



https://i0.wp.com/thedatascientist.com/wp-content/uploads/2018/05/recommender_systems.png

Lecture 3: Scalable Matrix Factorisation for Collaborative Filtering in RecSys

[COM6012: Scalable ML by Haiping Lu](#)

YouTube Playlist: <https://www.youtube.com/c/HaipingLu/>

Week 3 Contents / Objectives

- Recommender Systems
- Collaborative Filtering
- Matrix Factorisation for Collaborative Filtering
- Scalable Collaborative Filtering in Spark

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Many Decisions to Make



Recommendations Everywhere

Frequently bought together

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- This item: Thinking, Fast and Slow by Daniel Kahneman
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Recommender Systems (RecSys)

- Predict relevant items for a user, in a given context
 - Predict to what extent these items are relevant
 - A ranking task (searching as well)
 - Implicit, targeted, **intelligent** advertisement
 - Effective, popular marketing

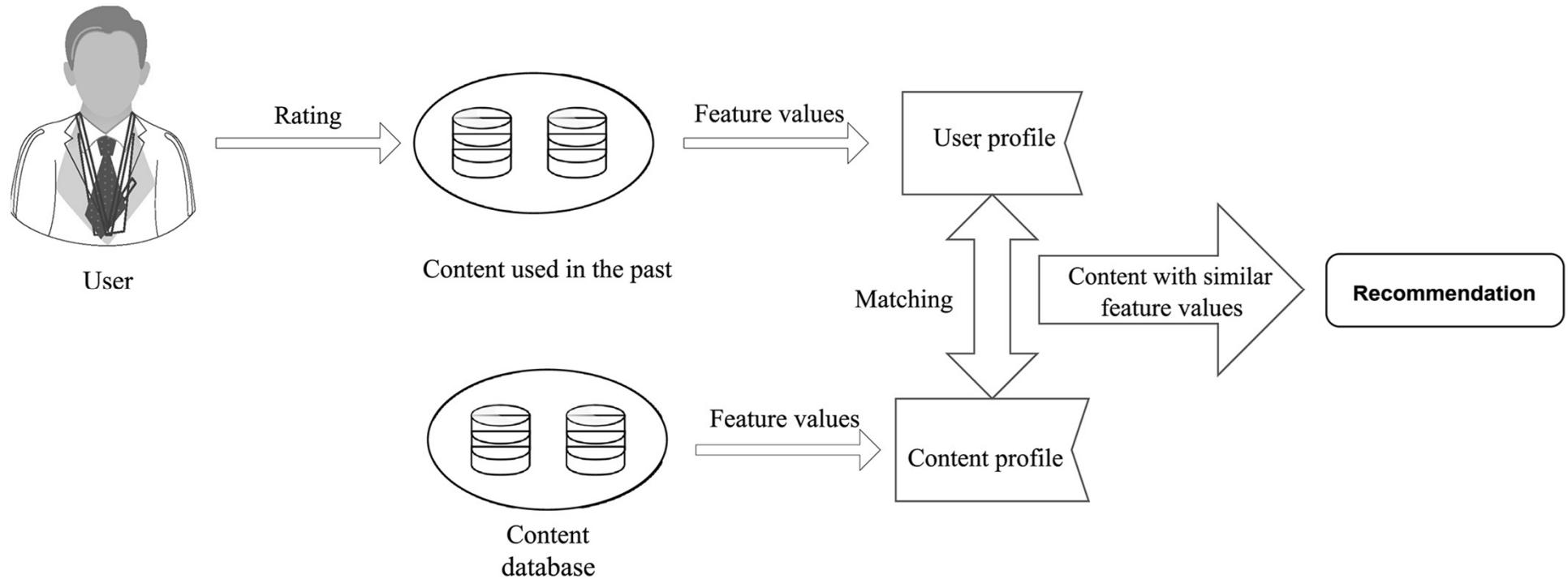


Two Classes of RecSys

- Content-based recommender systems
- Collaborative filtering recommender systems

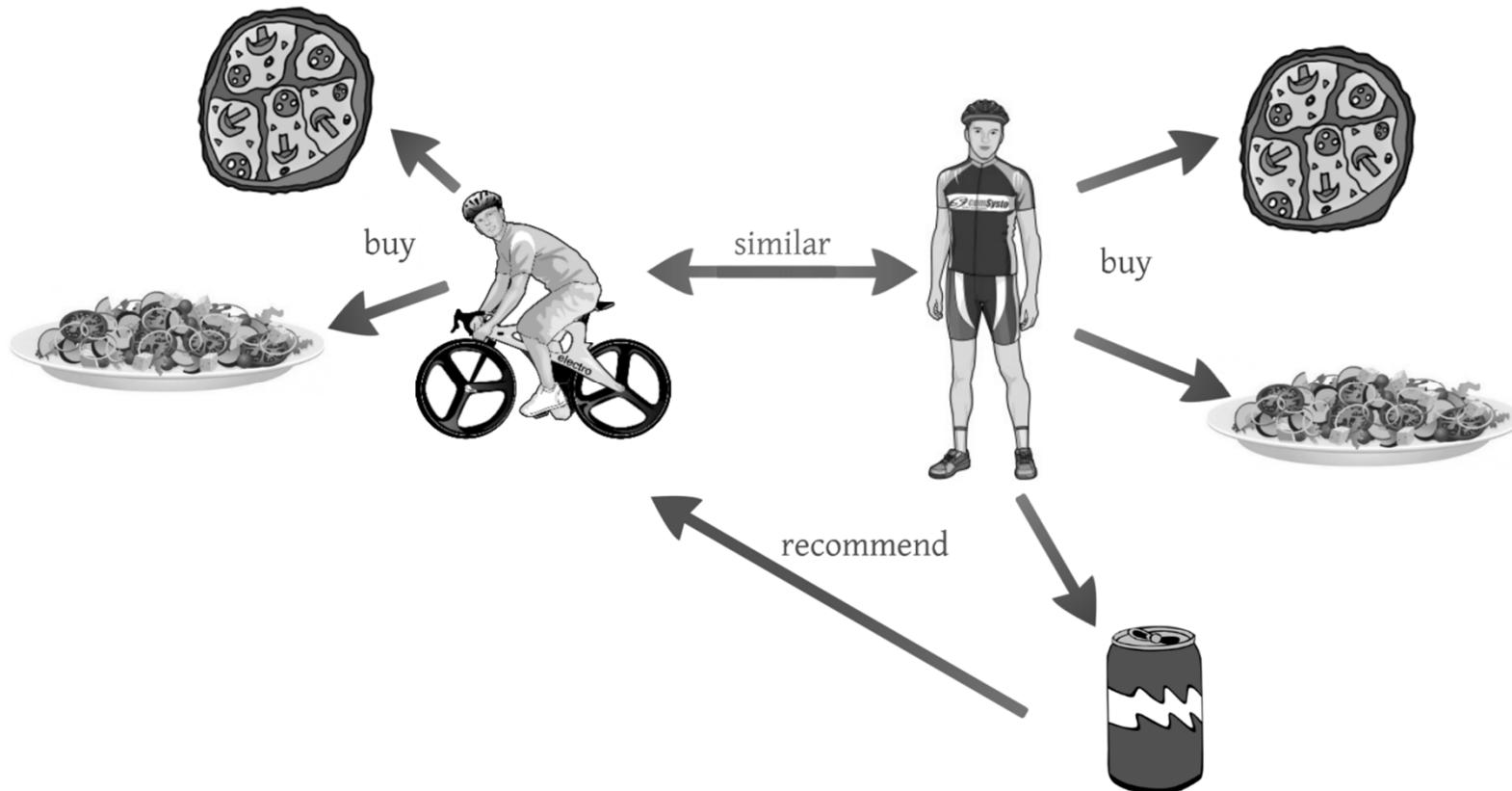


Content-based RecSys



[dac4058-fig-0010-m.jpg \(2128×789\) \(wiley.com\)](#)

Collaborative Filtering RecSys



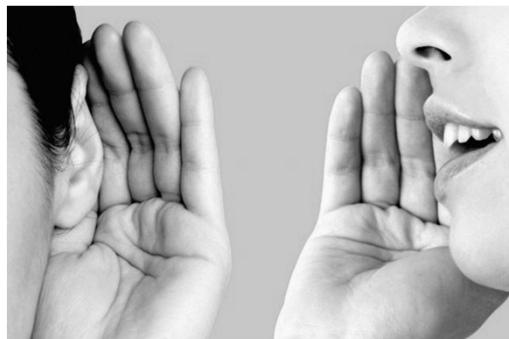
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What is Collaborative Filtering?

- Information filtering based on past records
 - Electronic word of mouth marketing
 - Turn visitors into customers (e-Salesman)
- Components
 - Users (customers): who provide ratings
 - Items (products): to be rated
 - Ratings (interest): core data



	John	Tom	Alice	
John	5	1	3	5
Tom	?	?	?	2
Alice	4	?	3	?

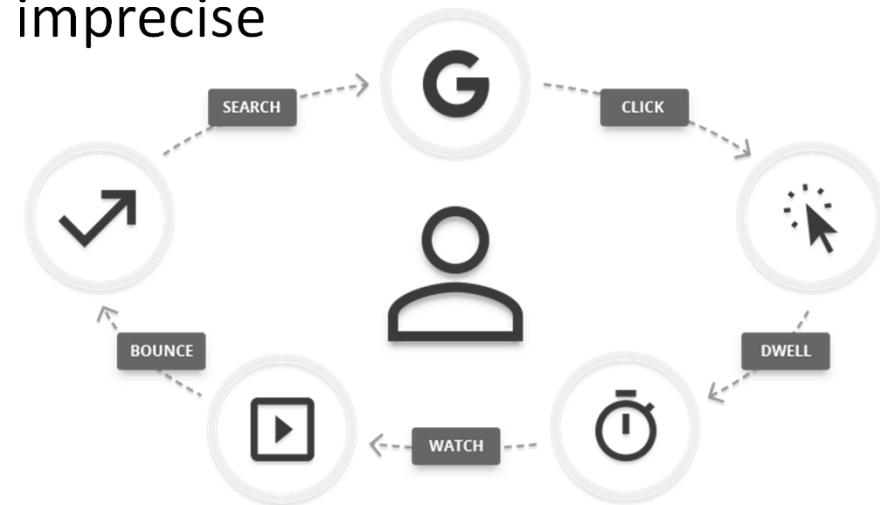
Collaborative Filtering (CF)

- Objective: predict how well a user will like an unrated item, given past ratings for a community of users
- How does CF work?
 - Input: many users' ratings for many items
 - Model: similar users \leftarrow ratings strongly correlate
 - Recommend items rated highly by similar users



Explicit vs Implicit Ratings

- Explicit (direct): users indicate levels of interest
 - Most accurate descriptions of a user's preference
 - Challenging in collecting data
- Implicit (indirect): observing user behavior
 - Can be collected with little or no cost to user
 - Ratings inference may be imprecise



Rating Scales

- Scalar ratings
 - Numerical scales
 - 1-5, 1-7, etc.
 - Binary ratings
 - Agree/Disagree, Good/Bad, etc.
 - Unary ratings
 - Presence/absence of an event, e.g., purchase/browsing history, search patterns, mouse movements
 - No info about the opposite $\neq 0$
- 
- 
- 

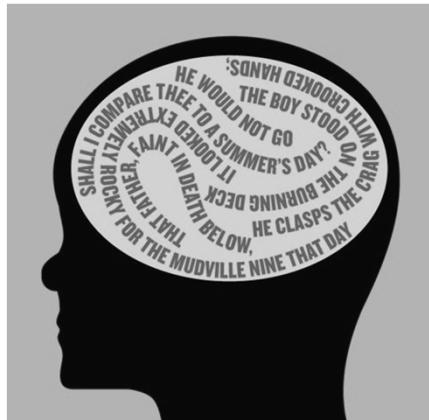
CF Preferences

- Many users, many items, many ratings
- Users rate multiple items
- Other users with similar needs/tastes
- Item evaluation requires personal taste
- Taste persists



CF Methods

- Memory-based: predict using past ratings directly
 - Weighted ratings given by other similar users
 - User-based & item-based (non-ML)
 - Model-based: model users based on past ratings
 - Predict ratings using the learned model



[iforget-465.jpg \(465x465\) \(newyorker.com\)](http://iforget-465.jpg (465x465) (newyorker.com))



neural-header.jpg (756×503) (utsouthwestern.edu)

Prediction Accuracy

- Mean absolute error (MAE)

$$MAE = \frac{\sum_{i,j} |p_{i,j} - r_{i,j}|}{n}$$

- Normalized MAE

$$NMAE = \frac{MAE}{r_{max} - r_{min}}$$

- Root mean squared error (RMSE)

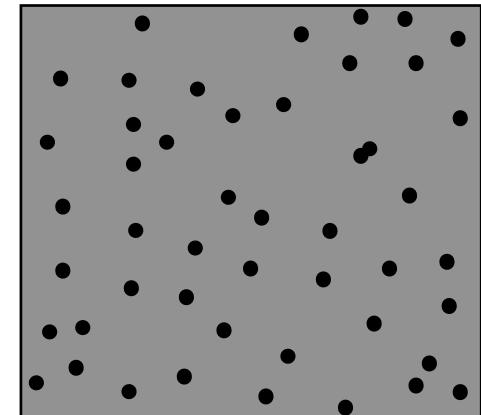
$$RMSE = \sqrt{\frac{1}{n} \sum_{i,j} (p_{i,j} - r_{i,j})^2}$$

Challenges

- Cold Start
 - New user
 - Rate some initial items
 - Non-personalized rec.
 - Describe tastes
 - Demographic info
 - New item
 - Randomly selecting items
 - Content analysis, metadata (non-CF)
- Sparsity: sparse user-item matrix
- Scalability: millions of users and items



[isbil+2.jpg \(490x303\) \(squarespace-cdn.com\)](#)



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Matrix Factorisation (MF) for CF

- Characterise items/users by vectors of factors learned from the rating matrix user x item
- High correlation between item and user factors → good recommendation
- Flexibility: incorporate implicit feedback, temporal effects, and confidence levels

John	5	1	3	5
Tom	?	?	?	2
Alice	4	?	3	?

Basic MF Model

- Map users & items to a joint latent factor space of dimensionality k
 - Item $i \rightarrow$ vector q_i : the extent to which the item possesses those k factors
 - User u : vector p_u : the extent of interest the user has on those k factors
- User-item interactions: the user's overall interest in the item's characteristics
 - Inner product $q_i^T p_u$: predicted user u 's rating of item i

$$\hat{r}_{u,i} = q_i^T p_u$$

How to Learn the MF Model

- To learn: item factors $\{q_i\}$ and user factors $\{p_u\}$
- Factorisation assuming full rating matrix
 - Factorise rating matrix R using SVD to obtain P, S, Q

$$R = PSQ^T$$

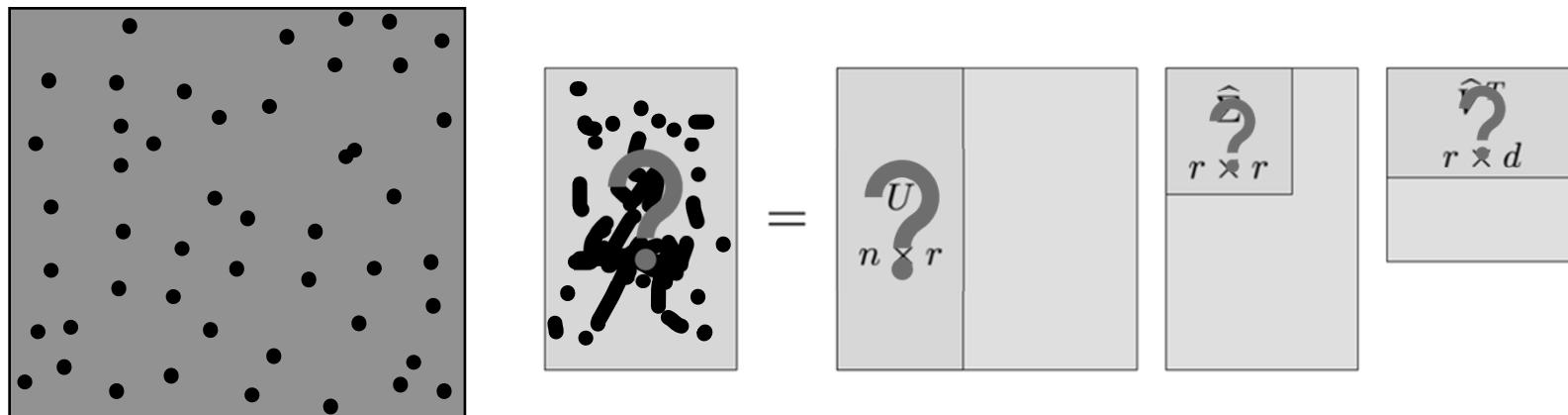
- Reduce the matrix S to dimension k , i.e. S_k
- $P \rightarrow P_k$ and $Q \rightarrow Q_k$: $P_k S_k \rightarrow \hat{P}$, and $S_k Q_k^T \rightarrow \hat{Q}^T$
- u th row of $\hat{P} \rightarrow p_u$, i th column of $\hat{Q}^T \rightarrow q_i$

$$\begin{array}{c|c|c|c} A & U & \Sigma & V^T \\ n \times d & n \times n & n \times d & d \times d \\ \hline & & \widehat{\Sigma} & \widehat{V}^T \\ & & r \times r & r \times d \\ & & & & \end{array}$$

$A: R$
 $U: P$
 $\Sigma: S$
 $V^T: Q$
 $r: k$

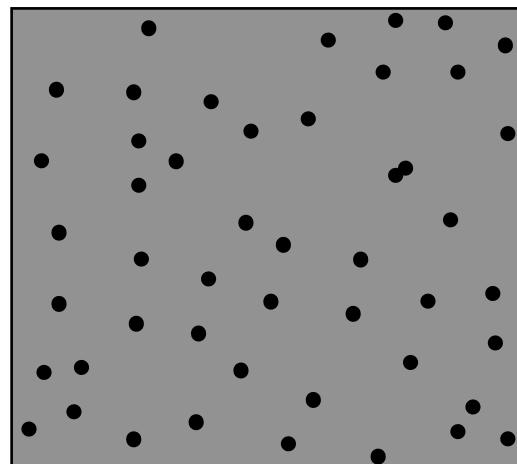
Challenges in MF for CF

- High portion of missing values caused by sparseness in the user-item rating matrix
- Conventional SVD is undefined when knowledge about the matrix is incomplete



How to Fill Missing Values

- Imputation: fill in missing ratings using the average ratings for user and item
- Problems
 - Expensive: significantly increases the amount of data
 - Inaccurate imputation might distort the data



MF with Missing Values

- Modelling directly the observed ratings only
 - Avoid overfitting through a regularised model
 - Minimize the regularised squared error on the set of known ratings to learn the factor vectors p_u and q_i

$$\min_{q^*, p^*} \sum_{(u,i) \in \kappa} (r_{ui} - q_i^T p_u)^2 + \lambda(\|q_i\|^2 + \|p_u\|^2)$$

- κ : the training set of the (u,i) pairs with known ratings
- λ : the regularisation parameter

Alternating Least Squares for MF-CF

$$\min_{q^*, p^*} \sum_{(u,i) \in \kappa} (r_{ui} - q_i^T p_u)^2 + \lambda(\| q_i \|_2^2 + \| p_u \|_2^2)$$

- Both p_u and q_i are unknown (non-convex function)
- Fix one of them → quadratic with optimal solution
- Alternating Least Squares (ALS): alternate between fixing q_i s and fixing p_u s
 - Fix $P(p_u)$ s as \hat{P} to recompute q_i s by solving a least-squares problem $\| R - P Q^T \|_F$ (Frobenius norm)

$$R = \hat{P} Q^T \Rightarrow Q^T = (\hat{P}^T \hat{P})^{-1} \hat{P}^T R$$

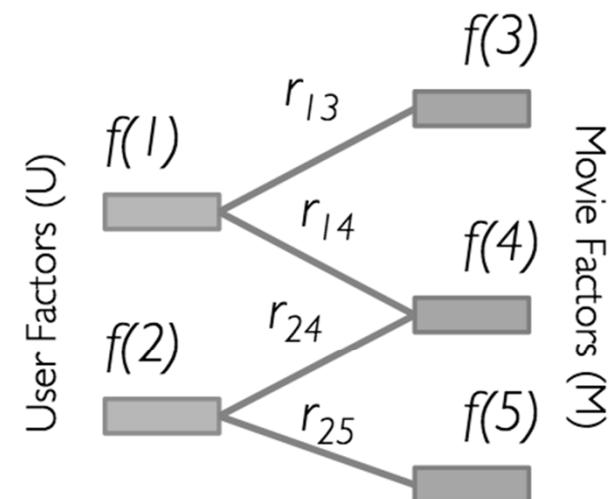
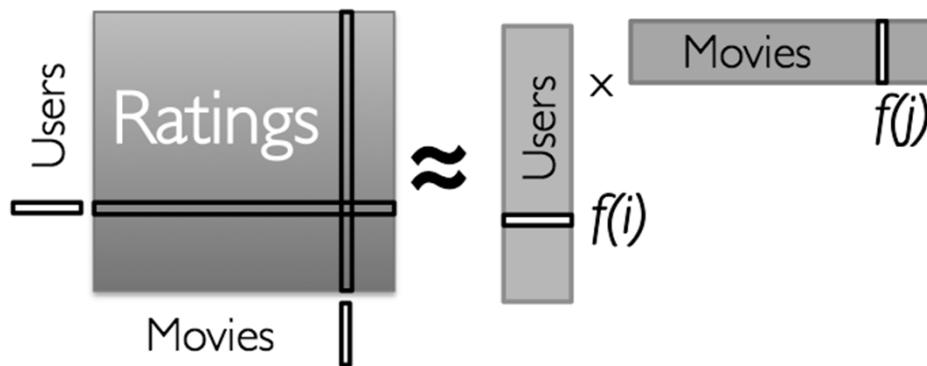
- Fix Q as \hat{Q} , we have

$$P = R \hat{Q} (\hat{Q}^T \hat{Q})^{-1}$$

- Random initialisation to start this iteration

MF for Movie Recommendation

Low-Rank Matrix Factorization:



Iterate:

$$f[i] = \arg \min_{w \in \mathbb{R}^d} \sum_{j \in \text{Nbrs}(i)} (r_{ij} - w^T f[j])^2 + \lambda ||w||_2^2$$

Figure from [spark-training/matrix_factorization.png at master · databricks/spark-training \(github.com\)](https://spark-training/databricks/spark-training.github.com/spark-training/matrix_factorization.png)

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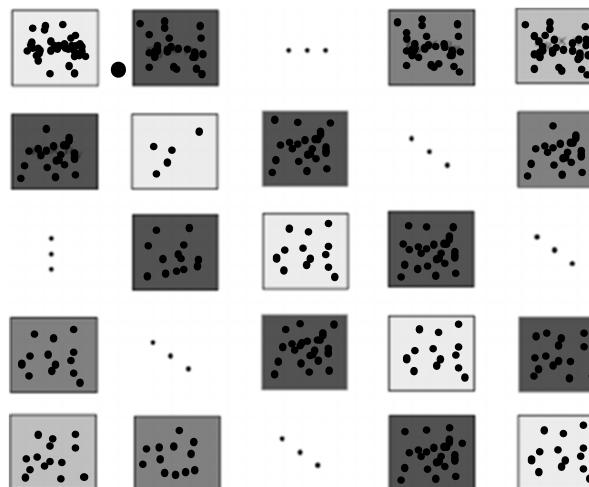
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Key in Scalable ML

- Computation and storage should be linear (in n , d)
→ Low-cost computation (time + space)
- Perform parallel and in-memory computation
→ Many working + reduce disk I/O
- Minimise network communication → Reduce overhead in parallelisation, not the more the better

Blocked Implementation of ALS

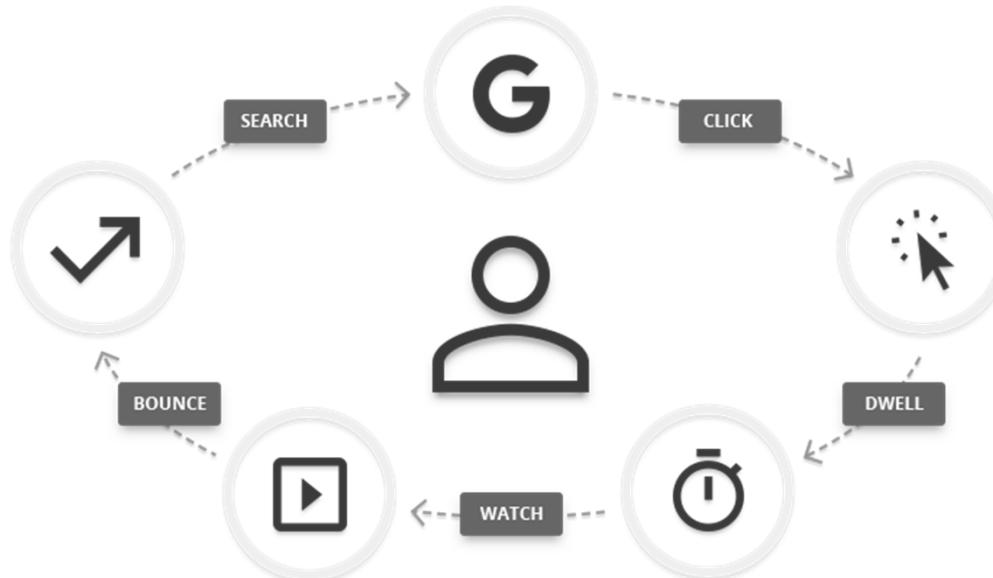
- Group users and items into blocks
 - Reduce communication: only send one copy of each user vector to each item block on each iteration, and only for the item blocks that need that user's feature vector
 - Pre-compute info: out-links of each user (which blocks of items it will contribute to); in-links for each item (which of the feature vectors it receives from each user block it will depend on)



[Color-online-A-symmetric-block-Toeplitz-matrix-Each-block-is-also-a-symmetric-Toeplitz.png \(488x369\) \(researchgate.net\)](#)

Implicit Feedback Modelling

- Implicit feedback: views, clicks, purchases, likes, shares
 - Rating r = strength in observations of user actions (#clicks, viewing duration) → confidence level in observed user preference
 - Construct a preference matrix P : e.g. 1 if $r > 0$ and 0 if $r = 0$
 - Factorisation of P → latent factors to predict the preference of a user for an item (details in an [ICDM08 paper](#))



The ALS API in Spark

- numUserBlocks/numItemBlocks: the number of blocks the users/items will be partitioned into to parallelize computation (defaults to 10)
- rank: the number of latent factors in the model (defaults to 10)
- regParam: the regularization parameter in ALS (defaults to 0.1)
- implicitPrefs: whether to use the explicit feedback ALS variant or one adapted for implicit feedback data (defaults to false: explicit ratings)
- alpha: the baseline confidence of implicit feedback (defaults to 1.0)
- nonnegative: whether to use nonnegative constraints (defaults to false)
- coldStartStrategy: “drop” → drop any rows in the DataFrame of predictions that contain NaN values (defaults to “nan”: assign NaN to a user and/or item factor is not present in the model)
- blockSize: the size of the user/product blocks in the blocked implementation of ALS to reduce communication

```
931     def train[ID: ClassTag]( // scalastyle:ignore
932         ratings: RDD[Rating[ID]],
933         rank: Int = 10,
934         numUserBlocks: Int = 10,
935         numItemBlocks: Int = 10,
936         maxIter: Int = 10,
937         regParam: Double = 0.1,
938         implicitPrefs: Boolean = false,
939         alpha: Double = 1.0,
940         nonnegative: Boolean = false,
941         intermediateRDDStorageLevel: StorageLevel = StorageLevel.MEMORY_AND_DISK,
942         finalRDDStorageLevel: StorageLevel = StorageLevel.MEMORY_AND_DISK,
943         checkpointInterval: Int = 10,
944         seed: Long = 0L)(
945         implicit ord: Ordering[ID]): (RDD[(ID, Array[Float])], RDD[(ID, Array[Float])]) = {
946
947         require(!ratings.isEmpty(), s"No ratings available from $ratings")
948         require(intermediateRDDStorageLevel != StorageLevel.NONE,
949                 "ALS is not designed to run without persisting intermediate RDDs.")
950
951         val sc = ratings.sparkContext
952
953         // Precompute the rating dependencies of each partition
954         val userPart = new ALSPartitioner(numUserBlocks)
955         val itemPart = new ALSPartitioner(numItemBlocks)
956         val blockRatings = partitionRatings(ratings, userPart, itemPart)
957             .persist(intermediateRDDStorageLevel)
958         val (userInBlocks, userOutBlocks) =
959             makeBlocks("user", blockRatings, userPart, itemPart, intermediateRDDStorageLevel)
960         userOutBlocks.count()      // materialize blockRatings and user blocks
```

CF in Spark ML

- Scala code (1800+ lines)
- Documentation: Collaborative Filtering in Spark
- DataBricks movie recommendations tutorial
- DataBricks: founded by the creators of Apache Spark
 - Their latest packages at their GitHub page
 - Databricks community edition: 15GB memory free



References

- Yehuda Koren, Robert Bell, and Chris Volinsky.
"Matrix factorization techniques for recommender systems." *Computer* 8 (2009): 30-37 (Yahoo & AT&T)
- Yifan Hu, Yehuda Koren, and Chris Volinsky.
"Collaborative filtering for implicit feedback datasets." *Eighth IEEE International Conference on Data Mining*, 2008
- Charu C. Aggarwal, *Recommender Systems: The Textbook*, April 2016