Summary Report (Include Cloud Service Set Up)

Building Movie Recommendation System Using Multiple Models

Introduction

Recommendation systems are one of the most widespread machine learning applications in the industry. They are not only built for movies and music streaming, but also for multiple products and services like e-commerce business, news and so on. Companies like Netflix, Youtube, and Amazon have leveraged recommendation systems to discover user preference and provide them with more relevant goods and services to enhance user experience and generate recurring revenue. No doubt, recommendation system is an indispensable part of their business success.

This assignment went through processes of building necessary elements for recommender engine, implementing an ensemble of machine learning algorithms and making use of AWS Sagemaker endpoint. The final pipeline is capable of offering specific movie suggestions for different users based on a combination result of three different models: ALS, AWS FM and Scikit-Surprise.

Dataset

The dataset used in this assignment is the famous MovieLens dataset. There are various versions available online(https://grouplens.org/datasets/movielens/), but for ease of use, ml-100k version is chosen to apply to those three models mentioned above. The dataset contains 100k ratings from 943 users on 1682 items. Features included in ml-100k version dataset are rating, genre, tag, movieid, userid, tagid and so on.

Model 1 : ALS Estimator Using Spark

The movielens dataset is downloaded from an grouplens online URL. After loading and unzip the movielens dataset from grouplens website, two dataframes (with features including userId, movieId, and rating) representing training and test data are created for further use.

According to the Spark ALS documentation, ALS(Alternating Least Squares) estimates the rating matrix as the product of two matrix with lower rank. During each iteration, one of the matrix is held constant while the other is solved using least squares. Then, the solved one is held constant while solving the other matrix using least squares.

To train an ALS estimator, initially we can simply use default parameters or set certain values, at the same time, specifying user, rating and item column respectively. For cold start strategy, users can choose between "drop" and `"NaN"`. In order for us to derive a performance metric to evaluate the recommendation system, we set the coldStartStrategy parameter as "drop" to drop rows in the prediction dataframe which contains NaN values. Further, cross validation with parameter tuning is applied to enhance ALS model. We set a parameter grid and apply the cross validation method, finally the best parameter with the smallest rmse is derived. When implementing the ALS model with the best parameter, the RMSE computed on the test data is 0.957.

The prediction result of the first model ALS estimator might not be satisfactory, but this is only from a single ALS model. We can expect further improvement later on when aggregating multiple effective models altogether.

Using als built-in functions recommendForAllUsers and recommendForAllItems, movies recommended and predicted rating for each user and user recommended for each movie can be easily obtained. The top 5 recommendation movieid are first stored in a list under the feature “recommendations”. For further comparison with other methods, the format of the final recommendation dataframe is adjusted, containing three features: userId, movieId and predicted_rating.

Model 2 : Scikit-Surprise

Surprise is a python Scikit used for recommdation system and it stands for Simple Python RecommendatIon System Engine. Users can use built-in datasets like movielens and custom dataset to build a recommendation system. There are various ready-to-use algorithms in Surprise package including collaborative filtering, matrix decomposition and so on. This package is a quite simple and easy to use. However, Surprise doesn’t support content-based information and implicit ratings.

The process of building recommendation system using Surprise is quite straightforward. After importing relevant modules and loading ml-100k dataset, trainset and testset are specified respectively for further use. Next, SVD algorithm, which also deals with Matrix factorization, is trained on the trainset and tested on the testset. The rmse of SVD model on the test set is 0.675, which is much smaller that that of AlS estimator. Next, a function called get_top_n is defined to return the top n (default number is five) recommendations for each user. The top 5 movid recommendations for all usered can be obtained using for loop. Again, just like the transformation shown in previous als recommendation result, the recommendations result using Surprise is adjusted to the same format.

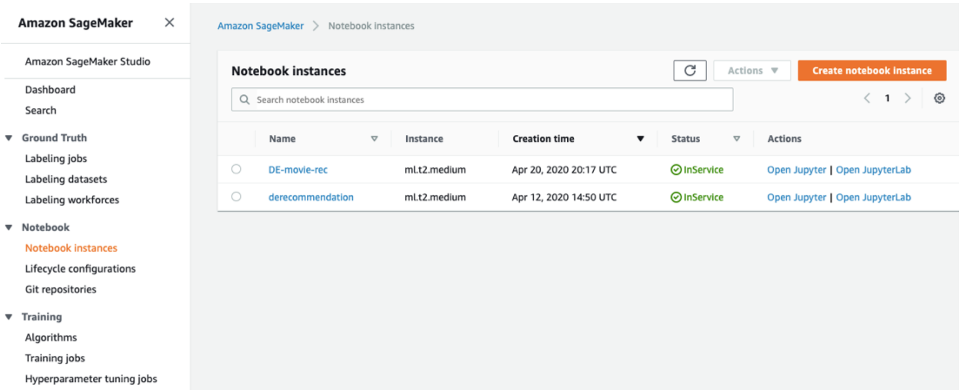
Model 3 : FM SageMaker

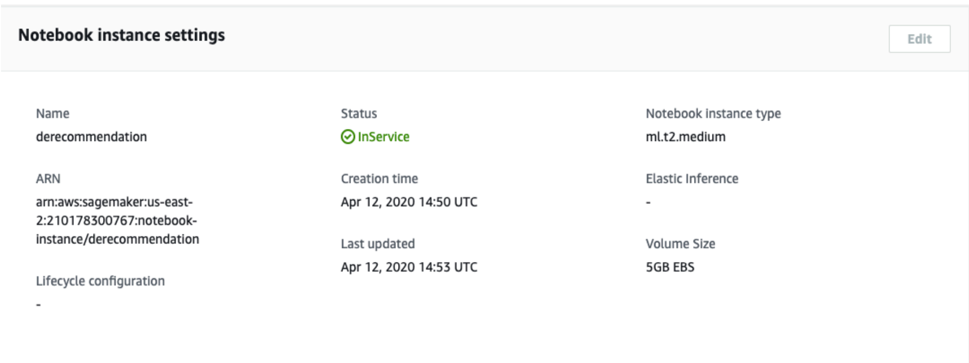
The final model built for this recommendation system is Factorization Machines(FM), the famous built-in algorithm of Amazon SageMaker, which is widely used for recommendation system (eg, FM models are used by Netflix to recommend movies for users). Factorization Machinesas is one class of collaborative filtering algorithms. As the name suggests, FM also uses matrix factorization to reduce problem dimensionality and thus, greatly boost computational efficiency on large sparse dataset.

In the movielens dataset (and also in real world practice !), the number of users and items are often large whereas users normally rate a small portion of all movies available. Therefore, the actual number of recommendations is quite small, resulting a large sparse dataset. The basic idea of factorization in FM model is that a sparse rating matrix can be decomposed into a dense user matrix and item matrix with lower dimension. Another benefit of using FM is that matrix factorization can also help us fill the blank values in the rating matrix, which means we can recommend new items to users.

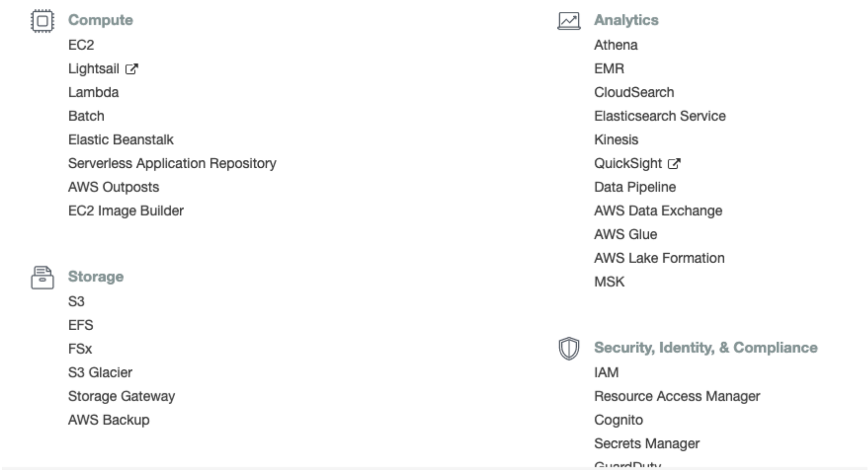
The pipeline of the recommendation system using sagemaker fm involves loading ml-100k data, data preprocessing stage (one hot-encoding user and movie for sparse matrix, and building binary label), converting data to protobuf and write to S3, and training, hyparameter tuning, deploying and finally predict using AWS SageMaker endpoint. The detailed code for building the pipeline is covered in the notebook. Here, a few steps to set up the cloud service are shown below.

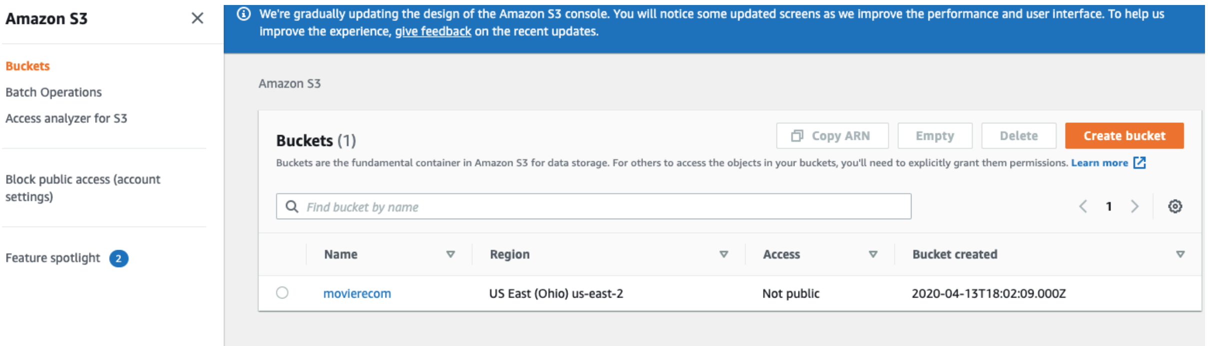
The first step is to create a notebook instance and specify the instance name and type. For example, for the notebook instance named derecommendation, the instane type is ml.t2.medium and the volume size is 5GB. Next we can open jupyter and create a 'conda_python 3' notebook to write the code and analysis.

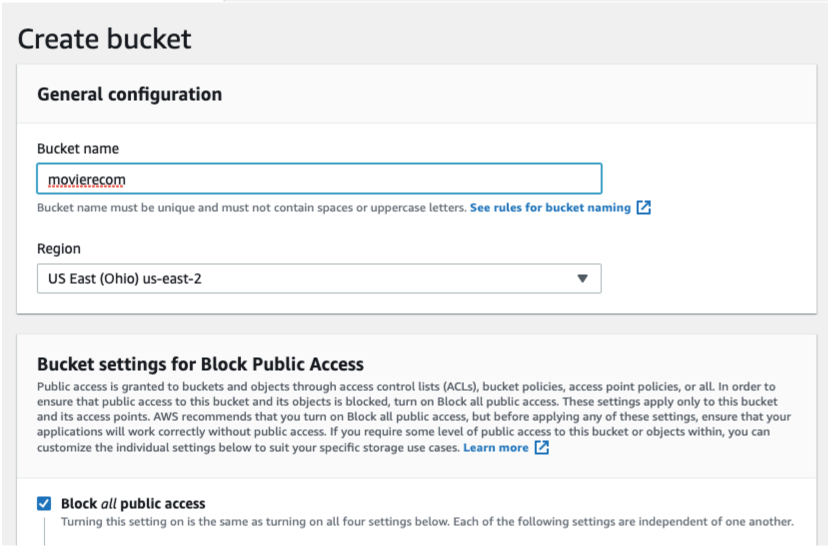




Another important step is to store the data in protobuf format to S3. To achieve this, first we need to create a bucket in Sagemaker service-Storage-S3 interface. Remember to notedown the bucket name as we need to specify the data storage bucket in the code.



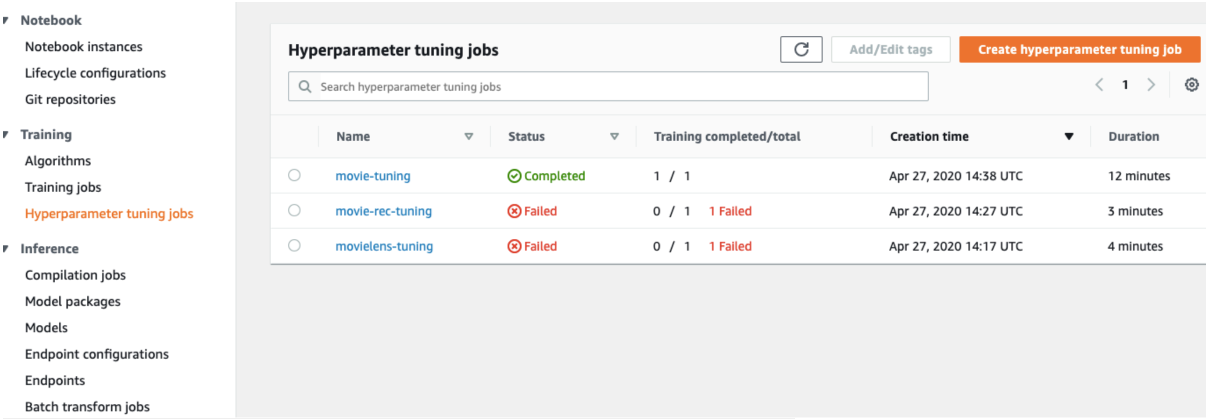


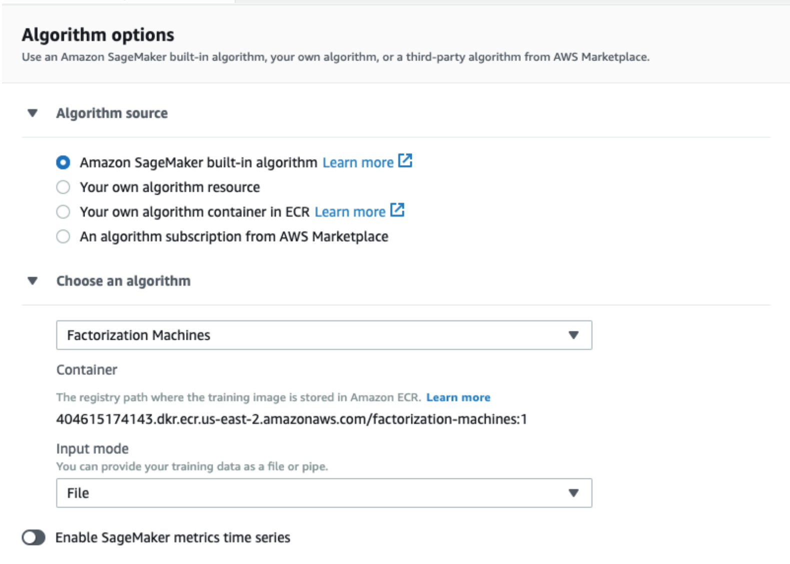


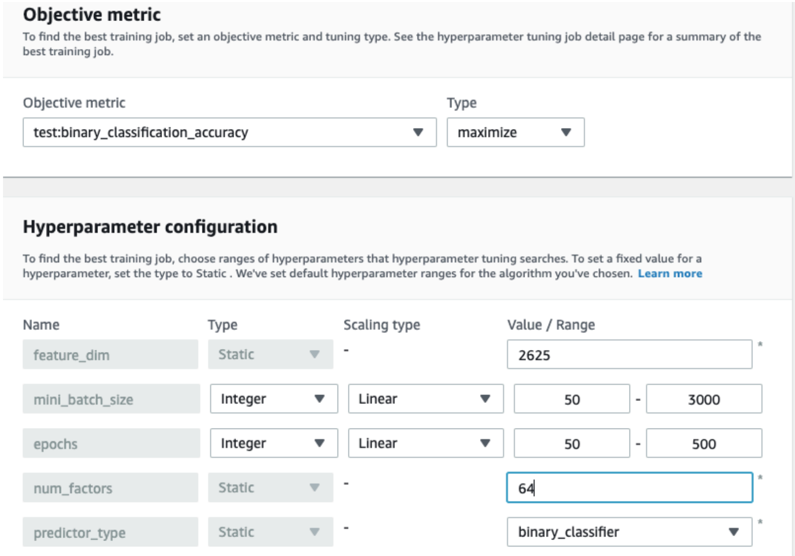

```python
#specify my personal bucket name
bucket = 'movierecom'
prefix = 'fm'

#write the key and prefix for train, test and output
train_key      = 'train.protobuf'
train_prefix   = '{}/{}'.format(prefix, 'train')

test_key       = 'test.protobuf'
test_prefix    = '{}/{}'.format(prefix, 'test')

output_prefix  = 's3://{}/{}/output'.format(bucket, prefix)
```

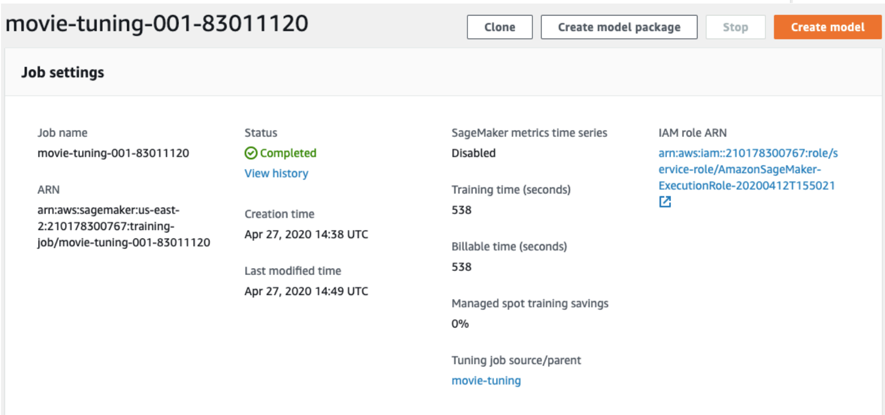
```
Training data S3 path:  s3://movierecom/fm/train/train.protobuf
Test data S3 path:  s3://movierecom/fm/test/test.protobuf
FM model output S3 path: s3://movierecom/fm/output
```

We can also use Sagemaker to tune hyperparamaters. After fitting the fm model using an initial set of hyperparameters, it is also quite convenient to do hyperparameter tuning jobs in Sagemaker training-hyperparameter tuning jobs interface. We need to create a tuning job and set configurations as shown in the screenshots. Note that the objective metric here is binary_classification_accuracy and the goal is to maximize it.

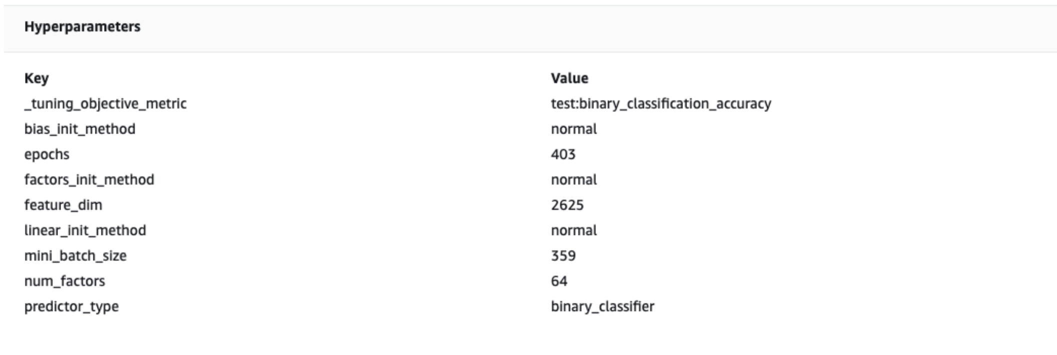








The best parameter which gives us the highest binary classification accuracy is shown below. Therefore it is optimal to set the hyperparameter as follows, deploying and predicting based on this model.



Hyperparameters

Key	Value
_tuning_objective_metric	test:binary_classification_accuracy
bias_init_method	normal
epochs	403
factors_init_method	normal
feature_dim	2625
linear_init_method	normal
mini_batch_size	359
num_factors	64
predictor_type	binary_classifier

Finishing the prediction using sagemaker endpoint, we can test on a particular record and a set of records. It is easy to get on-demand response for a particular userId and movieId pair, and compare the predicted scores and labels among different pairs. However, we need to derive the top n recommendations for each user, not just a single line response. In the notebook, three functions named ‘GetRecIndex’, ‘GetRecMovieID’, ‘UserFmDf’ to derive the final recommendations for each user (see the code in the notebook). The basic idea is to get all the response for each user and sort the positive response(predicted label=1) by score, and map the result to movieId in the test dataset to get the corresponding movieid for each response.

Model Combination : Scoring Strategy

Now the movie recommendations generated by the each model and corresponding predicted score/rating are available. We need to figure out a way to weight the result from different models and derive final top 5 movie recommendations for each user based on a combination score of those three models : ALS, Sagemaker FM, Surprise.

The scoring strategy takes both accuracy of each model and predicted score of each pair into consideration. To ensure the predicted scores of each pair in different models are comparable, standardization process is implemented since we only care about the relative distance of each predicted score in a model. Next, a weight metric is constructed using predicted score(after scaling) divided by the rmse of each model. The higher the weight is, the more accurate the recommendation result will be. Then, we add the weight of each pair(userid, movieid) generated by different models. By sorting the sum of weight of different pairs, we can easily get the top 5 recommendations for each user.

Reference:

[1]
https://spark.apache.org/docs/latest/api/java/org/apache/spark/ml/recommendation/ALS.html
[2]
https://surprise.readthedocs.io/en/stable/FAQ.html
[3]
https://aws.amazon.com/blogs/machine-learning/build-a-movie-recommender-with-factorization-machines-on-amazon-sagemaker/