Recommender Systems via Matrix Completion: Frank-Wolfe, Pairwise Frank-Wolfe, and Projected Gradient Methods

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Matrix Completion: Problem Formulation

- Goal: recover a low-rank matrix $X \in \mathbb{R}^{n_1 \times n_2}$ from a subset of observed entries $\{U_{ij}\}_{(i,j) \in J}$.
- Original non-convex formulation:

$$\min_{X \in \mathbb{R}^{n_1 \times n_2}} \sum_{(i,j) \in J} (X_{ij} - U_{ij})^2 \quad \text{s.t.} \quad \operatorname{rank}(X) \leq \delta$$

Relaxation: replace rank constraint with nuclear norm constraint

$$\min_{X \in \mathbb{R}^{n_1 \times n_2}} \sum_{(i,j) \in J} (X_{ij} - U_{ij})^2 \quad \text{s.t.} \quad \|X\|_* \le \delta$$

Feasible set: convex hull of rank-one matrices

$$C = \text{conv}\{\delta \, uv^{\top} : ||u|| = ||v|| = 1\}$$

Algorithms

- Projected gradient method: performs gradient descent steps followed by projection onto the feasible set to enforce constraints.
- Prank-Wolfe method: a projection-free algorithm that moves toward a solution of a linear minimization oracle over the constraint set.
- Pairwise Frank-Wolfe method: improves standard FW by selecting a pair of atoms (away and standard FW) and performing an update in their direction, accelerating convergence.

Linear Minimization Oracle (LMO)

• At each Frank-Wolfe iteration, solve:

$$LMO_{\mathcal{C}}(\nabla f(X_k)) = \arg\min_{\|X\|_* \leq \delta} \operatorname{tr}(\nabla f(X_k)^{\top} X)$$

Optimal solution:

$$S_k = \delta \cdot \mathsf{u}_1 \mathsf{v}_1^{\top}$$

where u_1 , v_1 are the top left and right singular vectors of $-\nabla f(X_k)$.

• In code, computed via:

 ARPACK is used for efficiency: it computes only the leading singular vectors, making it well-suited for large and sparse matrices.

Performance Tracking and Stopping Criteria

 Loss Function: Measures the squared error over observed entries:

$$f(X) = \sum_{(i,j)\in J} (X_{ij} - U_{ij})^2$$

 Duality Gap: Quantifies sub-optimality in Frank-Wolfe methods:

$$g_k = \langle \nabla f(X_k), X_k - S_k \rangle$$

where S_k is the solution of the Linear Minimization Oracle (LMO).

• Relative Change Between \hat{X}_k and X_k : Used as a stopping criterion for the Projected Gradient method:

$$\frac{\|\hat{X}_k - X_k\|_F}{\|X_k\|_F}$$

Stepsizes

We implemented the following stepsize strategies:

- Diminishing stepsize
- Exact line search stepsize
- Lipschitz constant dependent stepsize
- Armijo line search stepsize
- ⇒ The *Exact line search stepsize* has been used in the whole experiment

Tuning the δ parameter

- A validation-based approach was adopted to select the optimal value of the parameter δ .
- ullet δ controls the threshold in the matrix completion model.
- ullet A range of candidate δ values was tested.
- The δ yielding the best validation performance (lowest RMSE) was selected.
- ⇒ Maintaining a low-rank matrix has been preferred over lower error

Datasets

Amazon Gift Cards

- Sparse (4.9% density) with 377 users, 129 items (1-5 ratings)
- Latest two user interactions per user are used for training, the (N-1)-th for validation and the N-th for testing

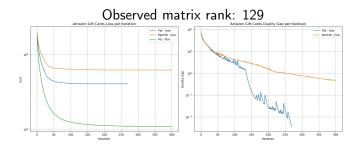
Netflix

- Integer movie ratings (1-5) from 1999-2005
- Subset created by selecting top 95% movies and 99% users (by rating count), further restricted to 2005 ratings to reduce bias
- Final dataset consisting of 4694 users and 225 movies

MovieLens 100K

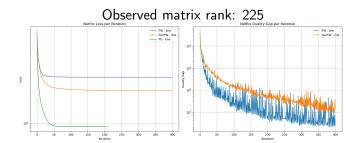
• 100,000 integer movie ratings (1-5) from 943 users and 1682 films, with a 6.3% density

Amazon Gift Cards



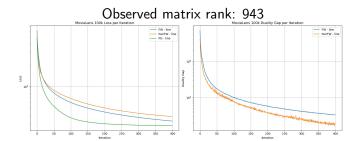
Algorithm	RMSE Test	Rank	Time(sec)
Projected Gradient	0.930	4	3.210
Pairwise FW	1.857	87	4.162
Standard FW	1.537	2	0.653

Netflix



Algorithm	RMSE Test	Rank	Time(sec)
Projected Gradient	0.889	96	19.380
Pairwise FW	1.089	188	101.972
Standard FW	1.263	68	11.622

MovieLens



Algorithm	RMSE Test	Rank	Time(sec)
Projected Gradient	0.951	115	260.403
Pairwise FW	0.980	379	2760.050
Standard FW	0.980	401	47.662