Big Data Analytics - Individual Project

By Muhammad Haris Choudhary

Movie Ratings and Recommendations

Pre-processing

Requirements

- Name -> length
- Separate Genre
- Remove Unknowns from episodes
- Changing Length to int
- Moving each item back to place
- Lastly, scaling

Procedure

- 1. Used Pandas, numpy
- 2. A function called preProcess()
- 3. Returns 2 ndarrays
- 4. X and Y values depending on the file name.

Task 1

Predict Ratings for each new telefilm

Procedure

Libraries

Numpy

Tensorflow

Keras

Plans

• Linear Regression

• Polynomial Regression

Neural Network

Tensorflow

```
class NeuralNetwork(object):
                                                                                                  def __init__(self, x, y):
ral(X, Y, X_pred):
                                                                                                     #parameters
                                                                                                     np.random.seed(0)
el = keras.Sequential([
                                                                                                     self.input = x
                                                                                                     self.size = x.shape[1]
keras.layers.Dense(7, activation=tf.nn.relu),
                                                                                                     self.w1 = 0.1 * np.random.rand(int(x.shape[1]), 89)
keras.layers.Dense(64, activation=tf.nn.relu),
                                                                                                     self.w2 = 0.1 * np.random.rand(89, 1)
keras.layers.Dense(64, activation=tf.nn.relu),
                                                                                                               = v
keras.layers.Dense(1)
                                                                                                     self.output = np.zeros(v.shape)
                                                                                                  def feedForward(self):
                                                                                                     #forward propogation through the network
el.compile(optimizer='adam',
                                                                                                     self.11 = np.dot(self.input, self.w1)
        loss='mean_squared_error',
                                                                                                     self.layer1 = sigmoid(self.l1) #Layer 1
        metrics=tf.keras.metrics.RootMeanSquaredError())
                                                                                                     self.output = sigmoid(np.dot(self.layer1, self.w2)) #Output
el.fit(X.astype('float32'), Y.astype('float32'), epochs=1000, verbose=0)
                                                                                                  def backprop(self):
                                                                                                     self.output_error = self.y - self.output # error in output
d_y = model.predict(X_pred.astype('float32'))
                                                                                                     self.output_delta = self.output_error * sigmoid(self.output, deriv=True)
                                                                                                     self.z2_error = self.output_delta.dot(self.w2.T) #z2 error; how much our hidden layer w
urn pred y
                                                                                                                                                                    ng derivative o
                                                        def Poly():
                                                                                                                                                                    -> hidden) weig
                                                             X, y = preprocess.preProcess()
                                                             y = np.reshape(y, (X.shape[0],1))
                                                             alpha = 0
                                                             deg = X.shape[1]
                                                             model = Ridge(alpha=alpha, solver='auto', random state = 42)
                                                             model = Pipeline([
                                                                      ("poly_features", PolynomialFeatures(degree=deg, include_bias=True)),
                                                                      ("std scaler", StandardScaler()),
       Results
                                                                      ("regul reg", model),
                                                                 1)
```

model.fit(X, y)

#y pred = model.predict(x test)

Task 2

Recommender System

Procedure

Libraries

pyspark

Plans

• Content based

Not as effective

• Collaborative-Filtering

Sufficient data

```
#Reading from the file
ratings_df = spark.read.csv("Rating.csv", header=True, inferSchema=True)
ratings_df = ratings_df.where("rating != -1")
#initialzing recommender
recommender = ALS(maxIter=25, regParam=0.1, userCol="user_id",
                      itemCol = "teleplay_id", ratingCol = "rating",
                      coldStartStrategy = "drop")
train, test = ratings_df.randomSplit([0.9, 0.1])
trained = recommender.fit(train)
prediction = trained.transform(test)
prediction.show()
# Create a user for recommending
user_input = ratings_df.select("user_id").where(col("user_id") == 53698)
user = trained.recommendForUserSubset(user_input, 100000)
user = user.withColumn("rec exp", explode("recommendations")).select('user id',
                        col("rec_exp.teleplay_id"),
                        col("rec exp.rating"))
user.show(10, False)
```

5214	148	6	6.37717
51013	148	6	6.9932
73135	148	3	5.39389
59186	148	6	7.344489
33175	148	8	6.96188
66105	148	5	6.3186
66563	148	7	6.281896
59311	148	7	7.5766
47582	148	9	7.250516
58646	148	8	6.72172
50558	148	5	6.175328
15629	148	4	6.046019
50766	148	6	6.85038
53640	148	9	7.206413
10744	148	8	6.073122
30587	148	6	7.160832
58570	148	4	6.84379
59172	148	8	7.87209
47935	463	10	8.50388
58944	463	8	7.86721

Results