

# Maximum Likelihood Estimation for RNA homology search

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# RNA Homology Search

- RFAM 9.1 contains 1371 families of non-coding RNAs
- Tons of newly sequenced genomes can be expected in next years
- ncRNA annotation of already sequenced genomes is still sparse in many cases.
- What is the phylogenic distribution of a certain ncRNA family?
- Derive model for a family based on known sequences, search for homologs.

## Search methods

- sequence based: `blastn`
- sequence + structure, automatic model learning: covariance models (`infern`, `RaveNnA`), `erpin`
- sequence + structure, descriptor-based programs: `RNAMotif`, `rnabob`, `PatSearch`, ...
  - manually model properties of a family, (usually) very fast

# Comparison

- difficulties in ncRNA homology search: structure conservation, length variation, frequent small indels

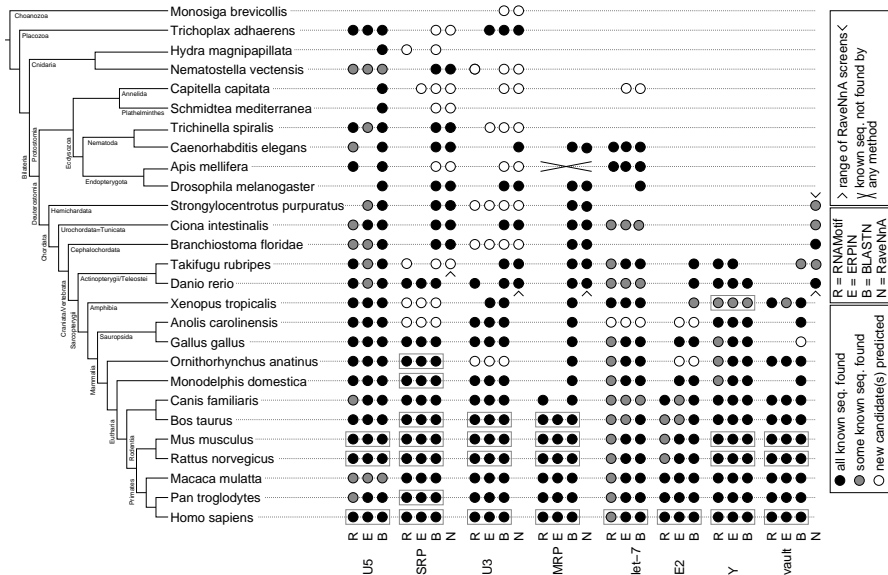
## Little experiment

- How well do those methods generalize?
- 8 ncRNA families, 28 genomes
- RNAMotif, blastn, erpin, RaveNnA
- Phylogenetic restricted training set (structure annotated alignment)
- Derive models
- Search all genomes
- RNAMotif: manually derive descriptors from alignment, iteratively search genomes and modify descriptors (3 rounds)

# Range of animal genomes



# Results



# Automatic descriptor design

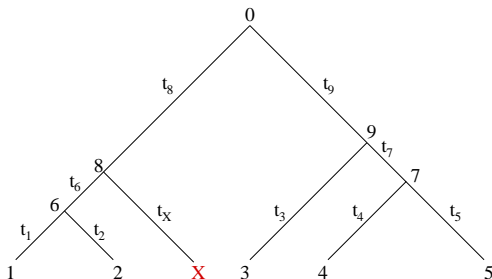
- Current problems in model design: Manually constructing descriptors for a specific ncRNA family is very hard for non-experts
- Tradeoff between specificity and sensitivity, small changes in the descriptor can dramatically affect number of hits
- What we want to have: Given a structure-annotated sequence alignment, automatically build the best descriptor for that family
- Even better: Build a descriptor aimed for searching in one target species

# Targeted descriptor design

## Idea

Which sequence and structure can be expected in a certain species?

- Knowing the relations between species, build a model optimized for a target organism
- Trade sensitivity off for specificity



# Framework

- Assume different evolutionary rates for different parts of the RNA molecule, e.g. loop regions are known to evolve faster than stems.
- Given a phylogenetic tree and a multiple alignment, calculate a mutation rate  $\mu$  for each paired and unpaired column which maximizes the likelihood of the tree
- Then calculate probabilities for base occurrences for a target species in the tree.
- High probability columns contribute to the model
- Derive descriptor (e.g. RNAMotif)

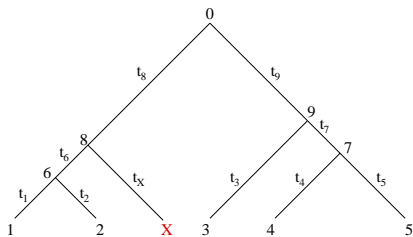


# Framework

# STOCKHOLM

```
Seq1      CCAUCCGUAAGGGCGGUUGG
#=GR Seq1 SS  (((((((((.....)))))).)))
Seq2      GCAUCCGUAAGGGCGGUUGC
#=GR Seq2 SS  ((.((((((.....)))))).))
Seq3      GCAUCCGGAAGGGCGGUAGC
#=GR Seq3 SS  ((.((((.....))))..))
Seq4      GCAUCCGGAAGGGGGUAGC
#=GR Seq4 SS  ((.((((.....))))..))
Seq5      GCAUC-----UAGC
#=GR Seq5 SS  ((.-----..))
#=GC SS_cons ((.((((((.....)))))).))

SeqX      ??????????????????????
#=GC SeqX SS ??????????????????????
```



# Algorithm

- 1 Delete leaf  $X$  (target species) from tree  $T$
- 2 Optimize a mutation rate  $\mu$  for each paired and unpaired column for maximizing the likelihood of the tree (root 0)

$$\hat{\mu} = \operatorname{argmax}_{\mu} L(\mu)$$

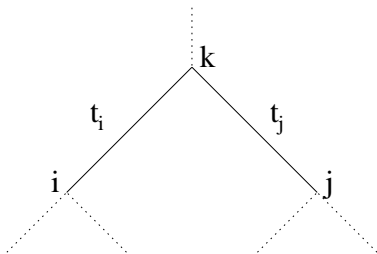
$$L(\mu) = \sum_{s_0} \pi_{s_0} L_{s_0}(\mu)$$

- 3 Add  $X$  to  $T$  and root  $T$  at  $X$
- 4 Using the estimated  $\hat{\mu}$ , recalculate likelihoods for all states  $s_0$  of the root node 0

# Algorithm

- Tree likelihood is calculated by post-order traversal of the tree (leaves are evaluated first)
- For interior nodes  $k$

$$L_{s_k}(\mu) = \left( \sum_{s_i} P_{s_k s_i}(t_i, \mu) L_{s_i}(\mu) \right) \cdot \left( \sum_{s_j} P_{s_k s_j}(t_j, \mu) L_{s_j}(\mu) \right)$$



# Algorithm

- Leaf nodes:  $L_{s_k}(\mu) = 1$  if state  $s_k$  is in alignment, otherwise  $L_{s_k}(\mu) = 0$
- Transition matrix  $P_{s_k s_i}(t_i, \mu)$  gives probability for changing  $s_i$  into  $s_k$  in time  $t_i$  given mutation rate  $\mu$
- derived from a rate matrix  $Q$  containing instantaneous substitution rates:  $P_{xy}(t, \mu) = [e^{t\mu Q}]_{xy}$
- $Q$  is a substitution rate model, unpaired and paired models, empirical models based on substitution rates derived from alignments (like RIBOSUM)

- Gaps not contained in most models, but in most of the alignments

Model ID no.	Frequency parameters	Rate parameters	Constraints	Free parameters	Reference
6A	6: $\pi_1, \pi_2 \dots \pi_6$	15: $\alpha_{ij}$	2	19	
6B	6: $\pi_1, \pi_2 \dots \pi_6$	3: $\alpha_a, \alpha_b, \beta$	2	7	
6C	3: $\pi_1, \pi_2, \pi_3$	3: $\alpha_a, \alpha_b, \beta$	2	4	TILLIER (1994)
6D	3: $\pi_1, \pi_2, \pi_3$	2: $\alpha_a, \beta$	2	3	TILLIER (1994)
7A	7: $\pi_1, \pi_2 \dots \pi_7$	21: $\alpha_{ij}$	2	26	HIGGS (2000)
7B	4: $\pi_1, \pi_2, \pi_3, \pi_7$	21: $\alpha_{ij}$	2	23	
7C	7: $\pi_1, \pi_2 \dots \pi_7$	10: $\alpha_{ij}$	2	15	
7D	7: $\pi_1, \pi_2 \dots \pi_7$	4: $\alpha_a, \alpha_b, \beta, \gamma$	2	9	TILLIER and COLLINS (1998)
7E	7: $\pi_1, \pi_2 \dots \pi_7$	2: $\alpha_a, \gamma$	2	7	TILLIER and COLLINS (1998)
7F	4: $\pi_1, \pi_2, \pi_3, \pi_7$	4: $\alpha_a, \alpha_b, \beta, \gamma$	2	6	
16A	10: $\pi_1 \dots \pi_{10}$	5: $\alpha_a, \alpha_b, \beta, \gamma, \epsilon$	2	19	
16B	16: $\pi_1, \pi_2 \dots \pi_{16}$	1: $\mu$	2	15	SCHÖNIGER and VON HAESLER (1994)
16C	7: $\pi_1 \dots \pi_6, \pi_m$	5: $\alpha_a, \alpha_b, \beta, \gamma, \epsilon$	2	10	
16D	4: $\pi_A, \pi_C, \pi_G, \pi_U$	4: $\alpha, \beta, \lambda, \phi$	2	6	
16E	4: $\pi_A, \pi_C, \pi_G, \pi_U$	3: $\alpha, \beta, \lambda$	2	5	MUSE (1995) modified HKY
16F	4: $\pi_A, \pi_C, \pi_G, \pi_U$	3: $\alpha, \beta, \lambda$	2	5	MUSE (1995) GU model
16G	0	3: $\alpha, \beta, \gamma$	1	2	RZHETSKY (1995)
16H	0	2: $\mu, \lambda$	1	1	MUSE (1995)

# Acknowledgements

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