Hajun Song Assessment 1B
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Problem 1. Person Re-Identification
Discussion of Pre-Processing

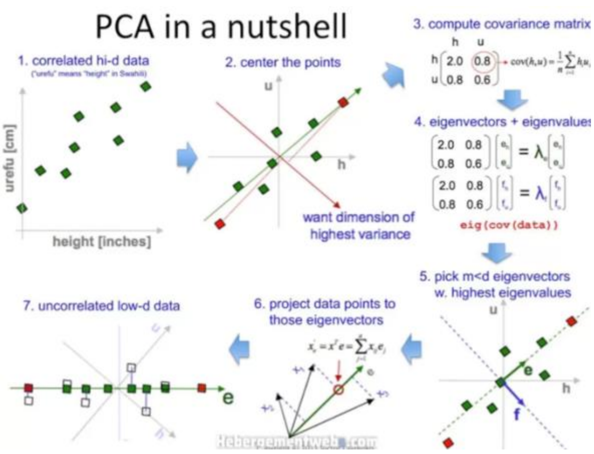
```
# resize data and convert to grayscale
gallery_X_small_gray = convert_to_grayscale(resize(gallery_X, (64, 32)))
print(gallery_X_small_gray.shape)
probe_X_small_gray = convert_to_grayscale(resize(probe_X, (64, 32)))
print(probe_X_small_gray.shape)

# plot some resized and grayscale images
plot_images(gallery_X_small_gray, gallery_Y)
```

```
Metal device set to: Apple M1 Pro
(301, 64, 32, 1)
(301, 64, 32, 1)
```

In re-identification problem, Market-1501 dataset was provided. Initially the image size is provided as 128 x 64. This image data has been cropped to 64x32 and converted into grayscale. This is because PCA requires the data to be aligned, in this case where location of whole entity (legs, arms, head, body) being in the same place in each images. Converting the resized images to grayscale reduces the colour information from RGB (Red, Green, Blue) channels to a single channel representing the intensity or brightness. This simplification allows to reduce the dimensionality without losing significant data. Additionally, working with grayscale images can reduce computational requirements and enhance the efficiency of the model training and matching process. Note that in the vectorized representation of images used for PCA/LDA, the spatial information is lost as the image is flattened into a single vector. This can limit the ability of vector-based approaches to effectively encode and utilize spatial relationships present in the original image. In contrast, DCNNs directly capture and leverage spatial information, allowing them to better capture the spatial relationships and patterns within images. Same pre-processing is performed on Deep-leaning model. This is to ensure the consistency and comparability with other methods. By applying the same pre-processing steps, the input data is standardized and normalized, allowing for fair comparisons between different models and techniques.

Discussion of selected non-deep-learning approaches.

PCA was selected mainly because it is widely used for non-deep learning approach for dimension reduction problems and feature extraction. PCA effectively reduces the dimensionality of the feature meanwhile preserving significant information.



1. Mean Centering: The first step in PCA is to subtract the mean of each feature from the data points. This ensures that the data is centered around zero.
2. Singular Value Decomposition (SVD): Instead of using eigenvalue decomposition, PCA can be efficiently computed using SVD. SVD factorizes the data matrix into three matrices: U, Σ, and V^T. The matrix Σ contains the singular values, which represent the square roots of the eigenvalues of the covariance matrix.
3. Selection of Principal Components: The principal components are determined by the singular vectors in the matrix V^T. These vectors represent the directions in the original feature space along which the data varies the most.
4. Projection: The selected principal components are used to transform the original data into a lower-dimensional space. This is done by projecting the data onto the principal components, resulting in a new set of coordinates called PC scores.

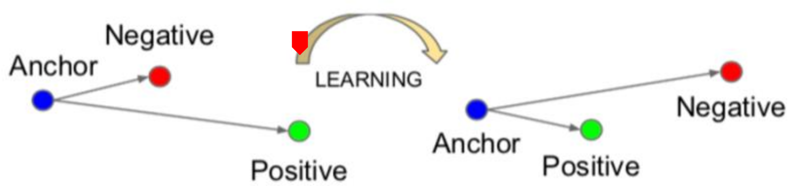
LDA approach was also considered however it was not used because of these result/reason.
PCA aims to find the orthogonal components that capture the maximum variance in the data, while LDA focuses on finding the linear combinations of features that maximize the class separability.

Supervised vs. Unsupervised: PCA is an unsupervised method that does not consider class labels, whereas LDA is a supervised method that utilizes class labels to guide the feature transformation process. LDA takes advantage of the class information to find discriminative features that can enhance classification performance.

Classification Performance: LDA is particularly effective when there is a significant overlap between class distributions, as it aims to find discriminative features that minimize intra-class variation and maximize inter-class variation. In contrast, PCA focuses on capturing the overall variance in the data and may not prioritize class separability.

Discussion of selected deep-learning approaches.

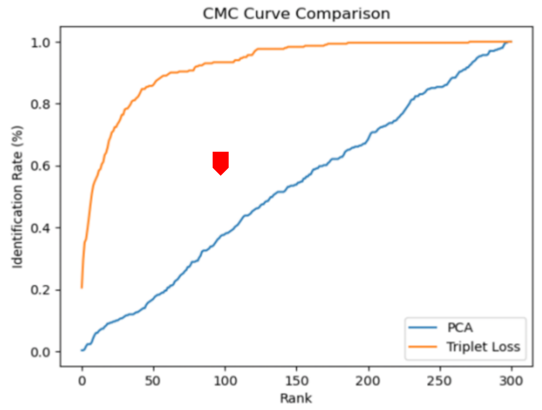
The triplet loss deep learning approach was chosen for this assessment. Triplet loss is to reduce the distance to positive images and increase the distance to negative images through learning



Simply put, it means seeing anchor images, positive images, and negative images.

It is effective in learning compact and discriminative embeddings for similarity-based tasks like person re-identification. It uses a Siamese network architecture and contrastive learning to capture inter-sample similarities and differences, while addressing intra-class variations. The evaluation metrics associated with triplet loss, such as Top-N accuracy and CMC curves, align well with the requirements of matching and ranking samples. Triplet Loss can simply be

An evaluation of two methods, (Top- 1, Top- 5, Top- 10)




```
Triplet Loss - Top N accuracy
Top 1 Rank - Percentage: 27.0%
Top 5 Rank - Percentage: 11.0%
Top 10 Rank - Percentage: 3.0%
PCA - Top N accuracy
Top 1 Rank - Percentage: 1.0%
Top 5 Rank - Percentage: 2.0%
Top 10 Rank - Percentage: 3.0%
```

The CMC plot shown above is a visualization of the cumulative match characteristic (CMC) curve for a particular recognition system. It plots the probability of the system correctly recognizing a queried identity against the rank of the true identity in the gallery, with the rank increasing from left to right.
In this particular case, the CMC plot compares the top N accuracy of two different methods: triplet loss and PCA. Triplet loss is a deep learning method for feature extraction that learns to separate images of different identities in the feature space. PCA, on the other hand, is a classical method for dimensionality reduction that projects the data onto a lower-dimensional space.

From the CMC plot, we can see that triplet loss outperforms PCA in terms of top N accuracy, with a higher probability of correctly recognizing the queried identity for all values of N. This suggests that triplet loss is a more effective method for feature extraction in this particular recognition system.

When evaluating the performance of the two methods, it is important to consider instances where one method outperforms the other. While the CMC plot shows that triplet loss generally performs better than PCA in terms of top N accuracy, there may be cases where PCA is more effective, such as when dealing with a smaller dataset or when computational efficiency is a concern.

In terms of strengths and weaknesses, triplet loss has the advantage of being a deep learning method that can learn complex representations of images, while PCA is a simpler, classical method that is computationally efficient and interpretable. However, triplet loss may require a larger dataset to train effectively and can be more computationally expensive than PCA. Overall, the choice between the two methods should be based on the specific needs of the recognition system and the available resources.

Ethical Discussion

Person re-identification involves identifying individuals across different camera views or locations and raises several ethical considerations. This article discusses the ethical concerns related to data collection for training person re-identification models, the potential uses of these models, and the limitations associated with them.

Data Collection: The collection of data for training person re-identification models can raise ethical concerns, particularly regarding privacy and consent. It is important to ensure that individuals whose data is used in training these models have provided informed consent and that the data used for training is diverse and representative of the population to avoid perpetuating biases. (K. Hao. 2020) Anonymization techniques should be employed to protect the privacy of individuals in the training data, and policies should be in place to ensure that surveillance systems are used responsibly. (M. Murgia. 2019)

Uses of Person Re-Identification Models: Person re-identification models can be applied in various contexts, such as authentication for digital devices and video surveillance. Ethical concerns arise in relation to how these models are used, including surveillance and privacy, discrimination and bias, and the potential for misuse or abuse.

Limitations of Person Re-Identification Models: It is essential to consider the limitations associated with person re-identification models, including accuracy and false positives/negatives, environmental factors, and contextual understanding. (Garbuzova, E. 2021).

In summary, ethical considerations in person re-identification involve responsible data collection, addressing biases and privacy concerns, ensuring proper use of the technology, and understanding its limitations. Ongoing research, open dialogue, and robust regulations are crucial to mitigate these ethical concerns and promote the responsible development and deployment of person re-identification systems.

References

M. Murgia. (2019) Who's using your face? the ugly truth about facial recognition. [Online]. Available: https://www.ft.com/content/cf19b956-60a2-11e9-b285-3acd5d43599e

Garbuzova, E. (2021). Ethical Concerns About Reidentification of Individuals from MRI Neuroimages. *Voices in Bioethics*, *7*. https://doi.org/10.52214/vib.v7i.8662

K. Hao. (2020) The two-year fight to stop amazon from selling face recognition to the police. [Online]. Available: https://www.technologyreview.com/2020/06/12/1003482/amazon-stopped-selling-police-face-recognition-fight/