

# Offline Handritting Word Recognition

Thijs Kooi, Davide Modolo

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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

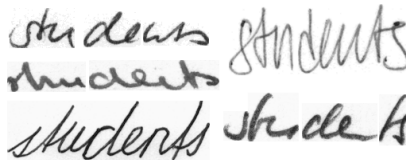


Figure: 'Students' written by different authors

# 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

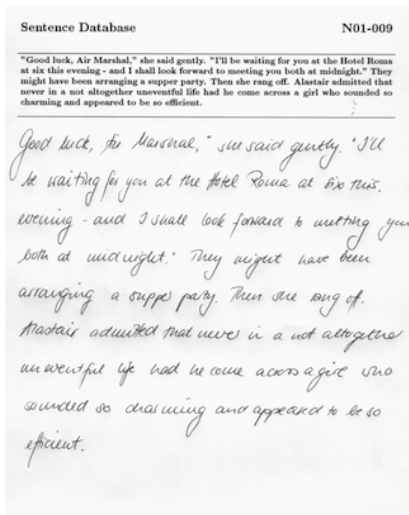
## The IAM Handwriting Database<sup>1</sup>

- 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)

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

## Example of a page of scanned text



## Implementation Details



# Pipeline

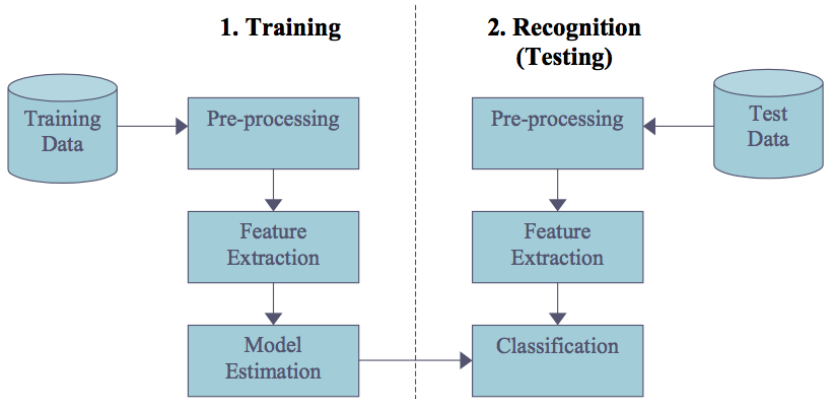


Figure: Pipeline of a word recognition system

## Implementation Details

### Pre-Processing

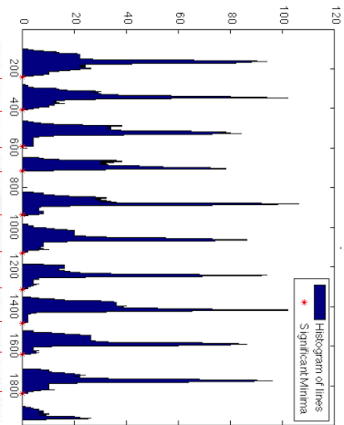
# Pre-processing

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

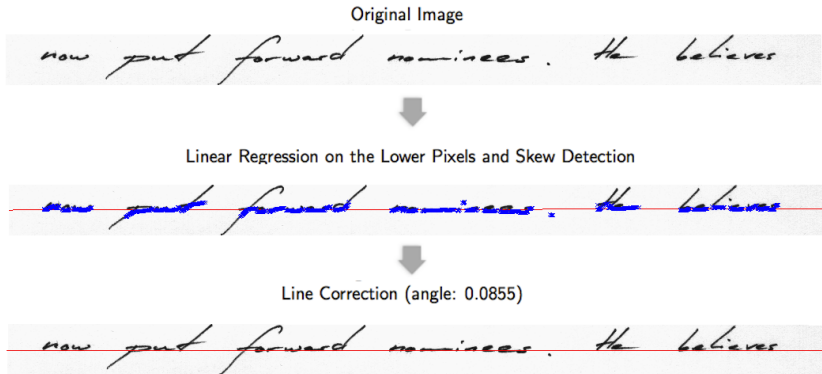
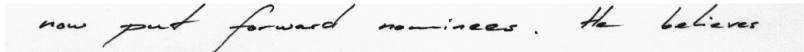


Figure: Skew detection and correction pipeline

# Slant detection and Correction

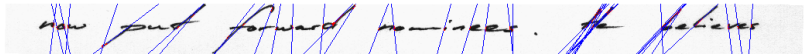
Image after skew correction



now put forward nominees. He believes



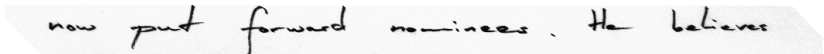
Slant Detection



now put forward nominees. He believes



Slant Correction



now put forward nominees. He believes

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

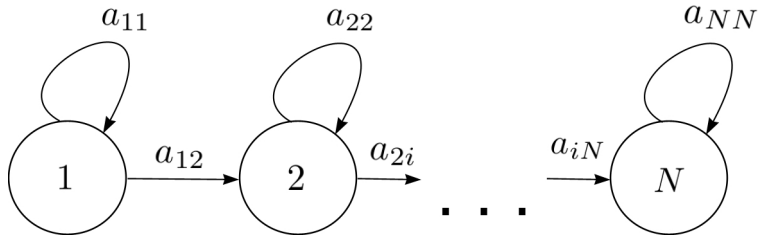


Figure: Left-to-right HMM with  $N$  states

# 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

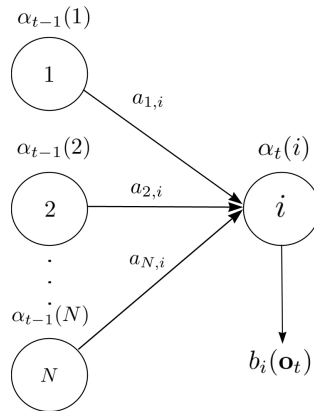
- 3 The most likely state sequence, underlying a given observation sequence and the model,  $Q^* = \max P(Q|\mathbf{O}, \lambda)$ .

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

# Updating the parameters

Comparison with GMM:

Model:	<b>GMM</b>	<b>HMM</b>
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

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

## Problems we ran into

Singularities. Consider the following observation:

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

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Singularities

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

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## Singularities

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

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

- Add some random noise, also to prevent variance from collapsing.

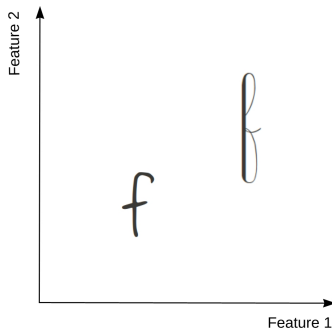
## Problems we ran into

Short words have less likelihood.

Harder to recognise, more subject to writer variations.

tried to solve this by using MOG.

## Within class variations



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



## Within class variations

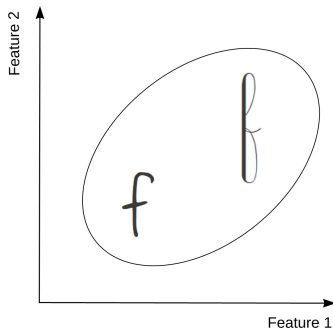


Figure: Fitting a single Gaussian

## Within class variations

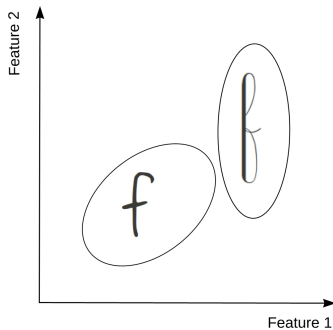


Figure: Fitting a mixture of 2 Gaussians

# Results

blabla

# Conclusions

blabla

blocs

## title of the bloc

bloc text

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