ICR - Identifying Age-Related Conditions Dataset

This notebook walks you through how to train a LightGBM on the ICR - Identifying Age-Related Conditions dataset made available for this competition. The goal of the model is to predict if a person has one or more of any of three medical conditions or none.

Dataset Description

The competition data comprises over fifty anonymized health characteristics linked to three age-related conditions. Your goal is to predict whether a subject has or has not been diagnosed with one of these conditions -- a binary classification problem.

Note that this is a Code Competition, in which the actual test set is hidden. In this version, we give some sample data in the correct format to help you author your solutions. When your submission is scored, this example test data will be replaced with the full test set. There are about 400 rows in the full test set.

Files and Field Descriptions train.csv - The training set. Id Unique identifier for each observation. AB-GL Fifty-six anonymized health characteristics. All are numeric except for EJ, which is categorical. Class A binary target: 1 indicates the subject has been diagnosed with one of the three conditions, 0 indicates they have not. test.csv - The test set. Your goal is to predict the probability that a subject in this set belongs to each of the two classes. greeks.csv - Supplemental metadata, only available for the training set. Alpha Identifies the type of age-related condition, if present. A No age-related condition. Corresponds to class 0. B, D, G The three age-related conditions. Correspond to class 1. Beta, Gamma, Delta Three experimental characteristics. Epsilon The date the data for this subject was collected. Note that all of the data in the test set was collected after the training set was collected. sample_submission.csv - A sample submission file in the correct format. See the Evaluation page for more details.

Import the libraries

```
import pandas as pd
import numpy as np

import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import plotly.offline as pyo

from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from imblearn.over_sampling import SMOTE
```

```
from sklearn.model_selection import train_test_split, GridSearchCV

import xgboost as xgb
from sklearn.ensemble import VotingClassifier
from lightgbm import LGBMClassifier
from sklearn.svm import SVC

from sklearn.metrics import confusion_matrix, classification_report,
accuracy_score, log_loss, make_scorer

!pip install kaleido
```

```
Requirement already satisfied: kaleido in
/usr/local/lib/python3.10/dist-packages (0.2.1)
```

Load the Dataset

```
train = pd.read_csv('train.csv')
greeks = pd.read_csv('greeks.csv')
print("Full train dataset shape is {}".format(train.shape))
```

```
Full train dataset shape is (617, 58)
```

The data is composed of 58 columns and 617 entries. We can see all 58 dimensions(results will be truncated since the number of columns is big) of our dataset by printing out the first 5 entries using the following code:

```
train.head()
```

```
             Id        AB          AF          AH         AM        AR
\
0  000ff2bfdfe9  0.209377  3109.03329   85.200147  22.394407  8.138688

1  007255e47698  0.145282   978.76416   85.200147  36.968889  8.138688

2  013f2bd269f5  0.470030  2635.10654   85.200147  32.360553  8.138688

3  043ac50845d5  0.252107  3819.65177  120.201618  77.112203  8.138688

4  044fb8a146ec  0.380297  3733.04844   85.200147  14.103738  8.138688


         AX        AY         AZ          BC  ...        FL       FR
\
0  0.699861  0.025578   9.812214    5.555634  ...  7.298162  1.73855

1  3.632190  0.025578  13.517790    1.229900  ...  0.173229  0.49706

2  6.732840  0.025578  12.824570    1.229900  ...  7.709560  0.97556
```

```
3  3.685344  0.025578  11.053708    1.229900  ...  6.122162   0.49706

4  3.942255  0.054810   3.396778  102.151980  ...  8.153058  48.50134


         FS         GB          GE            GF         GH         GI
\
0  0.094822  11.339138   72.611063   2003.810319  22.136229  69.834944

1  0.568932   9.292698   72.611063  27981.562750  29.135430  32.131996

2  1.198821  37.077772   88.609437  13676.957810  28.022851  35.192676

3  0.284466  18.529584   82.416803   2094.262452  39.948656  90.493248

4  0.121914  16.408728  146.109943   8524.370502  45.381316  36.262628


          GL  Class
0   0.120343      1
1  21.978000      0
2   0.196941      0
3   0.155829      0
4   0.096614      1

[5 rows x 58 columns]
```

```
greeks.head()
```

```
             Id Alpha Beta Gamma Delta    Epsilon
0  000ff2bfdfe9     B    C     G     D  3/19/2019
1  007255e47698     A    C     M     B    Unknown
2  013f2bd269f5     A    C     M     B    Unknown
3  043ac50845d5     A    C     M     B    Unknown
4  044fb8a146ec     D    B     F     B  3/25/2020
```

`Class` is the label column indicating if a person has one or more of any of the three medical conditions (i.e,`Class 1`), or none of the three medical conditions (i.e,`Class 0`). Given the features of the dataset, the goal of our model is to predict the value of `Class` for any person.

Quick basic dataset exploration

```
train.describe().T
```

```
       count         mean          std         min          25%  \
AB     617.0     0.477149     0.468388    0.081187     0.252107
AF     617.0  3502.013221  2300.322717  192.593280  2197.345480
AH     617.0   118.624513   127.838950   85.200147    85.200147
```

AM	617.0	38.968552	69.728226	3.177522	12.270314
AR	617.0	10.128242	10.518877	8.138688	8.138688
AX	617.0	5.545576	2.551696	0.699861	4.128294
AY	617.0	0.060320	0.416817	0.025578	0.025578
AZ	617.0	10.566447	4.350645	3.396778	8.129580
BC	617.0	8.053012	65.166943	1.229900	1.229900
BD	617.0	5350.388655	3021.326641	1693.624320	4155.702870
BN	617.0	21.419492	3.478278	9.886800	19.420500
BP	617.0	231.322223	183.992505	72.948951	156.847239
BQ	557.0	98.328737	96.479371	1.331155	27.834425
BR	617.0	1218.133238	7575.293707	51.216883	424.990642
BZ	617.0	550.632525	2076.371275	257.432377	257.432377
CB	615.0	77.104151	159.049302	12.499760	23.317567
CC	614.0	0.688801	0.263994	0.176874	0.563688
CD	617.0	90.251735	51.585130	23.387600	64.724192
CF	617.0	11.241064	13.571133	0.510888	5.066306
CH	617.0	0.030615	0.014808	0.003184	0.023482
CL	617.0	1.403761	1.922210	1.050225	1.050225
CR	617.0	0.742262	0.281195	0.069225	0.589575
CS	617.0	36.917590	17.266347	13.784111	29.782467
CU	617.0	1.383792	0.538717	0.137925	1.070298
CW	617.0	27.165653	14.645993	7.030640	7.030640
DA	617.0	51.128326	21.210888	6.906400	37.942520
DE	617.0	401.901299	317.745623	35.998895	188.815690
DF	617.0	0.633884	1.912384	0.238680	0.238680
DH	617.0	0.367002	0.112989	0.040995	0.295164
DI	617.0	146.972099	86.084419	60.232470	102.703553
DL	617.0	94.795377	28.243187	10.345600	78.232240
DN	617.0	26.370568	8.038825	6.339496	20.888264
DU	616.0	1.802900	9.034721	0.005518	0.005518
DV	617.0	1.924830	1.484555	1.743070	1.743070
DY	617.0	26.388989	18.116679	0.804068	14.715792
EB	617.0	9.072700	6.200281	4.926396	5.965392
EE	617.0	3.064778	2.058344	0.286201	1.648679
EG	617.0	1731.248215	1790.227476	185.594100	1111.160625
EH	617.0	0.305107	1.847499	0.003042	0.003042
EL	557.0	69.582596	38.555707	5.394675	30.927468
EP	617.0	105.060712	68.445620	78.526968	78.526968
EU	617.0	69.117005	390.187057	3.828384	4.324656
FC	616.0	71.341526	165.551545	7.534128	25.815384
FD	617.0	6.930086	64.754262	0.296850	0.296850
FE	617.0	10306.810737	11331.294051	1563.136688	5164.666260
FI	617.0	10.111079	2.934025	3.583450	8.523098
FL	616.0	5.433199	11.496257	0.173229	0.173229
FR	617.0	3.533905	50.181948	0.497060	0.497060
FS	615.0	0.421501	1.305365	0.067730	0.067730
GB	617.0	20.724856	9.991907	4.102182	14.036718
GE	617.0	131.714987	144.181524	72.611063	72.611063
GF	617.0	14679.595398	19352.959387	13.038894	2798.992584

GH	617.0	31.489716	9.864239	9.432735	25.034888
GI	617.0	50.584437	36.266251	0.897628	23.011684
GL	616.0	8.530961	10.327010	0.001129	0.124392
Class	617.0	0.175041	0.380310	0.000000	0.000000

	50%	75%	max
AB	0.354659	0.559763	6.161666
AF	3120.318960	4361.637390	28688.187660
AH	85.200147	113.739540	1910.123198
AM	20.533110	39.139886	630.518230
AR	8.138688	8.138688	178.943634
AX	5.031912	6.431634	38.270880
AY	0.025578	0.036845	10.315851
AZ	10.461320	12.969516	38.971568
BC	1.229900	5.081244	1463.693448
BD	4997.960730	6035.885700	53060.599240
BN	21.186000	23.657700	29.307300
BP	193.908816	247.803462	2447.810550
BQ	61.642115	134.009015	344.644105
BR	627.417402	975.649259	179250.252900
BZ	257.432377	257.432377	50092.459300
CB	42.554330	77.310097	2271.436167
CC	0.658715	0.772206	4.103032
CD	79.819104	99.813520	633.534408
CF	9.123000	13.565901	200.967526
CH	0.027860	0.034427	0.224074
CL	1.050225	1.228445	31.688153
CR	0.730800	0.859350	3.039675
CS	34.835130	40.529401	267.942823
CU	1.351665	1.660617	4.951507
CW	36.019104	37.935832	64.521624
DA	49.180940	61.408760	210.330920
DE	307.509595	507.896200	2103.405190
DF	0.238680	0.238680	37.895013
DH	0.358023	0.426348	1.060404
DI	130.050630	165.836955	1049.168078
DL	96.264960	110.640680	326.236200
DN	25.248800	30.544224	62.808096
DU	0.251741	1.058690	161.355315
DV	1.743070	1.743070	25.192930
DY	21.642456	34.058344	152.355164
EB	8.149404	10.503048	94.958580
EE	2.616119	3.910070	18.324926
EG	1493.817413	1905.701475	30243.758780
EH	0.085176	0.237276	42.569748
EL	71.949306	109.125159	109.125159
EP	78.526968	112.766654	1063.594578
EU	22.641144	49.085352	6501.264480
FC	36.394008	56.714448	3030.655824

```
FD         1.870155      4.880214    1578.654237
FE      7345.143424  10647.951650  143224.682300
FI         9.945452     11.516657      35.851039
FL         3.028141      6.238814     137.932739
FR         1.131000      1.512060    1244.227020
FS         0.250601      0.535067      31.365763
GB        18.771436     25.608406     135.781294
GE        72.611063    127.591671    1497.351958
GF      7838.273610  19035.709240  143790.071200
GH        30.608946     36.863947      81.210825
GI        41.007968     67.931664     191.194764
GL         0.337827     21.978000      21.978000
Class      0.000000      0.000000       1.000000
```

- The **mean (average)** values for each variable vary significantly, ranging from very small values (e.g., 0.03 for CH) to much larger values (e.g., 3502 for AF). This suggests that the variables have different scales and magnitudes.
- **Standard Deviation (Std)**: The standard deviation measures the variability or spread of data around the mean. Variables such as AF and GF have relatively high standard deviations, indicating that their data points are more spread out, while variables like CH and CL have lower standard deviations, suggesting less variability.
- **Minimum (Min) and Maximum (Max)**: The minimum and maximum values show the range of values within each variable. Some variables have a relatively small range (e.g., CH), while others have a wide range (e.g., AF and GF).
- **Outliers**: Some variables have a wide gap between the 75th percentile and the maximum value, indicating the possible presence of outliers in those variables. These outliers could significantly affect the statistical analysis and may need to be addressed.
- **Skewness**: Skewness is a measure of the asymmetry of the distribution of data. Some variables may exhibit skewness, as indicated by differences between the mean and median (50th percentile) which will probably require some transformations like log-level one.

```
missing_values = train.isna().sum()
total_rows = len(train)
missing_percentage = (missing_values / total_rows) * 100

missing_data = pd.DataFrame({
    'Missing Values': missing_values,
    'Missing Percentage': missing_percentage,
    'Data Type': train.dtypes
})
```

```python
print("Training Dataset Missing Values:\n")
missing_data[missing_data['Missing Percentage']!=0]
```

```
Training Dataset Missing Values:


    Missing Values  Missing Percentage Data Type
BQ              60            9.724473   float64
CB               2            0.324149   float64
CC               3            0.486224   float64
DU               1            0.162075   float64
EL              60            9.724473   float64
FC               1            0.162075   float64
FL               1            0.162075   float64
FS               2            0.324149   float64
GL               1            0.162075   float64
```

```python
print("Number of duplicate rows:")
train.duplicated().sum()
```

```
Number of duplicate rows:

0
```

```python
greeks.describe()
```

```
                  Id Alpha Beta Gamma Delta  Epsilon
count            617   617  617   617   617      617
unique           617     4    3     8     4      198
top     000ff2bfdfe9     A    C     M     B  Unknown
freq               1   509  407   445   456      144
```

```python
greeks.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 617 entries, 0 to 616
Data columns (total 6 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   Id       617 non-null    object
 1   Alpha    617 non-null    object
 2   Beta     617 non-null    object
 3   Gamma    617 non-null    object
 4   Delta    617 non-null    object
 5   Epsilon  617 non-null    object
dtypes: object(6)
memory usage: 29.0+ KB
```

```python
print("Number of duplicate rows:")
greeks.duplicated().sum()
```

```
Number of duplicate rows:
```

```
0
```

Donut chart for label column: Class

```
# Data
plot_df = train.Class.value_counts().reset_index()
plot_df.columns = ['Class', 'Count']

# Create a donut chart
fig = px.pie(plot_df, names='Class',
values='Count',hole=0.7,color_discrete_sequence=["Black","Red"] )
fig.update_layout(title='Class Proportion in Training Data',
showlegend=False)

fig.add_annotation(
    x=0.5,
    y=0.5,
    align="center",
    xref="paper",
    yref="paper",
    showarrow=False,
    font_size=22,
    text="Class<br>Imbalance",
)

fig.update_traces(
    hovertemplate=None,
    textposition="outside",
    texttemplate="Class %{label}<br>%{value}<br>%{percent}",
    textfont_size=16,
    rotation=-20,
    marker_line_width=25,
    marker_line_color="white",
)

# Show the chart
fig.show()
```

Important: From the pie chart we can see that the dataset is heavily imbalanced since the fraction of positive(`1`) samples is very small compared to the negative(`0`) samples.

Exploring the distribution

Correlation!!

```
pearson_corr = (
    train.drop("Class", axis=1).corr(numeric_only=True,
method="pearson").round(2)
)
```

```
mask = np.triu(np.ones_like(pearson_corr, dtype=bool))
lower_triangular_corr = (
    pearson_corr.mask(mask)
    .dropna(axis="index", how="all")
    .dropna(axis="columns", how="all")
)

heatmap = go.Heatmap(
    z=lower_triangular_corr,
    x=lower_triangular_corr.columns,
    y=lower_triangular_corr.index,
    text=lower_triangular_corr.fillna(""),
    texttemplate="%{text}",
    showscale=True,
    colorbar_len=1.02,
    hoverinfo="none",
)
fig = go.Figure(heatmap)
fig.update_layout(
    title="Pearson Correlation Matrix",
    title_font_size=18,
    width=840,
    height=840,
    xaxis_showgrid=False,
    yaxis_showgrid=False,
    yaxis_autorange="reversed",
)
fig.show()

corr_threshold = 0.7

# Create a mask for values above the correlation threshold
corr_mask = lower_triangular_corr.abs() > corr_threshold

# Filter the DataFrame to get pairs with correlations above the
threshold
highest_abs_corr = (
    lower_triangular_corr[corr_mask]
    .stack()
    .sort_values(ascending=False)
    .reset_index()
    .rename(columns={"level_0": "Feature 1", "level_1": "Feature 2",
0: "Absolute Pearson Correlation"})
)

# Display the highest absolute correlations
highest_abs_corr
```

	Feature 1	Feature 2	Absolute Pearson Correlation
0	FD	EH	0.97

1	DV	CL	0.95
2	BZ	BC	0.91
3	EH	DU	0.85
4	DV	AR	0.82
5	FD	DU	0.81
6	EP	CS	0.79
7	EP	AR	0.75
8	AR	AH	0.75
9	BD	BC	0.75
10	DV	AH	0.75
11	CL	AR	0.75
12	EB	AR	0.74
13	EP	EB	0.73
14	CS	AR	0.72
15	EP	DV	0.72
16	EB	AH	0.71

Highest Pearson Correlation - Pair Plots

```
n_cols = 5
n_rows = len(highest_abs_corr)//n_cols + 1

fig = make_subplots(
    rows=n_rows,
    cols=n_cols,
    horizontal_spacing=0.1,
    vertical_spacing=0.06,
)

r = 1
c = 1

for feature1, feature2 in zip(highest_abs_corr['Feature
1'],highest_abs_corr['Feature 2']):
    scatter_data = train[[feature1, feature2,'Class']]
    fig.add_scatter(
        x=train[train["Class"] == 0][feature1],
        y=train[train["Class"] == 0][feature2],
        mode="markers",
        name="Class 1",
        marker=dict(color="#010D36", size=2, symbol="circle",
opacity=0.5),
        legendgroup="Class 1",
        showlegend=False,
        row=r,
        col=c,
    )
    fig.add_scatter(
        x=train[train["Class"] == 1][feature1],
        y=train[train["Class"] == 1][feature2],
```

```
        mode="markers",
        name="Class 1",
        marker=dict(color="#FF2079", size=2, symbol="circle",
opacity=0.5),
        legendgroup="Class 1",
        showlegend=False,
        row=r,
        col=c,
    )
    fig.update_xaxes(
        type="log",
        title_text=feature1,
        titlefont_size=9,
        titlefont_family="Arial Black",
        tickfont_size=7,
        row=r,
        col=c,
    )
    fig.update_yaxes(
        type="log",
        title_text=feature2,
        titlefont_size=9,
        titlefont_family="Arial Black",
        tickfont_size=7,
        row=r,
        col=c,
    )

    c+=1
    if c > n_cols:
      c = 1
      r += 1
    if r>5:
        break

fig.update_annotations(font_size=14)
fig.update_layout(
    title="Highest Pearson Correlations - Pair Plots<br>Logarithmic
Scale",
    title_font_size=18,
        width=1400,
        height=800
    )

fig.show()
```

The highest correlation is between EH - FD (0.97), and this is clearly visible there. Moreover, values associated with Class 0 are shifted towards higher values. A similar situation occurs within DU - EH and DU - FD. Unfortunately, we don't know what these abbreviations mean.

Moreover, we can see that many different values of a given feature correspond to one specific value from the second one. It may account for a little problem for machine learning algorithms. Such a situation appears in each of the above relationships.

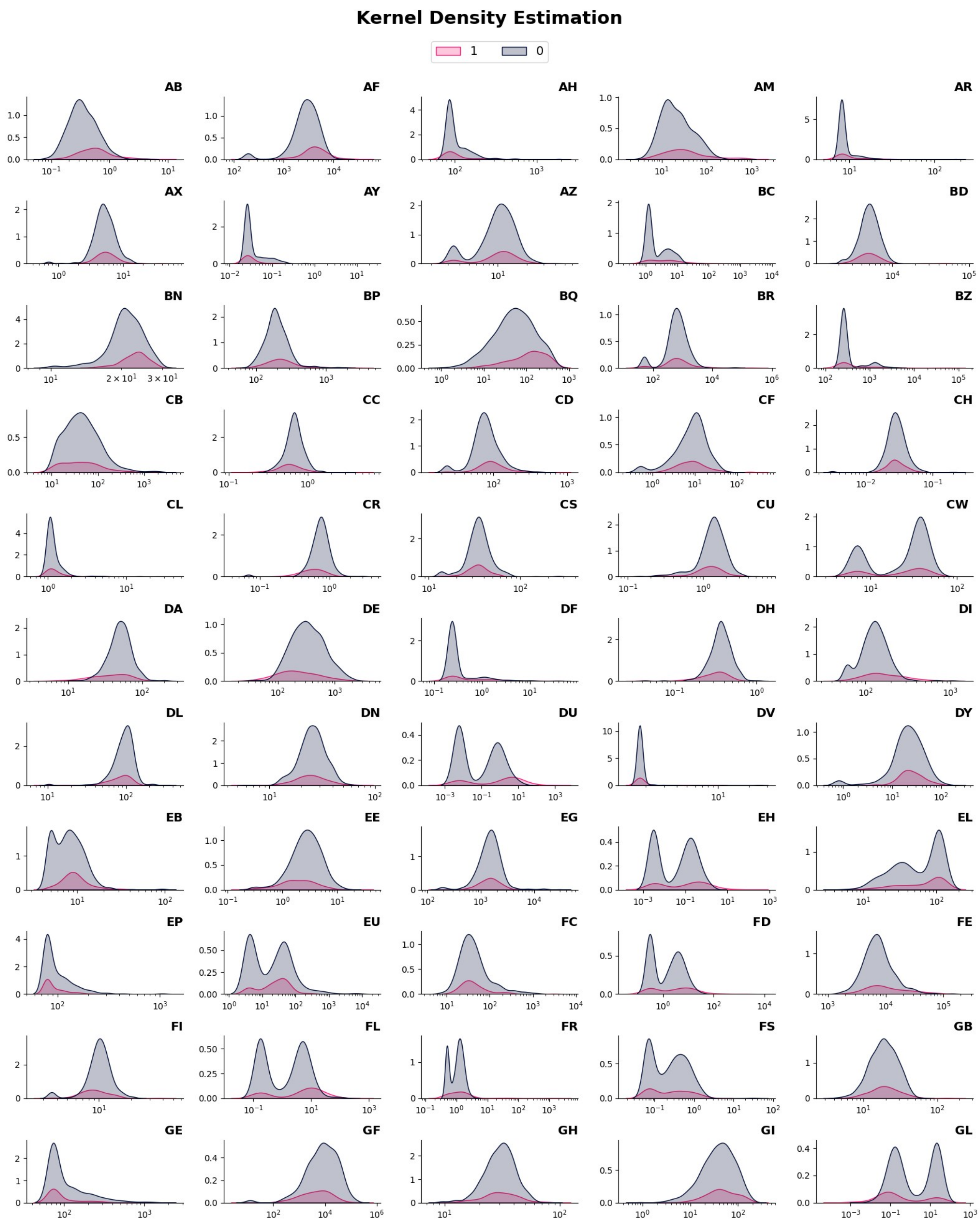
Pair Plots & Kernel Density Estimation

```
figsize = (4*4, 20)
fig = plt.figure(figsize=figsize)
numeric_columns = ['AB', 'AF', 'AH', 'AM', 'AR', 'AX', 'AY', 'AZ',
'BC', 'BD ', 'BN',
       'BP', 'BQ', 'BR', 'BZ', 'CB', 'CC', 'CD ', 'CF', 'CH', 'CL',
'CR', 'CS',
       'CU', 'CW ', 'DA', 'DE', 'DF', 'DH', 'DI', 'DL', 'DN', 'DU',
'DV', 'DY',
       'EB', 'EE', 'EG', 'EH', 'EL', 'EP', 'EU', 'FC', 'FD ', 'FE',
'FI',
       'FL', 'FR', 'FS', 'GB', 'GE', 'GF', 'GH', 'GI', 'GL']

for idx, col in enumerate(numeric_columns):
    ax = plt.subplot(11,5, idx + 1)
    sns.kdeplot(
        data=train, hue='Class', fill=True,
        x=col, palette=['#010D36','#FF2079'], legend=False,
log_scale=True
    )

    ax.set_ylabel(''); ax.spines['top'].set_visible(False),
    ax.set_xlabel(''); ax.spines['right'].set_visible(False)
    ax.set_title(f'{col}', loc='right',
                 weight='bold', fontsize=14)

fig.suptitle(f'Kernel Density Estimation\n\n\n', ha='center',
fontweight='bold', fontsize=21)
fig.legend([1, 0], loc='upper center', bbox_to_anchor=(0.5, 0.96),
fontsize=14, ncol=3)
plt.tight_layout()
plt.show()
```



Well, here we've got a diversity of variables, i.e. some of them probably relatively good fit a normal distribution, while some have long tails (and extremely long tails), like AR, AY, BR, BZ, etc. Moreover, there are even bimodal distributions. We will better understand the diversity between classes on the cumulative plots, as below.

Probability Plots & Transformations

A probability plot, also known as a probability-probability plot or P-P plot, is a graphical tool used in statistics to assess the similarity between the observed data and a specific probability distribution, typically a theoretical distribution like the normal distribution. It helps you visually compare the observed data to the expected distribution to check for goodness-of-fit.

On such a plot, samples which follow normal distribution are deployed on a diagonal straight line.

Some machine learning models assume that the variable follows a normal distribution. In turn, the mentioned technique helps to decide which transformations should be done within the given variable to improve the fit to that distribution.

```
import plotly.subplots as sp
import plotly.graph_objs as go
import pandas as pd
import scipy.stats as stats
import numpy as np

# Calculate the number of rows and columns for subplots
num_plots = len(numeric_columns)
num_rows = (num_plots + 4) // 5
num_cols = min(5, num_plots)
# Create subplots
fig = sp.make_subplots(rows=num_rows, cols=num_cols,
subplot_titles=numeric_columns)

# Loop through numeric columns and create PP plots
for i, col in enumerate(numeric_columns):
    row_idx = i // num_cols + 1  # Row index starts from 1
    col_idx = i % num_cols + 1   # Column index starts from 1

    # Create a PP plot using scipy's probplot function
    (osm, osr), (slope, intercept, R) =
stats.probplot(train[col].dropna(), rvalue=True)
    x_theory = np.array([osm[0], osm[-1]])
    y_theory = intercept + slope * x_theory
    R2 = f"R\u00b2 = {R * R:.2f}"

    fig.add_scatter(x=osm, y=osr, mode="markers", row=row_idx,
col=col_idx, name=col)
    fig.add_scatter(x=x_theory, y=y_theory, mode="lines", row=row_idx,
col=col_idx)
    fig.add_annotation(
        x=-1.25,
        y=osr[-1] * 0.75,
        text=R2,
        showarrow=False,
        row=row_idx,
```

```
        col=col_idx,
        font_size=9,
    )
    fig.update_yaxes(tickfont_size=7, row=row_idx, col=col_idx)
    fig.update_xaxes(
        titlefont_size=9,
        titlefont_family="Arial Black",
        tickfont_size=7,
        row=row_idx,
        col=col_idx,
    )

fig.update_layout(
    title="Numerical Features - Probability Plots against Normal 
Distribution",
    title_font_size=18,
    showlegend=False,
    width=800,
    height=1000,
)
fig.update_traces(
    marker=dict(size=1, symbol="x-thin", line=dict(width=2, 
color="#010D36")),
    line_color="#FF2079",
)
fig.show()
```

Some variables fit a normal distribution well, which manifests by a high coefficient of determination (R-squared) and evenly deployed samples around the straight line. These are for example DN or BN.

Nevertheless, there are a lot of features which do not fit the normal one. We can improve that by specific transformations:

- **Log Transformation** - generally works fine with right-skewed data. Requires non-negative numbers.
- **Square Root Transformation** - similarly to log-level transformation. Requires non-negative numbers.
- **Square Transformation** - helps to reduce left-skewed data.
- **Reciprocal Transformation** - used sometimes, when data is skewed, or there are obvious outliers. Not defined at zero.
- **Box-Cox Transformation** - used when data is skewed or has outliers. Requires strictly positive numbers.
- **Yeo-Johnson Transformation** - variation of Box-Cox transformation, but without restrictions concerning numbers.
- Let's check all of these transformations for our variables. We simply use the probplot() function to get R-squared coefficients for each transformation.

```
from collections import defaultdict
r2_scores = defaultdict(tuple)
for feature in numeric_columns:
    actual = train[feature].dropna()
    _, (*_, R_actual) = stats.probplot(actual, rvalue=True)
    _, (*_, R_log) = stats.probplot(np.log(actual), rvalue=True)
    _, (*_, R_sqrt) = stats.probplot(np.sqrt(actual), rvalue=True)
    _, (*_, R_reci) = stats.probplot(np.reciprocal(actual),
rvalue=True)
    _, (*_, R_boxcox) = stats.probplot(stats.boxcox(actual)[0],
rvalue=True)
    _, (*_, R_yeojohn) = stats.probplot(stats.yeojohnson(actual)[0],
rvalue=True)
    r2_scores[feature] = (
        R_actual * R_actual,
        R_log * R_log,
        R_sqrt * R_sqrt,
        R_reci * R_reci,
        R_boxcox * R_boxcox,
        R_yeojohn * R_yeojohn,
    )

r2_scores = pd.DataFrame(
    r2_scores, index=("Original", "Log", "Sqrt", "Reciprocal",
"BoxCox", "YeoJohnson")
).T

r2_scores["Max_R2"] = r2_scores.max(axis=1)
r2_scores["Winner"] = r2_scores.idxmax(axis=1)
r2_scores
```

```
     Original       Log      Sqrt  Reciprocal    BoxCox  YeoJohnson
Max_R2  \
AB   0.537195  0.976071  0.820288    0.919818  0.998107    0.991143
0.998107
AF   0.761133  0.871797  0.945411    0.344347  0.955054    0.955098
0.955098
AH   0.237829  0.567640  0.415764    0.678381  0.686058    0.686064
0.686064
AM   0.383144  0.958737  0.715838    0.903156  0.996761    0.995844
0.996761
AR   0.158397  0.421770  0.299171    0.505032  0.515449    0.515495
0.515495
AX   0.745500  0.917768  0.912345    0.488744  0.937514    0.950425
0.950425
AY   0.038600  0.572584  0.231879    0.641586  0.633691    0.626888
0.641586
AZ   0.942194  0.902788  0.953193    0.722089  0.956941    0.957626
0.957626
BC   0.057783  0.740394  0.308317    0.723142  0.738835    0.744935
```

```
0.744935
BD   0.412282  0.924370  0.730386    0.918367  0.961509    0.961520
0.961520
BN   0.982099  0.928739  0.961476    0.825362  0.993600    0.993580
0.993600
BP   0.461899  0.905478  0.712543    0.971848  0.986447    0.986567
0.986567
BQ   0.812398  0.977717  0.939916    0.485671  0.984550    0.983672
0.984550
BR   0.055811  0.885948  0.397579    0.457543  0.887074    0.887841
0.887841
BZ   0.086862  0.502319  0.346967    0.502719  0.481912    0.481920
0.502719
CB   0.317032  0.952747  0.690670    0.881848  0.978588    0.978439
0.978588
CC   0.673966  0.948966  0.868570    0.847414  0.952309    0.975135
0.975135
CD   0.686465  0.941333  0.871289    0.743286  0.941202    0.941889
0.941889
CF   0.453262  0.947208  0.870999    0.450216  0.968046    0.979463
0.979463
CH   0.599988  0.898763  0.825710    0.422958  0.900935    0.975738
0.975738
CL   0.151457  0.435171  0.277955    0.628105  0.721774    0.718286
0.721774
CR   0.835590  0.812355  0.913398    0.323328  0.912846    0.941255
0.941255
CS   0.531470  0.913486  0.792626    0.818609  0.920400    0.922159
0.922159
CU   0.948658  0.904454  0.972254    0.547978  0.974273    0.978779
0.978779
CW   0.805405  0.723434  0.765556    0.652644  0.801058    0.803982
0.805405
DA   0.909082  0.954343  0.976473    0.672694  0.979144    0.979560
0.979560
DE   0.806895  0.998046  0.941718    0.759547  0.998048    0.998064
0.998064
DF   0.179709  0.537371  0.409527    0.549016  0.529052    0.536364
0.549016
DH   0.965479  0.931629  0.982158    0.524439  0.983225    0.989231
0.989231
DI   0.655187  0.958293  0.850923    0.932682  0.977697    0.977845
0.977845
DL   0.904739  0.824056  0.924321    0.362192  0.928338    0.928656
0.928656
DN   0.957602  0.986776  0.988740    0.854012  0.992372    0.992653
0.992653
DU   0.145653  0.833323  0.610286    0.673193  0.821972    0.829112
0.833323
```

```
DV   0.096076  0.176720  0.137523    0.220881  0.253917    0.253675
0.253917
DY   0.853920  0.883918  0.974051    0.288298  0.979453    0.982654
0.982654
EB   0.465145  0.912420  0.755278    0.937628  0.949643    0.950555
0.950555
EE   0.854700  0.978933  0.976729    0.621592  0.995538    0.997789
0.997789
EG   0.358601  0.905506  0.710396    0.527721  0.905899    0.906060
0.906060
EH   0.094971  0.852936  0.580548    0.666167  0.850948    0.857032
0.857032
EL   0.799947  0.838279  0.827087    0.717439  0.819070    0.818347
0.838279
EP   0.356975  0.689508  0.557657    0.773526  0.771434    0.771460
0.773526
EU   0.104789  0.898208  0.476711    0.760645  0.897454    0.897554
0.898208
FC   0.258714  0.899376  0.598341    0.920140  0.990775    0.991654
0.991654
FD   0.046164  0.865867  0.408159    0.707177  0.853494    0.864380
0.865867
FE   0.521984  0.954013  0.778517    0.902705  0.992014    0.992018
0.992018
FI   0.909043  0.909730  0.942588    0.717941  0.942332    0.943853
0.943853
FL   0.410031  0.843535  0.789117    0.671201  0.847307    0.858882
0.858882
FR   0.023201  0.759319  0.132019    0.838942  0.890760    0.911057
0.911057
FS   0.138256  0.896390  0.682564    0.787605  0.889818    0.888394
0.896390
GB   0.826848  0.993463  0.958838    0.872173  0.993409    0.994011
0.994011
GE   0.445490  0.692298  0.594819    0.742418  0.730661    0.730683
0.742418
GF   0.678426  0.948683  0.920366    0.110029  0.996524    0.996596
0.996596
GH   0.961661  0.986407  0.991705    0.865216  0.994028    0.994194
0.994194
GI   0.900398  0.975590  0.983979    0.381367  0.997190    0.996976
0.997190
GL   0.656634  0.829559  0.703707    0.133046  0.832609    0.720029
0.832609

         Winner
AB       BoxCox
AF   YeoJohnson
AH   YeoJohnson
```

AM	BoxCox
AR	YeoJohnson
AX	YeoJohnson
AY	Reciprocal
AZ	YeoJohnson
BC	YeoJohnson
BD	YeoJohnson
BN	BoxCox
BP	YeoJohnson
BQ	BoxCox
BR	YeoJohnson
BZ	Reciprocal
CB	BoxCox
CC	YeoJohnson
CD	YeoJohnson
CF	YeoJohnson
CH	YeoJohnson
CL	BoxCox
CR	YeoJohnson
CS	YeoJohnson
CU	YeoJohnson
CW	Original
DA	YeoJohnson
DE	YeoJohnson
DF	Reciprocal
DH	YeoJohnson
DI	YeoJohnson
DL	YeoJohnson
DN	YeoJohnson
DU	Log
DV	BoxCox
DY	YeoJohnson
EB	YeoJohnson
EE	YeoJohnson
EG	YeoJohnson
EH	YeoJohnson
EL	Log
EP	Reciprocal
EU	Log
FC	YeoJohnson
FD	Log
FE	YeoJohnson
FI	YeoJohnson
FL	YeoJohnson
FR	YeoJohnson
FS	Log
GB	YeoJohnson
GE	Reciprocal
GF	YeoJohnson

```
GH   YeoJohnson
GI       BoxCox
GL       BoxCox
```

It seems that the Yeo-Johnson transformation is the most frequently chosen transformation method that produces the highest R-squared value. However, other methods like Box-Cox and Log also appear as winners in some cases.

```
#Getting columns corresponding to their winning transformations
no_transform_cols = r2_scores[r2_scores["Winner"] == "Original"].index
log_transform_cols = r2_scores[r2_scores["Winner"] == "Log"].index
sqrt_transform_cols = r2_scores[r2_scores["Winner"] == "Sqrt"].index
reciprocal_transform_cols = r2_scores[r2_scores["Winner"] ==
"Reciprocal"].index
boxcox_transform_cols = r2_scores[r2_scores["Winner"] ==
"BoxCox"].index
yeojohnson_transform_cols = r2_scores[r2_scores["Winner"] ==
"YeoJohnson"].index

train_transformed = train.copy()

def transformations(data):
    for col in log_transform_cols:
        data[col] = np.log(data[col])

    # Applying sqrt transformation to specific columns
    for col in sqrt_transform_cols:
        data[col] = np.sqrt(data[col])

    # Applying reciprocal transformation to specific columns
    for col in reciprocal_transform_cols:
        data[col] = 1 / data[col]

    # Applying Box-Cox transformation to specific columns
    for col in boxcox_transform_cols:
        index = data.index[data[col].notna()]
        null_index = data.index[data[col].isna()]
        data.loc[index,col] =
stats.boxcox(data.drop(null_index,axis=0)[col])[0]

    # Applying Yeo-Johnson transformation to specific columns
    for col in yeojohnson_transform_cols:
        index = data.index[data[col].notna()]
        null_index = data.index[data[col].isna()]
        data.loc[index,col] =
stats.yeojohnson(data.drop(null_index,axis=0)[col])[0]
    return data

train_transformed = transformations(train_transformed)
```

Probability Plots - Again!

```
import plotly.subplots as sp
import plotly.graph_objs as go
import pandas as pd
import scipy.stats as stats
import numpy as np

# Calculate the number of rows and columns for subplots
num_plots = len(numeric_columns)
num_rows = (num_plots + 4) // 5
num_cols = min(5, num_plots)
# Create subplots
fig = sp.make_subplots(rows=num_rows, cols=num_cols,
subplot_titles=numeric_columns)

semi_const = []
# Loop through numeric columns and create PP plots
for i, col in enumerate(numeric_columns):
    row_idx = i // num_cols + 1  # Row index starts from 1
    col_idx = i % num_cols + 1   # Column index starts from 1

    # Create a PP plot using scipy's probplot function
    (osm, osr), (slope, intercept, R) =
stats.probplot(train_transformed[col].dropna(), rvalue=True)
    x_theory = np.array([osm[0], osm[-1]])
    y_theory = intercept + slope * x_theory
    R2 = f"R\u00b2 = {R * R:.2f}"
    if R*R < 0.8:
        semi_const.append(col)

    fig.add_scatter(x=osm, y=osr, mode="markers", row=row_idx,
col=col_idx, name=col)
    fig.add_scatter(x=x_theory, y=y_theory, mode="lines", row=row_idx,
col=col_idx)
    fig.add_annotation(
        x=-1.25,
        y=osr[-1] * 0.75,
        text=R2,
        showarrow=False,
        row=row_idx,
        col=col_idx,
        font_size=9,
    )
    fig.update_yaxes(tickfont_size=7, row=row_idx, col=col_idx)
    fig.update_xaxes(
#         title_text=col,
        titlefont_size=9,
        titlefont_family="Arial Black",
        tickfont_size=7,
```

```
        row=row_idx,
        col=col_idx,
    )

fig.update_layout(
    title="Numerical Features - Probability Plots against Normal
Distribution",
    title_font_size=18,
    showlegend=False,
    width=800,
    height=1000,
)
fig.update_traces(
    marker=dict(size=1, symbol="x-thin", line=dict(width=2,
color="#010D36")),
    line_color="#FF2079",
)
fig.show()

#All the variables that did not improve on transformation
semi_const
```

```
['AH', 'AR', 'AY', 'BC', 'BZ', 'CL', 'DF', 'DV', 'EP', 'GE']
```

As you can see above, the transformations works perfectly for some variables. Sometimes models like SVC handle very well, and appropriate transformations for these algorithms are crucial. Let's look closely at these values we've got.

There is something problematic with some variables, i.e., these that have especially poor transformation results. Let's specify, and look at them closely:

AH,AY,AR, BZ, DF, and DV

```
#Let's see whats in there for the worst ones
train[["AH","AY","AR","BZ","DF","DV"]]
```

	AH	AY	AR	BZ	DF	DV
0	85.200147	0.025578	8.138688	257.432377	0.238680	1.74307
1	85.200147	0.025578	8.138688	257.432377	0.238680	1.74307
2	85.200147	0.025578	8.138688	257.432377	0.238680	1.74307
3	120.201618	0.025578	8.138688	257.432377	0.238680	1.74307
4	85.200147	0.054810	8.138688	257.432377	0.238680	1.74307
..	...	...	...	...	...	...
612	123.763599	0.077343	13.020852	257.432377	0.238680	2.41906
613	85.200147	0.025882	15.973224	257.432377	0.238680	1.74307
614	130.138587	0.025578	10.005552	257.432377	0.238680	1.74307
615	85.200147	0.025578	8.138688	257.432377	0.532818	1.74307
616	546.663930	0.116928	8.138688	257.432377	0.238680	1.74307

[617 rows x 6 columns]

```
problematic_cols = train[["AH","AY","AR","BZ","DF","DV"]]
print("% of Duplicate Entries",
problematic_cols.duplicated().sum()/problematic_cols.shape[0])

% of Duplicate Entries 0.29983792544570503
```

Okay, there we have just mostly the **same value for the whole variable**. That's the reason for weak transformations. **It's good to check other semi-constant variables.**

```
semi_const = ["AH","AY","AR","BC","BZ","CL","DF","DV","EP","GE"]
semi_const_class = semi_const + ["Class"]
train[semi_const_class].corr()["Class"]

AH        0.044645
AY        0.082420
AR        0.064380
BC        0.155882
BZ        0.112423
CL        0.016852
DF        0.064272
DV        0.015477
EP       -0.068383
GE       -0.070766
Class     1.000000
Name: Class, dtype: float64
```

Weak correlations with Class. These features can be binarized.

```
import pandas as pd

def binarize_columns_by_mean(data, columns_to_binarize,
threshold=None):
    """
    Binarize columns in a DataFrame based on their mean.
    """
    # Calculate the mean of each column
    column_means = data[columns_to_binarize].mean()
    if threshold is None:
        threshold = column_means
    data_binarized = data[columns_to_binarize] > threshold
    data = pd.concat([data, data_binarized], axis=1)
    data.drop(columns=columns_to_binarize, inplace=True)
    return data

train_transformed = binarize_columns_by_mean(train_transformed, ["AH",
"AY", "AR", "BC", "BZ", "CL", "DF", "DV", "EP", "GE"])
```

Categorical Variables: EJ

In the whole dataset, there is only one categorical feature - EJ. Let's focus on this.

```
import plotly.express as px

# Data
plot_df = train.groupby(["EJ","Class"])["Id"].count().reset_index()
plot_df.columns = ['EJ', 'Class', 'Count']

# Create a nested donut chart
fig = px.sunburst(
    plot_df,
    path=['EJ', 'Class'],
    values='Count',
    color='EJ',
    color_discrete_sequence=["Black", "Light Blue"],
)
fig.update_layout(title='Nested Donut Chart - EJ Value Proportion in
Training Data')

# Calculate proportions
total_counts = plot_df['Count'].sum()
plot_df['Proportion'] = plot_df['Count'] / total_counts

# Add custom labels with proportions and counts
fig.update_traces(
    textinfo='label+percent entry+value',
    texttemplate="Class %{label}<br>%{value}<br>%{percentParent}",
    hovertemplate='<b>%{label}</b><br>Count: %{value}<br>Proportion: %
{percentEntry}',
    textfont_size=14,
    insidetextorientation='horizontal',  # Horizontal percentage
labels
)

# Show the chart
fig.show()
```

Modelling

Started off with simple baseline models, and then used GridSearchCV to tune Hyperparameters. A combination of tree-based models and SVMs worked pretty well.

```
def balanced_log_loss(y_true,y_prob,y_pred=None,**kwargs):
    """Competition evaluation metric - balanced logarithmic loss.
    The overall effect is such that each class is roughly equally
    important for the final score."""
    if y_pred is None:
```

```
        y_pred = (y_prob >= 0.5).astype(int)

    N0, N1 = np.bincount(y_true)
    y0 = np.where(y_true == 0, 1, 0)
    y1 = np.where(y_true == 1, 1, 0)

    eps = kwargs.get("eps", 1e-15)
    y_pred = np.clip(y_pred, eps, 1 - eps)
    p0 = np.log(1 - y_pred)
    p1 = np.log(y_pred)

    return -(1 / N0 * np.sum(y0 * p0) + 1 / N1 * np.sum(y1 * p1)) *
0.5

def evaluate(y_true,y_pred):
    # Calculate the confusion matrix
    cm = confusion_matrix(y_true, y_pred)

    # Plot the confusion matrix with color using seaborn
    plt.figure(figsize=(4,4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', linewidths=0.5,
cbar=False)
    plt.title("Confusion Matrix")
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()

    # Generate and print the classification report
    class_report = classification_report(y_val, y_pred,
target_names=['Class 0', 'Class 1'])
    print("Classification Report:\n", class_report)
    print("Log_Loss:",balanced_log_loss(y_true,y_pred))

# from lightgbm import LGBMClassifier

# # Define the parameter grid for hyperparameter tuning, optimal
ranges were choosen after trial and error
# lgbm_params = {
#     "max_depth": [2,3,5],
#     "num_leaves": [2,4,6],
#     "min_child_samples": [11,13,17],
#     "n_estimators": [100,200,300],
#     "learning_rate": [0.10,0.15,0.20],
#     "colsample_bytree": [0.2,0.4,0.6],
#     "min_split_gain": [1e-2,1e-3,1e-4],
#     "reg_alpha": [1e-1,1e-2,1e-3],
#     "reg_lambda": [5e-1,5e-2,5e-3]
# }
# # Create a RandomForestClassifier
# lgbm_classifier = LGBMClassifier(random_state=42)
```

```
# # Create a GridSearchCV object with custom scoring function
# grid_search = GridSearchCV(
#     estimator=lgbm_classifier,
#     param_grid=lgbm_params,
#     scoring=make_scorer(balanced_log_loss, greater_is_better=False),
# Use the custom scoring function
#     cv=5,  # Cross-validation folds
#     n_jobs=-1  # Use all available CPU cores
# )

# # Fit the grid search to the data
# grid_search.fit(X_train, y_train)

# # Get the best estimator and best hyperparameters
# best_lgbm_classifier = grid_search.best_estimator_
# best_params = grid_search.best_params_

# # Calculate the average log loss across cross-validation folds
# log_loss_values = -grid_search.cv_results_['mean_test_score']
# average_log_loss = np.mean(log_loss_values)

# print("Average_Log_Loss:",average_log_loss)
# print("Best Random Forest Classifier:", best_lgbm_classifier)
# print("Best Hyperparameters:", best_params)

from sklearn.preprocessing import FunctionTransformer,
PowerTransformer

def splitXy(df, kind = "train"):
    df['EJ'].replace({"A": 0, "B": 1}, inplace=True)
    if kind == "train":
        X = df.drop(["Id", "Class"], axis=1).apply(lambda x:
x.fillna(x.mean()))
        y = df["Class"]
    else:
        X = df.drop(["Id"], axis=1).apply(lambda x:
x.fillna(x.mean()))
        y = np.nan

    return X, y

def binarize_columns_by_mean(data, columns_to_binarize,
threshold=None):
        column_means = data[columns_to_binarize].mean()
        if threshold is None:
            threshold = column_means
        data_binarized = data[columns_to_binarize] > threshold
        data = pd.concat([data, data_binarized], axis=1)
        data.drop(columns=columns_to_binarize, inplace=True)
```

```
        return data

X,y = splitXy(train)

# Split the data into training, validation, and test sets with
stratified sampling
Xtrain, Xval, ytrain, yval = train_test_split(X, y, test_size=0.2,
random_state=42, stratify=y)

# Define the log transformation function
log_transformer = FunctionTransformer(np.log1p, validate=True)
Xtrain[log_transform_cols] =
log_transformer.transform(Xtrain[log_transform_cols])
Xval[log_transform_cols] =
log_transformer.transform(Xval[log_transform_cols])

# Define the reciprocal transformation function
reciprocal_transformer = FunctionTransformer(lambda x: 1 / x,
validate=True)
Xtrain[reciprocal_transform_cols] =
reciprocal_transformer.transform(Xtrain[reciprocal_transform_cols])
Xval[reciprocal_transform_cols] =
reciprocal_transformer.transform(Xval[reciprocal_transform_cols])

# Initialize the PowerTransformer
box_cox_transformer = PowerTransformer(method='box-cox')

# Determine the constant offset
boffset = abs(np.min(Xtrain[boxcox_transform_cols])) + 0.1  # Adding
0.1 to ensure positivity

# Add the offset to both train and test data
Xtrain[boxcox_transform_cols] += boffset
Xval[boxcox_transform_cols] += boffset

Xtrain[boxcox_transform_cols] =
box_cox_transformer.fit_transform(Xtrain[boxcox_transform_cols])
Xval[boxcox_transform_cols] =
box_cox_transformer.transform(Xval[boxcox_transform_cols])

# Initialize the PowerTransformer
yoffset = abs(np.min(Xtrain[yeojohnson_transform_cols])) + 0.1  #
Adding 0.1 to ensure positivity
yeo_johnson_transformer = PowerTransformer(method='box-cox')
Xtrain[yeojohnson_transform_cols] += yoffset
Xval[yeojohnson_transform_cols] += yoffset

Xtrain[yeojohnson_transform_cols] =
yeo_johnson_transformer.fit_transform(Xtrain[yeojohnson_transform_cols
])
```

```
Xval[yeojohnson_transform_cols] =
yeo_johnson_transformer.transform(Xval[yeojohnson_transform_cols])

#Binarize
Xtrain = binarize_columns_by_mean(Xtrain,["AH", "AY", "AR", "BC",
"BZ", "CL", "DF", "DV", "EP", "GE"])
Xval = binarize_columns_by_mean(Xval,["AH", "AY", "AR", "BC", "BZ",
"CL", "DF", "DV", "EP", "GE"])
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432:
UserWarning:

X has feature names, but FunctionTransformer was fitted without
feature names

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432:
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feature names

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432:
UserWarning:

X has feature names, but FunctionTransformer was fitted without
feature names

/usr/local/lib/python3.10/dist-packages/numpy/core/fromnumeric.py:84:
FutureWarning:

In a future version, DataFrame.min(axis=None) will return a scalar min
over the entire DataFrame. To retain the old behavior, use
'frame.min(axis=0)' or just 'frame.min()'

/usr/local/lib/python3.10/dist-packages/numpy/core/fromnumeric.py:84:
FutureWarning:

In a future version, DataFrame.min(axis=None) will return a scalar min
over the entire DataFrame. To retain the old behavior, use
'frame.min(axis=0)' or just 'frame.min()'
```

```
# Scale the data using a scaler
scale = StandardScaler()
Xtrain = scale.fit_transform(Xtrain)
```

```python
Xval = scale.transform(Xval)

# Apply SMOTE to the training data only
smote = SMOTE(sampling_strategy='auto', random_state=42)
Xtrain_resampled, ytrain_resampled = smote.fit_resample(Xtrain,
ytrain)

# Define parameters here
xgb_params = {
    "max_depth": 2,
    "n_estimators": 200,
    "learning_rate": 0.4,
    "subsample": 0.6,
    "min_child_weight": 0.1,
    "max_delta_step": 0.35,
    "colsample_bytree": 0.3,
    "colsample_bylevel": 0.7,
    "min_split_loss": 1e-4,
    "reg_alpha": 2e-3,
    "reg_lambda": 6e-2,
}
svc_params = {
    "probability": True,
    "C": 3,
}
lgbm_params = {
    "max_depth": 3,
    "num_leaves": 8,
    "min_child_samples": 17,
    "n_estimators": 200,
    "learning_rate": 0.15,
    "colsample_bytree": 0.4,
    "min_split_gain": 1e-4,
    "reg_alpha": 1e-2,
    "reg_lambda": 5e-3,
}

# Create a pipeline with the VotingClassifier
current_ensemble = make_pipeline(
    VotingClassifier(
        estimators=[
            ("lgbm",LGBMClassifier(random_state=42, **lgbm_params)),
            ("xgb", xgb.XGBClassifier(random_state=42, **xgb_params)),
            ("svc", SVC(random_state=42, **svc_params)),
        ],
        voting="soft",
        weights=(0.46, 0.46, 0.08),
    ),
)
```

```
# Fit the ensemble on the training data
current_ensemble.fit(Xtrain_resampled, ytrain_resampled)

# Make predictions on the validation set
ypred_prob = current_ensemble.predict_proba(Xval)[:, 1]

# Convert probabilities to binary predictions
ypred = (ypred_prob >= 0.5).astype(int)

# Calculate Log Loss
logloss = log_loss(yval, ypred_prob)
print(f"Log Loss: {logloss:.4f}")

# Calculate accuracy
accuracy = accuracy_score(yval, ypred)
print(f"Accuracy: {accuracy:.4f}")
```

```
[LightGBM] [Info] Number of positive: 407, number of negative: 407
[LightGBM] [Warning] Auto-choosing col-wise multi-threading, the
overhead of testing was 0.000602 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 11144
[LightGBM] [Info] Number of data points in the train set: 814, number
of used features: 46
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 ->
initscore=0.000000
[LightGBM] [Warning] No further splits with positive gain, best gain:
-inf
[LightGBM] [Warning] No further splits with positive gain, best gain:
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[LightGBM] [Warning] No further splits with positive gain, best gain:
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
```

```
Log Loss: 0.1624
Accuracy: 0.9435
```

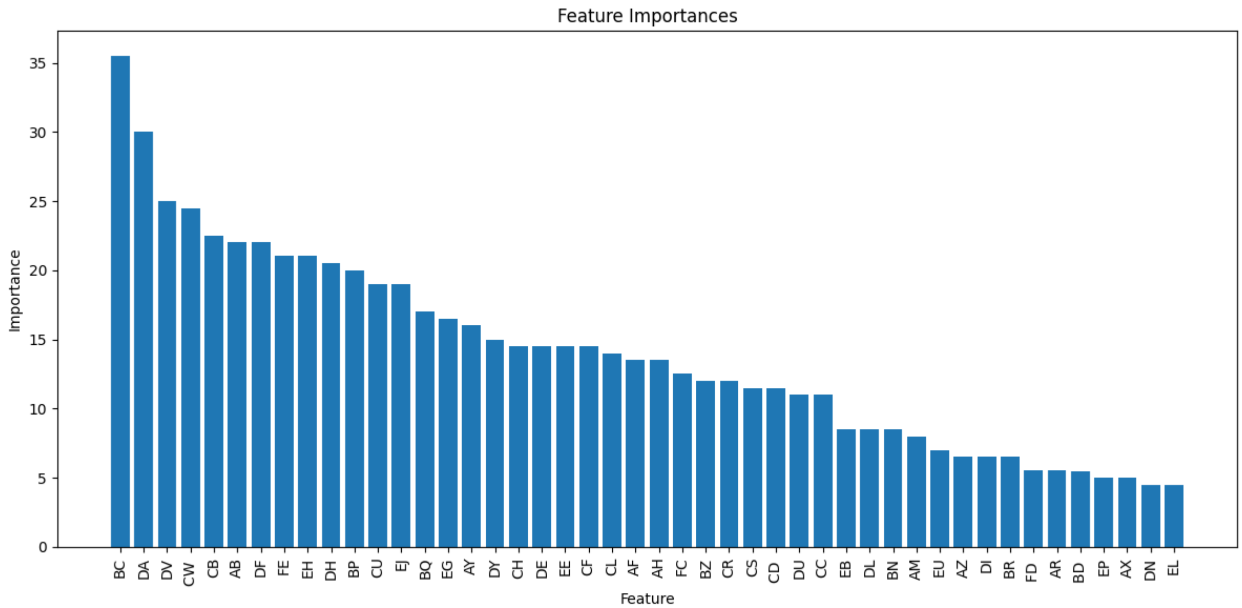
Visualize the model

```
# Extract feature importances from the individual models
lgbm_feature_importances =
current_ensemble.named_steps['votingclassifier'].estimators_[0].featur
e_importances_
xgb_feature_importances =
current_ensemble.named_steps['votingclassifier'].estimators_[1].featur
e_importances_
# Note: You may need to adjust the above lines depending on the naming
of your estimators in the VotingClassifier.

# Combine feature importances (you can use different strategies, such
as averaging or summing)
feature_importances = (lgbm_feature_importances +
xgb_feature_importances) / 2
feature_names = X.columns

# Sort feature importances and corresponding feature names in
descending order
sorted_indices = np.argsort(feature_importances)[::-1]
sorted_feature_importances = feature_importances[sorted_indices]
sorted_feature_names = feature_names[sorted_indices]

# Create a bar plot to visualize feature importances
plt.figure(figsize=(12, 6))
plt.bar(range(len(sorted_feature_importances)),
sorted_feature_importances)
plt.xticks(range(len(sorted_feature_importances)),
sorted_feature_names, rotation=90)
plt.xlabel('Feature')
plt.ylabel('Importance')
plt.title('Feature Importances')
plt.tight_layout()
plt.show()
```



Submission

```
test = pd.read_csv('test.csv')

Xtest,ytest = splitXy(test, kind="test")
Xtest[log_transform_cols] =
log_transformer.transform(Xtest[log_transform_cols])
Xtest[reciprocal_transform_cols] =
reciprocal_transformer.transform(Xtest[reciprocal_transform_cols])
Xtest[boxcox_transform_cols] =
box_cox_transformer.transform(Xtest[boxcox_transform_cols]+boffset)
Xtest[yeojohnson_transform_cols] =
yeo_johnson_transformer.transform(Xtest[yeojohnson_transform_cols]
+yoffset)
Xtest = binarize_columns_by_mean(Xtest,["AH", "AY", "AR", "BC", "BZ",
"CL", "DF", "DV", "EP", "GE"])

# Scale the data using a scaler
Xtest = scale.transform(Xtest)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432:
UserWarning:

X has feature names, but FunctionTransformer was fitted without
feature names

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432:
UserWarning:

X has feature names, but FunctionTransformer was fitted without
```

```
feature names

<ipython-input-30-7bc07b97278c>:32: RuntimeWarning:

divide by zero encountered in divide
```

```python
# Make predictions on the validation set
ypred_prob = current_ensemble.predict_proba(Xtest)[:, 1]

# Convert probabilities to binary predictions
ypred = (ypred_prob >= 0.5).astype(int)

class_1 = ypred_prob
class_0 = 1 - ypred_prob

sample_submission = pd.read_csv("sample_submission.csv")
sample_submission['class_0'] = class_0
sample_submission['class_1'] = class_1
sample_submission.to_csv('submission.csv', index=False)
sample_submission
```

	Id	class_0	class_1
0	00eed32682bb	0.912043	0.087957
1	010ebe33f668	0.912043	0.087957
2	02fa521e1838	0.912043	0.087957
3	040e15f562a2	0.912043	0.087957
4	046e85c7cc7f	0.912043	0.087957