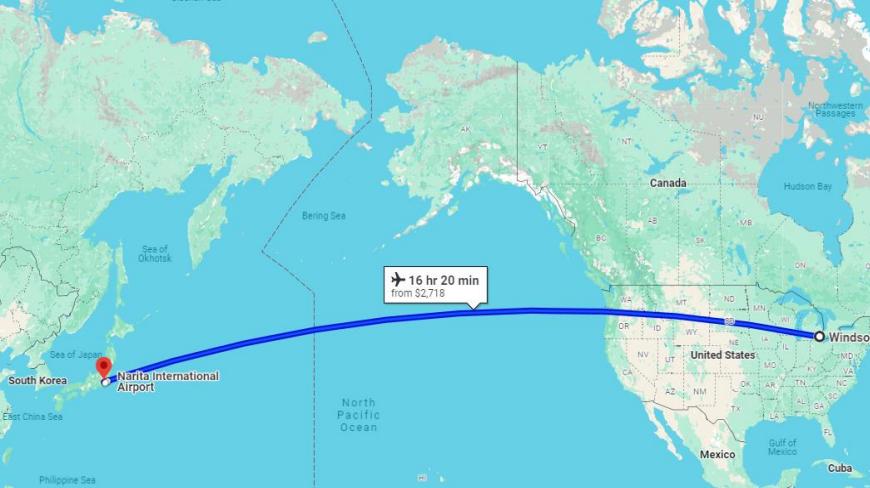




Paradigm Shifts in Team Recommendation  
**From Historical Subgraph Optimization to Emerging Graph Neural Network**  
Fani's Lab/ @SIGIR-AP24



“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



# Outline

- I) Introduction and Background (Hossein)
- II) Pioneering Techniques (Mahdis)
- III) Learning-based Heuristics (Mahdis)
- IV) Challenges and New Perspectives (Mahdis)
- V) Applications (Mahdis)

Hands-on: OpeNTF (Christine & Jamil)

# Outline

I) Introduction and Background

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III) Learning-based Heuristics

IV) Challenges and New Perspectives

V) Applications

Hands-on: OpeNTF

## What Is a Team?

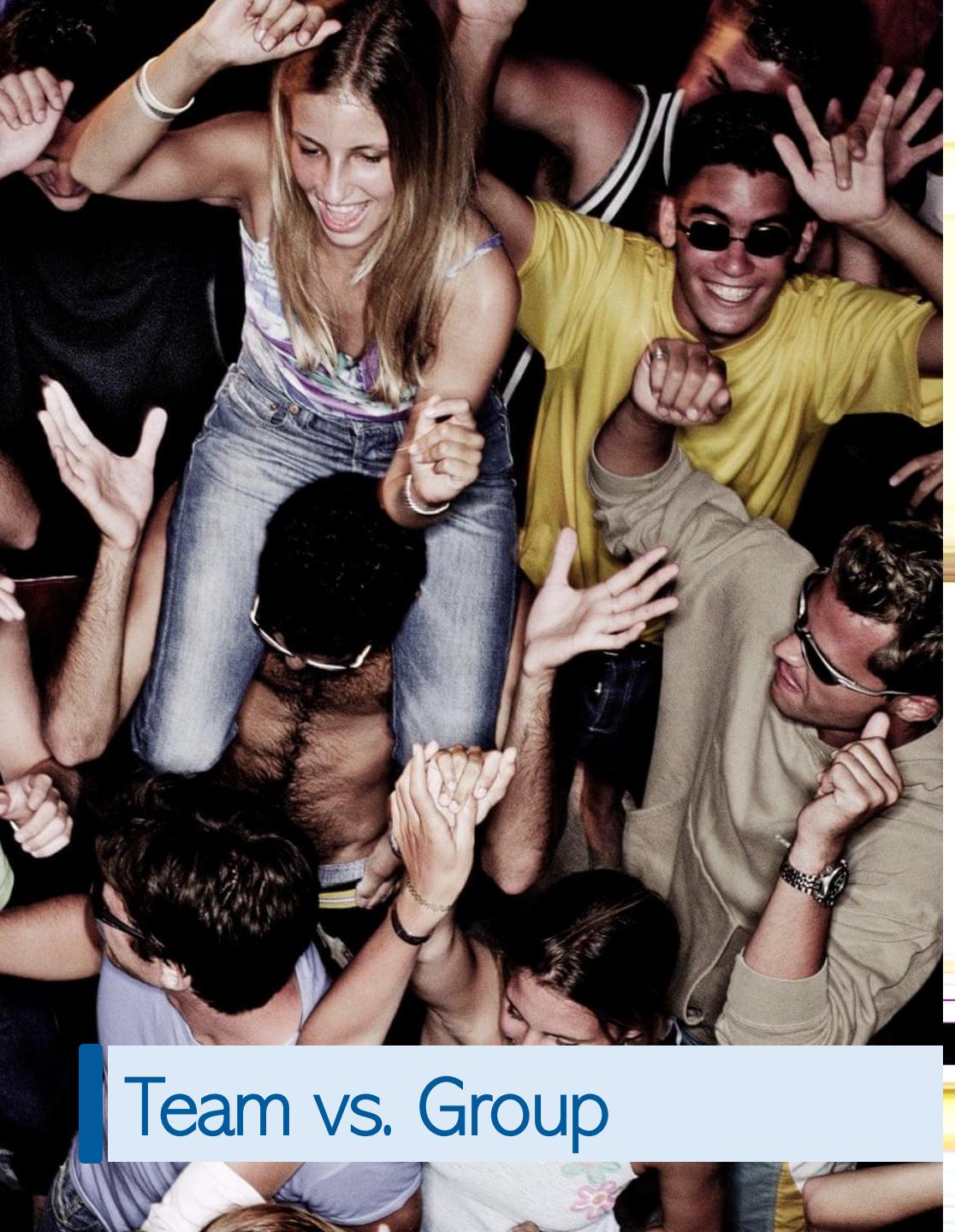
A group of users who **collaborate** together with a **common purpose** in order to accomplish the requirements of a task.

[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

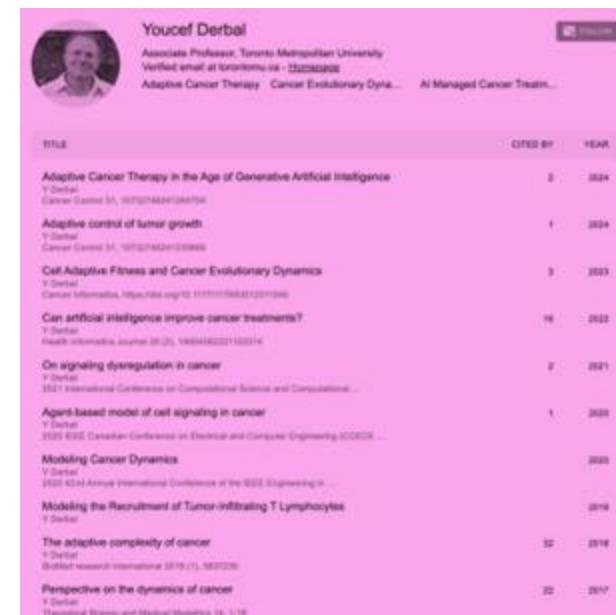
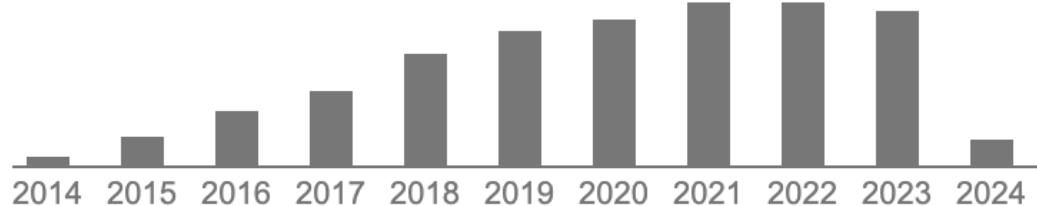
Authors Tomas Mikolov, Kai Chen, Greg Corrado, Jeffrey Dean

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



The Big Lebowski, 1998, Joel & Ethan Coen



## Entertainment Industry (Cast'nCrew)

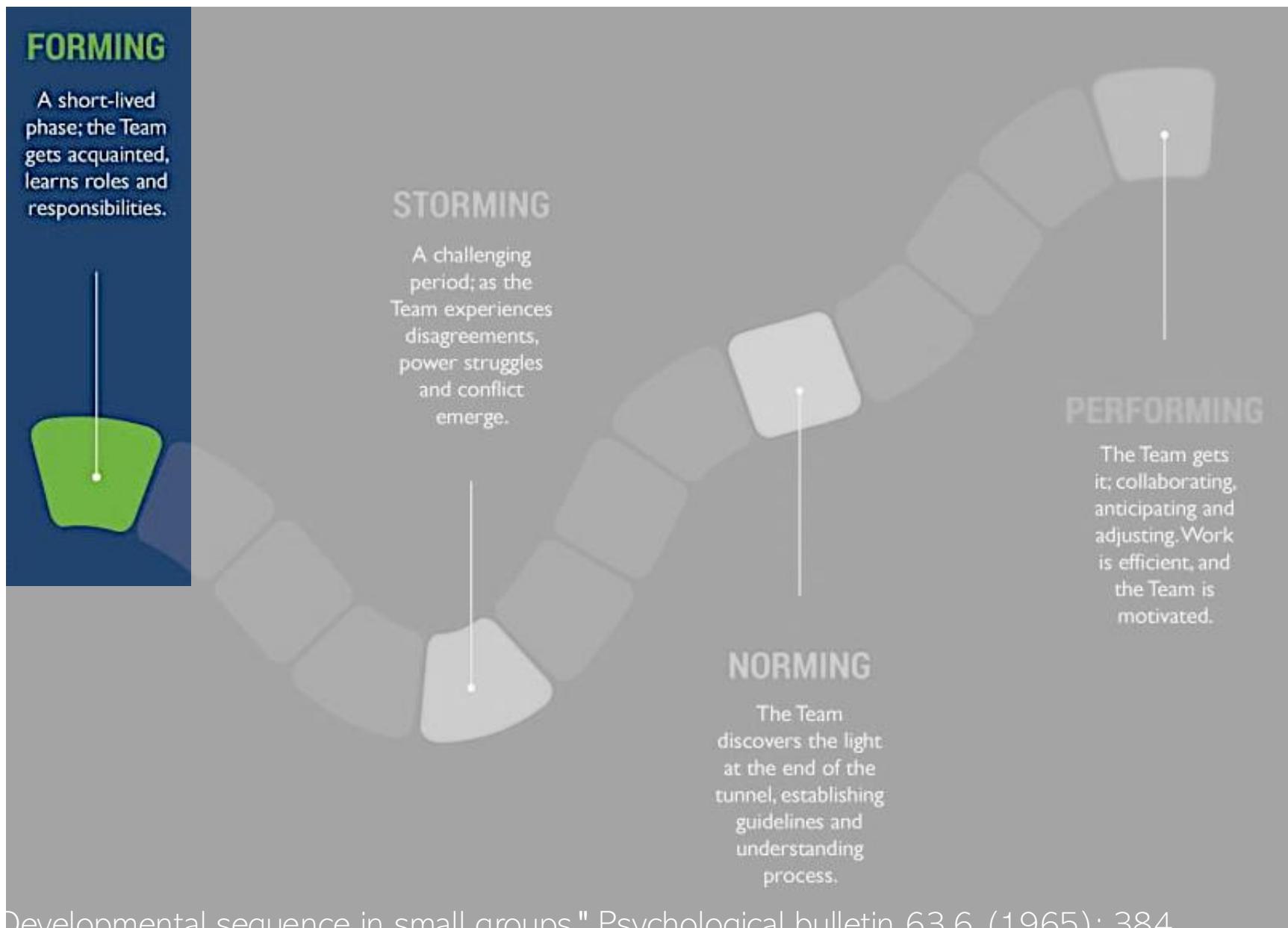


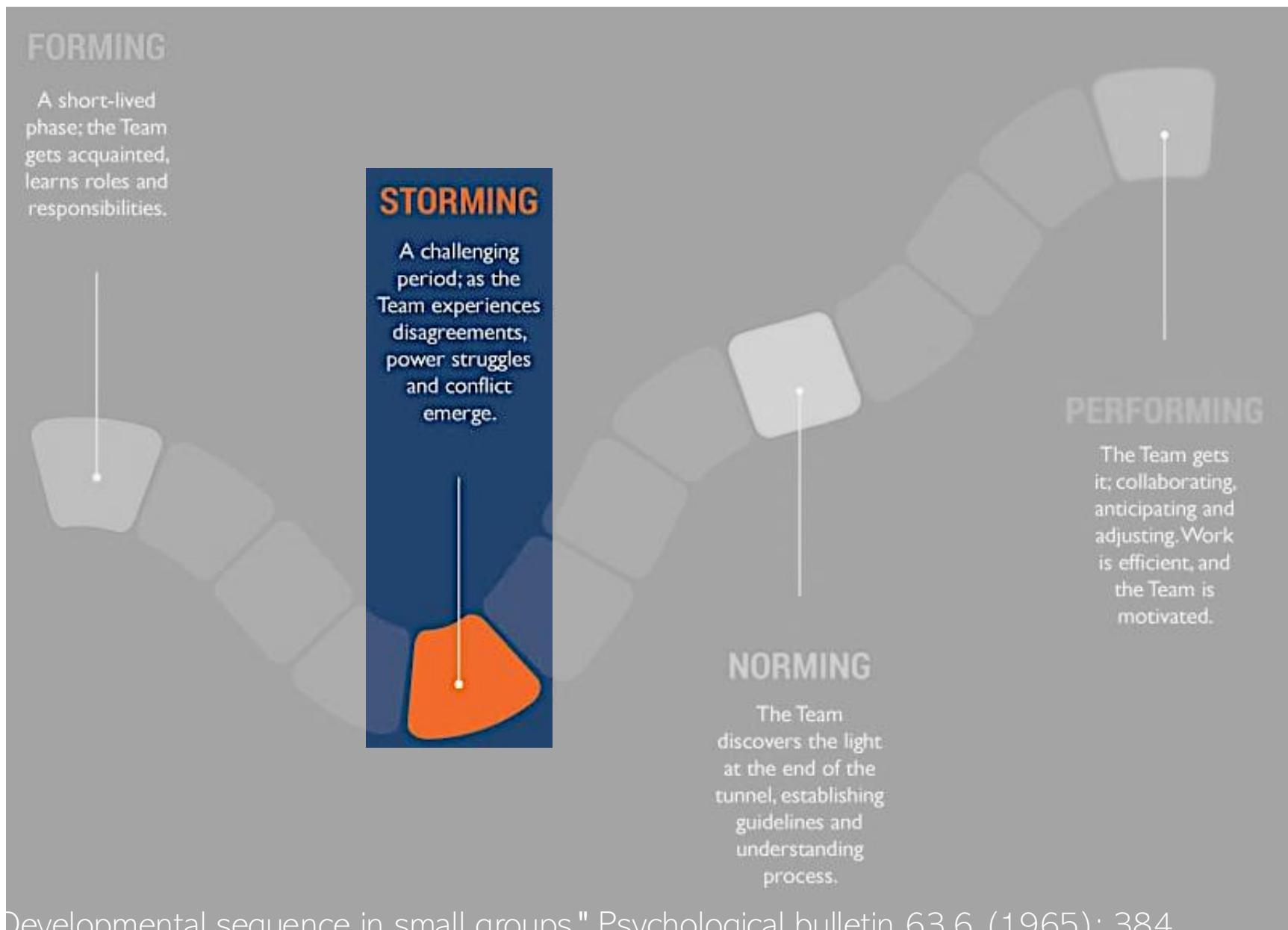
# Sport Teams

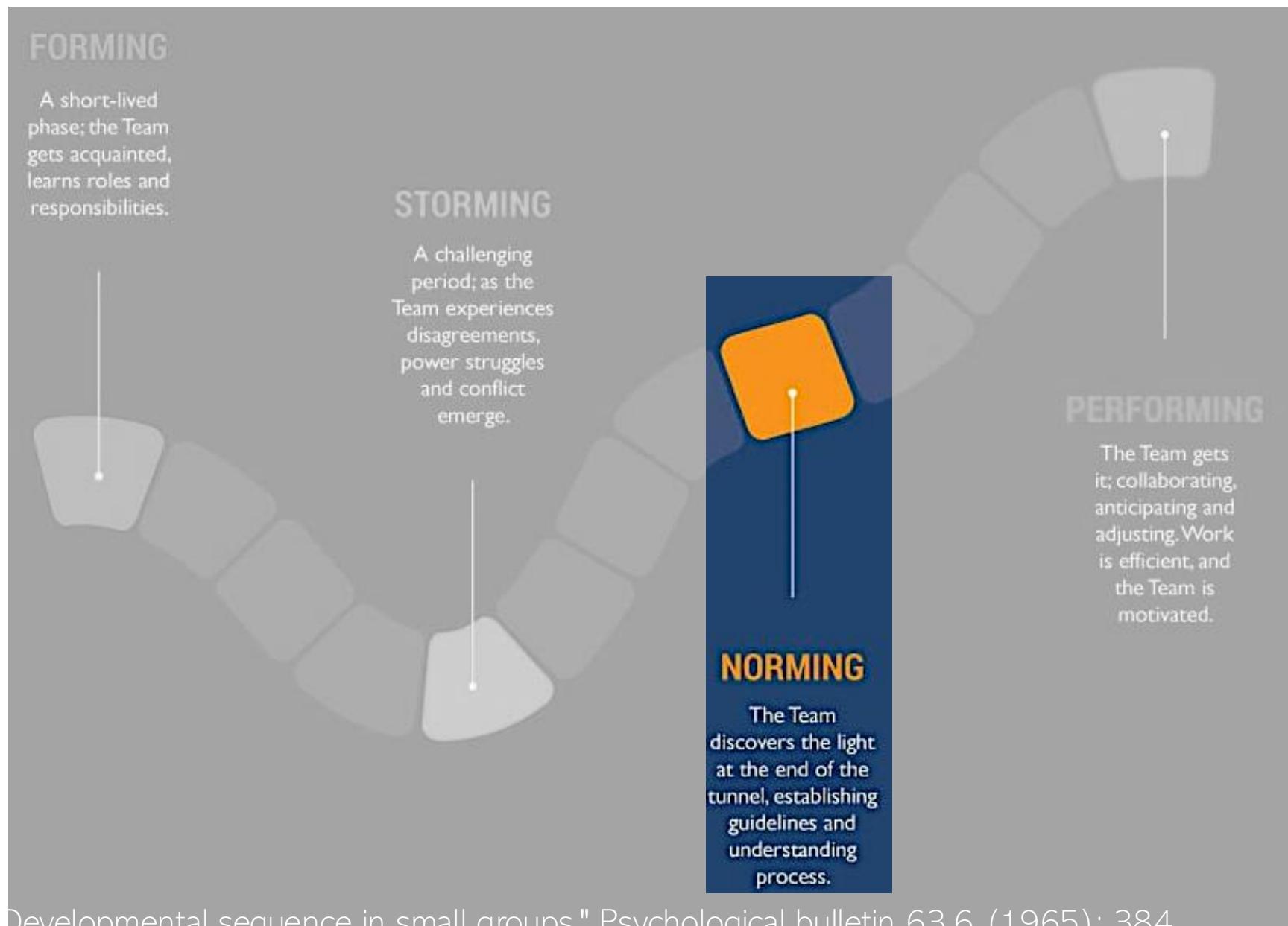
# Development for a Team

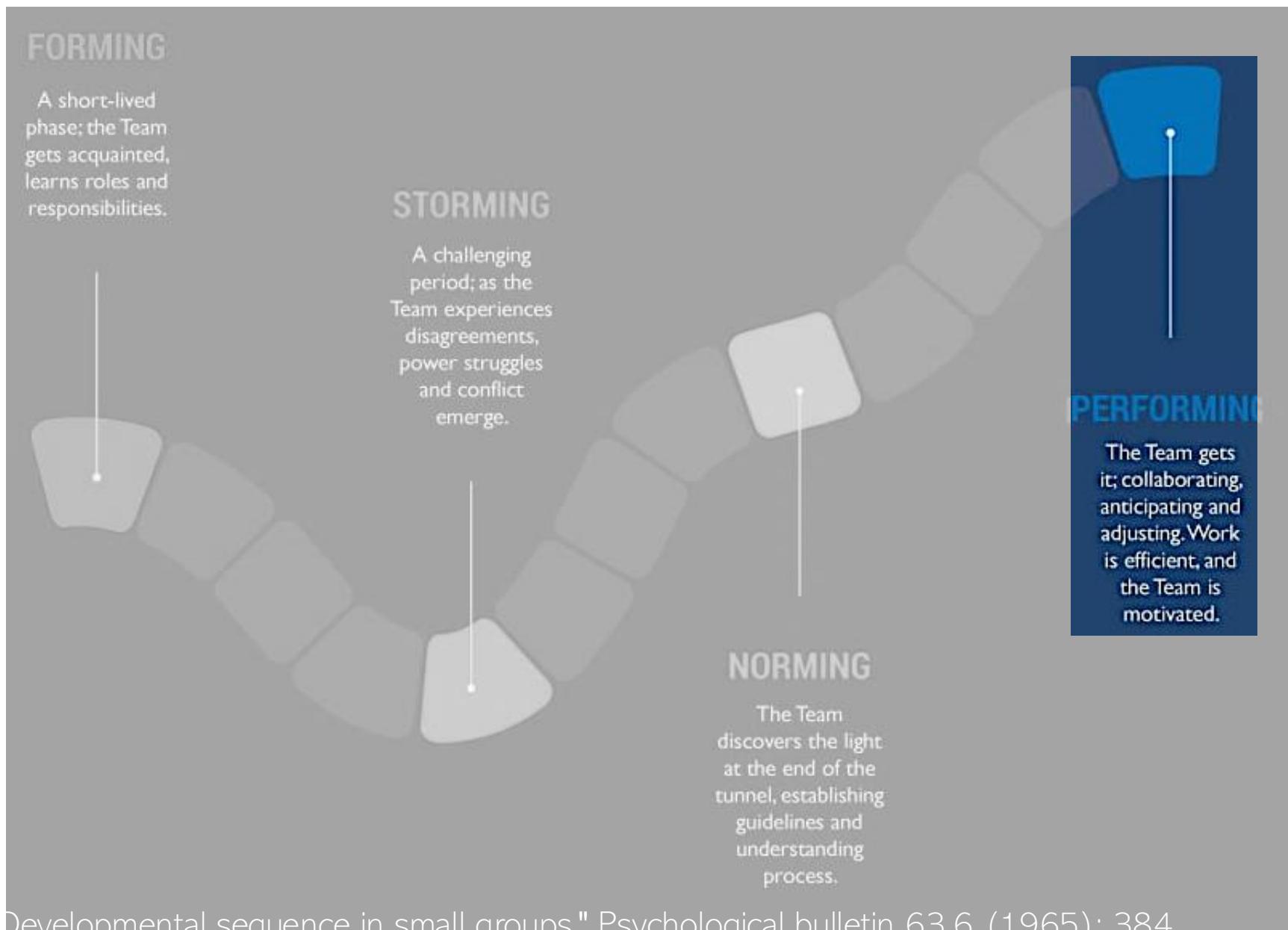
**Four distinct phases** of development for a team

[Tuckman et al., Psychological bulletin ,1965]









# 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](#)



297 ↗ 3,631

## 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>



### Abstract

We present Aardvark, a social search engine. Published: 01 April 2012 [Publication History](#)  
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 it. The challenge lies in finding the right document. Unlike a traditional 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.

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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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## 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!



Own Now on Digital  
Now Playing In Theaters



Tomas Mikolov

## Efficient estimation of word representations in vector space

Authors Tomas Mikolov, Kai Chen, Greg Corrado, Jeffrey Dean

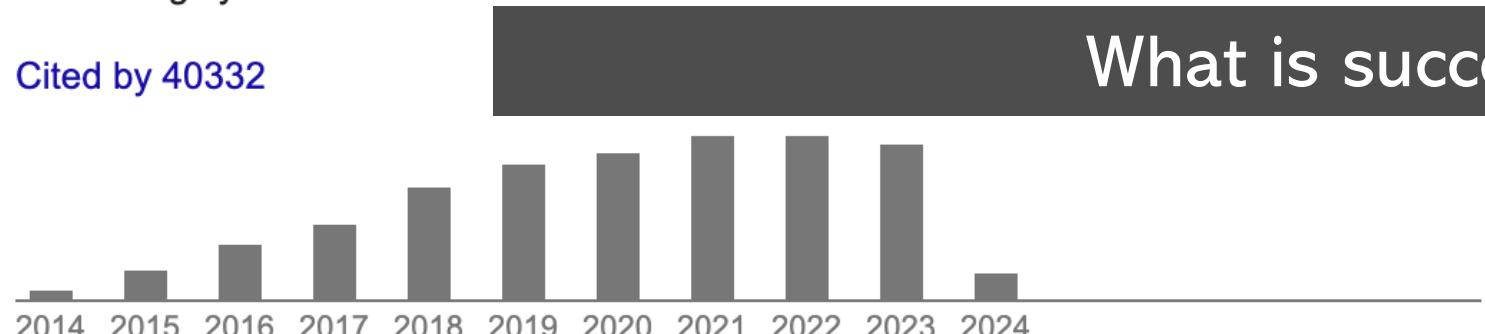
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What is success?



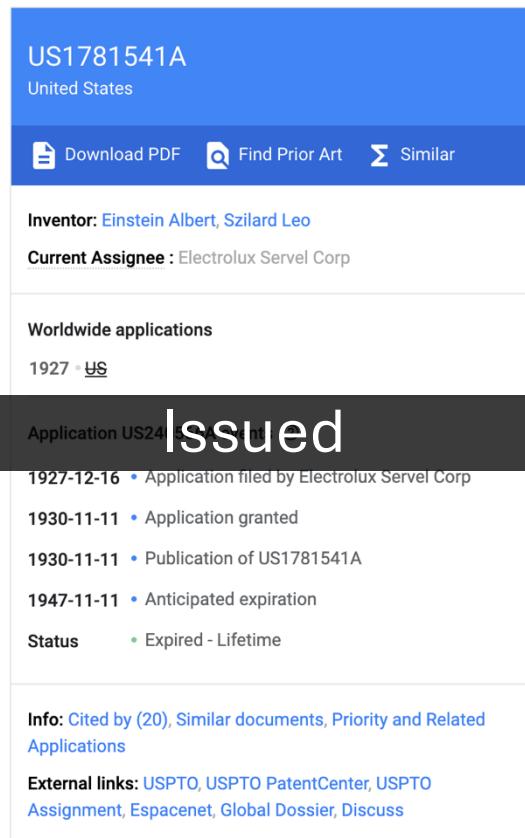
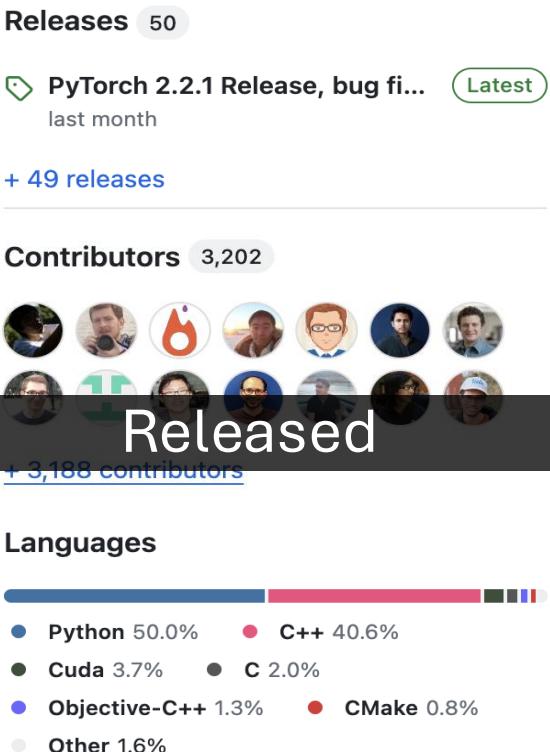
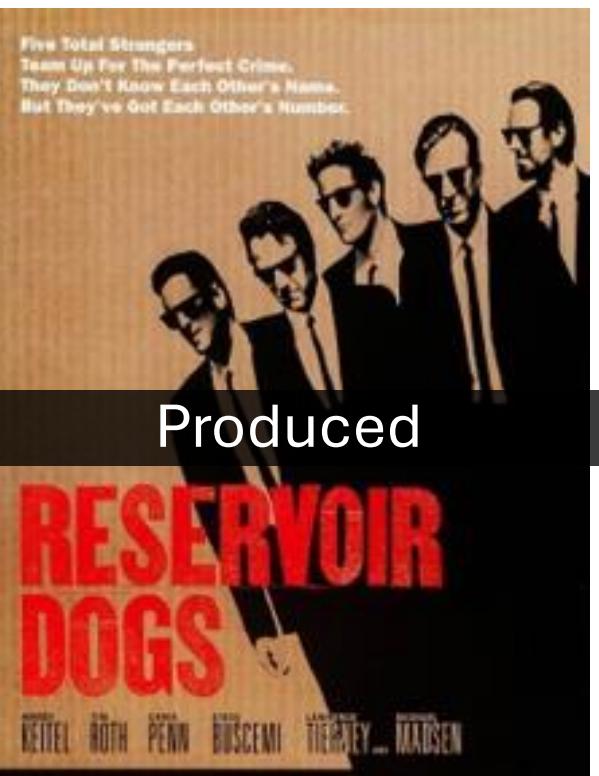
**Tomas Mikolov**

December 13, 2023 ·

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

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://www.facebook.com/share/p/kXYaYaRvRCr5K2Ze>**What is success?**



## A Streaming Approach to Neural Team Formation Training

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

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, we propose a neural team formation method that learn vector representations of experts' skills in a streaming fashion in a 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.

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

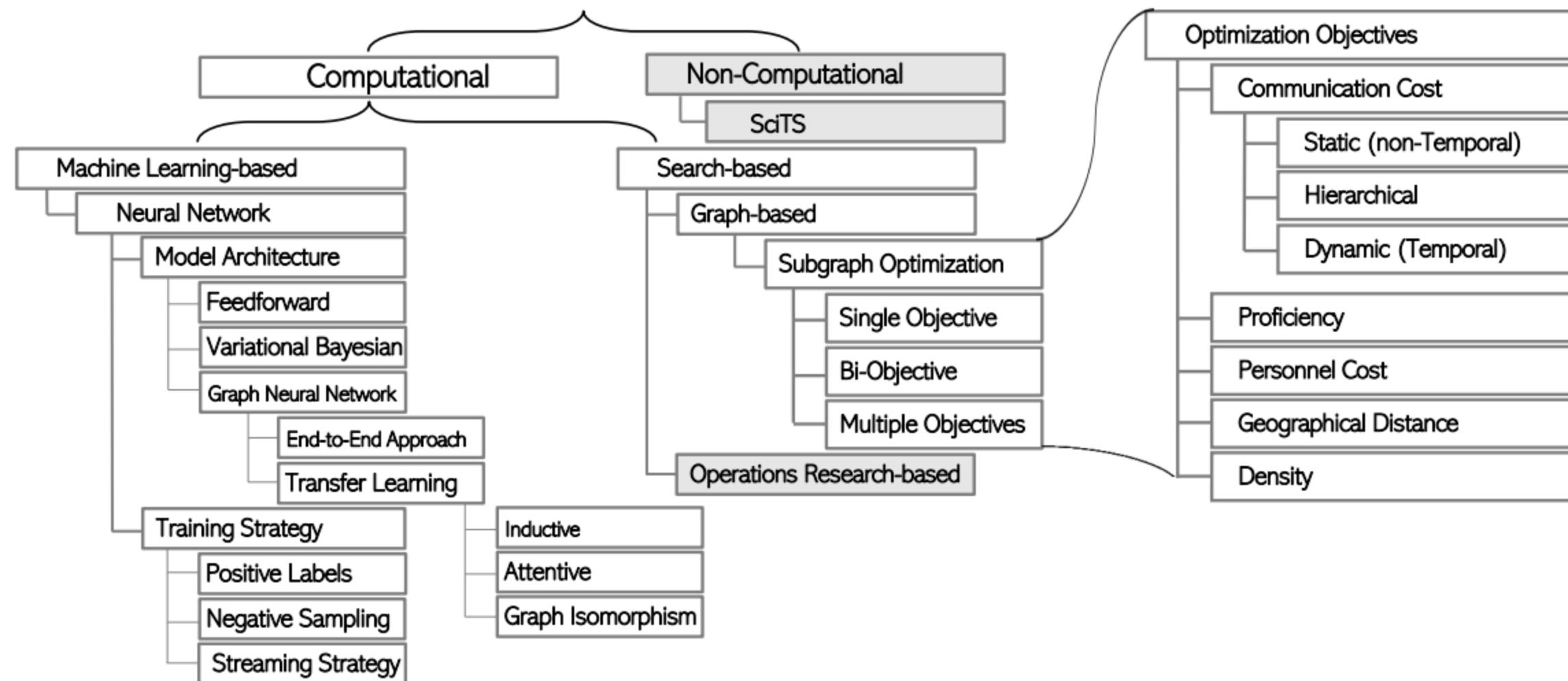
Teams were formed **manually** by relying on **human experience** and **instinct** in a **tedious**, **error-prone**, and **suboptimal** process.

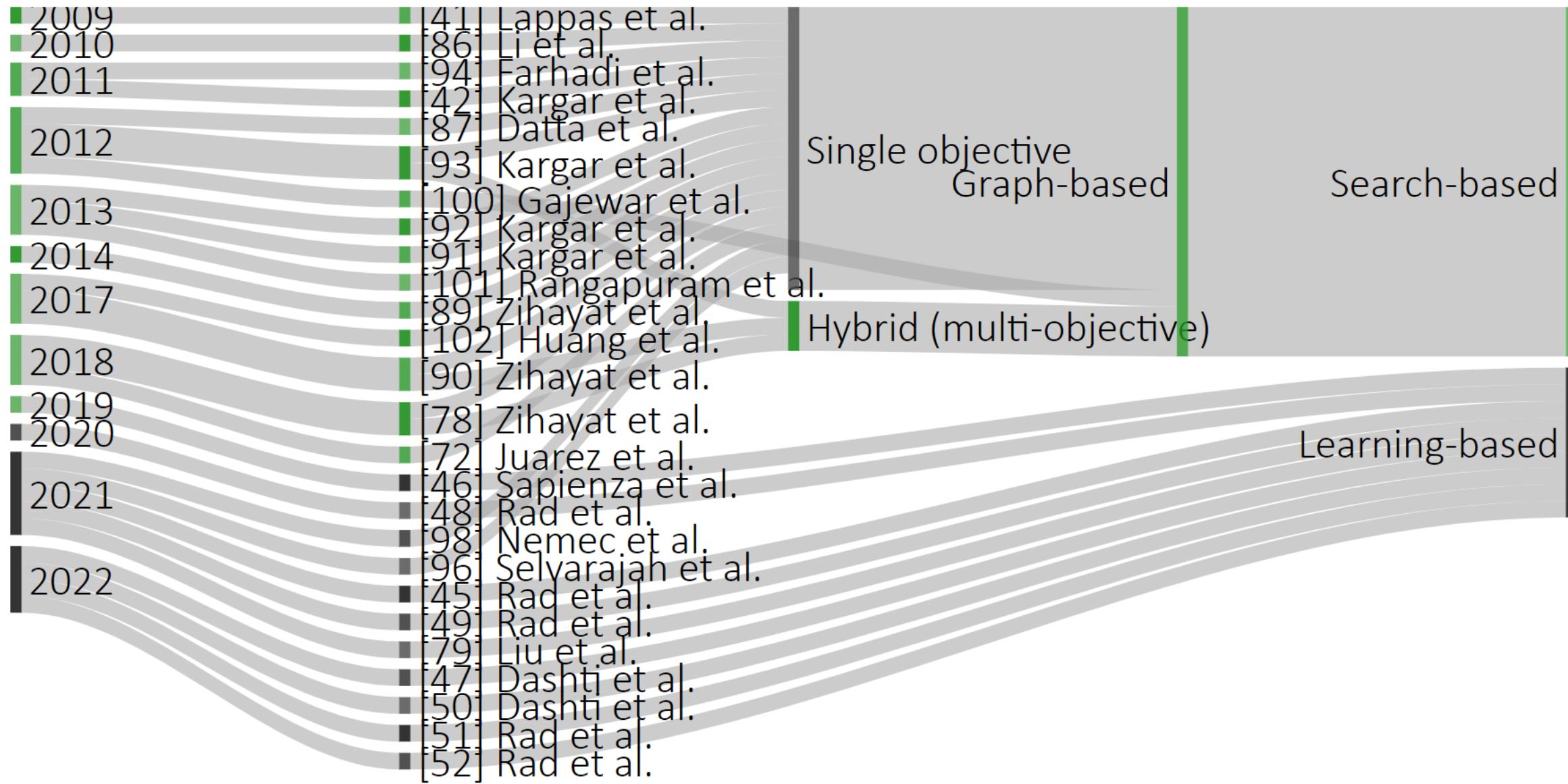
## Difficulties:

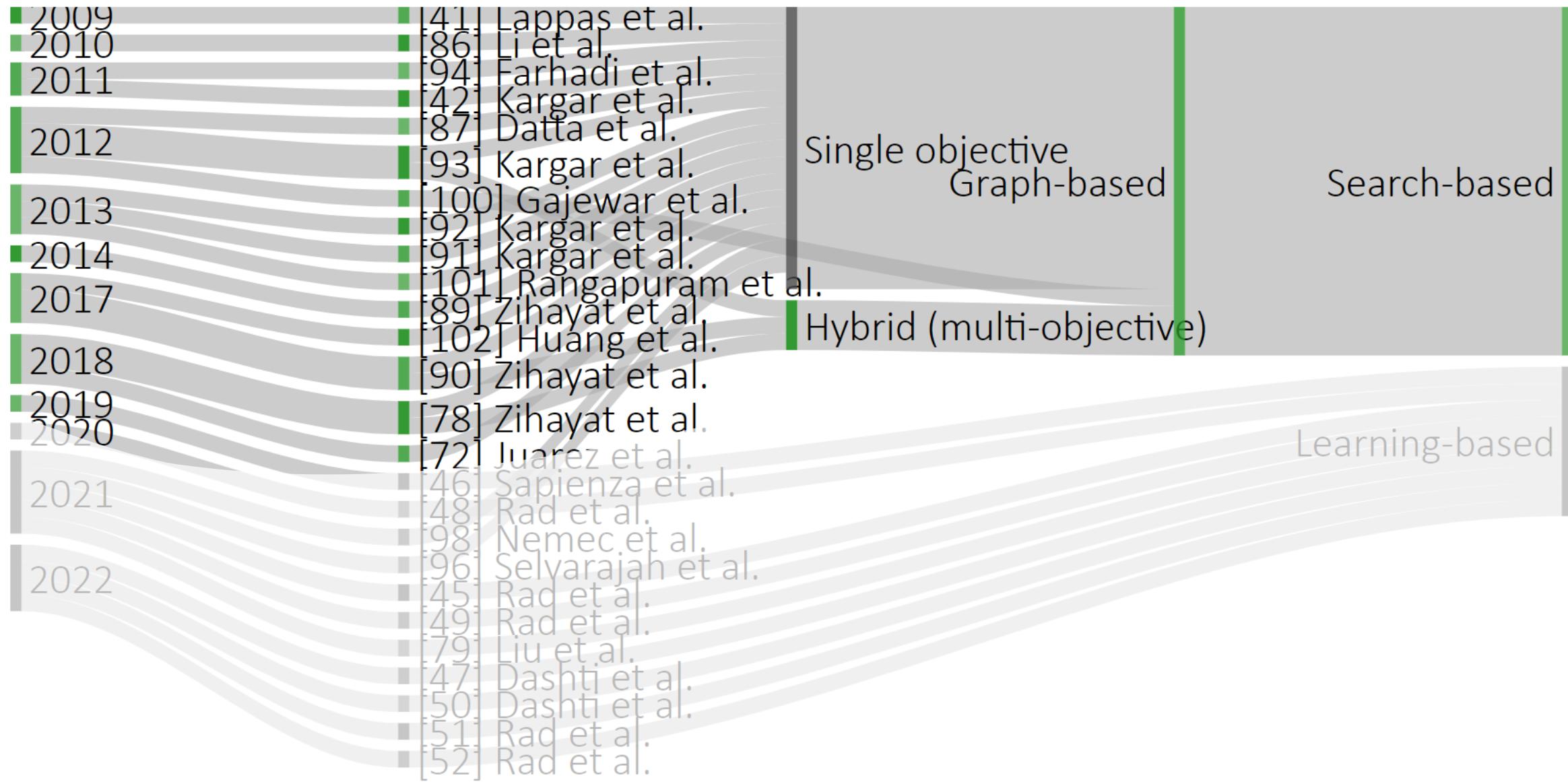
**Manual** team recommendation on a **large scale** is almost **impossible**

- Race
  - Gender
  - Popularity
- 
- o Multitude of criteria to optimize
    - Communication cost
    - Budget
    - Time

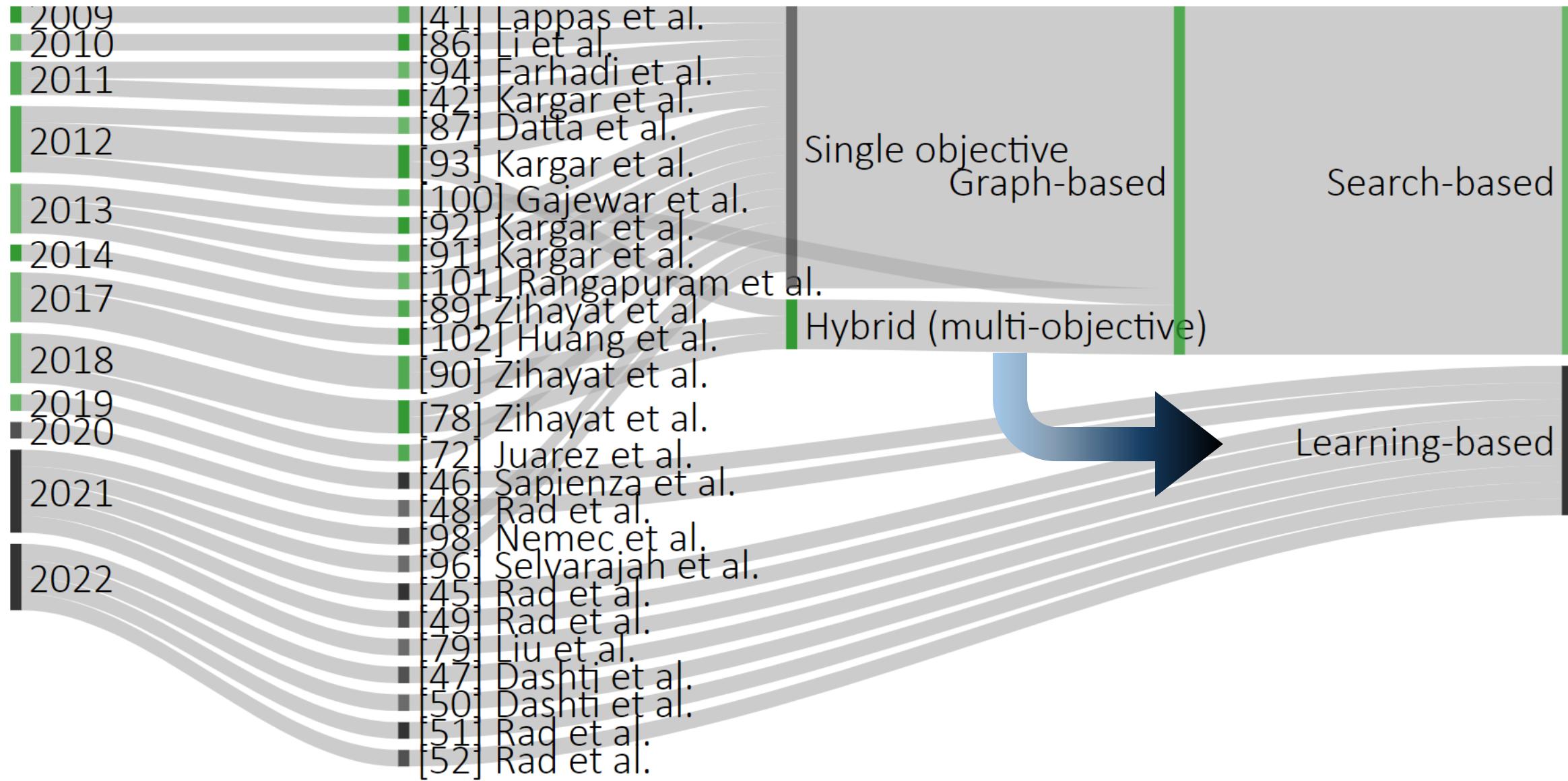
# Computational Approach







Computationally Prohibitive



# 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.

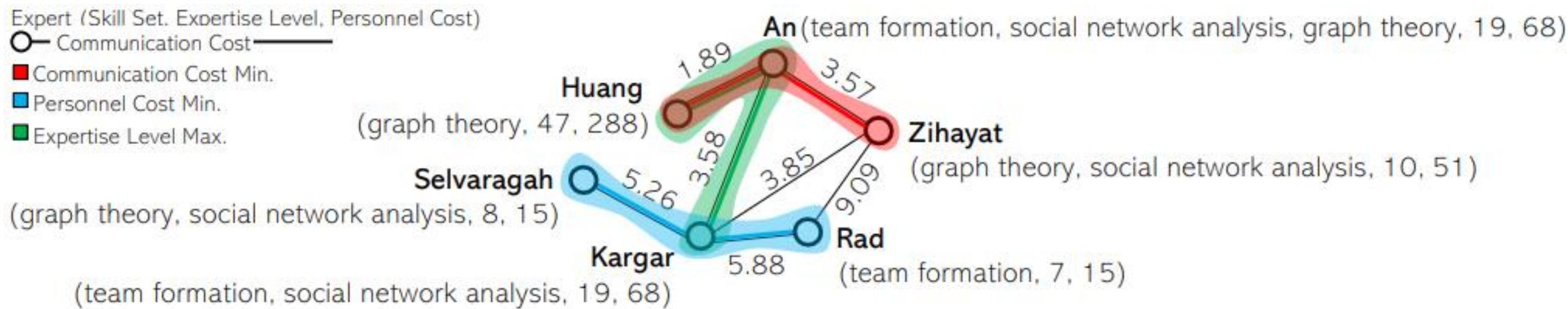
The problem of team recommendation has been translated into graph mining.

# 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
- Proficiency
- Personnel Cost
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- Multi-Objective

# Communication Cost ( $\varphi$ )

- 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 ( $\varphi$ )

Communication cost computations:

# Communication Cost ( $\varphi$ )

Communication cost computations:

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

# Communication Cost ( $\varphi$ )

Communication cost computations:

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

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
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						✓	✓				✓

# Communication Cost Minimization Methods

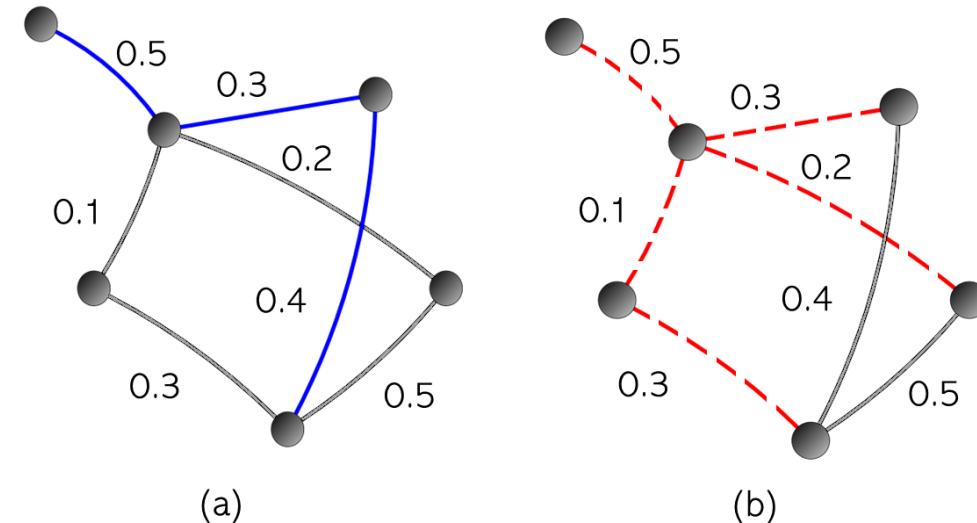
- Non-temporal (Static)
- Temporal (Dynamic)

# Communication Cost Minimization Algorithms ( $\varphi$ )

- 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.

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

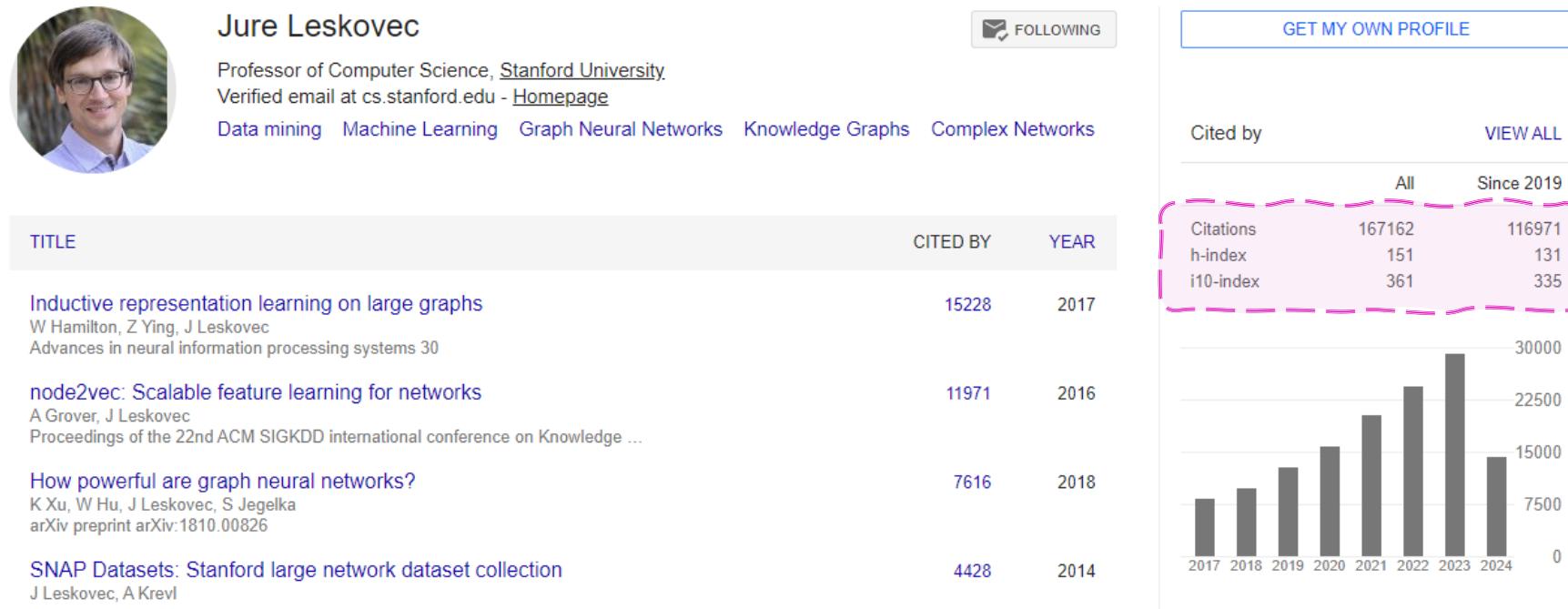
# Subgraph Optimization Objectives

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

# Proficiency( $\phi$ )

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

- h-index



- number of citations

# Proficiency( $\phi$ )

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

Sum of inverse of expertise level

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

Year	Hybrid	Communication Cost					Proficiency				Geographical Distance	Density
		Diameter	MST	Leader Distance	Sum of Edge Weights	Random Walk	Sum of Distance	Trust Score	Expertise Level	Connector Authority	Skill Holder Authority	
Lappas et al. [43]	2009	✓	✓									
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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						✓	✓				✓

# 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					Proficiency					
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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						✓	✓				✓

# 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

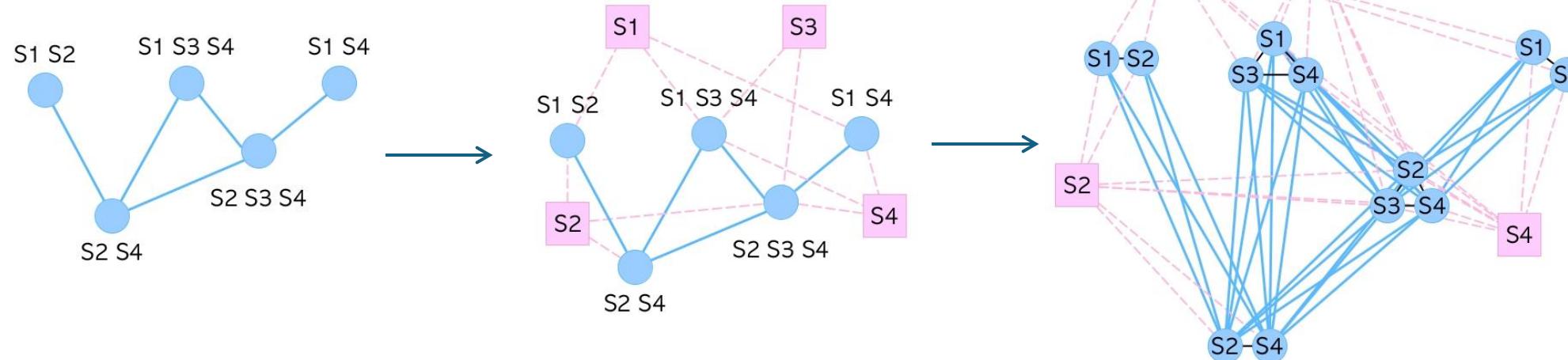
Lappas et al. is the **first attempt** to form a team based on the **subgraph optimization** on the user network. [Lappas et. al., KDD, 2009]

**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

I) Introduction and Background

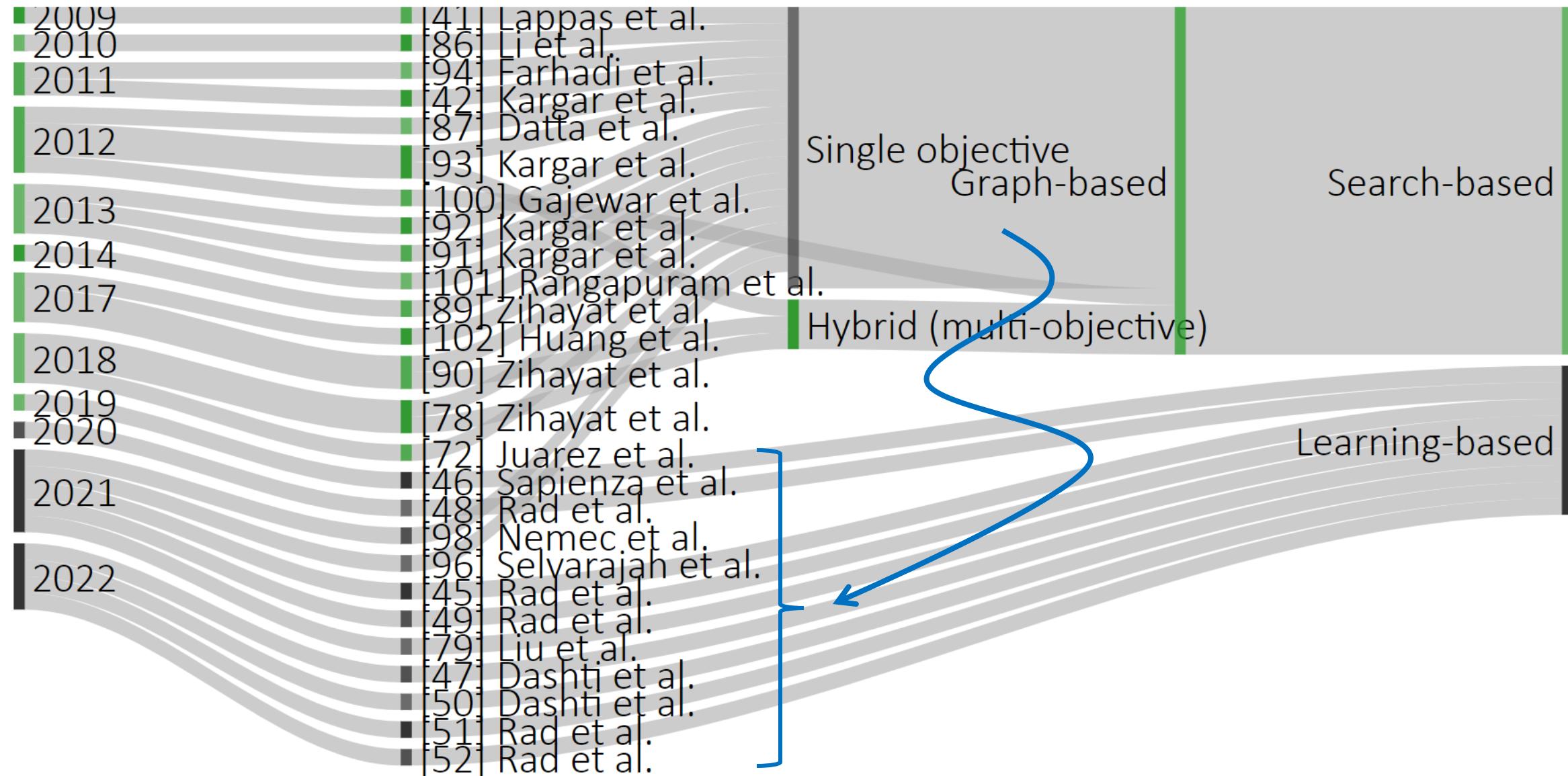
II) Pioneering Techniques

III) Learning-based Heuristics

IV) Challenges and New Perspectives

V) Applications

Hands-on: OpeNTF



Team Recommendation Works in Time

# Learning-based Heuristics

## Paradigm Shift to Learning-Based Methods



ORIGINAL RESEARCH  
published: 13 June 2019  
doi: 10.3389/fdata.2019.00014



### Deep Neural Networks for Optimal Team Composition

Anna Sapienza<sup>†</sup>, Palash Goyal<sup>†</sup> and Emilio Ferrara<sup>\*</sup>

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.

#### OPEN ACCESS

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Beijing Jiaotong University, China  
Jingrui He,  
Arizona State University,  
United States

*\*Correspondence:*  
Emilio Ferrara

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

# 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



ORIGINAL RESEARCH  
published: 13 June 2019  
doi: 10.3389/fdata.2019.00014



### Deep Neural Networks for Optimal Team Composition

**Anna Sapienza<sup>†</sup>, Palash Goyal<sup>†</sup> and Emilio Ferrara<sup>\*</sup>**

*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.

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# Learning-based Heuristics

## 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

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



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# Learning-based Heuristics

**Advantages** of Learning-Based Methods:

# Learning-based Heuristics

## Advantages of Learning-Based Methods:

- **Efficiency:** Enhanced by iterative and online learning procedures.

# Learning-based Heuristics

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- **Efficacy:** Improved prediction and team performance.

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- **Efficacy:** Improved prediction and team performance.
- **Scalability:** Can handle larger networks.

# Learning-based Heuristics

## Advantages of Learning-Based Methods:

- **Efficiency:** Enhanced by iterative and online learning procedures.
- **Efficacy:** Improved prediction and team performance.
- **Scalability:** Can handle larger networks.
- **Dynamic Adaptation:** Better suited for temporal conditions.

# Learning-based Heuristics

## Introductory Definitions:

- Team
- Team Recommendation

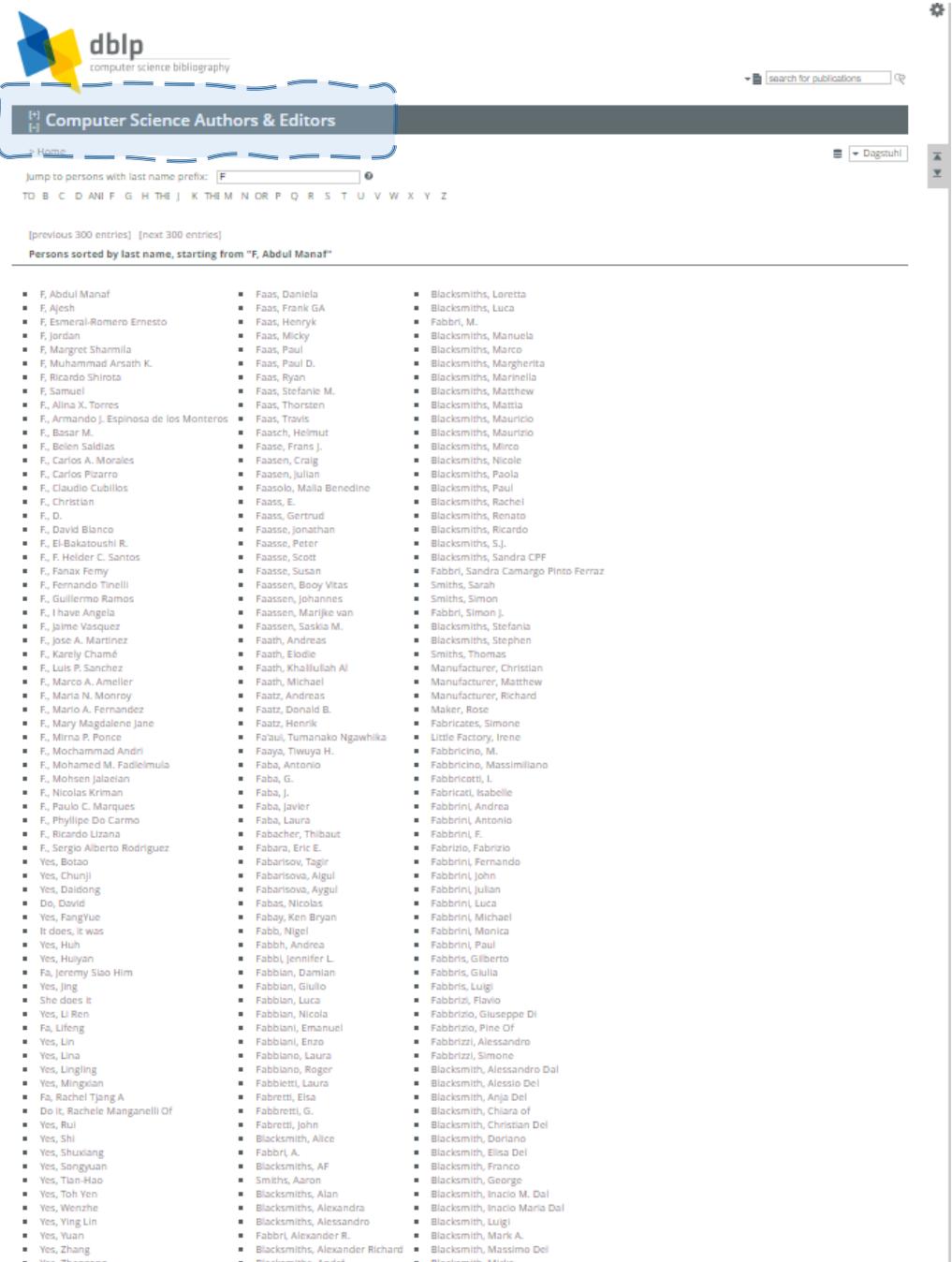
# Learning-based Heuristics

## Introductory Definitions:

- Team
- Team Recommendation

# Learning-based Heuristics

## Team



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F. Mohsen Jalaeian
F. Nicolas Kriman
F. Paulo C. Marques
F. Phyllipe Do Carmo
F. Ricardo Lirana
F. Sergio Alberto Rodriguez
Yes, Botao
Yes, Chunji
Yes, Daidong
Do, David
Yes, FangYue
It does, it was
Yes, Hu
Yes, Huiyan
Fa, Jeremy Siao Him
Yes, Jing
She does it
Yes, Li Ren
Fa, Lifeng
Yes, Lin
Yes, Lina
Yes, Lingling
Yes, Mingxian
Fa, Rachel Tjiang A
Do it, Rachelle Manganiell Of
Yes, Rui
Yes, Shl
Yes, Shuxiang
Yes, Songquan
Yes, Tian Hao
Yes, Toli Yen
Yes, Wenzhe
Yes, Ying Lin
Yes, Yuan
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# Learning-based Heuristics

Team

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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)
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Software Engineering
Sustainability Informatics
Theoretical Computer Science

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Given a set of **skills**  $S = \{i\}$  and a set of **users**  $E = \{j\}$ , a team of users  $e \in E$ ;  $e \neq \emptyset$  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<sup>(✉)</sup>, Reza Barzegar, Arman Dashti, and Mahdis Saeedi

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Keywords: Neural Team Formation • Training Strategy • OpeNTF

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

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# 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  $e^*$  such that their collaboration in the predicted team  $(s, e^*)$  is successful, that is  $(s, e^*)_{y=1}$ , while avoiding a subset of users  $e'$  resulting in  $(s, e')_{y=0}$ . More concretely, the Team Recommendation problem is to find a mapping function  $f$  of parameters  $\theta$  from the powerset of skills to the powerset of  $s$  such that  $f_\theta : P(S) \rightarrow P(E)$ ,  $f_\theta(s) = e^*$ .

Keywords: Neural Team Formation · Training Strategy · OpeNTF

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**Keywords:** Neural Team Formation · Training Strategy · OpeNTF

# Learning-based Heuristics

- Model Architecture
- Training Strategies

# Model Architecture

- Feedforward
- Variational Bayesian
- Graph Representation Learning

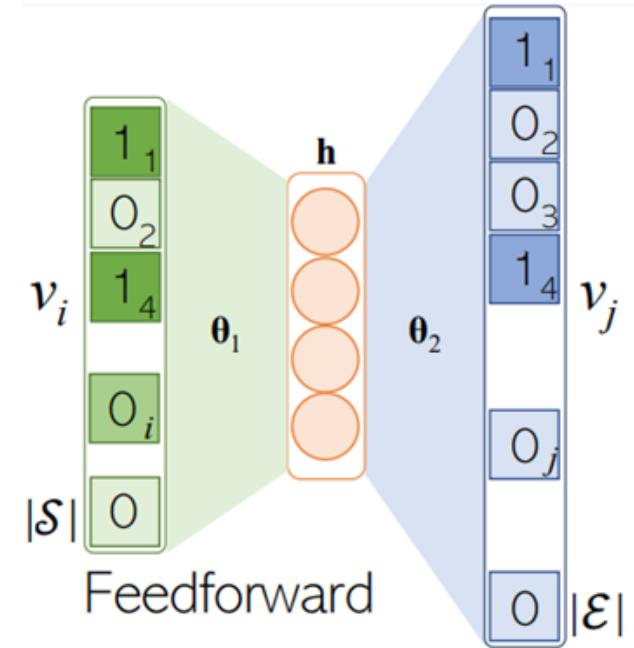
# Model Architecture

- Feedforward
- Variational Bayesian
- Graph Representation Learning

# Feedforward

## Neural Team Recommendation

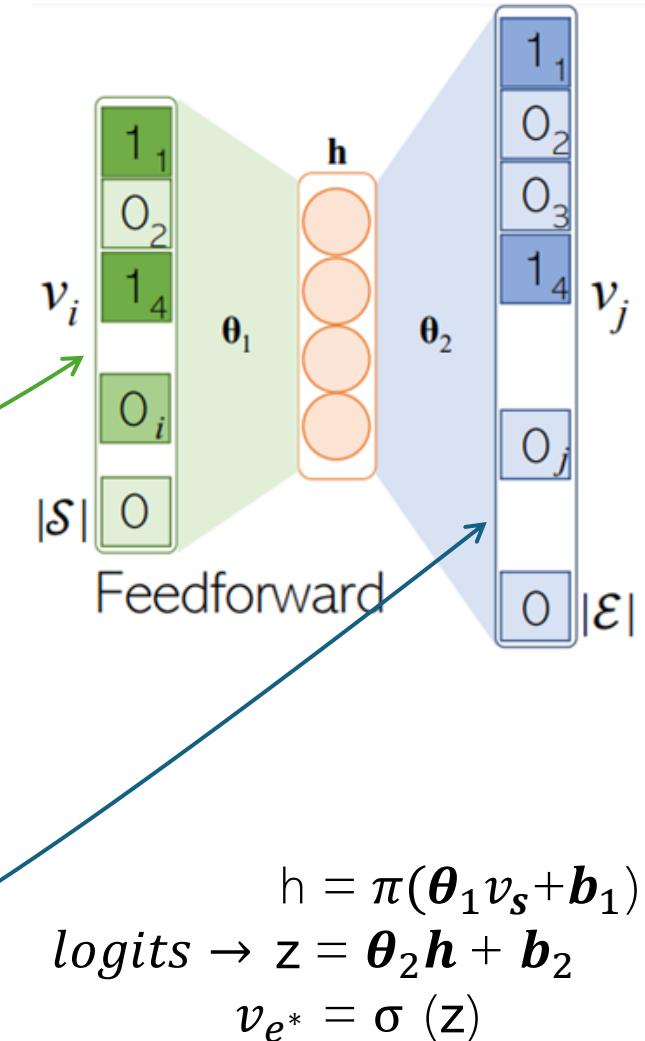
Given the training set  $T$ , Neural Team Recommendation estimates  $f_{\theta}(s)$  using a multi-layer neural network that learns, from  $T$ , to map a vector representation of subset of skills  $s$ , referred to as  $v_s$ , to a vector representation of subset of experts  $e^*$ , referred to as  $v_{e^*}$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



# Feedforward

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# Variational Bayesian

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

# Variational Bayesian

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

- 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

Idea:

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  $P(y|x, \theta)$ .

# Variational Bayesian

## Probabilistic model

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

- **Classification:**  $y$  is a set of classes,  $P(y|x, \theta)$  is a categorical distribution.
- **Regression:**  $y$  is a continuous variable,  $P(y|x, \theta)$  is a Gaussian distribution.

# Variational Bayesian

Goal:

Maximizing the likelihood function  $f$  of  $\theta$ :

# Variational Bayesian

## Goal:

Maximizing the likelihood function  $f$  of  $\theta$  :

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

# Variational Bayesian

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

# Variational Bayesian

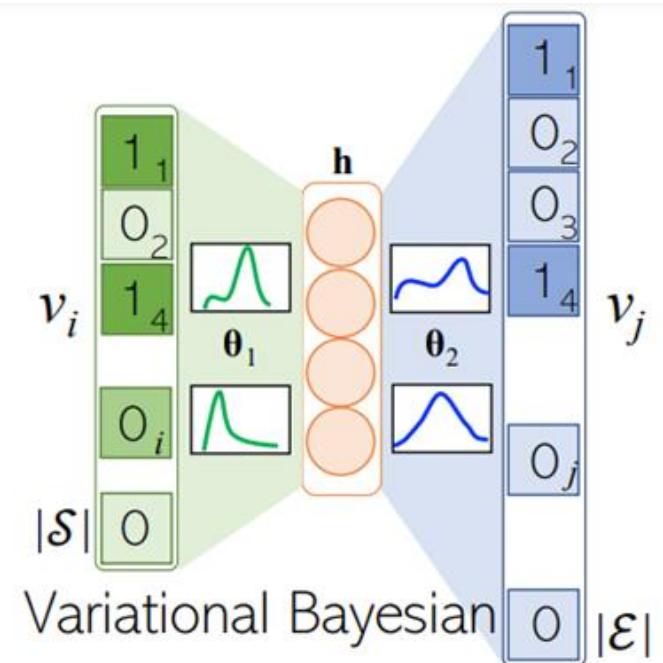
**By Bayes theorem:** Multiplying the likelihood with a prior distribution  $p(\theta)$ .

**Hint:** The true prior probability of weights  $p(\theta)$  **cannot** be calculated efficiently.

# Variational Bayesian

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**Hint:** The true prior probability of weights  $p(\theta)$  **cannot** be calculated efficiently.

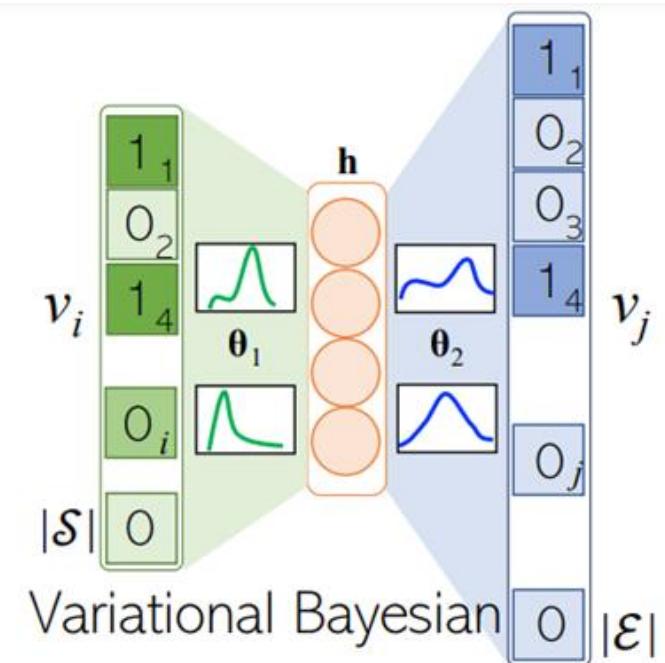


# Variational Bayesian

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

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

$$\begin{aligned} \text{KL}(q \parallel p(\theta | T)) &= \int q(\theta | \mu, \sigma) \log \left[ \frac{q}{p(\theta | T)} \right] d\theta \\ &= E_q \log \left[ \frac{q}{p(\theta | T)} \right], \quad \text{KL}(q \parallel p) \geq 0 \end{aligned}$$

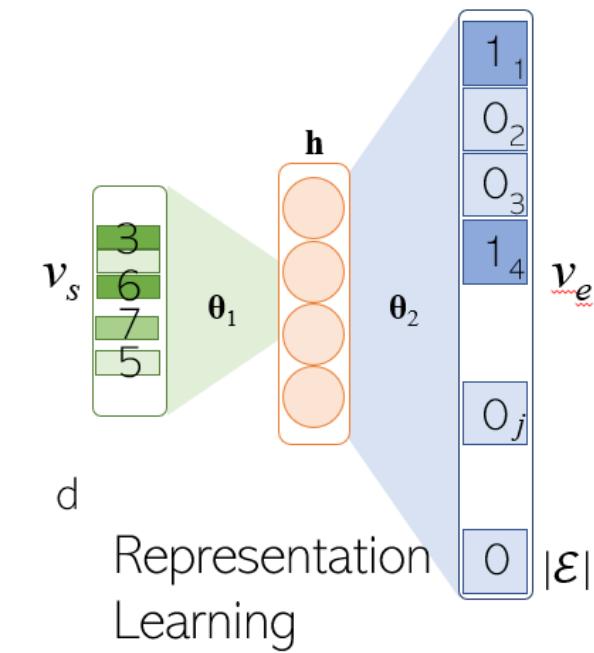


# Neural Architecture

- Feedforward
- Variational Bayesian
- Graph Representation Learning

# Graph Representation Learning

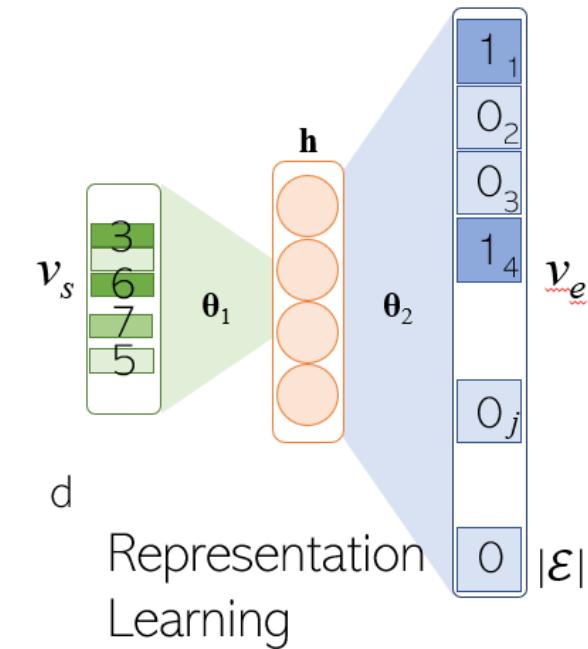
Dense Vector vs. Multi-hot vector



# Graph Representation Learning

## Dense Vector vs. Multi-hot vector

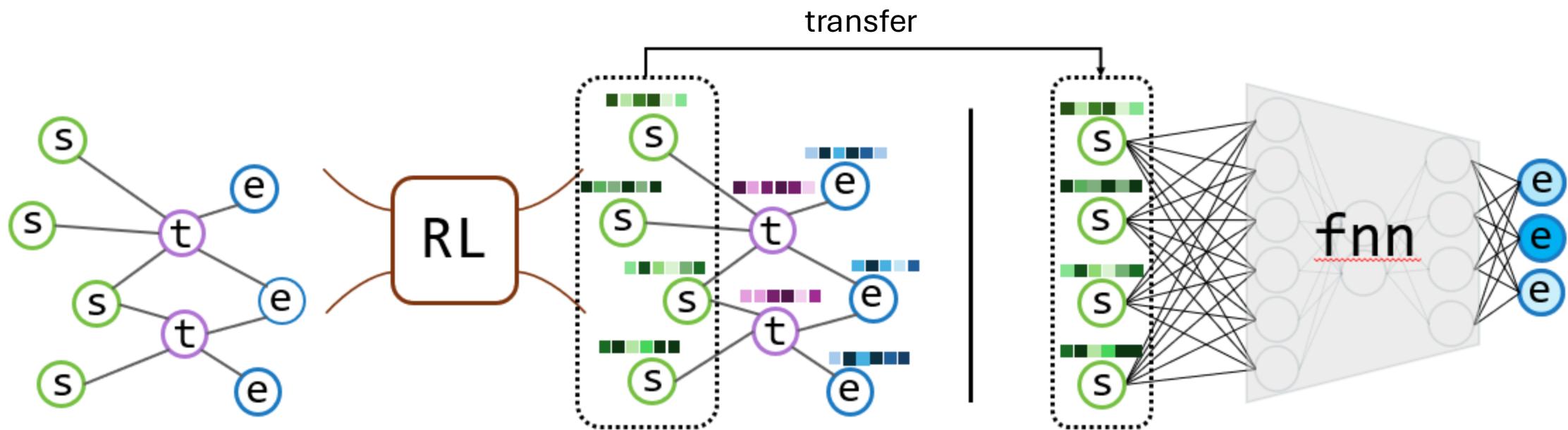
- **Dense Vector:** A vector with fewer dimension and continuous value rather than just 0 or 1.



Representation  
Learning

# Graph Representation Learning

Transfer learning-based



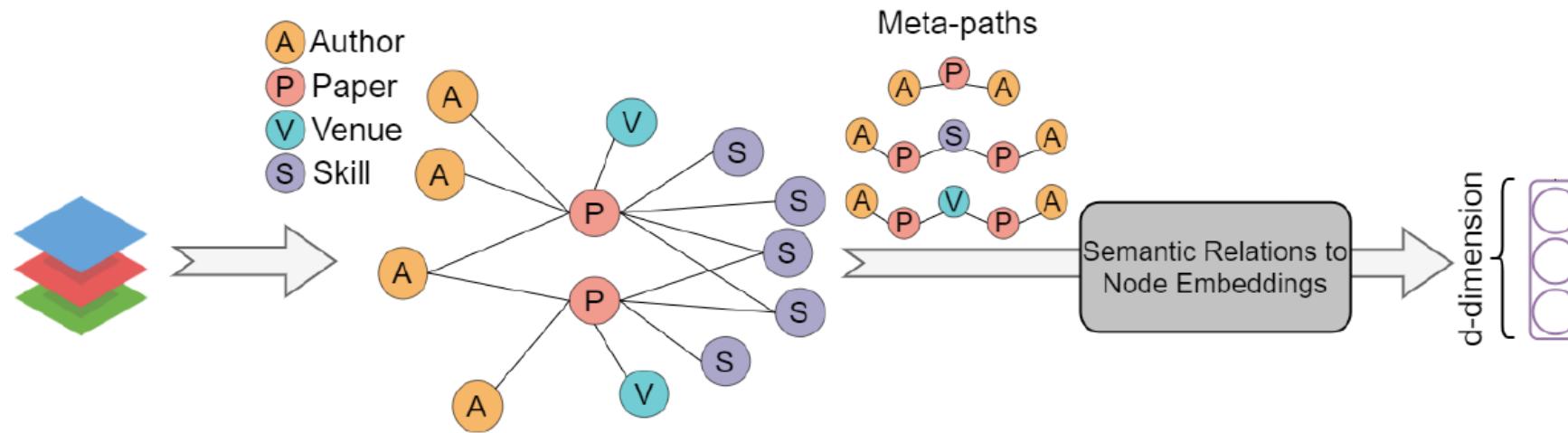
# Graph Representation Learning

## Analyzing Network Graph

- Metha Path-based Methods
- Message passing-based Methods

# Graph Representation Learning

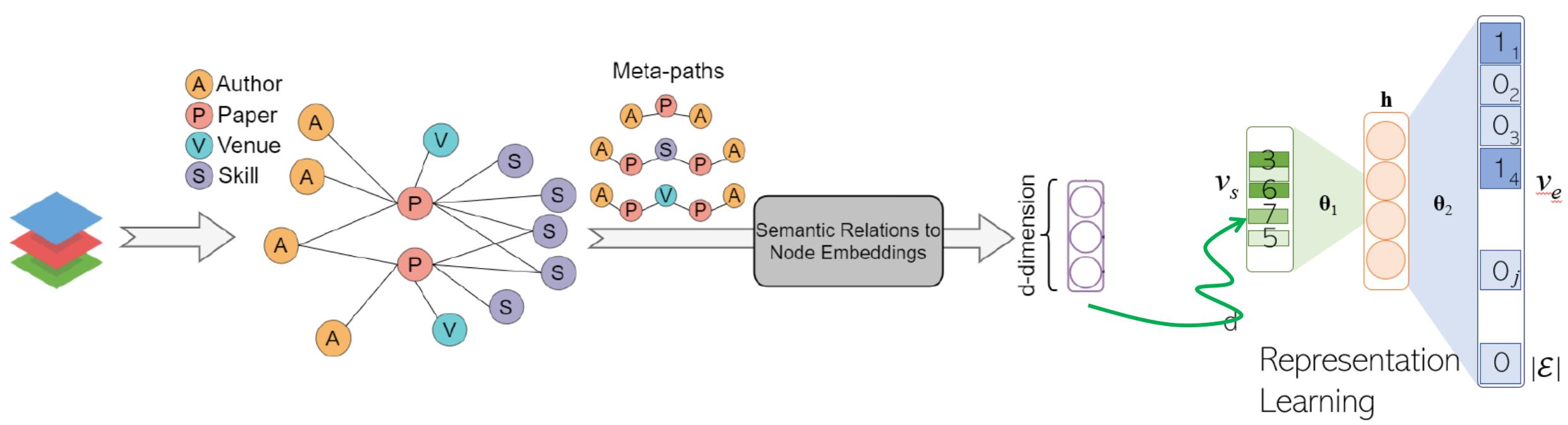
## Meta Path-based Methods



[Rad et. Al., Sigir ,2021]

# Graph Representation Learning

## Metha Path-based Methods



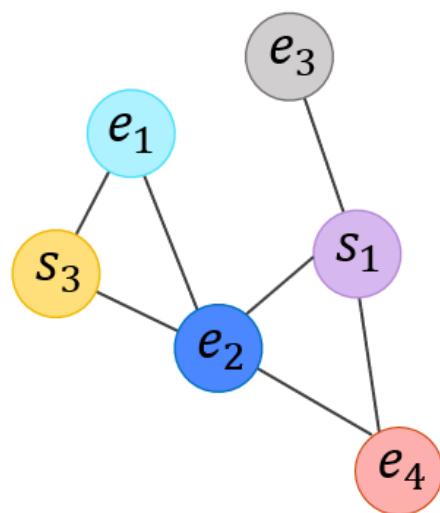
[Rad et. al., Sigir ,2021]

# Graph Representation Learning

Message Passing-based Methods ([Graph Neural Networks \(GNN\)](#))

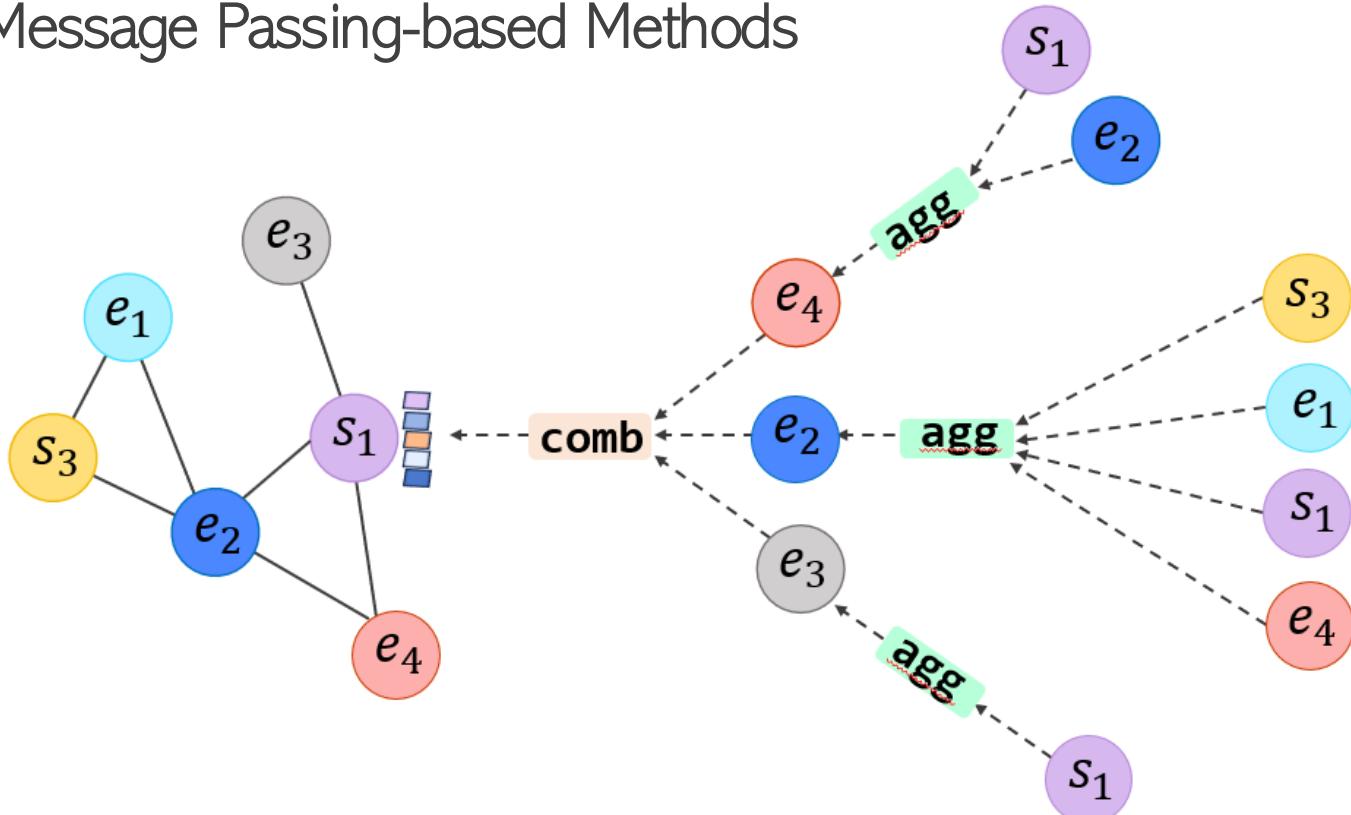
# Graph Representation Learning

## Message Passing-based Methods



# Graph Representation Learning

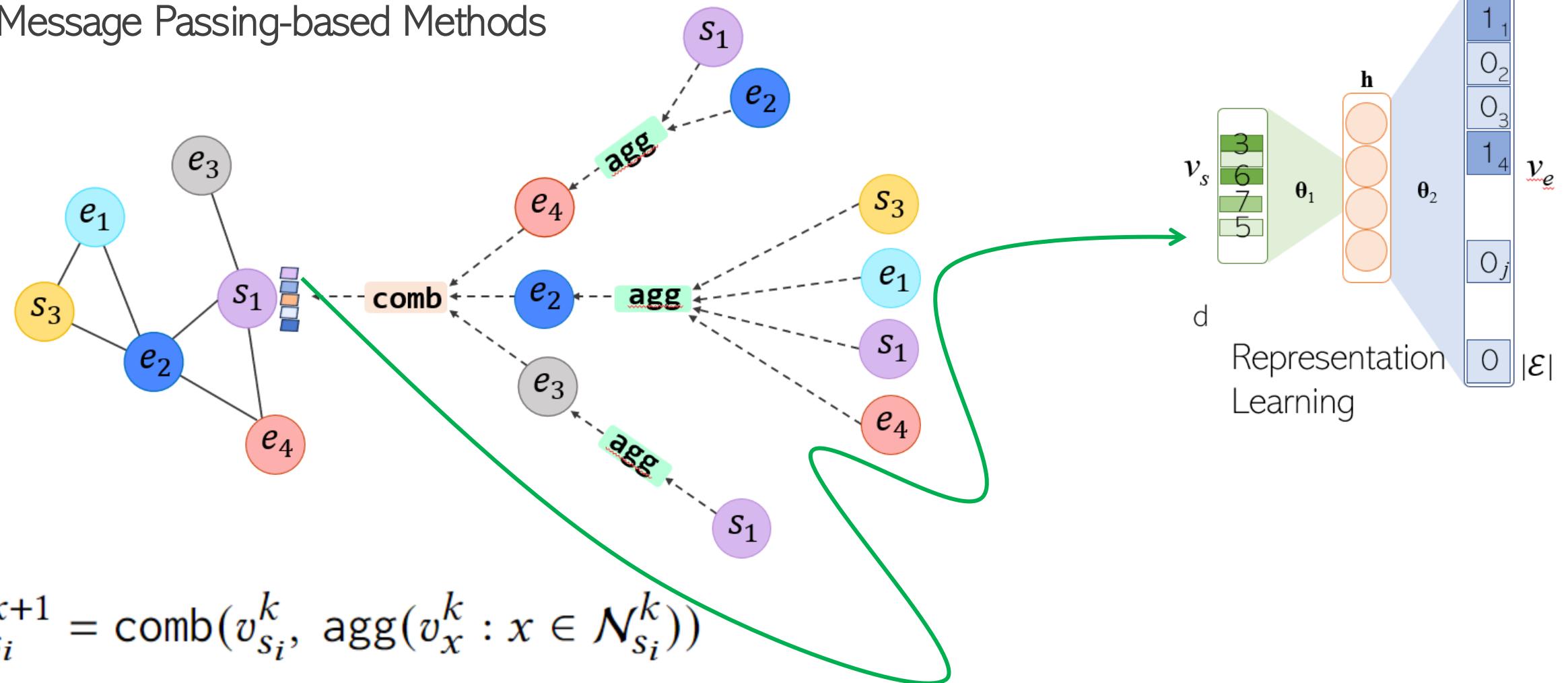
## Message Passing-based Methods



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

# Graph Representation Learning

## Message Passing-based Methods



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# Graph Representation Learning

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

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

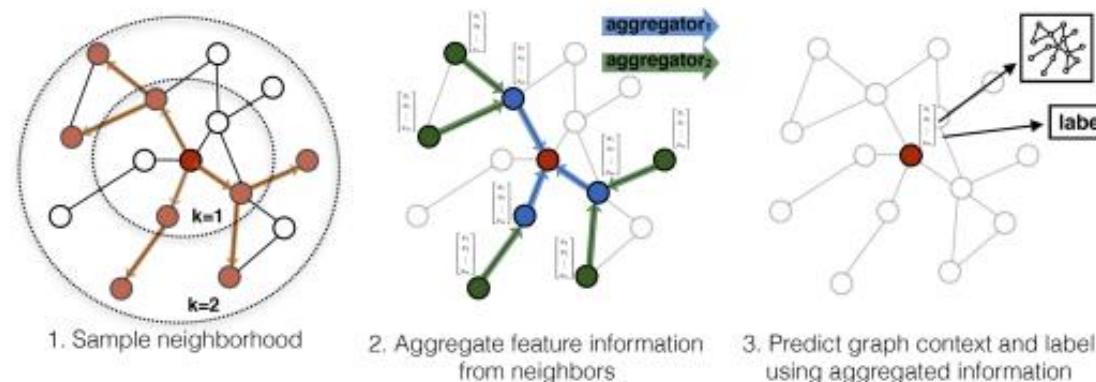
- **Inductive methods:** Can infer vector representations for unseen skill nodes based.

# Graph Representation Learning

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

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

## GraphSAGE



# Graph Representation Learning

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

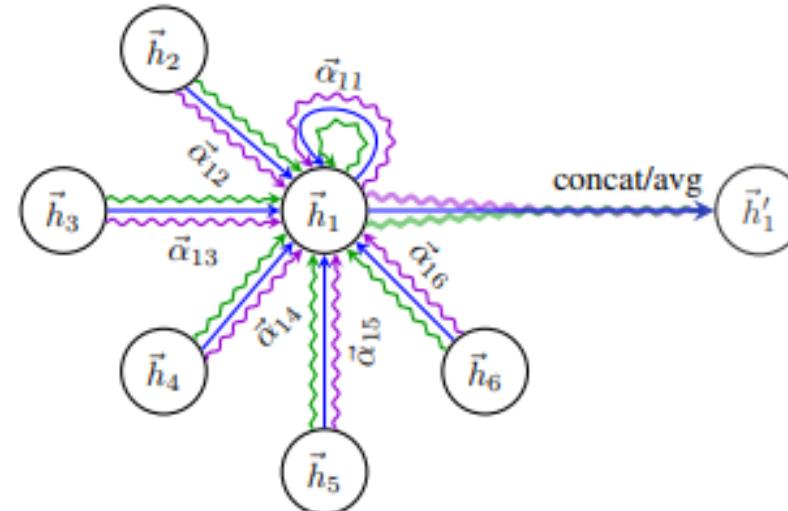
- **Attentive methods:** Allocate attention coefficients to a skill node's neighbours to signify their importance in updating the skill node's vector.

# Graph Representation Learning

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

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

GAT



# 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]

%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]	<b>77.84</b>	<b>1.39</b>	<u>1.09</u>	<u>0.83</u>	<b>0.84</b>	<u>1.64</u>	2.49	<b>1.46</b>	<b>1.56</b>	<b>1.96</b>	<b>0.67</b>	<b>0.93</b>	<b>1.05</b>
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													
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]	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]	<b>77.87</b>	<b>1.35</b>	<b>1.19</b>	<b>0.92</b>	<b>0.81</b>	<b>1.78</b>	<b>2.76</b>	<b>1.39</b>	<b>1.62</b>	<b>2.08</b>	<b>0.64</b>	<b>0.92</b>	<b>1.09</b>
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	<u>1.34</u>	<u>1.07</u>	<u>0.89</u>	<b>0.81</b>	<u>1.61</u>	<u>2.66</u>	<b>1.42</b>	<u>1.53</u>	<u>2.02</u>	<b>0.66</b>	<u>0.90</u>	<u>1.08</u>
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
gine [19]	76.70	1.18	1.02	0.83	0.69	1.52	2.49	1.16	1.35	1.80	0.51	0.76	0.92

Average performance of 3-fold fnn on test set in dblp

[Ahmed et. Al., WISE ,2024]

%aucroc		%precision			%recall			%ndcg			%map		
		@2	@5	@10	@2	@5	@10	@2	@5	@10	@2	@5	@10
skill-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]	70.38	0.46	0.41	0.39	0.29	0.63	1.20	0.47	0.57	0.83	0.22	0.32	0.40
gs [18]	75.05	0.70	0.63	0.58	0.42	0.95	1.75	0.71	0.85	1.22	0.32	0.47	0.59
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]	<b>76.99</b>	<b>1.00</b>	<b>0.87</b>	<b>0.74</b>	<b>0.59</b>	<b>1.32</b>	<b>2.23</b>	<b>1.03</b>	<b>1.20</b>	<b>1.62</b>	<b>0.47</b>	<b>0.68</b>	<b>0.83</b>
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]	<b>76.63</b>	<b>0.92</b>	<b>0.80</b>	<b>0.71</b>	<b>0.55</b>	<b>1.20</b>	<b>2.15</b>	<b>0.94</b>	<b>1.09</b>	<b>1.53</b>	<b>0.43</b>	<b>0.61</b>	<b>0.76</b>
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	<b>0.95</b>	<b>0.75</b>	<b>0.63</b>	<b>0.57</b>	<b>1.12</b>	1.90	<b>1.00</b>	<b>1.08</b>	<b>1.44</b>	<b>0.48</b>	<b>0.66</b>	<b>0.79</b>

Average performance of 3-fold bnn on test set in dblp

[Ahmed et. Al., WISE ,2024]

## Research Question

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

[Ahmed et. Al., WISE ,2024]

## fnn

	%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 [164331]	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]	<b>77.84</b>	<b>1.39</b>	<b>1.09</b>	<b>0.83</b>	<b>0.84</b>	<b>1.64</b>	<b>2.49</b>	<b>1.46</b>	<b>1.56</b>	<b>1.96</b>	<b>0.67</b>	<b>0.93</b>	<b>1.05</b>
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													
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 [164331]	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]	<b>77.87</b>	<b>1.35</b>	<b>1.19</b>	<b>0.92</b>	<b>0.81</b>	<b>1.78</b>	<b>2.76</b>	<b>1.39</b>	<b>1.62</b>	<b>2.08</b>	<b>0.64</b>	<b>0.92</b>	<b>1.09</b>
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	<b>0.81</b>	1.61	2.66	<b>1.42</b>	1.53	2.02	<b>0.66</b>	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
gine [19]	76.70	1.18	1.02	0.83	0.69	1.52	2.49	1.16	1.35	1.80	0.51	0.76	0.92

## bnn

	%aucroc	%precision			%recall			%ndcg			%map		
		@2	@5	@10	@2	@5	@10	@2	@5	@10	@2	@5	@10
skill-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 [164331]	72.86	<b>0.82</b>	<b>0.68</b>	<b>0.61</b>	<b>0.49</b>	<b>1.02</b>	<b>1.86</b>	<b>0.84</b>	<b>0.95</b>	<b>1.33</b>	0.39	<b>0.56</b>	<b>0.69</b>
m2v [38]	70.38	0.46	0.41	0.39	0.29	0.63	1.20	0.47	0.57	0.83	0.22	0.32	0.40
gs [18]	75.05	0.70	0.63	0.58	0.42	0.95	1.75	0.71	0.85	1.22	0.32	0.47	0.59
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gatv2 [5]	<b>76.99</b>	<b>1.00</b>	<b>0.87</b>	<b>0.74</b>	<b>0.59</b>	<b>1.32</b>	<b>2.23</b>	<b>1.03</b>	<b>1.20</b>	<b>1.62</b>	<b>0.47</b>	<b>0.68</b>	<b>0.83</b>
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
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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]	<b>76.63</b>	<b>0.92</b>	<b>0.80</b>	<b>0.71</b>	<b>0.55</b>	<b>1.20</b>	<b>2.15</b>	<b>0.94</b>	<b>1.09</b>	<b>1.53</b>	<b>0.43</b>	<b>0.61</b>	<b>0.76</b>
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	<b>0.95</b>	<b>0.75</b>	<b>0.63</b>	<b>0.57</b>	<b>1.12</b>	<b>1.90</b>	<b>1.00</b>	<b>1.08</b>	<b>1.44</b>	<b>0.48</b>	<b>0.66</b>	<b>0.79</b>

fnn vs bnn performances for dblp

# Learning-based Heuristics

- Model Architecture
- Training Strategies

# Training Strategies

- Negative Sampling
- Streaming Strategy

# Training Strategies

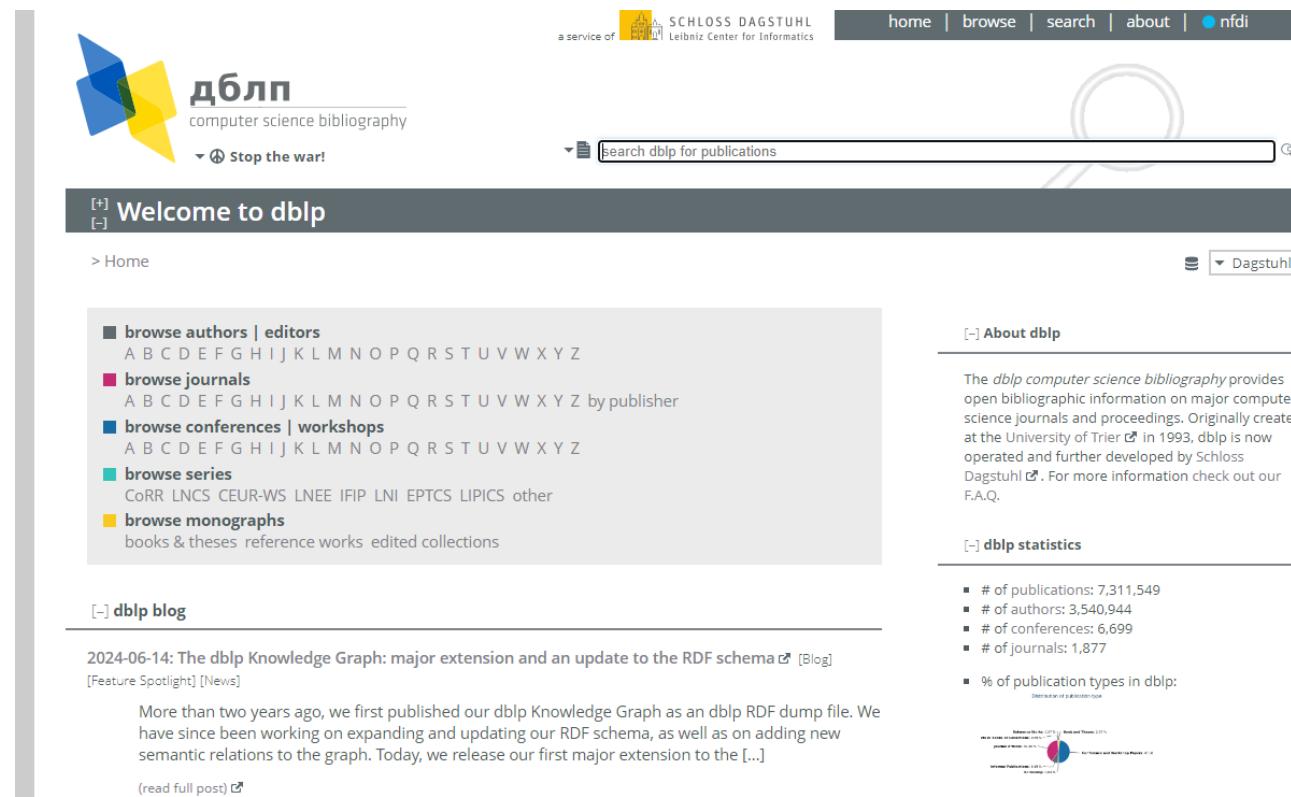
- Negative Sampling
- Streaming Strategy

# 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.



The screenshot shows the homepage of the dblp computer science bibliography. At the top, there's a navigation bar with links for 'home', 'browse', 'search', 'about', and 'nfdi'. Below the navigation is a search bar with the placeholder 'search dblp for publications'. To the left, there's a logo for 'дблп' (dblp) with the text 'computer science bibliography' and a link to 'Stop the war!'. A large circular graphic is centered above the search bar. On the left side, there's a sidebar with links for 'browse authors | editors' (with letters A-Z), 'browse journals' (with letters A-Z), 'browse conferences | workshops' (with letters A-Z), 'browse series' (listing CoRR, LNCS, CEUR-WS, LNEE, IFIP, LNI, EPTCS, LIPICS, other), and 'browse monographs' (listing books & theses, reference works, edited collections). Below this is a link to the 'dblp blog'. In the main content area, there's a section titled 'About dblp' with a paragraph of text about the history and operation of the service. There's also a section titled 'dblp statistics' with a list of metrics: # of publications: 7,311,549, # of authors: 3,540,944, # of conferences: 6,699, # of journals: 1,877, and % of publication types in dblp. A pie chart at the bottom illustrates the distribution of publication types.

# Negative Sampling

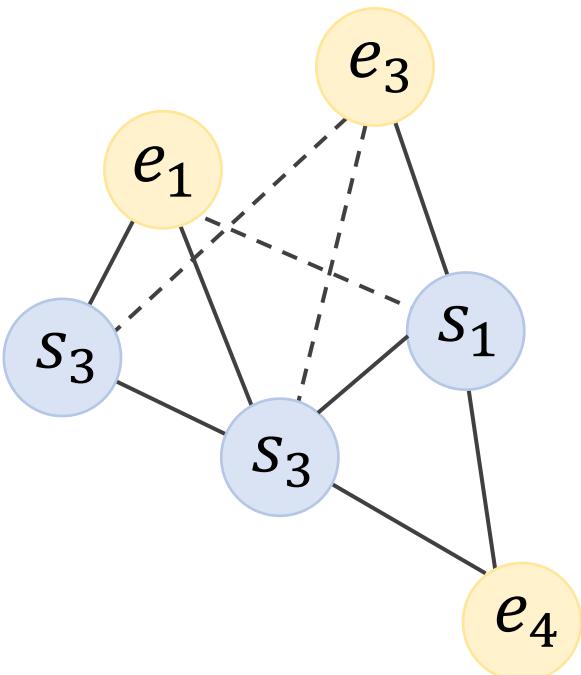
## Closed-World Assumption

- 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

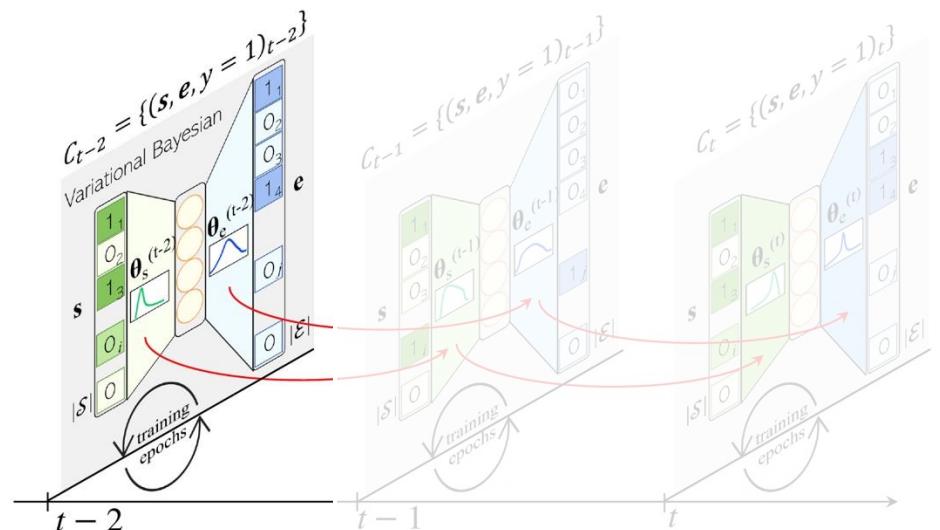
Predicting future successful teams of users who can effectively collaborate is challenging due to experts' **temporality** of

- Skill sets
- Levels of expertise
- Collaboration ties

# Streaming Strategy

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

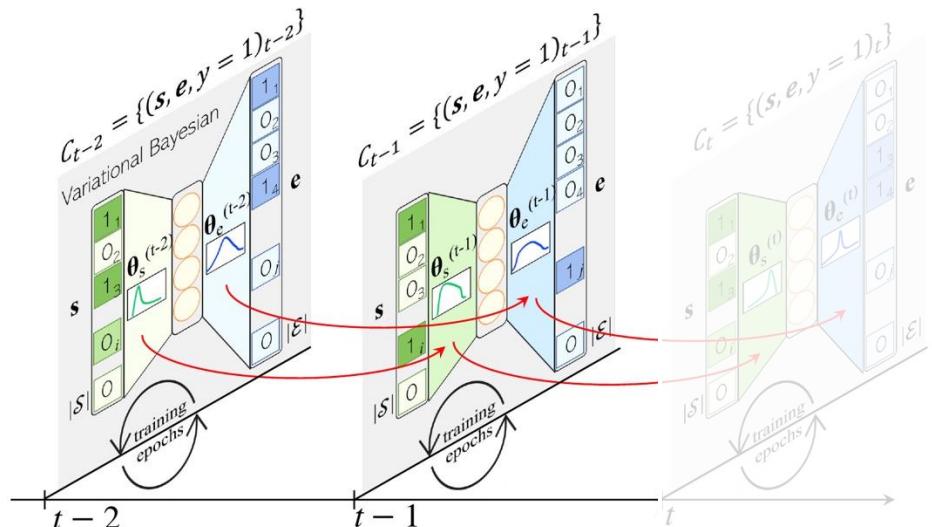
Initiates learning for the next time interval  $t + 1$



# Streaming Strategy

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

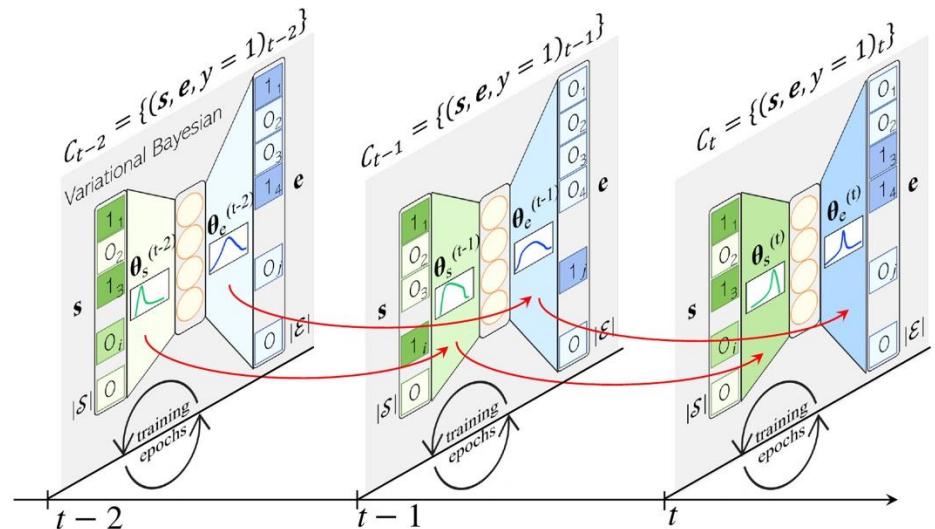
Initiates learning for the next time interval  $t + 1$



# Streaming Strategy

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

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



# Evaluation Methodology

- Dataset
- Effectiveness

# Evaluation Methodology

- Dataset
- Effectiveness

# Dataset

- DBLP
- IMDB
- USPT
- GitHub

# Dataset

○ DBLP

○ IMDB

○ USPT

○ GitHub

The screenshot shows the homepage of the dblp computer science bibliography. At the top, there is a navigation bar with links for 'home', 'browse', 'search', 'about', and 'nfdi'. Below the navigation bar, there is a search bar with the placeholder 'search dblp for publications'. On the left side, there is a logo for 'дблп' (dblp) with the subtitle 'computer science bibliography' and a link to 'Stop the war!'. In the center, there is a large button labeled '[+ Welcome to dblp]'. Below this button, there are several navigation links: 'browse authors | editors' (with letters A-Z), 'browse journals' (with letters A-Z), 'browse conferences | workshops' (with letters A-Z), 'browse series' (listing CoRR, LNCS, CEUR-WS, LNEE, IFIP, LNI, EPTCS, LIPICS, other), and 'browse monographs' (listing books & theses, reference works, edited collections). To the right, there is a section titled '[+] About dblp' which provides information about the history and operation of the database. Below this, there is a section titled '[+] dblp statistics' which lists various publication counts. At the bottom, there is a pie chart showing the distribution of publication types.

SCHLOSS DAGSTUHL  
Leibniz Center for Informatics

home | browse | search | about | nfdi

search dblp for publications

[+] Welcome to dblp

[+] Home

[+] About dblp

[+] dblp statistics

[+] dblp blog

2024-06-14: The dblp Knowledge Graph: major extension and an update to the RDF schema [Blog]  
[Feature Spotlight] [News]

More than two years ago, we first published our dblp Knowledge Graph as an dblp RDF dump file. We have since been working on expanding and updating our RDF schema, as well as on adding new semantic relations to the graph. Today, we release our first major extension to the [...]

(read full post)

# of publications: 7,311,549  
# of authors: 3,540,944  
# of conferences: 6,699  
# of journals: 1,877  
% of publication types in dblp:

Books and Theses: 2.81%  
Journal Articles: 67.41%  
Conference Proceedings: 29.78%  
Internal Publications: 0.80%

# Dataset

- DBLP
- IMDB
- USPT
- GitHub

The image shows the IMDb movie page for "The Matrix". The main title "The Matrix" is at the top, followed by the release year "1999", rating "R", and runtime "2 h 16m". Below the title is a movie poster featuring Keanu Reeves, Laurence Fishburne, and others. To the right of the poster is a large action-oriented still from the film showing Neo fighting. A "Play trailer 2:26" button is overlaid on this still. At the top right, there are links for "Cast & crew", "User reviews", "Trivia", "FAQ", "IMDbPro", "All topics", and a "Rate" button. Below the trailer button, the IMDb rating is shown as 8.7/10 (2.1M votes). To the right of the rating are sections for "YOUR RATING", "POPULARITY", and "152 Rate". On the far right, there are sections for "18 VIDEOS" and "99+ PHOTOS". The bottom of the page contains the movie's plot summary, director/writer information, star cast, and streaming/rental options.

The Matrix

1999 · R · 2 h 16m

+ ANU REEVES LAURENCE FISHBURNE

MATRIX

ON MARCH 31 THE FIGHT FOR THE FUTURE BEGINS

Action Sci-Fi

When a beautiful stranger leads computer hacker Neo to a forbidding underworld, he discovers the shocking truth—the life he knows is the elaborate deception of an evil cyber-intelligence.

Directors: [Lana Wachowski](#) · [Lilly Wachowski](#)

Writers: [Lilly Wachowski](#) · [Lana Wachowski](#)

Stars: [Keanu Reeves](#) · [Laurence Fishburne](#) · [Carrie-Anne Moss](#)

IMDbPro See production info at IMDbPro

Cast & crew · User reviews · Trivia · FAQ · IMDbPro · All topics · Rate

IMDb RATING YOUR RATING POPULARITY

8.7/10 2.1M ★ Rate 152 · 11

18 VIDEOS

99+ PHOTOS

STREAMING RENT/BUY

NOW prime video

from €2.99

Add to Watchlist

Added by 1.0M users

5K User reviews 226 Critic reviews 73 Metascore

# Dataset

○ DBLP

○ IMDB

○ USPT

○ GitHub

(12) INTERNATIONAL APPLICATION PUBLISHED UNDER THE PATENT COOPERATION TREATY (PCT)

(19) World Intellectual Property  
Organization  
International Bureau



(10) International Publication Number

**WO 2019/227238 A1**

(43) International Publication Date

05 December 2019 (05.12.2019)

**WIPO | PCT**

(51) International Patent Classification:

*G06Q 30/00* (2012.01)      *H04L 12/16* (2006.01)  
*G06F 16/903* (2019.01)      *H04L 12/58* (2006.01)  
*G06N 20/00* (2019.01)

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(21) International Application Number:

PCT/CA2019/050767

(22) International Filing Date:

03 June 2019 (03.06.2019)

(74) Agent: **BERESKIN & PARR LLP/S.E.N.C.R.L.,S.R.L.**;  
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3Y2 (CA).

(25) Filing Language:

English

(26) Publication Language:

English

(30) Priority Data:

62/679,099      01 June 2018 (01.06.2018)      US

(81) Designated States (*unless otherwise indicated, for every kind of national protection available*): AE, AG, AL, AM, AO, AT, AU, AZ, BA, BB, BG, BH, BN, BR, BW, BY, BZ, CA, CH, CL, CN, CO, CR, CU, CZ, DE, DJ, DK, DM, DO, DZ, EC, EE, EG, ES, FI, GB, GD, GE, GH, GM, GT, HN, HR, HU, ID, IL, IN, IR, IS, JO, JP, KE, KG, KH, KN, KP, KR, KW, KZ, LA, LC, LK, LR, LS, LU, LY, MA, MD, ME,

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Port Moody, British Columbia V3H 5H1 (CA).

# Dataset

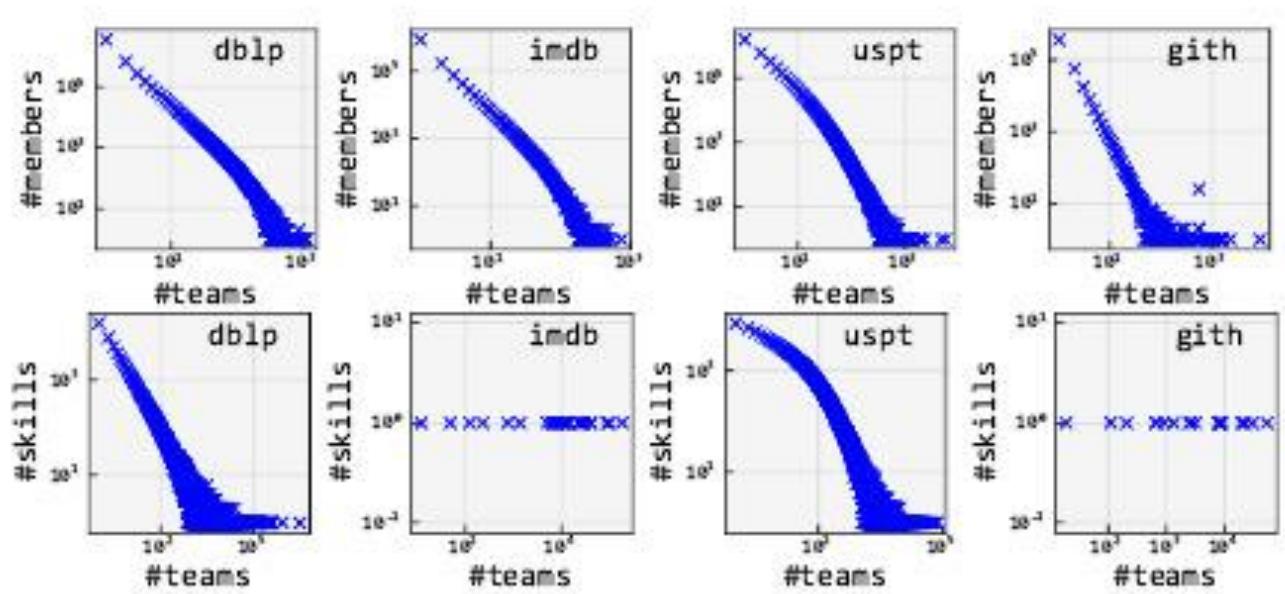
○ DBLP

○ IMDB

○ USPT

○ GitHub

The screenshot shows a user interface for a GitHub repository page. At the top, there is a header with the profile icon of 'Fani's Lab!' and the text 'Fani's Lab!'. Below the header, there is a navigation bar with links: Overview, Repositories (19), Projects, Packages, People (40). On the left side, there is a sidebar titled 'Repositories' with options: All (selected), Public, Sources, Forks, Archived, Templates. The main content area is titled 'All' and shows a search bar with the placeholder 'Search repositories'. It displays 19 repositories. The first repository listed is 'OpeNTF' (Public), which is described as 'Neural machine learning methods for Team Formation problem.' It has tags: machine-learning, pytorch, neural-team-formation. The second repository is 'Osprey' (Public), described as 'Online Predatory Conversation Detection', with tags: Python. The third repository is 'RePair' (Public), described as 'Extensible and Configurable Toolkit for Query Refinement Gold Standard Generation Using Transformers', with tags: information-retrieval, query-refinement, query-suggestions, query-refinement.



	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

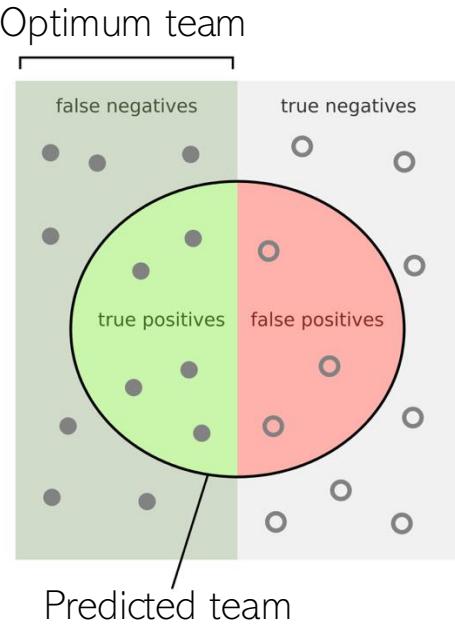
# Effectiveness

## Classification Metrics

Precision:

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

$$P(k) = \frac{|e^* \cap \hat{e}|}{k} = \frac{\text{True Positives}}{\text{Predicted team}}$$



Optimum team

Recall:

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

# Effectiveness

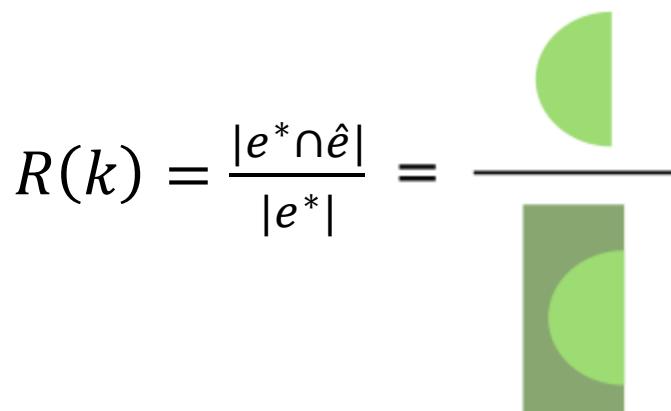
## Classification Metrics

Recall:

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

Predicted team

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



# Effectiveness

## Classification Metrics

Success:

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

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

# 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**

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

# 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  $e^*$ .

# Effectiveness

## Ranking Metrics

### Discounted Cumulative Gain:

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

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

# Effectiveness

## Ranking Metrics

### Discounted Cumulative Gain:

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

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

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.

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

Metrics	Sapienza <i>et al.</i> [2019]	Rad <i>et al.</i> [2020]	Rad <i>et al.</i> [2021b]	Dashti <i>et al.</i> [2022a]	Rad <i>et al.</i> [2022b]	Rad <i>et al.</i> [2022a]	Dashti <i>et al.</i> [2022b]	Rad <i>et al.</i> [2021a]
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

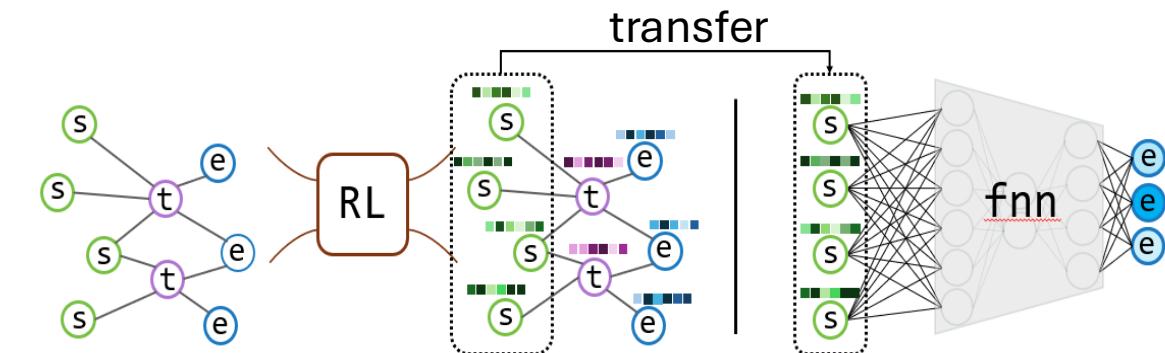
- End-to-End Graph Neural Network
- Fair and Diverse Team Recommendation
- Spatial Team Recommendation

# Challenges and New Perspectives

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

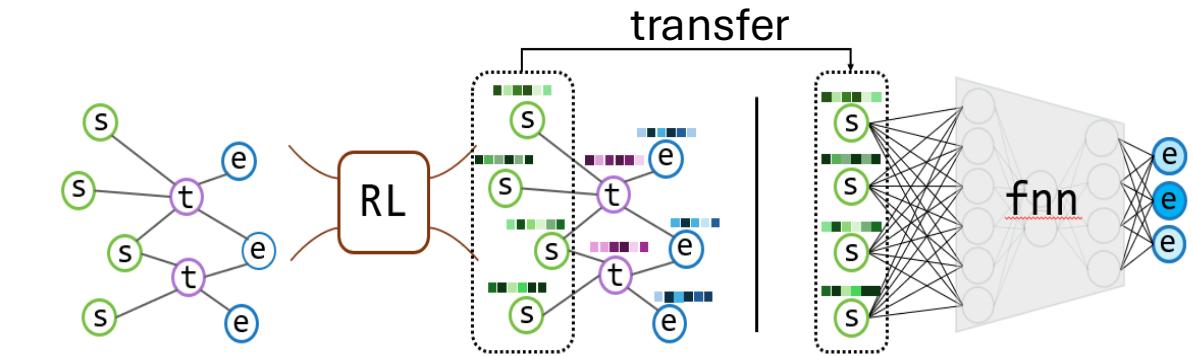
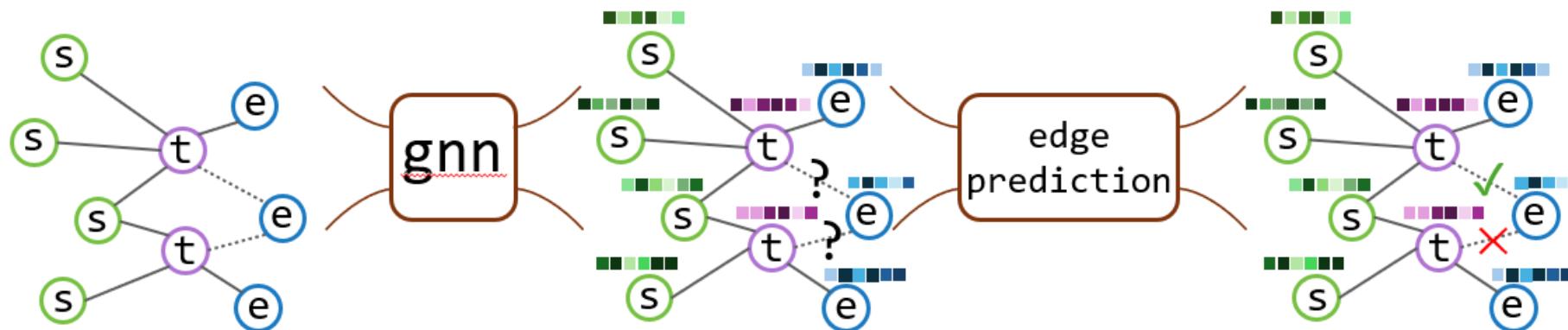
# End-to-End Graph Neural Network

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
transfer-fnn	han								
	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
transfer-fnn	han								
	mhot	0.75	0.70	0.86	1.59	0.84	1.19	0.41	0.52
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	lant	0.74	0.68	0.81	1.52	0.85	1.18	0.40	0.50
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transfer-bnn	mhot	0.83	0.74	0.95	1.71	0.92	1.28	0.45	0.57
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	gine	1.01	0.93	1.15	2.14	1.16	1.62	0.58	0.71
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# 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.

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Notions of **Group Fairness**:



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Notions of **Group Fairness**:

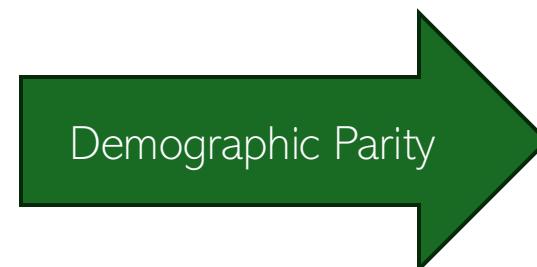
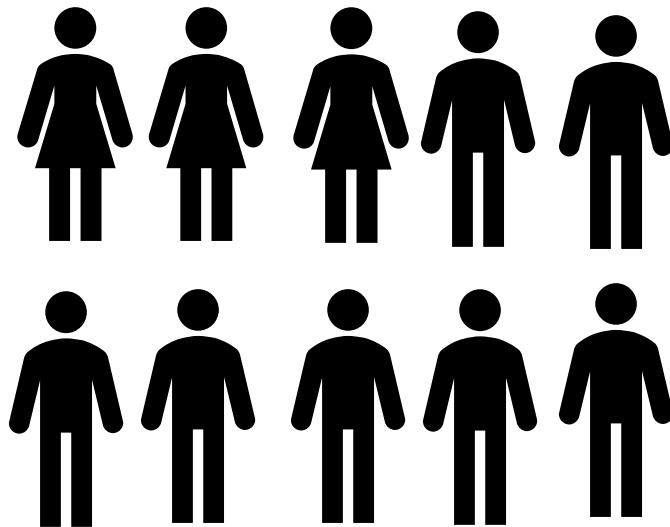
- Demographic Parity
- Equality of Opportunity



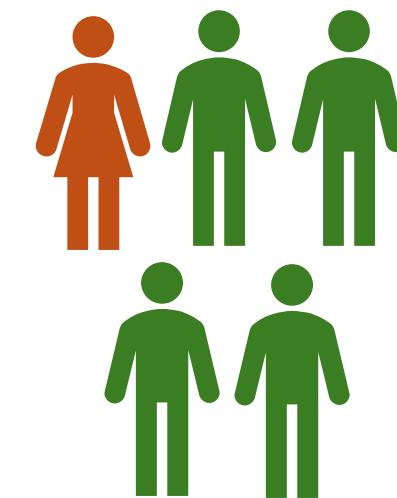
# Fair and Diverse Team Recommendation

## Demographic Parity

Candidate Pool



Final Team



- Male: 70%
- Female: 30%

# Fair and Diverse Team Recommendation

Demographic Parity :

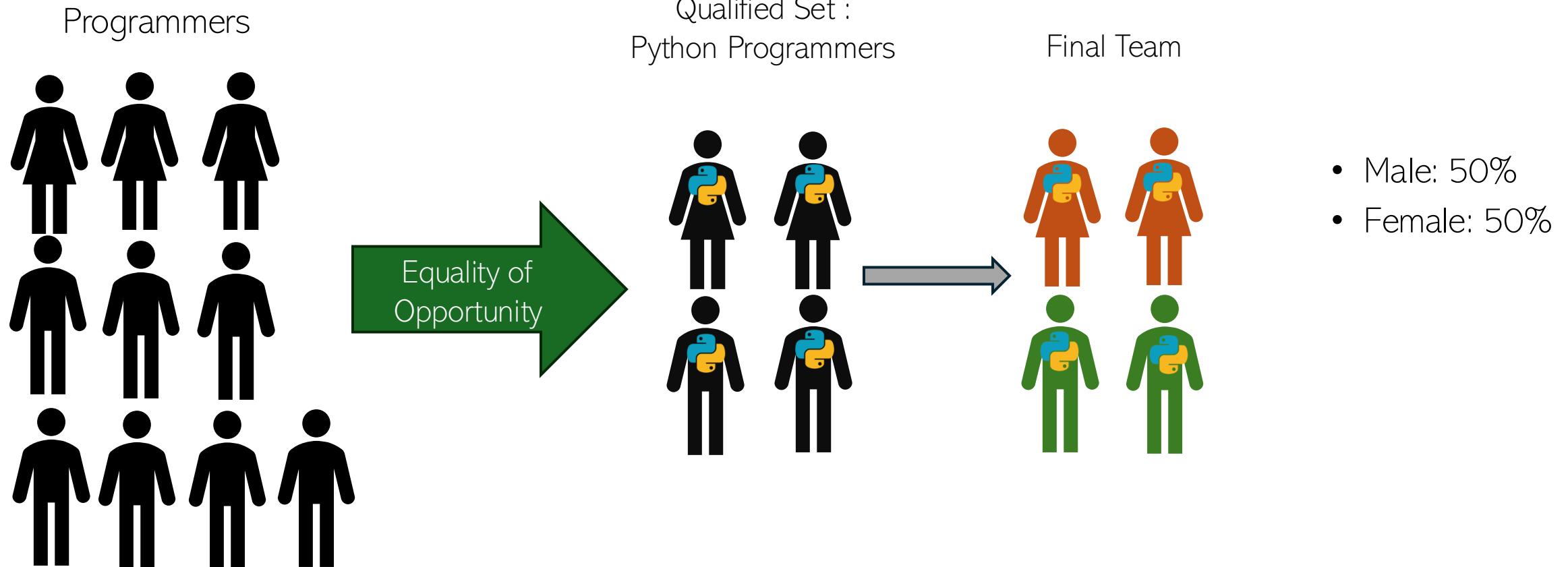
Enforces the membership in a team to be independent of values of a protected attribute for team members.

$$[P(e_0 \in T) = P(e'_1 \in T)] \wedge [P(e_0 \notin T) = P(e'_1 \notin T)]$$

↑  
Male                      ↑  
                            Female

# Fair and Diverse Team Recommendation

## Equality of Opportunity



# 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.

$$[P(e_0 \in T | e_0, S_{e_0} \cap S \neq \emptyset) = P(e'_1 \in T | e'_1, S_{e'_1} \cap S \neq \emptyset)]$$

↑  
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],

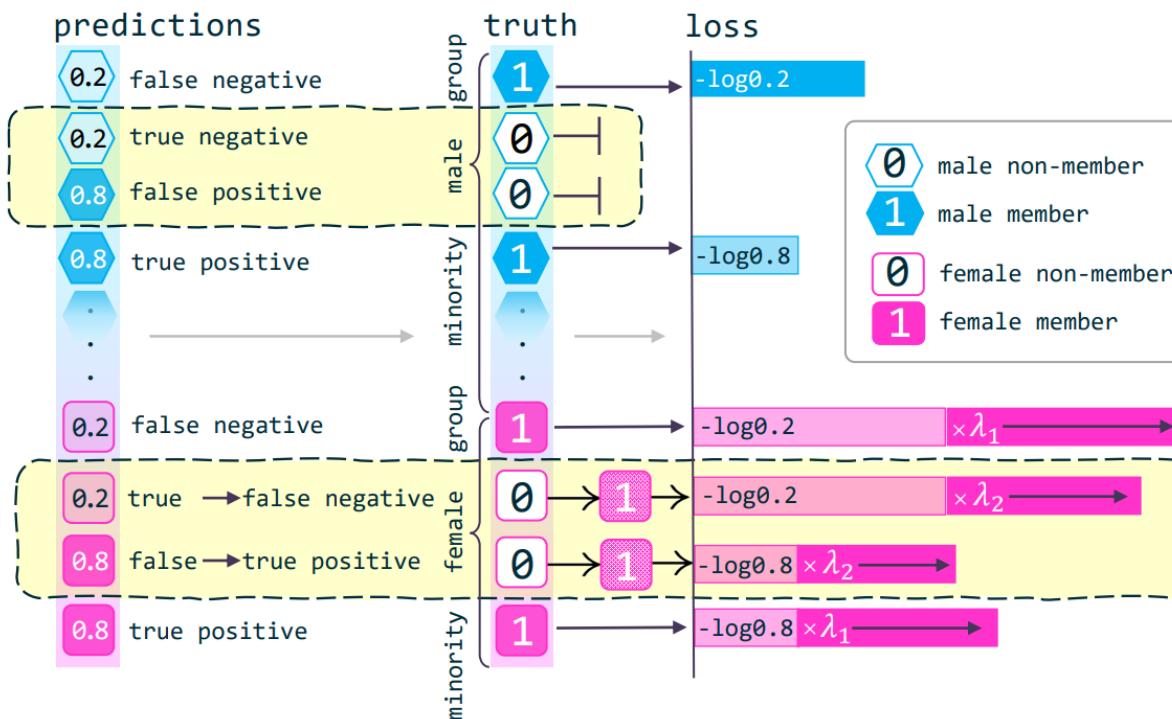
# Fair and Diverse Team Recommendation

- **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.

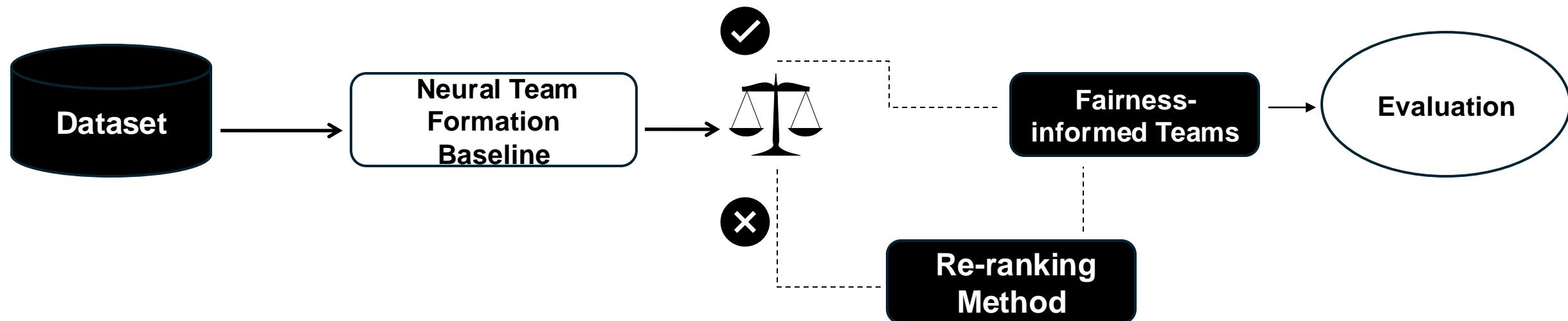
[Moasses et.al., BIAS-SIGIR, 2024]



# 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.

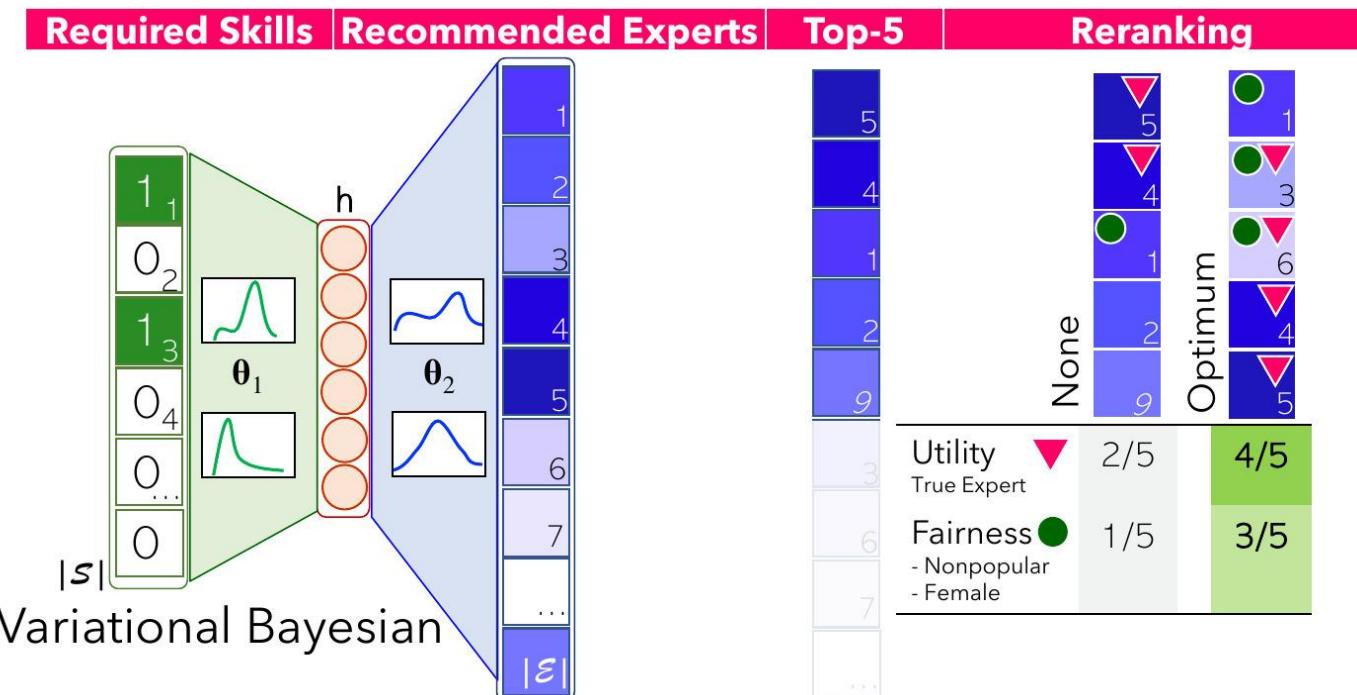
[Loghmani et.al., BIAS-ECIR, 2022], [Geyik et.al., KDD, 2019]



# Fair and Diverse Team Recommendation

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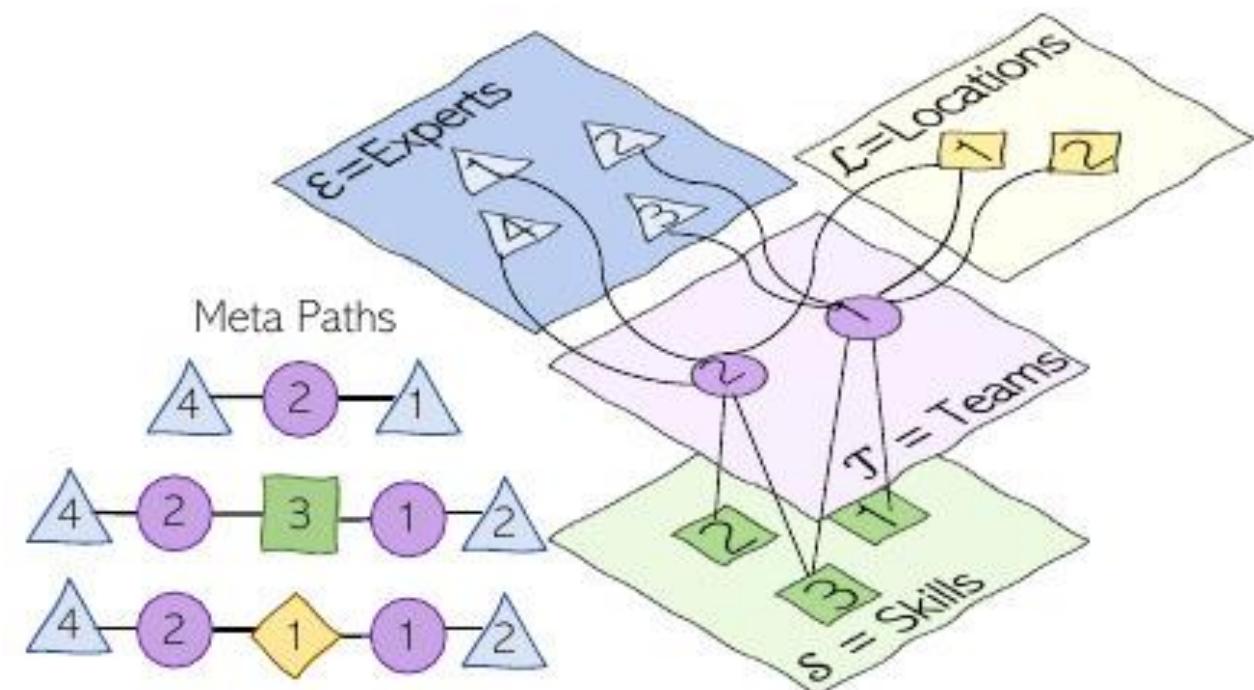
# Challenges and New Perspectives

- End-to-End Graph Neural Network
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# 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

I) Introduction and Background

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V) Applications

Hands-on: OpeNTF

# Applications

- Group Learning
- Reviewer Assignment
- Palliative Care

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# Group Learning

## Why group learning

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### Active Engagement:

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

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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

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- Integer linear programming (ILP)

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# Group Learning

## Prior Methods

- Integer linear programming (ILP)
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  - 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

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## 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.

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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

