Supplementary Material for:
A Survey on Hypergraph Representation Learning

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A METHODOLOGY

This section clarifies the data collection process and the inclusion criteria for the selected articles.

A.1 Data Collection

We conducted our literature review by in-depth reading, interpreting, and categorizing articles addressing the problem of generating a low-dimensional representation of a hypergraph. We carried out our search in the Scopus database since it represents a comprehensive and accurate database of peer-reviewed research articles in the fields relevant to this survey. Specifically, we submitted the following query: `TITLE-ABS-KEY ("hypergraph embedding" OR "hypergraph learning" OR "hypergraph representation learning" OR "hypergraph neural network*" OR "hypergraph convolution" OR "hypergraph attention")`, limiting the results to only English-written contributions. We repeated the same query by replacing the word `hypergraph` with the terms `hyper-network` and `high-order`, as well as trying out different spellings of these words. We did not limit either the subject areas or the publication year. The rationale behind this choice relies on two main reasons. First, hypergraphs—and, more generally, graphs—embody a tool to study emergent phenomena in a wide range of application domains. Second, hypergraphs rose to prominence only recently in the academic landscape, and the topic of hypergraph representation learning represents an even more novel research field. A total of 1, 338 non-duplicated articles met these criteria by June 2022.

A.2 Inclusion Criteria

We followed a standard two-step selection process to pick the final set of articles to include in this survey. First, we screened the original set by filtering each article based on its title and abstract. In this phase, we removed all articles related to (higher) student education and high-order neural networks [64, 86]. In the second step, we filtered the remaining articles based on their content, removing out-of-scope articles, such as hypergraph-regularized methods. After this process, the number of articles was narrowed down to 102. Figure 1 schematically shows the selection process, while Figure 2 provides an overview of the venues where the selected articles have been published.

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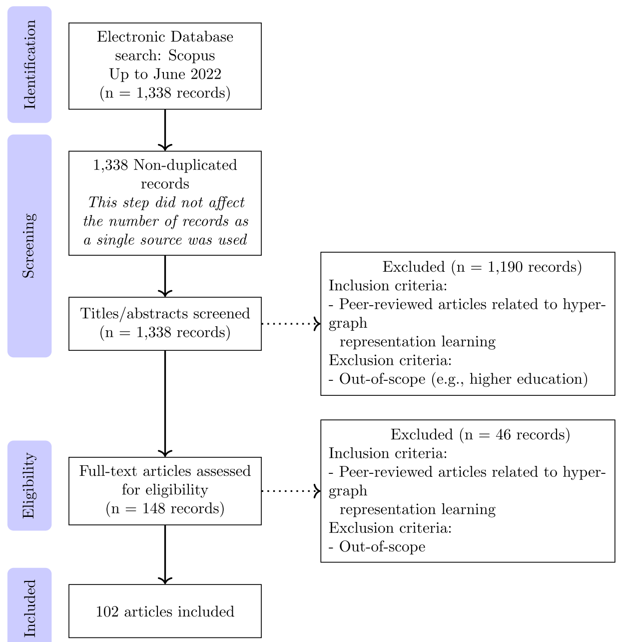


Fig. 1. PRISMA chart reporting the selection process of our systematic literature review.

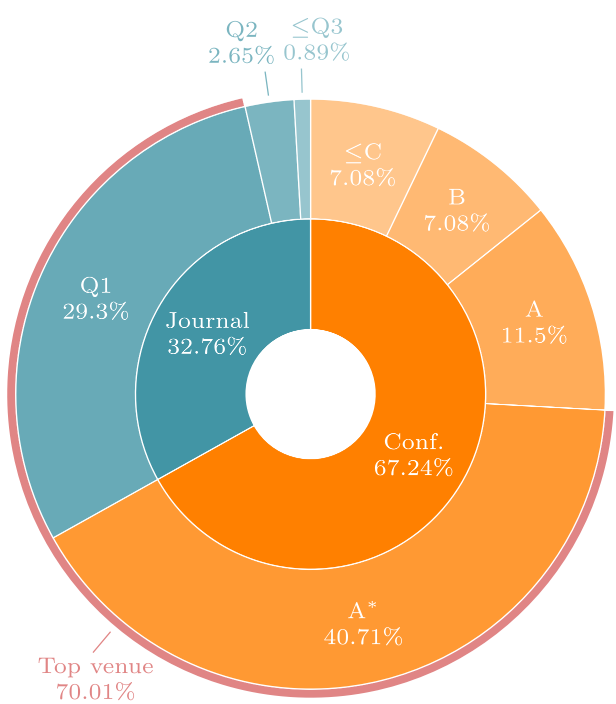
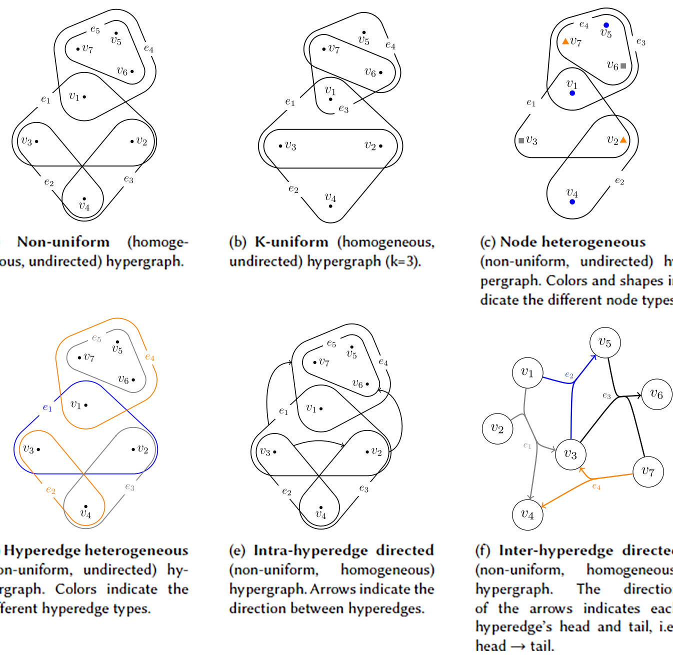


Fig. 2. Distribution of the ranking of the venues where the selected articles have been published. Conference and journal rankings have been evaluated according to CORE 2021 (A* > A > B > C > not ranked) and Scimago (Q1 > Q2 > Q3 > Q4), respectively.

B INPUT SETTING

B.1 Types of Input Hypergraphs

Figure 3 shows different examples of possible input hypergraphs.



(a) **Non-uniform** (homogeneous, undirected) hypergraph.

(b) **K-uniform** (homogeneous, undirected) hypergraph (k=3).

(c) **Node heterogeneous** (non-uniform, undirected) hypergraph. Colors and shapes indicate the different node types.

(d) **Hyperedge heterogeneous** (non-uniform, undirected) hypergraph. Colors indicate the different hyperedge types.

(e) **Intra-hyperedge directed** (non-uniform, homogeneous) hypergraph. Arrows indicate the direction between hyperedges.

(f) **Inter-hyperedge directed** (non-uniform, homogeneous) hypergraph. The direction of the arrows indicates each hyperedge's head and tail, i.e., head → tail.

Fig. 3. Types of input hypergraphs. An example of a dynamic hypergraph is not shown because it is usually represented as a sequence of static hypergraphs.

C HYPERGRAPH REPRESENTATION LEARNING METHODS

C.1 Input Settings

In this survey, we analyze the hypergraph embedding input along six axes: the nature of the high-order relation, its directionality, and size, the temporal dimension, whether nodes have attached additional information, and whether the hypergraph is converted into a graph. Figure 4 outlines the considered input settings.

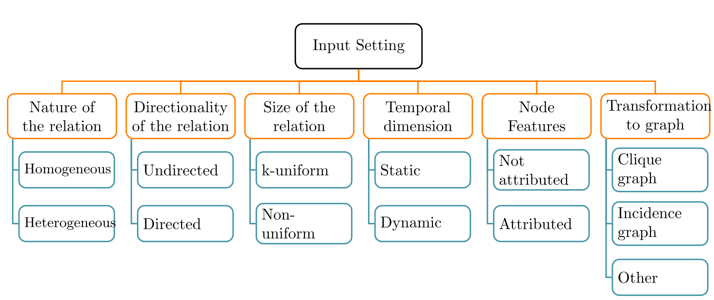


Fig. 4. Taxonomy of input settings.

C.2 Taxonomy of Hypergraph Embedding Methods

We divide hypergraph embedding techniques into three macro categories: spectral learning methods, proximity preserving methods, and (deep) neural networks-based methods. Figure 5 summarizes this taxonomy.

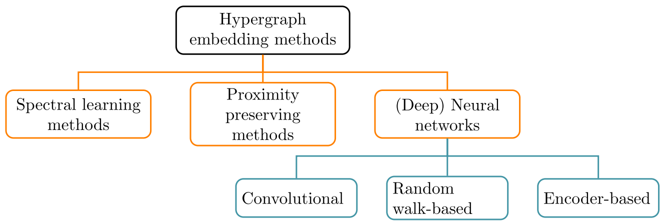


Fig. 5. Taxonomy of hypergraph embedding methods.

C.3 Temporal Distribution of the Literature about Hypergraph Embedding

Figure 6 provides the temporal distribution of the articles covered in this survey divided according to their category. The overall number of works from 2022 takes into account only the articles published by June of the same year (see Section A). Spectral learning methods were the first to appear in the literature (i.e., from the 1990s). Although the works before 2008 were primarily theoretical and did not strictly focus on learning hypergraph representations as we mean nowadays, their theoretical findings were essential to developing the most recent approaches. Besides rare exceptions traditionally linked to visualization tasks, spectral learning techniques fail when facing large-scale hypergraphs. This drawback should explain their disappearance in recent years. A different consideration must be made for the proximity-preserving family. While spectral learning methods are more mathematics-driven, we can consider proximity-preserving techniques to be more machine learning–driven as they follow the usual machine learning pipeline. However, the researchers' interest in these methods started when **deep neural networks (DNNs)** were already a big deal and, as for machine learning research in general, DNNs have stolen the show. The rise of DNN techniques began right after the introduction of Graph Convolutional Networks by Kipf and Welling in 2017 [63]. Over the past few years, the increase in computational power and experience working with graph convolutions has allowed a rapid escalation of DNN methods, currently representing the de facto technique for hypergraph representation learning.

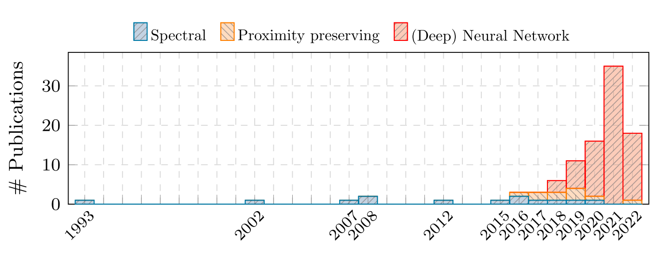


Fig. 6. Temporal distribution of the articles considered in this survey.

D SPECTRAL REPRESENTATION LEARNING METHODS

Table 1 provides an overview of the spectral methods described in the survey.

Table 1. Spectral-based Methods

Method	Input HG	Laplacian = $\mathbf{Z}(\mathbf{D}_v - \mathbf{S}_v)\mathbf{Z}^\top$	Learning Task	Venue	Year
Bolla [10]	Hom, NU	$\mathbf{S}_e = \mathbf{D}_e^{-1}$ and $\mathbf{Z} = \mathbf{I}_{\lvert\mathcal{V}\rvert}$	-	Discrete Mathematics	1993
Rodriguez [92]	Hom, NU	$\mathbf{D}_r = \mathrm{diag}(\mathbf{HWH}^\top - \mathbf{D}_v)$, $\mathbf{Z} = \mathbf{D}_r^{-1/2}$, $\mathbf{S}_e = \mathbf{W}$, $\mathbf{S}_v = \mathbf{HS}_e\mathbf{H}^\top - \mathbf{D}_r$	-	Linear & Multilinear Algebra	2002
Zhou et al. [149]	Hom, NU	$\mathbf{S}_e = \mathbf{WD}_e^{-1}$ and $\mathbf{Z} = \mathbf{D}_v^{-1/2}$	Clustering	NeurIPS	2007
Ren et al. [91]	Hom, NU	$\mathbf{S}_e = \frac{1}{2}\mathbf{I}_{\lvert\mathcal{E}\rvert}$ and $\mathbf{Z} = \sqrt{2}\mathbf{I}_{\lvert\mathcal{V}\rvert}$	Clustering	SSPR	2008
Sun et al. [103]	Hom, NU, A	Zhou's Laplacian	Classification	KDD	2008
Pu and Faltings [90]	Hom, NU	$\mathbf{S}_e = \mathbf{W}$ and $\mathbf{Z} = \mathbf{D}_v^{-1/2}$ (*)	Classification	ECML PKDD	2012
Yuan and Tang [144]	Hom, NU, A	Zhou's Laplacian (*)	Classification	IEEE GRSL	2015
Zhu et al. [150]	Het, NU	$\mathbf{Z} = \mathbf{I}_{\lvert\mathcal{V}\rvert}$ and $\mathbf{S}_e = \mathbf{WD}_e^{-1}$	Recommendation	Neurocomputing	2016
Huang et al. [53]	Hom, NU, A	Zhou's Laplacian (*)	Dimensionality reduction	Neurocomputing	2016
Sun et al. [107]	Hom, NU, A	$\mathbf{Z} = \mathbf{I}_{\lvert\mathcal{V}\rvert}$ and $\mathbf{S}_e = \mathbf{WD}_e^{-1}$	Classification	Remote Sensing	2017
Saito et al. [94]	Hom, NU	$\mathbf{Z} = \mathbf{D}_v^{-1/2}$, $\mathbf{S}_e = \mathbf{D}_e^{-1}\mathbf{W}$, $\mathbf{S}_v = \mathbf{A} - \mathrm{diag}(\mathbf{A})$, $\mathbf{A} = \mathbf{HS}_e\mathbf{H}^\top$	Clustering	AAAI	2018
Luo et al. [73]	Hom, NU, A	Zhou's Laplacian (*)	Classification	IEEE Trans. on Cybernetics	2019
Luo et al. [74]	Hom, NU, A	Zhou's Laplacian (*)	Classification	JSTARS	2020

As tasks, we only consider those directly using the node embeddings (standard output among these methods). All methods are transductive and work in a static and undirected input setting. `Hom/Het` stand for homogeneous/heterogeneous; `NU` stands for non-uniform; `A` stands for attributed nodes. (*) The formulation is related but does not directly fit the framework (3).

E PROXIMITY-PRESERVING METHODS

Table 2 summarizes the proximity-preserving methods described in the survey.

Table 2. Proximity-Preserving Methods

Method	Input HG	Proximity Model	Learning Task	Venue	Year	Code
HEBE [40]	Het, NU	Softmax of the dot-product	Classification	ICDM	2016	https://bitbucket.org/hgui/hebe/downloads/
HEBE-PO [41]	Het, NU	As HEBE	Classification	TKDE	2017	https://bitbucket.org/hgui/hebe/downloads/
HEBE-PE [41]	Het, NU	As HEBE	Link prediction	TKDE	2017	https://bitbucket.org/hgui/hebe/downloads/
HGE [141]	Het, NU	Multilinear map	Recommendation	CIKM	2018	https://github.com/chia-an/HGE
Event2vec [22]	Het, NU	Sigmoid of the weighted dot-product	Clustering, Class.	ICDMW	2018	-
FOBE [108]	Hom, NU	Sigmoid of the dot-product	Link prediction, Recom.	MLG	2019	https://github.com/JSybrandt/HypergraphEmbedding
HOBE [108]	Hom, NU	ReLU of the dot-product	Link prediction, Recom.	MLG	2019	https://github.com/JSybrandt/HypergraphEmbedding
LBSN2Vec [137]	Het, U	Cosine similarity	Link prediction, Recom.	WWW	2019	https://github.com/eXascaleInfolab/LBSN2Vec
LBSN2Vec++ [138]	Het, U	Cosine similarity	Link prediction, Recom.	TKDE	2020	https://github.com/eXascaleInfolab/LBSN2Vec
MSC-LBSN [111]	Het, U	Cosine similarity	Link prediction, Recom.	TKDE	2022	-

Node embedding is the standard output. All methods are transductive and work in a static and undirected input setting. `Hom/Het` stand for homogeneous/heterogeneous; `(N)U` stands for (non-)uniform. Task: `Class` stands for classification, and `Recom` for recommendation.

F (DEEP) NEURAL NETWORKS MODELS

Table 3 summarizes the (deep) neural-network-based methods described in the survey.

Table 3. (Deep) Neural Network Methods

Method	Input HG	Embedding Output	MPF	Skip-conn	Attention	Gated upd	Spectral	RW	Enc-based	Task	Venue	Year	Code (github.com/)
DHNE [112]	Het, U	$\mathcal{V}$							✓	Class, LP	AAAI	2018	tadpole/DHNE
DHHE [21]	Het, NU	$\mathcal{V}$						✓		Class, LP	ICME	2018	-
HHNE [5]	Het, NU	$\mathcal{V}$	✓	✓						LP	ICDM	2018	illidanlab/HHNE
HGNN [33]	Hom, NU	$\mathcal{V}$	✓	✓						Class	AAAI	2019	iMoonLab/HGNN
Hyper2Vec [48]	Hom, NU	$\mathcal{V}$						✓		Class	DASFAA	2019	jeffhj/NHNE
DHGNN [56]	Hom, NU	$\mathcal{V}$	✓		✓					Class	IJCAI	2019	iMoonLab/DHGNN
HpLapGCN [35]	Hom, NU	$\mathcal{V}$					✓			Class	Neurocom.	2019	-
Hyper-gram [51]	Het, U	$\mathcal{V}$						✓		LP	CIKM	2019	HKUST-KnowComp/HPHG
HyperGCN [134]	Hom, NU	$\mathcal{V}$	✓							Class	NeurIPS	2019	malllabiisc/HyperGCN
DHE [87]	Hom, NU, MC	$\mathcal{V}$, $\mathcal{E}$						✓	✓	Class	NeurIPS	2019	Josh-Payne/deep-hyperedges
Hyper-SAGNN [147]	Het, NU	$\mathcal{V}$			✓			✓	✓	LP	ICLR	2020	ma-compbio/Hyper-SAGNN
HyperRec [118]	Het, NU, D	$\mathcal{V}$	✓	✓		✓				Recom	SIGIR	2020	-
NHNE [47]	Hom, NU, MC	$\mathcal{V}$, $\mathcal{E}$						✓		Class, LP	TOIS	2020	jeffhj/NHNE
HNHN [28]	Hom, NU	$\mathcal{V}$, $\mathcal{E}$	✓							Class	ICMLW	2020	-
MGCN [15]	Hom, NU	$\mathcal{V}$	✓	✓						LP	KDD	2020	-
DHCF [54]	Hom, NU, MC	$\mathcal{V}$	✓	✓						Recom	KDD	2020	-
HGC-RNN [140]	Hom, NU	$\mathcal{V}$	✓		✓	✓				Regr	KDD	2020	-
NHP [135]	Het, NU, Dir	$\mathcal{V}$	✓							LP	CIKM	2020	-
AdaHGNN [126]	Hom, NU	$\mathcal{V}$	✓							Class	MM	2020	-
HyperGAT [26]	Het, NU, MC	$\mathcal{V}$, $\mathcal{E}$	✓		✓					Class	EMNLP	2020	kaize0409/HyperGAT
SHCN [17]	Het, U	$\mathcal{V}$	✓	✓						Recom	TOIS	2020	-
G-MPNN [133]	Hom, NU	$\mathcal{V}$	✓							Class, LP	NeurIPS	2020	naganandy/G-MPNN-R
HGAT [13]	Hom, NU	$\mathcal{V}$	✓		✓					Class	TrustCom	2020	-
HAIN [3]	Hom, NU	$\mathcal{V}$	✓	✓						Class	IEEE BigData	2020	-
HCR [55]	Het, NU	$\mathcal{V}$	✓		✓					Recom	ICDM	2021	-
HCHA [2]	Hom, NU	$\mathcal{V}$	✓	✓	✓					Class	Pat Rec	2021	-
DHCN [131]	Hom, NU	$\mathcal{V}$	✓		✓					Recom	AAAI	2021	xiaxin1998/DHCN
HWNN [104]	Het, NU, MC	$\mathcal{V}$					✓			Class	WSDM	2021	-
STHGCN [121]	Hom, NU, D, MC	$\mathcal{V}$	✓			✓				Regr	TITS	2021	-
HGCELM [72]	Hom, NU	$\mathcal{V}$	✓							Class	Appl Sci	2021	-
MHCN [142]	Het, NU, MC	$\mathcal{V}$	✓	✓						Recom	TheWebConf	2021	Coder-Yu/QRec
HNN [105]	Hom, NU	$\mathcal{V}$	✓		✓					LP	TheWebConf	2021	-
DualHGCN [132]	Hom, NU, MC	$\mathcal{V}$	✓	✓						Class, LP	TheWebConf	2021	xuehansheng/DualHGCN
KHNN [71]	Hom, NU, MC	$\mathcal{V}$	✓							Recom	DASFAA	2021	-
SSF [46]	Hom, U	$\mathcal{V}$	✓		✓					LP	DASFAA	2021	-
STHAN-SR [97]	Hom, U, D	$\mathcal{V}$	✓		✓					Regr	AAAI	2021	-
SHARE [119]	Hom, NU	$\mathcal{V}$, $\mathcal{E}$	✓		✓					Recom	SDM	2021	-
[101]	Hom, NU	$\mathcal{V}$, $\mathcal{E}$	✓							LP	SDM	2021	-
MHGNN [1]	Hom, NU	$\mathcal{V}$	✓							Class	TIP	2021	-
[130]	Het, NU, D	$\mathcal{V}$	✓		✓	✓				Regr	J IM	2021	-
HeteHG-VAE [31]	Het, NU	$\mathcal{V}$, $\mathcal{E}$			✓				✓	LP	PAMI	2021	haoyfan/HeteHG-VAE
UniGNN [52]	Hom, NU	$\mathcal{V}$, $\mathcal{E}$	✓	✓						Class	IJCAI	2021	OneForward/UniGNN
[38]	Het, NU	$\mathcal{V}$	✓		✓					LP	WWW	2021	-
S^{2}HCN [77]	Hom, NU, MC	$\mathcal{V}$	✓							Class	SPIE RS	2021	-
pLapHGNN* [76]	Het, NU	$\mathcal{V}$					✓			Class	TMM	2021	-
DualHGNN [125]	Hom, NU, MC	$\mathcal{V}$	✓		✓					Class	J Kno Sys	2021	-
(Res|Multi)HGNN [49]	Hom, NU	$\mathcal{V}$	✓	✓						Class	ICIP	2021	OneForward/ResMHGNN
HNN-HM [69]	Hom, U, Dir	$\mathcal{V}$							✓	Class	ICCV	2021	-
H^{2}SeqRec [68]	Het, NU, MC, D	$\mathcal{V}$	✓							Recom	CIKM	2021	Abigale001/h2seqrec
HHGR [146]	Hom, NU	$\mathcal{V}$	✓		✓					Recom	CIKM	2021	0411tony/HHGR
HyperCTR [45]	Hom, NU, D	$\mathcal{V}$	✓							Recom	CIKM	2021	-
HybridHGCN [50]	Hom, NU, MC	$\mathcal{V}$	✓							Class	PRVC	2021	-
HGDD [85]	Het, NU	$\mathcal{V}$	✓							Class, LP	ISBRA	2021	-
HGNNA [27]	Hom, NU	$\mathcal{V}$	✓		✓					Recom	JPCS	2021	-
HGWNN [81]	Hom, NU	$\mathcal{V}$					✓			Class	Neurocom.	2021	-
EHGNN [59]	Hom, NU	$\mathcal{V}$, $\mathcal{E}$	✓							Class	NeurIPS	2021	harryjo97/EHGNN
HOT [62]	Hom, U	$\mathcal{V}$	✓		✓					LP	NeurIPS	2021	jw9730/hot
HyperTeNet [115]	Het, U, MC	$\mathcal{V}$	✓		✓					Recom	ICDM	2021	mvijaikumar/HyperTeNet
HyperGroup [42]	Hom, NU	$\mathcal{E}$	✓	✓						Recom	TOIS	2021	-
F^{2}HNN [78]	Hom, NU, MC	$\mathcal{V}$	✓							Class	TGRS	2022	-
DHAT [75]	Hom, NU, Dir	$\mathcal{V}$	✓		✓					Regr	ITS	2022	-
[122]	Het, NU	$\mathcal{V}$	✓			✓				Recom	WWW	2022	-
HyperINF [57]	Hom, NU, D, MC	$\mathcal{V}$	✓	✓						Recom	TSUSC	2022	-
HEMR [66]	Het, NU, Dir	$\mathcal{V}$						✓		Recom	TNNLS	2022	picuslab/HEMR
GC-HGNN [88]	Hom, NU	$\mathcal{V}$	✓							Recom	J ECRA	2022	-
HRSC [151]	Het, NU	$\mathcal{V}$, $\mathcal{E}$						✓		Class, LP	Appl Sci	2022	-
IHGNN [18]	Het, U	$\mathcal{V}$, $\mathcal{E}$	✓							Recom	TheWebConf	2022	CDboyOne/IHGNN
AllSet [19]	Hom, NU	$\mathcal{V}$, $\mathcal{E}$	✓		✓					Class	ICLR	2022	jianhao2016/AllSet
HyperSaR [110]	Het, NU	$\mathcal{V}$, $\mathcal{E}$	✓							Recom	ECIR	2022	naver/hypersar
MT-HGCN [120]	Hom, NU, D, MC	$\mathcal{V}$	✓			✓				Regr	TITS	2022	-
[106]	Hom, NU, D	$\mathcal{V}$, $\mathcal{E}$	✓		✓					Class	TKDE	2022	-
HCCF [128]	Hom, NU	$\mathcal{V}$	✓	✓						Recom	SIGIR	2022	akaxlh/HCCF
HGNN$^+$ [37]	Hom, NU	$\mathcal{V}$	✓							Class, Recom	PAMI	2022	iMoonLab/DeepHypergraph
SHT [129]	Hom, NU	$\mathcal{V}$, $\mathcal{E}$	✓	✓	✓					Recom	KDD	2022	akaxlh/SHT
DH-HGCN [43]	Hom, NU	$\mathcal{V}$	✓		✓					Recom	SIGIR	2022	-
LE [136]	Hom, NU	$\mathcal{V}$	✓	✓						Class	CIKM	2022	ycq091044/LEGCN

Input HG: Hom/Het stands for homogeneous/heterogeneous, (N)U for (non-)uniform, MC for multi-channel, D for dynamic, and Dir for directed. Task: Class stands for classification, LP for link prediction, Regr for regression, and Recom for Recommendation. All methods can handle attributed nodes.

G DATASETS

Table 4 lists the datasets used by the works reviewed. For each dataset, we detail whether it belongs to a specific category, the link where it can be downloaded, a reference to the paper introducing it (if any), which methods have been tested on it and for which tasks, and how it has been modeled with a hypergraph.

Table 4. Most Commonly used Public Datasets by the Articles Reviewed

Dataset type	Dataset	Link (https://tinyurl.com/)	Class	Clus	LP	Recom	Regr	Other	Input setting	Used by
Bookmarks	Del.icio.us [39]	delicious-db				✓			Het, NU	[150]
	CiteULike [39, 116]	citeulike-db				✓			Hom/Het, NU, MC	[54, 150]
Co-authorship / Co-citation	AMiner [109]	aminer-db	✓	✓					Het, NU	[22]
	ACM [123]	acm-data			✓				Het, NU	[38]
	DBLP* [36, 139]	dblp-net | dblp-bip | aminer-dblp	✓		✓	✓			Hom/Het, NU, MC	[3, 19, 28, 31, 38, 40, 41, 47, 48, 52, 104, 105, 108, 125, 134, 135]
	Cora* [99]	cora-cit-network | cora-coauth	✓		✓				Hom/Het, NU, MC	[2, 3, 19, 33, 37, 38, 50, 52, 56, 87, 90, 104, 105, 125, 134, 136]
	Citeseer [93]	citeseer	✓						Hom, NU, MC	[2, 3, 19, 28, 35, 37, 50, 52, 56, 90, 125, 134, 136]
	PubMed* [99]	pubmed-db | pb-diabetes	✓						Hom/Het, NU, MC	[2, 3, 19, 28, 33, 37, 50, 52, 87, 104, 134, 136]
	WebKB [24]	webkb-net	✓						Hom, NU	[90]
Categorical	20newsgroup [60]	20newsgroup	✓	✓					Hom, NU	[2, 19, 90, 94, 118, 136]
	Cancer [102]	cancer-db		✓					Hom, NU	[72, 94]
	Chess [100]	chess-cat-db		✓					Hom, NU	[94]
	Congress [98]	congress-votes		✓					Hom, NU	[94]
	Covertype [9]	covertype	✓						Hom, NU	[90]
	Letter [34]	letterrecog	✓						Hom, NU	[90]
	Nursery [83]	nursery-db		✓					Hom, NU	[94]
	Scene [12]	scenedb	✓						Hom, NU, A	[103]
	Yeast [29]	yeastdataset	✓						Hom, NU, A	[103]
	Zoo [34]	zoodb	✓	✓					Hom, NU	[19, 90, 94, 136, 149]
Purchase	Alibaba [132]	-	✓		✓				Hom/Het, (N)U, MC	[18, 132]
	Amazon* [67, 80, 139]	amazon-meta | amzn-prod | amzn-rev	✓		✓	✓			Hom/Het, (N)U, D, MC	[17, 18, 68, 90, 108, 118, 128, 132]
	Diginetica	diginetica				✓			Hom/Het, (N)U	[18, 27, 88, 119, 131]
	Tmall	tmall-ijcai15				✓			Hom/Het, NU	[88, 122, 129, 135]
	YooChoose [7]	yoochoose				✓			Hom, U, D	[27, 119]
Biology / Chemistry	CMP	pmh-data-ch					✓		Het, NU, D	[130]
	CTD [143]	ctd-data	✓						Het, NU	[85]
	Drug-Drug Interactions [5]	-			✓				Het, NU	[5]
	Drug-Target Interactions	dt-inter	✓		✓				Hom, NU, MC	[132]
	FAERS	drug-faers	✓		✓				Het, (N)U	[5, 51, 62, 112, 147, 151]
	iAF1260 [32]	iAF1260			✓				Het, NU, D	[135]
	iJO1366 [84]	iJO1366-ecoli			✓				Het, NU, D	[135]
	USPTO [58]	uspto-db			✓				Het, NU, D	[135]
GPS	GPS [148]	-	✓		✓				Hom/Het, (N)U	[51, 62, 112, 147, 151]
	Gowalla [20]	gowalla-db			✓				Hom, NU	[129]
Images	AR	ar-database						✓	Hom, NU, A	[53]
	Botswana	botswana-img	✓						Hom, NU, A, MC	[74, 78, 107, 144]
	FERET [89]	color-feret						✓	Hom, NU, A	[53]
	Houses	house-img	✓	✓					Hom, (N)U, Dir	[69, 91]
	Indian Pines [4]	indian-pines	✓						Hom, NU, A, MC	[73, 77, 78, 107, 144]
	JAFFE [25]	jaffe-db						✓	Hom, NU, A	[53]
	KSC	ksc-db-img	✓						Hom, NU, A, MC	[74, 77, 78]
	LFW-A [124]	lfw-db-img						✓	Hom, NU, A	[53]
	ModelNet40 [127]	modelnet40	✓						Hom/Het, NU, MC	[1, 19, 33, 37, 49, 50, 76, 81, 136]
	MS-COCO [70]	mscoco-db			✓				Hom, NU	[126]
	NUS-WIDE [23]	nus-wide-db	✓		✓				Het, NU	[21, 126]
	NTU [14]	http://3d.csie.ntu.edu.tw/	✓						Hom/Het, NU, MC	[1, 19, 33, 37, 49, 50, 76, 81, 136]
	ORL [95]	faces-orl						✓	Hom, NU, A	[53]
	Pascal VOC [30]	pascal-voc-2007	✓		✓				Hom, (N)U, Dir	[69, 126]
	Pavia University	pavia-uni	✓						Hom, NU, A, MC	[73, 78, 107]
	Visual Genome [65]	visual-genome			✓				Hom, NU	[126]
	Yale [6]	yale-faces-db-img						✓	Hom, NU, A	[53]
Miscellanea	ReVerb45k [114]	reverb45k			✓				Het, U, D	[135]
Movies	CAMRa2011*	CAMRa2011				✓			Hom/Het, NU	[55, 146]
	IMDB*	imdb-movie-db	✓		✓				Hom/Het, NU, MC	[31, 47, 48, 59, 125]
	LDOS-CoMoDa [82]	ldos-comoda				✓			Het, NU	[141]
	Micro-Video 1.7M [16]	micro-video				✓			Hom, NU, D	[45]
	MovieLens* [44]	movie-lens	✓		✓	✓			Hom/Het, (N)U, MC, D	[37, 45, 51, 54, 62, 71, 110, 112, 128, 147, 151]
Q&A	Yahoo* [61, 113]	yahoo-db	✓						Hom, NU, A	[103]
Review	Goodreads* [117, 118]	goodreads-db				✓			Het, NU, D	[68, 115, 118]
	Movie review	movie-reviews-db	✓						Het, NU	[118]
	Yelp*	yelp-db	✓		✓	✓			Hom/Het, NU	[17, 19, 31, 38, 40–43, 105, 128, 129, 142]

(Continued)

Table 4. Continued

Dataset type	Dataset	Link (https://tinyurl.com/)	Class	Clus	LP	Recom	Regr	Other	Input setting	Used by
Social networks	Baidu (feed & news) [54]	-				✓			Hom, NU, MC	[54]
	Foursquare [137]	foursquare-net			✓	✓			Het, U	[111, 137, 138]
	Douban	douban-db			✓	✓			Hom/Het, (N)U, MC	[31, 42, 43, 46, 142, 146]
	Douban-Weibo [15]	-			✓				Hom, NU	[15]
	Facebook-Twitter [15]	-			✓				Hom, NU	[15]
	Friendster [139]	friendster-net			✓				Hom, NU	[108]
	LiveJournal [139]	livejournal-net			✓				Hom, NU	[108]
	MaFengWo	-				✓			Het, NU	[55]
	Sina	-	✓						Hom, NU, D	[106]
	Twitter	-	✓						Hom, NU, D	[106]
	YouTube [139]	youtube-net-comm			✓				Hom, NU	[108]
	Weeplace [96]	weeplace-sn				✓			Hom, NU	[146]
	Weibo	-			✓	✓			Hom, (N)U, D, MC	[46, 57]
Songs	#nowplaying [145]	nowplaying-db				✓			Hom, NU	[88, 131]
	Last.FM	last-fm-db				✓			Hom/Het, NU, MC	[71, 108, 110, 142]
	Spotify [8]	million-songs | spotify-db				✓			Het, NU, Dir	[66, 115]
Text	Ohsumed | Reuters	oh-r8-r52	✓						Het, NU	[118]
	wordnet [11, 79]	word-net	✓		✓				Het, (N)U	[51, 112, 147, 151]

Input setting: `Hom`/`Het` stands for homogeneous/heterogeneous, `(N)U` for (non-)uniform, `MC` for multi-channel, `D` for dynamic, and `Dir` for directed. The symbol * means that the specific dataset is available in multiple versions. † The NTU dataset is not reachable from our location. All links were accessed on the 12th of June, 2023.

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