

# Combinatorial Optimization in Bioinfo

## Folding RNA *in silico*

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# Outline

## Introduction

Dynamic programming 101

Dynamic programming framework

## Variations on RNA folding

Why RNA?

RNA folding

RNA Structure(s)

Some representations of RNA structure

Thermodynamics vs Kinetics

## Free-energy minimization

Nussinov-style RNA folding

Turner energy model

MFold/Unafold

Performances and the comparative approach

Towards a 3D ab-initio prediction

## Boltzmann ensemble

Nussinov: Minimisation  $\Rightarrow$  Counting

Computing the partition function

Statistical sampling

## Foreword ...

... or how to make a million bucks by giving change parsimoniously!!

**Problem:** You have access to unlimited amount of **1**, **20** and **50** cents coins. A client prefers to travel light, i.e. to **minimize the #coins**.

How to give **N** cents back in change without losing a customer?

**Strategy #1:** Start with *heaviest* coins, and then complete/fill-up with coins of *decreasing* value.

$$21 = ??$$

$$55$$

$$60$$

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$$\begin{aligned} 60 &= \text{€}50 + \text{€}20 + \text{€}10 ?? \\ &= \text{€}20 + \text{€}20 + \text{€}20 ! \end{aligned}$$

Problem *a priori* (?) non-solvable using such a *greedy* approach, as a (simpler) problem is already NP-complete (thus Efficient solution  $\Rightarrow$  1M\$).

## Foreword

**Strategy #2:** Brute force enumeration  $\rightarrow \#Coins^N$  (Ouch!)

**Strategy #3:** The following recurrence gives the minimal number of coins:

$$\text{Min}\#\text{Coins}(N) = \text{Min} \left\{ \begin{array}{l} \text{£1 coin} \rightarrow 1 + \text{Min}\#\text{Coins}(N - 1) \\ \text{£20 coin} \rightarrow 1 + \text{Min}\#\text{Coins}(N - 20) \\ \text{£50 coin} \rightarrow 1 + \text{Min}\#\text{Coins}(N - 50) \end{array} \right.$$

With some memory ( $N$  intermediate computations), the minimum number of coins can be obtained after  $N \times \#Coins$  operations. An actual set of coins can be reconstructing by **tracing back** the choices performed at each stage, leading to the minimum.

**Remark:** We still haven't won the million, as  $N$  has **exponential value compared to the length of its encoding**, so the algorithm does not qualify as **efficient** (i.e. polynomial).

Still, this approach is much more efficient than a brute-force enumeration:  
 $\Rightarrow$  Dynamic programming.

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# Dynamic programming: General principle

Dynamic programming = General optimization technique.

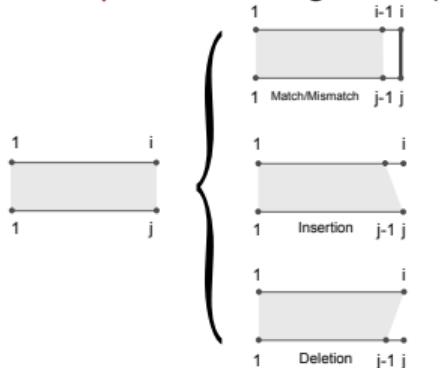
Prerequisite: Optimal solution for problem  $P$  can be derived from solutions to sub-problems of  $P$ .

Bioinformatics :

Discrete solution space (alignments, structures...)

- + Additively-inherited objective function (cost, log-odd score, energy...)
- ⇒ Efficient dynamic programming scheme

Example: Local Alignment(Smith/Waterman)



$$W(i, 0) = 0$$

$$W(0, j) = 0$$

$$W(i, j) = \max \begin{cases} W(i - 1, j - 1) + m_{i,j} \\ W(i - 1, j) + p_i \\ W(i, j - 1) + p_d \end{cases}$$

## Algorithmic details

Dynamic programming scheme defines a space of (sub)problems and a recurrence that relates the score of a problem to that of smaller problems.

Given a scheme, two steps :

- Matrix filling: Computation and tabulation of best scores (Computed from smaller problems to larger ones).
- Traceback: Reconstruct best solution from contributing subproblems.

Complexity of algorithm depends on:

- Cardinality of sub-problem space
- Number of alternatives considers at each step (#Terms in recurrence)

Smith&Waterman example:

- $i: 1 \rightarrow n + 1 \Rightarrow \Theta(n)$
- $j: 1 \rightarrow m + 1 \Rightarrow \Theta(m)$
- 3 operations at each step  
 $\Rightarrow \Theta(m.n)$  time/memory

$$W(i, 0) = 0$$
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## Properties of DP schemes

Necessary properties:

- ▶ **Correctness:**  $\forall$  sub-problem, the computed value must indeed maximize the objective function .

Proofs usually inductive, and quite technical, but very systematic.

Desirable properties of DP schemes:

- ▶ **Completeness** of space of solutions generated by decomposition.  
Algorithmic tricks, by *cutting branches*, may violate this property.
- ▶ **Unambiguity:** Each solution is generated at most once.  
⇒ Under these properties, one can enumerate solution space.

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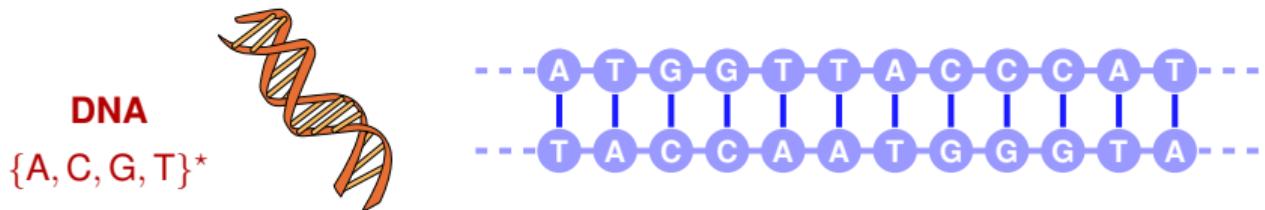
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Nussinov: Minimisation  $\Rightarrow$  Counting

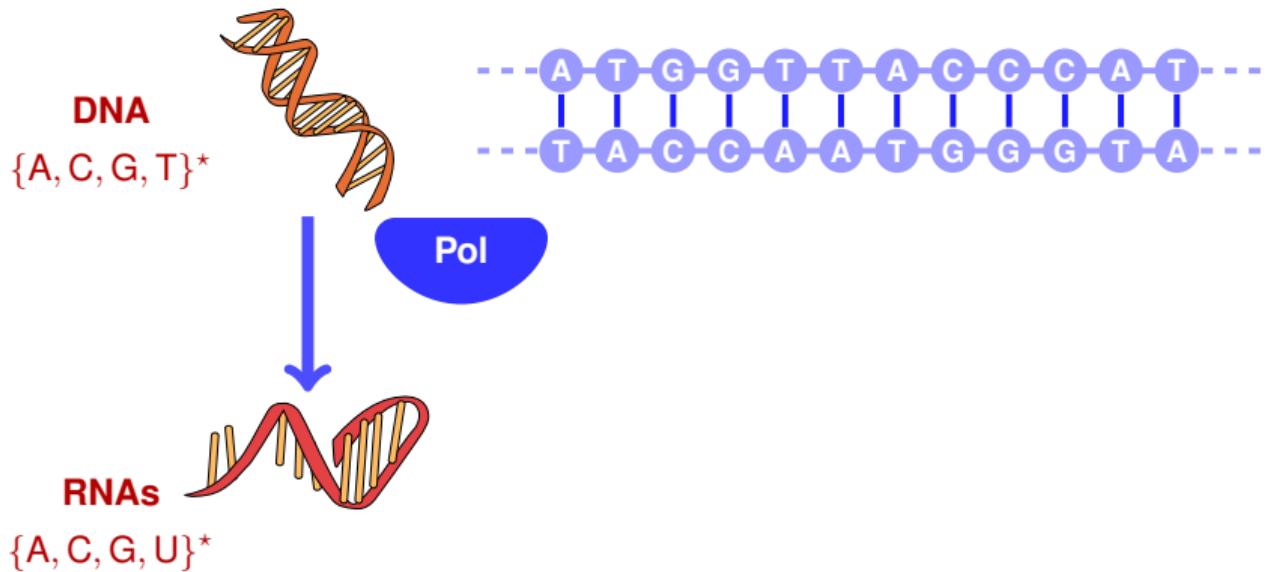
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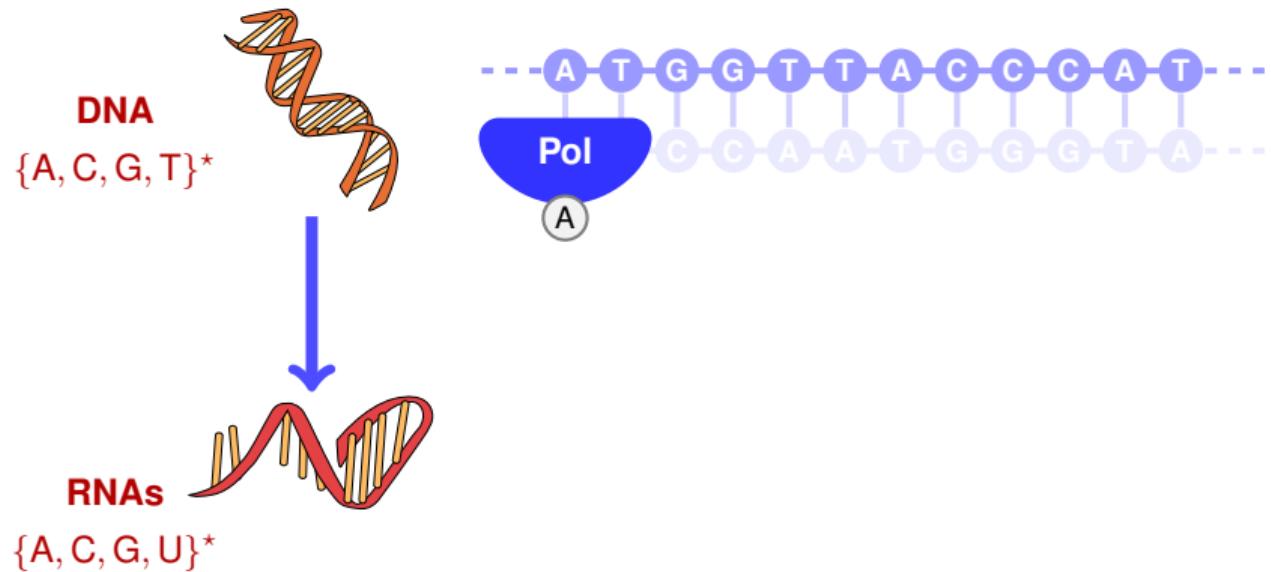
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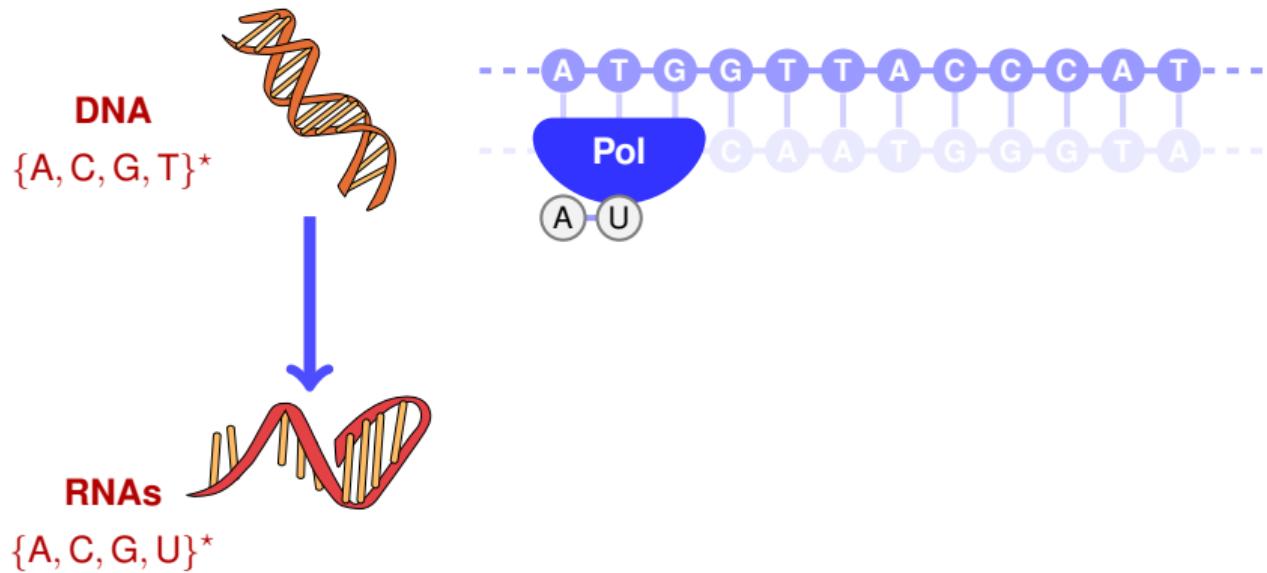
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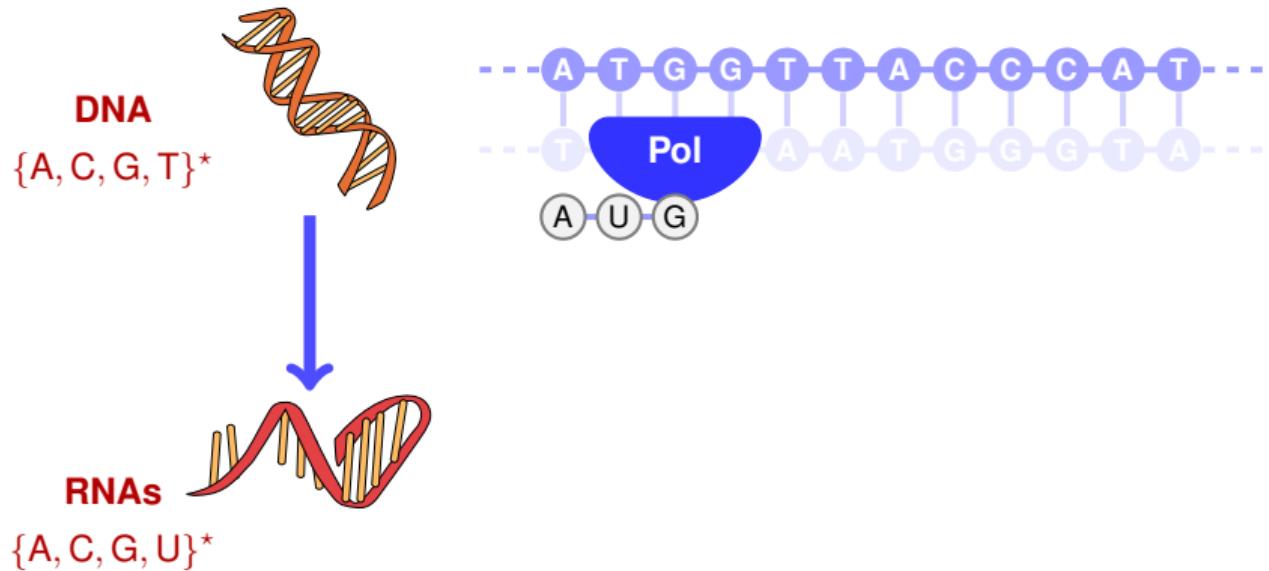
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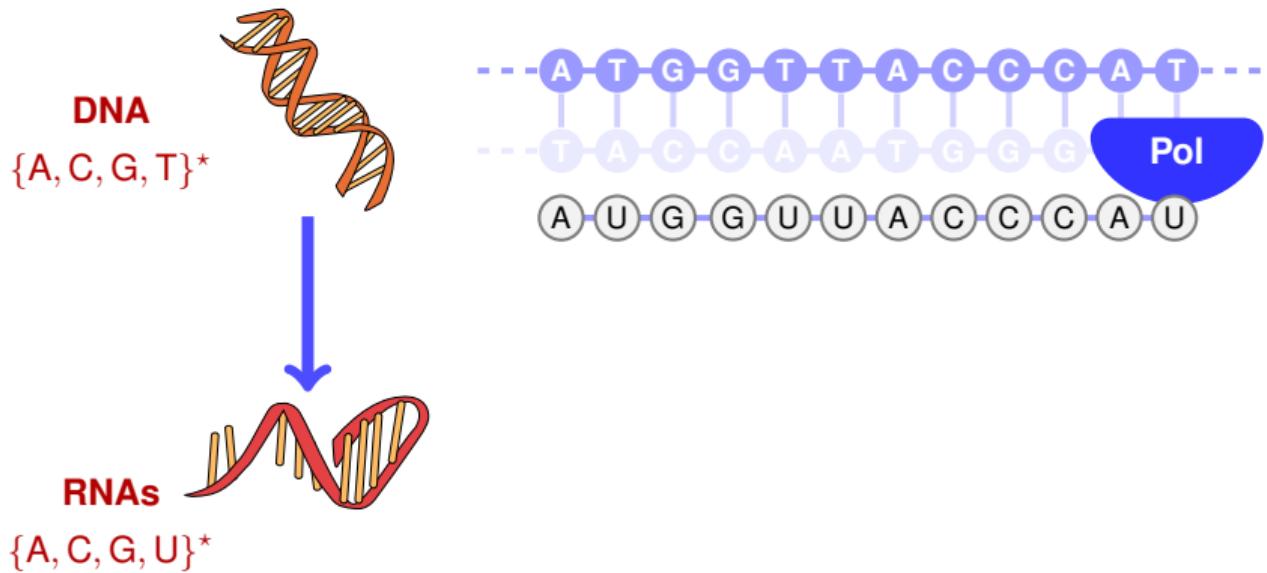
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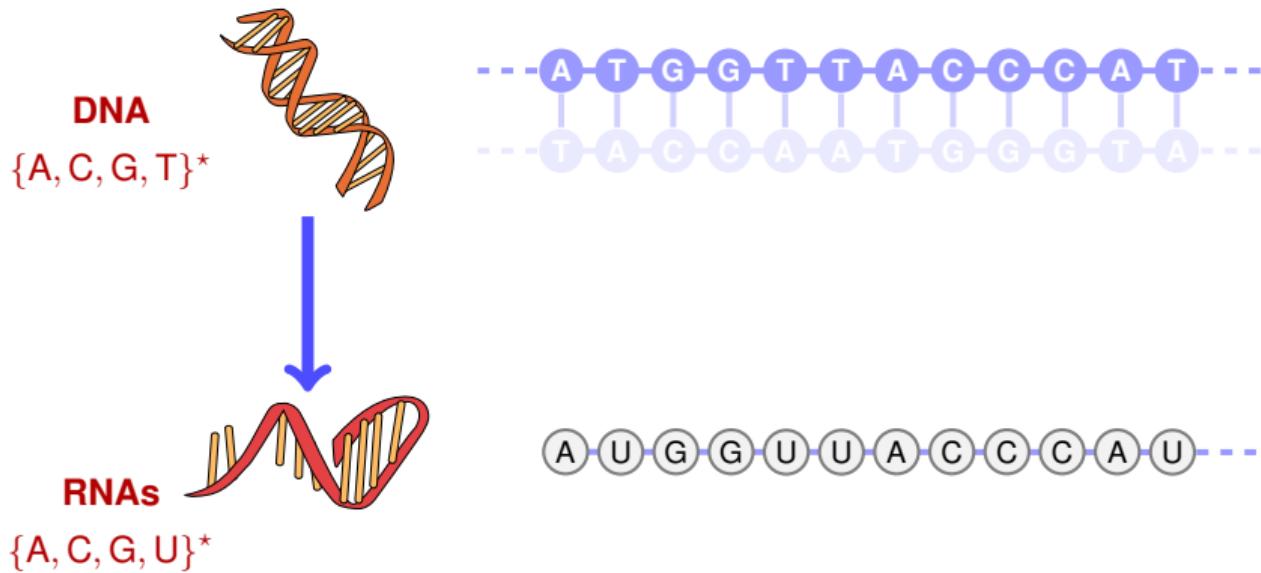
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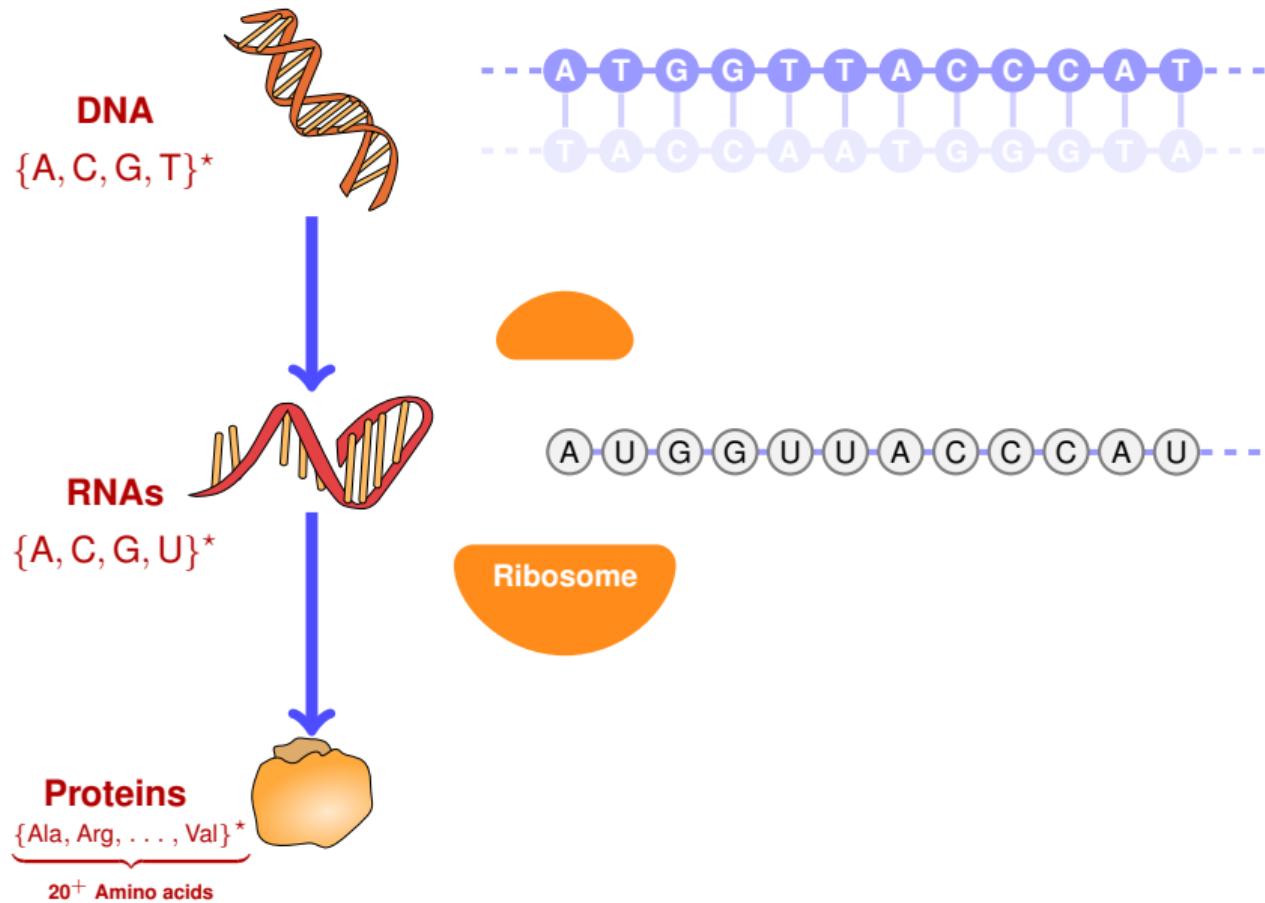
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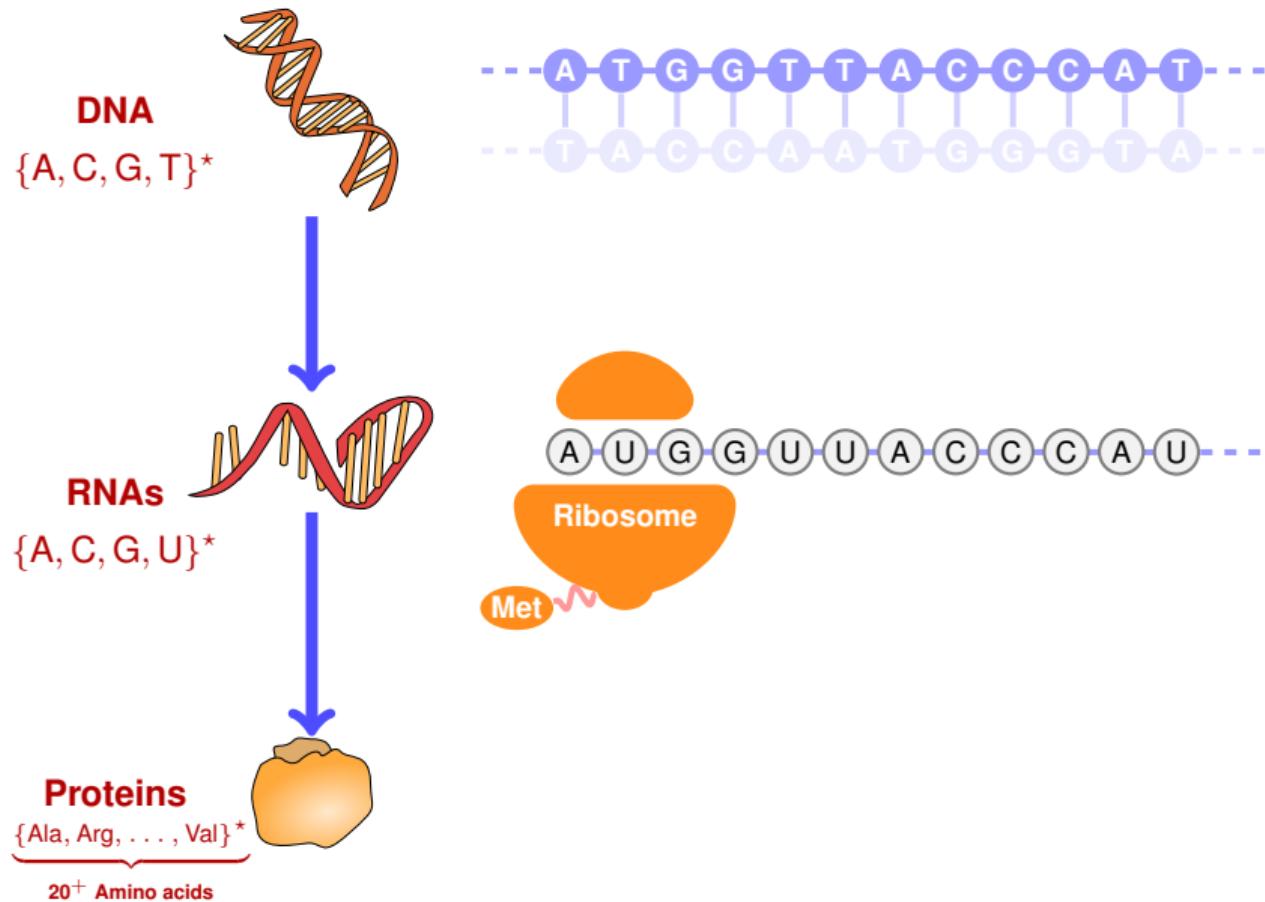
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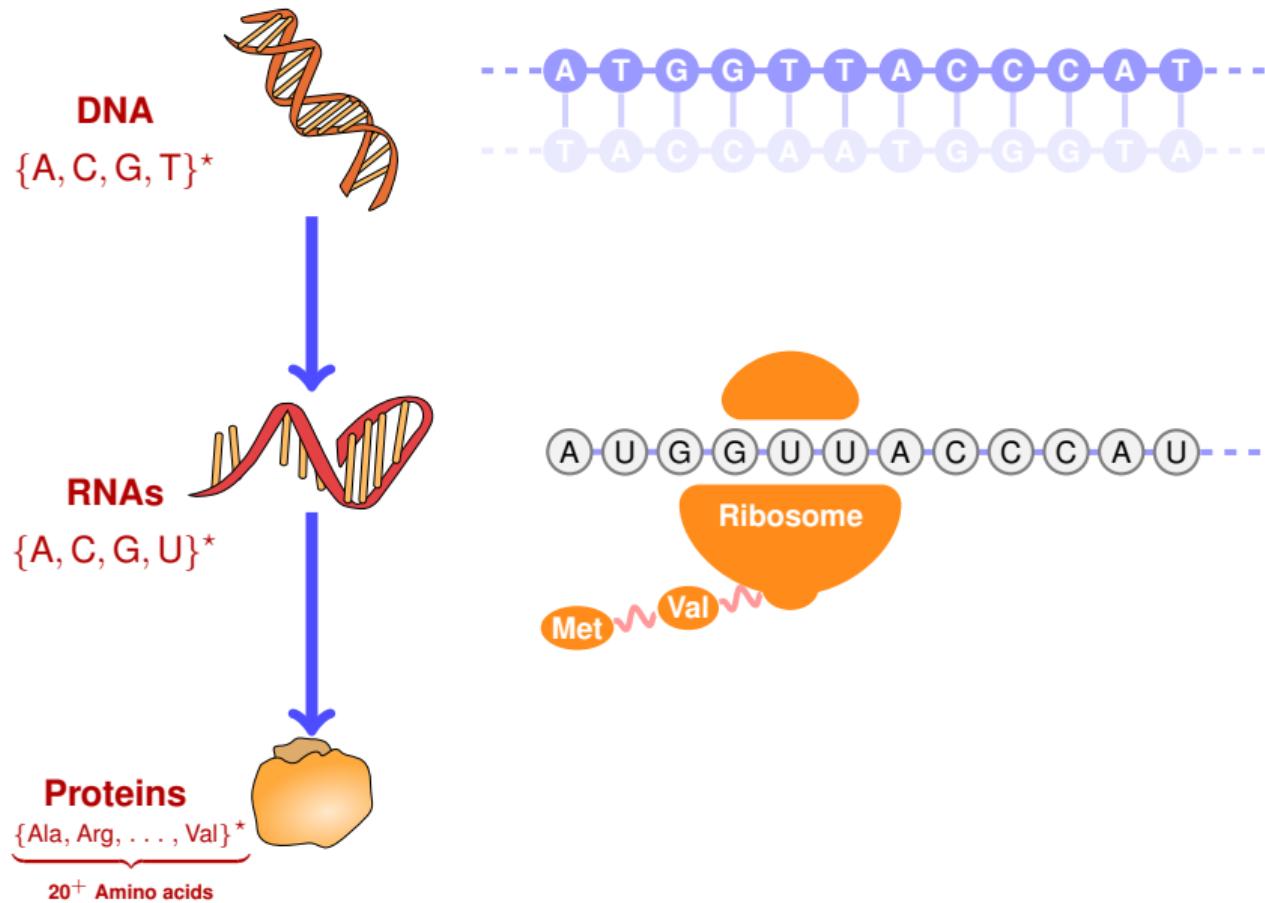
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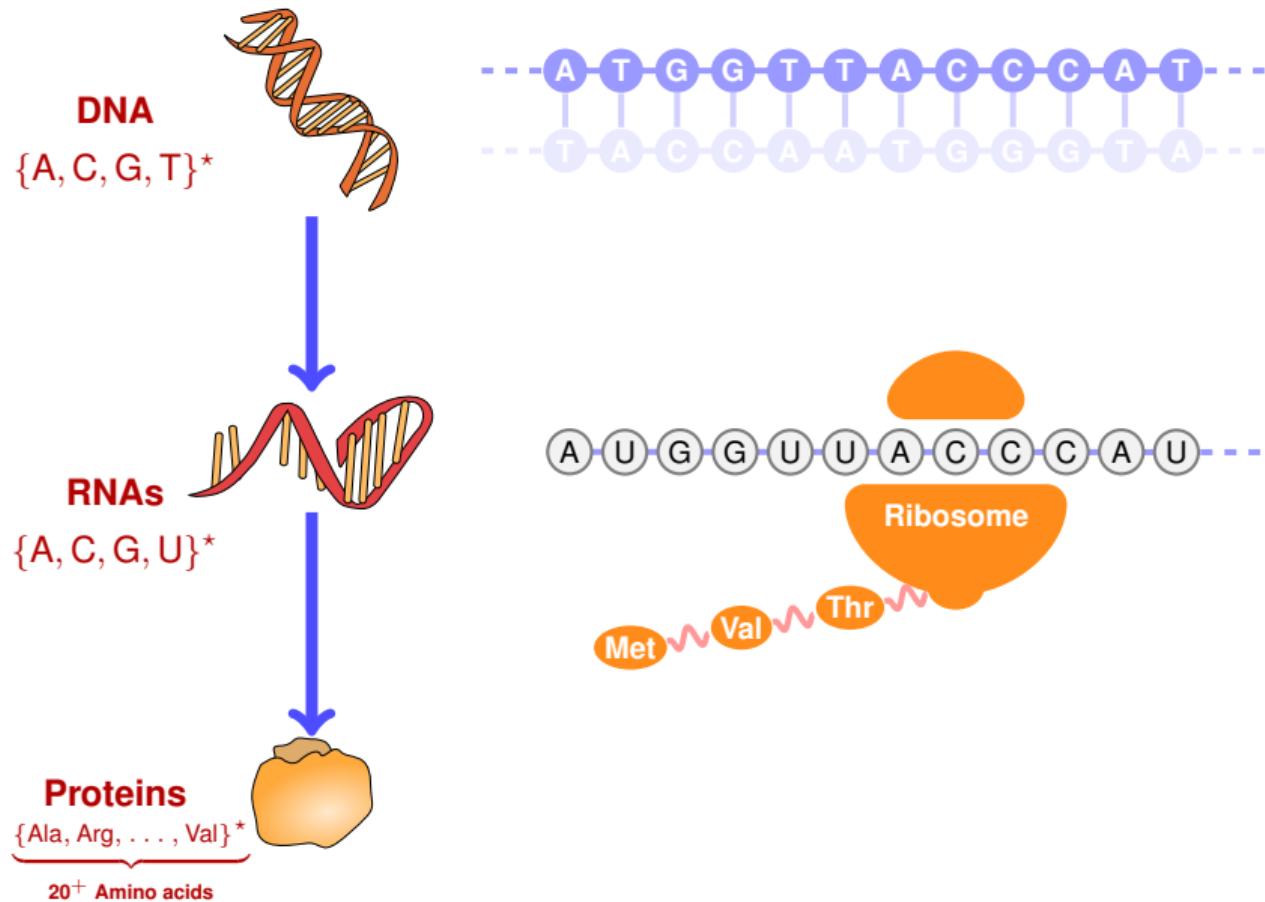
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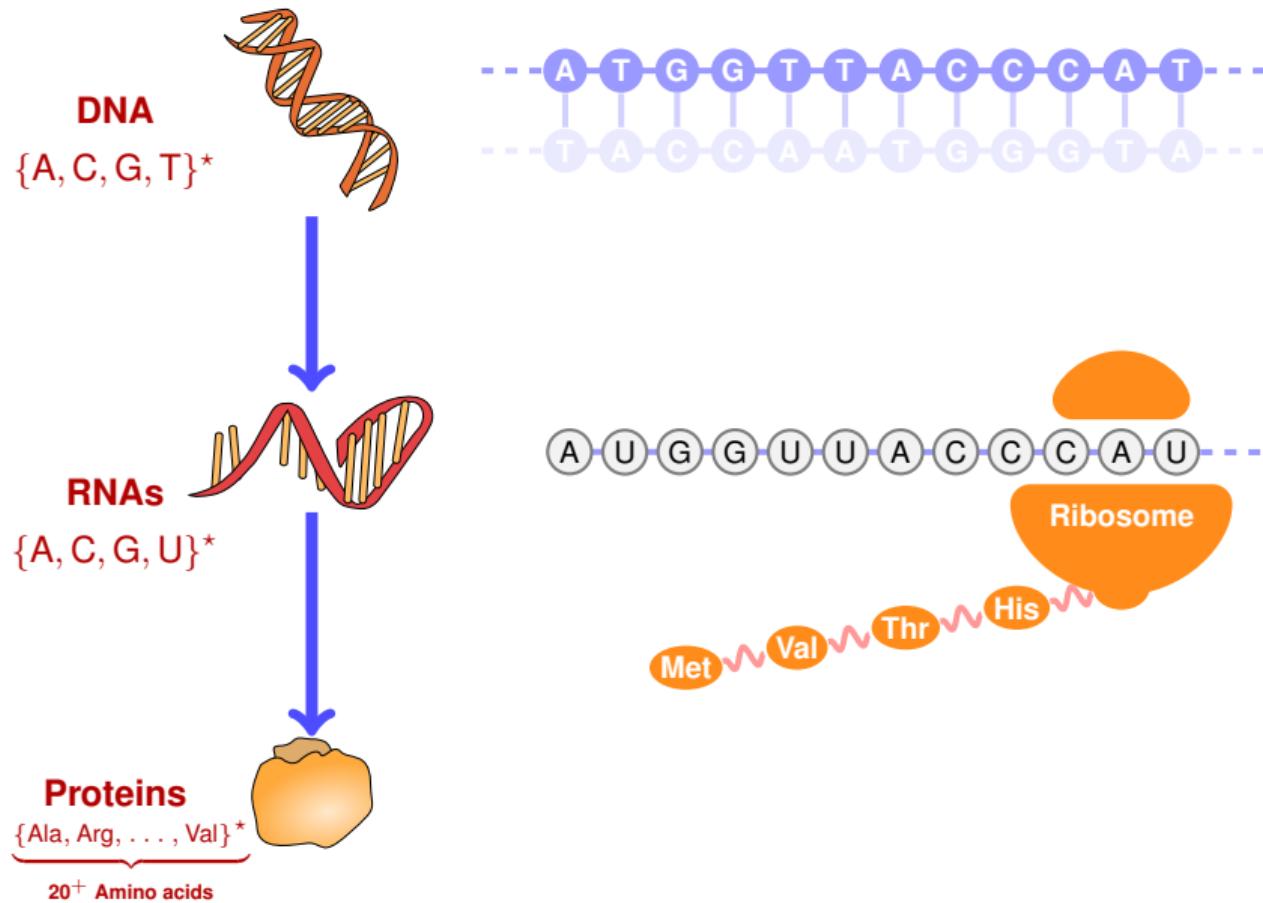
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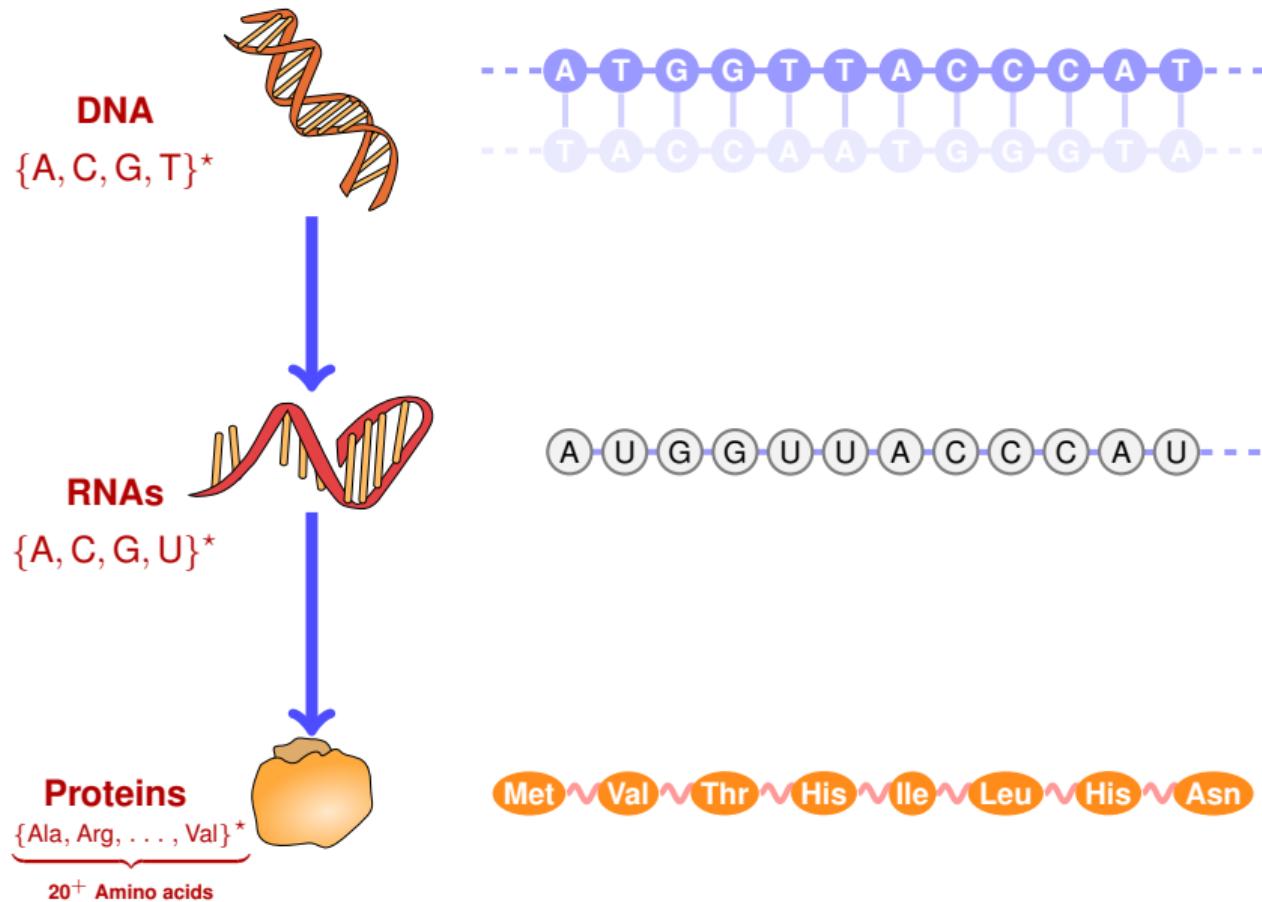
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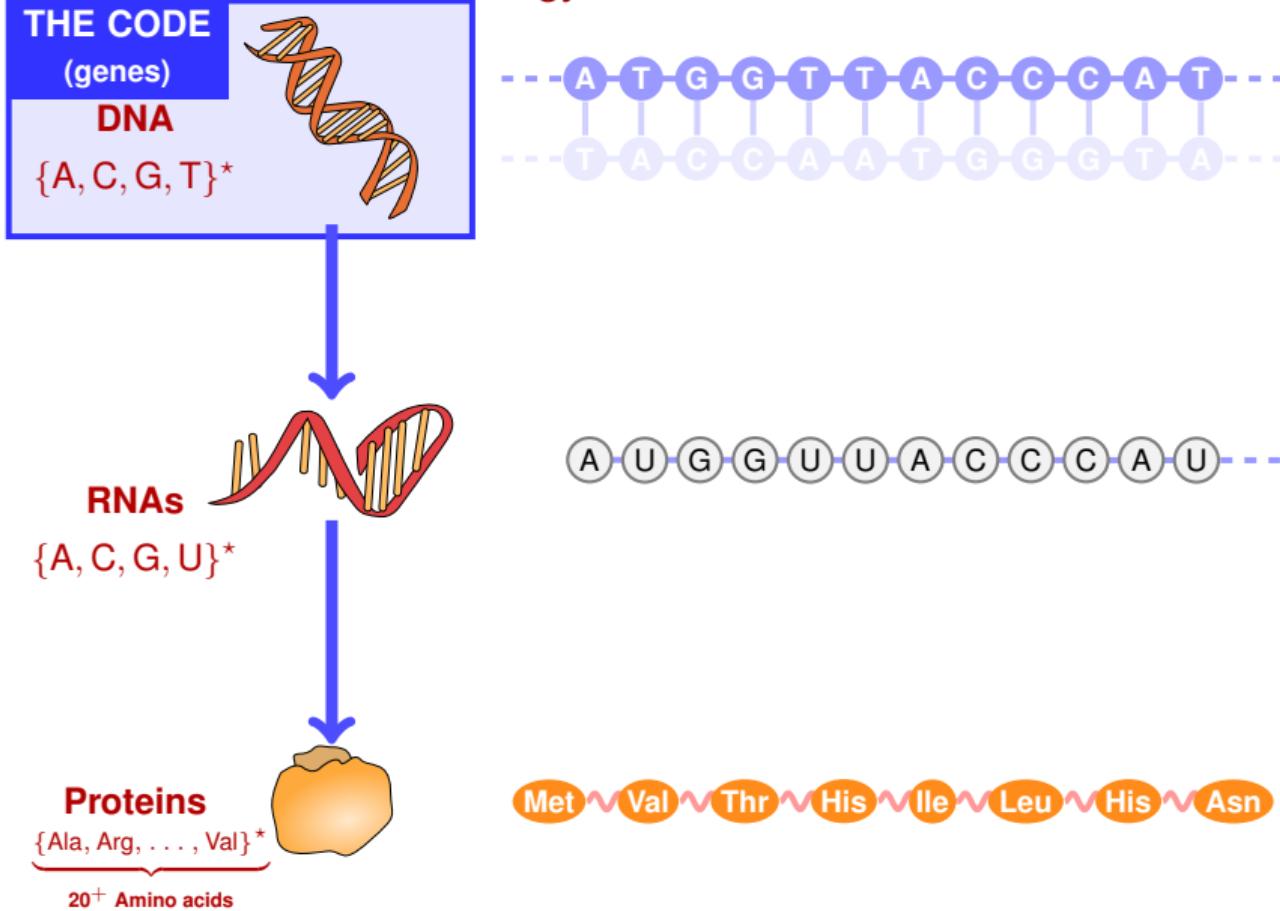
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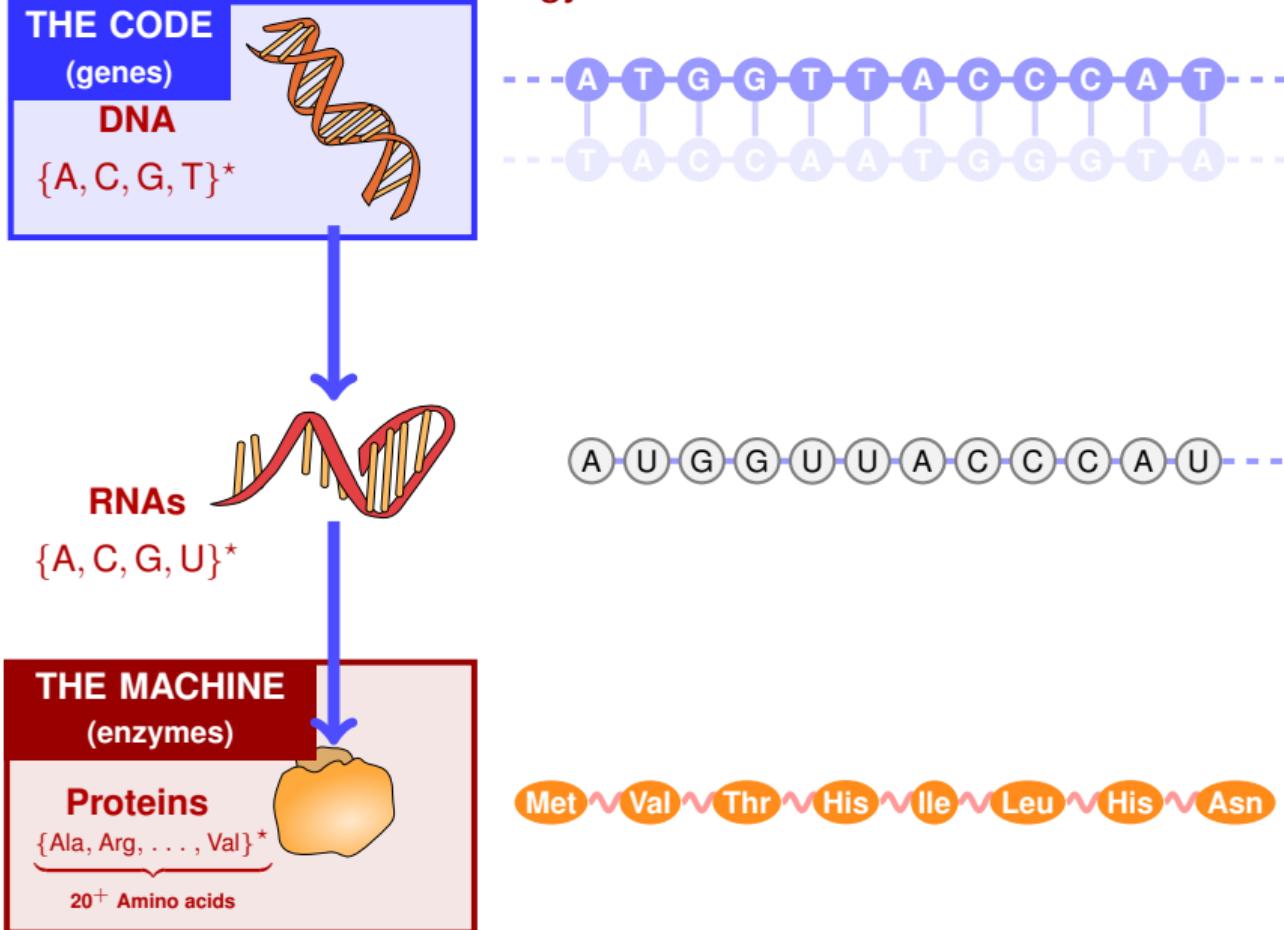
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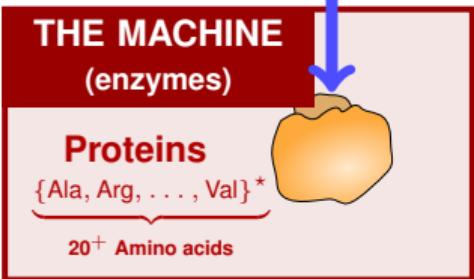
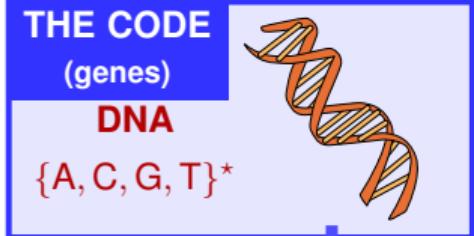
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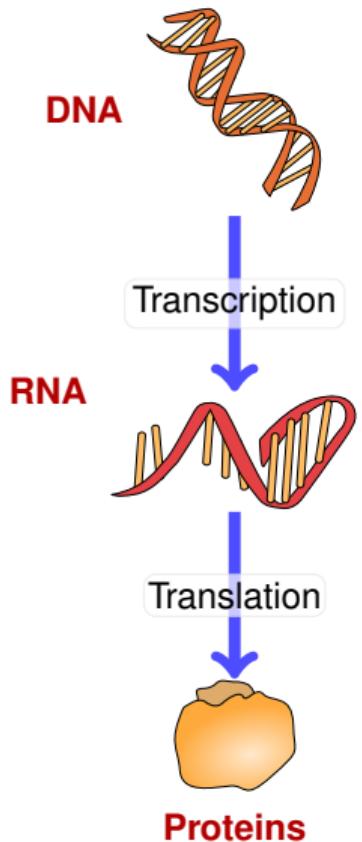


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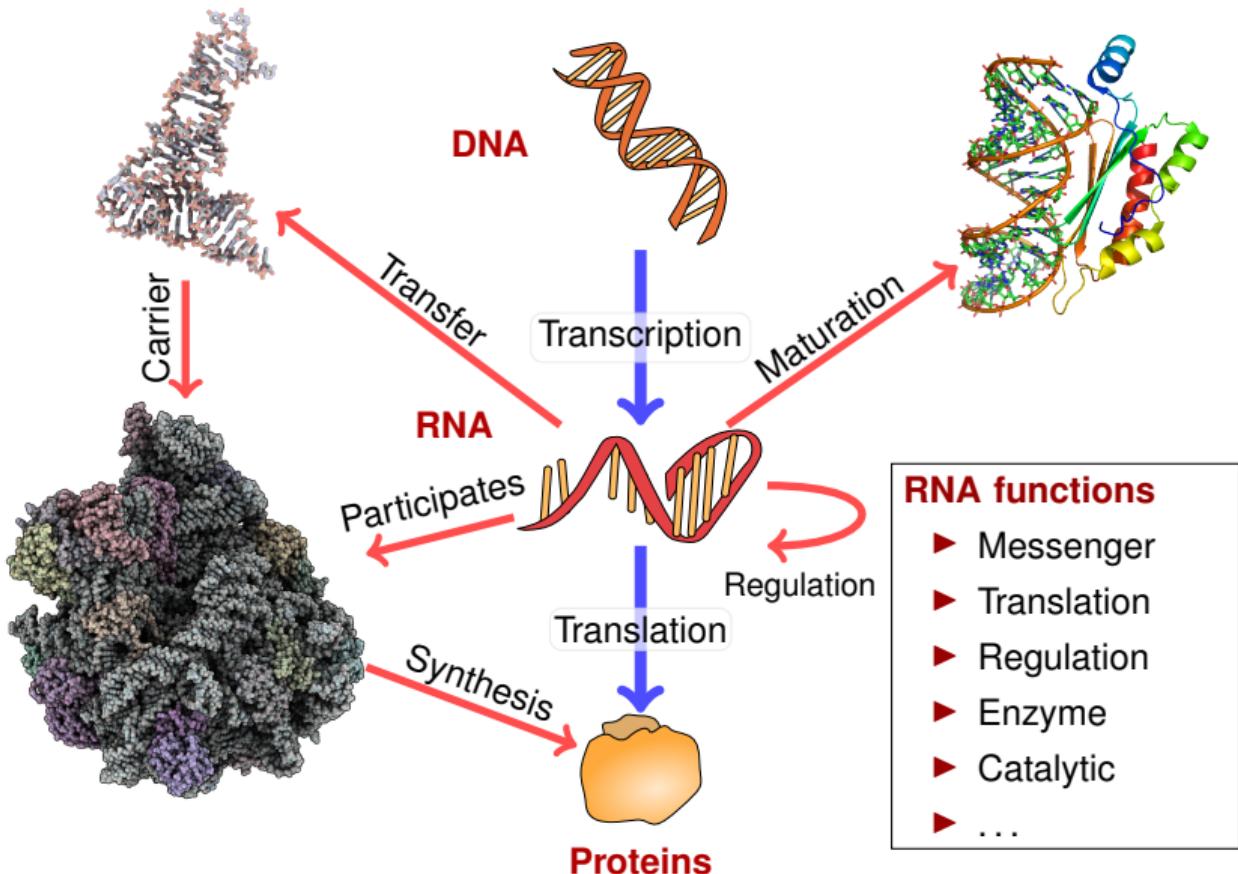


20+ Amino acids

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# RiboNucleic Acids (RNAs) in Human biology/health: Friends **and** Foes!

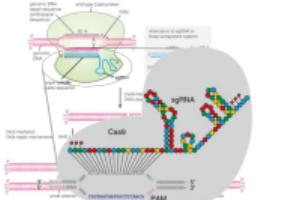


# RiboNucleic Acids (RNAs) in Human biology/health: Friends **and** Foes!

## Targeting system for DNA Editing

CRISPR therapies

Sickle-cell anemia,  $\beta$ -thalassamia, Leber congenital amaurosis (LCA), cancers...



Hendel et al, 2015; Agrotis & Ketteler, 2015

## RiboNucleic Acids (RNAs)



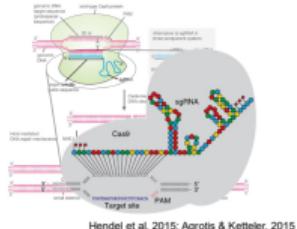
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mRNA Vaccines  
COVID-19, Malaria (Zika, CMV, Cancers?)

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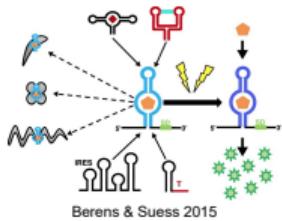
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Berens & Suess 2015  
Sensor of metabolites  
Riboswitches

## RiboNucleic Acids (RNAs)



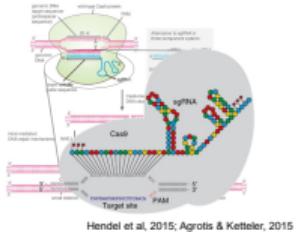
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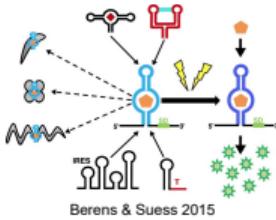
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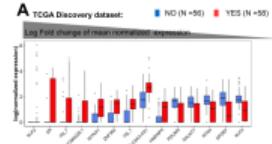


Sensor of metabolites  
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## Quantitative expression

Transcriptomic signatures

Cancer diagnosis/prognosis/relapse...



[NGuyen et al, 2021]

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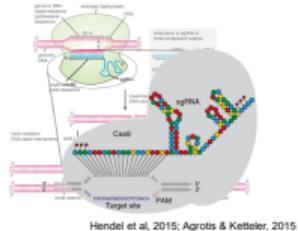
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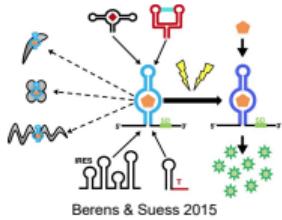
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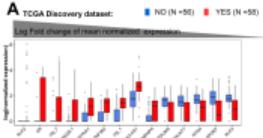


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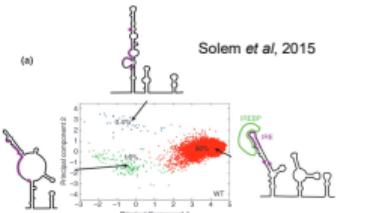


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## Non-coding mutations

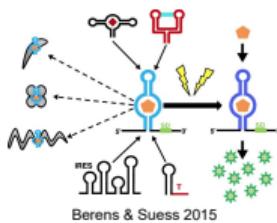
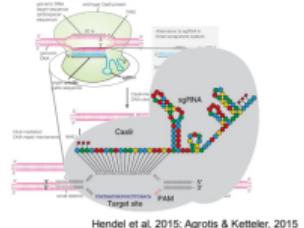
lncRNAs, miRNAs, structure-associated (RiboSnitches)  
 $\beta$ -thalassemia, duchenne muscular dystrophy,  
Cystic fibrosis, Rett syndrome...

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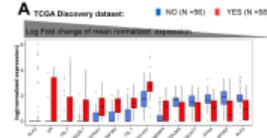


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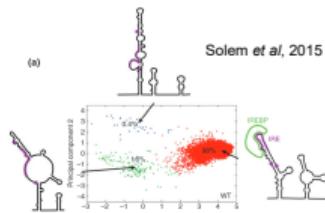
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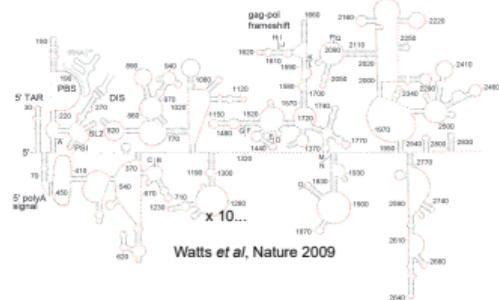


## No-coding mutations

lncRNAs, miRNAs, structure-associated (RiboSnitches)  
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## Genomic material for Human pathogens

HIV-1, SARS-CoV 2, HCoVs, MERS

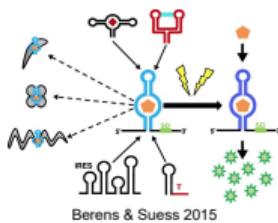
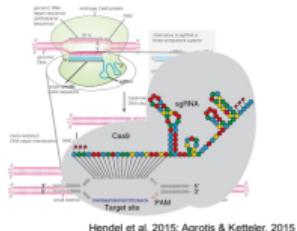


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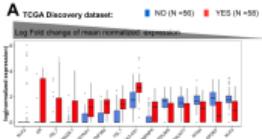


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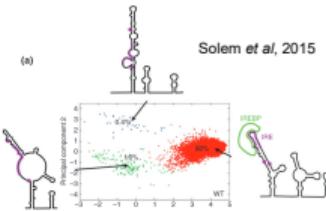
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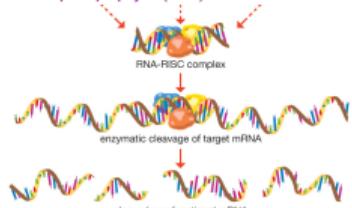
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## Regulation of gene expression

RNAi therapies (FDA approved)

Primary hyperoxaluria type 1 (PH1),  
Hereditary transthyretin amyloidosis (ATTRv),  
Acute hepatic porphyria (AHP)



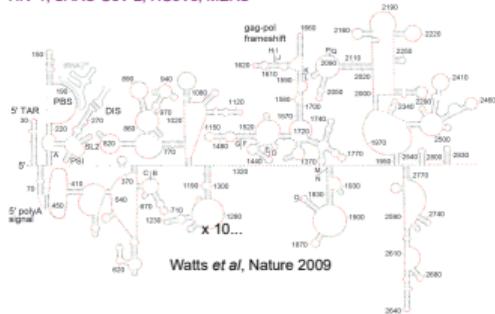
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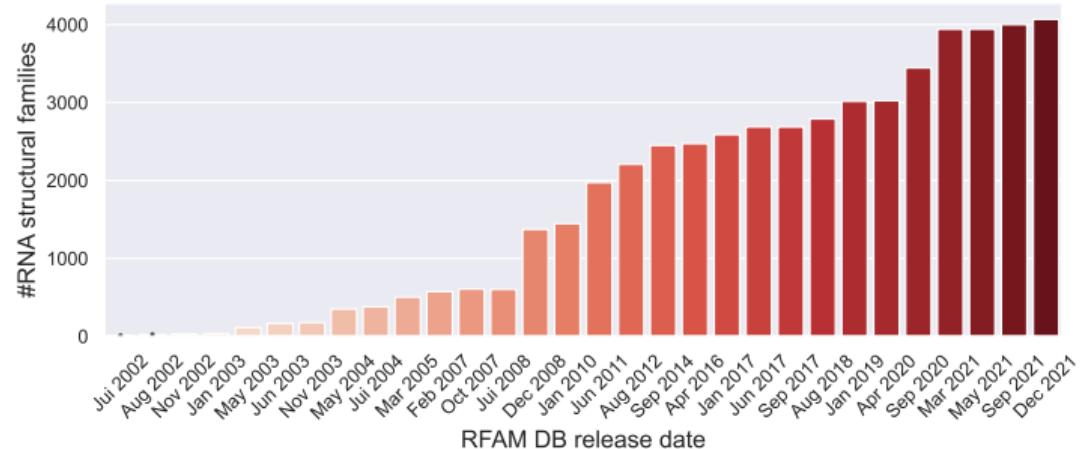
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(a)

Solem et al., 2015



RNA functional diversity is (largely) enabled by deep structural diversity

cleaved, nonfunctional mRNA

Encyclopaedia Britannica, Inc. 2013

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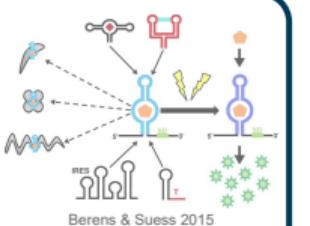
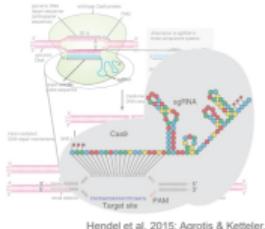
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## Targeting system for DNA Editing

CRISPR therapies

Sickle-cell anemia,  $\beta$ -thalassamia, Leber congenital amaurosis (LCA), cancers...

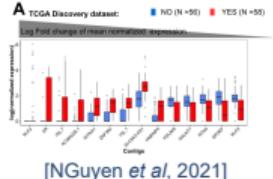


Sensor of metabolites  
Riboswitches

## Quantitative expression

Transcriptomic signatures

Cancer diagnosis/prognosis/relapse...



## Rational design

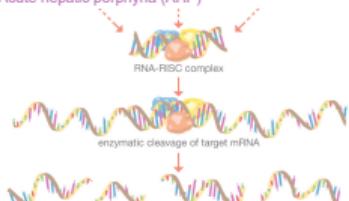
### Regulation of gene expression

RNAi therapies (FDA approved)

Primary hyperoxaluria type 1 (PH1),

Hereditary transthyretin amyloidosis (ATTRv),

Acute hepatic porphyria (AHP)

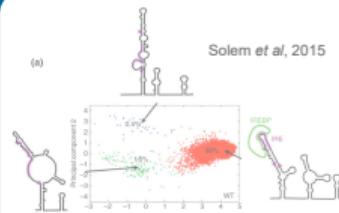


## RiboNucleic Acids (RNAs)



Encodes proteins  
mRNA Vaccines  
COVID-19, Malaria (Zika, CMV, Cancers?)

Solem et al, 2015



### Non-coding mutations

lncRNAs, miRNAs, structure-associated (RiboSnitches)

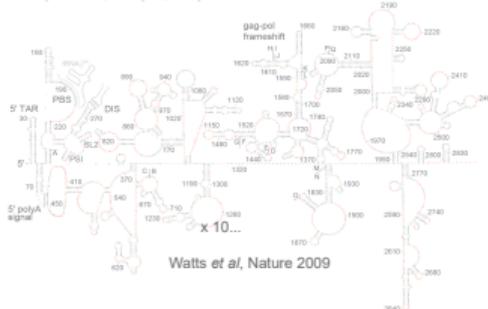
$\beta$ -thalassemia, duchenne muscular dystrophy,

Cystic fibrosis, Rett syndrome...

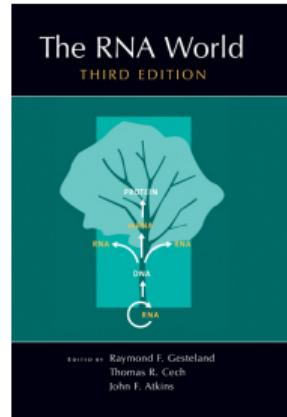
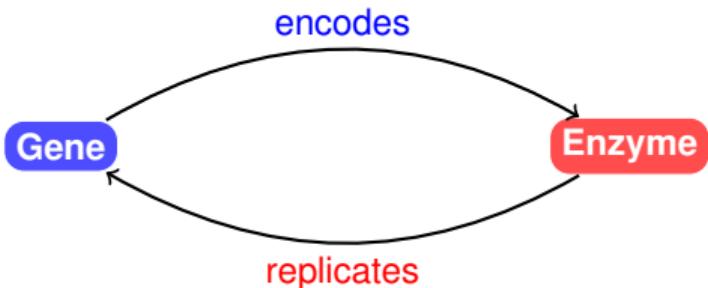
## (2D) Structure Modeling

### Genomic material for Human pathogens

HIV-1, SARS-CoV 2, HCoVs, MERS



## RNA world: Resolving the *chicken vs egg* paradox at the origin of life...

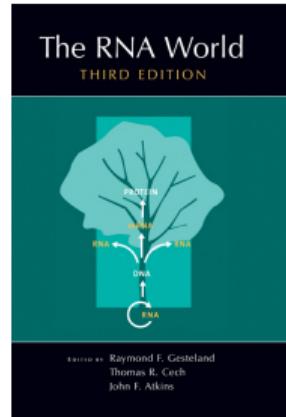
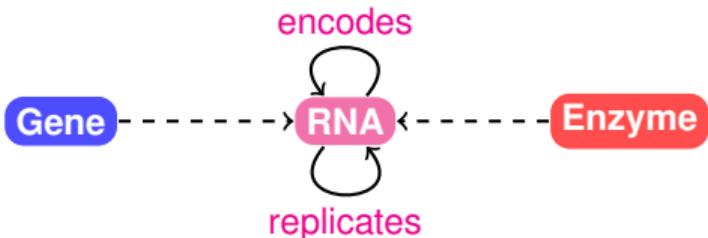


A gene big enough to specify an enzyme would be too big to replicate accurately without the aid of an enzyme of the very kind that it is trying to specify. So the system *apparently cannot get started*.

[...] This is the *RNA World*. To see how plausible it is, we need to look at why proteins are good at being enzymes but bad at being replicators; at why DNA is good at replicating but bad at being an enzyme; and finally why *RNA might just be good enough at both roles to break out of the Catch-22*.

R. Dawkins. *The Ancestor's Tale: A Pilgrimage to the Dawn of Evolution*

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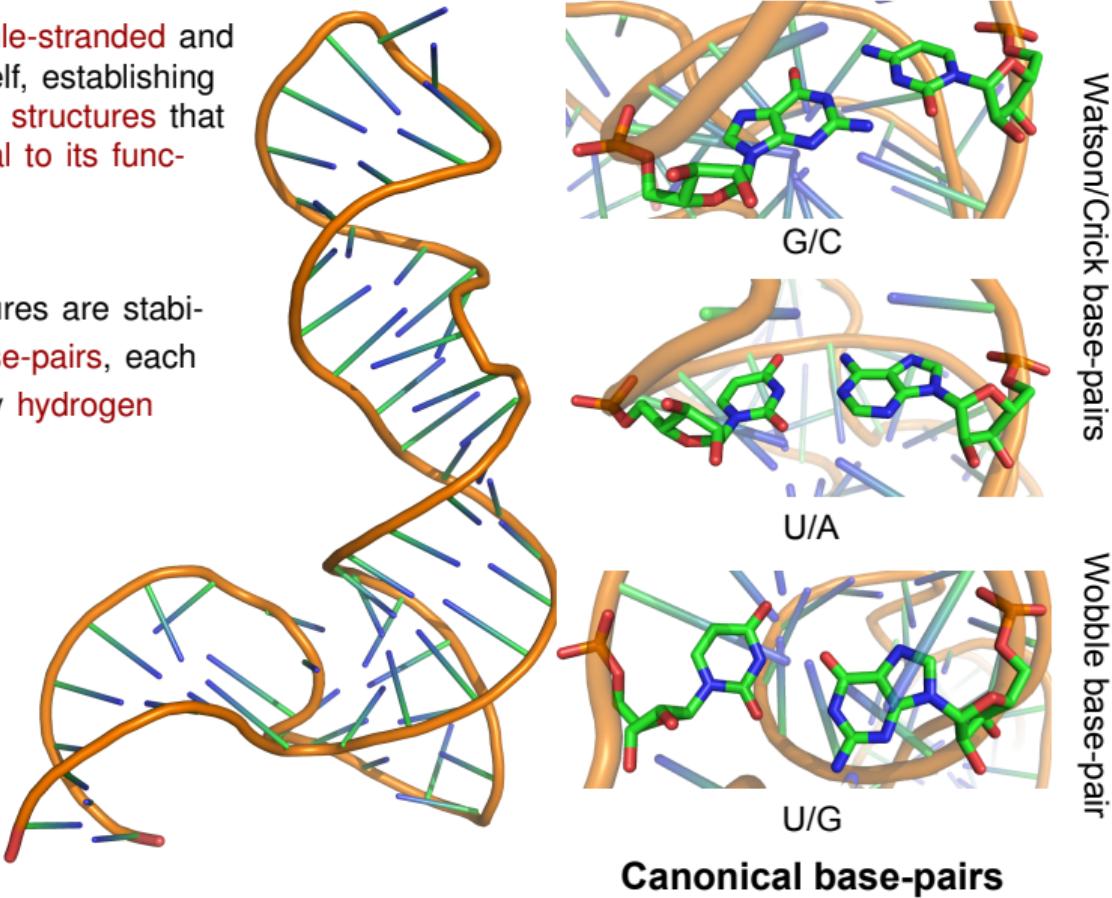
[...] This is the **RNA World**. To see how plausible it is, we need to look at why proteins are good at being enzymes but bad at being replicators; at why DNA is good at replicating but bad at being an enzyme; and finally why *RNA might just be good enough at both roles to break out of the Catch-22*.

R. Dawkins. *The Ancestor's Tale: A Pilgrimage to the Dawn of Evolution*

# RNA folding

RNA is **single-stranded** and folds on itself, establishing complex 3D structures that are **essential** to its function(s).

RNA structures are stabilized by **base-pairs**, each mediated by hydrogen bonds.

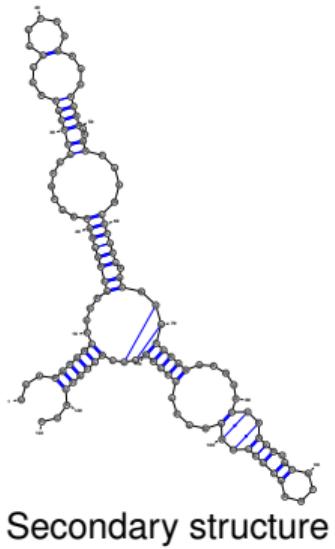


# RNA Structure(s)

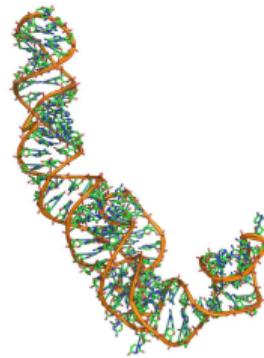
Three<sup>1</sup> levels of representation:

UUAGGCAGGCCACAGC  
GGUGGGGUUGCCUCC  
CGUACCCAUCCCGAA  
CACGGAAGAUAGCC  
CACCAAGCGUUCGGG  
GAGUACUGGAGUGCG  
CGAGCCUCUGGGAAA  
CCGGUUCGCCGCCA  
CC

Primary structure



Secondary structure



Tertiary structure

Source: 5s rRNA (PDB 1K73:B)

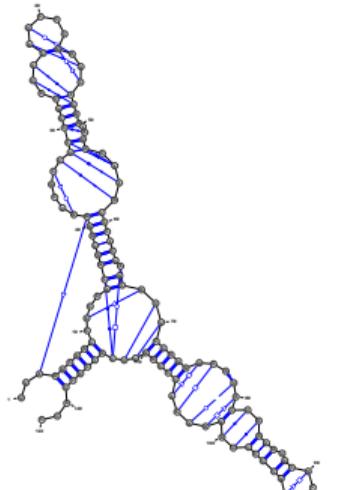
<sup>1</sup>Well, mostly...

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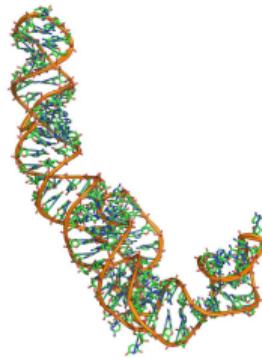
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GAGUACUGGAGUGCG  
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CCGGUUCGCCGCCA  
CC

Primary structure



Secondary<sup>+</sup> structure



Tertiary structure

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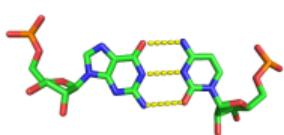
<sup>1</sup>Well, mostly...

## Ignored by secondary structure

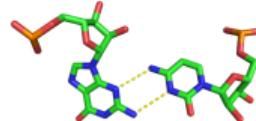
### ► Non-canonical base-pairs

Any base-pair **other than** {(A-U), (C-G), (G-U)}

Or interacting on non-standard edge ( $\neq$  WC/WC-Cis) [LW01].

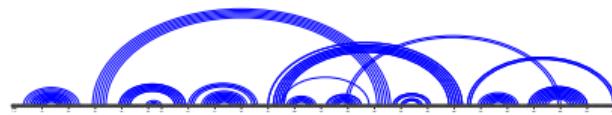


Canonique CG pair(WC/WC-Cis)



Non-canonique CG pair (Sugar/WC-Trans)

### ► Pseudoknots (PKs)



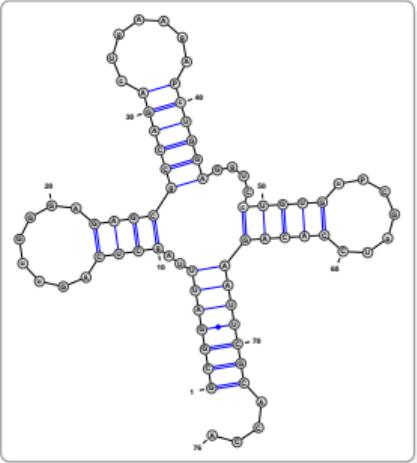
Pseudoknotted structure of group I ribozyme (PDBID: 1Y0Q:A)

Considering PKs may lead to better predictions, **but**:

- Some PK conformations are simply unfeasible;
- Folding *in silico* with general pseudoknots is NP-complete [LP00];

Still, folding on restricted classes of conformations seems promising [CDR<sup>+</sup>04].

# Various representations for a versatile biomolecule



Outer-planar graphs

Hamiltonian-path,  $\Delta(G) \leq 3$ , 2-connected\*

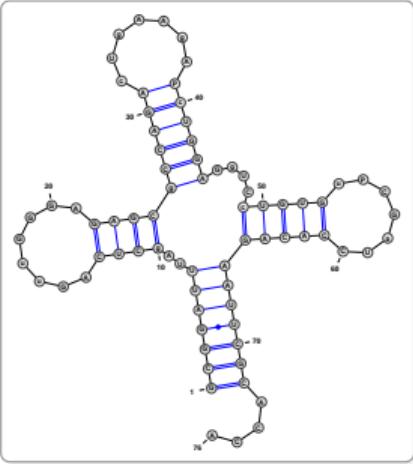
Supporting intuitions

Different representations

Common combinatorial structure

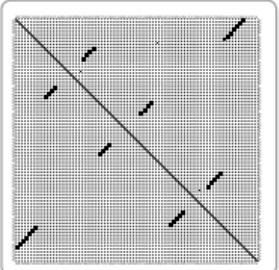
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Dot plots

Adjacency matrices\*

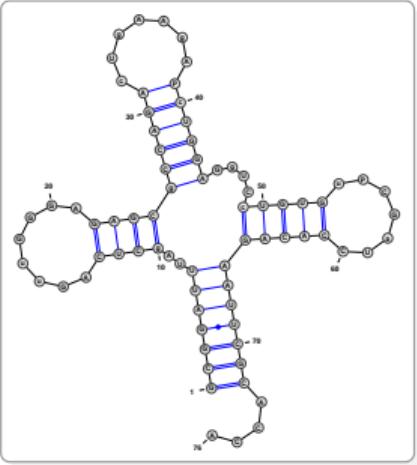
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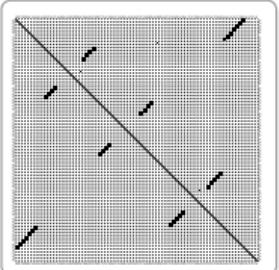
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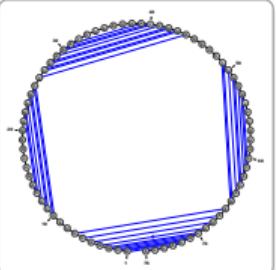


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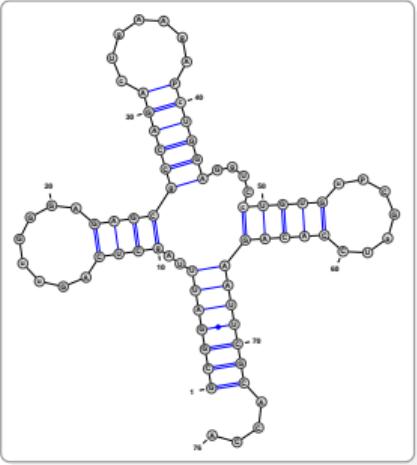
Non-crossing arc diagrams\*

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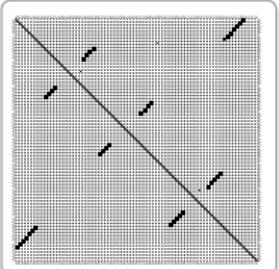


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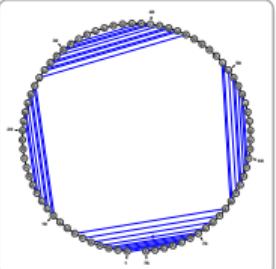
Motzkin words\*

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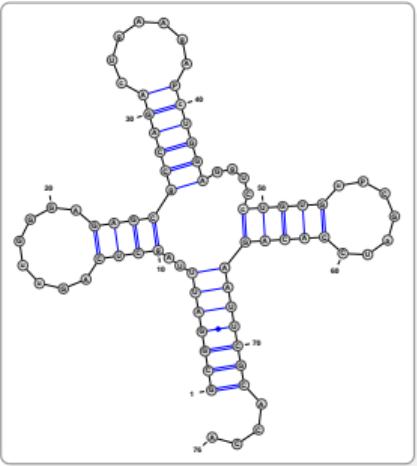
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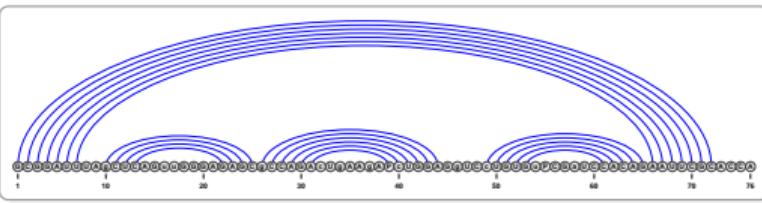


Outer-planar graphs

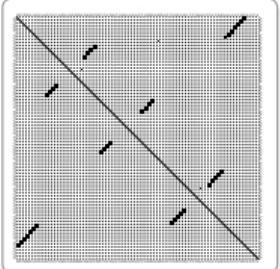
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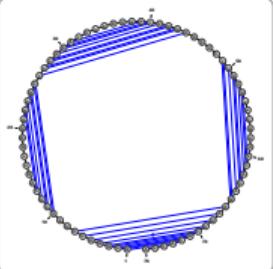
Motzkin words\*



Non-crossing arc-annotated sequences\*



Dot plots  
Adjacency matrices\*



Non-crossing arc diagrams\*

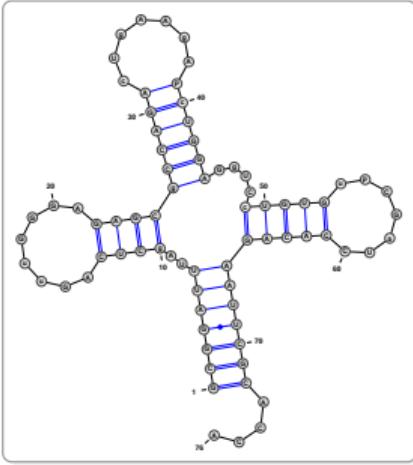
## Supporting intuitions

Different representations

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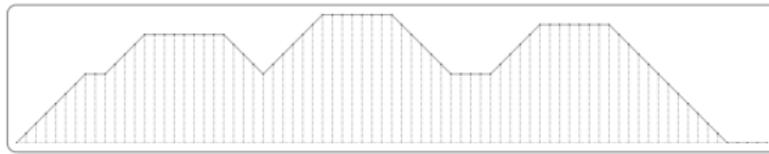


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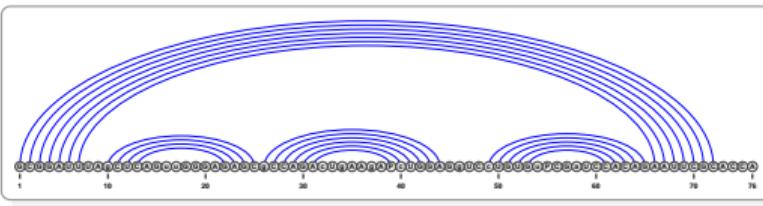
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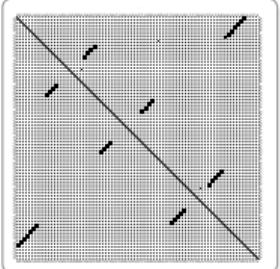
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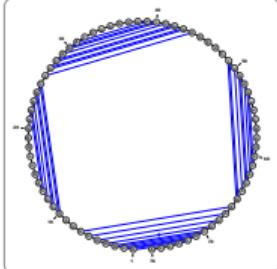
Positive 1D meanders\* over  $S = \{+1, -1, 0\}$



Non-crossing arc-annotated sequences\*



Dot plots  
Adjacency matrices\*



Non-crossing arc diagrams\*

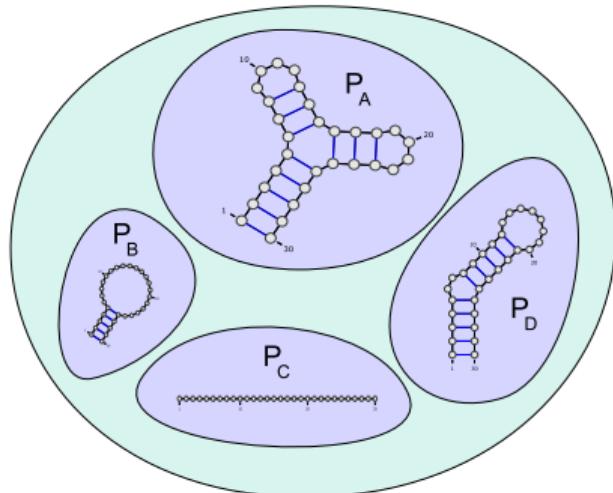
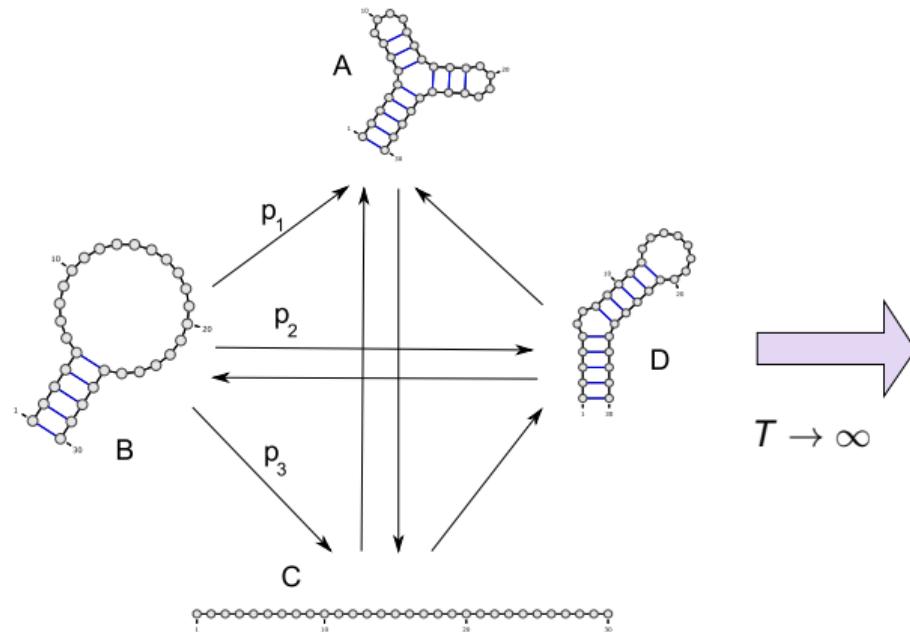
## Supporting intuitions

- Different representations
- Common combinatorial structure

\* Additional steric constraints

## Thermodynamics aparté

At the nanoscopic scale, RNA structure *fluctuates* ( $\approx$  Markov process).



Convergence towards a **stationary distribution** at the **Boltzmann equilibrium**, where the probability of a conformation only depends on its **free-energy**.

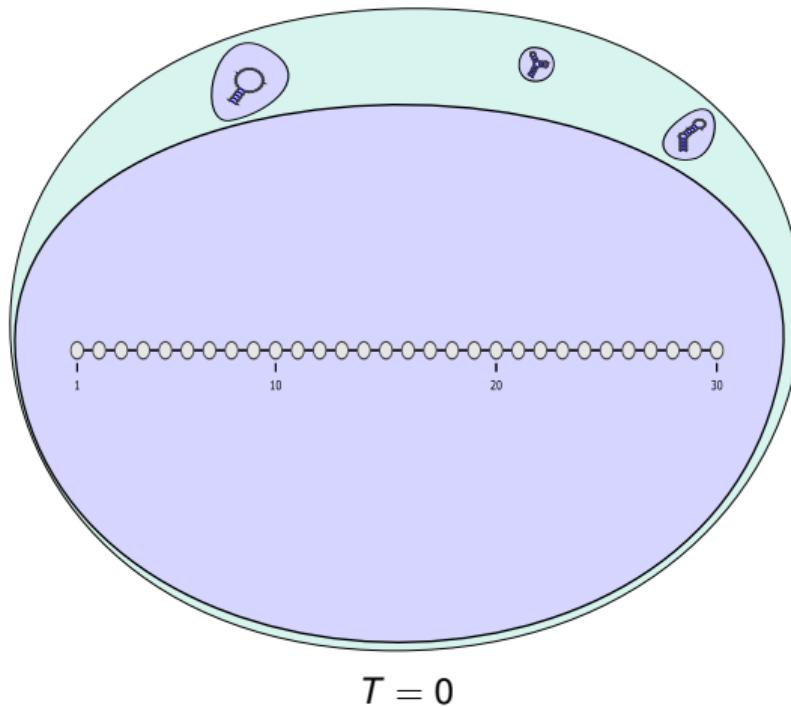
**Corollary:** Initial conformation does not matter.

**Questions:** For a given **conformation space** and **free-energy model**:

- A. Determine most stable (Minimum Free Energy) structure at equilibrium.

## Away from equilibrium

Transcription: RNA synthesized, supposedly without structure<sup>2</sup>

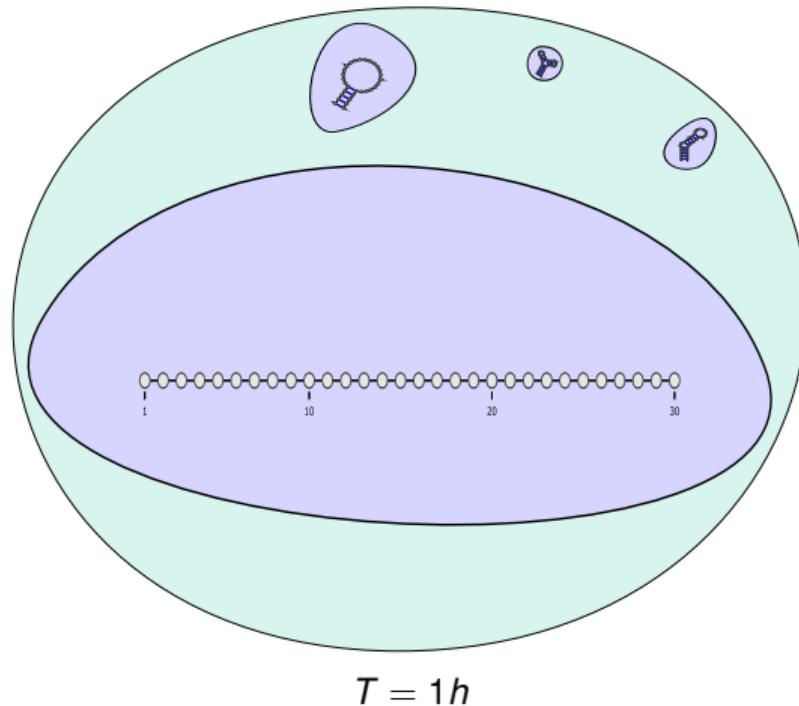


But most mRNAs are degrade before 7h (Org.: Souris [SSN<sup>+</sup>09]).

<sup>2</sup>Except for co-transcriptional folding...

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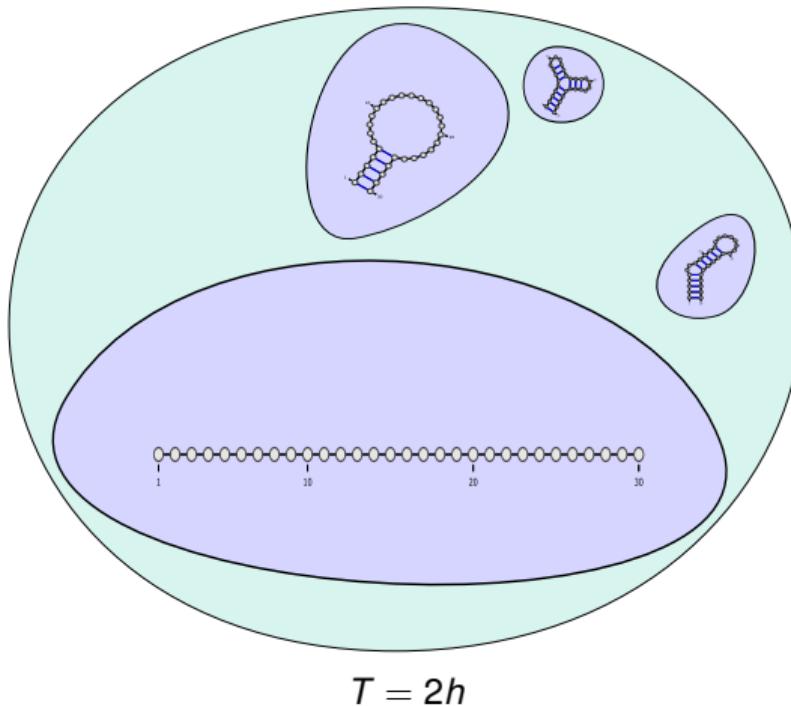


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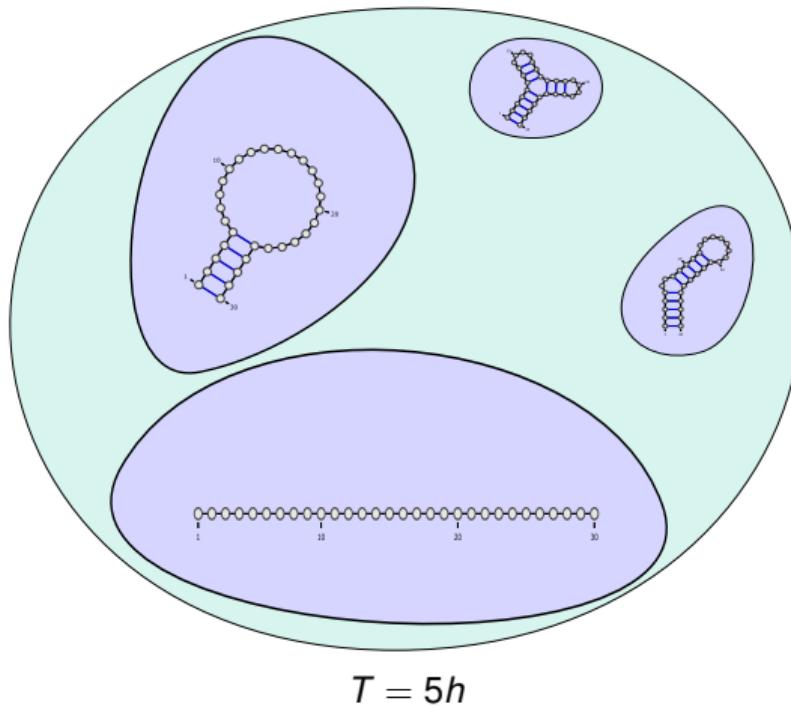


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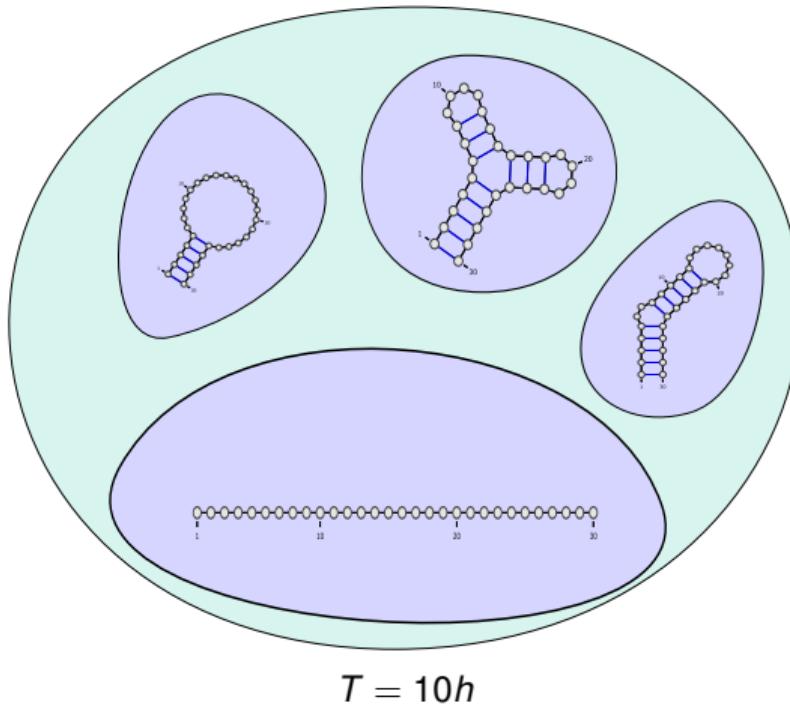


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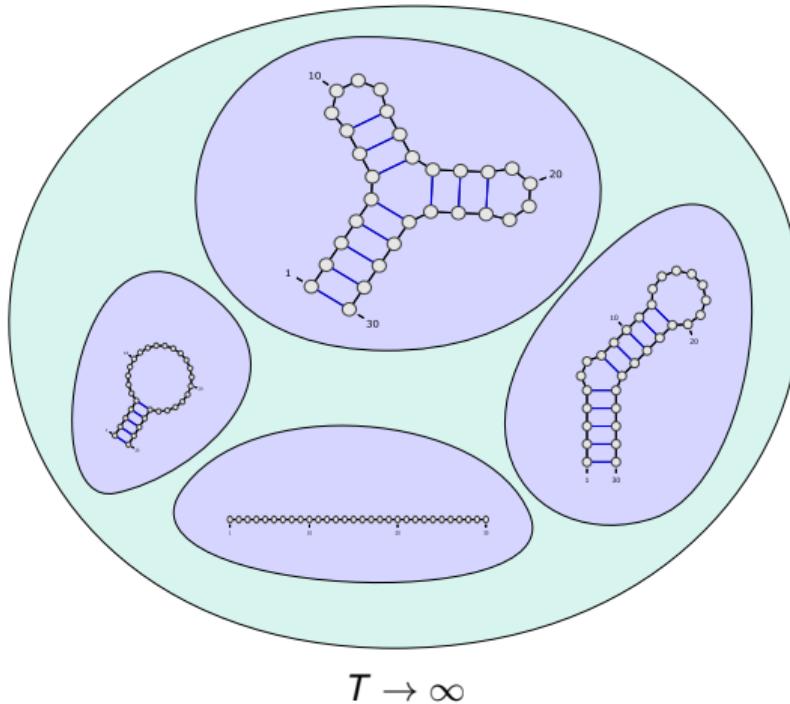


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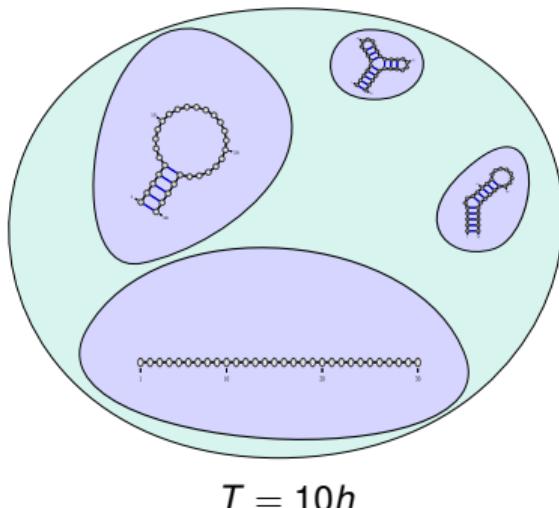


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Transcription: RNA synthesized, supposedly without structure<sup>2</sup>



But most mRNAs are degrade before 7h (Org.: Souris [SSN<sup>+09</sup>]).

- A. Determine most stable (Minimum Free-Energy) structure at equilibrium;
- B. Compute average properties of Boltzmann ensemble;
- C. Determine most likely structure at finite time  $T$ .

(c.f. H. Isambert through simulation, NP-complete deterministically [MTSC09])

<sup>2</sup>Except for co-transcriptional folding...

# Outline

## Introduction

- Dynamic programming 101
- Dynamic programming framework

## Variations on RNA folding

- Why RNA?
- RNA folding
- RNA Structure(s)
- Some representations of RNA structure
- Thermodynamics vs Kinetics

## Free-energy minimization

- Nussinov-style RNA folding
- Turner energy model
- MFold/Unafold
- Performances and the comparative approach
- Towards a 3D ab-initio prediction

## Boltzmann ensemble

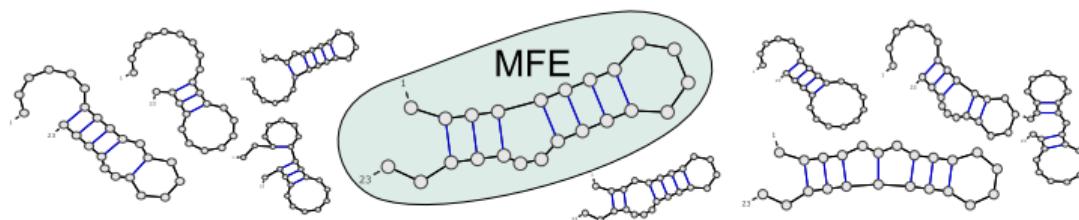
- Nussinov: Minimisation  $\Rightarrow$  Counting
- Computing the partition function
- Statistical sampling

# Folding by minimizing free-energy

Problem A: Determine Minimum Free-Energy structure (MFE).

Ab initio folding prediction =

Predict RNA structure from its sequence  $\omega$  only.



- ▶ **Conformations:** Set  $S_\omega$  of secondary structures compatible (w.r.t. base-pairing constraints) with primary structure  $\omega$ .
- ▶ **Free-Energy:** Function  $E_{\omega, S}$  (KCal.mol<sup>-1</sup>), additive on motifs occurring in any sequence/conformation couple ( $\omega, S$ ).
- ▶ **Native structure:** Functional conformation of the biomolecule.

Remarks:

- ▶ Not necessarily unique (Kinetics, or bi-stable structures);
- ▶ In presence of PKs → Ambiguous: Which is the native conformation?

# Nussinov/Jacobson model

## Nussinov/Jacobson energy model (NJ)

Base-pair maximization (with a twist):

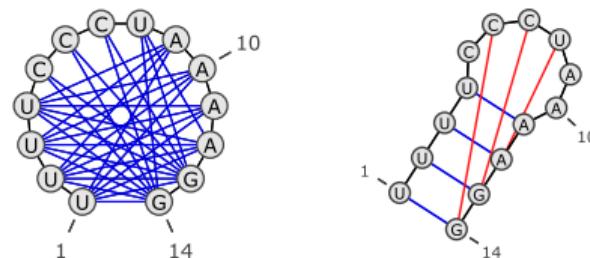
- ▶ Additive model on independently contributing base-pairs;
- ▶ Canonical base-pairs only: Watson/Crick (A/U,C/G) and Wobble (G/U)

$$\Rightarrow E_{\omega,S} = -\# \text{Paires}(S)$$

Folding in NJ model  $\Leftrightarrow$  Base-pair (weight) maximization

Example:

UUUUUCCCUAAAAGG



Variant: Weight each pair with  $-\#$  Hydrogen bonds

$$\Delta G(G \equiv C) = -3$$

$$\Delta G(A = U) = -2$$

$$\Delta G(G - U) = -1$$

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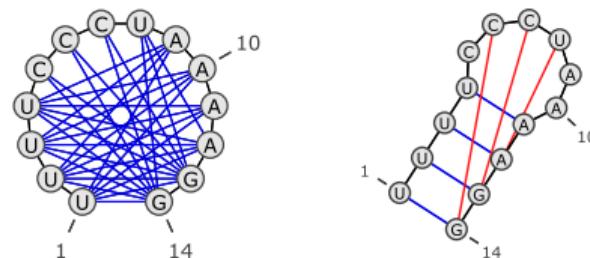
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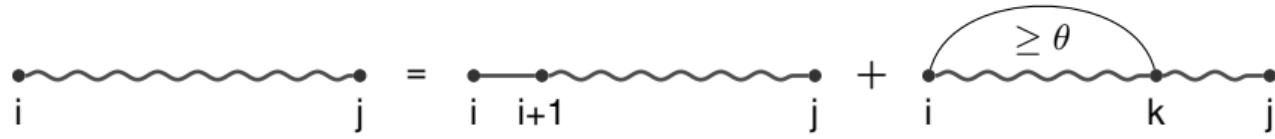
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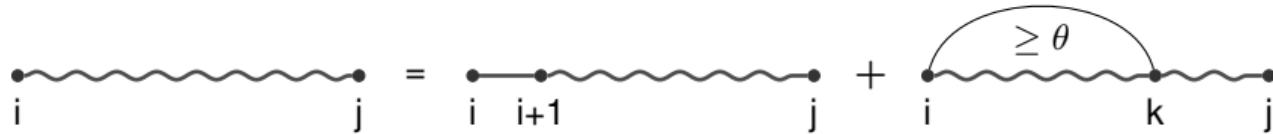
## Nussinov/Jacobson DP scheme



$$N_{i,t} = 0, \quad \forall t \in [i, i + \theta]$$

$$N_{i,j} = \min \begin{cases} N_{i+1,j} & i \text{ unpaired} \\ \min_{k=i+\theta+1}^j \Delta G_{i,k} + N_{i+1,k-1} + N_{k+1,j} & i \text{ paired with } k \end{cases}$$

## Nussinov/Jacobson DP scheme



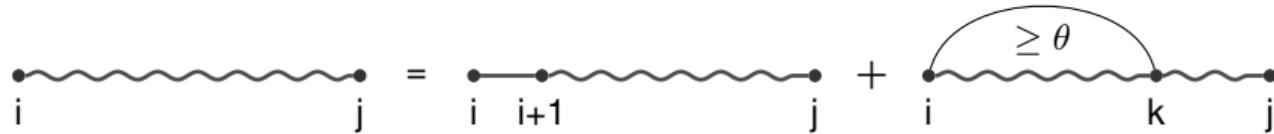
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**Correctness.** Goal = Show that MFE over interval  $[i, j]$  is indeed found in  $N_{i,j}$  after completing the computation. Proceed by induction:

- ▶ Assume that property holds for any  $[i', j']$  such that  $j' - i' < n$ .
- ▶ Consider  $[i, j], j - i = n$ . Let  $\text{MFE}_{i,j} := \text{Base-pairs of best struct. on } [i, j]$ . Then first position  $i$  in  $\text{MFE}_{i,j}$  is either:
  - ▶ Unpaired:  $\text{MFE}_{i,j} = \text{MFE}_{i+1,j}$  → free-energy =  $N_{i+1,j}$
  - ▶ Paired to  $k$ :  $\text{MFE}_{i,j} = \{(i, k)\} \cup \text{MFE}_{i+1,k-1} \cup \text{MFE}_{k+1,j}$ .  
(Indeed, any BP between  $[i+1, k-1]$  and  $[k+1, j]$  would cross  $(i, k)$ ) → free-energy =  $\Delta G_{i,k} + N_{i+1,k-1} + N_{k+1,j}$

## Nussinov/Jacobson DP scheme



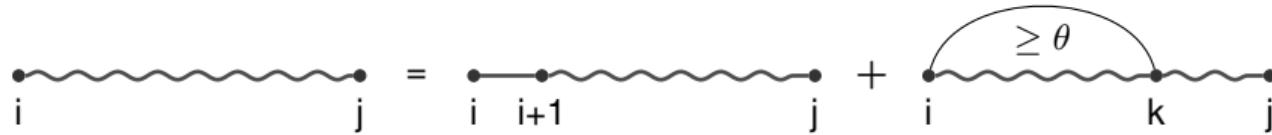
$$N_{i,t} = 0, \quad \forall t \in [i, i + \theta]$$

$$N_{i,j} = \min \begin{cases} N_{i+1,j} & i \text{ unpaired} \\ \min_{k=i+\theta+1}^j \Delta G_{i,k} + N_{i+1,k-1} + N_{k+1,j} & i \text{ paired with } k \end{cases}$$

**Correctness.** Goal = Show that MFE over interval  $[i, j]$  is indeed found in  $N_{i,j}$  after completing the computation. Proceed by induction:

- ▶ Assume that property holds for any  $[i', j']$  such that  $j' - i' < n$ .
- ▶ Consider  $[i, j], j - i = n$ . Let  $\text{MFE}_{i,j} :=$  Base-pairs of best struct. on  $[i, j]$ .  
Then first position  $i$  in  $\text{MFE}_{i,j}$  is either:
  - ▶ **Unpaired:**  $\text{MFE}_{i,j} = \text{MFE}_{i+1,j}$  → free-energy =  $N_{i+1,j}$
  - ▶ **Paired to  $k$ :**  $\text{MFE}_{i,j} = \{(i, k)\} \cup \text{MFE}_{i+1,k-1} \cup \text{MFE}_{k+1,j}$ .  
(Indeed, any BP between  $[i+1, k-1]$  and  $[k+1, j]$  would cross  $(i, k)$ )→ free-energy =  $\Delta G_{i,k} + N_{i+1,k-1} + N_{k+1,j}$

## Nussinov/Jacobson DP scheme



$$N_{i,t} = 0, \quad \forall t \in [i, i + \theta]$$

$$N_{i,j} = \min \begin{cases} N_{i+1,j} & i \text{ unpaired} \\ \min_{k=i+\theta+1}^j \Delta G_{i,k} + N_{i+1,k-1} + N_{k+1,j} & i \text{ paired with } k \end{cases}$$

**Correctness.** Goal = Show that MFE over interval  $[i, j]$  is indeed found in  $N_{i,j}$  after completing the computation. Proceed by induction:

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  - ▶ **Unpaired:**  $\text{MFE}_{i,j} = \text{MFE}_{i+1,j}$   $\rightarrow \text{free-energy} = N_{i+1,j}$
  - ▶ **Paired to  $k$ :**  $\text{MFE}_{i,j} = \{(i, k)\} \cup \text{MFE}_{i+1,k-1} \cup \text{MFE}_{k+1,j}$ .  
(Indeed, any BP between  $[i+1, k-1]$  and  $[k+1, j]$  would cross  $(i, k)$ )  $\rightarrow \text{free-energy} = \Delta G_{i,k} + N_{i+1,k-1} + N_{k+1,j}$

# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	0	0	2	2	2	2	4	4	4	5	7	7	8	10
U	0	0	0	0	0	0	0	0	2	2	4	5	7	7	7	8	10	
A	0	0	0	0	0	0	0	0	2	2	2	2	5	5	5	8	8	
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	8	8		
U	0	0	0	0	0	0	0	0	0	2	3	5	5	5	6	7		
U	0	0	0	0	0	0	0	0	0	2	3	5	5	5	5	7		
C	0	0	0	0	0	0	0	0	0	3	3	3	3	3	5	5		
U	0	0	0	0	0	0	0	0	0	0	2	2	2	2	2	3		
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2		
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	



# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	0	2	2	2	2	4	4	4	5	7	7	8	10	10
U	0	0	0	0	0	0	0	0	2	2	4	5	7	7	8	10	10	10
A	0	0	0	0	0	0	0	2	2	2	2	5	5	5	5	8	8	8
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	8	8	8	8
U	0	0	0	0	0	0	0	0	2	3	5	5	5	6	7	7	7	7
U	0	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7	7	7
C	0	0	0	0	0	0	0	0	3	3	3	3	3	5	5	5	5	5
U	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	3	3
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	2	2
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0



# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
C	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
G	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	2	2	2	2	4	4	5	7	7	7	8	10		
U	0	0	0	0	0	0	0	2	2	4	5	7	7	7	8	10		
A	0	0	0	0	0	0	0	2	2	2	5	5	5	5	8	8		
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	8	8		
U	0	0	0	0	0	0	0	2	3	5	5	5	5	6	7			
U	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7			
C	0	0	0	0	0	0	0	3	3	3	3	3	3	5	5			
U	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	3		
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2		
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
C	i		j	=	i		j		+	i		k	j	$\geq \theta$	0	0	0	
G																0	0	0
A																0	0	0

# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
C	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
G	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	11	11
G		0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A			0	0	0	0	2	2	2	2	4	4	5	7	7	8	10	
U				0	0	0	0	0	0	2	2	4	5	7	7	8	10	
A					0	0	0	0	0	2	2	2	2	5	5	5	8	8
C						0	0	0	0	0	0	2	5	5	5	8	8	
U							0	0	0	0	0	2	3	5	5	6	7	
U								0	0	0	0	2	3	5	5	5	7	
C									0	0	0	0	3	3	3	5	5	
U										0	0	0	0	2	2	2	3	
U											0	0	0	0	0	1	2	
A												0	0	0	0	0	0	
G													0	0	0	0	0	
A														0	0	0	0	
C															0	0	0	
G																0	0	
A																		0

# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
	(	.	.	.	.	.	.	.	.	.	.	.	.	.	.	)	.	
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	2	2	2	2	4	4	5	7	7	7	8	10		
U	0	0	0	0	0	0	0	2	2	4	5	7	7	7	8	10		
A	0	0	0	0	0	0	0	2	2	2	5	5	5	5	8	8		
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	8	8		
U	0	0	0	0	0	0	0	2	3	5	5	5	5	6	7			
U	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7			
C	0	0	0	0	0	0	0	3	3	3	3	3	3	5	5			
U	0	0	0	0	0	0	0	0	0	2	2	2	2	2	3			
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2		
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
	(	.	.	.	.	.	.	.	.	.	.	.	.	.	.	)	.	
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	0	2	2	2	2	4	4	4	5	7	7	8	10	10
U	0	0	0	0	0	0	0	0	2	2	4	5	7	7	8	10	10	10
A	0	0	0	0	0	0	0	2	2	2	2	5	5	5	5	8	8	8
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	5	8	8	8
U	0	0	0	0	0	0	0	2	3	5	5	5	5	6	7			
U	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7			
C	0	0	0	0	0	0	0	3	3	3	3	3	3	5	5			
U	0	0	0	0	0	0	0	0	0	2	2	2	2	2	3			
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2		
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			

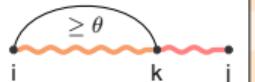


# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
	(	.	.	.	.	.	.	.	.	.	.	.	.	.	.	)	.	
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	0	2	2	2	2	4	4	5	7	7	8	10		
U	0	0	0	0	0	0	0	0	2	2	4	5	7	7	8	10		
A	0	0	0	0	0	0	0	2	2	2	5	5	5	5	8	8		
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	8	8		
U	0	0	0	0	0	0	0	2	3	5	5	5	5	6	7			
U	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7			
C	0	0	0	0	0	0	0	0	3	3	3	3	3	3	5	5		
U	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	3		
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2		
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			



# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
	(	.	.	.	.	.	.	.	.	.	.	.	.	.	.	)	.	
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	2	2	2	2	4	4	5	7	7	7	8	10		
U	0	0	0	0	0	0	0	2	2	4	5	7	7	7	8	10		
A	0	0	0	0	0	0	0	2	2	2	5	5	5	5	8	8		
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	8	8		
U	0	0	0	0	0	0	0	2	3	5	5	5	5	6	7			
U	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7			
C	0	0	0	0	0	0	0	0	3	3	3	3	3	3	5	5		
U	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	3		
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2		
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
G	i					j	=	i		i+1		j	+	i		k	j	0
A																		

# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
	(	.	.	.	.	.	.	.	.	.	.	.	.	.	.	)	.	
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11
G	0	0	0	0	0	3	3	3	5	5	5	5	5	6	8	10	10	10
A	0	0	0	0	2	2	2	2	4	4	5	7	7	7	8	10		
U	0	0	0	0	0	0	0	2	2	4	5	7	7	7	8	10		
A	0	0	0	0	0	0	0	2	2	2	5	5	5	5	8	8		
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	8	8		
U	0	0	0	0	0	0	0	2	3	5	5	5	5	6	7			
U	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7			
C	0	0	0	0	0	0	0	3	3	3	3	3	3	3	5	5		
U	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	3		
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2		
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		



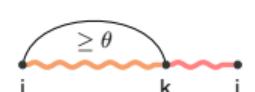
# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
	(	.	.	.	.	.	.	.	.	.	.	.	.	.	.	)	.	
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	2	2	2	2	4	4	5	7	7	7	8	10		
U	0	0	0	0	0	0	0	2	2	4	5	7	7	7	8	10		
A	0	0	0	0	0	0	0	2	2	2	5	5	5	5	8	8		
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	8	8		
U	0	0	0	0	0	0	0	2	3	5	5	5	5	6	7			
U	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7			
C	0	0	0	0	0	0	0	3	3	3	3	3	3	5	5			
U	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	3		
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2		
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
G	i					j	=	i		i+1		j	+	i		k	j	0
A																		

# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
	(	.	.	.	.	.	.	.	.	.	.	.	.	.	.	)	.	
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	2	2	2	2	2	4	4	4	5	7	7	8	10	10
U	0	0	0	0	0	0	0	0	2	2	4	5	7	7	8	10	10	10
A	0	0	0	0	0	0	0	2	2	2	2	5	5	5	5	8	8	8
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	8	8	8	8
U	0	0	0	0	0	0	0	2	3	5	5	5	5	6	7			
U	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7			
C	0	0	0	0	0	0	0	3	3	3	3	3	3	5	5			
U	0	0	0	0	0	0	0	0	2	2	2	2	2	2	3			
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2		
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	i				j	=	i		i+1		j	+	i	≥ θ	k	j		0
A																		0

# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
	(	.	.	.	.	.	.	.	.	.	.	.	.	.	.	)	.	
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	2	2	2	2	4	4	4	5	7	7	8	10		
U	0	0	0	0	0	0	0	2	2	4	5	7	7	8	10			
A	0	0	0	0	0	0	0	2	2	2	5	5	5	5	8	8		
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	8	8		
U	0	0	0	0	0	0	0	2	3	5	5	5	5	6	7			
U	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7			
C	0	0	0	0	0	0	0	3	3	3	3	3	3	5	5			
U	0	0	0	0	0	0	0	0	2	2	2	2	2	2	3			
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2		
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	i		j	=	i	i+1	j		+ 	k	j						0	
A																		

# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
	(	.	.	.	.	.	.	.	.	.	.	.	.	.	.	)	.	
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	0	0	2	2	2	2	4	4	5	7	7	8	10	
U	0	0	0	0	0	0	0	0	2	2	4	5	7	7	8	10		
A	0	0	0	0	0	0	0	0	2	2	2	5	5	5	5	8	8	
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	8	8		
U	0	0	0	0	0	0	0	0	0	2	3	5	5	5	6	7		
U	0	0	0	0	0	0	0	0	0	2	3	5	5	5	5	7		
C	0	0	0	0	0	0	0	0	0	3	3	3	3	3	5	5		
U	0	0	0	0	0	0	0	0	0	0	2	2	2	2	2	3		
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2		
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0



# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
	(	(	.	.	.	.	.	.	.	.	.	.	.	.	).	)	).	.
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	2	2	2	2	4	4	4	5	7	7	7	8	10	
U	0	0	0	0	0	0	0	2	2	4	5	7	7	7	8	10		
A	0	0	0	0	0	0	0	2	2	2	5	5	5	5	8	8		
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	8	8		
U	0	0	0	0	0	0	0	2	3	5	5	5	5	6	7			
U	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7			
C	0	0	0	0	0	0	0	3	3	3	3	3	3	5	5			
U	0	0	0	0	0	0	0	0	0	2	2	2	2	2	3			
U	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2			
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
G	i				j	=	i		i+1		j	+	i		$\geq \theta$	k	j	0
A																		

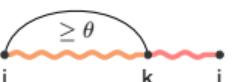
# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
	(	(	.	.	.	.	.	.	.	.	.	.	.	.	.	)	)	.
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	2	2	2	2	4	4	4	5	7	7	7	8	10	
U	0	0	0	0	0	0	0	2	2	4	5	7	7	7	8	10		
A	0	0	0	0	0	0	0	2	2	2	5	5	5	5	5	8	8	
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	5	8	8	
U	0	0	0	0	0	0	0	2	3	5	5	5	5	6	6	7		
U	0	0	0	0	0	0	0	2	3	5	5	5	5	5	5	7		
C	0	0	0	0	0	0	0	0	3	3	3	3	3	3	3	5	5	
U	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	3	
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2		
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	i		j	=	i	i+1	j			i	k	j		$\geq \theta$				0
A																		

# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
	(	(	.	.	.	.	.	.	.	.	.	.	.	.	.)	)	.	
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	0	0	0	2	2	2	2	4	4	5	7	7	8	10
U	0	0	0	0	0	0	0	0	2	2	4	5	7	7	7	8	10	
A	0	0	0	0	0	0	0	0	2	2	2	5	5	5	5	8	8	
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	5	8	8	
U	0	0	0	0	0	0	0	0	2	3	5	5	5	5	6	7		
U	0	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7		
C	0	0	0	0	0	0	0	0	0	3	3	3	3	3	3	5	5	
U	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	3	
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2		
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	i					j	=	i		i+1		j	+	i		k	j	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
C	(	(	(	.	.	.	)	.	.	.	.	.	.	.	)	)	.	
G	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	0	0	0	2	2	2	2	4	4	5	7	7	8	10
U	0	0	0	0	0	0	0	0	2	2	4	5	7	7	7	8	10	
A	0	0	0	0	0	0	0	0	2	2	2	5	5	5	5	8	8	
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	5	8	8	
U	0	0	0	0	0	0	0	0	2	3	5	5	5	6	7			
U	0	0	0	0	0	0	0	0	2	3	5	5	5	5	7			
C	0	0	0	0	0	0	0	0	0	3	3	3	3	3	5	5		
U	0	0	0	0	0	0	0	0	0	0	2	2	2	2	2	3		
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2		
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
A	i						j	=	i				j	+	i		j	0
C															0	0	0	
G															0	0	0	
A															0	0	0	

# Nussinov/Jacobson

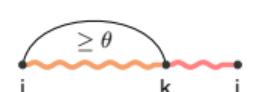
	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A	
	(	(	(	.	.	.	)	.	.	.	.	.	.	.	.	)	)	.	
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14	
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11	
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10	
A	0	0	0	0	0	0	0	2	2	2	2	2	4	4	5	7	7	8	10
U	0	0	0	0	0	0	0	0	0	2	2	2	4	5	7	7	8	10	
A	0	0	0	0	0	0	0	0	0	2	2	2	2	5	5	5	8	8	
C	0	0	0	0	0	0	0	0	0	0	2	5	5	5	5	8	8	8	
U	0	0	0	0	0	0	0	0	0	2	3	5	5	5	6	7			
U	0	0	0	0	0	0	0	0	0	2	3	5	5	5	5	7			
C	0	0	0	0	0	0	0	0	0	0	3	3	3	3	3	5	5		
U	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	3			
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2			
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
G	i					j	=	i		i+1		j	+	i	≥ θ	k	j	0	
A																		0	

# Nussinov/Jacobson

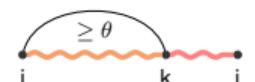
	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
C	(	(	(	.	.	.	)	.	.	.	.	.	.	.	.	)	)	.
G	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	0	0	0	2	2	2	2	4	4	5	7	7	8	10
U	0	0	0	0	0	0	0	0	2	2	4	5	7	7	7	8	10	
A	0	0	0	0	0	0	0	0	2	2	2	2	5	5	5	8	8	
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	5	8	8	
U	0	0	0	0	0	0	0	0	2	3	5	5	5	6	6	7		
U	0	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7		
C	0	0	0	0	0	0	0	0	3	3	3	3	3	3	5	5	5	
U	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	3	
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
C	i																	
G																		
A																		



# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A	
	(	(	(	.	.	.	)	.	.	.	.	.	.	.	.	)	)	.	
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14	
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11	
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10	
A	0	0	0	0	0	0	0	2	2	2	2	2	4	4	5	7	7	8	10
U	0	0	0	0	0	0	0	0	0	2	2	2	4	5	7	7	8	10	
A	0	0	0	0	0	0	0	0	0	2	2	2	2	5	5	5	8	8	
C	0	0	0	0	0	0	0	0	0	0	2	5	5	5	5	8	8	8	
U	0	0	0	0	0	0	0	0	0	2	3	5	5	5	6	6	7	7	
U	0	0	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7	7	
C	0	0	0	0	0	0	0	0	0	3	3	3	3	3	3	5	5	5	
U	0	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	3	3	
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
C	i						j	=	i				j	+	i		k	j	
G																			
A																		0	

# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A	
	(	(	(	.	.	.	)	.	.	.	.	.	.	.	.	)	)	.	
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14	
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11	
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10	
A	0	0	0	0	0	0	0	2	2	2	2	2	4	4	5	7	7	8	10
U	0	0	0	0	0	0	0	0	0	2	2	2	4	5	7	7	8	10	
A	0	0	0	0	0	0	0	0	0	2	2	2	2	5	5	5	8	8	
C	0	0	0	0	0	0	0	0	0	0	2	5	5	5	5	8	8	8	
U	0	0	0	0	0	0	0	0	0	2	3	5	5	5	6	6	7	7	
U	0	0	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7	7	
C	0	0	0	0	0	0	0	0	0	0	3	3	3	3	3	5	5	5	
U	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	2	3	3	
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	2	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	i					j	=	i		i+1		j	+	i		j	0		
A																		0	

# Nussinov/Jacobson

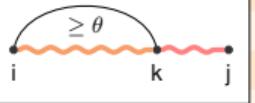
	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A	
	(	(	(	.	.	.	)	.	.	.	.	.	.	.	.	)	)	.	
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14	
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11	
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10	
A	0	0	0	0	0	0	0	2	2	2	2	2	4	4	5	7	7	8	10
U	0	0	0	0	0	0	0	0	0	2	2	2	4	5	7	7	8	10	
A	0	0	0	0	0	0	0	0	0	2	2	2	2	5	5	5	8	8	
C	0	0	0	0	0	0	0	0	0	0	2	5	5	5	5	8	8	8	
U	0	0	0	0	0	0	0	0	0	2	3	5	5	5	6	6	7	7	
U	0	0	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7	7	
C	0	0	0	0	0	0	0	0	0	0	0	3	3	3	3	5	5	5	
U	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	3	3	
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	2	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	



# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A	
	(	(	(	.	.	.	)	.	.	.	.	.	.	.	.	)	)	.	
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14	
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11	
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10	
A	0	0	0	0	0	0	0	2	2	2	2	2	4	4	5	7	7	8	10
U	0	0	0	0	0	0	0	0	0	2	2	2	4	5	7	7	8	10	
A	0	0	0	0	0	0	0	0	0	2	2	2	2	5	5	5	8	8	
C	0	0	0	0	0	0	0	0	0	0	2	5	5	5	5	8	8	8	
U	0	0	0	0	0	0	0	0	0	2	3	5	5	5	6	6	7	7	
U	0	0	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7	7	
C	0	0	0	0	0	0	0	0	0	3	3	3	3	3	3	5	5	5	
U	0	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	3	3	
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2	2	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	i					j	=	i		i+1		j	+	i	≥ θ	k	j	0	
A																		0	

# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
C	(	(	(	.	.	.	)	.	(	.	.	.	.	.	)	)	)	.
G	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	0	0	0	2	2	2	2	2	4	4	5	7	7	10
U	0	0	0	0	0	0	0	0	2	2	4	5	7	7	7	8	10	
A	0	0	0	0	0	0	0	0	2	2	2	2	5	5	5	8	8	
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	5	8	8	
U	0	0	0	0	0	0	0	0	2	3	5	5	5	6	6	7		
U	0	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7		
C	0	0	0	0	0	0	0	0	3	3	3	3	3	3	3	5	5	
U	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	3	
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
A	i				j	=	i		i+1		j	+	i		k	j	0	

# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A	
	(	(	(	.	.	.	)	.	(	.	.	.	.	.	)	)	)	.	
C	0	0	0	0	0	0	3	4	4	6	6	6	6	9	9	11	14	14	
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11	
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10	
A	0	0	0	0	0	0	0	2	2	2	2	2	4	4	5	7	7	8	10
U	0	0	0	0	0	0	0	0	0	2	2	2	4	5	7	7	8	10	
A	0	0	0	0	0	0	0	0	0	2	2	2	2	5	5	5	8	8	
C	0	0	0	0	0	0	0	0	0	0	2	5	5	5	5	8	8	8	
U	0	0	0	0	0	0	0	0	0	2	3	5	5	5	6	7			
U	0	0	0	0	0	0	0	0	0	2	3	5	5	5	5	7			
C	0	0	0	0	0	0	0	0	0	3	3	3	3	3	3	5	5		
U	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	3			
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2			
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
G	i					j	=	i	i+1			j	+	i	≥ θ	k	j	0	
A																		0	

# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
C	(	(	(	.	.	.	)	.	.	(	.	.	.	.	)	)	)	.
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	0	0	2	2	2	2	4	4	5	7	7	8	10	10
U	0	0	0	0	0	0	0	0	2	2	4	5	7	7	7	8	10	10
A	0	0	0	0	0	0	0	2	2	2	2	5	5	5	5	8	8	8
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	5	8	8	8
U	0	0	0	0	0	0	0	0	2	3	5	5	5	5	6	7	7	7
U	0	0	0	0	0	0	0	0	2	3	5	5	5	5	5	5	7	7
C	0	0	0	0	0	0	0	0	3	3	3	3	3	3	3	5	5	5
U	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	3	3
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	2
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A	i				j	=	i		i+1		j	+	i	≥ θ	k	j	0	0
C																0	0	0
G																0	0	0
A																0	0	0

# Nussinov/Jacobson

	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
C	(	(	(	.	.	.	)	.	(	(	.	.	.	)	)	)	)	.
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	0	0	2	2	2	2	4	4	5	7	7	8	10	10
U	0	0	0	0	0	0	0	0	2	2	4	5	7	7	7	8	10	10
A	0	0	0	0	0	0	0	2	2	2	2	5	5	5	5	8	8	8
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	5	8	8	8
U	0	0	0	0	0	0	0	0	2	3	5	5	5	6	6	7	7	7
U	0	0	0	0	0	0	0	0	2	3	5	5	5	5	5	7	7	7
C	0	0	0	0	0	0	0	0	3	3	3	3	3	3	3	5	5	5
U	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	3	3
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2	2
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A	i				j	=	i		i+1		j	+	i	≥ θ	k	j	0	0
C																0	0	0
G																0	0	0
A																0	0	0

# Nussinov/Jacobson

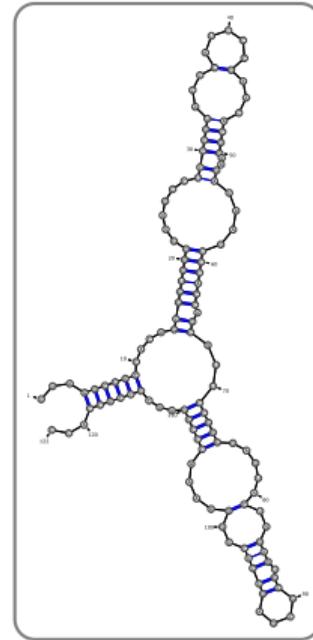
	C	G	G	A	U	A	C	U	U	C	U	U	A	G	A	C	G	A
C	(	(	(	.	.	.	)	.	(	(	.	.	.	)	)	)	)	.
G	0	0	0	0	0	0	3	4	4	6	6	6	6	7	9	11	11	11
G	0	0	0	0	0	0	3	3	3	5	5	5	5	6	8	10	10	10
A	0	0	0	0	0	0	2	2	2	2	4	4	5	7	7	8	10	10
U	0	0	0	0	0	0	0	0	2	2	4	5	7	7	7	8	10	10
A	0	0	0	0	0	0	0	2	2	2	2	5	5	5	5	8	8	8
C	0	0	0	0	0	0	0	0	0	2	5	5	5	5	5	8	8	8
U	0	0	0	0	0	0	0	0	2	3	5	5	5	6	6	7	7	7
U	0	0	0	0	0	0	0	2	3	5	5	5	5	5	5	7	7	7
C	0	0	0	0	0	0	0	0	3	3	3	3	3	3	3	5	5	5
U	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	3	3
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2	2
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C	i																	
G																		
A																		



## Turner energy model

Based on **unambiguous** decomposition of 2<sup>ary</sup> structure into **loops**:

- ▶ Internal loops
- ▶ Bulges
- ▶ Terminal loops
- ▶ Multi loops
- ▶ Stackings



Free-energy  $\Delta G$  of a loop depend on bases, assymmetry, dangles ...

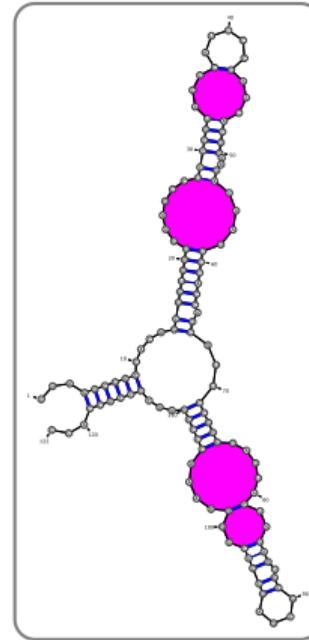
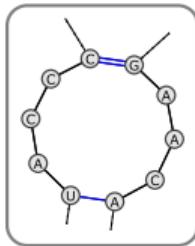
Experimentally determined  
+ Interpolated for larger loops.

Improved results by taking stacking into account.

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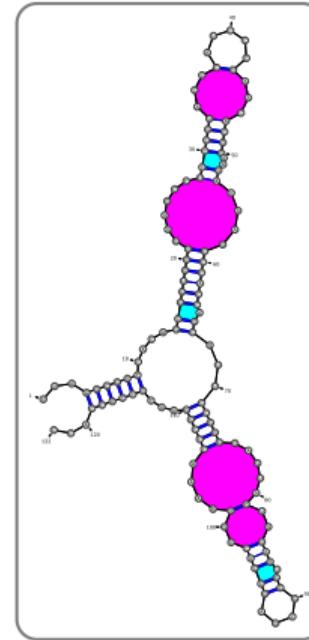
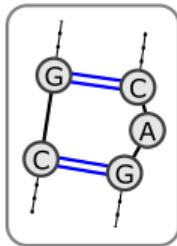
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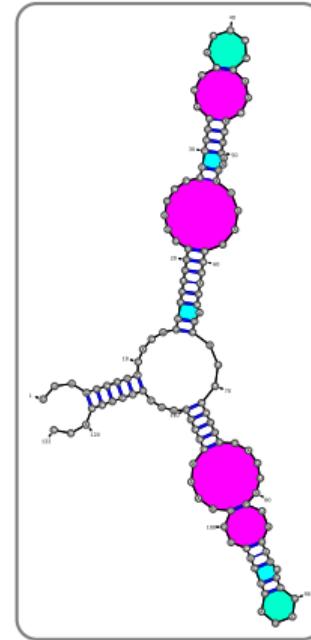
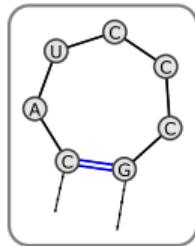
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Free-energy  $\Delta G$  of a loop depend on bases, assymmetry, dangles ...

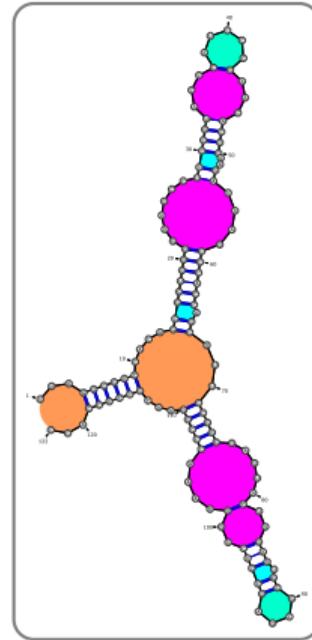
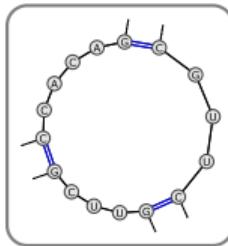
Experimentally determined  
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Free-energy  $\Delta G$  of a loop depend on  
bases, assymmetry, dangles ...

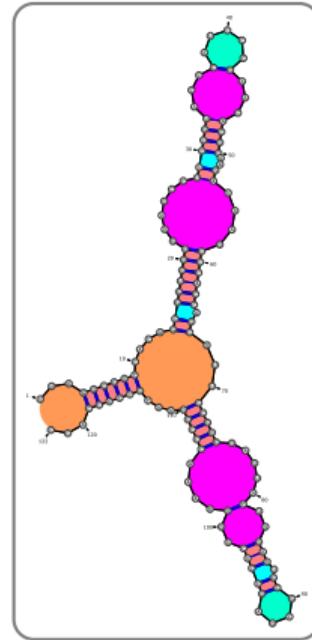
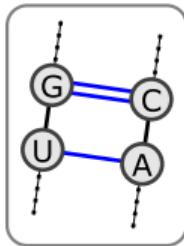
Experimentally determined  
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Improved results by taking stacking into account.

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Based on **unambiguous** decomposition of 2<sup>ary</sup> structure into **loops**:

- ▶ Internal loops
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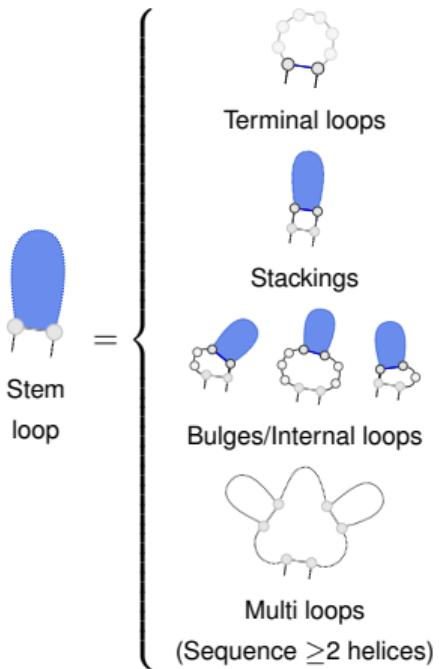


Free-energy  $\Delta G$  of a loop depend on bases, assymmetry, dangles ...

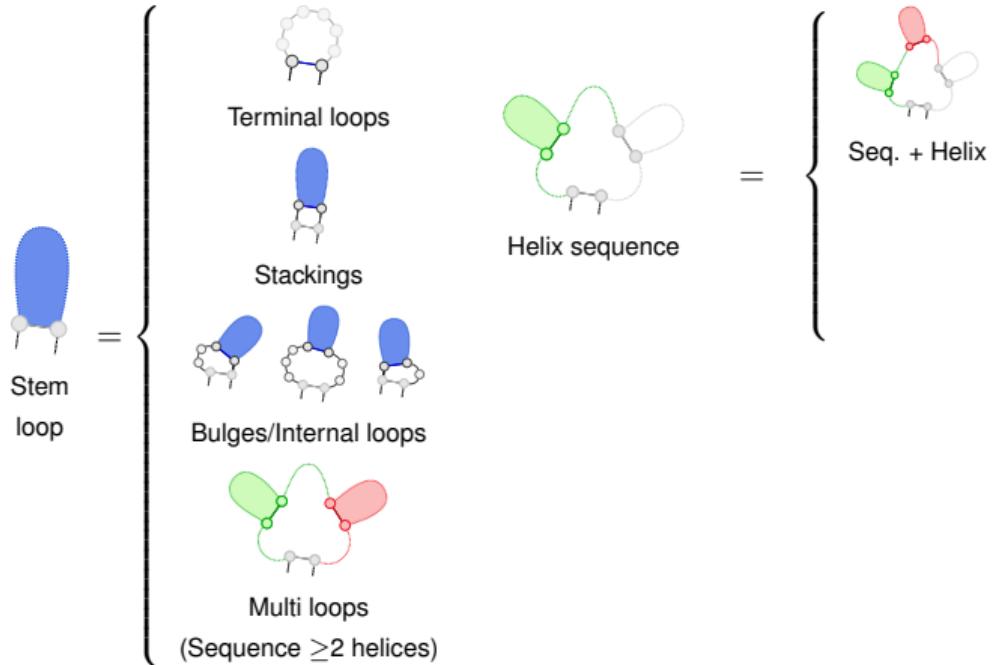
Experimentally determined  
+ Interpolated for larger loops.

Improved results by taking stacking into account.

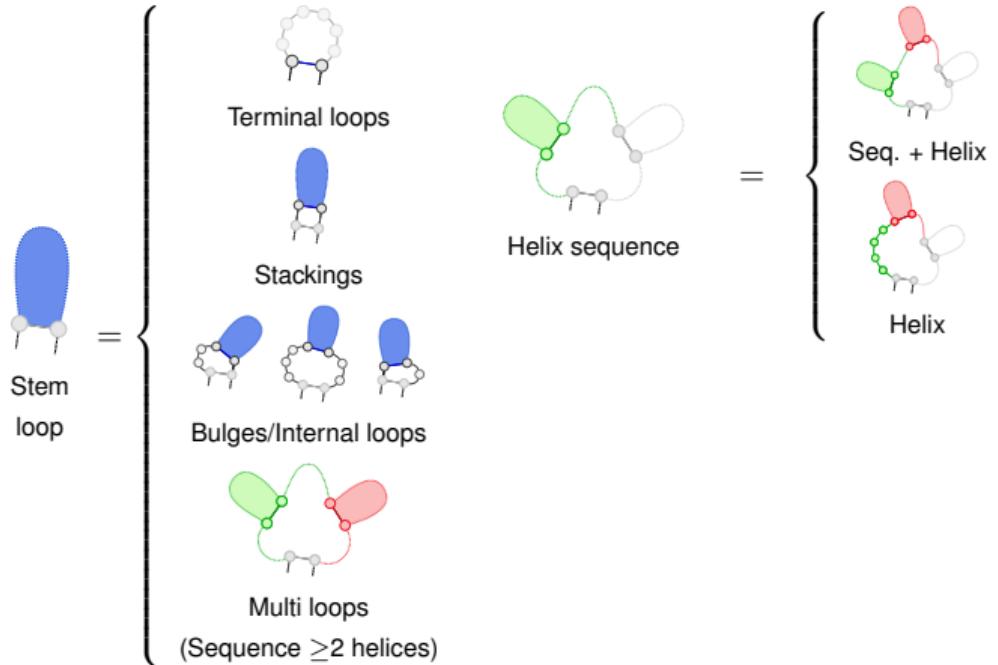
## MFE DP equations



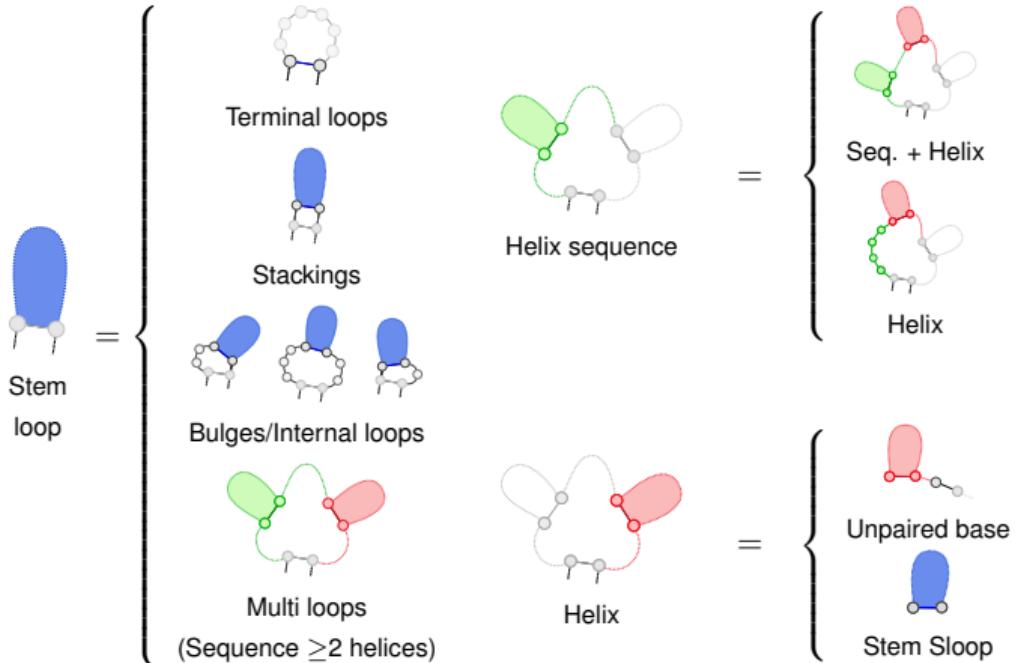
## MFE DP equations



## MFE DP equations

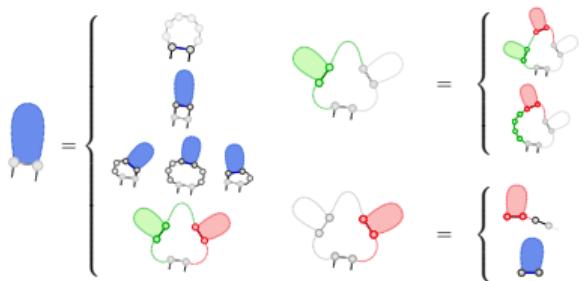


## MFE DP equations



## MFold Unafold

- ▶  $E_H(i, j)$ : Energy of terminal loop *enclosed by*  $(i, j)$  pair
- ▶  $E_{BL}(i, j)$ : Energy of bulge or internal loop *enclosed by*  $(i, j)$  pair
- ▶  $E_S(i, j)$ : Energy of stacking  $(i, j)/(i + 1, j - 1)$
- ▶ Penalty for multi loop (*a*), and occurrences of unpaired base (*b*) and helix (*c*) in multi loops.



## DP recurrence

$$\begin{aligned}\mathcal{M}'_{i,j} &= \min \left\{ \begin{array}{l} E_H(i, j) \\ E_S(i, j) + \mathcal{M}'_{i+1, j-1} \\ \text{Min}_{i', j'} (E_{BL}(i, i', j', j) + \mathcal{M}'_{i', j'}) \\ a + \text{Min}_k (\mathcal{M}_{i+1, k-1} + \mathcal{M}^1_{k, j-1}) \end{array} \right\} \\ \mathcal{M}_{i,j} &= \text{Min}_k \left\{ \min (\mathcal{M}_{i, k-1}, b(k-1)) + \mathcal{M}^1_{k, j} \right\} \\ \mathcal{M}^1_{i,j} &= \text{Min}_k \left\{ b + \mathcal{M}^1_{i, j-1}, c + \mathcal{M}'_{i, j} \right\}\end{aligned}$$

# Backtracking

Backtracking to reconstruct MFE structure:

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Complexity:

For each min,  $\mathcal{O}(n)$  potential contributors

⇒ Worst-case complexity in  $\mathcal{O}(n^2)$  for naive backtrack.

Keep best contributor for each Min ⇒ Backtracking in  $\mathcal{O}(n)$

⇒ UnaFold [MZ08]/RNAFold [HFS<sup>+</sup>94] compute the MFE for the Turner model  
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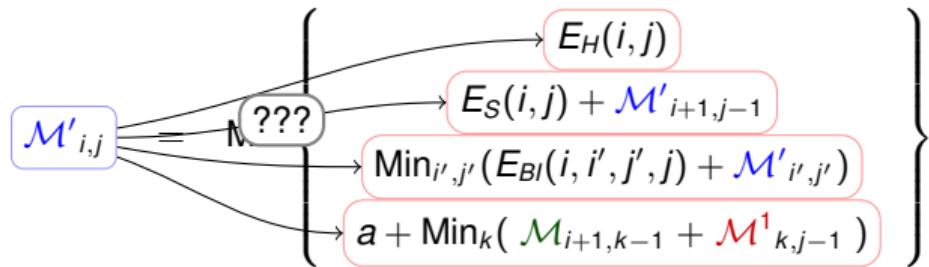
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### Definition (Ab initio folding)

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
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- ▶ Limited performances

### Definition (Comparative approach)

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

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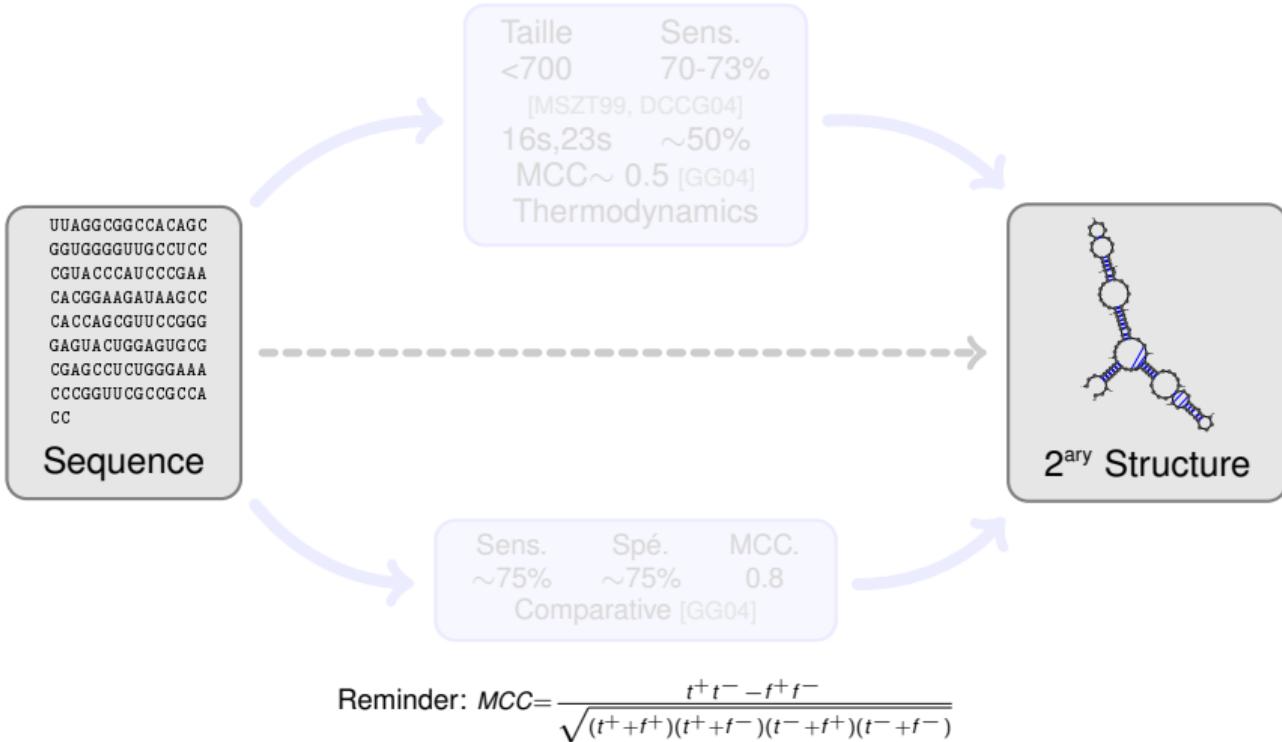
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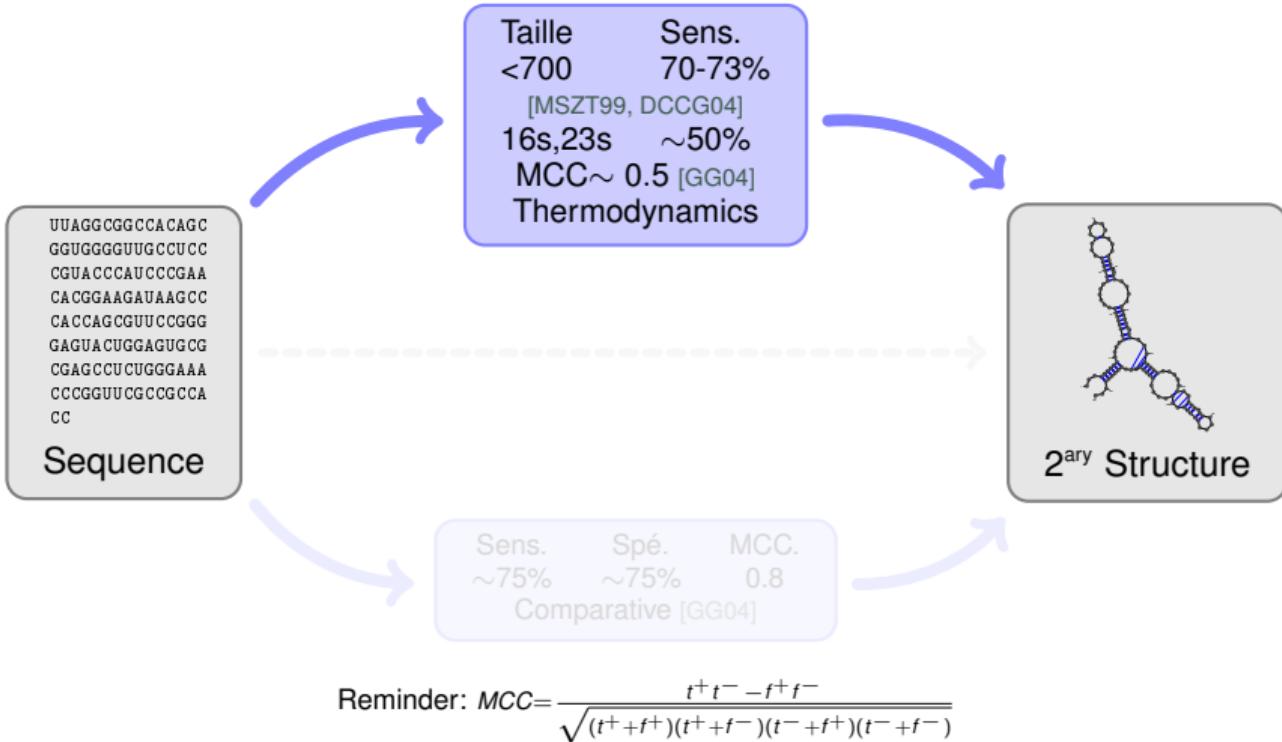
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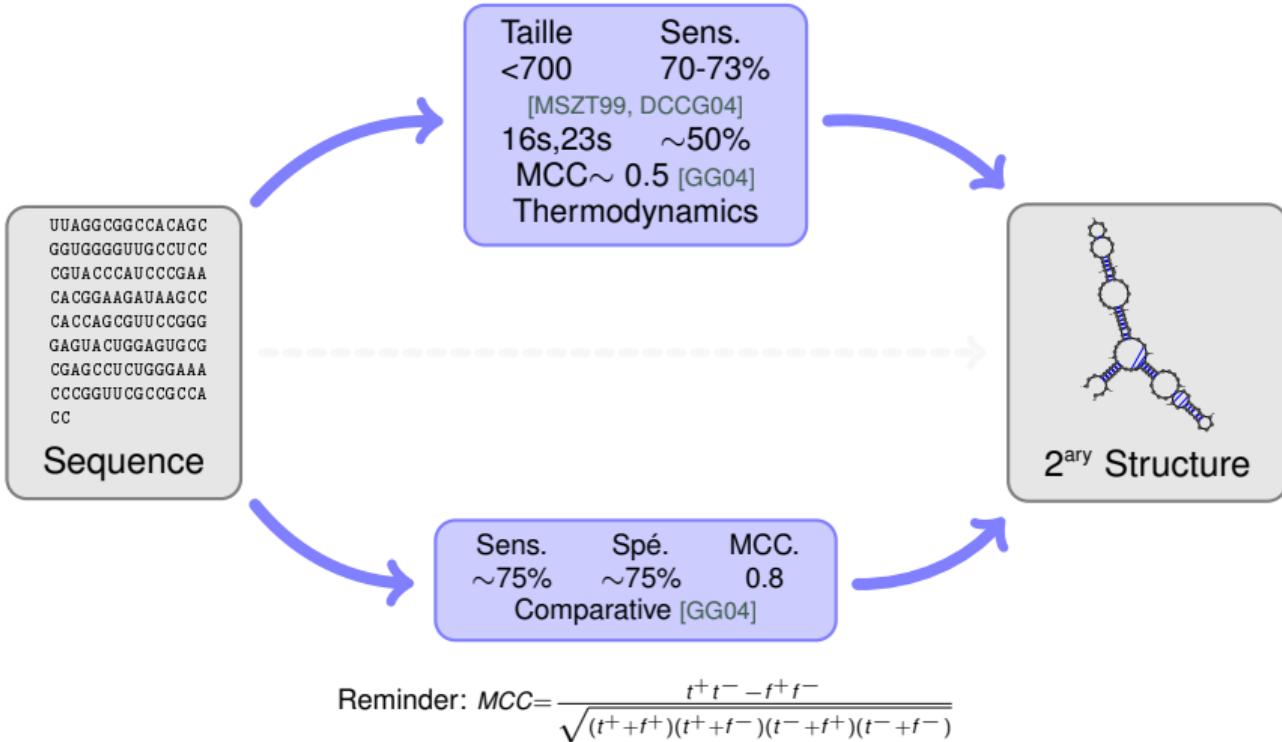
# Performances



## Performances



## Performances



# Towards a 3D ab-initio prediction

**Goal:** From sequence to all-atom/coarse grain 3D models!!!

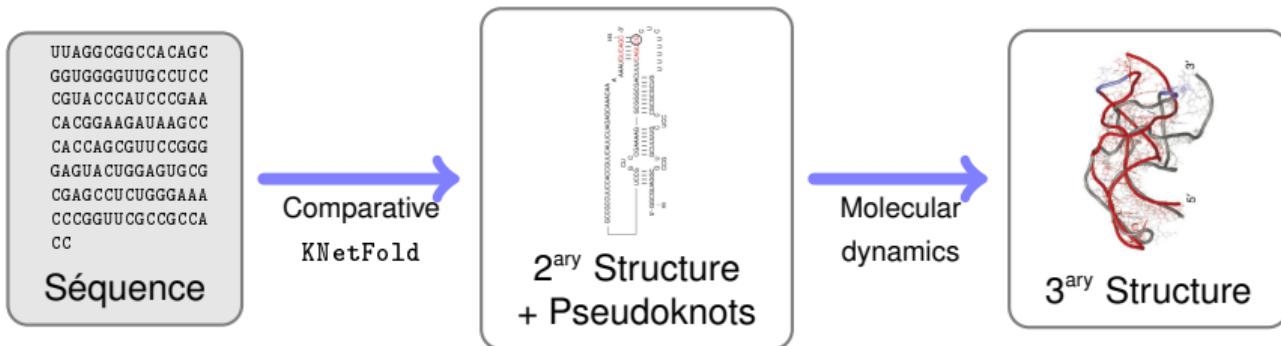
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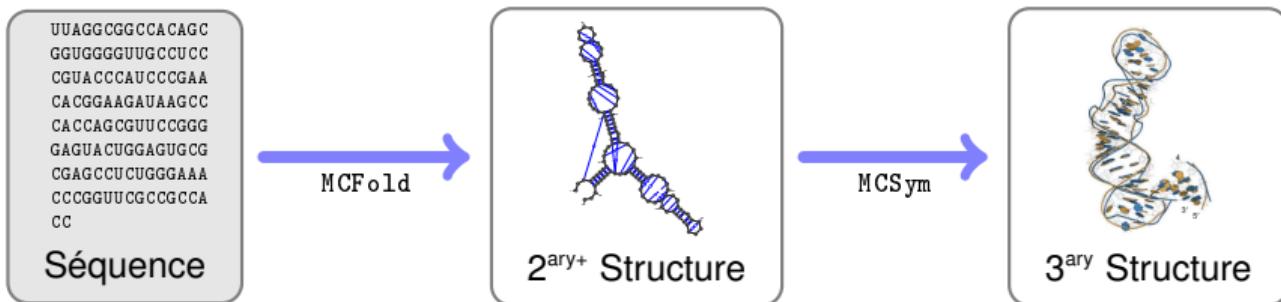
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# Outline

## Introduction

- Dynamic programming 101
- Dynamic programming framework

## Variations on RNA folding

- Why RNA?
- RNA folding
- RNA Structure(s)
- Some representations of RNA structure
- Thermodynamics vs Kinetics

## Free-energy minimization

- Nussinov-style RNA folding
- Turner energy model
- MFold/Unafold
- Performances and the comparative approach
- Towards a 3D ab-initio prediction

## Boltzmann ensemble

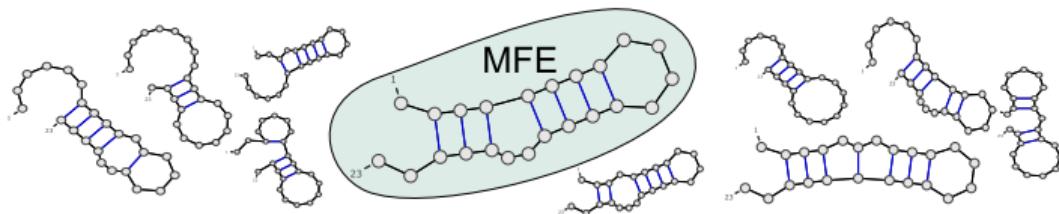
- Nussinov: Minimisation  $\Rightarrow$  Counting
- Computing the partition function
- Statistical sampling

# The canonical Boltzmann Ensemble

RNA *breathes*  $\Rightarrow$  There is no more than a single conformation.

## New paradigm

The conformations of an RNA **coexist** in the **Boltzmann distribution**.



**Consequence:** The MFE probability can be arbitrarily small.

$\Rightarrow$  To understand how RNA acts, one must account for the set of alternative structures.

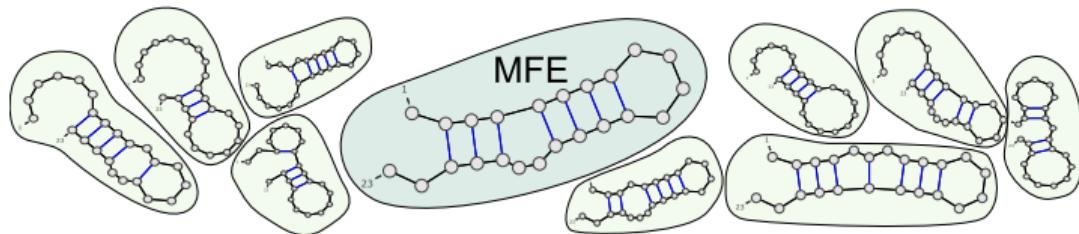
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## Boltzmann Distribution: Definition

For each structure  $S$  compatible with an RNA  $\omega$ , the Boltzmann distribution associates a **Boltzmann factor**  $\mathcal{B}_{S,\omega} = e^{\frac{-E_{S,\omega}}{RT}}$ , where:

- ▶  $E_{S,\omega}$  is the free-energy  $S$  ( $\text{kCal}\cdot\text{mol}^{-1}$ )
- ▶  $T$  is the temperature (K)
- ▶  $R$  is the perfect gaz constant ( $1.986 \cdot 10^{-3} \text{ kCal}\cdot\text{K}^{-1}\cdot\text{mol}^{-1}$ )

To obtain a distribution, one simply renormalizes by the **partition function**

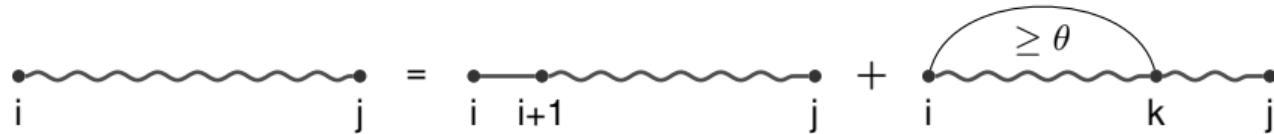
$$\mathcal{Z}_\omega = \sum_{S \in \mathcal{S}_\omega} e^{\frac{-E_{S,\omega}}{RT}}$$

where  $\mathcal{S}_\omega$  is the set of conformations that are compatibles with  $\omega$ .

The **Boltzmann probability** of a structure  $S$  is simply given by

$$P_{S,\omega} = \frac{e^{\frac{-E_{S,\omega}}{RT}}}{\mathcal{Z}_\omega}.$$

## Nussinov/Jacobson DP scheme



$$N_{i,t} = 0, \quad \forall t \in [i, i + \theta]$$

$$N_{i,j} = \min \begin{cases} N_{i+1,j} & i \text{ unpaired} \\ \min_{k=i+\theta+1}^j \Delta G_{i,k} + N_{i+1,k-1} + N_{k+1,j} & i \text{ paired with } k \end{cases}$$

**Ambiguity?** Consider  $i$ : Either **unpaired**, or **paired to  $k$** .

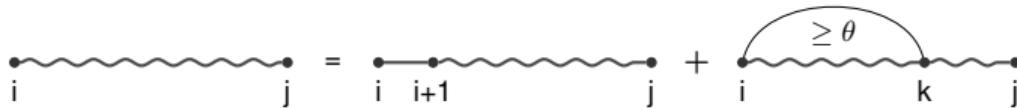
Sets of structures generated in these two cases are clearly disjoint.

(also holds for various values of  $k$ )  $\Rightarrow$  **Unambiguous** decomposition

**Completeness?** True, since scheme explores every possible outcome for  $i$ .

+ Induction on interval length  $\Rightarrow$  **Complete** decomposition

## Nussinov/Jacobson DP scheme



Recurrence for minimal free-energy of a fold :

$$N_{i,t} = 0, \quad \forall t \in [i, i + \theta]$$

$$N_{i,j} = \min \left\{ \begin{array}{ll} N_{i+1,j} & (i \text{ unpaired}) \\ \min_{k=i+\theta+1}^j E_{i,k} + N_{i+1,k-1} + N_{k+1,j} & (i \text{ comp. with } k) \end{array} \right.$$

Recurrence for counting compatible structures :

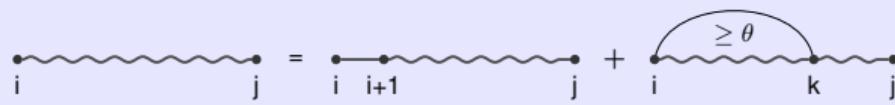
$$C_{i,t} = 1, \quad \forall t \in [i, i + \theta]$$

$$C_{i,j} = \sum \left\{ \begin{array}{ll} C_{i+1,j} & (i \text{ unpaired}) \\ \sum_{k=i+\theta+1}^j 1 \times C_{i+1,k-1} \times C_{k+1,j} & (i \text{ comp. with } k) \end{array} \right.$$

Decomposition matters, and the rest (MFE, count...) follows!

## Partition function

Partition function = Weighted count over compatible structures

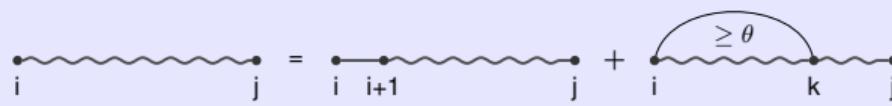


$$\mathcal{Z}_{i,t} = 1, \quad \forall t \in [i, i + \theta]$$

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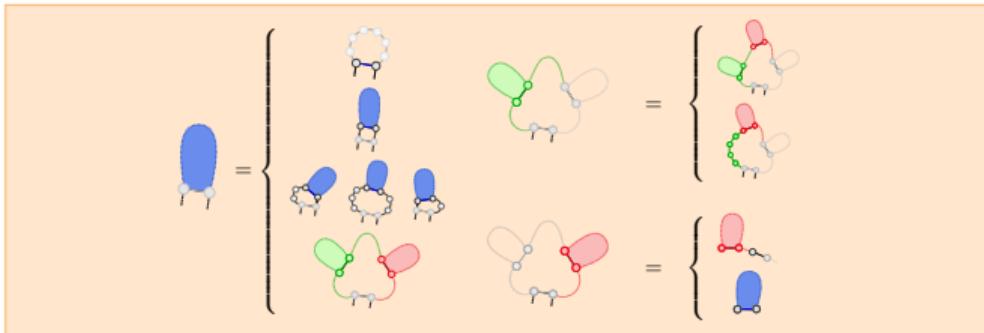


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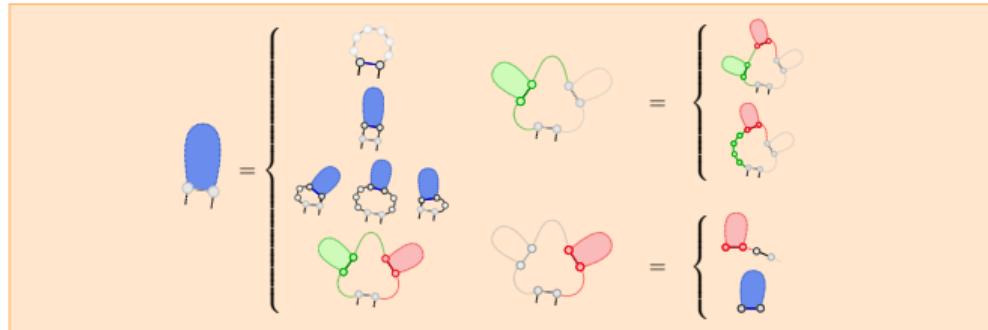
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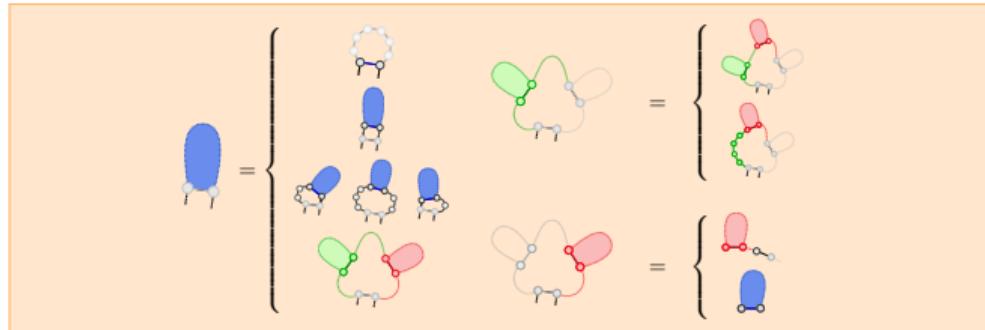
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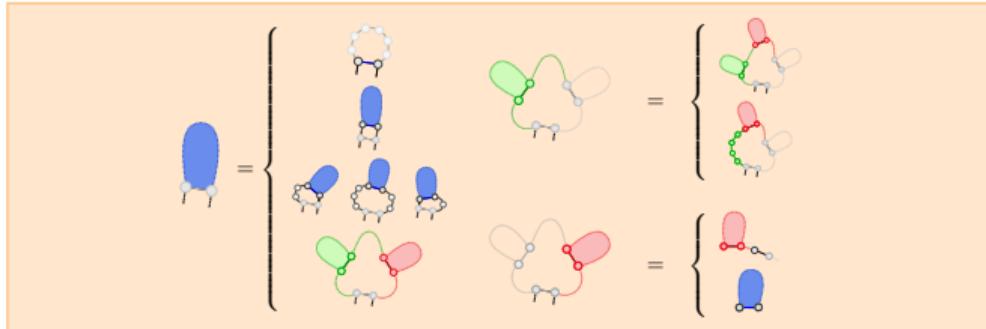
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$$\begin{aligned} \mathcal{Z}'(i,j) &= \sum \left\{ \begin{array}{l} e^{-E_H(i,j)} \\ e^{-E_S(i,j)} \mathcal{Z}'(i+1, j-1) \\ + \sum \left( e^{-E_B(i,i',j',j)} \mathcal{Z}'(i',j') \right) \\ + e^{-\frac{(a)}{RT}} \sum (\mathcal{Z}(i+1, k-1) \mathcal{Z}^1(k, j-1)) \end{array} \right\} \\ \mathcal{Z}(i,j) &= \sum \left( \mathcal{Z}(i, k-1) + e^{-\frac{b(k-1)}{RT}} \right) \mathcal{Z}^1(k, j) \\ \mathcal{Z}^1(i,j) &= e^{-\frac{b}{RT}} \mathcal{Z}^1(i, j-1) + e^{-\frac{c}{RT}} \mathcal{Z}'(i, j) \end{aligned}$$

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Validity of a partition function computation:

- ▶ Completeness/Unambiguity of decomposition scheme
- ▶ Correctness of Boltzmann factor

Weight induced by backtrack = Product of derivations weights

$e^{-E/RT} \rightarrow$  Weight products  $\Leftrightarrow$  Summing energy terms

$$\begin{aligned}e^{-E_{bp}(i,k)/RT} \times \mathcal{Z}_{i+1,k-1} \times \mathcal{Z}_{k+1,j} &= \cdot \sum_x e^{-E(x)/RT} \cdot \sum_y e^{-E(y)/RT} \\ &= \sum_{x,y} e^{-E(x)/RT} \cdot e^{-E(y)/RT} \\ &= \sum_{x,y} e^{-(E_{bp}(i,k) + E(x) + E(y))/RT}\end{aligned}$$

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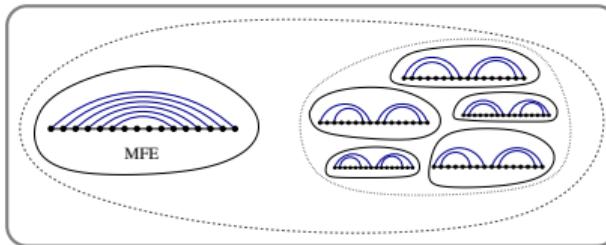
$e^{-E/RT} \rightarrow$  Weight products  $\Leftrightarrow$  Summing energy terms

$$\begin{aligned}e^{-E_{bp}(i,k)/RT} \times \mathcal{Z}_{i+1,k-1} \times \mathcal{Z}_{k+1,j} &= \cdot \sum_x e^{-E(x)/RT} \cdot \sum_y e^{-E(y)/RT} \\ &= \sum_{x,y} e^{-a/RT} \cdot e^{-E(x)/RT} \cdot e^{-E(y)/RT} \\ &= \sum_{x,y} e^{-(E_{bp}(i,k) + E(x) + E(y))/RT}\end{aligned}$$

## Statistical sampling of RNA 2<sup>ary</sup> structures

MFE ( $\Leftrightarrow$  Max probability) may be **heavily dominated** by a set  $\mathcal{B}$  of **structurally similar suboptimal structures**.

⇒ Functional conformation probably closer to  $\mathcal{B}$  than to MFE.



**Proof-of-concept:** [DCL05]

- ▶ Sample structures within Boltzmann probability
  - ▶ Cluster structures
  - ▶ Build and return consensus structure of the heaviest cluster
- ⇒ Relative improvement for specificity (+17.6%) and sensitivity (+21.74%, except group II introns)

### Problem

How to sample from the Boltzmann ensemble?

## Stochastic backtrack (adapted from SFold)

**Goal** [DL03]: From sequence  $\omega$ , draw  $S$  with prob.  $e^{-E_S/RT}/\mathcal{Z}$

**Principle:** Choose derivation with prob. prop. to its contribution to part. fun.

**Precomputation:** Compute part. fun. versions of matrices  $(\mathcal{Z}, \mathcal{Z}', \mathcal{Z}^1)$ .

Stochastic backtrack:

1. Draw uniform random number  $r \in [0, \mathcal{Z}'(i, j)]$
2. Subtract from  $r$  the contributions of  $\mathcal{Z}'(i, j)$  until  $r < 0$
3. Recurse over associated regions/matrices

$$\mathcal{Z}'(i, j) \in \boxed{???} \rightarrow \begin{cases} e^{-\frac{E_H(i, j)}{RT}} + e^{-\frac{E_S(i, j)}{RT}} \mathcal{Z}'(i+1, j-1) & \text{A} \\ \sum \left( e^{-\frac{E_B(i, i', j', j)}{RT}} \mathcal{Z}'(i', j') \right) & \text{B} \\ \rightarrow e^{-\frac{(a)}{RT}} \sum (\mathcal{Z}(i+1, k-1) \mathcal{Z}^1(k, j-1)) & \text{C} \end{cases}$$

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$$\mathcal{Z}'(i, j) = \sum \begin{cases} e^{\frac{-E_H(i, j)}{RT}} + e^{\frac{-E_S(i, j)}{RT}} \mathcal{Z}'(i+1, j-1) & \text{A} \\ \sum \left( e^{\frac{-E_B(i, i', j', j)}{RT}} \mathcal{Z}'(i', j') \right) & \text{B} \\ e^{\frac{-(a)}{RT}} \sum (\mathcal{Z}(i+1, k-1) \mathcal{Z}^1(k, j-1)) & \text{C} \end{cases}$$

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A1 | A2 | Bi | Bi+1 | ... | Bj-1 | Bj | Ci | Ci+1 | ... | Cj-1 | Cj

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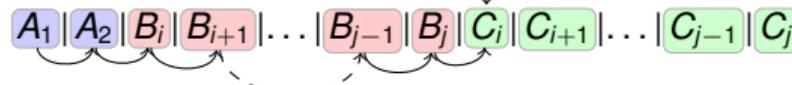
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**Correctness:** Each  $S \in \mathcal{S}_\omega$  uniquely generated (DP scheme unambiguity)  
Therefore the probability of generated  $S$  is

$$p_S = \frac{\mathcal{B}(E_1)}{\mathcal{B}(\mathcal{S}_\omega)} \cdot \frac{\mathcal{B}(E_2)}{\mathcal{B}(E_1)} \cdot \frac{\mathcal{B}(E_3)}{\mathcal{B}(E_2)} \cdots \frac{\mathcal{B}(\{S\})}{\mathcal{B}(E_m)}$$

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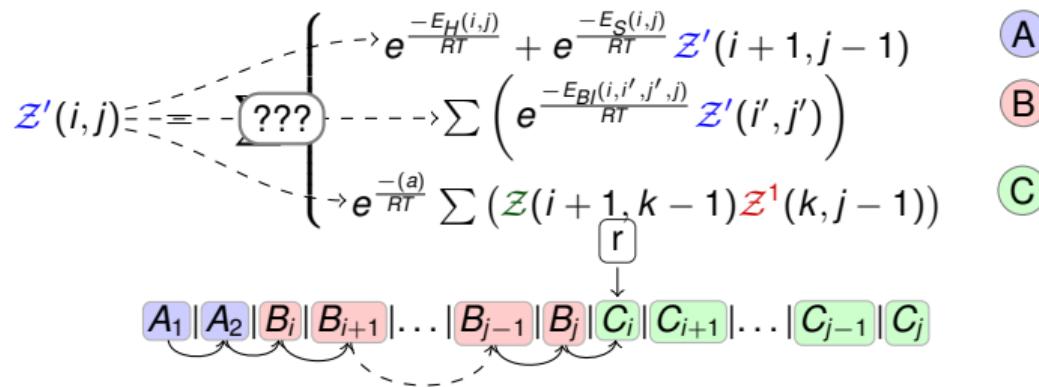
$$p_S = \frac{\mathcal{B}(\{S\})}{\mathcal{B}(\mathcal{S}_\omega)} = \frac{e^{-E_S/RT}}{\mathcal{Z}} = P_{S, \omega}$$

# Complexity

Goal [DL03]: From sequence  $\omega$ , draw  $S$  with prob.  $e^{-E_S/RT}/\mathcal{Z}$

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Average-case complexity in  $\Theta(k \times n\sqrt{n})$  (homopolymer model) [Pon08].  
Boustrophedon search  $\Rightarrow \mathcal{O}(k \times n \log n)$  worst-case [Pon08].

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$r$

After  $\Theta(n)$  operations, recurse over region of length  $n - 1$   
 $\Rightarrow$  Worst-case complexity in  $\mathcal{O}(k \times n^2)$  for  $k$  samples

Average-case complexity in  $\Theta(k \times n\sqrt{n})$  (homopolymer model) [Pon08].

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