Automatic Text Evaluation through the Lens of Wasserstein Barycenters

Oral Presentation at EMNLP 2021

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IBM

Importance of Evaluation of NLG

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What is automatic evaluation?

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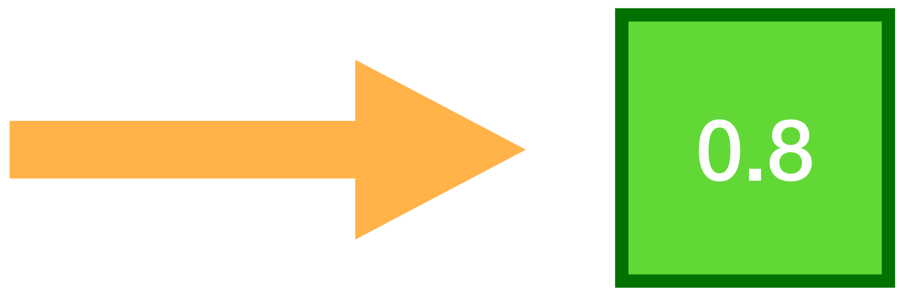
What is automatic evaluation?

R: The weather is cold today.

C: It is freezing today



Importance of Evaluation of NLG

What is automatic evaluation?

R: The weather is cold today.

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→ 0.8

R: I like those cats.

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1. Debug NLG systems without annotators

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Why do we need evaluation of NLG?

1. Debug NLG systems without annotators
2. Improve learning of systems by deriving new loss
3. Compare different systems

Existing Methods

Existing Methods

Edit Based

Existing Methods

Edit Based

Operations

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

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

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Distance is 4 !

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N-gram Based

C : I like these very nice pies !

R : I like those cakes !

Unigrams

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C : $\boxed{\text{I}}$ $\boxed{\text{like}}$ these very nice pies $\boxed{\text{!}}$

R : $\boxed{\text{I}}$ $\boxed{\text{like}}$ those cakes $\boxed{\text{!}}$

Bigrams

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Embedding Based

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Embedding Based

Word Mover distance

BertScore

MoverScore

Sentence Mover

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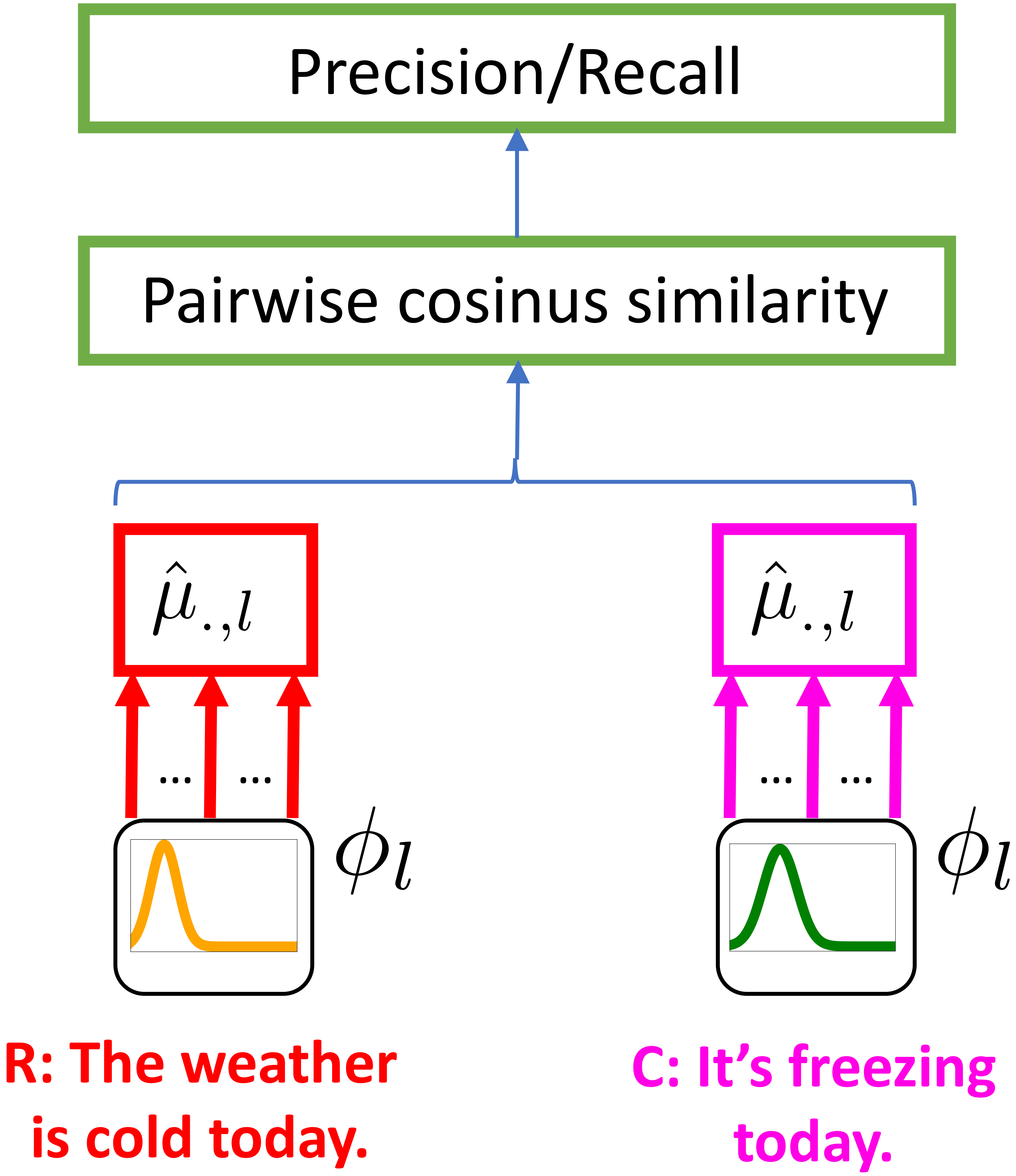
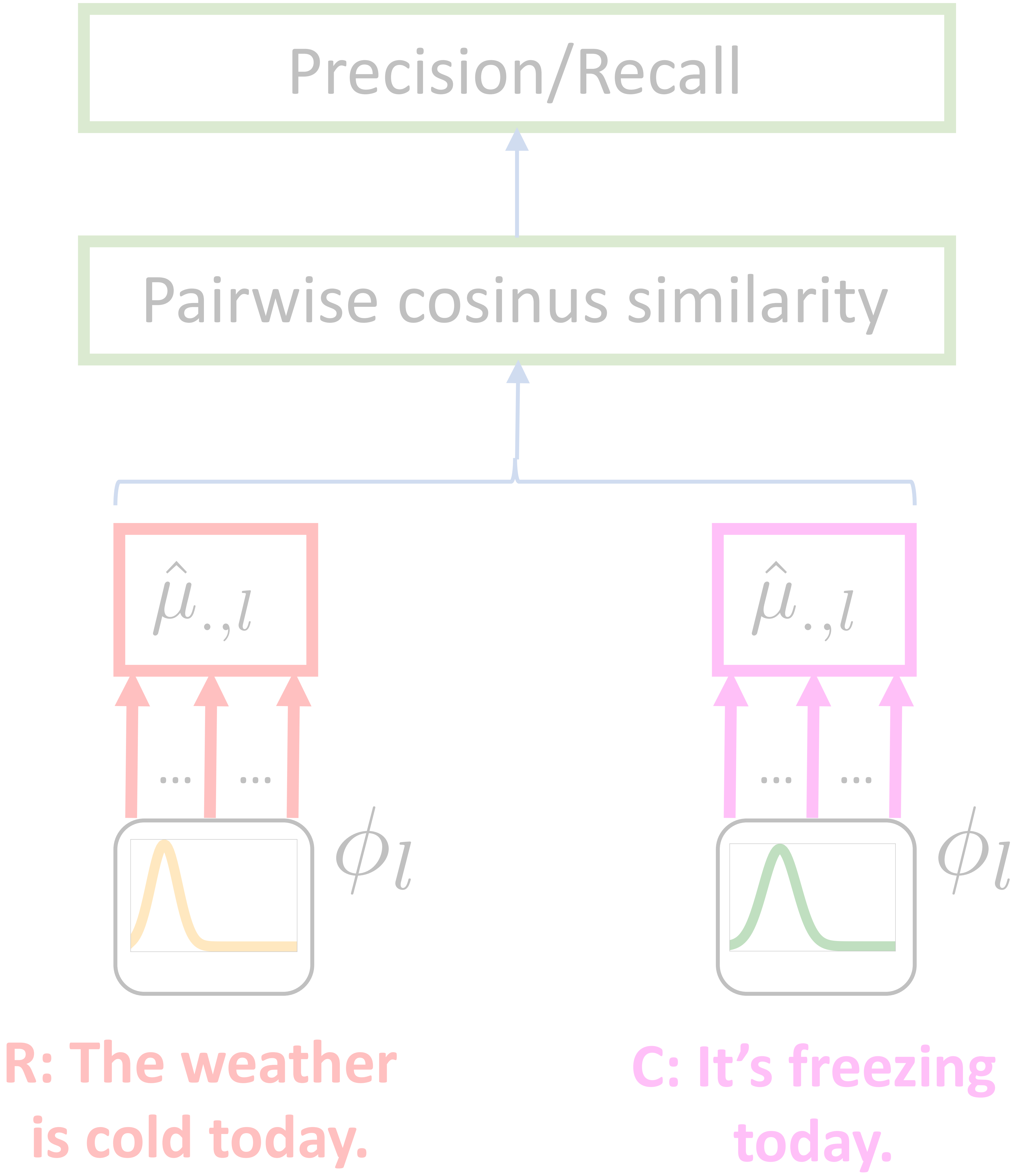


Precision/Recall
Pairwise cosinus similarity
$\hat{\mu}_{.,l}$
$\hat{\mu}_{.,l}$
...
...
...
...
ϕ_l
ϕ_l
R: The weather is cold today.
C: It's freezing today.

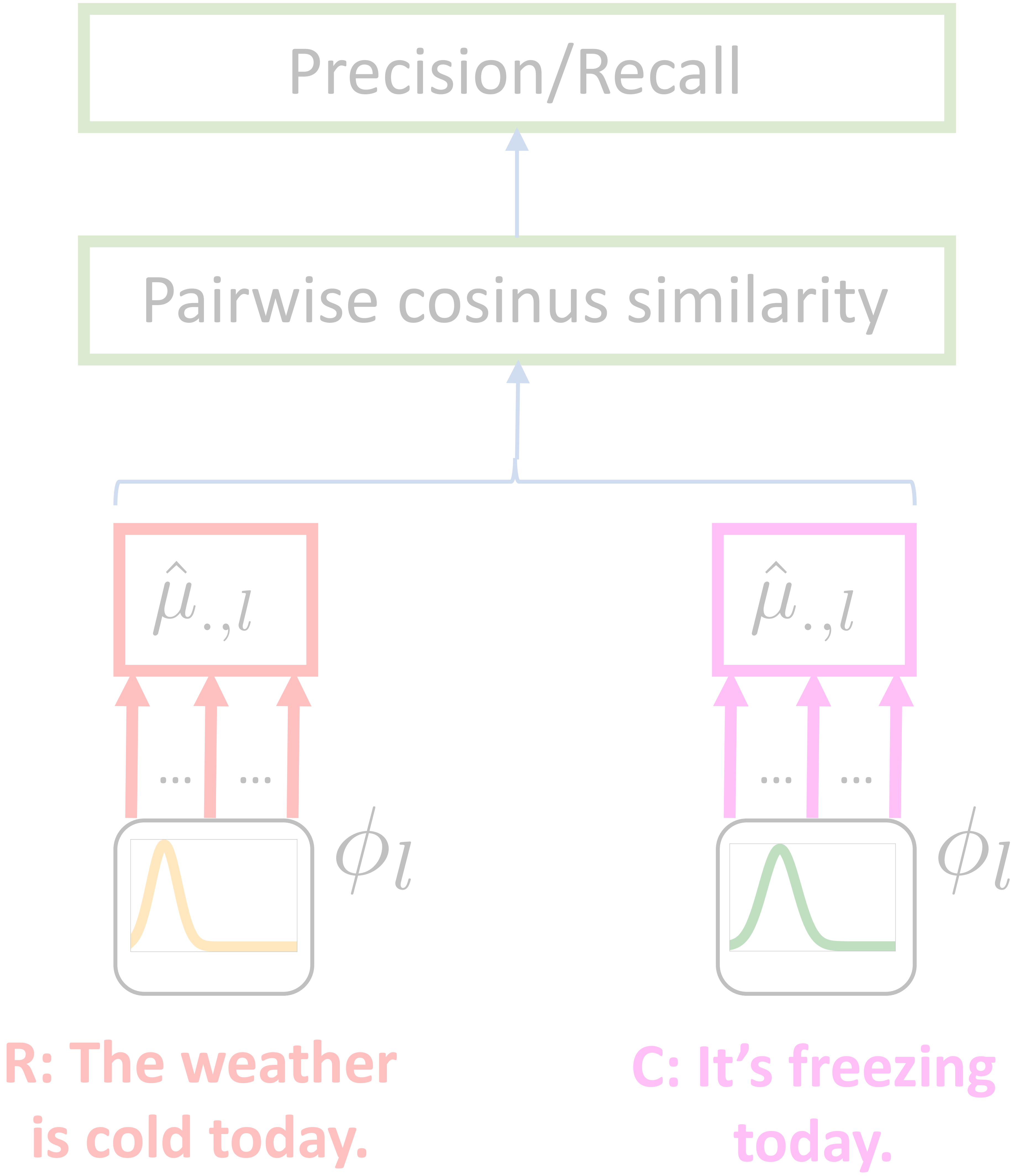
BertScore



Advantage

1. Deal with paraphrases
2. Include "semantic"

BertScore



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Limitations

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

Optimal Transport

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Goal Compute distance between probability measures (μ,ν)

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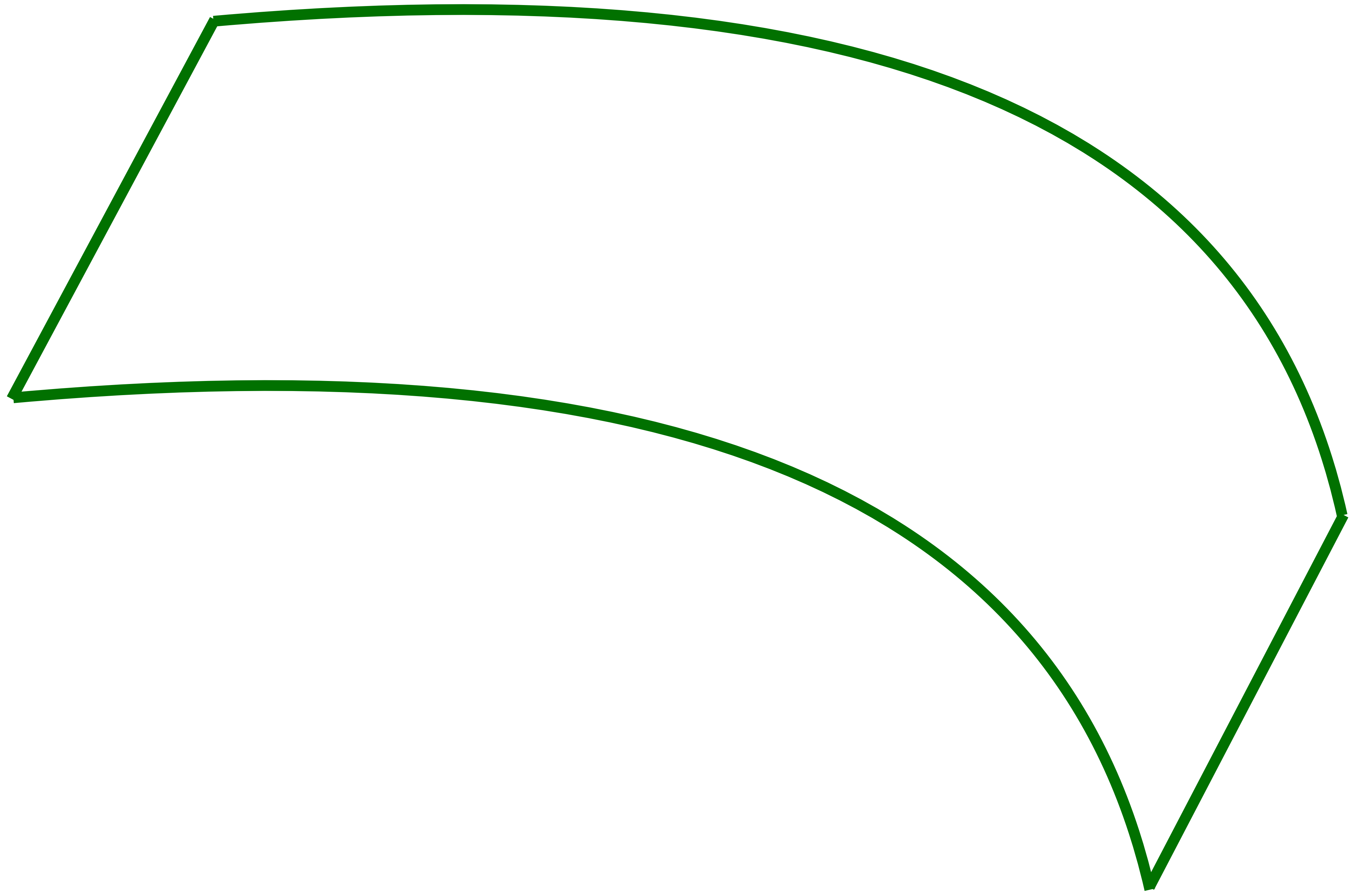
Input Discret Measures

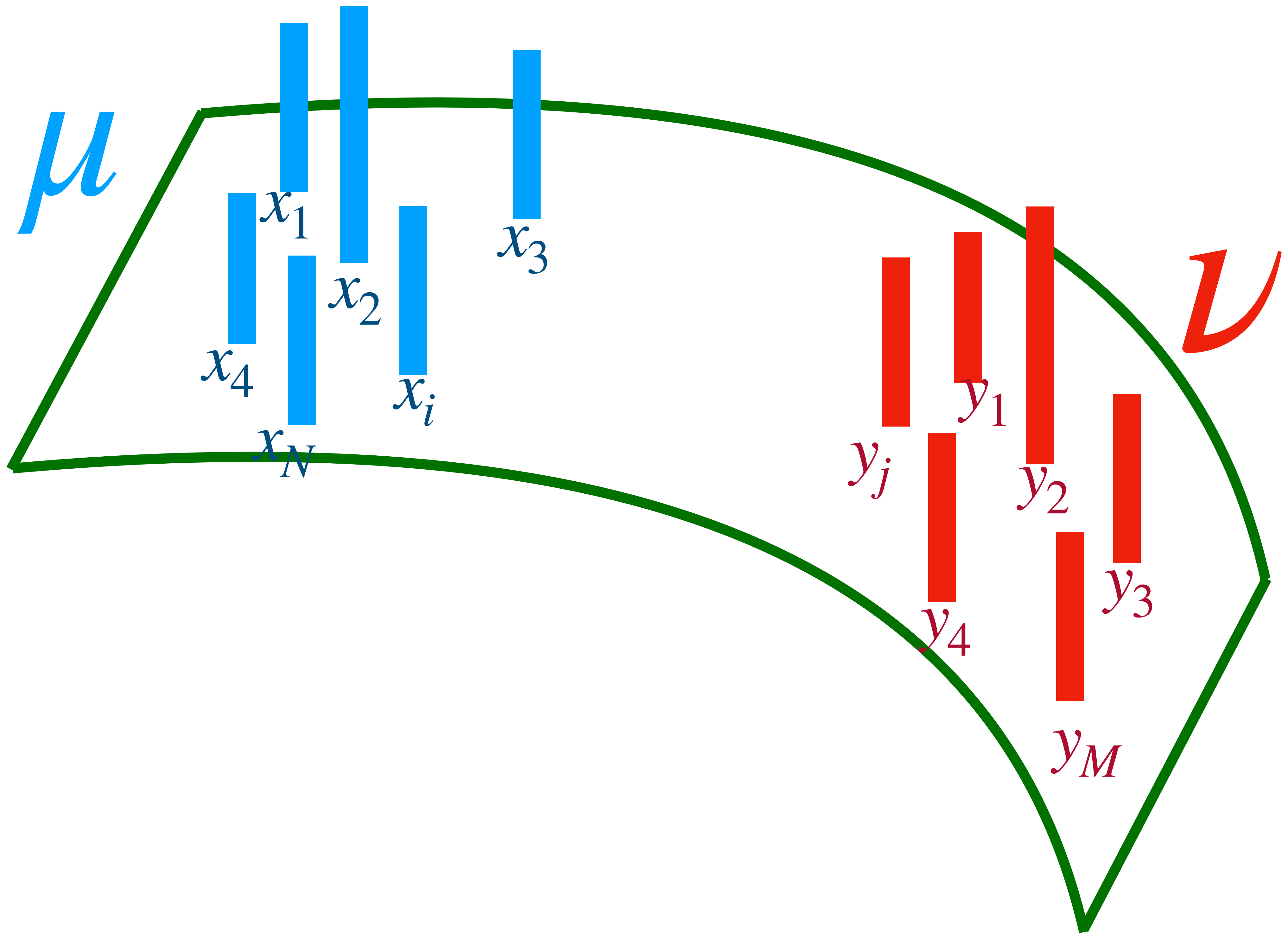


Optimal Transport

Goal Compute distance between probability measures (μ,ν)

Input Discret Measures

$$\nu = \sum_{j=1}^{M} \beta_j \delta_{x_j} \qquad \mu = \sum_{i=1}^{N} \alpha_i \delta_{x_i}$$



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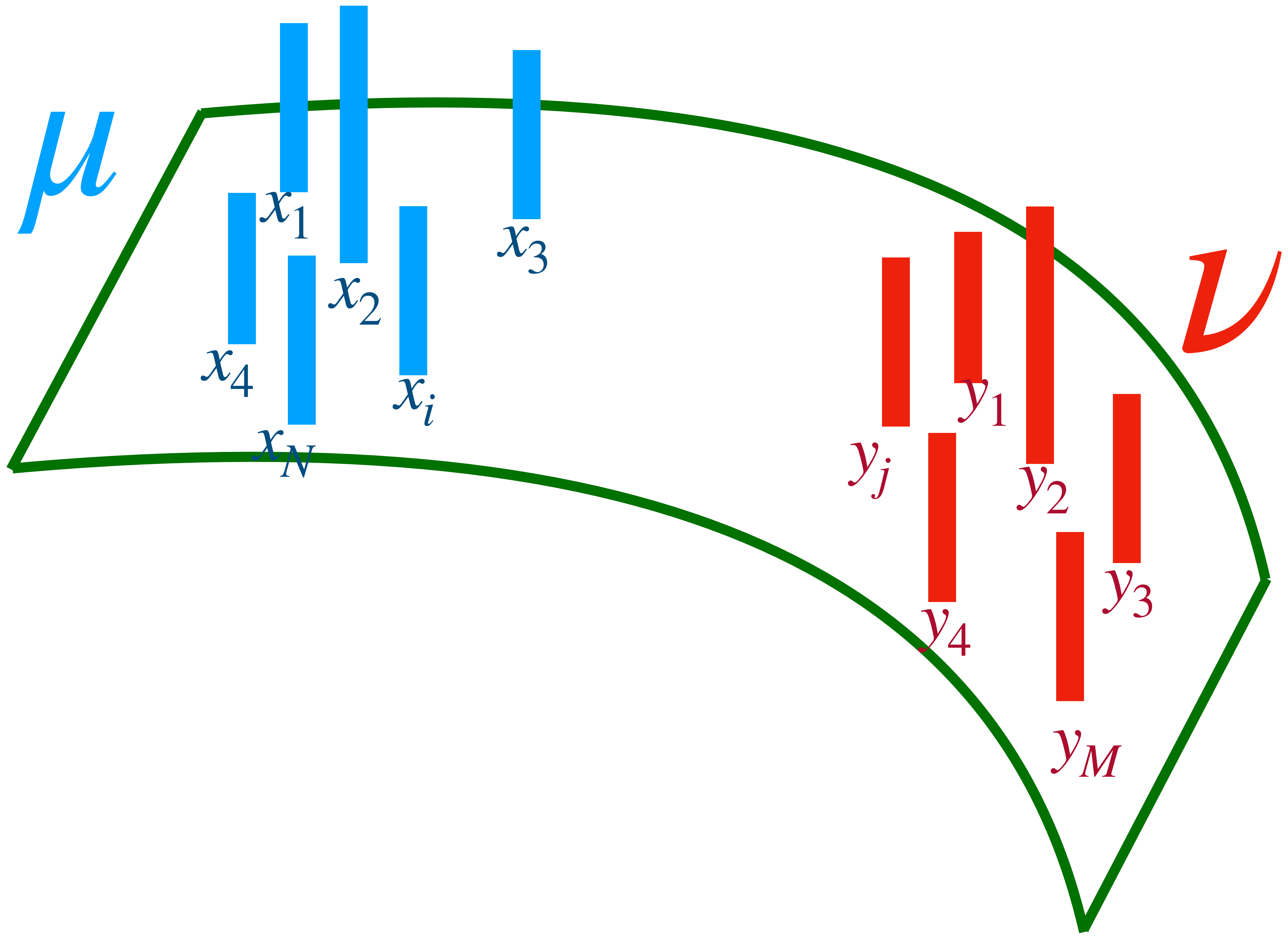
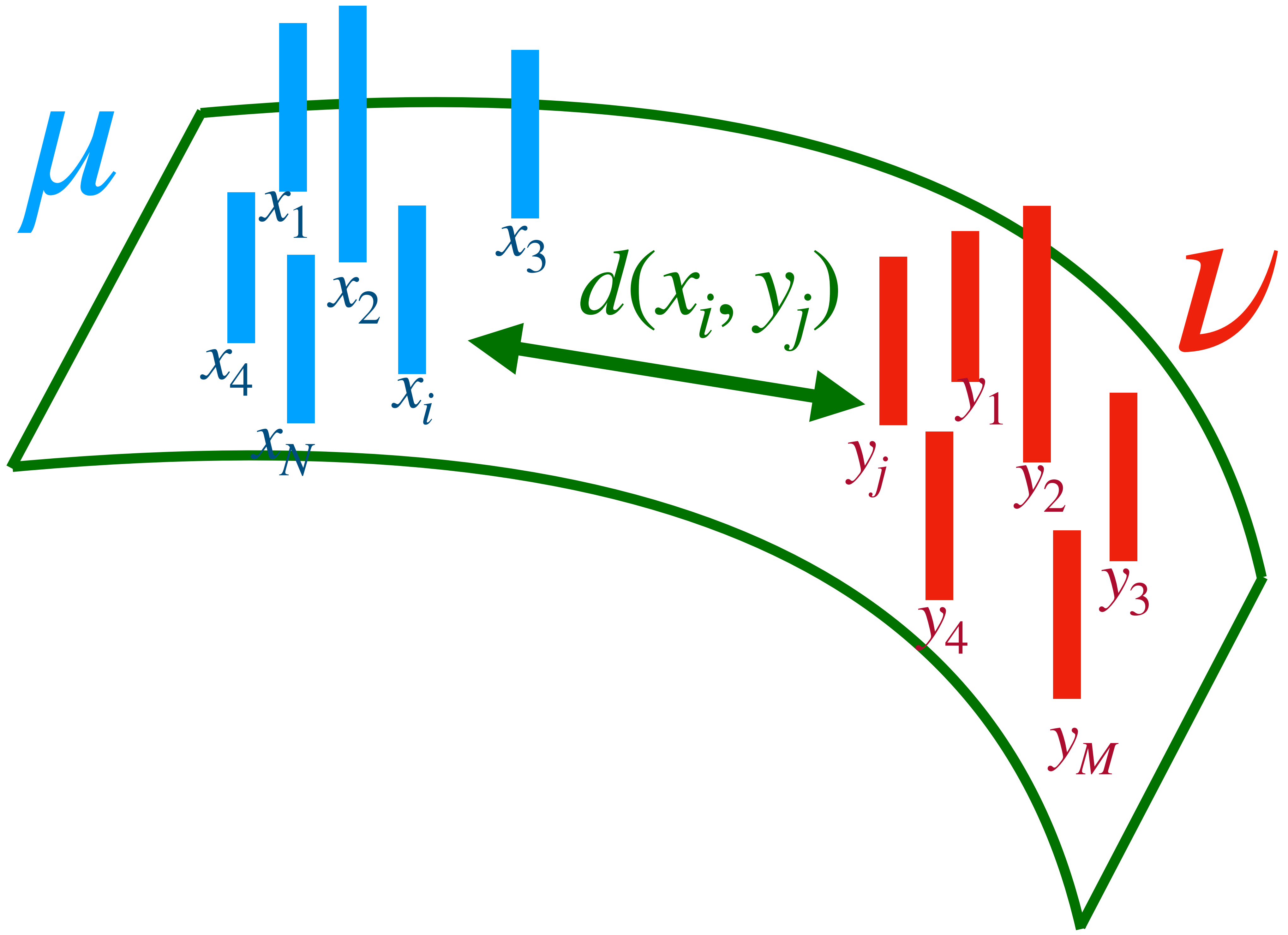


Cost Matrix

Optimal Transport

Goal Compute distance between probability measures (μ,ν)



Input Discret Measures

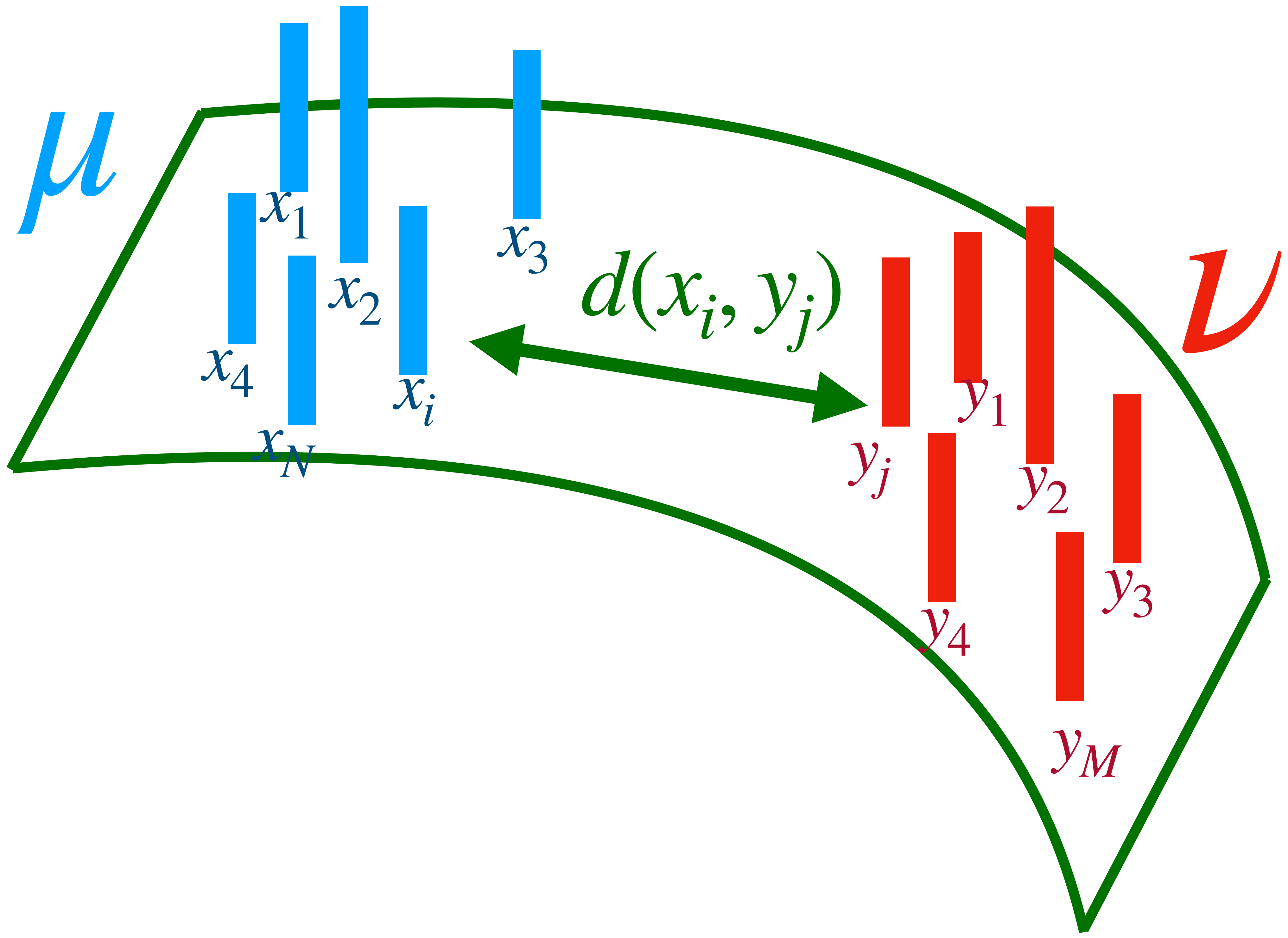
$$\nu = \sum_{j=1}^{M} \beta_j \delta_{x_j} \qquad \mu = \sum_{i=1}^{N} \alpha_i \delta_{x_i}$$

Cost Matrix

$$C = \begin{pmatrix} d(x_1, y_1) & \cdots & d(x_1, y_M) \\ \cdots & \cdots & \cdots \\ d(x_N, y_1) & \cdots & d(x_N, y_M) \end{pmatrix}$$

Optimal Transport

Goal **Compute distance between probability measures (μ,ν)**



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Transport Plan

$$\begin{array}{cc} \begin{array}{ccc} \alpha_1 & & \alpha_M \\ \uparrow & & \uparrow \end{array} & \\ \Pi = \begin{pmatrix} \pi_{11} & \cdots & \pi_{1M} \\ \cdots & \cdots & \cdots \\ \pi_{N1} & \cdots & \pi_{NM} \end{pmatrix} & \begin{array}{c} \longrightarrow \beta_1 \\ \\ \longrightarrow \beta_N \end{array} \end{array}$$

Optimal Transport

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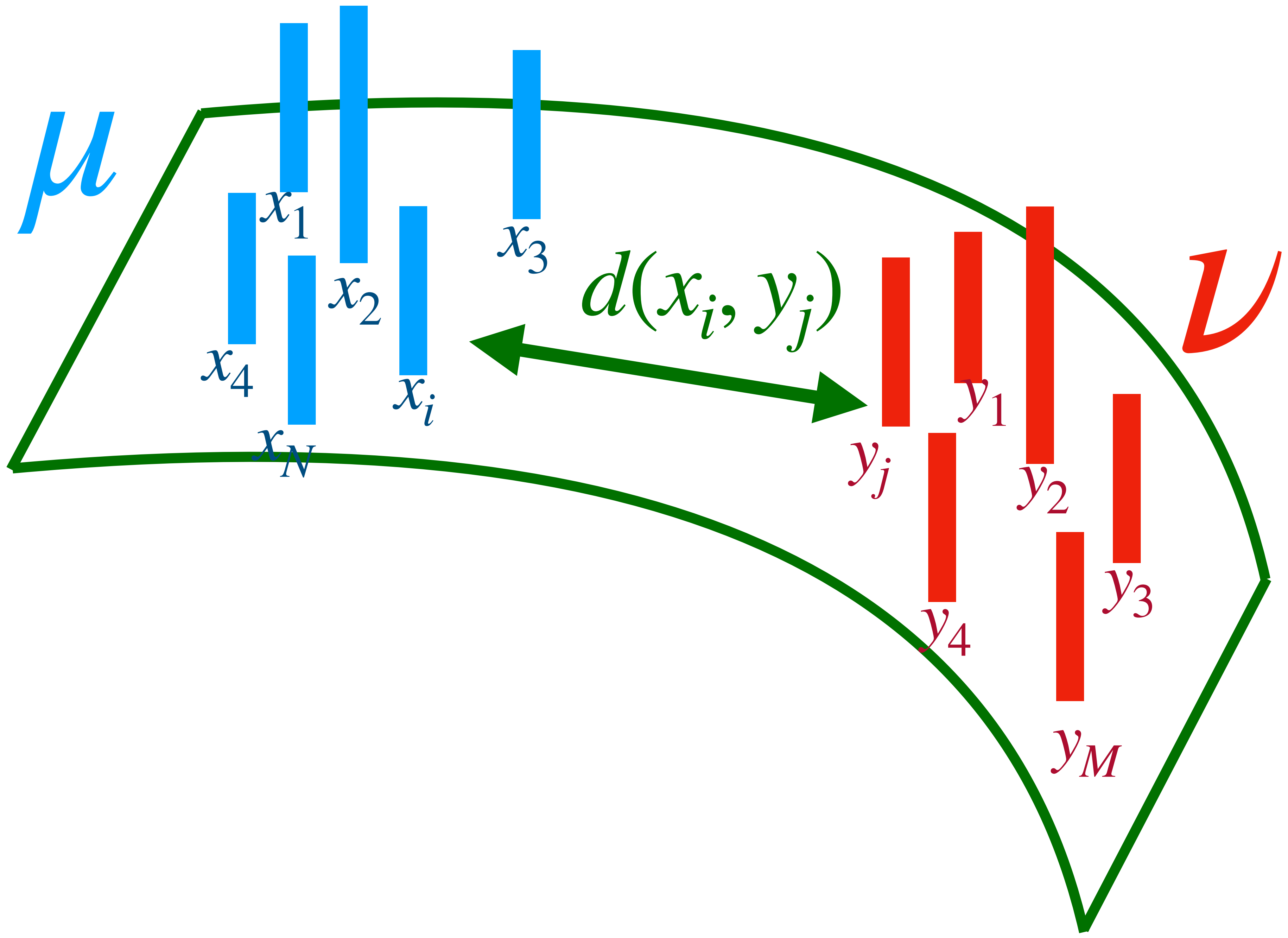

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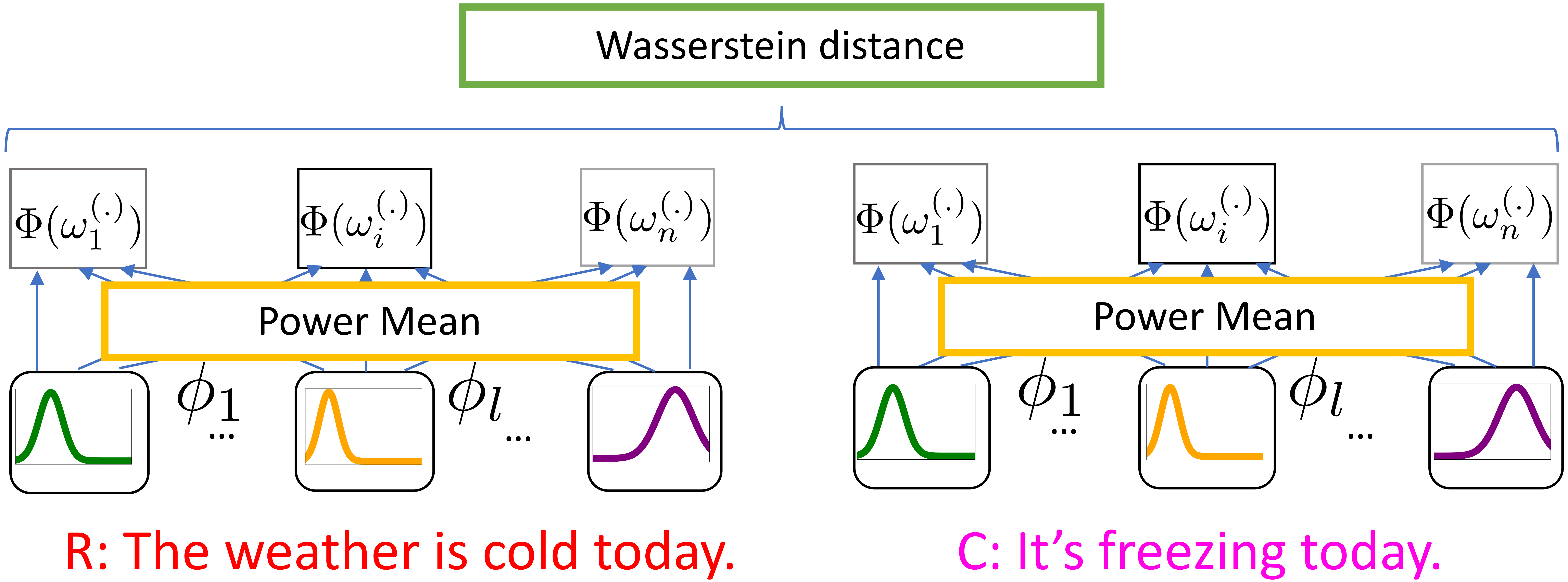
Wasserstein Distance

$$OT(\nu, \mu) = \min_{\Pi} \sum_{ij} C_{i,j} \times \Pi_{i,j}$$

$$\Pi 1 = \alpha, \Pi^T 1 = \beta$$

MoverScore

MoverScore



Wasserstein distance
$\Phi(\omega_1^{(.)})$
$\Phi(\omega_i^{(.)})$
$\Phi(\omega_n^{(.)})$
$\Phi(\omega_1^{(.)})$
$\Phi(\omega_i^{(.)})$
$\Phi(\omega_n^{(.)})$
Power Mean
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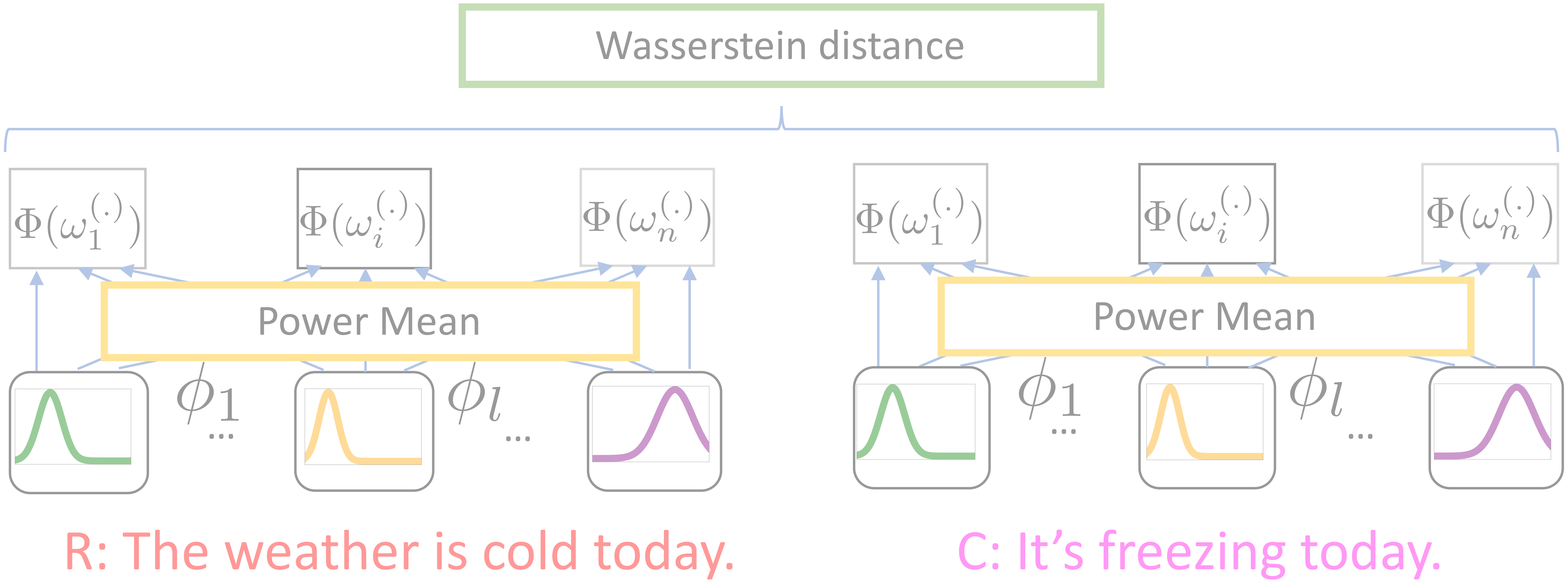
ϕ_1 ...
ϕ_l ...
ϕ_1 ...
ϕ_l ...
R: The weather is cold today.
C: It's freezing today.

MoverScore



Advantage

1. Deal with paraphrases
2. Include "semantic"
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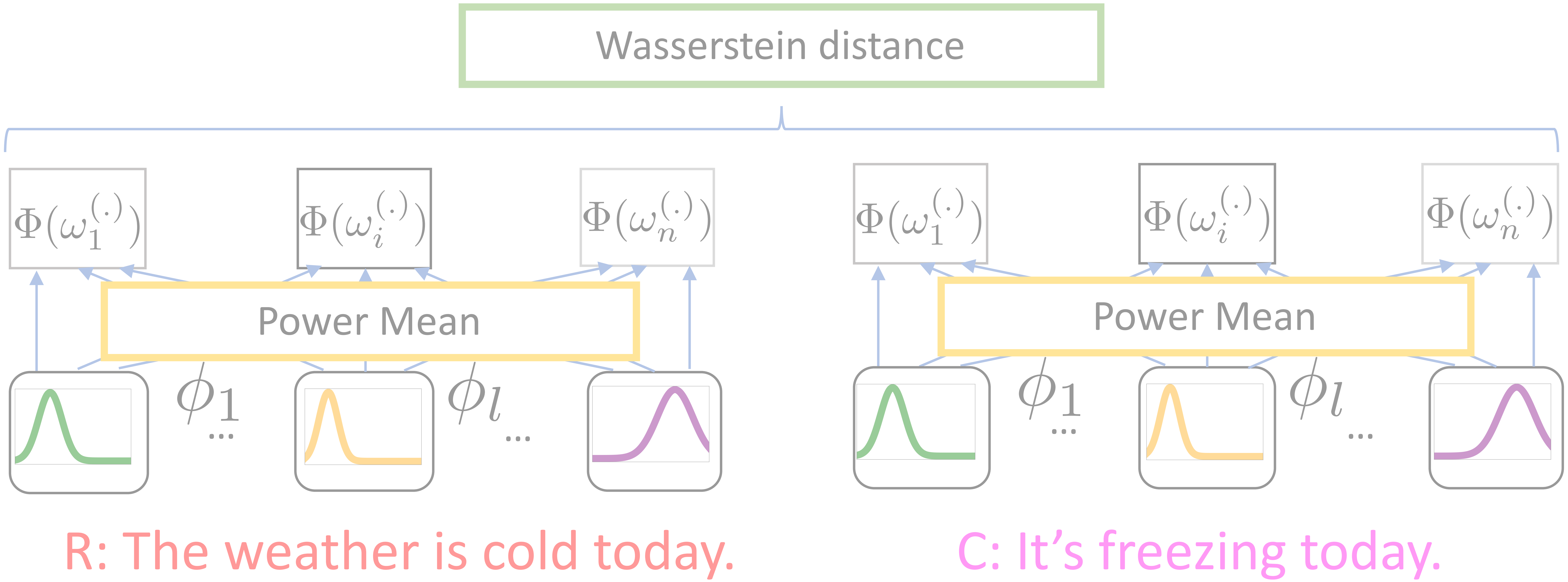
MoverScore



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Limitations

1. Use arbitrary sequence of operation

(euclidean aggregation function

Wasserstein distance)

Our Contributions

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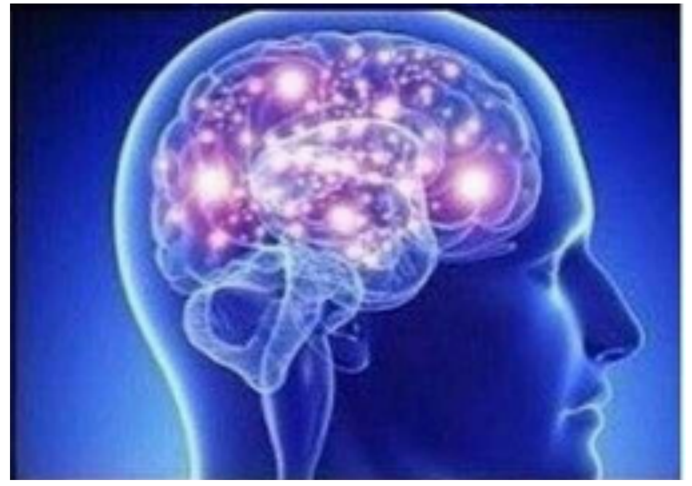
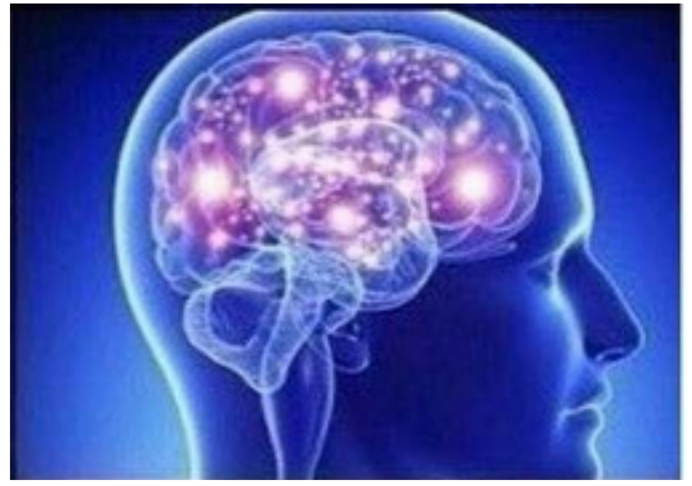


A novel metric called BaryScore

Our Contributions



A novel metric called BaryScore

Previously

1 Take one layer

2 Do a series of operations
(Wasserstein)

BertScore

Our Contributions

A novel metric called BaryScore

Previously

1 Take one layer	1 Take several layers
2 Do a series of operations (Wasserstein)	2 Aggregate using euclidean distance
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BertScore	**MoverScore**

Our Contributions

A novel metric called BaryScore

Previously

Best of all worlds

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BertScore

MoverScore

Our Contributions

A novel metric called BaryScore

Previously		Best of all worlds
1 Take one layer	1 Take several layers	1 Take several layers
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BertScore	MoverScore	BaryScore

Wasserstein Barycenters

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Euclidean Interpolation

$$\nu = \sum_{i=1}^{N} \alpha_i l_2(\mu_i, \mu)$$

Wasserstein Barycenters

Euclidean Interpolation

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Wasserstein Interpolation

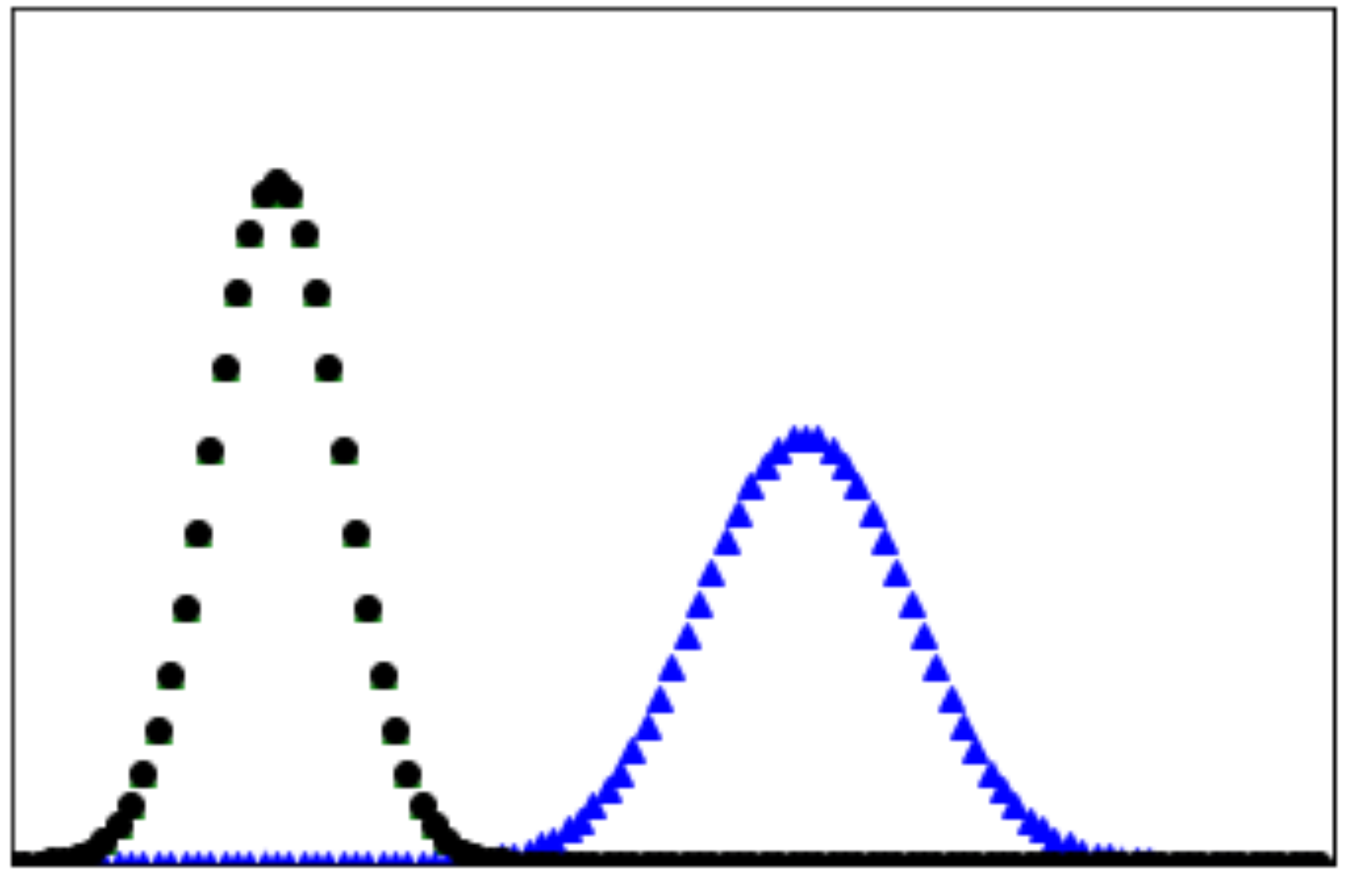
$$\nu = argmin_{\mu} \sum_{i=1}^{N} \alpha_i W(\mu_i, \mu)$$

Wasserstein Barycenters

Euclidean Interpolation

$$\nu = \sum_{i=1}^{N} \alpha_i l_2(\mu_i, \mu)$$

$$\nu = \alpha_i l_2(\mu_i, \mu) + (1 - \alpha_i) l_2(\mu_i, \mu)$$



α_i **Varies**

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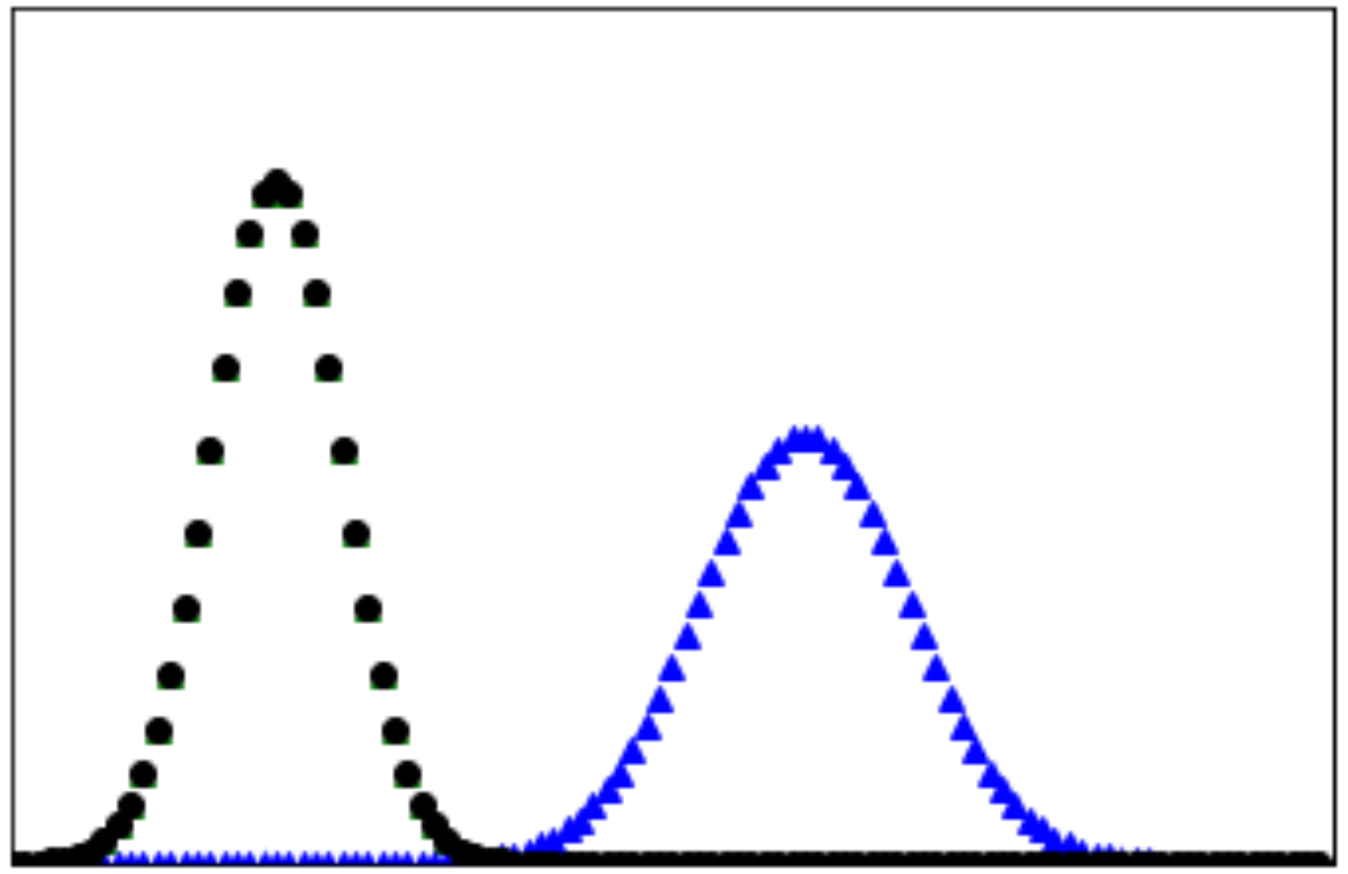

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Do not look like a gaussian !

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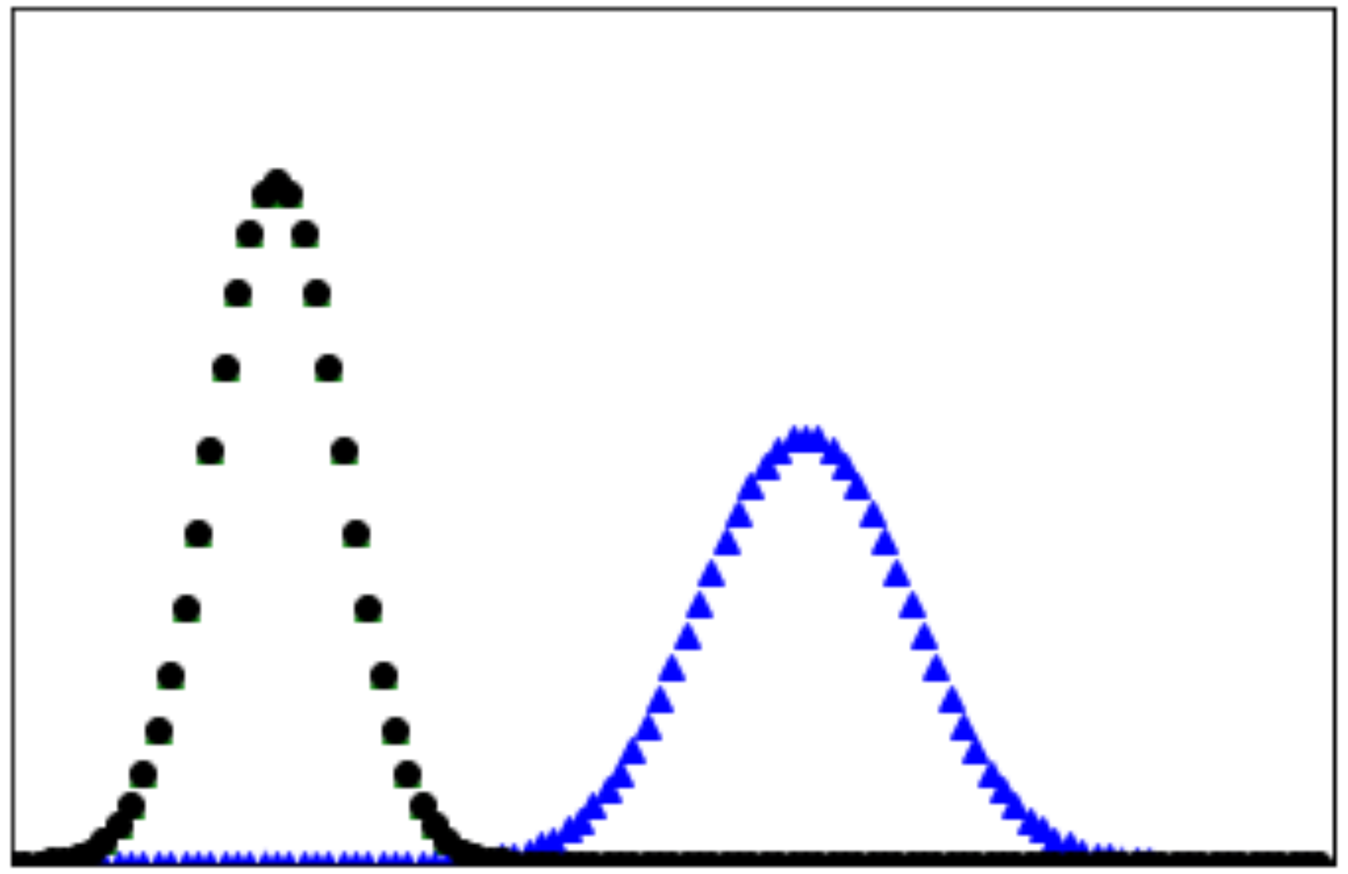

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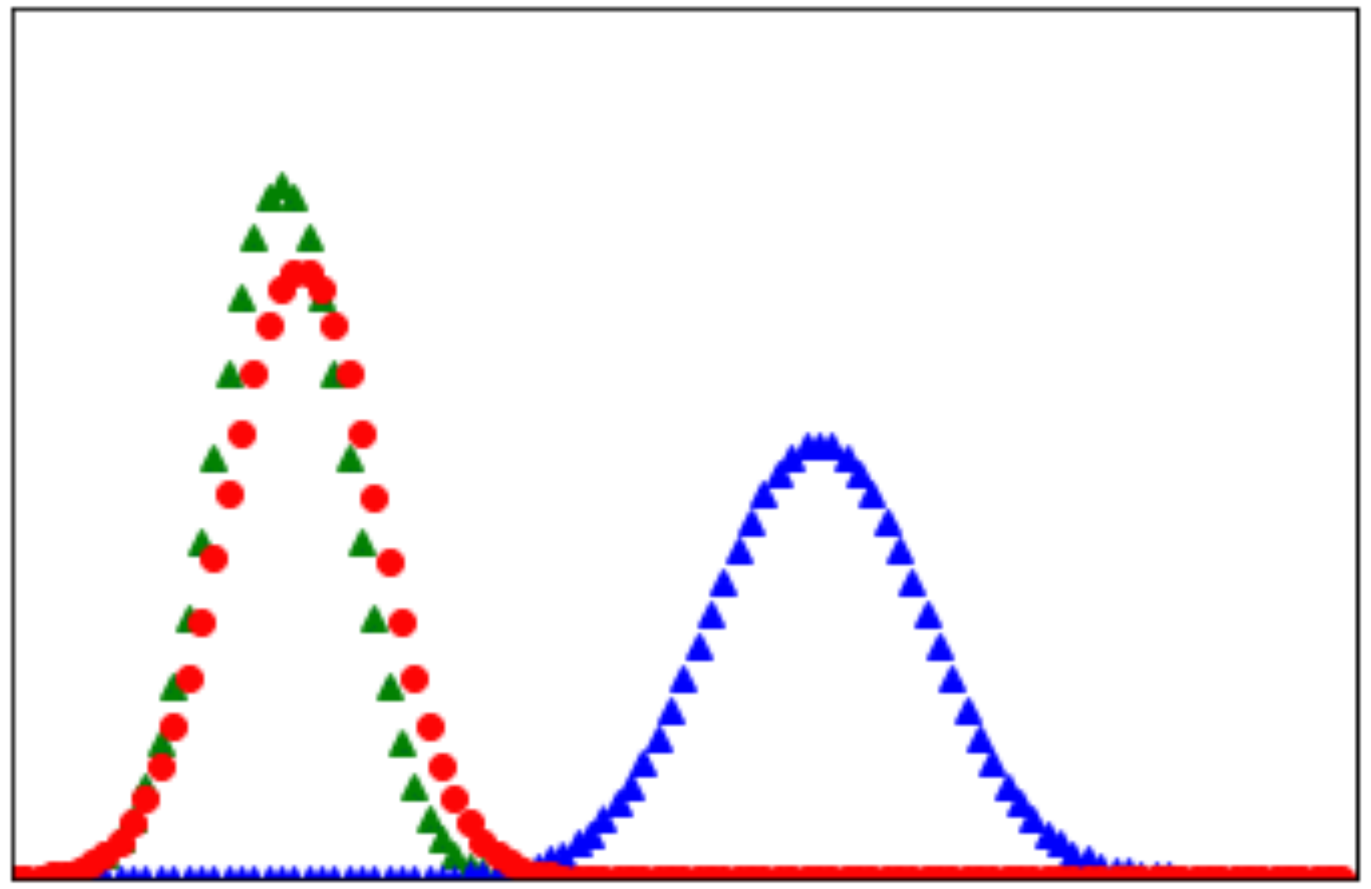

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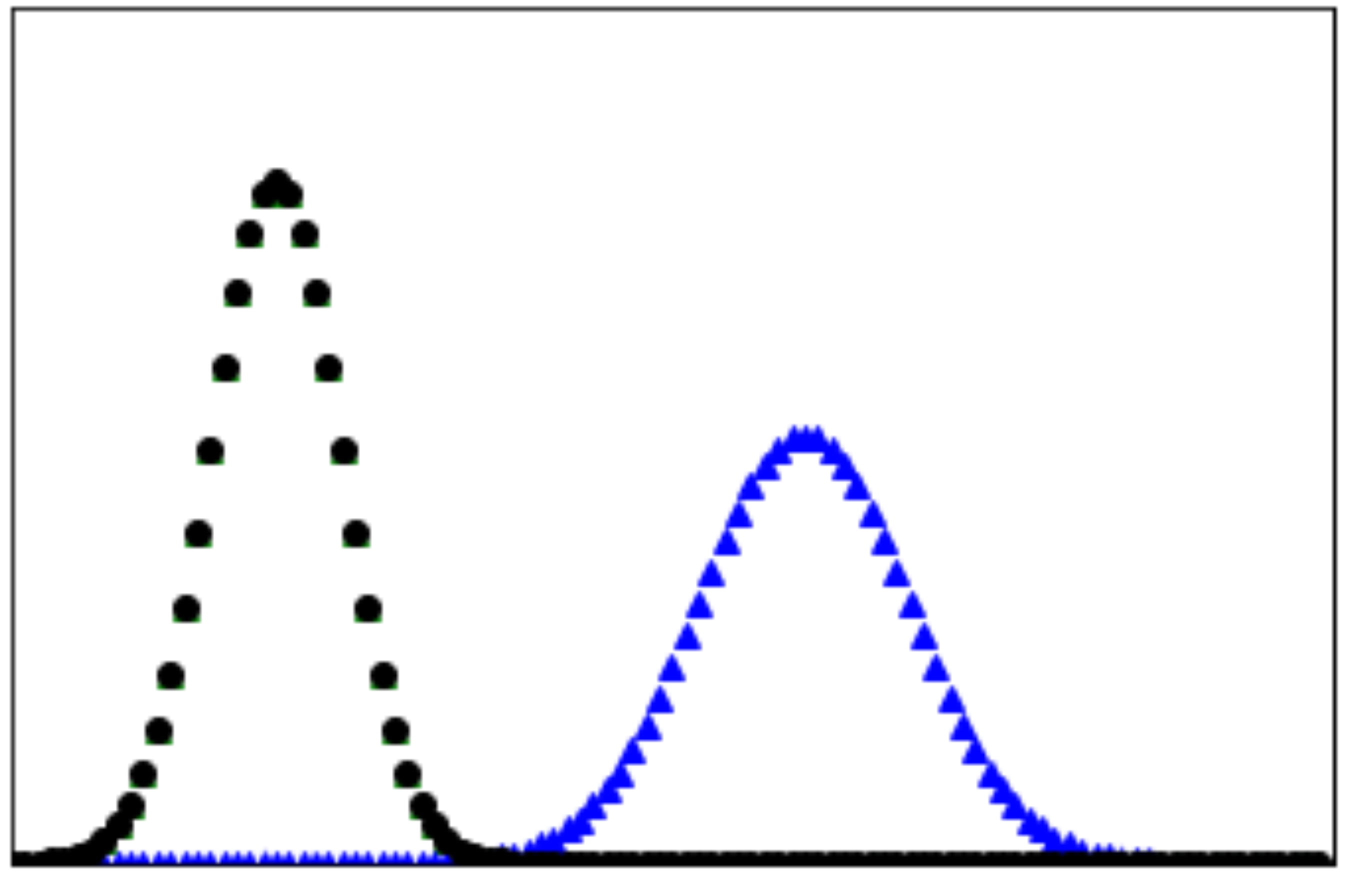

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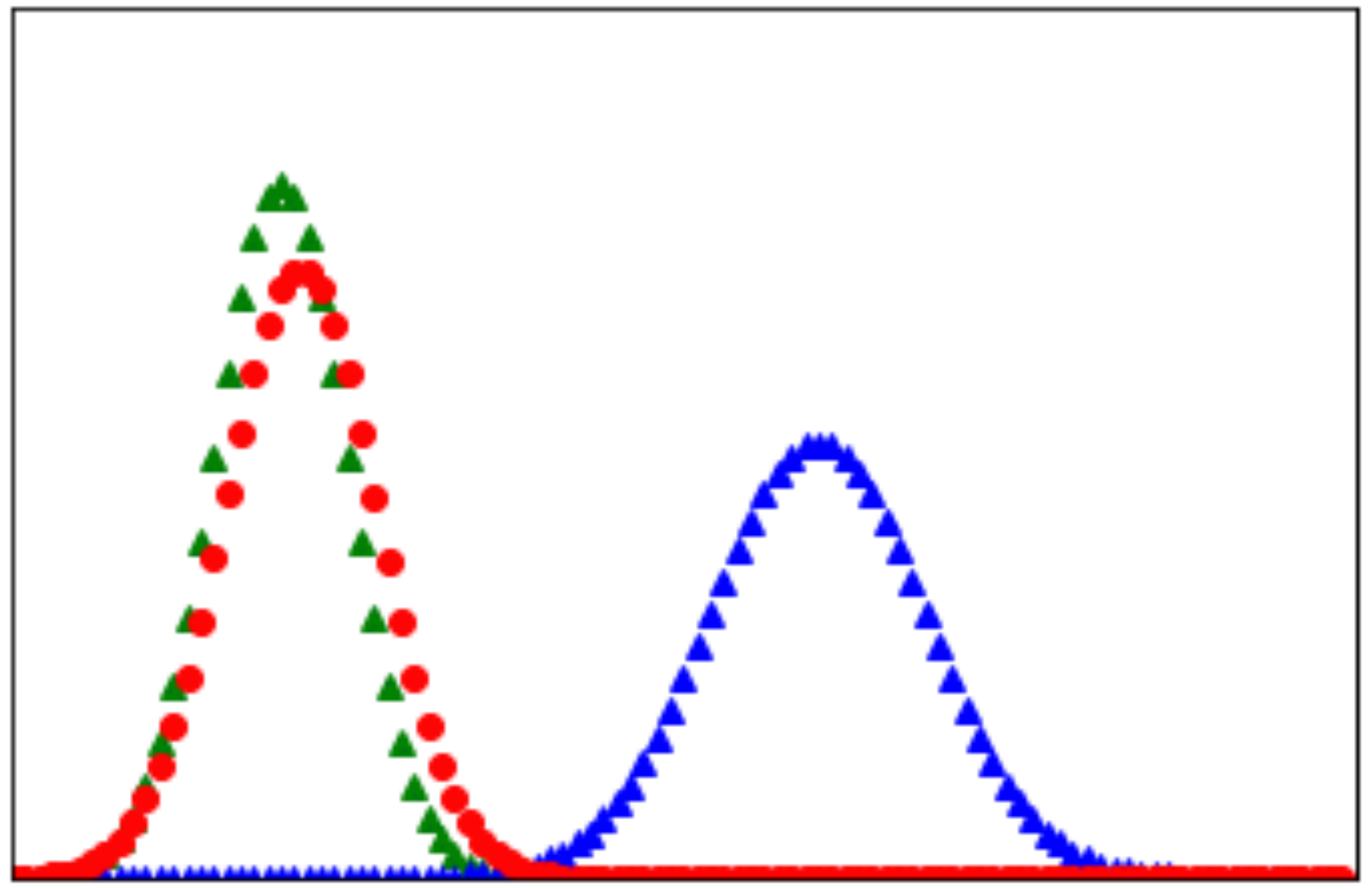

Do not look like a gaussian !

Preserve the gaussian!

BaryScore

BarySсore

Reference: R

BaryScore

Reference: R **Candidate:** C

BaryScore

Reference: R **Candidate:** C

Goal : metric $m : (\boxed{C}, \boxed{R}) \mapsto m(C, R) \in \mathbb{R}_+$

BaryScore

Reference: R **Candidate:** C

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Algorithm

Algorithm 1 `BaryScore`

INPUT: $C = \{\omega_1^c, \ldots, \omega_{n_c}^c\}$, $R = \{\omega_1^r, \ldots, \omega_{n_r}^r\}$, $(\phi_1, \ldots, \phi_L)$ pre-trained layers from BERT or ELMo.

Compute layers embeddings:
$\phi_\ell(C)$ and $\phi_\ell(R)$ for every $1 \le \ell \le L$.

Compute measures: $\{\hat{\mu}_{C,\ell}, \hat{\mu}_{R,\ell}\}_{\ell=1}^L$.

Compute Wasserstein barycenters:

$$\hat{\mu}_C = \underset{\hat{\mu}}{\operatorname{argmin}} \sum_{\ell=1}^{L} \mathcal{W}(\hat{\mu}_{C,\ell}, \hat{\mu}),$$

$$\hat{\mu}_R = \underset{\hat{\mu}}{\operatorname{argmin}} \sum_{\ell=1}^{L} \mathcal{W}(\hat{\mu}_{R,\ell}.\hat{\mu}),$$

OUTPUT: $\mathcal{W}(\hat{\mu}_R, \hat{\mu}_C)$.

BaryScore

Reference: R Candidate: C

Goal : metric $m : (\boxed{C}, \boxed{R}) \mapsto m(C, R) \in \mathbb{R}_+$

Algorithm

1. Find the Wasserstein barycentric distributions of BERT layers for C and R

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$\phi_\ell(C)$ and $\phi_\ell(R)$ for every $1 \leq \ell \leq L$.

Compute measures: $\{\hat{\mu}_{C,\ell}, \hat{\mu}_{R,\ell}\}_{\ell=1}^{L}$.

Compute Wasserstein barycenters:

$$\hat{\mu}_C = \underset{\hat{\mu}}{\text{argmin}} \sum_{\ell=1}^{L} \mathcal{W}(\hat{\mu}_{C,\ell}, \hat{\mu}),$$

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OUTPUT: $\mathcal{W}(\hat{\mu}_R, \hat{\mu}_C)$.

BaryScore

Reference: R Candidate: C

Goal : metric $m : (\boxed{C}, \boxed{R}) \mapsto m(C, R) \in \mathbb{R}_+$

Algorithm

1. Find the Wasserstein barycentric distributions of BERT layers for C and R

2. Evaluate these barycentric distributions using the Wasserstein distance.

Algorithm 1 `BaryScore`

INPUT: $C = \{\omega_1^c, \ldots, \omega_{n_c}^c\}$, $R = \{\omega_1^r, \ldots, \omega_{n_r}^r\}$, $(\phi_1, \ldots, \phi_L)$ pre-trained layers from BERT or ELMo.

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BaryScore vs BertScore vs MoverScore

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Comparison between aggregation functions

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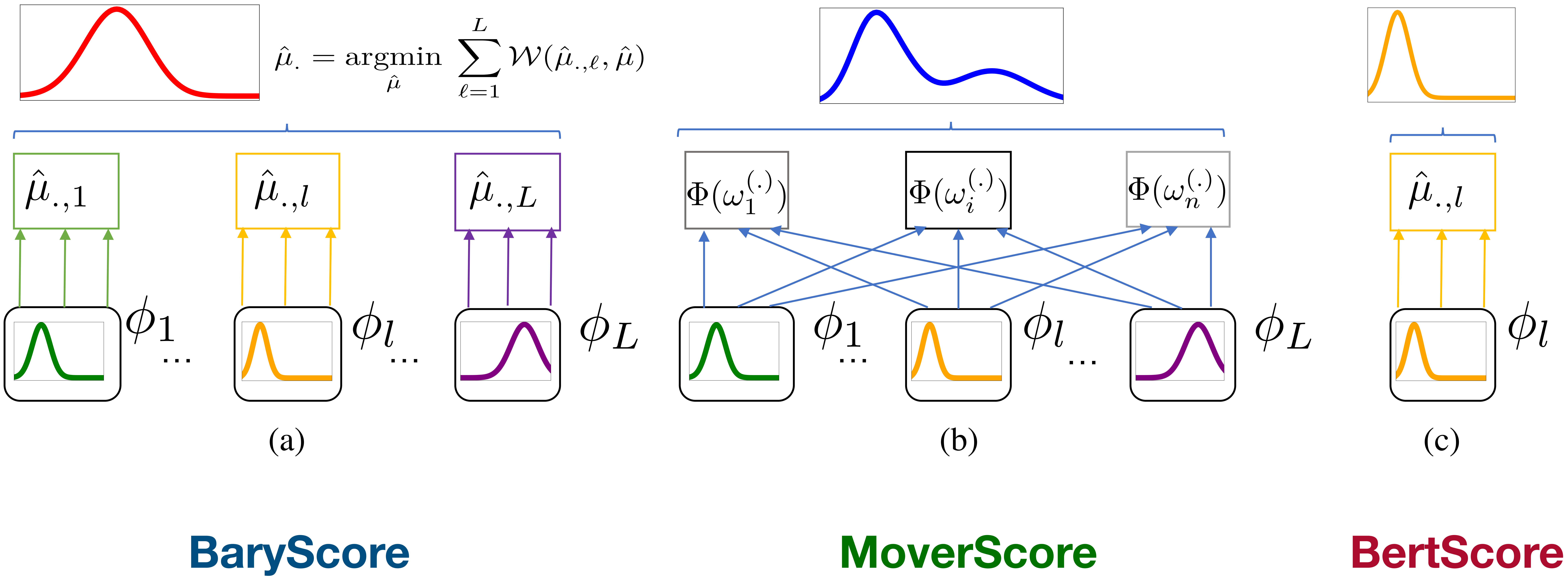

Evaluating Metric Scores

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Notations

S systems

N texts

R_i i-th reference

C_i^j i-th text candidate generated by j-th system

$h(C_i^j)$ human score

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Can the metric be used to compare the performance of two systems?

$$K_{sys} = K(M^{sy}, H^{sy})$$

$$M^{sy} = \left[\frac{1}{N}\sum_{i=1}^{N} m(R_i, C_i^1), \cdots, \frac{1}{N}\sum_{i=1}^{n} m(R_i, C_i^s)\right]$$

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System Aggregation !
Compare vector of length S

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Can the metric be used as a loss or reward of a system?

$$K_{text} = \frac{1}{N}\sum_{i=1}^{N} K(M_i^{text}, H_i^{text})$$

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Text Aggregation !
Averaged correlation

Experimental Setting

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Machine Translation

- Results on WMT17/WMT18
- All metrics are measures on en only
- Pairs includes cs-en de-en ru-en fi-en ro-en tr-en

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Task

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(John_Blaha birthDate 1942_08_26)
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John Blaha, born in San Antonio on 1942-08-26, worked as a pilot

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Metric	r	ρ	τ	r	ρ	τ	r	ρ	τ
Correct	100.0	100.0	100.0	97.6	85.2	73.3	99.1	89.7	75.0
DataC	85.2	97.6	73.3	100.0	100.0	100.0	96.0	93.8	81.6
Relev	89.7	99.1	75.0	96.0	93.8	81.6	100.0	100.0	100.0
BaryS	**91.7**	**90.0**	**78.3**	**87.8**	78.2	61.6	**89.4**	**82.6**	70.0
BaryS$^+$	90.5	89.5	76.6	87.7	**85.0**	**70.0**	89.2	86.4	71.6
BertS	85.5	83.4	73.3	74.7	68.2	53.3	83.3	79.4	65.0
MoverS	84.1	84.1	73.3	78.7	66.2	53.3	82.1	77.4	65.0
BLEU	77.6	66.3	60.0	55.7	50.2	36.6	63.0	65.2	51.6
R-1	80.6	65.0	65.0	76.5	76.3	60.3	64.3	69.2	56.7
R-2	73.6	63.3	58.3	54.7	43.1	35.0	62.0	60.8	46.7
R-WE	60.9	73.4	60.0	40.2	58.2	40.1	49.9	64.1	48.3
METEOR	86.5	66.3	70.0	77.3	50.2	46.6	82.1	65.2	58.6
TER	79.6	78.3	58.0	69.7	58.2	38.0	75.0	70.2	**77.6**

Correlation score for different coefficient Pearson r, Spearman ρ and Kendall τ

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Thanks for listening

Link to Paper

Title: **Automatic Text Evaluation through the Lens of Wasserstein Barycenters**

Corresponding Authors:

Pierre Colombo