Complex Systems

CS2024/problem_2.pdf

Results

The topic of this project is Zipf's phenomenological law applied to linguistics.

Visit the Project Gutenberg website *(https://www.gutenberg.org/)*, which is a library of over 70 000 free eBooks. Download four eBooks of your choice and conduct the Zipf analysis, and then:

1. Save the result of the analysis in the text file. The name of the file should include the title of the book and the number of words it contains. The file should contain four columns: (1) rank, (2) word, (3) number of a given word in the text, (4) frequency of a given word in the text. Why do I need both columns (3) and (4)? Think about it.

```
import re

word_count = {}

# Read the file content
with open('scrambledeggs.txt', 'r') as file:
    file_content = file.read()


def analyze_text():
    global word_count

    # Extract words of length 3 to 10 characters
    filtered_words = re.findall(r'\b[A-Za-z][a-z]{2,9}\b', file_content)
    for token in filtered_words:
        current_count = word_count.get(token, 0)
        word_count[token] = current_count + 1

    # Sort words by their frequency in descending order
    sorted_words = dict(
        sorted(word_count.items(), key=lambda item: item[1], reverse=True))
    total_words = len(filtered_words)
    output_data = ""

    # Generate the result string
    for index, (token, occurrence) in enumerate(sorted_words.items()):
        frequency_percentage = round(occurrence / total_words, 6)
        output_data += f"{index + 1}, {token}, {occurrence},
{frequency_percentage}\n"

    return output_data


# Save the analysis result to a file
with open('output.txt', 'w') as result_file:
    result_file.write(analyze_text())
```
main.ipynb, Python (version 3.11.7)

``` First 20 rows

```
1, the, 523, 0.057021
2, you, 244, 0.026603
3, and, 215, 0.023441
4, with, 127, 0.013846
5, that, 110, 0.011993
6, was, 100, 0.010903
7, her, 96, 0.010467
8, she, 95, 0.010358
9, for, 92, 0.010031
10, Project, 84, 0.009158
11, Gutenberg, 84, 0.009158
12, Eustace, 82, 0.00894
13, his, 82, 0.00894
14, this, 76, 0.008286
15, not, 68, 0.007414
16, have, 60, 0.006542
17, your, 53, 0.005778
18, The, 52, 0.005669
19, said, 51, 0.00556
20, all, 51, 0.00556
```

``` output.txt

2. Compare the empirical distribution from your analysis with the theoretical Zipf distribution by plotting both on the same graph in log-log scale (one graph for each book). Try to do the same in linear scale. What do you observe?

```
import re
import numpy as np
import matplotlib.pyplot as plt
from scipy.optimize import curve_fit

# Function to process text and compute word distributions


def extract_distributions(file_content):
    word_frequency = {}
    token_list = re.findall(r'\b[A-Za-z][a-z]{2,9}\b', file_content)

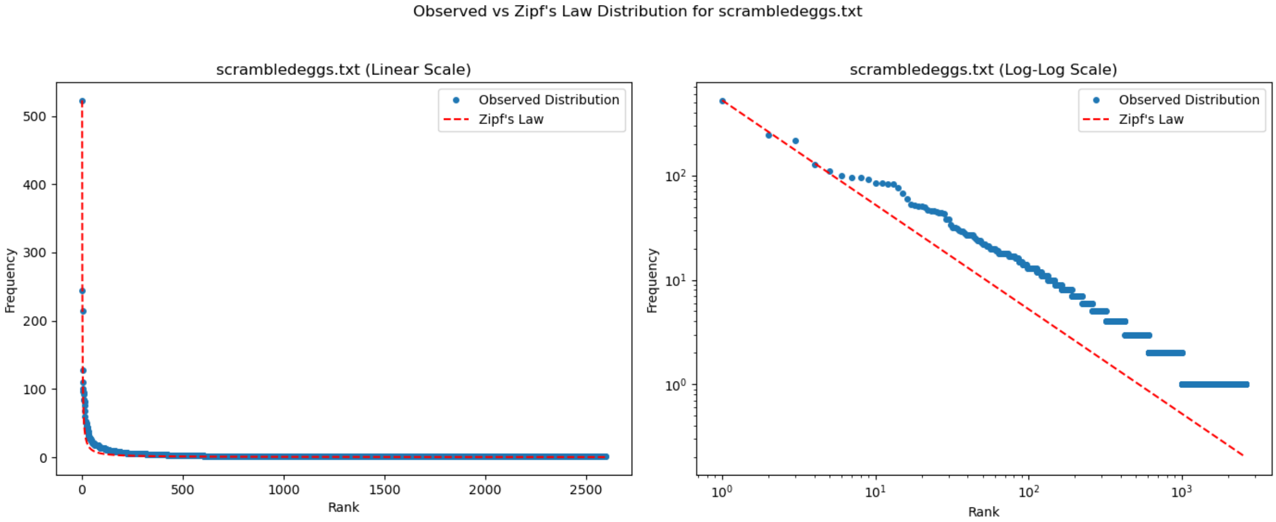
    # Count occurrences of each word
    for token in token_list:
        token_count = word_frequency.get(token, 0)
        word_frequency[token] = token_count + 1

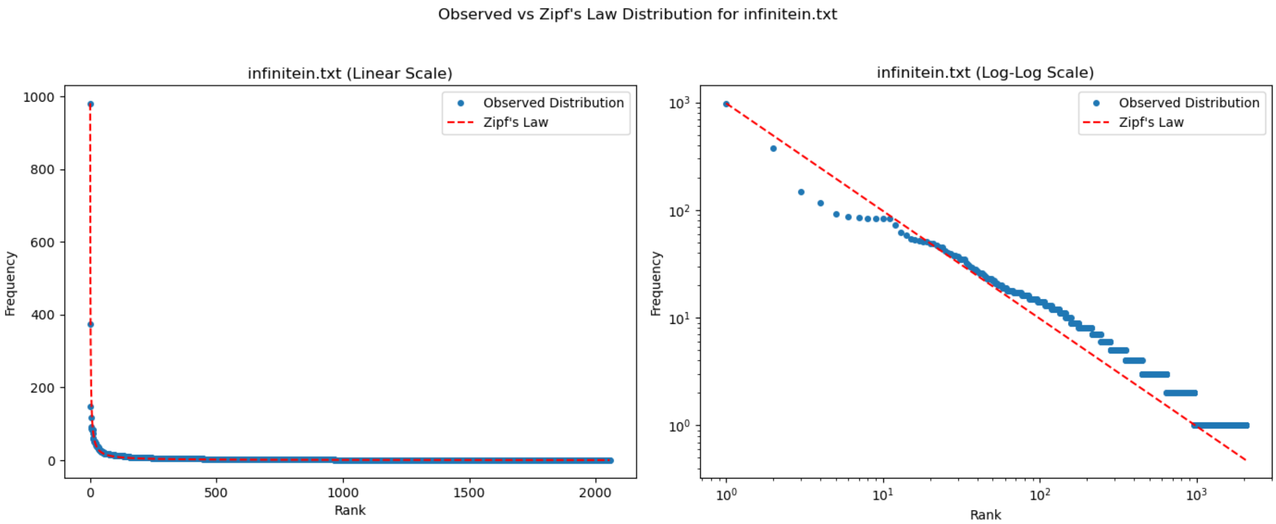
    # Sort word frequencies in descending order
    sorted_frequencies = sorted(word_frequency.values(), reverse=True)
    word_ranks = np.arange(1, len(sorted_frequencies) + 1)
    observed_frequencies = np.array(sorted_frequencies)
    # Zipf's Law: freq ~ 1/rank
    predicted_zipf = observed_frequencies[0] / word_ranks

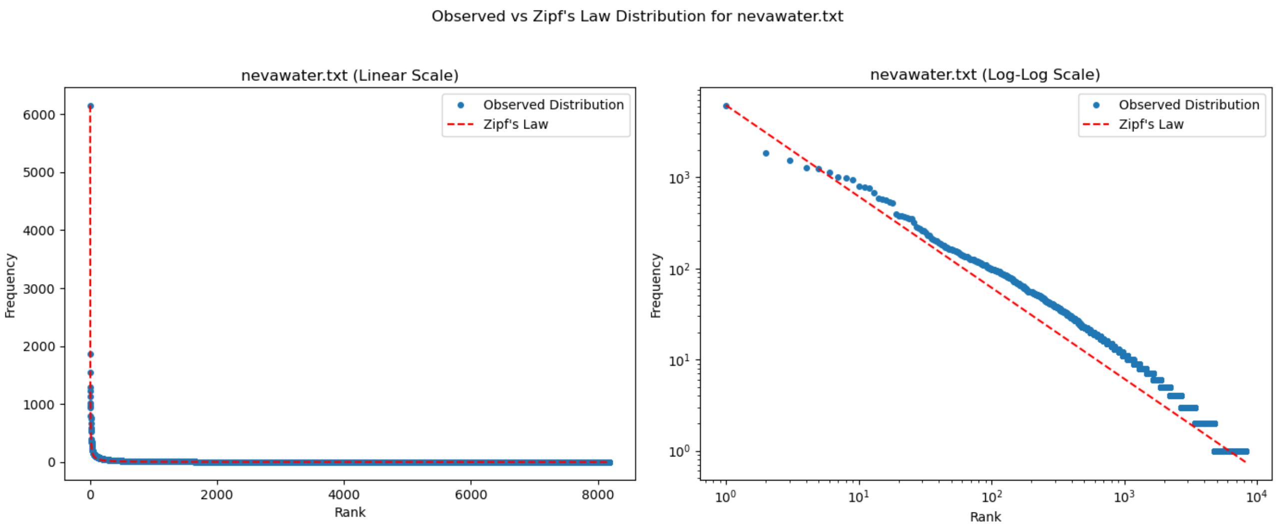
    return word_ranks, observed_frequencies, predicted_zipf

# Task 3: Define generalized Zipf-Mandelbrot law function
```

```python
def zipf_mandelbrot(rank, alpha, beta):
    return 1 / (rank + beta) ** alpha


# List of books to analyze
book_files = ['scrambledeggs.txt', 'infinitein.txt', 'nevawater.txt']

# Analyze each book in the list
for book_file in book_files:
    with open(book_file, 'r') as file:
        content = file.read()

    # Get rank, empirical frequencies, and theoretical Zipf frequencies
    ranks, observed_freqs, theoretical_zipf = extract_distributions(content)

    # Create plots
    fig, (linear_plot, loglog_plot) = plt.subplots(1, 2, figsize=(14, 6))

    # Linear scale plot
    linear_plot.plot(ranks, observed_freqs, label="Observed Distribution",
                     marker='o', linestyle='', markersize=4)
    linear_plot.plot(ranks, theoretical_zipf,
                     label="Zipf's Law", color='red', linestyle='--')
    linear_plot.set_xlabel("Rank")
    linear_plot.set_ylabel("Frequency")
    linear_plot.set_title(f"{book_file} (Linear Scale)")
    linear_plot.legend()

    # Log-log scale plot
    loglog_plot.loglog(ranks, observed_freqs, label="Observed Distribution",
                       marker='o', linestyle='', markersize=4)
    loglog_plot.loglog(ranks, theoretical_zipf,
                       label="Zipf's Law", color='red', linestyle='--')
    loglog_plot.set_xlabel("Rank")
    loglog_plot.set_ylabel("Frequency")
    loglog_plot.set_title(f"{book_file} (Log-Log Scale)")
    loglog_plot.legend()

    # Display the plots
    plt.suptitle(f"Observed vs Zipf's Law Distribution for {book_file}")
    plt.tight_layout(rect=[0, 0.03, 1, 0.95])
    plt.show()
```
``` main.ipynb, Python (version 3.11.7)
```







ANSWER: Log-log plot offers a more effective comparison between the observed data and the predicted Zipf's Law. For the third eBook, the graph exhibits the strongest alignment with the theoretical model, showing the closest resemblance to a straight-line pattern.

3. Try to fit a and b constants in Zipf-Mandelbrot law freq. $\propto 1/(rank+b)_a$ for two different languages. Is it possible to distinguish languages using a and b parameters only?

````
```
import re
from collections import Counter
from scipy.optimize import curve_fit
import matplotlib.pyplot as plt
import numpy as np

def rank_frequency_model(rank, scale_factor, exponent, offset):
    return scale_factor / (rank + offset) ** exponent

def calculate_word_occurrences(file_path):
    with open(file_path, 'r', encoding='utf-8') as f:
        content = f.read().lower()
        words = re.findall(r'\b\w+\b', content)
        word_frequencies = Counter(words)
    return word_frequencies

def derive_rank_frequency(word_frequencies):
    sorted_frequencies = word_frequencies.most_common()
    rank_positions = np.array([i + 1 for i in range(len(sorted_frequencies))])
    counts = np.array([freq for (_, freq) in sorted_frequencies])
    return rank_positions, counts

text_files = ['scrambledeggs.txt', 'dutch.txt', 'german.txt']
fit_results = {}

for text_file in text_files:
    word_frequencies = calculate_word_occurrences(text_file)
    ranks, counts = derive_rank_frequency(word_frequencies)
    initial_params = [max(counts), 1.0, 1.0]
    fit_results[text_file], _ = curve_fit(rank_frequency_model, ranks, counts,
p0=initial_params)

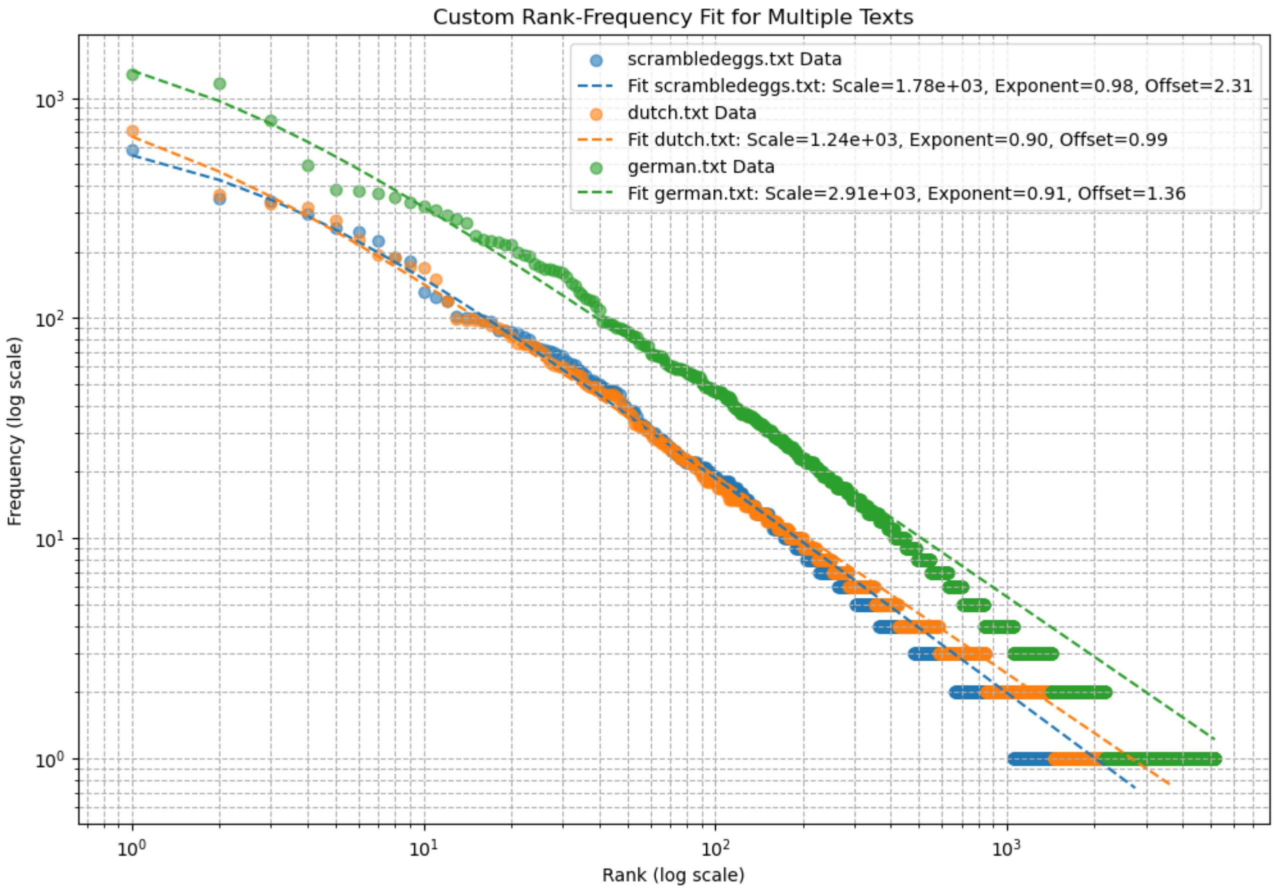
plt.figure(figsize=(12, 8))
for text_file in text_files:
    word_frequencies = calculate_word_occurrences(text_file)
    ranks, counts = derive_rank_frequency(word_frequencies)
    scale_factor, exponent, offset = fit_results[text_file]
    plt.scatter(ranks, counts, label=f'{text_file} Data', alpha=0.6, s=40)
    plt.plot(ranks, rank_frequency_model(ranks, *fit_results[text_file]),
             label=f'Fit {text_file}: Scale={scale_factor:.2e},
Exponent={exponent:.2f}, Offset={offset:.2f}',
             linestyle='--')
plt.xscale('log')
plt.yscale('log')
plt.xlabel('Rank (log scale)')
plt.ylabel('Frequency (log scale)')
plt.title('Custom Rank-Frequency Fit for Multiple Texts')
plt.legend()
plt.grid(True, which='both', linestyle='--')
plt.show()

for text_file in text_files:
    scale_factor, exponent, offset = fit_results[text_file]
    print(f'File: {text_file} - Scale: {scale_factor:.2e}, Exponent:
{exponent:.2f}, Offset: {offset:.2f}')

for i, file1 in enumerate(text_files):
    for j, file2 in enumerate(text_files):
        if i < j:
            scale1, exp1, off1 = fit_results[file1]
````
````

```
            scale2, exp2, off2 = fit_results[file2]
            print(f'Comparison between {file1} and {file2}:')
            print(f' Scale: {scale1:.2e} vs {scale2:.2e}')
            print(f' Exponent: {exp1:.2f} vs {exp2:.2f}')
            print(f' Offset: {off1:.2f} vs {off2:.2f}')
```

`` ``` `` main.ipynb, Python (version 3.11.7)




```
File: scrambledeggs.txt - Scale: 1.78e+03, Exponent: 0.98, Offset: 2.31
File: dutch.txt - Scale: 1.24e+03, Exponent: 0.90, Offset: 0.99
File: german.txt - Scale: 2.91e+03, Exponent: 0.91, Offset: 1.36
Comparison between scrambledeggs.txt and dutch.txt:
 Scale: 1.78e+03 vs 1.24e+03
 Exponent: 0.98 vs 0.90
 Offset: 2.31 vs 0.99
Comparison between scrambledeggs.txt and german.txt:
 Scale: 1.78e+03 vs 2.91e+03
 Exponent: 0.98 vs 0.91
 Offset: 2.31 vs 1.36
Comparison between dutch.txt and german.txt:
 Scale: 1.24e+03 vs 2.91e+03
 Exponent: 0.90 vs 0.91
 Offset: 0.99 vs 1.36
```
terminal output, zsh 5.9 (arm64-apple-darwin24.0)

ANSWER: I analyzed three texts written in Dutch, English, and German. The results show that the parameter 'a' varies significantly across languages, allowing us to differentiate them based on their distinct frequency distributions.