

# Empirical performances, ML/AI an advanced dynamic programming

Yann Ponty

AMIBio Team  
École Polytechnique/CNRS

# Historical paradigms towards 2D prediction

## Definition (Ab initio folding)

Starting from sequence, find conformation that minimizes free-energy.

### Advantages:

- ▶ Mechanical nature allows the (in)validation of models
- ▶ Reasonable complexity  $\mathcal{O}(n^3)/\mathcal{O}(n^2)$  time/space
- ▶ *Exhaustive* nature

### Limitations:

- ▶ Hard to include PKs
- ▶ Highly dependent on energy model
- ▶ No cooperativity
- ▶ Limited performances

## Definition (Comparative approach)

Starting from homologous sequences, postulate common structure and find best possible tradeoff between folding & alignment.

### Avantages :

- ▶ Better performances
- ▶ (Limited) cooperativity
- ▶ Self-improving

### Limitations

- ▶ Easily unreasonable complexity
- ▶ Non exhaustive search
- ▶ Captures *transient* structures

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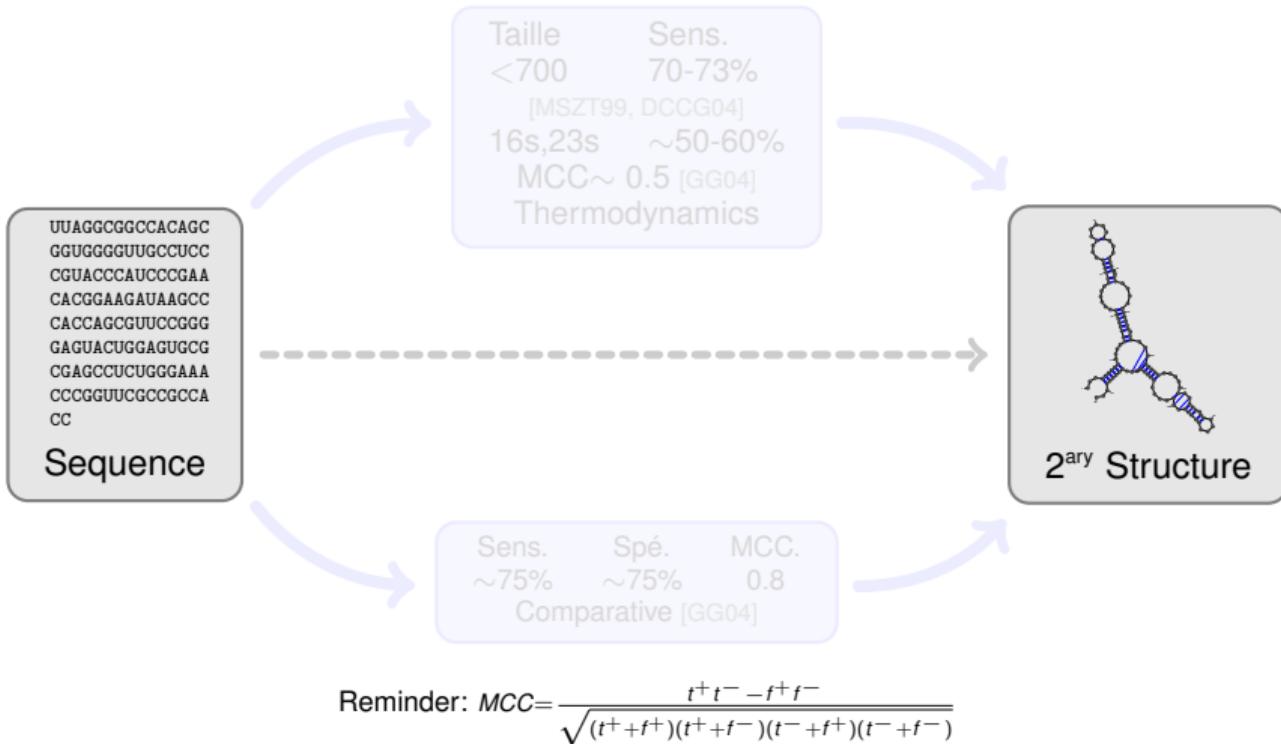
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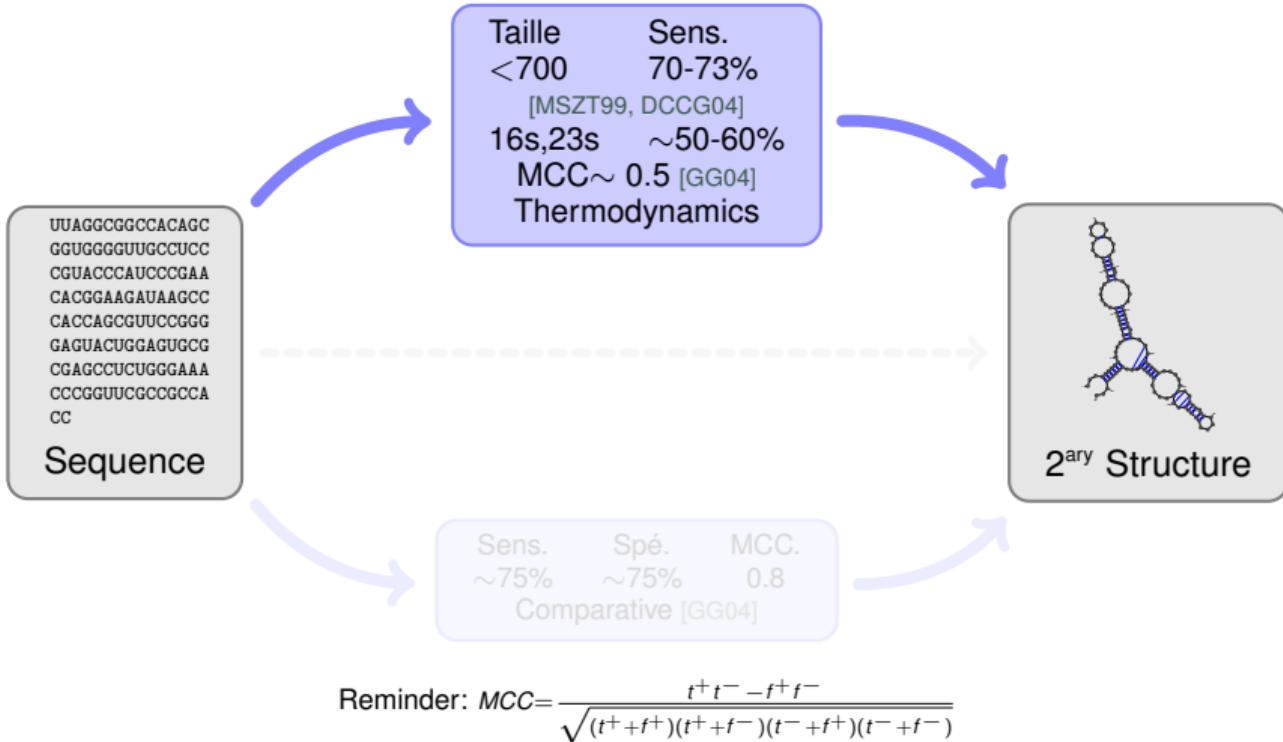
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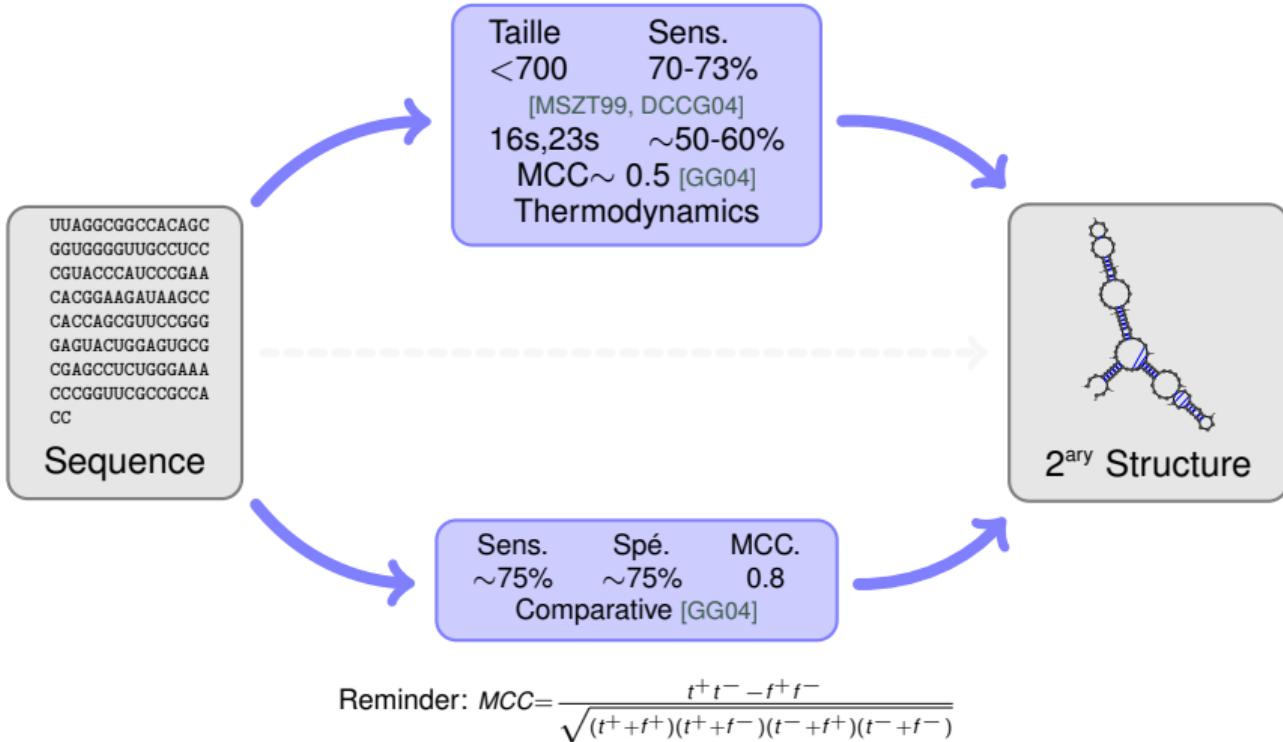
## Typical performances



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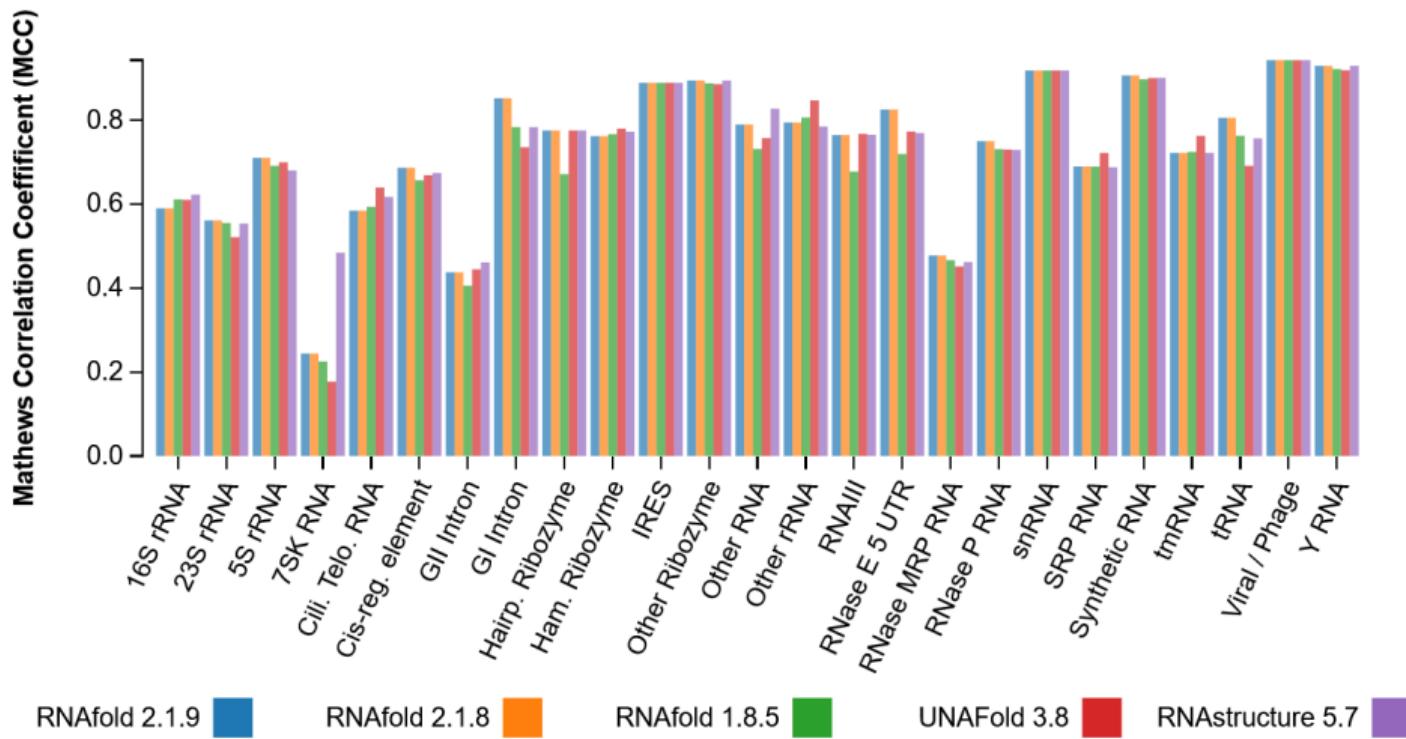


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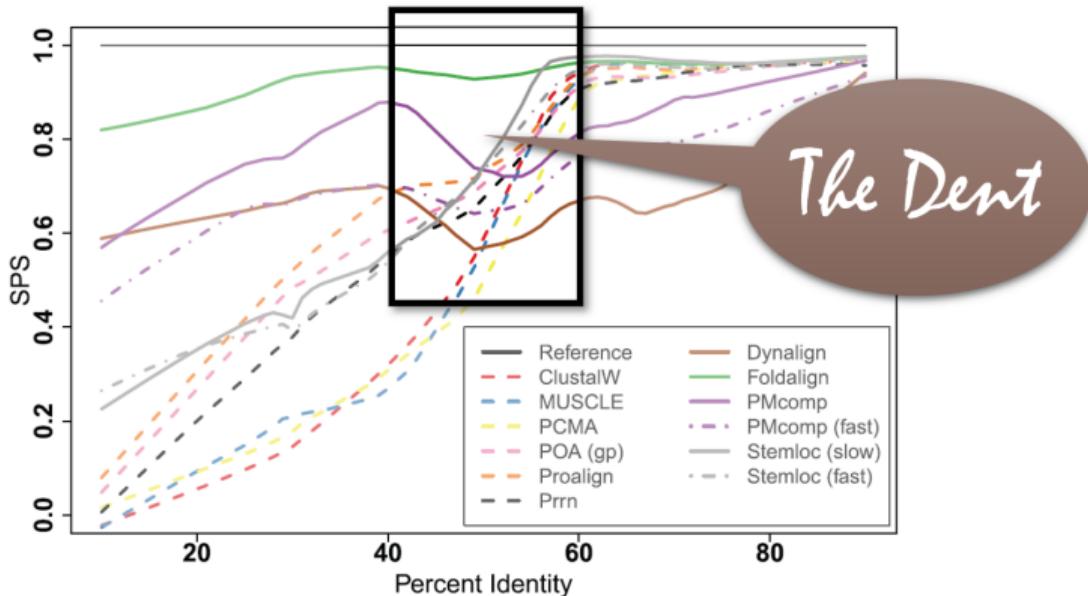
# Detailed performances of 2D folding algorithms

Performance Benchmark (by RNA class)



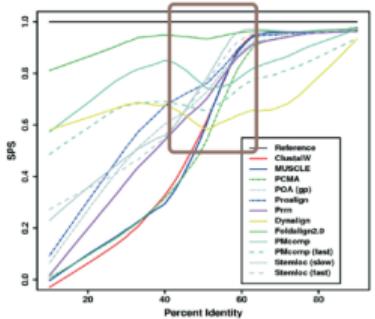
## Biased benchmarks: precedent in comparative folding/alignment

Bralibase: Benchmark for comp. RNA folding [Gardner,Wilm & Washietl, NAR 2005]

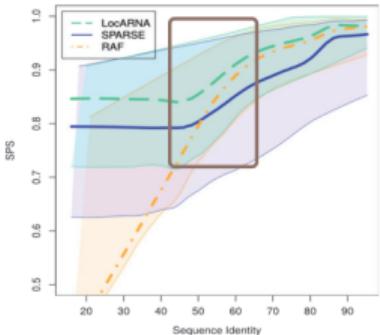


[Löwes *et al*, Briefings in Bioinfo 2016]

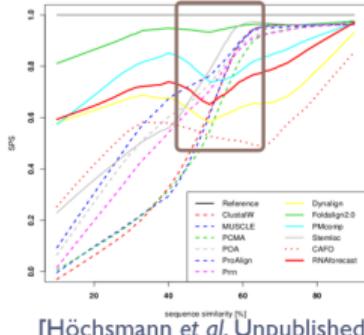
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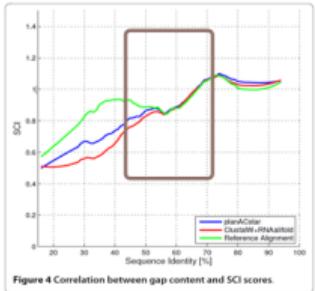
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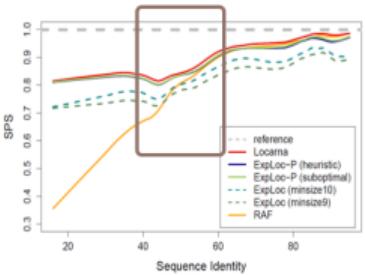
[Will et al, Bioinformatics 2015]



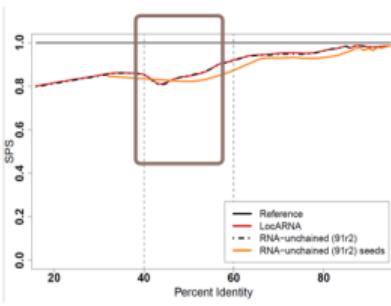
[Höchsmann et al, Unpublished]



[Bremges et al, BMC Bioinfo, 2010]



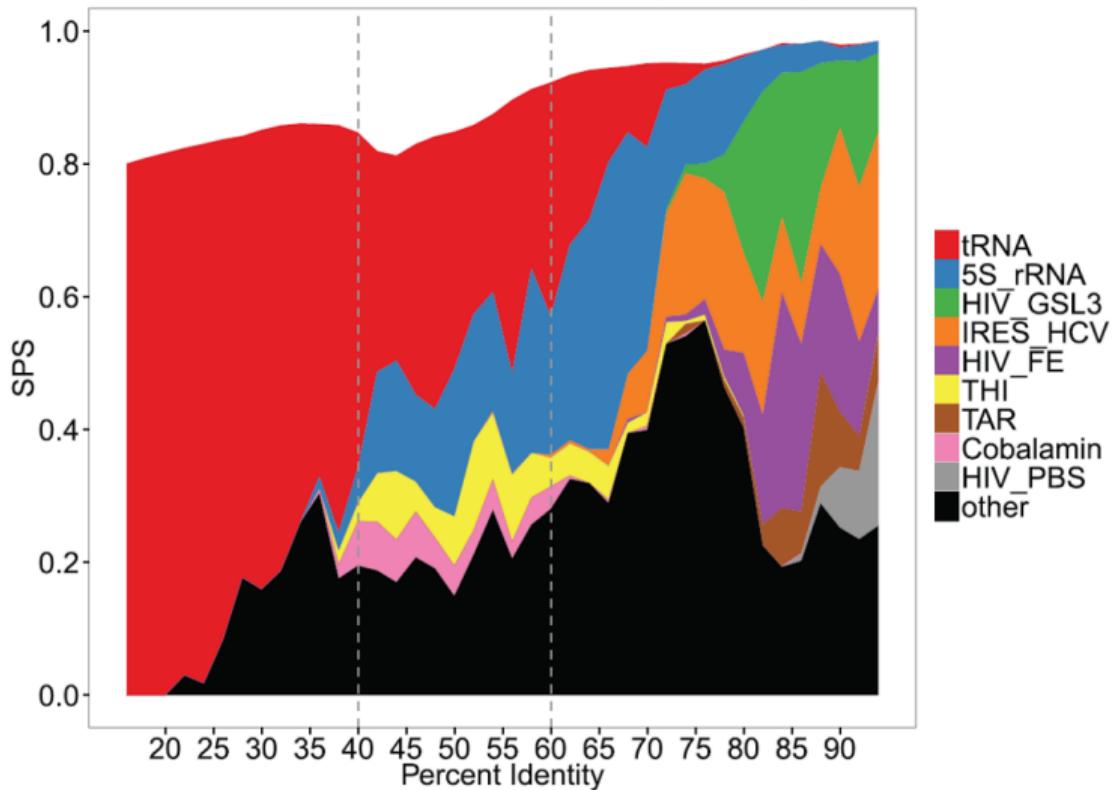
[Schmiedl et al, RECOMB 2012]



[Bourgeade et al, J Comp Biol, 2015]

[Löwes et al, Briefings in Bioinfo 2016]

## Biased benchmarks: precedent in comparative folding/alignment



[Löwes *et al*, *Briefings in Bioinfo* 2016]

## The elephant in the room – 2010s version



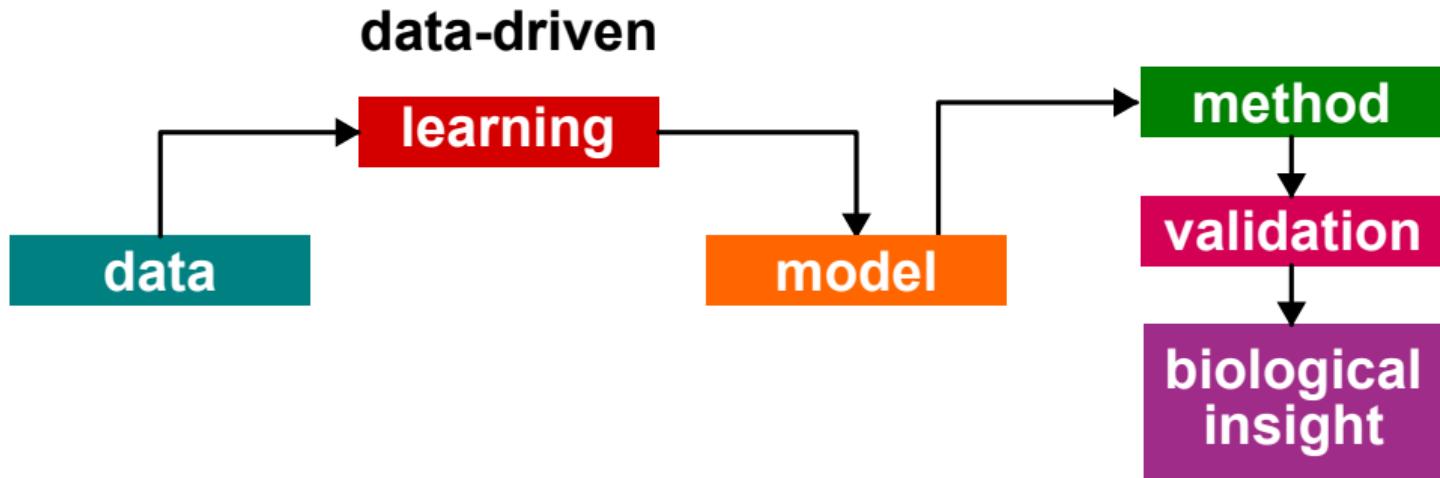
## The elephant in the room – 2020s version



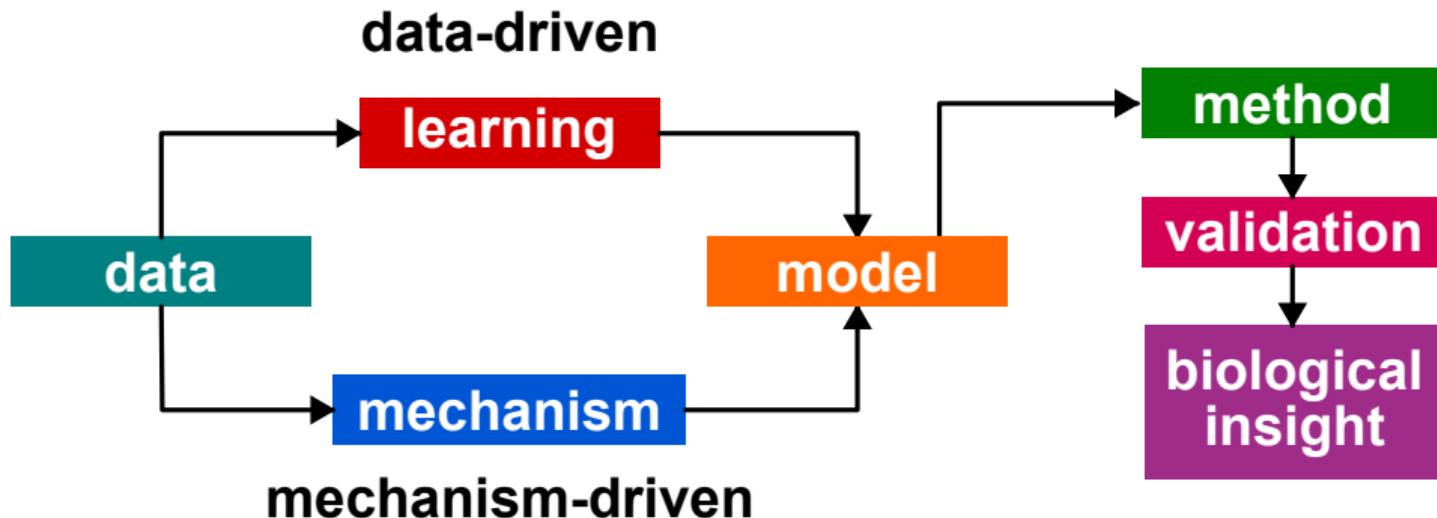
# A personal take on predictive Bioinformatics



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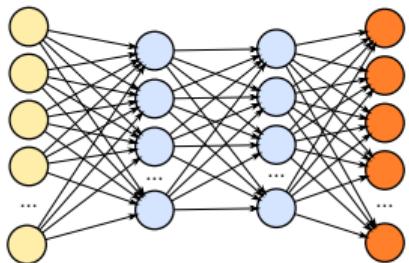
Method dev. as a modeling discipline:

Mechanism-driven model + Exact/deterministic algorithms  
→ Performance as (in)validation of model

# Machine Learning (ML): The beauty...

Machine Learning as a tool for scientific discovery

- ▶ Great promises
- ▶ Self-improving methods
- ▶ Generates/prioritizes hypotheses
- ▶ Available workforce (ubiquitous in curriculums)
- ▶ Highly promoted/funded by research institutions and glamorous journals...



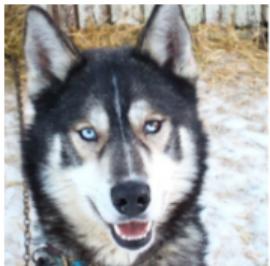
**Shut up and  
take my money**



# Machine Learning (ML): The beauty... and the beast

Multiple (potential) pitfalls for ML in Bio<sup>\*</sup>:

- ▶ Tricky evaluation (data leakage) → Extrapolation/generalization???
- ▶ Reproducibility issues (code/datasets availability, stability, retraining)
- ▶ Fishing expeditions/storytelling, selective reporting
- ▶ Educational deadend?
- ▶ Future(?) ecological disaster? Random blue checkmarks AI zealots on Twitter (grumble...)

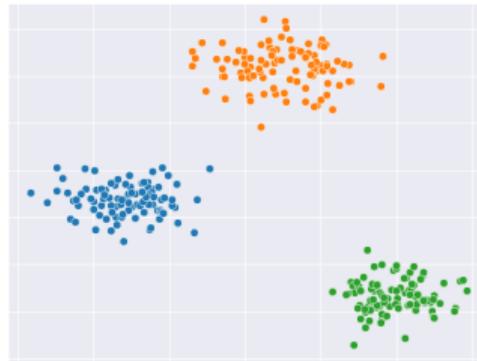


(a) Husky classified as wolf



(b) Explanation

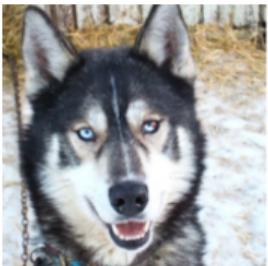
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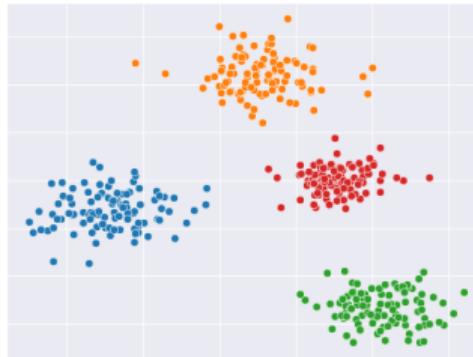


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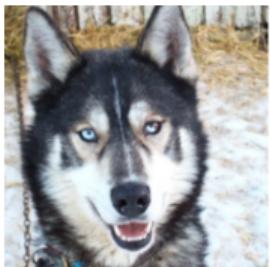
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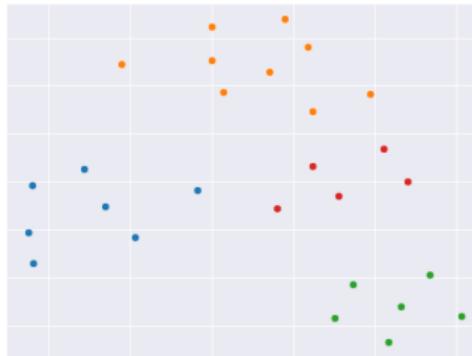


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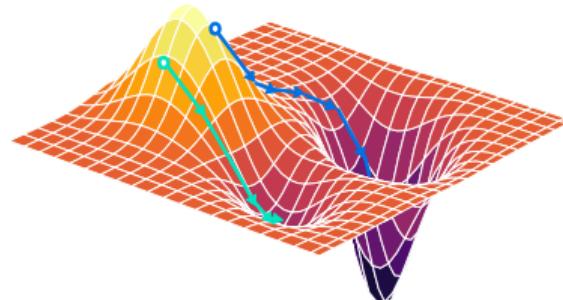
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**Available upon request**

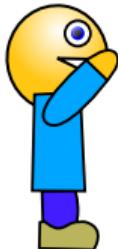
*aka iff I'm in a good mood,  
PhD/postdoc still in lab, HDDs haven't burned,  
pharma hasn't expressed interest in data...*



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**Fifth law of thermodynamics (continued)**

...

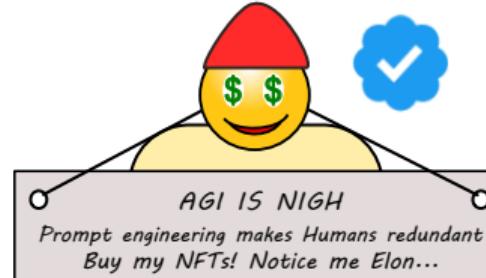
```
-0.31622776601683794 0.31622776601683794
-0.3157663248679193 0.3160839282916222
0.006806069733149146 0.17777128902976705
0.4472135954999579 1.433348584081719
-1.5736761136523203 1.433348584081719
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...
24235/1020400
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# A crowded ML field for RNA 2D prediction



Method	Output	PKs?	Architecture	Availability
CONTRAfold	Pairwise contacts	No	CLLM	Code+weights+webserver
EternaFold	Pairwise contacts	No	CLLM	Code+weights+webserver
DMfold	DBN	Yes	bi-LSTM	Code only
RNA-state-inf	Binary paired/unpaired	N/A	bi-LSTM	Code only
SPOT-RNA2	Pairwise contacts	Yes	CNN	Code+weights+webserver
CROSS	Binary paired/unpaired	N/A	CNN-like	Webserver
RPRes	Binary paired/unpaired	N/A	bi-LSTM+CNN	Code only
2dRNA	Pairwise contacts	Yes	bi-LSTM+CNN	Webserver
2dRNA-LD	Pairwise contacts	Yes	bi-LSTM+CNN	Webserver
SPOT-RNA	Pairwise contacts	Yes	CNN+bi-LSTM	Code+weights+webserver
MXfold2	Pseudo-dG	No	CNN+bi-LSTM	Code+weights+webserver
CNNFold	Pairwise contacts	Yes	CNN(NxN input)	Code+weights
UFold	Pairwise contacts	Yes	CNN(NxN input)	Code+weights+webserver
CDPfold	DBN	No	CNN(NxN input)	Code
E2Efold	Pairwise contacts	Yes	Transformer+CNN	Code+weights
ATTfold	Pairwise contacts	Yes	Transformer+CNN	No

[Wu *et al*, *Briefings in Bioinfo* 2023]

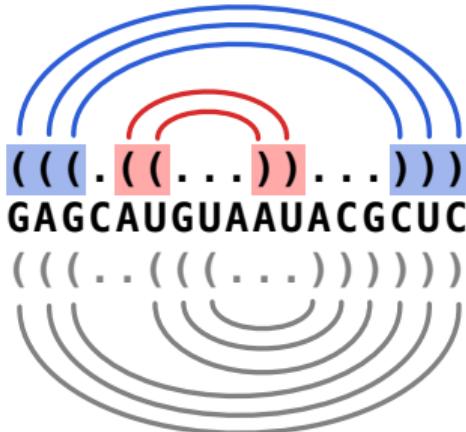
## Performances of 2D structure prediction

RNAStrand benchmark

[Adronescu *et al*, BMC Bioinf 2008]

Method	F <sub>1</sub>
RNAfold 1.8.5	0.737
UNAfold 3.8	0.725
RNAstructure 5.7	0.744

Candidate  
Sequence  
Reference



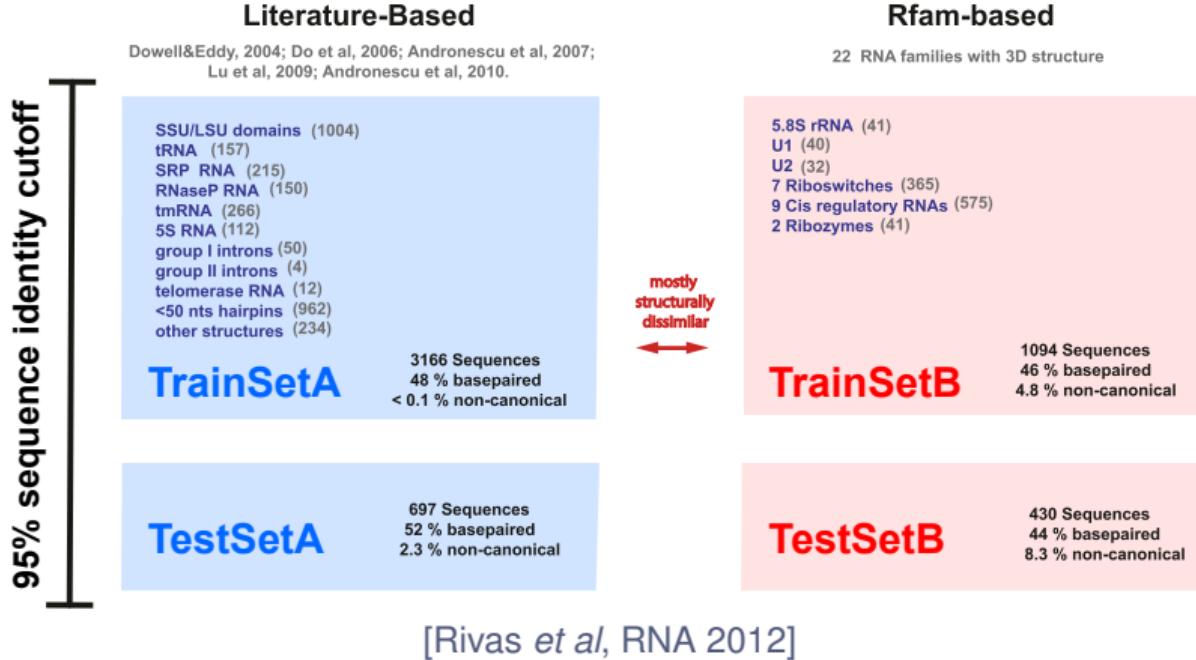
$$\text{Sens} = 3/6 = 0.5$$

$$\text{PPV} = 3/5 = 0.6$$

$$F_1 = 0.545\dots$$

$$F_1\text{-score} = \frac{2 \times \text{PPV} \times \text{Sens}}{\text{PPV} + \text{Sens}}$$

# The TORNADO dataset



[Rivas *et al*, RNA 2012]

TrainSetA vs TestSetA: 95% sim. cutoff → Learn  $k$ -mer to template association

(May happen even for extreme cutoffs)

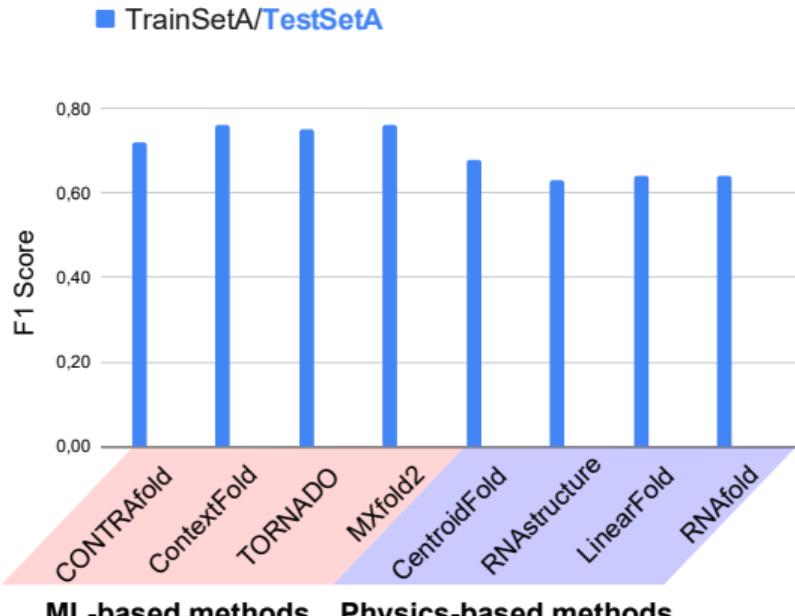
TrainSetA vs TestSetB: Rewards learning structurally generalizable models

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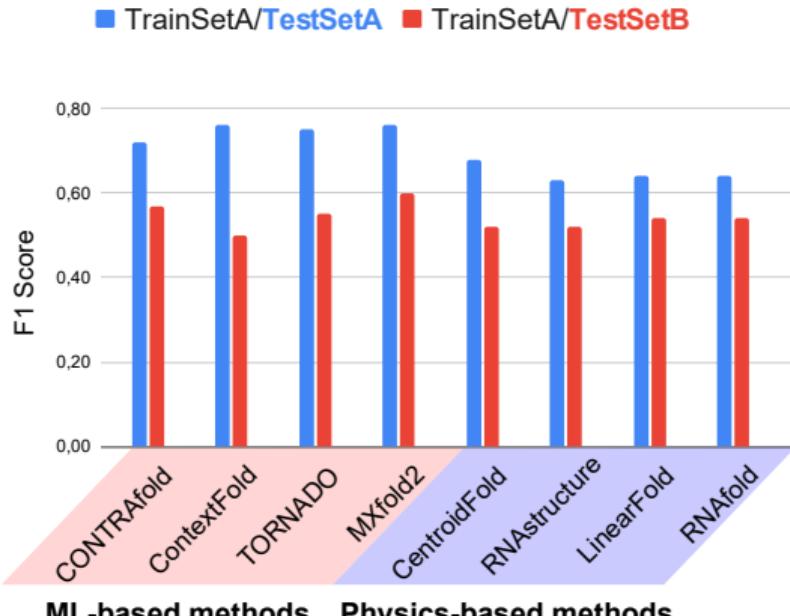
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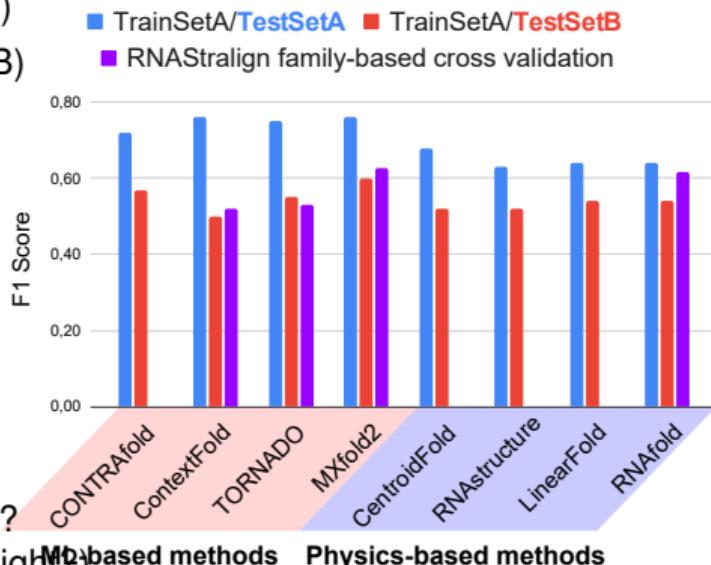
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# The (nc)RNA datasphere

- ▶ 34M sequences, inc 22M presumably structured (RNACentral)
- ▶ 4000+ functional ncRNA families (RFAM)
- ▶ 250-300 non-redundant 3D models (PDB)

Existing methods trained on datasets:

- ▶ highly-redundant sequence-wise
- ▶ low-diversity structure-wise

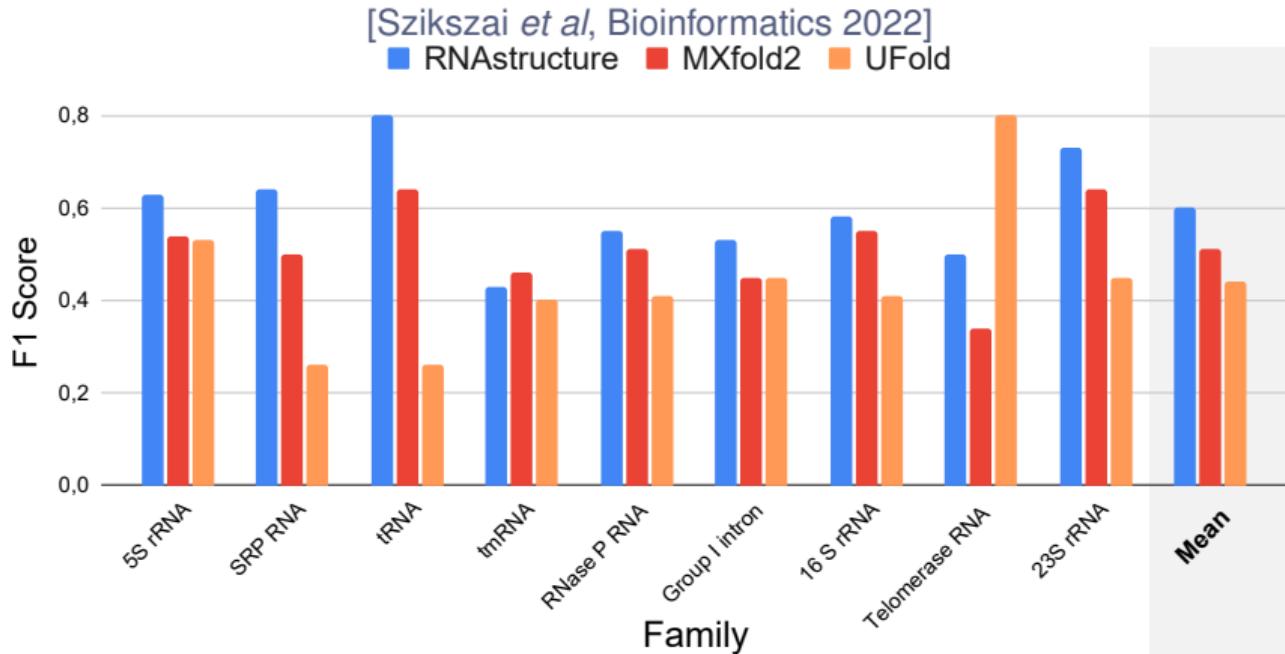


Do ML methods generalize to new structures?

(Do ML perfs translate into *new* biological insight?)

[Sato *et al*, Nature Comm 2021]

## Generalization to new families/structures remains problematic

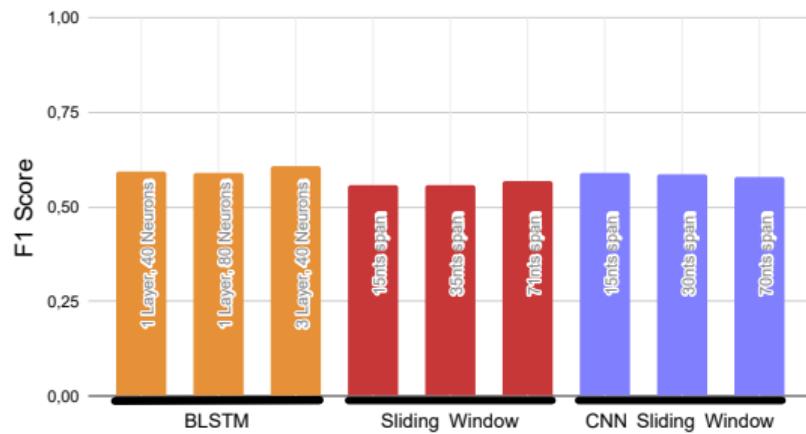


Family-fold cross-validation on **Archivell** dataset [Sloma & Mathews, RNA 2016]  
3974 RNAs of length 77-438 (large rRNAs split into smaller domains)

# What if you had access to (unbounded) additional data?

Idea: Assess NN models' capacity to emulate RNAfold on random sequences

[Flamm *et al*, Frontiers in Bioinfo 2022]

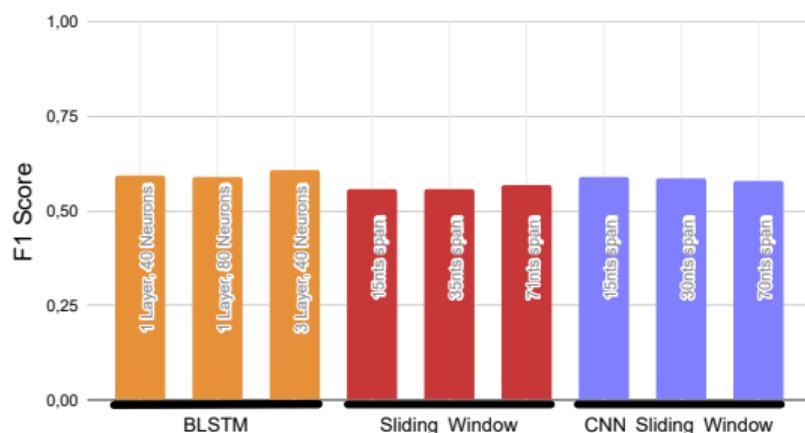


Perfs *plateau* at 80k seq/structs (70nts)

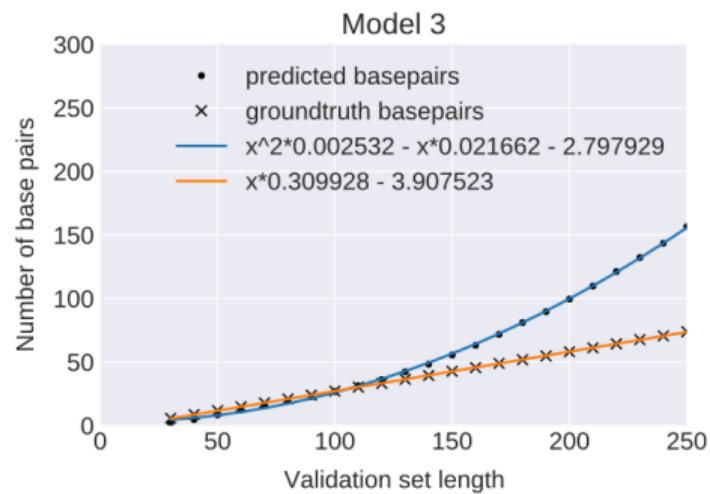
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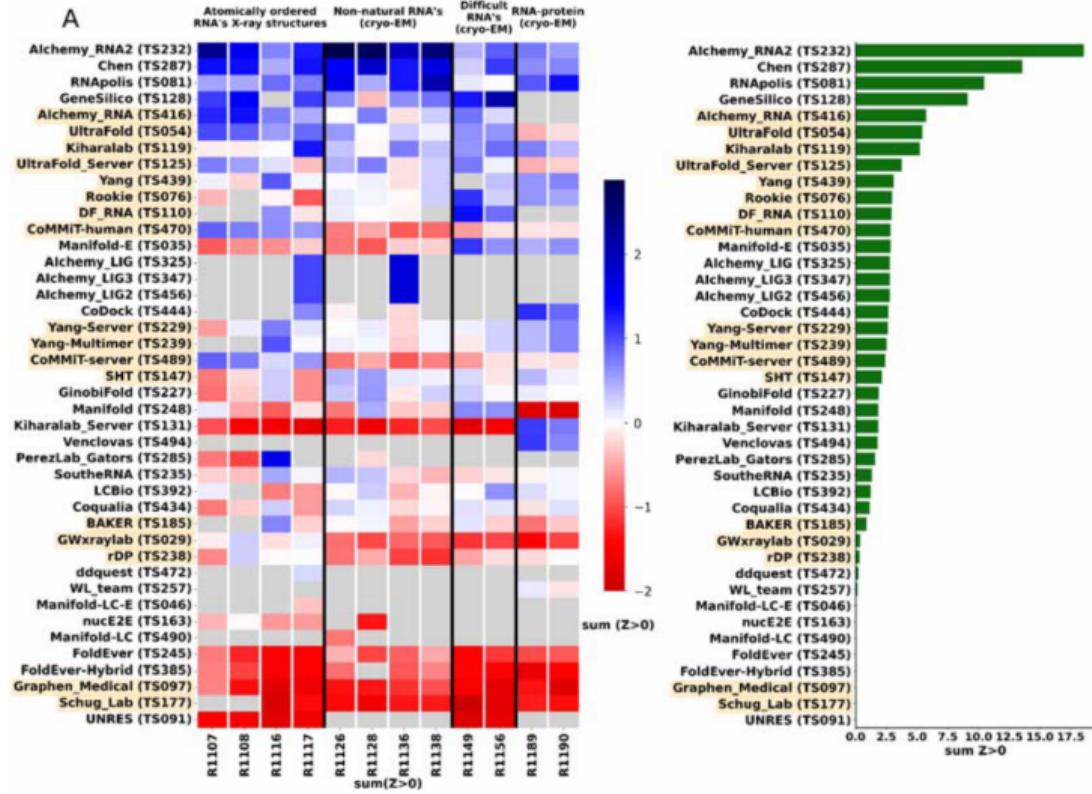


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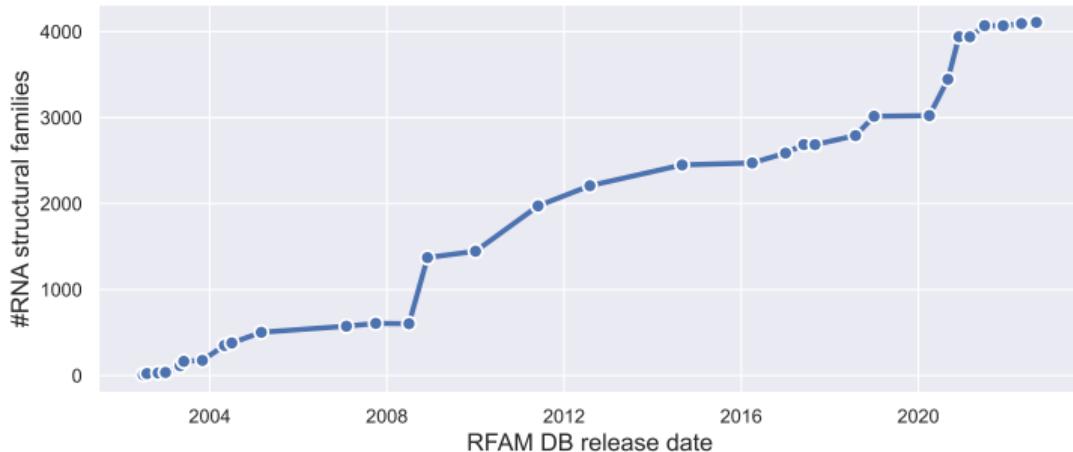
Popular CNN predicts  $\Theta(n^2)$  BPs!

# RNA 3D structure: No AlphaFold moment at CASP15



[Das *et al.*, under review]

## Conclusions and musings



- ▶ Still a need for improved RNA prediction (possibly ML-based)
- ▶ Purely combinatorial methods still ± state-of-the-art for new families...
- ▶ Hybrid approaches à la MxFold2: Best of both worlds?
- ▶ Assessing intrinsic limits of architectures: RNAFold as surrogate model

## Conclusions and musings

So what's special about RNA?

- ▶ Modular but combinatorial structure
- ▶ New folds being routinely discovered (+ can be designed)
- ▶ Relatively scarce 3D data
- ▶ Opportunity: Tons of probing data (ML)
- ▶ Potential of LLMs/transformers (incoming)
- ▶ Pseudoknots-ready algorithms

## Conclusions and musings

RNA/Bioinfo community needs to enforce stricter standards for ML publications:

- ▶ Enforce datasets and source code availability  
[Szikszai *et al*, Bioinfo'22] found 4/8 recent DL methods non-functional
- ▶ Realistic retraining mandatory  
Precondition for self-improvement, benchmarking of novel methods
- ▶ Consider mechanistic and ML methods as largely incomparable
- ▶ Better datasets/benchmarks needed, but perhaps not sufficient
- ▶ Sequence-based leakage should be systematically investigated

## Suboptimal structures

Prob.: Simplified energy model (no pseudoknots, only canonical BPs)

⇒ Native structure (functional) could be **overthrown**.

⇒ Investigate suboptimal structures (RNASubopt [WFHS99]),

i.e. build all structures within  $\Delta \text{ KCal.mol}^{-1}$  of MFE:

- ▶ Compute minimum free-energy matrices
- ▶ Backtrack on any contribution within  $\Delta$  of MFE;
- ▶ Update  $\Delta$  such that future backtracks create  $\geq 1$  struct.
- ▶ Recursively generate subopts and combine (brute-force ou Sort)

$$\mathcal{M}'_{1,n,\Delta} = \min \left( \begin{array}{l} \rightarrow a + c + \text{Min} \left( \mathcal{M}_{i+1,k_0-1} + \mathcal{M}^1_{k_0,j-1} \right) \\ \rightarrow a + c + \text{Min} \left( \mathcal{M}_{i+1,k_1-1} + \mathcal{M}^1_{k_1,j-1} \right) \\ \rightarrow a + c + \text{Min} \left( \mathcal{M}_{i+1,k_2-1} + \mathcal{M}^1_{k_2,j-1} \right) \end{array} \right)$$
$$E_0 - \mathcal{M}'_{1,n} = \varepsilon_0 \leq \Delta$$
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$$E_2 - \mathcal{M}'_{1,n} = \varepsilon_2 \leq \Delta$$

## Suboptimal structures

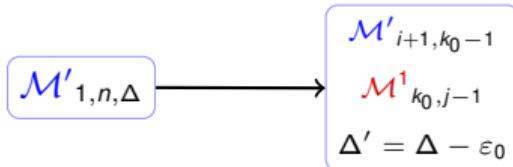
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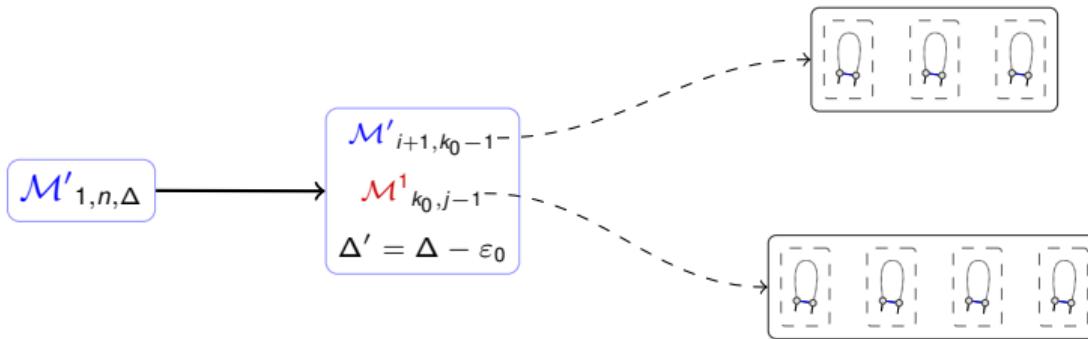
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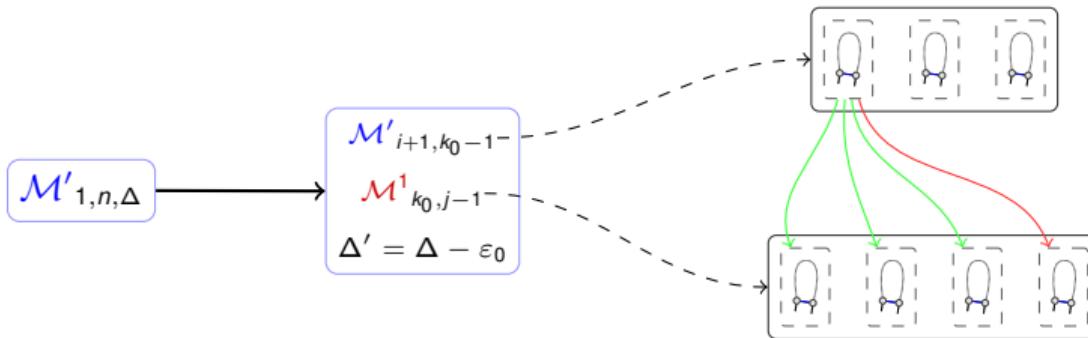
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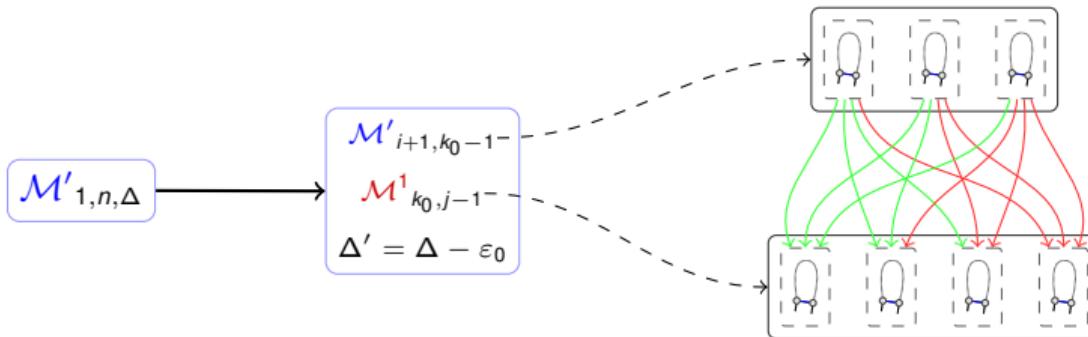
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- ▶ Recursively generate subopts and combine (brute-force ou Sort)



## Suboptimal structures

Prob.: Simplified energy model (no pseudoknots, only canonical BPs)

⇒ Native structure (functional) could be **overthrown**.

⇒ Investigate suboptimal structures (RNASubopt [WFHS99]),

i.e. build all structures within  $\Delta \text{ KCal.mol}^{-1}$  of MFE:

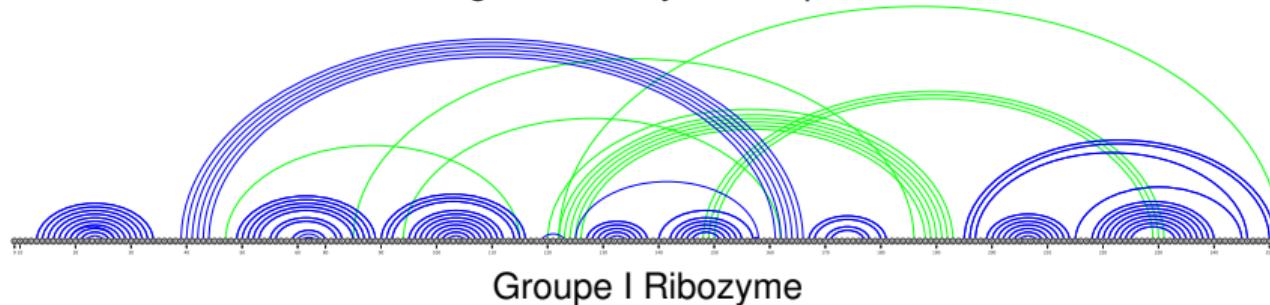
- ▶ Compute minimum free-energy matrices
- ▶ Backtrack on any contribution within  $\Delta$  of MFE;
- ▶ Update  $\Delta$  such that future backtracks create  $\geq 1$  struct.
- ▶ Recursively generate subopts and combine (**brute-force** ou **Sort**)

⇒ Time complexity (**Sort**) :  $\mathcal{O}(n^3 + n \cdot k \log(k))$

( $k$  grows exponentially fast with  $\Delta$ !)

## Predicting pseudoknotted structures

Pseudoknots are essential to the folding and activity of multiple RNA families.



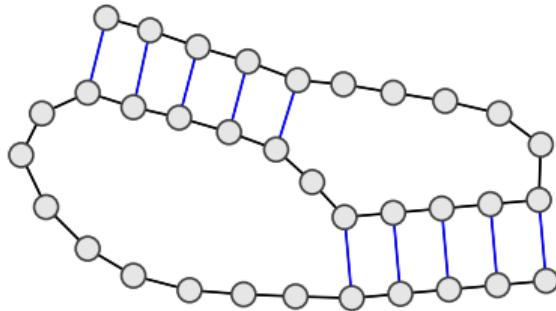
Their disregard within current folding algorithms stems both from **algorithmic** and **energetic** intricacies.

(**Pseudoknots** = Crossings  $\Rightarrow$  foldings delimited by base-pair can no longer be assumed to be independent)

Type	Complexity	Reference
Secondary structures	$\mathcal{O}(n^3)$	[MSZT99]
L&P	$\mathcal{O}(n^5)$	[LP00]
D&P	$\mathcal{O}(n^5)$	[DP03]
A&U	$\mathcal{O}(n^5)$	[Aku00]
R&E	$\mathcal{O}(n^6)$	[RE99]
Unconstrained	NP-complete	[LP00]

## Akutsu/Uemura Algorithm

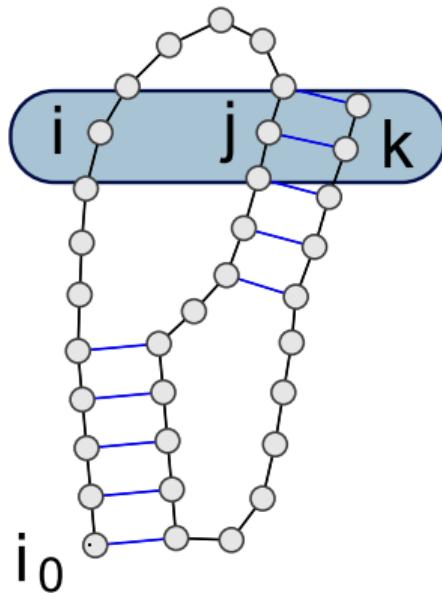
Goal: Capture a category of simple, yet recurrent, pseudoknots.



Idea: When such a PK motif is rotated, one can deduce the MFE of a triplet  $(i, j, k)$  from the MFE of triplets directly below it.

## Akutsu/Uemura Algorithm

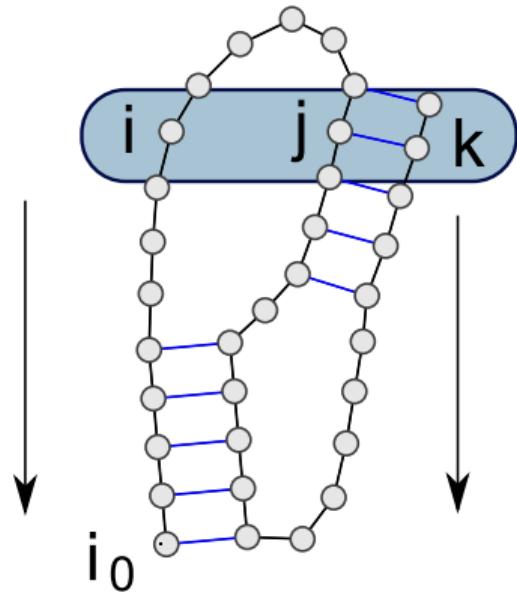
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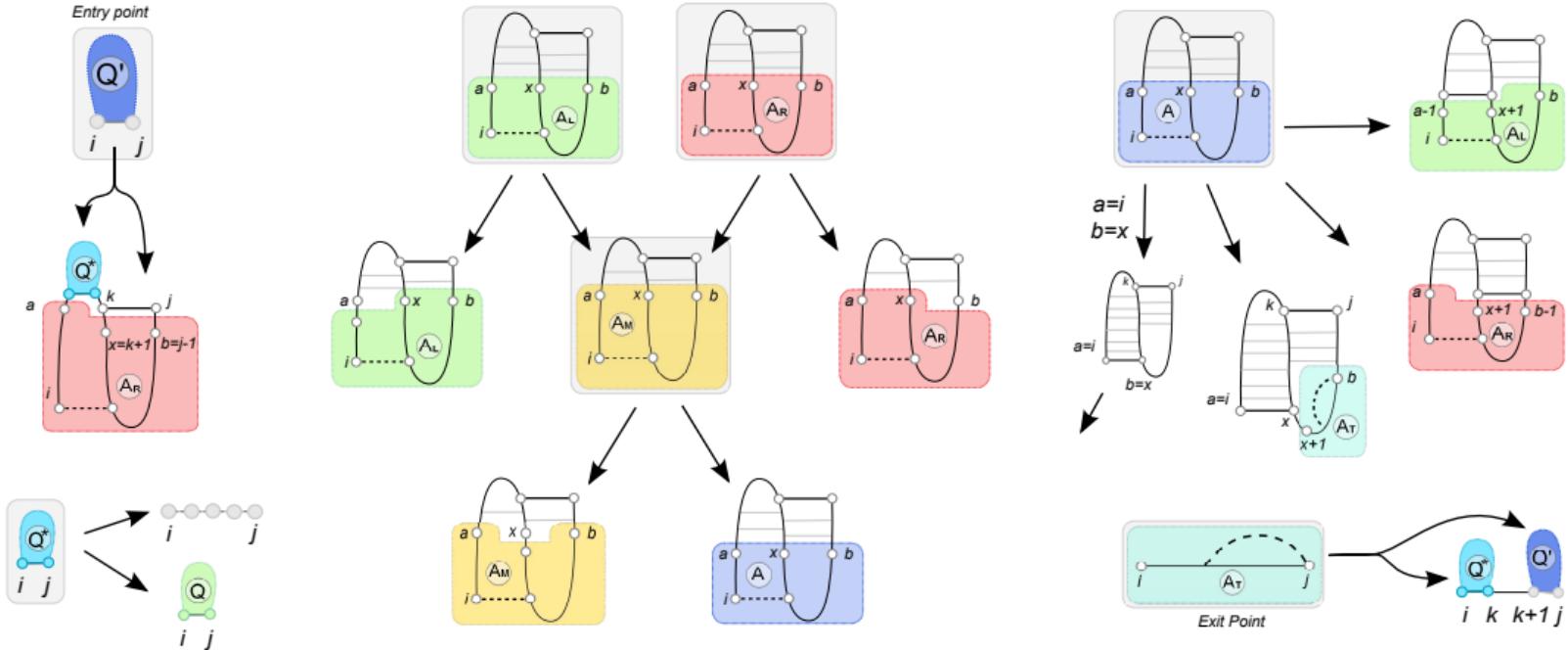
## Akutsu/Uemura Algorithm

Goal: Capture a category of simple, yet recurrent, pseudoknots.



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# Akutsu/Uemura: Dynamic programming



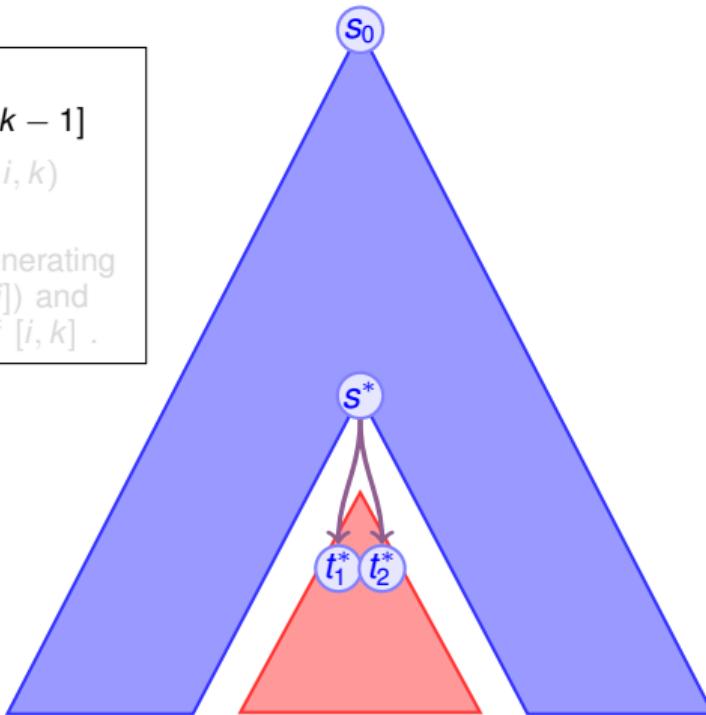
Application/Problem	Weight fun.	Time/Space	Ref.
Energy minimization	$\frac{\pi_{bp}}{RT}$	$\mathcal{O}(n^4)/\mathcal{O}(n^4)$	[Aku00]
Partition function	$e^{-\frac{\pi_{bp}}{RT}}$	$\mathcal{O}(n^4)/\mathcal{O}(n^4)$	$\Theta(n^6)$ [CC09]
BP probabilities	$e^{-\frac{\pi_{bp}}{RT}}$	$\mathcal{O}(n^4)/\mathcal{O}(n^4)$	-
Sampling ( $k$ -struct.)	$e^{-\frac{\pi_{bp}}{RT}}$	$\mathcal{O}(n^4 + kn \log n)/\mathcal{O}(n^4)$	-

Exercice: Write DP equation for MFE computation, counting and partition function.

## Inside/outside algorithm

Structure including base pair  $(i, k)$ :

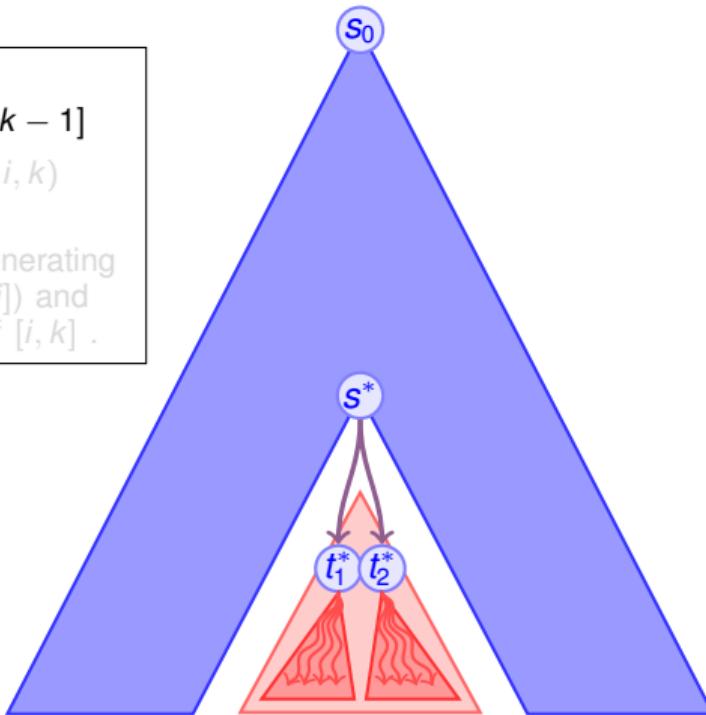
- ▶ **Inside:** Structures over  $[i + 1, k - 1]$
- ▶ **Outside:** Contexts of interval  $(i, k)$ 
  - ▶  $\forall$  interval  $[i, j], i < j \leq k$
  - ▶ Complete structure by generating brother intervals  $([k + 1, j])$  and recurse over the father of  $[i, k]$ .



## Inside/outside algorithm

Structure including base pair  $(i, k)$ :

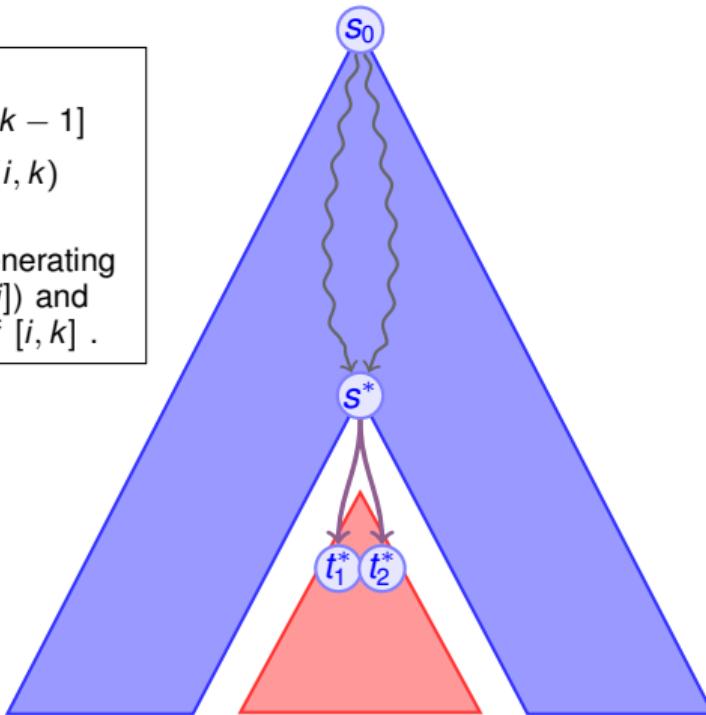
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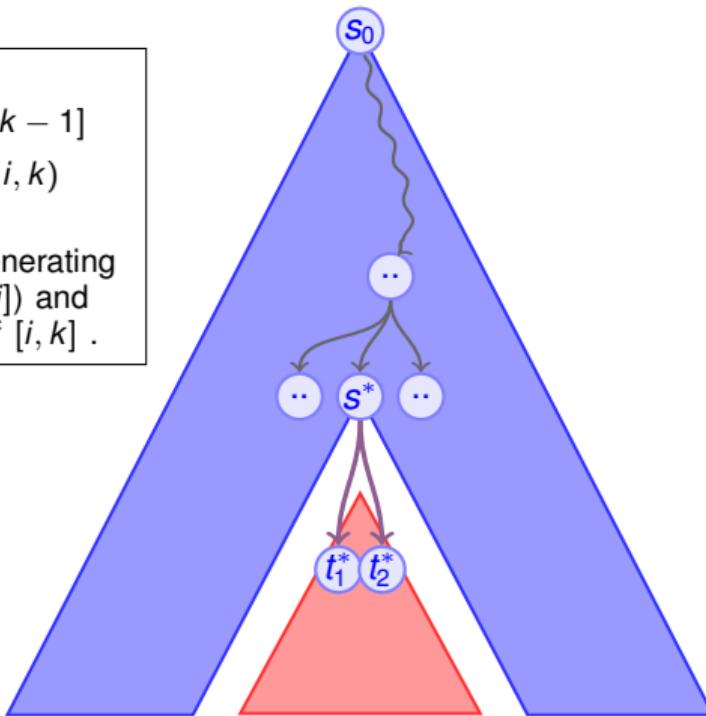
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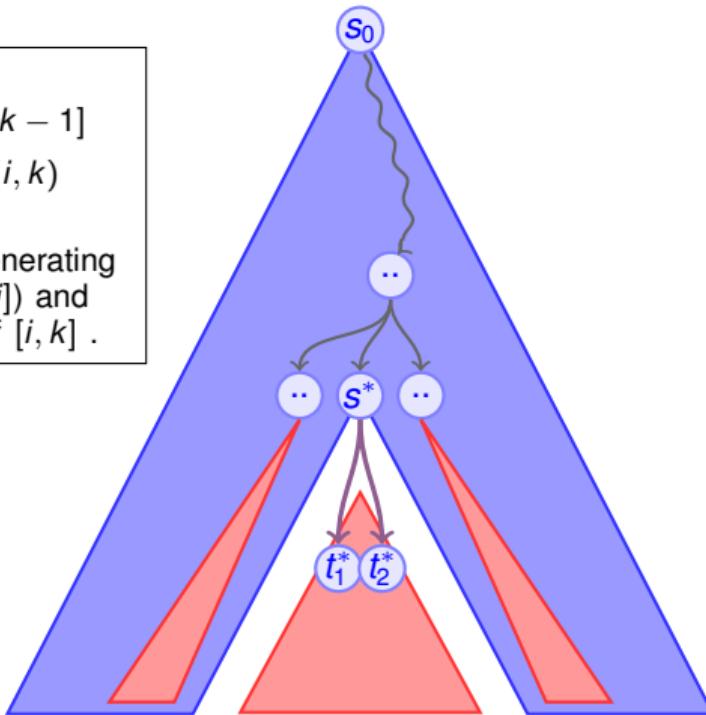
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Structure including base pair  $(i, k)$ :

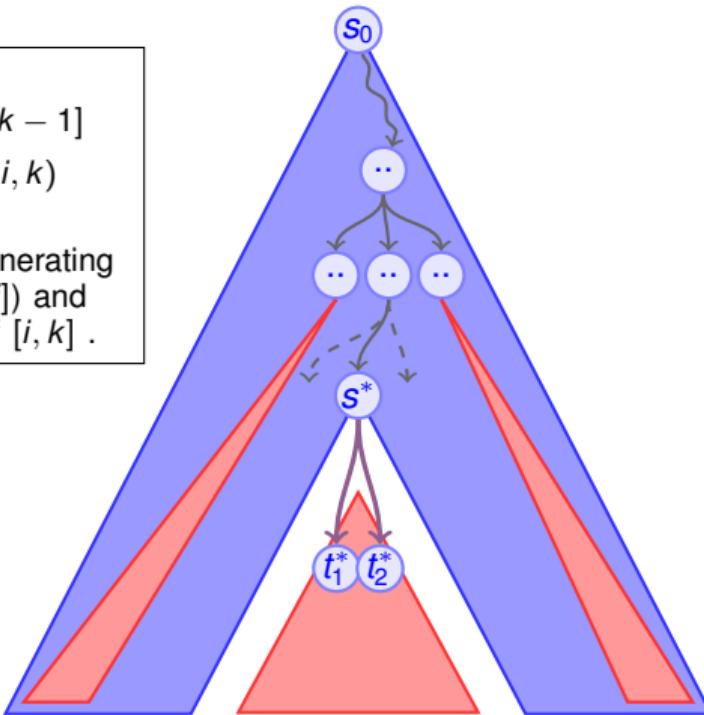
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## Inside/outside algorithm

Structure including base pair  $(i, k)$ :

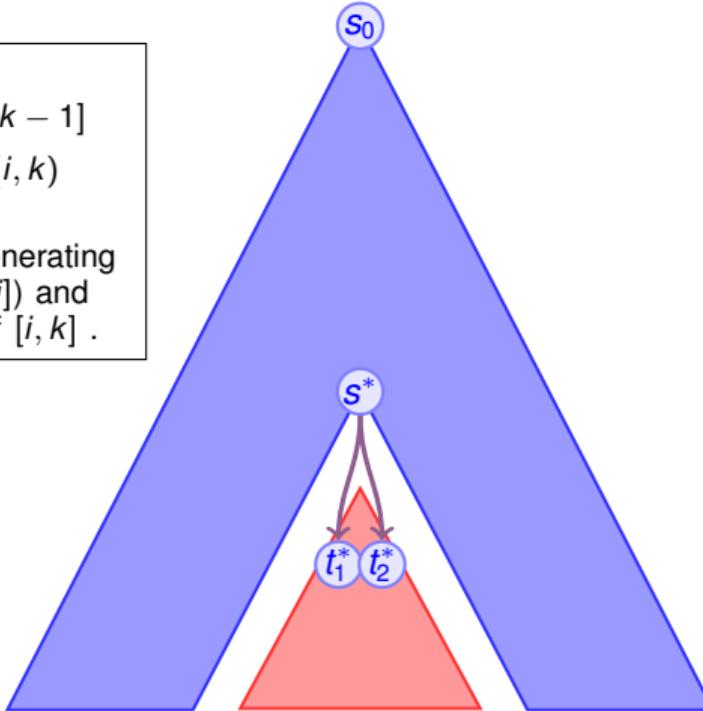
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## Inside/outside algorithm

Structure including base pair  $(i, k)$ :

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- ▶ **Outside:** Contexts of interval  $(i, k)$ 
  - ▶  $\forall$  interval  $[i, j], i < j \leq k$
  - ▶ Complete structure by generating **brother intervals**  $([k + 1, j])$  and recurse over the **father** of  $[i, k]$ .



Whenever some further **technical conditions** are satisfied, this decomposition is **complete** and **unambiguous**, and implies a **simple recurrence** for computing the base pair probability matrix in  $\Theta(n^3)$ .

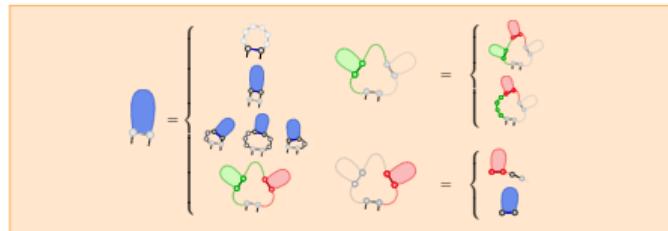
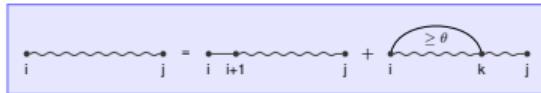
Alternatively: Duplicate sequence

# What is a good dynamic programming scheme?

Correction of a (Ensemble) dynamic programming scheme:

Objective function **correctly** computed/inherited at **local level**

- + All the conformations can be obtained
- ⇒ Correct algorithm (Induction)



Enumerating search space helps **but** does not constitute a proof.

Need to **show equivalence** of DP schemes, e.g. use one to simulate the other and vice versa.  
(Generating functions may help)

# What is a good dynamic programming scheme?

Correction of a (Ensemble) dynamic programming scheme:

Objective function correctly computed/inherited at local level

- + All the conformations can be obtained
- ⇒ Correct algorithm (Induction)

$$\begin{aligned}C_{i,t} &= 1, \quad \forall t \in [i, i + \theta] \\ C_{i,j} &= \sum \left\{ \sum_{k=i+\theta+1}^j 1 \times C_{i+1,k-1} \times C_{k+1,j} \right.\end{aligned}$$

Homopolymer (All pairs allowed) +  $\theta = 1$   
 $\Rightarrow C_{1,n} = 1, 1, 1, 2, 4, 8, 17, 32, 82, 185, 423, \dots$



$$\begin{aligned}\mathcal{C}'_{i,j} &= \sum \left\{ \begin{array}{l} 1 \\ \mathcal{C}'_{i+1,j-1} \\ \sum_{i',j'} \mathcal{C}'_{i',j'} \\ \sum_k \mathcal{C}_{i+1,k-1} \times \mathcal{C}^1_{k,j-1} \end{array} \right. \\ \mathcal{C}_{i,j} &= \sum_k ((\mathcal{C}_{i,k-1} + 1) \times \mathcal{C}^1_{k,j}) \\ \mathcal{C}^1_{i,j} &= \mathcal{C}^1_{i,j-1} + \mathcal{C}'_{i,j}\end{aligned}$$

Homopolymer +  $\theta = 1$   
 $\Rightarrow \mathcal{C}'_{1,n} = 0, 1, 1, 2, 4, 8, 17, 32, 82, 185, 423, \dots$

Enumerating search space helps but does not constitute a proof.

Need to show equivalence of DP schemes, e.g. use one to simulate the other and vice versa.  
(Generating functions may help)

## Structural alignment: Why?

**Hypothesis:** Common evolutionary pressure = Common function .

Within certain RNA families (ex.: RNase-P), low sequence conservation **yet** high structural conservation.

**Algorithmic problems:**

- ▶ **Editing:** Compute *distance* between two secondary structures *A* and *B*.  
Find minimal cost sequence of operations to turn *A* into *B*. Already NP-complete for two secondary structures [BFRS07].
- ▶ **Alignment:** Find minimal cost super-structure.  
Generalizes sequence alignment. Polynomial ( $\mathcal{O}(n^4)$ ) for secondary structures [BDD<sup>+</sup>08], NP-complete in 3D [SZS<sup>+</sup>08].  
**Alternatives:** Local/global alignment, motifs search (aka small-in-large).
- ▶ **Superimposition:** Find solid-body geometric transform (Rotation, translation, zoom) to superimpose *as well as possible* the coordinates of two RNAs having known matching.  
Polynomial in 3D [McL82].

**Remark:** Algorithmic hardness stems from finding the matching (i.e. combinatorial, not geometric).

## FR3D: A geometric approach

When 3D models are available, the alignment problem can be tackled in a **purely geometric setting**.

### Problem

**Input:** Motif  $m$ , target structure  $b$  (ordered set of 3D points).

**Output:** Matching of  $m$  versus a subset of  $b$  that minimizes a notion of geometric **discrepancy**.

**Geometric discrepancy:** In FR3D [SZS<sup>+</sup>08], a **discrepancy** function  $D$  combines two error functions  $L$  et  $A$ , respectively accounting for the **superimposability** ( $L$ ) and **base orientation** ( $A$ ) of  $m$  and  $b$ .

$$L = \sqrt{\min_{R, T} \sum_{i=1}^m \|b_i - R(T(m_i))\|^2} \quad A = \sqrt{\sum_{i=1}^m \alpha_i^2} \quad D = \frac{1}{m} \sqrt{L^2 + A^2}$$

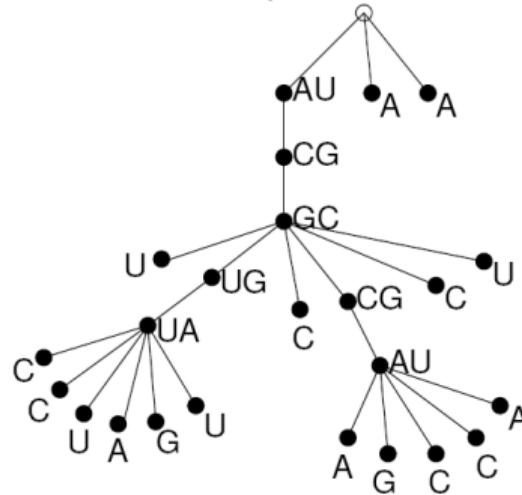
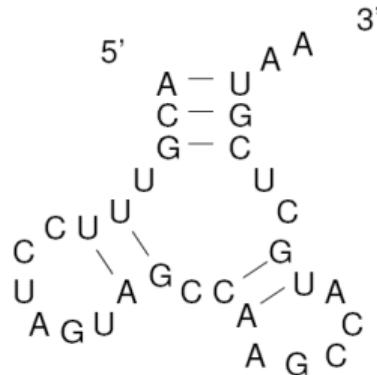
$R, T$ : Rotation and translation.  $c_i$ : Center of mass (CM) of base  $m_i$ .  $\alpha_i$ : Spread between orientation of CMs/bases in  $m_i$  et  $b_i$ .

Backtrack + Incremental pruning (Bounds on  $D$ )  $\Rightarrow$  Combinatorial explosion!

But exact search feasible for smaller motifs.

## Structures to Trees

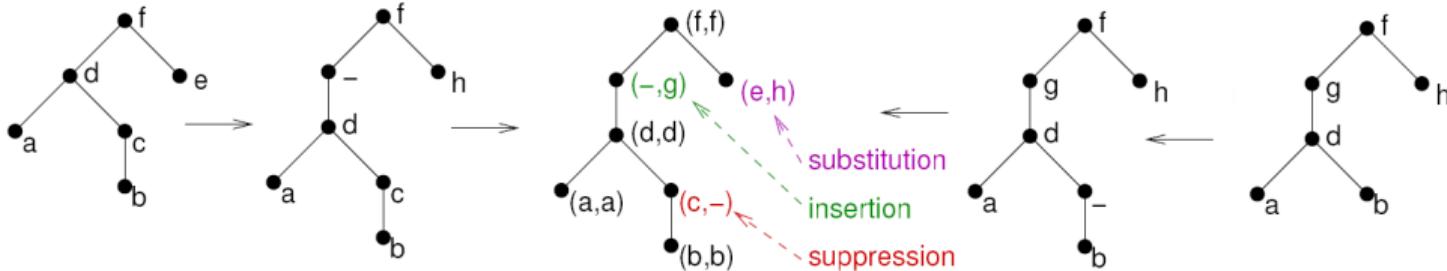
The alignment of two secondary structures is based on their tree-like representations<sup>1</sup>.



Base pairs  $\Rightarrow$  internal nodes

Unpaired bases  $\Rightarrow$  Leaves

Alignment = Complete matching having minimal cost.



## Aligning Trees<sup>2</sup>

$$\delta(\text{Tree}_1, \text{Tree}_2) = \min \left\{ \begin{array}{l} \delta(\text{Tree}_1, \text{Tree}_2) + \text{del}(\bullet) \\ \delta(\text{Tree}_1, \text{Tree}_2) + \text{ins}(\bullet) \\ \delta(\text{Tree}_1, \text{Tree}_2) + \text{subst}(\bullet, \bullet) \end{array} \right.$$

## Aligning Forests

$$\delta(\text{Forest}_1, \text{Forest}_2) = \min \left\{ \begin{array}{l} \min \{ \delta(\text{Tree}_1, \text{Tree}_2) + \delta(\text{Forest}_1 \setminus \text{Tree}_1, \text{Forest}_2 \setminus \text{Tree}_2) \mid \text{Forest}_1 \setminus \text{Tree}_1 = \text{Forest}_2 \setminus \text{Tree}_2 \} \\ \quad + \text{del}(\bullet) \\ \min \{ \delta(\text{Tree}_1, \text{Tree}_2) + \delta(\text{Forest}_1 \setminus \text{Tree}_1, \text{Forest}_2 \setminus \text{Tree}_2) \mid \text{Forest}_1 \setminus \text{Tree}_1 = \text{Forest}_2 \setminus \text{Tree}_2 \} \\ \quad + \text{ins}(\bullet) \\ \delta(\text{Forest}_1, \text{Forest}_2) + \delta(\text{Forest}_1 \setminus \text{Tree}_1, \text{Forest}_2 \setminus \text{Tree}_2) \end{array} \right.$$

Worst-case complexity in  $\mathcal{O}(n^4)$  [JWZ94], on average in  $\mathcal{O}(n^2)$  [HDD07].

**But** RNA-specific operations are lacking

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<sup>2</sup>Idem

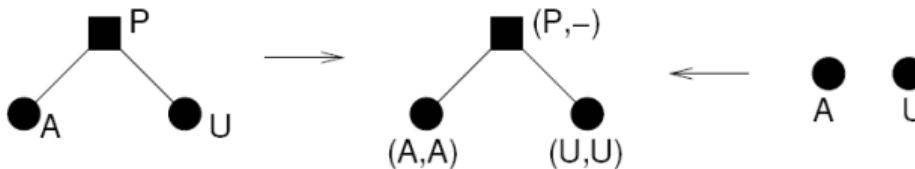
## RNAForester [HVG04]

Parametrization of operation costs, but some operations, atomic in a realistic model, must be composed from available ones.

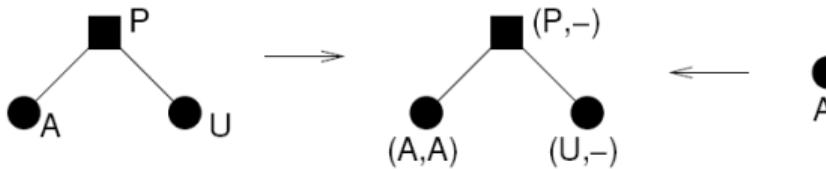
Example: To detach a base-pair, delete node (base-pair), and insert two leaves (bases).

RNAForester: Based on Jiang, Wang & Zhang algorithm  
+ Integration of RNA-specific operations<sup>3</sup>.

arc-breaking



arc-altering



<sup>3</sup>Idem

## NestedAlign [BDD<sup>+</sup>08]

$$\delta(\text{Tree}_1, \text{Tree}_2) = \min \left\{ \begin{array}{l} \delta(\text{Tree}_1, \text{Tree}_2) + \text{BDel}(\bullet) \\ \delta(\text{Tree}_1, \text{Tree}_2) + \text{BIns}(\bullet) \\ \delta(\text{Tree}_1, \text{Tree}_2) + \text{BSub}(\bullet, \bullet) \\ \min \{ \delta(\text{Tree}_1, \text{Tree}_2) + \delta(\text{Tree}_1, \text{Tree}_2) : \text{Tree}_1 = \text{Tree}_2 \} + \text{PDel}(\bullet) \\ \min \{ \delta(\text{Tree}_1, \text{Tree}_2) + \delta(\text{Tree}_1, \text{Tree}_2) : \text{Tree}_1 = \text{Tree}_2 \} + \text{PIns}(\bullet) \\ \delta(\text{Tree}_1, \text{Tree}_2) + \delta(\text{Tree}_1, \text{Tree}_2) + \text{PSub}(\bullet, \bullet) \\ \min \{ \delta(\text{Tree}_1, \text{Tree}_2) + \delta(\text{Tree}_1, \text{Tree}_2) : \text{Tree}_1 = \text{Tree}_2 \} + \text{Fus}(\bullet, \bullet, \bullet) \\ \min \{ \delta(\text{Tree}_1, \text{Tree}_2) + \delta(\text{Tree}_1, \text{Tree}_2) : \text{Tree}_1 = \text{Tree}_2 \} + \text{Sci}(\bullet, \bullet, \bullet) \\ \min \{ \delta(\text{Tree}_1, \text{Tree}_2) + \delta(\text{Tree}_1, \text{Tree}_2) : \text{Tree}_1 = \text{Tree}_2 \} + \text{GAlt}(\bullet, \bullet) \\ \min \{ \delta(\text{Tree}_1, \text{Tree}_2) + \delta(\text{Tree}_1, \text{Tree}_2) : \text{Tree}_1 = \text{Tree}_2 \} + \text{DAlt}(\bullet, \bullet) \\ \min \{ \delta(\text{Tree}_1, \text{Tree}_2) + \delta(\text{Tree}_1, \text{Tree}_2) : \text{Tree}_1 = \text{Tree}_2 \} + \text{GComp}(\bullet, \bullet) \\ \min \{ \delta(\text{Tree}_1, \text{Tree}_2) + \delta(\text{Tree}_1, \text{Tree}_2) : \text{Tree}_1 = \text{Tree}_2 \} + \text{DComp}(\bullet, \bullet) \end{array} \right\}$$

si  $\bullet$  base  
si  $\bullet$  base  
si  $\bullet$  et  $\bullet$  bases  
si  $\bullet$  paire  
si  $\bullet$  paire  
si  $\bullet$  et  $\bullet$  paires  
si  $\bullet$  paire et  $\bullet$  base  
si  $\bullet$  paire et  $\bullet$  base  
si  $\bullet$  paire et  $\bullet$  base  
si  $\bullet$  paire  
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si  $\bullet$  paire

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