## HMM for Alignments

### Laboratory of Bioinformatics I Module 2

26 March, 2019

Emidio Capriotti
http://biofold.org/

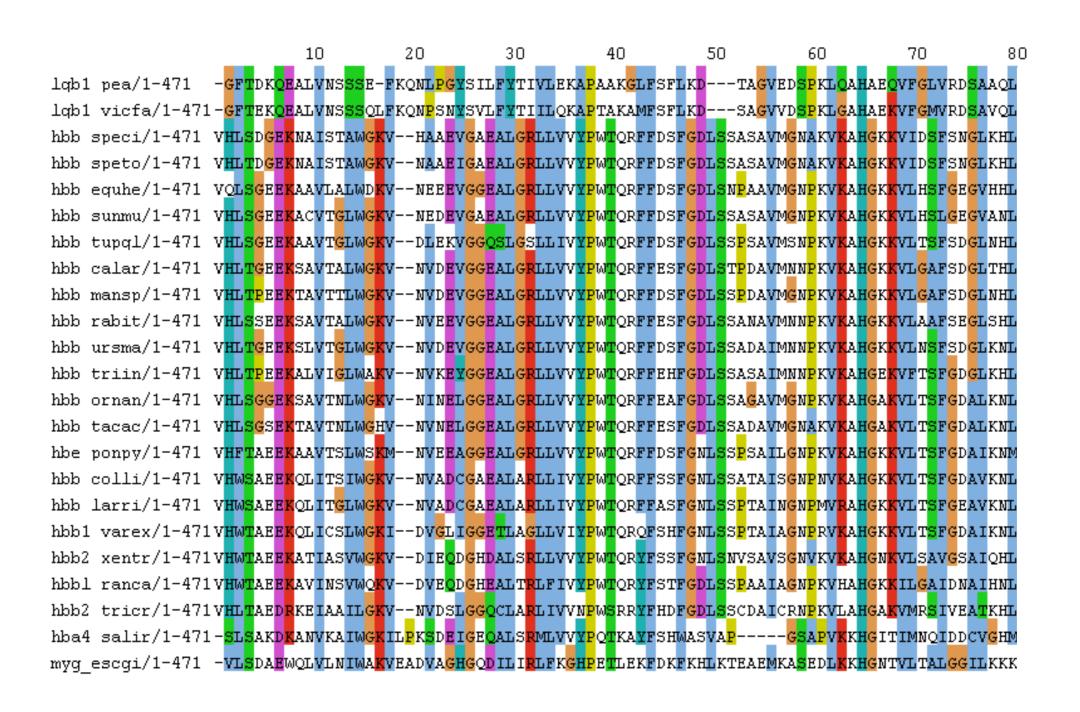


Department of Pharmacy and Biotechnology (FaBiT) University of Bologna



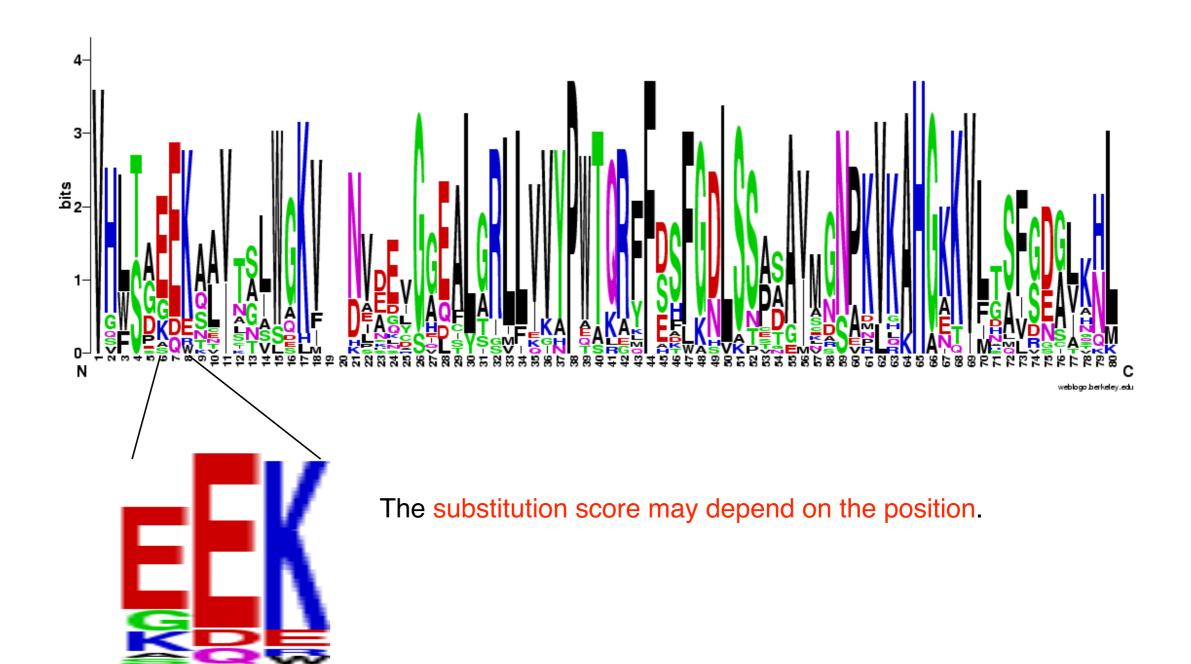
## Alignment of globins

#### Different positions are not equivalent



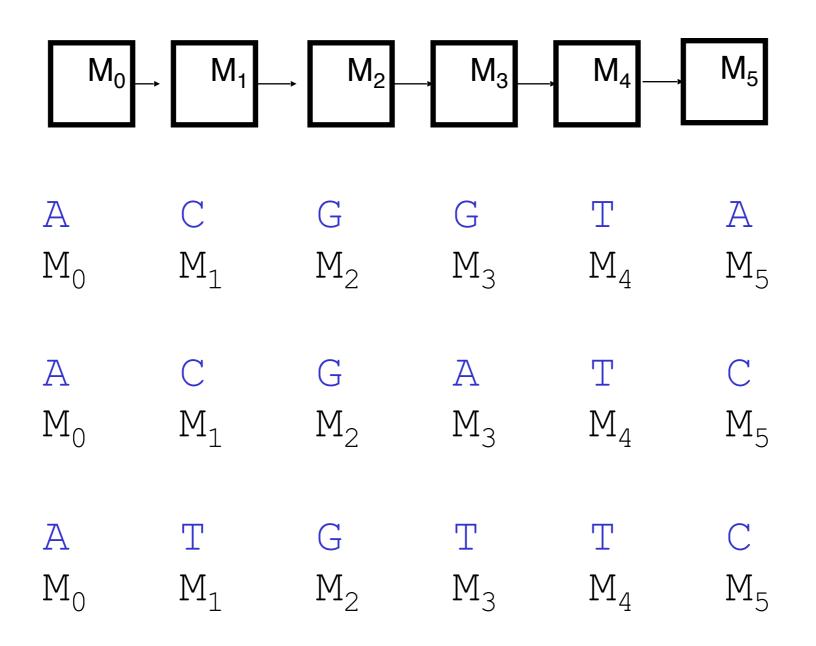
## Sequence logo

A more flexible alignment score is needed to align protein families



## How to Align?

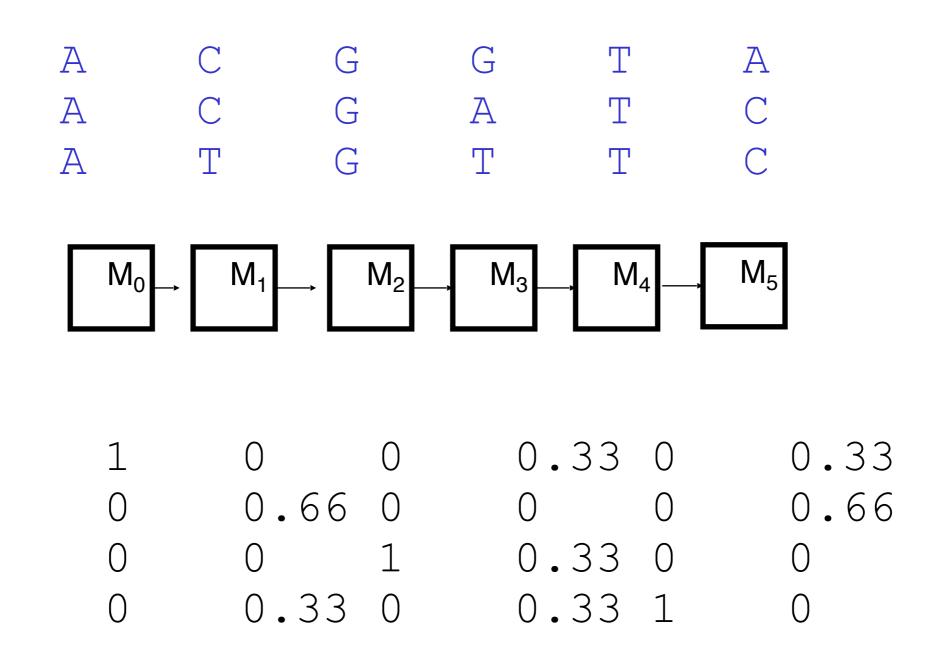
Each state represent a position in the alignment.



Each position has a peculiar composition

## From Sequences to Model

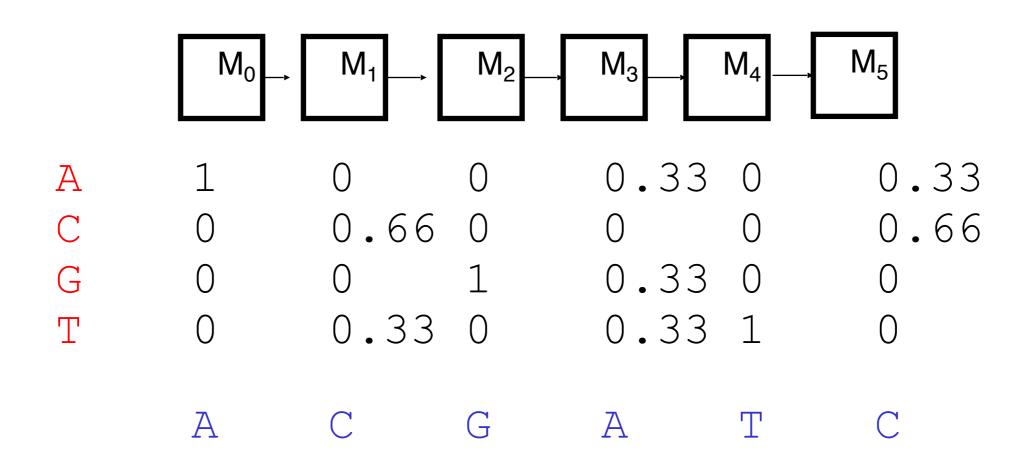
Given a set of sequences we can train a model by estimating the emission probability



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## Scoring a Sequence

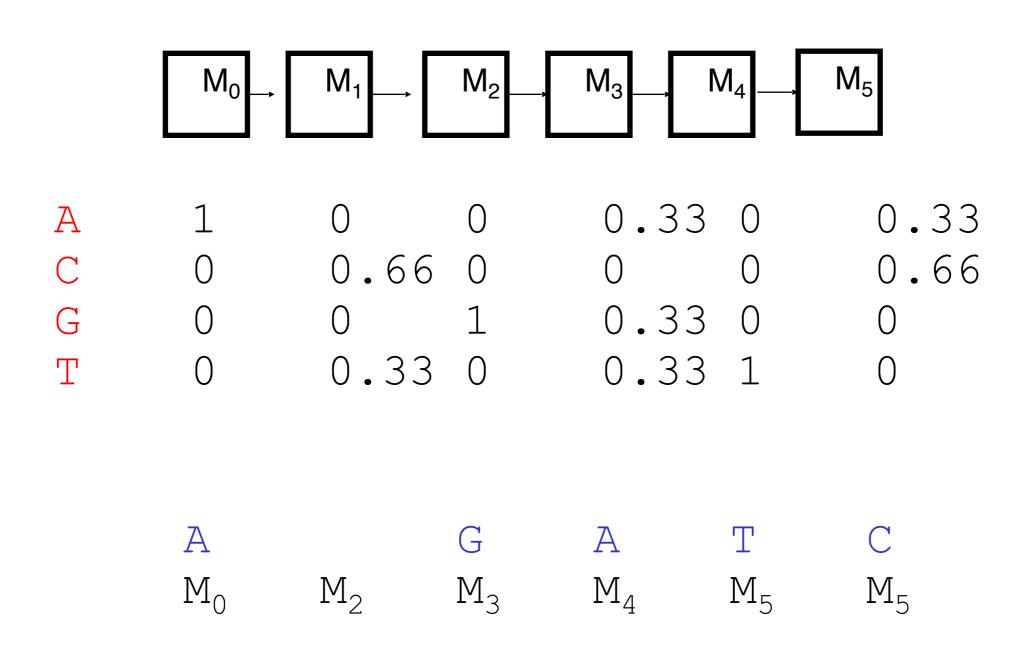
Given the model we can calculate the probability of the a new aligned sequence



$$P(s|M) = 1 \times 0.66 \times 1 \times 0.33 \times 1 \times 0.66$$

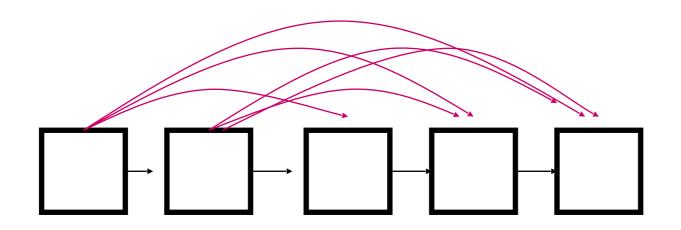
## Alignments with Gaps

A strategy to introduce gaps is needed

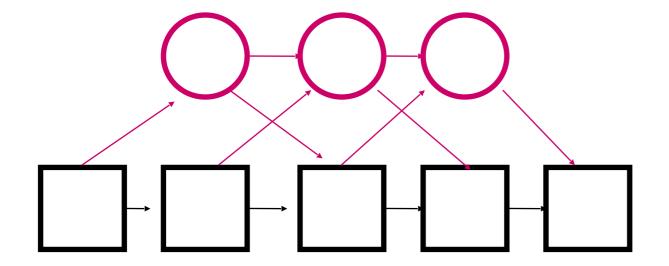


### Silent States

Different topology to model gaps

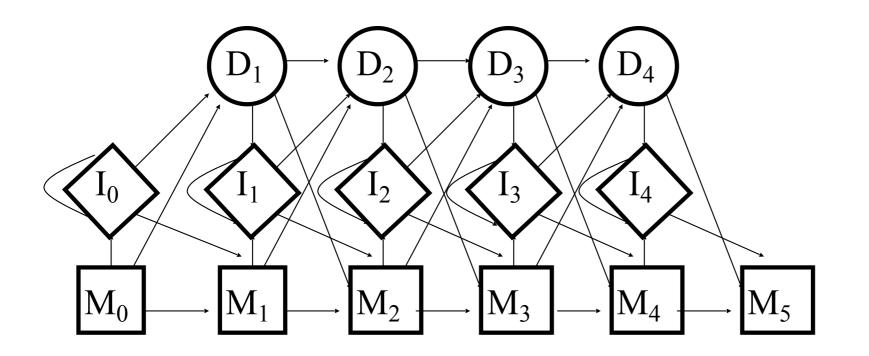


N(N-1)/2 transitions



To reduce the number of parameters we can use states that doesn't emit any character 4N-8 transitions

### **Profile HMM**



Delete states

Insert states

Match states

$$\mathbf{A}$$
 $\mathbf{M}_0$ 

$$M_1$$

$$\mathbf{G}$$
  $\mathbf{M}_2$ 

$$\mathbf{G}$$
 $\mathbf{M}_3$ 

$$M_4$$

$$\mathbf{A}$$
 $\mathbf{M}_5$ 

$$\begin{array}{ccccc} \textbf{A} & \textbf{C} & \textbf{G} & \textbf{C} \\ M_0 & I_0 & I_0 & M_1 \end{array}$$

$$\mathbf{A}$$
  $\mathbf{M}_2$ 

$$\mathbf{G}$$
 $\mathbf{M}_3$ 

A

$$M_5$$

$$M_0$$

$$\mathbf{D}_1$$

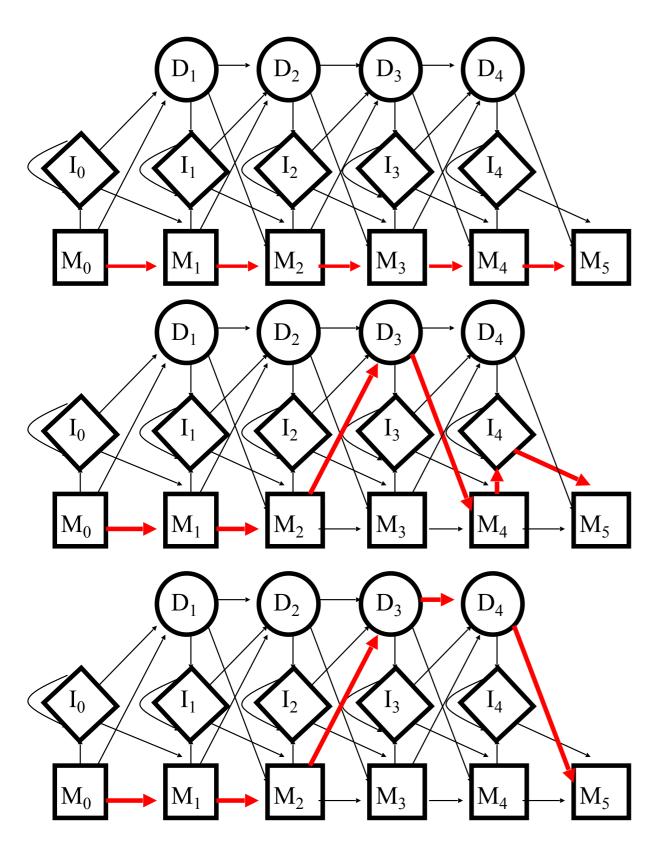
$$\mathbf{G}$$
 $\mathbf{M}_2$ 

$$M_3$$

$$M_4$$

$$M_5$$

# Example of Alignment



#### Sequence 1

A S T R A L Viterbi path

 $\mathbf{M}_0 \quad \mathbf{M}_1 \quad \mathbf{M}_2 \quad \mathbf{M}_3 \quad \mathbf{M}_4 \quad \mathbf{M}_5$ 

A S T R A L

#### Sequence 2

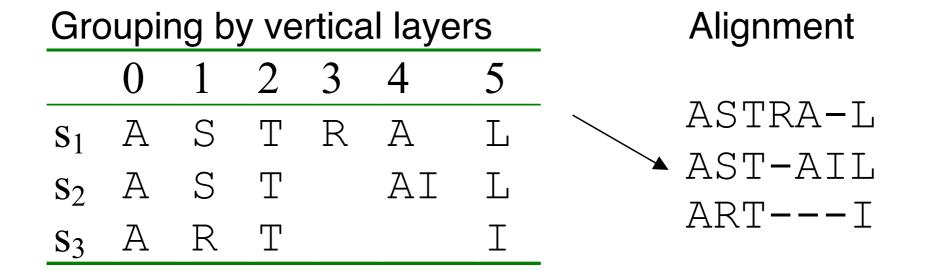
A S T A I L Viter bi path  $D_{1} M_{1} M_{2} D_{3} M_{4} I_{4} M_{5}$ 

#### Sequence 3

ARTI

## Alignment Calculation

M <sub>0</sub>	M <sub>1</sub> S	M <sub>2</sub> T	M <sub>3</sub> R	M <sub>4</sub> A	<b>M</b> <sub>5</sub> <b>L</b>	Sequence 1
M <sub>0</sub>	M <sub>1</sub>	M <sub>2</sub> T	D <sub>3</sub>	M <sub>4</sub> I <sub>4</sub> A I	M <sub>5</sub>	Sequence 2
M <sub>0</sub>	M <sub>1</sub>	M <sub>2</sub> T	D <sub>3</sub>	$D_4$	M <sub>5</sub>	Sequence 3



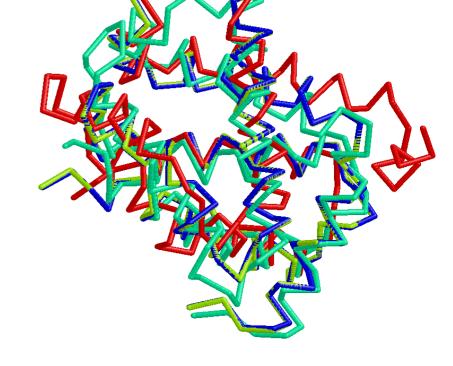
-Log P(s I M) Is an alignment score

## Alignment of Globins

#### 

F GG GG
S----HGSAQVKGHGKKVADALTNAVAHV---D--DMPNALSALSDLHAHKL--RVDPV
STPDAVMGNPKVKAHGKKVLGAFSDGLAHL---D--NLKGTFATLSELHCDKL--HVDPE
KSEAEMKASEDLKKHGVTVLTALGAILKK----K-GHHEAELKPLAQSHATKH--KIPIK
KDLESIKGTAPFETHANRIVGFFSKIIGEL--P---NIEADVNTFVASHKPRG---VTHD
TTADQLKKSADVRWHAERIINAVNDAVASM--DDTEKMSMKLRDLSGKHAKSF--QVDPQ
GTSEVPQNNPELQAHAGKVFKLVYEAAIQLQVTGVVVTDATLKNLGSVHVSKG---VADA

---AS---DPGVAALGAKVLAQIGVAVSHL--GDEGKMVAQMKAVGVRHKGYGNKHIKAQ



#### GGGGGGGGGGGGG

#### ННИННИННИННИННИННИННИННИНН

NFKLLSHCLLVTLAAHLPAEFTPAVHASLDKFLASVSTVLTSKYR----NFRLLGNVLVCVLAHHFGKEFTPPVQAAYQKVVAGVANALAHKYH----YLEFISEAIIHVLHSRHPADFGADAQGAMSKALELFRKDIAAKYKELGYQG
QLNNFRAGFVSYMKAHT--DFA-GAEAAWGATLDTFFGMIFSKM----YFKVLAAVIADTVAAG------DAGFEKLMSMICILLRSAY----HFPVVKEAILKTIKEVVGAKWSEELNSAWTIAYDELAIVIKKEMNDAA--YFEPLGASLLSAMEHRIGGKMNAAAKDAWAAAYADISGALISGLOS----

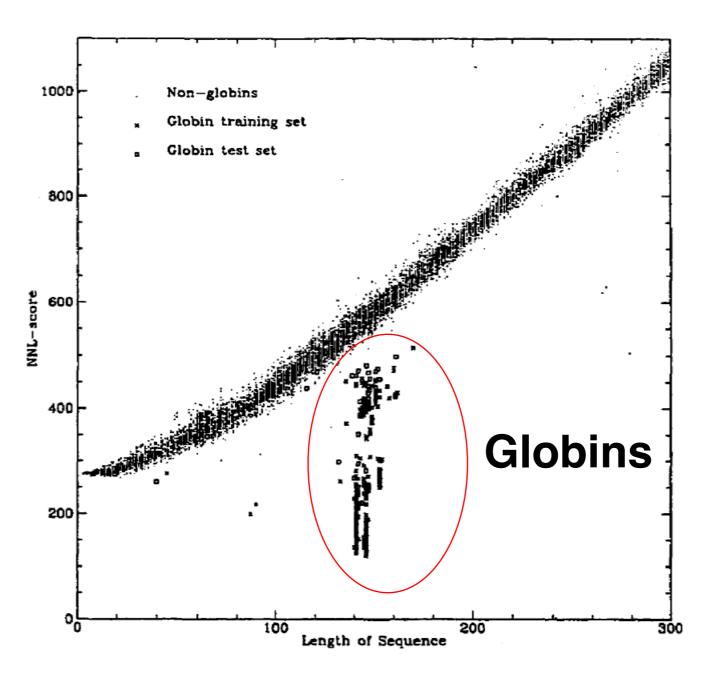
### Globins HMM

HMM are calculate from a training set of 400 unaligned sequences. After the HMM is built, it is used to obtain a multiple alignment of all the training sequences. This is the alignment of the 7 globins as aligned with the trained model.

AAAAAAAAAAAAAA	RRRRRRRRRRRRRRRCCCCCCCCCCCCCCCCCCCCCCC
<b>++++++++++++</b>	DDDD ******
	.HAGEYGAEALERMFLSFPTTKTYFPHFD-L
	.NVDEVGGEALGRLLVVYPWTQRFFESFGDL
	.DVAGHGQDILIRLFKSHPETLEKFDRFKHL
	.KGDPVGILYAVFKADPSIMAKFTQFAGK
	.TYETSGVDILVKFFTSTPAAQEFFPKFKGL
	.NIPKHTHRFFILVLEIAPAAKDLFSFLK-G
	dngagvgkDcLikfLsahpqmaavfg-f
O	MONOVORDOBINI BANIN MANO I
DDDDDDDEE EEEEEEEEEEEEEE	E FFFFFFFF FFFG
	F GGGG
*****	* ******* **
SHGSAQVKGH-GKKVADALTNAVA	HVDDMPNALSALSDLHAHKLRVD
STPDAVMGNPKVKA.HGKKVLGAFSDGLA	HLDNLKGTFATLSELHCDKLHVD
KTEA-EMKASEDLKKHGVTVLTALGAILK	KKGHHEAELKPLAQSHATKHKIP
DLES-IKGTAPFET.HANRIVGFFSKIIG	ELPNIEADVNTFVASHKPR-GVT
	SMDDtekMSMKLRDLSGKHAKSFQVD
	QLQVtgvvvTDATLKNLGSVHVSK-GVA
SGASDPGVAA.LGAKVLAQIGVAVS	HLGDegkMVAQMKAVGVRHKgygNK-HIK
GGGGGGGGGGGGGGGGGGGGGGGGGGGGGGGGGGGGGG	HHHHHHHHHHHHHHHHHH *******
PVNFKLLSHCLLVTLAAHLPAEFTPAVHA	
PENFRLLGNVLVCVLAHHFGKEFTPPVQA	
IKYLEFISEAIIHVLHSRHPGDFGADAQGA HDQLNNFRAGFVSYMKAHTDF-AGAEA	24.4
POYFKVLAAVIADTVAAGDA	
DAHFPVVKEAILKTIKEVVGAKWSEELNS	
AQYFEPLGASLLSAMEHRIGGKMNAAAKD	

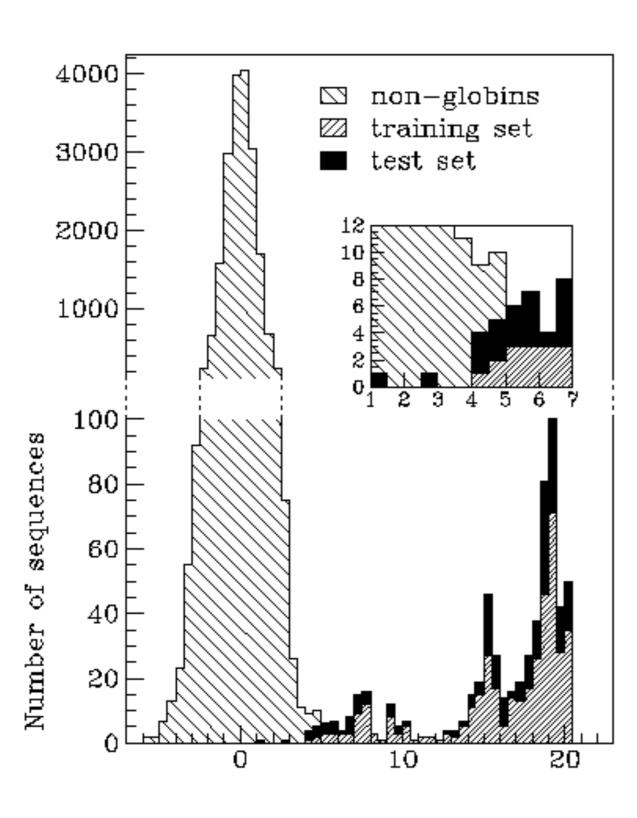
## Globin Classification

The NLL-score is calculated to discriminate between Globin and non-Globin protein sequences



NLLscore = -log P(sIM)

## Score distribution



$$Z\text{-score} = \frac{\text{NLL (s) - }}{\sigma \text{ (NLL)}}$$

With mean and standard deviation computed on sets of sequences with similar length

### **Confusion Matrix**

A 2x2 matrix for calculating the performance of prediction methods

		Condition (as determined by "Gold standard")	
	Total population	Condition positive	Condition negative
Test outcome	Test outcome positive	True positive	False positive (Type I error)
	Test outcome negative	False negative (Type II error)	True negative

## **Overall Accuracy**

How many predictions are correct on the overall?

Accuracy (ACC):
$$ACC = \frac{(TP+TN)}{(TP+FN+TN+FP)}$$

Is it an informative enough score?

### Dataset Unbalance

Accuracy can be strongly biased because of class unbalance. It is not very informative

	Class 1	Class -1
Prediction 1	90	10
Prediction -1	0	0

Acc = 0.9
ALL the examples are predicted in the class 1:
Very bad predictions

	Class 1	Class -1
Prediction 1	81	1
Prediction -1	9	9

Acc = 0.9 It seems a much more reasonable prediction

## Class Specific Measures

Sensitivity (Sn) or True Positive Rate (TPR):  $Sn = \frac{TP}{TP + FN}$ 

It answer to the question:

How many of the real positive examples are correctly predicted?

Precision or Positive Predictive Value (PPV):

$$PPV = \frac{TP}{TP + FP}$$

It answer to the question:

How many of the positive predictions are correct?

It is sometimes referred as Specificity

### **Matthews Correlation**

Matthews Correlation Coefficient (MCC):

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP) \times (TP + FN) \times (TN + FP) \times (TN + FN)}}$$

It answer to the question:

Is the prediction really correlated with the real classes?

It is 0 in case of random prediction
It is 1 only in case of perfect prediction
It is -1 only in case of completely wrong prediction

It is the Pearson's correlation coefficient for categorical classes

### MCC and Unbalance

MCC is not affected by dataset unbalance

	Class 1	Class -1
Prediction 1	90	10
Prediction -1	0	0

Acc = 0.9All the examples are predicted in the class 1: MCC = 0.0

Very bad predictions

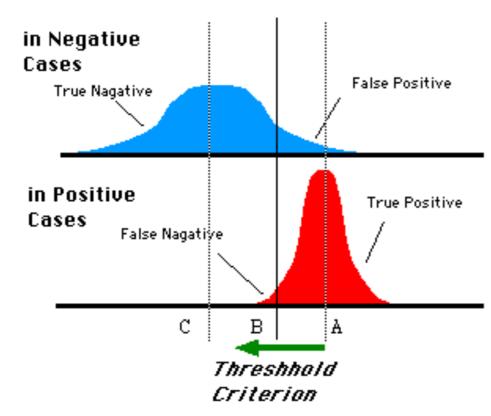
	Class 1	Class -1
Prediction 1	81	1
Prediction -1	9	9

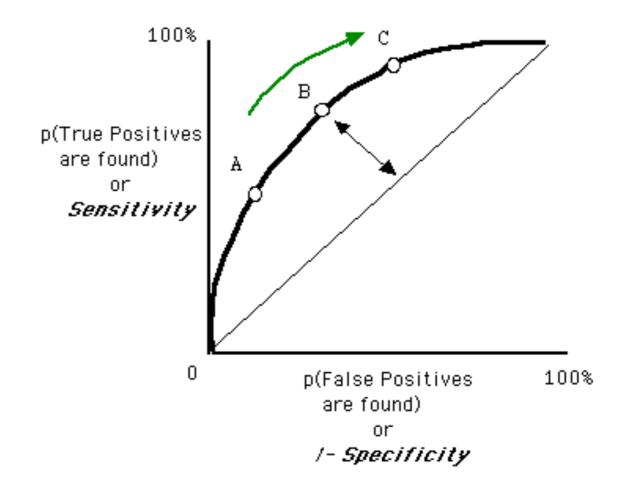
Acc = 0.9 MCC = 0.62 Predictions are good

### **ROC Curve**

The Receiver Operating Characteristics depends on a parameter, TPR and FPR can be plotted at varying values of the parameter

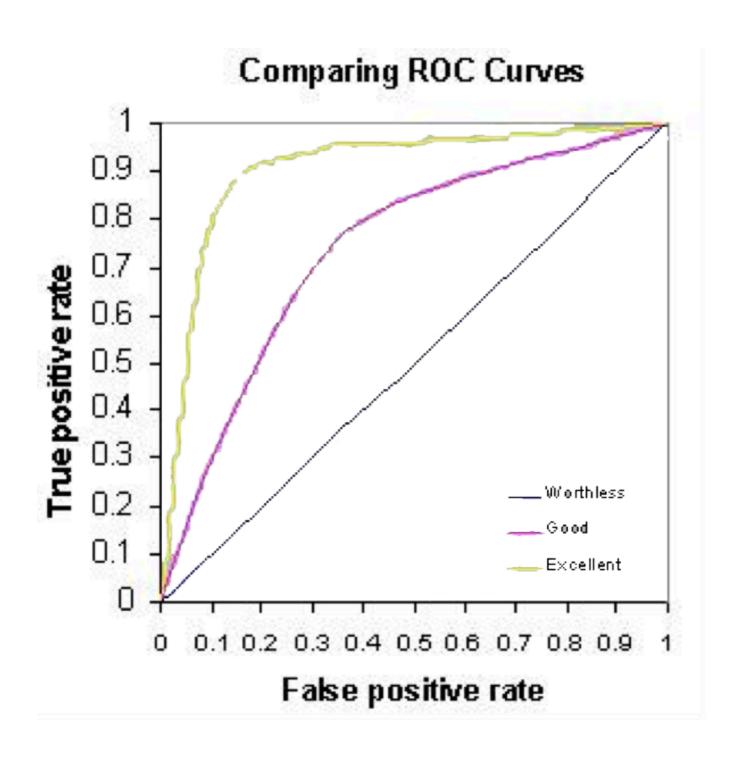
#### Distributions of the Observed signal strength





### Area Under Curve

The Area Under the ROC Curve (AUC) is used to measure the perforce of a predictor



AUC=0.5 → Random prediction

AUC=1 → Perfect prediction