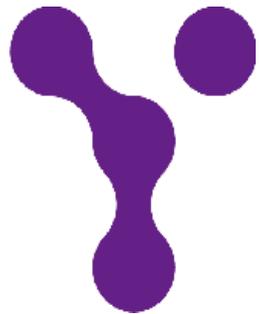
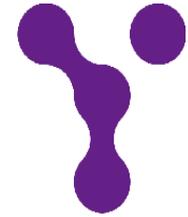


Ranking on Cross-Domain Manifold for Sketch-based 3D model Retrieval

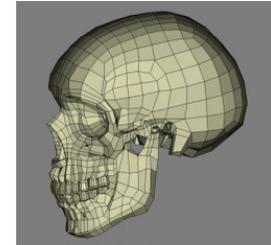


Takahiko Furuya, Ryutarou Ohbuchi
University of Yamanashi

Introduction



- 3D models are widely used.
 - Mechanical CAD, Games,...
 - 3D range scanners, 3D printers,...
 - User generated.
 - Trimble 3D warehouse, ...



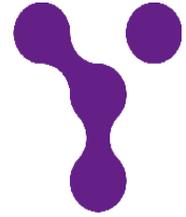
- 3D model retrieval is essential.

- High retrieval accuracy.
- Efficiency.
- Ease of use.

Focuses of this research

accurate
and
easy to use

Why sketch-based ?



■ Keywords

- ✓ Accessible for most people.
- ✗ 3D models lack textual tags.

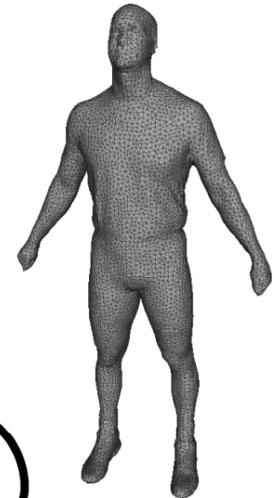
■ 3D model

- ✓ Sufficiently accurate for certain applications.
- ✗ 3D models often unavailable.

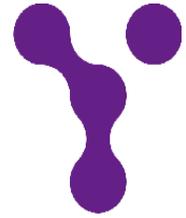
■ 2D hand-drawn sketch

- ✓ Accessible for most people.
- ✓ Intuitively specify 2D shape.
- ✗ Inaccurate.
 - Even the best method yields MAP = 11% using SHREC 2013 benchmark.

human search



Cross-domain matching problem

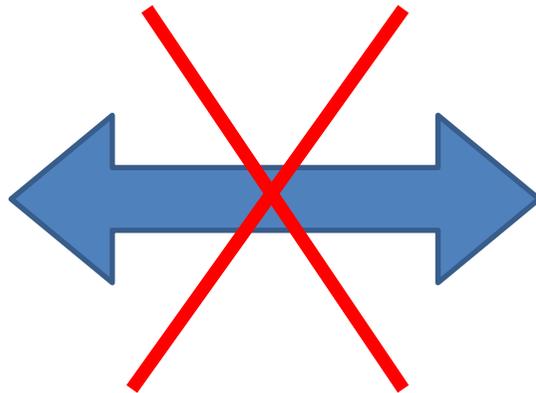


- How do we compare a 2D sketch and a 3D model?

Can't be compared directly.

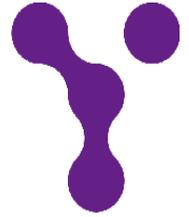


2D sketch



3D model

Cross-domain matching problem



- Approach 1 : Image feature-based comparison.
 - Renders 3D models into lines.
 - e.g., Suggestive contour [DeCarlo03], ...
 - Adopted by most.



Can be compared.



2D sketch

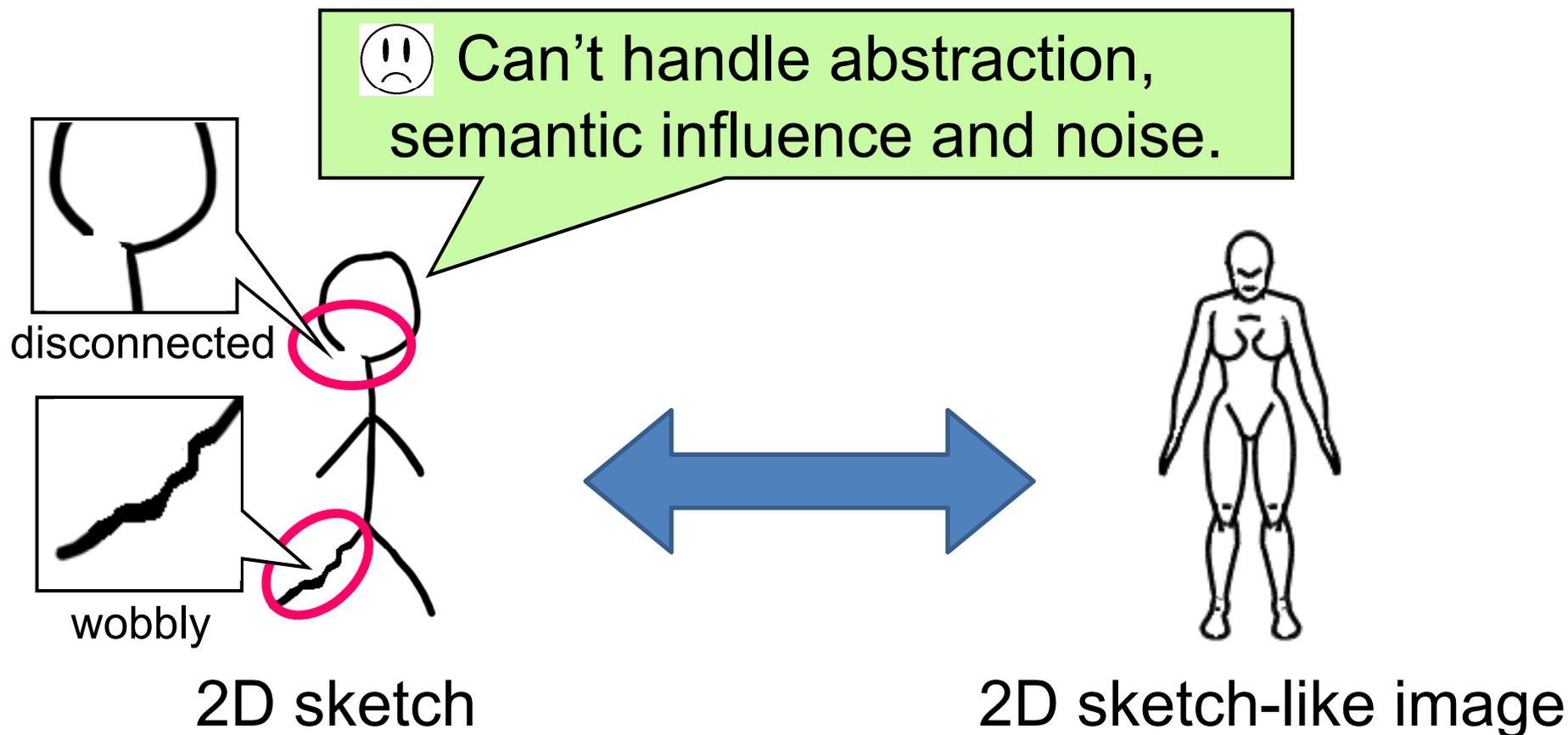


2D sketch-like image

Cross-domain matching problem



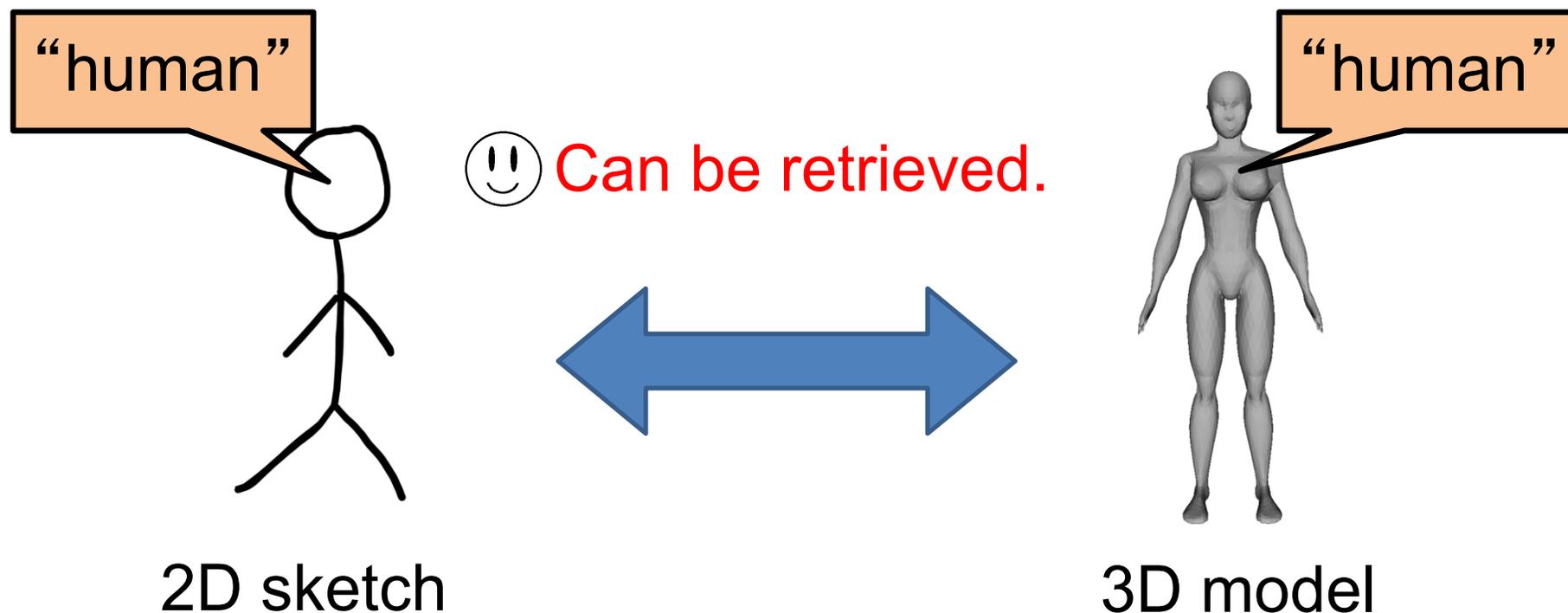
- Approach 1 : Image feature-based comparison.



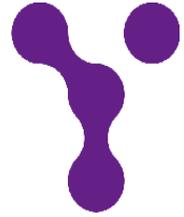
Cross-domain matching problem



- Approach 2 : Semantic label-based comparison.

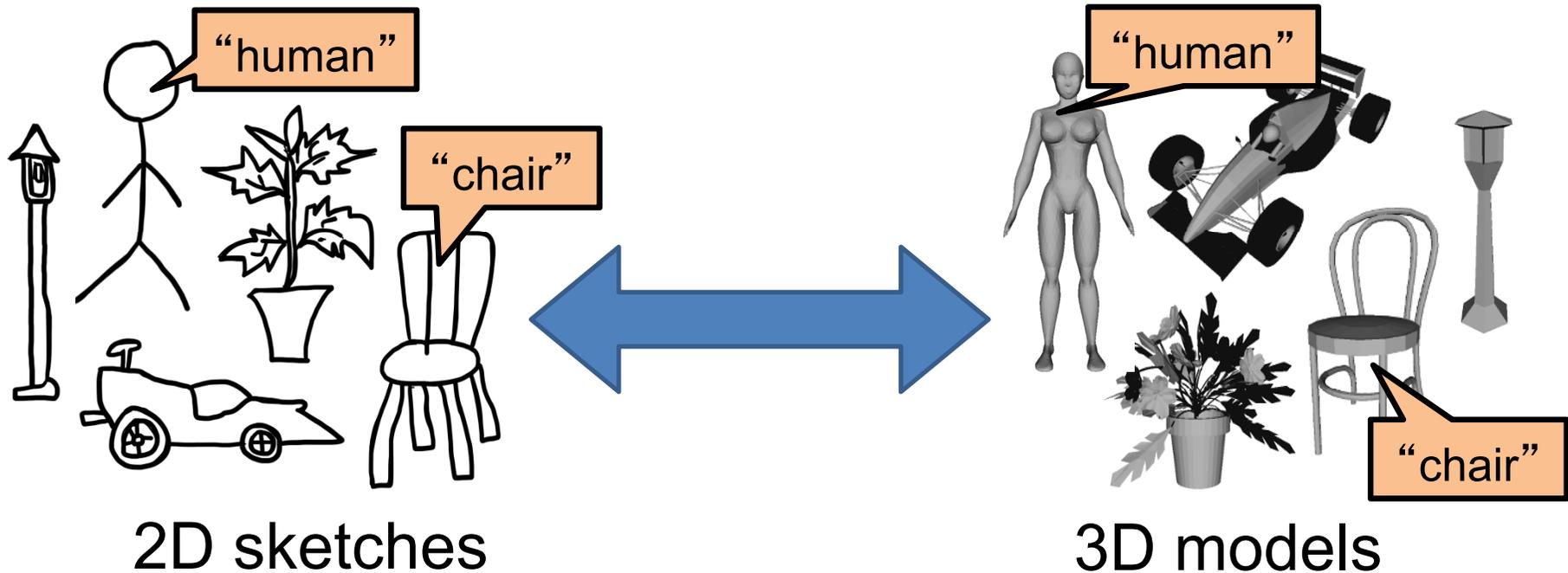


Cross-domain matching problem

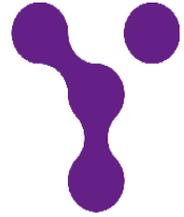


- Approach 2 : Semantic label-based comparison.

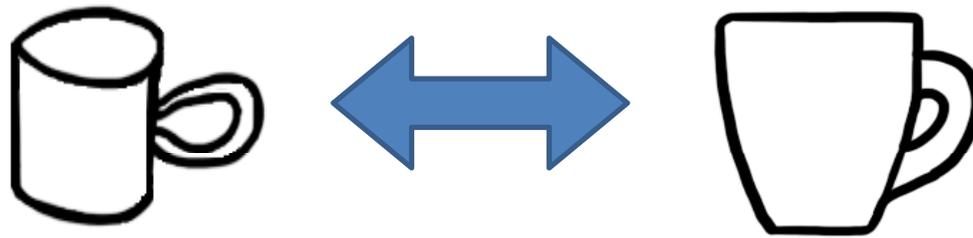
☹ Learning sparse labels is difficult.



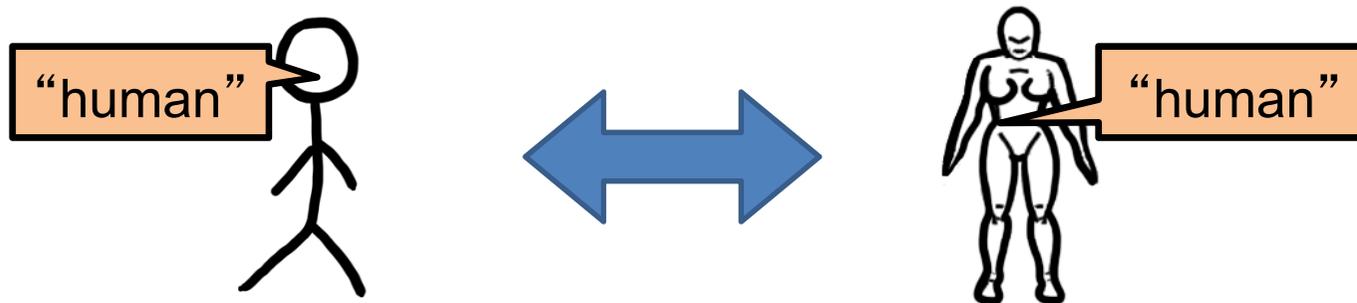
Our approach



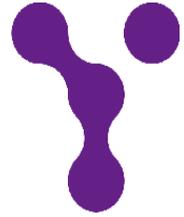
- **Combination of features and labels.**
 - ✓ Matching by image features.



- ✓ Matching by semantic labels.



Outline



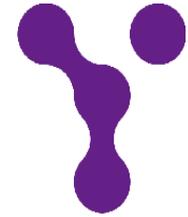
- Related work
 - BF-GALIF [Eitz12]
 - Algorithm for sketch-based 3D model retrieval
 - Manifold Ranking [Zhou03]
 - Algorithm for distance metric learning

- Proposed method

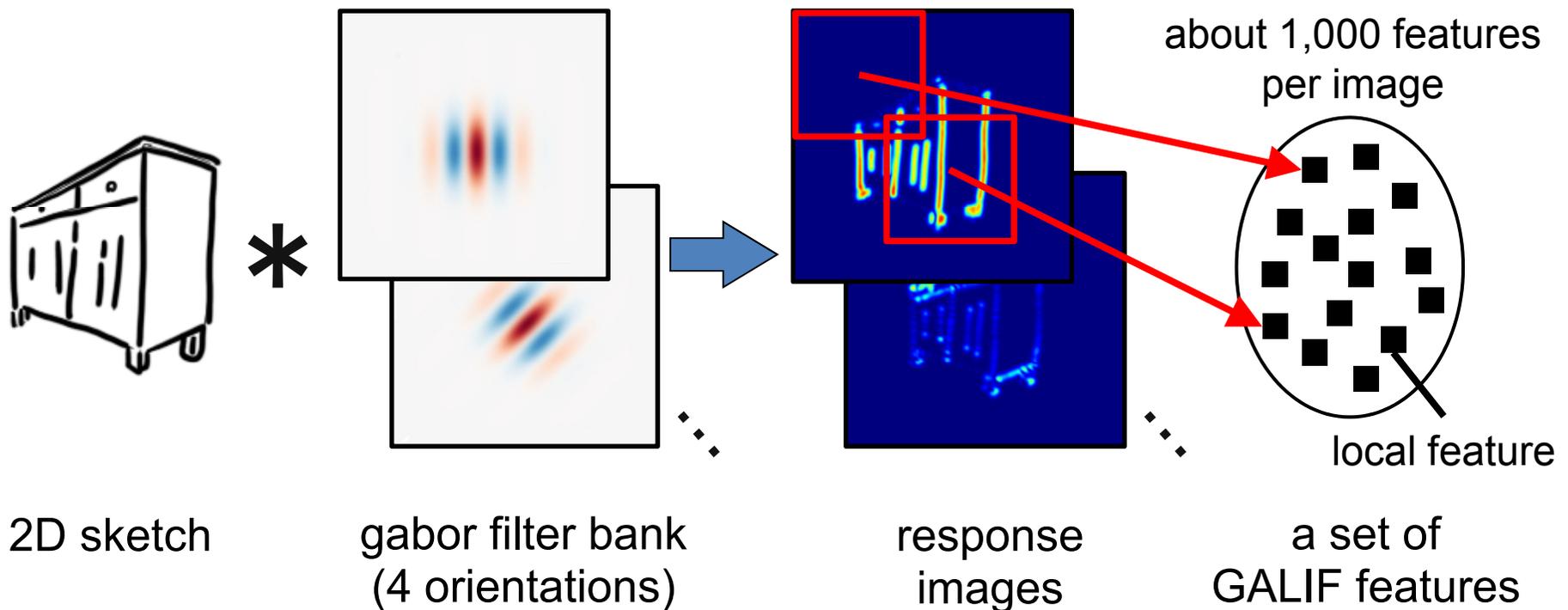
- Experiments and results

- Conclusion and future work

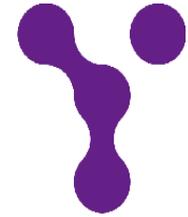
Related work : Sketch-to-3D model matching algorithm BF-GALIF [Eitz12]



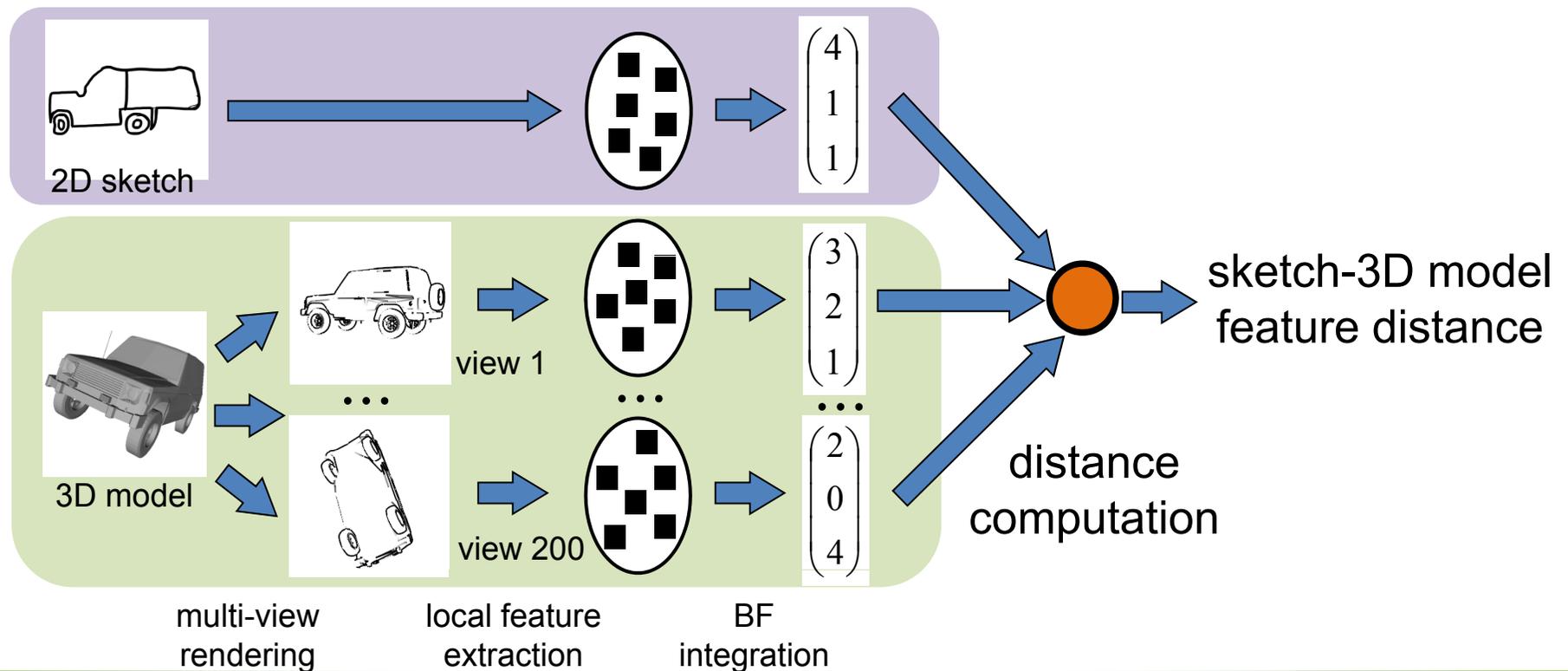
- Efficiently compares sets of local features.
 1. **Densely extracts Gabor filter-based local features.**
 2. Integrates local features into a vector by Bag-of-Features.



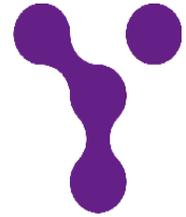
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- Efficiently compares sets of local features.
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Related work : Sketch-to-3D model matching algorithm BF-GALIF [Eitz12]



- Efficiently compares sets of local features.

😊 Robust against articulation of 2D shape.

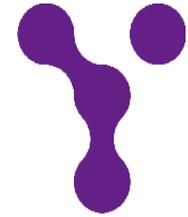
😊 Among the most accurate methods.

😞 Yet, insufficient ...

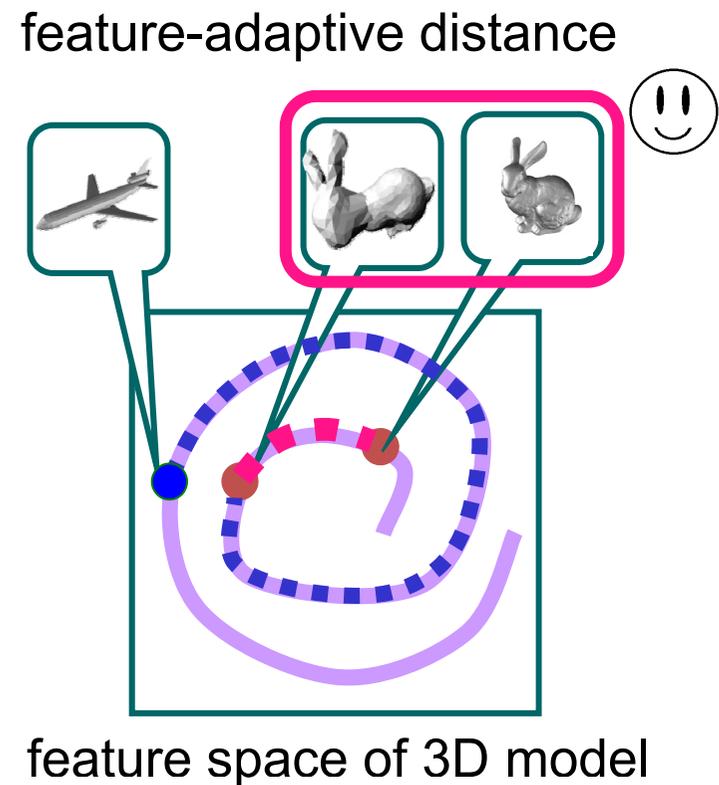
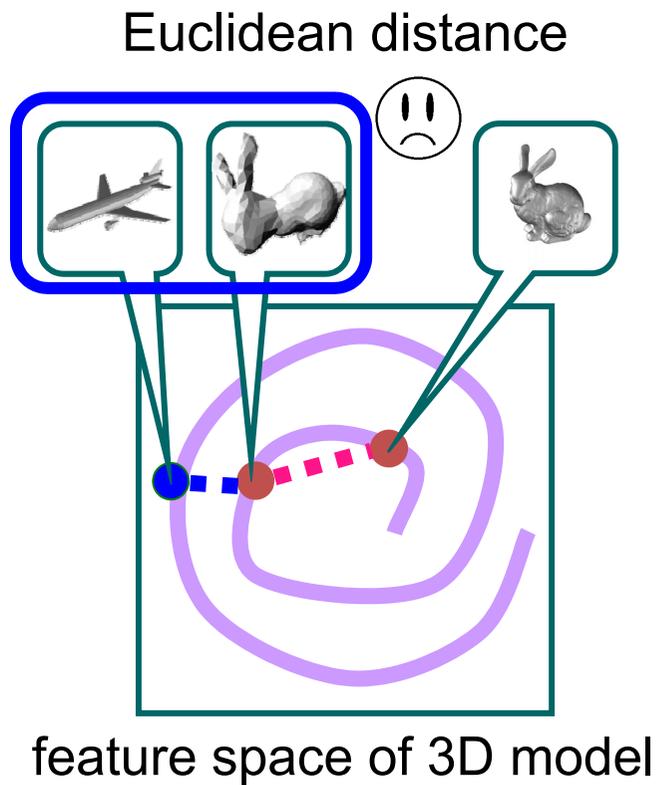
Our approach

- better feature comparison.
- semantic labels.

Improving single-domain feature comparison



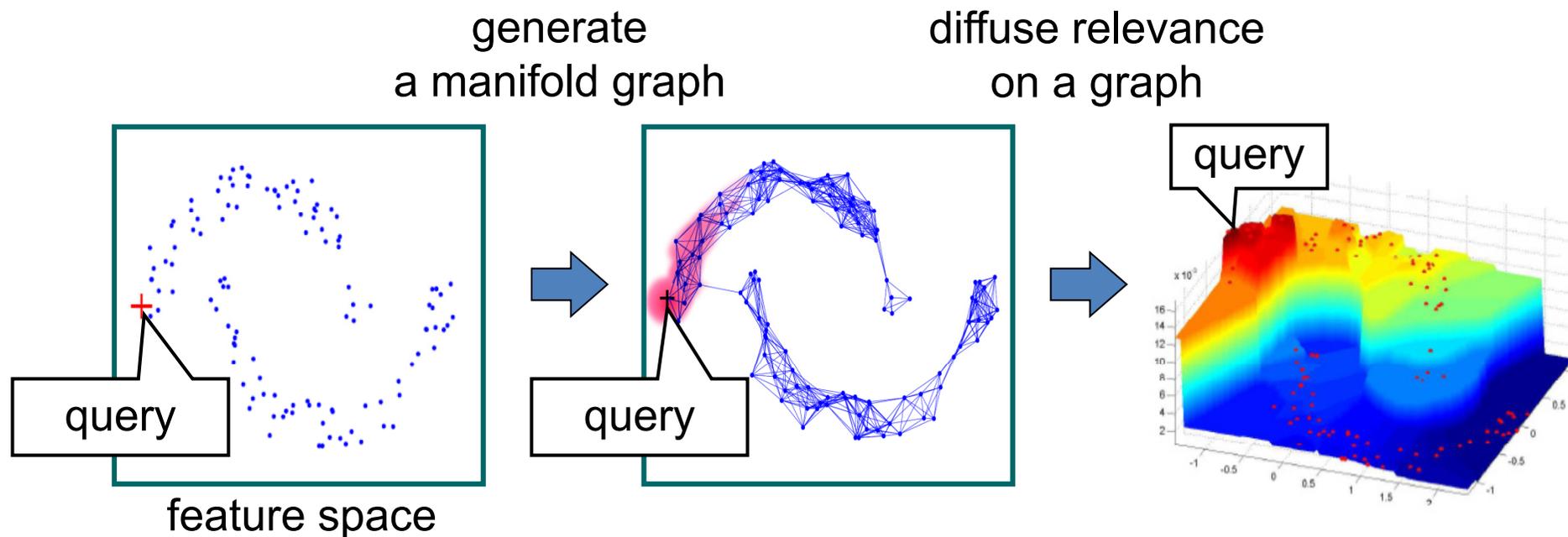
- Learns feature-adaptive distance metric on manifold.





Related work : Distance metric learning Manifold Ranking [Zhou03]

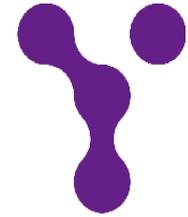
- Diffusion distance on a feature manifold graph.



Our approach

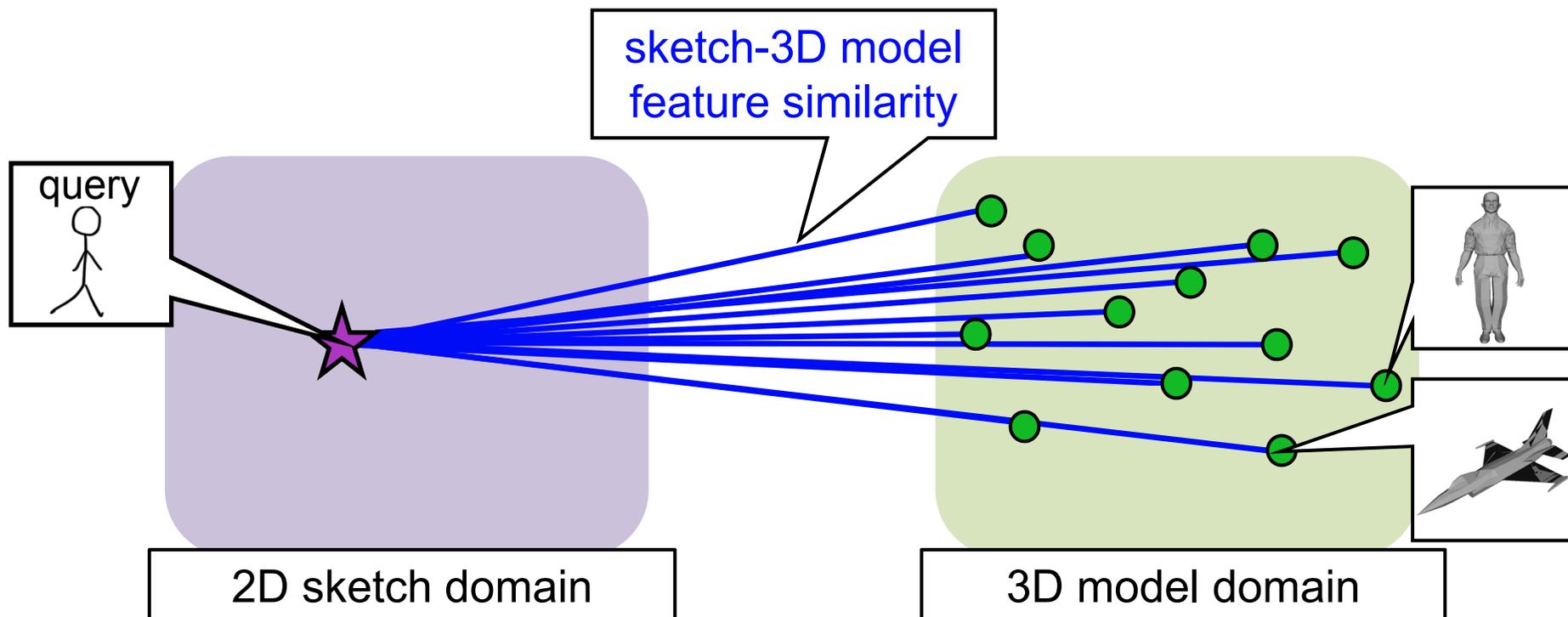
- extends Manifold Ranking to cross-domain.

Improving cross-domain feature comparison

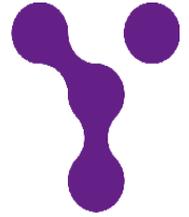


■ BF-GALIF [Eitz12]

- 😞 Structure of feature manifold is ignored.

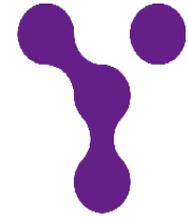


Outline

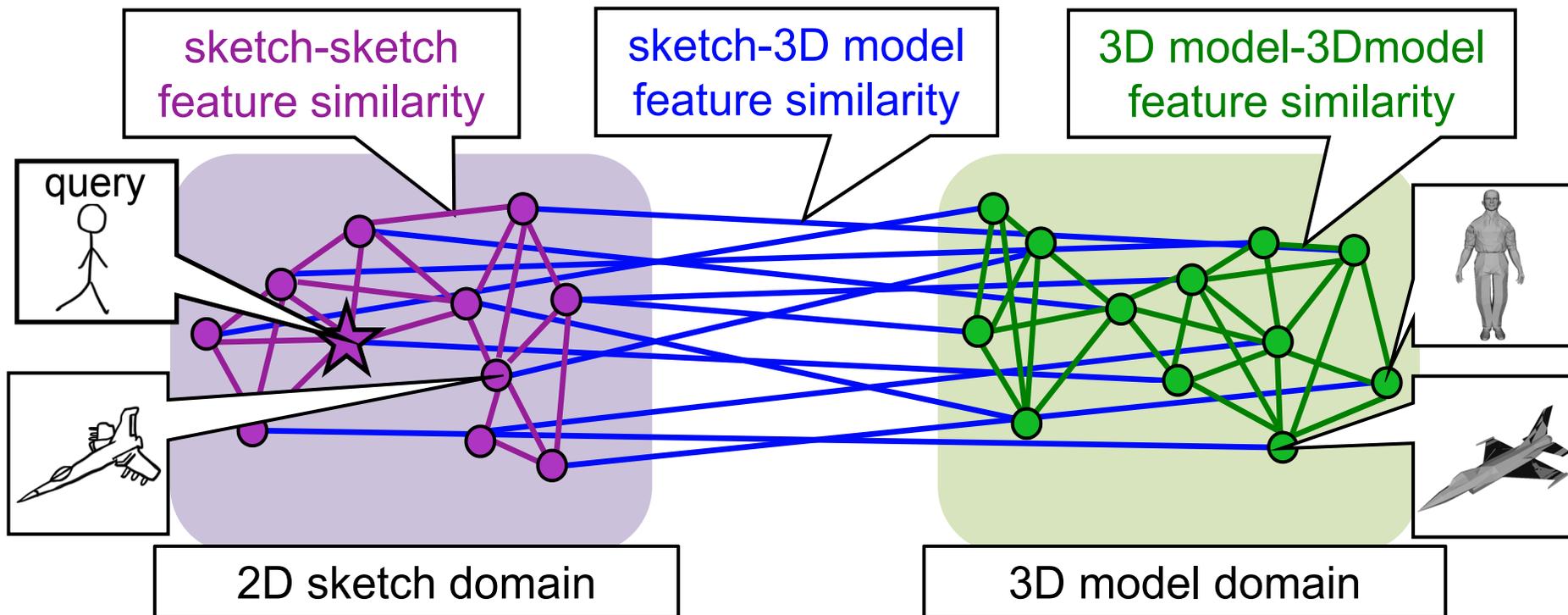


- Related work
- **Proposed method**
 - Cross-Domain Manifold Ranking (CDMR) algorithm
- Experiments and results
- Conclusion and future work

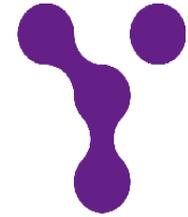
Improving cross-domain feature comparison



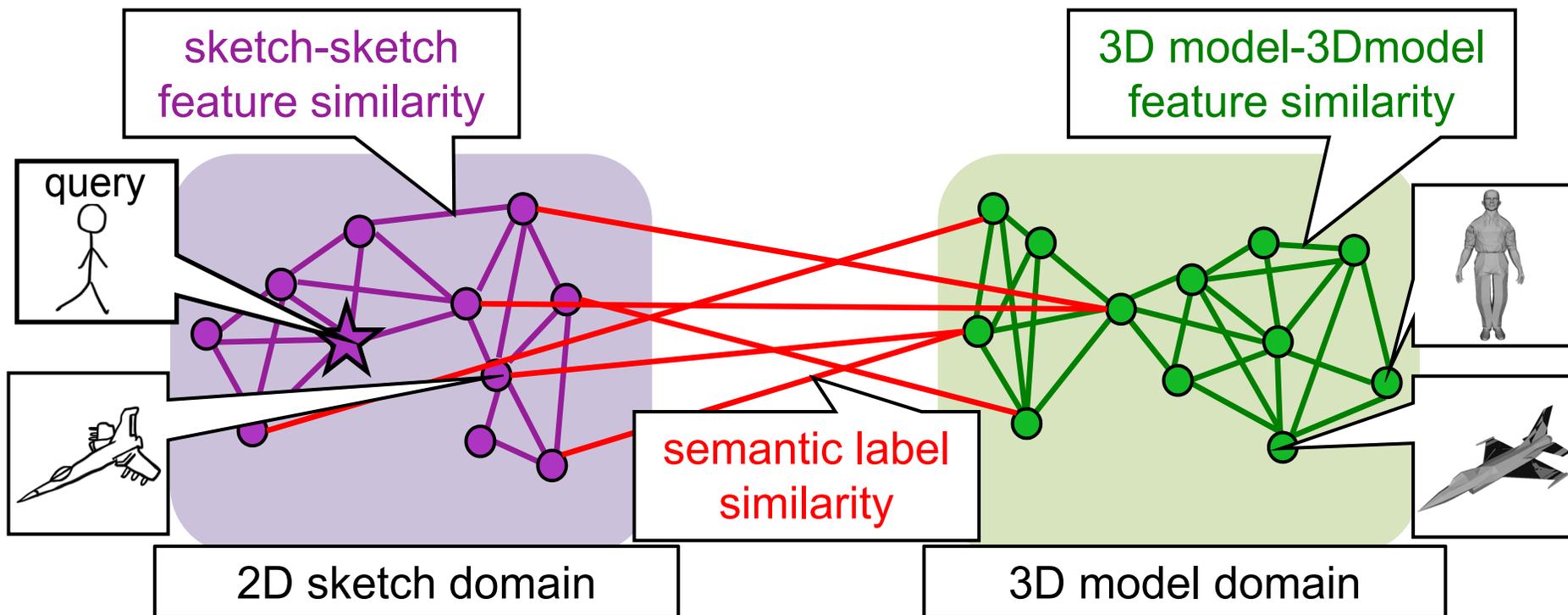
- Ranking by diffusion distance on a Cross-Domain Manifold (CDM).
 - 😊 Structure of each feature manifold is kept.



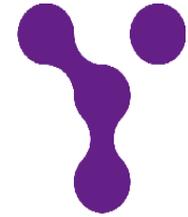
Improving cross-domain feature comparison



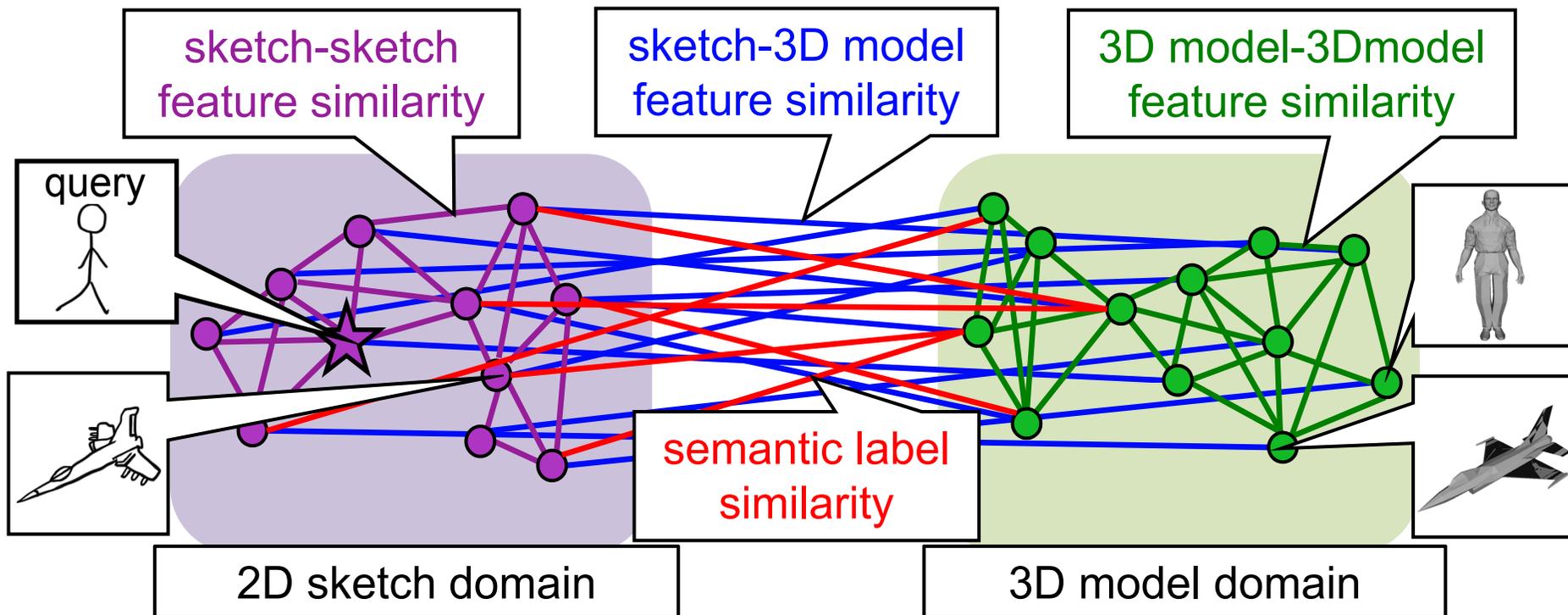
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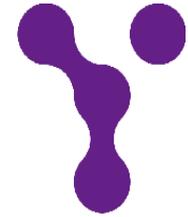


Improving cross-domain feature comparison

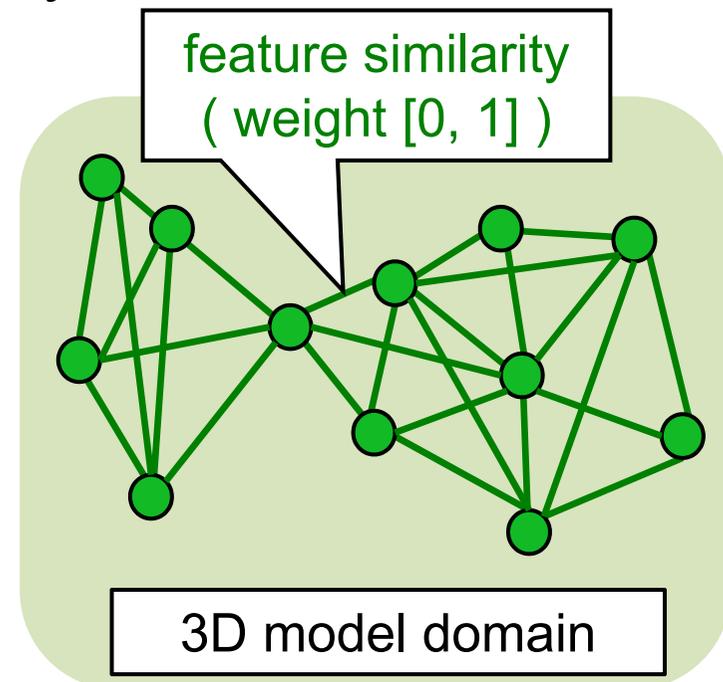
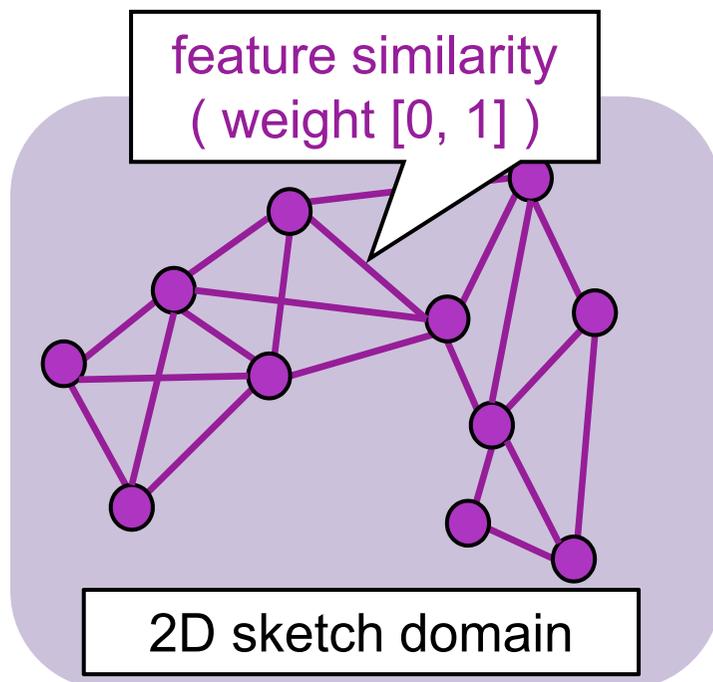


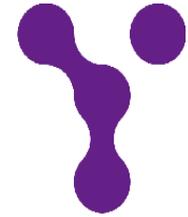
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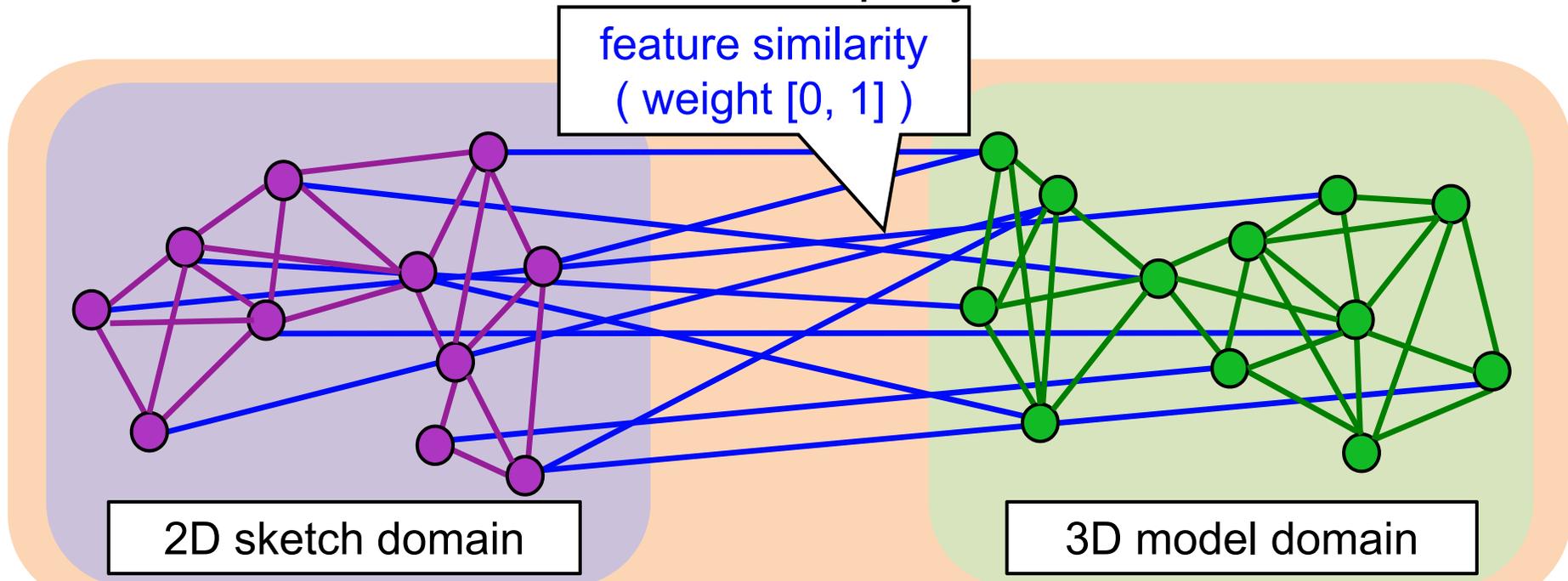


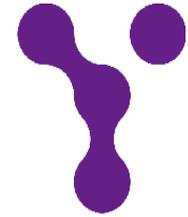
- Ranking by diffusion distance on the CDM.
 1. Generates a feature manifold on each domain.
 2. Links the two manifolds by feature and label similarity.
 3. Diffuses relevance from the query.



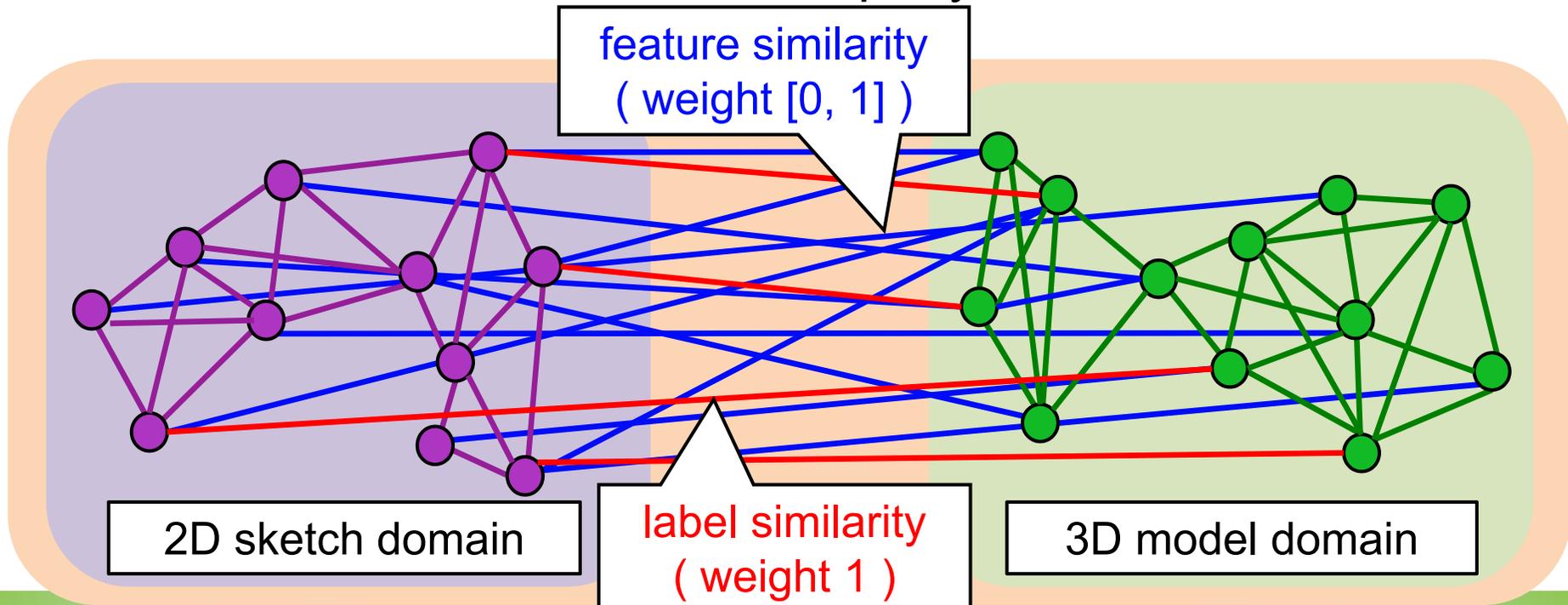


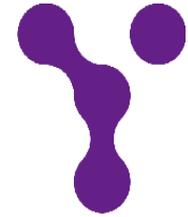
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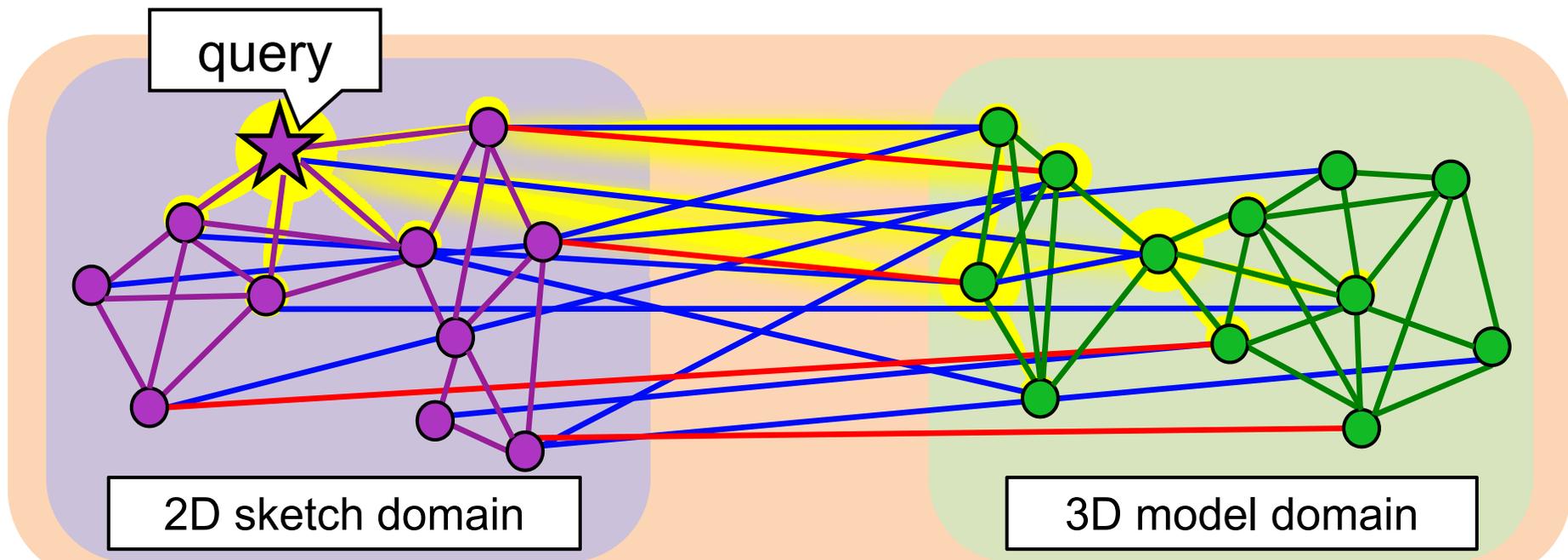


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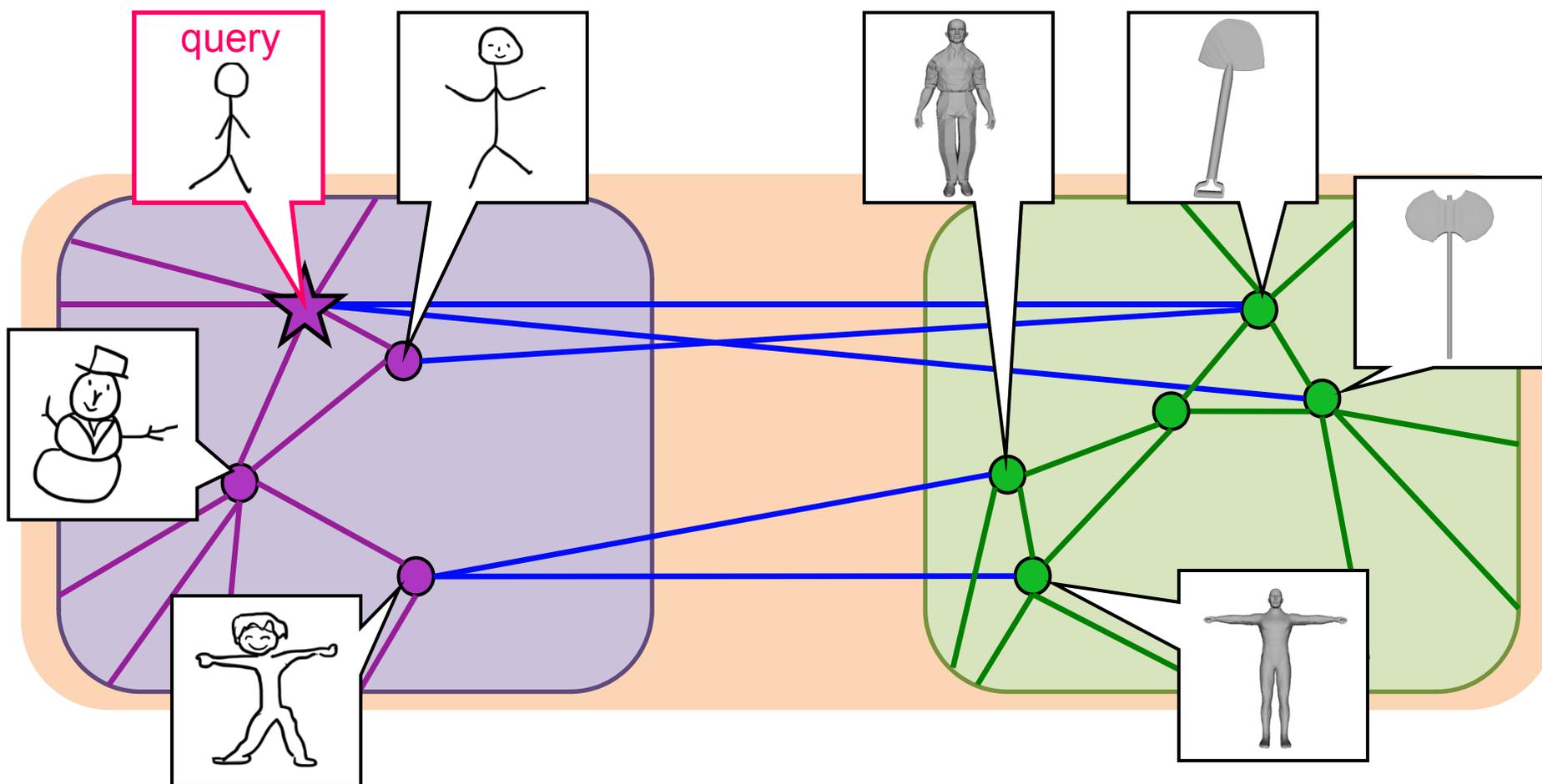
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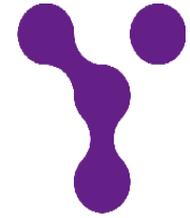


Proposed method Cross-Domain Manifold Ranking (CDMR)

- Example 1 : Ranking by label similarity.

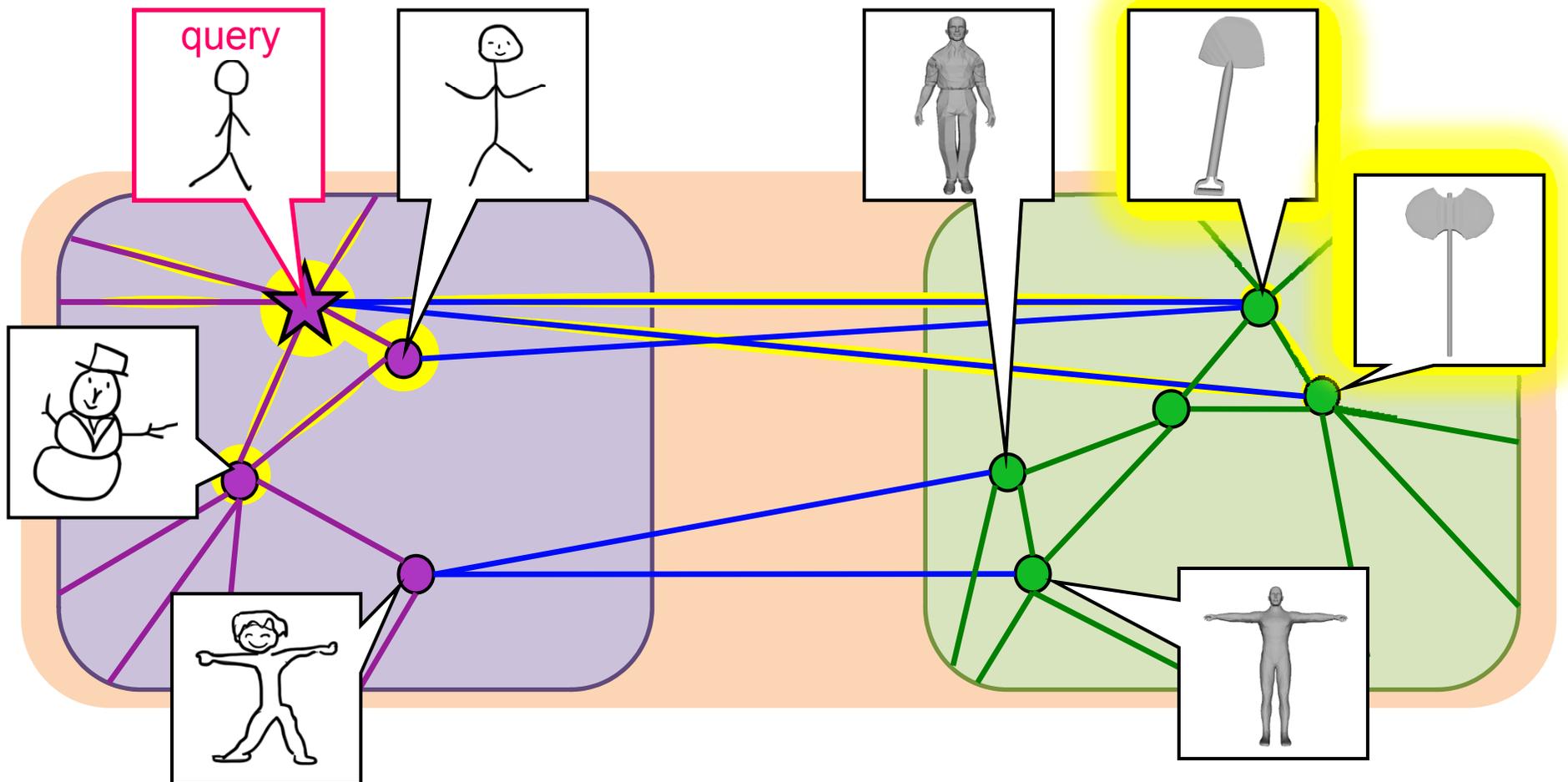


Proposed method Cross-Domain Manifold Ranking (CDMR)



- Example 1 : Ranking by label similarity.

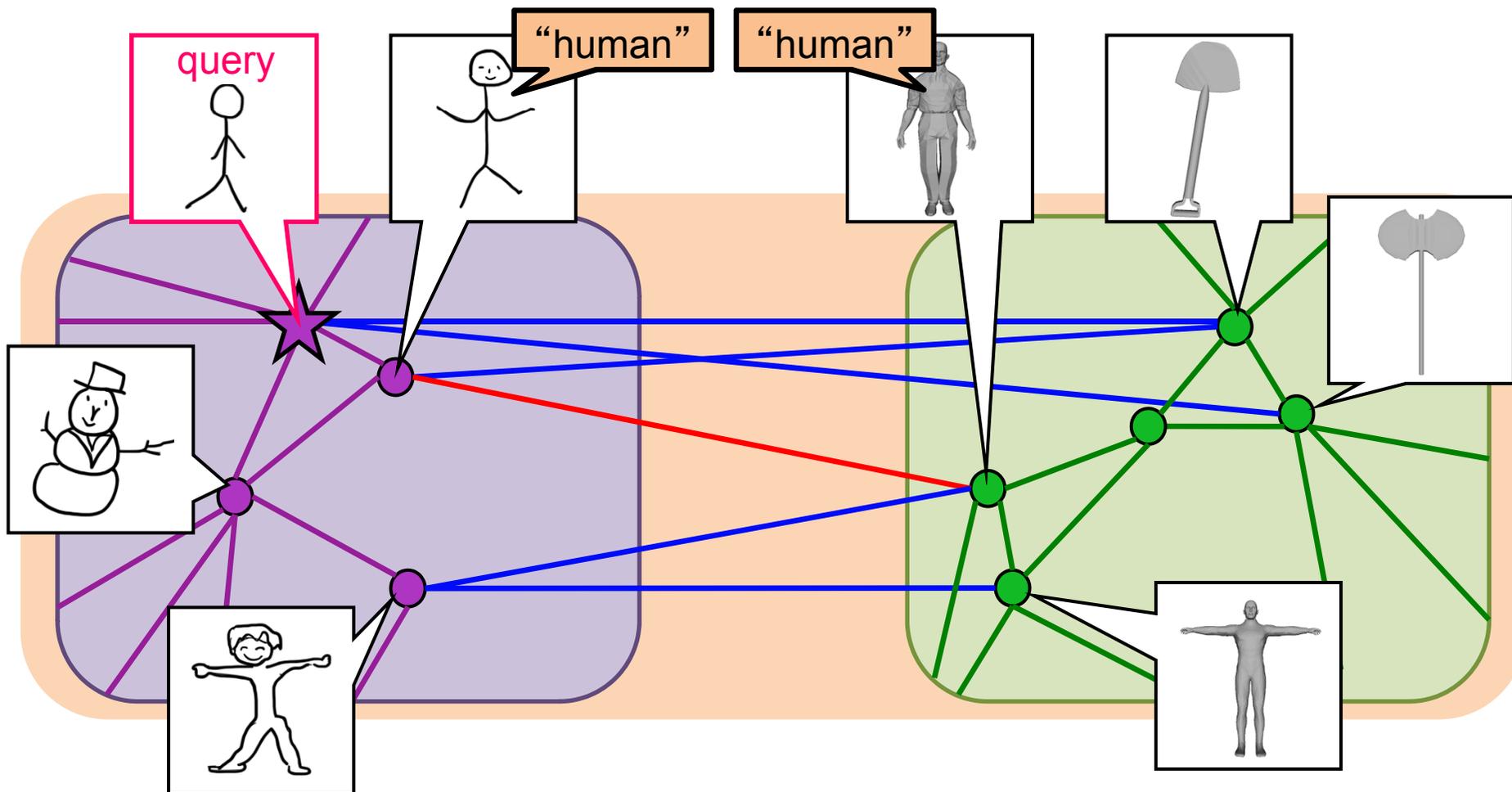
☹️ Incorrect results.



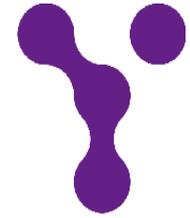
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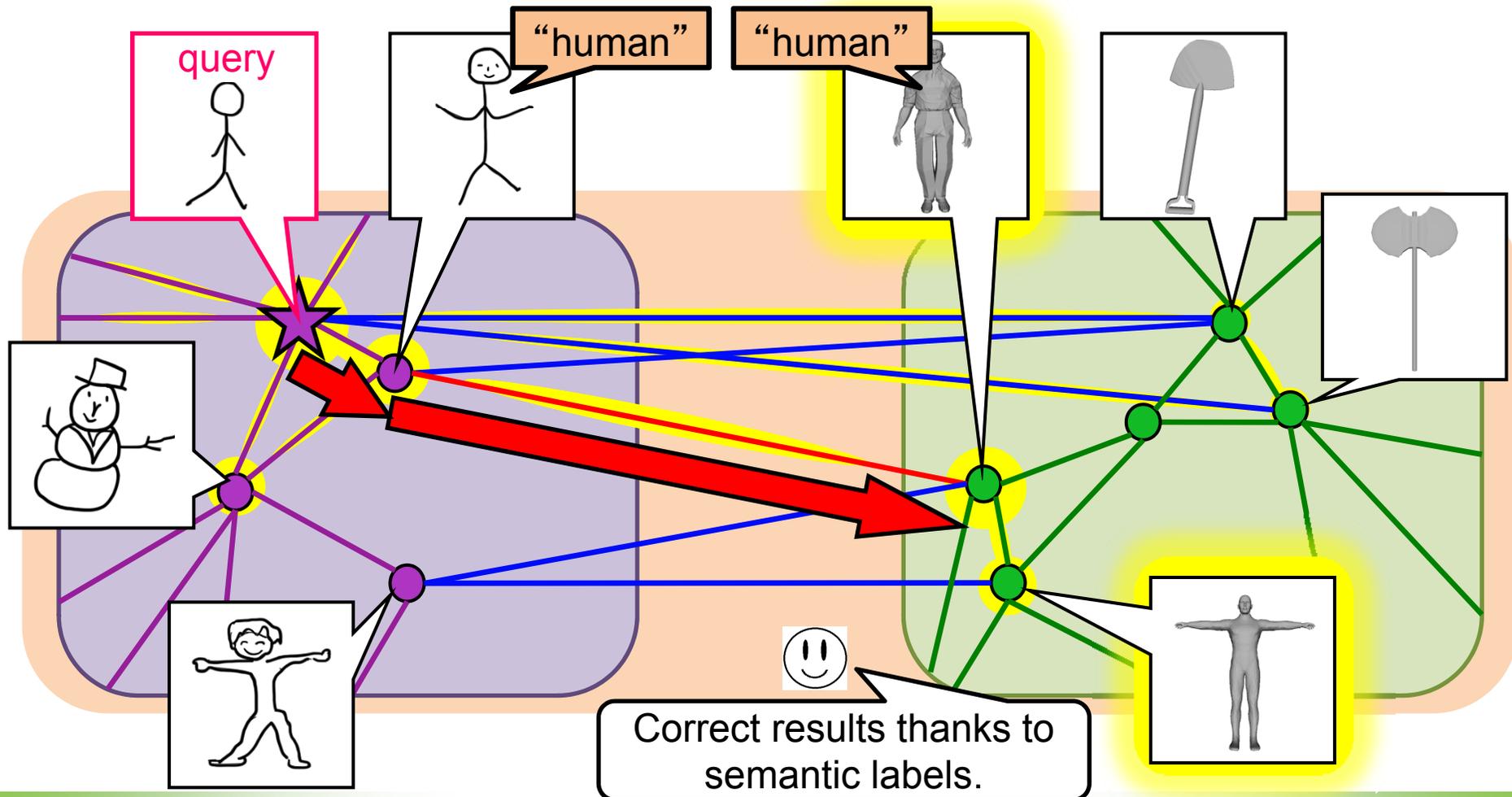
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Proposed method Cross-Domain Manifold Ranking (CDMR)



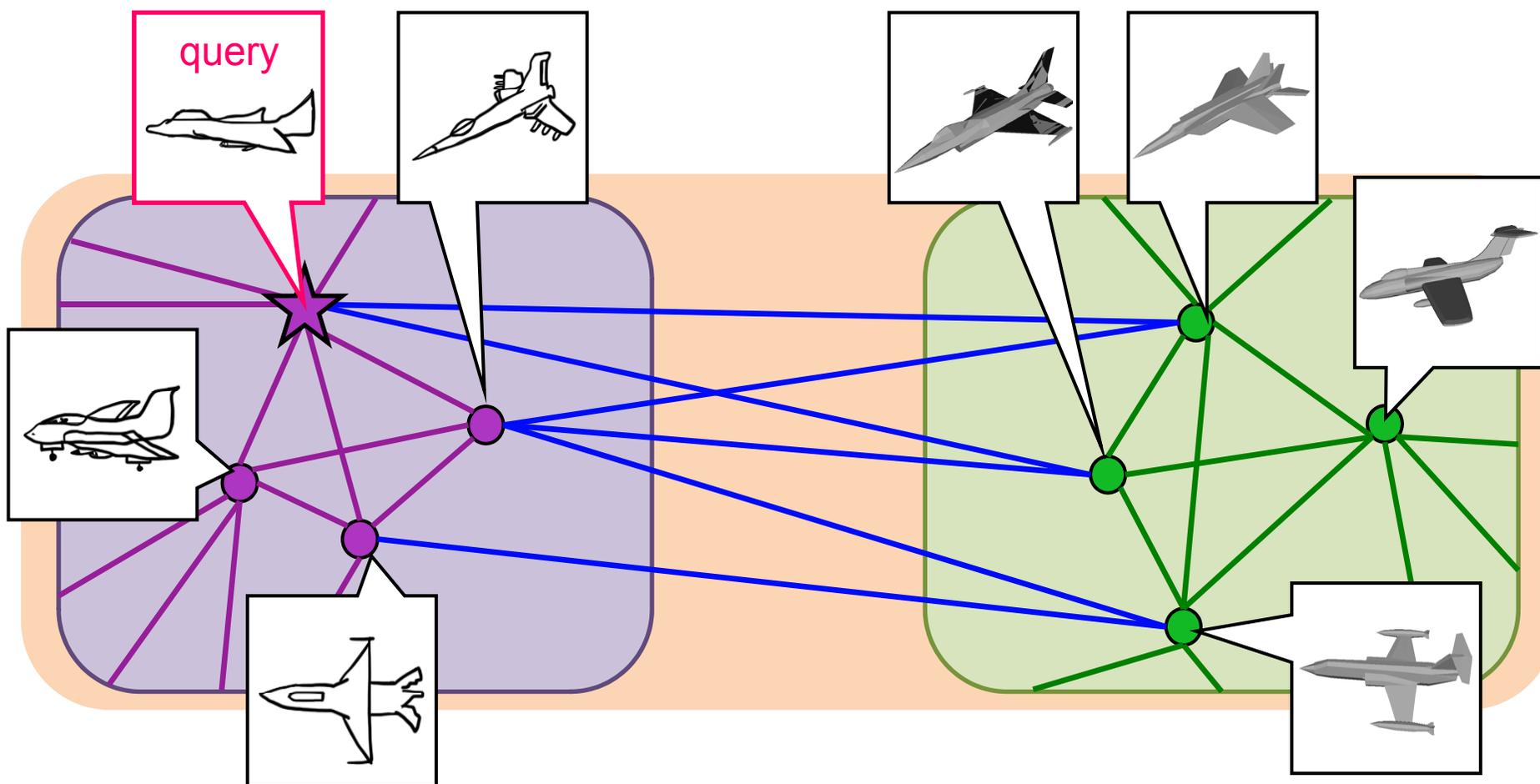
- Example 1 : Ranking by label similarity.





Proposed method Cross-Domain Manifold Ranking (CDMR)

- Example 2 : Ranking by feature similarity.



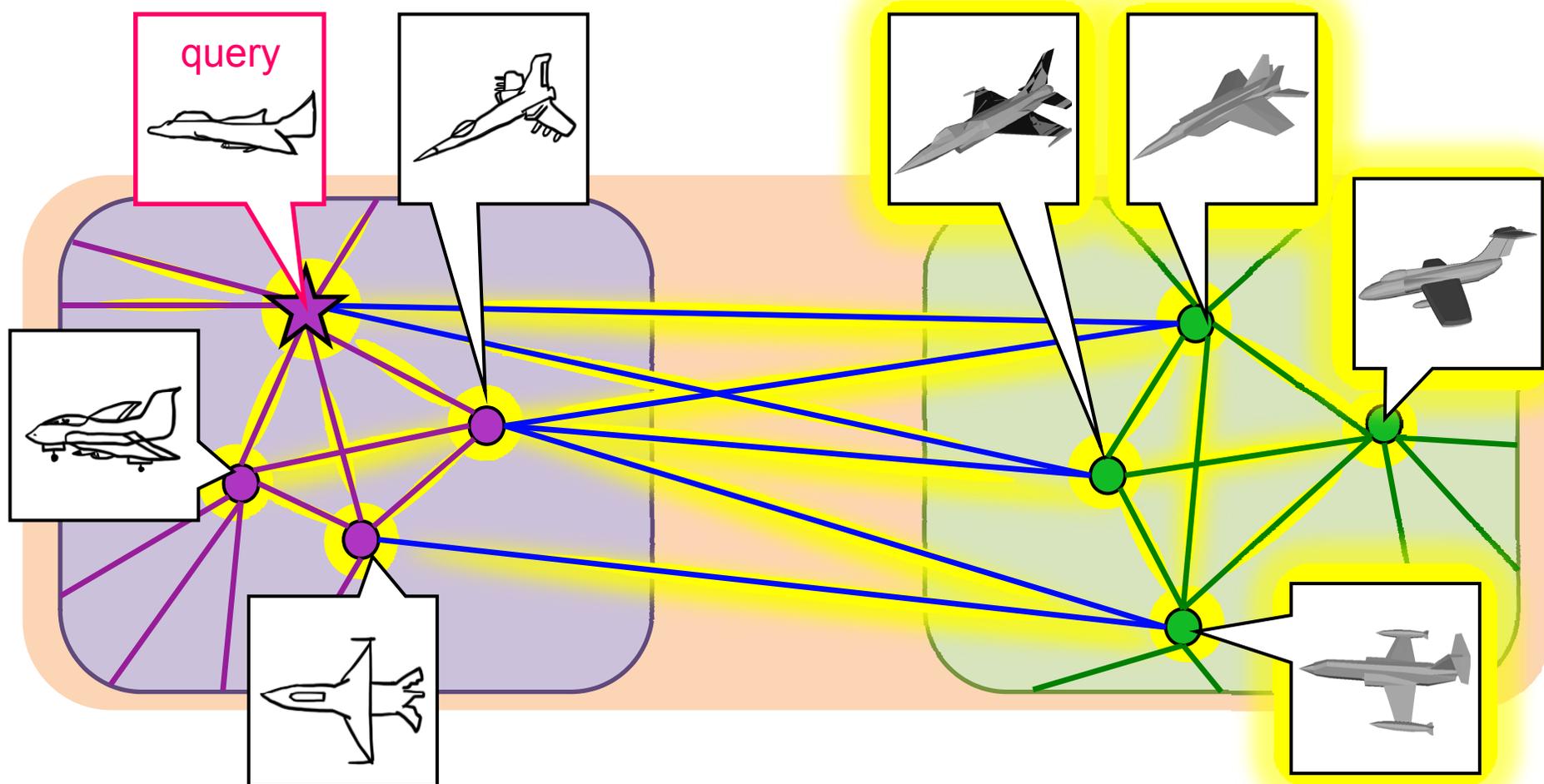


Proposed method Cross-Domain Manifold Ranking (CDMR)

- Example 2 : Ranking by feature similarity.



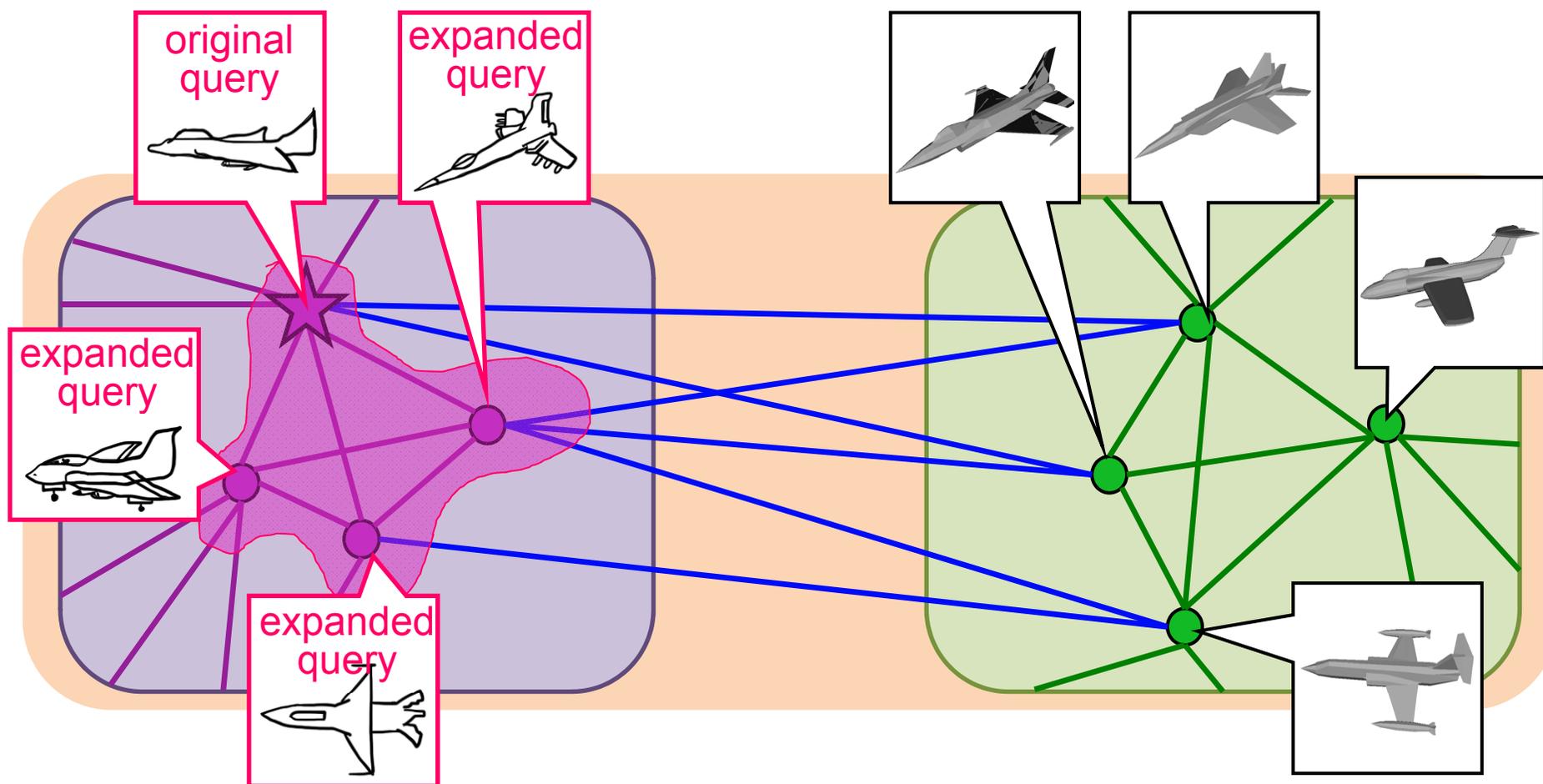
Correct results.



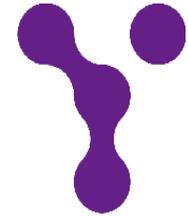


Proposed method Cross-Domain Manifold Ranking (CDMR)

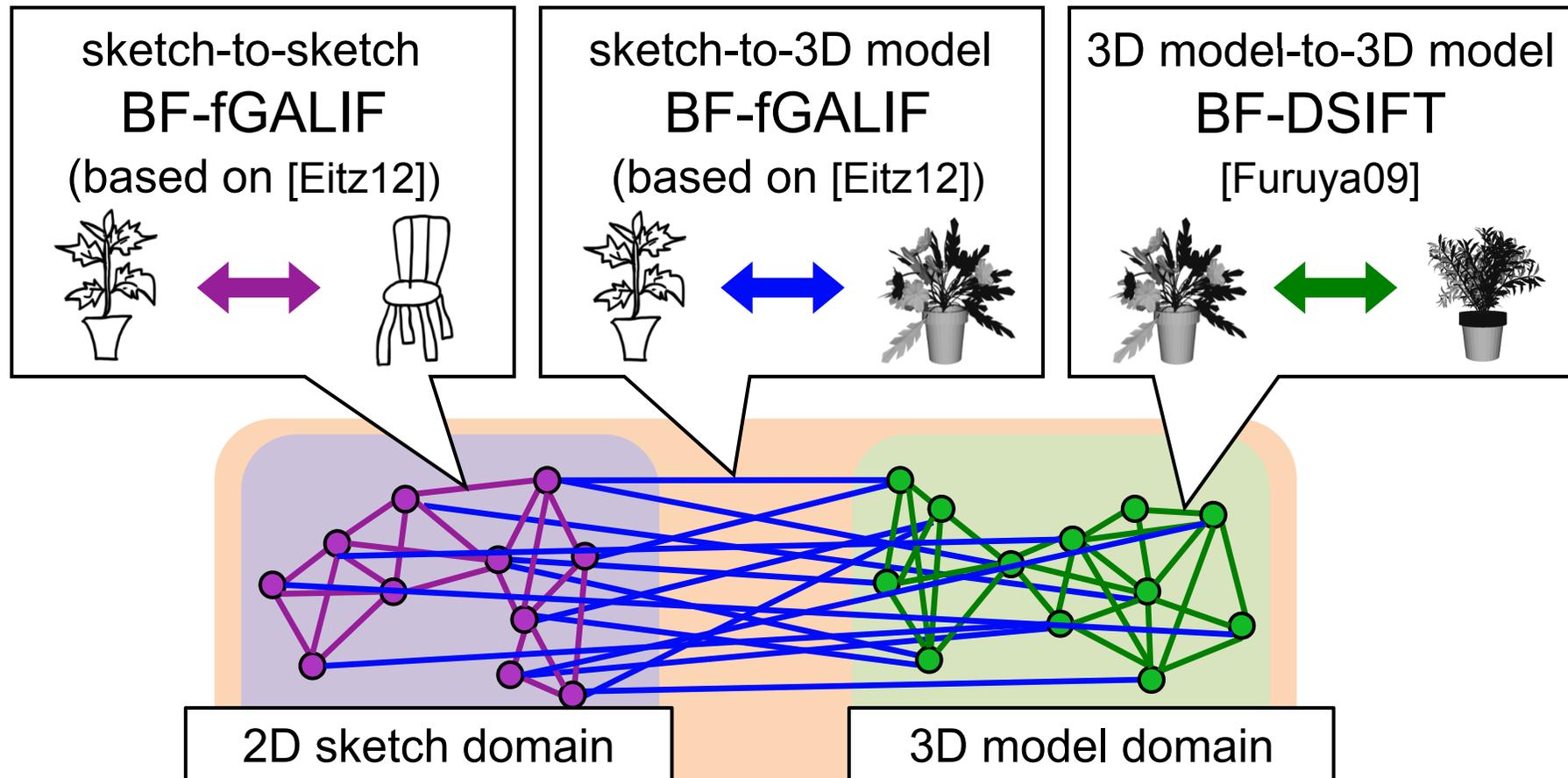
- CDMR embodies an automatic query expansion.



Proposed method Cross-Domain Manifold Ranking (CDMR)



- Feature comparison methods.

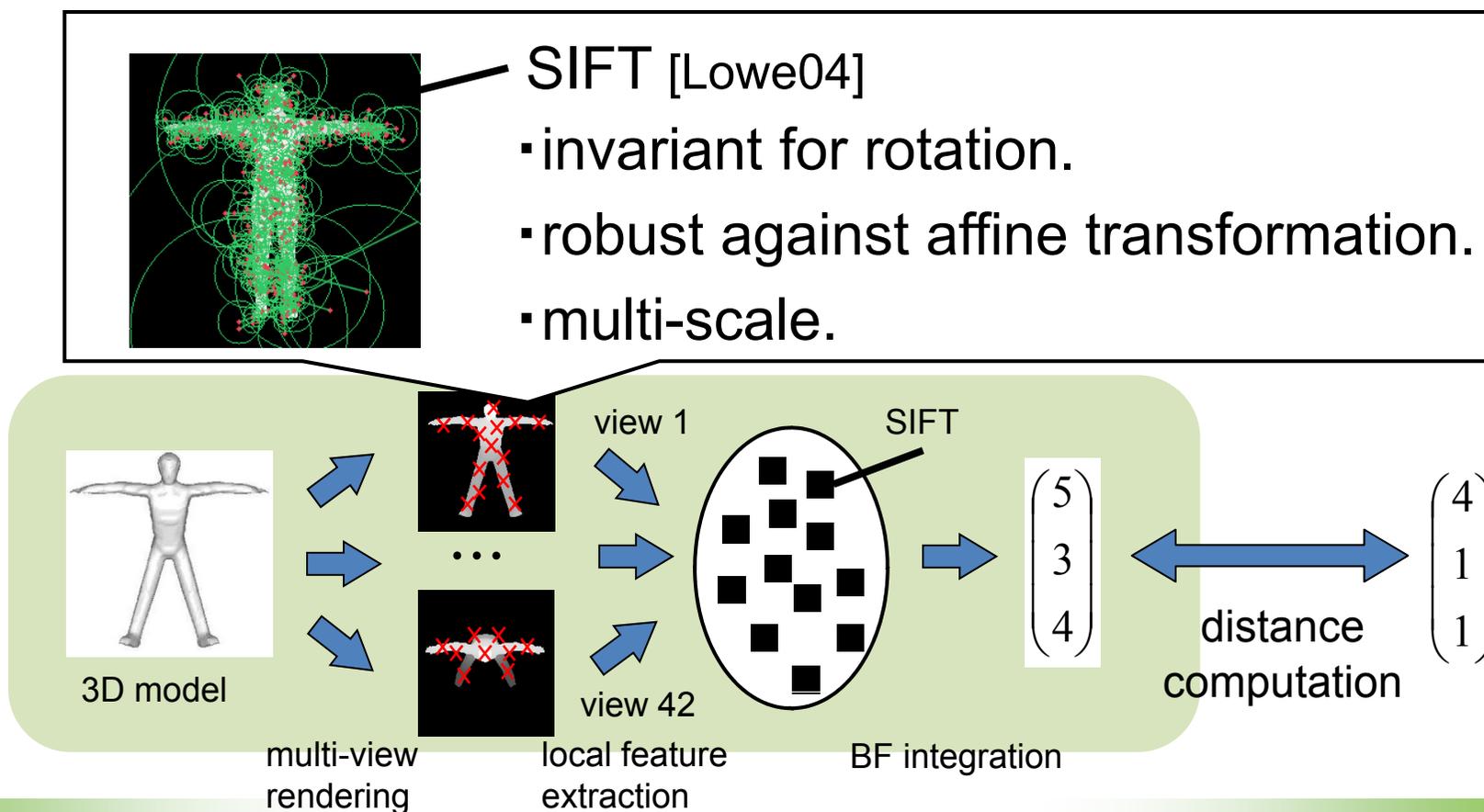




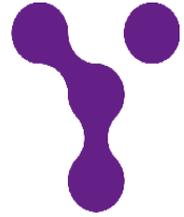
3D model-to-3D model comparison

BF-DSIFT [Furuya09]

- Dense and random extraction of local visual features.
- Per-model BF integration.



Outline



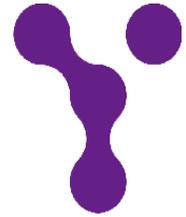
- Related work
 - BF-GALIF [Eitz12]
 - Algorithm for sketch-based 3D model retrieval
 - Manifold Ranking [Zhou03]
 - Algorithm for distance metric learning

- Proposed method
 - Cross-Domain Manifold Ranking (CDMR) algorithm

- Experiments and results

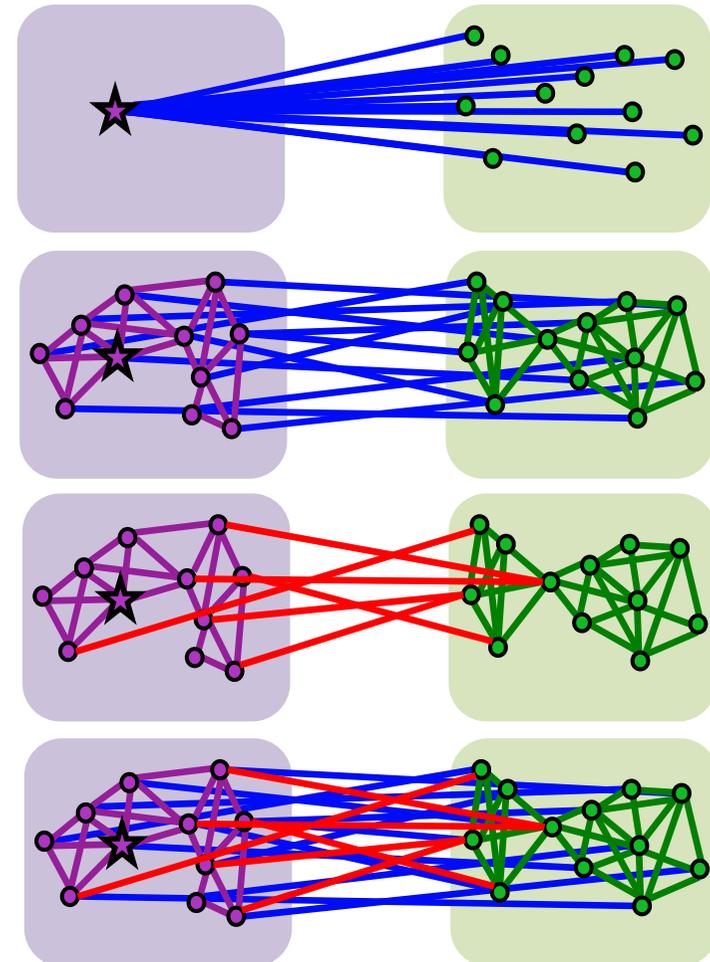
- Conclusion and future work

Experiments



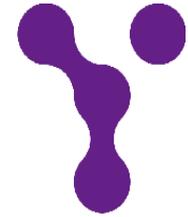
■ Evaluate retrieval accuracy.

- BF-fGALIF (≐ [Eitz12])
 - No distance metric learning.
 - Baseline
- CDMR-BF-fGALIF (F)
 - Unsupervised learning.
- CDMR-BF-fGALIF (L)
 - Supervised learning.
- CDMR-BF-fGALIF (F+L)
 - Semi-supervised learning.



Experiments

Benchmark databases



■ S-PSB [Eitz12]

• Test set (90 categories)

907 sketches

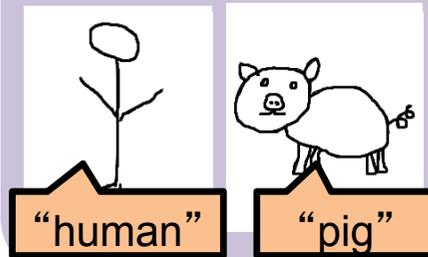


907 models

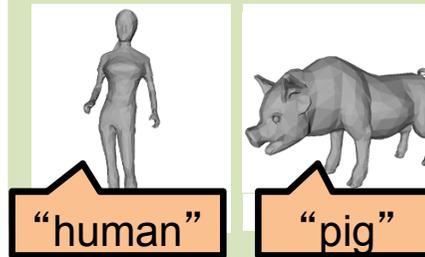


• Training set (92 categories)

907 sketches



907 models

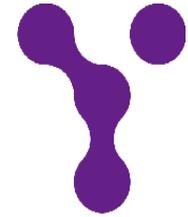


Difficult to learn labels.

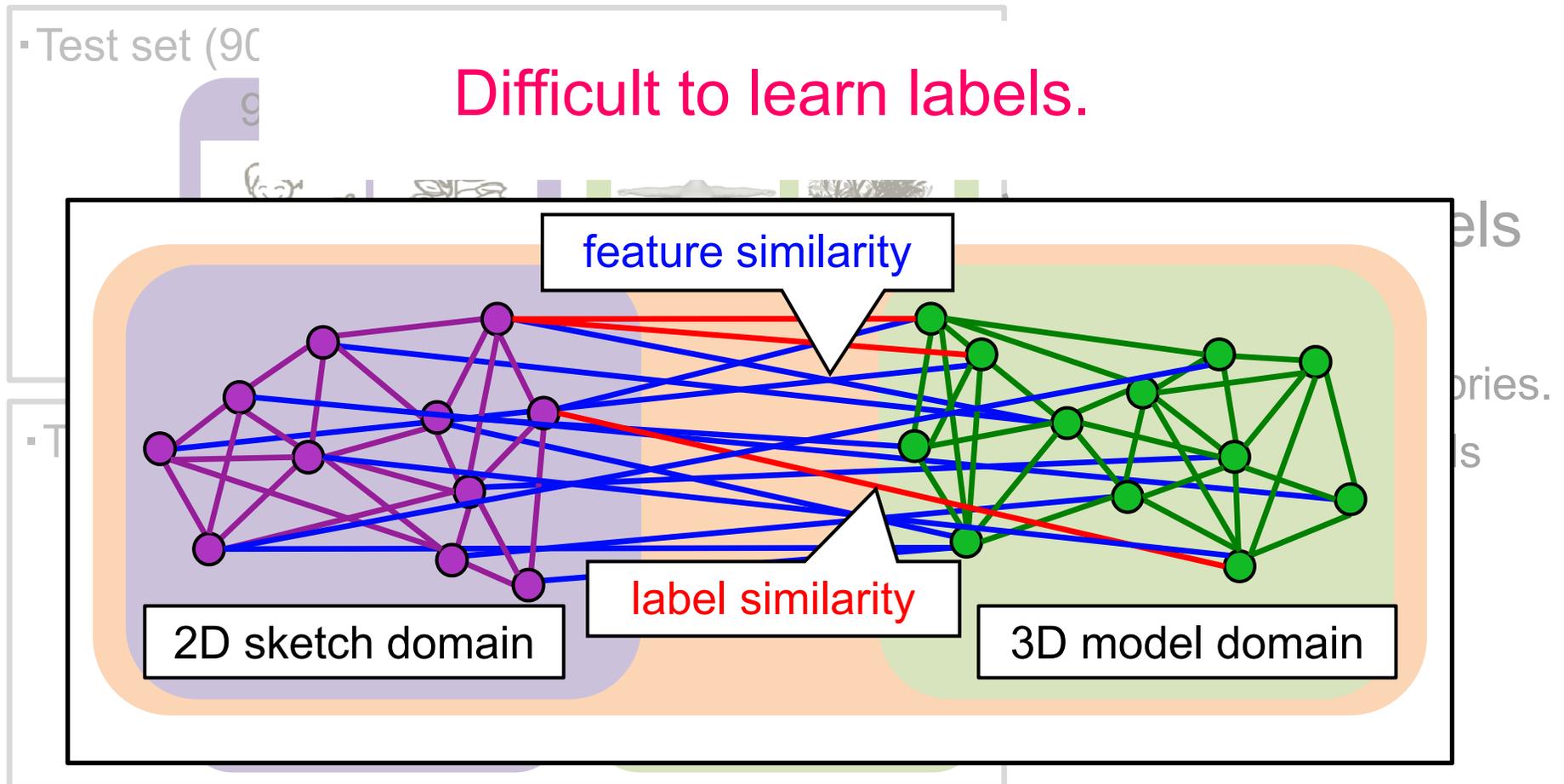
- 21 shared categories.
- As few as 4 labels per category.

Experiments

Benchmark databases

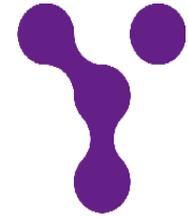


■ S-PSB [Eitz12]

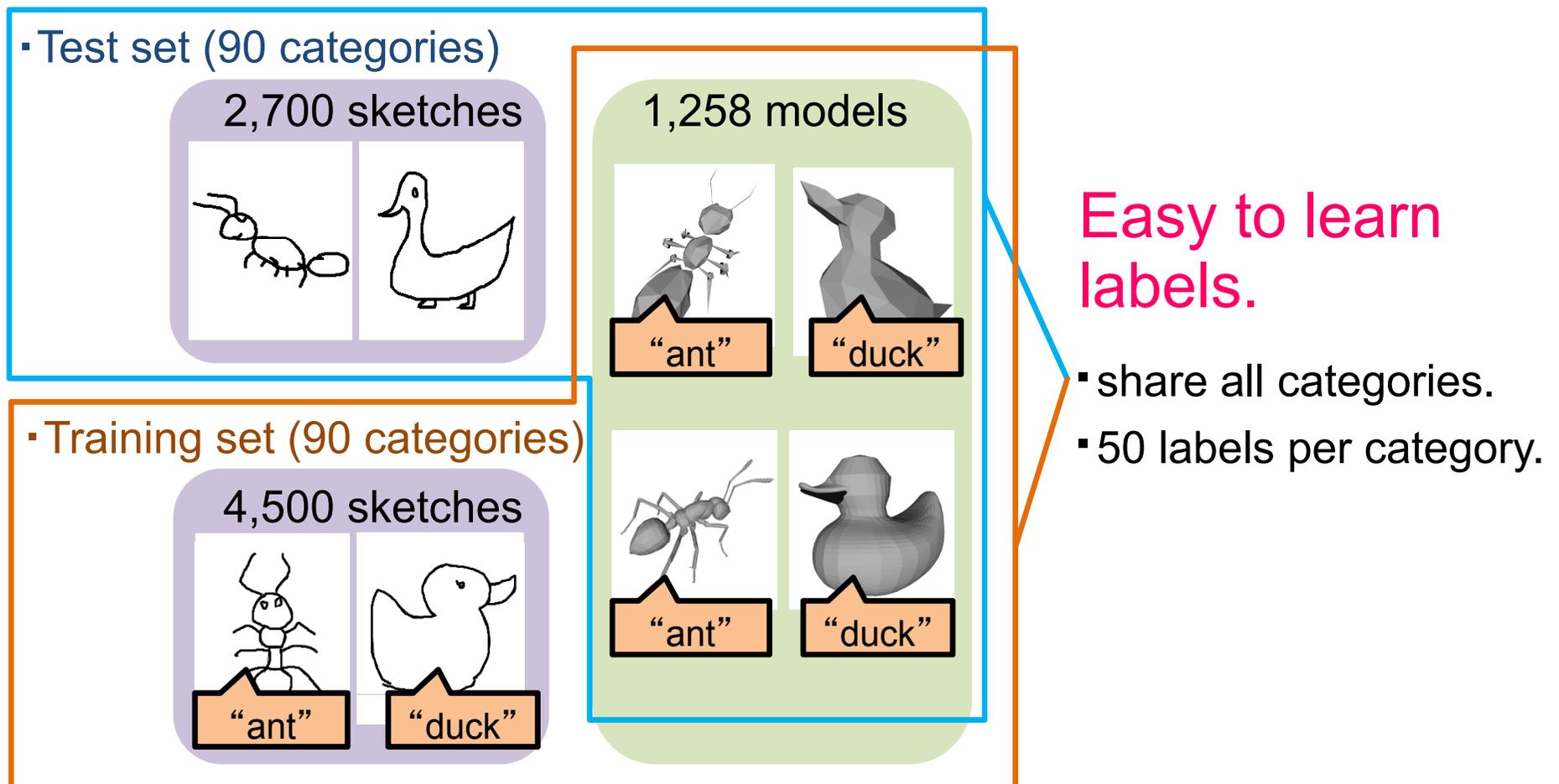


Experiments

Benchmark databases

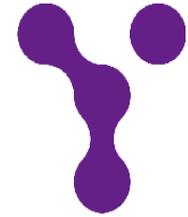


- SHREC2013 sketch-based 3D shape retrieval (SH13) [Li13]

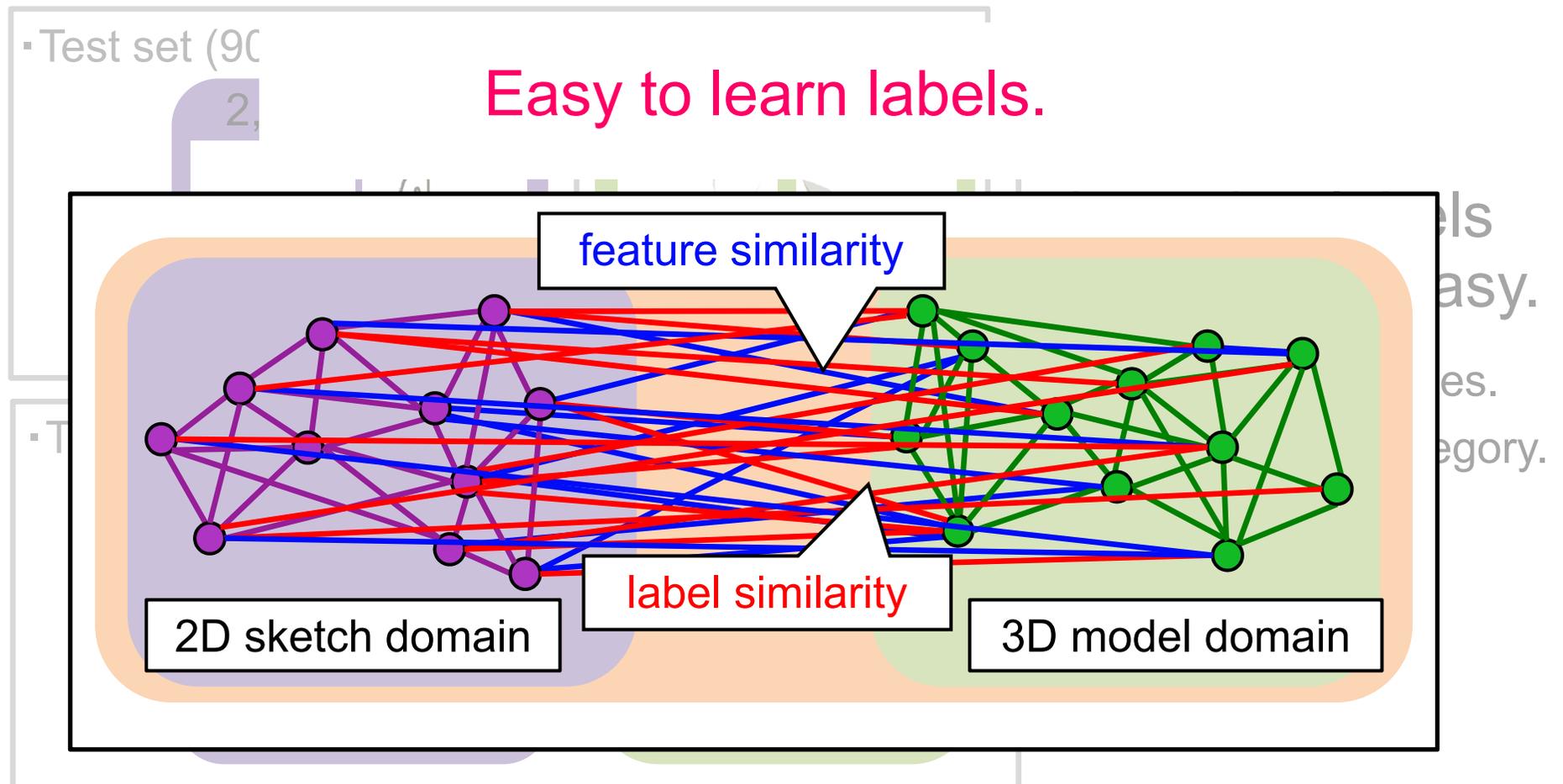


Experiments

Benchmark databases

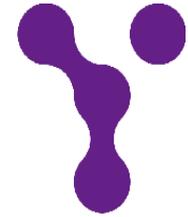


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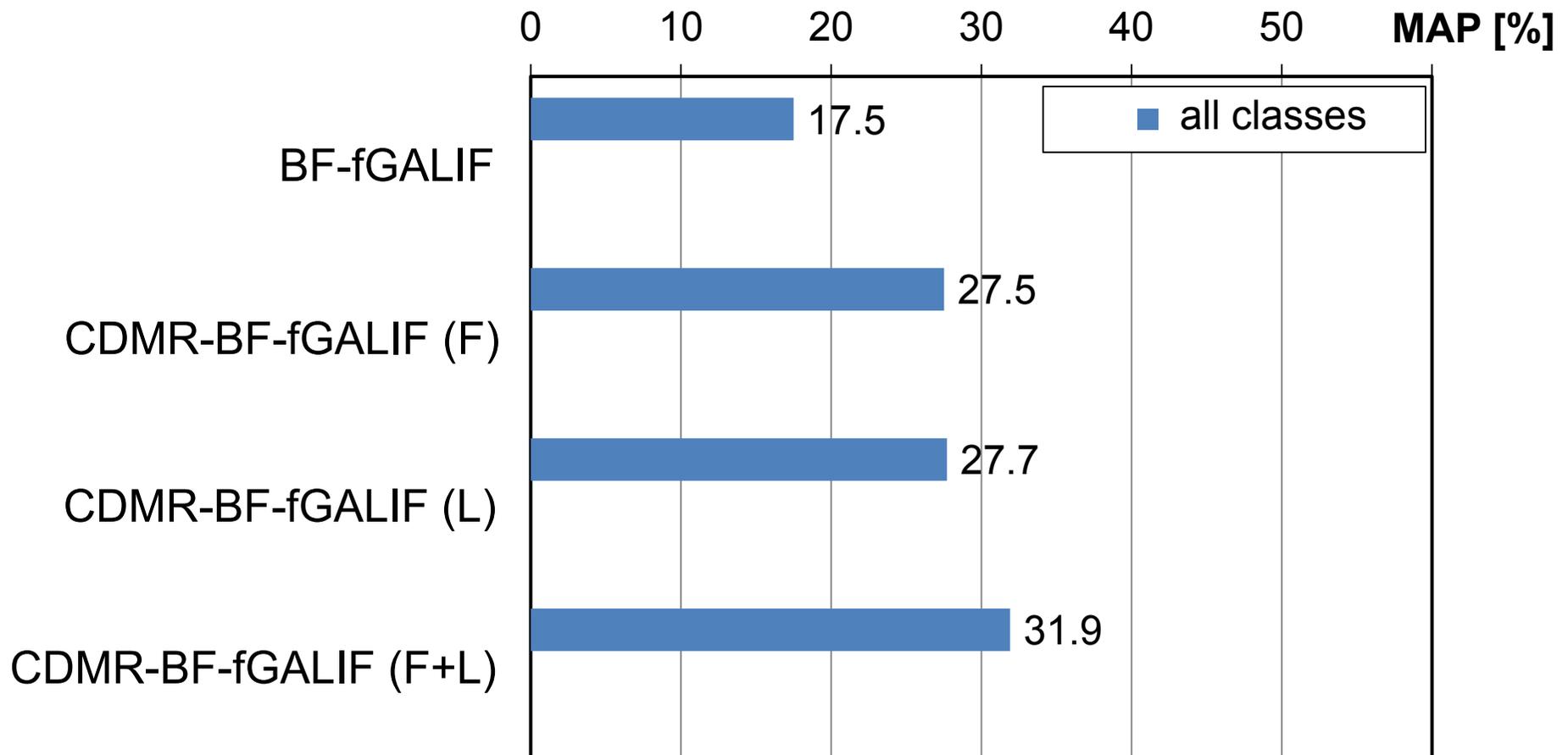


Experimental results

Effectiveness of CDMR for S-PSB

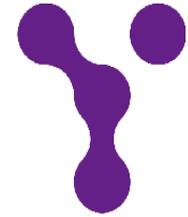


- CDMR is effective.

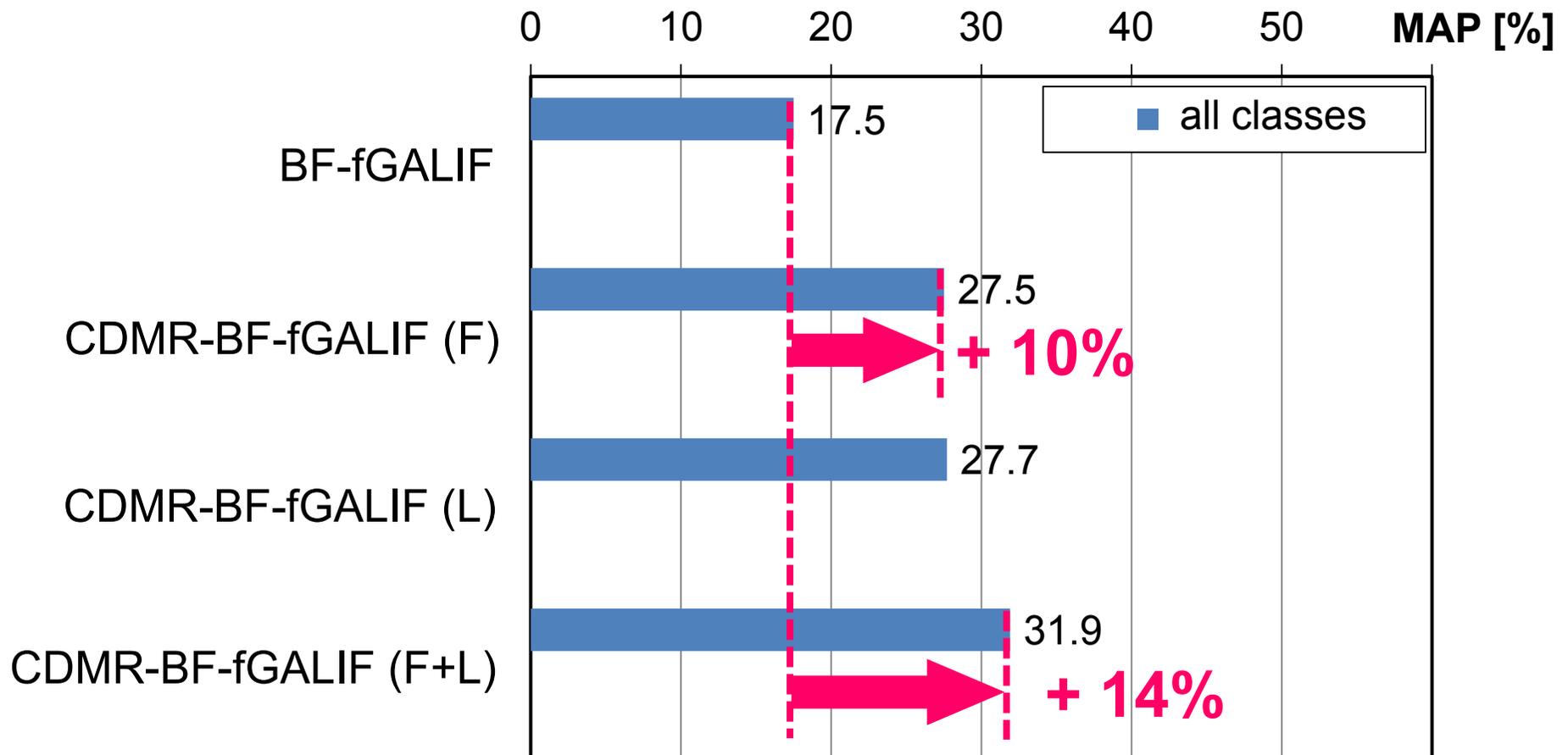


Experimental results

Effectiveness of CDMR for S-PSB

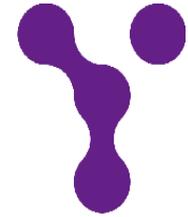


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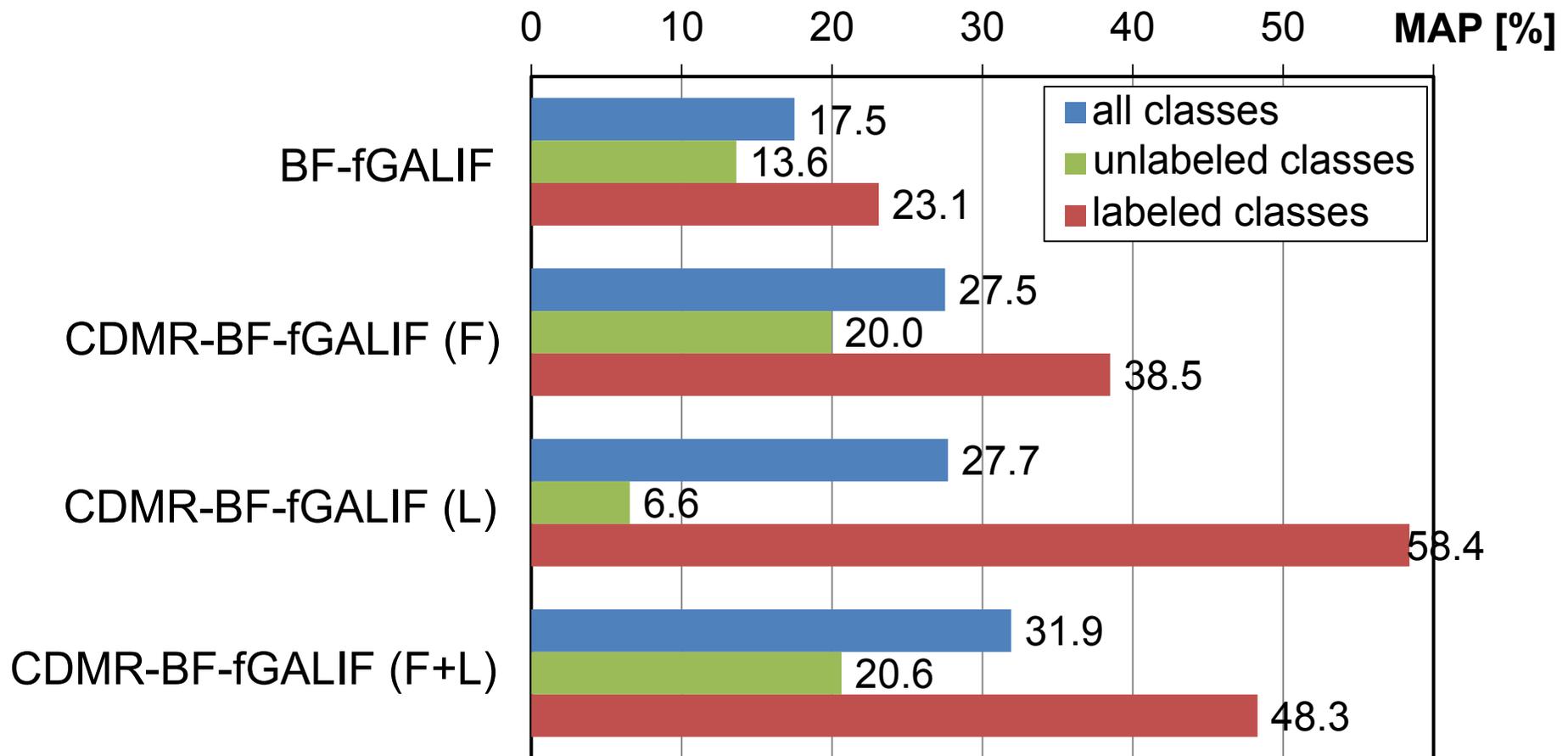


Experimental results

Effectiveness of CDMR for S-PSB

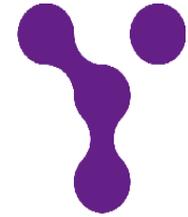


- CDMR (F+L) effectively learns sparse labeling.

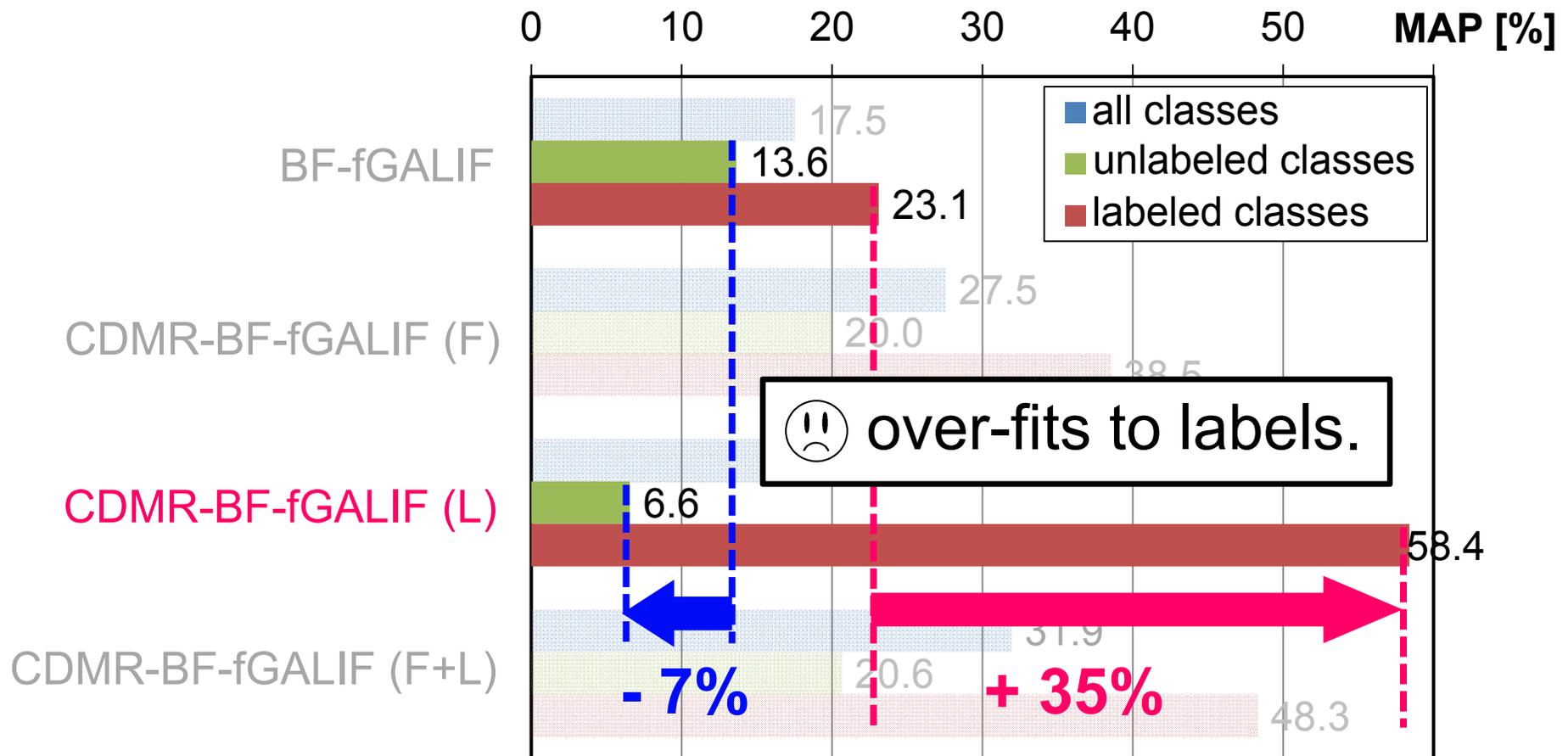


Experimental results

Effectiveness of CDMR for S-PSB

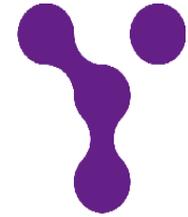


- CDMR (F+L) effectively learns sparse labeling.

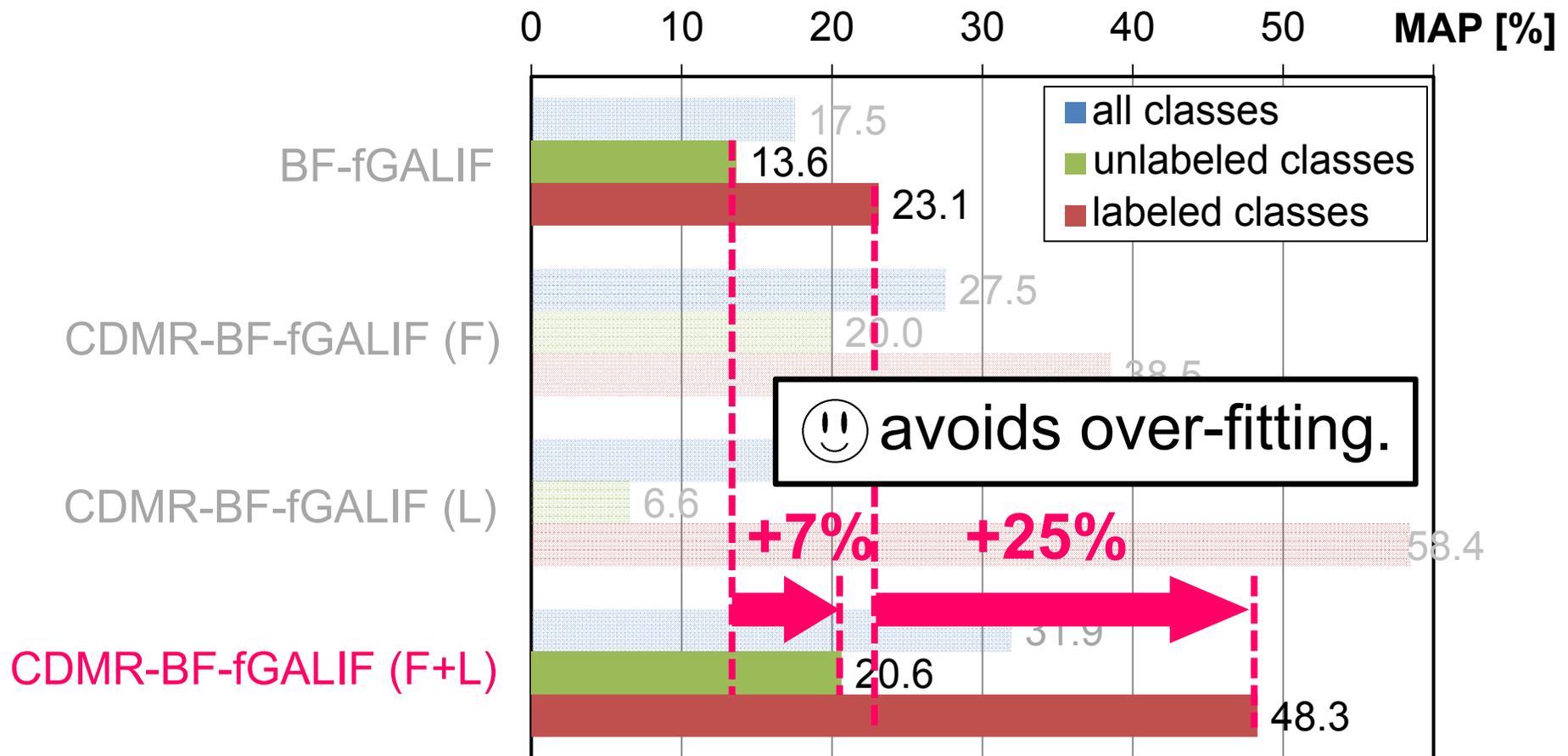


Experimental results

Effectiveness of CDMR for S-PSB

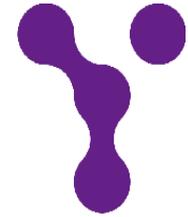


- CDMR (F+L) effectively learns sparse labeling.

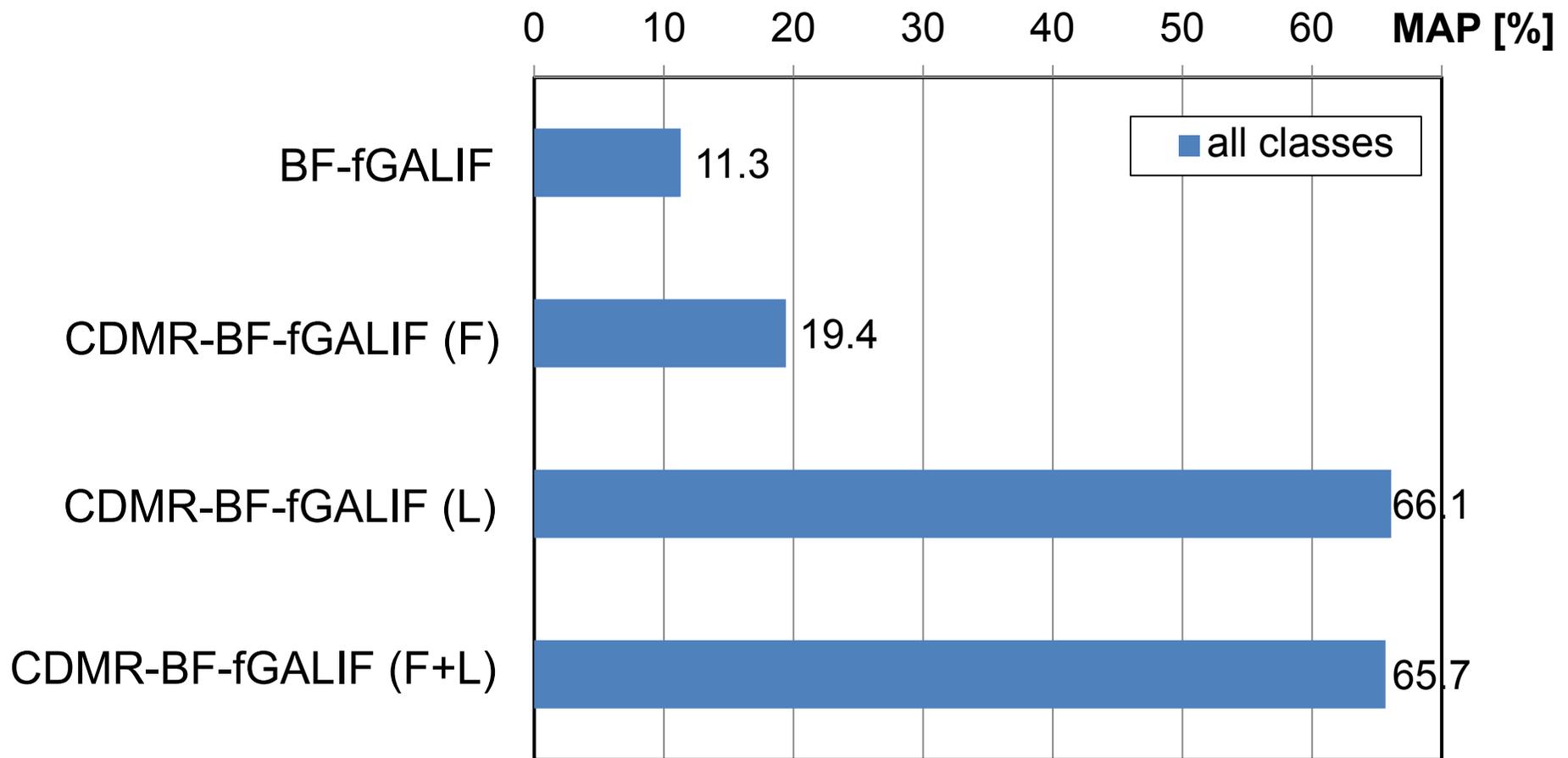


Experimental results

Effectiveness of CDMR for SH13

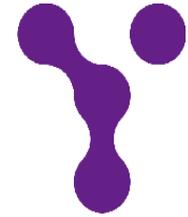


- Large improvement of MAP due to dense labeling.

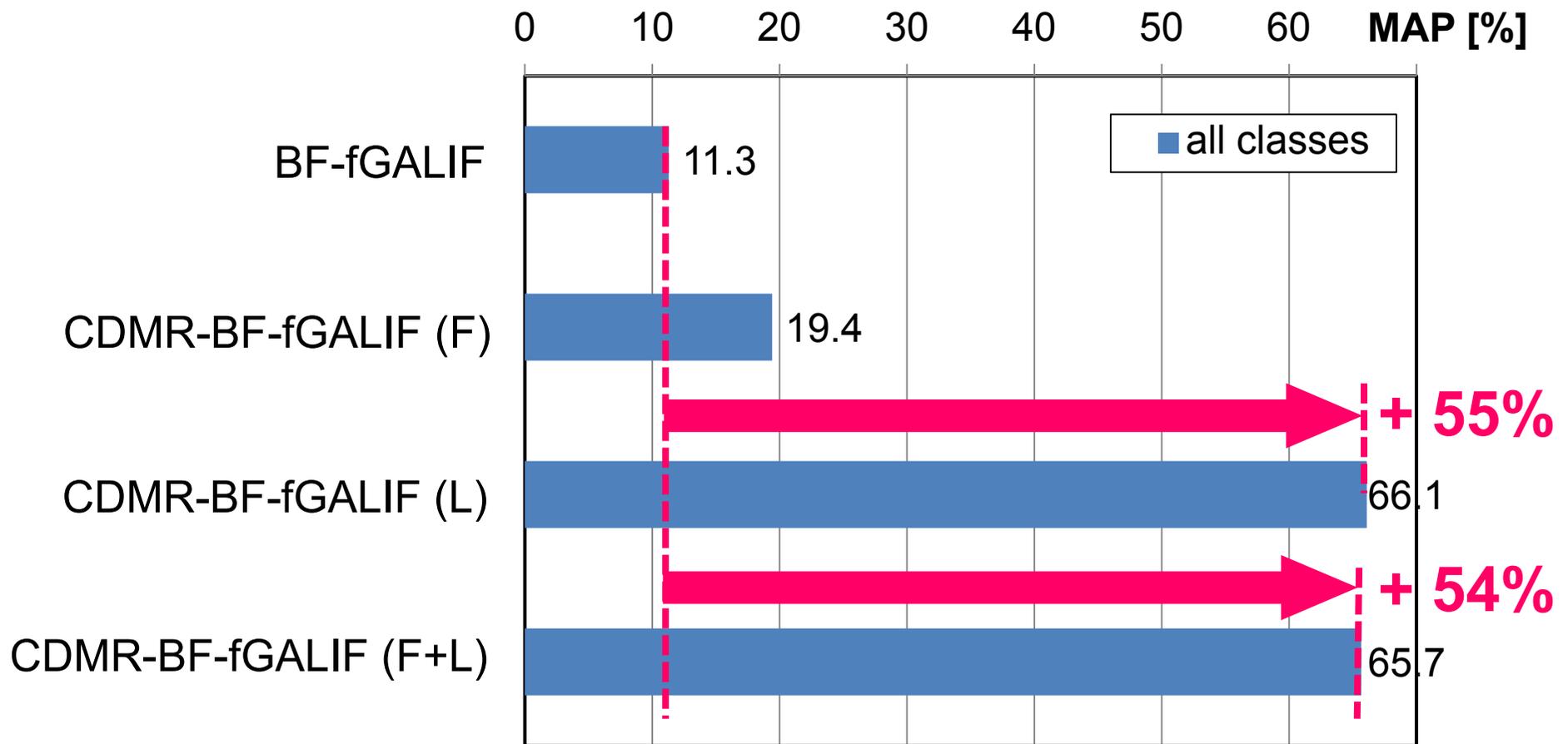


Experimental results

Effectiveness of CDMR for SH13

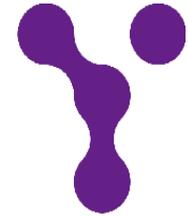


- Large improvement of MAP due to dense labeling.

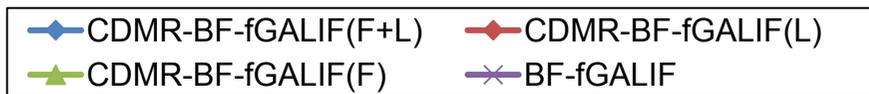
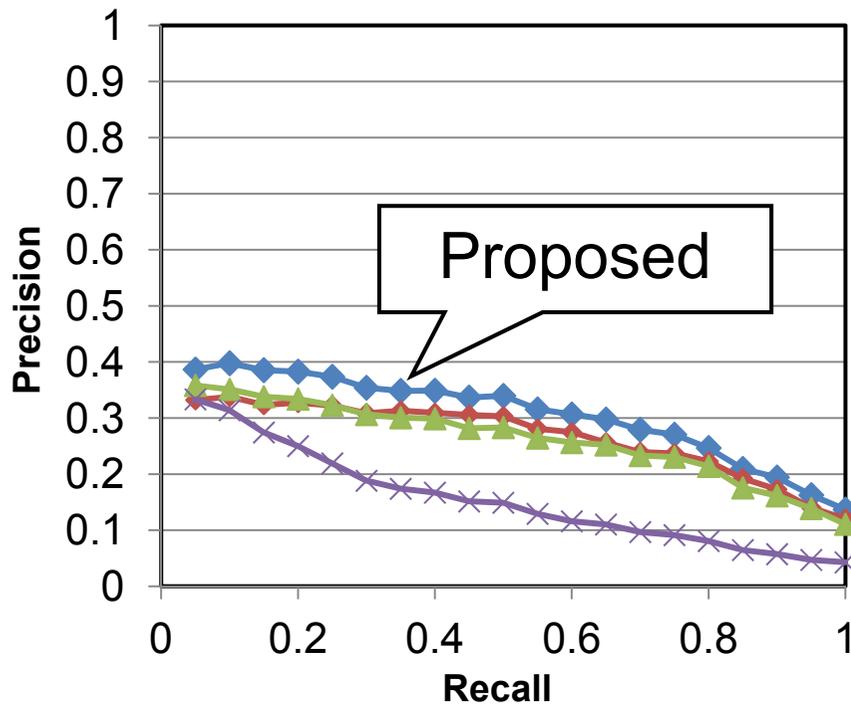


Experimental results

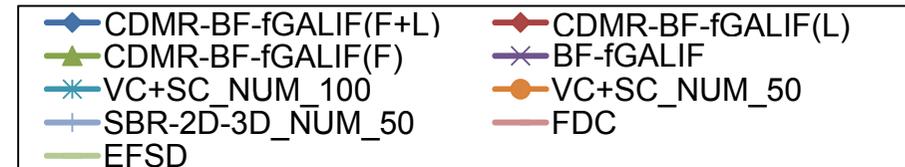
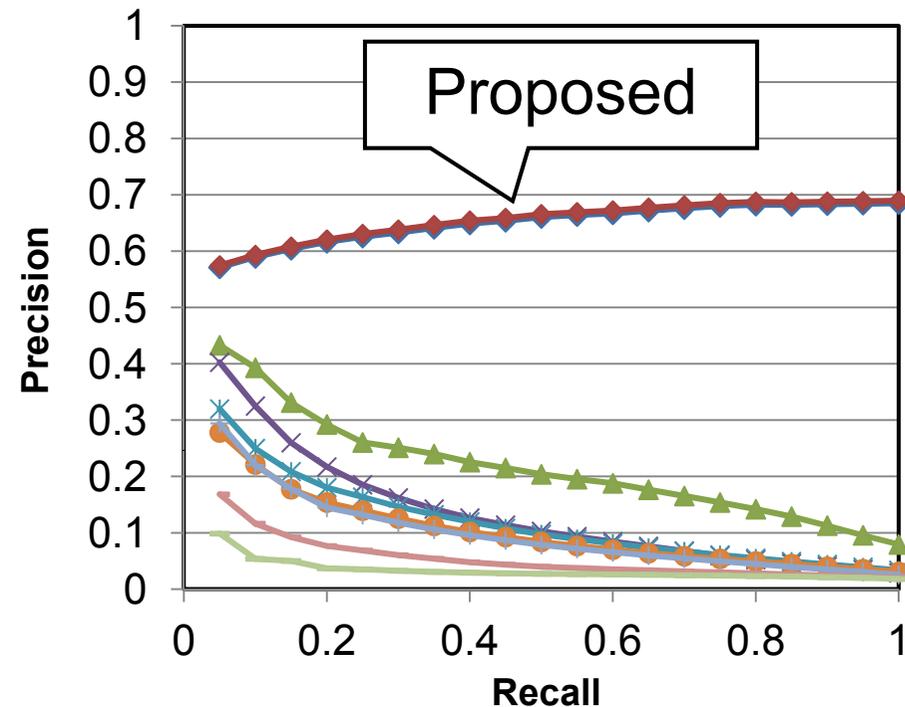
Comparison with other algorithms



S-PSB

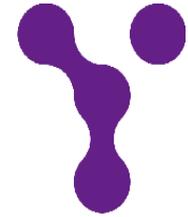


SH13



Experimental results

Retrieval results (S-PSB)

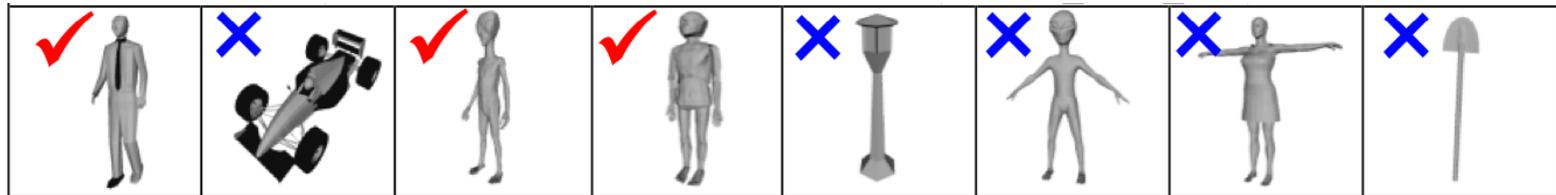


■ “human” (labeled category)

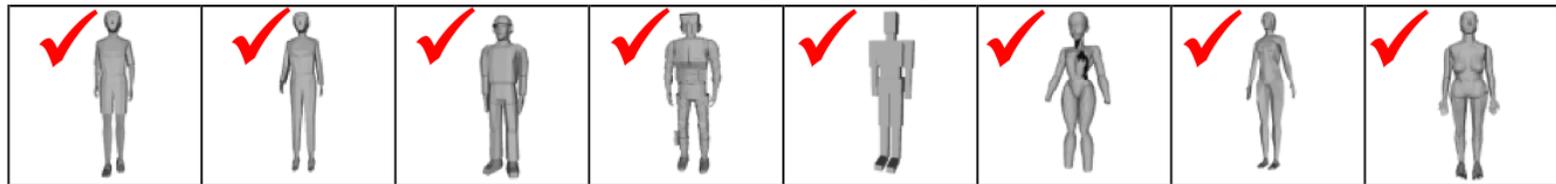
Query



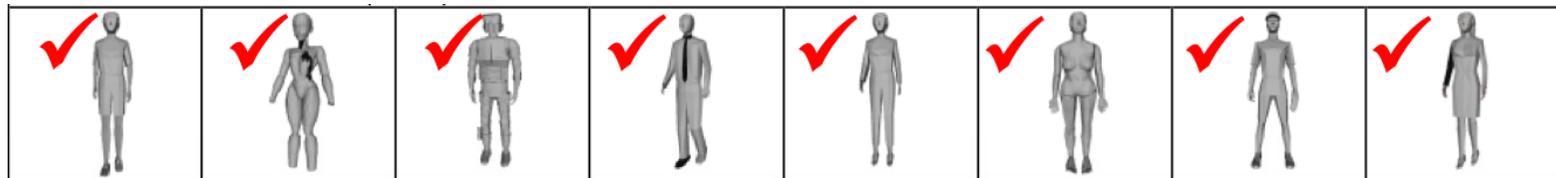
BF-GALIF [Eitz12]



CDMR-BF-GALIF (L) \doteq CMCP [Zhai12]

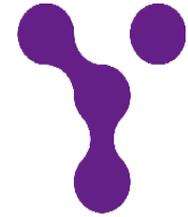


CDMR-BF-GALIF (F+L)



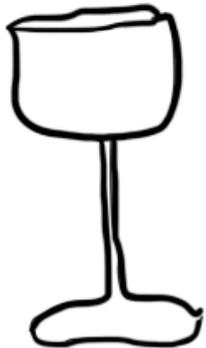
Experimental results

Retrieval results (S-PSB)

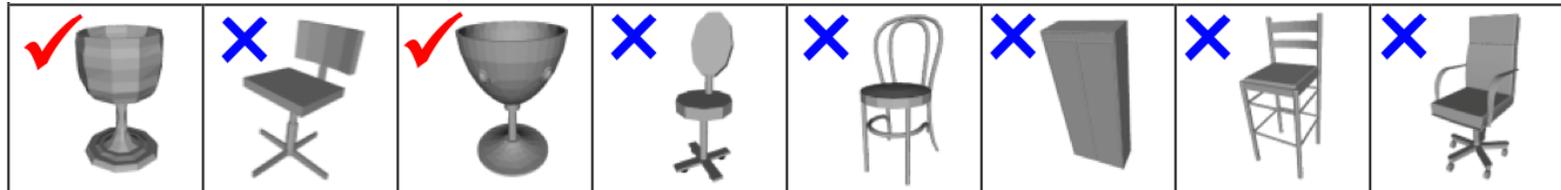


■ “glass_with_stem” (unlabeled category)

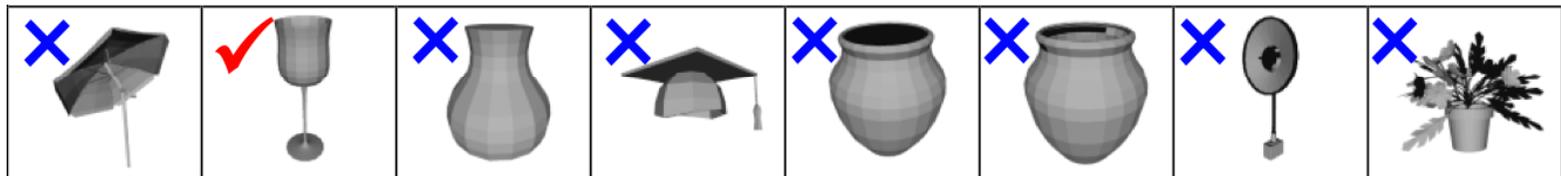
Query



BF-GALIF [Eitz12]



CDMR-BF-GALIF (L) \doteq CMCP [Zhai12]

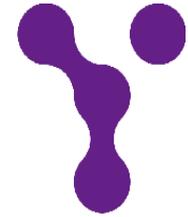


CDMR-BF-GALIF (F+L)



Experimental results

Computation time per query



Computation time per query for S-PSB [s]

methods	extract BF-GALIF	compute distance	CDMR (matrix size : 3,628 x 3,628)	total
BF-GALIF	0.11	1.59		1.70
CDMR-BF-GALIF	0.11	1.59	36.86	38.56



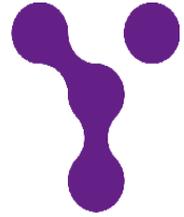
Computation time per query for SH13 [s]

methods	extract BF-GALIF	compute Distance	CDMR (matrix size : 8,458 x 8,458)	total
BF-GALIF	0.11	1.13		1.24
CDMR-BF-GALIF	0.11	1.17	659.93	661.21



measured by using: Intel Xeon E3-1245 @ 3.30 GHz, 32 GB of memory

Conclusion and Future work



■ Conclusion

- More accurate sketch-based 3D model retrieval.
 - Cross-Domain Manifold Ranking (CDMR)
 - Combines feature similarity and semantic similarity.
 - Outperforms previous methods.

■ Future work

- Faster computation (e.g., approximation of diffusion).
- More accurate feature comparison.