Handwriting Identification

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Abstract

After a week of learning and working, our group decided to build a **Handwriting Identification** model. In this paper, we introduced 2 general concepts of Machine Learning: **The Unified Framework** and **TEFPA**, discussed how the each concept was applied in our model, and described the Handwriting Identification model in detail.

Contents

1 Introduction to Machine Learning:

1.1 TEFPA:

TEFPA is the general model in Machine Learning, including

- T (Task) - input and output of the model
- E (Experience) - dataset used in the model
- F (Function) - functions used in the model
- P (Performance) - assessment of the model (loss/accuracy)
- A (Algorithm) - algorithms applied in the model

1.2 A Simplified yet Unified Framework:

A framework that is used to solve all problems with machine learning.

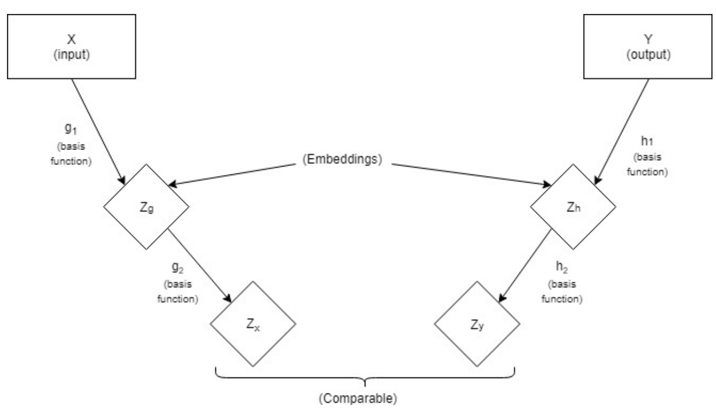

Image 1. Machine Learning Unified framework

Notes:

1. g_1: Basis function (linear function)
2. Z_g, Z_h: Embeddings/ Coordinate vector / Basis vector
3. g_2: Basis function
4. Z_x, Z_y: comparable vectors

Brief Description:

- Input goes through basis function g_1 to extract important features as embeddings (coordinate vectorS).
- Function g_2 projects embeddings into the same space to compare predicted output with the real output.

2 Handwriting Identification

Handwriting Identification is a program that identifies writer from an image of handwritten sentences.

2.1 Handwriting Identification in Unified Framework

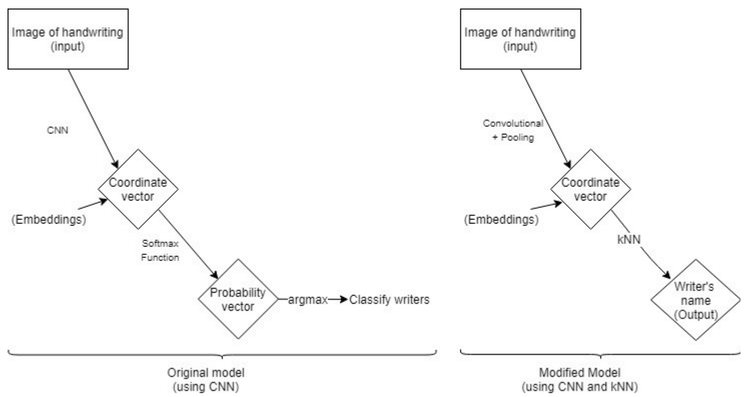

Image 2. Handwriting Identification's Unified framework

Brief Description:

- Original Model:
  + Image of handwriting goes through CNN to extract important features as embeddings (coordinate vectors).
  + Softmax function generates embeddings into probability vectors, using argmax to find writer that has the highest probability.

- Modified model:
  + Image of handwriting goes through CNN to extract important features as embeddings (coordinate vectors).
  + Embedding goes through kNN to find writer with the nearest coordinate vector to it in the vector space.

2.2 Handwriting Identification's Task:

- Input: Image of handwritten sentences
  - Output: Name of writer
  - Purpose: To identify writer based on images of handwriting.

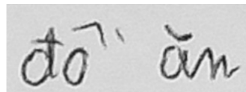

Image 3. Input image

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Writer_name :  Trung
```

Image 4. Output

2.3 Handwriting Identification's Experience:

- Dataset: IAM Handwriting Database
- Description: The dataset includes 657 writers contributed samples of their handwriting, which were scanned at a resolution of 300dpi and saved as PNG images with 256 gray levels.
- Each image is cropped into 113x113-size images, to increase the capability of the database.
- The dataset is split into train files, test files, and validation files with the ratio 4:1:1
- We imported images of handwritten sentences of our class's students as new data and used 'convert(mode= "L")' to convert images into grayscale.

2.4 Handwriting Identification's Function:

Structure: Consists of CNN (Convolutional Neural Network)

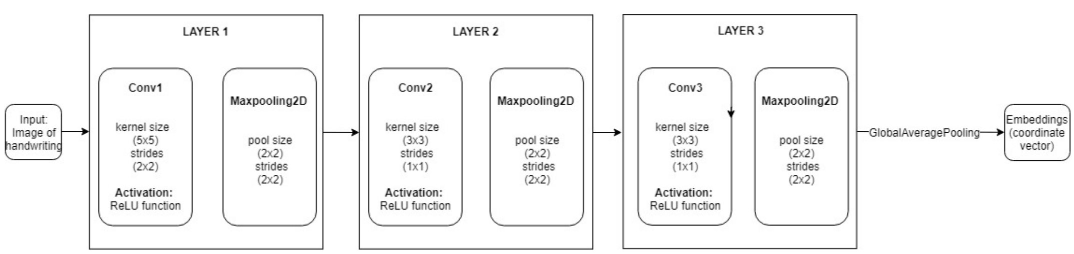

Image 5. CNN in Handwriting Identification

CNN was used for the machine to extract and learn the important features in the input image.
CNN consists of 3 main types of layers: Convolution Layer, Pooling Layer and Fully-connected Layer:

+ **Convolution Layer**: the objective of convolution is to extract high-level features of the image from the input image. The first convolution layer is responsible for extracting low-level features. As there are more convolution layers, the machine are able to learn higher-level features of the image.
+ **Pooling Layer**: is used to reduce the size of the convolved feature in the image, in order to reduce the computationtal power required to run the process.
+ **Fully-connected Layer**: performs classification based on the features extracted by previous layers. It typically contains softmax activation function in order to output a probability vector for each of the classification labels.

Our original model classified handwriting of 50 writers. In order to change to a recognition model, we changed the structure of the model by removing the last layer (Fully-Connected Layer) in CNN and adding kNN algorithm.

2.5 Handwriting Identification's Performance:

To measure the loss in the session we use **cross entropy** to measure the differences between the training datas (cropped images) and the samples (images from dataset)

2.6 Handwriting Identification's Algorithm:

-Optimizer : ADAM
-kNN (k Nearest Neighbors) : a supervised-learning that use K nearest data in the dataset to label new input data. We use this to calculate global average weights and label unseen handwritings (following major voting).

3 Resources

http://www.fki.inf.unibe.ch/databases/iam-handwriting-database