MIC: Mining Interclass Characteristics for Improved Metric Learning

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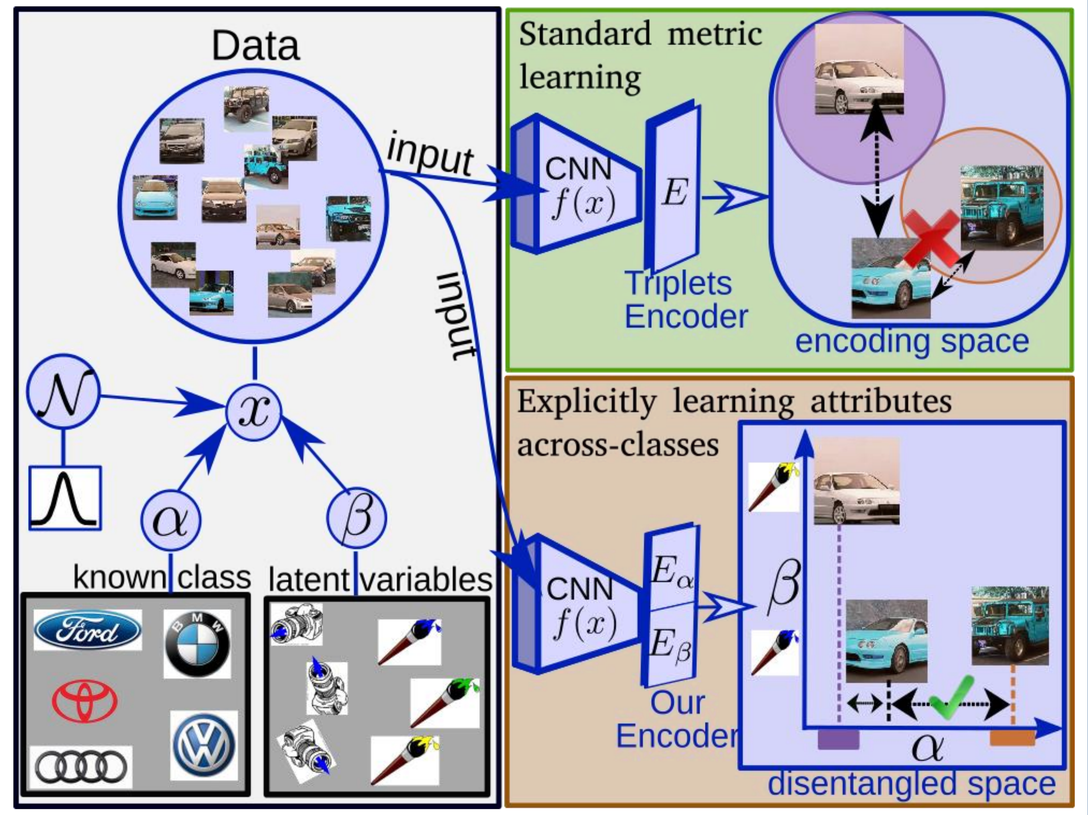
1 Introduction

Abstract

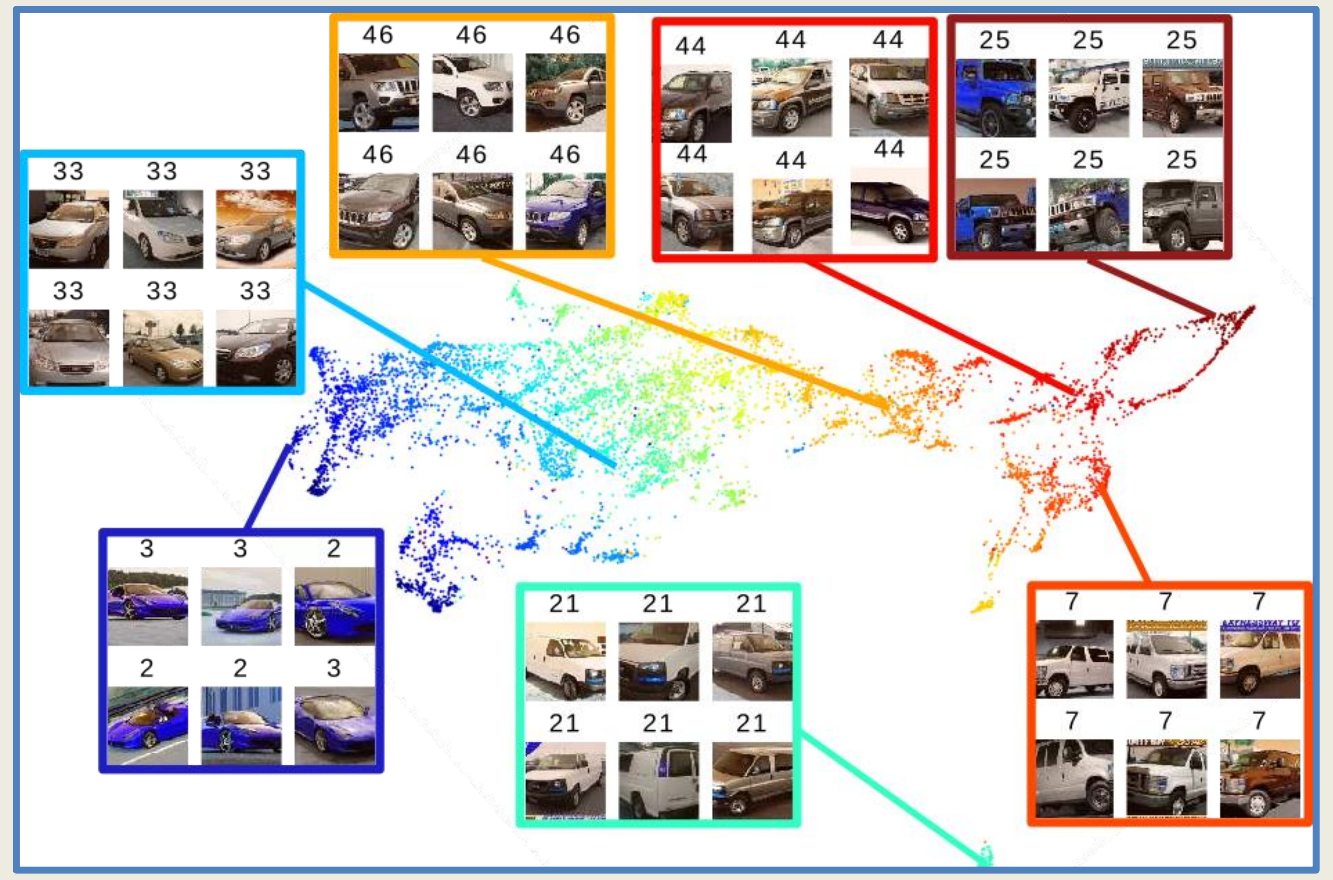
Goal of Metric learning:
Learn an embedding space in which semantically similar objects are grouped close together.

Problem:
Training relies only on **class-discriminative information.** Discards information shared across classes **(interclass characteristics)** as noise.

Proposal:
Explicitly learning structured shared characteristics provides extra information about the data. Furthermore, by explicitly explaining them away we emphasize discriminative features.

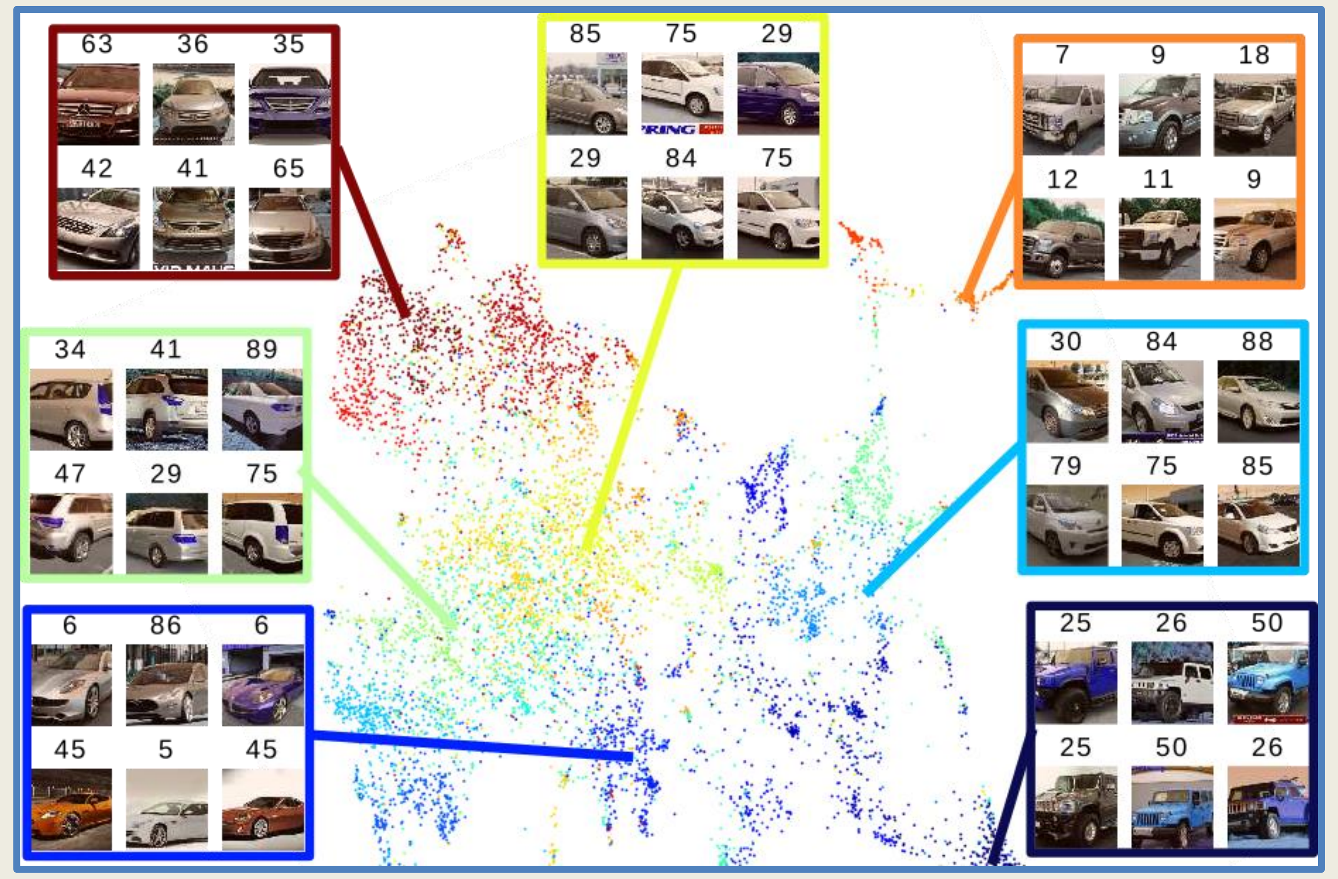


3 Embedding Characteristics



UMAP of learned class encoding.
Produces grouping by class, independently from e.g. orientation and color!

UMAP of learned intra-class encoding
Produces grouping by characteristics shared across classes, independently from class specific features.



4 Pipeline Ablation

Ablation of components:
Simply clustering does not benefit zero-shot performance. Using standardization and separating via mutual information loss does.

Clust	Stand	MutInfo	CARS	CUB	SOP
-	-	-	80.0	62.9	73.2
+	-	-	79.2	59.1	71.9
+	+	-	81.3	64.9	75.8
+	+	+	**82.6**	**66.3**	**76.9**

2 MIC: Mining Interclass Characteristics

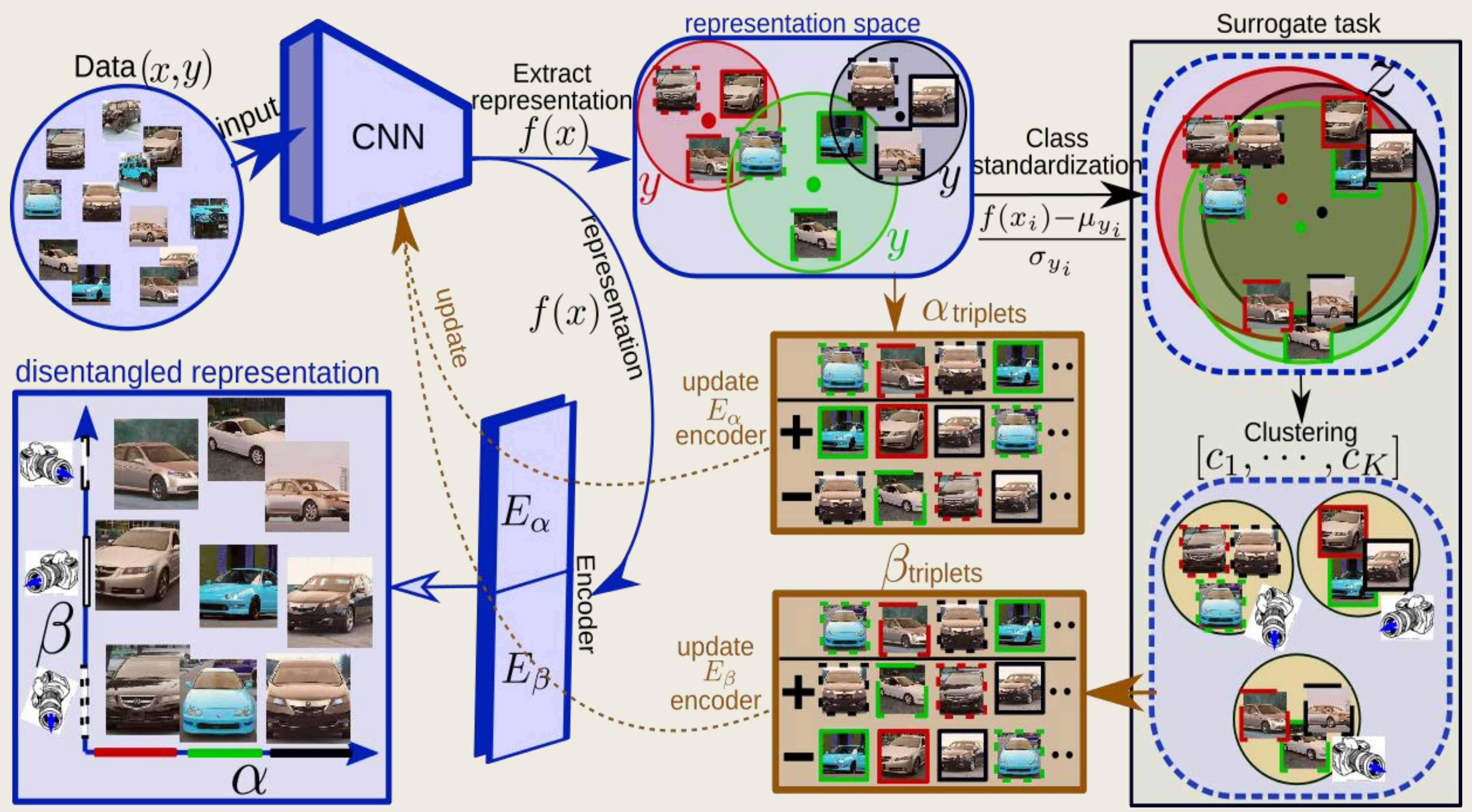
(1) For each train sample, extract features using a pre-trained model.

(2) Reduce the class bias by standardizing each class independently, moving all class embeddings to zero mean.

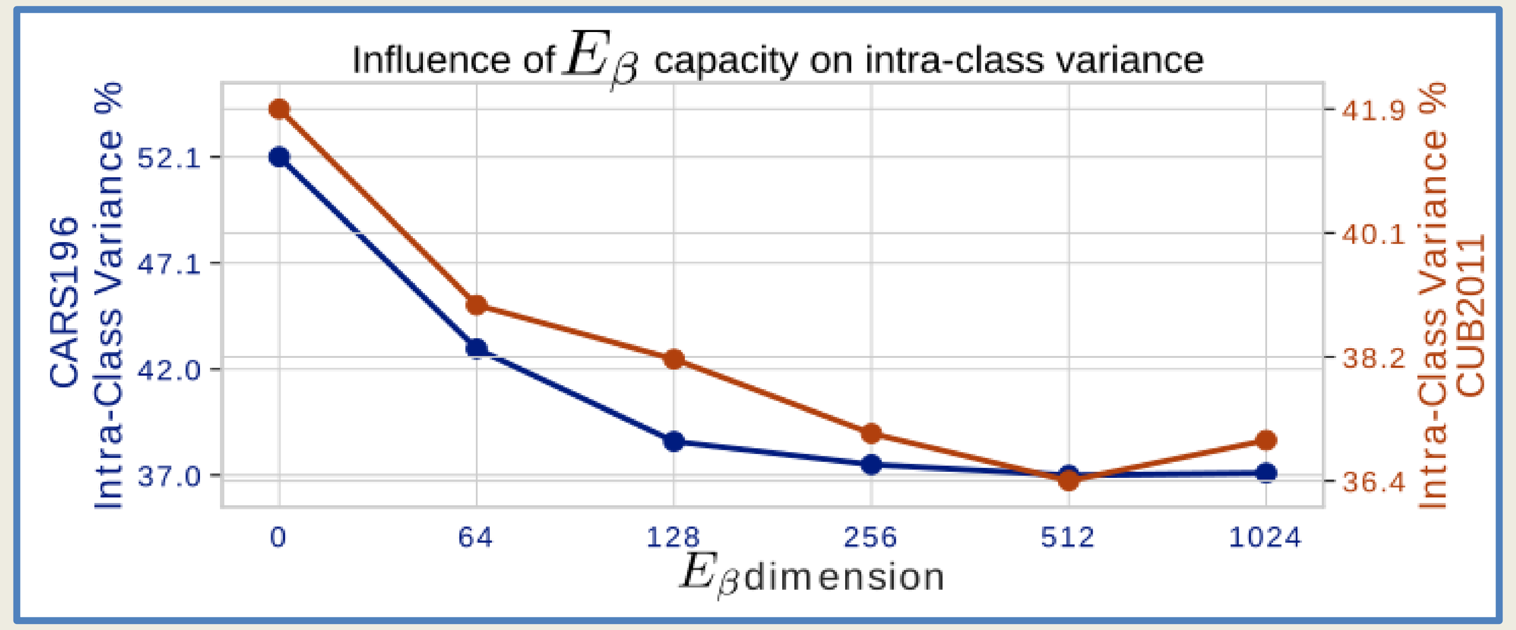
(3) Cluster this standardized feature space to produce new surrogate labels, corresponding to different shared characteristics in the dataset.

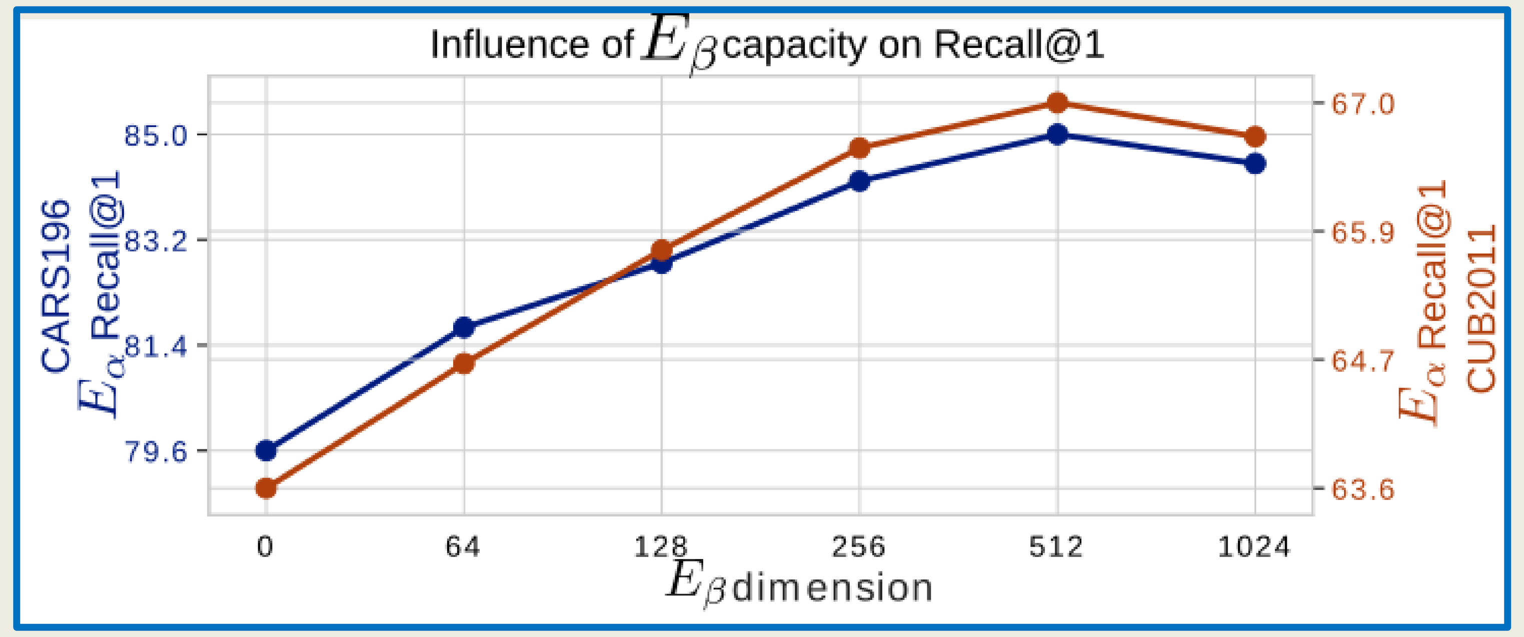
(4) Sample triplets based on class and surrogate labels.

(5) Both embeddings are updated with standard metric learning losses. A **mutual information loss** ensures contrastive features being learned.



5 Influence of Auxiliary Encoding





6 Results

CUB200-2011

R@k	Dim	1	2	4	NMI
DVML[19]	512	52.7	65.1	75.5	61.4
BIER[28]	512	55.3	67.2	76.9	-
HTL[9]	512	57.1	68.8	78.7	-
A-BIER[29]	512	57.5	68.7	78.3	-
HTG[39]	-	59.5	71.8	81.3	-
DREML[37]	9216	63.9	75.0	83.1	67.8
Semihard[31]	-	42.6	55.0	66.4	55.4
Semihard*	128	57.2	69.4	79.9	63.9
MIC+semih	128	58.8	70.8	81.2	66.0
ProxyNCA[22]	64	49.2	61.9	67.9	64.9
ProxyNCA*	128	57.4	69.2	79.1	62.5
MIC+ProxyNCA	128	60.6	72.2	81.5	64.9
Margin[36]	128	63.6	74.4	83.1	69.0
Margin*	128	62.9	74.1	82.9	66.3
MIC+margin	128	**66.3**	**77.2**	**85.5**	**69.4**

CARS196

R@k	Dim	1	2	4	NMI
HTG[39]	-	76.5	84.7	90.4	-
BIER[28]	512	78.0	85.8	91.1	-
HTL[9]	512	81.4	88.0	92.7	-
DVML[19]	512	82.0	88.4	93.3	67.6
A-BIER[29]	512	82.0	89.0	93.2	-
DREML[37]	9216	86.0	91.7	95.0	76.4
Semihard[31]	-	51.5	63.8	73.5	53.4
Semihard*	128	65.5	76.9	85.2	58.3
MIC+semih	128	70.5	80.5	87.4	61.6
ProxyNCA[22]	64	73.2	82.4	86.4	-
ProxyNCA*	128	73.0	81.3	87.9	59.5
MIC+ProxyNCA	128	75.9	84.1	90.1	60.5
Margin[36]	128	79.6	86.5	90.1	69.1
Margin*	128	80.0	87.7	92.3	66.3
MIC+margin	128	**82.6**	**89.0**	**93.1**	**69.2**

Stanford Online Products

R@k	Dim	1	10	100	NMI
DVML[19]	512	70.2	85.2	93.8	**90.8**
BIER[28]	512	72.7	86.5	94.0	-
ProxyNCA[22]	64	73.7	-	-	-
A-BIER[29]	512	74.2	86.9	94.0	-
HTL[9]	512	74.8	**88.3**	**94.8**	-
Margin[36]	128	72.7	86.2	93.8	**90.7**
Margin*	128	74.4	87.2	94.0	89.4
MIC+margin	128	**76.9**	**88.9**	**95.4**	89.9

In-Shop Clothes

R@k	Dim	1	10	30	50
BIER[28]	512	76.9	92.8	96.2	97.1
HTG[39]	-	80.3	93.9	96.6	97.1
HTL[9]	512	80.9	94.3	97.2	97.8
A-BIER[29]	512	83.1	95.1	97.5	98.0
DREML[37]	9216	78.4	93.7	96.7	-
Margin*	128	84.5	95.7	97.6	98.3
MIC+margin	128	**87.9**	**96.9**	**98.3**	**98.7**

Significant improvements in zero-shot retrievals across all datasets and loss functions!