

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

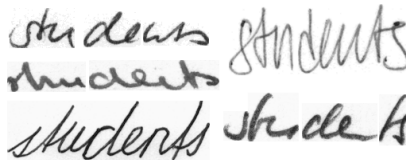


Figure: 'Students' written by different authors

Our AI 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

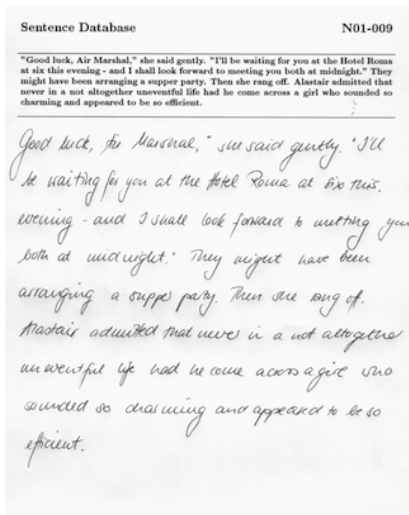
Dataset

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)

¹<http://www.iam.unibe.ch/fki/databases/iam-handwriting-database>

Example of a page of scanned text



Implementation Details

Pipeline

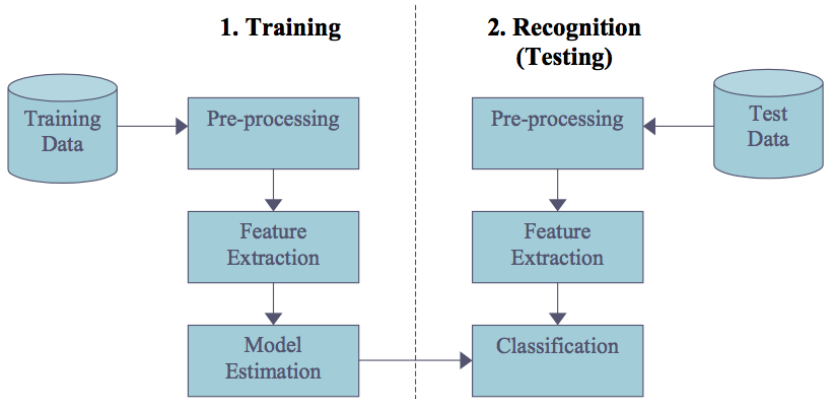


Figure: Pipeline of a word recognition system

Implementation Details

Pre-Processing

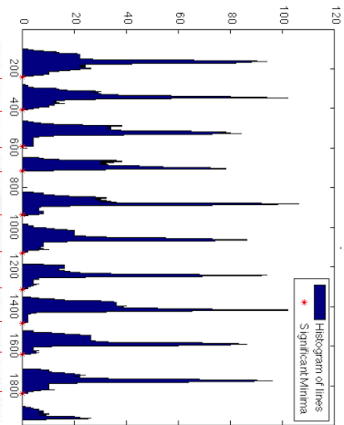
Pre-processing

Images/pipelinePP.png

Line Segmentation

Tough they may gather some Left-wing support, a large majority of Labour M P's are likely to turn down the Foot-Griffiths resolution. The Foot's line will be that as Labour M P's opposed the Government Bill which brought life gears into existence, they should not now put forward nominees. He believes that the House of Lords should be abolished and that Labour should not take any steps which would appear to "prop up" an out-dated institution.

Original image segmented in lines



Vertical histograms and significant minima

Figure: Example of line segmentation

Skew and Slope Correction

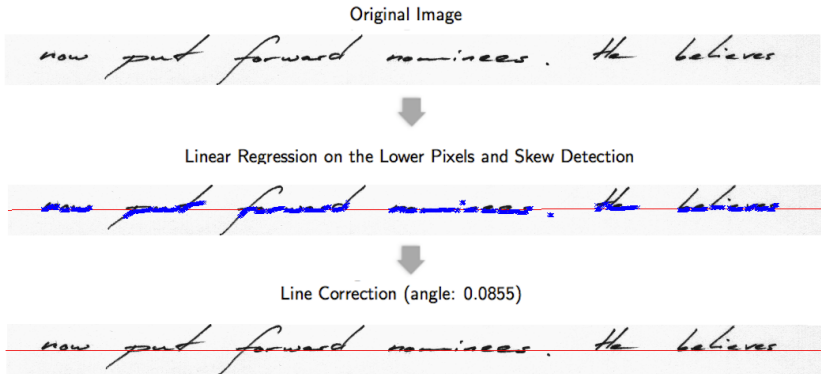
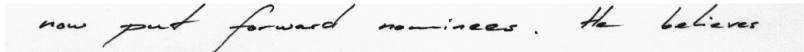


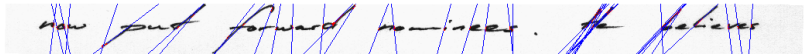
Figure: Skew detection and correction pipeline

Slant detection and Correction

Image after skew correction



Slant Detection



Slant Correction

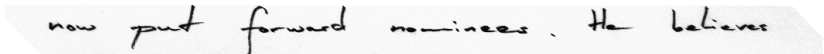


Figure: Slant detection and correction pipeline

Word segmentation

- We first detect white spaces:

Images/words_segm_wp.png

Vertical Scaling

Skeletonization

Remembering the entire pipeline....

Why do we repeat skew and slant correction twice?

Images/pipelinePPex.png

Because....

Images/pipelinePPex.png

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 against distortions caused by different handwriting styles. Moreover, we want to find low dimensional feature 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 orientation, we need rotation variant features to distinguish between for instance a 6 and a 9 and a b and an p, etc.

HMM

- A set of N states $S = (s_1, s_2, \dots, s_N)$, where the state of the system at time t is denoted q_t
- A set of priors $\pi = (\pi_1, \pi_2, \dots, \pi_N)$, providing the probability $P(q_1 = s_i)$.
- A transition function \mathbf{A} , where $a_{ij} = P(q_{t+1} = s_j | q_t = s_i)$.
- An observation function \mathbf{B} , mapping each observation at every state to a probability $b_i(\mathbf{o}_t) = P(\mathbf{o}_t | q_t = s_i, \lambda)$, where λ denotes the model parameters.

The model is trained to estimate the posterior probability $P(\mathbf{O}|\lambda)$ of an observation sequence \mathbf{O} , with D -dimensional observation vectors $\mathbf{o}_t = (o_1, o_2, \dots, o_D)$.

HMM

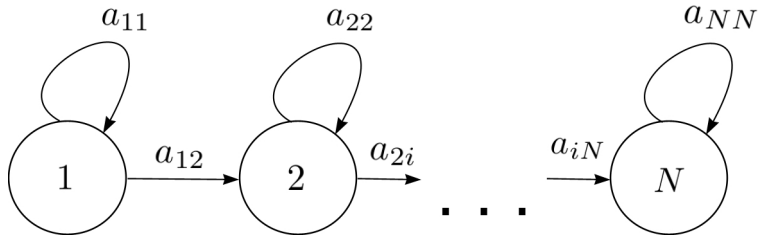


Figure: Left-to-right HMM with N states

Main problems in an HMM

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

Main problems in an HMM

- 1 The probability of an observation sequence, given the model, $P(\mathbf{O}|\lambda)$.

Sum-product algorithm: forward-backward algorithm

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

EM-algorithm: Baum-Welch reestimation

- 3 The most likely state sequence, underlying a given observation sequence and the model, $Q^* = \max P(Q|\mathbf{O}, \lambda)$.

Dynamic programming: Viterbi algorithm

Forward probability

$$\alpha_t(i) \equiv P(o_1, o_2, \dots, o_t | q_t = s_i, \lambda) = \left[\sum_{j=1}^N \alpha_{t-1}(j) a_{ij} \right] b_j(o_t) \quad (1)$$

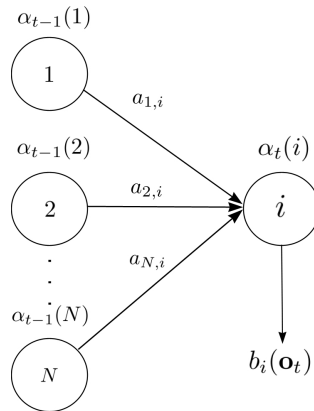


Figure: Computation of forward probability

Forward probability

$$\alpha_t(i) \equiv$$

$$P(o_1, o_2, \dots, o_t | q_t = s_i, \lambda) =$$

$$\left[\sum_{j=1}^N \alpha_{t-1}(j) a_{ij} \right] b_j(o_t) \quad (2)$$

$$P(\mathbf{O}|\lambda) = \sum_{i=1}^N \alpha_T(i) \quad (3)$$

Problem 1 solved.

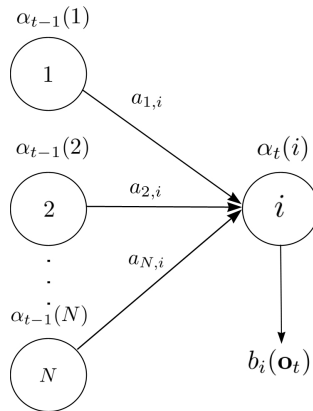


Figure: Computation of forward probability

Updating the parameters

The forward-backward algorithm also comes with a backward probability:

$$\beta_t(j) \equiv P(o_{t+1}, o_{t+2}, \dots, o_T | q_t = s_j, \lambda) = \sum_{i=1}^N a_{ij} b_i(o_{t+1}) \beta_i(o_{t+1}) \quad (4)$$

With this we can define the probability of being in a state at a timestep as:

$$\gamma_t(i, k) \equiv \gamma_t(i) \frac{b_{i,k}(\mathbf{o}_t)}{b_i(\mathbf{o}_t)} \quad (5)$$

Updating the parameters

Comparison with GMM:

Model:	GMM	HMM
Model parameters:	$\lambda = \pi, \mu, \Sigma$	$\lambda = \pi, \mathbf{A}, \mathbf{B}$
Hyper parameters:	Number of components	Topology (states, transitions)
Observed variables:	Data points	Observations
Latent variables:	Priors of a component	State sequence

Updating parameters

Model:	GMM	HMM
E-step:	Estimate the probability of a component, given the data and current parameters.	Estimate the probability of being in a state at a timestep and the probability of transferring from a state to another state.
M-step:	Maximise π , μ and Σ .	Maximise π , A and B

Problems we ran into

Consider the following observation:

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

Problems we ran into

$$\mathbf{O} = \begin{pmatrix} -1 & 0 \\ 2 & 0 \\ 1 & 0 \\ -2 & 0 \end{pmatrix}$$
$$\Sigma = \begin{pmatrix} 3\frac{1}{3} & 0 \\ 0 & 0 \end{pmatrix}$$

Problems we ran into

Singularities

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

$$\Sigma = \begin{pmatrix} 3\frac{1}{3} & 0 \\ 0 & 0 \end{pmatrix}$$

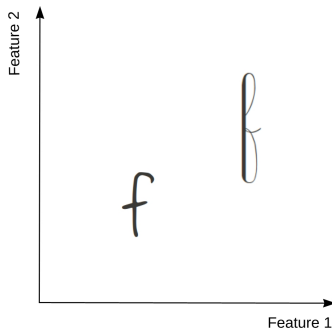
$$|\Sigma| = 0$$

Possible solution: Add some random noise.

Problems we ran into

Short words/long words.

Within class variations



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

Within class variations

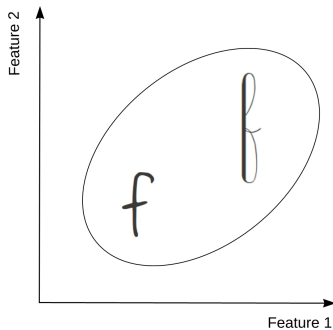


Figure: Fitting a single Gaussian

Within class variations

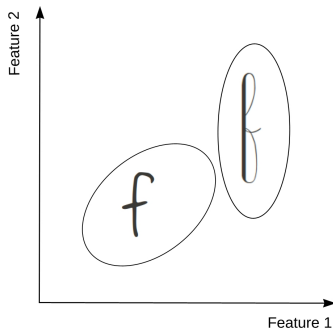


Figure: Fitting a mixture of 2 Gaussians

Results

blabla

Conclusions

blabla

blocs

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