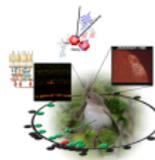
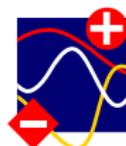


# Rare-event simulations for score statistics of multiple sequence alignments

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Leipzig, 28.11.2014



# Outline

1 Biological Background

2 Rare-Event Simulation

3 Results

4 Conclusion

# Biological Background

## Sequence Similarities

- Relations, ...
- Functional groups, protein structure...

## Evolution of DNA sequences

Copies by DNA polymerase:

- Inherit = match
- Replace = mismatch
- Insert/delete = gap

**A G C T A**

**A T T A**

*DNA alignment*

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<b>A</b>	<b>T</b>	<b>T</b>	<b>A</b>	

*DNA alignment*

# Biological Background

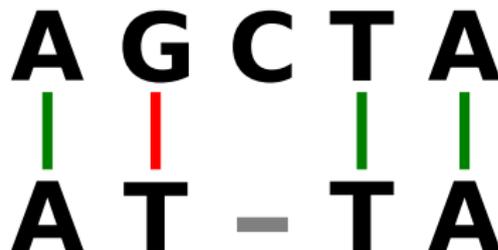
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*DNA alignment*

$$S = \sum_{\text{aligned}, k} s(x_{ik}, y_{jk}) - \sum_{\text{gaps}, g} d + (l_g - 1)e$$

## Scoring of Residue Pairs

Biologists provide *substitution matrices*

Reflect statistical model of substitutions

	A	...	W	Y	V
A	4	...	-3	-2	0
⋮	⋮	⋱			⋮
W	-3		11	2	-3
Y	-2		2	7	-1
V	0	...	-3	-1	4

BLOSUM62: extract

## Optimal Pairwise Alignment

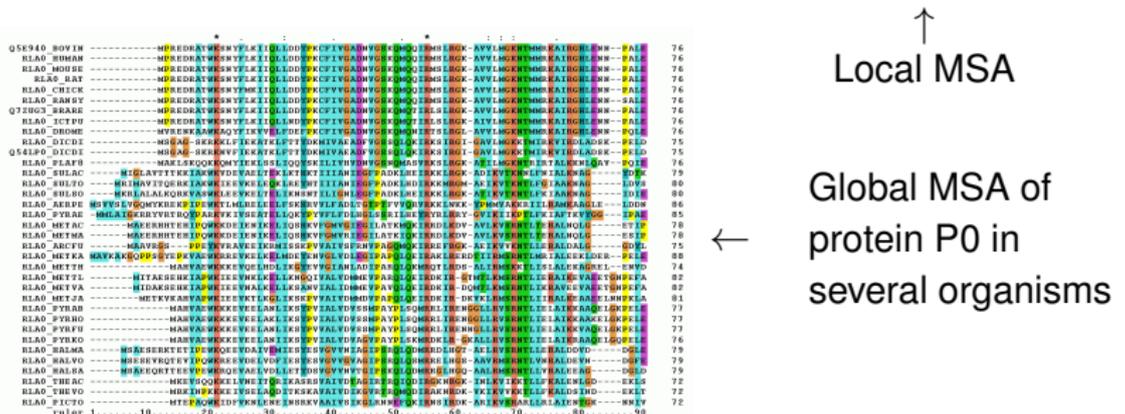
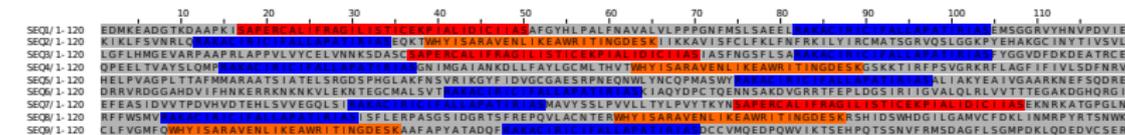
- Many possible alignments
- Find highest scoring one → most likely actual relation

⇒ Optimisation problem, solve by *dynamic programming*  $\mathcal{O}(L^2)$

[Smith, Waterman; J. Mol. Bio.; 1970]

# Multiple Sequence Alignments

- Find the optimal alignment of  $N > 2$  sequences
- Local alignment: best scoring mutual subsequence
- Dynamic programming in  $\mathcal{O}(L^N)$  for sequences of length  $L$



Miguel Andrade, [http://en.wikipedia.org/wiki/File:RPLP0\\_90\\_ClustalW\\_aln.gif](http://en.wikipedia.org/wiki/File:RPLP0_90_ClustalW_aln.gif)

# Rare Event Simulation

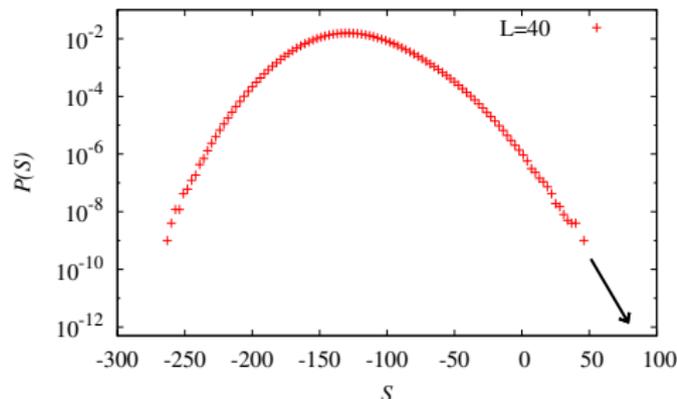
## Sequence Similarity

- Score so far only indicator for alignment optimization
- Relation or random agreements? How "good" is the obtained score  $S_{\text{obs}}$ ?

⇒ Score statistics as criterium:  $P(S \geq S_{\text{obs}})$

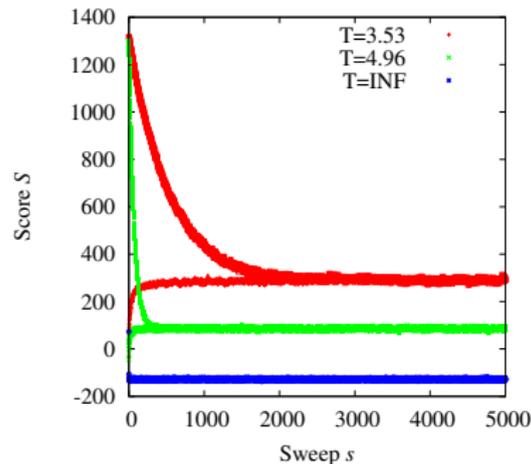
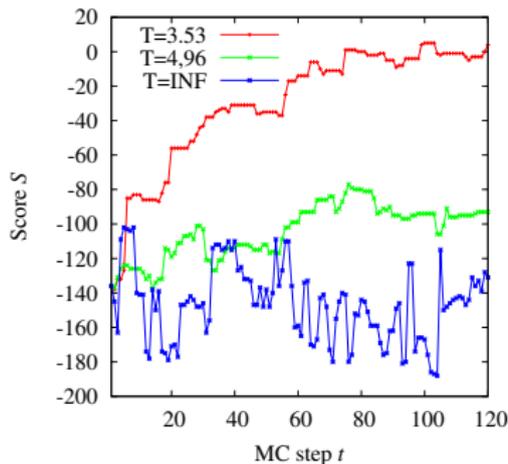
## Simple Sampling

- Only covers high probability region
- Biologically relevant: low probability, high scoring tail



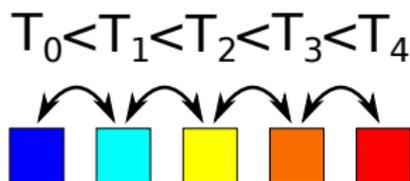
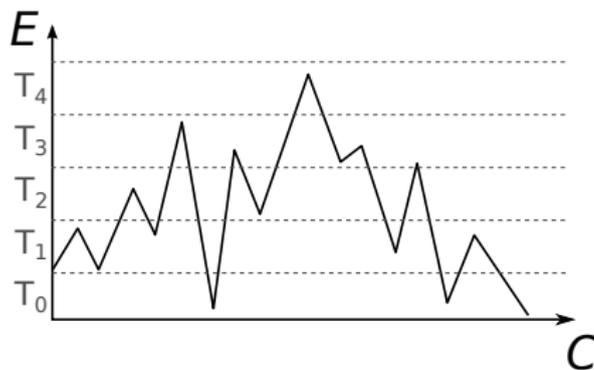
## Mapping to Statistical Mechanics [Hartmann;Phys.Rev.E;2002]

- Decrease energy  $\rightarrow$  increase score: Use  $E = -S$
- Simulate Markov Chain of sequences at finite “temperature” with probabilities  $P(S) \cdot \exp(\frac{S}{T})$ .



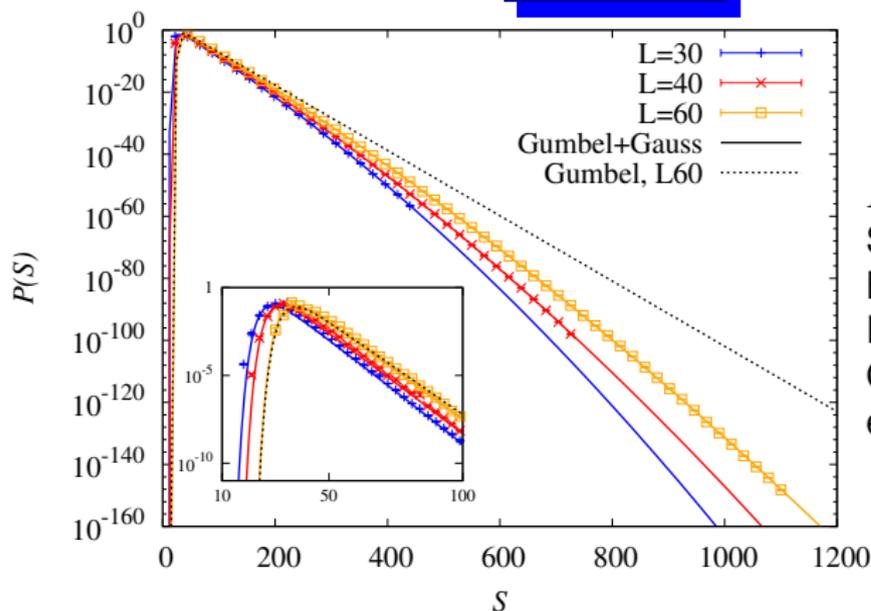
## Parallel Tempering

- To cover large score range: simulate at different temperatures
- After one sweep switch systems of neighboring temperatures with probability
 
$$P_{\text{sw}}(T_i) = \min(1, \exp(\Delta S_i \Delta \beta_i))$$
 with  $\Delta S_i = (S_i - S_{i+1}), \Delta \beta_i = \frac{1}{T_i} - \frac{1}{T_{i+1}}$
- Avoid trapping in local maxima



- Parallel simulation using MPI: 15 to 20 temperatures

# Results



$N = 3$

Substitution matrix:  
BLOSUM62

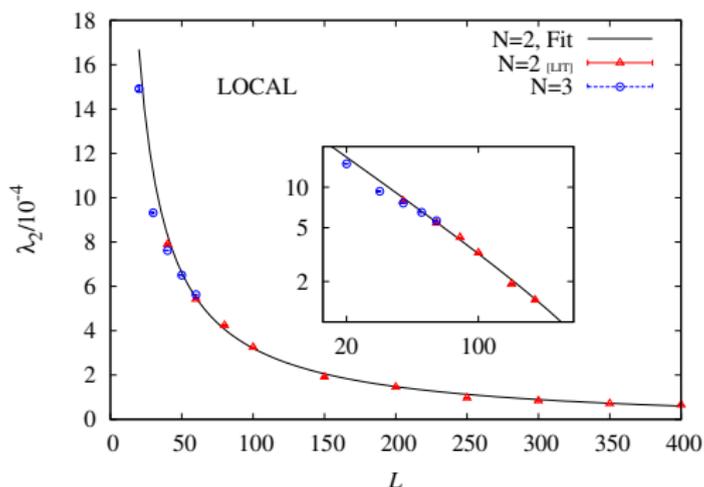
Penalties:

Gap open:  $d = 12$

extend:  $e = 1$

- Previous studies found Gumbel distribution with Gaussian correction for  $N = 2$  sequences: [Wolfsheimer, Burghardt, AKH; Alg. Mol. Bio.; 2007]

$$P(S) \propto \lambda \exp(-\lambda(S - S_0) - e^{-\lambda(S - S_0)}) \exp(-\lambda_2(S - S_0)^2)$$



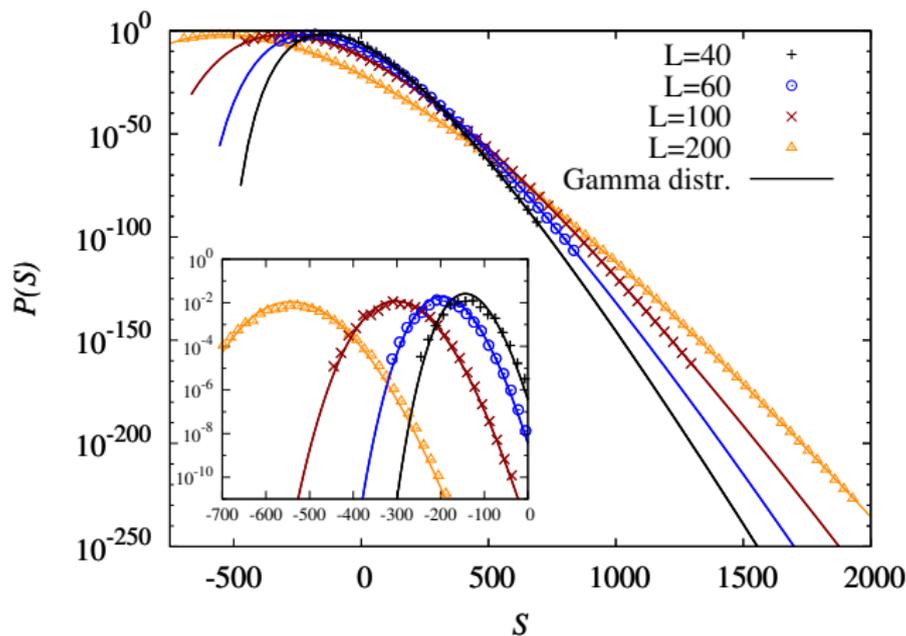
## Length-Dependence of Gaussian Correction

- Use score per pair  $\frac{S}{(N-1)(N-2)}$
- Calculate  $\lambda_2$

⇒ decreases with increasing sequence length

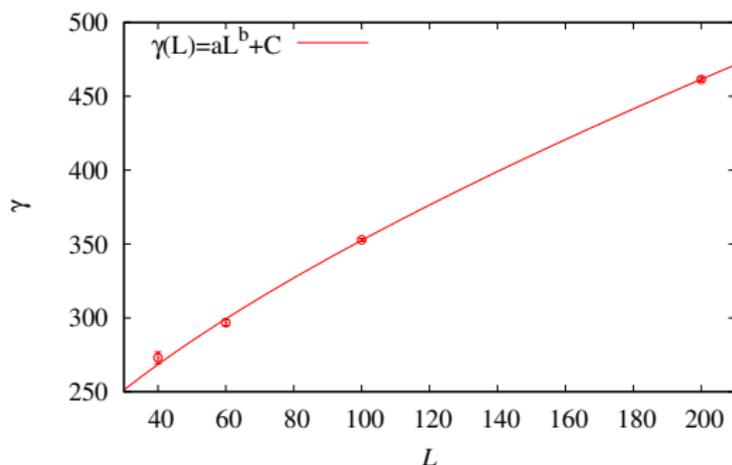
⇒ coincides so far with findings for  $N = 2$

[Wolfsheimer, Burghardt, Hartmann; Alg. Mol. Bio.; 2007]



Global MSA,  
 $N = 3$ ,  
 Gamma-  
 distribution  
 [Pang, Tang, Chen, Tao;  
 BMC Bioinf; 2005]

$$P_{\Gamma}(S) = \frac{\lambda^{\gamma}}{\Gamma(\gamma)} (S - \mu)^{\gamma-1} \exp(-\lambda(S - \mu))$$



## Length-Dependence of $\gamma$

- $\gamma$  increases with growing sequence length
- $\gamma = 1$ : exponential distribution
- $\gamma \rightarrow \infty$ : normal distribution

# Conclusion

## Large Deviation Simulation

- Mapping to statistical mechanics
- Successful approach to sample small probabilities

## Local Alignments

- Behavior for  $N = 2$  confirmed for  $N = 3$
- Gumbel distribution of scores with Gaussian correction in tail
- Deviation from the standard Gumbel distribution  
e.g. relevant in database searches

[Wolfsheimer, Herms, Rahmann, Hartmann; BMC Bioinformatics; 2011]

## Global Alignments

- No analytical solution
- Gamma distribution better candidate than Gumbel distribution

## Prospects

- Check if this holds for other substitution matrices
- Analyse dependence on gap penalties
- Develop heuristic for gapped local MSA
- Check results for sequence sets with  $N > 3$

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Thank you for your attention!

# Dynamic Programming

		H	E	A	G	A	W
	<b>0</b>	← <b>-8</b>	← -16	← -24	← -32	← -40	← -48
		↖	↖	↖		↖	
P	-8	-2	-9	<b>-17</b>	← <b>-25</b>	-33	← -41
	↑	↑	↖	↖		↖	
A	-16	-10	-3	-4	← -12	<b>-20</b>	← -28
	↑	↑	↑	↖	↖	↖	↖
W	-24	-18	-11	-6	-7	-15	<b>-5</b>
	↑	↖	↖	↖	↖	↖	↑
H	-32	-14	-18	-13	-8	-9	<b>-13</b>

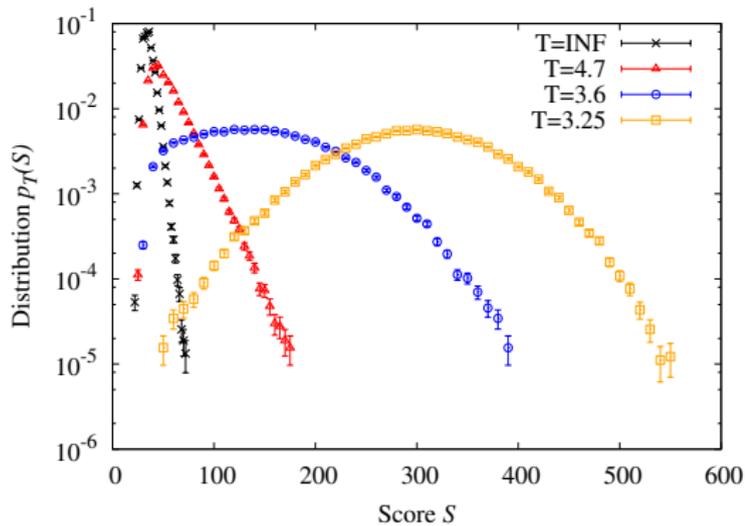
Dynamic Programming matrix for fixed gap costs [Durbin1998]

H	E	A	G	A	W	-
-	-	P	-	A	W	H

$$P(S) = p_T(S) Z_T \exp(-S/T)$$

## Obtaining $P(S)$

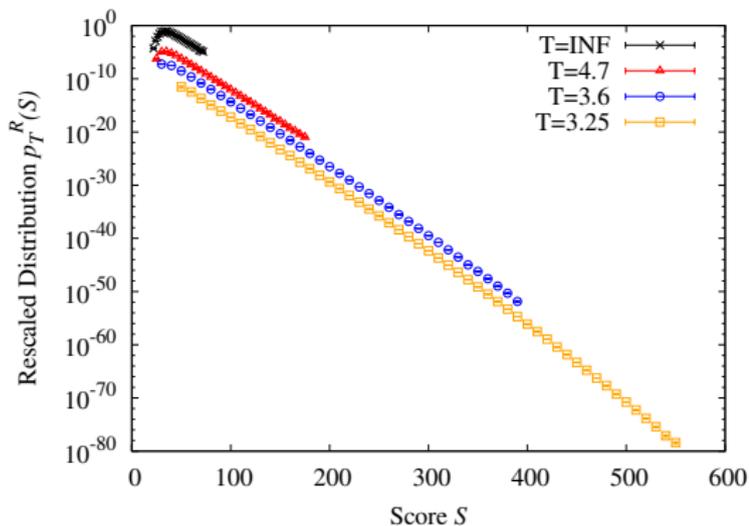
- Simulations give scaled distributions  $p_T(S)$



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## Obtaining $P(S)$

- Simulations give scaled distributions  $p_T(S)$
- Rescale with  $\exp(-S/T)$
- Assume  $P(S) = p_\infty(S)$
- $\rightarrow$  shift on logarithmic scale

