Similarity Learning with (or without) Convolutional Neural Network

Moitreya Chatterjee, Yunan Luo

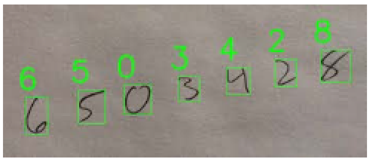
Image Source: Google

Outline – This Section

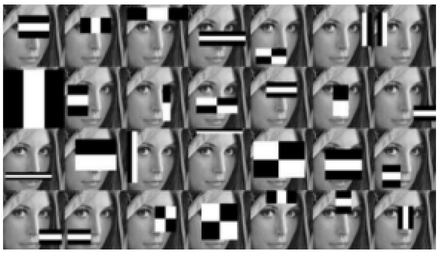
- **Why do we need Similarity Measures**
- **Metric Learning as a measure of Similarity**
  - **Notion of a metric**
  - **Unsupervised Metric Learning**
  - **Supervised Metric Learning**
- **Traditional Approaches for Matching**
- **Challenges with Traditional Matching Techniques**
- Deep Learning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

Need for Similarity Measures

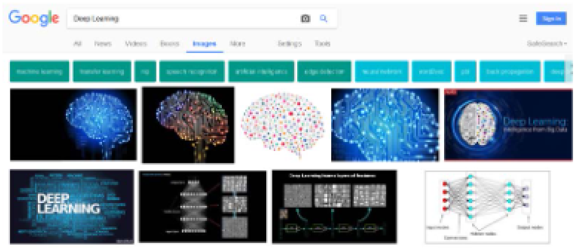
Several applications of Similarity Measures exists in today's world:



- 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.
  - $f(x, y) = (x - y)^T \Sigma^{-1} (x - y)$; where Σ is the mean-subtracted covariance matrix of all data points.

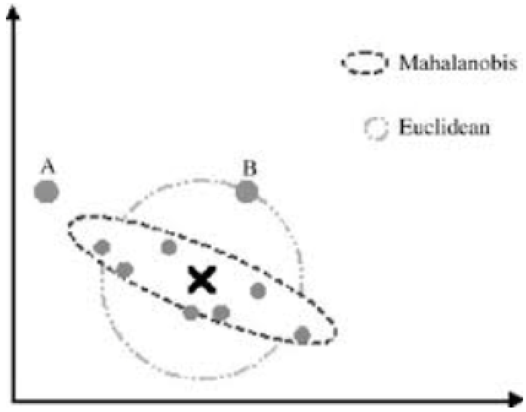


Image Source: Google

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.

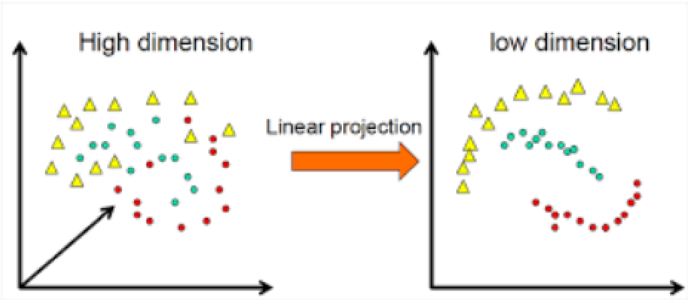


Image Source: Google

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: $J(w) = \max_w (w^T S_B w)/(w^T S_W w)$

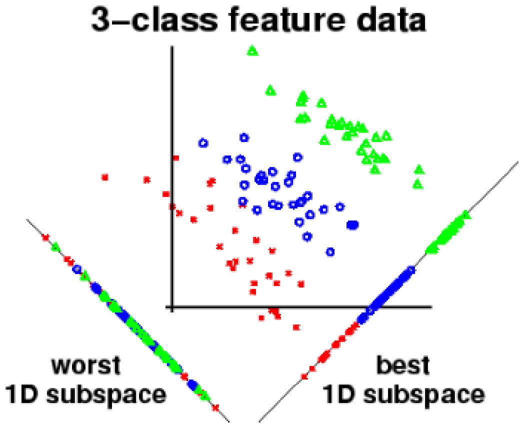


Image Source: Google

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