# cs109a_MS3_EDA

October 31, 2023

## 1 cs109a Final Project Milestone 3: EDA

[1]:

```
# Import libraries
import os
import time
import numpy as np
import pandas as pd
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer, KNNImputer
from sklearn.linear_model import LinearRegression, LogisticRegression,␣
  ↪LogisticRegressionCV
from sklearn.neighbors import KNeighborsRegressor
from sklearn.model_selection import train_test_split, cross_validate
from sklearn.metrics import r2_score, confusion_matrix, classification_report,␣
  ↪roc_curve
from sklearn.metrics import roc_auc_score, precision_recall_curve,␣
  ↪average_precision_score
import warnings
warnings.filterwarnings("ignore")
plt.style.use('seaborn-notebook')
sns.set_style('darkgrid')
# pandas tricks for better display
pd.options.display.max_columns = 50
pd.options.display.max_rows = 500
pd.options.display.max_colwidth = 100
pd.options.display.precision = 3
```

[2]:

```
# helper functions

def visualize_missingness(df, figsize=(6, 7)):
    # calculate missing data percentages
    missing_data_percentage = (df.isnull().sum() / len(df)) * 100
    # sort by percentage
    missing_data_percentage = missing_data_percentage.
 ↪sort_values(ascending=True)
    # visualize using horizontal barplot
    plt.figure(figsize=figsize)
    missing_data_percentage.plot(kind='barh')
    plt.title('Percentage of Missing Data by Column')
    plt.xlabel('Percentage Missing (%)')
    plt.ylabel('Columns')
    plt.show()

def visualize_class_imbalance(df, target_col, figsize=(5, 2)):
    # Visualize class imbalance
    plt.figure(figsize=figsize)
    df[target_col].value_counts().plot(kind='barh')
    plt.title('Class Distribution')
    plt.ylabel('Class Label')
    plt.xlabel('Number of Samples')
    plt.show()

def missing_values_table(df):
    # count the missing values for each column
    missing_values = df.isnull().sum()
    # calculate the percentage of missing values
    missing_percentage = (100 * df.isnull().sum() / len(df))
    # create a table with the results
    missing_values_table = pd.concat([missing_values, missing_percentage],␣
 ↪axis=1)
    # rename the columns
    missing_values_table_columns = missing_values_table.rename(
        columns = {0 : 'Missing Values', 1 : '% of Total Values'})
    # sort the table by percentage of missing in descending order
    missing_values_table_columns = missing_values_table_columns[
        missing_values_table_columns.iloc[:,1] != 0].sort_values(
        '% of Total Values', ascending=False).round(1)
    # print a summary
    print("Your selected dataframe has " + str(df.shape[1]) + " columns.\n"
          "There are " + str(missing_values_table_columns.shape[0]) +
          " columns that have missing values.")
    # return the dataframe with missing info
    return missing_values_table_columns

def handle_missing_data(df):
    # keep track of the original columns
    original_columns = df.columns.tolist()
    # create dummy columns only for columns with missing data
    for col in original_columns:
        if df[col].isna().any():
            df[col + "_is_missing"] = df[col].isna().astype(int)
    # define imputers
    numeric_imputer = SimpleImputer(strategy='median')
    categorical_imputer = SimpleImputer(strategy='most_frequent')
    # impute median values for numeric columns and most frequent value for non-numeric columns
    for col in original_columns:
        if df[col].dtype in [np.float64, np.int64]:
            df[col] = numeric_imputer.fit_transform(df[[col]]).flatten()
        else:
            df[col] = categorical_imputer.fit_transform(df[[col]]).flatten()
    return df

def scale_data(df, columns_to_scale):
    scaler = StandardScaler()
    df[columns_to_scale] = scaler.fit_transform(df[columns_to_scale])
    return df
```

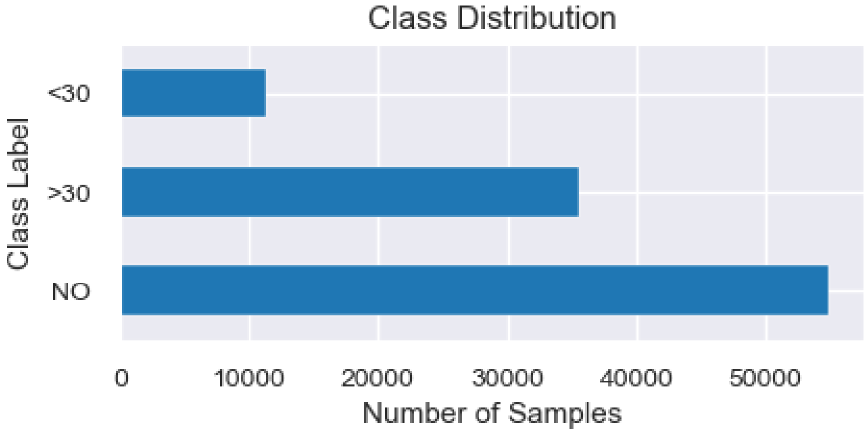
[3]:
```
# load data
df = pd.read_csv('../data/diabetic_data.csv', na_values='?')

# examine first 5 rows of dataframe
print(f'Shape of diabetic data: {df.shape}')
display(df.head())
```

```
Shape of diabetic data: (101766, 50)

   encounter_id  patient_nbr             race  gender      age weight  \
0       2278392      8222157        Caucasian  Female   [0-10)    NaN
1        149190     55629189        Caucasian  Female  [10-20)    NaN
2         64410     86047875  AfricanAmerican  Female  [20-30)    NaN
3        500364     82442376        Caucasian    Male  [30-40)    NaN
4         16680     42519267        Caucasian    Male  [40-50)    NaN

   admission_type_id  discharge_disposition_id  admission_source_id  \
0                  6                        25                    1
1                  1                         1                    7
2                  1                         1                    7
3                  1                         1                    7
4                  1                         1                    7

   time_in_hospital payer_code         medical_specialty  num_lab_procedures  \
0                 1        NaN  Pediatrics-Endocrinology                  41
1                 3        NaN                       NaN                  59
2                 2        NaN                       NaN                  11
3                 2        NaN                       NaN                  44
4                 1        NaN                       NaN                  51
```

```
   num_procedures  num_medications  number_outpatient  number_emergency  \
0               0                1                  0                 0
1               0               18                  0                 0
2               5               13                  2                 0
3               1               16                  0                 0
4               0                8                  0                 0

   number_inpatient  diag_1  diag_2 diag_3  number_diagnoses max_glu_serum  \
0                 0  250.83     NaN    NaN                 1           NaN
1                 0     276  250.01    255                 9           NaN
2                 1     648     250    V27                 6           NaN
3                 0       8  250.43    403                 7           NaN
4                 0     197     157    250                 5           NaN

  A1Cresult metformin repaglinide nateglinide chlorpropamide glimepiride  \
0       NaN        No          No          No             No          No
1       NaN        No          No          No             No          No
2       NaN        No          No          No             No          No
3       NaN        No          No          No             No          No
4       NaN        No          No          No             No          No

  acetohexamide glipizide glyburide tolbutamide pioglitazone rosiglitazone  \
0            No        No        No          No           No            No
1            No        No        No          No           No            No
2            No    Steady        No          No           No            No
3            No        No        No          No           No            No
4            No    Steady        No          No           No            No

  acarbose miglitol troglitazone tolazamide examide citoglipton insulin  \
0       No       No           No         No      No          No      No
1       No       No           No         No      No          No      Up
2       No       No           No         No      No          No      No
3       No       No           No         No      No          No      Up
4       No       No           No         No      No          No  Steady

  glyburide-metformin glipizide-metformin glimepiride-pioglitazone  \
0                  No                  No                       No
1                  No                  No                       No
2                  No                  No                       No
3                  No                  No                       No
4                  No                  No                       No

  metformin-rosiglitazone metformin-pioglitazone change diabetesMed readmitted
0                      No                     No     No          No         NO
1                      No                     No     Ch         Yes        >30
2                      No                     No     No         Yes         NO
3                      No                     No     Ch         Yes         NO
4                      No                     No     Ch         Yes         NO
```

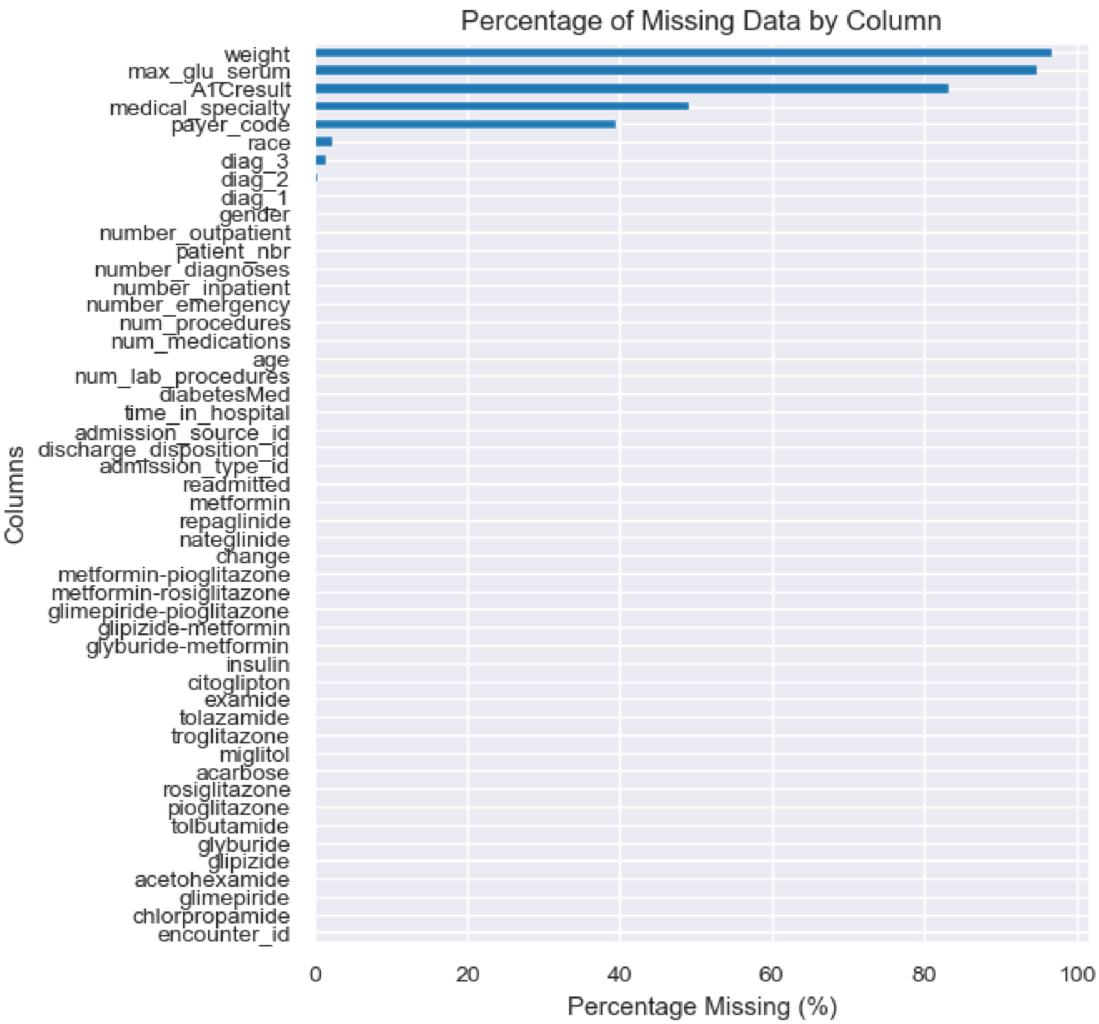
[4]:

```
# class imbalance
visualize_class_imbalance(df, target_col='readmitted')
```



[5]:

```
# visualize missingness
visualize_missingness(df)
```



[6]:
```
# missing values table
missing_values_table(df)
```

```
Your selected dataframe has 50 columns.
There are 9 columns that have missing values.
```

[6]:
```
                   Missing Values  % of Total Values
weight                      98569               96.9
max_glu_serum               96420               94.7
A1Cresult                   84748               83.3
medical_specialty           49949               49.1
payer_code                  40256               39.6
race                         2273                2.2
diag_3                       1423                1.4
diag_2                        358                0.4
```

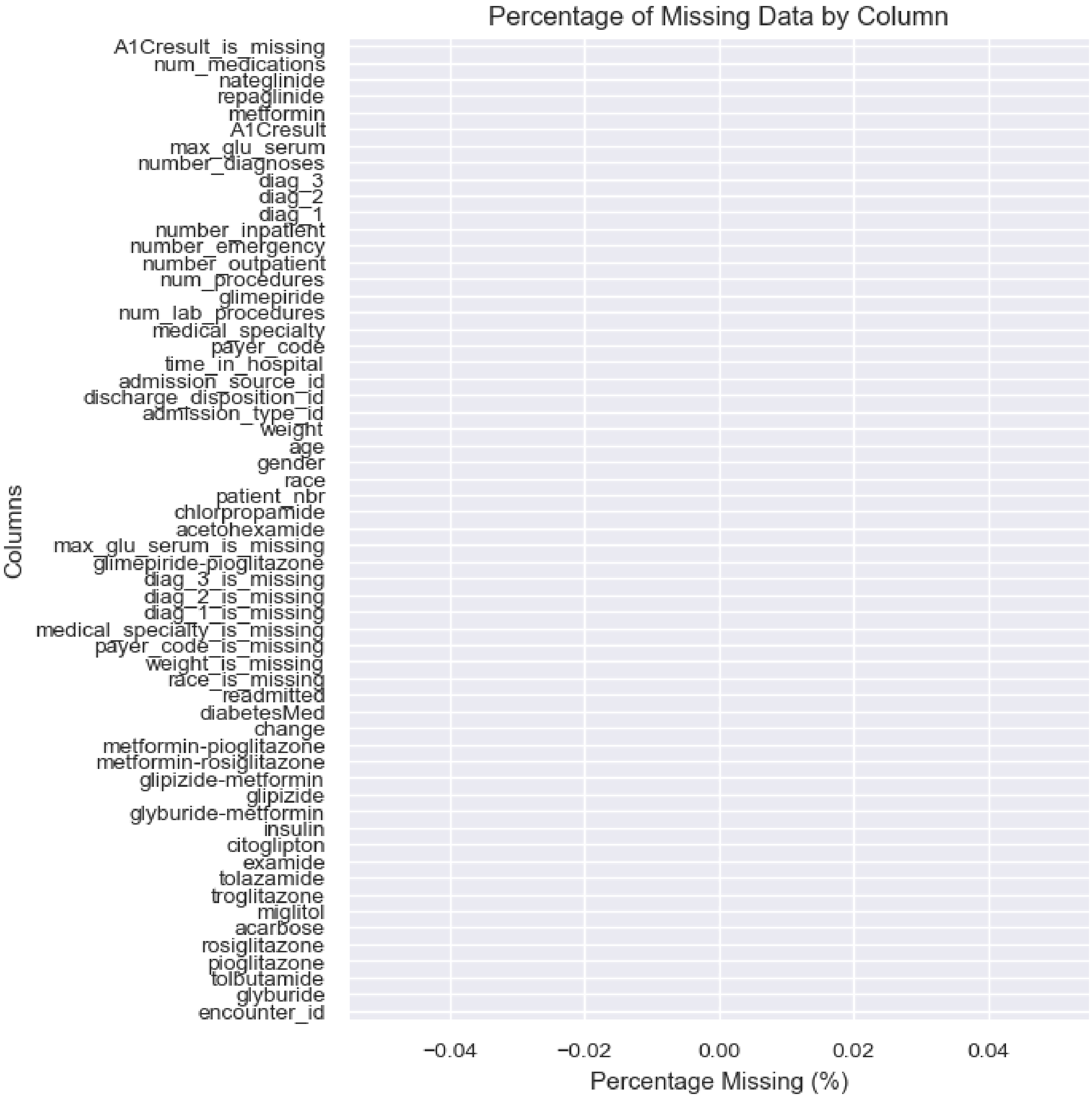
```
diag_1                                    21                 0.0
```

[7]:

```python
# deal with missing data
df_imp = handle_missing_data(df)
```

[8]:

```python
# look at imputed data
visualize_missingness(df_imp, figsize=(6, 8))
```



[9]:

```python
# standardize data
df_std = scale_data(df_imp, ['time_in_hospital'])
df_std.head()
```

```
[9]:    encounter_id  patient_nbr            race  gender      age    weight  \
     0     2.278e+06    8.222e+06       Caucasian  Female   [0-10)  [75-100)
     1     1.492e+05    5.563e+07       Caucasian  Female  [10-20)  [75-100)
     2     6.441e+04    8.605e+07 AfricanAmerican  Female  [20-30)  [75-100)
     3     5.004e+05    8.244e+07       Caucasian    Male  [30-40)  [75-100)
     4     1.668e+04    4.252e+07       Caucasian    Male  [40-50)  [75-100)

        admission_type_id  discharge_disposition_id  admission_source_id  \
     0                6.0                      25.0                  1.0
     1                1.0                       1.0                  7.0
     2                1.0                       1.0                  7.0
     3                1.0                       1.0                  7.0
     4                1.0                       1.0                  7.0

        time_in_hospital payer_code         medical_specialty  num_lab_procedures  \
     0            -1.138         MC  Pediatrics-Endocrinology                41.0
     1            -0.468         MC          InternalMedicine                59.0
     2            -0.803         MC          InternalMedicine                11.0
     3            -0.803         MC          InternalMedicine                44.0
     4            -1.138         MC          InternalMedicine                51.0

        num_procedures  num_medications  number_outpatient  number_emergency  \
     0             0.0              1.0                0.0               0.0
     1             0.0             18.0                0.0               0.0
     2             5.0             13.0                2.0               0.0
     3             1.0             16.0                0.0               0.0
     4             0.0              8.0                0.0               0.0

        number_inpatient  diag_1  diag_2 diag_3  number_diagnoses max_glu_serum  \
     0               0.0  250.83     276    250               1.0          Norm
     1               0.0     276  250.01    255               9.0          Norm
     2               1.0     648     250    V27               6.0          Norm
     3               0.0       8  250.43    403               7.0          Norm
     4               0.0     197     157    250               5.0          Norm

       A1Cresult metformin  … rosiglitazone acarbose miglitol troglitazone  \
     0        >8        No  …            No       No       No           No
     1        >8        No  …            No       No       No           No
     2        >8        No  …            No       No       No           No
     3        >8        No  …            No       No       No           No
     4        >8        No  …            No       No       No           No

       tolazamide examide citoglipton insulin glyburide-metformin  \
     0         No      No          No      No                  No
     1         No      No          No      Up                  No
     2         No      No          No      No                  No
     3         No      No          No      Up                  No
```

```
4         No      No          No  Steady                  No

  glipizide-metformin glimepiride-pioglitazone metformin-rosiglitazone  \
0                  No                       No                      No
1                  No                       No                      No
2                  No                       No                      No
3                  No                       No                      No
4                  No                       No                      No

  metformin-pioglitazone change diabetesMed readmitted race_is_missing  \
0                     No     No          No         NO               0
1                     No     Ch         Yes        >30               0
2                     No     No         Yes         NO               0
3                     No     Ch         Yes         NO               0
4                     No     Ch         Yes         NO               0

  weight_is_missing payer_code_is_missing medical_specialty_is_missing  \
0                 1                     1                            0
1                 1                     1                            1
2                 1                     1                            1
3                 1                     1                            1
4                 1                     1                            1

  diag_1_is_missing diag_2_is_missing diag_3_is_missing  \
0                 0                 1                 1
1                 0                 0                 0
2                 0                 0                 0
3                 0                 0                 0
4                 0                 0                 0

  max_glu_serum_is_missing A1Cresult_is_missing
0                        1                    1
1                        1                    1
2                        1                    1
3                        1                    1
4                        1                    1

[5 rows x 59 columns]
```

```
[ ]:
```