

Assignment 6: Text Analytics: String Distances

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In [4]: # Loading the necessary libraries
import pandas as pd
import numpy as np
import re
import matplotlib.pyplot as plt
import jellyfish
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In [5]: input_name = "Mukund" # initializing my name
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In [6]: babynames = pd.read_csv("babyNamesUSYOB-full.csv") # Loading the babynames dataset
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In [7]: babynames.head()
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Out[7]:
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	YearOfBirth	Name	Sex	Number
0	1880	Mary	F	7065
1	1880	Anna	F	2604
2	1880	Emma	F	2003
3	1880	Elizabeth	F	1939
4	1880	Minnie	F	1746

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In [8]: babynames.shape
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Out[8]: (1858689, 4)
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In [9]: # Preprocessing the babynames data
names = babynames['Name'].apply(lambda x: re.sub('[^a-zA-Z]', '', x.lower())).drop_duplicates()
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In [10]: # defining the distance metrics
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def hamming_distance(a, b):
    """Computes the Hamming distance between two strings."""
    if len(a) != len(b):
        raise ValueError("Strings must be of equal length.")
    return sum(1 for x, y in zip(a, b) if x != y)

def longest_common_substring_distance(a, b):
    """Computes the distance between two strings as the length of their longest common
    substrings = np.zeros((len(a) + 1, len(b) + 1))
    for i, x in enumerate(a):
        for j, y in enumerate(b):
            if x == y:
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        lengths[i + 1][j + 1] = lengths[i][j] + 1
    return len(a) + len(b) - 2 * lengths.max()

def levenshtein_distance(a, b):
    """Computes the Levenshtein distance between two strings."""
    return jellyfish.levenshtein_distance(a, b)

def damerau_levenshtein_distance(a, b):
    """Computes the full Damerau-Levenshtein distance between two strings."""
    return jellyfish.damerau_levenshtein_distance(a, b)

def restricted_damerau_levenshtein_distance(s1, s2):
    # Compute the standard Damerau-Levenshtein distance
    d = jellyfish.damerau_levenshtein_distance(s1, s2)

    # Count the number of adjacent transpositions
    transpositions = 0
    for i in range(min(len(s1), len(s2)) - 1):
        if s1[i] != s2[i] and s1[i+1] == s2[i] and s1[i] == s2[i+1]:
            transpositions += 1

    # Subtract the number of adjacent transpositions
    d_restricted = d - transpositions

    return d_restricted

def qgram_distance(a, b, q):
    """Computes the q-gram distance between two strings."""
    a_qgrams = set(a[i:i + q] for i in range(len(a) - q + 1))
    b_qgrams = set(b[i:i + q] for i in range(len(b) - q + 1))
    return 1 - len(a_qgrams & b_qgrams) / len(a_qgrams | b_qgrams)

def jaro_distance(a, b):
    """Computes the Jaro distance between two strings."""
    return jellyfish.jaro_distance(a, b)

def jaro_winkler_distance(a, b, weight=0.1):
    """Computes the Jaro-Winkler distance between two strings."""
    return jellyfish.jaro_winkler(a, b)

def jaccard_distance(a, b, q):
    """Computes the Jaccard distance between two strings based on their q-gram profile"""
    a_qgrams = set(a[i:i + q] for i in range(len(a) - q + 1))
    b_qgrams = set(b[i:i + q] for i in range(len(b) - q + 1))
    return 1 - len(a_qgrams & b_qgrams) / len(a_qgrams | b_qgrams)

def cosine_distance(a, b, q):
    """Computes the cosine distance between two strings based on their q-gram profiles"""
    a_qgrams = set(a[i:i + q] for i in range(len(a) - q + 1))
    b_qgrams = set(b[i:i + q] for i in range(len(b) - q + 1))
    intersection = len(a_qgrams & b_qgrams)
    norm_a = np.sqrt(len(a_qgrams))

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norm_b = np.sqrt(len(b_qgrams))
return 1 - intersection / (norm_a * norm_b)

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def soundex_distance(a, b):
    """Computes the distance between two strings based on their Soundex encoding."""
    soundex_a = jellyfish.soundex(a)
    soundex_b = jellyfish.soundex(b)
    return 0 if soundex_a == soundex_b else 1

```

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In [11]: def name_distance(name, distance_metric):
    """Computes the distance between the input name and another name based on a given
    return distance_metric(input_name, name)

```

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In [12]: # Computing the distance between the input name and each name in the dataset based on
# babynames['hamming_distance'] = names.apply(lambda x: name_distance(x, hamming_distance))
babynames['longest_common_substring_distance'] = names.apply(lambda x: name_distance(x, longest_common_substring_distance))
babynames['levenshtein_distance'] = names.apply(lambda x: name_distance(x, levenshtein_distance))
babynames['damerau_levenshtein_distance'] = names.apply(lambda x: name_distance(x, damerau_levenshtein_distance))
babynames['restricted_damerau_levenshtein_distance'] = names.apply(lambda x: name_distance(x, restricted_damerau_levenshtein_distance))
babynames['qgram_distance'] = names.apply(lambda x: name_distance(x, lambda a, b: qgram_distance(a, b)))
babynames['jaro_distance'] = names.apply(lambda x: name_distance(x, jaro_distance))
babynames['jaro_winkler_distance'] = names.apply(lambda x: name_distance(x, jaro_winkler_distance))
babynames['jaccard_distance'] = names.apply(lambda x: name_distance(x, lambda a, b: jaccard_distance(a, b)))
babynames['cosine_distance'] = names.apply(lambda x: name_distance(x, lambda a, b: cosine_distance(a, b)))
babynames['soundex_distance'] = names.apply(lambda x: name_distance(x, soundex_distance))

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In [14]: # Sorting the dataframes by each distance metric and selecting the top ten names
# top10_hamming = babynames.sort_values('hamming_distance').head(10)['Name']
top10_lcs = babynames.sort_values('longest_common_substring_distance').head(10)['Name']
top10_levenshtein = babynames.sort_values('levenshtein_distance').head(10)['Name']
top10_dl = babynames.sort_values('damerau_levenshtein_distance').head(10)['Name']
top10_restricted_dl = babynames.sort_values('restricted_damerau_levenshtein_distance').head(10)['Name']
top10_qgram = babynames.sort_values('qgram_distance').head(10)['Name']
top10_jaro = babynames.sort_values('jaro_distance', ascending=False).head(10)['Name']
top10_jaro_winkler = babynames.sort_values('jaro_winkler_distance', ascending=False).head(10)['Name']
top10_jaccard = babynames.sort_values('jaccard_distance').head(10)['Name']
top10_cosine = babynames.sort_values('cosine_distance').head(10)['Name']
top10_soundex = babynames.sort_values('soundex_distance').head(10)['Name']

# Printing the top ten names for each distance metric
# print('Top 10 names based on Hamming distance:')
# print(top10_hamming)
# print('')

print('Top 10 names based on longest common substring distance:')
print(top10_lcs)
print('')

print('Top 10 names based on Levenshtein distance:')
print(top10_levenshtein)
print('')

print('Top 10 names based on full Damerau-Levenshtein distance:')
print(top10_dl)
print('')

print('Top 10 names based on restricted Damerau-Levenshtein distance:')
print(top10_restricted_dl)

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print('')

print('Top 10 names based on q-gram distance:')
print(top10_qgram)
print('')

print('Top 10 names based on Jaro distance:')
print(top10_jaro)
print('')

print('Top 10 names based on Jaro-Winkler distance:')
print(top10_jaro_winkler)
print('')

print('Top 10 names based on Jaccard distance:')
print(top10_jaccard)
print('')

print('Top 10 names based on cosine distance:')
print(top10_cosine)
print('')

print('Top 10 names based on Soundex distance:')
print(top10_soundex)
```

Top 10 names based on longest common substring distance:

1272422	Mukund
1858055	Mukunda
1587092	Kuno
1303322	Kunj
1001470	Ku
835026	Un
1405960	Rund
805735	Lukus
62489	Sun
734248	Funda

Name: Name, dtype: object

Top 10 names based on Levenshtein distance:

1272422	Mukund
1858055	Mukunda
725904	Uland
1303322	Kunj
1689414	Rylund
625751	Duuna
1128	Edmund
1452989	Dukens
720816	Sukina
179470	Uuno

Name: Name, dtype: object

Top 10 names based on full Damerau-Levenshtein distance:

1272422	Mukund
1858055	Mukunda
179470	Uuno
1318435	Yukino
720816	Sukina
1303322	Kunj
547798	Osmund
1505530	Yukina
118981	Eugene
1711226	Yuuna

Name: Name, dtype: object

Top 10 names based on restricted Damerau-Levenshtein distance:

1272422	Mukund
185676	Ikuko
1858055	Mukunda
1380291	Yuuka
922049	Nikunj
1484079	Mukul
625751	Duuna
1331942	Luken
1587092	Kuno
720816	Sukina

Name: Name, dtype: object

Top 10 names based on q-gram distance:

1272422	Mukund
1858055	Mukunda
1777325	Kundana
1303322	Kunj
1587092	Kuno
1405960	Rund
101680	Lunda

704285 Mundy
1044456 Tunde
15887 Gunda
Name: Name, dtype: object

Top 10 names based on Jaro distance:

1272422 Mukund
1858055 Mukunda
1405960 Rund
179470 Uuno
721013 Yulunda
757396 Kindu
941209 Kendu
919282 Chukwudi
718862 Burgundy
1036098 Katelund

Name: Name, dtype: object

Top 10 names based on Jaro-Winkler distance:

1272422 Mukund
1858055 Mukunda
1405960 Rund
179470 Uuno
721013 Yulunda
757396 Kindu
941209 Kendu
919282 Chukwudi
718862 Burgundy
1036098 Katelund

Name: Name, dtype: object

Top 10 names based on Jaccard distance:

1272422 Mukund
1858055 Mukunda
1777325 Kundana
1303322 Kunj
1587092 Kuno
1405960 Rund
101680 Lunda
704285 Mundy
1044456 Tunde
15887 Gunda

Name: Name, dtype: object

Top 10 names based on cosine distance:

1272422 Mukund
1858055 Mukunda
1777325 Kundana
1405960 Rund
1303322 Kunj
1587092 Kuno
657408 Rundy
1758444 Kunsh
1448640 Kunga
822179 Kunte

Name: Name, dtype: object

Top 10 names based on Soundex distance:

1272422 Mukund
1207957 Majenta

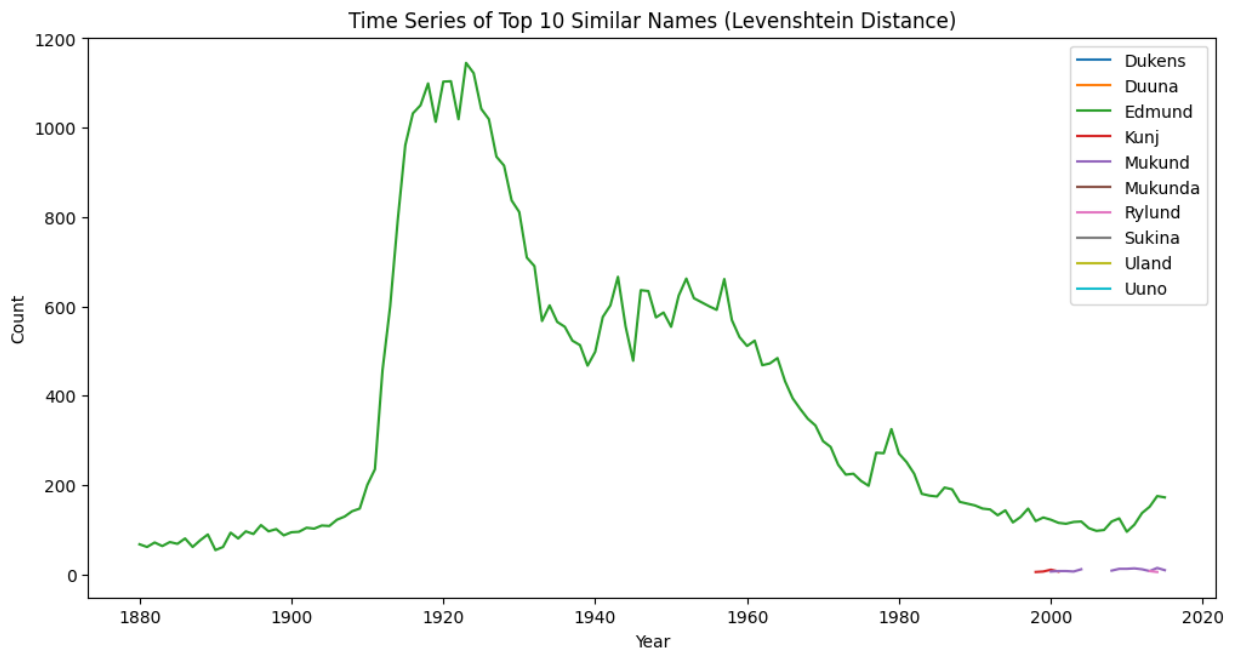
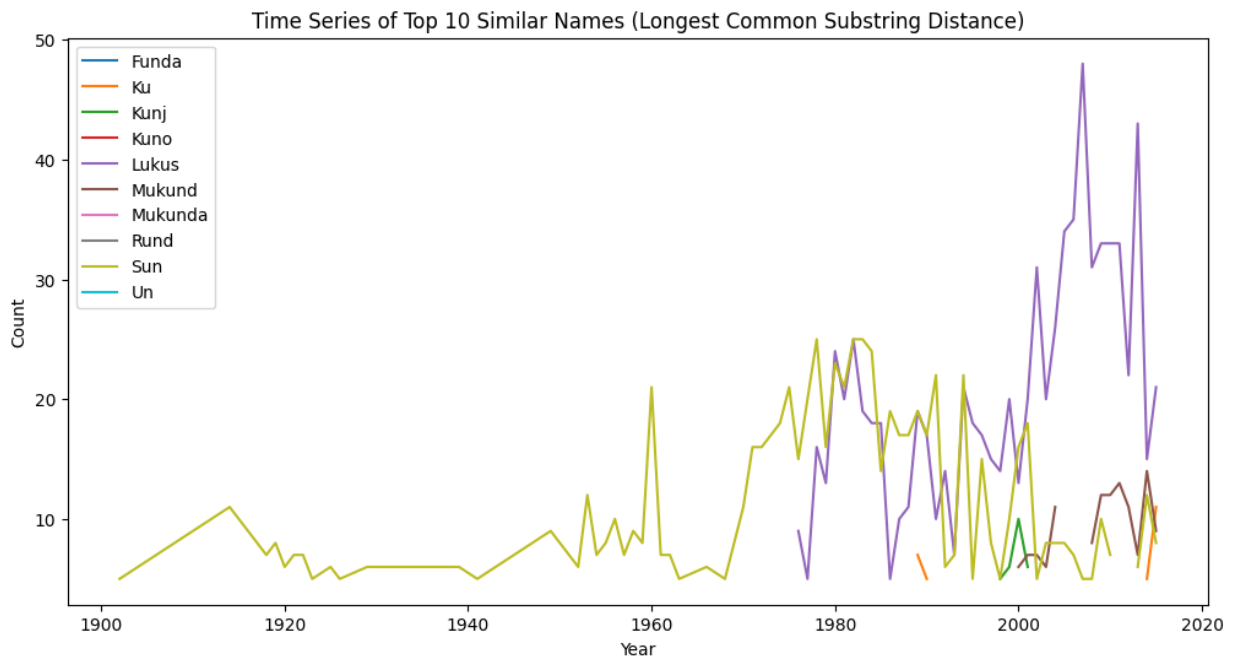
```
719346      Mashonda
875175      Magenta
835816      Mishonda
1285959     Makendra
933673      Mashaunda
677682      Mashanda
837281      Mashawnda
1405750     Mashanti
Name: Name, dtype: object
```

```
In [15]: # Plotting the time series
def plot_time_series(a, distance_metric):
    # Subset the data for the top 10 names
    subset = babynames[babynames['Name'].isin(a)]
    # subset = subset[subset['Name'] != input_name] # excluding the input name

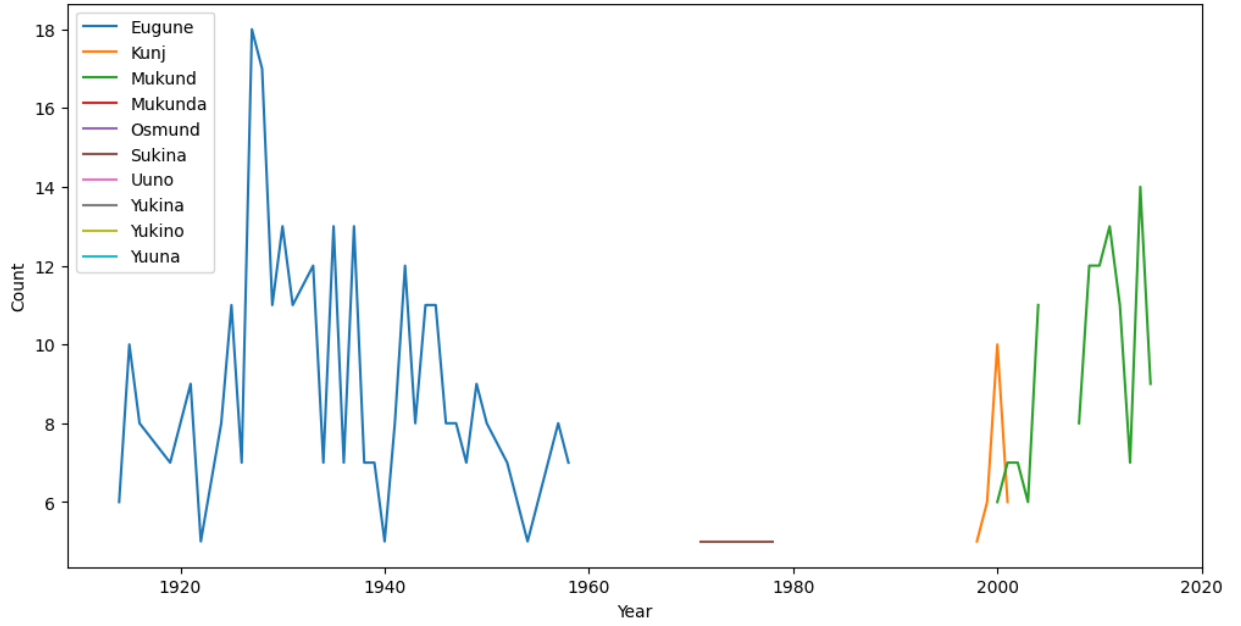
    # Pivot the data to create a time series
    pivoted = subset.groupby(['YearOfBirth', 'Name'])['Number'].sum().unstack()

    # Plot
    pivoted.plot(figsize=(12,6))
    plt.title('Time Series of Top 10 Similar Names (' + distance_metric + ')')
    plt.xlabel('Year')
    plt.ylabel('Count')
    plt.legend()
    plt.show()

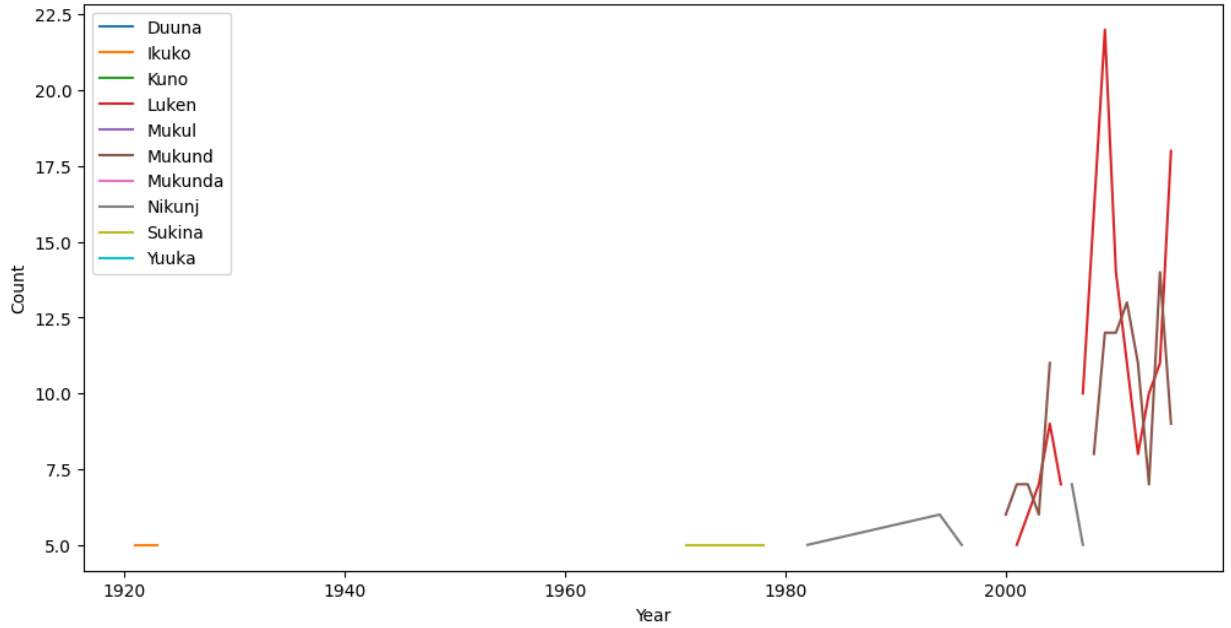
# Plotting the time series for each distance metric
# plot_time_series(top10_hamming, 'Hamming Distance')
plot_time_series(top10_lcs, 'Longest Common Substring Distance')
plot_time_series(top10_levenshtein, 'Levenshtein Distance')
plot_time_series(top10_dl, 'Damerau-Levenshtein Distance')
plot_time_series(top10_restricted_dl, 'Restricted Damerau-Levenshtein Distance')
plot_time_series(top10_qgram, 'q-gram Distance')
plot_time_series(top10_jaro, 'Jaro Distance')
plot_time_series(top10_jaro_winkler, 'Jaro-Winkler Distance')
plot_time_series(top10_jaccard, 'Jaccard Distance')
plot_time_series(top10_cosine, 'Cosine Distance')
plot_time_series(top10_soundex, 'Soundex Distance')
```



Time Series of Top 10 Similar Names (Damerau-Levenshtein Distance)



Time Series of Top 10 Similar Names (Restricted Damerau-Levenshtein Distance)



Count

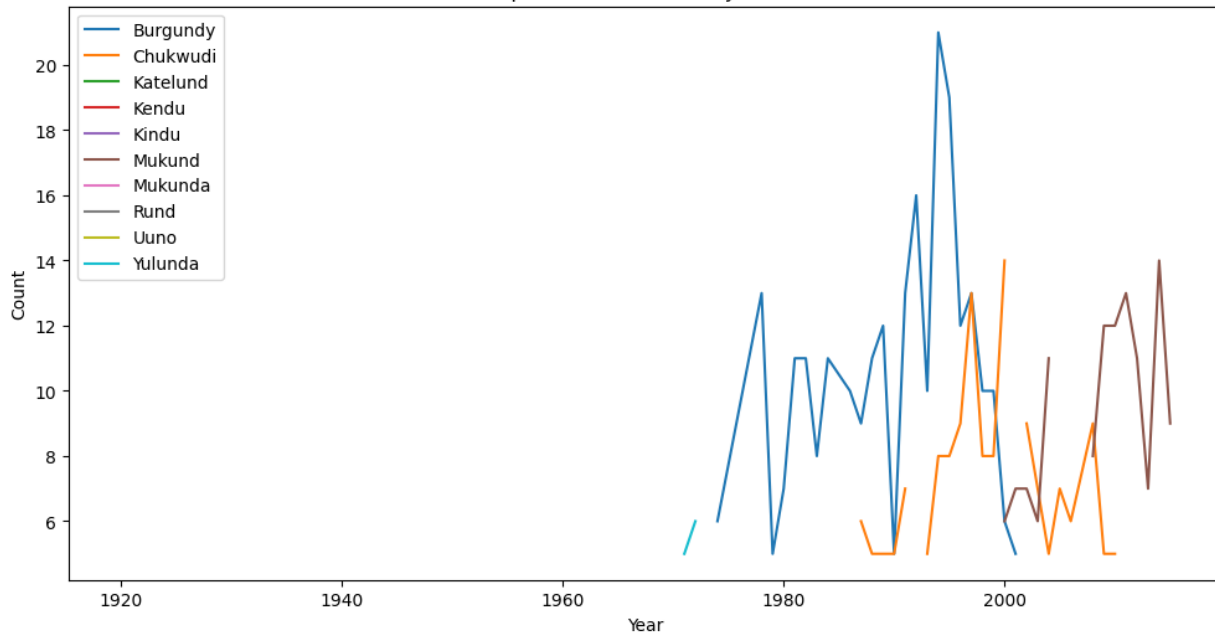
Year

Legend:

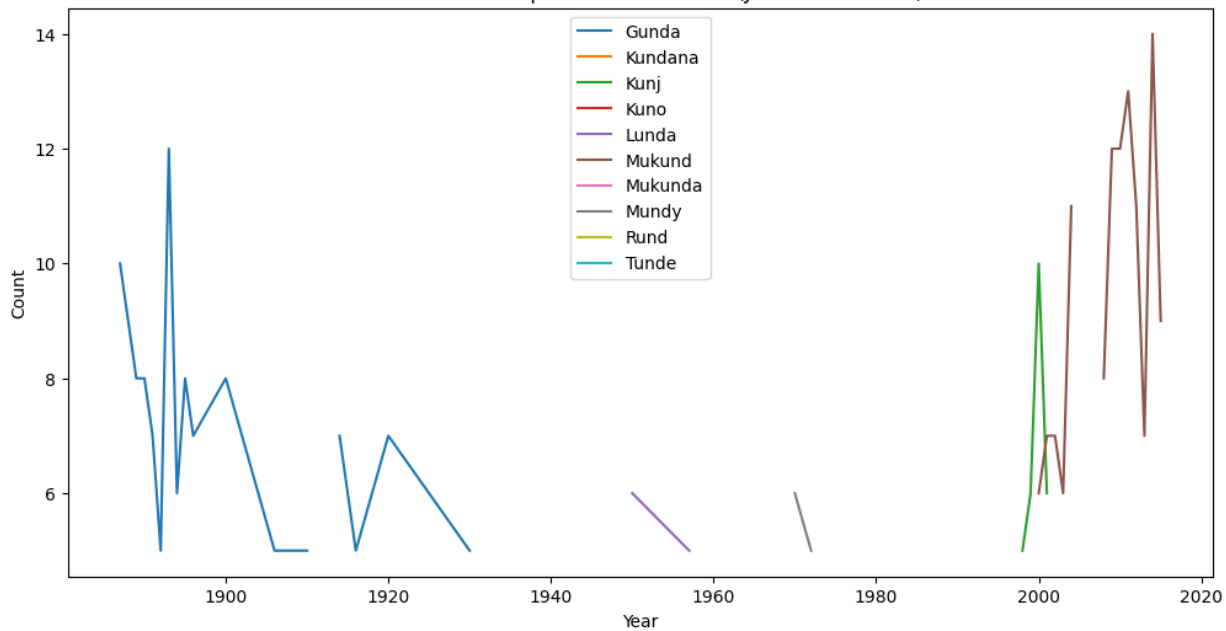
- Gunda
- Kundana
- Kunj
- Kuno
- Lunda
- Mukund
- Mukunda
- Mundy
- Rund
- Tunde

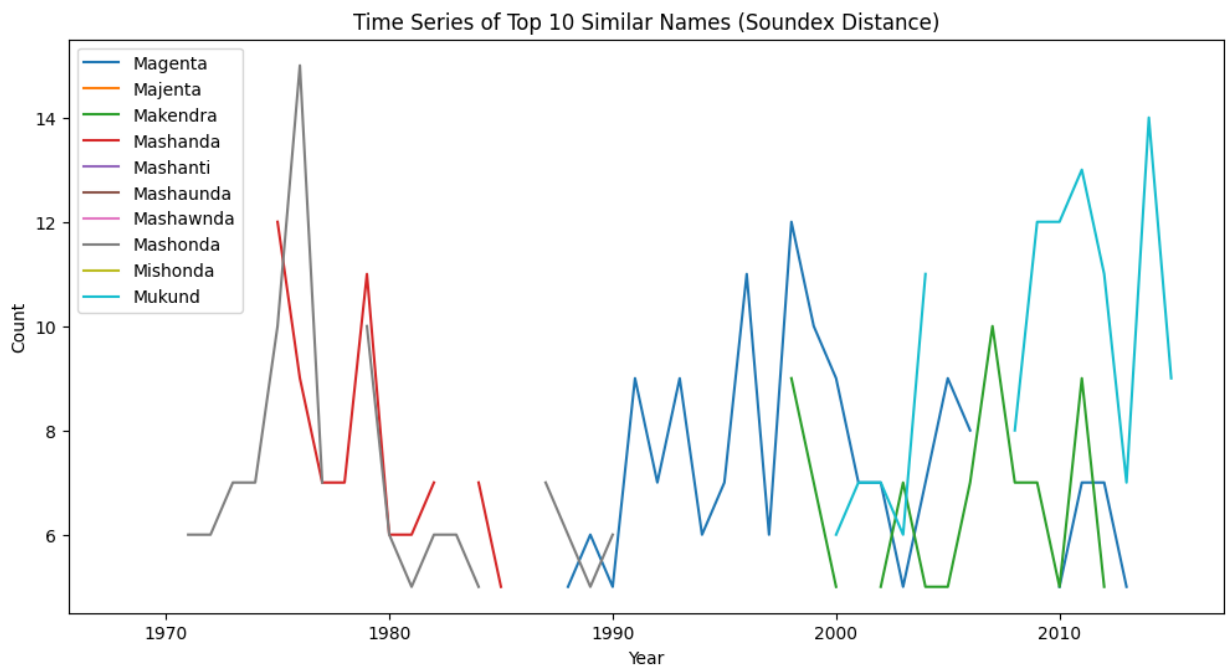
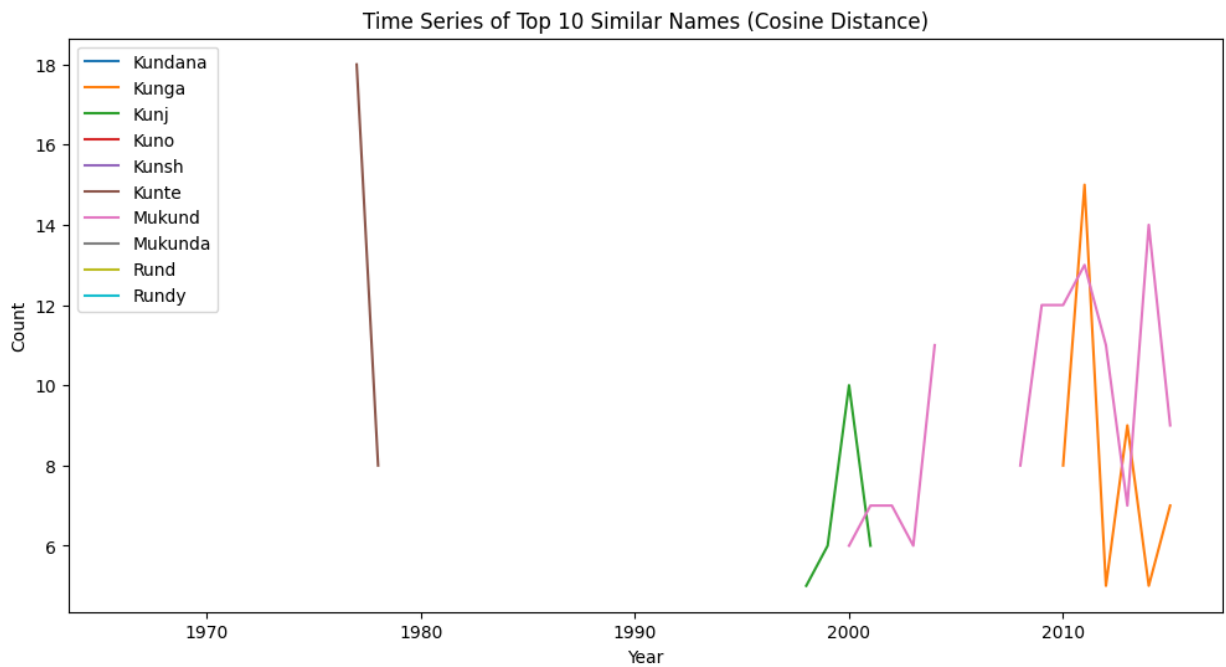
The graph displays the count of 1000s of records for ten datasets over time. The Y-axis is labeled 'Count' and ranges from 0 to 20. The X-axis is labeled 'Year' and ranges from 1920 to 2015. The legend identifies the datasets by color: Burgundy (blue), Chukwudi (orange), Katelund (green), Kendu (red), Kindu (purple), Mukund (brown), Mukunda (pink), Rund (grey), Uuno (yellow-green), and Yulunda (cyan). Burgundy shows a significant peak around 1995, reaching a count of approximately 21. Chukwudi and Mukund show peaks around 2000 and 2010 respectively, both reaching a count of approximately 14. Most other datasets have counts below 10.

Time Series of Top 10 Similar Names (Jaro-Winkler Distance)



Time Series of Top 10 Similar Names (Jaccard Distance)





It is easy to note that the first name "Mukund" is not so common in the US and it has only started to appear after the 2000s. The "babynames" dataset consists of a large collection of names and their frequency of occurrence over the years. Therefore, the distance metrics that work well with longer strings and are capable of taking into account the semantic meaning of the symbols are likely to perform better on this dataset. Regarding which distance metrics to use for finding the related baby names and their similarities and differences, following are my observations:

The Levenshtein distance, Full Damerau-Levenshtein distance, and q-gram distance are examples of metrics that work well with longer strings and are capable of taking into account the semantic meaning of the symbols. The Levenshtein distance and Full Damerau-Levenshtein distance are capable of handling the insertion, deletion, and substitution of symbols in a string, which is especially useful for measuring the distance between names with different lengths or

with common phonemes but different spellings. The q-gram distance, on the other hand, breaks the names into substrings of a fixed length, which helps to capture the semantic meaning of the symbols and is less sensitive to the order of the symbols.

The Longest Common Substring distance and Jaro distance, while still useful, may not be as effective on this dataset due to the large variation in the length of names and the high degree of variation in the order of the symbols. However, the Jaro-Winkler distance, which gives more weight to the initial characters, may be more effective as it can capture the similarities between names that share a common prefix.

The Hamming distance, while useful in certain contexts, is not as applicable to this dataset as it only works on strings of the same length, and doesn't take into account the semantic meaning of the symbols.

The Jaccard distance and cosine distance between q-gram profiles, while useful for comparing the similarity of short strings, may not be the best choice for the babynames dataset, as names can vary significantly in length, and the size of the q-grams may need to be adjusted to ensure accurate results.

Finally, the distance based on Soundex encoding is useful for comparing the similarity of names that sound alike but are spelled differently. It can help to identify common phonemes and group similar sounding names together, but it may not be as effective in capturing the semantic meaning of the symbols as some of the other distance metrics.