A Recommender System

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Obvious Applications

We are now advanced enough that we can aspire to a serious application. One of the most significant applications for some very large websites (Netflix, Amazon, etc.) are recommender systems.

“Customers who bought this product also bought these.”

“Here are some movies you might like…”

As well as many types of targeted advertising. However those of you with less commercial ambitions will find the core concepts here widely applicable to many types of data that require dimensionality reduction techniques.

Let’s go all Netflix

Netflix once (2009) had a $1,000,000 contest to with just this very problem[1]. We will start with a similar dataset. It looks like:

Movie Dataset (Movie ID, Title, Genre):
31,Dangerous Minds (1995),Drama
32,Twelve Monkeys (a.k.a. 12 Monkeys) (1995),Mystery|Sci-Fi|Thriller
34,Babe (1995),Children|Drama

Ratings Dataset (User ID, Movie ID, Rating, Timestamp):
2,144,3.0,835356016
2,150,5.0,835355395
2,153,4.0,835355441
2,161,3.0,835355493

We won’t use the genres or timestamp fields for our analysis.

1) https://en.wikipedia.org/wiki/Netflix_Prize

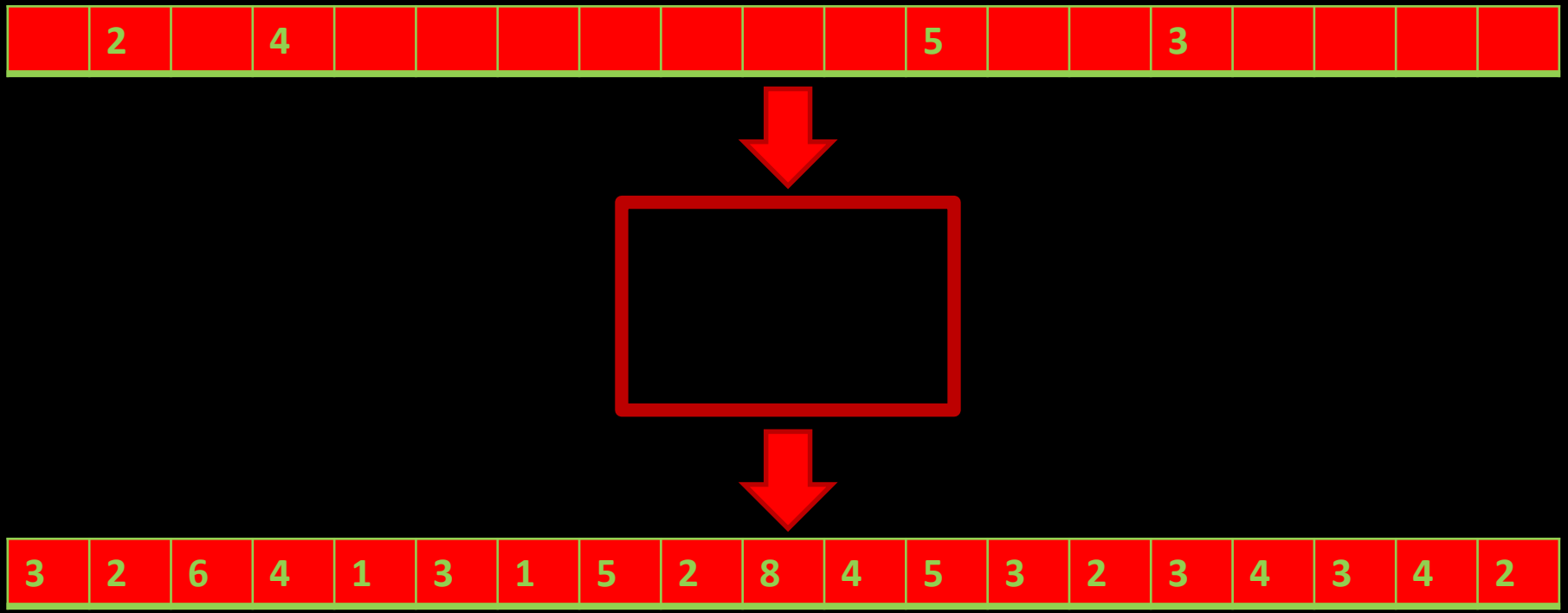
Objective

For any given user we would like to use their ratings, in combination with all the existing user ratings, to determine which movies they might prefer. For example, a user might really like *Annie Hall* and *The Purple Rose of Cairo* (both Woody Allen movies, although our database doesn't have that information). Can we infer from other users that they might like *Zelig*? That would be finding a latent variable. These might also include affinities for an actor, or director, or genre, etc.

So what we have is a (sparse) list of ratings for a user:

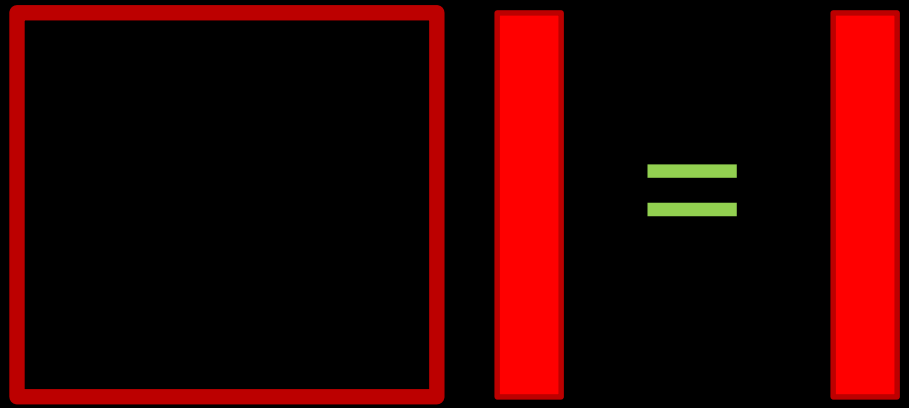
Black Box

We want to run that through a black box and get a list of projected ratings.



Matrix Multiply

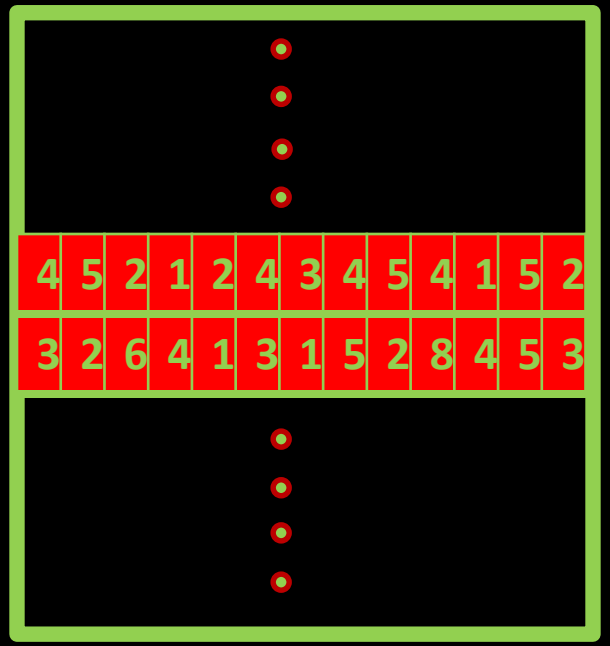
This might have the feel of a matrix multiply. Linear algebra is the language of machine learning, but you won't need to do more than recall the basics today.



This isn't our answer. It would be difficult for such a matrix to deal with the sparsity of the input vector for one thing. We can do something even more direct.

User Item Association Matrix

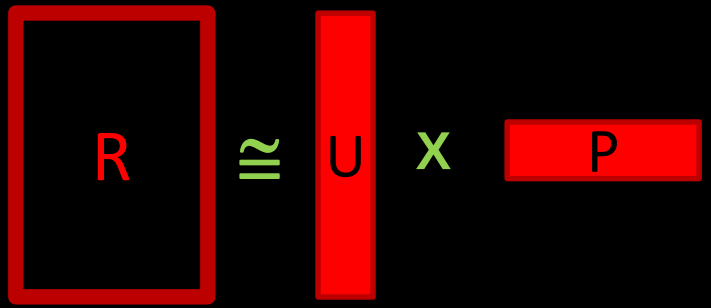
We will construct a matrix that is simply a spreadsheet containing all of our users' projected ratings.



This will be a very large matrix (all movies X all users). The way we construct it will allow us to save it in a much more compact form.

Lossy Compression Becomes Approximate Solution

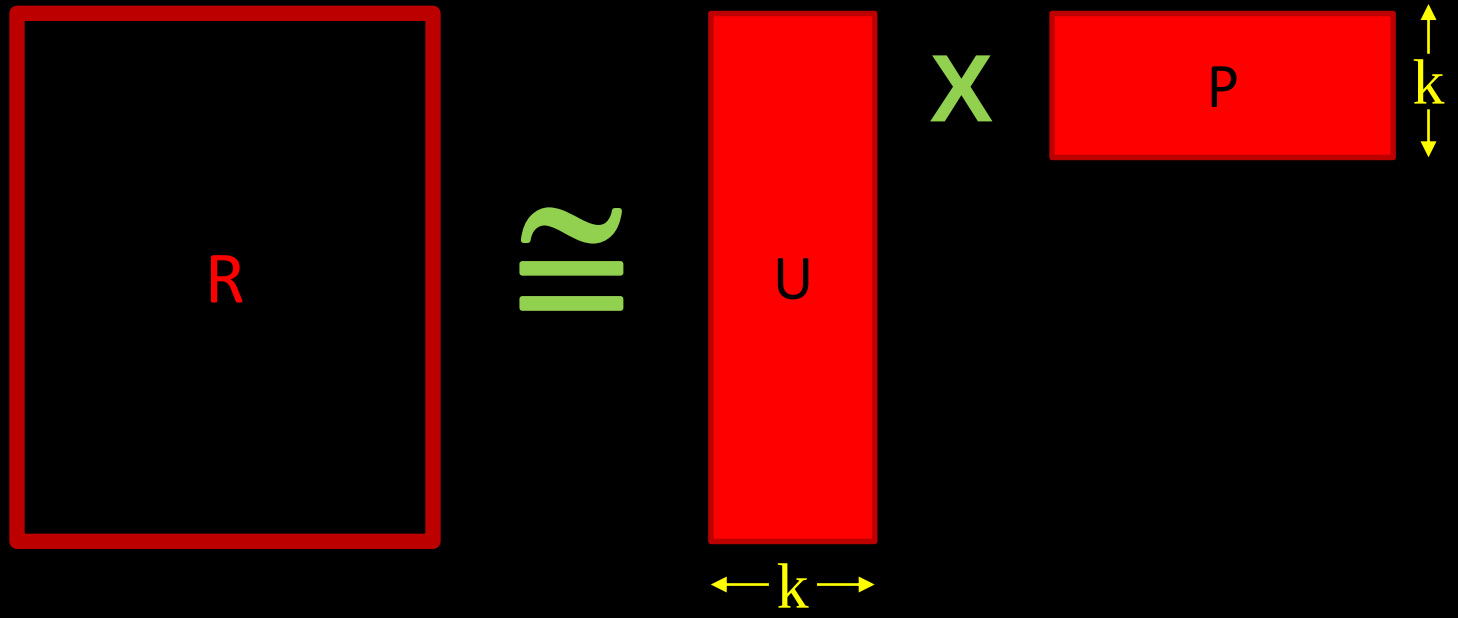
The answer to the problem of compressing this matrix to a reasonable size is also going to provide us a means to construct it.



We are going to approximate our given, sparse, R matrix as the product of two smaller matrices. You can consider them a *user feature matrix* and an *item feature matrix*. *This approximation is also going to smooth out the zeros and in the process give us our projected ratings.* But we'll get to that.

Matrix Factorization

There are different ways to decompose a matrix. We will approximate this matrix as the product of two smaller matrices. The rank, k, of the new matrices will determine how many *effects* we are incorporating.



Why not SVD?

For those of you familiar with these kinds of techniques, you may wonder why we aren't using Singular Value Decomposition. This is another common technique to decompose matrices and is also part of Spark's mllib.

SVD reduces the matrix to three submatrices, a diagonal matrix and two orthonormal matrices. These have some nice properties to work with.

However, there are two major drawbacks for this application:

- More expensive, which matters for these potentially immense matrices.
- Original matrix must be dense. Our given matrix will have lots of missing values (corresponding to the many unrated movies for any user).

Defining our error

In ML, defining the *error* (or *loss*, or *cost*) is often the core of defining the objective solution. Once we define the error, we can usually plug it into a canned solver which can minimize it. Defining the error can be obvious, or very subtle.

Clustering: For k-means we simply used the geometrical distance. It was actually the sum of the squared distances, but you get the idea.

Image Recognition: If our algorithm tags a picture of a cat as a dog, is that a larger error than if it tags it as a horse? Or a car? How would you quantify these?

Recommender: We will take the Mean Square Error distance between our given matrix and our approximation as a starting point.

Mean Square Error plus Regularization

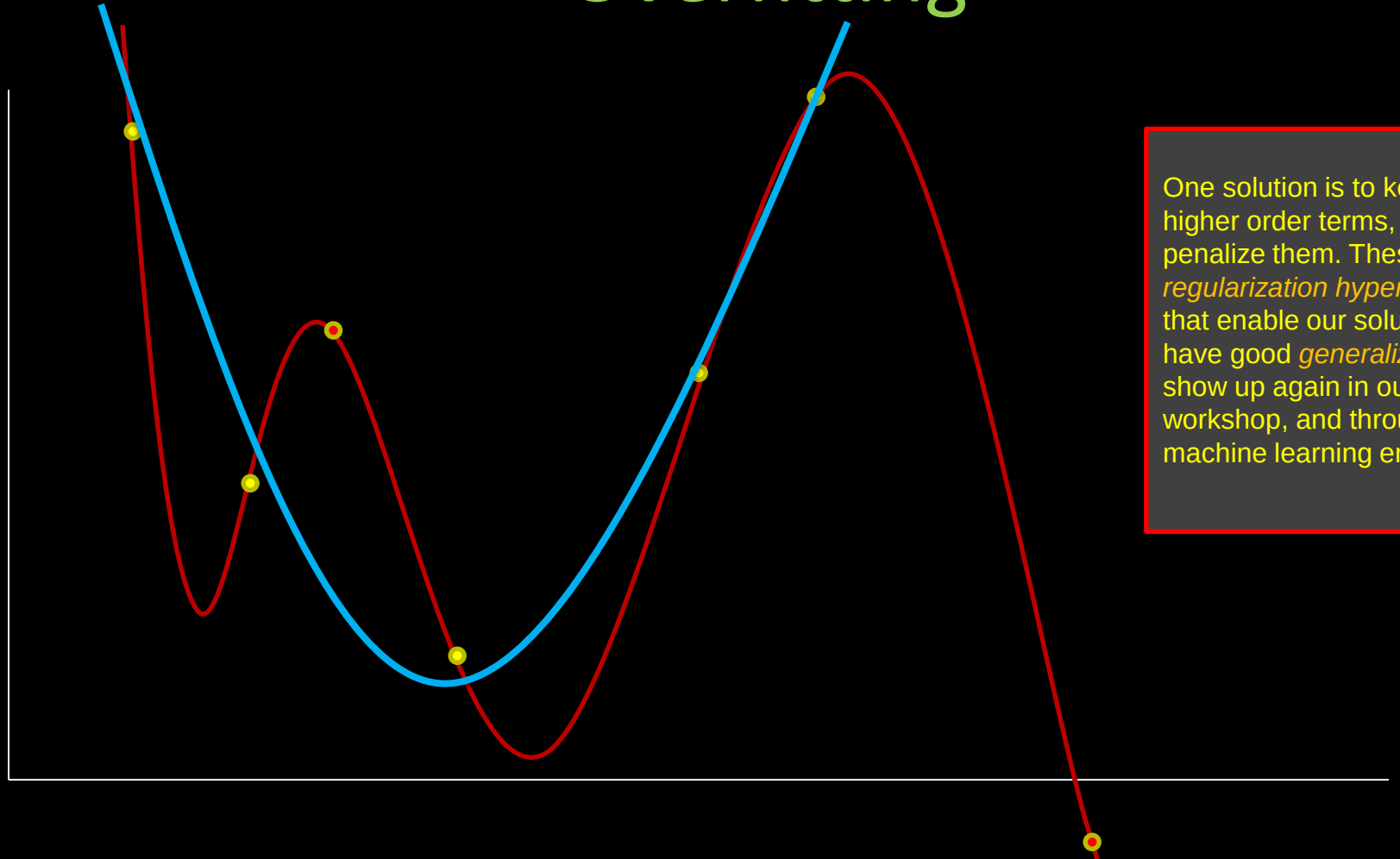
We will also add a term to discourage *overfitting* by damping large elements of U or P. This is called regularization and versions appear frequently in error functions.

$$\text{Error} = | R - UxP |^2 + \lambda(\text{Penalty for large elements})$$

The $||$ notation means "sum the squares of all the elements and then take the square root".

You may wonder how we can have "too little" error – the pursuit of which leads to overfitting. Think back to our clustering problem. We could drive the error as low as we wanted by adding more clusters (up to 5000!). But we weren't really finding new clusters. Variations of this phenomena occur throughout machine learning.

Overfitting



One solution is to keep using higher order terms, but to penalize them. These *regularization hyperparameters* that enable our solution to have good *generalization* will show up again in our workshop, and throughout your machine learning endeavors.

Training, Validation and Test Data

We use the training data to create our solution, the UxP matrix here.

The validation data is used to verify we are not overfitting: to stop training after enough iterations, to adjust λ or k here, or to optimize the many other *hyperparameters* you will encounter in ML.

The test data must be saved to judge our final solution.

Reusing, or subtly mixing, the training, validation and test data is a frequently cause of confusion.

What proportions of your data to use for each of these is somewhat empirical and you might want to start by copying from similar work or examples using your same solver.

Mean Square Error plus Regularization

Here is exactly our error term with regularization. MLLIB scales this factor for us based on the number of ratings (this tweak is called ALS-WR).

$$\text{Error} = | R - UxP |^2 + \lambda(|U|^2 + |P|^2)$$

The $||$ notation means "sum the squares of all the elements and then take the square root".

Additionally, we need to account for our missing (unrated) values. We just zero out those terms. Here it is term-by-term:

$$\text{Error} = \Sigma_{I,j}\, w_{I,j}\, (R_{I,j} - (UxP)_{ij})^2 + \lambda(|U|^2 + |P|^2) \qquad w_{I,j} = 0 \text{ if } R_{I,j} \text{ is unknown}$$

Note that we now have two hyperparameters, k and λ, that we need to select intelligently.

Alternating Least Squares

To actually find the U and P that minimize this error we need a solving algorithm.

SGD, a go-to for many ML problems and one we will use later, is not practical for billions of parameters, which we can easily reach with these types of problems. We are dealing with *Users X Items* elements here.

Instead we use Alternating Least Squares (ALS), also built into MLLIB.

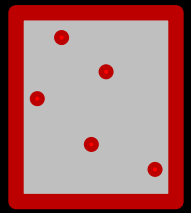
- Alternating least squares cheats by holding one of the arrays constant and then doing a classic least squares fit on the other array parameters. Then it does this for the other array.
- This is easily parallelized.
- It works well with sparse inputs. The algorithm scales linearly with observed entries.

Here Is Our Plan

Given Ratings

Use ALS

Predicted Ratings



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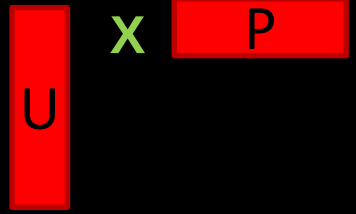

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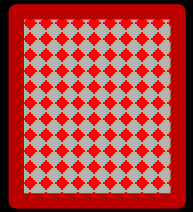
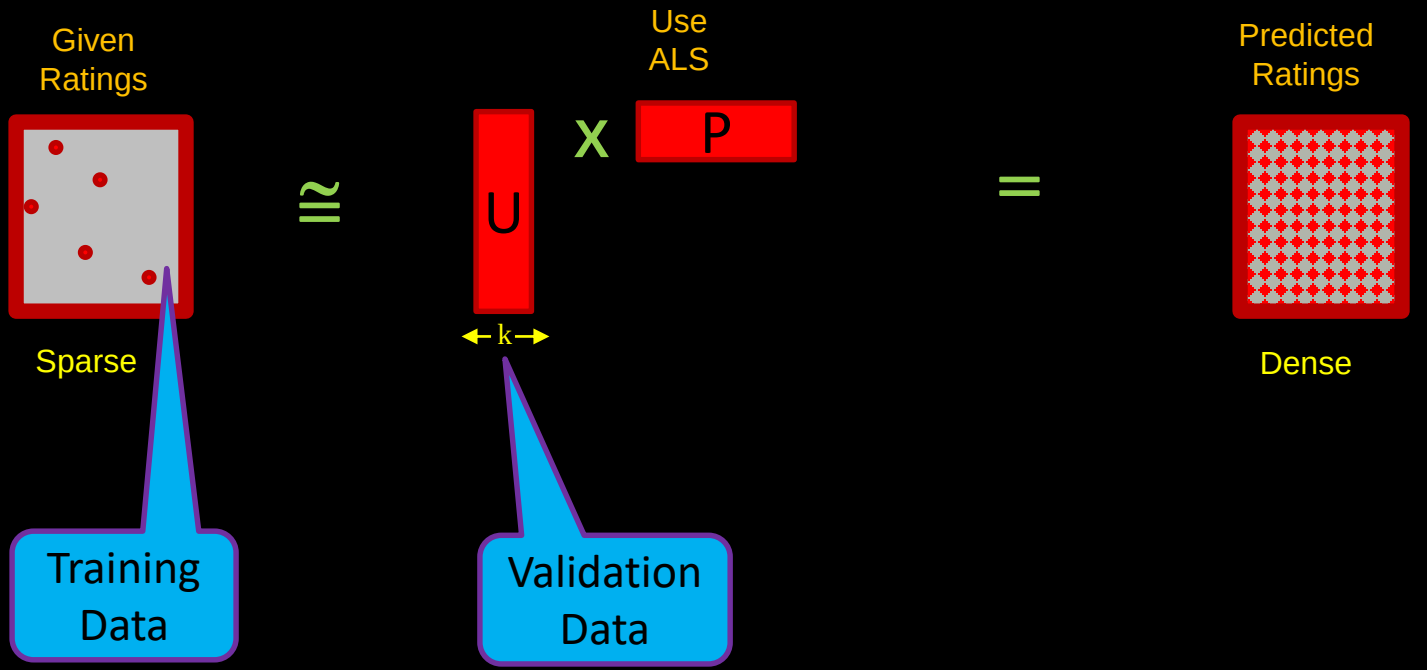


Sparse

Dense

Where does our data come into play?



Let’s Build A Recommender

We have all the tools we need, so let’s fire up PySpark and make create a scalable recommender. Our plan is:

1. Load and parse data files
2. Create ALS model
3. Train it with varying ranks (k) to find reasonable values

4. Add a new user
5. Get top recommendations for new user

Building a Recommender

```
br06% interact
...
r288%
r288% module load spark
r288% pyspark
```

```
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 1.6.0
      /_/

Using Python version 2.7.5 (defa
SparkContext available as sc, Hi
>>>
>>> ratings_raw_RDD = sc.textFil
>>> ratings_RDD = ratings_raw_RD                                    float(tokens[2])))
>>>
>>> training_RDD, validation_RDD
>>>
>>> predict_validation_RDD = val
>>> predict_test_RDD = test_RDD.
```

```
>>> training_RDD.take(4)
[(1, 1029, 3.0), (1, 1061, 3.0),
>>> predict_validation_RDD.take(
[(1, 1129), (1, 1172), (1, 1405), (1, 2105)]
>>>
```

ovie,rating) data.

Ds.

data for our prediction RDDs.

```
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 1.6.0
      /_/

Using Python version 2.7.5 (default, Nov 20 2015 02:00:19)
SparkContext available as sc, HiveContext available as sqlContext.
>>>
>>> ratings_raw_RDD = sc.textFile('ratings.csv')
>>> ratings_RDD = ratings_raw_RDD.map(lambda line: line.split(",")).map(lambda tokens: (int(tokens[0]),int(tokens[1]),float(tokens[2])))
>>>
>>> training_RDD, validation_RDD, test_RDD = ratings_RDD.randomSplit([3, 1, 1], 0)
>>>
>>> predict_validation_RDD = validation_RDD.map(lambda x: (x[0], x[1]))
>>> predict_test_RDD = test_RDD.map(lambda x: (x[0], x[1]))
>>>
>>>
>>> from pyspark.mllib.recommendation import ALS
>>> import math
>>>
>>> seed = 5
>>> iterations = 10
>>> regularization = 0.1
>>> ranks = [4, 8, 12]
>>> errors = [0, 0, 0]
>>> err = 0
>>> min_error = float('inf')
>>> best_rank = -1
```

Import mllib and set some variables we are about to use.

```
>>> ratings_raw_RDD = sc.textFile('ratings.csv')
>>> ratings_RDD = ratings_raw_RDD.map(lambda line: line.split(",")).map(lambda tokens: (int(tokens[0]),int(tokens[1]),float(tokens[2])))
>>>
>>> training_RDD, validation_RDD, test_RDD = ratings_RDD.randomSplit([3, 1, 1], 0)
>>>
>>> predict_validation_RDD = validation_RDD.map(lambda x: (x[0], x[1]))
>>> predict_test_RDD = test_RDD.map(lambda x: (x[0], x[1]))
>>>
>>>
>>> from pyspark.mllib.recommendation import ALS
>>> import math
>>>
>>> seed = 5
>>> iterations = 10
>>> regularization = 0.1
>>> ranks = [4, 8, 12]
>>> errors = [0, 0, 0]
>>> err = 0
>>> min_error = float('inf')
>>> best_rank = -1
>>>
>>> for rank in ranks:
...     model = ALS.train(training_RDD, rank, seed=seed, iterations=iterations, lambda_=regularization)
...     predictions_RDD = model.predictAll(predict_validation_RDD).map(lambda r: ((r[0], r[1]), r[2]))
...     ratings_and_preds_RDD = validation_RDD.map(lambda r: ((r[0], r[1]), r[2])).join(predictions_RDD)
...     error = math.sqrt(ratings_and_preds_RDD.map(lambda r: (r[1][0] - r[1][1])**2).mean())
...     errors[err] = error
...     err += 1
...     print 'For rank %s the RMSE is %s' % (rank, error)
...     if error < min_error:
...         min_error = error
...         best_rank = rank
...
For rank 4 the RMSE is 0.93683749317
For rank 8 the RMSE is 0.952092733983
For rank 12 the RMSE is 0.951914636563
>>>
>>> print 'The best model was trained with rank %s' % best_rank
The best model was trained with rank 4
```

Run our ALS model on various ranks to see which is best.

```
>>>
>>> for rank in ranks:
>>>     model = ALS.train(training_RDD, rank, seed=seed, iterations=iterations, lambda_=regularization)
>>>     predictions_RDD = model.predictAll(predict_validation_RDD).map(lambda r: ((r[0], r[1]), r[2]))
>>>     ratings_and_preds_RDD = validation_RDD.map(lambda r: ((r[0], r[1]), r[2])).join(predictions_RDD)
>>>     error = math.sqrt(ratings_and_preds_RDD.map(lambda r: (r[1][0] - r[1][1])**2).mean())
>>>     errors[err] = error
>>>     err += 1
>>>     print 'For rank %s the RMSE is %s' % (rank, error)
>>>     if error < min_error:
>>>         min_error = error
>>>         best_rank = rank
>>>
>>> print 'The best model was trained with rank %s' % best_rank
>>>
For rank 4 the RMSE is 0.93683749317
For rank 8 the RMSE is 0.952092733983
For rank 12 the RMSE is 0.951914636563
>>>
The best model was trained with rank 4
```

```
>>> model.predictAll(predict_validation_RDD).take(2)
[Rating(user=463, product=4844, rating=2.7640960482284322), Rating(user=380, product=4844, rating=2.399938320644199)]
>>>
>>> model.predictAll(predict_validation_RDD).map(lambda r: ((r[0], r[1]), r[2])).take(2)  # predictions_RDD
[((463, 4844), 2.
>>>
>>> validation_RD
[(1, 1129), 2.0),
>>>
>>> validation_RD
[((1, 1129), 2.0)
```

```
>>> predictions_RDD.take(2)
[((463, 4844), 2.7640960482284322), ((380, 4844), 2.399938320644199)]
>>>
>>> validation_RDD.map(lambda r: ((r[0], r[1]), r[2])).take(2)
[((1, 1129), 2.0), ((1, 1172), 4.0)]
>>>
>>> ratings_and_preds_RDD.take(2)     # validation_RDD joined predictions_RDD
[((119, 145), (4.0, 2.903215714486778)), ((407, 5995), (4.5, 4.604779028840272))]
```

```
>>> for rank in ranks:
>>>     model = ALS.train(training_RDD, rank, seed=seed, iterations=iterations, lambda_=regularization)
>>>     predictions_RDD = model.predictAll(predict_validation_RDD).map(lambda r: ((r[0], r[1]), r[2]))
>>>     ratings_and_preds_RDD = validation_RDD.map(lambda r: ((r[0], r[1]), r[2])).join(predictions_RDD)
>>>     error = math.sqrt(ratings_and_preds_RDD.map(lambda r: (r[1][0] - r[1][1])**2).mean())
>>>     errors[err] = error
>>>     err += 1
>>>     print 'For rank %s the RMSE is %s' % (rank, error)
>>>     if error < min_error:
>>>         min_error = error
>>>         best_rank = rank
>>>
>>> print 'The best model was trained with rank %s' % best_rank
>>>
For rank 4 the RMSE is 0.93683749317
For rank 8 the RMSE is 0.952092733983
For rank 12 the RMSE is 0.951914636563
>>>
The best model was trained with rank 4
>>>
>>> model = ALS.train(training_RDD, best_rank, seed=seed, iterations=iterations, lambda_=regularization)
>>> predictions_RDD = model.predictAll(predict_test_RDD).map(lambda r: ((r[0], r[1]), r[2]))
>>> ratings_and_preds_RDD = test_RDD.map(lambda r: ((r[0], r[1]), r[2])).join(predictions_RDD)
>>> error = math.sqrt(ratings_and_preds_RDD.map(lambda r: (r[1][0] - r[1][1])**2).mean())
>>> print 'For testing data the RMSE is %s' % (error)
>>> For testing data the RMSE is 0.932684762873
```

This is our fully tested model (smallest dataset).

Adding a User

```
.
.
.
>>>
>>> new_user_ID = 0
>>> new_user = [
        (0,100,4), # City Hall (1996)
        (0,237,1), # Forget Paris (1995)
        (0,44,4), # Mortal Kombat (1995)
        (0,25,5), # etc....
        (0,456,3),
        (0,849,3),
        (0,778,2),
        (0,909,3),
        (0,478,5),
        (0,248,4)
       ]
>>>
>>> new_user_RDD = sc.parallelize(new_user)
>>> updated_ratings_RDD = ratings_RDD.union(new_user_RDD)
>>>
>>> updated_model = ALS.train(updated_ratings_RDD, best_rank, seed=seed, iterations=iterations, lambda_=regularization)
>>>
```

We assume User ID 0 is unused, but could check with `ratings_RDD.filter(lambda x: x[0]=='0').count()"`

Let’s get some predictions…

```
.
.
.
>>>
>>> movies_raw_RDD = sc.textFile('movies.csv')
>>> movies_RDD = movies_raw_RDD.map(lambda line: line.split(",")).map(lambda tokens: (int(tokens[0]),tokens[1]))
>>>
>>> new_user_rated_movie_ids = map(lambda x: x[1], new_user)
>>> new_user_unrated_movies_RDD = movies_RDD.filter(lambda x: x[0] not in new_user_rated_movie_ids).map(lambda x: (new_user_ID, x[0]))
>>> new_user_recommendations_RDD = updated_model.predictAll(new_user_unrated_movies_RDD)
```

```
>>> new_user_unrated_movies_RDD.take(3)
[(0, 1), (0, 2), (0, 3)]
>>> new_user_recommendations_RDD.take(2)
[Rating(user=0, product=4704, rating=3.606560950463134), Rating(user=0, product=4844, rating=2.1368358868224036)]
```

Let see some titles

```
.
.
.
>>>
>>> product_rating_RDD = new_user_recommendations_RDD.map(lambda x: (x.product, x.rating))
>>> new_user_recommendations_titled_RDD = product_rating_RDD.join(movies_RDD)
>>> new_user_recommendations_formatted_RDD = new_user_recommendations_titled_RDD.map(lambda x: (x[1][1],x[1][0]))
>>>
>>> top_recomends = new_user_recommendations_formatted_RDD.takeOrdered(10, key=lambda x: -x[1])
>>> for line in top_recomends: print line
...
(u'Maelstr\xf6m (2000)', 6.2119957527973355)
(u'"King Is Alive', 6.2119957527973355)
(u'Innocence (2000)', 6.2119957527973355)
(u'Dangerous Beauty (1998)', 6.189751978239315)
(u'"Bad and the Beautiful', 6.005879185976944)
(u"Taste of Cherry (Ta'm e guilass) (1997)", 5.960748198887891)
(u'The Lair of the White Worm (1988)', 5.958594728894122)
(u"Mifune's Last Song (Mifunes sidste sang) (1999)", 5.934820295566816)
(u'"Business of Strangers', 5.899232655788708)
>>>
>>> one_movie_RDD = sc.parallelize([(0, 800)]) # Lone Star (1996)
>>> rating_RDD = updated_model.predictAll(one_movie_RDD)
>>> rating_RDD.take(1)
[Rating(user=0, product=800, rating=4.100848893773136)]
```

Looks like we can sort by value after all! Behind the scenes takeOredered() just does the key swap and SortByKey that we did ourselves.

```
>>> new_user_recommendations_titled_RDD.take(2)
[(111360, (1.0666741148393921, u'Lucy (2014)')), (49530, (1.8020006042285814, u'Blood Diamond (2006)'))]
>>> new_user_recommendations_formatted_RDD.take(2)
[(u'Lucy (2014)', 1.0666741148393921), (u'Blood Diamond (2006)', 1.8020006042285814)]
```

Exercises

1) We noticed that out top ranked movies have ratings higher than 5. This makes perfect sense as there is no ceiling implied in our algorithm and one can imagine that certain combinations of factors would combine to create “better than anything you’ve seen yet” ratings.

Maybe you have a friend that really likes Anime. Many of her ratings for Anime are 5. And she really likes Scarlett Johansson and gives her movies lots of 5s. Wouldn’t it be fair to consider her rating for *Ghost in the Shell* to be a 7/5?

Nevertheless, we may have to constrain our ratings to a 1-5 range. Can you normalize the output from our recommender such that our new users only sees ratings in that range?

2) We haven’t really investigated our convergence rate. We specify 10 iterations, but is that reasonable? Graph your error against iterations and see if that is a good number.

3) I mentioned that our larger dataset does benefit from a rank of 12 instead of 4 (as one might expect). The larger datasets (ratings-large.csv and movies-large.csv) are available to you in ~training/LargeMovies. Prove that the error is less with a larger rank. How does this dataset benefit from more iterations? Is it more effective to spend the computation cycles on more iterations or larger ranks?