In [122]:
```
#adding neccessary packages


import pandas as pd
import string

import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy import stats

from matplotlib import pyplot as plt
%matplotlib inline



from numpy import array
from pickle import dump

from keras.preprocessing.text import Tokenizer
from keras.utils import to_categorical
from keras.models import Sequential
from keras.layers import Dense
from keras.preprocessing.sequence import pad_sequences

from keras.layers import LSTM
from keras.layers import Embedding


from keras.models import load_model


from random import randint
from pickle import load
```

In [123]:
```
# creating a fucntion to import data from a text file--
# opening the file as read only and then reading the text


def load_file(filename):

    file = open(filename, 'r')

    text = file.read()

    file.close()

    return text
```

In [124]:
```
# turn contents into clean tokens by removing unwanted punctuations and non-alphabet characters
# all text is then returned as a small case text with only alphabets.

def clean_file(text_file):

    text_file = text_file.replace('--', ' ')

    tokens = text_file.split()

    table = str.maketrans('', '', string.punctuation)
    tokens = [w.translate(table) for w in tokens]

    tokens = [word for word in tokens if word.isalpha()]

    tokens = [word.lower() for word in tokens]

    return tokens
```

In [125]:
```
# save tokens to file, one dialog per line


def save_file(lines, filename):

    data = '\n'.join(lines)
    file = open(filename, 'w')

    file.write(data)
    file.close()
```

In [126]:
```
# using the function to load training document
text_file = load_file('JekyllHyde.txt')
print(text_file[250:839])
```

```
NDOW

 THE LAST NIGHT

 DR. LANYON’S NARRATIVE

 HENRY JEKYLL’S FULL STATEMENT OF THE CASE


STORY OF THE DOOR

Mr. Utterson the lawyer was a man of a rugged countenance that was
never lighted by a smile; cold, scanty and embarrassed in discourse;
backward in sentiment; lean, long, dusty, dreary and yet somehow
lovable. At friendly meetings, and when the wine was to his taste,
something eminently human beaconed from his eye; something indeed which
never found its way into his talk, but which spoke not only in these
silent symbols of the after-dinner face, but more often and loudly
```

In [127]:
```
# clean file tokens nad print unique ones

tokens = clean_file(text_file)
print(tokens[:100])
print('Total Tokens: %d' % len(tokens))
print('Unique Tokens: %d' % len(set(tokens)))
```

```
['the', 'strange', 'case', 'of', 'dr', 'jekyll', 'and', 'mr', 'hyde', 'by', 'robert', 'louis', 'stevenson',
'contents', 'story', 'of', 'the', 'door', 'search', 'for', 'mr', 'hyde', 'dr', 'jekyll', 'was', 'quite', 'a
t', 'ease', 'the', 'carew', 'murder', 'case', 'incident', 'of', 'the', 'letter', 'incident', 'of', 'dr', 'lan
yon', 'incident', 'at', 'the', 'window', 'the', 'last', 'night', 'dr', 'narrative', 'henry', 'full', 'stateme
nt', 'of', 'the', 'case', 'story', 'of', 'the', 'door', 'mr', 'utterson', 'the', 'lawyer', 'was', 'a', 'man',
'of', 'a', 'rugged', 'countenance', 'that', 'was', 'never', 'lighted', 'by', 'a', 'smile', 'cold', 'scanty',
'and', 'embarrassed', 'in', 'discourse', 'backward', 'in', 'sentiment', 'lean', 'long', 'dusty', 'dreary', 'a
nd', 'yet', 'somehow', 'lovable', 'at', 'friendly', 'meetings', 'and', 'when', 'the']
Total Tokens: 24550
Unique Tokens: 3871
```

In [128]:
```
# organize into sequences of tokens by selecting the  sequence of tokens. Converting and storing them as line
s

length = 50 + 1
sequences = list()
for i in range(length, len(tokens)):

    seq = tokens[i-length:i]

    line = ' '.join(seq)

    sequences.append(line)

print('Total Sequences: %d' % len(sequences))
```

```
Total Sequences: 24499
```

In [129]:
```
# save sequences to file

out_filename = 'JekyllHyde_sequences.txt'
save_file(sequences, out_filename)
```

In [130]:
```
text_file = load_file('JekyllHyde_sequences.txt')
lines = text_file.split('\n')
```

In [131]:
```
# integer encode sequences of words using tokenizer, then creating a vocabulary size

tokenizer = Tokenizer()
tokenizer.fit_on_texts(lines)
sequences = tokenizer.texts_to_sequences(lines)

vocab_size = len(tokenizer.word_index) + 1
```

In [132]:
```
# # separate into input and output

sequences = array(sequences)
X, y = sequences[:,:-1], sequences[:,-1]
y = to_categorical(y, num_classes=vocab_size)
seq_length = X.shape[1]
```

In [133]:
```
#Creating a RNN model using Long-short term memory
#Adding layes to the model using Rectified Linear Unit and Softmax, as there are multiclases

model = Sequential()
model.add(Embedding(vocab_size, 50, input_length = seq_length))
model.add(LSTM(100, return_sequences=True))
model.add(LSTM(100))
model.add(Dense(100, activation='relu'))
model.add(Dense(vocab_size, activation='softmax'))
print(model.summary())


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


# Fitting the model using batches and for 100epochs
model.fit(X, y, batch_size=128, epochs=100)

# save the model to file
model.save('model.h5')
# save the tokenizer
dump(tokenizer, open('tokenizer.pkl', 'wb'))
```

```
________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_2 (Embedding)      (None, 50, 50)            193600
________________________________________________________________
lstm_3 (LSTM)                (None, 50, 100)           60400
________________________________________________________________
lstm_4 (LSTM)                (None, 100)               80400
________________________________________________________________
dense_3 (Dense)              (None, 100)               10100
________________________________________________________________
dense_4 (Dense)              (None, 3872)              391072
=================================================================
Total params: 735,572
Trainable params: 735,572
Non-trainable params: 0
________________________________________________________________
None
Epoch 1/100
24499/24499 [==============================] - 41s 2ms/step - loss: 6.6255 - acc: 0.0625
Epoch 2/100
24499/24499 [==============================] - 37s 2ms/step - loss: 6.1855 - acc: 0.0652
Epoch 3/100
24499/24499 [==============================] - 37s 2ms/step - loss: 6.0151 - acc: 0.0680
Epoch 4/100
24499/24499 [==============================] - 37s 2ms/step - loss: 5.8692 - acc: 0.0827
Epoch 5/100
24499/24499 [==============================] - 37s 1ms/step - loss: 5.7742 - acc: 0.0868
Epoch 6/100
24499/24499 [==============================] - 37s 1ms/step - loss: 5.7004 - acc: 0.0894
Epoch 7/100
24499/24499 [==============================] - 37s 1ms/step - loss: 5.6356 - acc: 0.0933
Epoch 8/100
24499/24499 [==============================] - 37s 1ms/step - loss: 5.5742 - acc: 0.0963
Epoch 9/100
24499/24499 [==============================] - 37s 1ms/step - loss: 5.5171 - acc: 0.0980
Epoch 10/100
24499/24499 [==============================] - 37s 1ms/step - loss: 5.4635 - acc: 0.1002
Epoch 11/100
24499/24499 [==============================] - 37s 1ms/step - loss: 5.4198 - acc: 0.1015
Epoch 12/100
24499/24499 [==============================] - 36s 1ms/step - loss: 5.3745 - acc: 0.1046
Epoch 13/100
```

```
24499/24499 [==============================] - 36s 1ms/step - loss: 5.3319 - acc: 0.1058
Epoch 14/100
24499/24499 [==============================] - 36s 1ms/step - loss: 5.2945 - acc: 0.1085
Epoch 15/100
24499/24499 [==============================] - 36s 1ms/step - loss: 5.2523 - acc: 0.1094
Epoch 16/100
24499/24499 [==============================] - 36s 1ms/step - loss: 5.2108 - acc: 0.1104
Epoch 17/100
24499/24499 [==============================] - 36s 1ms/step - loss: 5.1678 - acc: 0.1104
Epoch 18/100
24499/24499 [==============================] - 36s 1ms/step - loss: 5.1186 - acc: 0.1148
Epoch 19/100
24499/24499 [==============================] - 36s 1ms/step - loss: 5.0692 - acc: 0.1156
Epoch 20/100
24499/24499 [==============================] - 36s 1ms/step - loss: 5.0187 - acc: 0.1189
Epoch 21/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.9647 - acc: 0.1207
Epoch 22/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.9124 - acc: 0.1236
Epoch 23/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.8640 - acc: 0.1270
Epoch 24/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.8121 - acc: 0.1281
Epoch 25/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.7645 - acc: 0.1318
Epoch 26/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.7234 - acc: 0.1316
Epoch 27/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.6735 - acc: 0.1363
Epoch 28/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.6258 - acc: 0.1380
Epoch 29/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.5831 - acc: 0.1384
Epoch 30/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.5418 - acc: 0.1429
Epoch 31/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.5002 - acc: 0.1431
Epoch 32/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.4573 - acc: 0.1457
Epoch 33/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.4162 - acc: 0.1472
Epoch 34/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.3814 - acc: 0.1493
```

```
Epoch 35/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.3406 - acc: 0.1518
Epoch 36/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.3015 - acc: 0.1545
Epoch 37/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.2617 - acc: 0.1561
Epoch 38/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.2262 - acc: 0.1600
Epoch 39/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.1862 - acc: 0.1620
Epoch 40/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.1493 - acc: 0.1626
Epoch 41/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.1112 - acc: 0.1656
Epoch 42/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.0764 - acc: 0.1711
Epoch 43/100
24499/24499 [==============================] - 36s 1ms/step - loss: 4.0349 - acc: 0.1736
Epoch 44/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.9961 - acc: 0.1773
Epoch 45/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.9612 - acc: 0.1811
Epoch 46/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.9216 - acc: 0.1840
Epoch 47/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.8873 - acc: 0.1872
Epoch 48/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.8493 - acc: 0.1930
Epoch 49/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.8146 - acc: 0.1953
Epoch 50/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.7805 - acc: 0.1993
Epoch 51/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.7465 - acc: 0.2039
Epoch 52/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.7159 - acc: 0.2071
Epoch 53/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.6840 - acc: 0.2084
Epoch 54/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.6588 - acc: 0.2132
Epoch 55/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.6239 - acc: 0.2203
Epoch 56/100
```

```
24499/24499 [==============================] - 36s 1ms/step - loss: 3.5939 - acc: 0.2222
Epoch 57/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.5695 - acc: 0.2245
Epoch 58/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.5399 - acc: 0.2303
Epoch 59/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.5123 - acc: 0.2367
Epoch 60/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.4851 - acc: 0.2384
Epoch 61/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.4612 - acc: 0.2422
Epoch 62/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.4283 - acc: 0.2482
Epoch 63/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.3996 - acc: 0.2508
Epoch 64/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.3828 - acc: 0.2548
Epoch 65/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.3587 - acc: 0.2577
Epoch 66/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.3367 - acc: 0.2601
Epoch 67/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.3096 - acc: 0.2655
Epoch 68/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.2836 - acc: 0.2700
Epoch 69/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.2596 - acc: 0.2758
Epoch 70/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.2322 - acc: 0.2789
Epoch 71/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.2145 - acc: 0.2816
Epoch 72/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.4727 - acc: 0.2603
Epoch 73/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.2988 - acc: 0.2792
Epoch 74/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.3167 - acc: 0.2788
Epoch 75/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.2698 - acc: 0.2837
Epoch 76/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.2289 - acc: 0.2878
Epoch 77/100
24499/24499 [==============================] - 51s 2ms/step - loss: 3.2834 - acc: 0.2830
```

```
Epoch 78/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.2979 - acc: 0.2810
Epoch 79/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.2532 - acc: 0.2832
Epoch 80/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.1629 - acc: 0.2931
Epoch 81/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.1222 - acc: 0.3012
Epoch 82/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.0788 - acc: 0.3093
Epoch 83/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.0436 - acc: 0.3132
Epoch 84/100
24499/24499 [==============================] - 36s 1ms/step - loss: 3.0109 - acc: 0.3154
Epoch 85/100
24499/24499 [==============================] - 36s 1ms/step - loss: 2.9742 - acc: 0.3257
Epoch 86/100
24499/24499 [==============================] - 36s 1ms/step - loss: 2.9503 - acc: 0.3293
Epoch 87/100
24499/24499 [==============================] - 36s 1ms/step - loss: 2.9248 - acc: 0.3310
Epoch 88/100
24499/24499 [==============================] - 36s 1ms/step - loss: 2.8919 - acc: 0.3374
Epoch 89/100
24499/24499 [==============================] - 36s 1ms/step - loss: 2.8706 - acc: 0.3390
Epoch 90/100
24499/24499 [==============================] - 36s 1ms/step - loss: 2.8398 - acc: 0.3465
Epoch 91/100
24499/24499 [==============================] - 35s 1ms/step - loss: 2.8656 - acc: 0.3447
Epoch 92/100
24499/24499 [==============================] - 35s 1ms/step - loss: 2.8315 - acc: 0.3519
Epoch 93/100
24499/24499 [==============================] - 36s 1ms/step - loss: 2.7956 - acc: 0.3581
Epoch 94/100
24499/24499 [==============================] - 35s 1ms/step - loss: 2.7714 - acc: 0.3623
Epoch 95/100
24499/24499 [==============================] - 35s 1ms/step - loss: 2.7387 - acc: 0.3650
Epoch 96/100
24499/24499 [==============================] - 35s 1ms/step - loss: 2.7086 - acc: 0.3685
Epoch 97/100
24499/24499 [==============================] - 36s 1ms/step - loss: 2.6761 - acc: 0.3756
Epoch 98/100
24499/24499 [==============================] - 35s 1ms/step - loss: 2.6488 - acc: 0.3803
Epoch 99/100
```

```
24499/24499 [==============================] - 36s 1ms/step - loss: 2.6396 - acc: 0.3830
Epoch 100/100
24499/24499 [==============================] - 35s 1ms/step - loss: 2.6082 - acc: 0.3919
```

In [134]:
```
# save the model to file
model.save('JekyllHyde_model.h5')
# save the tokenizer
dump(tokenizer, open('JekyllHyde_tokenizer.pkl', 'wb'))
```

In [135]:
```
# using load_model from keras we load the saved model


seq_length = len(lines[0].split()) - 1

#load the model
model = load_model('JekyllHyde_model.h5')

tokenizer = load(open('JekyllHyde_tokenizer.pkl', 'rb'))
```

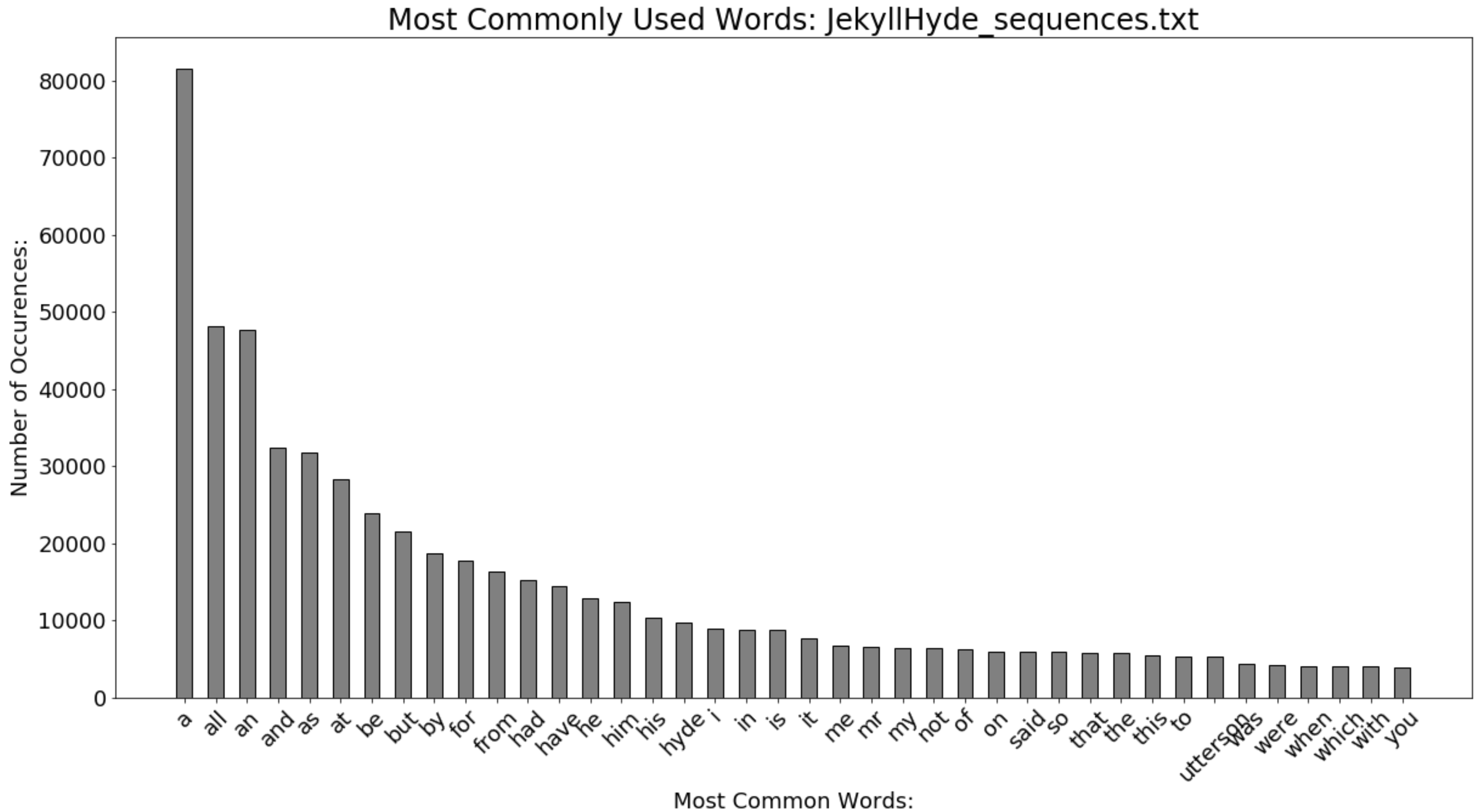
In [136]:
```
# We then create a language model using the sequences and generate new text by selecting random sequences

# generate a sequence from a language model
def generate_seq(model, tokenizer, seq_length, seed_text, n_words):
    result = list()
    in_text = seed_text

    # generate a fixed number of words
    for _ in range(n_words):

        # encode the text as integer
        encoded = tokenizer.texts_to_sequences([in_text])[0]

        # truncate sequences to a fixed length
        encoded = pad_sequences([encoded], maxlen=seq_length, truncating='pre')

        # predict probabilities for each word
        yhat = model.predict_classes(encoded, verbose=0)

        # map predicted word index to word
        out_word = ''
        for word, index in tokenizer.word_index.items():
            if index == yhat:
                out_word = word
                break

        # append to input
        in_text += ' ' + out_word
        result.append(out_word)
    return ' '.join(result)
```

In [137]:
```
# load cleaned text sequences

text_file = load_file('JekyllHyde_sequences.txt')
lines = text_file.split('\n')
seq_length = len(lines[0].split()) - 1

# load the model
model = load_model('JekyllHyde_model.h5')

# load the tokenizer
tokenizer = load(open('JekyllHyde_tokenizer.pkl', 'rb'))

# select a seed text
seed_text = lines[randint(0,len(lines))]
print(seed_text + '\n')

# generate new text
generated = generate_seq(model, tokenizer, seq_length, seed_text, 50)
print(generated[:])
```

```
it almost rivalled the brightness of hope i was stepping leisurely across the court after breakfast drinking
the chill of the air with pleasure when i was seized again with those indescribable sensations that heralded
the change and i had but the time to gain the shelter of my cabinet before

two ahead now anatomical was long overthrown the screaming and obligation at least fumes of smiling and to be
forced and you are not see it was a fine clear to the lawyer have been learning his clasped room i had come u
p with a tempest and the whole business
```

In [138]:

```
def plotWordFrequency(file):
    f = open(file,'r')
    words = [x for y in [l.split() for l in f.readlines()] for x in y]
    data = sorted([(w, words.count(w)) for w in set(words)], key = lambda x:x[1], reverse=True)[:40]
    most_words = [x[0] for x in data]
    times_used = [int(x[1]) for x in data]
    plt.figure(figsize=(20,10))
    plt.bar(x=sorted(most_words), height=times_used, color = 'grey', edgecolor = 'black',  width=.5)
    plt.xticks(rotation=45, fontsize=18)
    plt.yticks(rotation=0, fontsize=18)
    plt.xlabel('Most Common Words:', fontsize=18)
    plt.ylabel('Number of Occurences:', fontsize=18)
    plt.title('Most Commonly Used Words: %s' % (file), fontsize=24)
    plt.show()



file = 'JekyllHyde_sequences.txt'
plotWordFrequency(file)
```


Most Commonly Used Words: JekyllHyde_sequences.txt
Number of Occurences:
0
10000
20000
30000
40000
50000
60000
70000
80000
a
all
an
and
as
at
be
but
by
for
from
had
have
he
him
his
hyde
i
in
is
it
me
mr
my
not
of
on
said
so
that
the
this
to
utterson
was
were
when
which
with
you
Most Common Words: