Random Sampling LDA for Face Recognition

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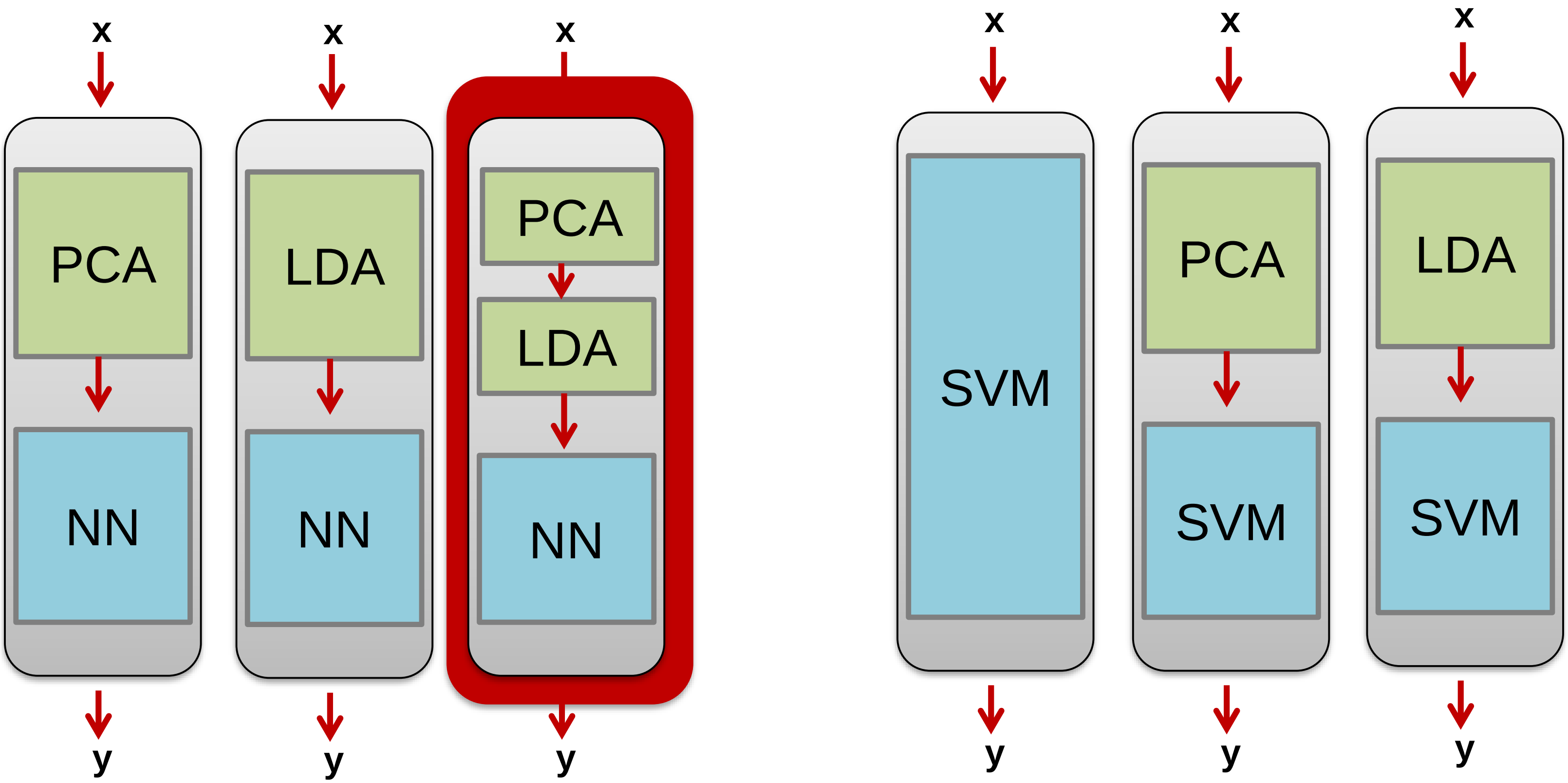
https://labicvl.github.io/

X. Wang and X. Tang, Random Sampling for Subspace Face Recognition, IJCV, 70(1), 91–104, 2006

A base model for ensemble learning is



More discriminative than PCA

When $\mathbf{S}_W^{-1}$ is not attainable

SVM is a global optimiser?

PCA helps the computational complexity of SVM, but accuracy?

Two discriminative parts in a sequence?

https://goo.gl/m6Mnov for questions

Random sampling on training data

- In bagging, random bootstrap replicates are generated by sampling the training set, so each replicate has a smaller number of (unique) training samples.
- We first project the high dimensional image data to the N−1 dimension PCA subspace. For N training samples, there are at most N−1 eigenvectors with nonzero eigenvalues.

- (1) Apply PCA to the face training set with N samples for c classes.

  Project all the face data to the N−1 eigenfaces $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_{\mathrm{N}-1}]$.

- (2) Generate *T* bootstrap replicates $\{S_t\}_{t=1}^{T}$.

  Each replicate contains the training images of c1 individuals randomly selected from the c classes, or a random subset of images for each of the c classes.

- (3) Construct a PCA-LDA classifier from each replicate and combine the multiple classifiers using a fusion rule.

  Mpca and Mlda need to be chosen.

Random sampling in feature space

- We first project the high dimensional image data to the N−1 dimension PCA subspace before random sampling.
- In Fisherface, overfitting happens when the training set is relatively small compared to the high dimensionality of the feature vector.
- In order to construct a stable LDA classifier, we sample a small subset of features.
- By the random sampling, we construct multiple stable LDA classifiers.
- We then combine these classifiers to construct a more powerful classifier that covers the entire feature space without losing discriminant information.

Random sampling in feature space

At the training stage:

Consider N images $\{\mathbf{x}_n\}$, n = 1,...,N and $\mathbf{x}_n \in R^D$ in an D-dimensional image space, and assume that each image belongs to one of c classes.

- (1) Apply PCA to the face training set:

  All the eigenfaces with zero eigenvalues are removed, and N−1 eigenfaces $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_{N-1}]$ are retained.

- (2) Generate T random subspaces $\{R_t\}_{t=1}^{T}$:

  Each random subspace R_t is spanned by M0 + M1 dimensions.

  The first M0 dimensions are fixed as the M0 largest eigenfaces in $\mathbf{W}$.

  The remaining M1 dimensions are randomly selected from the other N−1−M0 eigenfaces in $\mathbf{W}$.

- (3) T LDA classifiers $\{y_t^R(\mathbf{x})\}_{t=1}^{T}$ are constructed from the T random subspaces.

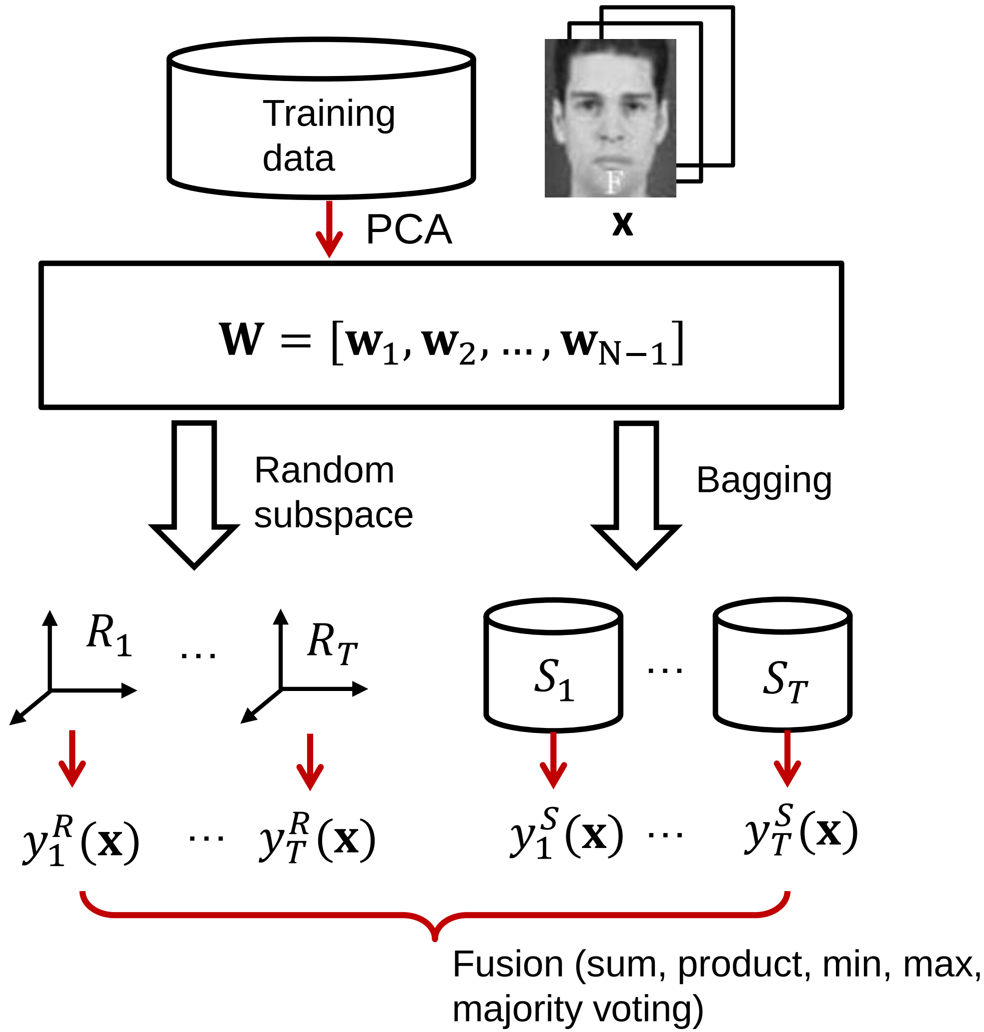
  Mpca (=M0+M1) and Mlda need to be chosen.

Random sampling in feature space

At the testing stage:

- (1) The input face data is projected to *T* random subspaces and fed to *T* PCA-LDA classifiers in parallel.
- (2) The outputs of the *T* PCA-LDA classifiers are combined using a fusion scheme (e.g. sum, product, min, max, majority voting) to make the final decision.

Random sampling based PCA-LDA (Fisherface)



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