A Parallel Recommender System Using A Collaborative Filtering Algorithm For Movie Recommender System

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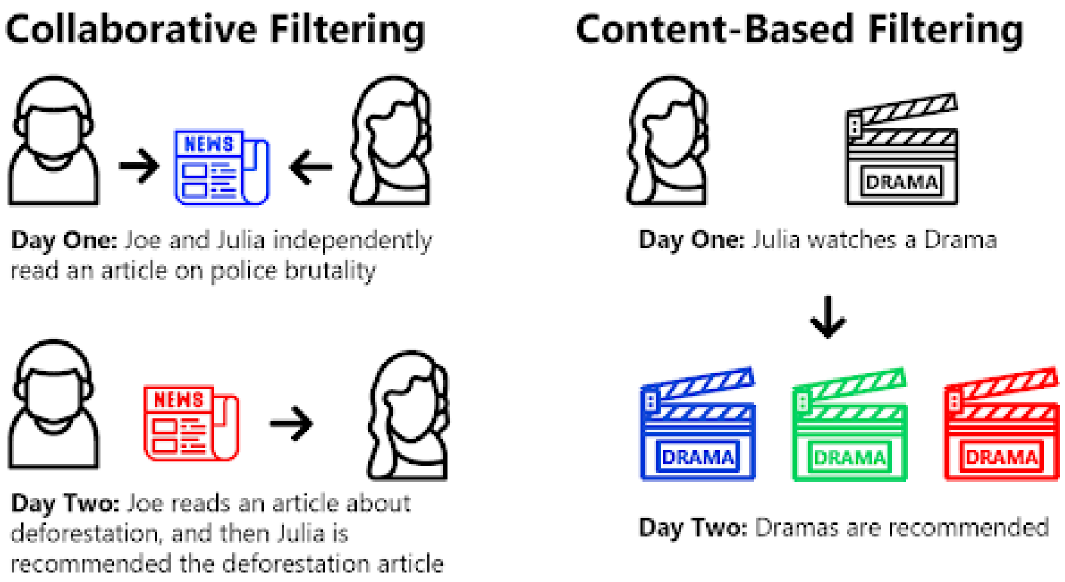
Types of Recommendation Systems

- **Content-Based Filtering:**

  Content-Based recommender system tries to guess the features or behavior of a user given the item’s features, he/she reacts positively to [1].
- **Collaborative Filtering:**

  Collaborative does not need the features of the items to be given. Every user and item is described by a feature vector or embedding [2].



Collaborative Filtering
NEWS
Day One: Joe and Julia independently read an article on police brutality
NEWS
Day Two: Joe reads an article about deforestation, and then Julia is recommended the deforestation article
Content-Based Filtering
DRAMA
Day One: Julia watches a Drama
DRAMA
DRAMA
DRAMA
Day Two: Dramas are recommended

Image Source

Literature Review

Similarity Computation

- Cosine Vector (CV) Similarity [3]
- Pearson Correlation (PC) Similarity [4][5]
- Spearman Correlation (SC)[6]
- JacRA Similarity [7]

Rating Prediction

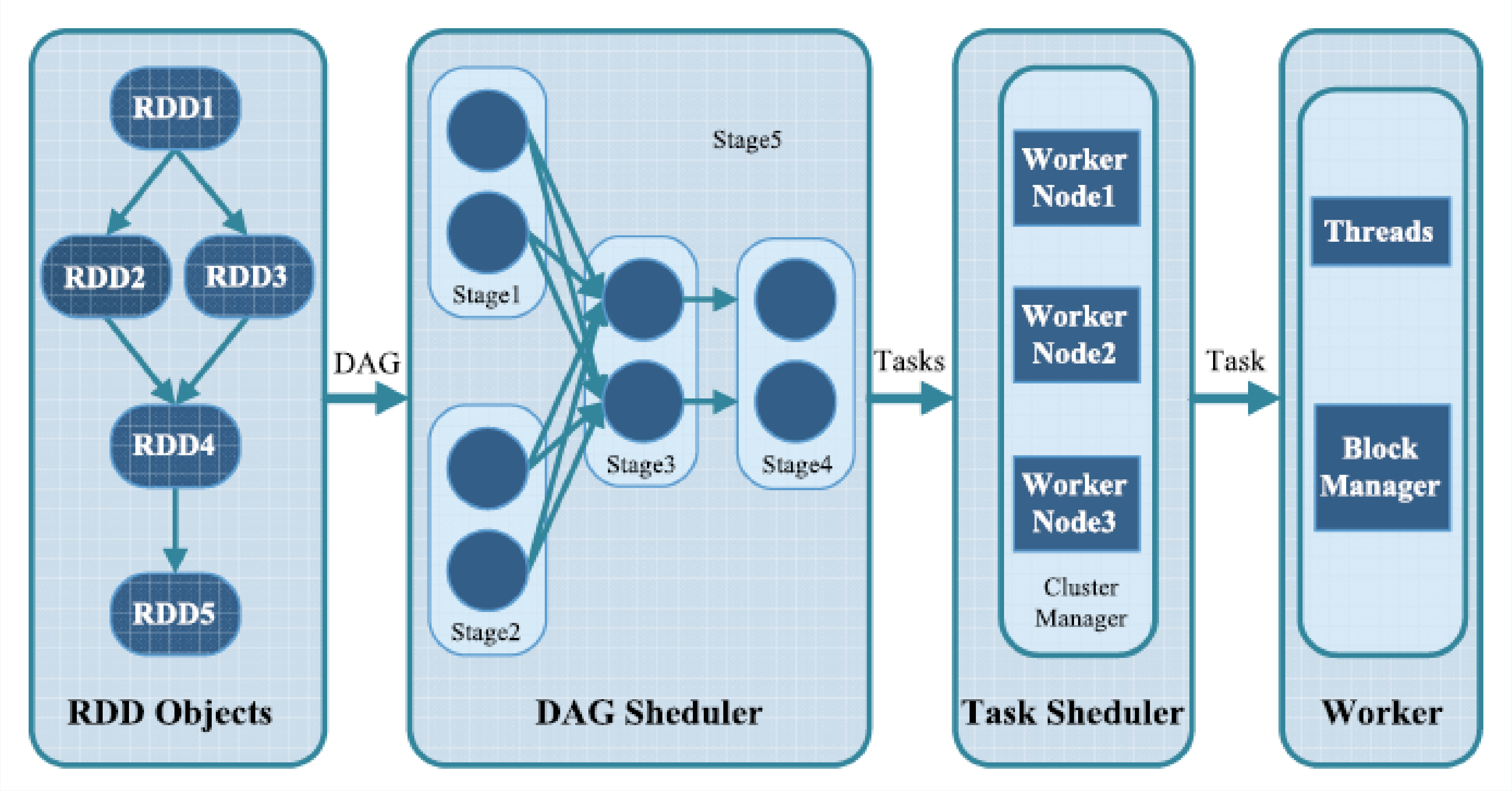
- Weighted Average (WA) [8]
- Mean-Centering (MC) [9][10]
- Z-Score (ZS) [11]

Hadoop vs Apache [12]

- Hadoop
  - Processing data using MapReduce in Hadoop is slow
  - Performs batch processing of data
  - Hadoop has more lines of code. Since it is written in Java, it takes more time to execute.
  - Hadoop supports Kerberos authentication, which is difficult to manage

- Apache
  - Spark processes data 100 times faster than MapReduce as it is dome in-memory
  - Performs both batch processing and real-time processing of data
  - Spark has fewer lines of code as it is implemented in Scala
  - Spark supports authentication via a shared secret. It can also run-on YARN leveraging the capability of Kerberos

The Task Scheduling Procedure In Spark [13]



Methodology

Algorithms That We Have Used

K-nearest neighbors (KNN) Algorithm

The k-nearest neighbors (KNN) algorithm is a simple, easy-to-implement supervised machine learning algorithm that can be used to solve both classification and regression problems [14].

Alternating Least Square (ALS)

Alternating Least Square (ALS) is also a matrix factorization algorithm and it runs itself in a parallel fashion. ALS is implemented in Apache Spark ML and built for a larges-scale collaborative filtering problems [15].

Linear Regression Analysis

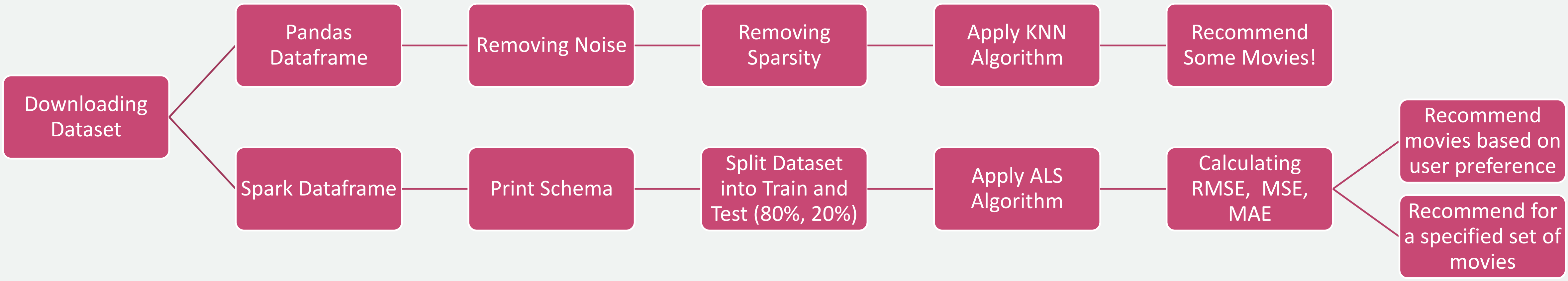
Linear regression analysis is used to predict the value of a variable based on the value of another variable. The variable you want to predict is called the dependent variable [16].

Our Dataset Statistics vs The Paper We Followed!

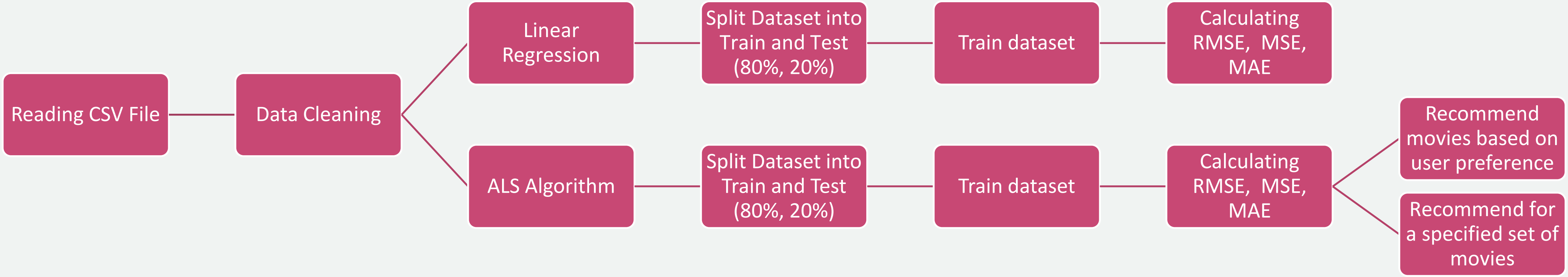
	Datasets	# of users	# of items	# of ratings	Sparsity
Our Dataset	MovieLens-100k	943	1682	100000	6.3%
	Netflix-6.2M	95325	412	6198103	15%

	Datasets	# of users	# of items	# of ratings	Sparsity
Dataset of The Paper We Followed [13]	WikiLens	326	5111	26937	1.6%
	MovieLens-100k	943	1682	100000	6.3%
	MovieLens-1M	6040	3900	1000209	4.2%

Methodology for MovieLens-100k Dataset



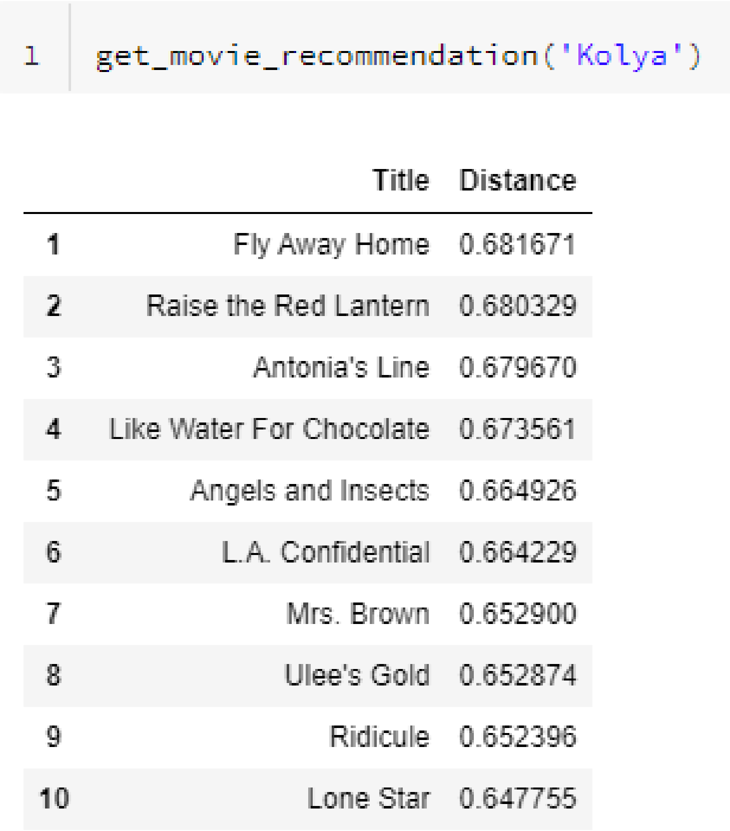
Methodology for Netflix-6.2M Dataset


Reading CSV File
Data Cleaning
Linear Regression
Split Dataset into Train and Test (80%, 20%)
Train dataset
Calculating RMSE, MSE, MAE
ALS Algorithm
Split Dataset into Train and Test (80%, 20%)
Train dataset
Calculating RMSE, MSE, MAE
Recommend movies based on user preference
Recommend for a specified set of movies

Experimental Results

Movie Recommender System using KNN Algorithm :: MovieLens-100k

- Used KNN algorithm to compute similarity with Cosine Distance metric.
- We first check if the movie name input is in the database (CSV)
- If exists, then we use our recommendation system to find similar movies
- Sort them based on their similarity distance and output only the top 10 movies with their distances from the input movie
- All the movies in the top 10 are just like “Kolya” itself, therefore I think the result, in this case, is also good.

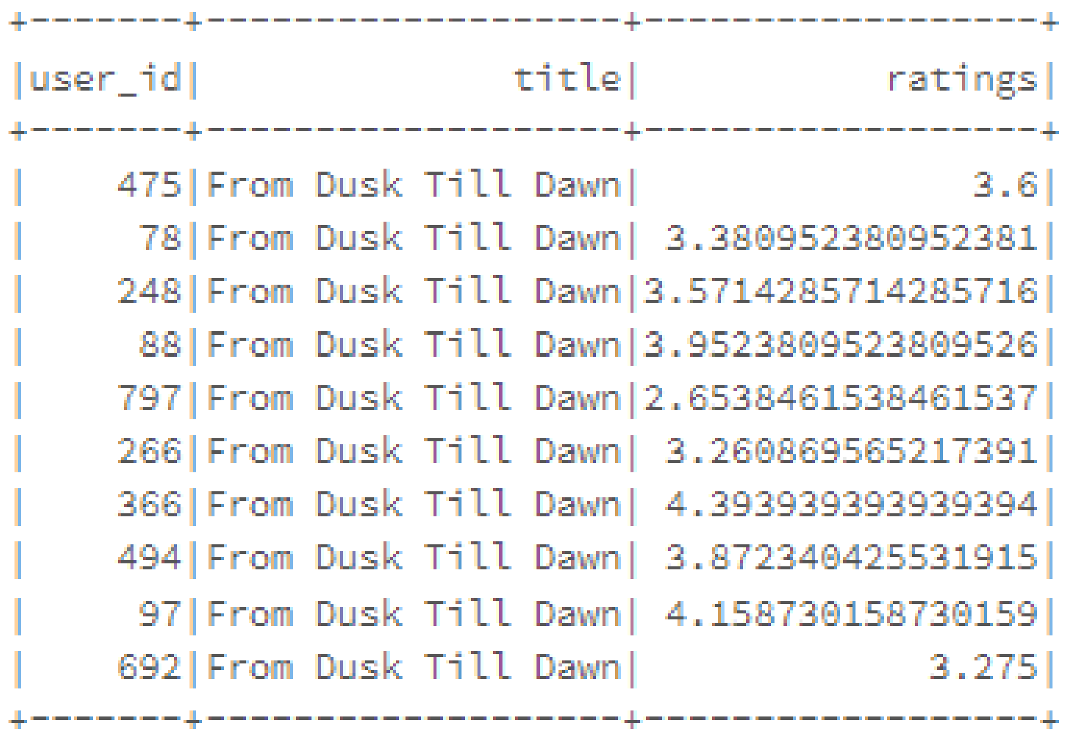


```
get_movie_recommendation('Kolya')
```

	Title	Distance
1	Fly Away Home	0.681671
2	Raise the Red Lantern	0.680329
3	Antonia's Line	0.679670
4	Like Water For Chocolate	0.673561
5	Angels and Insects	0.664926
6	L.A. Confidential	0.664229
7	Mrs. Brown	0.652900
8	Ulee's Gold	0.652874
9	Ridicule	0.652396
10	Lone Star	0.647755

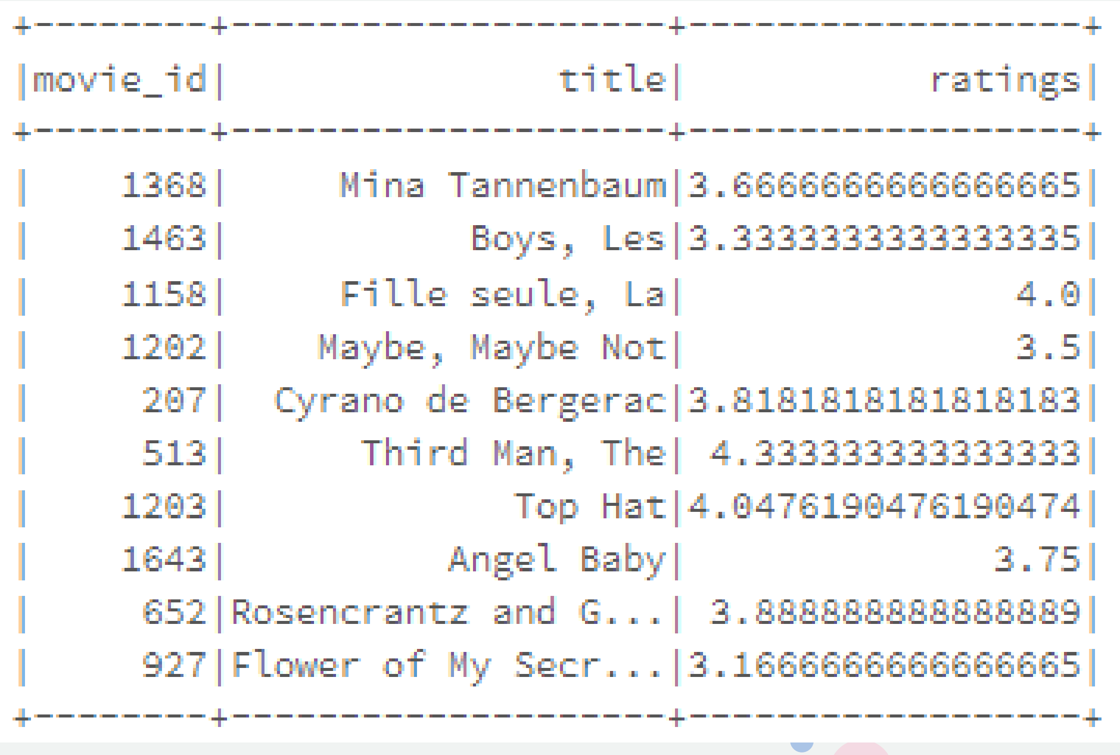
Movie Recommender System using ALS Algorithm :: MovieLens-100k

Selecting the list of users for the movie which id is 17



```
+-------+-------------------+------------------+
|user_id|              title|           ratings|
+-------+-------------------+------------------+
|    475|From Dusk Till Dawn|               3.6|
|     78|From Dusk Till Dawn| 3.380952380952381|
|    248|From Dusk Till Dawn|3.5714285714285716|
|     88|From Dusk Till Dawn|3.9523809523809526|
|    797|From Dusk Till Dawn|2.6538461538461537|
|    266|From Dusk Till Dawn| 3.260869565217391|
|    366|From Dusk Till Dawn| 4.393939393939394|
|    494|From Dusk Till Dawn| 3.872340425531915|
|     97|From Dusk Till Dawn| 4.158730158730159|
|    692|From Dusk Till Dawn|             3.275|
+-------+-------------------+------------------+
```

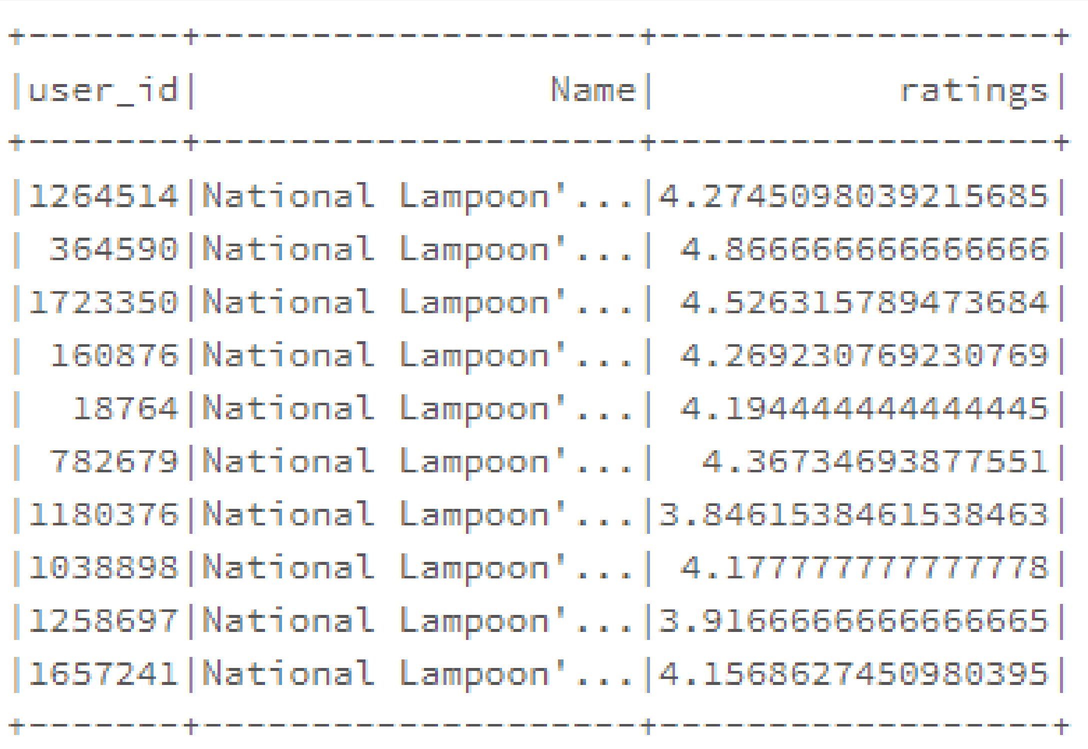
- Selecting the list of movies for the user whose id is 6



```
+--------+--------------------+------------------+
|movie_id|               title|           ratings|
+--------+--------------------+------------------+
|    1368|     Mina Tannenbaum|3.6666666666666665|
|    1463|           Boys, Les|3.3333333333333335|
|    1158|     Fille seule, La|               4.0|
|    1202|    Maybe, Maybe Not|               3.5|
|     207|  Cyrano de Bergerac|3.8181818181818183|
|     513|      Third Man, The| 4.333333333333333|
|    1203|             Top Hat|4.0476190476190474|
|    1643|          Angel Baby|              3.75|
|     652|Rosencrantz and G...| 3.888888888888889|
|     927|Flower of My Secr...|3.1666666666666665|
+--------+--------------------+------------------+
```

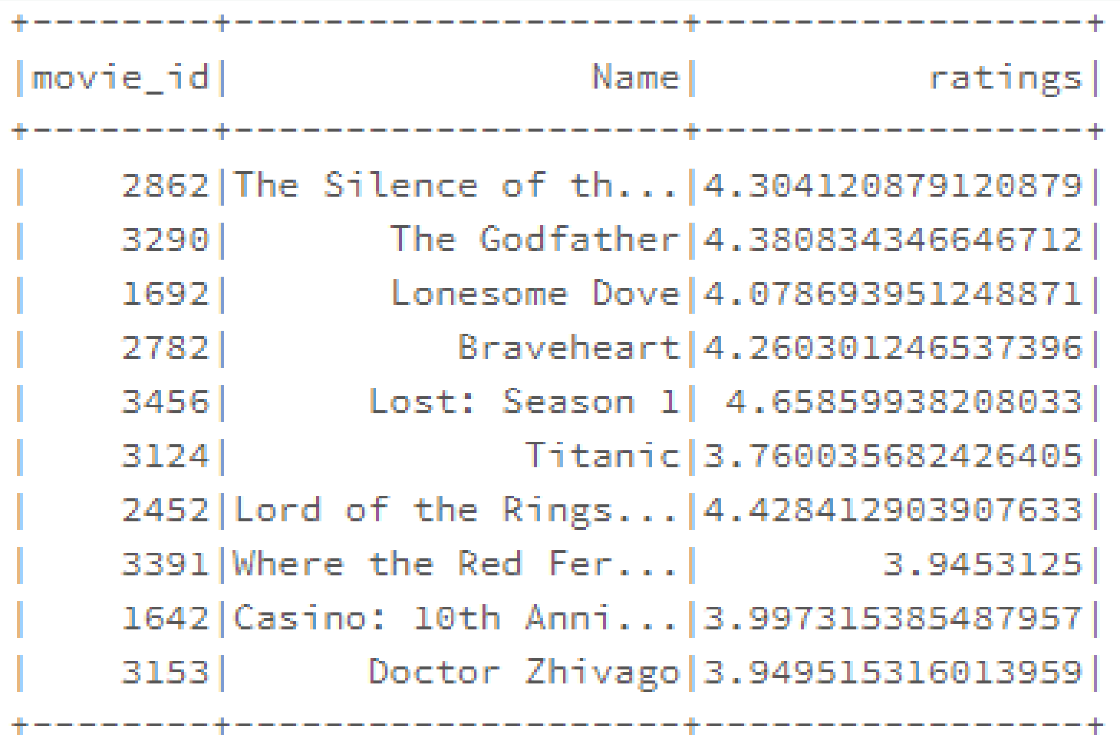
Movie Recommender System using ALS Algorithm :: Netflix-6.2M

Selecting the list of users for the movie which id is 17



```
+-------+--------------------+------------------+
|user_id|                Name|           ratings|
+-------+--------------------+------------------+
|1264514|National Lampoon'...|4.2745098039215685|
| 364590|National Lampoon'...| 4.866666666666666|
|1723350|National Lampoon'...| 4.526315789473684|
| 160876|National Lampoon'...| 4.269230769230769|
|  18764|National Lampoon'...| 4.194444444444445|
| 782679|National Lampoon'...|  4.36734693877551|
|1180376|National Lampoon'...|3.8461538461538463|
|1038898|National Lampoon'...| 4.177777777777778|
|1258697|National Lampoon'...|3.9166666666666665|
|1657241|National Lampoon'...|4.1568627450980395|
+-------+--------------------+------------------+
```

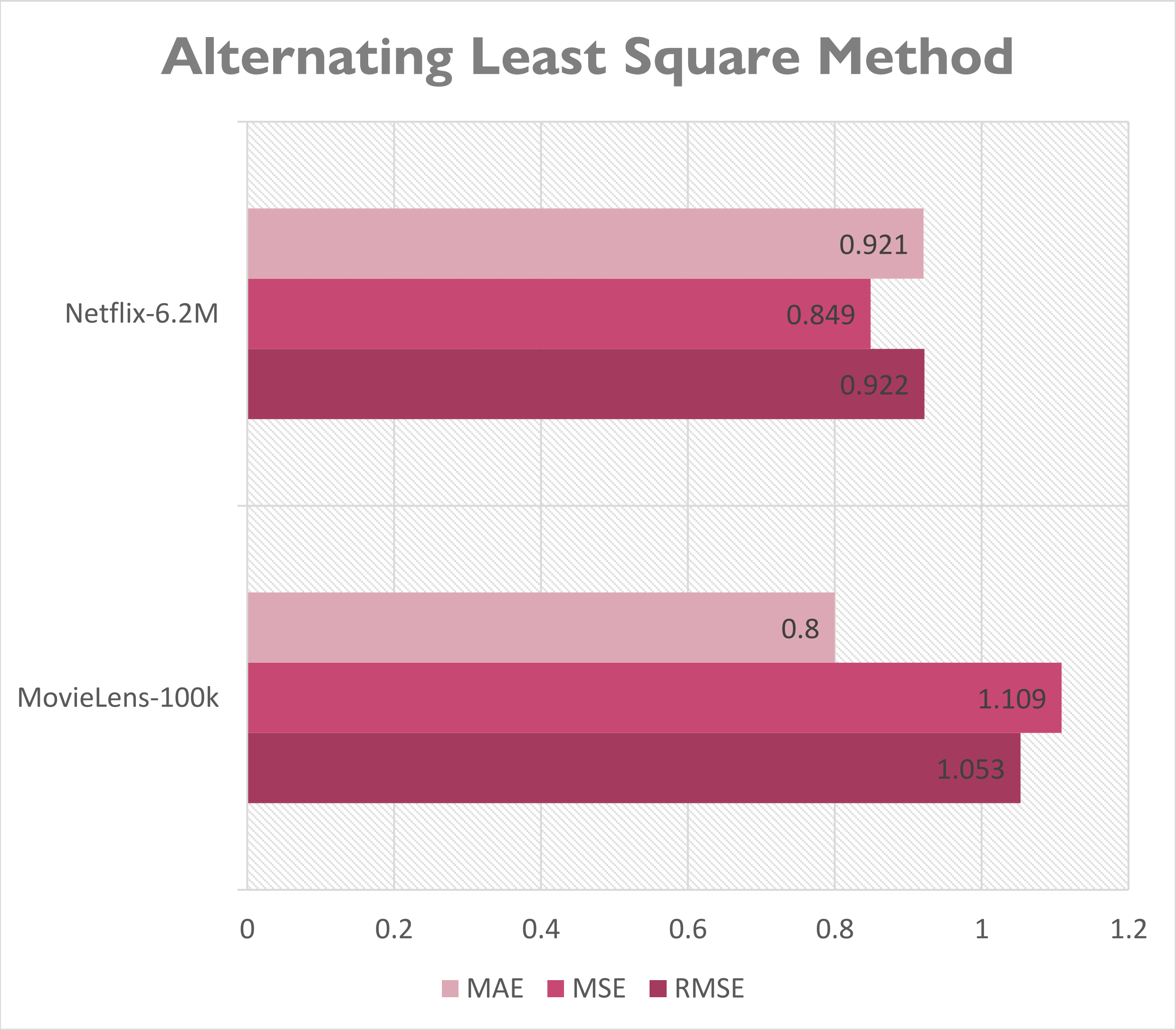
- Selecting the list of movies for the user whose id is 6



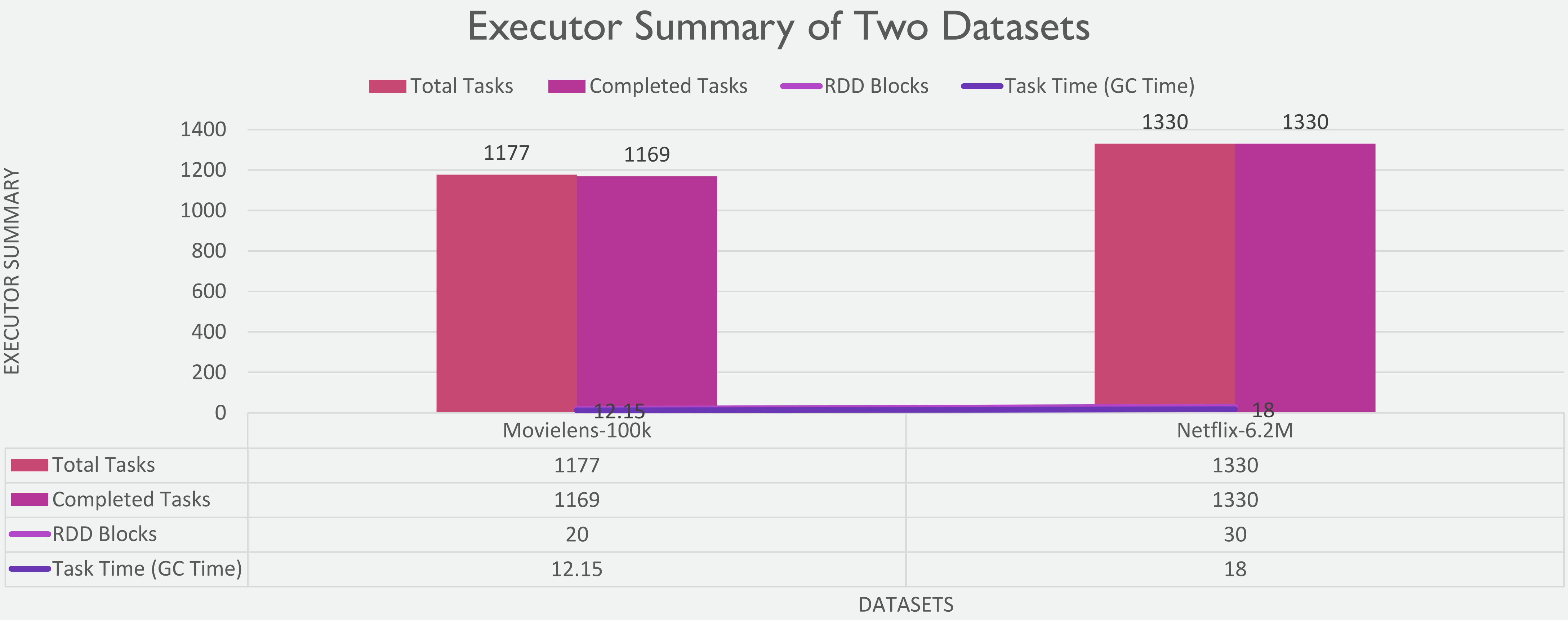
```
+--------+--------------------+-----------------+
|movie_id|                Name|          ratings|
+--------+--------------------+-----------------+
|    2862|The Silence of th...|4.304120879120879|
|    3290|       The Godfather|4.380833466467 12|
|    1692|       Lonesome Dove|4.078693951248871|
|    2782|          Braveheart|4.260301246537396|
|    3456|      Lost: Season 1| 4.65859938208033|
|    3124|             Titanic|3.760035682426405|
|    2452|Lord of the Rings...|4.428412903907633|
|    3391|Where the Red Fer...|        3.9453125|
|    1642|Casino: 10th Anni...|3.997315385487957|
|    3153|      Doctor Zhivago|3.949515316013959|
+--------+--------------------+-----------------+
```

Comparison Between Netflix-6.2M & ML-100K Datasets ALS Method

RMSE, MSE, MAE



Executor Summary of Two Datasets

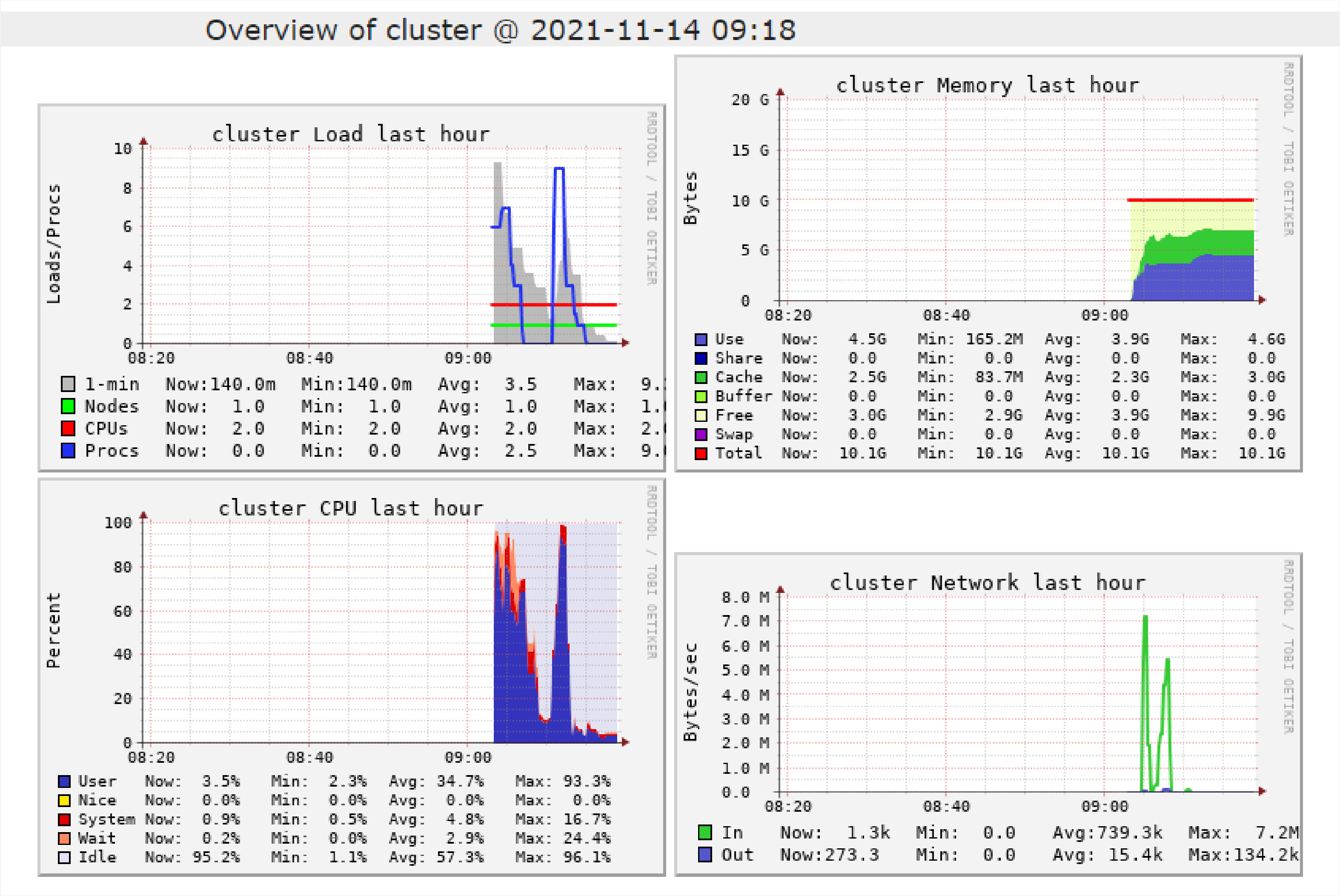


	Movielens-100k	Netflix-6.2M
Total Tasks	1177	1330
Completed Tasks	1169	1330
RDD Blocks	20	30
Task Time (GC Time)	12.15	18

Ganglia Cluster Report

Ganglia Cluster Report :: MovieLens-100k (Host View)

Databricks Runtime Version:
10.1 (includes Apache Spark 3.2.0, Scala 2.12)



Overview of cluster @ 2021-11-14 09:18

```
■ 1-min  Now:140.0m  Min:140.0m  Avg:  3.5  Max:  9.
■ Nodes  Now:  1.0   Min:  1.0   Avg:  1.0  Max:  1.
■ CPUs   Now:  2.0   Min:  2.0   Avg:  2.0  Max:  2.
■ Procs  Now:  0.0   Min:  0.0   Avg:  2.5  Max:  9.
```

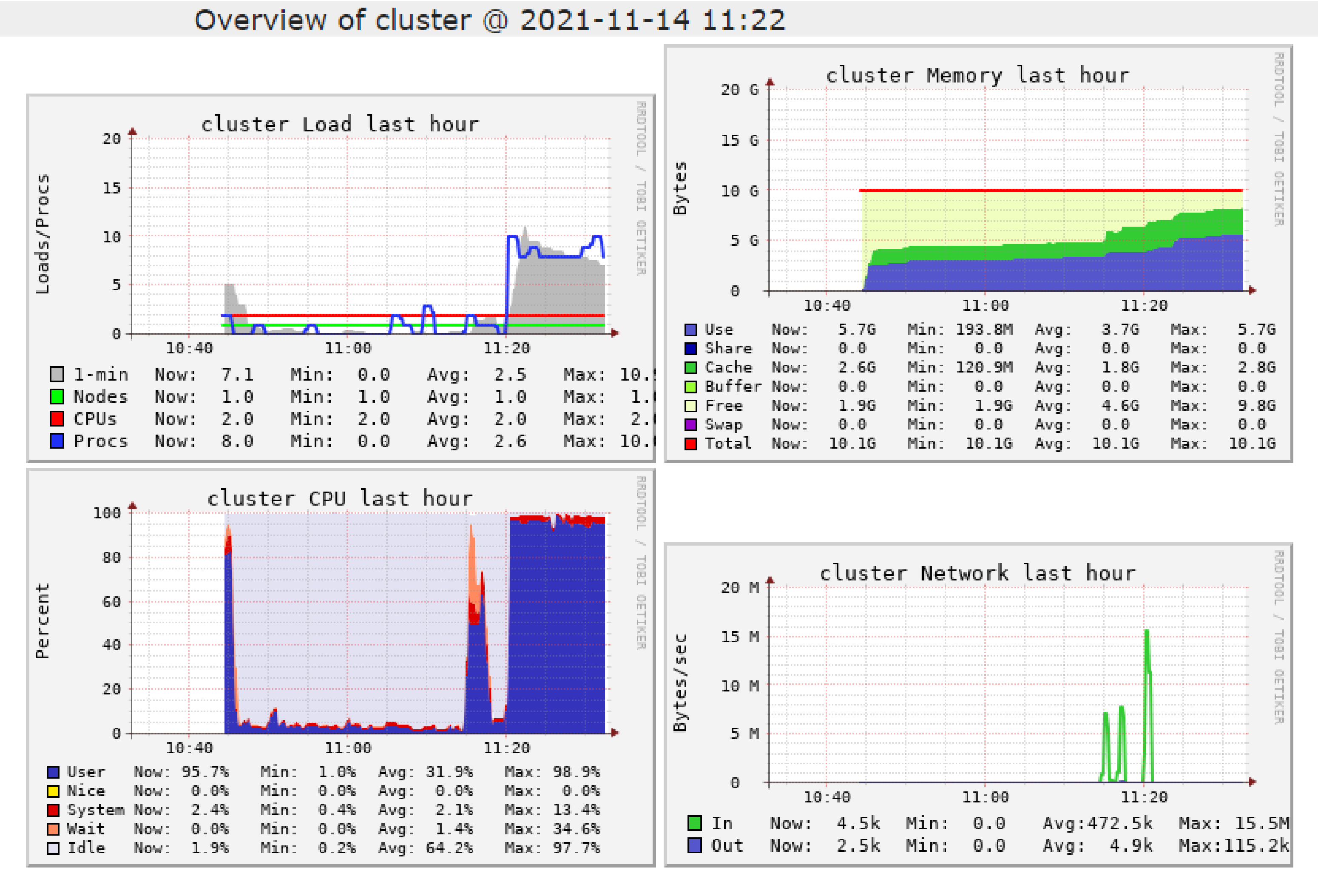
```
■ Use    Now:   4.5G  Min: 165.2M  Avg:   3.9G  Max:   4.6G
■ Share  Now:   0.0   Min:   0.0   Avg:   0.0   Max:   0.0
■ Cache  Now:   2.5G  Min:  83.7M  Avg:   2.3G  Max:   3.0G
■ Buffer Now:   0.0   Min:   0.0   Avg:   0.0   Max:   0.0
□ Free   Now:   3.0G  Min:   2.9G  Avg:   3.9G  Max:   9.9G
■ Swap   Now:   0.0   Min:   0.0   Avg:   0.0   Max:   0.0
■ Total  Now:  10.1G  Min:  10.1G  Avg:  10.1G  Max:  10.1G
```

```
■ User   Now:  3.5%   Min:  2.3%   Avg: 34.7%   Max: 93.3%
■ Nice   Now:  0.0%   Min:  0.0%   Avg:  0.0%   Max:  0.0%
■ System Now:  0.9%   Min:  0.5%   Avg:  4.8%   Max: 16.7%
■ Wait   Now:  0.2%   Min:  0.0%   Avg:  2.9%   Max: 24.4%
□ Idle   Now: 95.2%   Min:  1.1%   Avg: 57.3%   Max: 96.1%
```

```
■ In   Now:  1.3k  Min:  0.0   Avg:739.3k  Max:  7.2M
■ Out  Now:273.3   Min:  0.0   Avg: 15.4k  Max:134.2k
```

Ganglia Cluster Report :: Netflix-6.2M (Host View)

Databricks Runtime Version:
10.1 (includes Apache Spark 3.2.0, Scala 2.12)



Overview of cluster @ 2021-11-14 11:22

cluster Load last hour

```
■ 1-min  Now:  7.1   Min:  0.0   Avg:  2.5   Max: 10.
■ Nodes  Now:  1.0   Min:  1.0   Avg:  1.0   Max:  1.
■ CPUs   Now:  2.0   Min:  2.0   Avg:  2.0   Max:  2.
■ Procs  Now:  8.0   Min:  0.0   Avg:  2.6   Max: 10.
```

cluster Memory last hour

```
■ Use    Now:   5.7G   Min: 193.8M  Avg:   3.7G   Max:   5.7G
■ Share  Now:   0.0    Min:   0.0   Avg:   0.0    Max:   0.0
■ Cache  Now:   2.6G   Min: 120.9M  Avg:   1.8G   Max:   2.8G
■ Buffer Now:   0.0    Min:   0.0   Avg:   0.0    Max:   0.0
■ Free   Now:   1.9G   Min:   1.9G  Avg:   4.6G   Max:   9.8G
■ Swap   Now:   0.0    Min:   0.0   Avg:   0.0    Max:   0.0
■ Total  Now:  10.1G   Min:  10.1G  Avg:  10.1G   Max:  10.1G
```

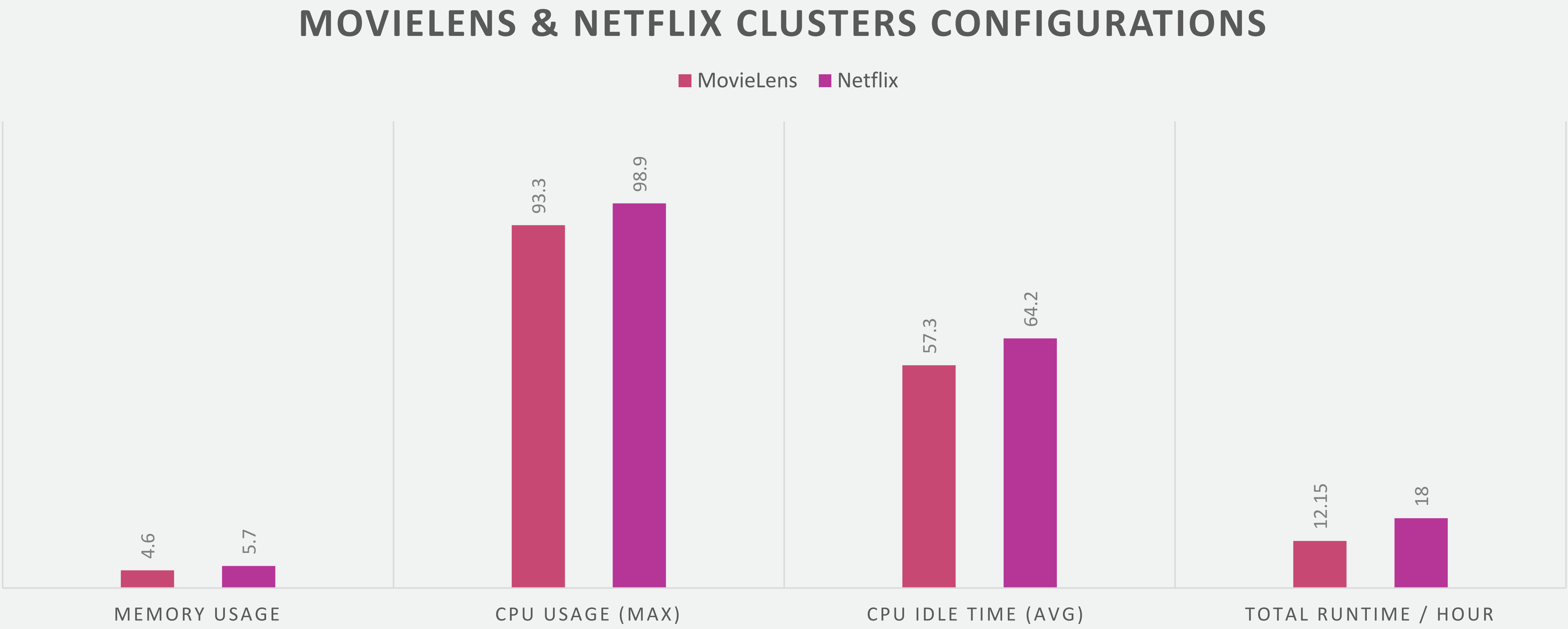
cluster CPU last hour

```
■ User   Now: 95.7%   Min:  1.0%  Avg: 31.9%   Max: 98.9%
■ Nice   Now:  0.0%   Min:  0.0%  Avg:  0.0%   Max:  0.0%
■ System Now:  2.4%   Min:  0.4%  Avg:  2.1%   Max: 13.4%
■ Wait   Now:  0.0%   Min:  0.0%  Avg:  1.4%   Max: 34.6%
□ Idle   Now:  1.9%   Min:  0.2%  Avg: 64.2%   Max: 97.7%
```

cluster Network last hour

```
■ In   Now:  4.5k  Min:  0.0   Avg:472.5k  Max: 15.5M
■ Out  Now:  2.5k  Min:  0.0   Avg:  4.9k  Max:115.2k
```

MovieLens and Netflix Clusters Configurations - usage Overall



Limitations & Future Work

Unable to create multiple master / worker node in Microsoft Azure Cloud as a student

Databricks Community Edition only permits cluster with 8-core CPU with node 2

Future Work

Hybrid recommender systems

Reducing dataset size and user-item segmentation

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Discussion

How is Apache Spark different from MapReduce?

Why is Apache Spark faster than Apache Hadoop?

Is it possible to run Apache Spark without Hadoop?

What role does worker node play in Apache Spark Cluster? And what is the need to register a worker node with the driver program?

How can you trigger automatic clean-ups in Spark to handle accumulated metadata?

Thank You