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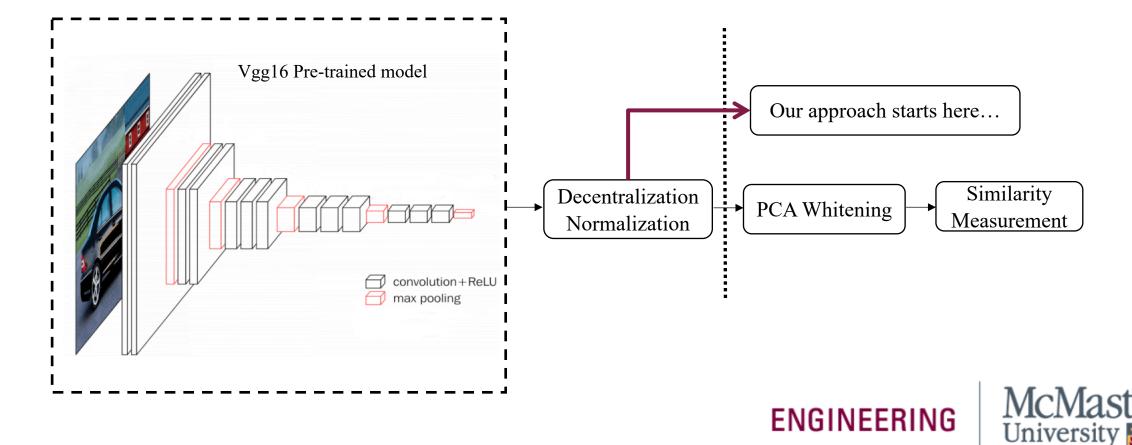
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The basic image retrieval process based on convolutional neutral network.



#### Dataset Structure

- Matching pairs:
  - $\mathbf{X}^{M} = [\mathbf{x}_{1}, \mathbf{x}_{2}, \mathbf{x}_{3}, \mathbf{x}_{4} ..., \mathbf{x}_{L}]_{512xL}$
  - $\mathbf{Y}^{M} = [\mathbf{y}_{1}, \mathbf{y}_{2}, \mathbf{y}_{3}, \mathbf{y}_{4}..., \mathbf{y}_{L}]_{512xL}$
- Non-matching pairs:
  - $\mathbf{X}^N = [\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \mathbf{x}_4..., \mathbf{x}_L]_{512xL}$
  - $\mathbf{Y}^N = [\mathbf{y}_4, \mathbf{y}_8, \mathbf{y}_1, \mathbf{y}_{10}..., \mathbf{y}_{L-4}]_{512xL}$
- $\mathbf{x}_i$  matches  $\mathbf{y}_j$  when i = j. Otherwise, they doesn't match.



- Correlation analysis and canonical vectors
  - Step 1 Building covariance matrix :

$$\mathbf{\Phi}^{M} = \frac{1}{2(L-1)} \mathbf{H}^{M} (\mathbf{H}^{M})^{T} = \begin{bmatrix} \mathbf{\Sigma}_{auto} & \mathbf{\Sigma}^{M} \\ \mathbf{\Sigma}^{M} & \mathbf{\Sigma}_{auto} \end{bmatrix}, \text{ where } \mathbf{H}^{M} = \begin{bmatrix} X^{M} & Y^{M} \\ Y^{M} & X^{M} \end{bmatrix}_{1024 \text{x} 2L}$$

$$\mathbf{\Phi}^{N} = \frac{1}{2(L-1)} \mathbf{H}^{N} (\mathbf{H}^{N})^{T} = \begin{bmatrix} \mathbf{\Sigma}_{auto} & \mathbf{\Sigma}^{N} \\ \mathbf{\Sigma}^{N} & \mathbf{\Sigma}_{auto} \end{bmatrix}, \text{ where } \mathbf{H}^{N} = \begin{bmatrix} X^{N} & Y^{N} \\ Y^{N} & X^{N} \end{bmatrix}_{1024 \text{x} 2L}$$

Note: 
$$\Sigma_{auto} = \frac{X^{M} (X^{M})^{T} + Y^{M} (Y^{M})^{T}}{2(L-1)} = \frac{X^{N} (X^{N})^{T} + Y^{N} (Y^{N})^{T}}{2(L-1)},$$

$$\Sigma^{M} = \frac{X^{M} (Y^{M})^{T} + Y^{M} (X^{M})^{T}}{2(L-1)}, \Sigma^{N} = \frac{X^{N} (Y^{N})^{T} + Y^{N} (X^{N})^{T}}{2(L-1)}.$$



- Correlation analysis and canonical vectors
  - Step 2 Removing autocorrelation:

$$\widehat{\mathbf{\Phi}}^{M} = \mathbf{\Sigma}_{auto}^{-\frac{1}{2}} \mathbf{\Phi}^{M} \mathbf{\Sigma}_{auto}^{-\frac{1}{2}} = \mathbf{\Sigma}_{auto}^{-\frac{1}{2}} \begin{bmatrix} \mathbf{\Sigma}_{auto} & \mathbf{\Sigma}^{M} \\ \mathbf{\Sigma}^{M} & \mathbf{\Sigma}_{auto} \end{bmatrix} \mathbf{\Sigma}_{auto}^{-\frac{1}{2}} = \begin{bmatrix} \mathbf{I} & \mathbf{J}^{M} \\ \mathbf{J}^{M} & \mathbf{I} \end{bmatrix},$$

$$\widehat{\mathbf{\Phi}}^{N} = \mathbf{\Sigma}_{auto}^{-\frac{1}{2}} \mathbf{\Phi}^{N} \mathbf{\Sigma}_{auto}^{-\frac{1}{2}} = \mathbf{\Sigma}_{auto}^{-\frac{1}{2}} \begin{bmatrix} \mathbf{\Sigma}_{auto} & \mathbf{\Sigma}^{N} \\ \mathbf{\Sigma}^{N} & \mathbf{\Sigma}_{auto} \end{bmatrix} \mathbf{\Sigma}_{auto}^{-\frac{1}{2}} = \begin{bmatrix} \mathbf{I} & \mathbf{J}^{N} \\ \mathbf{J}^{N} & \mathbf{I} \end{bmatrix}.$$

Where 
$$\mathbf{J}^M = \mathbf{\Sigma}_{auto}^{-\frac{1}{2}} \mathbf{\Sigma}^M \mathbf{\Sigma}_{auto}^{-\frac{1}{2}}, \ \mathbf{J}^N = \mathbf{\Sigma}_{auto}^{-\frac{1}{2}} \mathbf{\Sigma}^N \mathbf{\Sigma}_{auto}^{-\frac{1}{2}}.$$



- Correlation analysis and canonical vectors
  - Step 3 Deriving matching and non-matching coefficients :
    - 1) Applying eigen-decomposition on  $\mathbf{J}^{M}$ :

$$\mathbf{J}^{M}=\mathbf{U}\boldsymbol{\Lambda}\mathbf{U}^{T}.$$

2) Left- and right- multiplication of  $\mathbf{J}^{M}$  and  $\mathbf{J}^{N}$  by  $\mathbf{U}^{T}$  and  $\mathbf{U}$ :

$$\mathbf{\Lambda} = \mathbf{U}^T \mathbf{J}^M \mathbf{U}; \, \mathbf{\Pi} = \mathbf{U}^T \mathbf{J}^N \mathbf{U}.$$



- Correlation analysis and canonical vectors
  - Step 3 Deriving matching and non-matching coefficients :

$$\Lambda = \begin{bmatrix} c_1^M & 0 & \dots & 0 \\ 0 & c_1^M & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & c_{512}^M \end{bmatrix}, \Pi = \begin{bmatrix} c_1^N & \pi_{1,2} & \dots & \pi_{1,512} \\ \pi_{1,2} & c_2^N & \dots & \pi_{2,512} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{512,1} & \pi_{512,1} & \dots & c_{512}^N \end{bmatrix}$$

Matching coefficient:  $c_t^M = [\Lambda]_{tt}$ ,

Non-matching coefficient:  $c_t^N = [\Pi]_{tt}$ , where  $t \in \{1,2,...,512\}$ .



Chernoff information for canonical vector selection

Step 1 – The Chernoff information  $CI(S_t^M || S_t^N)$  is defined as

$$CI(\boldsymbol{S}_t^M || \boldsymbol{S}_t^N) = D(\boldsymbol{S}_t^{\lambda} || \boldsymbol{S}_t^M) = D(\boldsymbol{S}_t^{\lambda} || \boldsymbol{S}_t^M),$$

where 
$$\boldsymbol{S}_t^M = \begin{bmatrix} 1 & c_t^M \\ c_t^M & 1 \end{bmatrix}$$
,  $\boldsymbol{S}_t^N = \begin{bmatrix} 1 & c_t^M \\ c_t^M & 1 \end{bmatrix}$ ,

$$(S_t^{\lambda})^{-1} = \lambda_t (S_t^M)^{-1} + (1 - \lambda_t) (S_t^N)^{-1},$$

$$\lambda_t \in [0,1], t \in [1,512].$$



• Chernoff information for canonical vector selection

Step 2 – We express the "distance" between distributions  $S_t^{\lambda}$  and  $S_t^{M}$ ,  $S_t^{N}$  by using

Kullback–Leibler (KL) divergence:

$$D(\boldsymbol{S}_{t}^{\lambda} \parallel \boldsymbol{S}_{t}^{M}) = \frac{1}{2} \log_{e} \frac{|\boldsymbol{S}_{t}^{M}|}{|\boldsymbol{S}_{t}^{\lambda}|} + \frac{1}{2} \operatorname{tr}((\boldsymbol{S}_{t}^{M})^{-1} \boldsymbol{S}_{t}^{\lambda}) - 1,$$

$$D(\boldsymbol{S}_t^{\lambda} \parallel \boldsymbol{S}_t^N) = \frac{1}{2} \log_e \frac{|\boldsymbol{S}_t^N|}{|\boldsymbol{S}_t^{\lambda}|} + \frac{1}{2} \operatorname{tr}((\boldsymbol{S}_t^N)^{-1} \boldsymbol{S}_t^{\lambda}) - 1.$$

Setting  $D(S_t^{\lambda} || S_t^M) = D(S_t^{\lambda} || S_t^N)$  helps find the optimal  $\lambda_t = \lambda_t^*$ .





- Chernoff information for canonical vector selection
  - Step 3 Feature selection:

By solving for each  $\lambda_t^*$ , the Chernoff information of all 512 pairs could be evaluated, leading to a ranking of the most different pairs  $(c_t^M, c_t^N)$ , and the most discriminative k-vectors of **U**. The selected canonical vectors from **U** build new matrix  $\widetilde{\mathbf{U}}$ . In additional, the top k different pairs from  $(c_t^M, c_t^N)$  are selected.



- Similarity measurement with hypothesis testing
  - Step 1 Feature transformation:

Given any two feature vectors  $(x_r, y_c)$ , the transformed feature column vectors

are computed as follows:

$$\mathbf{w} = [\mathbf{w}_{1}, \mathbf{w}_{2}, ..., \mathbf{w}_{k}]^{T} = \widetilde{\mathbf{U}}^{T} \mathbf{\Sigma}_{auto}^{-\frac{1}{2}} \mathbf{x}_{r},$$

$$\mathbf{v} = [\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_k]^T = \widetilde{\mathbf{U}}^T \mathbf{\Sigma}_{auto}^{-\frac{1}{2}} \mathbf{y}_c.$$



- Similarity measurement with hypothesis testing
  - Step 2 Hypothesis testing:

We assume  $(x_r, y_c)$  comes from jointly gaussian distribution. Hence,  $(w_i, v_i)$  for  $i \in$ 

{1,2,...,k} are jointly Gaussian, and independent from each other.

$$P_{M}(w_{i}, v_{i}) = \frac{e^{-\frac{1}{2}[w_{i} \ v_{i}]\begin{bmatrix} 1 & \tilde{c}_{i}^{M} \\ \tilde{c}_{i}^{M} & 1 \end{bmatrix}\begin{bmatrix} w_{i} \\ v_{i} \end{bmatrix}}}{\sqrt{(2\pi)^{2} \begin{vmatrix} 1 & \tilde{c}_{i}^{M} \\ \tilde{c}_{i}^{M} & 1 \end{vmatrix}}}, P_{N}(w_{i}, v_{i}) = \frac{e^{-\frac{1}{2}[w_{i} \ v_{i}]\begin{bmatrix} 1 & \tilde{c}_{i}^{N} \\ \tilde{c}_{i}^{N} & 1 \end{bmatrix}\begin{bmatrix} w_{i} \\ v_{i} \end{bmatrix}}}{\sqrt{(2\pi)^{2} \begin{vmatrix} 1 & \tilde{c}_{i}^{N} \\ \tilde{c}_{i}^{N} & 1 \end{vmatrix}}}.$$



- Similarity measurement with hypothesis testing
  - Step 2 Hypothesis testing:

Confidence score = 
$$\sum_{i=1}^{k} \log \frac{P_M(w_i, v_i)}{P_N(w_i, v_i)}$$
.

The higher the score is, the more likely the two images are a match. And we rank the

confidence scores in descending order to obtain the image retrieval results.



#### EVALUATION RESULTS FROM 30K-SFM LEARNING DATABASE ON OXFORD5K

Learning dataset: 30k-SfM													
Oxford5k	Dim	MAC				SPoC				SD			
		LDA	PCAw	S-CCA	G-CCA	LDA	PCAw	S-CCA	G-CCA	LDA	PCAw	S-CCA	G-CCA
	25	_	0.3504	0.2424	0.3901	_	0.4796	0.2511	0.4879		0.4993	0.3355	0.5008
	50		0.4264	0.3290	0.4690		0.5153	0.3149	0.5437		0.5129	0.4542	0.5856
	100		0.4980	0.4106	0.5064		0.5217	0.4549	0.6219		0.6038	0.5292	0.6300
	200		0.5547	0.4933	0.5592		0.6072	0.5123	0.6658		0.6580	0.6838	0.6877
	300	_	0.5710	0.5400	0.5406		0.6433	0.5274	0.6723		0.6728	0.6610	0.6824
	400		0.5726	0.5614	0.5463		0.6516	0.5373	0.6713		0.6825	0.6699	0.6831
	450	_	0.5731	0.5618	0.5424		0.6549	0.5333	0.6696		0.6869	0.6750	0.6812
, <u> </u>	512	_	0.5620	0.5621	0.5418		0.6535	0.6535	0.6704		0.6805	0.6786	0.6815

#### EVALUATION RESULTS FROM 120K-SFM LEARNING DATABASE ON OXFORD5K.

Learning dataset: 120k-SfM												
Dim	MAC					SI	PoC		SD			
	LDA	PCAw	S-CCA	G-CCA	LDA	PCAw	S-CCA	G-CCA	LDA	PCAw	S-CCA	G-CCA
25	0.3603	0.3830			0.4758	0.4472	0.3203	0.4783	0.4759	0.4779	0.3262	0.5017
50	0.4760	0.4277		0.4780	0.5612	0.4930	0.4085	0.5627	0.5375	0.5129		0.5688
100	0.5157	0.5185		0.5432	0.6017	0.5675	0.5379	0.6338	0.6429	0.6038		0.6597
200	0.5887	0.5443	0.5516	0.6182	0.6571	0.6399	0.6440	0.6947	0.6861	0.6337	0.6485	0.7176
300	0.6028	0.5619	0.5723	0.6246	0.6643	0.6575	0.6651	0.7089	0.7030	0.6638	0.6770	0.7325
400	0.5974	0.5793	0.5680	0.6251	0.6688	0.6808	0.6699	0.7116	0.7020	0.6933	0.6824	0.7381
450	0.5939	0.5819	0.5777	0.6233	0.6678	0.6862	0.6754	0.7124	0.6972	0.6952	0.6894	0.7391
512	0.5868	0.5765	0.5765	0.6229	0.6613	0.6851	0.6851	0.7131	0.6958	0.6900	0.6900	0.7393
_ _ _ _	25 50 100 200 300 400	25 0.3603 50 0.4760 100 0.5157 200 0.5887 300 0.6028 400 0.5974 450 0.5939	LDA         PCAw           25         0.3603         0.3830           50         0.4760         0.4277           100         0.5157         0.5185           200         0.5887         0.5443           300         0.6028         0.5619           400         0.5974         0.5793           450         0.5939         0.5819	Dim         LDA         PCAw         S-CCA           25         0.3603         0.3830         0.2682           50         0.4760         0.4277         0.3720           100         0.5157         0.5185         0.4510           200         0.5887         0.5443         0.5516           300         0.6028         0.5619         0.5723           400         0.5974         0.5793         0.5680           450         0.5939         0.5819         0.5777	Dim         MAC           LDA         PCAw         S-CCA         G-CCA           25         0.3603         0.3830         0.2682 <b>0.4235</b> 50         0.4760         0.4277         0.3720 <b>0.4780</b> 100         0.5157         0.5185         0.4510 <b>0.5432</b> 200         0.5887         0.5443         0.5516 <b>0.6182</b> 300         0.6028         0.5619         0.5723 <b>0.6246</b> 400         0.5974         0.5793         0.5680 <b>0.6251</b> 450         0.5939         0.5819         0.5777 <b>0.6233</b>	Dim         MAC           LDA         PCAw         S-CCA         G-CCA         LDA           25         0.3603         0.3830         0.2682 <b>0.4235</b> 0.4758           50         0.4760         0.4277         0.3720 <b>0.4780</b> 0.5612           100         0.5157         0.5185         0.4510 <b>0.5432</b> 0.6017           200         0.5887         0.5443         0.5516 <b>0.6182</b> 0.6571           300         0.6028         0.5619         0.5723 <b>0.6246</b> 0.6643           400         0.5974         0.5793         0.5680 <b>0.6251</b> 0.6688           450         0.5939         0.5819         0.5777 <b>0.6233</b> 0.6678	Dim         MAC         SI           LDA         PCAw         S-CCA         G-CCA         LDA         PCAw           25         0.3603         0.3830         0.2682 <b>0.4235</b> 0.4758         0.4472           50         0.4760         0.4277         0.3720 <b>0.4780</b> 0.5612         0.4930           100         0.5157         0.5185         0.4510 <b>0.5432</b> 0.6017         0.5675           200         0.5887         0.5443         0.5516 <b>0.6182</b> 0.6571         0.6399           300         0.6028         0.5619         0.5723 <b>0.6246</b> 0.6643         0.6575           400         0.5974         0.5793         0.5680 <b>0.6251</b> 0.6688         0.6808           450         0.5939         0.5819         0.5777 <b>0.6233</b> 0.6678         0.6862	Dim         LDA         PCAw         S-CCA         G-CCA         LDA         PCAw         S-CCA           25         0.3603         0.3830         0.2682 <b>0.4235</b> 0.4758         0.4472         0.3203           50         0.4760         0.4277         0.3720 <b>0.4780</b> 0.5612         0.4930         0.4085           100         0.5157         0.5185         0.4510 <b>0.5432</b> 0.6017         0.5675         0.5379           200         0.5887         0.5443         0.5516 <b>0.6182</b> 0.6571         0.6399         0.6440           300         0.6028         0.5619         0.5723 <b>0.6246</b> 0.6643         0.6575         0.6651           400         0.5974         0.5793         0.5680 <b>0.6251</b> 0.6688         0.6808         0.6699           450         0.5939         0.5819         0.5777 <b>0.6233</b> 0.6678         0.6862         0.6754	Dim         MAC         SPoC           LDA         PCAw         S-CCA         G-CCA         LDA         PCAw         S-CCA         G-CCA           25         0.3603         0.3830         0.2682 <b>0.4235</b> 0.4758         0.4472         0.3203 <b>0.4783</b> 50         0.4760         0.4277         0.3720 <b>0.4780</b> 0.5612         0.4930         0.4085 <b>0.5627</b> 100         0.5157         0.5185         0.4510 <b>0.5432</b> 0.6017         0.5675         0.5379 <b>0.6338</b> 200         0.5887         0.5443         0.5516 <b>0.6182</b> 0.6571         0.6399         0.6440 <b>0.6947</b> 300         0.6028         0.5619         0.5723 <b>0.6246</b> 0.6643         0.6575         0.6651 <b>0.7089</b> 400         0.5974         0.5793         0.5680 <b>0.6251</b> 0.6688         0.6808         0.6699 <b>0.7116</b> 450         0.5939         0.5819         0.5777 <b>0.6233</b> 0.6678         0.6862         0.6754 <b>0.7124</b>	Dim         MAC         SPoC           LDA         PCAw         S-CCA         G-CCA         LDA         PCAw         S-CCA         G-CCA         LDA           25         0.3603         0.3830         0.2682 <b>0.4235</b> 0.4758         0.4472         0.3203 <b>0.4783</b> 0.4759           50         0.4760         0.4277         0.3720 <b>0.4780</b> 0.5612         0.4930         0.4085 <b>0.5627</b> 0.5375           100         0.5157         0.5185         0.4510 <b>0.5432</b> 0.6017         0.5675         0.5379 <b>0.6338</b> 0.6429           200         0.5887         0.5443         0.5516 <b>0.6182</b> 0.6571         0.6399         0.6440 <b>0.6947</b> 0.6861           300         0.6028         0.5619         0.5723 <b>0.6246</b> 0.6643         0.6575         0.6651 <b>0.7089</b> 0.7030           400         0.5974         0.5793         0.5680 <b>0.6251</b> 0.6688         0.6802         0.6754 <b>0.7124</b> 0.6972	Dim         MAC         SPoC         S           LDA         PCAw         S-CCA         G-CCA         LDA         PCAw         S-CCA         G-CCA         LDA         PCAw           25         0.3603         0.3830         0.2682 <b>0.4235</b> 0.4758         0.4472         0.3203 <b>0.4783</b> 0.4759         0.4779           50         0.4760         0.4277         0.3720 <b>0.4780</b> 0.5612         0.4930         0.4085 <b>0.5627</b> 0.5375         0.5129           100         0.5157         0.5185         0.4510 <b>0.5432</b> 0.6017         0.5675         0.5379 <b>0.6338</b> 0.6429         0.6038           200         0.5887         0.5443         0.5516 <b>0.6182</b> 0.6571         0.6399         0.6440 <b>0.6947</b> 0.6861         0.6337           300         0.6028         0.5619         0.5723 <b>0.6246</b> 0.6643         0.6575         0.6651 <b>0.7089</b> 0.7030         0.6638           400         0.5939         0.5819         0.5777 <b>0.6233</b> 0.6678         0.6862         0.6754 <b>0.7124</b> 0.6972         0.6952	Dim         MAC         SPoC         SD           LDA         PCAw         S-CCA         G-CCA         LDA         PCAw         S-CCA         G-CCA         LDA         PCAw         S-CCA           25         0.3603         0.3830         0.2682 <b>0.4758</b> 0.4758         0.4472         0.3203 <b>0.4783</b> 0.4759         0.4779         0.3262           50         0.4760         0.4277         0.3720 <b>0.4780</b> 0.5612         0.4930         0.4085 <b>0.5627</b> 0.5375         0.5129         0.4521           100         0.5157         0.5185         0.4510 <b>0.5432</b> 0.6017         0.5675         0.5379 <b>0.6338</b> 0.6429         0.6038         0.5547           200         0.5887         0.5443         0.5516 <b>0.6182</b> 0.6571         0.6399         0.6440 <b>0.6947</b> 0.6861         0.6337         0.6485           300         0.6028         0.5619         0.5723 <b>0.6246</b> 0.6643         0.6575         0.6651 <b>0.7089</b> 0.7030         0.6638         0.6824           450         0.5939         0.5819         0.5777 <b>0.6233</b>

Thank you! Q&A...

