

Exploiting Relational Information in Social Networks using Geometric Deep Learning on Hypergraphs

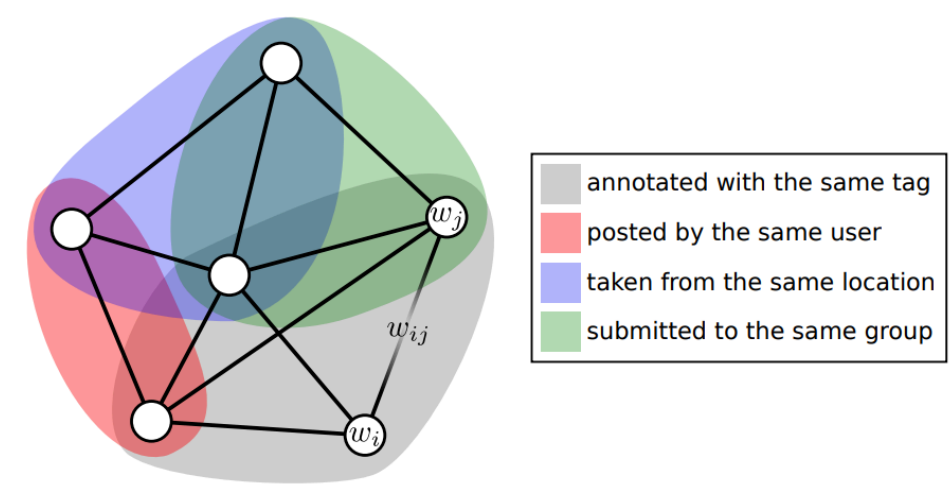


UNIVERSITEIT VAN AMSTERDAM

Devanshu Arya, Stevan Rudinac & Marcel Worring
Informatics Institute, University of Amsterdam

Introduction

In a social network, the neighbourhood of an entity which can be image, post or user often carry sufficient information for tasks such as classification, recommendation or link prediction



Goal

Learn one type of relations between entities to predict other type of relations in a social network

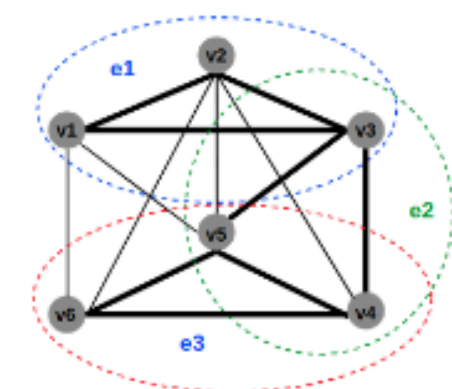


Challenges

1. Representation - To avoid any loss in information
2. Information Flow - To transfer neighbourhood features across entities
3. Generalizability - To cover all kinds of social networks

Background

Hypergraph is a generalisation of a graph in which an edge can connect any number of vertices.



Matrix Completion (Candès et al. 2008)

$$\min_{\mathbf{X} \in \mathbb{R}^{m \times n}} \|\mathbf{X}\|_* + \mu \|\Omega \circ (\mathbf{X} - \mathbf{A})\|_F^2$$

$L(\mathbf{X})$

Geometric Matrix Completion (Kalofolias et al. 2014)

$$\min_{\mathbf{X} \in \mathbb{R}^{m \times n}} L(\mathbf{X}) + \mu_c \underbrace{\text{tr}(\mathbf{X} \Delta_c \mathbf{X}^T)}_{\|\mathbf{X}\|_{\Delta_c}^2} + \mu_r \underbrace{\text{tr}(\mathbf{X}^T \Delta_r \mathbf{X})}_{\|\mathbf{X}\|_{\Delta_r}^2}$$

with Δ_r, Δ_c the row and column graph laplacians.

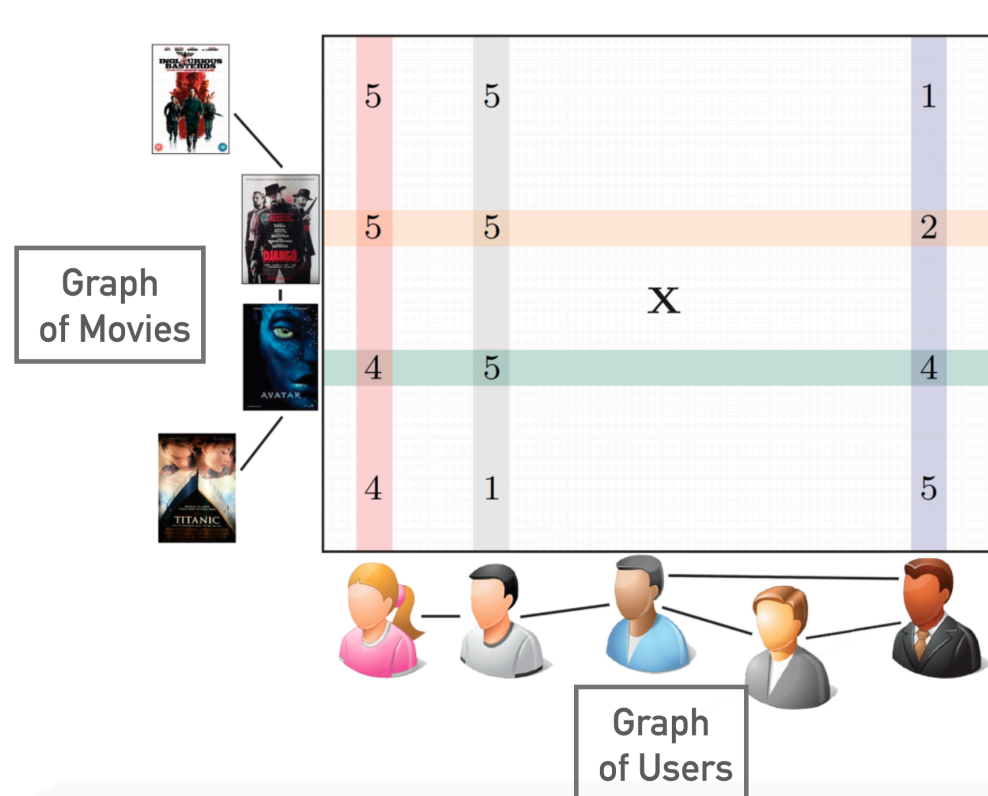
Multi- Graph Convolutional Neural Networks (MGCNN)^[2]

A multi-graph convolution can be obtained as:

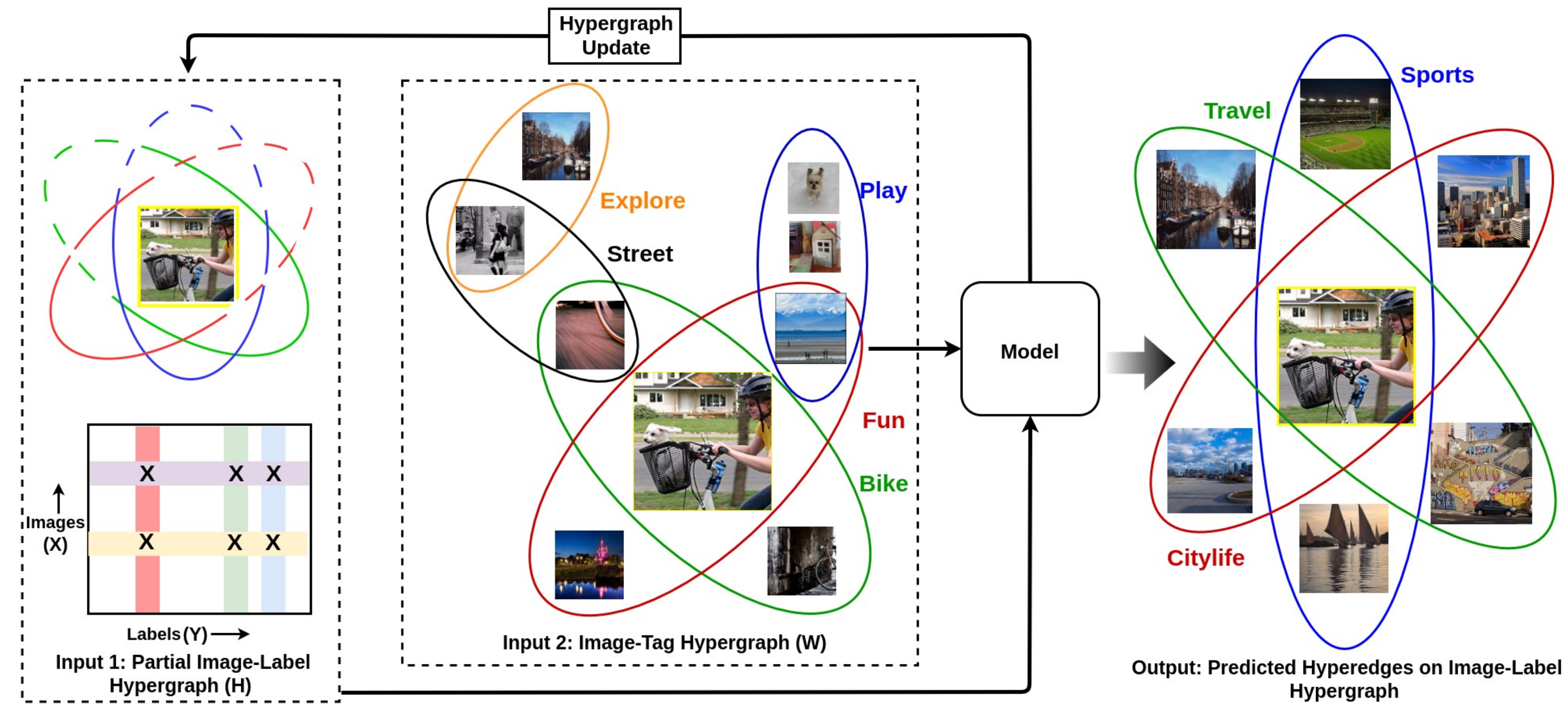
$$\mathbf{X} * \mathbf{Y} = \Phi_r(\hat{\mathbf{X}} \circ \hat{\mathbf{Y}}) \Phi_c^T$$

which simplifies matrix completion problem on graphs to minimising

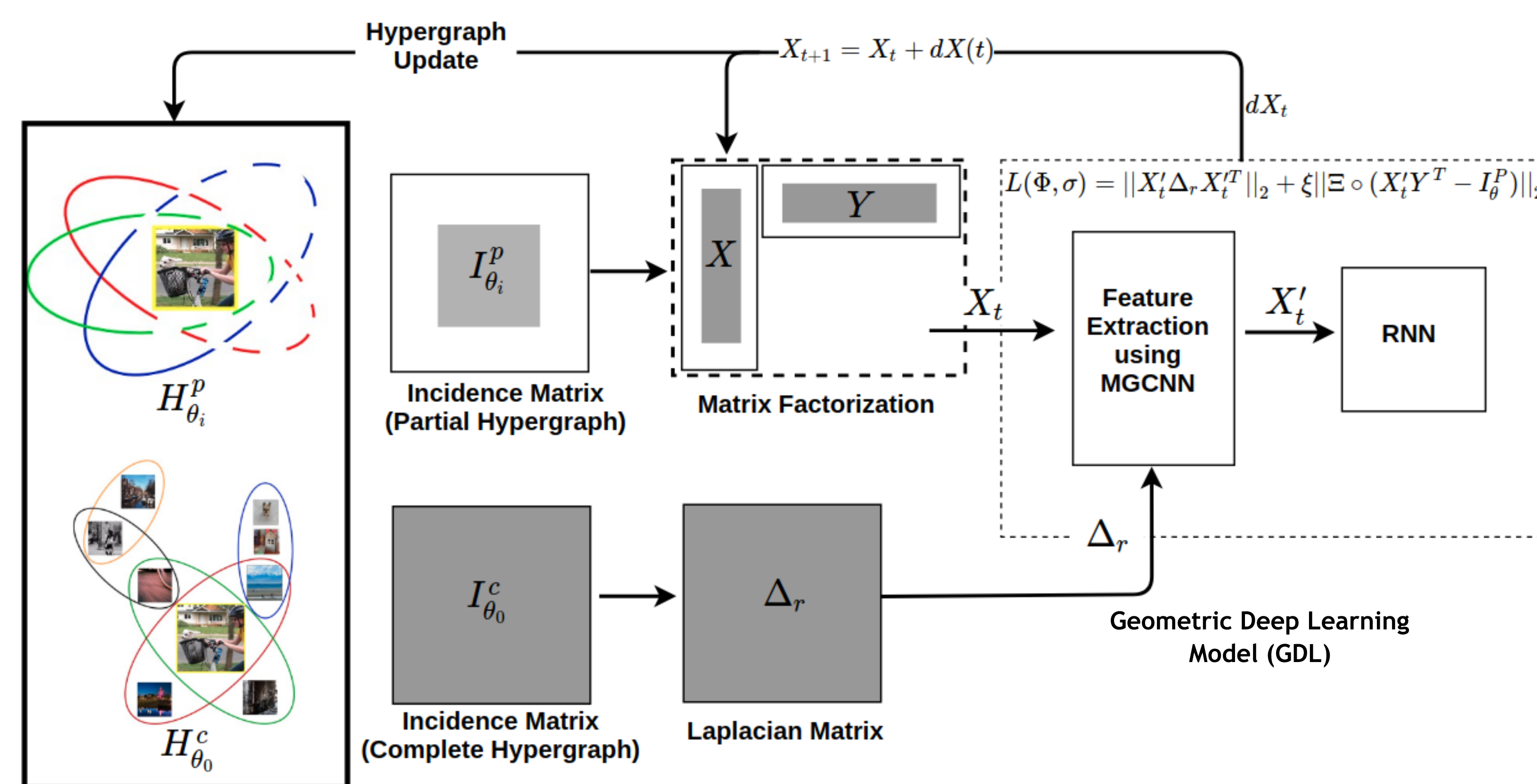
$$\ell(\Theta) = \|\mathbf{X}_\Theta^{(T)}\|_{\Delta_r}^2 + \|\mathbf{X}_\Theta^{(T)}\|_{\Delta_c}^2 + \mu L(\mathbf{X}_\Theta^{(T)})$$



Overview



Proposed Approach



Experimental Setup

Dataset

Entities	Count	Total number of relations formed
Tags	21,192	91,485,864
Groups	10,575	70,226,414
Users	2,663	52,804
Labels	99	613,014

Tasks

- *Task1*: Multi-Label Image Classification
- *Task2*: Image-User Link Prediction
- *Task3*: Group Recommendation
- *Task4*: Tag Recommendation

Evaluation

Training: Randomly sample 60% of Entity-Target Metadata + All Entity-Known Metadata Relations

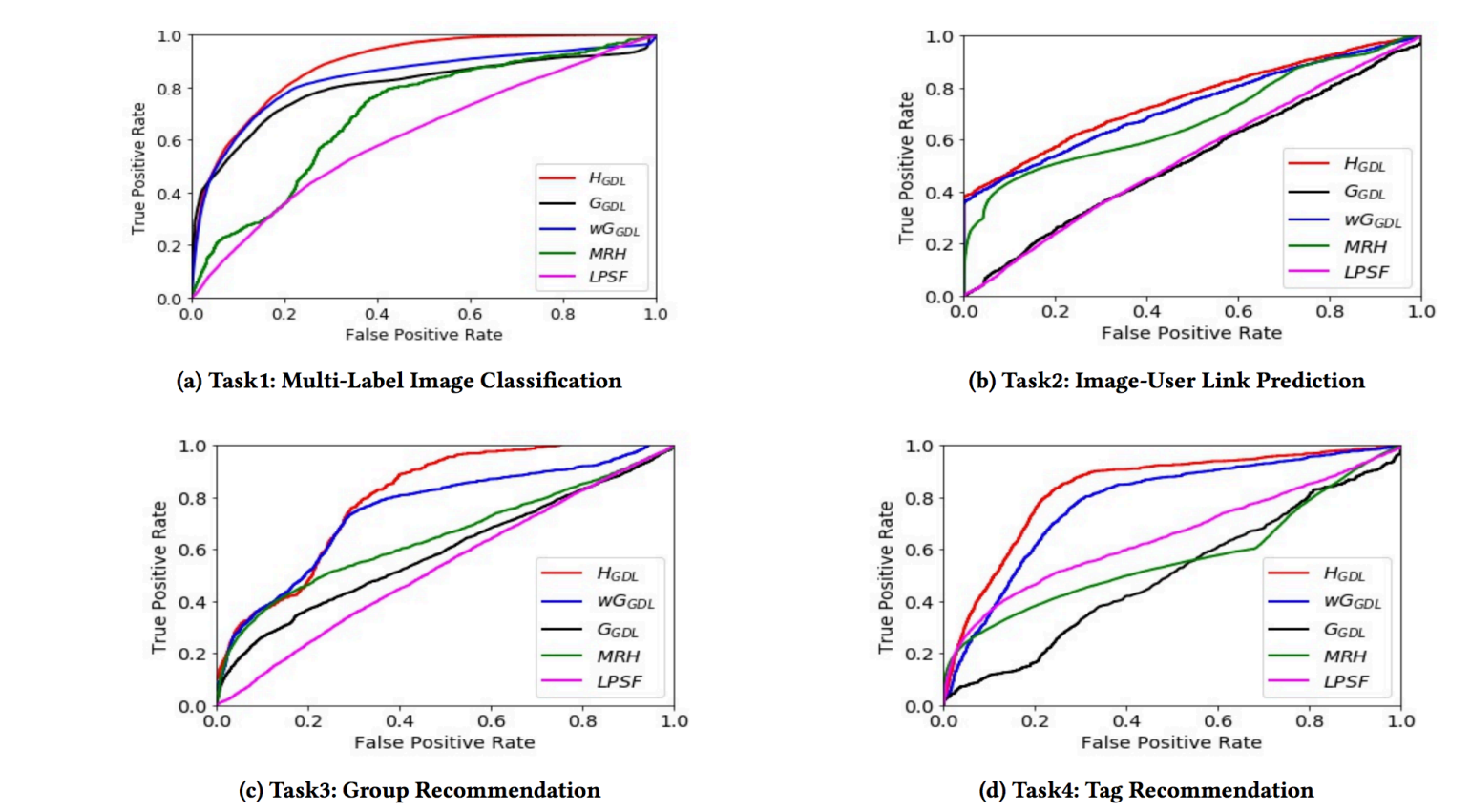
Testing: Based on the ability to reconstruct of the rest of the 40% Entity-Target Metadata relations

Comparison

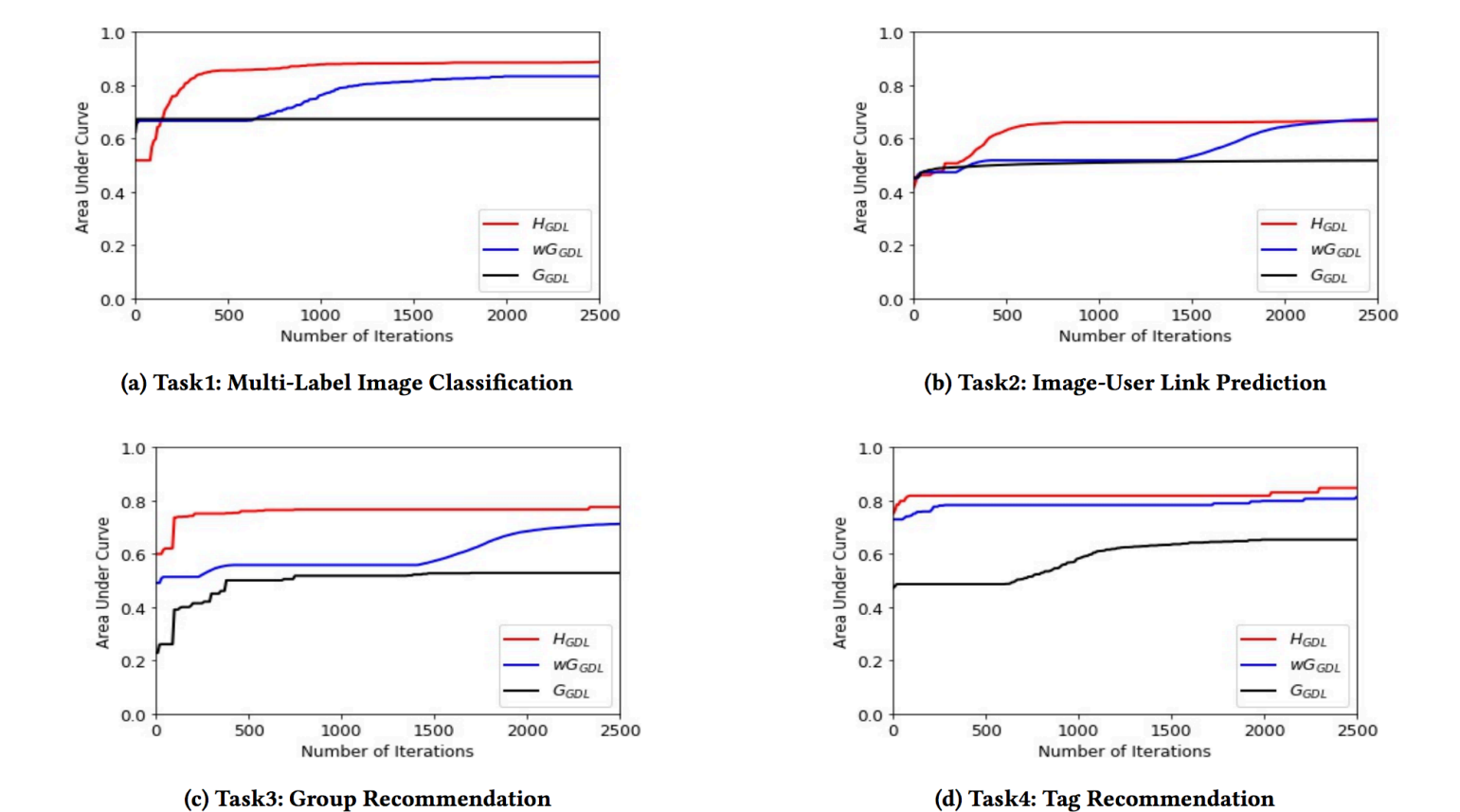
- H_{GDL} Hyper graph based framework with GDL model
- G_{GDL} Graph based framework with GDL model
- wG_{GDL} Weighted Graph based framework with GDL model
- MRH Context based recommendation on hyper graph framework
- LPSF Link Prediction using social network features

Results

Experiment 1: Performance in predicting relations between entities



Experiment 2: Efficiency in learning relational information



Conclusion

- The neighbourhood of an entity in a social network carries invaluable information that can be utilised for multiple tasks
- Our proposed framework exploits the contextual metadata by learning relational information most
- Hypergraph is the most efficient way to represent data in a social network
- Our Geometric Deep Learning (*GDL*) based model outperforms existing algorithms on hypergraph (*MRH*) and graph based feature extraction on social network (*LPSF*)

References

- [1] McAuley et al. Image labelling on a network: Using social-network metadata for image classification. In ECCV, 2012
- [2] Monti et al. Geometric matrix completion with recurrent multi-graph neural networks. In Advances in NIPS 2017.
- [3] Bu et al. Music recommendation by unified hypergraph: combining social media information and music content. In ACM Multimedia, 2010
- [4] Li et al. Link prediction in social networks based on hypergraph. In International Conference on World Wide Web. ACM, 2013

Acknowledgement

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 700381

