SOCIAL MEDIA ANALYSIS

ACTOR NETWORK ANALYSIS & COOPERATION PREDICTION

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AGENDA

1. Motivation
2. Literature Review
3. Dataset
4. Method & Experimental Results
5. Conclusion & Future Work

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The right cast determines the success

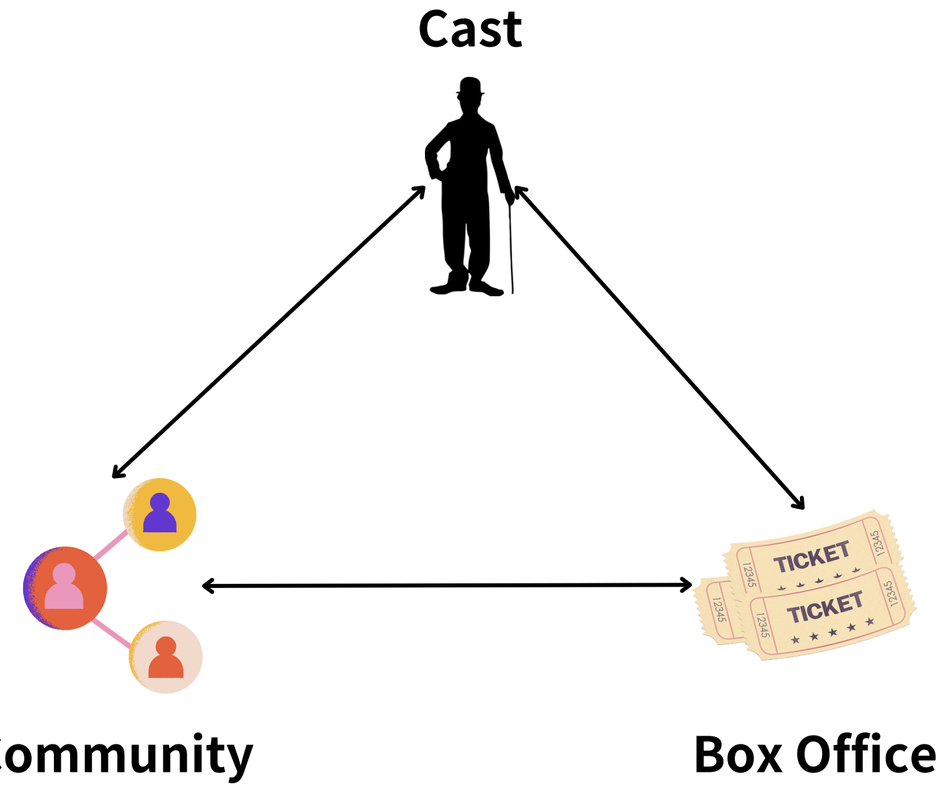
Success Example

Robert Downey Jr. and Chris Evans, portraying Iron Man and Captain America respectively in the Marvel Cinematic Universe, brought immense success to the franchise.

However, choosing the casts is difficult……

What is Difficult?

- Assessing the suitability of actors
- Evaluate whether the combination of actors would be liked by the audience
- Predicting the box office performance



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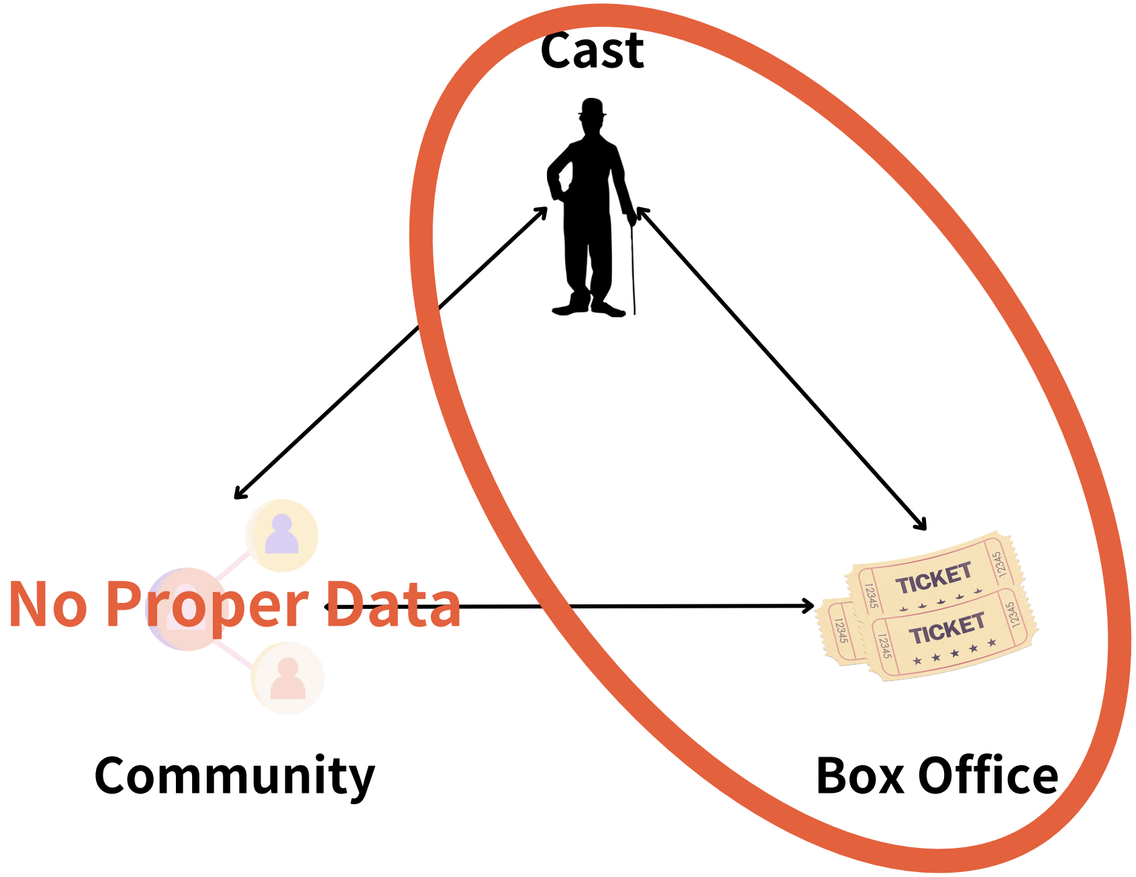
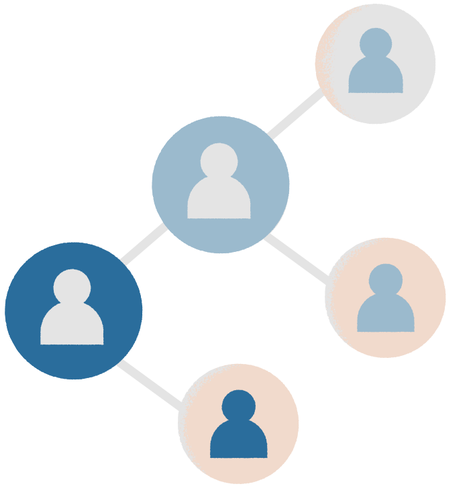


So, this study aims to……

Goal 1

analyze collaboration data among movie actors and construct networks of their collaboration relationships



Goal 2

predicting potential actor combinations and collaborative relationships

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Link Prediction Paradigms

Embedding

Preserves the edge structure of the graph.

- **EGES**
- metapath2vec, struc2vec, node2vec
- LINE, DeepWalk

Heuristic

- PPR, Graph distance

GNN

Encodes topological structures of graphs.

Autoencoder

- NESS
- VGAE

Subgraph

- BUDDY, ELPH
- **SEAL**
- GraphSAGE

Representation Learning Methods

	Training paradigm	Dataset	Release date
NESS	Autoencoder	Cora, Citeseer, PubMed (homophilous) WebKB, Chameleon (heterogeneous)	Mar 2023
BUDDY, ELPH	Subgraph	Cora, Citeseer, PubMed, OGB	Sep 2022
EGES	Embedding	Amazon Reviews, Taobao (private)	Mar 2018
SEAL	Subgraph	USAir, NS, PB, Yeast, C.ele, Power, Router, E.coli	Feb 2018
metapath2vec	Embedding	AMiner CS, DBIS	Aug 2017

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Dataset Overview

Movie Data	source	TMDB 15000 Movies Dataset (with credits) from Kaggle, Supplementary data from The Numbers website
	volume	2686 movies from 2000/01 to 2023/05
Actor Data	source	Movie_Actor Database from Data.World
	volume	1943 actors

How can we define a "successful" movie?

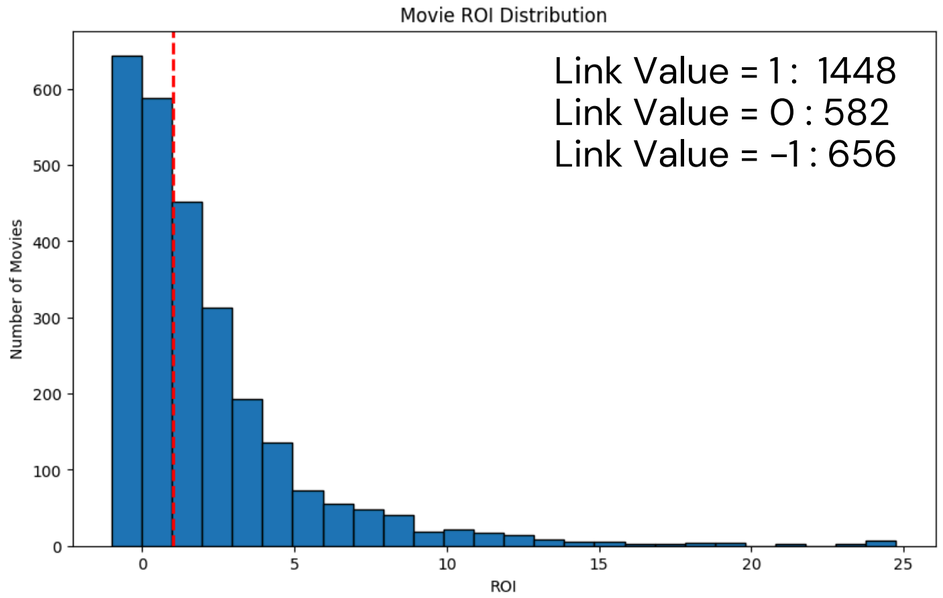
" A general rule of thumb for qualifying a movie as a “financial success” is to compare its gross revenue to twice its reported budget - in other words, an ROI of at least 1. "

ROI = **Gross - Budget** / **Budget**

ROI >= 1 -> Link Value = 1

1>ROI >= 0 -> Link Value = 0

ROI < 0 -> Link Value = -1



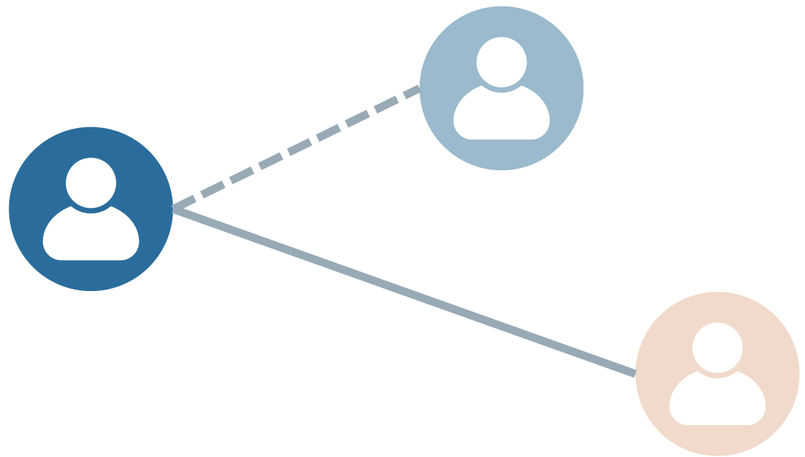
Actor_Network.json

Node


```
{
    "id": 0,
    "name": "AnneHathaway",
    "gender": 1.0,
    "popularity": "43.687",
    "Birth Country": "USA",
    "Height (Inches)": 68.0,
    "Ethnicity": "White",
    "NetWorth": 60000000.0,
    "Age": 43.0
}
```


Link


```
{
    "source": 0,
    "target": 2,
    "value": 1
 }
```

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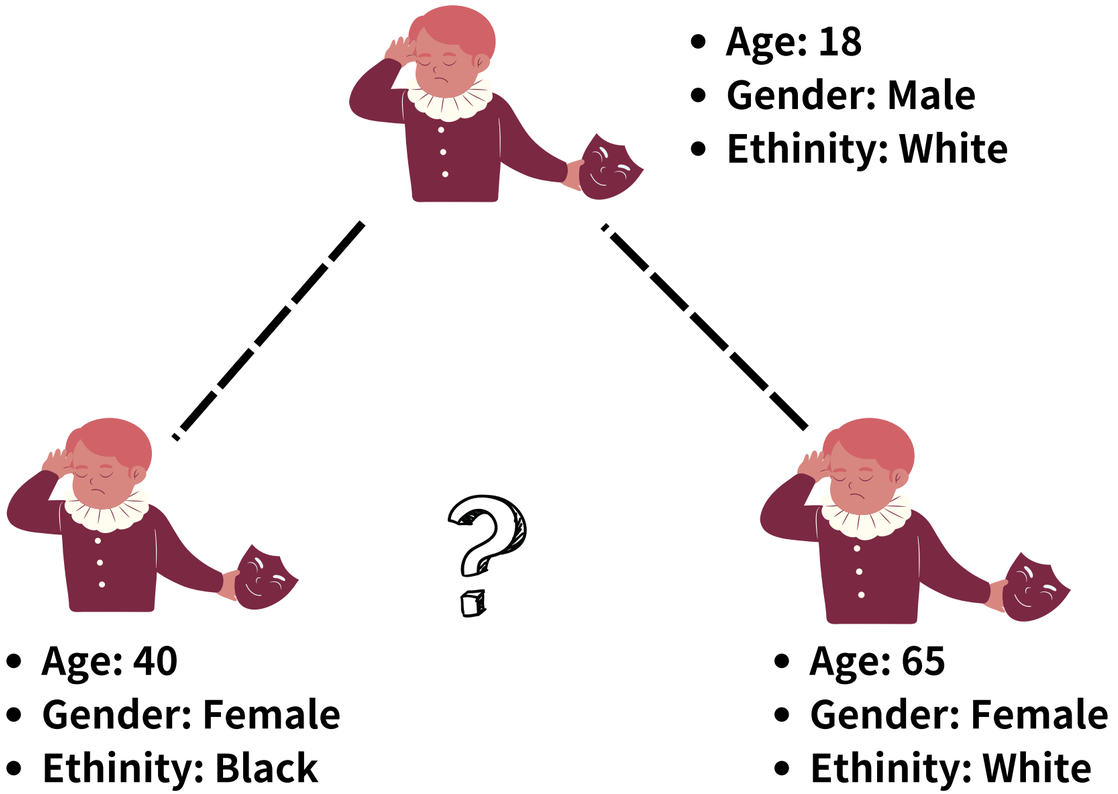
Link Prediction

predict the probability of success cooperation

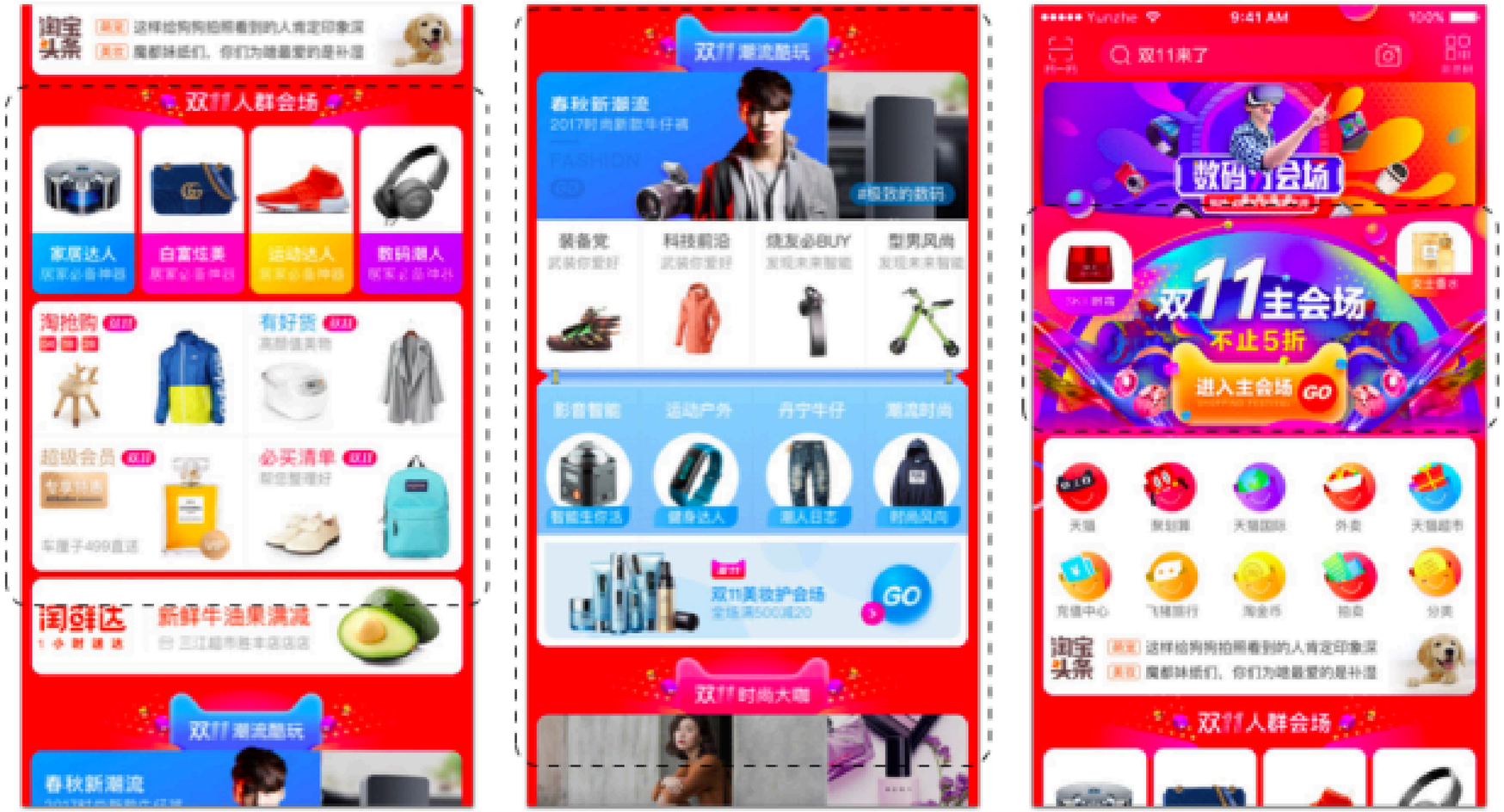
Link Prediction

EGES

SEAL



Node Embedding - EGES



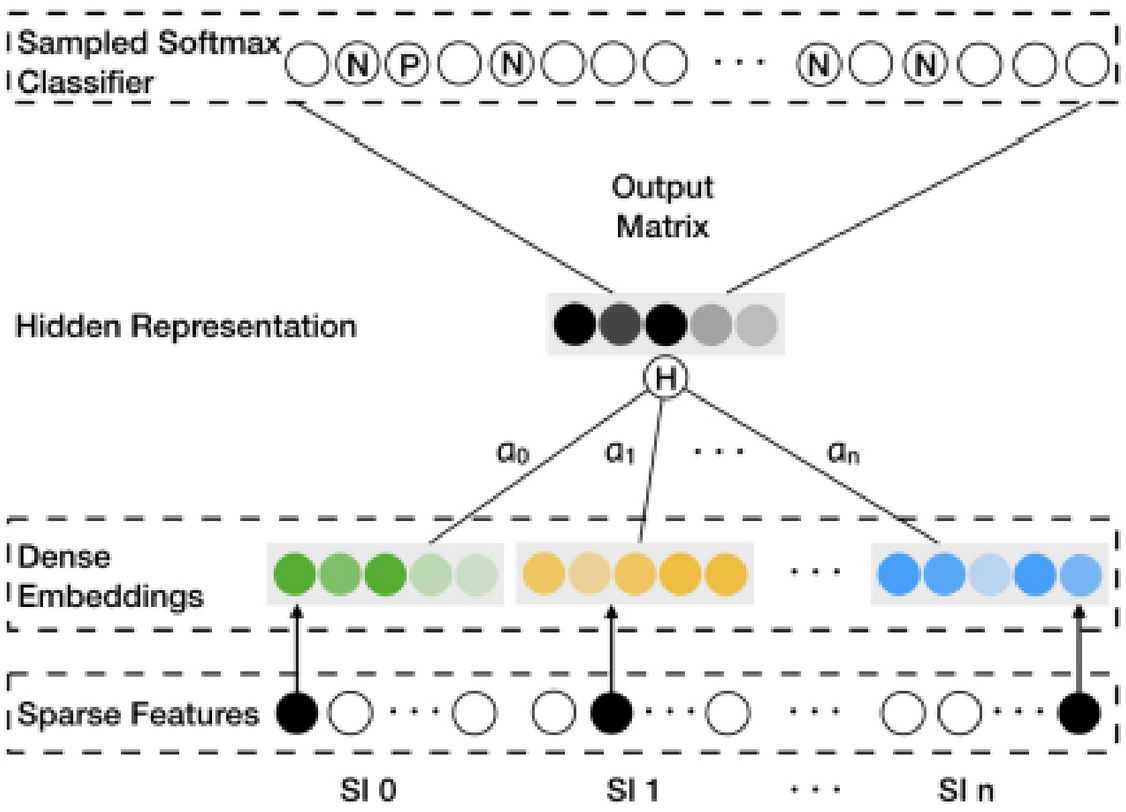
Reference: Billion-scale Commodity Embedding for E-commerce Recommendation in Alibaba

Node Embedding - EGES

Solve Cold-start issue

Add side information to embeddings

Enhanced = weighted



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Node Embedding - EGES Implementation

Graph Definition	
Property	• directed -> undirected • weighted -> unweighted
Node	• actors
Other side information	• convert to categorical data
Link	• defined by popularity

Link Prediction Methods
XGBoost
Similarity Threshold
Similarity Ranking

Message Passing - GCN

Based on node embeddings, previous research often designed diverse message passing mechanisms to effectively consider other neighboring nodes in the network.

Initialize Node2Vec + Side Information

Information Propagation Graph Convolutional Network (GCN)

$$f^{gcn}(x_i) = \sum_{j \in N(i) \cup (j)} \frac{e_{j,i}}{\sqrt{\hat{d}_j \cdot \hat{d}_i}} x_j$$

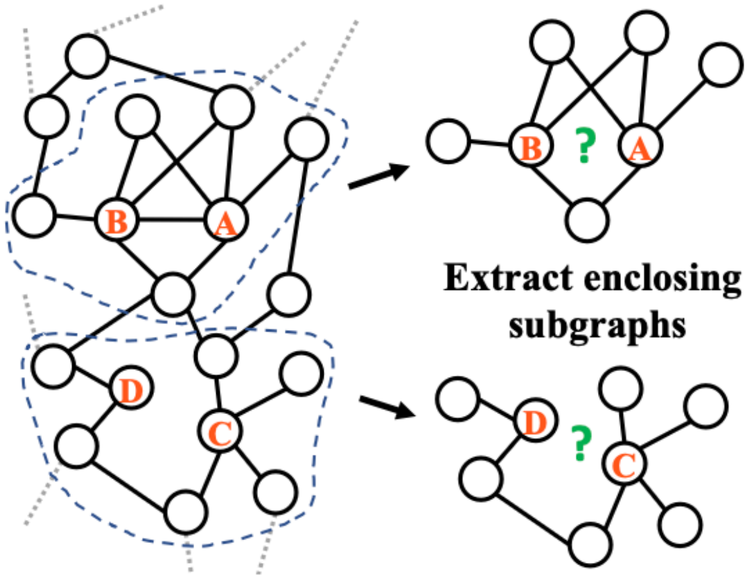
Prediction dense layer

Message Passing - SEAL

We implemented the SEAL (Subgraphs, Embeddings, and Attributes for Link prediction) algorithm proposed by Muhan Zhang and Yixin Chen, 2018.

It contains three steps:

1. **enclosing subgraph extraction**
   - Construct subgraph with nodes around target link
2. **node information matrix construction**
   - Node labeling (from subgraph) + node attributes + node embedding
3. **GNN learning**
   - GCN + dense layer



Experiment Results - Settings

Data Split

- Link Type: (+1), (0), (−1)
- Node Pairs w/o Link: (x)
- Split Ratio = 8:1:1

We utilize "Failure link(−1)" as negative samples in training set!

Train	Valid	Test
Pos: 1,051(+1) Neg: 651(-1)+400(x)	Pos: 131(+1) Neg: 131(x)	Pos: 131(+1) Neg: 131(x)

Evaluation Metrics : ROC-AUC

RQ1: How do our models perform?

- SEAL outperforms all the benchmark models.
- Models using graph information can perform better in this task.

	baseline	benchmark		best
	ML-based	**EGES**	**GCN**	**SEAL**
Valid	0.611	0.592	0.672	**0.845**
Test	0.553	0.592	0.676	**0.801**

RQ2: How does side information affect model performance?

- Actors' static features can help improve the collaboration recommendation

	Without Side Inforamtion			With Side Information		
Model	**EGES**	**GCN**	**SEAL**	**EGES**	**GCN**	**SEAL**
Valid	0.520	0.617	0.808	0.592	0.672	**0.845**
Test	0.565	0.609	0.770	0.592	0.676	**0.801**

RQ3: How does our model perform in application?

- Our model can accurately predict existing relationships

Cillian Murphy. & **Emily Blunt**

Oppenheimer (2023),
not in the dataset but is correctly predicted

RQ3: How does our model perform in application?

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Emma Stone & **Mark Ruffalo**

Poor Things (2024),
not in the dataset but is correctly predicted

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Finally…

We used open source movie dataset to construct actor collaborative network, and achieved 80.1% ROC-AUC score by implementing GNN-based models.

Managerial Implication

We demonstrated a data-driven approach that allows online streaming platforms to find more suitable movie leads from a profitability perspective in film production.

Future Work

- More precise and directly relevant definition of “successful collaboration”
- Consideration of movie category and more comprehensive actor profile data
- Consideration of temporal relation and heterogeneous information

Thanks for Listening

PROPOSAL

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