# Self-Supervised Spatial-Temporal Feature Learning for Video Correspondence — NeurIPS 2022 Supplementary Material

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- 1 The supplementary material contains: 1) ablation study of different contrastive models; 2) ablation
- 2 study of entropy-based selection; 3) more qualitative examples for video object segmentation.

#### 3 1 Ablation study of different contrastive models

- 4 Given a query point randomly sampled in the target frame, we visualize the result of computing the
- b local correlation and global correlation map w.r.t. reference frame. The dashed line in red represents
- 6 the range of computing correlation map w.r.t. query point. The reference frame is randomly sampled
- 7 in the memory bank of inference strategy. Given a query point randomly sampled in the target frame,
- we visualize the result of computing the local correlation and global correlation map w.r.t. reference
- frame. The dashed line in red represents the range of computing correlation map w.r.t. query point.
- The reference frame is randomly sampled in the memory bank of inference strategy. Given a query
- point randomly sampled in the target frame, we visualize the result of computing the local correlation
- and global correlation map w.r.t. reference frame. The dashed line in red represents the range of
- computing correlation map w.r.t. query point. The reference frame is randomly sampled in the
- 14 memory bank of inference strategy

## 2 Ablation study of entropy-based selection

We make detailed ablation study for our entropybased selection in terms of both visual perception and quantitative comparison. As shown in Figure 1, the entropy map has a higher response on moving objects involved in severe deformation and occlusions, which should be paid more attention to. In Table 1, we adopt different thresholds to generate the mask m with high entropy. The baseline is to apply local correlation distillation for all queries,

| Method  | Dataset | $\mathcal{J}\&\mathcal{F}_m\uparrow$ |
|---------|---------|--------------------------------------|
| T = 0.1 | YTV     | 67.4                                 |
| T = 0.4 | YTV     | 68.3                                 |
| T = 0.7 | YTV     | 69.0                                 |
| T = 1.0 | YTV     | 68.1                                 |

Table 1: **The quantitative results on the validation set of DAVIS-2017.** The Dataset represents dataset(s) used for training. YTV:YouTube-VOS []

- *i.e.*, T = 1.0. When setting T with 0.1, the performance drops to 67.4% due to the underutilization of
- 27 the supervision from finest pyramid level. The results of setting T with 0.4 and 0.7 indicate applying
- distillation in the region with high entropy exhibits a performance gain.

### More qualitative examples for video object segmentation

30 We do the most of experiments

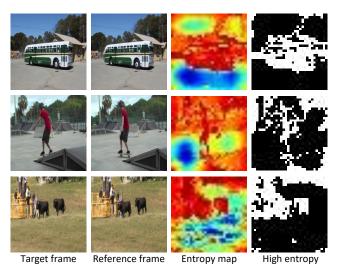


Figure 1: **Visualization of the entropy map.** We compute the entropy for each query in target frame using Eq 8 in our main paper. The mask with high entropy is generated by setting a threshold.