# 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

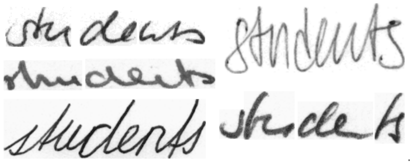


Figure: 'Students' written by different authors

## 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

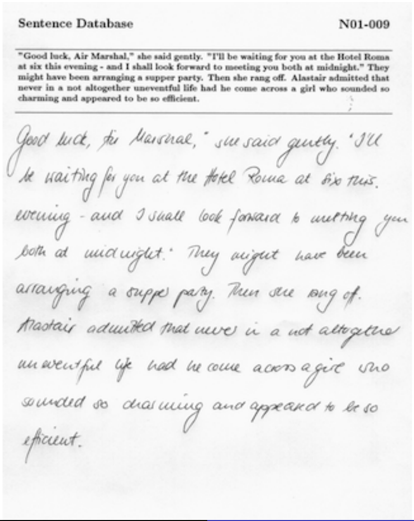
## Dataset

The IAM Handwriting Database 3.0[1]

- 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

[1]http://www.iam.unibe.ch/fki/databases/iam-handwriting-database

## Example of a page of scanned text



**Sentence Database** **N01-009**

"Good luck, Air Marshal," she said gently. "I'll be 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 a supper party. Then she rang off. Alastair admitted that never in a not altogether uneventful life had he come across a girl who sounded so charming and appeared to be so efficient.

Good luck, Air Marshal," she said gently. "I'll
be waiting for you at the Hotel Roma at six this
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## Implementation Details

## Pipeline

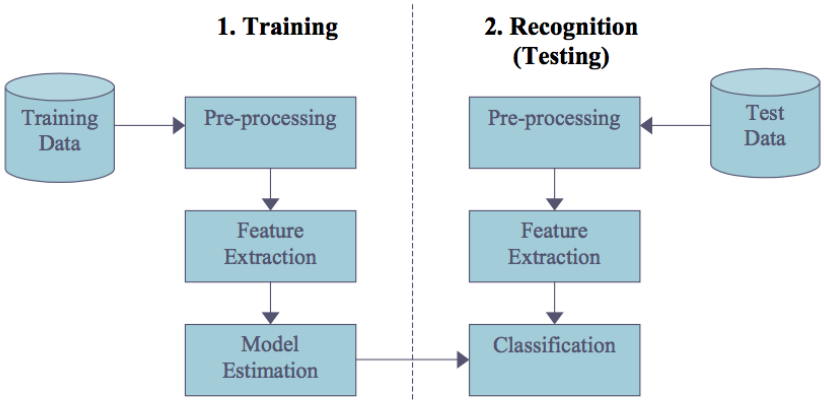


Figure: Pipeline of a word recognition system

## Implementation Details

Pre-Processing

## Pre-processing

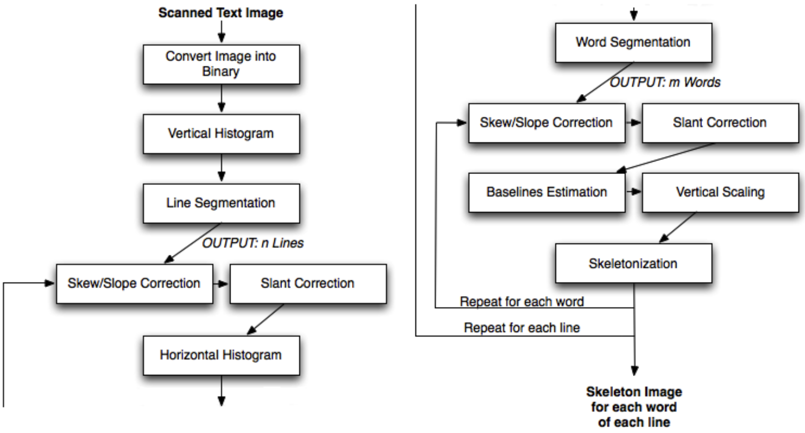
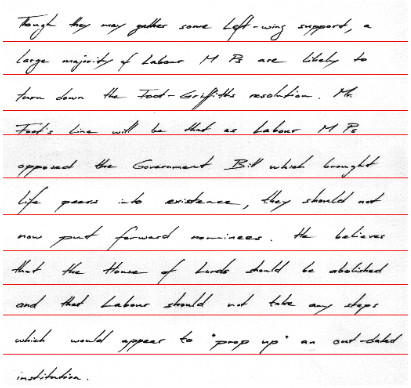


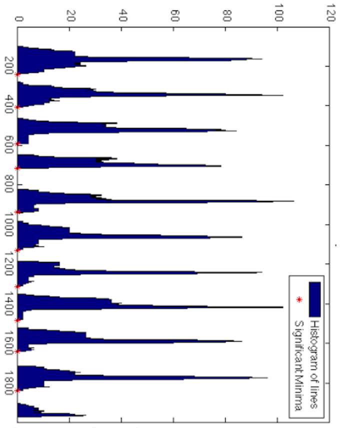
Figure: Pipeline for the pre-processing/normalization step

## Line Segmentation



Though they may gather some Left-wing support, a
large majority of Labour MPs are likely to
turn down the Foot-Griffiths resolution. Mr.
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

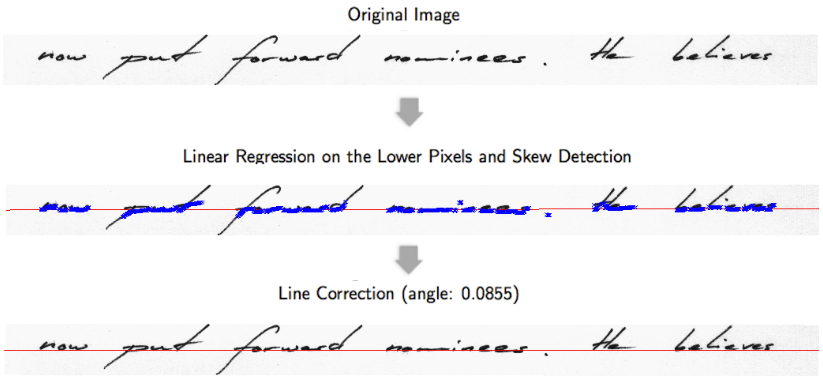

Original Image
Linear Regression on the Lower Pixels and Skew Detection
Line Correction (angle: 0.0855)

Figure: Skew detection and correction pipeline

## Slant Correction

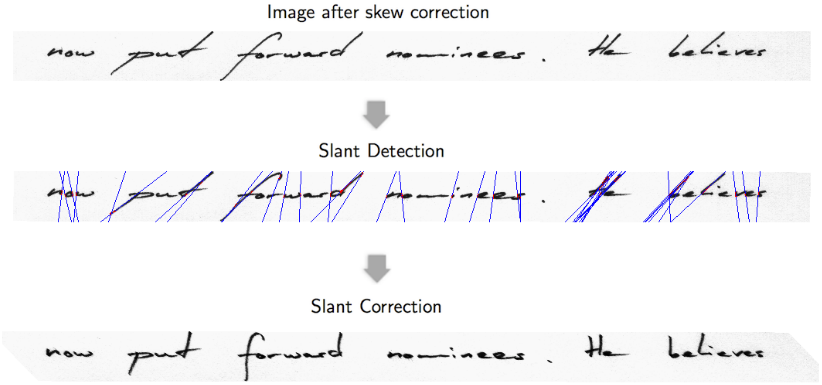
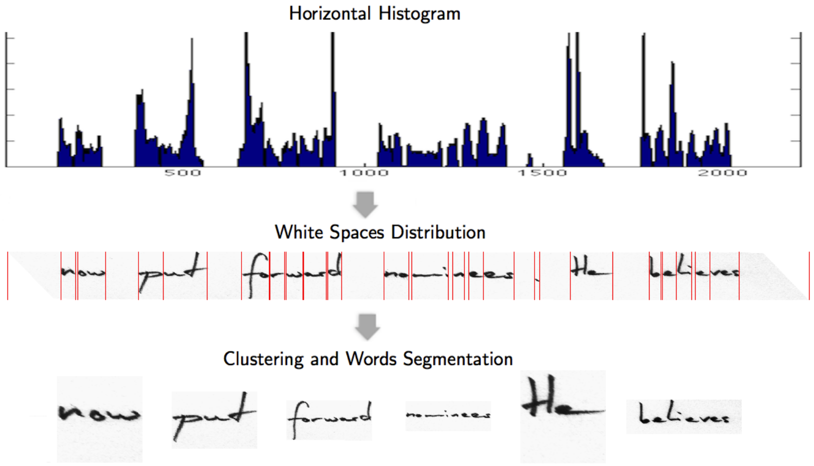


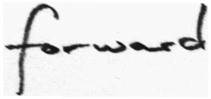
Image after skew correction
now put forward nominees. He believes
Slant Detection
Slant Correction

Figure: Slant detection and correction pipeline

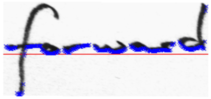
## Word segmentation



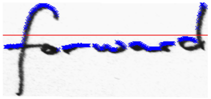
## Baseline Estimation



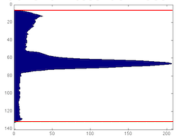
Lower Baseline

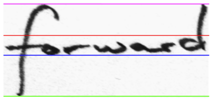


Upper Baseline



Ascender and Descender Baselines





## Vertical Scaling

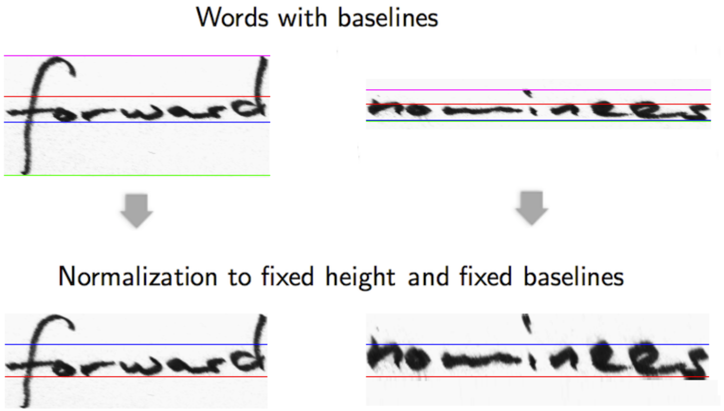


Figure: Examples of vertical scaling process

## Skeletonization

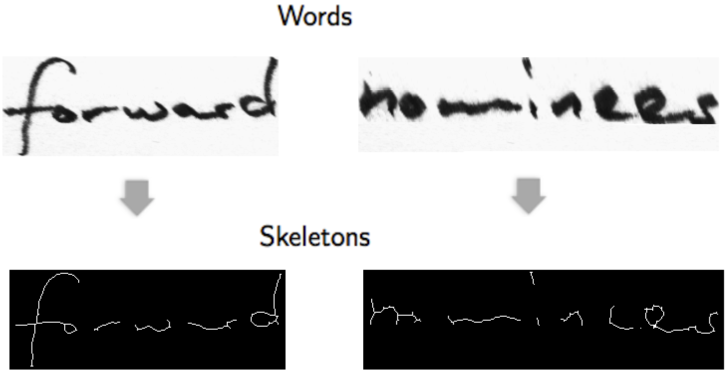
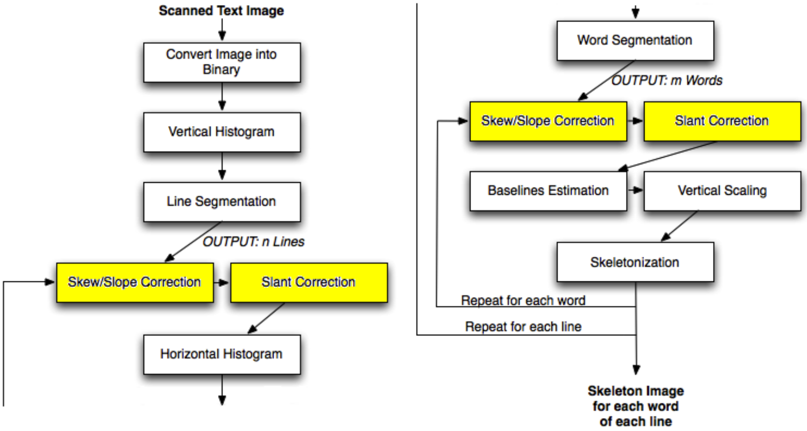


Figure: Skeletonization process

## Remembering the entire pipeline....

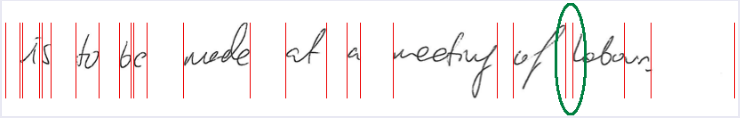
**Why repeating skew and slant correction twice?**



## The normalizations are necessary for:

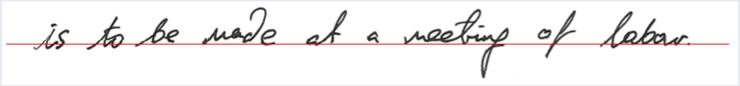
### First

Words segmentation



### Second

Not all the words have the same slope, slant and lower baseline



## 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:

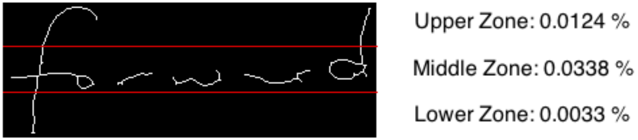


Figure: Example

## 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.

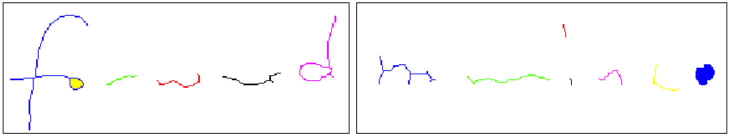
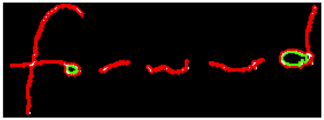


Figure: Example of words divided in different components (colors)

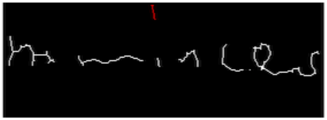
## Morphological Features

We extract:

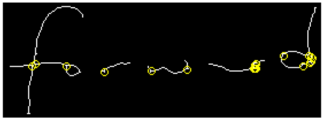
Loops



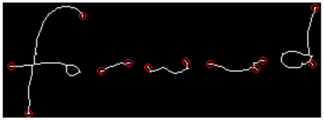
Dots



Junctions



Endpoints



## HMM

- A set of $N$ states $S = (s_1, s_2, \ldots, s_N)$, where the state of the system at time $t$ is denoted $q_t$
- A set of priors $\pi = (\pi_1, \pi_2, \ldots, \pi_N)$, 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 $\mathbf{o}_t = (o_1, o_2, \ldots, o_D)$.

## HMM

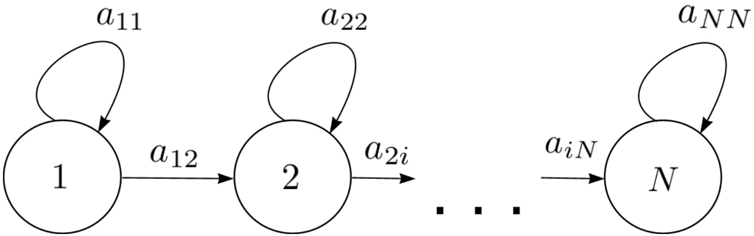


Figure: Left-to-right HMM with N states

## 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 $X = (\mathbf{O}_1, \mathbf{O}_2, \ldots, \mathbf{O}_M)$.
3. The most likely state sequence, underlying a given observation sequence and the model, $Q^* = \max P(Q|\mathbf{O}, \lambda)$.

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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

## Forward probability

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

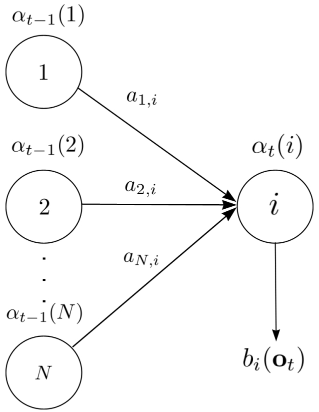

Figure: Computation of forward probability

## Forward probability

$$\alpha_t(i) \equiv$$
$$P(o_1, o_2, \ldots, o_t | q_t = s_i, \lambda) =$$
$$\left[\sum_{j=1}^{N} \alpha_{t-1}(j) a_{ij}\right] b_j(o_t) \tag{2}$$

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

Problem 1 solved.

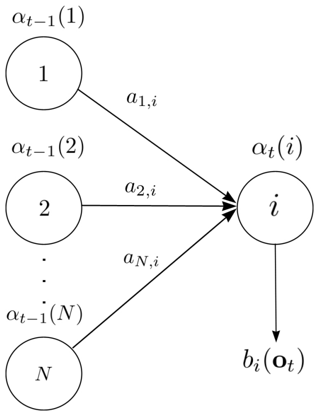

Figure: Computation of forward probability

## Learning the parameters

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

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

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

$$\gamma_t(i) \equiv (P(\mathbf{O}|\lambda))^{-1} \alpha_t(i) \beta_t(i) \tag{5}$$

Where normalisation constant
$P(\mathbf{O}|\lambda) = \sum_{j=1}^{N} \alpha_t(i)\beta_t(i) = \sum_{j=1}^{N} \alpha_T(j)$.

## Learning the parameters

$\hat{a}_{ij} = \mathit{frac}$Prob. of being in i and transfering to jProb. of begin in i $=$

$$\hat{a}_{ij} = \frac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{t=1}^{T-1} \gamma_t(i)} \tag{6}$$

The priors remain fixed, for the left-to-right model.

## 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), observation function |
| 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 transfering from a state to another state. |
| M-step: | Maximise $\pi$, $\mu$ and $\Sigma$. | Maximise $\pi$, **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

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

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.

## Results on simple task

Simple experiment, train the model on intensity features and run it on typewritten words. Feed features from letter to both models.

Table: Results for simple typewritten words, avg over 40 runs

| **Word** | Letter | Number | Differe |
|---|---|---|---|
| LL Intensity N=6 K=1 10EM | 121.68 | 106.36 | 15 |
| LL All features N=6 K=1 10EM | 795.45 | 14.08 | 781 |
| LL All features N=1 K=1 10EM | 602.22 | -90.02 | 692 |
| LL All features N=6 K=3 10EM | -186.45 | -330.14 | 143 |
| LL All features N=6 K=3 30EM | 226.96 | -820.30 | 1.0 |
| LL ALL , N=6, K=1, 10EM, diagonal cov | 871.16 | 531.27 | 487 |
| LL ALL , N=6, K=1, 10EM, isotropc cov | -179.00 | -272.23 | 197 |
| ... | ... | ... | |

## Results on simple task

Step 2, take cursive words of the same length.

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

| **Word** | Before | People |
|---|---|---|
| LL All features N=6 K=1 10EM | $1.17e+03$ | $1.19e+03$ |
| LL All features N=1 K=1 10EM | 602.22 | -90.02 |
| LL All features N=6 K=3 10EM | -186.45 | -330.14 |
| LL All features N=6 K=3 30EM | 226.96 | -820.30 |
| LL ALL , N=6, K=1, 10EM, diagonal cov | 871.16 | 531.27 |
| LL ALL , N=6, K=1, 10EM, isotropc cov | -179.00 | -272.23 |
| ... | ... | ... |

## Conclusions

blabla