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Offline Handritting Word Recognition

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Overview of the Project

Off-line handwriting recognition

- It involves the automatic conversion of text in an image into letter codes which are usable within computer and text-processing applications
- Off-line handwriting recognition is comparatively difficult, as different people have different handwriting styles

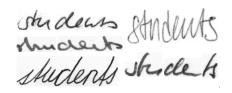


Figure: 'Students' written by different authors



Our Al Project

A lot of research has been done over the past years.

We explored the topic and implemented a full pipeline for the task. The research touched different fields:

- Data Collection
- Image Processing
- Features extraction
- Machine Learning techniques
- Word Recognition using Hidden Markov Models



Dataset

The IAM Handwriting Database¹

- Unconstrained handwritten text (scanned at a resolution of 300dpi and saved as PNG images with 256 gray levels)
- 1'539 pages of scanned text of 657 writers
- We extracted 35 instances of the 300 most frequent words (20 as training set and 15 as test set)

Example of a page of scanned text

Sentence Database

N01-009

"Good lack, Air Marshal," she said geath. "The waiting for you at the Hotel Roma at six this evening - and I shall look forward to meeting you both at midnight." They might have been arranging supper party. Then she rang off. Alastair admitted that never in a not altogether uneventful life had be come across a girl who sounded so charming and appeared to be so efficient.

Good buck, to Marshal, " sur said gently "I'll be Haiting for you at the total Roma at the time the Roma at the total wind you both at midwight." They aright have been alranging a supple pary. Then the long of that a decorate an area of the had we can a give in a sure of the world so chasting and appeared to be so efficient.

Overview Implementation Details Results Conclusions Section no. 4

Pipeline Pre-Processing Feature Extraction Hidden-Markov Model

Implementation Details

Pipeline

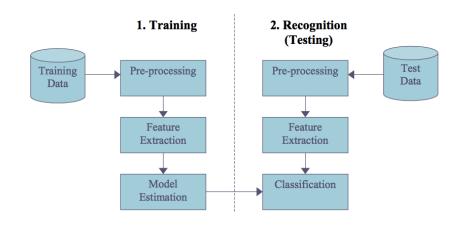


Figure: Pipeline of a word recognition system

Pipeline Pre-Processing Feature Extraction Hidden-Markov Model

Implementation Details

Pre-Processing

Pipeline

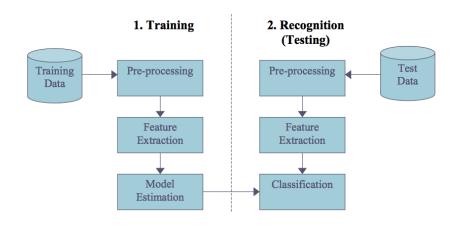
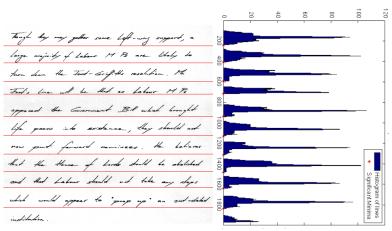


Figure: Pipeline of a word recognition system

Line Segmentation



Original image segmented in lines

Vertical histograms and significant minima

Skew and Slope Correction

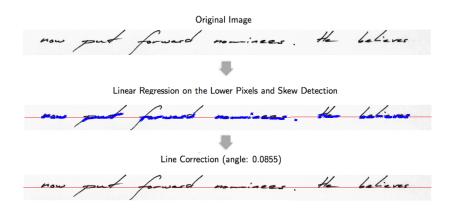


Figure: Skew detection and correction pipeline

Slant detection and Correction

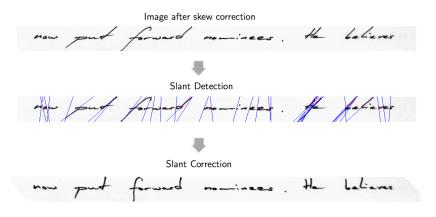


Figure: Slant detection and correction pipeline

Word segmentation

Vertical Scaling

Pipeline Pre-Processing Feature Extraction Hidden-Markov Model

Implementation Details

Feature Extraction

Features

We want to find features that minimise the within-class variability and maximise the between class variability. On top of this, the features should be robust againts distortions caused by different handwriting styles. Moreover, we want to find low dimensional featur vectors and would therefore like features to be highly descriptive. The selection of features depends both on the pre-processing and the classifier to use. If all characters are assumed to have the same oriention, we need rotation variant features to distinguish between for instance a 6 and a 9 and a b and an p, etc.

HMM

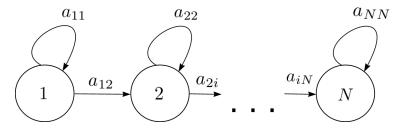


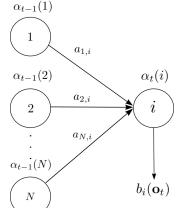
Figure: Left-to-right HMM with N states

Main problems in an HMM

- The probability of an observation sequence, given the model, $P(\mathbf{O}|\lambda)$.
- ② The most likely state sequence, underlying a given observation sequence and the model, $Q^* = \max P(Q|\mathbf{0}, \lambda)$.
- **3** The most likely parameters of the model $\lambda^* = \max P(X|\lambda)$, given a training set of M observation sequences $X = (\mathbf{O}_1, \mathbf{O}_2, \dots, \mathbf{O}_M)$.

Forward probability

Solution to the first problem, use *forward-backward* algorithm, a special instance of the sum-product algorithm

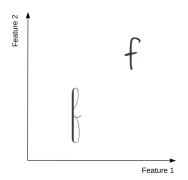


Updating the parameters

Use EM-algorithm

Updating parameters

Within class variations



Using features such as loops, this will give quite different feature vector.



Within class variations

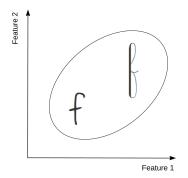


Figure: Fitting a single Gaussian

Within class variations

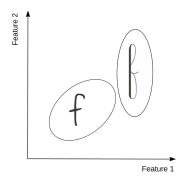


Figure: Fitting a mixture of 2 Gaussians

Problems we ran into

$$X = \begin{pmatrix} -1 & 0 \\ 2 & 0 \\ 1 & 0 \\ -2 & 0 \end{pmatrix}$$

Problems we ran into

$$X = \begin{pmatrix} -1 & 0 \\ 2 & 0 \\ 1 & 0 \\ -2 & 0 \end{pmatrix}$$

$$\Sigma = \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix}$$

Results

blabla



Conclusions

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