

Optimizing Recommendation Systems with the Frank-Wolfe Algorithm

Optimization for Data Science

Anna Putina¹

¹Università degli Studi di Padova

February 5th, 2025



UNIVERSITÀ
DEGLI STUDI
DI PADOVA

Table of Contents

- 1 Frank-Wolfe Method
- 2 Matrix Completion
- 3 Datasets
- 4 Implementation Details
- 5 Results



Table of Contents

- 1 Frank-Wolfe Method
- 2 Matrix Completion
- 3 Datasets
- 4 Implementation Details
- 5 Results



Frank-Wolfe Algorithm

Algorithm 1: Frank-Wolfe Method

Input: Convex function $f(x)$, feasible region C , initial point $x_0 \in C$

for $k = 0, 1, \dots$ **do**

 Compute $s_k = \arg \min_{s \in C} \langle \nabla f(x_k), s \rangle$ using LMO;

 Set direction $d_k^{FW} = s_k - x_k$;

 Choose step size $\alpha_k \in (0, 1]$;

 Update $x_{k+1} = x_k + \alpha_k d_k^{FW}$;

if *stopping condition is met* **then**

 break;



Table of Contents

- 1 Frank-Wolfe Method
- 2 Matrix Completion**
- 3 Datasets
- 4 Implementation Details
- 5 Results



Matrix Completion Problem

Objective: Retrieve a low-rank matrix $X \in \mathbb{R}^{n_1 \times n_2}$ from a sparse set of observed matrix entries $\{U_{ij}\}_{(i,j) \in J}$, where $J \subset [1 : n_1] \times [1 : n_2]$.

Formulation:

$$\min_{X \in \mathbb{R}^{n_1 \times n_2}} f(X) := \sum_{(i,j) \in J} (X_{ij} - U_{ij})^2$$

subject to $\text{rank}(X) \leq \delta$.

Relaxation:

$$\min_{X \in \mathbb{R}^{n_1 \times n_2}} \sum_{(i,j) \in J} (X_{ij} - U_{ij})^2$$

subject to $\|X\|_* \leq \delta$.



Solution Approach

Convex Optimization Formulation:

$$C = \{X \in \mathbb{R}^{n_1 \times n_2} : \|X\|_* \leq \delta\} = \text{conv}\{\delta \mathbf{u} \mathbf{v}^T : \mathbf{u} \in \mathbb{R}^{n_1}, \mathbf{v} \in \mathbb{R}^{n_2}, \|\mathbf{u}\| = \|\mathbf{v}\| = 1\}.$$

Linear Minimization Oracle (LMO):

$$\text{LMO}_C(\nabla f(X_k)) \in \arg \min_{\|X\|_* \leq \delta} \text{tr}(\nabla f(X_k)^T X).$$

Implementation:

- Compute the gradient $\nabla f(X_k)$.
- Find the rank-one matrix $\delta \mathbf{u}_1 \mathbf{v}_1^T$, where $\mathbf{u}_1, \mathbf{v}_1$ are the left and right singular vectors of $-\nabla f(X_k)$ corresponding to its top singular value.
- Approximate X as a sparse combination of rank-one matrices.



Table of Contents

- 1 Frank-Wolfe Method
- 2 Matrix Completion
- 3 Datasets**
- 4 Implementation Details
- 5 Results



Datasets Overview

MovieLens 20M Dataset

- A widely recognized benchmark in recommendation systems research.
- Contains **20 million** ratings from **138,000** users for over **27,000** movies.
- Ratings range from **0.5 to 5.0**, with metadata (titles, genres, timestamps).

Anime User Score Dataset

- Focuses on the anime domain with **16,500** anime titles.
- Contains ratings from **270,033** users.
- Ratings range from **1 to 10**.
- Presents challenges such as **diverse user base** and **varying popularity**.



Table of Contents

- 1 Frank-Wolfe Method
- 2 Matrix Completion
- 3 Datasets
- 4 Implementation Details**
- 5 Results



Algorithm Tracking and Stopping Criteria

The algorithm monitors key metrics during execution:

- **Loss Function:** Measures squared error over observed entries:

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

- **Dual Gap:** Indicates sub-optimality:

$$\text{Dual Gap} = \langle \nabla f(X_k), X_k - S_k \rangle,$$

where S_k is the solution from the LMO.

- **Relative Change Between Iterates:**

$$\frac{\|X_{k+1} - X_k\|_F}{\|X_k\|_F}.$$

Stopping thresholds balance accuracy and efficiency.



Learning Rate Strategies

Several learning rate strategies determine the step size α_k at each iteration:

- **Diminishing Step Size:** Standard for Frank-Wolfe:

$$\alpha_k = \frac{2}{k+2}.$$

- **Exact Line Search:** Minimizes the loss function:

$$\alpha_k = \arg \min_{\alpha \in [0,1]} f(X_k + \alpha(S_k - X_k)).$$

- **Armijo Rule:** Ensures sufficient descent:

$$f(X_k + \alpha_k d_k) \leq f(X_k) + c\alpha_k \langle \nabla f(X_k), d_k \rangle,$$

where $d_k = S_k - X_k$ and $c \in (0, 1)$ is a constant.



Performance Tracking

The algorithm's performance was evaluated using:

- **Loss Function:** Tracks error over iterations.
- **Dual Gap:** Monitors convergence to optimality.

Key results:

- Comparison of loss and dual gap for different learning rate strategies.
- Showcases the effectiveness and efficiency of the Frank-Wolfe algorithm for matrix completion.



Table of Contents

- 1 Frank-Wolfe Method
- 2 Matrix Completion
- 3 Datasets
- 4 Implementation Details
- 5 Results**



Convergence Results

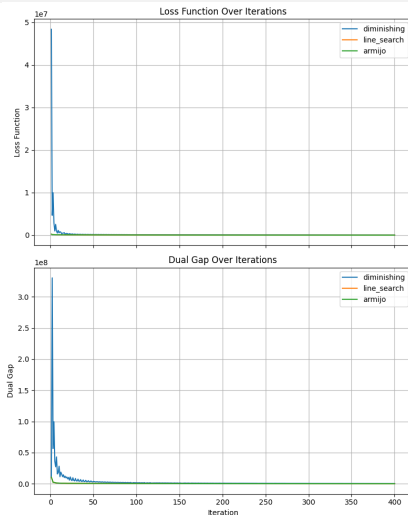
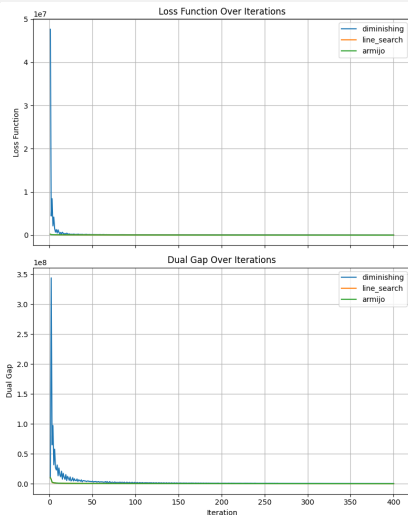


Figure 1. Comparison of loss and dual gap for different step sizes. Left: MovieLens dataset. Right: Anime dataset.



MovieLens

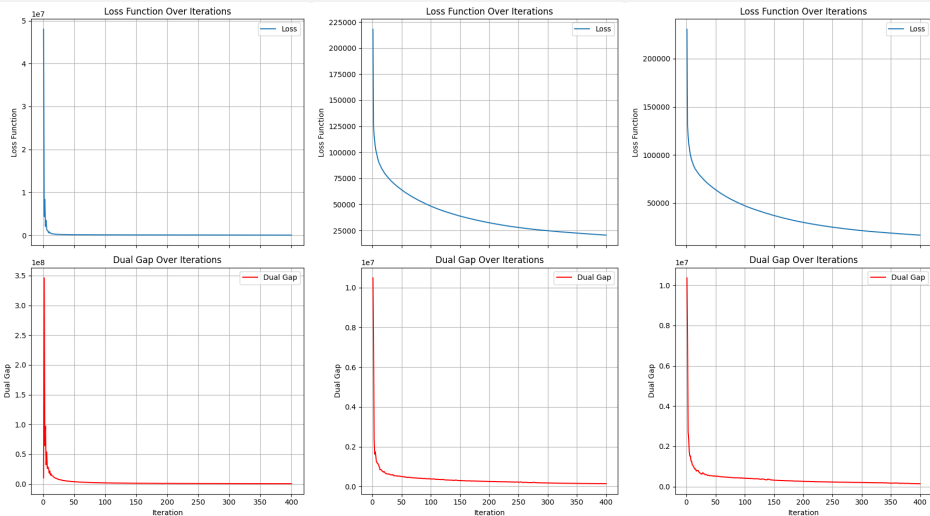


Figure 2. MovieLens dataset with different step size strategies: Diminishing, Exact Line Search, and Armijo Rule.



Anime

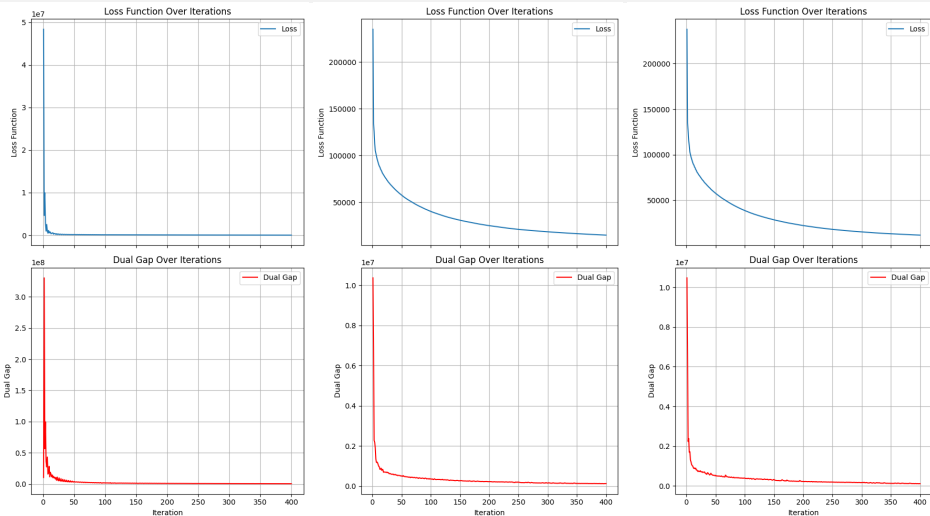


Figure 3. Anime dataset with different step size strategies: Diminishing, Exact Line Search, and Armijo Rule.



Relative Accuracy Function and Results

Function Description: The function computes the percentage of predictions (y_{pred}) that fall within a given **tolerance** of the true values (y_{true}).

Results:

Dataset	Step Size Strategy	Relative Accuracy (%)
MovieLens	Diminishing	62
MovieLens	Line Search	82
MovieLens	Armijo	88
Anime	Diminishing	82
Anime	Line Search	98
Anime	Armijo	99

