# EXPLOITING RELATIONAL INFORMATION IN SOCIAL NETWORKS USING GEOMETRIC DEEP LEARNING ON HYPERGRAPHS

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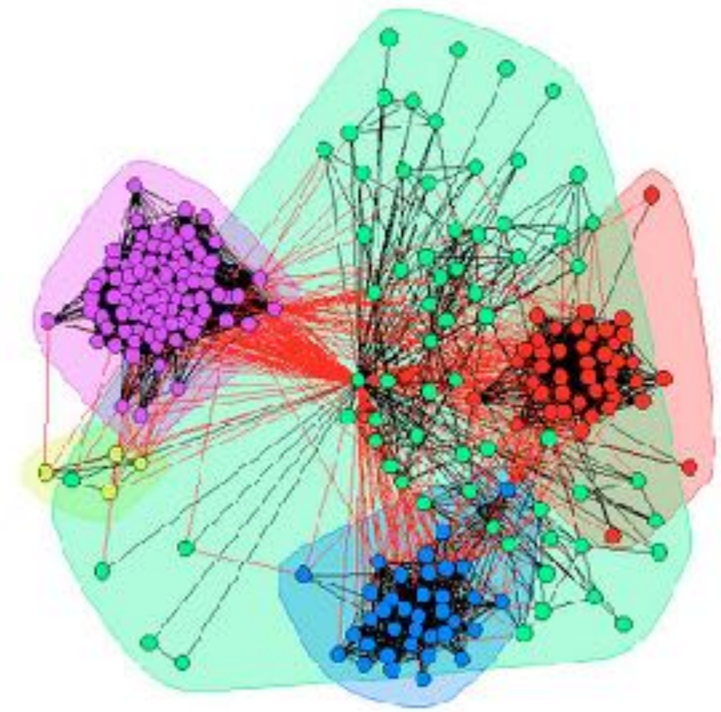
# OUTLINE

- Motivation
- Research Question
- Challenges
- Proposed Model
- Experiments
- Conclusion

# MOTIVATION

- In a social network, the neighborhood of an **entity** (image, post, user) often carry sufficient information for tasks such as classification, recommendation or link prediction

- The scale-free property of social network can be utilised to develop a context-only model that can exploit the relations between entities

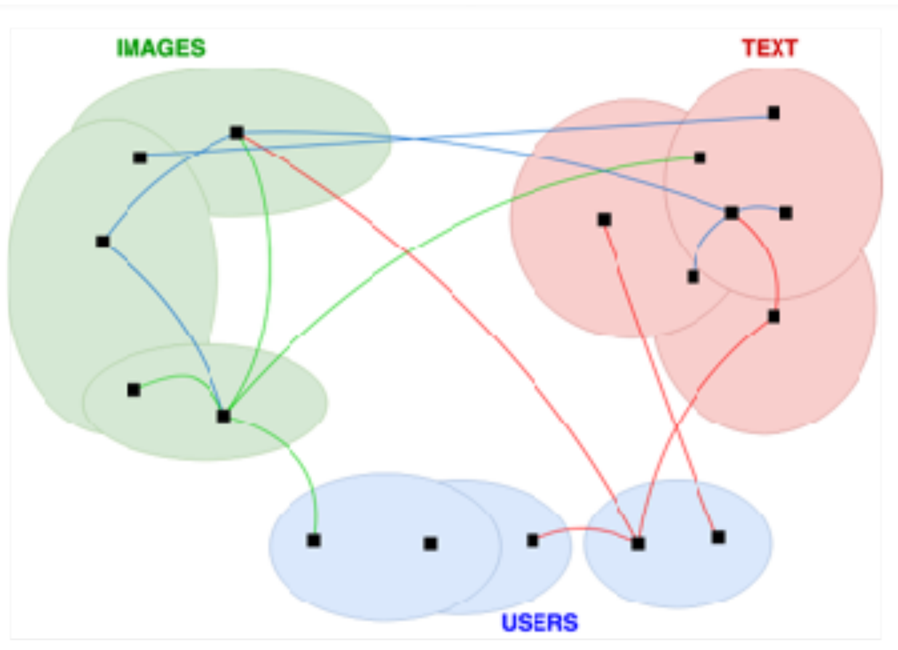


# SOCIAL MULTIMEDIA NETWORK

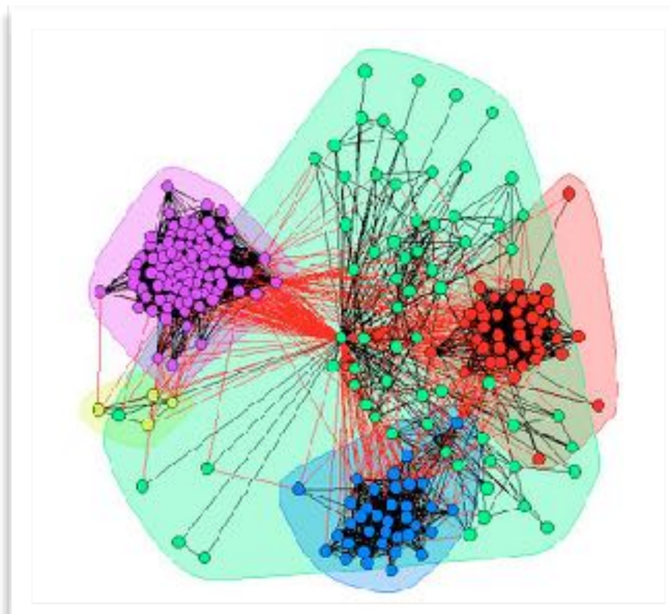
- Presence of a diverse set of entities makes social multimedia network, in particular, a different field of study as compared to other networks

| Types of Social Network | Examples | Main Entity |
|---|---|---|
| Social Communication Network | Facebook, Twitter | Users |
| Discussion Forums | Reddit, Quora | Posts |
| Media Sharing Networks | Instagram, Flickr | Images/Videos |
| Sharing Economy Network | Airbnb, Uber | Resources |

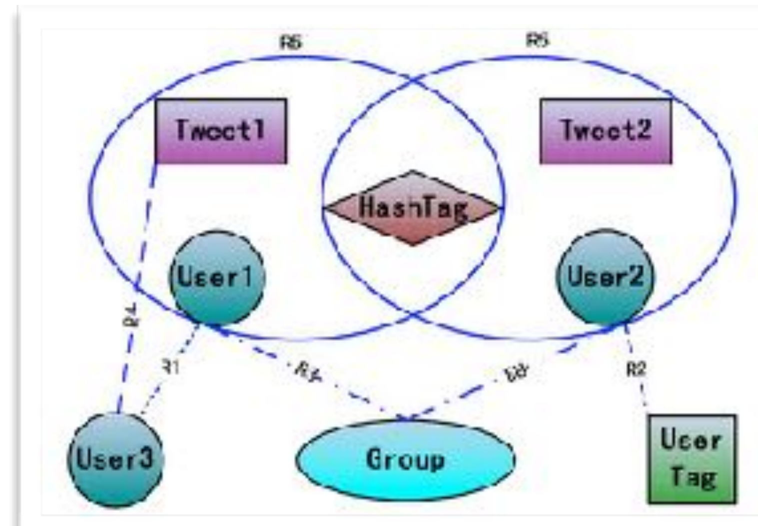
# SOCIAL MULTIMEDIA NETWORK




*Multimodal Entities*



*Overlapping Community*
*Scale-Free Network*




*Higher-Order*
*Relations*

# RESEARCH QUESTION

- How to learn one type of relations between entities to predict other type of relations in a social network?

# CHALLENGES

- Representation - To avoid any loss in information

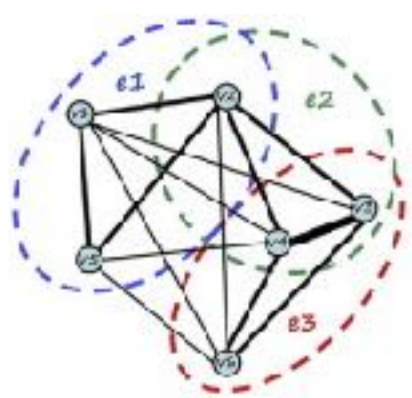
- Information Flow - To transfer information between entities

- Generalisability - To cover all kinds of social networks

# REPRESENTATION: HYPER GRAPH

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


- $H = (V, E)$ where:
  - $V$ is a set of entities called vertices
  - $E$ is a set of non-empty subsets of $V$ called hyper edges




(a)

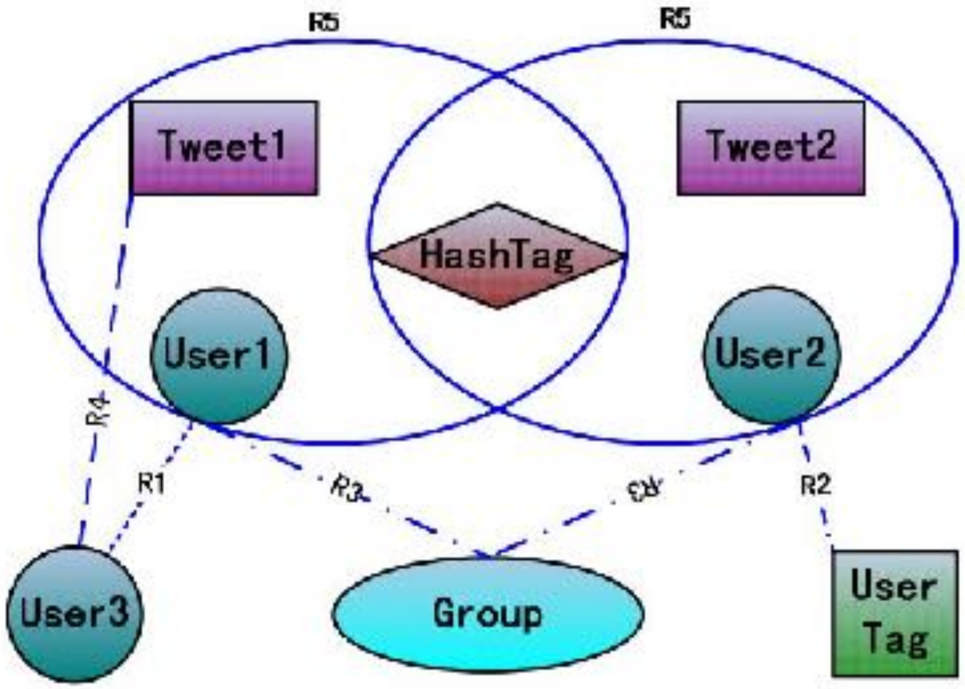
*Hypergraph with nodes( $v_i$ ) and hyperedges ( $e_i$ )*

| | e1 | e2 | e3 | e4 | e5 | ... | e16 | e17 | e18 |
|---|---|---|---|---|---|---|---|---|---|
| v1 | 1 | 0 | 0 | 1 | 1 | | 0 | 0 | 0 |
| v2 | 1 | 1 | 0 | 1 | 0 | | 0 | 0 | 0 |
| v3 | 0 | 1 | 1 | 0 | 1 | | 1 | 1 | 0 |
| v4 | 0 | 1 | 1 | 0 | 0 | | 1 | 0 | 0 |
| v5 | 1 | 0 | 0 | 0 | 0 | | 0 | 1 | 1 |
| v6 | 0 | 0 | 1 | 0 | 0 | | 0 | 0 | 1 |

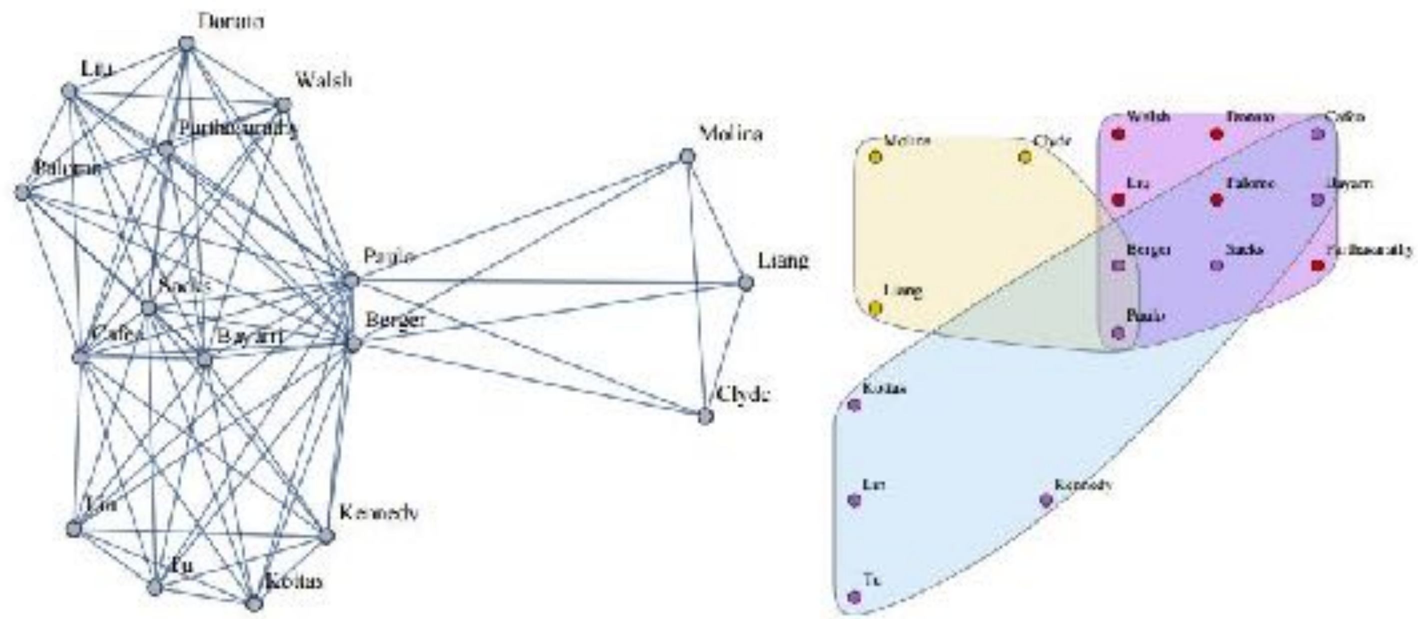
(b)

*Incidence Matrix*

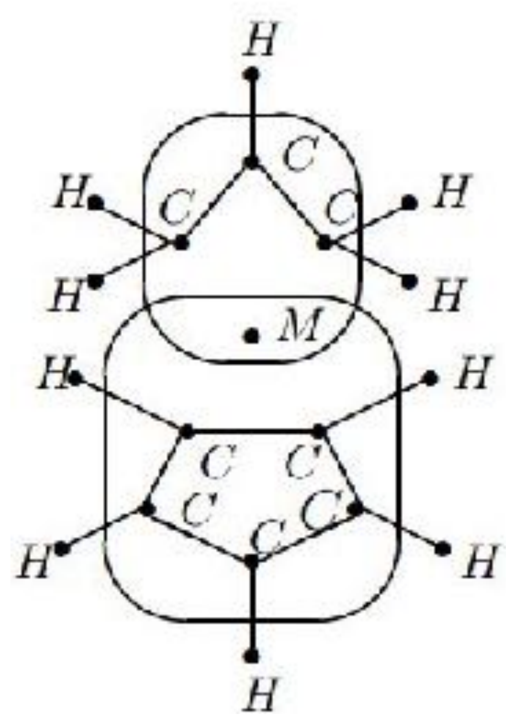
# EXAMPLES




Social Interactions



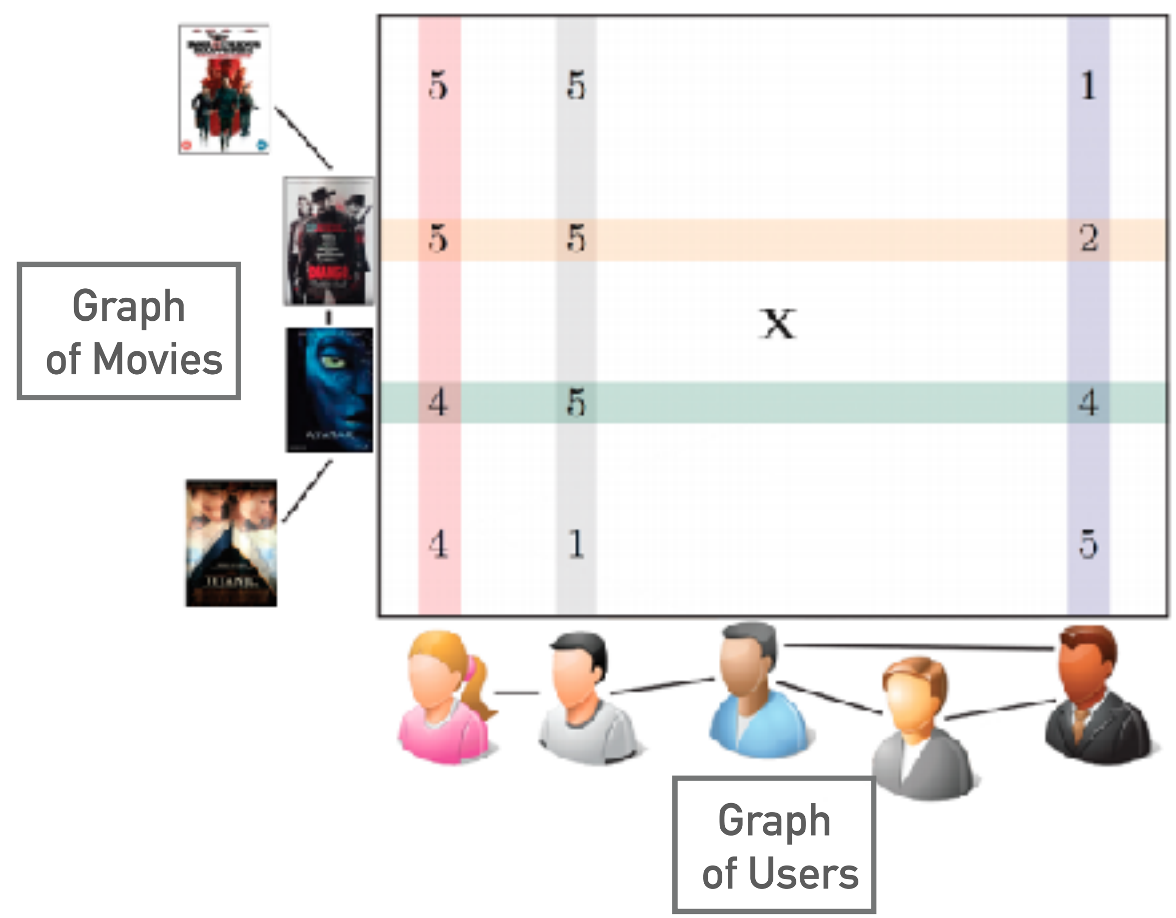

Citation Networks




Chemical Processes

# INFORMATION FLOW: MULTI-GRAPH CNN (MGCNN)[1]

- Deep learning approach for matrix completion based on one of recent geometric deep learning architecture namely multigraph convolutional neural network
- Works on the basic principle: two-dimensional Fourier transform of an image (matrix) can be thought of as applying a one-dimensional Fourier transform to its rows and columns.



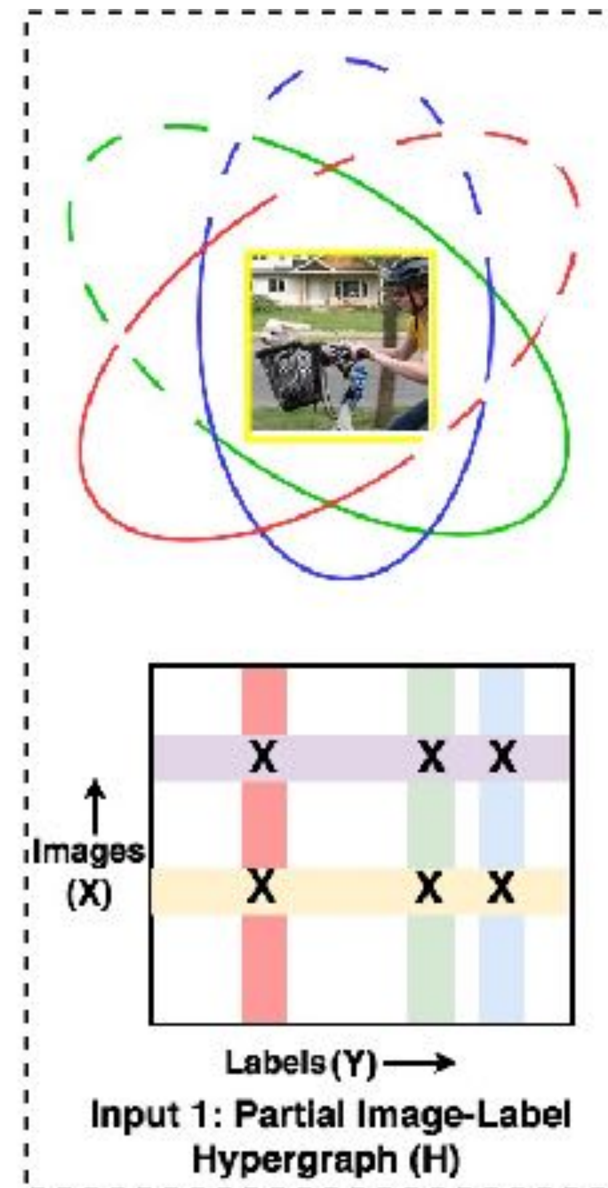

1. Federico Monti, Michael Bronstein, and Xavier Bresson. 2017. Geometric matrix completion with recurrent multi-graph neural networks. In Advances in Neural Information Processing Systems. 3700-3710.

# GENERALIZABILITY: FORMULATING THE PROBLEM AS MATRIX COMPLETION

- Matrix completion is the task of finding the missing values of a partially observed low-rank matrix

- Construct a hyper graph from partially known relations, between entities and a metadata

- Exploit relations from sub-space of entity and the known
  metadata, using them as side information



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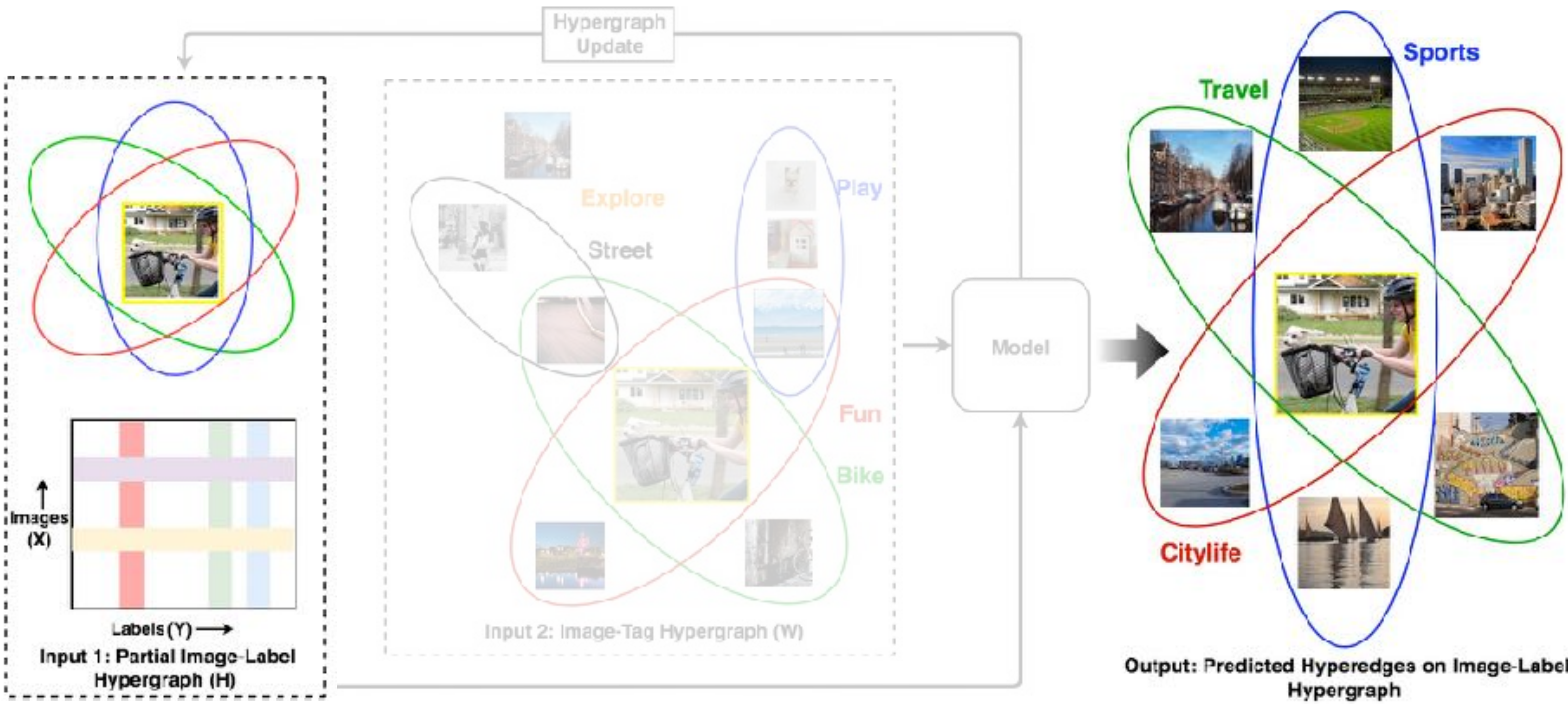
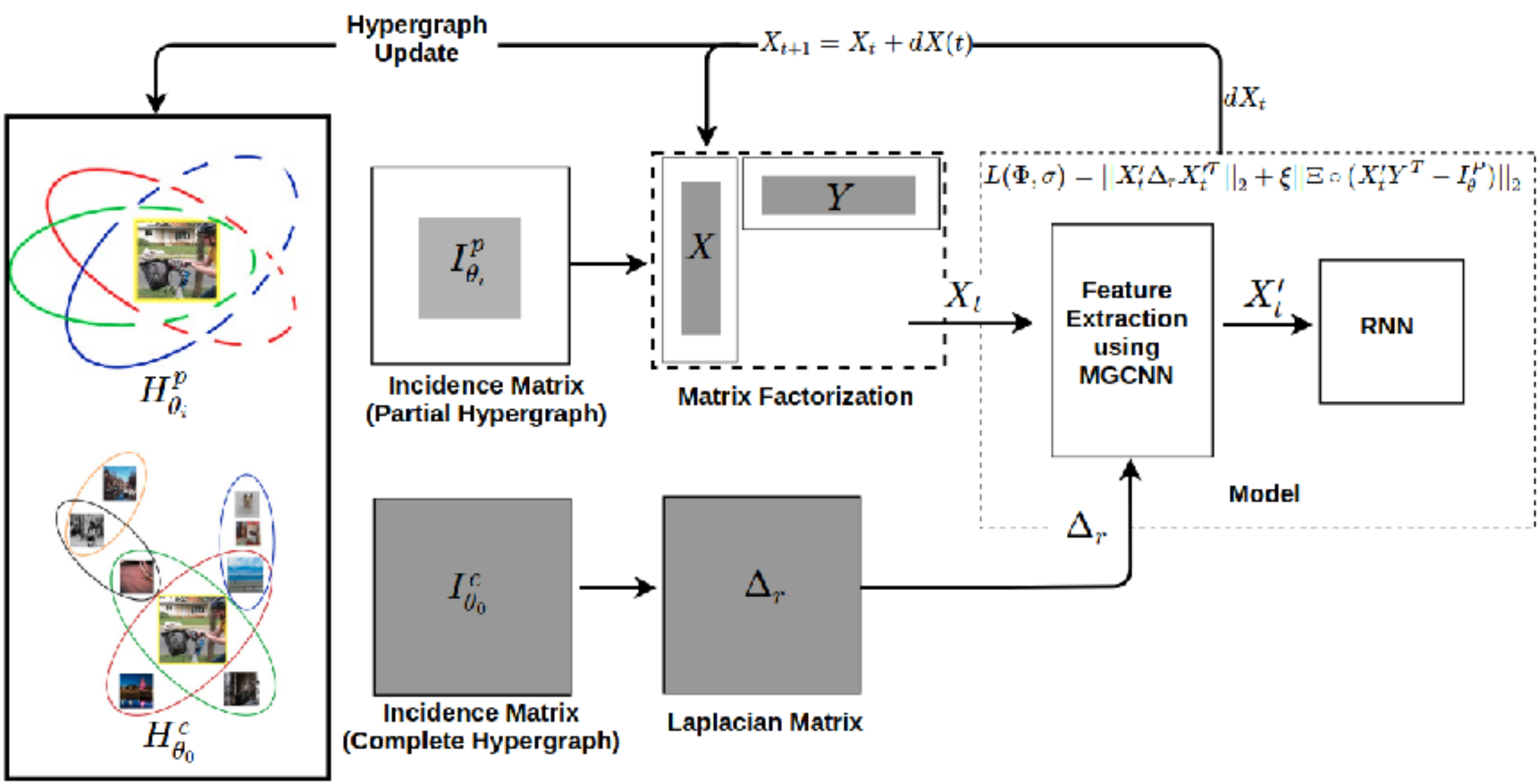


# OVERVIEW OF THE PROPOSED MODEL



# DATA SETUP AND TASKS

- CLEF Dataset[2] containing images from Flickr
  - 4,546 images
  - 99 labels
  - 21,192 tags
  - 10,575 groups
  - 2,663 users
- Tasks
  - *Task1*: Multi-Label Image Classification
  - *Task2*: Image-User Link Prediction
  - *Task3*: Group Recommendation
  - *Task4*: Tag Recommendation

2. J. McAuley and J. Leskovec. Image Labeling on a Network: Using Social-Network Metadata for Image Classification. ECCV, 2012.

# TRAINING

- Multitude of relations formed even for small number of images
- Train Set:

A. All the relations ($rel_{\theta_0}$) between the images and known metadata ($\theta_0$) depicted by

1. Hypergraph (H)
2. Weighted Graph (wG)
3. Simple Graph (G)

| | Task1 | Task2 | Task3 | Task4 |
|---|---|---|---|---|
| $\theta_0$ | Tags ($t$) | Tags($t$) | Tags ($t$) | Labels ($l$) |
| $\theta_i$ | Labels ($l$) | User ($u$) | Groups ($g$) | Tags ($t$) |
| $\|\|rel_{\theta_i}\|\|$ | 613,014 | 51,804 | 70,226,414 | 91,485,864 |
| $\|\|rel(H^c_{\theta_0})\|\|$ | 45,766 | 45,766 | 45,766 | 55,396 |
| $\|\|rel(G^c_{\theta_0})\|\|$ | 85,802 | 85,802 | 85,802 | 45,766 |

B. Randomly sampled 60% of the relations ($rel_{\theta_i}$) between the images and the target metadata ($\theta_i$)

# EVALUATION

1. **Representation:** To show the efficiency in representation by hypergraph, we evaluate our model on relations represented by hypergraph (H), weighted graph (wG) and simple graph(G)

2. **Information Flow:** We compare our model to link prediction in social networks based on hypergraph (MRH)

3. **Generalizability:** We compare our model with traditional feature extraction on graph based model for social networks (LPSF)

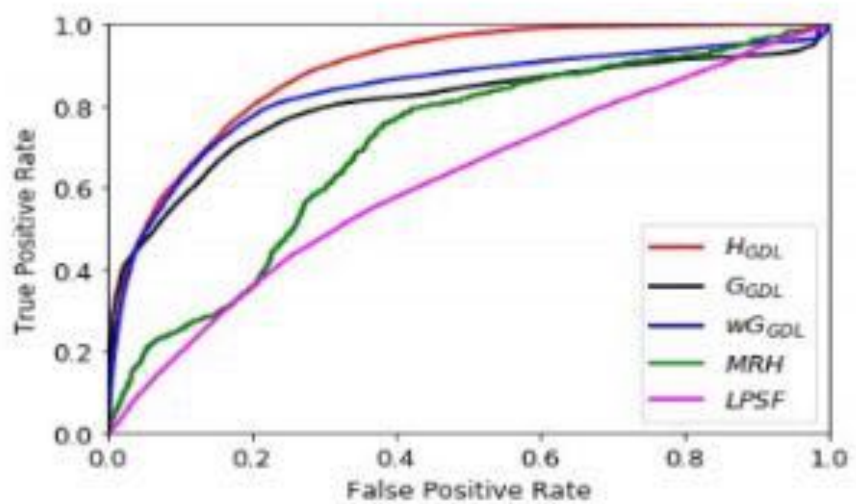
# COMPARISONS

- Framework
  - Weighted Graph
  - Simple Graph
- Model
  - MRH1 - Recommendation using hyper graph framework
  - LPSF2  - Link Prediction using social network features like page rank, number of common neighbours, preferential attachment etc..

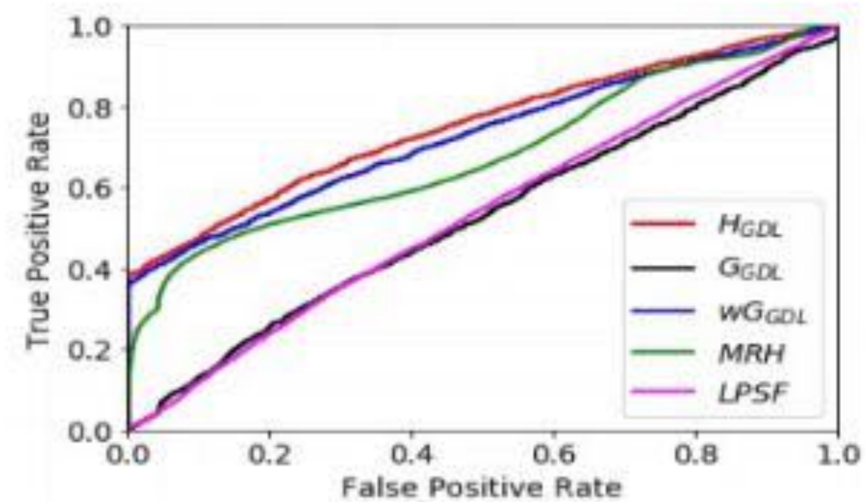
1. Jiajun Bu, Shulong Tan, Chun Chen, Can Wang, Hao Wu, Lijun Zhang, and Xiaofei He. 2010. Music recommendation by uni ed hypergraph: combining social media information and music content. In Proceedings of the 18th ACM international conference on Multimedia. ACM, 391–400.

2. DwXi Wang and Gita Sukthankar. 2014. Link prediction in heterogeneous collabo- ration networks. In Social network analysis-community detection and evolution. Springer, 165–192.

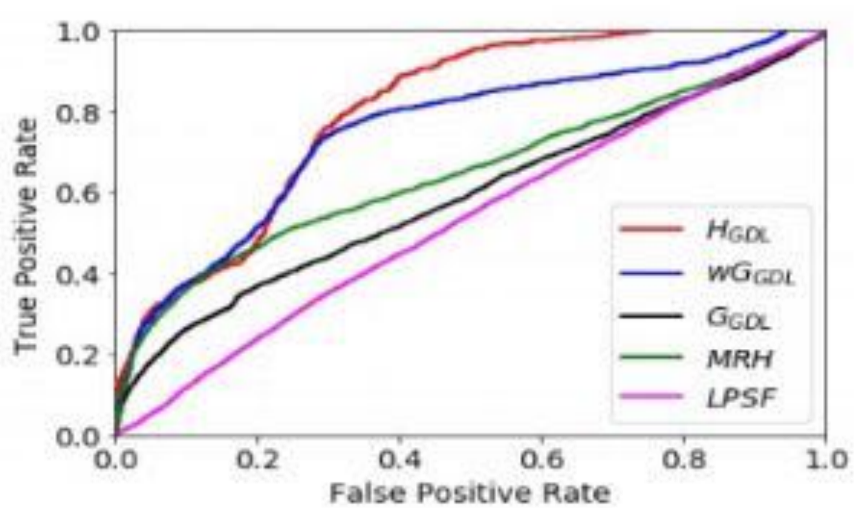
# RESULTS



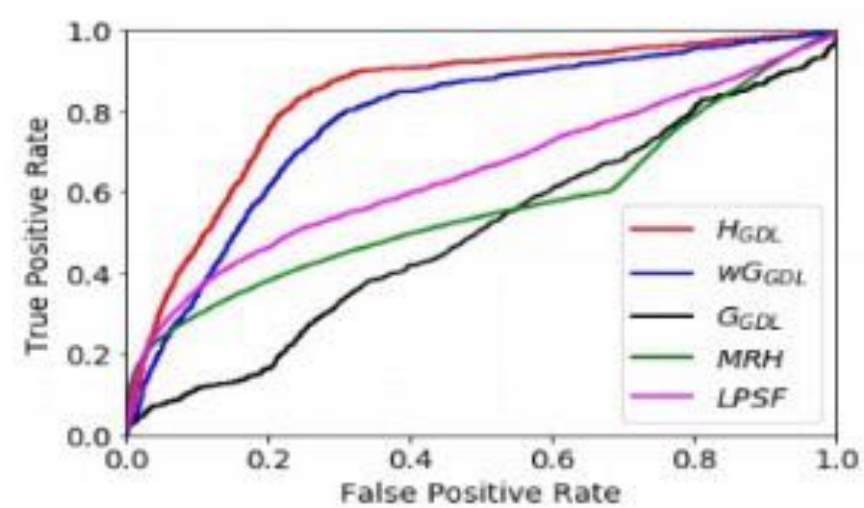

(a) Task1: Multi-Label Image Classification




(b) Task2: Image-User Link Prediction




(c) Task3: Group Recommendation




(d) Task4: Tag Recommendation

**Figure 4: Experiment 1 - Receiver Operating Characteristics (ROC) curve showing the performance of the models on each of the 4 tasks. The hypergraph-based geometric deep learning model ($H_{GDL}$) has significant advantage as compared to other methods.**

# CONCLUSION

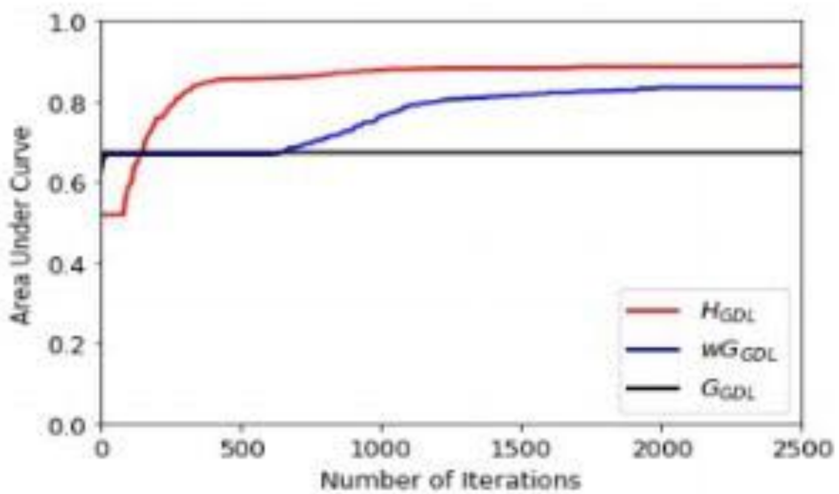
- Proposed framework learns relational information in a network which is content independent, hence generalizable and can be used to perform multiple tasks

- Hypergraph is the most efficient way to represent data on a social network

- Our deep Learning based model on hypergraph outperforms existing algorithms on hypergraph (*MRH)* and graph based feature extraction on social network (*LPSH)*

# THANK YOU!

# RESULTS

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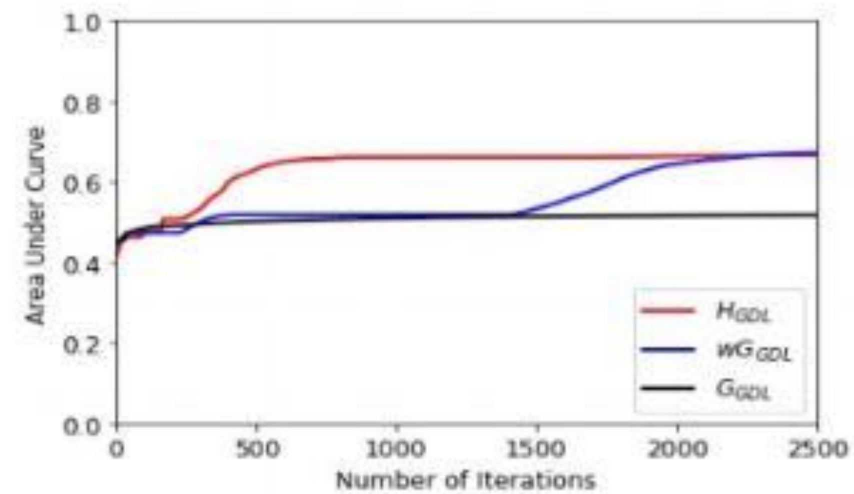
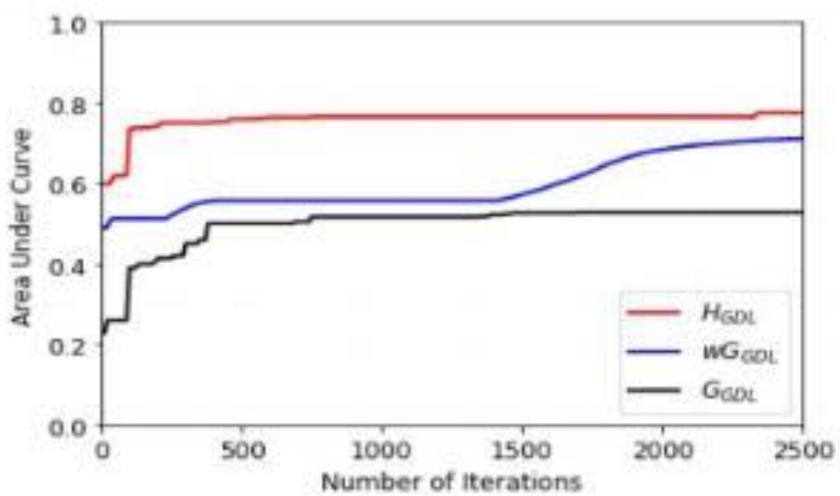



**(b) Task2: Image-User Link Prediction**

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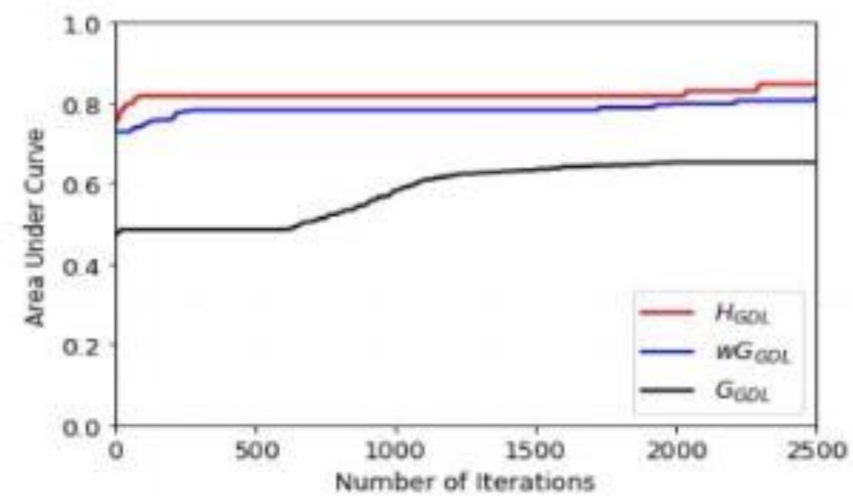


**(d) Task4: Tag Recommendation**

**Figure 5: Experiment 2 - Figure showing the rate of learning with each iteration of the proposed model using hypergraph ($H_{GDL}$), weighted graph ($wG$) and simple graph ($G$). As can be seen, the hypergraph-based model converges faster for all the 4 tasks implying a better representation to learn relational information.**

# CROSS-DOMAIN COLLABORATIVE FILTERING

- Borrows rating knowledge for each user from some related auxiliary domains

- Rating matrices are relatively dense, to alleviate the rating sparsity problem in the sparse target domain

# EXPERIMENTS

We designed the experiments to investigate:

1. Performance of the proposed generic framework to predict multiple types of relations between entities
2. Advantages of using geometric deep learning over existing simple graph as well as hypergraph-based learning
3. Efficiency in representing relational information of a network using hypergraphs as compared to pairwise simple graph representation