Photo: https://www.instagram.com/daviddoubilet/

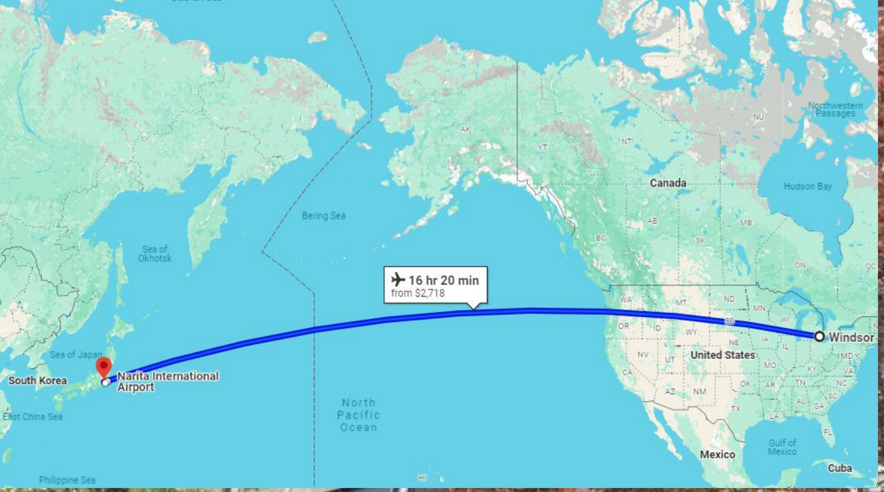
Paradigm Shifts in Team Recommendation

From Historical Subgraph Optimization to Emerging Graph Neural Network

Fani's Lab/ @SIGIR-AP24

Eternal Sunshine of the Spotless Mind, Michel Gondry, 2004

“What does team recommendation have to do with information retrieval?”



Fani's Lab!, School of Computer Science, University of Windsor, Canada

Organizers:    

Director: **Mahdis Saeedi**, PhD., Research Associate

Actors: **Christine Wong**, BSc., Research Assistant

Md. Jamil Ahmed, MSc., Research Assistant

Producer: **Hossein Fani**, PhD., Assistant Professor

Schindler's List, Steven Spielberg, 1993

Outline

Outline

I) Introduction and Background

II) Pioneering Techniques

III) Learning-based Heuristics

IV) Challenges and New Perspectives

V) Applications

Hands-on: OpeNTF

What Is a Team?

A group of users who collaborate together with a common purpose in order to accomplish the requirements of a task.

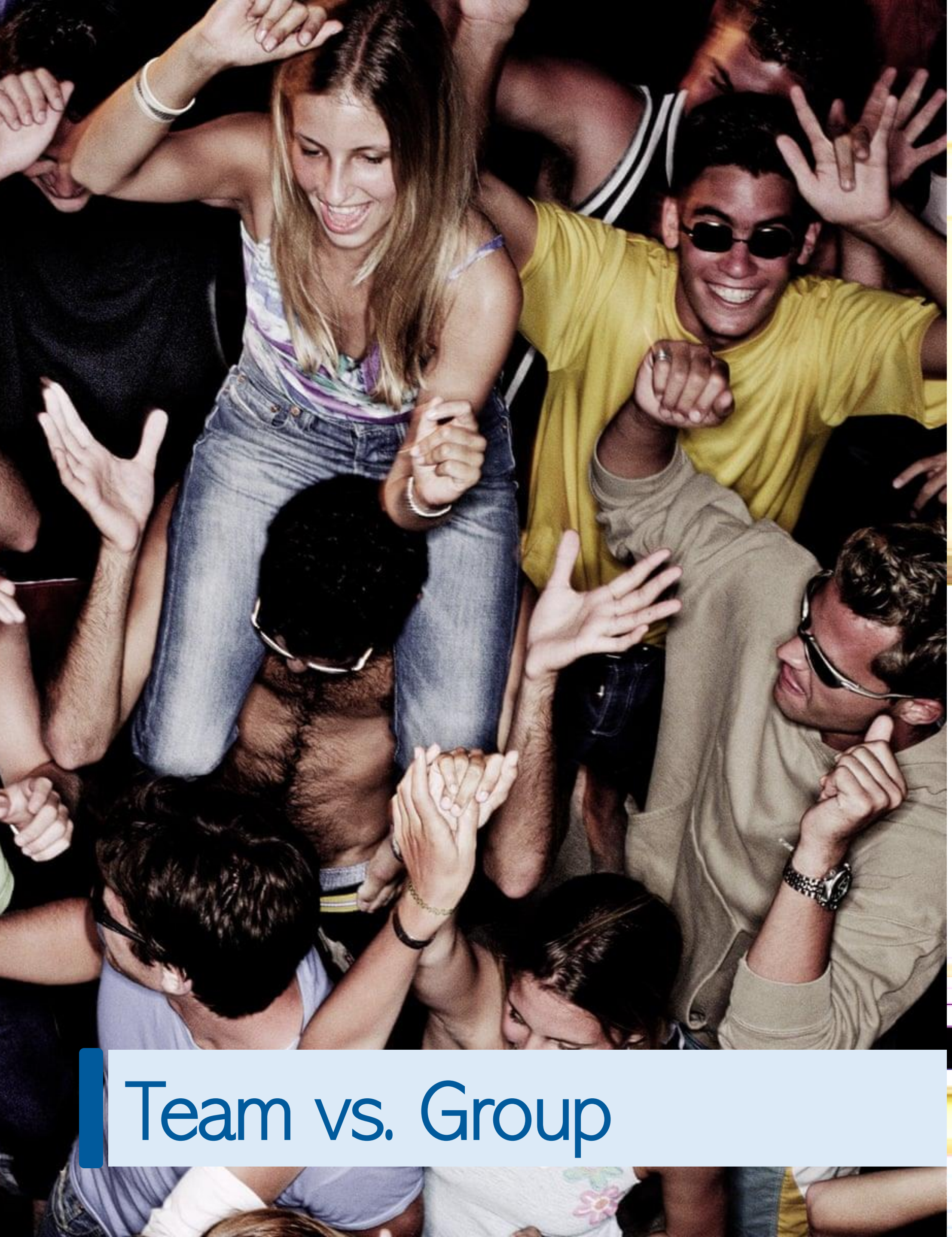
[Brannik et al., Psychology Press, 1997]

What Is a Team?

A group of users who **independently** endeavor to accomplish their individual tasks to reach a **shared goal** or value, while **actively interacting and adapting**.

[Zzkarian et. Al., IIE transactions,1999]

Team vs. Group

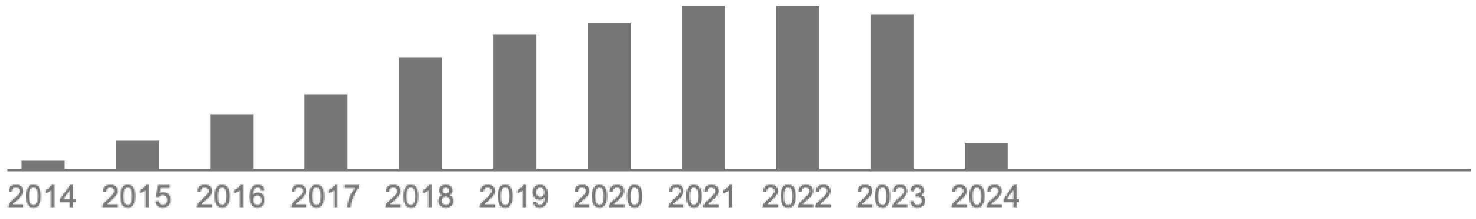


Dead Poet Society, 1998, Peter Weir
Robin Williams: *“we don’t read and write poetry because it’s cute …”*

Group Learning Teams

Efficient estimation of word representations in vector space

Authors	Tomas Mikolov, Kai Chen, Greg Corrado, Jeffrey Dean
Publication date	2013/1/16
Journal	arXiv preprint arXiv:1301.3781
Description	We propose two novel model architectures for computing continuous vector representations of words from very large data sets. The quality of these representations is measured in a word similarity task, and the results are compared to the previously best performing techniques based on different types of neural networks. We observe large improvements in accuracy at much lower computational cost, i.e. it takes less than a day to learn high quality word vectors from a 1.6 billion words data set. Furthermore, we show that these vectors provide state-of-the-art performance on our test set for measuring syntactic and semantic word similarities.
Total citations	Cited by 40332



Science Research Teams

The Big Lebowski, 1998, Joel & Ethan Coen

Entertainment Industry (Cast’nCrew)

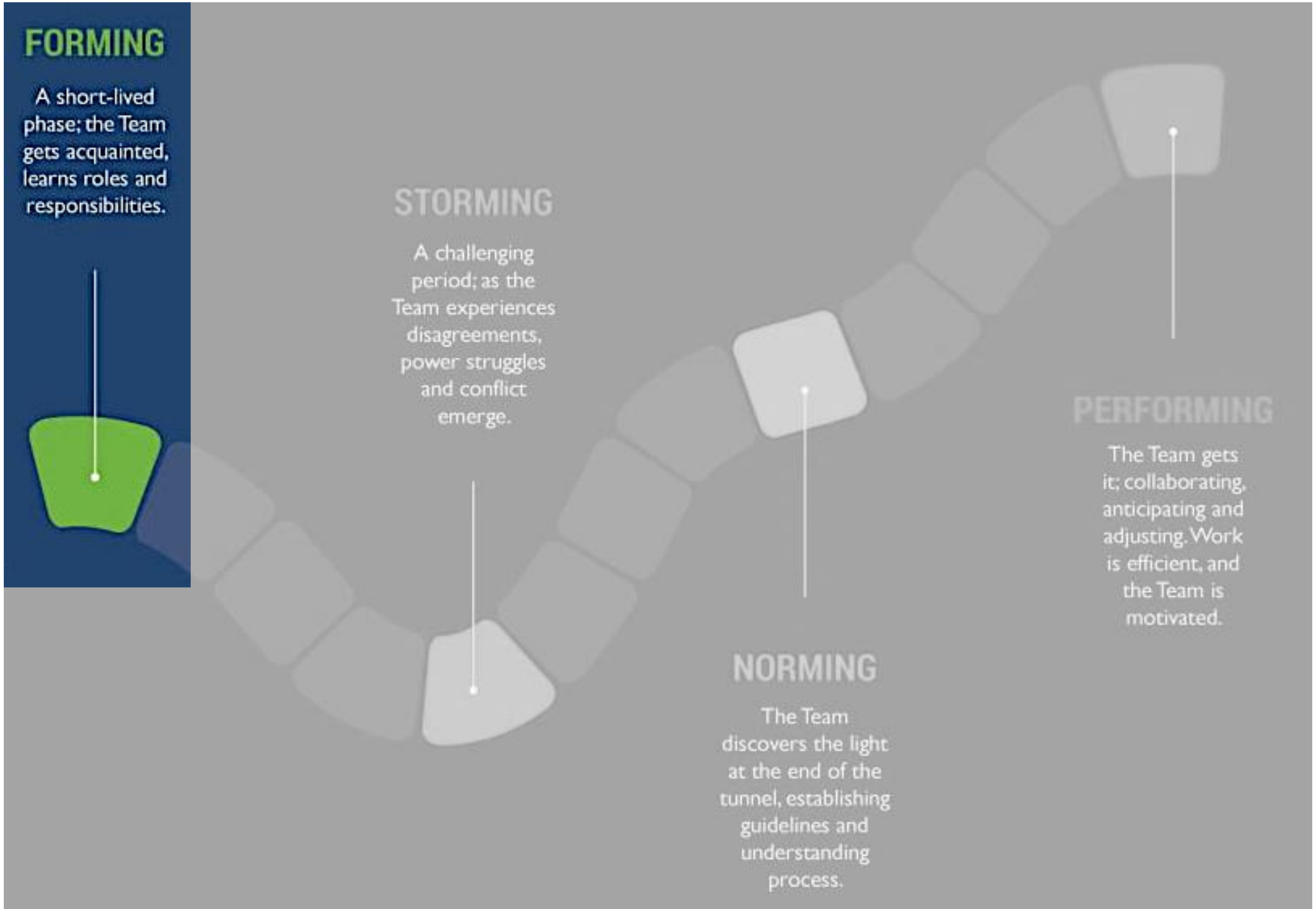

FIFA
WORLD CHAMPIONS
2011
CHAMPIONS
FIFA WOMEN'S WORLD CUP 2011™
GERMANY 2011
FIFA
WOMEN'S WORLD CUP

Sport Teams

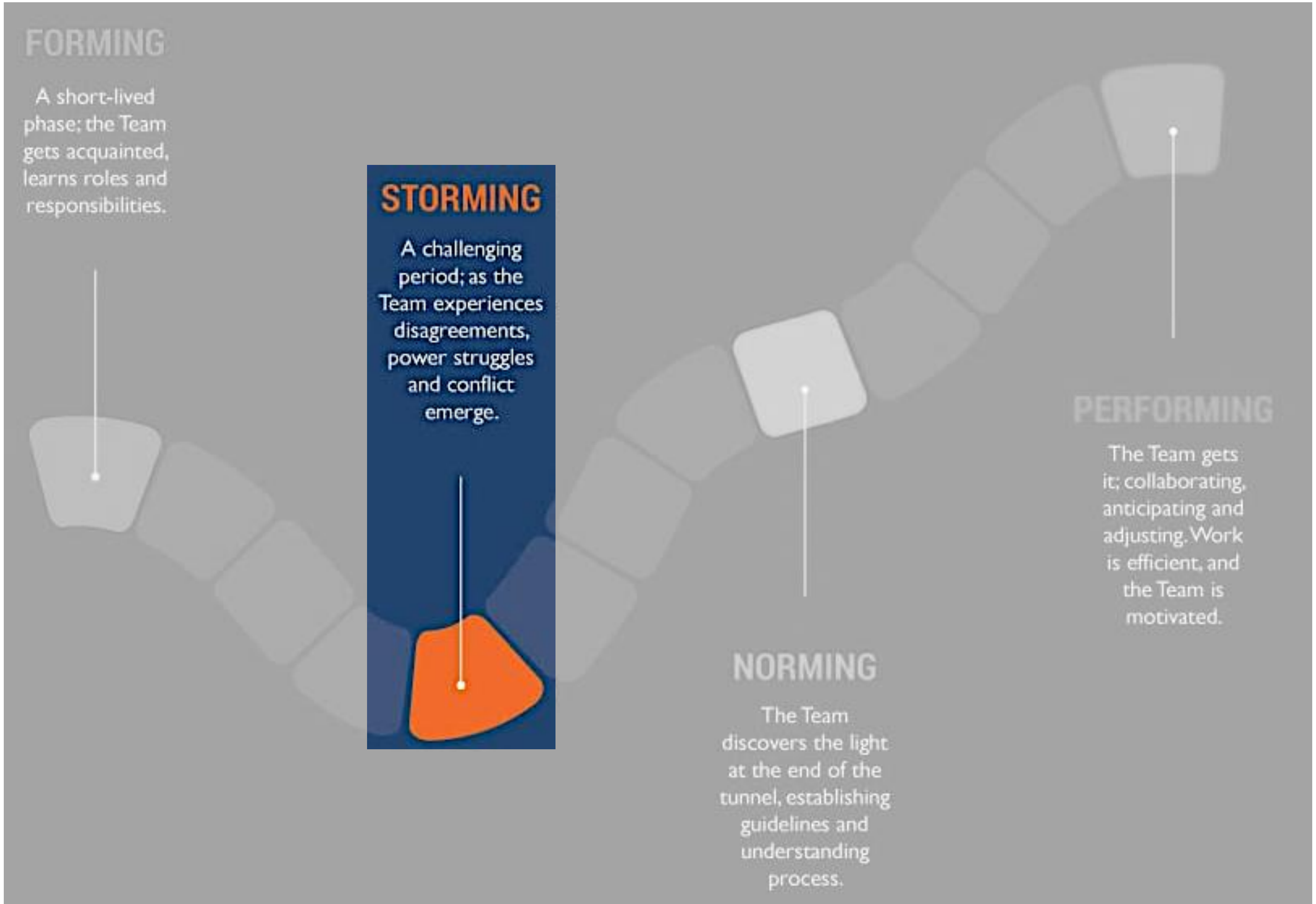
Development for a Team

Four distinct phases of development for a team

[Tuckman et al., Psychological bulletin ,1965]



Developmental sequence in small groups." Psychological bulletin 63.6 (1965): 384.



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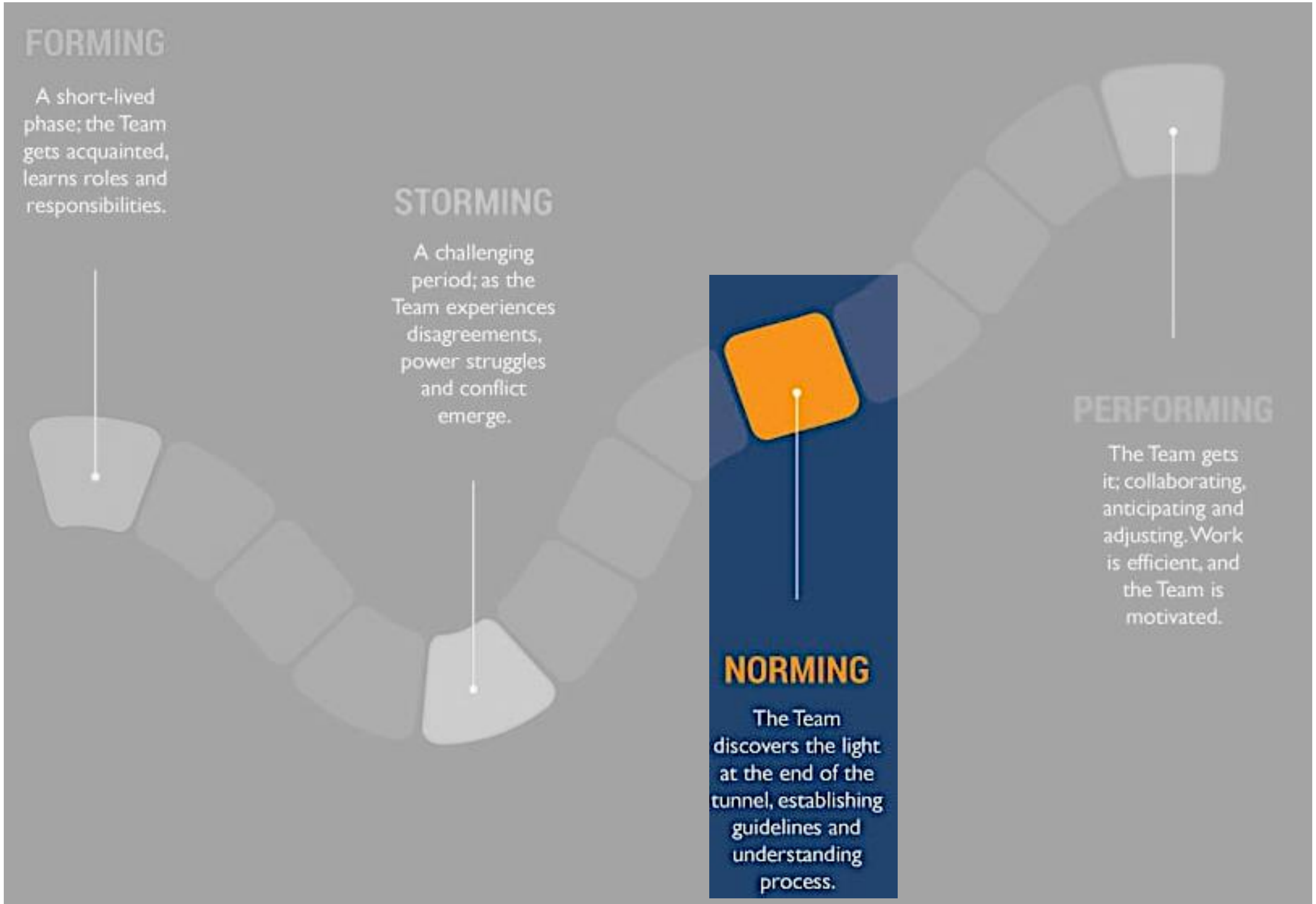

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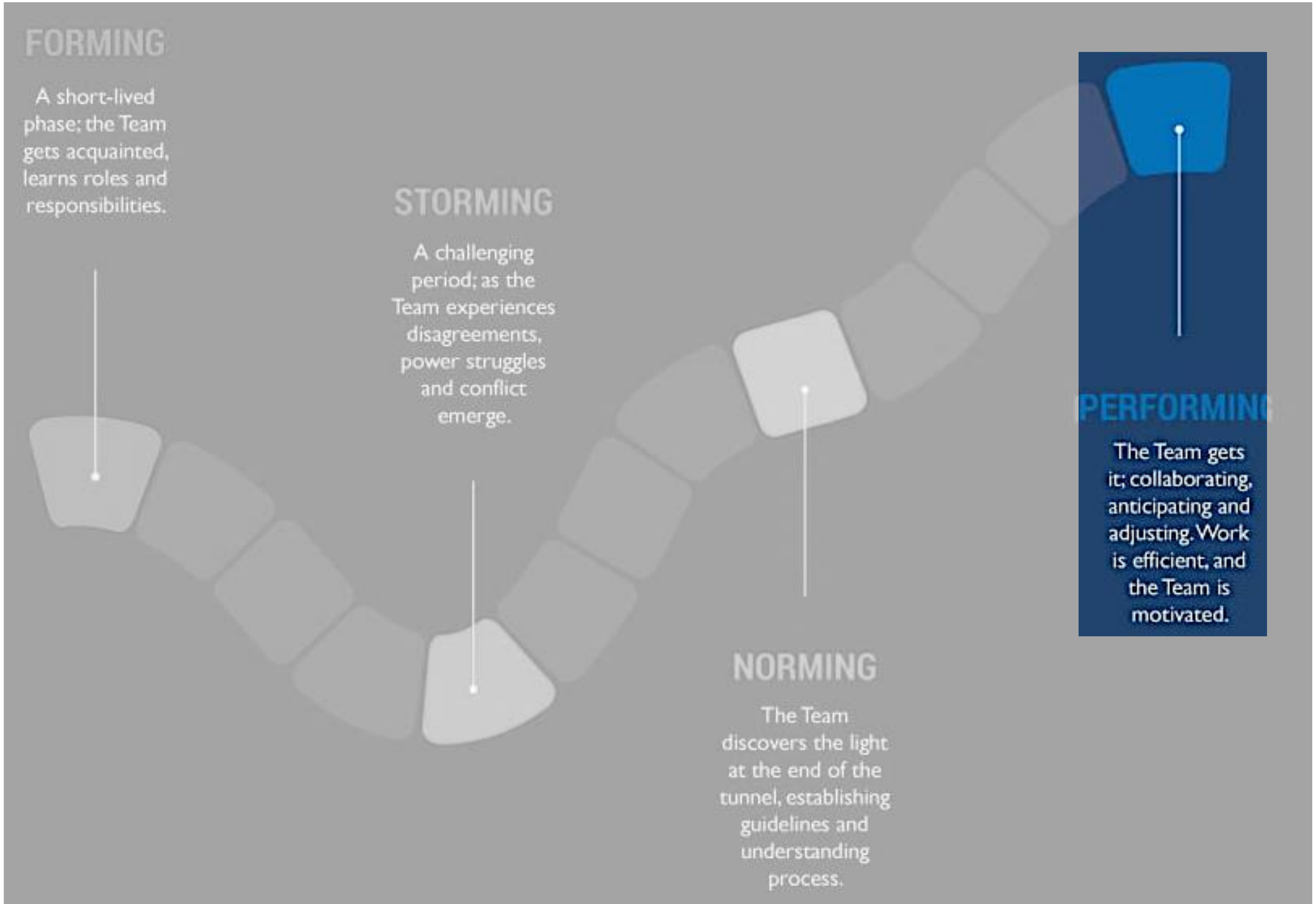

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Team Recommendation

Team Recommendation ↔ Information Retrieval

The anatomy of a large-scale social search engine

Authors: Damon Horowitz, Sepandar D. Kamvar Authors Info & Claims

WWW '10: Proceedings of the 19th international conference on World wide web • Pages 431 - 440
https://doi.org/10.1145/1772690.1772735

Published: 26 April 2010 Publication History

Abstract

We present Aardvark, a social search eng
web input, text message, or voice. Aardva
network most likely to be able to answer
challenge lies in finding the right docume
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Searching the village: models and methods for social search

Authors: Damon Horowitz, Sepandar D. Kamvar Authors Info & Claims

Communications of the ACM, Volume 55, Issue 4 • Pages 111 - 118 • https://doi.org/10.1145/2133806.2133830

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Abstract

We describe Aardvark, a social search engine. With Aardvark, users ask a question, either by instant message, e-mail, Web input, text message, or voice. Aardvark then routes the question to the person in the user's extended social network most likely to be able to answer that question. As compared to a traditional Web search engine, where the challenge lies in finding the right *document* to satisfy a user's information need, the challenge in a social search engine like Aardvark lies in finding the right *person* to satisfy a user's information need. Further, while trust in a traditional search engine is based on authority, in a social search engine like Aardvark, trust is based on intimacy. We describe how these considerations inform the architecture, algorithms, and user interface of Aardvark, and how they are reflected in the behavior of Aardvark users.

Eternal Sunshine of the Spotless Mind, Michel Gondry, 2004

Information Retrieval in a Library: Web Search

Team Recommendation ↔ Information Retrieval

The anatomy of a large-scale social search engine

Authors: Damon Horowitz, Sepandar D. Kamvar | Authors Info & Claims

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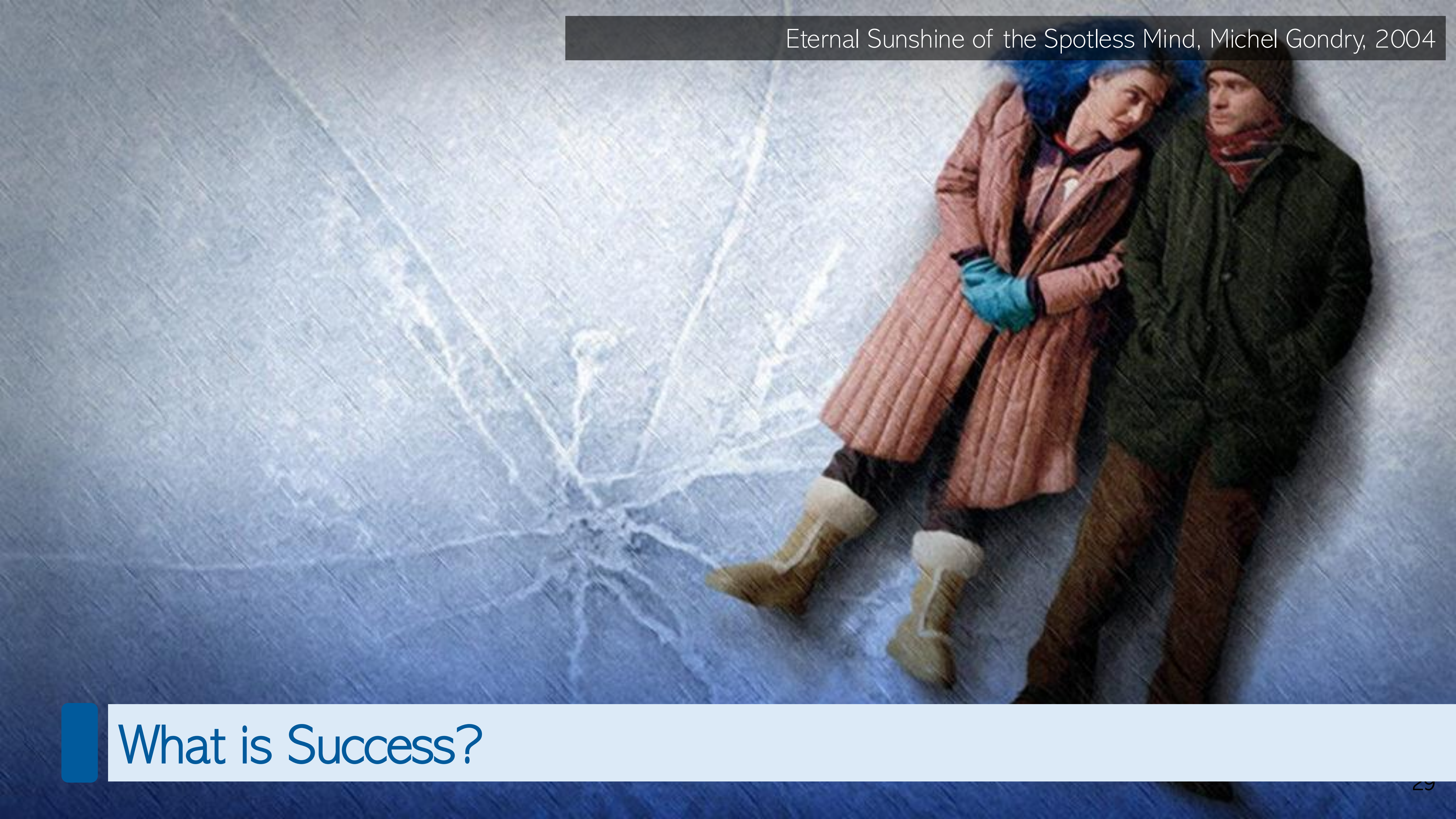
Eternal Sunshine of the Spotless Mind, Michel Gondry, 2004

Information Retrieval in a Village: Social Search

Social Information Retrieval (Social IR)

Eternal Sunshine of the Spotless Mind, Michel Gondry, 2004



What is Success?

What is success?

Japan, Women World Cup 2011

What is success?

US$1.446 billion vs. no Oscar!

Tomas Mikolov

Efficient estimation of word representations in vector space

Authors	Tomas Mikolov, Kai Chen, Greg Corrado, Jeffrey Dean
Publication date	2013/1/16
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Description	We propose two novel model architectures for computing continuous vector representations of words from very large data sets. The quality of these representations is measured in a word similarity task, and the results are compared to the previously best performing techniques based on different types of neural networks. We observe large improvements in accuracy at much lower computational cost, i.e. it takes less than a day to learn high quality word vectors from a 1.6 billion words data set. Furthermore, we show that these vectors provide state-of-the-art performance on our test set for measuring syntactic and semantic word similarities.
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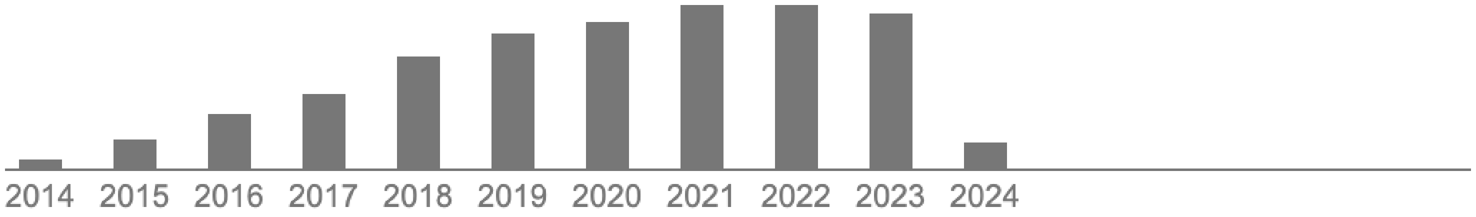


Tomas Mikolov

December 13, 2023 ·

Yesterday we received a Test of Time Award at NeurIPS for the word2vec paper from ten years ago. I'm really happy about it! I think it's the first "best paper" type of award I ever received. In fact, the original word2vec paper was rejected at the first ICLR conference in 2013 (despite the acceptance rate of around 70%), so it made me think how difficult it is for reviewers to predict future impact of research papers.

https://openreview.net/forum?id=idpCdOWtqXd60

https://www.facebook.com/share/p/kXYaYaRvRCr5K2Ze

What is success?

Produced

Releases 50

PyTorch 2.2.1 Release, bug fi... Latest
last month

+ 49 releases

Contributors 3,202

+ 3,188 contributors

Languages

- Python 50.0%
- C++ 40.6%
- Cuda 3.7%
- C 2.0%
- Objective-C++ 1.3%
- CMake 0.8%
- Other 1.6%

Released

US1781541A
United States

Download PDF | Find Prior Art | Similar

Inventor: Einstein Albert, Szilard Leo
Current Assignee : Electrolux Servel Corp

Worldwide applications
1927 · US

Application US24

1927-12-16	Application filed by Electrolux Servel Corp
1930-11-11	Application granted
1930-11-11	Publication of US1781541A
1947-11-11	Anticipated expiration
Status	Expired - Lifetime

Info: Cited by (20), Similar documents, Priority and Related Applications

External links: USPTO, USPTO PatentCenter, USPTO Assignment, Espacenet, Global Dossier, Discuss

Issued

A Streaming Approach to Neural Team Formation Training

Hossein Fani[0000-0002-6033-6564], Reza Barzegar[0009-0002-2831-4143], Arman Dashti[0000-0001-9022-5403], and Mahdis Saeedi[0000-0002-6297-3794]

University of Windsor, Windsor, ON., Canada
{hfani, barzegar, vaghehd, msaeedi}@uwindsor.ca

Abstract. Predicting *future* successful teams of experts who can effectively collaborate is challenging due to the experts' temporality of skill sets, levels of expertise, and collaboration ties, which is overlooked by prior work. Specifically, state-of-the-art neural-based methods learn vector representations of experts and skills in a *static* latent space, falling short of incorporating the possible drift and variability of experts' skills and collaboration ties in time. In this paper, we propose (1) a streaming-based training strategy for neural models to capture the evolution of experts' skills and collaboration ties over time and (2) to consume time information as an additional signal to the model for predicting future successful teams. We empirically benchmark our proposed method against state-of-the-art neural team formation methods and a strong temporal recommender system on datasets from varying domains with distinct distributions of skills and experts in teams. The results demonstrate neural models that utilize our proposed training strategy excel at efficacy in terms of classification and information retrieval metrics. The codebase is available at `https://github.com/fani-lab/OpeNTF/tree/ecir24`.

Keywords: Neural Team Formation · Training Strategy · OpeNTF.

Published

Success

Traditional approach

Teams were formed manually by relying on human experience and instinct in a tedious, error-prone, and suboptimal process.

Difficulties:

- Large number of candidates
  - Different knowledge
  - Different culture
  - Different characteristic
- Hidden personal and societal biases
  - Race
  - Gender
  - Popularity
- Multitude of criteria to optimize
  - Communication cost
  - Budget
  - Time

Traditional approach

Teams were formed manually by relying on human experience and instinct in a tedious, error-prone, and suboptimal process.

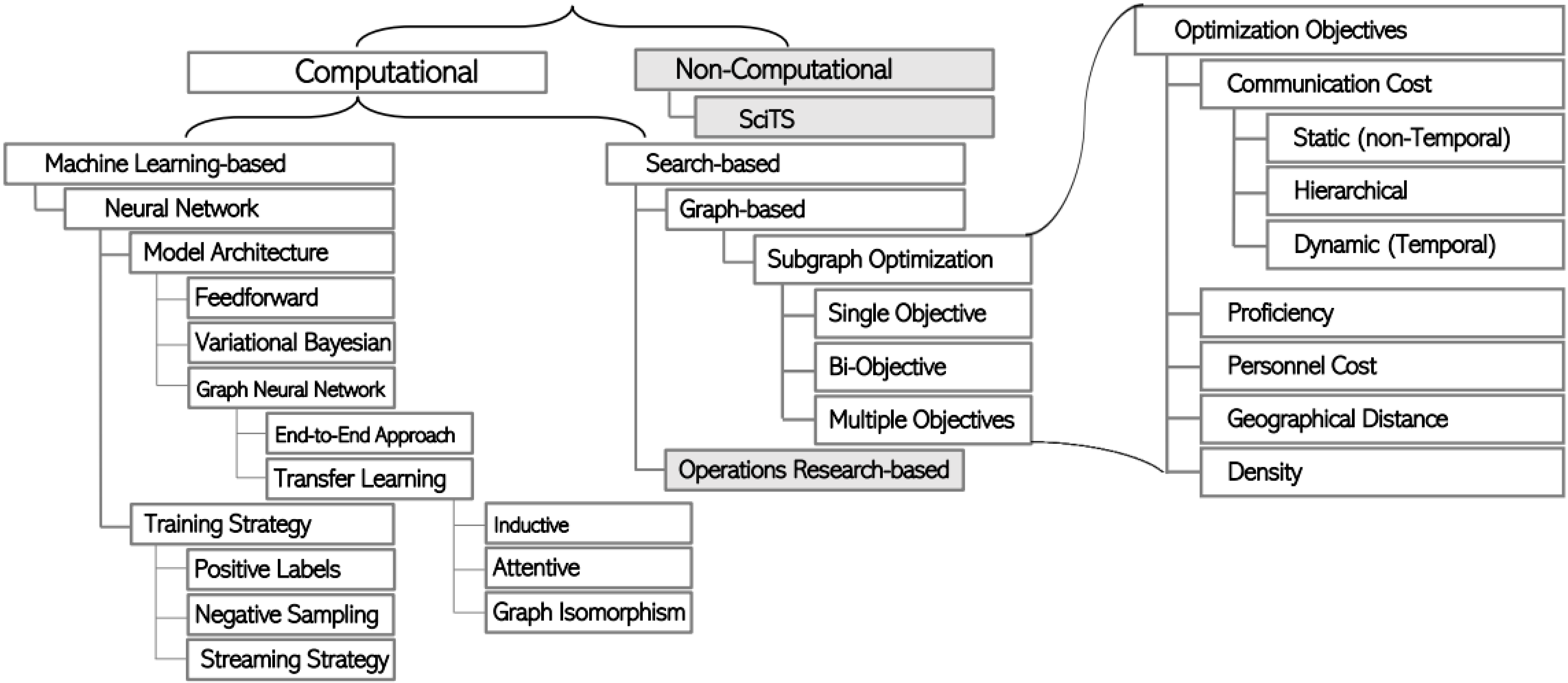
Difficulties:

Manual team recommendation on a large scale is almost impossible

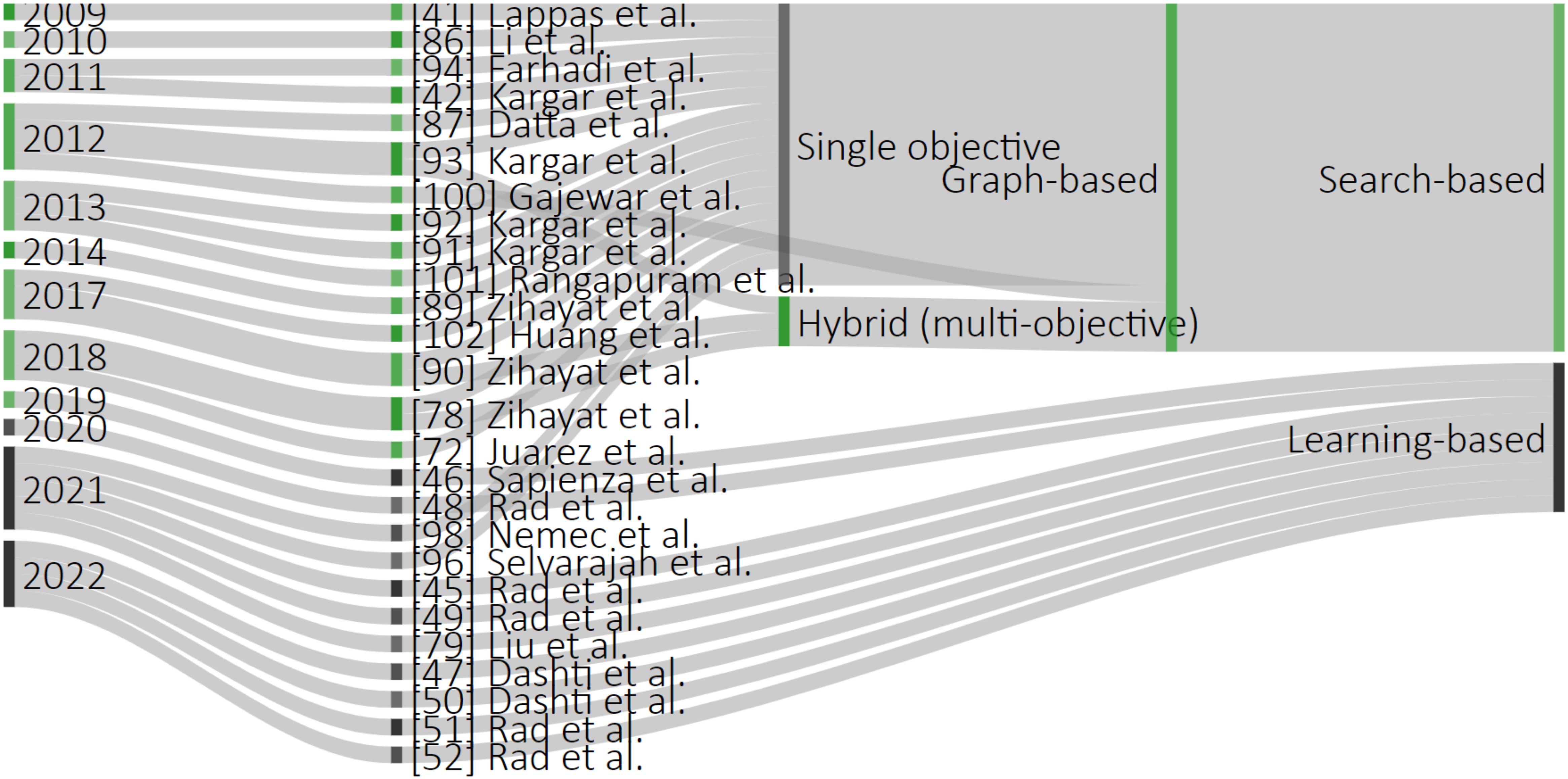
- Race
- Gender
- Popularity

- Multitude of criteria to optimize
  - Communication cost
  - Budget
  - Time

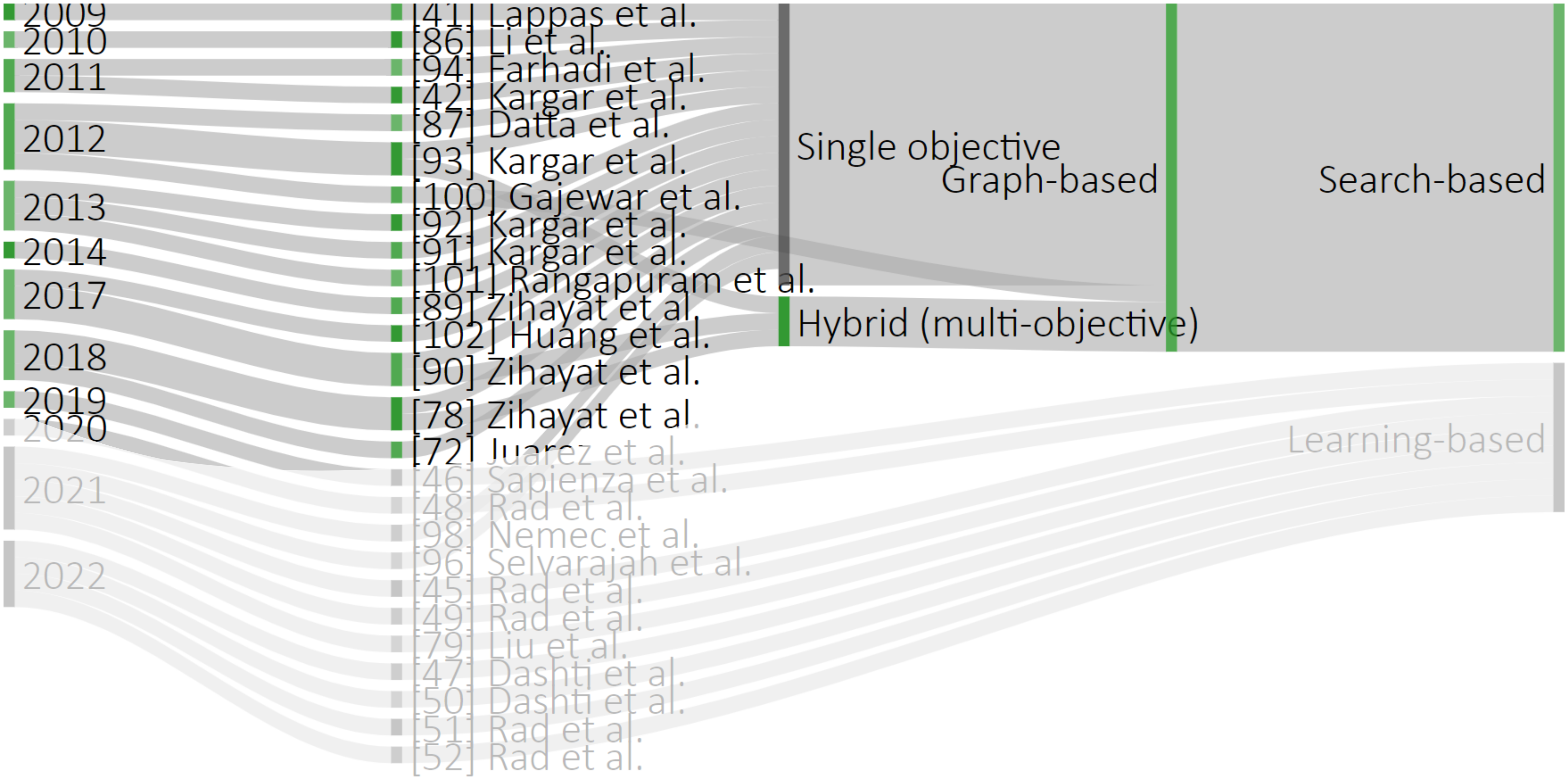
Computational Approach



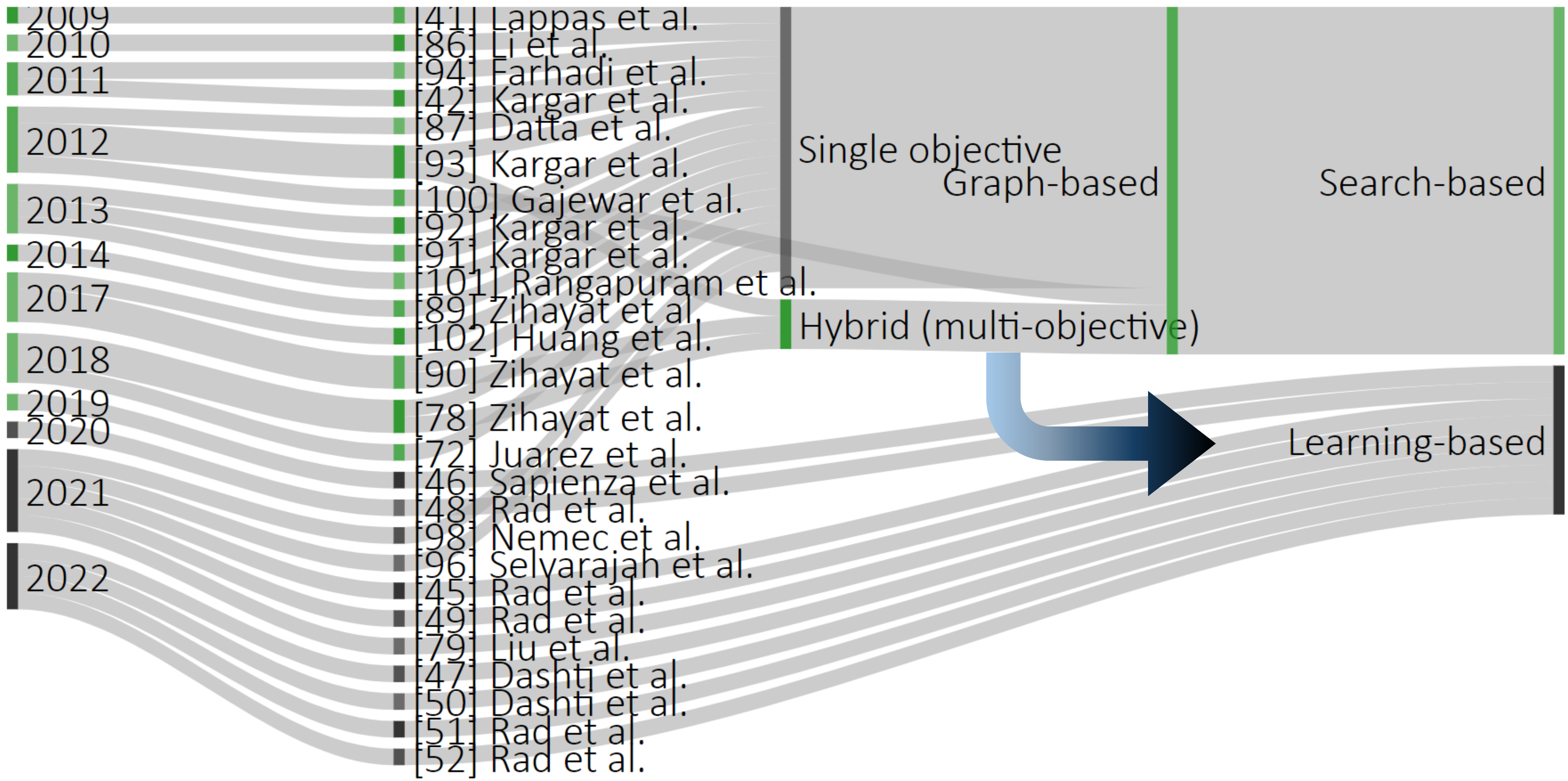
Team Allocation, Team Selection, Team Composition, Team Configuration, Team Recommendation, Team Formation



Team Recommendation Methods in Time



Computationally Prohibitive



Transfer | Distill the Knowledge for Neural Team Recommendation

Outline

I) Introduction and Background

II) Pioneering Techniques

III) Learning-based Heuristics

IV) Challenges and New Perspectives

V) Applications

Hands-on: OpeNTF

Essential Reminder

Core Objective of the Tutorial

Motivation for transforming
strong graph-based optimization technique
into
learning-based methods
for enhanced adaptability and performance.

Graph-based Team Recommendation

Underlying network structure is a key factor to form an effective team.

[Miller, Computational Modeling and Organization Theories. AAAI Press, 2001]
[Gaston et al., Proceedings of the 1st NAACSOS Conference, 2003]
[Gaston et al., AAAI Technical Report, 2004]
[Chen, INCoS, 2010]

- Organizations' inherent hierarchical structure.
- Experts' social and collaborative ties.

Expert Network

The expert network is considered as an attributed graph:
Experts as nodes,
skills as node attributes,
edges as ties between experts.

Synergistic interdisciplinary discoveries from social network analysis and graph theory.

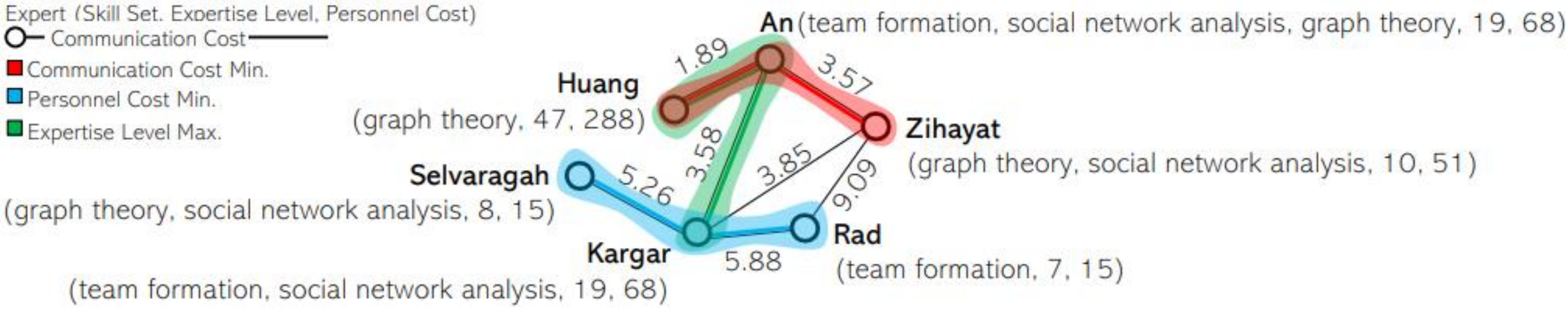
The problem of team recommendation has been translated into graph mining.

Subgraph Optimization

What is the specific implication of this statement?

Subgraph Optimization

What is the specific implication of this statement?



Subgraph Optimization Objectives

- Communication Cost
- Proficiency
- Personnel Cost
- Geographical Distance
- Density
- Multi-Objective

Subgraph Optimization Objectives

- Communication Cost
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- Multi-Objective

Communication Cost (φ)

- A metric to measures how effectively users communicate.
- lower communication cost in a team indicates easier communication, better understanding and collaborations among team members.
- Communication cost ⟷ Team performance

Communication Cost (φ)

Communication cost computations:

Communication Cost (φ)

Communication cost computations:

- $W_{\downarrow}(e) = W(u, v) = 1 - |\frac{P_u \cap P_v}{P_u \cup P_v}| \in R^{[0,1]}$

Communication Cost (φ)

Communication cost computations:

- $W_{\downarrow}(e) = W(u,v) = 1 - |\frac{P_u \cap P_v}{P_u \cup P_v}| \in R^{[0,1]}$

- $W_{\downarrow}(e) = |\frac{1}{P_u \cap P_v}| \in R^{(0,1] \cup \{\infty\}}$

	Year	Hybrid	Communication Cost						Proficiency						
			Diameter	MST	Leader Distance	Sum of Edge Weights	Random Walk	Sum of Distance	Trust Score	Expertise Level	Connector Authority	Skill Holder Authority	Personnel Cost	Geographical Distance	Density
Lappas et al. [43]	2009		✓	✓											
Li et al. [92]	2010			✓											
Farhadi et al. [99] (2011)	2011		✓												
Kargar et al. [44]	2011				✓			✓							
Datta et al. [93] (2012)	2012		✓	✓											
Kargar et al. [98]	2012							✓					✓		
Gajewar et al. [105]	2012														✓
Kargar et al. [97]	2013		✓					✓					✓		
Kargar et al. [96]	2013		✓					✓					✓		
Rangapuram et al. [106]	2013													✓	✓
Zihayat et al. [94]	2014							✓		✓			✓		
Huang et al. [107]	2016				✓			✓							
Zihayat et al. [95]	2017					✓					✓	✓			
Zihayat et al. [84]	2018					✓					✓	✓	✓		
Juarez et al. [78]	2018									✓					✓
Nemec et al. [103]	2021						✓								
Selvarajah et al. [101]	2021							✓	✓					✓	

Objective overview

Communication Cost Minimization Methods

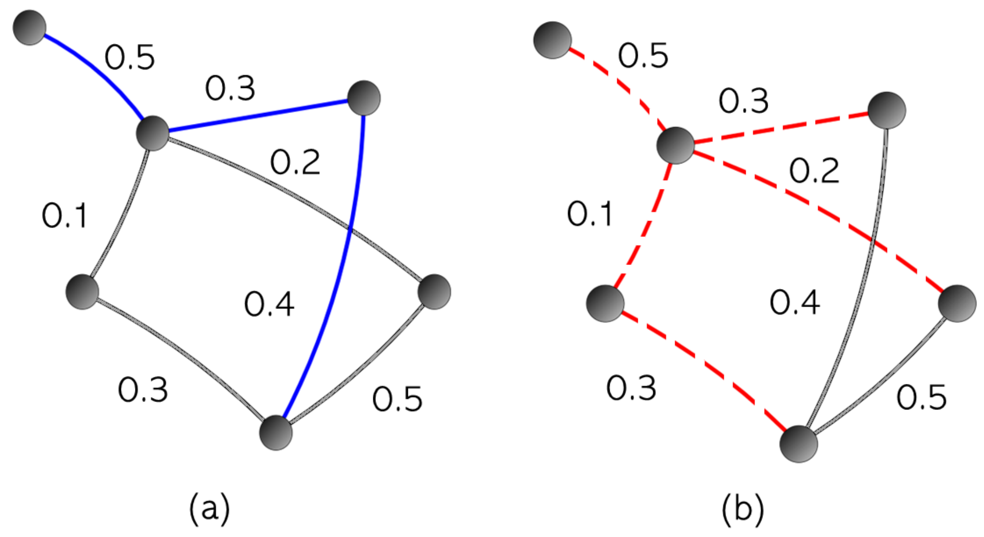
- Non-temporal (Static)
- Temporal (Dynamic)

Communication Cost Minimization Algorithms (φ)

- Non-temporal (Static)
- Temporal (Dynamic)

Non-temporal (Static) Communication Cost

- Sum of distances
- Sum of edge weights
- Diameter of the subgraph
- Cost of the spanning tree



Minimum subgraph based on (a) diameter (solid blue edges) vs. (b) spanning tree (dashed red edges)

Communication Cost Minimization Algorithms

- Non-temporal (Static)

- Temporal (Dynamic)

Temporal (Dynamic) Communication Cost

Temporal (dynamic) communication cost is based on the fact that the least communication cost exists between users who could maintain many successful collaborations over time till recently or currently.

$$\min_{V_P \in \mathcal{P}(G)} \varphi_{DT}(G[V_P]) = \sum_{v,v' \in V_P} d(v,v') + \alpha(t - t')$$

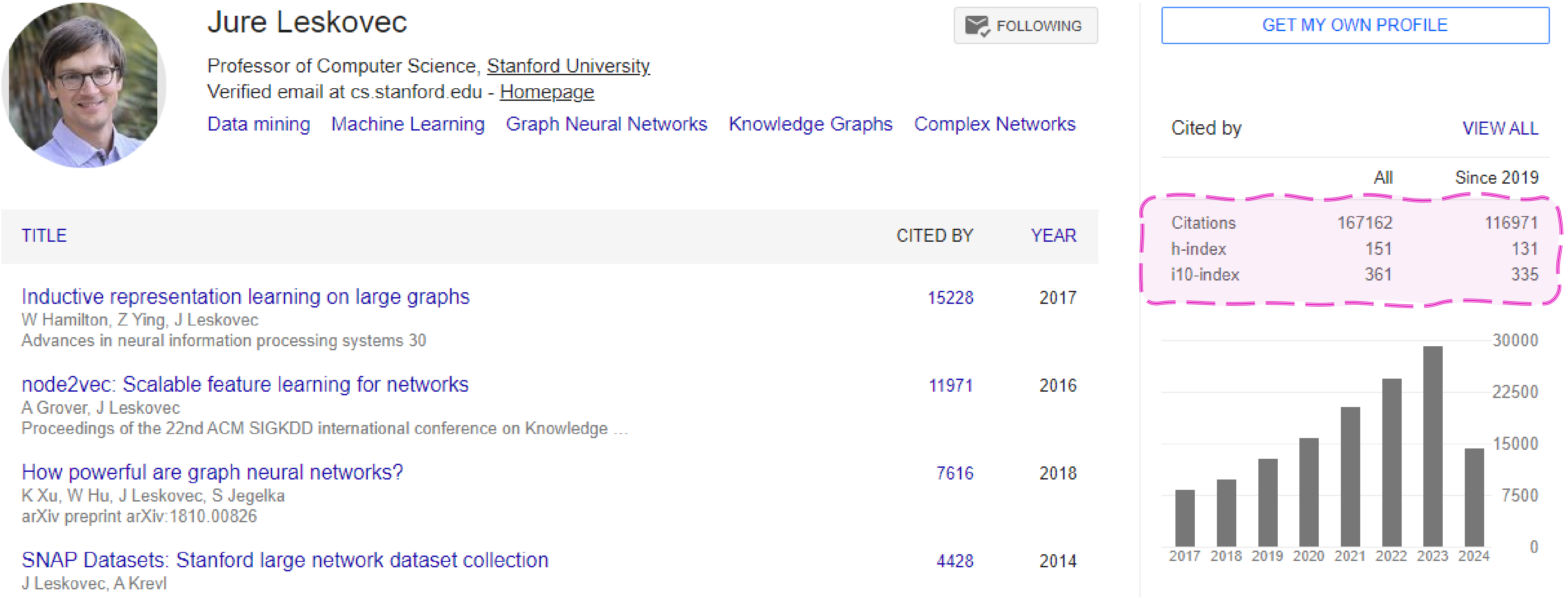
Subgraph Optimization Objectives

- Communication Cost
- Proficiency
- Personnel Cost
- Geographical Distance
- Density
- Multi-Objective

Proficiency(ϕ)

Proficiency of users indicates **the level of expertise** in a particular profession or a skill.

- h-index
- number of citations



Proficiency(ϕ)

Authority [Zihayat et. Al., EDBT, 2017]

Sum of inverse of expertise level

$$\min_{V_P \in \mathcal{P}(G)} \phi(G[V_P]) = \sum_{v \in A} \frac{1}{a_v}$$

			Communication Cost						Proficiency						
	Year	Hybrid	Diameter	MST	Leader Distance	Sum of Edge Weights	Random Walk	Sum of Distance	Trust Score	Expertise Level	Connector Authority	Skill Holder Authority	Personnel Cost	Geographical Distance	Density
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Kargar et al. [44]	2011				✓			✓							
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Gajewar et al. [105]	2012														✓
Kargar et al. [97]	2013		✓					✓					✓		
Kargar et al. [96]	2013		✓					✓					✓		
Rangapuram et al. [106]	2013													✓	✓
Zihayat et al. [94]	2014							✓		✓			✓		
Huang et al. [107]	2016				✓			✓							
Zihayat et al. [95]	2017					✓					✓	✓			
Zihayat et al. [84]	2018					✓					✓	✓	✓		
Juarez et al. [78]	2018									✓					✓
Nemec et al. [103]	2021						✓								
Selvarajah et al. [101]	2021							✓	✓					✓	

Objective overview

Multi-Objective Optimization

- Communication cost and proficiency
  [Zihayat et. al., AMW, 2018]
  [Zihayat et. al., EDBT, 2017]

- Communication cost and personnel cost
  [Aijun et. al., SDM, 2013]
  [Kargar et. al., CSE, 2013]
  [Zihayat et. al., AMW, 2018]

- Density and proficiency
  [Juarez et. al., GECCO., 2018]

- Communication cost, personnel cost and proficiency
  [Zihayat et. al., WI-IAT, 2014]

- Dynamic communication cost, geographical proximity, and proficiency
  [Selvarajah et. al., Expert Syst. Appl., 2021]

	Year	Hybrid	Communication Cost: Diameter	Communication Cost: MST	Communication Cost: Leader Distance	Communication Cost: Sum of Edge Weights	Communication Cost: Random Walk	Communication Cost: Sum of Distance	Proficiency: Trust Score	Proficiency: Expertise Level	Proficiency: Connector Authority	Proficiency: Skill Holder Authority	Personnel Cost	Geographical Distance	Density
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Kargar et al. [98]	2012							✓					✓		
Gajewar et al. [105]	2012														✓
Kargar et al. [97]	2013		✓					✓					✓		
Kargar et al. [96]	2013		✓					✓					✓		
Rangapuram et al. [106]	2013													✓	✓
Zihayat et al. [94]	2014							✓		✓			✓		
Huang et al. [107]	2016				✓			✓							
Zihayat et al. [95]	2017					✓					✓	✓			
Zihayat et al. [84]	2018					✓					✓	✓	✓		
Juarez et al. [78]	2018									✓					✓
Nemec et al. [103]	2021						✓								
Selvarajah et al. [101]	2021							✓	✓					✓	

Objective overview

Pioneering Techniques

- Subgraph Optimization Objectives
- Subgraph Optimization Algorithms

Subgraph Optimization Algorithms

Subgraph optimization problems are proven to be NP-hard
[Karp, Complexity of computer computations, Springer, 2010]

Heuristics have been developed to solve this problem in polynomial time through greedy and approximation algorithms.

Communication Cost Minimization Algorithms

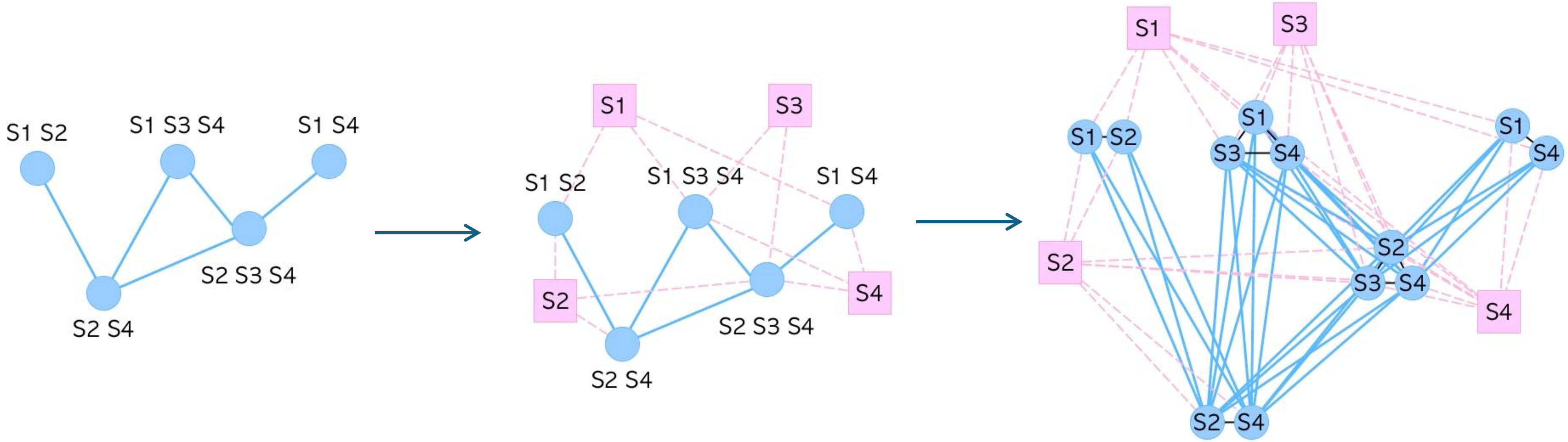
Lappas et al. is the first attempt to form a team based on the subgraph optimization on the user network. [Lappas et. al., KDD, 2009]

Key Concept: Reducing the cost of communication between team members.

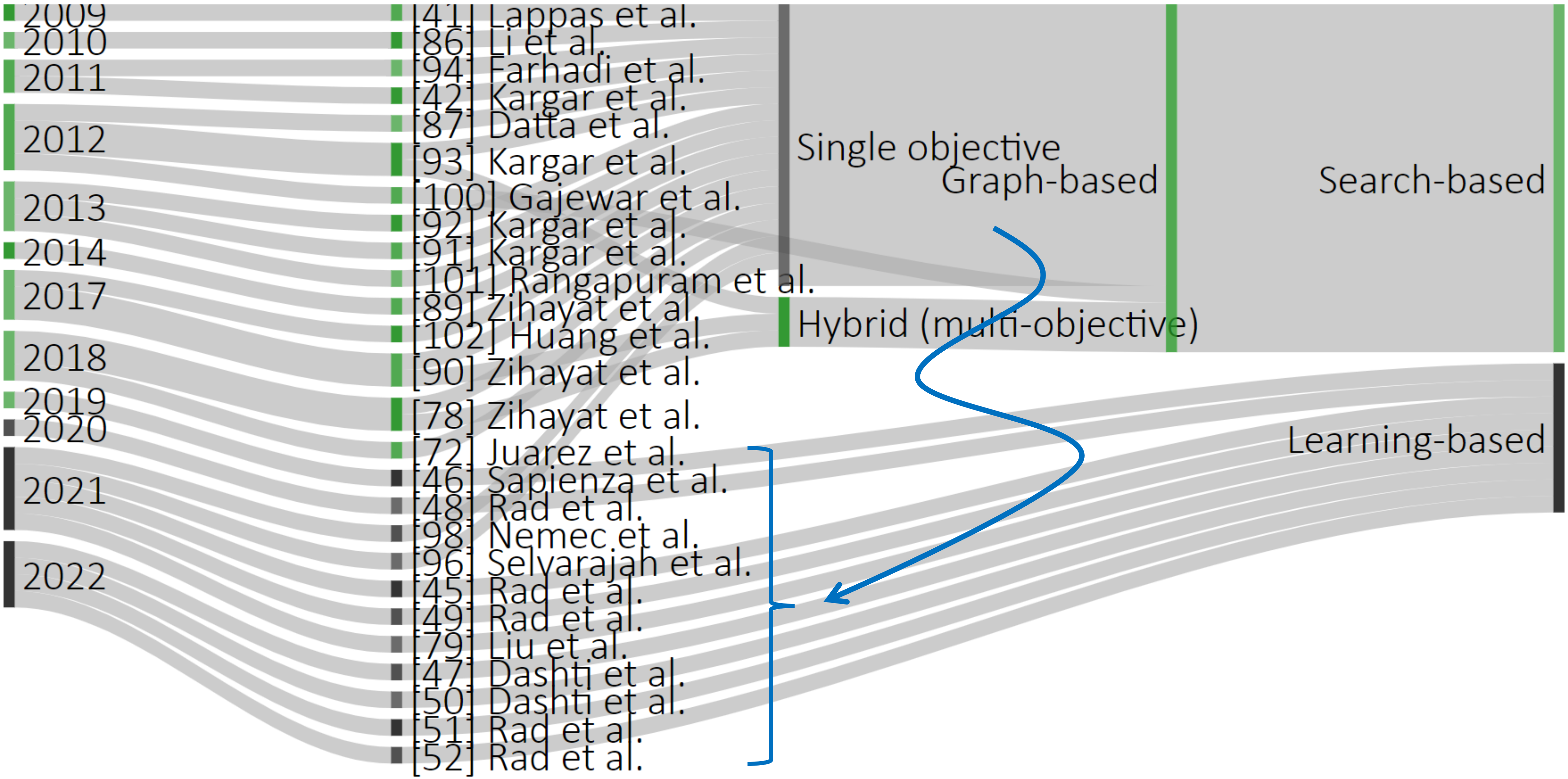
- Diameter-Based Optimization RarestFirst
- Spanning Tree-Based Optimization CoverSteiner and EnhancedSteiner

Communication Cost Minimization Algorithms

Graph extension of EnhancedSteiner Algorithm



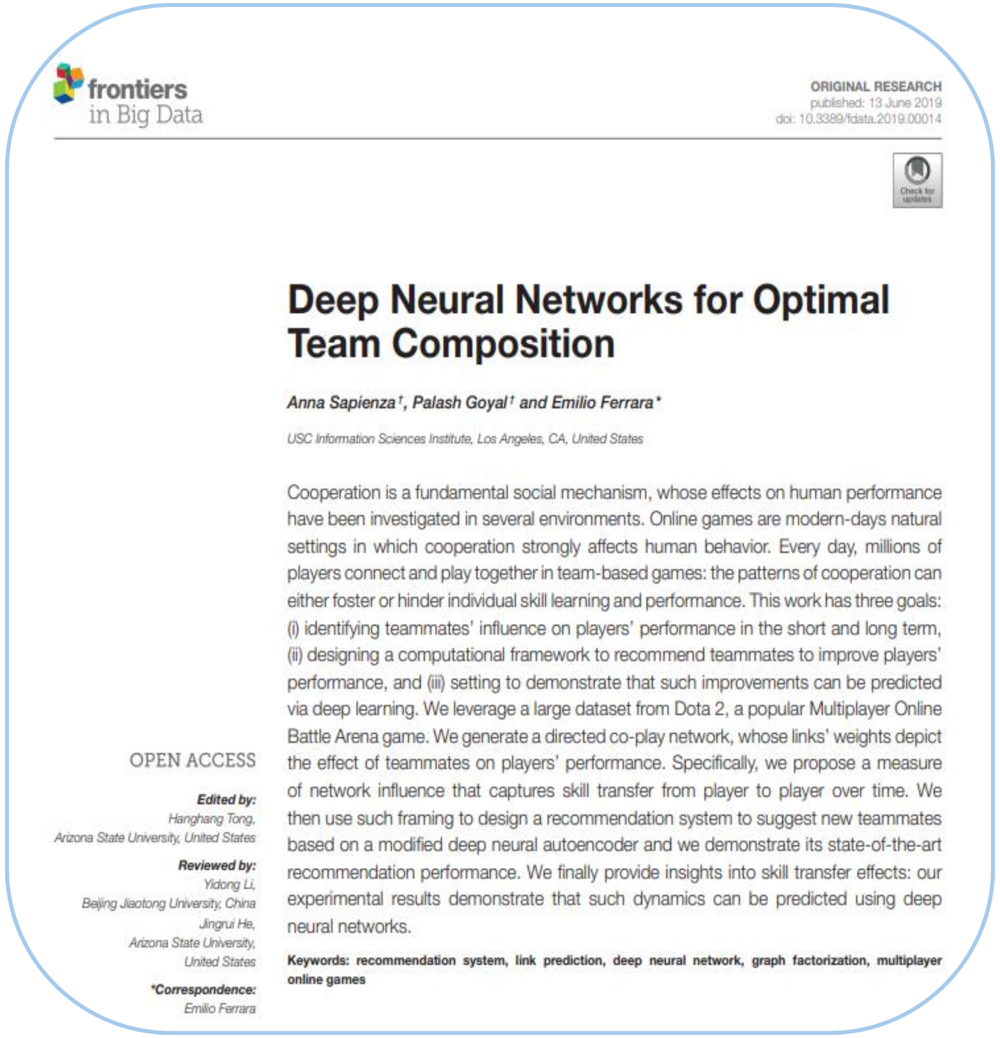
Outline



Team Recommendation Works in Time

Learning-based Heuristics

Paradigm Shift to Learning-Based Methods


frontiers in Big Data
ORIGINAL RESEARCH
published: 13 June 2019
doi: 10.3389/fdata.2019.00014

Check for updates

Deep Neural Networks for Optimal Team Composition

Anna Sapienza[†], Palash Goyal[†] and Emilio Ferrara*

USC Information Sciences Institute, Los Angeles, CA, United States

Cooperation is a fundamental social mechanism, whose effects on human performance have been investigated in several environments. Online games are modern-days natural settings in which cooperation strongly affects human behavior. Every day, millions of players connect and play together in team-based games: the patterns of cooperation can either foster or hinder individual skill learning and performance. This work has three goals: (i) identifying teammates' influence on players' performance in the short and long term, (ii) designing a computational framework to recommend teammates to improve players' performance, and (iii) setting to demonstrate that such improvements can be predicted via deep learning. We leverage a large dataset from Dota 2, a popular Multiplayer Online Battle Arena game. We generate a directed co-play network, whose links' weights depict the effect of teammates on players' performance. Specifically, we propose a measure of network influence that captures skill transfer from player to player over time. We then use such framing to design a recommendation system to suggest new teammates based on a modified deep neural autoencoder and we demonstrate its state-of-the-art recommendation performance. We finally provide insights into skill transfer effects: our experimental results demonstrate that such dynamics can be predicted using deep neural networks.

Keywords: recommendation system, link prediction, deep neural network, graph factorization, multiplayer online games

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Learning-based Heuristics

Paradigm Shift to Learning-Based Methods

- Autoencoder architecture
- Using the history of past teams for a game
- Form a new successful team

frontiers in Big Data
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Deep Neural Networks for Optimal Team Composition

Anna Sapienza†, *Palash Goyal*† *and Emilio Ferrara**

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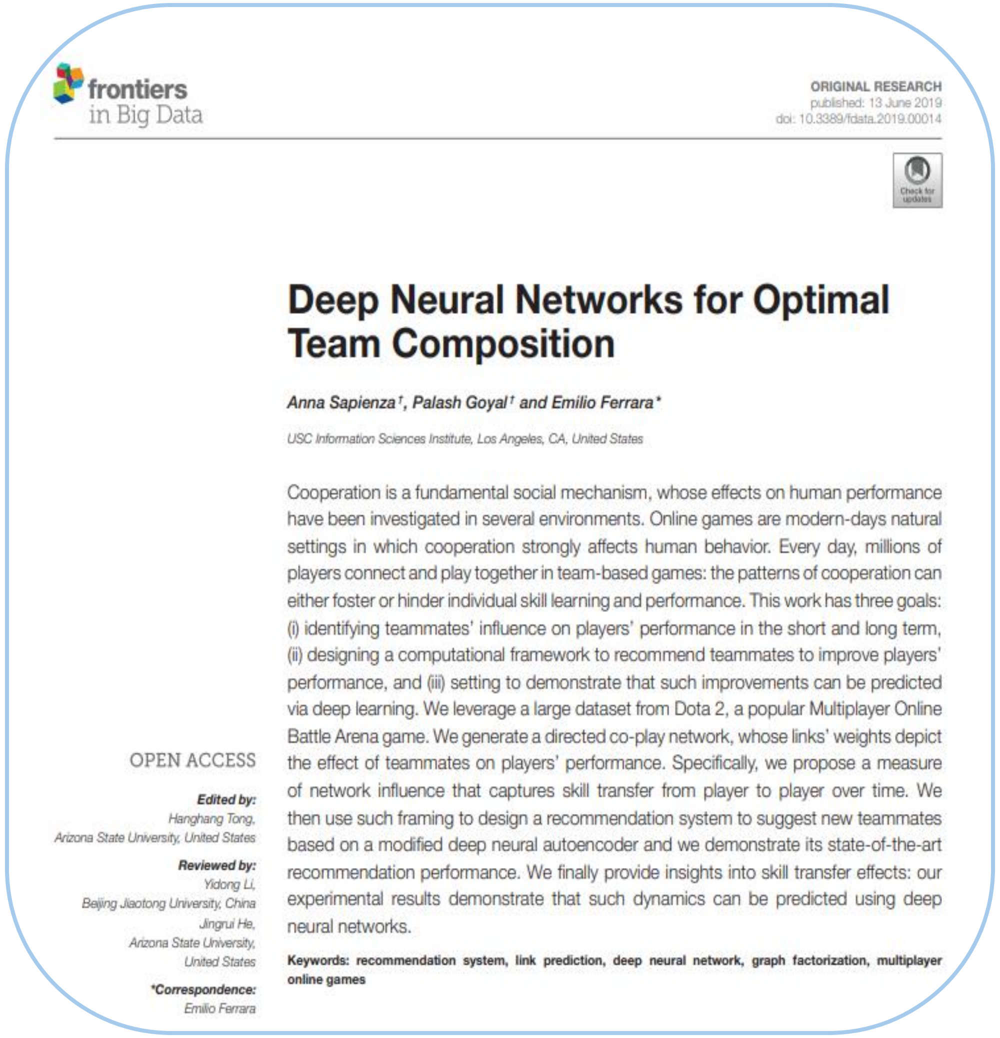
Paradigm Shift to Learning-Based Methods

- Learn the inherent structure of ties among users and their skills.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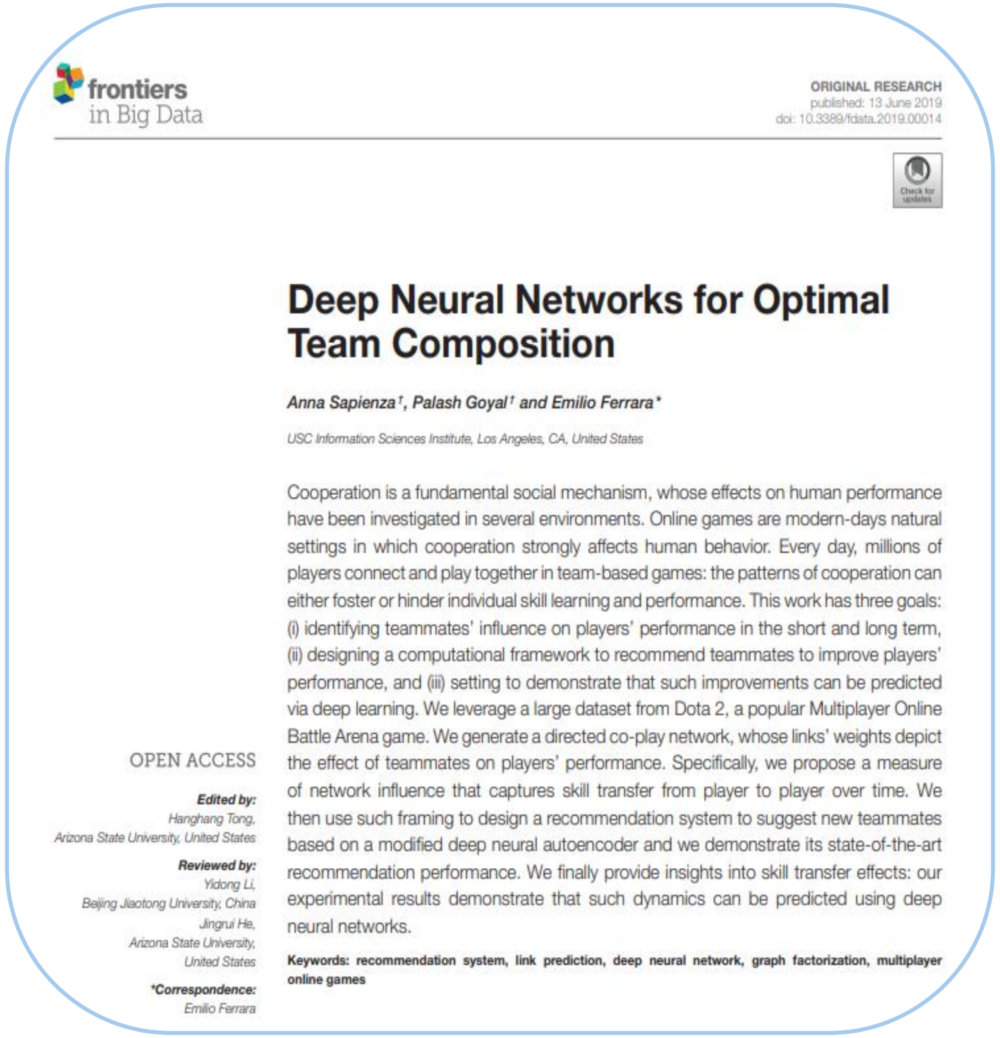
Learning-based Heuristics

Paradigm Shift to Learning-Based Methods

- Learn the inherent structure of ties among users and their skills.
- Utilize all past (un)successful team compositions as training samples.



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Learning-based Heuristics

Paradigm Shift to Learning-Based Methods

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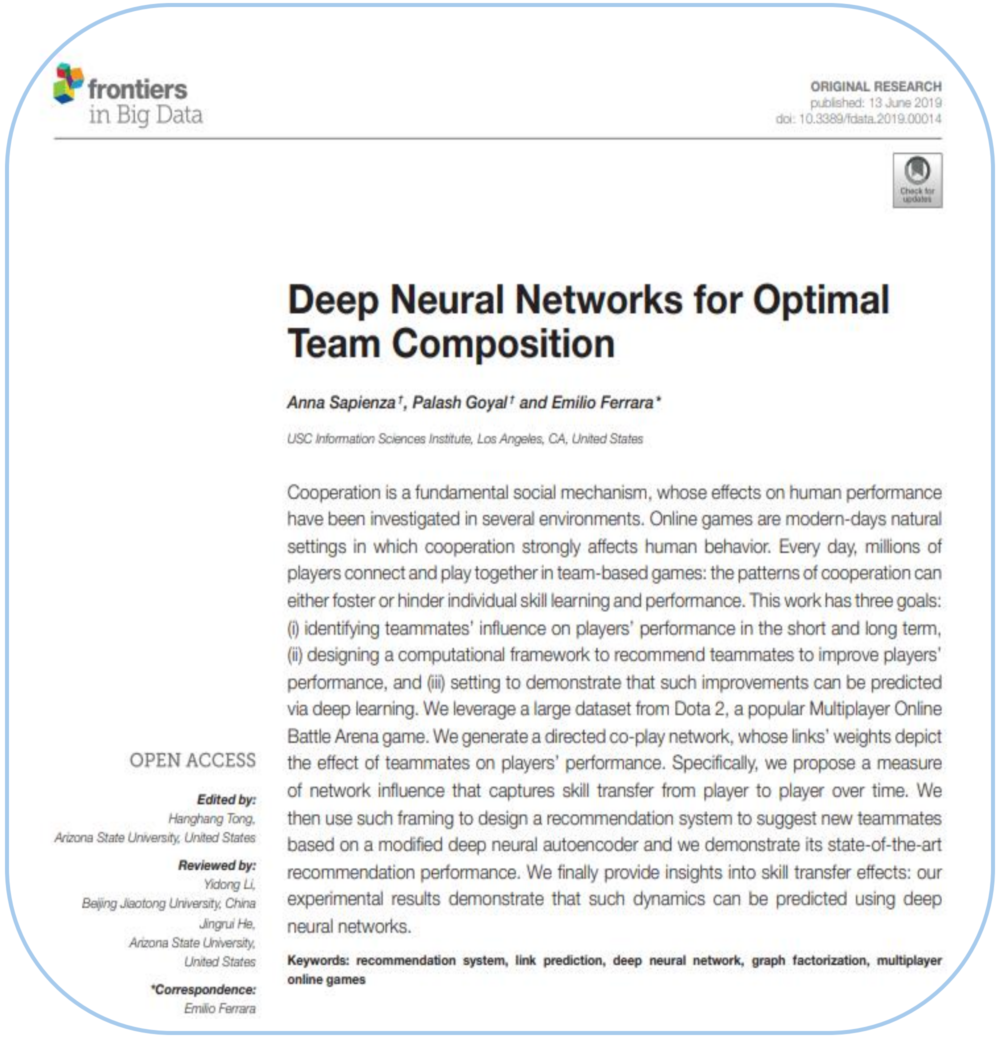
- Utilize all past (un)successful team compositions as training samples.
- Predict future teams and their performance.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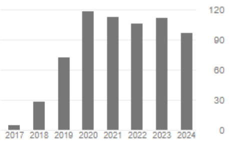

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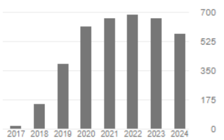

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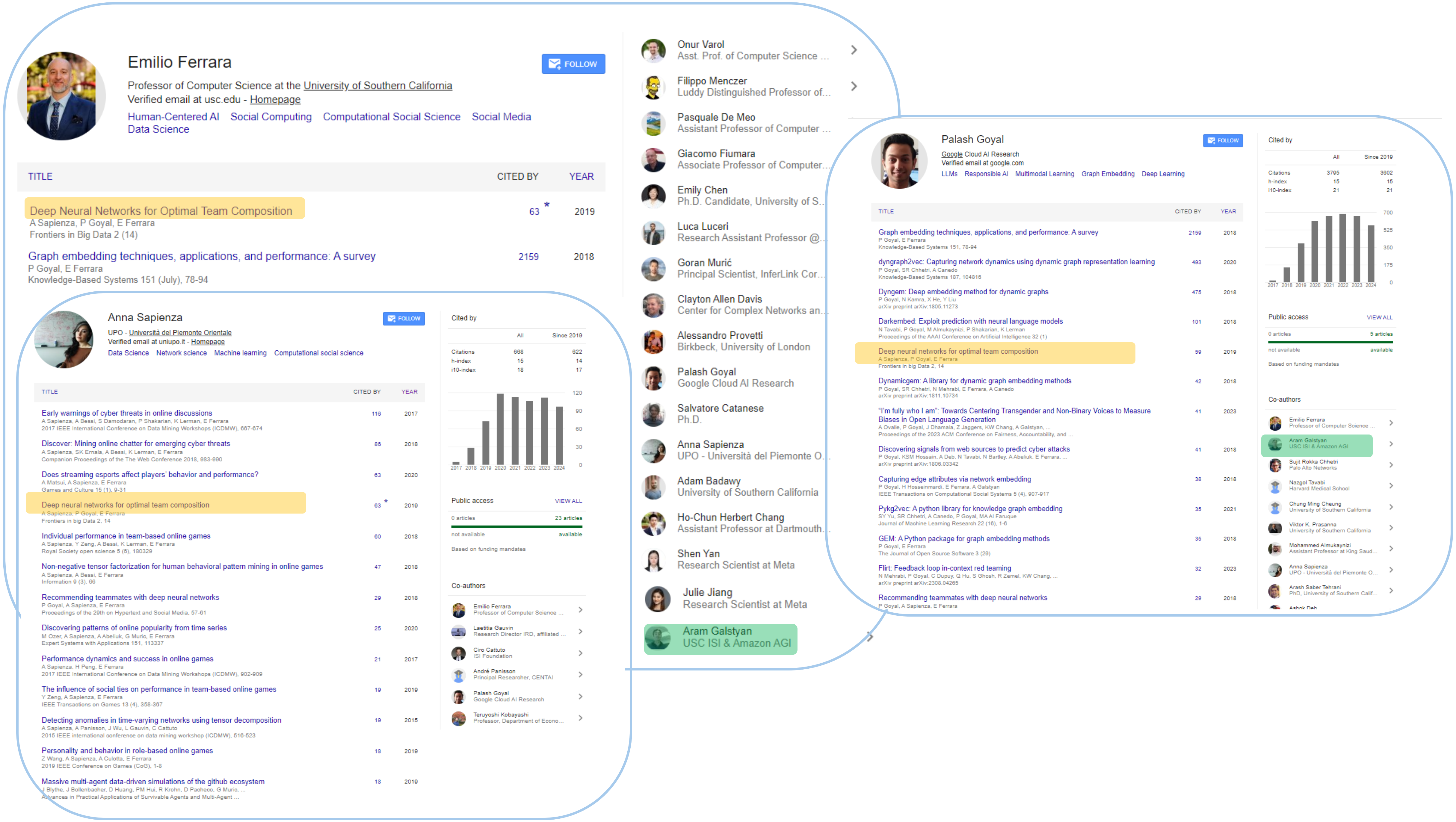
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Learning-based Heuristics

Advantages of Learning-Based Methods:

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- Dynamic Adaptation: Better suited for temporal conditions.

Learning-based Heuristics

Introductory Definitions:

- Team
- Team Recommendation

Learning-based Heuristics

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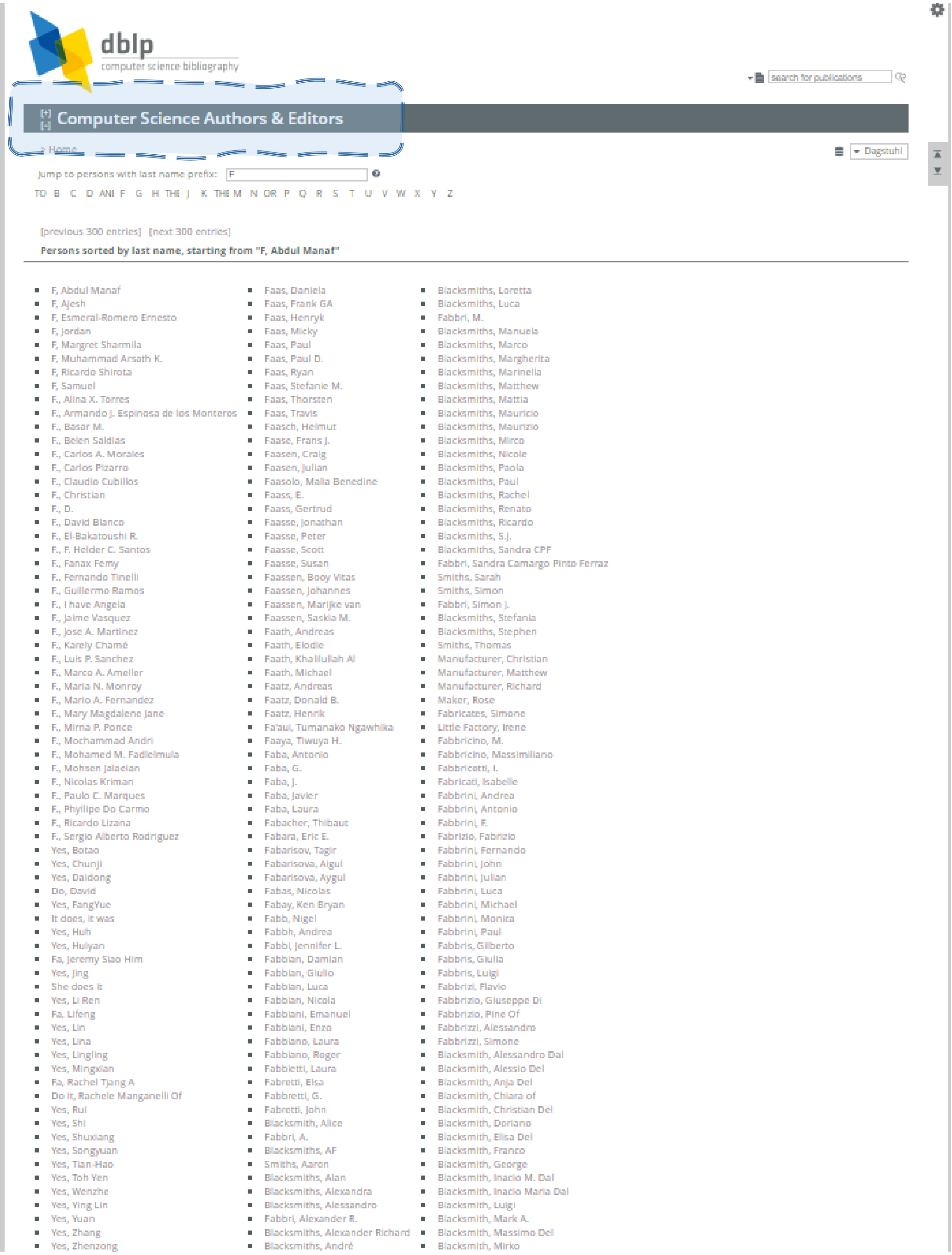
Learning-based Heuristics

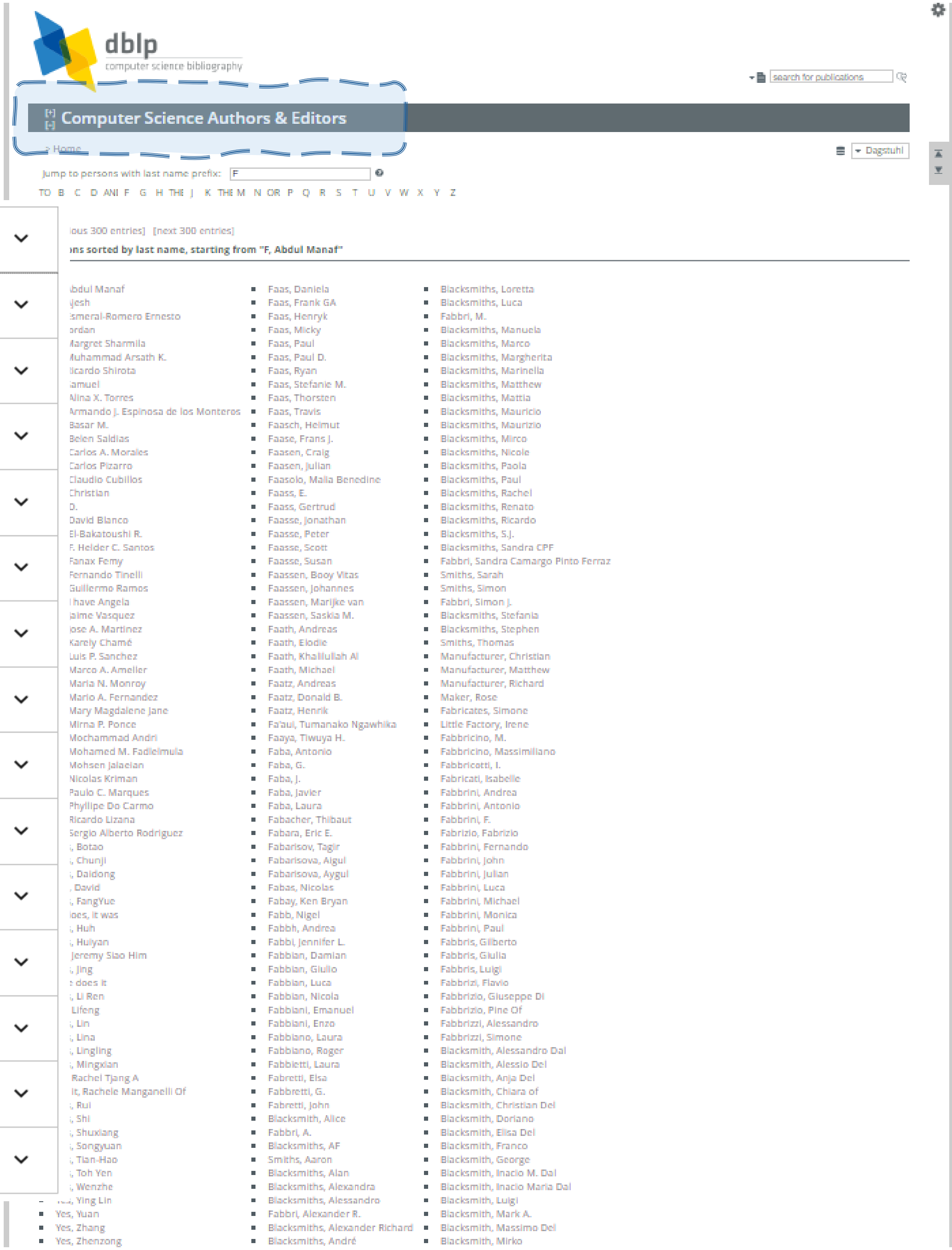
Team



Learning-based Heuristics

Team

- Artificial Intelligence (AI)
- Computational Biology
- Computational Medicine
- Computer Graphics
- Computer Science & Education
- Data Management Systems
- Human-Computer Interaction (HCI)
- Programming Languages & Formal Methods
- Quantum Computing
- Scientific Computing (SC)
- Systems & Networks (SN)
- Social Networks
- Software Engineering
- Sustainability Informatics
- Theoretical Computer Science



Learning-based Heuristics

Team

Given a set of **skills** $S=\{i\}$ and a set of **users** $E=\{j\}$, a team of users $e \subset E$; $e \neq \emptyset$ that collectively cover the skill set $s \subset S$; $s \neq \emptyset$ is shown by (s,e) along with its **success status** $y \in \{0,1\}$. Further, $T = \{(s,e)_y : y \in \{0,1\}\}$ indexes all previous teams.

Hossein Fani[✉], Reza Barzegar, Arman Dashti, and Mahdis Saeedi

Learning-based Heuristics

Team

Given a set of skills S ={i} and a set of users E ={j}, a team of users e⊂E ; e ≠ ∅ that collectively cover the skill set s⊆S ; s ≠ ∅ is shown by (s,e) along with its success status y∈{0,1}. Further, $T = \{(s,e)_y$: y∈{0,1}} indexes all previous teams.

Hossein Fani(✉), Reza Barzegar, Arman Dashti, and Mahdis Saeedi

Keywords: Neural Team Formation · Training Strategy · OpeNTF

Learning-based Heuristics

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A Streaming Approach to Neural Team Formation Training

Hossein Fani(✉), Reza Barzegar, Arman Dashti, and Mahdis Saeedi

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Abstract. Predicting *future* successful teams of experts who can effectively collaborate is challenging due to the experts' temporality of skill sets, levels of expertise, and collaboration ties, which is overlooked by prior work. Specifically, state-of-the-art neural-based methods learn vector representations of experts and skills in a *static* latent space, falling short of incorporating the possible drift and variability of experts' skills and collaboration ties in time. In this paper, we propose (1) a streaming-based training strategy for neural models to capture the evolution of experts' skills and collaboration ties over time and (2) to consume time information as an additional signal to the model for predicting future successful teams. We empirically benchmark our proposed method against state-of-the-art neural team formation methods and a strong temporal recommender system on datasets from varying domains with distinct distributions of skills and experts in teams. The results demonstrate neural models that utilize our proposed training strategy excel at efficacy in terms of classification and information retrieval metrics. The codebase is available at https://github.com/fani-lab/OpeNTF/tree/ecir24.

Keywords: Neural Team Formation · Training Strategy · OpeNTF

Learning-based Heuristics

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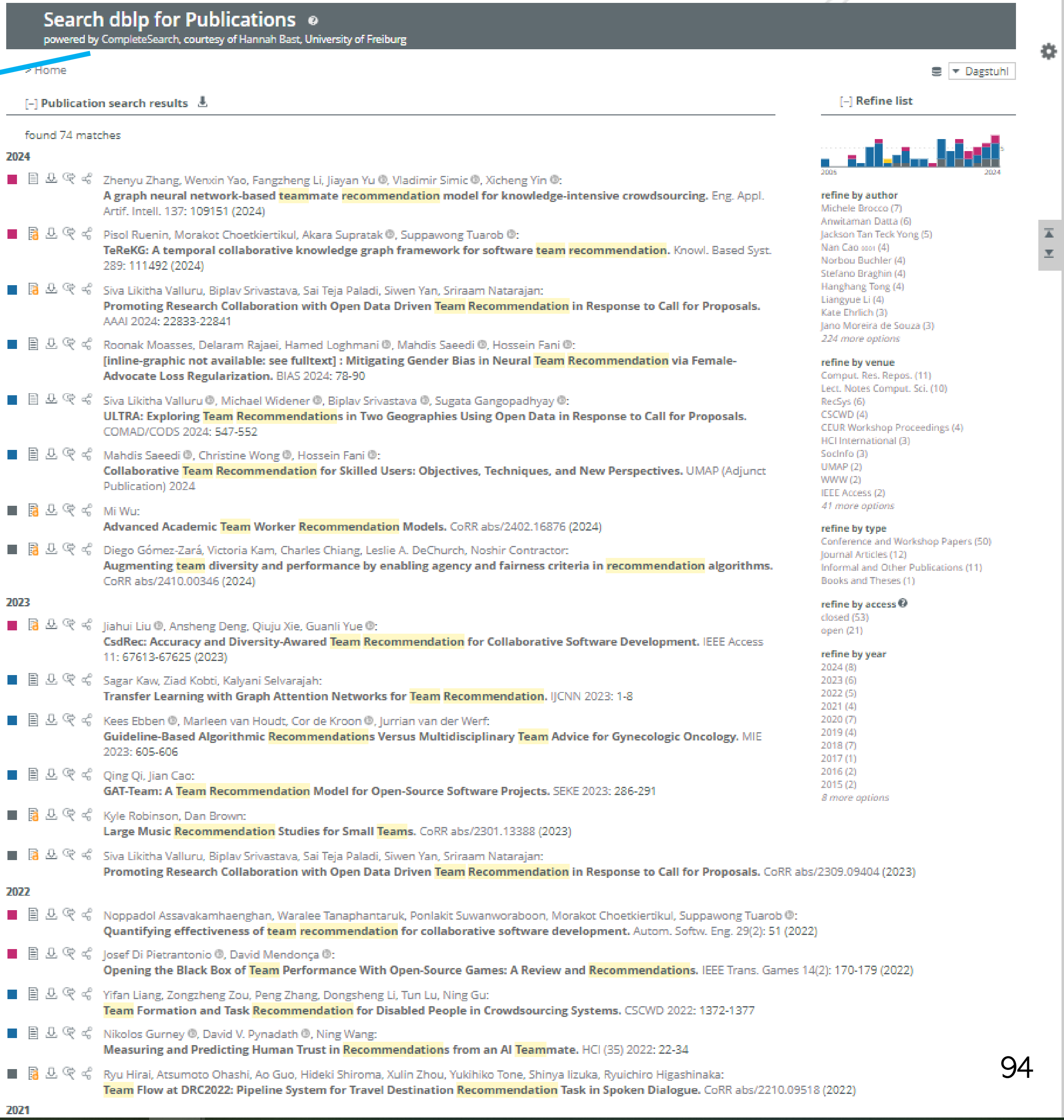
Given a set of **skills** S ={i} and a set of **users** E ={j}, a team of users e⊂E ; e ≠ ∅ that collectively cover the skill set s⊂S ; s ≠ ∅ is shown by (s,e) along with its **success status** y∈{0,1}. Further, T = $\{(s,e)_y$: y∈{0,1}} indexes all previous teams.



Learning-based Heuristics

Introductory Definitions:

- Team
- Team Recommendation

Learning-based Heuristics

Team Recommendation

Given a subset of skills s and all teams *T*, the Team Recommendation problem aims at identifying an optimal subset of users $\boldsymbol{e}^*$ such that their collaboration in the predicted team (s, $\boldsymbol{e}^*$) is successful, that is $(\mathbf{s}, \boldsymbol{e}^*)_{y=1}$, while avoiding a subset of users $\boldsymbol{e}'$ resulting in $(\mathbf{s}, \boldsymbol{e}')_{y=0}$. More concretely, the Team Recommendation problem is to find a mapping function f of parameters $\boldsymbol{\theta}$ from the powerset of skills to the powerset of s such that $f_{\boldsymbol{\theta}} : P(S) \rightarrow P(E)$, $f_{\boldsymbol{\theta}}(\mathrm{s}) = e^*$.

Keywords: Neural Team Formation · Training Strategy · OpeNTF

Learning-based Heuristics

Team Recommendation

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Keywords: Neural Team Formation · Training Strategy · OpeNTF

Learning-based Heuristics

Team Recommendation

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f

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Keywords: Neural Team Formation · Training Strategy · OpeNTF

Learning-based Heuristics

Team Recommendation

Given a subset of skills s and all teams $\mathcal{T}$, the Team Recommendation problem aims at identifying an optimal subset of users $\boldsymbol{e}^*$ such that their collaboration in the predicted team $(\mathrm{s}, \boldsymbol{e}^*)$ is successful, that is $(\mathbf{s}, \boldsymbol{e}^*)_{y=1}$, while avoiding a subset of users $\boldsymbol{e}'$ resulting in $(\mathbf{s}, \boldsymbol{e}')_{y=0}$. More concretely, the Team Recommendation problem is to find a mapping function f of parameters $\boldsymbol{\theta}$ from the powerset of skills to the powerset of s such that $f_{\boldsymbol{\theta}} : P(S) \rightarrow P(E)$, $f_{\boldsymbol{\theta}}(\mathrm{s}) = e^*$.

f

A Streaming Approach to Neural Team Formation Training

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Abstract. Predicting *future* successful teams of experts who can effectively collaborate is challenging due to the experts' temporality of skill sets, levels of expertise, and collaboration ties, which is overlooked by prior work. Specifically, state-of-the-art neural-based methods learn vector representations of experts and skills in a *static* latent space, falling short of incorporating the possible drift and variability of experts' skills and collaboration ties in time. In this paper, we propose (1) a streaming-based training strategy for neural models to capture the evolution of experts' skills and collaboration ties over time and (2) to consume time information as an additional signal to the model for predicting future successful teams. We empirically benchmark our proposed method against state-of-the-art neural team formation methods and a strong temporal recommender system on datasets from varying domains with distinct distributions of skills and experts in teams. The results demonstrate neural models that utilize our proposed training strategy excel at efficacy in terms of classification and information retrieval metrics. The codebase is available at https://github.com/fani-lab/OpeNTF/tree/ecir24.

Keywords: Neural Team Formation · Training Strategy · OpeNTF

Learning-based Heuristics

- Model Architecture
- Training Strategies

Model Architecture

- Feedforward
- Variational Bayesian
- Graph Representation Learning

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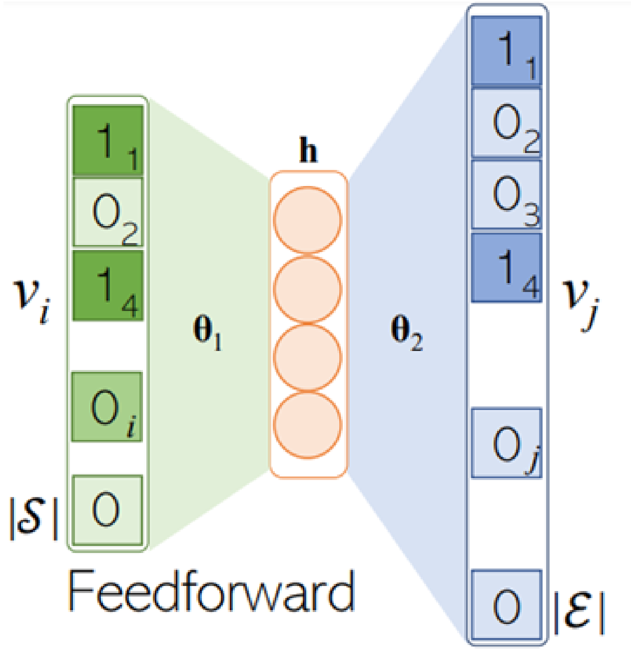
Feedforward

Neural Team Recommendation

Given the training set T, Neural Team Recommendation estimates $\boldsymbol{f_\theta}(\mathrm{s})$ using a multi-layer neural network that learns, from T, to map a vector representation of subset of skills $\mathbf{s}$, referred to as $\boldsymbol{v_s}$,to a vector representation of subset of experts $\boldsymbol{e}^*$, referred to as $\boldsymbol{v_{e^*}}$, by maximizing the posterior (MAP) probability of $\boldsymbol{\theta}$ in $\boldsymbol{f_\theta}$ over T, that is, $\boldsymbol{argmax}_{\boldsymbol{\theta}}\ \mathrm{p}(\boldsymbol{\theta} \mid T)$



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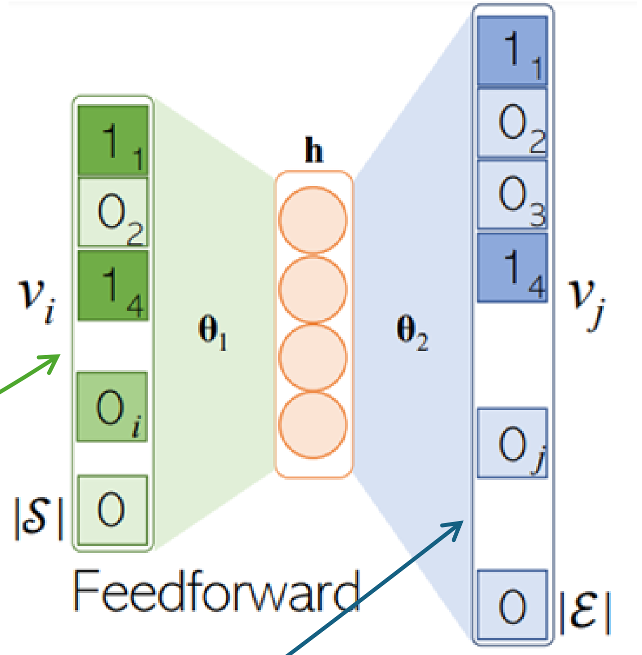

$$h = \pi(\boldsymbol{\theta}_1 v_s + \boldsymbol{b}_1)$$
$$logits \rightarrow z = \boldsymbol{\theta}_2 \boldsymbol{h} + \boldsymbol{b}_2$$
$$v_{e^*} = \sigma\ (z)$$

Variational Bayesian

Traditional FNNs can overfit and provide overconfident predictions, especially with limited or noisy data because:

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- Training sets in team recommendation models suffer from popularity bias;

- The majority of experts (non-popular experts) have scarcely participated in the teams , whereas few experts (popular ones) are in many teams.

Variational Bayesian

A feedforward model overfits to the popular experts, giving them higher scores and recommend them more frequently, leading to systematic discrimination against already disadvantaged nonpopular experts.

Neural Architecture

- Feedforward
- Variational Bayesian
- Graph Representation Learning

Variational Bayesian

Idea:

Using probabilistic weights as opposed to single real-valued weights.

Variational Bayesian

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Using probabilistic weights as opposed to single real-valued weights.

- Treating the network's weights as probability distributions instead of fixed values.

- Distribution of predictions rather than a single deterministic output.

Variational Bayesian

Probabilistic model

A neural network can be viewed as probabilistic model $P(y|x, \boldsymbol{\theta})$.

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Probabilistic model

A neural network can be viewed as probabilistic model $P(y|x, \boldsymbol{\theta})$.

- **Classification**: y is a set of classes, $P(y|x, \boldsymbol{\theta})$ is a categorical distribution.

- **Regression**: y is a continuous variable, $P(y|x, \boldsymbol{\theta})$ is a Gaussian distribution.

Variational Bayesian

Goal:

Maximizing the likelihood function f of θ :

Variational Bayesian

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Maximizing the likelihood function f of $\boldsymbol{\theta}$:

- Cross entropy (Classification)
- Sum of squares error (Regression)

Variational Bayesian

By Bayes theorem: Multiplying the likelihood with a prior distribution $p(\theta)$.

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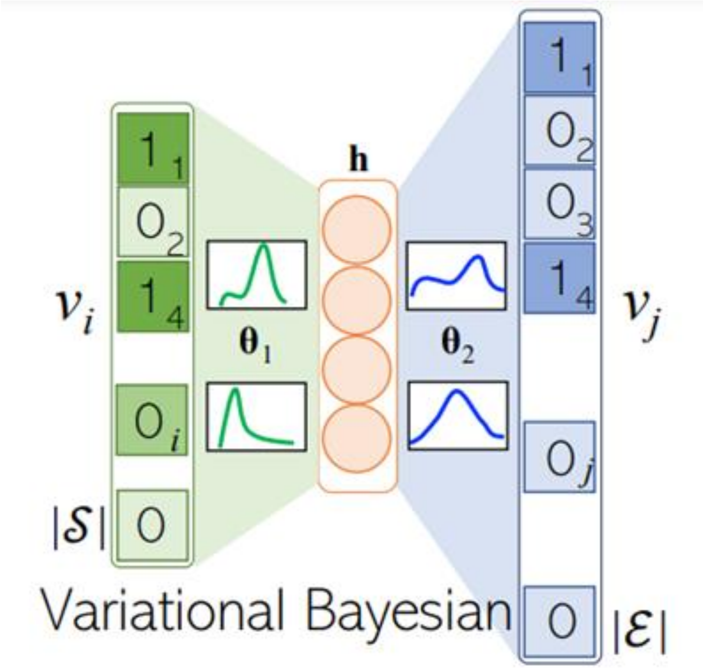


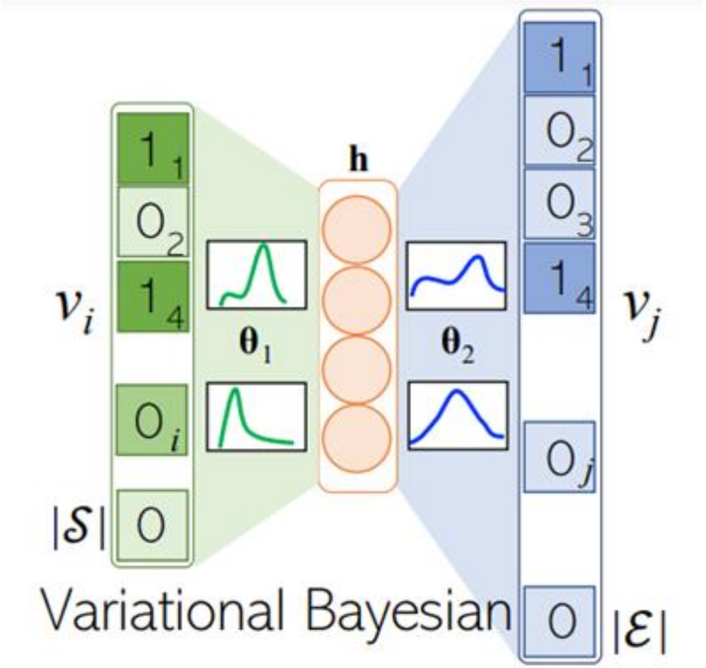
Variational Bayesian

$\theta \sim (\mu, \sigma)$　　　　q(θ)=$\mathcal{N}(\mu, \sigma)$

Parameters' means and variances are estimated by minimizing the Kullback-Leibler divergence between q and p

$$\mathrm{KL}(q \| p(\theta \mid T)) = \int q(\theta \mid \mu, \sigma) \log\left[\frac{q}{p(\theta|T)}\right] d\theta$$

$$= E_q \log\left[\frac{q}{p(\theta|T)}\right] \quad , \mathrm{KL}(q\| p) \geq 0$$



Neural Architecture

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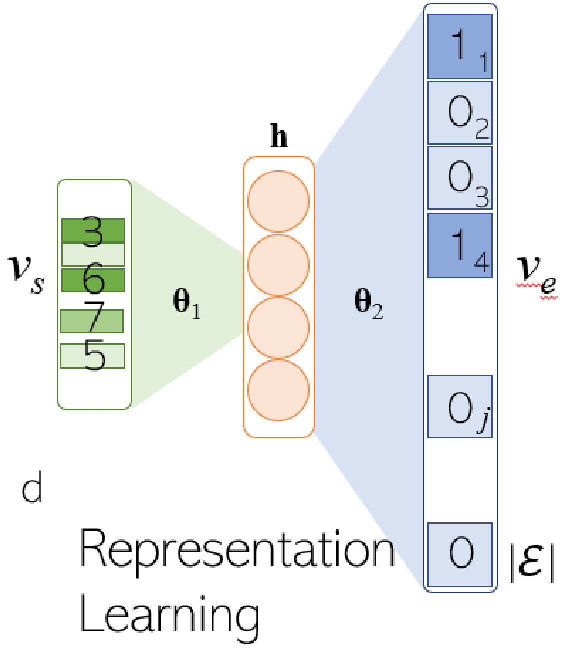
Graph Representation Learning

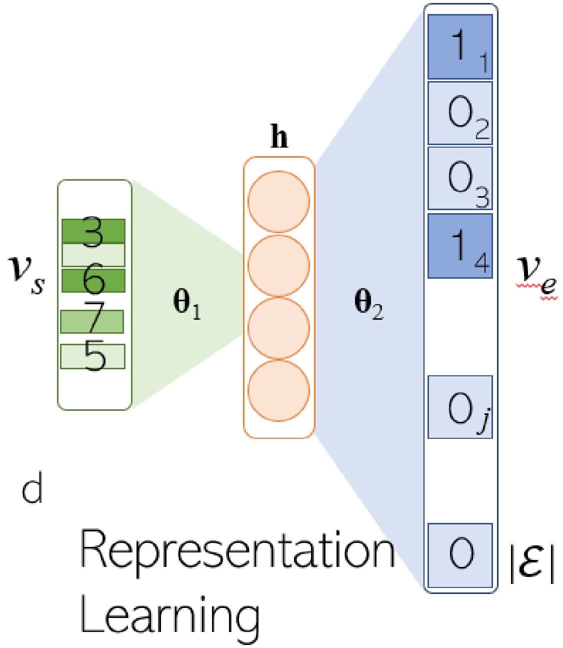
Dense Vector vs. Multi-hot vector



Graph Representation Learning

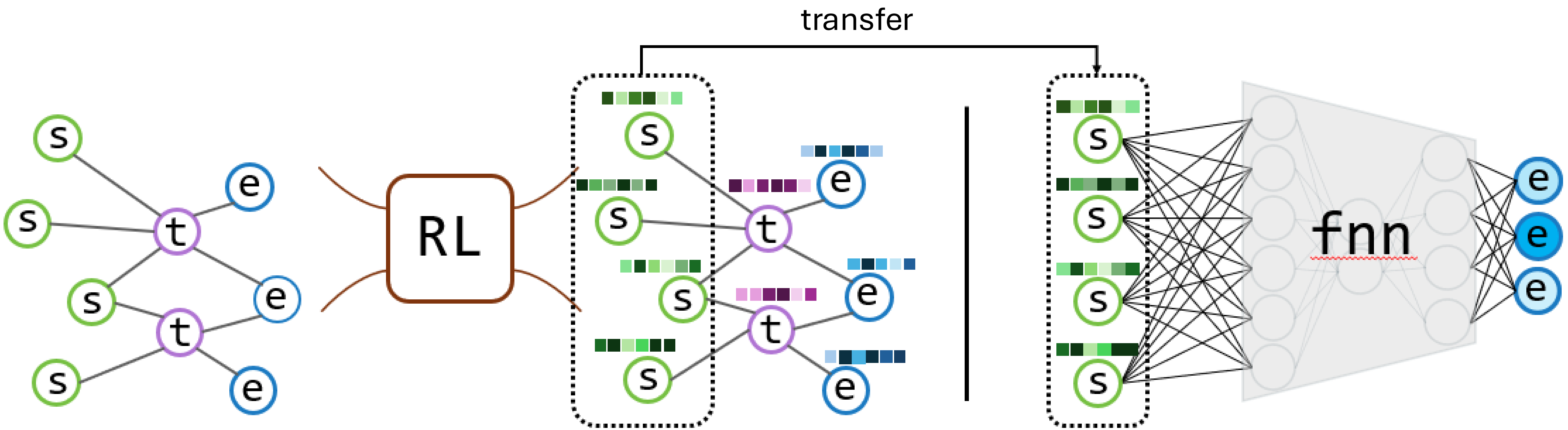
Dense Vector vs. Multi-hot vector

- **Dense Vector**: A vector with fewer dimension and continuous value rather than just 0 or 1.



Graph Representation Learning

Transfer learning-based



Graph Representation Learning

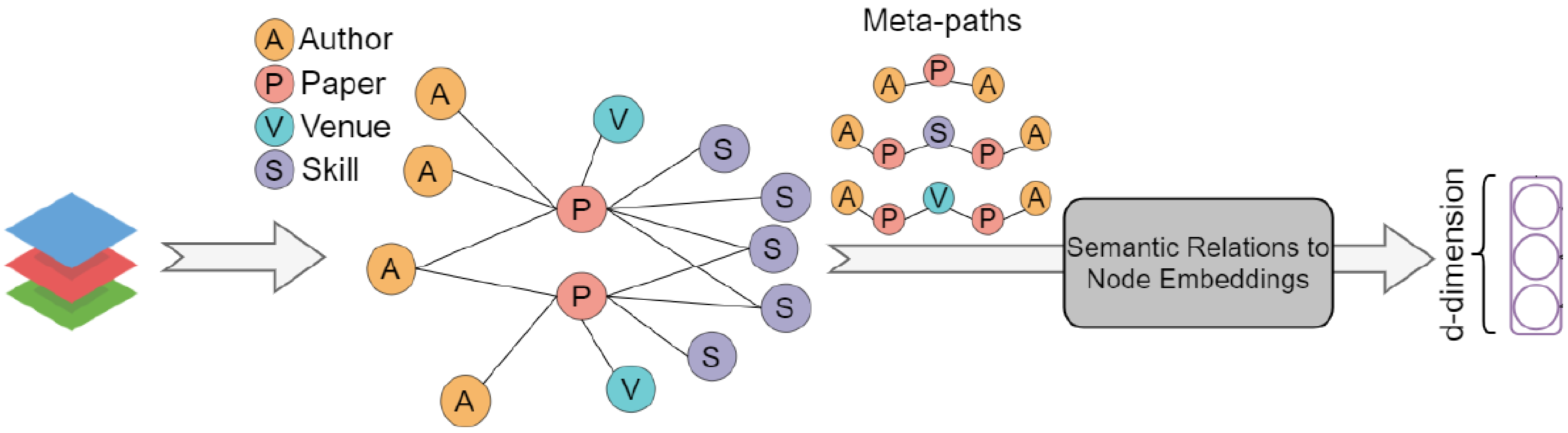
Analyzing Network Graph

- Metha Path-based Methods

- Message passing-based Methods

Graph Representation Learning

Meta Path-based Methods



[Rad et. Al., Sigir ,2021]

Graph Representation Learning

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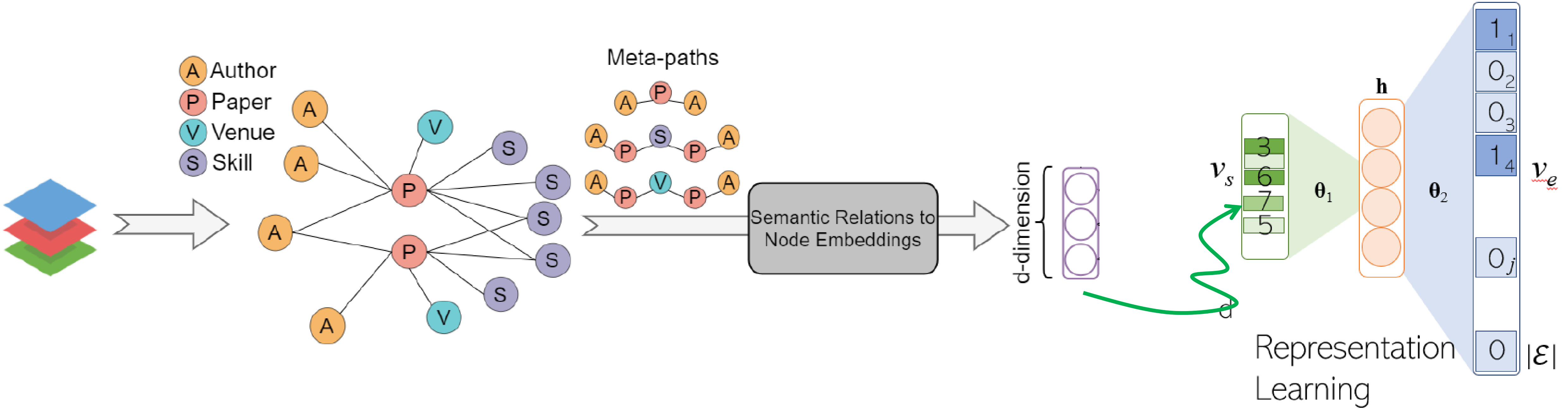


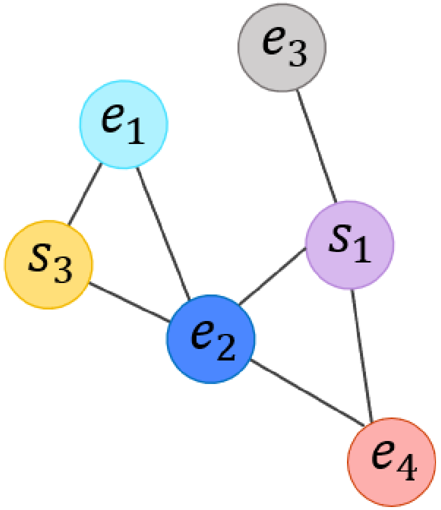
[Rad et. al., Sigir ,2021]

Graph Representation Learning

Message Passing-based Methods (Graph Neural Networks (GNN))

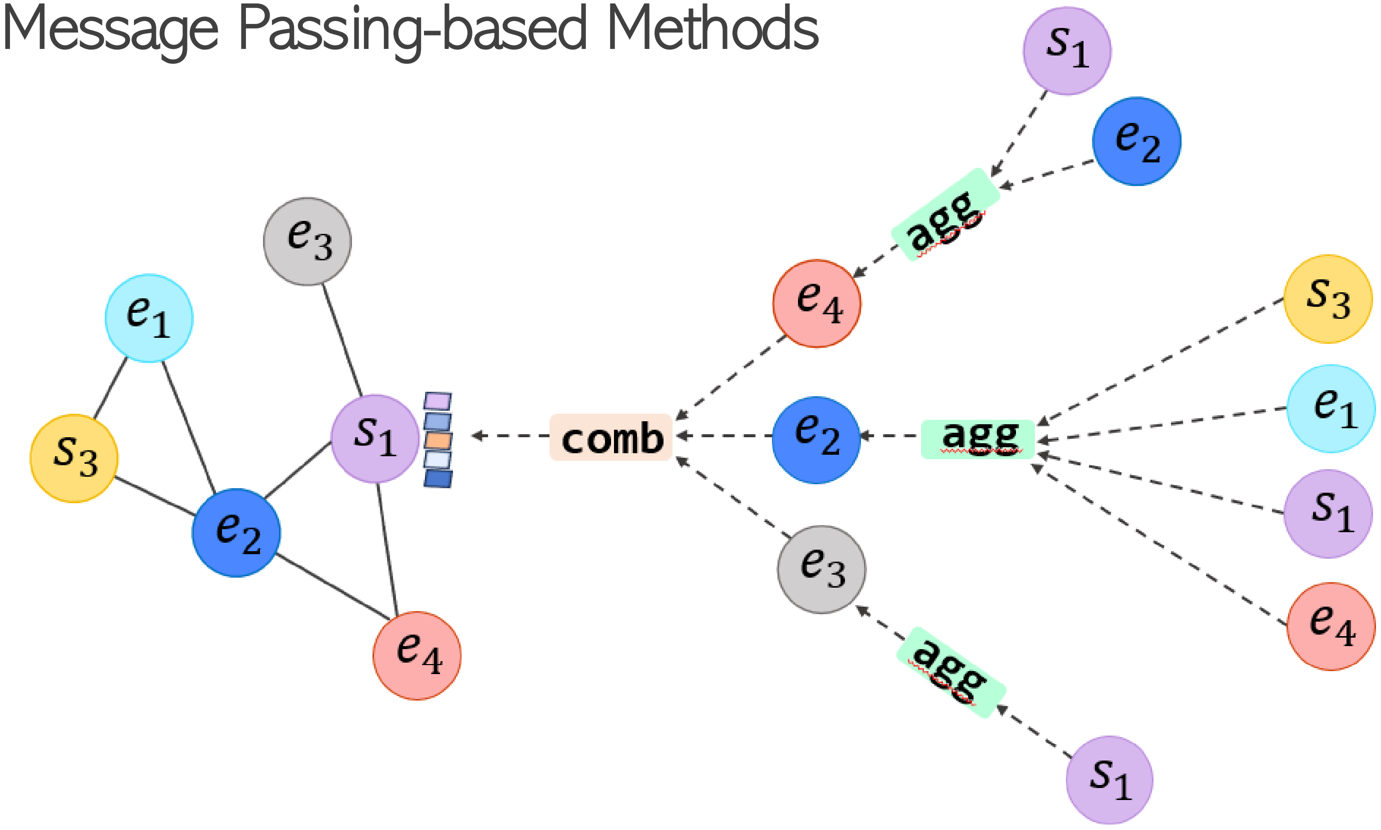
Graph Representation Learning

Message Passing-based Methods



Graph Representation Learning

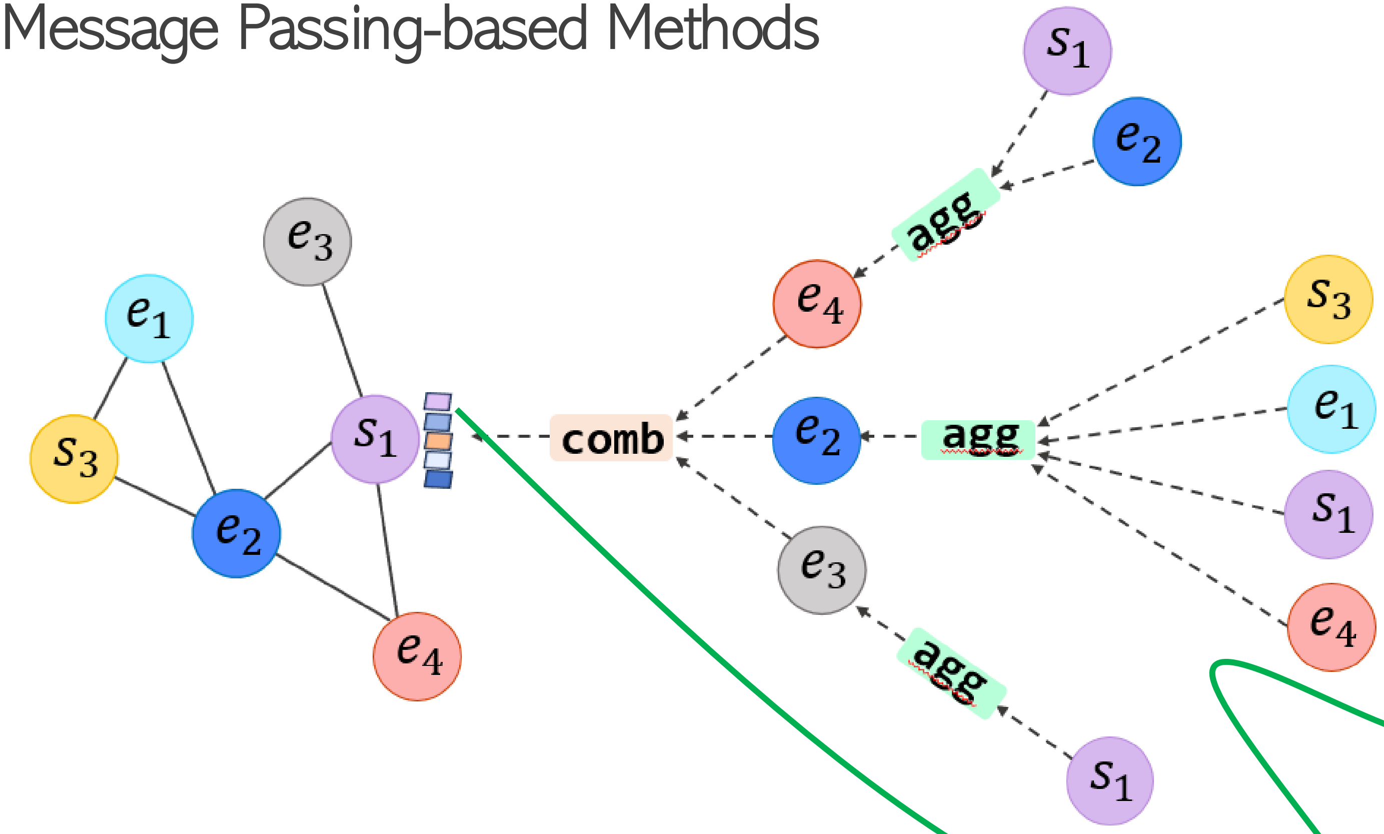
Message Passing-based Methods

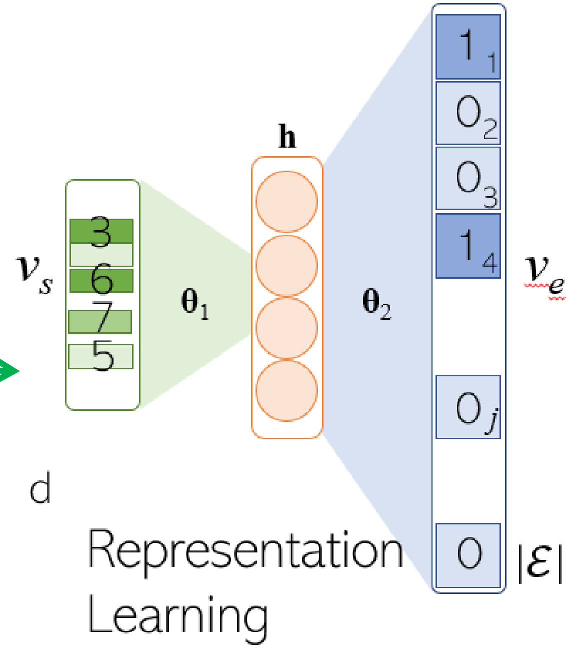


$$v_{s_i}^{k+1} = \mathrm{comb}(v_{s_i}^{k},\ \mathrm{agg}(v_x^k : x \in N_{s_i}^k))$$

Graph Representation Learning

Message Passing-based Methods





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Message Passing-based Methods differ in their aggr and comb functions.

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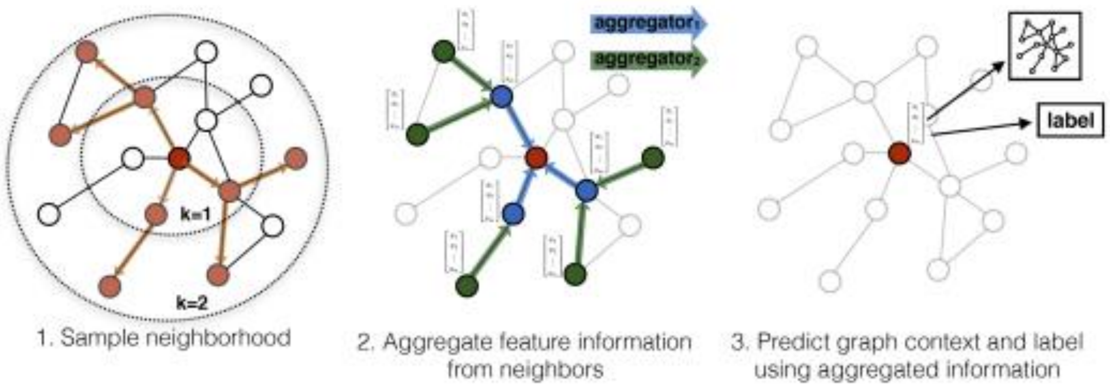
- Inductive methods: Can infer vector representations for unseen skill nodes based on existing nodes residing in the neighbourhood of the unseen skill node.

GraphSAGE



[Hamilton et. al., Annual Conference on Neural Information Processing Systems, 2017]

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- Attentive methods: Allocate attention coefficients to a skill node's neighbours to signify their importance in updating the skill node's vector.

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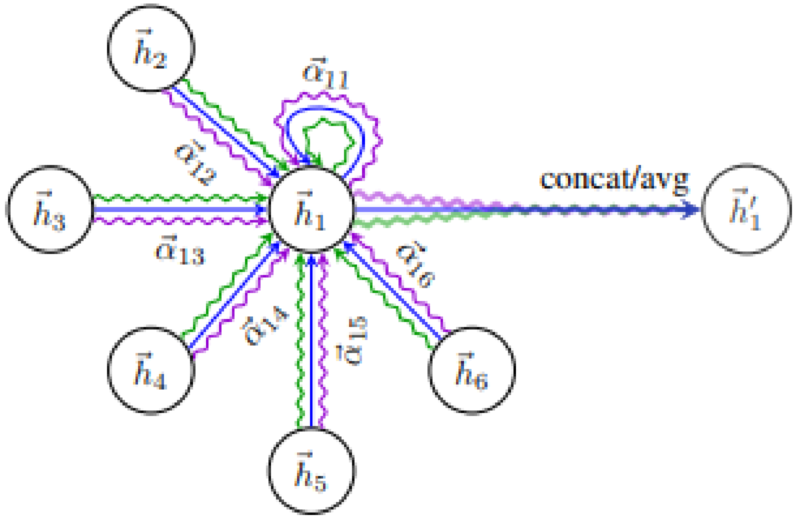
GAT



[Velickovic et. al., ICLR, 2018]

Graph Representation Learning

Message Passing-based Methods differ in their aggr and comb functions.

- Graph isomorphism methods: wherein, next to the skill vectors, the agg and comb functions are also parameterized and learnable based on Weisfeiler-Lehman graph isomorphism test.

Graph Neural Network For Team Recommendation

Research Question

Which dense vector representation is of the best quality across neural team recommenders and datasets?

[Ahmed et. Al., WISE ,2024]

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	%aucroc	%precision			%recall			%ndcg			%map		
		@2	@5	@10	@2	@5	@10	@2	@5	@10	@2	@5	@10
skill-expert													
m-hot [43]	77.54	0.78	0.70	0.65	0.49	1.07	1.96	0.79	0.96	1.37	0.37	0.53	0.66
d2v [16,43,31]	76.36	1.05	0.83	0.72	0.64	1.27	2.21	1.09	1.18	1.62	0.51	0.72	0.88
m2v [38]	76.88	1.21	1.01	0.80	0.73	1.54	2.44	1.25	1.42	1.83	0.58	0.84	0.99
gs [18]	77.81	1.01	0.92	0.83	0.60	1.38	2.51	1.05	1.24	1.76	0.51	0.72	0.90
gat [51]	77.62	1.30	**1.10**	**0.85**	0.79	**1.66**	**2.57**	1.29	1.49	1.92	0.59	0.84	0.98
gatv2 [5]	77.57	1.28	0.96	0.81	0.78	1.44	2.45	1.33	1.39	1.85	0.62	0.82	0.97
han [53]	**77.84**	**1.39**	1.09	0.83	**0.84**	1.64	2.49	**1.46**	**1.56**	**1.96**	**0.67**	**0.93**	**1.05**
gin [55]	77.25	0.44	0.63	0.69	0.27	0.93	2.07	0.41	0.72	1.25	0.18	0.37	0.53
gine [19]	77.53	1.15	0.92	0.79	0.68	1.37	2.35	1.15	1.26	1.72	0.51	0.71	0.87
skill-team-expert													
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d2v [16,43,31]	75.51	0.97	0.82	0.70	0.59	1.24	2.13	1.00	1.13	1.55	0.46	0.66	0.82
m2v [38]	74.65	0.81	0.74	0.68	0.50	1.14	2.07	0.83	1.01	1.44	0.39	0.59	0.75
gs [18]	77.73	1.12	0.87	0.74	0.67	1.31	2.24	1.19	1.26	1.69	0.55	0.73	0.88
gat [51]	**77.87**	**1.35**	**1.19**	**0.92**	**0.81**	**1.78**	**2.76**	1.39	**1.62**	**2.08**	0.64	**0.92**	**1.09**
gatv2 [5]	77.75	1.27	0.92	0.80	0.77	1.39	2.40	1.29	1.32	1.80	0.59	0.77	0.94
han [53]	77.86	1.34	1.07	0.89	**0.81**	1.61	2.66	**1.42**	1.53	2.02	**0.66**	0.90	1.08
gin [55]	77.77	1.31	0.95	0.78	0.78	1.43	2.35	1.35	1.37	1.80	0.61	0.78	0.92
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Average performance of 3-fold fnn on test set in dblp

[Ahmed et. Al., WISE ,2024]

	%aucroc	%precision @2	%precision @5	%precision @10	%recall @2	%recall @5	%recall @10	%ndcg @2	%ndcg @5	%ndcg @10	%map @2	%map @5	%map @10
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Research Question

Do neural team recommenders of different architectures benefit from dense vectors equally?

[Ahmed et. Al., WISE ,2024]

fnn

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bnn

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gat [51]	75.41	0.54	0.54	0.53	0.32	0.82	1.60	0.54	0.70	1.06	0.24	0.38	0.49
gatv2 [5]	**76.99**	**1.00**	**0.87**	**0.74**	**0.59**	**1.32**	**2.23**	**1.03**	**1.20**	**1.62**	**0.47**	**0.68**	**0.83**
han [53]	75.29	0.59	0.52	0.51	0.35	0.79	1.54	0.60	0.71	1.05	0.28	0.40	0.51
gin [55]	72.33	0.80	0.61	0.52	0.48	0.92	1.57	0.83	0.88	1.18	0.40	0.54	0.64
gine [19]	74.10	0.76	0.63	0.56	0.46	0.96	1.71	0.78	0.88	1.23	0.37	0.52	0.63
skill-team-expert													
m-hot [43]	71.42	0.60	0.53	0.49	0.37	0.82	1.51	0.61	0.73	1.05	0.30	0.43	0.54
d2v [16,43,31]	72.86	0.82	0.68	0.61	0.49	1.02	1.86	0.84	0.95	1.33	0.39	0.56	0.69
m2v [38]	66.77	0.33	0.31	0.32	0.20	0.48	0.98	0.34	0.42	0.65	0.15	0.23	0.30
gs [18]	76.34	0.75	0.71	0.66	0.46	1.08	2.00	0.74	0.94	1.36	0.34	0.52	0.65
gat [51]	76.29	0.72	0.66	0.62	0.44	0.99	1.86	0.72	0.87	1.28	0.33	0.49	0.62
gatv2 [5]	74.82	0.73	0.64	0.54	0.44	0.96	1.64	0.75	0.87	1.19	0.35	0.49	0.58
han [53]	**76.63**	0.92	**0.80**	**0.71**	0.55	**1.20**	**2.15**	0.94	**1.09**	**1.53**	0.43	0.61	0.76
gin [55]	71.39	0.69	0.60	0.52	0.42	0.91	1.59	0.73	0.84	1.15	0.35	0.49	0.60
gine [19]	74.31	**0.95**	0.75	0.63	**0.57**	1.12	1.90	**1.00**	1.08	1.44	**0.48**	**0.66**	**0.79**

fnn vs bnn performances for dblp

Learning-based Heuristics

- Model Architecture
- Training Strategies

Training Strategies

- Negative Sampling
- Streaming Strategy

Training Strategies

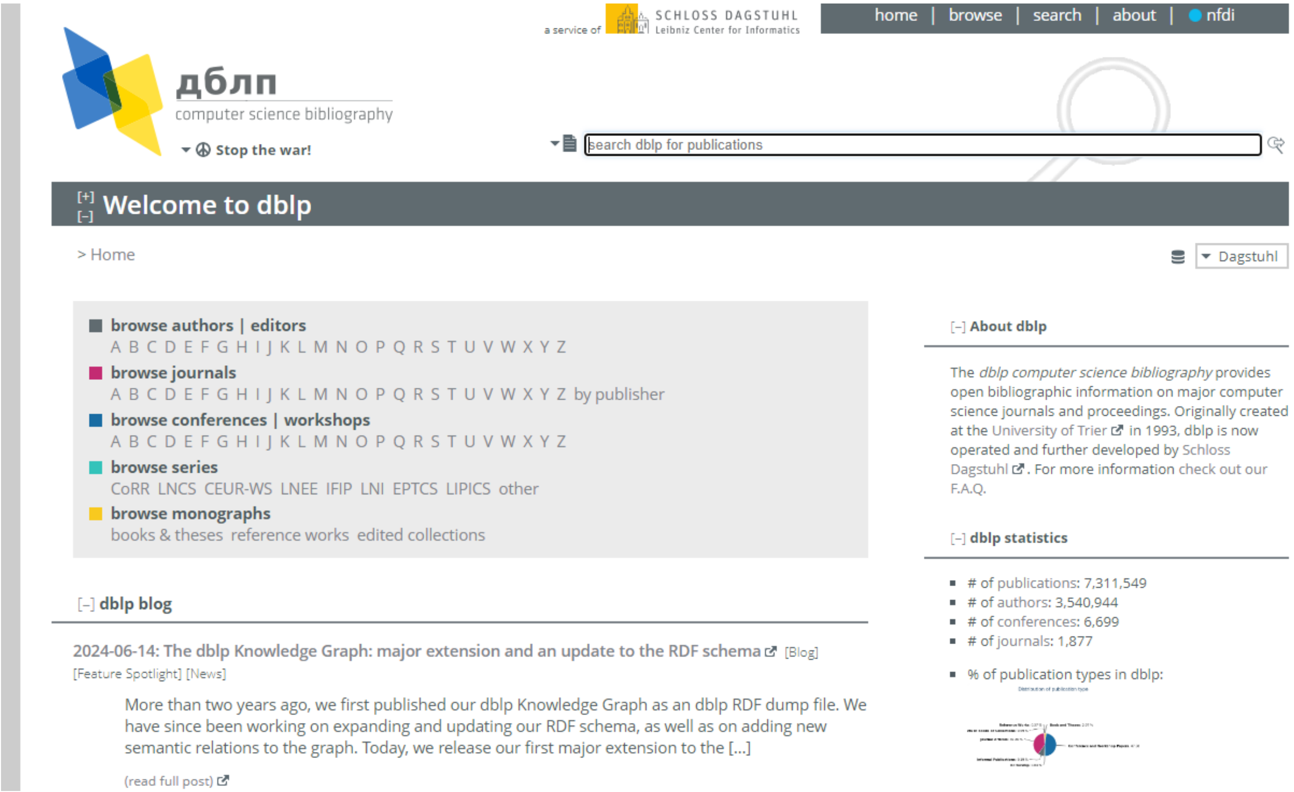
- Negative Sampling
- Streaming Strategy

Negative Sampling

Most available data in team recommendation domain only consists of successful teams.

Negative Sampling

Most available data in team recommendation domain only consists of successful teams.



Negative Sampling

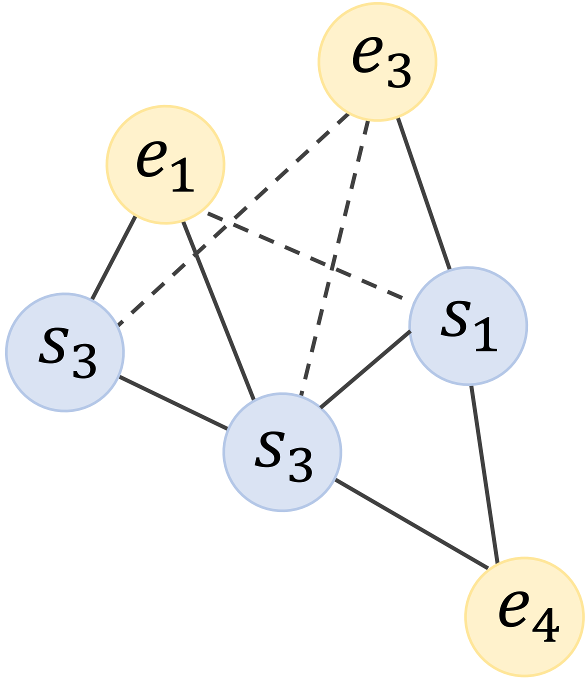
Closed-World Assumption

- No currently known successful team is considered unsuccessful

Negative Sampling

Closed-World Assumption

- No currently known successful team is considered unsuccessful



Negative team: experts e_1, e_3

skills s_1, s_2, s_3

Negative Sampling

Optimization function discriminates successful from unsuccessful teams through negative sampling.

Positive Samples

$$\sum_{t_{se} \in \mathcal{T}} [\log \sigma(v_e^\top \cdot v_s) + \sum_{t_{se'} \sim \mathbb{P} : t_{se'} \notin \mathcal{T}}^{k} \log \sigma(-v_{e'}^\top \cdot v_s)]$$

Probability Distribution

Negative Samples

[Dashti et. al., CIKM, 2022]

Training Strategies

- Negative Sampling
- Streaming Strategy

Streaming Strategy

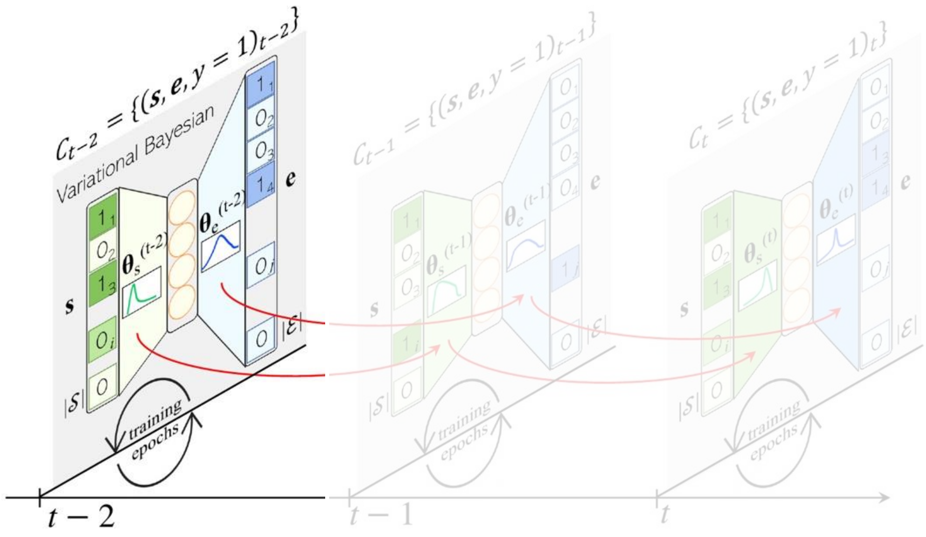
Predicting future successful teams of users who can effectively collaborate is challenging due to experts' temporality of

- Skill sets
- Levels of expertise
- Collaboration ties

Streaming Strategy

Neural model learns vector representations for users and skills at time interval t

Initiates learning for the next time interval $t + 1$

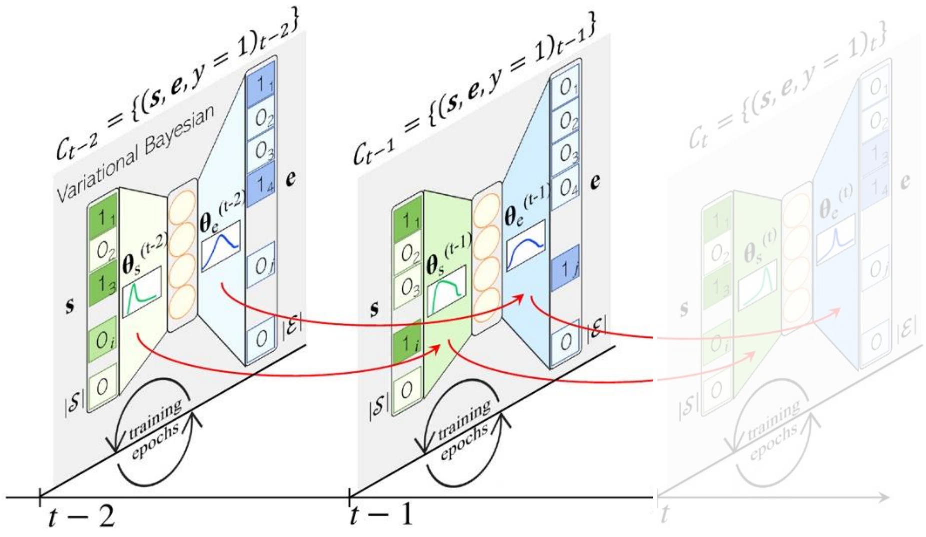


[Fani et. al., ECIR, 2024]

Streaming Strategy

Neural model learns vector representations for users and skills at time interval t

Initiates learning for the next time interval $t + 1$



[Fani et. al., ECIR, 2024]

Streaming Strategy

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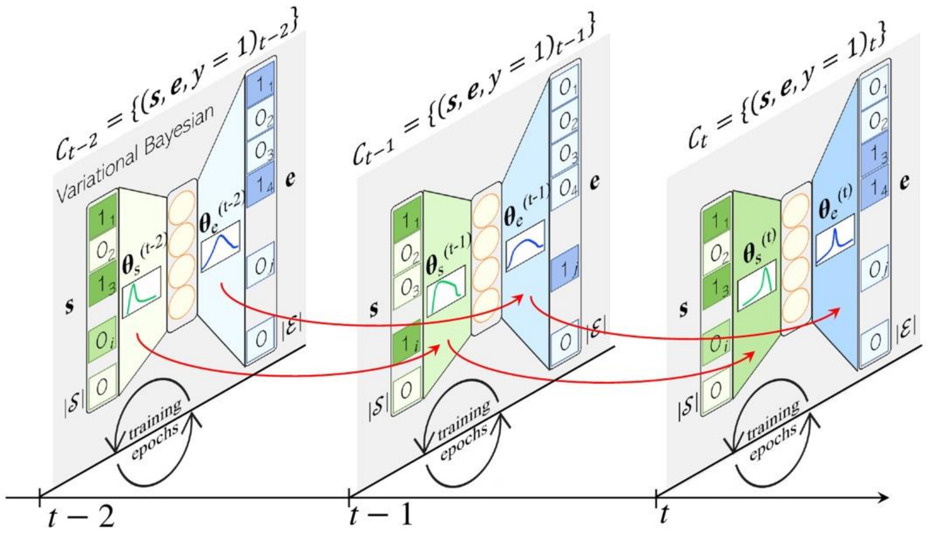

[Fani et. al., ECIR, 2024]

Evaluation Methodology

- Dataset
- Effectiveness

Evaluation Methodology

- Dataset
- Effectiveness

Dataset

- DBLP
- IMDB
- USPT
- GitHub

Dataset

- DBLP
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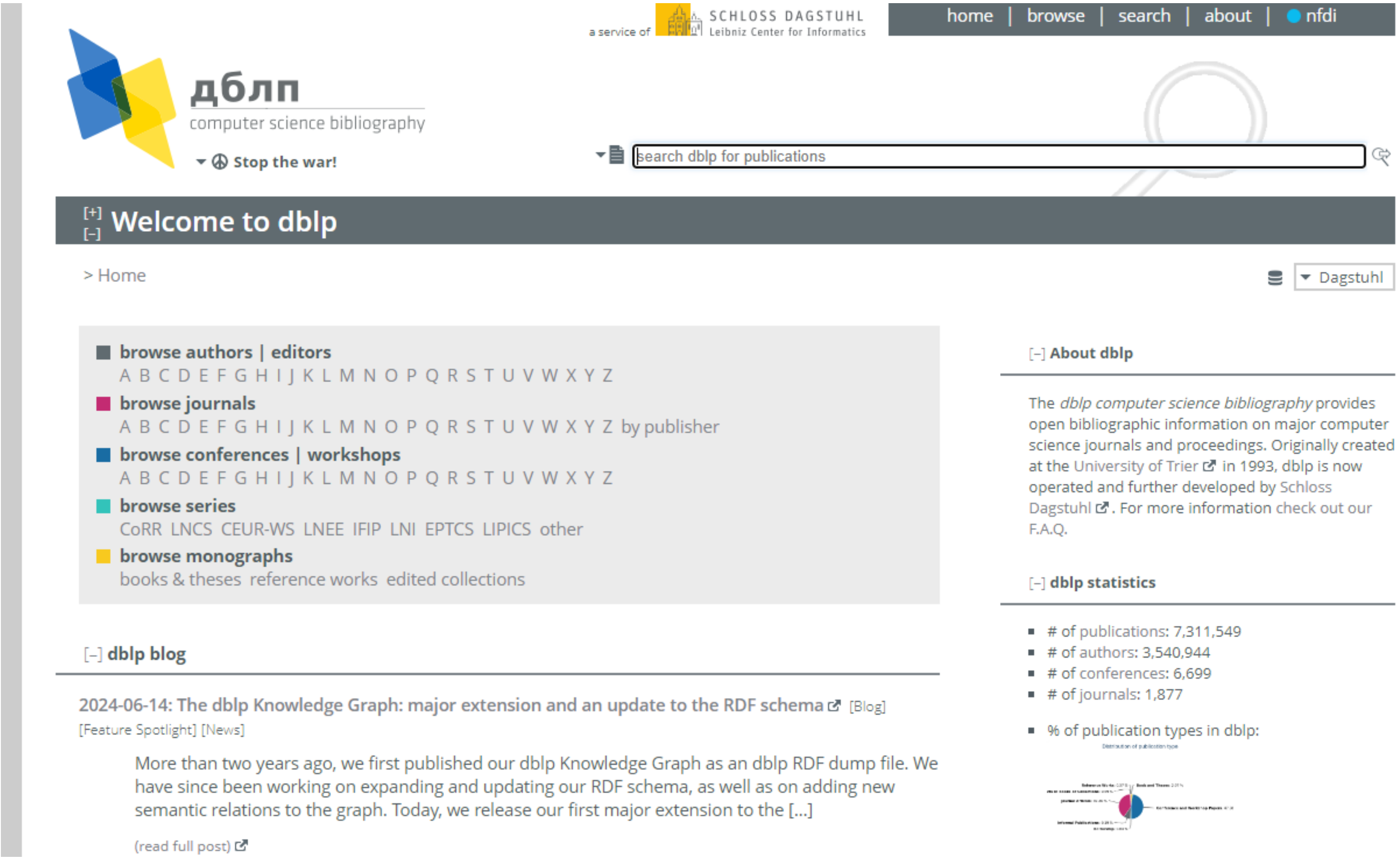
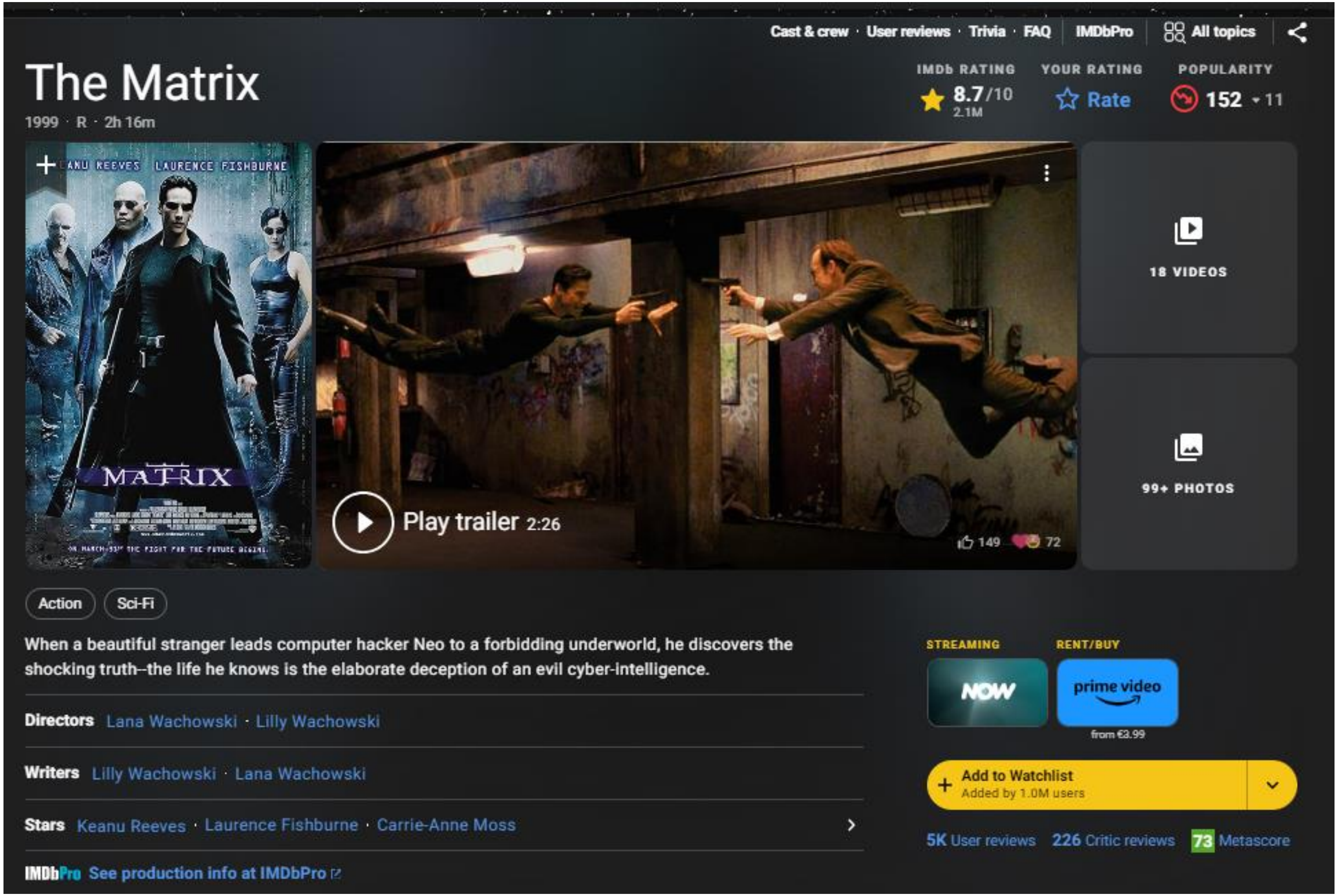


Dataset

- DBLP
- IMDB
- USPT
- GitHub



Dataset

- DBLP
- IMDB
- USPT
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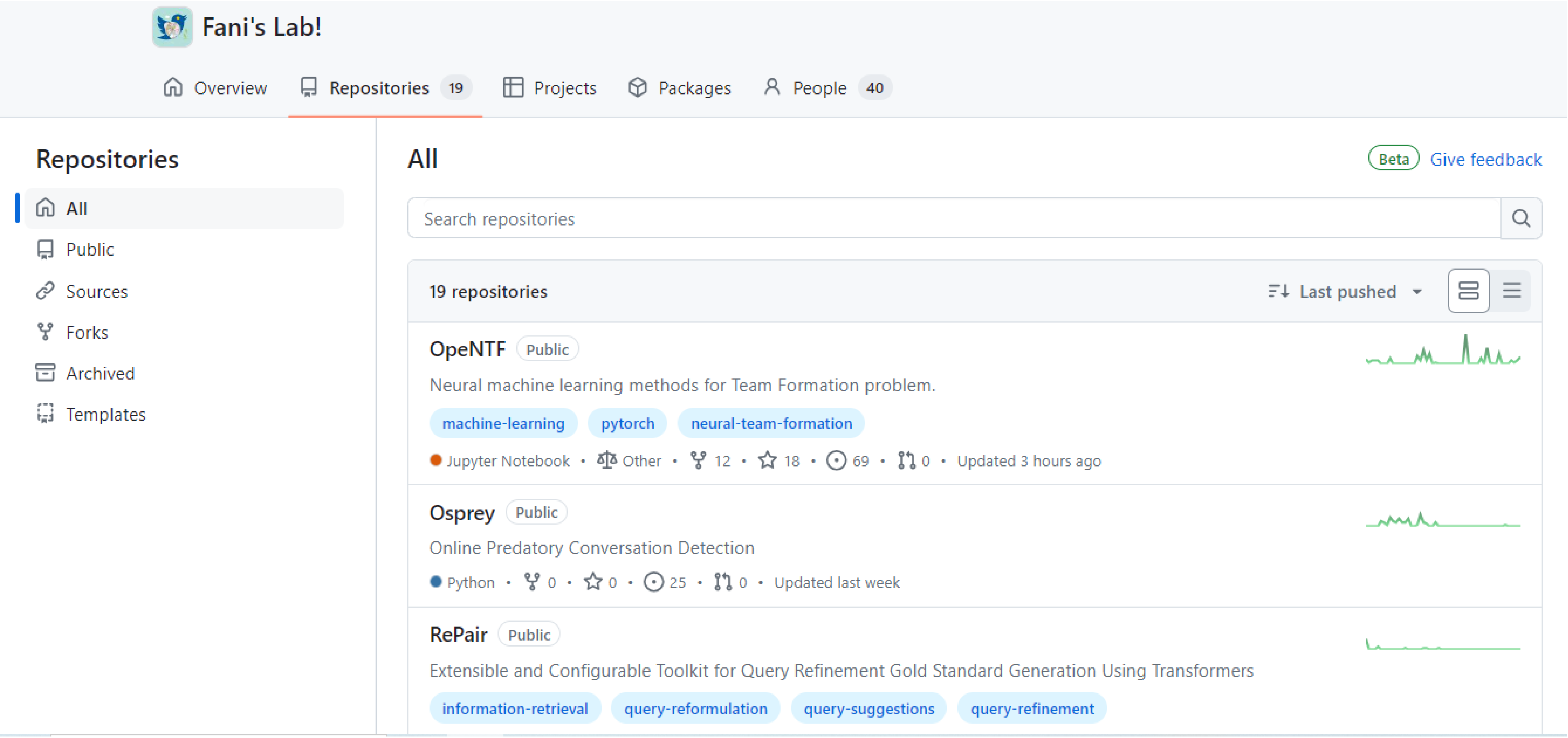
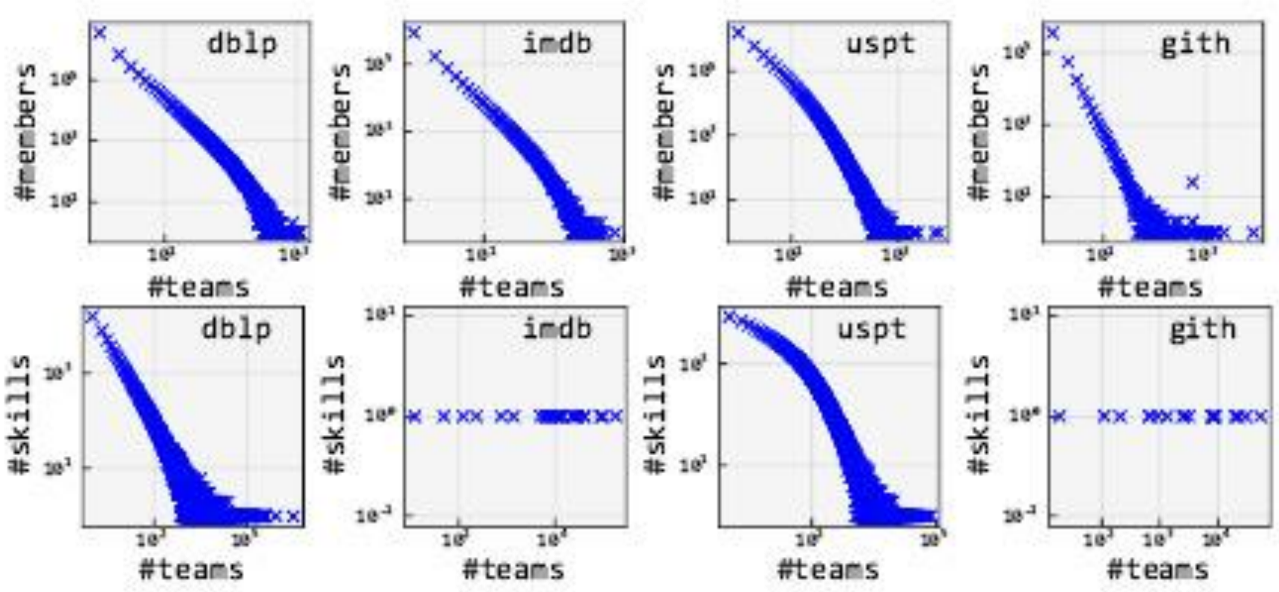
Dataset

- DBLP
- IMDB
- USPT
- GitHub





	dblp	uspt	imdb	gith
#teams	4,877,383	7,068,508	507,034	132,851
#unique experts	5,022,955	3,508,807	876,981	452,606
#unique skills	89,504	241,961	28	20
Avg #expert per team	3.06	2.51	1.88	5.52
Avg #skill per team	8.57	6.29	1.54	1.37
Avg #team per expert	2.97	5.05	1.09	1.62
Avg #skill per expert	16.73	19.49	1.59	2.03
#team w/ single expert	768,956	2,578,898	322,918	0
#team w/ single skill	5,569	939,955	315,503	69,131

Dataset Statistics and Distribution

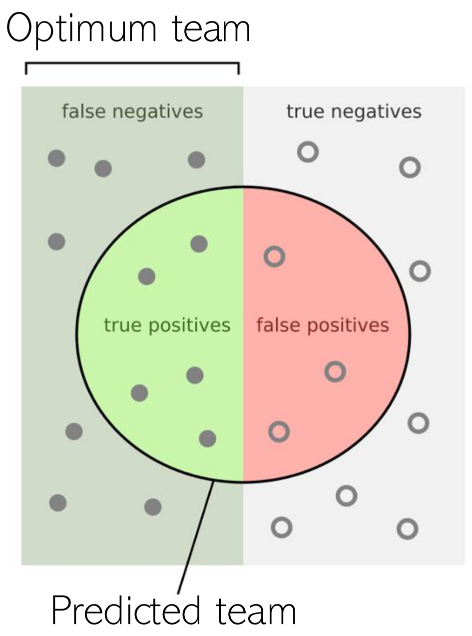
Evaluation Methodology

- Dataset
- Effectiveness

Effectiveness

Classification Metrics

Effectiveness

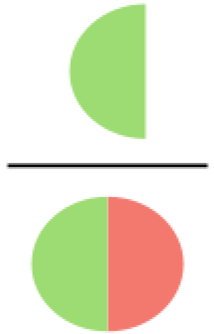


Classification Metrics

Precision:

How many of the k predicted experts $\hat{e}$ are correctly identified from the optimum team e^*.

$$P(k) = \frac{|e^* \cap \hat{e}|}{k} =$$



Optimum team

Recall:

How many of the experts in the optimum team e^* has been predicted in $\hat{e}$.

$R(k) = \frac{|e^* \cap \hat{e}|}{|e^*|}$

Predicted team

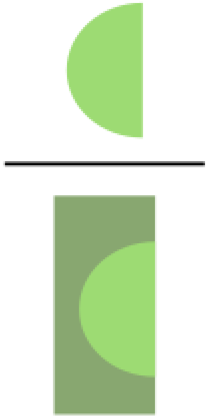
Effectiveness

Classification Metrics

Recall:

How many of the experts in the optimum team e^* has been predicted in $\hat{e}$.

$$R(k) = \frac{|e^* \cap \hat{e}|}{|e^*|} =$$



Effectiveness

Classification Metrics

Success:

Is there at least one expert from $\boldsymbol{e}^*$ in the predicted k experts $\hat{\boldsymbol{e}}$.

$$S(k) = |e^* \cap \hat{e}| > 0$$

Effectiveness

Ranking Metrics

Reciprocal Rank:

Reciprocal Rank is the first position on the predicted rank list that an expert from the optimum is found.

Intuitively, the lower rank a model finds an expert of the optimum team, the better

$$RR(k) = \begin{cases} \dfrac{1}{rank} & renk \leq k \\ 0 & otherwise \end{cases}$$

Effectiveness

Ranking Metrics

Average Precision:

$$AP(k) = \frac{\sum_{i=1}^{k} P(i) \times \delta_{e^*}(i)}{|e^* \cap \hat{e}|}$$

where $\delta_{e^*}(i)$ returns 1 if the i-th predicted expert is in $\boldsymbol{e}^*$.

Effectiveness

Ranking Metrics

Discounted Cumulative Gain:

Ranking quality metric used to evaluate the effectiveness of algorithms in returning relevant items.

$$\mathrm{DCG}(k) = \sum_{i=1}^{k} \frac{\delta_{e^*}(i)}{\log(i+1)}$$

Effectiveness

Ranking Metrics

Discounted Cumulative Gain:

Ranking quality metric used to evaluate the effectiveness of algorithms in returning relevant items.

$$\mathrm{DCG}(k) = \sum_{i=1}^{k} \frac{\delta_{e^*}(i)}{\log(i+1)}$$

This metric can be normalized relative to the ideal case (Ideal DCG) when the top-k predicted experts include members of the optimum team e^* at the lowest possible ranks.

$$\mathrm{nDCG}(k) = \frac{DCG(k)}{\sum_{i=1}^{|e^*|} \frac{1}{\log(i+1)}}$$

	Metrics	Sapienza *et al.* [2019]	Rad *et al.* [2020]	Rad *et al.* [2021b]	Dashti *et al.* [2022a]	Rad *et al.* [2022b]	Rad *et al.* [2022a]	Dashti *et al.* [2022b]	Rad *et al.* [2021a]
+Optimum Teams	Average Precision		✓	✓	✓	✓	✓	✓	✓
	Reciprocal Rank		✓	✓		✓	✓		✓
	Discounted Cumulative Gain		✓	✓	✓	✓	✓	✓	✓
	Recall		✓	✓	✓	✓	✓	✓	✓
	Precision				✓			✓	
	Area Under Curve				✓			✓	
	Squared Error	✓							
	Skill Coverage			✓			✓		
	Communication Cost					✓			

Evaluation Metrics

Outline

I) Introduction and Background

II) Pioneering Techniques

III) Learning-based Heuristics

IV) Challenges and New Perspectives

V) Applications

Hands-on: OpeNTF

Challenges and New Perspectives

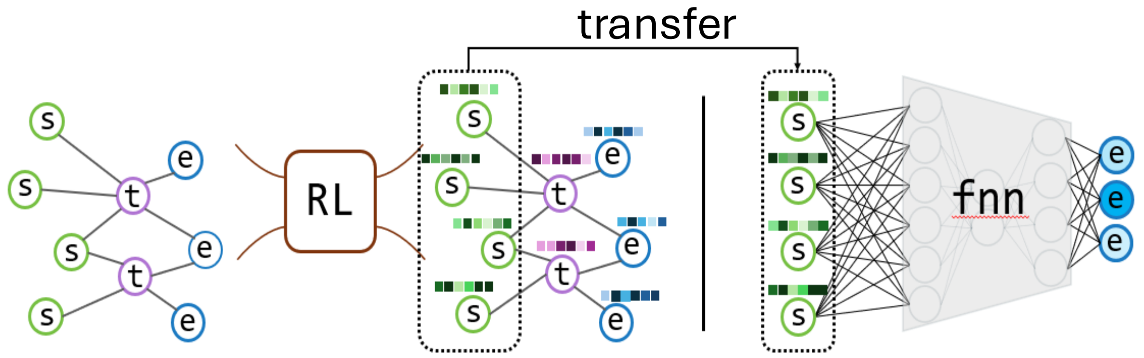
- End-to-End Graph Neural Network
- Fair and Diverse Team Recommendation
- Spatial Team Recommendation

Challenges and New Perspectives

- End-to-End Graph Neural Network
- Fair and Diverse Team Recommendation
- Spatial Team Recommendation

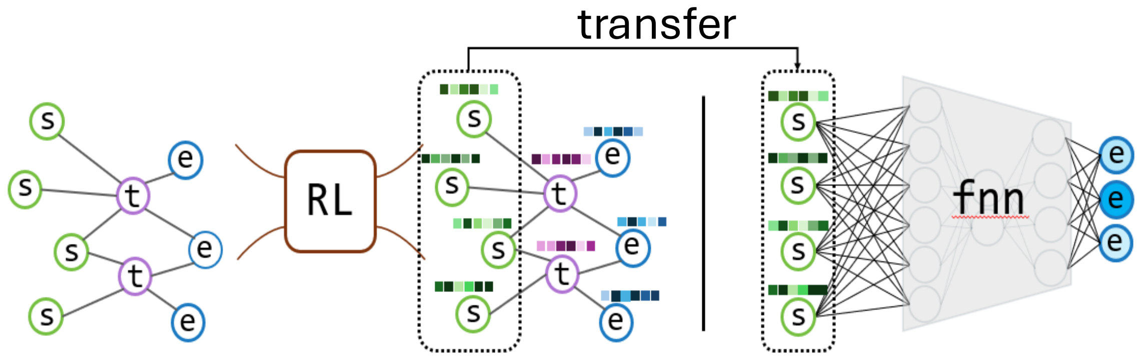
End-to-End Graph Neural Network

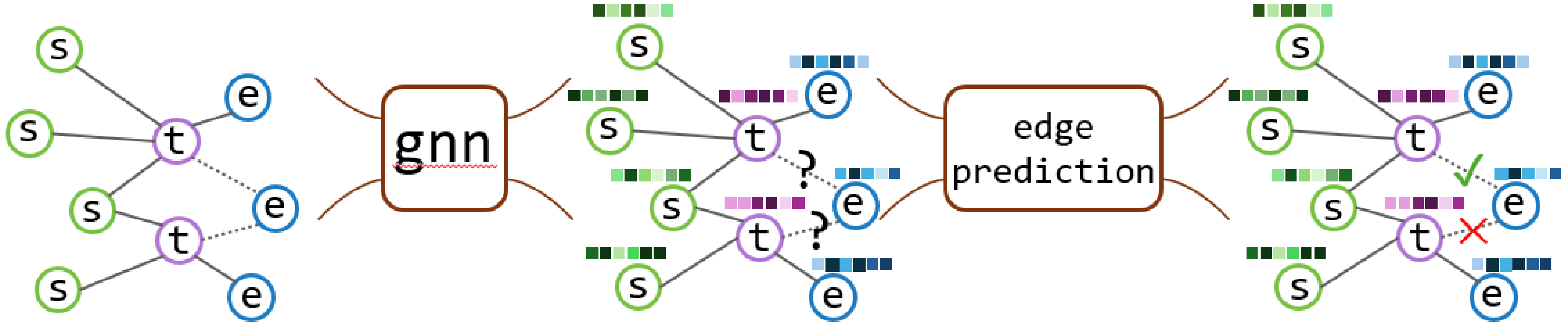
Transfer learning vs. End-to-End



End-to-End Graph Neural Network

Transfer learning vs. End-to-End





End-to-End Graph Neural Network

Research Question

Does end-to-end approach outperform transfer learning-based approach for team recommendation?

End-to-End Graph Neural Network

		dblp-ste							
		%precision		%recall		%ndcg		%map	
approach	gnn	@5	@10	@5	@10	@5	@10	@5	@10
e2e	m2v								
	lant								
	gs	14.40	9.24	54.00	67.80	33.20	38.40	25.20	28.10
	gin	**14.50**	9.07	**54.70**	67.00	31.50	36.10	22.70	25.40
	gine								
	gat	14.30	9.46	53.80	68.90	**38.10**	43.80	**31.40**	34.70
	gatv2	14.00	**9.48**	52.70	**69.00**	37.90	**44.00**	31.40	**34.90**
	han								
transfer-fnn	mhot	0.70	0.65	1.07	1.96	0.96	1.37	0.53	0.66
	d2v	0.83	0.72	1.27	2.21	1.18	1.62	0.72	0.88
	m2v	0.82	0.70	1.24	2.13	1.13	1.55	0.66	0.82
	lant	0.90	0.83	1.35	2.48	1.17	1.69	0.67	0.84
	gs	0.87	0.74	1.30	2.24	1.26	1.63	0.60	0.76
	gin	0.95	0.78	1.43	2.35	1.37	1.57	0.59	0.76
	gine	1.02	0.83	1.52	2.49	1.35	1.80	0.76	0.92
	gat	1.19	0.92	1.78	2.75	1.62	2.08	0.92	1.09
	gatv2	1.01	0.83	1.51	2.51	1.41	1.88	0.80	0.96
	han	0.93	0.82	1.42	2.49	1.33	1.82	0.80	0.97
transfer-bnn	mhot	0.53	0.49	0.82	1.51	0.73	1.05	0.43	0.54
	d2v	0.68	0.61	1.02	1.86	0.95	1.33	0.56	0.69
	m2v	0.31	0.32	0.48	0.98	0.42	0.65	0.23	0.30
	lant	0.66	0.61	1.01	1.87	0.88	1.28	0.49	0.61
	gs	0.71	0.66	1.08	2.00	0.94	1.36	0.52	0.65
	gin	0.60	0.52	0.91	1.59	0.84	1.15	0.49	0.60
	gine	0.75	0.63	1.12	1.90	1.08	1.44	0.66	0.79
	gat	0.66	0.62	0.99	1.86	0.87	1.28	0.49	0.62
	gatv2	0.64	0.54	0.96	1.64	0.87	1.19	0.49	0.58
	han	0.80	0.71	1.20	2.15	1.09	1.53	0.61	0.76

		imdb-ste							
		%precision		%recall		%ndcg		%map	
approach	gnn	@5	@10	@5	@10	@5	@10	@5	@10
e2e	m2v								
	lant								
	gs	**15.40**	9.16	**49.70**	57.40	33.70	36.80	27.00	29.00
	gin	14.10	8.91	45.30	56.50	28.50	32.80	21.80	24.30
	gine								
	gat	14.70	**9.17**	47.40	**57.50**	33.50	37.40	27.20	29.70
	gatv2	14.50	9.09	46.70	57.20	**33.80**	**37.90**	**27.90**	**30.40**
	han								
transfer-fnn	mhot	0.75	0.70	0.86	1.59	0.84	1.19	0.41	0.52
	d2v	0.84	0.76	0.93	1.72	0.95	1.32	0.45	0.57
	m2v	0.84	0.77	0.95	1.76	0.95	1.33	0.46	0.57
	lant	0.74	0.68	0.81	1.52	0.85	1.18	0.40	0.50
	gs	0.83	0.73	0.91	1.64	0.95	1.27	0.44	0.55
	gin	0.76	0.68	0.84	1.56	0.87	1.19	0.40	0.51
	gine	0.73	0.64	0.82	1.45	0.85	1.14	0.41	0.50
	gat	0.92	0.82	1.00	1.83	1.06	1.43	0.50	0.62
	gatv2	0.87	0.80	0.96	1.80	0.98	1.37	0.47	0.59
	han	0.77	0.72	0.86	1.63	0.85	1.21	0.39	0.50
transfer-bnn	mhot	0.83	0.74	0.95	1.71	0.92	1.28	0.45	0.57
	d2v	0.87	0.81	0.99	1.84	0.98	1.38	0.47	0.60
	m2v	0.76	0.71	0.83	1.58	0.85	1.20	0.41	0.52
	lant	1.01	0.96	1.14	2.18	1.18	1.66	0.58	0.73
	gs	0.99	0.90	1.12	2.03	1.12	1.55	0.54	0.67
	gin	0.90	0.83	1.04	1.92	1.07	1.47	0.52	0.65
	gine	1.01	0.93	1.15	2.14	1.16	1.62	0.58	0.71
	gat	0.96	0.86	1.07	1.94	1.10	1.50	0.53	0.66
	gatv2	0.93	0.80	1.05	1.84	1.05	1.41	0.51	0.62
	han	1.06	0.99	1.19	2.25	1.21	1.70	0.59	0.74

Challenges and New Perspectives

- End-to-End Graph Neural Network
- Fair and Diverse Team Recommendation
- Spatial Team Recommendation

Fair and Diverse Team Recommendation

The primary focus of existing team recommendation methods is maximizing the models' efficacy, largely ignoring diversity in the recommended users.

Fair and Diverse Team Recommendation

The primary focus of existing team recommendation methods is maximizing the models' efficacy, largely ignoring diversity in the recommended users.

Fairness in machine learning algorithms guarantees where a disadvantaged group also known as a protected group, should be treated similarly to the advantaged group as a whole.

[Altenburger et.al., AAAI Conference on Web and Social Media, 2017]

Fair and Diverse Team Recommendation

There is little to no diversity-aware algorithmic method that mitigates unfair societal biases in team recommendation models.

Fair and Diverse Team Recommendation

There is little to no diversity-aware algorithmic method that mitigates unfair societal biases in team recommendation models.

Notions of **Group** Fairness:

Fair and Diverse Team Recommendation

There is little to no diversity-aware algorithmic method that mitigates unfair societal biases in team recommendation models.

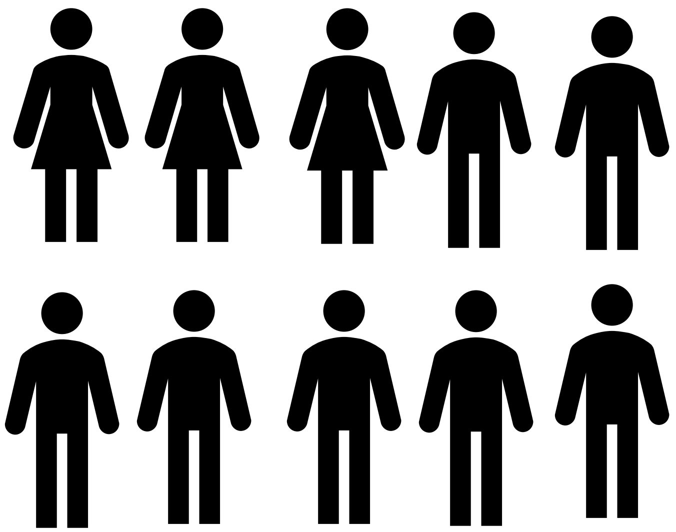
Notions of **Group** Fairness:

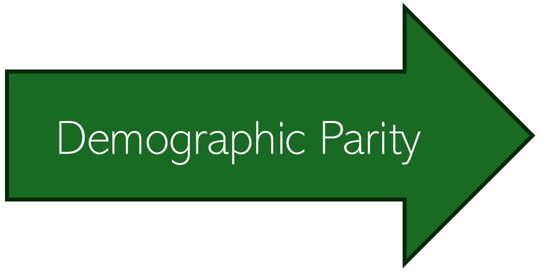
- Demographic Parity
- Equality of Opportunity

Fair and Diverse Team Recommendation

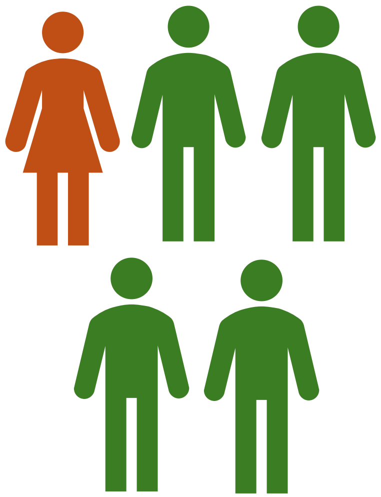
Demographic Parity

Candidate Pool





Final Team



- Male: 70%
- Female: 30%

Fair and Diverse Team Recommendation

Demographic Parity :

Enforces the membership in a team to be independent of values of a protected attribute for team members.

$$[\mathrm{P}(e_0 \in T) = \mathrm{P}(e_1' \in T)] \wedge [\mathrm{P}(e_0 \notin T) = \mathrm{P}(e_1' \notin T)]$$

Male

Female

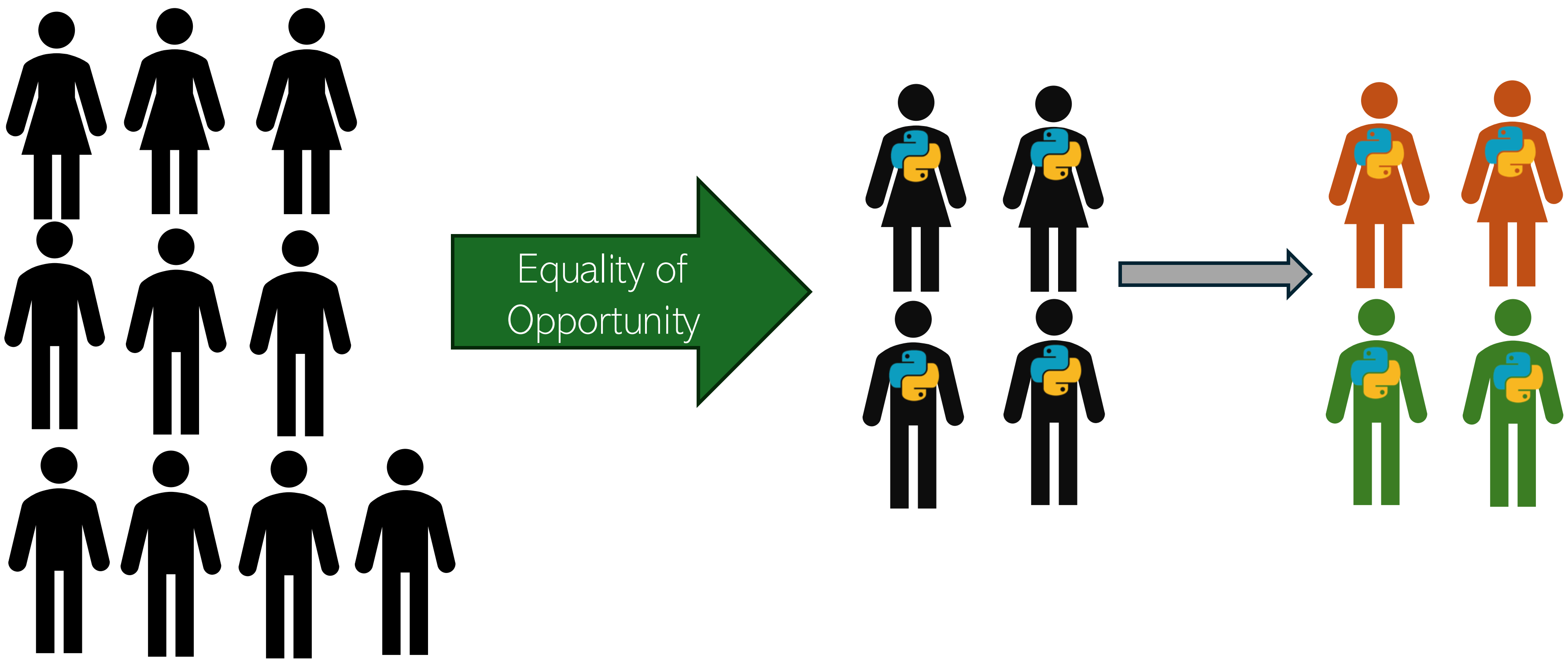
Fair and Diverse Team Recommendation

Equality of Opportunity

Programmers

Qualified Set :
Python Programmers

Final Team



- Male: 50%
- Female: 50%

Fair and Diverse Team Recommendation

Equality of Opportunity:

Enforces the skilled membership in a team to be independent of values of a protected attribute for team members.

$$[\mathrm{P}(e_0 \in T | e_0 , S_{e_0} \cap S \neq \emptyset) = \mathrm{P}(e_1' \in T | e_1' , S_{e_1'} \cap S \neq \emptyset)]$$

Skilled Male

Skilled Female

Fair and Diverse Team Recommendation

Debiasing algorithms can be categorized based on their integration into the machine learning pipeline:

- **Pre-process**: No work, to the best of our knowledge
- **In-process**: Little work, *vivaFemme* [Moasses et.al., BIAS-SIGIR, 2024]
- **Post-process**: Little work, Adila [Loghmani et.al., BIAS-ECIR, 2022], [Geyik et.al., KDD, 2019],

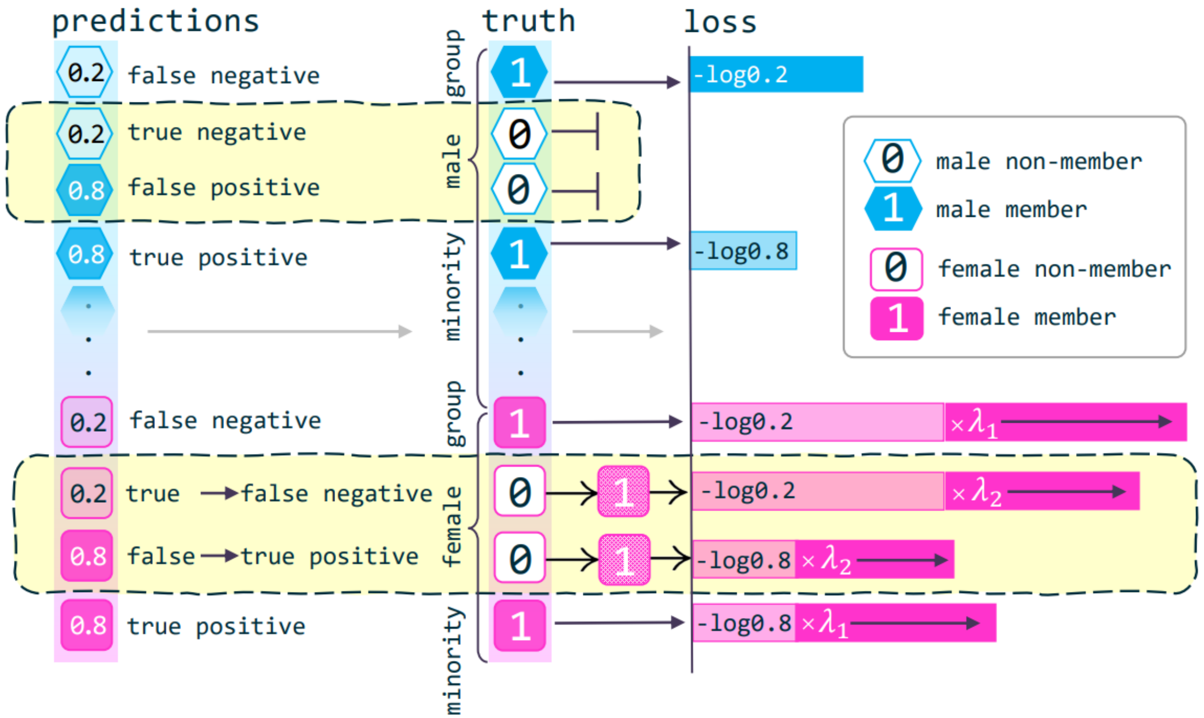
Fair and Diverse Team Recommendation

- Pre-processing methods modify data or label through re-sampling heuristics before model training.

Fair and Diverse Team Recommendation

- In-processing techniques adjust the optimization process of models to balance accuracy and fairness.

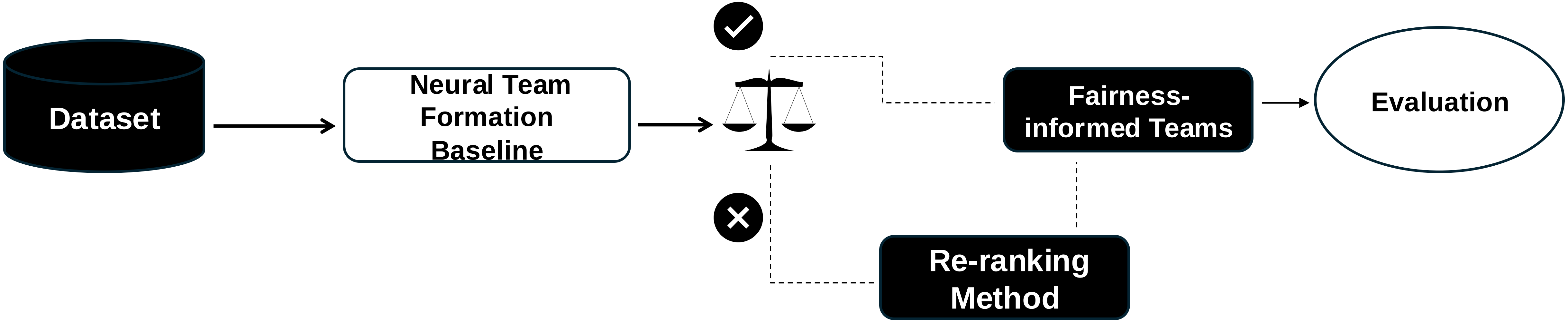
[Moasses et.al., BIAS-SIGIR, 2024]



Fair and Diverse Team Recommendation

- Post-processing methods modify model outputs during inference, which may involve altering thresholds, scoring rules, or reranking the recommended list of items.

[Loghmani et.al., BIAS-ECIR, 2022], [Geyik et.al., KDD, 2019]



Fair and Diverse Team Recommendation

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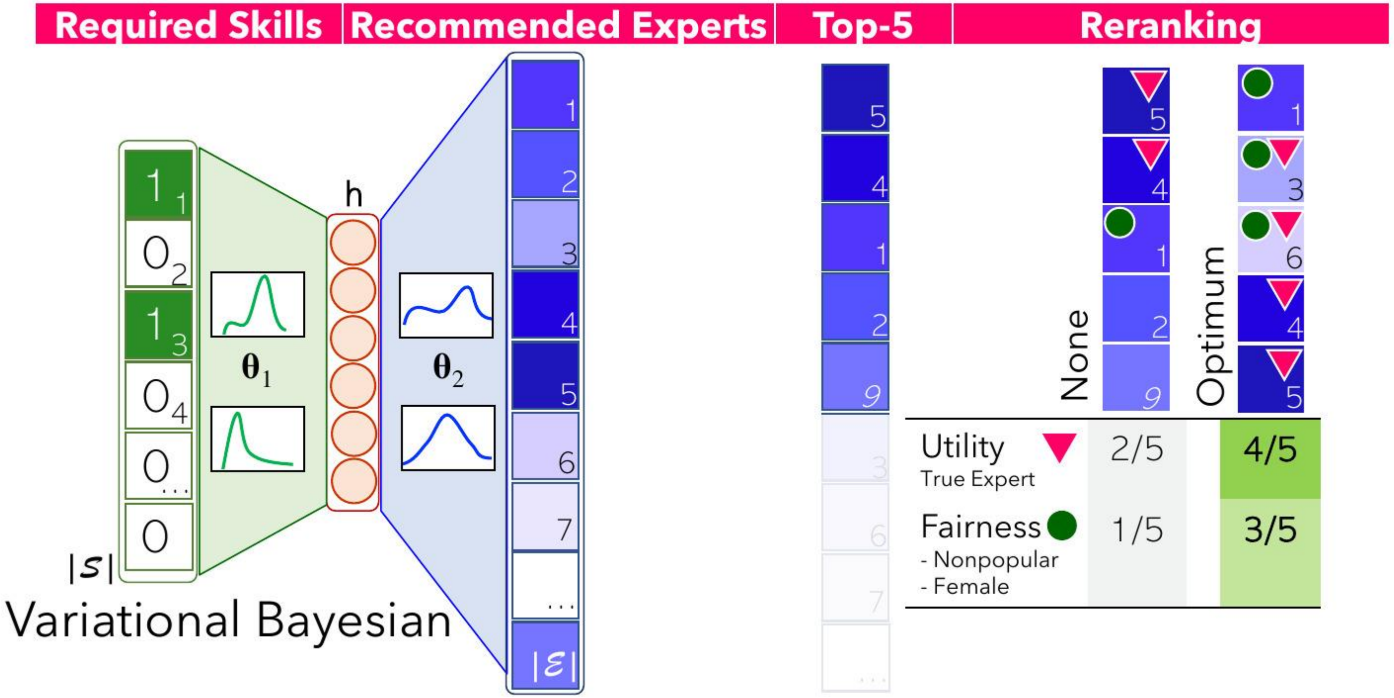


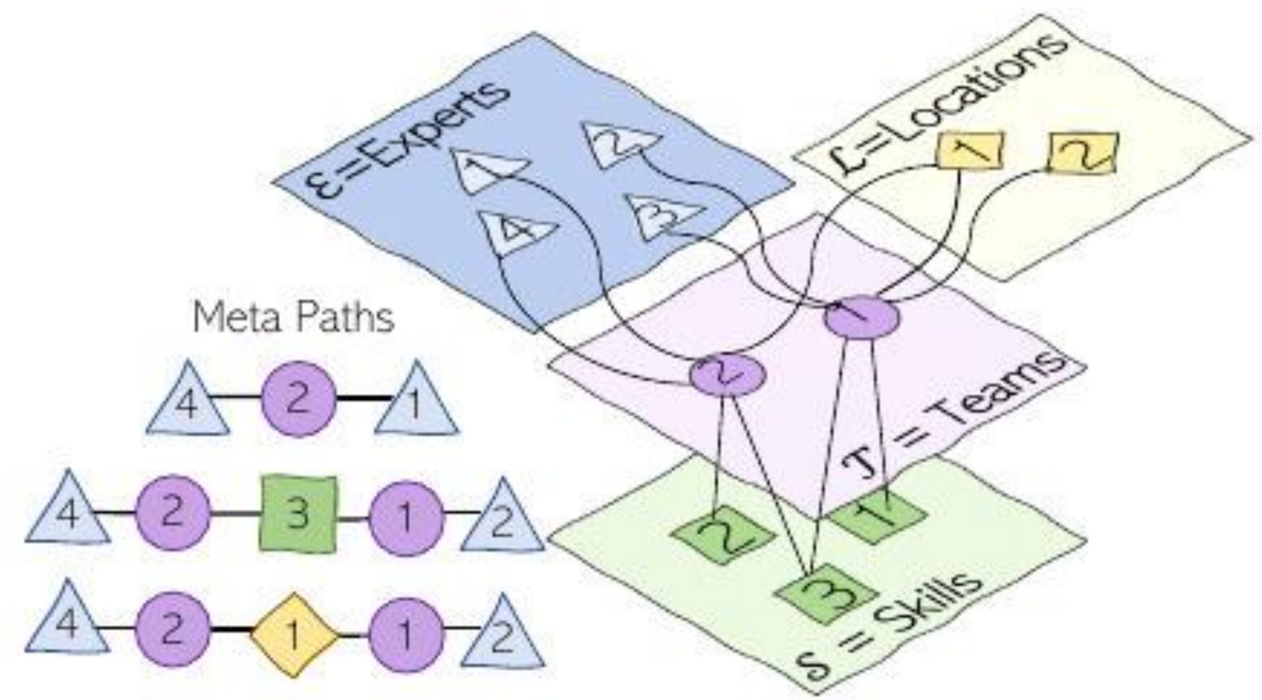
Challenges and New Perspectives

- End-to-End Graph Neural Network
- Fair and Diverse Team Recommendation
- Spatial Team Recommendation

Spatial Team Recommendation

The majority of existing methods use skills as a primary factor while overlooking geographical location and the corresponding ties it leads to between users in a team.

- Time zone
- Region



Outline

Applications

- Group Learning
- Reviewer Assignment
- Palliative Care

Applications

- Group Learning
- Reviewer Assignment
- Palliative Care

Group Learning

Why group learning

Group Learning

Why group learning

Active Engagement:

Working in groups helps students engage deeply with the material and share their knowledge

Group Learning

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Accountability:

Teamwork motivates students to enhance problem solving skills, stay on track and meet deadlines.

Group Learning

Why group learning

Active Engagement:

Working in groups helps students engage deeply with the material and share their knowledge

Accountability:

Teamwork motivates students to enhance problem solving skills, stay on track and meet deadlines.

Essential Skills:

Develops time management and communication skills for future success.

Group Learning

Not all student groups work well.

Group Learning

Not all student groups work well. Why?

Group Learning

Not all student groups work well. Why?

Groups are not systematically formed.

Group Learning

Team recommendation approaches in the classroom

- Average grade

Group Learning

Team recommendation approaches in the classroom

- Average grade
- Availability for work

Group Learning

Team recommendation approaches in the classroom

- Average grade
- Availability for work
- Personality and behavior

Group Learning

Prior Methods

Group Learning

Prior Methods

- Integer linear programming (ILP)

Group Learning

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- Integer linear programming (ILP)
- Genetic Algorithm

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Group Learning

Prior Methods

- Integer linear programming (ILP)
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    - Resource allocation [Vecina et al, HAIS 2022]
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    - Task assignment to agents based on their capabilities [Crawford et al, AAMAS 2016]

Group Learning

Prior Methods

- Integer linear programming (ILP)
- Genetic Algorithm
  - Resource allocation [Vecina et al, HAIS 2022]
  - Matching of students to supervisors [Sanchez et al, Appl. Soft Comput. 2019]
  - Task assignment to agents based on their capabilities [Crawford et al, AAMAS 2016]
  - Project allocation to individuals according to their skills [Camelo et al, Comput. Oper. Res., 2021]

Applications

- Group Learning
- Reviewer Assignment
- Palliative Care

Reviewer Assignment

Background

Reviewer Assignment

Background

- Peer review is a critical part of the academic publishing process and is closely tied to the quality and integrity of academic journals.

[Mandviwalla et. Al., Decision Support Systems, 2008]
[Zhang et. Al., Information Processing and Management, 2023]

Reviewer Assignment

Background

- Peer review is a critical part of the academic publishing process and is closely tied to the quality and integrity of academic journals.
- Assigning reviewers to a manuscript is crucial for determining the quality and suitability of submitted manuscript.

[Mandviwalla et. Al., Decision Support Systems, 2008]
[Zhang et. Al., Information Processing and Management, 2023]

Reviewer Assignment

Approaches

Reviewer Assignment Approaches

Reviewer-paper matching degree

Reviewer Assignment Approaches

Reviewer-paper matching degree

- Manual methods such as asking reviewers to bid on papers. [Shah et. Al., Journal of Machine Learning Research, 2018]

Reviewer Assignment Approaches

Reviewer-paper matching based

- Text information-based method to compared the similarity between potential reviewers and manuscripts. [yang et. Al., Applied Soft Computing, 2020]

Reviewer Assignment Approaches

Retrieval-based reviewer assignment

Reviewer Assignment Approaches

Retrieval-based reviewer assignment

- Developed a recommendation framework that employs information retrieval techniques to collate publications, keywords, and abstracts by integrating cosine similarity assessments between keywords and full-text indices to generate final recommendations. [Arabzadeh et. Al., CIKM, 2024]

Applications

- Group Learning
- Reviewer Assignment
- Palliative Care

Palliative Care

Background

- Palliative care is caring holistically for patients and families to improve their quality of life.

[Manalu et. Al., International Journal of Medical and Health Sciences, 2022]
[Selvarajah et. Al., Innovations in Intelligent Systems and Applications (INISTA), 2018]

Palliative Care

Background

- Palliative care is caring holistically for patients and families to improve their quality of life.
- It provides an active and comprehensive integrated health approach, which is a multidisciplinary approach that integrates doctors, nurses, physiotherapists, psychologists, nutritionists and other professions as needed.

[Manalu et. Al., International Journal of Medical and Health Sciences, 2022]
[Selvarajah et. Al., Innovations in Intelligent Systems and Applications (INISTA), 2018]

Palliative Care

Background

- The care system takes a team-based approach to address the needs of patients and their families.

[Manalu et. Al., International Journal of Medical and Health Sciences, 2022]
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Palliative Care

Background

- The care system takes a team-based approach to address the needs of patients and their families.

Challenges:

- Each care provider has limited capabilities and can provide special type of services.
- Several barriers such as geographical distance, communication costs, time availability, etc.

[Manalu et. Al., International Journal of Medical and Health Sciences, 2022]
[Selvarajah et. Al., Innovations in Intelligent Systems and Applications (INISTA), 2018]

Palliative Care as a Team Recommendation Problem

- Care providers as experts.
- Services they can provide as skills.

[Manalu et. Al., International Journal of Medical and Health Sciences, 2022]
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Palliative Care as a Team Recommendation Problem

- Care providers as experts.
- Services they can provide as skills.
- Based on the structure of the network, and relationship among the care providers in the network, the best team of support/care can be identified. (efficient team)

[Manalu et. Al., International Journal of Medical and Health Sciences, 2022]
[Selvarajah et. Al., Innovations in Intelligent Systems and Applications (INISTA), 2018]

Palliative Care as a Team Recommendation Problem

Mapping the Care Network:

- The care network is mapped to a weighted graph, considering factors such as distance, communication, and contact costs.

[Manalu et. Al., International Journal of Medical and Health Sciences, 2022]
[Selvarajah et. Al., Innovations in Intelligent Systems and Applications (INISTA), 2018]

Palliative Care Approaches

Evolutionary Modelling

- Cultural Algorithm [Selvarajah et. Al., Innovations in Intelligent Systems and Applications (INISTA), 2018]

Resources

https://fani-lab.github.io/OpeNTF/tutorial/sigir-ap24/

All materials are available on the tutorial website.

- List of related papers
- Slides
- Video
- Link to libraries