What are the best systems?

New Perspectives on NLP Benchmarking.

Nathan Noiry & Pierre Colombo

Datacraft 8. March 2022.

Takeaway of the presentation

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Classical AI pipeline:

Takeaway of the presentation

Classical AI pipeline:

Data collection

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Classical AI pipeline:

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Features extraction

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ML Model

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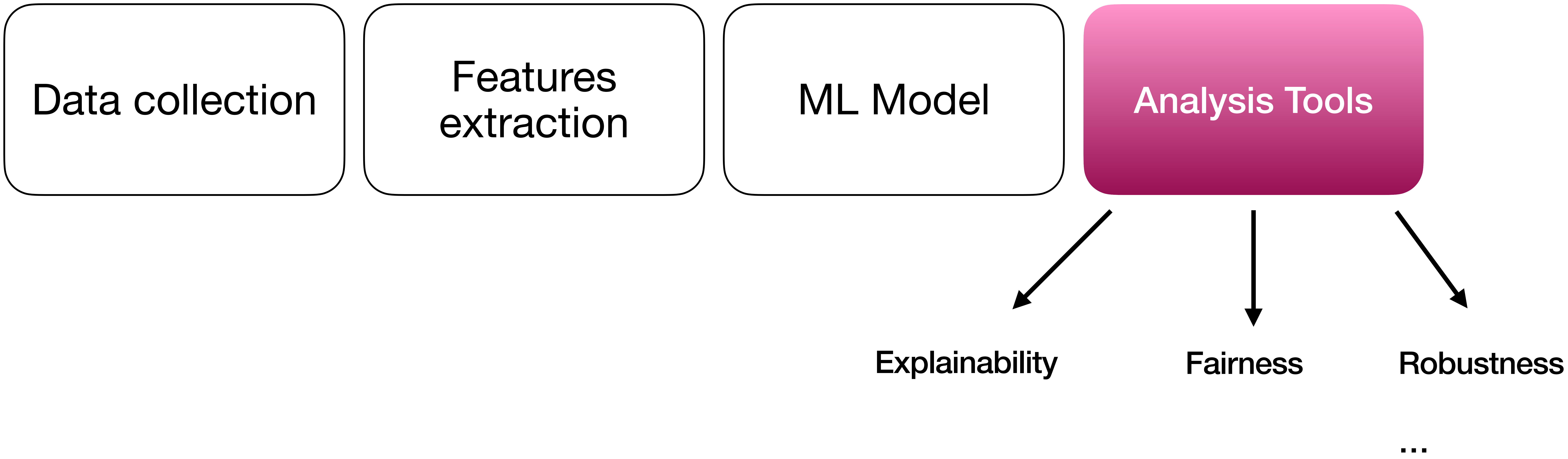
Analysis Tools

Takeaway of the presentation

Classical AI pipeline:



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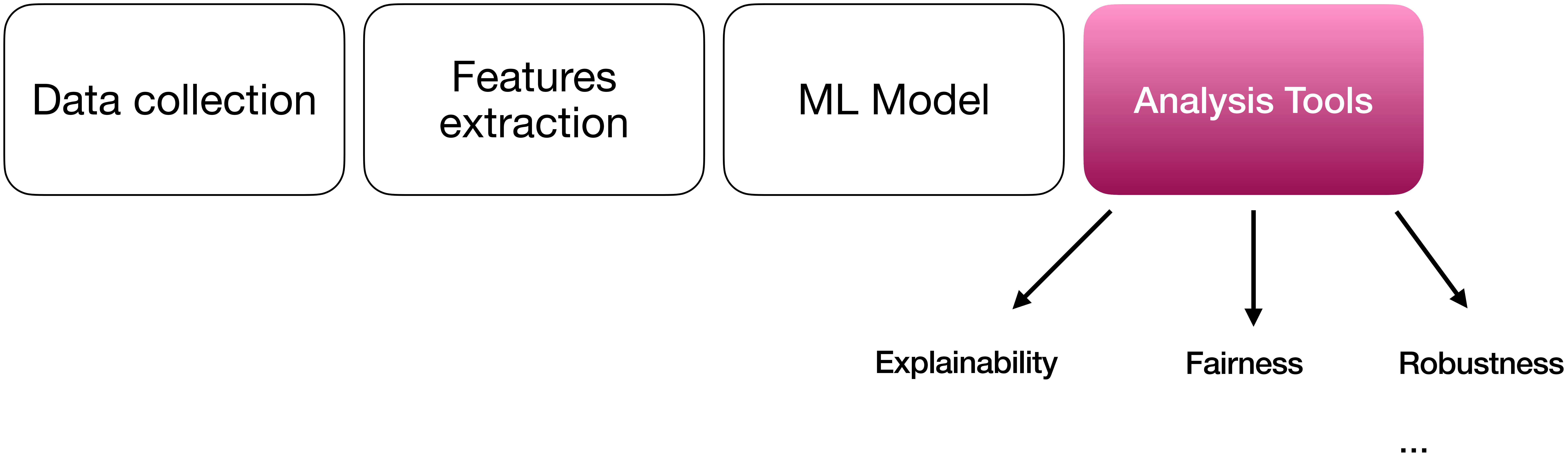

Stop focusing on the models!

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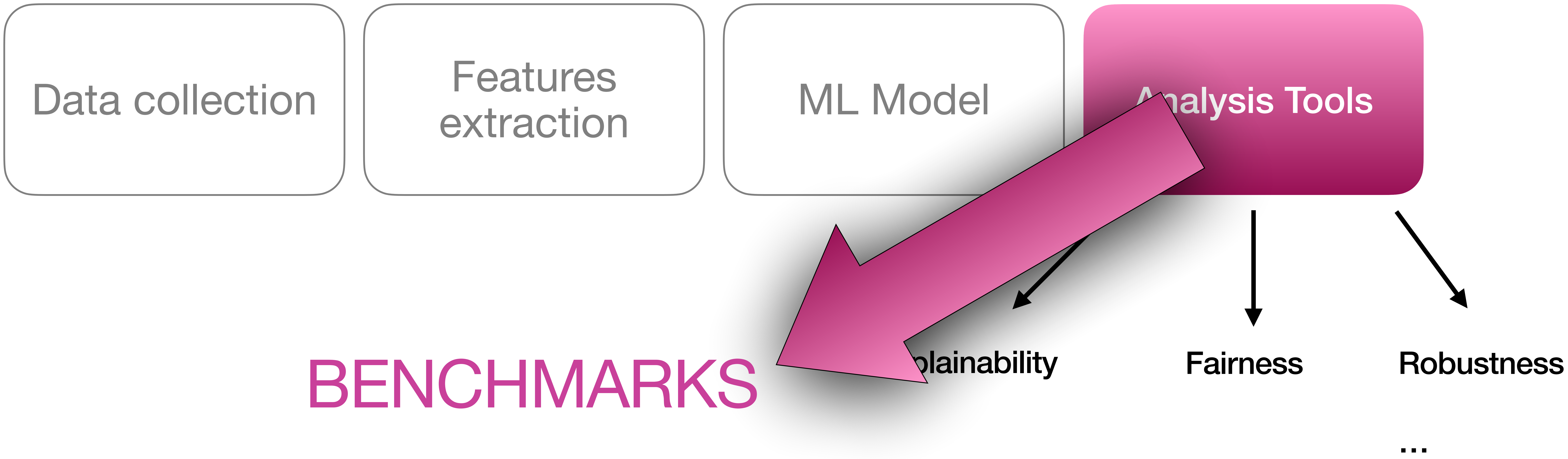

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Warmup

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What is a benchmark?

1. An ensemble of datasets
2. One or multiple metrics
3. A way to aggregate performances

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Why are benchmark vitals?

Research advances in Machine Learning are crucially fueled by *reliable evaluation procedures*

Outline

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1. **How to evaluate Natural Language Generation?**

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1.1 Context: problems, evaluation of automatic evaluation.

1.2 What are the main metrics to do reference based evaluation of NLG?

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1.2 Task Level Aggregation

1.3 Instance Level Aggregation

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3. Conclusions

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Karpinska et al. 2021

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Why do we need human evaluation?

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4. Easy to use (e.g no annotator training, no form design).

Let’s formalize the problem of Automatic Evaluation

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S_1: The weather is cold today.

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Dissimilar

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We want to build a metric m

$$m : \mathcal{S} \times \mathcal{S} \to [0,1]$$

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Correlation with human scores

Koehn 2009; Specia, Raj, and Turchi 2010; Chatzikoumi 2020

Reference based vs reference free evaluation

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Scenario 1: Let's assume we have a reference

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Edit Based

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N-gram Based

Embedding Based

Existing Methods

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Edit Based

Snover et al. 2006

Operations

- Insertion (I)
- Deletion (D)
- Substitution (S).

tailor -> sailor (S)
sailor -> sailir (S)
sailir -> sailin (S)
sailin_ -> sailing (I)

Distance is 4 !

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N-gram Based

Papineni et al. 2002

C : I like these very nice pies !

R : I like those cakes !

Unigrams

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Embedding Based

Word Mover distance
Kusner et al. 2015

BertScore
Zhang et al. 2019

MoverScore
Zhao et al. 2019

Sentence Mover
Clark et al. 2019

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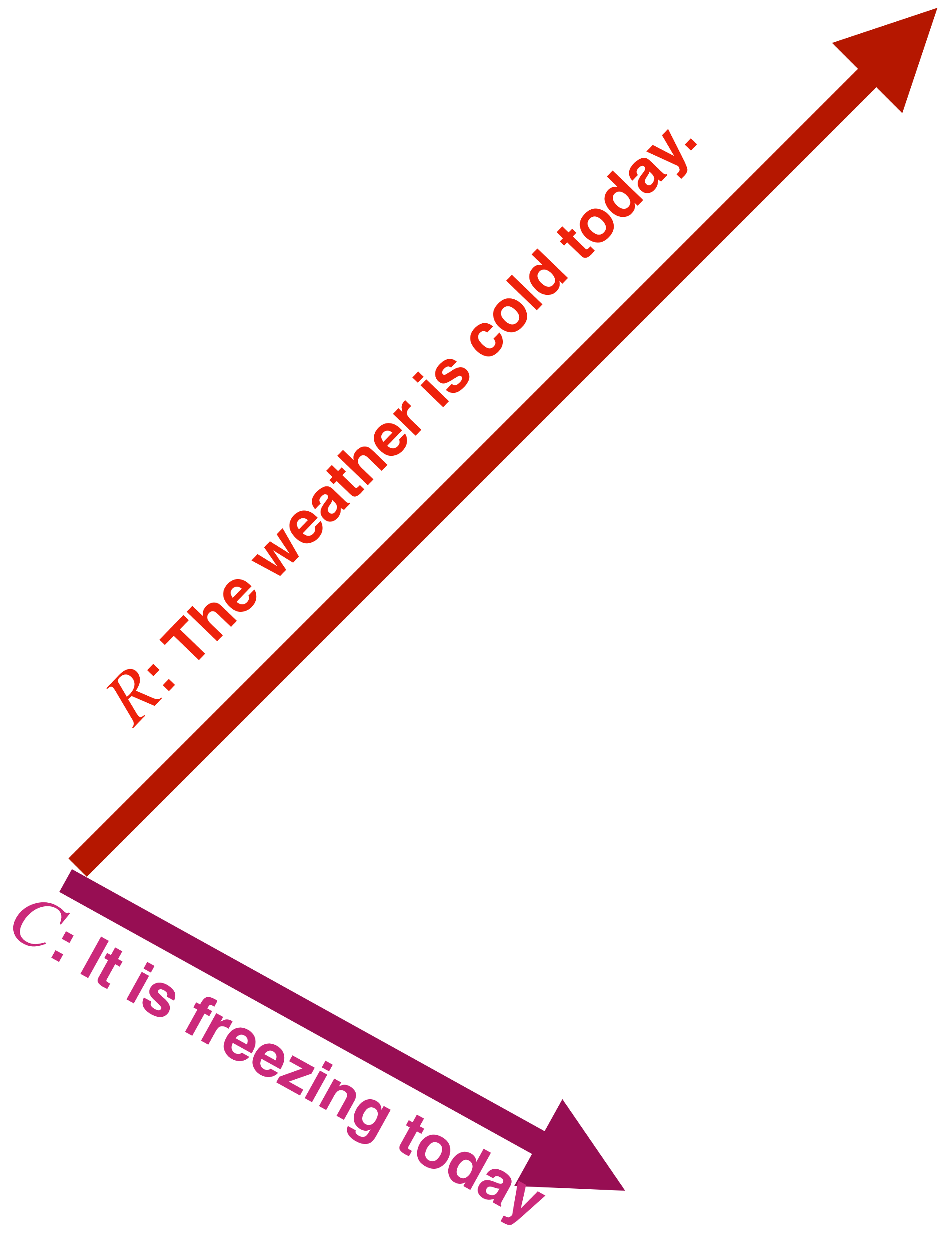

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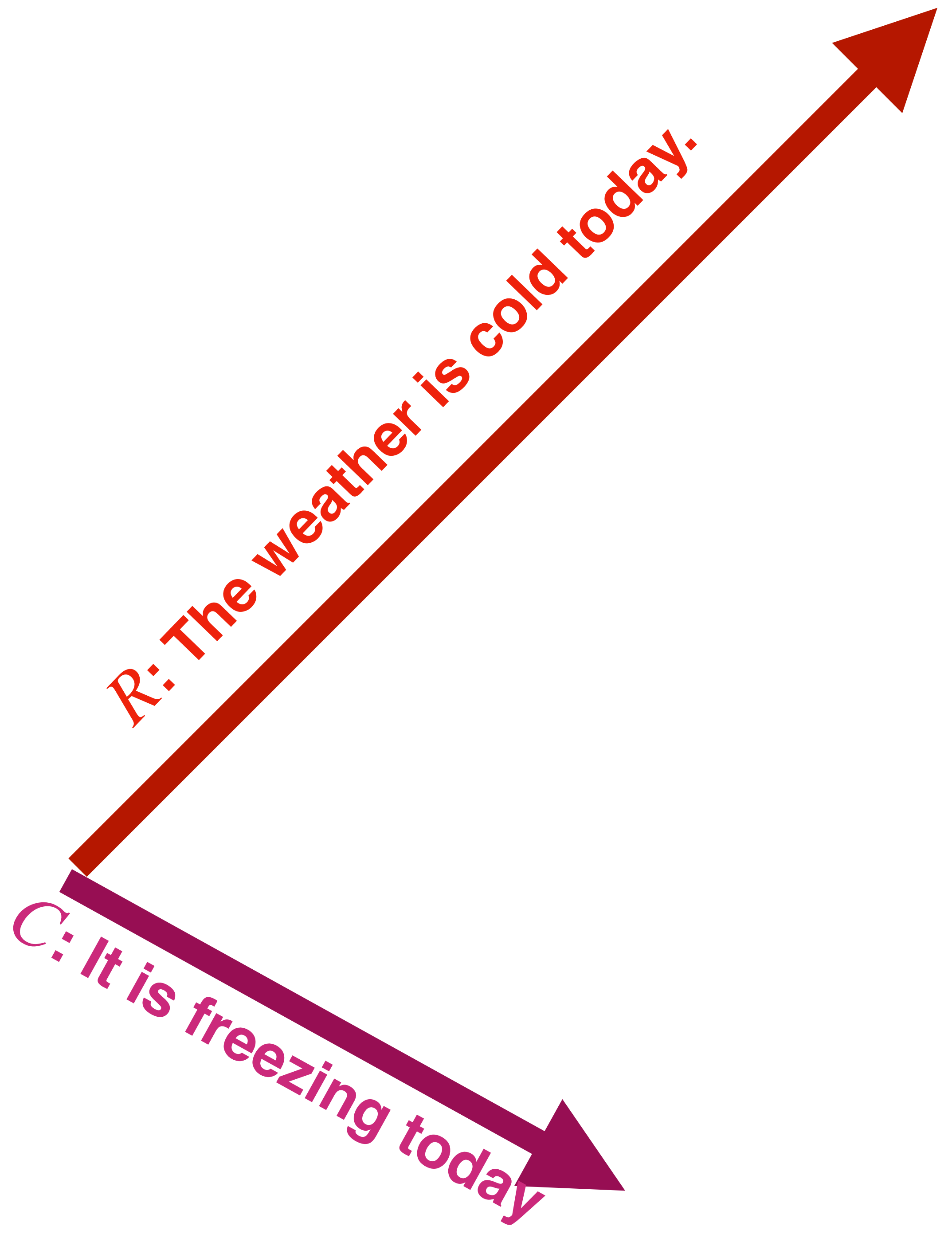
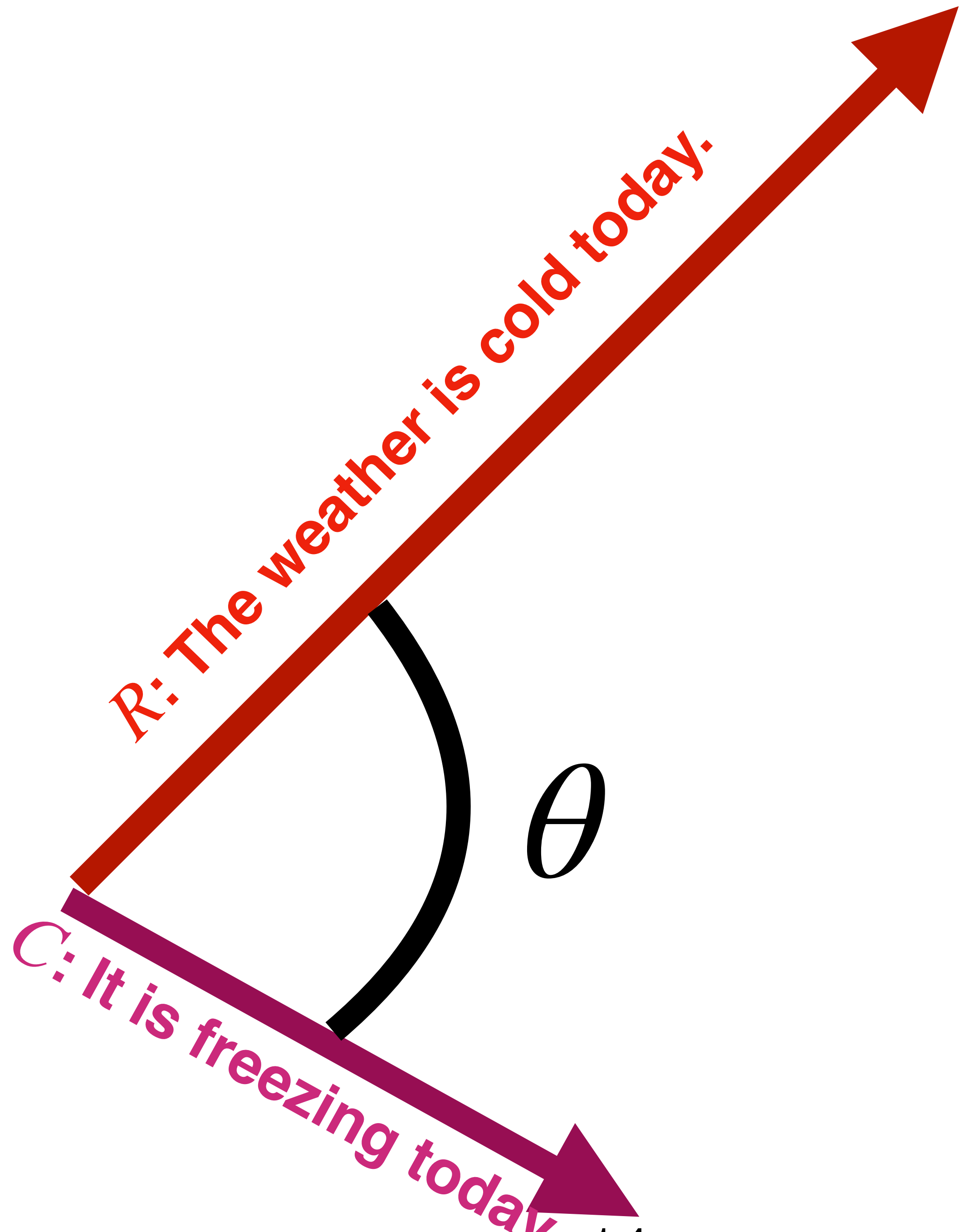


2. Choose a similarity function



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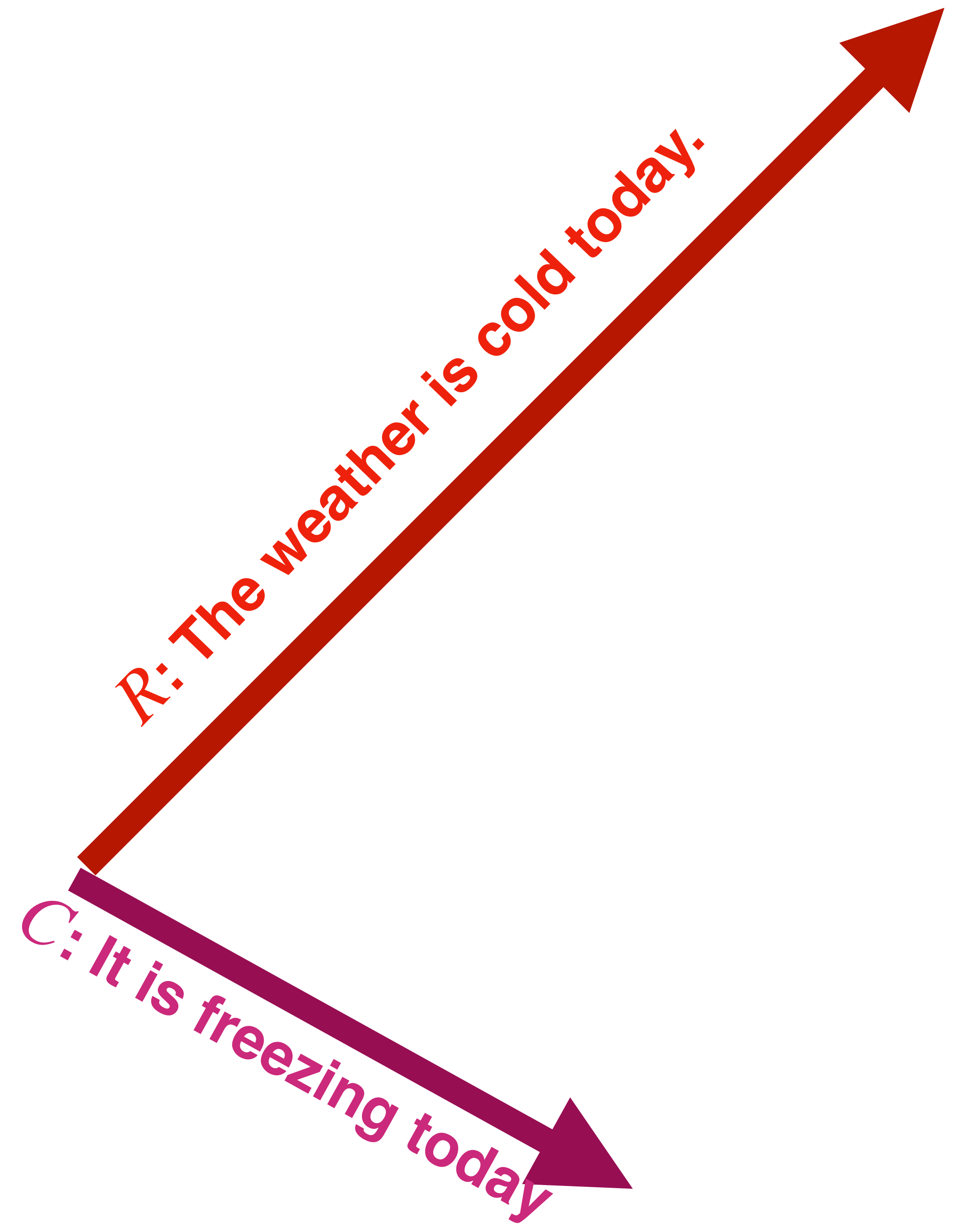

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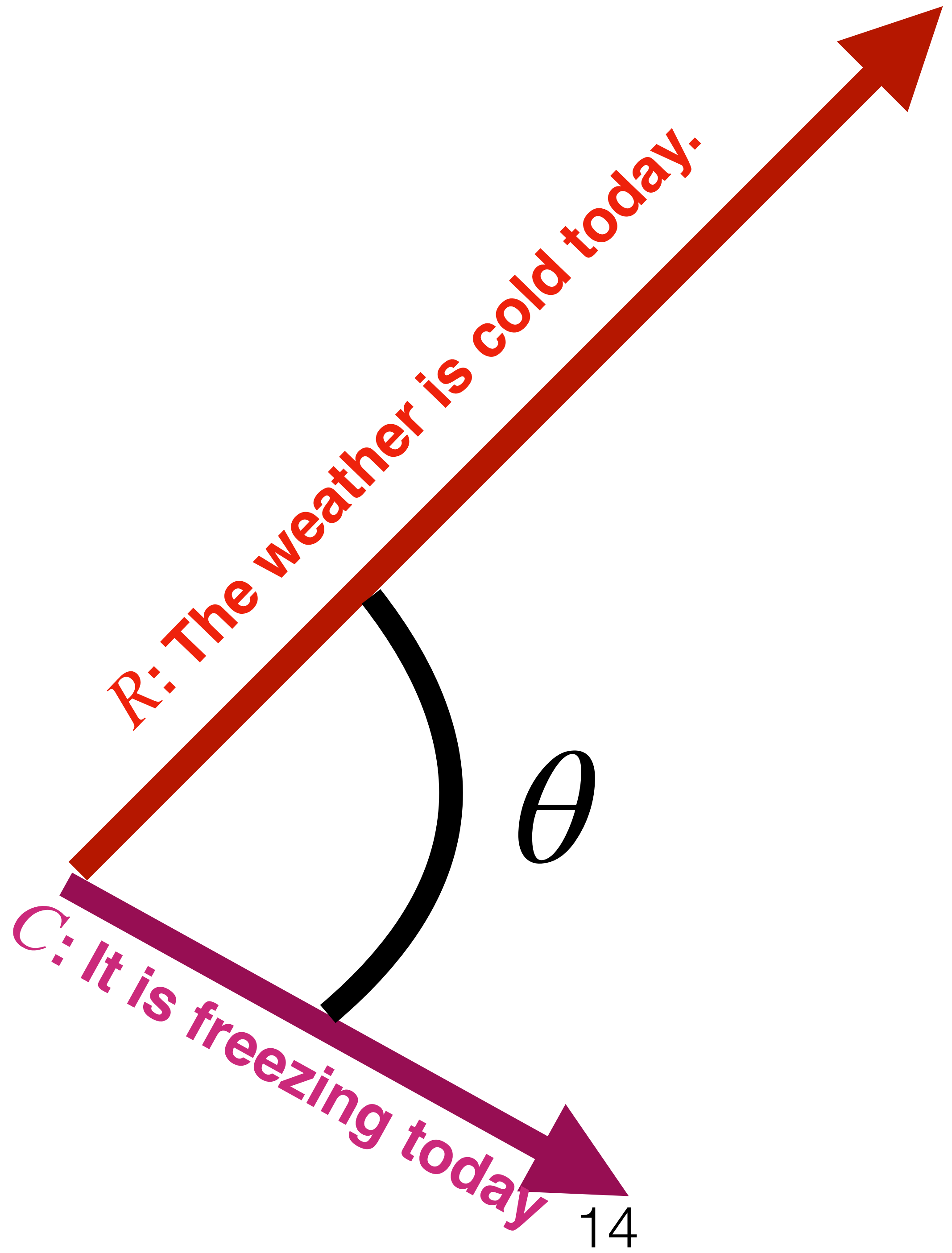

Advantage

1. Deal with paraphrases
2. Include "semantic"

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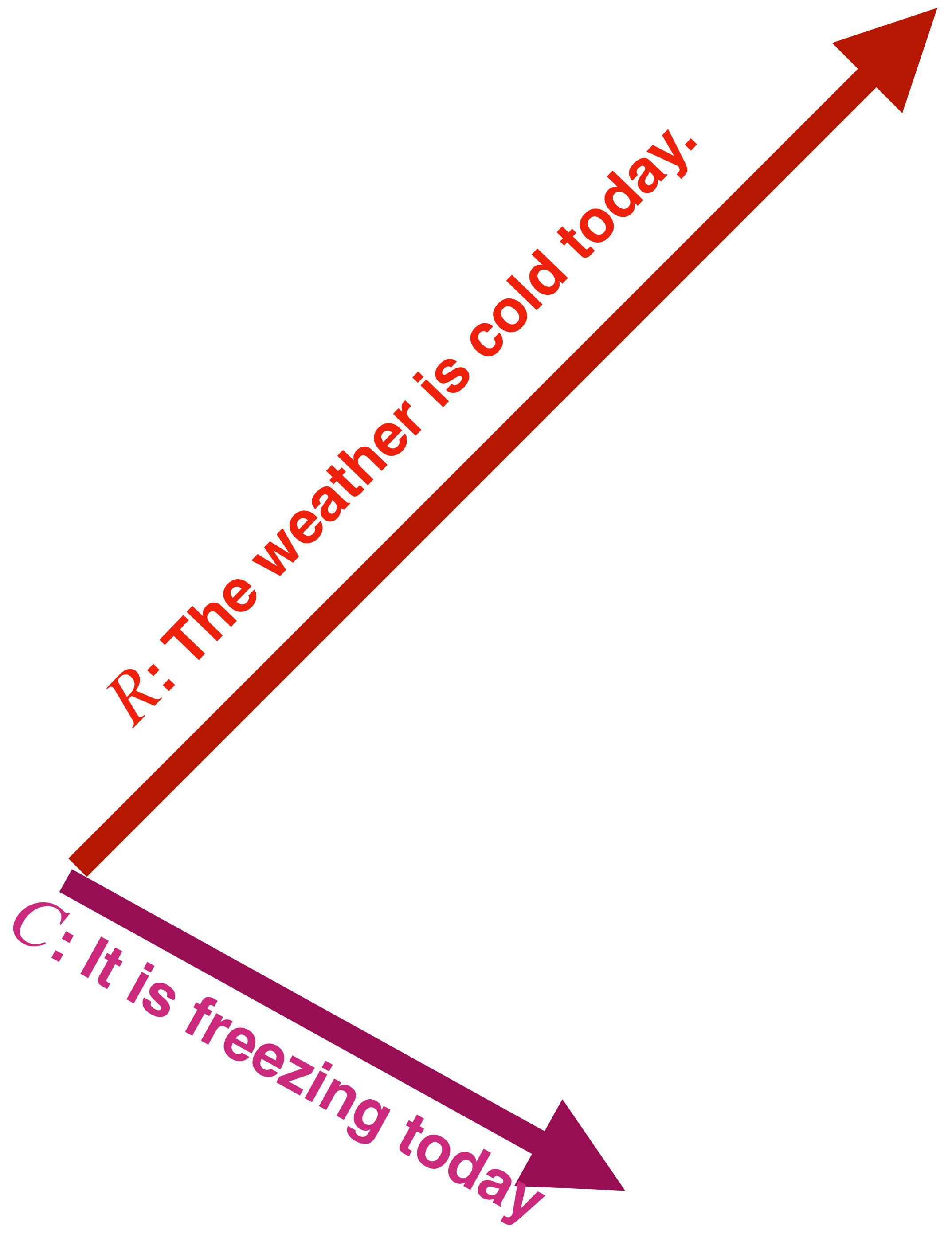

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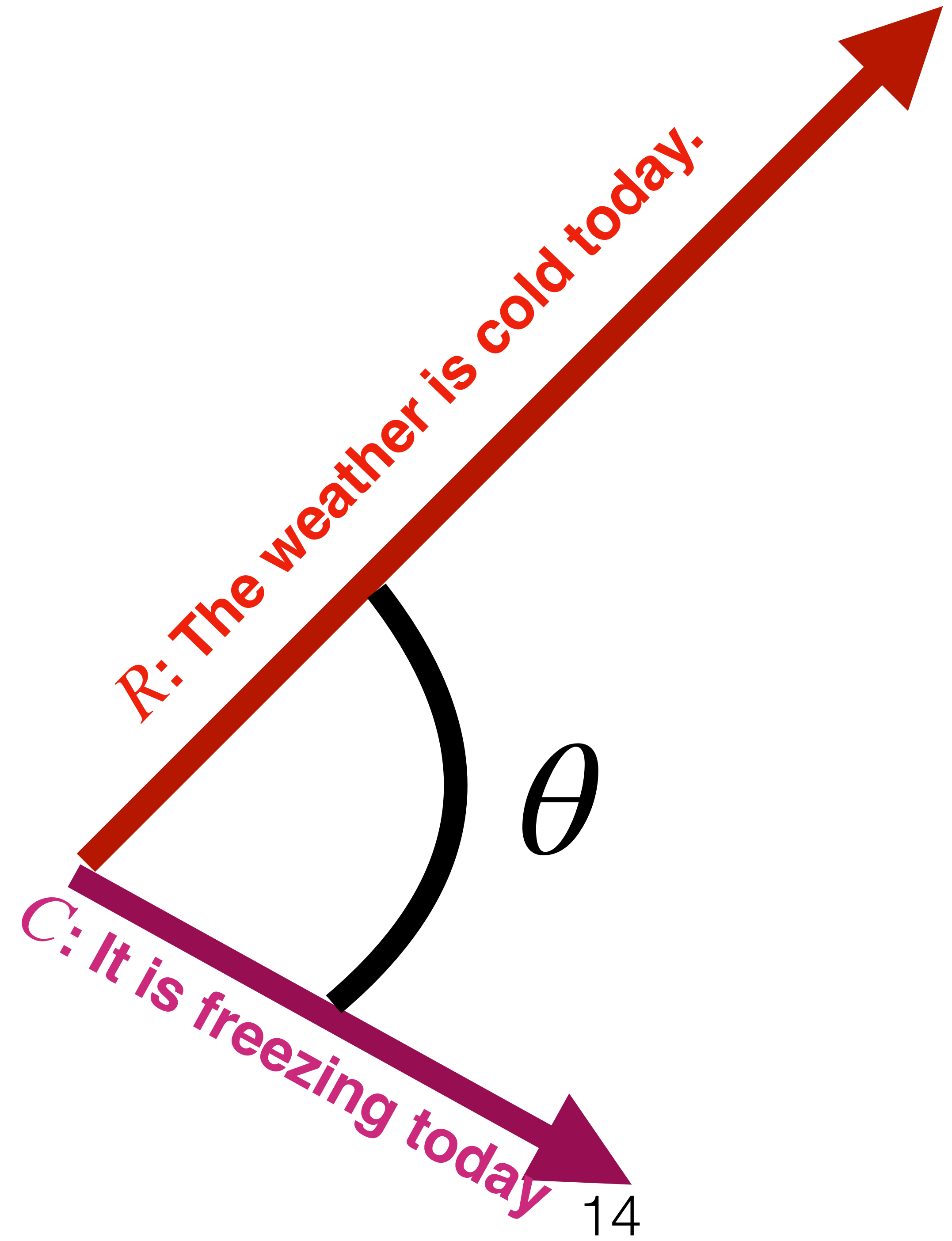

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Limitation

1. Not interpretable

BertScore

Zhang et al. 2019

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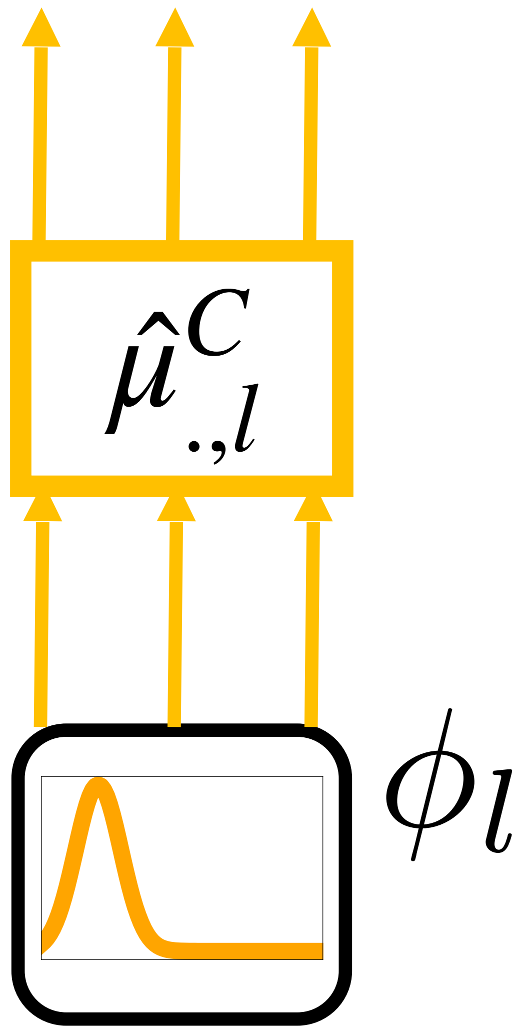

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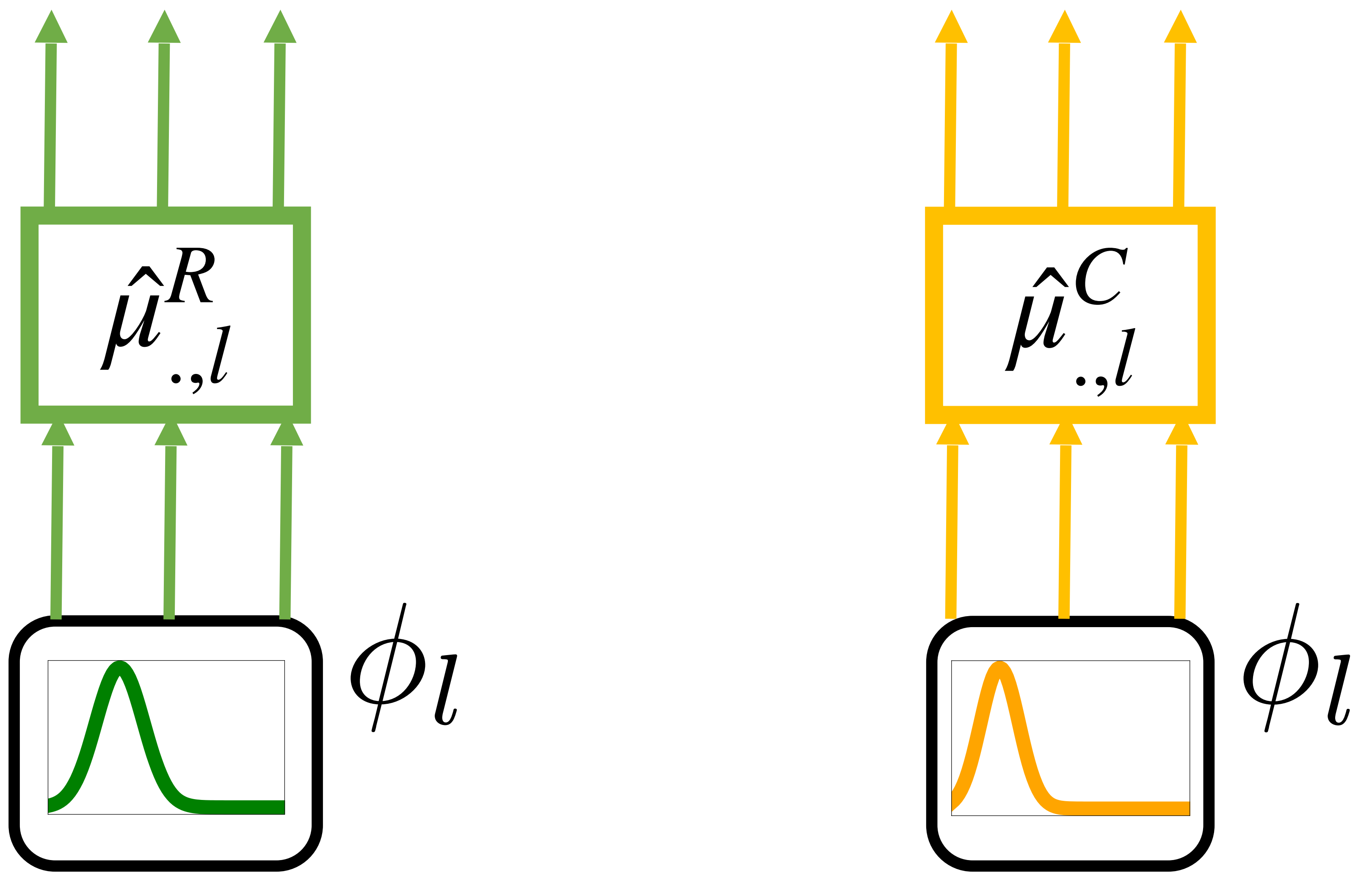

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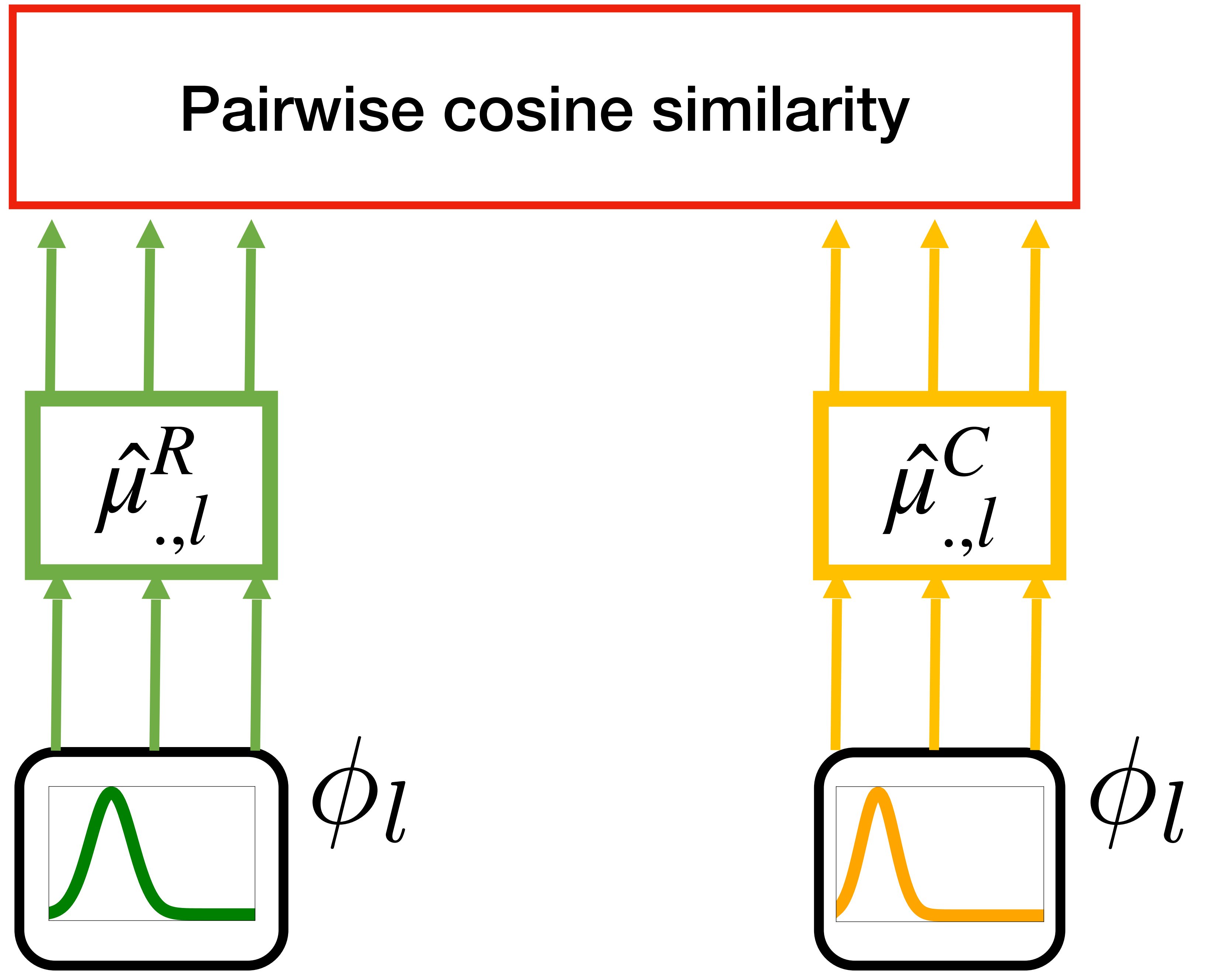

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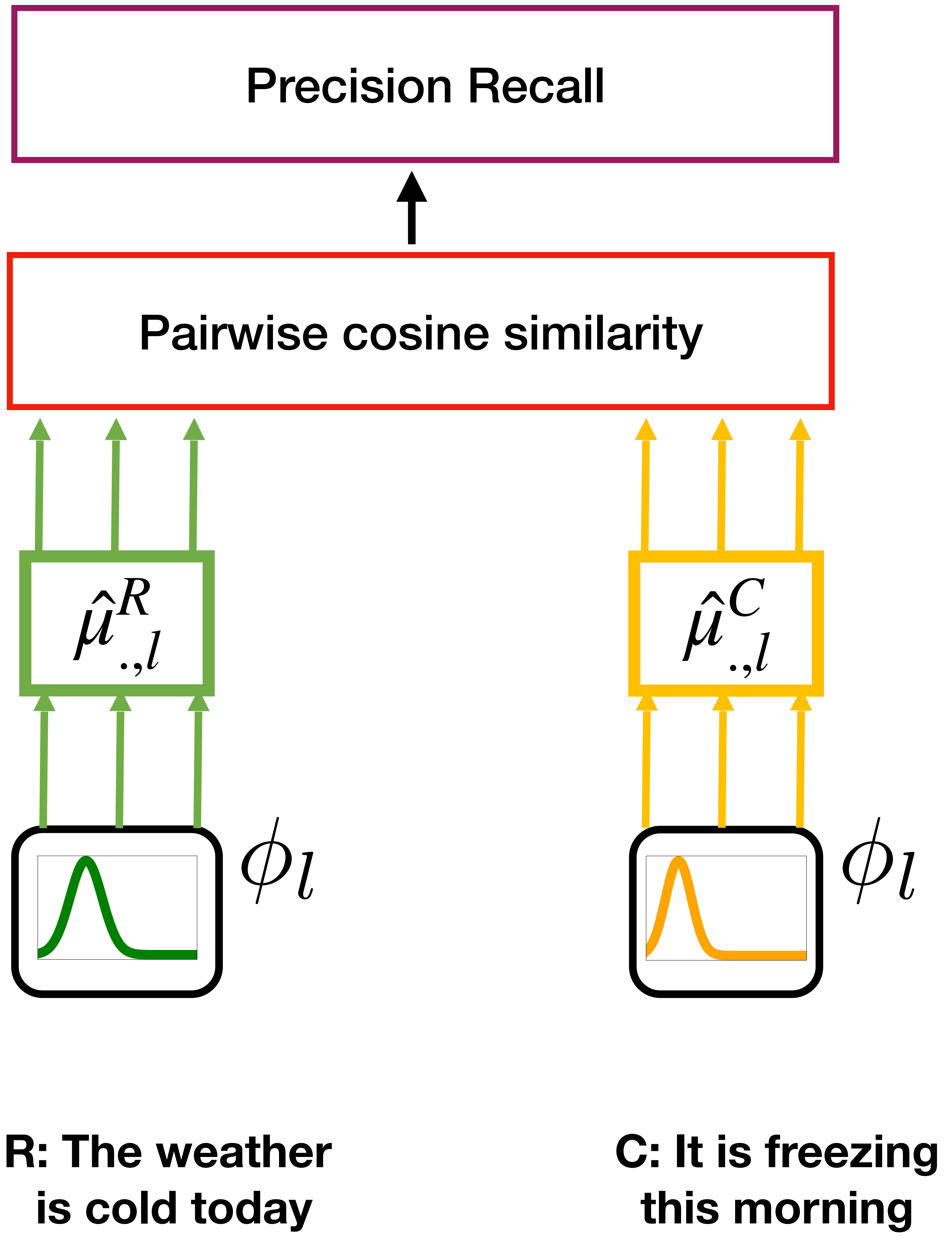

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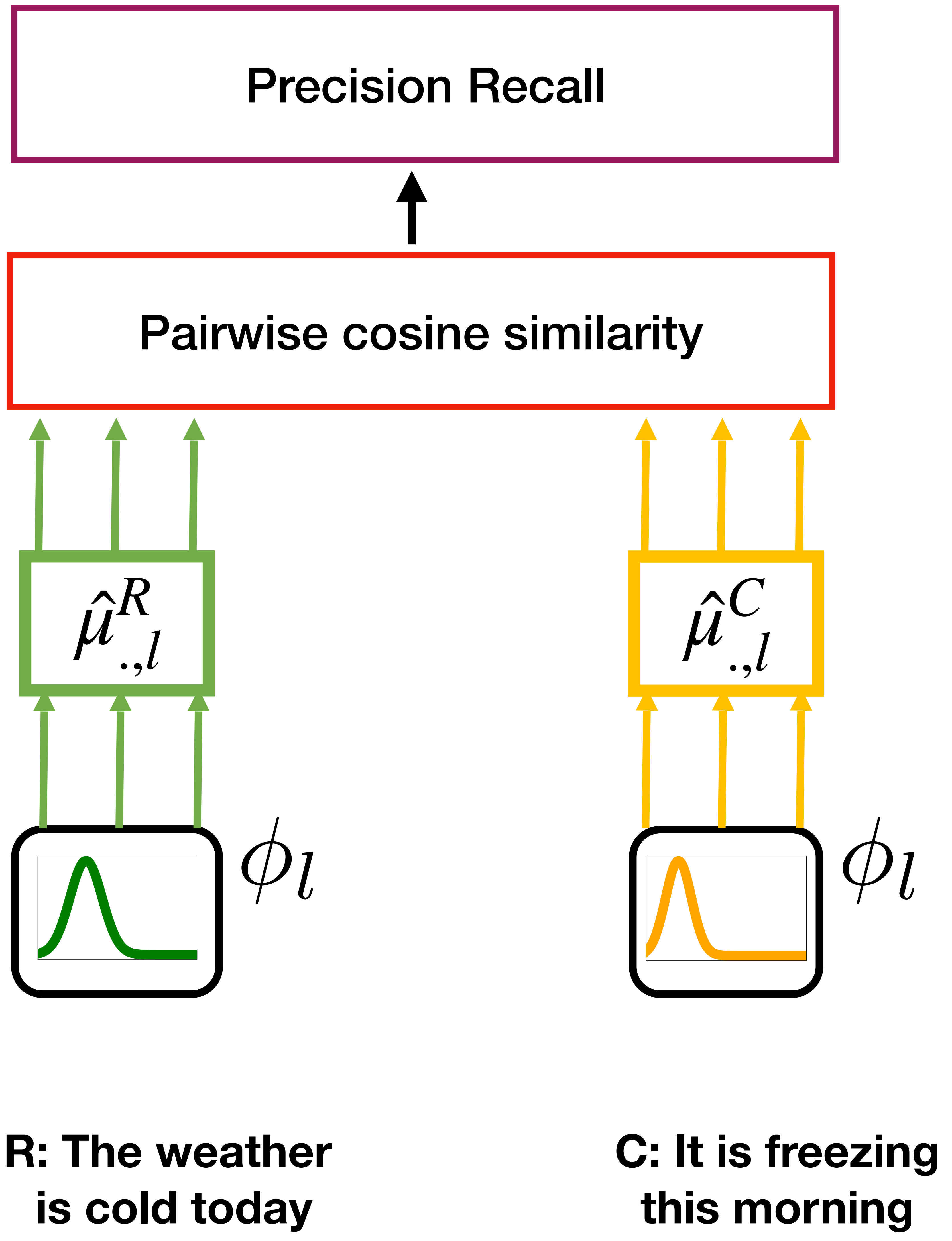

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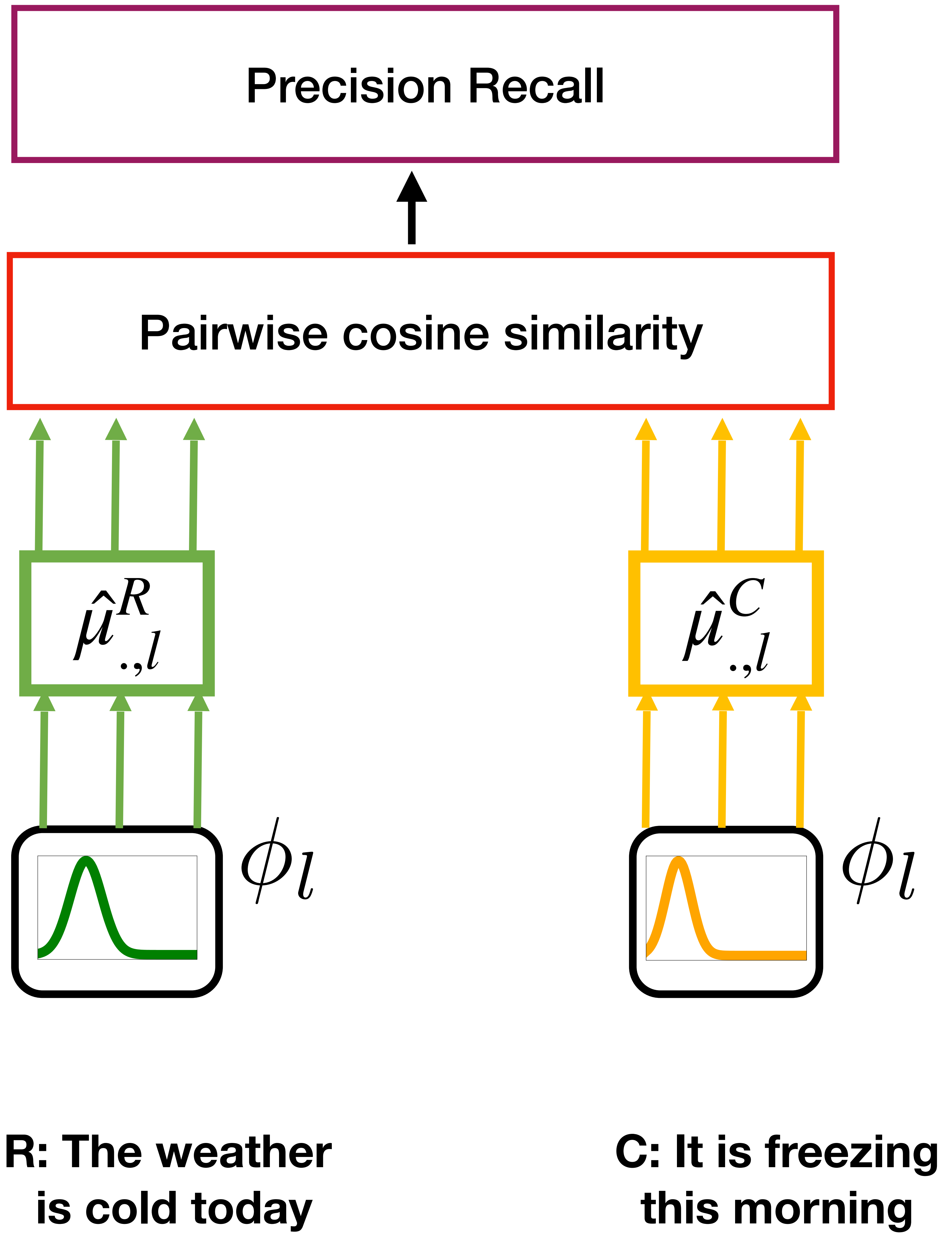

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Limitations

1. Use only one layer
2. Use arbitrary sequence of operation

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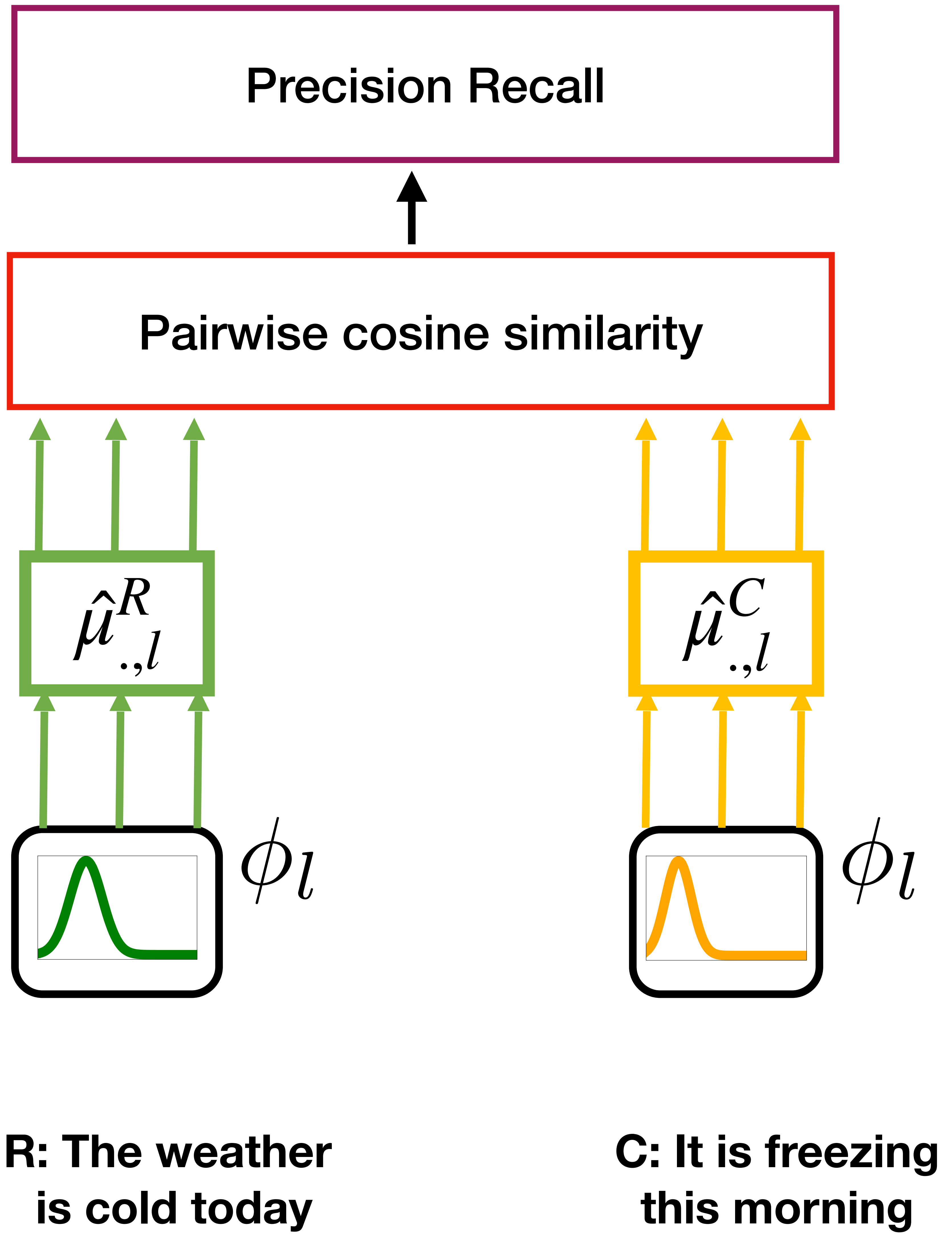

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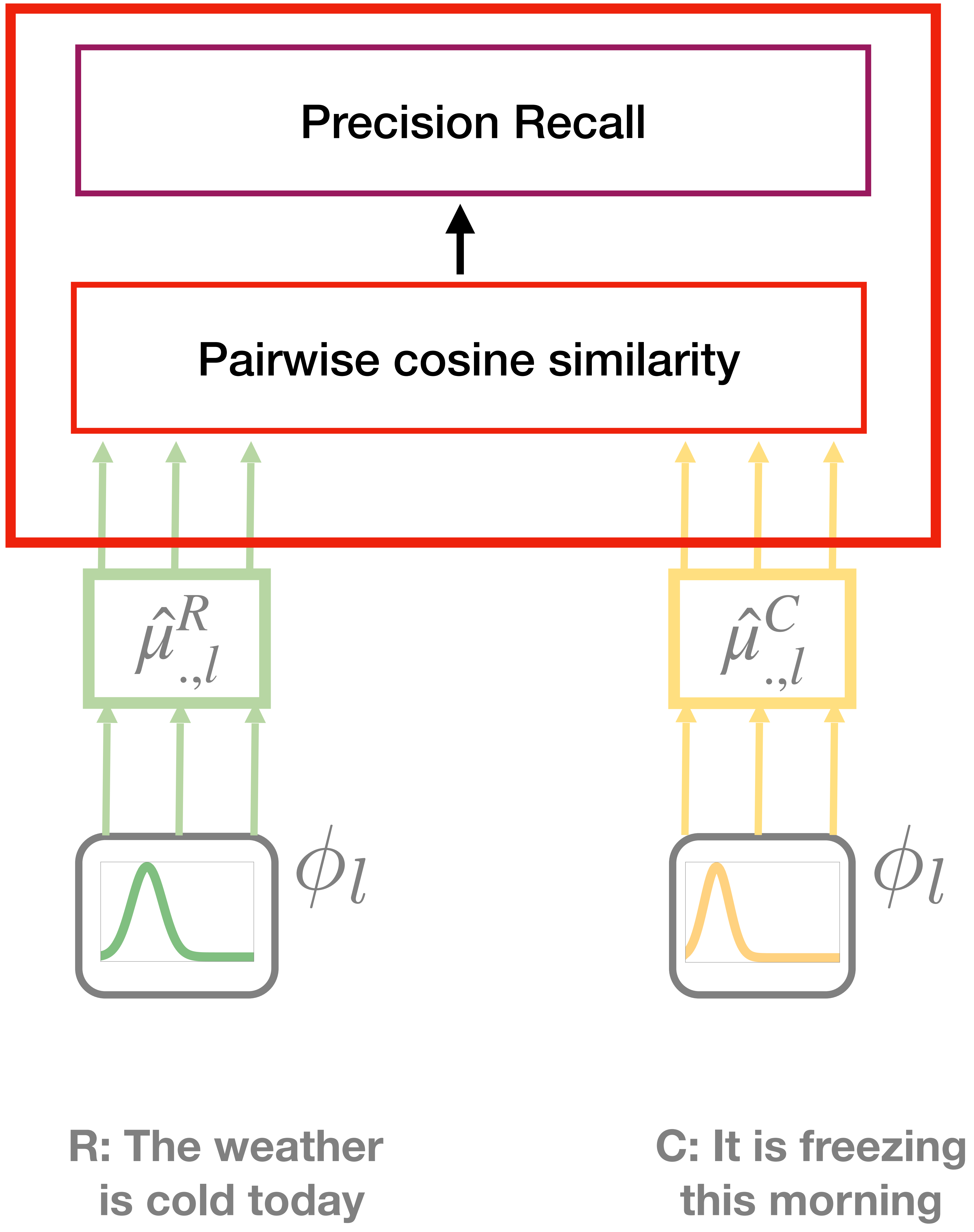

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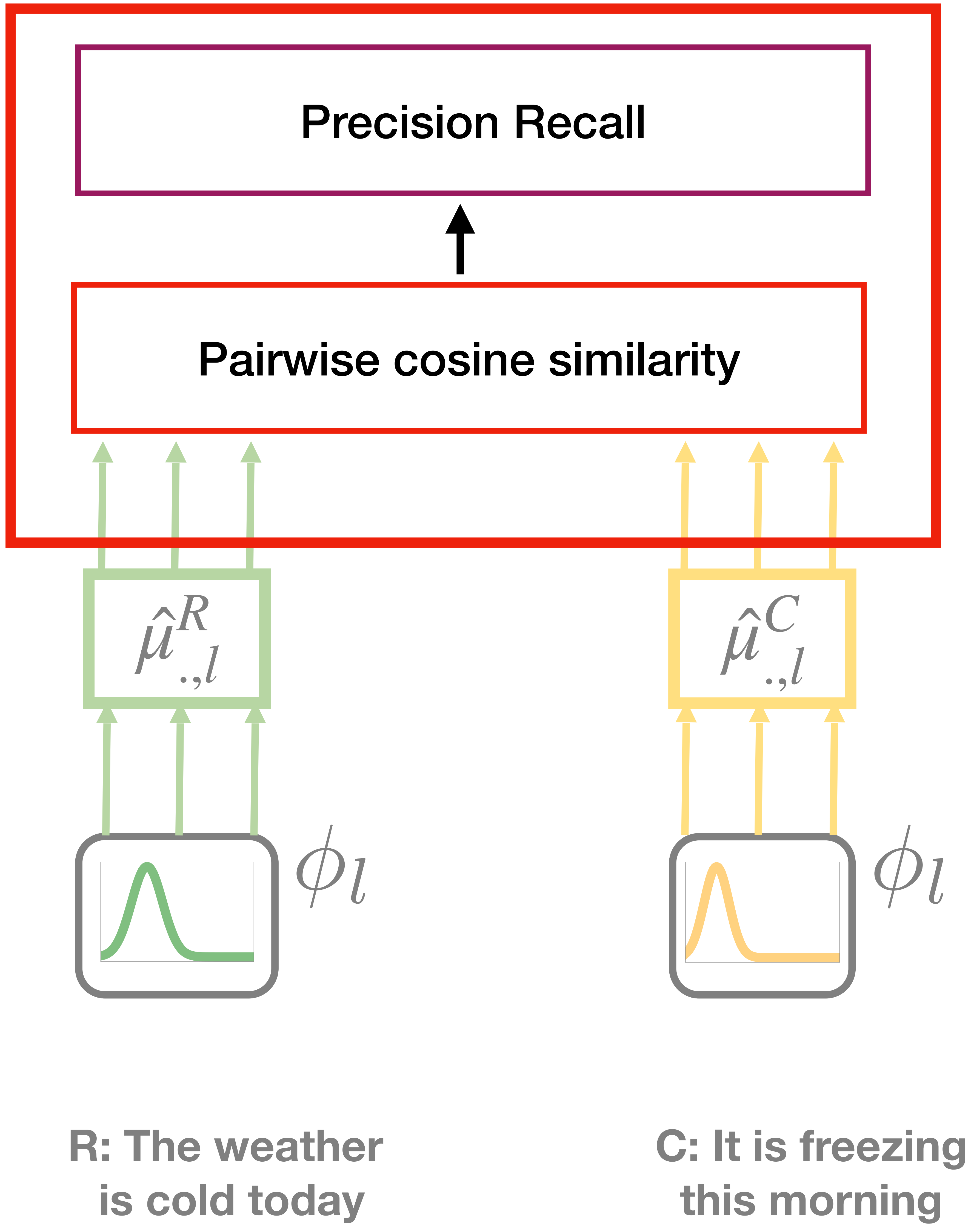

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G. Staerman, P. Mozharovskyi, P. Colombo, S. Clémençon, F. d'Alché-Buc. A Pseudo-Metric between Probability Distributions based on Depth-Trimmed Regions.

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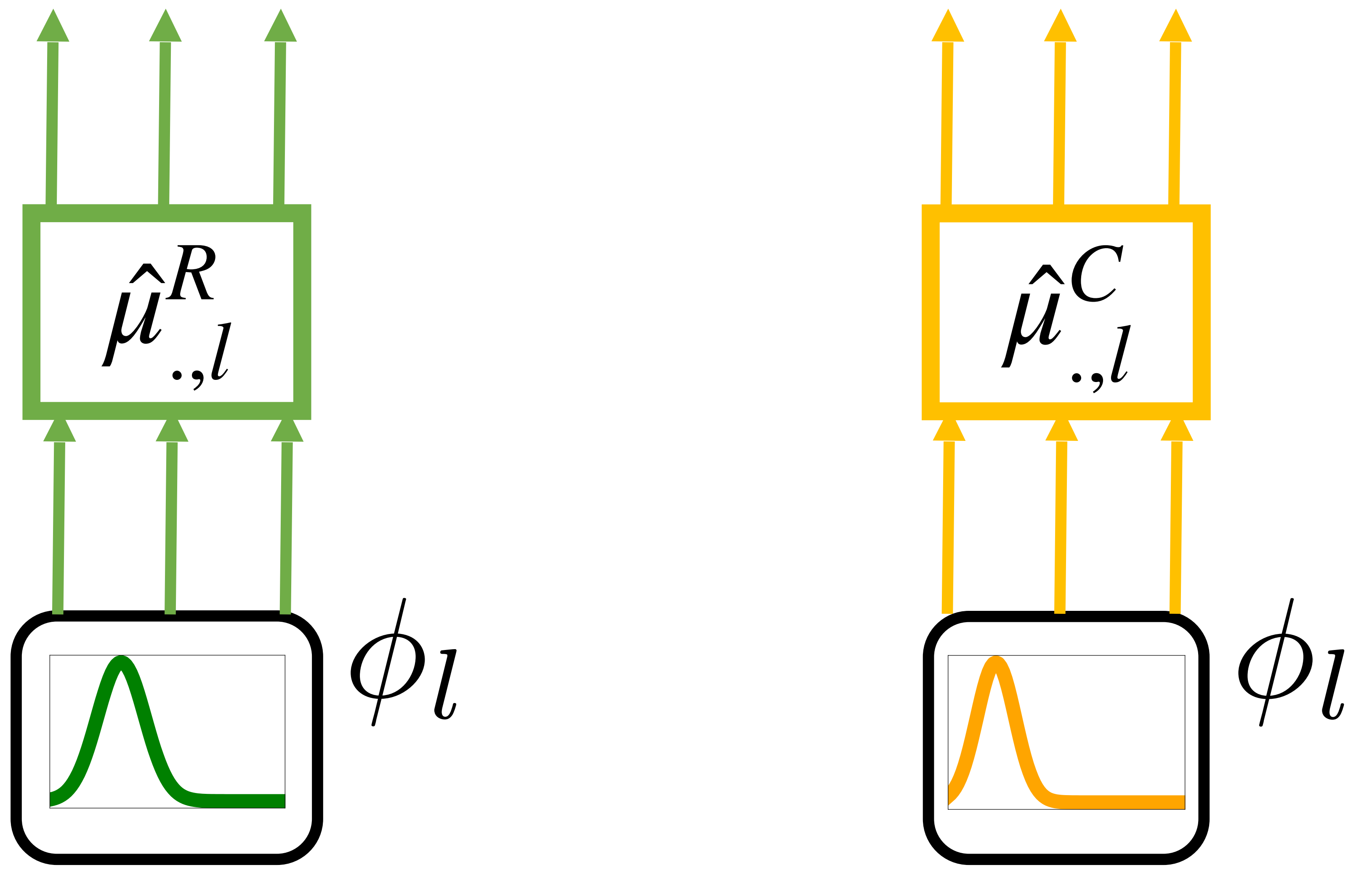

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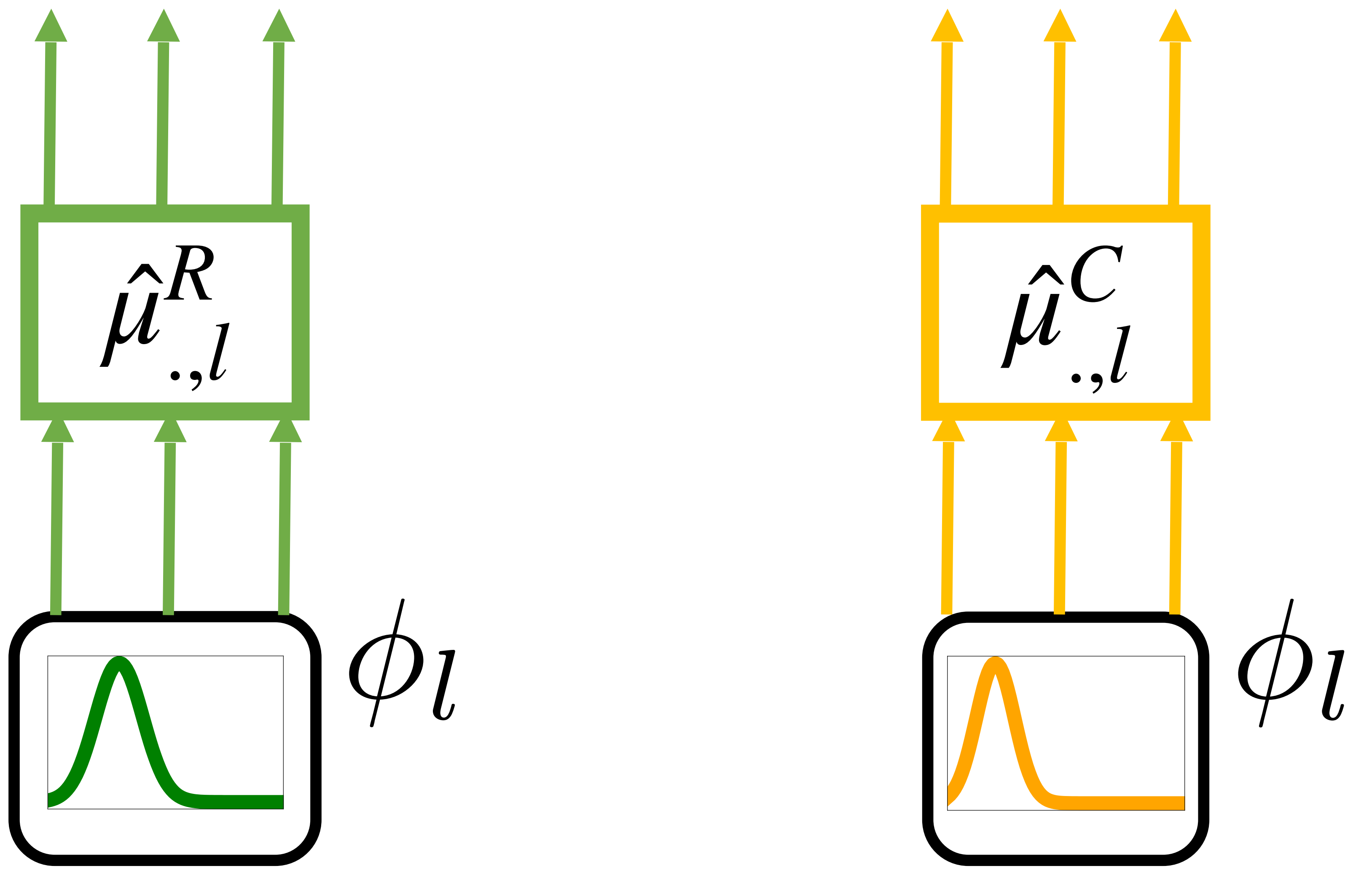

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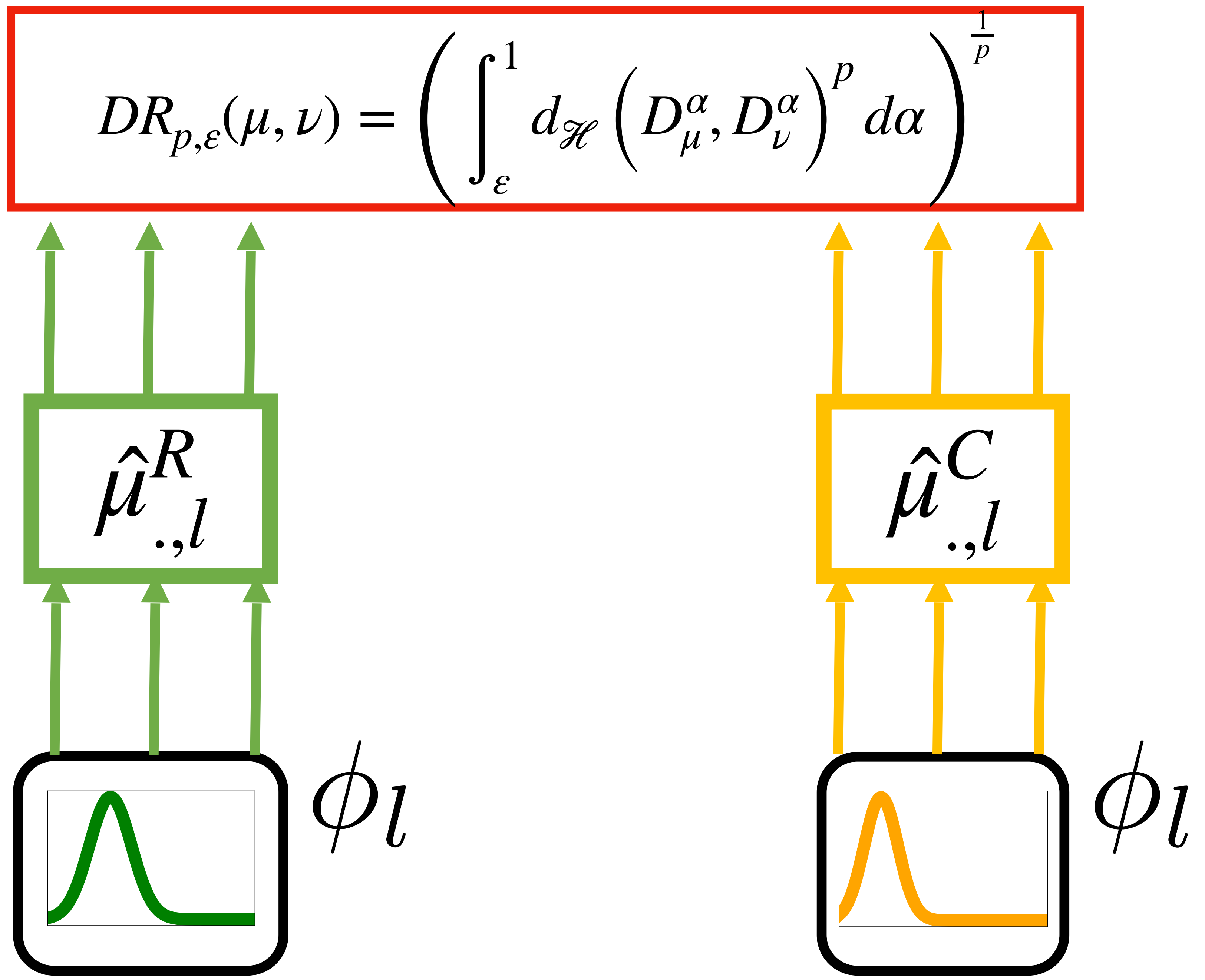

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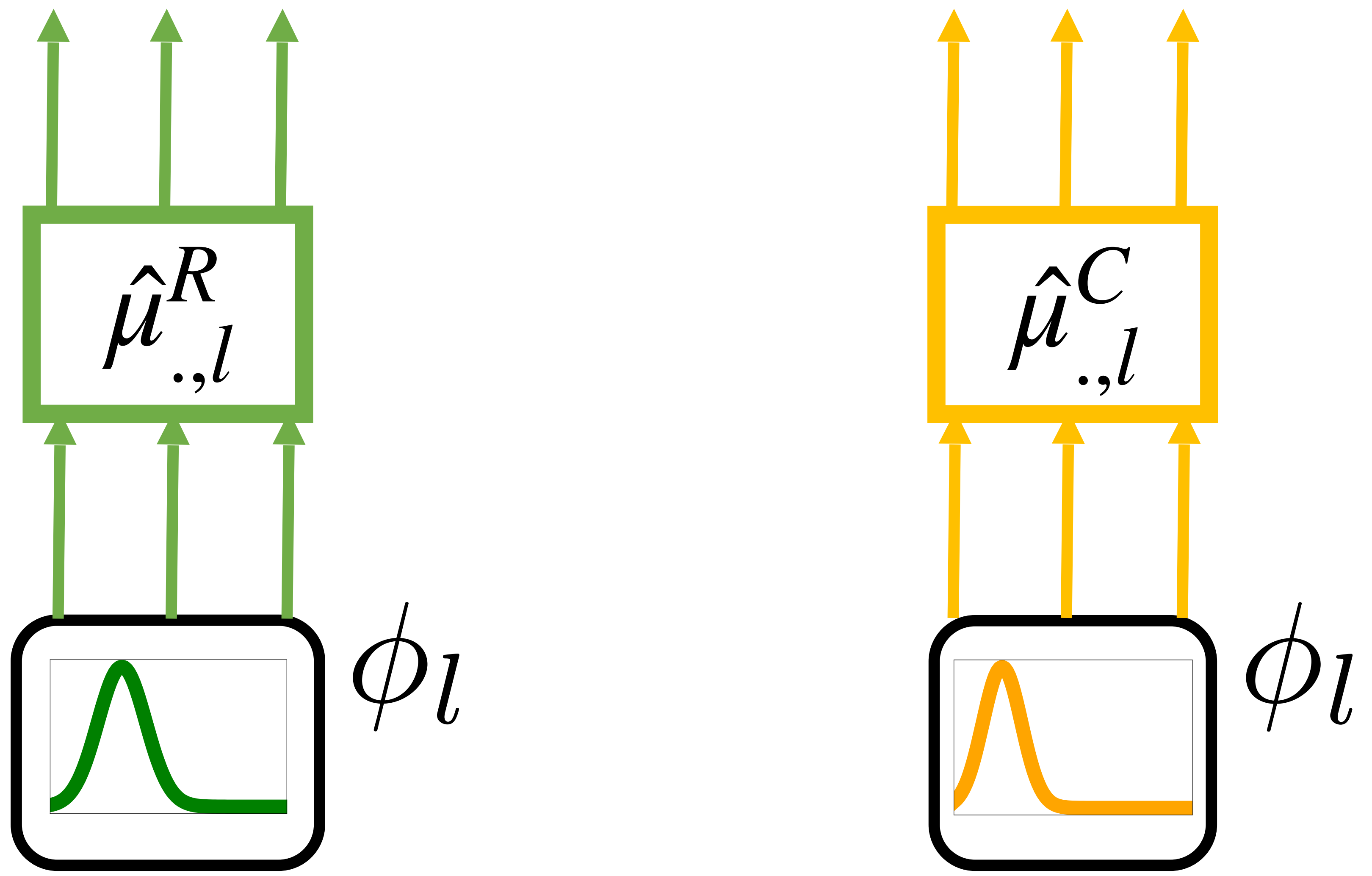

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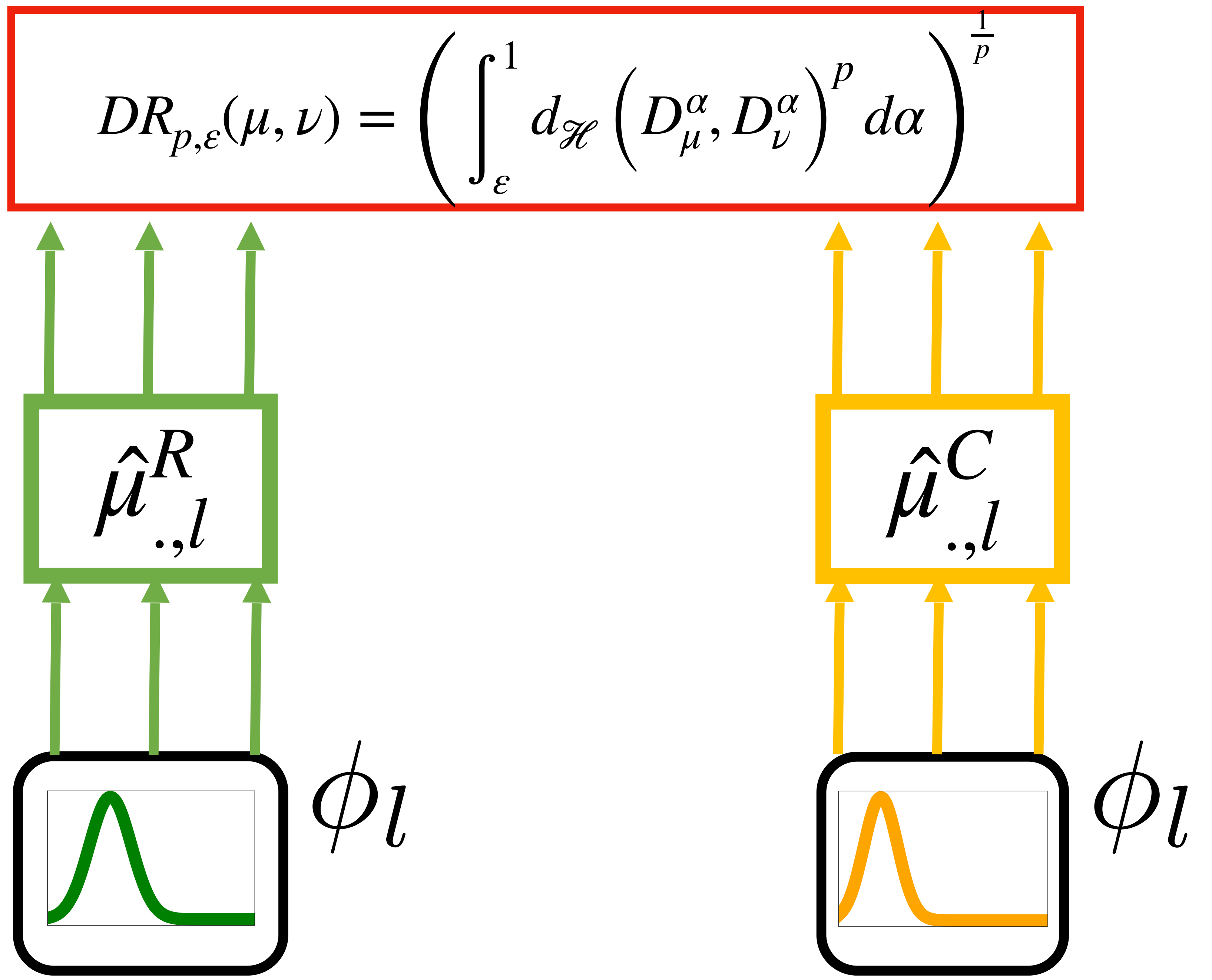

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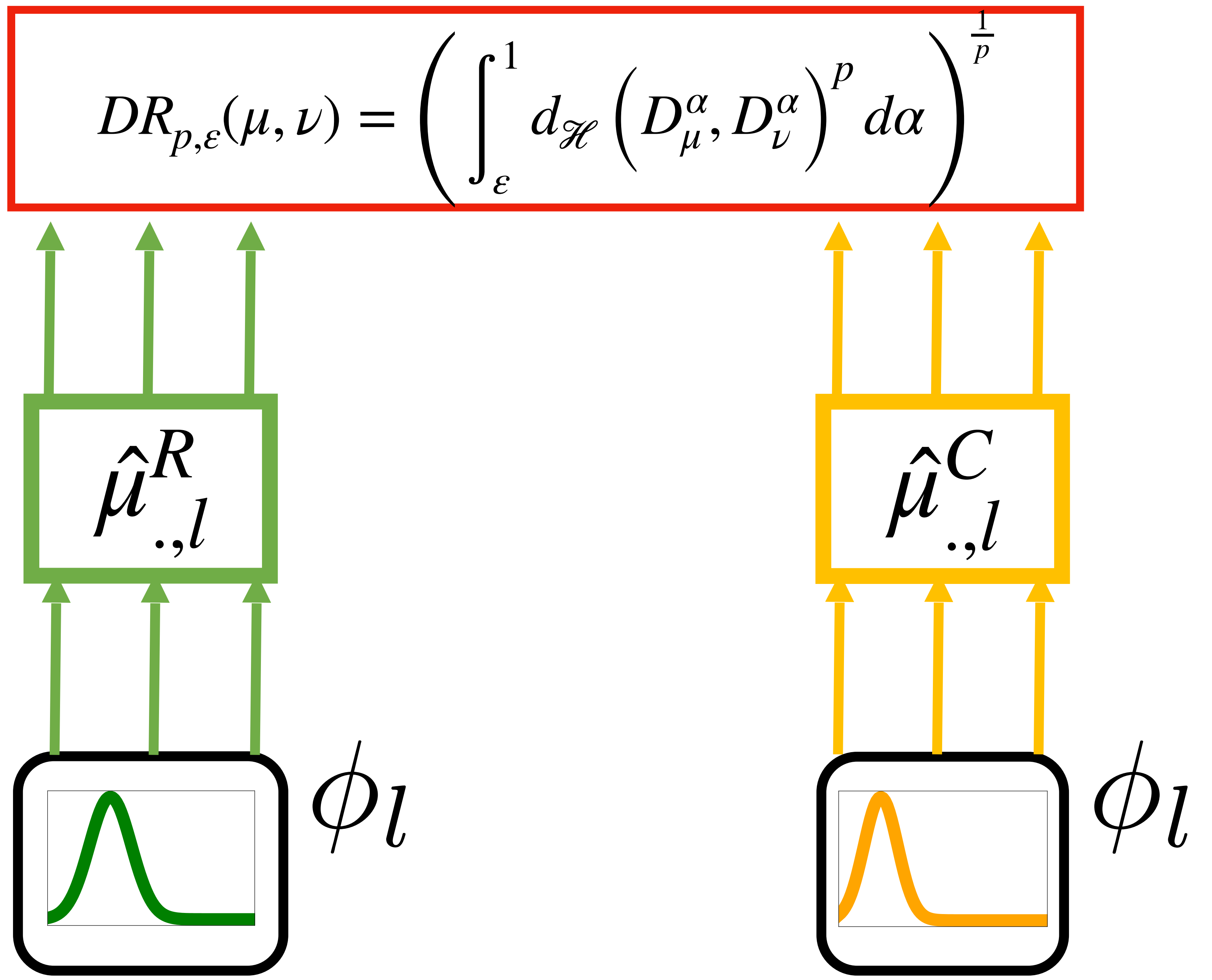

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Embedding Based Metric With Neural Networks

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0.8

Embedding Based Metric With Neural Networks

Intuition

R: The weather is cold today.

C: It is freezing today

0.8

1. Choose your multi-layer encoder

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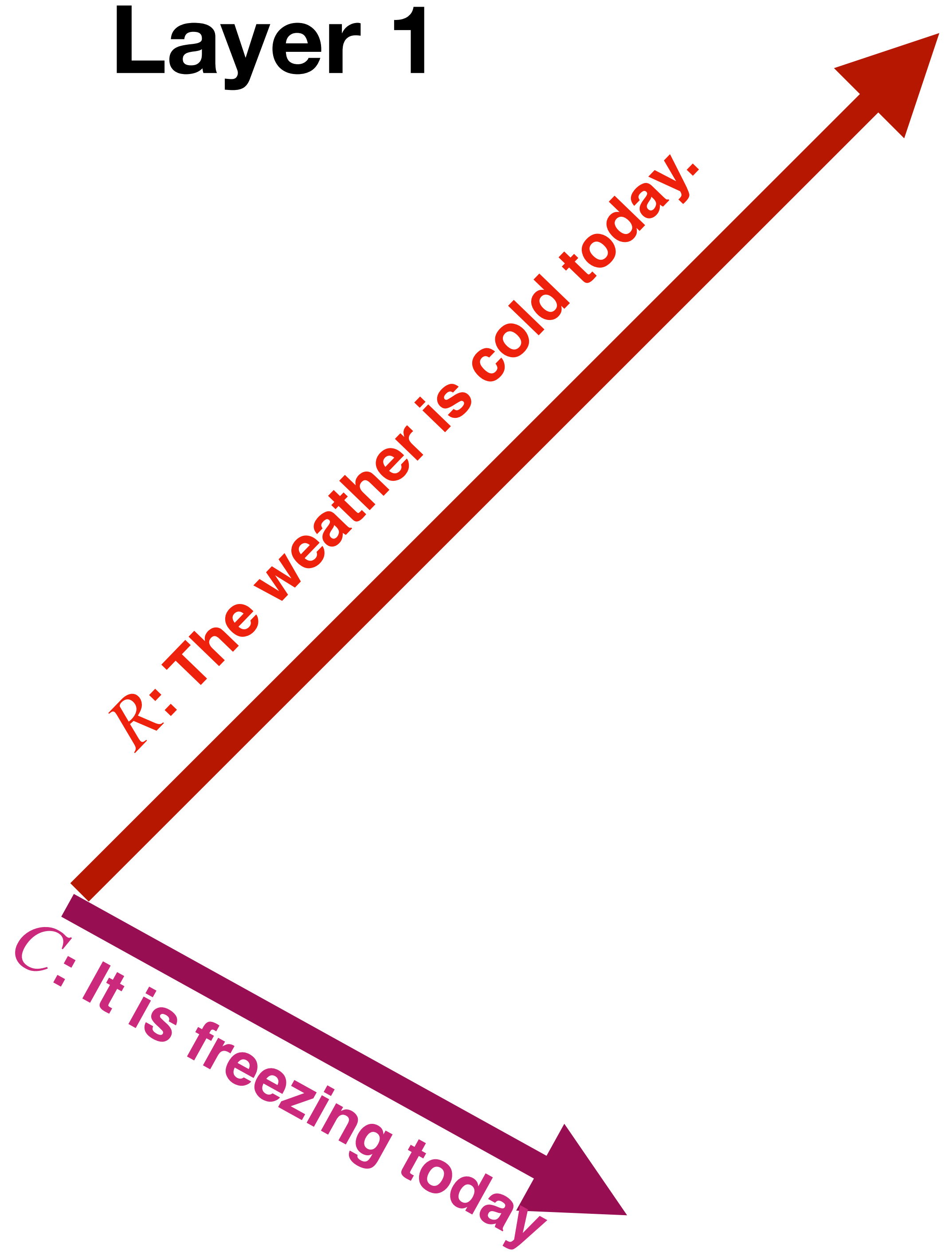
Layer 1



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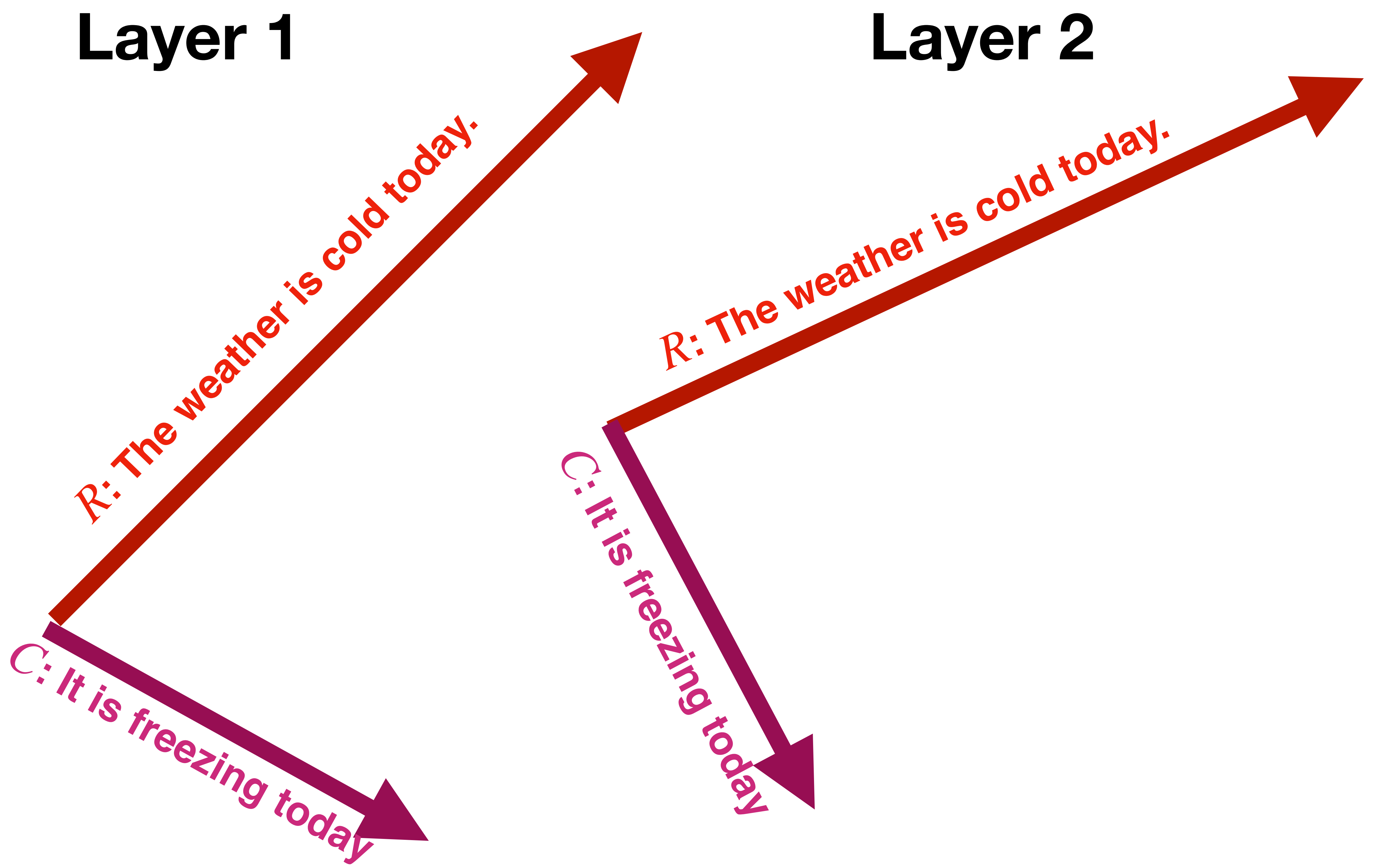

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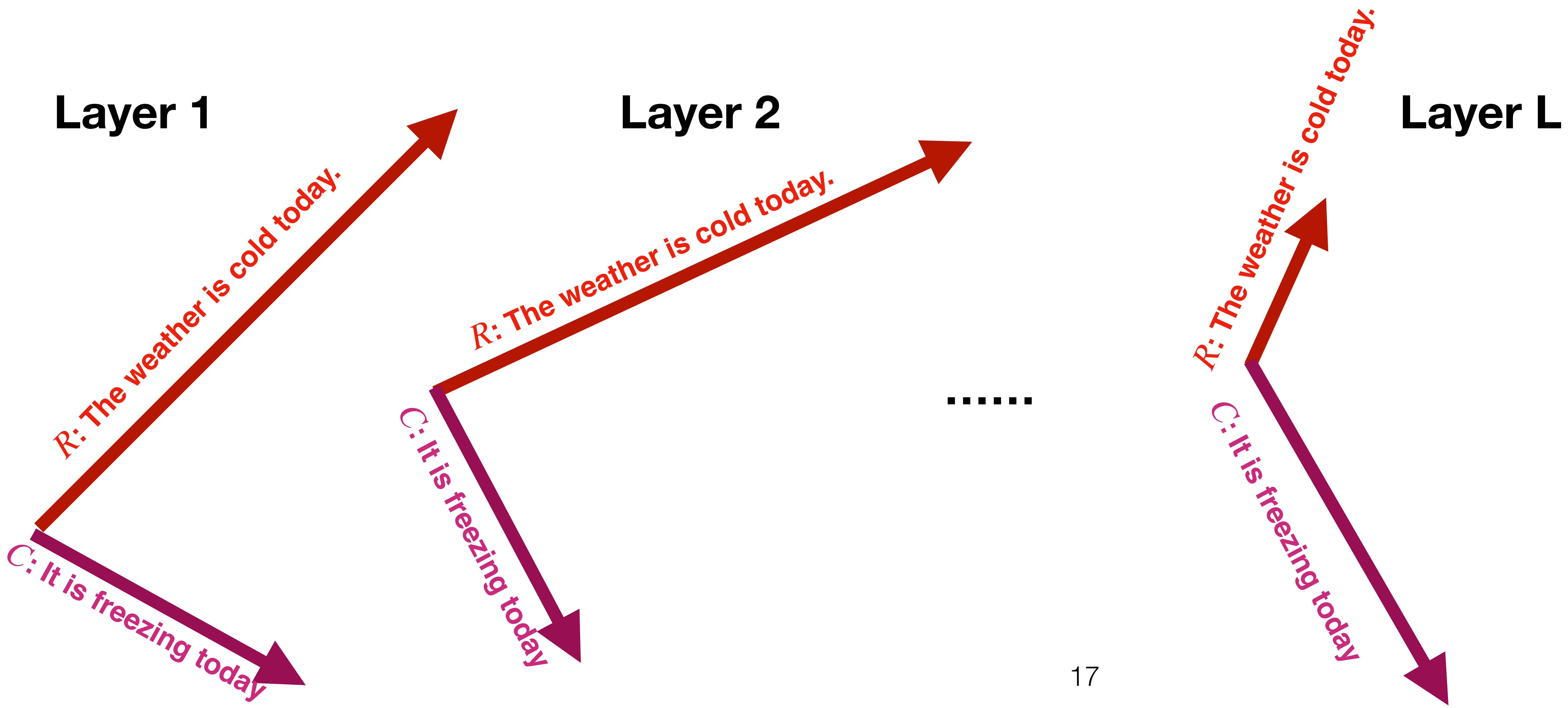

Embedding Based Metric With Neural Networks

Intuition

R: The weather is cold today.

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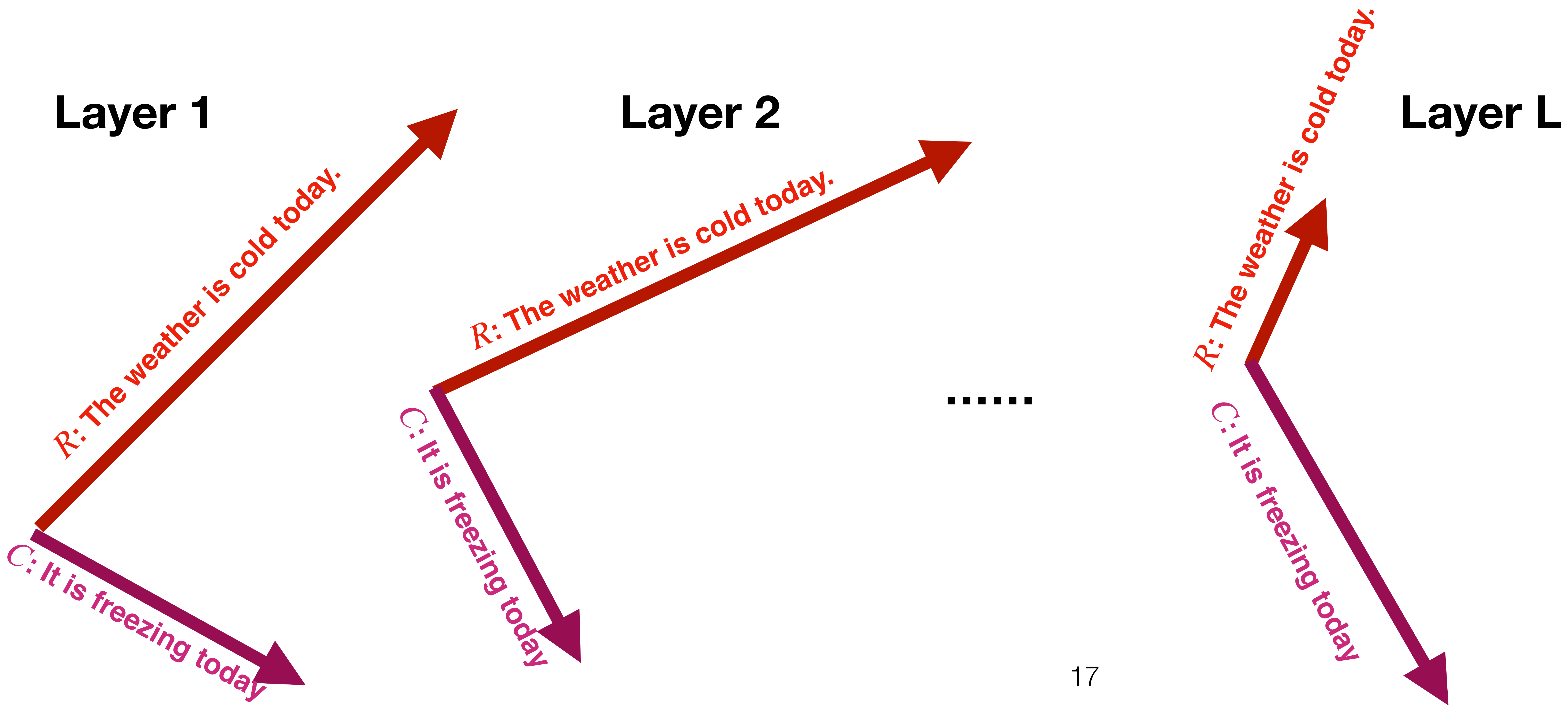
1. Choose your multi-layer encoder

2. Choose a similarity function euh??



?

BaryScore vs BertScore vs MoverScore

Pierre Colombo, Guillaume Staerman, Chloé Clavel, Pablo Piantanida. Automatic Text Evaluation through the Lens of Wasserstein Barycenters.

BaryScore vs BertScore vs MoverScore

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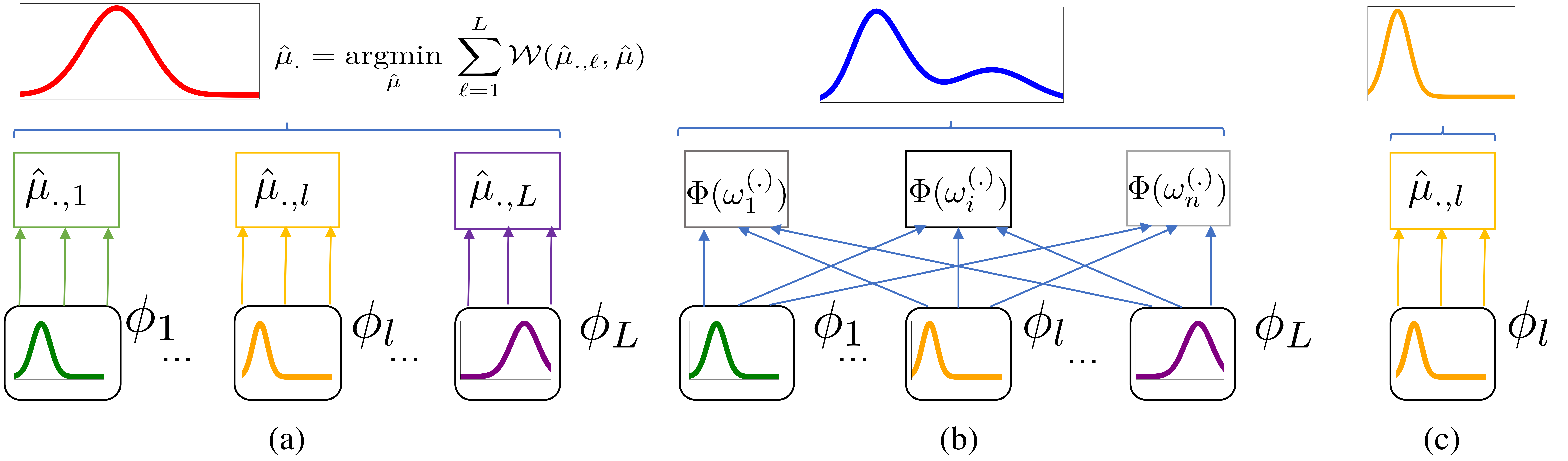

BaryScore **MoverScore** **BertScore**

1. How to evaluate Natural Language Generation?

1.1 Context: problems, evaluation of automatic evaluation.

1.2 What are the main metrics to do reference based evaluation of NLG?

1.3 Reference based evaluation of NLG using embedding based metrics.

1.4 Beyond embedding based metrics.

Pierre Colombo, Chloé Clavel and Pablo Piantanida. InfoLM: A New Metric to Evaluate Summarization & Data2Text Generation. AAAI 2022

Statistical Measures of Similarity

Statistical Measures of Similarity

Hello, Chicago.
If there is anyone out there who still doubts that America is a place where all things are possible, who still wonders if the dream of our founders is alive in our time, [….].
Yes we can!

Input Text

Statistical Measures of Similarity

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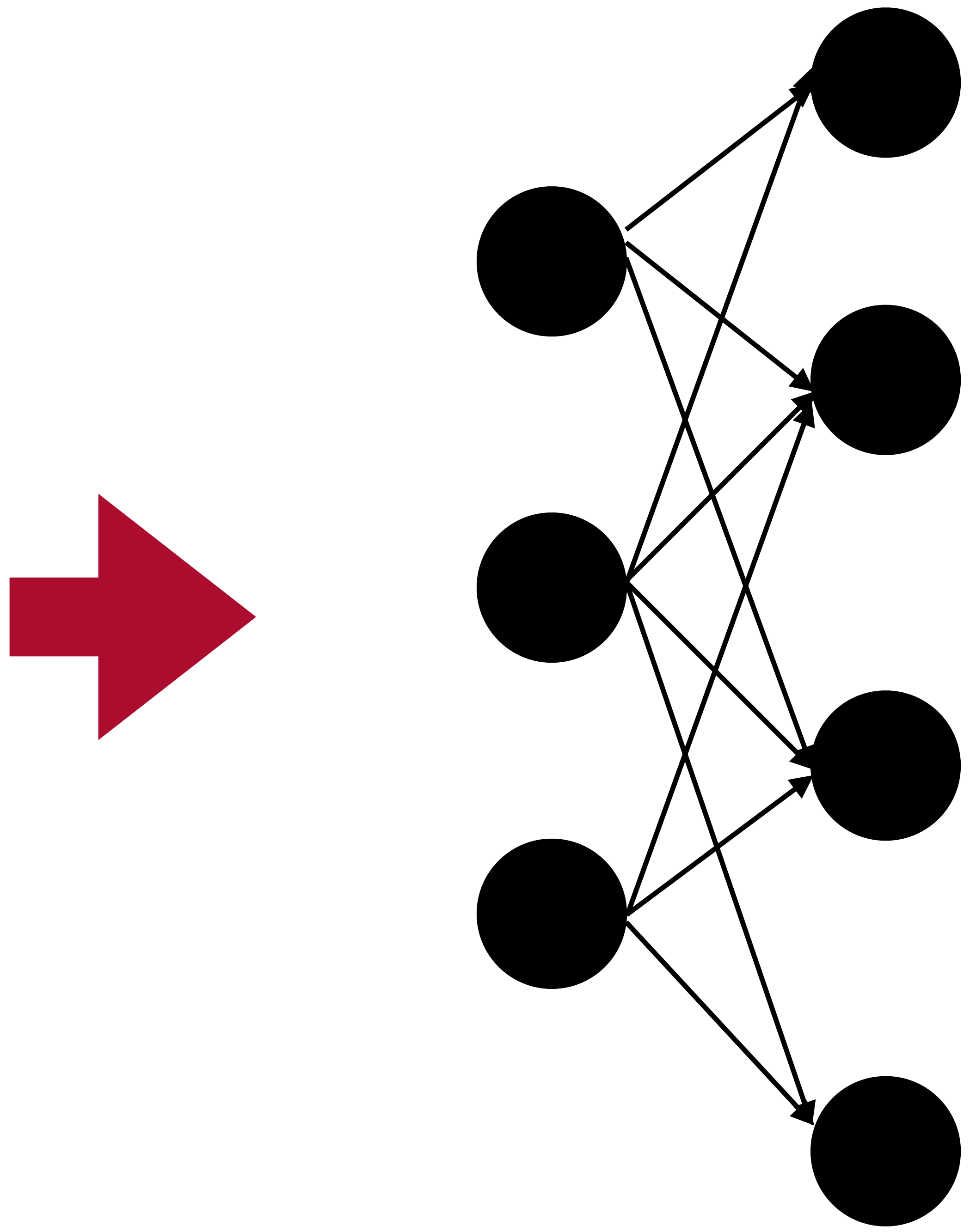

Input Text

Neural Network

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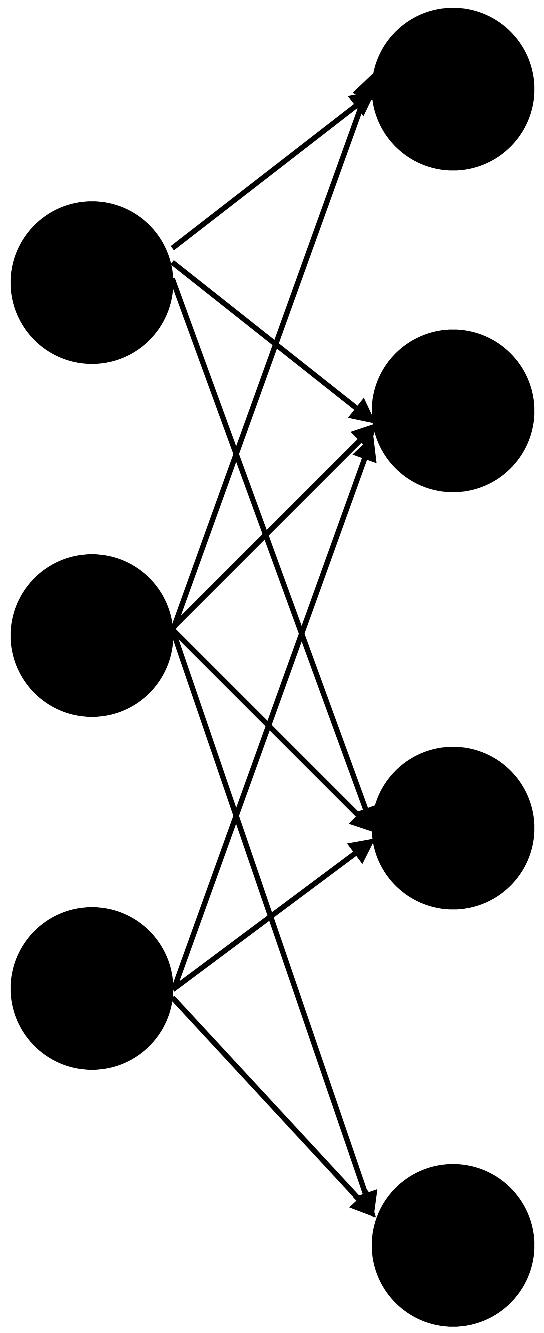
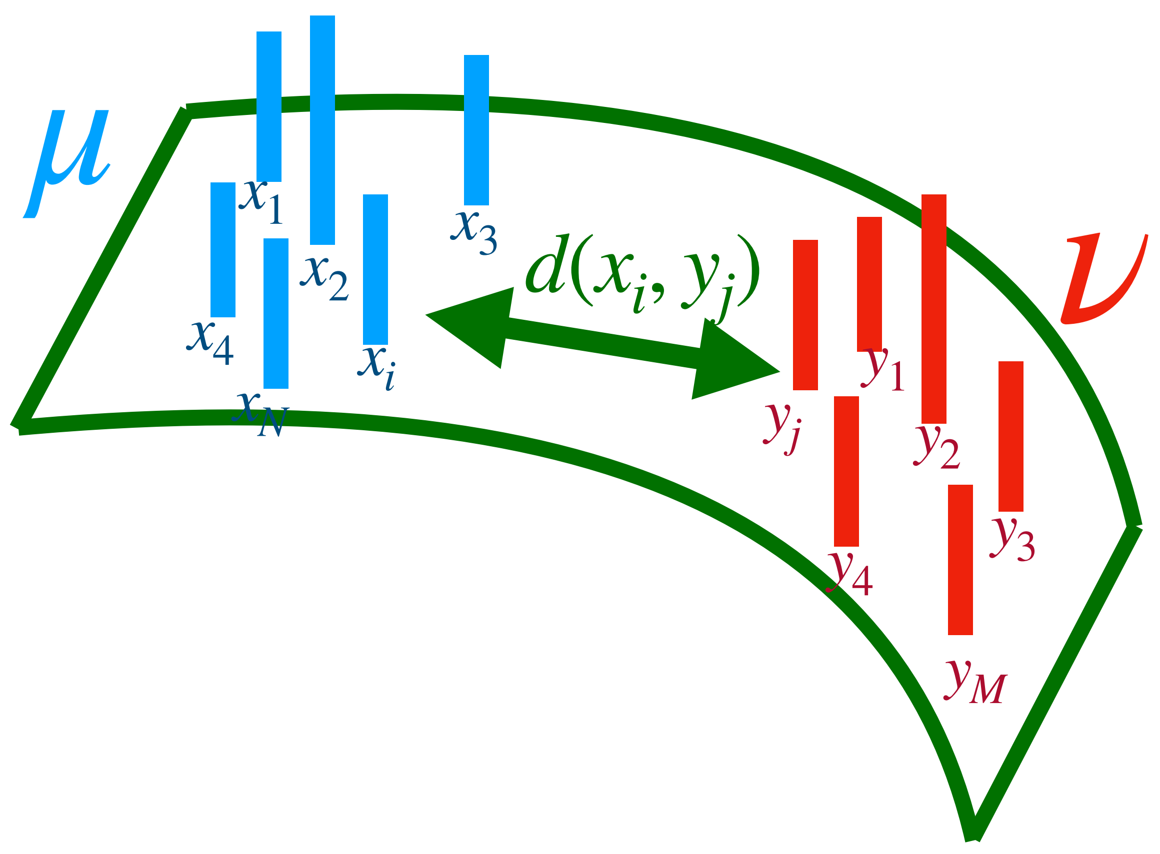


Neural Network

High dimensional data



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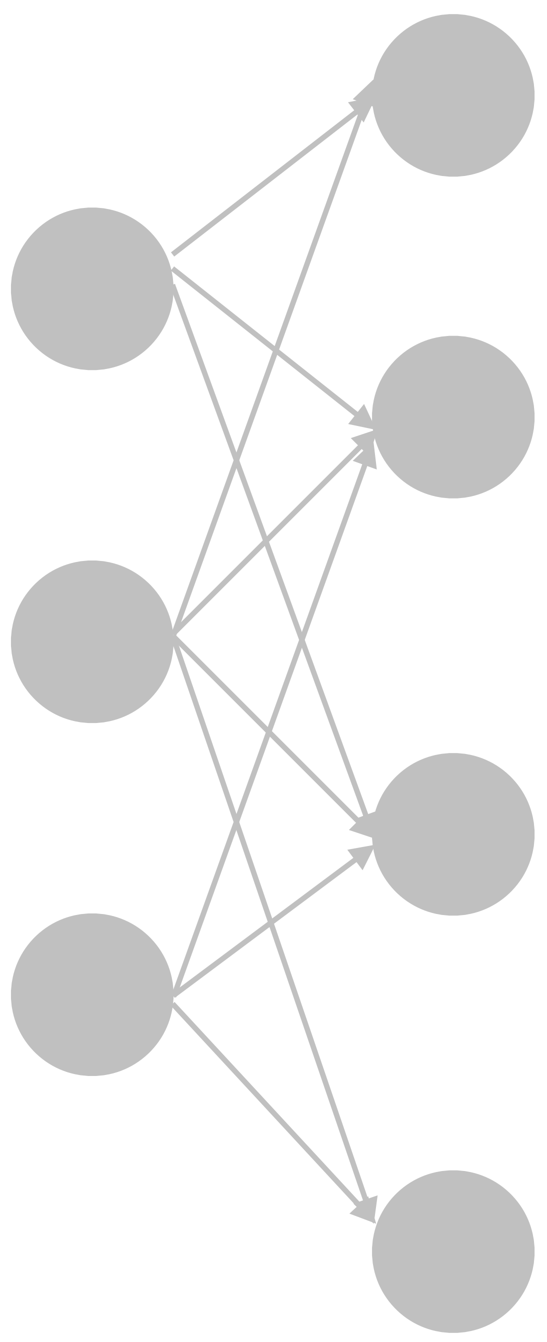

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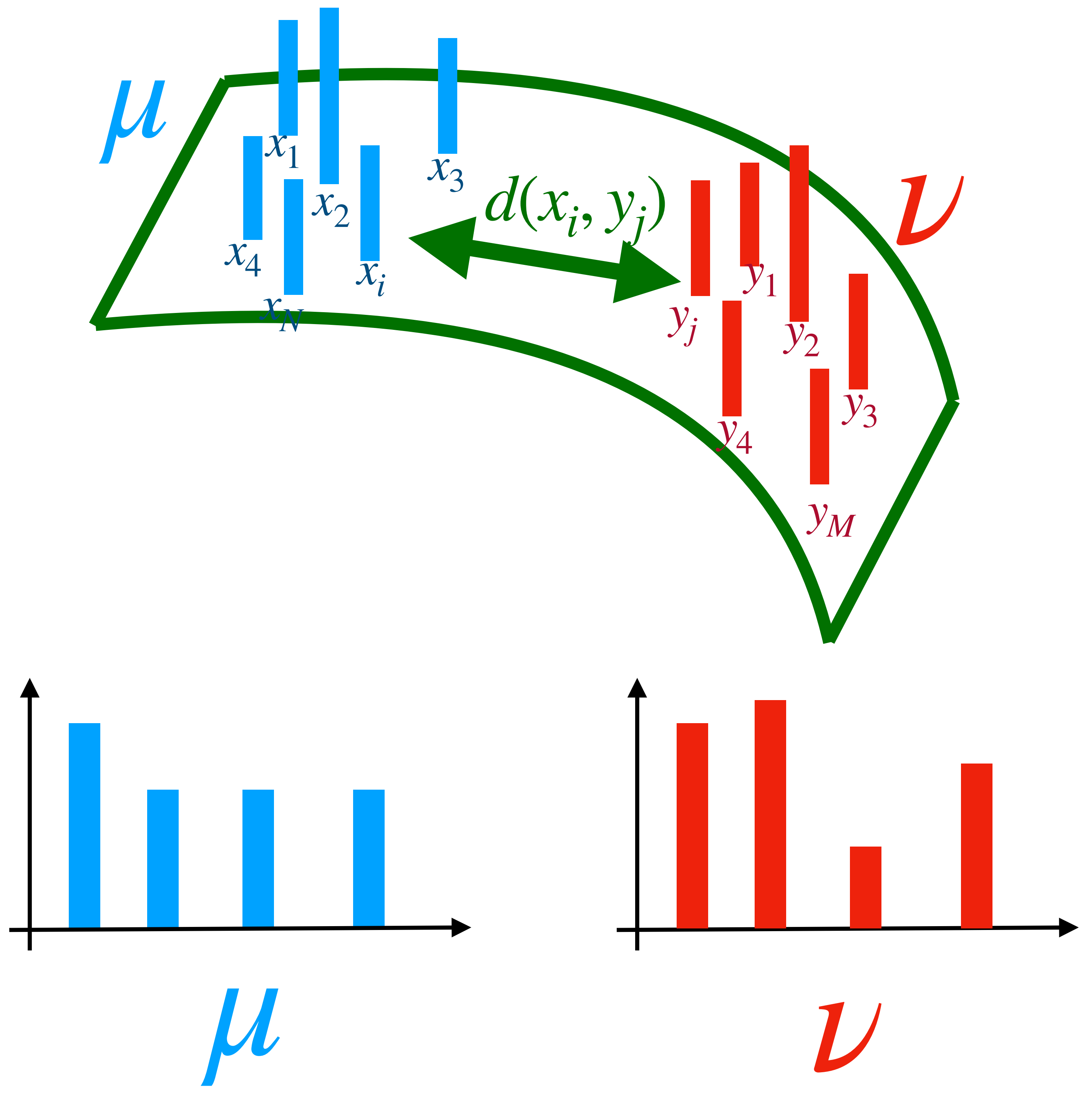

Soft Probabilities

Statistical Measures of Similarity

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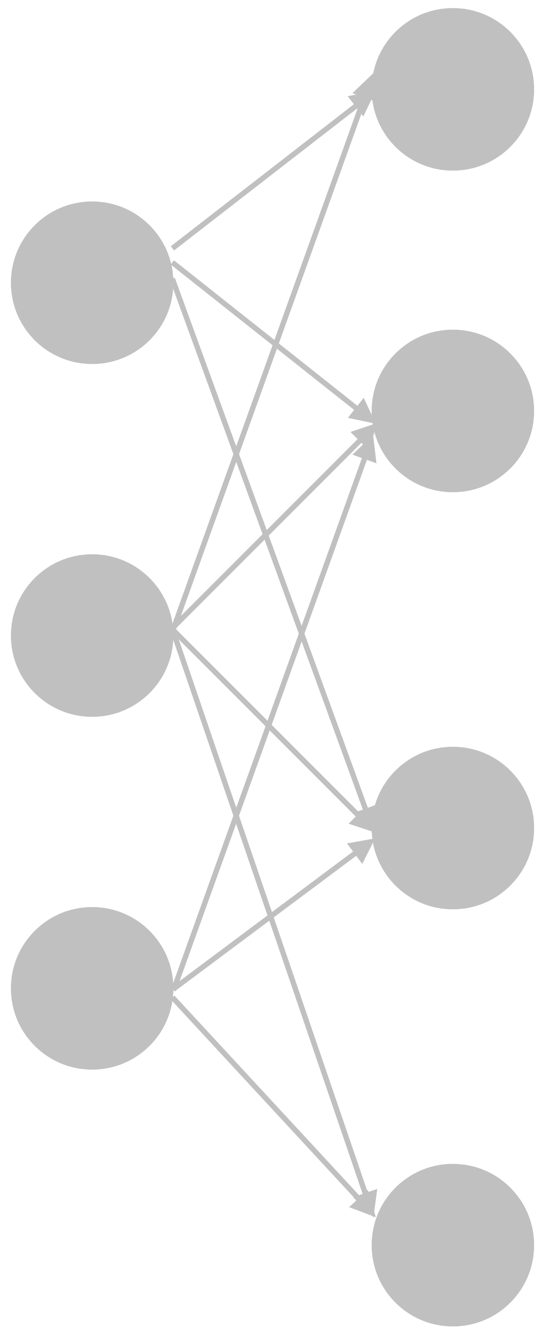

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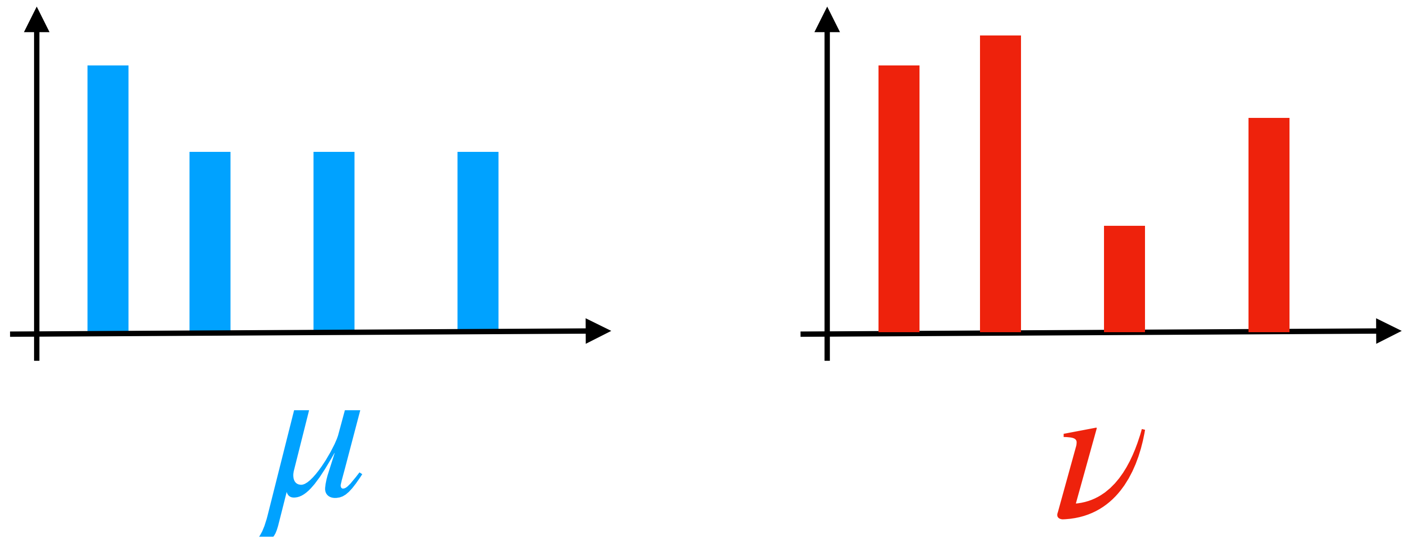

Input Text

Neural Network

Soft Probabilities

Existing Methods

Edit Based

Snover et al. 2006

Operations

- Insertion (I)
- Deletion (D)
- Substitution (S).

tailor -> sailor (S)
sailor -> sailir (S)
sailir -> sailin (S)
sailin_ -> sailing (I)

Distance is 4 !

Existing Methods

InfoLM

Edit Based

Snover et al. 2006

Operations

- Insertion (I)
- Deletion (D)
- Substitution (S).

tailor -> sailor (S)
sailor -> sailir (S)
sailir -> sailin (S)
sailin -> sailing (I)

Distance is 4 !

N-gram Based

Papineni et al. 2002

C : I like these very nice pies !

R : I like those cakes !

Unigrams

C : I like these very nice pies !

R : I like those cakes !

Bigrams

C : I like these very nice pies !

R : I like those cakes !

Embedding Based

Word Mover distance
Kusner et al. 2015

BertScore
Zhang et al. 2019

MoverScore
Zhao et al. 2019

Sentence Mover
Clark et al. 2019

Assumptions for InfoLM

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Goal **Compute a similarity score between R and C.**

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Goal Compute a similarity score between R and C.

Tools Use a pretrained MLM

Assumptions for InfoLM

Goal **Compute a similarity score between R and C.**

MLM predicts a distribution over Ω

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$$\mathcal{I} : [0,1]^{|\Omega|} \times [0,1]^{|\Omega|}$$

Assumptions for InfoLM

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Use a measure of information

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Use a **measure of information**

$$\mathcal{I} : [0,1]^{|\Omega|} \times [0,1]^{|\Omega|}$$

Name	Notation	Domain	Expression
α-divergence (Csiszár 1967)	$\mathcal{D}_\alpha$	$\alpha \notin \{0,1\}$	$\frac{1}{\alpha(\alpha-1)}(1-\sum q_i^{1-\alpha} p_i^\alpha)$
γ divergence (Fujisawa and Eguchi 2008)	$\mathcal{D}_\gamma^\beta$	$\beta \notin \{0,-1\}$	$\frac{1}{\beta(\beta+1)} \log \sum p_i^{\beta+1} + \frac{1}{\beta+1} \log \sum q_i^{\beta+1} - \frac{1}{\beta} \log \sum p_i q_i^\beta$
AB Divergence (Cichocki, Cruces, and Amari 2011)	$\mathcal{D}_{sAB}^{\alpha,\beta}$	$(\alpha,\beta) \in (\mathbb{R}^*)^2$, $\beta+\alpha \neq 0$	$\frac{1}{\beta(\beta+\alpha)} \log \sum p_i^{\beta+\alpha} + \frac{1}{\beta+\alpha} \log \sum q_i^{\beta+\alpha} - \frac{1}{\beta} \log \sum p_i^\alpha q_i^\beta$
$\mathcal{L}_1$ distance	$\mathcal{L}_1$		$\sum \lvert p_i - q_i \rvert$
$\mathcal{L}_2$ distance	$\mathcal{L}_2$		$\sqrt{\sum (p_i - q_i)^2}$
$\mathcal{L}_\infty$ distance	$\mathcal{L}_\infty$		$\max_i \lvert p_i - q_i \rvert$
Fisher-Rao distance	R		$\frac{2}{\pi} \arccos \sum \sqrt{p_i \times q_i}$

Intuition of InfoLM

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Goal **Compute a similarity score between R and C.**

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Equivalence for masked contexts $\mathcal{I} : [0,1]^{|\Omega|} \times [0,1]^{|\Omega|}$

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MLM

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Similar context

R: It is [MASK] today.

C: It is [MASK] this morning !

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Similar context

MLM

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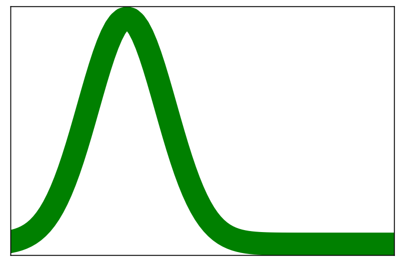
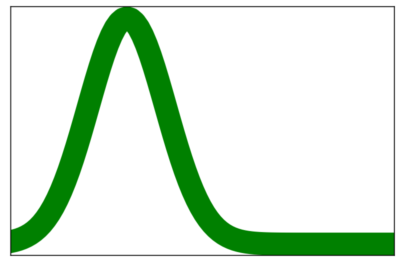


$p_\Omega(\cdot \mid [C]^2)$



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$p_\Omega(\cdot \,|\, [R]^2)$

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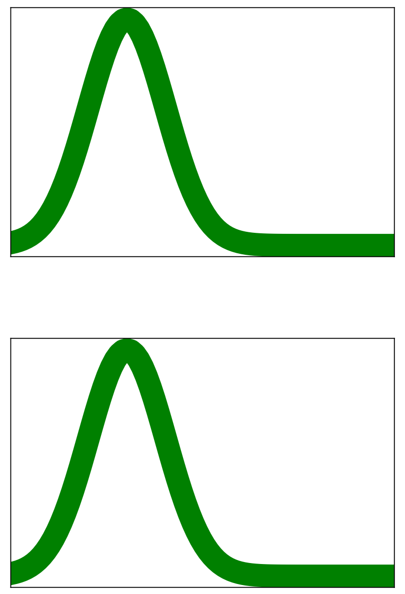

$$\mathcal{I}\left(p_\Omega(\cdot \,|\, [R]^2), p_\Omega(\cdot \,|\, [C]^2)\right) \sim 0$$

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Equivalence for masked contexts $\mathcal{I} : [0,1]^{|\Omega|} \times [0,1]^{|\Omega|}$

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Similar context

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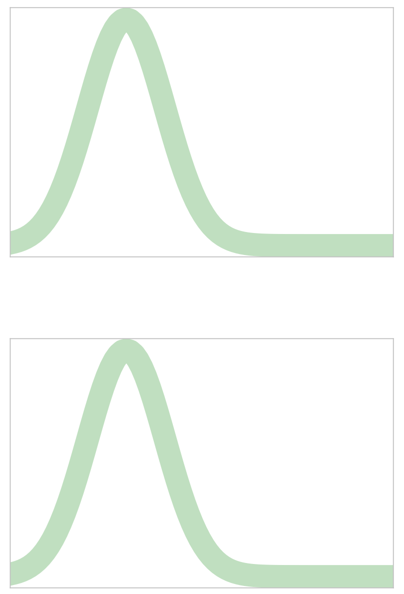

$\mathcal{I}\left(p_\Omega(\cdot \,|\, [R]^2), p_\Omega(\cdot \,|\, [C]^2)\right) \sim 0$

Dissimilar context

R: It is cold [MASK]

C: It is [MASK] this morning !

Intuition of InfoLM

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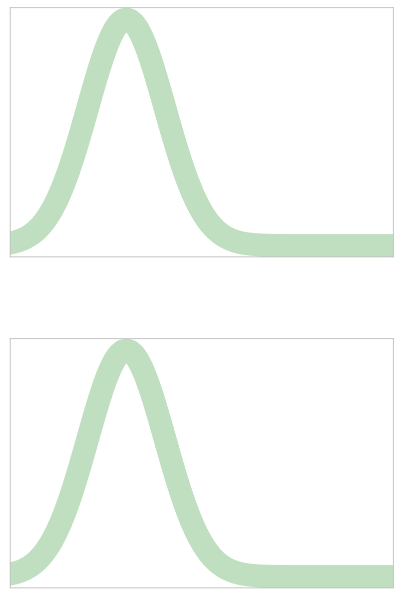

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Dissimilar context

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$p_\Omega(\cdot \mid [R]^3)$

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Intuition of InfoLM

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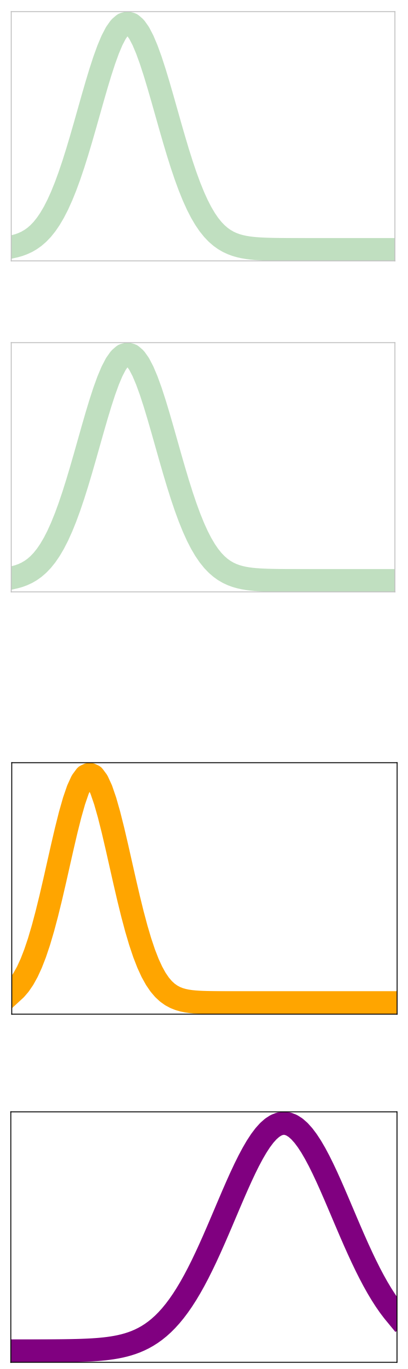

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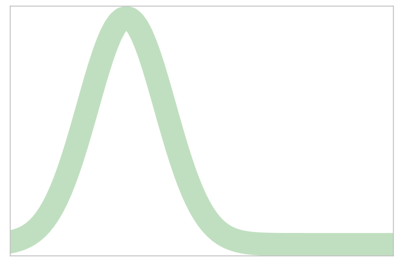
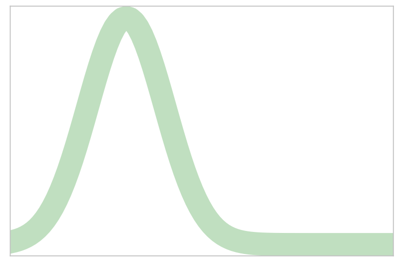
$p_\Omega(\cdot \mid [R]^2) \rightarrow$



$p_\Omega(\cdot \mid [C]^2) \rightarrow$



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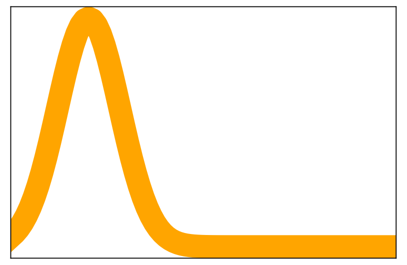

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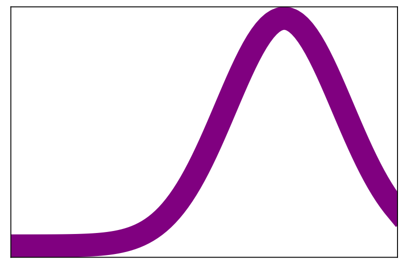

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Context Aggregation

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Goal **Compute a similarity score between R and C.**

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How to aggregate contexts?

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Goal Compute a similarity score between R and C.

How to aggregate contexts? → **Weighted Sum!**

Context Aggregation

Goal Compute a similarity score between R and C.

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Reference

[MASK] is cold today.

...

It is [MASK] today.

...

It is cold today [MASK]

Context Aggregation

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Reference

[MASK] is cold today.

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Candidate

[MASK] is freezing this morning !

...

It is [MASK] this morning !

...

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Goal Compute a similarity score between R and C.

How to aggregate contexts? → Weighted Sum!

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[MASK] is cold today.

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$$P \triangleq \frac{1}{5}\sum_{k=0}^{4} \gamma_k \times p_\Omega(\,\cdot \mid [R]^k)$$

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It is [MASK] this morning !

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Goal Compute a similarity score between R and C.

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Candidate

[MASK] is freezing this morning !

...

It is [MASK] this morning !

...

It is freezing this morning [MASK]

$$Q \triangleq \frac{1}{6} \sum_{k=0}^{5} \gamma_k \times p_\Omega(\,\cdot\,|\,[C]^k)$$

Context Aggregation

Goal Compute a similarity score between R and C.

How to aggregate contexts? → **Weighted Sum!**

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$$P \triangleq \frac{1}{5}\sum_{k=0}^{4} \gamma_k \times p_\Omega(\cdot \mid [R]^k)$$

$$InfoLM\,(R, C) \triangleq \mathcal{I}\left(P, Q\right)$$

Candidate

[MASK] is freezing this morning !

...

It is [MASK] this morning !

...

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$$Q \triangleq \frac{1}{6}\sum_{k=0}^{5} \gamma_k \times p_\Omega(\cdot \mid [C]^k)$$

Experimental Setting

Experimental Setting

Data2text Generation

- Results on WebNLG 2020
- Correctness / Data Coverage / Relevance
Fluency / Text Structure
- Results on English only

Gardent et al. 2017

Ferreira et al. (2020)

Perez-Beltrachini et al 2016

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Summary Generation

- Results on SummEval
- Correlation with pyramid score
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Bhandari et al. (2020)

Nenkova and Passonneau 2004

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Results

Results

Task

(John_Blaha birthDate 1942_08_26)
(John_Blaha birthPlace San_Antonio)
(John_E_Blaha job Pilot)

John Blaha, born in San Antonio on 1942-08-26, worked as a pilot

Results

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John Blaha, born in San Antonio on 1942-08-26, worked as a pilot

Metric	Correctness			Data Coverage			Fluency			Relevance			Text Structure		
	r	ρ	τ	r	ρ	τ	r	ρ	τ	r	ρ	τ	r	ρ	τ
Correct	100.0	100.0	100.0	97.6	85.2	73.3	80.0	81.1	61.6	99.1	89.7	75.0	80.1	80.8	60.0
DataC	85.2	97.6	73.3	100.0	100.0	100.0	71.8	51.7	38.3	96.0	93.8	81.6	71.6	51.4	36.6
Fluency	81.1	80.0	61.6	71.8	51.7	38.3	100.0	100.0	100.0	77.0	61.4	46.6	99.5	99.7	98.3
Relev	89.7	99.1	75.0	96.0	93.8	81.6	77.0	61.4	46.6	100.0	100.0	100.0	77.2	61.1	45.0
TextS	80.8	80.1	60.0	71.6	51.4	36.6	99.5	99.7	98.3	77.2	61.1	45.0	100.0	100.0	100.0
$\mathcal{D}_{AB}$	88.8	**89.3**	**76.6**	**81.8**	**82.6**	**70.0**	86.6	92.0	76.6	**89.8**	**87.9**	73.3	86.6	91.4	75.0
$\mathcal{D}_{\alpha}$	88.8	**89.3**	**76.6**	**81.8**	**82.6**	**70.0**	86.6	92.0	76.6	**89.8**	**87.9**	73.3	86.6	91.4	75.0
$\mathcal{D}_{\beta}$	81.4	50.0	71.6	48.4	79.7	65.0	44.8	84.7	76.6	49.3	72.3	60.0	48.0	83.8	75.0
$\mathcal{L}_1$	75.2	33.8	61.6	32.4	53.8	40.0	22.7	83.5	73.3	32.2	57.9	45.0	25.6	83.2	71.6
$\mathcal{R}$	**89.7**	86.0	75.0	78.7	70.5	51.6	**93.3**	**95.7**	**85.3**	87.6	84.4	70.0	**92.4**	93.8	81.6
JS	79.4	81.1	70.0	69.3	75.5	60.0	89.4	91.4	75.0	81.7	70.5	60.0	91.9	91.1	73.3
BertS	85.5	83.4	73.3	74.7	68.2	53.3	92.3	95.5	85.0	83.3	79.4	65.0	91.9	**95.0**	**83.3**
MoverS	84.1	84.1	73.3	78.7	66.2	53.3	91.2	92.1	78.3	82.1	77.4	65.0	90.1	91.4	76.3
BLEU	77.6	66.3	60.0	55.7	50.2	36.6	89.4	90.5	78.3	63.0	65.2	51.6	88.5	89.1	76.6
R-1	80.6	65.0	65.0	61.1	59.6	48.3	76.5	76.3	60.3	64.3	69.2	56.7	75.9	77.5	58.3
METEOR	86.5	66.3	70.0	77.3	50.2	46.6	86.7	90.5	78.3	82.1	65.2	58.6	86.2	89.1	76.6
TER	79.6	78.3	58.0	69.7	58.2	38.0	89.1	93.5	80.0	75.0	70.2	**77.6**	89.5	91.1	78.6

Results

Task

(John_Blaha birthDate 1942_08_26)
(John_Blaha birthPlace San_Antonio)
(John_E_Blaha job Pilot)

John Blaha, born in San Antonio on 1942-08-26, worked as a pilot

Parameter Free

Metric	Correctness			Data Coverage			Fluency			Relevance			Text Structure		
	r	ρ	τ	r	ρ	τ	r	ρ	τ	r	ρ	τ	r	ρ	τ
Correct	100.0	100.0	100.0	97.6	85.2	73.3	80.0	81.1	61.6	99.1	89.7	75.0	80.1	80.8	60.0
DataC	85.2	97.6	73.3	100.0	100.0	100.0	71.8	51.7	38.3	96.0	93.8	81.6	71.6	51.4	36.6
Fluency	81.1	80.0	61.6	71.8	51.7	38.3	100.0	100.0	100.0	77.0	61.4	46.6	99.5	99.7	98.3
Relev	89.7	99.1	75.0	96.0	93.8	81.6	77.0	61.4	46.6	100.0	100.0	100.0	77.2	61.1	45.0
TextS	80.8	80.1	60.0	71.6	51.4	36.6	99.5	99.7	98.3	77.2	61.1	45.0	100.0	100.0	100.0
$\mathcal{D}_{AB}$	88.8	**89.3**	**76.6**	**81.8**	**82.6**	**70.0**	86.6	92.0	76.6	**89.8**	**87.9**	73.3	86.6	91.4	75.0
$\mathcal{D}_{\alpha}$	88.8	**89.3**	**76.6**	**81.8**	**82.6**	**70.0**	86.6	92.0	76.6	**89.8**	**87.9**	73.3	86.6	91.4	75.0
$\mathcal{D}_{\beta}$	81.4	50.0	71.6	48.4	79.7	65.0	44.8	84.7	76.6	49.3	72.3	60.0	48.0	83.8	75.0
$\mathcal{L}_1$	75.2	33.8	61.6	32.4	53.8	40.0	22.7	83.5	73.3	32.2	57.9	45.0	25.6	83.2	71.6
$\mathcal{R}$	**89.7**	86.0	75.0	78.7	70.5	51.6	**93.3**	**95.7**	**85.3**	87.6	84.4	70.0	**92.4**	93.8	81.6
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Multitask: To evaluate on system on different tasks we need different metrics (data2text vs Translation)

Let's speak about how to aggregate different metrics to obtain stronger evaluation procedures.

2. How to aggregate several metrics?

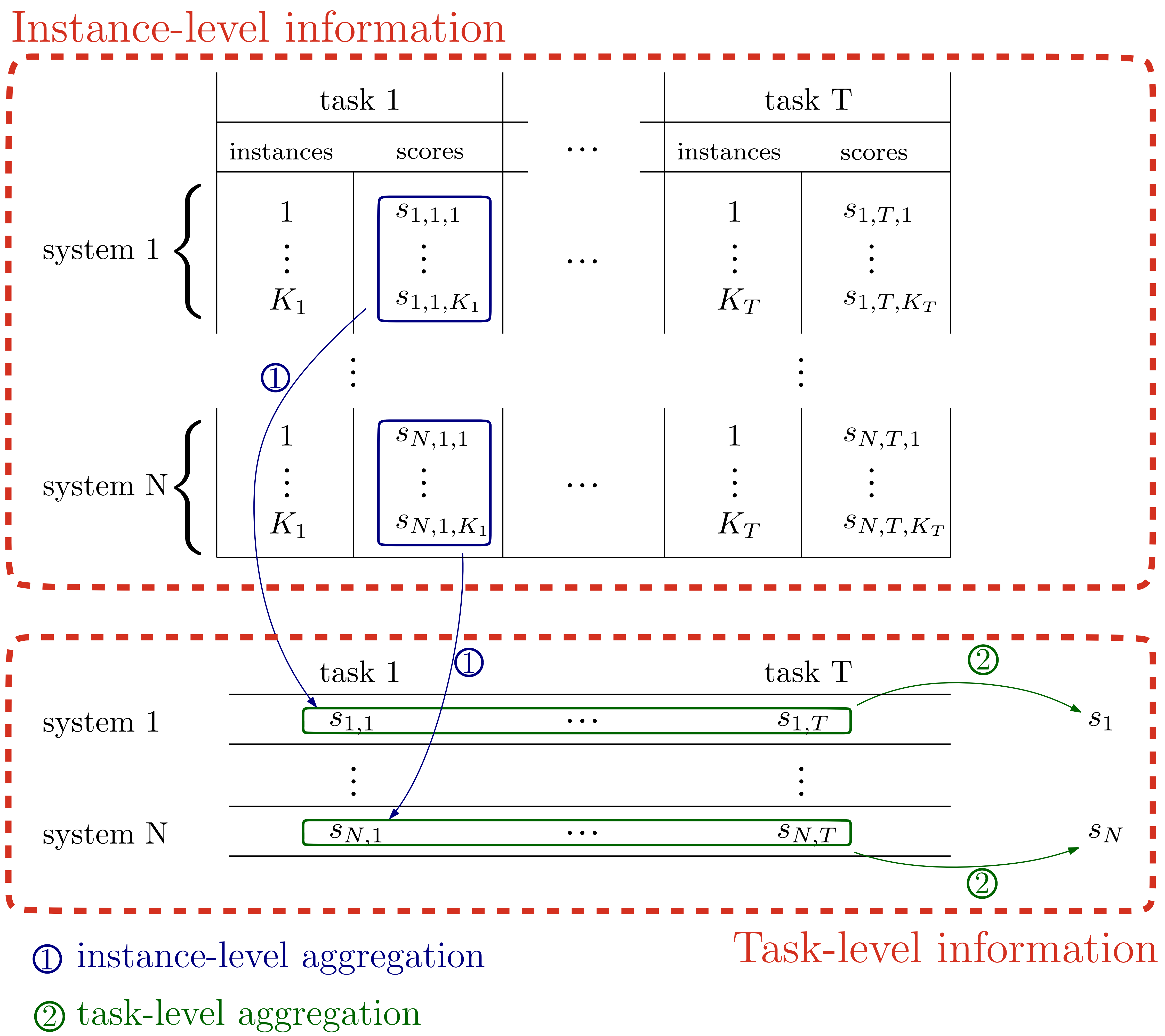
1.1 Framework

1.2 Task Level Aggregation

1.3 Instance Level Aggregation

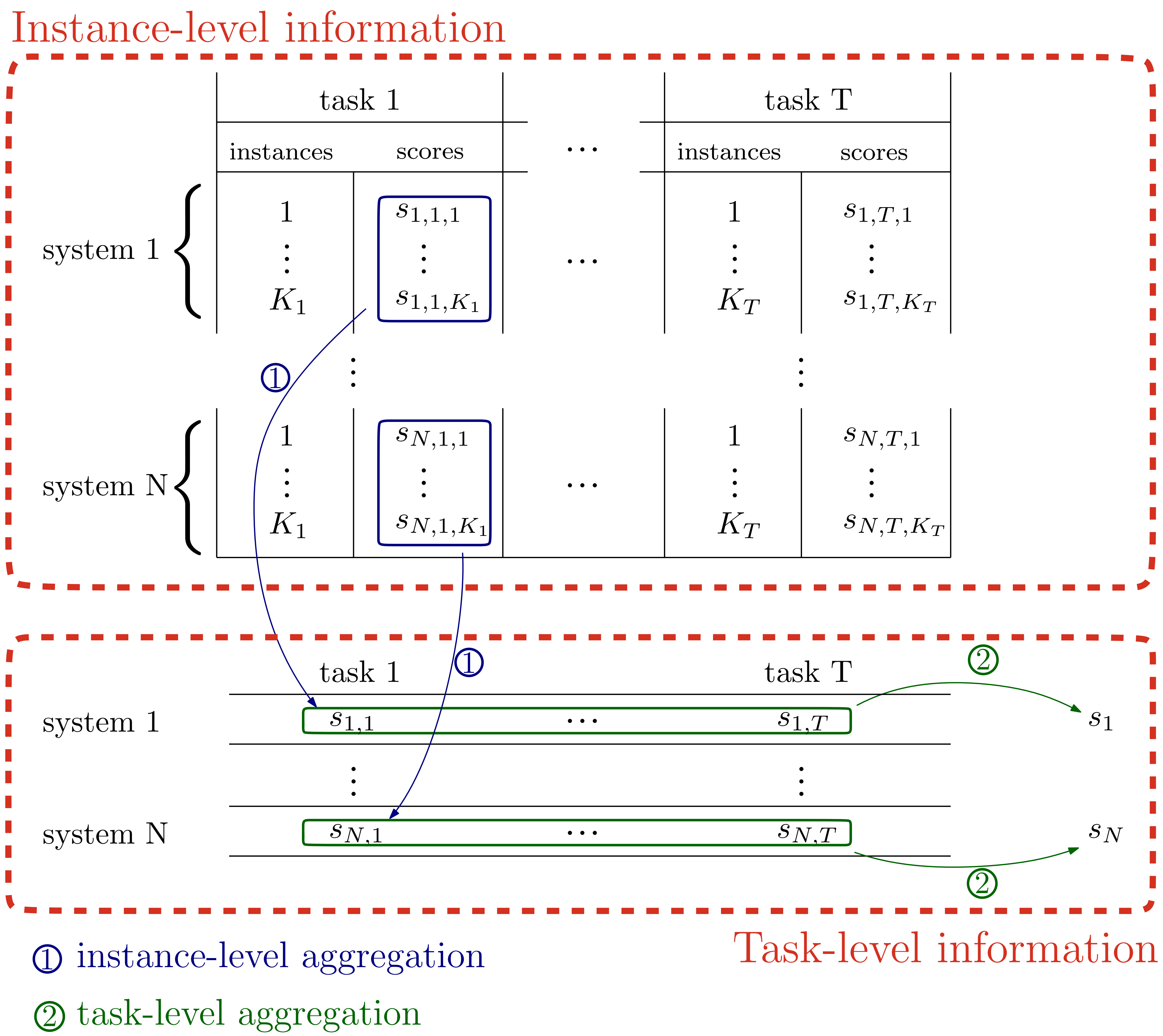
Pierre Colombo, Nathan Noiry, Ekhine Irurozki and Stephan Clemencon. What are the best Systems? New Perspectives on NLP Benchmarking.

Framework



Instance-level information
task 1
task T
instances
scores
...
system 1
1
K_1
$s_{1,1,1}$
$s_{1,1,K_1}$
$s_{1,T,1}$
s_{1,T,K_T}
K_T
system N
$s_{N,1,1}$
$s_{N,1,K_1}$
$s_{N,T,1}$
s_{N,T,K_T}
①
②
$s_{1,1}$
$s_{1,T}$
$s_{N,1}$
$s_{N,T}$
s_1
s_N
Task-level information
① instance-level aggregation
② task-level aggregation

Framework



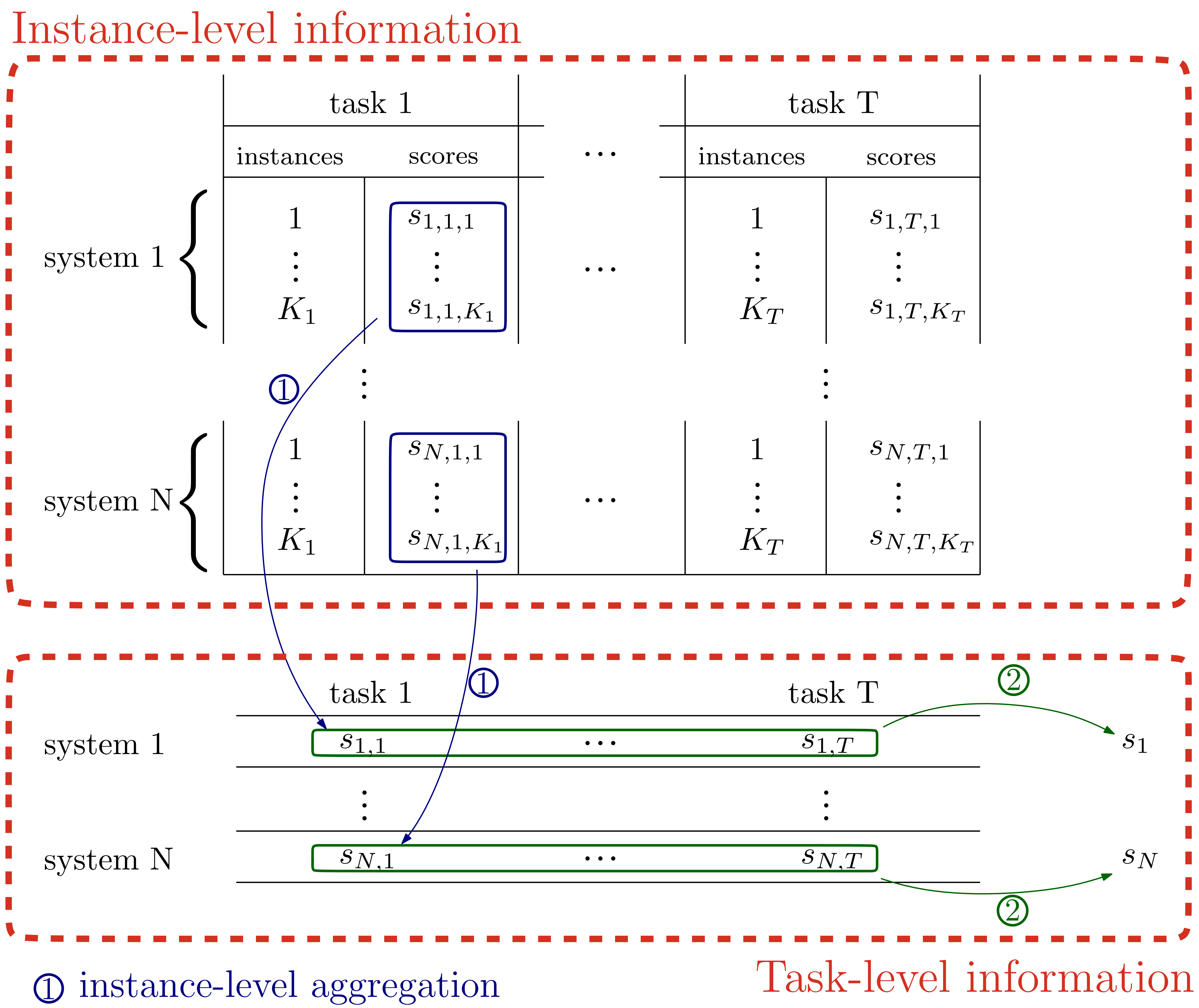
Setting:

1. One has access to the scores of N systems across T tasks.

2. Each task t being associated with a metric and a test set of size K_t.

3. We have $s_{n,t,k} \in \mathbb{R}$

First problem: task-level ranking



① instance-level aggregation

② task-level aggregation

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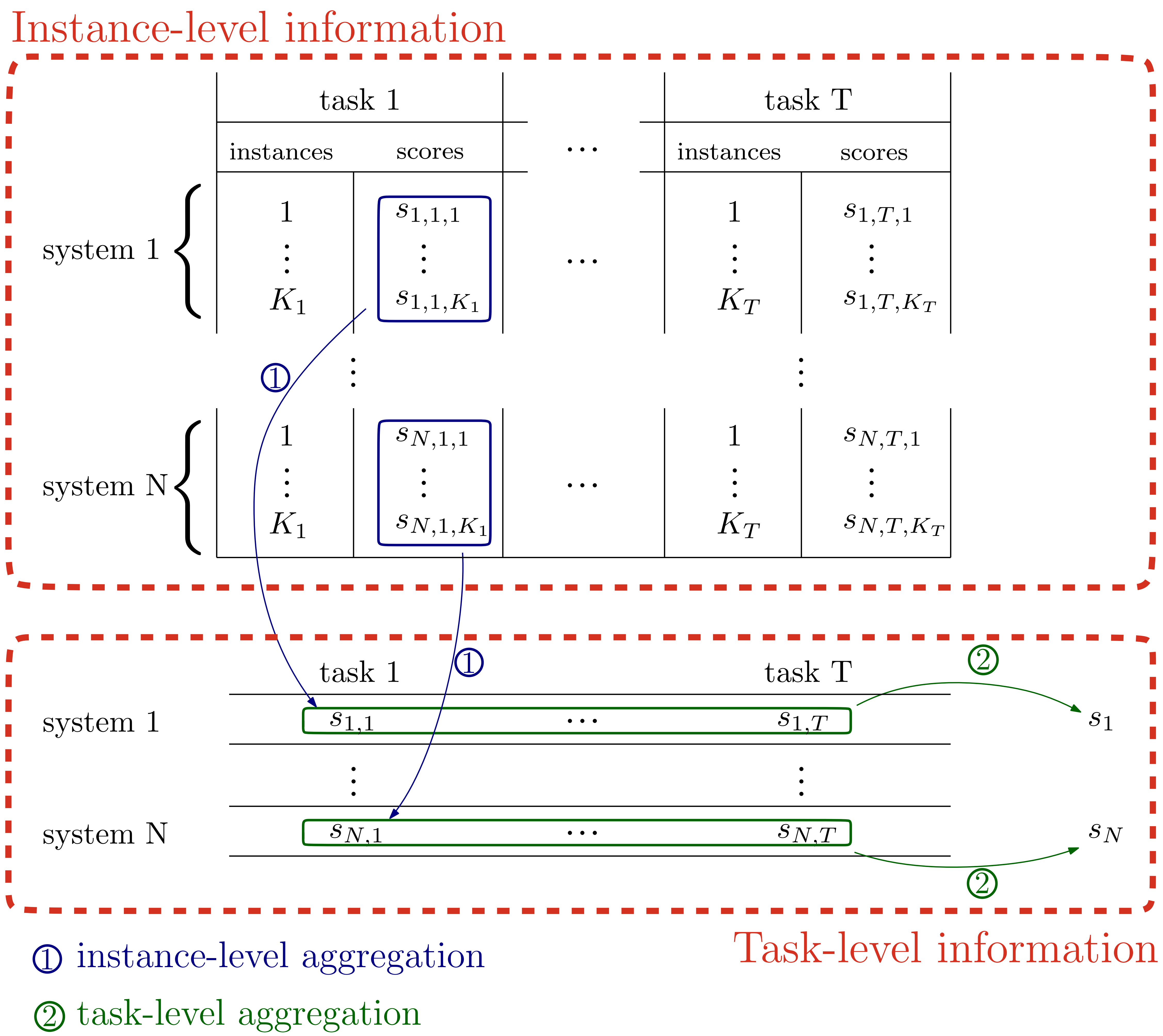

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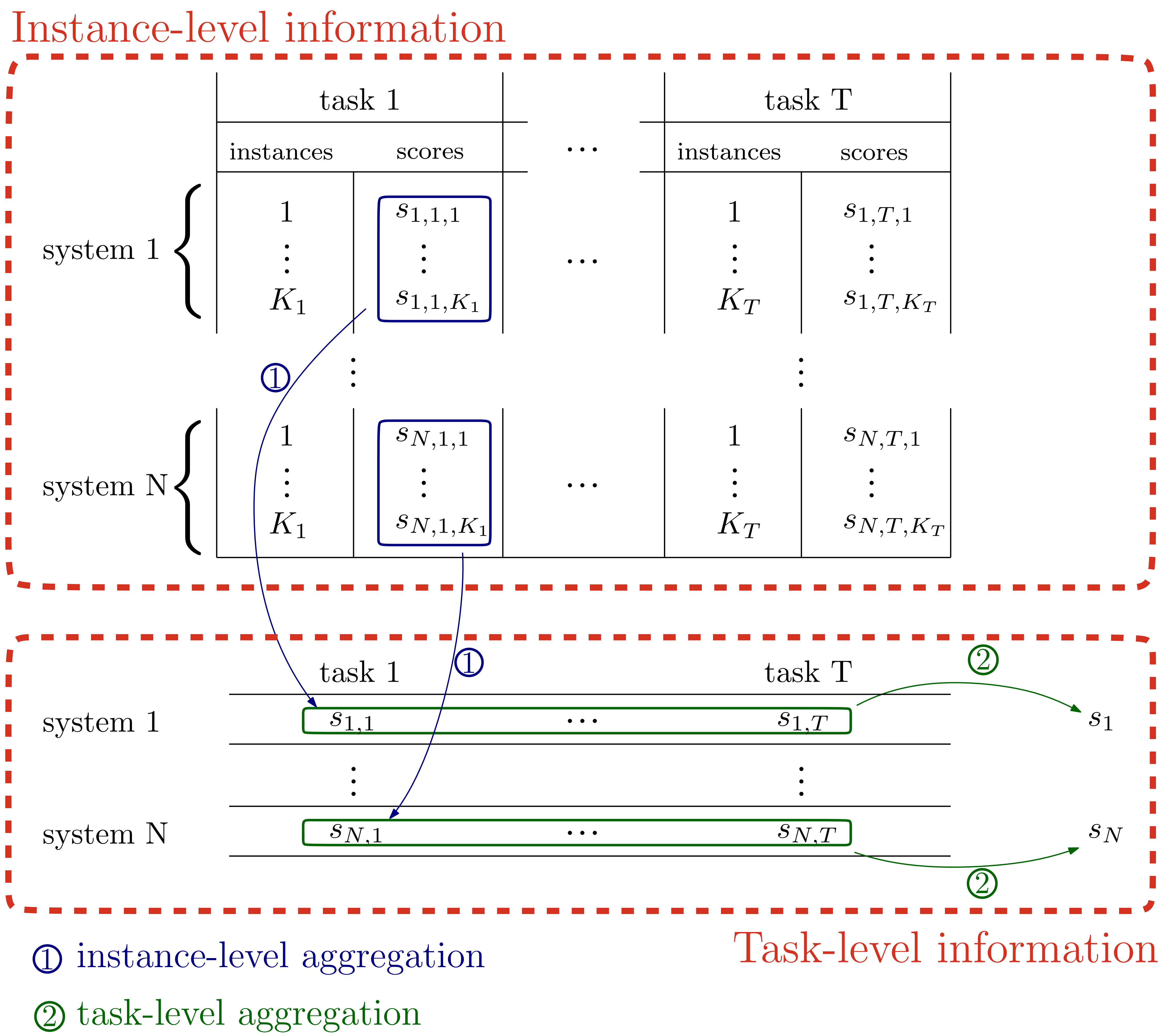

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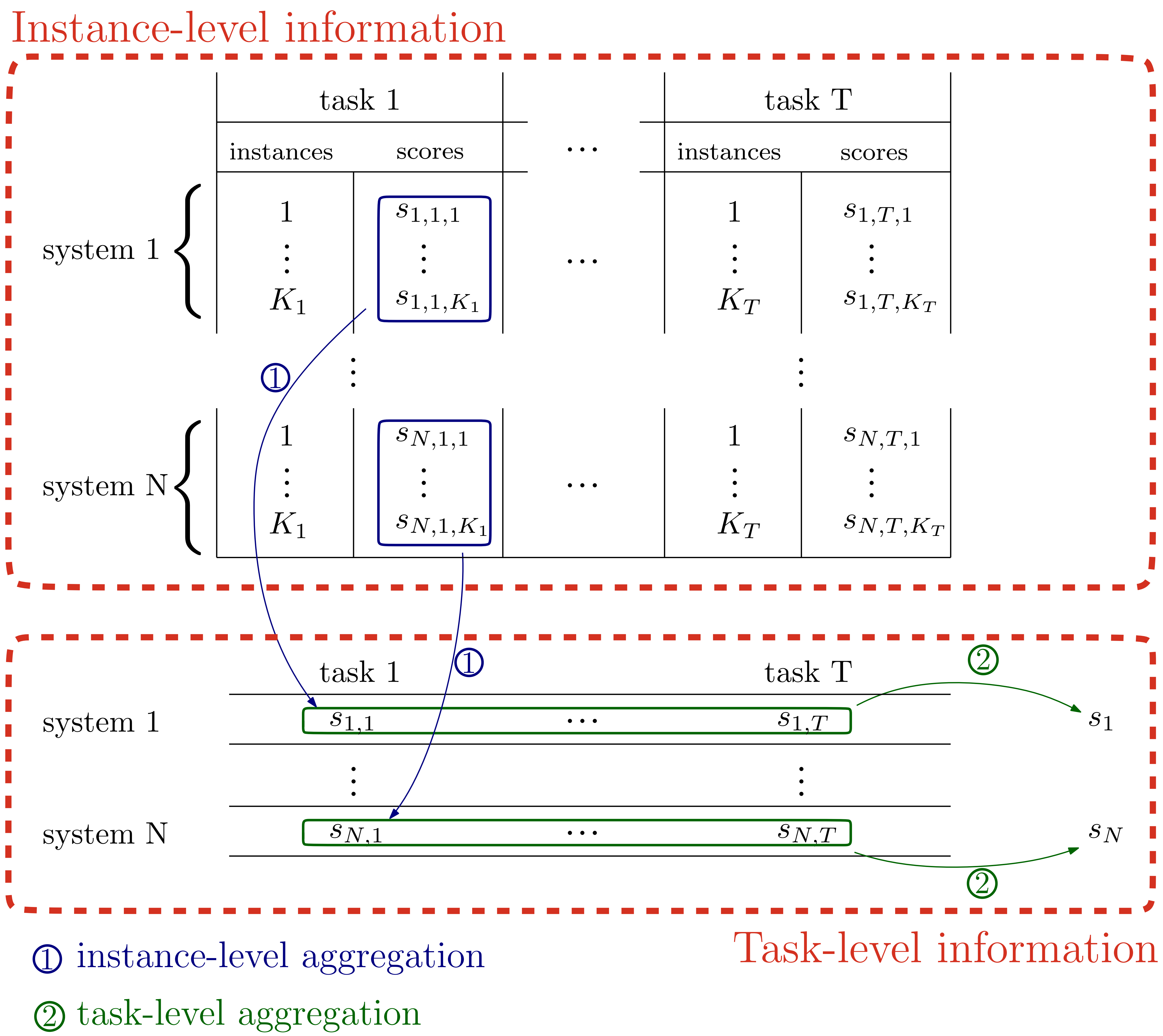

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Goal: find an aggregation procedure that orders the systems.

Second problem: instance-level ranking

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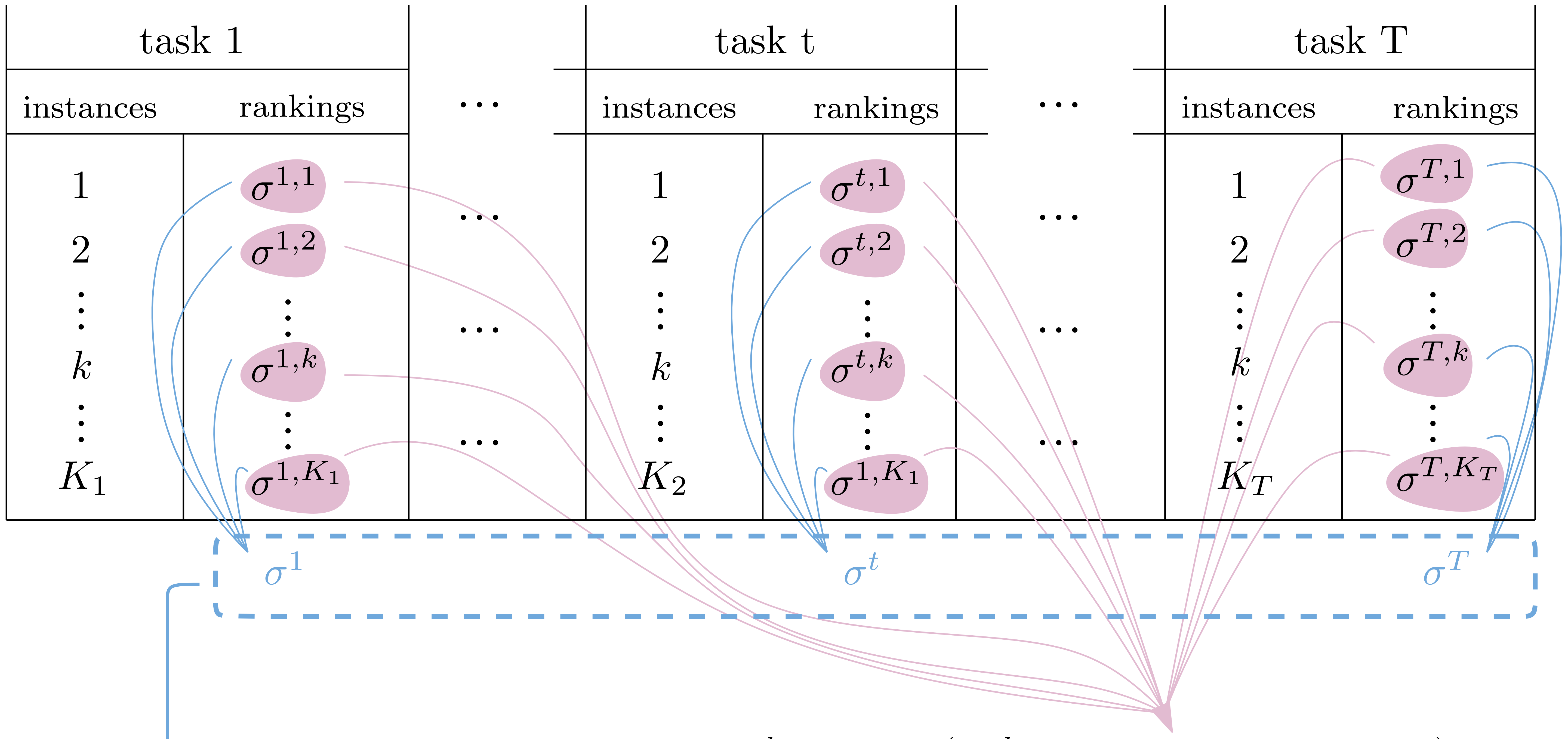

One level aggregation: $\sigma^l = \text{Borda}\big(\sigma^{t,k},\, 1 \le t \le T,\, 1 \le k \le K_t\big)$

Two level aggregation: $\forall 1 \le t \le T, \quad \sigma^t = \text{Borda}\big(\sigma^{t,k},\, 1 \le k \le K_t\big)$

$\sigma^{2l} = \text{Borda}\big(\sigma^t,\, 1 \le t \le T\big)$

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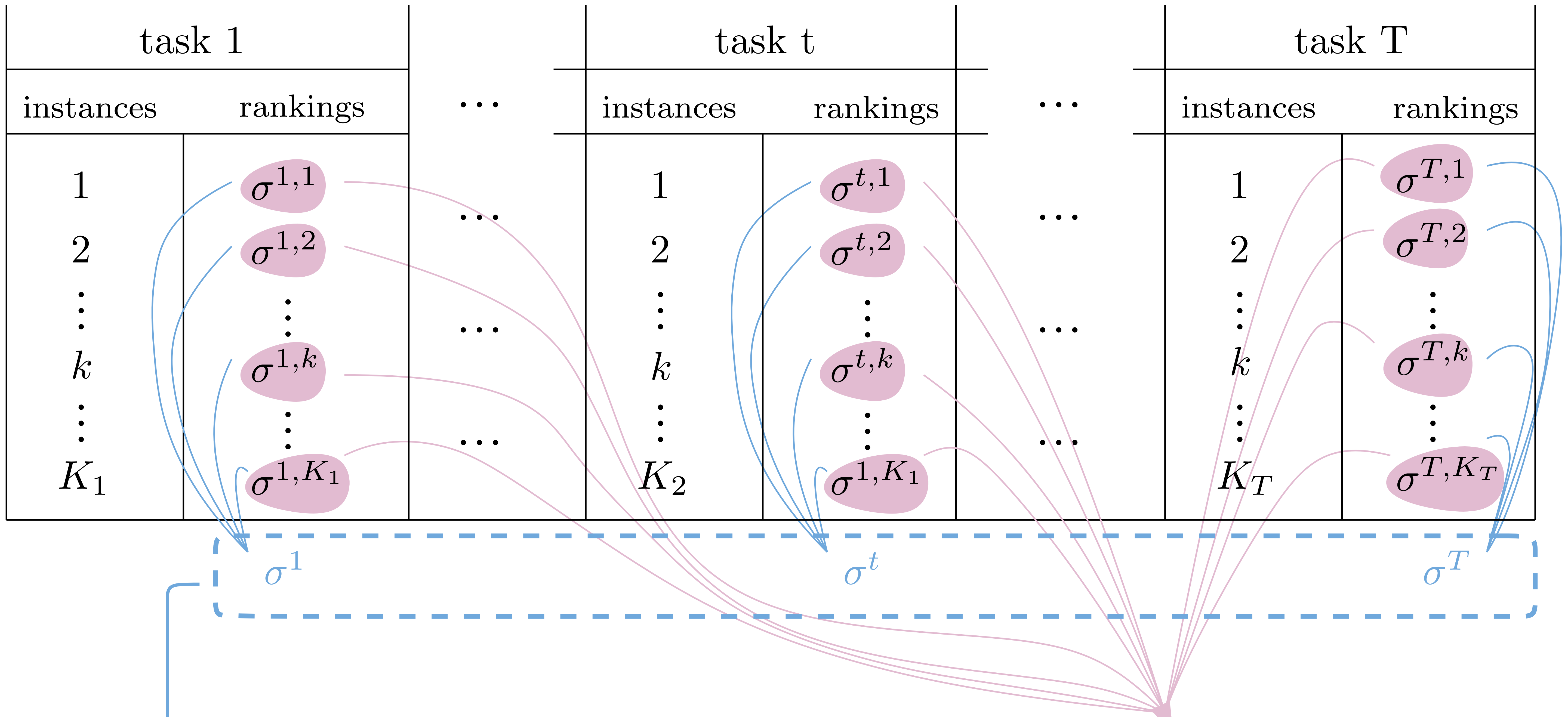

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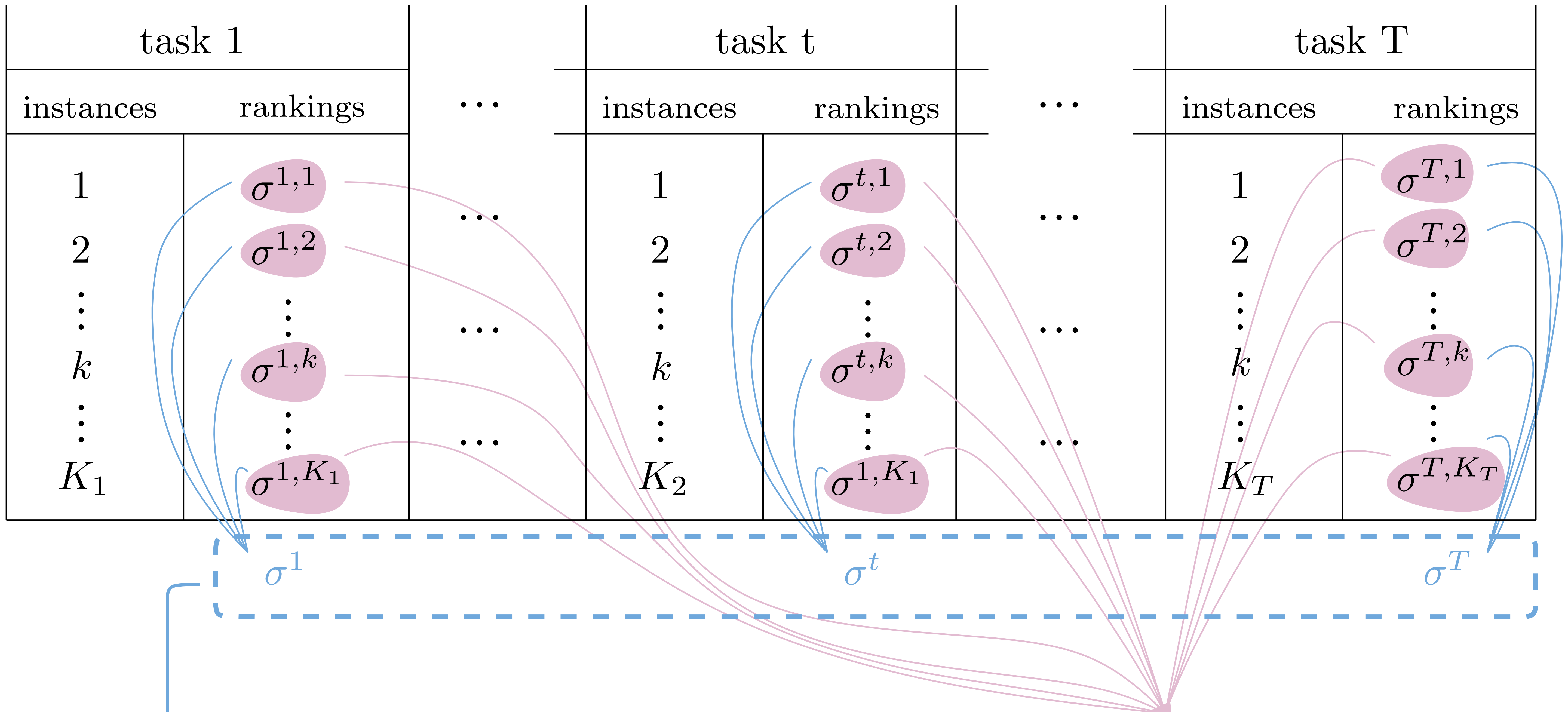

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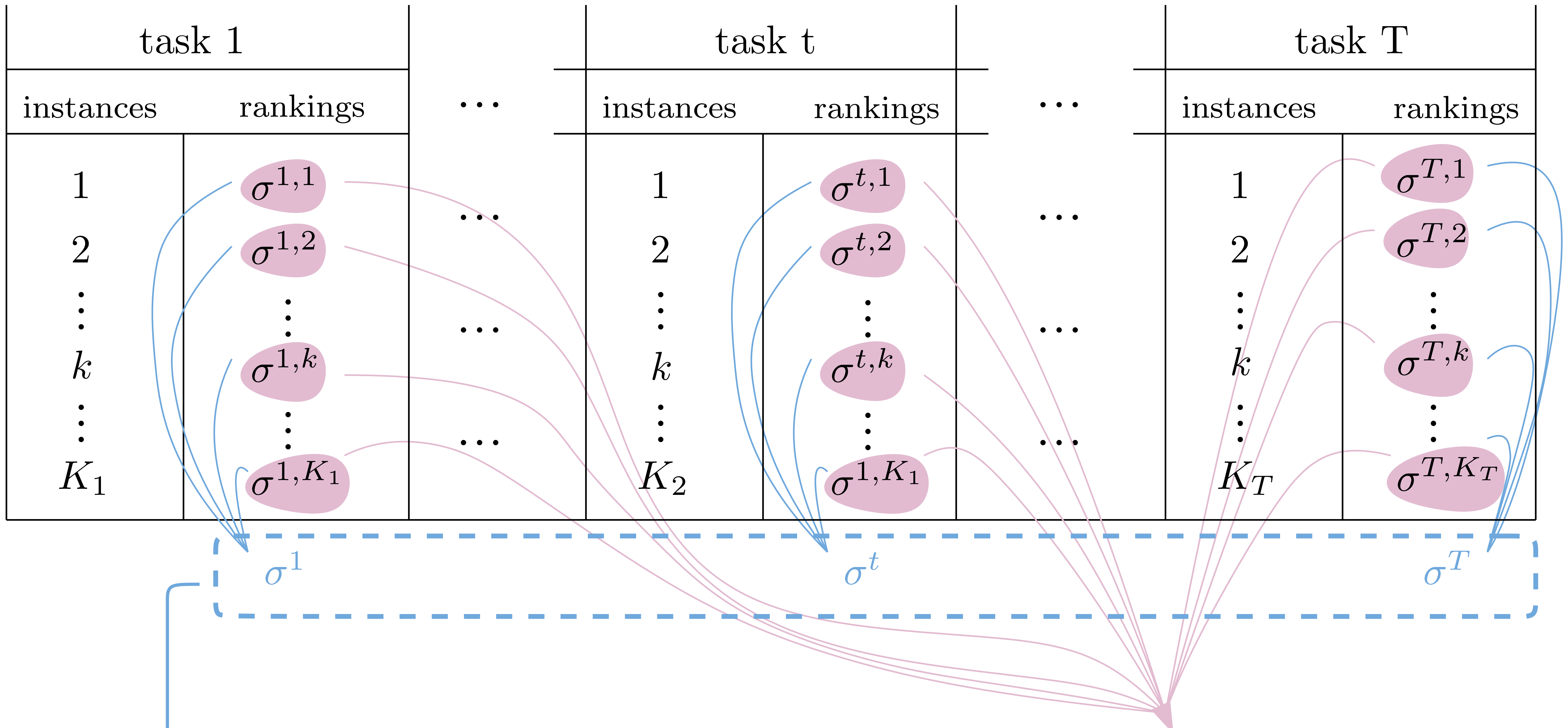

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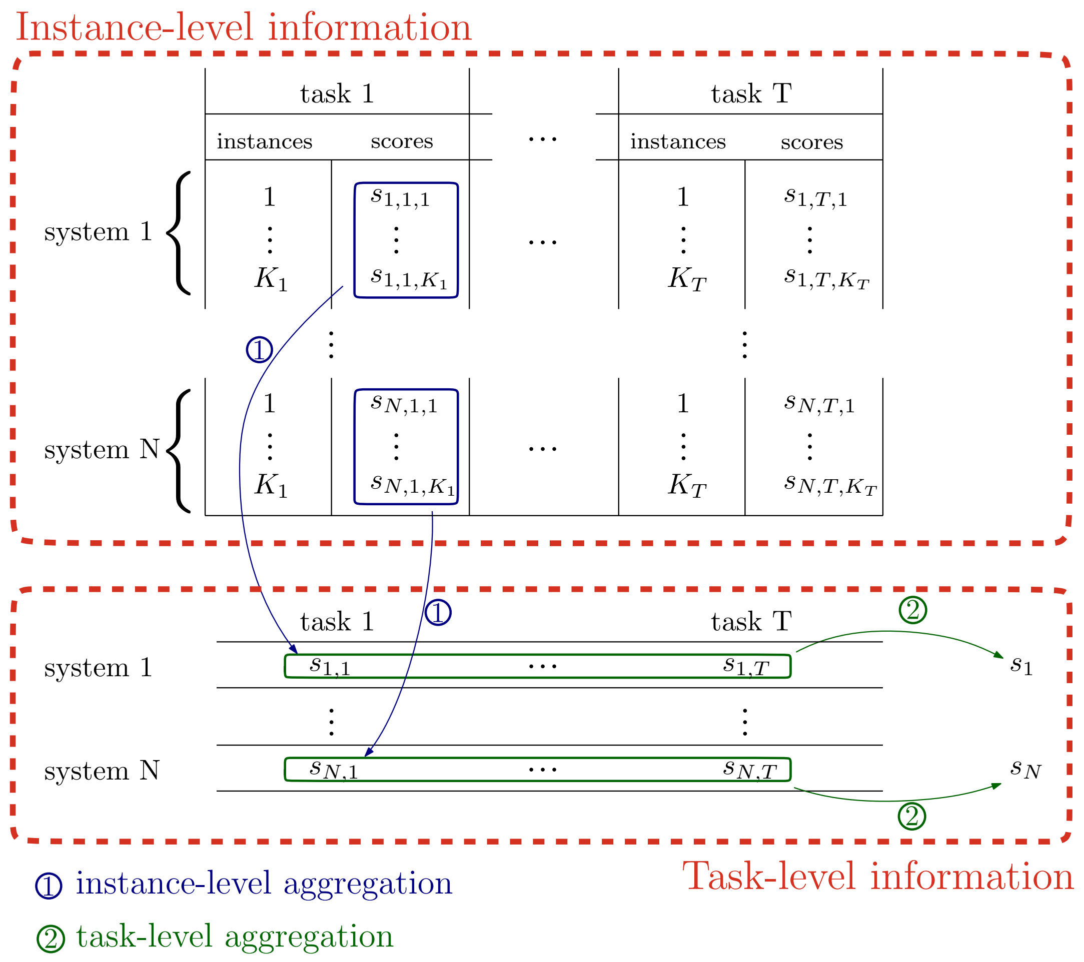

Initial information: $s_{n,t} \in \mathbb{R}$

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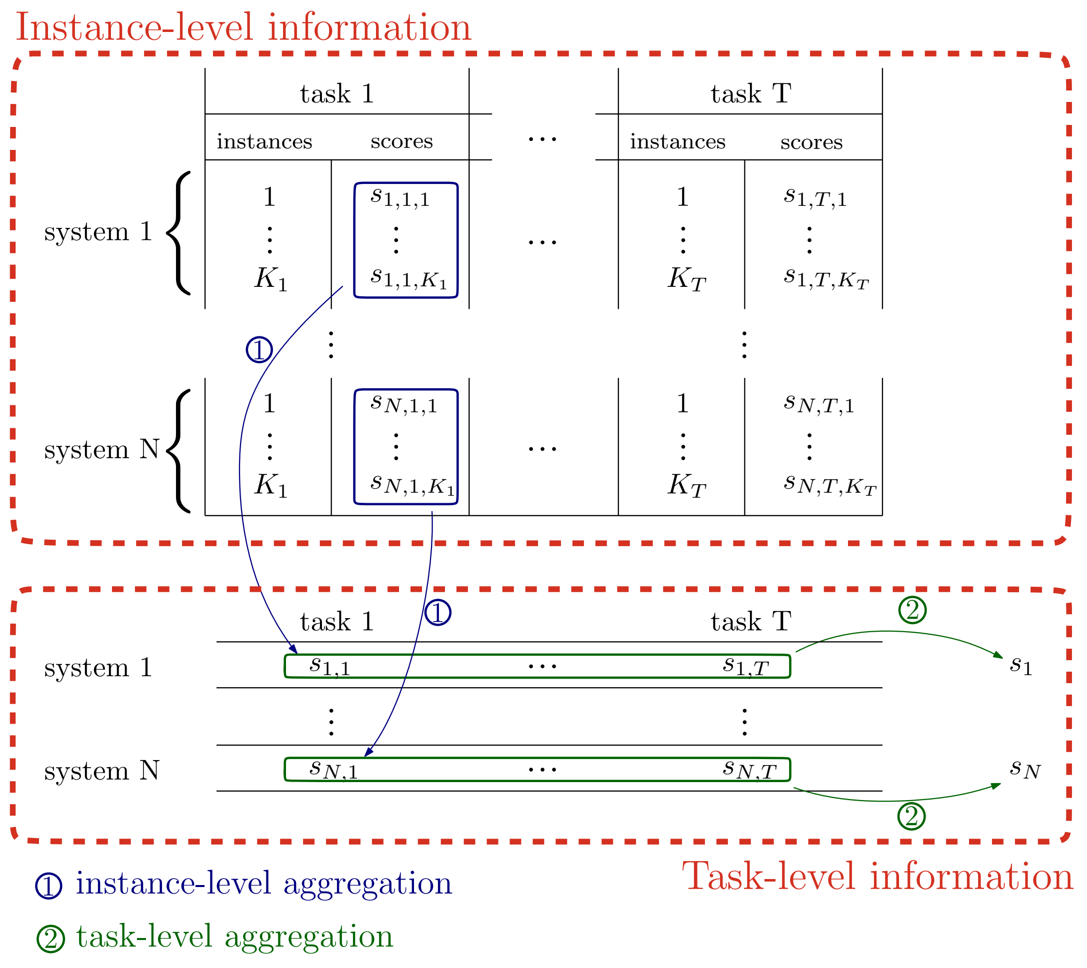

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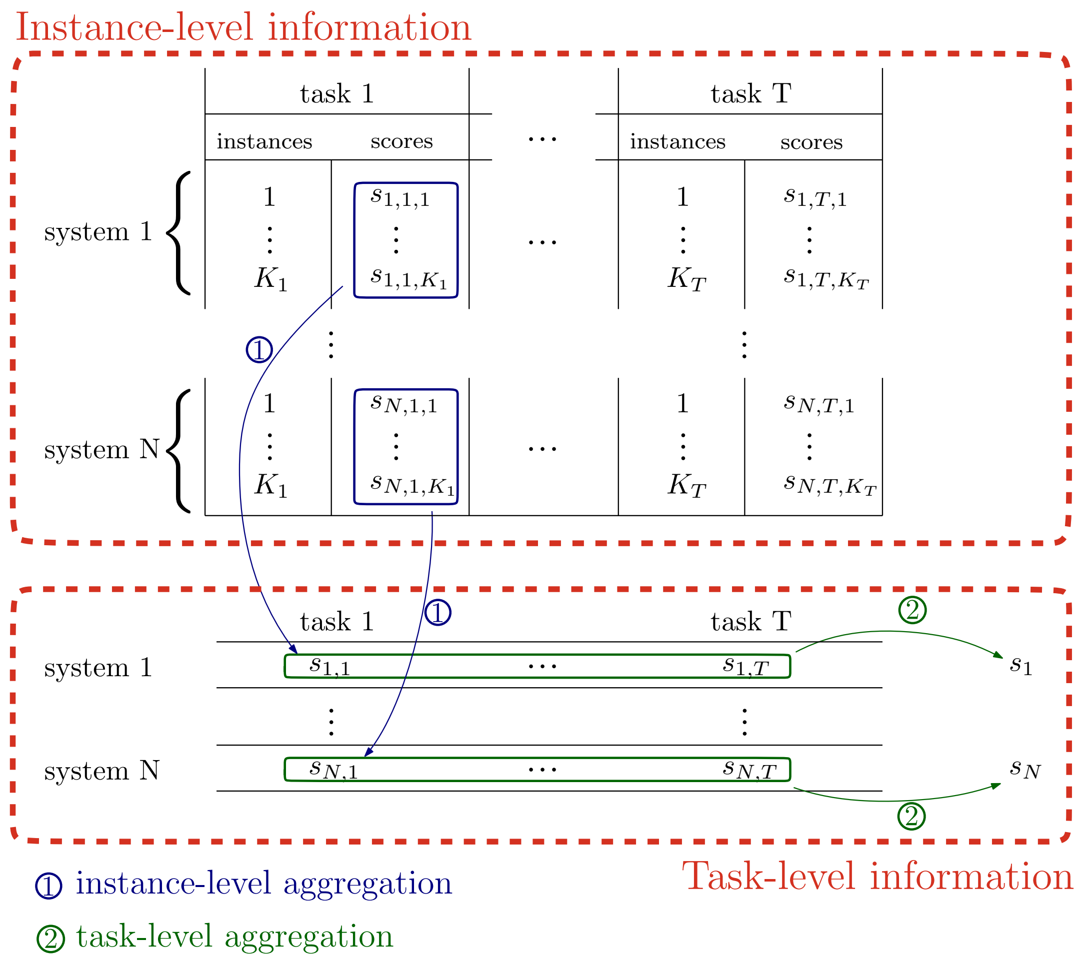
First attempt: mean-aggregation

1. **Compute aggregated scores:**

$$s_n = \sum_{t=1}^{T} s_{n,t}$$

2. **Rank systems accordingly**

Focus on task-level ranking



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Weaknesses

1. **Scale dependent**

2. **Non-relative score**

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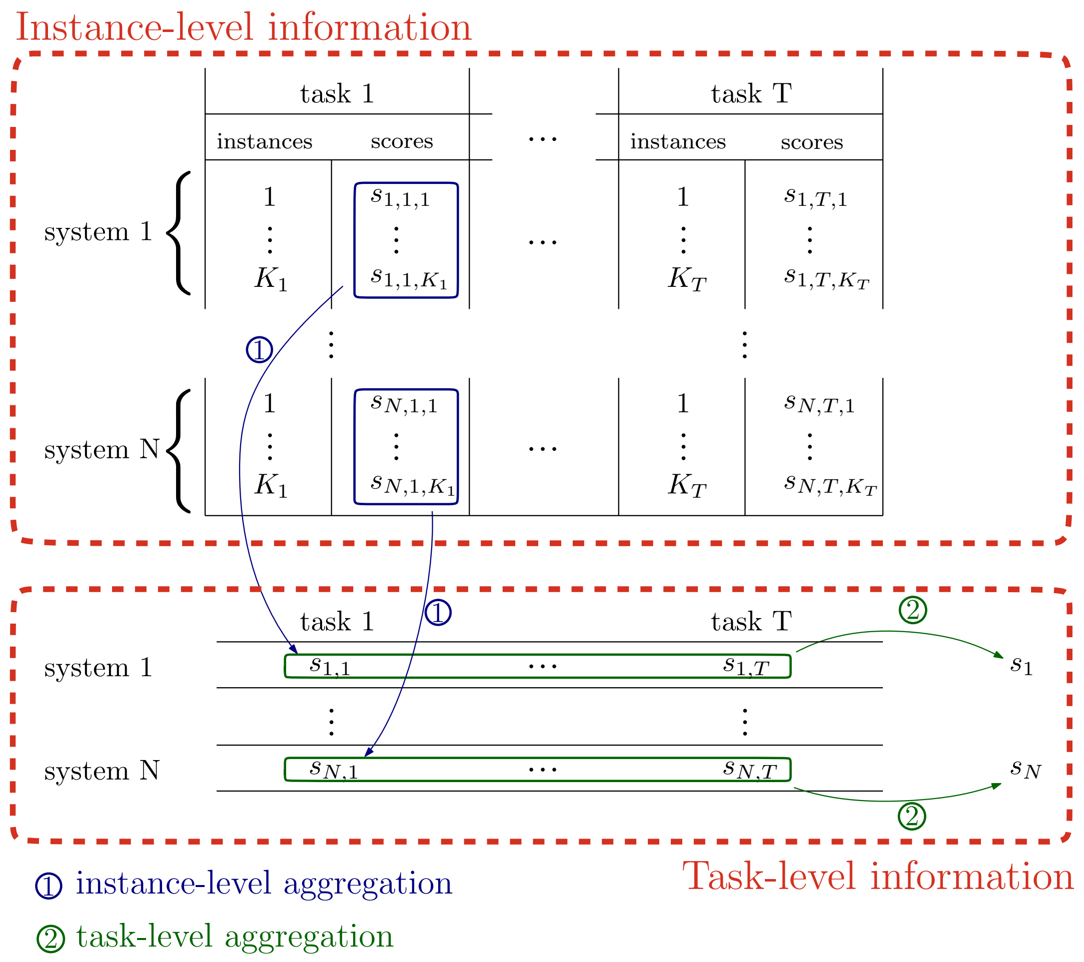

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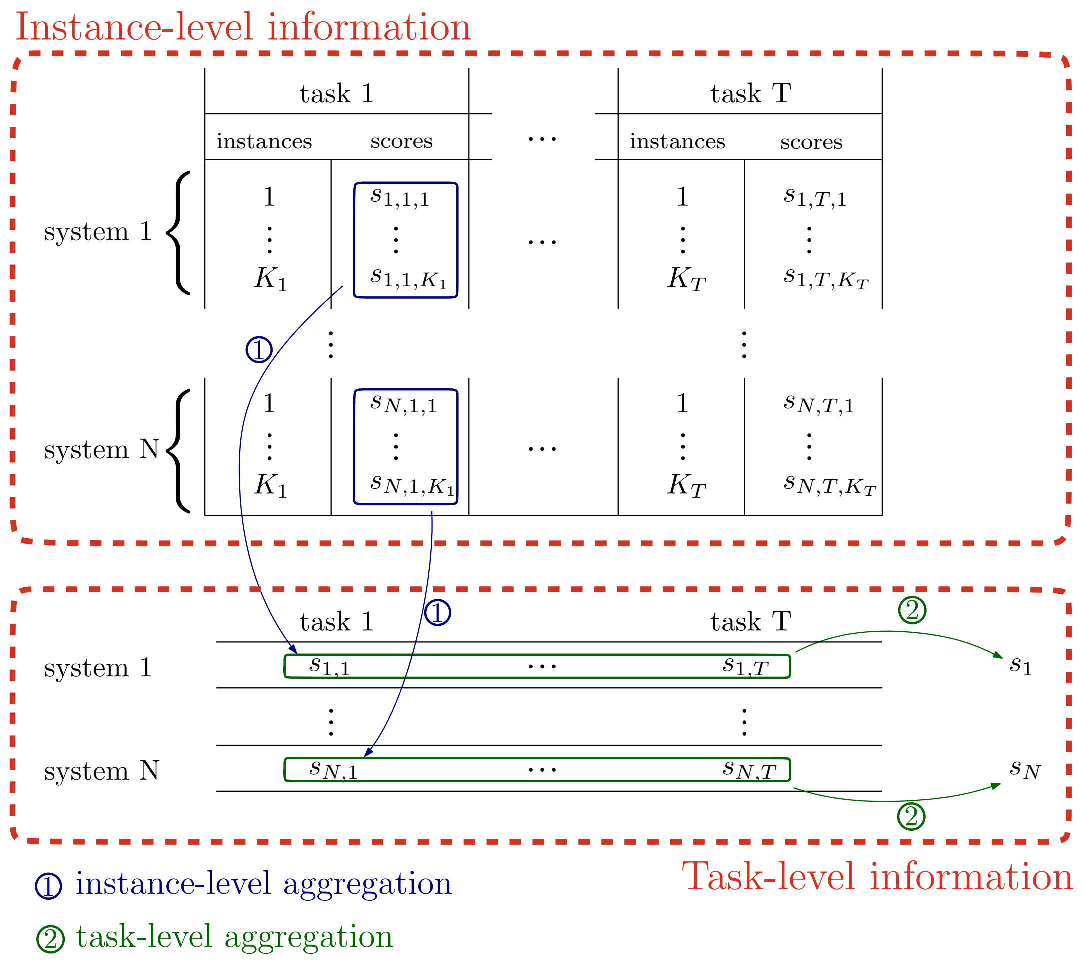


Initial information: $s_{n,t} \in \mathbb{R}$

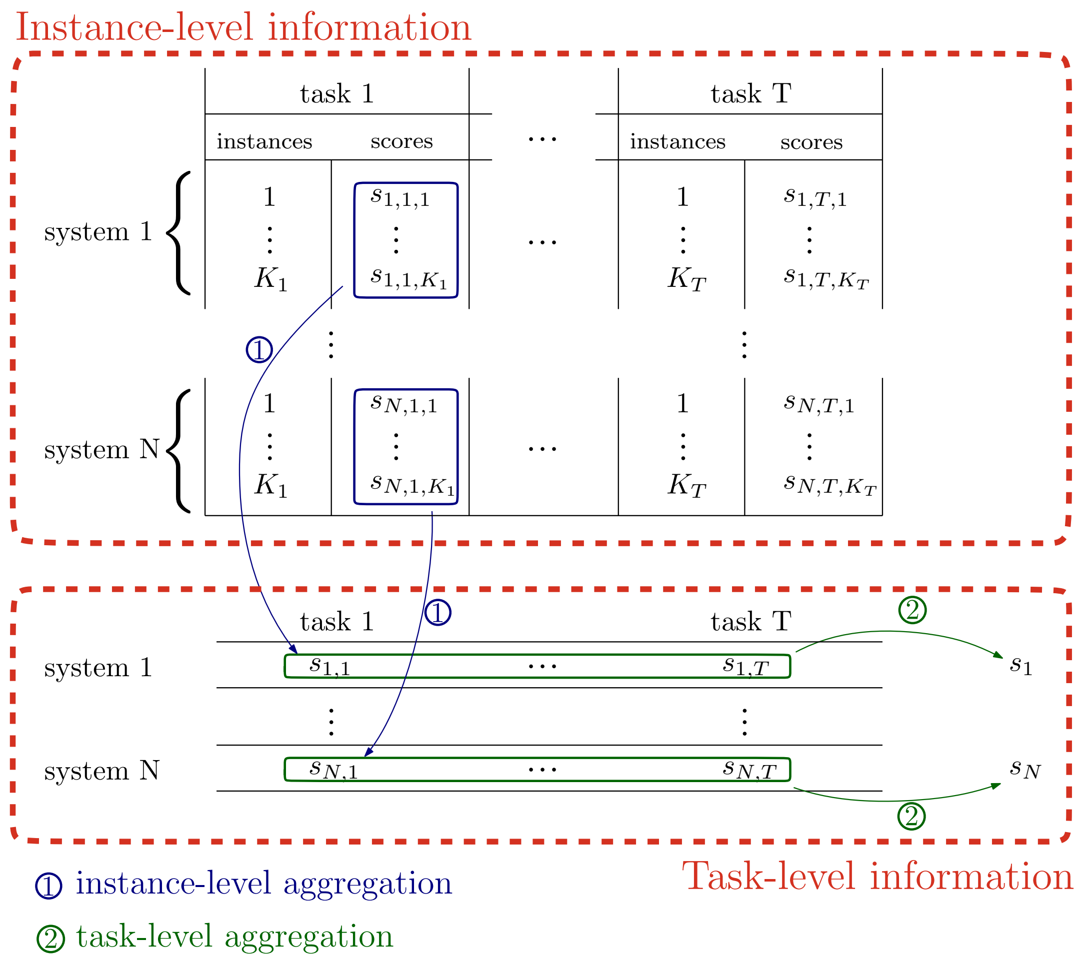
Second attempt: pairwise ranking

1. **Compute pairwise ranking:**

$$\lambda_A = \sum_{t=1}^{T} \mathbf{1}_{s_{A,t} > s_{B,t}}$$

2. **Rank A>B if and only if $\lambda_A > \lambda_B$**

Focus on task-level ranking



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Weaknesses

1 Restricted to two systems

2 Can lead to paradoxes

A toy example

	task 1	task 2	task 3	task 4	task 5	task 6	sum
A	$0,3$ 3	5 3	10 1	$0,02$ 2	$1,0$ 1	$0,4$ 3	$16,72$ 13
B	$0,1$ 2	4 2	13 2	$0,01$ 1	$2,2$ 3	$0,3$ 2	$19,61$ 12
C	$0,0$ 1	3 1	15 3	$0,03$ 3	$2,0$ 2	$0,2$ 1	$20,23$ 11

mean-aggregation: $A > B > C$

pairwise ranking: $B > A, \ C > B, \ A = C$

our ranking: $C > B > A$

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Solution: define a distance d on the permutation group, and find a permutation σ^* that minimizes the sum of distances:

$$\sigma^* \in \operatorname*{argmin}_{\sigma \in \mathfrak{S}_N} \sum_{t=1}^{T} d(\sigma, \sigma^t)$$

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Relaxation of the problem: Borda count!

+ 2-approximation
+ Small complexity
+ Simple interpretation

Numerical Results

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Ranking Analysis

GLUE			XTREM		
σ^*	Team	σ^{mean}	σ^*	Team	σ^{mean}
0 (1430)	Ms Alex	0 (88.6)	0 (55)	ULR	0 (83.2)
1 (1405)	ERNIE	1 (88.0)	1 (50)	CoFe	1 (82.6)
2 (1397)	DEBERTA	2 (87.9)	2 (44)	InfoLXL	3 (80.6)
3 (1391)	AliceMind	3 (87.8)	3 (42)	VECO	4 (80.3)
4 (1375)	PING-AH	5 (87.6)	4 (35)	Unicoder	5 (79.4)
5 (1362)	HFL	4 (87.7)	5 (34)	PolyGlot	2 (80.6)
6 (1361)	T5	6 (87.5)	6 (31)	ULR-v2	6 (79.4)
7 (1358)	DIRL	10 (86.7)	7 (29)	HiCTL	8 (79.1)
8 (1331)	Zihan	7 (87.6)	8 (29)	Ernie	7 (79.1)
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0 (1430)	Ms Alex	0 (88.6)	0 (55)	ULR	0 (83.2)
1 (1405)	ERNIE	1 (88.0)	1 (50)	CoFe	1 (82.6)
2 (1397)	DEBERTA	2 (87.9)	2 (44)	InfoLXL	3 (80.6)
3 (1391)	AliceMind	3 (87.8)	3 (42)	VECO	4 (80.3)
4 (1375)	PING-AH	5 (87.6)	4 (35)	Unicoder	5 (79.4)
5 (1362)	HFL	4 (87.7)	5 (34)	PolyGlot	2 (80.6)
6 (1361)	T5	6 (87.5)	6 (31)	ULR-v2	6 (79.4)
7 (1358)	DIRL	10 (86.7)	7 (29)	HiCTL	8 (79.1)
8 (1331)	Zihan	7 (87.6)	8 (29)	Ernie	7 (79.1)
9 (1316)	ELECTRA	11 (86.7)	9 (21)	Anony	10 (78.3)

Numerical Results

Ranking Analysis

GLUE			XTREM		
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Aggregation procedure matters a lot!

Numerical Results

Ranking Analysis

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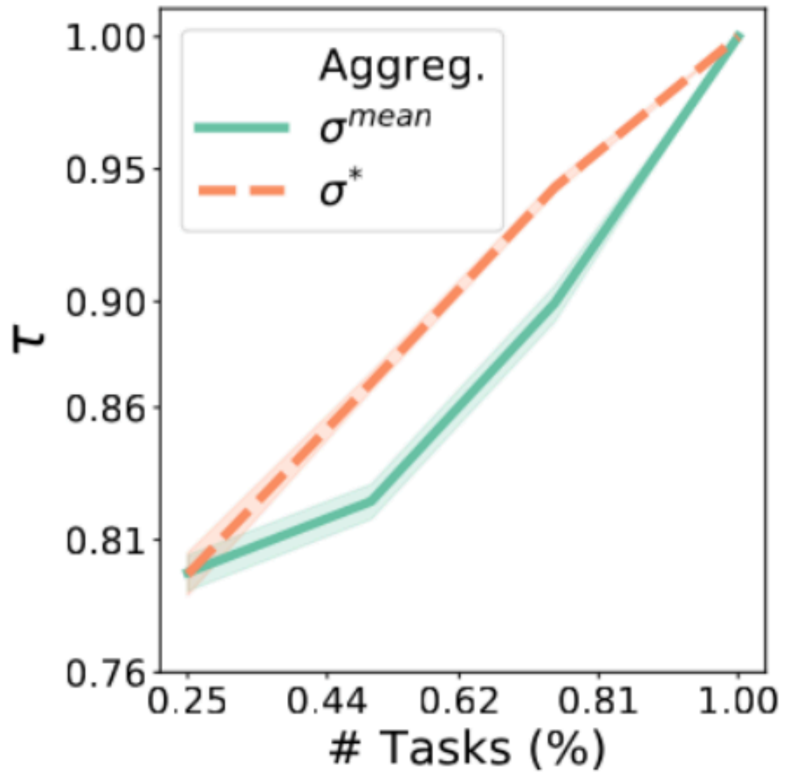
Aggregation procedure matters a lot!

Robustness Analysis

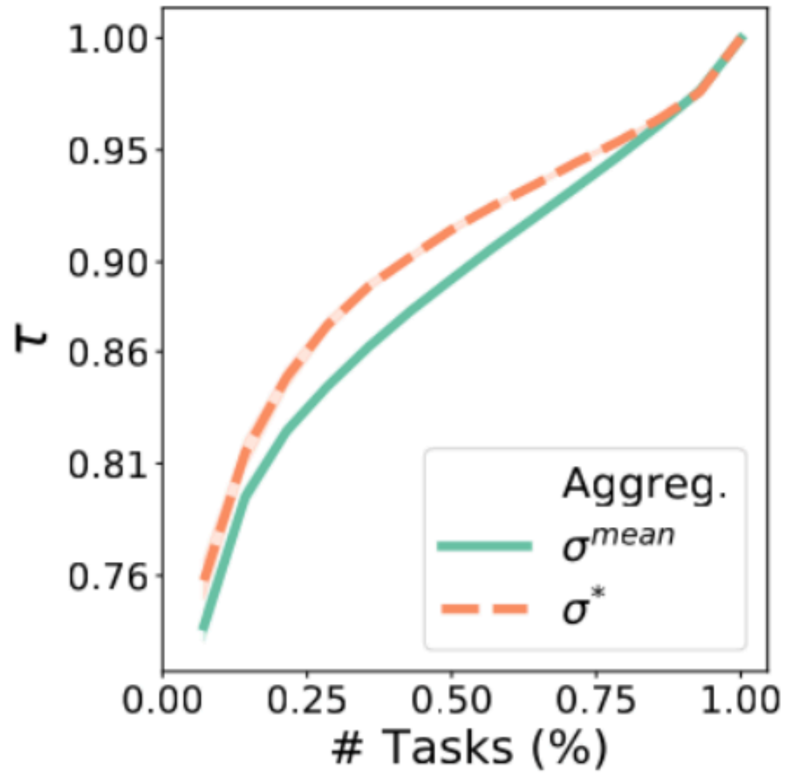
Setting:

For an increasing % of task, compute the Kendall's tau correlation coefficient between the obtained ranking and the one obtained with all the tasks

Higher is better



(f) EXTREM



(a) GLUE

Numerical Results

Ranking Analysis

GLUE			XTREM		
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Aggregation procedure matters a lot!

Robustness Analysis

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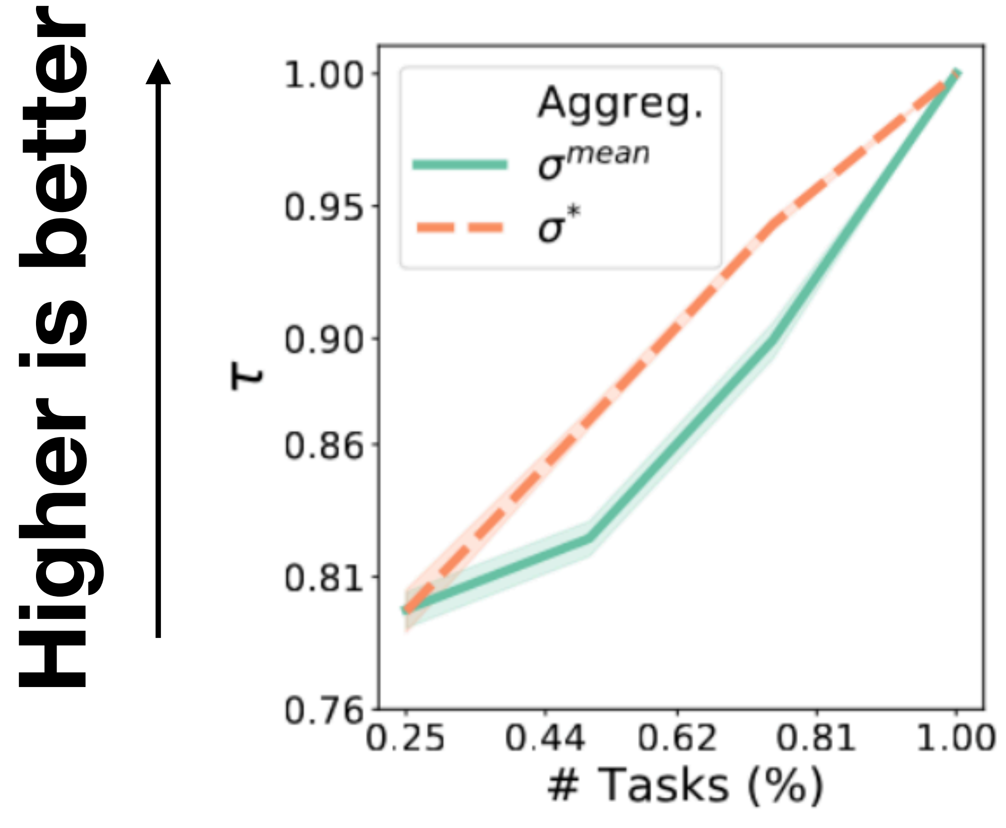
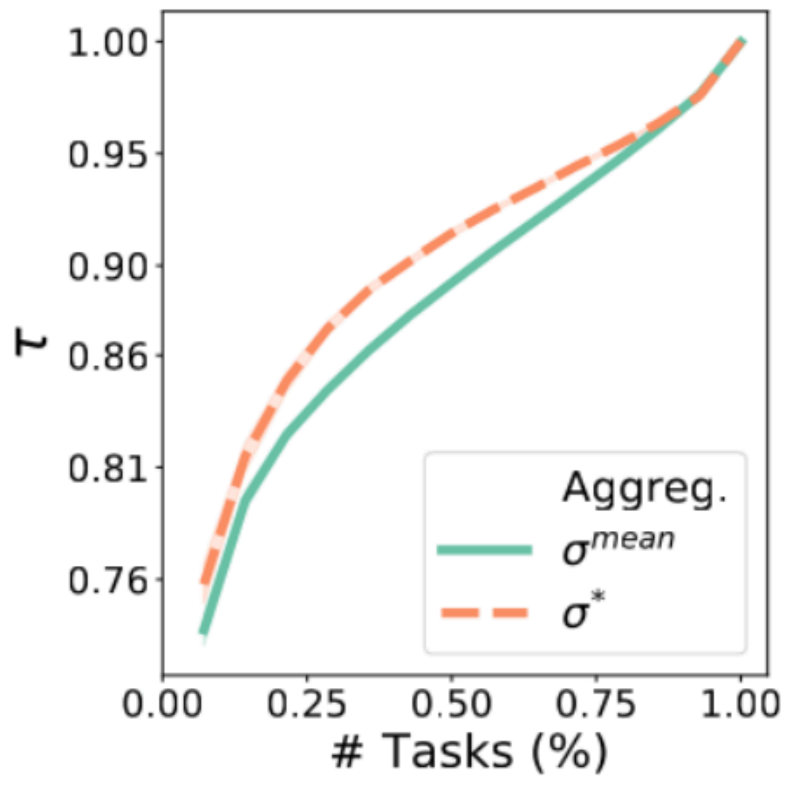


(f) EXTREM



(a) GLUE

Relying on Borda count is more reliable

2. How to aggregate several metrics?

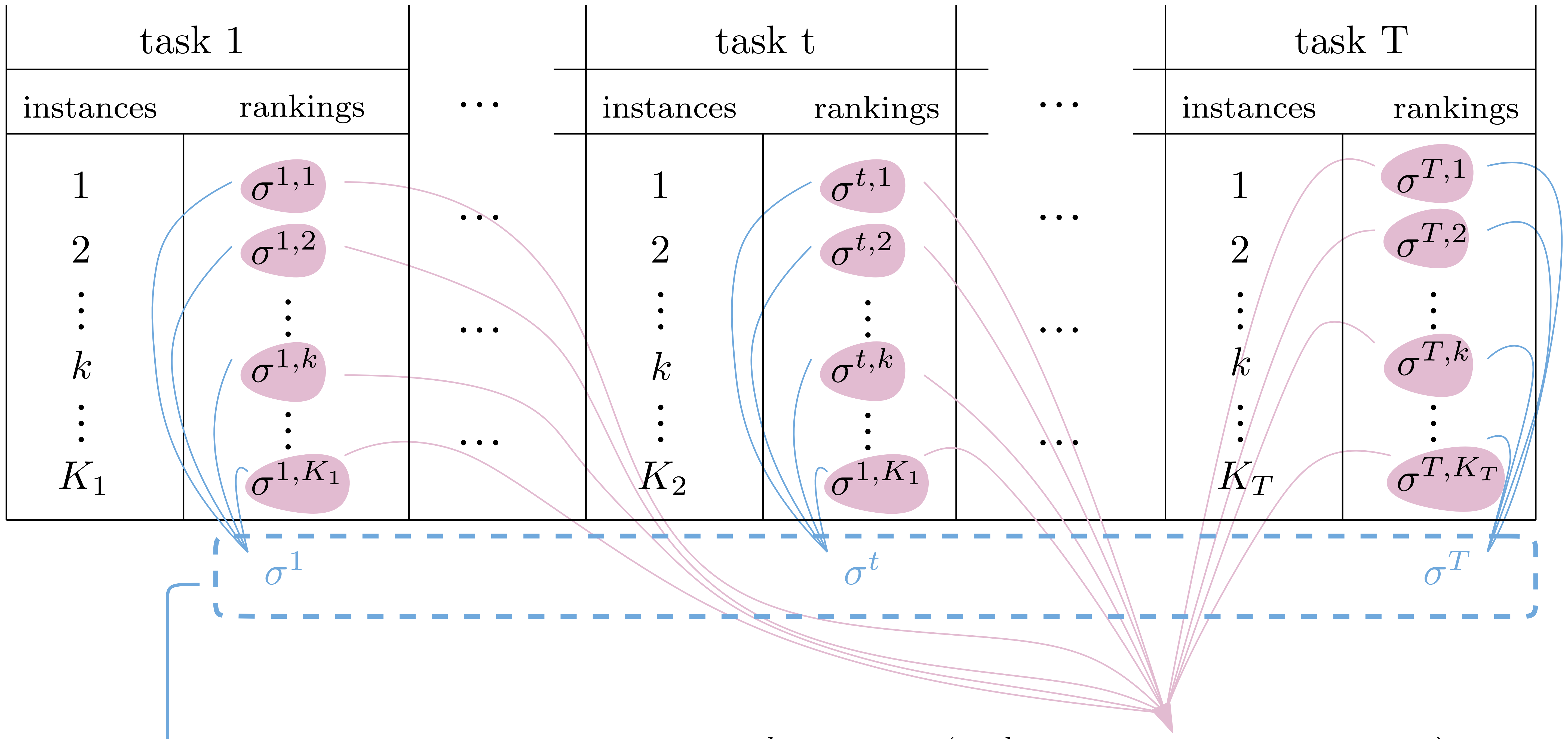
1.1 Framework

1.2 Task Level Aggregation

1.3 Instance Level Aggregation

What about instance-level aggregation?

What about instance-level aggregation?

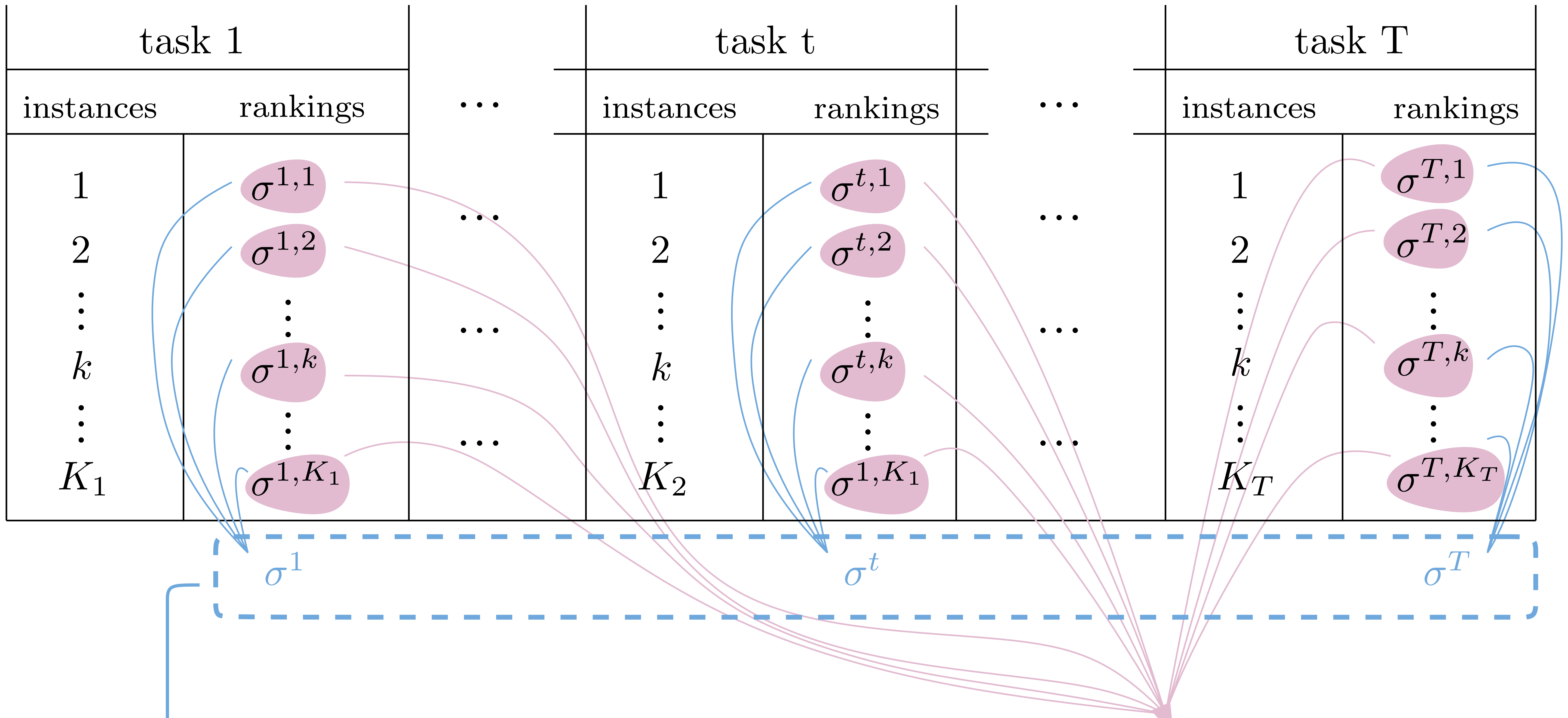


One level aggregation: $\sigma^l = \mathrm{Borda}\big(\sigma^{t,k},\ 1 \leq t \leq T,\ 1 \leq k \leq K_t\big)$

Two level aggregation: $\forall 1 \leq t \leq T, \quad \sigma^t = \mathrm{Borda}\big(\sigma^{t,k},\ 1 \leq k \leq K_t\big)$

$\sigma^{2l} = \mathrm{Borda}\big(\sigma^t,\ 1 \leq t \leq T\big)$

What about instance-level aggregation?



For every n, every t and every k, access to the aggregated performance of system n on instance k of task t

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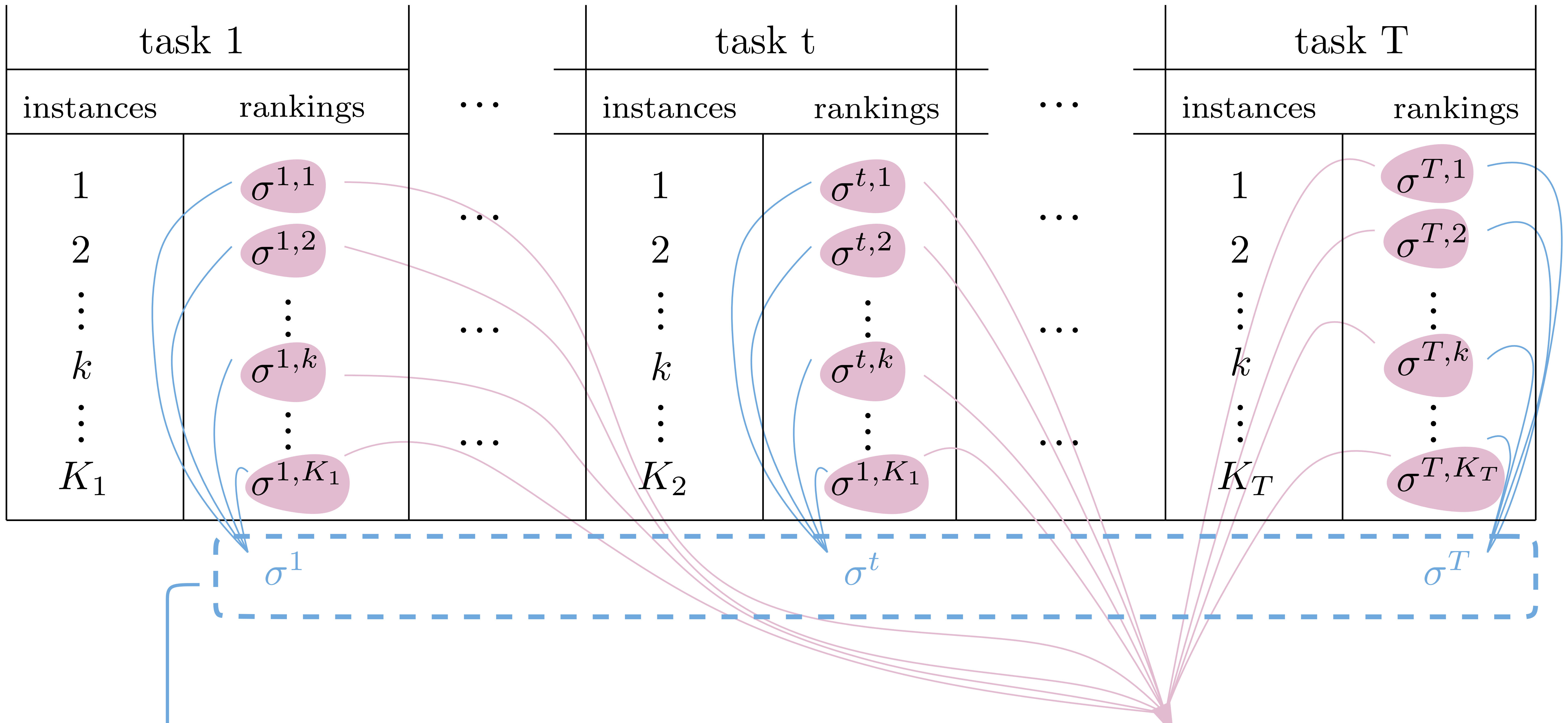

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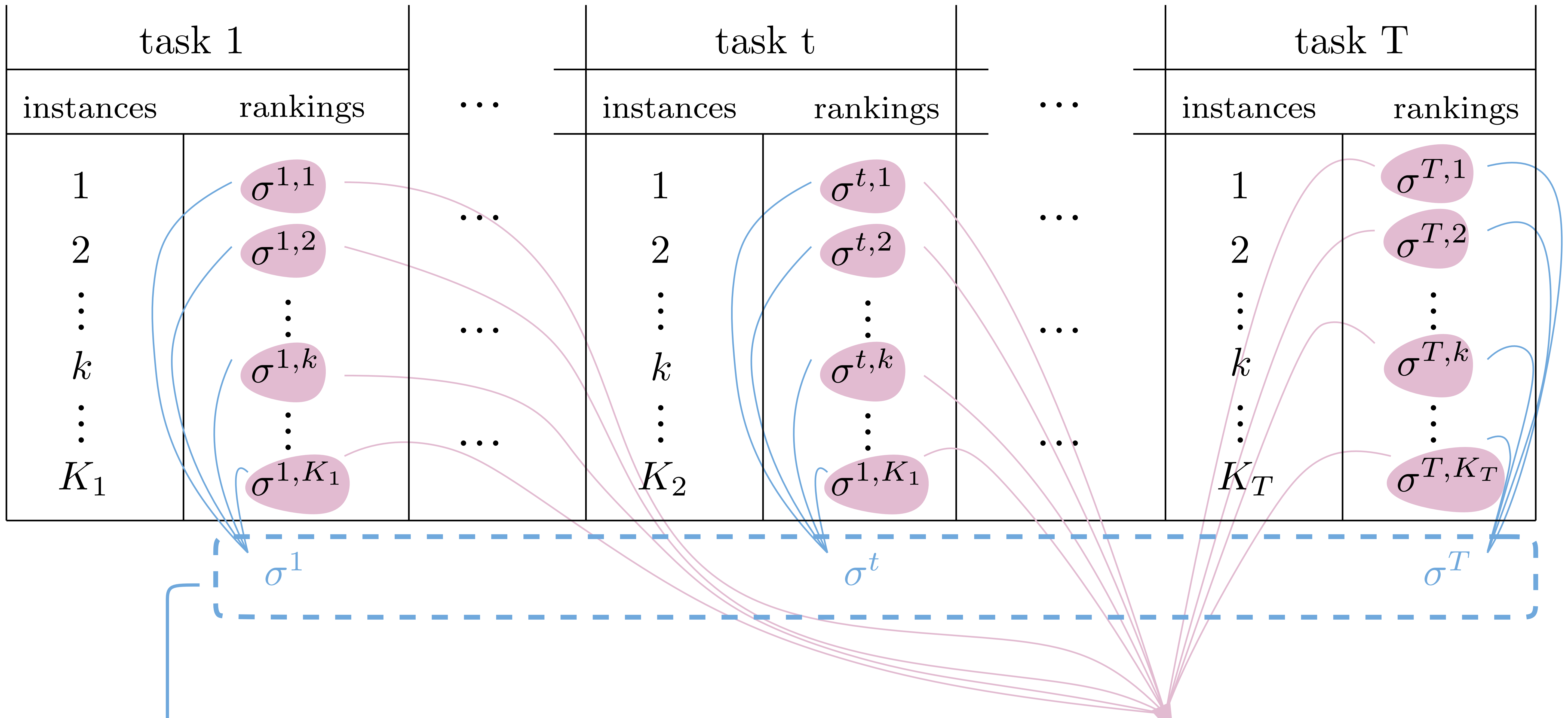
$$s_{n,t,k} \in \mathbb{R}$$

What about instance-level aggregation?



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For every n, every t and every k, access to the aggregated performance of system n on instance k of task t

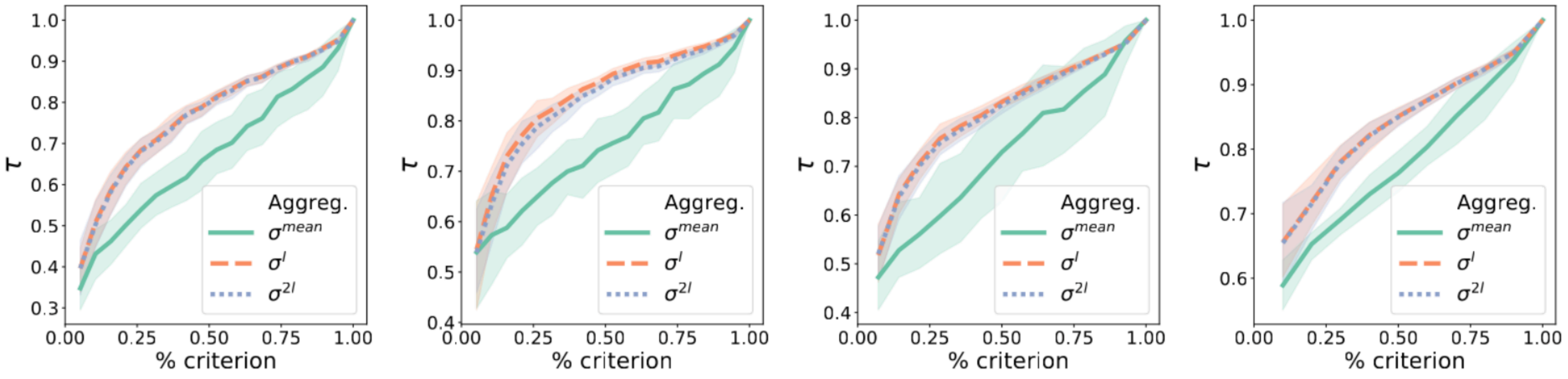
$$s_{n,t,k} \in \mathbb{R}$$

Goal: find an aggregation procedure that orders the systems.

Numerical Results

Numerical Results

Robustness Analysis

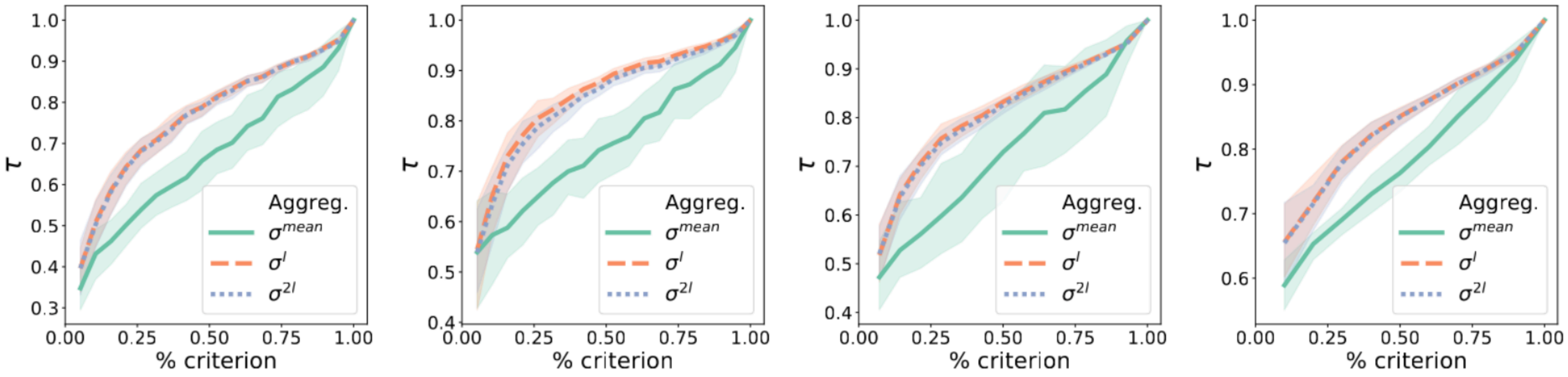


(b) Persona Chat (c) Topic Chat (d) FLICKR (e) MLQE

Numerical Results

Robustness Analysis

Relying on Borda count is more reliable. An 1 or 2 level are equivalents.



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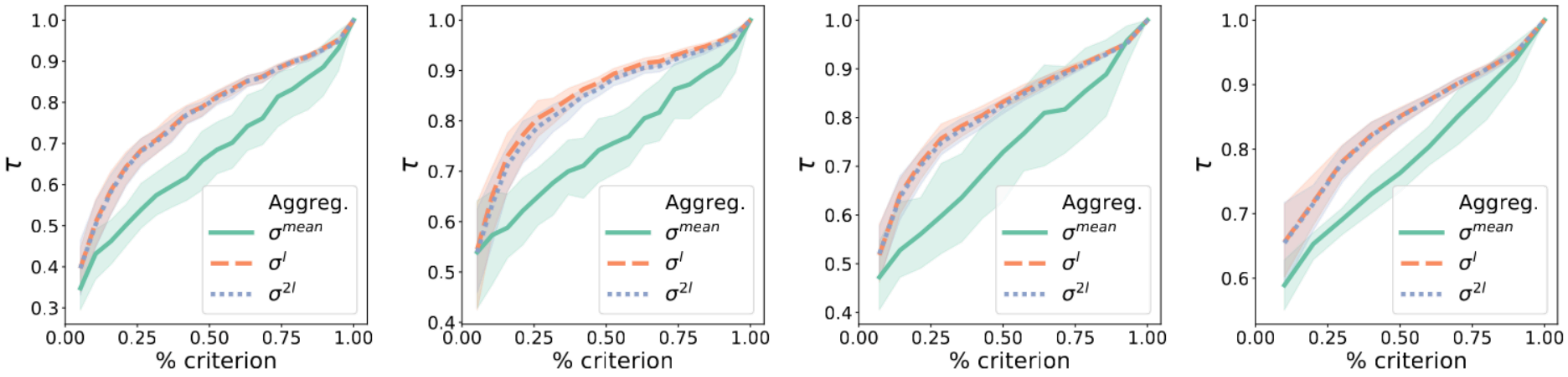

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Ranking Correlation

	PC	TC	FLI.	MLQE
$\tau(\sigma^{l}, \sigma^{2l})$	-0.08	-0.01	0	-0.03
$\tau(\sigma^{mean}, \sigma^{2l})$	0.32	0.27	0.29	0.01
$\tau(\sigma^{mean}, \sigma^{l})$	-0.10	-0.15	-0.04	0.00
RSUM	SEVAL	TAC08	TAC09	TAC11
0.04	0.14	0.28	0.06	-0.06
0.07	0.52	0.32	0.37	0.37
0	0.10	0.23	0.19	0.07

Numerical Results

Robustness Analysis

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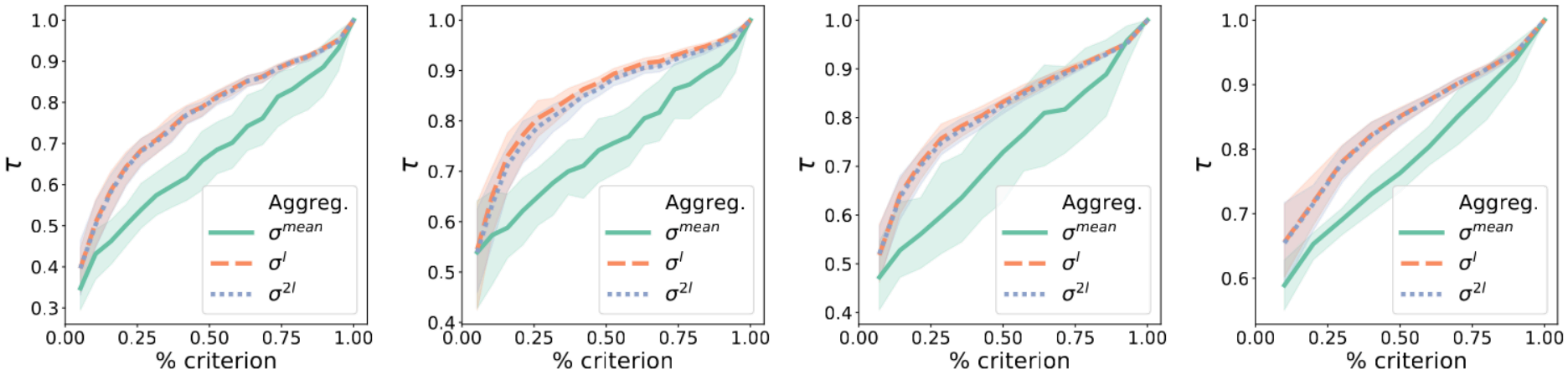

(b) Persona Chat (c) Topic Chat (d) FLICKR (e) MLQE

Ranking Correlation

Aggregation procedure matters a lot!

σ^l disagrees from σ^{2l} and σ^{mean} both on top systems and on their orders.

σ^{2l} and σ^{mean} select similar systems but rank them differently.

	PC	TC	FLI.	MLQE
$\tau(\sigma^l, \sigma^{2l})$	-0.08	-0.01	0	-0.03
$\tau(\sigma^{mean}, \sigma^{2l})$	0.32	0.27	0.29	0.01
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3. Conclusions