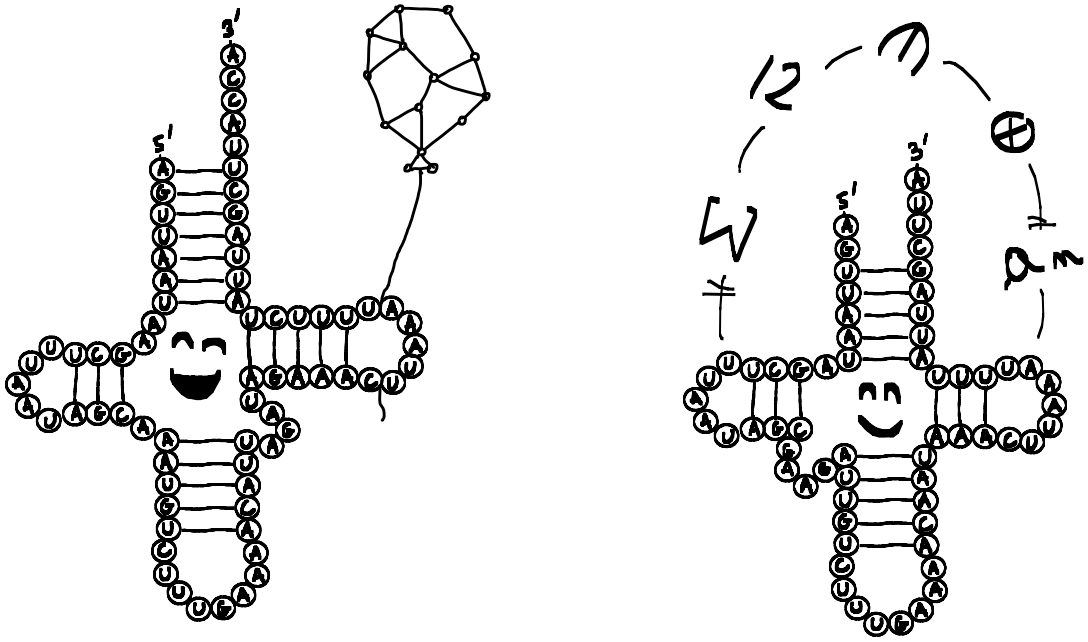
GENERATING TREE ALIGNMENTS

HOW COMBINATORICS CAN HELP BIOINFORMATICS

Julien COURTIEL (PIMS/Univ. of British Columbia, Vancouver)

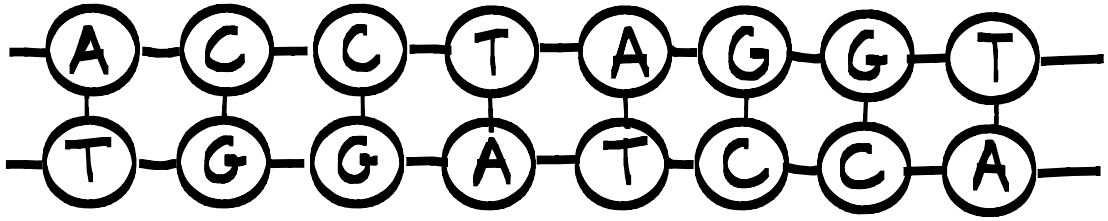
2016 SFU Symposium on Mathematics and Computation



Co-authors: Cedric CHAUVE (Simon Fraser University, Vancouver)
Yann PONTY (CNRS/LIX, Ecole Polytechnique, Inria Saclay)

WHAT IS RNA?

DNA
the code



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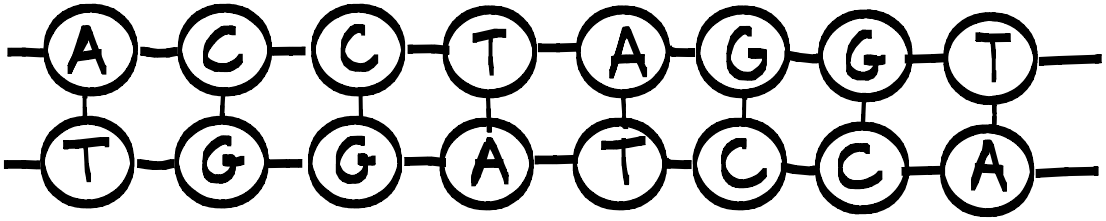

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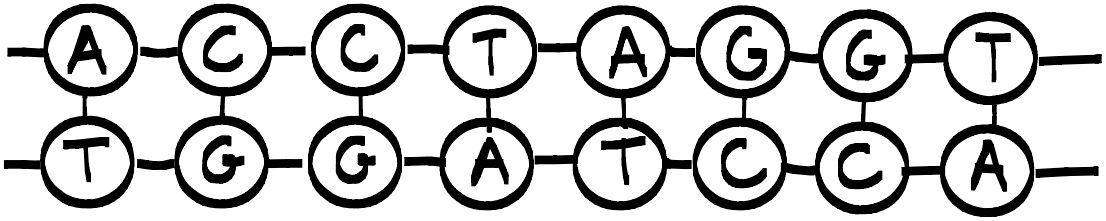
RNA

WHAT IS RNA?

BETTER CALL POL

DNA
the code



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Pol

RNA

WHAT IS RNA?

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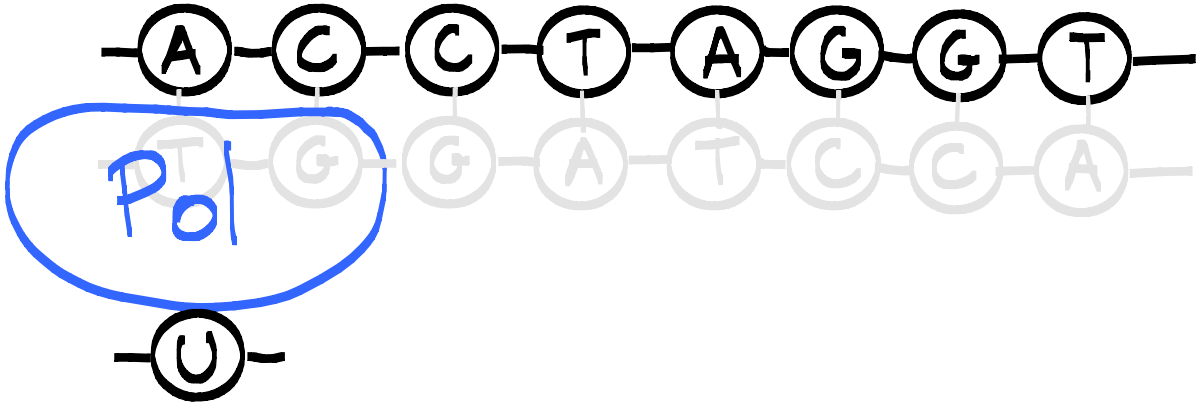
RNA



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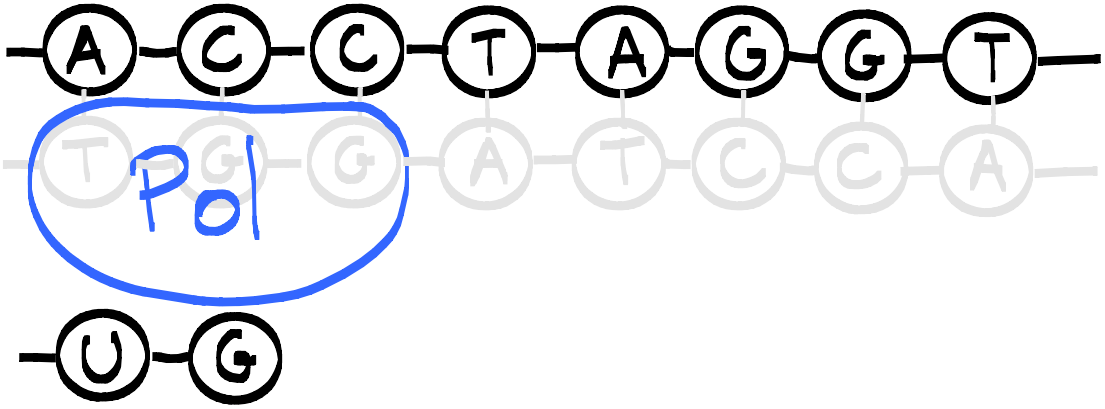
RNA



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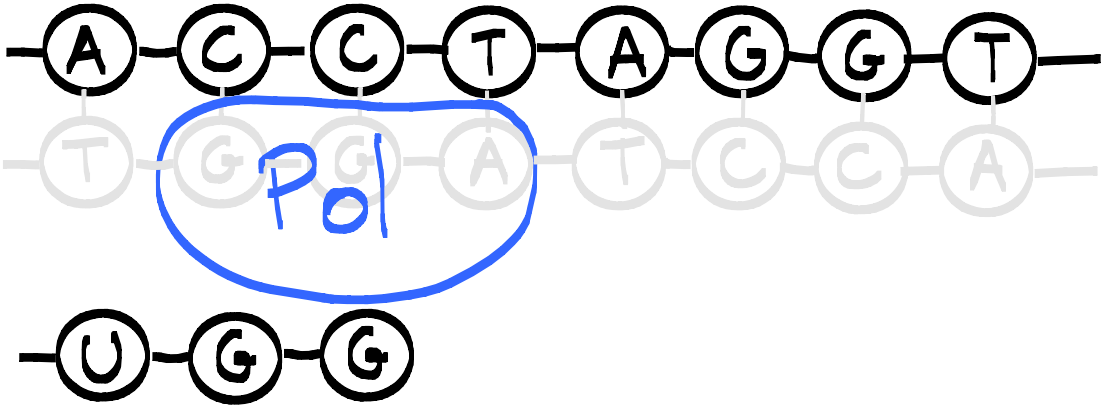
RNA



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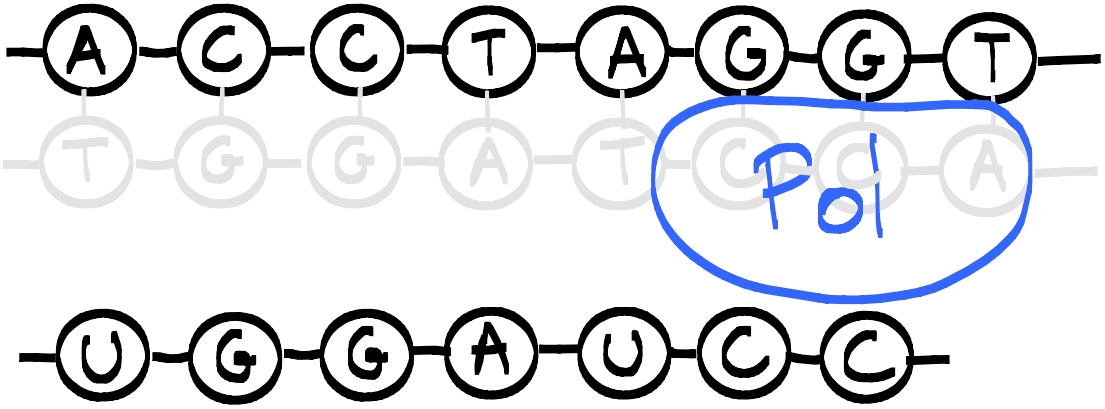
RNA



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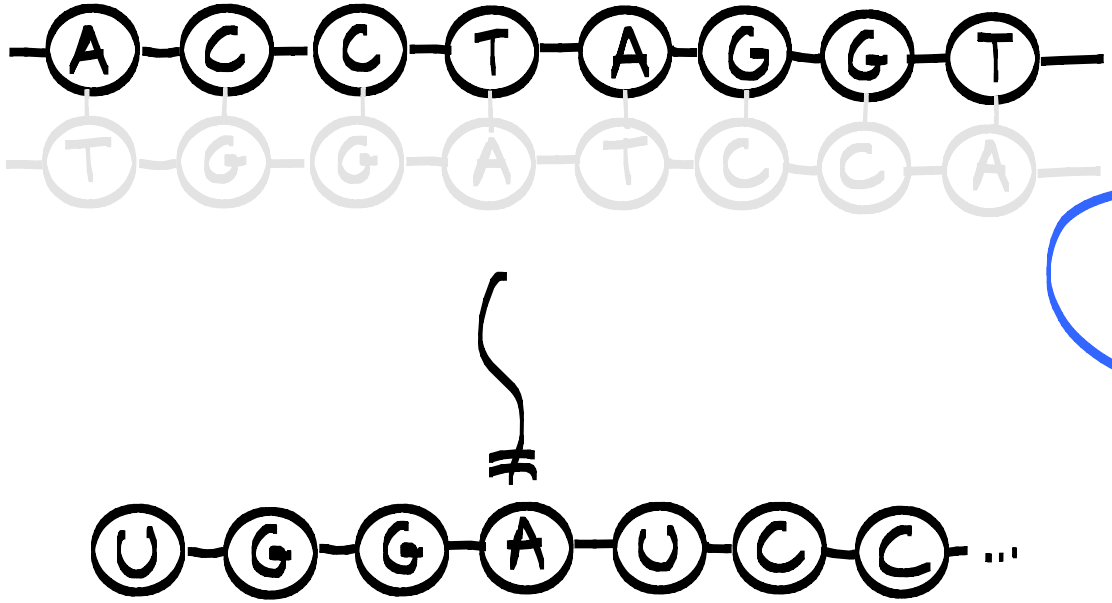

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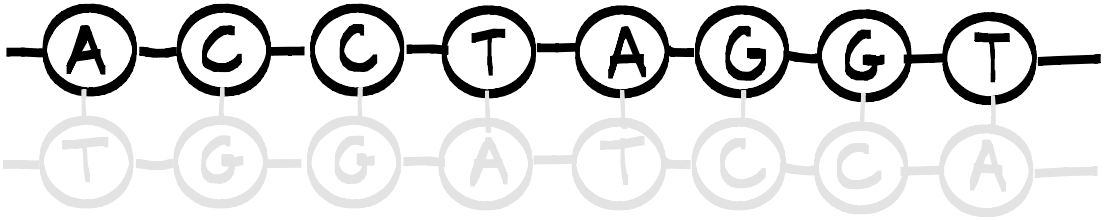

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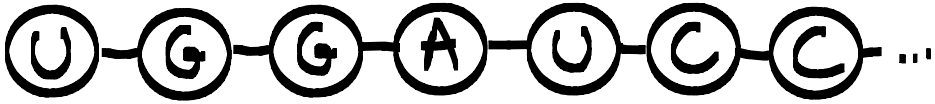
RNA



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proteins

WHAT IS RNA?

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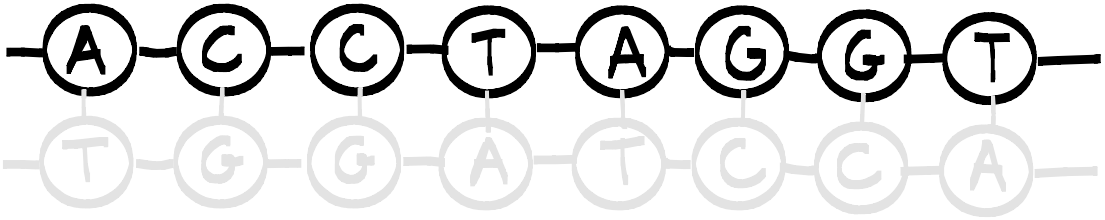

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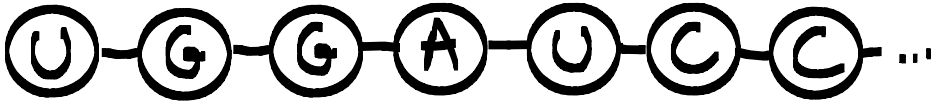
RNA



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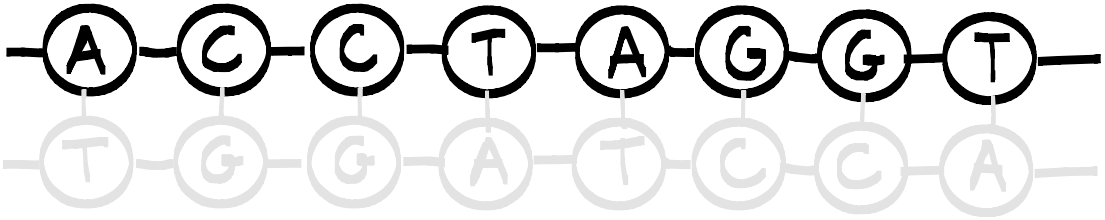

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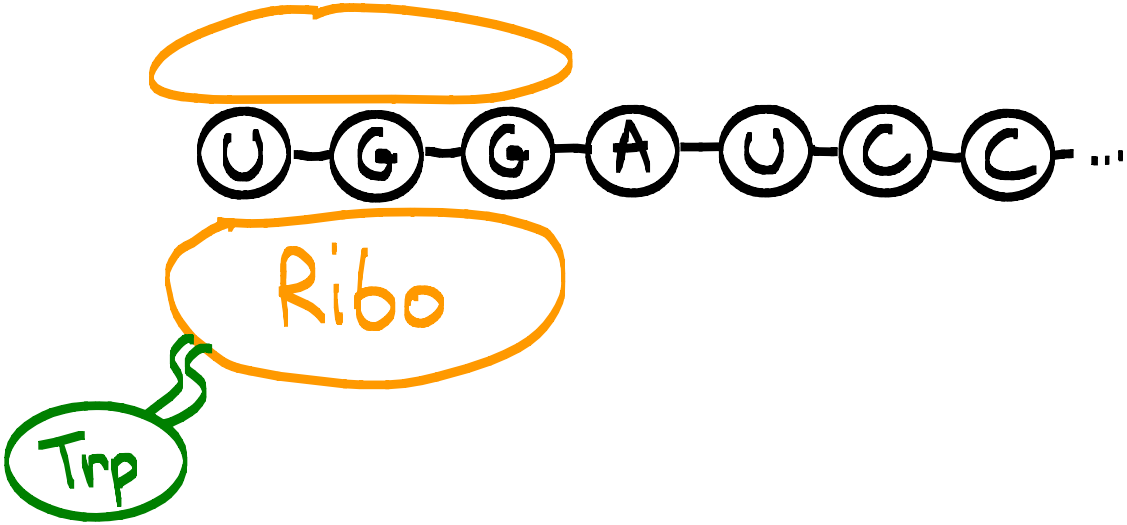

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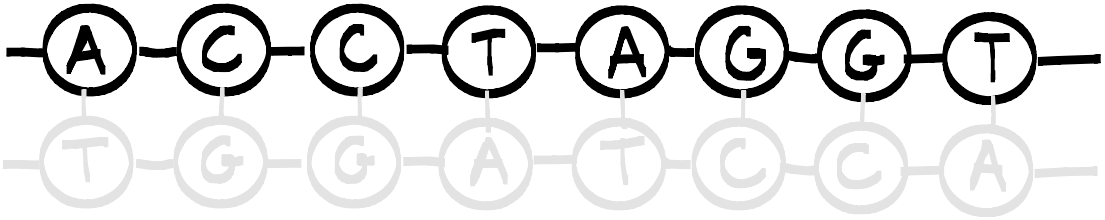

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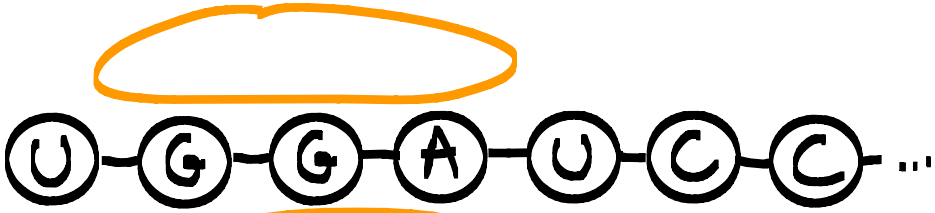

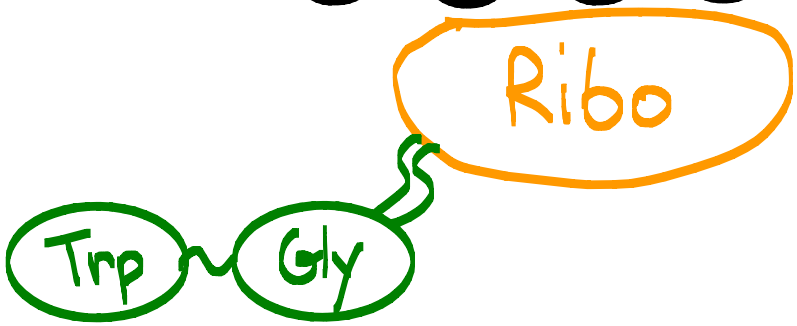

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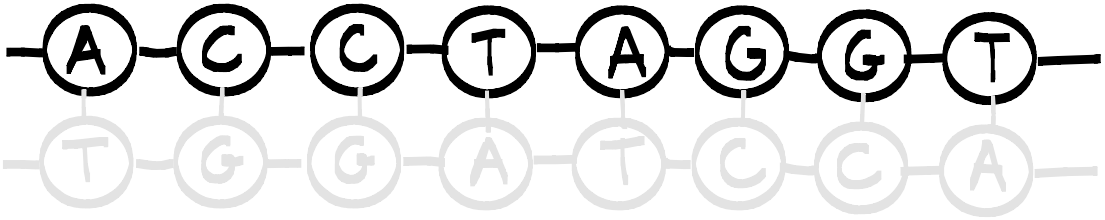

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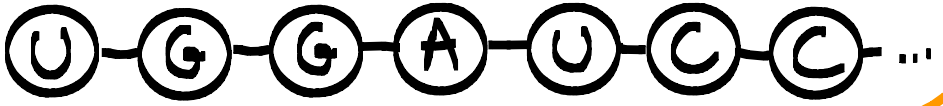

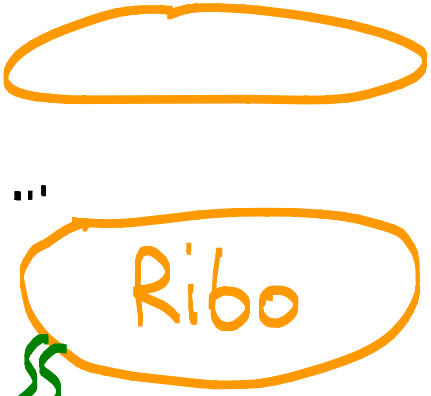

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proteins

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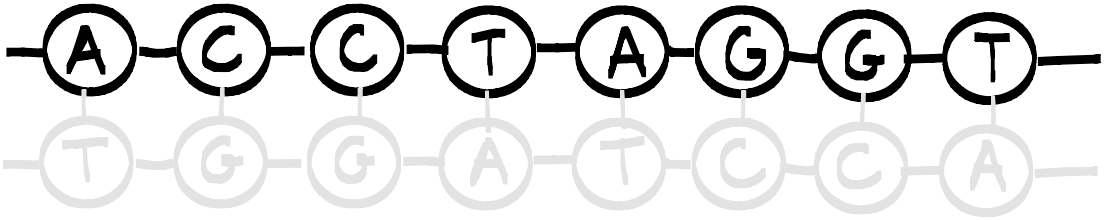

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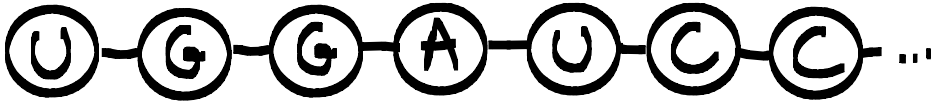

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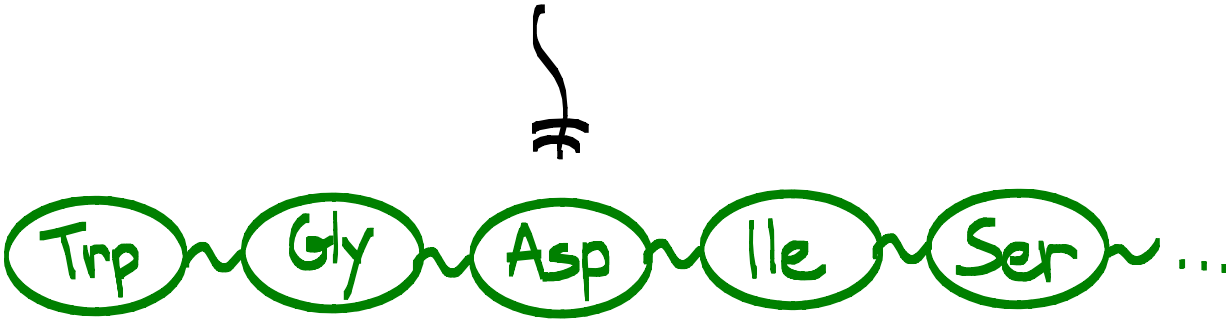
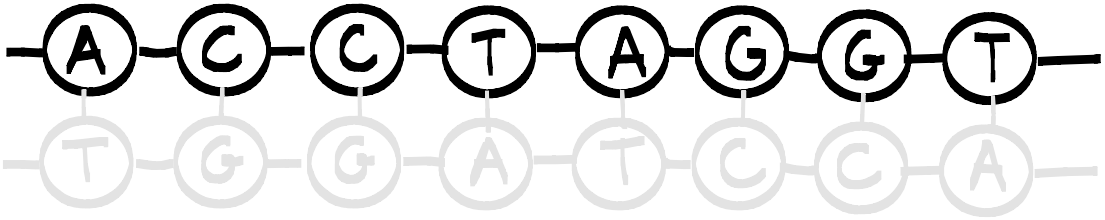
proteins



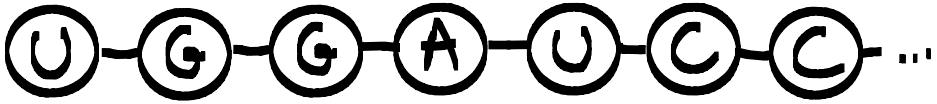
Classic dogma

WHAT IS RNA?

DNA
the code



RNA
the messenger

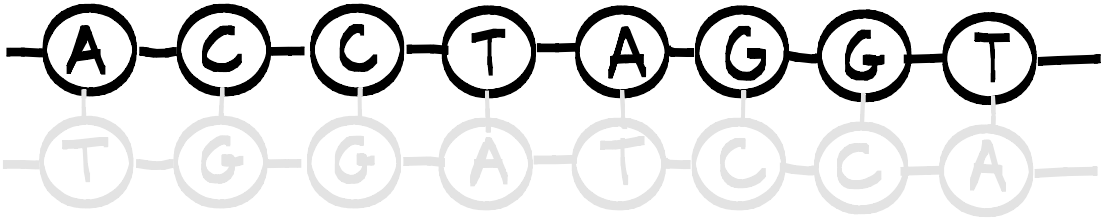


proteins
the machine

Classic dogma

WHAT IS RNA?

DNA
the code



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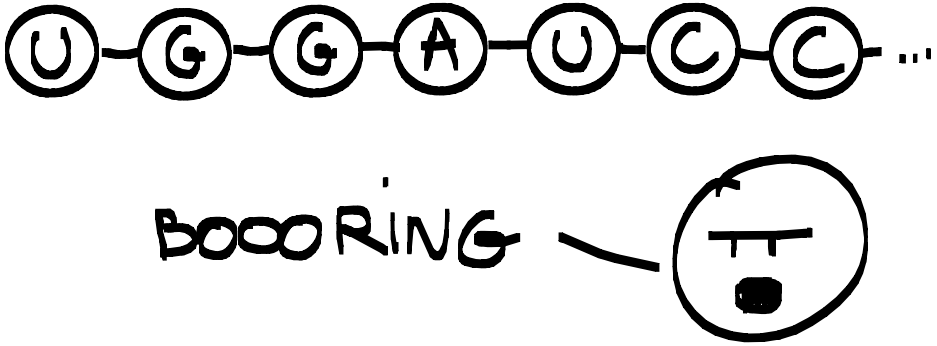
RNA
the messenger?



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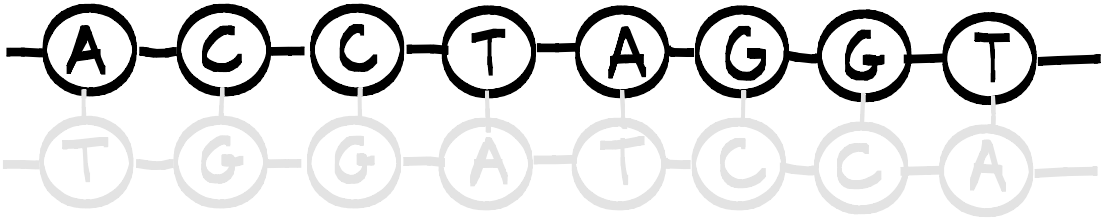
proteins
the machine

Dogma 2.0

WHAT IS RNA?

DNA
the code



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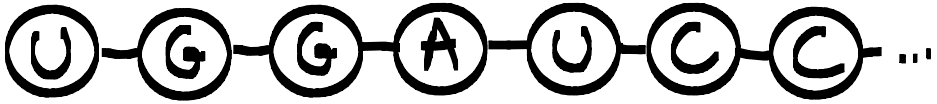


actually also... translator, enzyme,
↑ regulator, catalyst...
recent
breakthrough

↓

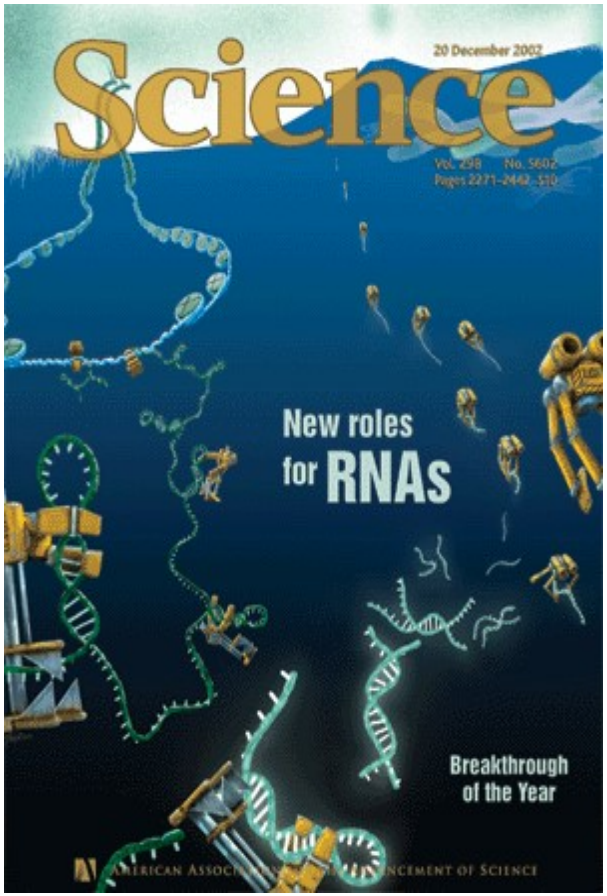
proteins
the machine

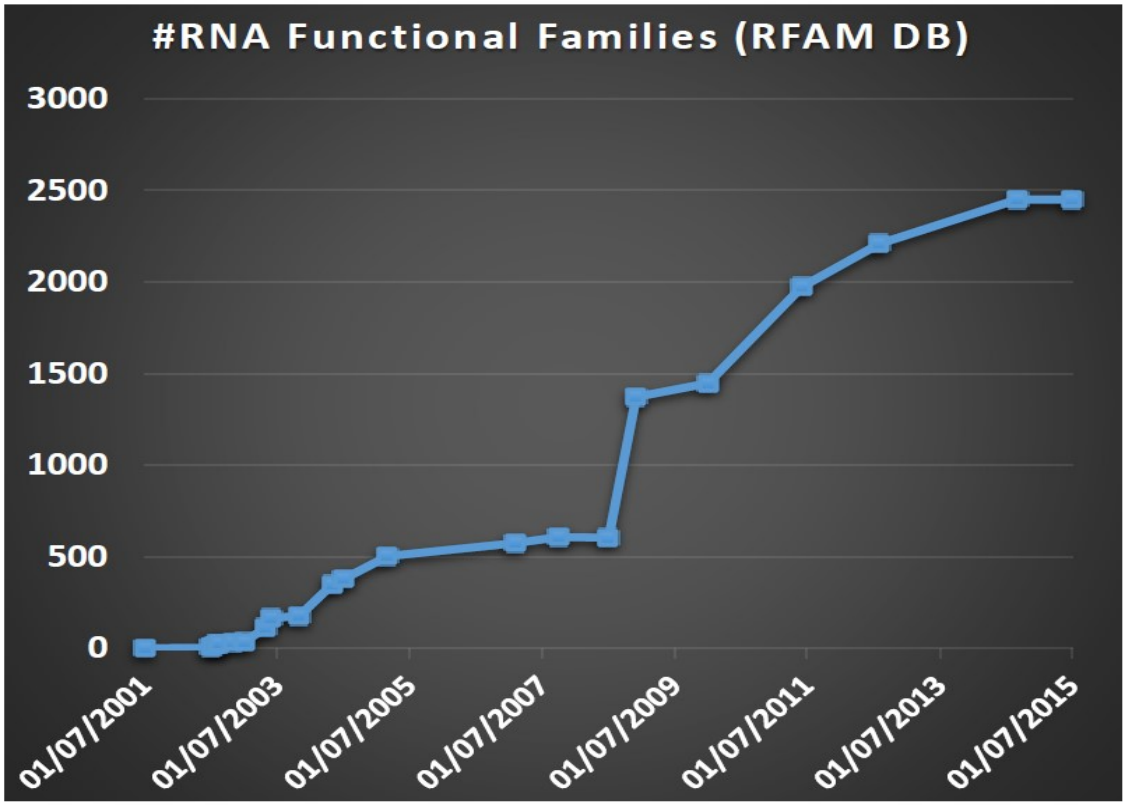
WHAT IS RNA?

RNA
the messenger

U-G-G-A-U-C-C-...

actually also... translator, regulator; enzyme, catalyst...

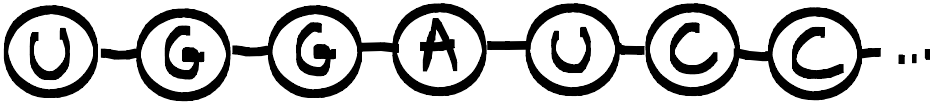




So what is RNA?

RNA is

a single-stranded molecule (chain of nucleotides)...



So what is RNA?

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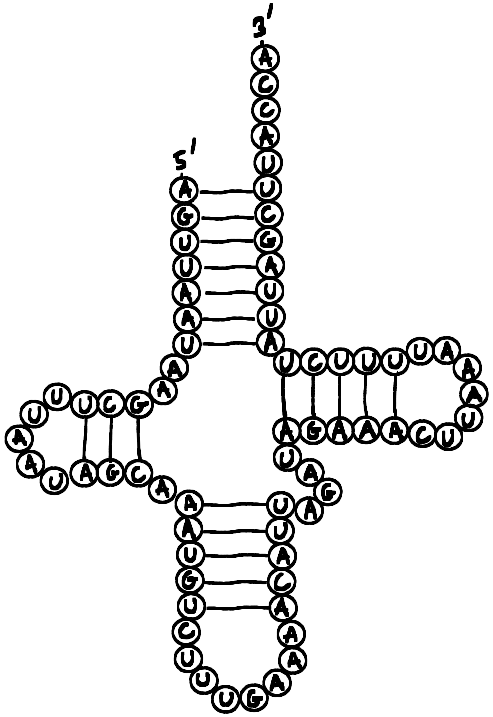
... stabilized by hydrogen bonds...



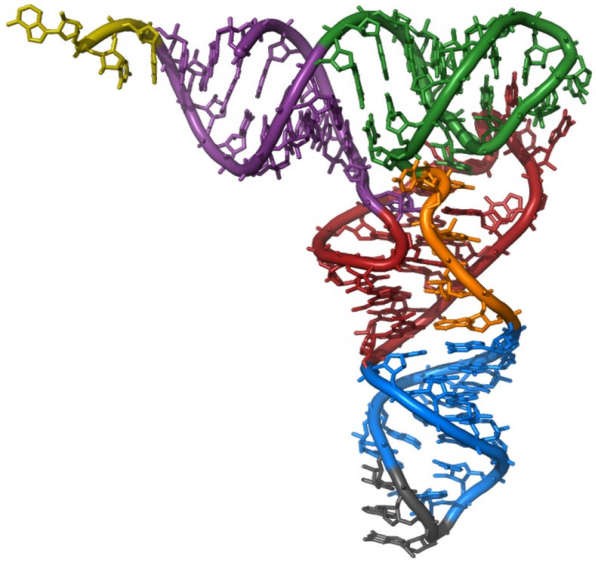
So what is RNA?

RNA is

a single-stranded molecule (chain of nucleotides)...

... stabilized by hydrogen bonds...

...which folds onto itself.



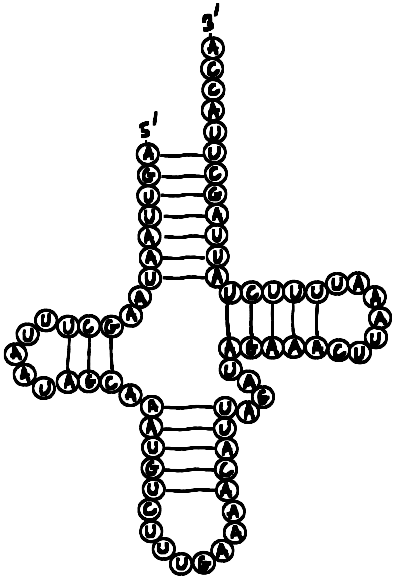
So what is RNA?

RNA is

a single-stranded molecule (chain of nucleotides)...

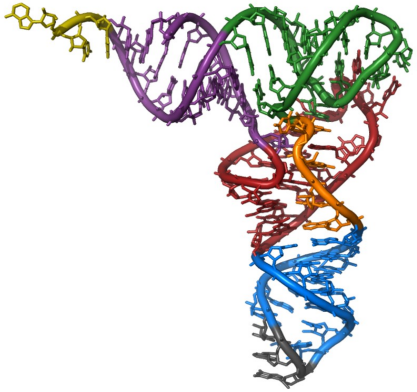
primary structure

...stabilized by hydrogen bonds...



secondary structure

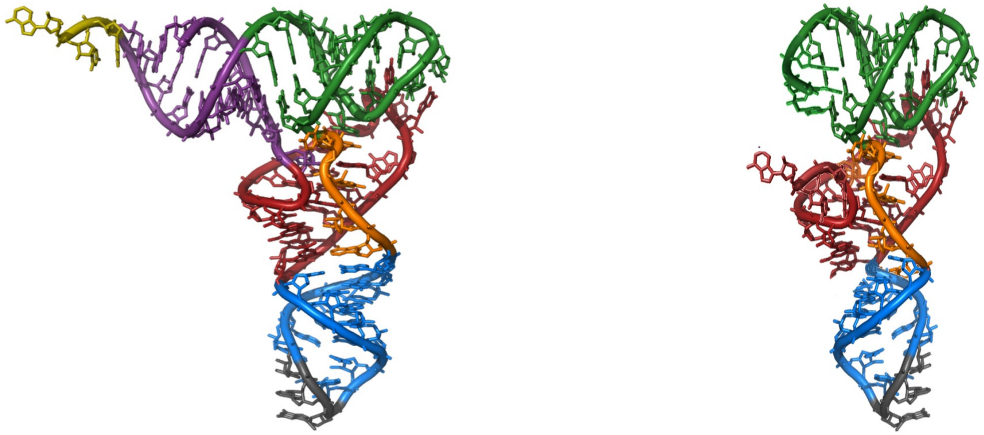
...which folds onto itself.



tertiary structure

RNA COMPARISON

Interesting problem: evaluating similarity between two RNAs.



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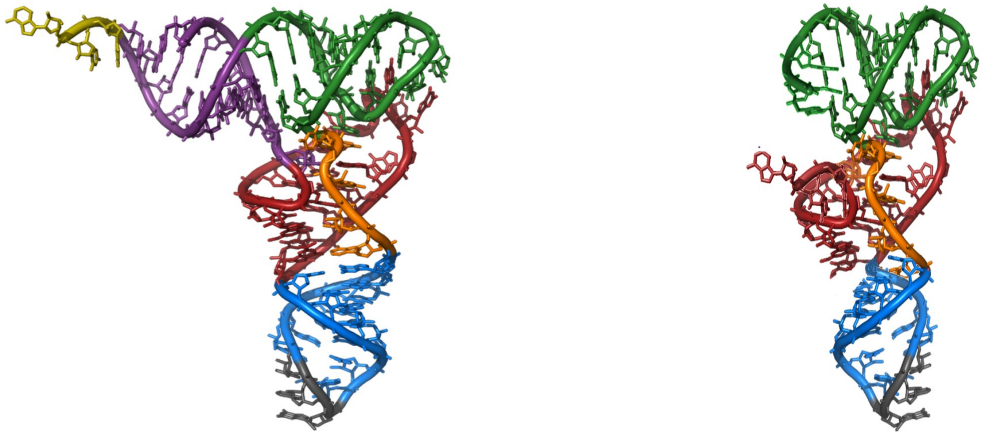

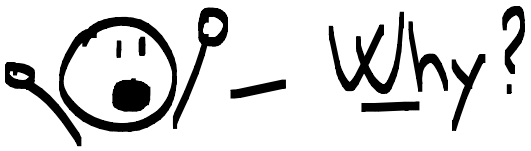

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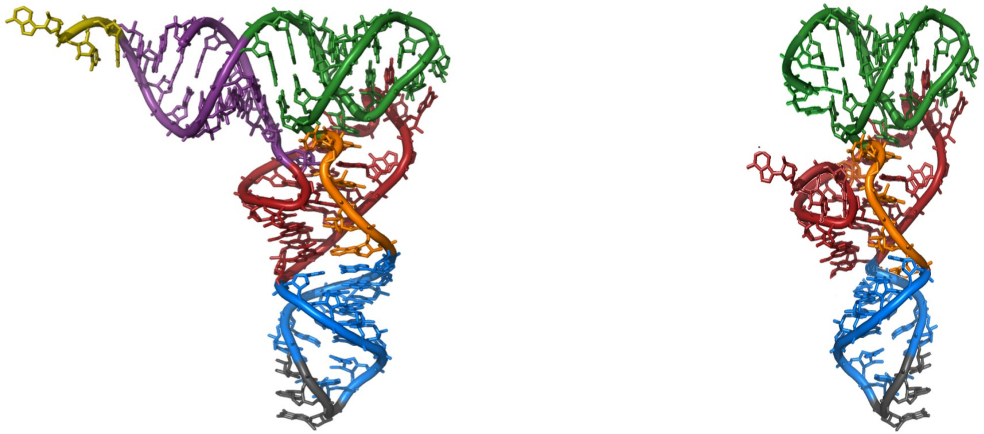
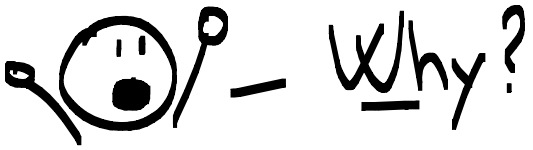
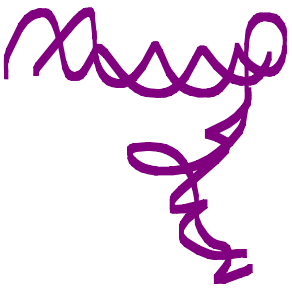


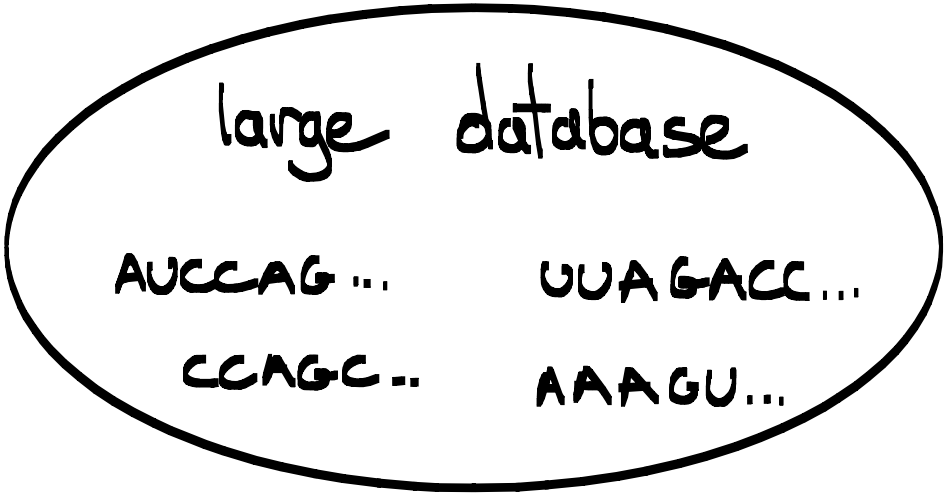


Typical situation:

New RNA →



ACAGUACC...



RNA COMPARISON

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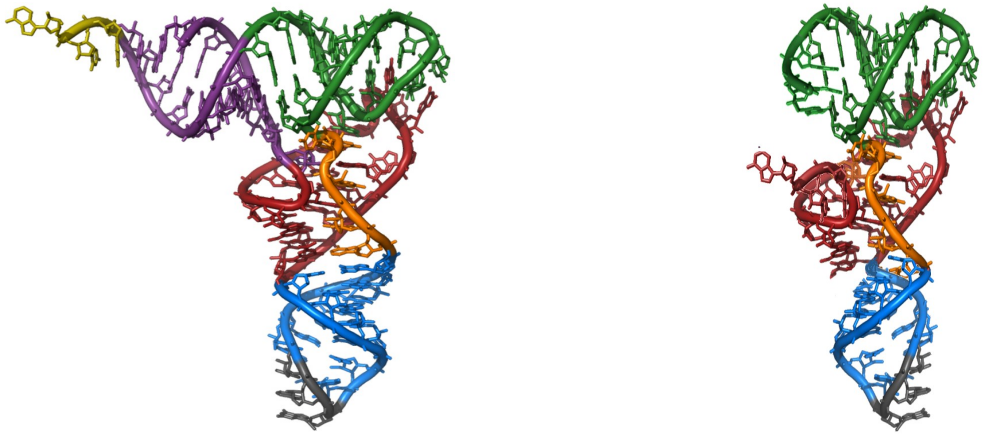

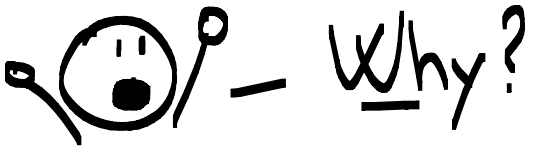

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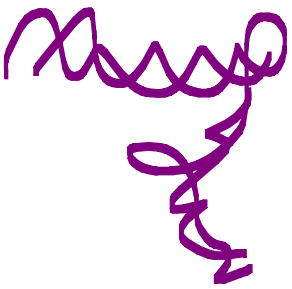
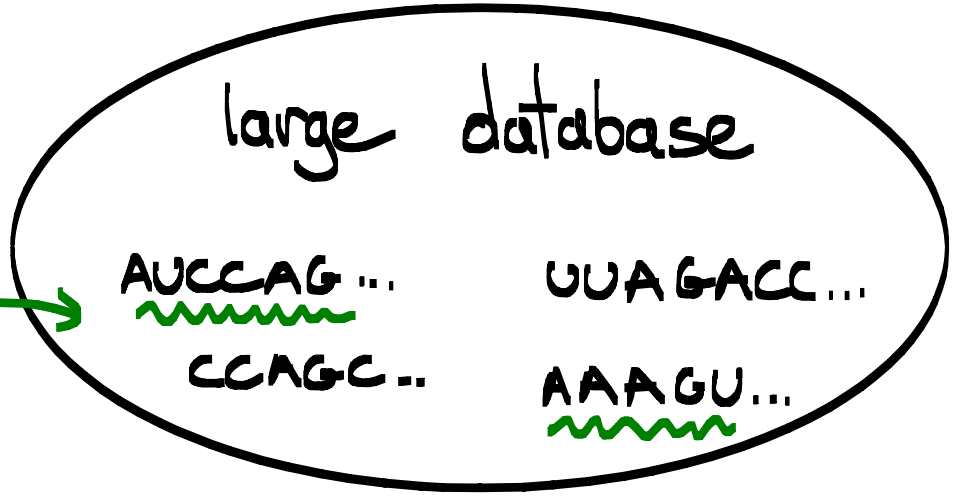


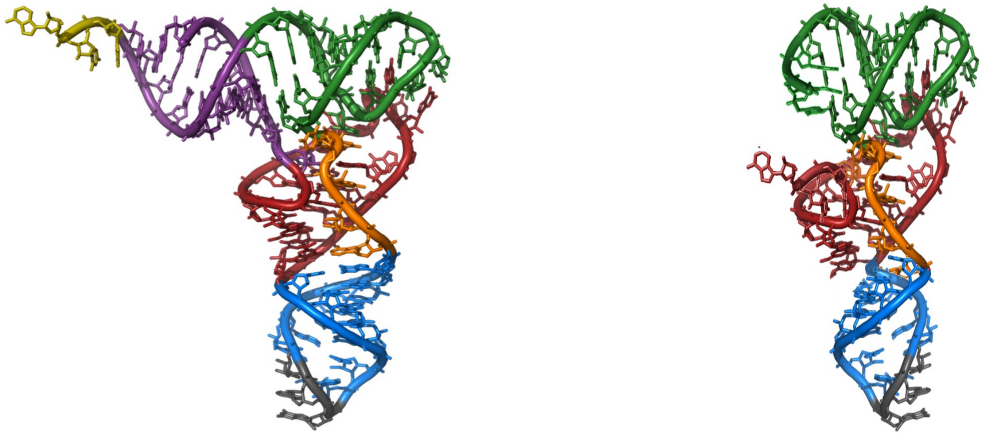
ACAGUACC...

finding similar RNAs



MOTIVATION: RNA COMPARISON

Question: how to measure similarity between two RNAs?



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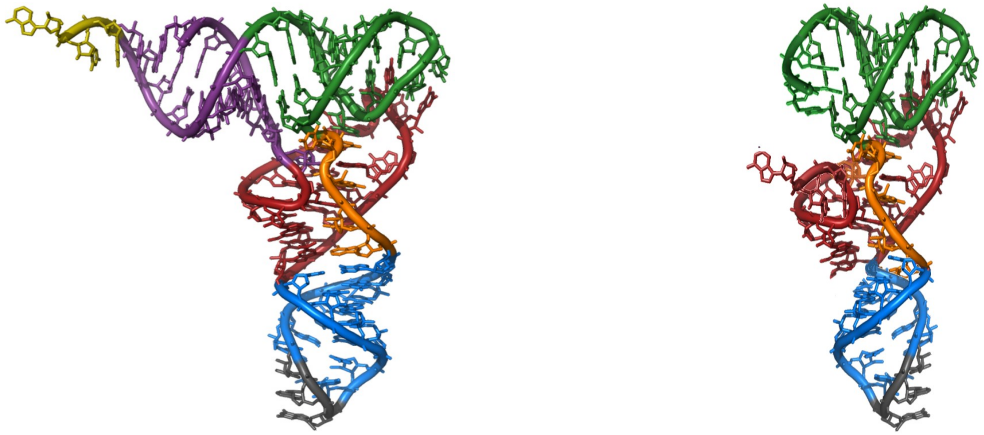


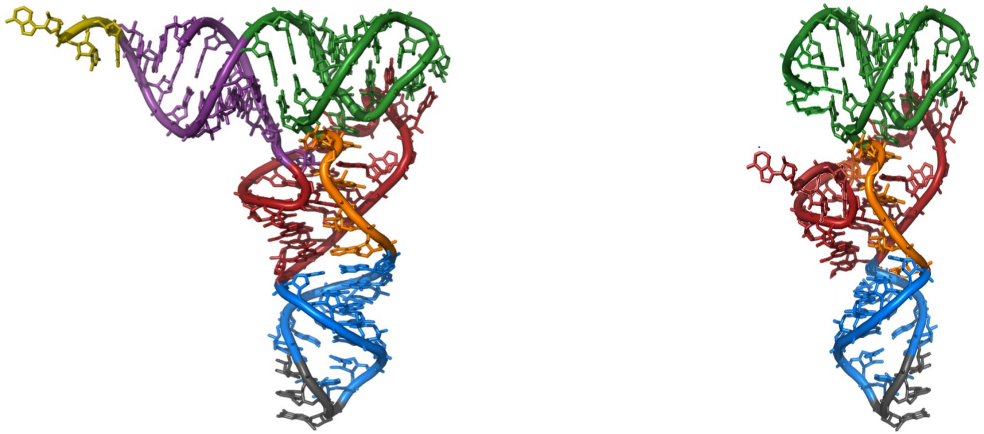
First idea: compare the primary structures.

RNA 1: AUUCGAUUA...

RNA 2: ACCAUGAUUA...

MOTIVATION: RNA COMPARISON

Question: how to measure similarity between two RNAs?



First idea: compare the primary structures.
→ sequence alignment

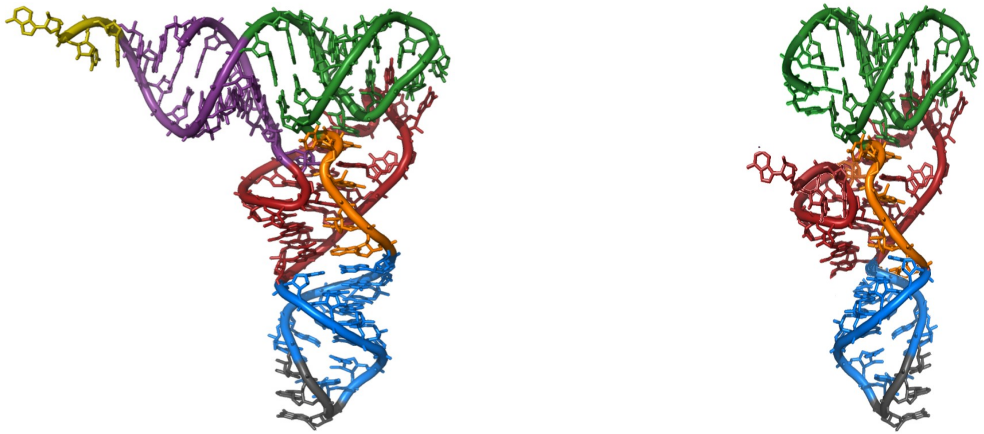
RNA 1: AUUCGAUUA...

RNA 2: ACCAUGAUUA...

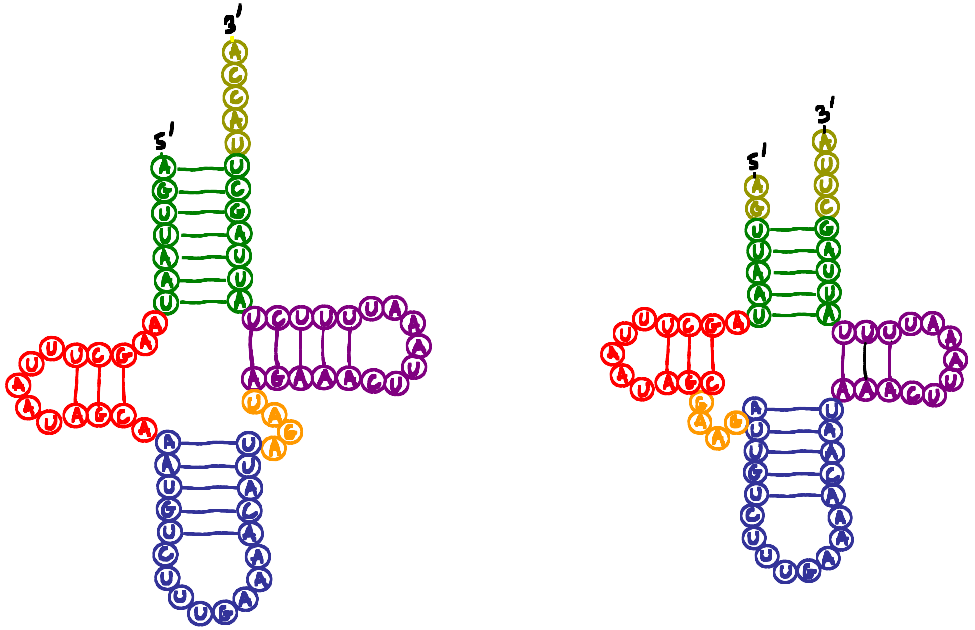
alignment: $\binom{A}{A}\binom{U}{-}\binom{-}{C}\binom{U}{-}\binom{C}{C}\binom{-}{A}\binom{-}{U}\binom{G}{G}\binom{A}{A}\binom{U}{U}\binom{U}{U}\binom{A}{A}\ldots$

MOTIVATION: RNA COMPARISON

Question: how to measure similarity between two RNAs?

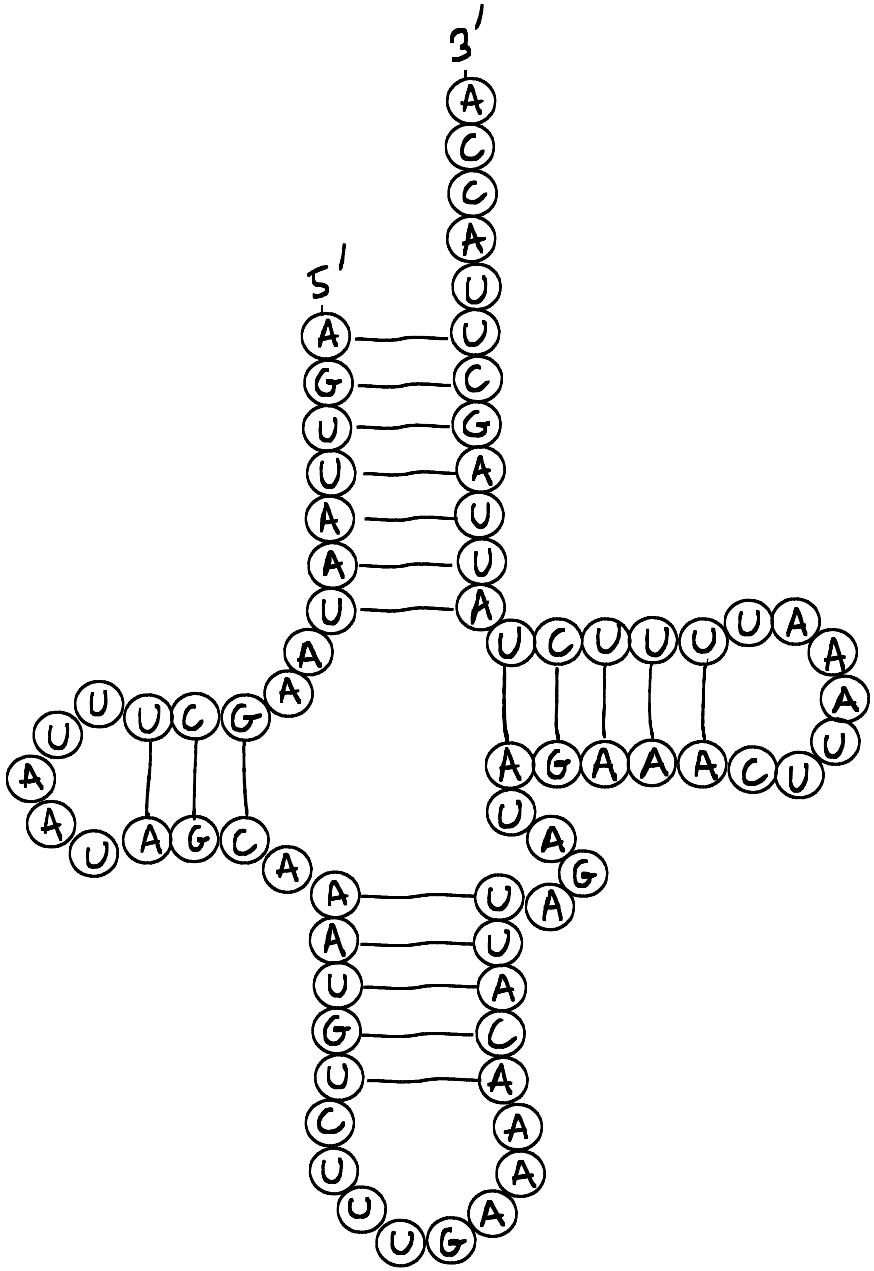


Second idea: compare secondary structures.

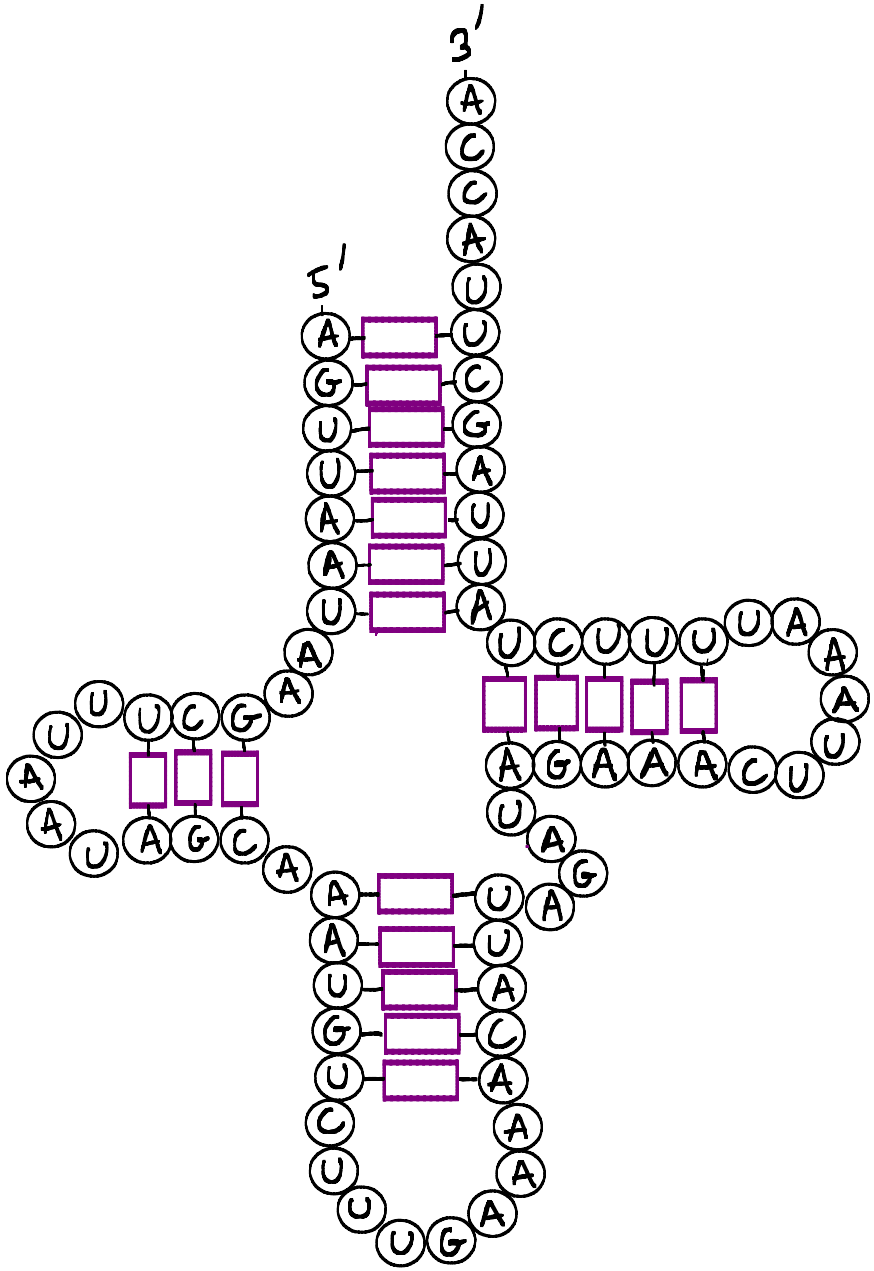


→ notion of tree alignment [Jiang, Wang, Zhang]

FROM SECONDARY STRUCTURES TO TREES



FROM SECONDARY STRUCTURES TO TREES



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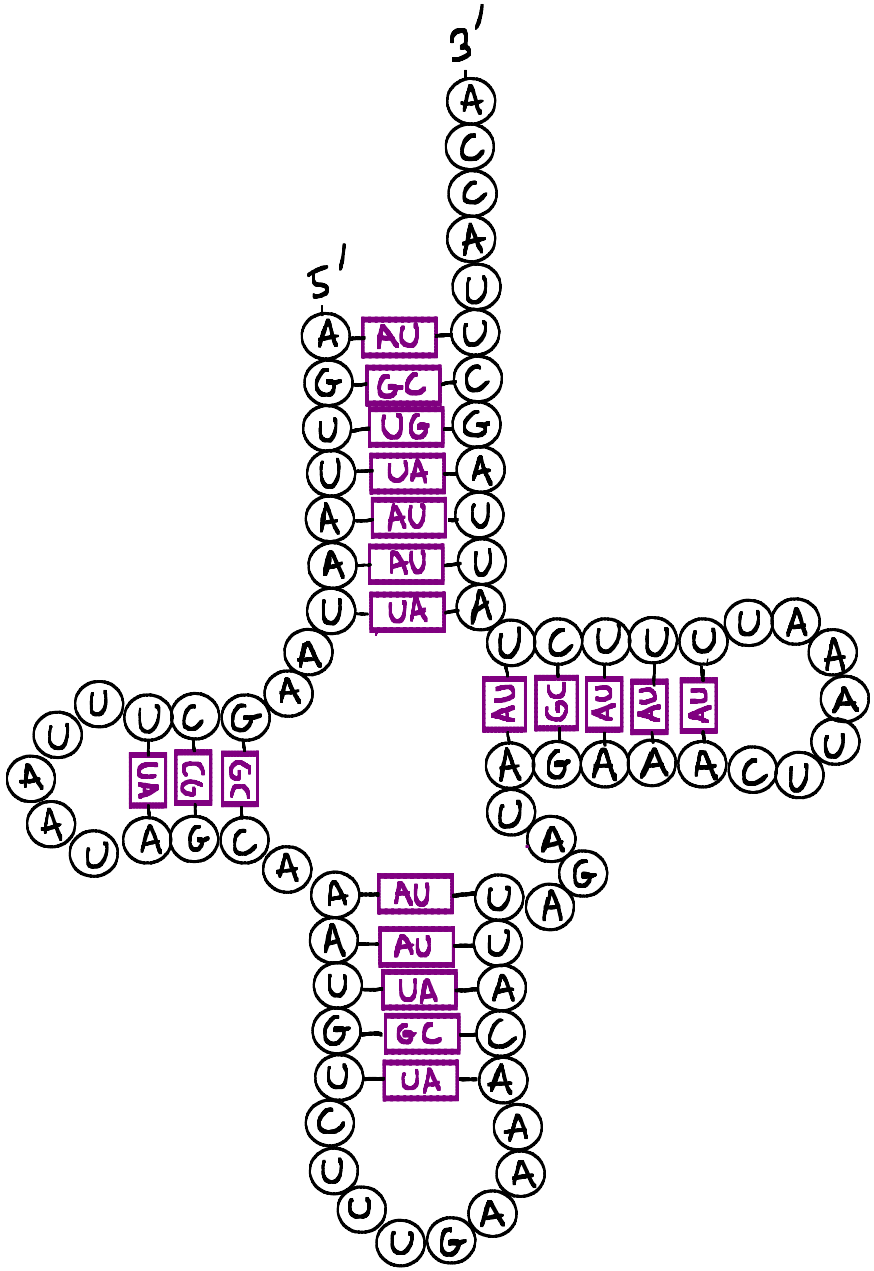

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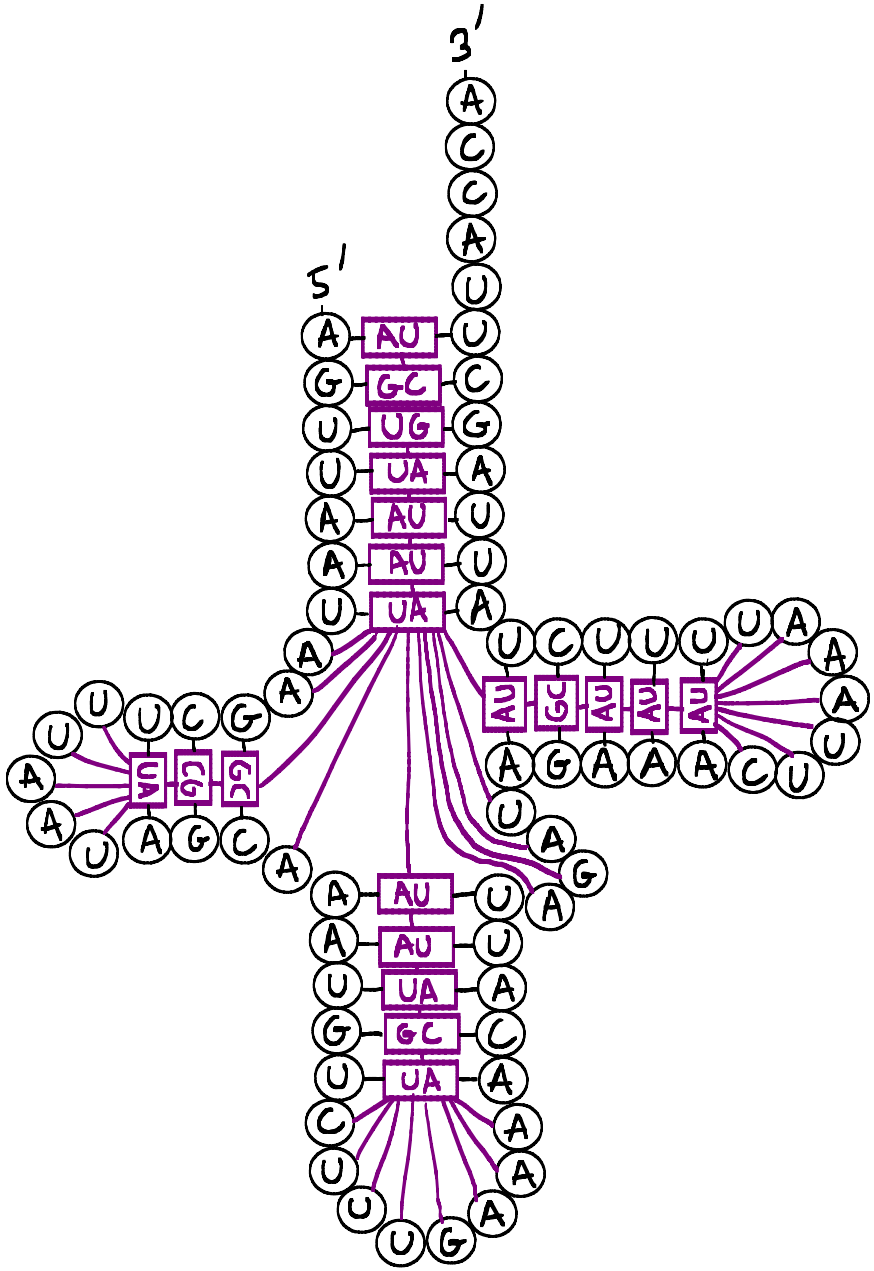

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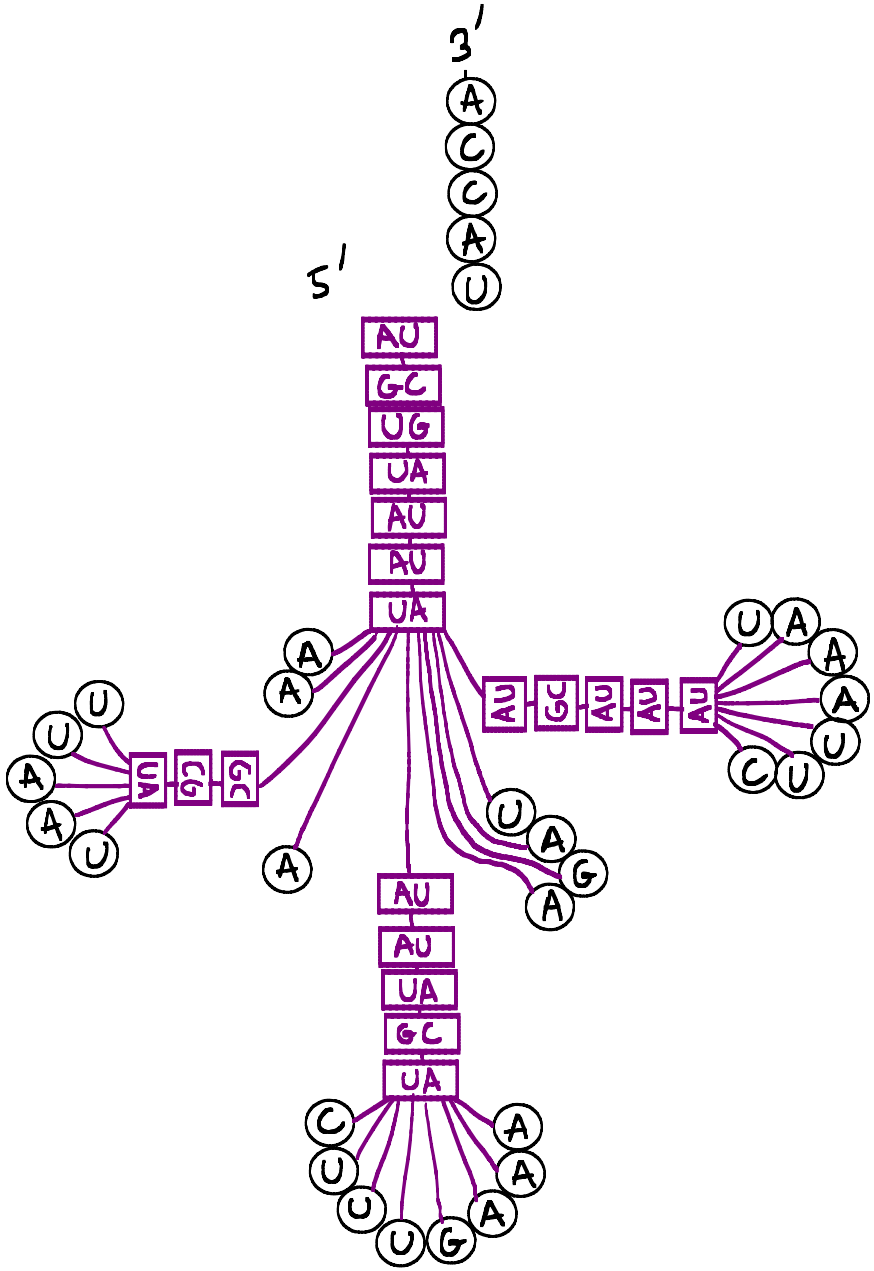

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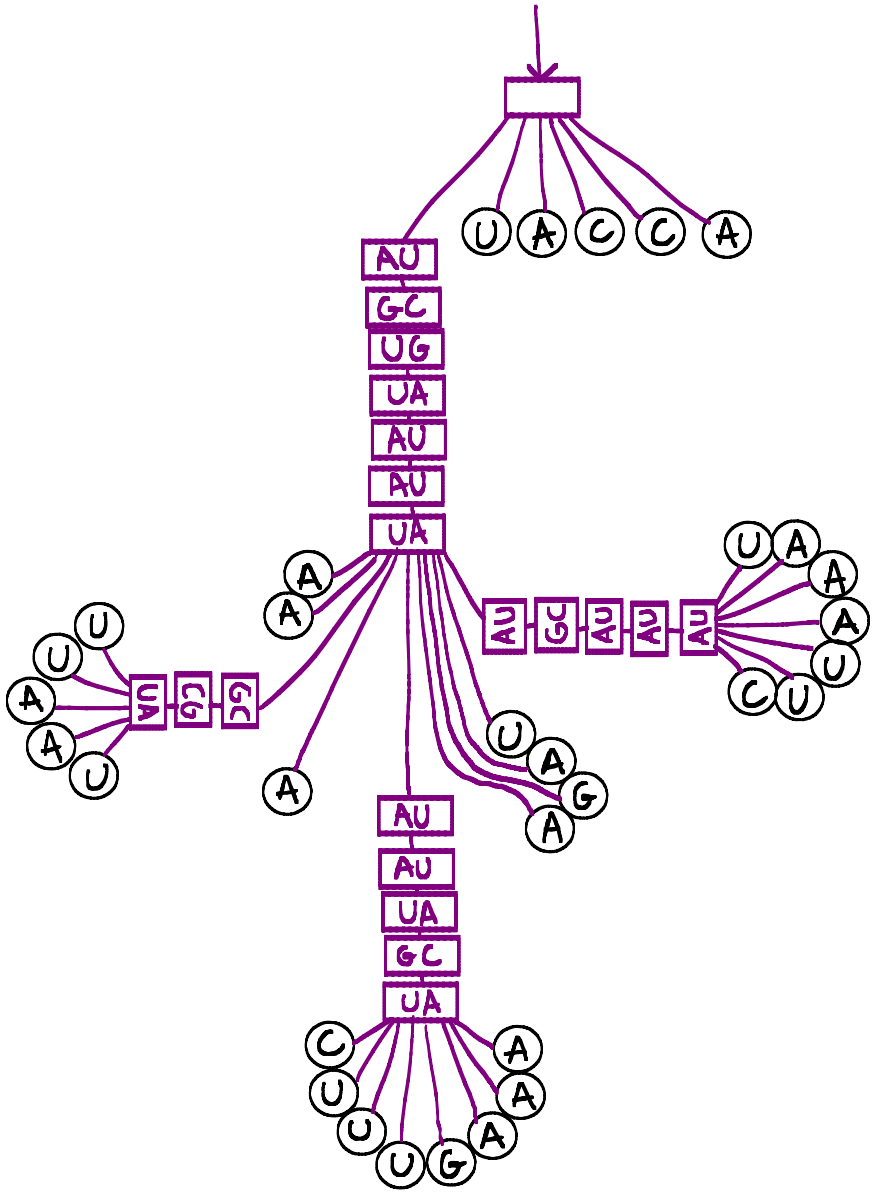

FROM SECONDARY STRUCTURES TO TREES

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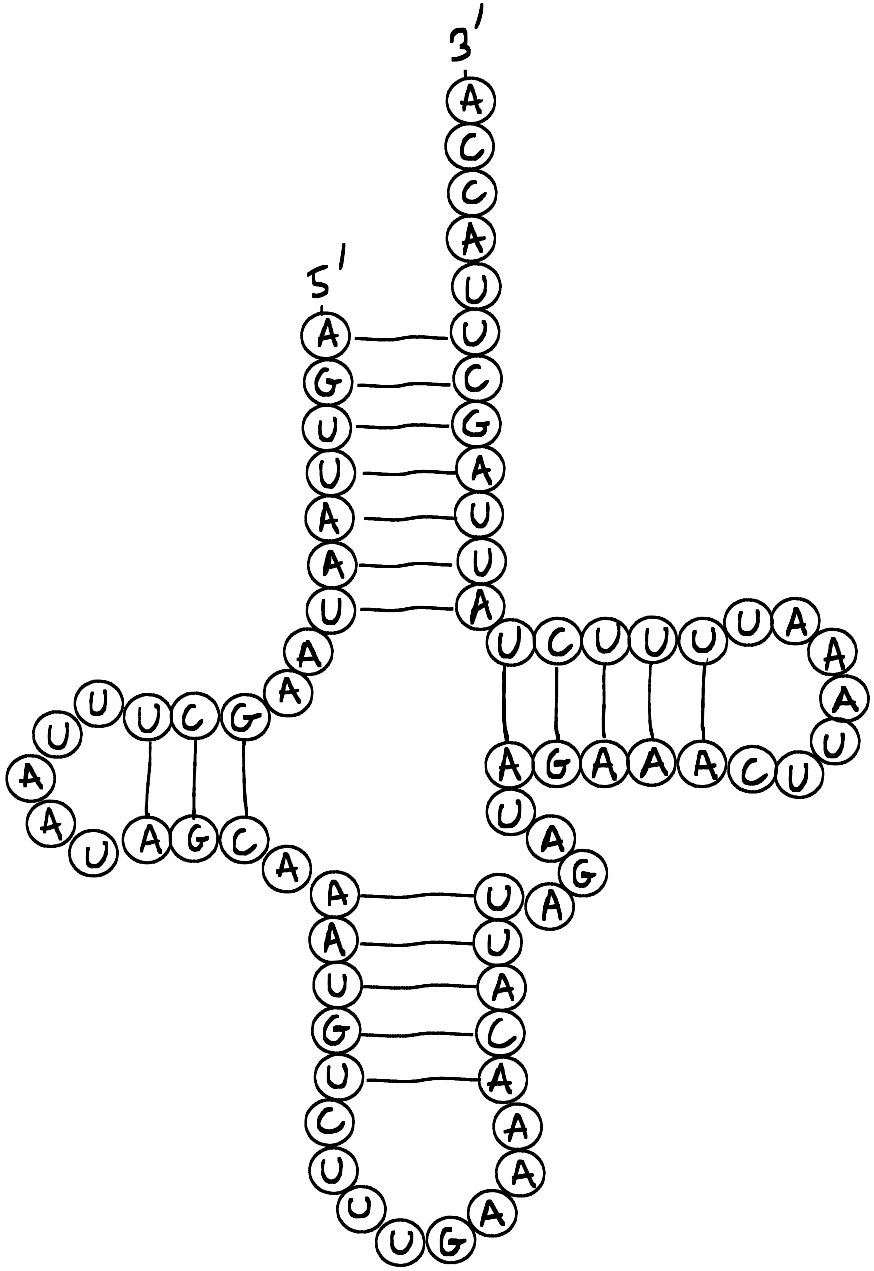

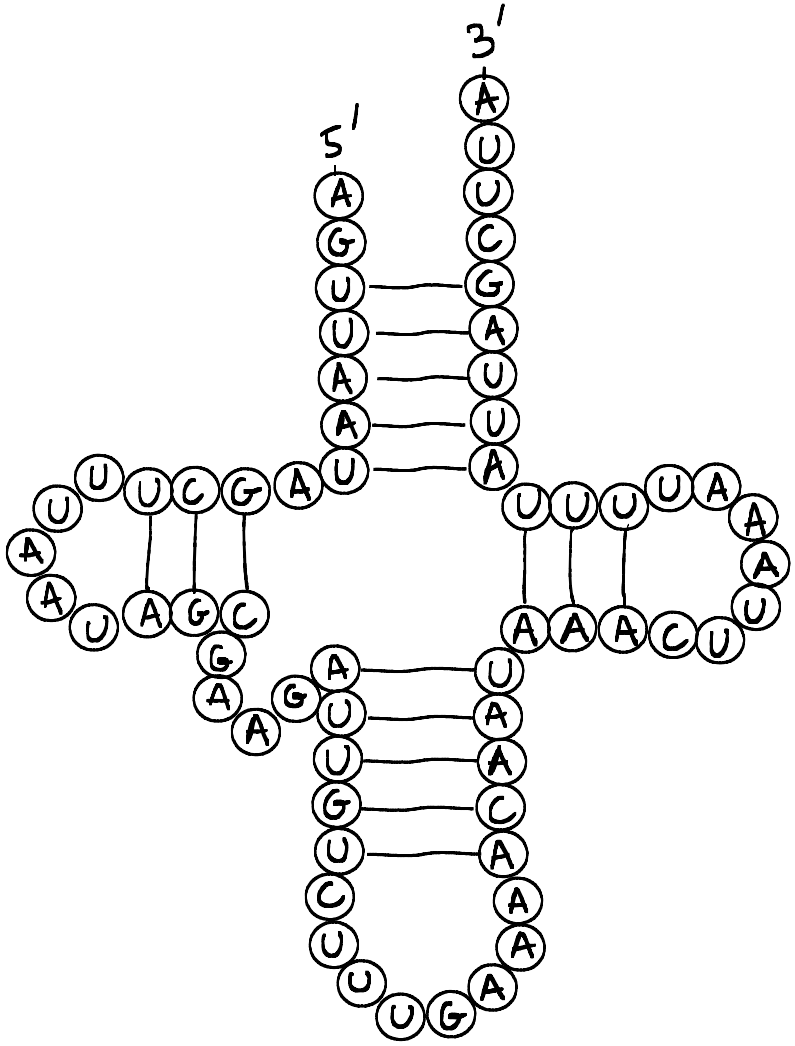

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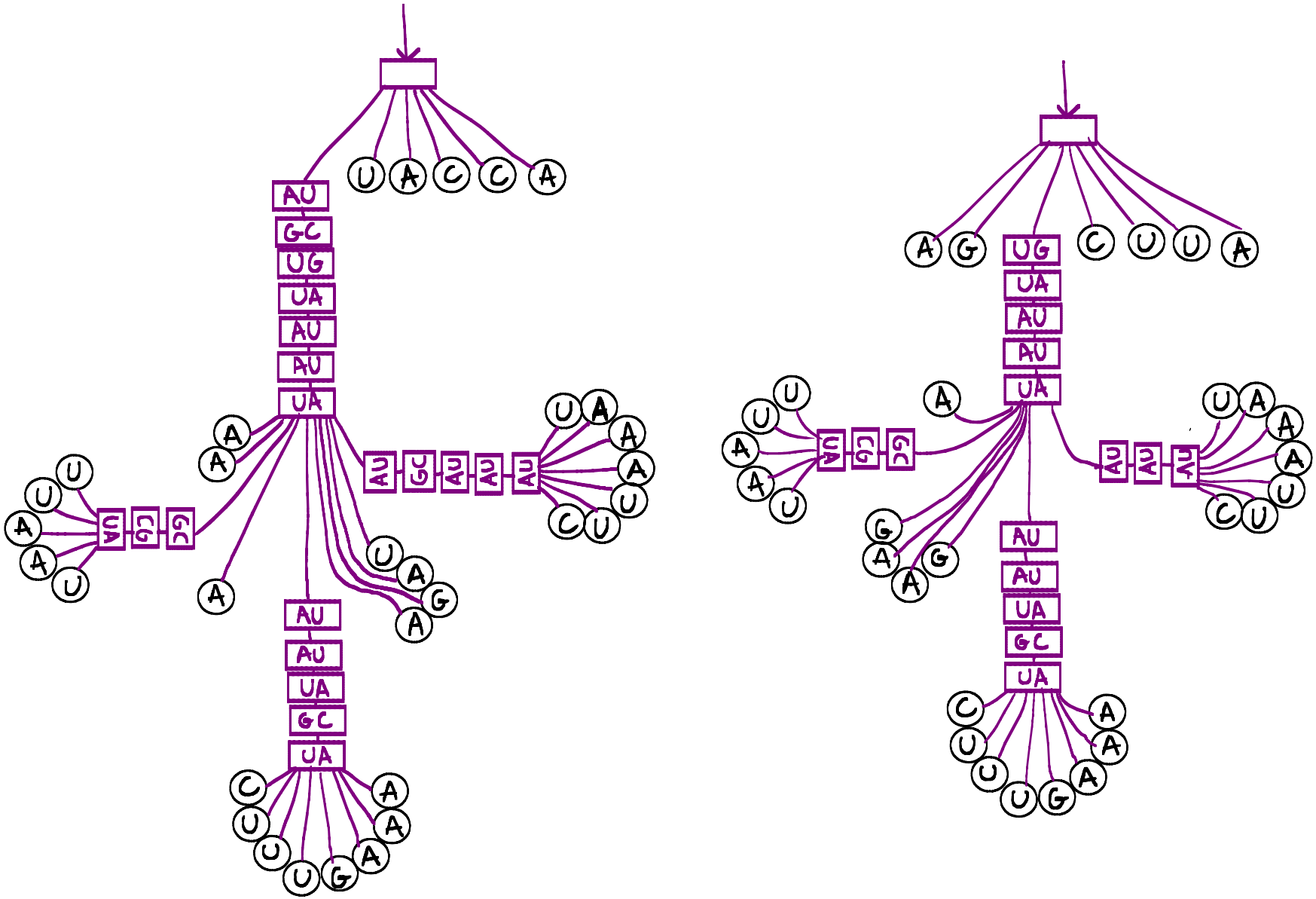
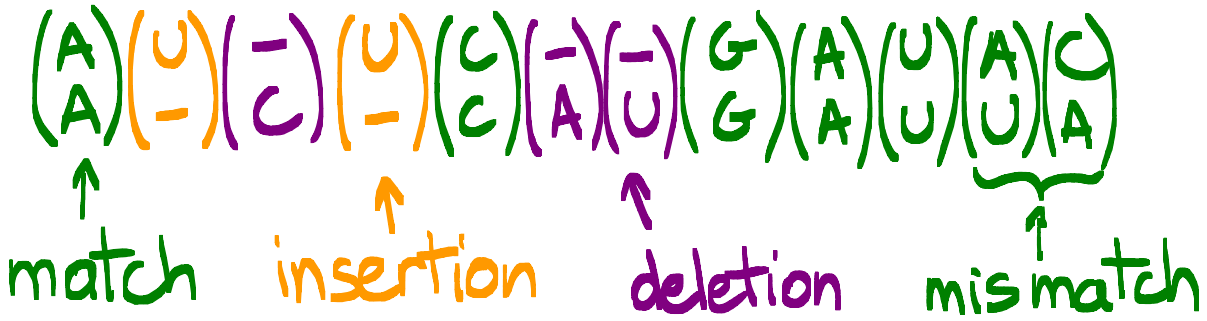


SEQUENCE ALIGNMENT

super sequence = word on $\Sigma \times \Sigma \oplus \Sigma \times \{-\} \oplus \{-\} \times \Sigma$



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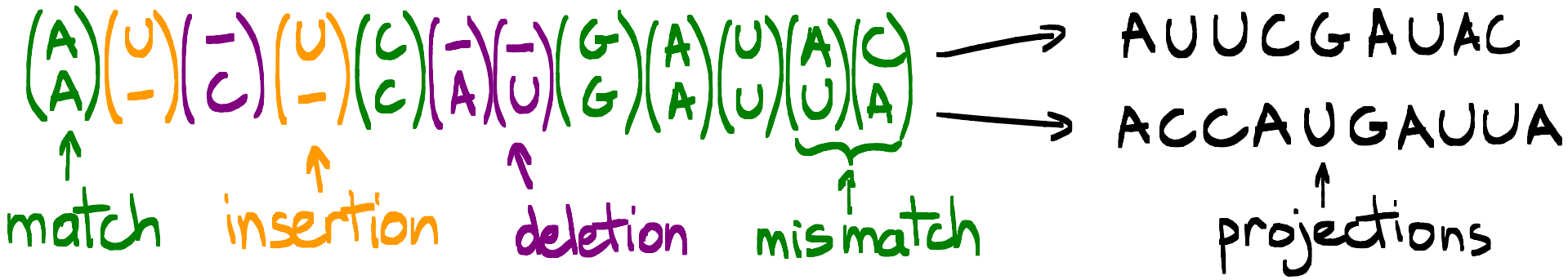

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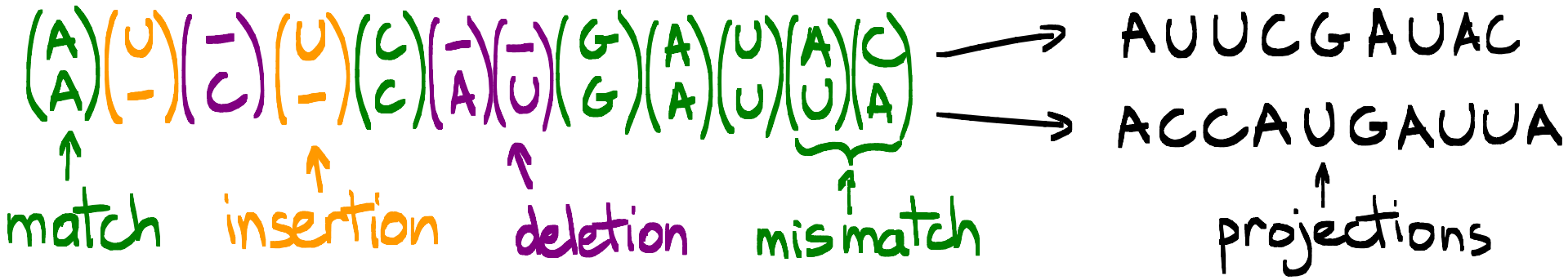

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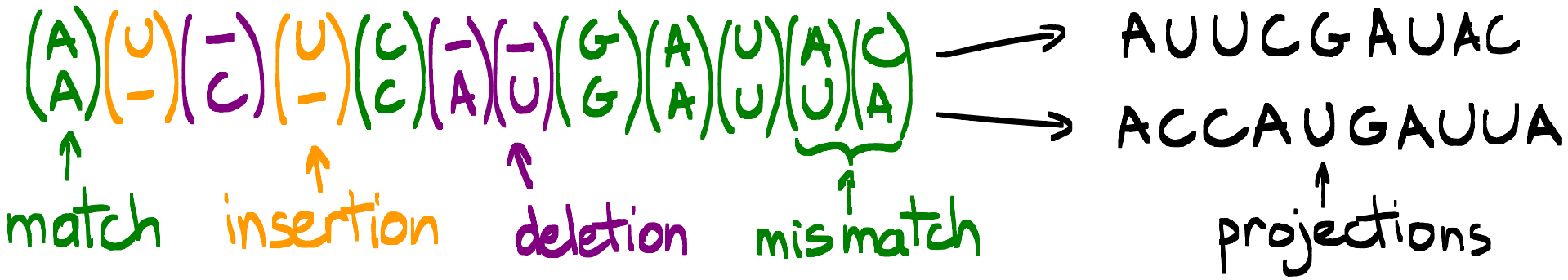

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cost of an alignment = nb of insertions + deletions + mismatches

OPTIMAL ALIGNMENT

Classical problem: Given S_1 and S_2, find one optimal alignment between S_1 and S_2.

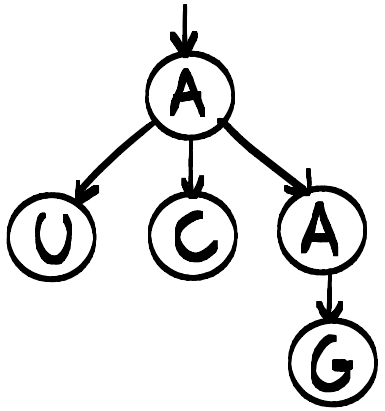
Solvable by Dynamic Programming:

- → Needleman-Wunsch algorithm
- → Smith-Waterman algorithm
- → BLAST (heuristic)

Worst case and average time: $O(n^2)$

TREES AND SUPERTREES

Trees are plane, rooted, and vertices are labeled by an alphabet $\sum$.

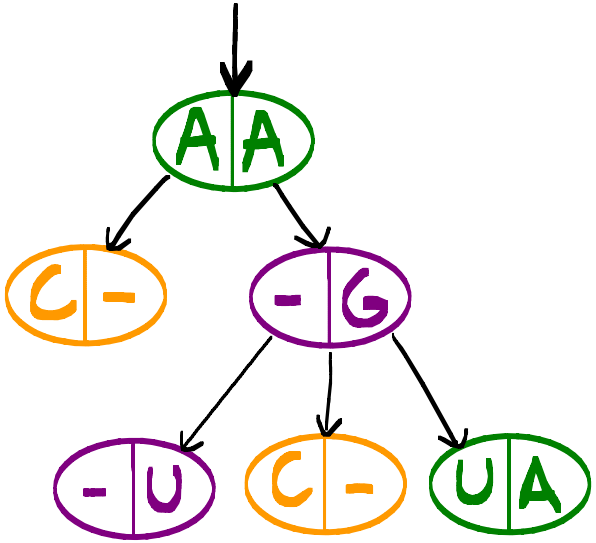


Supertree = tree with 3 types of vertices:

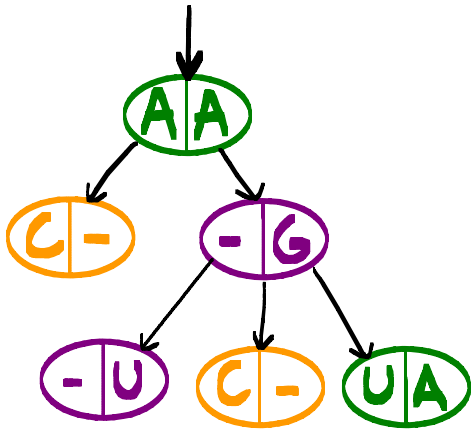
(mis)match

insertion

deletion



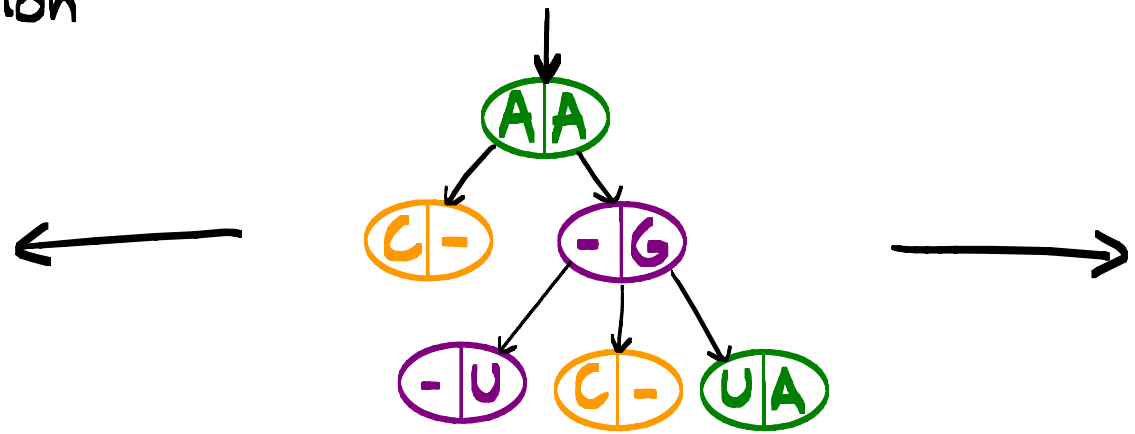
TREE ALIGNMENTS



TREE ALIGNMENTS

first projection

second projection



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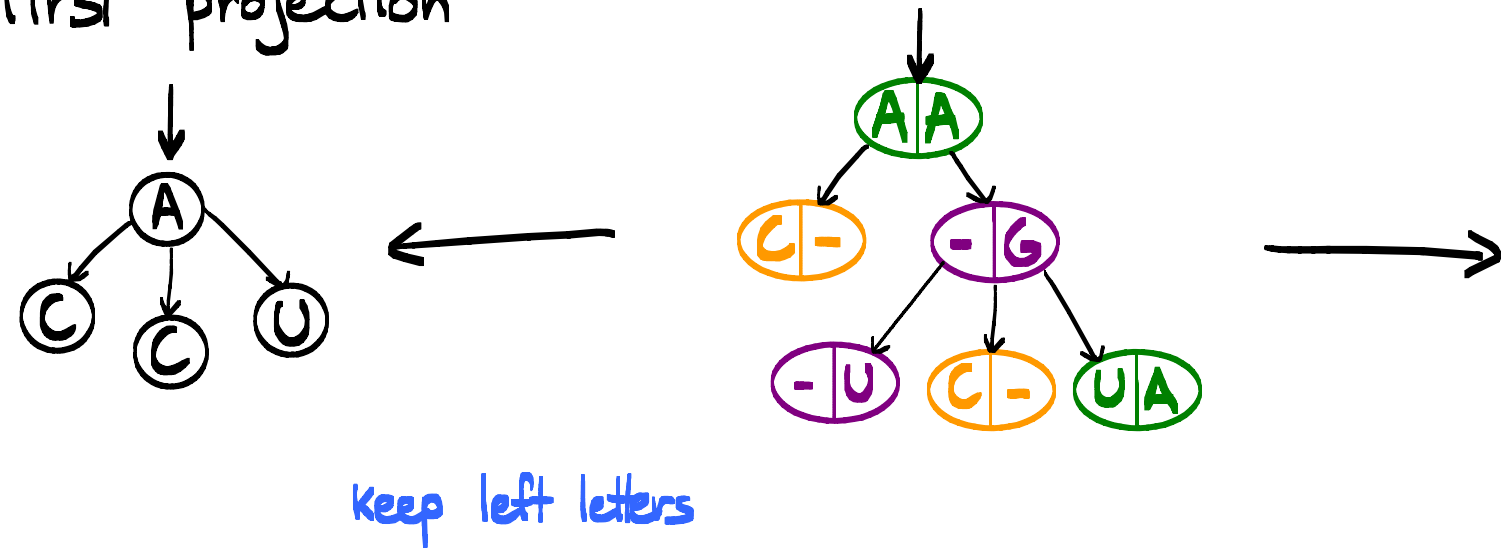
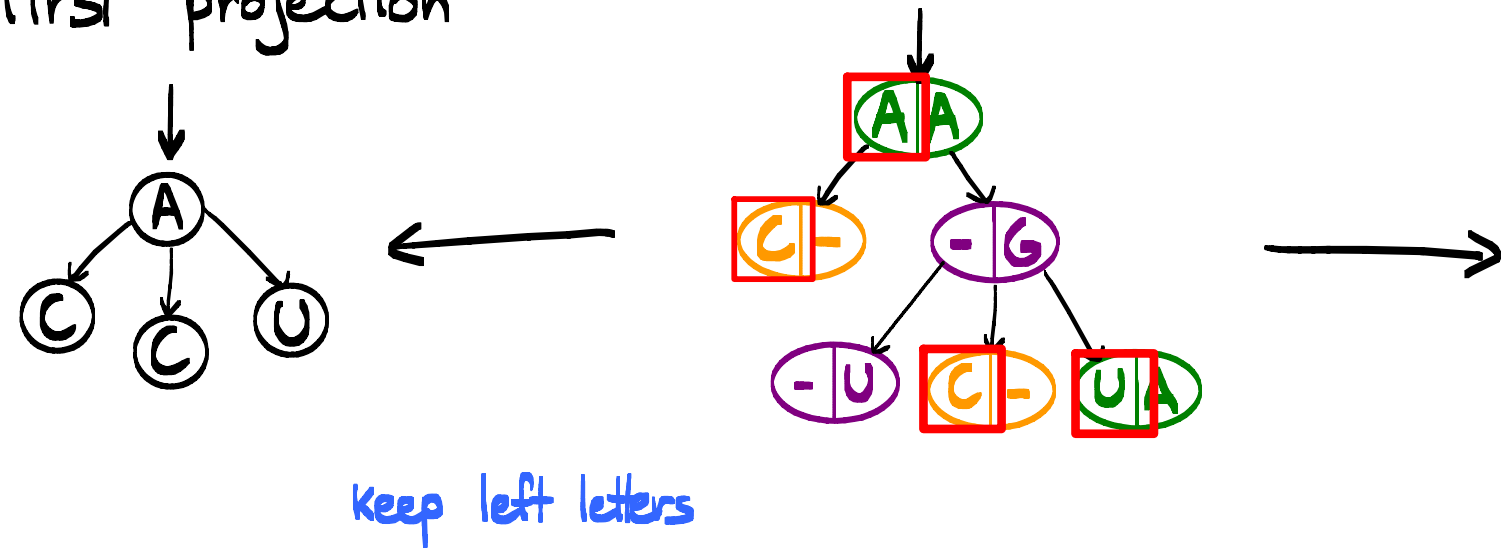


Keep left letters

TREE ALIGNMENTS

first projection

second projection



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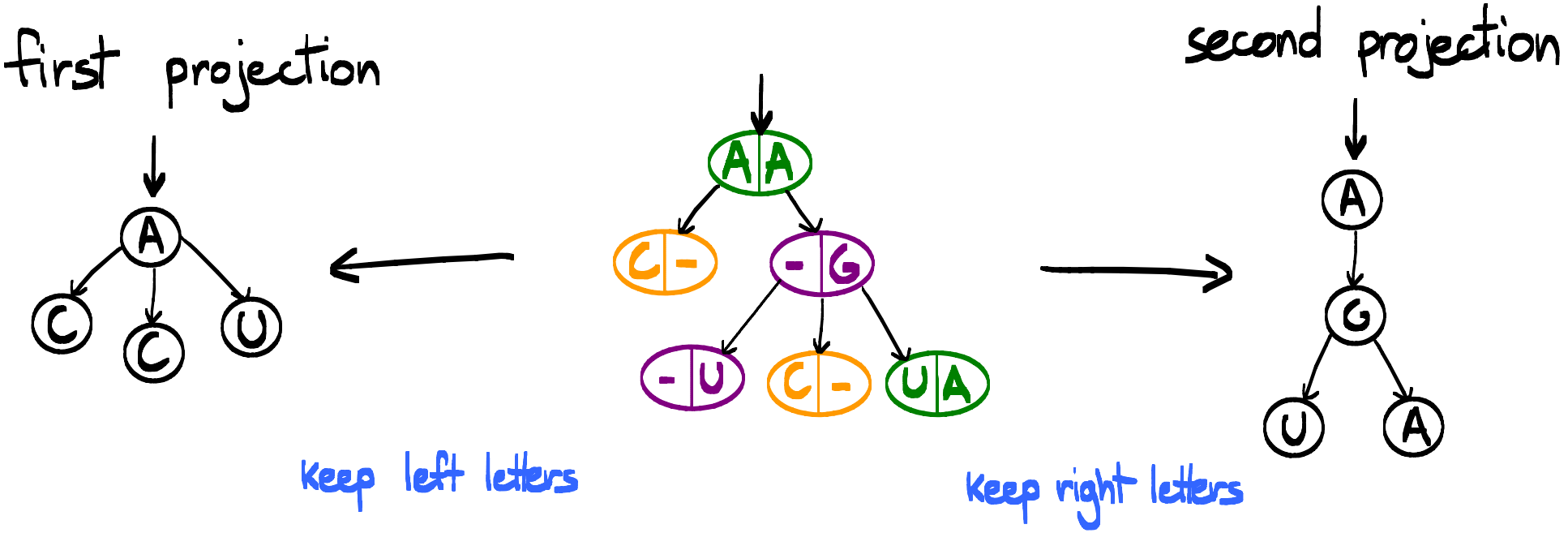

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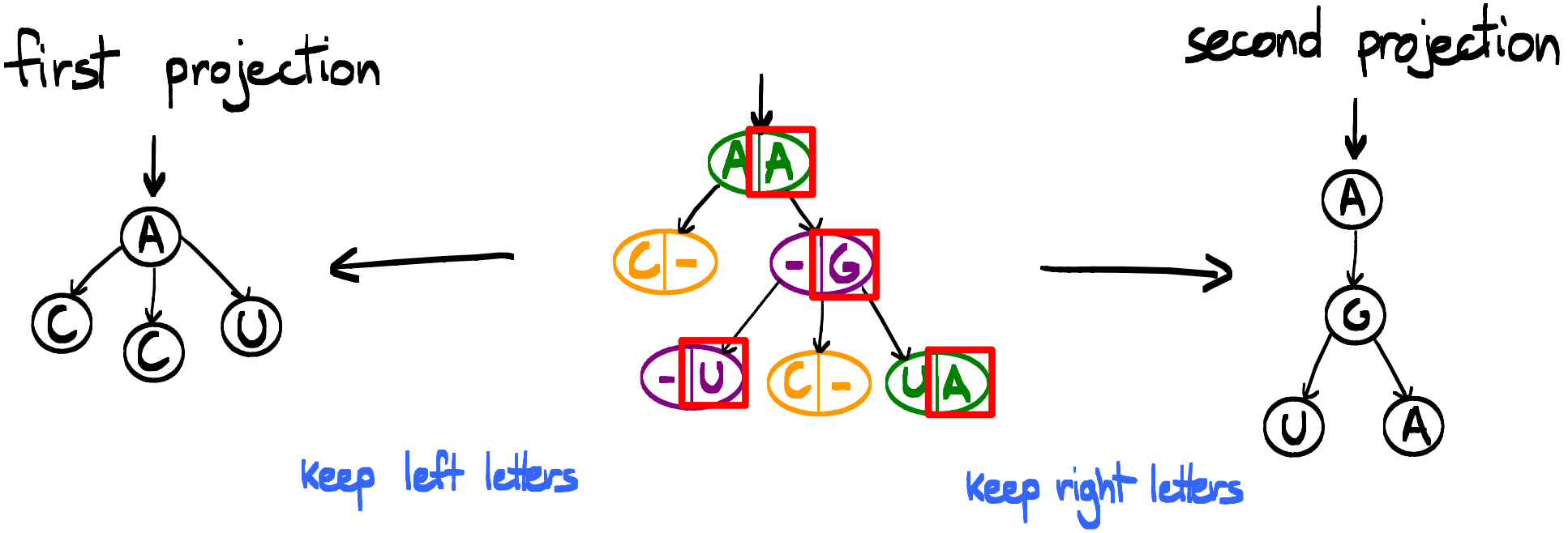

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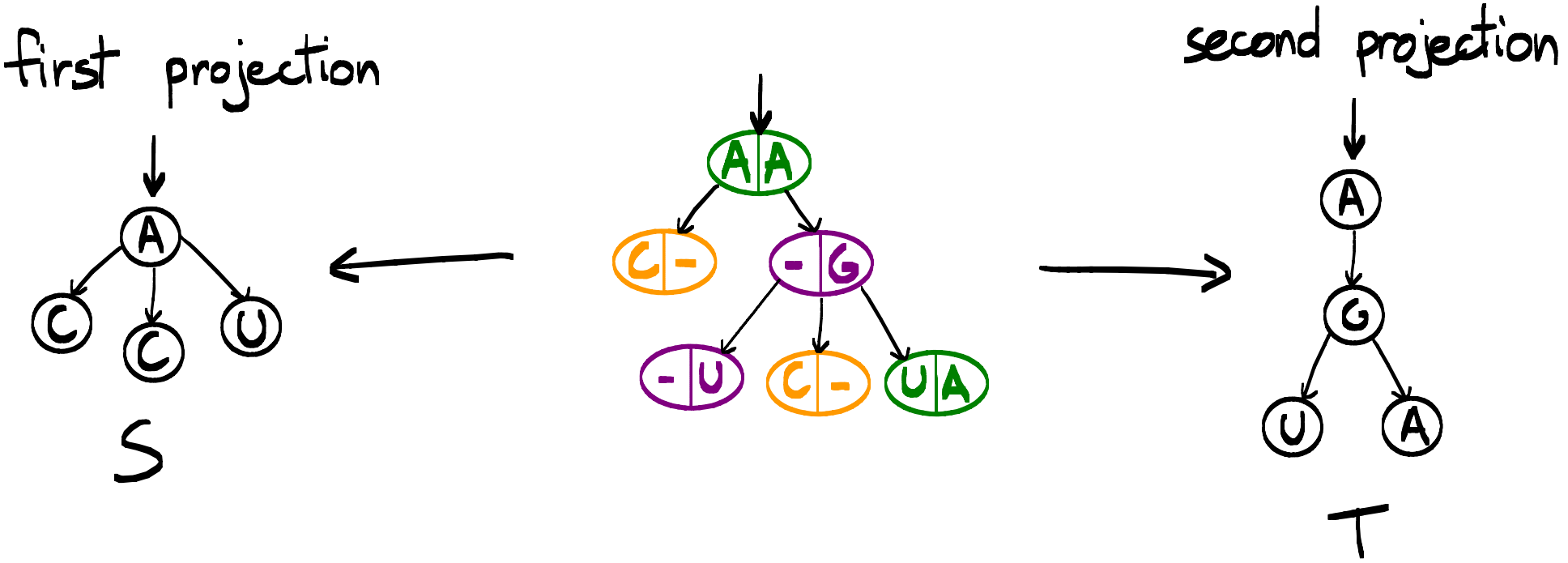
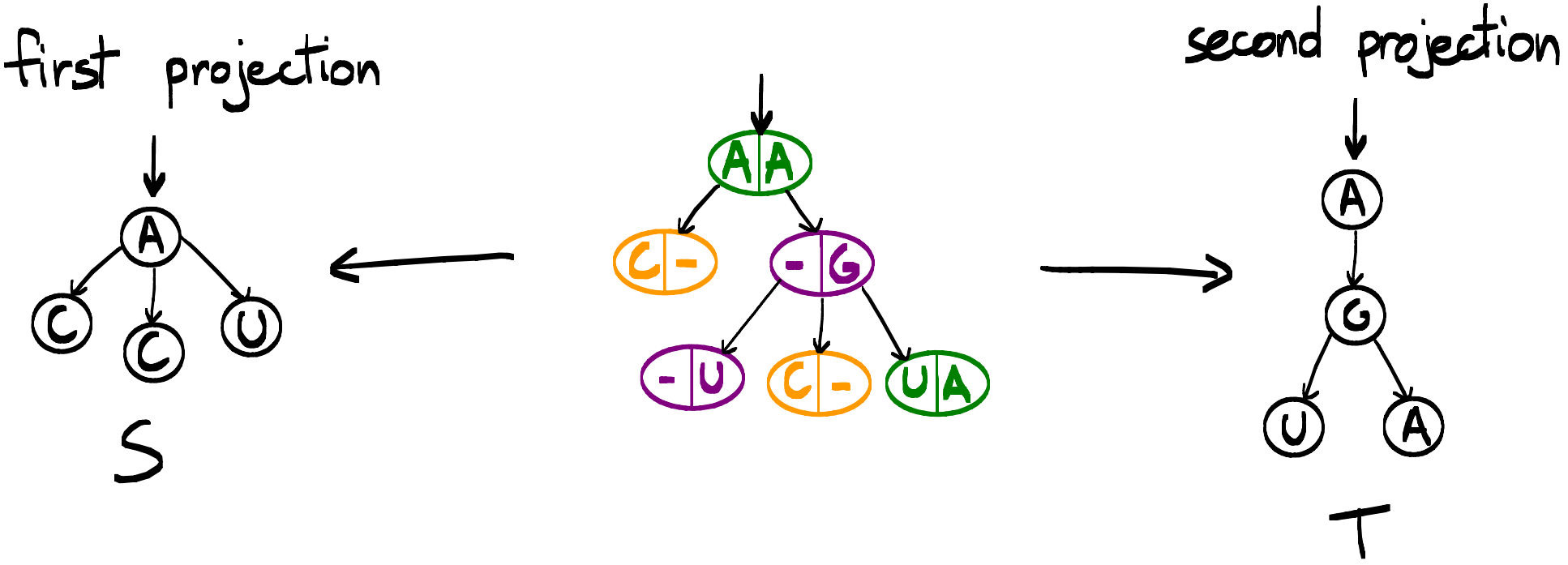


Given two trees S and T,

alignment between S and T = supertree whose projections are S and T.

TREE ALIGNMENTS



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CONNECTION WITH SEQUENCE ALIGNMENTS

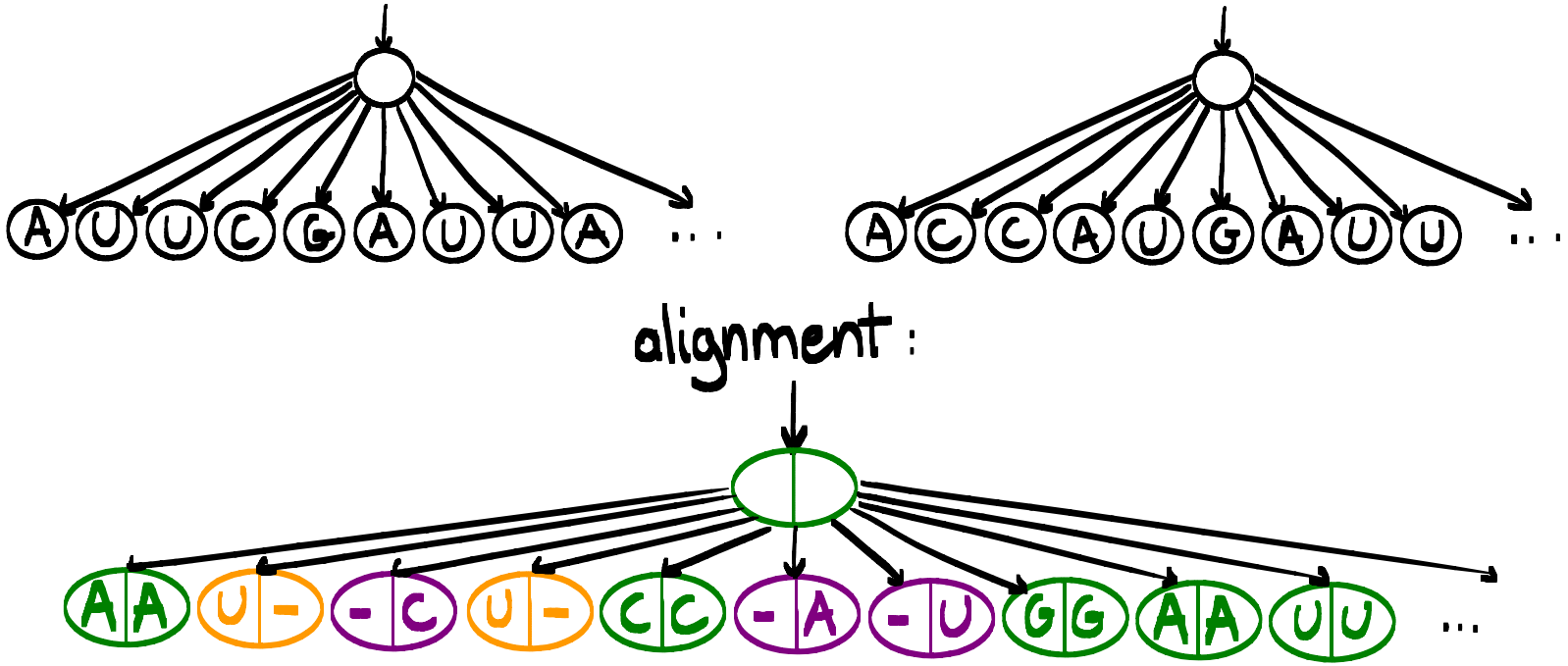
Tree alignments generalize sequence alignments.

SEQUENCE

AUUCGAUUA... ACCAUGAUUA...

alignment :

TREE



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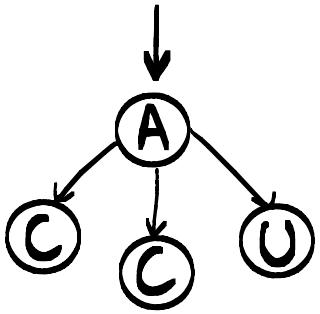
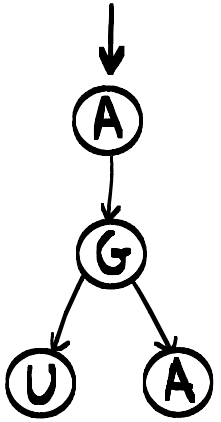
Solvable by Dynamic Programming:

Worst case time
$O(n^4)$
[Jiang, Wang, Zhang]

Average time
$O(n^2)$
[Herrbach, Denise, Dulucq]

SPACE OF ALIGNMENTS

Which alignment between 

and 

is the most likely?

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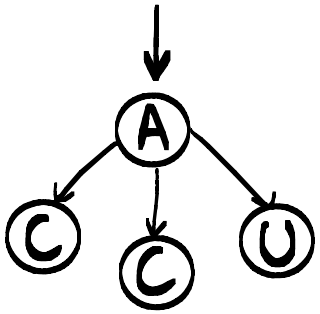

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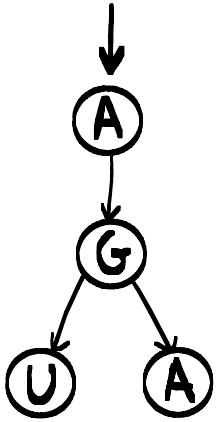

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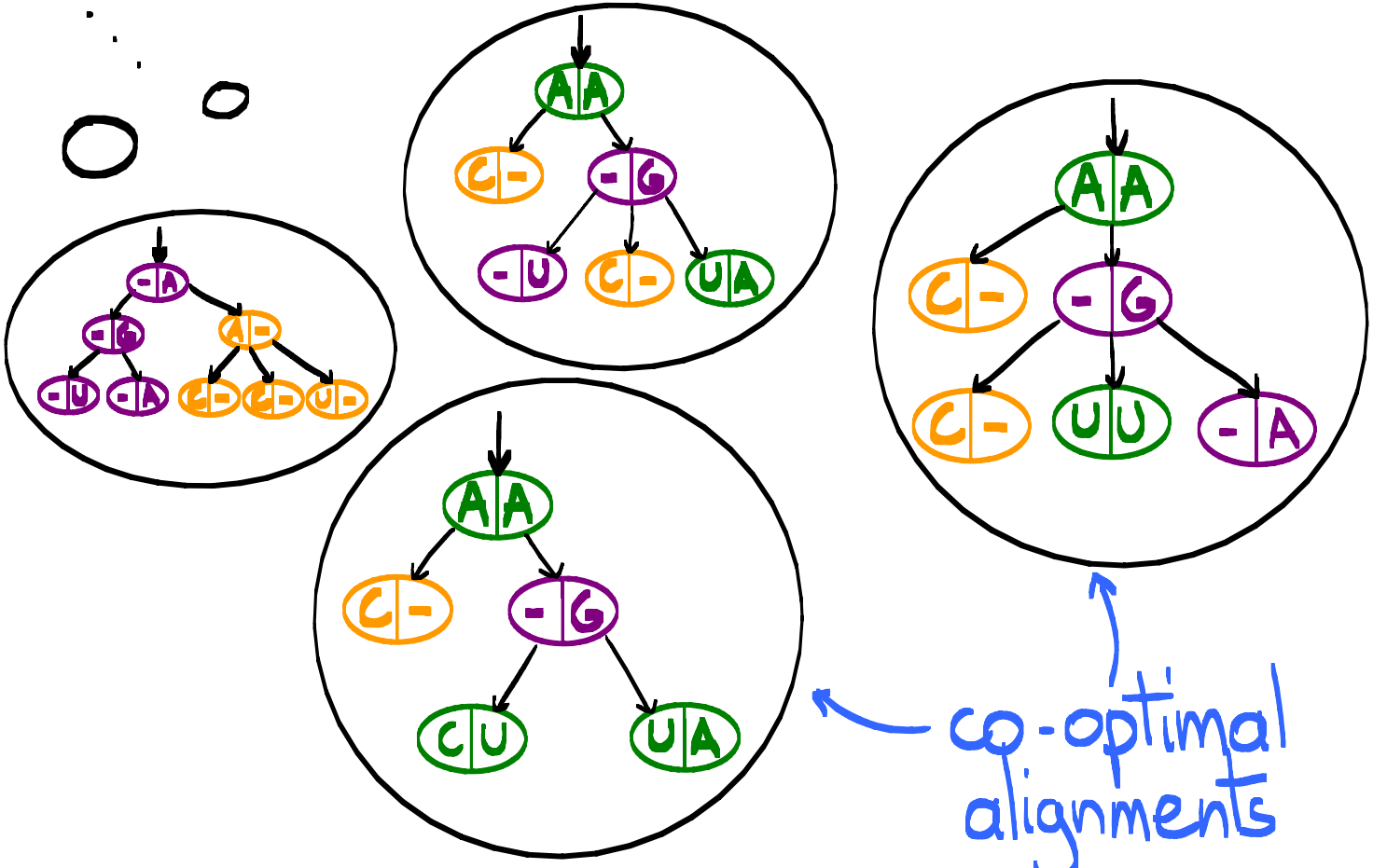


SPACE OF ALIGNMENTS

Why finding one optimal alignment may be inadequate:

- Co-optimal alignments can be very different.
- Exploring the space of alignments enables the detection of high probability features.

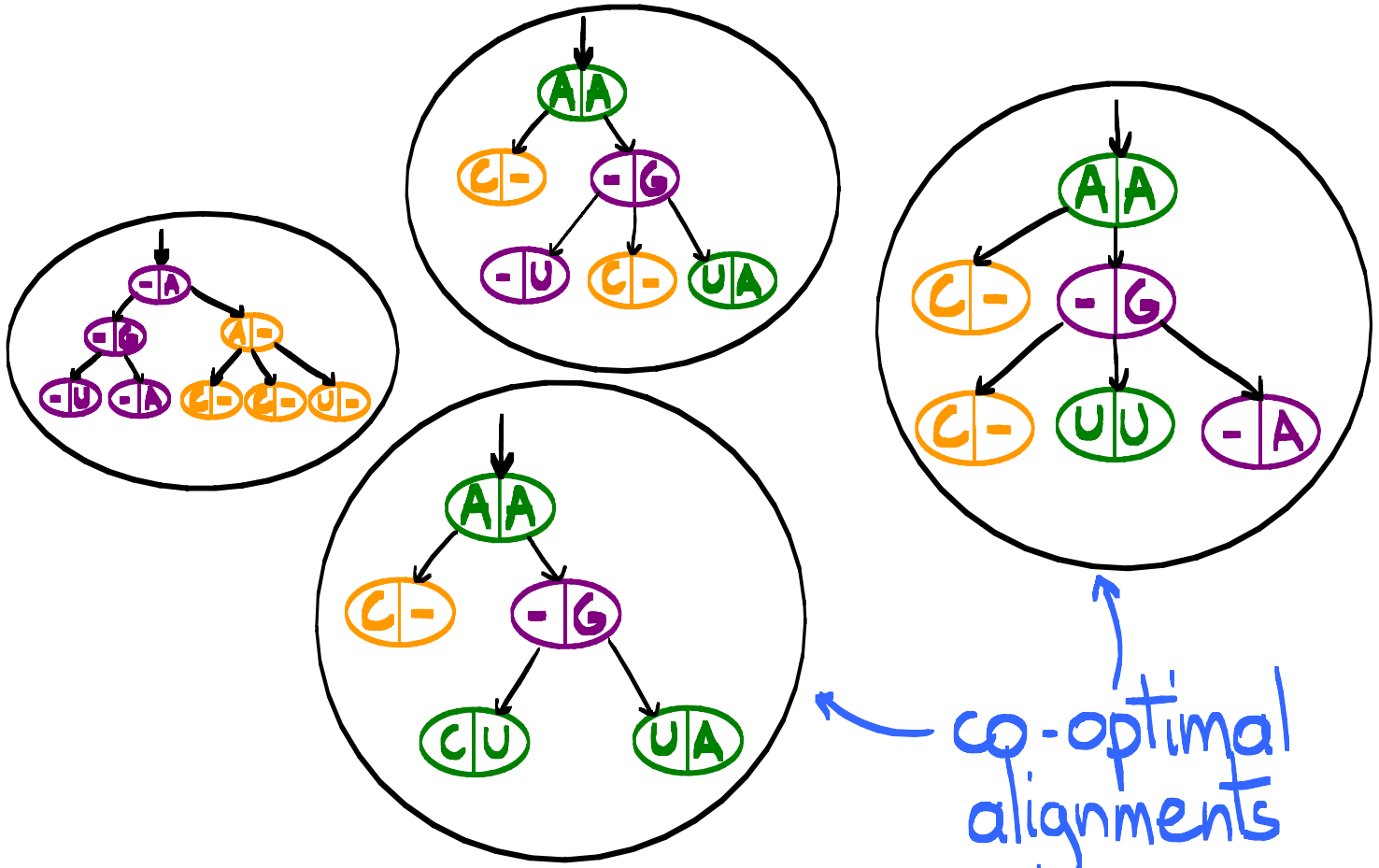
SPACE OF ALIGNMENTS

Objective: Sampling alignments under the Gibbs-Boltzmann probability distribution.

probability of an alignment A

$$\propto e^{-\frac{cost(A)}{k}}$$

(Gibbs-Boltzmann distribution)



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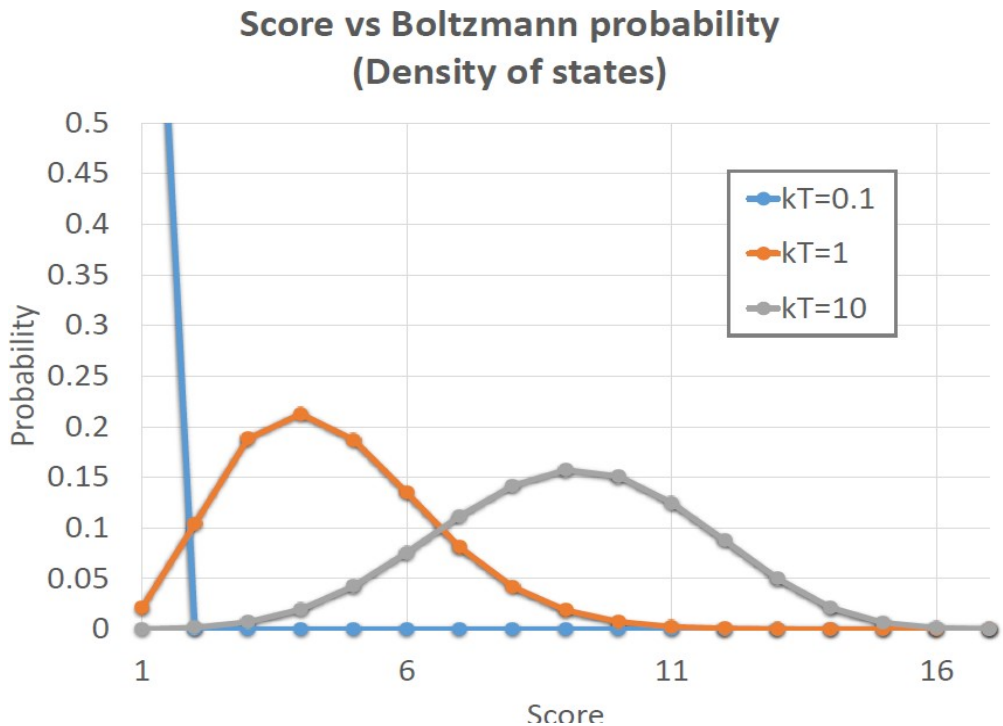

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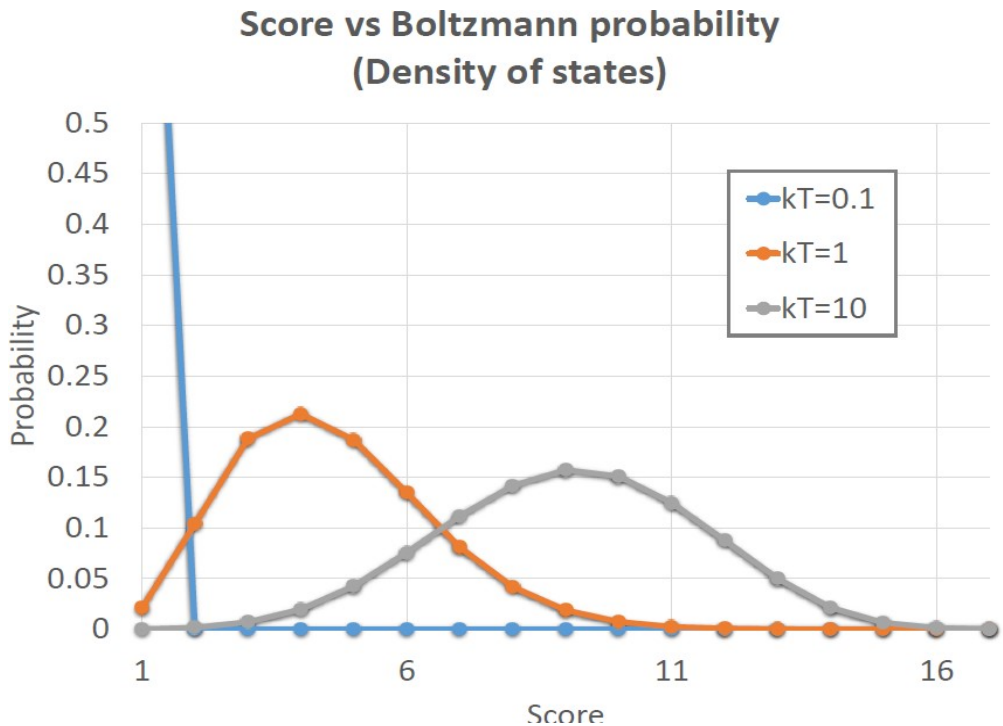

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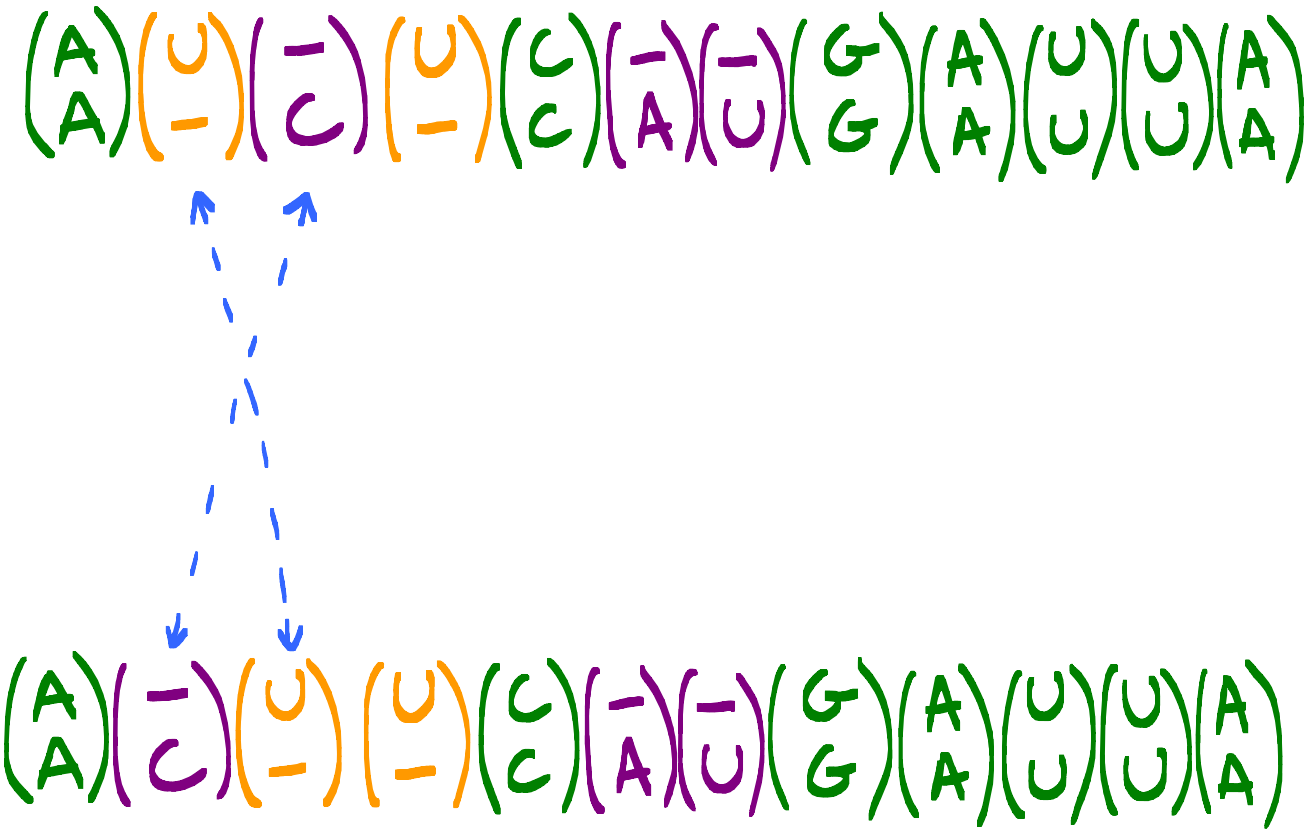
AMBIGUITY OF ALIGNMENTS

For sequences,



is the same alignment as

AMBIGUITY OF ALIGNMENTS

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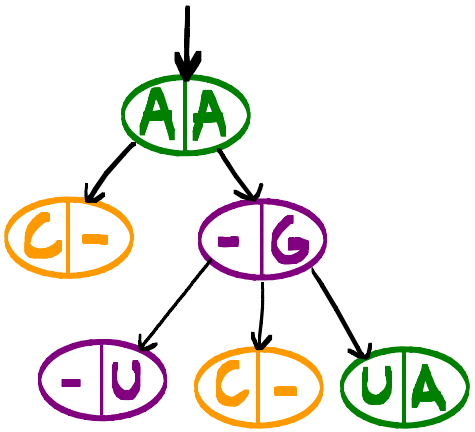

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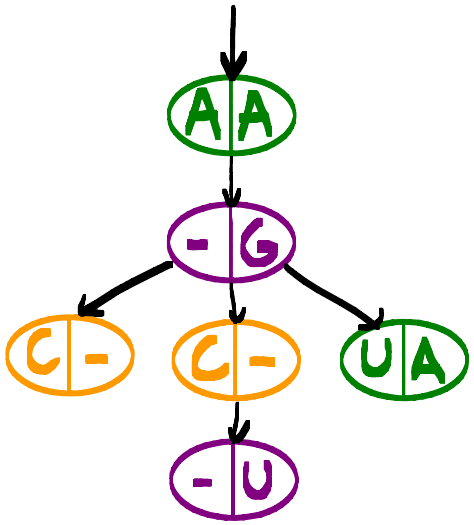
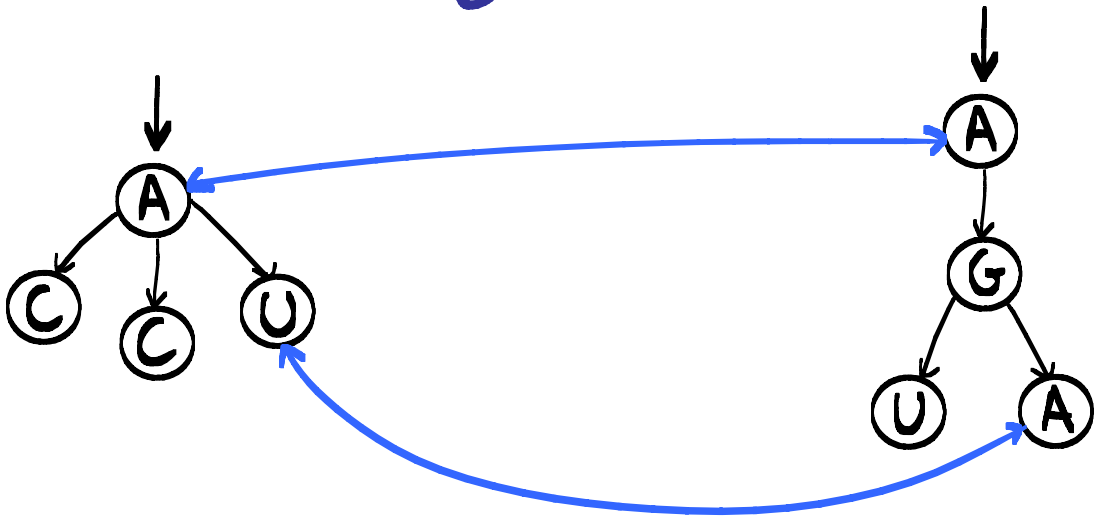
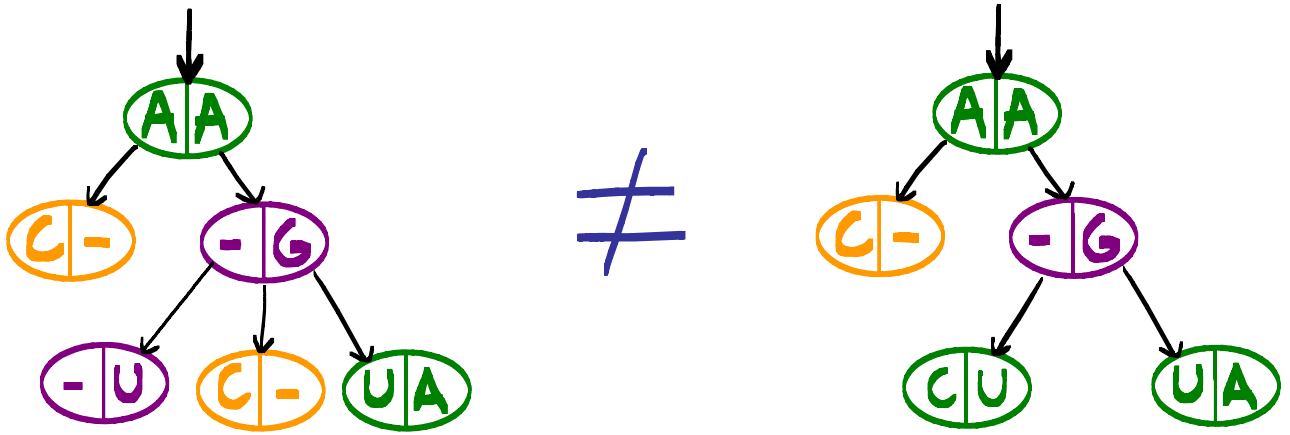


induce the same alignment between

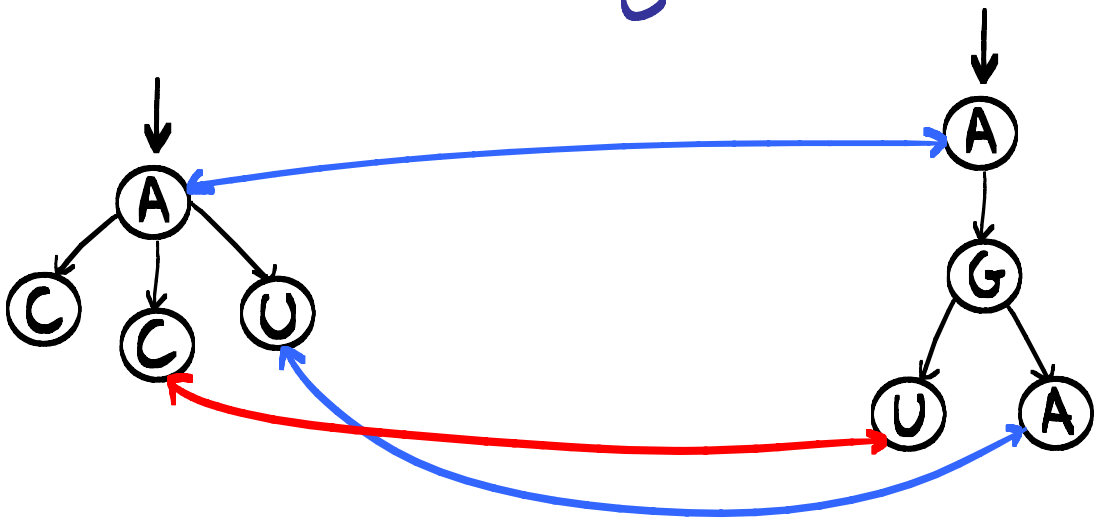


AMBIGUITY OF ALIGNMENTS

The two supertrees



do not induce the same alignment between the trees



PROBLEM RAISED BY THE AMBIGUITY

For sequences, we can deal with the ambiguity by defining canonical alignments.

Ex :

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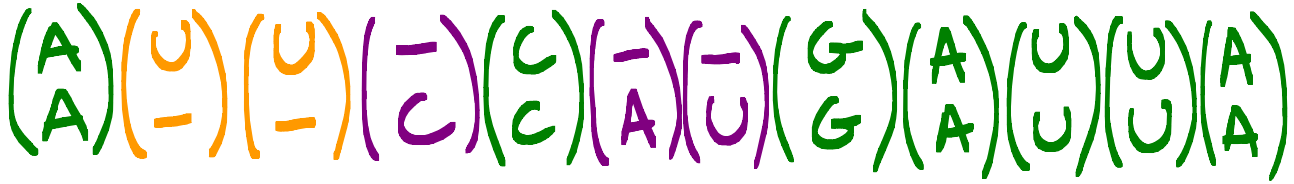

Insertions before Deletions.

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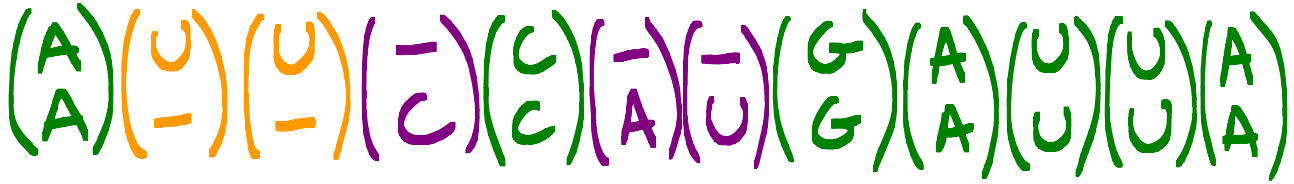

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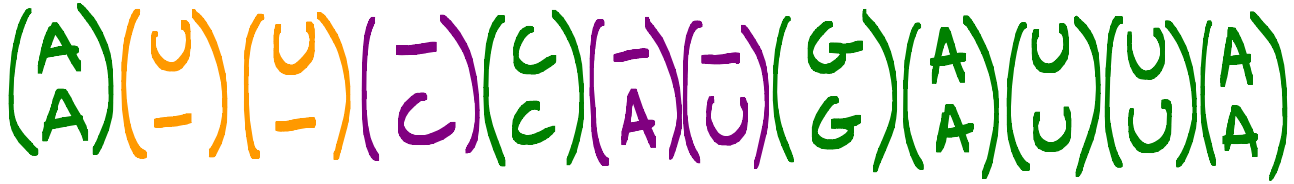

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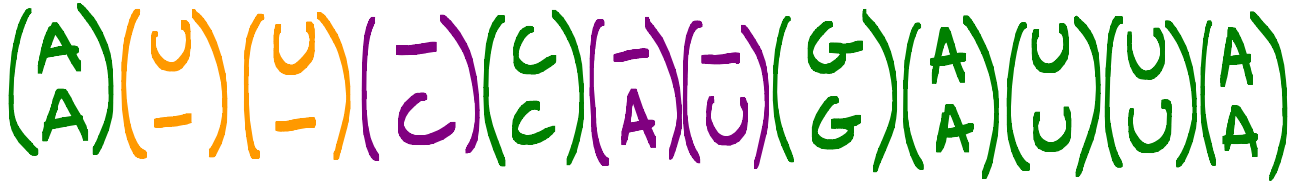


Insertions before Deletions.

For trees, it is much more complicated!

Strategy: COMBINATORICS!

Build a context-free grammar that generates every alignment exactly once

GRAMMARS FOR SEQUENCE ALIGNMENTS

Ambiguous grammar:

$$\mathcal{S} \leftarrow \binom{x}{y}\boxed{\mathcal{S}} \oplus \binom{x}{-}\boxed{\mathcal{S}} \oplus \binom{-}{y}\boxed{\mathcal{S}} \oplus \varepsilon$$

Non-ambiguous grammar:

$$\mathcal{S} \leftarrow \binom{x}{y}\boxed{\mathcal{S}} \oplus \binom{x}{-}\boxed{\mathcal{S}} \oplus \binom{-}{y}\boxed{\mathcal{S}^D} \oplus \varepsilon$$

$$\mathcal{S}^D \leftarrow \binom{x}{y}\boxed{\mathcal{S}} \oplus \binom{-}{y}\boxed{\mathcal{S}^D} \oplus \varepsilon$$

A GRAMMAR FOR ALIGNMENTS

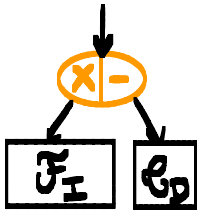
For trees, an ambiguous grammar can be derived from [Jiang, Wang, Zhang].

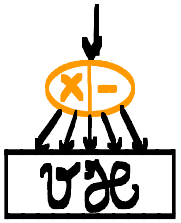
Our result:

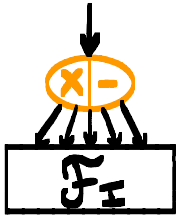
Theorem: The set of generated by the following grammar contains every tree alignment exactly once.

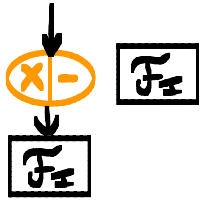
A GRAMMAR FOR ALIGNMENTS

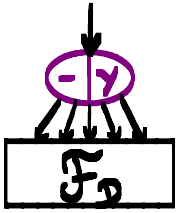
Our (complicated) non-ambiguous grammar:

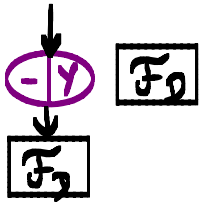
$$\mathcal{A} \leftarrow \mathcal{U}^{\phi} \mid \mathcal{C}_I \mid \mathcal{C}_D \mid$$ 

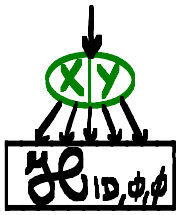
$$\mathcal{U}^{\phi} \leftarrow \mathcal{U}^{\uparrow} \mid$$ 

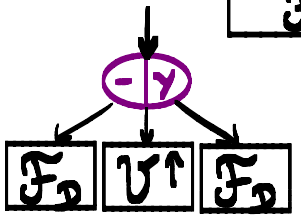
$$\mathcal{C}_I \leftarrow$$ 

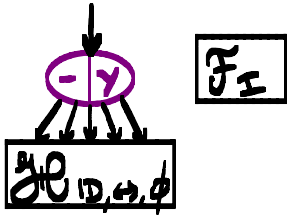
$$\mathcal{F}_I \leftarrow \varepsilon \mid$$ 

$$\mathcal{C}_D \leftarrow$$ 

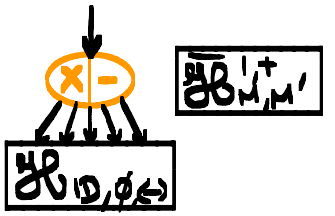
$$\mathcal{F}_D \leftarrow \varepsilon \mid$$ 

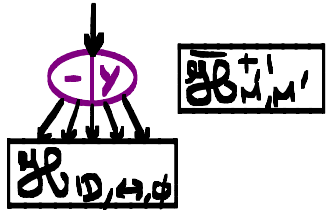
$$\mathcal{U}^{\uparrow} \leftarrow$$ 

$\mid$ 

$$\mathcal{U}\mathcal{H} \leftarrow \mathcal{F}_I\ \mathcal{U}\mathcal{H} \mid \mathcal{U}^{\phi}\ \mathcal{F}_I \mid$$ 

For $J \in \{D, \underline{D}\}$, $(M, M') \in \{\phi, \rightarrow, \leftrightarrow\}^2$:

$$\mathcal{H}_{J,M,M'} \leftarrow \varepsilon \mid \mathcal{C}_I\ \mathcal{H}_{J,M,M'} \mid \mathcal{C}_D\ \mathcal{H}_{D,M,M'} \mid \mathcal{U}^{\phi}\ \overline{\mathcal{H}}^{J,M,M'} \mid$$ 

$\overline{\mathcal{H}}^{J,M,M'}$ $\mid$ 

$\overline{\mathcal{H}}^{J,M,M'}$

only if $(M,M') = (\phi,\phi)$

only if $J \neq D$ and $M \neq \leftrightarrow$

only if $M' \neq \leftrightarrow$

no room for $\overline{\mathcal{H}}^{i,j}_{M,M'}$...

APPLICATION 1. COUNTING.

Theorem There are on average $C \times 1.5^n$ alignments between two random trees of cumulative size n where $C = 0.299\ldots$

Corollary: A same alignment was repeated $\sim 0.875 \times 1.412^n$ times on average in Jiang et al.'s ambiguous grammar.

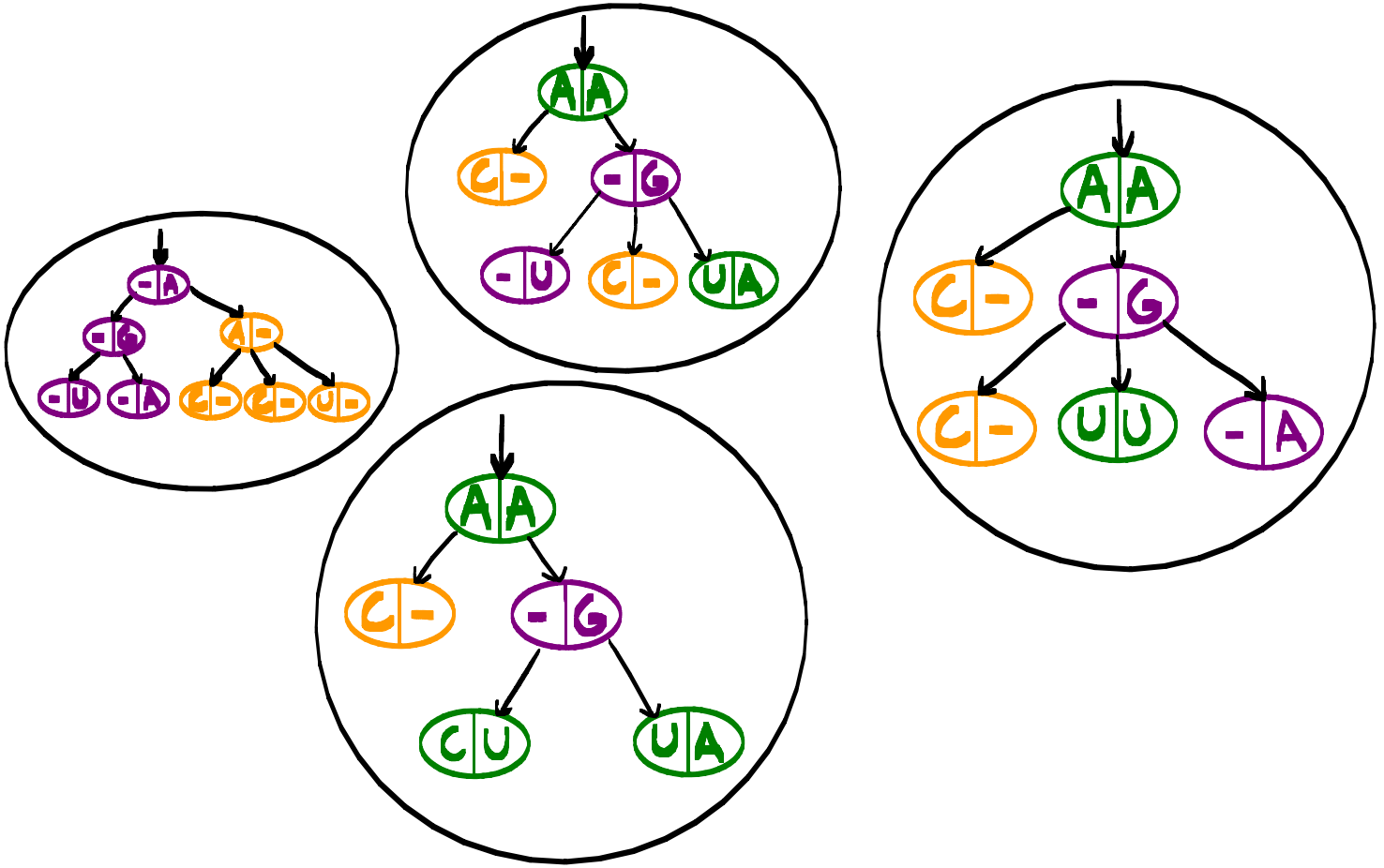
APPLICATION 2. SAMPLING

Objective: Sampling alignments under the Gibbs-Boltzmann probability distribution.

probability of an alignment A

$$\propto e^{-\frac{cost(A)}{K}}$$

(Gibbs-Boltzmann distribution)



APPLICATION 2. SAMPLING

Objective: Sampling alignments under the Gibbs-Boltzmann probability distribution.

Strategy:

→ Filter the grammar to obtain a new grammar that only generates alignments between two fixed trees S and T

→ Use dynamic programming.

SAMPLING

Theorem Let S and T be two trees of size n_1 and n_2. Sampling alignments between S and T under the Gibbs-Boltzmann distribution can be done with worst-case time and space complexities $O(n_1 n_2 (n_1 + n_2)^2)$ and with average-case time and space complexities $O(n_1 n_2)$.

SAMPLING

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Upsides:

- No additional complexity cost (except constants, moderate)
- Flexibility of the sampling algorithm.
- Already implemented.

Downside

- Complicated DP scheme.

CONCLUSION

"Combinatorics is a powerful tool to solve algorithmic problems."

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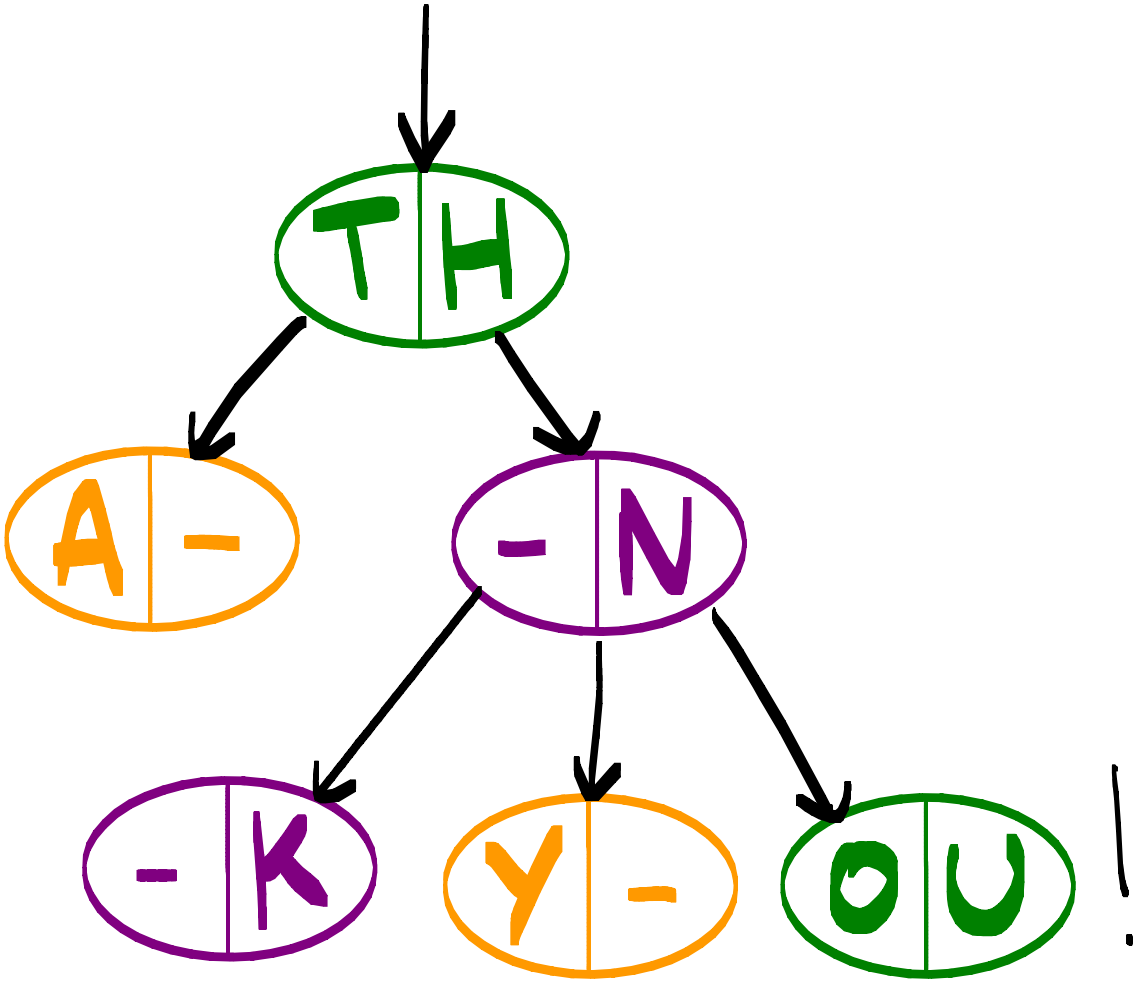
"Combinatorics is a powerful tool to solve algorithmic problems."

Open questions:

→ Existence of easier decompositions?

→ Alignment problem for arc-annoted sequences?


TH
A-
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!

APPLICATION 1: COUNTING.

Theorem: The generating function $A(z,u)$ of tree alignments satisfies

$$A(z,u) = \left(z^2 + z - uz^2 + \frac{z}{\sqrt{1-4z}}\right) \times B(z,u)$$

where

$$\left(uzC(z)^2 - z^2C(z)^2 + 2z\right)B(z,u)^2 + \left(z^2C^4(z) - 2zC(z)^2 - 1\right)B(z,u) + C^2(z) = 0$$

and

$$C(z) = \frac{1-\sqrt{1-4z}}{2z}$$ Catalan generating function