# Binary Classification with a Software Defects Dataset

Your Goal: Predict defects in C programs given various various attributes about the code.

https://www.kaggle.com/competitions/playground-series-s3e23/overview

## Imports

In [57]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

## Data Exploration

In [58]:
```
df_train = pd.read_csv('train.csv')
df_train.head()
```

Out[58]:

| | id | loc | v(g) | ev(g) | iv(g) | n | v | l | d | i | ... | lOCode |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 22.000000 | 3.000000 | 1.000000 | 2.000000 | 60.000000 | 278.630000 | 0.060000 | 19.560000 | 14.250000 | ... | 17 |
| **1** | 1 | 14.000000 | 2.000000 | 1.000000 | 2.000000 | 32.000000 | 151.270000 | 0.140000 | 7.000000 | 21.110000 | ... | 11 |
| **2** | 2 | 11.000000 | 2.000000 | 1.000000 | 2.000000 | 45.000000 | 197.650000 | 0.110000 | 8.050000 | 22.760000 | ... | 8 |
| **3** | 3 | 8.000000 | 1.000000 | 1.000000 | 1.000000 | 23.000000 | 94.010000 | 0.190000 | 5.250000 | 17.860000 | ... | 4 |
| **4** | 4 | 11.000000 | 2.000000 | 1.000000 | 2.000000 | 17.000000 | 60.940000 | 0.180000 | 5.630000 | 12.440000 | ... | 7 |

5 rows × 23 columns

In [59]:
```
df_train=df_train.drop(['id'],axis=1)
```

In [60]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 101763 entries, 0 to 101762
Data columns (total 22 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   loc                101763 non-null  float64
 1   v(g)               101763 non-null  float64
 2   ev(g)              101763 non-null  float64
 3   iv(g)              101763 non-null  float64
 4   n                  101763 non-null  float64
 5   v                  101763 non-null  float64
 6   l                  101763 non-null  float64
 7   d                  101763 non-null  float64
 8   i                  101763 non-null  float64
 9   e                  101763 non-null  float64
 10  b                  101763 non-null  float64
 11  t                  101763 non-null  float64
 12  lOCode             101763 non-null  int64  
 13  lOComment          101763 non-null  int64  
 14  lOBlank            101763 non-null  int64  
 15  locCodeAndComment  101763 non-null  int64  
 16  uniq_Op            101763 non-null  float64
 17  uniq_Opnd          101763 non-null  float64
 18  total_Op           101763 non-null  float64
 19  total_Opnd         101763 non-null  float64
 20  branchCount        101763 non-null  float64
 21  defects            101763 non-null  bool   
dtypes: bool(1), float64(17), int64(4)
memory usage: 16.4 MB
```

In [61]:
```
df_train.isnull().sum()
```

Out[61]:
```
loc                  0
v(g)                 0
ev(g)                0
iv(g)                0
n                    0
v                    0
l                    0
d                    0
i                    0
e                    0
b                    0
t                    0
lOCode               0
lOComment            0
lOBlank              0
locCodeAndComment    0
uniq_Op              0
uniq_Opnd            0
total_Op             0
total_Opnd           0
branchCount          0
defects              0
dtype: int64
```

In [62]:
```
df_train.describe()
```

Out[62]:

| | loc | v(g) | ev(g) | iv(g) | n | v | l |
|---|---|---|---|---|---|---|---|
| **count** | 101763.000000 | 101763.000000 | 101763.000000 | 101763.000000 | 101763.000000 | 101763.000000 | 101763.000000 |
| **mean** | 37.347160 | 5.492684 | 2.845022 | 3.498826 | 96.655995 | 538.280956 | 0.111634 |
| **std** | 54.600401 | 7.900855 | 4.631262 | 5.534541 | 171.147191 | 1270.791601 | 0.100096 |
| **min** | 1.000000 | 1.000000 | 1.000000 | 1.000000 | 0.000000 | 0.000000 | 0.000000 |
| **25%** | 13.000000 | 2.000000 | 1.000000 | 1.000000 | 25.000000 | 97.670000 | 0.050000 |
| **50%** | 22.000000 | 3.000000 | 1.000000 | 2.000000 | 51.000000 | 232.790000 | 0.090000 |
| **75%** | 42.000000 | 6.000000 | 3.000000 | 4.000000 | 111.000000 | 560.250000 | 0.150000 |
| **max** | 3442.000000 | 404.000000 | 165.000000 | 402.000000 | 8441.000000 | 80843.080000 | 1.000000 |

8 rows × 21 columns

In [63]:

```
pd.set_option('float_format', '{:f}'.format)
```

In [64]:

```
# checking the variance of the data
df_train.var()
```

Out[64]:

```
loc                          2981.203824
v(g)                           62.423511
ev(g)                          21.448584
iv(g)                          30.631145
n                           29291.360964
v                         1614911.293984
l                               0.010019
d                             199.411281
i                             522.430662
e                     36317460566.283279
b                               0.177953
t                        97274734.515400
lOCode                       1485.409423
lOComment                      34.838465
lOBlank                        40.734496
locCodeAndComment               0.997814
uniq_Op                        45.556417
uniq_Opnd                     326.317523
total_Op                    10928.122408
total_Opnd                   5139.787142
branchCount                   207.727916
defects                         0.175278
dtype: float64
```

## Apparently they'll need standardization later on using our StandardScaler, let's check the correlation

In [65]:

```
corr = df_train.corr()
corr
```

Out[65]:

| | loc | v(g) | ev(g) | iv(g) | n | v | l | d | |
|---|---|---|---|---|---|---|---|---|---|
| **loc** | 1.000000 | 0.761509 | 0.544569 | 0.696327 | 0.759605 | 0.758069 | -0.388018 | 0.599474 | 0.486 |
| **v(g)** | 0.761509 | 1.000000 | 0.729249 | 0.790553 | 0.631041 | 0.618267 | -0.387270 | 0.574305 | 0.304 |
| **ev(g)** | 0.544569 | 0.729249 | 1.000000 | 0.545255 | 0.390504 | 0.367697 | -0.325488 | 0.357735 | 0.160 |
| **iv(g)** | 0.696327 | 0.790553 | 0.545255 | 1.000000 | 0.589718 | 0.585134 | -0.291631 | 0.487112 | 0.319 |
| **n** | 0.759605 | 0.631041 | 0.390504 | 0.589718 | 1.000000 | 0.928390 | -0.300350 | 0.808291 | 0.725 |
| **v** | 0.758069 | 0.618267 | 0.367697 | 0.585134 | 0.928390 | 1.000000 | -0.254087 | 0.748121 | 0.673 |
| **l** | -0.388018 | -0.387270 | -0.325488 | -0.291631 | -0.300350 | -0.254087 | 1.000000 | -0.426309 | -0.162 |
| **d** | 0.599474 | 0.574305 | 0.357735 | 0.487112 | 0.808291 | 0.748121 | -0.426309 | 1.000000 | 0.515 |
| **i** | 0.486427 | 0.304531 | 0.160594 | 0.319971 | 0.725408 | 0.673386 | -0.162300 | 0.515402 | 1.000 |
| **e** | 0.501281 | 0.430184 | 0.275179 | 0.394291 | 0.569544 | 0.582332 | -0.091764 | 0.471276 | 0.286 |
| **b** | 0.739926 | 0.611954 | 0.360889 | 0.563969 | 0.918254 | 0.935263 | -0.254245 | 0.755130 | 0.681 |
| **t** | 0.512228 | 0.472080 | 0.280391 | 0.414640 | 0.602202 | 0.590431 | -0.097000 | 0.493976 | 0.300 |
| **lOCode** | 0.803460 | 0.641835 | 0.382541 | 0.636895 | 0.911761 | 0.899258 | -0.289713 | 0.778856 | 0.677 |
| **lOComment** | 0.528029 | 0.379520 | 0.292689 | 0.337728 | 0.566374 | 0.531985 | -0.187982 | 0.486619 | 0.435 |
| **lOBlank** | 0.670751 | 0.461759 | 0.282293 | 0.426030 | 0.775345 | 0.735278 | -0.288838 | 0.676297 | 0.654 |
| **locCodeAndComment** | 0.246244 | 0.208324 | 0.164563 | 0.178546 | 0.262916 | 0.242057 | -0.125480 | 0.268184 | 0.214 |
| **uniq_Op** | 0.367068 | 0.389917 | 0.200460 | 0.378869 | 0.618021 | 0.544283 | -0.399440 | 0.782781 | 0.527 |
| **uniq_Opnd** | 0.637582 | 0.532358 | 0.279100 | 0.550633 | 0.818994 | 0.798964 | -0.283644 | 0.690652 | 0.803 |
| **total_Op** | 0.764612 | 0.639125 | 0.394963 | 0.591597 | 0.963373 | 0.936446 | -0.294469 | 0.808275 | 0.702 |
| **total_Opnd** | 0.761662 | 0.606453 | 0.372867 | 0.567097 | 0.953080 | 0.942189 | -0.290559 | 0.784738 | 0.740 |
| **branchCount** | 0.762755 | 0.966702 | 0.774752 | 0.747870 | 0.626009 | 0.608678 | -0.416185 | 0.575155 | 0.313 |
| **defects** | 0.342642 | 0.301187 | 0.259928 | 0.245618 | 0.258080 | 0.231179 | -0.253237 | 0.241936 | 0.208 |

22 rows × 22 columns

In [66]:

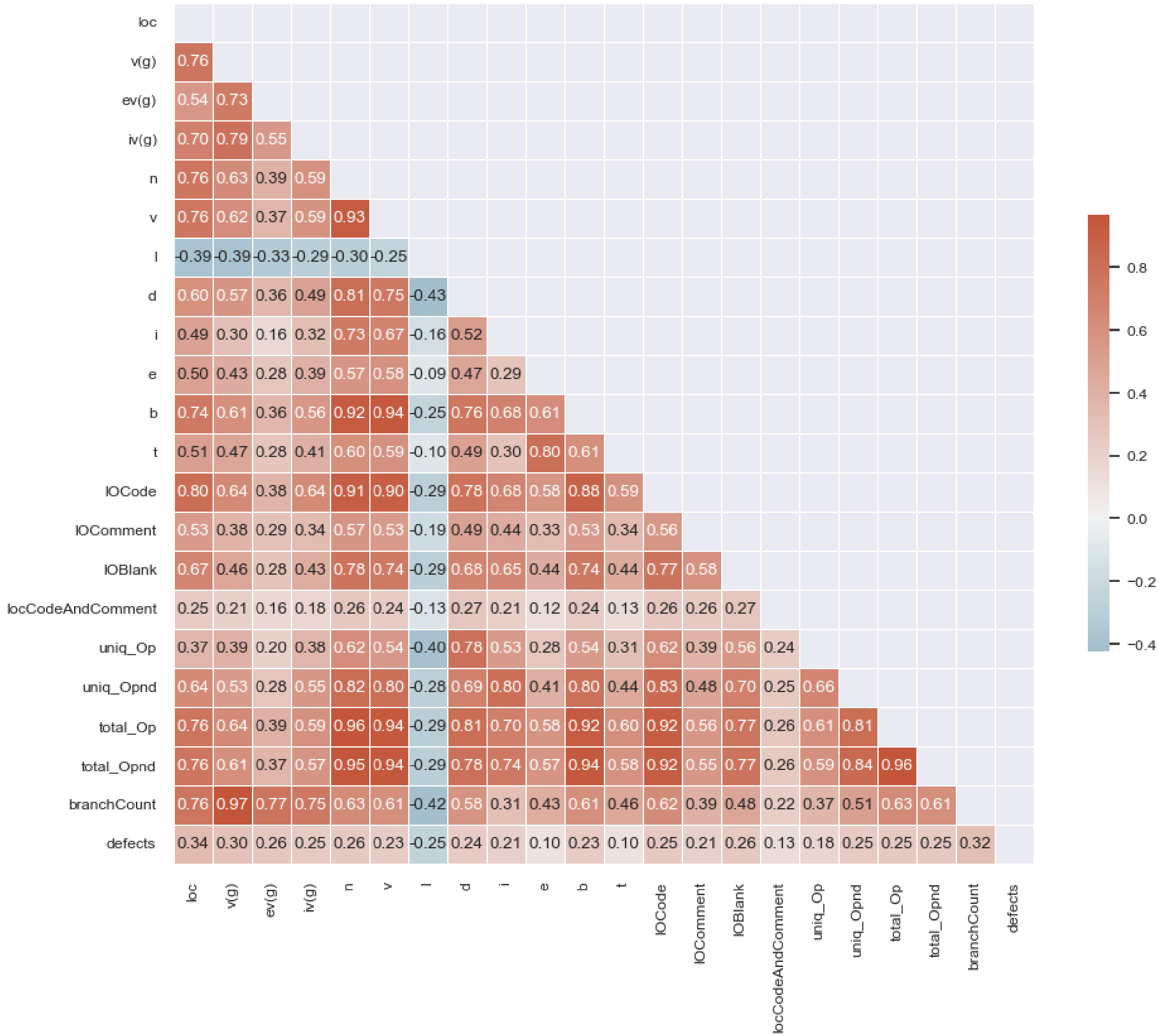
```
corr['defects'].sort_values(ascending=False)
```

Out[66]:
```
defects              1.000000
loc                  0.342642
branchCount          0.322827
v(g)                 0.301187
ev(g)                0.259928
n                    0.258080
lOBlank              0.257819
total_Opnd           0.252752
lOCode               0.250604
total_Op             0.250533
uniq_Opnd            0.246113
iv(g)                0.245618
d                    0.241936
b                    0.232594
v                    0.231179
i                    0.208577
lOComment            0.205402
uniq_Op              0.178474
locCodeAndComment    0.133150
t                    0.099592
e                    0.095366
l                   -0.253237
Name: defects, dtype: float64
```

## t and e columns should be dropped since they don't help that much compared to other features, we should check our heatmap

In [67]:
```
# plotting heatmap
mask = np.triu(np.ones_like(corr, dtype=bool))
f, ax = plt.subplots(figsize=(11, 9))
cmap = sns.diverging_palette(230, 20, as_cmap=True)
sns.set(font_scale=0.8)
sns.heatmap(corr, mask=mask, cmap=cmap, center=0, square=True, linewidths=.5, cbar_kws={"shrink"
```

Out[67]:
```
<AxesSubplot: >
```




## As we can see there're a lot of features that are highly correlated to each other, they're like redundant info which won't help our model much so we should drop them.

In [68]:

```
# drop columns that have high correlation with at least 3 columns
columns_to_drop = []
for column in corr.columns:
    if (corr[column] > 0.9).sum() >= 3:
        columns_to_drop.append(column)

df_train_filtered = df_train.drop(columns_to_drop, axis=1)
df_train_filtered.head()
```

Out[68]:

| | loc | v(g) | ev(g) | iv(g) | l | d | i | e | t | lOComment |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 22.000000 | 3.000000 | 1.000000 | 2.000000 | 0.060000 | 19.560000 | 14.250000 | 5448.790000 | 302.710000 | 1 |
| **1** | 14.000000 | 2.000000 | 1.000000 | 2.000000 | 0.140000 | 7.000000 | 21.110000 | 936.710000 | 52.040000 | 0 |
| **2** | 11.000000 | 2.000000 | 1.000000 | 2.000000 | 0.110000 | 8.050000 | 22.760000 | 1754.010000 | 97.450000 | 0 |
| **3** | 8.000000 | 1.000000 | 1.000000 | 1.000000 | 0.190000 | 5.250000 | 17.860000 | 473.660000 | 26.310000 | 0 |
| **4** | 11.000000 | 2.000000 | 1.000000 | 2.000000 | 0.180000 | 5.630000 | 12.440000 | 365.670000 | 20.310000 | 0 |

In [69]:
```
df_train_filtered.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 101763 entries, 0 to 101762
Data columns (total 16 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   loc                101763 non-null  float64
 1   v(g)               101763 non-null  float64
 2   ev(g)              101763 non-null  float64
 3   iv(g)              101763 non-null  float64
 4   l                  101763 non-null  float64
 5   d                  101763 non-null  float64
 6   i                  101763 non-null  float64
 7   e                  101763 non-null  float64
 8   t                  101763 non-null  float64
 9   lOComment          101763 non-null  int64  
 10  lOBlank            101763 non-null  int64  
 11  locCodeAndComment  101763 non-null  int64  
 12  uniq_Op            101763 non-null  float64
 13  uniq_Opnd          101763 non-null  float64
 14  branchCount        101763 non-null  float64
 15  defects            101763 non-null  bool   
dtypes: bool(1), float64(12), int64(3)
memory usage: 11.7 MB
```

In [70]:
```
filtered_corr = df_train_filtered.corr()
filtered_corr['defects'].sort_values(ascending=False)
```

Out[70]:
```
defects              1.000000
loc                  0.342642
branchCount          0.322827
v(g)                 0.301187
ev(g)                0.259928
lOBlank              0.257819
uniq_Opnd            0.246113
iv(g)                0.245618
d                    0.241936
i                    0.208577
lOComment            0.205402
uniq_Op              0.178474
locCodeAndComment    0.133150
t                    0.099592
e                    0.095366
l                   -0.253237
Name: defects, dtype: float64
```

In [71]:
```
#dropp features with correlation between -0.1 and 0.1
#dropping features with correlation between -0.1 and 0.1
df_train_filtered = df_train_filtered.drop(filtered_corr[(filtered_corr['defects'] > -0.1) & (fi
df_train_filtered.head()
```

Out[71]:

| | loc | v(g) | ev(g) | iv(g) | l | d | i | lOComment | lOBlank | locCodeAndCon |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 22.000000 | 3.000000 | 1.000000 | 2.000000 | 0.060000 | 19.560000 | 14.250000 | 1 | 1 | |
| **1** | 14.000000 | 2.000000 | 1.000000 | 2.000000 | 0.140000 | 7.000000 | 21.110000 | 0 | 1 | |
| **2** | 11.000000 | 2.000000 | 1.000000 | 2.000000 | 0.110000 | 8.050000 | 22.760000 | 0 | 1 | |
| **3** | 8.000000 | 1.000000 | 1.000000 | 1.000000 | 0.190000 | 5.250000 | 17.860000 | 0 | 2 | |
| **4** | 11.000000 | 2.000000 | 1.000000 | 2.000000 | 0.180000 | 5.630000 | 12.440000 | 0 | 2 | |

In [72]:
```python
filtered_corr = df_train_filtered.corr()
filtered_corr['defects'].sort_values(ascending=False)
```

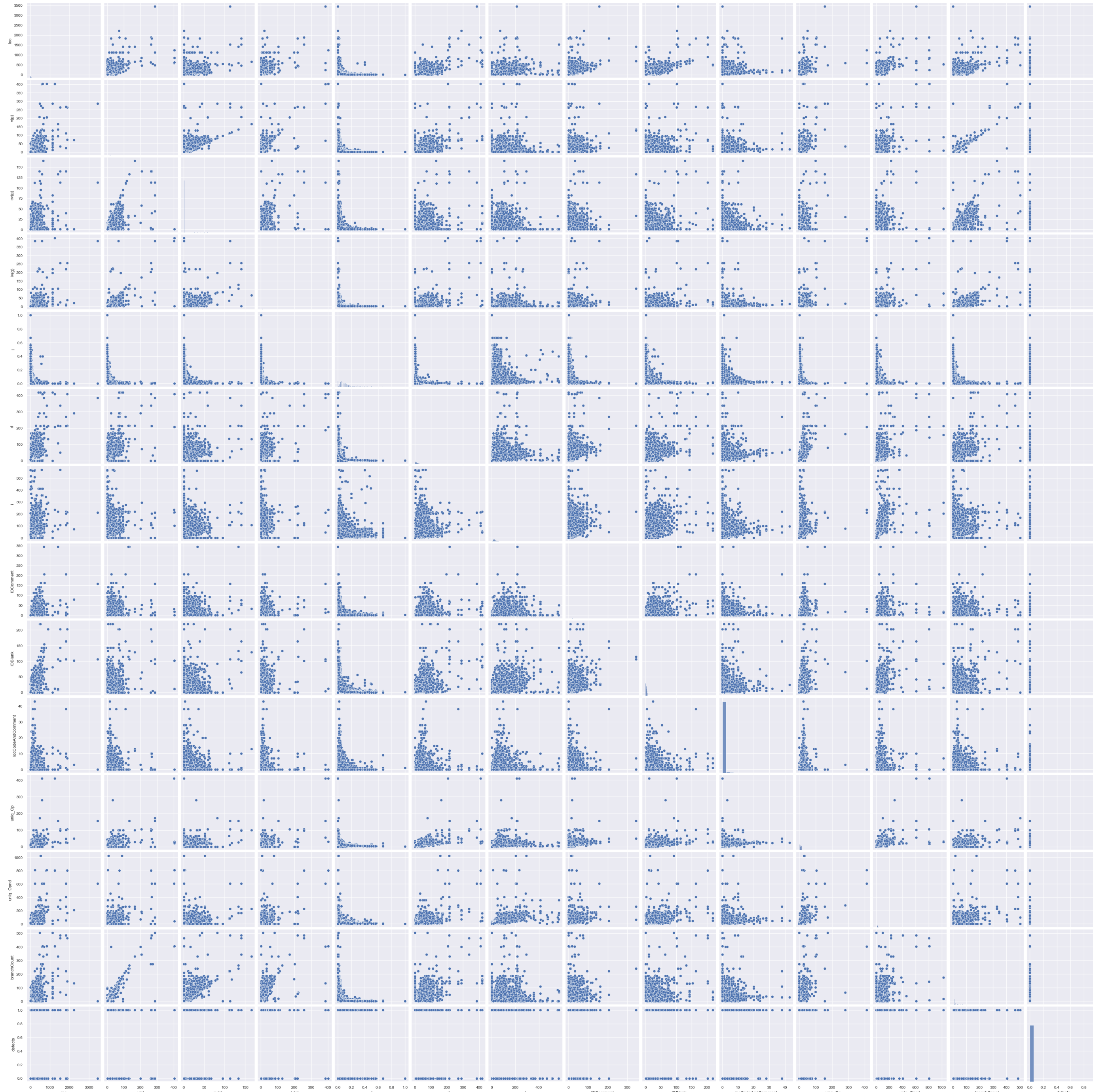
Out[72]:
```
defects              1.000000
loc                  0.342642
branchCount          0.322827
v(g)                 0.301187
ev(g)                0.259928
lOBlank              0.257819
uniq_Opnd            0.246113
iv(g)                0.245618
d                    0.241936
i                    0.208577
lOComment            0.205402
uniq_Op              0.178474
locCodeAndComment    0.133150
l                   -0.253237
Name: defects, dtype: float64
```

### I think we're good to go now, let's create a pairplot to check things out first.

In [73]:
```python
# create a pairplot to see the distribution of the data
sns.pairplot(df_train_filtered)
```

```
<__array_function__ internals>:180: RuntimeWarning: Converting input from bool to <class 'numpy.uint8'> for compatibility.
```

Out[73]:
```
<seaborn.axisgrid.PairGrid at 0x2f78808af50>
```



In [74]:
```
# convert defects to binary
df_train_filtered['defects'] = df_train_filtered['defects'].apply(lambda x: 1 if x == True else (
df_train_filtered.head()
```

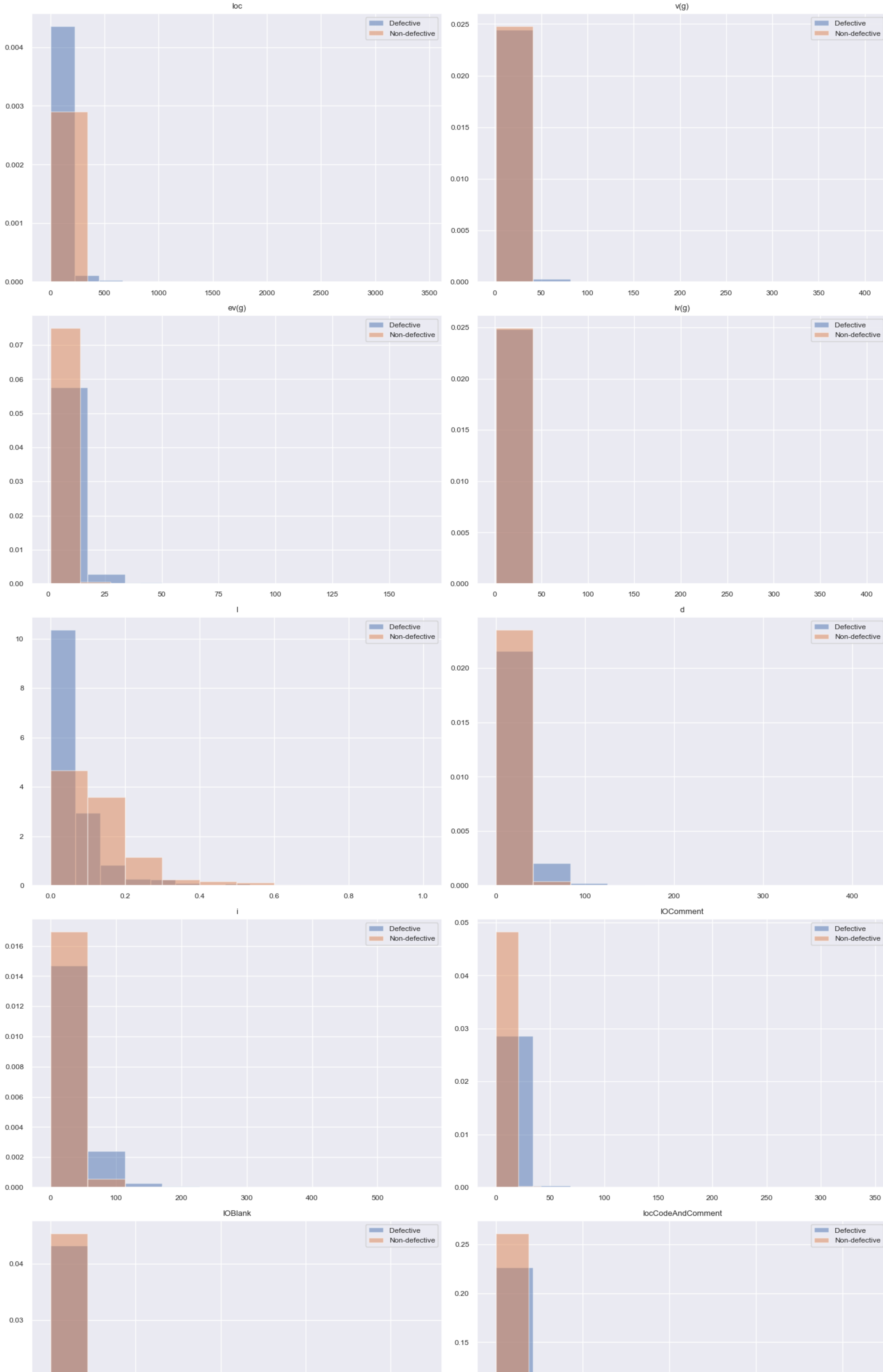
Out[74]:

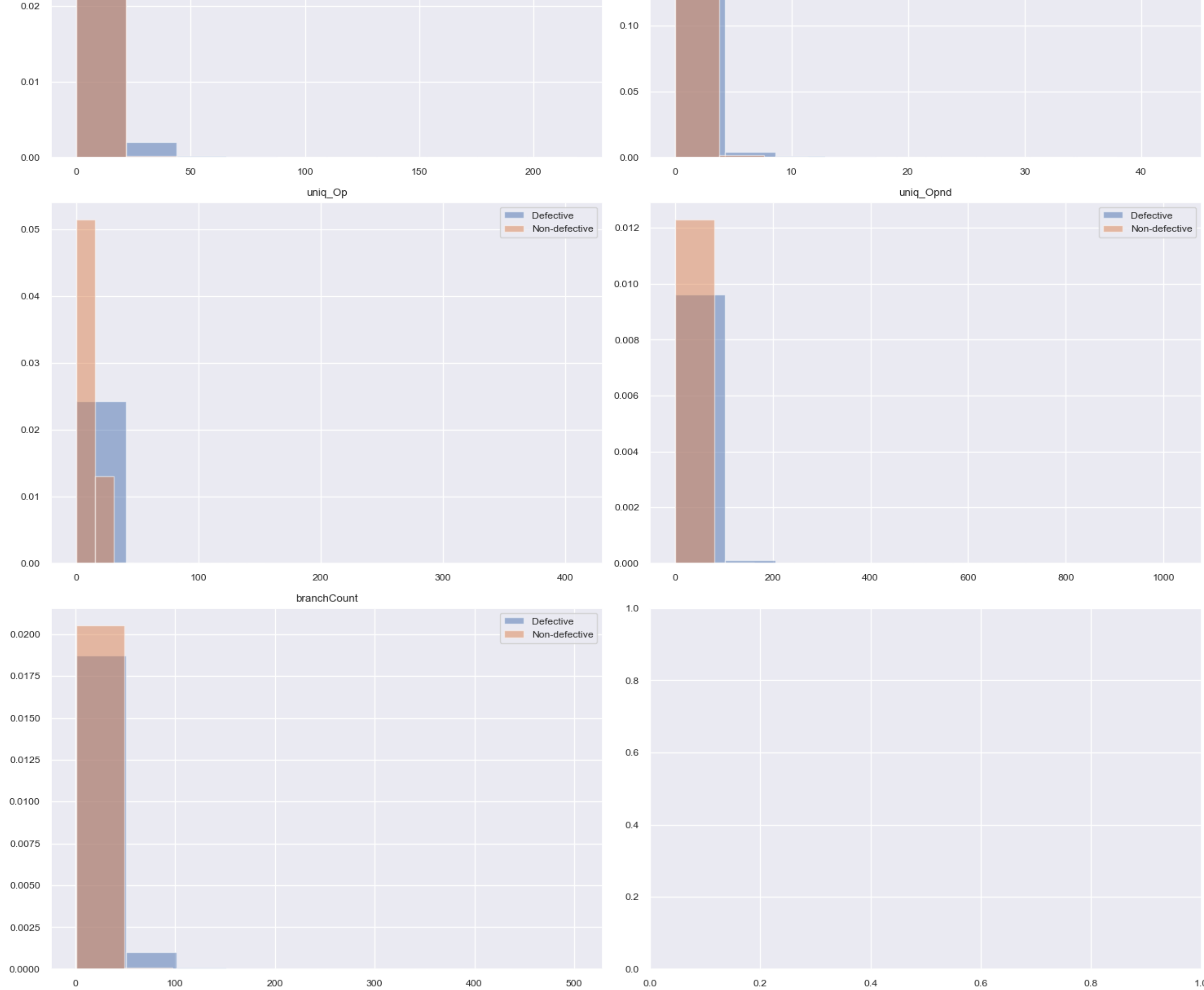
| | loc | v(g) | ev(g) | iv(g) | l | d | i | lOComment | lOBlank | locCodeAndCom |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 22.000000 | 3.000000 | 1.000000 | 2.000000 | 0.060000 | 19.560000 | 14.250000 | 1 | 1 | |
| 1 | 14.000000 | 2.000000 | 1.000000 | 2.000000 | 0.140000 | 7.000000 | 21.110000 | 0 | 1 | |
| 2 | 11.000000 | 2.000000 | 1.000000 | 2.000000 | 0.110000 | 8.050000 | 22.760000 | 0 | 1 | |
| 3 | 8.000000 | 1.000000 | 1.000000 | 1.000000 | 0.190000 | 5.250000 | 17.860000 | 0 | 2 | |
| 4 | 11.000000 | 2.000000 | 1.000000 | 2.000000 | 0.180000 | 5.630000 | 12.440000 | 0 | 2 | |

## Let's plot the distribution of our features according defectiveness

In [75]:
```
# plot the distribution of each features with defects in subplots
def plot_feature_distribution(df, feature_columns, target_column):
```

```
    num_features = len(feature_columns)
    num_plots_per_row = 2
    num_rows = (num_features + num_plots_per_row - 1) // num_plots_per_row

    fig, axs = plt.subplots(num_rows, num_plots_per_row, figsize=(15, 5*num_rows))

    for i, feature in enumerate(feature_columns):
        row = i // num_plots_per_row
        col = i % num_plots_per_row
        ax = axs[row, col] if num_rows > 1 else axs[col]
        ax.hist(df[df[target_column] == 1][feature], label='Defective', alpha=0.5, density=True)
        ax.hist(df[df[target_column] == 0][feature], label='Non-defective', alpha=0.5, density=Tr
        ax.set_title(feature)
        ax.legend()

    plt.tight_layout()
    plt.show()

feature_columns = df_train_filtered.columns.drop('defects')
target_column = 'defects'

plot_feature_distribution(df_train_filtered, feature_columns, target_column)
```


loc
Defective
Non-defective
v(g)
Defective
Non-defective
ev(g)
Defective
Non-defective
iv(g)
Defective
Non-defective
l
Defective
Non-defective
d
Defective
Non-defective
i
Defective
Non-defective
lOComment
Defective
Non-defective
lOBlank
Defective
Non-defective
locCodeAndComment
Defective
Non-defective




# Modeling

let's start creating our model

In [76]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler, PolynomialFeatures
from sklearn.decomposition import PCA
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, roc_curve, r
from sklearn.pipeline import Pipeline
```

### Splitting data, making sure to stratify the splitting to y in order to balance the classes in both training and testing

In [77]:
```
# splitting the data into train and test
X = df_train_filtered.drop('defects', axis=1)
y = df_train_filtered['defects']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,stratify=y, random_state
```

### We'll create a pipeline with polynomialfeatures to get the best of our features, then we scale our data preparing it to go through PCA for dimensionality reduction, and then fit our Random Forest Classifier with a little hyperparameter tuning.

In [78]:
```
# Creating my pipeline which consists of polynomial features, standardscaling as a method for sta
```

```python
rf_pipe = Pipeline([
    ('poly', PolynomialFeatures()),
    ('scaler', StandardScaler()),
    ('pca', PCA()),
    ('classifier', RandomForestClassifier(n_estimators=100, min_weight_fraction_leaf=0.001,n_job
#fitting the pipeline
rf_pipe.fit(X_train, y_train)
```

Out[78]:

```
Pipeline
  PolynomialFeatures
  StandardScaler
  PCA
  RandomForestClassifier
```

## Checking the explained variance ration our PCA got

In [79]:

```python
print(rf_pipe[2].explained_variance_ratio_)
```

```
[3.83002406e-01 9.83239125e-02 6.67211909e-02 6.40802816e-02
 5.44741248e-02 4.87529071e-02 3.78771791e-02 2.62081189e-02
 2.23472375e-02 1.86726727e-02 1.77456129e-02 1.53826146e-02
 1.29284299e-02 1.22553321e-02 1.11672387e-02 9.40986959e-03
 7.97595769e-03 7.53473877e-03 6.23373978e-03 6.03654570e-03
 5.50211724e-03 4.74469913e-03 4.23283550e-03 3.99595977e-03
 3.40385115e-03 3.08187802e-03 2.95584303e-03 2.89041500e-03
 2.56721304e-03 2.43112690e-03 2.31587605e-03 2.08249626e-03
 1.97673696e-03 1.95804385e-03 1.84837826e-03 1.68226729e-03
 1.63173679e-03 1.56330748e-03 1.45814457e-03 1.36978078e-03
 1.25745751e-03 1.12120090e-03 1.03059834e-03 1.00952315e-03
 9.33678889e-04 8.36359474e-04 8.21912835e-04 7.96949274e-04
 7.37926538e-04 7.21374674e-04 6.77663447e-04 6.45793634e-04
 6.06414826e-04 5.30347543e-04 5.12404567e-04 4.76722421e-04
 4.45651225e-04 4.18454261e-04 3.91900575e-04 3.70450964e-04
 3.51349634e-04 3.33736447e-04 3.00718845e-04 2.76634230e-04
 2.64439009e-04 2.49735657e-04 2.34043609e-04 2.29984672e-04
 2.20246149e-04 1.95005087e-04 1.85194214e-04 1.69231331e-04
 1.60694468e-04 1.43537473e-04 1.33506066e-04 1.25255091e-04
 1.21012747e-04 1.11208110e-04 1.08083567e-04 9.97455151e-05
 9.83869695e-05 8.93332803e-05 8.37809979e-05 7.54205060e-05
 6.86073538e-05 5.64769404e-05 5.27385085e-05 4.71043566e-05
 4.20341919e-05 3.88126867e-05 3.49315214e-05 2.89839162e-05
 2.33624032e-05 1.90373433e-05 1.40227874e-05 1.06517713e-05
 8.83704595e-06 7.47271718e-06 6.93956800e-06 4.59510620e-06
 4.10816813e-06 2.77583838e-06 1.60563042e-06 1.01580443e-06
 2.72575164e-33]
```

## Checking at which component should we be able to reach at least 0.9, looks like it's in the 17th component (0.90732509)

In [80]:

```python
print(rf_pipe[2].explained_variance_ratio_.cumsum())
```

```
[0.38300241 0.48132632 0.54804751 0.61212779 0.66660192 0.71535482
 0.753232   0.77944012 0.80178736 0.82046003 0.83820564 0.85358826
 0.86651669 0.87877202 0.88993926 0.89934913 0.90732509 0.91485983
 0.92109356 0.92713011 0.93263223 0.93737693 0.94160976 0.94560572
 0.94900957 0.95209145 0.95504729 0.95793771 0.96050492 0.96293605
 0.96525193 0.96733442 0.96931116 0.9712692  0.97311758 0.97479985
 0.97643158 0.97799489 0.97945304 0.98082282 0.98208028 0.98320148
 0.98423207 0.9852416  0.98617528 0.98701164 0.98783355 0.9886305
 0.98936842 0.9900898  0.99076746 0.99141326 0.99201967 0.99255002
 0.99306242 0.99353915 0.9939848  0.99440325 0.99479515 0.9951656
 0.99551695 0.99585069 0.99615141 0.99642804 0.99669248 0.99694222
 0.99717626 0.99740624 0.99762649 0.9978215  0.99800669 0.99817592
 0.99833662 0.99848015 0.99861366 0.99873891 0.99885993 0.99897114
 0.99907922 0.99917896 0.99927735 0.99936668 0.99945047 0.99952589
 0.99959449 0.99965097 0.99970371 0.99975081 0.99979285 0.99983166
 0.99986659 0.99989558 0.99991894 0.99993798 0.999952   0.99996265
 0.99997149 0.99997896 0.9999859  0.99999049 0.9999946  0.99999738
 0.99999898 1.         1.        ]
```

## Evaluating Our Model

In [81]:
```
# predicting the values
y_pred = rf_pipe.predict(X_test)
# checking the accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.8132148893518336
```

In [82]:
```
# confusion matrix
confusion_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(confusion_matrix)
```

```
Confusion Matrix:
[[18533  1142]
 [ 3610  2156]]
```

In [83]:
```
# classification report
classification_report = classification_report(y_test, y_pred)
print("Classification Report:")
print(classification_report)
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.94      0.89     19675
           1       0.65      0.37      0.48      5766

    accuracy                           0.81     25441
   macro avg       0.75      0.66      0.68     25441
weighted avg       0.80      0.81      0.79     25441
```

In [84]:
```
# roc curve
y_pred_proba = rf_pipe.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)

plt.plot(fpr, tpr)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
```

```
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic Curve')
plt.show()
```


### Getting our ROC AUC Score as the metric this competition proposed to measure our model's performance

In [85]:
```
# roc auc score
roc_auc = roc_auc_score(y_test, y_pred_proba)
print("ROC AUC Score:", roc_auc)
```

```
ROC AUC Score: 0.7902229738276476
```

**0.7902 is pretty great for this task! now let's submit our model's results on the proposed test data for the competition.**

# Submission

In [86]:
```
df_test_org = pd.read_csv('test.csv')
df_test_org.head()
```

Out[86]:

| | id | loc | v(g) | ev(g) | iv(g) | n | v | l | d | i | ... |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 101763 | 33.000000 | 5.000000 | 1.000000 | 4.000000 | 144.000000 | 824.820000 | 0.040000 | 26.960000 | 30.050000 | ... |
| **1** | 101764 | 27.000000 | 8.000000 | 8.000000 | 2.000000 | 125.000000 | 646.240000 | 0.040000 | 22.820000 | 27.220000 | ... |
| **2** | 101765 | 130.000000 | 11.000000 | 7.000000 | 10.000000 | 545.000000 | 3831.400000 | 0.020000 | 48.150000 | 66.170000 | ... |
| **3** | 101766 | 65.000000 | 7.000000 | 1.000000 | 7.000000 | 156.000000 | 855.710000 | 0.060000 | 17.230000 | 49.890000 | ... |
| **4** | 101767 | 22.000000 | 3.000000 | 1.000000 | 3.000000 | 52.000000 | 238.420000 | 0.100000 | 9.600000 | 26.700000 | ... |

5 rows × 22 columns

In [87]:
```
# select only the features that we used for training
df_test = df_test_org[X_train.columns]
```

In [91]:
```
# predicting the values
y_pred_test = rf_pipe.predict_proba(df_test)
# getting the positive class probabilities
y_pred_test = y_pred_test[:, 1]
```

In [92]:
```
# saving the predictions
df_submission = pd.DataFrame({'id': df_test_org['id'], 'defects': y_pred_test})
df_submission.to_csv('submission.csv', index=False)
```

In [93]:
```
df_submission.head(20)
```

Out[93]:

| | id | defects |
|---|---|---|
| **0** | 101763 | 0.283111 |
| **1** | 101764 | 0.177130 |
| **2** | 101765 | 0.604668 |
| **3** | 101766 | 0.407093 |
| **4** | 101767 | 0.159537 |
| **5** | 101768 | 0.485797 |
| **6** | 101769 | 0.092344 |
| **7** | 101770 | 0.627196 |
| **8** | 101771 | 0.425210 |
| **9** | 101772 | 0.064896 |
| **10** | 101773 | 0.553594 |
| **11** | 101774 | 0.665572 |
| **12** | 101775 | 0.263819 |
| **13** | 101776 | 0.568118 |
| **14** | 101777 | 0.294554 |
| **15** | 101778 | 0.415679 |
| **16** | 101779 | 0.682313 |
| **17** | 101780 | 0.183711 |
| **18** | 101781 | 0.672612 |
| **19** | 101782 | 0.137161 |

### Results with more than 0.5 are "True" meanwhile less than 0.5 are "False", since True(1) is our positive class.

# Great Work!