EE542 PROJ DIE I





```
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 import java.io.File
 import scala.io.Source
 import org.apache.log4j.Logger
 import org.apache.log4j.Level
 import org.apache.spark.SparkConf
 import org.apache.spark.SparkContext
 import org.apache.spark.SparkContext._
 import org.apache.spark.rdd._
 import org.apache.spark.mllib.recommendation.{ALS, Rating, MatrixFactorizationModel}
import java.io.File
import scala.io.Source
import org.apache.log4j.Logger
import org.apache.log4j.Level
import org.apache.spark.SparkConf
import org.apache.spark.SparkContext
import org.apache.spark.SparkContext._
import org.apache.spark.rdd._
import org.apache.spark.mllib.recommendation.{ALS, Rating, MatrixFactorizationModel}
Took 2 seconds.
```

```
val movieLensHomeDir = "s3://ee542proj/input/"
                                                                         FINISHED ▷ 牂 圓 ۞
 val movies = sc.textFile(movieLensHomeDir + "movies.dat").map { line =>
   val fields = line.split("::")
   // format: (movieId, movieName)
   (fields(0).toInt, fields(1))
 }.collect.toMap
 val ratings = sc.textFile(movieLensHomeDir + "ratings.dat").map { line =>
   val fields = line.split("::")
   // format: (timestamp % 10, Rating(userId, movieId, rating))
   (fields(3).toLong % 10, Rating(fields(0).toInt, fields(1).toInt, fields(2).toDouble))
movieLensHomeDir: String = s3://ee542proj/
movies: scala.collection.immutable.Map[Int,String] = Map(2163 -> Attack of the Killer Tomat
oes! (1980), 8607 -> Tokyo Godfathers (2003), 645 -> Nelly & Monsieur Arnaud (1995), 42900
-> Cul-de-sac (1966), 892 -> Twelfth Night (1996), 69 -> Friday (1995), 53550 -> Rescue Daw
n (2006), 37830 -> Final Fantasy VII: Advent Children (2004), 5385 -> Last Waltz, The (1978
), 5810 -> 8 Mile (2002), 7375 -> Prince & Me, The (2004), 5659 -> Rocking Horse Winner, Th
e (1950), 2199 -> Phoenix (1998), 8062 -> Dahmer (2002), 3021 -> Funhouse, The (1981), 8536
 -> Intended, The (2002), 5437 -> Manhattan Project, The (1986), 1322 -> Amityville 1992: I
t's About Time (1992), 1665 -> Bean (1997), 5509 -> Biggie and Tupac (2002), 5686 -> Russia
n Ark (Russkiy Kovcheg) (2002), 1036 -> Die Hard (1988), 2822 -> Medi...ratings: org.apache
```

```
.spark.rdd.RDD[(Long, org.apache.spark.mllib.recommendation.Rating)] = MapPartitionsRDD[11]
at map at <console>:52
Took 12 seconds. (outdated)
```

```
val training = ratings.filter(x \Rightarrow x._1 < 6)
                                                                           FINISHED ▷ 光 圓 ۞
   .values
   .cache()
 val validation = ratings.filter(x => x._1 >= 6 \& x._1 < 8)
   .values
   .cache()
 val test = ratings.filter(x \Rightarrow x._1 \Rightarrow 8).values.cache()
 val numTraining = training.count()
 val numValidation = validation.count()
 val numTest = test.count()
println("Training: " + numTraining + ", validation: " + numValidation + ", test: " +
training: org.apache.spark.rdd.RDD[org.apache.spark.mllib.recommendation.Rating] = MapParti
tionsRDD[21] at values at <console>:54
validation: org.apache.spark.rdd.RDD[org.apache.spark.mllib.recommendation.Rating] = MapPar
titionsRDD[23] at values at <console>:54
test: org.apache.spark.rdd.RDD[org.apache.spark.mllib.recommendation.Rating] = MapPartition
sRDD[25] at values at <console>:53
numTraining: Long = 6002473
numValidation: Lona = 1999675
numTest: Long = 1997906
Training: 6002473, validation: 1999675, test: 1997906
Took 23 seconds.
```

```
/** Compute RMSE (Root Mean Squared Error). */

def computeRmse(model: MatrixFactorizationModel, data: RDD[Rating], n: Long): Double = {
   val predictions: RDD[Rating] = model.predict(data.map(x => (x.user, x.product)))
   val predictionsAndRatings = predictions.map(x => ((x.user, x.product), x.rating))
   .join(data.map(x => ((x.user, x.product), x.rating))).values
   math.sqrt(predictionsAndRatings.map(x => (x._1 - x._2) * (x._1 - x._2)).reduce(_ + _)
   / n)

computeRmse: (model: org.apache.spark.mllib.recommendation.MatrixFactorizationModel, data:
```

```
val ranks = List(8, 12)
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 val lambdas = List(0.1, 10.0)
 val numIters = List(10, 20)
 var bestModel: Option[MatrixFactorizationModel] = None
 var bestValidationRmse = Double.MaxValue
 var bestRank = 0
 var bestLambda = -1.0
 var bestNumIter = -1
 for (rank <- ranks; lambda <- lambdas; numIter <- numIters) {</pre>
   val model = ALS.train(training, rank, numIter, lambda)
   val validationRmse = computeRmse(model, validation, numValidation)
   println("RMSE (validation) = " + validationRmse + " for the model trained with rank = "
     + \text{ rank } + \text{", lambda} = \text{" } + \text{ lambda} + \text{", and numIter} = \text{" } + \text{ numIter} + \text{"."})
   if (validationRmse < bestValidationRmse) {</pre>
     bestModel = Some(model)
     bestValidationRmse = validationRmse
     bestRank = rank
     bestLambda = lambda
     bestNumIter = numIter
   }
ranks: List[Int] = List(8, 12)
lambdas: List[Double] = List(0.1, 10.0)
numIters: List[Int] = List(10, 20)
bestModel: Option[org.apache.spark.mllib.recommendation.MatrixFactorizationModel] = None
bestValidationRmse: Double = 1.7976931348623157E308
bestRank: Int = 0
bestLambda: Double = -1.0
bestNumIter: Int = -1
RMSE (validation) = 0.8236100381645034 for the model trained with rank = 8, lambda = 0.1, a
nd numIter = 10.
RMSE (validation) = 0.8189231812579648 for the model trained with rank = 8, lambda = 0.1, a
nd numIter = 20.
RMSE (validation) = 3.667982949261605 for the model trained with rank = 8, lambda = 10.0, a
nd numIter = 10.
RMSE (validation) = 3.667982949261605 for the model trained with rank = 8, lambda = 10.0, a
nd numIter = 20.
RMSE (validation) = 0.8192026516236711 for the model trained with rank = 12, lambda = 0.1,
and numIter = 10.
RMSE (validation) = 0.8154603688946302 for the model trained with rank = 12, lambda = 0.1,
and numIter = 20.
RMSE (validation) = 3.667982949261605 for the model trained with rank = 12, lambda = 10.0,
and numIter = 10.
RMSE (validation) = 3.667982949261605 for the model trained with rank = 12, lambda = 10.0,
and numIter = 20.
Took 459 seconds.
```

```
val testRmse = computeRmse(bestModel.get, test, numTest)

testRmse: Double = 0.8155943302828965
The best model was trained with rank = 12 and lambda = 0.1, and numIter = 20, and its RMSE on the test set is 0.8155943302828965.
Took 16 seconds.
```

```
// create a naive baseline and compare it with the best model ring and value meanRating = training.union(validation).map(_.rating).mean value baselineRmse = math.sqrt(test.map(x => (meanRating - x.rating) * (meanRating - x.rating)).mean) value improvement = (baselineRmse - testRmse) / baselineRmse * 100 println("The best model improves the baseline by " + "%1.2f".format(improvement) + "%.") meanRating: Double = 3.5123623057208624 baselineRmse: Double = 1.0597828264660583 improvement: Double = 23.041371315426044 The best model improves the baseline by 23.04%. Took 3 seconds.
```

```
val candidates = sc.parallelize(movies.keys.toSeq)
                                                                          FINISHED ▷ 光 圓 贷
 val recommendations = bestModel.get
   .predict(candidates.map((100, _)))
   .collect()
   .sortBy(- _.rating)
   .take(10)
 var i = 1
 println("Movies recommended for you:")
 recommendations.foreach { r \Rightarrow
   println("%2d".format(i) + ": " + movies(r.product))
   i += 1
candidates: org.apache.spark.rdd.RDD[Int] = ParallelCollectionRDD[2611] at parallelize at <
console>:53
recommendations: Array[org.apache.spark.mllib.recommendation.Rating] = Array(Rating(100,609
83,4.321957638468641), Rating(100,61742,3.802899742530066), Rating(100,42783,3.748203027639
5695), Rating(100,53883,3.729625669769619), Rating(100,32090,3.6831572695067334), Rating(10
0,60291,3.5688352736060587), Rating(100,296,3.526813877388885), Rating(100,64280,3.52117897
37280452), Rating(100,858,3.5161860620303176), Rating(100,1221,3.5152962996050747))
i: Int = 1
Movies recommended for you:
 1: Eve and the Fire Horse (2005)
 2: Maradona by Kusturica (2008)
 3: Shadows of Forgotten Ancestors (1964)
 4: Power of Nightmares: The Rise of the Politics of Fear, The (2004)
 5: Low Life, The (1995)
 6: Gonzo: The Life and Work of Dr. Hunter S. Thompson (2008)
 7: Pulp Fiction (1994)
 8: Hospital (1970)
 9: Godfather, The (1972)
```

```
10: Godfather: Part II, The (1974)
Took 3 seconds.
```

Comedy Movies recommended for you:

1: Pulp Fiction (1994)

```
val moviesWithGenres = sc.textFile(movieLensHomeDir + "movies.dat").map finisimeD=≥ 岽 国 墩
   val fields = line.split("::")
   // format: (movieId, movieName, genre information)
   (fields(0).toInt, fields(2))
}.collect.toMap
moviesWithGenres: scala.collection.immutable.Map[Int,String] = Map(2163 -> ComedylHorror, 8
607 -> Adventure|Animation|Drama, 645 -> Drama, 42900 -> Comedy|Crime|Drama|Thriller, 892 -
> Comedy|Drama|Romance, 69 -> Comedy, 53550 -> Action|Adventure|Drama|War, 37830 -> Action|
Adventure | Animation | Fantasy | Sci-Fi, 5385 -> Documentary, 5810 -> Drama, 7375 -> Comedy | Roma
nce, 5659 -> DramalHorror, 2199 -> CrimelDrama, 8062 -> DramalHorrorlThriller, 3021 -> Horr
or, 8536 -> Drama|Thriller, 5437 -> Comedy|Thriller, 1322 -> Horror, 1665 -> Comedy, 5509 -
> Documentary, 5686 -> DramalFantasylWar, 1036 -> Action|CrimelThriller, 2822 -> Adventure|
Romance, 7304 -> Animation|Comedy|Fantasy|Musical, 54999 -> Action|Adventure|Thriller, 2630
 -> Drama, 6085 -> Comedy|Drama, 3873 -> Comedy|Western, 4188 -> Chil...
Took 1 seconds.
 val comedyMovies = moviesWithGenres.filter(_._2.matches(".*Comedy.*")). kennshed D 法 国 您
 val candidates = sc.parallelize(comedyMovies.toSeq)
 val recommendations = bestModel.get
   .predict(candidates.map((100, _)))
   .collect()
   .sortBy(- _.rating)
   .take(5)
 var i = 1
 println("Comedy Movies recommended for you:")
 recommendations.foreach { r \Rightarrow
   println("%2d".format(i) + ": " + movies(r.product))
   i += 1
}
comedyMovies: Iterable[Int] = Set(2163, 42900, 892, 69, 7375, 5437, 1665, 7304, 6085, 3873,
 26413, 4201, 4447, 33004, 3962, 5422, 5469, 3944, 6387, 3883, 62851, 5116, 4094, 6167, 508
8, 2889, 59858, 2295, 2306, 4571, 5857, 4464, 101, 2109, 1454, 4909, 2031, 5896, 59625, 207
2, 8663, 4062, 3399, 54256, 33675, 6544, 4169, 4899, 53578, 6712, 55020, 5950, 3167, 31160,
4183, 909, 4290, 3477, 333, 3979, 2463, 3397, 49110, 3581, 8784, 3830, 6317, 518, 7990, 24
99, 8843, 1083, 468, 54193, 5205, 6172, 4015, 26842, 234, 6690, 2331, 3566, 4728, 6954, 487
7, 6014, 5582, 4992, 5131, 6374, 88, 50354, 47047, 32289, 352, 53993, 33145, 1855, 45722, 5
454, 56176, 1211, 3990, 7888, 4714, 1158, 582, 762, 3072, 8883, 1005, 5141, 115, 6944, 3317
, 5168, 4500, 65027, 7409, 5718, 34018, 37384, 46976, 276, 2622, 4402...candidates: org.apa
che.spark.rdd.RDD[Int] = ParallelCollectionRDD[2715] at parallelize at <console>:55
recommendations: Array[org.apache.spark.mllib.recommendation.Rating] = Array(Rating(100,296
,3.526813877388885), Rating(100,3030,3.331894391300624), Rating(100,750,3.2978257339389936)
, Rating(100,50949,3.248493364773723), Rating(100,6119,3.2032888900258034))
i: Int = 1
```

2: Yojimbo (1961)3: Dr. Strangelove or: How I Learned to Stop Worrying and Love the Bomb (1964)

```
4: Mafioso (1962)
5: Père Noël est une Ordure, Le (1982)
Took 2 seconds.
```

```
val comedyMovies = moviesWithGenres.filter(_._2.matches(".*Action.*")). kæmsshed ▷ 💥 🗉 ‡
 val candidates = sc.parallelize(comedyMovies.toSeq)
 val recommendations = bestModel.get
   .predict(candidates.map((100, _)))
   .collect()
   .sortBy(- _.rating)
   .take(5)
 var i = 1
 println("Action Movies recommended for you:")
 recommendations.foreach \{ r = > \}
   println("%2d".format(i) + ": " + movies(r.product))
   i += 1
}
comedyMovies: Iterable[Int] = Set(53550, 37830, 1036, 54999, 1586, 26413, 809, 7373, 7766,
58627, 2094, 5469, 6387, 7272, 1168, 4005, 63433, 7569, 4262, 7445, 54256, 479, 51077, 3434
, 2412, 6283, 3698, 54686, 7143, 6317, 2427, 50147, 36519, 34645, 26842, 6448, 5999, 27611,
7072, 8646, 4682, 56167, 555, 6566, 6014, 1110, 4166, 6808, 2363, 1200, 45722, 6057, 170,
5898, 3681, 6587, 7040, 26746, 46335, 6576, 6177, 7164, 7409, 4339, 1882, 2808, 31553, 5069
, 6219, 2527, 3153, 8811, 27828, 6900, 2947, 3959, 8118, 33672, 49651, 1544, 48319, 51935,
1591, 379, 511, 5691, 4614, 64508, 8045, 26152, 861, 1497, 10, 4543, 1788, 61132, 8733, 560
67, 59840, 1608, 3439, 6764, 56921, 384, 3745, 64231, 26950, 7573, 533, 4011, 4026, 1867, 4
528, 1275, 4638, 7345, 1233, 3781, 4440, 4564, 6078, 8370, 2476, 6996...candidates: org.apa
che.spark.rdd.RDD[Int] = ParallelCollectionRDD[2775] at parallelize at <console>:55
recommendations: Array[org.apache.spark.mllib.recommendation.Rating] = Array(Rating(100,575
1,3.482584374718392), Rating(100,27376,3.4506631353117534), Rating(100,1208,3.3443345063216
37), Rating(100,3030,3.331894391300624), Rating(100,2019,3.3181241628444287))
i: Int = 1
Action Movies recommended for you:
 1: Goodbye Pork Pie (1981)
2: Tunnel, The (Der Tunnel) (2001)
3: Apocalypse Now (1979)
4: Yojimbo (1961)
 5: Seven Samurai (Shichinin no samurai) (1954)
Took 3 seconds.
```

```
i += 1
comedyMovies: Iterable[Int] = Set(8607, 53550, 37830, 2822, 54999, 809, 7373, 33004, 2094,
6405, 1168, 4571, 3345, 4005, 101, 63433, 7569, 3930, 4899, 26085, 3698, 1031, 54686, 1899,
7143, 6317, 6512, 6448, 27611, 941, 3927, 6986, 6566, 31934, 6527, 5582, 3172, 6808, 45722
, 2077, 1750, 170, 5898, 52328, 8883, 8450, 8723, 7164, 4339, 6162, 44022, 6106, 31553, 506
9, 50601, 40815, 3417, 3285, 3153, 8811, 6458, 8682, 2947, 3959, 1544, 48319, 2099, 1591, 7
332, 58105, 26152, 10, 4543, 5967, 61132, 6764, 56, 5361, 6401, 3745, 8635, 4575, 7573, 533
, 3332, 1867, 3175, 47124, 1275, 2141, 4638, 7345, 26483, 51575, 26792, 40339, 31617, 340,
153, 4980, 5192, 4941, 1196, 52287, 3629, 5227, 2723, 4142, 2046, 8898, 1127, 54001, 45431,
 709, 33558, 34520, 1359, 2173, 8678, 1967, 4467, 2405, 63853, 1254, ...candidates: org.apa
che.spark.rdd.RDD[Int] = ParallelCollectionRDD[2765] at parallelize at <console>:55
recommendations: Array[org.apache.spark.mllib.recommendation.Rating] = Array(Rating(100,575
1,3.482584374718392), Rating(100,1201,3.2594467304885155), Rating(100,25798,3.2484933647737
23), Rating(100,4993,3.2462897675533324), Rating(100,7153,3.239427986275163))
i: Int = 1
Adventure Movies recommended for you:
 1: Goodbye Pork Pie (1981)
2: Good, the Bad and the Ugly, The (Buono, il brutto, il cattivo, Il) (1966)
 3: Island of Lost Souls (1932)
4: Lord of the Rings: The Fellowship of the Ring, The (2001)
 5: Lord of the Rings: The Return of the King, The (2003)
Took 2 seconds.
```

val comedyMovies = moviesWithGenres.filter(_._2.matches(".*Action|Roman@N的Dkbys类 国 袋

```
val candidates = sc.parallelize(comedyMovies.toSeq)
 val recommendations = bestModel.get
   .predict(candidates.map((100, _)))
   .collect()
   .sortBy(- _.rating)
   .take(5)
 var i = 1
 println("Action and Romance Movies recommended for you:")
 recommendations.foreach \{ r = > \}
   println("%2d".format(i) + ": " + movies(r.product))
   i += 1
}
comedyMovies: Iterable[Int] = Set(58627, 1110, 6177, 8118, 4614, 1497, 1137, 5316, 3414, 88
16, 1475, 4637, 3442, 4866, 6095, 6723, 2708, 4568, 6130, 638, 1514, 1398, 34538, 26696, 63
276, 7268, 1714, 5084, 4001, 623, 7376, 5156, 821, 7899, 2833, 64999, 2965, 4892, 4853, 419
9, 4531, 6588, 2737, 894, 1666, 5826, 6163, 4947, 6556, 1159, 43987, 2157, 980, 4636, 9, 88
00, 1493, 1424, 2196, 3541, 2497, 1599, 2756, 1434, 1170, 1071, 6192, 36392, 4438, 4503, 32
83, 7704, 1520, 2817, 204, 71, 3796, 1669, 4099, 4764, 5580, 5212, 1574, 64368, 64997, 6280
3, 4569, 7892, 251, 964, 932, 983, 8131, 32617, 1477, 1102, 3444, 4441, 6417, 3206, 64030,
145, 3376, 4035, 6472, 4950, 4200, 4630, 4092, 1658, 3769, 4106, 1749, 7192, 4651, 976, 593
4, 4738, 4542, 62334, 3368, 5922, 63647, 667, 5409, 4387, 2258, 2534,...candidates: org.apa
che.spark.rdd.RDD[Int] = ParallelCollectionRDD[2785] at parallelize at <console>:55
recommendations: Array[org.apache.spark.mllib.recommendation.Rating] = Array(Rating(100,636
47,3.309619538780511), Rating(100,62803,3.106653546147294), Rating(100,6082,2.7761122259552
766), Rating(100,4438,2.7225535165937966), Rating(100,6192,2.7211811068702954))
i: Int = 1
```

Action and Romance Movies recommended for you:

- 1: Hanzo the Razor: Sword of Justice (Goyôkiba) (1972)
- 2: Lone Wolf and Cub: Baby Cart in Peril (Kozure Ôkami: Oya no kokoro ko no kokoro) (1972)
- 3: Grey Fox, The (1982)
- 4: Chinese Connection, The (a.k.a. Fist of Fury) (Jing wu men) (1972)
- 5: Open Hearts (Elsker dig for evigt) (2002)

Took 1 seconds.

sameModel: org.apache.spark.mllib.recommendation.MatrixFactorizationModel = org.apache.spar k.mllib.recommendation.MatrixFactorizationModel@4a3c98d1

Took 14 seconds.

READY ▷ 牂 圓 ⑳