

# Offline Handwriting 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

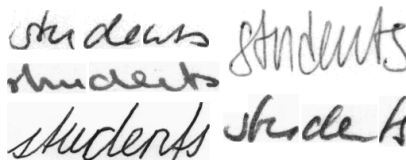


Figure: 'Students' written by different authors

# 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

# Dataset

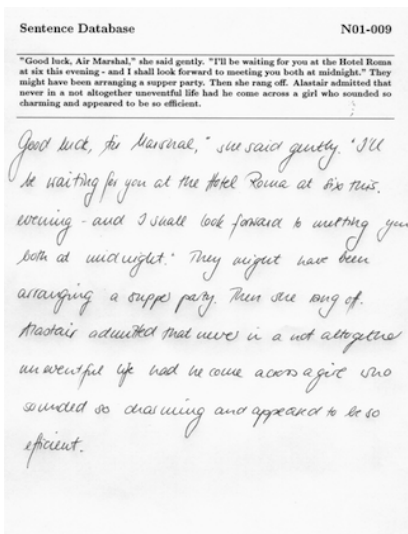
## The IAM Handwriting Database 3.0<sup>1</sup>

- 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
- 13'353 isolated and labeled text lines
- 115'320 isolated and labeled words

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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

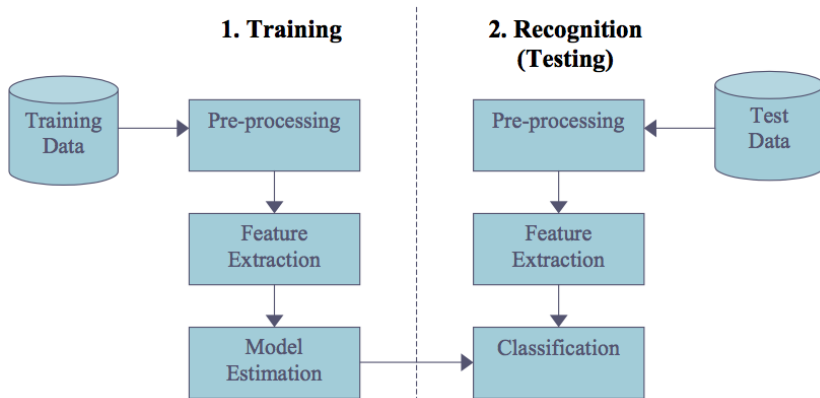


Figure: Pipeline of a word recognition system

## Implementation Details

### Pre-Processing

# Pre-processing

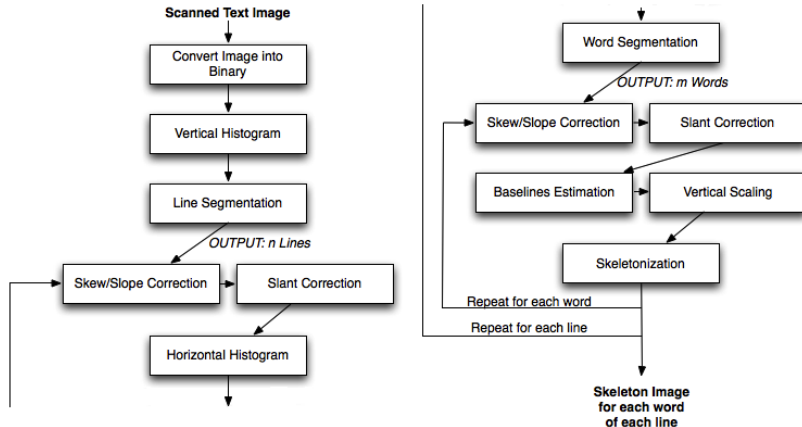
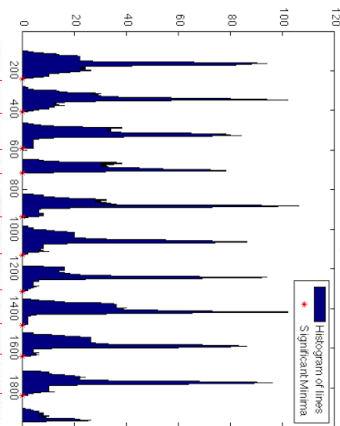


Figure: Pipeline for the pre-processing/normalization step

# Line Segmentation

Tough they may gather some left-wing support, a large majority of Labour MPs are likely to turn down the Foot-Griffiths resolution. The Foot's line will be that as Labour MPs opposed the Government Bill which brought life peers 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

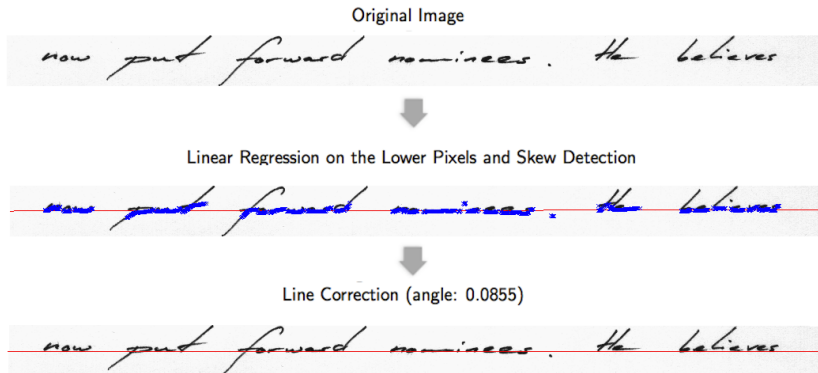


Figure: Skew detection and correction pipeline

# Slant Correction

Image after skew correction

now put forward nominees. He believes



Slant Detection

now put forward nominees. He believes



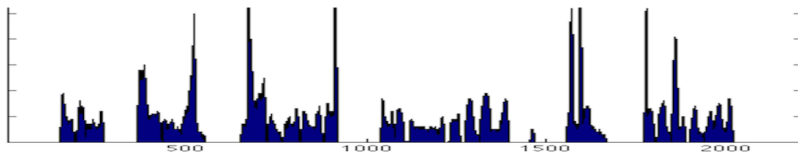
Slant Correction

now put forward nominees. He believes

Figure: Slant detection and correction pipeline

# Word segmentation

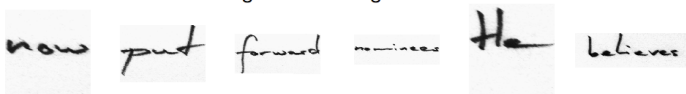
Horizontal Histogram



White Spaces Distribution



Clustering and Words Segmentation

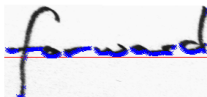


# Baseline Estimation

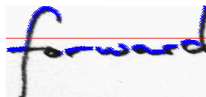
forward



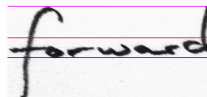
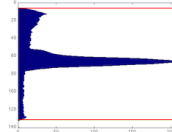
Lower Baseline



Upper Baseline



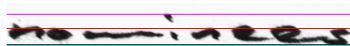
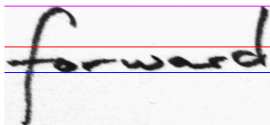
Ascender and Descender Baselines





# Vertical Scaling

Words with baselines



Normalization to fixed height and fixed baselines

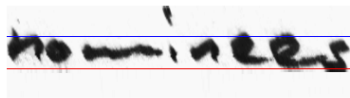
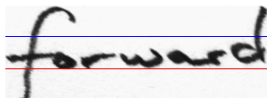


Figure: Examples of vertical scaling process

# Skeletonization

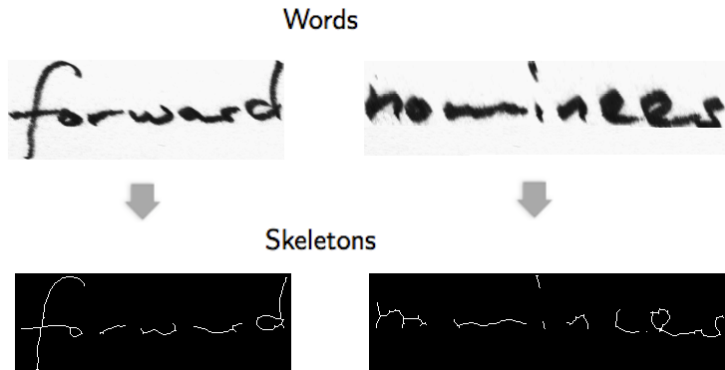
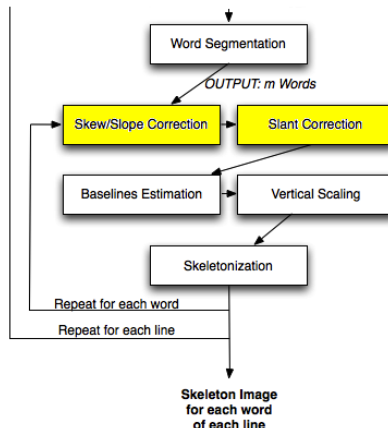
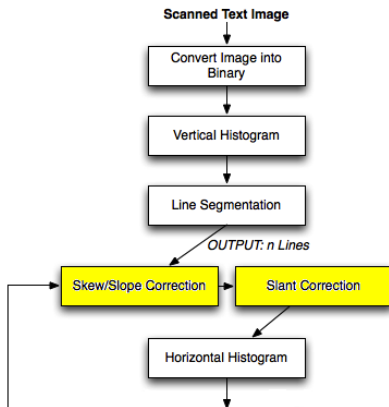


Figure: Skeletonization process

# Remembering the entire pipeline....

## Why repeating skew and slant correction twice?



# The normalizations are necessary for:

First

Words segmentation

Images/problem1.png

## Implementation Details

### Feature Extraction

# Features

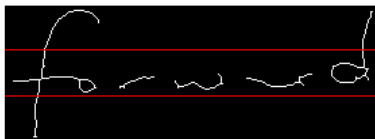
Extracted from the skeleton of the words.

Mainly 2 types:

- Statistical
- Morphological

# Statistical Features

Percentage of white pixels in the 3 zones of the word:



Upper Zone: 0.0124 %

Middle Zone: 0.0338 %

Lower Zone: 0.0033 %

Figure: Example

# Morphological Features

Obtained by **connected component analysis**.

- A connected component it is a subgraph in which any two vertices are connected to each other by paths, and which is connected to no additional vertices.





# Morphological Features

We extract:

Images/morpho\_features.png

## Implementation Details

### Hidden-Markov Model for Word Recognition

# 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 **A**, where  $a_{ij} = P(q_{t+1} = s_j | q_t = s_i)$ .
- An observation function **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  $\lambda$  denotes the model parameters.

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

# HMM

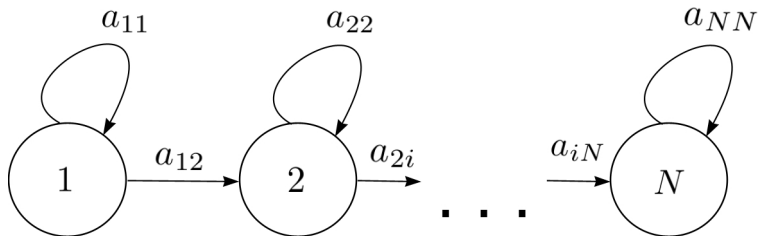


Figure: Left-to-right HMM with  $N$  states

# 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

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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

### 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), observation function
Observed variables:	Data points	Observations
Latent variables:	Priors of a component	State sequence

# Updating parameters

Model:	<b>GMM</b>	<b>HMM</b>
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 $\pi$ , <b>A</b> and <b>B</b>





# Problems we ran into

Singularities. Consider the following observation:

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

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

# 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

Length of the word. Short words seem to be harder to find.

Possible causes:

- During the testing, the model does not execute a complete sequence, e.g. when looking for 'the' in 'therefore' it might end before 'r'.
- Short words may be more difficult to recognise as they are more sensible to inter-writer variations.

Possible solutions:

- Force the model to end the observations sequence in the final state.
- Use a more complex observation model. E.g., a MOG.

# Mixture of Gaussians

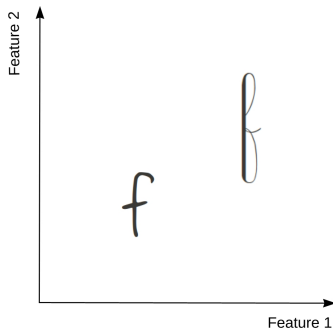


Figure: Two letters plotted in a two dimensional feature space

# Mixture of Gaussians

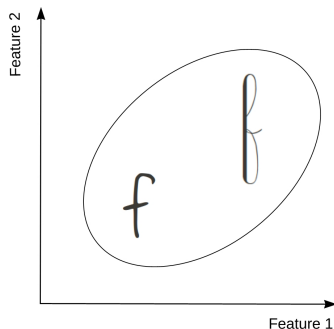


Figure: Two letters plotted in a two dimensional feature space

# Mixture of Gaussians

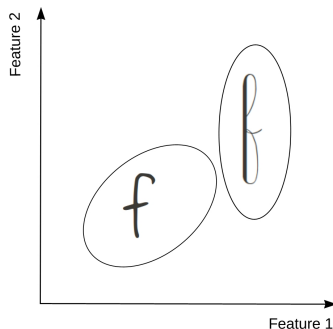


Figure: Two letters plotted in a two dimensional feature space

## Experiments and Results



# Experiments

We run 2 type of experiments:

- 1 vs 1 word recognition
  - We build models for 2 words and we test both models for new instances of the 2 words from novel authors
  - *GOAL*: Test how much the likelihoods of the 2 words differ
- all vs all words recognition
  - We build models for every word and for every word in the test set we rank all the models by loglikelihood
  - *GOAL*: Compute general accuracy for a small dataset

For both experiments the model of a word is built using 30 samples from 30 authors of the word.

# Experiment 1 - Typewritten words

- Done to check the correctness of the pipeline.
- Only used intensity features.
- Used words 'Letter' and 'Number' (same length)

Table: Results averaged over 40 runs

Word	Letter	Number	Difference
LL Intensity N=6 K=1	121.68	106.36	15.32
LL All features N=6 K=1	795.45	14.08	781.37
LL All features N=1 K=1	602.22	-90.02	692.22
LL All features N=6 K=3	226.96	-820.30	$1.04e^3$
LL ALL , N=6, K=1, diagonal cov	871.16	531.27	487.75
LL ALL , N=6, K=1, isotropic cov	-179.00	-272.23	197.35
...	...	...	...

## Experiment 1 - Handwritten Words (same length)

- Used words 'Before' and 'People' (same length)

**Table:** Results for simple handwritten words, avg over 40 runs

Word	Before	People	Difference
LL All features N=6 K=1	$1.17e + 03$	$1.19e + 03$	480.16
LL All features N=1 K=1	699.56	$1.0124e + 03$	422.78
LL All features N=6 K=3	226.96	-820.30	$1.04e^3$

# Experiment 1 - Handwritten Words (short vs long)

## Experiments 2

- Used a small dataset of 100 words
- Tested on 200 words of novel authors

Num. States	Num. Gaussian Comp.	Accuracy 1 <sup>2</sup>	Accuracy 2 <sup>3</sup>
lengthWord	1	0.2400	0.3400
1	1	0.2000	0.3600
1	5	0.0800	0.1800
lengthWord	5	0.1200	0.3000

<sup>2</sup>Correct if in 1st position of the ranked list

<sup>3</sup>Correct if in 1st or 2nd position of the ranked list

# Evaluation

- short vs long...
- More GMM components seems to decrease the accuracy because of ....

## Conclusions

# Conclusions about the AI project

- The full pipeline is working, however a lot of improvements are possible:
  - Extract more features
  - Eventually apply PCA to the feature vector
  - Optimize the parameters of the HMM (i.e. using a validation set).
- Built models for letters instead of models for words (it requires letters segmentation)
- Use a language model



# Personal Evaluation

- We built a full working pipeline
- We read and learnt a lot about a new topic
- We had the chance to apply a lot of techniques that we had only been studied in theory
- We improved our skills in programming

Questions?