Proof of concept

A proof-of-concept of the main "originality score" algorithm: preprocessing a sample paper, performing analytics, saving the document's hash, and returning a score.

!pip install keras gensim

In [41]:

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

import os
import nltk
import numpy as np
import pandas as pd
```

Read in dataset

Load the Reuter 50_50 training dataset (https://archive.ics.uci.edu/ml/datasets/Reuter_50_50).

TODO: download and extract directly from website

In [2]:

```
# source modified from:
# https://github.com/devanshdalal/Author-Identification-task/blob/master/learner
.py
path = 'data/C50/C50train/'
authors = os.listdir(path)
data = []

for author in authors:
  texts = os.listdir(path + author + '/')
  for text in texts:
    f=open(path + author + '/' + text, 'r')
    data.append([author, f.read()])
    f.close()

df = pd.DataFrame(data, columns=["author", "text"])
df.head()

# TODO: add more author, text pairs
```

Out[2]:

	author	text
0	RobinSidel	Drugstore giant Revco D.S. Inc. said Monday it...
1	RobinSidel	Mattel Inc., seeking to expand in the market f...
2	RobinSidel	A financial agreement between Barney's Inc and...
3	RobinSidel	An independent shareholder advisory firm recom...
4	RobinSidel	Raising the stakes in the escalating battle fo...

Preprocess data

Process text

In [3]:

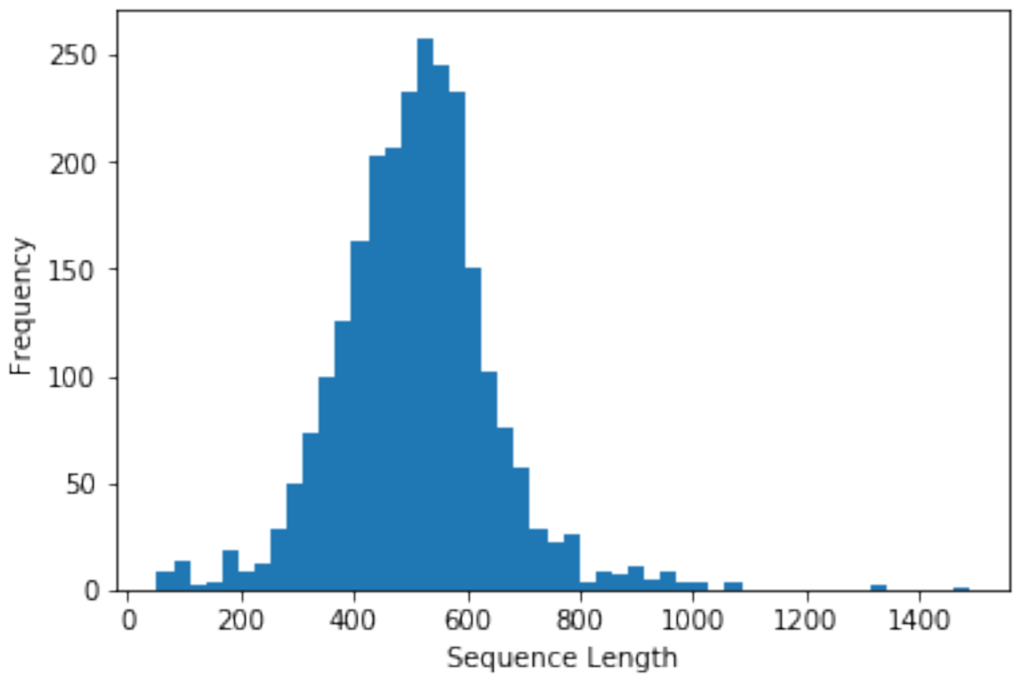
```
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
import matplotlib.pyplot as plt
%matplotlib inline

tokenizer = Tokenizer(nb_words=20000, filters='!"#$%&()*+,-./:;<=>?@[\\]^_`{|}~\
t\n',
                                  lower=True,split=' ')

tokenizer.fit_on_texts(df["text"])
X = tokenizer.texts_to_sequences(df["text"])

# plot histogram
num_words = [len(n) for n in X]
plt.hist(num_words, 50)
plt.xlabel('Sequence Length')
plt.ylabel('Frequency')
plt.show()
```

```
Using TensorFlow backend.
```



In [4]:

```
# Pad sequences, use 500 as maximum length.
X = pad_sequences(X, maxlen=500)

print("Here is the first text tokenized, size {}:\n".format(len(X[0])), X[0])
```

```
Here is the first text tokenized, size 500:
 [   203     64      9   1864     10      1     41     27     14    694      8
47
    57  10446   1881    235    203     64    224  10446     80   1297     40
307
    89    272     15   1133    216      4     64      9      1     36    393
```

```
80
   250   201  8975    84    42    15   505    40  1487   565   272
5
  1364   180     9  1316    13 10446   112   860  4841  2325     6
462
     6    87  6499    37   115   868  1032   120   933   288   954
764
     6   256   120    87   470   391    72  5156    34  1743    22
579
     1   933    41     2  2096   264    59     4  1432   764     3
861
 17281     7   201   682     7    12    22   311    13  4011     2
1506
     4  3542  1199   234   171    72   528  7482  3754   201   682
24
    46  2640   523    10    25  5157     1  6500  4592     3  1708
719
  2139    70     6   582  2266  1578    12    24    46  1691    16 1
2794
   123   801     6    87     6    17   156    25  1940   645   558
71
  1099   191  4011    11   197  2326     2  5744   125     5     1
3543
    16   546  1381     3   201  8975 17282  1278   739     6  1767
6781
   861     5  5745  4011    22    14   543     2  5320   201   682
676
  1208     7  4842 14659     3  4979   518 14660    74   201  8975
123
   801   814     2  7863    55    28   294     2  5746     5  7864
1
   701     3   273  6211   137   775    16  1708  2139  1382   397
12
  1780 17283     5     4    36   195   239     2   389  1507   123
801
   118  3671    13     1    41    25     7    17  1960  3486  1278
739
    11   284    15   141   509    26     3   689    54     7    45
3
 10446    63  2097    22    14     2  5511  1069  5747   913     5
5745
   229  4011  2195  3231   861     6   201   682    24  2747   861
633
    43   265     1  1278     6     1   861   868    12    22    14
4
   530   123   739     8  4011     7   610  5158     3   185  2793
301
  5158   112    74  4011    49     7    12    22  5748     6  2748
17
  2225   224     8   201   682    84   362  2920   235     1   224
35
    46   211     2  7865   198     1    61    70    49     7    90
3357
```

```
   136   214    22    14  5512    53    60  7866    52   498  4011
228
    34   184  1079     4  5321   333    13   201   682   619     4 1
7284
    15    17  2466     6  3544  6782   157    12   751     1   201
682
   367  1289    59     1  1455     6  2166     1    36     6   244
224
    20  4011   685     3    72  1104    42    32  1424   641   397 1
1469
    68    19  1979    18     4   470  3004 11469   347     2   442
201
   682   109  2195 14661  1209  1725     1  7867   131   163  4011
2195
    66  4843   861     5   378 14662  7867     6  2140   163     1
107
    13   201   682    19   344    18     4   731   454     8  4011
31
   228    34    28    19   927     5     4   928   987    13  4711
1959
     1    61    70    35  1079     4  1210     8  4711  1959     2
287
  4011     8    39   161    44    23     1   107  3927    53   843
1606
  1053    10     1   441    27   746   425   137]
```

Process authors

In [5]:

```
from sklearn.preprocessing import LabelEncoder
from keras.utils import to_categorical

encoder = LabelEncoder()
encoded = encoder.fit_transform(df["author"])
y = to_categorical(encoded)

print("Author {} is one-hot encoded as:\n".format(df["author"][0]), y[0])
```

```
Author RobinSidel is one-hot encoded as:
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0
. 0.
 0. 0.]
```

Train Network

Create training and test sets

In [51]:

```
from sklearn.model_selection import train_test_split

# Keeps some authors aside for hash testing
x_train, x_new, y_train, y_new = train_test_split(X, y, train_size=0.8, shuffle=
False)

# Split remainder into 70% training and 30% testing and shuffle
x_train, x_test, y_train, y_test = train_test_split(x_train, y_train, train_size
=0.7, random_state=1)

print("New:  {} text from {} authors".format(x_new.shape[0], len(np.unique(y_new
, axis=0))))
print("Train: {} text from {} authors".format(x_train.shape[0], len(np.unique(y_
train, axis=0))))
print("Test:  {} text from {} authors".format(x_test.shape[0], len(np.unique(y_t
est, axis=0))))
```

```
New:  500 text from 10 authors
Train: 1400 text from 40 authors
Test:  600 text from 40 authors
```

In [105]:

```
print("Sample training data, showing authors")
print(np.argmax(y_train, axis=1)[:100])
```

```
Sample training data, showing authors
[ 6 39 40 45  3 46 23  3  5  8  1 10 20 41 25 49 21 15 14  7 10 13 2
8 22
  0 39 20 14 25 22 40  7 35  5 33  8 33 29 35 38  1 28 16 40 15 10 2
7  9
 23 13  5 46 41 27 10 33  5 40 45  9 10 18 20 45 21 29 45 36 31 41 2
1  0
 14 18 40 27 12 33 19 41 20  8 23 13  8 27 34 14 16 27 22 16 19 28 1
6 15
 10 17 16 36]
```

Create network model

In [14]:

```
from keras.models import Sequential
from keras.layers import Dense, Dropout
from keras.layers import Embedding
from keras.layers import LSTM, SimpleRNN, RepeatVector
import keras

RUN_NAME = "run 4 with LSTM 128, embed 128, batch_size=10"
max_features = 20000

model = Sequential()
model.add(Embedding(max_features, 128, name='embed'))
model.add(LSTM(32, dropout=0.8, recurrent_dropout=0.2, name='lstm'))
model.add(Dense(50, activation='softmax', name='dense'))

model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])

model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embed (Embedding)            (None, None, 128)         2560000
_________________________________________________________________
lstm (LSTM)                  (None, 32)                20608
_________________________________________________________________
dense (Dense)                (None, 50)                1650
=================================================================
Total params: 2,582,258
Trainable params: 2,582,258
Non-trainable params: 0
_________________________________________________________________
```

Train network

In [15]:

```
logger = keras.callbacks.TensorBoard(
    log_dir='logs/{}'.format(RUN_NAME),
    write_graph=True,
    histogram_freq=5
)

model.fit(x_train,
          y_train,
          epochs=30,
          validation_split=0.2,
#           callbacks=[logger],
          shuffle=True)
```

```
Train on 1120 samples, validate on 280 samples
Epoch 1/30
1120/1120 [==============================] - 19s 17ms/step - loss: 3
.9005 - acc: 0.0455 - val_loss: 3.8867 - val_acc: 0.1143
Epoch 2/30
1120/1120 [==============================] - 18s 16ms/step - loss: 3
.8360 - acc: 0.0616 - val_loss: 3.8166 - val_acc: 0.0179
Epoch 3/30
1120/1120 [==============================] - 17s 15ms/step - loss: 3
.7217 - acc: 0.0455 - val_loss: 3.7102 - val_acc: 0.0750
Epoch 4/30
1120/1120 [==============================] - 17s 16ms/step - loss: 3
.6289 - acc: 0.0982 - val_loss: 3.6156 - val_acc: 0.1071
Epoch 5/30
1120/1120 [==============================] - 17s 15ms/step - loss: 3
.5035 - acc: 0.1545 - val_loss: 3.4953 - val_acc: 0.1750
Epoch 6/30
1120/1120 [==============================] - 17s 15ms/step - loss: 3
.3575 - acc: 0.1839 - val_loss: 3.3904 - val_acc: 0.1714
Epoch 7/30
1120/1120 [==============================] - 18s 16ms/step - loss: 3
.2056 - acc: 0.2241 - val_loss: 3.2824 - val_acc: 0.1857
Epoch 8/30
1120/1120 [==============================] - 17s 15ms/step - loss: 2
.9926 - acc: 0.2768 - val_loss: 3.1555 - val_acc: 0.2393
Epoch 9/30
1120/1120 [==============================] - 17s 15ms/step - loss: 2
.8313 - acc: 0.3009 - val_loss: 3.0405 - val_acc: 0.2286
Epoch 10/30
1120/1120 [==============================] - 18s 16ms/step - loss: 2
.6458 - acc: 0.3509 - val_loss: 2.9049 - val_acc: 0.2714
Epoch 11/30
1120/1120 [==============================] - 18s 16ms/step - loss: 2
.4466 - acc: 0.4232 - val_loss: 2.8368 - val_acc: 0.2893
Epoch 12/30
1120/1120 [==============================] - 18s 16ms/step - loss: 2
.3260 - acc: 0.4571 - val_loss: 2.7575 - val_acc: 0.3000
Epoch 13/30
```

```
1120/1120 [==============================] - 17s 15ms/step - loss: 2
.1583 - acc: 0.4982 - val_loss: 2.6947 - val_acc: 0.3107
Epoch 14/30
1120/1120 [==============================] - 17s 15ms/step - loss: 2
.0012 - acc: 0.5545 - val_loss: 2.6363 - val_acc: 0.3214
Epoch 15/30
1120/1120 [==============================] - 17s 16ms/step - loss: 1
.8773 - acc: 0.5875 - val_loss: 2.5684 - val_acc: 0.3357
Epoch 16/30
1120/1120 [==============================] - 17s 15ms/step - loss: 1
.7443 - acc: 0.6321 - val_loss: 2.5947 - val_acc: 0.3250
Epoch 17/30
1120/1120 [==============================] - 18s 16ms/step - loss: 1
.6312 - acc: 0.6643 - val_loss: 2.5357 - val_acc: 0.3429
Epoch 18/30
1120/1120 [==============================] - 17s 15ms/step - loss: 1
.5236 - acc: 0.6821 - val_loss: 2.4975 - val_acc: 0.3429
Epoch 19/30
1120/1120 [==============================] - 17s 16ms/step - loss: 1
.3982 - acc: 0.7152 - val_loss: 2.5123 - val_acc: 0.3250
Epoch 20/30
1120/1120 [==============================] - 18s 16ms/step - loss: 1
.3265 - acc: 0.7375 - val_loss: 2.4991 - val_acc: 0.3536
Epoch 21/30
1120/1120 [==============================] - 18s 16ms/step - loss: 1
.2645 - acc: 0.7384 - val_loss: 2.4996 - val_acc: 0.3643
Epoch 22/30
1120/1120 [==============================] - 18s 16ms/step - loss: 1
.1545 - acc: 0.7848 - val_loss: 2.4928 - val_acc: 0.3857
Epoch 23/30
1120/1120 [==============================] - 17s 15ms/step - loss: 1
.1012 - acc: 0.7982 - val_loss: 2.4119 - val_acc: 0.3607
Epoch 24/30
1120/1120 [==============================] - 17s 15ms/step - loss: 1
.0354 - acc: 0.8009 - val_loss: 2.4981 - val_acc: 0.3714
Epoch 25/30
1120/1120 [==============================] - 17s 15ms/step - loss: 0
.9638 - acc: 0.8179 - val_loss: 2.4708 - val_acc: 0.3714
Epoch 26/30
1120/1120 [==============================] - 18s 16ms/step - loss: 0
.9084 - acc: 0.8214 - val_loss: 2.4786 - val_acc: 0.3857
Epoch 27/30
1120/1120 [==============================] - 17s 15ms/step - loss: 0
.8602 - acc: 0.8464 - val_loss: 2.4985 - val_acc: 0.3750
Epoch 28/30
1120/1120 [==============================] - 17s 16ms/step - loss: 0
.8147 - acc: 0.8455 - val_loss: 2.4927 - val_acc: 0.3786
Epoch 29/30
1120/1120 [==============================] - 18s 16ms/step - loss: 0
.7342 - acc: 0.8652 - val_loss: 2.5473 - val_acc: 0.3893
Epoch 30/30
1120/1120 [==============================] - 18s 16ms/step - loss: 0
.7321 - acc: 0.8634 - val_loss: 2.5506 - val_acc: 0.3893
```

Out[15]:

<keras.callbacks.History at 0x1a2e4c3e80>

Test network

In [16]:

```
score, acc = model.evaluate(x_test, y_test, batch_size=200)

print('Test score:', score)
print('Test accuracy:', acc)
```

```
600/600 [==============================] - 0s 796us/step
Test score: 2.616125742594401
Test accuracy: 0.39666666587193805
```

Create and compare hashes

In [70]:

```
from sklearn.metrics.pairwise import cosine_similarity

def get_author(index):
    one_hot = y_new[index]
    i = np.argmax(one_hot)
    return encoder.inverse_transform(i)

def get_hash(text):
    prediction = model.predict(text)
    prediction = prediction[-1]
    return prediction

def get_similarity(hash1, hash2):
    return float(cosine_similarity([hash1], [hash2]))

x_hash = [get_hash(x) for x in x_new]
```

In [96]:

```
def get_similarity_from_index(i, j):
    return get_similarity(x_hash[i], x_hash[j])

def print_similarity(i, j):
    similarity = get_similarity_from_index(i, j)

    if get_author(i) == get_author(j):
        print("Comparision of text {} and {} \tfor same author {} is: \t\t{}".fo
rmat(
             i, j, get_author(i), similarity))
    else:
        print("Comparision of text {} and {} \tfor authors {} and {} is: \t{}".f
ormat(
             i, j, get_author(i), get_author(j), similarity))

print_similarity(0,2)
print_similarity(0,11)
print_similarity(0,60)
print_similarity(0,110)
```

```
Comparision of text 0 and 2     for same author MatthewBunce is:
1.0
Comparision of text 0 and 11    for same author MatthewBunce is:
1.0
Comparision of text 0 and 60    for authors MatthewBunce and ToddNis
sen is:         0.834044337272644
Comparision of text 0 and 110   for authors MatthewBunce and PeterHu
mphrey is:      0.759009063243866
```

In [136]:

```
true_positive, true_negative, false_positive, false_negative = 0,0,0,0
margin = 0.8
num_texts = len(x_new)

for i in range(num_texts):
    for j in range(min(i+1, num_texts), num_texts):
        similarity = get_similarity_from_index(i, j)

        if similarity >= margin:
            if get_author(i) == get_author(j):
                true_positive += 1
            else:
                false_positive += 1
        else:
            if get_author(i) == get_author(j):
                false_negative += 1
            else:
                true_negative += 1

print("True positives ", true_positive)
print("False positives", false_positive)
print("True negatives ", true_negative)
print("False negatives", false_negative)
```

```
True positives  8273
False positives 58658
True negatives  53842
False negatives 3977
```

In [140]:

```
# Comparison just for the same author
y_new_ints = np.unique(np.argmax(y_new, axis=1))
y_new_authors = encoder.inverse_transform(y_new_ints)
new_authors = {name:{"correct":0, "incorrect":0} for name in y_new_authors}

for i in range(num_texts):
    author_i = get_author(i)

    for j in range(min(i+1, num_texts), num_texts):
        if author_i == get_author(j):
            similarity = get_similarity_from_index(i, j)
            if similarity >= margin:
                new_authors[author_i]["correct"] += 1
            else:
                new_authors[author_i]["incorrect"] += 1

print("Number of correctly identified text belonging to each author:")
new_authors
```

```
Number of correctly identified text belonging to each author:
```

Out[140]:

```
{'AlexanderSmith': {'correct': 524, 'incorrect': 701},
 'BernardHickey': {'correct': 636, 'incorrect': 589},
 'GrahamEarnshaw': {'correct': 952, 'incorrect': 273},
 'KirstinRidley': {'correct': 567, 'incorrect': 658},
 'LydiaZajc': {'correct': 1086, 'incorrect': 139},
 'MatthewBunce': {'correct': 976, 'incorrect': 249},
 'PeterHumphrey': {'correct': 982, 'incorrect': 243},
 'SarahDavison': {'correct': 745, 'incorrect': 480},
 'TimFarrand': {'correct': 649, 'incorrect': 576},
 'ToddNissen': {'correct': 1156, 'incorrect': 69}}
```

In [146]:

```
[new_authors[d]["correct"] for d in new_authors]
```

Out[146]:

```
[524, 636, 952, 567, 1086, 976, 982, 745, 649, 1156]
```

In [158]:

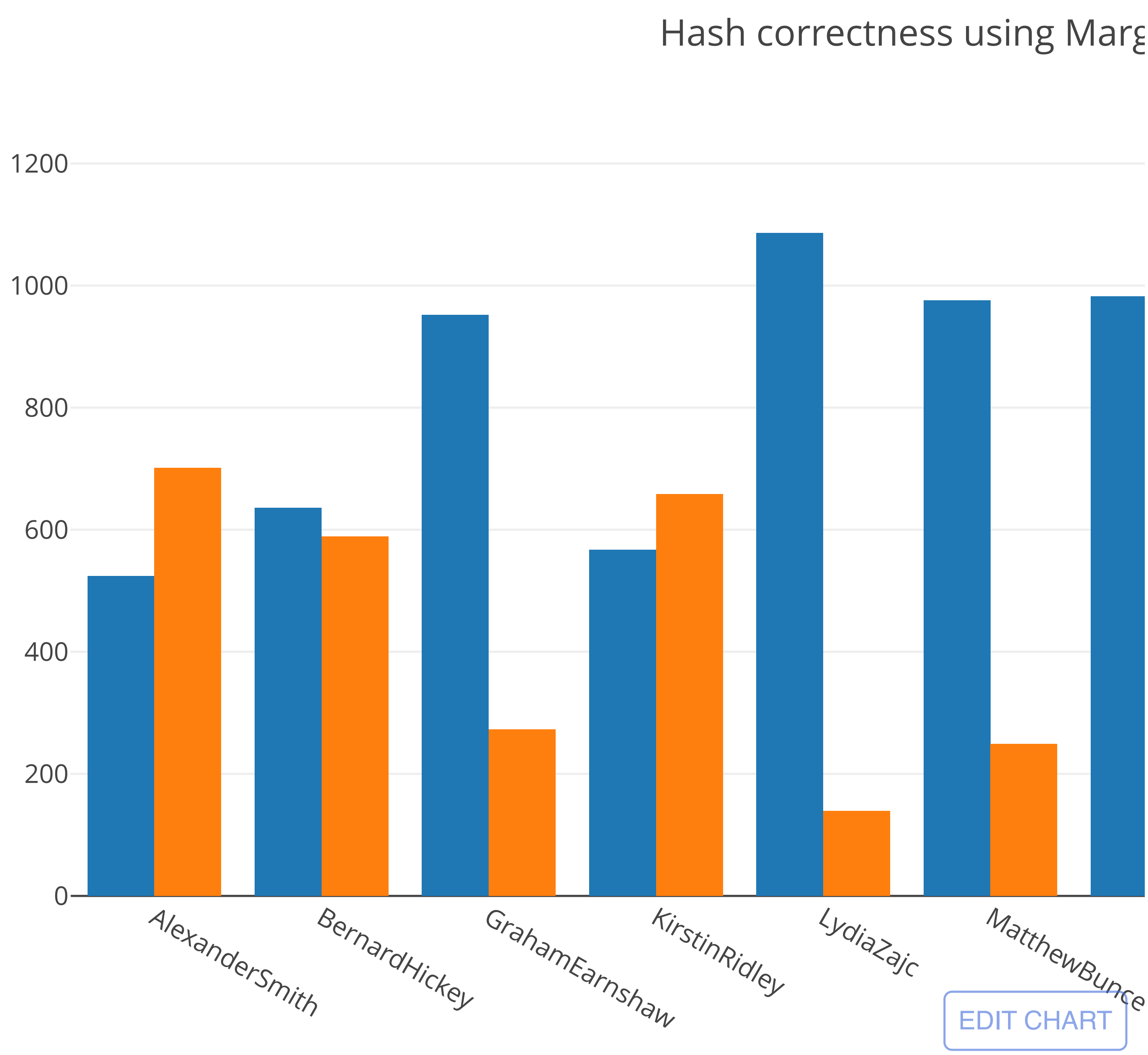
```
import plotly.plotly as py
import plotly.graph_objs as go

trace1 = go.Bar(
    x=y_new_authors,
    y=[new_authors[d]["correct"] for d in new_authors],
    name='Correct'
)
trace2 = go.Bar(
    x=y_new_authors,
    y=[new_authors[d]["incorrect"] for d in new_authors],
    name='Incorrect'
)

data = [trace1, trace2]
layout = go.Layout(
    title='Hash correctness using Margin=0.8',
    barmode='group'
)

fig = go.Figure(data=data, layout=layout)
py.iplot(fig, filename='jupyter-basic_bar')
```

Out[158]:



Analysis

The chart above shows that the neural network does a great job of identifying the text written by Lydia and Todd and a good job identifying the text from Graham, Matthew, and Peter. For the other authors, it does not perform as well; in two cases (Alexander and Kristin) it is wrong more than it is right. Another issue is the large percentage of false positives when compared to other author texts. While some text from different authors may share certain characteristics, the goal of the algorithm is to maximize their differences.

More work will be coming in two areas: (1) improving the network to have > 80% test accuracy (if possible) and improving the comparison algorithm's ability to differentiate texts.