

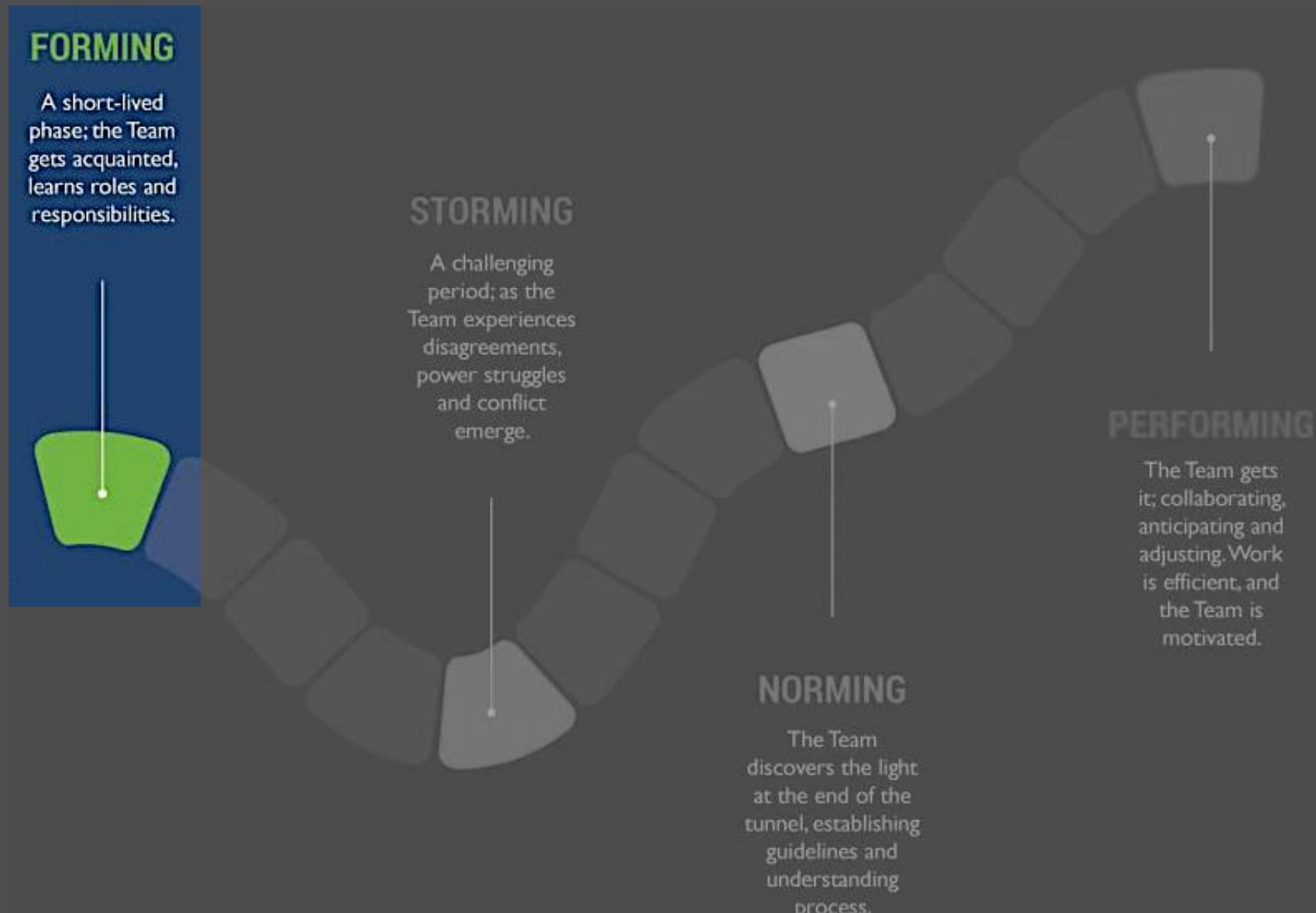


## A Streaming Approach to Neural Team Formation Training

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



5 MB hard drive being shipped by IBM - 1956.



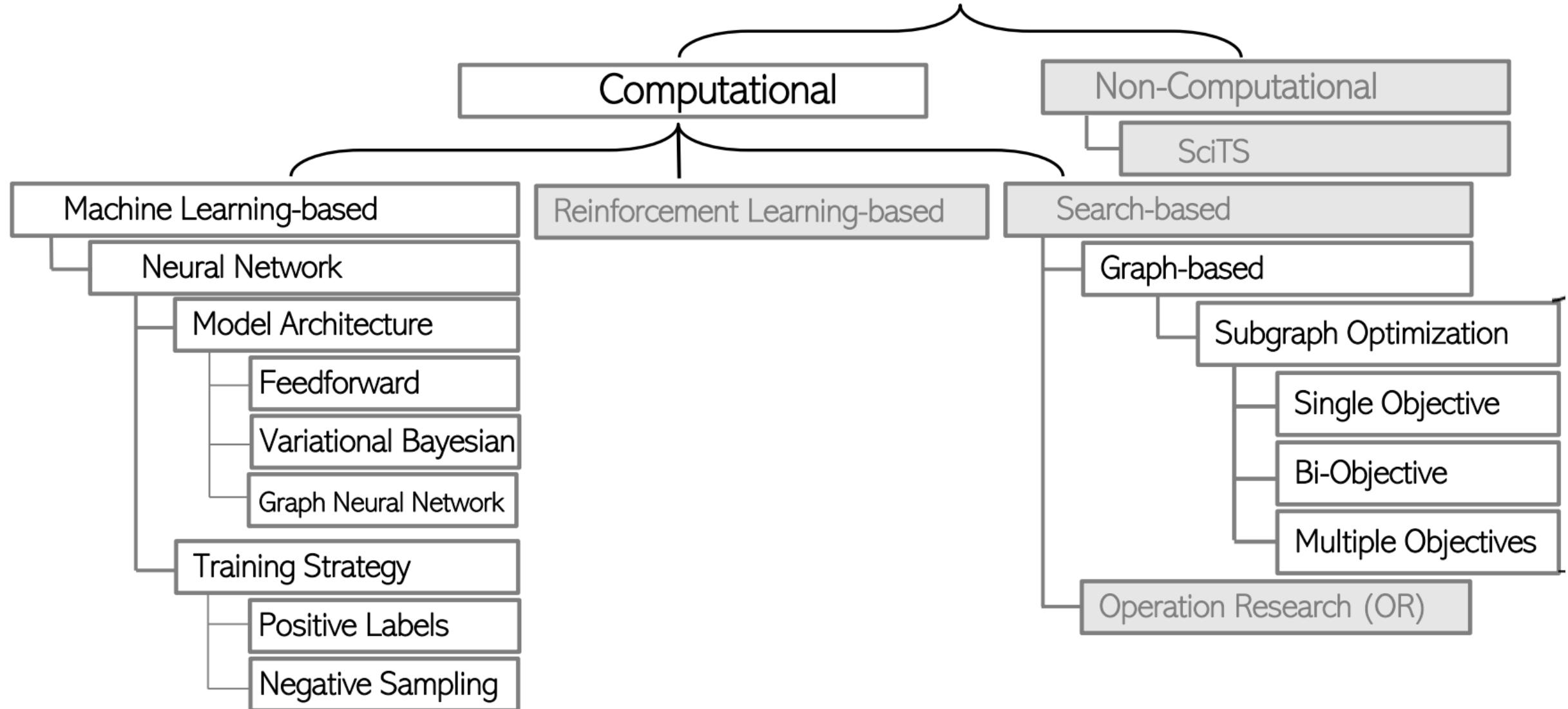
Tuckman, Bruce W. "Developmental sequence in small groups." Psychological bulletin 63.6 (1965): 384.

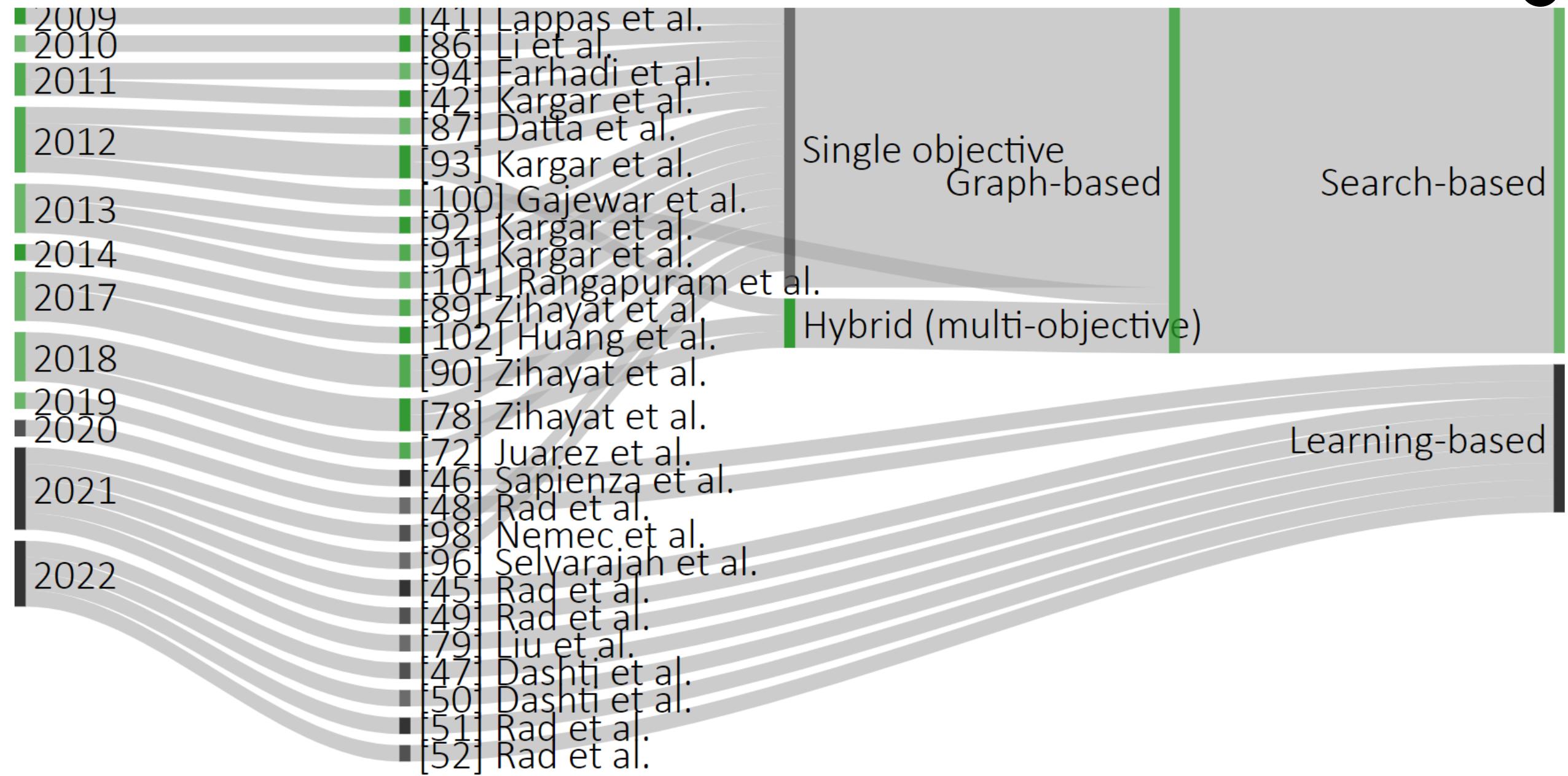


Photo: unknown

**Conventionally Manual by a Human Selector:**

- Large number of expert candidates
  - Different background
  - Different traits (night owls vs. early birds)
- Multitude criteria to optimize
  - Budget/Salary
  - Time/Availability
  - Communication costs
- Biases
  - Popularity
  - Gender
  - Race







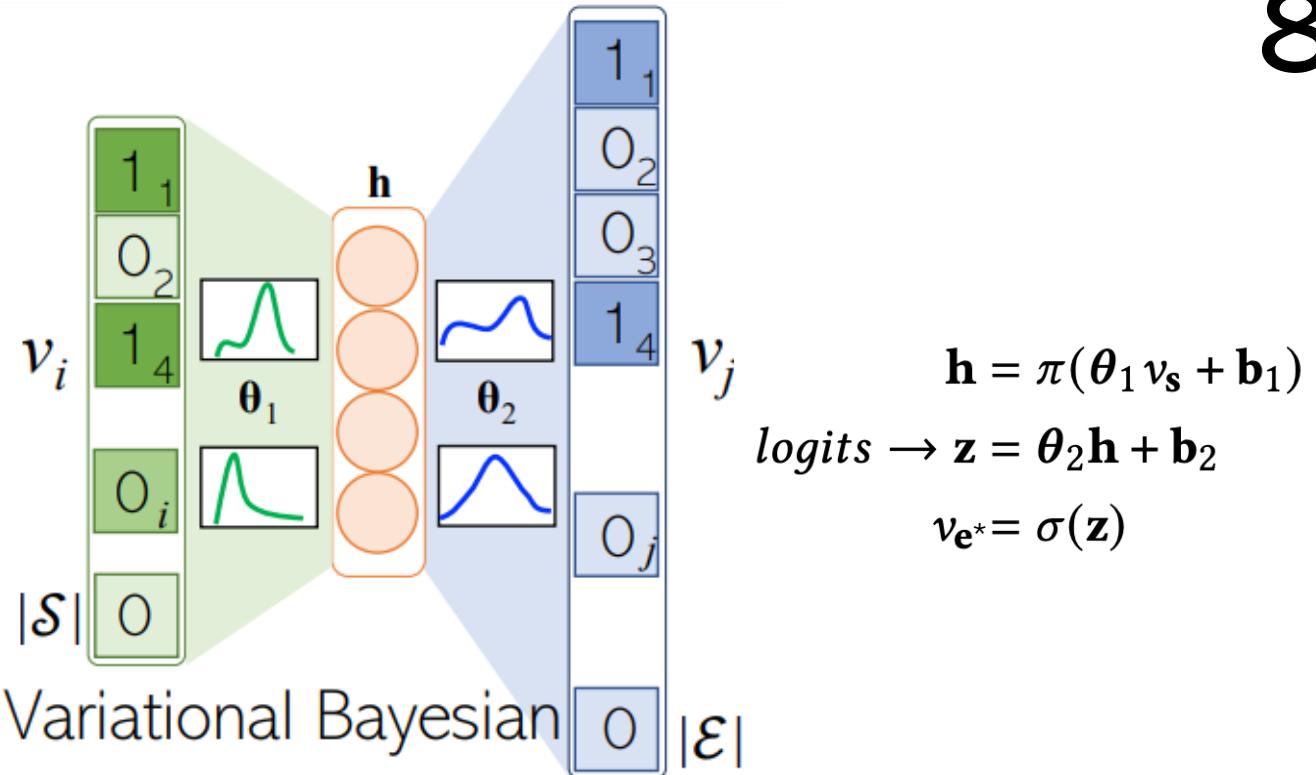
**Neural Team Formation**

Photo by: Julia Wimmerlin

**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  $s \subseteq \mathcal{S}$ ;  $s \neq \emptyset$  is shown by  $(s, \mathbf{e})$  along with its success status  $y \in \{0, 1\}$ . Further,  $\mathcal{T} = \{(s, \mathbf{e})_y : y \in \{0, 1\}\}$  indexes all previous teams.

**Definition 2 (Team Formation).** Given a subset of skills  $s$  and all teams  $\mathcal{T}$ , the Team Formation problem aims at identifying an optimal subset of experts  $\mathbf{e}^*$  such that their collaboration in the predicted team  $(s, \mathbf{e}^*)$  is successful, that is  $(s, \mathbf{e}^*)_{y=1}$ , while avoiding a subset of experts  $\mathbf{e}'$  resulting in  $(s, \mathbf{e}')_{y=0}$ . More concretely, the Team Formation problem is to find a mapping function  $f$  of parameters  $\theta$  from the powerset of skills to the powerset of experts such that  $f_\theta : \mathcal{P}(\mathcal{S}) \rightarrow \mathcal{P}(\mathcal{E}), f_\theta(s) = \mathbf{e}^*$ .

**Definition 3 (Neural Team Formation).** Given the training set  $\mathcal{T}$ , Neural Team Formation estimates  $f_\theta(s)$  using a multi-layer neural network that learns, from  $\mathcal{T}$ , to map a vector representation of subset of skills  $s$ , referred to as  $v_s$ , to a vector representation of subset of experts  $\mathbf{e}^*$ , referred to as  $v_{\mathbf{e}^*}$ , by maximizing the posterior (MAP) probability of  $\theta$  in  $f_\theta$  over  $\mathcal{T}$ , that is,  $\underset{\theta}{\operatorname{argmax}} p(\theta | \mathcal{T})$ .



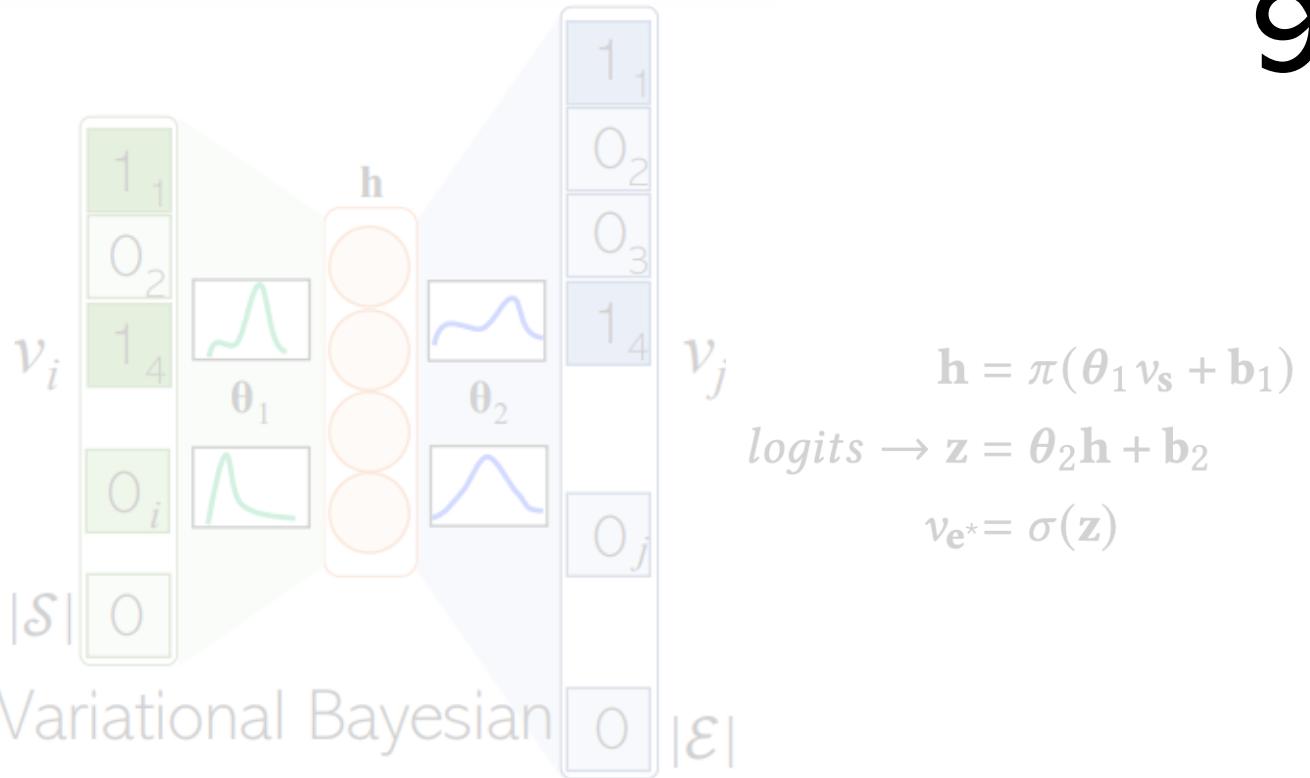
$$\underset{\theta}{\operatorname{argmax}} p(\theta | \mathcal{T}) \propto p(\mathcal{T} | \theta) p(\theta) = p(\theta) \prod_{(s, \mathbf{e}^*) \in \mathcal{T}^+} p(\mathbf{e}^* | s, \theta)$$

$$p(\mathbf{e} | s, \theta) = \prod_{j \in \mathbf{e}^*} \sigma(\mathbf{z}[j]) \propto \sum_{j \in \mathbf{e}^*} \log \sigma(\mathbf{z}[j])$$

**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.

**Definition 2 (Team Formation).** Given a subset of skills  $\mathbf{s}$  and all teams  $\mathcal{T}$ , the Team Formation problem aims at identifying an optimal subset of experts  $\mathbf{e}^*$  such that their collaboration in the predicted team  $(\mathbf{s}, \mathbf{e}^*)$  is successful, that is  $(\mathbf{s}, \mathbf{e}^*)_{y=1}$ , while avoiding a subset of experts  $\mathbf{e}'$  resulting in  $(\mathbf{s}, \mathbf{e}')_{y=0}$ . More concretely, the Team Formation problem is to find a mapping function  $f$  of parameters  $\theta$  from the powerset of skills to the powerset of experts such that  $f_\theta : \mathcal{P}(\mathcal{S}) \rightarrow \mathcal{P}(\mathcal{E}), f_\theta(\mathbf{s}) = \mathbf{e}^*$ .

**Definition 3 (Neural Team Formation).** Given the training set  $\mathcal{T}$ , Neural Team Formation estimates  $f_\theta(\mathbf{s})$  using a multi-layer neural network that learns, from  $\mathcal{T}$ , to map a vector representation of subset of skills  $\mathbf{s}$ , referred to as  $v_s$ , to a vector representation of subset of experts  $\mathbf{e}^*$ , referred to as  $v_{e^*}$ , by maximizing the posterior (MAP) probability of  $\theta$  in  $f_\theta$  over  $\mathcal{T}$ , that is,  $\underset{\theta}{\operatorname{argmax}} p(\theta | \mathcal{T})$ .



$$\mathbf{h} = \pi(\theta_1 v_s + \mathbf{b}_1)$$

$$\text{logits} \rightarrow \mathbf{z} = \theta_2 \mathbf{h} + \mathbf{b}_2$$

$$v_{\mathbf{e}^*} = \sigma(\mathbf{z})$$

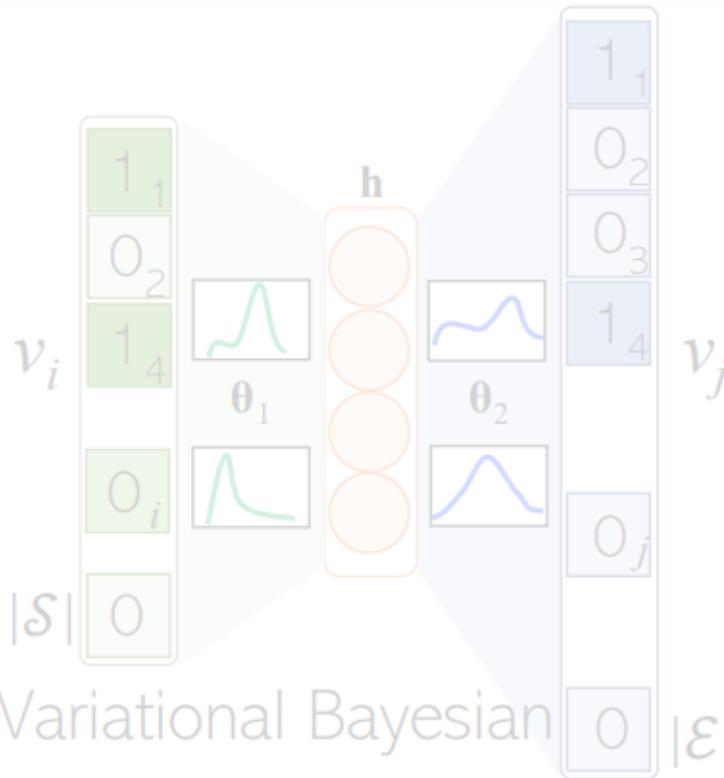
$$\operatorname{argmax}_{\theta} p(\theta | \mathcal{T}) \propto p(\mathcal{T} | \theta) p(\theta) = p(\theta) \prod_{(\mathbf{s}, \mathbf{e}^*) \in \mathcal{T}^+} p(\mathbf{e}^* | \mathbf{s}, \theta)$$

$$p(\mathbf{e} | \mathbf{s}, \theta) = \prod_{j \in e^*} \sigma(z[j]) \propto \sum_{j \in e^*} \log \sigma(z[j])$$

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

**Definition 2 (Team Formation).** Given a subset of skills  $s$  and all teams  $\mathcal{T}$ , the Team Formation problem aims at identifying an optimal subset of experts  $e^*$  such that their collaboration in the predicted team  $(s, e^*)$  is successful, that is  $(s, e^*)_{y=1}$ , while avoiding a subset of experts  $e'$  resulting in  $(s, e')_{y=0}$ . More concretely, the Team Formation problem is to find a mapping function  $f$  of parameters  $\theta$  from the powerset of skills to the powerset of experts such that  $f_\theta : \mathcal{P}(\mathcal{S}) \rightarrow \mathcal{P}(\mathcal{E}), f_\theta(s) = e^*$ .

**Definition 3 (Neural Team Formation).** Given the training set  $\mathcal{T}$ , Neural Team Formation estimates  $f_\theta(s)$  using a multi-layer neural network that learns, from  $\mathcal{T}$ , 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  $\mathcal{T}$ , that is,  $\underset{\theta}{\operatorname{argmax}} p(\theta|\mathcal{T})$ .



$$\mathbf{h} = \pi(\theta_1 v_s + \mathbf{b}_1)$$

$$\text{logits} \rightarrow \mathbf{z} = \theta_2 \mathbf{h} + \mathbf{b}_2$$

$$v_{e^*} = \sigma(\mathbf{z})$$

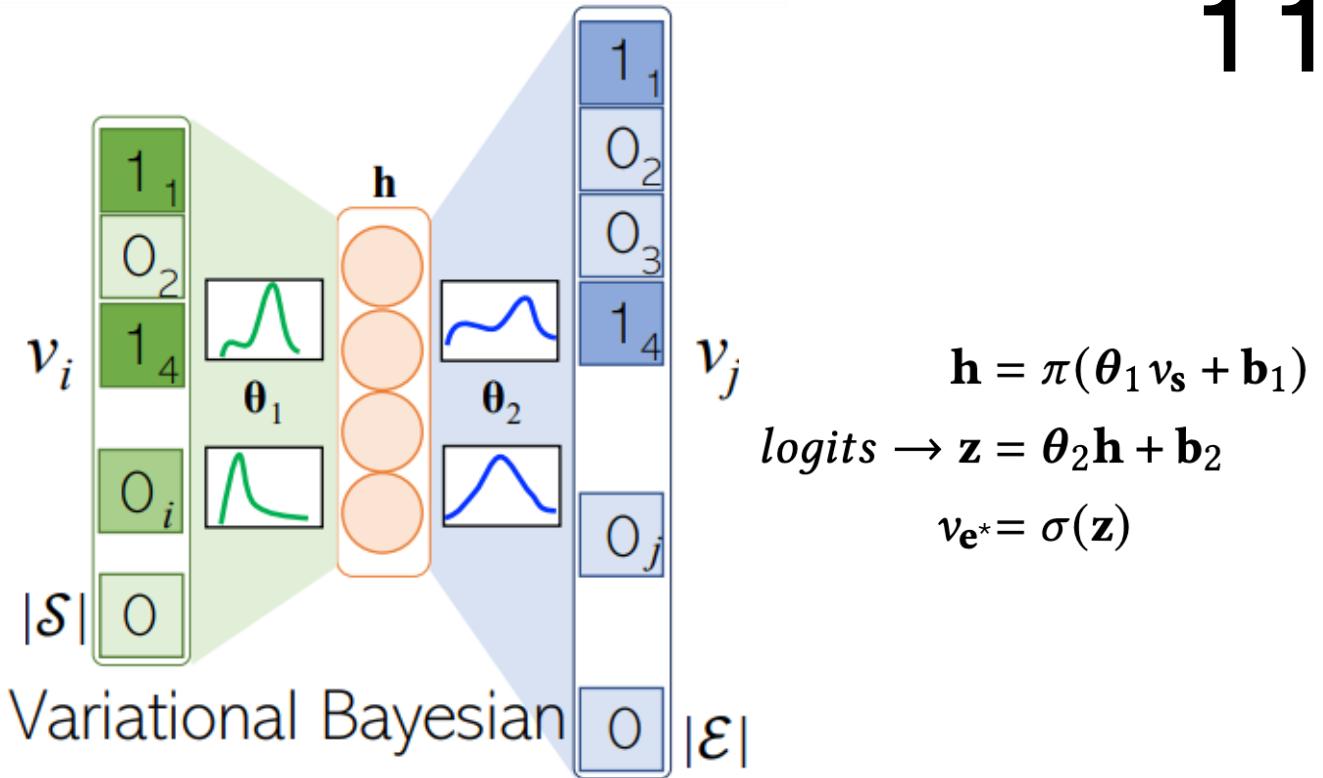
$$\operatorname{argmax}_{\theta} p(\theta|\mathcal{T}) \propto p(\mathcal{T}|\theta)p(\theta) = p(\theta) \prod_{(s,e^*) \in \mathcal{T}^+} p(e^*|s, \theta)$$

$$p(\mathbf{e}|\mathbf{s}, \theta) = \prod_{j \in e^*} \sigma(\mathbf{z}[j]) \propto \sum_{j \in e^*} \log \sigma(\mathbf{z}[j])$$

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

**Definition 2 (Team Formation).** Given a subset of skills  $s$  and all teams  $\mathcal{T}$ , the Team Formation problem aims at identifying an optimal subset of experts  $e^*$  such that their collaboration in the predicted team  $(s, e^*)$  is successful, that is  $(s, e^*)_{y=1}$ , while avoiding a subset of experts  $e'$  resulting in  $(s, e')_{y=0}$ . More concretely, the Team Formation problem is to find a mapping function  $f$  of parameters  $\theta$  from the powerset of skills to the powerset of experts such that  $f_\theta : \mathcal{P}(\mathcal{S}) \rightarrow \mathcal{P}(\mathcal{E}), f_\theta(s) = e^*$ .

**Definition 3 (Neural Team Formation).** Given the training set  $\mathcal{T}$ , Neural Team Formation estimates  $f_\theta(s)$  using a multi-layer neural network that learns, from  $\mathcal{T}$ , 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  $\mathcal{T}$ , that is,  $\underset{\theta}{\operatorname{argmax}} p(\theta|\mathcal{T})$ .



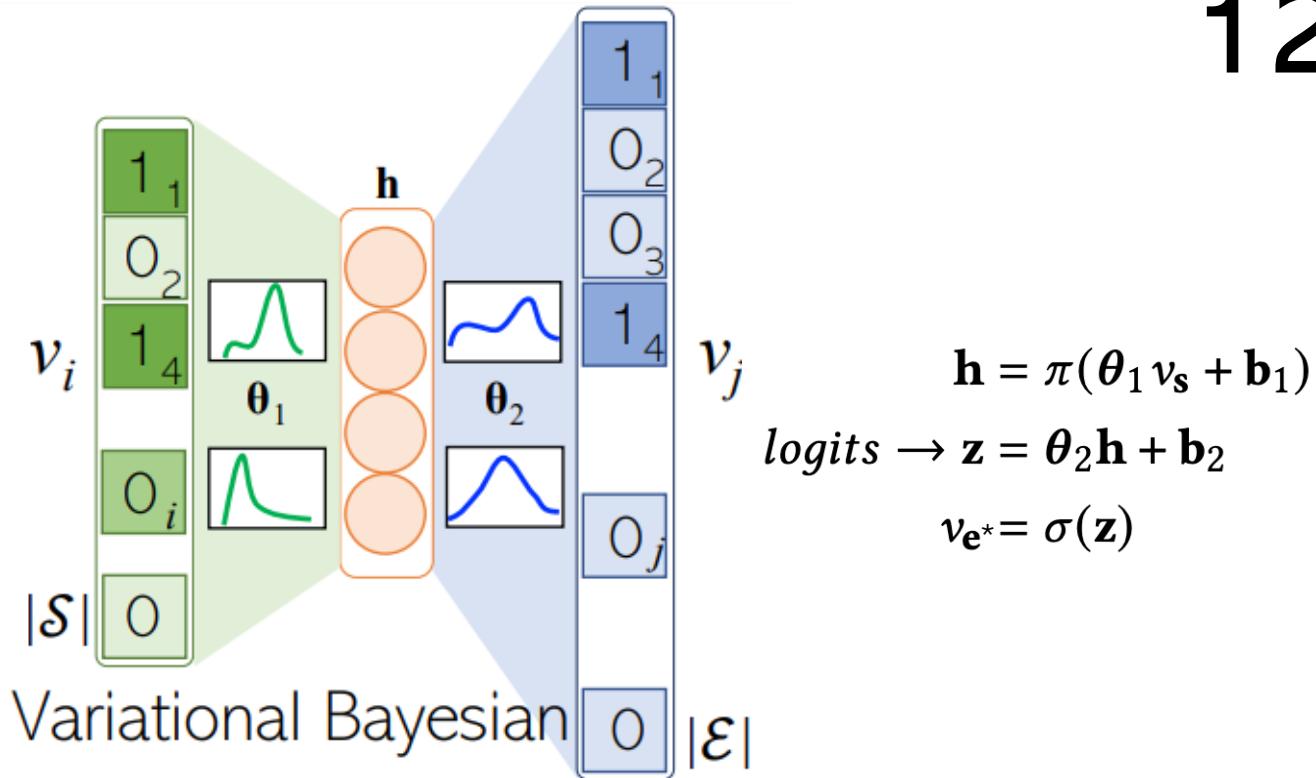
$$\operatorname{argmax}_{\theta} p(\theta|\mathcal{T}) \propto p(\mathcal{T}|\theta)p(\theta) = p(\theta) \prod_{(s,e^*) \in \mathcal{T}^+} p(e^*|s, \theta)$$

$$p(e|s, \theta) = \prod_{j \in e^*} \sigma(z[j]) \propto \sum_{j \in e^*} \log \sigma(z[j])$$

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

**Definition 2 (Team Formation).** Given a subset of skills  $s$  and all teams  $\mathcal{T}$ , the Team Formation problem aims at identifying an optimal subset of experts  $e^*$  such that their collaboration in the predicted team  $(s, e^*)$  is successful, that is  $(s, e^*)_{y=1}$ , while avoiding a subset of experts  $e'$  resulting in  $(s, e')_{y=0}$ . More concretely, the Team Formation problem is to find a mapping function  $f$  of parameters  $\theta$  from the powerset of skills to the powerset of experts such that  $f_\theta : \mathcal{P}(\mathcal{S}) \rightarrow \mathcal{P}(\mathcal{E}), f_\theta(s) = e^*$ .

**Definition 3 (Neural Team Formation).** Given the training set  $\mathcal{T}$ , Neural Team Formation estimates  $f_\theta(s)$  using a multi-layer neural network that learns, from  $\mathcal{T}$ , 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  $\mathcal{T}$ , that is,  $\underset{\theta}{\operatorname{argmax}} p(\theta|\mathcal{T})$ .



$$\mathbf{h} = \pi(\theta_1 v_s + \mathbf{b}_1)$$

$$\text{logits} \rightarrow \mathbf{z} = \theta_2 \mathbf{h} + \mathbf{b}_2$$

$$v_{e^*} = \sigma(\mathbf{z})$$

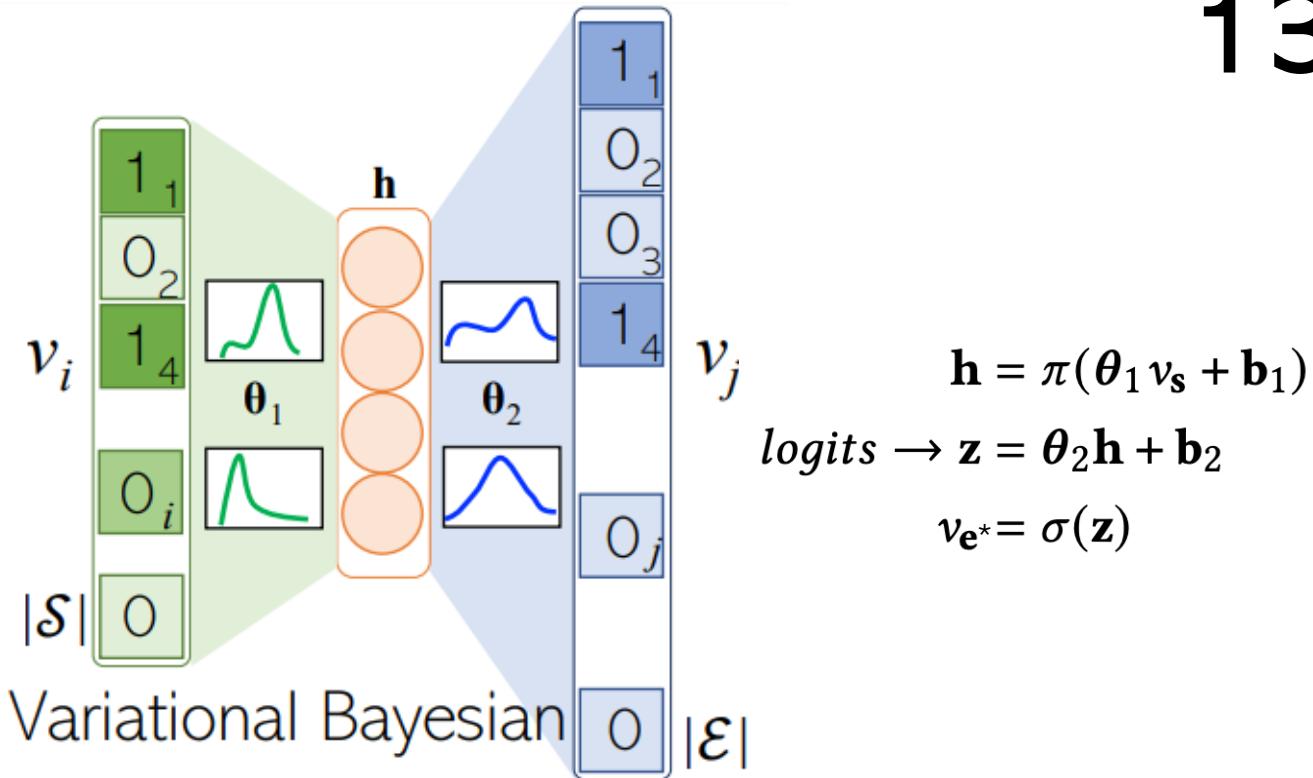
$$\operatorname{argmax}_{\theta} p(\theta|\mathcal{T}) \propto p(\mathcal{T}|\theta)p(\theta) = p(\theta) \prod_{(s, e^*) \in \mathcal{T}^+} p(e^*|s, \theta)$$

$$p(e|s, \theta) = \prod_{j \in e^*} \sigma(z[j]) \propto \sum_{j \in e^*} \log \sigma(z[j])$$

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

**Definition 2 (Team Formation).** Given a subset of skills  $s$  and all teams  $\mathcal{T}$ , the Team Formation problem aims at identifying an optimal subset of experts  $e^*$  such that their collaboration in the predicted team  $(s, e^*)$  is successful, that is  $(s, e^*)_{y=1}$ , while avoiding a subset of experts  $e'$  resulting in  $(s, e')_{y=0}$ . More concretely, the Team Formation problem is to find a mapping function  $f$  of parameters  $\theta$  from the powerset of skills to the powerset of experts such that  $f_\theta : \mathcal{P}(\mathcal{S}) \rightarrow \mathcal{P}(\mathcal{E}), f_\theta(s) = e^*$ .

**Definition 3 (Neural Team Formation).** Given the training set  $\mathcal{T}$ , Neural Team Formation estimates  $f_\theta(s)$  using a multi-layer neural network that learns, from  $\mathcal{T}$ , 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  $\mathcal{T}$ , that is,  $\underset{\theta}{\operatorname{argmax}} p(\theta|\mathcal{T})$ .



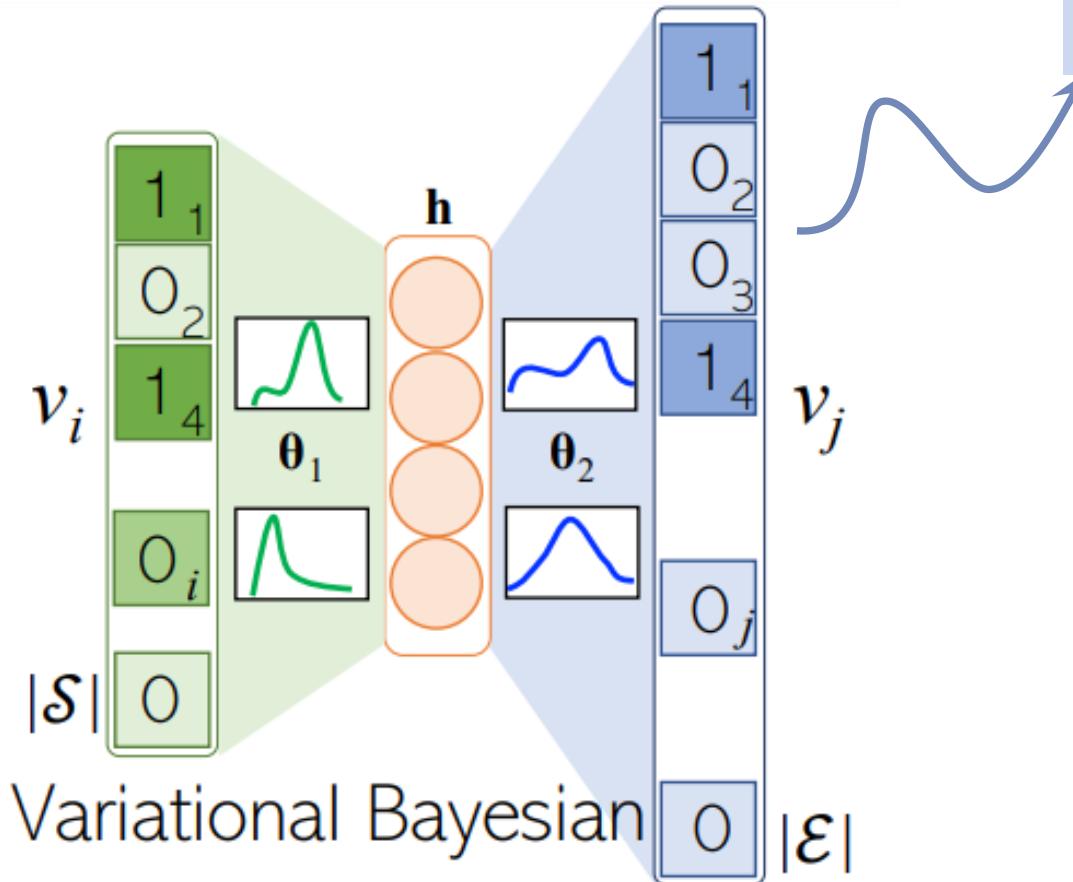
$$\operatorname{argmax}_{\theta} p(\theta|\mathcal{T}) \propto p(\mathcal{T}|\theta)p(\theta) = p(\theta) \prod_{(s, e^*) \in \mathcal{T}^+} p(e^*|s, \theta)$$

$$p(\mathbf{e}|\mathbf{s}, \theta) = \prod_{j \in e^*} \sigma(\mathbf{z}[j]) \propto \sum_{j \in e^*} \log \sigma(\mathbf{z}[j])$$

## A Streaming Approach to Neural Team Formation Training

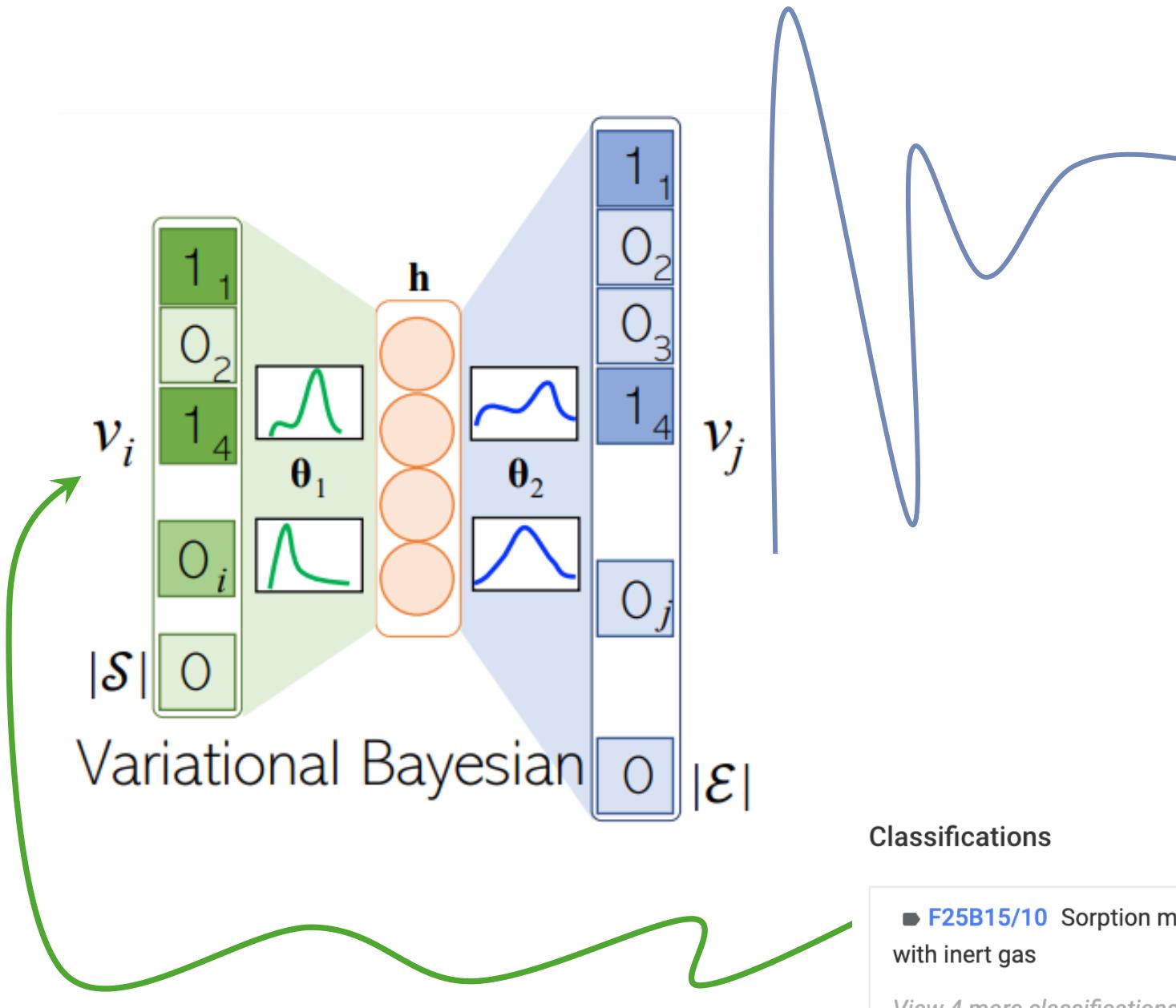
Hossein Fani<sup>[0000-0002-6033-6564]</sup>, Reza Barzegar<sup>[0009-0002-2831-4143]</sup>, Arman Dashti<sup>[0000-0001-9022-5403]</sup>, and Mahdis Saeedi<sup>[0000-0002-6297-3794]</sup>

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

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



US1781541A  
United States

[Download PDF](#) [Find Prior Art](#) [Similar](#)

Inventor: Einstein Albert, Szilard Leo

Current Assignee : Electrolux Servel Corp

Worldwide applications

1927 • US

Application US240566A events ②

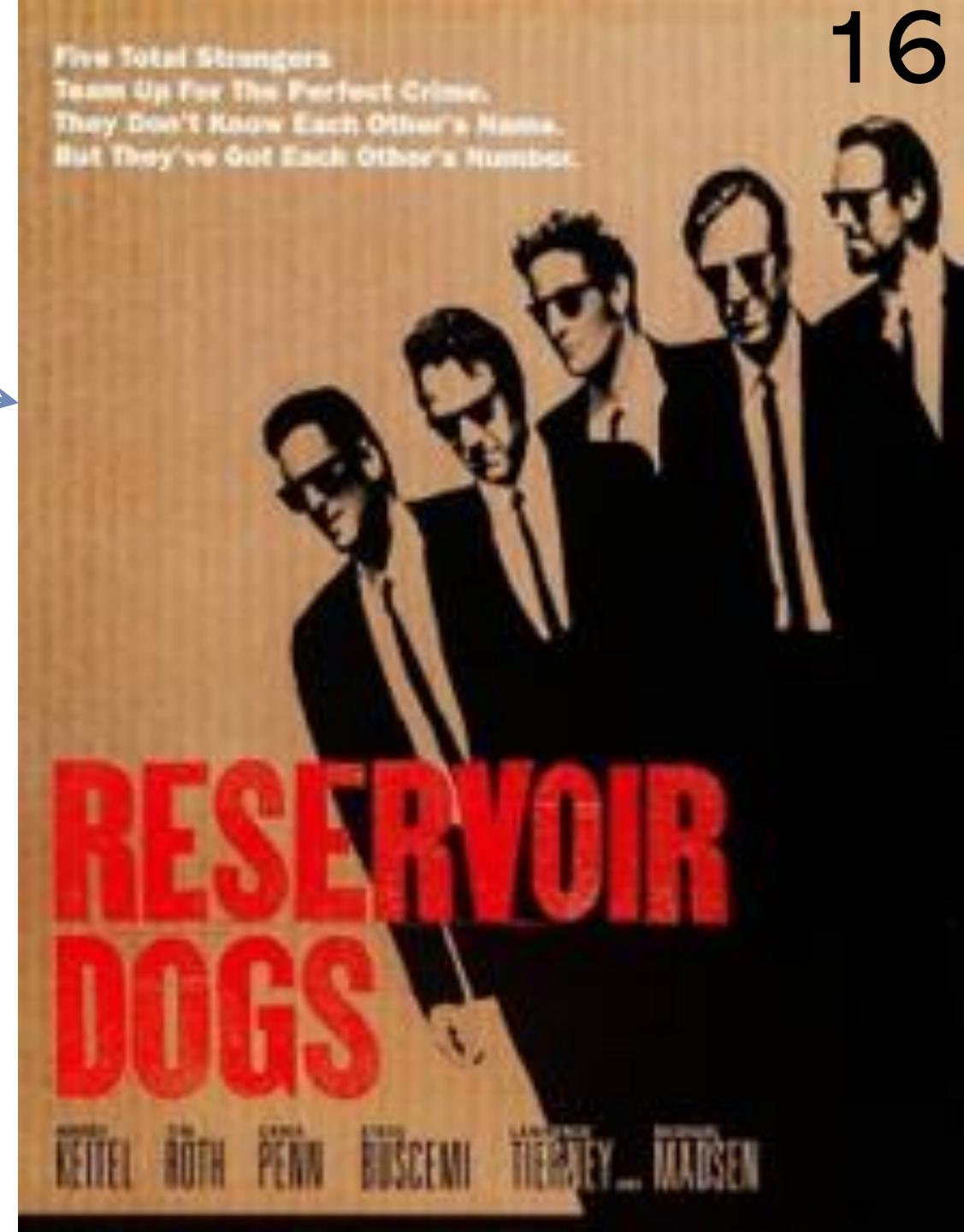
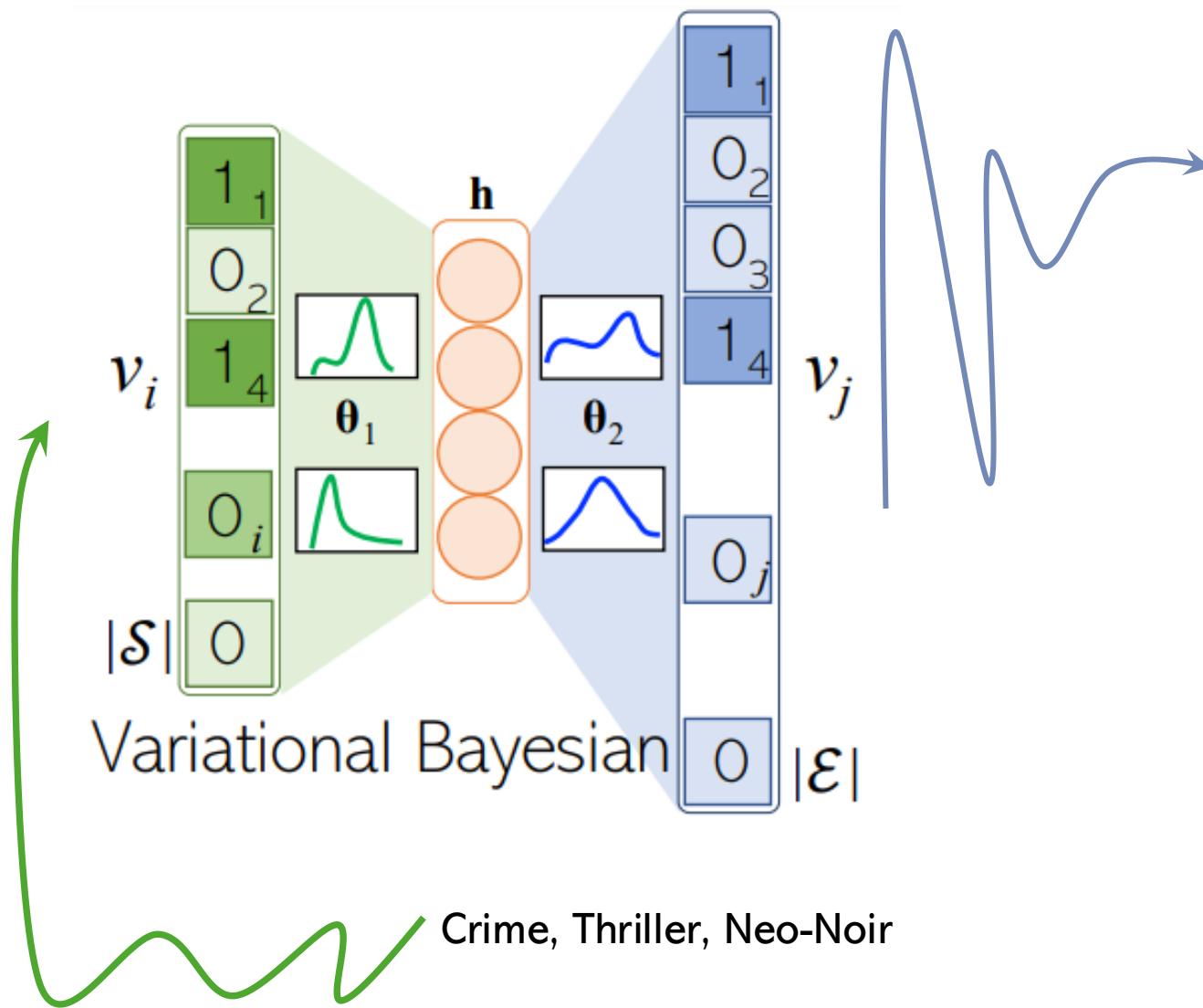
- 1927-12-16 • Application filed by Electrolux Servel Corp
- 1930-11-11 • Application granted
- 1930-11-11 • Publication of US1781541A
- 1947-11-11 • Anticipated expiration

Status • Expired - Lifetime

Classifications

- F25B15/10 Sorption machines, plants or systems, operating continuously, e.g. absorption type with inert gas

[View 4 more classifications](#)



Releases 50

PyTorch 2.2.1 Release, bug fi... Latest

last month

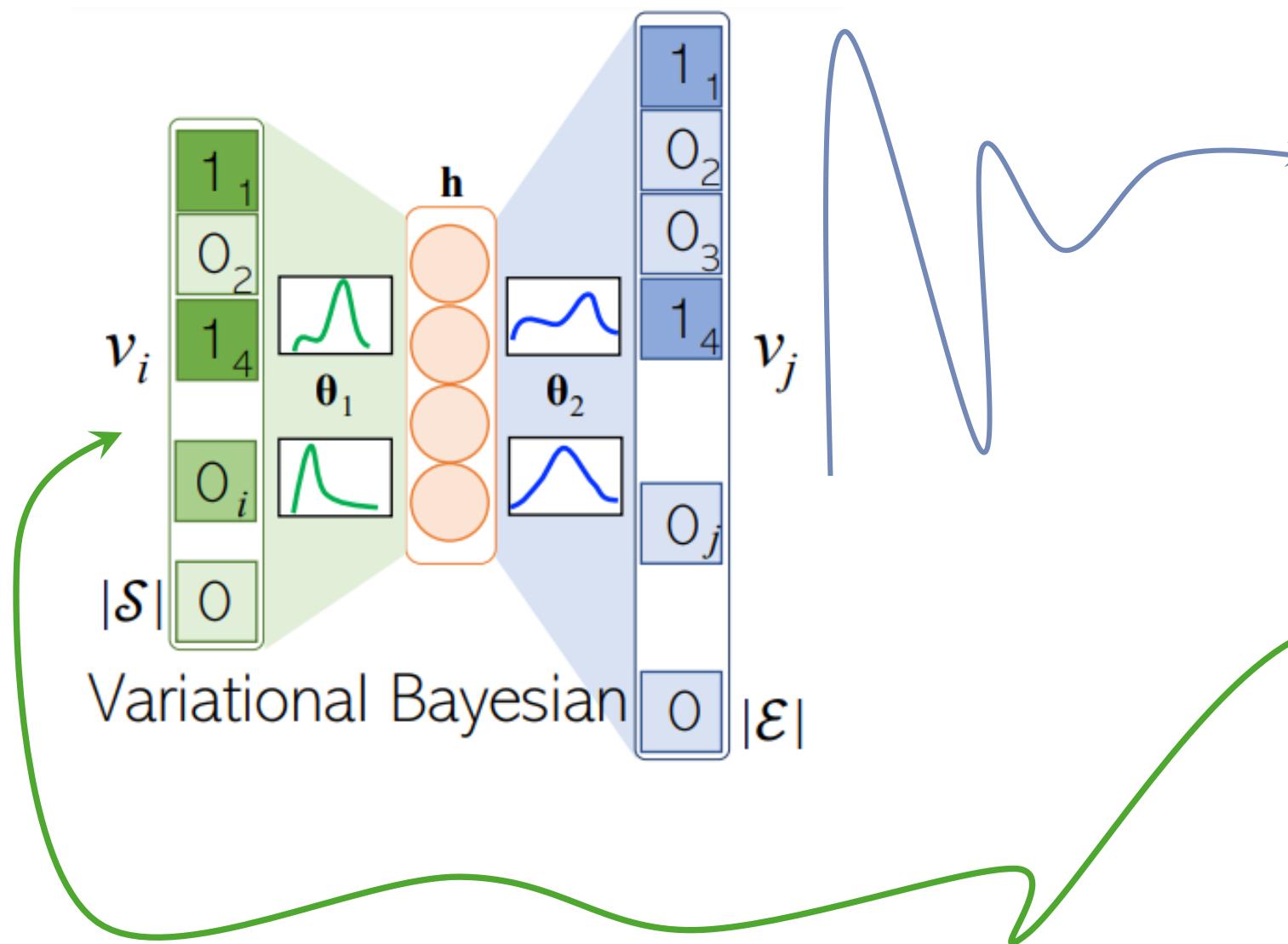
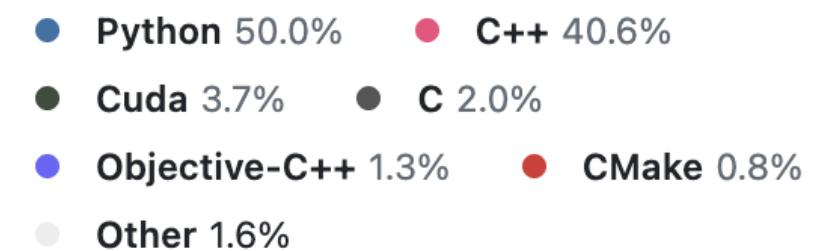
+ 49 releases

Contributors 3,202



+ 3,188 contributors

### Languages



Small vs. large set  
- Future RQ

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

**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.

What does it mean for a team to be successful?

Challenges ...



Tomas Mikolov

## Efficient estimation of word representations in vector space

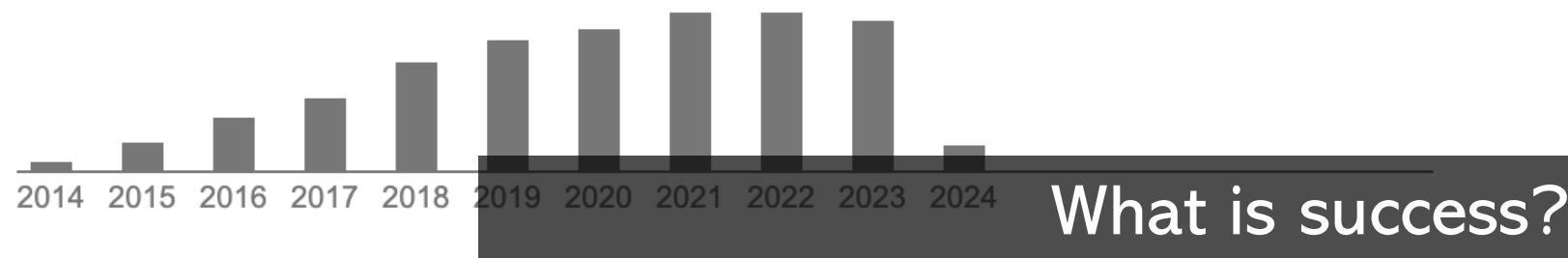
Authors Tomas Mikolov, Kai Chen, Greg Corrado, Jeffrey Dean

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](#)





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?



Own Now on Digital  
Now Playing In Theaters

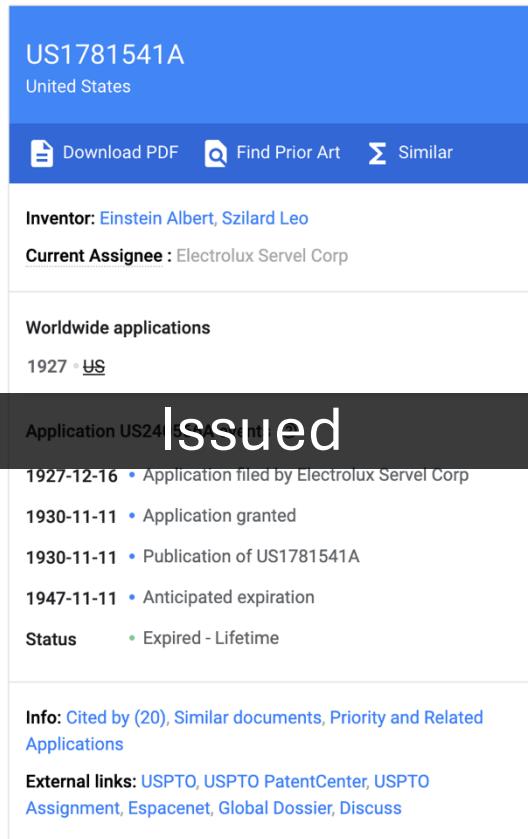
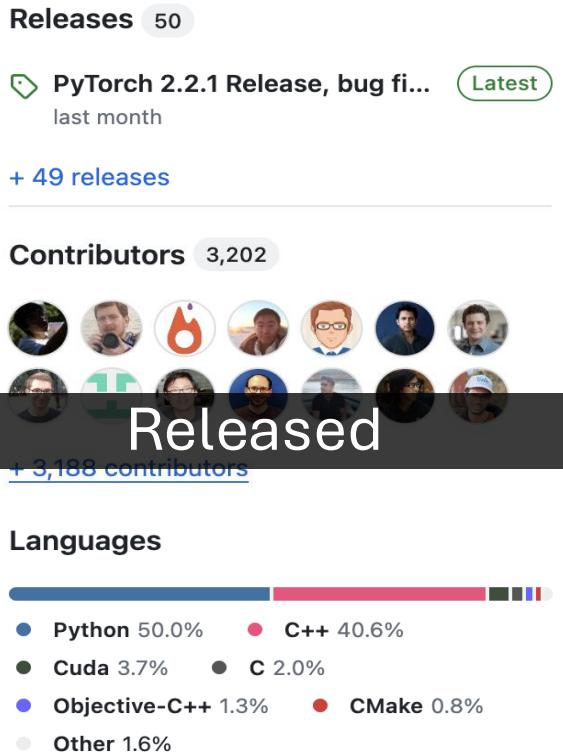
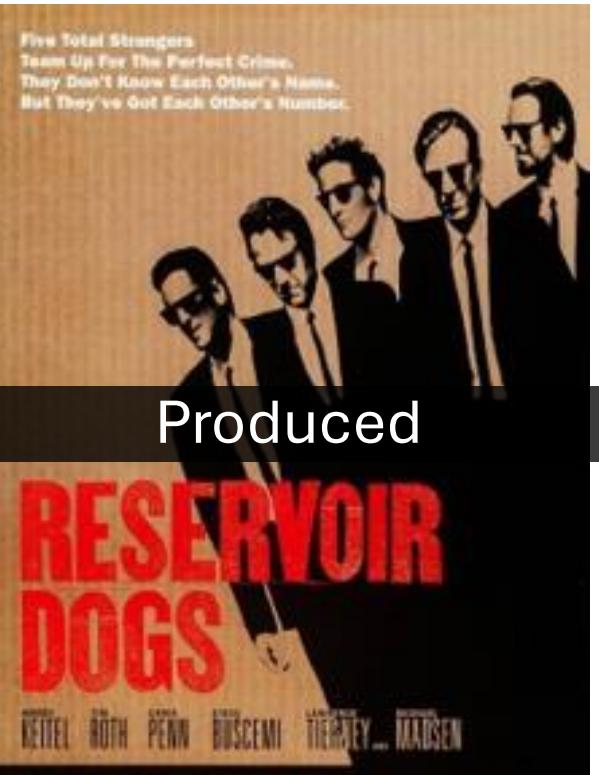
US\$1.446 billion vs. no Oscar!



The Big Lebowski, 1998

Joel & Ethan Coen

Jeff Bridges, John Goodman, Steve Buscemi



## 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

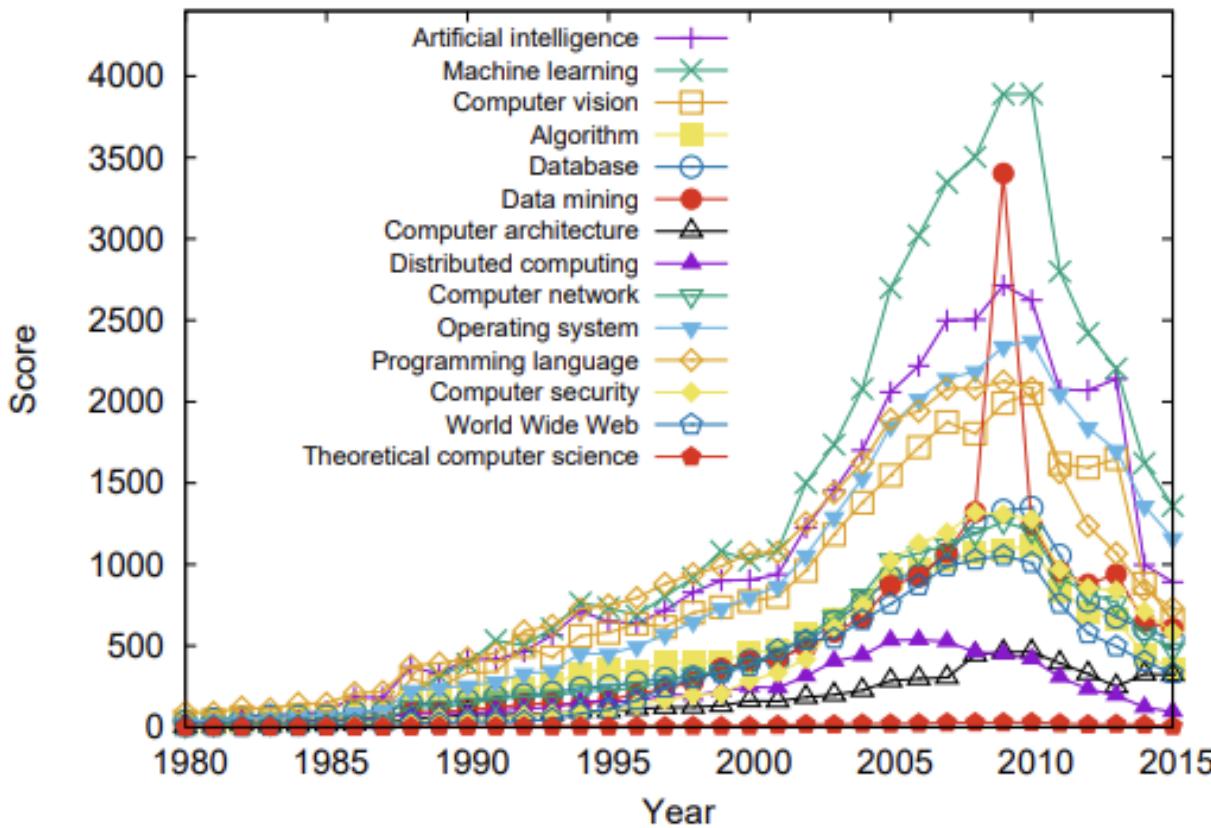
**Abstract.** Predicting *future* successful teams of experts who can effectively collaborate is challenging due to the experts' temporality of skill sets, levels of expertise, and collaboration ties, which is overlooked by prior work. Specifically, we propose a streaming-based training method that learn vector representations of experts' skills in a dynamic and sequential 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.

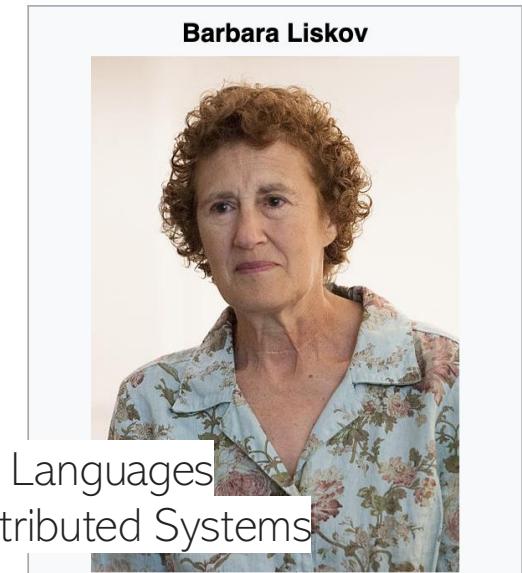
Success

(a) General trend (absolute).

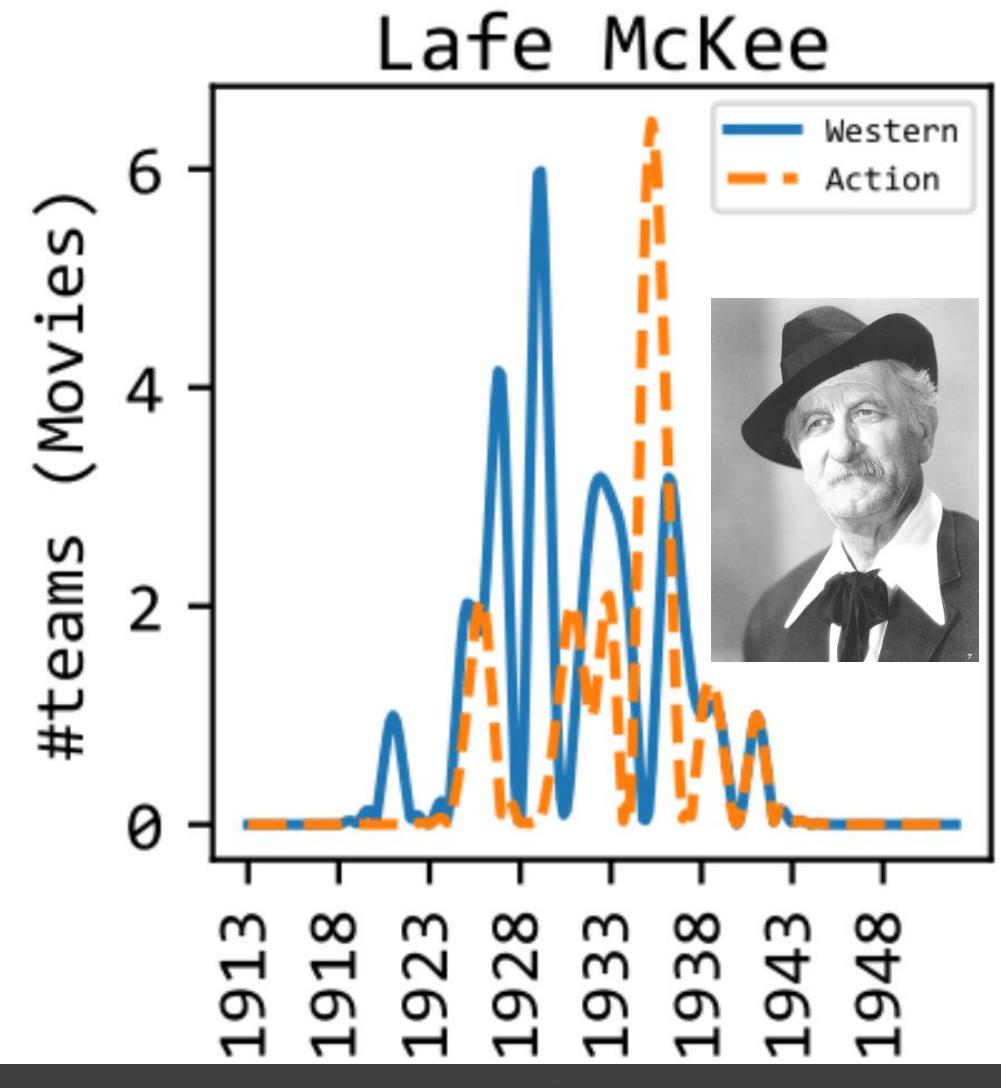
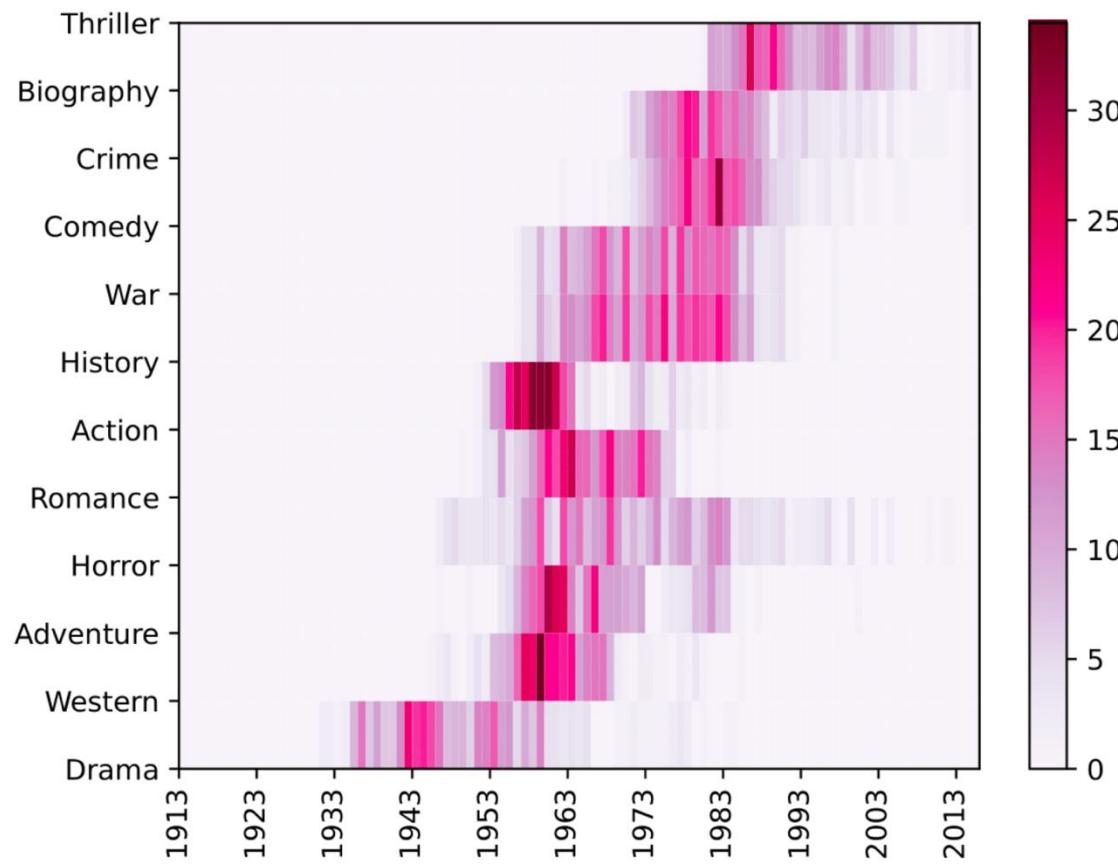


Effendy et al. Analysing trends in computer science research: A preliminary study using the microsoft academic graph. WWW 2017.

Operating Systems  
Programming Languages  
Distributed Systems



<b>Born</b>	Barbara Jane Huberman November 7, 1939 (age 84) Los Angeles, California, US
<b>Alma mater</b>	University of California, Berkeley (BA) Stanford University (PhD)
<b>Known for</b>	Venus (operating system) CLU Argus Thor (object-oriented database) Liskov substitution principle
<b>Spouse</b>	Nathan Liskov (1970–)
<b>Children</b>	1
<b>Awards</b>	ACM SIGART Award (1990) A. M. Turing Award (2008) Computer Pioneer Award (2018)
<b>Scientific career</b>	Fields Computer science

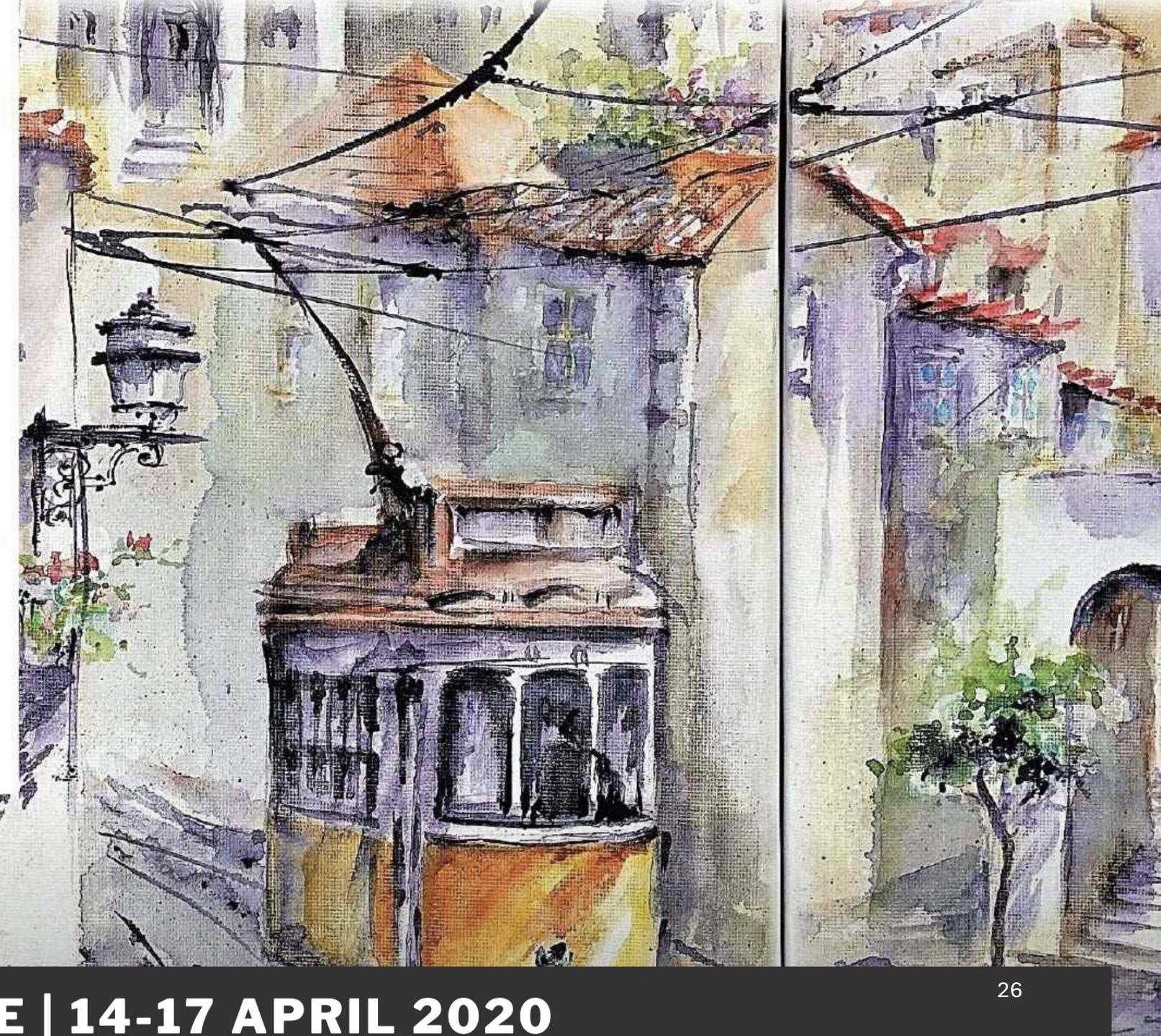


Temporal Evolutions in Skills & Expert's Skills



# ECIR 2020

42<sup>nd</sup> EUROPEAN CONFERENCE  
ON INFORMATION RETRIEVAL



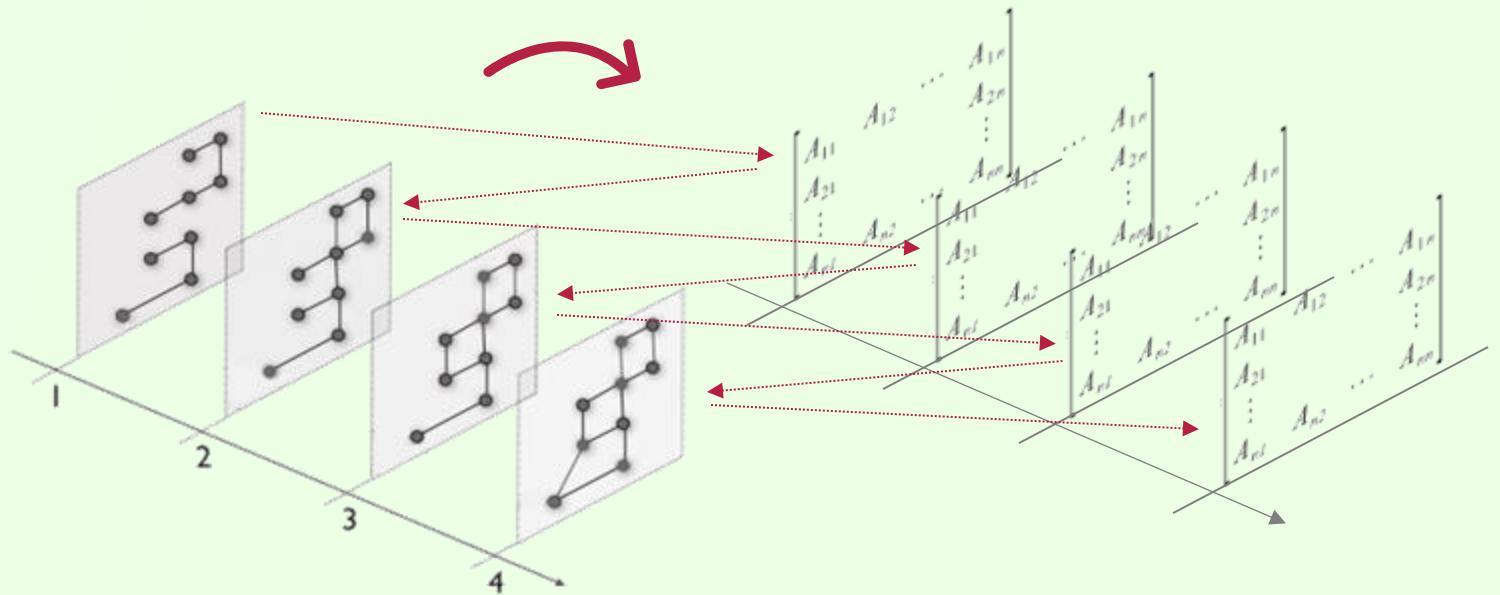
ECIR 2020 | ONLINE | 14-17 APRIL 2020

# TEMPORAL LATENT SPACE MODELING

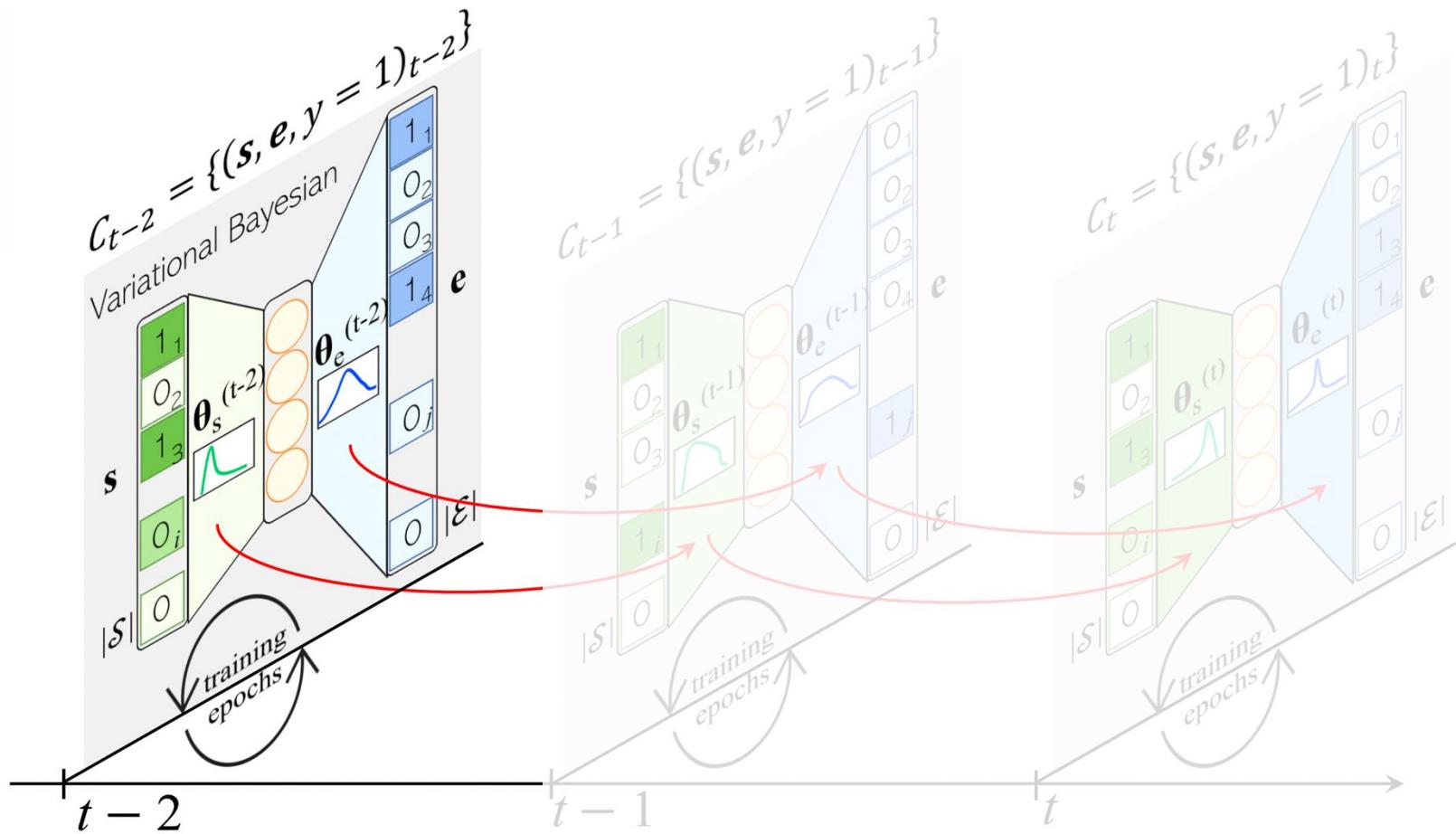
*local* Block Coordinate Gradient Descent (Zhu et al.TKDE 2016)

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

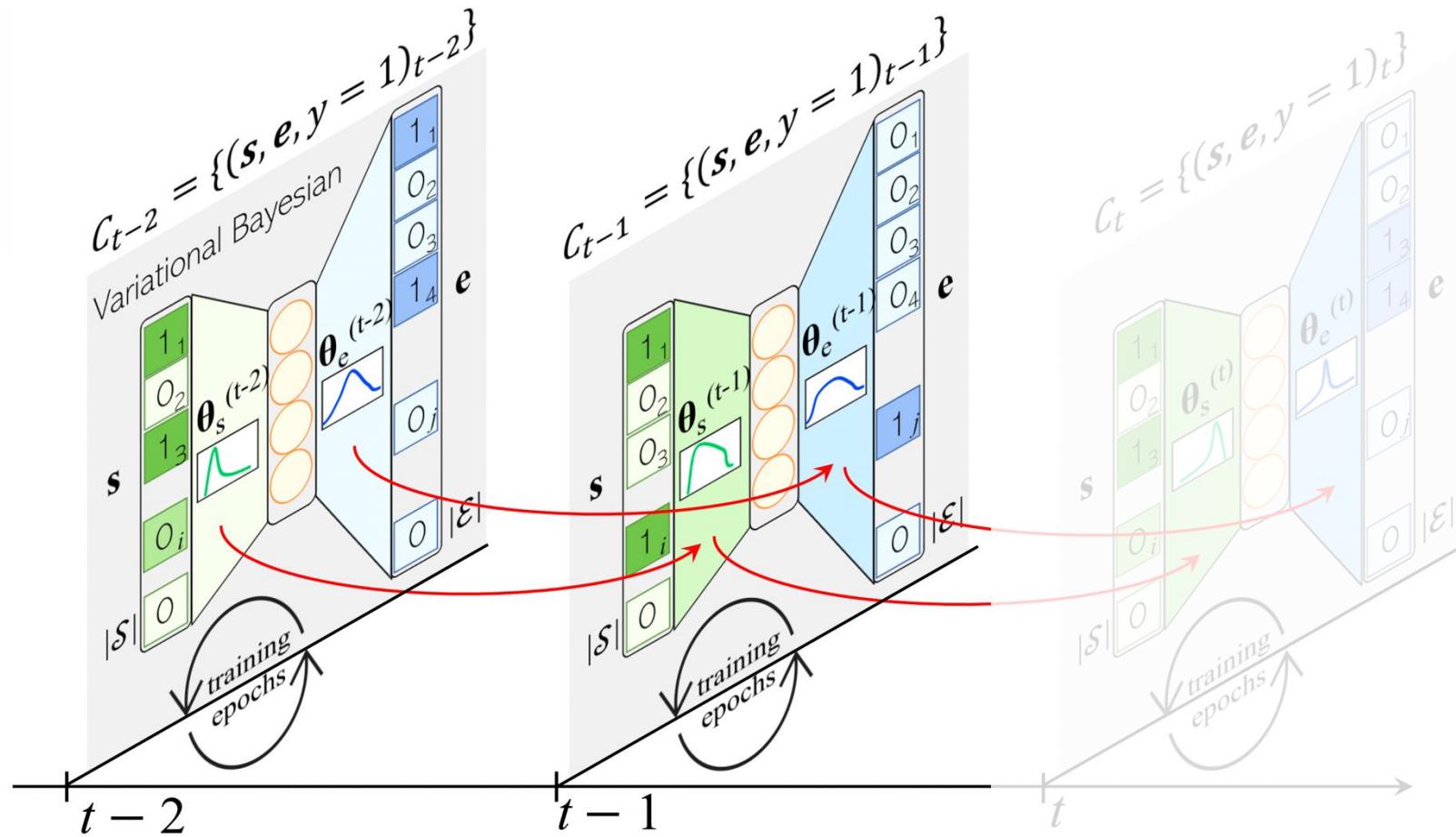
$$\forall u \in \mathbb{U}; \mathbf{y}_{ut} \geq 0, \mathbf{y}_{ut} \mathbf{y}_{ut}^\top = 1$$



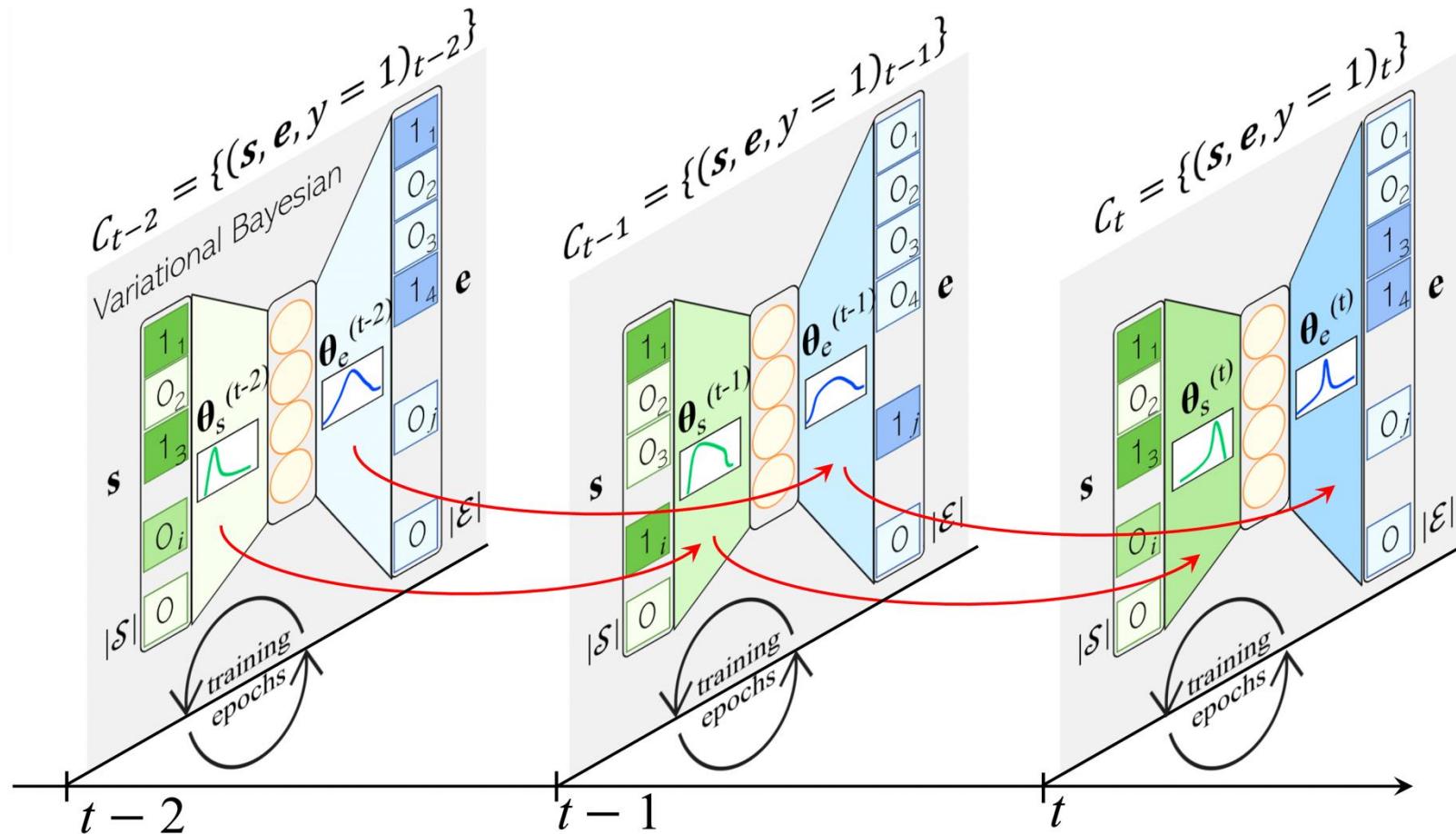
Fani et al. Temporal latent space modeling for community prediction. ECIR 2020

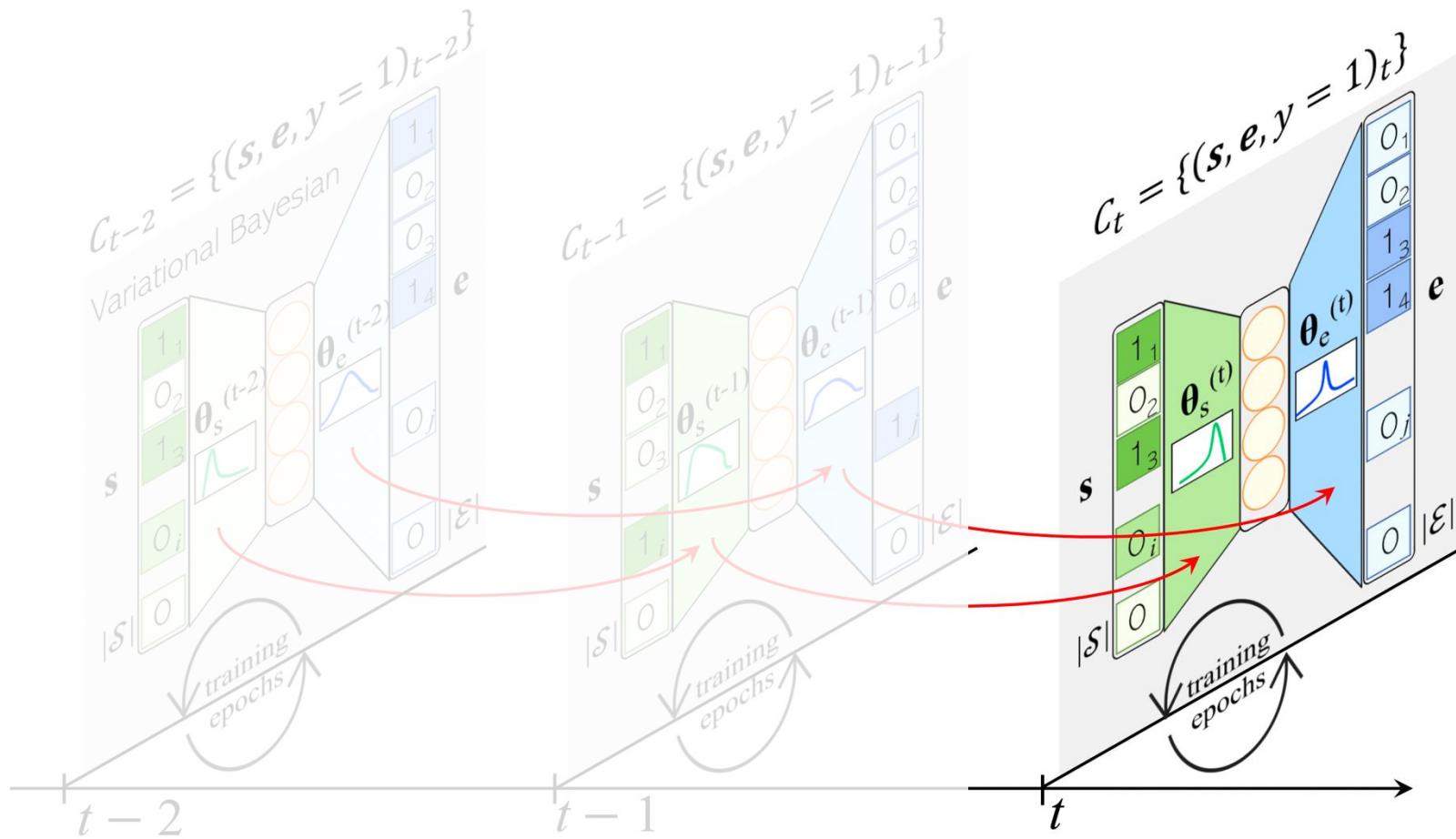


Streaming Training Strategy



Streaming Training Strategy





$T+1$

Streaming Training Strategy

Table 1: Statistics of the raw and preprocessed datasets.

	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	

Table 1: Statistics of the raw and preprocessed datasets.

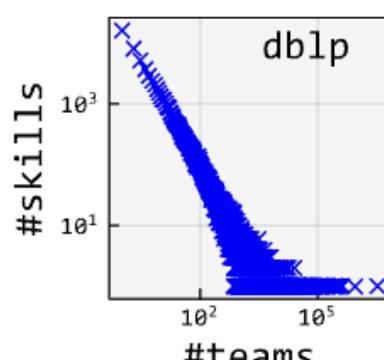
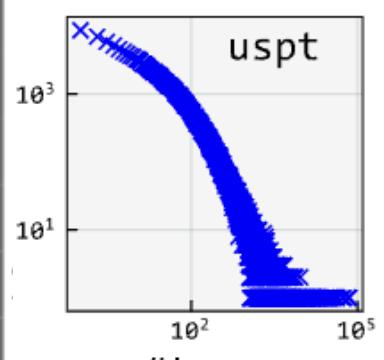
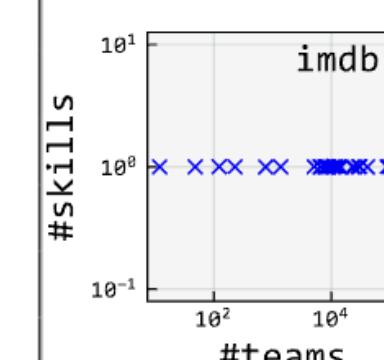
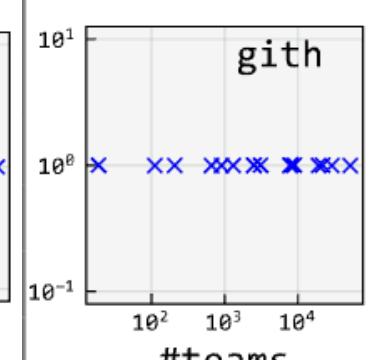
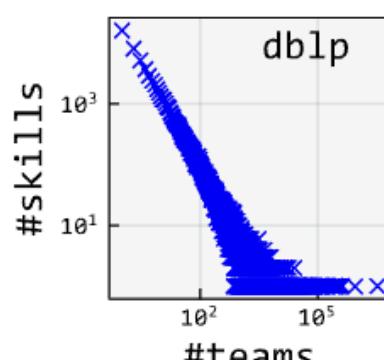
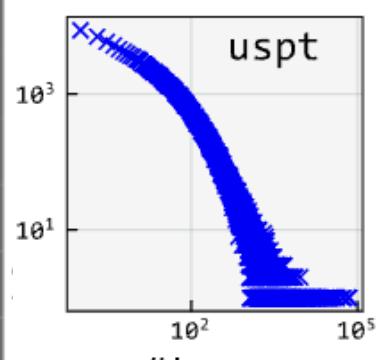
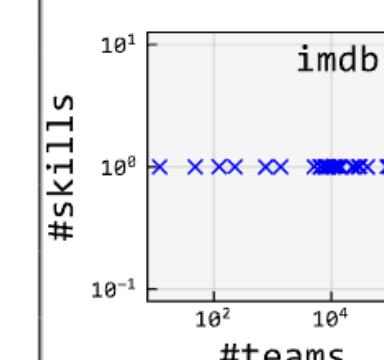
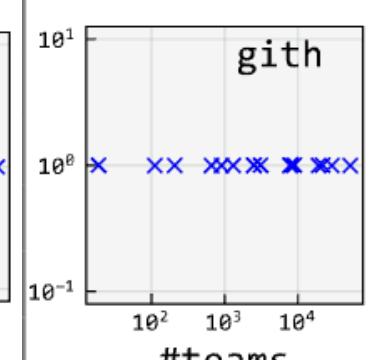
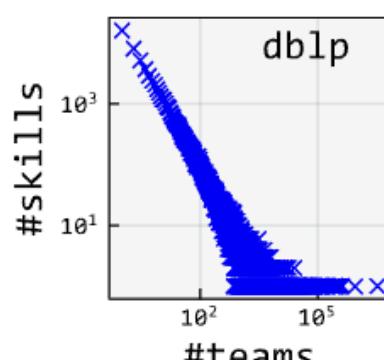
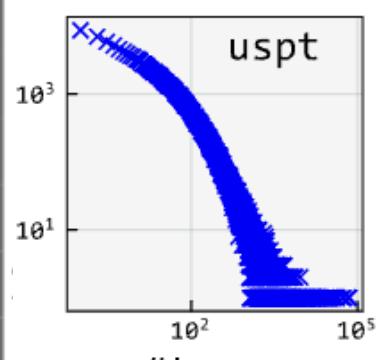
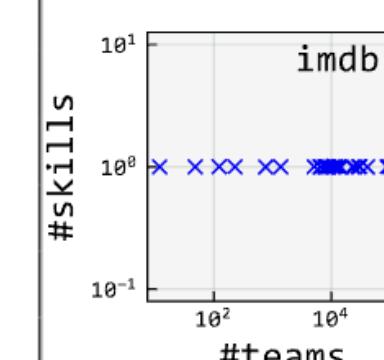
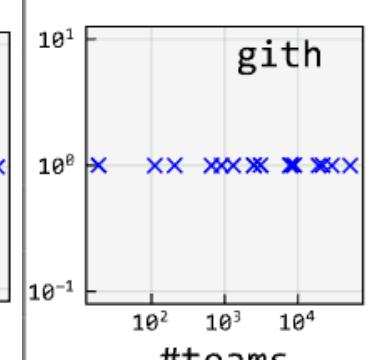
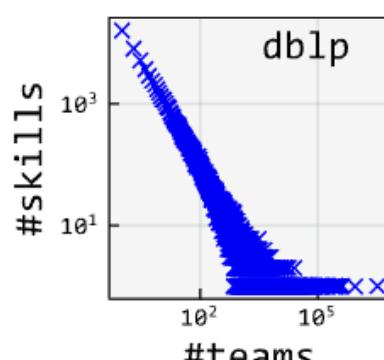
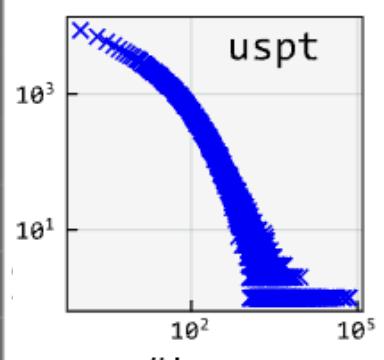
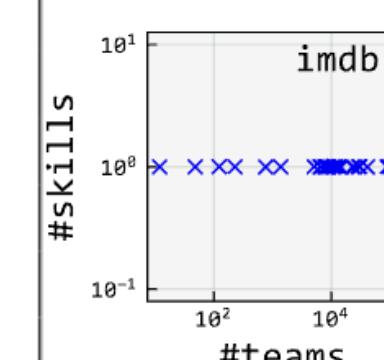
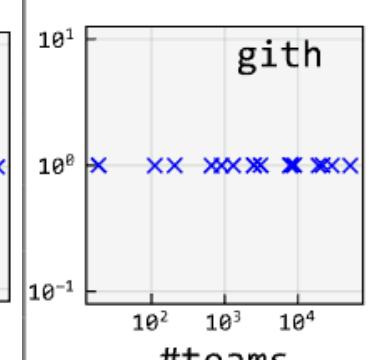
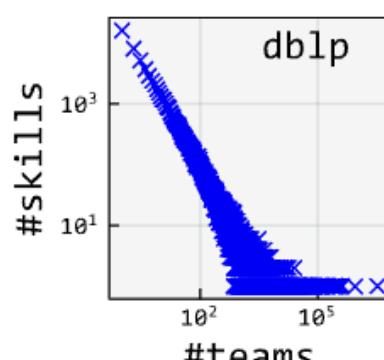
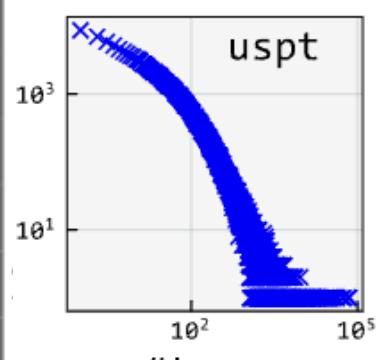
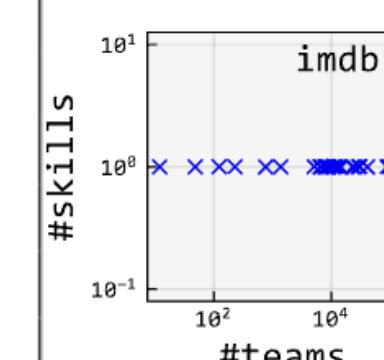
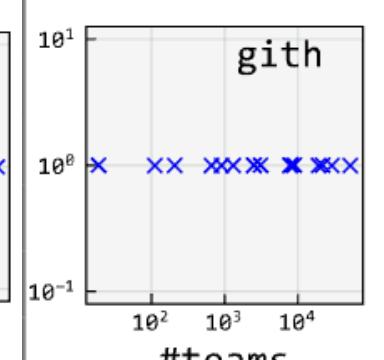
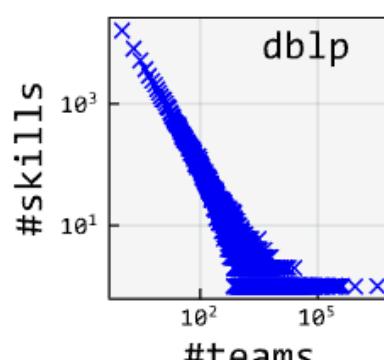
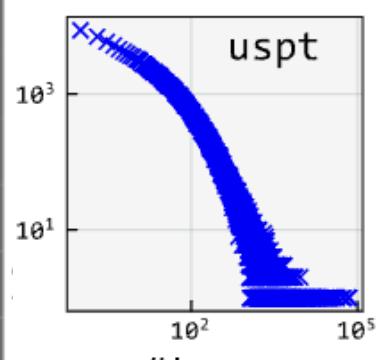
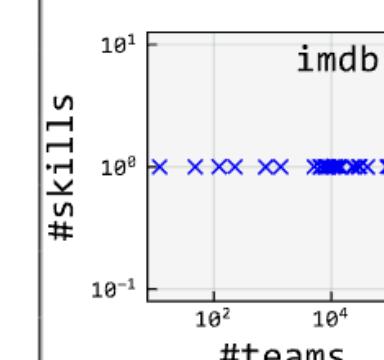
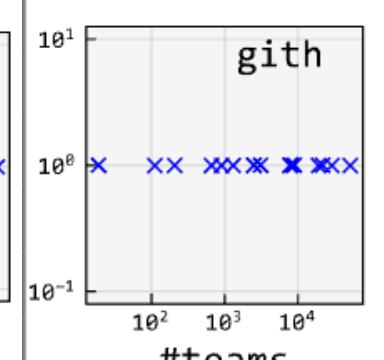
	dblp		uspt		imdb		gith	
	raw	filtered	raw	filtered	raw	filtered	raw	filtered
#teams	4,877,383	99,375	7,068,508	152,317	507,034	32,059	132,851	11,312
#unique experts	5,022,955	14,214	3,508,807	12,914	876,981	2,011	452,606	2,686
#unique skills	89,504	29,661	241,961	67,315	28	23	20	19
avg #expert per team								
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	

Table 1: Statistics of the raw and preprocessed datasets.

	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	

**RQ1:** Does moving embeddings of experts and skill through time in the latent space improve the performance of neural models for the prediction of future successful teams?

**RQ2:** Does adding time explicitly to the input embeddings of skills boost neural models performance?

**RQ3:** Is the impact of our proposed training strategy consistent across datasets from various domains with distinct statistical distributions?

## Low values of evaluation metrics for practical application

- Primarily due to the simplicity of the architectures
- Small number of epochs

Our main goal is not to report state-of-the-art results for a novel model  
But to showcase the synergistic effects of streaming training strategy

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

# RQ1: Randomly Shuffled vs. Streaming?

Variational Bayesian neural network with streaming (tbnn-\*) and lack thereof (bnn-\*)

--

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	<b>0.4299</b>	<b>0.3973</b>	<b>0.3612</b>	<b>0.2601</b>	<b>0.5963</b>	<b>1.0801</b>	<b>0.4284</b>	<b>0.5221</b>	<b>0.7465</b>	<b>0.1947</b>	<b>0.2864</b>	<b>0.3520</b>	<b>77.01</b>
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	<b>1.2268</b>	<b>1.0583</b>	<b>0.9324</b>	<b>0.6037</b>	<b>1.2928</b>	<b>2.2518</b>	<b>1.2322</b>	<b>1.2960</b>	<b>1.7348</b>	<b>0.4626</b>	<b>0.6659</b>	<b>0.8118</b>	<b>85.34</b>

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

| Model | 1st | 2nd | 3rd | 4th | 5th | 6th | 7th | 8th | 9th | 10th | 11th | 12th | 13th | 14th | 15th | 16th | 17th | 18th | 19th | 20th | 21st | 22nd | 23rd | 24th | 25th | 26th | 27th | 28th | 29th | 30th | 31st | 32nd | 33rd | 34th | 35th | 36th | 37th | 38th | 39th | 40th | 41st | 42nd | 43rd | 44th | 45th | 46th | 47th | 48th | 49th | 50th | 51st | 52nd | 53rd | 54th | 55th | 56th | 57th | 58th | 59th | 60th | 61st | 62nd | 63rd | 64th | 65th | 66th | 67th | 68th | 69th | 70th | 71st | 72nd | 73rd | 74th | 75th | 76th | 77th | 78th | 79th | 80th | 81st | 82nd | 83rd | 84th | 85th | 86th | 87th | 88th | 89th | 90th | 91st | 92nd | 93rd | 94th | 95th | 96th | 97th | 98th | 99th | 100th | 101st | 102nd | 103rd | 104th | 105th | 106th | 107th | 108th | 109th | 110th | 111st | 112nd | 113rd | 114th | 115th | 116th | 117th | 118th | 119th | 120th | 121st | 122nd | 123rd | 124th | 125th | 126th | 127th | 128th | 129th | 130th | 131st | 132nd | 133rd | 134th | 135th | 136th | 137th | 138th | 139th | 140th | 141st | 142nd | 143rd | 144th | 145th | 146th | 147th | 148th | 149th | 150th | 151st | 152nd | 153rd | 154th | 155th | 156th | 157th | 158th | 159th | 160th | 161st | 162nd | 163rd | 164th | 165th | 166th | 167th | 168th | 169th | 170th | 171st | 172nd | 173rd | 174th | 175th | 176th | 177th | 178th | 179th | 180th | 181st | 182nd | 183rd | 184th | 185th | 186th | 187th | 188th | 189th | 190th | 191st | 192nd | 193rd | 194th | 195th | 196th | 197th | 198th | 199th | 200th | 201st | 202nd | 203rd | 204th | 205th | 206th | 207th | 208th | 209th | 210th | 211st | 212nd | 213rd | 214th | 215th | 216th | 217th | 218th | 219th | 220th | 221st | 222nd | 223rd | 224th | 225th | 226th | 227th | 228th | 229th | 230th | 231st | 232nd | 233rd | 234th | 235th | 236th | 237th | 238th | 239th | 240th | 241st | 242nd | 243rd | 244th | 245th | 246th | 247th | 248th | 249th | 250th | 251st | 252nd | 253rd | 254th | 255th | 256th | 257th | 258th | 259th | 260th | 261st | 262nd | 263rd | 264th | 265th | 266th | 267th | 268th | 269th | 270th | 271st | 272nd | 273rd | 274th | 275th | 276th | 277th | 278th | 279th | 280th | 281st | 282nd | 283rd | 284th | 285th | 286th | 287th | 288th | 289th | 290th | 291st | 292nd | 293rd | 294th | 295th | 296th | 297th | 298th | 299th | 300th | 301st | 302nd | 303rd | 304th | 305th | 306th | 307th | 308th | 309th | 310th | 311st | 312nd | 313rd | 314th | 315th | 316th | 317th | 318th | 319th | 320th | 321st | 322nd | 323rd | 324th | 325th | 326th | 327th | 328th | 329th | 330th | 331st | 332nd | 333rd | 334th | 335th | 336th | 337th | 338th | 339th | 340th | 341st | 342nd | 343rd | 344th | 345th | 346th | 347th | 348th | 349th | 350th | 351st | 352nd | 353rd | 354th | 355th | 356th | 357th | 358th | 359th | 360th | 361st | 362nd | 363rd | 364th | 365th | 366th | 367th | 368th | 369th | 370th | 371st | 372nd | 373rd | 374th | 375th | 376th | 377th | 378th | 379th | 380th | 381st | 382nd | 383rd | 384th | 385th | 386th | 387th | 388th | 389th | 390th | 391st | 392nd | 393rd | 394th | 395th | 396th | 397th | 398th | 399th | 400th | 401st | 402nd | 403rd | 404th | 405th | 406th | 407th | 408th | 409th | 410th | 411st | 412nd | 413rd | 414th | 415th | 416th | 417th | 418th | 419th | 420th | 421st | 422nd | 423rd | 424th | 425th | 426th | 427th | 428th | 429th | 430th | 431st | 432nd | 433rd | 434th | 435th | 436th | 437th | 438th | 439th | 440th | 441st | 442nd | 443rd | 444th | 445th | 446th | 447th | 448th | 449th | 450th | 451st | 452nd | 453rd | 454th | 455th | 456th | 457th | 458th | 459th | 460th | 461st | 462nd | 463rd | 464th | 465th | 466th | 467th | 468th | 469th | 470th | 471st | 472nd | 473rd | 474th | 475th | 476th | 477th | 478th | 479th | 480th | 481st | 482nd | 483rd | 484th | 485th | 486th | 487th | 488th | 489th | 490th | 491st | 492nd | 493rd | 494th | 495th | 496th | 497th | 498th | 499th | 500th | 501st | 502nd | 503rd | 504th | 505th | 506th | 507th | 508th | 509th | 510th | 511st | 512nd | 513rd | 514th | 515th | 516th | 517th | 518th | 519th | 520th | 521st | 522nd | 523rd | 524th | 525th | 526th | 527th | 528th | 529th | 530th | 531st | 532nd | 533rd | 534th | 535th | 536th | 537th | 538th | 539th | 540th | 541st | 542nd | 543rd | 544th | 545th | 546th | 547th | 548th | 549th | 550th | 551st | 552nd | 553rd | 554th | 555th | 556th | 557th | 558th | 559th | 560th | 561st | 562nd | 563rd | 564th | 565th | 566th | 567th | 568th | 569th | 570th | 571st | 572nd | 573rd | 574th | 575th | 576th | 577th | 578th | 579th | 580th | 581st | 582nd | 583rd | 584th | 585th | 586th | 587th | 588th | 589th | 590th | 591st | 592nd | 593rd | 594th | 595th | 596th | 597th | 598th | 599th | 600th | 601st | 602nd | 603rd | 604th | 605th | 606th | 607th | 608th | 609th | 610th | 611st | 612nd | 613rd | 614th | 615th | 616th | 617th | 618th | 619th | 620th | 621st | 622nd | 623rd | 624th | 625th | 626th | 627th | 628th | 629th | 630th | 631st | 632nd | 633rd | 634th | 635th | 636th | 637th | 638th | 639th | 640th | 641st | 642nd | 643rd | 644th | 645th | 646th | 647th | 648th | 649th | 650th | 651st | 652nd | 653rd | 654th | 655th | 656th | 657th | 658th | 659th | 660th | 661st | 662nd | 663rd | 664th | 665th | 666th | 667th | 668th | 669th | 670th | 671st | 672nd | 673rd | 674th | 675th | 676th | 677th | 678th | 679th | 680th | 681st | 682nd | 683rd | 684th | 685th | 686th | 687th | 688th | 689th | 690th | 691st | 692nd | 693rd | 694th | 695th | 696th | 697th | 698th | 699th | 700th | 701st | 702nd | 703rd | 704th | 705th | 706th | 707th | 708th | 709th | 710th | 711st | 712nd | 713rd | 714th | 715th | 716th | 717th | 718th | 719th | 720th | 721st | 722nd | 723rd | 724th | 725th | 726th | 727th | 728th | 729th | 730th | 731st | 732nd | 733rd | 734th | 735th | 736th | 737th | 738th | 739th | 740th | 741st | 742nd | 743rd | 744th | 745th | 746th | 747th | 748th | 749th | 750th | 751st | 752nd | 753rd | 754th | 755th | 756th | 757th | 758th | 759th | 760th | 761st | 762nd | 763rd | 764th | 765th | 766th | 767th | 768th | 769th | 770th | 771st | 772nd | 773rd | 774th | 775th | 776th | 777th | 778th | 779th | 780th | 781st | 782nd | 783rd | 784th | 785th | 786th | 787th | 788th | 789th | 790th | 791st | 792nd | 793rd | 794th | 795th | 796th | 797th | 798th | 799th | 800th | 801st | 802nd | 803rd | 804th | 805th | 806th | 807th | 808th | 809th | 810th | 811st | 812nd | 813rd | 814th | 815th | 816th | 817th | 818th | 819th | 820th | 821st | 822nd | 823rd | 824th | 825th | 826th | 827th | 828th | 829th | 830th | 831st | 832nd | 833rd | 834th | 835th | 836th | 837th | 838th | 839th | 840th | 841st | 842nd | 843rd | 844th | 845th | 846th | 847th | 848th | 849th | 850th | 851st | 852nd | 853rd | 854th | 855th | 856th | 857th | 858th | 859th | 860th | 861st | 862nd | 863rd | 864th | 865th | 866th | 867th | 868th | 869th | 870th | 871st | 872nd | 873rd | 874th | 875th | 876th | 877th | 878th | 879th | 880th | 881st | 882nd | 883rd | 884th | 885th | 886th | 887th | 888th | 889th | 890th | 891st | 892nd | 893rd | 894th | 895th | 896th | 897th | 898th | 899th | 900th | 901st | 902nd | 903rd | 904th | 905th | 906th | 907th | 908th | 909th | 910th | 911st | 912nd | 913rd | 914th | 915th | 916th | 917th | 918th | 919th | 920th | 921st | 922nd | 923rd | 924th | 925th | 926th | 927th | 928th | 929th | 930th | 931st | 932nd | 933rd | 934th | 935th | 936th | 937th | 938th | 939th | 940th | 941st | 942nd | 943rd | 944th | 945th | 946th | 947th | 948th | 949th | 950th | 951st | 952nd | 953rd | 954th | 955th | 956th | 957th | 958th | 959th | 960th | 961st | 962nd | 963rd | 964th | 965th | 966th | 967th | 968th | 969th | 970th | 971st | 972nd | 973rd | 974th | 975th | 976th | 977th | 978th | 979th | 980th | 981st | 982nd | 983rd | 984th | 985th | 986th | 987th | 988th | 989th | 990th | 991st | 992nd | 993rd | 994th | 995th | 996th | 997th | 998th | 999th | 1000th | 1001st | 1002nd | 1003rd | 1004th | 1005th | 1006th | 1007th | 1008th | 1009th | 1010th | 1011st | 1012nd | 1013rd | 1014th | 1015th | 1016th | 1017th | 1018th | 1019th | 1020th | 1021st | 1022nd | 1023rd | 1024th | 1025th | 1026th | 1027th | 1028th | 1029th | 1030th | 1031st | 1032nd | 1033rd | 1034th | 1035th | 1036th | 1037th | 1038th | 1039th | 1040th | 1041st | 1042nd | 1043rd | 1044th | 1045th | 1046th | 1047th | 1048th | 1049th | 1050th | 1051st | 1052nd | 1053rd | 1054th | 1055th | 1056th | 1057th | 1058th | 1059th | 1060th | 1061st | 1062nd | 1063rd | 1064th | 1065th | 1066th | 1067th | 1068th | 1069th | 1070th | 1071st | 1072nd | 1073rd | 1074th | 1075th | 1076th | 1077th | 1078th | 1079th | 1080th | 1081st | 1082nd | 1083rd | 1084th | 1085th | 1086th | 1087th | 1088th | 1089th | 1090th | 1091st | 1092nd | 1093rd | 1094th | 1095th | 1096th | 1097th | 1098th | 1099th | 1100th | 1101st | 1102nd | 1103rd | 1104th | 1105th | 1106th | 1107th | 1108th | 1109th | 1110th | 1111st | 1112nd | 1113rd | 1114th | 1115th | 1116th | 1117th | 1118th | 1119th | 1120th | 1121st | 1122nd | 1123rd | 1124th | 1125th | 1126th | 1127th | 1128th | 1129th | 1130th | 1131st | 1132nd | 1133rd | 1134th | 1135th | 1136th | 1137th | 1138th | 1139th | 1140th | 1141st | 1142nd | 1143rd | 1144th | 1145th | 1146th | 1147th | 1148th | 1149th | 1150th | 1151st | 1152nd | 1153rd | 1154th | 1155th | 1156th | 1157th | 1158th | 1159th | 1160th | 1161st | 1162nd | 1163rd | 1164th | 1165th | 1166th | 1167th | 1168th | 1169th | 1170th | 1171st | 1172nd | 1173rd | 1174th | 1175th | 1176th | 1177th | 1178th | 1179th | 1180th | 1181st | 1182nd | 1183rd | 1184th | 1185th | 1186th | 1187th | 1188th | 1189th | 1190th | 1191st | 1192nd | 1193rd | 1194th | 1195th | 1196th | 1197th | 1198th | 1199th | 1200th | 1201st | 1202nd | 1203rd | 1204th | 1205th | 1206th | 1207th | 1208th | 1209th |<
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |

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	<b>0.4299</b>	<b>0.3973</b>	<b>0.3612</b>	<b>0.2601</b>	<b>0.5963</b>	<b>1.0801</b>	<b>0.4284</b>	<b>0.5221</b>	<b>0.7465</b>	<b>0.1947</b>	<b>0.2864</b>	<b>0.3520</b>	<b>77.01</b>
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	<b>1.2268</b>	<b>1.0583</b>	<b>0.9324</b>	<b>0.6037</b>	<b>1.2928</b>	<b>2.2518</b>	<b>1.2322</b>	<b>1.2960</b>	<b>1.7348</b>	<b>0.4626</b>	<b>0.6659</b>	<b>0.8118</b>	<b>85.34</b>

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

	Model	dblp	uspt	imdb	gith	Model	dblp	uspt	imdb	gith	Model	dblp	uspt	imdb	gith
1	Baseline	0.50	0.50	0.50	0.50	Baseline	0.50	0.50	0.50	0.50	Baseline	0.50	0.50	0.50	0.50
2	Proposed	0.50	0.50	0.50	0.50	Proposed	0.50	0.50	0.50	0.50	Proposed	0.50	0.50	0.50	0.50
3	Proposed	0.50	0.50	0.50	0.50	Proposed	0.50	0.50	0.50	0.50	Proposed	0.50	0.50	0.50	0.50

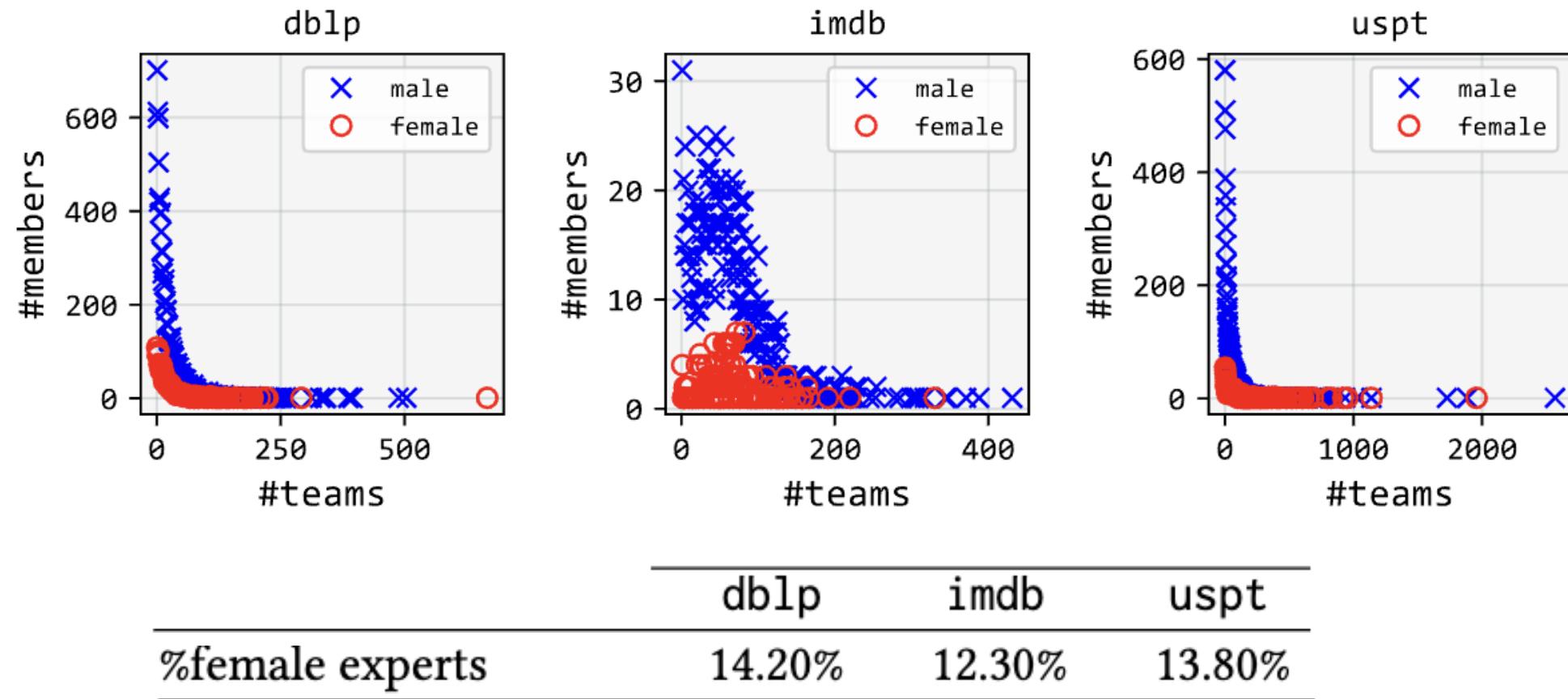
### RQ3: Is the impact consistent across datasets?

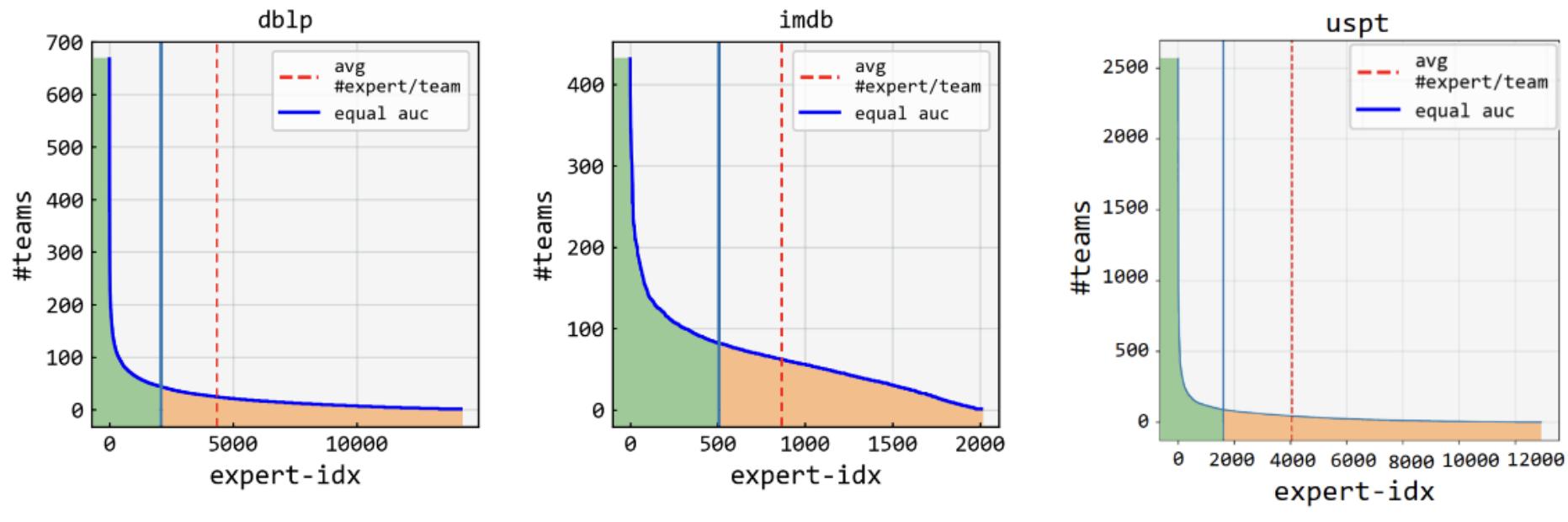
dblp, uspt vs. imdb, gith

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	<b>1.5319</b>	<u>1.4043</u>	0.5319	<b>2.4610</b>	<u>4.4965</u>	0.7548	<u>1.7381</u>	<u>2.6829</u>	0.3369	<u>0.8215</u>	<u>1.1674</u>	63.46	
tbnn_emb	<u>0.8511</u>	1.1064	1.0638	<u>0.5674</u>	1.7518	1.3262	<u>0.9474</u>	1.4848	2.2007	<u>0.4965</u>	0.8138	1.0099	<b>66.87</b>	
tbnn_dt2v_emb	<b>1.9149</b>	<u>1.1915</u>	<b>1.4468</b>	<b>1.2411</b>	<u>1.9504</u>	<b>4.5532</b>	<b>1.8667</b>	<b>1.8703</b>	<b>3.0303</b>	<b>0.9043</b>	<b>1.1099</b>	<b>1.4293</b>	<u>66.56</u>	
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]	<b>7.3267</b>	<b>4.7129</b>	<u>3.3861</u>	<b>3.5441</b>	<b>5.1580</b>	<b>6.1885</b>	<b>6.4753</b>	<b>5.8418</b>	<b>6.2665</b>	<b>2.3424</b>	<b>3.0822</b>	<b>3.3837</b>	<u>62.65</u>	
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	<u>1.8025</u>	2.3978	<u>2.8768</u>	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	<u>5.7426</u>	<u>4.5941</u>	<b>3.8020</b>	<u>2.1874</u>	<u>3.8474</u>	<u>4.7855</u>	<u>5.6081</u>	<u>5.3287</u>	<u>5.6670</u>	1.7131	<u>2.4258</u>	2.7858	<b>64.89</b>	



Future Direction: Bias

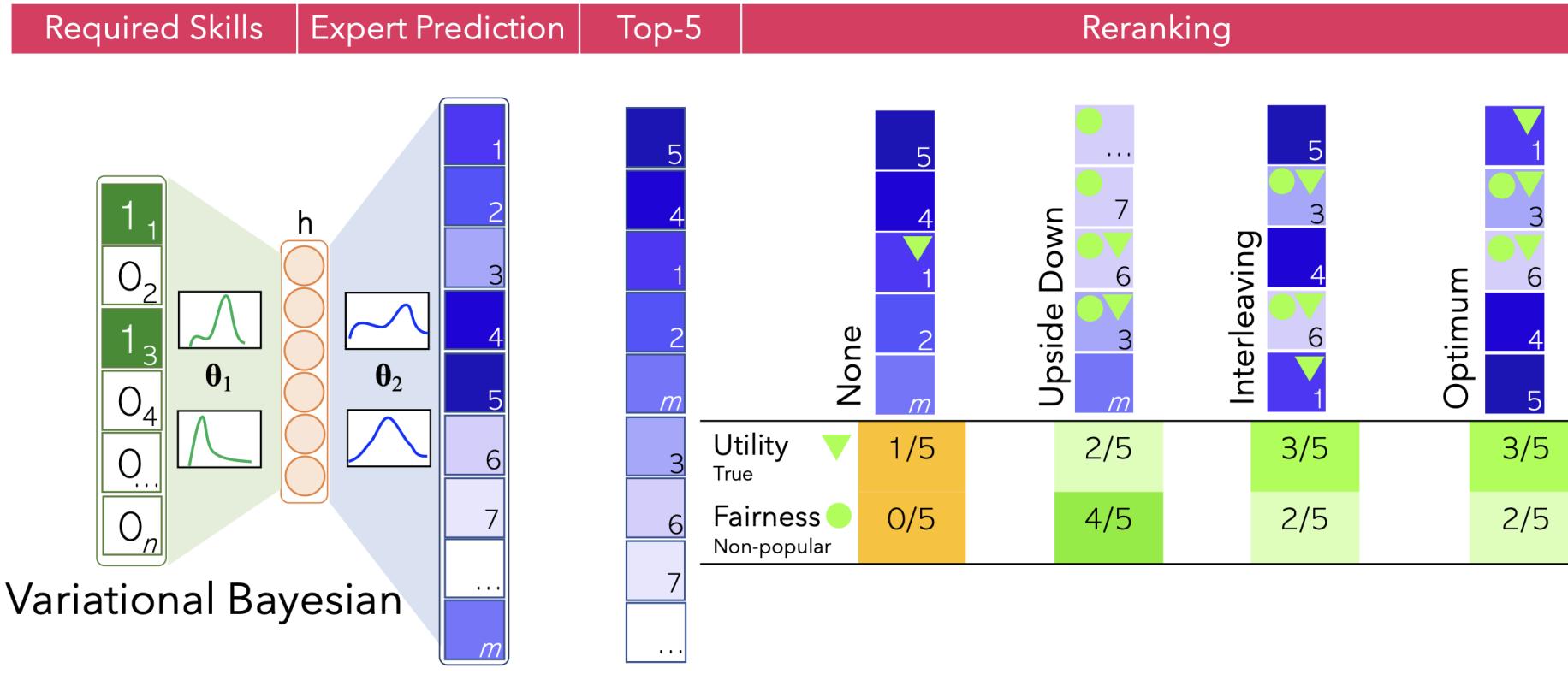




	dblp	imdb	uspt
%popular experts (avg)	31.30%	42.60%	31.40%

# Adila\*: Fairness-Aware Team Formation

feminine Arabic given name, meaning just and fair ، عادلة \*



Post-processing Fair Reranking

fani-lab / OpeNTF

Code Issues 58 Pull requests Discussions Actions Projects Wiki Security 656 Insights Settings

**OpeNTF** (Public)

Edit Pins Unwatch 4 Fork 10 Star 15 Publish your first package

[README](#) License

# OpeNTF : An Open-Source Neural Team Formation Benchmark Library

Team formation involves selecting a team of skillful experts who will, more likely than not, accomplish a task. Researchers have proposed a rich body of computational methods to automate the traditionally tedious and error-prone manual process. We previously released OpeNTF, an open-source framework hosting canonical neural models as the cutting-edge class of approaches, along with large-scale training datasets from varying domains. In this paper, we contribute OpeNTF2 that extends the initial release in two prime directions. (1) The first of its kind in

- [Fairness aware Team Formation](#)
- [Datasets and Parallel Preprocessing](#)
- [Non-Temporal Neural Team Formation](#)
- [Temporal Neural Team Prediction](#)
- [Model Architecture](#)
- [Negative Sampling Strategies](#)

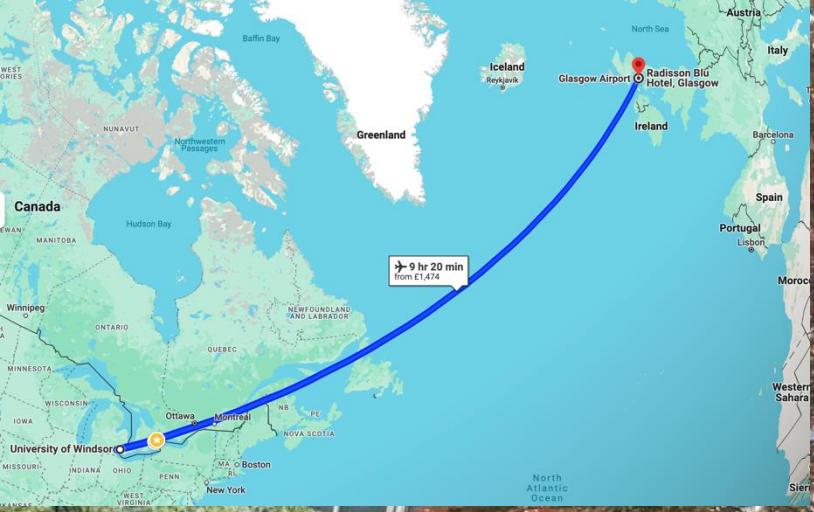
```

classDiagram
    class OpeNTF {
        Fnn
    }
    class Ntf {
        +device
        +run()
        +learn()
        +test()
        +evaluate()
    }
    class tNtf {
        +model: Ntf
        +step_ahead
        learn()
        run()
    }
    class Nmt {
        +prepare_data()
        +build_vocab()
        learn()
        test()
        eval()
        run()
    }
    class Bnn
    Ntf <|-- tNtf
    Ntf <|-- Nmt
    Ntf --> Fnn
    Ntf --> Bnn
    tNtf --> Fnn
    Nmt --> Fnn
    
```

**Contributors** 13

**Deployments** 27

✓ **github-pages** last month  
+ 26 deployments



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



Reza

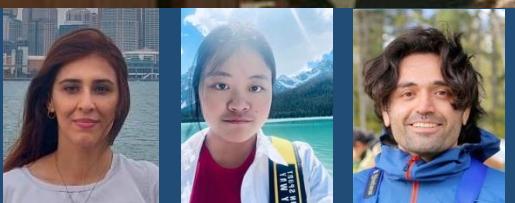
Arman

Mahdis

Hossein



[Home](#)   [Key Dates](#)   [Calls](#) ▾   [Program](#) ▾   [Attend](#) ▾   [Organizers](#)   [Sponsors](#) ▾



## Collaborative Team Recommendation for Skilled Users: Objectives, Techniques, and New perspectives



A slide for people affected by the disaster of wars ...  
Embrace - Sculpted by Hans Schleeh, born in Germany and emigrated to Canada in 1951