San Diego Street Conditions Classification

A Cloud Computing Project by Leonid Shpaner, Jose Luis Estrada, and Kiran Singh

[1]:
```python
import boto3
import sagemaker
from pyathena import connect

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from prettytable import PrettyTable
from imblearn.over_sampling import SMOTE, ADASYN
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split

import warnings
warnings.filterwarnings('ignore')
```

Data Wrangling

[2]:
```python
# create athena database
sess = sagemaker.Session()
bucket = sess.default_bucket()
role = sagemaker.get_execution_role()
region = boto3.Session().region_name
# s3 = boto3.Session().client(service_name="s3", region_name=region)

# ec2 = boto3.Session().client(service_name="ec2", region_name=region)
# sm = boto3.Session().client(service_name="sagemaker", region_name=region)
```

[3]:
```python
ingest_create_athena_db_passed = False
```

[4]:
```python
# set a database name
database_name = "watersd"
```

[5]:
```python
# Set S3 staging directory -- this is a temporary directory used for Athena queries
s3_staging_dir = "s3://{0}/athena/staging".format(bucket)
```

[6]:
```python
conn = connect(region_name=region, s3_staging_dir=s3_staging_dir)
```

[7]:
```python
statement = "CREATE DATABASE IF NOT EXISTS {}".format(database_name)
print(statement)
pd.read_sql(statement, conn)
```

```
CREATE DATABASE IF NOT EXISTS watersd
```

[7]:
```
Empty DataFrame
Columns: []
Index: []
```

[8]:
```python
water_dir = 's3://waterteam1/raw_files'
```

[9]:
```python
# SQL statement to execute the analyte tests drinking water table

table_name ='oci_2015_datasd'
pd.read_sql(f'DROP TABLE IF EXISTS {database_name}.{table_name}', conn)


create_table = f"""
CREATE EXTERNAL TABLE IF NOT EXISTS {database_name}.{table_name}(
                seg_id string,
                oci float,
                street string,
                street_from string,
                street_to string,
                seg_length_ft float,
                seg_width_ft float,
                func_class string,
                pvm_class string,
                area_sq_ft float,
                oci_desc string,
                oci_wt float
                )

                ROW FORMAT DELIMITED
                FIELDS TERMINATED BY ','
                LOCATION '{water_dir}/{table_name}'
                TBLPROPERTIES ('skip.header.line.count'='1')
"""

pd.read_sql(create_table, conn)

pd.read_sql(f'SELECT * FROM {database_name}.{table_name} LIMIT 5', conn)
```

[9]:
```
      seg_id    oci street street_from street_to  seg_length_ft  seg_width_ft  \
0  SA-000003  65.14  ALLEY                              772.7258          30.0
1  SA-000004  67.45  ALLEY                              196.0025          30.0
2  SA-000005  70.88  ALLEY                              395.0049          30.0
3  SA-000006  84.00  ALLEY                              192.0025          30.0
4  SA-000008  79.24  ALLEY                              251.7540          30.0

  func_class             pvm_class  area_sq_ft oci_desc      oci_wt
0      Alley  PCC Jointed Concrete   23181.773     Fair  1510060.80
1      Alley  PCC Jointed Concrete    5880.075     Fair   396611.06
2      Alley  PCC Jointed Concrete   11850.147     Good   839938.44
3      Alley  PCC Jointed Concrete    5760.075     Good   483846.30
4      Alley  PCC Jointed Concrete    7552.620     Good   598469.60
```

[10]:
```python
# SQL statement to execute the analyte tests drinking water table

table_name2 ='sd_paving_datasd'
pd.read_sql(f'DROP TABLE IF EXISTS {database_name}.{table_name2}', conn)
```

```
create_table = f"""
CREATE EXTERNAL TABLE IF NOT EXISTS {database_name}.{table_name2}(
                pve_id int,
                seg_id string,
                project_id string,
                title string,
                project_manager string,
                project_manager_phone string,
                status string,
                type string,
                resident_engineer string,
                address_street string,
                street_from string,
                street_to string,
                seg_cd int,
                length int,
                width int,
                date_moratorium date,
                date_start date,
                date_end date,
                paving_miles float
                )

                ROW FORMAT DELIMITED
                FIELDS TERMINATED BY ','
                LOCATION '{water_dir}/{table_name2}'
                TBLPROPERTIES ('skip.header.line.count'='1')
"""

pd.read_sql(create_table, conn)

pd.read_sql(f'SELECT * FROM {database_name}.{table_name2} LIMIT 5', conn)
```

[10]:

```
       pve_id     seg_id project_id             title  \
0  1073577074  SA-000319       UTLY  Public Works CIP
1  1792486183  SA-000345       UTLY  Public Works CIP
2  1173780646  SA-000375       UTLY  Public Works CIP
3  1276790298  SA-000378       UTLY  Public Works CIP
4    27170959  SA-001081       UTLY  Public Works CIP

            project_manager project_manager_phone             status  \
0  Engineering@sandiego.gov          858-627-3200  post construction
1  Engineering@sandiego.gov          858-627-3200  post construction
2  Engineering@sandiego.gov          858-627-3200  post construction
3  Engineering@sandiego.gov          858-627-3200  post construction
4  Engineering@sandiego.gov          858-627-3200  post construction

      type resident_engineer address_street street_from street_to  seg_cd  \
0  Overlay               ECP          ALLEY                              2
1   Slurry               ECP          ALLEY                              2
```

```
2    Slurry               ECP          ALLEY                              2
3    Slurry               ECP          ALLEY                              2
4  Concrete               ECP          ALLEY                              9

   length  width date_moratorium  date_start    date_end  paving_miles
0       0    NaN      2019-02-02  2019-02-02  2019-02-02      0.000000
1     938   30.0      2019-01-30  2019-01-30  2019-01-30      0.177652
2     674   30.0      2018-08-01  2018-08-01  2018-08-01      0.127652
3     658   30.0      2018-08-01  2018-08-01  2018-08-01      0.124621
4     680   30.0            None  2020-08-13  2020-08-13      0.128788
```

[11]:
```
# SQL statement to execute the analyte tests drinking water table

table_name3 ='traffic_counts_datasd'
pd.read_sql(f'DROP TABLE IF EXISTS {database_name}.{table_name3}', conn)


create_table = f"""
CREATE EXTERNAL TABLE IF NOT EXISTS {database_name}.{table_name3}(
                id string,
                street_name string,
                limits string,
                northbound_count int,
                southbound_count int,
                eastbound_count int,
                westbound_count int,
                total_count int,
                file_no string,
                date_count date
                )

                ROW FORMAT DELIMITED
                FIELDS TERMINATED BY ','
                LOCATION '{water_dir}/{table_name3}'
                TBLPROPERTIES ('skip.header.line.count'='1')
"""

pd.read_sql(create_table, conn)

pd.read_sql(f'SELECT * FROM {database_name}.{table_name3} LIMIT 5', conn)
```

[11]:
```
           id street_name            limits  northbound_count  \
0  01AV018207       01 AV      A ST - ASH ST             18010
1  01AV015210       01 AV      A ST - ASH ST             20060
2  01AV018213       01 AV      A ST - ASH ST             19597
3  01AV007721       01 AV      A ST - ASH ST             10640
4  01AV088812       01 AV  ASH ST - BEECH ST              2298

  southbound_count eastbound_count westbound_count  total_count  file_no  \
0             None            None            None        18010  0182-07
1             None            None            None        20060  0152-10
```

```
2           None           None           None       19597   0182-13
3           None           None           None       10640   0077-21
4           None           None           None        2298   0888-12

   date_count
0  2007-03-13
1  2010-03-18
2  2013-03-12
3  2021-03-10
4  2012-12-11
```

[12]:
```
statement = "SHOW DATABASES"
df_show = pd.read_sql(statement, conn)
df_show.head(5)
```

[12]:
```
  database_name
0       default
1        dsoaws
2       watersd
```

[13]:
```
if database_name in df_show.values:
    ingest_create_athena_db_passed = True
```

[14]:
```
%store ingest_create_athena_db_passed
```

```
Stored 'ingest_create_athena_db_passed' (bool)
```

[15]:
```
pd.read_sql(f'SELECT * FROM {database_name}.{table_name} t1 INNER JOIN \
                            {database_name}.{table_name2} t2 ON t1.seg_id \
                            = t2.seg_id LIMIT 5', conn)
```

[15]:
```
      seg_id    oci street  street_from  street_to  seg_length_ft  \
0  SA-000345  34.14  ALLEY                                937.9261
1  SA-000375  97.25  ALLEY                                673.3209
2  SA-000378  62.67  ALLEY                                657.2000
3  SA-001081  68.86  ALLEY                                679.1060
4  SA-001083  28.67  ALLEY                                660.0917

   seg_width_ft func_class             pvm_class  area_sq_ft  …  \
0          30.0      Alley           AC Improved   28137.783  …
1          30.0      Alley  PCC Jointed Concrete   20199.627  …
2          30.0      Alley  PCC Jointed Concrete   19716.000  …
3          30.0      Alley  PCC Jointed Concrete   20373.180  …
4          30.0      Alley  PCC Jointed Concrete   19802.752  …

  address_street  street_from  street_to seg_cd length width date_moratorium  \
0          ALLEY                              2    938    30      2019-01-30
1          ALLEY                              2    674    30      2018-08-01
2          ALLEY                              2    658    30      2018-08-01
3          ALLEY                              9    680    30            None
4          ALLEY                              9    661    30            None
```

```
   date_start    date_end paving_miles
0  2019-01-30  2019-01-30     0.177652
1  2018-08-01  2018-08-01     0.127652
2  2018-08-01  2018-08-01     0.124621
3  2020-08-13  2020-08-13     0.128788
4  2020-07-31  2020-07-31     0.125189

[5 rows x 31 columns]
```

[16]:
```
df = pd.read_sql(f'SELECT * FROM (SELECT * FROM {database_name}.{table_name} \
                          t1 INNER JOIN {database_name}.{table_name2} t2 \
                          ON t1.seg_id = t2.seg_id) m1 LEFT JOIN (SELECT street_name,␣
 ↪\
                                                                    SUM(total_count)␣
 ↪total_count \
                                                                    FROM␣
 ↪{database_name}.{table_name3} \
                                                                    GROUP BY␣
 ↪street_name) t3 \
                          ON m1.address_street = t3.street_name', conn)
```

[17]:
```
df.head(5)
```

[17]:
```
      seg_id    oci  street  street_from street_to  seg_length_ft  seg_width_ft  \
0  SA-000345  34.14   ALLEY                              937.9261          30.0
1  SA-000375  97.25   ALLEY                              673.3209          30.0
2  SA-000378  62.67   ALLEY                              657.2000          30.0
3  SA-001081  68.86   ALLEY                              679.1060          30.0
4  SA-001083  28.67   ALLEY                              660.0917          30.0

  func_class             pvm_class  area_sq_ft  … street_to  seg_cd  length  \
0      Alley           AC Improved   28137.783  …                  2     938
1      Alley  PCC Jointed Concrete   20199.627  …                  2     674
2      Alley  PCC Jointed Concrete   19716.000  …                  2     658
3      Alley  PCC Jointed Concrete   20373.180  …                  9     680
4      Alley  PCC Jointed Concrete   19802.752  …                  9     661

  width date_moratorium  date_start    date_end paving_miles street_name  \
0    30      2019-01-30  2019-01-30  2019-01-30     0.177652        None
1    30      2018-08-01  2018-08-01  2018-08-01     0.127652        None
2    30      2018-08-01  2018-08-01  2018-08-01     0.124621        None
3    30            None  2020-08-13  2020-08-13     0.128788        None
4    30            None  2020-07-31  2020-07-31     0.125189        None

  total_count
0         NaN
1         NaN
2         NaN
3         NaN
4         NaN
```

```
[5 rows x 33 columns]
```

[18]:
```python
# remove duplicated columns
df = df.loc[:,~df.columns.duplicated()]
```

Exploratory Data Analysis (EDA)

[19]:
```python
# get number of rows and columns
print('Number of Rows:', df.shape[0])
print('Number of Columns:', df.shape[1], '\n')

# inspect datatypes and nulls
data_types = df.dtypes
data_types = pd.DataFrame(data_types)
data_types = data_types.assign(Null_Values =
                               df.isnull().sum())
data_types.reset_index(inplace = True)
data_types.rename(columns={0:'Data Type',
                          'index': 'Column/Variable',
                          'Null_Values': "# of Nulls"})
```

```
Number of Rows: 23005
Number of Columns: 30
```

[19]:

	Column/Variable	Data Type	# of Nulls
0	seg_id	object	0
1	oci	float64	0
2	street	object	0
3	street_from	object	0
4	street_to	object	0
5	seg_length_ft	float64	0
6	seg_width_ft	float64	0
7	func_class	object	0
8	pvm_class	object	0
9	area_sq_ft	float64	0
10	oci_desc	object	0
11	oci_wt	float64	0
12	pve_id	int64	0
13	project_id	object	0
14	title	object	0
15	project_manager	object	0
16	project_manager_phone	object	0
17	status	object	0
18	type	object	0
19	resident_engineer	object	0
20	address_street	object	0
21	seg_cd	int64	0
22	length	int64	0
23	width	int64	0
24	date_moratorium	object	4426
25	date_start	object	1

```
26              date_end    object           7
27           paving_miles   float64          0
28            street_name    object      16874
29            total_count   float64      16874
```

Bias Exploration

To explore potential areas of bias, we will endeavor to trace class imbalance on the target feature of "oci_desc."

[20]:
```
oci_desc_fair = df['oci_desc'].value_counts()['Fair']
oci_desc_good = df['oci_desc'].value_counts()['Good']
oci_desc_poor = df['oci_desc'].value_counts()['Poor']
oci_desc_total = oci_desc_fair  + oci_desc_good + oci_desc_poor

table1 = PrettyTable() # build a table
table1.field_names = ['Fair Condition', 'Good Condition',
                      'Poor Condition', 'Total']
table1.add_row([oci_desc_fair, oci_desc_good, oci_desc_poor,
                oci_desc_total])
table1
```

[20]:
```
+----------------+----------------+----------------+-------+
| Fair Condition | Good Condition | Poor Condition | Total |
+----------------+----------------+----------------+-------+
|      6105      |     15758      |      1142      | 23005 |
+----------------+----------------+----------------+-------+
```

[21]:
```
perc_good = oci_desc_good /(oci_desc_total)
perc_fair = oci_desc_fair /(oci_desc_total)
perc_poor = oci_desc_poor /(oci_desc_total)
print(round(perc_good, 2)*100, '% of streets '
                      'are in good condition ')
print(round(perc_fair, 2)*100, '% of streets '
                      'are in fair condition ')
print(round(perc_poor, 2)*100, '% of streets '
                      'are in poor condition ')
```

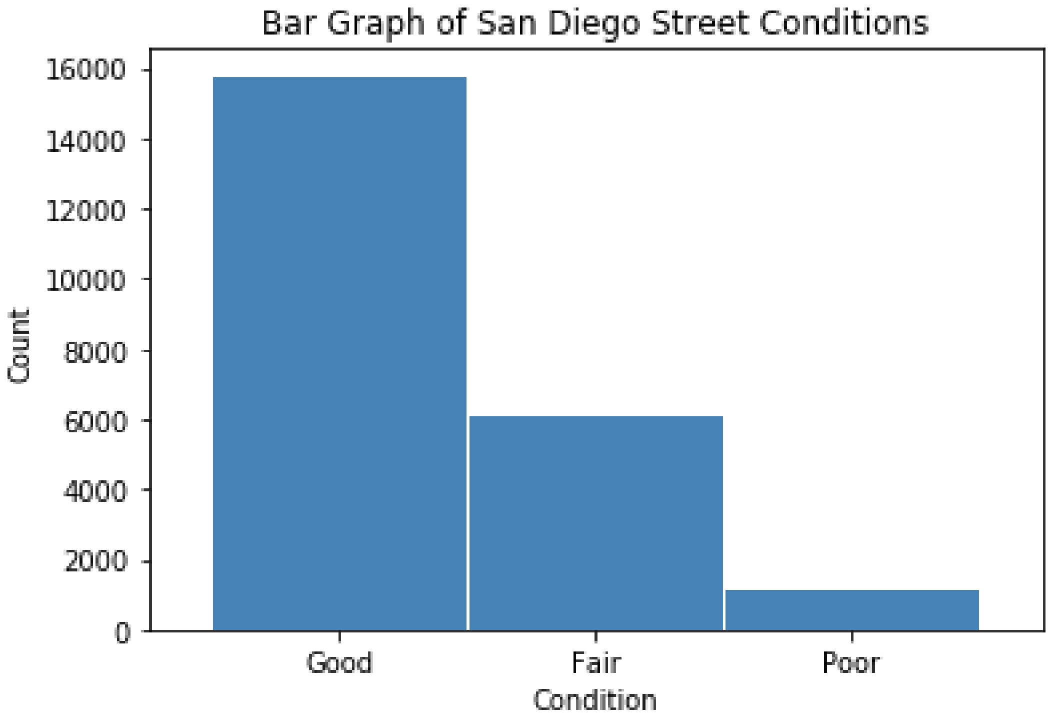
```
68.0 % of streets are in good condition
27.0 % of streets are in fair condition
5.0 % of streets are in poor condition
```

Considerably more than half of the streets are in good condition. A little less than a third are in fair condition. Only 5% are in poor condition.

[22]:
```
# accidents injury bar graph
conditions = df['oci_desc'].value_counts()
fig = plt.figure()
conditions.plot.bar(x ='lab', y='val', rot=0, width=0.99,
                    color="steelblue")
plt.title ('Bar Graph of San Diego Street Conditions')
plt.xlabel('Condition')
plt.ylabel('Count')
```

```
plt.show()

conditions
```



[22]:
```
Good    15758
Fair     6105
Poor     1142
Name: oci_desc, dtype: int64
```

Whereas a method can be used to classify street conditions into multiple classes, it is easier to re-classify streets in “fair” and “good” condition into one category in comparison with the poor class. This, in turn, becomes a binary classification problem. Thus, there are now 21,863 streets in good condition and 1,142 in poor condition (only 5% of all streets). This presents a definitive example of class imbalance.

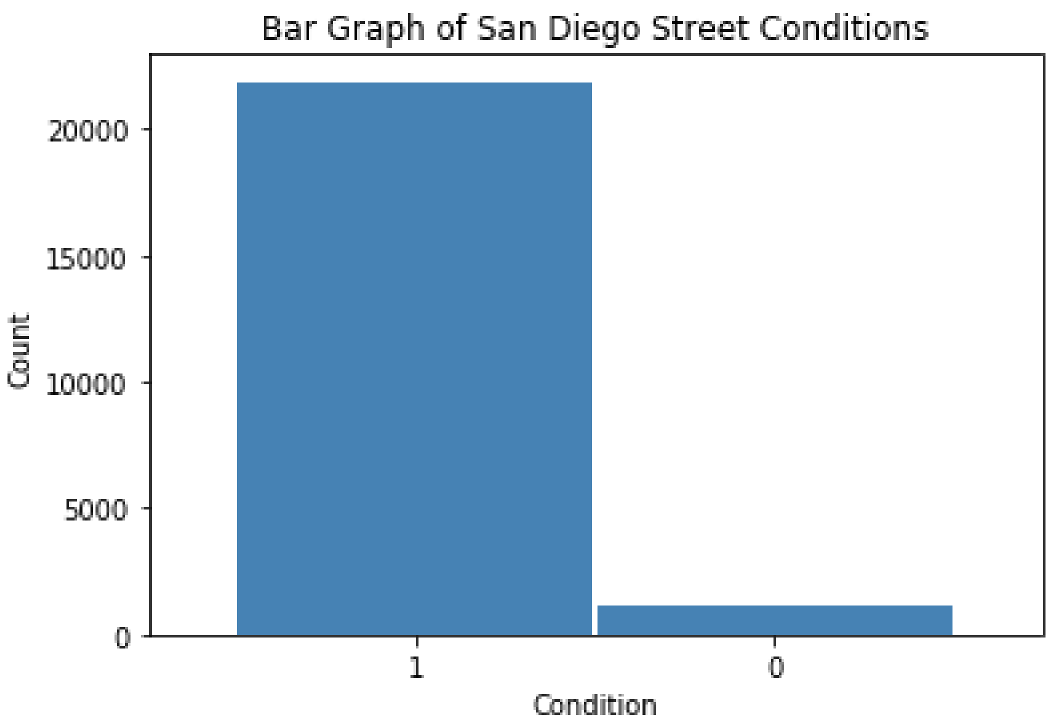
[23]:
```
df['oci_cat'] = df['oci_desc'].map({'Good':1, 'Fair':1,
                                    'Poor':0})
cond = df['oci_cat'].value_counts()
cond
```

[23]:
```
1    21863
0     1142
Name: oci_cat, dtype: int64
```

[24]:
```
# oci ratings bar graph
fig = plt.figure()
cond.plot.bar(x ='lab', y='val', rot=0, width=0.99,
                        color="steelblue")
plt.title ('Bar Graph of San Diego Street Conditions')
```

```
plt.xlabel('Condition')
plt.ylabel('Count')
plt.show()

cond
```



[24]:
```
1    21863
0     1142
Name: oci_cat, dtype: int64
```

[25]:
```
# cast oci info into range of values
labels = [ "{0} - {1}".format(i, i + 5) for i in range(0, 100, 10) ]
df['OCI Range'] = pd.cut(df.oci, range(0, 105, 10),
                                right=False,
                                labels=labels).astype(object)
# inspect the new dataframe with this info
df[['oci', 'OCI Range']]
```

[25]:

	oci	OCI Range
0	34.14	30 - 35
1	97.25	90 - 95
2	62.67	60 - 65
3	68.86	60 - 65
4	28.67	20 - 25
…	…	…
23000	93.40	90 - 95
23001	91.01	90 - 95
23002	97.26	90 - 95

```
23003  95.00   90 - 95
23004  80.83   80 - 85

[23005 rows x 2 columns]
```

[26]:
```
print("\033[1m"+'Street Conditions by Condition Index Range'+"\033[1m")
def oci_cond():
    oci_desc_good = df.loc[df.oci_desc == 'Good'].groupby(
                           ['OCI Range'])[['oci_desc']].count()
    oci_desc_good.rename(columns = {'oci_desc':'Good'}, inplace=True)

    oci_desc_fair = df.loc[df.oci_desc == 'Fair'].groupby(
                           ['OCI Range'])[['oci_desc']].count()
    oci_desc_fair.rename(columns = {'oci_desc':'Fair'}, inplace=True)

    oci_desc_poor = df.loc[df.oci_desc == 'Poor'].groupby(
                           ['OCI Range'])[['oci_desc']].count()
    oci_desc_poor.rename(columns = {'oci_desc':'Poor'}, inplace=True)

    oci_desc_comb = pd.concat([oci_desc_good, oci_desc_fair, oci_desc_poor],
    axis = 1)
    # sum row totals
    oci_desc_comb.loc['Total']= oci_desc_comb.sum(numeric_only=True, axis=0)
    # sum column totals
    oci_desc_comb.loc[:,'Total'] = oci_desc_comb.sum(numeric_only=True, axis=1)

    oci_desc_comb.fillna(0, inplace = True)
    return oci_desc_comb.style.format("{:,.0f}")

oci_cond = oci_cond().data # retrieve dataframe
oci_cond
```

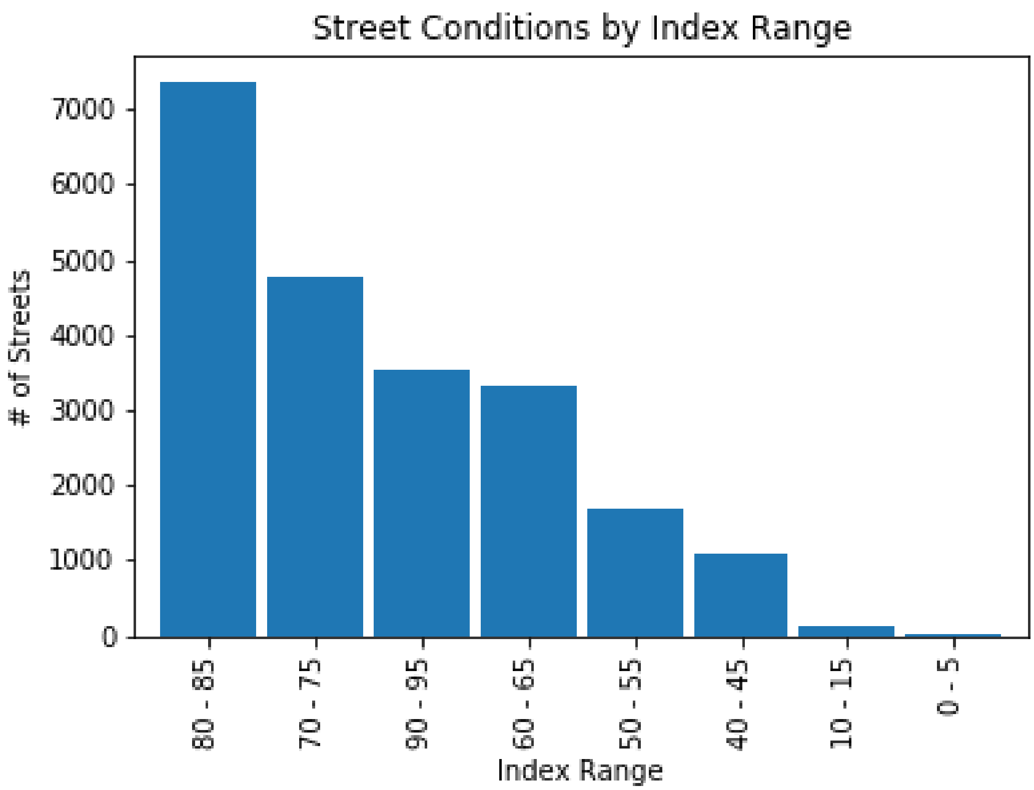
Street Conditions by Condition Index Range

[26]:

	Good	Fair	Poor	Total
70 - 75	4766.0	3.0	0.0	4769.0
80 - 85	7341.0	0.0	0.0	7341.0
90 - 95	3541.0	0.0	0.0	3541.0
40 - 45	0.0	1095.0	0.0	1095.0
50 - 55	0.0	1685.0	0.0	1685.0
60 - 65	0.0	3322.0	0.0	3322.0
0 - 5	0.0	0.0	37.0	37.0
10 - 15	0.0	0.0	135.0	135.0
20 - 25	0.0	0.0	259.0	259.0
30 - 35	0.0	0.0	711.0	711.0
Total	15648.0	6105.0	1142.0	22895.0

[27]:
```
oci_plt = oci_cond['Total'][0:8].sort_values(ascending=False)
oci_plt.plot(kind='bar', width=0.90)
plt.title('Street Conditions by Index Range')
plt.xlabel('Index Range')
plt.ylabel('# of Streets')
```

```
plt.show()
```



Summary Statistics

[28]:
```
# summary statistics
summ_stats = pd.DataFrame(df['oci'].describe()).T
summ_stats
```

[28]:

	count	mean	std	min	25%	50%	75%	max
oci	23005.0	74.791413	16.784048	0.0	66.3	79.06	87.3	100.0

[29]:
```
IQR = summ_stats['75%'][0] - summ_stats['25%'][0]
low_outlier = summ_stats['25%'][0] - 1.5*(IQR)
high_outlier = summ_stats['75%'][0] + 1.5*(IQR)
print('Low Outlier:', low_outlier)
print('High Outlier:', high_outlier)
```

```
Low Outlier: 34.8
High Outlier: 118.8
```

[30]:
```
print("\033[1m"+'Overall Condition Index (OCI) Summary'+"\033[1m")
def oci_by_range():
    pd.options.display.float_format = '{:,.2f}'.format
    new = df.groupby('OCI Range')['oci']\
    .agg(["mean", "median", "std", "min", "max"])
    new.loc['Total'] = new.sum(numeric_only=True, axis=0)
```

```
    column_rename = {'mean': 'Mean', 'median': 'Median',
                     'std': 'Standard Deviation',\
                     'min':'Minimum','max': 'Maximum'}
    dfsummary = new.rename(columns = column_rename)
    return dfsummary
oci_by_range = oci_by_range()
oci_by_range
```

Overall Condition Index (OCI) Summary

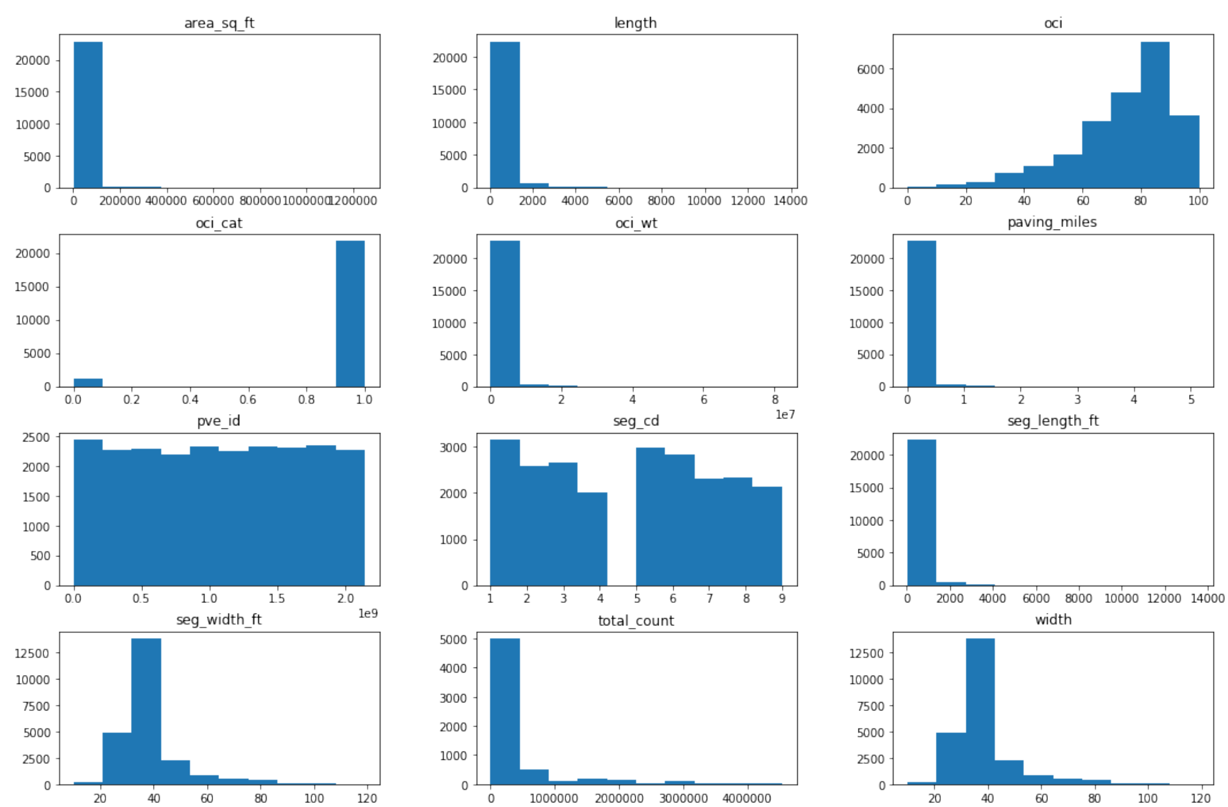
[30]:

OCI Range	Mean	Median	Standard Deviation	Minimum	Maximum
0 - 5	6.13	8.00	3.70	0.00	9.69
10 - 15	15.66	16.40	2.82	10.11	19.84
20 - 25	25.77	26.17	2.91	20.12	29.96
30 - 35	35.63	36.04	2.80	30.04	39.98
40 - 45	45.37	45.58	2.88	40.00	49.98
50 - 55	55.62	56.00	2.88	50.00	59.98
60 - 65	65.56	65.80	2.82	60.00	69.99
70 - 75	75.11	75.16	2.97	70.00	79.99
80 - 85	85.14	85.15	2.84	80.00	89.99
90 - 95	93.44	92.89	2.57	90.00	99.33
Total	503.42	507.19	29.18	450.27	548.73

Histogram Distributions

[31]:

```
# histograms
df.hist(grid=False, figsize=(18,12))
plt.show()
```



Boxplot Distribution (OCI)

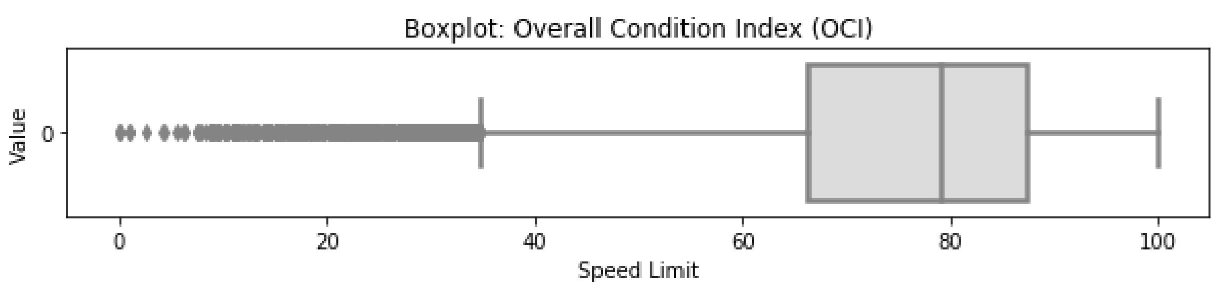
[32]:
```
# selected boxplot distribution for oci values
print("\033[1m"+'Boxplot Distribution'+"\033[1m")

# Boxplot of age as one way of showing distribution
fig = plt.figure(figsize = (10,1.5))
plt.title ('Boxplot: Overall Condition Index (OCI)')
plt.xlabel('Speed Limit')
plt.ylabel('Value')
sns.boxplot(data=df['oci'],
            palette="coolwarm", orient='h',
            linewidth=2.5)
plt.show()

IQR = summ_stats['75%'][0] - summ_stats['25%'][0]

print('The first quartile is %s. '%summ_stats['25%'][0])
print('The third quartile is %s. '%summ_stats['75%'][0])
print('The IQR is %s.'%round(IQR,2))
print('The mean is %s. '%round(summ_stats['mean'][0],2))
print('The standard deviation is %s. '%round(summ_stats['std'][0],2))
print('The median is %s. '%round(summ_stats['50%'][0],2))
```

Boxplot Distribution

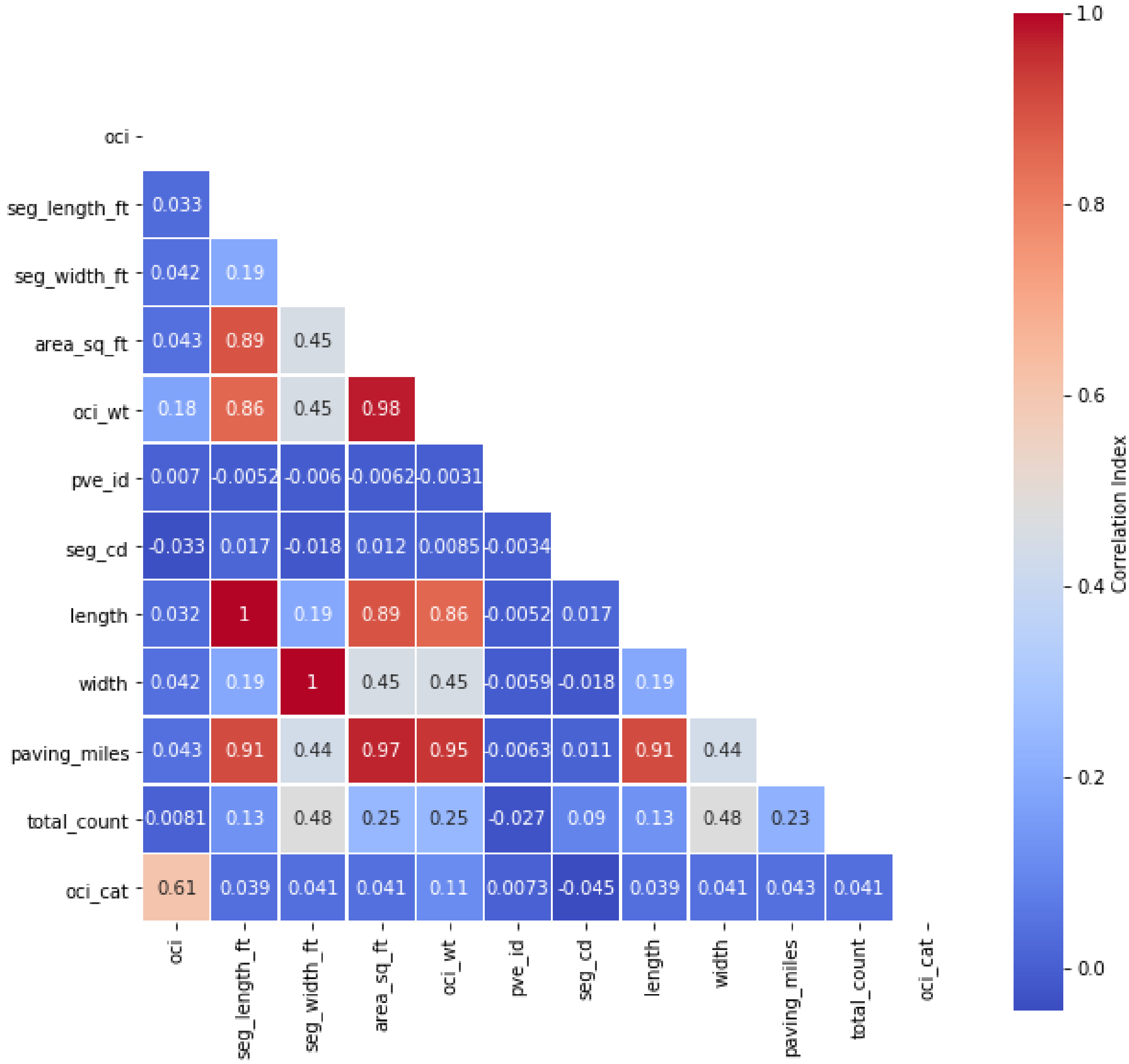



```
The first quartile is 66.3.
The third quartile is 87.3.
The IQR is 21.0.
The mean is 74.79.
The standard deviation is 16.78.
The median is 79.06.
```

Correlation Matrix

[33]:
```
# assign correlation function to new variable
corr = df.corr()
matrix = np.triu(corr) # for triangular matrix
```

```
plt.figure(figsize=(10,10))
# parse corr variable intro triangular matrix
sns.heatmap(df.corr(method='pearson'),
            annot=True, linewidths=.5,
            cmap="coolwarm", mask=matrix,
            square = True,
            cbar_kws={'label': 'Correlation Index'})
plt.show()
```



Multicollinearity

Let us narrow our focus by removing highly correlated predictors and passing the rest into a new dataframe.

[34]:
```
cor_matrix = df.corr().abs()
upper_tri = cor_matrix.where(np.triu(np.ones(cor_matrix.shape),
                                     k=1).astype(np.bool))
```

```
to_drop = [column for column in upper_tri.columns if
           any(upper_tri[column] > 0.75)]
print('These are the columns prescribed to be dropped: %s'%to_drop)
```

```
These are the columns prescribed to be dropped: ['area_sq_ft', 'oci_wt', 'length',
'width', 'paving_miles']
```

Pre-Processing

Feature Engineering

The residential, collector, major, prime, local, and alley functional classes are converted to dummy variables.

[35]:
```
df['func_class'].value_counts()
df['func_cat'] = df['func_class'].map({'Residential': 1,
                                       'Collector': 2,
                                       'Major': 3, 'Prime':4,
                                       'Local':5, 'Alley':6})
```

The AC Improved, PCC Jointed Concrete, AC Unimproved, and UnSurfaced pavement classes are converted to dummy variables.

[36]:
```
df['pvm_class'].value_counts()
df['pvm_cat'] = df['pvm_class'].map({'AC Improved': 1,
                                     'PCC Jointed Concrete': 2,
                                     'AC Unimproved': 3,
                                     'UnSurfaced':4})
```

The current status of the job (i.e., post construction, design, bid/award, construction, and planning) is also converted to dummy variables.

[37]:
```
df['status'].value_counts()
df['status_cat'] = df['status'].map({'post construction': 1,
                                     'design': 2,
                                     'bid / award': 3,
                                     'construction':4,
                                     'planning': 5})
```

The start date is subtracted from the end date and converted to number of days as one column.

[38]:
```
df['date_end'] = pd.to_datetime(df['date_end'])
df['date_start'] = pd.to_datetime(df['date_start'])
day_diff = df.dropna(subset=['date_end', 'date_start'],
                     inplace=True)
df['day_diff'] = (df['date_end'] - df['date_start']).dt.days.astype(int)
```

Dropping Non-Useful/Re-classed Columns

Columns with explicit titles (i.e., names) and non-convertible/non-meaningful strings are dropped. Redundant columns (columns that have been cast to dummy variables) have also been dropped in conjunction with the index column which serves no purpose for this experiment.

[39]:
```
# drop unnecessary columns
df = df.drop(columns=['street_from','street_to',
                      'street_name','total_count',
                      'seg_id', 'street',
                      'pve_id', 'title','project_manager',
                      'project_manager_phone', 'project_id',
                      'resident_engineer', 'address_street',
                      'date_moratorium', 'OCI Range'])
df = df.reset_index(drop=True)

# drop re-classed columns
df = df.drop(columns=['func_class', 'pvm_class', 'status', 'type',
                      'date_end', 'date_start', 'oci_desc'])
```

The original dataframe is copied into a new dataframe *df1* in order to continue the final steps in the pre-processing endeavor. This is to avoid any mis-steps or adverse/unintended effects on the original dataframe.

[40]:
```
# create new dataframe for final pre-processing steps
df1 = df.copy()
```

The dataframe can now be prepared as a flat .csv file if so desired.

[41]:
```
# output to csv file as backup
# df.to_csv('sd_roads_dataframe.csv')
```

Handling Class Imbalance

Multiple methods for balancing a dataset exist like "undersampling the majority classes" (Fregly & Barth, 2021, p. 178). To account for the large gap (95%) of mis-classed data on the "poor" condition class, "oversampling the minority class up to the majority class" (p. 179) is commenced. However, such endeavor cannot proceed in good faith without the unsupervised dimensionality reduction technique of Principal Component Analysis (PCA), which is carried out "to compact the dataset and eliminate irrelevant Features" (Naseriparsa & Kashani, 2014, p. 33). In this case, a new dataframe is reduced down into the first two principal components since the largest percent variance explained exists therein.

[42]:
```
# the first two principal components are used
pca = PCA(n_components=2, random_state=777)
data_2d = pd.DataFrame(pca.fit_transform(df1.iloc[:,0:9]))
```

The dataframe is prepared for scatterplot analysis as follows.

[43]:
```
data_2d= pd.concat([data_2d, df1['oci_cat']], axis=1)
data_2d.columns = ['x', 'y', 'oci_cat']; data_2d
```

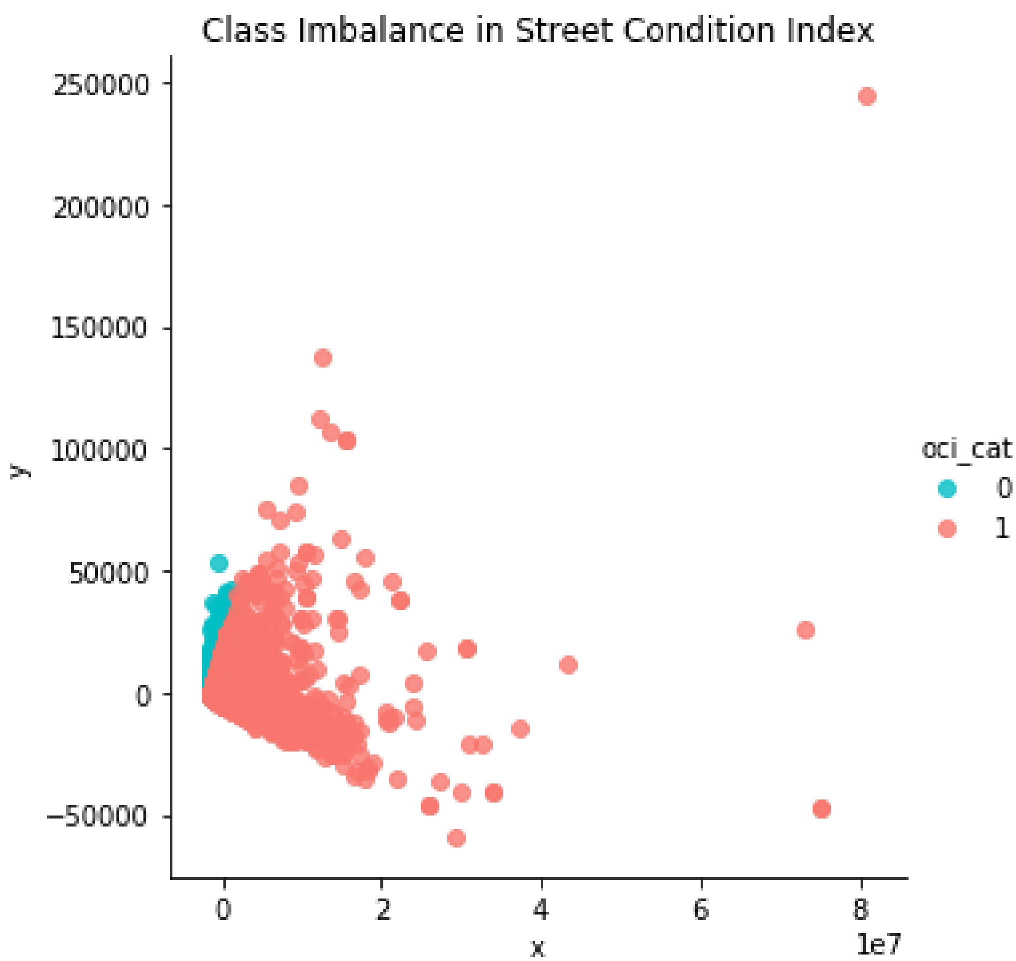
[43]:

	x	y	oci_cat
0	-565,511.24	14,903.90	0
1	438,106.89	-5,292.13	1
2	-290,656.73	3,118.86	1
3	-123,365.87	1,734.80	1
4	-958,462.83	11,356.77	0
…	…	…	…
22993	-1,120,094.45	-2,138.79	1
22994	1,469,689.03	-5,161.03	1

```
22995  1,321,569.31 -6,995.59        1
22996   -846,170.55 -2,671.76        1
22997   -932,156.28 -1,420.73        1

[22998 rows x 3 columns]
```

[44]:
```
sns.lmplot('x','y', data_2d,fit_reg=False,hue='oci_cat',
                    palette=['#00BFC4','#F8766D'])
plt.title('Class Imbalance in Street Condition Index'); plt.show()
```



The dataset is oversampled into a new dataframe *df2.*

The adaptive synthetic sampling approach is leveraged in conjunction with the Synthetic Minority Oversampling (SMOTE) technique to "balance the class distribution and increase the variety of sample domain" (p. 33). This allows for the minority class to be more closely matched (up-sampled) to the majority class for an approximately even 50/50 weight distribution.

[45]:
```
ada = ADASYN(random_state=777)
X_resampled, y_resampled = ada.fit_resample(df1.iloc[:,0:13], df1['oci_cat'])
```

[46]:
```
df2 = pd.concat([pd.DataFrame(X_resampled), pd.DataFrame(y_resampled)], axis=1)
df2.columns = df1.columns
```

The classes are re-balanced in a new dataframe using oversampling:

[47]:
```
# rebalanced classes in new df
df2['oci_cat'].value_counts()
zero_count = df2['oci_cat'].value_counts()[0]
one_count = df2['oci_cat'].value_counts()[1]
zero_plus_one = zero_count + one_count

print('Poor Condition Size:', zero_count)
print('Good Condition Size:', one_count)
print('Percent in Poor Condition:', round(zero_count/zero_plus_one,2))
print('Percent in Good Condition:', round(one_count/zero_plus_one,2))
```

```
Poor Condition Size: 21844
Good Condition Size: 21858
Percent in Poor Condition: 0.5
Percent in Good Condition: 0.5
```

Train-Test-Validation Split

[48]:
```
#Divide train set by .7, test set by .15, and valid set .15
size_train = 30592
size_test = 6555
size_valid = 6555
size_total = size_test + size_valid + size_train
train, test = train_test_split(df2, train_size = size_train,
                               random_state = 777)
valid, test = train_test_split(df2, train_size = size_test,
                               random_state = 777)

print('training size:', size_train)
print('validation size:', size_valid)
print('test size:', size_test)
print('training percentage:', round(size_train/(size_total),2))
print('validation percentage:', round(size_valid/(size_total),2))
print('test percentage:', round(size_test/(size_total),2))
```

```
training size: 30592
validation size: 6555
test size: 6555
training percentage: 0.7
validation percentage: 0.15
test percentage: 0.15
```

[49]:
```
X_var = list(df2.columns)
target = 'oci_cat'
X_var.remove(target)
X_train = train[X_var]
y_train = train[target]
X_test = test[X_var]
y_test = test[target]
X_valid = valid[X_var]
y_valid = valid[target]
```

References

Amazon Web Services. (n.d.). *Amazon Athena.*
https://aws.amazon.com/athena/?whats-new-cards.sort-by=item.additionalFields.postDateTime&whats-new-cards.sort-order=desc

Fregly, C., & Barth, A. (2021). *Data Science on AWS.* O'Reilly.

Garrick, D. (2021, September 12). San Diego to spend $700K assessing street conditions to spend repair money wisely. *The San Diego Union-Tribune.*
https://www.sandiegouniontribune.com/news/politics/story/2021-09-12/san-diego-to-spend-700k-assessing-street-conditions-to-spend-repair-money-wisely

Naseriparsa, M. & Kashani, M.M.R. (2014). Combination of PCA with SMOTE Resampling to Boost the Prediction Rate in Lung Cancer Dataset.
International Journal of Computer Applications, 77(3) 33-38. https://doi.org/10.5120/13376-0987