General Info

This notebook contains a record linkage process using different kinds of preprocessing, blockings and classifier approaches for the FEII 2016 challenge.
All information about the challenge are available at this link: https://ir.nist.gov/feiii/2016-challenge.html

All datasets provided contains information about financial entities from different sources.

This challenge also provides us partial ground truths to evaluate our matchings.

Goals

The goals of this challenge are:

- **identify matching records between FFIEC and LEI datasets (FFIEC ▯ LEI)**
- **identify matching records between FFIEC and SEC datasets (FFIEC ▯ SEC)**

Tools and workflow

Our record linkage process makes use of the Python Record Linkage Toolkit (Documentation: https://recordlinkage.readthedocs.io/en/latest/about.html).
The package contains indexing (or blocking) methods, functions to compare records and machine learning classifiers to classify matching and not matching records. We also use standalone machine learning classifiers for a supervised learning approach.

The workflow adopted for this project is the following:

Imports

In [1]:

```
import recordlinkage
from recordlinkage.preprocessing import clean
from recordlinkage.compare import Exact, String, VariableA, VariableB
import pandas as pd
import nltk
from cleanco import cleanco
from collections import Counter
import re
import time
import math
import random
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, make_scorer
from sklearn.model_selection import GridSearchCV, StratifiedKFold, train_test_split
from sklearn.ensemble import RandomForestClassifier
```

Read Datasets

In this section we read all datasets needed:

- **FFIEC**

- LEI
- SEC
- ground truths

Read FFIEC

In [2]:

```
df1 = pd.read_csv('./data/FFIEC.csv')
```

In [3]:

```
df1.head(5)
```

Out[3]:

	IDRSSD	FDIC Certificate Number	OCC Charter Number	OTS Docket Number	Primary ABA Routing Number	Financial Institution Name	Financial Institution Name Cleaned	Financial Institution Address	Financial Institution City	Financial Institution State	Financ Instituti Zip Co
0	37	10057	0	16553	61107146	BANK OF HANCOCK COUNTY	BANK OF HANCOCK COUNTY	12855 BROAD STREET	SPARTA	GA	310
1	242	3850	0	0	81220537	FIRST COMMUNITY BANK XENIA-FLORA	FIRST COMMUNITY BANK XENIA-FLORA	260 FRONT STREET	XENIA	IL	628
2	279	28868	0	2523	311972526	MINEOLA COMMUNITY BANK, SSB	MINEOLA COMMUNITY BANK, SSB	215 W BROAD	MINEOLA	TX	757
3	354	14083	0	0	101107475	BISON STATE BANK	BISON STATE BANK	223 MAIN STREET	BISON	KS	675
4	457	10202	0	0	91208332	LOWRY STATE BANK	LOWRY STATE BANK	400 FLORENCE AVE.	LOWRY	MN	563

Read LEI

In [4]:

```
df2 = pd.read_csv('./data/LEI.csv', engine='python')
```

In [5]:

```
df2.head(5)
```

Out[5]:

	LOU	LOU_ID	LEI	LegalName	LegalNameCleaned	AssociatedLEI	AssociatedEntityName	LegalA
0	5493	GMEI	549300D5GJV4HUX52B25	Black Diamond BGWB14 Inc.	Black Diamond BGWB14 Inc.	NaN	NaN	Cor
1	2138	IEI	213800AEWHVA48PG1673	INFIGEN ENERGY US PARTNERSHIP	INFIGEN ENERGY US PARTNERSHIP	NaN	NaN	COI
2	5493	GMEI	5493001BP0K5C4YI1257	Nextgen Finance, LLC	Nextgen Finance, LLC	NaN	NaN	2711 (
3	5493	GMEI	549300O17WX08AA1BA13	pControl North	pControl North	NaN	NaN	615 S

	LOU	LOU_ID	LEI	LegalName	LegalNameCleaned	AssociatedLEI	AssociatedEntityName	LegalA
3	5493	GMEI	549300O17WX08AATRA13	America Inc.	America Inc.	NaN	NaN	615 S
4	5493	GMEI	549300S6SBBS482XV369	RYCO Hydraulics, Inc.	RYCO Hydraulics, Inc.	NaN	NaN	615 S

5 rows × 39 columns

Read SEC

In [6]:

```
df3 = pd.read_csv('./data/SEC.csv', engine='python')
```

In [7]:

```
df3.head(5)
```

Out[7]:

	CIK	IRS_NUMBER	CONFORMED_NAME	MinOfFILING_DATE	FORMER_CONFORMED_NAME	FORMER_NAME_CHANGED
0	20	221759452.0	K TRON INTERNATIONAL INC	20080722	NaN	NaN
1	1750	362334820.0	AAR CORP	20080605	ALLEN AIRCRAFT RADIO INC	19700204.0
2	1800	360698440.0	ABBOTT LABORATORIES	20080703	NaN	NaN
3	1841	132833083.0	ABEL/NOSER CORPORATION	20090317	ABEL NOSER CORP ...	20000101.0
4	1853	826008492.0	MOTIVNATION, INC.	20080612	ABERDEEN IDAHO MINING CO	20000101.0

5 rows × 24 columns

Read ground truths

FFIEC ▯ LEI

In [8]:

```
FFIEC_LEI_gt = pd.read_csv('./data/FFIEC-LEI-GroundTruth.csv', sep='\t')
FFIEC_LEI_gt = FFIEC_LEI_gt.set_index(['FFIEC_ID','LEI_ID'])
```

In [9]:

```
FFIEC_LEI_gt.head(5)
```

Out[9]:

TYPE

FFIEC_ID	LEI_ID	TYPE
68756	549300465MKS092D6K02	TP
63069	593C3GZG957YOJPS2Z63	TP
3560783	549300KIB2BK64XF5262	TP
1356768	5493008ZK5SW6NTWB533	TP
3470985	549300DCFF8W6ZAEKH70	TP

FFIEC ▯ SEC

In [10]:

```
FFIEC_SEC_gt = pd.read_csv('./data/FFIEC-SEC-GroundTruth.csv', sep='\t')
FFIEC_SEC_gt = FFIEC_SEC_gt.set_index(['FFIEC_ID','SEC_ID'])
```

In [11]:

```
FFIEC_SEC_gt.head(5)
```

Out[11]:

		TYPE
FFIEC_ID	SEC_ID	
436711	1430521	TP
618740	1594492	TP
63069	275216	TP
3348888	1552682	TP
895710	1520684	TP

Preprocessing

Here we define all the function needed for the preprocessing phase: cleaning data, normalization and other operations.

By analyzing our data we found:

- **inconsistent addresses information.**
  e.g: SEC contains, in the same address attribute, information about the P.O. BOX addresses which is not present in other datasets.
  e.g: normalization of words for example st ▯ street
- **zipcodes length not uniform.**
- **There is implicit semantic knowledge included in a name, e.g., a name may contain “National Association” or “State Bank of” in its name. This complicates matching based on a similarity score.**
- **Stopwords and punctuation differ between the same abbreviations or words.**

Utils functions

In [12]:

```
def normalizeAddress(sentence):
    # normalize road types
    for key in road_types:
        sentence = re.sub(r"\s*\b"+re.escape(key)+r"\b\s*", ' '+road_types[key]+' ', sen
tence)
```

```python
    # normalize road orientations
    for key in road_orientations:
        sentence = re.sub(r"\s*\b"+re.escape(key)+r"\b\s*", ' '+road_orientations[key]+'
', sentence)
    sentence = re.sub(r"\s*\bpo box \d{0,}\b\s*",' ', sentence)
    sentence = re.sub(r"\s*\bbox \d{0,}\b\s*",' ', sentence)
    sentence = sentence.strip()
    return sentence

def normalizeZipCode(zip_code):
    if zip_code == 'NaN':
        return zip_code
    # takes first "5" digits
    zip_code = zip_code.split('-')[0]

    # adding initial zeros to partial zip codes
    zeros = 5 - len(zip_code)
    while zeros > 0:
        zip_code = '0' + zip_code
        zeros -= 1
    return zip_code


def normalizeNameModifier(sentence):
    modifier = None
    for key in name_modifiers:
        if re.search(r"\b"+re.escape(key)+r"\b", sentence):
            modifier = name_modifiers[key]
            sentence = re.sub(r"\s*\b"+re.escape(key)+r"\b\s*",' ', sentence)

    for key in name_modifiers:
        if re.search(r"\b"+re.escape(name_modifiers[key])+r"\b", sentence):
            modifier = name_modifiers[key]
            sentence = re.sub(r"\s*\b"+re.escape(name_modifiers[key])+r"\b\s*",' ', sent
ence)
    sentence = re.sub('\s+',' ',sentence).strip()
    return sentence, modifier

def removeStopWords(sentence):
    tokens = nltk.tokenize.word_tokenize(sentence)
    tokens = [word for word in tokens if word not in stop_words]
    ret = ' '.join(tokens)
    return ret

def flatten(listoflists):
    return [item for list in listoflists for item in list]

def mostCommonWords(names):
    tokens = names.apply(nltk.tokenize.word_tokenize)
    tokens = tokens.apply(lambda x: [word for word in x if word not in stop_words])
    ugs = Counter(flatten(tokens.apply(lambda x : list(nltk.ngrams(x, 1)))))
    bgs = Counter(flatten(tokens.apply(lambda x : list(nltk.ngrams(x, 2)))))
    tgs = Counter(flatten(tokens.apply(lambda x : list(nltk.ngrams(x, 3)))))
    return ugs, bgs, tgs

# stop words list
stop_words = nltk.corpus.stopwords.words('english')

# name modifiers dictionary
name_modifiers = {'corp': 'corporation', 'co': 'company', 'fsb': 'federal savings bank',
                  'na': 'national association', 'inc': 'incorporated', 'ta': 'trust asso
ciation'}

# orientation dictionary
road_orientations = {'north': 'n', 'south': 's', 'east': 'e', 'west': 'w',
                'northeast': 'ne', 'northwest': 'nw', 'southeast': 'se', 'southwest': 's
w'}

# road types dictionary
road_types = {'street': 'st', 'road': 'rd', 'avenue': 'ave', 'square': 'sq',
              'lane': 'la', 'suite': 'su', 'plaza': 'pl' }
```

Cleaning functions

Here we defined cleaning functions which use the previously defined preprocessing functions for an easier utilization later on.

FFIEC

In [13]:

```
# verify IDs uniqueness
print('FFIEC:')
print(df1['IDRSSD'].value_counts())
print('\nNo removes needed...')
```

```
FFIEC:
399357     1
17978      1
448040     1
640554     1
3482166    1
          ..
375650     1
734051     1
28406      1
533124     1
3045383    1
Name: IDRSSD, Length: 6652, dtype: int64

No removes needed...
```

In [14]:

```
def preprocessFFIEC(df, name=True, stopwords=True, modifier=True, address=True):
    # filter out unwanted columns from dataframe
    df = pd.DataFrame(df[['IDRSSD', 'Financial Institution Name Cleaned', \
                          'Financial Institution Address', 'Financial Institution City',
\
                          'Financial Institution State', 'Financial Institution Zip Code
5']])
    # set id index
    df = df.set_index('IDRSSD')
    # clean Name
    if name:
        df['Financial Institution Name Cleaned'] = df['Financial Institution Name Cleane
d'].str.replace('&', ' and ')
        df['Financial Institution Name Cleaned'] = clean(df['Financial Institution Name
Cleaned'])
        # remove stopwords
        if stopwords:
            df['Financial Institution Name Cleaned'] = df['Financial Institution Name Cl
eaned'].apply(removeStopWords)
        # remove name modifier
        if modifier:
            df[['Financial Institution Name Cleaned', 'MODIFIER']] = df.apply(lambda x:
pd.Series(normalizeNameModifier(x['Financial Institution Name Cleaned'])), axis=1)
    # clean address
    if address:
        df['Financial Institution Address'] = clean(df['Financial Institution Address'])
.apply(normalizeAddress)
    # clean city
    df['Financial Institution City'] = clean(df['Financial Institution City'])
    # clean postal code
    df['Financial Institution Zip Code 5'] = df['Financial Institution Zip Code 5'].asty
pe(str).apply(normalizeZipCode)
    return df
```

LEI

In [15]:

```
print('LEI:')
print(df2['LEI'].value_counts())
print('\n Need to remove record with LEI =', '9.598E+19' )
```

```
LEI:
9.598E+19               9
549300DT8SH0CF6BTT37    1
5493007KJQJ3YKET6L74    1
6M5VVHP54K5BPR2GI852    1
549300CW9L0BVQY20W81    1
                       ..
54930005OOZ1ZPIEB793    1
549300MG78OMJG7UHF07    1
549300EZHHTTDNQF5G02    1
549300TS75MG79QT5F80    1
549300SBN40YH05GIW70    1
Name: LEI, Length: 53950, dtype: int64

 Need to remove record with LEI = 9.598E+19
```

In [16]:

```
def preprocessLEI(df, name=True, stopwords=True, modifier=True, address=True):
    # filter out unwanted columns from dataframe
    df = pd.DataFrame(df[['LEI', 'LegalNameCleaned', 'LegalAddress_Line_Cleaned', \
                         'LegalAddress_City', 'LegalAddress_Region_2', 'LegalAddress_Coun
try', 'LegalAddress_PostalCode_5']])

    # set id as index
    df = df.set_index('LEI')

    # remove invalid records
    df = pd.DataFrame(df.drop('9.598E+19'))

    # clean Name
    if name:
        df['LegalNameCleaned'] = df['LegalNameCleaned'].str.replace('&', ' and ')
        df['LegalNameCleaned'] = clean(df['LegalNameCleaned'])
        # remove stopwords
        if stopwords:
            df['LegalNameCleaned'] = df['LegalNameCleaned'].apply(removeStopWords)
        # remove name modifier
        if modifier:
            df[['LegalNameCleaned', 'MODIFIER']] = df.apply(lambda x: pd.Series(normaliz
eNameModifier(x['LegalNameCleaned'])), axis=1)
    # clean address
    if address:
        df['LegalAddress_Line_Cleaned'] = clean(df['LegalAddress_Line_Cleaned']).apply(n
ormalizeAddress)
    # clean city
    df['LegalAddress_City'] = clean(df['LegalAddress_City'])
    # clean postal code
    df['LegalAddress_PostalCode_5'] = df['LegalAddress_PostalCode_5'].apply(lambda x : s
tr(int(x) if str(x) != 'nan' else x))\
                                                                      .apply(normalizeZi
pCode)
    return df
```

SEC

In [17]:

```
# verify IDs uniqueness
print('SEC:')
print(df3['CIK'].value_counts())
print('\nNo removes needed...')
```

```
SEC:
```

```
790526     1
1596732    1
1501174    1
1133076    1
1482745    1
          ..
1625266    1
215740     1
1524413    1
744126     1
1312769    1
Name: CIK, Length: 129312, dtype: int64

No removes needed...
```

In [18]:

```python
def preprocessSEC(df, name=True, stopwords=True, modifier=True, address=True):
    # filter out unwanted columns from dataframe
    df = pd.DataFrame(df[['CIK', 'CONFORMED_NAME', 'B_STREET', \
                          'B_CITY', 'B_STPR', 'B_POSTAL']])
    # set id as index
    df = df.set_index('CIK')
    # clean Name
    if name:
        df['CONFORMED_NAME'] = df['CONFORMED_NAME'].str.replace('&', ' and ')
        df['CONFORMED_NAME'] = clean(df['CONFORMED_NAME'])
        # remove stopwords
        if stopwords:
            df['CONFORMED_NAME'] = df['CONFORMED_NAME'].apply(removeStopWords)
        # remove name modifier
        if modifier:
            df[['CONFORMED_NAME', 'MODIFIER']] = df.apply(lambda x: pd.Series(normalizeN
ameModifier(x['CONFORMED_NAME'])), axis=1)
    # clean address
    if address:
        # TODO: define clean address
        df['B_STREET'] = clean(df['B_STREET']).apply(normalizeAddress)
    # clean city
    df['B_CITY'] = clean(df['B_CITY'])
    # clean postal code
    df['B_POSTAL'] = df['B_POSTAL'].astype(str).apply(normalizeZipCode)
    return df
```

preprocessAll

In [19]:

```python
def preprocessAll(df_FFIEC, df_LEI, df_SEC, name=True, stopwords=True, modifier=True, add
ress=True):
    df_FFIEC = preprocessFFIEC(df_FFIEC, name, stopwords, modifier, address)
    df_LEI = preprocessLEI(df_LEI, name, stopwords, modifier, address)
    df_SEC = preprocessSEC(df_SEC, name, stopwords, modifier, address)
    return df_FFIEC, df_LEI, df_SEC
```

Blocking

Here we define functions which make use of the Python Record Linkage Toolkit to implement different blocking strategies. A blocking strategy is used to create and limit the number of record pairs which needs to be compared later on to indentify the matching ones. We considered:

- **Full Indexing: no blocking strategy is applied. A full index is an index with all possible combinations of record pairs. Returns the cartesian products of the records from each dataset. This is usually not the best choice in terms of performance.**

- **Exact Blocking: returns all record pairs that agree on the given variable(s).**

- Sorted Neighbourhood Blocking: sorts records based on a sorting key and moves a window of size *n* over the sorted records. Records within the window are paired with each other to form the candidate record pair list. The Sorted Neighbourhood Blocking method is a great method when there is relatively large amount of spelling mistakes.

Functions definitions

In [20]:

```
# full indexing, computationally expensive
def fullIndexing(df_A, df_B):
    start_time = time.time()
    indexer = recordlinkage.Index()
    indexer.full()
    candidate_links = indexer.index(df_A, df_B)
    print("Execution time: %s seconds " % (time.time() - start_time))
    return candidate_links

# exact blocking
def exactBlocking(df_A, df_B, column_A, column_B):
    start_time = time.time()
    indexer = recordlinkage.Index()
    indexer.block(left_on=[column_A], right_on=[column_B])
    candidate_links = indexer.index(df_A, df_B)
    print("Execution time: %s seconds " % (time.time() - start_time))
    return candidate_links

# sorted neighbourhood indexing
def sortedNeighbourhoodIndexing(df_A, df_B, column_A, column_B, window=3):
    start_time = time.time()
    indexer = recordlinkage.Index()
    indexer = recordlinkage.SortedNeighbourhoodIndex(
            left_on=column_A, right_on=column_B, window=window
        )
    candidate_links = indexer.index(df_A, df_B)
    print("Execution time: %s seconds " % (time.time() - start_time))
    return candidate_links
```

Comparison

Here we define the compare function which makes use of the **Python Record Linkage Toolkit**.

It's possibile to define how attributes are compared with each other:

- Exact matching: the similarity is 1 in case of agreement and 0 otherwise.
- String matching: different similarity algorithms are available **jaro**, **jarowinkler**, **levenshtein**, **damerau_levenshtein**, **qgram** or **cosine**. In case of agreement, the similarity is 1 and in case of complete disagreement it is 0.

Other matching methods are available but our function doesn't implement those because are not needed for our datasets.

- Numeric matching
- Geographic matching
- Data matching

Functions definitions

In [21]:

```
# str_comp = {'method': [{'col_names': ['col_A', 'col_B'], 'threshold': n}, {'col_names':
['col_A', 'col_B'], 'threshold': n}]}
# exact_comp = [{'col_names': ['col_A', 'col_B']}]

def compareRecords(df_A, df_B, candidate_links, str_comp, exact_comp):
    comp = recordlinkage.Compare()

    for method in str_comp:
        for columns in str_comp[method]:
            col_A = columns['col_names'][0]
            col_B = columns['col_names'][1]
            if 'threshold' in columns:
                threshold = columns['threshold']
                comp.add(String(col_A, col_B,
                                    method = method,
                                    threshold = threshold,
                                    label = col_A))
            else:
                comp.add(String(col_A, col_B,
                                    method = method,
                                    label = col_A))

    for columns in exact_comp:
            col_A = columns['col_names'][0]
            col_B = columns['col_names'][1]
            comp.add(Exact(col_A, col_B, label = col_A))
    start_time = time.time()
    features = comp.compute(candidate_links, df_A, df_B)
    print("Execution time: %s seconds " % (time.time() - start_time))
    return features
```

Classification

Here we define functions to determine which records are Matching Records and which are not.

We considered different approaches:

- **Deterministic: a matching record is one that agrees on at least a certain amount of attributes according to the comparing rules we previously defined.**
- **Unsupervised Machine Learning: we used k-means and ECM (Expectation/Conditional Maximisation) models for an unsupervised ML approach. Unsupervised learning is a good approach for record linkage when data isn't labeled since it doesn't need a training set. Our ground truth is partial and as we'll see later on it isn't really reliable.**
- **Supervised Machine Learning: we used a Random Forest classifier to try and make use of the ground truth available as a training set for this approach. We also used a stratified 10-fold cross validation to evaluate the performance because of the small dataset available as training.**

Functions definitions

In [22]:

```
def getDeterministicMatches(features, threshold=0):
    if threshold == 0:
        n_columns = len(features.columns)
        if n_columns % 2 == 0:
            threshold = n_columns / 2 + 1
        else:
            threshold = math.ceil(n_columns / 2)
    links_pred = features[features.sum(axis=1) >= threshold]
    return links_pred

def getMachineLearningMatches(method, features):
    classifier = None
    if method == 'kmeans':
        classifier = recordlinkage.KMeansClassifier()
    elif method == 'ECM':
        classifier = recordlinkage.KMeansClassifier()
    else:
        print('Invalid classifier')
        return
    links_pred = classifier.fit_predict(features)
    return links_pred

def balanceFFIEC_SEC(df, features):
    links_found = df[df.index.isin(features.index)]
    np.random.seed(10)
    sampled_TN = links_found[links_found.TYPE=='TN'].sample(120)
    np.random.seed(10)
    sampled_TP = links_found[links_found.TYPE=='TP'].sample(120)
    balanced_df = pd.concat([sampled_TN, sampled_TP, links_found[links_found['TYPE'] ==
'Ambiguous']])
    return balanced_df

def convertTargetToNumber(target_str):
    if target_str == 'TN':
        return 0
    if target_str == 'TP':
        return 1
    if target_str == 'Ambiguous':
        return 2

def preprocessForSupervised(features, ground_truth):
    fig, axs = plt.subplots(1,2)
    ground_truth['TYPE'].value_counts().plot(kind='bar', title='Target - original', ax=a
xs[0])
    ground_truth_balanced = balanceFFIEC_SEC(ground_truth, features)
    ground_truth_balanced['TYPE'].value_counts().plot(kind='bar', title= 'Target - sampl
ed', ax=axs[1])
    features_subset = features[features.index.isin(ground_truth_balanced.index)]
    features_subset = features_subset.merge(ground_truth_balanced,
                      left_on=features_subset.index.values,
                      right_on=ground_truth_balanced.index.values)
    features_subset = features_subset.set_index('key_0')
    features_subset.index = pd.MultiIndex.from_tuples(features_subset.index, names=['FFI
EC_ID', 'SEC_ID'])
    features_subset['TYPE'] = features_subset['TYPE'].apply(convertTargetToNumber)
    return features_subset
```

Evaluation

In this section we define functions to evalute our results.

If a ground truth is available we report a Confusion Matrix and the performance measure of Precision, Recall and F-Score.

We also define functions which help us identify which records we misclassified as matching (False positive) or which we identified as not matching but they were instead matching (False negative) all relying on the availability of a ground truth.

Functions definitions

In [23]:

```
# get confusion matrix
def getConfusionMatrix(ground_truth, links_pred):
    return recordlinkage.confusion_matrix(ground_truth[ground_truth.TYPE == 'TP'].index,
links_pred)
```

```
# get precision measure
def getPrecision(ground_truth, links_pred):
    return recordlinkage.precision(ground_truth[ground_truth.TYPE == 'TP'].index, links_
pred)

# get recall measure
def getRecall(ground_truth, links_pred):
    return recordlinkage.recall(ground_truth[ground_truth.TYPE == 'TP'].index, links_pre
d)

# get precision measure
def getFScore(ground_truth, links_pred):
    return recordlinkage.fscore(ground_truth[ground_truth.TYPE == 'TP'].index, links_pre
d)

# get all performance measures
def getPerformance(ground_truth, links_pred):
    conf_matrix = getConfusionMatrix(ground_truth, links_pred)
    precision = getPrecision(ground_truth, links_pred)
    recall = getRecall(ground_truth, links_pred)
    fscore = getFScore(ground_truth, links_pred)
    return conf_matrix, precision, recall, fscore

# get false positives
def getFalsePositives(ground_truth, links_pred):
    false_positive_links_gt = list(set(list(links_pred.index.values)) & set(list(ground_t
ruth[ground_truth.TYPE != 'TP'].index.values)))
    false_positive_links_gt = pd.DataFrame(ground_truth.loc[ground_truth.index.isin(fals
e_positive_links_gt)])
    false_positive_links_ngt = links_pred[~links_pred.index.isin(ground_truth.index.valu
es)]
    false_positive_links = pd.concat([false_positive_links_gt, false_positive_links_ngt]
)
    false_positive_links = pd.DataFrame(false_positive_links['TYPE'])
    return false_positive_links

# get false negatives. It includes FN generated by our comparison and those excluded from
our blocking strategy
def getFalseNegatives(ground_truth, links_pred, candidate_links):
    false_negatives_links_gt = pd.DataFrame(ground_truth.loc[~ground_truth.index.isin(li
nks_pred.index.values)])
    false_negatives_links_gt = false_negatives_links_gt.loc[false_negatives_links_gt.TYPE
== 'TP']
    false_negatives_links_gt['CAUSE'] = 'compare'
    false_negatives_links_bl = pd.DataFrame(ground_truth.loc[~ground_truth.index.isin(ca
ndidate_links)])
    false_negatives_links_bl = false_negatives_links_bl.loc[false_negatives_links_bl.TYPE
== 'TP']
    false_negatives_links_bl['CAUSE'] = 'blocking'
    false_negatives_links = pd.concat([false_negatives_links_gt, false_negatives_links_b
l])
    false_negatives_links = false_negatives_links[~false_negatives_links.index.duplicate
d(keep='last')]
    return false_negatives_links

# check a record pair. Indexes is a tuple containing the record indices
def checkRecordPair(df_A, df_B, features, indexes):
    record_A = df_A[df_A.index == indexes[0]].values
    record_B = df_B[df_B.index == indexes[1]].values
    features_AB = features[(features.index.get_level_values(0) == indexes[0]) & (feature
s.index.get_level_values(1) == indexes[1])]
    return record_A, record_B, features_AB
```

Record linkage FFIEC LEI

In this section we execute the workflow previosly explained to identify the matching records between FFIEC and LEI datasets.

Attribute pairs

- **Financial Institution Name Cleaned LegalNameCleaned**
- **Financial Institution Address LegalAddress_Line_Cleaned**
- **Financial Institution City LegalAddress_City**
- **Financial Institution State LegalAddress_Region_2**
- **Financial Institution Zip Code 5 LegalAddress_PostalCode_5**

Preprocessing

In [24]:

```
FFIEC, LEI, _ = preprocessAll(df1, df2, df3, name=True, stopwords=True, modifier=True, address=True)
```

Blocking (Choose one of the two blocking strategies)

Exact Blocking

In [25]:

```
candidate_links = exactBlocking(FFIEC, LEI, 'Financial Institution Name Cleaned', 'LegalNameCleaned')
```

```
Execution time: 0.07483386993408203 seconds
```

Then jump to Exact Blocking Compare section.

Sorted Neighbourhood Blocking

In [26]:

```
candidate_links = sortedNeighbourhoodIndexing(FFIEC, LEI, 'Financial Institution Name Cleaned', 'LegalNameCleaned')
```

```
Execution time: 0.1686689853668213 seconds
```

Then jump to Sorted Blocking Compare section.

In [27]:

```
len(candidate_links)
```

Out[27]:

```
8701
```

Compare (Reminder: choose only one of the two comparison)

Exact Blocking Compare

In [28]:

```
# Compare Det
str_comp = {'jarowinkler': [
    {
        'col_names': ['Financial Institution Address', 'LegalAddress_Line_Cleaned'],
        'threshold': 0.75
    },
    {
        'col_names': ['Financial Institution City', 'LegalAddress_City'],
        'threshold': 0.90
    }
]}
exact_comp = [
    {'col_names': ['Financial Institution Zip Code 5', 'LegalAddress_PostalCode_5']},
    {'col_names': ['Financial Institution State', 'LegalAddress_Region_2']}
]
features_det = compareRecords(FFIEC, LEI, candidate_links, str_comp, exact_comp)

# Compare ML
str_comp = {'jarowinkler': [
    {
        'col_names': ['Financial Institution Address', 'LegalAddress_Line_Cleaned']
    },
    {
        'col_names': ['Financial Institution City', 'LegalAddress_City']
    }
]}
features_ml = compareRecords(FFIEC, LEI, candidate_links, str_comp, exact_comp)
```

```
Execution time: 0.08975982666015625 seconds
Execution time: 0.08078360557556152 seconds
```

Sorted Blocking Compare

In [29]:

```
# Compare Det
str_comp = {'jarowinkler': [
    {
        'col_names': ['Financial Institution Name Cleaned', 'LegalNameCleaned'],
        'threshold': 0.90
    },
    {
        'col_names': ['Financial Institution Address', 'LegalAddress_Line_Cleaned'],
        'threshold': 0.85
    },
    {
        'col_names': ['Financial Institution City', 'LegalAddress_City'],
        'threshold': 0.90
    }
]}
exact_comp = [
    {'col_names': ['Financial Institution Zip Code 5', 'LegalAddress_PostalCode_5']}
]
features_det = compareRecords(FFIEC, LEI, candidate_links, str_comp, exact_comp)

# Compare ML
str_comp = {'jarowinkler': [
    {
        'col_names': ['Financial Institution Name Cleaned', 'LegalNameCleaned']
    },
    {
        'col_names': ['Financial Institution Address', 'LegalAddress_Line_Cleaned']
    },
    {
        'col_names': ['Financial Institution City', 'LegalAddress_City']
    }
]}

features_ml = compareRecords(FFIEC, LEI, candidate_links, str_comp, exact_comp)
```

```
Execution time: 0.11070489883422852 seconds
Execution time: 0.10471892356872559 seconds
```

Classification

Deterministic

In [30]:

```
links_pred_det = getDeterministicMatches(features_det)
```

Perfomance measures based on the ground truth available:

In [31]:

```
cm_det, prec_det, rec_det, fscore = getPerformance(FFIEC_LEI_gt, links_pred_det.index)
print(cm_det)
print('PRECISION: ', prec_det)
print('RECALL: ', rec_det)
print('F-SCORE: ', fscore)
```

```
[[482.  14.]
 [ 65.  nan]]
PRECISION:  0.8811700182815356
RECALL:  0.9717741935483871
F-SCORE:  0.9242569511025887
```

Unsupervised Machine Learning

K-means

In [32]:

```
links_pred_km = getMachineLearningMatches('kmeans', features_ml)
```

Perfomance measures based on the ground truth available:

In [33]:

```
cm_km, prec_km, rec_km, fscore = getPerformance(FFIEC_LEI_gt, links_pred_km)
print(cm_km)
print('PRECISION: ', prec_km)
print('RECALL: ', rec_km)
print('F-SCORE: ', fscore)
```

```
[[469.  27.]
 [114.  nan]]
PRECISION:  0.8044596912521441
RECALL:  0.9455645161290323
F-SCORE:  0.8693234476367006
```

ECM

In [34]:

```
links_pred_ecm = getMachineLearningMatches('ECM', features_ml)
```

Perfomance measures based on the ground truth available:

In [35]:

```
cm_ecm, prec_ecm, rec_ecm, fscore = getPerformance(FFIEC_LEI_gt, links_pred_ecm)
print(cm_ecm)
print('PRECISION: ', prec_ecm)
print('RECALL: ', rec_ecm)
print('F-SCORE: ', fscore)
```

```
[[469.  27.]
 [114.  nan]]
PRECISION:  0.8044596912521441
RECALL:  0.9455645161290323
F-SCORE:  0.8693234476367006
```

Record linkage FFIEC SEC

In this section we execute the workflow previosly explained to identify the matching records between FFIEC and SEC datasets.

- **Financial Institution Name Cleaned CONFORMED_NAME**
- **Financial Institution Address B_STREET**
- **Financial Institution City B_CITY**
- **Financial Institution State B_STPR**
- **Financial Institution Zip Code 5 B_POSTAL**

Preprocessing

In [36]:

```
FFIEC, _, SEC = preprocessAll(df1, df2, df3, name=True, stopwords=True, modifier=True, ad
dress=True)
```

Blocking (Choose one of the two blocking strategies)

Exact Blocking

In [37]:

```
candidate_links = exactBlocking(FFIEC, SEC, 'Financial Institution Name Cleaned', 'CONFOR
MED_NAME')
```

```
Execution time: 0.11670708656311035 seconds
```

Then jump to Exact Blocking Compare section.

Sorted Neighbourhood Blocking

In [38]:

```
candidate_links = sortedNeighbourhoodIndexing(FFIEC, SEC, 'Financial Institution Name Cle
aned', 'CONFORMED_NAME')
```

```
Execution time: 0.347886323928833 seconds
```

Then jump to Sorted Blocking Compare section.

In [39]:

```
len(candidate_links)
```

Out[39]:

```
9163
```

Compare (Reminder: choose only one of the two comparison)

Exact Blocking Compare

In [40]:

```
# Compare Det
str_comp = {'jarowinkler': [
    {
        'col_names': ['Financial Institution Address', 'B_STREET'],
        'threshold': 0.75
    },
    {
        'col_names': ['Financial Institution City', 'B_CITY'],
        'threshold': 0.90
    }
]}
exact_comp = [
    {'col_names': ['Financial Institution Zip Code 5', 'B_POSTAL']},
    {'col_names': ['Financial Institution State', 'B_STPR']}
]
features_det = compareRecords(FFIEC, SEC, candidate_links, str_comp, exact_comp)

# Compare ML
str_comp = {'jarowinkler': [
    {
        'col_names': ['Financial Institution Address', 'B_STREET']
    },
    {
        'col_names': ['Financial Institution City', 'B_CITY']
    }
]}

features_ml = compareRecords(FFIEC, SEC, candidate_links, str_comp, exact_comp)
```

```
Execution time: 0.10272479057312012 seconds
Execution time: 0.07878971099853516 seconds
```

Sorted Blocking Compare

In [41]:

```
# Compare Det
str_comp = {'jarowinkler': [
    {
        'col_names': ['Financial Institution Name Cleaned', 'CONFORMED_NAME'],
        'threshold': 0.90
    },
    {
        'col_names': ['Financial Institution Address', 'B_STREET'],
        'threshold': 0.85
    },
    {
        'col_names': ['Financial Institution City', 'B_CITY'],
        'threshold': 0.90
    }
]}
exact_comp = [
    {'col_names': ['Financial Institution Zip Code 5', 'B_POSTAL']}
]
features_det = compareRecords(FFIEC, SEC, candidate_links, str_comp, exact_comp)

# Compare ML
str_comp = {'jarowinkler': [
    {
        'col_names': ['Financial Institution Name Cleaned', 'CONFORMED_NAME']
    },
    {
        'col_names': ['Financial Institution Address', 'B_STREET']
    },
    {
        'col_names': ['Financial Institution City', 'B_CITY']
    }
]}

features_ml = compareRecords(FFIEC, SEC, candidate_links, str_comp, exact_comp)
```

```
Execution time: 0.11469483375549316 seconds
Execution time: 0.11220407485961914 seconds
```

Classification

Deterministic

In [42]:

```
links_pred_det = getDeterministicMatches(features_det)
```

Perfomance measures based on the ground truth available:

In [43]:

```
cm_det, prec_det, rec_det, fscore = getPerformance(FFIEC_SEC_gt, links_pred_det.index)
print(cm_det)
print('PRECISION: ', prec_det)
print('RECALL: ', rec_det)
print('F-SCORE: ', fscore)
```

```
[[184.  46.]
 [471.  nan]]
PRECISION:  0.28091603053435116
RECALL:  0.8
F-SCORE:  0.415819209039548
```

Unsupervised Machine Learning

K-means

In [44]:

```
links_pred_km = getMachineLearningMatches('kmeans', features_ml)
```

Perfomance measures based on the ground truth available:

In [45]:

```
cm_km, prec_km, rec_km, fscore = getPerformance(FFIEC_SEC_gt, links_pred_km)
print(cm_km)
print('PRECISION: ', prec_km)
print('RECALL: ', rec_km)
print('F-SCORE: ', fscore)
```

```
[[175.  55.]
 [505.  nan]]
PRECISION:  0.25735294117647056
RECALL:  0.7608695652173914
F-SCORE:  0.38461538461538464
```

ECM

In [46]:

```
links_pred_ecm = getMachineLearningMatches('ECM', features_ml)
```

Perfomance measures based on the ground truth available:

In [47]:

```
cm_ecm, prec_ecm, rec_ecm, fscore = getPerformance(FFIEC_SEC_gt, links_pred_ecm)
print(cm_ecm)
print('PRECISION: ', prec_ecm)
print('RECALL: ', rec_ecm)
print('F-SCORE: ', fscore)
```

```
[[175.   55.]
 [505.   nan]]
PRECISION:  0.25735294117647056
RECALL:  0.7608695652173914
F-SCORE:  0.38461538461538464
```

Supervised Machine Learning

We decided to implement a supervised machine learning approach only for these two datasets because of a bigger and more balanced ground truth available to use as a training set.

In this case we have a multi class supervised classification. The target values are TP (Matches), TN (Not Matches), Ambiguous

Blocking

This time we considered a bigger window for the blocking algorithm to have more examples to classify.

In [48]:

```
candidate_links = sortedNeighbourhoodIndexing(FFIEC, SEC, 'Financial Institution Name Cle
aned', 'CONFORMED_NAME', window=15)
```

```
Execution time: 0.5510342121124268 seconds
```

Compare

We also decided to compare all attributes for a better classification.

In [49]:

```
str_comp = {'jarowinkler': [
    {
        'col_names': ['Financial Institution Name Cleaned', 'CONFORMED_NAME'],
        #'threshold': 0.90
    },
    {
        'col_names': ['Financial Institution Address', 'B_STREET'],
        #'threshold': 0.85
    },
    {
        'col_names': ['Financial Institution City', 'B_CITY'],
        #'threshold': 0.85
    }
]}
exact_comp = [
    {'col_names': ['Financial Institution Zip Code 5', 'B_POSTAL']},
    {'col_names': ['Financial Institution State', 'B_STPR']}
]
features = compareRecords(FFIEC, SEC, candidate_links, str_comp, exact_comp)
```

```
Execution time: 0.656287670135498 seconds
```

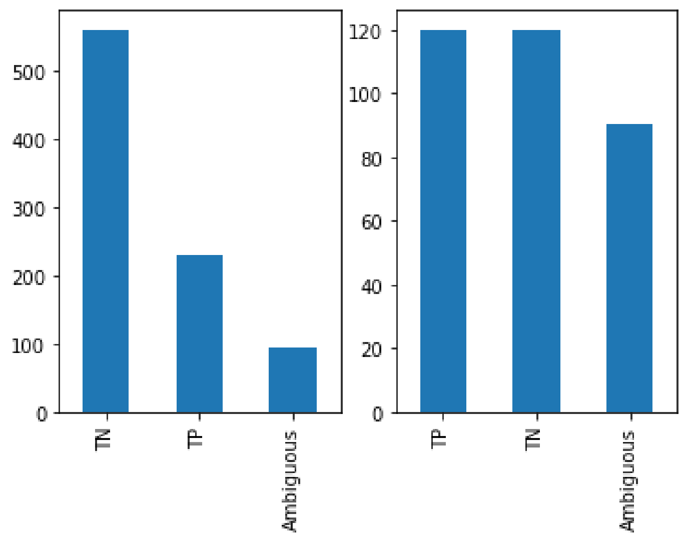
Preprocessing

The ground truth is still unbalanced so we proceed to balance the minority class (Ambiguous) with the majority classes (FN and TP) with a process of undersampling.

In [50]:

```
features = preprocessForSupervised(features, FFIEC_SEC_gt)
```

Target - original   Target - sampled



Supervised classification with Random Forest classifier

In [51]:

```
skf = StratifiedKFold(n_splits=10, random_state=100, shuffle=True)
clf = RandomForestClassifier(random_state=100)
params = {}
gs = GridSearchCV(clf, cv=skf, param_grid=params, scoring=['precision_macro', 'recall_ma
cro', 'f1_macro'], refit='f1_macro')
```

Subset data in training set and test set

In [52]:

```
X_train, X_test, y_train, y_test = train_test_split(features.iloc[:,0:len(features.colum
ns) - 1], features['TYPE'], test_size=0.25, random_state=100)
```

Train on trainining data

In [53]:

```
y_pred = clf.fit(X_train, y_train).predict(X_test)
```

Evaluate on test set

In [54]:

```
confusion_matrix(y_test, y_pred)
```

Out[54]:

```
array([[17,  5,  4],
       [ 3, 20,  5],
       [ 9, 12,  8]], dtype=int64)
```

Some predicted match status examples:

In [55]:

```
examples = pd.DataFrame(y_test)
examples['PREDICTION'] = y_pred
print('Record classified as matches:')
examples_TP = examples[examples.PREDICTION == 1].head(10)
examples_TP
```

```
Record classified as matches:
```

Out[55]:

		TYPE	PREDICTION
FFIEC_ID	SEC_ID		
2868352	1145956	1	1
3058114	1299582	1	1
463735	879089	2	1
2713920	1135986	1	1
972406	829937	2	1
480228	1102113	2	1
3547131	1537720	1	1
509811	1291629	1	1
930358	1506985	0	1
991340	356264	2	1

In [56]:

```
checkRecordPair(FFIEC, SEC, features, (930358,1506985))
```

Out[56]:

```
(array([['united bankers bank', '1650 w 82nd st su 1500', 'bloomington',
         'MN', '55431', None]], dtype=object),
 array([['united bankers bancorporation', '1650 w 82nd st su 1500',
         'bloomington', 'MN', '55431', 'incorporated']], dtype=object),
                          Financial Institution Name Cleaned  \
 FFIEC_ID SEC_ID
 930358   1506985                                 0.913612

                          Financial Institution Address  Financial Institution City  \
 FFIEC_ID SEC_ID
 930358   1506985                                 1.0                         1.0

                          Financial Institution Zip Code 5  \
 FFIEC_ID SEC_ID
 930358   1506985                                        1

                          Financial Institution State  TYPE
 FFIEC_ID SEC_ID
 930358   1506985                                 1     0  )
```

Since we have a very small amount of data a better evaluation is estimated with a stratified 10-fold cross validation

In [57]:

```
y_pred = gs.fit(features.iloc[:,0:len(features.columns) - 1], features['TYPE'])
```

In [58]:

```
gs.cv_results_
```

Out[58]:

```
{'mean_fit_time': array([0.09101467]),
 'std_fit_time': array([0.00808395]),
 'mean_score_time': array([0.0081352]),
 'std_score_time': array([0.00022919]),
 'params': [{}],
 'split0_test_precision_macro': array([0.58333333]),
 'split1_test_precision_macro': array([0.41595442]),
 'split2_test_precision_macro': array([0.65201465]),
 'split3_test_precision_macro': array([0.65509259]),
 'split4_test_precision_macro': array([0.61805556]),
 'split5_test_precision_macro': array([0.68868169]),
 'split6_test_precision_macro': array([0.50980392]),
 'split7_test_precision_macro': array([0.59920635]),
 'split8_test_precision_macro': array([0.71428571]),
 'split9_test_precision_macro': array([0.48148148]),
 'mean_test_precision_macro': array([0.59179097]),
 'std_test_precision_macro': array([0.09091296]),
 'rank_test_precision_macro': array([1]),
 'split0_test_recall_macro': array([0.58333333]),
 'split1_test_recall_macro': array([0.52777778]),
 'split2_test_recall_macro': array([0.64814815]),
 'split3_test_recall_macro': array([0.64814815]),
 'split4_test_recall_macro': array([0.62037037]),
 'split5_test_recall_macro': array([0.68518519]),
 'split6_test_recall_macro': array([0.48148148]),
 'split7_test_recall_macro': array([0.59259259]),
 'split8_test_recall_macro': array([0.68518519]),
 'split9_test_recall_macro': array([0.44444444]),
 'mean_test_recall_macro': array([0.59166667]),
 'std_test_recall_macro': array([0.0791599]),
 'rank_test_recall_macro': array([1]),
 'split0_test_f1_macro': array([0.58333333]),
 'split1_test_f1_macro': array([0.46222222]),
 'split2_test_f1_macro': array([0.64666667]),
 'split3_test_f1_macro': array([0.64098973]),
 'split4_test_f1_macro': array([0.6092437]),
 'split5_test_f1_macro': array([0.68605475]),
 'split6_test_f1_macro': array([0.44698979]),
 'split7_test_f1_macro': array([0.59188034]),
 'split8_test_f1_macro': array([0.69192211]),
 'split9_test_f1_macro': array([0.44761905]),
 'mean_test_f1_macro': array([0.58069217]),
 'std_test_f1_macro': array([0.09056989]),
 'rank_test_f1_macro': array([1])}
```