Language Classification

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Part 1: Learning weights in logistic regression

You are training a classifier for reviews of a new product recently released by a company. You design a couple of features,

$$\text{Initialize } w_1 = w_2 = b = 0$$
$$\eta = 0.2$$
$$\hat{y}_i = w_1 x_{1i} + w_2 x_{2i} + b$$
$$\text{Minimize } L_{CE}(\hat{y}, y) = -\log p\,(y \mid x) = -\left[y \log \hat{y} + (1 - y) \log(1 - \hat{y})\right]$$

For $x_1 = 2, x_2 = 1, y = 1$

$$\begin{aligned} L &= -\left[1 \log \sigma\,(0)) + (1 - y) \log(1 - \sigma\,(0))\right] \\ &= -\left[\log(0.5) + 0\right] = 0.69 \end{aligned}$$

The update or recurrence equation is

$$w_{t+1} = w_t - \eta \frac{d}{dw} L_{CE}$$
$$b_{t+1} = b_t - \eta \frac{d}{db} L_{CE}$$

$$\frac{dL}{dw_j} = \left[\sigma(wx + b) - y\right] x_j$$
$$\frac{dL}{db} = \left[\sigma(wx + b) - y\right]$$

Let’s implement the sigmoid equation and the update equation in a function `update_lr_weights`

```
sigmoid <- function(x) {
  1 / (1 + exp(-x))
}
```

```r
update_lr_weights <- function(data, lr){
  # assumes weights start with w
  weight_cols <- data %>%
    select(starts_with('w')) %>%
    colnames()

  # assumes features start with x
  feature_cols <- data %>%
    select(starts_with('x')) %>%
    colnames()

  # look at each x1, x2, y tuple
  for (i in 1:nrow(data)){
    weights <- data[,weight_cols]
    x <- data[,feature_cols]
    y <- data[i,'y'] %>% pull(y)
    j <- 1
    b <- data[i,'b'] %>% pull(b)

    # update weights and gradients for each tuple, for each weight
    for (weight_col in weight_cols){
      covariate <- x[i,j] %>% pull()
      weight <- data[i, weight_col] %>% pull()
      data[i+1, weight_col] <- weight - lr*((sigmoid(sum(weights[i,] * x[i,]) + b) - y)*covariate)
      data[i, paste0('eta_dl.d', weight_col)] <- lr*((sigmoid(sum(weights[i,] * x[i,]) + b) - y)*covariate)
      j <- j + 1
    }
    # update bias, gradient for each tuple
    data[i+1, 'b'] <- b - lr*(sigmoid(sum(weights[i,] * x[i,]) + b) - y)
    data[i, 'eta_dl.db'] <- lr*(sigmoid(sum(weights[i,] * x[i,]) + b) - y)

    # get error for each tuple
    data[i, 'error'] <- -(y*log(sigmoid(sum(weights[i,] * x[i,]) + b)) + (1-y) * log(1 - sigmoid(sum(weights[i,] * x[i,]) +
b)))
  }
  return(data)
}

data <- tibble(x1 = c(2,1,0), x2 = c(1,3,4), y = c(1,0,0),
               w1 = 0, w2 = 0, b = 0, error = 0, eta_dl.dw1 = 0, eta_dl.dw2 = 0, eta_dl.db = 0)


update <- update_lr_weights(data, lr = 0.2)
```

```
update %>%
  mutate(t = seq(0,nrow(update)-1,1)) %>%
  relocate(t) %>%
  kableExtra::kable() %>%
  kableExtra::kable_styling()
```

t	x1	x2	y	w1	w2	b	error	eta_dl.dw1	eta_dl.dw2	eta_dl.db
0	2	1	1	0.0000000	0.0000000	0.0000000	0.6931472	-0.2000000	-0.1000000	-0.1000000
1	1	3	0	0.2000000	0.1000000	0.1000000	1.0374880	0.1291313	0.3873938	0.1291313
2	0	4	0	0.0708687	-0.2873938	-0.0291313	0.2682519	0.0000000	0.1882279	0.0470570
3	NA	NA	NA	0.0708687	-0.4756217	-0.0761882	NA	NA	NA	NA

This table shows the weights at each timestep, the learning rate adjusted gradients at each timestep, and the error at each timestep. Timestep indexes the x, y, w, b tuples, starting at 0 and ending at 3. Interestingly, we get the largest updates when error is largest and smaller updates when error is smallest. We can also observe that the update for a weight is 0 when the covariate on a given observation is 0. In these three observations, it appears estimates are nudged upwards when the outcome is 1 and downwards when the outcome is 0. However, whether or not the updates will be positive or negative will always depend on the current values of the covariates, the weights and bias, and the outcome. The updates will always follow the opposite direction of the steepest increase in the Loss function with respect to the parameters (and therefore the values of the covariates and outcomes that influence their derivative).

Part 2, The Politeness Dataset

In [ ]:
```
import pandas as pd
import numpy as np
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.model_selection import GridSearchCV
import nltk
from sklearn.linear_model import LogisticRegression
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score, make_scorer, precision_score, recall_score, f1_score
from sklearn.model_selection import cross_validate
from sklearn.pipeline import Pipeline
from sklearn.metrics import confusion_matrix
from sklearn import metrics
import matplotlib.pyplot as plt
import seaborn as sns
from gensim.models import Word2Vec
```

In [ ]:
```
nltk.download('punkt') # this is needed to use NLTK's `word_tokenize` function
nltk.download('stopwords')
```

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\benja\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\benja\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Out[ ]:
```
True
```

In [ ]:
```
polite = pd.read_csv('politeness_data.csv')
```

In [ ]:
```
polite.head
```

```
Out[ ]: <bound method NDFrame.head of           id                                               text  polite
0       1331  Try to add an `import pycuda` line at the top ...       1
1     196858  Hello, our project has begun to fall a little ...       1
2      25622  Picking up your challenge. You a big fan of sk...       0
3       4161  @Herbert: Still I think your answer is very co...       1
4     526013  Thanks for continuing to look over the article...       1
...      ...                                                ...     ...
4927    6485  You never mentioned how far it is to work? How...       0
4928    3637  Why are the results bad? Can you elaborate on ...       0
4929     765  Thank you, after some experimenting, this seem...       1
4930     991  Why are you using that in the first place? Why...       0
4931    6458  Why on earth would that make for bad chicken s...       0

[4932 rows x 3 columns]>
```

```
In [ ]: x=polite.text
        y=polite.polite
```

Logistic Regression

```
In [ ]: scoring = {
            'accuracy': make_scorer(accuracy_score),
            'precision': make_scorer(precision_score),
            'recall': make_scorer(recall_score),
            'f1_score': make_scorer(f1_score)
        }
```

```
In [ ]: pipe_bow = Pipeline([('vec',CountVectorizer()),
                             ('lr', LogisticRegression(C = 1, penalty='l2',solver='saga',max_iter=1000))])
```

```
In [ ]: pipe_tfidf = Pipeline([('vec',TfidfVectorizer()),
                               ('lr', LogisticRegression(C = 1, penalty='l2',solver='saga',max_iter=1000))])
        pipe_binary = Pipeline([('vec',CountVectorizer(binary=True)),
                               ('lr', LogisticRegression(C = 1, penalty='l2',solver='saga',max_iter=1000))])
```

```
In [ ]: cv_bow = cross_validate(pipe_bow, x, y, cv=5, scoring = scoring)
        cv_tfidf = cross_validate(pipe_tfidf, x, y, cv=5, scoring = scoring)
        cv_binary = cross_validate(pipe_binary, x, y, cv=5, scoring = scoring)
```

```
In [ ]: lr_models = pd.concat([pd.DataFrame(cv_bow), pd.DataFrame(cv_tfidf), pd.DataFrame(cv_binary)])
        lr_models['model'] = np.repeat(['bow','tfidf','binary'], 5)
        lr_models.groupby('model').mean()
```

Out[ ]:

model	fit_time	score_time	test_accuracy	test_precision	test_recall	test_f1_score
binary	0.326193	0.023488	0.701542	0.703966	0.695873	0.699767
bow	0.627263	0.022621	0.696880	0.699391	0.691004	0.695107
tfidf	0.101053	0.021685	0.710667	0.704289	0.727091	0.715381

For each feature or change in input text processing: Describe your motivation for including the feature Discussion of results: Did it improve performance or not? (Either result is fine. It is not necessary to beat logistic regression with unigram features.)

My models are as follows:

- Baseline model, L2 normalized logistic regression with word counts as features
- Tf-idf model, L2 normalized logistic regression with tf-idf weighted word features. My motivation for attempting this is that it will downweight or outright eliminate unimportant, highly frequent words (e.g., 'the'), "biasing" the model estimation process towards rarer, reasonably more informative words.
- Binary model, same as the baseline model except with binary word presence indicators instead of counts. My motivation for attempting this is that it is a simpler model than using counts. For instance, it may be beneficial to indicate whether or word occurs vs. how many times it occurs, because the number of times a word appears may not scale with an increase in odds that the text is polite or impolite. Therefore, this would add some noise to the model estimation process.
- Other ideas: obtain or make a "politeness" lexicon indicator. Things that I know for certain should be correlated with politeness/impoliteness, e.g., the use of the word `please` or `thank you` bigram or the use of the word `stupid` or a `you suck` bigram.

For a feature-based model of your choice:

List the top 2 most informative features that are mostly strongly positively and negatively associated with politeness. Discuss if you find these surprising and any other comments you might have. You may adapt code provided by the instructor in the Naive Bayes example (notebook here), use another source online, or write your own.

I will give this information for my TF-IDF logistic regression model because it performed the best

In [ ]:

```
pipe_tfidf.fit(x, y)

# Define the most_informative_features function
def most_informative_features(vectorizer, classifier, n=10):
    feature_names = vectorizer.get_feature_names_out()
    topn_class1 = sorted(zip(classifier.coef_[0], feature_names))[-n:]
    topn_class0 = sorted(zip(-classifier.coef_[0], feature_names))[-n:]

    print("Class 1:")
```

```
    for coef, feat in reversed(topn_class1):
        print(feat, coef)

    print("\nClass 0:")
    for coef, feat in reversed(topn_class0):
        print(feat, coef)


most_informative_features(pipe_tfidf.named_steps['vec'], pipe_tfidf.named_steps['lr'], n=2)
```

```
Class 1:
thanks 5.645505067725689
could 3.348128349104262

Class 0:
why 6.488065432838999
homework 2.7116534979864335
```

That `thanks` is important to politeness is unsurprising. `Could` is also possibly unsurprising, because it can be the start of a polite question.

That `why` is important to impoliteness is interesting because one connotation of this is that `why` questions on StackOverflow usually come from questioning the judgment of the questioner by the answerer. That `homework` is also predictive of impoliteness is interesting because Stackoverflow is a website for people to try answering their own problems first, failing, and then saying why they are stuck. That someone might mention homework in an impolite response might mean they were responding to someone curtly about doing their own homework.

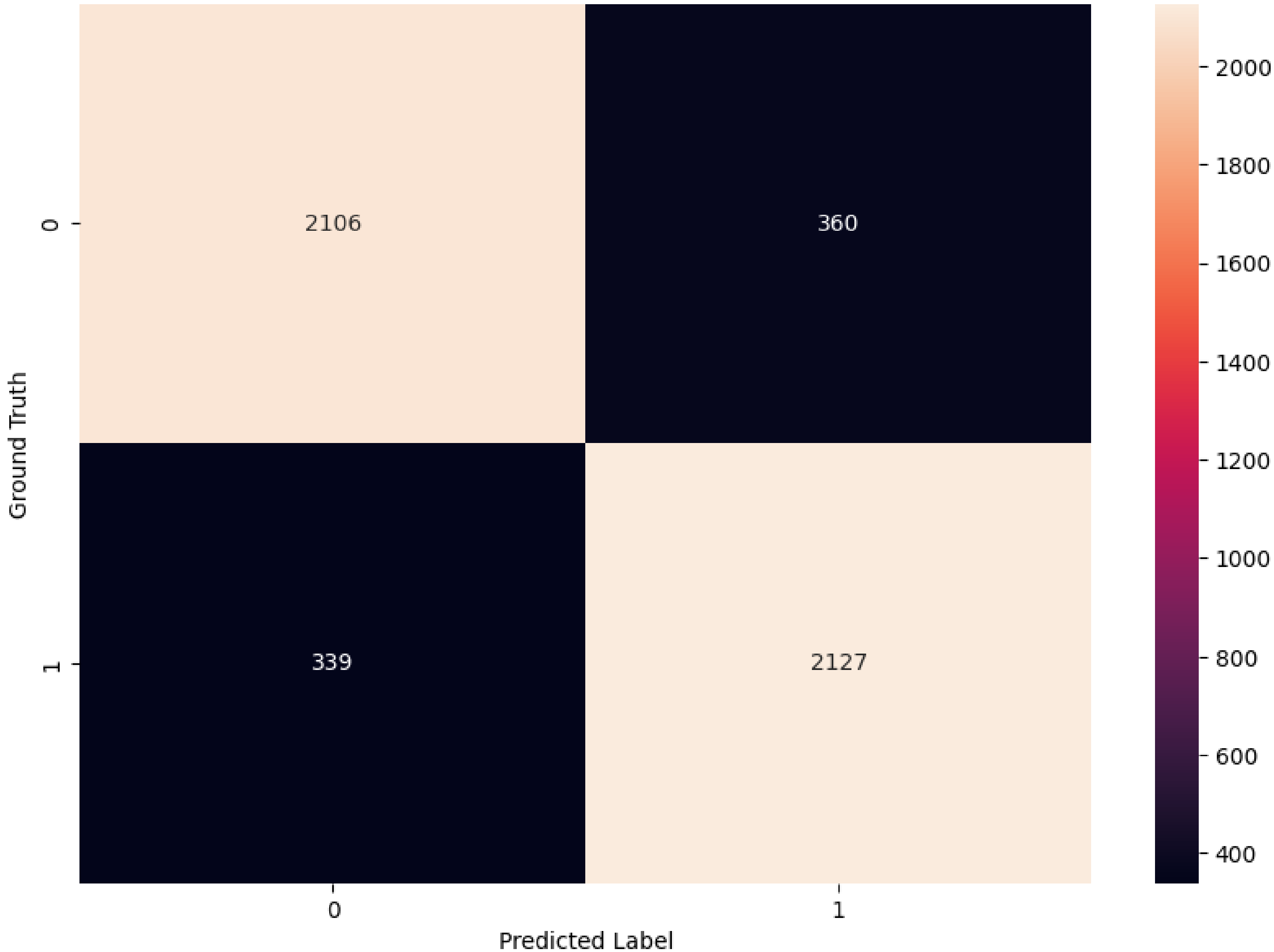
Do an error analysis. Provide a confusion matrix.

In [ ]:
```
pred_y = pipe_tfidf.predict(x)
cm = confusion_matrix(y, pred_y)

print(cm)
```

```
[[2106  360]
 [ 339 2127]]
```

In [ ]:
```
plt.figure(figsize=(10,7))
sns.heatmap(cm, annot=True, fmt='d')
plt.xlabel('Predicted Label')
plt.ylabel('Ground Truth')
plt.show()
```



The model is about 70% correct, as our accuracy metric indicates. The errors are split approximately 50/50 between false negatives and false positives

Sample multiple examples from both false negatives and false positives. Do you see any patterns in these errors? How might these errors be addressed with different features or if the system could understand something else? (You don't have to implement these, just speculate.)

In [ ]:
```
def get_misses(outcome, outcome_hat, text_data):
    false_negatives = [i for i, outcome in enumerate(outcome) if ((outcome == 1) & (outcome_hat[i] == 0))]
    false_positives = [i for i, outcome in enumerate(outcome) if ((outcome == 0) & (outcome_hat[i] == 1))]
    top10_positive = ['thanks', 'could', 'hi', 'can', 'for', 'thank', 'help', 'great', 'good', 'would']
    top10_negative = ['why', 'homework', 'really', 'not', 'don', 'who', 'wikipedia', 'what', 'shouldn', 'no']
    neg_in_fn = 0
```

```python
    pos_in_fn = 0
    neg_in_fp = 0
    pos_in_fp = 0

    print("False Negatives:")
    for i in false_negatives[0:10]:
        print(text_data[i])
        print('Negative Words? ' + str(any(word in text_data[i] for word in top10_negative)))
        if any(word in text_data[i] for word in top10_negative):
            neg_in_fn += 1
        print('Positive Words? ' + str(any(word in text_data[i] for word in top10_positive)))
        if any(word in text_data[i] for word in top10_positive):
            pos_in_fn += 1


    print("\nFalse Positives:")
    for i in false_positives[0:10]:
        print(text_data[i])
        print('Negative Words? ' + str(any(word in text_data[i] for word in top10_negative)))
        print('Positive Words? ' + str(any(word in text_data[i] for word in top10_positive)))
        if any(word in text_data[i] for word in top10_negative):
            neg_in_fp += 1
        if any(word in text_data[i] for word in top10_positive):
            pos_in_fp += 1

    print(f'The number of false negative examples with a top 10 informative negative word was {neg_in_fn} out of 10')
    print(f'The number of false negative examples with a top 10 informative positive words was {pos_in_fn} out of 10')
    print(f'The number of false positive examples with a top 10 informative negative words was {neg_in_fp} out of 10')
    print(f'The number of false positive examples with a top 10 informative positive words was {pos_in_fp} out of 10')

get_misses(y, pred_y, x)
```

```
False Negatives:
What are you trying to say? You want a Registry Editor?
Negative Words? False
Positive Words? False
Not sure what you are referring to when you say you need an SQL query builder for "Python". Do you mean to say you need an ORM like SQL
Alchemy (http://www.sqlalchemy.org/) to connect with databases without having to write SQL statements yourself?
Negative Words? True
Positive Words? True
I confess, no. What's exactly to be read in the docs you are referring to?
Negative Words? True
Positive Words? False
I read the diff upside down or something... Glad someone is keeping an eye on me :) I'm mainly doing stuff over here <url> these days,
what are you up to currently? Still concentrating on the Ui Imair?
Negative Words? True
Positive Words? True
What version of bash are you using? Is it 4.x or 3.x?
Negative Words? False
Positive Words? False
At what point in this process did you discover the MBP was unplugged? Is the problem continuing to happen after the MBP is fully rechar
ged?
Negative Words? True
Positive Words? True
How are `g_rx_buffer` and `BYTE` defined?  What compiler are you using?
Negative Words? False
Positive Words? False
What would stop the algorithm from just producing a regular expression that is the "or" of all the possible substrings?  Or would you b
e comfortable with this regular expression from being produced?
Negative Words? False
Positive Words? True
Ditto "look professional". What does that mean to you, exactly?
Negative Words? False
Positive Words? False
@Ivo Wetzel So, you are saying there is not way to get all objects attributes and values ? Or to convert such object to an associative
array ?
Negative Words? True
Positive Words? False

False Positives:
You could specify whether you need an introduction on applied statistics, or one on (theoretical) statistical inference. I.e., do you w
ant the framework of testing, regression and ANOVA explained or do you want to know what the central limit theorem and the inequality o
f Chebiyshev have to do with the weak law of large numbers?
Negative Words? True
Positive Words? True
I guess this could lead to another set of advertising answers. There are a good range of vendors providing high quality services in thi
s industry, but you might want to update your question with region, country etc?
Negative Words? True
Positive Words? True
@There: That's a lot of code to wade through.  Are you saying you can't possibly simplify it in any further?
Negative Words? False
```

```
Positive Words? True
Re: <url> and <url>, if you think they are better off as redirects to the suburb/town rather than substubs on the lakes with a <nowiki>
<person></nowiki> tagline, you only need to overwrite the article with a redirect (or revert to a previous version that was a redirec
t), leaving the substub in the article history. How come you speedied them before redirecting?
Negative Words? True
Positive Words? True
Sorry @klox I don't understand. Could you explain a bit more?
Negative Words? True
Positive Words? False
There cant be a general solution. What do you do when the stack has 10 entries and you need to output a number, but the last number has
nt arrived yet?
Negative Words? False
Positive Words? True
Hi, although I agree with you, please check the following <url> in process. Why can't the darn thing work, in the first place?
Negative Words? False
Positive Words? True
If the ads are script elements, does it really matter where you place them? Perhaps you can give an example?
Negative Words? True
Positive Words? True
The sources are ref'd in the article. Can you be more specific?
Negative Words? False
Positive Words? False
Further to what Stefan said, the tocloft package might be sensitive to other things you have in your preamble.  Could you post a [minim
um working example](http://meta.tex.stackexchange.com/questions/228/ive-just-been-told-i-have-to-write-a-minimal-example-what-is-that),
please?
Negative Words? True
Positive Words? True
The number of false negative examples with a top 10 informative negative word was 5 out of 10
The number of false negative examples with a top 10 informative positive words was 4 out of 10
The number of false positive examples with a top 10 informative negative words was 6 out of 10
The number of false positive examples with a top 10 informative positive words was 8 out of 10
```

In 8 out of 10 false positive examples, there was a positive word that was in the top10 most informative positive words. In 5 out of 10 false negative examples, there was a negative word that was in the top10 most informative negative words.

At the same time, both false positive examples and false negative examples also had the presence of informative positive and negative words. Two false positive examples contain the words "can't", which my tokenizer tokenizes partially into the word 'can'. This is a clear example of how preprocessing can affect the downstream prediction task. If I had included 'can't' as its own, full token, this might've helped the model distinguish between someone saying something polite containing 'can' and someone saying something impolite with 'can't' (e.g., "can't you do this?").

Another way that the features could be improved is to use larger n-grams. For instance, even if I use the same tokenizer, it could've helped the model if it saw "can" and "'t" as a bigram feature compared to "can" and "'t" as independent and uncorrelated unigram features.

Neural Network

In this section, you will build and evaluate a feedforward neural network that uses pre-trained static word embeddings (word2vec, GloVe, FastText, etc) as input. To represent the document, you can take the average word embeddings of the input sentence or choose another function. You can choose which activation function to use and other hyperparameters. You will again use 5-fold cross validation on the dataset. There is no need for this model to outperform the logistic regression model you made.

Tasks for section 2.2 Implement a feedforward neural network with static word embeddings as input.

In [ ]:
```
sentences = [nltk.word_tokenize(sentence) for sentence in x]
model = Word2Vec(sentences)
def sentence_to_avg_vector(sentence):
    words = sentence.split()
    word_vectors = [model.wv[word] for word in words if word in model.wv.key_to_index]
    if not word_vectors:
        return np.zeros(model.vector_size)
    return np.mean(word_vectors, axis=0)

polite['text_avg_embedding'] = polite['text'].apply(sentence_to_avg_vector)
```

In [ ]:
```
nn = MLPClassifier(max_iter=1000, random_state=42)

nn_x = np.stack(polite['text_avg_embedding'].values)
nn_y = polite['polite'].values

cv_nn = cross_validate(nn, nn_x, nn_y, cv=5, scoring = scoring)
```

In [ ]:
```
nn_model = pd.DataFrame(cv_nn)
nn_model['model'] = np.repeat(['nn'], 5)
all_models = pd.concat([lr_models, nn_model])
```

In the report, please provide:

Performance scores for this model. Include accuracy as well as precision, recall, and f1-score for the positive (polite) class. This can be an additional row in the table with other performance scores.

In [ ]:
```
all_models.groupby('model').mean()
```

Out[ ]:

model	fit_time	score_time	test_accuracy	test_precision	test_recall	test_f1_score
binary	0.326193	0.023488	0.701542	0.703966	0.695873	0.699767
bow	0.627263	0.022621	0.696880	0.699391	0.691004	0.695107
nn	3.998432	0.006944	0.610710	0.614305	0.616010	0.611709
tfidf	0.101053	0.021685	0.710667	0.704289	0.727091	0.715381

The tf-idf model is still the best performing model, logistic regression or otherwise.

Discuss the motivation for any choices you made as far as word embedding types, pretraining dataset, and/or how you represented the document, or if you experimented with multiple of these options.

I used word2vec because it is an easily understandable way to embed words based on their 'positive' contexts. I also estimated embeddings using the polite dataset using the word2vec algorithm because it was easiest. I then represented each sentence/documents as the average embedding of the words it contains because it was straightforward to do so. These motivations are not very virtuous and it shows in the performance of the neural network, although there are also the architectural factors to consider with regards to the performance. I did not experiment with any other embedding or representation options. However, if I were to experiment with different embeddings, I would find a pre-trained embedding obtained from a larger corpus with documents similar to the one in this dataset (code Q&A forum) or another somewhat conversational corpus. For experimenting with representations, perhaps the sum of embeddings would be a better representation than the averages.

Discuss the motivation for any choices you made as far as network architecture (number and dimensions of hidden layers) or hyperparameters (learning rate, number of epochs, etc). Note if you experimented with any of these options.

I don't know why I would choose one architecture and set of hyperparameters over another, so I used default parameters (i.e., one hidden layer with `100 neurons` and the `relu` activation function). This is where hyperparameter tuning comes in so let's try that

In [ ]:
```
param_grid = {
    'hidden_layer_sizes': [(50,50,50), (50,100,50), (10,10)],
    'activation': ['tanh', 'relu'],
    'solver': ['sgd', 'adam'],
    'alpha': [0.0001, .001, 0.01, 0.05],
    'learning_rate': ['constant','adaptive'],
}

nn_2 = MLPClassifier(max_iter=300, random_state=42)

nn_grid = GridSearchCV(nn_2, param_grid, cv=5, n_jobs=-1)
```

```
# Fit the model to the data
nn_grid.fit(nn_x, nn_y)  # replace X and y with your data
```

Out[ ]:

```
GridSearchCV
estimator: MLPClassifier
MLPClassifier
```

In [ ]:

```
best_nn_params = nn_grid.best_params_
print("Best parameters:", best_nn_params)

best_nn = MLPClassifier(**best_nn_params, max_iter=300)
best_nn.fit(nn_x, nn_y)  # replace X and y with your data
```

```
Best parameters: {'activation': 'relu', 'alpha': 0.0001, 'hidden_layer_sizes': (50, 50, 50), 'learning_rate': 'constant', 'solver': 'ad
am'}
```

Out[ ]:

```
MLPClassifier
MLPClassifier(hidden_layer_sizes=(50, 50, 50), max_iter=300)
```

In [ ]:

```
pred_nn_y = best_nn.predict(nn_x)
cm = confusion_matrix(nn_y, pred_nn_y)

print(cm)
```

```
[[1769  697]
 [1132 1334]]
```

Even after some minor hyperparameter searching, the neural network still performs poorly with the embeddings I used. This goes to show that the quality of input matters just as much as the model predicting the output. My best guess to improve the input quality is to use a higher quality pre-trained embedding from online, as opposed to a "word2vectorization" of the words in the politeness dataset.