# Deep Joint Discriminative Learning for Vehicle Re-identification and Retrieval

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2017.09.18

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# **Outline**

Background
Deep Joint Discriminative Learning
Experimental Results
Conclusion



# Deep Joint Discriminative Learning for Vehicle Re-identification and Retrieval

# **Outline**

#### **Background**

Deep Joint Discriminative Learning

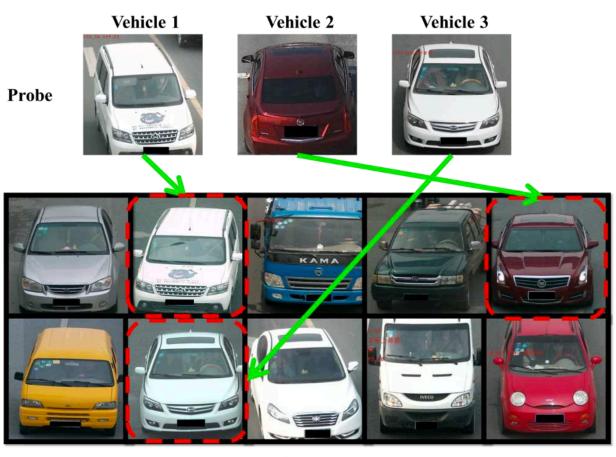
Experimental Results

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# Vehicle search and re-identification



**Gallery** 

#### Vehicle search and re-identification

- Practical applications in video surveillance systems
- Challenge

005

- License plate is not clear
  - Low-resolution
  - Occluded or removed
- → Vehicle ReID based on **appearance information**

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#### Vehicle search and re-identification

■ VehicleID dataset

006

- Labeled in identity level
- Remove license plate



- Most identification works focus on face or person
  - Face recognition
  - Person re-identification
- Target: learn discriminative representations
  - State-of-art → Deep CNN based
  - DeepID [Sun et. al, 2014]
    - Directly classify identities  $(\sim 1 \text{ w})$
  - DeepID2 [Sun et. al, 2014]
    - Pairwise verification loss
  - Triplet loss [Schroff et. al, 2015, Ding et. al 2015]
    - Triplet relationship between positive and negative pairs

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- Difference of vehicle identification
  - Previous works focus on model classification
    - Recognize models instead of identities
  - Vehicles of same model  $\rightarrow$  similar visual appearance
  - Capture special marks



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  - Vehicles of same model  $\rightarrow$  similar visual appearance
  - Capture special marks
- Large scale vehicle identification dataset
  - VehicleID [Liu et al. 2016]
  - Facilitate deep learning models

- Difference of vehicle identification
  - Previous works focus on model classification
    - Recognize model instead of identities
  - Vehicles of same model  $\rightarrow$  similar visual appearance
  - Capture special marks
- Large scale vehicle identification dataset
  - VehicleID [Liu et al. 2016]
  - Facilitate deep learning models
- Deep Joint Discriminative Learning (DJDL) model
  - A unified framework to extract discriminative features

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**Triplet** 

**Triplet Loss** 

 $\triangle$ 

#### **Architecture Overview**

- Unified framework for four tasks
  - Shared base convolution network
    - A common CNN pretrained on ImageNet
  - Classification tasks
    - Identification
    - Attribute recognition
  - Verification subnetwork
    - Two images
  - Triplet subnetwork
    - Three images

- Identification subnetwork
  - Each input image → Identity label
  - Conventional recognition task
    - Softmax + cross-entropy loss

$$L_{identi}(f_i) = -\sum_{j=1}^n p_j \log \hat{p_j}$$
 target label Predicted probability

- Attribute recognition subnetwork
  - Jointly recognize vehicle attributes
    - Such as color and vehicle model

$$L_{attri}(f_i) = -\sum_{k=1}^{n_{attri}} \sum_{j=1}^{n_k} a_j^k \log \hat{a_j^k}$$

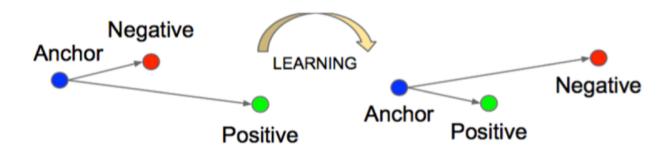
- Verification subnetwork
  - Pair-wise siamese network
    - Use Euclidean distance after normalization
      - Distance  $\rightarrow$  small if same identity
      - Distance → large if different identity

$$L_{verif}(f_i, f_j) = \begin{cases} \frac{1}{2} \|f_i - f_j\|_2^2, & v_i == v_j, \\ \frac{1}{2} max(0, \alpha - \|f_i - f_j\|_2)^2, & v_i \neq v_j, \end{cases}$$
Margin parameter enforce distance > \alpha

- Triplet subnetwork
  - Anchor + positive + negative

$$L_{triplet}(f_i, f_j, f_k) = max(0, ||f_i - f_j||_2^2 - ||f_i - f_k||_2^2 + \beta)$$

Margin parameter



Objective function

$$L = L_{identi} + L_{attri} + L_{verif} + L_{triplet}$$

- SGD optimization
- Jointly learning in a single batch
  - Specific batch composition design

- Batch composition design
  - Satisfy four tasks at the same time
    - Half positive pairs + half random samples

Positive pairs O-O O-O

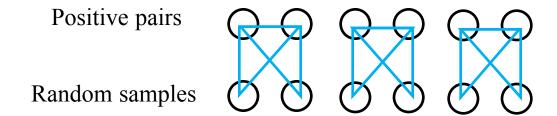
Random samples O O O O O

- Batch composition design
  - Satisfy four tasks at the same time
    - Verification samples

Positive pairs

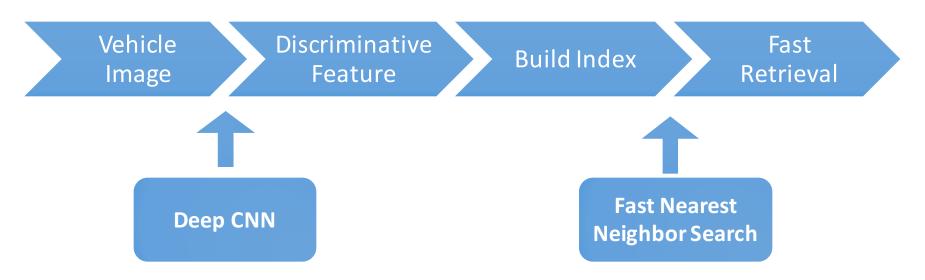
Random samples

- Batch composition design
  - Satisfy four tasks at the same time
    - Triplet samples





- $\blacksquare$  Discriminative features  $\rightarrow$  Build index
  - Vehicle Retrieval
    - Nearest neighbor search



Marius Muja and David G Lowe, "Fast approximate nearest neighbors with automatic algorithm configuration," in VISAPP, 2009.

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# Experimental settings

- VehicleID Dataset
  - 221763 images of 26267 vehicles
  - Three test sets
    - Small, medium, large size
- Two tasks
  - Vehicle retrieval
  - Vehicle re-identification

# **Experimental settings**

- Implementation Details
  - MXNet platform
  - Base convolutional network
    - Inception-BN
  - Augmentation
    - Random crop
    - Random flip
  - Batch size: 64
  - Margin parameters  $\alpha$ ,  $\beta$  as 0.9

#### Vehicle Retrieval

- Evaluation protocol
  - Mean average precision (MAP)
- Ablation results

Method	Small	Medium	Large
Identi	0.712	0.684	0.670
Identi+Attri	0.718	0.686	0.672
Identi+Attri+Verifi	0.731	0.705	0.689
Identi+Attri+Verifi+Triplet	0.786	0.747	0.720

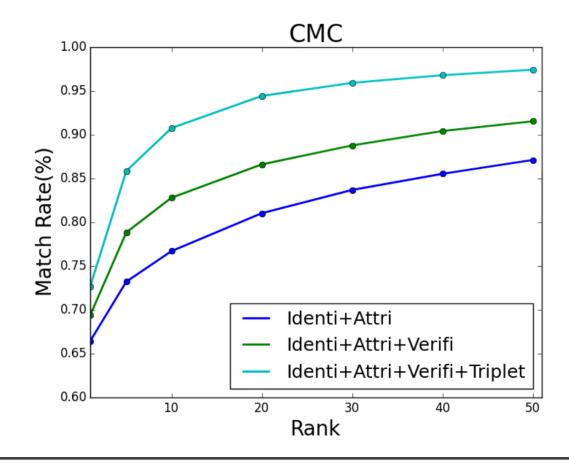
#### Vehicle Retrieval

■ Compare with state-of-art

Method	Small	Medium	Large
VGG+CCL [1]	0.492	0.448	0.386
Mixed Diff+CCL [1]	0.546	0.481	0.455
HDC + Contrastive [16]	0.655	0.631	0.575
Identi+Attri+Verifi+Triplet	0.786	0.747	0.720



- Evaluation protocols
  - CMC curve



#### Vehicle Re-identification

- Evaluation protocols
  - Top1 and Top 5 match rates

Protocol	Small	Medium	Large
	0.436	0.370	0.329
	0.490	0.428	0.382
Top 1	0.670	0.667	0.651
	0.689	0.687	0.661
	0.723	0.708	0.680
	0.642	0.571	0.533
	0.735	0.668	0.616
Top 5	0.735	0.729	0.716
	0.781	0.765	0.737
	0.857	0.818	0.789
	Top 1	0.436 0.490 Top 1 0.670 0.689 <b>0.723</b> 0.642 0.735 Top 5 0.735 0.781	0.436 0.370 0.490 0.428 Top 1 0.670 0.667 0.689 0.687 <b>0.723 0.708</b> 0.642 0.571 0.735 0.668 Top 5 0.735 0.729 0.781 0.765

#### Conclusion

- A novel Deep Joint Discriminative Learning model
  - For vehicle re-identification and retrieval
  - A unified framework by incorporating four tasks
    - Different properties → benefit each other
    - Jointly optimize
      - specific designed batch composition
- Experiments validate the effectiveness of DJDL model
  - State-of-the-art results on two tasks



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Project Page: http://www.icst.pku.edu.cn/struct/Projects/djdl.html

