Hierarchical Learning of Dependent Concepts for Human Activity Recognition

Aomar Osmani [1], **Massinissa Hamidi** [1], and Pegah Alizadeh [2]
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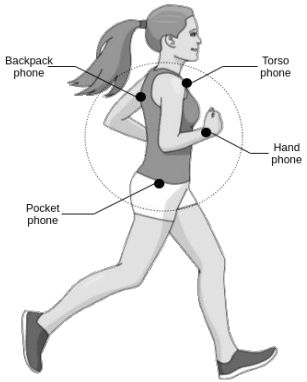
[2] DeVinci Research Center, Pôle Universitaire De Vinci

Concepts Dependency in Real Applications



Topology of the wearable sensors deployment in a real-world application

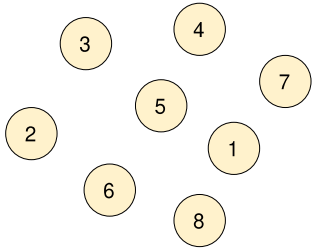
Running

Walking

Driving a car

Being in a bus

...



Concepts

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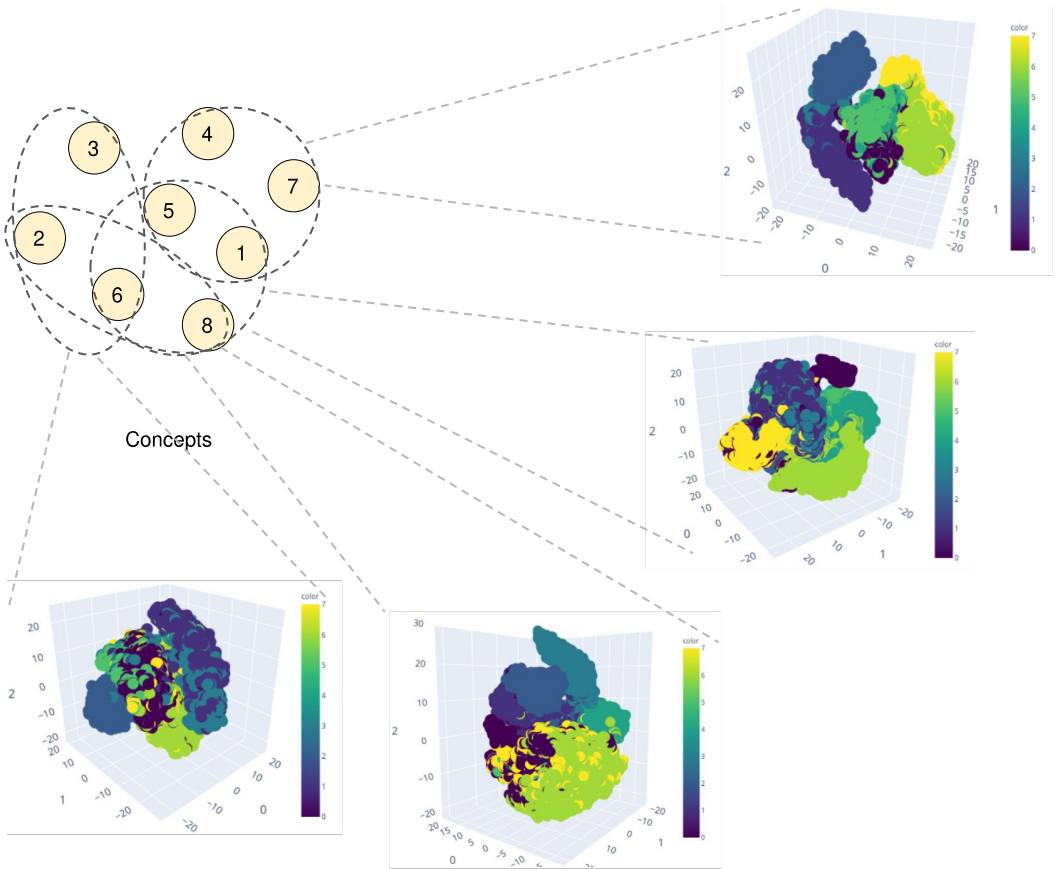
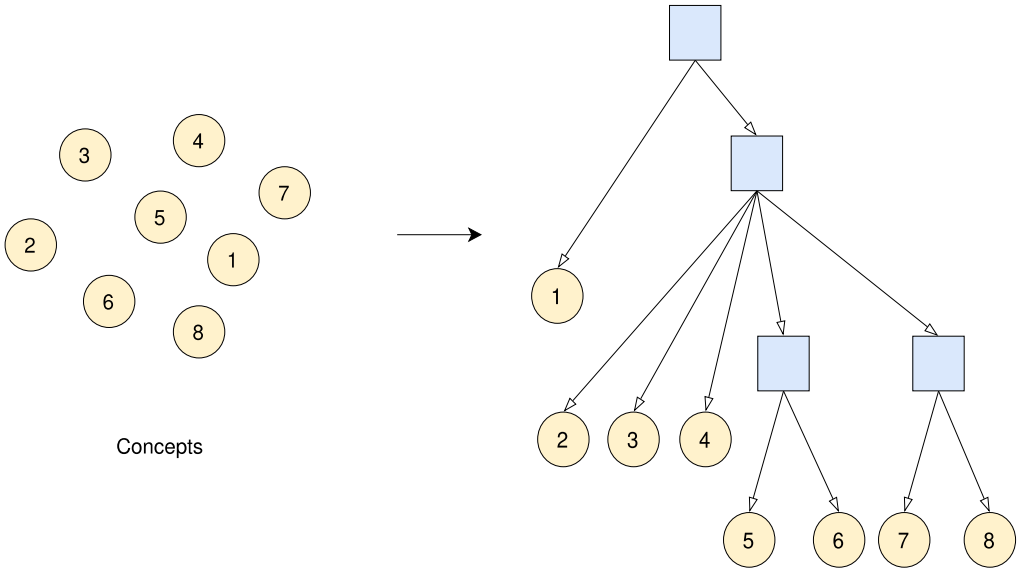


Structuring the Concepts



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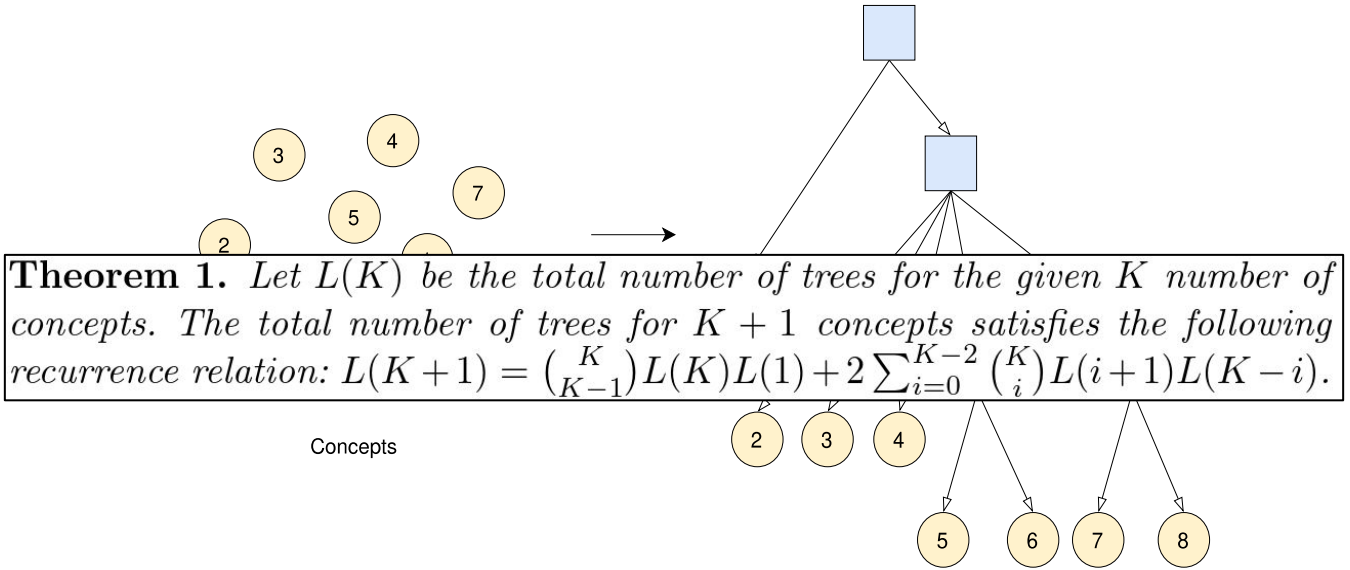

Theorem 1. *Let $L(K)$ be the total number of trees for the given K number of concepts. The total number of trees for $K+1$ concepts satisfies the following recurrence relation:* $L(K+1) = \binom{K}{K-1} L(K)L(1) + 2\sum_{i=0}^{K-2} \binom{K}{i} L(i+1)L(K-i)$.

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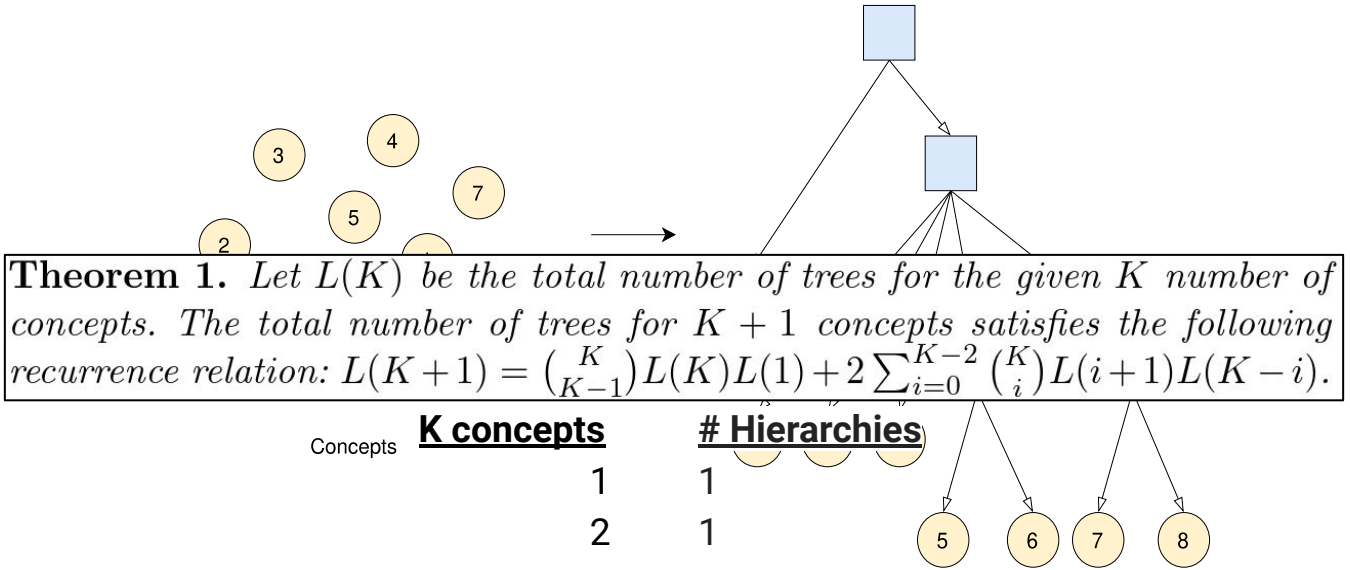

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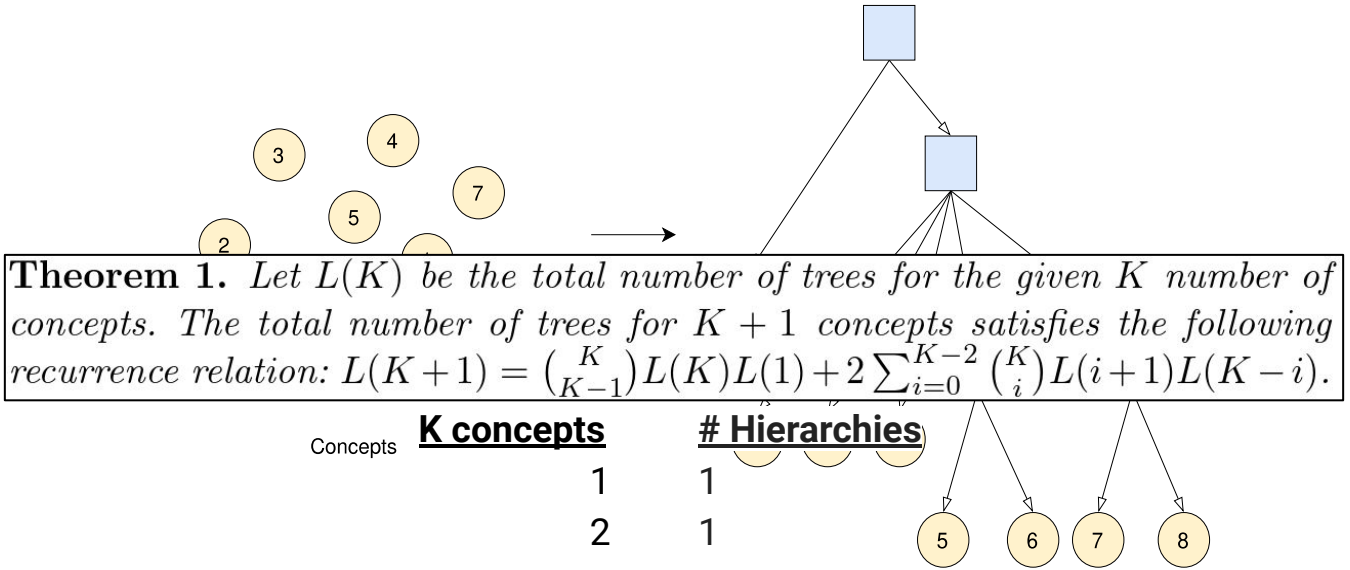
Concepts

K concepts	# Hierarchies
1	1
2	1
3	4
...	...
8	660.032
9	12.818.912
10	282.137.824

Structuring the Concepts



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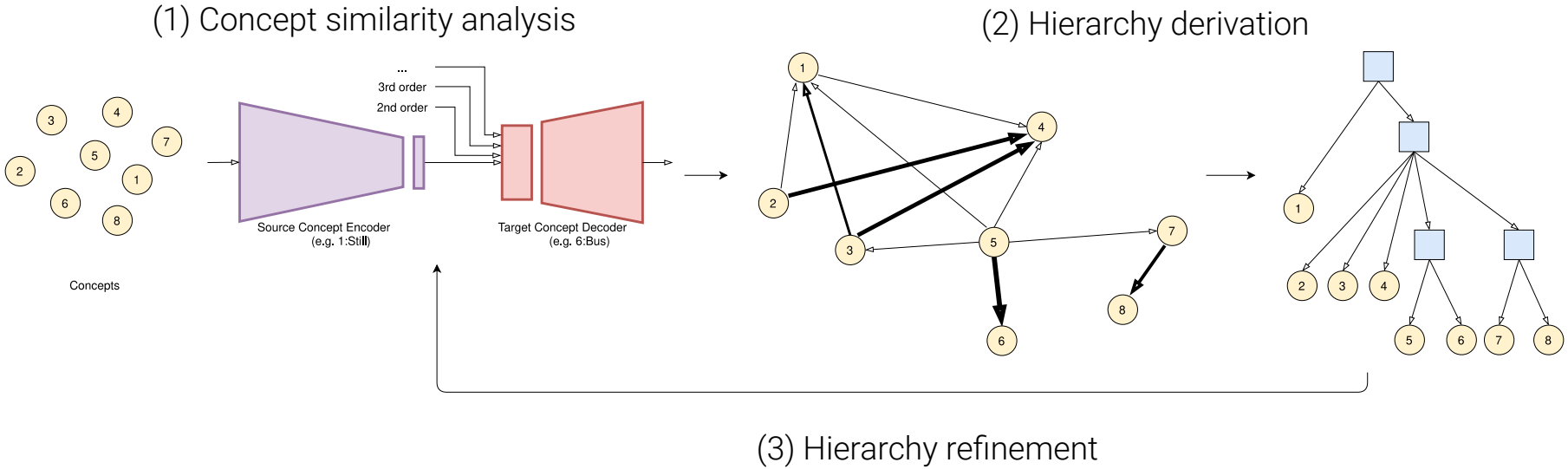
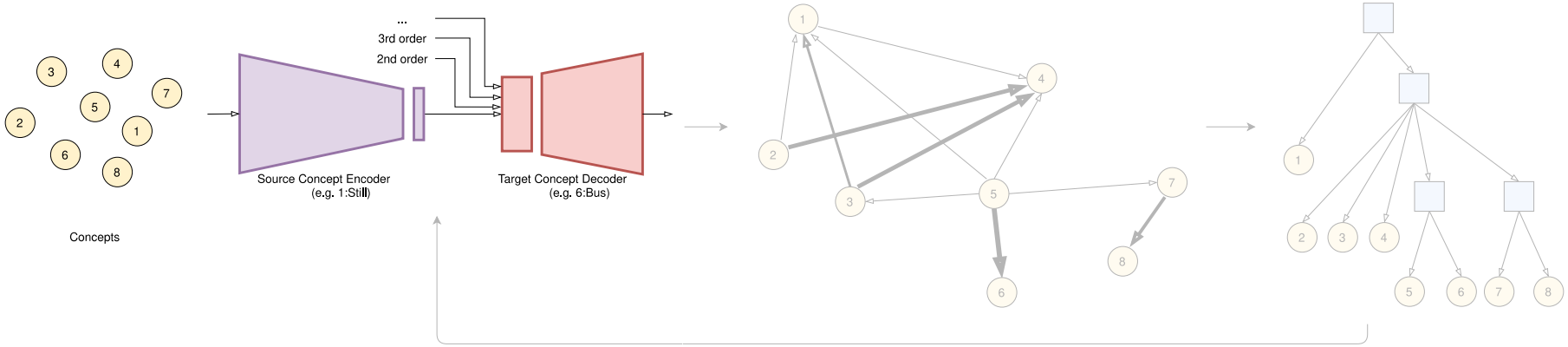
Concepts Structuring Based on Transfer Affinity

Transfer Affinity-Based Concepts Structuring



Concept Similarity Analysis



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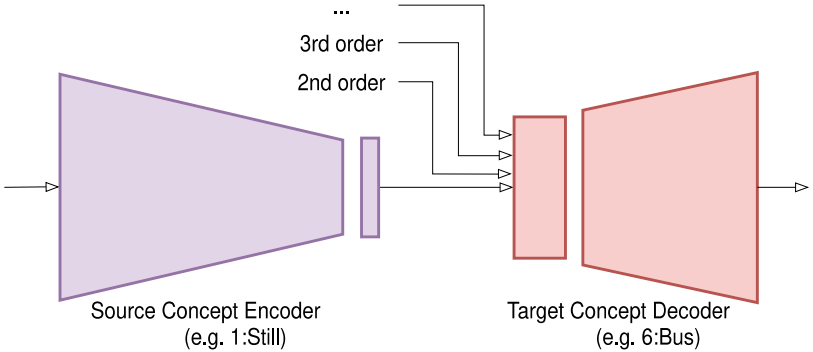


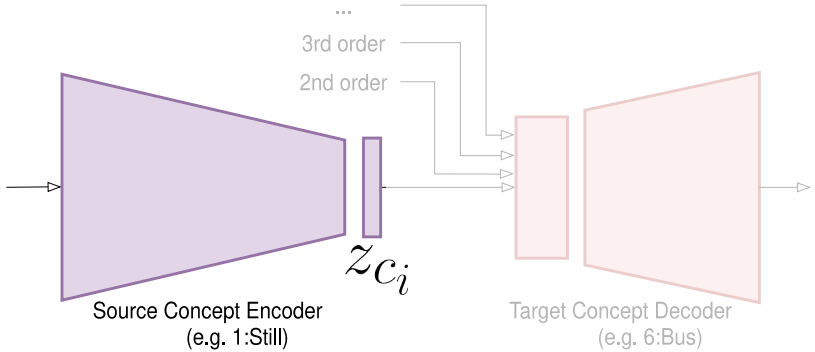
c_i Source concept

c_j Target concept

$p_{c_i \rightarrow c_j}$

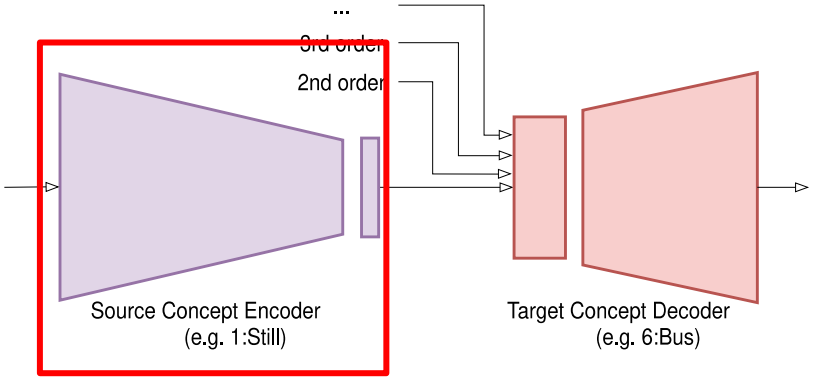
Affinity score

Concept Similarity Analysis



$$\underset{\theta,\theta'}{\operatorname{argmin}} \mathbb{E}_{x,c\sim X,C|c=c_i} \mathcal{L}(g_{\theta'}^{c_i}(f_{\theta}^{c_i}(x)), x)$$

Concept Similarity Analysis



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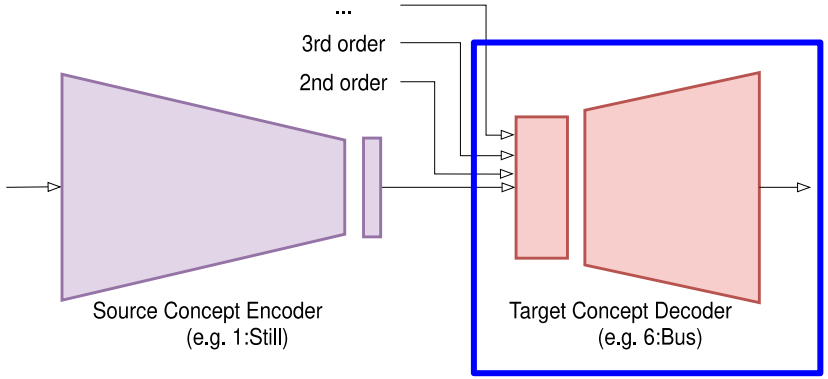

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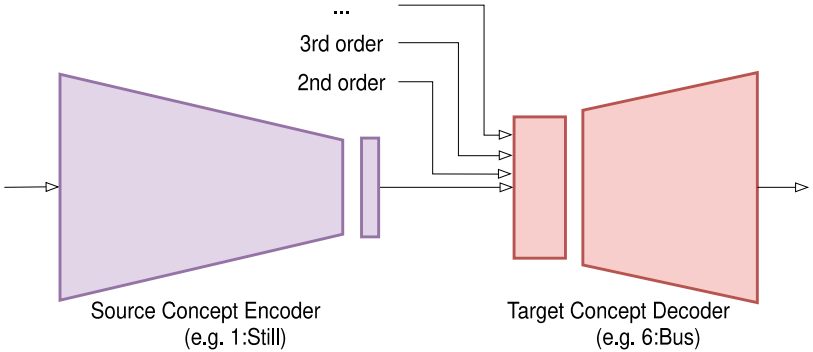
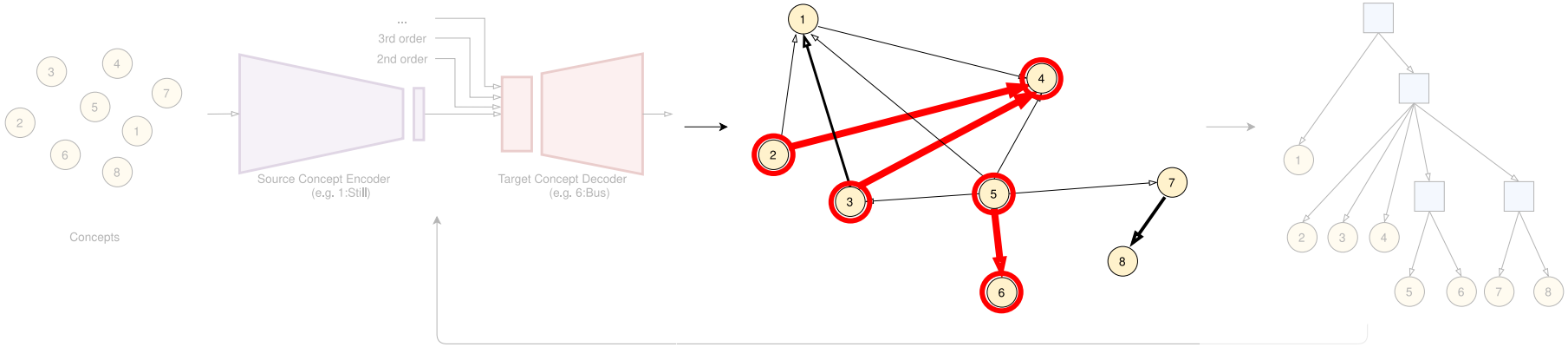


The final affinity score $\frac{\alpha \cdot p_{c_i \rightarrow c_j} + \beta \cdot b}{\alpha + \beta}$

b the supervision budget during fine-tuning

Concept Similarity Analysis



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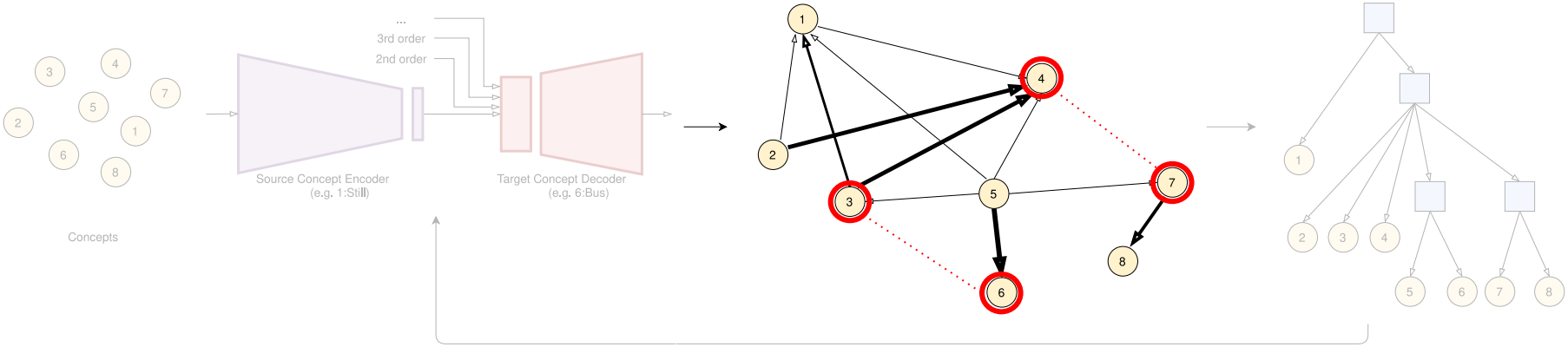
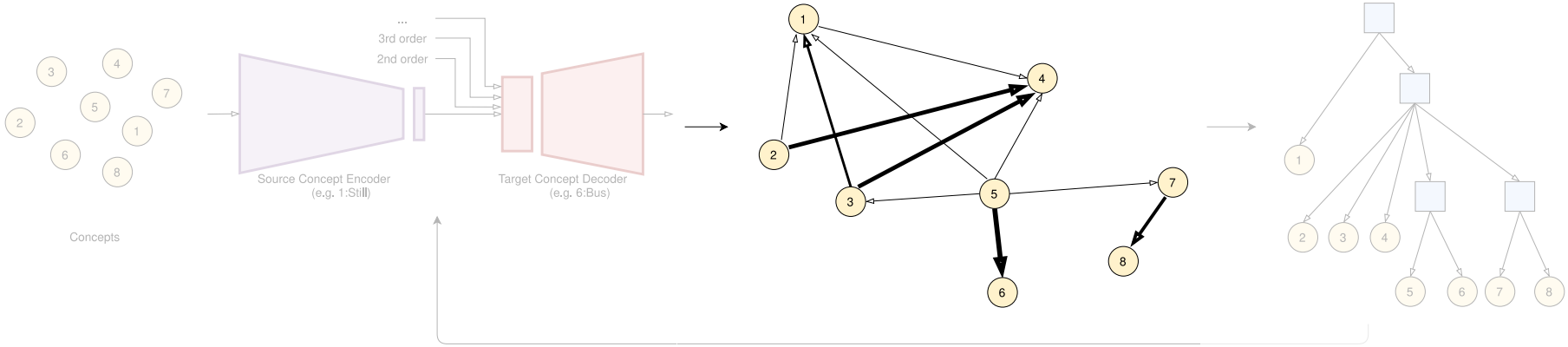


Hierarchy Derivation



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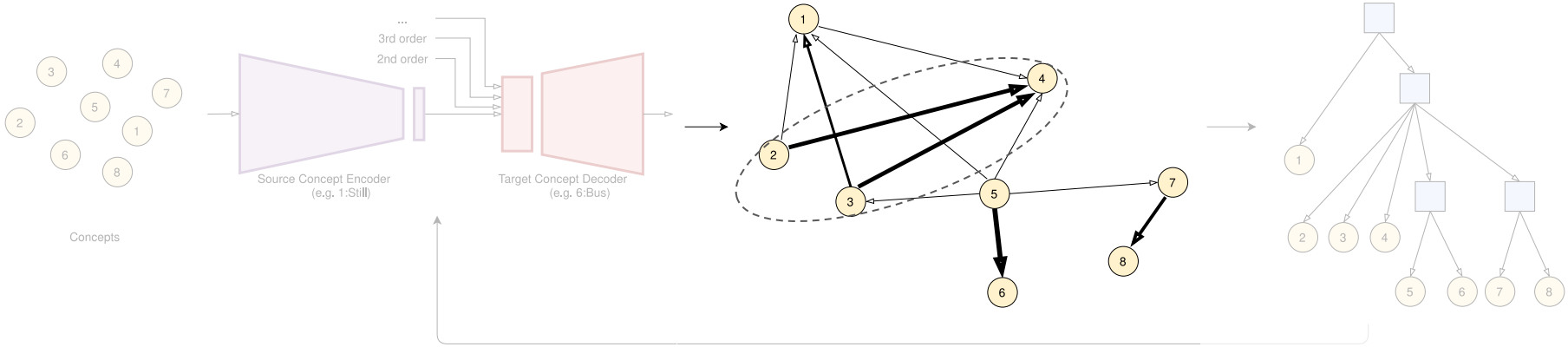
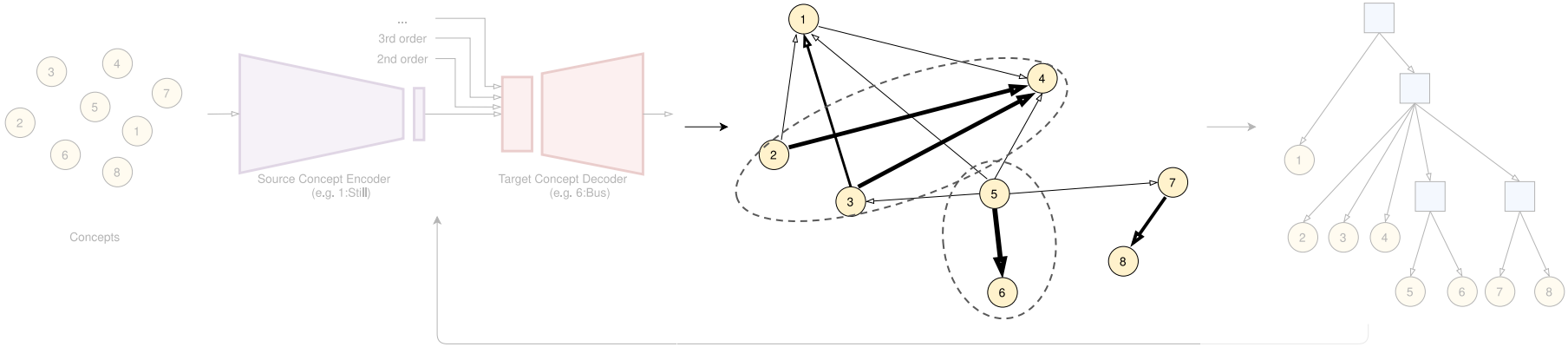


$$d_{k(ij)} = \alpha_i d_{ki} + \alpha_j d_{kj} + \beta d_{ij} + \gamma |d_{ki} - d_{kj}|$$

Hierarchy Derivation



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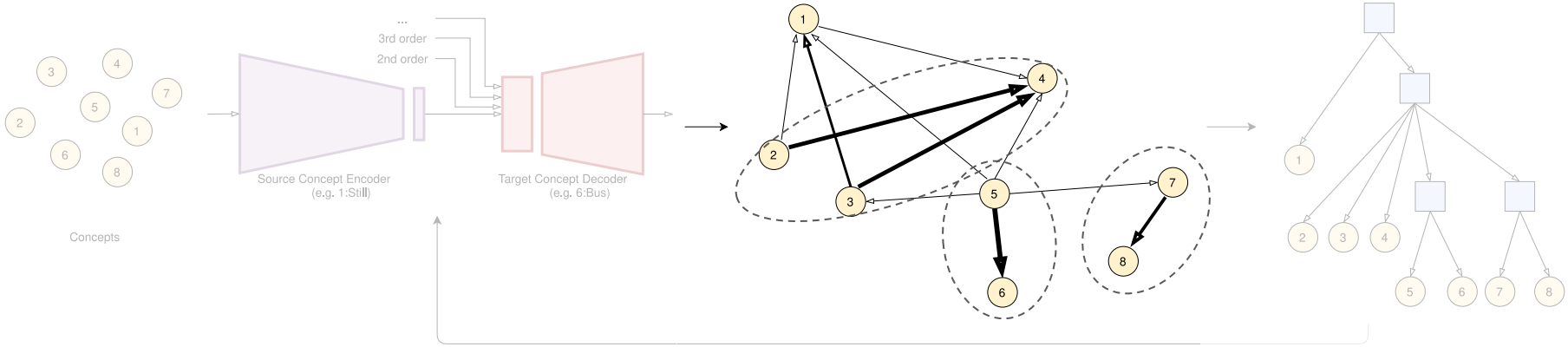

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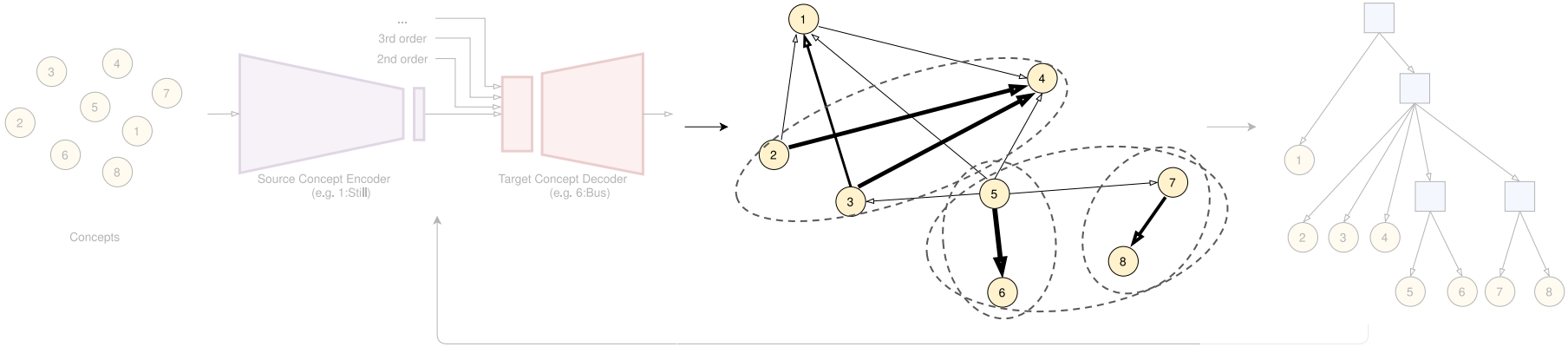

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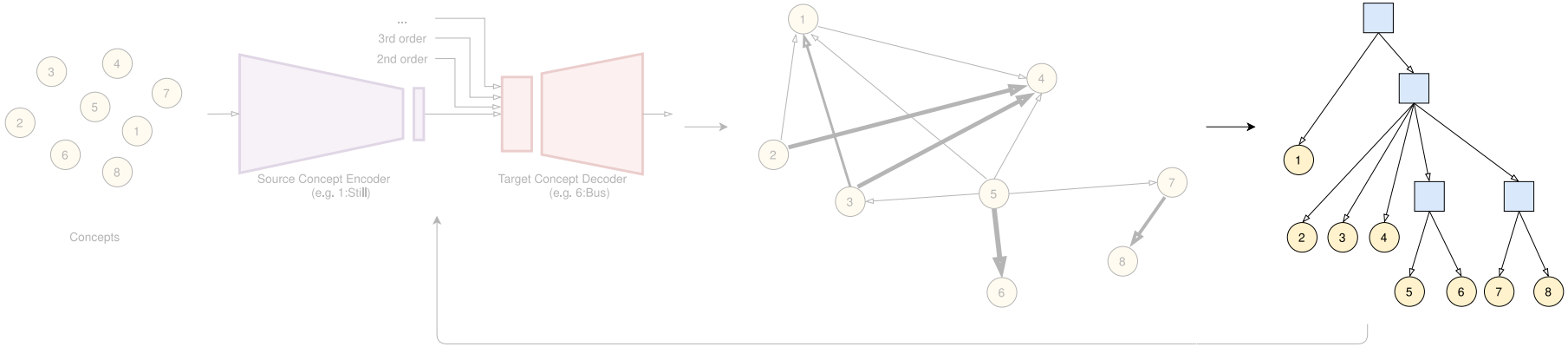

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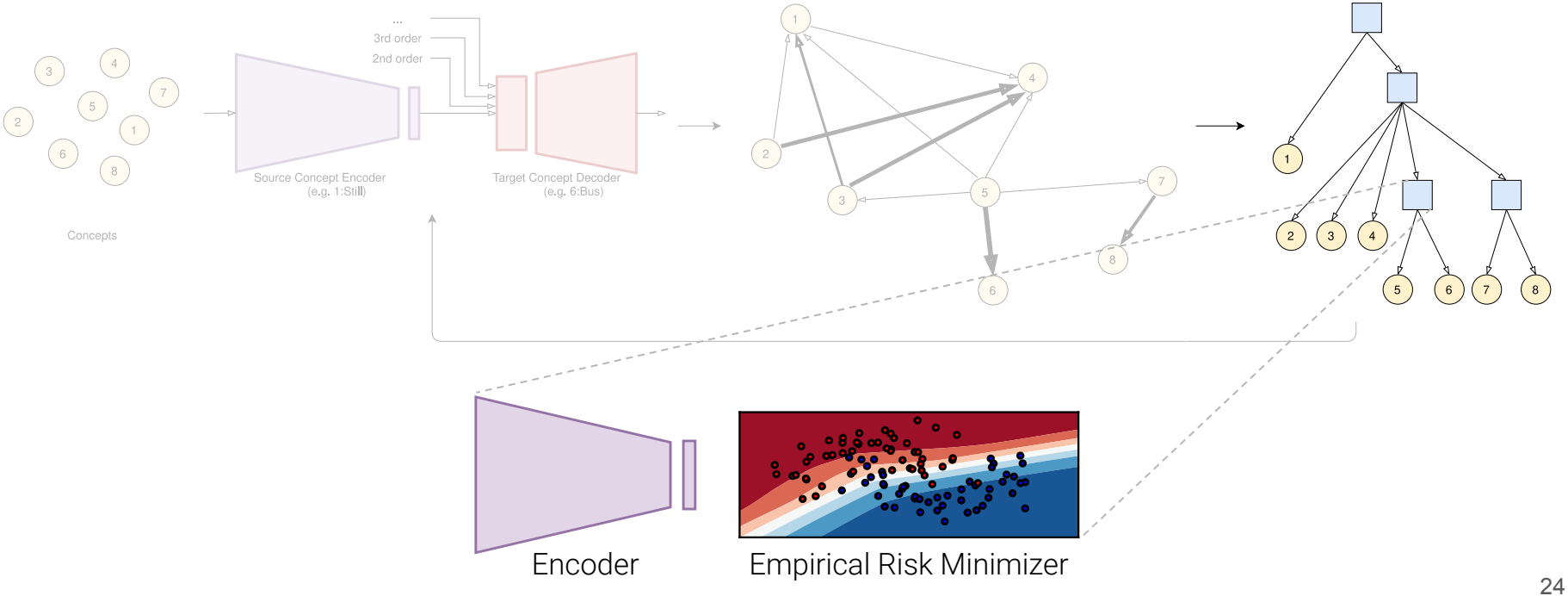

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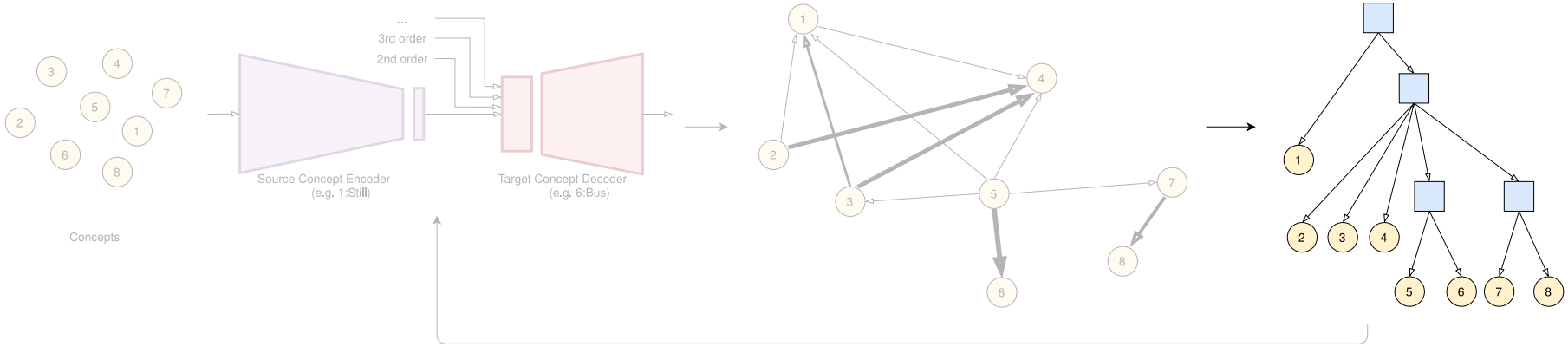
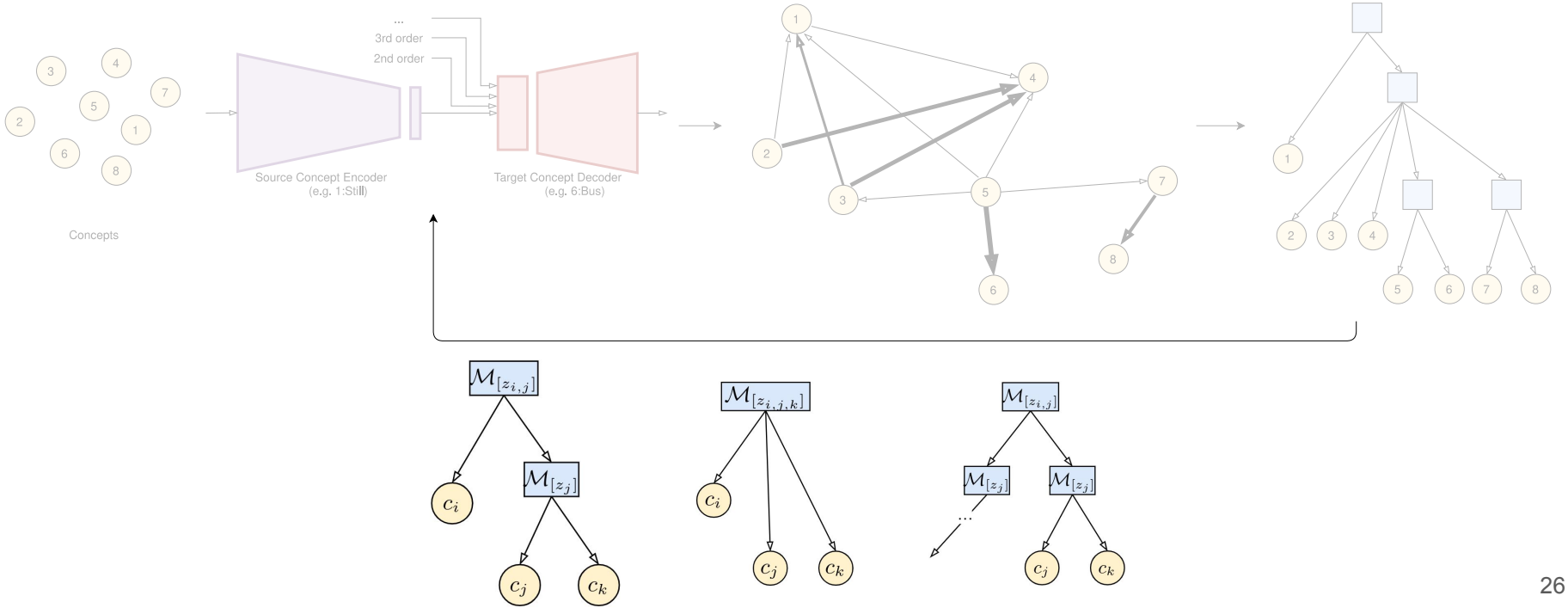


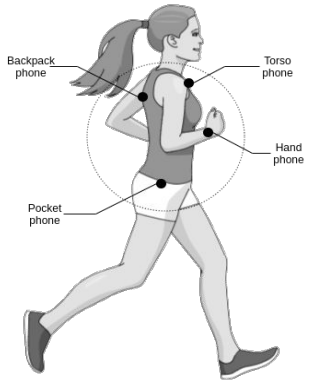
Hierarchy Refinement



Experiments

Experimental Setup

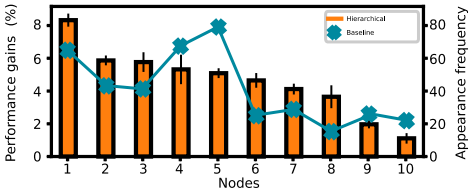
- Dataset
  - SHL dataset;
  - Multimodal and multilocation data;
- Training details
  - Stacking of Conv1d/ReLU/MaxPool blocks (Tensorflow);
  - SVMs are associated to the non-leaf nodes;
  - Hyperparameter optimization (scikit-optimize/Microsoft NNI);

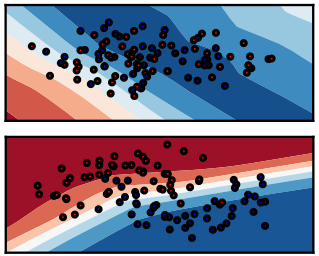


Topology of the wearable sensors deployment in a real-world application

Experimental Evaluation

(i) Evaluation of the hierarchical classification performances





(ii) Evaluation of the affinity analysis stage

(iii) Universality and Stability of the derived hierarchies

Method	Agree.	perf. avg.± std.
Expertise	-	72.32±0.17
Random	0.32	48.17±5.76
Proposed	0.77	75.92±1.13

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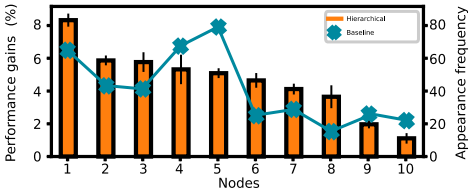

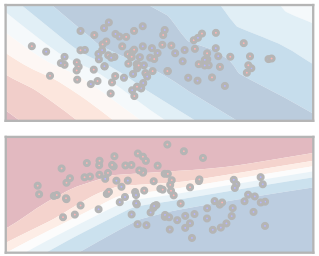

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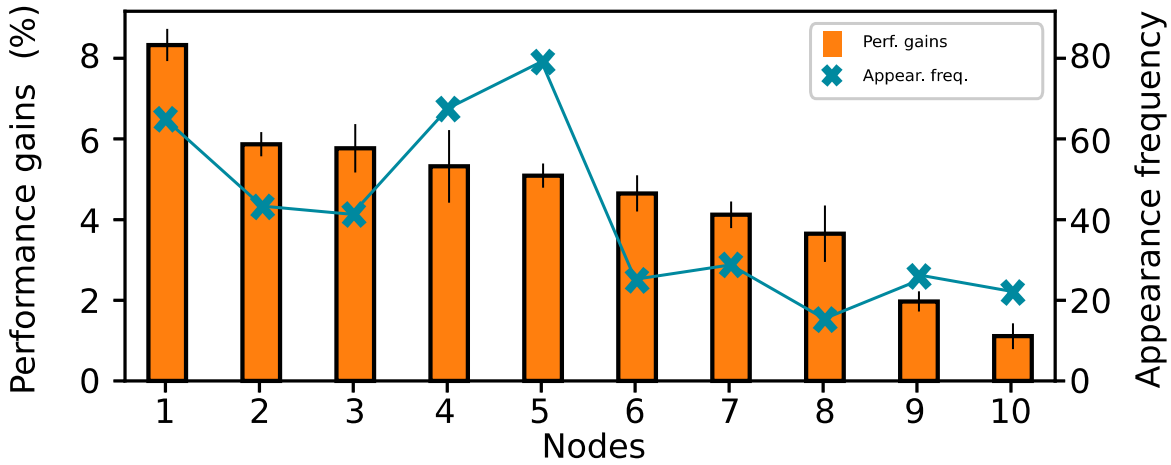
Evaluation of the Hierarchical Classification Performances

Per-node performances



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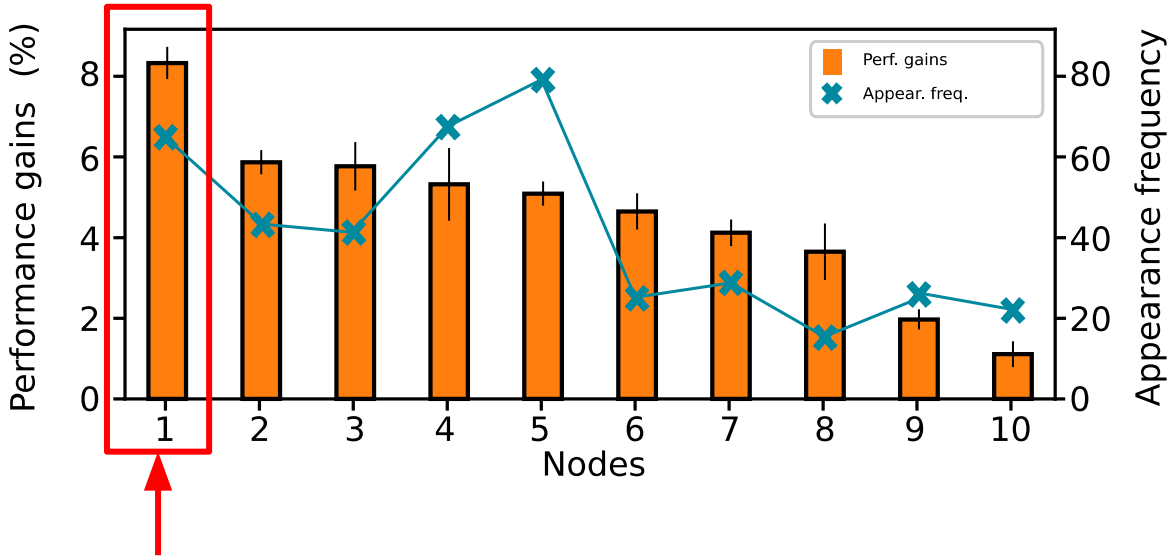
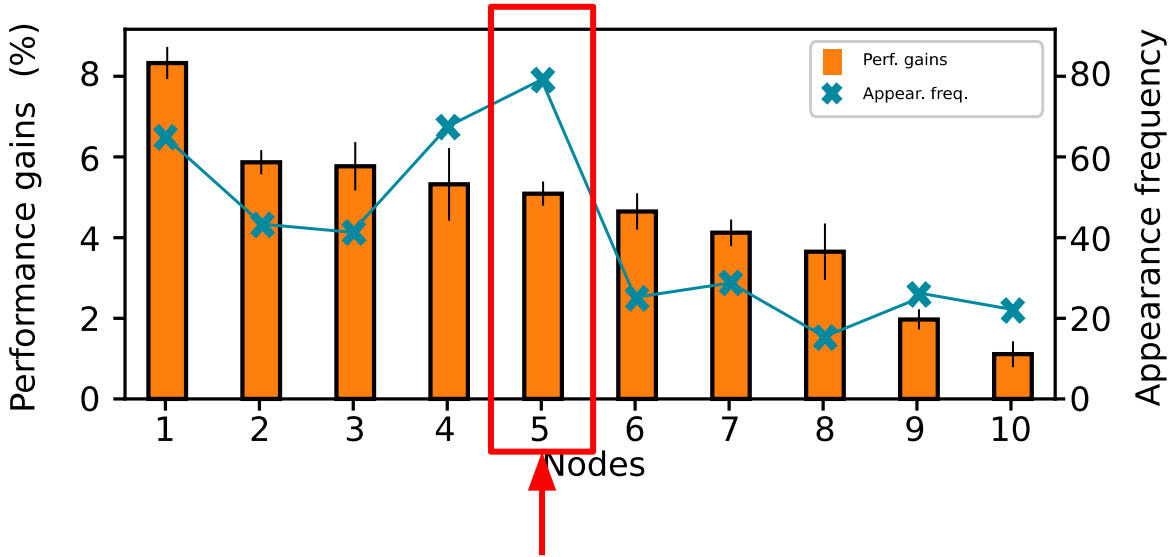


Concepts: *still* vs. *rest*
Perf. gains: 8.13±0.5%
Appear. freq.: >60

Evaluation of the Hierarchical Classification Performances

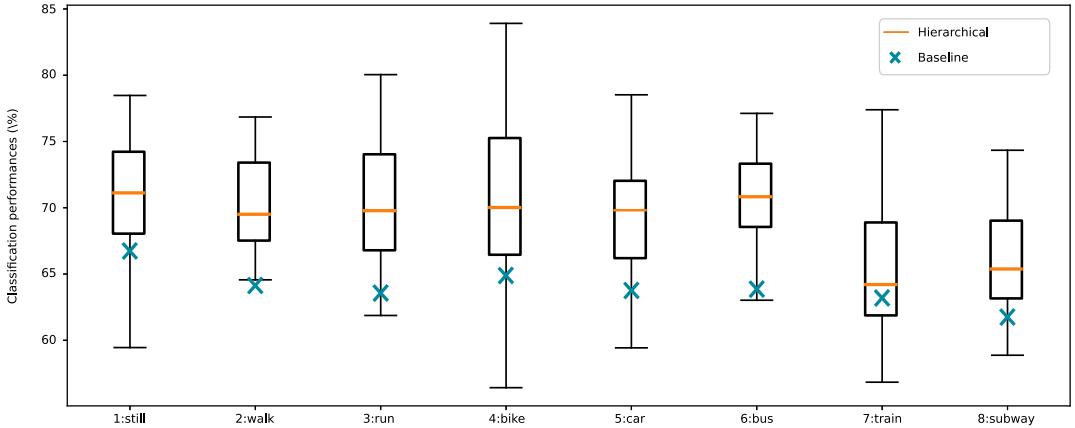
Per-node performances



concepts: *bike*, *car*, *bus*
Perf. gains: 5.09±0.3%
Appear. freq.: 80

Evaluation of the Hierarchical Classification Performances

Per-concept performances



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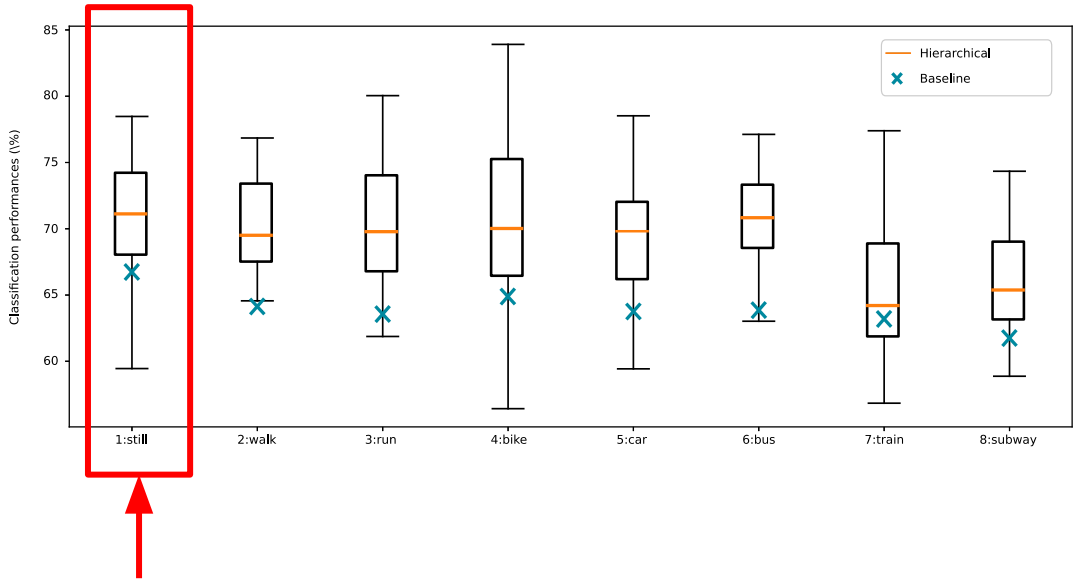
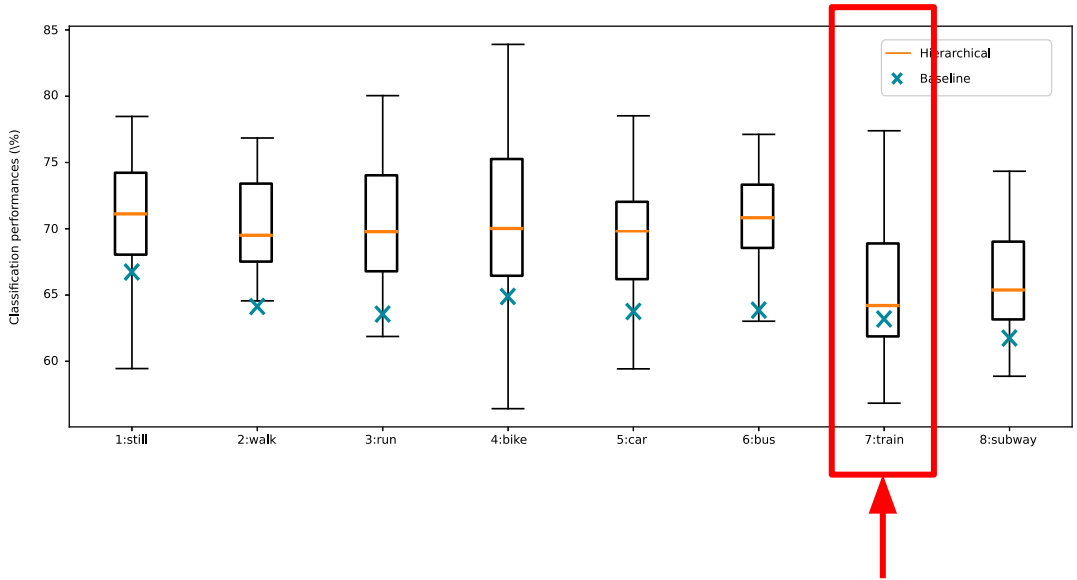


Concept: *still*
Classification rate: 72.32±3.45%

Evaluation of the Hierarchical Classification Performances

Per-concept performances



Concept: *train*
Classification rate: 64.43±4.45%

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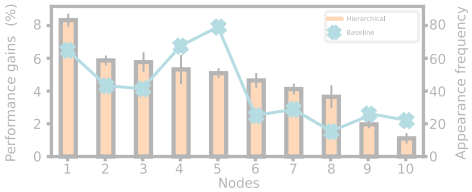

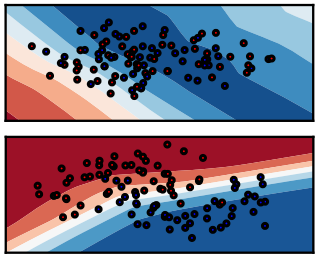

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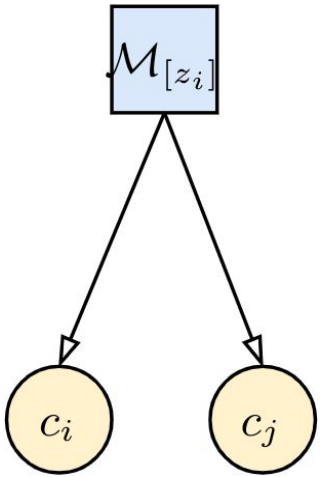
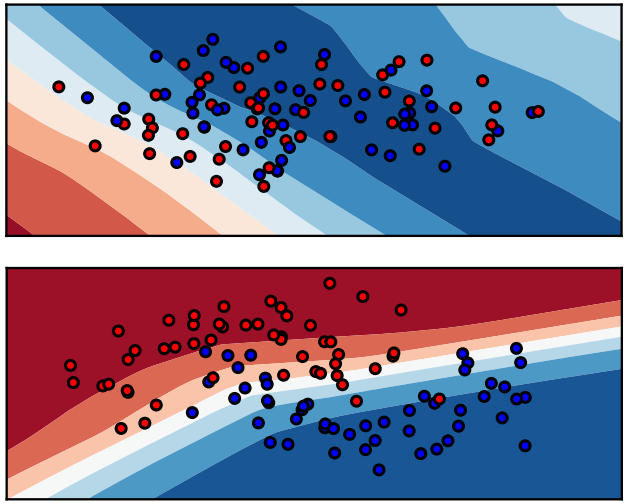
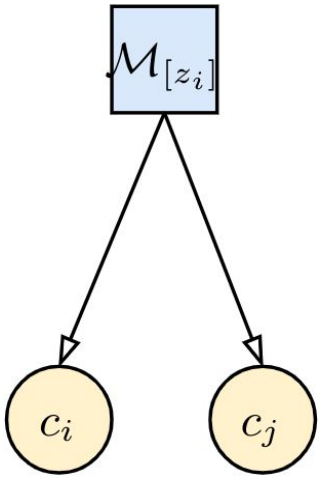
Separability of the Grouped Concepts

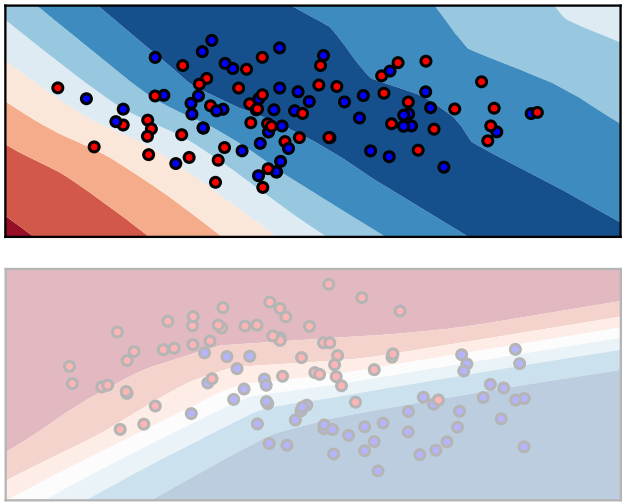




Separability of the Grouped Concepts



low affinity score



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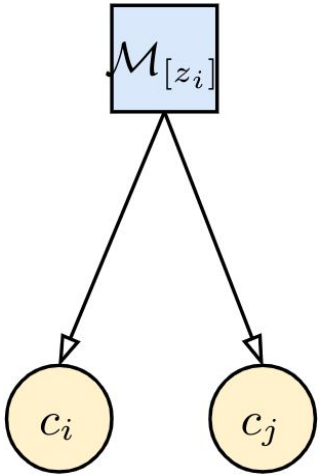

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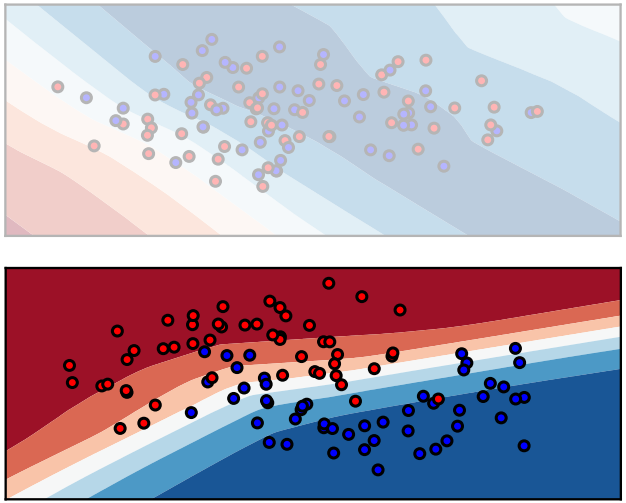
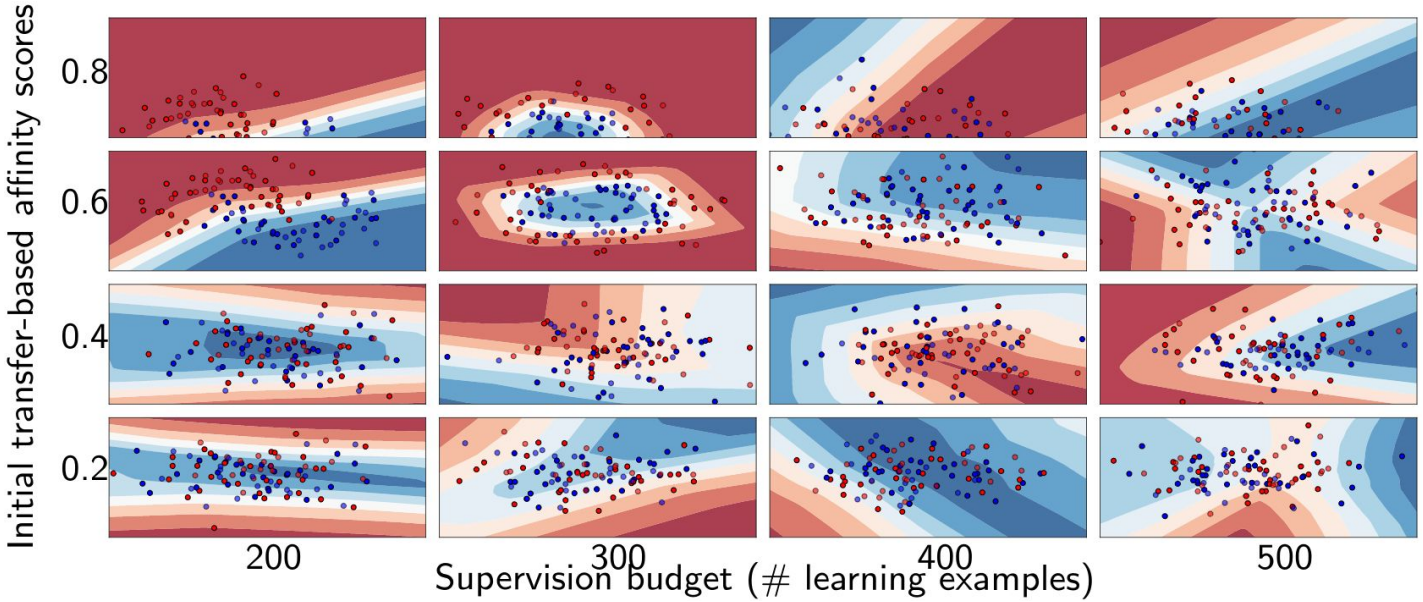


Impact of the Supervision Budget



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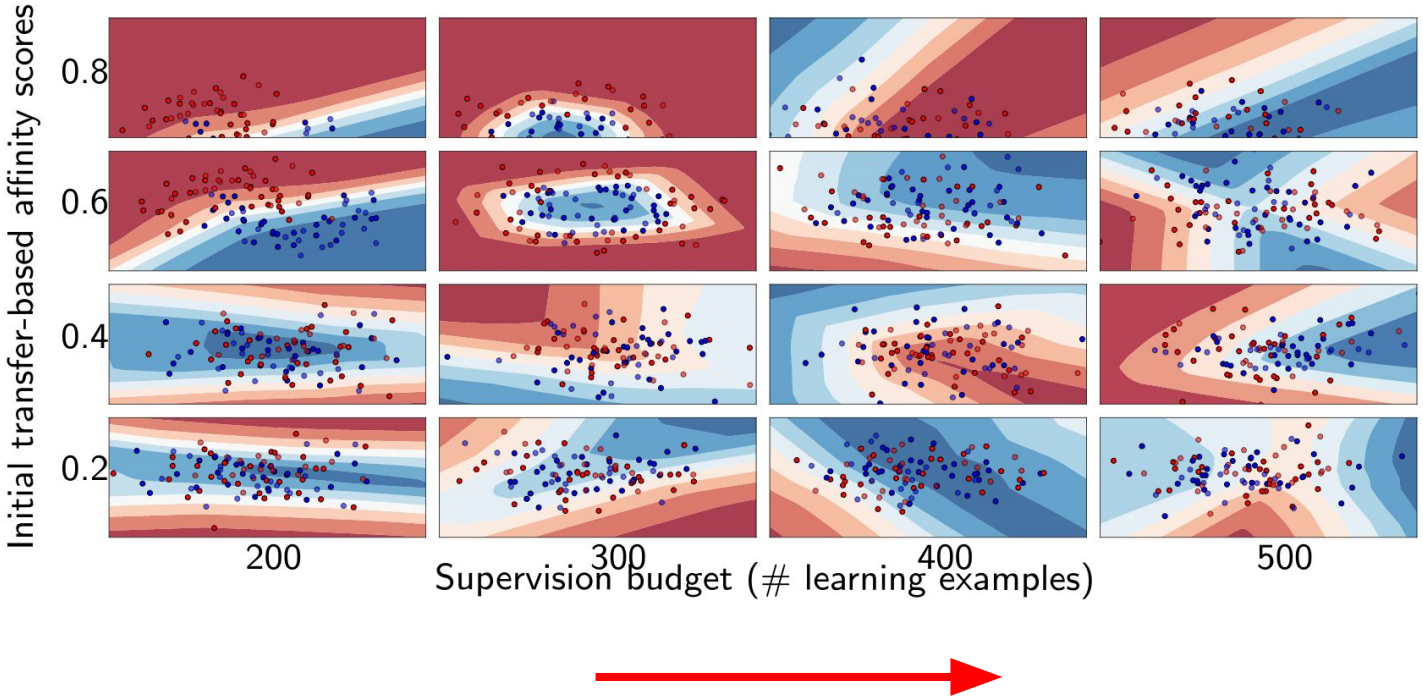

Summary

- We proposed an approach based on transfer affinity to determine an optimal organization of the concepts;
- We get a substantial improvement of recognition performances over a baseline which uses a flat classification setting;
- Comparative analysis raises interesting questions about concept dependencies and the required amount of supervision

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