test_df['stem-width']+1)
<ipython-input-17-a2d19164d0d7>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  test_df['cap-diam-div-stem-height'] = test_df['cap-diameter']/(test_df['stem-height']+1)
```

4. Data Processing

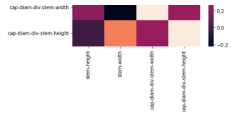
```
[18] from sklearn.pipeline import Pipeline
     from sklearn.preprocessing import StandardScaler, OneHotEncoder
     from sklearn.compose import ColumnTransformer, make_column_transformer
```

```
[19] # 1. Convert the "class" column into labels: 'p' (poisonous) -> 0,  'e' (edible) -> 1
     converted_labels = labels.replace({'p': 0, 'e': 1})
```

```
[20] # 2. You can drop columns if you see fit
     #dropped cap diameter due to high correlation
     #consider dropping veil color
     features = train_df.drop(remove_features, axis=1)
     train_x = features.drop(remove_features2, axis=1)
     test_x = test_df.drop(remove_features, axis=1)
```

```
[21] sns.heatmap(train_x.corr())
     #features are pretty good
```

```
<AxesSubplot:>
```



[22] # 3. See any incomplete data? We learned how to deal with them in project 1.
train_x.isnull().sum()

```
cap-shape                   0
cap-surface             12298
cap-color                   0
does-bruise-or-bleed        0
gill-attachment          7766
gill-color                  0
stem-height                 0
stem-width                  0
stem-root               42800
stem-surface            30301
stem-color                  0
has-ring                    0
ring-type                1765
habitat                     0
season                      0
cap-diam-div-stem-width     0
cap-diam-div-stem-height    0
dtype: int64
```

[23] nulled_features = ['stem-root']
train_x2 = train_x.drop(nulled_features, axis=1)
test_x2 = test_x.drop(nulled_features, axis=1)
train_x2.dropna()

	cap-shape	cap-surface	cap-color	does-bruise-or-bleed	gill-attachment	gill-color	stem-height	stem-width	stem-surface	stem-color	has-ring	ring-type	habitat	season	cap-diam-div-stem-width	cap-diam-div-stem-height
0	x	g	o	f	e	w	16.95	17.09	y	w	t	g	d	w	0.843560	0.850139
1	x	g	o	f	e	w	17.99	18.19	y	w	t	g	d	u	0.865034	0.874144
2	x	g	o	f	e	w	17.80	17.74	y	w	t	g	d	w	0.750800	0.748404
3	f	h	e	f	e	w	15.77	15.98	y	w	t	p	d	w	0.834511	0.844961
4	x	h	o	f	e	w	16.53	17.20	y	w	t	p	d	w	0.804396	0.835140
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
48443	f	k	n	f	p	n	3.83	5.94	k	n	t	f	d	u	0.940922	1.351967
48444	s	k	n	f	p	n	4.32	7.18	k	n	t	f	d	u	0.707024	1.088346
48445	f	k	y	f	p	n	3.72	5.76	k	n	t	f	d	u	0.659763	0.944915
48446	s	k	y	f	p	n	4.41	5.35	k	n	t	f	d	u	0.870866	1.022181
48447	f	k	n	f	p	n	3.43	5.08	k	n	t	f	d	u	0.828947	1.137698

14264 rows × 16 columns

[24] X_train, X_test, y_train, y_test = train_x2, test_x2, converted_labels.iloc[:50213], converted_labels.iloc[50213:]

[25] print (X_train.shape, y_train.shape)
print (X_test.shape, y_test.shape)

```
(50213, 16) (50213,)
(10856, 16) (10856,)
```

[26] numerical_features = ['stem-height', 'stem-width', 'cap-diam-div-stem-width', 'cap-diam-div-stem-width']
categorical_features = ['cap-shape', 'cap-color', 'does-bruise-or-bleed', 'gill-color', 'stem-color', 'has-ring', 'habitat', 'season']

```
num_pipeline = Pipeline([
        ('std_scaler', StandardScaler())
    ])

full_pipeline = ColumnTransformer([
        ("num", num_pipeline, numerical_features),
        ("cat", OneHotEncoder(categories='auto', handle_unknown='ignore'), categorical_features),
    ])

prep_train = full_pipeline.fit_transform(X_train).toarray()
prep_test = full_pipeline.transform(X_test).toarray()
```

6. Logistic Regression & Statistical Hypothesis Testing

[27] from sklearn.linear_model import LogisticRegression
from sklearn import metrics

```
log_reg = LogisticRegression(solver='liblinear')
log_reg.fit(prep_train, y_train)
```

LogisticRegression(solver='liblinear')

predicted_log = log_reg.predict(prep_test)
print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(y_test, predicted_log)))
print("%-12s %f" % ('Precision:', metrics.precision_score(y_test, predicted_log)))
print("%-12s %f" % ('Recall:', metrics.recall_score(y_test, predicted_log)))
print("%-12s %f" % ('F1:', metrics.f1_score(y_test, predicted_log)))

```
Accuracy:    0.437638
Precision:   0.513827
Recall:      0.314171
F1:          0.389927
```

[29] import statsmodels.api as sm

```
stats_data = train_df[['stem-height', 'stem-width', 'cap-diam-div-stem-width', 'cap-diam-div-stem-height']]
stats_data
```

	stem-height	stem-width	cap-diam-div-stem-width	cap-diam-div-stem-height
0	16.95	17.09	0.843560	0.850139
1	17.99	18.19	0.865034	0.874144
2	17.80	17.74	0.750800	0.748404
3	15.77	15.98	0.834511	0.844961
4	16.53	17.20	0.804396	0.835140
...	...	...	...	...
50208	3.93	6.22	0.163435	0.239351
50209	3.18	5.43	0.197512	0.303828
50210	3.86	6.37	0.172320	0.261317
50211	3.56	5.44	0.192547	0.271930
50212	3.25	5.45	0.181395	0.275294

50213 rows × 4 columns

[30] y_train

```
0        0
1        0
2        0
3        0
4        0
        ..
50208    0
50209    0
50210    0
50211    0
50212    0
Name: class, Length: 50213, dtype: int64
```

[31] sm_x = sm.add_constant(stats_data)
logit_mod = sm.Logit(y_train, sm_x)
logit_res = logit_mod.fit()
print(logit_res.summary())

```
Optimization terminated successfully.
         Current function value: 0.666947
         Iterations 5
                           Logit Regression Results
==============================================================================
Dep. Variable:                  class   No. Observations:                50213
Model:                          Logit   Df Residuals:                    50208
Method:                           MLE   Df Model:                            4
Date:                Mon, 06 Mar 2023   Pseudo R-squ.:                0.01050
Time:                        23:00:08   Log-Likelihood:                -33489.
converged:                       True   LL-Null:                       -33841.
Covariance Type:            nonrobust   LLR p-value:                 4.323e-272
===========================================================================================
                              coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------------
const                      -1.2328      0.038    -32.352      0.000      -1.307      -1.158
stem-height                 0.0352      0.005      7.527      0.000       0.026       0.044
stem-width                  0.0146      0.003      4.424      0.000       0.008       0.021
cap-diam-div-stem-width     0.3881      0.084      4.618      0.000       0.223       0.553
cap-diam-div-stem-height    0.3517      0.043      8.225      0.000       0.268       0.435
===========================================================================================
```

7. Dimensionality Reduction using PCA

[32] # PCA: https://scikit-learn.org/stable/modules/generated/sklearn.decomposition.PCA.html
prep_train.shape

```
(50213, 63)
```

[33] from sklearn import decomposition

[34] pca = decomposition.PCA(n_components=5)
pca_train = pca.fit_transform(prep_train)
pca_train.shape

```
(50213, 5)
```

[35] log_reg.fit(pca_train, y_train)

LogisticRegression(solver='liblinear')

[36] log_reg.fit(pca_train, y_train)
pca_test = pca.transform(prep_test)
predicted_pca = log_reg.predict(pca_test)
print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(y_test, predicted_pca)))
print("%-12s %f" % ('Precision:', metrics.precision_score(y_test, predicted_pca)))
print("%-12s %f" % ('Recall:', metrics.recall_score(y_test, predicted_pca)))
print("%-12s %f" % ('F1:', metrics.f1_score(y_test, predicted_pca)))

```
Accuracy:    0.446007
Precision:   0.524819
Recall:      0.314976
F1:          0.393680
```

8. Experiment with any 2 other models (Non-Ensemble)

```
[37] # Models: https://scikit-learn.org/stable/supervised_learning.html
     from sklearn.neighbors import KNeighborsClassifier
     neigh = KNeighborsClassifier(n_neighbors=10001)
     neigh.fit(pca_train, y_train)
     neigh_predicted = neigh.predict(pca_test)
     print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(y_test, neigh_predicted)))
     print("%-12s %f" % ('Precision:', metrics.precision_score(y_test, neigh_predicted)))
     print("%-12s %f" % ('Recall:', metrics.recall_score(y_test, neigh_predicted)))
     print("%-12s %f" % ('F1:', metrics.f1_score(y_test, neigh_predicted)))

     Accuracy:    0.611551
     Precision:   0.725606
     Recall:      0.516103
     F1:          0.603181
```

```
[38] from sklearn.tree import DecisionTreeClassifier
     tree = DecisionTreeClassifier(max_depth=2)
     tree.fit(pca_train, y_train)
     tree_predicted = tree.predict(pca_test)
     print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(y_test, tree_predicted)))
     print("%-12s %f" % ('Precision:', metrics.precision_score(y_test, tree_predicted)))
     print("%-12s %f" % ('Recall:', metrics.recall_score(y_test, tree_predicted)))
     print("%-12s %f" % ('F1:', metrics.f1_score(y_test, tree_predicted)))

     Accuracy:    0.671942
     Precision:   0.650607
     Recall:      0.543639
     F1:          0.592333
```

9. Experiment with 1 Ensemble Method

```
[39] # Ensemble Methods: https://scikit-learn.org/stable/modules/ensemble.html
     from sklearn.ensemble import RandomForestClassifier
     forest = RandomForestClassifier(n_estimators=15)
     forest.fit(pca_train, y_train)
     forest_predicted = forest.predict(pca_test)
     print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(y_test, forest_predicted)))
     print("%-12s %f" % ('Precision:', metrics.precision_score(y_test, forest_predicted)))
     print("%-12s %f" % ('Recall:', metrics.recall_score(y_test, forest_predicted)))
     print("%-12s %f" % ('F1:', metrics.f1_score(y_test, forest_predicted)))

     Accuracy:    0.591194
     Precision:   0.766304
     Recall:      0.410467
     F1:          0.534606
```

10. Cross-Validation & Hyperparameter Tuning for All 3 Models

```
[40] # Cross-Validation: https://scikit-learn.org/stable/modules/cross_validation.html
     from sklearn.model_selection import KFold
     from sklearn.model_selection import cross_val_score

     kf = KFold(n_splits = 10, random_state=42, shuffle=True)

     knn_clf = KNeighborsClassifier()
     knn_results = cross_val_score(knn_clf, pca_train, y_train, cv=kf)
     print("KNN CV Accuracy: %.2f%%" % (knn_results.mean()*100.0))

     tree_clf = DecisionTreeClassifier()
     tree_results = cross_val_score(tree_clf, pca_train, y_train, cv=kf)
     print("Decision Tree CV Accuracy: %.2f%%" % (tree_results.mean()*100.0))

     forest_clf = RandomForestClassifier()
     forest_results = cross_val_score(forest_clf, pca_train, y_train, cv=kf)
     print("Decision Tree CV Accuracy: %.2f%%" % (forest_results.mean()*100.0))

     KNN CV Accuracy: 92.92%
     Decision Tree CV Accuracy: 90.66%
     Decision Tree CV Accuracy: 95.21%
```

```
[41] # Hyperparameter Tuning: https://scikit-learn.org/stable/modules/grid_search.html
     from sklearn.model_selection import GridSearchCV

     knn_params = [
        { 'n_neighbors': [5, 55, 555, 5555],
          'weights': ['uniform', 'distance'],
          'algorithm': ['brute', 'kd_tree', 'ball_tree', 'auto']
        }
     ]
     knn_clf_grid = GridSearchCV(estimator=knn_clf, param_grid=knn_params, cv=kf, verbose=True)
     knn_clf_grid.fit(pca_train, y_train)
     print(knn_clf_grid.best_estimator_.get_params())

     Fitting 10 folds for each of 32 candidates, totalling 320 fits
     {'algorithm': 'brute', 'leaf_size': 30, 'metric': 'minkowski', 'metric_params': None, 'n_jobs': None, 'n_neighbors': 5, 'p': 2, 'weights': 'distance'}
```

```
[42] tree_params = [
        { 'max_depth': [2, 5, 8],
          'criterion': ['gini', 'entropy', 'log_loss'],
        }
     ]
     tree_clf_grid = GridSearchCV(estimator=tree_clf, param_grid=tree_params, cv=kf, verbose=True)
     tree_clf_grid.fit(pca_train, y_train)
     print(tree_clf_grid.best_estimator_.get_params())

     Fitting 10 folds for each of 9 candidates, totalling 90 fits
     {'ccp_alpha': 0.0, 'class_weight': None, 'criterion': 'gini', 'max_depth': 8, 'max_features': None, 'max_leaf_nodes': None, 'min_impurity_decrease': 0.0, 'min_samples_leaf': 1, 'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0, 'random_state': None, 'splitter': 'best'}
```

```
[43] forest_params = [
        { 'n_estimators': [1, 5, 15],
          'max_features': [None, 1.0],
        }
     ]
     forest_clf_grid = GridSearchCV(estimator=forest_clf, param_grid=forest_params, cv=kf, verbose=True)
     forest_clf_grid.fit(pca_train, y_train)
     print(forest_clf_grid.best_estimator_.get_params())

     Fitting 10 folds for each of 6 candidates, totalling 60 fits
     {'bootstrap': True, 'ccp_alpha': 0.0, 'class_weight': None, 'criterion': 'gini', 'max_depth': None, 'max_features': None, 'max_leaf_nodes': None, 'max_samples': None, 'min_impurity_decrease': 0.0, 'min_samples_leaf': 1, 'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0, 'n_estimators': 15, 'n_jobs': None, 'oob_score': False, 'random_state': None, 'verbose': 0, 'warm_start': False}
```

11. Report Final Results

```
[44] # e.g. Accuracy, Precision etc.
     final_neigh = KNeighborsClassifier(algorithm='brute', leaf_size=30, metric='minkowski', metric_params=None, n_jobs=None, n_neighbors=5, p=2, weights='distance')
     final_neigh.fit(pca_train, y_train)
     final_neigh_predicted = final_neigh.predict(pca_test)
     print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(y_test, final_neigh_predicted)))
     print("%-12s %f" % ('Precision:', metrics.precision_score(y_test, final_neigh_predicted)))
     print("%-12s %f" % ('Recall:', metrics.recall_score(y_test, final_neigh_predicted)))
     print("%-12s %f" % ('F1:', metrics.f1_score(y_test, final_neigh_predicted)))

     Accuracy:    0.462878
     Precision:   0.540536
     Recall:      0.480524
     F1:          0.464309
```

```
[45] final_tree = DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini', max_depth=8, max_features=None, max_leaf_nodes=None,
                                         min_impurity_decrease=0.0, min_samples_leaf=1, min_samples_split=2, min_weight_fraction_leaf=0.0,
                                         random_state=None, splitter='best')
     final_tree.fit(pca_train, y_train)
     final_tree_predicted = final_tree.predict(pca_test)
     print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(y_test, final_tree_predicted)))
     print("%-12s %f" % ('Precision:', metrics.precision_score(y_test, final_tree_predicted)))
     print("%-12s %f" % ('Recall:', metrics.recall_score(y_test, final_tree_predicted)))
     print("%-12s %f" % ('F1:', metrics.f1_score(y_test, final_tree_predicted)))

     Accuracy:    0.506448
     Precision:   0.638492
     Recall:      0.338264
     F1:          0.423002
```

```
[46] final_forest = RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None, criterion='gini', max_depth=None, max_features=None, max_leaf_nodes=None,
                                           max_samples=None, min_impurity_decrease=0.0, min_samples_leaf=1, min_samples_split=2, min_weight_fraction_leaf=0.0, n_estimators=15, n_jobs=None,
                                           oob_score=False, random_state=None, warm_start=False)
     final_forest.fit(pca_train, y_train)
     final_forest_predicted = final_forest.predict(pca_test)
     print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(y_test, final_forest_predicted)))
     print("%-12s %f" % ('Precision:', metrics.precision_score(y_test, final_forest_predicted)))
     print("%-12s %f" % ('Recall:', metrics.recall_score(y_test, final_forest_predicted)))
     print("%-12s %f" % ('F1:', metrics.f1_score(y_test, final_forest_predicted)))

     Accuracy:    0.545965
     Precision:   0.690114
     Recall:      0.374396
     F1:          0.485437
```

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