EDA_practice

January 25, 2021

1 Exploratory Data Analysis for Machine Learning

1.1 Peer Review Project 1

This project uses the publically available **Breast Cancer Wisconsin (Diagnostic) Data set** hosted on Kaggle

https://www.kaggle.com/uciml/breast-cancer-wisconsin-data

Features are computed from a digitized image of a fine needle aspirate (FNA) of a breast mass. They describe characteristics of the cell nuclei present in the image.

K. P. Bennett and O. L. Mangasarian: "Robust Linear Programming Discrimination of Two Linearly Inseparable Sets", Optimization Methods and Software 1, 1992, 23-34.

I intend to apply the steps taught in the last 2 weeks ie;

1. Data retrieval
2. Data cleaning (removing/imputing missing values and outliers if present)
3. Checking features using plots/ visualisations
4. Feature engineering such as transformations for linear regression modelling
5. Hypothesis testing for features that are associated with Benign vs Malignant tissue

1.1.1 Module Imports

[1]:
```
%pylab inline
%config InlineBackend.figure_formats = ['retina']

import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
```

```
Populating the interactive namespace from numpy and matplotlib
```

1.1.2 Importing the data

[2]:
```python
# Importing the data
filepath = "data.csv"
df = pd.read_csv(filepath)
df.info()
```

```
<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
```

[3]:
```
df.head()
```

[3]:
```
         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]
```

1.1.3 For purposes of prediction, unique features such as the ID will not be useful and can be dropped

[4]:
```
df1 = df.copy()
df1.drop('id',axis=1,inplace=True)
df1.head()
```

[4]:

```
  diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
0         M        17.99         10.38          122.80     1001.0
1         M        20.57         17.77          132.90     1326.0
2         M        19.69         21.25          130.00     1203.0
3         M        11.42         20.38           77.58      386.1
4         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

   symmetry_mean  …  texture_worst  perimeter_worst  area_worst  \
0         0.2419  …          17.33           184.60      2019.0
1         0.1812  …          23.41           158.80      1956.0
2         0.2069  …          25.53           152.50      1709.0
3         0.2597  …          26.50            98.87       567.7
4         0.1809  …          16.67           152.20      1575.0

   smoothness_worst  compactness_worst  concavity_worst  concave points_worst  \
0            0.1622             0.6656           0.7119                0.2654
1            0.1238             0.1866           0.2416                0.1860
2            0.1444             0.4245           0.4504                0.2430
3            0.2098             0.8663           0.6869                0.2575
4            0.1374             0.2050           0.4000                0.1625

   symmetry_worst  fractal_dimension_worst  Unnamed: 32
0          0.4601                  0.11890          NaN
1          0.2750                  0.08902          NaN
2          0.3613                  0.08758          NaN
3          0.6638                  0.17300          NaN
4          0.2364                  0.07678          NaN

[5 rows x 32 columns]
```

1.1.4 Since there aren't any missing values or cateogorical variables other than the diagnosis in the dataset, we can look at some basic descriptive statistics

[5]:

```python
df1.describe().T
```

[5]:

```
                         count        mean         std         min  \
radius_mean              569.0   14.127292    3.524049    6.981000
texture_mean             569.0   19.289649    4.301036    9.710000
perimeter_mean           569.0   91.969033   24.298981   43.790000
area_mean                569.0  654.889104  351.914129  143.500000
```

smoothness_mean	569.0	0.096360	0.014064	0.052630
compactness_mean	569.0	0.104341	0.052813	0.019380
concavity_mean	569.0	0.088799	0.079720	0.000000
concave points_mean	569.0	0.048919	0.038803	0.000000
symmetry_mean	569.0	0.181162	0.027414	0.106000
fractal_dimension_mean	569.0	0.062798	0.007060	0.049960
radius_se	569.0	0.405172	0.277313	0.111500
texture_se	569.0	1.216853	0.551648	0.360200
perimeter_se	569.0	2.866059	2.021855	0.757000
area_se	569.0	40.337079	45.491006	6.802000
smoothness_se	569.0	0.007041	0.003003	0.001713
compactness_se	569.0	0.025478	0.017908	0.002252
concavity_se	569.0	0.031894	0.030186	0.000000
concave points_se	569.0	0.011796	0.006170	0.000000
symmetry_se	569.0	0.020542	0.008266	0.007882
fractal_dimension_se	569.0	0.003795	0.002646	0.000895
radius_worst	569.0	16.269190	4.833242	7.930000
texture_worst	569.0	25.677223	6.146258	12.020000
perimeter_worst	569.0	107.261213	33.602542	50.410000
area_worst	569.0	880.583128	569.356993	185.200000
smoothness_worst	569.0	0.132369	0.022832	0.071170
compactness_worst	569.0	0.254265	0.157336	0.027290
concavity_worst	569.0	0.272188	0.208624	0.000000
concave points_worst	569.0	0.114606	0.065732	0.000000
symmetry_worst	569.0	0.290076	0.061867	0.156500
fractal_dimension_worst	569.0	0.083946	0.018061	0.055040
Unnamed: 32	0.0	NaN	NaN	NaN

	25%	50%	75%	max
radius_mean	11.700000	13.370000	15.780000	28.11000
texture_mean	16.170000	18.840000	21.800000	39.28000
perimeter_mean	75.170000	86.240000	104.100000	188.50000
area_mean	420.300000	551.100000	782.700000	2501.00000
smoothness_mean	0.086370	0.095870	0.105300	0.16340
compactness_mean	0.064920	0.092630	0.130400	0.34540
concavity_mean	0.029560	0.061540	0.130700	0.42680
concave points_mean	0.020310	0.033500	0.074000	0.20120
symmetry_mean	0.161900	0.179200	0.195700	0.30400
fractal_dimension_mean	0.057700	0.061540	0.066120	0.09744
radius_se	0.232400	0.324200	0.478900	2.87300
texture_se	0.833900	1.108000	1.474000	4.88500
perimeter_se	1.606000	2.287000	3.357000	21.98000
area_se	17.850000	24.530000	45.190000	542.20000
smoothness_se	0.005169	0.006380	0.008146	0.03113
compactness_se	0.013080	0.020450	0.032450	0.13540
concavity_se	0.015090	0.025890	0.042050	0.39600
concave points_se	0.007638	0.010930	0.014710	0.05279

```
symmetry_se                  0.015160    0.018730     0.023480     0.07895
fractal_dimension_se         0.002248    0.003187     0.004558     0.02984
radius_worst                13.010000   14.970000    18.790000    36.04000
texture_worst               21.080000   25.410000    29.720000    49.54000
perimeter_worst             84.110000   97.660000   125.400000   251.20000
area_worst                 515.300000  686.500000  1084.000000  4254.00000
smoothness_worst             0.116600    0.131300     0.146000     0.22260
compactness_worst            0.147200    0.211900     0.339100     1.05800
concavity_worst              0.114500    0.226700     0.382900     1.25200
concave points_worst         0.064930    0.099930     0.161400     0.29100
symmetry_worst               0.250400    0.282200     0.317900     0.66380
fractal_dimension_worst      0.071460    0.080040     0.092080     0.20750
Unnamed: 32                       NaN         NaN          NaN         NaN
```

1.1.5 Whew, that's a lot of data. Maybe a pair plot with diagnosis as the hue can tell us more. Since the variables are so many, let's use only 6 of them for now.

[18]:
```
smaller_df = df1.loc[:,['diagnosis','concave␣
↪points_mean','compactness_mean','concavity_mean','radius_mean','area_mean','texture_mean']]
smaller_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 7 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   diagnosis             569 non-null    object
 1   concave points_mean   569 non-null    float64
 2   compactness_mean      569 non-null    float64
 3   concavity_mean        569 non-null    float64
 4   radius_mean           569 non-null    float64
 5   area_mean             569 non-null    float64
 6   texture_mean          569 non-null    float64
dtypes: float64(6), object(1)
memory usage: 31.2+ KB
```

[19]:
```
sns.set_context('talk')
sns.pairplot(smaller_df, hue='diagnosis')
```

[19]: <seaborn.axisgrid.PairGrid at 0x18e204cab20>

1.1.6 There seems to be a linear relationship between dimensions and the diagnosis of the cancer. That would be an interesting hypothesis to test.

1.1.7 But we need to engineer these features into a normal distribution for linear regression modelling

[8]:
```
# Check for skewed distributions before hypothesis testing
skew_vals = smaller_df.skew()
skew_limit = 0.75 # define a limit above which we will log transform
```

[9]:
```
# Showing the skewed columns
skew_cols = (skew_vals
             .sort_values(ascending=False)
             .to_frame()
             .rename(columns={0:'Skew'})
```

```
                .query('abs(Skew) > {}'.format(skew_limit)))

skew_cols
```

[9]:

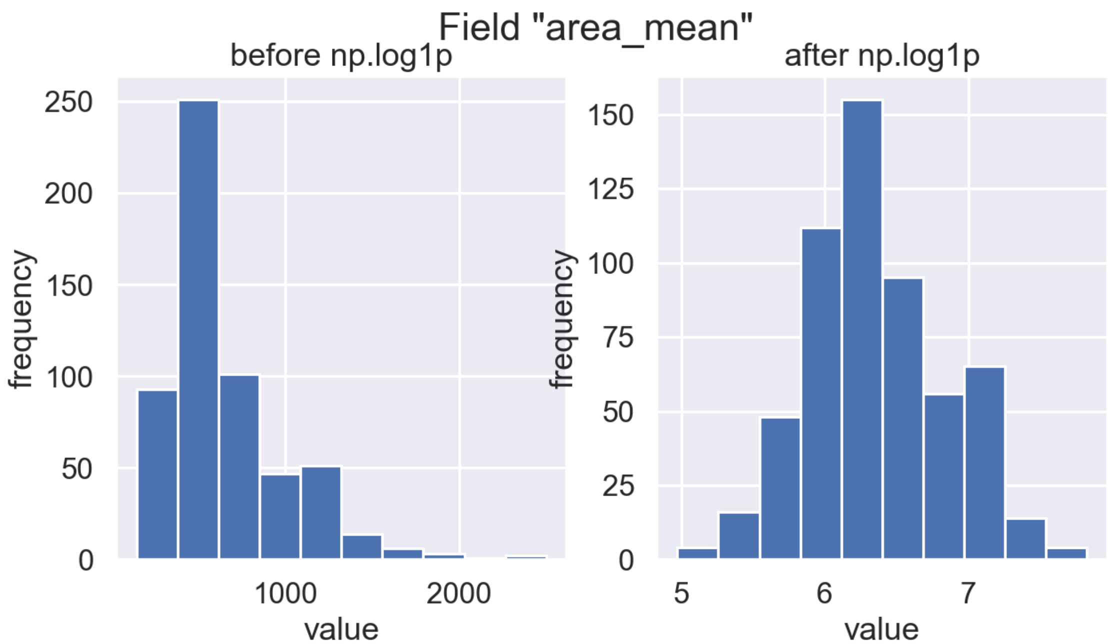
	Skew
area_mean	1.645732
concavity_mean	1.401180
compactness_mean	1.190123
perimeter_mean	0.990650
radius_mean	0.942380

1.1.8 All features except texture are skewed. So we shall apply Log transformation to them before hypothesis testing

[10]:

```
# Let's look at what happens to one of these features, when we apply np.log1p␣
↪visually.

# Choose a field
field = "area_mean"

# Create two "subplots" and a "figure" using matplotlib
fig, (ax_before, ax_after) = plt.subplots(1, 2, figsize=(10, 5))

# Create a histogram on the "ax_before" subplot
df[field].hist(ax=ax_before)

# Apply a log transformation (numpy syntax) to this column
df[field].apply(np.log1p).hist(ax=ax_after)

# Formatting of titles etc. for each subplot
ax_before.set(title='before np.log1p', ylabel='frequency', xlabel='value')
ax_after.set(title='after np.log1p', ylabel='frequency', xlabel='value')
fig.suptitle('Field "{}"'.format(field))
```

[10]: Text(0.5, 0.98, 'Field "area_mean"')




```
[11]: # Perform the skew transformation:

      for col in skew_cols.index.values:
          if col == "diagnosis":
              continue
          smaller_df[col] = smaller_df[col].apply(np.log1p)
```

```
[12]: smaller_df.head()
```

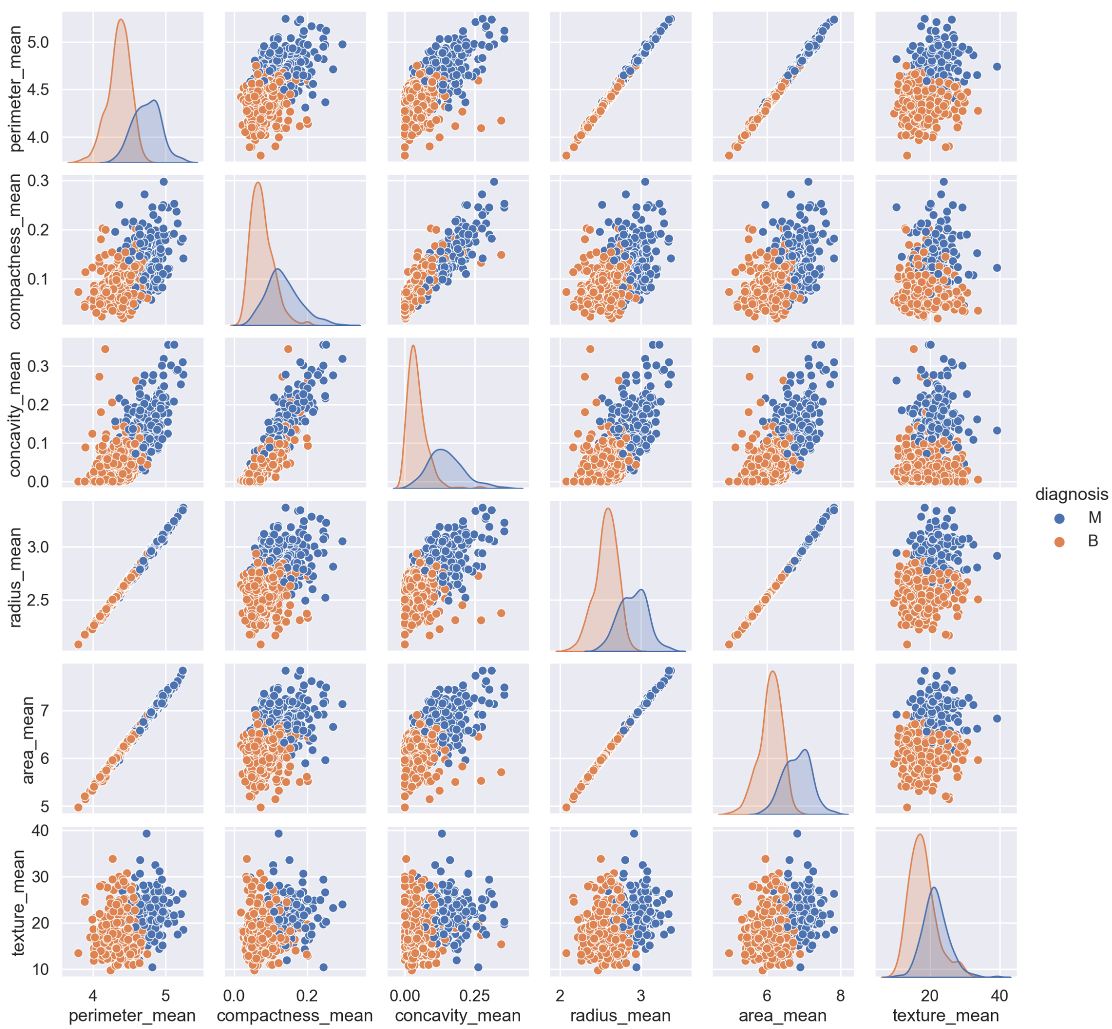
```
[12]:   diagnosis  perimeter_mean  compactness_mean  concavity_mean  radius_mean  \
      0         M        4.818667          0.244983        0.262441     2.943913
      1         M        4.897093          0.075701        0.083330     3.071303
      2         M        4.875197          0.148334        0.180153     3.029650
      3         M        4.364117          0.249902        0.216240     2.519308
      4         M        4.913390          0.124692        0.180653     3.058237

         area_mean  texture_mean
      0   6.909753         10.38
      1   7.190676         17.77
      2   7.093405         21.25
      3   5.958683         20.38
      4   7.168580         14.34
```

```
[13]: smaller_df.describe().T
```

[13]:
```
                   count       mean       std       min        25%        50%  \
perimeter_mean     569.0   4.500683  0.248328  3.801985   4.332968   4.468663
compactness_mean   569.0   0.098145  0.046646  0.019195   0.062900   0.088588
concavity_mean     569.0   0.082552  0.070113  0.000000   0.029132   0.059721
radius_mean        569.0   2.691235  0.222226  2.077064   2.541602   2.665143
area_mean          569.0   6.365109  0.482274  4.973280   6.043345   6.313729
texture_mean       569.0  19.289649  4.301036  9.710000  16.170000  18.840000

                         75%        max
perimeter_mean      4.654912   5.244389
compactness_mean    0.122572   0.296691
concavity_mean      0.122837   0.355434
radius_mean         2.820188   3.371082
area_mean           6.664026   7.824846
texture_mean       21.800000  39.280000
```

[14]:
```
# Checking to see how the feature engineering has improved the distribution of␣
↪attributes
sns.pairplot(smaller_df, hue='diagnosis')
```

[14]:
```
<seaborn.axisgrid.PairGrid at 0x18e205b9730>
```



1.2 Hypotheses

Ho - The concave points mean of bengin and malignant tissue is the same

Ho - The compactness mean of bengin and malignant tissue is the same

Ho - The perimeter mean of bengin and malignant tissue is the same

1.2.1 Hypothesis testing

Ho - The perimeter mean of bengin and malignant tissue is the same

H1 - The perimeter mean of bengin and malignant tissue is not the same

[15]:
```
# To test this hypothesis, we shall carry out a t-test on the two diagnoses

from scipy.stats import ttest_ind
```

```python
mal = smaller_df[smaller_df['diagnosis'] == 'M']
ben = smaller_df[smaller_df['diagnosis'] == 'B']

ttest_ind(mal['perimeter_mean'],ben['perimeter_mean'])
```

[15]: Ttest_indResult(statistic=26.35462190815133, pvalue=1.5372483643273375e-100)

Such a low p-value leads us to reject the null hypothesis. Tissues of benign and malignant breast cancer have different perimeters. Next steps;

1. Check how other features correlate with the cancer being benign or malignant.
2. This data set contained only 569 samples. More data would be needed to confirm or refute these findings
3. A model can be trained to look for these key features in identifying benign or malignant cancer tissue.

Thank you!