

## CHIN-TING KO FALL 2016

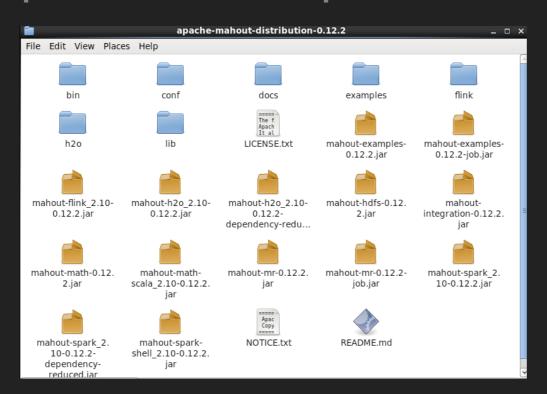
# APACHE MAHOUT 605.788 FINAL PROJECT

#### WHAT IS APACHE MAHOUT?

- Apache Mahout is a library of scalable machine learning algorithms on top of Hadoop and using MapReduce paradigm.
- Build an environment for quickly creating scalable performant machine learning applications
- Popular machine learning techniques such as
  - Recommendation
  - Classification
  - Clustering
- Once big data stored no the HDFS, Mahout makes it faster and easier to turn big data into big information

### **SETTING UP MAHOUT**

- Install Java and IDE
- Install Hadoop
- Install Mahout (0.12.2)
- Edit .bash\_profile to set up Mahout\_HOME





#### Latest release version 0.12.2 has

#### **Apache Mahout Samsara Environment includes**

- Distributed Algebraic optimizer
- · R-Like DSL Scala API
- Linear algebra operations
- Ops are extensions to Scala
- · IScala REPL based interactive shell
- Integrates with compatible libraries like MLLib
- Runs on distributed Spark, H2O, and Flink
- fastutil to speed up sparse matrix and vector computations
- Matrix to tsv conversions for integration with Apache Zeppelin

#### **Apache Mahout Samsara Algorithms included**

- Stochastic Singular Value Decomposition (ssvd, dssvd)
- Stochastic Principal Component Analysis (spca, dspca)
- Distributed Cholesky QR (thinQR)
- Distributed regularized Alternating Least Squares (dals)
- Collaborative Filtering: Item and Row Similarity
- Naive Bayes Classification
- Distributed and in-core

#### MOVIE RECOMMENDER USING MAHOUT

- Gather Input File (UserID, ItemID, Rating)
- Recommender Engine (Pick a similarity measure)
- Run Mahout Command
- Making Use of the Output File

#### **INPUT DATASET**

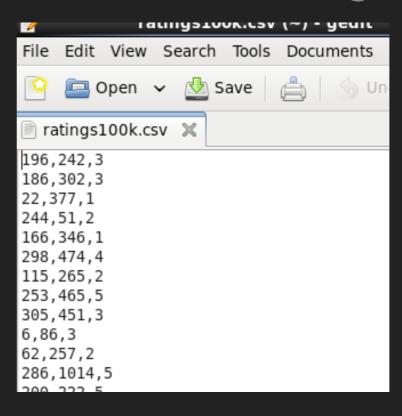
- http://grouplens.org/datasets/movielens/
- ml-100k.zip/u.data (UserID ItemID Rating Timestamp)

```
File Edit View Search Terminal Help

[hdadmin@hdserver ~]$ cat ml-100k/u.data | sed 's/\t/,/g' | cut -f1-3 -d, > ratings100k.csv

[hdadmin@hdserver ~]$
```

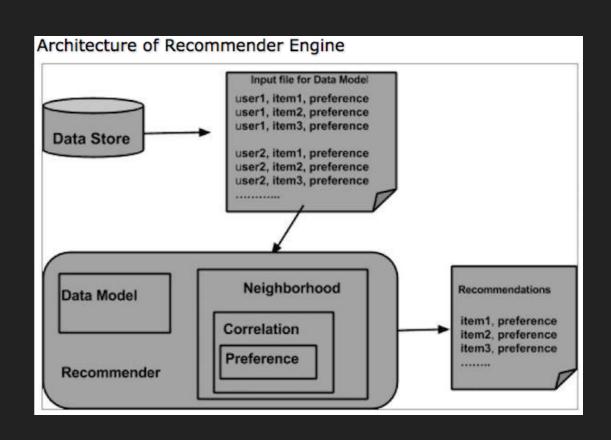
- ml-1m.zip/rating.dat (UserID::ItemID::Rating::Timestamp)
- UserID, ItemID, Rating



#### MAHOUT RECOMMENDER ENGINE

- Collaborative Filtering
  - Look for users who share same rating patterns
  - Use the ratings from those like-minded users found to calculate prediction

- Building a Recommender using Mahout
  - Create DataModel Object
  - Create UserSimilarity Object
  - Create Recommender Object
  - Recommend Items to User



### RECOMMENDER ENGINE

Copy File to HDFS:

```
File Edit View Search Terminal Help

-rw-r--r-- 1 hdadmin supergroup 979173 2016-11-22 15:28 /ratings100k.csv
-rw-r--r-- 1 hdadmin supergroup 11553456 2016-11-22 15:27 /ratings1m.csv

drwxrwx--- - hdadmin supergroup 0 2016-11-13 11:41 /tmp

drwxr-xr-x - hdadmin supergroup 0 2016-11-06 11:12 /user
```

#### Run Mahout Recommendation Job:

```
hdadmin@hdserver:~
                                                                                                                              □ X
File Edit View Search Terminal Help
[hdadmin@hdserver ~]$ mahout recommenditembased --input /ratings100k.csv --output recommendations100k --numRecommendations 25 --s
imilarityClassname SIMILARITY COSINE
Running on hadoop, using /usr/local/hadoop/hadoop-2.7.2/bin/hadoop and HADOOP CONF DIR=
MAHOUT-JOB: /usr/local/hadoop/apache-mahout-distribution-0.12.2/mahout-examples-0.12.2-job.jar
16/11/22 15:49:54 INFO AbstractJob: Command line arguments: {--booleanData=[false], --endPhase=[2147483647], --input=[/ratings100
k.csv], --maxPrefsInItemSimilarity=[500], --maxPrefsPerUser=[10], --maxSimilaritiesPerItem=[100], --minPrefsPerUser=[1], --numRec
pmmendations=[25], --output=[recommendations100k], --similarityClassname=[SIMILARITY COSINE], --startPhase=[0], --tempDir=[temp]}
16/11/22 15:49:54 INFO AbstractJob: Command line arguments: {--booleanData=[false], --endPhase=[2147483647], --input=[/ratings100
k.csv], --minPrefsPerUser=[1], --output=[temp/preparePreferenceMatrix], --ratingShift=[0.0], --startPhase=[0], --tempDir=[temp]}
Java HotSpot(TM) Server VM warning: You have loaded library /usr/local/hadoop/hadoop-2.7.2/lib/native/libhadoop.so.1.0.0 which mi
ght have disabled stack quard. The VM will try to fix the stack quard now.
It's highly recommended that you fix the library with 'execstack -c <libfile>', or link it with '-z noexecstack'.
16/11/22 15:49:55 WARN NativeCodeLoader: Unable to load native-hadoop library for your platform... using builtin-java classes whe
re applicable
16/11/22 15:49:55 INFO deprecation: mapred.input.dir is deprecated. Instead, use mapreduce.input.fileinputformat.inputdir
16/11/22 15:49:55 INFO deprecation: mapred.compress.map.output is deprecated. Instead, use mapreduce.map.output.compress
16/11/22 15:49:55 INFO deprecation: mapred.output.dir is deprecated. Instead, use mapreduce.output.fileoutputformat.outputdir
16/11/22 15:49:55 INFO RMProxy: Connecting to ResourceManager at /0.0.0.0:8032
16/11/22 15:49:58 INFO FileInputFormat: Total input paths to process : 1
16/11/22 15:49:58 INFO JobSubmitter: number of splits:1
16/11/22 15:49:59 INFO JobSubmitter: Submitting tokens for job: job 1479854934870 0002
16/11/22 15:49:59 INFO YarnClientImpl: Submitted application application 1479854934870 0002
16/11/22 15:49:59 INFO Job: The url to track the job: http://localhost:8088/proxy/application 1479854934870 0002/
16/11/22 15:49:59 INFO Job: Running job: job 1479854934870 0002
16/11/22 15:50:14 INFO Job: Job job 1479854934870 0002 running in uber mode : false
16/11/22 15:50:14 INFO Job: map 0% reduce 0%
16/11/22 15:50:22 INFO Job: map 100% reduce 0%
16/11/22 15:50:31 INFO Job: map 100% reduce 100%
16/11/22 15:50:31 INFO Job: Job job 1479854934870 0002 completed successfully
16/11/22 15:50:31 INFO Job: Counters: 49
```

#### **OUTPUT FILE**

 Each line represents UserID with associated recommended ItemID and their scores.

#### SPARK - MLLIB



- MLlib is Apache Spark's scalable machine learning library.
- MLlib was built on top of Spark to take advantage of Spark's efficiency when running iterative Machine Learning algorithms.
- MLlib uses the alternating least squares (ALS) algorithm to learn these latent factors.
  - Alternating Least Squares (ALS) is an optimization technique to solve matrix factorization problems.
  - ALS works by iteratively solving a series of least squares regression problems. In each iteration, one of the user- or item-factor matrices is treated as fixed, while the other one is updated using the fixed factor and the rating data. Then, the factor matrix that was solved for is, in turn, treated as fixed, while the other one is updated. This process continues until the model has converged (or for a fixed number of iterations).

(https://www.packtpub.com/books/content/building-recommendation-engine-spark)

# **OUTPUT FILE (SPARK MLLIB)**

Each line represents UserID with associated recommended ItemID and their scores.

```
hdadmin@hdserver:~/MovieRecommendation
File Edit View Search Terminal Help
scala> val topRecsForUser1 = model.recommendProducts(1,10)
topRecsForUser1: Array[org.apache.spark.mllib.recommendation.Rating] = Array(Rating(1,618,6.774438867943637), Rating(1,3867,6.6489927917
52741), Rating(1,966,6.522484173964295), Rating(1,572,6.427094942354792), Rating(1,3149,6.347160717816235), Rating(1,3523,6.245779377862
082), Rating(1,2962,6.0278801095579695), Rating(1,2482,5.900282961200457), Rating(1,1685,5.892318867776706), Rating(1,3933,5.75546569128
9622))
scala> val topRecsForUser1 = model.recommendProducts(2,10)
topRecsForUser1: Array[org.apache.spark.mllib.recommendation.Rating] = Array(Rating(2,1872,6.832084684845792), Rating(2,864,6.7293577321
87241), Rating(2,572,6.13254322790024), Rating(2,1058,5.730026263746217), Rating(2,2503,5.370907329267695), Rating(2,1574,5.347824820420
602), Rating(2,1436,5.295925227379191), Rating(2,687,5.278860715744662), Rating(2,3670,5.2319661479476185), Rating(2,3245,5.149588571716
scala> val topRecsForUser1 = model.recommendProducts(3,10)
topRecsForUser1: Array[org.apache.spark.mllib.recommendation.Rating] = Array(Rating(3,811,11.1624144104375), Rating(3,751,11.05831602680
2977), Rating(3,197,10.829263737951194), Rating(3,2913,9.877369870311949), Rating(3,1549,9.303079940465825), Rating(3,974,9.234115368084

    Rating(3,939,9.163269248141692), Rating(3,1529,9.006818203338263), Rating(3,1898,8.998920132163294), Rating(3,632,8.959103487192792)

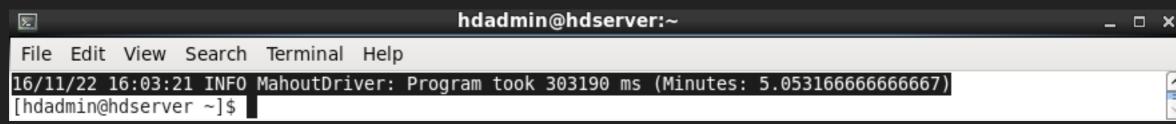
scala> val topRecsForUser1 = model.recommendProducts(4,10)
topRecsForUser1: Array[org.apache.spark.mllib.recommendation.Rating] = Array(Rating(4,1000,10.47886024462249), Rating(4,2342,9.929486630
314619), Rating(4,3245,9.022109081705754), Rating(4,2238,8.827577460318551), Rating(4,831,8.811759641124747), Rating(4,3944,8.6624112673
7358), Rating(4,2192,8.617173358848197), Rating(4,2773,8.514338413500267), Rating(4,3951,8.16717151759865), Rating(4,3224,8.162175315542
scala> val topRecsForUser1 = model.recommendProducts(5,10)
topRecsForUser1: Array[org.apache.spark.mllib.recommendation.Rating] = Array(Rating(5,503,5.788375141269848), Rating(5,1002,5.7112524913
53883), Rating(5,3645,5.695299660152859), Rating(5,3776,5.586769089511085), Rating(5,1144,5.414294176773753), Rating(5,1423,5.3554156874
888434), Rating(5,1664,5.330862239434492), Rating(5,702,5.282304519114816), Rating(5,557,5.235724554946875), Rating(5,1153,5.23539494641
scala> val topRecsForUser1 = model.recommendProducts(6,10)
topRecsForUser1: Array[org.apache.spark.mllib.recommendation.Rating] = Array(Rating(6,2933,7.906932108263031), Rating(6,1872,7.148926771
2952795), Rating(6,2129,7.053008226427211), Rating(6,2056,7.035079732165646), Rating(6,1471,6.632216980420657), Rating(6,638,6.476366184
663778), Rating(6,2913,6.351026973095998), Rating(6,687,6.296795083953017), Rating(6,2332,6.244670194409402), Rating(6,2503,6.2298639191
964815))
scala> val topRecsForUser1 = model.recommendProducts(7,10)
topRecsForUser1: Array[org.apache.spark.mllib.recommendation.Rating] = Array(Rating(7,2964,9.710648821264051), Rating(7,1471,7.819228601
9784625), Rating(7,2063,7.78771032750209), Rating(7,2129,7.746815693528694), Rating(7,958,7.717085278713771), Rating(7,618,7.57059447208
84055), Rating(7,3636,7.547774995633008), Rating(7,811,7.417765929041326), Rating(7,2933,7.3167072524981505), Rating(7,1232,7.2766931329
87369))
scala> val topRecsForUser1 = model.recommendProducts(8,10)
topRecsForUser1: Array[org.apache.spark.mllib.recommendation.Rating] = Array(Rating(8,1685,6.436333469169517), Rating(8,108,5.9160031231
82164), Rating(8,3803,5.6484589181330325), Rating(8,557,5.60014498876392), Rating(8,572,5.5432001728285965), Rating(8,2309,5.42043940559
1808), Rating(8,296,5.138825191285687), Rating(8,2964,5.133273427686358), Rating(8,966,5.115977196882945), Rating(8,925,5.11470551297196
```

## SUMMARY/ OBSERVATION

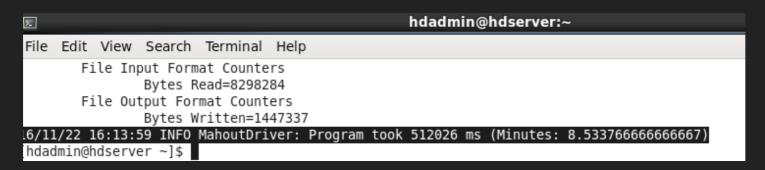
- Mahout was build to run on top of Hadoop. Hadoop writes to disk on every iteration, this makes Mahout run very slowly.
- Spark also has a machine learning library (MLlib) to address this issue.(processing using distributed memory)
- Mahout is moving away from MapReduce
  - 11 April 2015 Apache Mahout 0.10.0 released
  - The Hadoop MapReduce versions of Mahout algorithms are still maintained but no new MapReduce contributions are accepted. From this release onwards contributions must be Mahout Samsara based or at least run on Spark.

## SUMMARY/ OBSERVATION

ml-100k: 5 minutes (Mahout)



ml-1m: 8.5 minutes (Mahout)



- ml-1m: less than 1 min (Spark MLlib)
  - train the model: less than 30 second
  - query: 1~2 second

#### REFERENCE

http://mahout.apache.org/

https://www.manning.com/books/mahout-in-action

http://www.tutorialspoint.com/mahout/

https://en.wikipedia.org/wiki/Apache\_Mahout

https://www.youtube.com/watch?v=bXtX6IPoBME

https://www.youtube.com/watch?v=iMAMYzfRiS4

http://leoyeh.me:8080/2014/12/20/%E8%B3%87%E6%96%99%E5%88%86%E6%9E%90-

Mahout-%E8%99%95%E7%90%86-1/

http://blog.csdn.net/huhui\_cs/article/details/8596388

http://blog.cloudera.com/blog/2011/11/recommendation-with-apache-mahout-in-cdh3/

https://www.quora.com/When-should-one-use-Sparks-MLlib-and-not-Apache-Mahout

https://databricks-training.s3.amazonaws.com/movie-recommendation-with-mllib.html

http://spark.apache.org/docs/latest/mllib-collaborative-filtering.html

https://www.packtpub.com/books/content/building-recommendation-engine-spark