In [2]:
```
# imports
#All finalised needed imports
import pandas as pd
import itertools
from sklearn.model_selection import cross_val_score
from sklearn import linear_model
import matplotlib.pyplot as plt
import numpy as np
from sklearn.ensemble import RandomForestClassifier
import warnings
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from sklearn.svm import SVC
from sklearn.metrics import classification_report, accuracy_score
from imblearn.over_sampling import SMOTE
nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')

our_custom_stop_words = stopwords.words('english')
# removing these words from the stop words array since they are related to gender.
our_custom_stop_words.remove("he")
our_custom_stop_words.remove("him")
our_custom_stop_words.remove("himself")
our_custom_stop_words.remove("his")
our_custom_stop_words.remove("she")
our_custom_stop_words.remove("she's")
our_custom_stop_words.remove("her")
our_custom_stop_words.remove("hers")
our_custom_stop_words.remove("herself")
our_custom_stop_words.remove("they")
our_custom_stop_words.remove("them")
our_custom_stop_words.remove("their")
our_custom_stop_words.remove("theirs")
our_custom_stop_words.remove("themselves")
```

```
# Suppress warnings
warnings.filterwarnings("ignore")
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

In [3]:
```
# Author: Jeziel Banos Gonzalez
# Before actual training, split data into columns and split data into X and Y train and test

All_data = pd.read_csv('edos_labelled_data.csv')

# x is the actual text, y is the sexist or not sexist label
# training data
X_train = All_data[All_data['split'] == 'train'].drop(columns=['label'])
y_train = All_data[All_data['split'] == 'train']['label']

# testing data
X_test = All_data[All_data['split'] == 'test'].drop(columns=['label'])
y_test = All_data[All_data['split'] == 'test']['label']
```

In [4]:
```
#Author: Jeziel Banos Gonzalez
from nltk.stem import PorterStemmer
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer

# This is the pre processing cell that actually removes and edits the text column

def remove_unwanted_text(dataframe_to_edit):
  # removes the pattern "[something here]" from the column 'text'
  # these are users, and links
  for ind in dataframe_to_edit.index:

    og_text = dataframe_to_edit['text'][ind]
    text = word_tokenize(og_text)
    cleaned_text = ""

    for word in text:

      if( not word.isnumeric() and not word.isspace()):
        if(word[0] != "[" ):
          cleaned_text +=  word+ " "
    # replace the text column with the cleaned version
    dataframe_to_edit['text'][ind] = cleaned_text.lower()



def remove_stop_words(dataframe_to_edit):
  # removes the stop words from the text column

  stop_words = set(our_custom_stop_words)
  # looping through every row
  for ind in dataframe_to_edit.index:

      og_text = dataframe_to_edit['text'][ind]
      word_tokens = word_tokenize(og_text)
      cleaned_text = ""

      for word in word_tokens:
        if not word.lower() in stop_words:
          cleaned_text += word.lower() + " "
      # replace the text column with the cleaned version
      dataframe_to_edit['text'][ind] = cleaned_text
```

```
def stem_words(dataframe_to_edit):
  # stems all the words that are left after removing stop words and unwanted patterns
  ps = PorterStemmer()
  # looping through every row
  for ind in dataframe_to_edit.index:

    og_words = dataframe_to_edit['text'][ind]
    text = word_tokenize(og_words)
    stemmed_words = ""

    for word in text:
      stemmed_words += ps.stem(word) + " "
    # replace the text column with the cleaned version
    dataframe_to_edit['text'][ind] = stemmed_words


# clean up the training data
remove_unwanted_text(X_train)
stem_words(X_train)
remove_stop_words(X_train)

# clean up the testung data
remove_unwanted_text(X_test)
stem_words(X_test)
remove_stop_words(X_test)
```

In [5]:

```
#Author: Jeziel Banos Gonzalez
#N-gram aproach (Unigrams)
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.linear_model import LogisticRegression

# uses unigrams
vectors = CountVectorizer(min_df=1, ngram_range=(1,1)).fit(X_train['text'])
X_train_vectored = vectors.transform(X_train['text'])


# fitting the data to a logisitical regression model
LR_model = LogisticRegression()
LR_model.fit(X_train_vectored, y_train)

# predict on the testing data
test_predictions = LR_model.predict(vectors.transform(X_test['text']))
print("The accuracy of the LogisticRegression N-gram model is (test data):", accuracy_score(test_pr
print("\nClassification Report:\n", classification_report(y_test, test_predictions))
```

```
The accuracy of the LogisticRegression N-gram model is (test data): 0.8075506445672191

Classification Report:
               precision    recall  f1-score   support

  not sexist       0.83      0.92      0.87       789
      sexist       0.70      0.52      0.60       297

    accuracy                           0.81      1086
   macro avg       0.77      0.72      0.73      1086
weighted avg       0.80      0.81      0.80      1086
```

In [6]:

```
coefs = np.logspace(-3, 3, 50)
max_acc = None
best_coef = None

for coef in coefs:
    svm = SVC(kernel='linear', C=coef)
    # run 2 fold cv, any higher results in large runtimes
    scores = cross_val_score(svm, X_train_vectored, y_train, cv=2)
    mean = np.mean(scores)

    # update max accuracy if new coefficient raises it
    if max_acc is None or mean > max_acc:
```

```
        max_acc = mean
        best_coef = coef
```

In [7]:
```
# Author: Jeziel Banos Gonzalez

# fitting the data to a SVC/SVM model (still using n-gram approach)
N_SVM = SVC(kernel='linear', C=best_coef)
N_SVM.fit(X_train_vectored, y_train)

# predicting with model on the testing data
X_test_transformed_N_gram_SVM = vectors.transform(X_test['text'])
predictions_N_SVM = N_SVM.predict(X_test_transformed_N_gram_SVM)

print("Accuracy of the SVC model using n-grams:", accuracy_score(y_test, predictions_N_SVM))
print("\nClassification Report:\n", classification_report(y_test, predictions_N_SVM))
```

```
Accuracy of the SVC model using n-grams: 0.8112338858195212

Classification Report:
               precision    recall  f1-score   support

  not sexist       0.82      0.96      0.88       789
      sexist       0.79      0.42      0.55       297

    accuracy                           0.81      1086
   macro avg       0.80      0.69      0.72      1086
weighted avg       0.81      0.81      0.79      1086
```

In [8]:
```
# Author: Jeziel Banos Gonzalez

# fitting the training data to the random forest model
forest_model = RandomForestClassifier()
forest_model.fit(X_train_vectored, y_train)

# predicting with the forest model on the testing data
forest_predictions = forest_model.predict(vectors.transform(X_test['text']))
print("Accuracy of the Random Forest model using n-grams:", accuracy_score(y_test, forest_predictic
print("\nClassification Report:\n", classification_report(y_test, forest_predictions))
```

```
Accuracy of the Random Forest model using n-grams: 0.8241252302025782

Classification Report:
               precision    recall  f1-score   support

  not sexist       0.81      0.98      0.89       789
      sexist       0.89      0.41      0.56       297

    accuracy                           0.82      1086
   macro avg       0.85      0.69      0.72      1086
weighted avg       0.84      0.82      0.80      1086
```

In [9]:
```
#Author: Adan Baca
# encoding labels with TF-IDF
from sklearn.feature_extraction.text import TfidfVectorizer

corpus = X_train['text']
vectorizer = TfidfVectorizer()

#transforming and fitting the training data
vector = vectorizer.fit_transform(corpus)

#transforming the testing data
X_test_transformed = vectorizer.transform(X_test['text'])
```

In [10]:
```
# Author: Adan Baca
# cross validation for optimizing regularization coefficient for SVM model

# time/performance tradeoff: shrinking this interval allowed me to run 3-fold cv
```

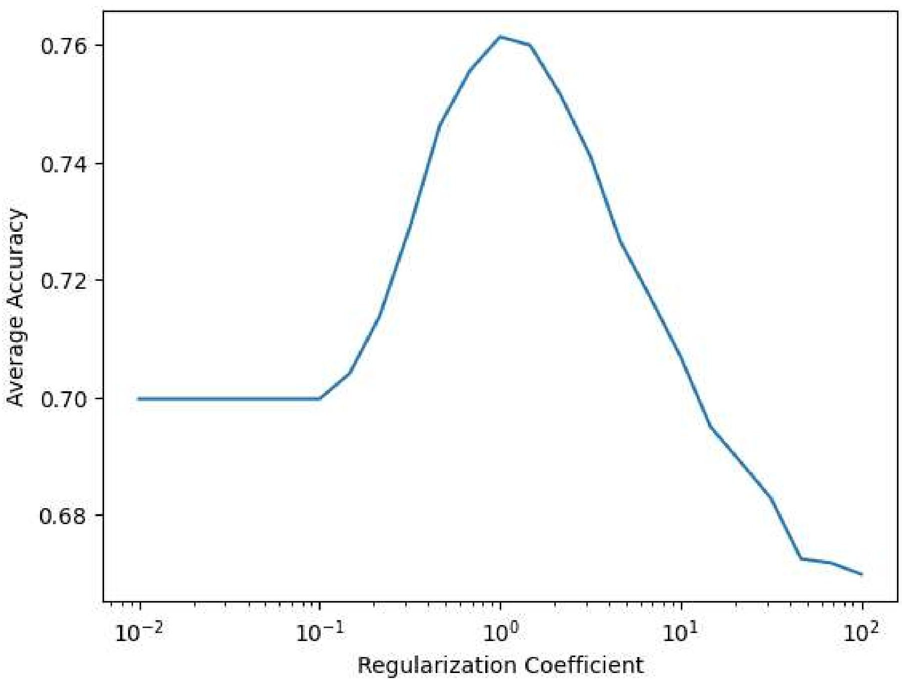
```
coefs = np.logspace(-2, 2, 25)

acc = [] # accuracy array to use for graphing
max_acc = None
best_coef = None

for coef in coefs:
    svm = SVC(kernel='sigmoid', C=coef)
    scores = cross_val_score(svm, vector, y_train, cv=3)
    mean = np.mean(scores)

    # update max accuracy if new coefficient raises it
    if max_acc is None or mean > max_acc:
        max_acc = mean
        best_coef = coef
    acc.append(mean)
plt.plot(coefs, acc)
plt.xscale('log')
plt.ylabel("Average Accuracy")
plt.xlabel("Regularization Coefficient")
print(f"Maximum accuracy: {max_acc}")
print(f"Best coefficient: {best_coef}")
```

```
Maximum accuracy: 0.7612698919853123
Best coefficient: 1.0
```



In [11]:
```
# Adan Baca
# SVC using TF-IDF
SVM_og = SVC(kernel='sigmoid', C=best_coef)
SVM_og.fit(vector, y_train)
y_pred = SVM_og.predict(X_test_transformed)

print("Accuracy of SVC using TF-IDF:", accuracy_score(y_test, y_pred))
print("Classification Report of SVC using TF-IDF:\n", classification_report(y_test, y_pred))
```

```
Accuracy of SVC using TF-IDF: 0.8149171270718232
Classification Report of SVC using TF-IDF:
               precision    recall  f1-score   support

  not sexist       0.82      0.96      0.88       789
      sexist       0.79      0.44      0.57       297

    accuracy                           0.81      1086
   macro avg       0.80      0.70      0.72      1086
weighted avg       0.81      0.81      0.80      1086
```

In [12]:

```
# Author: Adan Baca
# Logistic Regression Model using TF-IDF

LR_model_TFIDF = LogisticRegression(penalty='l1', solver='liblinear')
LR_model_TFIDF.fit(vector, y_train)

test_predictions_TFIDF = LR_model_TFIDF.predict(X_test_transformed)

print("Accuracy of Logistic Regression using TF-IDF:", accuracy_score(y_test, test_predictions_TFID
print("Classification Report of Logistic Regression using TF-IDF:\n", classification_report(y_test,
```

```
Accuracy of Logistic Regression using TF-IDF: 0.8149171270718232
Classification Report of Logistic Regression using TF-IDF:
               precision    recall  f1-score   support

  not sexist       0.82      0.96      0.88       789
      sexist       0.79      0.44      0.56       297

    accuracy                           0.81      1086
   macro avg       0.81      0.70      0.72      1086
weighted avg       0.81      0.81      0.80      1086
```

In [13]:

```
# Author: Adan Baca
# Random Forest Classifier using TF-IDF

rand_forest_TFIDF = RandomForestClassifier()
rand_forest_TFIDF.fit(vector, y_train)

rand_forest_TFIDF_pred = rand_forest_TFIDF.predict(X_test_transformed)

print("Accuracy of Random Forest Classifier using TF-IDF:", accuracy_score(y_test, rand_forest_TFID
print("\nClassification Report of Random Forest Classifier using TFIDF:\n", classification_report(y
```

```
Accuracy of Random Forest Classifier using TF-IDF: 0.8213627992633518

Classification Report of Random Forest Classifier using TFIDF:
               precision    recall  f1-score   support

  not sexist       0.81      0.98      0.89       789
      sexist       0.89      0.39      0.55       297

    accuracy                           0.82      1086
   macro avg       0.85      0.69      0.72      1086
weighted avg       0.83      0.82      0.80      1086
```

In [22]:

```
# When attempting to raise our F1 scores, we realized that a big issue was the
# low f1 score for sexist data. We then realized this was caused by an imbalance
# of data, with most of the data being non sexist.

smote = SMOTE()
X_train_smote, y_train_smote = smote.fit_resample(vector, y_train)
```

In [23]:

```
# Logistic Regression using SMOTE and TF-IDF

LR_model_TFIDF_SMOTE = LogisticRegression(penalty='l1', solver='liblinear')
LR_model_TFIDF_SMOTE.fit(X_train_smote, y_train_smote)
```

```
test_predictions_TFIDF_SMOTE = LR_model_TFIDF_SMOTE.predict(X_test_transformed)

print("Accuracy of Logistic Regression using TF-IDF:", accuracy_score(y_test, test_predictions_TFID
print("Classification Report of Logistic Regression using TF-IDF:\n", classification_report(y_test,
```

```
Accuracy of Logistic Regression using TF-IDF: 0.8038674033149171
Classification Report of Logistic Regression using TF-IDF:
               precision    recall  f1-score   support

  not sexist       0.88      0.85      0.86       789
      sexist       0.63      0.68      0.65       297

    accuracy                           0.80      1086
   macro avg       0.75      0.76      0.76      1086
weighted avg       0.81      0.80      0.81      1086
```

In [24]:
```
cols = [
    'Sexist Precision',
    'Sexist Recall',
    'Sexist F1',
    'Non-sexist Precision',
    'Non-sexist Recall',
    'Non-sexist F1',
    'Weighted Average Precision',
    'Weighted Average Recall',
    'Weighted Average F1'
]
models = [
    'N-grams + SVM',
    'N-grams + Logistic Regression',
    'N-grams + Random Forest',
    'TF-IDF + SVM',
    'TF-IDF + Logistic Regression',
    'TF-IDF + Random Forest',
    'TF-IDF + SMOTE + Logistic Regression'
]
results = pd.DataFrame(columns=cols, index=models)
```

In [25]:
```
results.loc['N-grams + SVM', 'Sexist Precision'] = 0.79
results.loc['N-grams + SVM', 'Sexist Recall'] = 0.42
results.loc['N-grams + SVM', 'Sexist F1'] = 0.55

results.loc['N-grams + SVM', 'Non-sexist Precision'] = 0.82
results.loc['N-grams + SVM', 'Non-sexist Recall'] = 0.96
results.loc['N-grams + SVM', 'Non-sexist F1'] = 0.88

results.loc['N-grams + SVM', 'Weighted Average Precision'] = 0.81
results.loc['N-grams + SVM', 'Weighted Average Recall'] = 0.81
results.loc['N-grams + SVM', 'Weighted Average F1'] = 0.79

results.loc['N-grams + Logistic Regression', 'Sexist Precision'] = 0.70
results.loc['N-grams + Logistic Regression', 'Sexist Recall'] = 0.52
results.loc['N-grams + Logistic Regression', 'Sexist F1'] = 0.60

results.loc['N-grams + Logistic Regression', 'Non-sexist Precision'] = 0.83
results.loc['N-grams + Logistic Regression', 'Non-sexist Recall'] = 0.92
results.loc['N-grams + Logistic Regression', 'Non-sexist F1'] = 0.87

results.loc['N-grams + Logistic Regression', 'Weighted Average Precision'] = 0.80
results.loc['N-grams + Logistic Regression', 'Weighted Average Recall'] = 0.81
results.loc['N-grams + Logistic Regression', 'Weighted Average F1'] = 0.80

results.loc['N-grams + Random Forest', 'Sexist Precision'] = 0.89
results.loc['N-grams + Random Forest', 'Sexist Recall'] = 0.39
results.loc['N-grams + Random Forest', 'Sexist F1'] = 0.54

results.loc['N-grams + Random Forest', 'Non-sexist Precision'] = 0.81
results.loc['N-grams + Random Forest', 'Non-sexist Recall'] = 0.98
results.loc['N-grams + Random Forest', 'Non-sexist F1'] = 0.89
```

```
results.loc['N-grams + Random Forest', 'Weighted Average Precision'] = 0.83
results.loc['N-grams + Random Forest', 'Weighted Average Recall'] = 0.82
results.loc['N-grams + Random Forest', 'Weighted Average F1'] = 0.79


results.loc['TF-IDF + SVM', 'Sexist Precision'] = 0.79
results.loc['TF-IDF + SVM', 'Sexist Recall'] = 0.44
results.loc['TF-IDF + SVM', 'Sexist F1'] = 0.57

results.loc['TF-IDF + SVM', 'Non-sexist Precision'] = 0.82
results.loc['TF-IDF + SVM', 'Non-sexist Recall'] = 0.96
results.loc['TF-IDF + SVM', 'Non-sexist F1'] = 0.88

results.loc['TF-IDF + SVM', 'Weighted Average Precision'] = 0.81
results.loc['TF-IDF + SVM', 'Weighted Average Recall'] = 0.81
results.loc['TF-IDF + SVM', 'Weighted Average F1'] = 0.80


results.loc['TF-IDF + Logistic Regression', 'Sexist Precision'] = 0.79
results.loc['TF-IDF + Logistic Regression', 'Sexist Recall'] = 0.44
results.loc['TF-IDF + Logistic Regression', 'Sexist F1'] = 0.56

results.loc['TF-IDF + Logistic Regression', 'Non-sexist Precision'] = 0.82
results.loc['TF-IDF + Logistic Regression', 'Non-sexist Recall'] = 0.96
results.loc['TF-IDF + Logistic Regression', 'Non-sexist F1'] = 0.88

results.loc['TF-IDF + Logistic Regression', 'Weighted Average Precision'] = 0.81
results.loc['TF-IDF + Logistic Regression', 'Weighted Average Recall'] = 0.81
results.loc['TF-IDF + Logistic Regression', 'Weighted Average F1'] = 0.80


results.loc['TF-IDF + Random Forest', 'Sexist Precision'] = 0.88
results.loc['TF-IDF + Random Forest', 'Sexist Recall'] = 0.37
results.loc['TF-IDF + Random Forest', 'Sexist F1'] = 0.52

results.loc['TF-IDF + Random Forest', 'Non-sexist Precision'] = 0.81
results.loc['TF-IDF + Random Forest', 'Non-sexist Recall'] = 0.98
results.loc['TF-IDF + Random Forest', 'Non-sexist F1'] = 0.89

results.loc['TF-IDF + Random Forest', 'Weighted Average Precision'] = 0.83
results.loc['TF-IDF + Random Forest', 'Weighted Average Recall'] = 0.81
results.loc['TF-IDF + Random Forest', 'Weighted Average F1'] = 0.79


results.loc['TF-IDF + SMOTE + Logistic Regression', 'Sexist Precision'] = 0.63
results.loc['TF-IDF + SMOTE + Logistic Regression', 'Sexist Recall'] = 0.68
results.loc['TF-IDF + SMOTE + Logistic Regression', 'Sexist F1'] = 0.65

results.loc['TF-IDF + SMOTE + Logistic Regression', 'Non-sexist Precision'] = 0.88
results.loc['TF-IDF + SMOTE + Logistic Regression', 'Non-sexist Recall'] = 0.85
results.loc['TF-IDF + SMOTE + Logistic Regression', 'Non-sexist F1'] = 0.86

results.loc['TF-IDF + SMOTE + Logistic Regression', 'Weighted Average Precision'] = 0.81
results.loc['TF-IDF + SMOTE + Logistic Regression', 'Weighted Average Recall'] = 0.80
results.loc['TF-IDF + SMOTE + Logistic Regression', 'Weighted Average F1'] = 0.81
```

In [26]:
```
results
```

Out[26]:

	Sexist Precision	Sexist Recall	Sexist F1	Non-sexist Precision	Non-sexist Recall	Non-sexist F1	Weighted Average Precision	Weighted Average Recall	Weighted Average F1
N-grams + SVM	0.79	0.42	0.55	0.82	0.96	0.88	0.81	0.81	0.79
N-grams + Logistic Regression	0.7	0.52	0.6	0.83	0.92	0.87	0.8	0.81	0.8
N-grams + Random Forest	0.89	0.39	0.54	0.81	0.98	0.89	0.83	0.82	0.79
TF-IDF + SVM	0.79	0.44	0.57	0.82	0.96	0.88	0.81	0.81	0.8
TF-IDF + Logistic Regression	0.79	0.44	0.56	0.82	0.96	0.88	0.81	0.81	0.8
TF-IDF + Random Forest	0.88	0.37	0.52	0.81	0.98	0.89	0.83	0.81	0.79
TF-IDF + SMOTE + Logistic Regression	0.63	0.68	0.65	0.88	0.85	0.86	0.81	0.8	0.81