```
In [29]: ## we will now load our data
In [169...
         import random
          ## create set values
         class Sentiment:
             NEGATIVE = "NEGATIVE"
              NEUTRAL = "NEUTRAL
              POSITIVE = "POSITIVE"
          class Review:
             def __init__(self, text, score):
                  self.text = text
                  self.score = score
                  self.sentiment = self.get_sentiment()
              def get_sentiment(self):
                  if self.score <= 2:</pre>
                      return Sentiment.NEGATIVE
                  elif self.score == 3:
                     return Sentiment.NEUTRAL
                  else: #Score of 4 or 5
                      return Sentiment.POSITIVE
          class ReviewContainer:
             def init__(self, reviews):
                  self.reviews = reviews
             def get text(self):
                  return [x.text for x in self.reviews]
              def get sentiment(self):
                  return [x.sentiment for x in self.reviews]
              def evenly_distribute(self):
                  negative = list(filter(lambda x: x.sentiment == Sentiment.NEGATIVE, self.reviews))
                  positive = list(filter(lambda x: x.sentiment == Sentiment.POSITIVE, self.reviews))
                  positive_shrunk = positive[:len(negative)]
                  self.reviews = negative + positive_shrunk
                  random.shuffle(self.reviews)
In [178... ## We are building this data model to extract the reviews and the overall rating
          import json
          file name='./Books small 10000.json'
          reviews =[]
         with open(file_name) as f:
              for line in f:
                  review=json.loads(line)
                  reviews.append(Review(review['reviewText'], review['overall']))
          reviews[5].sentiment
Out[170]: 'POSITIVE'
In [191… ## Now we will divide our data into training data to train the Algo and Test data to see if it accurately
         ##depicts the Sentiment Data Prep
          from sklearn.model_selection import train_test_split
         Training, Test =train test split(reviews, test size=0.33, random state=42)
          train_container=ReviewContainer(Training)
         test container=ReviewContainer(Test)
          cont.evenly_distribute()
          len(cont.reviews)
         It was okay. I have read all the Duggars books and they sorta overlap each other and it's like the same book! N
         ot thrilled with ALOT of there views and actually got the book to find out more...let's just say I seen all I n
         eed to. Not a big fan.
         436
         436
Out[191]: 872
In [172... print(Training[0].sentiment)
         POSITIVE
In [192... train_container.evenly_distribute()
         train_x = train_container.get_text()
          train y = train container.get sentiment()
          test_container.evenly_distribute()
          test x = test_container.get_text()
          test y = test container.get sentiment()
```

```
print(train y.count(Sentiment.POSITIVE))
                              print(train_y.count(Sentiment.NEGATIVE))
                              436
                              #Now we will use a method called bag of words method to extract features from text documents.
 In [224...
                               #These features can be used for training machine learning algorithms.
                              from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
                              vectorizer = TfidfVectorizer ()
                               train x vector= vectorizer.fit transform(train x)
                              print(train x[0])
                               print(train_x_vector[0])
                               test x vectors = vectorizer.transform(test x)
                              Colton - Annoying and too ControllingMelanie - submissive to his kisses and his lovemaking. Hated the book. Don'
                              t buy
                                     (0, 1177)
                                                                                 0.21907036353461787
                                     (0, 2383)
                                                                                 0.16289068338656323
                                     (0, 991)
                                                                                 0.07581628283131062
                                     (0, 7929)
                                                                                 0.061685676591184666
                                     (0, 3660)
                                                                                 0.2876533689028302
                                      (0, 4787)
                                                                                 0.36526329916498107
                                     (0, 4486)
                                                                                 0.36526329916498107
                                     (0, 3793)
                                                                                 0.2913499890150326
                                                                                 0.0670584054770816
                                     (0, 8052)
                                      (0, 7610)
                                                                                 0.3443414245118173
                                      (0, 1732)
                                                                                 0.36526329916498107
                                     (0, 8079)
                                                                                 0.15107091897051994
                                      (0, 423)
                                                                                 0.1305119101535069
                                                                                 0.25796475629751126
                                     (0, 447)
                                     (0, 1550)
                                                                                 0.3443414245118173
 In [225...
                              ##Classfication this is Linear SVM to predict the sentiment of some data
                              from sklearn import svm
                               clf svm =svm.SVC(kernel='linear')
                               clf_svm.fit(train_x_vector,train_y)
                               test x[0]
                              clf_svm.predict(test_x_vectors[0])
Out[225]: array(['NEGATIVE'], dtype='<U8')
                              Decison Tree
 In [226... from sklearn.tree import DecisionTreeClassifier
                               clf_dec =DecisionTreeClassifier()
                               clf_dec.fit(train_x_vector,train_y)
                              clf_dec.predict(test_x_vectors[0])
Out[226]: array(['NEGATIVE'], dtype='<U8')
                              ## Logistic Regression
 In [227...
                              from sklearn.linear model import LogisticRegression
                               clf_log =LogisticRegression()
                               clf log.fit(train x vector,train y)
                              clf_log.predict(test_x_vectors[0])
Out[227]: array(['NEGATIVE'], dtype='<U8')
                              Evaluation
 In [228... ## Mean Accuracy
                              print(clf svm.score(test x vectors,test y))
                              print(clf dec.score(test x vectors,test y))
                              print(clf_log.score(test_x_vectors,test_y))
                              0.8076923076923077
                              0.6634615384615384
                              0.8052884615384616
 In [229... ## F1 scores to see if our model predicts the values based of sentiment
                              from sklearn.metrics import f1 score
                              print(f1\_score(test\_y, clf\_svm.predict(test\_x\_vectors), average \verb=None, labels=[Sentiment.POSITIVE, Sentiment.NEUTRA]) and the substitution of t
                               \#\#print(f1\_score(test\_y,clf\_dec.predict(test\_x\_vectors),average=None, labels=[Sentiment.POSITIVE,Sentiment.NEUT]
                              \#\#print(f1\_score(test\_y, clf\_log.predict(test\_x\_vectors), average=None, \ labels=[Sentiment.POSITIVE, Sentiment.NEUT] + (f1\_score(test\_y, clf\_log.predict(test\_x\_vectors), average=None, \ labels=[Sentiment.POSITIVE, Sentiment.NEUT] + (f1\_score(test\_x\_vectors), \ labels=[Sentiment.POSITIVE, Sentiment.NEUT] + (f1\_score(test\_x\_vectors), \ labels=[Sentiment.POSITIVE, Sentiment.NEUT] + (f1\_score(test\_x\_vectors), \ labels=[Sentiment.POSITIVE, Sentiment.POSITIVE, Sentiment.NEUT] + (f1\_score(test\_x\_vectors), \ labels=[Sentiment.POSITIVE, Sent
                              [0.80582524 0.
                                                                                                       0.80952381]
                              C: \ Users \\ cold\\ an a conda \\ lib\\ site-packages\\ sklearn\\ metrics\\ \_classification.py: 1580: \ Undefined \\ Metric \\ Warning: F-size \\ F-size \\ Long \\ Size \\ S
                              core is ill-defined and being set to 0.0 in labels with no true nor predicted samples. Use `zero division` para
                              meter to control this behavior.
                                _warn_prf(average, "true nor predicted", "F-score is", len(true_sum))
 In [230... print(test_y.count(Sentiment.POSITIVE))
                              print(test_y.count(Sentiment.NEGATIVE))
```

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208
208
```

```
### Now we will create and run some test data to see how well our machine learning model correctly predicts the
   In [232...
             ## of these reviews
             test_set=['It was okay. I have read all the Duggars books and they sorta overlap each other and its like the sa
             test_set = ['very fun', "bad book do not buy", 'horrible waste of time']
test_set3 =['Very Bad','I Loved it','it was okay', 'it needs better story writing','Ada Sucks','I was so good']
             new_test = vectorizer.transform(test_set)
             new test2 = vectorizer.transform(test set2)
             new_test3 = vectorizer.transform(test_set3)
             print(clf_svm.predict(new_test))
             print(clf_svm.predict(new_test2))
             print(clf_svm.predict(new_test3))
             ['POSITIVE' 'NEGATIVE' 'NEGATIVE']
             ['NEGATIVE']
             ['NEGATIVE' 'POSITIVE' 'NEGATIVE' 'NEGATIVE' 'POSITIVE' 'POSITIVE']
   In [237... ## now we will try to improve the machine learning model one more time by making the model determine which para
             ## is best for the model at that moment
             from sklearn.model_selection import GridSearchCV
             parameters = {'kernel':('linear', 'rbf'), 'C': (1,4,8,16,32)}
             svc = svm.SVC()
             clf = GridSearchCV(svc,parameters,cv=5)
             clf.fit(train x vector, train y)
  Out[237]: GridSearchCV(cv=5, estimator=SVC(),
                            param grid={'C': (1, 4, 8, 16, 32), 'kernel': ('linear', 'rbf')})
   In [252... print(clf.score(test_x_vectors, test_y))
             0.8197115384615384
   In [274... print(clf_svm.predict(test_x_vectors[4]))
             ['POSITIVE']
Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js
```