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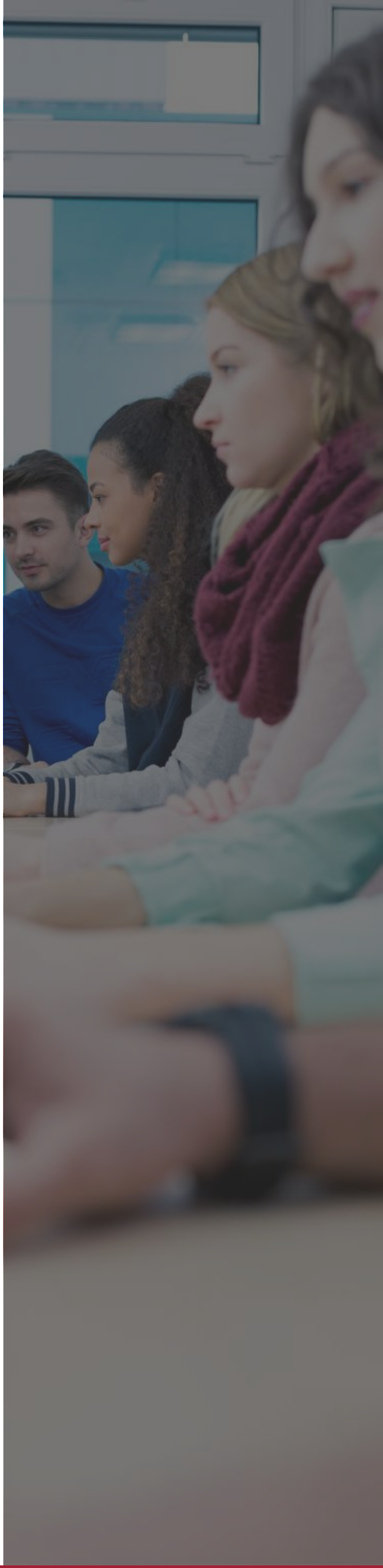
Case Study: Build Your Own Recommendation System for Movies



WHAT WILL YOU GET OUT OF THIS CASE STUDY?

This case study is extracted from MIT's online course for professionals, Data Science and Big Data Analytics: Making Data-Driven Decisions.

After going through this case study, you'll be able to:

- Analyze data to develop your own version of a recommendation engine, which forms the basis of content systems used at companies like Netflix, Pandora, Spotify, etcetera
- Experience a hands-on approach to advance your data science skills
- Access to a series of resources and tools, including sample data basis, that will enable you to build your recommendation system
- Get a sneak peak at the content included in MIT's online professional course on data science

IMPORTANT:
Don't get discouraged if some of the steps described seem too complicated! Remember, this is an extract of the online course that will provide you with all the background necessary to successfully complete this case study.

Learn more about the course here.

WHY THIS CASE STUDY?

By following some simple steps, you can develop your own version of a recommendation engine, which forms the basis of several content recommendation systems, e.g. Netflix, Pandora, Spotify etc. You can now apply this acquired skill to all sorts of domains of your choice, e.g. restaurant recommendations.

Self-Help Documentation: In this document, we walk through some helpful tips to get you started with building your own Recommendation engine based on the case studies discussed in the Recommendation systems module. In this tutorial, we provide examples and some pseudo-code for the following programming environments: R, Python. In case you need extra help on coding, you can download the Jupyter software and read this file where you will find the code needed to solve the case study.

Time Required: The time required todo this activity varies depending on your experience in the required programming background. We suggest to plan somewhere between 1 & 3 hours. Remember, this is an optional activity for participants looking for hands-on experience.

Before You Start: Watch this video! It's taken also from the course and it provides context and knowledge you will need to complete this activity If link above doesn't work, copy and paste this on your browser: **https://www.youtube.com/watch?v=m9gESMWWb5Q**

MEET YOUR INSTRUCTOR, PROF. DEVAVRAT SHAH

Co-director of the MIT online course Data Science and Big Data Analytics: Making Data-Driven Decisions

As a professor in the department of electrical engineering and computer science at MIT, Dr. Shah's current research is on the theory of large complex networks. He is a member of the Laboratory for Information and Decision Systems and the Director the Statistics and Data Science Center in MIT Institute for Data, Systems, and Society. Dr. Shah received his Bachelor of Technology in Computer Science and Engineering from the Indian Institute of Technology, Bombay, in 1999. He received the Presidents of India Gold Medal, awarded to the best graduating student across all engineering disciplines. He received his Ph.D. in CS from Stanford University. His doctoral thesis won the George B. Dantzig award from INFORMS for best dissertation. In 2005, he started teaching at MIT. In 2013, he co-founded Celect, Inc.

DISCLAIMER:

This case study will require some prior knowledge and experience with the programming language you choose to use for reproducing case study results. Generally, participants with 6 months of experience using "R"or"Python" should be successful ingoing through these exercises. MIT is not responsible for errors in these tutorials or in external, publicly available data sets, code, and implementation libraries. Please note that any links to external, publicly available websites, data sets, code, and implementation libraries are provided as a courtesy for the student. They should not be construed as an endorsement of the content or views of the linked materials.

INTRODUCTION

In this document, we walk through some helpful tips to get you started with building your own Recommendation engine based on the case studies discussed in the Recommendation systems module. In this tutorial, we provide examples and some pseudo-code for the following programming environments: **R, Python**. We cover the following:

1. **Getting the data**
2. **Working with the dataset**
3. **Recommender libraries in R, Python**
4. **Data partitions (Train, Test)**
5. **Integrating a Popularity Recommender**
6. **Integrating a Collaborative Filtering Recommender**
7. **Integrating an Item-Similarity Recommender**
8. **Getting Top-K recommendations**
9. **Evaluation: RMSE**
10. **Evaluation: Confusion Matrix/Precision-Recall**

Remember to watch this video first: **https://www.youtube.com/watch?v=m9gESMWWb5Q**

1 GETTING THE DATA

For this tutorial, we use the dataset(s) provided by MovieLens. MovieLens has several datasets. You can choose any. For this tutorial, we will use the 100K dataset dataset. This dataset set consists of:

- **100,000 ratings (1-5) from 943 users on 682 movies.**
- **Each user has rated at least 20 movies.**
- **Simple demographic info for the users (age, gender, occupation, zip)**

Download the "u.data" file. To view this file you can use Microsoft Excel, for example. It has the following tab-separated format: **user id | item id | rating | timestamp**. The timestamps are in Unix seconds since 1/1/1970 UTC, EPOCH format.

2 WORKING WITH THE DATA SET

The first task is to explore the dataset. You can do so using a programming environment of your choice, e.g. **Python** or **R**.

In R, you can read the data by simply calling the read.table() function:

```
data = read.table('u.data')
```

You can rename the column names as desired:

```
olnames(data) = c("user_id", "item_id", "rating", "timestamp")
```

Since we don't need the timestamps,
we can drop them:

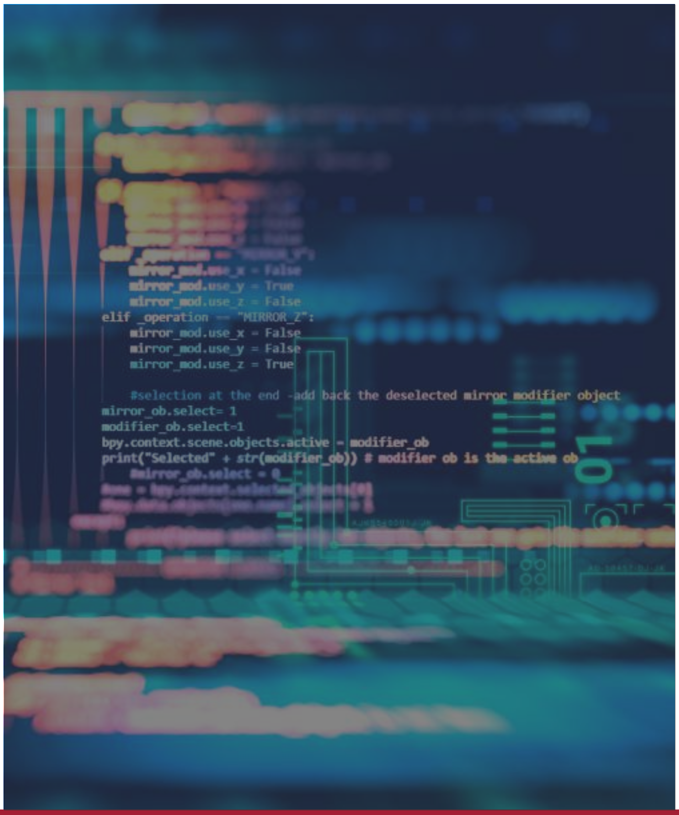
```
data = data[ , -which(names(data) %in%  c("timestamp"))]
```

You can look at the data properties by using:

```
str(data)
summary(data)
```

Plot a histogram of the data:

```
hist(data$rating)
```



```
elif _operation == "MIRROR_Z":
    mirror_mod.use_x = False
    mirror_mod.use_y = False
    mirror_mod.use_z = True

    #selection at the end -add back the deselected mirror modifier object
mirror_ob.select= 1
modifier_ob.select=1
bpy.context.scene.objects.active = modifier_ob
print("Selected" + str(modifier_ob)) # modifier ob is the active ob
```

In Python, you can convert the data to a Pandas dataframe to organize the dataset. For plotting in Python, you can use MatplotLib. You can do all the operations above (described for R), in Python using Pandas in the following way:

```
import matplotlib as mpl
mpl.use('TkAgg')
from matplotlib import pyplot as plt
import pandas as pd
import numpy as np

col_names = ["user_id", "item_id", "rating", "timestamp"]
data = pd.read_table(“u.data”, names=col_names)
data = data.drop(“timestamp”, 1)
data.info()

plt.hist(data[“rating”])
plt.show()
```

DATA SPARSITY

The dataset sparsity can be calculated as:

$$\text{Sparsity} = \frac{\text{Number of Ratings in the Dataset}}{\text{(Number of movies/Columns) * (Number of Users/Rows)}} * 100\%$$

In R, you can calculate these quantities as follows:

```
Number_Ratings = nrows(data)
Number_Movies = length(unique(data$item_id))
Number_Users = length(unique(data$user_id))
```

In Python, while using Pandas, can you do the same:

```
Number_Ratings = len(data)
Number_Movies = len(np.unique(data[“item_id”]))
Number_Users = len(np.unique(data[“user_id”]))
```

SUB-SETTING THE DATA:

If you want the data to be less sparse, for example, a good way to achieve that is to subset the data where you only select Users/Movies that have at least a certain number of observations in the dataset.

In R, for example, if you wanted to subset the data such that only users with 50 or more ratings remained, you would do the following:

```
data = data[ data$user_id %in%  names(table(data$user_id))
[table(data$user_id) > 50] , ]
```

3 RECOMMENDERS

If you want to build your own Recommenders from scratch, you can consult the vast amounts of academic literature available freely. There are also several self-help guides which can be useful, such as these:

- Collaborative Filtering with R;
- How to build a Recommender System;

On the other hand, why build a recommender from scratch when there is a vast array of publicly available Recommenders (in all sorts of programming environments) ready for use? Some examples are:

- RecommenderLab for R;
- Graphlab-Create for Python (has a free license for personal and academic use);
- Apache Spark's Recommendation module;
- Apache Mahout;

For this tutorial, we will reference **RecommenderLab** and **Graphlab-Create**.

4 SPLITTING DATA RANDOMLY (TRAIN/TEST)

A random split can be created in R and Pandas (Python).

In R, you can do the following to create a 70/30 split for Train/Test:

```
library(caTools)
spl = sample.split(data$rating, 0.7)
train = subset (data, spl == TRUE)
test = subset (data, spl == FALSE)
```

In Pandas (Python), using the **SciKit-Learn** library, we can do the same via:

```
import pandas as pd
import numpy as np
from sklearn.cross_validation import train_test_split
# assuming pdf is the pandas dataframe with the data
train, test = train_test_split(pdf, test_size = 0.3)
```

Alternatively, one can use the Recommender libraries (discussed earlier) to create the data splits.

For RecommenderLab in R, the documentation in Section 5.6 provides examples that will allow random data splits.

Graphlab's Sframe objects also have a random_split() function which works similarly.

5 POPULARITY RECOMMENDER

RecommenderLab, provides a popularity recommender out of the box. Section 5.5 of the RecommenderLab guide provides examples and sample code to help do this.

GraphLab-Create also provides a Popularity Recommender. If the dataset is in Pandas, it can easily integrate with GraphLab's Sframe datatype as noted here. Some more information on the Popularity Recommender and its usage is provided on the popularity recommender's online documentation.

6 COLLABORATIVE FILTERING

Most recommender libraries will provide an implementation for Collaborative Filtering methods. The RecommenderLab in R and GraphLab in Python both provide implementations of Collaborative Filtering methods, as noted next:

For RecommenderLab, use the "UBCF" (user-based collaborative filtering) to train the model, as noted in the documentation.

For GraphLab, use the "Factorization Recommender".

Often, a regularization parameter is used with these models. The best value for this regularization parameter is chosen using a Validations set. Here is how this can be done:

1. If the Train/Test split has already been performed (as detailed earlier), split the Train set further (75%/25%) in to Train/Validation sets. Now we have three sets: Train, Validation, Test.
2. Train several models, each using a different value of the regularization parameter (usually in the range: (1e-5, 1e-1).
3. Use the Validation set to determine which model results in the lowest RMSE (see Evaluation section below).
4. Use the regularization value that corresponds to the lowest Validation-set RMSE (see Evaluation section below).
5. Finally, with that parameter value fixed, use the trained model to get a final RMSE value on the Test set.
6. It can also help plotting the Validation set RMSE values vs the Regularization parameter values to determine the best one.

IMPORTANT:
Don't get discouraged if some of the steps described seem too complicated! Remember, this is an extract of the online course that will provide you with all the background necessary to successfully complete this case study.

7 ITEM SIMILARITY FILTERING

Several recommender libraries will also provide Item-Item similarity based methods.

For RecommenderLab, use the "IBCF" (item-based collaborative filtering) to train the model.

For GraphLab, use the "Item-Item Similarity Recommender".

Item Similarity recommenders can use the "0/1" ratings model to train the algorithms (where 0 means the item was not rated by the user and 1 means it was). No other information is used. For these types of recommenders, a ranked list of items **recommended** for each user is made available as the output, based on "similar" items. Instead of RMSE, a Precision/Recall metric can be used to evaluate the accuracy of the model (see details in the Evaluation Section below).

8 TOP-K RECOMMENDATIONS

Based on scores assigned to User-Item pairs, each recommender algorithm makes available functions that will provide a sorted list of top-K items most highly recommended for each user (from among those items not already rated by the user).

In RecommenderLab, the parameter type='topNlist' to the evaluate() function will produce such a list.

In GraphLab, the recommend(K) function for each type of recommender object will do the same.

9 EVALUATION: RMSE (ROOT MEAN SQUARED ERROR)

Once the model is trained on the Training data, and any parameters determined using a Validation set, if required, the model can be used to compute the error (RMSE) on predictions made on the Test data.

RecommenderLab in R, uses the predict() and calcPredictionAccuracy() functions to compute the predictions (based on the trained model) and evaluate RMSE (and MSE and MAE).

GraphLab in Python, also has a predict() function to get predictions. It provides a suite of functions to evaluate metrics such as rmse (evaluation.rmse(), for example).

10 EVALUATION: PRECISION/RECALL, CONFUSION MATRIX

For the top-K recommendations based evaluation, such as in Item Similarity recommenders, we can evaluate using a Confusion Matrix or Precision/Recall values. Specifically,

- Precision: out of K top recommendations, how many of the true best K songs were recommended.
- Recall: out of the K best recommendations, how many were recommended.

For RecommenderLab, the getConfusionMatrix (results), where results is the output of the evaluate() function discussed earlier, will provide the True Positives, False Negatives, False Positives and True Negatives matrix from which Precision and Recall can be calculated.

In Graphlab, the following function will also produce the Confusion Matrix: evaluation.confusion_matrix(). Also, if comparing models, e.g. Popularity Recommender and Item-Item Similarity Recommender, a precision/recall plot can be generated by using the following function: recommender.util.compare_models(metric='precion _recall'). This will produce a Precision/Recall plot (and list of values) for various values of K (the number of recommendations for each user).