

Machine Learning: Recommender System

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Contents

1 Introduction

2 Memory-based Collaborative Filtering

3 Model-based Collaborative Filtering

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Contents

1 Introduction

2 Memory-based Collaborative Filtering

3 Model-based Collaborative Filtering

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Example: Recommender System

YouTube JP

recommender system

INSIDE OUT
DESPICABLE ME 2
THE AVENGERS: AGE OF ULTRON
ANT-MAN

	Animated	Marvel	Super Villain	
Animated	Yes	No	No	No
Marvel	No	No	Yes	Yes
Super Villain	No	Yes	Yes	Yes

3:13 / 13:47

Recommender Systems

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1 323 6 分享 ...

Formal Model
• $C \times$ set of customers
• $S \times$ set of items
• Utility Function $u: C \times S \rightarrow R$
• R is a set of ratings
• I is a discrete ordered set
• e.g., 1 to 5 stars, real number in [0,1]

Overview of Recommender Systems | Stanford University
Video Tutorials - All in One
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Collaborative Filtering | Stanford University
Video Tutorials - All in One
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Option 2: Cosine similarity
• $\text{sim}(u_i, u_j) = \frac{\sum_{k=1}^n u_{ik} u_{jk}}{\sqrt{\sum_{k=1}^n u_{ik}^2} \sqrt{\sum_{k=1}^n u_{jk}^2}}$
• $\text{sim}(u_i, u_j) \in [0, 1]$
• $\text{sim}(u_i, u_j) = 1 \Leftrightarrow u_i = u_j$
• $\text{sim}(u_i, u_j) = 0 \Leftrightarrow u_i \perp u_j$
• Problem: Inverse document frequency

8 Recommender Systems - Machine Learning Class 10-701
Alex Smola
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1:16:26

From the Labs: Winning the Netflix Prize
AT&T Tech Channel
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How to build a machine learning recommender systems and how
BYU Analytics
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7:02

A red arrow points from the video player to the sidebar.

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Example: Recommender System

Hello, Kristina. We have [recommendations](#) for you.

Kristina's Amazon.com | [Today's Deals](#) | [Gifts & Wish Lists](#) | [Gift Cards](#)

Shop All Departments | Search All Departments

Your Amazon.com Your Browsing History Recommended For You Rate These Items Improve Your

Kristina, Welcome to Your Amazon.com

Today's Recommendations For You

Here's a daily sample of items recommended for you. Click here to [see all recommendations](#).

[Street Food of India: The 50...](#)
(Hardcover) by Sephi Bergerson
★★★★★ (4) \$19.17
Fix this recommendation

[Lavazza Tierra! 100% Arabica Whole Bean Espresso...](#)
★★★★★ (38) \$34.41
Fix this recommendation

[Entourage: The Complete Fou... DVD ~ Adrian Grenier](#)
★★★★★ (44) \$16.49
Fix this recommendation

New For You®

[The Race \(Isaac Bell\)](#)
Clive Cussler, Justin Scott
Hardcover
\$27.95 \$14.97
Fix this recommendation

[Multisensory Teaching of Basic...](#)
Judith R. Birsh, Sally E. Shaywitz
Hardcover
\$79.95 \$44.99

[Kill Shot \(Mitch Rapp\)](#)
Vince Flynn
Hardcover
\$27.99 \$16.62
Fix this recommendation

[Limitless \(Unrated Extended Cut\)](#)
Bradley Cooper, Anna Friel, Abbie...
DVD
\$29.99 \$15.19

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Recommender System

Recommender System applies **statistical** and **knowledge discovery techniques** to the problem of making product recommendations.

Advantages of recommender systems:

- **Improve conversion rate:**
 - Help customers find what they want to buy.
- **Cross-selling:**
 - Suggest additional products.
- **Improve customer loyalty:**
 - Create a value-added relationship.

Use Cases of Recommendation Systems

- **Netflix:** **2/3** of the watched movies are recommended.
- **Amazon:** **35%** sales come from recommendations.
- **Google News:** recommendations generate **38%** more click-throughs.
- **Choicestream:** **28%** of the people would buy more music if they found what they liked.

Collaborative Filtering

Make **automatic predictions (filtering)** about the interests of a user by collecting preferences or taste information **from many other users (collaboration)**.

Type of CF Algorithms

- **Memory-based CF:** utilize the entire user-item database to generate a prediction.
 - **User-based CF:** find similar users to predict ratings.
 - **Item-based CF:** use similar items to predict ratings.
- **Model-based CF:** build a model from the rating data(Matrix factorization, etc.) and use this model to predict missing ratings.

Contents

1 Introduction

2 Memory-based Collaborative Filtering

3 Model-based Collaborative Filtering

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User-based CF

Recommendations based on the **relationship between users**.

The basic steps

- Identify **set of items** rated by the target user u .
- Identify which **other users (neighbors)** were rated by the items set.
- Compute **similarity** between each neighbor and select k **most similar neighbors**.
- Predict ratings for the target user.

User-based CF

	Item1	Item2	Item3	Item4	Item5	Item6
User1	2			4	5	
User2	5		4			1
User3			5		2	
User4		1		5		4
User5			4			2
User6	4	5		1		

1. For the target user5, identify the relevant items set $\mathcal{D} = \{\text{item3, item6}\}$.

User-based CF

	Item1	Item2	Item3	Item4	Item5	Item6
User1	2			4	5	
User2	5		4			1
User3			5		2	
User4		1		5		4
User5			4			2
User6	4	5		1		

2. Identify users set $\mathcal{M} = \{\text{user2}, \text{user3}, \text{user4}\}$ were rated by the items in set $\mathcal{N} = \{\text{item3}, \text{item6}\}$.

3. Compute **similarity** between each user (neighbor) and select k **most similar neighbors**.

- **Pearson correlation coefficient**
- Cosine similarity
- Others

Pearson correlation coefficient between user u and v :

$$sim(u, v) = \frac{\sum_{i \in \mathcal{I}} (r_{ui} - \bar{r}_u)(r_{vi} - \bar{r}_v)}{\sqrt{\sum_{i \in \mathcal{I}} (r_{ui} - \bar{r}_u)^2} \sqrt{\sum_{i \in \mathcal{I}} (r_{vi} - \bar{r}_v)^2}}$$

- \mathcal{I} denotes relevant items set.
- r_{ui} and r_{vi} denote the ratings of user u and v for item i .
- \bar{r}_u and \bar{r}_v denote the average ratings of user u and v .

User-based CF

	Item1	Item2	Item3	Item4	Item5	Item6	
User1	2			4	5		
User2	5		4			1	sim = 0.87
User3			5		2		sim = 1
User4		1		5		4	sim = -1
User5			4			2	
User6	4	5		1			

- Compute **similarity** between each neighbor based on **Pearson correlation coefficient**.
- For example, compute similarity between user2 and user5:

\bar{r}_{user2} (average rating) is $(5+4+1)/3 = 3.34$

\bar{r}_{user5} (average rating) is $(4+2)/2 = 3$

$$sim(user2, user5) = \frac{(4-3.34)\cdot(4-3)+(1-3.34)\cdot(2-3)}{\sqrt{((4-3.34)^2 + (1-3.34)^2)((4-3.34)^2 + (2-3.34)^2)}} = 0.87$$

4. Make predictions based on the k nearest neighbors for user u .

Predict rating $r_{u,i}$ by

$$r_{u,i} = \bar{r}_u + \frac{\sum_{v \in \mathcal{K}} \text{sim}(v, u)(r_{vi} - \bar{r}_v)}{\sum_{v \in \mathcal{K}} |\text{sim}(v, u)|}$$

- \mathcal{K} denotes the set of k nearest neighbors.
- $|\text{sim}(v, u)|$ denotes the absolute value of similarity.
- \bar{r}_u denotes the average rating of user u .
- \bar{r}_v denotes the average rating of user v .
- r_{vi} denote the ratings of user v for item i
- $\text{sim}(v, u)$ denotes the similarity between user v and u .

User-based CF

	Item1	Item2	Item3	Item4	Item5	Item6	
User1	2			4	5		
User2	5		4			1	sim = 0.87
User3			5		2		sim = 1
User4		1		5		4	sim = -1
User5	3.51	3.81	4	2.42	2.48	2	
User6	4	5		1			

- Make predictions based on the k nearest neighbors
- For example, make prediction of user5 for item1:

$$r_{user5,item1} = (4 + 2)/2 + \frac{0.87 \cdot (5 - (5 + 4 + 1)/3)}{|0.87|} = 3.51$$

Recommendations based on the **relationship between items**.

The basic steps

- Identify set of users rated by the target item u .
- Identify which other items (neighbors) were rated by the users set.
- Compute similarity between each neighbor and select k most similar neighbors.
- Predict ratings for the target item.

Item-based CF

	Item1	Item2	Item3	Item4	Item5	Item6
User1	2			4	5	
User2	5		4			1
User3			5		2	
User4		1		5		4
User5			4			2
User6	4	5		1		

1. For the target item6, identify the relevant set $\mathcal{U} = \{\text{user2}, \text{user4}, \text{user5}\}$.

Item-based CF

	Item1	Item2	Item3	Item4	Item5	Item6
User1	2			4	5	
User2	5		4			1
User3			5		2	
User4		1		5		4
User5			4			2
User6	4	5		1		

2. Identify items set {item1, item2, item3, item4} were rated by the users in set \mathcal{U} .

3. Compute **similarity** between each item (neighbor) and select k **most similar neighbors**.

- Pearson correlation coefficient
- Cosine similarity
- Others

Pearson correlation coefficient between item \mathcal{I} and \mathcal{H} :

$$sim(I, H) = \frac{\sum_{u \in \mathcal{U}} (r_{ui} - \bar{r}_i)(r_{uh} - \bar{r}_h)}{\sqrt{\sum_{u \in \mathcal{U}} (r_{ui} - \bar{r}_i)^2} \sqrt{\sum_{u \in \mathcal{U}} (r_{uh} - \bar{r}_h)^2}}$$

- \mathcal{U} denotes relevant users set.
- r_{ui} and r_{uh} denote the ratings of user u for item \mathcal{I} and \mathcal{H} .
- \bar{r}_i and \bar{r}_h denote the average ratings of item \mathcal{I} and \mathcal{H} .

Item-based CF

	Item1	Item2	Item3	Item4	Item5	Item6
User1	2			4	5	
User2	5		4			1
User3			5		2	
User4		1		5		4
User5			4			2
User6	4	5		1		

sim = -1 sim = -1 sim = 0.86 sim = 1

- Compute **similarity** between each neighbor based on **Pearson correlation coefficient**.
- For example, compute similarity between item3 and item6:

\bar{r}_{item3} (average rating) is $(4+5+4)/3 = 4.34$

\bar{r}_{item6} (average rating) is $(1+4+2)/3 = 2.34$

$$sim(item3, item6) = \frac{(4-4.34) \cdot (1-2.34) + (4-4.34) \cdot (2-2.34)}{\sqrt{((4-4.34)^2 + (4-4.34)^2) \cdot ((1-2.34)^2 + (2-2.34)^2)}} = 0.86$$

4. Make predictions based on the k nearest neighbors for item i .

Predict rating $r_{u,i}$ by

$$r_{u,i} = \bar{r}_i + \frac{\sum_{h \in K} sim(h, i)(r_{u,h} - \bar{r}_h)}{\sum_{h \in K} |sim(h, i)|}$$

- K denotes the set of k nearest neighbors.
- $|sim(h, i)|$ denotes the absolute value of similarity.
- \bar{r}_i denotes the average rating of item i .
- \bar{r}_h denotes the average rating of item h .
- $sim(h, i)$ denotes the similarity between item h and i .

Item-based CF

	Item1	Item2	Item3	Item4	Item5	Item6
User1	2			4	5	2.94
User2	5		4			1
User3			5		2	2.48
User4		1		5		4
User5			4			2
User6	4	5		1		1.12

sim = -1 sim = -1 sim = 0.86 sim = 1

- Make predictions based on the k nearest neighbors
- For example, make prediction of item6 for user1:

$$r_{item6,user1} = \frac{1 + 4 + 2}{3} + \frac{-1 \cdot \left(2 - \frac{2+5+4}{3}\right) + 1 \cdot \left(4 - \frac{4+5+1}{3}\right)}{|-1| + |1|}$$
$$= 2.94$$

Memory-based CF

Differences between Item-based CF and User-based CF

User-based similarity is more **dynamic**.

- Precompute user neighborhood may lead to poor predictions.

Item-based similarity is **static**.

- Precompute item neighborhood may provide accurate results.

Memory-based CF

Strengths

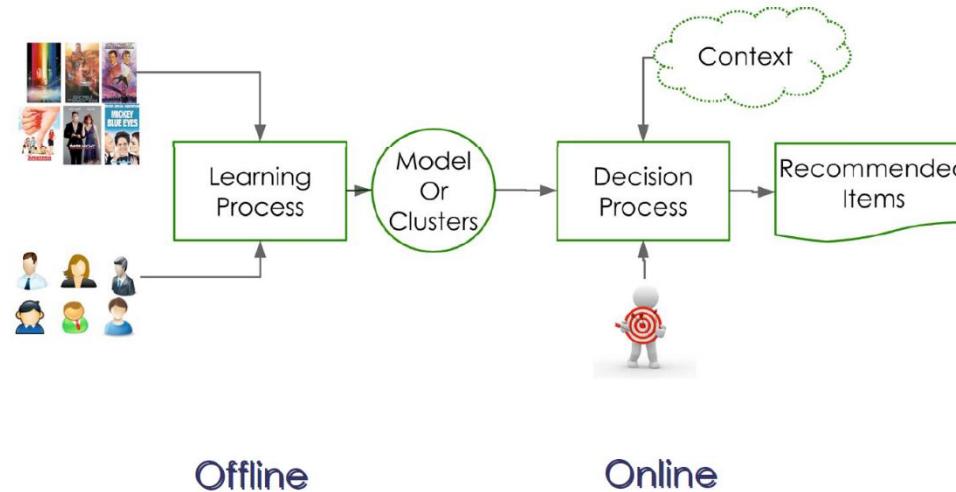
- Require minimal knowledge engineering efforts.
- Users and products are symbols without any internal structure or characteristics.
- Produce good-enough results in most cases.

Weaknesses

- Require **a large number** of explicit and reliable ratings.
- **Highly time consuming** to compute similarity with millions of users & items.

Challenges of Memory-based CF

Two-step process



- **Two-step process:** similarity computation in the offline setting and prediction process in the online setting.
- **Accuracy problem:** difficult to make accurate predictions based on nearest neighbors.
- **Sparsity problem:** the number of observed samples is less than 1%.

Contents

1 Introduction

2 Memory-based Collaborative Filtering

3 Model-based Collaborative Filtering

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Model-based CF Algorithms

Models are learned from the **underlying data** rather than heuristics

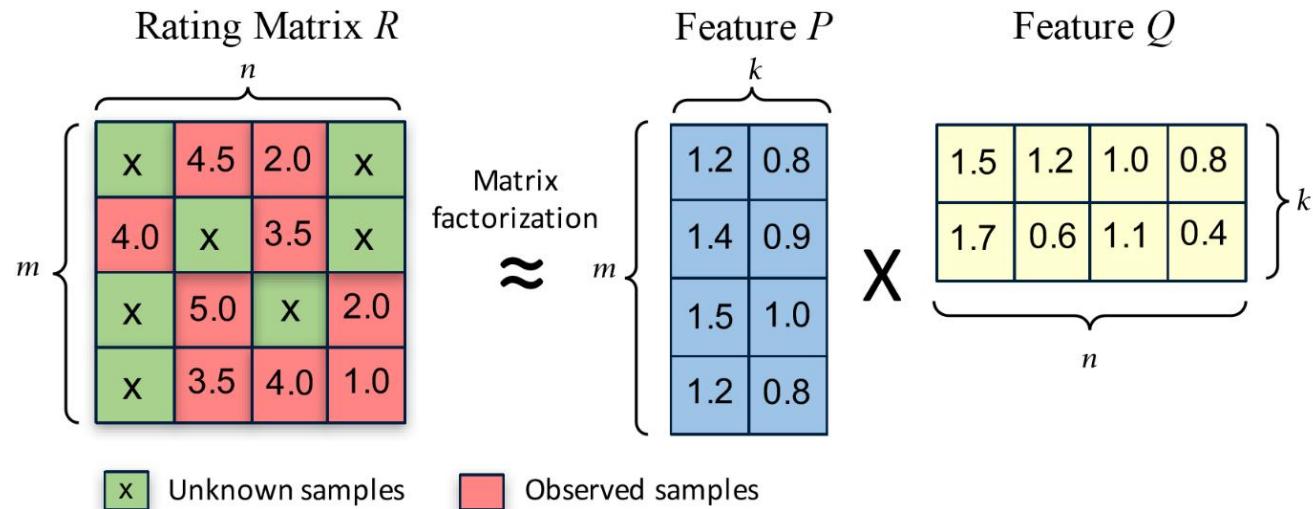
Models of user ratings (or purchases):

- **Matrix Factorization**
- Clustering (classification)
- Association Rules
- Deep learning based methods
- Other models

Matrix Factorization is the most widely used algorithm.

Matrix Factorization

- Give a rating matrix $\mathbf{R} \in \mathbb{R}^{m \times n}$, with sparse ratings from m users to n items.
- Assume rating matrix \mathbf{R} can be factorized into the multiplication of two **low-rank feature matrices** $\mathbf{P} \in \mathbb{R}^{m \times k}$ and $\mathbf{Q} \in \mathbb{R}^{k \times n}$.



An example of matrix factorization ($m = 4$, $n = 4$, $k = 2$).

Determine Objective Function

- Determine an **objective function**.

- Squared error loss:

$$\mathcal{L}(r_{ui}, \hat{r}_{ui}) = (r_{ui} - \hat{r}_{ui})^2$$

- Binary hinge loss:

$$\mathcal{L}(r_{ui}, \hat{r}_{ui}) = \max(0, 1 - r_{ui}\hat{r}_{ui})$$

- Notes: r_{ui} denotes the **actual rating** of user u for item i and \hat{r}_{ui} denotes the **prediction**.

Alternating Least Square (ALS) for MF

ALS is to minimize the following objective function:

$$\mathcal{L} = \sum_{u,i} (r_{u,i} - \mathbf{p}_u^T \mathbf{q}_i)^2 + \lambda \left(\sum_u \|\mathbf{p}_u\|^2 + \sum_i \|\mathbf{q}_i\|^2 \right)$$

- $\mathbf{P} = [\mathbf{p}_1, \mathbf{p}_2 \cdots, \mathbf{p}_m]^T \in \mathbb{R}^{m \times k}$.
- $\mathbf{Q} = [\mathbf{q}_1, \mathbf{q}_2 \cdots, \mathbf{q}_n] \in \mathbb{R}^{k \times n}$.
- $r_{u,i}$ denotes the **actual rating** of user u for item i , $u = 1 \cdots m$, $i = 1 \cdots n$.
- λ is **regularization parameter** to avoid overfitting.

General Steps of ALS

Algorithm 1 General Steps of ALS

- 1: **Require** rating matrix \mathbf{R} , feature matrices \mathbf{P} , \mathbf{Q} and regularization parameter λ .
 - 2: **Optimize** \mathbf{P} while fixing \mathbf{Q} .
 - 3: **Optimize** \mathbf{Q} while fixing \mathbf{P} .
 - 4: **Repeat** the above processes until **convergence**.
-

Optimize P while Fixing Q

- Objective function:

$$\mathcal{L} = \sum_{u,i} (r_{u,i} - \mathbf{p}_u^T \mathbf{q}_i)^2 + \lambda (\sum_u \|\mathbf{p}_u\|^2 + \sum_i \|\mathbf{q}_i\|^2)$$

- Optimize \mathbf{P} while fixing \mathbf{Q} :

The first order optimality:

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial \mathbf{p}_u} &= 0 \\ \Rightarrow \sum_i (\mathbf{q}_i \mathbf{q}_i^T + \lambda \mathbf{I}) \mathbf{p}_u &= \mathbf{Q} \mathbf{R}_{u*}^T \\ \Rightarrow \mathbf{p}_u &= (\mathbf{Q} \mathbf{Q}^T + \lambda \mathbf{I})^{-1} \mathbf{Q} \mathbf{R}_{u*}^T\end{aligned}$$

- \mathbf{R}_{u*} denotes the u -th row of rating matrix \mathbf{R} .
- Update all \mathbf{p}_u with the above formula.

Optimize Q while Fixing P

- Objective function:

$$\mathcal{L} = \sum_{u,i} (r_{u,i} - \mathbf{p}_u^T \mathbf{q}_i)^2 + \lambda (\sum_u \|\mathbf{p}_u\|^2 + \sum_i \|\mathbf{q}_i\|^2)$$

- Optimize **Q** while fixing **P**:

The first order optimality:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{q}_i} = 0$$

$$\Rightarrow \sum_u (\mathbf{p}_u \mathbf{p}_u^T + \lambda \mathbf{I}) \mathbf{q}_i = \mathbf{P}^T \mathbf{R}_{*i}$$

$$\Rightarrow \mathbf{q}_i = (\mathbf{P}^T \mathbf{P} + \lambda \mathbf{I})^{-1} \mathbf{P}^T \mathbf{R}_{*i}$$

- \mathbf{R}_{*i} denotes the i -th column of rating matrix **R**.
- Update all \mathbf{q}_i with the above formula.

Algorithm 2 ALS Algorithm

- 1: **Require** rating matrix \mathbf{R} , feature matrices \mathbf{P} , \mathbf{Q} and regularization parameter λ .
 - 2: **Optimize** \mathbf{P} while fixing \mathbf{Q} :
$$\mathbf{p}_u = (\mathbf{Q}\mathbf{Q}^T + \lambda\mathbf{I})^{-1}\mathbf{Q}\mathbf{R}_{u*}^T$$
 - 3: **Optimize** \mathbf{Q} while fixing \mathbf{P} :
$$\mathbf{q}_i = (\mathbf{P}^T\mathbf{P} + \lambda\mathbf{I})^{-1}\mathbf{P}^T\mathbf{R}_{*i}$$
 - 4: **Repeat** the above processes until **convergence**.
-

Why SGD?

Time complexity per iteration of ALS:

$$O(|\Omega|k^2 + (m+n)k^3)$$

- $|\Omega|$ denotes the number of observed samples.
- k denotes the rank.
- m and n denote the number of users and items.
- ALS is **not scalable** to **large-scale** datasets.

Time complexity per iteration of SGD:

$$O(|\Omega|k)$$

- SGD is **scalable** to **large-scale** datasets.

SGD is to minimize the following objective function:

$$\mathcal{L} = \sum_{u,i \in \Omega} (r_{u,i} - \mathbf{p}_u^T \mathbf{q}_i)^2 + \lambda_p \|\mathbf{p}_u\|^2 + \lambda_q \|\mathbf{q}_i\|^2$$

- $\mathbf{P} = [\mathbf{p}_1, \mathbf{p}_2 \cdots, \mathbf{p}_m]^T \in \mathbb{R}^{m \times k}$.
- $\mathbf{Q} = [\mathbf{q}_1, \mathbf{q}_2 \cdots, \mathbf{q}_n] \in \mathbb{R}^{k \times n}$.
- $r_{u,i}$ denotes the **actual rating** of user u for item i .
- Ω denotes the set of **observed samples** from rating matrix \mathbf{R} .
- λ_p and λ_q are **regularization parameters** to avoid overfitting.

General Steps of SGD

Algorithm 3 General Steps of SGD

- 1: **Require** feature matrices \mathbf{P} , \mathbf{Q} , observed set Ω , regularization parameters λ_p , λ_q and learning rate α .
 - 2: **Randomly** select an observed sample $r_{u,i}$ from observed set Ω .
 - 3: Calculate the **gradient** w.r.t to the objective function.
 - 4: Update the feature matrices \mathbf{P} and \mathbf{Q} with learning rate α and gradient.
 - 5: **Repeat** the above processes until **convergence**.
-

Gradient Computation

- Objective function:

$$\mathcal{L} = \sum_{u,i \in \Omega} (r_{u,i} - \mathbf{p}_u^T \mathbf{q}_i)^2 + \lambda_p \|\mathbf{p}_u\|^2 + \lambda_q \|\mathbf{q}_i\|^2$$

- Randomly select an observed sample $r_{u,i}$.
- Calculate the **prediction error**:

$$E_{u,i} = r_{u,i} - \mathbf{p}_u^T \mathbf{q}_i$$

- Calculate the **gradient**:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{p}_u} = 2(E_{u,i}(-\mathbf{q}_i) + \lambda_p \mathbf{p}_u)$$
$$\frac{\partial \mathcal{L}}{\partial \mathbf{q}_i} = 2(E_{u,i}(-\mathbf{p}_u) + \lambda_q \mathbf{q}_i)$$

Update Feature Matrices

- Objective function:

$$\mathcal{L} = \sum_{u,i \in \Omega} (r_{u,i} - \mathbf{p}_u^T \mathbf{q}_i)^2 + \lambda_p \|\mathbf{p}_u\|^2 + \lambda_q \|\mathbf{q}_i\|^2$$

- Randomly select an observed sample $r_{u,i}$.

- Calculate the **prediction error**:

$$E_{u,i} = r_{u,i} - \mathbf{p}_u^T \mathbf{q}_i$$

- Calculate the **gradient**:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{p}_u} = 2(E_{u,i}(-\mathbf{q}_i) + \lambda_p \mathbf{p}_u)$$
$$\frac{\partial \mathcal{L}}{\partial \mathbf{q}_i} = 2(E_{u,i}(-\mathbf{p}_u) + \lambda_q \mathbf{q}_i)$$

- Update the feature matrices **P** and **Q** with **learning rate α** :

$$\mathbf{p}_u = \mathbf{p}_u + 2\alpha(E_{u,i}\mathbf{q}_i - \lambda_p \mathbf{p}_u)$$

$$\mathbf{q}_i = \mathbf{q}_i + 2\alpha(E_{u,i}\mathbf{p}_u - \lambda_q \mathbf{q}_i)$$

Algorithm 4 SGD Algorithm

- 1: **Require** feature matrices \mathbf{P} , \mathbf{Q} , observed set Ω , regularization parameters λ_p , λ_q and learning rate α .
- 2: **Randomly** select an observed sample $r_{u,i}$ from observed set Ω .
- 3: Calculate the **gradient** w.r.t to the objective function:

$$\begin{aligned}E_{u,i} &= r_{u,i} - \mathbf{p}_u^T \mathbf{q}_i \\ \frac{\partial \mathcal{L}}{\partial \mathbf{p}_u} &= 2(E_{u,i}(-\mathbf{q}_i) + \lambda_p \mathbf{p}_u) \\ \frac{\partial \mathcal{L}}{\partial \mathbf{q}_i} &= 2(E_{u,i}(-\mathbf{p}_u) + \lambda_q \mathbf{q}_i)\end{aligned}$$

- 4: **Update** the feature matrices \mathbf{P} and \mathbf{Q} with learning rate α and gradient.

$$\begin{aligned}\mathbf{p}_u &= \mathbf{p}_u + 2\alpha(E_{u,i}\mathbf{q}_i - \lambda_p \mathbf{p}_u) \\ \mathbf{q}_i &= \mathbf{q}_i + 2\alpha(E_{u,i}\mathbf{p}_u - \lambda_q \mathbf{q}_i)\end{aligned}$$

- 5: **Repeat** the above processes until **convergence**.
-

Matrix Factorization

Comparison between SGD and ALS

- ALS is easier to **parallelize** than SGD.
- ALS **converges faster** than the SGD.
- SGD has less **storage complexity** than ALS.
(ALS needs to store the rating matrix **R**)
- SGD has less **computational complexity** than ALS.
(ALS needs to compute the matrix-vector multiplication)

Accuracy Measures

Mean Absolute Error (MAE) computes the deviation between predicted ratings and actual ratings.

$$MAE = \frac{1}{|\Omega|} \sum_{u,i \in \Omega} |\hat{r}_{u,i} - r_{u,i}|$$

- Ω denotes the **observed set**.
- $|\Omega|$ denotes the **number of observed set**.
- $r_{u,i}$ denotes the **actual rating** and $\hat{r}_{u,i}$ denotes the prediction.

Root Mean Square Error (RMSE) is similar to MAE, but places more emphasis on larger deviation.

$$RMSE = \sqrt{\frac{1}{|\Omega|} \sum_{u,i \in \Omega} (\hat{r}_{u,i} - r_{u,i})^2}$$

Riemannian Pursuit for Big Matrix Recovery

Riemannian Pursuit for Big Matrix Recovery

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Abstract

Low rank matrix recovery is a fundamental task in many real-world applications. The performance of existing methods, however, deteriorates significantly when applied to ill-conditioned or large-scale matrices. In this paper, we therefore propose an efficient method, called Riemannian Pursuit (RP), that aims to address these two problems simultaneously. Our method consists of a sequence of fixed-rank optimization problems. Each subproblem, solved by a nonlinear Riemannian conjugate gradient method, aims to correct the solution in the most important subspace of increasing size. Theoretically, RP converges linearly under mild conditions and experimental results show that it substantially outperforms existing methods when applied to large-scale and ill-conditioned matrices.

Definition 1. Given a linear operator $\mathcal{A} : \mathbb{R}^{m \times n} \rightarrow \mathbb{R}^l$, let $b = \mathcal{A}(\hat{\mathbf{X}}) + e$ be l linear measurements of an unknown rank- \hat{r} matrix $\hat{\mathbf{X}} \in \mathbb{R}^{m \times n}$, where e denotes noise. Then the task of MR is to recover $\hat{\mathbf{X}}$ by solving

$$\min_{\mathbf{X}} f(\mathbf{X}), \quad \text{s.t. } \text{rank}(\mathbf{X}) \leq r, \quad (1)$$

where $l \ll mn$, $r \geq \hat{r}$, and $f(\mathbf{X}) = \frac{1}{2} \|b - \mathcal{A}(\mathbf{X})\|_F^2$.

The definition of \mathcal{A} depends on the application context, such as matrix completion, quantum state tomography, matrix factorizations; see, e.g., (Recht et al., 2010; Candès & Plan, 2010a; Recht, 2011; Keshavan et al., 2010b; Laue, 2012). Although our derivation is valid for any \mathcal{A} that allows for MR, in the numerical experiments, we will focus on *matrix completion* (MC) as a specific application. In this case, $\mathcal{A}(\mathbf{X})$ is defined as the element-wise restriction of \mathbf{X} on Ξ , a subset of the complete set of entries of \mathbf{X} .

Problem (1) is known to be NP-hard. To address it, many researchers proposed to solve the nuclear-norm convex re-

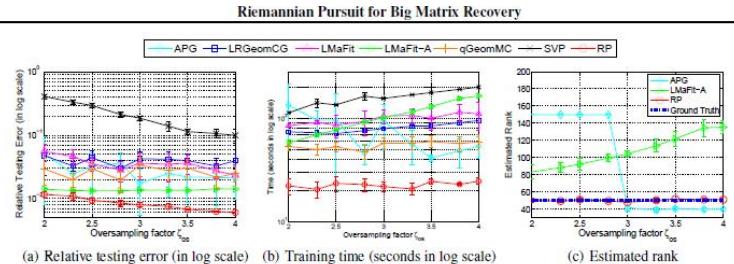


Figure 2. Comparison on medium-sized problems of rank $\hat{r} = 50$. The results are obtained by averaging over 10 independent trials.

APG, LRGeomCG, qGeomMC, Lmafit, Lmafit-A, GECO, Jaggi's method and Lau's method.

In general, collaborative filtering data are very noisy. As a result, the singular values of the matrices tend to be long-tail. Therefore, we need to set larger stopping tolerances to alleviate over-fitting. For this experiment, we set $\lambda_F = 0.2$ and $\epsilon_{out} = 10^{-4}$. We set $\eta = 0.65$, and the detected ranks by RP are used as the rank estimations for the fixed-rank methods, namely LRGeomCG, qGeomMC and LMaFIT. Finally, we constrain the maximum rank for all methods to 100. For comparison, we report the testing RMSE of different methods over 10 random 80/20 train/test partitions as explained in (Laue, 2012).

Comparison results are shown in Table 3. From the table, we can observe that RP performs the best among all the methods in terms of RMSE and computational efficiency. It is worth mentioning that we use the rank detected by RP as the rank estimation for LRGeomCG and qGeomMC. Therefore, RP can be much faster than these two methods if the cost of the model selection is considered.

atures are similar to ours, thus the comparison is fair. In addition, we list the training time, the times of speedup, RMSE and the CPU details in Table 4 for reference.

Table 4. Performance comparison on Movie-10M dataset				
Methods	Time (in seconds)	Speedup	RMSE	CPU(GHz)
GLasso	784,941	9,000x	0.821	2.5
Lau	2,663	30x	0.815	2.5
Jaggi	3,120	38x	0.862	2.4
RP	81	—	0.817	2.8

From Table 4, we observe that on the Movie-10M dataset, RP obtains comparable or better performance to the baseline methods in terms of RMSE, but can achieve great speedup with similar CPUs. Particularly, RP is orders of magnitude faster than all the other methods. With these comparisons, we can conclude that RP can achieve much faster training speed over the comparison methods.

6. Conclusion

We propose a Riemannian Pursuit (RP) method for tackling big MR problems. In contrast to nuclear-norm based methods, RP only needs to compute rank- ρ truncated SVD with ρ very small per iteration, as opposed to APG which may take hundreds of high-dimensional SVDs. By exploiting the Riemannian geometry of the fixed-rank manifold, RP uses a more efficient master solver. Moreover, RP increases the rank of the matrix by $\rho > 1$ per iteration, thus it exhibits good scalability for big MR problems with large ranks. Finally, RP automatically detects the rank with appropriate stopping conditions, and performs well on ill-conditioned problems. Extensive experimental results show that RP achieves superb scalability and maintain similar or better MR performance compared with state-of-the-art methods.

Table 3. Experimental results on real-world datasets.

Dataset	Movie-10M		Netflix	
	RMSE	Time (seconds)	RMSE	Time (seconds)
APG	1.096	1048±17	0.867	3128±3
LRGeomCG	0.824	338±11	0.887	—
QgeomMC	0.850	189±7	0.880	3063±74
Lmafit	0.837	307±1	0.875	3798±50
Lmafit-A	0.969	421±16	0.962	5286±165
RP	0.817	81±1	0.859	1332±27

* Result of APG on Netflix is absent due to out-of-memory issue. The standard deviations of RMSE are not reported since they are not significant. The average ranks estimated by APG, Lmafit-A and RP on Movie are 100, 77 and 10, respectively. The average ranks estimated by Lmafit-A and RP on Netflix are 81 and 12, respectively.

Code available at: <https://tanmingkui.github.io/files/sourcecode/Riemannian.rar>

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Riemannian Pursuit For Big Matrix Recovery

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The source codes are available [HERE](#)

Please cite the following paper if you find the codes are useful:

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