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### Motivations

**Ranking loss treats all negatives "equally"**  $\rightarrow$  Resulting in a large semantic discrepancy



#### Semantic relevance



# SEMANTIC-PRESERVING METRIC LEARNING FOR VIDEO-TEXT RETRIEVAL

### **Proposed method**

### **Objectives: Place each negative embeddings** according to proposed semantic relevance



**Dotted circle: learned embeddings by ranking loss** Solid circle: learned embeddings by the proposed method

#### **Proposed loss for a cross-modal triplet**



### **Overall loss by applying bidirectional loss** and hardest negative sampling



 $\max loss_{t \to v}(p, n)$ 

+ max  $loss_{v \to t}(p, n)$ 

## **Experimental results**

#### Present a close alignment between the learned metric space and the semantic space

#### **Qualitative results: semantically similar** videos are embedded close to each other

Text query : a man is riding a horse at top speed in a race

**Ranking loss** 



#### **Proposed method**



#### **Quantitative results: Improve text-to-video** retrieval performance on six video-text datasets

Dataset	Loss	Text to video						Gain
		R@1	R@5	R@10	MedR	MeanR	Sum of R	Gaill
LSMDC	Rank	10.6	25.5	33.1	33	122.8	69.2	+16.5%
	Semantic	12.7	29.2	38.7	25	103.2	80.6	
DiDeMo	Rank	13.8	33.4	44.8	15	68.2	92.0	+11.6%
	Semantic	15.1	37.2	50.4	10	45.1	102.7	
ANet	Rank	12.8	34.5	48.6	11	68.7	95.9	+9.2%
	Semantic	14.2	37.8	52.8	9	46.6	104.7	
VTT	Rank	8.6	24.4	34.1	29	210.0	67.1	+7.6%
	Semantic	9.1	26.2	37.0	22	163.8	72.2	
TGIF	Rank	5.9	14.8	20.6	122	729.1	41.3	+4.0%
	Semantic	6.0	15.4	21.6	93	563.9	43.0	
VATEX	Rank	35.2	71.5	80.8	2	18.9	187.4	+2.0%
	Semantic	35.3	73.2	82.7	2	15.8	191.2	

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#### (Rank) and the proposed method on MSR-VTT (Top-5)

#### Comparison text-to-video retrieval result of ranking loss (Rank) and the proposed method (Semantic)