GraphConfRec: A Graph Neural Network-Based Conference Recommender System

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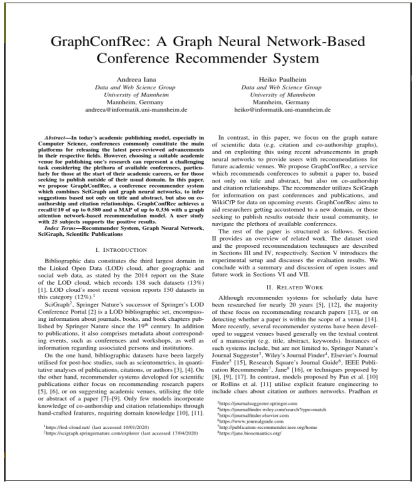
Conference Recommendation



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***Abstract*—In today's academic publishing model, especially in Computer Science, conferences commonly constitute the main platforms for releasing the latest peer-reviewed advancements in their respective fields. However, choosing a suitable academic venue for publishing one's research can represent a challenging task considering the plethora of available conferences, particularly for those at the start of their academic careers, or for those seeking to publish outside of their usual domain. In this paper, we propose GraphConfRec, a conference recommender system which combines SciGraph and graph neural networks, to infer suggestions based not only on title and abstract, but also on co-authorship and citation relationships. GraphConfRec achieves a recall@10 of up to 0.580 and a MAP of up to 0.336 with a graph attention network-based recommendation model. A user study with 25 subjects supports the positive results.**

***Index Terms*—Recommender System, Graph Neural Network, SciGraph, Scientific Publications**

I. Introduction

Bibliographic data constitutes the third largest domain in the Linked Open Data (LOD) cloud, after geographic and social web data, as stated by the 2014 report on the State of the LOD cloud, which records 138 such datasets (13%) [1]. LOD cloud's most recent version reports 150 datasets in this category (12%).[1]

SciGraph[2], Springer Nature's successor of Springer's LOD Conference Portal [2] is a LOD bibliographic set, encompassing information about journals, books, and book chapters published by Springer Nature since the 19^{th} century. In addition to publications, it also comprises metadata about corresponding events, such as conferences and workshops, as well as information regarding associated persons and institutions.

On the one hand, bibliographic datasets have been largely utilised for post-hoc studies, such as scientometrics, in quantitative analyses of publications, citations, or authors [3], [4]. On the other hand, recommender systems developed for scientific publications either focus on recommending research papers [5], [6], or on suggesting academic venues, utilising the title or abstract of a paper [7]–[9]. Only few models incorporate knowledge of co-authorship and citation relationships through hand-crafted features, requiring domain knowledge [10], [11].

In contrast, in this paper, we focus on the graph nature of scientific data (e.g. citation and co-authorship graphs), and on exploiting this using recent advancements in graph neural networks to provide users with recommendations for future academic venues. We propose GraphConfRec, a service which recommends conferences to submit a paper to, based not only on title and abstract, but also on co-authorship and citation relationships. The recommender utilizes SciGraph for information on past conferences and publications, and WikiCfP for data on upcoming events. GraphConfRec aims to aid researchers getting accustomed to a new domain, or those seeking to publish results outside their usual community, to navigate the plethora of available conferences.

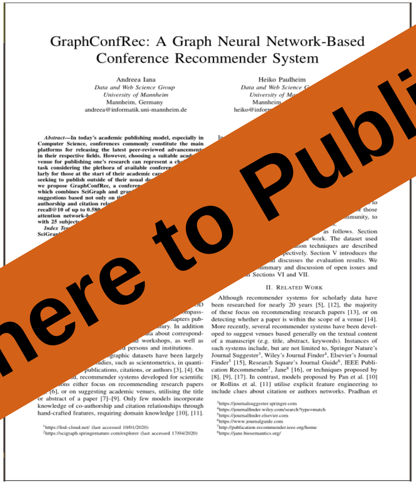
The rest of the paper is structured as follows. Section II provides an overview of related work. The dataset used and the proposed recommendation techniques are described in Sections III and IV, respectively. Section V introduces the experimental setup and discusses the evaluation results. We conclude with a summary and discussion of open issues and future work in Sections VI and VII.

II. Related Work

Although recommender systems for scholarly data have been researched for nearly 20 years [5], [12], the majority of these focus on recommending research papers [13], or on detecting whether a paper is within the scope of a venue [14]. More recently, several recommender systems have been developed to suggest venues based generally on the textual content of a manuscript (e.g. title, abstract, keywords). Instances of such systems include, but are not limited to, Springer Nature's Journal Suggester[3], Wiley's Journal Finder[4], Elsevier's Journal Finder[5] [15], Research Square's Journal Guide[6], IEEE Publication Recommender[7], Jane[8] [16], or techniques proposed by [8], [9], [17]. In contrast, models proposed by Pan et al. [10] or Rollins et al. [11] utilise explicit feature engineering to include clues about citation or authors networks. Pradhan et

[1]https://lod-cloud.net/ (last accessed 10/01/2020)
[2]https://scigraph.springernature.com/explorer (last accessed 17/04/2020)
[3]https://journalsuggester.springer.com
[4]https://journalfinder.wiley.com/search?type=match
[5]https://journalfinder.elsevier.com
[6]https://www.journalguide.com
[7]http://publication-recommender.ieee.org/home
[8]https://jane.biosemantics.org/

Conference Recommendation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II. Related Work

Where to Publish?

Status Quo

Limitations of academic venue recommenders

1. Heavy focus on textual content (e.g. title, abstract, keywords)
2. Explicit feature engineering (e.g. meta-path features)

Limitations of knowledge base recommenders

1. Use of handcrafted features
2. Use of shallow transductive graph embedding techniques (e.g. TransE, RDF2Vec)

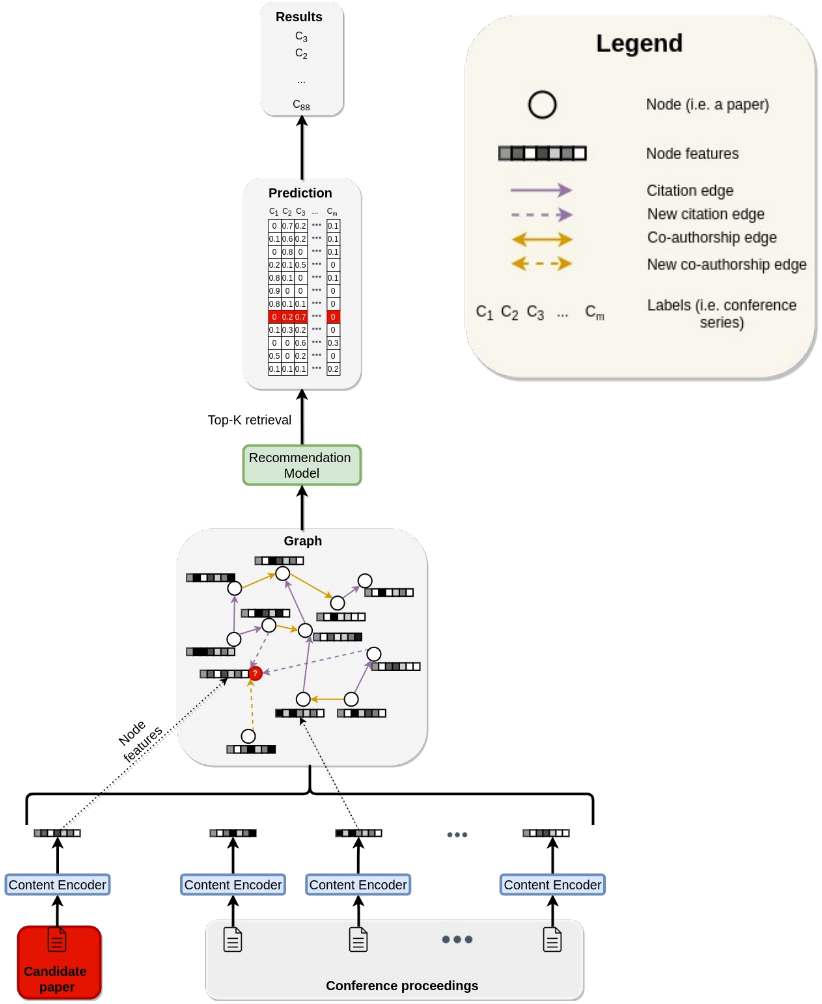
GraphConfRec

Task: node classification

Recommendation module: inductive graph embedding model – Graph Neural Networks (GNNs)

Input: target manuscript and existing conference proceedings modelled as a **graph**

Output: top *K* recommendations



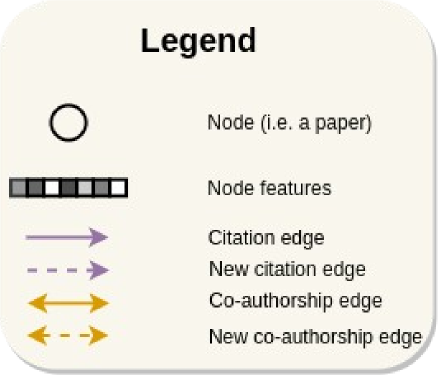
GraphConfRec: Graph Construction

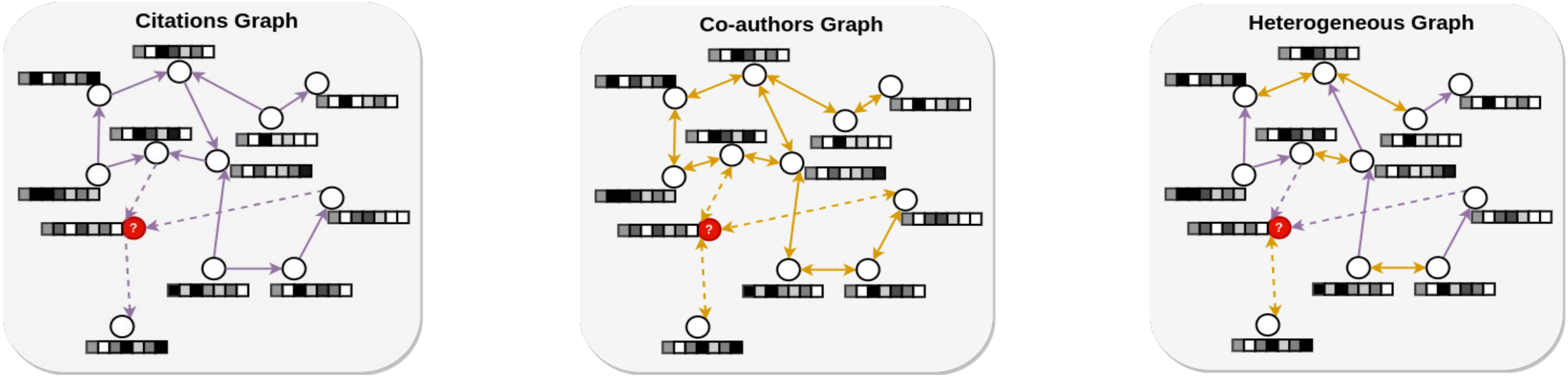
Nodes

- Features - textual content
- Labels – conference series

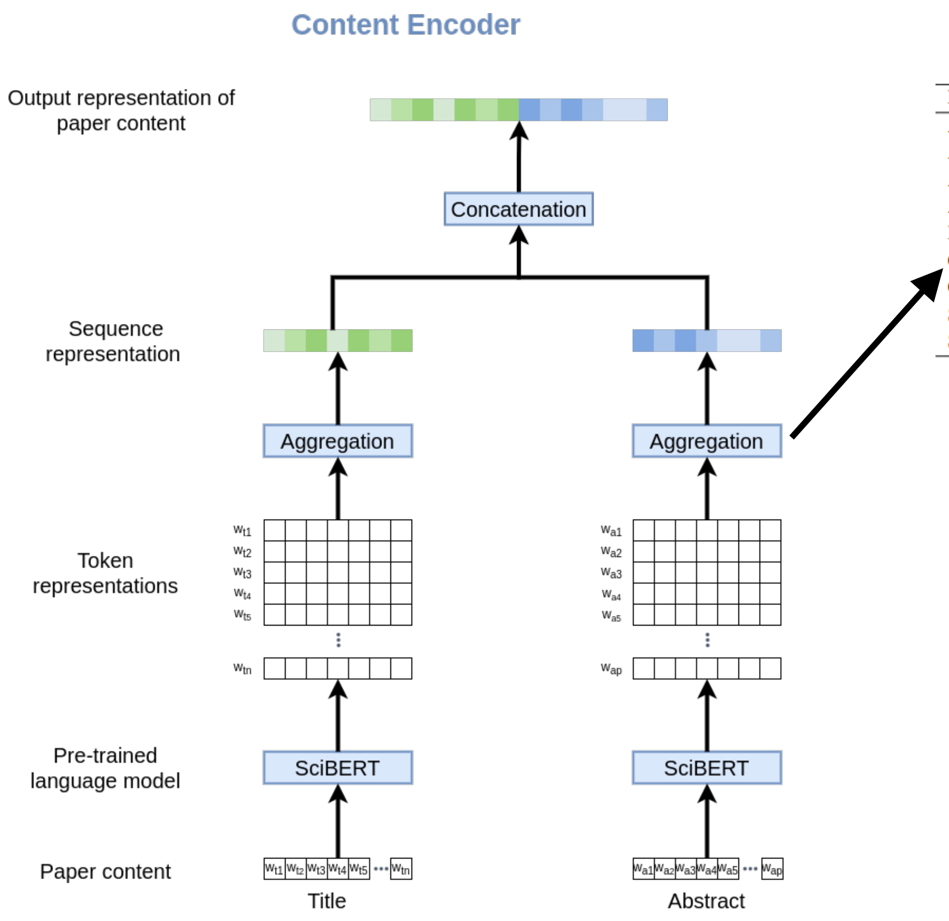
Edges

- Citations – directed, from citing to cited publication
- Co-authorship – undirected, min. 2 shared authors



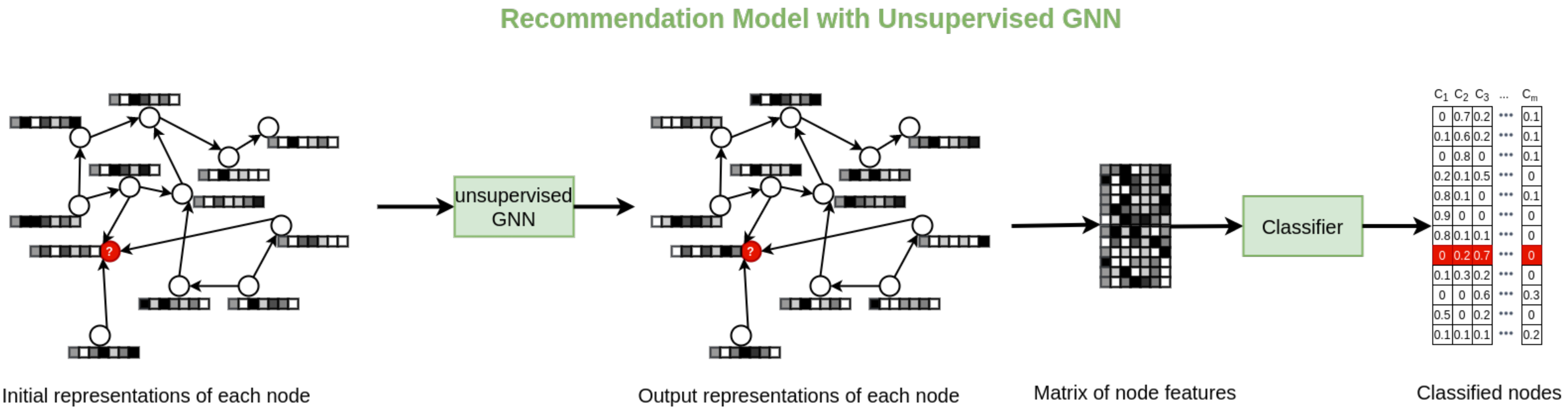


GraphConfRec: Content Encoder



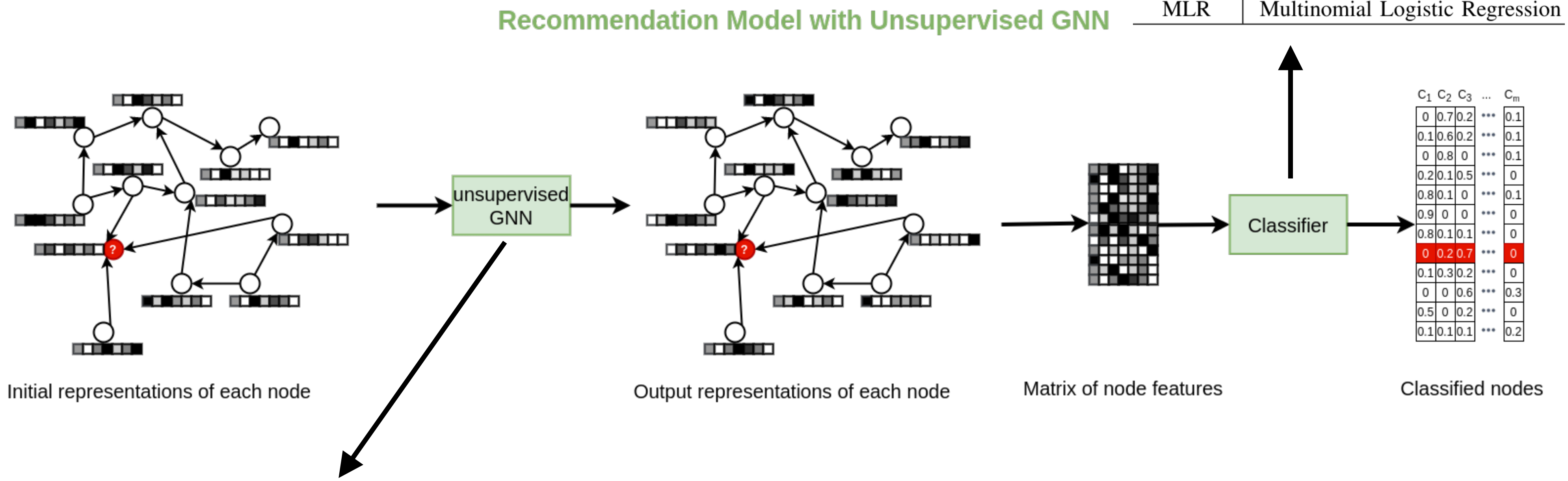
Notation	Description
AVG_L	Mean of last hidden layer representation of all tokens
AVG_2L	Mean of second-to-last hidden layer representation of all tokens
AVG_SUM_L4	Mean of the sum of the last four hidden layers representation of all tokens
AVG_SUM_ALL	Mean of the sum of all the hidden layers representation of all tokens
MAX_2L	Max pool over the second-to-last hidden layer representation of all tokens
CONC_AVG_MAX_2L	Concatenation of the AVG_2L and MAX_2L vectors
CONC_AVG_MAX_SUM_L4	Concatenation of the AVG_SUM_L4 and MAX_SUM_L4 vectors
SUM_L	Sum of the last hidden layer representation of all the tokens
SUM_2L	Sum of the second-to-last hidden layer representation of all the tokens

GraphConfRec: Recommendation Module



GraphConfRec: Recommendation Module

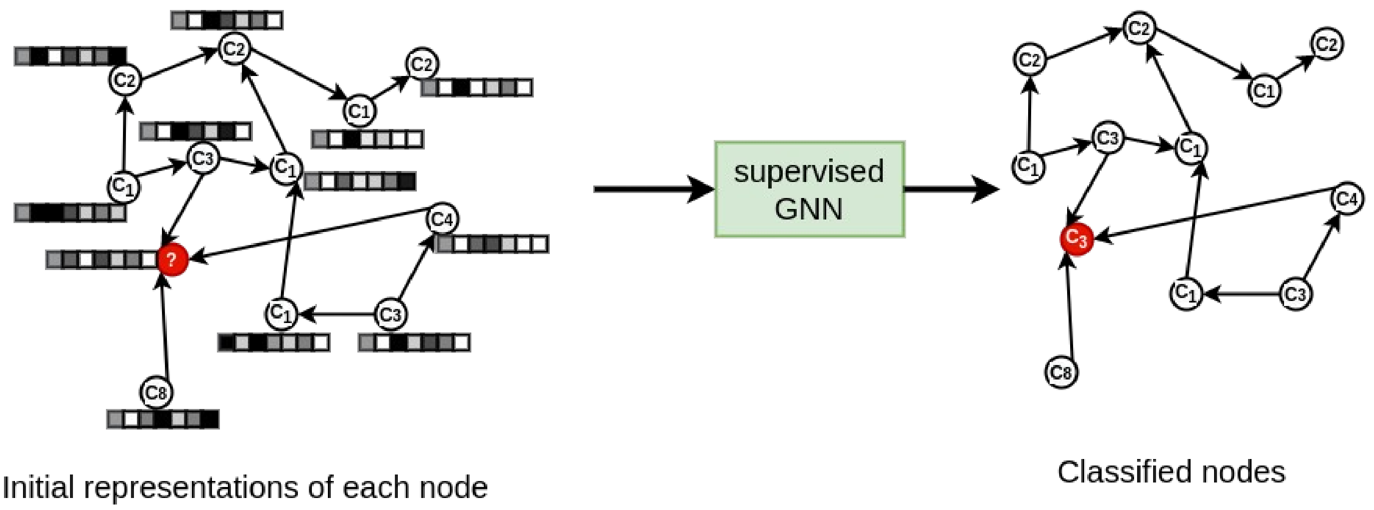
Notation	Model
KNN	K-Nearest Neighbour
GNB	Gaussian Naive Bayes
MLP	Multilayer Perceptron
MLR	Multinomial Logistic Regression



Base Model	Node embedding technique
GraphSAGE (Hamilton et al., 2017)	Learn functions to aggregate feature information of nodes in uniformly sampled, fixed-size neighbourhood
GraphSAGE_RL (Oh et al., 2019)	Sample neighbourhoods using non-linear regression function, where a reinforcement learning policy (RL) determins the weight of each combination of node and neighbourhood, from the negative classification loss output of a GraphSAGE model

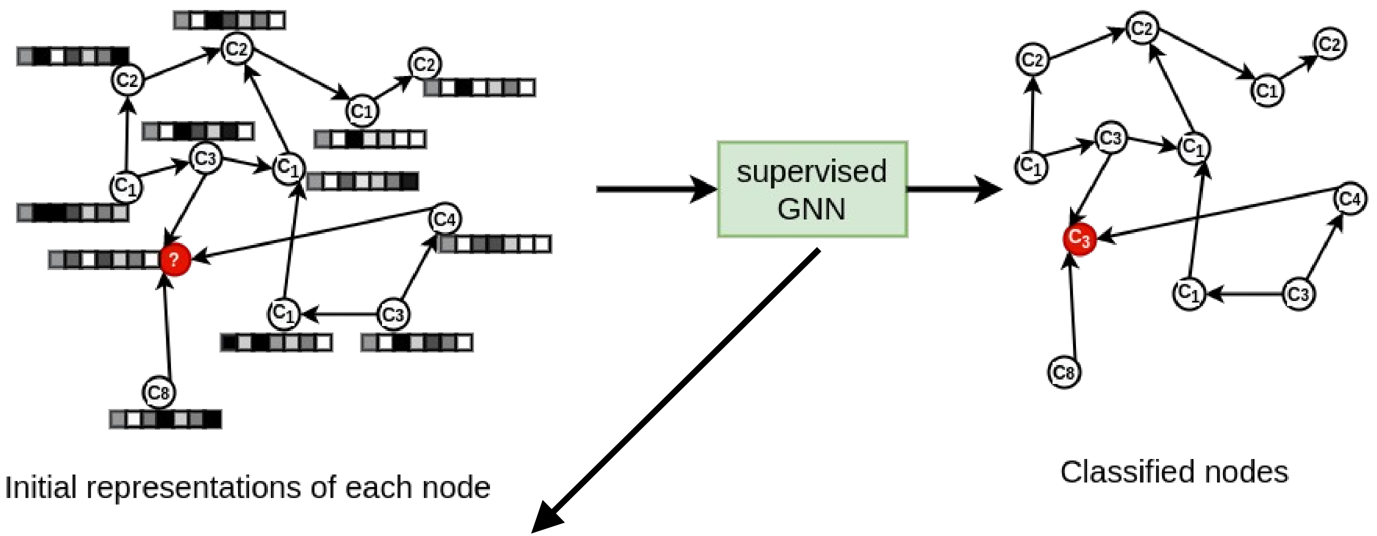
GraphConfRec: Recommendation Module

Recommendation Model with Supervised GNN



GraphConfRec: Recommendation Module

Recommendation Model with Supervised GNN



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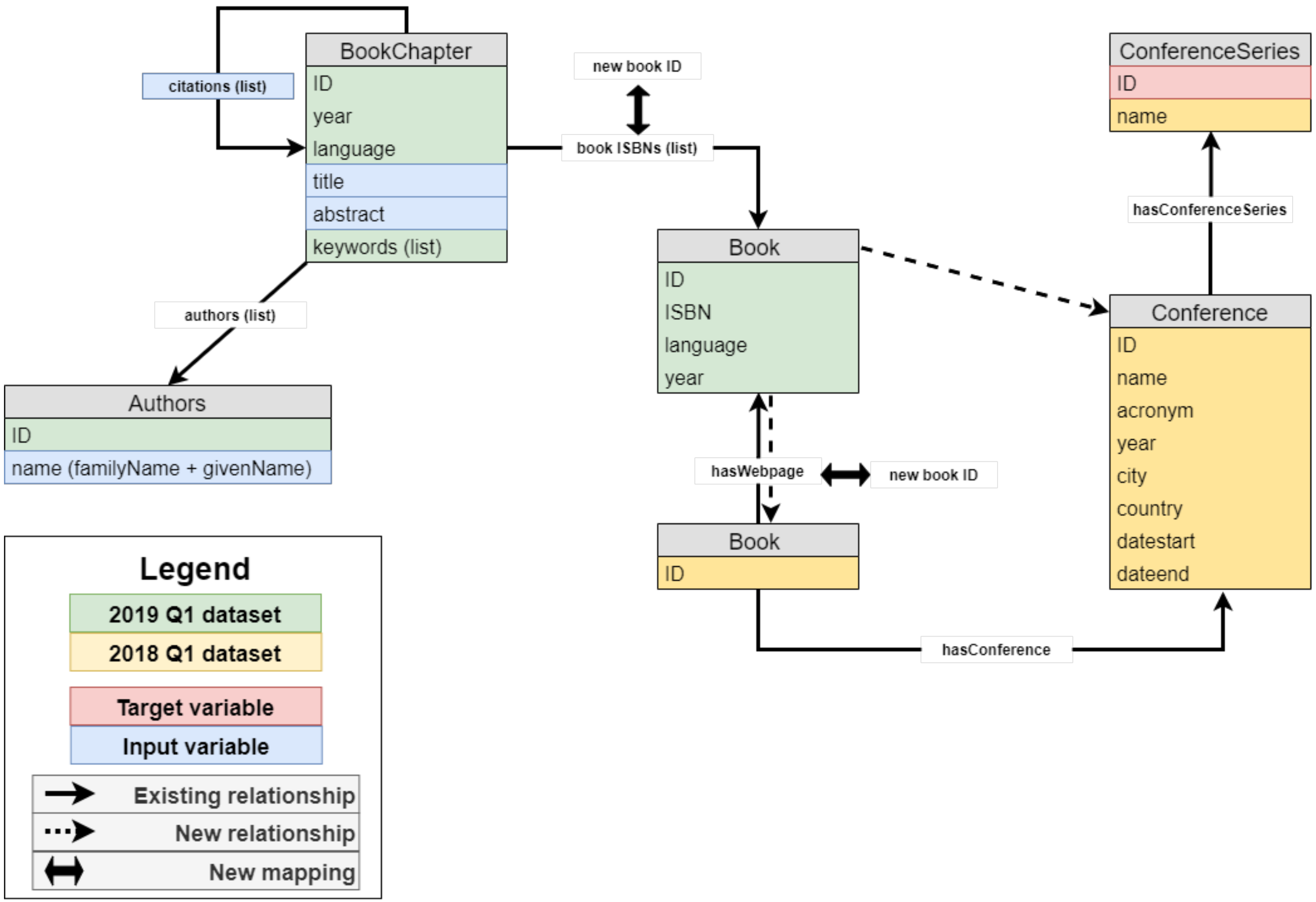
GAT (Veličković et al., 2017)	A self-attention mechanism is applied over the features of the node's neighbours
HAN (Wang et al., 2019)	Combination of node-level attention weighting meta-path-based neighbours and semantic-level attention weighting meta-paths in heterogeneous graph
SciBERT-ARGA (Pan et al., 2018)	Abstracts embedded with SciBERT and graph nodes with an adversarially regularized graph autoencoder

SciGraph Dataset



SciGraph Dataset

Remarks

- Only a subset of author names are disambiguated in SciGraph
- We only consider citations towards other conference publications contained in SciGraph
- Overlap: repeating conference series

	Training (1975-2014)	Validation (2015)	Test (2016)	Overlap (training - test)
Distinct conference series IDs	1,122	311	518	394
Distinct author names	164,103	19,994	30,175	14,639
All papers	293,836	130,002	213,000	–
Papers w/ English abstracts	290,877	12,990	21,223	–
Papers w/ English abstracts and citations in SciGraph	137,376	7,511	11,600	–

Evaluation: Setup

Setup: 10 recommendations per model, 1 ground truth

Evaluation metrics: Recall@10, MAP@*K*

Best case scenario

- Recall: 0.761 (true value always contained)
- MAP: 0.761 (true value always on position 1)

Two baselines

- *Authors model:* recommendations based on publication history of the manuscripts's authors
- *GraphSage Neighbour:* unsupervised GraphSage on co-authorship graph + cosine similarity

Evaluation: Quantitative Results

Model	Model configuration		Training statistics		Evaluation results			
	Embedding type	Parameter settings	Avg. time (s) per epoch	Epochs trained	Recall@10	MAP@10	MAP@5	MAP@3
Authors (1st baseline)	–	–	–	–	0.458	0.308	0.302	0.290
GraphSAGE Neighbour (2nd baseline)	CONC_AVG_MAX_SUM_L4	maxpool aggregator	11,994.46	10	0.259	0.096	0.082	0.072
GraphSAGE Classifier (citations graph)	CONC_AVG_MAX_2L	GCN aggregator + MLR	4,991.29	10	0.414	0.244	0.234	0.221
GraphSAGE Classifier (co-authorship graph)	AVG_SUM_ALL	maxpool aggregator + MLR	9,010.57	10	0.054	0.019	0.015	0.014
GraphSAGE Classifier Concat	SUM_L	GCN aggregator + KNN (n=30)	3,271.12	10	0.395	0.237	0.228	0.215
GraphSAGE supervised (citations graph)	AVG_2L	GCN aggregator	29.63	20	0.417	0.246	0.236	0.223
GraphSAGE supervised (heterogeneous graph)	AVG_SUM_ALL	GCN aggregator	32.48	20	0.440	0.258	0.247	0.234
GraphSAGE_RL Classifier (citations graph)	SUM_L	GCN aggregator + MLR	10,699.81	10	0.414	0.242	0.231	0.220
GraphSAGE_RL supervised (citations graph)	AVG_L	mean-concat aggregator + last-hop reward	36.43	10	0.531	0.298	0.284	0.266
GraphSAGE_RL supervised (heterogeneous graph)	SUM_L	mean-concat aggregator + all-hops reward	56.49	10	0.546	0.306	0.292	0.273
GAT (citations graph)	AVG_L	8 attention heads with 64 hidden units each	93.53	367	0.572	0.327	0.312	0.295
GAT (heterogeneous graph)	SUM_2L	8 attention heads with 64 hidden units each	147.25	503	**0.580**	**0.336**	**0.322**	**0.303**
HAN	AVG_L	8 attention heads with 128 hidden units each	226.34	301	0.540	0.300	0.285	0.267
SciBERT-ARGA (citations graph)	AVG_2L	ARGVA + FFNN with 500 hidden units	5.71	200	0.530	0.293	0.278	0.261
SciBERT-ARGA (heterogeneous graph)	AVG_L	ARGA + FFNN with 500 hidden units	6.57	200	0.534	0.295	0.280	0.263

Experiments

- Different SciBERT aggregation strategies
- 3 types of input graphs
- Wide range of model specific parameters

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Experiments

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- Wide range of model specific parameters

Evaluation: User Study

Limitation quantitative evaluation: 1 conference is *correct*

Participants: 25 academic researchers

- 80% Master or PhD students
- 16% contained in SciGraph

Setup: test 4 models with papers of their own choice

- Recommendation suitability rating from 1 (worst) to 5 (best)
- (Optional) comment on the quality of recommendations

Model	Authors	HAN	GAT (cit.)	GAT (het.)
Raters	16	21	25	22
Avg. rating	2.75	**3.76**	3.68	3.55

Limitations and Outlook

Limitations	Outlook
Exclusion of ACM, IEEE, AAAI, ACL conference proceedings due to publisher-dependent dataset	Publisher-independent dataset (e.g. Microsoft Academic Knowledge Graph)
Low internal confidence scores and ranking for suitable recommendations	Re-scaling of confidence scores for top recommendations Re-ranking of top recommendations by clustering similar conference series
Inclusion of niche conferences and workshops	Fine-tuning results based on additional features

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Code & Data

https://github.com/andreeaiana/graph_confrec