Semidefinite Programming

Applications in approximating NP-Complete problems & Matrix Completetion

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Presentation Overview

- Semidefinite Programming
- 2 Travelling Salesman

Overview Relaxation

Experimental Result

Visualization

3 Matrix Completetion

Overview

Relaxation

Fashion-MNIST

4 Referencing



Reviewing TSP

The Traveling Salesman Problem (TSP) is an optimization problem in which the objective is to find the shortest possible route for a salesman to visit a given set of cities, passing through each city exactly once, and returning to the starting city. It is a well-known NP-hard problem.

Semidefinite Programming Methods for the Symmetric Traveling Salesman Problem , 1999

Let $C \in \mathbb{R}^{n \times n}$ denote the matrix of edge costs. Let J denote the all-ones matrix, and e denote the all-ones vector.

minimize
$$\frac{1}{2} \operatorname{trace}(CX)$$

subject to $Xe = 2e$
 $X_{ii} = 0, \quad i = 1, \dots, n$
 $0 \le X_{ij} \le 1, \quad i, j = 1, \dots, n$
 $2I - X + (2 - 2\cos\left(\frac{2\pi}{n}\right))(J - I) \succeq 0$
 X is a real, symmetric $n \times n$ matrix.

X is a fractional adjacency matrix, meaning for $e = \{i, j\}$, $x_{ij} = x_{ji}$ is the proportion of edge e used.

Integrality Gap And Running Time

| # Of Nodes | SDP Time | BF Time | SDP Objective Value | BF Objective Value | Integrity Gap | Time Ratio |
|------------|----------|----------|---------------------|--------------------|---------------|------------|
| 10 | 0.7101 | 0.0156 | 53224.4854 | 53228.3976 | 0.9999 | 45.519 |
| 15 | 0.6776 | 0.8224 | 65753.5934 | 67299.5625 | 0.9770 | 0.8239 |
| 20 | 1.2271 | 97.2059 | 69558.9865 | 76199.4928 | 0.9129 | 0.0126 |
| 21 | 1.3689 | 266.7778 | 73969.6527 | 77373.6362 | 0.9560 | 0.0051 |
| 22 | 5.4774 | 657.7847 | 66459.7265 | 68245.9576 | 0.9738 | 0.0083 |

Visualization

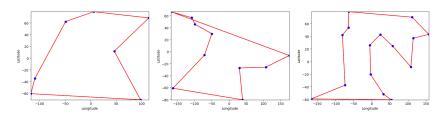


Figure: reasonable solution

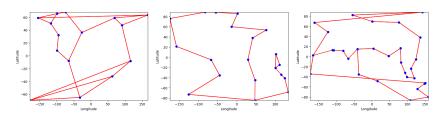
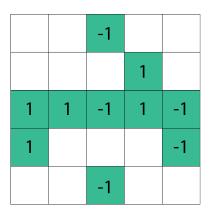


Figure: unreasonable solution

Low rank matrices

Given an incomplete matrix, can we recover the missing values?



| 1 | 1 | -1 | 1 | -1 |
|---|---|----|---|----|
| 1 | 1 | -1 | 1 | -1 |
| 1 | 1 | -1 | 1 | -1 |
| 1 | 1 | -1 | 1 | -1 |
| 1 | 1 | -1 | 1 | -1 |

Yes! Given:

- The matrix is low rank
- We have enough sample data
- and more ... (needle in haystack)

Why is this useful

- Netflix has an incomplete set of user preferences based off their past watch history. They
- 2 Recommendation Engine
- 3 Images

Relaxing Matrix Completetion to SDP

Suppose we have a low rank matrix \mathbf{M} . We have a set of location Ω describing our sampling. That is, if $(i,j) \in \Omega$, we observe entry M_{ij} . Given \mathbf{M} is low rank, it seems resonable that we would like to solve the following optimization problem

minimize
$$\operatorname{rank}(\mathbf{X})$$

subject to $X_{ij} = M_{ij} \quad (i,j) \in \Omega$
 $\mathbf{X} \in \mathbb{R}^{n \times n}$

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But...

Rank is not a convex. This turns out to be an NP-Hard Problem.

Introduce the nuclear norm

Nuclear Norm

The nuclear norm is a close approximation of the rank.

The nuclear norm of a matrix \mathbf{X} is defined as the sum of the eigenvalues.

$$\|\mathbf{X}\|_* = \sum_{k=1}^n \sigma_k \mathbf{X}$$

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For a symmetric positive semi-definite (SPSD) matricies, the nuclear norm is equal to the trace.

A better relaxation

What if our matrix is not SPSD

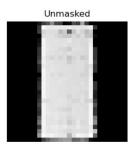
We introduce two matricies W₁ and W₂

A better relaxation

$$\begin{split} \text{minimize} & & \text{trace}(\mathbf{W}_1) + \text{trace}(\mathbf{W}_2) \\ \text{subject to} & & X_{ij} = M_{ij} \quad (i,j) \in \Omega \\ & & & \begin{bmatrix} \mathbf{W}_1 & \mathbf{X} \\ \mathbf{X}^\top & \mathbf{W}_2 \end{bmatrix} \succeq 0 \end{split}$$

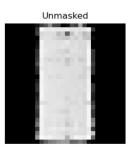






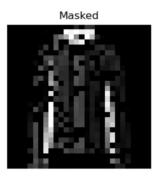
Original (rank=14)





Masked

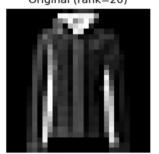




Unmasked



Original (rank=20)



Masked



Unmasked



Lists

Bullet Points and Numbered Lists

- Lorem ipsum dolor sit amet, consectetur adipiscing elit
- Aliquam blandit faucibus nisi, sit amet dapibus enim tempus
 - Lorem ipsum dolor sit amet, consectetur adipiscing elit
 - Nam cursus est eget velit posuere pellentesque
- Nulla commodo, erat quis gravida posuere, elit lacus lobortis est, quis porttitor odio mauris at libero
- 1 Nam cursus est eget velit posuere pellentesque
- Vestibulum faucibus velit a augue condimentum quis convallis nulla gravida

Citing References

An example of the \cite command to cite within the presentation:

This statement requires citation [Smith, 2022, Kennedy, 2023].

References



John Smith (2022) Publication title Journal Name 12(3), 45 – 678.



Annabelle Kennedy (2023) Publication title Journal Name 12(3), 45 – 678.

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