INSURANCE COMPANIES SETTLEMENT ANALYSIS BY MELU-AKEKUE BARINATAMKEE

OBJECTIVE

- Perform Data Cleaning
- Perform Feature Engineering
- Get the best ML Classifier for the sample

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```
%matplotlib inline
```

In [3]:

```
df = pd.read_csv('sample.csv')
df.head()
```

Out[3]:

	Claim No	Occurrence No	Claim Financial Year	Agency NN	Incident Date	Finalised Date	Total Paid	Paid Days Lost	Service Start Date	Service End Date	...	Mechanism	Na
0	13/005096	1	2013	7069	01-11-12	24-01-13	$8,580.00	26.01	02-11-12	18-12-12	...	Muscular stress-lift, carry, put down objects	Spr and str of jo mus
1	21/013033	1	2021	63246	29-04-21	10-06-21	$573.66	2	29-04-21	30-04-21	...	Falls on the same level	C wound inclu traum amputa
2	16/005676	1	2016	2043954	16-11-15	04-01-16	$796.97	2.02	16-11-15	17-11-15	...	Being assaulted by a person or persons	C wound inclu traum amputa
3	15/002879	1	2015	63246	04-09-14	18-02-15	$5,570.19	26	05-09-14	10-10-14	...	Muscular stress with no objects handled	Spr and str of jo mus
4	14/020489	2	2014	63246	08-05-14	29-01-16	$35,406.63	75.09	03-10-14	12-01-15	...	Falls on the same level	Spr and str of jo mus

5 rows × 25 columns

In [4]:

```
# Let's build a reference list of all columns and their indexes
```

```
col_mapping = [f"{c[0]}:{c[1]}" for c in enumerate(df.columns)]
col_mapping
```

Out[4]:

```
['0:Claim No',
 '1:Occurrence No',
 '2:Claim Financial Year',
 '3:Agency NN',
 '4:Incident Date',
 '5:Finalised Date',
 '6:Total Paid',
 '7:Paid Days Lost',
 '8:Service Start Date',
 '9:Service End Date',
 '10:Injury Agency Group',
 '11:Bodily Location Group',
 '12:Mechanism Group',
 '13:Nature Group',
 '14:Bodily Location',
 '15:Mechanism',
 '16:Nature',
 '17:Major',
 '18:Occupation',
 '19:Gender',
 '20:Date of Birth',
 '21:Days to RTW',
 '22:RTW Category',
 '23:Age at Accident Date',
 '24:Settled']
```

In [5]:

```
df.dtypes
```

Out[5]:

```
Claim No                   object
Occurrence No               int64
Claim Financial Year        int64
Agency NN                   int64
Incident Date              object
Finalised Date             object
Total Paid                 object
Paid Days Lost             object
Service Start Date         object
Service End Date           object
Injury Agency Group        object
Bodily Location Group      object
Mechanism Group            object
Nature Group               object
Bodily Location            object
Mechanism                  object
Nature                     object
Major                      object
Occupation                 object
Gender                     object
Date of Birth              object
Days to RTW                 int64
RTW Category               object
Age at Accident Date        int64
Settled                    object
dtype: object
```

In [6]:

```
df.isna().sum()
```

Out[6]:

```
Claim No                     0
Occurrence No                0
Claim Financial Year         0
```

```
Agency NN                  0
Incident Date              0
Finalised Date             0
Total Paid                 0
Paid Days Lost             0
Service Start Date       475
Service End Date         475
Injury Agency Group        0
Bodily Location Group      0
Mechanism Group            0
Nature Group               0
Bodily Location            0
Mechanism                  0
Nature                     0
Major                      0
Occupation                 0
Gender                     0
Date of Birth              1
Days to RTW                0
RTW Category               0
Age at Accident Date       0
Settled                    0
dtype: int64
```

In [7]:

```python
df[df['Date of Birth'].isna()]
```

Out[7]:

	Claim No	Occurrence No	Claim Financial Year	Agency NN	Incident Date	Finalised Date	Total Paid	Paid Days Lost	Service Start Date	Service End Date	...	Mechanism	
12155	14/013142	1	2014	1801385	17-02-14	16-06-14	$5,049.83	18.66	NaN	NaN	...	Muscular stress while handling object	Sup

1 rows × 25 columns

In [8]:

```python
# Subtract columns to get Duration of Incident and Duration of Service
import datetime as dt
x = pd.to_datetime(df['Finalised Date'], dayfirst=True) - pd.to_datetime(df['Incident Da
te'], dayfirst=True)
df['Duration of Service'] = pd.to_datetime(df['Service End Date'], dayfirst=True) - pd.t
o_datetime(df['Service Start Date'], dayfirst=True)
df['Duration of Incident'] = pd.to_datetime(df['Finalised Date'], dayfirst=True) - pd.to
_datetime(df['Incident Date'], dayfirst=True)
df.head()
```

Out[8]:

	Claim No	Occurrence No	Claim Financial Year	Agency NN	Incident Date	Finalised Date	Total Paid	Paid Days Lost	Service Start Date	Service End Date	...	Major	Occ
0	13/005096	1	2013	7069	01-11-12	24-01-13	$8,580.00	26.01	02-11-12	18-12-12	...	Intermediate Clerical, Sales and Service Workers	F A
1	21/013033	1	2021	63246	29-04-21	10-06-21	$573.66	2	29-04-21	30-04-21	...	Intermediate Clerical, Sales and Service Workers	T (Ec As
2	16/005676	1	2016	2043954	16-11-15	04-01-16	$796.97	2.02	16-11-15	17-11-15	...	Associate Professionals	Res

	Claim No	Occurrence No	Claim Financial Year	Agency NN	Incident Date	Finalised Date	Total Paid	Paid Days Lost	Service Start Date	Service End Date	...	Major	Oc
3	15/002879	1	2015	63246	04-09-14	18-02-15	$5,570.19	26	05-09-14	10-10-14	...	Intermediate Clerical, Sales and Service Workers	(Ec As
4	14/020489	2	2014	63246	08-05-14	29-01-16	$35,406.63	75.09	03-10-14	12-01-15	...	Tradespersons and Related Workers	G

5 rows × 27 columns

In [9]:

```python
# Let's remove columns Claim No, Incident Date, Finalised Date, Service Start Date and Se
rvice End Date
# df.drop(['column_nameA', 'column_nameB'], axis=1, inplace=True)
df_filtered = df.drop(['Claim No', 'Incident Date', 'Finalised Date', 'Service Start Dat
e', 'Service End Date'], axis=1)
df_filtered.head()
```

Out[9]:

	Occurrence No	Claim Financial Year	Agency NN	Total Paid	Paid Days Lost	Injury Agency Group	Bodily Location Group	Mechanism Group	Nature Group	Bodily Location	...	
0	1	2013	7069	$8,580.00	26.01	Mobile Plant and Transport	Trunk (inc. Back)	Body Stressing	Sprains, Strains and Dislocations	Stomach	...	In Cle a
1	1	2021	63246	$573.66	2	Non-powered Handtools, Appliances and Equipment	Head	Falls, Slips and Trips of a Person	Open Wound	Head - unspecified locations	...	In Cle a
2	1	2016	2043954	$796.97	2.02	Animal, Human and Biological Agencies	Head	Being Hit by Moving Objects	Open Wound	Face	...	Pr
3	1	2015	63246	$5,570.19	26	Animal, Human and Biological Agencies	Lower Limbs	Body Stressing	Sprains, Strains and Dislocations	Knee	...	In Cle a
4	2	2014	63246	$35,406.63	75.09	Environmental Agencies	Upper Limbs	Falls, Slips and Trips of a Person	Sprains, Strains and Dislocations	Shoulder	...	Trac a

5 rows × 22 columns

In [10]:

```python
print(df_filtered.columns)
```

```
Index(['Occurrence No', 'Claim Financial Year', 'Agency NN', 'Total Paid',
       'Paid Days Lost', 'Injury Agency Group', 'Bodily Location Group',
       'Mechanism Group', 'Nature Group', 'Bodily Location', 'Mechanism',
       'Nature', 'Major', 'Occupation', 'Gender', 'Date of Birth',
       'Days to RTW', 'RTW Category', 'Age at Accident Date', 'Settled',
       'Duration of Service', 'Duration of Incident'],
      dtype='object')
```

In [11]:

```python
# Observing the value counts for each column
for col in df_filtered.columns:
    if df_filtered[col].dtype == 'object':
        print(df_filtered[col].value_counts())
```

```
$0.00          62
$645.50         4
$961.41         3
$966.92         3
$295.44         3
               ..
$13,712.79      1
$99,596.72      1
$5,182.77       1
$273.59         1
$1,074.67       1
Name: Total Paid, Length: 22941, dtype: int64
1         1140
2         1101
3          773
4          573
5          492
          ...
318.83       1
600.47       1
75.56        1
264          1
429.06       1
Name: Paid Days Lost, Length: 7392, dtype: int64
Animal, Human and Biological Agencies                7098
Non-powered Handtools, Appliances and Equipment      5988
Environmental Agencies                               3789
Other and Unspecified Agencies                       2405
Mobile Plant and Transport                           1174
Materials and Substances                             1143
Powered Equipment, Tools and Appliances              1034
Machinery and (Mainly) Fixed Plant                    321
Chemicals and Chemical Products                       187
Name: Injury Agency Group, dtype: int64
Upper Limbs                                      6216
Lower Limbs                                      5255
Trunk (inc. Back)                                4450
Multiple Locations                               2799
Non-physical Locations (Psychological)           2075
Head                                             1637
Neck                                              574
Systemic Locations (eg. Nervous, Digestive)       107
Unspecified Locations                              26
Name: Bodily Location Group, dtype: int64
Body Stressing                                  8358
Falls, Slips and Trips of a Person              5637
Being Hit by Moving Objects                     5016
Mental Stress                                   1909
Hitting Objects with a Part of the Body         1118
Other and Unspecified Mechanisms of Injury       328
Chemicals and Other Substances                   295
Heat, Radiation and Electricity                  246
Biological Factors                               205
Sound and Pressure                                27
Name: Mechanism Group, dtype: int64
Sprains, Strains and Dislocations                 10132
Musculoskeletal System and Connective Tissue       3525
Contusion and Crushing                             2476
Mental Disorders                                   2197
Fractures                                          1551
All Other Diseases                                 1126
Open Wound                                          966
Superficial Injury                                  796
Burns                                               232
Foreign body, Ear, Eye, Nose, Respiratory            88
Multiple Injuries                                    50
Name: Nature Group, dtype: int64
Lower back                             2810
Knee                                   2235
Psychological system in general        2075
Shoulder                               2048
```

```
Other specified multiple locations    1425
                                      ...
Other internal chest organs              1
Liver and intrapepatic ducts             1
Kidney                                   1
Bladder                                  1
Large intestine                          1
Name: Bodily Location, Length: 83, dtype: int64
Falls on the same level                             3913
Muscular stress-lift, carry, put down objects       3010
Muscular stress while handling object               2652
Being assaulted by a person or persons              2644
Muscular stress with no objects handled             1598
Repetitive movement, low muscle loading             1098
Stepping, kneeling  or sitting on objects           1016
Being hit by moving objects                          973
Hitting stationary objects                           784
Falls from a height                                  708
Exposure to a traumatic event                        598
Being hit by a person accidentally                   477
Harassment                                           440
Work Pressure                                        412
Being trapped between stationary & moving obj        392
Hitting moving objects                               317
Other Mental stress factors                          282
Being hit by falling objects                         261
Vehicle accident                                     197
Single contact with chemical or substance            195
Exposure to workplace/occupational violence          165
Contact with hot objects                             162
Being trapped by moving machinery or equip           124
Contact with bio factors of human origin             114
Contact with bio factors of non-human origin          91
Being hit by an animal                                90
Unspecified mechanisms of injury                      81
Contact with electricity                              55
Insect and spider bites and stings                    51
Being bitten by an animal                             51
Other and multiple mechanisms of injury               48
Long term contact with chemicals or substance         27
Exposure to environmental heat                        25
Other & unspecified contact with chem or sub          21
Rubbing and chafing                                   17
Exposure to single, sudden sound                      14
Long term exposure to sounds                           9
Suicide or attempted suicide                           7
Mental stress relating to Coronavirus COVID19          5
Other variations in pressure                           4
Exposure to mechanical vibration                       4
Slide or cave-in                                       2
Exposure to non-ionising radiation                     2
Exposure to environmental cold                         1
Contact with poisonous parts of plant or mari          1
Contact with cold objects                              1
Name: Mechanism, dtype: int64
Sprains and strains of joints and muscles           9992
Disorders muscles, tendons, other soft tissue       3453
Contusion with intact skin and crushing             2476
Mental disorders                                    2197
Fractures                                           1527
Open wound not including traumatic amputation        966
Superficial injury                                   796
Burns                                                232
Intracranial injury including concussion             210
Other and unspecified injuries                       193
Dislocation                                          140
Poisoning & toxic effects of substances               99
Foreign body - eye, ear, nose, respiratory            88
Hernia                                                85
Other diseases                                        60
Other respiratory conditions due to substance         53
Multiple injuries                                     50
```

```
Other diseases of skin & subcutaneous tissue      48
Dorsopathies - disorders of vertebrae & discs     46
Effects of weather, exposure, air pressure        40
Injuries to nerves & spinal cord                  37
Other diseases of respiratory system              33
Other infectious and parasitic diseases           32
Contact dermatitis                                31
Disorders nerve roots, plexuses                   28
Disorders of the conjunctiva and cornea           27
Fracture of vertebral column                      24
Arthopathies and related disorders                20
Other disorders of the eye                        17
Internal injury chest, abdomen and pelvis         16
Asthma                                            13
Other unspecified dermatitis or eczema            13
Other diseases digestive system                   12
Deafness                                          11
Other diseases of ear & mastoid process            9
Adverse event following immunisation               8
Intestinal infectious diseases                     8
Other diseases circulatory system                  7
Viral diseases exc hepatitis, STD, AIDS            7
Traumatic amputation including eye                 6
Osteopathies, chondropathies & acquired muscl      6
Neoplasms of uncertain behaviour                   3
Other malignant neoplasms and carcinomas           3
Ischaemic heart disease                            2
Damage to artificial aid(s)                        2
Other heart disease exc ischaemic heart            2
Anxiety/stress disorder                            2
Mental diseases unspecified                        1
Novel coronavirus (COVID-19)                       1
Malignant neoplasm of pleura (mesothelioma)        1
Mycoses                                            1
Hypertension (high blood pressure)                 1
Diseases brain, spinal cord                        1
Cerebrovascular disease                            1
Depression                                         1
Post-traumatic stress disorder                     1
Name: Nature, dtype: int64
Intermediate Clerical, Sales and Service Workers    8159
Professionals                                       7428
Associate Professionals                             2179
Labourers and Related Workers                       1797
Tradespersons and Related Workers                   1527
Elementary Clerical, Sales and Service Workers       930
Managers and Administrators                          551
Intermediate Production and Transport Workers        480
Advanced Clerical and Service Workers                 65
Non ASCO Codes                                        22
Unknown                                                1
Name: Major, dtype: int64
Teachers Aide (Education Assistant)            2898
Prison Officer                                 2594
Registered Nurse                               2183
Primary School Teacher                         1300
Secondary School Teacher                       1213
                                               ...
Sales Assistant (Other Personal and Household     1
Bank Worker                                       1
Sales Clerk                                       1
Software Designer                                 1
Personnel Consultant                              1
Name: Occupation, Length: 446, dtype: int64
Female     14492
Male        8646
Unknown        1
Name: Gender, dtype: int64
21-10-71    16
26-06-64    16
08-09-56    13
14-04-72    13
```

```
12-03-71     13
             ..
24-06-75      1
15-11-68      1
31-12-64      1
01-07-92      1
04-12-83      1
Name: Date of Birth, Length: 10877, dtype: int64
RTW 13 Weeks        15113
Not RTW 26 Weeks     5535
RTW 26 Weeks         2491
Name: RTW Category, dtype: int64
N    20261
Y     2878
Name: Settled, dtype: int64
```

In [12]:

```
df_filtered['Gender'].value_counts()
```

Out[12]:

```
Female      14492
Male         8646
Unknown         1
Name: Gender, dtype: int64
```

In [13]:

```
# Let's move Settled to the last column
column_to_move = df_filtered.pop("Settled")
df_filtered.insert(21, "Settled", column_to_move)
df_filtered.head(1)
```

Out[13]:

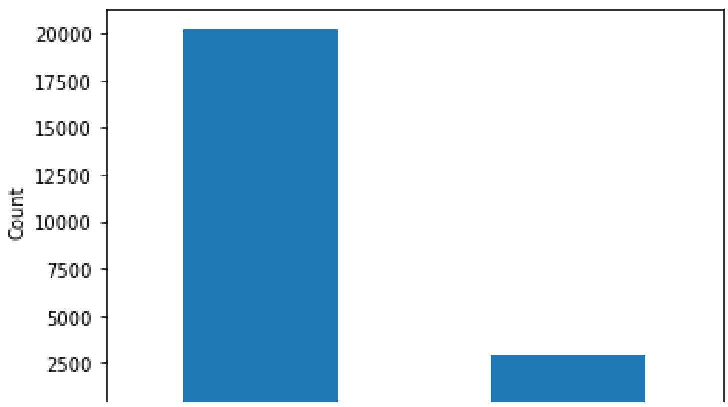
	Occurrence No	Claim Financial Year	Agency NN	Total Paid	Paid Days Lost	Injury Agency Group	Bodily Location Group	Mechanism Group	Nature Group	Bodily Location	...	Major
0	1	2013	7069	$8,580.00	26.01	Mobile Plant and Transport	Trunk (inc. Back)	Body Stressing	Sprains, Strains and Dislocations	Stomach	...	Intermediate Clerical, Sales and Service Workers

1 rows × 22 columns

Making use of Bar Charts and Box plots to see the correlation between the columns and the Settled column

In [14]:

```
df_filtered['Settled'].value_counts().plot(kind='bar', xlabel='Settled', ylabel='Count',
rot=0)
plt.show()
```



Using Chi-Squared Test to pick the best features to use

In [15]:

```
# # split into train and test sets
# X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=
1)
# # summarize
# print('Train', X_train.shape, y_train.shape)
# print('Test', X_test.shape, y_test.shape)

# Retrieve numpy array
dataset = df_filtered.values
# Split into input (X) and output (y) variables
X = dataset[:, :-1]
y = dataset[:,-1]
# format all fields as string
X = X.astype(str)
print(X, y)
```

```
[['1' '2013' '7069' ... '55' '46 days 00:00:00' '84 days 00:00:00']
 ['1' '2021' '63246' ... '49' '1 days 00:00:00' '42 days 00:00:00']
 ['1' '2016' '2043954' ... '48' '1 days 00:00:00' '49 days 00:00:00']
 ...
 ['1' '2019' '2623845' ... '49' '3 days 00:00:00' '49 days 00:00:00']
 ['1' '2013' '2253554' ... '57' '2 days 00:00:00' '344 days 00:00:00']
 ['1' '2022' '2623920' ... '53' '298 days 00:00:00' '389 days 00:00:00']] ['N' 'N' 'N' ..
. 'N' 'N' 'Y']
```

In [16]:

```
from sklearn.model_selection import train_test_split
# Split data into train and test sets, using 67% of data for training and 33% for testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=1
)
# Summarize
print('Train', X_train.shape, y_train.shape)
print('Test', X_test.shape, y_test.shape)
```

```
Train (15503, 21) (15503,)
Test (7636, 21) (7636,)
```

Prepare the Input data

In [17]:

```
from sklearn.preprocessing import OrdinalEncoder
oe = OrdinalEncoder(handle_unknown='use_encoded_value', unknown_value=-1)
oe.fit(X_train)
X_train_enc = oe.transform(X_train)
X_test_enc = oe.transform(X_test)
print(X_train_enc, X_test_enc)
```

```
[[2.000e+00 1.000e+00 1.080e+02 ... 2.000e+01 3.340e+02 7.270e+02]
 [2.000e+00 1.000e+00 1.080e+02 ... 3.900e+01 8.110e+02 6.200e+01]
 [3.000e+00 1.000e+00 2.000e+01 ... 2.300e+01 9.200e+01 7.310e+02]
 ...
 [0.000e+00 8.000e+00 1.080e+02 ... 4.400e+01 7.950e+02 1.534e+03]
 [0.000e+00 6.000e+00 8.400e+01 ... 4.200e+01 9.390e+02 1.659e+03]
 [0.000e+00 5.000e+00 1.080e+02 ... 3.800e+01 7.740e+02 1.070e+02]] [[   0.    0.   56. .
..   30.  587.  188.]
 [   0.    0.  108. ...   40.  334.  667.]
 [   0.    6.  108. ...   25.  795.  596.]
 ...
 [   0.    7.  108. ...   51. 1103.  991.]
 [   0.    3.   20. ...   40.  674. 1677.]
```

```
[   0.     9.    83. ...    45. 1094.   314.]]
```

Prepare the Output data

In [18]:

```
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
le.fit(y_train)
y_train_enc = le.transform(y_train)
y_test_enc = le.transform(y_test)
print(y_train_enc, y_test_enc)
```

```
[0 1 0 ... 0 1 1] [0 0 0 ... 0 0 0]
```

Now that we have loaded and prepared the dataset, we can explore feature selection.

Chi-Squared Feature Selection

Pearson’s chi-squared statistical hypothesis test is an example of a test for independence between categorical variables.

In [19]:

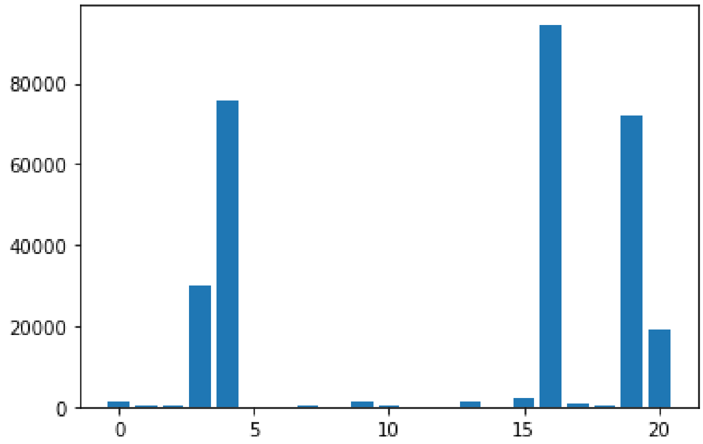
```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
fs = SelectKBest(score_func=chi2, k='all')
fs.fit(X_train_enc, y_train_enc)
X_train_fs = fs.transform(X_train_enc)
X_test_fs = fs.transform(X_test_enc)
```

We can then print the scores for each variable (largest is better), and plot the scores for each variable as a bar graph to get an idea of how many features we should select.

In [20]:

```
# Get the scores for each feature
import matplotlib.pyplot as plt
for i in range(len(fs.scores_)):
    print('Feature %d: %f' % (i, fs.scores_[i]))
# Plot the scores
plt.bar([i for i in range(len(fs.scores_))], fs.scores_)
plt.show()
```

```
Feature 0: 1494.877961
Feature 1: 140.987184
Feature 2: 149.032149
Feature 3: 30019.821978
Feature 4: 75622.256117
Feature 5: 1.231208
Feature 6: 18.164627
Feature 7: 282.887569
Feature 8: 0.213988
Feature 9: 1480.395651
Feature 10: 251.080662
Feature 11: 22.389234
Feature 12: 1.681745
Feature 13: 1403.654780
Feature 14: 7.614364
Feature 15: 2292.660728
Feature 16: 94588.371797
Feature 17: 982.976218
Feature 18: 537.350621
Feature 19: 72113.337707
Feature 20: 19245.663535
```



In [21]:

```
len(df_filtered.columns)
```

Out[21]:

```
22
```

In [22]:

```
# Print the scores with the name of the respective feature
feature_scores = {}
for (score,feature) in zip(fs.scores_, df_filtered.columns):
    #print("Feature: ", feature ,"; Score: ", score)
    feature_scores[feature] = []
    feature_scores[feature].append(score)
print(feature_scores)
```

```
{'Occurrence No': [1494.877960704207], 'Claim Financial Year': [140.98718449221423], 'Age
ncy NN': [149.03214924108906], 'Total Paid': [30019.82197784309], 'Paid Days Lost': [7562
2.25611730787], 'Injury Agency Group': [1.2312075049117401], 'Bodily Location Group': [18
.16462735010077], 'Mechanism Group': [282.88756947524524], 'Nature Group': [0.21398804896
14825], 'Bodily Location': [1480.3956511522208], 'Mechanism': [251.08066249432255], 'Natu
re': [22.389234004571243], 'Major': [1.6817454089103652], 'Occupation': [1403.65477980584
82], 'Gender': [7.614363904368194], 'Date of Birth': [2292.6607275935044], 'Days to RTW':
[94588.37179683124], 'RTW Category': [982.9762176274314], 'Age at Accident Date': [537.35
06210862328], 'Duration of Service': [72113.33770704552], 'Duration of Incident': [19245.
66353498628]}
```

From our Chi Square, there are 5 major features, so let's pick the top 5 features from the feature score dictionary

In [23]:

```
# To get the top 5 features
from heapq import nlargest
top_5_features = nlargest(5, feature_scores, key = feature_scores.get)
print(top_5_features)
```

```
['Days to RTW', 'Paid Days Lost', 'Duration of Service', 'Total Paid', 'Duration of Incid
ent']
```

The null hypothesis for chi2 test is that "two categorical variables are independent". So a higher value of chi2 statistic means "two categorical variables are dependent" and MORE USEFUL for classification.

In [24]:

```
# We edit the chi square feature selection to pick the top 5 values(Days to RTW, Paid Day
s Lost, Duration of Service, Total Paid, Duration of Incident)
fs = SelectKBest(score_func=chi2, k=5)
fs.fit(X_train_enc, y_train_enc)
X_train_fs = fs.transform(X_train_enc)
X_test_fs = fs.transform(X_test_enc)
```

```python
# Print the features and scores
for i in range(len(fs.scores_)):
    print('Feature %d: %f' % (i, fs.scores_[i]))
```

```
Feature 0: 1494.877961
Feature 1: 140.987184
Feature 2: 149.032149
Feature 3: 30019.821978
Feature 4: 75622.256117
Feature 5: 1.231208
Feature 6: 18.164627
Feature 7: 282.887569
Feature 8: 0.213988
Feature 9: 1480.395651
Feature 10: 251.080662
Feature 11: 22.389234
Feature 12: 1.681745
Feature 13: 1403.654780
Feature 14: 7.614364
Feature 15: 2292.660728
Feature 16: 94588.371797
Feature 17: 982.976218
Feature 18: 537.350621
Feature 19: 72113.337707
Feature 20: 19245.663535
```

In [25]:

```python
print(X_train_fs)
```

```
[[12827.  2673.   334.   334.   727.]
 [11799.  3987.   811.   811.    62.]
 [ 9079.  3248.    92.    92.   731.]
 ...
 [  661.  3385.   795.   795.  1534.]
 [ 6285.  3980.   939.   939.  1659.]
 [ 8610.  3567.   774.   774.   107.]]
```

Now Let's use the features gotten from Chi Square and fit the model.

The following Classification models will be used

- **Logistic Regression**
- **Support Vector Machines**
- **Decision Tree**
- **KNN**

Logistic Regression Model

In [26]:

```python
# Logistic Regression classification algorithm
from sklearn.linear_model import LogisticRegression
# Support Vector Machine classification algorithm
from sklearn.svm import SVC
# Decision Tree classification algorithm
from sklearn.tree import DecisionTreeClassifier
# K Nearest Neighbors classification algorithm
from sklearn.neighbors import KNeighborsClassifier
```

In [27]:

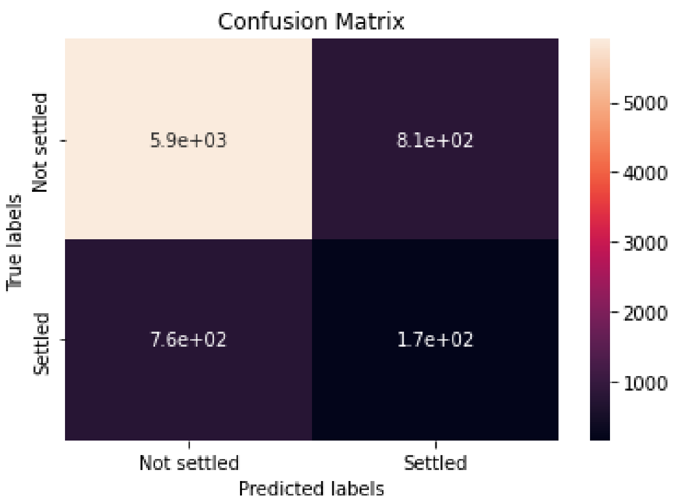
```python
# Function for plotting CONFUSION MATRIX
def plot_confusion_matrix(y,y_predict):
    "this function plots the confusion matrix"
    from sklearn.metrics import confusion_matrix
```

```
    cm = confusion_matrix(y, y_predict)
    ax=plt.subplot()
    sns.heatmap(cm, annot=True, ax=ax); #annot=True to annotate cells
    ax.set_xlabel('Predicted labels')
    ax.set_ylabel('True labels')
    ax.set_title('Confusion Matrix');
    ax.xaxis.set_ticklabels(['Not settled', 'Settled']); ax.yaxis.set_ticklabels(['Not se
ttled', 'Settled'])
```

In [29]:

```
lr=LogisticRegression()

# Train the model
lr.fit(X_train_fs, y_train_enc)

# Get the accuracy score of the model
lr_score = lr.score(X_test_fs, y_test_enc)
print("Logistic Regression accuracy is ", lr_score)

# Plot the confusion matrix
yhat=lr.predict(X_test_fs)
threshold = 0.2
lr_yhat= (lr.predict_proba(X_test_fs)[:,1] >= threshold).astype(bool)
plot_confusion_matrix(y_test_enc,lr_yhat)
```

```
Logistic Regression accuracy is  0.8791251964379256
```



In [30]:

```
from sklearn.metrics import accuracy_score, balanced_accuracy_score, f1_score

print('Scoring based on tuned threshold')
print('-'*50)
print(f'Accuracy score:          {accuracy_score(y_test_enc, lr_yhat > threshold)}')
print(f'Balanced accuracy score: {balanced_accuracy_score(y_test_enc, lr_yhat > threshold
)}')
print(f'F1 score:                {f1_score(y_test_enc, lr_yhat > threshold)}')
print('-'*50)
```

```
Scoring based on tuned threshold
--------------------------------------------------
Accuracy score:          0.7949188056574122
Balanced accuracy score: 0.5301351705322979
F1 score:                0.17578947368421052
--------------------------------------------------
```

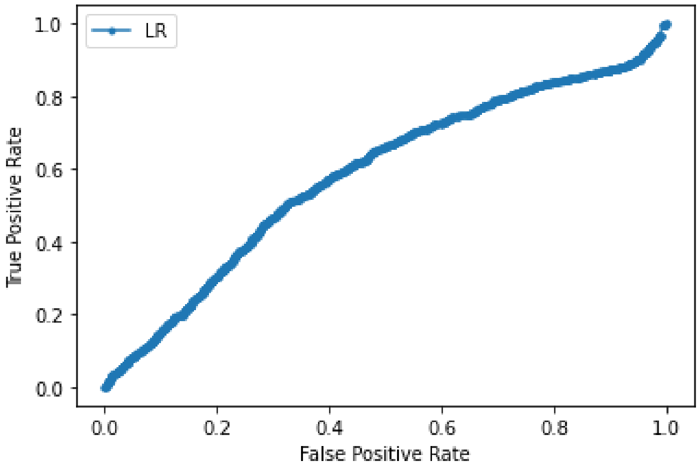
ROC FOR LOGISTIC REGRESSION MODEL

In [31]:

```
from sklearn.metrics import roc_auc_score
```

```
from sklearn.metrics import roc_curve
# predict the probability
lr_probs = lr.predict_proba(X_test_fs)
# keep probabilities for the positive outcome only
lr_probs = lr_probs[:, 1]
# calculate scores
lr_auc = roc_auc_score(y_test_enc, lr_probs)
# summarize scores
print('LR: ROC AUC=%.3f' % (lr_auc))
# calculate roc scores
lr_fpr, lr_tpr, thresholds = roc_curve(y_test_enc, lr_probs)
# plot the curve
plt.plot(lr_fpr, lr_tpr, marker='.', label='LR')
# axis labels
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
# show the legend
plt.legend()
# show the plot
plt.show()
```

```
LR: ROC AUC=0.586
```

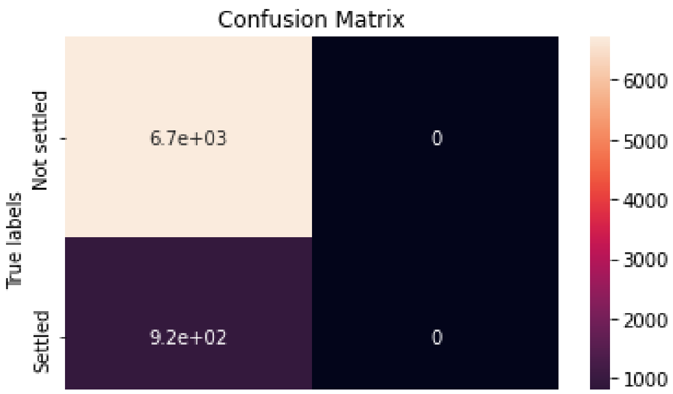


SVM Model

In [32]:

```
svm = SVC()

# Train the model
svm.fit(X_train_fs, y_train_enc)

# Get the accuracy score of the model
svm_score = svm.score(X_test_fs, y_test_enc)
print('SVM accuracy is ', svm_score)

# Plot the confusion matrix
svm_yhat=svm.predict(X_test_fs)
plot_confusion_matrix(y_test_enc,svm_yhat)
```

```
SVM accuracy is  0.8791251964379256
```



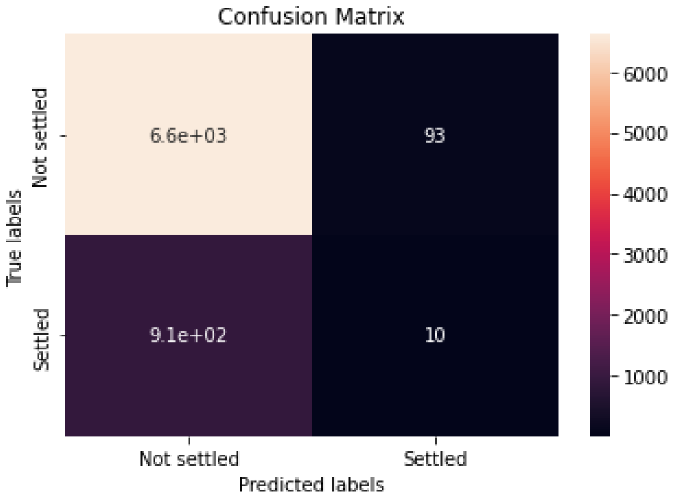
ROC CURVE FOR SVM MODEL

Decision Tree Model

In [33]:

```
tree=DecisionTreeClassifier()

# Train the model
tree.fit(X_train_fs, y_train_enc)

# Get the accuracy score of the model
tree_score = lr.score(X_test_fs, y_test_enc)
print("Decision Tree accuracy is ", tree_score)

# Plot the confusion matrix
threshold = 0.2
tree_yhat= (tree.predict_proba(X_test_fs)[:,1] >= threshold).astype(bool)
#tree_yhat=lr.predict(X_test_fs)
plot_confusion_matrix(y_test_enc,tree_yhat)
```

```
Decision Tree accuracy is  0.8791251964379256
```



In [34]:

```
from sklearn.metrics import accuracy_score, balanced_accuracy_score, f1_score

print('Scoring based on tuned threshold')
print('-'*50)
print(f'Accuracy score:          {accuracy_score(y_test_enc, tree_yhat > threshold)}')
print(f'Balanced accuracy score: {balanced_accuracy_score(y_test_enc, tree_yhat > thresho
ld)}')
print(f'F1 score:                {f1_score(y_test_enc, tree_yhat > threshold)}')
print('-'*50)
```

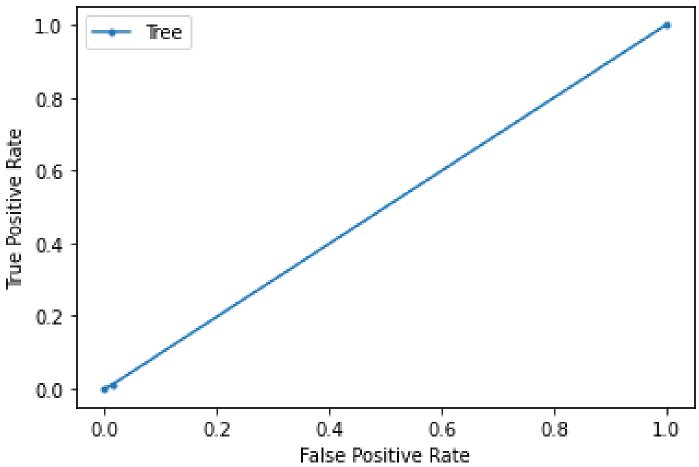
```
Scoring based on tuned threshold
--------------------------------------------------
Accuracy score:          0.8682556312205343
Balanced accuracy score: 0.49849025975859973
F1 score:                0.019493177387791423
--------------------------------------------------
```

ROC CURVE FOR TREE MODEL

In [35]:

```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
# predict the probability
tree_probs = tree.predict_proba(X_test_fs)
# keep probabilities for the positive outcome only
tree_probs = tree_probs[:, 1]
# calculate scores
tree_auc = roc_auc_score(y_test_enc, tree_probs)
# summarize scores
print('Tree: ROC AUC=%.3f' % (tree_auc))
# calculate roc scores
tree_fpr, tree_tpr, thresholds = roc_curve(y_test_enc, tree_probs)
# plot the curve
plt.plot(tree_fpr, tree_tpr, marker='.', label='Tree')
# axis labels
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
# show the legend
plt.legend()
# show the plot
plt.show()
```

```
Tree: ROC AUC=0.498
```

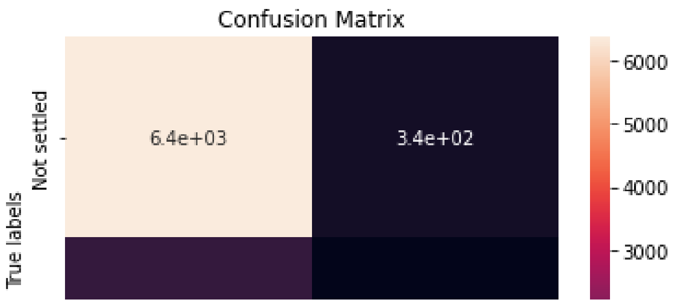


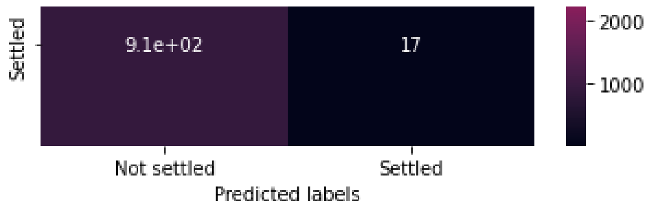
KNN Model

In [36]:

```
KNN=KNeighborsClassifier()

# Train the model
KNN.fit(X_train_fs, y_train_enc)

# Get the accuracy score of the model
KNN_score = KNN.score(X_test_fs, y_test_enc)
print("KNN accuracy is ", KNN_score)

# Plot the confusion matrix
threshold = 0.2
KNN_yhat= (KNN.predict_proba(X_test_fs)[:,1] >= threshold).astype(bool)
# KNN_yhat= (KNN.predict_proba(X_test_fs)[:,1] >= 0.2).astype(bool)
plot_confusion_matrix(y_test_enc,KNN_yhat)
```

```
KNN accuracy is  0.8791251964379256
```





In [37]:

```
from sklearn.metrics import accuracy_score, balanced_accuracy_score, f1_score

print('Scoring based on tuned threshold')
print('-'*50)
print(f'Accuracy score:          {accuracy_score(y_test_enc, KNN_yhat > threshold)}')
print(f'Balanced accuracy score: {balanced_accuracy_score(y_test_enc, KNN_yhat > threshol
d)}')
print(f'F1 score:                {f1_score(y_test_enc, KNN_yhat > threshold)}')
print('-'*50)
```

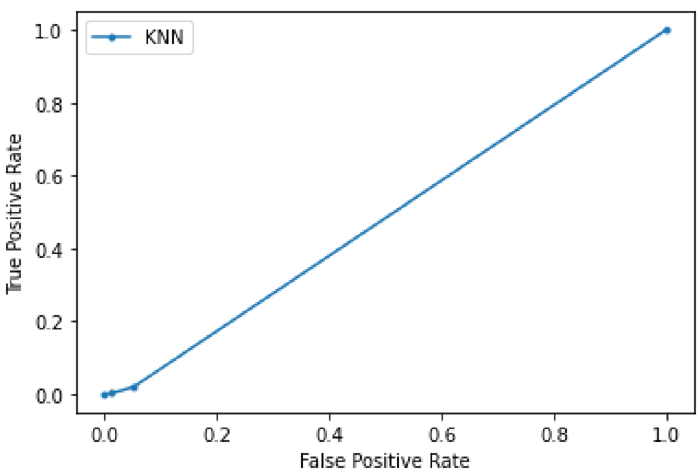
```
Scoring based on tuned threshold
--------------------------------------------------
Accuracy score:          0.8366946045049765
Balanced accuracy score: 0.4838106201982893
F1 score:                0.026541764246682278
--------------------------------------------------
```

ROC CURVE FOR KNN MODEL

In [38]:

```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
# predict the probability
KNN_probs = KNN.predict_proba(X_test_fs)
# keep probabilities for the positive outcome only
KNN_probs = KNN_probs[:, 1]
# calculate scores
KNN_auc = roc_auc_score(y_test_enc, KNN_probs)
# summarize scores
print('KNN: ROC AUC=%.3f' % (KNN_auc))
# calculate roc scores
KNN_fpr, KNN_tpr, thresholds = roc_curve(y_test_enc, KNN_probs)
# plot the curve
plt.plot(KNN_fpr, KNN_tpr, marker='.', label='KNN')
# axis labels
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
# show the legend
plt.legend()
# show the plot
plt.show()
```

```
KNN: ROC AUC=0.484
```



So the model with the best performance is the Logistic Regression Model

In [52]:

```
accuracy = accuracy_score(y_test_enc, lr_yhat)
print(f'Accuracy of Logistic Regression Model: {(accuracy*100)}%')
```

```
Accuracy of Logistic Regression Model: 79.49188056574123%
```