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Not All Pairs are Equal: Hierarchical Learning for Average-Precision-Oriented Video Retrieval

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Alignment of the Objective with the Metric

Evaluation Metric: Average Precision (AP)

- Evaluates the overall rankings of relevant videos
- Assigns larger weights on higher-ranked instances

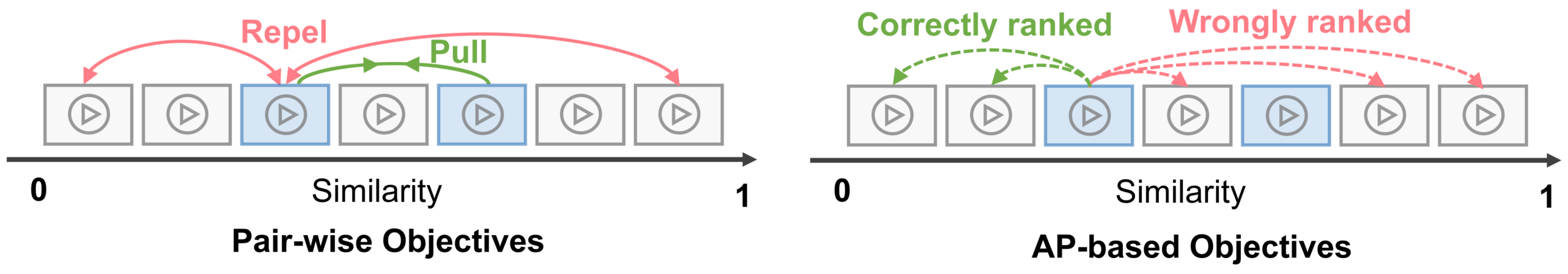
$$AP = \frac{1}{n}\sum_{i=1}^{n}\frac{i}{r_i}$$

Previous Training Objectives: Pair-wise Objectives

- Pull the positive instances closer and repel the negative ones
- ✗ Treat all mis-ranked pairs equally
- ✗ Mismatch with the evaluation metric

New Training Objectives: AP-based Objectives

- Rectify the wrongly ranked positive-negative pairs in the list
- ✓ Fill the gap between training objectives and evaluation metrics



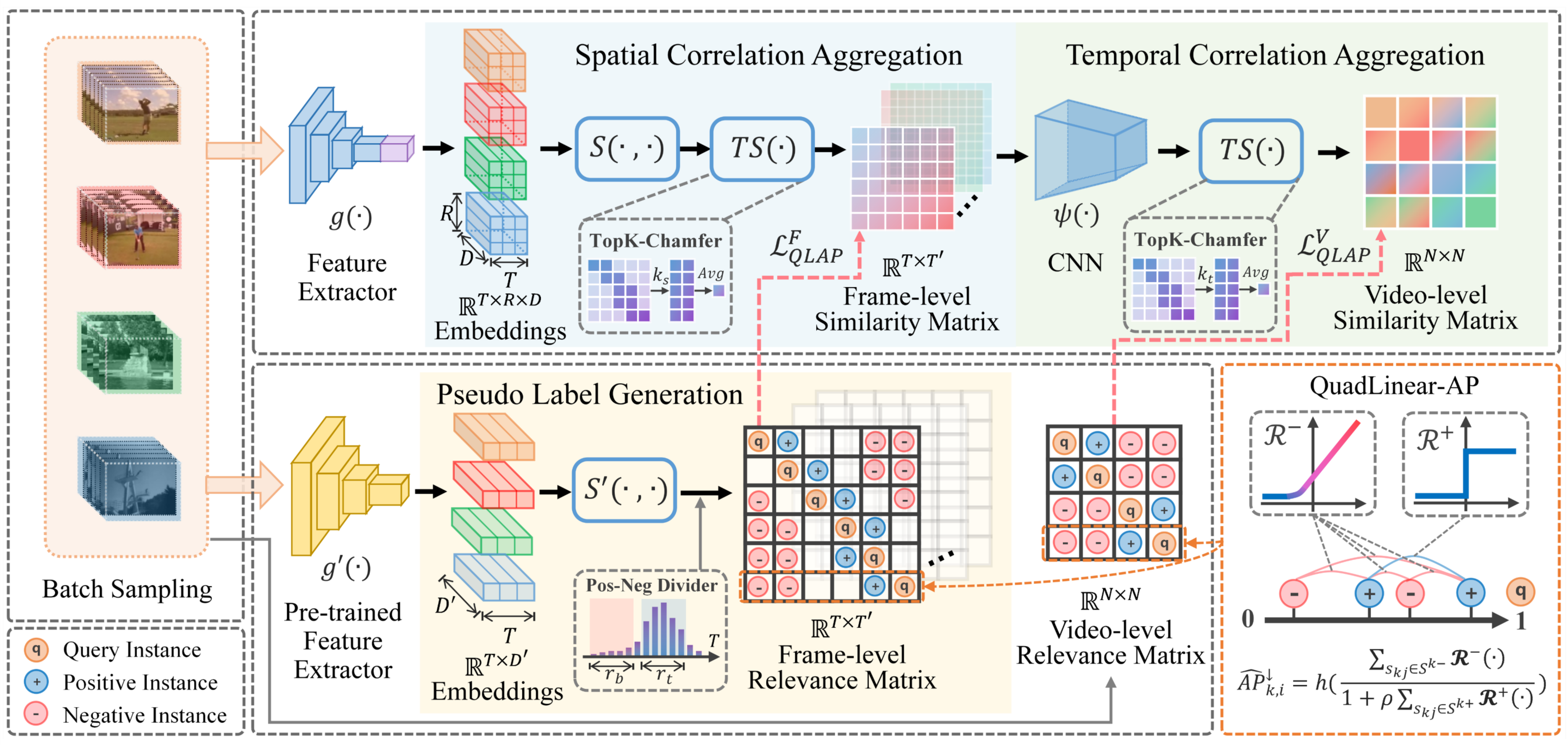
Two Challenges for Video-Oriented AP Optimization

- Current AP losses are suboptimal for **video-level** retrieval
- Noisy **frame-level** matching leads to a biased AP estimation

Hierarchical Learning Framework

Overall Framework: HAP-VR

Hierarchical learning for Average-Precision-oriented Video Retrieval



Video-Oriented AP Optimization Algorithm

- **Step1**: Bottom-up video similarity measure
- **Step2**: Pseudo-label generation
- **Step3**: Hierarchical AP optimization

$$\mathcal{L} = \underbrace{\lambda_f \mathcal{L}^F_{QLAP}}_{frame-level} + \underbrace{\lambda_v \mathcal{L}^V_{QLAP}}_{video-level} + \mathcal{L}_{base}$$

Gradient-Enhanced AP Optimization

Optimization Problem:

- Maximizing the AP score

$$\max_f \quad AP(f) = \frac{1}{N}\sum_{k=1}^{N} AP_k(f)$$

$$AP_k(f) = \frac{1}{|\boldsymbol{S}^{k+}|}\sum_{s_{ki}\in\boldsymbol{S}^{k+}} \frac{\mathcal{R}(s_{ki}, \boldsymbol{S}^{k+})}{\mathcal{R}(s_{ki}, \boldsymbol{S}^{k+}\cup\boldsymbol{S}^{k-})} = \frac{1}{|\boldsymbol{S}^{k+}|}\sum_{s_{ki}\in\boldsymbol{S}^{k+}} \frac{1+\sum_{s_{kj}\in\boldsymbol{S}^{k+}}\mathcal{H}(d^k_{ji})}{1+\sum_{s_{kj}\in\boldsymbol{S}^{k+}\cup\boldsymbol{S}^{k-}}\mathcal{H}(d^k_{ji})}$$

Objective Reformation:

- Minimizing the AP risk

$$\min_f \quad AP^{\downarrow}(f) = \frac{1}{N}\sum_{k=1}^{N} AP^{\downarrow}_k(f)$$

$$\boxed{\mathcal{R}(s, \boldsymbol{S}) = 1 + \sum_{s'\in\boldsymbol{S}}\mathcal{H}(s'-s) \qquad d^k_{ji} = s_{kj} - s_{ki} \quad h(x) = \frac{x}{1+x}}$$

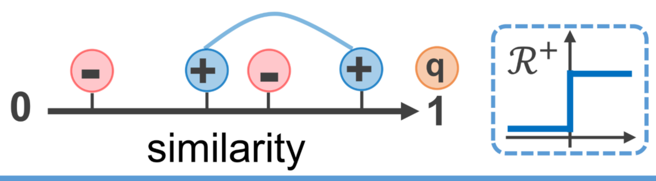
$$AP^{\downarrow}_k(f) = 1 - \frac{1}{|\boldsymbol{S}^{k+}|}\sum_{s_{ki}\in\boldsymbol{S}^{k+}} \frac{1+\sum_{s_{kj}\in\boldsymbol{S}^{k+}}\mathcal{H}(d^k_{ji})}{1+\sum_{s_{kj}\in\boldsymbol{S}^{k+}\cup\boldsymbol{S}^{k-}}\mathcal{H}(d^k_{ji})} = \frac{1}{|\boldsymbol{S}^{k+}|}\sum_{s_{ki}\in\boldsymbol{S}^{k+}} \frac{\sum_{s_{kj}\in\boldsymbol{S}^{k-}}\mathcal{H}(d^k_{ji})}{1+\sum_{s_{kj}\in\boldsymbol{S}^{k+}\cup\boldsymbol{S}^{k-}}\mathcal{H}(d^k_{ji})} = \frac{1}{|\boldsymbol{S}^{k+}|}\sum_{s_{ki}\in\boldsymbol{S}^{k+}} h\left(\boxed{\frac{\sum_{s_{kj}\in\boldsymbol{S}^{k-}}\mathcal{H}(d^k_{ji})}{1+\sum_{s_{kj}\in\boldsymbol{S}^{k+}}\mathcal{H}(d^k_{ji})}}\right)$$

Rethinking the Components of AP Risk: QuadLinear-AP

$$AP^{\downarrow}_k(f) = \frac{1}{|\boldsymbol{S}^{k+}|}\sum_{s_{ki}\in\boldsymbol{S}^{k+}} h\left(\frac{\sum_{s_{kj}\in\boldsymbol{S}^{k-}}\mathcal{H}(d^k_{ji})}{1+\sum_{s_{kj}\in\boldsymbol{S}^{k+}}\mathcal{H}(d^k_{ji})}\right) \Rightarrow \widehat{AP}^{\downarrow}_k(f) = \frac{1}{|\boldsymbol{S}^{k+}|}\sum_{s_{ki}\in\boldsymbol{S}^{k+}} h\left(\frac{\sum_{s_{kj}\in\boldsymbol{S}^{k-}}\mathcal{R}^-(d^k_{ji};\delta)}{1+\rho\sum_{s_{kj}\in\boldsymbol{S}^{k+}}\mathcal{R}^+(d^k_{ji})}\right)$$

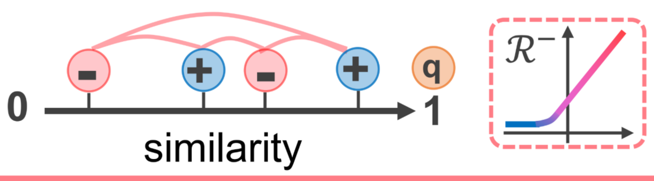
Positive-positive Pairs

- Serve as weights
- No need for optimization
- $\mathcal{R}^+(x) = \mathcal{H}(x) = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{if } x \le 0 \end{cases}$



Positive-negative Pairs

- Rankings should be corrected
- Need proper gradients for optimization
- $\mathcal{R}^-(x;\delta) = \begin{cases} \mathcal{H}(-x)\cdot\frac{1}{\delta^2}x^2 + \frac{2}{\delta}x + 1, & \text{if } x \ge -\delta \\ 0, & \text{if } x < -\delta \end{cases}$



Original AP

$$\frac{\sum_{s_{kj}\in\boldsymbol{S}^{k-}}\mathcal{H}(d^k_{ji})}{1+\sum_{s_{kj}\in\boldsymbol{S}^{k+}}\mathcal{H}(d^k_{ji})}$$

Non-differentiability

Smooth-AP

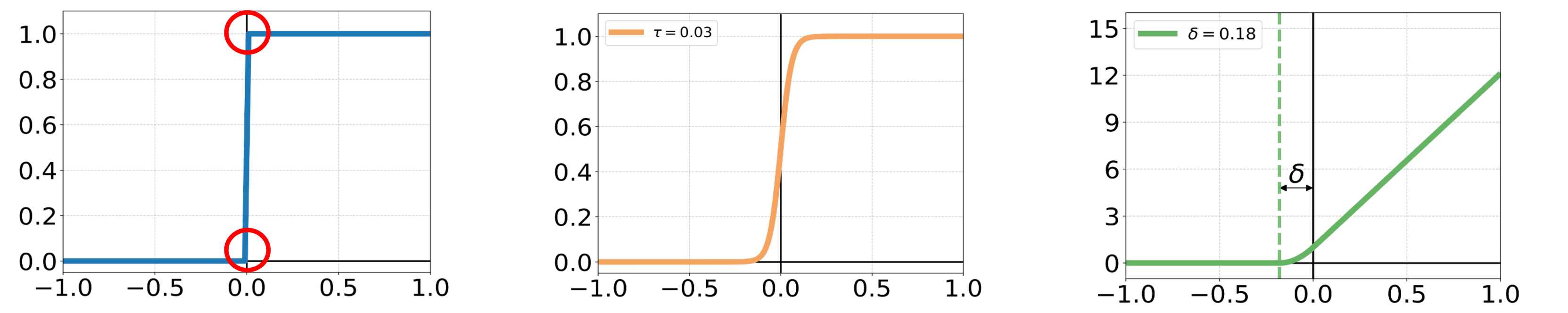
$$\frac{\sum_{s_{kj}\in\boldsymbol{S}^{k-}}\mathcal{G}(d^k_{ji};\tau)}{1+\sum_{s_{kj}\in\boldsymbol{S}^{k+}}\mathcal{G}(d^k_{ji};\tau)}$$

Gradient Vanishing

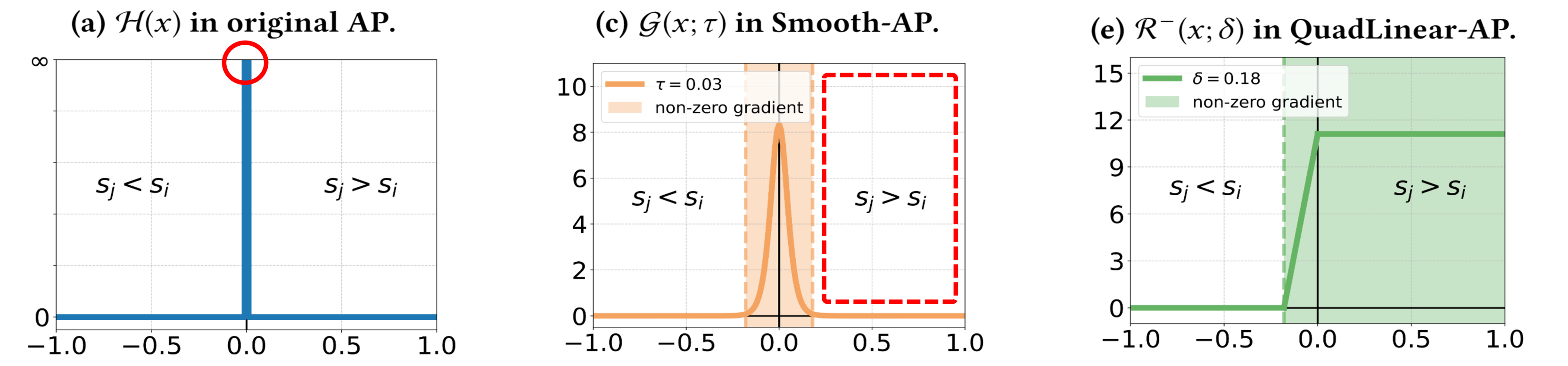
QuadLinear-AP (Ours)

$$\frac{\sum_{s_{kj}\in\boldsymbol{S}^{k-}}\mathcal{R}^-(d^k_{ji};\delta)}{1+\rho\sum_{s_{kj}\in\boldsymbol{S}^{k+}}\mathcal{R}^+(d^k_{ji})}$$

Favorable properties



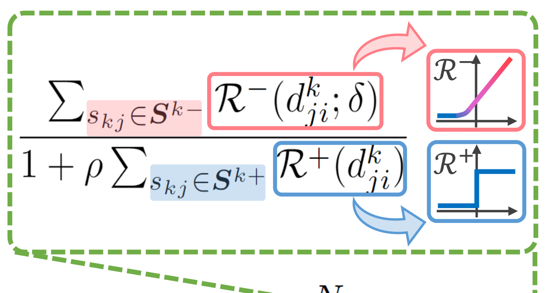
(a) $\mathcal{H}(x)$ in original AP. (c) $\mathcal{G}(x;\tau)$ in Smooth-AP. (e) $\mathcal{R}^-(x;\delta)$ in QuadLinear-AP.



(b) Derivative of $\mathcal{H}(x)$. (d) Derivative of $\mathcal{G}(x;\tau)$. (f) Derivative of $\mathcal{R}^-(x;\delta)$.

Favorable Properties of QuadLinear-AP

- Differentiable AP optimization
- Suitable gradients for low AP area
- Continuous, Smooth, and Convex
- Monotonically increasing (non-strictly)
- Upper bound of Heaviside function



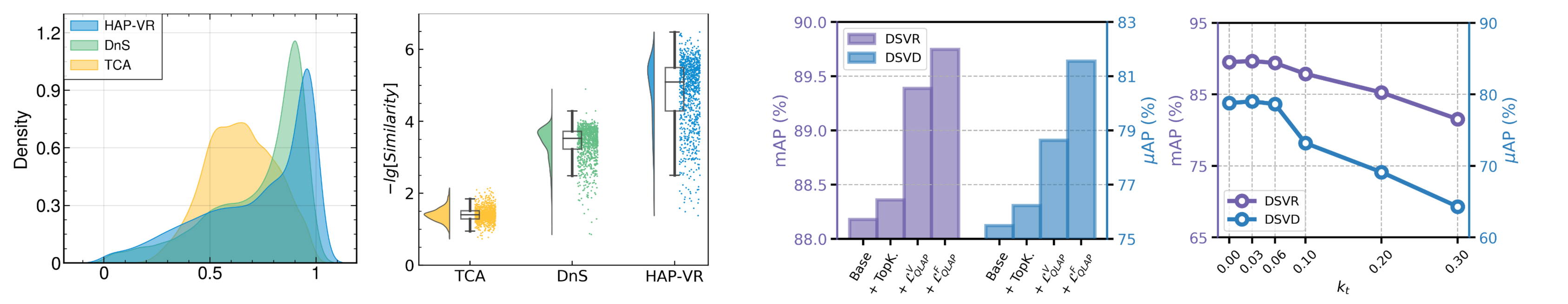
$$\mathcal{L}_{QLAP} = \frac{1}{N}\sum_{k=1}^{N}\widehat{AP}^{\downarrow}_k(f)$$

Evaluation Results

Overall Performance of Our Proposed HAP-VR

- HAP-VR improves mAP and μAP effectively on multiple tasks

Method	Label	Trainset	Retrieval (mAP)					Detection (μAP)				
			EVVE	SVD	FIVR-200K DSVR	FIVR-200K CSVR	FIVR-200K ISVR	EVVE	SVD	FIVR-200K DSVD	FIVR-200K CSVD	FIVR-200K ISVD
DML† [32]	✓	VCDB ($\mathcal{C}$&$\mathcal{D}$)	61.10	85.00	52.80	51.40	44.00	75.50	/	39.00	36.50	30.00
TMK† [46]	✓	internal	61.80	86.30	52.40	50.70	42.50	/	/	/	/	/
TCA [53]	✓	VCDB ($\mathcal{C}$&$\mathcal{D}$)	63.08	89.82	86.81	82.31	69.61	76.90	56.93	69.09	62.28	49.24
ViSiL† [30]	✓	VCDB ($\mathcal{C}$&$\mathcal{D}$)	65.80	88.10	89.90	85.40	72.30	79.10	/	75.80	69.00	53.00
DnS (S_a) [34]	✓	DnS-100K	65.33	90.20	92.09	87.54	74.08	74.56	72.24	79.66	69.51	54.20
DnS (S_b) [34]	✓	DnS-100K	64.41	89.12	90.89	86.28	72.87	75.80	66.53	78.05	68.52	53.48
LAMV† [2]	✗	YFCC100M	62.00	88.00	61.90	58.70	47.90	80.60	/	55.40	50.00	38.80
VRL† [24]	✗	internal	/	/	90.00	85.80	70.90	/	/	/	/	/
ViSiL$_f$† [30]	✗	ImageNet	62.70	/	89.00	84.80	72.10	74.60	/	66.90	59.50	45.90
S^{2}VS [33]	✗	VCDB ($\mathcal{D}$)	67.17	88.40	92.53	87.73	74.51	80.72	65.04	86.12	77.41	63.26
HAP-VR (Ours)	✗	VCDB ($\mathcal{D}$)	69.15	89.00	92.83	88.21	74.72	82.88	67.87	88.41	79.85	64.79

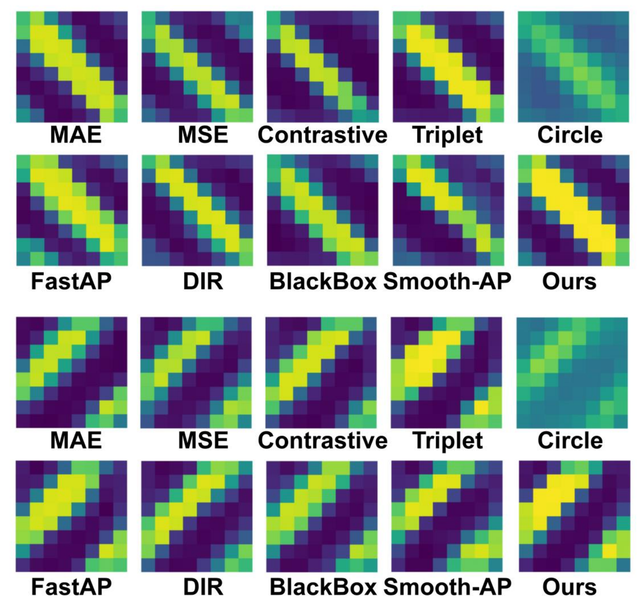


(a) Relevant pair distribution. (b) Irrelevant pair distribution. (c) Effect of components. (d) Impact of k_γ.

Effectiveness of Our Proposed QuadLinear-AP

- QuadLinear-AP outperforms previous pair-wise/AP-based losses

Losses	Retrieval (mAP)			Detection (μAP)		
	DSVR	CSVR	ISVR	DSVD	CSVD	ISVD
MAE	89.07	88.03	80.86	78.08	75.69	65.26
MSE	89.22	88.26	80.80	78.66	76.07	65.44
Contrastive [18]	88.67	88.09	80.97	75.12	74.23	67.41
Triplet [50]	88.11	87.77	81.21	72.94	73.18	69.23
Circle [55]	87.53	86.11	78.77	73.26	71.15	59.33
FastAP [6]	89.30	88.42	81.16	78.83	77.51	69.95
DIR [47]	89.65	88.57	80.64	78.50	76.22	65.42
BlackBox [45]	89.70	88.55	80.53	80.07	77.37	66.00
Smooth-AP [4]	89.36	88.33	80.73	79.85	77.75	68.42
QuadLinear-AP (**Ours**)	90.80	89.68	81.31	82.92	80.03	71.45



Conclusions

- **Methodologically**: Propose a self-supervised framework (**HAP-VR**) for video retrieval to **bridge the gap** of the objective and metric.
- **Analytically**: Introduce a gradient-enhanced AP surrogate loss (**QuadLinear-AP**) and design a **hierarchical learning strategy** for **AP optimization** on both video and frame levels.
- **Empirically**: Experimental results demonstrate the effectiveness of our proposed framework on various video retrieval tasks.

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