HANDS-ON RECOMMENDER SYSTEM ON PYSPARK

PySpark Collaborative Filtering with ALS

Understand data munging in PySpark while building a recommender system that utilises matrix factorisation technique — Alternating Least Squares (ALS)

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Photo by Nathan Dumlao (https://unsplash.com/@nate_dumlao) product a user will like, and based on that, recommends a few products to the users. For example, Amazon can recommend new shopping items to buy, Netflix can recommend new movies to watch, and Google can recommend news that a user might be interested in. The two widely used approaches for building a recommender system are the content-based filtering (CBF) and collaborative filtering (CF).

To understand the concept of recommender systems, let us look at an example. The below table shows the user-item *utility matrix* Y where the value Rui denotes how item i has been rated by user u on a scale of 1–5. The missing entries (shown by **?** in Table) are the items that have not been rated by the respective user.

	item1	item2	item3	item4
user1	2	5	1	3
user2	4	?	?	1
user3	?	4	2	?
user4	2	4	3	1
user5	1	3	2	?

user-item utility matrix

The objective of the recommender system is to predict the ratings for these items. Then the highest rated items can be recommended to the respective users. In real world problems, the utility matrix is expected to be very sparse, as each user only encounters a small fraction of items among the vast pool of options available. The code for this project can be found here.

Explicit v.s. Implicit ratings

There are two ways to gather user preference data to recommend items, the first method is to ask for **explicit ratings** from a user, typically on a concrete rating scale (such as rating a movie from one to five stars) making it easier to make extrapolations from data to predict future ratings. However, the drawback with explicit data is that it puts the responsibility of data collection on the user, who may not want to take time to enter ratings. On the other hand, **implicit data** is easy to collect in large quantities without any extra effort on the part of the user. Unfortunately, it is much more difficult to work with.

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In real world problems, the utility matrix is expected to be very sparse, as each user only encounters a small fraction of items among the vast pool of options available. Cold-Start problem can arise during addition of a new user or a new item where both do not have history in terms of ratings. Sparsity can be calculated using the below function.

```
def get_mat_sparsity(ratings):
    # Count the total number of ratings in the dataset
    count_nonzero = ratings.select("rating").count()

    # Count the number of distinct userIds and distinct movieIds
    total_elements = ratings.select("userId").distinct().count() * ratings.select("m

    # Divide the numerator by the denominator
    sparsity = (1.0 - (count_nonzero *1.0)/total_elements)*100
    print("The ratings dataframe is ", "%.2f" % sparsity + "% sparse.")

get_mat_sparsity(ratings)
```

calculate_sparsity hosted with ❤ by **GitHub** **view raw**

1. Dataset with Explicit Ratings (MovieLens)

MovieLens is a recommender system and virtual community website that recommends movies for its users to watch, based on their film preferences using collaborative filtering. MovieLens 100M datatset is taken from the MovieLens website, which customizes user recommendation based on the ratings given by the user. To understand the concept of recommendation system better, we will work with this dataset. This dataset can be downloaded from here.

There are 2 tuples, movies and ratings which contains variables such as MovieID::Genre::Title and UserID::MovieID::Rating::Timestamp respectively.

Let’s load the data and explore the data. To load the data as a spark dataframe, import pyspark and instantiate a spark session.

```
from pyspark.sql import SparkSession
spark =
SparkSession.builder.appName('Recommendations').getOrCreate()

movies = spark.read.csv("movies.csv",header=True)
ratings = spark.read.csv("ratings.csv",header=True)
```

```
+------+-------+------+
|userId|movieId|rating|
+------+-------+------+
|     1|     31|   2.5|
|     1|   1029|   3.0|
|     1|   1061|   3.0|
|     1|   1129|   2.0|
|     1|   1172|   4.0|
|     1|   1263|   2.0|
```

Movie lens data with explicit ratings given by the user for movies watched.

```
# Join both the data frames to add movie data into ratings
movie_ratings = ratings.join(movies, ['movieId'], 'left')
movie_ratings.show()
```

```
+-------+------+------+----------+--------------------+--------------------+
|movieId|userId|rating| timestamp|               title|              genres|
+-------+------+------+----------+--------------------+--------------------+
|     31|     1|   2.5|1260759144|Dangerous Minds (...|               Drama|
|   1029|     1|   3.0|1260759179|        Dumbo (1941)|Animation|Childre...|
|   1061|     1|   3.0|1260759182|     Sleepers (1996)|            Thriller|
|   1129|     1|   2.0|1260759185|Escape from New Y...|Action|Adventure|...|
|   1172|     1|   4.0|1260759205|Cinema Paradiso (...|               Drama|
|   1263|     1|   2.0|1260759151|Deer Hunter, The ...|           Drama|War|
|   1287|     1|   2.0|1260759187|       Ben-Hur (1959)|Action|Adventure|...|
```

Ratings and movie data combined for better visualisation

Let's calculate the data sparsity to understand the sparsity of the data. Please function that we built in the beginning of this article to get the sparsity. The movie lens data is 98.36% sparse.

```
get_mat_sparsity(ratings)
```

Before moving into recommendations, split the dataset into train and test. Please set the seed to reproduce results. We will look at different recommendation techniques in detail in the below sections.

```
# Create test and train set
(train, test) = ratings.randomSplit([0.8, 0.2], seed = 2020)
```

2. Dataset with Binary Ratings (MovieLens)

add implicit ratings using explicit ratings by adding 1 for watched and 0 for not watched. We aim the model to give high predictions for movies watched.

Please note this is not the right dataset for implict ratings since there may be movies in the not watched set, which the user has actually watched but not given a rating.

```
def get_binary_data(ratings):
    ratings = ratings.withColumn('binary', fn.lit(1))
    userIds = ratings.select("userId").distinct()
    movieIds = ratings.select("movieId").distinct()

    user_movie = userIds.crossJoin(movieIds).join(ratings, ['userId', 'movieId'], "l
    user_movie = user_movie.select(['userId', 'movieId', 'binary']).fillna(0)
    return user_movie

user_movie = get_binary_data(ratings)
```

get_binary_data hosted with ❤ by **GitHub** **view raw**

```
user_movie.show()
```

```
+------+-------+------+
|userId|movieId|binary|
+------+-------+------+
|   148|   1580|     1|
|   148|   2659|     0|
|   148|   3794|     0|
|   148|   3175|     1|
```

Approaches to Recommendation

The two widely used approaches for building a recommender system are the content-based filtering (CBF) and collaborative filtering (CF), of which CBF is the most widely used.

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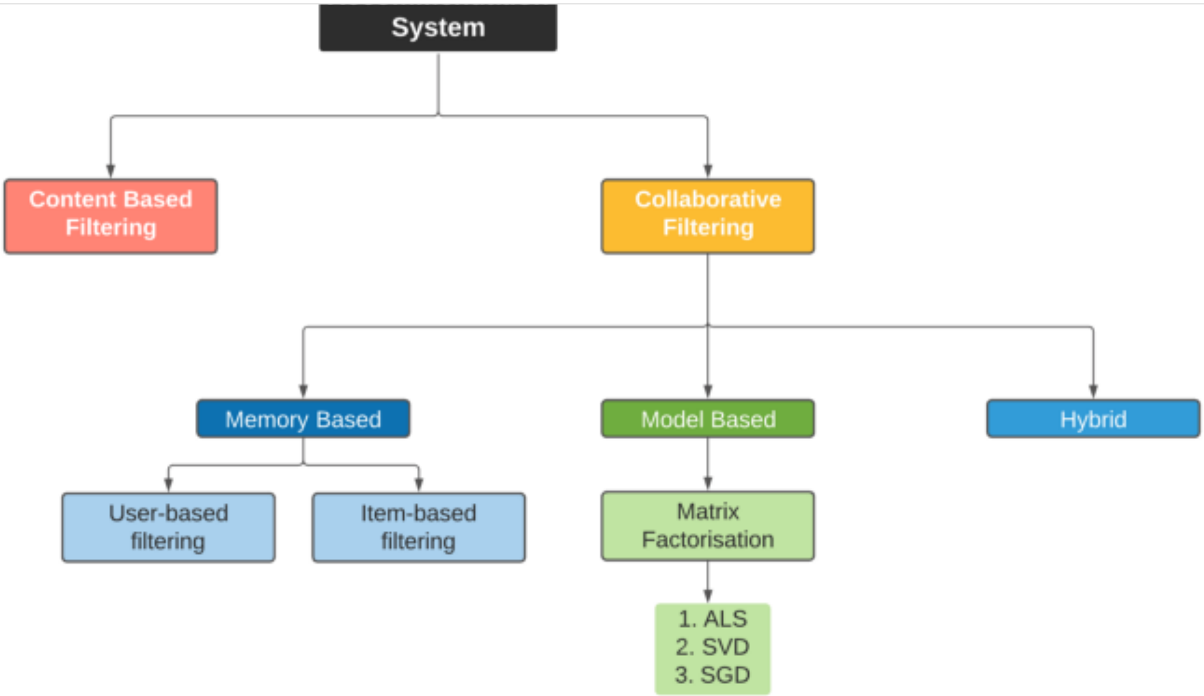


The below figure illustrates the concepts of CF and CBF. The primary difference between these two approaches is that CF looks for similar users to recommend items while CBF looks for similar contents to recommend items.

Content-based Filtering (CBF)

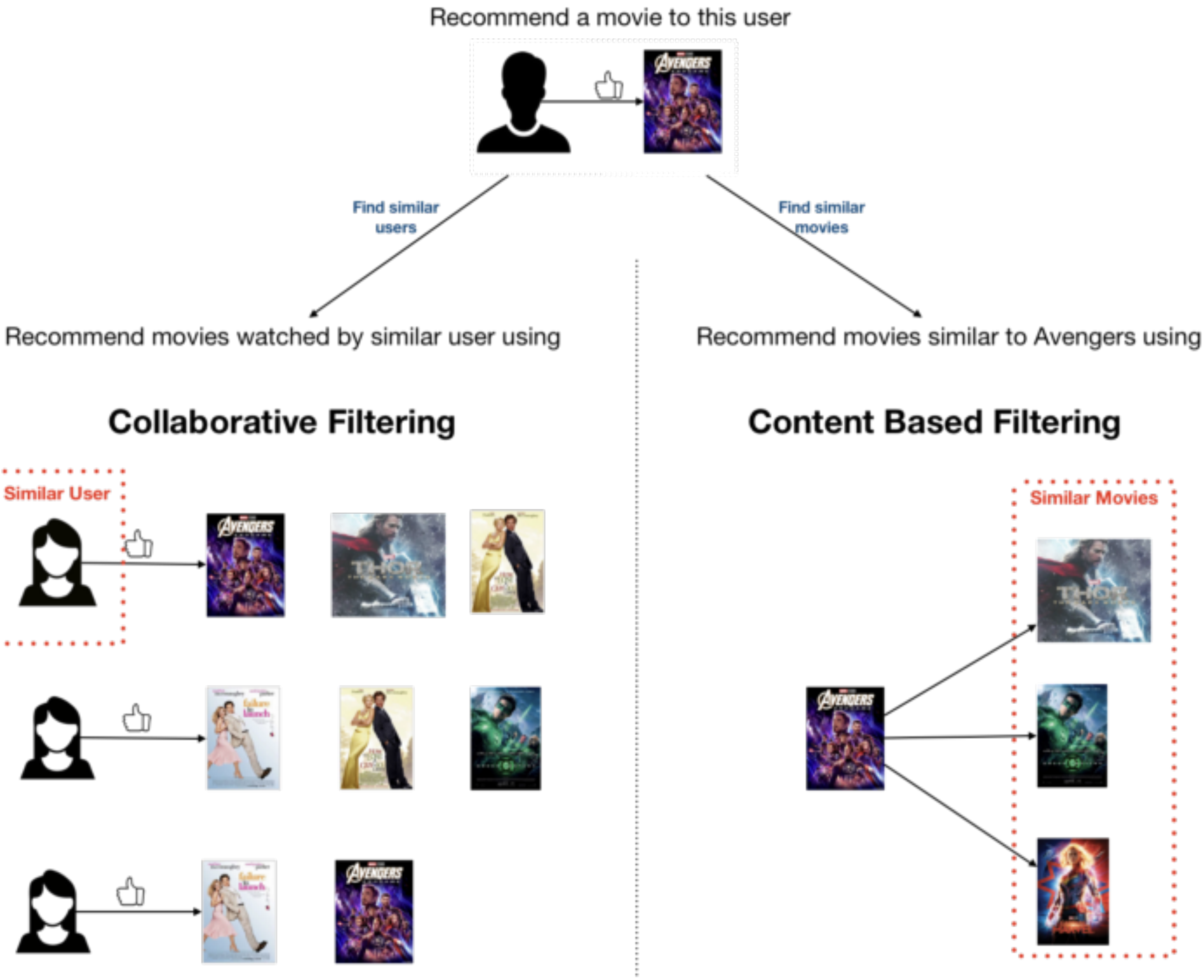
The main idea behind CBF is to recommend items similar to the items previously liked by the user. For example, if the user have rated some items in the past, then these items are used for *user-modeling* where the user's interests are quantified. Traditionally, the item iis represented by a *feature vector* xi, which can be boolean or real valued, and the user is represented by a weight vector ✓u of same dimension. Given a new item x⇤, represented in the same feature vector space, the likeliness, e.g., rating of the item is predicted using the user model.

This can be achieved in two different ways:

• Predicting ratings using parametric models like regression or logistic regression for multiple ratings and binary ratings respectively based on the previous ratings.

• Similarity based techniques using distance measures to find similar items to the items liked by the user based on item features.

CB can be applied even when a strong user-base is not built, as it depends on the item's meta data (features) therefore does not suffer from cold-start problem. However, this the item that the user already knows about, it leaves no room for serendipity and causes over specialisation. CB also ignores popularity of an item and other users feedbacks.



Collaborative filtering (CF)

Collaborative filtering aggregates the past behaviour of all users. It recommends items to a user based on the items liked by another set of users whose likes (and dislikes) are similar to the user under consideration. This approach is also called the *user-user* based CF.

item-item based CF became popular later, where to recommend an item to a user, the similarity between items liked by the user and other items are calculated. The user-user CF and item-item CF can be achieved by two different ways, **memory-based** (neighbourhood approach) and **model-based** (latent factor model approach).

1. The memory-based approach

sparse which hinders scalability, and second, they perform poorly in terms of reducing the RMSE (root-mean-squared-error) compared to other complex methods. User-based Filtering and Item-based Filtering are the two ways to approach memory-based collaborative filtering.

User-based Filtering: To recommend items to user u1 in the user-user based neighborhood approach first a set of users whose likes and dislikes similar to the useru1 is found using a similarity metrics which captures the intuition that sim(u1, u2) >sim(u1, u3) where user u1 and u2 are similar and user u1 and u3 are dissimilar. similar user is called the neighbourhood of user u1.

Item-based Filtering: To recommend items to user u1 in the item-item based neighborhood approach the similarity between items liked by the user andother items are calculated.

2. The model-based approach

Latent factor model based collaborative filtering learns the (latent) user and item profiles (both of dimension K) through matrix factorization by minimizing the RMSE (Root Mean Square Error) between the available ratings yand their predicted values y^. Here each item i is associated with a latent (feature) vector xi, each user u is associated

$$\hat{y}_{ui} = \mu + b_u + b_i + \theta_u^\top \mathbf{x}_i$$

Image Source: https://developers.google.com/machine-learning/recommendation/collaborative/matrix

Latent methods deliver prediction accuracy superior to other published CF techniques. It also addresses the sparsity issue faced with other neighbourhood models in CF. The memory efficiency and ease of implementation via gradient based matrix factorization model (SVD) have made this the method of choice within the Netflix Prize competition. However, the latent factor models are only effective at estimating the association between all items at once but fails to identify strong association among a small set of closely related items.

Recommendation using Alternating Least Squares (ALS)

Alternating Least Squares (ALS) matrix factorisation attempts to estimate the ratings matrix R as the product of two lower-rank matrices, X and Y, i.e. X * Yt = R. Typically these approximations are called 'factor' matrices. The general approach is iterative. During each iteration, one of the factor matrices is held constant, while the other is solved for using least squares. The newly-solved factor matrix is then held constant while solving for the other factor matrix.

In the below section we will instantiate an ALS model, run hyperparameter tuning, cross validation and fit the model.

1. Build out an ALS model

To build the model explicitly specify the columns. Set nonnegative as '*True*', since we are looking at rating greater than 0. The model also gives an option to select implicit ratings. Since we are working with explicit ratings, set it to '*False*'.

it is actually very common to encounter users and/or items in the evaluation set that are not in the training set. By default, Spark assigns `NaN` predictions during `ALSModel.transform` when a user and/or item factor is not present in the model.*We set cold start strategy to 'drop' to ensure we don't get NaN evaluation metrics*

```
# Import the required functions
from pyspark.ml.evaluation import RegressionEvaluator
from pyspark.ml.recommendation import ALS
from pyspark.ml.tuning import ParamGridBuilder, CrossValidator

# Create ALS model
als = ALS(
         userCol="userId",
         itemCol="movieId",
         ratingCol="rating",
         nonnegative = True,
         implicitPrefs = False,
         coldStartStrategy="drop"
)
```

2. Hyperparameter tuning and cross validation

```
# Import the requisite packages
from pyspark.ml.tuning import ParamGridBuilder, CrossValidator
from pyspark.ml.evaluation import RegressionEvaluator
```

ParamGridBuilder: We will first define the tuning parameter using param_grid function, please feel free experiment with parameters for the grid. I have only chosen 4 parameters for each grid. This will result in 16 models for training.

```
# Add hyperparameters and their respective values to param_grid
param_grid = ParamGridBuilder() \
            .addGrid(als.rank, [10, 50, 100, 150]) \
            .addGrid(als.regParam, [.01, .05, .1, .15]) \
            .build()
```

RegressionEvaluator: Then define the evaluator, select rmse as metricName in evaluator.

```
# Define evaluator as RMSE and print length of evaluator
evaluator = RegressionEvaluator(
           metricName="rmse",
           labelCol="rating",
           predictionCol="prediction")
print ("Num models to be tested: ", len(param_grid))
```

CrossValidator: Now feed both param_grid and evaluator into the crossvalidator including the ALS model. I have chosen number of folds as 5. Feel free to experiement with parameters.

```
# Build cross validation using CrossValidator
cv = CrossValidator(estimator=als, estimatorParamMaps=param_grid,
evaluator=evaluator, numFolds=5)
```

4. Check the best model parameters

Let us check, which parameters out of the 16 parameters fed into the crossvalidator, resulted in the best model.

```
print("**Best Model**")

# Print "Rank"
print("  Rank:", best_model._java_obj.parent().getRank())

# Print "MaxIter"
print("  MaxIter:", best_model._java_obj.parent().getMaxIter())

# Print "RegParam"
print("  RegParam:", best_model._java_obj.parent().getRegParam())
```

```
**Best Model**
  Rank: 16
  MaxIter: 10
  RegParam: 0.16
```

3. Fit the best model and evaluate predictions

Now fit the model and make predictions on test dataset. As discussed earlier, based on the range of parameters chosen we are testing 16 models, so this might take while.

```
#Fit cross validator to the 'train' dataset
model = cv.fit(train)

#Extract best model from the cv model above
best_model = model.bestModel

# View the predictions
test_predictions = best_model.transform(test)

RMSE = evaluator.evaluate(test_predictions)
print(RMSE)
```

The RMSE for the best model is 0.866 which means that on average the model predicts 0.866 above or below values of the original ratings matrix. Please note, matrix factorisation unravels patterns that humans cannot, therefore you can find ratings for a few users are a bit off in comparison to others.

4. Make Recommendations

Lets go ahead and make recommendations based on our best model. recommendForAllUsers(n) function in als takes n recommedations. Lets go with 5 recommendations for all users.

```
# Generate n Recommendations for all users
recommendations = best_model.recommendForAllUsers(5)
recommendations.show()
```

```
+------+--------------------+
|userId|     recommendations|
+------+--------------------+
|   471|[[3379, 4.816196]...|
|   463|[[3379, 4.994439]...|
|   496|[[3379, 4.5707183...|
|   148|[[33649, 4.504622...|
|   540|[[3379, 5.4063077...|
|   392|[[3379, 4.65679],...|
|   243|[[3379, 5.7590547...|
|    31|[[3379, 5.100943]...|
|   516|[[4429, 4.8041797...|
|   580|[[3379, 4.756224]...|
+------+--------------------+
```

5. Convert recommendations into interpretable format

The recommendations are generated in a format that easy to use in pyspark. As seen in recommendations make sense, we will want to add more information like movie name and genre, then explode array to get rows with single recommendations.

```
nrecommendations = nrecommendations\
    .withColumn("rec_exp", explode("recommendations"))\
    .select('userId', col("rec_exp.movieId"), col("rec_exp.rating"))

nrecommendations.limit(10).show()
```

userId	movieId	rating
471	3379	4.816196
471	8477	4.6407275
471	33649	4.5224075
471	171495	4.4964633
471	86781	4.482169
463	3379	4.994439
463	131724	4.7216597
463	33649	4.709987
463	171495	4.703137
463	78836	4.6359744

Do the recommendations make sense?

To check if the recommendations make sense, join movie name and genre to the above table. Lets randomly pick 100th user to check if the recommendations make sense.

100th User's ALS Recommendations:

movieId	userId	rating	title	genres
67618	100	5.1405735	Strictly Sexual (...	Comedy|Drama|Romance
3379	100	5.006642	On the Beach (1959)	Drama
33649	100	5.0065255	Saving Face (2004)	Comedy|Drama|Romance
42730	100	4.9775596	Glory Road (2006)	Drama
74282	100	4.915519	Anne of Green Gab...	Children|Drama|Ro...
26073	100	4.874221	Human Condition I...	Drama|War
184245	100	4.874221	De platte jungle ...	Documentary
84273	100	4.874221	Zeitgeist: Moving...	Documentary
7071	100	4.874221	Woman Under the I...	Drama
117531	100	4.874221	Watermark (2014)	Documentary

100th User's Actual Preference:

```
ratings.join(movies, on='movieId').filter('userId = 100').sort('rating',
ascending=False).limit(10).show()
```

movieId	userId	rating	title	genres
1101	100	5.0	Top Gun (1986)	Action|Romance
1958	100	5.0	Terms of Endearme...	Comedy|Drama
2423	100	5.0	Christmas Vacatio...	Comedy
4041	100	5.0	Officer and a Gen...	Drama|Romance
5620	100	5.0	Sweet Home Alabam...	Comedy|Romance
368	100	4.5	Maverick (1994)	Adventure|Comedy|...
934	100	4.5	Father of the Bri...	Comedy
539	100	4.5	Sleepless in Seat...	Comedy|Drama|Romance
16	100	4.5	Casino (1995)	Crime|Drama
553	100	4.5	Tombstone (1993)	Action|Drama|Western

The movie recommended to the 100th user primarily belongs to comedy, drama, war and romance genres, and the movies preferred by the user as seen in the above table, match very closely with these genres.

I hope you enjoyed reading. Please find the detailed codes in the Github Repository.

References:

http://spark.apache.org/docs/2.2.0/ml-collaborative-filtering.html