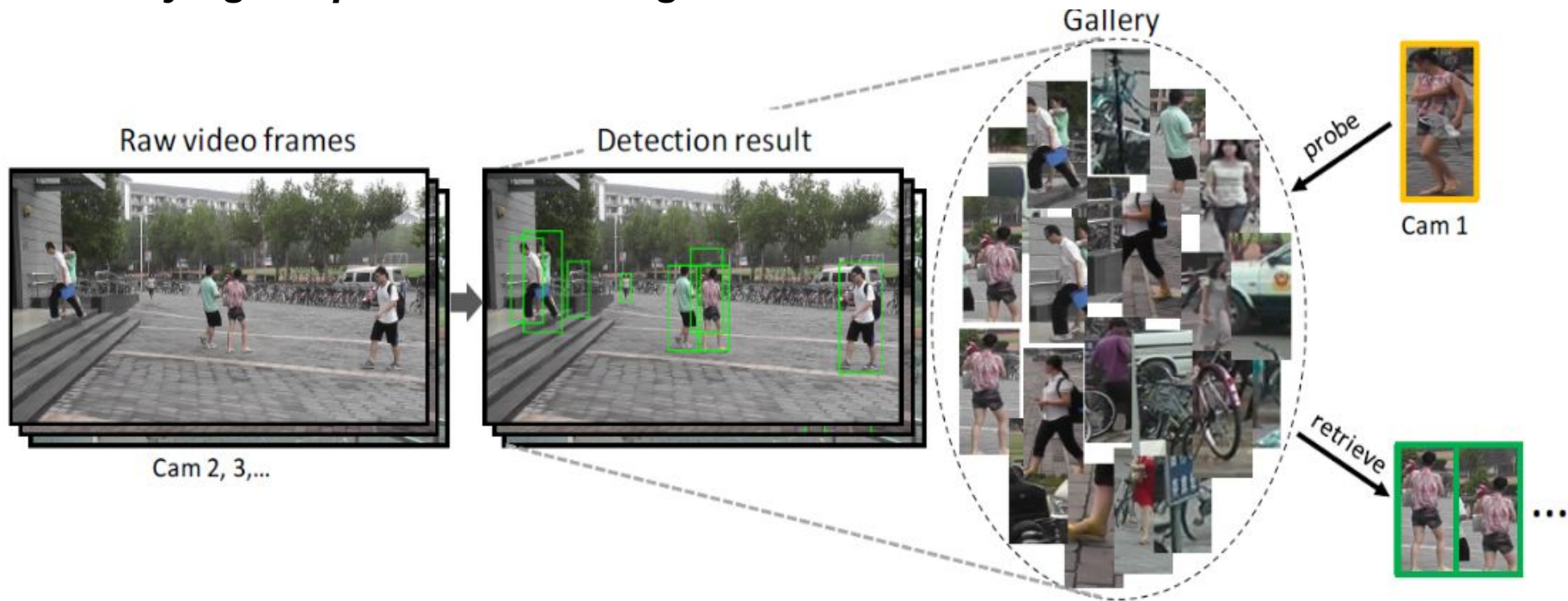


# Person re-identification by Local Maximal Occurrence representation and metric learning

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Experiment Presenter: Zhenpei Yang

**Person Re-identification: Given an image of a person from one camera, identifying the person from images taken from different cameras**



(a) Pedestrian Detection

(b) Person Re-identification

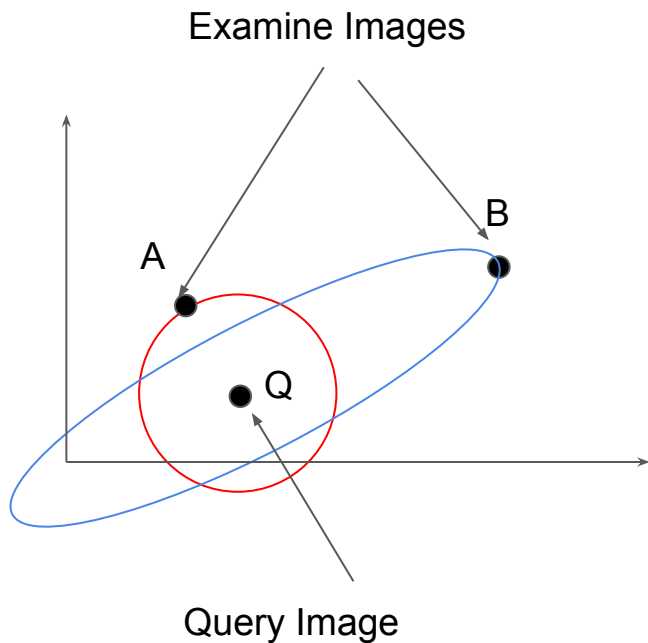
Person re-identification is a challenging problem because:

- Big Intra-class variance due to pose, viewpoint, illumination change.
- Need a proper metric to compute cross-class distance.

Contribution

- Extract good features *Local Occurrence Maximum (LOMO)*
- Use good distance metric *Cross-view Quadratic Discriminant Analysis (XQDA)*

# About distance metric



Which image is more likely correspond to image Q? A or B?

***Model the distribution for intra-class distance and extra-class distance!***

# Discriminative model

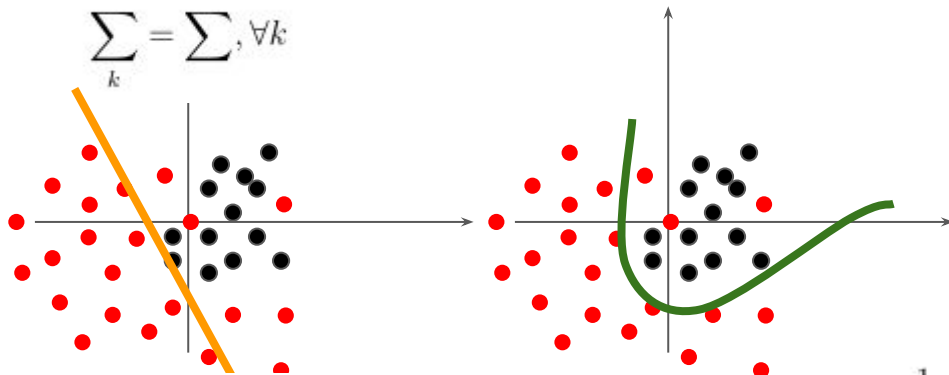
*Intuition: model the covariance for Intra-class distance and extra-class distance respectively using gaussian*

$$f_k(x) = \frac{1}{(2\pi)^{p/2} |\Sigma_k|^{1/2}} \exp^{-\frac{1}{2}(x-\mu_k)^T \Sigma_k^{-1} (x-\mu_k)}$$

Linear  
Discriminant  
Analysis (LDA)

Quadratic  
Discriminant  
Analysis (QDA)

Cross-view Quadratic  
Discriminant Analysis  
(XQDA)



$$d = \log \frac{\pi_k}{\pi_l} - \frac{1}{2} (\mu_k + \mu_l)^T \Sigma^{-1} (\mu_k - \mu_l) + x^T \Sigma^{-1} x (\mu_k - \mu_l), x = \Delta$$

$$d = -\frac{1}{2} x^T \Sigma^{-1} x - \frac{1}{2} \log \frac{|\Sigma_k|}{|\Sigma_l|} + \log \frac{\pi_k}{\pi_l}$$

# Cross-view Quadratic Discriminant Analysis (XQDA)

**Intuition: Original feature space is too high dimension.  
Maybe it's helpful to consider the problem in subspace**

$$P(\Delta|\Omega_I) = \frac{1}{(2\pi)^{d/2}|\Sigma_I|^{1/2}} e^{-\frac{1}{2}\Delta^T \Sigma_I^{-1} \Delta},$$

$$P(\Delta|\Omega_E) = \frac{1}{(2\pi)^{d/2}|\Sigma_E|^{1/2}} e^{-\frac{1}{2}\Delta^T \Sigma_E^{-1} \Delta},$$

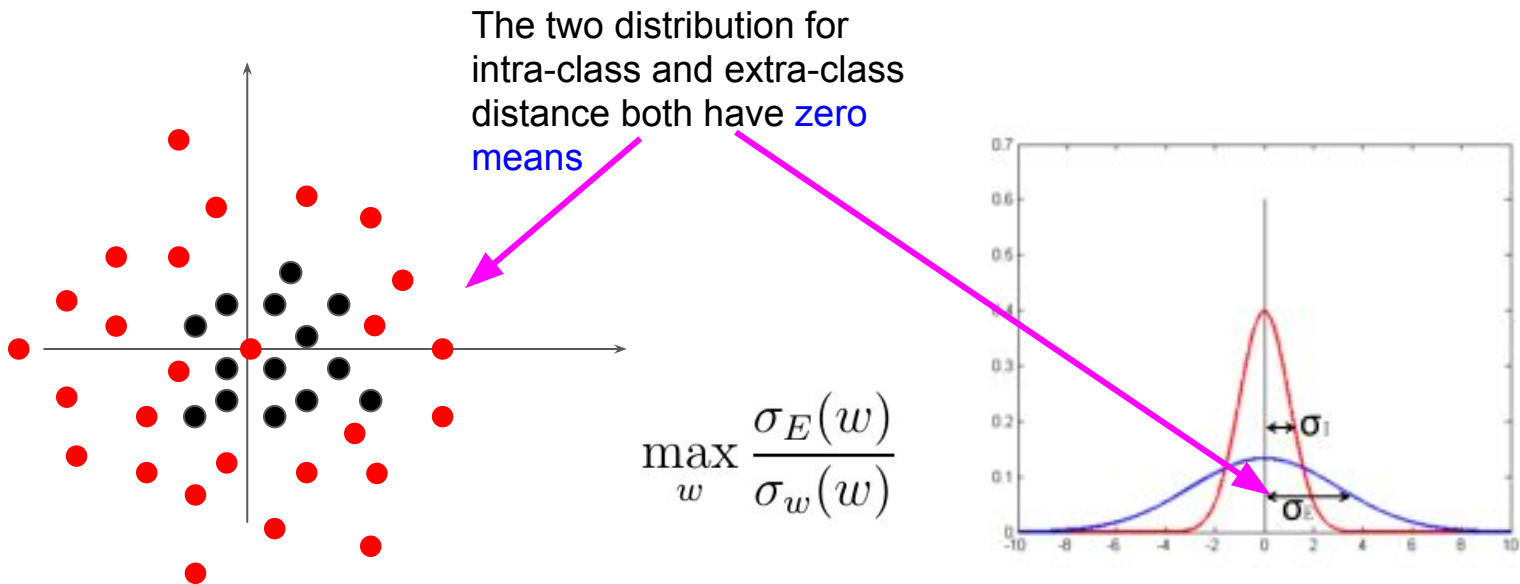
Hard to measure precisely  
in high dimension space

Measure this in subspace!

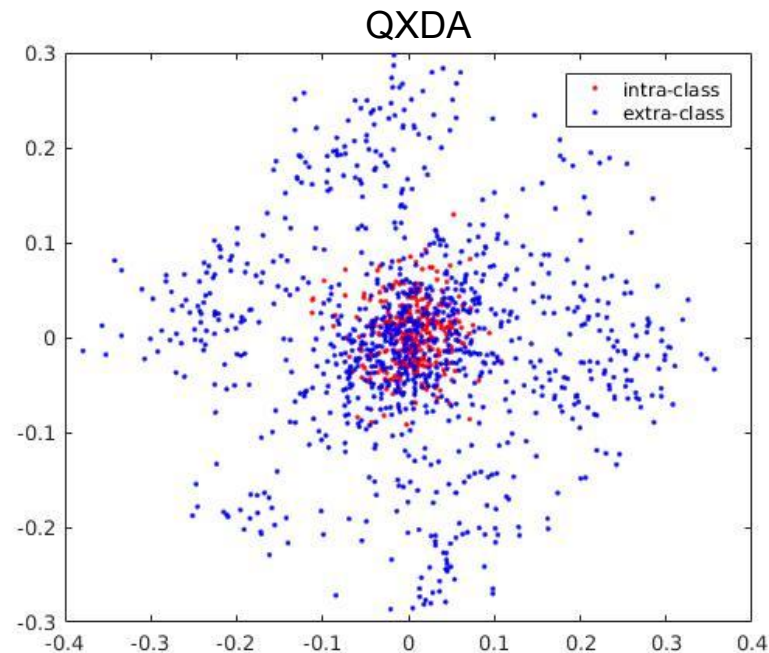
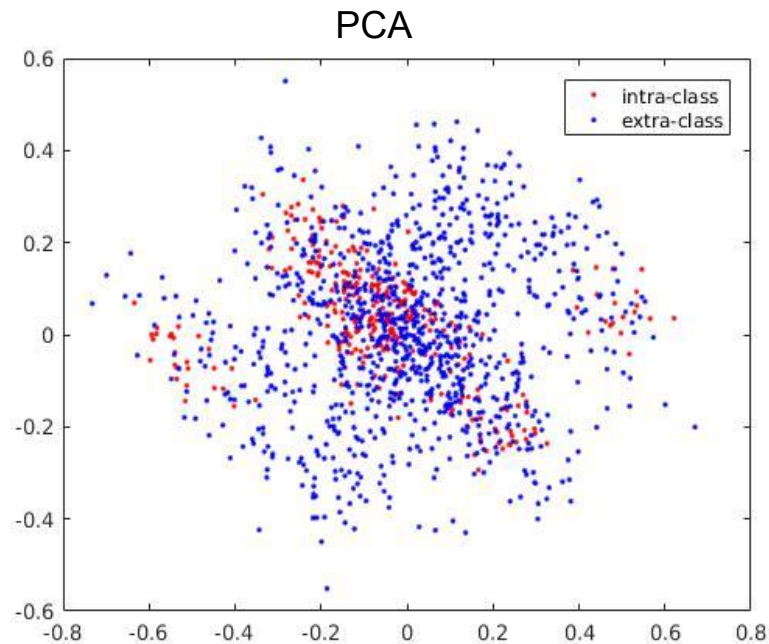
Which subspace ?

What about ?  
PCA

# Cross-view Quadratic Discriminant Analysis (XQDA)



The QXDA chose subspace that maximize the two classes' variance ratio





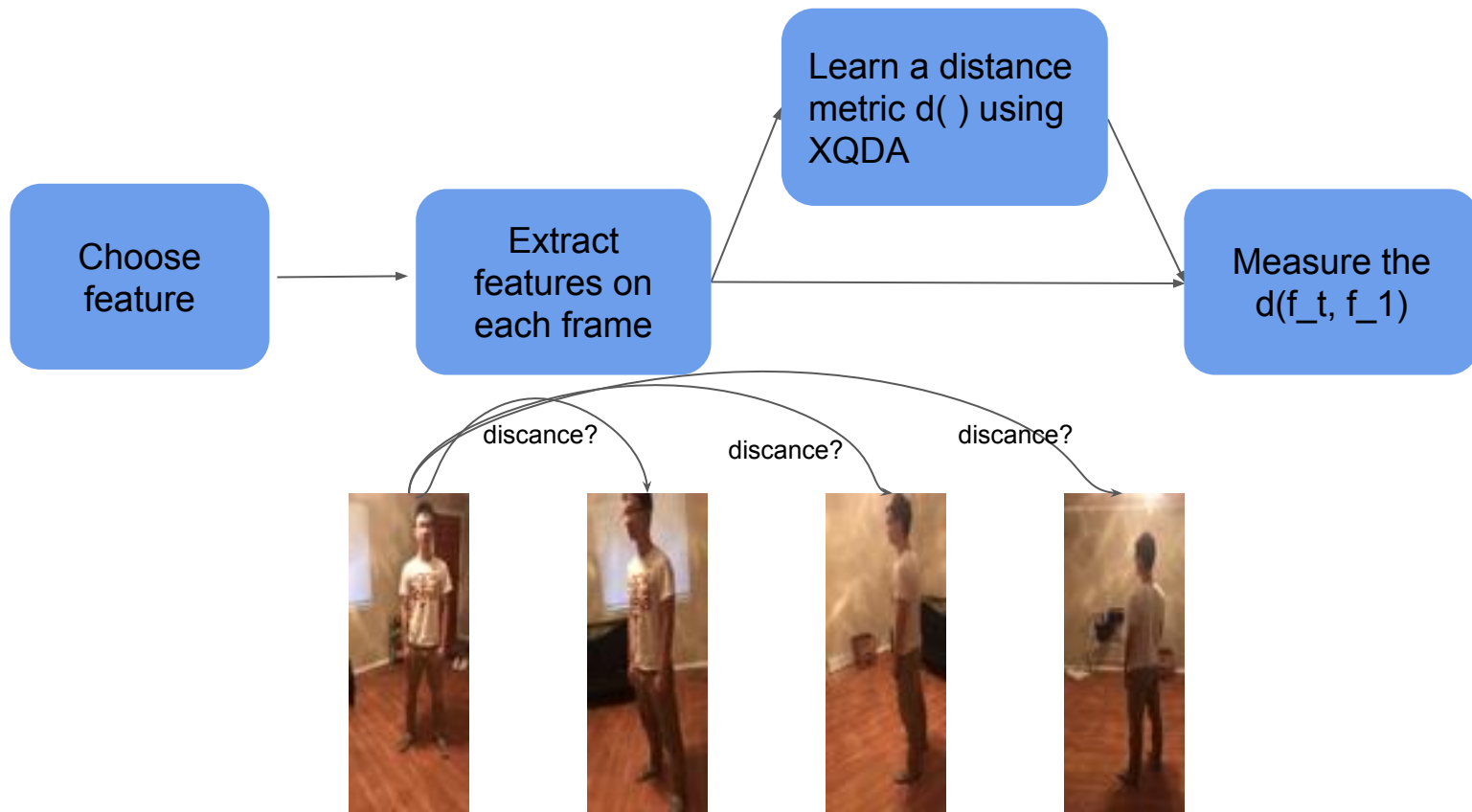
# Viewpoint Invariance Analysis

- Video taken by hand-hold camera
- #Total 23 seconds/705 frames(48\*128)
- 0-360 degree view



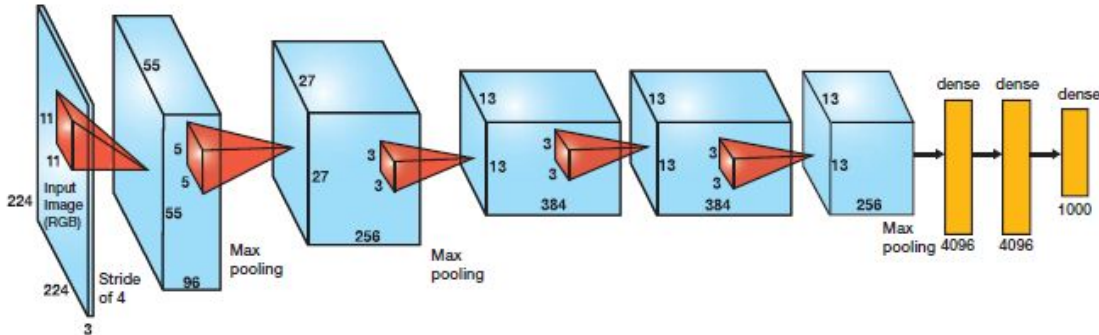
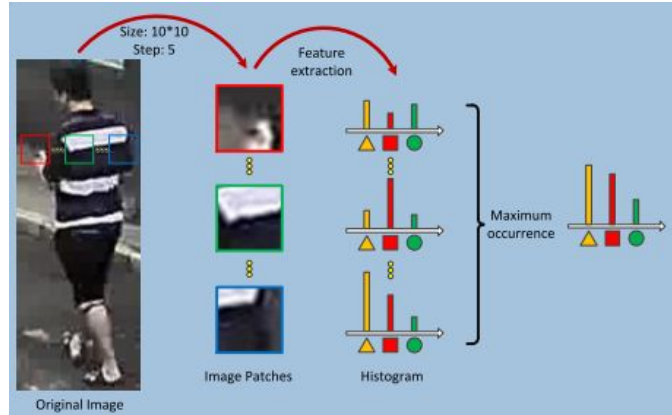
Slides credit: my roommate

# Viewpoint Invariance Analysis



# Investigated Features

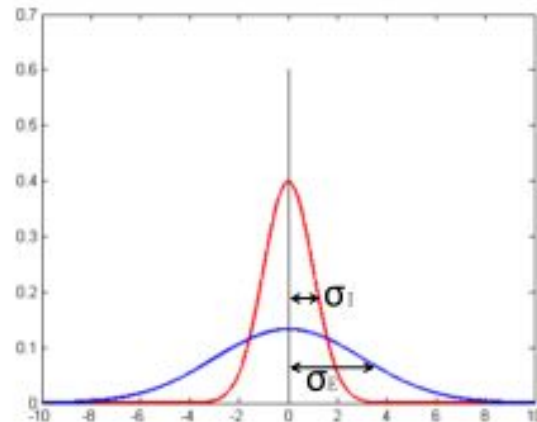
- Local Maximum Occurrence (LOMO)
- LOMO without Maximum Operator
- Convolutional Neural Network Feature (CNN)



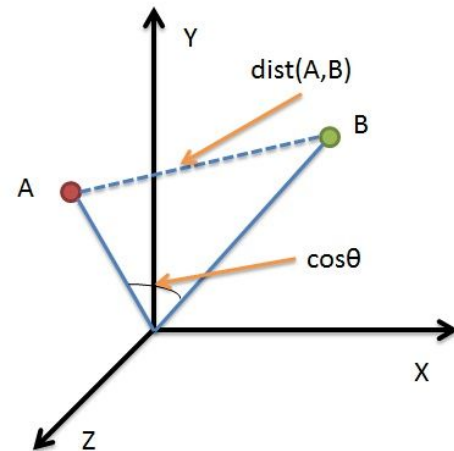
# Distance Metric

- Quadratic Discriminant Analysis (XQDA)
- Cosine Similarity

$$\max_w \frac{\sigma_E(w)}{\sigma_w(w)}$$

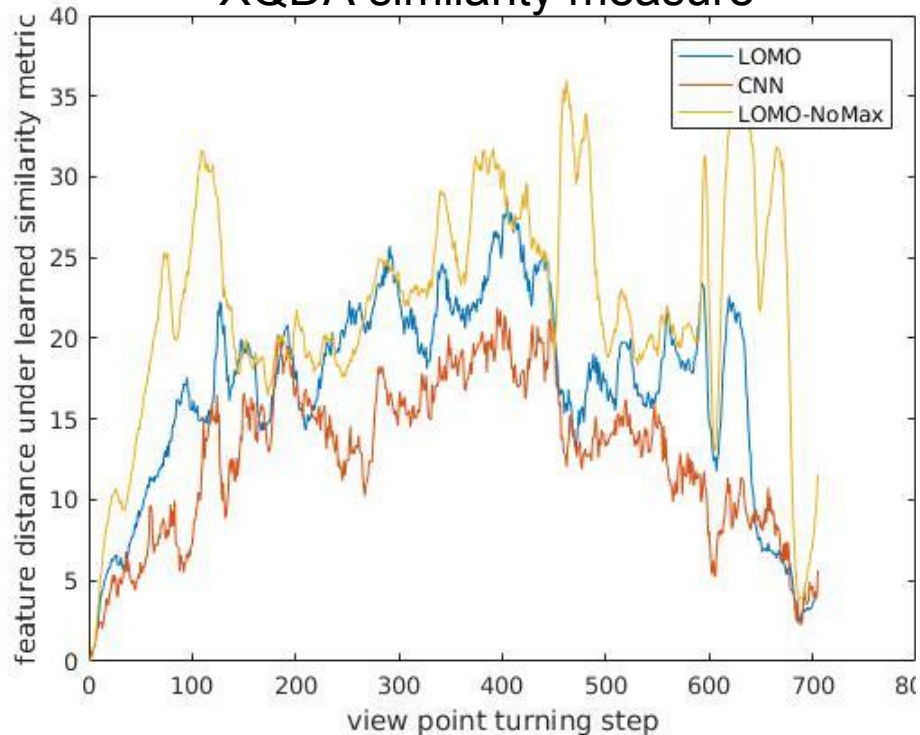


$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}}$$

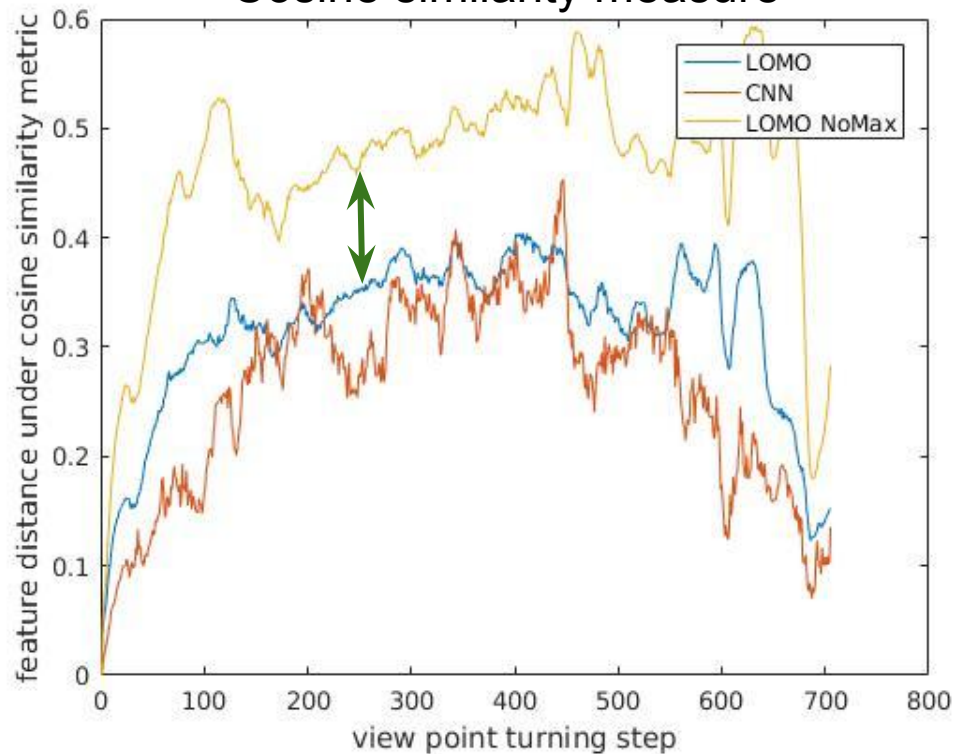


- ***The max operation in LOMO makes it more robust to viewpoint change***
- ***XQDA can learn more robust metric against viewpoint variation***

XQDA similarity measure



Cosine similarity measure

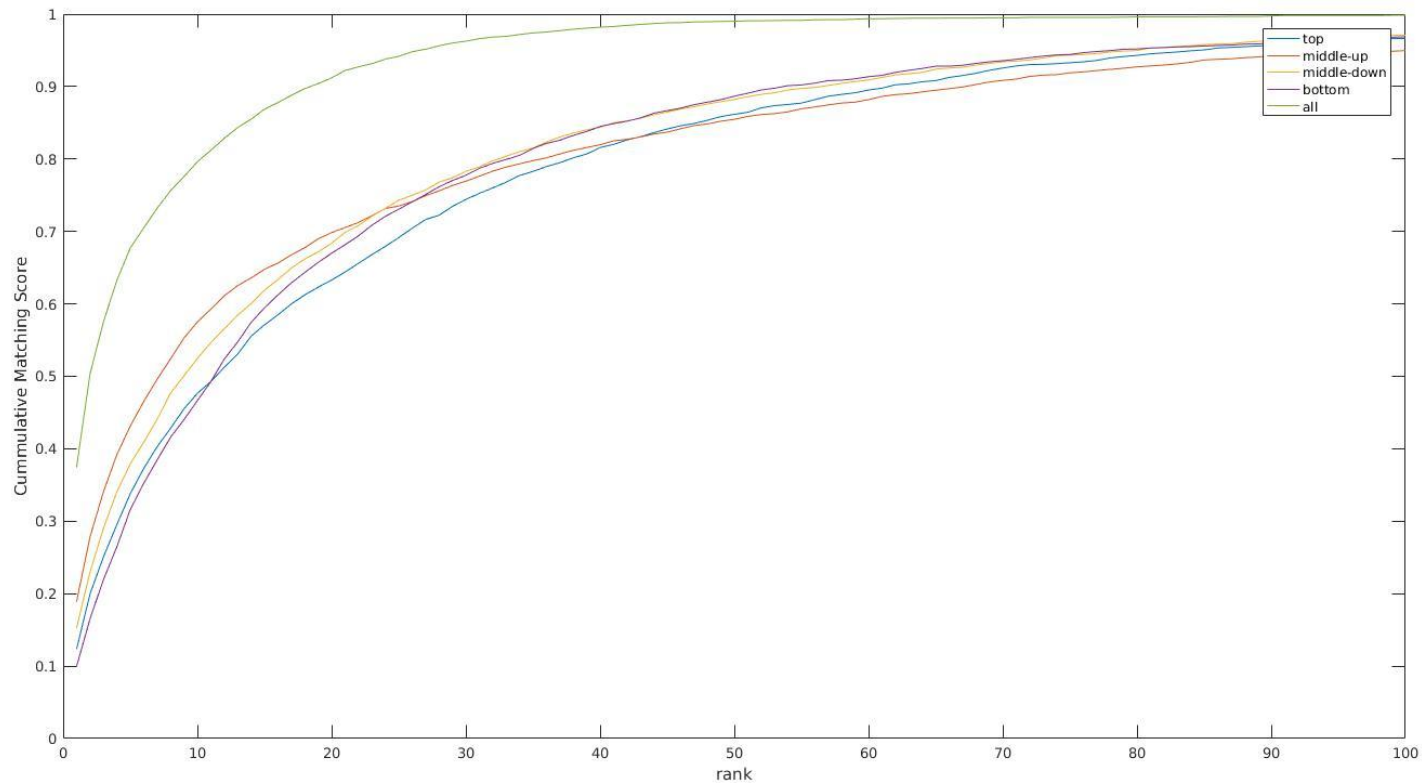


# Which region contribute mostly?

- Conduct training on four different body parts
- Compute the matching performance using each body parts

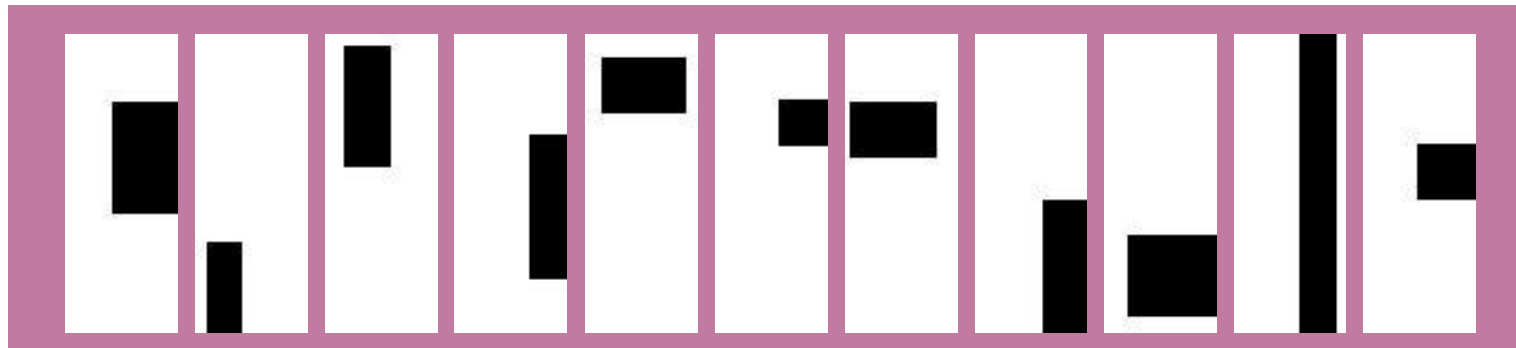


# The upper body is the most distinguishable part



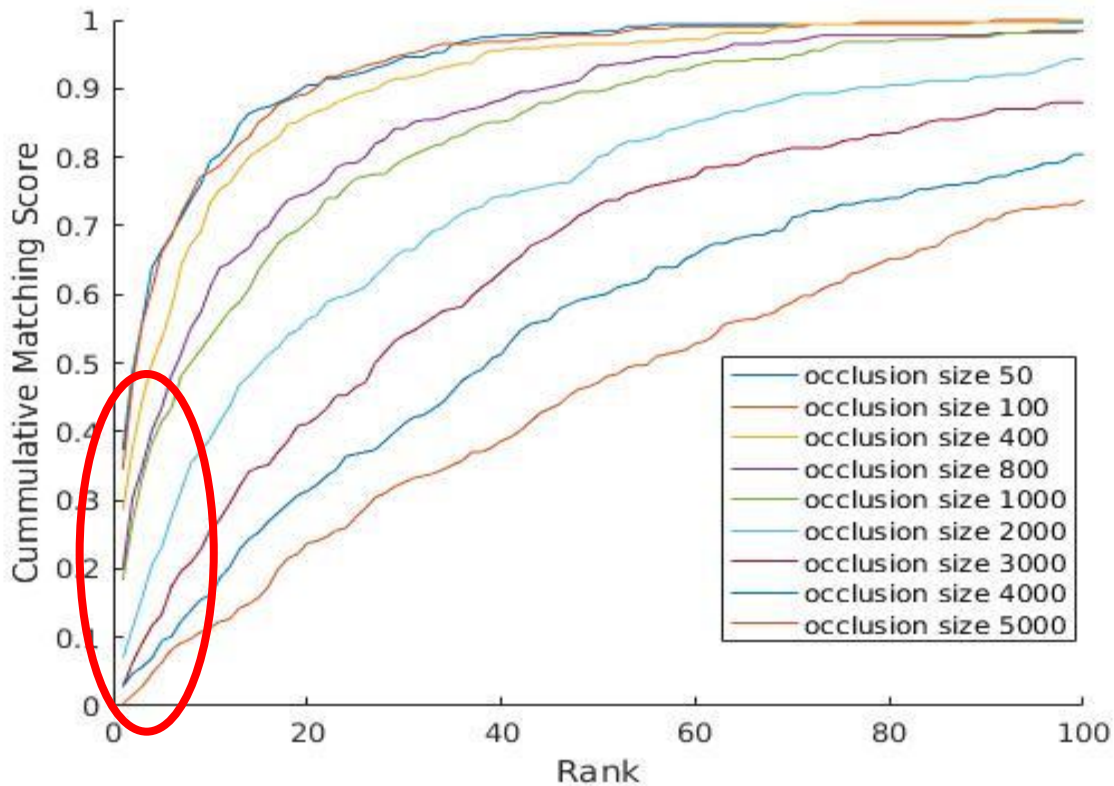
# Sensitivity to Occlusion

Parameter: *the size of occlusion area*

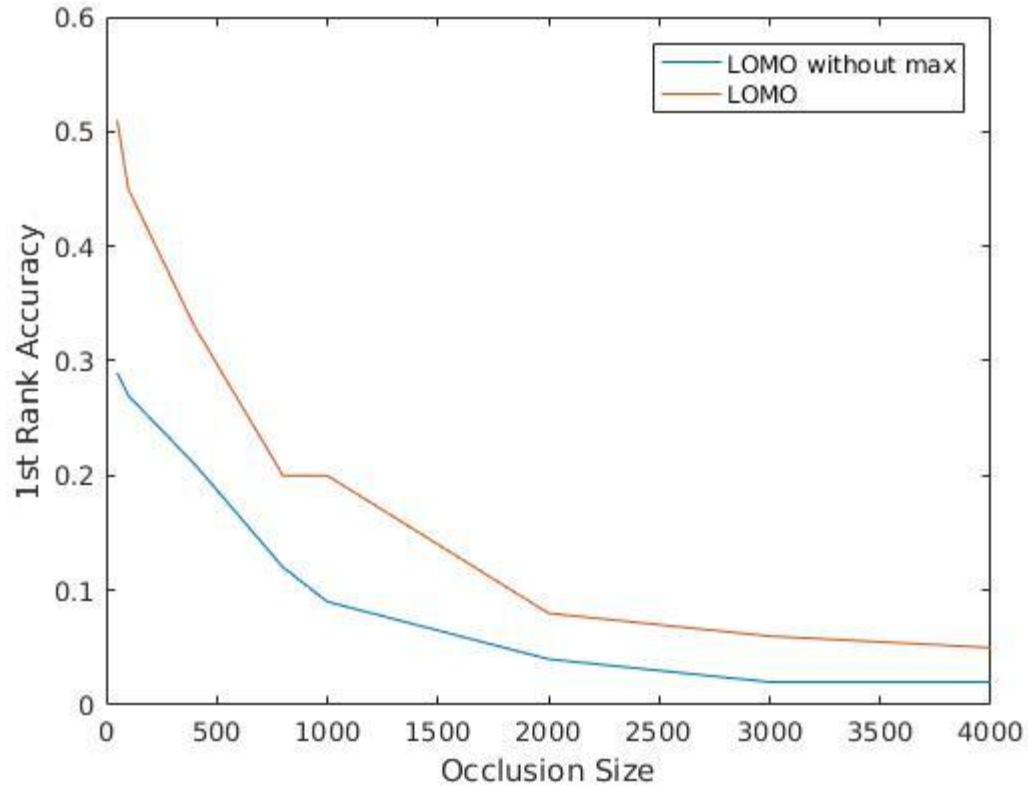




The performance degrades monotonous as occlusion become more severe



1st rank accuracy degrades monotonous as occlusion become more severe



# Conclusion

- *XQDA find the subspace that maximize the covariance odds of intra-class and extra-class distance.*
- *Doesn't robust to occlusion.*
- *LOMO feature has some viewpoint invariance due to the max operation.*
- *XQDA can learn more robust metric against viewpoint variation*
- *Upper body is the most distinct part for person-reidentification*