Proyect Structure

- 1. Data exploration and processing
- 2. Sexism detector:
 - 2.1 Dictionary—Based Sentiment Analysis to create sexism score
 - 2.2 Quicksort to organize data by sexism score
 - 2.3 Markov Chains for word predictions
 - 2.4 Algorithm for matrix multiplication (Strassen)
 - 2.5 Logistic regression with Strassen matrix multiplication and Gradient Descent
 - 2.6 Co-ocurrence tree to analyze words commonly used together in sexist tweets

Import Libraries

```
In [32]: #Import the neccesary libraries
         # fasttext: commonly used for natural language processing tasks
         # io: for inout/output operations needed for interacting with data. Reading from
         # re: regular expressions are sequences of characters that define a search pat
         # nltk: the "stopwords" module from the NLTK library provides a predefined lis
         # PrettyTable: allows us to visualize the Markov Chain in a simple way
         import fasttext
         import io
         import re
         import nltk
         nltk.download('stopwords')
         import pandas as pd
         import seaborn as sns
         import matplotlib.pyplot as plt
         import numpy as np
         import random
         import csv
         import sys
         #All of these were used for the logistic regression with matrix multiplication
         from sklearn.linear_model import LogisticRegression
         from sklearn.model_selection import train_test_split
         from sklearn.metrics import accuracy score, classification report
         from sklearn.compose import ColumnTransformer
         from sklearn.pipeline import Pipeline
```

```
# #This library was ONLY used in step 2.5.1 (this is a bonus algorithm I include
# from sklearn.feature_extraction.text import TfidfVectorizer

[nltk_data] Downloading package stopwords to
[nltk_data] /Users/mclevesluna/nltk_data...
[nltk_data] Package stopwords is already up-to-date!

In [2]: stopwords = nltk.corpus.stopwords
```

1. Data exploration and processing

```
In [3]: # Function to read CSV file with error handling and a custom delimiter
        def read csv with error handling(file path, delimiter=';'):
            data = []
            with open(file_path, 'r', encoding='utf-8', errors='ignore') as file:
                reader = csv.reader(file, delimiter=delimiter)
                for line num, row in enumerate(reader, start=1):
                        data.append(row)
                    except csv.Error as e:
                        print(f'Error at line {line_num}: {e}')
            return data
        # Import training data with error handling and semicolon delimiter
        df_tra = pd.DataFrame(read_csv_with_error_handling("../Project/EXIST_2021_Data
        df_training = df_tra.sample(frac=0.1, random_state=42)
        # Make sure that "source" and "task1" are read as strings
        df training[2] = df training[2].astype(str)
        df_training[5] = df_training[5].astype(str)
        # Testing data with error handling and semicolon delimiter
        df tes = pd.DataFrame(read csv with error handling("../Project/EXIST 2021 Data
        df_test = df_tes.sample(frac=0.1, random_state=42)
        # Make sure that "source" and "task1" are read as strings
        df_test[2] = df_test[2].astype(str)
        df test[5] = df test[5].astype(str)
```

```
In [4]: print(df_training.head())
```

3

1

```
2908 EXIST2021 2935 twitter
        2666 EXIST2021 2693
                              twitter
        5809 EXIST2021 5887 twitter
                                        es
        5832 EXIST2021 5910 twitter
                                        es
        3710 EXIST2021 3760 twitter
        2908 Ex-#Cuomo Aide: He '#Sexually #Harassed Me for...
                                                                     sexist
        2666
                     @Cannedbirds I dont hit women but probably
                                                                     sexist
        5809 @ldpsincompleios Va saliendo todo a la luz. la...
                                                                     sexist
        5832 Esta Claudia no es más que una lagartona que t...
                                                                     sexist
        3710 @Toni0084 abortar no es desear la muerte, nadi...
                                                                 non-sexist
        2908
                           sexual-violence
        2666 misogyny-non-sexual-violence
        5809 misogyny-non-sexual-violence
        5832
              misogyny-non-sexual-violence
        3710
                                non-sexist
        print(df_test.head())
In [5]:
                                      2
                                          3 \
                             1
        2347
              EXIST2021
                          9324
                                twitter
                                         es
        2399 EXIST2021
                          9376 twitter
                                         es
        1564 EXIST2021
                          8541 twitter
        3989 EXIST2021 10966 twitter
        3279 EXIST2021 10256 twitter es
        2347
              @anluma99 @abulelrafas Mal que lo hubiera hech...
                                                                 non-sexist
        2399 Me explicaron que cuando los hombres abren las...
                                                                     sexist
        1564 @olamiposiabeni @mobolajinafisa1 @FaisalokoMor...
                                                                 non-sexist
        3989 Eu segurando o choro quando o Chris canta 'ÄúV...
                                                                 non-sexist
        3279
              @maic00n__ Mitoooo #mgtow #gayscombolsonaro #lgbt
                                                                 non-sexist
        2347
                          non-sexist
        2399
              ideological-inequality
        1564
                          non-sexist
        3989
                          non-sexist
        3279
                          non-sexist
        For future reference:
        2 = "source" 3 = "language" 4 = "text" 5 = "task1" 6 = "task2"
In [6]: #Clean both spanish and english tweets (remove spaces, tags, links, make every
        def clean_text(text, language):
            if language == "en":
                # keep only words
                remove_links = re.sub(r"(https?\://)\S+", "link", text)
                remove_tags = re.sub(r"(?:\@)\S+", "tag", text)
                letters_only_text = re.sub("[^a-zA-Z]", " ", remove_links)
                # convert to lower case and split
                words = letters only text.lower().split()
                # remove stopwords
                stopword set = set(stopwords.words("english"))
```

```
meaningful_words = [w for w in words if w not in stopword_set]
        # join the cleaned words in a list
        return " ".join(meaningful_words)
    #what do clean if its in spanish
    else:
        # keep only words
        remove links = re.sub(r"(https?\://)\S+", "link", text)
        remove_tags = re.sub(r"(?:\@)\S+", "tag", text)
        letters_only_text = re.sub("[^abcdefghijklmnñopqrstuvwxyzABCDEFGHIJKLM]
        # convert to lower case and split
        words = letters only text.lower().split()
        # remove stopwords
        stopword_set = set(stopwords.words("spanish"))
        meaningful words = [w for w in words if w not in stopword set]
        # ioin the cleaned words in a list
        return " ".join(meaningful_words)
# Create a new column for cleaned text in the training set bases off of current
df training['clean text'] = df training.apply(lambda row: clean text(row[4], re
# Create a new column for cleaned text in the test set
df_test['clean_text'] = df_test.apply(lambda row: clean_text(row[4], row[3]), {
#Make sure "task1" has no trailing or leading spaces
df_training[5] = df_training[5].str.strip()
df test[5] = df test[5].str.strip()
```

2. Sexism detector

Sentiment analysis to calculate a sexism score

```
In [7]: # Create dictionary of sexist words using the task1 in our training set
        sexist_words = df_training[df_training[5] == 'sexist']['clean_text'].str.split
        df_sexist_dict = set(sexist_words)
In [8]: # Create function to analyze and score sexism based on the number of sexist wo
        def sentiment analysis(text, df sexist dict):
             # Split the cleaned tweet into words
            words = text.split()
            # Calculate the total sentiment score for the tweet
            total score = sum([word in df sexist dict for word in words])
            # Define a threshold for classification (0 because we won't tolerate even
            threshold = 0
            return total score
        #The complecity for this algorithm is: O(N + M * N), where N is the number of V
In [9]: # Apply sentiment analysis to our training and test dataset and add as a column
        df training["sexism score"] = df training["clean text"].apply(lambda x: sentime
        df_training.head()
```

Out[9]:

```
df_test["sexism_score"] = df_test["clean_text"].apply(lambda x: sentiment_analy
df_test.head()
```

	0	1	2	3	4	5	6	clean_text	s
234	17 EXIST2021	9324	twitter	es	@anluma99 @abulelrafas Mal que lo hubiera hech	non- sexist	non-sexist	anluma abulelrafas mal hecho miembro partido j	
239	99 EXIST2021	9376	twitter	es	Me explicaron que cuando los hombres abren las	sexist	ideological- inequality	explicaron hombres abren piernas locomoci n p	
156	64 EXIST2021	8541	twitter	en	@olamiposiabeni @mobolajinafisa1 @FaisalokoMor	non- sexist	non-sexist	olamiposiabeni mobolajinafisa faisalokomori ab	
398	39 EXIST2021	10966	twitter	es	Eu segurando o choro quando o Chris canta ,ÄúV	non- sexist	non-sexist	eu segurando choro quando chris canta úvamo te	
327	79 EXIST2021	10256	twitter	es	@maic00n_ Mitoooo #mgtow #gayscombolsonaro #lgbt	non- sexist	non-sexist	maic n mitoooo mgtow gayscombolsonaro Igbt	

Quicksort to organize by sexism score

```
In [10]: #Organize the data by the sexism score we created in our sentiment analysis alo
         def randomized_quicksort(data, column='sexism_score'):
             if len(data) <= 1:</pre>
                  return data
             # Randomly choose a pivot index
             pivot_index = np.random.randint(0, len(data))
             pivot = data[column].iloc[pivot_index]
             # Split the DataFrame
             less = data[data[column] < pivot]</pre>
             equal = data[data[column] == pivot]
             greater = data[data[column] > pivot]
             # Sort the split data
             return pd.concat([randomized_quicksort(less, column), equal, randomized_qui
         # Sort the DataFrame by the 'sexism_score' column
         sorted dfTrain = randomized quicksort(df training, 'sexism score')
         # Display the sorted DataFrame
         print(sorted_dfTrain)
```

```
1
                                 3
0
     EXIST2021
                4108
                      twitter
                                es
1
     EXIST2021
                1128
                      twitter
2
     EXIST2021
                  95
                      twitter
                                en
3
     EXIST2021
                 709
                      twitter
                                en
4
     EXIST2021
                 406
                           gab
                                en
                 . . .
685
     EXIST2021
                1383
                      twitter
                                en
686
     EXIST2021
                6484
                      twitter es
687
     EXIST2021
                2645
                      twitter
                                en
688
     EXIST2021
                1781
                      twitter
689
     EXIST2021
                2612
                      twitter
                                en
                                                                   5
0
     @soysi tambien @gabrielboric Retaquardia Estrecha non-sexist
1
     this is my cockits harder than a rockhorny hou...
                                                          non-sexist
2
        @holyquor @Answerforu2 #NotAllMen admit defeat
                                                          non-sexist
3
                      @FaisalokoMori Bearded women nko
                                                         non-sexist
4
     @jodecivante And I highly doubt you're ugly be...
                                                          non-sexist
     these boys start dating one day & expect t...
                                                              sexist
     @ainhoaeus @BcnInsania @Eritacus @ilusocial @m...
686
                                                              sexist
687
     @EXPELincels @beeonroids @shahjoffe @Ponderer ...
                                                          non-sexist
688
     @NinjaSocialist @MqtowRadical @CrossBiddy @nat...
                                                          non-sexist
689
     @CrossBiddy @NinjaSocialist @SR Duncan @Shotgu...
                                                              sexist
                          6
0
                 non-sexist
1
                 non-sexist
2
                 non-sexist
3
                 non-sexist
4
                 non-sexist
685
     stereotyping-dominance
686
     stereotyping-dominance
687
                 non-sexist
688
                 non-sexist
689
            sexual-violence
                                             clean text
                                                          sexism score
       soysi tambien gabrielboric retaguardia estrecha
0
                                                                     0
1
     cockits harder rockhorny hours clockin bathroo...
                                                                     0
2
            holyquor answerforu notallmen admit defeat
                                                                     0
3
                       faisalokomori bearded women nko
                                                                     1
4
                  jodecivante highly doubt ugly bestie
                                                                     1
. .
     boys start dating one day amp expect partner l...
                                                                    33
     ainhoaeus bcninsania eritacus ilusocial mariam...
                                                                    34
686
687
     expelincels beeonroids shahjoffe ponderer purg...
                                                                    56
     ninjasocialist mgtowradical crossbiddy natspra...
688
                                                                    57
     crossbiddy ninjasocialist sr duncan shotgunrai...
689
                                                                    86
[690 rows x 9 columns]
```

#The complexity of this quicksort algorithm is: O(n log n), where 'n' is the n In [11]: #Because we are selecting hte pivot randomnly, the worst case scenario is very

Markov chain to predict future words from user

```
#We first need to tokenize our "clean_text" column to separate it into individu
In [12]:
         tokenized_data = [clean_text(tweet, language) for tweet, language in zip(df_transport)
         # Build Markov Chain
In [13]:
         def build_markov_chain(inputtext):
              chain = \{\}
              for tweet in inputtext:
                  words = tweet.split()
                  for i in range(len(words) - 1):
                      current word = words[i]
                      next_word = words[i + 1]
                      if current word in chain:
                          chain[current_word].append(next_word)
                          chain[current_word] = [next_word]
              return chain
         markov_chain = build_markov_chain(tokenized_data)
         # Convert Markov Chain to DataFrame
         df markov chain = pd.DataFrame(list(markov chain.items()), columns=['Word', 'No
         # Display the DataFrame
         print(df_markov_chain)
                          Word
                                                      Next Words
         0
                            ex [cuomo, reina, girlfriend, wife]
         1
                                                           [aide]
                         cuomo
         2
                                                       [sexually]
                          aide
         3
                                                       [harassed]
                      sexually
         4
                     harassed
                                           [years, theestallion]
                         lizzo
                                                         [saying]
         5773
                                                         [weiaht]
         5774
                        loose
         5775
                       weiaht
                                                      [healthier]
                                                        [somehow]
         5776
                     healthier
         5777 discriminating
                                                            [fat]
         [5778 rows x 2 columns]
In [14]: #Now, also using our training data, we will calculate the transition probabili
         probabilities = {}
         def calculate_transition_probabilities(chain):
              for current_word, next_words in chain.items():
                  total_next_words = len(next_words)
                  probabilities[current word] = {word: next words.count(word) / total next
              return probabilities
         transition_probabilities = calculate_transition_probabilities(markov_chain)
         # Convert probabilities to DataFrame
         df_transition_probabilities = pd.DataFrame(list(transition_probabilities.items
```

```
words = df_transition_probabilities['Word'].tolist()
probabilities_matrix = df_transition_probabilities['Next Words'].apply(pd.Seric
# Assuming you have a list of words (cleaned_text)
cleaned_text = " ".join(df_training['clean_text'])

In [15]: len(cleaned_text)

Out[15]: #Next we have to generate the future sequences
```

woman bet would love white women sammy club dejan pueden ser jóvenes imprudent es creemos sabemos todas

In [17]: #Complexity of the full Markov chain: O(N * M). The where N is the number of to

Strassen's Algorithm for Matrix Multiplication

Extract words and probabilities

```
In [18]: def split matrix(matrix):
              # Check if the matrix has only one dimension
              if matrix.ndim == 1:
                  # If it's a 1D array, convert it to a 2D column vector
                  matrix = matrix.reshape((-1, 1))
              # the matrixes must be split into quadrants first
              row, col = matrix.shape
              row2, col2 = row // 2, col // 2
              upper left = matrix[:row2, :col2]
              upper_right = matrix[:row2, col2:]
              lower_left = matrix[row2:, :col2]
              lower_right = matrix[row2:, col2:]
              return upper left, upper right, lower left, lower right
         def strassen_multiply(A, B,threshold=50000):
              # Base case: switch to a more efficient algorithm (e.g., NumPy)
              if A.shape[0] <= threshold:</pre>
                  return np.dot(A, B)
```

```
# Split matrices into four quadrants
a, b, c, d = split_matrix(A)
e, f, g, h = split_matrix(B)
# Recursive steps for Strassen's algorithm
p1 = strassen multiply(a, f - h)
p2 = strassen_multiply(a + b, h)
p3 = strassen_multiply(c + d, e)
p4 = strassen_multiply(d, g - e)
p5 = strassen multiply(a + d, e + h)
p6 = strassen_multiply(b - d, g + h)
p7 = strassen_multiply(a - c, e + f)
# Compute the quadrants of the result matrix
upper_left = p5 + p4 - p2 + p6
upper_right = p1 + p2
lower_left = p3 + p4
lower_right = p1 + p5 - p3 - p7
# Combine the quadrants to get the result matrix
result = np.vstack((np.hstack((upper_left, upper_right)),
                    np.hstack((lower_left, lower_right))))
return result
```

```
In [19]: #Create some quick test matrices to ensure our Strassen's Algorithm for Matrix
         # Define two matrices A and B
         A = np.array([[4, 3], [5, 2]])
         B = np.array([[5, 1], [5, 6]])
         # Multiply matrices using Strassen's algorithm
         result = strassen_multiply(A,B)
         print("A_matrix:")
         print(A)
         print("B")
         print(B)
         print("\nResult of Matrix Multiplication:")
         print(result)
         A matrix:
         [[4 3]
          [5 2]]
         [[5 1]
          [5 6]]
         Result of Matrix Multiplication:
         [[35 22]
          [35 17]]
In [20]: #0verall time complexity of the algorithm: 0(n**log(2)7)=0(n**2.81), where n is
```

Logistic Regression with Matrix Multiplication (Strassen) and Gradient Descent

In order to use two algorithms in one task, we will be doing a manual logistic regression with matrix multiplication. Our matrix multiplication will be conducted using the Strassen's

Algorithm defined in the previous function.

```
In [21]: df training[2]
                   2908
                                    twitter
Out[21]:
                   2666
                                    twitter
                   5809
                                    twitter
                   5832
                                    twitter
                   3710
                                    twitter
                   3257
                                    twitter
                   1599
                                    twitter
                   4536
                                    twitter
                   1009
                                    twitter
                   734
                                            gab
                   Name: 2, Length: 690, dtype: object
In [22]: #Convert binary categoric variables (sources and language) into numeric ones
                   df_training['numeric_language'] = df_training[3].apply(lambda x: 1 if x == 'en'
                   df test['numeric language']=df test[3].apply(lambda x: 1 if x == 'en' else (2 :
                   df_training['numeric_source'] = df_training[2].apply(lambda x: 1 if x == 'twitte
                   df_test['numeric_source']=df_test[2].apply(lambda x: 1 if x == 'twitter' else
                   df test['sexism score'] = pd.to numeric(df test['sexism score'], errors='coerce')
                   df_training['sexism_score'] = pd.to_numeric(df_training['sexism_score'], error
                   df test['numeric language'] = pd.to numeric(df test['numeric language'], error
                   df_training['numeric_language'] = pd.to_numeric(df_training['numeric_language']
                   df_test['numeric_source'] = pd.to_numeric(df_test['numeric_source'], errors='colored")
                   df training['numeric source'] = pd.to numeric(df training['numeric source'], e
                   df_{training}[5] = df_{training}[5].apply(lambda x: 1 if x == 'sexist' else (0 if x)
                   df_{test}[5] = df_{test}[5].apply(lambda x: 1 if x == 'sexist' else (0 if x == 'non-sexist') | df_{test}[5] |
                   X = df_training[['numeric_source', 'numeric_language', 'sexism_score']]
                   # Convert our sexism output into a NumPy array for matrix multiplication
                   y = df training[5].values
                   # Convert our variables array for matrix multiplication
                   X \text{ matrix} = X.\text{values}
                   #Gettting my aprameters ready
                   # Initialize and transposing theta
                   theta = np.zeros(X matrix.shape[1])
                    thetaT = np.transpose(theta)
In [23]: # Define the sigmoid function
                   def sigmoid(z):
                            return 1 / (1 + np.exp(-z))
                   # Define the cost function
                   def cost_function(X, y, theta):
                            m = len(y)
                            h = sigmoid(strassen_multiply(X, theta,threshold=50000))
                            cost = y * np.log(h) + (1 - y) * np.log(1-h)
                            cost = -np.sum(cost)/m
                            return cost
```

```
# Define the gradient descent function
def gradient_descent(X, y, theta, learning_rate, epochs):
    m = len(y)
    for epoch in range(epochs):
    h = sigmoid(strassen_multiply(X, theta,threshold=50000))
    gradient = (1/m) * strassen_multiply(X.T,(h - y),threshold=50000)
    theta = theta - learning_rate * gradient
    cost = cost_function(X, y, theta)

    if epoch % 2000 == 0:
        print(f'Epoch {epoch}, Cost: {cost}')

return theta
```

```
In [24]: # Train the model
         learning rate = 0.01
         epochs = 50000
         def normalize(X):
              return (X-np.min(X))/(np.max(X)-np.min(X)+1e-6)
         X = np.float16(X matrix)
         y = df_training[5].values
         y = np.float16(y[:,np.newaxis])
         for i in range(2):
             print(np.min(X[:,i]), np.max(X[:,i]))
             X[:,i] = normalize(X[:,i])
         X = np.hstack((X, np.ones((X.shape[0], 1), dtype=X.dtype)))
         y = normalize(y)
         theta = np.zeros(X.shape[1])
         theta = theta[:,np.newaxis]
         theta_final = gradient_descent(X, y, theta, learning_rate, epochs)
         theta final
```

```
1.0 2.0
         1.0 2.0
         Epoch 0, Cost: 0.6584125201751524
         Epoch 2000, Cost: 0.5609166082909162
         Epoch 4000, Cost: 0.5519517053232531
         Epoch 6000, Cost: 0.5494692204507458
         Epoch 8000, Cost: 0.5486331269132615
         Epoch 10000, Cost: 0.548323119111504
         Epoch 12000, Cost: 0.548195805362609
         Epoch 14000, Cost: 0.5481367127968545
         Epoch 16000. Cost: 0.5481054932049796
         Epoch 18000, Cost: 0.548087041764228
         Epoch 20000, Cost: 0.5480752299946972
         Epoch 22000, Cost: 0.5480672895848695
         Epoch 24000, Cost: 0.5480618046599061
         Epoch 26000, Cost: 0.5480579614902177
         Epoch 28000, Cost: 0.548055249080892
         Epoch 30000, Cost: 0.5480533277982507
         Epoch 32000, Cost: 0.5480519644677279
         Epoch 34000, Cost: 0.5480509962167659
         Epoch 36000, Cost: 0.5480503082689888
         Epoch 38000, Cost: 0.5480498193829668
         Epoch 40000, Cost: 0.5480494719286608
         Epoch 42000, Cost: 0.5480492249818979
         Epoch 44000, Cost: 0.548049049466964
         Epoch 46000, Cost: 0.5480489247213733
         Epoch 48000, Cost: 0.5480488360599325
         array([[ 0.1776294 ],
Out[24]:
                 [ 0.26705672],
                 [ 0.17877411],
                 [-1.98711691]]
In [25]: #Define test matrices
         y \text{ test} = df \text{ test}[5]
         y_test = np.array(y_test)
         X_test = df_test[['numeric_source','numeric_language','sexism_score']]
In [26]: # Make predictions on test set
         predictions = np.array(sigmoid(np.dot(X, theta final)))
         y_{test} = df_{test}[5]
         # print(predictions[:,0])
          print(cost function(X, y, theta final))
         0.5480487730716307
In [27]: predictions
```

```
array([[0.36425949],
Out[27]:
                  [0.25100747],
                  [0.94921657],
                  [0.26796661],
                  [0.6862784],
                  [0.60473387],
                  [0.42803636],
                  [0.92893993],
                  [0.98736114],
                  [0.4065732],
                  [0.16388946].
                  [0.42803636],
                  [0.20383235]
                  [0.30445136],
                  [0.30445136],
                  [0.70542544].
                  [0.23438079],
                  [0.89327964],
                  [0.28608555],
                  [0.62614658],
                  [0.34357218],
                  [0.77396156],
                  [0.21891158],
                  [0.15186341],
                  [0.95340552],
                  [0.93987339],
                  [0.98202635],
                  [0.53946088],
                  [0.32394556],
                  [0.9161956],
                  [0.90140822],
                  [0.99967268],
                  [0.4065732],
                  [0.51691378],
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```

[0.86476246],[0.81725716], [0.90140822], [0.93468636], [0.53946088],[0.47225524], [0.56102188],[0.25100747], [0.45032052], [0.47225524],[0.92288707]. [0.25100747], [0.30445136], [0.9161956], [0.75773942], [0.92893993]. [0.26796661], [0.18987931], [0.64657166], [0.95717404], [0.6862784][0.94921657], [0.23438079], [0.47225524], [0.87500038], [0.64657166], [0.47225524], [0.21891158],[0.89327964], [0.34357218], [0.4065732], [0.18987931], [0.32394556],[0.64657166], [0.77396156], [0.85410158],[0.56130378], [0.20383235], [0.64657166], [0.30445136], [0.6862784], [0.32369492][0.34357218], [0.94921657], [0.18987931], [0.72343234], [0.53946088],[0.53946088],[0.45032052], [0.74116702], [0.56130378], [0.42803636], [0.70542544], [0.58344862], [0.84246016], [0.85410158],[0.42803636], [0.62614658], [0.74116702], [0.51691378],

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[0.30445136],
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[0.58344862].
[0.97665281],
[0.38493786],
[0.18987931],
[0.49456362]])
```

In [28]: #The complexity of this algorithm depends mostly on the Gradient Descent and the #Complexity: $0(Matrix\ Multiplication+Gradient\ Descent)=0(n**2.81)+k\cdot n\cdot (d+1))$ #Where k is the number of epochs, n is the number of instances, and d is the number of the following stances.

Creating a co-ocurrences tree

```
In [29]: # Remember, this is the sexist word dictionary we created in our sentiment ana
# Remember, we had tokenized our tweet data to create our Markov Chains: token.
#Convert our df_sexist_dict into list
sexist_words = list(df_sexist_dict)
```

```
In [30]: # Set a threshold for the sexism score
    threshold = 11  # This corresponds to the mean sexism score in our test data

# Filter tweets based on the threshold
    high_sexism_tweets = df_test[df_test['sexism_score'] > threshold]

# Convert the 'text' column to strings
    high_sexism_tweets['tokenized_text'] = high_sexism_tweets[4].astype(str).apply

# Display the tokenized text
    print(high_sexism_tweets[[4, 'tokenized_text']])

# Tokenize the text into words for high sexism tweets
    tokenized_high_sexism_tweets = [text.split() for text in high_sexism_tweets['tokenized_according to the sexism that it is the sex
```

```
co_occurrence_matrix = {}
for words in tokenized high sexism tweets:
    for i, word_i in enumerate(words):
        for j, word_j in enumerate(words):
            if i != j and (word_i in sexist_words or word_j in sexist_words):
                key = (word_i, word_j)
                co_occurrence_matrix[key] = co_occurrence_matrix.get(key, 0) +
# Print the 50 pairs with the highest weight (most common word combinations in
top_edges = sorted(co_occurrence_matrix.items(), key=lambda x: x[1], reverse=T
for edge, weight in top edges:
    print(f"{edge[0]} -- {edge[1]}: {weight}")
#You can activate this part to visualize the network, but it will print out a
# for edge, weight in co_occurrence_matrix.items():
     print(f"{edge[0]} -- {edge[1]}: {weight}")
# The warning that appears is NOT critical or relevant so we will ignore it
                                                      4 \
4291 Al quionista de Superlópez no le da la puta g...
1886
     @xlizagx I will take the handles hun.. serious...
3364 Michelle Bachelet reconoce violación de derec...
4368 @elmundoes A Pablo es que ya no le hacen caso ...
4347 @vania vargas Concuerdo... Mi hija y el resto ...
1904 Best explanation I, Äôve seen of whole Google s...
1338 @HayliNic Grown ass woman, playing video games...
     @CatfishKristen6 wields a psychosexual power o...
903
2252
     @Berro con limon @MarioPscherer Así son los m...
893
     I hate when bitches say they gone beat my ass ...
                                         tokenized text
4291 quionista superl pez da puta gana rodar blas l...
1886 xlizagx i will take the handles hun seriously ...
3364 michelle bachelet reconoce violaci n derechos ...
4368 elmundoes pablo hacen caso consejos soltar ton...
4347 vania vargas concuerdo hija resto mujeres debe...
1904 best explanation i ve seen of whole google sag...
1338 haylinic grown ass woman playing video games t...
903
      catfishkristen wields psychosexual power over ...
2252
     berro limon mariopscherer as machistas mujer c...
893
      i hate when bitches say they gone beat my ass ...
[99 rows x 2 columns]
/var/folders/cc/24m71qvx7n14q697ws0scfb40000qn/T/ipykernel 6557/1946314466.py:
8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row indexer,col indexer] = value instead
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/st
able/user_guide/indexing.html#returning-a-view-versus-a-copy
 high sexism tweets['tokenized text'] = high sexism tweets[4].astype(str).app
ly(clean text, language=2)
```

```
to -- women: 62
women -- to: 62
t -- i: 60
i -- t: 60
to -- s: 49
s -- to: 49
the -- women: 43
women -- the: 43
s -- s: 42
the -- in: 42
in -- the: 42
i -- hate: 40
hate -- i: 40
i -- in: 37
the -- t: 37
in -- i: 37
t -- the: 37
i -- women: 36
men -- women: 36
women -- i: 36
women -- men: 36
s -- the: 36
the -- s: 36
to -- men: 36
men -- to: 36
like -- i: 35
i -- like: 35
is -- s: 35
s -- is: 35
you -- t: 34
t -- you: 34
i -- s: 34
is -- women: 34
women -- is: 34
s -- i: 34
t -- it: 33
it -- t: 33
i -- at: 33
at -- i: 33
of -- women: 33
women -- of: 33
to -- t: 32
to -- in: 32
t -- to: 32
in -- to: 32
like -- to: 32
to -- like: 32
men -- men: 32
i -- love: 32
love -- i: 32
```

In []:

For a later time, we will finish constructing the following:

Predicting wether the string of words generated by our Markov Chain will be sexist according to our logistic regression**

1. Preprocess the Generated String: Tokenize the generated string into words.

- 2. Apply any necessary cleaning or preprocessing steps that you used during the training of your logistic regression model.
- 3. Feature Extraction: Extract the same features from the generated string that were used as input features during the training of your logistic regression model. This may include word frequencies, presence of specific words, or any other relevant features.
- 4. Use Logistic Regression Model:Input the extracted features into your trained logistic regression model to obtain a prediction.

```
In [31]: # # Preprocess the string generated by the Markov Chain
         # tokenized_text = generated_sequence.split()
         # processed_generated_sequence = " ".join(tokenized_text)
         # # Convert X matrix to a list of strings
         # X texts = [" ".join(map(str, row)) for row in X matrix]
         # # Fit and transform the processed text
         # tfidf vectorizer.fit(X texts)
         # generated_features = tfidf_vectorizer.transform([processed_generated_sequence
         # # Add a constant term for bias to the features
         # generated features with bias = np.hstack([generated features.toarray(), np.ol
         # # Assuming you have three features (numeric_source, numeric_language, sexism)
         # num features = 3
         # # Ensure that the number of features matches the size of theta final
         # assert generated features with bias.shape[1] == num features + 1, "Number of
         # # Now, make predictions using the logistic regression model
         # generated_predictions = sigmoid(np.dot(generated_features_with_bias, theta_fl
         # # Print the predictions
         # print("Generated Predictions:", generated_predictions)
         # # Print the feature names (words)
         # print("Feature names:", tfidf vectorizer.get feature names out())
         # # Print the TF-IDF matrix
         # print("TF-IDF matrix:\n", generated_features.toarray())
         # Make predictions on the TF-IDF features
         #predictions = predictions
         # Print the predictions
         #print("Predictions:", predictions)
```