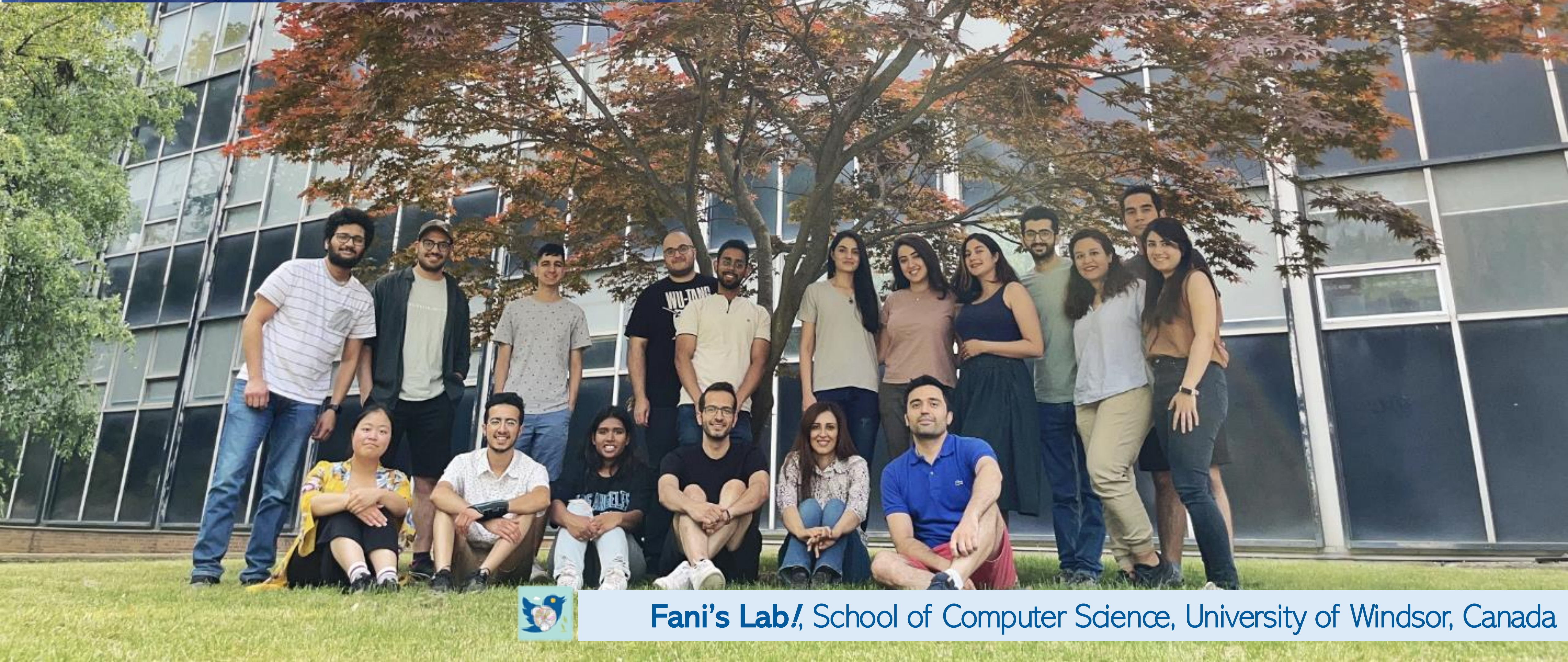
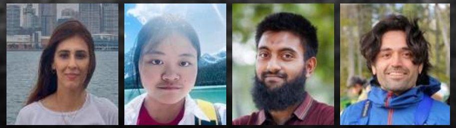
Photo: Bird Murmuration, James Crombie, https://www.jamescrombie.ie/

Bridging Historical Subgraph Optimization & Modern Graph Neural Network in Team Recommendations



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

Schindler's List, Steven Spielberg, 1993

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

5

Outline

What Is a Team?

A group of users who **collaborate** together with a **common purpose** 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]

Group vs. Team

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

Group Learning → Learning Teams

A. M. Turing (1950) Computing Machinery and Intelligence. *Mind 49:* 433-460.

COMPUTING MACHINERY AND INTELLIGENCE

By A. M. Turing

1. The Imitation Game

Beyond the Imitation Game: Quantifying and extrapolating the capabilities of language models

Alphabetic author list:*

Aarohi Srivastava, Abhinav Rastogi, Abhishek Rao, Abu Awal Md Shoeb, Abubakar Abid, Adam Fisch, Adam R. Brown, Adam Santoro, Aditya Gupta, Adrià Garriga-Alonso, Agnieszka Kluska, Aitor Lewkowycz, Akshat Agarwal, Alethea Power, Alex Ray, Alex Warstadt, Alexander W. Kocurek, Ali Safaya, Ali Tazarv, Alice Xiang, Alicia Parrish, Allen Nie, Aman Hussain, Amanda Askell, Amanda Dsouza, Ambrose Slone, Ameet Rahane, Anantharaman S. Iyer, Anders Andreassen, Andrea Madotto, Andrea Santilli, Andreas Stuhlmüller, Andrew Dai, Andrew La, Andrew Lampinen, Andy Zou, Angela Jiang, Angelica Chen, Anh Vuong, Animesh Gupta, Anna Gottardi, Antonio Norelli, Anu Venkatesh, Arash Gholamidavoodi, Arfa Tabassum, Arul Menezes, Arun Kirubarajan, Asher Mullokandov, Ashish Sabharwal, Austin Herrick, Avia Efrat, Aykut Erdem, Ayla Karakaş, B. 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Chi, Ethan Dyer, Ethan Jerzak, Ethan Kim, Eunice Engefu Manyasi, Evgenii Zheltonozhskii, Fanyue Xia, Fatemeh Siar, Fernando Martínez-Plumed, Francesca Happé, Francois Chollet, Frieda Rong, Gaurav Mishra, Genta Indra Winata, Gerard de Melo, Germán Kruszewski, Giambattista Parascandolo, Giorgio Mariani, Gloria Wang, Gonzalo Jaimovitch-López, Gregor Betz, Guy Gur-Ari, Hana Galijasevic, Hannah Kim, Hannah Rashkin, Hannaneh Hajishirzi, Harsh Mehta, Hayden Bogar, Henry Shevlin, Hinrich Schütze, Hiromu Yakura, Hongming Zhang, Hugh Mee Wong, Ian Ng, Isaac Noble, Jaap Jumelet, Jack Geissinger, Jackson Kernion, Jacob Hilton, Jaehoon Lee, Jaime Fernández Fisac, James B. Simon, James Koppel, James Zheng, James Zou, Jan Kocoń, Jana Thompson, Janelle Wingfield, Jared Kaplan, Jarema Radom, Jascha Sohl-Dickstein, Jason Phang, Jason Wei, Jason Yosinski, Jekaterina Novikova, Jelle Bosscher, Jennifer Marsh, Jeremy Kim, Jeroen Taal, Jesse Engel, Jesujoba Alabi, Jiacheng Xu, Jiaming Song, Jillian Tang, Joan Waweru, John Burden, John Miller, John U. Balis, Jonathan Batchelder, Jonathan Berant, Jörg Frohberg, Jos Rozen, Jose Hernandez-Orallo, Joseph Boudeman, Joseph Guerr, Joseph Jones, Joshua B. Tenenbaum, Joshua S. Rule, Joyce Chua, Kamil Kanclerz, Karen Livescu, Karl Krauth, Karthik Gopalakrishnan, Katerina Ignatyeva, Katja Markert, Kaustubh D. 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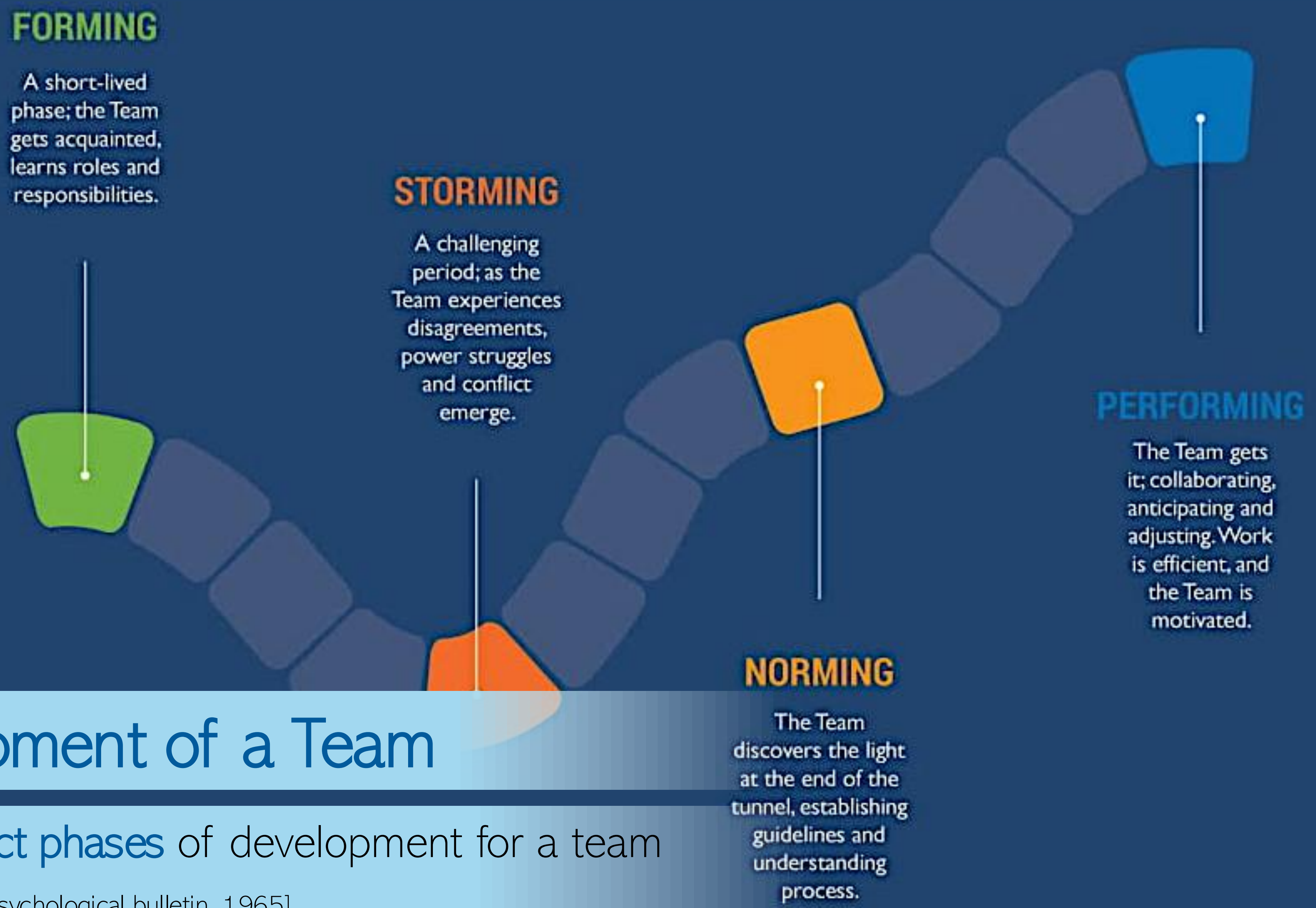
Yee, Michael Cohen, Michael Gu, Michael Ivanitskiy, Michael Starritt, Michael Strube, Michał Swędrowski, Michele Bevilacqua, Michihiro Yasunaga, Mihir Kale, Mike Cain, Mimee Xu, Mirac Suzgun, Mitch Walker, Mo Tiwari, Mohit Bansal, Moin Aminnaseri, Mor Geva, Mozhdeh Gheini, Mukund Varma T, Nanyun Peng, Nathan A. Chi, Nayeon Lee, Neta Gur-Ari Krakover, Nicholas Cameron, Nicholas Roberts, Nick Doiron, Nicole Martinez, Nikita Nangia, Niklas Deckers, Niklas Muennighoff, Nitish Shirish Keskar, Niveditha S. Iyer, Noah Constant, Noah Fiedel, Nuan Wen, Oliver Zhang, Omar Agha, Omar Elbaghdadi, Omer Levy, Owain Evans, Pablo Antonio Moreno Casares, Parth Doshi, Pascale Fung, Paul Pu Liang, Paul Vicol, Pegah Alipoormolabashi, Peiyuan Liao, Percy Liang, Peter Chang, Peter Eckersley, Phu Mon Htut, Pinyu Hwang, Piotr Miłkowski, Piyush Patil, Pouya Pezeshkpour, Priti Oli, Qiaozhu Mei, Qing Lyu, Qinlang Chen, Rabin Banjade, Rachel Etta Rudolph, Raefer Gabriel, Rahel Habacker, Ramon Risco, Raphaël Millière, Rhythm Garg, Richard Barnes, Rif A. Saurous, Riku Arakawa, Robbe Raymaekers, Robert Frank, Rohan Sikand, Roman Novak, Roman Sitelew, Ronan LeBras, Rosanne Liu, Rowan Jacobs, Rui Zhang, Ruslan Salakhutdinov, Ryan Chi, Ryan Lee, Ryan Stovall, Ryan Teehan, Rylan Yang, Sahib Singh, Saif M. Mohammad, Sajant Anand, Sam Dillavou, Sam Shleifer, Sam Wiseman, Samuel Gruetter, Samuel R. Bowman, Samuel S. Schoenholz, Sanghyun Han, Sanjeev Kwatra, Sarah A. Rous, Sarik Ghazarian, Sayan Ghosh, Sean Casey, Sebastian Bischoff, Sebastian Gehrmann, Sebastian Schuster, Sepideh Sadeghi, Shadi Hamdan, Sharon Zhou, Shashank Srivastava, Sherry Shi, Shikhar Singh, Shima Asaadi, Shixiang Shane Gu, Shubh Pachchigar, Shubham Toshniwal, Shyam Upadhyay, Shyamolima (Shammie) Debnath, Siamak Shakeri, Simon Thormeyer, Simone Melzi, Siva Reddy, Sneha Priscilla Makini, Soo-Hwan Lee, Spencer Torene, Sriharsha Hatwar, Stanislas Dehaene, Stefan Divic, Stefano Ermon, Stella Biderman, Stephanie Lin, Stephen Prasad, Steven T. Piantadosi, Stuart M. Shieber, Summer Misherghi, Svetlana Kiritchenko, Swaroop Mishra, Tal Linzen, Tal Schuster, Tao Li, Tao Yu, Tariq Ali, Tatsu Hashimoto, Te-Lin Wu, Théo Desbordes, Theodore Rothschild, Thomas Phan, Tianle Wang, Tiberius Nkinyili, Timo Schick, Timofei Kornev, Titus Tunduny, Tobias Gerstenberg, Trenton Chang, Trishala Neeraj, Tushar Khot, Tyler Shultz, Uri Shaham, Vedant Misra, Vera Demberg, Victoria Nyamai, Vikas Raunak, Vinay Ramasesh, Vinay Uday Prabhu, Vishakh Padmakumar, Vivek Srikumar, William Fedus, William Saunders, William Zhang, Wout Vossen, Xiang Ren, Xiaoyu Tong, Xinran Zhao, Xinyi Wu, Xudong Shen, Yadollah Yaghoobzadeh, Yair Lakretz, Yangqiu Song, Yasaman Bahri, Yejin Choi, Yichi Yang, Yiding Hao, Yifu Chen, Yonatan Belinkov, Yu Hou, Yufang Hou, Yuntao Bai, Zachary Seid, Zhuoye Zhao, Zijian Wang, Zijie J. Wang, Zirui Wang, Ziyi Wu

Science Research Teams

The Big Lebowski, 1998, Joel & Ethan Coen

11 Entertainment Industry (Cast'nCrew)

12 Sport Teams

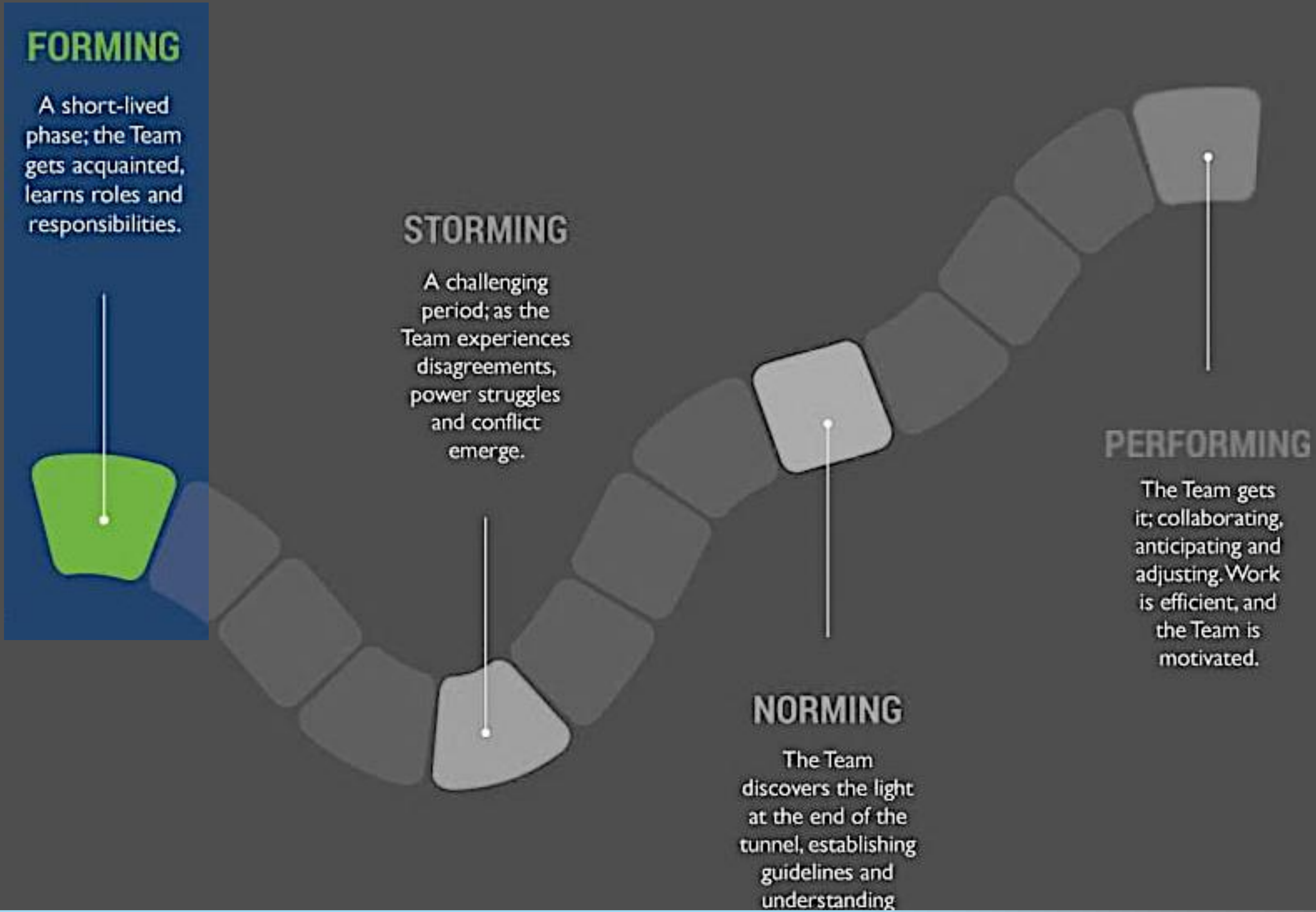


13

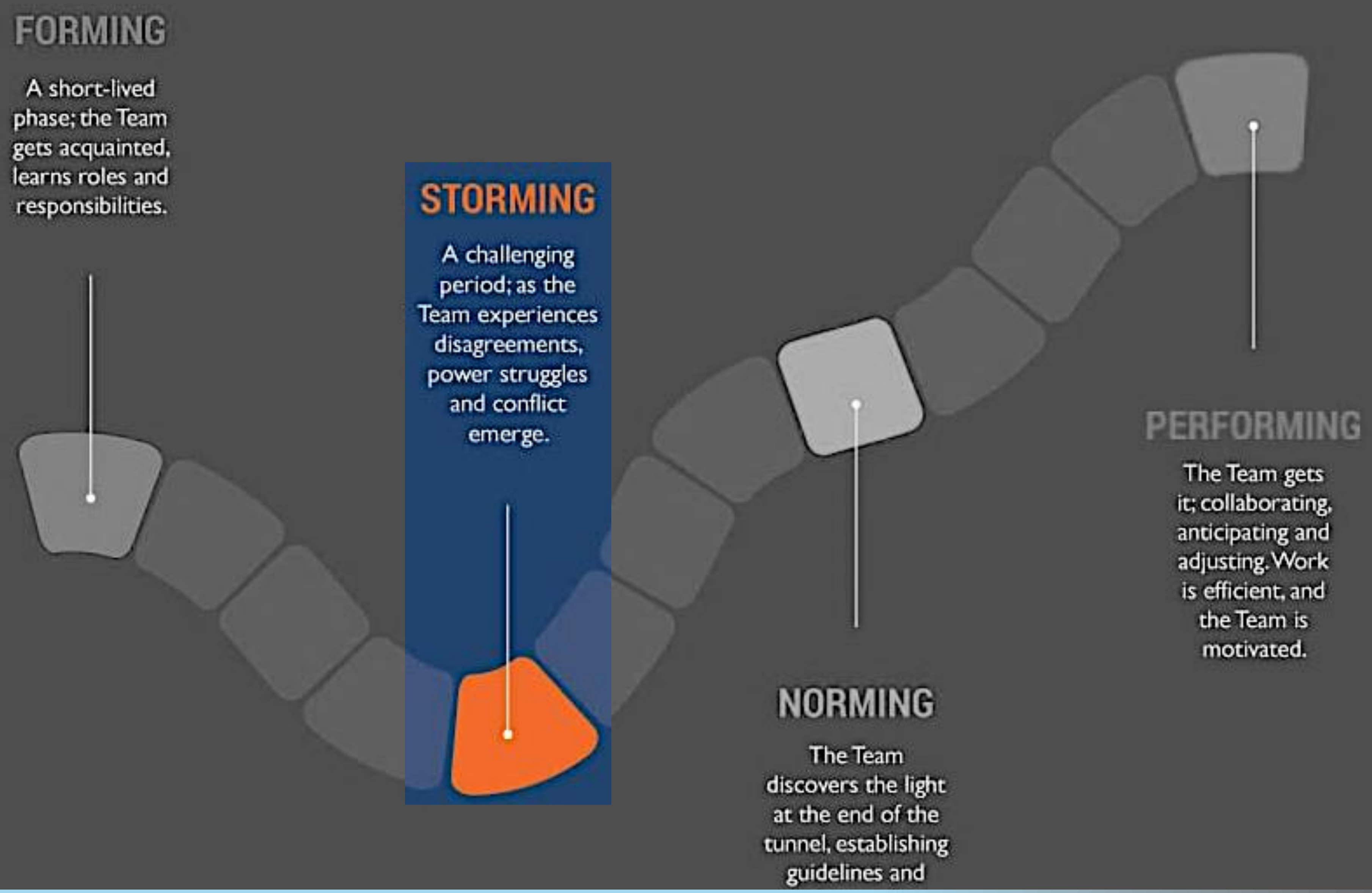
Development of a Team

Four distinct phases of development for a team

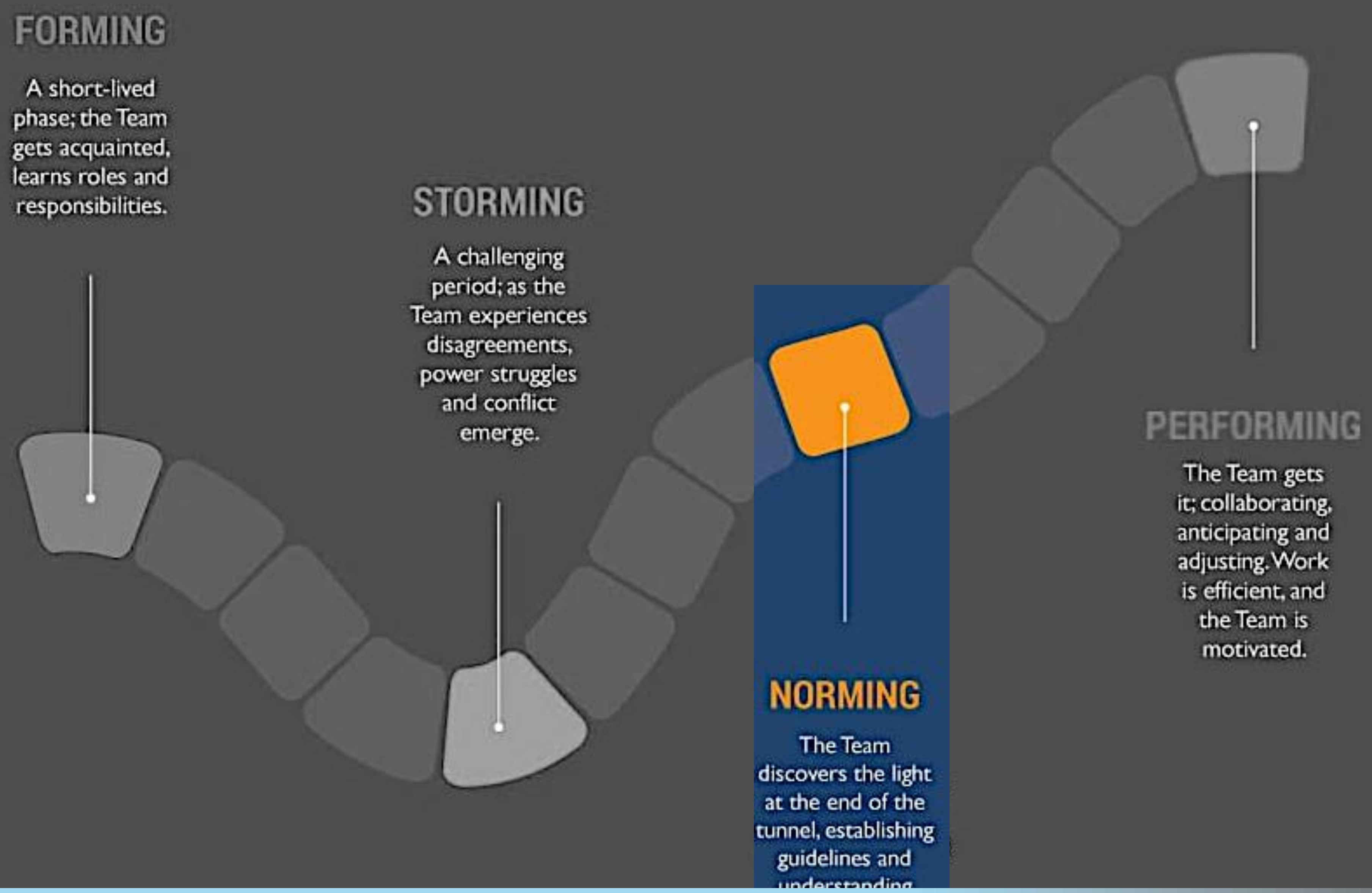
[Tuckman et al., Psychological bulletin ,1965]



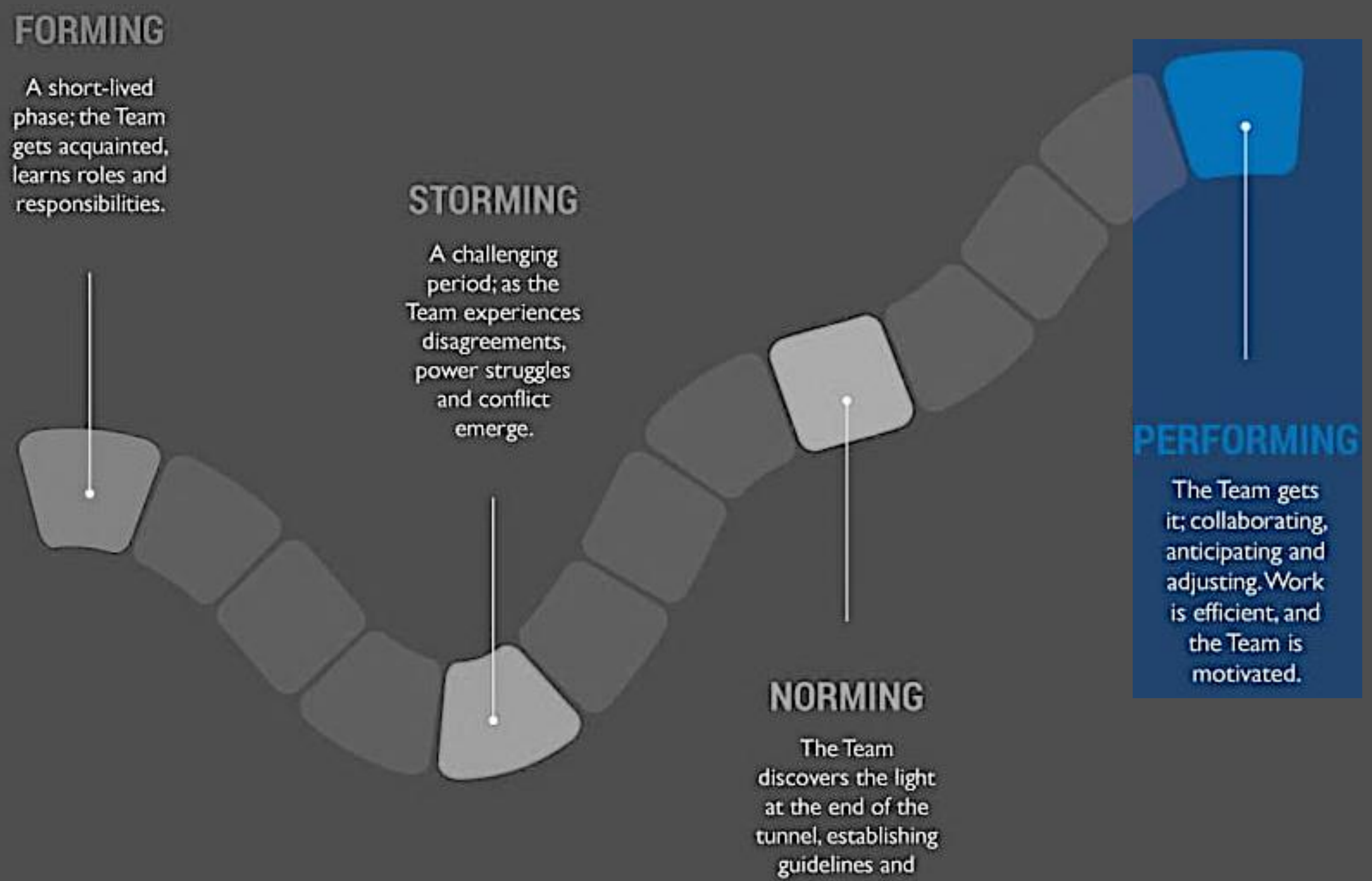
Tuckman, Bruce W. "Developmental sequence in small groups." Psychological bulletin 63.6 (1965): 384.



Tuckman, Bruce W. "Developmental sequence in small groups." Psychological bulletin 63.6 (1965): 384.



Tuckman, Bruce W. "Developmental sequence in small groups." Psychological bulletin 63.6 (1965): 384.



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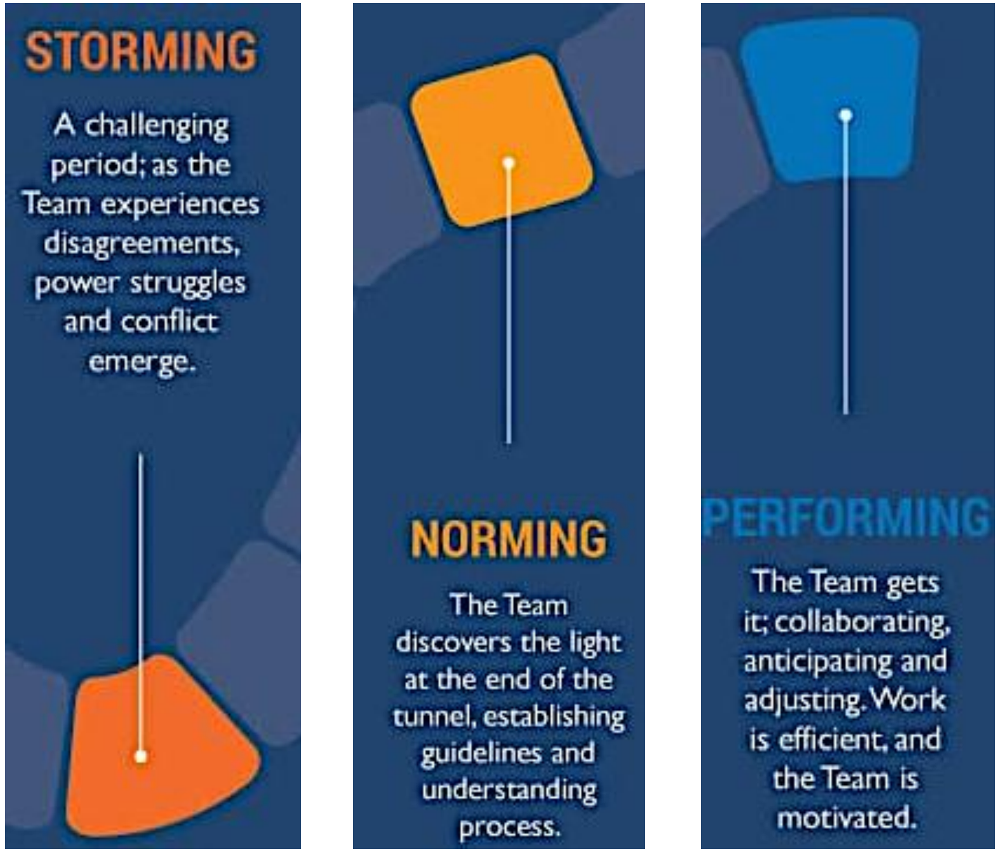
Team Recommendation → Team Formation

Team Recommendation → Team Refinement



Eternal Sunshine of the Spotless Mind, Michel Gondry, 2004

Information Retrieval in a Library: Web Search

Eternal Sunshine of the Spotless Mind, Michel Gondry, 2004

Information Retrieval in a Village: Social Search

Social Information Retrieval (Social IR)

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

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297 3,631

Get Access

Abstract

We present Aardvark, a social search engine. With Aardvark, users ask a question, either by instant message, email, 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.

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

Published: 01 April 2012 Publication History

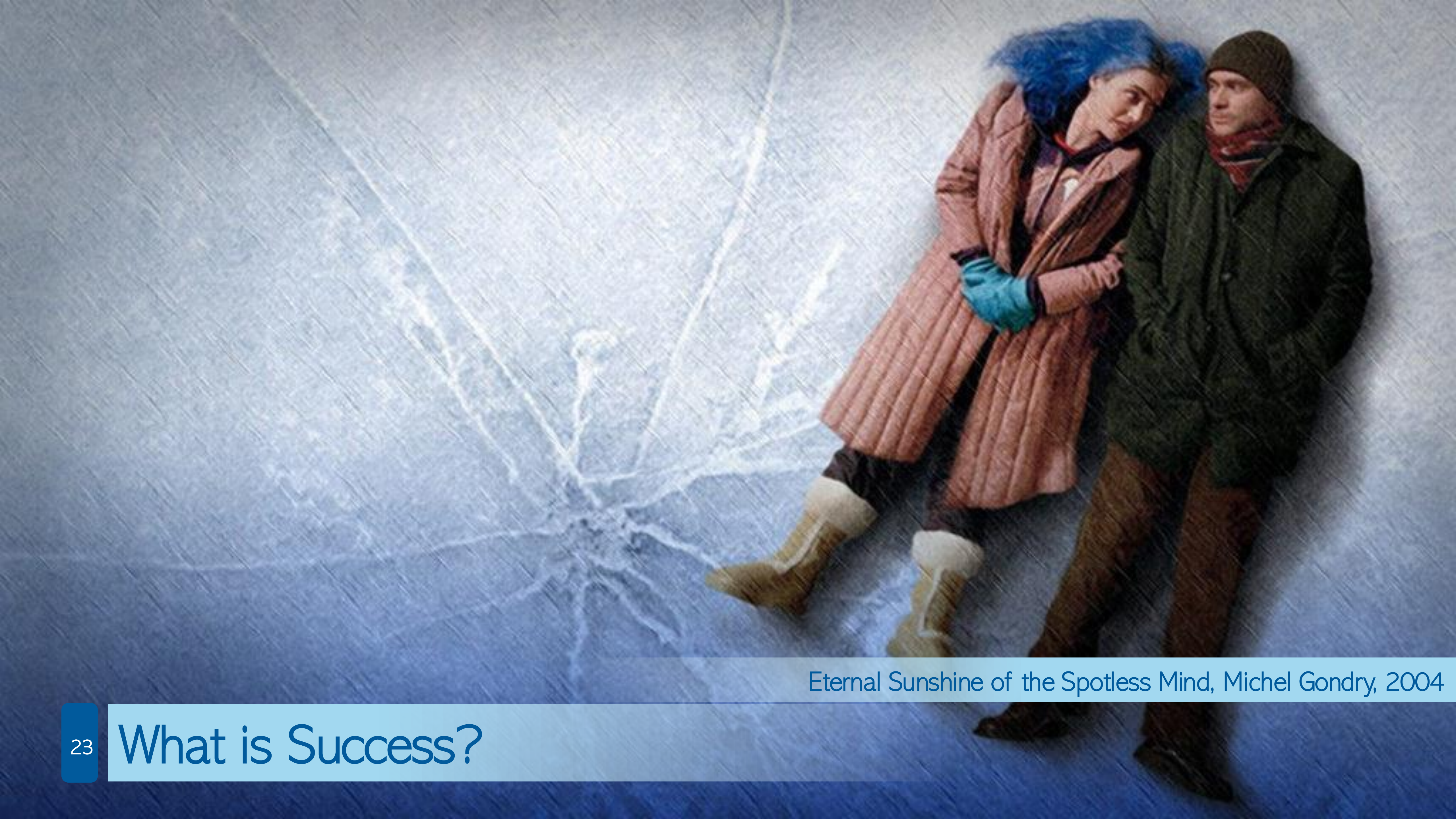
Check for updates

13 6,389

All formats PDF

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

What is Success?

24

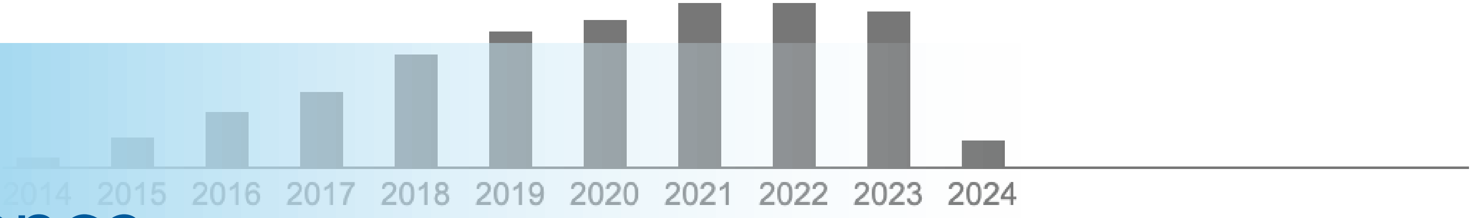
What is Success?
Germany, Women World Cup 2007

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
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



What is Success?
Peer-review Acceptance ...

Tomas Mikolov
December 13, 2023 ·

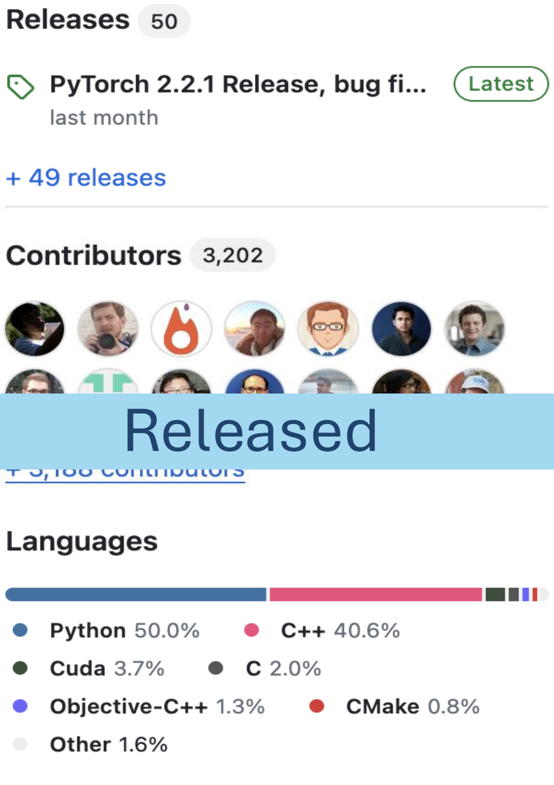
Yesterday we received a Test of Time Award at NeurIPS for the word2vec paper from ten years ago. I'm really happy about it! I think it's the first "best paper" type of award I ever received. In fact, the original word2vec paper was rejected at the first ICLR conference in 2013 (despite the acceptance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

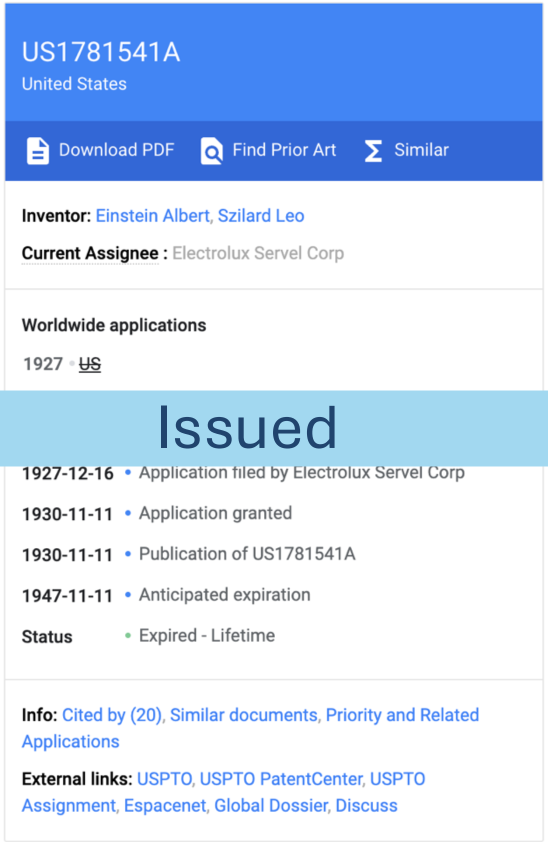
https://openreview.net/forum?id=idpCdOWtqXd60

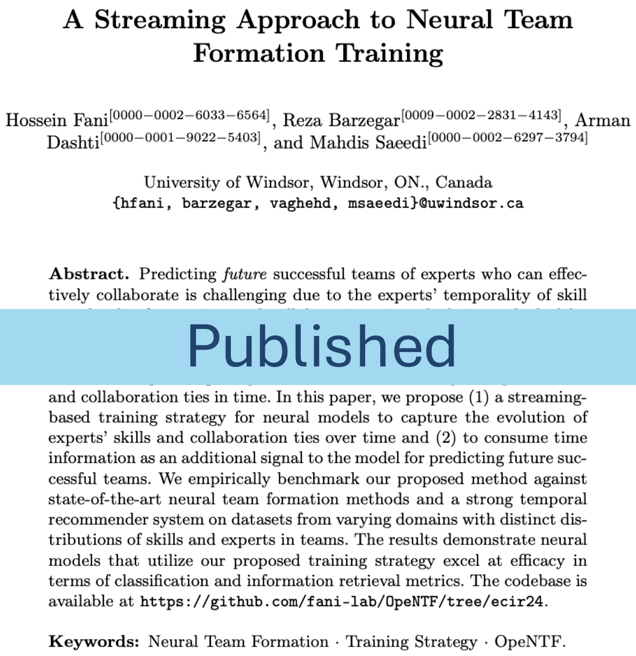
https://www.facebook.com/share/p/kXYaYaRvRCr5K2Ze

What is Success?
Peer-review Acceptance …

28 What is Success?







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 ... 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.

Produced | Released | Issued | Published

Traditional Approach

Manual, based on human experience, instinct; error-prone, and suboptimal

- 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

5 MB HDD, IBM, 1956

Traditional Approach

Manual, based on human experience, instinct; error-prone, and suboptimal

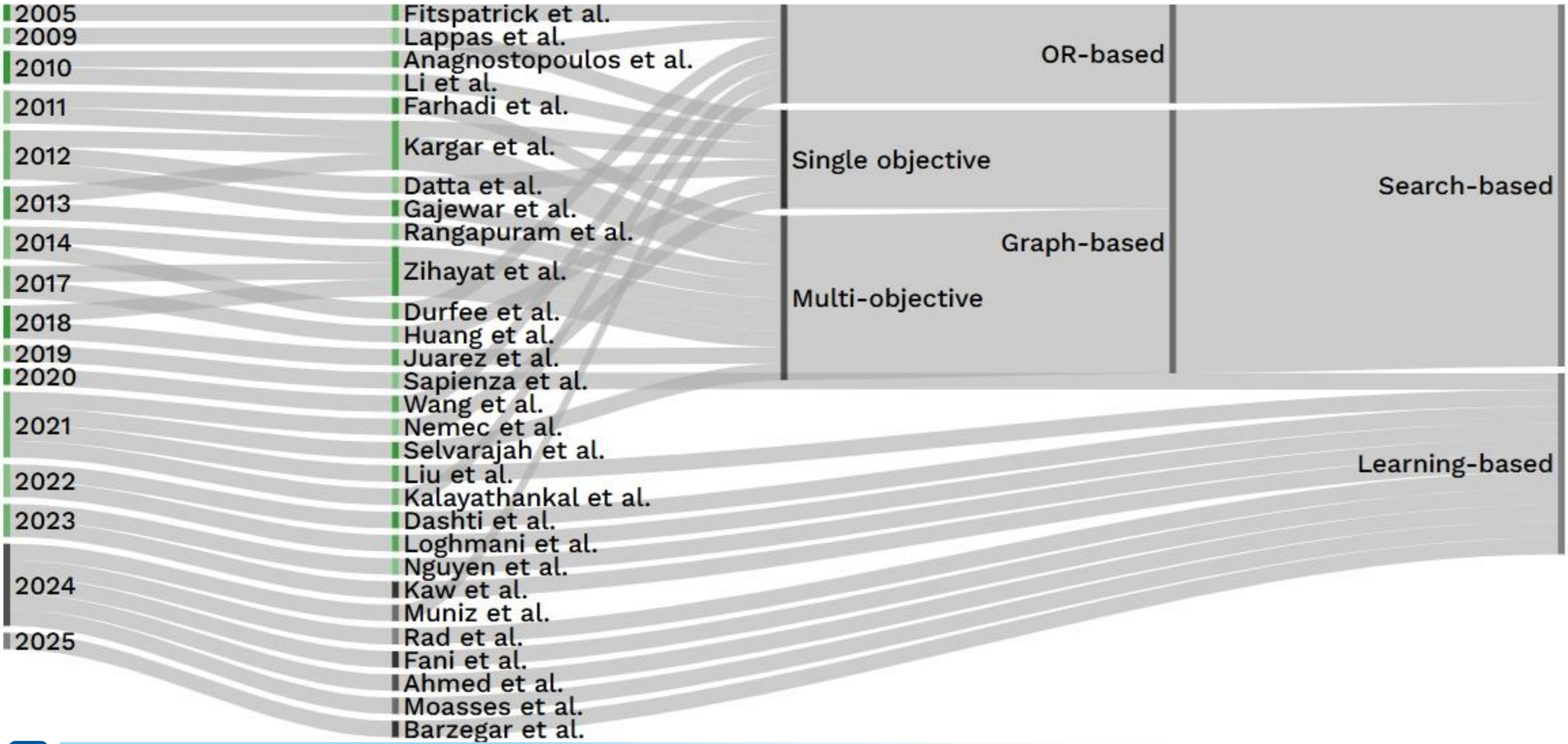
- Large number of candidates
  - Different knowledge
  - Different culture
  - Different characteristic
- Hidden pers … nd societal biases
  - Race
  - Gender
  - Popularity
- Multitude of criteria to optimize
  - Communication cost
  - Budget
  - Time

Manual team recommendation on a large scale is almost impossible!

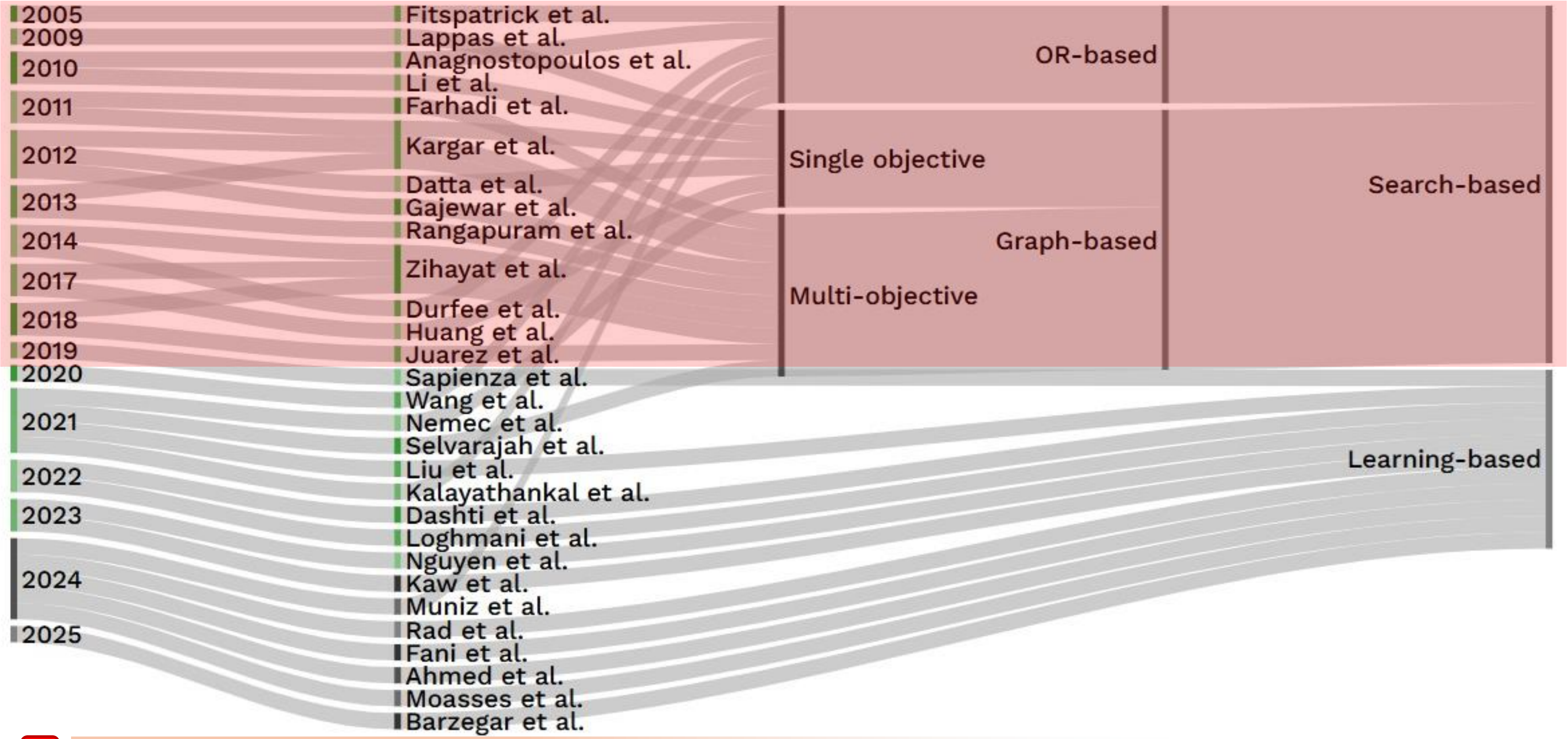
Computational Approach

- **Computational**
  - Refinement
    - Reinforcement Learning
  - **Formation**
    - **Search-based**
      - Subgraph Optimization
      - Operations Research
        - Single Objective
          - Communication Cost
            - Static (non-Temporal)
            - Hierarchical
            - Dynamic (Temporal)
        - Multiple Objectives
          - Proficiency
          - Personnel Cost
          - Geographical Distance
          - Density
    - **Learning-based**
      - Model Architecture
        - Feedforward
        - Variational Bayesian
        - Graph Neural Network
          - Transfer Learning
          - End-to-End Approach
      - Training Strategy
        - Positive Labels
        - Negative Sampling
        - Streaming Strategy
        - Curriculum
- non-Computational
  - Science of Team Science (SciTS)

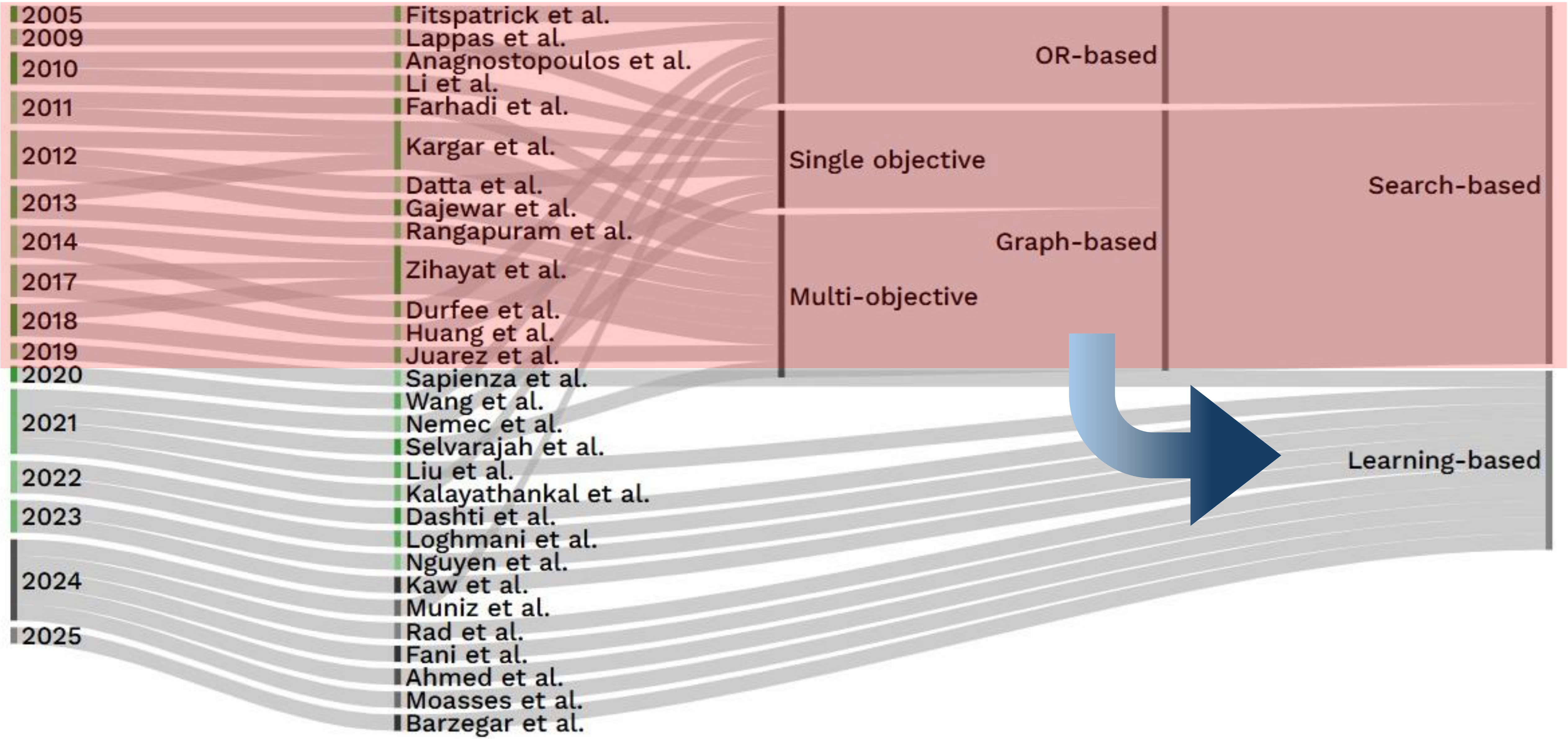
Team Allocation, Team Selection, Team Composition, Team Configuration, Team Recommendation, Team Formation



Computational Approach in Time



Computationally Prohibitive



Distill the Knowledge for Neural Team Recommendation

35 Outline

I) Introduction and Background

II) Pioneering Techniques

III) Learning-based Heuristics

IV) Challenges and New Perspectives

V) Applications

Hands-on: OpeNTF

Computational Approach

- Computational
  - Refinement
    - Reinforcement Learning
  - Formation
    - Search-based
      - Subgraph Optimization
        - Single Objective
          - Communication Cost
            - Static (non-Temporal)
            - Hierarchical
            - Dynamic (Temporal)
        - Multiple Objectives
          - Proficiency
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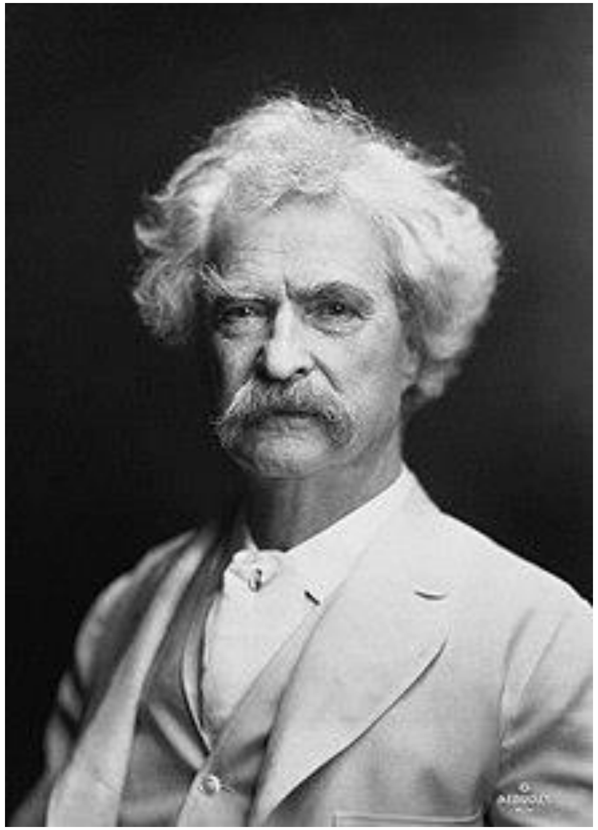
        - Negative Sampling
        - Streaming Strategy
        - Curriculum
- non-Computational
  - Science of Team Science (SciTS)

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

Core Objective of this Tutorial

> "There is no such thing as a new idea. It is impossible. We simply take a lot of old ideas and put them into a sort of mental kaleidoscope. We give them a turn and they make new and curious combinations. We keep on turning and making new combinations indefinitely; but they are the same old pieces of colored glass that have been in use through all the ages."



Samuel Langhorne Clemens (1835 – 1910)
Mark Twain, American Writer

Graph-based Approach

Underlying network structure is a key for Effective Team

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

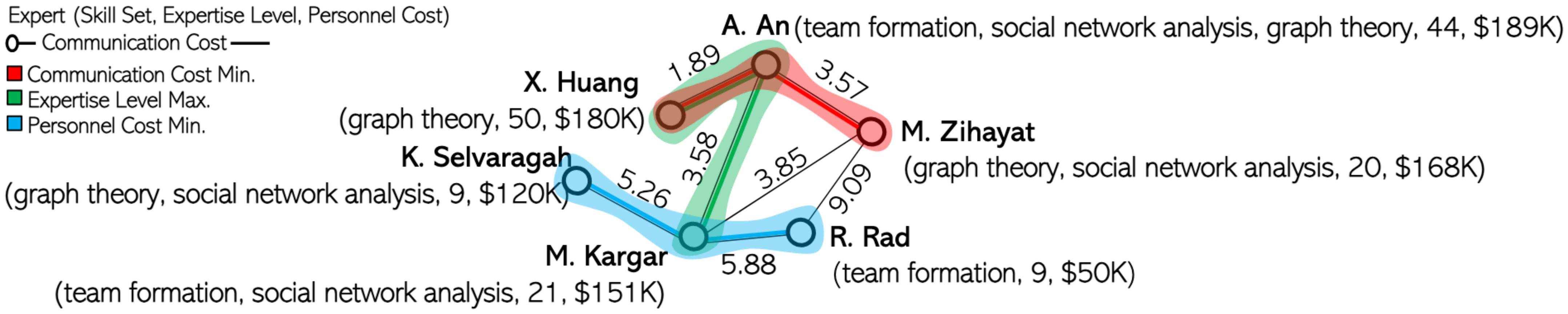
Team Recommendation

→ Social Network Analysis

→ Graph Theory

[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]

Subgraph Optimization on Expert Network



Undirected Homogeneous Weighted Attributed Graph:

Nodes	→	Experts
Node Attributes	→	Expert Skills, Salary, Expertise Level, …
Weighted Edges	→	Depends on the Optimization Objective

			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
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							✓	✓					✓	

Optimization Objectives

			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				✓			✓							
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 ↔ Team Performance

42 Communication Cost ↔ Team Performance

Effective Team

→ Effective Understanding among Team Members

→ Efficient (Easy, Fast, ...) Communication

→ Low Communication

Communication Cost ↔ Team Performance

More Joint Teamwork

→ Effective Understanding among Team Members

→ Efficient (Easy, Fast, …) Communication

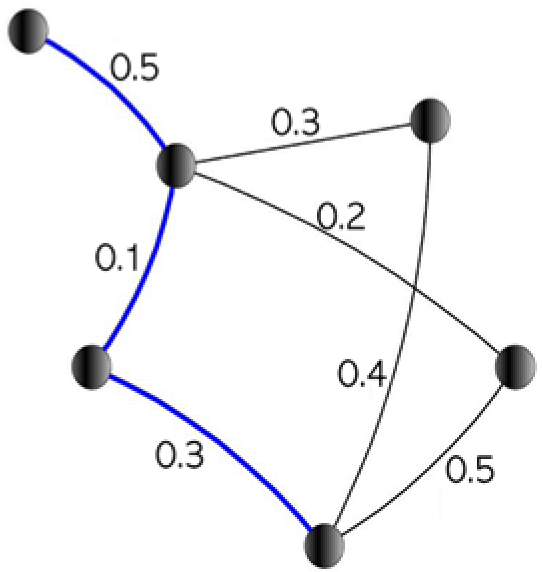
→ Low Communication

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

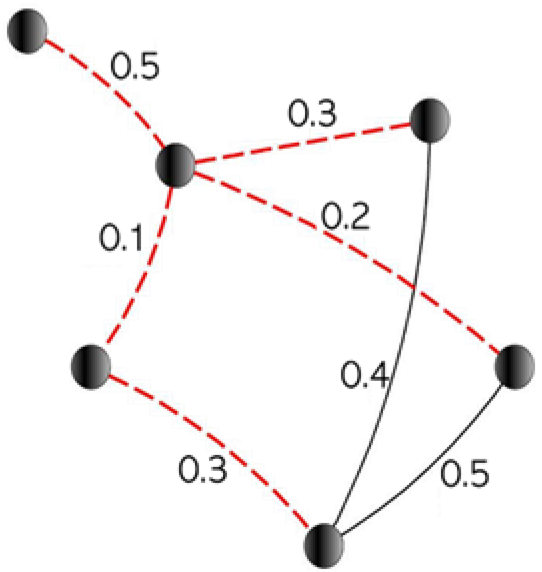
$$\omega_{\downarrow}(u, v) = \left|\frac{1}{P_u \cap P_v}\right| \in \Re^{(0,1] \cup \{\infty\}}$$

Communication Cost ↔ Team Performance

Subgraph w/ Minimum Sum of Distances
Subgraph w/ Minimum Sum of Edge Weights
Subgraph w/ Minimum Diameter
Subgraph w/ Minimum Spanning Tree



Minimum Diameter



Minimum Spanning Tree

45 Communication Cost ↔ Team Performance

More Joint Teamwork Recently

→ Effective Understanding among Team Members

→ Efficient (Easy, Fast, ...) Communication

→ Low Communication

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

			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
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 + Other Factors ↔ Team Performance

Multi-Objective Optimization

Communication Cost + Proficiency (e.g., h-index, #citations)

[Zihayat et. al., AMW, 2018], [Zihayat et. al., EDBT, 2017]

Communication Cost + Personnel Cost

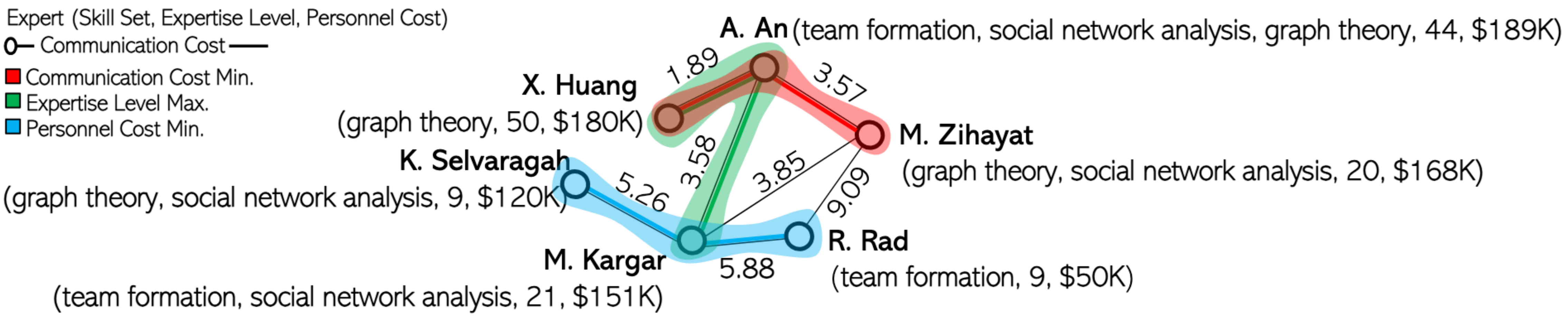
[Aijun et. al., SDM, 2013], [Kargar et. al., CSE, 2013], [Zihayat et. al., AMW, 2018]

Communication Cost + Personnel Cost + Proficiency

[Zihayat et. al., WI-IAT, 2014]

Communication Cost + Geographical Proximity + Proficiency

[Selvarajah et. al., Expert Syst. Appl., 2021]



48 Optimization Objective → Optimizer

Subgraph Optimization is NP-hard

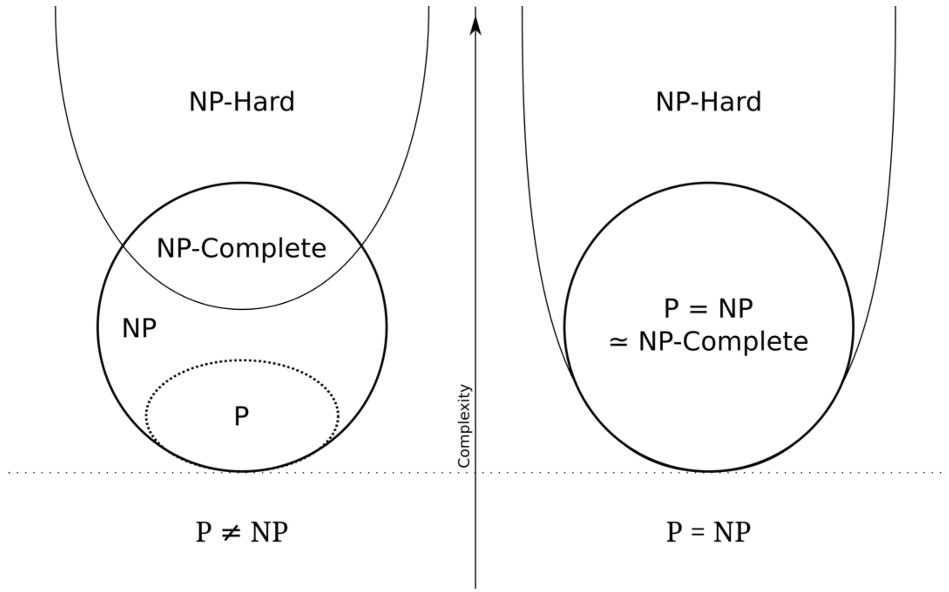
[Karp, Complexity of computer computations, Springer, 2010]

↓

Heuristics for Polynomial Time

Greedy

Approximation



Optimization Objective → Optimizer

Lappas et al. Finding a team of experts in social networks, KDD 2009.

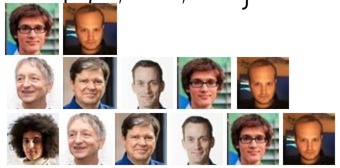
Algorithm 1 The RarestFirst algorithm for the DIAMETER-TF problem.

Input: Graph $G(\mathcal{X}, E)$; individuals' skill vectors $\{X_1, \ldots, X_n\}$ and task T.
Output: Team $\mathcal{X}' \subseteq \mathcal{X}$ and subgraph $G[\mathcal{X}']$.

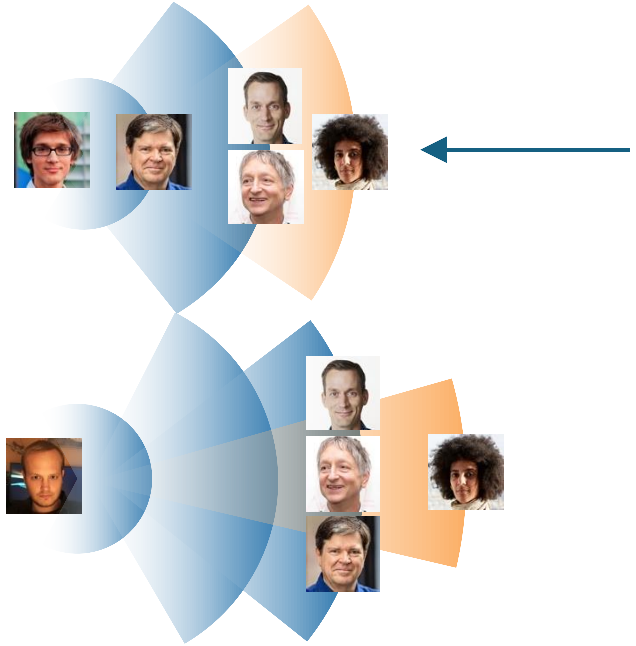
for every $a \in T$ **do**
  $S(a) = \{i \mid a \in X_i\}$
$a_{rare} \leftarrow \arg\min_{a \in T} |S(a)|$
for every $i \in S(a_{rare})$ **do**
  for $a \in T$ and $a \neq a_{rare}$ **do**
    $R_{ia} \leftarrow d(i, S(a))$
  $R_i \leftarrow \max_a R_{ia}$
$i^* \leftarrow \arg\min R_i$
$\mathcal{X}' = i^* \cup \{Path(i^*, S(a)) \mid a \in T\}$

$$\mathcal{O}(|S(a_{rare})| \times n) \xrightarrow{|S(a_{rare})| = \mathcal{O}(n)} \mathcal{O}(n^2)$$

Required Skills: T = {gn, nn, ml}
Support (gn) =
Support (nn) =
Support (ml) =



Subgraph of Experts that Covers Required Skills
Start with Experts with the Rarest Skills as Seed Support Group



50

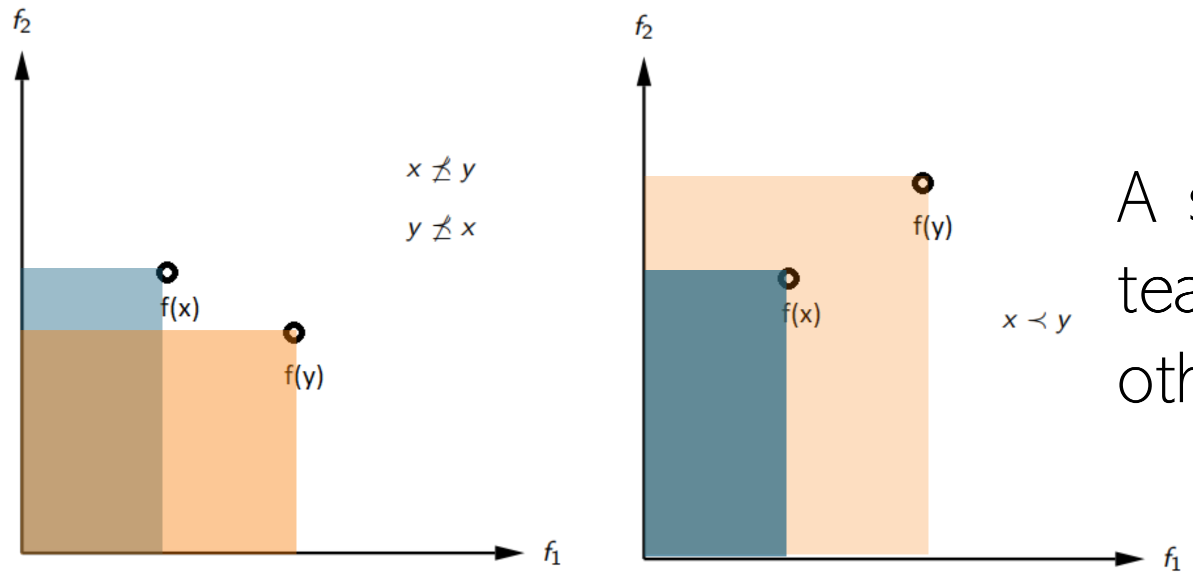
Multi-Objective → Optimizer

Interpolate (mainly linear) to a single edge weights

$$\omega_{\downarrow}(u, v) = \alpha f_1(u, v) + (1 - \alpha) f_2(u, v)$$

Pareto Optimality in Team Recommendation

[An et al. Finding affordable and collaborative teams from a network of experts. SIAM 2013.]



A subgraph is a Pareto Optimum team if it is not dominated by any other subgraphs.

A Survey of Subgraph Optimization for Expert Team Formation

ACM Computing Surveys, Pending Peer-review, R1, R2 Revisions Submitted …

Outline

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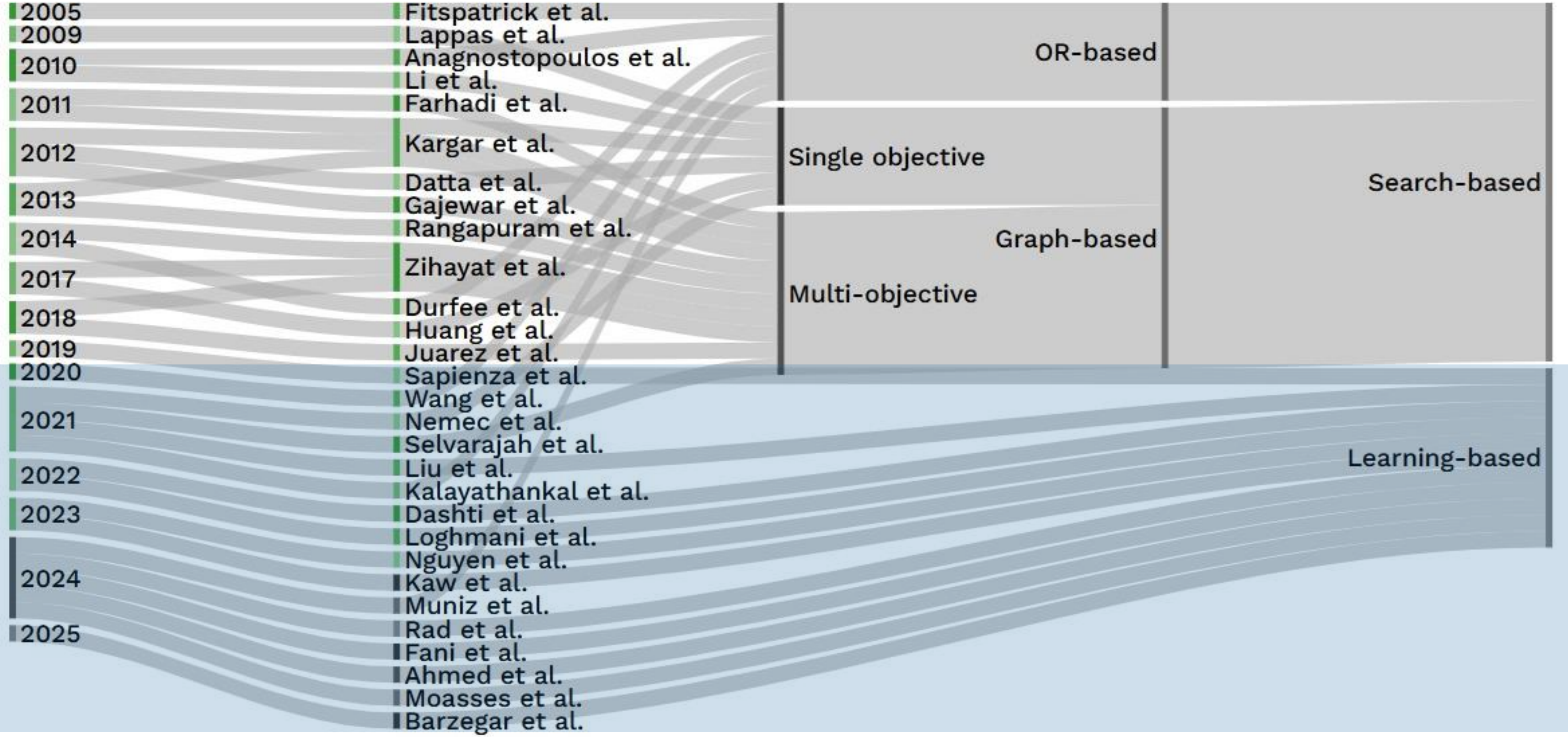
Computational Approach

- Computational
  - Refinement
    - Reinforcement Learning
  - Formation
    - Search-based
      - Subgraph Optimization
      - Operations Research
        - Single Objective
          - Communication Cost
            - Static (non-Temporal)
            - Hierarchical
            - Dynamic (Temporal)
        - Multiple Objectives
          - Proficiency
          - Personnel Cost
          - Geographical Distance
          - Density
    - Learning-based
      - Model Architecture
        - Feedforward
        - Variational Bayesian
        - Graph Neural Network
          - Transfer Learning
          - End-to-End Approach
      - Training Strategy
        - Positive Labels
        - Negative Sampling
        - Streaming Strategy
        - Curriculum
- non-Computational
  - Science of Team Science (SciTS)

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



Neural Team Recommendation

Neural Team Recommendation

The Seventh Seal, Ingmar Bergman, 1957

1957: The Seventh Seal, Ingmar Bergman, Gunnar Fischer, Max von Sydow, Gunnar Björnstrand, Bengt Ekerot, Bibi Andersson, Nils Poppe
1957: Wild Strawberries, Ingmar Bergman, Gunnar Fischer, Sjöström, Bibi Andersson, Ingrid Thulin, Gunnar Björnstrand, Jullan Kindahl
1966: Persona, Ingmar Bergman, Sven Nykvist, Bibi Andersson, Liv Ullmann, Margaretha Krook, Gunnar Björnstrand, Jörgen Lindström
1972: Cries and Whispers, Ingmar Bergman, Sven Nykvist, Harriet Andersson, Ingrid Thulin, Liv Ullmann, Kari Sylwan, Erland Josephson
1982: Fanny and Alexander, Ingmar Bergman, Sven Nykvist, Bertil Guve, Pernilla Allwin, Ewa Fröling, Jan Malmsjö, Gunn Wållgren

Neural Team Recommendation

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57 Neural Team Recommendation

The Seventh Seal, Ingmar Bergman, 1957

1984: After the Rehearsal, Ingmar Bergman, […],

Neural Team Recommendation

Utilize past (un)successful teams as training samples.
Predict future teams whose success is almost surely guaranteed!

Efficiency: iterative and online learning procedures
Efficacy: improved prediction and team performance
Scalability: can handle larger pool of experts
Dynamic Adaptation: better suited for temporal studies

Neural Team Recommendation → Team

Experts Pool

Skill Pool

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

Team is a subset of experts
for a subset of required skills

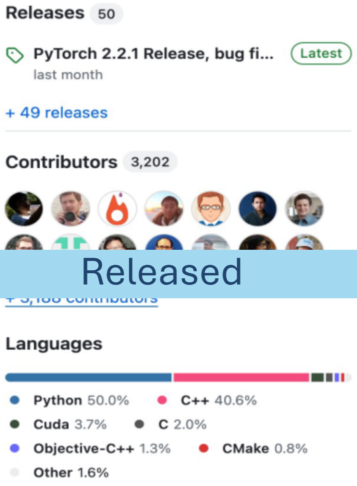
Label of Success

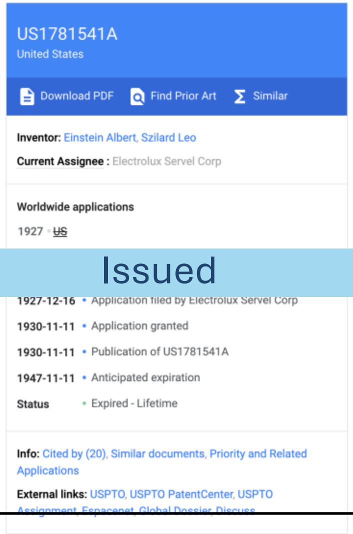
Neural Team Recommendation → Problem

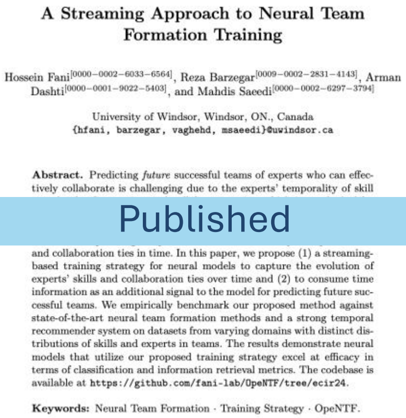
The Seventh Seal, Ingmar Bergman, 1957

Learn a function f of parameters θ from the powerset of skills $\mathcal{S}$ to the powerset of $\mathcal{E}$

$$f_\theta(s) = e^* \rightarrow (s, e^*)_{y=1} \;;\; f_\theta(s) \neq e' \rightarrow (s, e')_{y=0}$$







Produced	Released	Issued	Published

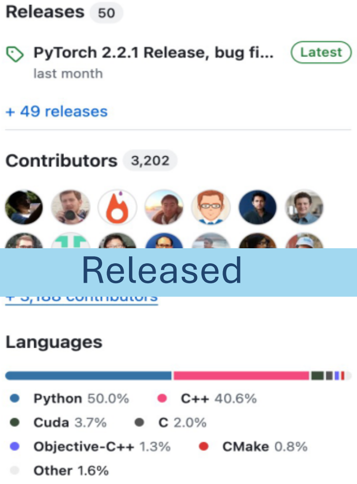
Teams	Movies	Software Repos	Patents	Papers
Skills	Genres	Programing Languages	Subclasses	Keywords
Experts	Cast'nCrew	Programmers	Inventors	Authors

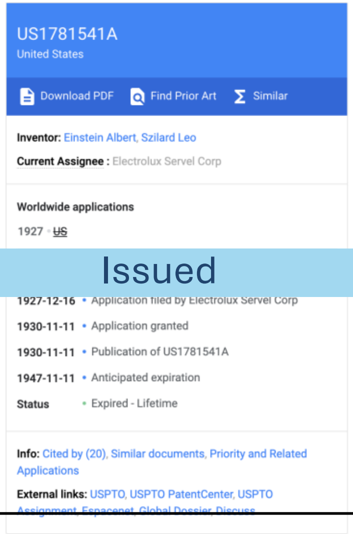
Neural Team Recommendation → Solutions

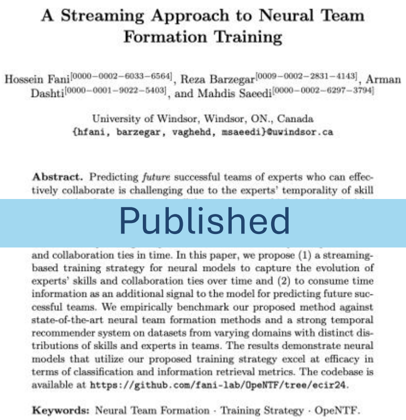
The Seventh Seal, Ingmar Bergman, 1957

Maximizing A Posterior (MAP) of $\boldsymbol{\theta}$ in $f_{\boldsymbol{\theta}}$ over training set $\mathcal{T}$ in a multilayer neural network

$$\mathtt{argmax}_{\boldsymbol{\theta}}\ p(\boldsymbol{\theta}|\mathcal{T}) \propto p(\mathcal{T}|\boldsymbol{\theta})p(\boldsymbol{\theta}) = p(\boldsymbol{\theta}) \prod_{(\mathbf{s},\mathbf{e})\in\mathcal{T}} p(\mathbf{e}|\mathbf{s},\boldsymbol{\theta})$$






A Streaming Approach to Neural Team Formation Training

Hossein Fani, Reza Barzegar, Arman Dashti, and Mahdi Saeedi

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

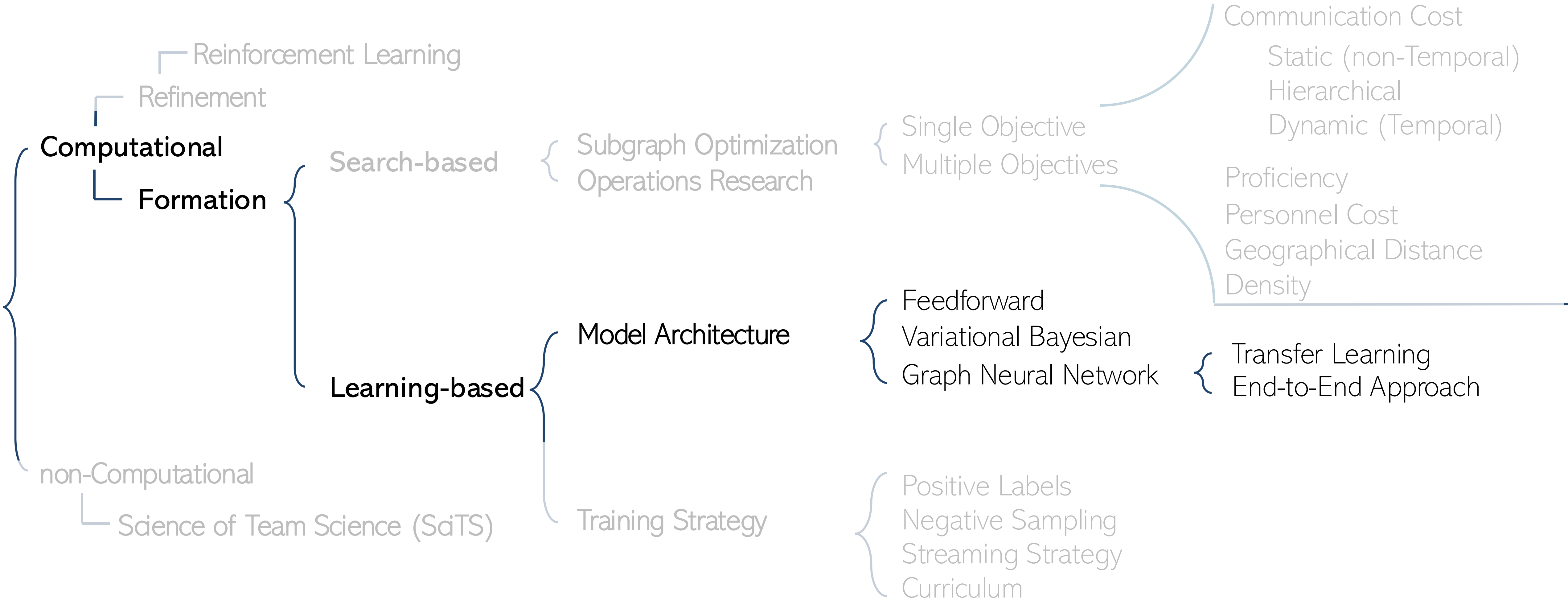
Abstract. Predicting future successful teams of experts who can effectively collaborate is challenging due to the experts' temporality of skill ... and collaboration ties in time. In this paper, we propose (1) a streaming-based training strategy for neural models to capture the evolution of experts' 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.

Produced | Released | Issued | Published

Teams	Movies	Software Repos	Patents	Papers
Skills	Genres	Programing Languages	Subclasses	Keywords
Experts	Cast'nCrew	Programmers	Inventors	Authors

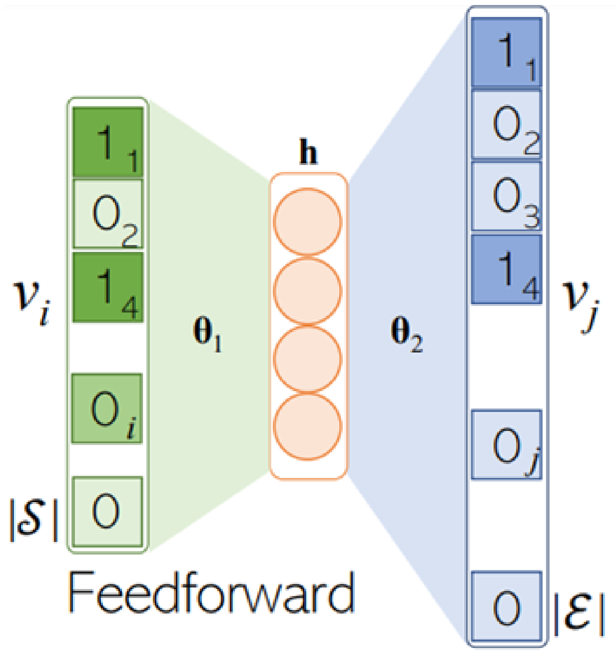
62 Computational Approach



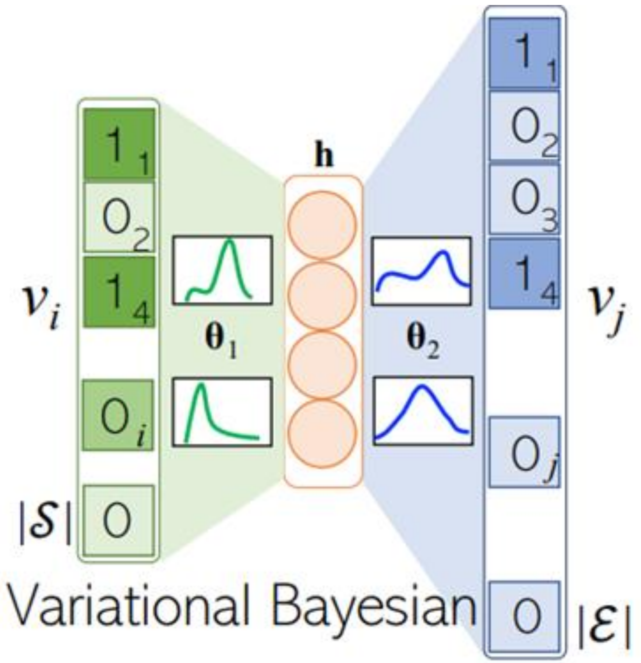
Team Allocation, Team Selection, Team Composition, Team Configuration, Team Recommendation, Team Formation

Rad et al. CIKM2020, CIKM2021, TOIS2023

Learning to Form Skill-based Teams of Experts. CIKM 2020.
PyTFL: A Python-based Neural Team Formation Toolkit. CIKM 2021.
A Variational Neural Architecture for Skill-based Team Formation. TOIS, 42(1): 1-28, 2023.



$$\mathbf{h} = \pi(\theta_1 v_s + \mathbf{b}_1)$$
$$logits \rightarrow \mathbf{z} = \theta_2 \mathbf{h} + \mathbf{b}_2$$
$$v_e = \sigma(\mathbf{z})$$



$\theta \sim (\mu, \sigma)$; $q(\theta) = \mathcal{N}(\mu, \sigma) \rightarrow$ min KL$(q \parallel p)$

Minimizing the Kullback-Leibler Divergence between $q(\theta)$ and $p(\theta)$

intel labs https://github.com/IntelLabs/bayesian-torch

Challenges

Learning to Form Skill-based Teams of Experts. CIKM 2020.
PyTFL: A Python-based Neural Team Formation Toolkit. CIKM 2021.
A Variational Neural Architecture for Skill-based Team Formation. TOIS, 42(1): 1-28, 2023.

Small vs. **Large** set
- Dense Representation Learning
  - GNN-based (Rad et al. SIGIR 2021)

Large set
- Future RQ

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

Lack of negative samples (unsuccessful teams)

Challenges

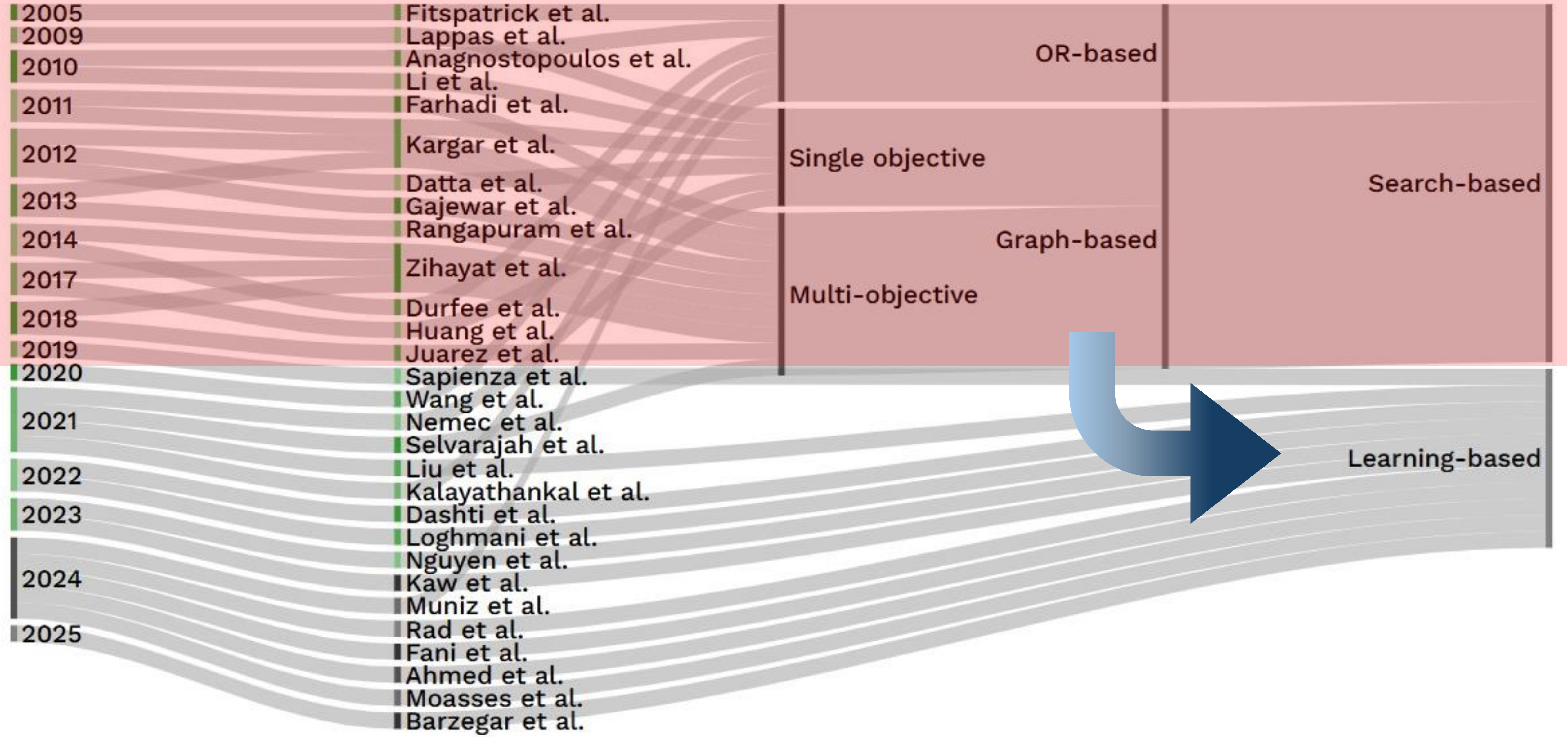
Learning to Form Skill-based Teams of Experts. CIKM 2020.
PyTFL: A Python-based Neural Team Formation Toolkit. CIKM 2021.
A Variational Neural Architecture for Skill-based Team Formation. TOIS, 42(1): 1-28, 2023.

Large set
- Future RQ

Small vs. Large set
- Dense Representation Learning
  - GNN-based (Rad et al. SIGIR 2021)

Biases
Popularity Bias
Gender Bias (Male Dominant)

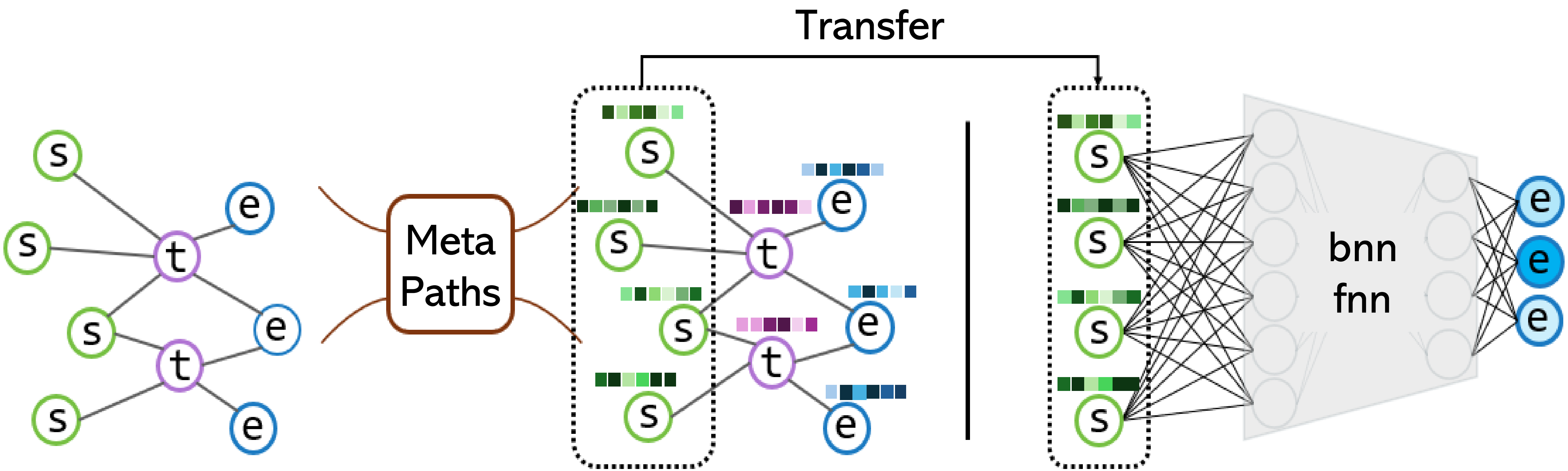
Lack of negative samples (unsuccessful)



Distill the Knowledge for Neural Team Recommendation

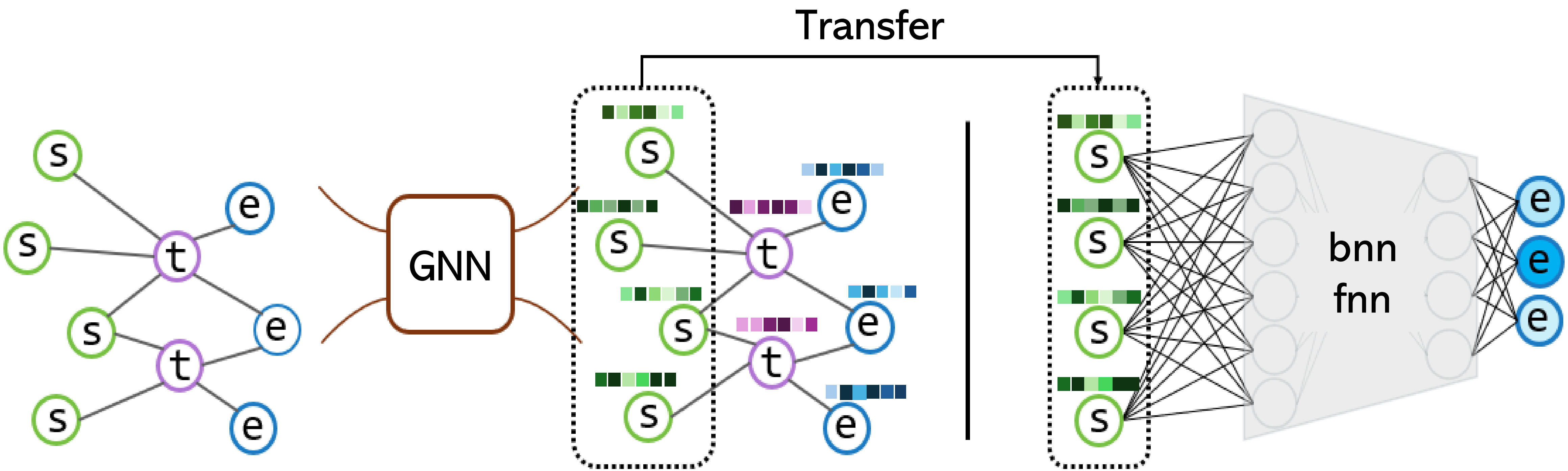
Graph Representation Learning → Skills

Rad et. al., Retrieving skill-based teams from collaboration networks. SIGIR 2021.



Graph Representation Learning → Skills

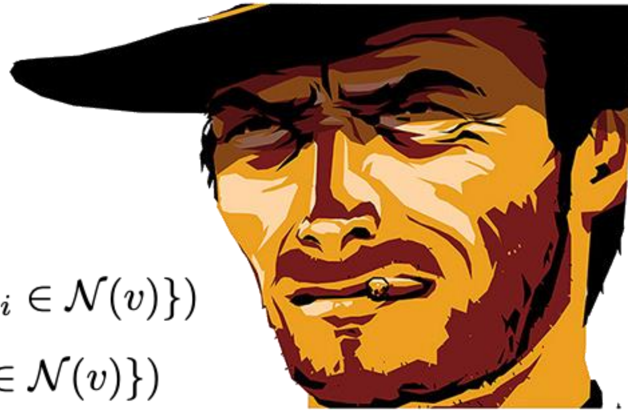
Ahmed et. al., Skill Vector Representation Learning for Collaborative Team Recommendation: A Comparative Study. WISE 2024.



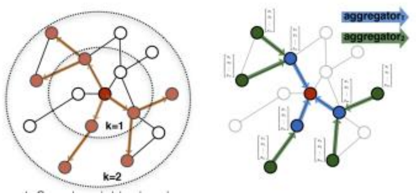
Message Passing-based GNN

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

Graph Neural Network → Skills



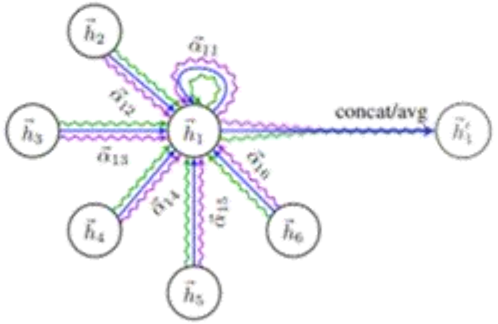
Graph SAmple-aggreGatE (GraphSAGE) [Hamilton et. al., NIPS 2017]



$$\mathbf{h}^k_{\mathcal{N}(v)} \leftarrow \text{AGGREGATE}_k(\{\mathbf{h}^{k-1}_u, \forall u \in \mathcal{N}(v)\}); \quad \begin{cases} \textbf{LSTM} \\ \max(\{\sigma\left(\mathbf{W}_{\text{pool}}\mathbf{h}^k_{u_i} + \mathbf{b}\right), \forall u_i \in \mathcal{N}(v)\}) \\ \text{MEAN}(\{\mathbf{h}^{k-1}_v\} \cup \{\mathbf{h}^{k-1}_u, \forall u \in \mathcal{N}(v)\}) \end{cases}$$

$$\mathbf{h}^k_v \leftarrow \sigma\left(\mathbf{W}^k \cdot \text{CONCAT}(\mathbf{h}^{k-1}_v, \mathbf{h}^k_{\mathcal{N}(v)})\right)$$

Graph Attention Network (GAT) [Velickovic et. al., ICLR 2018]



$$\vec{h}'_i = \sigma\left(\frac{1}{K}\sum_{k=1}^{K}\sum_{j\in\mathcal{N}_i}\alpha^k_{ij}\mathbf{W}^k\vec{h}_j\right) \quad \alpha_{ij} = \frac{\exp\left(\text{LeakyReLU}\left(\vec{\mathbf{a}}^T[\mathbf{W}\vec{h}_i \| \mathbf{W}\vec{h}_j]\right)\right)}{\sum_{k\in\mathcal{N}_i}\exp\left(\text{LeakyReLU}\left(\vec{\mathbf{a}}^T[\mathbf{W}\vec{h}_i \| \mathbf{W}\vec{h}_k]\right)\right)}$$

Graph Isomorphism Network (GIN) [Xu et al. ICLR 2019]

$$h_v^{(k)} = \phi\left(h_v^{(k-1)}, f\left(\left\{h_u^{(k-1)} : u \in \mathcal{N}(v)\right\}\right)\right)$$

The Good, the Bad and the Ugly - Sergio Leone, 1966
Music: Ennio Morricone

Graph Neural Network → Skills

Ahmed et. al., Skill Vector Representation Learning for Collaborative Team Recommendation: A Comparative Study. WISE 2024.

	%aucroc	%precision			%recall			%ndcg			%map		
		@2	@5	@10	@2	@5	@10	@2	@5	@10	@2	@5	@10
	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]	**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
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

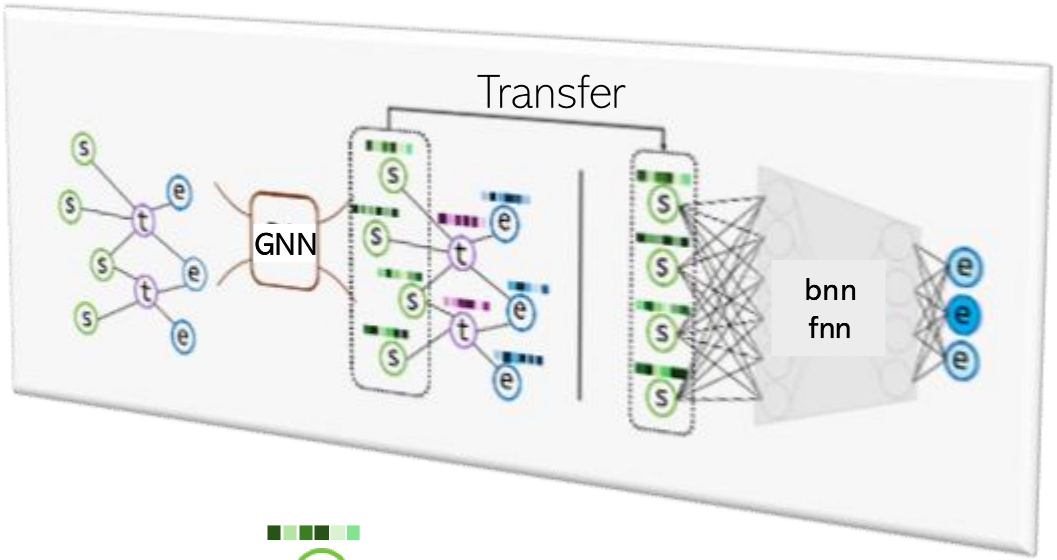
3-fold **fnn** on test set in **dblp**

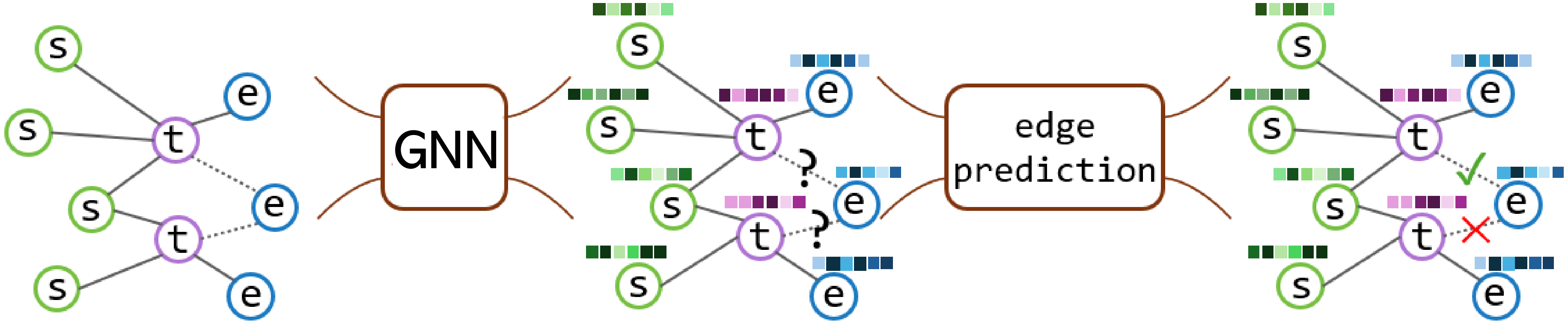
	%aucroc	%precision			%recall			%ndcg			%map		
		@2	@5	@10	@2	@5	@10	@2	@5	@10	@2	@5	@10
	skill-team-expert												
m-hot [43]	71.42	0.60	0.53	0.49	0.37	0.82	1.51	0.61	0.73	1.05	0.30	0.43	0.54
d2v [16,43,31]	72.86	0.82	0.68	0.61	0.49	1.02	1.86	0.84	0.95	1.33	0.39	0.56	0.69
m2v [38]	66.77	0.33	0.31	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**

3-fold **bnn** on test set in **dblp**

Graph Neural Network → End-to-End

Ahmed et. al., Graph Neural Team Recommendation: An End-to-End Approach via Heterogeneous Graph Neural Networks. SIGIR 2025.





End-to-End Graph Neural Network

skill-team-expert

		dblp								imdb							
		%precision		%recall		%ndcg		%map		%precision		%recall		%ndcg		%map	
		@5	@10	@5	@10	@5	@10	@5	@10	@5	@10	@5	@10	@5	@10	@5	@10
e2e	gs	14.37	9.24	54.00	67.79	33.21	38.39	25.18	28.10	15.39	9.16	49.73	57.44	33.70	36.78	27.00	29.03
	gin	14.47	9.07	54.68	66.95	31.50	36.12	22.74	25.36	14.08	8.91	45.34	56.49	28.49	32.79	21.76	24.30
	gine	7.66	7.65	21.56	44.17	16.50	24.74	12.67	16.18	19.33	12.21	53.14	66.25	38.80	43.86	31.13	34.07
	gat	14.33	9.46	53.81	68.86	38.11	43.78	31.44	34.65	14.66	9.17	47.44	57.47	33.45	37.40	27.17	29.68
	gatv2	14.03	9.48	52.73	69.01	37.87	43.98	31.43	34.86	14.49	9.09	46.72	57.18	33.81	37.88	27.86	30.39
	han	**28.97**	**15.17**	**83.19**	**86.38**	**70.42**	**71.74**	**64.28**	**65.27**	**23.37**	**15.42**	**57.82**	**74.15**	**45.58**	**52.38**	**37.42**	**42.21**
t-fnn	mhot	0.70	0.65	1.07	1.96	0.96	1.37	0.53	0.66	0.75	0.70	0.86	1.59	0.84	1.19	0.41	0.52
	d2v	0.83	0.72	1.27	2.21	1.18	1.62	0.72	0.88	0.84	0.76	0.93	1.72	0.95	1.32	0.45	0.57
	m2v	0.82	0.70	1.24	2.13	1.13	1.55	0.66	0.82	0.84	0.77	0.95	1.76	0.95	1.33	0.46	0.57
	lant	0.90	0.83	1.35	2.48	1.17	1.69	0.67	0.84	0.74	0.68	0.81	1.52	0.85	1.18	0.40	0.50
	gs	0.87	0.74	1.30	2.24	1.26	1.63	0.60	0.76	0.83	0.73	0.91	1.64	0.95	1.27	0.44	0.55
	gin	0.95	0.78	1.43	2.35	1.37	1.57	0.59	0.76	0.76	0.68	0.84	1.56	0.87	1.19	0.40	0.51
	gine	1.02	0.83	1.52	2.49	1.35	1.80	0.76	0.92	0.73	0.64	0.82	1.45	0.85	1.14	0.41	0.50
	gat	1.19	0.92	1.78	2.75	1.62	2.08	0.92	1.09	0.92	0.82	1.00	1.83	1.06	1.43	0.50	0.62
	gatv2	1.01	0.83	1.51	2.51	1.41	1.88	0.80	0.96	0.87	0.80	0.96	1.80	0.98	1.37	0.47	0.59
	han	0.93	0.82	1.42	2.49	1.33	1.82	0.80	0.97	0.77	0.72	0.86	1.63	0.85	1.21	0.39	0.50
t-bnn	mhot	0.53	0.49	0.82	1.51	0.73	1.05	0.43	0.54	0.83	0.74	0.95	1.71	0.92	1.28	0.45	0.57
	d2v	0.68	0.61	1.02	1.86	0.95	1.33	0.56	0.69	0.87	0.81	0.99	1.84	0.98	1.38	0.47	0.60
	m2v	0.31	0.32	0.48	0.98	0.42	0.65	0.23	0.30	0.76	0.71	0.83	1.58	0.85	1.20	0.41	0.52
	lant	0.66	0.61	1.01	1.87	0.88	1.28	0.49	0.61	1.01	0.96	1.14	2.18	1.18	1.66	0.58	0.73
	gs	0.71	0.66	1.08	2.00	0.94	1.36	0.52	0.65	0.99	0.90	1.12	2.03	1.12	1.55	0.54	0.67
	gin	0.60	0.52	0.91	1.59	0.84	1.15	0.49	0.60	0.90	0.83	1.04	1.92	1.07	1.47	0.52	0.65
	gine	0.75	0.63	1.12	1.90	1.08	1.44	0.66	0.79	1.01	0.93	1.15	2.14	1.16	1.62	0.58	0.71
	gat	0.66	0.62	0.99	1.86	0.87	1.28	0.49	0.62	0.96	0.86	1.07	1.94	1.10	1.50	0.53	0.66
	gatv2	0.64	0.54	0.96	1.64	0.87	1.19	0.49	0.58	0.93	0.80	1.05	1.84	1.05	1.41	0.51	0.62
	han	0.80	0.71	1.20	2.15	1.09	1.53	0.61	0.76	1.06	0.99	1.19	2.25	1.21	1.70	0.59	0.74

skill-team-expert-location

e2e	gs	14.63	9.15	52.91	64.97	35.37	39.90	28.27	30.88
	gin	11.80	8.78	42.44	62.46	26.28	33.65	19.51	23.54
	gine	7.66	7.65	21.56	44.17	16.50	24.74	12.67	16.17
	gat	13.69	**9.39**	50.24	**66.50**	35.57	41.74	29.10	32.62
	gatv2	**15.46**	9.22	**56.15**	65.38	**42.58**	**46.13**	**36.62**	**38.75**
	han	6.77	7.93	13.90	29.40	13.85	20.50	10.15	13.39
t-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	0.87	0.66	1.24	2.17	1.13	1.57	0.66	0.84
	lant	0.88	0.77	1.33	2.31	1.20	1.65	0.67	0.82
	gs	0.54	0.54	0.82	1.65	0.71	1.10	0.38	0.50
	gin	0.94	0.80	1.43	2.44	1.28	1.75	0.73	0.88
	gine	0.83	0.73	1.24	2.19	1.09	1.53	0.60	0.75
	gat	0.77	0.70	1.18	2.12	1.04	1.47	0.57	0.71
	gatv2	0.96	0.79	1.45	2.40	1.25	1.69	0.69	0.83
	han	0.92	0.79	1.38	2.36	1.26	1.72	0.72	0.87
t-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	0.51	0.55	0.70	1.30	0.58	0.65	0.27	0.40
	lant	0.65	0.60	0.99	1.84	0.87	1.26	0.48	0.60
	gs	0.85	0.73	1.28	2.20	1.14	1.56	0.64	0.78
	gin	0.46	0.42	0.70	1.27	0.62	0.89	0.34	0.42
	gine	0.51	0.47	0.76	1.40	0.68	0.97	0.38	0.46
	gat	0.59	0.53	0.90	1.61	0.81	1.14	0.46	0.57
	gatv2	0.52	0.52	0.77	1.56	0.67	1.04	0.37	0.48
	han	0.62	0.58	0.94	1.76	0.81	1.19	0.44	0.56

N/A

Neural Team Recommendation → Pioneer

Paradigm Shift to Learning-based Methods
- Autoencoder
- Teams for Online Games

frontiers in Big Data

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

OPEN ACCESS

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Deep Neural Networks for Optimal Team Composition

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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

Computational Approach

- Computational
  - Refinement
    - Reinforcement Learning
  - Formation
    - Search-based
      - Subgraph Optimization
      - Operations Research
        - Single Objective
        - Multiple Objectives
          - Communication Cost
            - Static (non-Temporal)
            - Hierarchical
            - Dynamic (Temporal)
          - Proficiency
          - Personnel Cost
          - Geographical Distance
          - Density
    - Learning-based
      - Model Architecture
        - Feedforward
        - Variational Bayesian
        - Graph Neural Network
          - Transfer Learning
          - End-to-End Approach
      - Training Strategy
        - Positive Labels
        - Negative Sampling
        - Streaming Strategy
        - Curriculum
- non-Computational
  - Science of Team Science (SciTS)

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

Negative Sampling

Most training sets only consists of successful teams!

Hamid Sourian, 59KG Greco-Roman Wrestler, Iran, Rio Olympic 2016
7 - 0 ⟶ Lost to a Fall (Pin)

Negative Sampling → Closed-World Assumption

No currently known (successful) team

↓

Unsuccessful

Medal record			[hide]
Representing Iran			
Men's Greco-Roman Wrestling			
Event	1st	2nd	3rd
Olympic Games	1	0	0
World Championships	6	0	0
World Junior Championship	1	0	0
World Cup	1	1	0
Other	6	1	2
Total	**15**	**2**	**2**

Negative Sampling → Inspired by ?

Dashti et. al., Effective Neural Team Formation via Negative Samples. CIKM 2022.

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

Positive Samples

Probability Distribution

Negative Samples

2.2 Negative Sampling

An alternative to the hierarchical softmax is Noise Contrastive Estimation (NCE), which was introduced by Gutmann and Hyvarinen [4] and applied to language modeling by Mnih and Teh [11]. NCE posits that a good model should be able to differentiate data from noise by means of logistic regression. This is similar to hinge loss used by Collobert and Weston [2] who trained the models by ranking the data above noise.

While NCE can be shown to approximately maximize the log probability of the softmax, the Skip-gram model is only concerned with learning high-quality vector representations, so we are free to simplify NCE as long as the vector representations retain their quality. We define Negative sampling (NEG) by the objective

$$\log \sigma({v'_{w_O}}^\top v_{w_I}) + \sum_{i=1}^{k} \mathbb{E}_{w_i \sim P_n(w)} \left[\log \sigma(-{v'_{w_i}}^\top v_{w_I})\right] \quad (4)$$

Table 1: Average performance of 5-fold neural models on test set in dblp.v12.

	%map2	%map5	%map10	%ndcg2	%ndcg5	%ndcg10	%pr2	%pr5	%pr10	%rec2	%rec5	%rec10	rocauc
random	0.0001	0.0001	0.0002	0.0002	0.0002	0.0004	0.0001	0.0002	0.0002	0.0001	0.0003	0.0006	0.4992
fnn	0.0045	0.0307	0.0612	0.0082	0.0227	0.0369	0.0045	0.0113	0.0155	0.0067	0.0188	0.0188	0.5000
fnn-uniform	0.0487	0.0741	0.0943	0.1074	0.1350	0.1993	0.1020	0.1030	0.0986	0.0597	0.1522	0.2913	0.6512
fnn-unigram	0.0437	0.0677	0.0880	0.0952	0.1249	0.1907	0.0932	0.0985	0.0971	0.0552	0.1447	0.2854	0.6505
fnn-unigram-b	0.0436	0.0665	0.0847	0.1005	0.1249	0.1846	0.0993	0.0979	0.0932	0.0569	0.1429	0.2702	0.6500
fnn-emb	0.0084	0.0402	0.0688	0.0134	0.0302	0.0428	0.0073	0.0174	0.0209	0.0134	0.0255	0.0215	0.4999
fnn-emb-uniform	0.0668	0.1043	0.1305	0.1537	0.1901	0.2716	0.1543	0.1505	0.1346	0.0870	0.2179	0.3925	0.6313
fnn-emb-unigram	0.0700	0.1084	0.1356	0.1564	0.1942	0.2803	0.1523	0.1500	0.1378	0.0884	0.2194	0.4038	0.6331
fnn-emb-unigram-b	0.0656	0.1015	0.1277	0.1444	0.1782	0.2607	0.1415	0.1374	0.1291	0.0830	0.2011	0.3770	0.6322
bnn	0.0061	0.0254	0.0569	0.0123	0.0204	0.0365	0.0061	0.0107	0.0155	0.0101	0.0161	0.0195	0.5000
bnn-uniform	0.0487	0.0741	0.0943	0.1074	0.1350	0.1993	**0.4005**	**0.3555**	**0.3102**	**0.2297**	**0.5124**	**0.8974**	0.7150
bnn-unigram	0.0437	0.0677	0.0880	0.0952	0.1249	0.1907	0.3388	0.2885	0.2670	0.1944	0.4175	0.7737	0.7132
bnn-unigram-b	0.1757	0.2499	0.3039	0.3983	0.4505	0.6312	0.3904	0.3402	0.3017	0.2256	0.4929	0.8774	**0.7168**
bnn-emb	0.0112	0.0326	0.0634	0.0175	0.0267	0.0413	0.0089	0.0145	0.0186	0.0168	0.0201	0.0201	0.5000
bnn-emb-uniform	0.1620	0.2296	0.2817	0.3663	0.4176	0.5895	0.3656	0.3405	0.2909	0.2121	0.4934	0.8463	0.7123
bnn-emb-unigram	**0.1792**	**0.2569**	0.3060	0.4022	0.4623	0.6205	0.3783	0.3298	0.2858	0.2213	0.4802	0.8313	0.7077
bnn-emb-unigram-b	0.1752	0.2537	**0.3094**	**0.4069**	**0.4728**	**0.6515**	0.3938	0.3518	0.3033	0.2252	0.5065	0.8775	0.7090

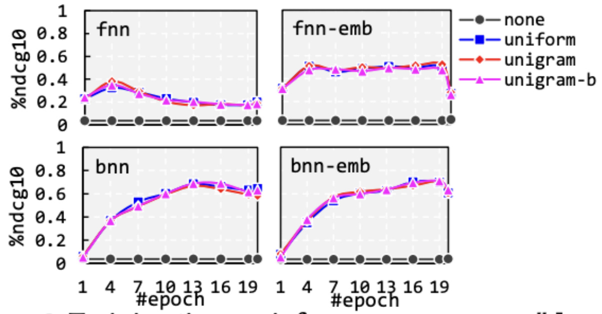
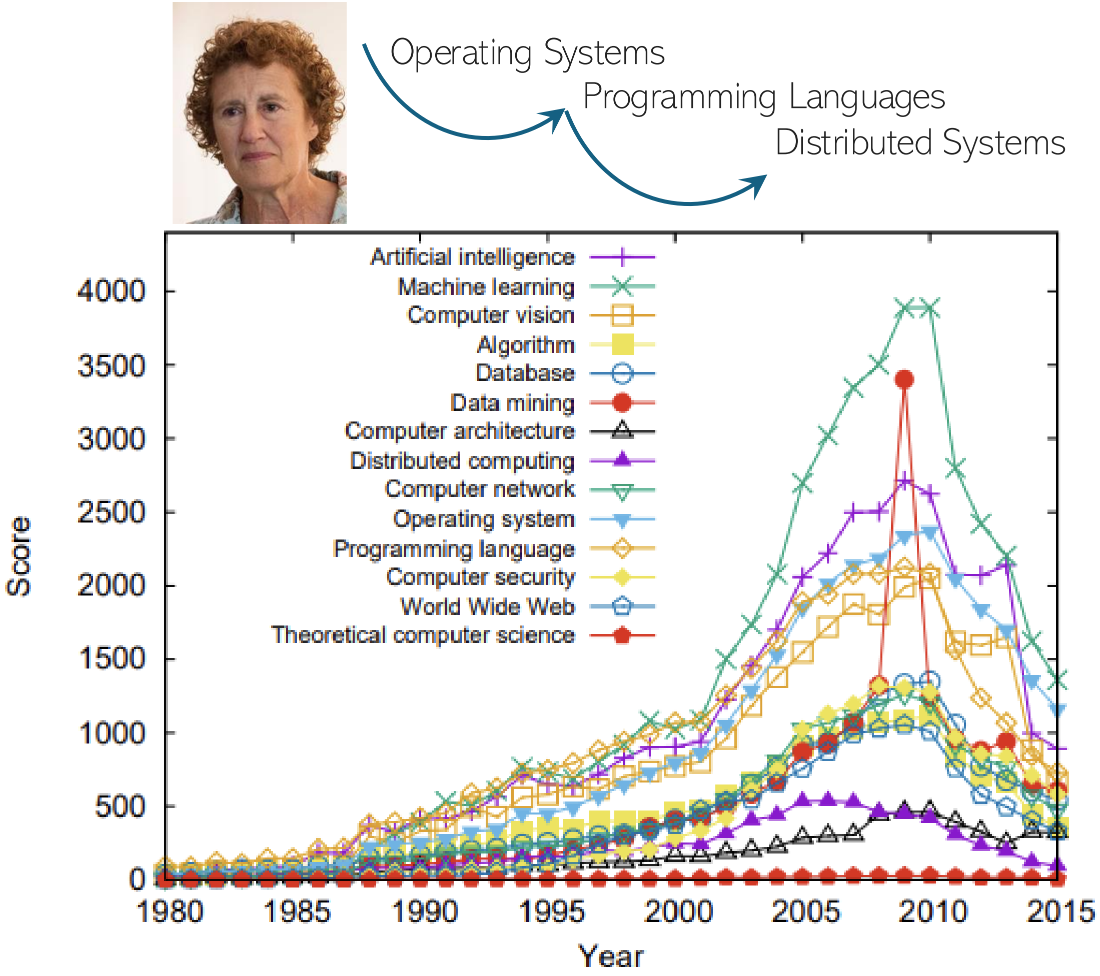


Figure 2: Training time vs. inference accuracy on dblp.v12.

Temporal Neural Team Recommendation



Effendy et al. WWW 2017.

Streaming Training Strategy

[Fani et. al., ECIR, 2024]

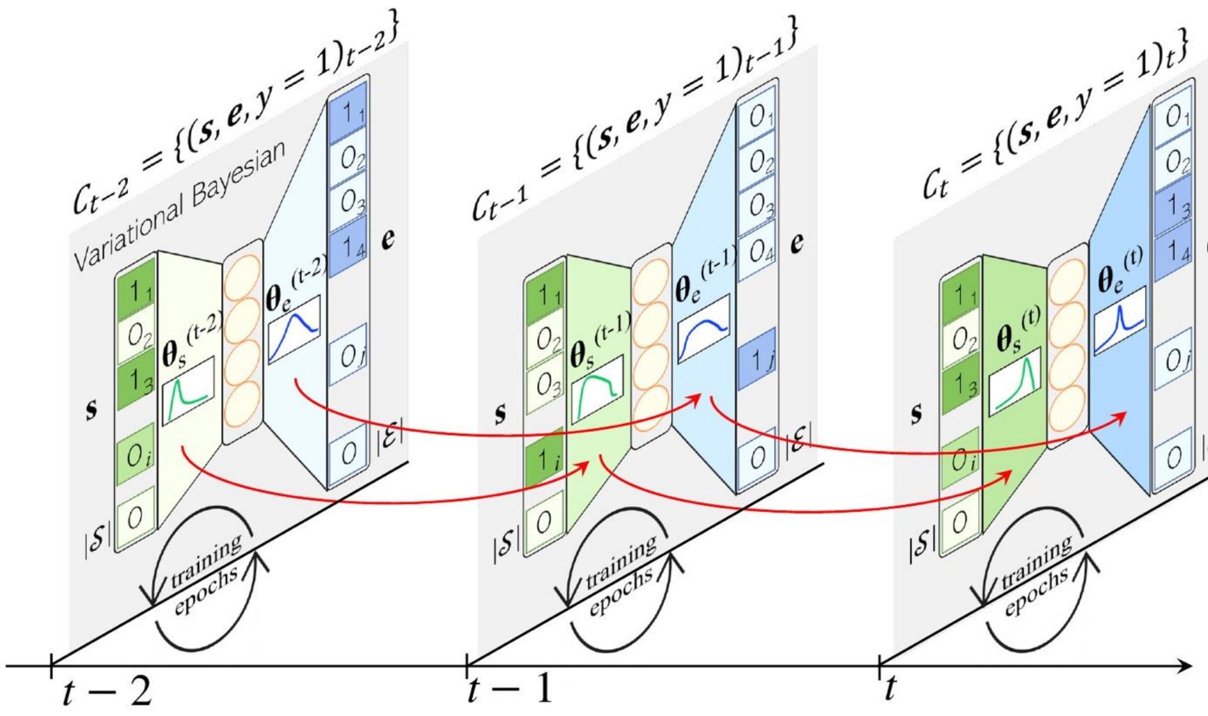


Table 2: Average performance of 5-fold neural models on the test set.

dblp	%pr2	%pr5	%pr10	%rec2	%rec5	%rec10	%ndcg2	%ndcg5	%ndcg10	%map2	%map5	%map10	%aucroc
bnn [36]	0.0570	0.0663	0.0710	0.0351	0.0993	0.2118	0.0538	0.0806	0.1330	0.0242	0.0411	0.0558	63.52
bnn_emb [35]	0.1124	0.1290	0.1251	0.0668	0.1909	0.3699	0.1083	0.1555	0.2397	0.0474	0.0792	0.1033	66.81
rrn [44]	0.0570	0.0391	0.0472	0.0380	0.0630	0.1552	0.0478	0.0523	0.0959	0.0217	0.0281	0.0446	50.73
tbnn	0.1189	0.1413	0.1664	0.0706	0.2090	0.4984	0.1126	0.1689	0.3031	0.0484	0.0845	0.1223	73.08
tbnn_emb	0.2996	0.2938	0.2811	0.1816	0.4433	0.8431	0.3048	0.3860	0.5721	0.1411	0.2095	0.2635	74.83
tbnn_dt2v_emb	**0.4299**	**0.3973**	**0.3612**	**0.2601**	**0.5963**	**1.0801**	**0.4284**	**0.5221**	**0.7465**	**0.1947**	**0.2864**	**0.3520**	**77.01**
imdb													
bnn [36]	0.2128	0.5106	0.4255	0.1418	0.8511	1.3050	0.1646	0.5699	0.7848	0.0709	0.2600	0.3148	51.16
bnn_emb [35]	0.4255	0.5106	0.6383	0.2837	0.8511	1.9574	0.3292	0.5923	1.1358	0.1418	0.2813	0.4389	51.82
rrn [44]	0.0000	0.8511	0.8511	0.0000	1.4184	2.8369	0.0000	0.8163	1.4606	0.0000	0.3191	0.6265	52.22
tbnn	0.8511	**1.5319**	1.4043	0.5319	**2.4610**	4.4965	0.7548	1.7381	2.6829	0.3369	0.8215	1.1674	63.46
tbnn_emb	0.8511	1.1064	1.0638	0.5674	1.7518	1.3262	0.9474	1.4848	2.2007	0.4965	0.8138	1.0099	**66.87**
tbnn_dt2v_emb	**1.9149**	1.1915	**1.4468**	**1.2411**	1.9504	**4.5532**	**1.8667**	**1.8703**	**3.0303**	**0.9043**	**1.1099**	**1.4293**	66.56
uspt													
bnn [36]	0.0657	0.0769	0.0910	0.0353	0.0976	0.2212	0.0655	0.0883	0.1481	0.0266	0.0433	0.0592	64.54
bnn_emb [35]	0.3663	0.4123	0.3748	0.1608	0.4509	0.8141	0.3652	0.4531	0.6094	0.1212	0.2027	0.2583	69.85
rrn [44]	0.0239	0.0383	0.0654	0.0140	0.0500	0.1370	0.0221	0.0408	0.0868	0.0096	0.0186	0.0340	51.60
tbnn	0.1843	0.1841	0.2029	0.0933	0.2321	0.5158	0.1794	0.2152	0.3481	0.0681	0.1056	0.1429	75.44
tbnn_emb	0.8272	0.7539	0.7042	0.3970	0.9021	1.6933	0.8457	0.9057	1.2657	0.3104	0.4533	0.5679	83.59
tbnn_dt2v_emb	**1.2268**	**1.0583**	**0.9324**	**0.6037**	**1.2928**	**2.2518**	**1.2322**	**1.2960**	**1.7348**	**0.4626**	**0.6659**	**0.8118**	**85.34**
gith													
bnn [36]	3.0693	2.8515	2.6931	1.2164	2.8846	5.1174	3.1365	3.2893	4.2340	1.0104	1.5706	2.1633	56.18
bnn_emb [35]	**7.3267**	**4.7129**	3.3861	**3.5441**	**5.1580**	**6.1885**	**6.4753**	**5.8418**	**6.2665**	**2.3424**	**3.0822**	**3.3837**	62.65
rrn [44]	0.0000	0.1980	0.0990	0.0000	0.0619	0.0619	0.0000	0.1679	0.1090	0.0000	0.0206	0.0206	52.26
tbnn	3.8614	2.8515	2.3564	1.8801	3.1525	4.5754	4.3319	3.9721	4.5031	1.8025	2.3978	2.8768	56.65
tbnn_emb	4.9505	3.5248	3.1287	1.9434	3.0770	4.3718	5.0849	4.4715	4.9844	1.6957	2.1431	2.5949	62.20
tbnn_dt2v_emb	5.7426	4.5941	**3.8020**	2.1874	3.8474	4.7855	5.6081	5.3287	5.6670	1.7131	2.4258	2.7858	**64.89**

Short timespan in the dataset

Computational Approach

- **Computational**
  - Refinement
    - Reinforcement Learning
  - Formation
    - Search-based
      - Subgraph Optimization
      - Operations Research
        - Single Objective
          - Communication Cost
            - Static (non-Temporal)
            - Hierarchical
            - Dynamic (Temporal)
        - Multiple Objectives
          - Proficiency
          - Personnel Cost
          - Geographical Distance
          - Density
    - Learning-based
      - Model Architecture
        - Feedforward
        - Variational Bayesian
        - Graph Neural Network
          - Transfer Learning
          - End-to-End Approach
      - Training Strategy
        - Positive Labels
        - Negative Sampling
        - Streaming Strategy
        - Curriculum
- non-Computational
  - Science of Team Science (SciTS)

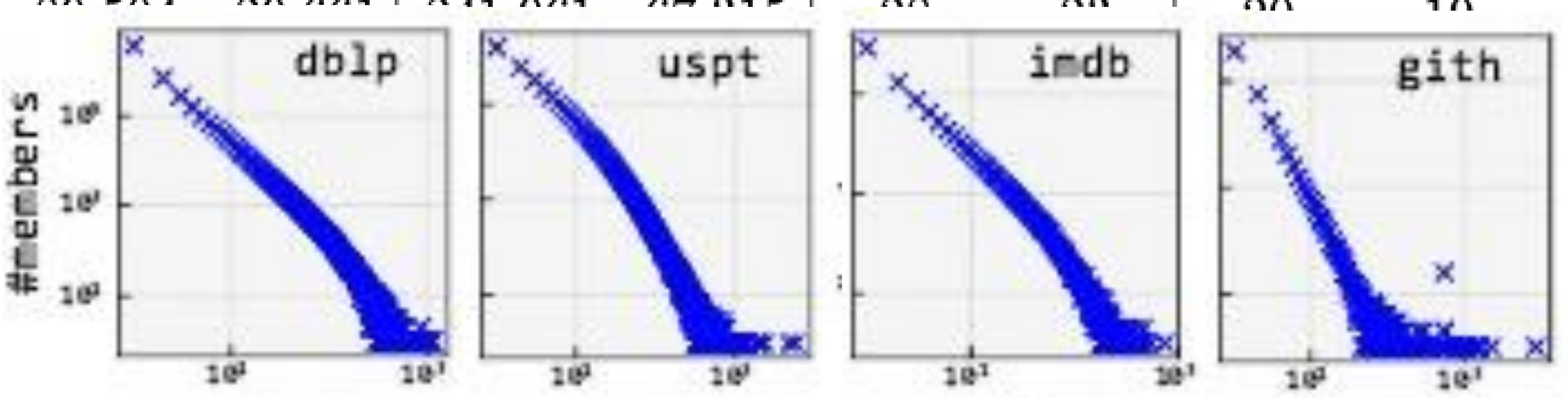
Team Allocation, Team Selection, Team Composition, Team Configuration, Team Recommendation, Team Formation

Experimental Setup → Dataset

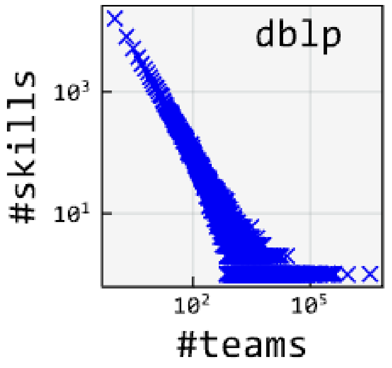
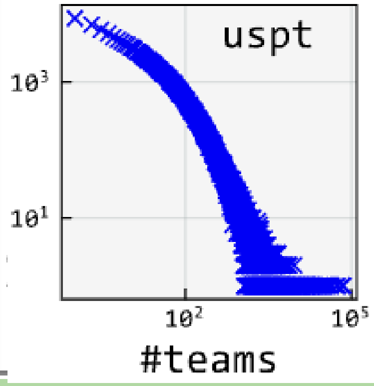
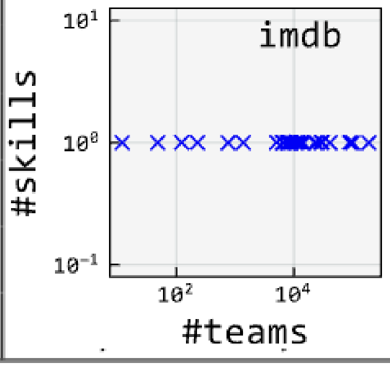
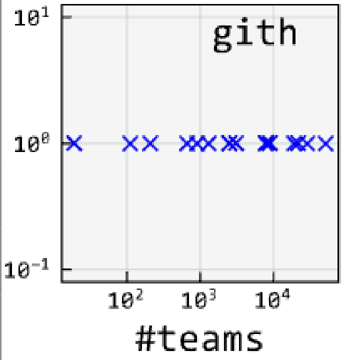
	dblp		uspt		imdb		gith	
	raw	filtered	raw	filtered	raw	filtered	raw	filtered
#teams	4,877,383	99,375	7,068,508	152,317	507,034	32,059	132,851	11,312
#unique experts	5,022,955	14,214	3,508,807	12,914	876,981	2,011	452,606	2,686
#unique skills	89,504	29,661	241,961	67,315	28	23	20	19
avg #expert per team	3.06	3.29	2.51	3.79	1.88	3.98	5.52	7.53
avg #skill per team	8.57	9.71	6.29	9.97	1.54	1.76	1.37	1.57
avg #team per expert	2.97	23.02	5.05	44.69	1.09	62.45	1.62	31.72
avg #skill per expert	16.73	96.72	19.49	102.53	1.59	10.85	2.03	5.18
#team w/ single expert	768,956	0	2,578,898	0	322,918	0	0	0
#team w/ single skill	5,569	56	939,955	8,110	315,503	15,180	69,131	6014
timespan (raw)	1979 – 2018		1976 – 2019		1914 – 2020		2008 – 2022	

Dataset

	dblp		uspt		imdb		gith	
	raw	filtered	raw	filtered	raw	filtered	raw	filtered
#teams	4,877,383	99,375	7,068,508	152,317	507,034	32,059	132,851	11,312
#unique experts	5,022,955	14,214	3,508,807	12,914	876,981	2,011	452,606	2,686
#unique skills								
avg #expert per team								
avg #skill per team								
avg #team per expert								
avg #skill per expert								
#team w/ single expert								
#team w/ single skill								
timespan (raw)	1979 – 2018		1976 – 2019		1914 – 2020		2008 – 2022	



84 Dataset

	dblp		uspt		imdb		gith	
	raw	filtered	raw	filtered	raw	filtered	raw	filtered
#teams	4,877,383	99,375	7,068,508	152,317	507,034	32,059	132,851	11,312
#unique experts	5,022,955	14,214	3,508,807	12,914	876,981	2,011	452,606	2,686
#unique skills	89,504	29,661	241,961	67,315	28	23	20	19
avg #expert per team								
avg #skill per team								
avg #team per expert								
avg #skill per expert								
#team w/ single expert								
#team w/ single skill								
Timespan (raw)	1979 – 2018		1976 – 2019		1914 – 2020		2008 – 2022	

85

Dataset

	dblp		uspt		imdb		gith	
	raw	filtered	raw	filtered	raw	filtered	raw	filtered
#teams	4,877,383	99,375	7,068,508	152,317	507,034	32,059	132,851	11,312
#unique experts	5,022,955	14,214	3,508,807	12,914	876,981	2,011	452,606	2,686
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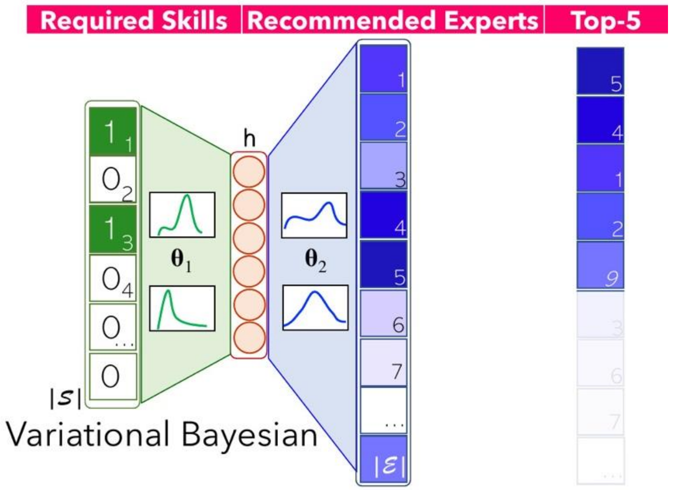
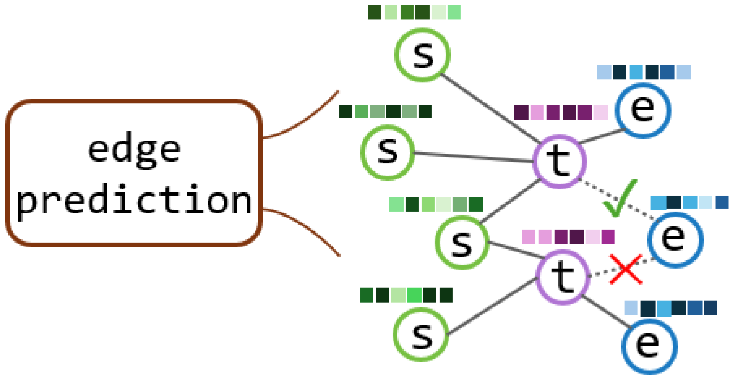
#team w/ single expert	768,956	0	2,578,898	0	322,918	0	0	0
#team w/ single skill	5,569	56	939,955	8,110	315,503	15,180	69,131	6014
Timespan (raw)	1979 – 2018		1976 – 2019		1914 – 2020		2008 – 2022	

Experimental Setup → Metrics

	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					✓			





Metrics → Classification

Given a test team (s, e)

Precision: How many of the k predicted experts $\hat{e}$ are correctly in e: $\mathrm{P(k)} = \frac{|\mathrm{e} \cap \hat{\mathrm{e}}|}{\mathrm{k}}$

Recall: How many of the correct experts e has been predicted in $\hat{e}$: $\mathrm{R(k)} = \frac{|\mathrm{e} \cap \hat{\mathrm{e}}|}{|\mathrm{e}|}$

Success: Did we at least predict one expert from e: $\mathrm{S(k)} = |\mathrm{e} \cap \hat{\mathrm{e}}| > 0$

Metrics → Ranking

Reciprocal Rank: the position of first correct expert. The higher rank, the better!

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

Average Precision:

$$\mathrm{AP(k)} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{k}} \mathrm{P(i)} \times \delta_e(\mathrm{i})}{|e|}$$

$\delta_\mathrm{e}(\mathrm{i})$ returns 1 if the $\mathbf{i}$-th expert is in $\boldsymbol{e}$.

Boolean Relevance

normalized Discounted Cumulative Gain: $$\mathrm{nDCG(k)} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{k}} \frac{\delta_\mathrm{e}(\mathrm{i})}{\log(\mathrm{i+1})}}{\sum_{\mathrm{i=1}}^{|\mathrm{e}|} \frac{1}{\log(\mathrm{i+1})}}$$

Metrics → Ranking

Evaluation Metrics

Jaime Arguello
INLS 509: Information Retrieval
jarguell@email.unc.edu

March 25, 2013

https://ils.unc.edu/courses/2013_spring/inls509_001/lectures/10-EvaluationMetrics.pdf

average-precision

rank (K)	ranking	R@K	P@K
1		0.10	1.00
2		0.10	0.50
3		0.20	0.67
4		0.30	0.75
5		0.40	0.80
6		0.50	0.83
7		0.60	0.86
8		0.60	0.75
9		0.70	0.78
10		0.70	0.70
11		0.80	0.73
12		0.80	0.67
13		0.80	0.62
14		0.90	0.64
15		0.90	0.60
16		0.90	0.56
17		0.90	0.53
18		0.90	0.50
19		0.90	0.47
20		1.00	0.50
total	10.00	average-precision	0.76

rank (K)	ranking	R@K	P@K
1		0.10	1.00
2		0.20	1.00
3		0.30	1.00
4		0.40	1.00
5		0.50	1.00
6		0.60	1.00
7		0.70	1.00
8		0.80	1.00
9		0.90	1.00
10		1.00	1.00
11		1.00	0.91
12		1.00	0.83
13		1.00	0.77
14		1.00	0.71
15		1.00	0.67
16		1.00	0.63
17		1.00	0.59
18		1.00	0.56
19		1.00	0.53
20		1.00	0.50
total	10.00	average-precision	1.00

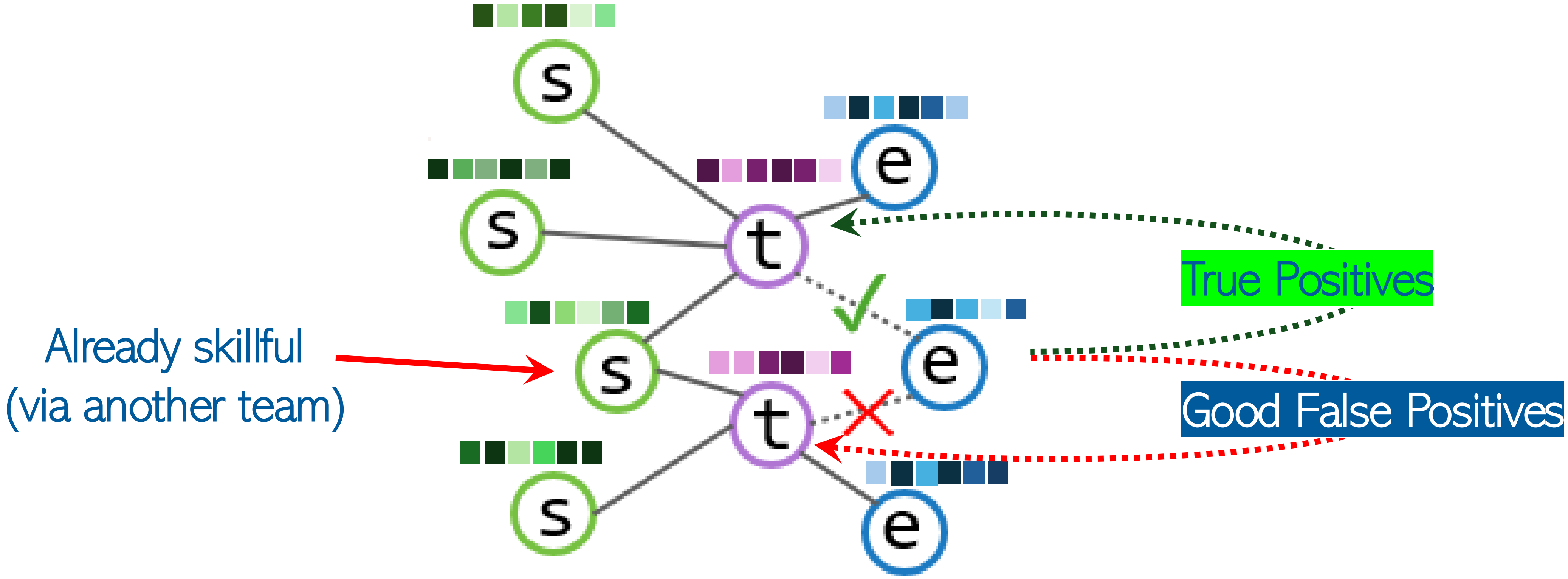
- Advantages:
  - no need to choose K
  - accounts for both precision and recall
  - ranking mistakes at the top of the ranking are more influential
  - ranking mistakes at the bottom of the ranking are still accounted for
- Disadvantages
  - not quite as easy to interpret as P/R@K

Metrics → Ranking

C/C++ → https://github.com/usnistgov/trec_eval

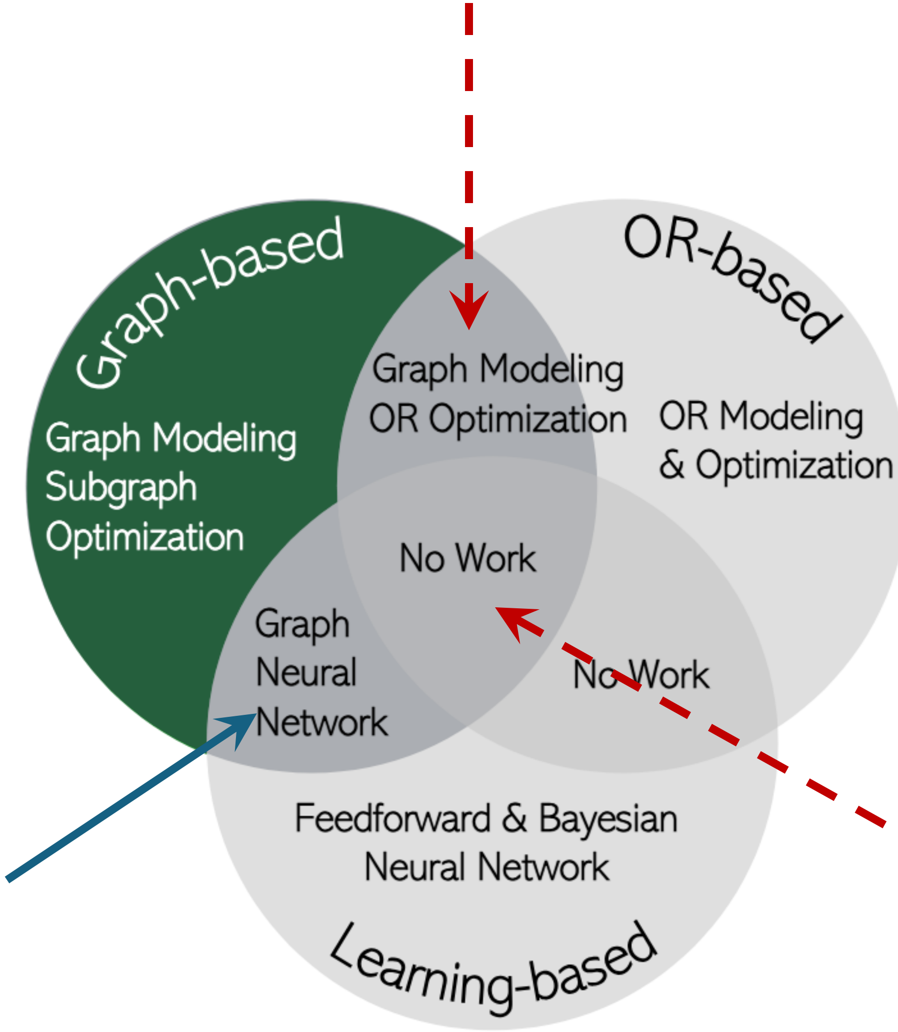
Cython → https://github.com/cvangysel/pytrec_eval

Metrics → Skill Coverage
How Bad is a False Positive Expert



Outline

Immediate RQs



Temporal End-to-End Graph Neural Network

[Fani et. al., ECIR 2024] + [Ahmed et al. WISE 2024]

Spatial Team Recommendation

- Time Zones
- Regions

94 Immediate RQs

Temporal End-to-End Graph Neural Network

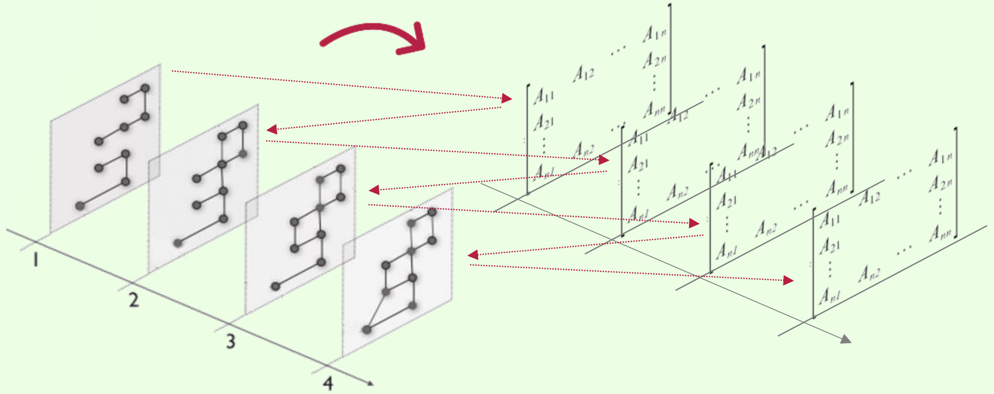
[Fani et. al., ECIR 2024] + [Ahmed et al. WISE 2024]

TEMPORAL LATENT SPACE MODELING

local Block Coordinate Gradient Descent (Zhu et al. TKDE 2016)

$$\arg\min \Big[\sum_{t=1}^{\mathrm{T}} \sum_{u,v \in \mathbb{U}} |w(u,v:t) - \mathbf{y}_{ut}\mathbf{y}_{vt}^{\top}|_F^2 + \lambda \sum_{t=1}^{\mathrm{T}} \sum_{u \in \mathbb{U}} (1 - \mathbf{y}_{ut}\mathbf{y}_{u(t-1)}^{\top}) \Big]$$

$$\forall u \in \mathbb{U}; \mathbf{y}_{ut} \geq 0, \mathbf{y}_{ut}\mathbf{y}_{ut}^{\top} = 1$$

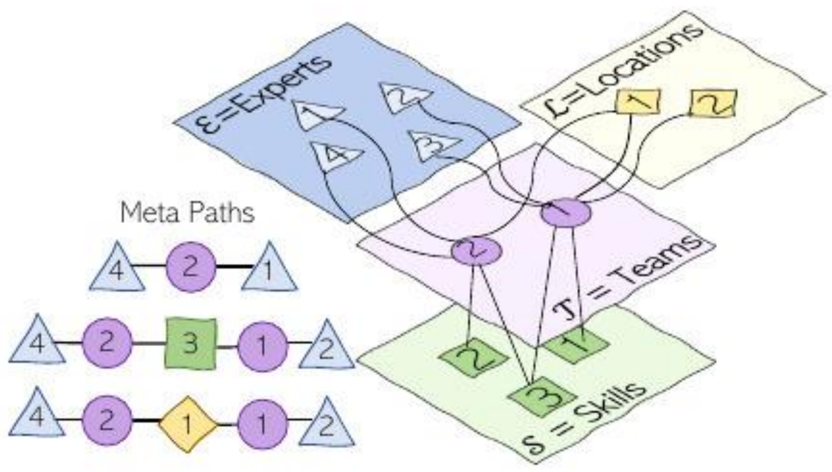


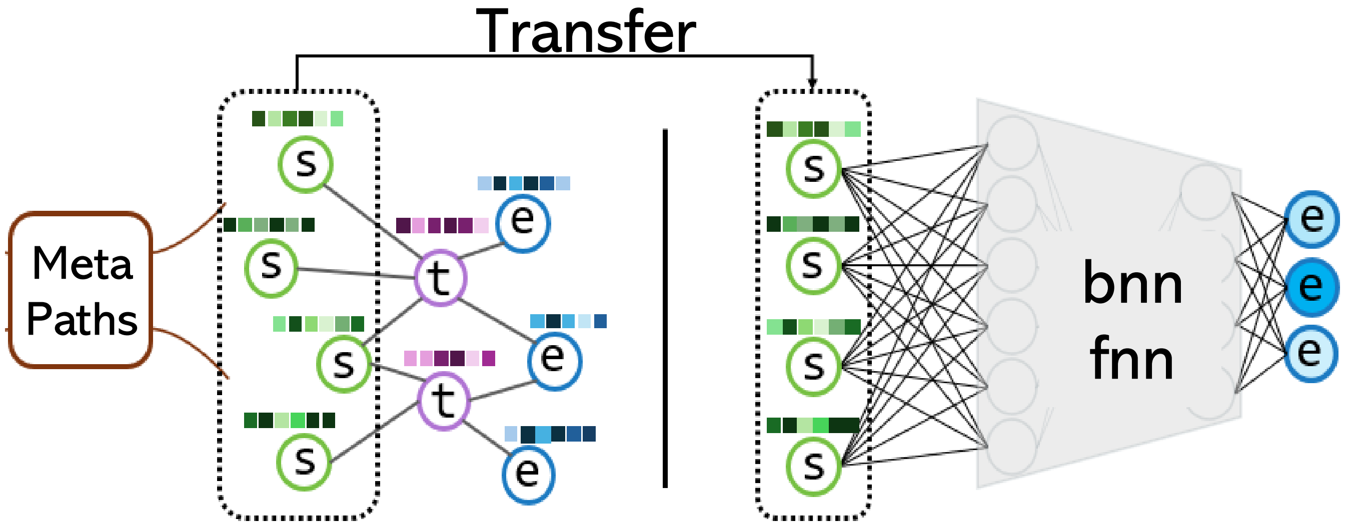
Fani et al. Temporal latent space modeling for community prediction. ECIR 2020

Immediate RQs

Geolocations used only for better skill vectors!

[Rad et. al., SIGIR 2021]





Fair and Diverse Team Recommendation

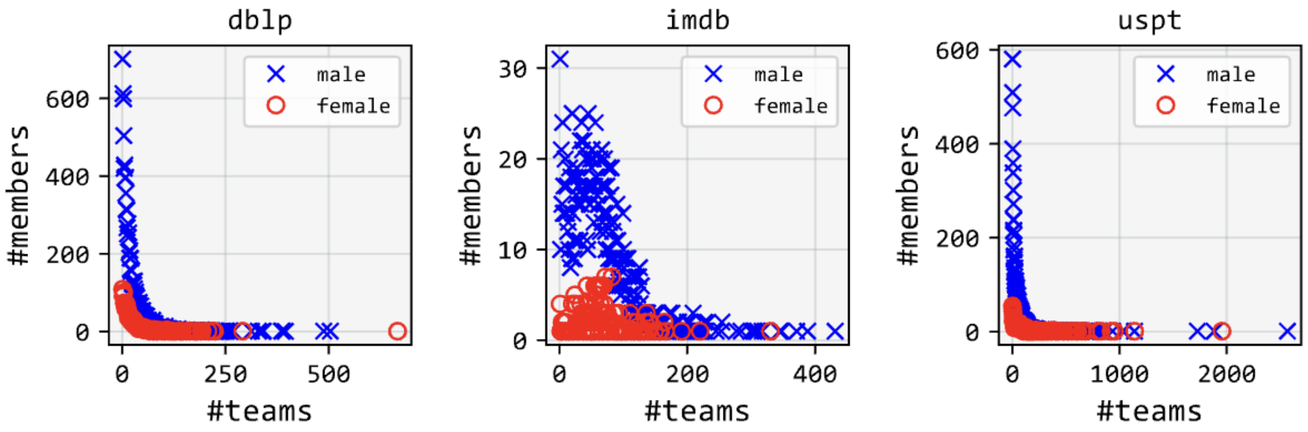
Salima Mazari, female Afghan governor, Leading a Taliban resistance

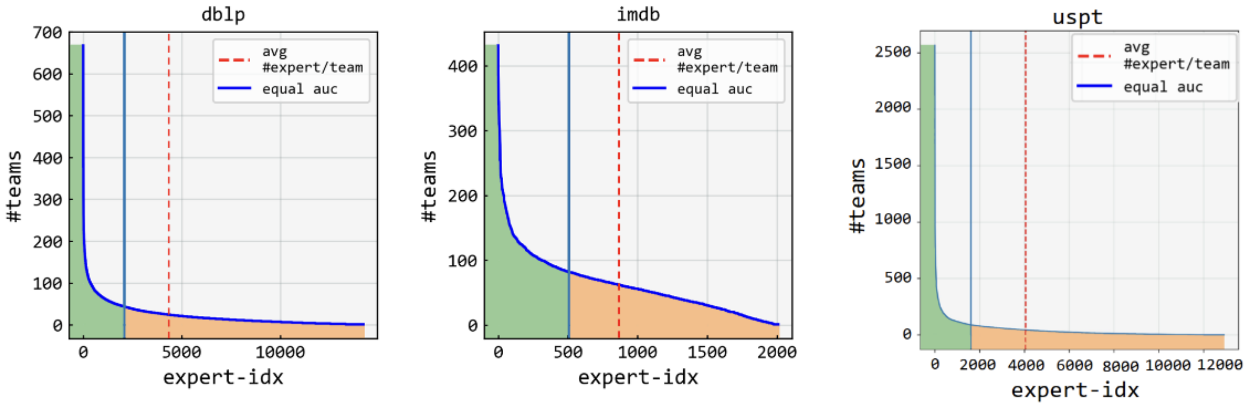
“Sometimes I'm in the office in Charkint, and other times I have to pick up a gun and join the battle”

https://people.com/politics/meet-salima-mazari-afghan-governor-who-led-a-taliban-resistance/ - 2021

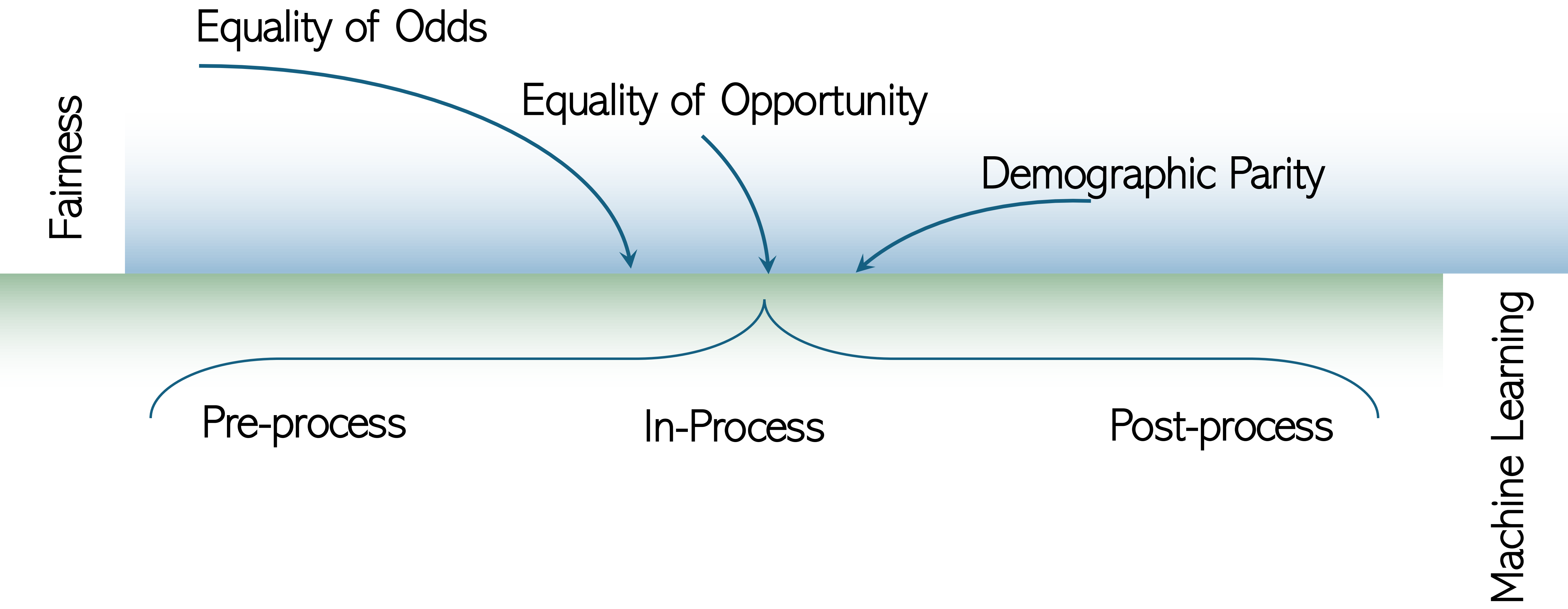
Fair and Diverse Team Recommendation

	dblp	imdb	uspt
%female experts	14.20%	12.30%	13.80%
%popular experts (avg)	31.30%	42.60%	31.40%





Fair and Diverse Team Recommendation



Fair and Diverse Team Recommendation

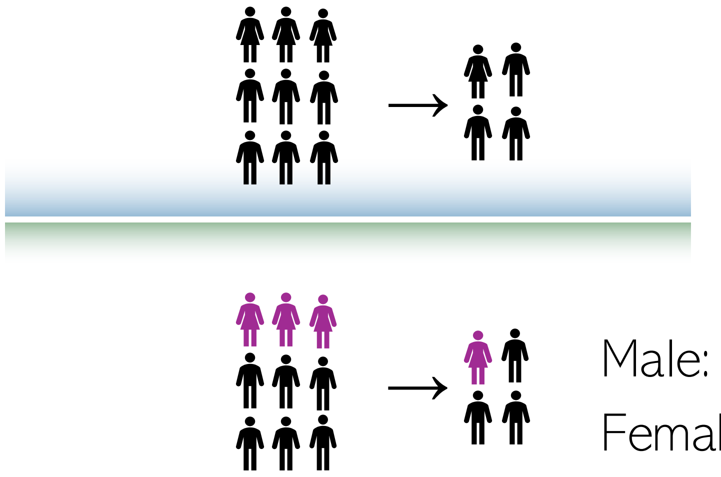
Demographic Parity: Membership of an expert is independent of any attribute

P(recommended | male) = P(recommended | female)

P(recommended | popular) = P(recommended | non-popular)

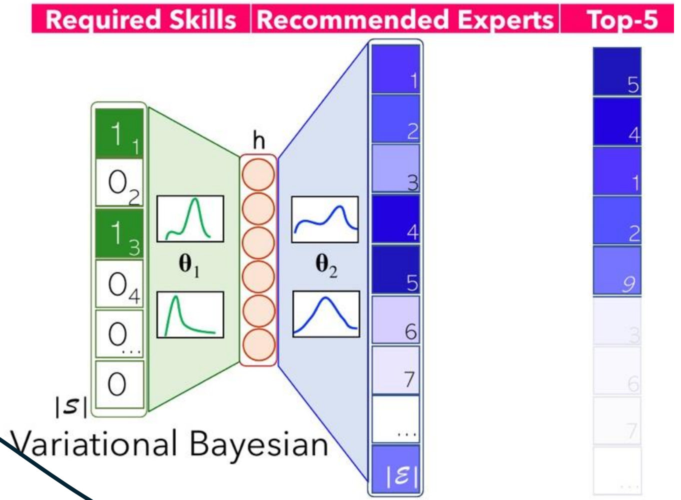
↓

P(recommended | whoever you are) = P(recommended)



Male: 70%

Female: 30%



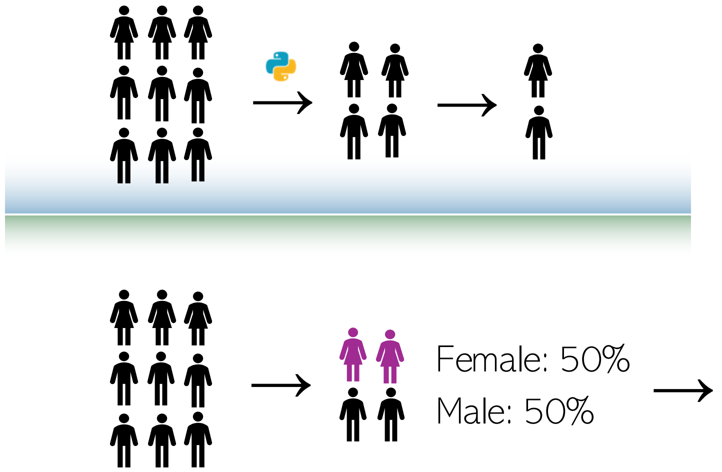
Male: 70%

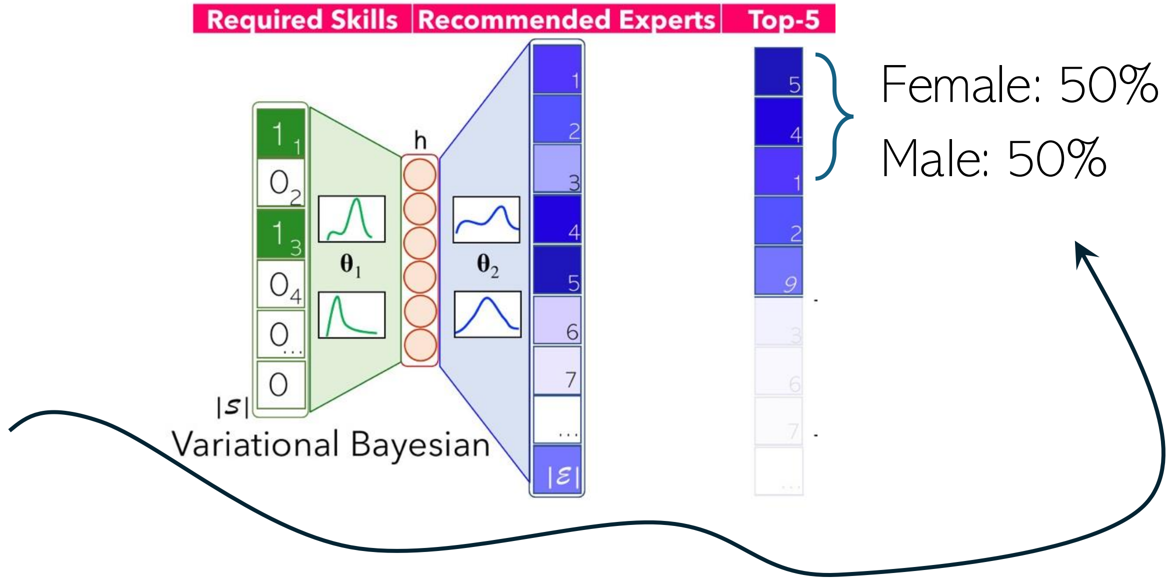
Female: 30%

01 Fair and Diverse Team Recommendation

Equality of Opportunity: Membership of a skilled expert is independent of any attribute

$$P(\text{recommended} \mid \text{true male}) = P(\text{recommended} \mid \text{true female})$$
$$P(\text{recommended} \mid \text{true popular}) = P(\text{recommended} \mid \text{true non-popular})$$
$$\downarrow$$
$$P(\text{recommended} \mid \text{whoever you are as long as you have the skill}) = P(\text{recommended})$$

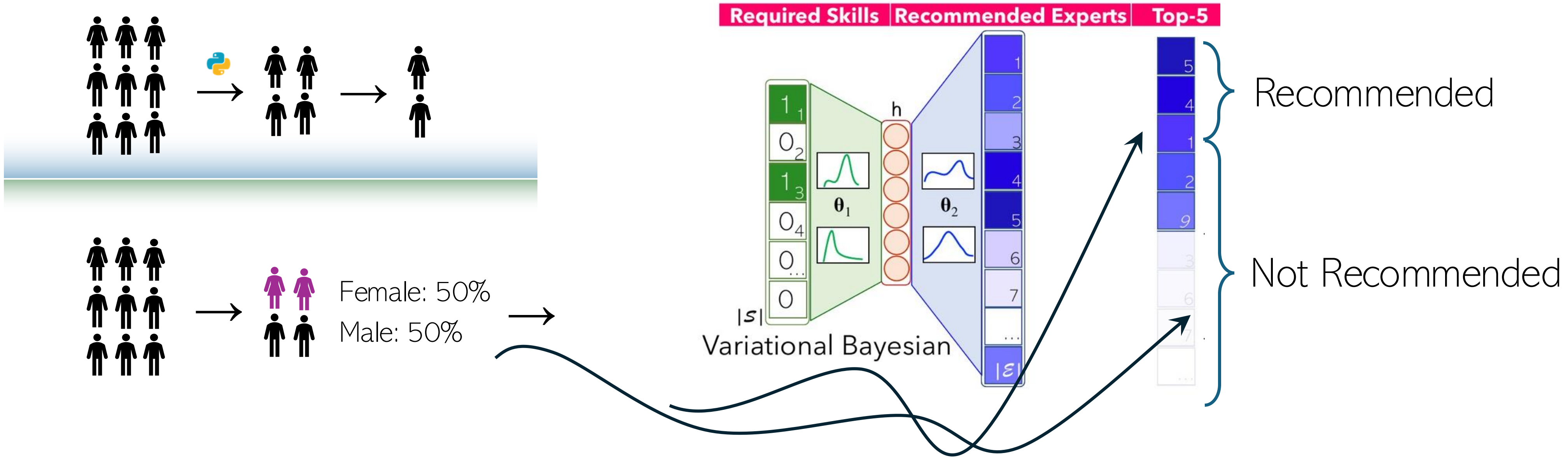




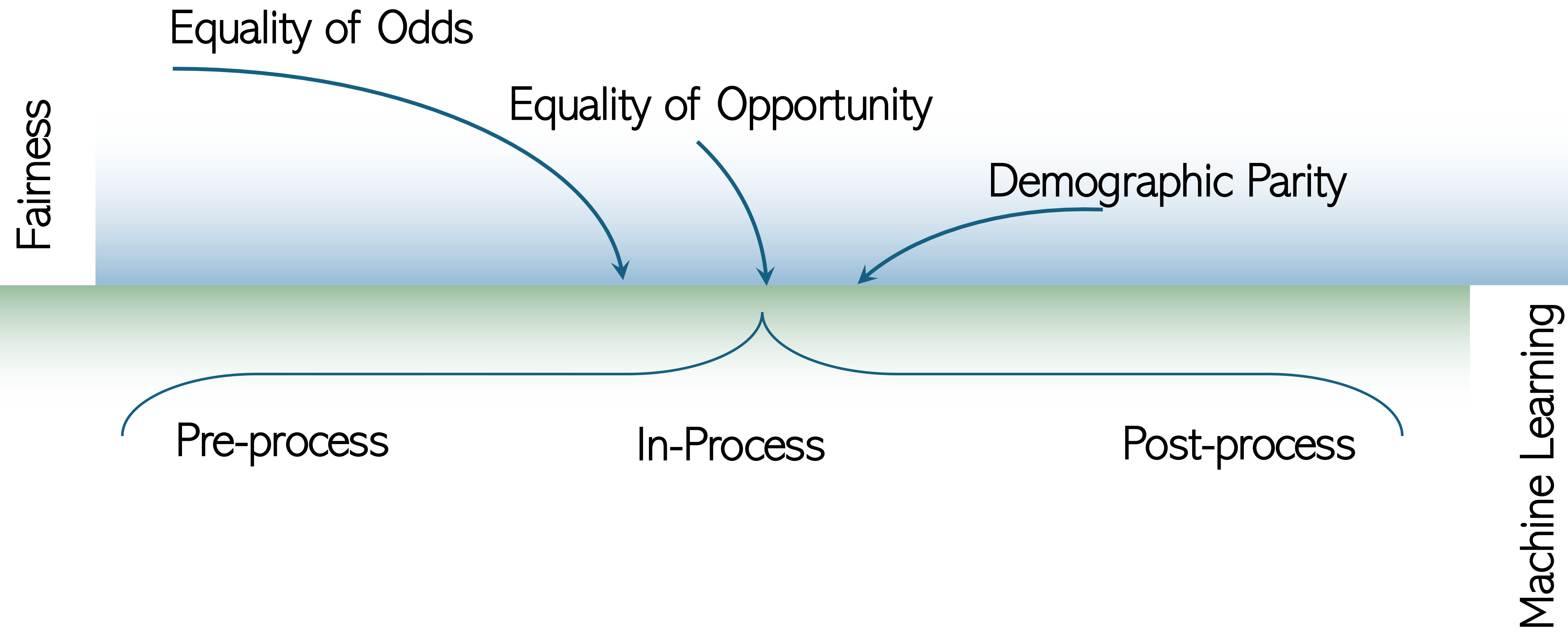
02 Fair and Diverse Team Recommendation

Equality of Odds

Membership of a skilled expert is independent of any attribute ⟶ True Positive Rate
Rejection of a skilled expert is independent of any attribute ⟶ False Positive Rate



103 Fair and Diverse Team Recommendation



Fair and Diverse Team Recommendation

Debiasing Algorithms

- **Pre-process**: Re-sampling (over/under sampling) heuristics before model training

  No work!

- **In-process**: Adjust the loss to balance efficacy and fairness

  [Moasses et.al., BIAS-SIGIR, 2024]
  [Barzegar et.al., WSDM 2025]

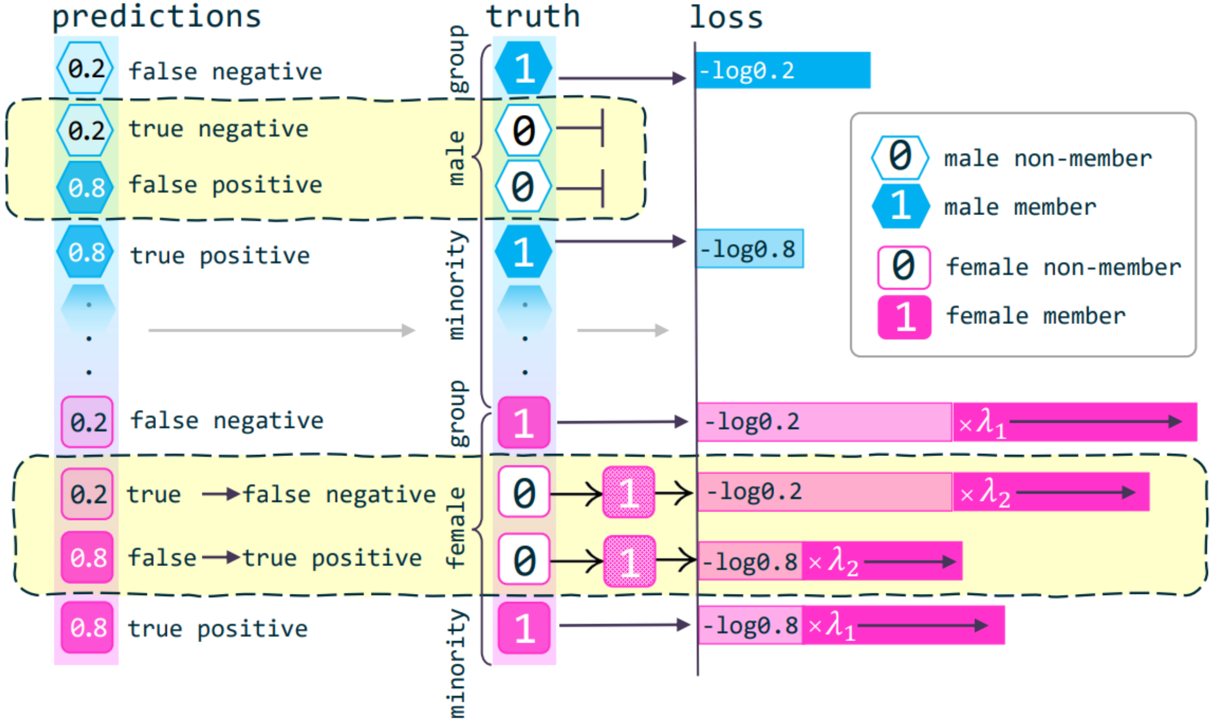
- **Post-process**:

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

Fair and Diverse Team Recommendation

Debiasing Algorithms → In-Process

Moasses et.al., vivafemme: Mitigating Gender Bias in Neural Team Recommendation via Female-Advocate Loss Regularization. BIAS-SIGIR 2024



Increase the loss of female predictions regardless of truth!

Fair and Diverse Team Recommendation

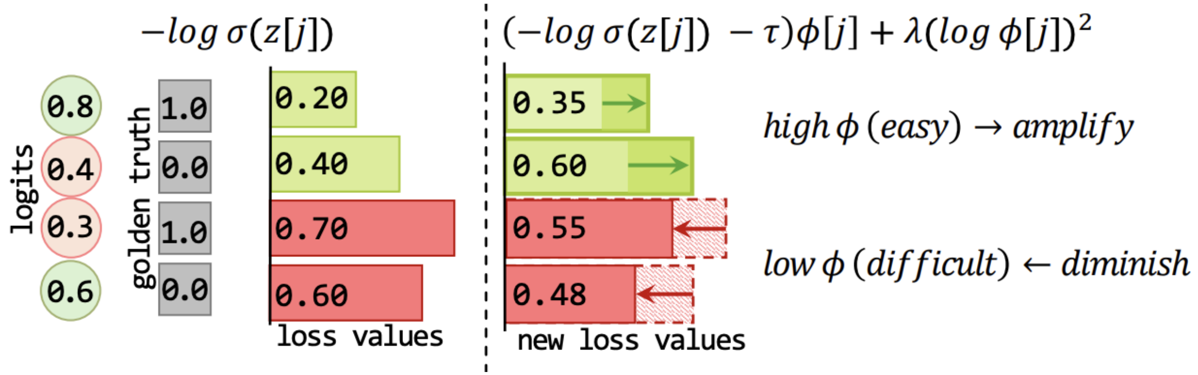
Debiasing Algorithms → In-Process

Barzegar et.al., Adaptive Loss-based **Curricula** for Neural Team Recommendation. WSDM 2025.

Easy Popular Experts vs. Difficult non-Popular Experts

Poster Session 9, March 13, Thursday, 4:00 PM – 5:45 PM,

dataset		neural model	our proposed curricula: static (sc)	parametric (pc)	non-parametric (npc)
dataset	dblp	non-variational	✗	✗	✓
		variational	✓	✓	✓
	imdb	non-variational	✗	✗	✓
		variational	✗	✗	✗



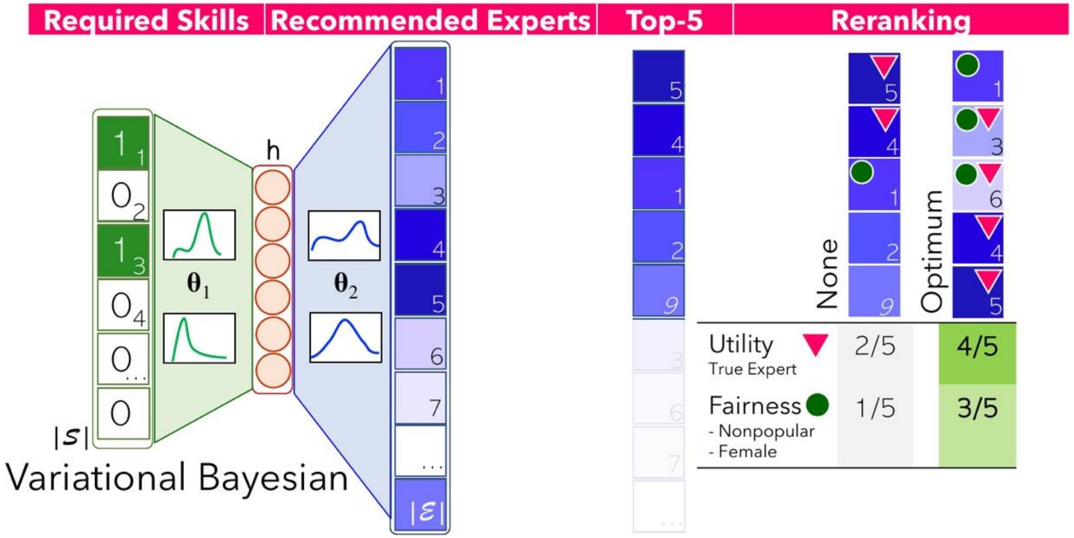
Saxena et al., **Data Parameters**: A New Family of Parameters for Learning a Differentiable Curriculum. NIPS 2019.
Castells et al., **SuperLoss**: A Generic Loss for Robust Curriculum Learning. NeurIPS 2020.

107 Fair and Diverse Team Recommendation

Debiasing Algorithms → Post-Process

Loghmani et.al., Bootless Application of Greedy Re-ranking Algorithms in Fair Neural Team Formation, BIAS-ECIR 2022.

Geyik et al., Fairness-aware ranking in search recommendation systems with application to **linkedin talent search**. KDD 2019



Fair and Diverse Team Recommendation

Fairness

Equality of Odds

Equality of Opportunity

Demographic Parity

Pre-process

In-Process

Post-process

Machine Learning

Fairness ⟺ Efficacy ⟺ Efficiency

Fairness maybe Unfair for Success

Outline

Group Learning

Active Engagement
Share Knowledge
Accountability
Time Management
Communication Skills
Conflict Resolution
Risk Management
Fairness
what else . . .

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]

Reviewer Assignment

"one of the first and potentially most important stage is the one that attempts to distribute submitted manuscripts to competent referees."

Rodriguez et al. Mapping the bid behavior of conference referees. Journal of Informetrics 2007.

Stelmakh et al., PeerReview4All: Fair and accurate reviewer assignment in peer review. Journal of Machine Learning Research 2021.

Arabzadeh et al., Reviewerly: Modeling the Reviewer Assignment Task as an Information Retrieval Problem, CIKM 2024.

Palliative Care

Symptom Management: Helps relieve pain, fatigue, and other distressing symptoms

Emotional Support: Provides counseling and mental health support

Spiritual Care: Addresses existential concerns based on personal or religious beliefs

Family Support: Helps with decision-making

Coordination of Care: Ensures smooth communication between healthcare providers

Salins et al. Palliative and end-of-life care practices for critically ill patients and their families in a peri-intensive care setting: a protocol for an umbrella review. Palliative & supportive care 2024.

Patients
Families

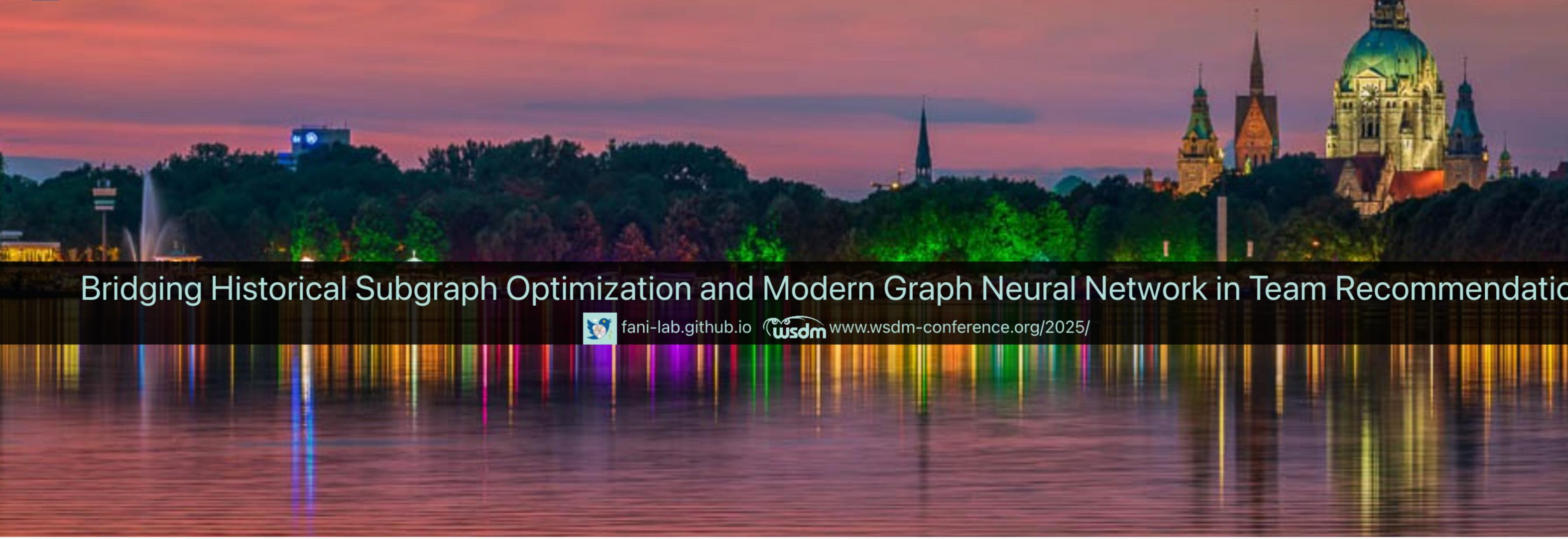
⟺

Doctors
Nurses
Physiotherapists
Psychologists
Nutritionists
Volunteers

geographical distance, communication costs, time availability

Selvarajah et al. Cultural Algorithms for Social Network Analysis: Case Studies in Team Formation." Cultural Algorithms: Tools to Model Complex Dynamic Social Systems 2020.

https://fani-lab.github.io/OpeNTF/tutorial/wsdm25/



Bridging Historical Subgraph Optimization and Modern Graph Neural Network in Team Recommendatio

fani-lab.github.io wsdm www.wsdm-conference.org/2025/

TIME AND LOCATION

Afternoon 1:30 PM - 5:00 PM (GMT+1)
Half-day, Monday, March 10, 2025
Konferenzraum 16, Hannover Congress Centre (HCC), Hannover, Germany

[Full Outline] [Slides] [Recording]