Ordinal regression is a classification method for categories on an ordinal scale -- e.g. [1, 2, 3, 4, 5] or [G, PG, PG-13, R]. This notebook implements ordinal regression using the method of Frank and Hal 2001, which transforms a k-multiclass classifier into k-1 binary classifiers (each of which predicts whether a data point is above a threshold in the ordinal scale -- e.g., whether a movie is "higher" than PG). This method can be used with any binary classification method that outputs probabilities; here L2-regularizaed binary logistic regression is used.

This notebook trains a model (on `train.txt`), optimizes L2 regularization strength on `dev.txt`, and evaluates performance on `test.txt`. Reports test accuracy with 95% confidence intervals.

```
from scipy import sparse
from sklearn import linear_model
from collections import Counter
import numpy as np
import operator
import nltk
import math
from scipy.stats import norm
import pandas as pd
```

```
!python -m nltk.downloader punkt
```

```
/usr/lib/python3.10/runpy.py:126: RuntimeWarning: 'nltk.downloader' found in sys.modules after import of package 'nltk', but
  warn(RuntimeWarning(msg))
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
```

```
def load_ordinal_data(filename, ordering):
    X = []
    Y = []
    orig_Y = []
    for ordinal in ordering:
        Y.append([])

    with open(filename, encoding="utf-8") as file:
        for line in file:
            cols = line.split("\t")
            idd = cols[0]
            label = cols[2].lstrip().rstrip()
            text = cols[3]

            X.append(text)

            index=ordering.index(label)
            # print(label)
            for i in range(len(ordering)):
                if index > i:
                    Y[i].append(1)
                else:
                    Y[i].append(0)
            orig_Y.append(label)


    return X, Y, orig_Y
```

```
class OrdinalClassifier:

    def __init__(self, ordinal_values, feature_method, trainX, trainY, devX, devY, testX, testY, orig_trainY, orig_devY, orig_te
        self.ordinal_values=ordinal_values
        self.feature_vocab = {}
        self.feature_method = feature_method
        self.min_feature_count=2
        self.log_regs = [None]* (len(self.ordinal_values)-1)

        self.trainY=trainY
        self.devY=devY
        self.testY=testY

        self.orig_trainY=orig_trainY
        self.orig_devY=orig_devY
        self.orig_testY=orig_testY

        self.trainX = self.process(trainX, training=True)
        self.devX = self.process(devX, training=False)
        self.testX = self.process(testX, training=False)

    # Featurize entire dataset
    def featurize(self, data):
        featurized_data = []
        for text in data:
            feats = self.feature_method(text)
            featurized_data.append(feats)
        return featurized_data

    # Read dataset and returned featurized representation as sparse matrix + label array
    def process(self, X_data, training = False):

        data = self.featurize(X_data)

        if training:
            fid = 0
            feature_doc_count = Counter()
            for feats in data:
                for feat in feats:
                    feature_doc_count[feat]+= 1

            for feat in feature_doc_count:
                if feature_doc_count[feat] >= self.min_feature_count:
                    self.feature_vocab[feat] = fid
                    fid += 1

        F = len(self.feature_vocab)
        D = len(data)
        X = sparse.dok_matrix((D, F))
        for idx, feats in enumerate(data):
            for feat in feats:
                if feat in self.feature_vocab:
                    X[idx, self.feature_vocab[feat]] = feats[feat]

        return X


    def train(self):
        (D,F) = self.trainX.shape


        for idx, ordinal_value in enumerate(self.ordinal_values[:-1]):
            best_dev_accuracy=0
            best_model=None
            for C in [0.1, 1, 10, 100]:

                log_reg = linear_model.LogisticRegression(C = C, max_iter=1000)
                log_reg.fit(self.trainX, self.trainY[idx])
                development_accuracy = log_reg.score(self.devX, self.devY[idx])
                if development_accuracy > best_dev_accuracy:
                    best_dev_accuracy=development_accuracy
                    best_model=log_reg


            self.log_regs[idx]=best_model

    def test(self):
        cor=tot=0
        counts=Counter()
        preds=[None]*(len(self.ordinal_values)-1)
        for idx, ordinal_value in enumerate(self.ordinal_values[:-1]):
            preds[idx]=self.log_regs[idx].predict_proba(self.testX)[:,1]

        preds=np.array(preds)
        test_prediction =[]

        for data_point in range(len(preds[0])):


            ordinal_preds=np.zeros(len(self.ordinal_values))
            for ordinal in range(len(self.ordinal_values)-1):
                if ordinal == 0:
                    ordinal_preds[ordinal]=1-preds[ordinal][data_point]
                else:
                    ordinal_preds[ordinal]=preds[ordinal-1][data_point]-preds[ordinal][data_point]

            ordinal_preds[len(self.ordinal_values)-1]=preds[len(preds)-1][data_point]

            prediction=np.argmax(ordinal_preds)
            counts[prediction]+=1
            if prediction == self.ordinal_values.index(self.orig_testY[data_point]):
                cor+=1
            tot+=1
            test_prediction.append(prediction)

        return cor/tot, test_prediction


def binary_bow_featurize(text):
    feats = {}
    words = nltk.word_tokenize(text)

    for word in words:
        word=word.lower()
        feats[word]=1

    return feats


def confidence_intervals(accuracy, n, significance_level):
    critical_value=(1-significance_level)/2
    z_alpha=-1*norm.ppf(critical_value)
    se=math.sqrt((accuracy*(1-accuracy))/n)
    return accuracy-(se*z_alpha), accuracy+(se*z_alpha)


from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt
def print_confusion(y_pred, y_val):
    fig, ax = plt.subplots(figsize=(10,10))

    # Compute the confusion matrix
    cm = confusion_matrix(y_val, y_pred)

    # Define the display labels in the desired order
    display_labels = ['average', 'excellent', 'good', 'poor']

    # Use ConfusionMatrixDisplay to plot with customized display labels
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=display_labels)
    disp.plot(ax=ax, xticks_rotation="vertical", values_format="d")
    plt.title('Confusion Matrix')

    plt.show()



def run(trainingFile, devFile, testFile, ordinal_values):


    trainX, trainY, orig_trainY=load_ordinal_data(trainingFile, ordinal_values)
    devX, devY, orig_devY=load_ordinal_data(devFile, ordinal_values)
    testX, testY, orig_testY=load_ordinal_data(testFile, ordinal_values)
    print(len(orig_testY))

    simple_classifier = OrdinalClassifier(ordinal_values, binary_bow_featurize, trainX, trainY, devX, devY, testX, testY, orig_tr
    simple_classifier.train()
    accuracy, test_prediction=simple_classifier.test()

    lower, upper=confidence_intervals(accuracy, len(testY[0]), .95)
    print("Test accuracy for best dev model: %.3f, 95%% CIs: [%.3f %.3f]\n" % (accuracy, lower, upper))

    mapping = {0: 'poor', 1: 'average', 2: 'good', 3: 'excellent'}
    y_pred_label = [mapping[numerical] for numerical in test_prediction]
    print_confusion(y_pred_labels, orig_testY)
```

```
from google.colab import drive
drive.mount('/content/drive')

%cd "/content/drive/MyDrive/Annotation project"
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=Tr
/content/drive/MyDrive/Annotation project
```

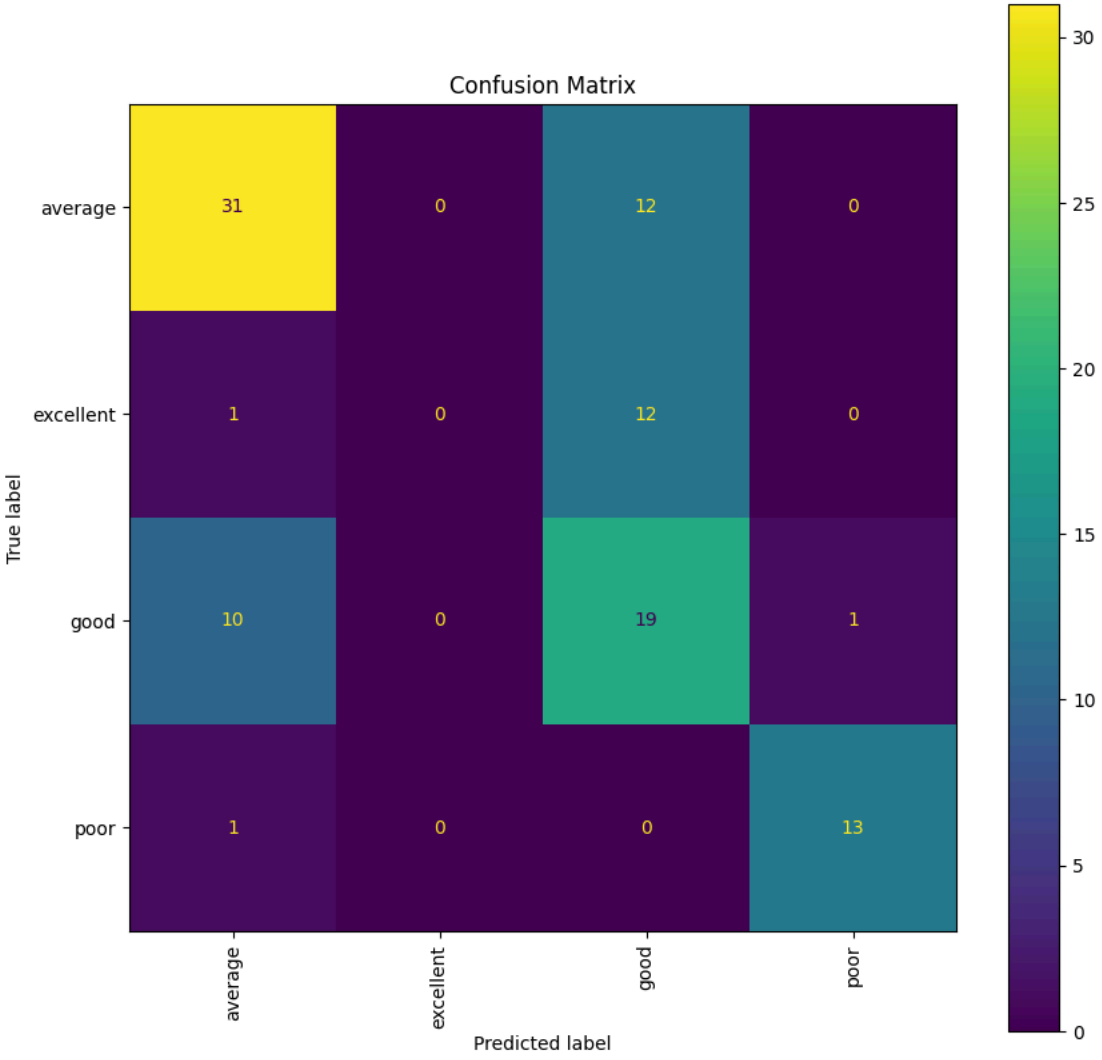
```
trainingFile = "train.txt"
devFile = "dev.txt"
testFile = "test.txt"

# ordinal values must be in order *as strings* from smallest to largest, e.g.:
# ordinal_values=["G", "PG", "PG-13", "R"]

ordinal_values=["poor", "average", "good", "excellent"]

run(trainingFile, devFile, testFile, ordinal_values)
```

```
100
Test accuracy for best dev model: 0.630, 95% CIs: [0.535 0.725]
```


Confusion Matrix
True label
average
excellent
good
poor
Predicted label
average
excellent
good
poor