Payment Date Prediction

```
#importing the essential libraries.
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
import datetime as dt
import warnings
warnings.filterwarnings("ignore")
from fast_ml.feature_selection import get_constant_features
import plotly.express as px
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
import xgboost as xgb
from sklearn.svm import SVR

#Store the dataset into the Dataframe
df = pd.read_csv('dataset_for_ML_Model.csv')

#checking the shape of dataframe
df.shape

(50000, 19)

#Check the Detail information of the dataframe
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 19 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   business_code           50000 non-null  object
 1   cust_number             50000 non-null  object
 2   name_customer           50000 non-null  object
 3   clear_date              40000 non-null  object
 4   buisness_year           50000 non-null  float64
 5   doc_id                  50000 non-null  float64
 6   posting_date            50000 non-null  object
 7   document_create_date    50000 non-null  int64
 8   document_create_date.1  50000 non-null  int64
 9   due_in_date             50000 non-null  float64
 10  invoice_currency        50000 non-null  object
 11  document type           50000 non-null  object
 12  posting_id              50000 non-null  float64
 13  area_business           0 non-null      float64
 14  total_open_amount       50000 non-null  float64
 15  baseline_create_date    50000 non-null  float64
```

```
 16  cust_payment_terms      50000 non-null  object
 17  invoice_id              49994 non-null  float64
 18  isOpen                  50000 non-null  int64
dtypes: float64(8), int64(3), object(8)
memory usage: 7.2+ MB
```

```
#Display All the column names
print(df.columns)
```

```
Index(['business_code', 'cust_number', 'name_customer', 'clear_date',
       'buisness_year', 'doc_id', 'posting_date',
'document_create_date',
       'document_create_date.1', 'due_in_date', 'invoice_currency',
       'document type', 'posting_id', 'area_business',
'total_open_amount',
       'baseline_create_date', 'cust_payment_terms', 'invoice_id',
'isOpen'],
      dtype='object')
```

```
#Describe the entire dataset
df.describe()
```

```
       buisness_year        doc_id  document_create_date  \
count   50000.000000  5.000000e+04          5.000000e+04
mean     2019.305700  2.012238e+09          2.019351e+07
std         0.460708  2.885235e+08          4.496041e+03
min      2019.000000  1.928502e+09          2.018123e+07
25%      2019.000000  1.929342e+09          2.019050e+07
50%      2019.000000  1.929964e+09          2.019091e+07
75%      2020.000000  1.930619e+09          2.020013e+07
max      2020.000000  9.500000e+09          2.020052e+07

       document_create_date.1   due_in_date  posting_id  area_business
\
count            5.000000e+04  5.000000e+04     50000.0            0.0

mean             2.019354e+07  2.019368e+07         1.0            NaN

std              4.482134e+03  4.470614e+03         0.0            NaN

min              2.018123e+07  2.018122e+07         1.0            NaN

25%              2.019051e+07  2.019052e+07         1.0            NaN

50%              2.019091e+07  2.019093e+07         1.0            NaN

75%              2.020013e+07  2.020022e+07         1.0            NaN

max              2.020052e+07  2.020071e+07         1.0            NaN
```

```
       total_open_amount  baseline_create_date    invoice_id
isOpen
count       50000.000000          5.000000e+04  4.999400e+04
50000.000000
mean        32337.021651          2.019354e+07  2.011340e+09
0.200000
std         39205.975231          4.482701e+03  2.766335e+08
0.400004
min             0.720000          2.018121e+07  1.928502e+09
0.000000
25%          4928.312500          2.019050e+07  1.929342e+09
0.000000
50%         17609.010000          2.019091e+07  1.929964e+09
0.000000
75%         47133.635000          2.020013e+07  1.930619e+09
0.000000
max        668593.360000          2.020052e+07  2.960636e+09
1.000000
```

Data Cleaning

```
#Showing top 5 records from the dataset
df.head(5)
```

```
  business_code cust_number       name_customer
clear_date  \
0          U001  0200769623        WAL-MAR corp  2020-02-11 00:00:00

1          U001  0200980828              BEN E   2019-08-08 00:00:00

2          U001  0200792734          MDV/ trust  2019-12-30 00:00:00

3          CA02  0140105686            SYSC llc                  NaN

4          U001  0200769623  WAL-MAR foundation  2019-11-25 00:00:00


   buisness_year        doc_id posting_date  document_create_date  \
0         2020.0  1.930438e+09   2020-01-26              20200125
1         2019.0  1.929646e+09   2019-07-22              20190722
2         2019.0  1.929874e+09   2019-09-14              20190914
3         2020.0  2.960623e+09   2020-03-30              20200330
4         2019.0  1.930148e+09   2019-11-13              20191113

   document_create_date.1  due_in_date invoice_currency document type
\
0                20200126   20200210.0              USD            RV
```

```
1                20190722   20190811.0              USD            RV

2                20190914   20190929.0              USD            RV

3                20200330   20200410.0              CAD            RV

4                20191113   20191128.0              USD            RV
```

```
   posting_id  area_business  total_open_amount  baseline_create_date
\
0         1.0            NaN           54273.28            20200126.0

1         1.0            NaN           79656.60            20190722.0

2         1.0            NaN            2253.86            20190914.0

3         1.0            NaN            3299.70            20200331.0

4         1.0            NaN           33133.29            20191113.0
```

```
  cust_payment_terms    invoice_id  isOpen
0               NAH4  1.930438e+09       0
1               NAD1  1.929646e+09       0
2               NAA8  1.929874e+09       0
3               CA10  2.960623e+09       1
4               NAH4  1.930148e+09       0
```

```
#Displaying the Null values percentage against every columns
percent_missing = df.isnull().sum() * 100 / len(df)
missing_value_df = pd.DataFrame({'column_name':
df.columns,'percent_missing': percent_missing})
missing_value_df
```

```
                                  column_name  percent_missing
business_code                   business_code            0.000
cust_number                       cust_number            0.000
name_customer                   name_customer            0.000
clear_date                         clear_date           20.000
buisness_year                   buisness_year            0.000
doc_id                                 doc_id            0.000
posting_date                    posting_date            0.000
document_create_date      document_create_date            0.000
document_create_date.1  document_create_date.1            0.000
due_in_date                       due_in_date            0.000
invoice_currency             invoice_currency            0.000
document type                   document type            0.000
posting_id                         posting_id            0.000
```

```
area_business                    area_business          100.000
total_open_amount             total_open_amount           0.000
baseline_create_date       baseline_create_date           0.000
cust_payment_terms           cust_payment_terms           0.000
invoice_id                           invoice_id           0.012
isOpen                                   isOpen           0.000
```

```
#Display Invoice_id and Doc_Id
df[['invoice_id','doc_id']]
```

```
         invoice_id        doc_id
0      1.930438e+09  1.930438e+09
1      1.929646e+09  1.929646e+09
2      1.929874e+09  1.929874e+09
3      2.960623e+09  2.960623e+09
4      1.930148e+09  1.930148e+09
...             ...           ...
49995  1.930797e+09  1.930797e+09
49996  1.929744e+09  1.929744e+09
49997  1.930537e+09  1.930537e+09
49998  1.930199e+09  1.930199e+09
49999  1.928576e+09  1.928576e+09

[50000 rows x 2 columns]
```

```
#Please check, Column 'posting_id' is constant columns or not
df.nunique()
```

```
business_code                6
cust_number               1425
name_customer             4197
clear_date                 403
buisness_year                2
doc_id                   48839
posting_date               506
document_create_date       507
document_create_date.1     506
due_in_date                547
invoice_currency             2
document type                2
posting_id                   1
area_business                0
total_open_amount        44349
baseline_create_date       506
cust_payment_terms          74
invoice_id               48833
isOpen                       2
dtype: int64
```

```
# we dropped the following columns
'area_business','posting_id','invoice_id',
```

```
'document_create_date','isOpen', 'document type',
'document_create_date.1'
df.drop(columns=['area_business','posting_id','invoice_id',
'document_create_date','isOpen', 'document type',
'document_create_date.1'], inplace=True)

#ensuring that the dataframe does not have the above columns.
df.columns
```

```
Index(['business_code', 'cust_number', 'name_customer', 'clear_date',
       'buisness_year', 'doc_id', 'posting_date', 'due_in_date',
       'invoice_currency', 'total_open_amount',
'baseline_create_date',
       'cust_payment_terms'],
      dtype='object')
```

```
#showing all duplicate rows from dataframe.
duplicate = df[df.duplicated()]
duplicate
```

```
      business_code cust_number        name_customer
clear_date  \
1041          U001  0200769623           WAL-MAR in  2019-03-12
00:00:00
2400          U001  0200769623         WAL-MAR trust  2019-08-28
00:00:00
2584          U001  0200769623  WAL-MAR corporation  2019-12-16
00:00:00
3755          U001  0200769623              WAL-MAR   2019-11-22
00:00:00
3873          CA02  0140104409       LOB associates
NaN
...             ...         ...                  ...
...
49928         U001  0200915438           GROC trust  2019-08-15
00:00:00
49963         U001  0200759878                SA us  2019-01-29
00:00:00
49986         U001  0200772670  ASSOCIAT foundation  2019-06-12
00:00:00
49990         U001  0200765011           MAINES llc  2019-06-06
00:00:00
49991         U001  0200704045             RA trust  2019-10-25
00:00:00

       buisness_year        doc_id posting_date  due_in_date
invoice_currency  \
1041          2019.0  1.928870e+09   2019-02-28   20190315.0
USD
2400          2019.0  1.929758e+09   2019-08-18   20190902.0
USD
```

```
2584          2019.0  1.930217e+09   2019-12-04   20191219.0
USD
3755          2019.0  1.930137e+09   2019-11-12   20191127.0
USD
3873          2020.0  2.960629e+09   2020-04-14   20200425.0
CAD
...              ...           ...          ...          ...
...
49928         2019.0  1.929646e+09   2019-07-25   20190809.0
USD
49963         2019.0  1.928614e+09   2019-01-13   20190128.0
USD
49986         2019.0  1.929403e+09   2019-05-29   20190613.0
USD
49990         2019.0  1.929365e+09   2019-05-22   20190606.0
USD
49991         2019.0  1.930001e+09   2019-10-10   20191025.0
USD

       total_open_amount  baline_create_date cust_payment_terms
1041           19557.41           20190228.0                NAH4
2400            5600.41           20190818.0                NAH4
2584           35352.17           20191204.0                NAH4
3755            2982.64           20191112.0                NAH4
3873           82975.82           20200415.0                CA10
...                 ...                  ...                 ...
49928           6969.00           20190725.0                NAA8
49963          10968.24           20190113.0                NAH4
49986         155837.53           20190529.0                NAU5
49990           4008.05           20190522.0                NAA8
49991          73002.24           20191010.0                NAA8

[1161 rows x 12 columns]
```

```
#displaying the number of duplicate rows.
duplicate.shape
```

```
(1161, 12)
```

```
#dropping duplicate rows from dataframe.
df.drop_duplicates(inplace=True)
```

```
df
```

```
      business_code cust_number       name_customer
clear_date  \
0              U001  0200769623        WAL-MAR corp  2020-02-11
00:00:00
1              U001  0200980828              BEN E   2019-08-08
00:00:00
2              U001  0200792734          MDV/ trust  2019-12-30
```

```
00:00:00
3              CA02  0140105686            SYSC llc
NaN
4              U001  0200769623  WAL-MAR foundation  2019-11-25
00:00:00
...             ...         ...                 ...                  .
..
49995          U001  0200561861      CO corporation
NaN
49996          U001  0200769623          WAL-MAR co  2019-09-03
00:00:00
49997          U001  0200772595    SAFEW associates  2020-03-05
00:00:00
49998          U001  0200726979           BJ'S  llc  2019-12-12
00:00:00
49999          U001  0200020431            DEC corp  2019-01-15
00:00:00

       buisness_year        doc_id posting_date  due_in_date
invoice_currency  \
0             2020.0  1.930438e+09   2020-01-26   20200210.0
USD
1             2019.0  1.929646e+09   2019-07-22   20190811.0
USD
2             2019.0  1.929874e+09   2019-09-14   20190929.0
USD
3             2020.0  2.960623e+09   2020-03-30   20200410.0
CAD
4             2019.0  1.930148e+09   2019-11-13   20191128.0
USD
...              ...           ...          ...          ...
...
49995         2020.0  1.930797e+09   2020-04-21   20200506.0
USD
49996         2019.0  1.929744e+09   2019-08-15   20190830.0
USD
49997         2020.0  1.930537e+09   2020-02-19   20200305.0
USD
49998         2019.0  1.930199e+09   2019-11-27   20191212.0
USD
49999         2019.0  1.928576e+09   2019-01-05   20190124.0
USD

       total_open_amount  baseline_create_date cust_payment_terms
0               54273.28            20200126.0                NAH4
1               79656.60            20190722.0                NAD1
2                2253.86            20190914.0                NAA8
3                3299.70            20200331.0                CA10
4               33133.29            20191113.0                NAH4
...                  ...                   ...                 ...
```

```
49995            3187.86            20200421.0                NAA8
49996            6766.54            20190815.0                NAH4
49997            6120.86            20200219.0                NAA8
49998              63.48            20191127.0                NAA8
49999            1790.30            20190101.0                NAM4

[48839 rows x 12 columns]
```

```
#duplicate rows are 0 now.
duplicate.shape
```

```
(1161, 12)
```

```
#checking number of rows and columns in df
df.shape
```

```
(48839, 12)
```

```
#checking number of null values in each column
df.isnull().sum()
```

```
business_code             0
cust_number               0
name_customer             0
clear_date             9681
buisness_year             0
doc_id                    0
posting_date              0
due_in_date               0
invoice_currency          0
total_open_amount         0
baseline_create_date      0
cust_payment_terms        0
dtype: int64
```

Data type Conversion

```
#checking the datatype of each column in dataframe.
df.dtypes
```

```
business_code            object
cust_number              object
name_customer            object
clear_date               object
buisness_year           float64
doc_id                  float64
posting_date             object
due_in_date             float64
invoice_currency         object
total_open_amount       float64
baseline_create_date    float64
```

```
cust_payment_terms       object
dtype: object
```

```
#checking the datatype format of specific columns
dt_clear_date=df['clear_date'].dtype
dt_posting_date=df['posting_date'].dtype
dt_due_in_date=df['due_in_date'].dtype
dt_baseline_create_date=df['baseline_create_date'].dtype
print("clear_date:",dt_clear_date)
print("posting_date:",dt_posting_date)
print("due_in_date:",dt_due_in_date)
print("baseline_create_date:",dt_baseline_create_date)
```

```
clear_date: object
posting_date: object
due_in_date: float64
baseline_create_date: float64
```

```
#converting date columns into date time formats
df['clear_date'] = pd.to_datetime(df['clear_date']).dt.normalize()
df['posting_date'] = pd.to_datetime(df['posting_date']).dt.normalize()
df['due_in_date'] = pd.to_datetime(df['due_in_date'], format = '%Y%m
%d',errors = 'coerce')
df['baseline_create_date'] =
pd.to_datetime(df['baseline_create_date'],format = '%Y%m%d',errors =
'coerce')
```

```
#again checking the datatype of each column in dataframe.
df.dtypes
```

```
business_code                   object
cust_number                     object
name_customer                   object
clear_date              datetime64[ns]
buisness_year                  float64
doc_id                         float64
posting_date            datetime64[ns]
due_in_date             datetime64[ns]
invoice_currency                object
total_open_amount              float64
baseline_create_date    datetime64[ns]
cust_payment_terms              object
dtype: object
```

```
#performing a count on each currency
df["invoice_currency"].value_counts()
```

```
USD    45011
CAD     3828
Name: invoice_currency, dtype: int64
```

```
#display the "total_open_amount" column value
df['total_open_amount']
```

```
0        54273.28
1        79656.60
2         2253.86
3         3299.70
4        33133.29
           ...
49995     3187.86
49996     6766.54
49997     6120.86
49998       63.48
49999     1790.30
Name: total_open_amount, Length: 48839, dtype: float64
```

```
#Convert all CAD into USD currency of "total_open_amount" column
df['converted_usd']=""
df.loc[df['invoice_currency'] =='CAD', 'converted_usd'] = 0.7 *
df['total_open_amount']
df.loc[df['invoice_currency'] =='USD', 'converted_usd'] =
df['total_open_amount']

#displaying the new "converted_usd" column.to_numeric will convert the
dtype from object to float.
df['converted_usd']=pd.to_numeric(df['converted_usd'],errors='coerce')
df["converted_usd"]
```

```
0        54273.28
1        79656.60
2         2253.86
3         2309.79
4        33133.29
           ...
49995     3187.86
49996     6766.54
49997     6120.86
49998       63.48
49999     1790.30
Name: converted_usd, Length: 48839, dtype: float64
```

```
#display year wise record of buisness_year.
df.sort_values(["buisness_year"])
```

```
      business_code cust_number        name_customer clear_date  \
24693          U001  0200707005            KING S co 2019-03-27
30055          CA02  0140104440        SO foundation 2019-05-21
30056          U001  0200750051            ALBER llc 2019-05-20
30057          U001      CCU013           KRAFT F us 2019-11-01
30058          U001  0200749225    SUPER  associates 2019-01-29
...             ...         ...                  ...        ...
```

```
11258          U001  0200772670  ASSOCIAT associates 2020-01-22
11261          U001  0200769623          WAL-MAR llc        NaT
33206          CA02  0140104440               SO in        NaT
33217          U001  0200700919              US  co        NaT
0              U001  0200769623         WAL-MAR corp 2020-02-11

       buisness_year        doc_id posting_date due_in_date
invoice_currency  \
24693         2019.0  1.928933e+09   2019-03-12  2019-03-27
USD
30055         2019.0  2.960546e+09   2019-05-03  2019-05-13
CAD
30056         2019.0  1.929249e+09   2019-05-03  2019-05-18
USD
30057         2019.0  1.929915e+09   2019-09-28  2019-09-28
USD
30058         2019.0  1.928618e+09   2019-01-14  2019-01-29
USD
...              ...           ...          ...         ...
...
11258         2020.0  1.930362e+09   2020-01-06  2020-01-21
USD
11261         2020.0  1.930662e+09   2020-03-19  2020-04-03
USD
33206         2020.0  2.960624e+09   2020-03-30  2020-04-11
CAD
33217         2020.0  1.930760e+09   2020-04-07  2020-04-22
USD
0             2020.0  1.930438e+09   2020-01-26  2020-02-10
USD

       total_open_amount baseline_create_date cust_payment_terms  \
24693            8195.84           2019-03-12               NAA8
30055           80920.24           2019-05-03               CA10
30056           84027.27           2019-05-03               NAA8
30057           31739.22           2019-09-28               NAX2
30058           25542.56           2019-01-14               NAA8
...                  ...                  ...                ...
11258           60088.90           2020-01-06               NAU5
11261            3270.04           2020-03-19               NAH4
33206           40288.97           2020-04-01               CA10
33217           40497.33           2020-04-07               NAA8
0               54273.28           2020-01-26               NAH4

       converted_usd
24693       8195.840
30055      56644.168
30056      84027.270
30057      31739.220
30058      25542.560
```

```
...              ...
11258      60088.900
11261       3270.040
33206      28202.279
33217      40497.330
0          54273.280

[48839 rows x 13 columns]
```

```
#delete "invoice_currency", "total_open_amount" columns.
df.drop(columns = ["invoice_currency", "total_open_amount"],
inplace=True)
```

```
#checking number of columns in dataframe.
df.shape[1]
```

```
11
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 48839 entries, 0 to 49999
Data columns (total 11 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   business_code         48839 non-null  object
 1   cust_number           48839 non-null  object
 2   name_customer         48839 non-null  object
 3   clear_date            39158 non-null  datetime64[ns]
 4   buisness_year         48839 non-null  float64
 5   doc_id                48839 non-null  float64
 6   posting_date          48839 non-null  datetime64[ns]
 7   due_in_date           48839 non-null  datetime64[ns]
 8   baseline_create_date  48839 non-null  datetime64[ns]
 9   cust_payment_terms    48839 non-null  object
 10  converted_usd         48839 non-null  float64
dtypes: datetime64[ns](4), float64(3), object(4)
memory usage: 5.5+ MB
```

Splitting the Dataset

```
#Checking the null values.
df.columns[df.isna().any()].tolist()
```

```
['clear_date']
```

```
#displaying the number of null values in "clear_date".
df["clear_date"].isnull().sum()
```

```
9681
```

```
#putting all the notnull() "clear_date" values in train data and
null() values in test data.
train = df[df['clear_date'].notnull()]
test = df[df['clear_date'].isnull()]

#checking the rows and columns of both dataframes.
print(train.shape)
print(test.shape)
```

```
(39158, 11)
(9681, 11)
```

```
train.head(5)
```

```
  business_code cust_number       name_customer clear_date
buisness_year  \
0          U001  0200769623        WAL-MAR corp 2020-02-11
2020.0
1          U001  0200980828              BEN E  2019-08-08
2019.0
2          U001  0200792734          MDV/ trust 2019-12-30
2019.0
4          U001  0200769623  WAL-MAR foundation 2019-11-25
2019.0
5          CA02  0140106181    THE  corporation 2019-12-04
2019.0

         doc_id posting_date due_in_date baseline_create_date  \
0  1.930438e+09   2020-01-26  2020-02-10           2020-01-26
1  1.929646e+09   2019-07-22  2019-08-11           2019-07-22
2  1.929874e+09   2019-09-14  2019-09-29           2019-09-14
4  1.930148e+09   2019-11-13  2019-11-28           2019-11-13
5  2.960581e+09   2019-09-20  2019-10-04           2019-09-24

  cust_payment_terms  converted_usd
0               NAH4      54273.280
1               NAD1      79656.600
2               NAA8       2253.860
4               NAH4      33133.290
5               CA10      15558.088
```

```
test.head(5)
```

```
   business_code cust_number     name_customer clear_date
buisness_year  \
3           CA02  0140105686          SYSC llc        NaT
2020.0
7           U001  0200744019           TARG us        NaT
2020.0
10          U001  0200418007               AM         NaT
2020.0
```

```
14          U001  0200739534        OK systems        NaT
2020.0
15          U001  0200353024  DECA corporation        NaT
2020.0

          doc_id posting_date due_in_date baseline_create_date  \
3   2.960623e+09   2020-03-30  2020-04-10           2020-03-31
7   1.930659e+09   2020-03-19  2020-04-03           2020-03-19
10  1.930611e+09   2020-03-11  2020-03-26           2020-03-11
14  1.930788e+09   2020-04-15  2020-04-30           2020-04-15
15  1.930817e+09   2020-04-23  2020-04-26           2020-04-16

   cust_payment_terms  converted_usd
3                CA10        2309.79
7                NAA8       11173.02
10               NAA8        3525.59
14               NAA8      121105.65
15               NAM2        3726.06
```

```
#creating a new column "delay"
train['delay']=df['clear_date']-df['due_in_date']

#displaying the delay values.
train["delay"]
```

```
0        1 days
1       -3 days
2       92 days
4       -3 days
5       61 days
          ...
49994    0 days
49996    4 days
49997    0 days
49998    0 days
49999   -9 days
Name: delay, Length: 39158, dtype: timedelta64[ns]
```

```
#creating new column "avg_delay"
train['avg_delay'] = train.groupby('name_customer')
['delay'].transform('mean', numeric_only=False)
train['avg_delay']
```

```
0       -3 days +07:08:49.779837776
1                 19 days 00:00:00
2         8 days 02:10:54.545454545
4       -3 days +19:33:27.692307693
5                 71 days 10:40:00
                    ...
49994             -1 days +14:45:00
49996   -3 days +12:40:08.540925267
```

```
49997     1 days 01:08:34.285714285
49998     1 days 13:36:42.985074626
49999   -4 days +02:20:52.173913044
Name: avg_delay, Length: 39158, dtype: timedelta64[ns]
```

```
#converting avg_delay into secs.
train['avg_delay'] = train['avg_delay'].dt.total_seconds()
```

```
#displaying the train dataframe.
train
```

```
      business_code cust_number       name_customer clear_date
buisness_year  \
0              U001  0200769623        WAL-MAR corp 2020-02-11
2020.0
1              U001  0200980828              BEN E  2019-08-08
2019.0
2              U001  0200792734          MDV/ trust 2019-12-30
2019.0
4              U001  0200769623  WAL-MAR foundation 2019-11-25
2019.0
5              CA02  0140106181    THE  corporation 2019-12-04
2019.0
...             ...         ...                 ...        ...
...
49994          U001  0200762301        C&S WH trust 2019-07-25
2019.0
49996          U001  0200769623          WAL-MAR co 2019-09-03
2019.0
49997          U001  0200772595    SAFEW associates 2020-03-05
2020.0
49998          U001  0200726979           BJ'S  llc 2019-12-12
2019.0
49999          U001  0200020431            DEC corp 2019-01-15
2019.0

             doc_id posting_date due_in_date baseline_create_date  \
0      1.930438e+09   2020-01-26  2020-02-10           2020-01-26
1      1.929646e+09   2019-07-22  2019-08-11           2019-07-22
2      1.929874e+09   2019-09-14  2019-09-29           2019-09-14
4      1.930148e+09   2019-11-13  2019-11-28           2019-11-13
5      2.960581e+09   2019-09-20  2019-10-04           2019-09-24
...             ...          ...         ...                  ...
49994  1.929601e+09   2019-07-10  2019-07-25           2019-07-10
49996  1.929744e+09   2019-08-15  2019-08-30           2019-08-15
49997  1.930537e+09   2020-02-19  2020-03-05           2020-02-19
49998  1.930199e+09   2019-11-27  2019-12-12           2019-11-27
49999  1.928576e+09   2019-01-05  2019-01-24           2019-01-01

      cust_payment_terms  converted_usd   delay     avg_delay
0                   NAH4      54273.280  1 days -2.334702e+05
```

```
1                   NAD1      79656.600 -3 days  1.641600e+06
2                   NAA8       2253.860 92 days  6.990545e+05
4                   NAH4      33133.290 -3 days -1.887923e+05
5                   CA10      15558.088 61 days  6.172800e+06
...                  ...            ...     ...           ...
49994               NAC6      84780.400  0 days -3.330000e+04
49996               NAH4       6766.540  4 days -2.135915e+05
49997               NAA8       6120.860  0 days  9.051429e+04
49998               NAA8         63.480  0 days  1.354030e+05
49999               NAM4       1790.300 -9 days -3.371478e+05

[39158 rows x 13 columns]
```

```
#dropping 'clear_date','delay' columns.
train.drop(columns=['clear_date','delay'],inplace=True)
```

```
X = train[["business_code", "cust_number", "name_customer",
"buisness_year", "doc_id", "posting_date", "due_in_date",
"baseline_create_date", "cust_payment_terms", "converted_usd"]]
y = train["avg_delay"]
```

```
X.head()
```

```
  business_code cust_number       name_customer  buisness_year
doc_id  \
0          U001  0200769623        WAL-MAR corp         2020.0
1.930438e+09
1          U001  0200980828              BEN E          2019.0
1.929646e+09
2          U001  0200792734          MDV/ trust         2019.0
1.929874e+09
4          U001  0200769623  WAL-MAR foundation         2019.0
1.930148e+09
5          CA02  0140106181    THE  corporation         2019.0
2.960581e+09

  posting_date due_in_date baseline_create_date cust_payment_terms  \
0   2020-01-26  2020-02-10           2020-01-26               NAH4
1   2019-07-22  2019-08-11           2019-07-22               NAD1
2   2019-09-14  2019-09-29           2019-09-14               NAA8
4   2019-11-13  2019-11-28           2019-11-13               NAH4
5   2019-09-20  2019-10-04           2019-09-24               CA10

   converted_usd
0      54273.280
1      79656.600
2       2253.860
4      33133.290
5      15558.088
```

```
X_train, X_loc_test, y_train, y_loc_test= train_test_split(X, y,
train_size=0.60, random_state=42)

X_train.head(5)
```

```
      business_code cust_number       name_customer  buisness_year  \
44556          U001  0200756072         REINHA corp         2019.0
36713          U001  0200776463          KROGE corp         2020.0
2639           U001  0200794332        COST systems         2019.0
49682          U001  0200780383     MEIJ foundation         2020.0
45201          U001  0200769623  WAL-MAR foundation         2019.0

             doc_id posting_date due_in_date baseline_create_date  \
44556  1.929516e+09   2019-06-20  2019-07-05           2019-06-20
36713  1.930432e+09   2020-01-23  2020-02-07           2020-01-23
2639   1.928699e+09   2019-01-30  2019-02-14           2019-01-30
49682  1.930341e+09   2019-12-31  2020-01-15           2019-12-31
45201  1.929881e+09   2019-09-17  2019-10-02           2019-09-17

      cust_payment_terms  converted_usd
44556               NAA8       54315.10
36713               NAA8       52725.92
2639                NAAX       21126.47
49682               NAA8      143649.72
45201               NAH4       14864.00
```

```
X_loc_test.head(5)
```

```
      business_code cust_number        name_customer  buisness_year  \
44405          U001  0200865666            RESTAU us         2020.0
15496          U001  0200762301       C&S WH systems         2019.0
18468          U001  0200769623  WAL-MAR corporation         2019.0
35095          U001  0200759082      INGL associates         2019.0
11539          U001   200780825  SYSCO FO associates         2019.0

             doc_id posting_date due_in_date baseline_create_date  \
44405  1.930516e+09   2020-02-12  2020-02-27           2020-02-12
15496  1.930066e+09   2019-10-29  2019-11-13           2019-10-29
18468  1.930254e+09   2019-12-09  2019-12-24           2019-12-09
35095  1.929724e+09   2019-08-08  2019-08-23           2019-08-08
11539  1.928702e+09   2019-01-31  2019-02-15           2019-01-31

      cust_payment_terms  converted_usd
44405               NAA8        2761.12
15496               NAC6        1308.66
18468               NAH4        7589.15
35095               NAA8       19661.32
11539               NAA8       15987.49
```

```
y_loc_test.head(5)
```

```
44405         0.000000
15496   -108000.000000
18468   -218946.589595
35095     64800.000000
11539    151200.000000
Name: avg_delay, dtype: float64
```

```
y_train.head(5)
```

```
44556     48000.000000
36713     43200.000000
2639     -55408.695652
49682    184320.000000
45201   -188792.307692
Name: avg_delay, dtype: float64
```

```
X_train.shape
```

```
(23494, 10)
```

```
X_loc_test.shape
```

```
(15664, 10)
```

```
y_loc_test.shape
```

```
(15664,)
```

```
y_train.shape
```

```
(23494,)
```

```
X_val, X_test, y_val, y_test = train_test_split(X_loc_test,
y_loc_test, train_size=0.50, random_state=42)
```

```
X_val.shape
```

```
(7832, 10)
```

```
X_test.shape
```

```
(7832, 10)
```

```
y_val.shape
```

```
(7832,)
```

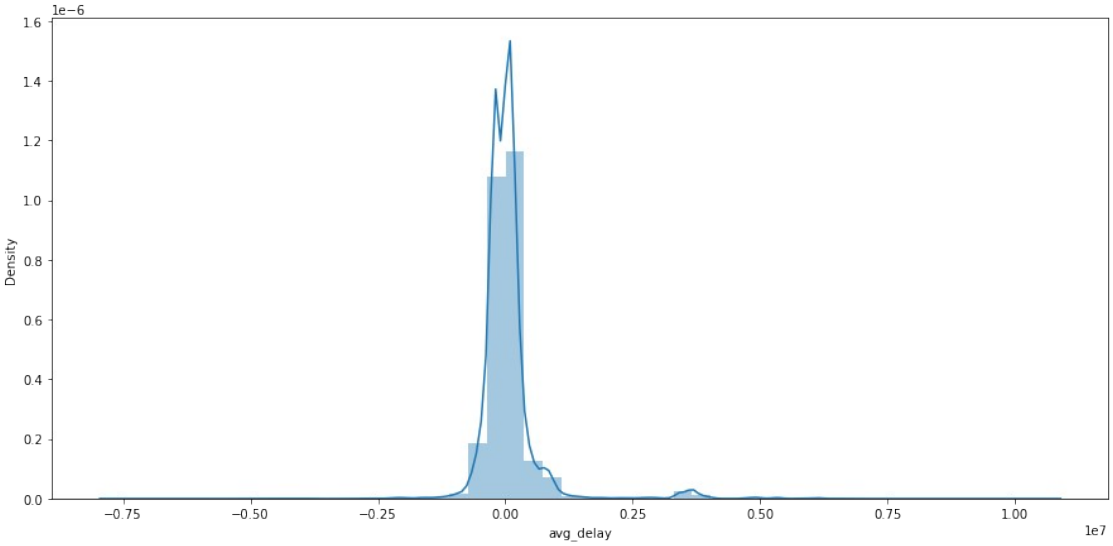
```
y_test.shape
```

```
(7832,)
```

Exploratory Data Analysis (EDA)

```
plt.subplots(figsize=(15,7))
sns.distplot(y_train)
```

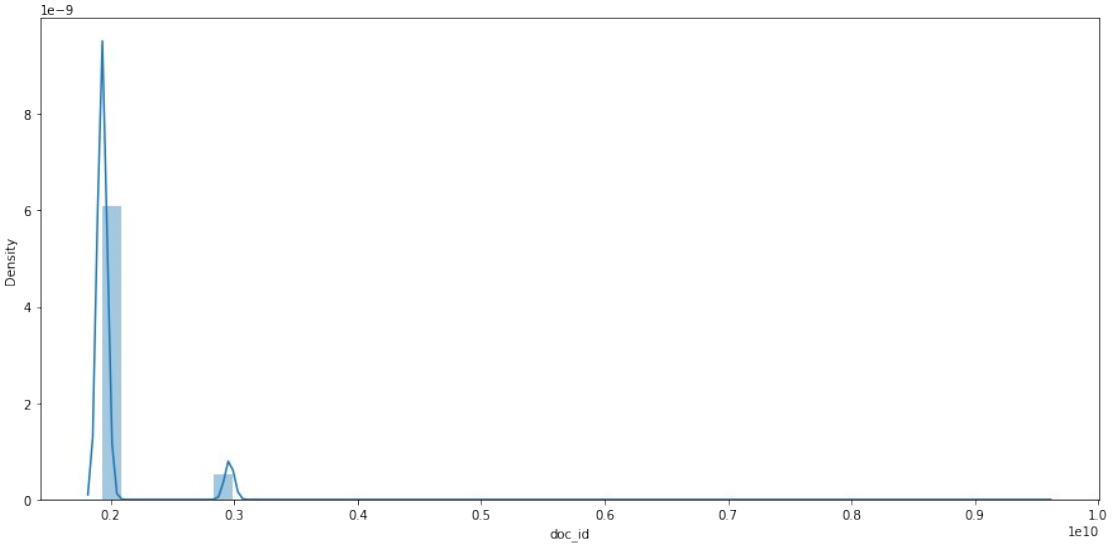
```
<AxesSubplot:xlabel='avg_delay', ylabel='Density'>
```




```
dt = X_train.groupby(by=['name_customer'], as_index=False)
['doc_id'].count()
```

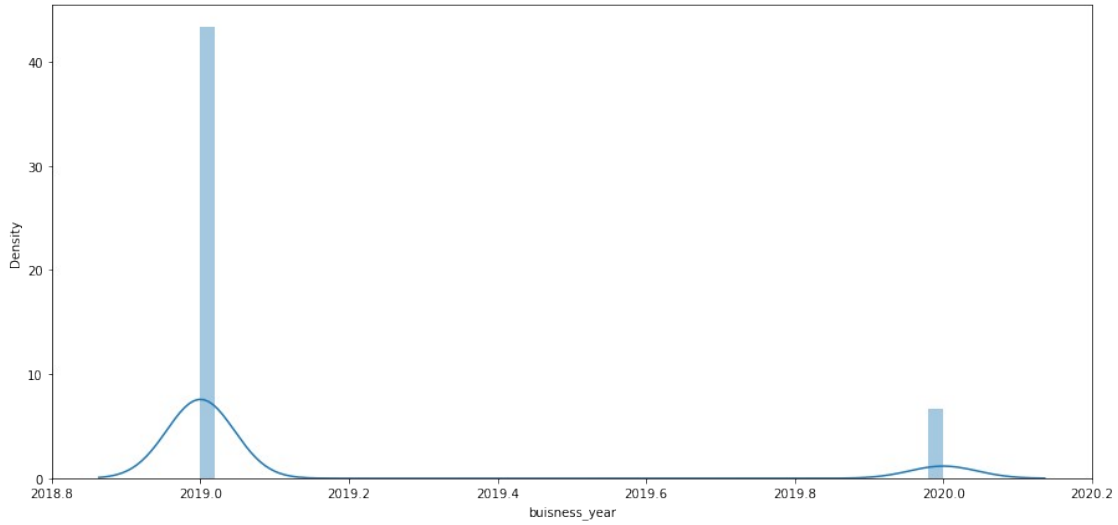
```
plt.subplots(figsize=(15,7))
sns.distplot(X_train["doc_id"])
```

```
<AxesSubplot:xlabel='doc_id', ylabel='Density'>
```




```
plt.subplots(figsize=(15,7))
sns.distplot(X_train["buisness_year"])
```

```
<AxesSubplot:xlabel='buisness_year', ylabel='Density'>
```



#draw distplot btw doc_id and buisness_year

Feature Engineering

#Display and describe the X_train dataframe

```
X_train
```

```
      business_code cust_number       name_customer  buisness_year  \
44556          U001  0200756072         REINHA corp         2019.0
36713          U001  0200776463          KROGE corp         2020.0
2639           U001  0200794332        COST systems         2019.0
49682          U001  0200780383     MEIJ foundation         2020.0
45201          U001  0200769623  WAL-MAR foundation         2019.0
...             ...         ...                 ...            ...
7745           U013  0140103699             L&E IN         2019.0
14076          U001  0200900909           SYSCO co         2019.0
48693          U001  0200769623       WAL-MAR trust         2020.0
1054           U001  0200764795   SYSCO  associates         2019.0
19783          U001  0200803720              DEC in         2019.0

            doc_id posting_date due_in_date baseline_create_date  \
44556  1.929516e+09   2019-06-20  2019-07-05           2019-06-20
36713  1.930432e+09   2020-01-23  2020-02-07           2020-01-23
2639   1.928699e+09   2019-01-30  2019-02-14           2019-01-30
49682  1.930341e+09   2019-12-31  2020-01-15           2019-12-31
45201  1.929881e+09   2019-09-17  2019-10-02           2019-09-17
...             ...          ...         ...                  ...
7745   1.991835e+09   2019-11-15  2019-12-15           2019-11-15
14076  1.929117e+09   2019-04-12  2019-04-27           2019-04-12
48693  1.930413e+09   2020-01-20  2020-02-04           2020-01-20
1054   1.929948e+09   2019-10-03  2019-10-18           2019-10-03
19783  1.928590e+09   2019-01-08  2019-01-08           2019-01-01
```

```
      cust_payment_terms  converted_usd
44556               NAA8       54315.10
36713               NAA8       52725.92
2639                NAAX       21126.47
49682               NAA8      143649.72
45201               NAH4       14864.00
...                  ...            ...
7745                NAVE       20131.46
14076               NAA8        2363.61
48693               NAH4        6663.73
1054                NAA8        3010.12
19783               NAM1        4524.65

[23494 rows x 10 columns]
```

```
X_train.describe()
```

```
       buisness_year        doc_id  converted_usd
count   23494.000000  2.349400e+04   23494.000000
mean     2019.134077  2.011913e+09   30618.192289
std         0.340742  2.852458e+08   36500.609654
min      2019.000000  1.928502e+09       0.790000
25%      2019.000000  1.929174e+09    4569.665750
50%      2019.000000  1.929732e+09   16795.265000
75%      2019.000000  1.930209e+09   45472.520500
max      2020.000000  9.500000e+09  668593.360000
```

```
from sklearn.preprocessing import LabelEncoder
business_coder = LabelEncoder()
business_coder.fit(X_train["business_code"])
```

```
LabelEncoder()
```

```
X_train['business_code_enc'] =
business_coder.fit_transform(X_train['business_code'])

X_val['business_code_enc'] =
business_coder.transform(X_val['business_code'])
X_test['business_code_enc'] =
business_coder.transform(X_test['business_code'])

X_train[["business_code", "business_code_enc"]]
```

```
      business_code  business_code_enc
44556          U001                  1
36713          U001                  1
2639           U001                  1
49682          U001                  1
45201          U001                  1
...             ...                ...
7745           U013                  5
```

```
14076          U001                 1
48693          U001                 1
1054           U001                 1
19783          U001                 1

[23494 rows x 2 columns]
```

```
def custom(col ,traindf = X_train,valdf = X_val,testdf = X_test):
    traindf.drop(col, axis =1,inplace=True)
    valdf.drop(col,axis=1 , inplace=True)
    testdf.drop(col,axis=1 , inplace=True)

    return traindf,valdf ,testdf

X_train ,X_val, X_test = custom(['business_code'])

X_train['cust_number'] =
X_train['cust_number'].str.replace('CCCA',"1").str.replace('CCU',"2").
str.replace('CC',"3").astype(int)
X_test['cust_number'] =
X_test['cust_number'].str.replace('CCCA',"1").str.replace('CCU',"2").s
tr.replace('CC',"3").astype(int)
X_val['cust_number'] =
X_val['cust_number'].str.replace('CCCA',"1").str.replace('CCU',"2").st
r.replace('CC',"3").astype(int)

#For encoding unseen labels
class EncoderExt(object):
    def __init__(self):
        self.label_encoder = LabelEncoder()
    def fit(self, data_list):
        self.label_encoder = self.label_encoder.fit(list(data_list) +
['Unknown'])
        self.classes_ = self.label_encoder.classes_
        return self
    def transform(self, data_list):
        new_data_list = list(data_list)
        for unique_item in np.unique(data_list):
            if unique_item not in self.label_encoder.classes_:
                new_data_list = ['Unknown' if x==unique_item else x
for x in new_data_list]
        return self.label_encoder.transform(new_data_list)

label_encoder = EncoderExt()
label_encoder.fit(X_train['name_customer'])
X_train['name_customer_enc']=label_encoder.transform(X_train['name_cus
tomer'])
X_val['name_customer_enc']=label_encoder.transform(X_val['name_custome
r'])
X_test['name_customer_enc']=label_encoder.transform(X_test['name_custo
mer'])
```

```
X_train ,X_val, X_test = custom(['name_customer'])

label_encoder1 = EncoderExt()
label_encoder1.fit(X_train['cust_payment_terms'])
X_train['cust_payment_terms_enc']=label_encoder1.transform(X_train['cu
st_payment_terms'])
X_val['cust_payment_terms_enc']=label_encoder1.transform(X_val['cust_p
ayment_terms'])
X_test['cust_payment_terms_enc']=label_encoder1.transform(X_test['cust
_payment_terms'])

X_train ,X_val, X_test = custom(['cust_payment_terms'])

X_train.dtypes

cust_number                      int32
buisness_year                  float64
doc_id                         float64
posting_date            datetime64[ns]
due_in_date             datetime64[ns]
baseline_create_date    datetime64[ns]
converted_usd                  float64
business_code_enc                int32
name_customer_enc                int32
cust_payment_terms_enc           int32
dtype: object

X_val.dtypes

cust_number                      int32
buisness_year                  float64
doc_id                         float64
posting_date            datetime64[ns]
due_in_date             datetime64[ns]
baseline_create_date    datetime64[ns]
converted_usd                  float64
business_code_enc                int32
name_customer_enc                int32
cust_payment_terms_enc           int32
dtype: object

X_test.dtypes

cust_number                      int32
buisness_year                  float64
doc_id                         float64
posting_date            datetime64[ns]
due_in_date             datetime64[ns]
baseline_create_date    datetime64[ns]
converted_usd                  float64
business_code_enc                int32
name_customer_enc                int32
```

```
cust_payment_terms_enc             int32
dtype: object
```

```
X_train['day_of_postingdate'] = X_train['posting_date'].dt.day
X_train['month_of_postingdate'] = X_train['posting_date'].dt.month
X_train['year_of_postingdate'] = X_train['posting_date'].dt.year

X_val['day_of_postingdate'] = X_val['posting_date'].dt.day
X_val['month_of_postingdate'] = X_val['posting_date'].dt.month
X_val['year_of_postingdate'] = X_val['posting_date'].dt.year


X_test['day_of_postingdate'] = X_test['posting_date'].dt.day
X_test['month_of_postingdate'] = X_test['posting_date'].dt.month
X_test['year_of_postingdate'] = X_test['posting_date'].dt.year

X_train ,X_val, X_test = custom(['posting_date'])

X_train['day_of_baseline'] = X_train['baseline_create_date'].dt.day
X_train['month_of_baseline'] =
X_train['baseline_create_date'].dt.month
X_train['year_of_baseline'] = X_train['baseline_create_date'].dt.year

X_val['day_of_baseline'] = X_val['baseline_create_date'].dt.day
X_val['month_of_baseline'] = X_val['baseline_create_date'].dt.month
X_val['year_of_baseline'] = X_val['baseline_create_date'].dt.year

X_test['day_of_baseline'] = X_test['baseline_create_date'].dt.day
X_test['month_of_baseline'] = X_test['baseline_create_date'].dt.month
X_test['year_of_baseline'] = X_test['baseline_create_date'].dt.year

X_train ,X_val, X_test = custom(['baseline_create_date'])

X_train['day_of_duedate'] = X_train['due_in_date'].dt.day
X_train['month_of_duedate'] = X_train['due_in_date'].dt.month
X_train['year_of_duedate'] = X_train['due_in_date'].dt.year

X_val['day_of_duedate'] = X_val['due_in_date'].dt.day
X_val['month_of_duedate'] = X_val['due_in_date'].dt.month
X_val['year_of_duedate'] = X_val['due_in_date'].dt.year

X_test['day_of_duedate'] = X_test['due_in_date'].dt.day
X_test['month_of_duedate'] = X_test['due_in_date'].dt.month
X_test['year_of_duedate'] = X_test['due_in_date'].dt.year

X_train ,X_val, X_test = custom(['due_in_date'])

print(X_train.dtypes,'\n\n')
print(X_val.dtypes,'\n\n')
print(X_test.dtypes)
```

```
cust_number                int32
buisness_year            float64
doc_id                   float64
converted_usd            float64
business_code_enc          int32
name_customer_enc          int32
cust_payment_terms_enc     int32
day_of_postingdate         int64
month_of_postingdate       int64
year_of_postingdate        int64
day_of_baseline            int64
month_of_baseline          int64
year_of_baseline           int64
day_of_duedate             int64
month_of_duedate           int64
year_of_duedate            int64
dtype: object
```

```
cust_number                int32
buisness_year            float64
doc_id                   float64
converted_usd            float64
business_code_enc          int32
name_customer_enc          int32
cust_payment_terms_enc     int32
day_of_postingdate         int64
month_of_postingdate       int64
year_of_postingdate        int64
day_of_baseline            int64
month_of_baseline          int64
year_of_baseline           int64
day_of_duedate             int64
month_of_duedate           int64
year_of_duedate            int64
dtype: object
```

```
cust_number                int32
buisness_year            float64
doc_id                   float64
converted_usd            float64
business_code_enc          int32
name_customer_enc          int32
cust_payment_terms_enc     int32
day_of_postingdate         int64
month_of_postingdate       int64
year_of_postingdate        int64
day_of_baseline            int64
month_of_baseline          int64
```

```
year_of_baseline            int64
day_of_duedate              int64
month_of_duedate            int64
year_of_duedate             int64
dtype: object
```

Feature Selection

```
from sklearn.feature_selection import VarianceThreshold
constant_filter = VarianceThreshold(threshold=0)
constant_filter.fit(X_train)
len(X_train.columns[constant_filter.get_support()])
```

```
16
```

```
constant_columns = [column for column in X_train.columns
                    if column not in
X_train.columns[constant_filter.get_support()]]
print(len(constant_columns))
```

```
0
```

```
x_train_T = X_train.T
print(x_train_T.duplicated().sum())
duplicated_columns = x_train_T[x_train_T.duplicated()].index.values
```

```
0
```

```
def handling_correlation(X_train,threshold=0.8):
    corr_features = set()
    corr_matrix = X_train.corr()
    for i in range(len(corr_matrix .columns)):
        for j in range(i):
            if abs(corr_matrix.iloc[i, j]) >threshold:
                colname = corr_matrix.columns[i]
                corr_features.add(colname)
    return list(corr_features)
```

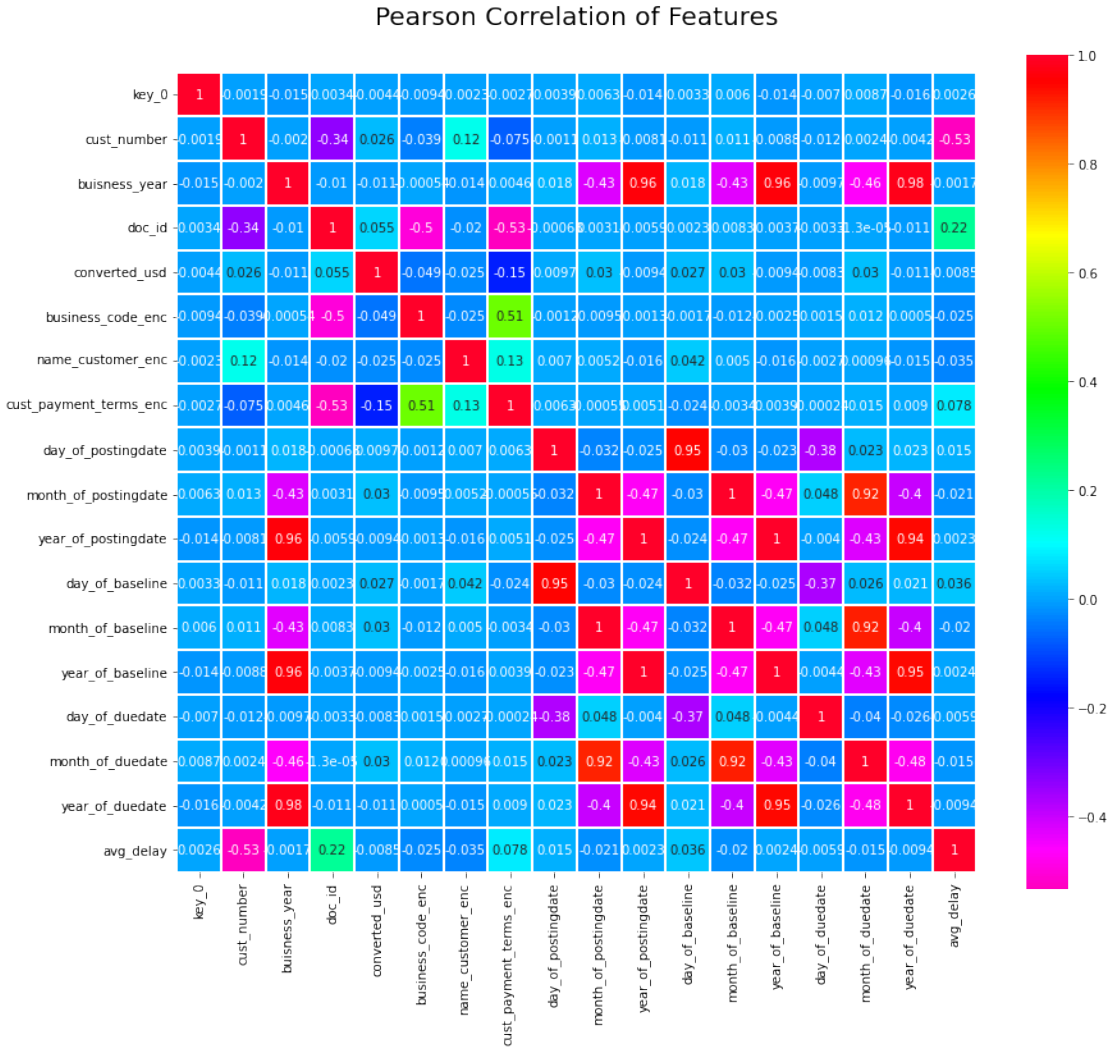
```
train=X_train.copy()
handling_correlation(train.copy(),0.85)
```

```
['month_of_baseline',
 'year_of_postingdate',
 'year_of_duedate',
 'day_of_baseline',
 'year_of_baseline',
 'month_of_duedate']
```

```
colormap = plt.cm.RdBu
plt.figure(figsize=(14,12))
plt.title('Pearson Correlation of Features', y=1.05, size=20)
sns.heatmap(X_train.merge(y_train , on =
```

```
X_train.index ).corr(),linewidths=0.1,vmax=1.0,
            square=True, cmap='gist_rainbow_r', linecolor='white',
annot=True)
```

```
<AxesSubplot:title={'center':'Pearson Correlation of Features'}>
```




```
from sklearn.feature_selection import VarianceThreshold
sel = VarianceThreshold(0.8)
sel.fit(X_train)
```

```
VarianceThreshold(threshold=0.8)
```

```
sel.variances_
```

```
array([1.73096954e+15, 1.16100201e-01, 8.13617218e+16, 1.33223780e+09,
       2.80596482e-01, 1.05187609e+06, 1.23314110e+02, 7.59077911e+01,
       1.23199874e+01, 1.16288980e-01, 7.75034812e+01, 1.23305592e+01,
       1.16501724e-01, 7.61464282e+01, 1.21259307e+01, 1.19305793e-
01])
```

Modelling

```
MSE_Score = []
R2_Score = []
Algorithm = []
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score

from sklearn.linear_model import LinearRegression
Algorithm.append('LinearRegression')
regressor = LinearRegression()
regressor.fit(X_train, y_train)
predicted= regressor.predict(X_test)

MSE_Score.append(mean_squared_error(y_test, predicted))
R2_Score.append(r2_score(y_test, predicted))

predict_test= regressor.predict(X_val)
mean_squared_error(y_val, predict_test, squared=False)

515943.3375777222

for i in Algorithm, MSE_Score, R2_Score:
    print(i,end=',')

['LinearRegression'],[320162589027.4911],[0.32175339197316966],

Algorithm.append('SVR')
regressor = SVR()
regressor.fit(X_train, y_train)
predicted= regressor.predict(X_test)

MSE_Score.append(mean_squared_error(y_test, predicted))
R2_Score.append(r2_score(y_test, predicted))

predict_test= regressor.predict(X_val)
mean_squared_error(y_val, predict_test, squared=False)

651773.9014090378

for i in Algorithm, MSE_Score, R2_Score:
    print(i,end=',')

['LinearRegression', 'SVR'],[320162589027.4911, 477086250513.25867],
[0.32175339197316966, -0.010680642387832728],

Algorithm.append('DecisionTreeRegressor')
regressor = DecisionTreeRegressor()
regressor.fit(X_train, y_train)
predicted= regressor.predict(X_test)

MSE_Score.append(mean_squared_error(y_test, predicted))
R2_Score.append(r2_score(y_test, predicted))
```

```
predict_test= regressor.predict(X_val)
mean_squared_error(y_val, predict_test, squared=False)
```

```
457910.14064372925
```

```
for i in Algorithm, MSE_Score, R2_Score:
    print(i,end=',')
```

```
['LinearRegression', 'SVR', 'DecisionTreeRegressor'],
[320162589027.4911, 477086250513.25867, 209273088399.6044],
[0.32175339197316966, -0.010680642387832728, 0.5566666212018201],
```

```
Algorithm.append('RandomForestRegressor')
regressor = RandomForestRegressor()
regressor.fit(X_train, y_train)
predicted= regressor.predict(X_test)

MSE_Score.append(mean_squared_error(y_test, predicted))
R2_Score.append(r2_score(y_test, predicted))

predict_test= regressor.predict(X_val)
mean_squared_error(y_val, predict_test, squared=False)
```

```
345049.21440526535
```

```
for i in Algorithm, MSE_Score, R2_Score:
    print(i,end=',')
```

```
['LinearRegression', 'SVR', 'DecisionTreeRegressor',
'RandomForestRegressor'],[320162589027.4911, 477086250513.25867,
209273088399.6044, 116469691984.98811],[0.32175339197316966, -
0.010680642387832728, 0.5566666212018201, 0.7532654462637267],
```

```
Algorithm.append('XGB Regressor')
regressor = xgb.XGBRegressor()
regressor.fit(X_train, y_train)
predicted = regressor.predict(X_test)

MSE_Score.append(mean_squared_error(y_test, predicted))
R2_Score.append(r2_score(y_test, predicted))

predict_test= regressor.predict(X_val)
mean_squared_error(y_val, predict_test, squared=False)
```

```
328868.64712268143
```

```
for i in Algorithm, MSE_Score, R2_Score:
    print(i,end=',')
```

```
['LinearRegression', 'SVR', 'DecisionTreeRegressor',
'RandomForestRegressor', 'XGB Regressor'],[320162589027.4911,
477086250513.25867, 209273088399.6044, 116469691984.98811,
```

```
111304108996.19151],[0.32175339197316966, -0.010680642387832728,
0.5566666212018201, 0.7532654462637267, 0.7642084460416663],

comp_df=pd.DataFrame([Algorithm,MSE_Score,
R2_Score],index=['Algorithm','MSE_Score','R2_Score'])
comp_df
```

```
                             0                   1
2  \
Algorithm     LinearRegression                 SVR
DecisionTreeRegressor
MSE_Score  320162589027.491089  477086250513.258667
209273088399.604401
R2_Score              0.321753           -0.010681
0.556667

                               3                   4
Algorithm  RandomForestRegressor        XGB Regressor
MSE_Score    116469691984.988113  111304108996.191513
R2_Score                0.753265            0.764208
```

```
regressorfinal = xgb.XGBRegressor()
regressorfinal.fit(X_train, y_train)
predictedfinal = regressorfinal.predict(X_test)
predict_testfinal = regressorfinal.predict(X_val)

print(mean_squared_error(y_test,predictedfinal,squared=False))
print(mean_squared_error(y_val, predict_testfinal, squared=False))
```

```
333622.70455739595
328868.64712268143
```

```
print("Accuracy for test dataset: ",r2_score(y_test,
predictedfinal)*100,"%")
print("Accuracy for val dataset: ",r2_score(y_val,
predict_testfinal)*100,"%")
print("Margin: ",r2_score(y_test, predictedfinal)-r2_score(y_val,
predict_testfinal))
```

```
Accuracy for test dataset:  76.42084460416663 %
Accuracy for val dataset:  74.34851029193163 %
Margin:  0.020723343122349913
```

Reason for choosing XGB

I chose XGB regressor because it provided minimum MSE and maximum R2 value.

Passing the null dataframe into the machine learning model.

```
test
```

```
      business_code cust_number        name_customer clear_date  \
3              CA02  0140105686             SYSC llc        NaT
7              U001  0200744019              TARG us        NaT
10             U001  0200418007                  AM         NaT
14             U001  0200739534           OK systems        NaT
15             U001  0200353024     DECA corporation        NaT
...             ...         ...                  ...        ...
49975          U001  0200769623           WAL-MAR in        NaT
49980          U001  0200769623  WAL-MAR corporation        NaT
49982          U001  0200148860             DOLLA co        NaT
49992          U001  0200900909             SYSCO co        NaT
49995          U001  0200561861       CO corporation        NaT

       buisness_year        doc_id posting_date due_in_date  \
3             2020.0  2.960623e+09   2020-03-30  2020-04-10
7             2020.0  1.930659e+09   2020-03-19  2020-04-03
10            2020.0  1.930611e+09   2020-03-11  2020-03-26
14            2020.0  1.930788e+09   2020-04-15  2020-04-30
15            2020.0  1.930817e+09   2020-04-23  2020-04-26
...              ...           ...          ...         ...
49975         2020.0  1.930625e+09   2020-03-10  2020-03-25
49980         2020.0  1.930851e+09   2020-05-03  2020-05-18
49982         2020.0  1.930638e+09   2020-03-11  2020-03-26
49992         2020.0  1.930702e+09   2020-03-25  2020-04-09
49995         2020.0  1.930797e+09   2020-04-21  2020-05-06

      baseline_create_date cust_payment_terms  converted_usd
3               2020-03-31               CA10        2309.79
7               2020-03-19               NAA8       11173.02
10              2020-03-11               NAA8        3525.59
14              2020-04-15               NAA8      121105.65
15              2020-04-16               NAM2        3726.06
...                    ...                ...            ...
49975           2020-03-10               NAH4       13114.99
49980           2020-05-03               NAH4        8899.71
49982           2020-03-11               NAA8        4967.06
49992           2020-03-25               NAA8        1998.64
49995           2020-04-21               NAA8        3187.86

[9681 rows x 11 columns]

test.shape

(9681, 11)

print(test.describe(),"\n\n\n")
print(test.info())

       buisness_year        doc_id  converted_usd
count         9681.0  9.681000e+03    9681.000000
mean          2020.0  2.006165e+09   32065.681125
```

```
std              0.0  2.673629e+08   35419.613688
min           2020.0  1.930535e+09       0.720000
25%           2020.0  1.930658e+09    5607.190000
50%           2020.0  1.930731e+09   19024.190000
75%           2020.0  1.930818e+09   47752.640000
max           2020.0  2.960636e+09  653644.800000
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9681 entries, 3 to 49995
Data columns (total 11 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   business_code          9681 non-null   object
 1   cust_number            9681 non-null   object
 2   name_customer          9681 non-null   object
 3   clear_date             0 non-null      datetime64[ns]
 4   buisness_year          9681 non-null   float64
 5   doc_id                 9681 non-null   float64
 6   posting_date           9681 non-null   datetime64[ns]
 7   due_in_date            9681 non-null   datetime64[ns]
 8   baseline_create_date   9681 non-null   datetime64[ns]
 9   cust_payment_terms     9681 non-null   object
 10  converted_usd          9681 non-null   float64
dtypes: datetime64[ns](4), float64(3), object(4)
memory usage: 907.6+ KB
None
```

```
backup = test
```

```
business_codern = LabelEncoder()
business_codern.fit(test['business_code'])
test['business_code_enc'] =
business_codern.transform(test['business_code'])
```

```
test['cust_number'] =
test['cust_number'].str.replace('CCCA',"1").str.replace('CCU',"2").str
.replace('CC',"3").astype(int)
```

```
test['day_of_clear_date'] = test['clear_date'].dt.day
test['month_of_clear_date'] = test['clear_date'].dt.month
test['year_of_clear_date'] = test['clear_date'].dt.year
```

```
test['day_of_posting_date'] = test['posting_date'].dt.day
test['month_of_posting_date'] = test['posting_date'].dt.month
test['year_of_posting_date'] = test['posting_date'].dt.year
```

```
test['day_of_create_date'] = test['baseline_create_date'].dt.day
test['month_of_create_date'] = test['baseline_create_date'].dt.month
test['year_of_create_date'] = test['baseline_create_date'].dt.year
```

```
test['day_of_due'] = test['due_in_date'].dt.day
test['month_of_due'] = test['due_in_date'].dt.month
test['year_of_due'] = test['due_in_date'].dt.year

test['cust_payment_terms_enc']=label_encoder1.transform(test['cust_pay
ment_terms'])
test['business_code_enc']=label_encoder1.transform(test['business_code
'])
test['name_customer_enc']=label_encoder.transform(test['name_customer'
])

test.dtypes

business_code                    object
cust_number                       int32
name_customer                    object
clear_date               datetime64[ns]
buisness_year                   float64
doc_id                          float64
posting_date             datetime64[ns]
due_in_date              datetime64[ns]
baseline_create_date     datetime64[ns]
cust_payment_terms               object
converted_usd                   float64
business_code_enc                 int32
day_of_clear_date               float64
month_of_clear_date             float64
year_of_clear_date              float64
day_of_posting_date               int64
month_of_posting_date             int64
year_of_posting_date              int64
day_of_create_date                int64
month_of_create_date              int64
year_of_create_date               int64
day_of_due                        int64
month_of_due                      int64
year_of_due                       int64
cust_payment_terms_enc            int32
name_customer_enc                 int32
dtype: object

test.drop(columns=['business_code','baseline_create_date','due_in_date
','posting_date','name_customer','clear_date',

'cust_payment_terms','day_of_clear_date','month_of_clear_date','year_o
f_clear_date'],inplace=True)

test.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 9681 entries, 3 to 49995
```

```
Data columns (total 16 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   cust_number             9681 non-null   int32  
 1   buisness_year           9681 non-null   float64
 2   doc_id                  9681 non-null   float64
 3   converted_usd           9681 non-null   float64
 4   business_code_enc       9681 non-null   int32  
 5   day_of_posting_date     9681 non-null   int64  
 6   month_of_posting_date   9681 non-null   int64  
 7   year_of_posting_date    9681 non-null   int64  
 8   day_of_create_date      9681 non-null   int64  
 9   month_of_create_date    9681 non-null   int64  
 10  year_of_create_date     9681 non-null   int64  
 11  day_of_due              9681 non-null   int64  
 12  month_of_due            9681 non-null   int64  
 13  year_of_due             9681 non-null   int64  
 14  cust_payment_terms_enc  9681 non-null   int32  
 15  name_customer_enc       9681 non-null   int32  
dtypes: float64(3), int32(4), int64(9)
memory usage: 1.1 MB
```

```
X_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7832 entries, 6118 to 44809
Data columns (total 16 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   cust_number             7832 non-null   int32  
 1   buisness_year           7832 non-null   float64
 2   doc_id                  7832 non-null   float64
 3   converted_usd           7832 non-null   float64
 4   business_code_enc       7832 non-null   int32  
 5   name_customer_enc       7832 non-null   int32  
 6   cust_payment_terms_enc  7832 non-null   int32  
 7   day_of_postingdate      7832 non-null   int64  
 8   month_of_postingdate    7832 non-null   int64  
 9   year_of_postingdate     7832 non-null   int64  
 10  day_of_baseline         7832 non-null   int64  
 11  month_of_baseline       7832 non-null   int64  
 12  year_of_baseline        7832 non-null   int64  
 13  day_of_duedate          7832 non-null   int64  
 14  month_of_duedate        7832 non-null   int64  
 15  year_of_duedate         7832 non-null   int64  
dtypes: float64(3), int32(4), int64(9)
memory usage: 917.8 KB
```

```
X_test.columns
```

```
Index(['cust_number', 'buisness_year', 'doc_id', 'converted_usd',
       'business_code_enc', 'name_customer_enc',
'cust_payment_terms_enc',
       'day_of_postingdate', 'month_of_postingdate',
'year_of_postingdate',
       'day_of_baseline', 'month_of_baseline', 'year_of_baseline',
       'day_of_duedate', 'month_of_duedate', 'year_of_duedate'],
      dtype='object')
```

```
test.columns
```

```
Index(['cust_number', 'buisness_year', 'doc_id', 'converted_usd',
       'business_code_enc', 'day_of_posting_date',
'month_of_posting_date',
       'year_of_posting_date', 'day_of_create_date',
'month_of_create_date',
       'year_of_create_date', 'day_of_due', 'month_of_due',
'year_of_due',
       'cust_payment_terms_enc', 'name_customer_enc'],
      dtype='object')
```

```
test2=test[['cust_number', 'buisness_year', 'doc_id', 'converted_usd',
       'business_code_enc', 'name_customer_enc',
'cust_payment_terms_enc',
       'day_of_posting_date', 'month_of_posting_date',
'year_of_posting_date',
       'day_of_create_date', 'month_of_create_date',
'year_of_create_date',
       'day_of_due', 'month_of_due', 'year_of_due']]
```

```
test2
```

```
       cust_number  buisness_year        doc_id  converted_usd  \
3        140105686         2020.0  2.960623e+09        2309.79
7        200744019         2020.0  1.930659e+09       11173.02
10       200418007         2020.0  1.930611e+09        3525.59
14       200739534         2020.0  1.930788e+09      121105.65
15       200353024         2020.0  1.930817e+09        3726.06
...            ...            ...           ...            ...
49975    200769623         2020.0  1.930625e+09       13114.99
49980    200769623         2020.0  1.930851e+09        8899.71
49982    200148860         2020.0  1.930638e+09        4967.06
49992    200900909         2020.0  1.930702e+09        1998.64
49995    200561861         2020.0  1.930797e+09        3187.86

       business_code_enc  name_customer_enc  cust_payment_terms_enc  \
3                     65               2694                       5
7                     65               2777                      21
10                    65                 96                      21
14                    65               2008                      21
15                    65                729                      36
```

```
...                  ...                ...                      ...
49975                 65               2979                       34
49980                 65               2977                       34
49982                 65                803                       21
49992                 65               2738                       21
49995                 65                541                       21

       day_of_posting_date  month_of_posting_date
year_of_posting_date  \
3                      30                     3
2020
7                      19                     3
2020
10                     11                     3
2020
14                     15                     4
2020
15                     23                     4
2020
...                   ...                   ...                    ..
.
49975                  10                     3
2020
49980                   3                     5
2020
49982                  11                     3
2020
49992                  25                     3
2020
49995                  21                     4
2020

       day_of_create_date  month_of_create_date
year_of_create_date  \
3                      31                     3                2020

7                      19                     3                2020

10                     11                     3                2020

14                     15                     4                2020

15                     16                     4                2020

...                   ...                   ...                 ...

49975                  10                     3                2020

49980                   3                     5                2020
```

```
49982                  11                     3                  2020

49992                  25                     3                  2020

49995                  21                     4                  2020


       day_of_due  month_of_due  year_of_due
3              10             4         2020
7               3             4         2020
10             26             3         2020
14             30             4         2020
15             26             4         2020
...           ...           ...          ...
49975          25             3         2020
49980          18             5         2020
49982          26             3         2020
49992           9             4         2020
49995           6             5         2020

[9681 rows x 16 columns]
```

```
regressorfinal = xgb.XGBRegressor()
regressorfinal.fit(X_train, y_train)
final_result = regressorfinal.predict(test2)

final_result = pd.Series(final_result,name='avg_delay')

final_result
```

```
0       1.434917e+06
1       5.126310e+05
2      -2.319441e+05
3       4.599519e+05
4      -2.844167e+05
           ...
9676    1.335793e+06
9677    1.105565e+06
9678   -3.803205e+05
9679    4.217559e+05
9680    7.891307e+04
Name: avg_delay, Length: 9681, dtype: float32
```

```
backup.reset_index(drop=True,inplace=True)
Final = backup.merge(final_result , on = test2.index )

Final
```

```
      key_0  cust_number  buisness_year        doc_id
converted_usd  \
```

```
0         3    140105686         2020.0  2.960623e+09        2309.79

1         7    200744019         2020.0  1.930659e+09       11173.02

2        10    200418007         2020.0  1.930611e+09        3525.59

3        14    200739534         2020.0  1.930788e+09      121105.65

4        15    200353024         2020.0  1.930817e+09        3726.06

...     ...          ...            ...           ...             ...

9676  49975    200769623         2020.0  1.930625e+09       13114.99

9677  49980    200769623         2020.0  1.930851e+09        8899.71

9678  49982    200148860         2020.0  1.930638e+09        4967.06

9679  49992    200900909         2020.0  1.930702e+09        1998.64

9680  49995    200561861         2020.0  1.930797e+09        3187.86


      business_code_enc  day_of_posting_date  month_of_posting_date  \
0                    65                   30                      3
1                    65                   19                      3
2                    65                   11                      3
3                    65                   15                      4
4                    65                   23                      4
...                 ...                  ...                    ...
9676                 65                   10                      3
9677                 65                    3                      5
9678                 65                   11                      3
9679                 65                   25                      3
9680                 65                   21                      4

      year_of_posting_date  day_of_create_date
month_of_create_date  \
0                     2020                  31                     3

1                     2020                  19                     3

2                     2020                  11                     3

3                     2020                  15                     4

4                     2020                  16                     4
```

```
...                    ...                 ...                    ...

9676                   2020                 10                     3

9677                   2020                  3                     5

9678                   2020                 11                     3

9679                   2020                 25                     3

9680                   2020                 21                     4
```

```
      year_of_create_date  day_of_due  month_of_due  year_of_due  \
0                    2020          10             4         2020
1                    2020           3             4         2020
2                    2020          26             3         2020
3                    2020          30             4         2020
4                    2020          26             4         2020
...                   ...         ...           ...          ...
9676                 2020          25             3         2020
9677                 2020          18             5         2020
9678                 2020          26             3         2020
9679                 2020           9             4         2020
9680                 2020           6             5         2020

      cust_payment_terms_enc  name_customer_enc     avg_delay
0                          5               2694  1.434917e+06
1                         21               2777  5.126310e+05
2                         21                 96 -2.319441e+05
3                         21               2008  4.599519e+05
4                         36                729 -2.844167e+05
...                      ...                ...           ...
9676                      34               2979  1.335793e+06
9677                      34               2977  1.105565e+06
9678                      21                803 -3.803205e+05
9679                      21               2738  4.217559e+05
9680                      21                541  7.891307e+04

[9681 rows x 18 columns]
```

```
Final.shape
```

```
(9681, 18)
```

```
Final['clear_date']=''
Final['posting_date']=''
Final['due_in_date']=''
Final['baseline_create_date']=''
Final['due_in_date']=pd.to_datetime(Final.year_of_due*10000+Final.mont
```

```
h_of_due*100+Final.day_of_due,format='%Y%m%d')
Final['posting_date']=pd.to_datetime(Final.year_of_posting_date*10000+
Final.month_of_posting_date*100+Final.day_of_posting_date,format='%Y%m
%d')
Final['baseline_create_date']=pd.to_datetime(Final.year_of_create_date
*10000+Final.month_of_create_date*100+Final.day_of_create_date,format=
'%Y%m%d')
```

```
Final
```

```
      key_0  cust_number  buisness_year        doc_id
converted_usd  \
0         3    140105686         2020.0  2.960623e+09        2309.79

1         7    200744019         2020.0  1.930659e+09       11173.02

2        10    200418007         2020.0  1.930611e+09        3525.59

3        14    200739534         2020.0  1.930788e+09      121105.65

4        15    200353024         2020.0  1.930817e+09        3726.06

...     ...          ...            ...           ...            ...

9676  49975    200769623         2020.0  1.930625e+09       13114.99

9677  49980    200769623         2020.0  1.930851e+09        8899.71

9678  49982    200148860         2020.0  1.930638e+09        4967.06

9679  49992    200900909         2020.0  1.930702e+09        1998.64

9680  49995    200561861         2020.0  1.930797e+09        3187.86


      business_code_enc  day_of_posting_date  month_of_posting_date  \
0                    65                   30                      3
1                    65                   19                      3
2                    65                   11                      3
3                    65                   15                      4
4                    65                   23                      4
...                 ...                  ...                    ...
9676                 65                   10                      3
9677                 65                    3                      5
9678                 65                   11                      3
9679                 65                   25                      3
9680                 65                   21                      4

      year_of_posting_date  day_of_create_date  ...  day_of_due
```

```
month_of_due  \
0                    2020                  31  ...          10
4
1                    2020                  19  ...           3
4
2                    2020                  11  ...          26
3
3                    2020                  15  ...          30
4
4                    2020                  16  ...          26
4
...                   ...                 ...  ...         ...
...
9676                 2020                  10  ...          25
3
9677                 2020                   3  ...          18
5
9678                 2020                  11  ...          26
3
9679                 2020                  25  ...           9
4
9680                 2020                  21  ...           6
5

      year_of_due  cust_payment_terms_enc  name_customer_enc
avg_delay  \
0            2020                       5               2694
1.434917e+06
1            2020                      21               2777
5.126310e+05
2            2020                      21                 96 -
2.319441e+05
3            2020                      21               2008
4.599519e+05
4            2020                      36                729 -
2.844167e+05
...           ...                     ...                ...
...
9676         2020                      34               2979
1.335793e+06
9677         2020                      34               2977
1.105565e+06
9678         2020                      21                803 -
3.803205e+05
9679         2020                      21               2738
4.217559e+05
9680         2020                      21                541
7.891307e+04

      clear_date  posting_date due_in_date baseline_create_date
```

```
0                   2020-03-30  2020-04-10           2020-03-31
1                   2020-03-19  2020-04-03           2020-03-19
2                   2020-03-11  2020-03-26           2020-03-11
3                   2020-04-15  2020-04-30           2020-04-15
4                   2020-04-23  2020-04-26           2020-04-16
...          ...           ...         ...                  ...
9676                2020-03-10  2020-03-25           2020-03-10
9677                2020-05-03  2020-05-18           2020-05-03
9678                2020-03-11  2020-03-26           2020-03-11
9679                2020-03-25  2020-04-09           2020-03-25
9680                2020-04-21  2020-05-06           2020-04-21

[9681 rows x 22 columns]
```

```
Final['clear_date'] = pd.to_datetime(Final['due_in_date']) +
pd.to_timedelta(Final['avg_delay'], unit='s')
```

```
Final['avg_delay'] = Final.apply(lambda row: row.avg_delay//(24 *
3600), axis = 1)
```

```
Final['avg_delay'] = abs(Final['avg_delay'])
```

```
bins=  [0,15,30,45,60,100]
labels = ['0-15','16-30','31-45','46-60','Greatar than 60']
Final['Aging Bucket'] = pd.cut(Final['avg_delay'], bins=bins,
labels=labels, right=False)
```

```
Final.drop(columns = ["avg_delay", "key_0"], inplace=True)
```

```
Final['Aging Bucket'].value_counts()
```

```
0-15               6667
16-30              2929
31-45                80
Greatar than 60       4
46-60                 1
Name: Aging Bucket, dtype: int64
```

```
Final.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9681 entries, 0 to 9680
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   cust_number             9681 non-null   int32
 1   buisness_year           9681 non-null   float64
 2   doc_id                  9681 non-null   float64
 3   converted_usd           9681 non-null   float64
 4   business_code_enc       9681 non-null   int32
 5   day_of_posting_date     9681 non-null   int64
 6   month_of_posting_date   9681 non-null   int64
```

```
 7   year_of_posting_date    9681 non-null   int64
 8   day_of_create_date      9681 non-null   int64
 9   month_of_create_date    9681 non-null   int64
 10  year_of_create_date     9681 non-null   int64
 11  day_of_due              9681 non-null   int64
 12  month_of_due            9681 non-null   int64
 13  year_of_due             9681 non-null   int64
 14  cust_payment_terms_enc  9681 non-null   int32
 15  name_customer_enc       9681 non-null   int32
 16  clear_date              9681 non-null   datetime64[ns]
 17  posting_date            9681 non-null   datetime64[ns]
 18  due_in_date             9681 non-null   datetime64[ns]
 19  baseline_create_date    9681 non-null   datetime64[ns]
 20  Aging Bucket            9681 non-null   category
dtypes: category(1), datetime64[ns](4), float64(3), int32(4), int64(9)
memory usage: 1.4 MB
```

Final

	cust_number	buisness_year	doc_id	converted_usd	business_code_enc	day_of_posting_date	month_of_posting_date	year_of_posting_date	day_of_create_date	month_of_create_date	...
0	140105686	2020.0	2.960623e+09	2309.79	65	30	3	2020	31	3	...
1	200744019	2020.0	1.930659e+09	11173.02	65	19	3	2020	19	1	...
2	200418007	2020.0	1.930611e+09	3525.59	65	11	3				
3	200739534	2020.0	1.930788e+09	121105.65	65	15	4				
4	200353024	2020.0	1.930817e+09	3726.06	65	23	4				
...	...	...	...	...	...	...	...				
9676	200769623	2020.0	1.930625e+09	13114.99	65	10	3				
9677	200769623	2020.0	1.930851e+09	8899.71	65	3	5				
9678	200148860	2020.0	1.930638e+09	4967.06	65	11	3				
9679	200900909	2020.0	1.930702e+09	1998.64	65	25	3				
9680	200561861	2020.0	1.930797e+09	3187.86	65	21	4				

```
3  ...
2                  2020                  11
3  ...
3                  2020                  15
4  ...
4                  2020                  16
4  ...
...                 ...                 ...                   ...
...
9676               2020                  10
3  ...
9677               2020                   3
5  ...
9678               2020                  11
3  ...
9679               2020                  25
3  ...
9680               2020                  21
4  ...

      day_of_due  month_of_due  year_of_due  cust_payment_terms_enc  \
0             10             4         2020                       5
1              3             4         2020                      21
2             26             3         2020                      21
3             30             4         2020                      21
4             26             4         2020                      36
...          ...           ...          ...                     ...
9676          25             3         2020                      34
9677          18             5         2020                      34
9678          26             3         2020                      21
9679           9             4         2020                      21
9680           6             5         2020                      21

      name_customer_enc                    clear_date posting_date  \
0                  2694 2020-04-26 14:35:17.000000000   2020-03-30
1                  2777 2020-04-08 22:23:51.031250000   2020-03-19
2                    96 2020-03-23 07:34:15.859375000   2020-03-11
3                  2008 2020-05-05 07:45:51.906250000   2020-04-15
4                   729 2020-04-22 16:59:43.281250000   2020-04-23
...                 ...                          ...          ...
9676               2979 2020-04-09 11:03:12.875000000   2020-03-10
9677               2977 2020-05-30 19:06:05.000000000   2020-05-03
9678                803 2020-03-21 14:21:19.468750000   2020-03-11
9679               2738 2020-04-13 21:09:15.875000000   2020-03-25
9680                541 2020-05-06 21:55:13.070312500   2020-04-21

     due_in_date baseline_create_date Aging Bucket
0     2020-04-10           2020-03-31        16-30
1     2020-04-03           2020-03-19         0-15
2     2020-03-26           2020-03-11         0-15
```

```
3     2020-04-30           2020-04-15         0-15
4     2020-04-26           2020-04-16         0-15
...          ...                  ...          ...
9676  2020-03-25           2020-03-10        16-30
9677  2020-05-18           2020-05-03         0-15
9678  2020-03-26           2020-03-11         0-15
9679  2020-04-09           2020-03-25         0-15
9680  2020-05-06           2020-04-21         0-15

[9681 rows x 21 columns]
```

```
Final.to_csv('C:/Users/SyberNautics-11/Desktop/High
Radius_ML_Model/HRC81592W_MilindPruthi.csv')
```