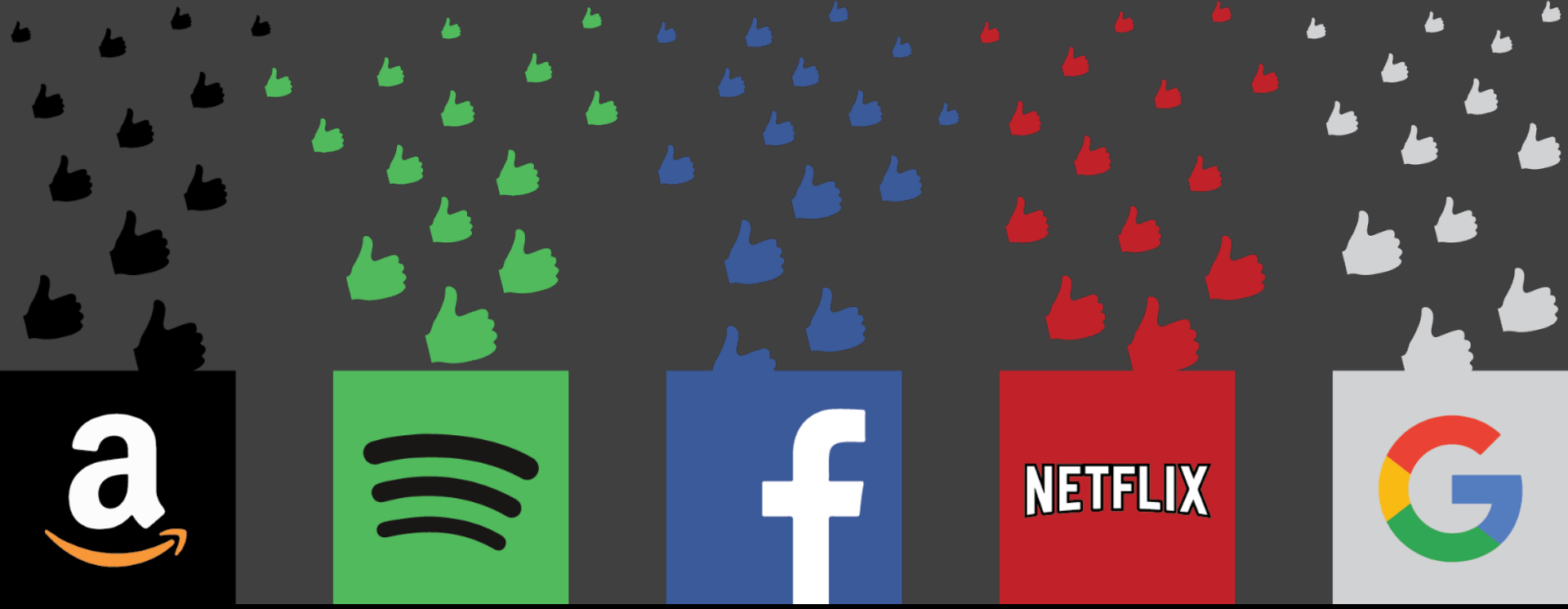

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Lecture 7: Scalable Matrix Factorisation for Collaborative Filtering in RecSys

COM6012: Scalable ML by

Slides courtesy of Haiping Lu

Week 7 Contents / Objectives

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

Many Decisions to Make

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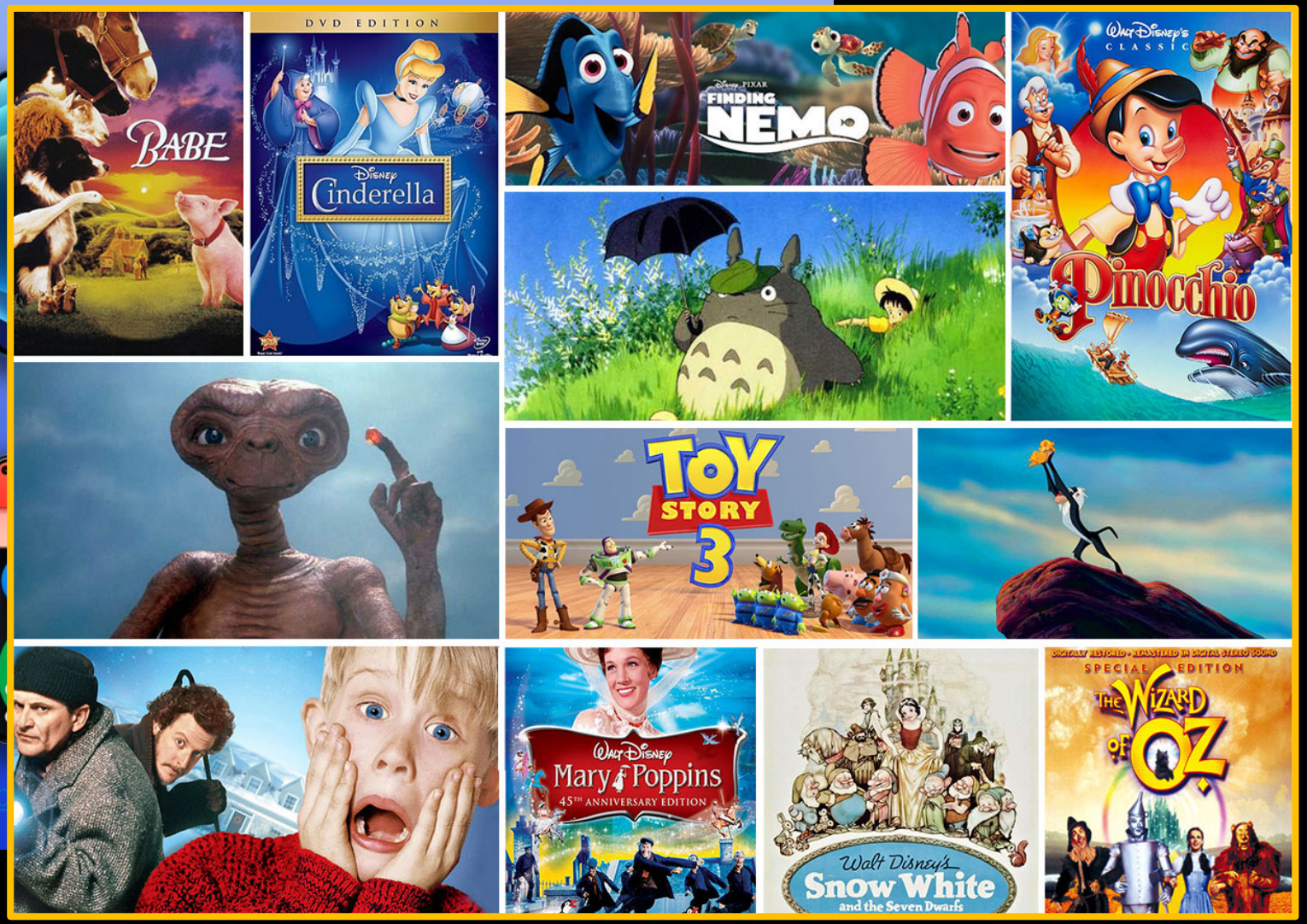
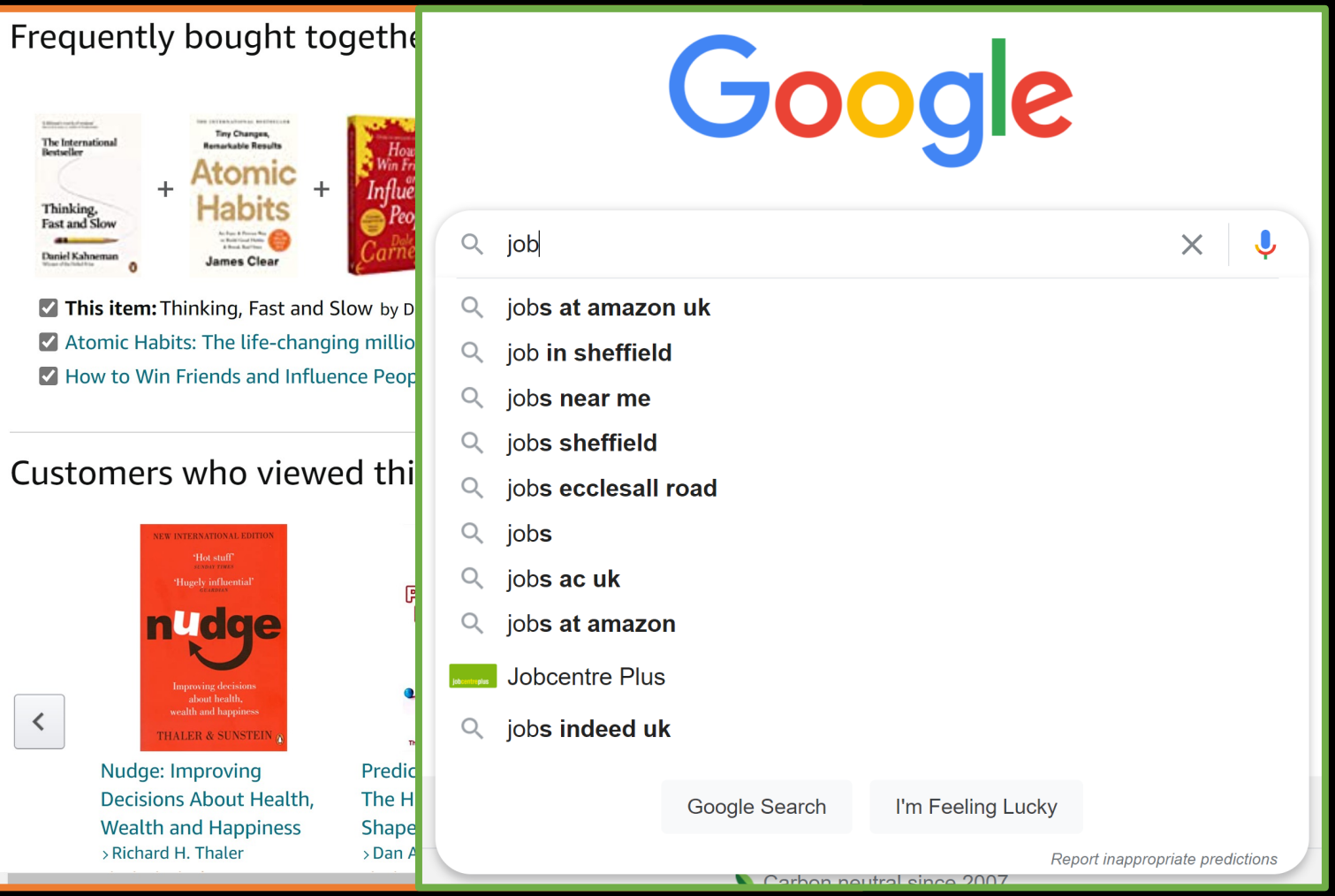
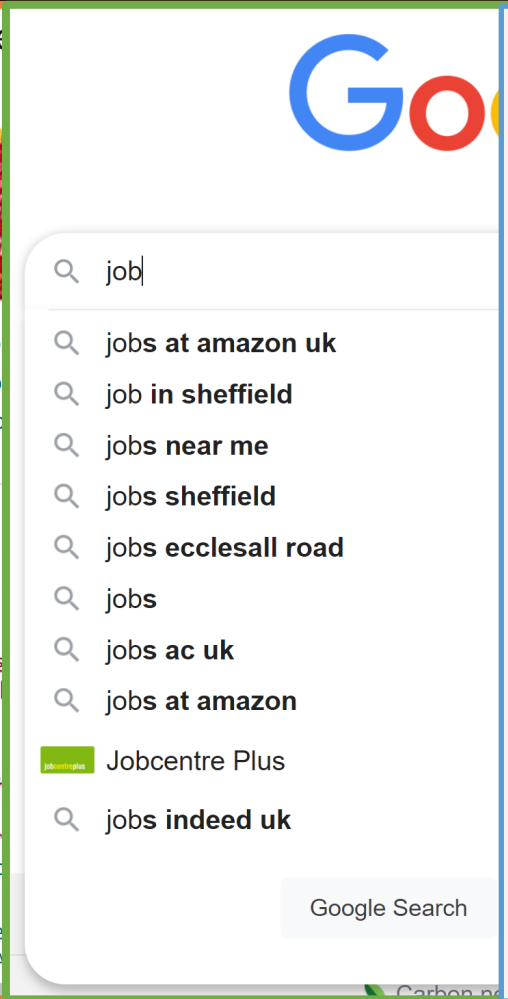
Many Decisions to Make

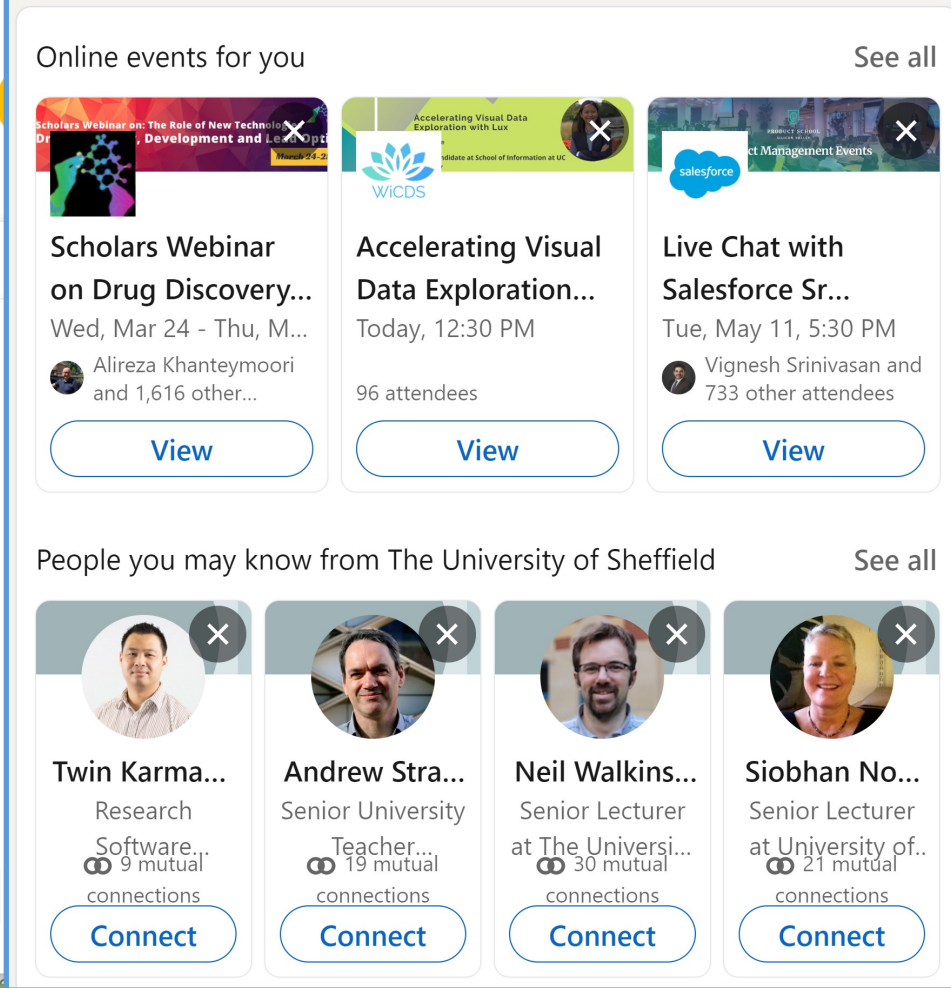


Recommendations Everywhere



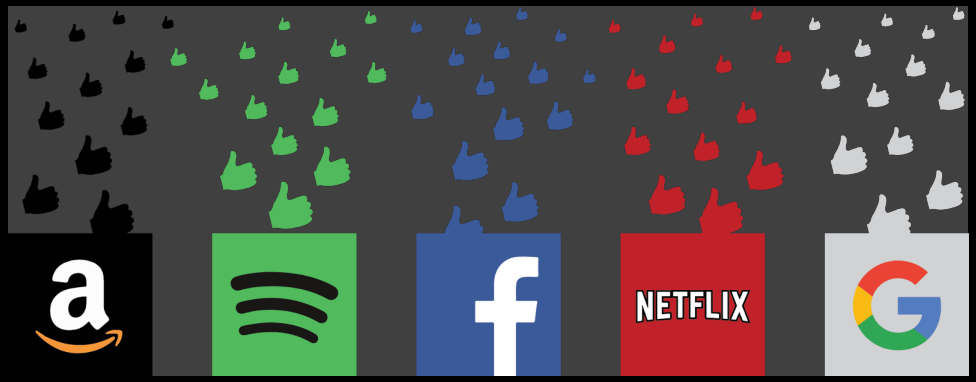
Recommendations Everywhere





Recommender Systems (RecSys)

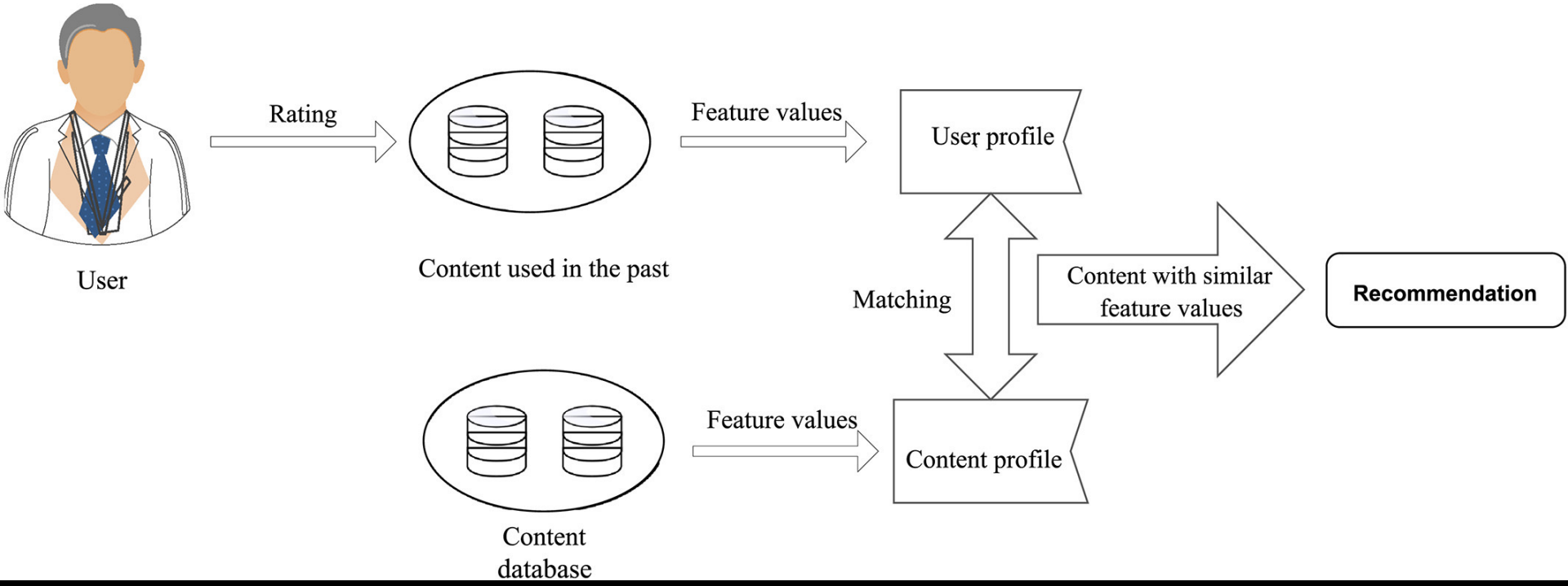
- Predict relevant items for a user, in a given context
- Predict to what extent these items are relevant
- A ranking task (searching as well)
- Implicit, targeted, **intelligent** advertisement
- Effective, popular marketing



Two Classes of RecSys

- Content-based – use known features of users/items
- Collaborative filtering – leverage other users

Content-based RecSys



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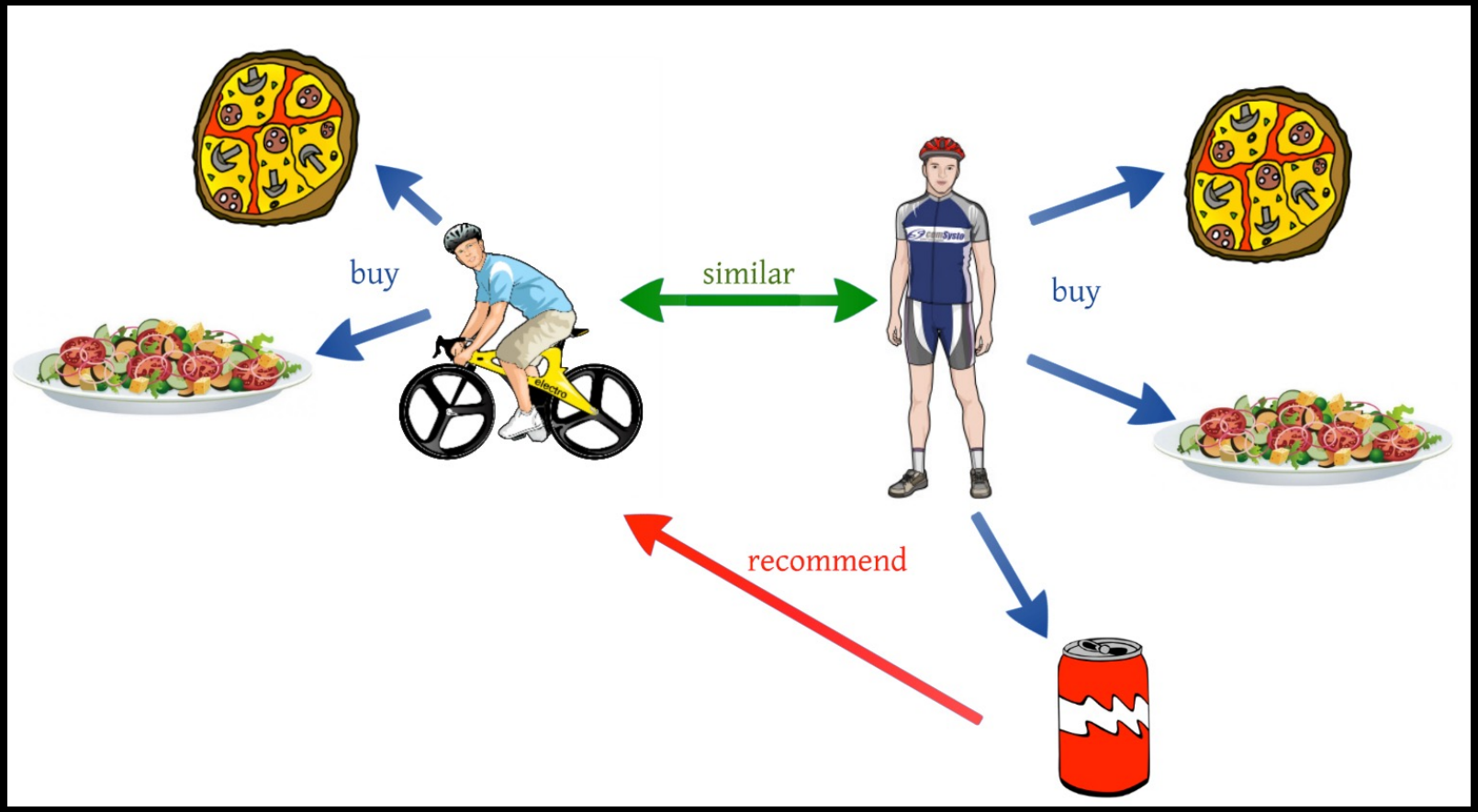
Collaborative Filtering RecSys



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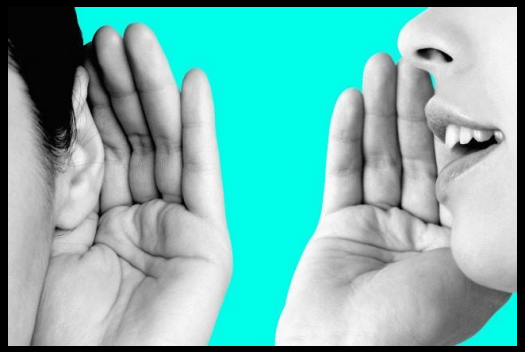
What is Collaborative Filtering?

- Base recommendations on the ratings of other users with similar tastes
- Components
  - Users (customers): who provide ratings
  - Items (products): to be rated
  - Ratings: the training data



Collaborative Filtering (CF)

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

Collaborative Filtering (CF)

- Objective: predict how a user will rate an item, given a set D of past ratings by a community of users
- CF for RecSys:
  - Input: many user-item-rating tuples in D
  - Model: similar users ← ratings strongly correlate
  - Recommend items rated highly by similar users

Collaborative Filtering (CF)

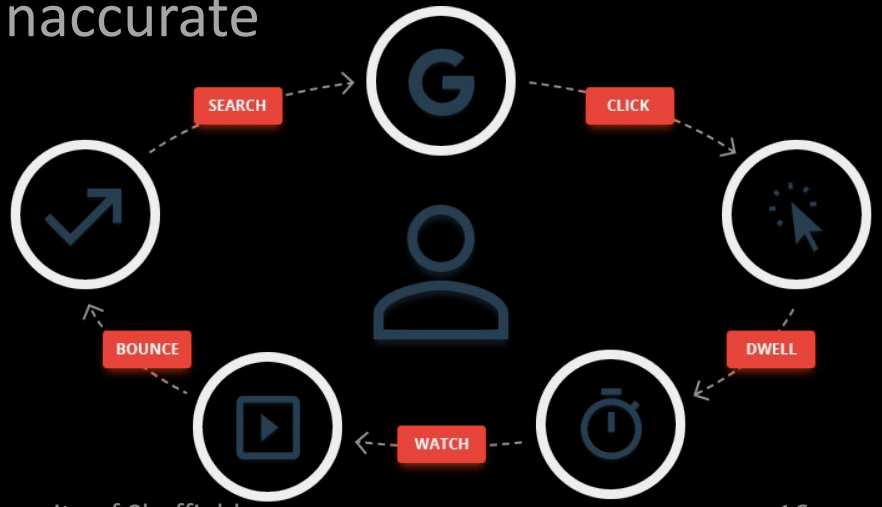
- Memory-based: predict using past ratings directly
  - Weighted ratings given by other similar users
  - User-based & item-based (non-ML)
- Model-based: model users based on past ratings
  - Predict ratings using the learned model

iforget-465.jpg (465×465) (newyorker.com)

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

Explicit vs Implicit Ratings

- Explicit: users directly indicate levels of interest
  - Most accurate descriptions of a user's preference
  - Challenging to collect such data
- Implicit: infer from observed user behavior
  - Can be collected with little or no cost to user
  - Inference ratings may be inaccurate



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 explicit “negative” examples

Prediction Accuracy

- Mean absolute error (MAE)
  - Where $n = |D|$

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

- 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

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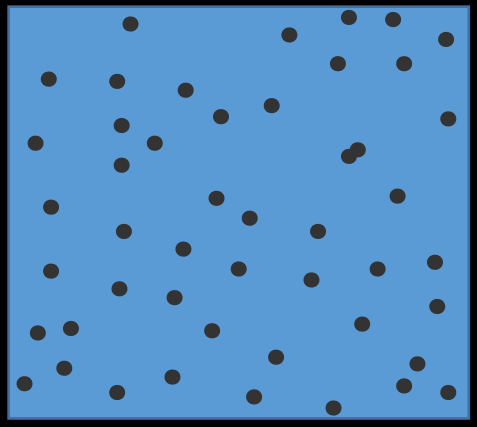

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Latent Factor Models

- Map users and items to a joint latent factor space of dimensionality k
- Describe each user/item by a vector of k "factors"
- We can think of each factor as describing some "topic" that a user might be interested in
- High correlation between user and item factors → *good recommendation*

Latent Factor Models

- To learn – item factors $\{q_i\}$ and user factors $\{p_u\}$:
  - Each user u → vector p_u: the user's degree of interest in each of the k factors
  - Each Item i → vector q_i: the degree to which the item possesses those k factors
- Define the prediction $\hat{r}_{u,i}$ of user u's rating of item i as

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

Matrix Factorisation (MF) for CF

- Let R be the user x item rating matrix

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

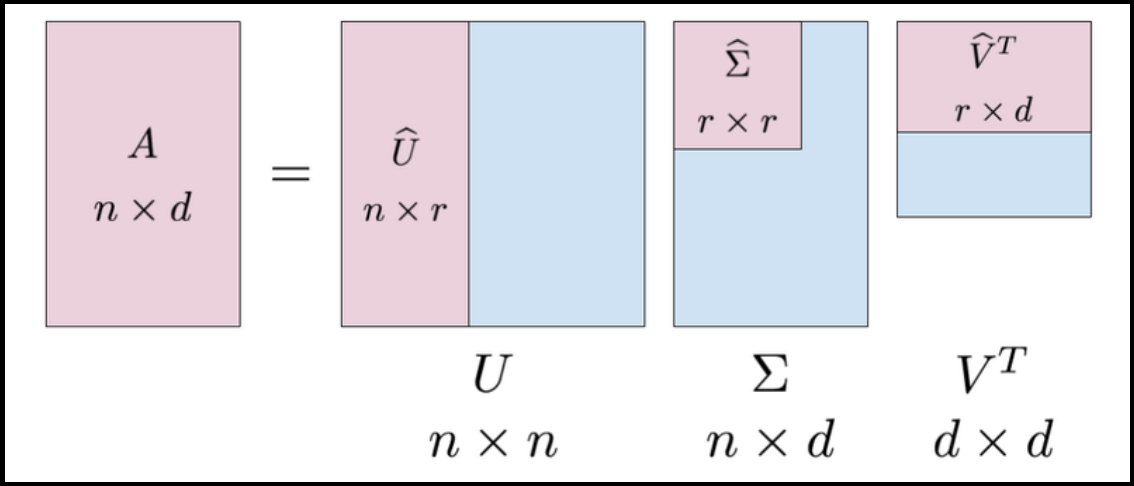
- Approximate rating matrix as $R \approx PQ^T$ where
  - P is the matrix with rows p_u
  - Q is the matrix with rows q_i

Singular Value Decomposition

- Factorise the ***full*** rating matrix R using SVD
  - Obtain matrices P, S, Q such that

$$R = PSQ^T$$

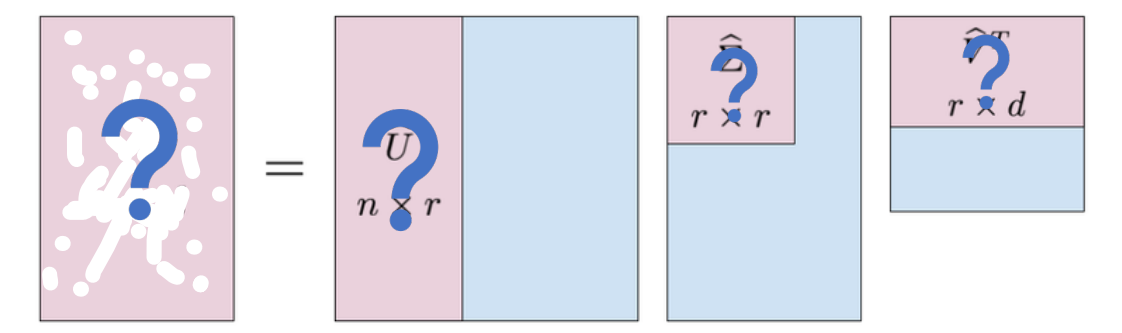
- Reduce the diagonal matrix S to the $k \times k$ matrix S_k
  - Likewise Reduce $P \rightarrow P_k$ and $Q \rightarrow Q_k$
  - Then uth row of $P_k S_k = p_u$ and ith row of $Q_k = q_i$



A: R
U: P
Σ: S
V: Q
r: k

Singular Value Decomposition

- The SVD is undefined when the rating matrix is not completely known – we only know ratings in κ
- Imputation – fill in ratings with user's average
  - Potentially expensive as this creates a lot more rating data
  - Inaccurate imputed values could distort the data



Factorisation with Missing Values

- Learn to predict the observed ratings only
  - Avoid ***overfitting*** through ℓ_2 regularisation
  - Minimize the regularised squared error on the set of known ratings to learn the factor vectors p_u and q_i

$$\min_{Q,P} \sum_{(u,i)\in D} \left(r_{ui} - q_i^T p_u\right)^2 + \lambda(\|q_i\|^2 + \|p_u\|^2)$$

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

Alternating Least Squares for CF

$$\mathcal{L}(Q, P\ ;\ D) = \sum_{(u,i)\in D} \left(r_{ui} - q_i^T p_u\right)^2 + \lambda(\|q_i\|^2 + \|p_u\|^2)$$

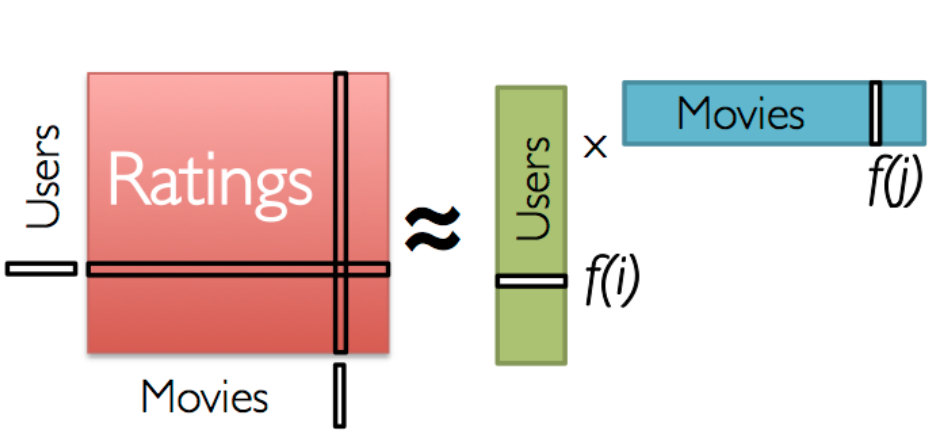
- Both p_u and q_i are unknown (loss is non-convex)
- Fix either p_u or q_i → loss becomes quadratic
- Alternating Least Squares (ALS) – alternate between fixing the q_i's and fixing p_u's
  - Fix P and find Q by solving a ***least-squares*** problem $\|R - PQ^T\|_F$ - (the Frobenius norm)

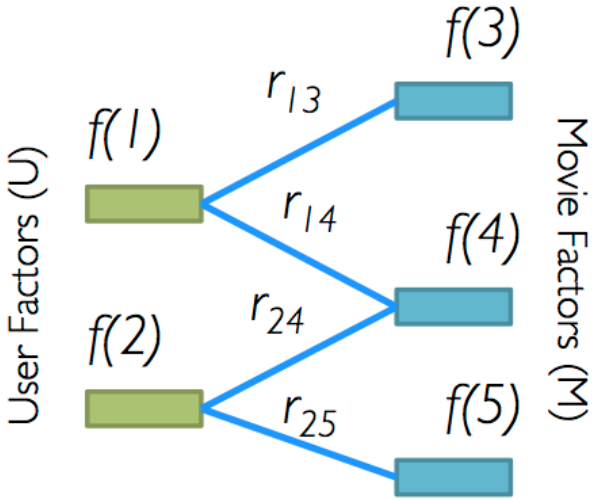
$$Q^T = (P^T P)^{-1} P^T R$$

  - Fix Q and update P as $P = R\hat{Q}(\hat{Q}^T\hat{Q})^{-1}$

MF for Movie Recommendations

Low-Rank Matrix Factorization:





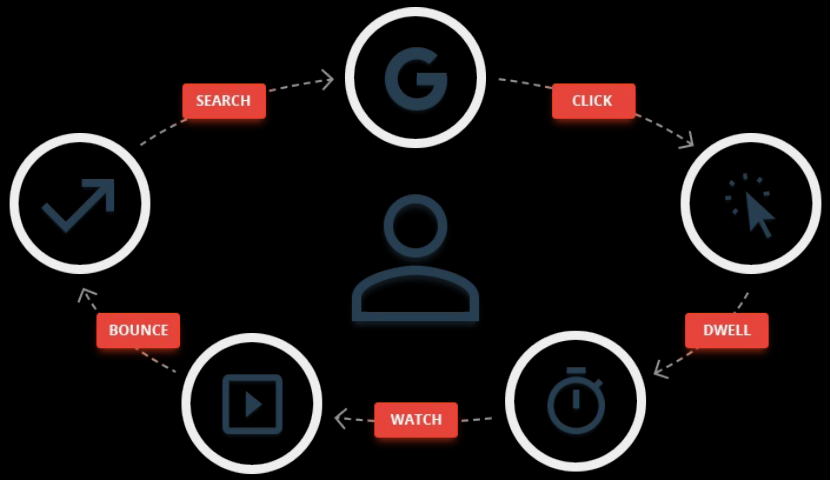
Iterate:

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

https://github.com/databricks/spark-training

Implicit Feedback

- Implicit feedback: views, clicks, purchases, shares
  - Rating $r =$ "strength" of actions (no. of clicks, viewing duration) → confidence level of observed preference
  - Preference matrix *P* with $p = 1$ if $r > 0$ and 0 if $r = 0$
  - Factorise of *P* with ratings ***weighted*** by their confidence (for details see this ICDM08 paper)



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Key in Scalable ML

- Computation and storage should be linear (in D, k)
  → 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

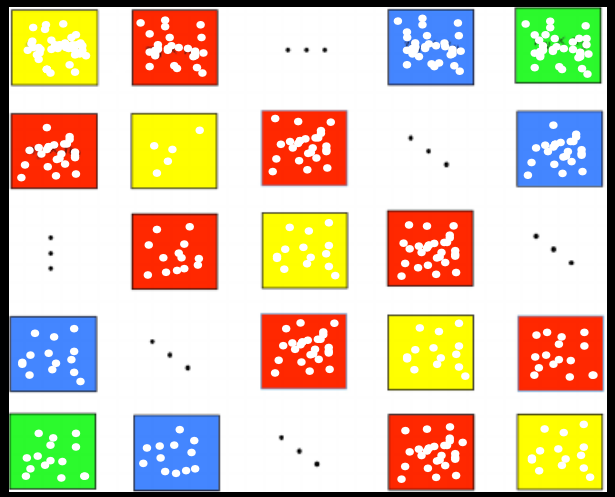
Blocked Implementation of ALS

$$\mathcal{L}(Q, P\ ;\ D) = \sum_{(u,i)\in D} \left(r_{ui} - q_i^T p_u\right)^2 + \lambda(\|q_i\|^2 + \|p_u\|^2)$$

How can we parallelize this?

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 (488×369) (researchgate.net)

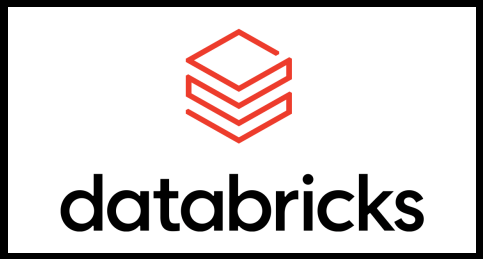
The ALS API in Spark

- 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

```scala
944   def train[ID: ClassTag]( // scalastyle:ignore
945       ratings: RDD[Rating[ID]],
946       rank: Int = 10,
947       numUserBlocks: Int = 10,
948       numItemBlocks: Int = 10,
949       maxIter: Int = 10,
950       regParam: Double = 0.1,
951       implicitPrefs: Boolean = false,
952       alpha: Double = 1.0,
953       nonnegative: Boolean = false,
954       intermediateRDDStorageLevel: StorageLevel = StorageLevel.MEMORY_AND_DISK,
955       finalRDDStorageLevel: StorageLevel = StorageLevel.MEMORY_AND_DISK,
956       checkpointInterval: Int = 10,
957       seed: Long = 0L)(
958       implicit ord: Ordering[ID]): (RDD[(ID, Array[Float])], RDD[(ID, Array[Float])]) = {
959
960     require(!ratings.isEmpty(), s"No ratings available from $ratings")
961     require(intermediateRDDStorageLevel != StorageLevel.NONE,
962       "ALS is not designed to run without persisting intermediate RDDs.")
963
964     val sc = ratings.sparkContext
965
966     // Precompute the rating dependencies of each partition
967     val userPart = new ALSPartitioner(numUserBlocks)
968     val itemPart = new ALSPartitioner(numItemBlocks)
969     val blockRatings = partitionRatings(ratings, userPart, itemPart)
970       .persist(intermediateRDDStorageLevel)
971     val (userInBlocks, userOutBlocks) =
972       makeBlocks("user", blockRatings, userPart, itemPart, intermediateRDDStorageLevel)
973     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: 14 days free on AWS, Microsoft Azure or Google Cloud.



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- 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