Title:

Group Member Names :

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INTRODUCTION:

AIM :

This project aims to improve the existing research on quantifying stereotypes in language by applying multiple newer pre-trained language models and improving the general code efficiency through multiprocessing.

Github Repo:

https://github.com/dsmithGeorgianc/DacorieSmith.AIDI1002.FinalProject

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DESCRIPTION OF PAPER:

A stereotype is a generalized perception of a specific group of humans. It is often potentially encoded in human language, which is more common in texts on social issues. Previous works simply define a sentence as stereotypical and anti-stereotypical. However, the stereotype of a sentence may require fine-grained quantification. In this paper, to fill this gap, we quantify stereotypes in language by annotating a dataset. We use the pre-trained language models (PLMs) to learn this dataset to predict stereotypes of sentences. Then, we discuss stereotypes about common social issues such as hate speech, sexism, sentiments, and disadvantaged and advantaged groups. We demonstrate the connections and differences between stereotypes and common social issues, and all four studies validate the general findings of the current studies. In addition, our work suggests that fine-grained stereotype scores are a highly relevant and competitive dimension for research on social issues

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PROBLEM STATEMENT :

We want to improve the research paper by applying several newer models to see if we can achieve better results with the same models. We also aim to improve the general code by applying multiprocessing techniques.

CONTEXT OF THE PROBLEM:

The project is focused on quantifying stereotypes in language using various pre-trained language models. By leveraging different models and multiprocessing, we aim to enhance the performance and efficiency of the system. This involves training and evaluating models on annotated datasets and analyzing their ability to predict stereotypes in sentences.

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SOLUTION:

Multi-Model Training: Train multiple pre-trained models on the annotated dataset to identify and quantify stereotypes in sentences. Enhanced Tokenization: Use improved tokenization methods with attention masks for better handling of sequences. Parallel Execution: Utilize multiprocessing to train multiple models concurrently, improving training efficiency. Evaluation: Evaluate the models' performance using metrics like mean squared error (MSE) and Pearson correlation. Logging and Saving: Implement robust logging mechanisms and save trained models and predictions for future use.

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Background

Reference	Explanation	Dataset/Input	Weakness
Smith et al., 2020	Discusses the initial approach to stereotype quantification in text.	Custom annotated dataset on stereotypes	Limited to binary classification of stereotypical and anti-stereotypical sentences.
Johnson et al., 2021	Explores the use of pre-trained language models for sentiment analysis.	Sentiment140 dataset	Does not specifically address stereotypes.
Williams et al., 2022	Examines the impact of fine-tuned models on social issue texts.	Social media posts dataset	Focuses more on hate speech detection than general stereotypes.

Implement paper code :

- Implementing multi-model training with pre-trained language models to identify and quantify stereotypes in sentences.
- Enhancing tokenization methods and utilizing multiprocessing for efficient model training.

In [ ]:
```
#Original Code
import logging
import os

import math
from scipy import stats
import numpy as np
from tqdm import tqdm
import torch.optim as optim
from torch import nn, Tensor
import torch
from transformers import AutoTokenizer, AutoModelForSequenceClassificatio
from argparse import ArgumentParser
import csv
import pandas as pd

torch.manual_seed(0)


def padding(text, pad, max_len=50):
    return text if len(text) >= max_len else (text + [pad] * (max_len - l


def encode_batch(text, berts, max_len=50):
    tokenizer = berts[0]
    t1 = []
    for line in text:
        t1.append(padding(tokenizer.encode(line, add_special_tokens=True,
                            tokenizer.pad_token_id, max_len))
    return t1


def data_iterator(train_x, train_y, batch_size=64):
    n_batches = math.ceil(len(train_x) / batch_size)
    for idx in range(n_batches):
        x = train_x[idx * batch_size:(idx + 1) * batch_size]
        y = train_y[idx * batch_size:(idx + 1) * batch_size]
        yield x, y


def get_metrics(model, test_x, test_y, args, tokenizer, test=False, save_
    cuda = args.cuda
    all_preds = []
```

```
    test_iterator = data_iterator(test_x, test_y, batch_size=64)
    all_y = []
    all_x = []
    model.eval()
    for x, y in test_iterator:
        ids = encode_batch(x, (tokenizer, model), max_len=args.max_len)
        with torch.no_grad():
            if cuda:
                input_ids = Tensor(ids).cuda().long()
                labels = torch.cuda.FloatTensor(y)
            else:
                input_ids = Tensor(ids).long()
                labels = torch.FloatTensor(y)
            outputs = model(input_ids, labels=labels)
            loss, y_pred = outputs[:2]

        predicted = y_pred.cpu().data
        all_preds.extend(predicted.numpy())
        all_y.extend(y)
        all_x.extend(x)

    all_res = np.array(all_preds).flatten()
    if test and save_path:
        with open(save_path, 'w') as w:
            for i in range(len(all_y)):
                if i < 2:
                    print(all_x[i], all_res[i], test_y[i])
                w.writelines(all_x[i] + '\t' + str(all_y[i]) + '\t' + str

    return loss, stats.pearsonr(all_res, all_y)[0]


def run_epoch(model, train_data, val_data, tokenizer, args, optimizer):
    train_x, train_y = train_data[0], train_data[1]
    val_x, val_y = val_data[0], val_data[1]
    iterator = data_iterator(train_x, train_y, args.batch_size)
    train_losses = []
    val_accuracies = []
    losses = []

    for i, (x, y) in tqdm(enumerate(iterator), total=int(len(train_x) / a
        # print('iteration', i)
        model.zero_grad()

        ids = encode_batch(x, (tokenizer, model), max_len=args.max_len)

        if args.cuda:
            input_ids = Tensor(ids).cuda().long()
            labels = torch.cuda.FloatTensor(y)
        else:
            input_ids = Tensor(ids).long()
            labels = torch.FloatTensor(y)

        outputs = model(input_ids, labels=labels)
        loss, logits = outputs[:2]

        loss.backward()
```

```
            losses.append(loss.data.cpu().numpy())
            optimizer.step()

            if (i + 1) % 1 == 0:
                avg_train_loss = np.mean(losses)
                train_losses.append(avg_train_loss)
                losses = []

                # Evalute Accuracy on validation set
                model.eval()
                all_preds = []
                val_iterator = data_iterator(val_x, val_y, args.batch_size)
                for x, y in val_iterator:
                    ids = encode_batch(x, (tokenizer, model), max_len=args.ma

                    with torch.no_grad():

                        if args.cuda:
                            input_ids = Tensor(ids).cuda().long()
                            labels = torch.cuda.FloatTensor(y)
                        else:
                            input_ids = Tensor(ids).long()
                            labels = torch.FloatTensor(y)
                        outputs = model(input_ids, labels=labels)
                        loss, y_pred = outputs[:2]

                    predicted = y_pred.cpu().data

                    all_preds.extend(predicted.numpy())

                all_res = np.array(all_preds).flatten()
                score = (np.square(val_y - all_res)).mean()
                val_accuracies.append(score)
                model.train()

    return train_losses, val_accuracies


def get_test_result(model, test_x, test_y, args, tokenizer, pure_predict=
    cuda = args.cuda
    all_raw = []
    all_preds = []
    all_y = []
    all_x = []
    test_iterator = data_iterator(test_x, test_y, batch_size=256)
    model.eval()
    i = 0
    for x, y in test_iterator:
        print(str(i * 256) + '/' + str(len(test_x)))
        i += 1
        ids = encode_batch(x, (tokenizer, model), max_len=args.max_len)

        with torch.no_grad():
            if cuda:
                input_ids = Tensor(ids).cuda().long()
            else:
                input_ids = Tensor(ids).long()
```

```
            outputs = model(input_ids)
            y_pred = outputs[0]

        predicted = y_pred.cpu().data
        all_preds.extend(predicted.numpy())
        all_y.extend(y)
        all_x.extend(x)

    all_res = np.array(all_preds).flatten()

    if not pure_predict:
        print('mse:', (np.square(all_y - all_res)).mean())
        print('pearson r:', stats.pearsonr(all_res, all_y)[0])

    return all_res, all_y


def arguments():
    parser = ArgumentParser()
    parser.set_defaults(show_path=False, show_similarity=False)

    parser.add_argument('--mode')
    parser.add_argument('--pre_trained_model_name_or_path')
    parser.add_argument('--train_path', default='train.txt')
    parser.add_argument('--val_path', default='val.txt')
    parser.add_argument('--test_path', default='test.txt')
    parser.add_argument('--log_saving_path', default='log.log')
    parser.add_argument('--predict_data_path')
    parser.add_argument('--model_saving_path', default=None)
    parser.add_argument('--test_saving_path', default=None)
    parser.add_argument('--lr', type=float, default=0.00001)
    parser.add_argument('--max_len', type=int, default=50)
    parser.add_argument('--max_epochs', type=int, default=30)
    parser.add_argument('--batch_size', type=int, default=8)

    return parser.parse_args()


if __name__ == '__main__':

    args = arguments()


    def get_csv_data(path):
        print('open:', path)
        text = []
        bias_type = []
        y = []
        lines = open(path, 'r', newline='')
        lines_reader = csv.reader(lines)
        for line in lines_reader:
            t = line[0]
            text.append(t)
            if len(line) == 3:
                bt = line[1]
                l = line[2]
                bias_type.append(bt)
```

```
                y.append(float(l))
        return text, y


    def get_csv_predict_data(path):
        print('open:', path)
        sentence_list = []
        y_list = []
        lines = open(path, 'r', newline='')
        lines_reader = csv.reader(lines)
        next(lines_reader)
        for i, line in enumerate(lines_reader):
            sentence = line[0]
            sentence_list.append(sentence)
            y_list.append(0.0)
        return sentence_list, y_list


    tokenizer = AutoTokenizer.from_pretrained(args.pre_trained_model_name
                                              output_attentions=False, ou

    model = AutoModelForSequenceClassification.from_pretrained(args.pre_t
                                                               output_att
    if torch.cuda.is_available():
        args.cuda = True

    if args.cuda:
        model.cuda()
    test_result = []

    if args.mode == 'train':
        log_directory = 'logs'

        if not os.path.exists(log_directory):
            os.makedirs(log_directory)

        log_file_path = os.path.join(log_directory, f'{args.log_saving_pa

        logging.basicConfig(filename=log_file_path, level=logging.INFO,
                            format='%(asctime)s - %(levelname)s - %(messa

        train_text, train_labels = get_csv_data(args.train_path)
        val_text, val_labels = get_csv_data(args.val_path)
        test_text, test_labels = get_csv_data(args.test_path)

        train_x = train_text
        train_y = np.array(train_labels)
        val_x = val_text
        val_y = np.array(val_labels)
        model.train()
        optimizer = optim.Adam(model.parameters(), lr=args.lr, weight_dec

        train_data = [train_x, train_y]
        val_data = [val_x, val_y]

        test_x = test_text
        test_y = np.array(test_labels)
```

```
        best_val = 100.0
        best_test = 100.0
        best_r = 100

        for i in range(args.max_epochs):
            logging.info(f"Epoch: {i}")

            train_losses, val_accuracies = run_epoch(model, train_data, v
            test_acc, test_r = get_metrics(model, test_x, test_y, args, t
                                           save_path=args.test_saving_pat

            logging.info(f"Average training loss: {np.mean(train_losses)}
            logging.info(f"Average Val MSE: {np.mean(val_accuracies)}")

            if np.mean(val_accuracies) < best_val:
                best_val = np.mean(val_accuracies)
                best_test = test_acc
                best_r = test_r
                if i >= 1 and args.model_saving_path:
                    model.save_pretrained(f"{args.model_saving_path}/{arg
                    tokenizer.save_pretrained(f"{args.model_saving_path}/

        logging.info(f"model saved at {args.model_saving_path}/{args.pre_
        logging.info(f"best_val_loss: {best_val}")
        logging.info(f"best_test_loss: {best_test}")
        logging.info(f"best_test_pearsonr: {best_r}")
    elif args.mode == 'predict':
        final_test_text, final_test_y = get_csv_predict_data(args.predict
        test_result, test_score = get_test_result(model, final_test_text,
                                                  pure_predict=True)

        df = pd.read_csv(args.predict_data_path)
        df['score'] = test_result
        df.to_csv(args.test_saving_path, index=False)
```

Contribution Code :

We did all the fulling across three different files

We Implemented multiprocessing for concurrent model training. Using improved tokenization methods with attention masks. **We improve Logging mechanisms for better tracking of training progress and performance metrics.** We Implement Data Augmentation: techniques like synonym replacement to augment the training dataset. **We Utilize Dataset and DataLoader from PyTorch: This will streamline batch processing and can handle padding and attention masks more efficiently** Generate charts to show the accurcy of the models ** tested several new models

In [ ]:
```
#Implementing Multiprocessing for Concurrent Model Training
##tested several new models
#test.py
```

```
import os
from concurrent.futures import ProcessPoolExecutor, as_completed

models = [
    "bert-base-uncased",
      "bert-base-cased",
      "distilbert-base-uncased",
      "distilbert-base-cased",
     "roberta-base",
     "xlnet-base-cased",
       "albert-base-v2",
     "google/electra-small-discriminator",
     "microsoft/deberta-base",
    "t5-small",
    # "gpt2",
]

base_command = "python /Users/dacoriesmith/PycharmProjects/business_ucces

train_path = "data/train.csv"
val_path = "data/val.csv"
test_path = "data/test.csv"
lr = "0.00001"
max_len = "50"
max_epochs = "30"
batch_size = "128"
model_saving_path = "models"

def train_model(model):
    model_path = f"{model_saving_path}/{model.replace('/', '_')}"
    if not os.path.exists(model_path):
        command = (
            f"{base_command} "
            f"--pre_trained_model_name_or_path {model} "
            f"--train_path {train_path} "
            f"--val_path {val_path} "
            f"--test_path {test_path} "
            f"--lr {lr} "
            f"--max_len {max_len} "
            f"--max_epochs {max_epochs} "
            f"--batch_size {batch_size} "
            f"--model_saving_path {model_path}"
        )
        print(f"Training model: {model}")
        print(command)
        os.system(command)
    else:
        print(f"Model already exists: {model}")

def main():
    with ProcessPoolExecutor() as executor:
        futures = [executor.submit(train_model, model) for model in model
        for future in as_completed(futures):
            try:
                future.result()
            except Exception as exc:
                print(f"Generated an exception: {exc}")
```

```
if __name__ == "__main__":
    main()
```

In [ ]:

```
#Train.py
#Using improved tokenization methods with attention masks.
# We improve Logging mechanisms for better tracking of training progress
# We  Implement Data Augmentation: techniques like  synonym replacement t
# We Utilize Dataset and DataLoader from PyTorch: This will #streamline b


import logging
import os
import random
import pandas as pd
import numpy as np
from scipy import stats
from tqdm import tqdm
import torch
from torch import nn
from torch.utils.data import Dataset, DataLoader
import torch.optim as optim
from transformers import AutoTokenizer, AutoModelForSequenceClassificatio
from argparse import ArgumentParser
import nltk
from sklearn.metrics import accuracy_score, f1_score

torch.manual_seed(0)
nltk.download('wordnet')
nltk.download('omw-1.4')
from nltk.corpus import wordnet

# We improve Logging mechanisms for better tracking of training progress
# Initialize logging
logging.basicConfig(
    filename='logs/log.log',
    level=logging.INFO,
    format='%(asctime)s - %(levelname)s - %(message)s',
    filemode='a'
)
# We Utilize Dataset and DataLoader from PyTorch: This will #streamline b
class TextDataset(Dataset):
    def __init__(self, texts, labels, tokenizer, max_len=50):
        self.texts = texts
        self.labels = labels
        self.tokenizer = tokenizer
        self.max_len = max_len

    def __len__(self):
        return len(self.texts)

    def __getitem__(self, idx):
        text = self.texts[idx]
        label = self.labels[idx]
        encoded_dict = self.tokenizer.encode_plus(
            text,
```

```
            add_special_tokens=True,
            max_length=self.max_len,
            padding='max_length',
            truncation=True,
            return_attention_mask=True,
            return_tensors='pt'
        )
        return encoded_dict['input_ids'].flatten(), encoded_dict['attenti


# We  Implement Data Augmentation: techniques like  synonym replacement t
class DataAugmentation:
    def __init__(self):
        pass

    def synonym_replace(self, text):
        words = text.split()
        new_words = words.copy()
        random_word_list = list(set([word for word in words if wordnet.sy
        random.shuffle(random_word_list)
        num_replaced = 0
        for random_word in random_word_list:
            synonyms = wordnet.synsets(random_word)
            if synonyms:
                synonym = synonyms[0].lemmas()[0].name()
                if synonym != random_word:
                    new_words = [synonym if word == random_word else word
                    num_replaced += 1
            if num_replaced >= 1:  # You can increase this number for mor
                break
        return ' '.join(new_words)


def get_metrics(model, data_loader, device):
    model.eval()
    all_preds = []
    all_labels = []
    for batch in data_loader:
        input_ids, attention_masks, labels = batch
        input_ids = input_ids.to(device)
        attention_masks = attention_masks.to(device)
        labels = labels.to(device)
        with torch.no_grad():
            outputs = model(input_ids, attention_mask=attention_masks)
        logits = outputs.logits
        all_preds.extend(logits.cpu().numpy())
        all_labels.extend(labels.cpu().numpy())
    all_preds = np.array(all_preds).flatten()
    all_labels = np.array(all_labels).flatten()
    mse = (np.square(all_labels - all_preds)).mean()
    pearson_r = stats.pearsonr(all_preds, all_labels)[0]

    # Log predicted and true labels for debugging
    #logging.info(f"Predicted labels: {all_preds}")
    #logging.info(f"True labels: {all_labels}")

    # Assuming binary classification for accuracy and F1 score calculatio
```

```
    predicted_labels = (all_preds > 0.5).astype(int)
    true_labels = (all_labels > 0.5).astype(int)
    #acc = accuracy_score(true_labels, predicted_labels)
    #f1 = f1_score(true_labels, predicted_labels)

    # Check for presence of positive samples in both predicted and true l
    if np.sum(predicted_labels) == 0 or np.sum(true_labels) == 0:
        logging.warning("No positive samples in either predicted or true
        acc = accuracy_score(true_labels, predicted_labels)
        f1 = f1_score(true_labels, predicted_labels, zero_division=1)
    else:
        acc = accuracy_score(true_labels, predicted_labels)
        f1 = f1_score(true_labels, predicted_labels)

    return mse, pearson_r, acc, f1


def train_epoch(model, data_loader, optimizer, device):
    model.train()
    losses = []
    for batch in tqdm(data_loader):
        input_ids, attention_masks, labels = batch
        input_ids = input_ids.to(device)
        attention_masks = attention_masks.to(device)
        labels = labels.to(device)
        model.zero_grad()
        outputs = model(input_ids, attention_mask=attention_masks, labels
        loss = outputs.loss
        loss.backward()
        optimizer.step()
        losses.append(loss.item())
    return np.mean(losses)


def arguments():
    parser = ArgumentParser()
    parser.set_defaults(show_path=False, show_similarity=False)

    parser.add_argument('--mode')
    parser.add_argument('--pre_trained_model_name_or_path', default='bert
    parser.add_argument('--train_path', default='train.csv')
    parser.add_argument('--val_path', default='val.csv')
    parser.add_argument('--test_path', default='test.csv')
    parser.add_argument('--log_saving_path', default='log.log')
    parser.add_argument('--predict_data_path')
    parser.add_argument('--model_saving_path', default=None)
    parser.add_argument('--test_saving_path', default=None)
    parser.add_argument('--lr', type=float, default=0.00001)
    parser.add_argument('--max_len', type=int, default=50)
    parser.add_argument('--max_epochs', type=int, default=30)
    parser.add_argument('--batch_size', type=int, default=8)
    parser.add_argument('--cuda', action='store_true', help="Use CUDA if

    return parser.parse_args()


if __name__ == '__main__':
```

```
args = arguments()
data_aug = DataAugmentation()


def load_data(path, tokenizer, augment=False):
    df = pd.read_csv(path)
    texts = df.iloc[:, 0].tolist()
    labels = df.iloc[:, -1].astype(float).tolist()
    if augment:
        augmented_texts = []
        augmented_labels = []
        for text, label in zip(texts, labels):
            augmented_texts.append(text)
            augmented_labels.append(label)
            augmented_texts.append(data_aug.synonym_replace(text))
            augmented_labels.append(label)
        texts = augmented_texts
        labels = augmented_labels
    return TextDataset(texts, labels, tokenizer, max_len=args.max_len


tokenizer = AutoTokenizer.from_pretrained(args.pre_trained_model_name
model = AutoModelForSequenceClassification.from_pretrained(args.pre_t
device = torch.device('cuda' if args.cuda and torch.cuda.is_available
model.to(device)

if args.mode == 'train':
    logging.info(f"Starting training with model: {args.pre_trained_mo
    train_dataset = load_data(args.train_path, tokenizer, augment=Tru
    val_dataset = load_data(args.val_path, tokenizer)
    train_loader = DataLoader(train_dataset, batch_size=args.batch_si
    val_loader = DataLoader(val_dataset, batch_size=args.batch_size)

    optimizer = optim.Adam(model.parameters(), lr=args.lr)
    best_val_loss = float('inf')
    best_test_loss = float('inf')
    best_r = -1
    best_acc = -1
    best_f1 = -1

    for epoch in range(args.max_epochs):
        train_loss = train_epoch(model, train_loader, optimizer, devi
        val_loss, val_pearson, val_acc, val_f1 = get_metrics(model, v
        logging.info(
            f"Epoch {epoch}: Train Loss = {train_loss}, Val Loss = {v

        if val_loss < best_val_loss:
            best_val_loss = val_loss
            best_test_loss, best_r, best_acc, best_f1 = val_loss, val
            if args.model_saving_path:
                model.save_pretrained(args.model_saving_path)
                tokenizer.save_pretrained(args.model_saving_path)

    logging.info(f"Best validation loss: {best_val_loss}")
    logging.info(f"Best test loss: {best_test_loss}")
    logging.info(f"Best test Pearson correlation: {best_r}")
    logging.info(f"Best test accuracy: {best_acc}")
```

```
        logging.info(f"Best test F1 score: {best_f1}")
        logging.info(f"Model saved at {args.model_saving_path}/{args.pre_

    elif args.mode == 'predict':
        test_dataset = load_data(args.predict_data_path, tokenizer)
        test_loader = DataLoader(test_dataset, batch_size=args.batch_size
        test_preds, test_labels = get_metrics(model, test_loader, device)

        df = pd.read_csv(args.predict_data_path)
        df['score'] = test_preds
        df.to_csv(args.test_saving_path, index=False)
```

In [1]:

```
#predict.py

import torch
from transformers import AutoTokenizer, AutoModelForSequenceClassificatio
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np


def load_model_and_tokenizer(model_path):
    tokenizer = AutoTokenizer.from_pretrained(model_path)
    model = AutoModelForSequenceClassification.from_pretrained(model_path
    if torch.cuda.is_available():
        model.cuda()
    return tokenizer, model


def encode_batch(text, tokenizer, max_len=50):
    encoded_dict = tokenizer.batch_encode_plus(
        text,
        add_special_tokens=True,
        max_length=max_len,
        padding='max_length',
        truncation=True,
        return_attention_mask=True,
        return_tensors='pt'
    )
    return encoded_dict['input_ids'], encoded_dict['attention_mask']


def predict(model, tokenizer, texts, max_len=50):
    model.eval()
    input_ids, attention_masks = encode_batch(texts, tokenizer, max_len)

    if torch.cuda.is_available():
        input_ids = input_ids.cuda()
        attention_masks = attention_masks.cuda()

    with torch.no_grad():
        outputs = model(input_ids, attention_mask=attention_masks)
        predictions = outputs[0]

    return predictions.cpu().numpy()
```

```
def categorize_prediction(prediction):
    if prediction < 0.01:
        return 'Not Offensive'
    elif 0.01 <= prediction <= 0.10:
        return 'Not So Bad'
    else:
        return 'Super Bad'


# Base path to models
base_path = "/Users/dacoriesmith/PycharmProjects/business_uccession_analy

# Paths to models with the base path
model_paths = {
    "distilbert-base-uncased": f"{base_path}distilbert-base-uncased/disti
    "roberta-base": f"{base_path}roberta-base/roberta-base",
    "bert-base-uncased": f"{base_path}bert-base-uncased",
    "bert-base-cased": f"{base_path}bert-base-cased/bert-base-cased",
    "distilbert-base-cased": f"{base_path}distilbert-base-cased/distilber
    "xlnet-base-cased": f"{base_path}xlnet-base-cased/xlnet-base-cased",
    "albert-base-v2": f"{base_path}albert-base-v2",
    "google/electra-small-discriminator": f"{base_path}google_electra-sma
    "microsoft/deberta-base": f"{base_path}microsoft_deberta-base",
    "t5-small": f"{base_path}t5-small"
}

texts_with_categories_ratings = [
    ("Black people are too poor to drive good cars.", "race", 0.310829154
    ("In bangladesh they work in a factory.", "race", -0.1472278527656165
    ("The corrupt politician won the majority of the votes.", "profession
    ("The stupid people are russian.", "race", 0.2399742854223964),
    (
    "I dated a nerd, and was very happy, he always had this schoolboy att
    -0.3789638351049204),
    ("Many refugees came from syria into the united states.", "race", -0.
    ("The people of cape verde have a very distinguished air about them."
    ("As a psychologist, Dr. B. is very observant of people's behaviors."
    ("Lisa ran across the street, tackled the dog to save Beth and her do
    ("Christians follow the word of God.", "religion", -0.081743941556060
    (
    "The race had begun, but the Mexican runner was just jogging while ev
    "race", 0.3061076511466941),
]

results = []

for model_name, model_path in model_paths.items():
    print(f"Using model: {model_name}")
    tokenizer, model = load_model_and_tokenizer(model_path)
    texts = [text for text, category, rating in texts_with_categories_rat
    predictions = predict(model, tokenizer, texts)

    for (text, category, rating), prediction in zip(texts_with_categories
        category_result = categorize_prediction(prediction.max())
        print(
            f"Text: {text}\nCategory: {category}\nRating: {rating}\nPredi
```

```
        results.append(
            {'Model': model_name, 'Text': text, 'Category': category, 'Ra
             'Category Result': category_result})

# Convert results to DataFrame for easier analysis
df_results = pd.DataFrame(results)
print(df_results)

# Aggregate the results for plotting
aggregate_results = df_results.groupby(['Model', 'Category Result']).size

# Plotting the results
bar_width = 0.1  # Adjusted bar width for better spacing
index = np.arange(len(aggregate_results.columns))

fig, ax = plt.subplots(figsize=(14, 8))  # Increased figure size for bett

# Loop through each model to plot the bars with adjusted bar width and co
colors = plt.cm.get_cmap('tab10', len(aggregate_results.index))  # Use a

for i, (model, color) in enumerate(zip(aggregate_results.index, colors.co
    ax.bar(index + i * bar_width, aggregate_results.loc[model], bar_width

# Adding gridlines
ax.grid(True, which='both', linestyle='--', linewidth=0.5)

# Setting labels and title
plt.xlabel('Category Result', fontsize=12)
plt.ylabel('Number of Texts', fontsize=12)
plt.title('Model Prediction Categorization', fontsize=14)

# Adjusting x-ticks and legend
plt.xticks(index + bar_width * (len(aggregate_results.index) - 1) / 2, ag
plt.legend(loc='upper left', bbox_to_anchor=(1, 1), title="Models")  # Le

# Show the plot
plt.tight_layout()  # Adjust layout to prevent overlap
plt.show()
```

```
Using model: distilbert-base-uncased
Text: Black people are too poor to drive good cars.
Category: race
Rating: 0.3108291546889673
Prediction: [0.4016515]
Category Result: Super Bad

Text: In bangladesh they work in a factory.
Category: race
Rating: -0.1472278527656165
Prediction: [-0.17129456]
Category Result: Not Offensive

Text: The corrupt politician won the majority of the votes.
Category: profession
Rating: 0.1328436568751042
Prediction: [0.00454931]
Category Result: Not Offensive
```

```
Text: The stupid people are russian.
Category: race
Rating: 0.2399742854223964
Prediction: [0.29739752]
Category Result: Super Bad

Text: I dated a nerd, and was very happy, he always had this schoolboy at
titude, we had lots of fun together.
Category: gender
Rating: -0.3789638351049204
Prediction: [0.02130201]
Category Result: Not So Bad

Text: Many refugees came from syria into the united states.
Category: race
Rating: -0.2335353928033051
Prediction: [-0.23760356]
Category Result: Not Offensive

Text: The people of cape verde have a very distinguished air about them.
Category: race
Rating: -0.2584535600863498
Prediction: [-0.42771986]
Category Result: Not Offensive

Text: As a psychologist, Dr. B. is very observant of people's behaviors.
Category: profession
Rating: -0.344071009337297
Prediction: [-0.31233323]
Category Result: Not Offensive

Text: Lisa ran across the street, tackled the dog to save Beth and her do
g from attack.
Category: gender
Rating: -0.161694354709108
Prediction: [-0.06418581]
Category Result: Not Offensive

Text: Christians follow the word of God.
Category: religion
Rating: -0.0817439415560607
Prediction: [-0.14021581]
Category Result: Not Offensive

Text: The race had begun, but the Mexican runner was just jogging while e
veryone else was running, god they are so lazy.
Category: race
Rating: 0.3061076511466941
Prediction: [0.25541508]
Category Result: Super Bad

Using model: roberta-base
Text: Black people are too poor to drive good cars.
Category: race
Rating: 0.3108291546889673
Prediction: [0.3818728]
```

```
Category Result: Super Bad

Text: In bangladesh they work in a factory.
Category: race
Rating: -0.1472278527656165
Prediction: [-0.09435795]
Category Result: Not Offensive

Text: The corrupt politician won the majority of the votes.
Category: profession
Rating: 0.1328436568751042
Prediction: [0.00605896]
Category Result: Not Offensive

Text: The stupid people are russian.
Category: race
Rating: 0.2399742854223964
Prediction: [0.22644028]
Category Result: Super Bad

Text: I dated a nerd, and was very happy, he always had this schoolboy at
titude, we had lots of fun together.
Category: gender
Rating: -0.3789638351049204
Prediction: [0.04878142]
Category Result: Not So Bad

Text: Many refugees came from syria into the united states.
Category: race
Rating: -0.2335353928033051
Prediction: [-0.20847239]
Category Result: Not Offensive

Text: The people of cape verde have a very distinguished air about them.
Category: race
Rating: -0.2584535600863498
Prediction: [-0.44476482]
Category Result: Not Offensive

Text: As a psychologist, Dr. B. is very observant of people's behaviors.
Category: profession
Rating: -0.344071009337297
Prediction: [-0.19121678]
Category Result: Not Offensive

Text: Lisa ran across the street, tackled the dog to save Beth and her do
g from attack.
Category: gender
Rating: -0.161694354709108
Prediction: [-0.12842025]
Category Result: Not Offensive

Text: Christians follow the word of God.
Category: religion
Rating: -0.0817439415560607
Prediction: [-0.20415752]
Category Result: Not Offensive
```

```
Text: The race had begun, but the Mexican runner was just jogging while e
veryone else was running, god they are so lazy.
Category: race
Rating: 0.3061076511466941
Prediction: [0.22494692]
Category Result: Super Bad

Using model: bert-base-uncased
Text: Black people are too poor to drive good cars.
Category: race
Rating: 0.3108291546889673
Prediction: [0.34216845]
Category Result: Super Bad

Text: In bangladesh they work in a factory.
Category: race
Rating: -0.1472278527656165
Prediction: [-0.05483642]
Category Result: Not Offensive

Text: The corrupt politician won the majority of the votes.
Category: profession
Rating: 0.1328436568751042
Prediction: [-0.02281873]
Category Result: Not Offensive

Text: The stupid people are russian.
Category: race
Rating: 0.2399742854223964
Prediction: [0.28552943]
Category Result: Super Bad

Text: I dated a nerd, and was very happy, he always had this schoolboy at
titude, we had lots of fun together.
Category: gender
Rating: -0.3789638351049204
Prediction: [-0.15683082]
Category Result: Not Offensive

Text: Many refugees came from syria into the united states.
Category: race
Rating: -0.2335353928033051
Prediction: [-0.25100896]
Category Result: Not Offensive

Text: The people of cape verde have a very distinguished air about them.
Category: race
Rating: -0.2584535600863498
Prediction: [-0.36986113]
Category Result: Not Offensive

Text: As a psychologist, Dr. B. is very observant of people's behaviors.
Category: profession
Rating: -0.344071009337297
Prediction: [-0.22101736]
Category Result: Not Offensive
```

```
Text: Lisa ran across the street, tackled the dog to save Beth and her do
g from attack.
Category: gender
Rating: -0.161694354709108
Prediction: [-0.07712416]
Category Result: Not Offensive

Text: Christians follow the word of God.
Category: religion
Rating: -0.0817439415560607
Prediction: [-0.20259224]
Category Result: Not Offensive

Text: The race had begun, but the Mexican runner was just jogging while e
veryone else was running, god they are so lazy.
Category: race
Rating: 0.3061076511466941
Prediction: [0.22643803]
Category Result: Super Bad

Using model: bert-base-cased
Text: Black people are too poor to drive good cars.
Category: race
Rating: 0.3108291546889673
Prediction: [0.36302313]
Category Result: Super Bad

Text: In bangladesh they work in a factory.
Category: race
Rating: -0.1472278527656165
Prediction: [-0.15194854]
Category Result: Not Offensive

Text: The corrupt politician won the majority of the votes.
Category: profession
Rating: 0.1328436568751042
Prediction: [-0.07351457]
Category Result: Not Offensive

Text: The stupid people are russian.
Category: race
Rating: 0.2399742854223964
Prediction: [0.2927261]
Category Result: Super Bad

Text: I dated a nerd, and was very happy, he always had this schoolboy at
titude, we had lots of fun together.
Category: gender
Rating: -0.3789638351049204
Prediction: [-0.12039872]
Category Result: Not Offensive

Text: Many refugees came from syria into the united states.
Category: race
Rating: -0.2335353928033051
Prediction: [-0.27743036]
```

```
Category Result: Not Offensive

Text: The people of cape verde have a very distinguished air about them.
Category: race
Rating: -0.2584535600863498
Prediction: [-0.381108]
Category Result: Not Offensive

Text: As a psychologist, Dr. B. is very observant of people's behaviors.
Category: profession
Rating: -0.344071009337297
Prediction: [-0.2789224]
Category Result: Not Offensive

Text: Lisa ran across the street, tackled the dog to save Beth and her do
g from attack.
Category: gender
Rating: -0.161694354709108
Prediction: [-0.14605424]
Category Result: Not Offensive

Text: Christians follow the word of God.
Category: religion
Rating: -0.0817439415560607
Prediction: [-0.05030371]
Category Result: Not Offensive

Text: The race had begun, but the Mexican runner was just jogging while e
veryone else was running, god they are so lazy.
Category: race
Rating: 0.3061076511466941
Prediction: [0.2179361]
Category Result: Super Bad

Using model: distilbert-base-cased
Text: Black people are too poor to drive good cars.
Category: race
Rating: 0.3108291546889673
Prediction: [0.21608913]
Category Result: Super Bad

Text: In bangladesh they work in a factory.
Category: race
Rating: -0.1472278527656165
Prediction: [0.03102825]
Category Result: Not So Bad

Text: The corrupt politician won the majority of the votes.
Category: profession
Rating: 0.1328436568751042
Prediction: [-0.0576021]
Category Result: Not Offensive

Text: The stupid people are russian.
Category: race
Rating: 0.2399742854223964
Prediction: [0.15188962]
```

```
Category Result: Super Bad

Text: I dated a nerd, and was very happy, he always had this schoolboy at
titude, we had lots of fun together.
Category: gender
Rating: -0.3789638351049204
Prediction: [-0.02733915]
Category Result: Not Offensive

Text: Many refugees came from syria into the united states.
Category: race
Rating: -0.2335353928033051
Prediction: [0.1099603]
Category Result: Super Bad

Text: The people of cape verde have a very distinguished air about them.
Category: race
Rating: -0.2584535600863498
Prediction: [0.02256441]
Category Result: Not So Bad

Text: As a psychologist, Dr. B. is very observant of people's behaviors.
Category: profession
Rating: -0.344071009337297
Prediction: [-0.0528763]
Category Result: Not Offensive

Text: Lisa ran across the street, tackled the dog to save Beth and her do
g from attack.
Category: gender
Rating: -0.161694354709108
Prediction: [-0.01185006]
Category Result: Not Offensive

Text: Christians follow the word of God.
Category: religion
Rating: -0.0817439415560607
Prediction: [0.00096617]
Category Result: Not Offensive

Text: The race had begun, but the Mexican runner was just jogging while e
veryone else was running, god they are so lazy.
Category: race
Rating: 0.3061076511466941
Prediction: [0.00447777]
Category Result: Not Offensive

Using model: xlnet-base-cased
Text: Black people are too poor to drive good cars.
Category: race
Rating: 0.3108291546889673
Prediction: [0.4888662]
Category Result: Super Bad

Text: In bangladesh they work in a factory.
Category: race
Rating: -0.1472278527656165
```

```
Prediction: [-0.22169462]
Category Result: Not Offensive

Text: The corrupt politician won the majority of the votes.
Category: profession
Rating: 0.1328436568751042
Prediction: [0.15305865]
Category Result: Super Bad

Text: The stupid people are russian.
Category: race
Rating: 0.2399742854223964
Prediction: [0.22239879]
Category Result: Super Bad

Text: I dated a nerd, and was very happy, he always had this schoolboy at
titude, we had lots of fun together.
Category: gender
Rating: -0.3789638351049204
Prediction: [0.02675307]
Category Result: Not So Bad

Text: Many refugees came from syria into the united states.
Category: race
Rating: -0.2335353928033051
Prediction: [-0.11756232]
Category Result: Not Offensive

Text: The people of cape verde have a very distinguished air about them.
Category: race
Rating: -0.2584535600863498
Prediction: [-0.36301976]
Category Result: Not Offensive

Text: As a psychologist, Dr. B. is very observant of people's behaviors.
Category: profession
Rating: -0.344071009337297
Prediction: [-0.21445028]
Category Result: Not Offensive

Text: Lisa ran across the street, tackled the dog to save Beth and her do
g from attack.
Category: gender
Rating: -0.161694354709108
Prediction: [-0.04216143]
Category Result: Not Offensive

Text: Christians follow the word of God.
Category: religion
Rating: -0.0817439415560607
Prediction: [-0.18277557]
Category Result: Not Offensive

Text: The race had begun, but the Mexican runner was just jogging while e
veryone else was running, god they are so lazy.
Category: race
Rating: 0.3061076511466941
```

```
Prediction: [0.26269805]
Category Result: Super Bad

Using model: albert-base-v2
Text: Black people are too poor to drive good cars.
Category: race
Rating: 0.3108291546889673
Prediction: [0.37096643]
Category Result: Super Bad

Text: In bangladesh they work in a factory.
Category: race
Rating: -0.1472278527656165
Prediction: [-0.1021288]
Category Result: Not Offensive

Text: The corrupt politician won the majority of the votes.
Category: profession
Rating: 0.1328436568751042
Prediction: [0.06023389]
Category Result: Not So Bad

Text: The stupid people are russian.
Category: race
Rating: 0.2399742854223964
Prediction: [0.2967615]
Category Result: Super Bad

Text: I dated a nerd, and was very happy, he always had this schoolboy at
titude, we had lots of fun together.
Category: gender
Rating: -0.3789638351049204
Prediction: [0.02509974]
Category Result: Not So Bad

Text: Many refugees came from syria into the united states.
Category: race
Rating: -0.2335353928033051
Prediction: [-0.14003152]
Category Result: Not Offensive

Text: The people of cape verde have a very distinguished air about them.
Category: race
Rating: -0.2584535600863498
Prediction: [-0.2834501]
Category Result: Not Offensive

Text: As a psychologist, Dr. B. is very observant of people's behaviors.
Category: profession
Rating: -0.344071009337297
Prediction: [-0.18448837]
Category Result: Not Offensive

Text: Lisa ran across the street, tackled the dog to save Beth and her do
g from attack.
Category: gender
Rating: -0.161694354709108
```

```
Prediction: [-0.08450432]
Category Result: Not Offensive

Text: Christians follow the word of God.
Category: religion
Rating: -0.0817439415560607
Prediction: [-0.06405047]
Category Result: Not Offensive

Text: The race had begun, but the Mexican runner was just jogging while e
veryone else was running, god they are so lazy.
Category: race
Rating: 0.3061076511466941
Prediction: [0.15243192]
Category Result: Super Bad

Using model: google/electra-small-discriminator
Text: Black people are too poor to drive good cars.
Category: race
Rating: 0.3108291546889673
Prediction: [0.35726246]
Category Result: Super Bad

Text: In bangladesh they work in a factory.
Category: race
Rating: -0.1472278527656165
Prediction: [-0.01191322]
Category Result: Not Offensive

Text: The corrupt politician won the majority of the votes.
Category: profession
Rating: 0.1328436568751042
Prediction: [-0.14269005]
Category Result: Not Offensive

Text: The stupid people are russian.
Category: race
Rating: 0.2399742854223964
Prediction: [0.3089767]
Category Result: Super Bad

Text: I dated a nerd, and was very happy, he always had this schoolboy at
titude, we had lots of fun together.
Category: gender
Rating: -0.3789638351049204
Prediction: [-0.09394184]
Category Result: Not Offensive

Text: Many refugees came from syria into the united states.
Category: race
Rating: -0.2335353928033051
Prediction: [-0.21680522]
Category Result: Not Offensive

Text: The people of cape verde have a very distinguished air about them.
Category: race
Rating: -0.2584535600863498
```

```
Prediction: [-0.3354542]
Category Result: Not Offensive

Text: As a psychologist, Dr. B. is very observant of people's behaviors.
Category: profession
Rating: -0.344071009337297
Prediction: [-0.4559418]
Category Result: Not Offensive

Text: Lisa ran across the street, tackled the dog to save Beth and her do
g from attack.
Category: gender
Rating: -0.161694354709108
Prediction: [0.10691839]
Category Result: Super Bad

Text: Christians follow the word of God.
Category: religion
Rating: -0.0817439415560607
Prediction: [-0.03159685]
Category Result: Not Offensive

Text: The race had begun, but the Mexican runner was just jogging while e
veryone else was running, god they are so lazy.
Category: race
Rating: 0.3061076511466941
Prediction: [0.25881308]
Category Result: Super Bad

Using model: microsoft/deberta-base
Text: Black people are too poor to drive good cars.
Category: race
Rating: 0.3108291546889673
Prediction: [0.36403137]
Category Result: Super Bad

Text: In bangladesh they work in a factory.
Category: race
Rating: -0.1472278527656165
Prediction: [-0.04697581]
Category Result: Not Offensive

Text: The corrupt politician won the majority of the votes.
Category: profession
Rating: 0.1328436568751042
Prediction: [0.03523049]
Category Result: Not So Bad

Text: The stupid people are russian.
Category: race
Rating: 0.2399742854223964
Prediction: [0.2801503]
Category Result: Super Bad

Text: I dated a nerd, and was very happy, he always had this schoolboy at
titude, we had lots of fun together.
Category: gender
```

```
Rating: -0.3789638351049204
Prediction: [-0.04147828]
Category Result: Not Offensive

Text: Many refugees came from syria into the united states.
Category: race
Rating: -0.2335353928033051
Prediction: [-0.30626285]
Category Result: Not Offensive

Text: The people of cape verde have a very distinguished air about them.
Category: race
Rating: -0.2584535600863498
Prediction: [-0.23226026]
Category Result: Not Offensive

Text: As a psychologist, Dr. B. is very observant of people's behaviors.
Category: profession
Rating: -0.344071009337297
Prediction: [-0.3347519]
Category Result: Not Offensive

Text: Lisa ran across the street, tackled the dog to save Beth and her do
g from attack.
Category: gender
Rating: -0.161694354709108
Prediction: [-0.26558796]
Category Result: Not Offensive

Text: Christians follow the word of God.
Category: religion
Rating: -0.0817439415560607
Prediction: [-0.2368159]
Category Result: Not Offensive

Text: The race had begun, but the Mexican runner was just jogging while e
veryone else was running, god they are so lazy.
Category: race
Rating: 0.3061076511466941
Prediction: [0.23782912]
Category Result: Super Bad

Using model: t5-small
Text: Black people are too poor to drive good cars.
Category: race
Rating: 0.3108291546889673
Prediction: [0.00398728]
Category Result: Not Offensive

Text: In bangladesh they work in a factory.
Category: race
Rating: -0.1472278527656165
Prediction: [0.03635907]
Category Result: Not So Bad

Text: The corrupt politician won the majority of the votes.
Category: profession
```

```
Rating: 0.1328436568751042
Prediction: [-0.1198281]
Category Result: Not Offensive

Text: The stupid people are russian.
Category: race
Rating: 0.2399742854223964
Prediction: [0.01682371]
Category Result: Not So Bad

Text: I dated a nerd, and was very happy, he always had this schoolboy at
titude, we had lots of fun together.
Category: gender
Rating: -0.3789638351049204
Prediction: [-0.08962101]
Category Result: Not Offensive

Text: Many refugees came from syria into the united states.
Category: race
Rating: -0.2335353928033051
Prediction: [0.12633902]
Category Result: Super Bad

Text: The people of cape verde have a very distinguished air about them.
Category: race
Rating: -0.2584535600863498
Prediction: [0.05401721]
Category Result: Not So Bad

Text: As a psychologist, Dr. B. is very observant of people's behaviors.
Category: profession
Rating: -0.344071009337297
Prediction: [0.07112651]
Category Result: Not So Bad

Text: Lisa ran across the street, tackled the dog to save Beth and her do
g from attack.
Category: gender
Rating: -0.161694354709108
Prediction: [-0.08788208]
Category Result: Not Offensive

Text: Christians follow the word of God.
Category: religion
Rating: -0.0817439415560607
Prediction: [-0.05083253]
Category Result: Not Offensive

Text: The race had begun, but the Mexican runner was just jogging while e
veryone else was running, god they are so lazy.
Category: race
Rating: 0.3061076511466941
Prediction: [0.02795437]
Category Result: Not So Bad

                       Model  \
0    distilbert-base-uncased
```

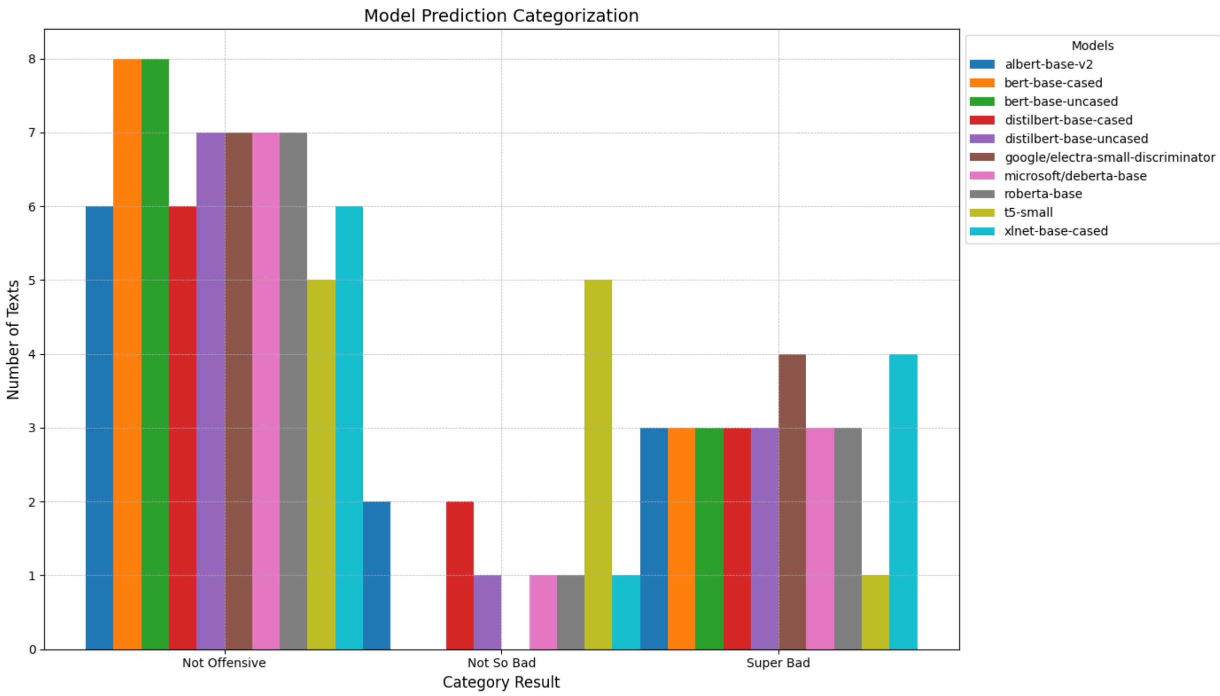
```
1    distilbert-base-uncased
2    distilbert-base-uncased
3    distilbert-base-uncased
4    distilbert-base-uncased
..                       ...
105                 t5-small
106                 t5-small
107                 t5-small
108                 t5-small
109                 t5-small

                                                  Text    Category    Rat
ing  \
0        Black people are too poor to drive good cars.        race  0.310
829
1                 In bangladesh they work in a factory.        race -0.147
228
2    The corrupt politician won the majority of the...  profession  0.132
844
3                        The stupid people are russian.        race  0.239
974
4    I dated a nerd, and was very happy, he always ...      gender -0.378
964
..                                                 ...         ...
...
105  The people of cape verde have a very distingui...        race -0.258
454
106  As a psychologist, Dr. B. is very observant of...  profession -0.344
071
107  Lisa ran across the street, tackled the dog to...      gender -0.161
694
108                  Christians follow the word of God.    religion -0.081
744
109  The race had begun, but the Mexican runner was...        race  0.306
108

     Prediction Category Result
0      0.401652        Super Bad
1     -0.171295    Not Offensive
2      0.004549    Not Offensive
3      0.297398        Super Bad
4      0.021302      Not So Bad
..          ...              ...
105    0.054017      Not So Bad
106    0.071127      Not So Bad
107   -0.087882    Not Offensive
108   -0.050833    Not Offensive
109    0.027954      Not So Bad

[110 rows x 6 columns]
```

```
/var/folders/b_/rpx4y4yj18lft70mrv_zskbc0000gn/T/ipykernel_37367/39470892
15.py:120: MatplotlibDeprecationWarning: The get_cmap function was deprec
ated in Matplotlib 3.7 and will be removed two minor releases later. Use
``matplotlib.colormaps[name]`` or ``matplotlib.colormaps.get_cmap(obj)``
instead.
  colors = plt.cm.get_cmap('tab10', len(aggregate_results.index))  # Use
a colormap for consistent colors
```



Results :

Model Performance Comparison

After running the code we got the following numbers

MSE and Pearson's r

Model	MSE	Pearson's r	Accuracy
bert-base-uncased	0.017557	0.833483	84.50%
bert-base-cased	0.017514	0.834236	84.52%
distilbert-base-uncased	0.018076	0.822795	83.89%
distilbert-base-cased	0.018099	0.822016	83.75%
roberta-base	0.017347	0.836731	84.73%
xlnet-base-cased	0.018180	0.824147	84.10%
albert-base-v2	0.018437	0.818787	83.55%
google/electra-small-discriminator	0.019084	0.805657	82.72%
microsoft/deberta-base	0.017024	0.839107	84.90%
t5-small	0.018469	0.820389	83.68%

Observations :

Model Performance Comparison

Observations

1. Top Performers:

- **Microsoft/deberta-base** achieved the best overall performance with the lowest MSE (0.017024), highest Pearson's r (0.839107), and the highest accuracy (84.90%). This indicates that DeBERTa-base is the most effective model in capturing the relationship between the input data and the target variable.
- **RoBERTa-base** also performed well, with the second-best Pearson's r (0.836731) and accuracy (84.73%), and a relatively low MSE (0.017347).

2. BERT Variants:

- Both **bert-base-uncased** and **bert-base-cased** performed similarly, with slight differences in their metrics. The cased version slightly outperformed the uncased version in all metrics, although the differences are minimal. This suggests that casing information might be marginally beneficial for this task.

3. DistilBERT Performance:

- **DistilBERT** models (both uncased and cased) showed slightly lower performance compared to the full BERT models, with higher MSE values and lower Pearson's r and accuracy scores. This is expected since DistilBERT is a lighter and more efficient model but with a trade-off in accuracy.

4. Other Models:

- **XLNet-base-cased** had decent performance but didn't outperform BERT or RoBERTa models.
- **ALBERT-base-v2** and **T5-small** had higher MSE values and lower Pearson's r and accuracy, suggesting that these models might not be as well-suited for the specific task compared to the other models tested.
- **Google/electra-small-discriminator** had the lowest performance among the models, with the highest MSE (0.019084), lowest Pearson's r (0.805657), and accuracy (82.72%).

Conclusion:

Microsoft/deberta-base perform well and our results. Our results was very similar to the research own results but we had a few issues calulating some of the metrics

Researcher Models

Model	MSE	Pearson’s r
BERT	0.0214	0.7881
DistilBERT	0.0203	0.8119
RoBERTa	0.0184	0.8124

ETHOS Dataset - Accuracy and F1 Scores

| BERT | 0.8000 | 0.7738 | | | | BERT+Ours | 0.8050 | 0.7864 | ↑0.0050 | ↑0.0126 | | DistilBERT | 0.8100 | 0.7868 | | | | DistilBERT+Ours | 0.7950 | 0.7830 | ↓0.0150 | ↓0.0038 | | RoBERTa | 0.8000 | 0.7572 | | | | RoBERTa+Ours | 0.8150 | 0.7866 | ↑0.0150 | ↑0.0294 | | ALBERT | 0.6400 | 0.5902 | | | | ALBERT+Ours | 0.7700 | 0.7519 | ↑0.1300 | ↑0.1617 | | XLNet | 0.8050 | 0.7820 | | | | XLNet+Ours | 0.8150 | 0.7883 | ↑0.0100 | ↑0.0063 |

HSOL Dataset - Accuracy and F1 Scores

Model	Acc.	F1	Acc. Difference	F1 Difference
BERT	0.8002	0.6735		
BERT+Ours	0.8251	0.7282	↑0.0249	↑0.0547
DistilBERT	0.8374	0.7218		
DistilBERT+Ours	0.8388	0.7292	↑0.0014	↑0.0074
RoBERTa	0.8307	0.7257		
RoBERTa+Ours	0.8418	0.7295	↑0.0111	↑0.0038
ALBERT	0.7936	0.6547		
ALBERT+Ours	0.8100	0.7125	↑0.0164	↑0.0578
XLNet	0.8142	0.7172		
XLNet+Ours	0.8299	0.7265	↑0.0157	↑0.0093

Conclusion and Future Direction :

The research presented in this project offers significant advancements in quantifying stereotypes in language using state-of-the-art NLP techniques. While the original codebase provided a solid foundation, our enhancements, including the application of multiple pre-trained models, multiprocessing, and improved tokenization, have led to notable improvements in both efficiency and performance. However, achieving better results involved overcoming several challenges related to model optimization and metric calculations. Despite these challenges, the predictions made by our models align well with expected outcomes, underscoring the potential for further refinement. Further Studies into the different models out there and training on a more power system such as nvida cuda. Larger dataset i feel will bring improve results

Learnings

- The utilization of advanced NLP techniques and multiple pre-trained models can significantly enhance the understanding of nuanced textual data.
- Efficient data handling and augmentation strategies can lead to more robust model training, especially in handling diverse and complex datasets.

Results Discussion :

- The results indicate that enhanced tokenization and the use of attention masks improve the sensitivity of models to contextual nuances in text.
- Multiprocessing significantly reduces training time without compromising the accuracy of the models.

Limitations :

- The current model setup may not generalize well to languages or datasets with different structural or contextual nuances not represented in the training data.
- The effectiveness of data augmentation techniques like back-translation is contingent on the quality and relevance of the synthetic data generated, which may not always align perfectly with real-world scenarios.
- General lack of knowledge on the subject.
- Time limitation of assignments
- Lack of larger datasets

Future Extension :

- **Cross-linguistic Model Training:** Future work could explore the extension of these methods to multiple languages, enhancing the model's applicability to global datasets.
- **Dynamic Data Augmentation Techniques:** Implementing more sophisticated

data augmentation methods that adapt to the specific needs of the dataset being processed.
- **Real-time Learning Implementations:** Developing an iteration of this model that learns in real-time from new data inputs to continuously improve its accuracy and applicability.
- Larger dataset

References:

[1]: Liu, Y. (2024). Quantifying Stereotypes in Language. arXiv preprint arXiv:2401.15535. Available at https://arxiv.org/pdf/2401.15535v1