Similarity Learning with (or without) Convolutional Neural Network

Moitreya Chatterjee, Yunan Luo

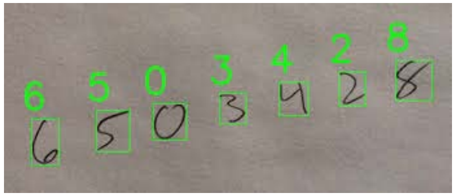
Image Source: Google

Outline – This Section

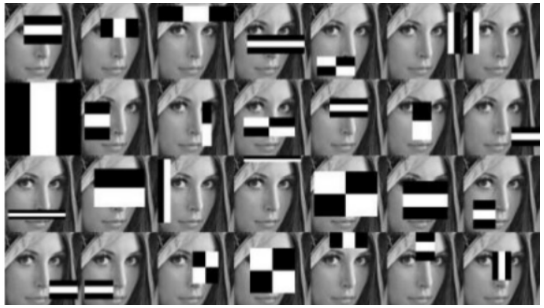
- **Why do we need Similarity Measures**
- **Metric Learning as a measure of Similarity**
  - **Notion of a metric**
  - **Unsupervised Metric Learning**
  - **Supervised Metric Learning**
- **Traditional Approaches for Matching**
- **Challenges with Traditional Matching Techniques**
- Deep Learning as a Potential Solution
- Application of Siamese Network for different tasks

Need for Similarity Measures

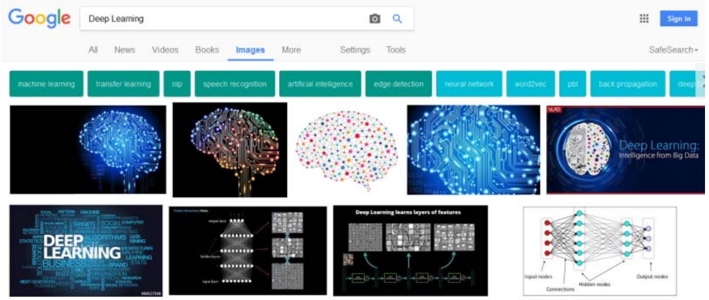
Several applications of Similarity Measures exists in today's world:



- Recognizing handwriting in checks.



- Automatic detection of faces in a camera image.



- Search Engines, such as Google, matching a **query** (could be text, image, etc.) with a set of **indexed documents** on the web.

Image Source: Google, PyImageSearch

Notion of a Metric

- A **Metric** is a function that quantifies a "distance" between every pair of elements in a set, thus inducing a measure of similarity.
- A metric f(x,y) must satisfy the following properties for all x, y, z belonging to the set:
  - *Non-negativity*: $f(x, y) \geq 0$
  - *Identity of Discernible*: $f(x, y) = 0 \iff x = y$
  - *Symmetry*: $f(x, y) = f(y, x)$
  - *Triangle Inequality*: $f(x, z) \leq f(x, y) + f(y, z)$

Types of Metrics

In broad strokes metrics are of two kinds:

- **Pre-defined Metrics**: Metrics which are fully specified without the knowledge of data.

  E.g. Euclidian Distance: $f(\mathbf{x}, \mathbf{y}) = (\mathbf{x} - \mathbf{y})^T(\mathbf{x} - \mathbf{y})$

- **Learned Metrics**: Metrics which can only be defined with the **knowledge** of the **data**.

  E.g. Mahalanobis Distance: $f(\mathbf{x}, \mathbf{y}) = (\mathbf{x} - \mathbf{y})^T\mathbf{M}(\mathbf{x} - \mathbf{y})$; where **M** is a matrix that is estimated from the data.

  Learned Metrics are of two types:

  - **Unsupervised** : Use unlabeled data
  - **Supervised** : Use labeled data

UNSUPERVISED METRIC LEARNING

Mahalanobis Distance

- Mahalanobis Distance weighs the Euclidian distance between two points, by the standard deviation of the data.
  - $f(\mathbf{x}, \mathbf{y}) = (\mathbf{x} - \mathbf{y})^T \Sigma^{-1} (\mathbf{x} - \mathbf{y})$; where Σ is the mean-subtracted covariance matrix of all data points.

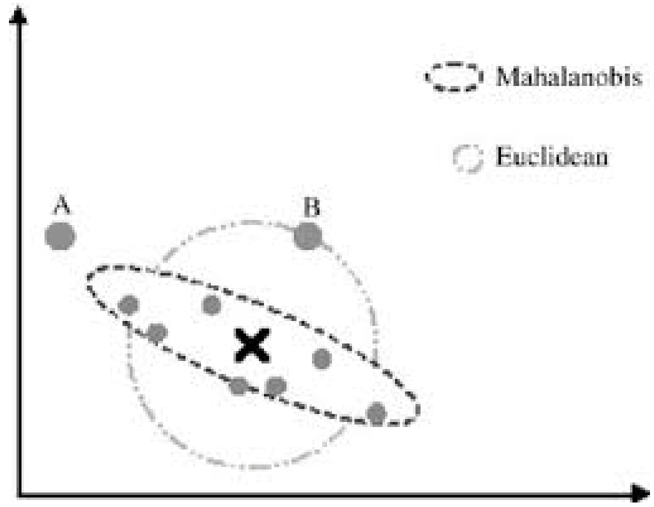


Image Source: Google

Chandra, M.P., 1936. On the generalised distance in statistics. In *Proceedings of the National Institute of Sciences of India* (Vol. 2, No. 1, pp. 49-55).

SUPERVISED METRIC LEARNING

Supervised Metric Learning

- In this setting, we have access to **labeled** data samples (z = {x, y}).
- The typical strategy is to use a 2-step procedure:
  - Apply some **supervised** domain transform.
  - Then use one of the unsupervised metrics for performing the mapping.

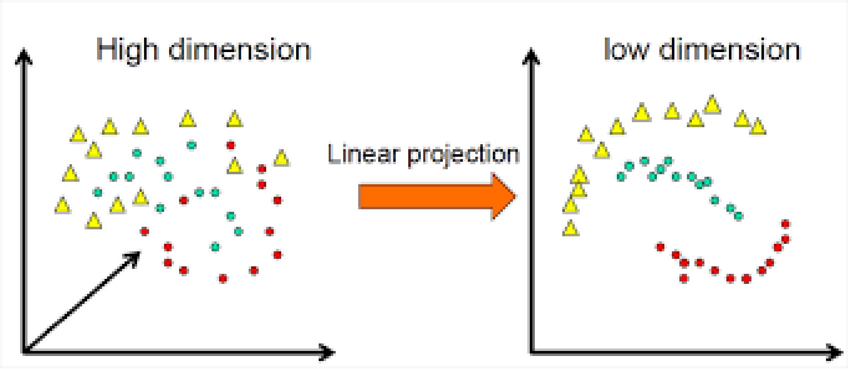


Image Source: Google

Bellet, A., Habrard, A. and Sebban, M., 2013. A survey on metric learning for feature vectors and structured data. *arXiv preprint arXiv:1306.6709*.

Linear Discriminant Analysis (LDA)

- In Fisher-LDA, the goal is to project the data to a space such that the ratio of "**between class covariance**" to "**within class covariance**" is maximized.
- This is given by: $J(w) = \max_w (w^T S_B w)/(w^T S_W w)$

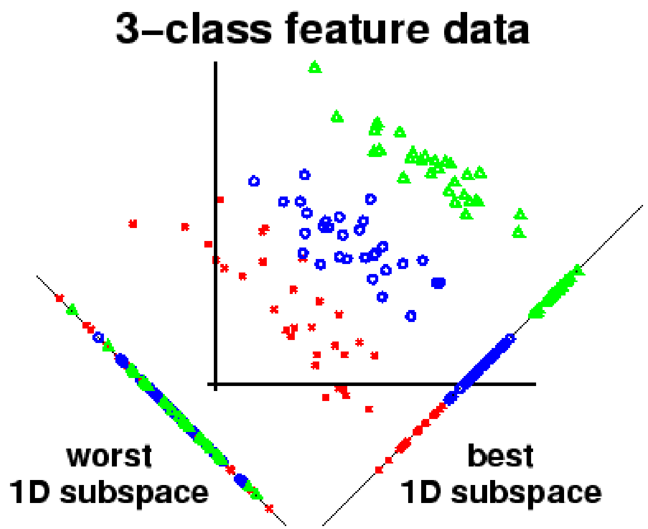


Image Source: Google

Fisher, R.A., 1936. The use of multiple measurements in taxonomic problems. *Annals of eugenics*, *7*(2), pp.179-188.

TRADITIONAL MATCHING TECHNIQUES

Traditional Approaches for Matching

The traditional approach for matching images, relies on the following pipeline:

1. **Extract Features**: For instance, color histograms of the input images.
2. **Learn Similarity**: Use L_1-norm on the features.

Stricker, M.A. and Orengo, M., 1995, March. Similarity of color images. In *IS&T/SPIE's Symposium on Electronic Imaging: Science & Technology* (pp. 381-392). International Society for Optics and Photonics.

Challenges with Traditional Methods for Matching

The principal shortcoming of traditional metric learning based methods is that the **feature representation** of the data and the **metric** are **not learned jointly**.

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- Metric Learning as a measure of Similarity
- Traditional Approaches for Similarity Learning
- Challenges with Traditional Similarity Measures
- **Deep Learning as a Potential Solution**
  - **Siamese Networks**
    - **Architectures**
    - **Loss Function**
    - **Training Techniques**
- Application of Siamese Network to different tasks

Deep Learning to the Rescue!

CNNs can **jointly optimize** the representation of the input data conditioned on the "similarity" measure being used, aka end-to-end learning.

Image Source: Google

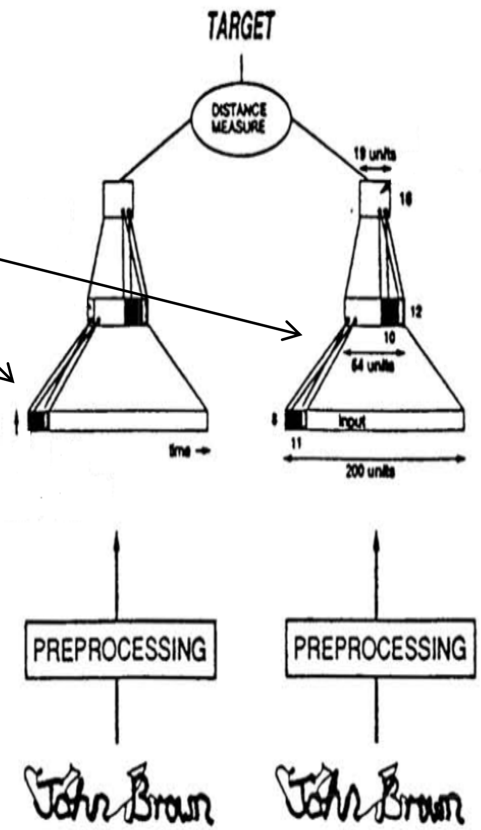
Revisit the Problem

- **Input**: Given a pair of input images, we want to know how “similar” they are to each other.
- **Output**: The output can take a variety of forms:
  - Either a binary label, i.e. 0 (same) or 1 (different).
  - A **Real** number indicating how similar a pair of images are.

Typical Siamese CNN

- **Input**: A pair of input signatures.
- **Output (Target)**: A label, 0 for **similar, 1 else**.

Share Weights



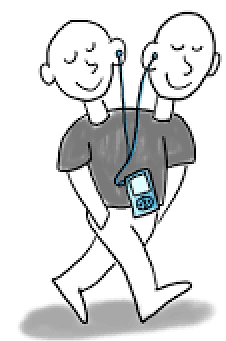
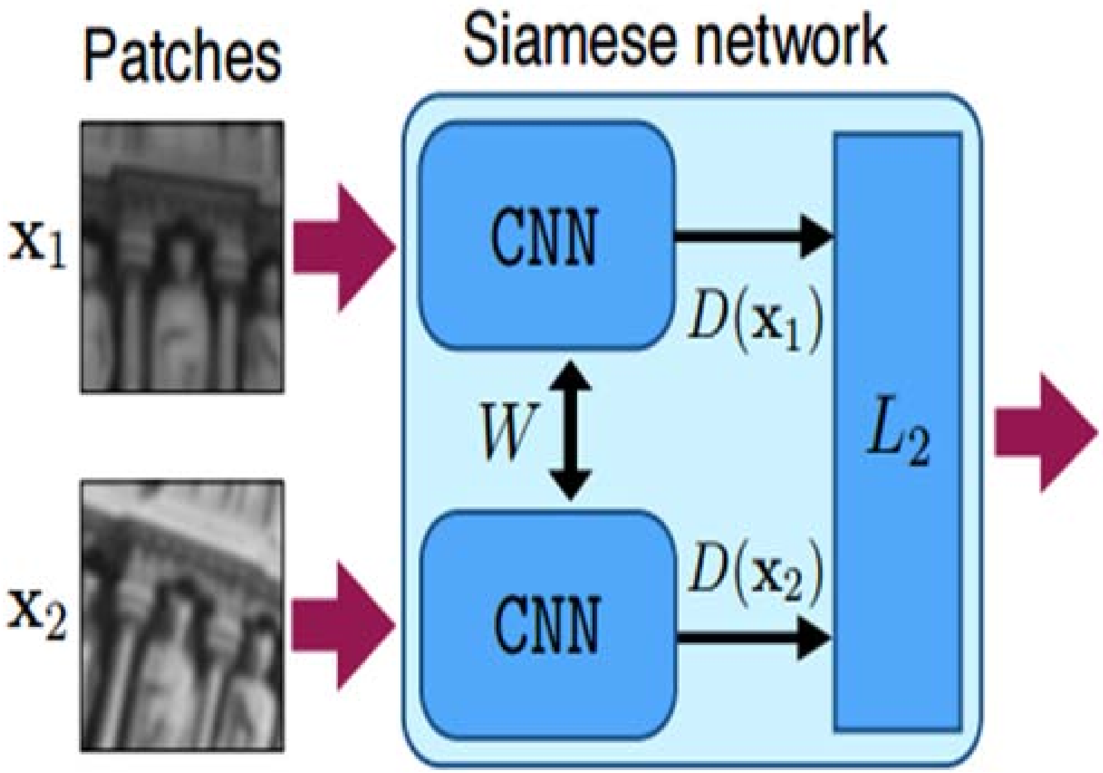


Image Source: Google

Bromley, J., Bentz, J.W., Bottou, L., Guyon, I., LeCun, Y., Moore, C., Säckinger, E. and Shah, R., 1993. Signature Verification Using A "Siamese" Time Delay Neural Network. *IJPRAI*, *7*(4), pp.669-688.

SIAMESE CNN - ARCHITECTURE

Standard architecture of Siamese CNN

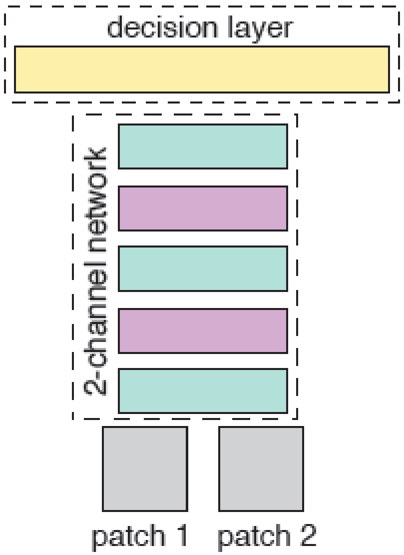


$||D(x_1) - D(x_2)||_2$

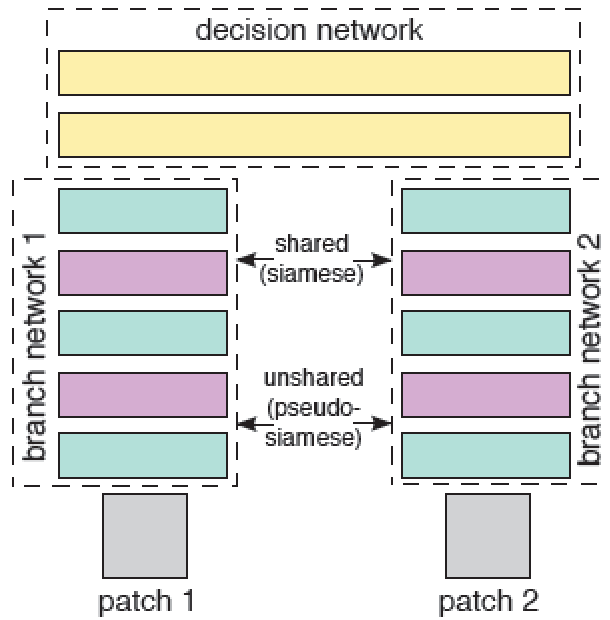
Simo-Serra, E., Trulls, E., Ferraz, L., Kokkinos, I., Fua, P. and Moreno-Noguer, F., 2015. Discriminative learning of deep convolutional feature point descriptors. In *Proceedings of the IEEE International Conference on Computer Vision* (pp. 118-126).

Popular Architecture Varieties

- No one “architecture” fits all!
- Design largely governed by what performs well empirically on the task at hand.



Inputs are merged right at the onset

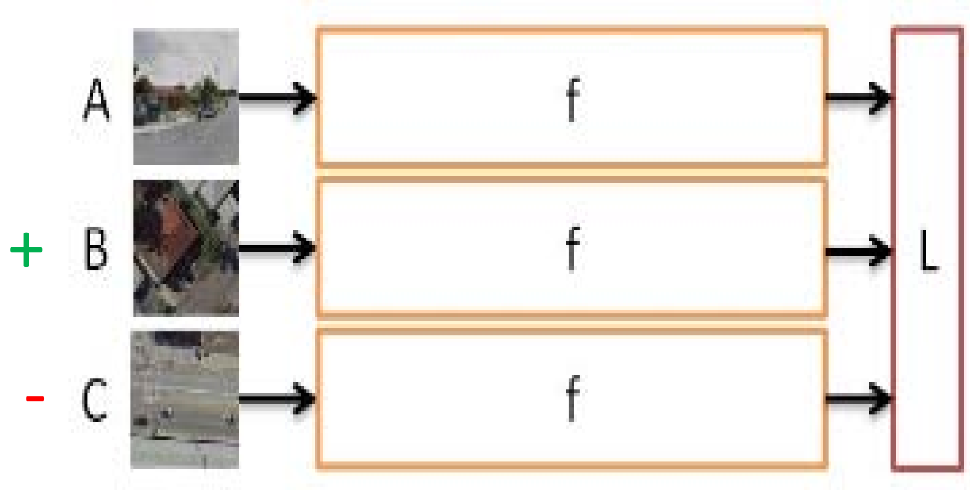


Inputs are first embedded independently, then merged.

Zagoruyko, S. and Komodakis, N., 2015. Learning to compare image patches via convolutional neural networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 4353-4361).

Siamese CNN – Variants

TRIPLET NETWORK



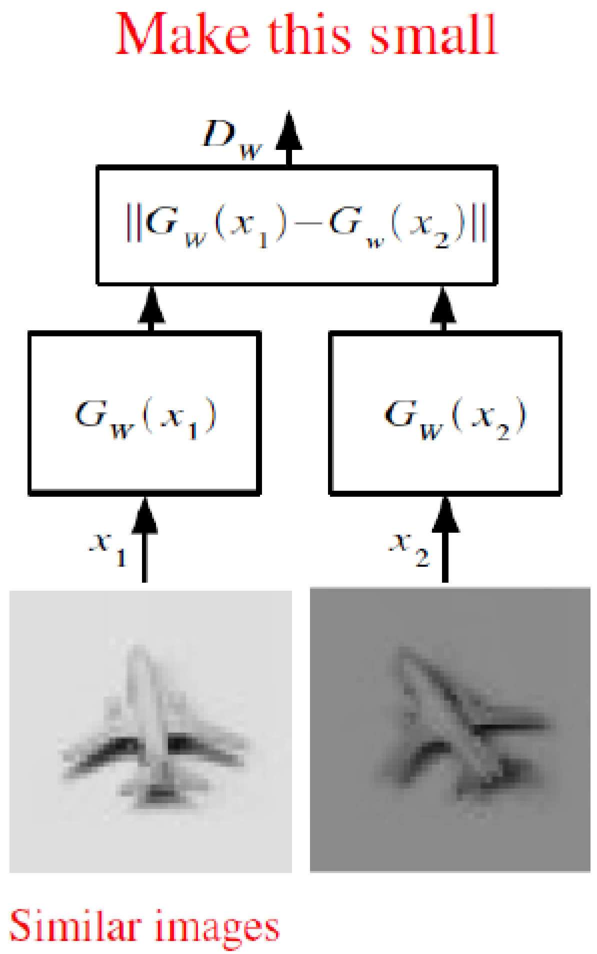
$\mathbf{D}(f(A), f(B)) < \mathbf{D}(f(A), f(C))$

- Compare triplets in one go.
- Check if the sample in the **topmost** channel, is more similar to the one in the middle or the one in the bottom.
- Allows us to learn ranking between samples.

Vo, N.N. and Hays, J., 2016, October. Localizing and orienting street views using overhead imagery. In European Conference on Computer Vision (pp. 494-509).

SIAMESE CNN – LOSS FUNCTION

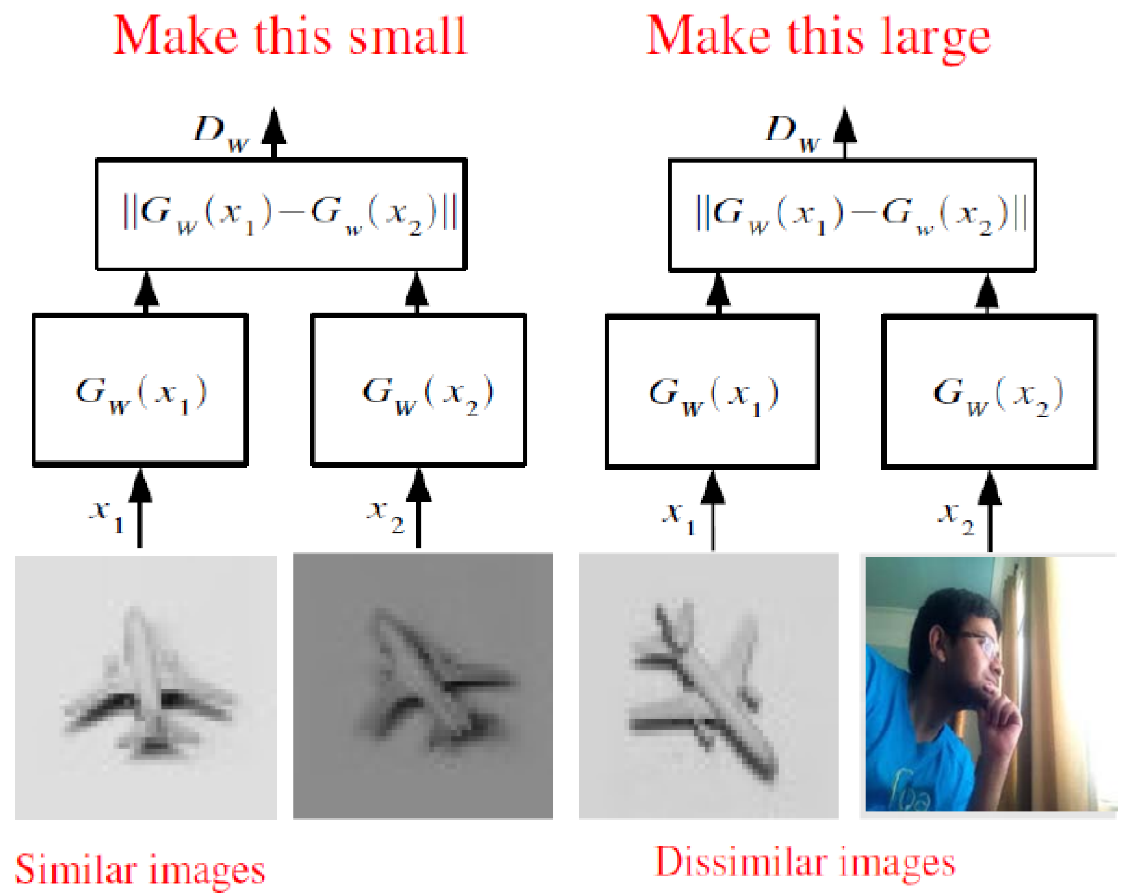
Siamese CNN – Loss Function



- **Is there a problem with this formulation?**
  - Yes.
  - The model could learn to embed every input to the same point, i.e. predict a **constant** as **output**.
  - In such a case, every pair of input would be categorized as a positive pair.

Chopra, S., Hadsell, R. and LeCun, Y., 2005, June. Learning a similarity metric discriminatively, with application to face verification. In *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on* (Vol. 1, pp. 539-546). IEEE.

Siamese CNN – Loss Function



The final loss is defined as :

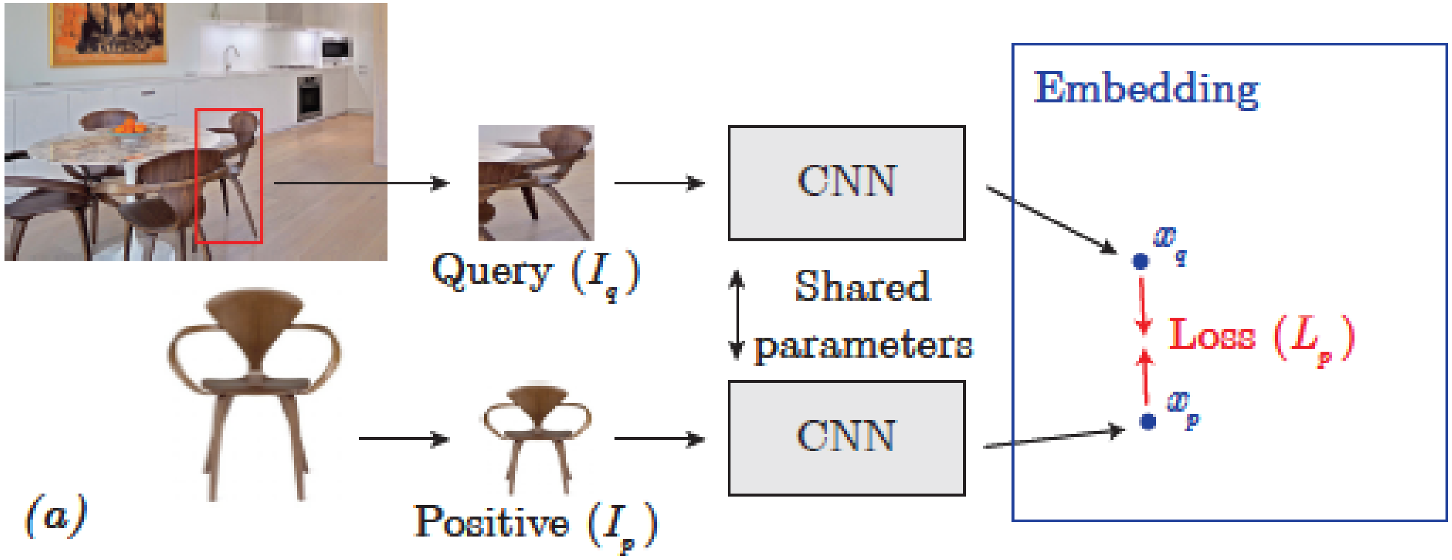
L = ∑loss of positive pairs + ∑ loss of negative pairs

Chopra, S., Hadsell, R. and LeCun, Y., 2005, June. Learning a similarity metric discriminatively, with application to face verification. In *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on* (Vol. 1, pp. 539-546). IEEE.

Siamese CNN – Loss Function

We can use different loss functions for the two types of input pairs.

- Typical positive pair (x_p, x_q) loss: $L(x_p, x_q) = ||x_p - x_q||^2$
  (Euclidian Loss)

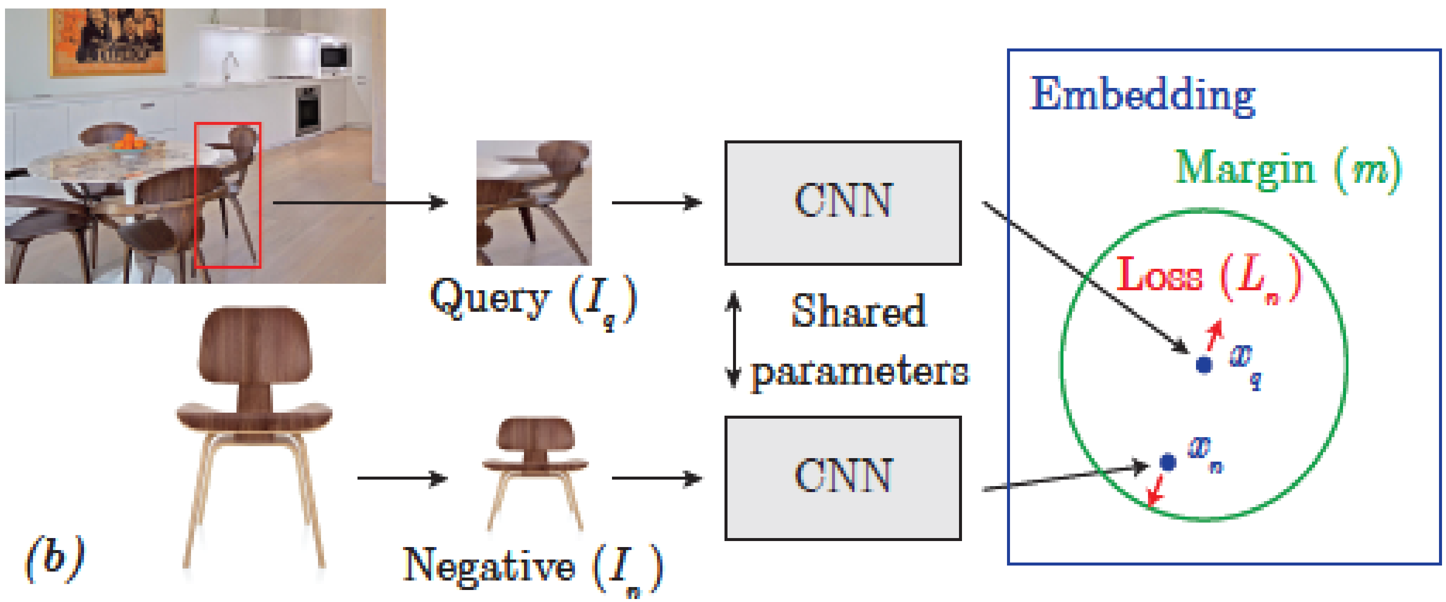


Bell, S. and Bala, K., 2015. Learning visual similarity for product design with convolutional neural networks. *ACM Transactions on Graphics (TOG)*, *34*(4), p.98.

Siamese CNN – Loss Function

- Typical negative pair (x_n, x_q) loss :

$$L(x_n, x_q) = \max(0, m^2 - ||x_n - x_q||^2) \text{ (Hinge Loss)}$$



Bell, S. and Bala, K., 2015. Learning visual similarity for product design with convolutional neural networks. *ACM Transactions on Graphics (TOG)*, *34*(4), p.98.

Choices of Loss Function

- Several choices for the Loss Functions are available. Choice depends on the task at hand.
- Loss Functions for **2-Stream Networks**:
  - **Margin Based:**
    - Contrastive Loss: Loss(x_p, x_q, y) =

      $y * ||x_p - x_q||^2 + (1 - y) * \max(0, m^2 - ||x_p - x_q||^2)$
      - Allows us to learn a margin of separation.
      - Extensible for Triplet Networks
  - **Non-Margin Based:**
    - Distance-Based Logistic Loss:

      $P(x_p, x_q) = (1 + \exp(-m)) / (1 + \exp(||x_p - x_q|| - m))$

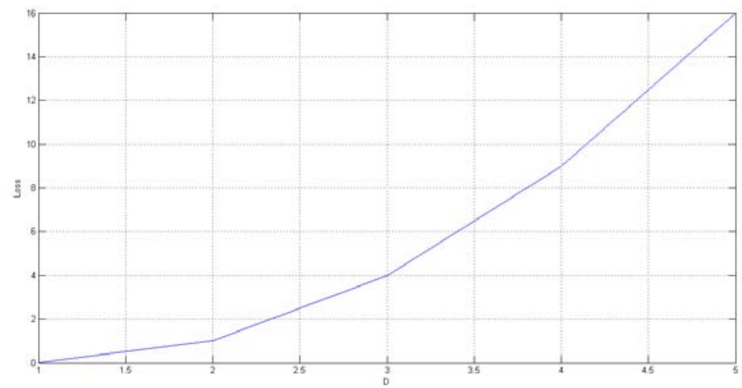
      $\text{Loss}(x_p, x_q, y) = \text{LogLoss}(P(x_p, x_q), y)$
      - Good for quicker convergence.

Choices of Loss Function

- Contrastive Loss:

For similar samples:

$\text{Loss}(x_p, x_q) = ||x_p - x_q||^2$

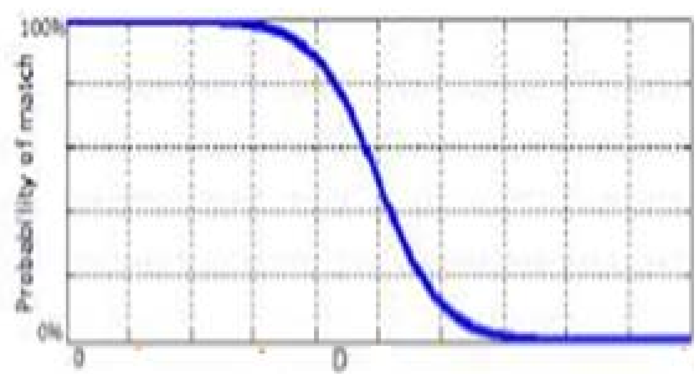


- Distance-Based Logistic Loss:

For similar pairs

$P(x_p, x_q) = (1 + \exp(-m)) / (1 + \exp(||x_p - x_q|| - m))$ -> 1 quickly

$\text{Loss}(x_p, x_q, y) = \text{LogLoss}(P(x_p, x_q), y)$

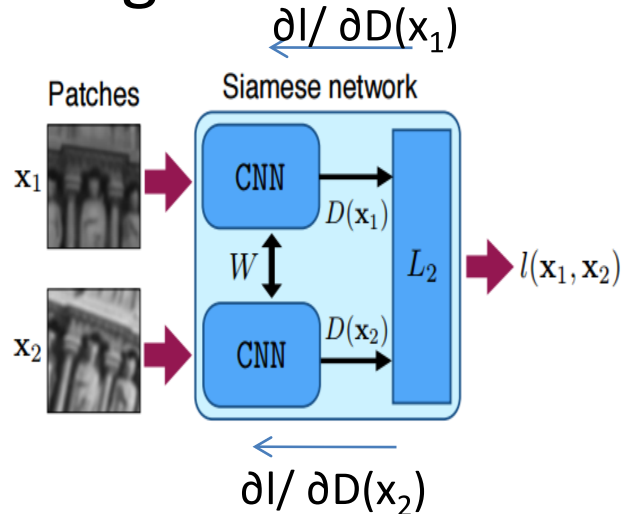


Vo, N.N. and Hays, J., 2016, October. Localizing and orienting street views using overhead imagery. In European Conference on Computer Vision (pp. 494-509).

SIAMESE CNN – TRAINING

Siamese CNN – Training

- Update each of the two streams independently and then average the weights.



- Does this technique remind us of anything?
  - Training in RNNs.
- Data augmentation may be used for more effective training.
  - Typically we hallucinate more examples by performing random crops, image flipping, etc.

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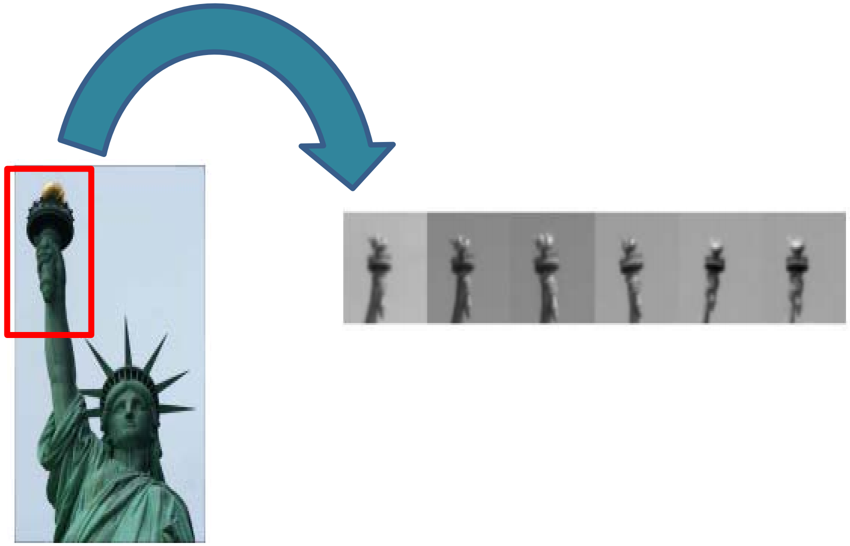
- **Application of Siamese Network to different tasks**
  - **Generating invariant and robust descriptors**
  - **Person Re-Identification**
  - **Rendering a street from Different Viewpoints**
  - **Newer nets for Person Re-Id, Viewpoint Invariance and Multimodal Data.**
  - **Use of Siamese Networks for Sentence Matching**

APPLICATIONS

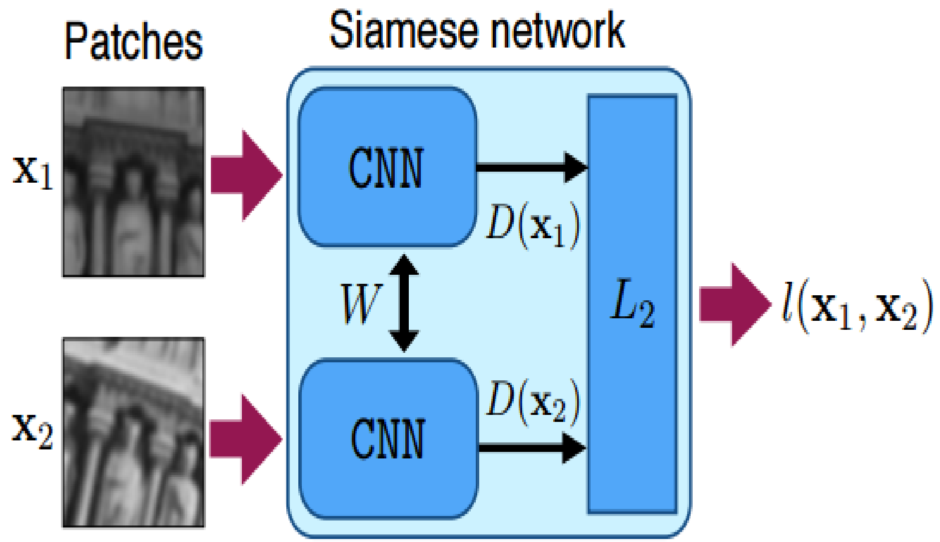
Discriminative Descriptors for Local Patches



Learn a discriminative representation of patches from different views of 3D points

Simo-Serra, E., Trulls, E., Ferraz, L., Kokkinos, I., Fua, P. and Moreno-Noguer, F., 2015. Discriminative learning of deep convolutional feature point descriptors. In *Proceedings of the IEEE International Conference on Computer Vision* (pp. 118-126).

Deep Descriptor



$$l(x_1, x_2) = \begin{cases} \|D(x_1) - D(x_2)\|_2, & p_1 = p_2 \\ \max\left(0, C - \|D(x_1) - D(x_2)\|_2\right), & p_1 \neq p_2 \end{cases}$$

Use the CNN outputs of our Siamese networks as descriptor

Simo-Serra, E., Trulls, E., Ferraz, L., Kokkinos, I., Fua, P. and Moreno-Noguer, F., 2015. Discriminative learning of deep convolutional feature point descriptors. In *Proceedings of the IEEE International Conference on Computer Vision* (pp. 118-126).

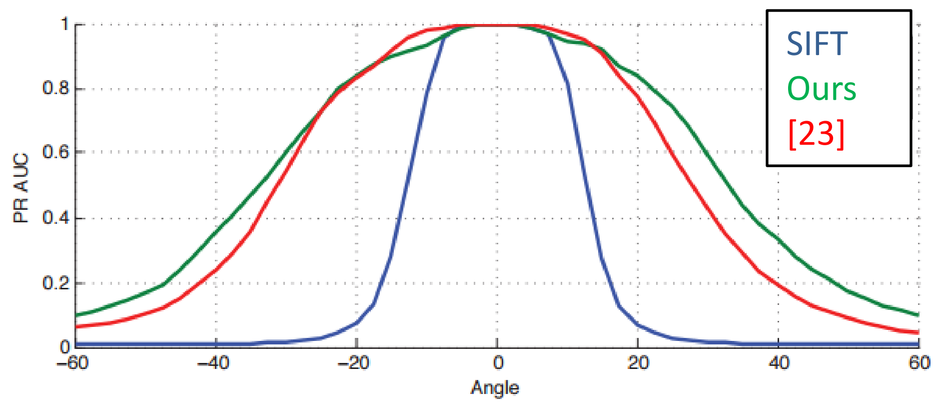
Evaluation

Comparison of area under precision-recall curve

Dataset	SIFT (Non-deep)	[23](Non-deep)	Ours
ND	0.346	0.663	**0.667**
TO	0.425	**0.709**	0.545
LY	0.226	0.558	**0.608**
All	0.370	0.693	**0.756**

SIFT: hand-crafted features
[23]: descriptor via convex optimization

Robustness to Rotation



Simo-Serra, E., Trulls, E., Ferraz, L., Kokkinos, I., Fua, P. and Moreno-Noguer, F., 2015. Discriminative learning of deep convolutional feature point descriptors. In *Proceedings of the IEEE International Conference on Computer Vision* (pp. 118-126).

Person Re-Identification

CUHK03 Dataset

Quick Test

Are they the same person?

Ahmed, E., Jones, M. and Marks, T.K., 2015. An improved deep learning architecture for person re-identification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 3908-3916).

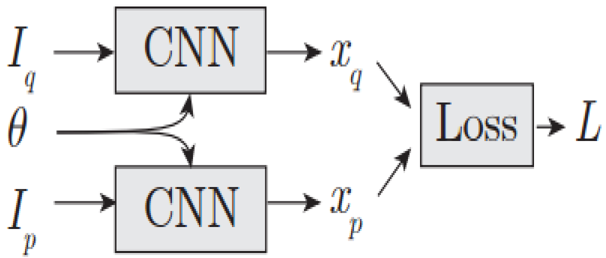
Person Re-Identification

True positive

True negative

Ahmed, E., Jones, M. and Marks, T.K., 2015. An improved deep learning architecture for person re-identification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 3908-3916).

Proposed Architecture



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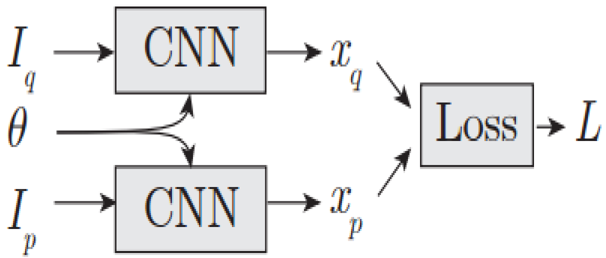

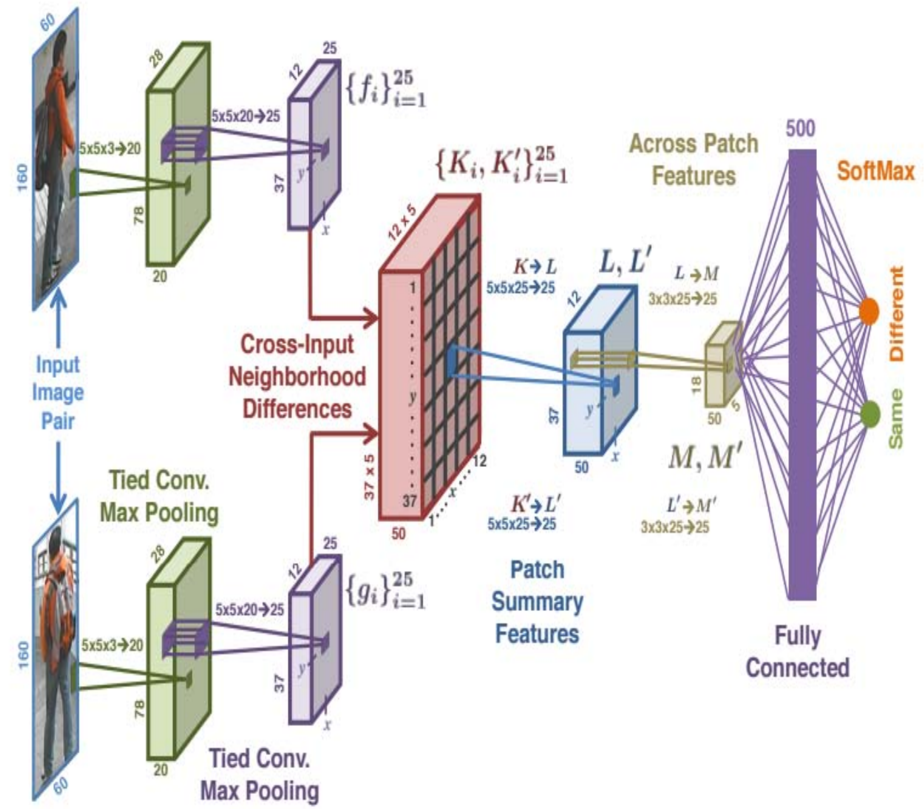

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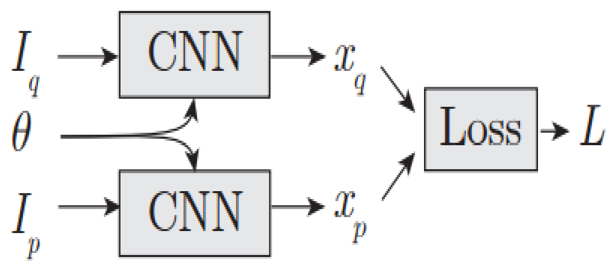

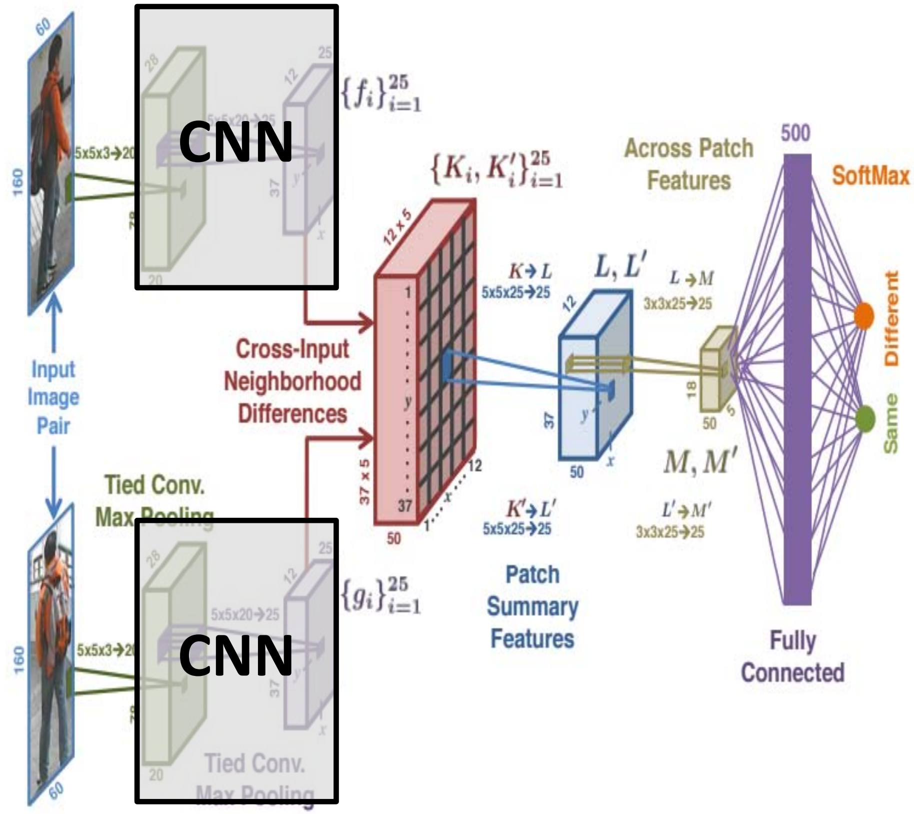

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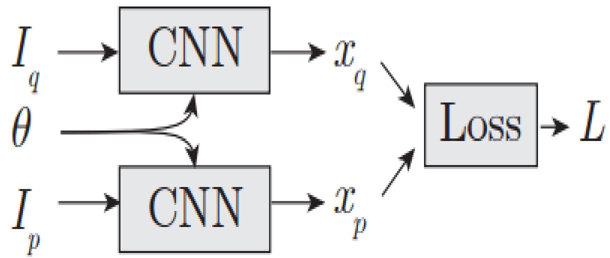

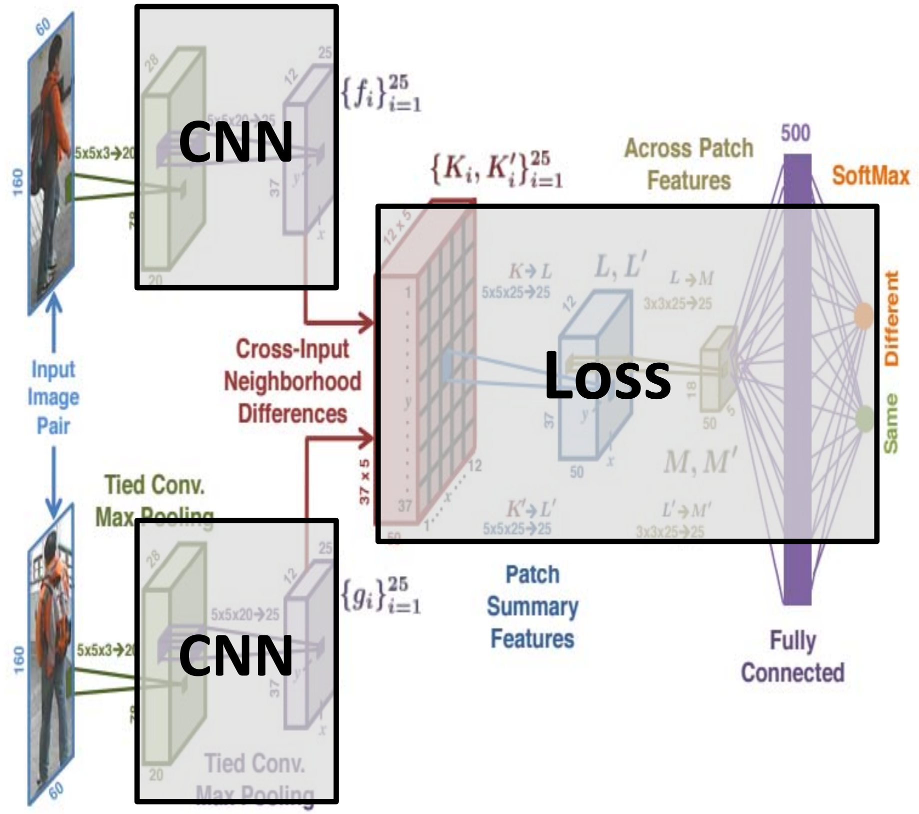

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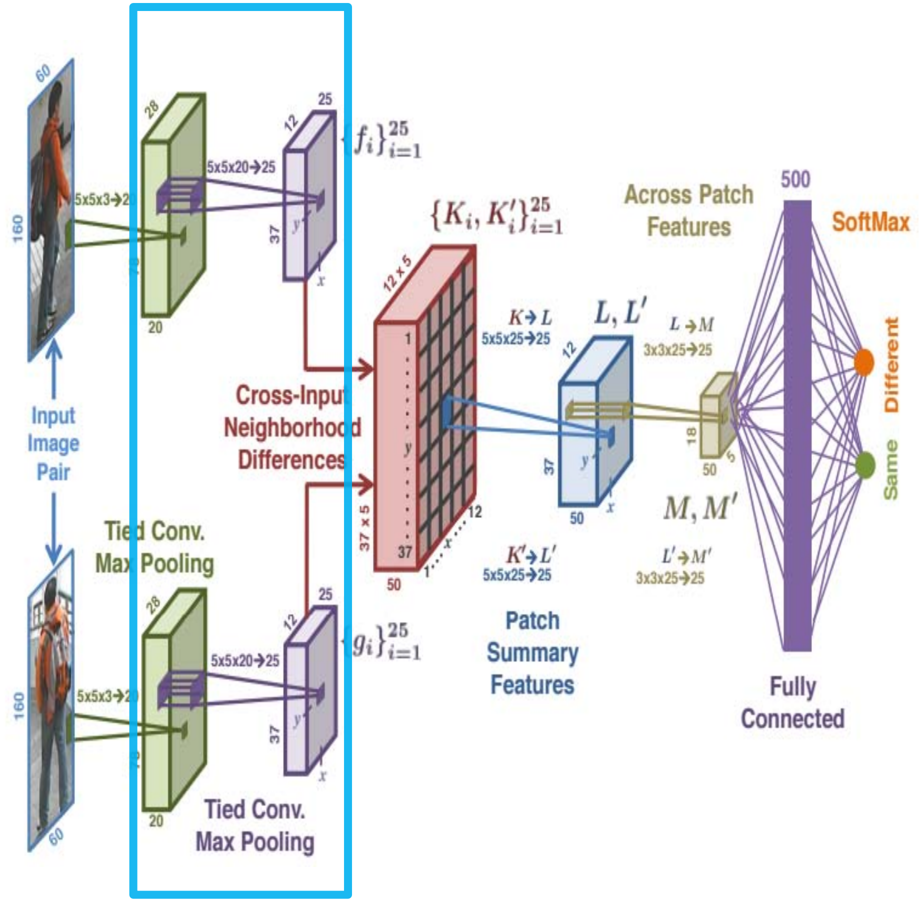
Tied Convolution

- Use convolutional layers to compute higher-order features
- Shared weights



Ahmed, E., Jones, M. and Marks, T.K., 2015. An improved deep learning architecture for person re-identification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 3908-3916).

Cross-Input Neighborhood Differences

- Compute *neighborhood difference* of two feature maps, instead of elementwise difference.

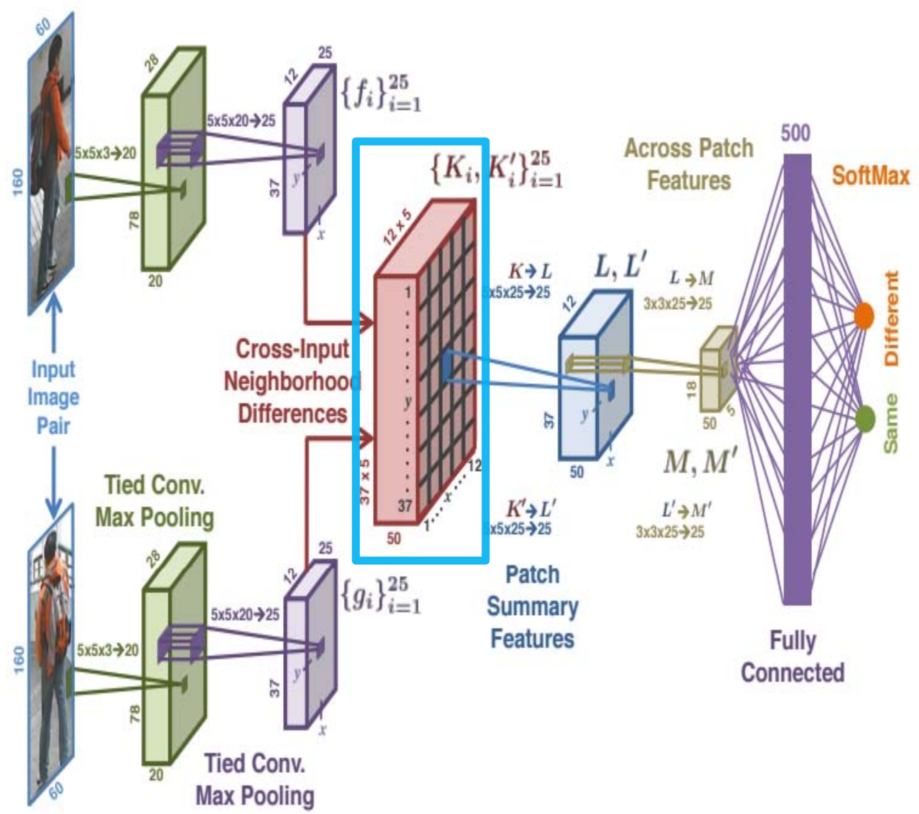
Example: f, g are feature maps of two input images

f

5	7	2
1	4	2
3	4	4

g

1	4	1
2	3	5
1	2	3



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Example: f, g are feature maps of two input images

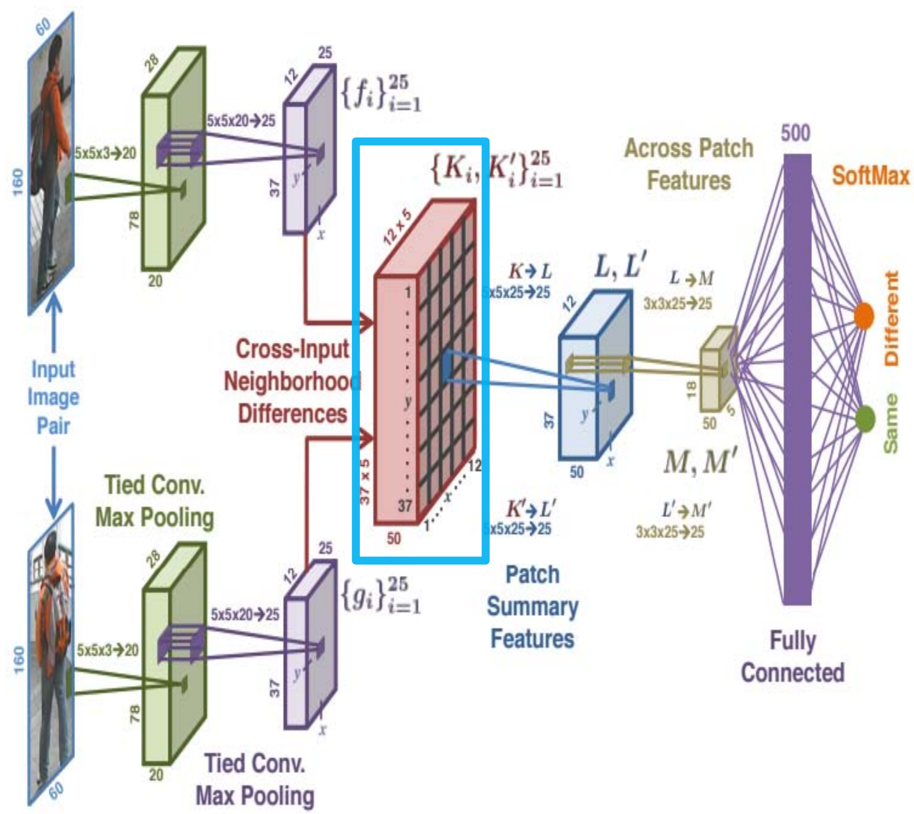
f

5	7	2
1	4	2
3	4	4

g

1	4	1
2	3	5
1	2	3

$$K(1,1) = \begin{bmatrix} 5 & 5 \\ 5 & 5 \end{bmatrix} - \begin{bmatrix} 1 & 4 \\ 2 & 3 \end{bmatrix} = \begin{bmatrix} 4 & 4 \\ 3 & 2 \end{bmatrix}$$



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Cross-Input Neighborhood Differences

- Compute *neighborhood difference* of two feature maps, instead of elementwise difference.

- A neighborhood-patch size of 5 was used in the paper:

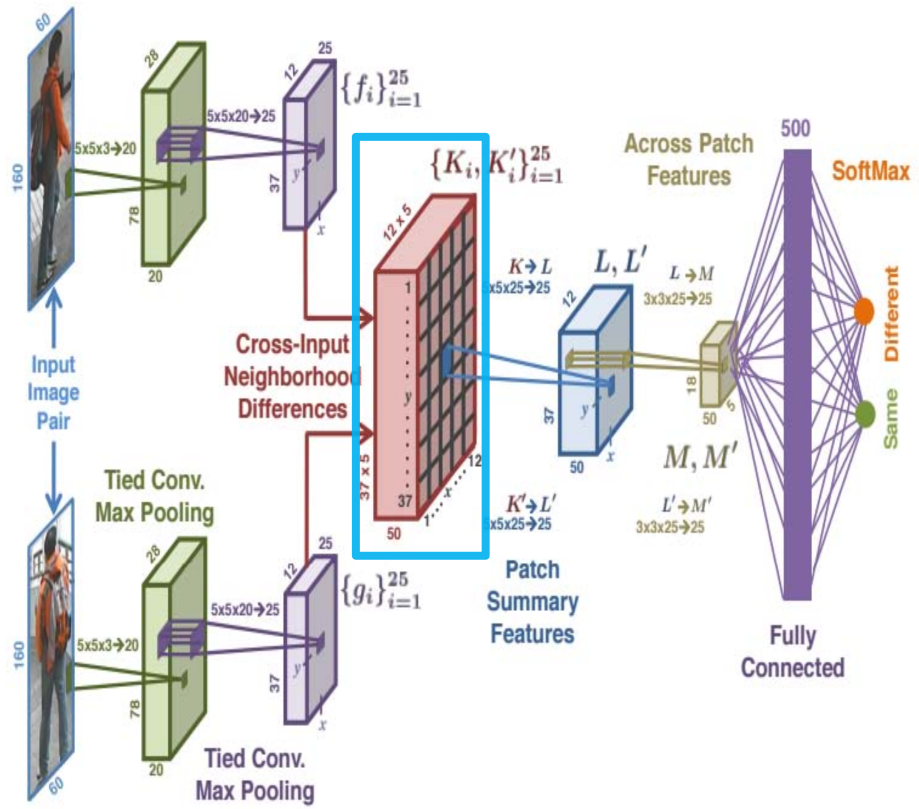
$$K_i(x,y)=f_i(x,y)I(5,5)-N[g_i(x,y)]$$

where

$I(5,5)$ is a 5x5 matrix of 1s,

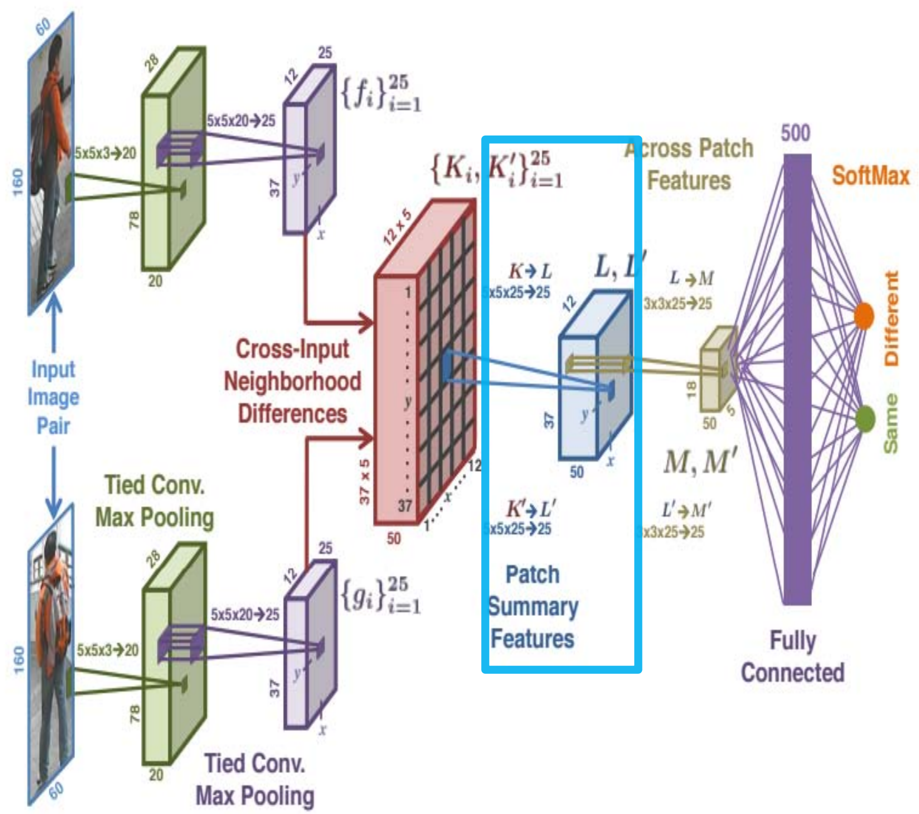
$N[g_i(x,y)]$ is the 5x5 neighborhood of g_i centered at (x,y)

- Another neighborhood difference map *K’* was also computed where *f* and *g* were revised.



Patch Summary Features

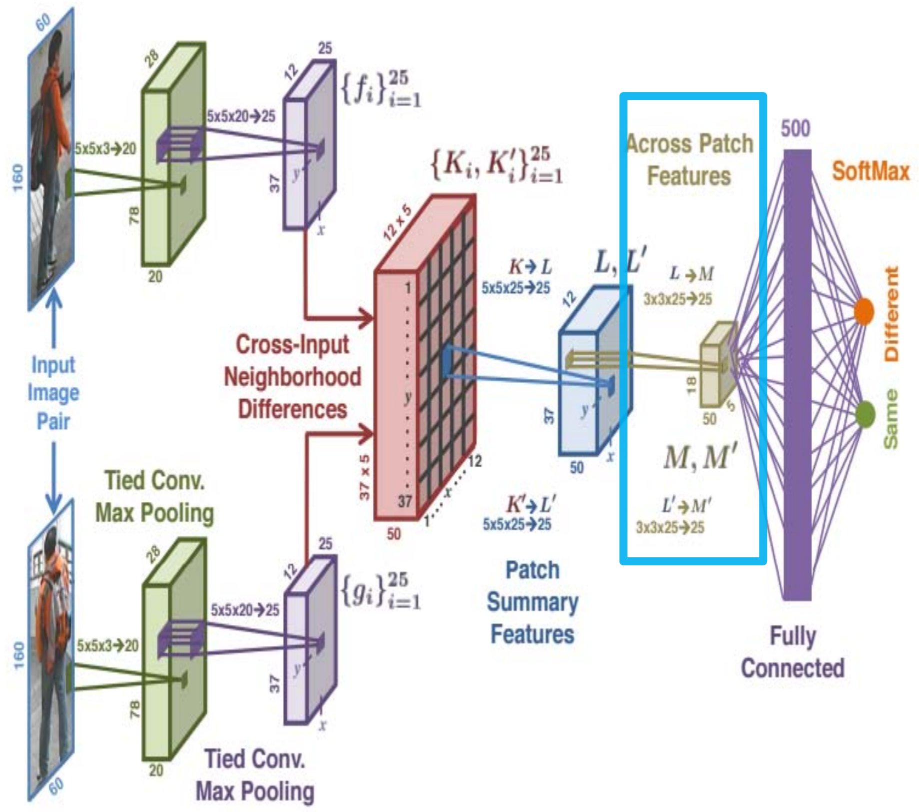
- Convolutional layers with 5x5 filters and stride 5 (the size of neighborhood patch).
- Provides a high-level summary of the cross-input differences in a neighborhood patch.



Ahmed, E., Jones, M. and Marks, T.K., 2015. An improved deep learning architecture for person re-identification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 3908-3916).

Across-Patch Features

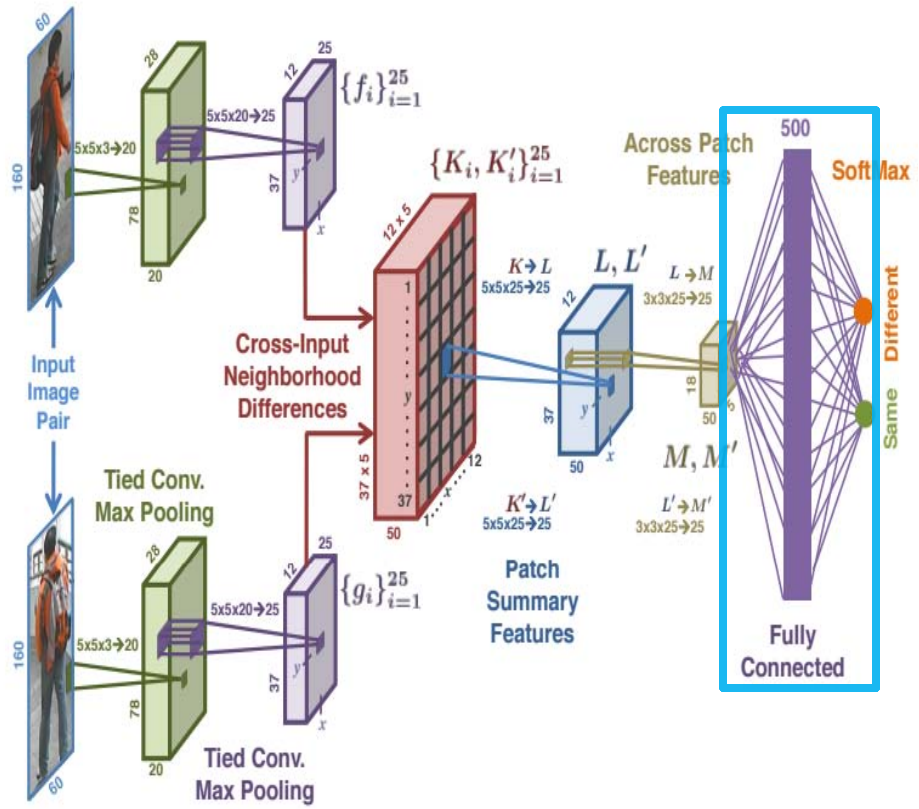
- Convolutional layers with 3x3 filters and stride 1.
- Learn spatial relationships across neighborhood differences



Ahmed, E., Jones, M. and Marks, T.K., 2015. An improved deep learning architecture for person re-identification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 3908-3916).

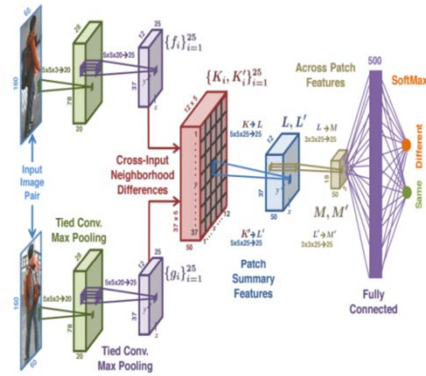
Across-Patch Features

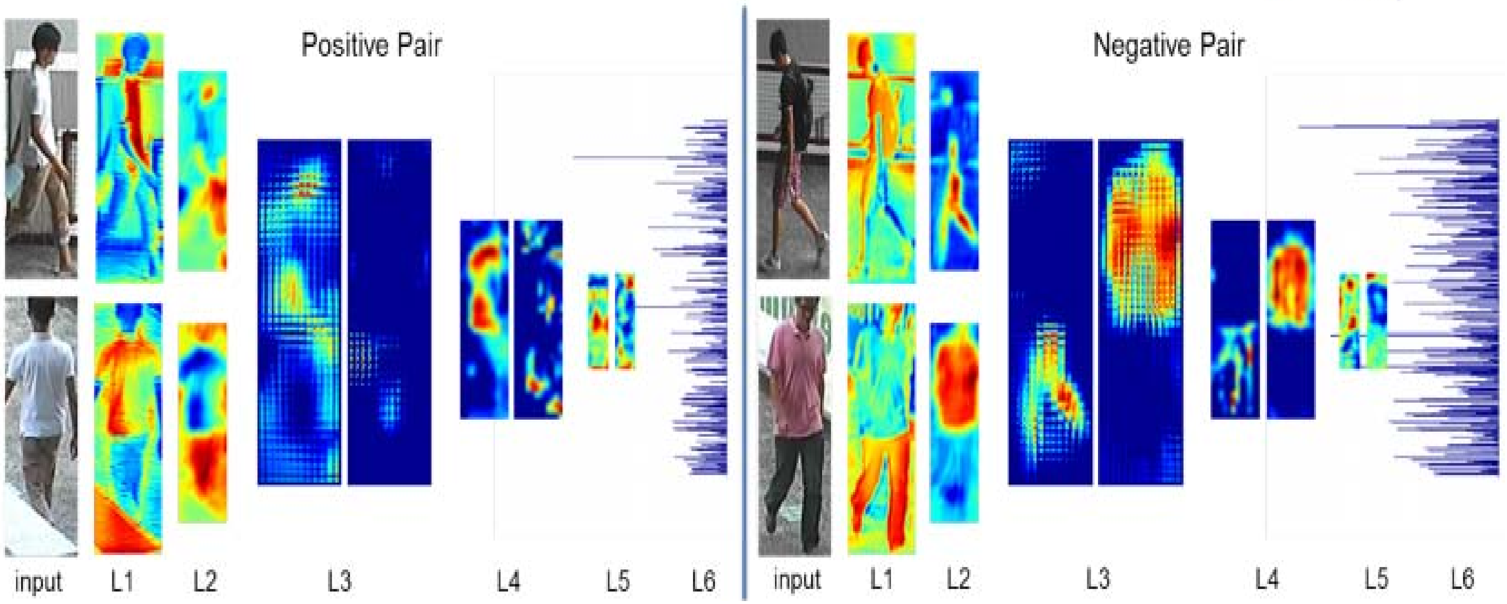
- Fully connected layer.
- Combine information from patches that are far from each other.
- Output: 2 softmax units



Ahmed, E., Jones, M. and Marks, T.K., 2015. An improved deep learning architecture for person re-identification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 3908-3916).

Visualization of Learned Features



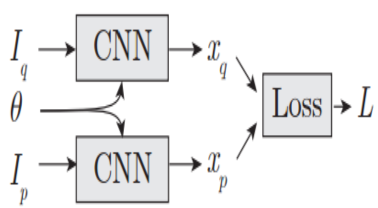


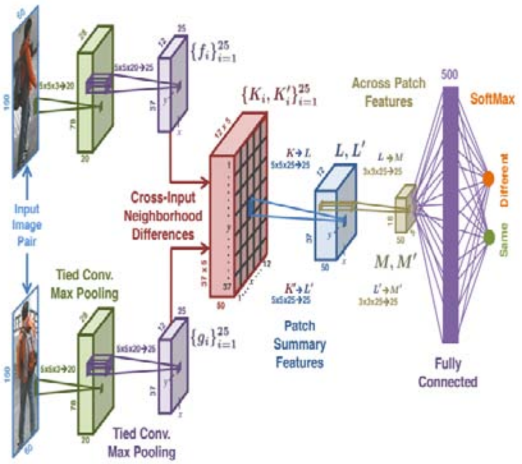
Ahmed, E., Jones, M. and Marks, T.K., 2015. An improved deep learning architecture for person re-identification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 3908-3916).

Evaluation

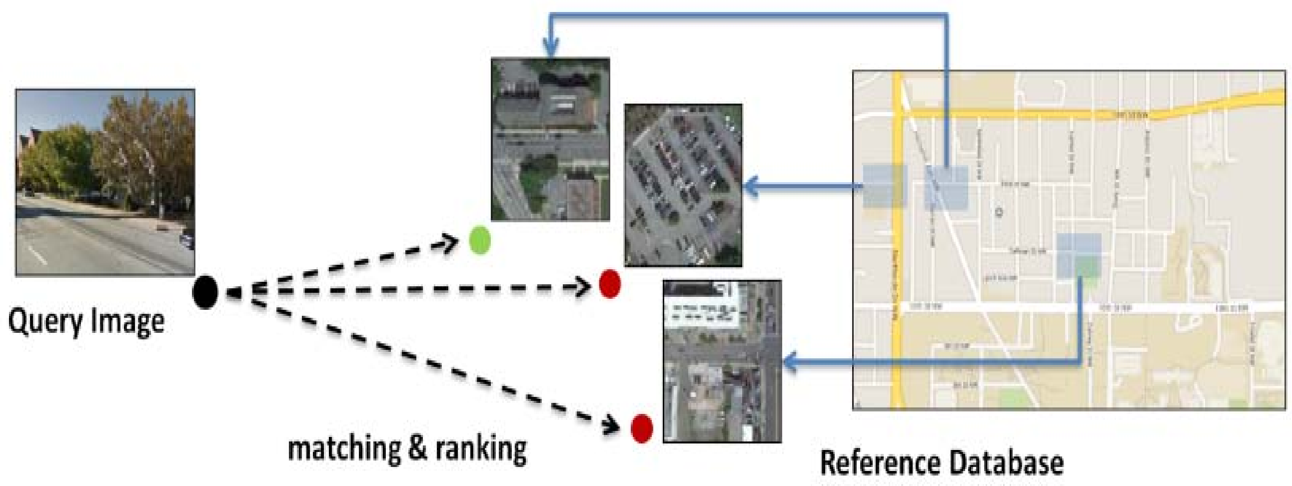
Method	Elementwise Difference	Neighborhood Difference
Identification rate	27.66%	54.74%

Method	Regular Siamese Network	This work
Identification rate	42.19%	54.74%





Street-View to Overhead-View Image Matching



Vo, N.N. and Hays, J., 2016, October. Localizing and orienting street views using overhead imagery. In European Conference on Computer Vision (pp. 494-509).

Street-View to Overhead-View Image Matching

Query:

Matching Image:

Vo, N.N. and Hays, J., 2016, October. Localizing and orienting street views using overhead imagery. In European Conference on Computer Vision (pp. 494-509).

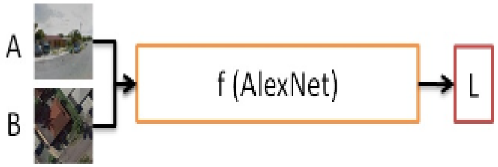
Quick Test

Which one is the correct match?

Vo, N.N. and Hays, J., 2016, October. Localizing and orienting street views using overhead imagery. In European Conference on Computer Vision (pp. 494-509).

CNN Architectures

Classification CNN:



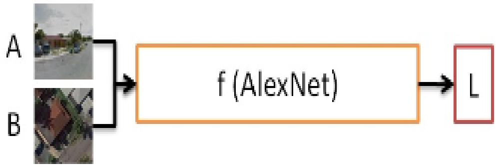
$$L(A, B, l) = LogLossSoftMax(f(I), l)$$

I = concatenation(A, B)
f = AlexNet
l = {0, 1}, label

Vo, N.N. and Hays, J., 2016, October. Localizing and orienting street views using overhead imagery. In European Conference on Computer Vision (pp. 494-509).

CNN Architectures

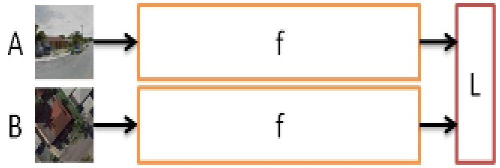
Classification CNN:



$$L(A, B, l) = LogLossSoftMax(f(I), l)$$

$I = concatenation(A, B)$
$f = AlexNet$
$l = \{0, 1\}$, *label*

Siamese-like CNN:



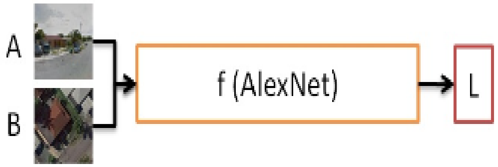
$$L(A, B, l) = l * D + (1 - l) * max(0, m - D)$$

$D = ||f(A) - f(B)||_2$
m = *margin parameter*

Vo, N.N. and Hays, J., 2016, October. Localizing and orienting street views using overhead imagery.
In European Conference on Computer Vision (pp. 494-509).

CNN Architectures

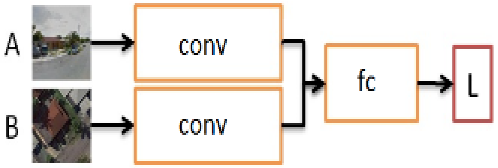
Classification CNN:



$$L(A, B, l) = LogLossSoftMax(f(I), l)$$

I = concatenation(A, B)
f = AlexNet
$l = \{0, 1\}$, label

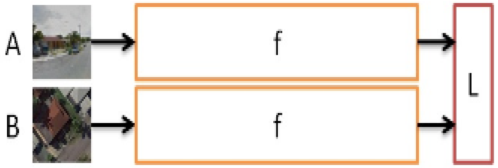
Siamese-classification hybrid network:



$$L(A, B, l) = LogLossSoftMax(f_{fc}(I_{conv}), l)$$

$I_{conv} = concatenation(f_{conv}(A), f_{conv}(B))$

Siamese-like CNN:



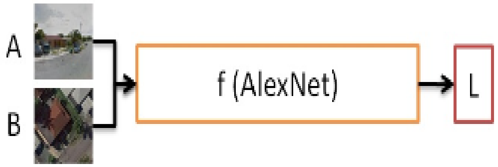
$$L(A, B, l) = l * D + (1- l) * max(0, m – D)$$

$D = ||f(A) – f(B)||_2$
m = margin parameter

Vo, N.N. and Hays, J., 2016, October. Localizing and orienting street views using overhead imagery.
In European Conference on Computer Vision (pp. 494-509).

CNN Architectures

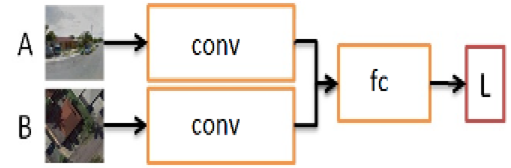
Classification CNN:



$$L(A, B, l) = LogLossSoftMax(f(I), l)$$

I = concatenation(A, B)
f = AlexNet
$l = \{0, 1\}$, label

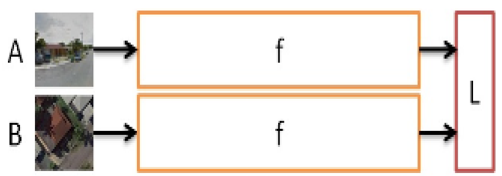
Siamese-classification hybrid network:



$$L(A, B, l) = LogLossSoftMax(f_{fc}(I_{conv}), l)$$

$I_{conv} = concatenation(f_{conv}(A), f_{conv}(B))$

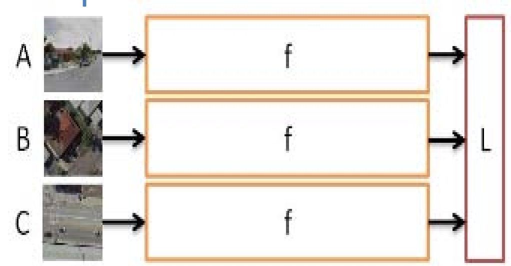
Siamese-like CNN:



$$L(A, B, l) = l * D + (1- l) * max(0, m - D)$$

$D = ||f(A) - f(B)||_2$
m = margin parameter

Triplet network CNN:



$$L(A, B, C) = max(0, m + D(A, B) - D(A, C))$$

(A, B) is a match pair
(A, C) is a non-match pair

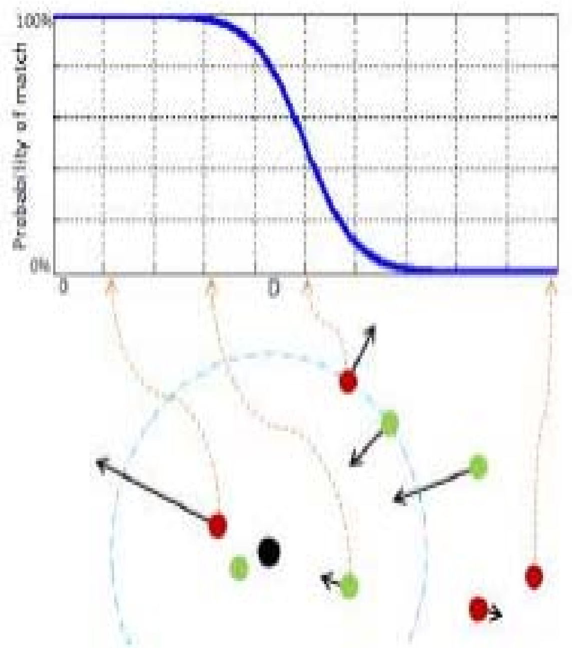
Vo, N.N. and Hays, J., 2016, October. Localizing and orienting street views using overhead imagery.
In European Conference on Computer Vision (pp. 494-509).

Distance-based Logistic Loss

$$p(A,B) = \frac{1 + exp(-m)}{1 + exp(D - m)}$$

$$L(A, B, l) = LogLoss\ (p(A, B), l)$$

where
$D = ||f(A) - f(B)||_2$
$m = margin\ parameter$



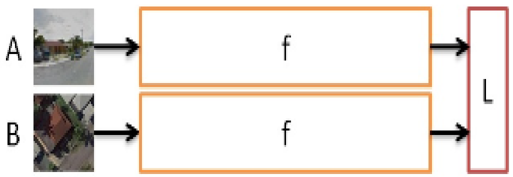
Matched/Nonmatched instances are pushed away from the "boundary" in the inward/outward direction.

Performance of Different Networks

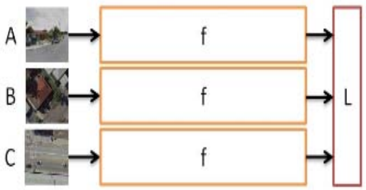
Matching accuracy

Test set	Denver	Detroit	Seattle
Siamese	85.6	83.2	82.9
Triplet	**88.8**	**86.8**	**86.4**

Siamese-like CNN:



Triplet network CNN:



Observation 1:

- Triplet network outperforms the Siamese by a large margin

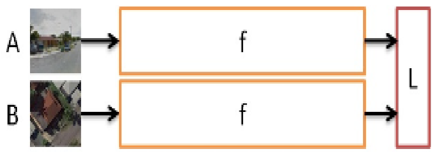
Vo, N.N. and Hays, J., 2016, October. Localizing and orienting street views using overhead imagery. In European Conference on Computer Vision (pp. 494-509).

Performance of Different Networks

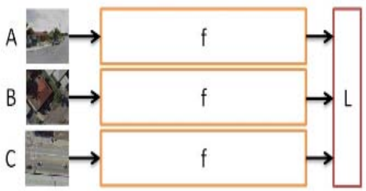
Matching accuracy

Test set	Denver	Detroit	Seattle
Siamese	85.6	83.2	82.9
Siamese-DBL	**90.0**	**88.0**	**88**
Triplet	88.8	86.8	86.4
Triplet-DBL	**90.2**	**88.4**	**87.6**

Siamese-like CNN:



Triplet network CNN:



Distance-based logistic (DBL) loss:

$$p(A,B) = \frac{1 + exp(-m)}{1 + exp(D - m)}$$

$$L(A, B, l) = LogLoss\,(p(A, B), l)$$

Observation 2:

- Distance-based logistic (DBL) Nets significantly outperform the original network.

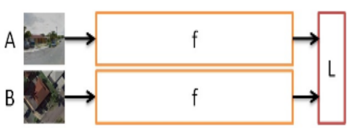
Vo, N.N. and Hays, J., 2016, October. Localizing and orienting street views using overhead imagery. In European Conference on Computer Vision (pp. 494-509).

Performance of Different Networks

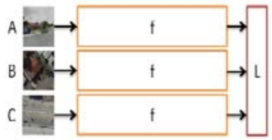
Matching accuracy

Test set	Denver	Detroit	Seattle
Siamese Net	85.6	83.2	82.9
Triplet Net	88.8	86.8	86.4
Classification Net	**90.0**	**87.8**	**87.7**
Hybrid Net	**91.5**	**88.7**	**89.4**

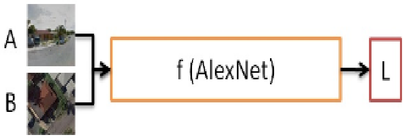
Siamese-like CNN:



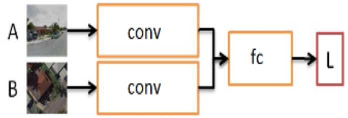
Triplet network CNN:



Classification CNN:



Classification-siamese hybrid:



Observation 3:

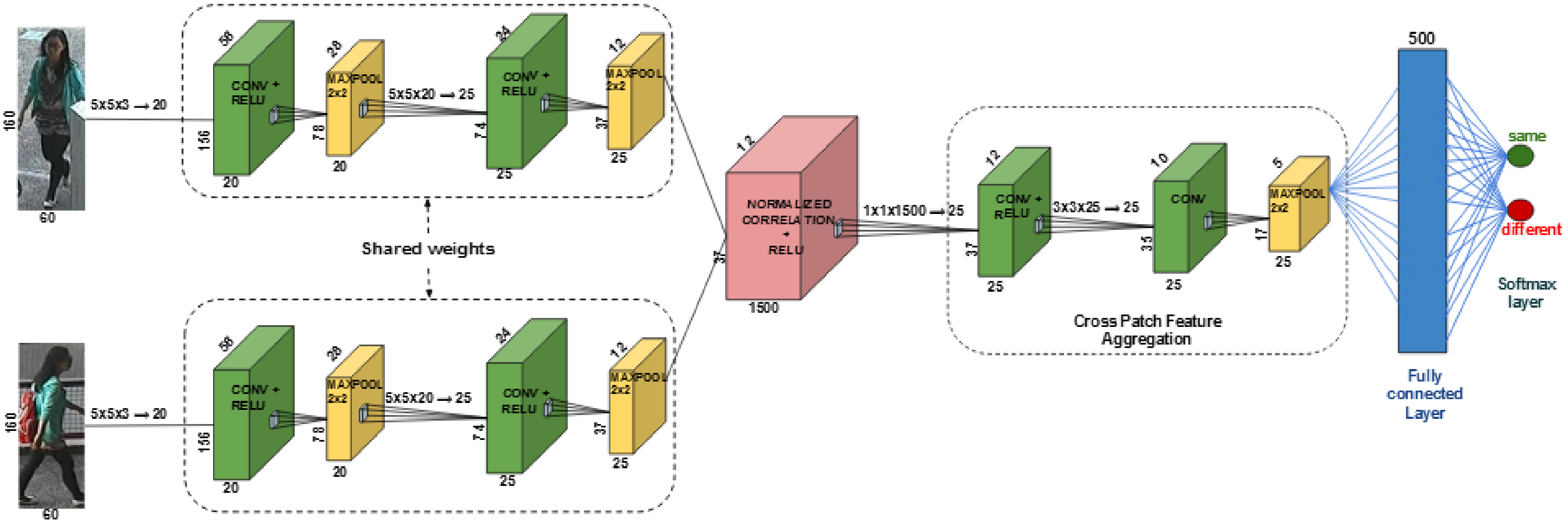
- Classification networks achieved better accuracy than Siamese and triplet networks.
- Jointly extract and exchange information from both input images.

Vo, N.N. and Hays, J., 2016, October. Localizing and orienting street views using overhead imagery. In European Conference on Computer Vision (pp. 494-509).

MORE VARIANTS OF SIAMESE CNNs

Siamese CNN – Variants

SIAMESE CNN – INTERMEDIATE MERGING



- Combining at an **intermediate stage** allows us to capture patch-level variability.
- Performing inexact (soft) matching yields superior performance. $\text{Match}(X, Y) = (X-\mu_X)(Y-\mu_Y)/\sigma_X\sigma_Y$

Subramaniam, A., Chatterjee, M. and Mittal, A., 2016. Deep Neural Networks with Inexact Matching for Person Re-Identification. In *Advances in Neural Information Processing Systems* (pp. 2667-2675).

Siamese CNN – Variants

SIAMESE CNN – INTERMEDIATE MERGING

Results:

- Handling Partial Occlusion:

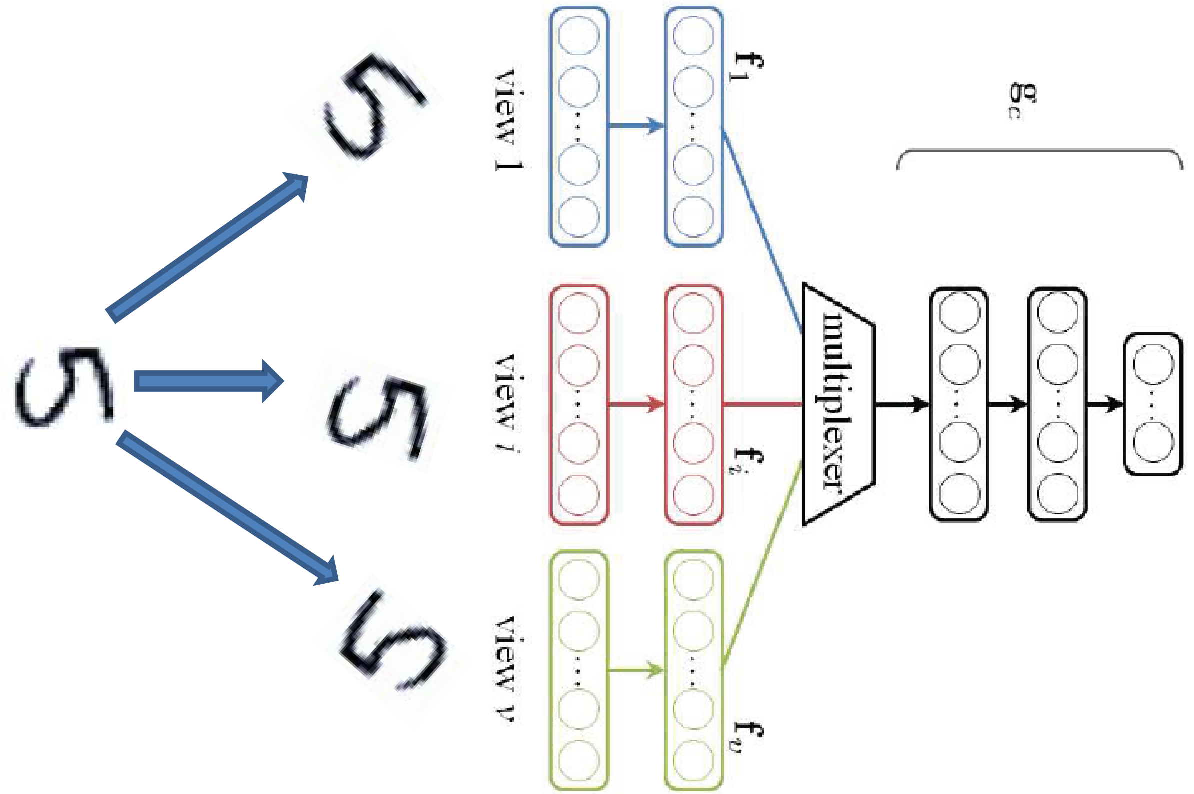
Baseline:

Proposed Method:

Subramaniam, A., Chatterjee, M. and Mittal, A., 2016. Deep Neural Networks with Inexact Matching for Person Re-Identification. In *Advances in Neural Information Processing Systems* (pp. 2667-2675).

Siamese CNN – Variants

SIAMESE CNN – FOR VIEWPOINT INVARIANCE



Viewpoint invariance is incorporated by considering the similarity of response across the individual streams.

Kan, M., Shan, S. and Chen, X., 2016. Multi-view deep network for cross-view classification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 4847-4855).

Siamese CNN – Variants

SIAMESE CNN – FOR VIEWPOINT INVARIANCE

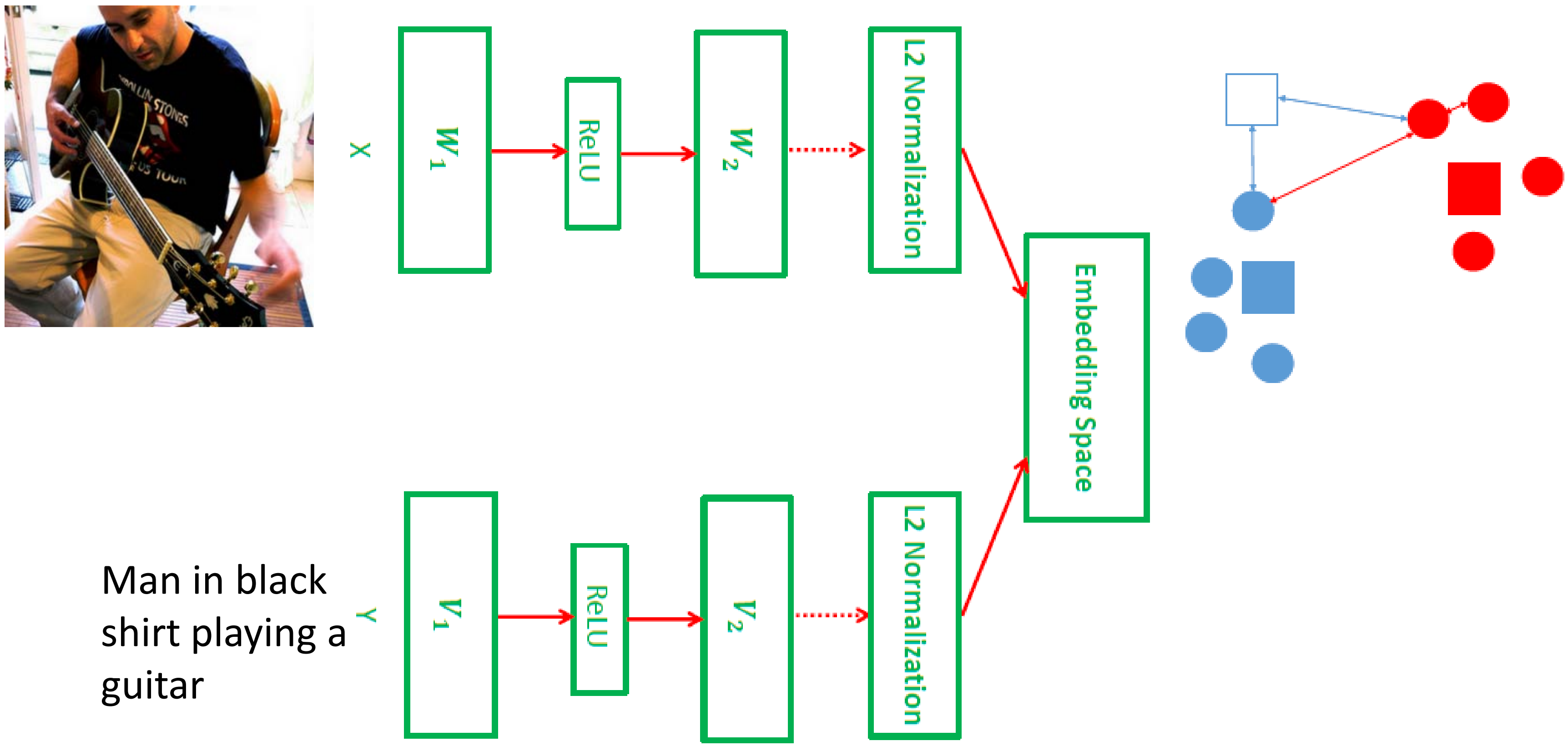
Results on the CMU MultiPIE Dataset, for recognition across 7 poses.

Methods	-45 deg	-30 deg	-15 deg	15deg	30 deg	45 deg
CCA	0.73	0.96	1.00	0.99	0.96	0.69
KCCA (RBF)	0.80	0.98	0.99	1.00	0.98	0.72
FIP+LDA	0.93	0.96	1.00	0.99	0.96	0.90
MVP+LDA	0.93	**1.00**	1.00	1.00	0.99	0.96
Proposed	**0.99**	0.99	**1.00**	**1.00**	**0.99**	**0.98**

Kan, M., Shan, S. and Chen, X., 2016. Multi-view deep network for cross-view classification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 4847-4855).

Siamese CNN – Variants

TWO STREAM CNN – FOR CROSS-MODAL EMBEDDING



Two stream networks have also been used for cross-modal embedding tasks. Here inputs from different modalities are mapped to a common space.

Wang, L., Li, Y. and Lazebnik, S., 2016. Learning deep structure-preserving image-text embeddings. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 5005-5013).

Siamese CNN - Variants

Application: Sentence completion, response to tweet, paraphrase identification

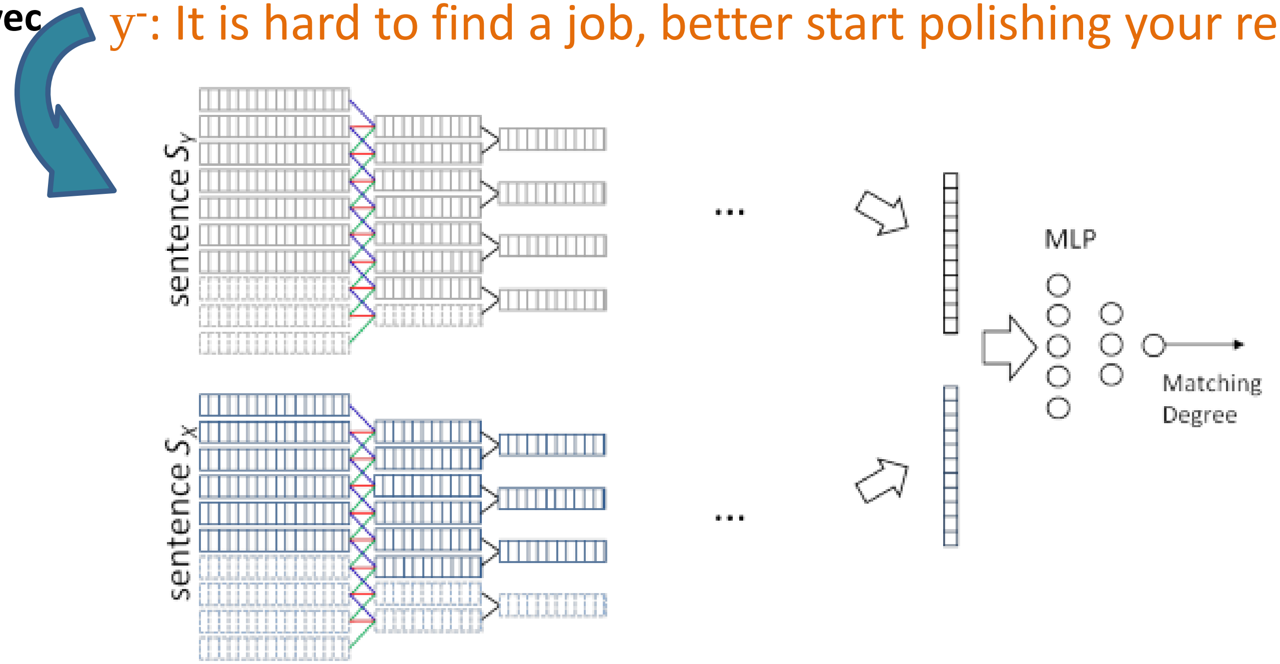
Example:

x : Damn, I have to work overtime this weekend!

y^{+}: Try to have some rest buddy.

y^{-}: It is hard to find a job, better start polishing your resume.

word2vec

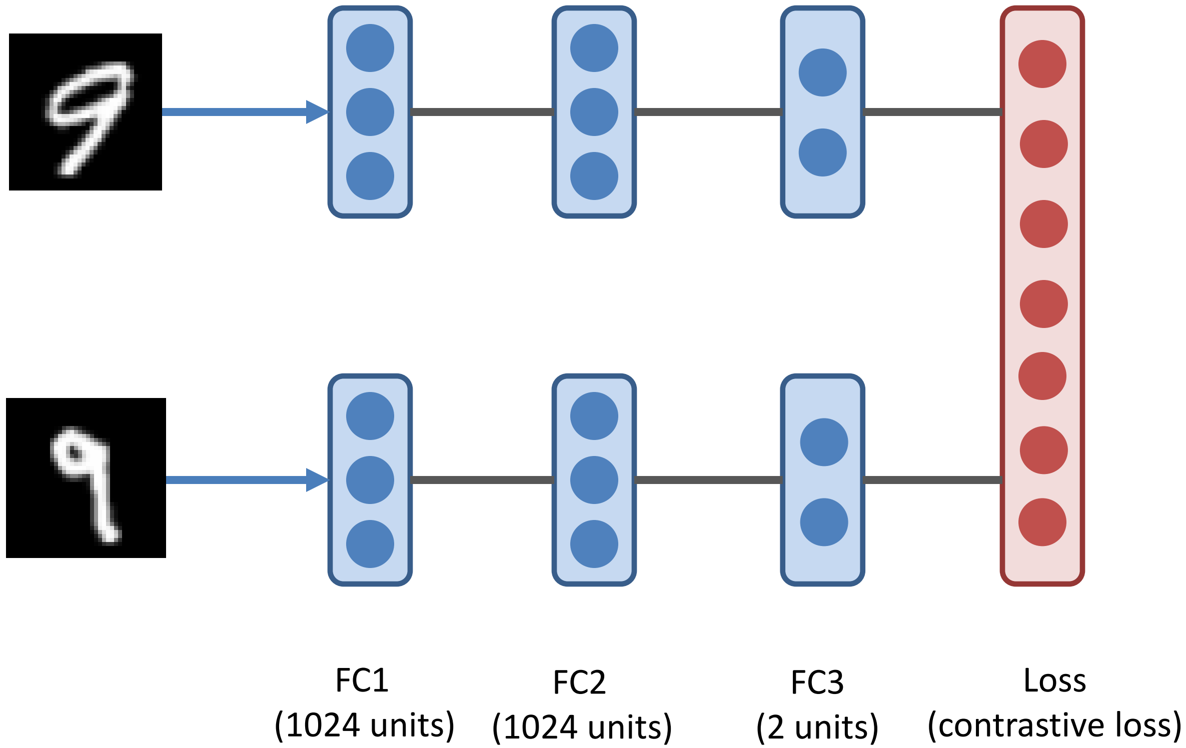


Hu, Baotian, et al., Convolutional neural network architectures for matching natural language sentences, NIPS 2014

DEMO OF SIAMESE NETWORK

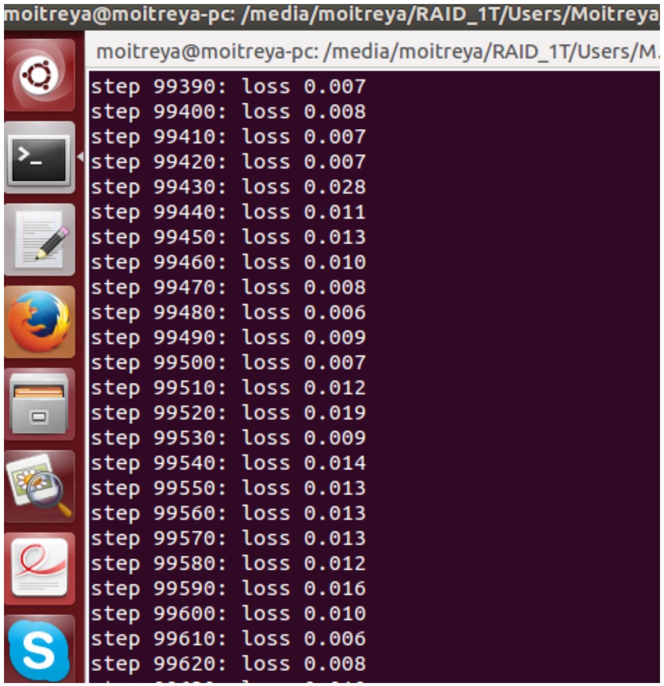
Demo: Architecture

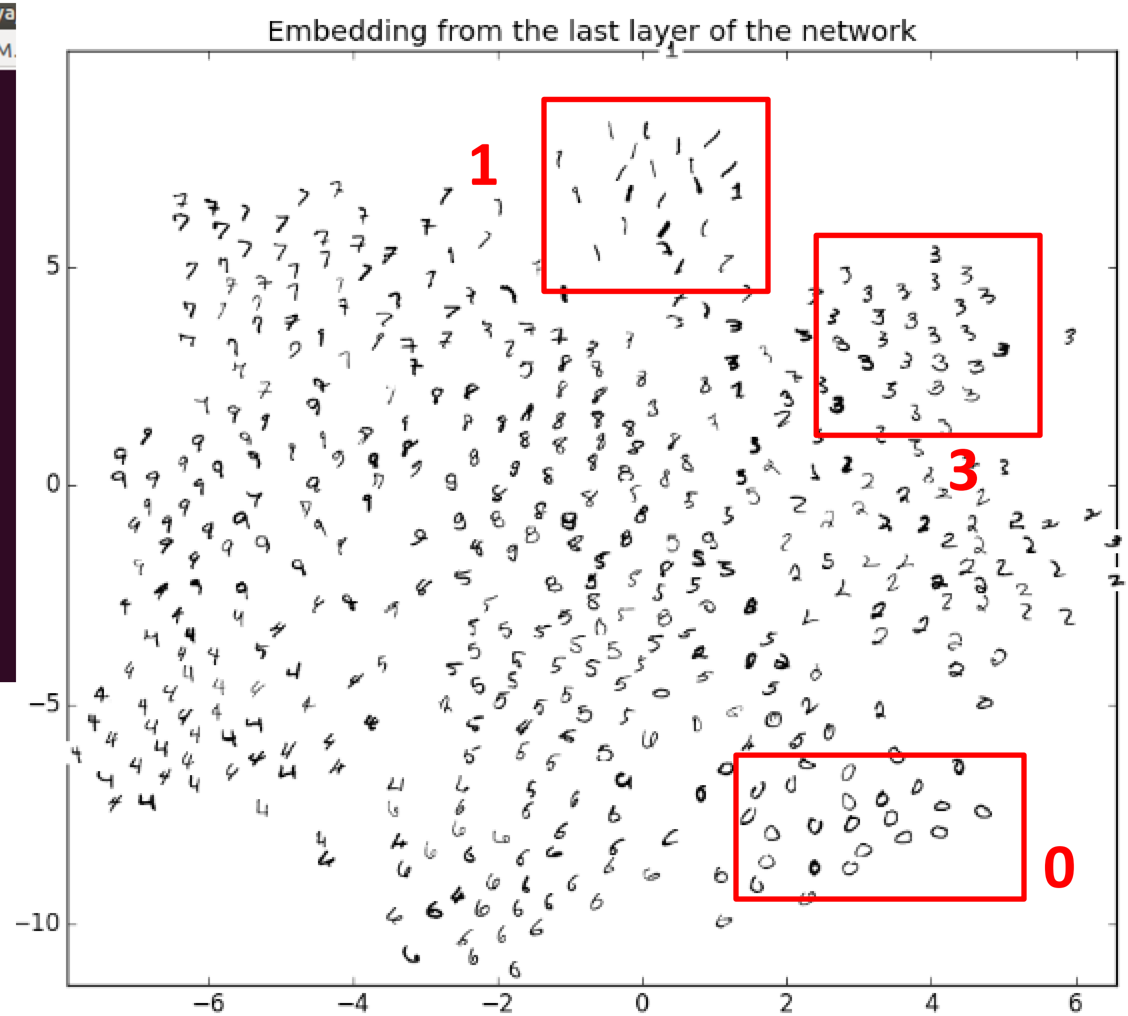
MNIST Digit Similarity Assessment



Code: @ywpkwon

Demo: Results





Code: @ywpkwon

Summary

- Quantifying “similarity” is an essential component of data analytics.
- Deep Learning approaches, such as “Siamese” Convolution Neural Nets, have shown promise recently.
- Several variants of Siamese CNN are available for making our life easier for a variety of tasks.

Reading List

- Bell, Sean, and Kavita Bala, Learning visual similarity for product design with convolutional neural networks, ACM Transactions on Graphics (TOG), 2015
- Chopra, Sumit, Raia Hadsell, and Yann LeCun, Learning a similarity metric discriminatively, with application to face verification, CVPR 2005
- Zagoruyko, Sergey, and Nikos Komodakis, Learning to compare image patches via convolutional neural networks, CVPR 2015
- Hoffer, Elad, and Nir Ailon, Deep metric learning using triplet network, arXiv:1412.6622
- Simo-Serra, Edgar, et al., Discriminative Learning of Deep Convolutional Feature Point Descriptors, ICCV 2015
- Vo, Nam N., and James Hays, Localizing and Orienting Street Views Using Overhead Imagery, ECCV 2016
- Ahmed, Ejaz, Michael Jones, and Tim K. Marks, An Improved Deep Learning Architecture for Person Re-Identification, CVPR 2015
- Hu, Baotian, et al., Convolutional neural network architectures for matching natural language sentences, NIPS 2014
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- Su, Hang, et al., Multi-view convolutional neural networks for 3d shape recognition, ICCV 2015
- Zheng, Yi, et al., Time Series Classification Using Multi-Channels Deep Convolutional Neural Networks, WAIM 2014
- Yi, Kwang Moo, et al., LIFT: Learned Invariant Feature Transform, arXiv:1603.09114
- Stricker, M.A. and Orengo, M. Similarity of color images. In *IS&T/SPIE's Symposium on Electronic Imaging: Science & Technology* (pp. 381-392), 1995.

Appreciate your kind attention!