What is the Project?

- This project is an attempt to create a machine learning model that can accurately classify whether a tumor is malignant or benign using PCA and then applying those results to other models.

Dataset Citation - MLA

- Learning, UCI Machine. “Breast Cancer Wisconsin (Diagnostic) Data Set.” Kaggle, 25 Sept. 2016, www.kaggle.com/datasets/uciml/breast-cancer-wisconsin-data.

About the Dataset

This dataset is from the UCI machine learning repository and uploaded to kaggle where I downloaded it. The dataset is already clean; however, the data does include two unneccessary columns and it may need to be transformed or rebalanced to be used for PCA analysis.

- The dataset has 33 features with diagnosis being the only categorical feature.
- There are 569 records in this dataset.
- At this point I do not have any background information or prior knowledge on the data.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import math
import seaborn as sns
import statsmodels.formula.api as smf
import statsmodels.api as sm
from sklearn.decomposition import PCA
```

In [2]:
```
data = pd.read_csv("BC_data.csv")

data.shape
```

Out[2]:
```
(569, 33)
```

In [3]:
```
print(data.info())
print(data.head())
print(data.nunique())
print(data.isnull())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 33 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   id                       569 non-null    int64  
 1   diagnosis                569 non-null    object 
 2   radius_mean              569 non-null    float64
 3   texture_mean             569 non-null    float64
 4   perimeter_mean           569 non-null    float64
 5   area_mean                569 non-null    float64
 6   smoothness_mean          569 non-null    float64
 7   compactness_mean         569 non-null    float64
 8   concavity_mean           569 non-null    float64
 9   concave points_mean      569 non-null    float64
 10  symmetry_mean            569 non-null    float64
 11  fractal_dimension_mean   569 non-null    float64
 12  radius_se                569 non-null    float64
 13  texture_se               569 non-null    float64
 14  perimeter_se             569 non-null    float64
 15  area_se                  569 non-null    float64
 16  smoothness_se            569 non-null    float64
 17  compactness_se           569 non-null    float64
 18  concavity_se             569 non-null    float64
 19  concave points_se        569 non-null    float64
 20  symmetry_se              569 non-null    float64
 21  fractal_dimension_se     569 non-null    float64
 22  radius_worst             569 non-null    float64
 23  texture_worst            569 non-null    float64
 24  perimeter_worst          569 non-null    float64
 25  area_worst               569 non-null    float64
 26  smoothness_worst         569 non-null    float64
 27  compactness_worst        569 non-null    float64
 28  concavity_worst          569 non-null    float64
 29  concave points_worst     569 non-null    float64
 30  symmetry_worst           569 non-null    float64
 31  fractal_dimension_worst  569 non-null    float64
 32  Unnamed: 32              0 non-null      float64
dtypes: float64(31), int64(1), object(1)
memory usage: 146.8+ KB
None
         id diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
0    842302         M        17.99         10.38          122.80     1001.0
1    842517         M        20.57         17.77          132.90     1326.0
2  84300903         M        19.69         21.25          130.00     1203.0
3  84348301         M        11.42         20.38           77.58      386.1
4  84358402         M        20.29         14.34          135.10     1297.0

   smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
0          0.11840           0.27760          0.3001              0.14710
1          0.08474           0.07864          0.0869              0.07017
2          0.10960           0.15990          0.1974              0.12790
3          0.14250           0.28390          0.2414              0.10520
4          0.10030           0.13280          0.1980              0.10430

   ...  texture_worst  perimeter_worst  area_worst  smoothness_worst  \
0  ...          17.33           184.60      2019.0            0.1622
1  ...          23.41           158.80      1956.0            0.1238
2  ...          25.53           152.50      1709.0            0.1444
3  ...          26.50            98.87       567.7            0.2098
4  ...          16.67           152.20      1575.0            0.1374

   compactness_worst  concavity_worst  concave points_worst  symmetry_worst  \
0             0.6656           0.7119                0.2654          0.4601
1             0.1866           0.2416                0.1860          0.2750
2             0.4245           0.4504                0.2430          0.3613
3             0.8663           0.6869                0.2575          0.6638
4             0.2050           0.4000                0.1625          0.2364

   fractal_dimension_worst  Unnamed: 32
0                  0.11890          NaN
1                  0.08902          NaN
2                  0.08758          NaN
3                  0.17300          NaN
4                  0.07678          NaN

[5 rows x 33 columns]
id                         569
diagnosis                    2
radius_mean                456
```

```
texture_mean               479
perimeter_mean             522
area_mean                  539
smoothness_mean            474
compactness_mean           537
concavity_mean             537
concave points_mean        542
symmetry_mean              432
fractal_dimension_mean     499
radius_se                  540
texture_se                 519
perimeter_se               533
area_se                    528
smoothness_se              547
compactness_se             541
concavity_se               533
concave points_se          507
symmetry_se                498
fractal_dimension_se       545
radius_worst               457
texture_worst              511
perimeter_worst            514
area_worst                 544
smoothness_worst           411
compactness_worst          529
concavity_worst            539
concave points_worst       492
symmetry_worst             500
fractal_dimension_worst    535
Unnamed: 32                  0
dtype: int64
        id  diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
0    False      False        False         False           False      False
1    False      False        False         False           False      False
2    False      False        False         False           False      False
3    False      False        False         False           False      False
4    False      False        False         False           False      False
..     ...        ...          ...           ...             ...        ...
564  False      False        False         False           False      False
565  False      False        False         False           False      False
566  False      False        False         False           False      False
567  False      False        False         False           False      False
568  False      False        False         False           False      False

     smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
0              False             False           False                False
1              False             False           False                False
2              False             False           False                False
3              False             False           False                False
4              False             False           False                False
..               ...               ...             ...                  ...
564            False             False           False                False
565            False             False           False                False
566            False             False           False                False
567            False             False           False                False
568            False             False           False                False

     ...  texture_worst  perimeter_worst  area_worst  smoothness_worst  \
0    ...          False            False       False             False
1    ...          False            False       False             False
2    ...          False            False       False             False
3    ...          False            False       False             False
4    ...          False            False       False             False
..   ...            ...              ...         ...               ...
564  ...          False            False       False             False
565  ...          False            False       False             False
```

```
566  ...              False              False         False                 False
567  ...              False              False         False                 False
568  ...              False              False         False                 False

     compactness_worst  concavity_worst  concave points_worst  symmetry_worst  \
0                False            False                 False           False
1                False            False                 False           False
2                False            False                 False           False
3                False            False                 False           False
4                False            False                 False           False
..                 ...              ...                   ...             ...
564              False            False                 False           False
565              False            False                 False           False
566              False            False                 False           False
567              False            False                 False           False
568              False            False                 False           False

     fractal_dimension_worst  Unnamed: 32
0                      False         True
1                      False         True
2                      False         True
3                      False         True
4                      False         True
..                       ...          ...
564                    False         True
565                    False         True
566                    False         True
567                    False         True
568                    False         True

[569 rows x 33 columns]
```

Data Usefulness

- In the current state, this data is not very useful. It has 32 features. Before starting any analysis ID will be removed and also the blank column at the end.

In [4]:
```
data = data.drop(['id', 'Unnamed: 32'], axis = 1)
```

We will use PCA to try to reduce the dimensions significantly. This will hopefully result in a large reduction of dimensions and possibly produce a good model as well.

In [5]:
```
data.shape
```

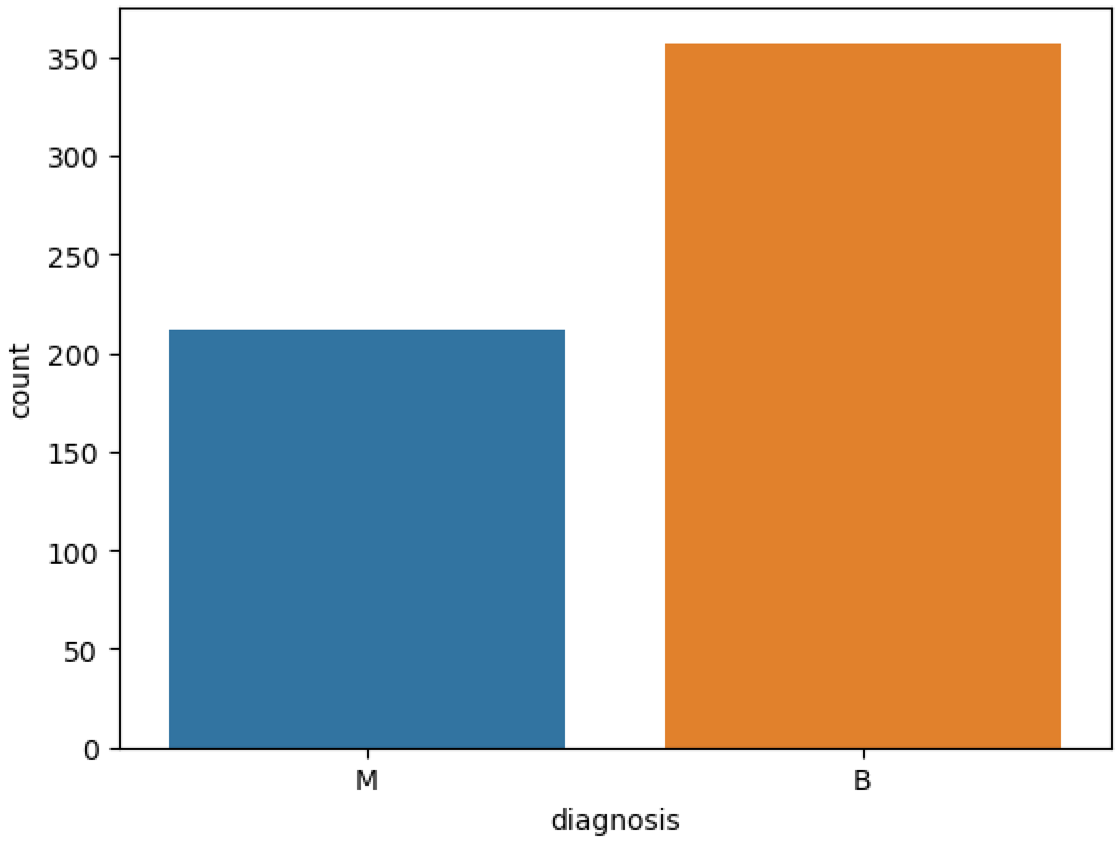
Out[5]:
```
(569, 31)
```

In [6]:
```
X = data.drop(['diagnosis'], axis = 1)
y = data[['diagnosis']]
```

Looking at the plot below we can see that the data is unbalanced to a degree. We will need to solve this before making any analysis.

In [7]:
```
sns.countplot(data = y, x = 'diagnosis')
```

Out[7]:
```
<AxesSubplot:xlabel='diagnosis', ylabel='count'>
```



The below code is just scaling for using PCA.

In [8]:
```
from scipy.stats import zscore
X1 = X.apply(zscore)
```

In [9]:
```
cov_mat = np.cov(X1, rowvar = False)
```

If we want to account for 95% of the variance we use the below code.

In [10]:
```
pca = PCA(n_components=0.95)
```

In [11]:
```
pca.fit(X1)
```

Out[11]:
```
PCA(n_components=0.95)
```

In [12]:
```
print(pca.explained_variance_ratio_)
```

```
[0.44272026 0.18971182 0.09393163 0.06602135 0.05495768 0.04024522
 0.02250734 0.01588724 0.01389649 0.01168978]
```

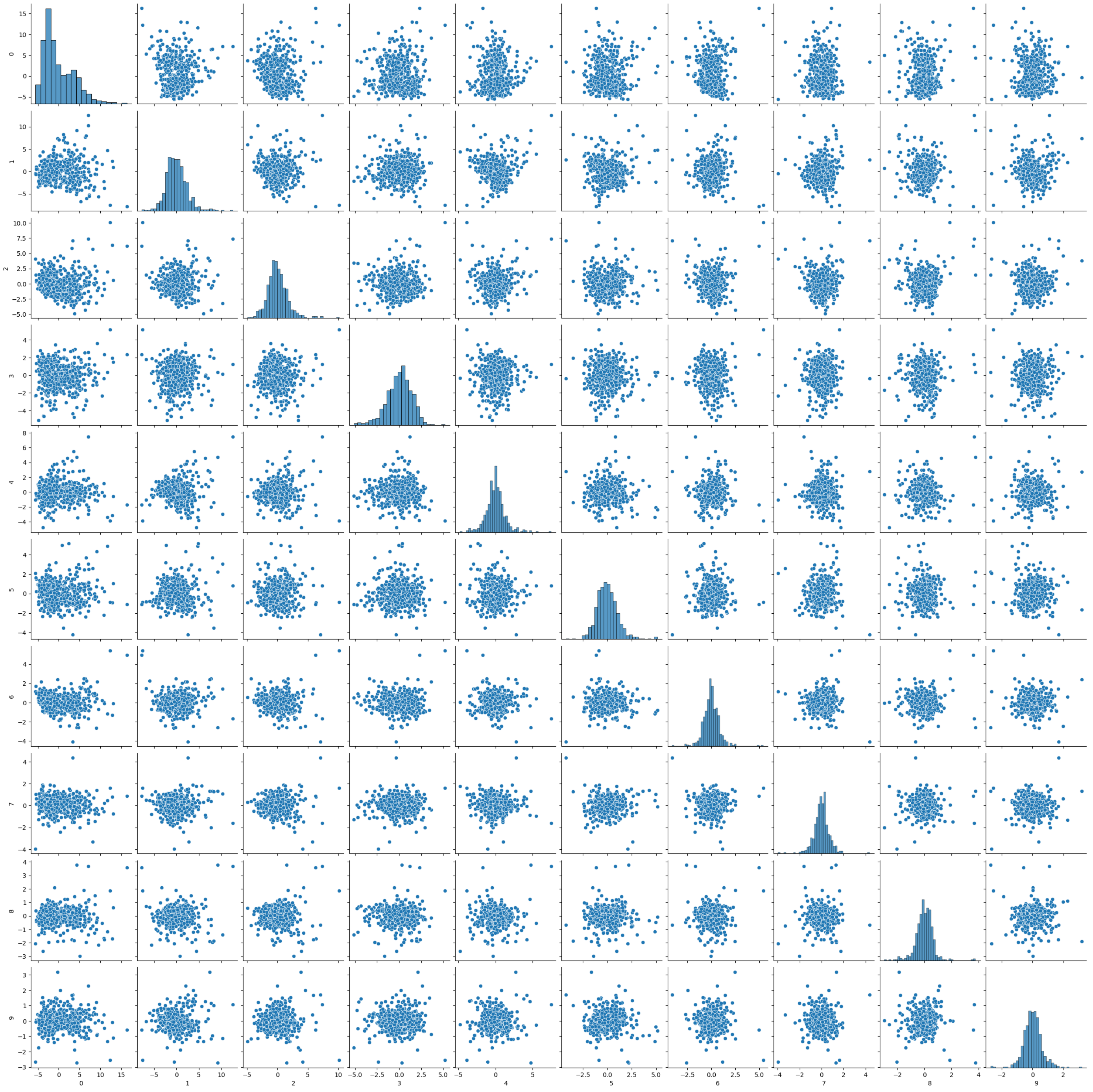
In [13]:
```
print(sum(pca.explained_variance_ratio_))
```

```
0.9515688143366667
```

In [14]:
```
pcafin = pca.transform(X1)
```

In [15]:
```
sns.pairplot(pd.DataFrame(pcafin))
```

Out[15]:
```
<seaborn.axisgrid.PairGrid at 0x2996541e790>
```



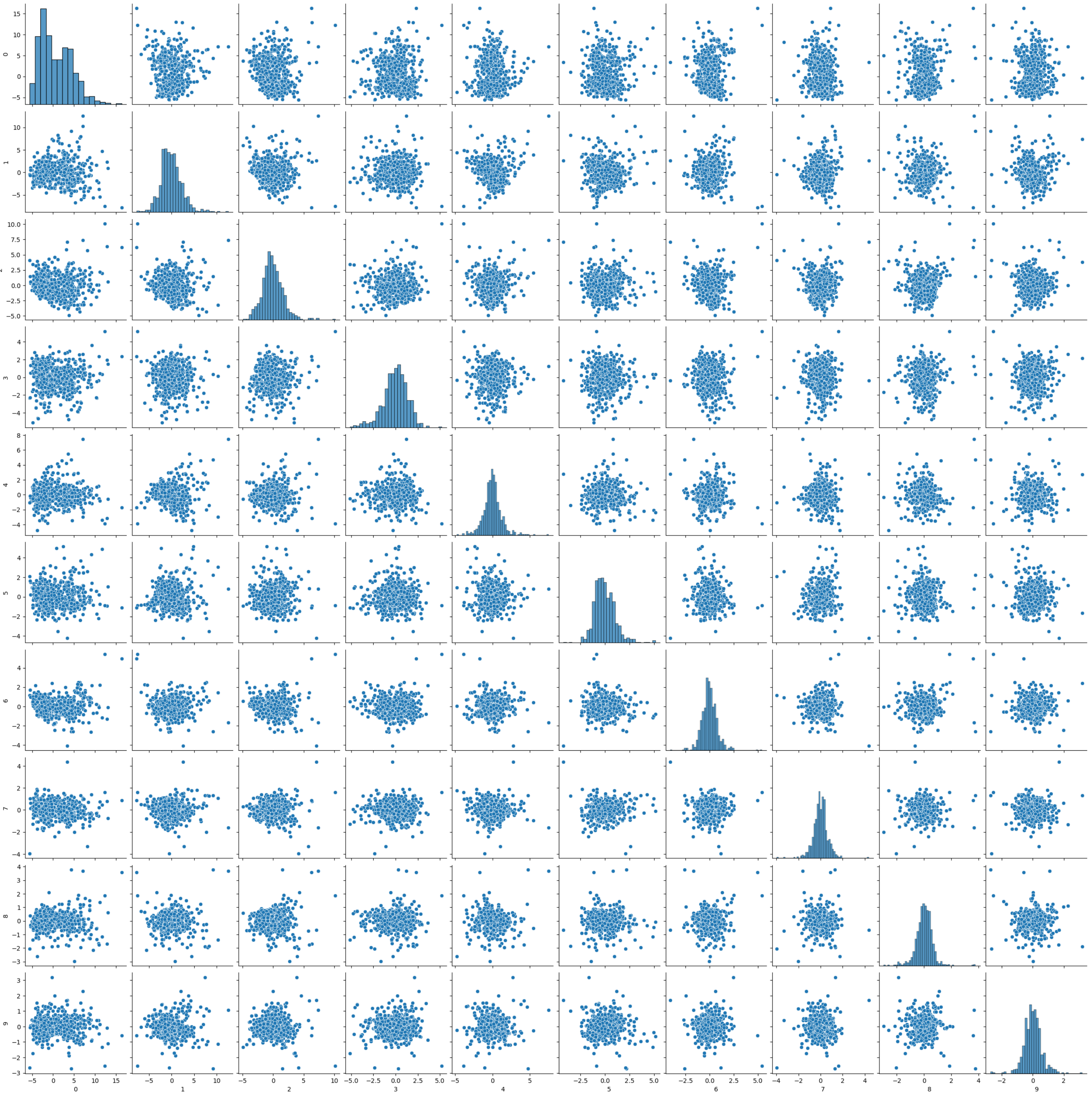
This distribution looks fairly unbalanced, so in order to use PCA most effectively we will have to balance it to some degree.

```
In [16]: from imblearn.over_sampling import SMOTE

         s = SMOTE()
         X_bal, y_bal = s.fit_resample(pcafin, y)
```

```
In [17]: sns.pairplot(pd.DataFrame(X_bal))
```

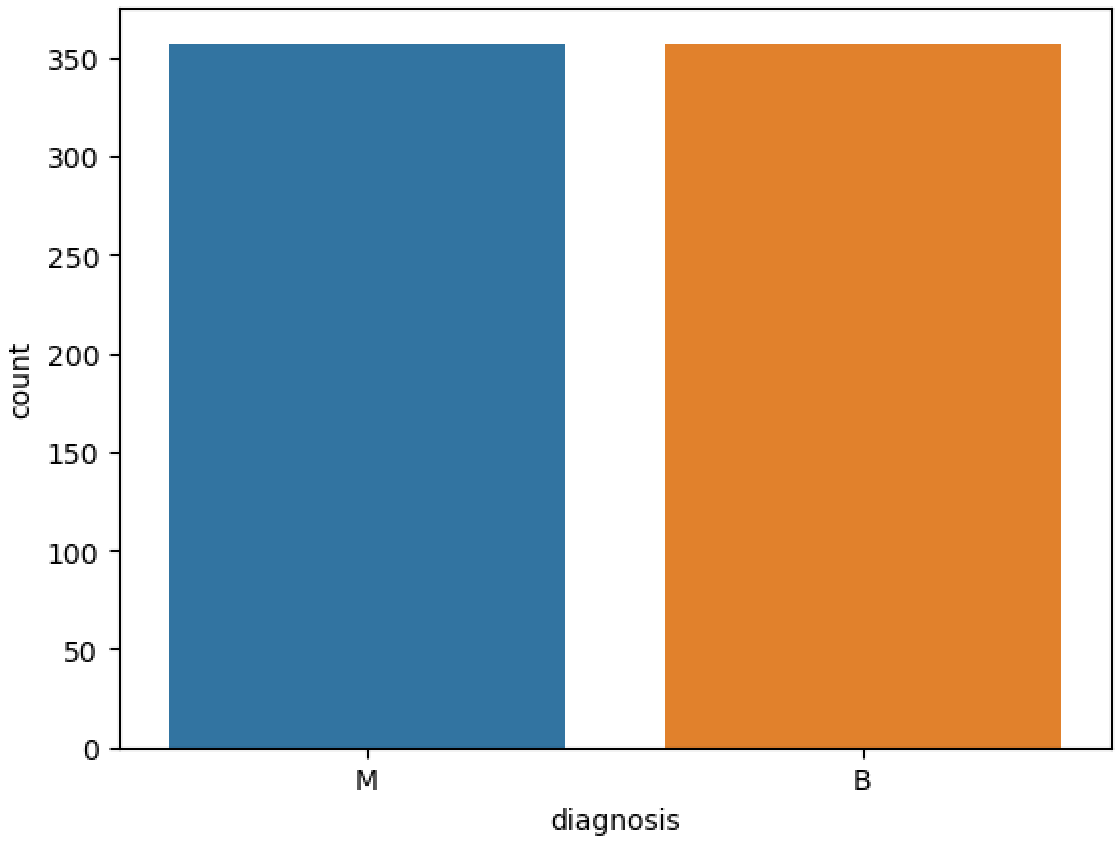
```
Out[17]: <seaborn.axisgrid.PairGrid at 0x2996f85a2e0>
```



We balance the data using SMOTE which is an oversampling technique that is designed to avoid potential overfitting caused by random oversampling. This should be very helpful in using PCA.

```
In [18]: sns.countplot(data = y_bal, x = 'diagnosis')
```

```
Out[18]: <AxesSubplot:xlabel='diagnosis', ylabel='count'>
```



In [19]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X_bal, y_bal, test_size = 0.25, rand

y_train
```

Out[19]:

	diagnosis
416	B
346	B
517	M
553	B
21	B
...	...
218	M
223	M
271	B
474	B
355	B

535 rows × 1 columns

Data Modeling

- As a side note, PCA is the unsupervised learning method used here. The rest of these models will be to compare how useful the PCA is for this dataset

- At this point we've balanced the dataset and used PCA to get new features, we should see how accurate models are. To do this we'll use a random forest and logistic regression model. We'll then go back and see what the results would have been without using PCA.

```
In [20]: from sklearn.ensemble import RandomForestRegressor
         from sklearn.linear_model import LogisticRegression

         rf = RandomForestRegressor(max_depth = 10, random_state = 5)

         # This is to convert y_train to numeric values. Categorical values will not work.
         y_trainrf = y_train['diagnosis'].apply(lambda val: 1 if val == 'M' else 0)
         y_testrf = y_test['diagnosis'].apply(lambda val: 1 if val == 'M' else 0)
```

```
In [21]: rf_fit = rf.fit(X_train, y_trainrf)
```

```
In [22]: print(rf_fit.score(X_test, y_testrf))
```

```
0.884937776303943
```

```
In [23]: pca_mod = LogisticRegression()
         pca_mod.fit(X_train, y_train)
         y_pred = pca_mod.predict(X_test)
         train_score = pca_mod.score(X_train, y_train)
         test_score = pca_mod.score(X_test, y_test)
```

```
C:\Users\joeyc\anaconda3\lib\site-packages\sklearn\utils\validation.py:993: DataConversi
onWarning: A column-vector y was passed when a 1d array was expected. Please change the
shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

```
In [24]: print(train_score)
```

```
0.9757009345794393
```

```
In [25]: print(test_score)
```

```
0.9832402234636871
```

This test score is very good at 0.98 after using PCA and logistic regression.

Models w/o PCA

- Since the models above use PCA we need base models without PCA to compare to. We will create those below.

```
In [26]: X_bal1, y_bal1 = s.fit_resample(X, y)
```

```
In [27]: X_train1, X_test1, y_train1, y_test1 = train_test_split(X_bal1, y_bal1, test_size = 0.25
```

```
In [28]: y_trainrf1 = y_train1['diagnosis'].apply(lambda val: 1 if val == 'M' else 0)
         y_testrf1 = y_test1['diagnosis'].apply(lambda val: 1 if val == 'M' else 0)
```

```
In [29]: rf_fit1 = rf.fit(X_train1, y_trainrf1)
```

```
In [30]: print(rf_fit1.score(X_test1, y_testrf1))
```

```
0.9283977647352647
```

So we can see that a random forest model really does not benefit from the use of PCA. This could be somewhat expected since random forest models are not necessarily suited to this type of problem.

Realistically it is a binary problem, M or B, so the real interesting model would be the logistic regression one we'll do next.

In [31]:
```
mod1 = LogisticRegression(max_iter=10000)
mod1.fit(X_train1, y_train1)
y_pred1 = mod1.predict(X_test1)
train_score1 = mod1.score(X_train1, y_train1)
test_score1 = mod1.score(X_test1, y_test1)
```

```
C:\Users\joeyc\anaconda3\lib\site-packages\sklearn\utils\validation.py:993: DataConversi
onWarning: A column-vector y was passed when a 1d array was expected. Please change the
shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

In [32]:
```
print(train_score1)
```

```
0.9570093457943926
```

In [33]:
```
print(test_score1)
```

```
0.9608938547486033
```

Final Results

- Final Test Scores for each model type
  - Logistic Regression
    - PCA = 0.98
    - Non-PCA = 0.96
  - Random Forest
    - PCA = 0.88
    - Non-PCA = 0.93

      ```
      - These results do vary slightly if the code is re-ran, but the general
      premise remains the same.
      ```

Conclusion

- PCA provided a significant boost to test score when it came to logistic regression and no boost to the random forest model.
- Overall this project showed significant value to using PCA when it comes to feature reduction. The model started with 31 real columns, not including ID or the blank column, and PCA brought it down to 10 features. This allowed us to make a significantly more accurate logistic regression model.
- I think the biggest improvement to this project would be more data. The dataset is small with only 569 entries, so it would be interesting to see if the model performed as well on a larger dataset.