Twitter Airlines Analysis

Data Preparation

Data is downloaded from

https://www.kaggle.com/crowdflower/twitter-airline-sentiment

A sentiment analysis job about the problems of each major U.S. airline. Twitter data was scraped from February of 2015 and contributors were asked to first classify positive, negative, and neutral tweets, followed by categorizing negative reasons (such as "late flight" or "rude service").

It contains the following fields:

- 1. tweet_id
- 2. airline_sentiment
- 3. airline_sentiment_confidence
- 4. negativereason
- 5. negativereason_confidence
- 6. airline
- 7. airline_sentiment_gold
- 8. name
- 9. negativereason_gold
- 10. retweet count
- 11. text
- 12. tweet_coord
- 13. tweet_created
- 14. tweet_location
- 15. user_timezone

```
Firstly, we load the data.
          val df = spark.read.
                             format("csv")
                             .option("header","true")
                             .option("inferSchema","true")
             .load("/home/harsh/Desktop/twitter airlines/Tweets.csv")
Selecting only required fields:
val raw =
df.select($"airline_sentiment".alias("label"),$"text".alias("tweet"))
Removing null values:
val nr = raw.na.drop()
Converting categorical features to numerical:
val indexer = new StringIndexer()
                .setInputCol("label")
                 .setOutputCol("labelIndex")
val indexed = indexer.fit(nr).transform(nr)
Making a user defined function for pre-processing (removing special
characters, emojis, website links):
def lo(d:String) :String = { d.replace("\"","").toLowerCase()
   .replaceAll("\n", "")
   .replaceAll("rt\\s+", "")
   .replaceAll("\s+@\w+", "")
   .replaceAll("@\w+", "")
   .replaceAll("\s+\#\w+", "")
   .replaceAll("#\\w+", "")
```

```
.replaceAll("(?:https?|http?)://[\\w/%.-]+", "")
   . replace All ("(?:https?|http?)://[\w/\%.-]+\s+", "")
   .replaceAll("(?:https?|http?)//[\w/\%.-]+\s+", "")
   .replaceAll("(?:https?|http?)//[\\w/%.-]+", "")
   .replaceAll("[^\u0000-\uFFFF]","")
   .replaceAll("(\u00a9|\u00ae|[\u2000-\u3300]|\ud83c[\ud000-\u000-\u000]]
.trim()
}
val lco = udf(lo _)
Pre-processing data using udf:
val f = indexed.select($"label", $"labelIndex",
lco($"tweet").alias("tweet"))
After loading and pre-processing, we need to convert tweets into
feature vectors.
val tokenizer = new
Tokenizer().setInputCol("tweet").setOutputCol("words")
val wordsData = tokenizer.transform(f)
val hashingTF = new HashingTF()
.setInputCol("words").setOutputCol("rawFeatures").setNumFeat
ures(10000)
```

val featurizedData = hashingTF.transform(wordsData)

```
val idf = new
IDF().setInputCol("rawFeatures").setOutputCol("features")
val idfModel = idf.fit(featurizedData)
```

val rescaledData = idfModel.transform(featurizedData)

Then we split the transformed data into two subsets i.e. training and test(ratio 0.8:0.2)

```
val Array(training, test) =
rescaledData.randomSplit(Array[Double](0.8,0.2))
```

Model Selection and Model Tuning

We tried Logistic Regression and MultiLayer Perceptron for classification.

val Ir = new LogisticRegression()

```
.setMaxIter(10)
.setRegParam(0.01)
.setLabelCol("labelIndex")
.setElasticNetParam(0.5)
```

```
val layers = Array[Int](20,15, 10, 3)
val trainer = new MultilayerPerceptronClassifier()
.setLayers(layers)
```

.setLabelCol("labelIndex")

```
val model = Ir.fit(training)
val model2 = trainer.fit(training)
```

val Ir_predictions = model.transform(test)

val mlp_predictions = model2.transform(test)

Conclusion

We evaluated accuracy for Logistic Regression and MultiLayer Perceptron using MultiClassClassification Evaluator and got 77 % accuracy for Logistic Regression and 74 % for MultiLayer Perceptron.

val evaluator = new MulticlassClassificationEvaluator()

.setLabelCol("label")

.setPredictionCol("prediction")

.setMetricName("accuracy")

val Ir_accuracy = evaluator.evaluate(Ir_predictions)

val mlp_accuracy = evaluator.evaluate(mlp_predictions)