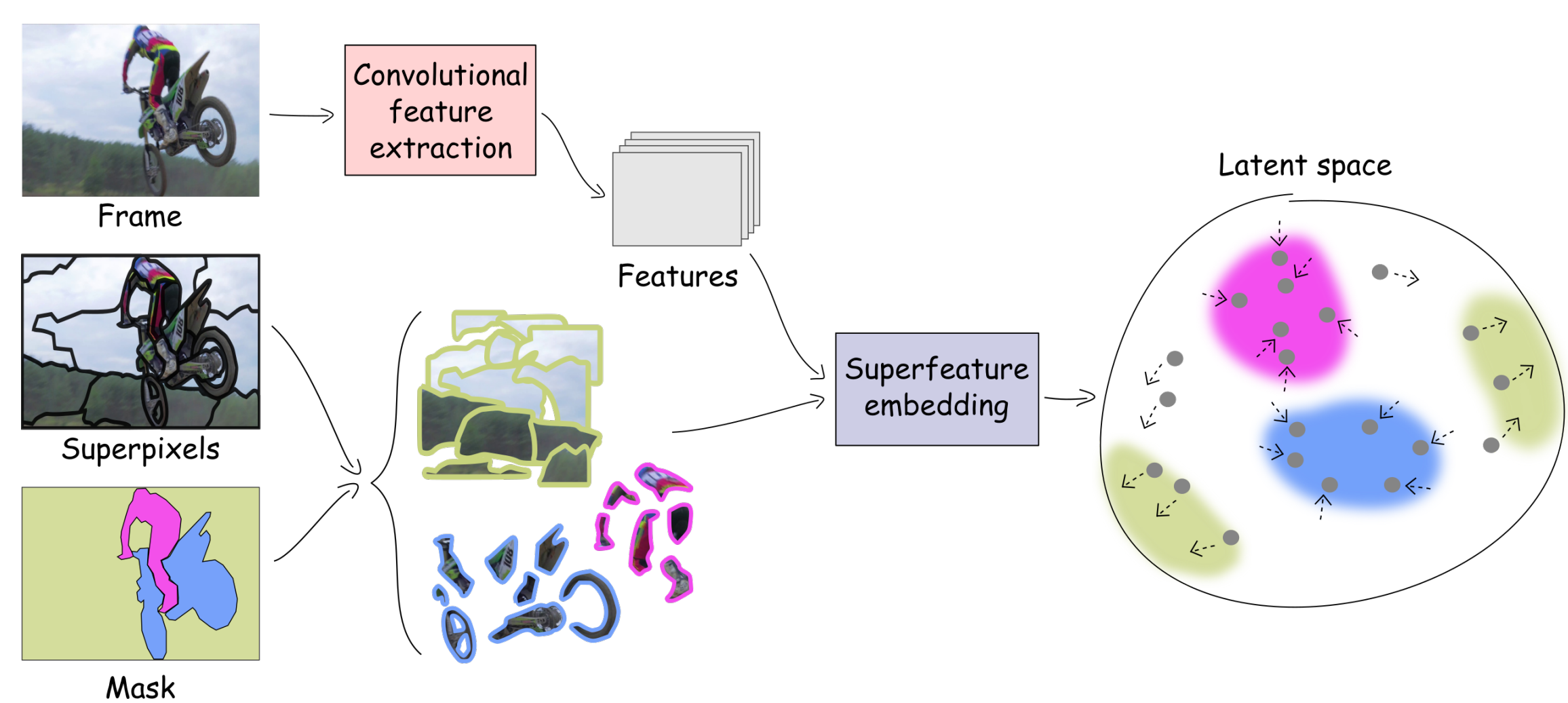




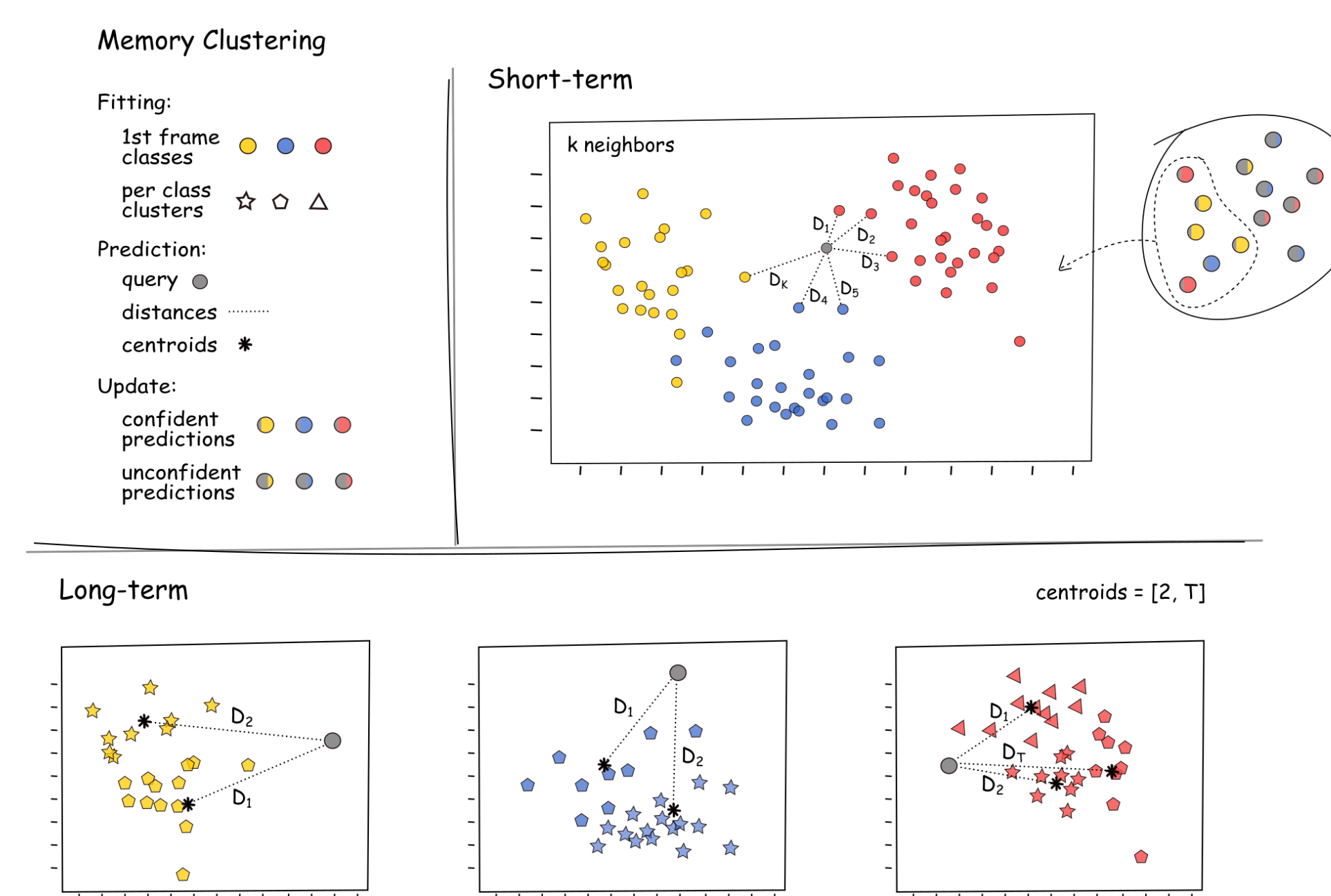
Superfeatures in a Highly Compressed Latent Space

A novel approach that embeds convolutional features into the corresponding superpixel areas through metric learning. The resulting ultra-compact image representations enable us to learn video object segmentation (VOS) from a small dataset of unlabeled still images.



Memory Clustering

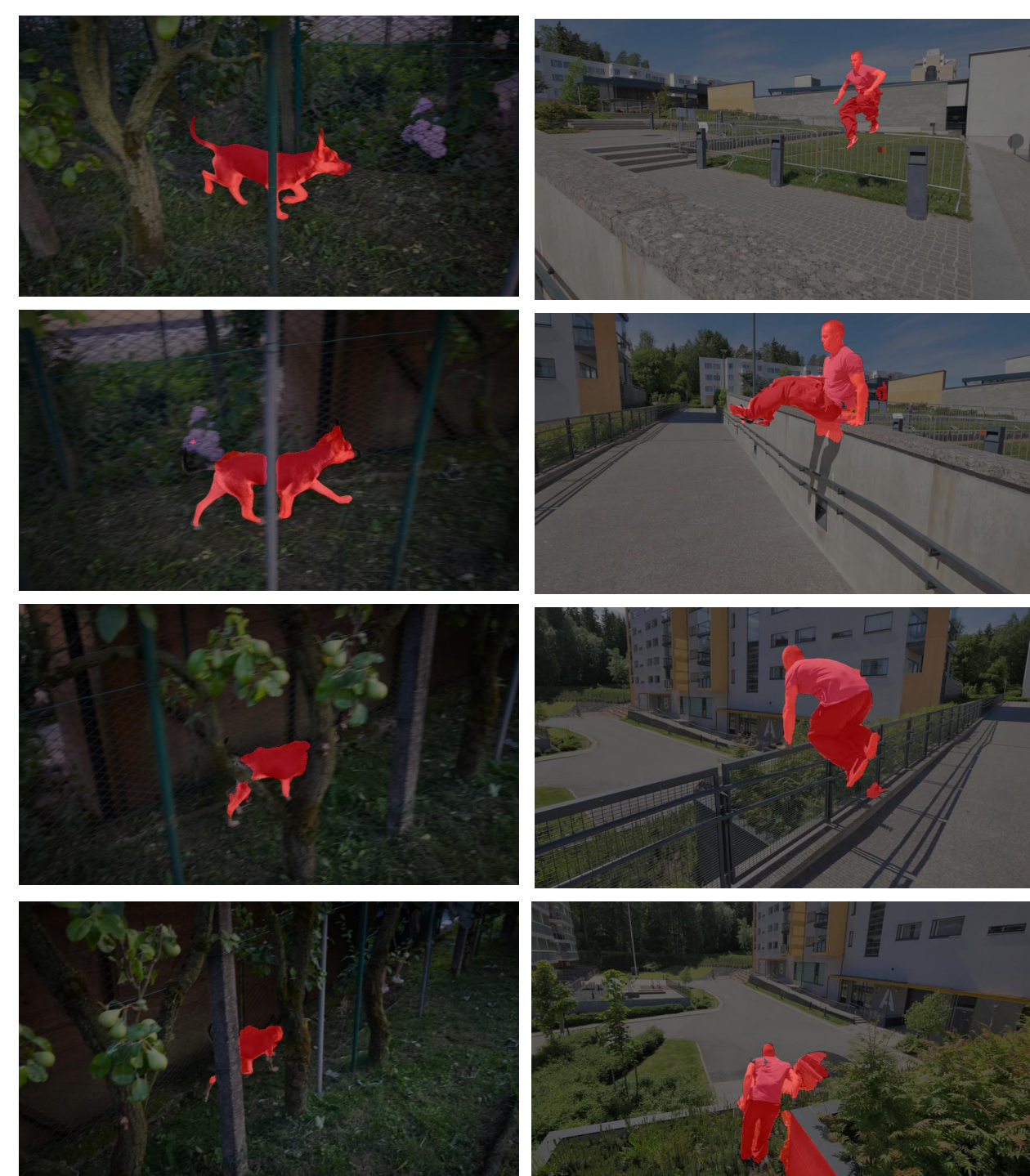
Our memory clustering mechanism provides short- and long-term information by measuring similarity distances among superfeatures in the latent space.



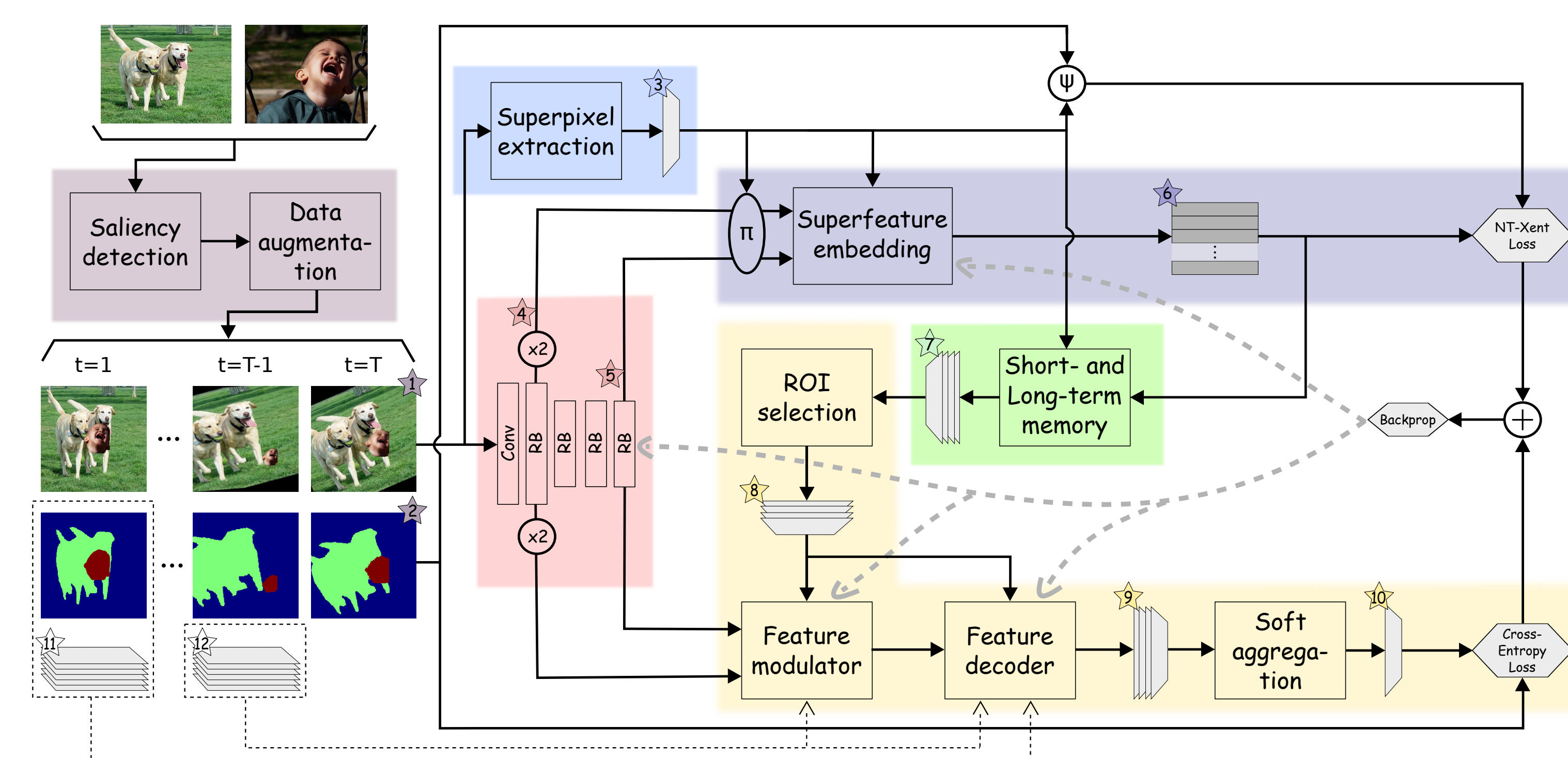
Short-term: is based on k-NN searches and responds quickly to immediate changes in the objects during short intervals.

Long-term: computes distances from the query superfeatures to the centroids of class-specific clusters.

Single-object Segmentation

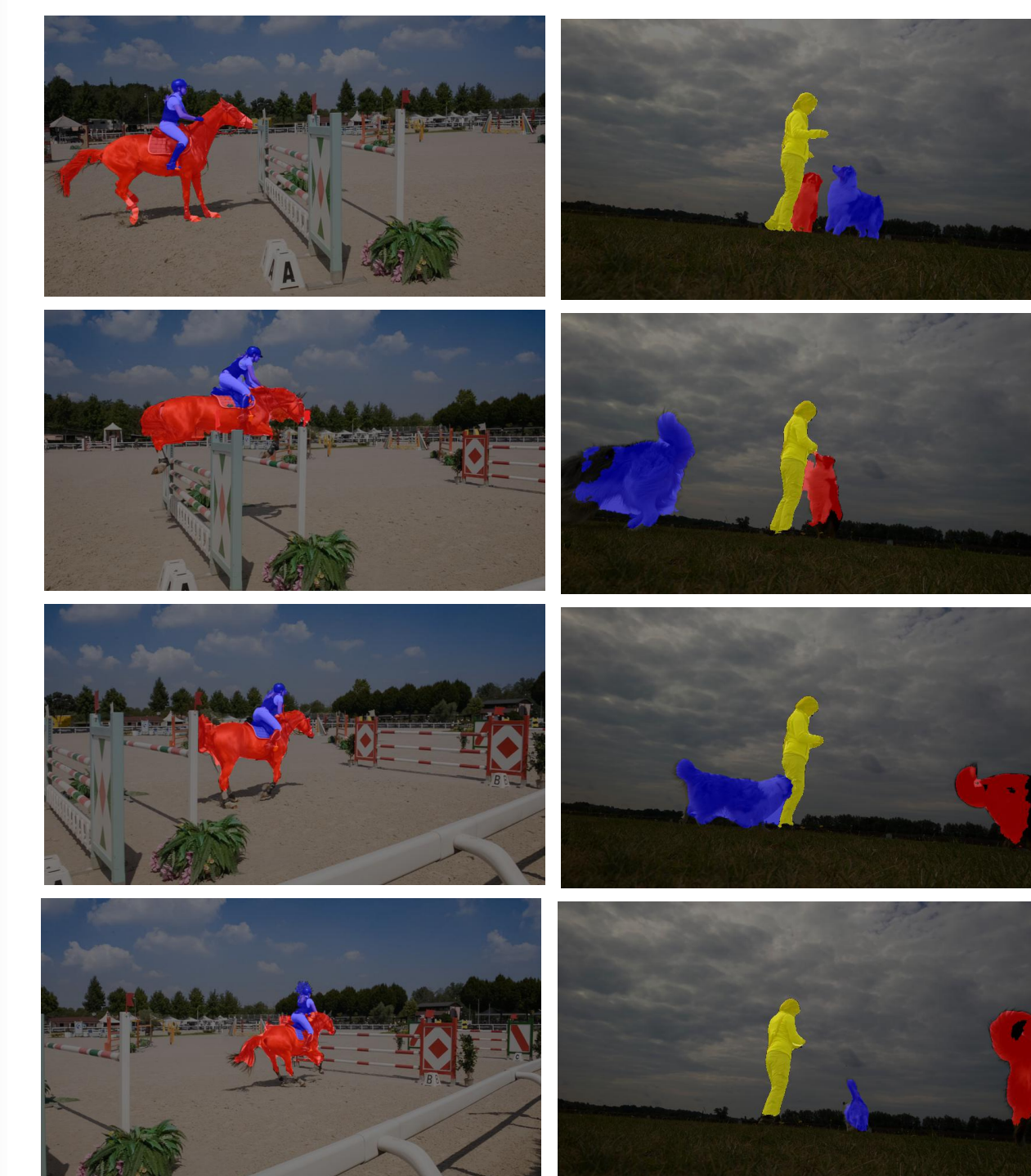


SHLS Training



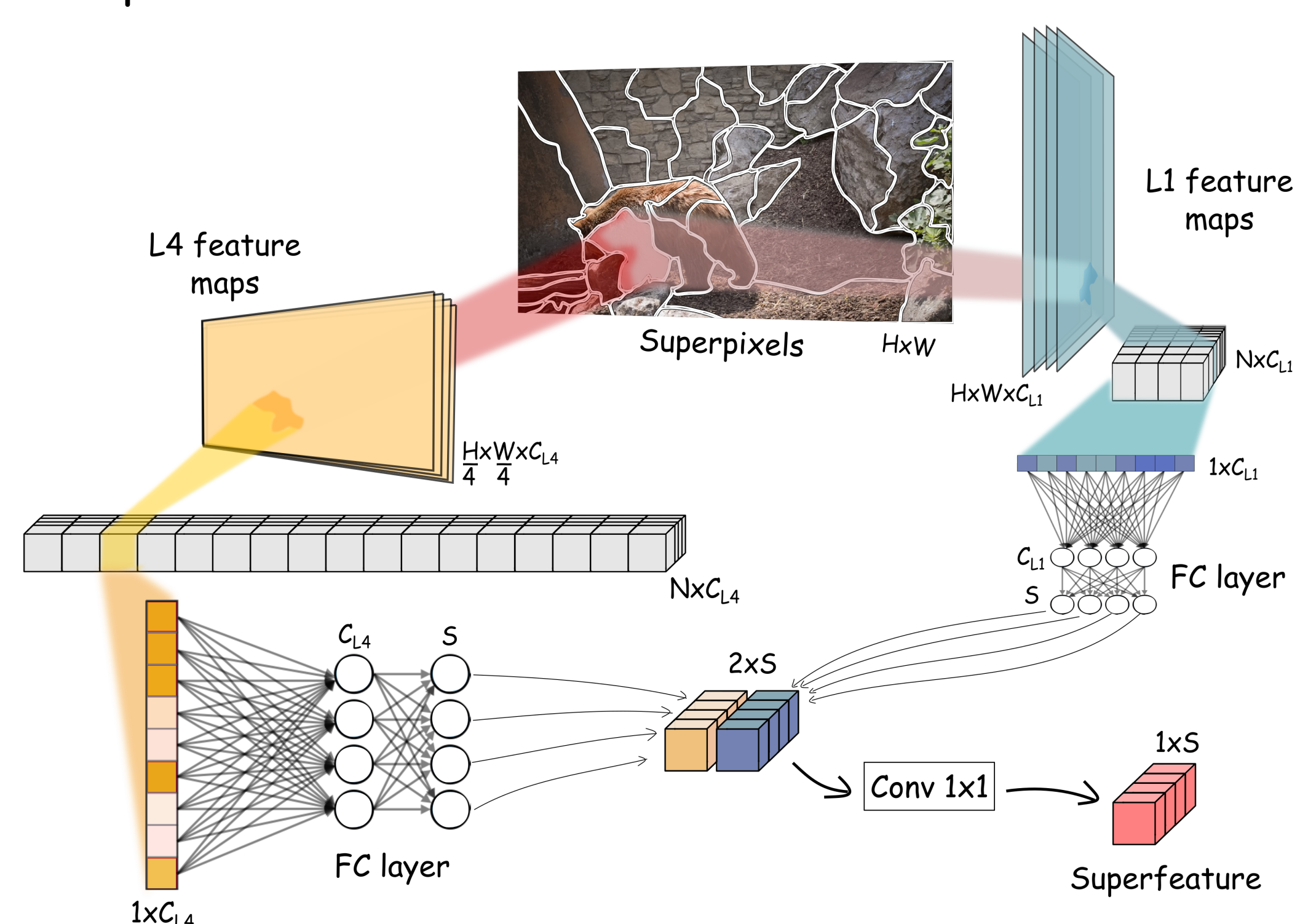
Offline phase: frame-mask sequences are synthesized using saliency detection and data augmentation; superpixels are extracted.
Online phase: Convolutional features are shared between two branches, one for superfeature generation with a contrastive NT-Xent loss and the other for segmentation refinement with a cross-entropy loss. A memory clustering module is used to store and retrieve information from past frames.

Multi-object Segmentation



Combining superpixels and features in superfeatures

The features inside a superpixel are averaged, for each channel, yielding $N \times C_{L1}$ and $N \times C_{L4}$ vectors. These vectors are fed into fully-connected layers, resulting in a $2 \times S$ vector, which is passed through a 1×1 convolution to generate the superfeature.

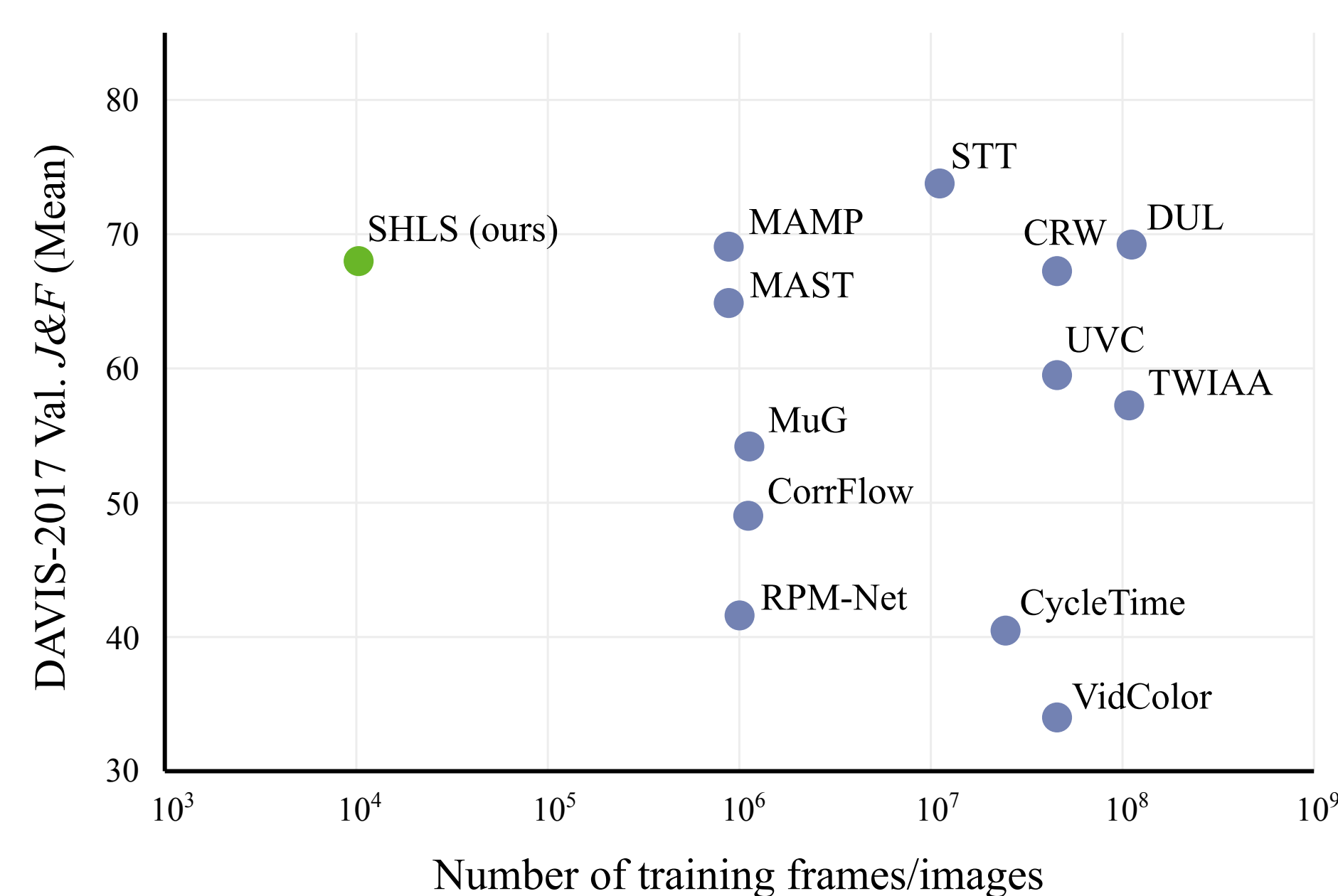


Takeaways

- A superfeature model that provides highly compressed superpixel-based representations.
- A memory clustering approach for retrieving information from past frames efficiently.
- A fully self-supervised VOS method trained with only 10k still images.

Quantitative Results

Benchmark on DAVIS-2017 validation set. SHLS is trained with at least 10^2 orders of magnitude fewer images than other self-supervised methods.



Acknowledgements

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References

- [1] MENDONÇA, M.; OLIVEIRA, L. ISEC: Iterative over-segmentation via edge clustering. IMAVIS, 2018.
- [2] FONTINELE, J.; MENDONÇA, M.; RUIZ, M.; PAPA, J.; OLIVEIRA, L. Faster α -expansion via dynamic programming and image partitioning. IJCNN, 2020.