

Fighting SARS-CoV-2 and other viruses with RNA bioinformatics

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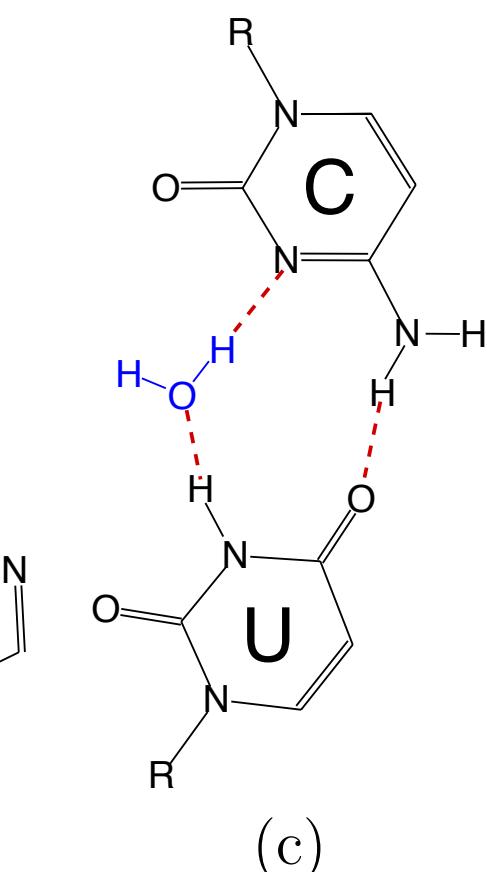
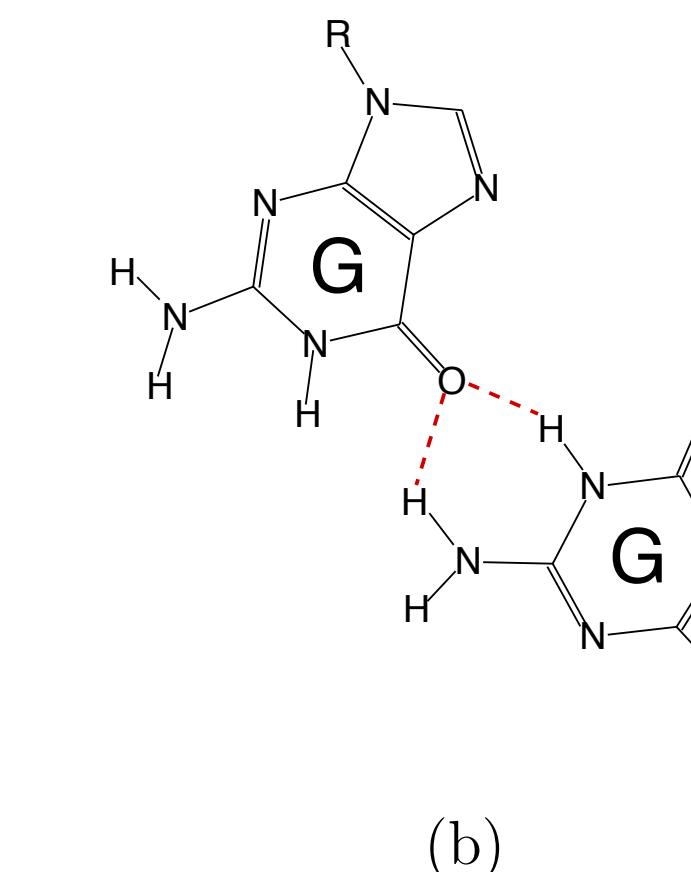
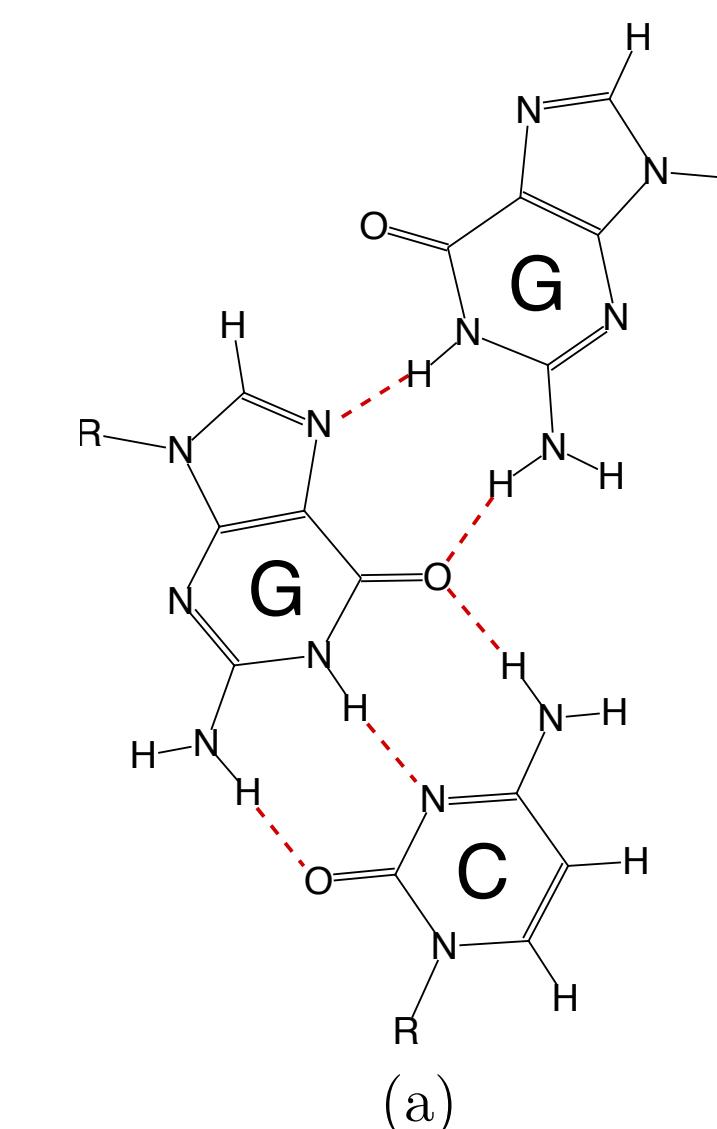
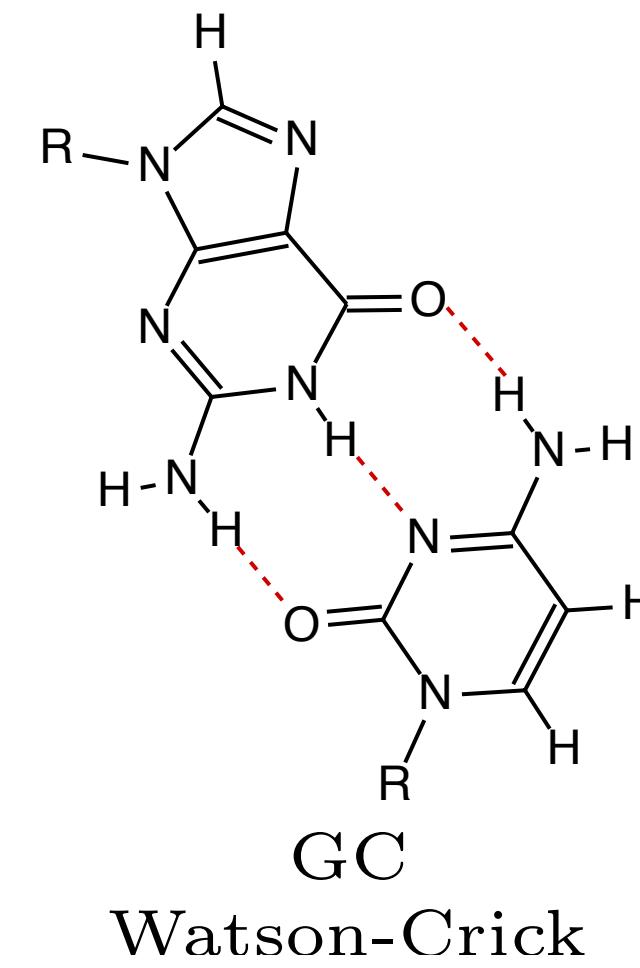
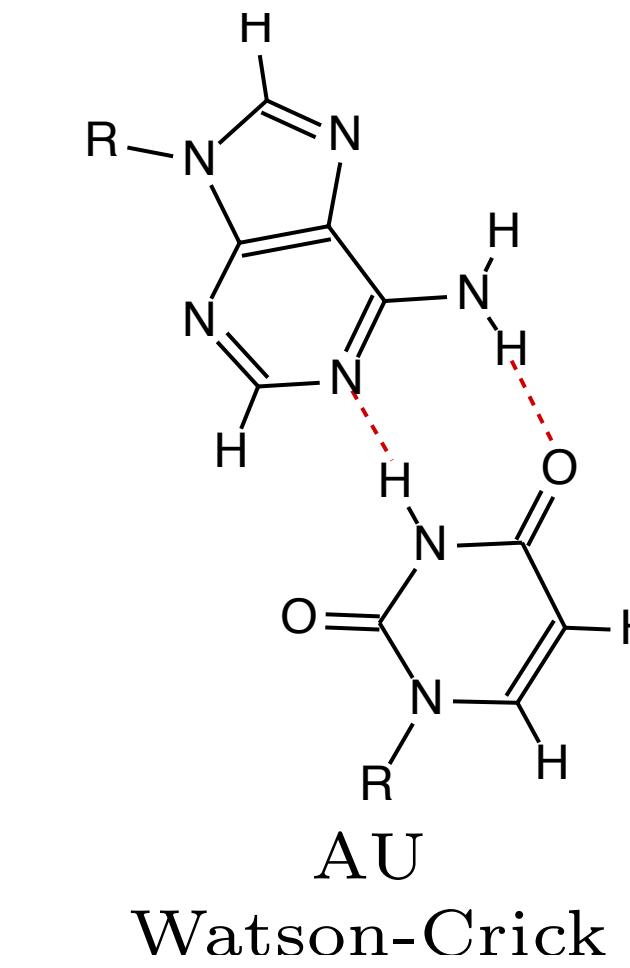
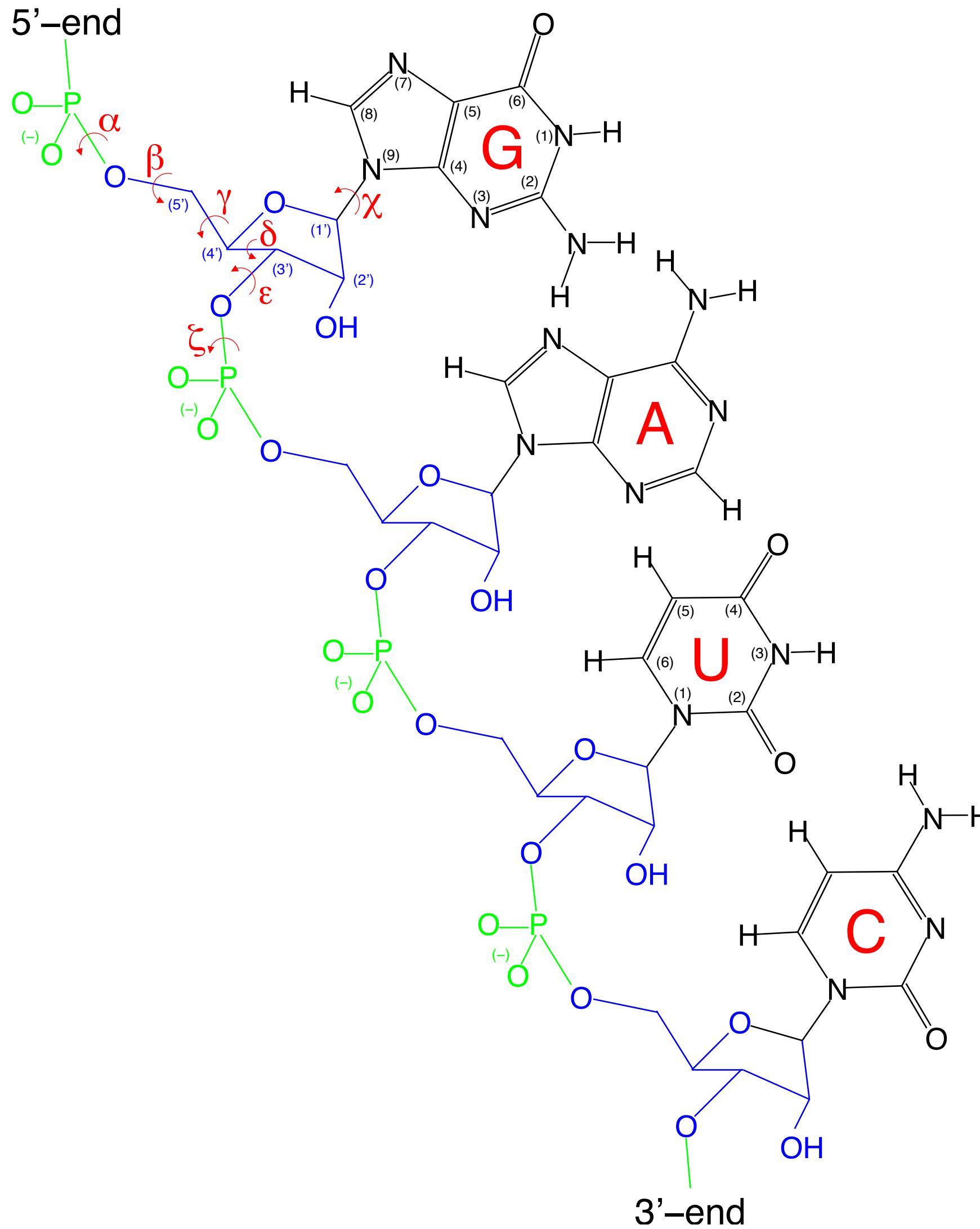
Chulalongkorn University
Bangkok
11 March 2020

Recent Virus Outbreaks

- 2012: MERS CoV in Saudi Arabia
- 2014/2015: Ebola virus (EBOV) in West Africa
- 2015/2016: Zika virus (ZIKV) in Brazil
- 2017: Yellow fever virus (YFV) in Brazil
- 2018: EBOV in DRC
- 2018/2019: Polio virus in Pakistan
- 2019: EEEV in USA
- 2019/2020: SARS-CoV-2 in China



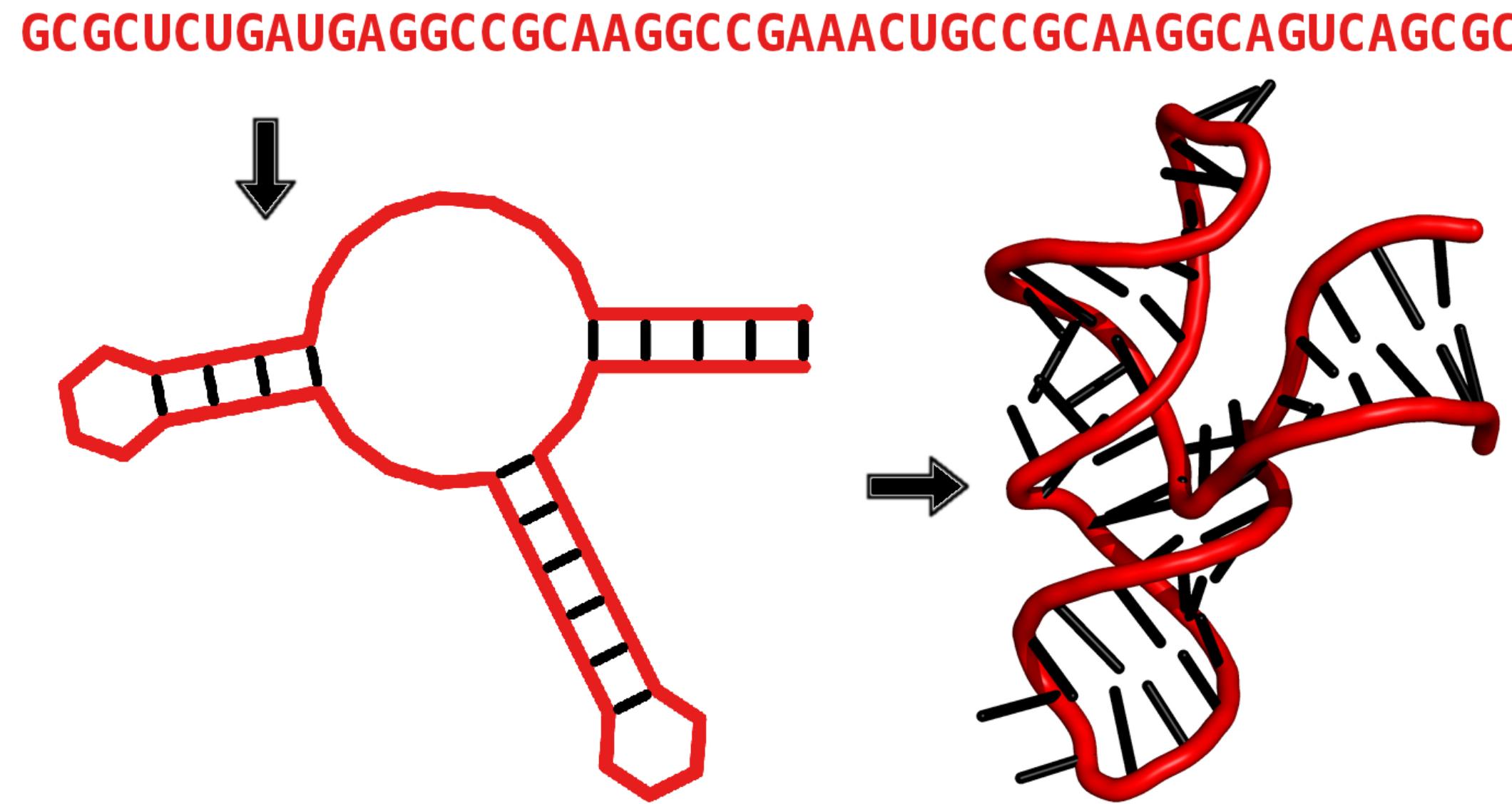
The Chemical Structure of RNA



Part I:

RNA structure prediction

The RNA Folding Problem

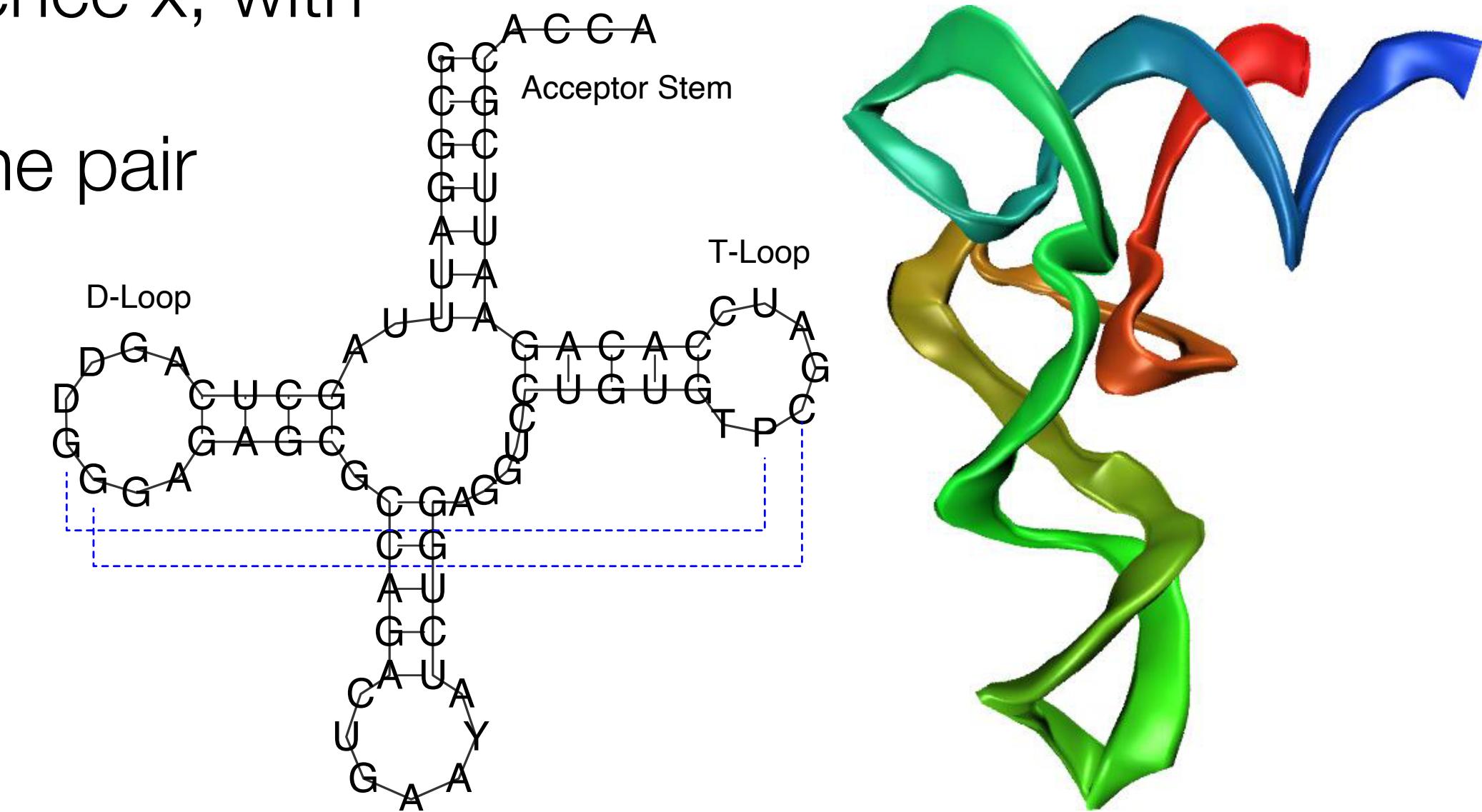


- Hierarchical folding: Secondary structure forms first then helices arrange to form tertiary structure
- Secondary structures cover most of the folding energy
- Convenient and biologically useful description
- Computationally easy to handle
- Tertiary structure prediction needs knowledge of secondary structure

Secondary Structures

A **secondary structure** is a list of base pairs (i,j) on a sequence x , with

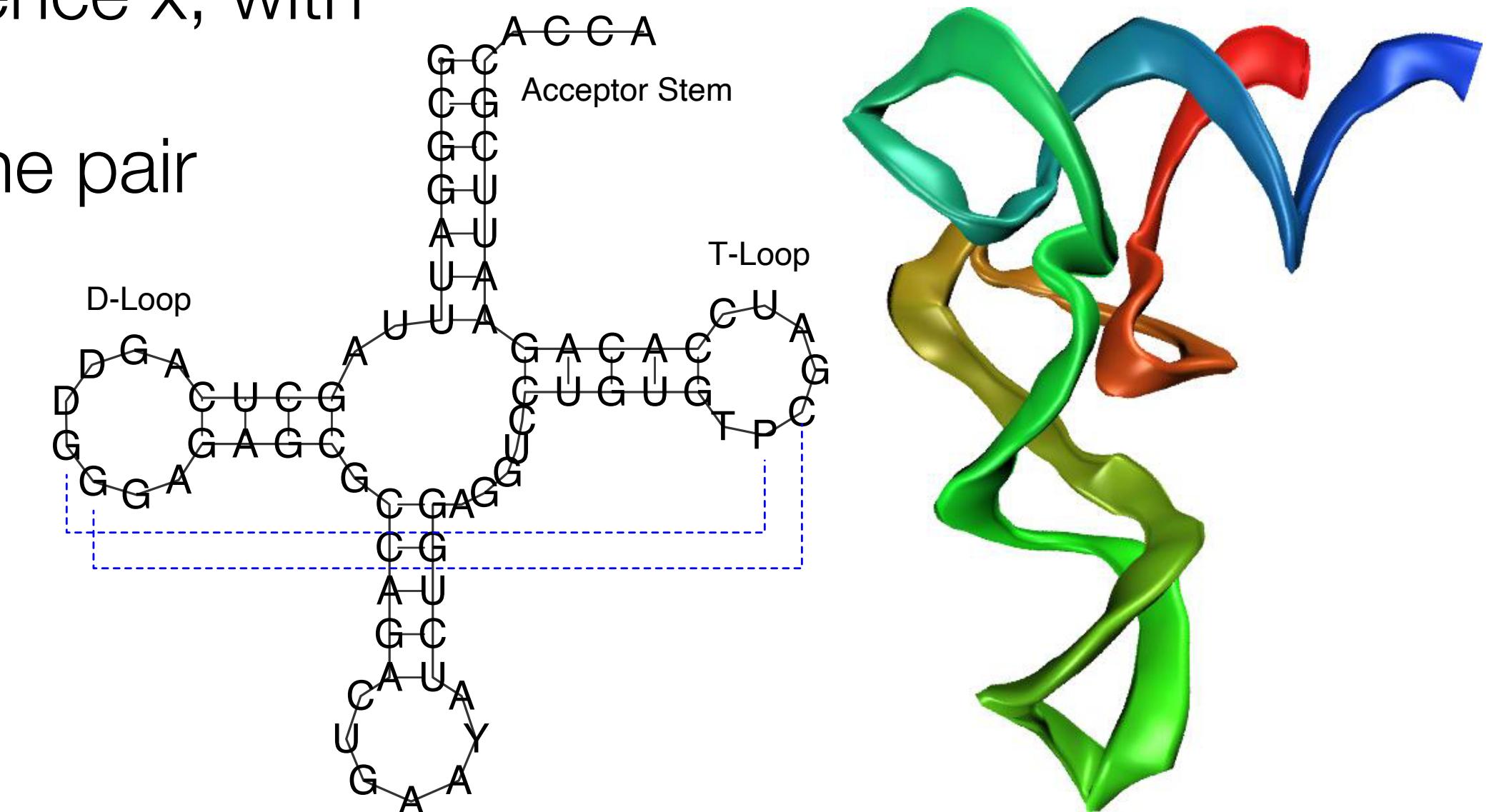
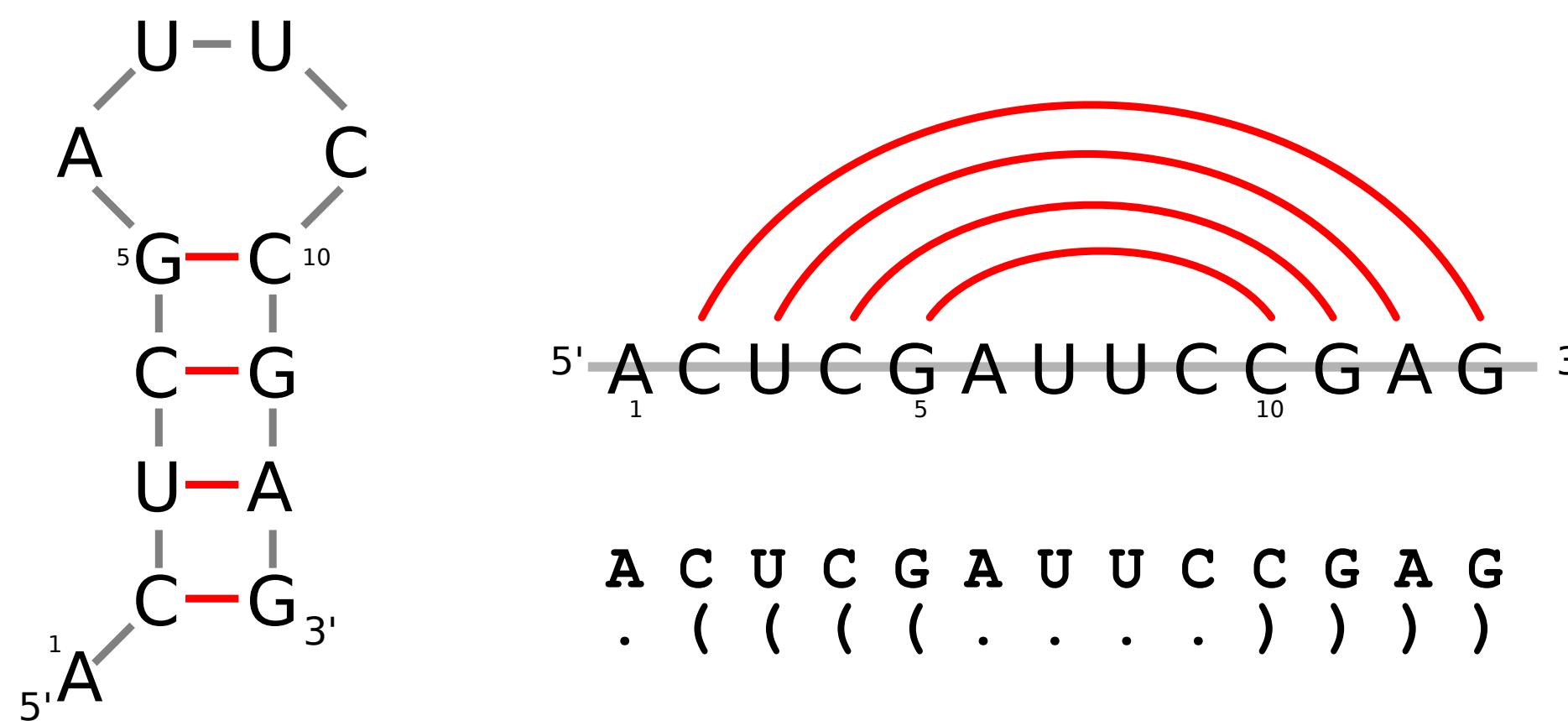
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- If (i,j) is a pair then $x_i x_j \in \{GC, CG, AU, UA, GU, UG\}$
- If (i,j) is a base pair, then $j - i > 3$
- No pseudo-knots: No pairs (i,j) and (k,l) with $i < k < j < l$



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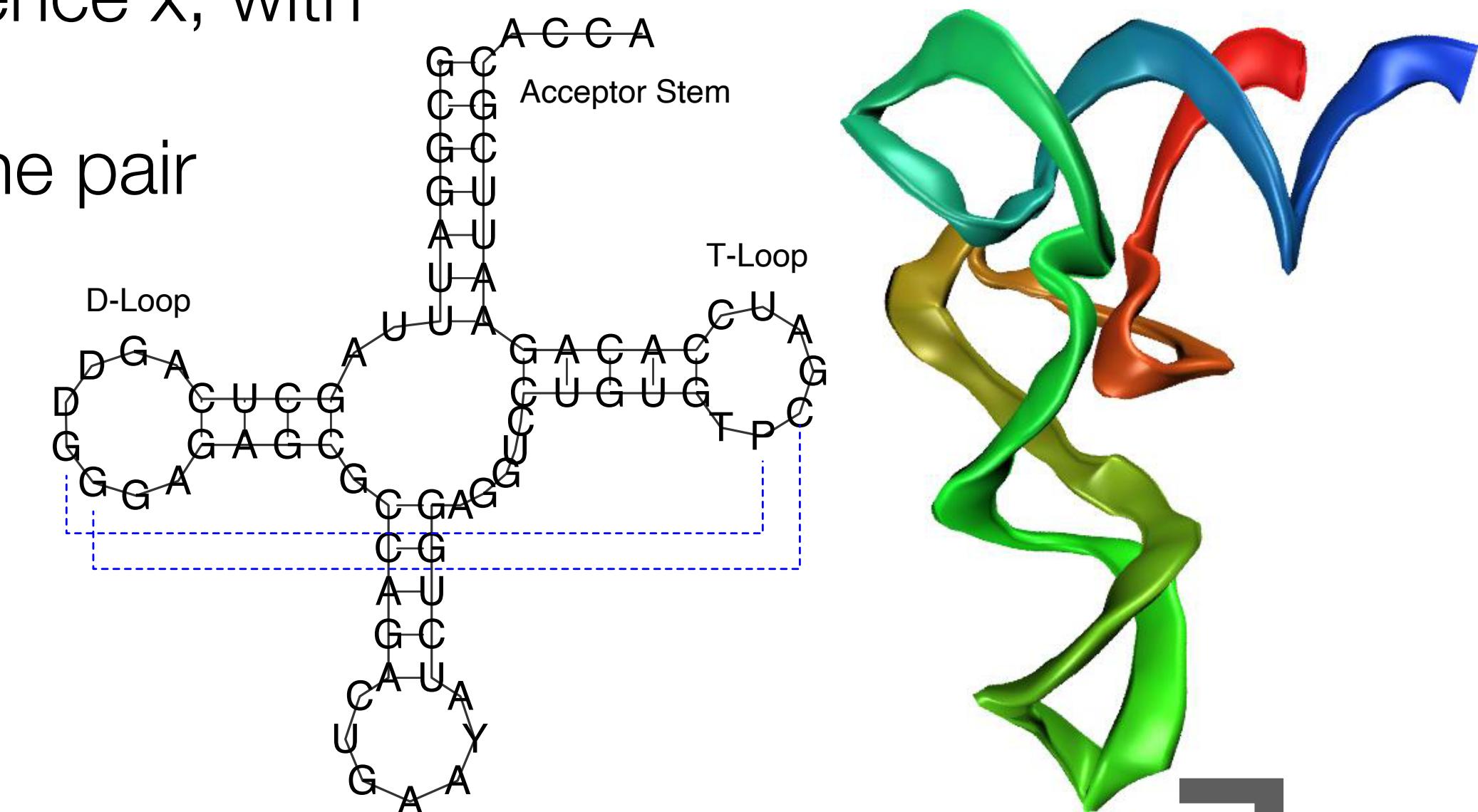
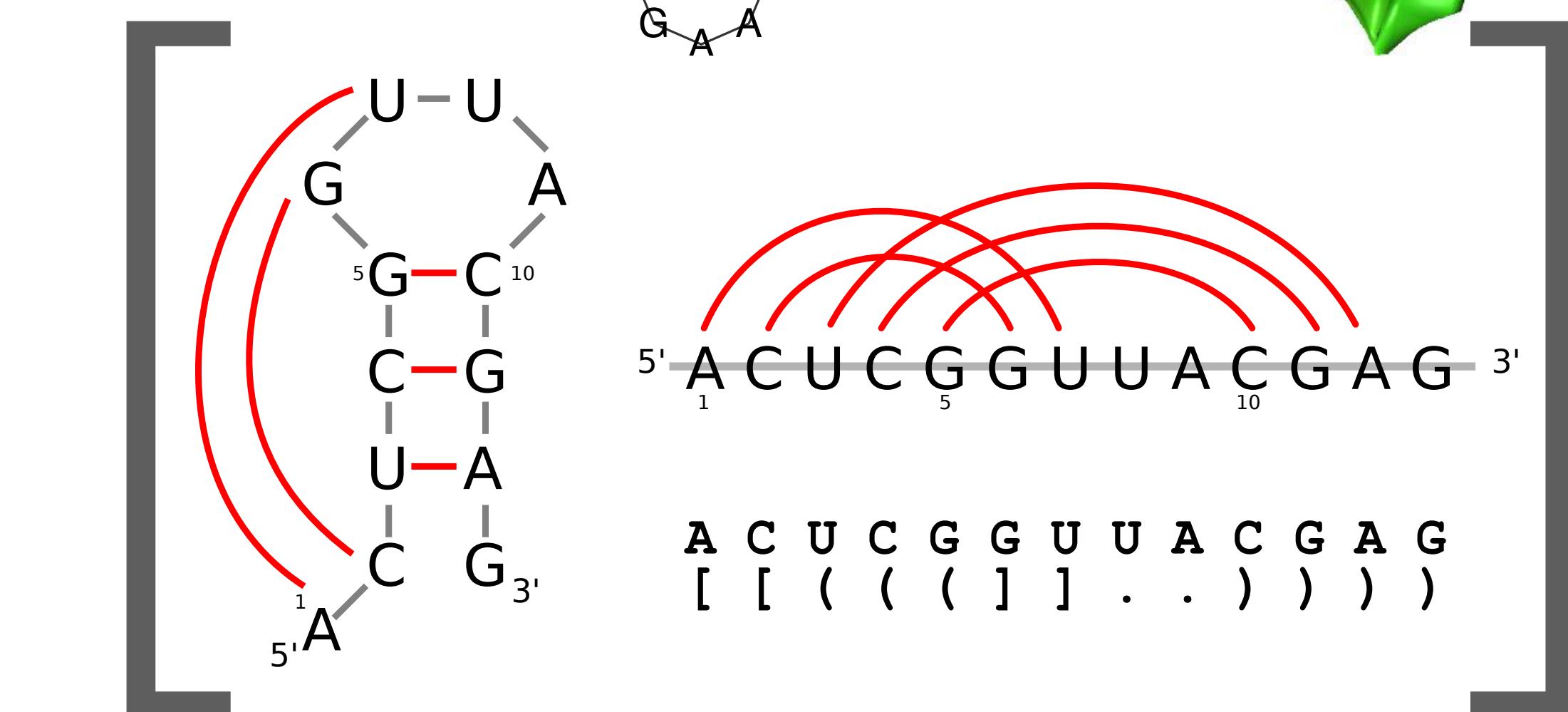
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Conformation Space

The number of secondary structures for a sequence $x = x_1 \dots x_n$ can be computed recursively



$$S_{ij} = S_{i+1,j} + \sum_{k=i+m}^j S_{i+1,k-1} S_{k+1,j} \Pi_{kj}$$

$\Pi_{ik} = 1$ if $x_i x_k \in \{\text{GC}, \text{CG}, \text{AU}, \text{UA}, \text{GU}, \text{UG}\}$, otherwise $\Pi_{ik} = 0$

For sequences with equal {A,U,G,C} content, the number of conformations grows asymptotically with sequence length

$$\bar{S}(n) \sim n^{-\frac{3}{2}} 1.85^n$$

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Conformation Space

The number of secondary structures for a sequence $x = x_1 \dots x_n$ can be computed recursively

Many sequences fold into the same structure

Nature ‘exploits’ this property

$$S_n = S_{n-1} + \sum_{k=1}^{j-1} S_{k-1} \Pi_{ki}$$

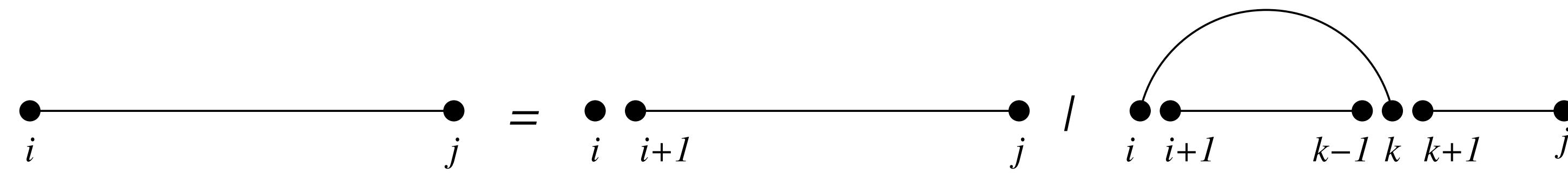
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Solving the RNA Folding Problem

Toy model for RNA folding: assign energies to base pairs $\varepsilon(x, y)$

Easily solved by **Dynamic Programming**: recursive computation with tabulation of intermediate results



$$E_{ij} = \min_{i < k \leq j} \left\{ E_{i+1,j}; \left(E_{i+1,k-1} + E_{k+1,j} + \varepsilon(x_i, x_k) \right) \right\}$$

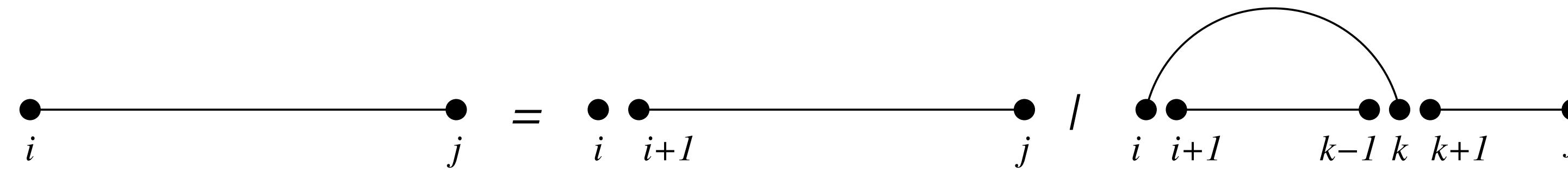
- E_{1n} is the best possible energy for our sequence
- Backtracing through the E table yields the corresponding structure
- The algorithm requires $\mathcal{O}(n^2)$ memory and $\mathcal{O}(n^3)$ CPU time

In practice this toy model is not good enough !
We need loop-dependent energies for serious predictions

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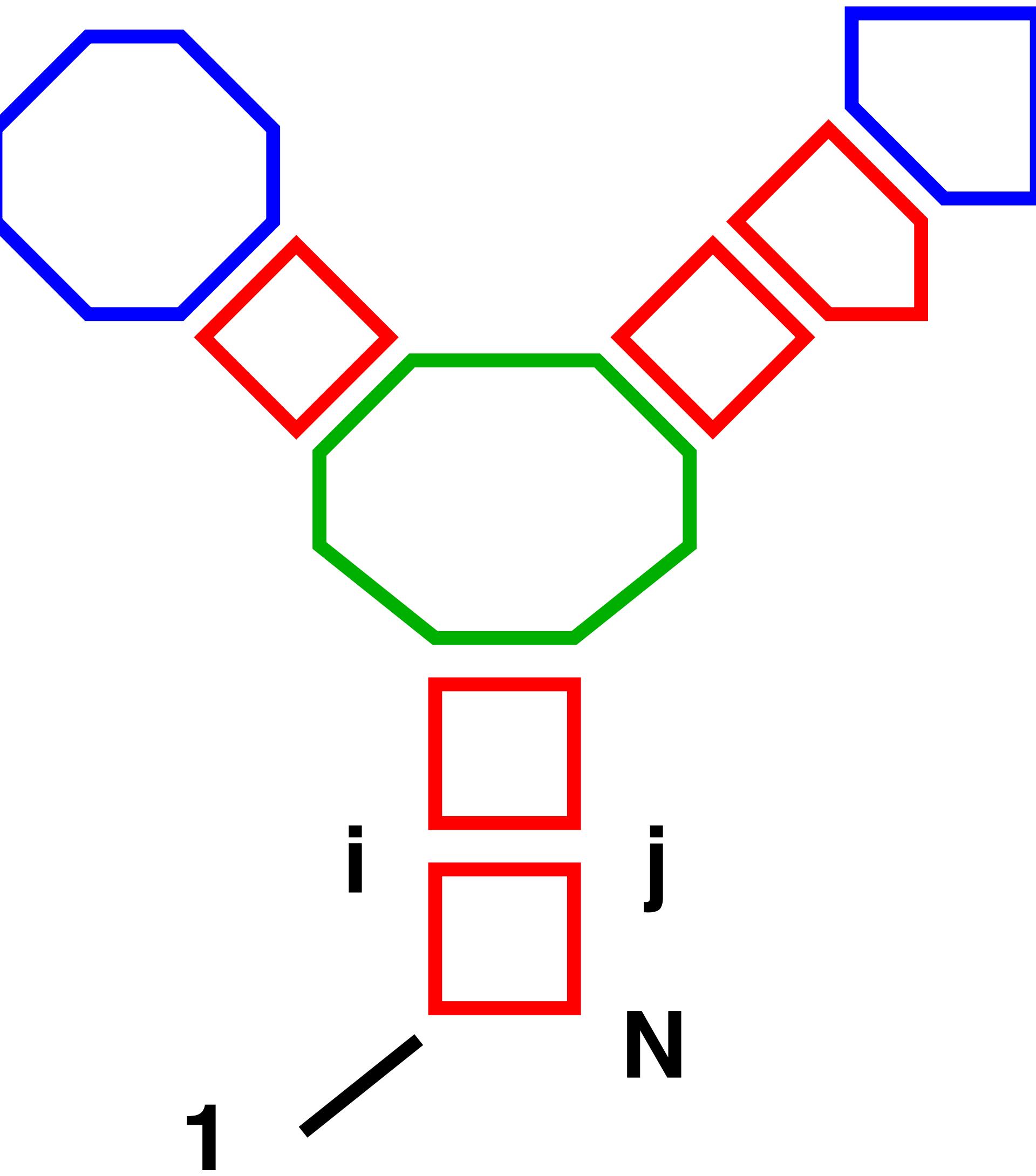


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Loop Decomposition

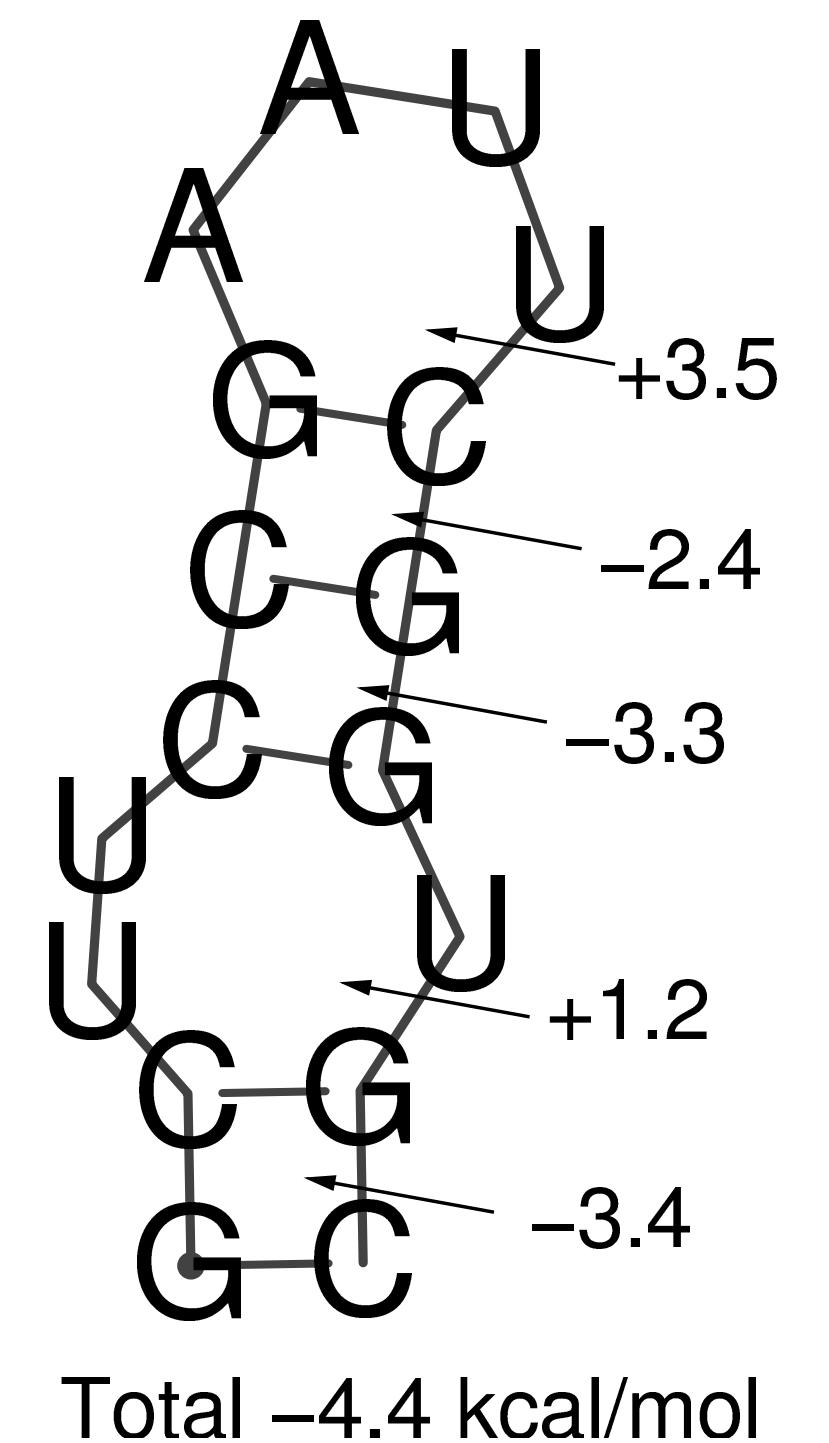


Nearest Neighbour Model

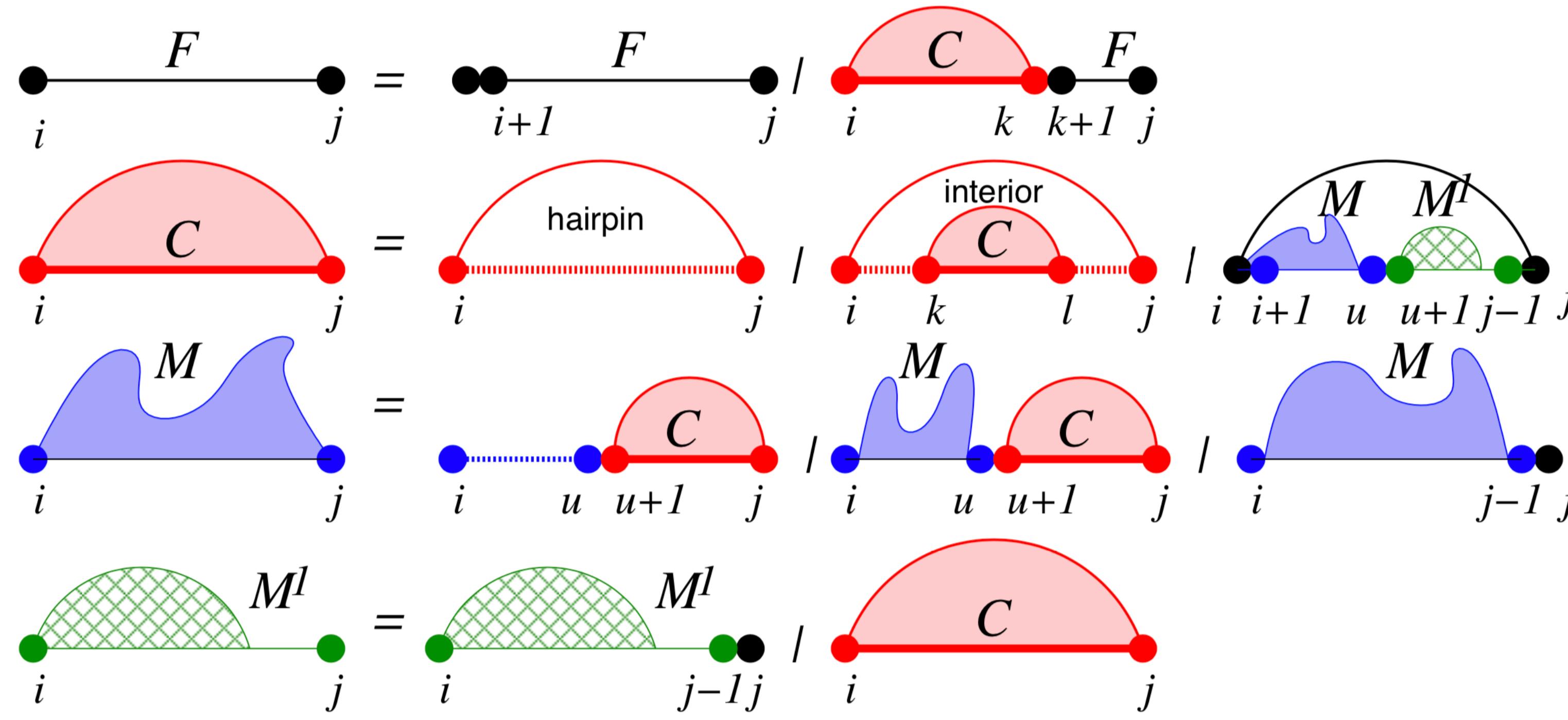
The standard energy model expresses the free energy of a structure as the sum over its loop energies

$$E(S) = \sum_{l \in S} E(l)$$

- Good approximation for most oligonucleotides
- Loop energies depend on loop type/size and some sequence dependence
- Most relevant parameters are experimentally measured; some still guesswork
- Secondary structures are macro-states, hence energies are **temperature-dependent free energies**
- Training parameters is becoming a viable alternative to experiment



Folding with Loop Based Energies



F_{ij} free energy of the optimal substructure on the subsequence $x[i..j]$.

C_{ij} optimal free energy on $x[i..j]$, where (i, j) pair.

M_{ij} $x[i..j]$ is part of a multiloop and contains at least one pair.

M_{ij}^l same as M_{ij} but contains exactly one component closed by (i, h) .

Partition Function

Recall: $\bar{S}(n) \sim n^{-\frac{3}{2}} 1.85^n$

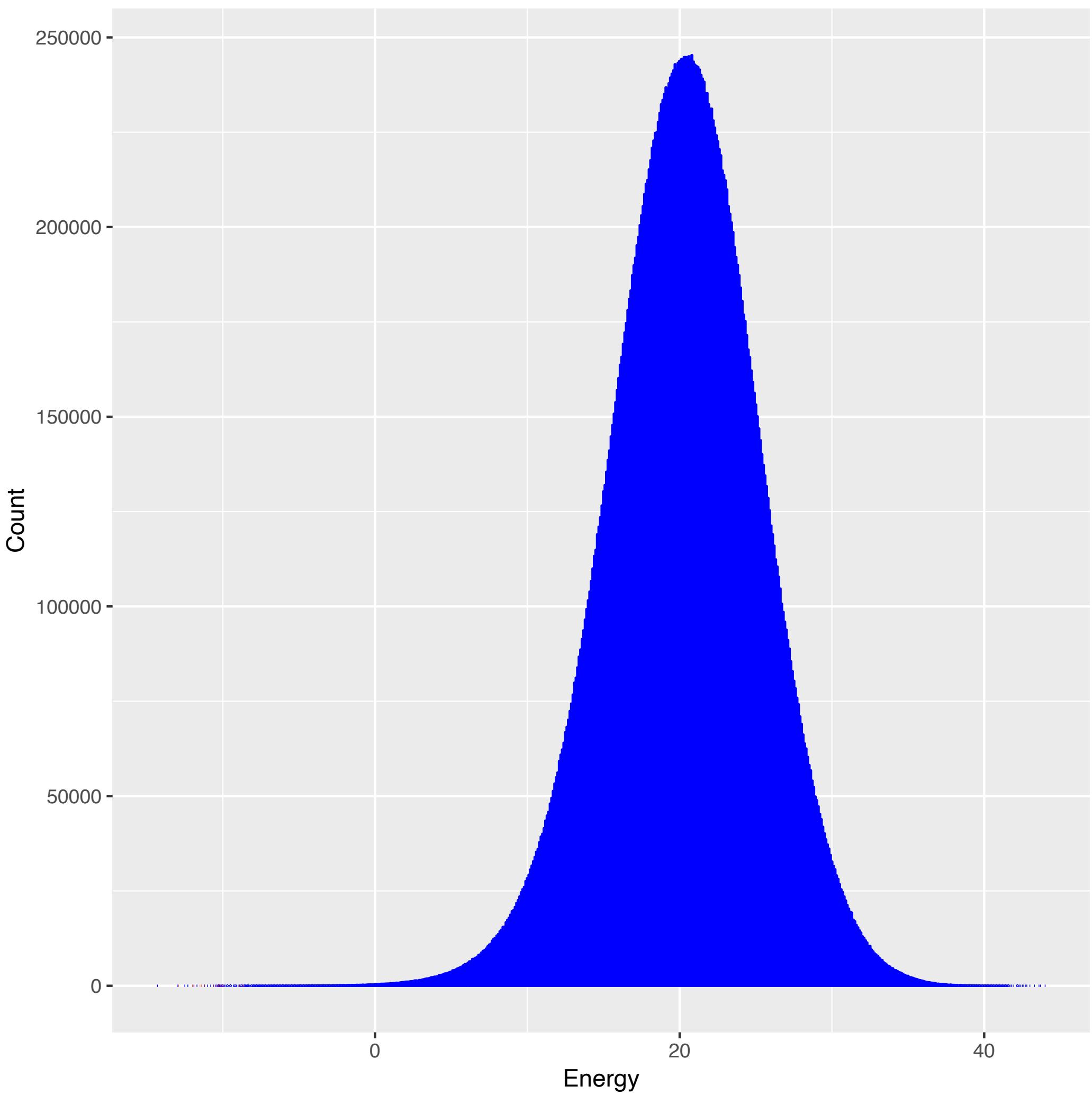
RNA is a biopolymer and ruled by thermodynamics

The **partition function** is the fundamental quantity of statistical mechanics and all thermodynamic properties can be derived from it

$$Z = \sum_{\Psi} \exp\left(-\frac{E(\Psi)}{RT}\right)$$

E.g. the free energy of formation is given by

$$\Delta G = -RT \ln Z$$



Partition Function

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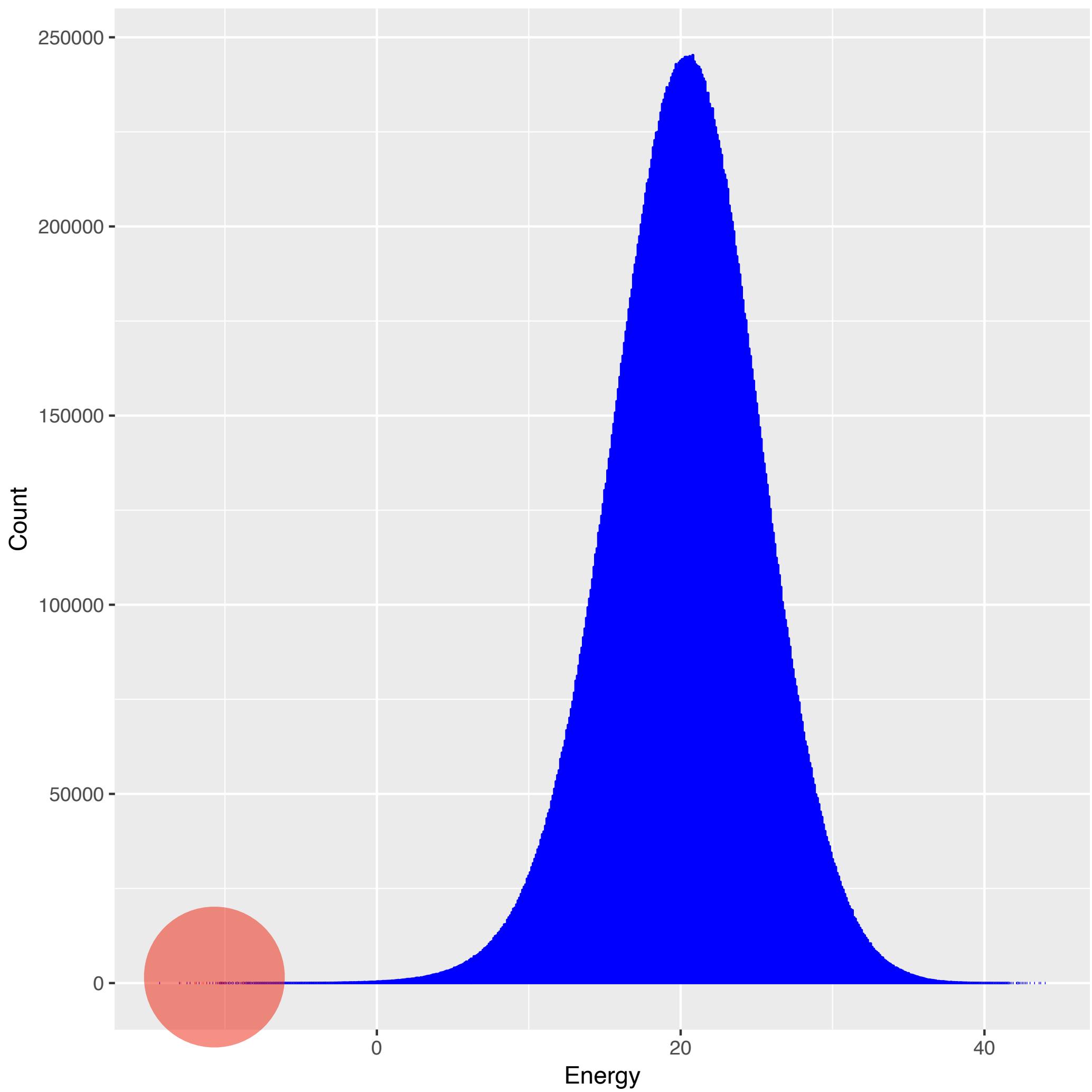
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Computing the Partition Function

The recursion has the same structure as for energy minimisation, with two differences

- replace minimum operation by sums
- addition of energies by products of partition functions

$$E_{ij} = \min_{i < k \leq j} \left\{ E_{i+1,j} ; \left(E_{i+1,k-1} + E_{k+1,j} + \varepsilon(x_i, x_k) \right) \right\}$$

$$Z_{ij} = Z_{i+1,j} + \sum_{k, (i,k) \text{ pairs}} Z_{i+1,k-1} Z_{k+1,j} \exp(-\varepsilon(x_i, x_k)/RT)$$

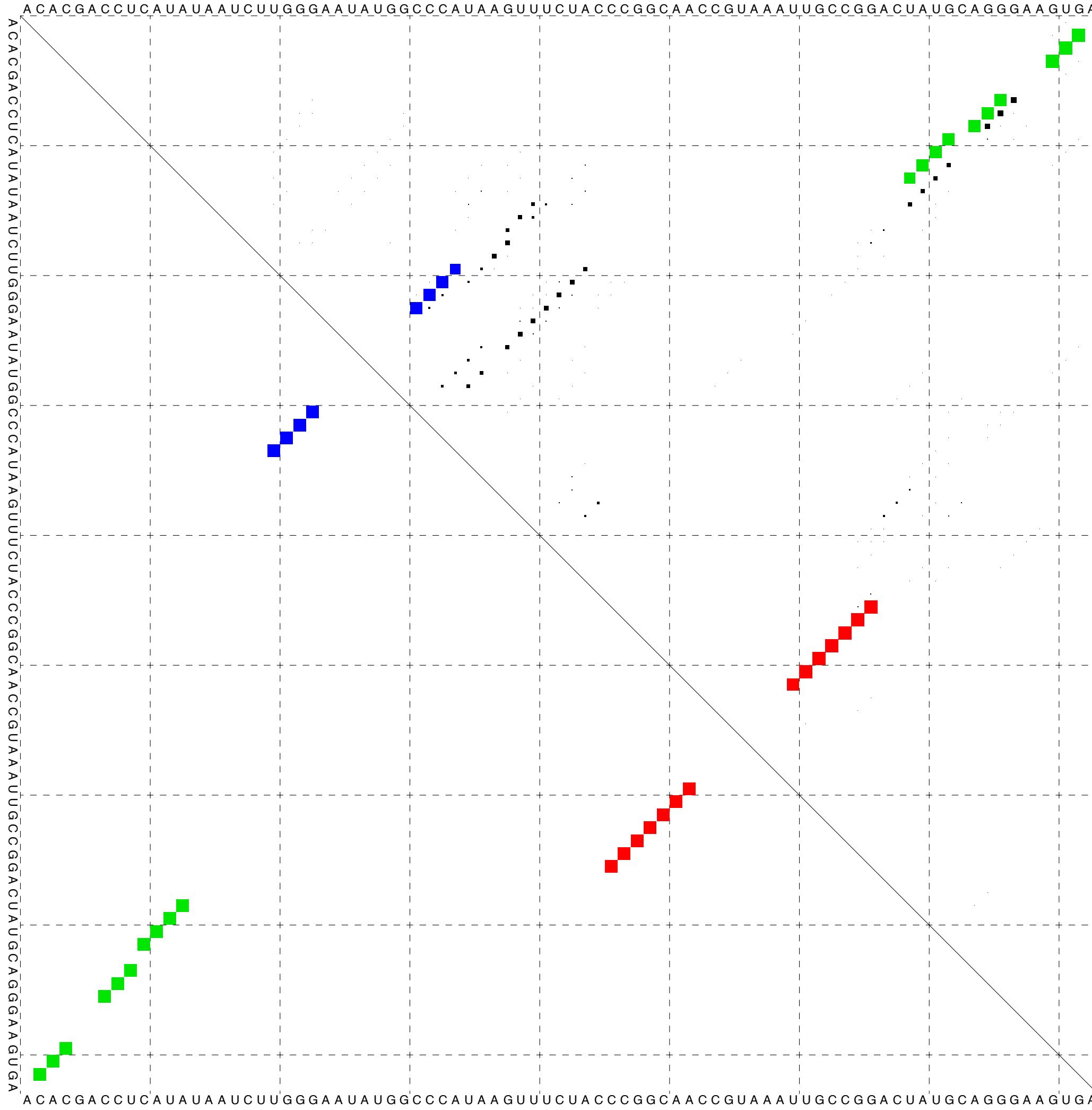
The probability of structure features can be computed from Z , e.g. the probability that a pair is formed

$$p_{ij} = \sum_{\Psi, (i,j) \in \Psi} p(S)$$

For efficient computation define the partition function \widehat{Z}_{ij} for structures outside the subsequence $x[i..j]$

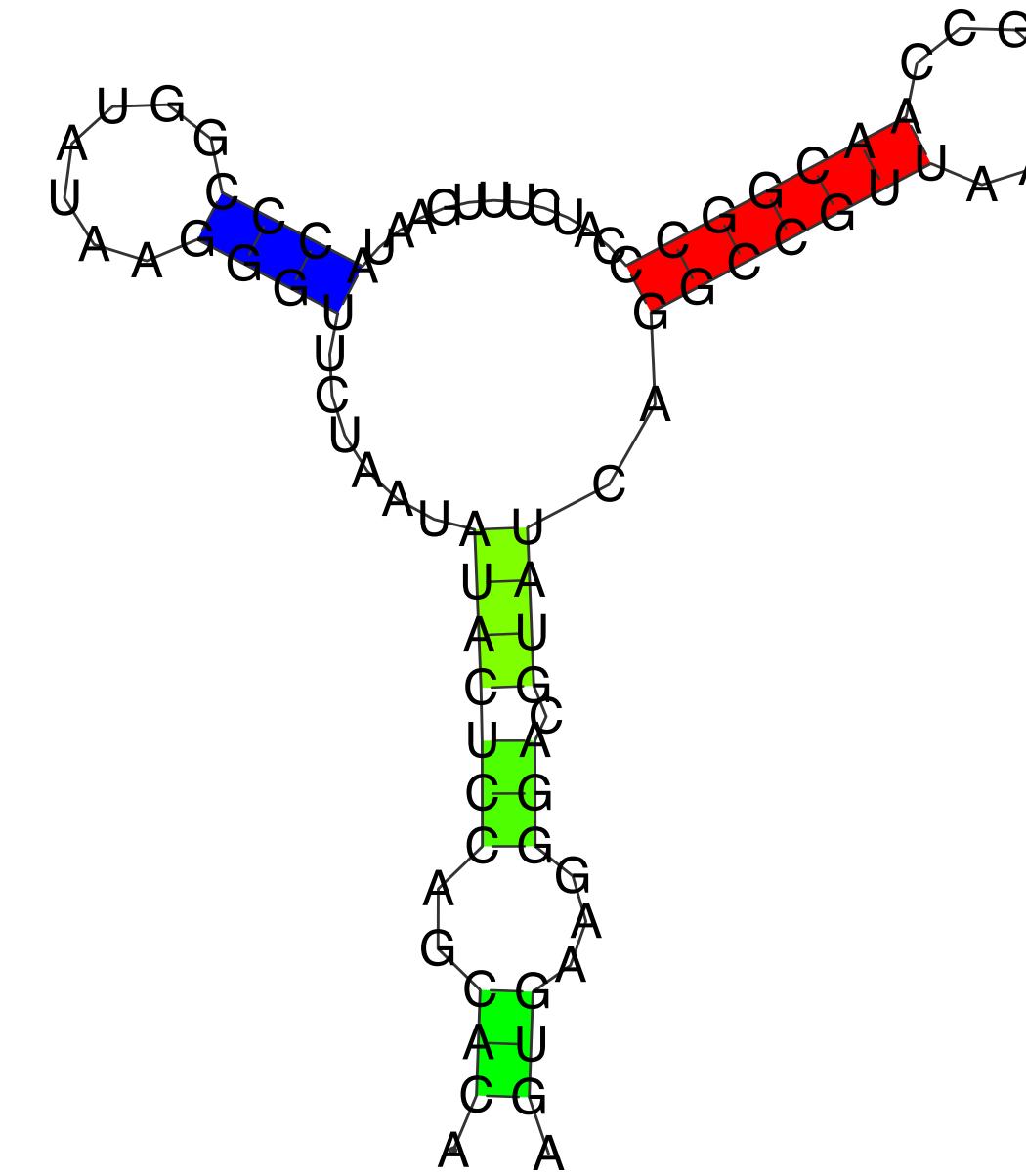
$$p_{ij} = \widehat{Z}_{ij} Z_{i+1,j-1} \exp(-\varepsilon_{ij}/RT) / Z$$

Representing Ensembles of RNA Structures



Ensembles of structures (thermodynamic equilibrium) are best represented by base pair probabilities.

A pair (i, j) with probability p is represented by a square in row i and column j with area p .



The Vienna RNA Package

- Minimum free energy and partition function folding
- Complete suboptimal folding
- Inverse folding / RNA design
- Comparison of secondary structures
- Specific heat curves
- Inclusion of structure probing data
- Analysis of folding kinetics / co-transcriptional folding
- Utilities for plotting and annotation structures
- 2.5D prediction: G-quadruplexes and pseudo-knots
- Prediction of consensus structures

For the programmer:

- A C library to link against your programs
- Python/Perl scripting language interface

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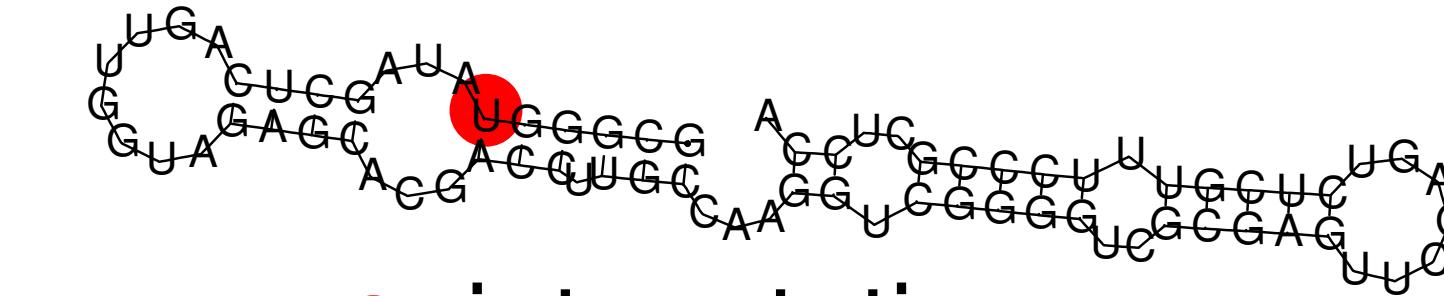
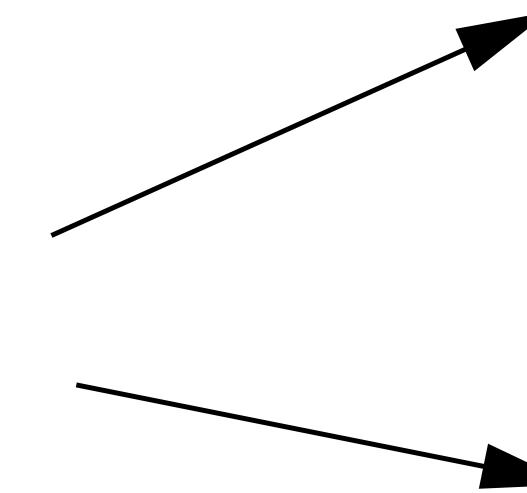
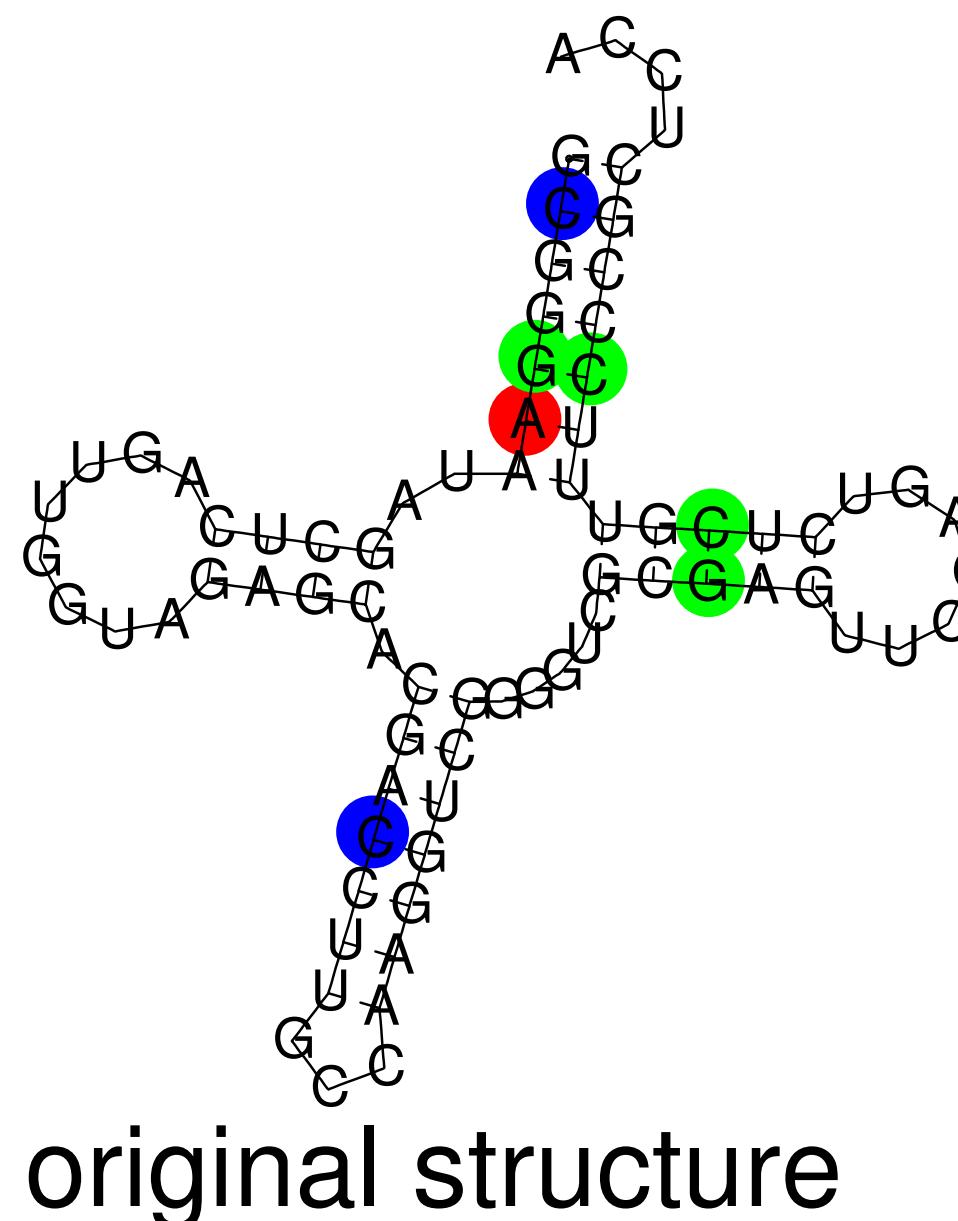
Free software, C source code and fold server available at

<http://www.tbi.univie.ac.at/RNA/>

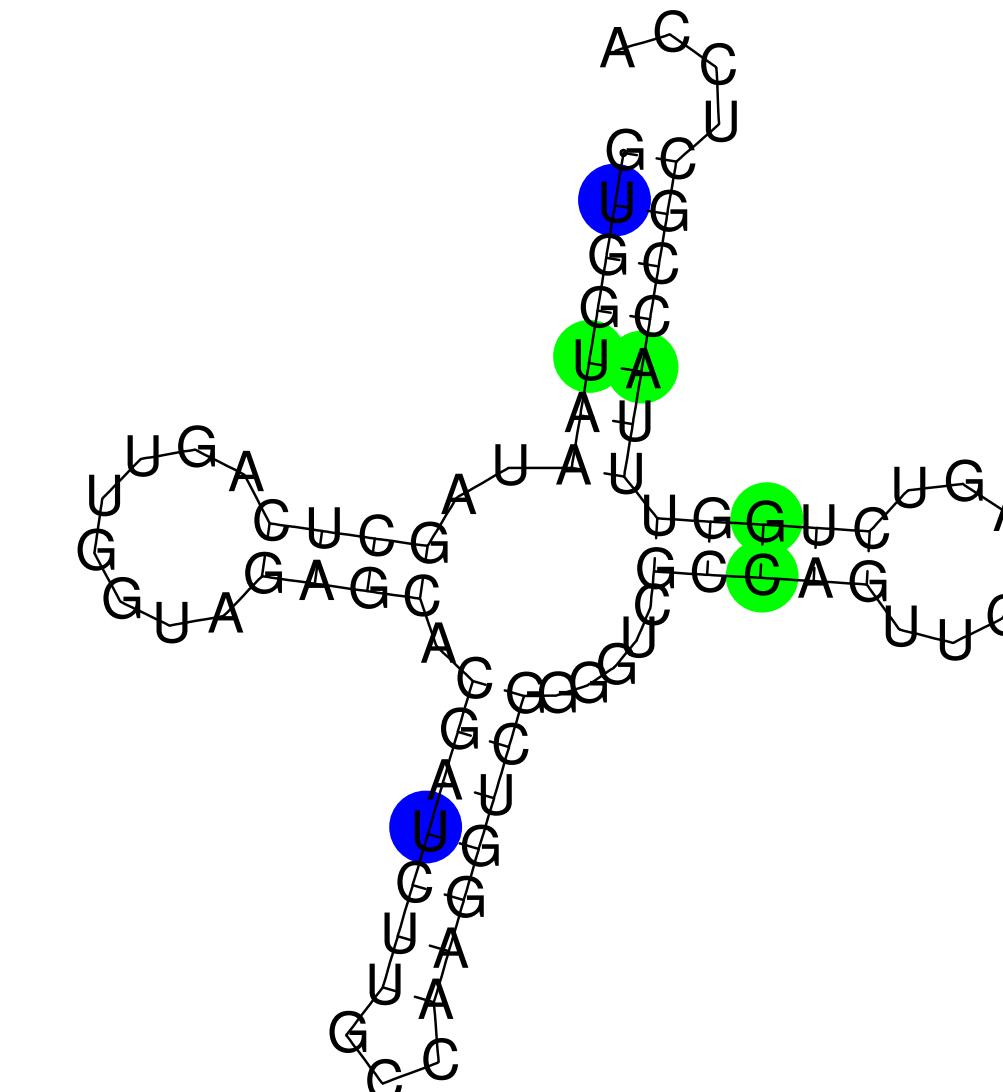
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Functional Structures: Point Mutations



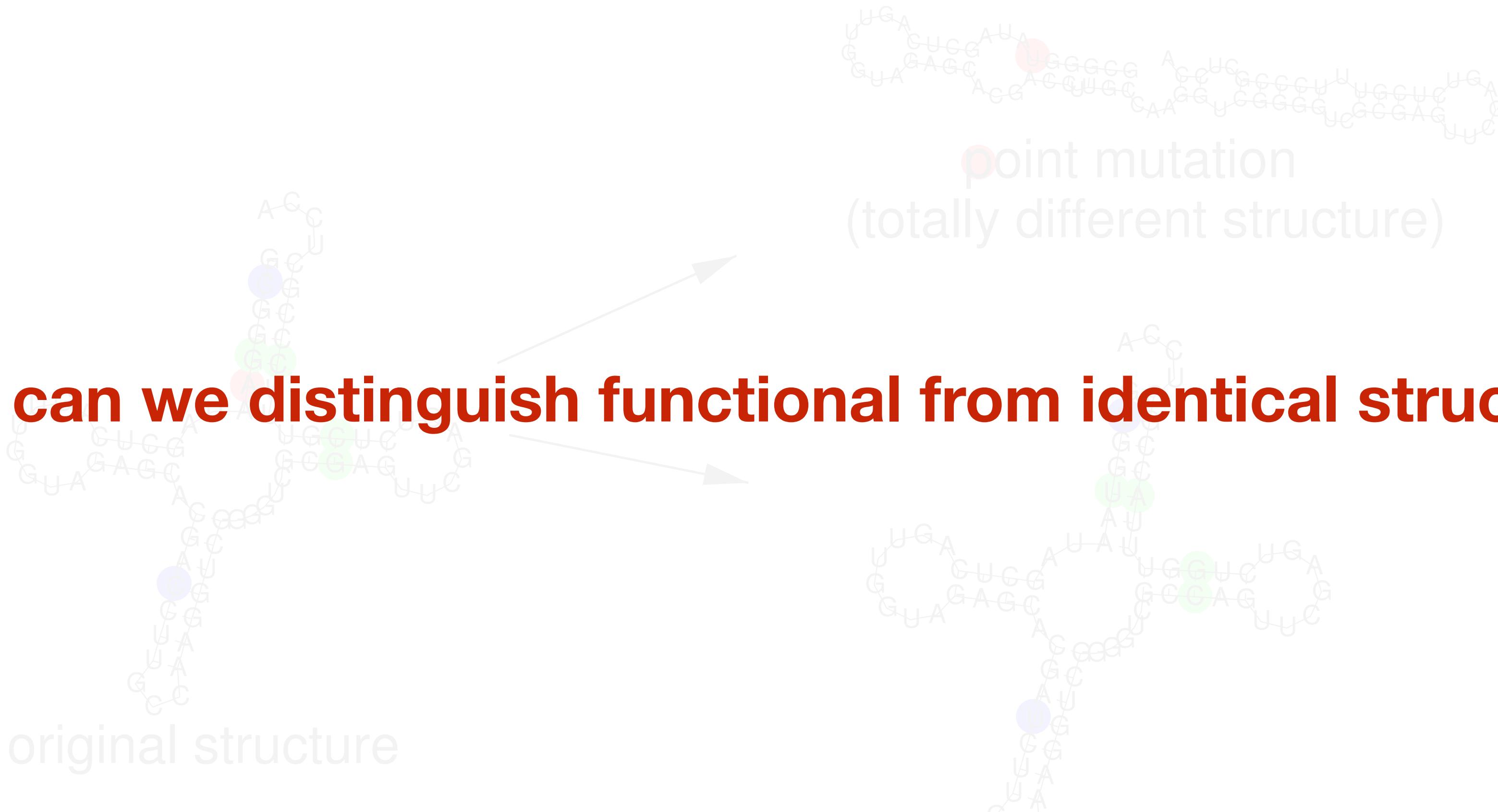
point mutation
(totally different structure)



compensatory and consistent mutations
(no structural change)

Functional Structures: Point Mutations

How can we distinguish functional from identical structures?



compensatory and consistent mutations
(no structural change)

Consensus Structures: Alignment Folding

Combine covariance analysis and folding into one DP algorithm

- Apply conventional folding algorithm to alignment
- Use a modified energy function that includes covariance score

$$E_c(A, \Psi) = \sum_k E(A_k, \Psi) + cv \cdot \sum_{(i,j) \in \Psi} B_{ij}$$

- Can be used for all variants: MFE, partition function, ...
- Efficient: $\mathcal{O}(N \cdot n^2 + n^3)$ CPU and $\mathcal{O}(n^2)$ memory for alignment length n and N sequences
- Same results as RNAfold for single sequences



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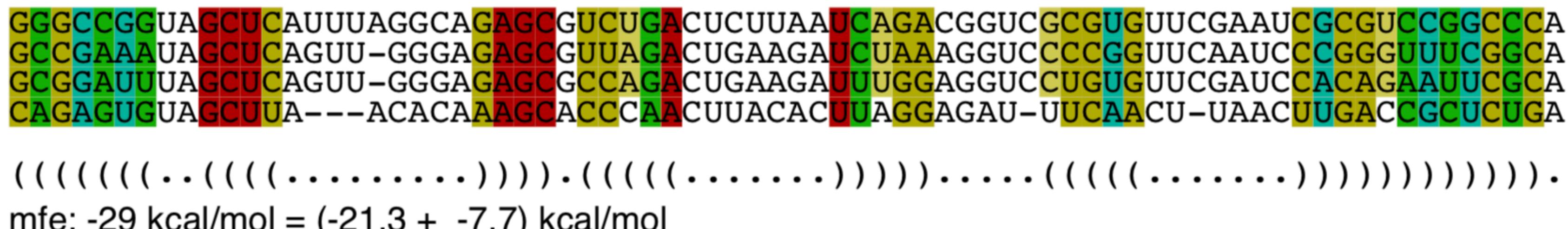
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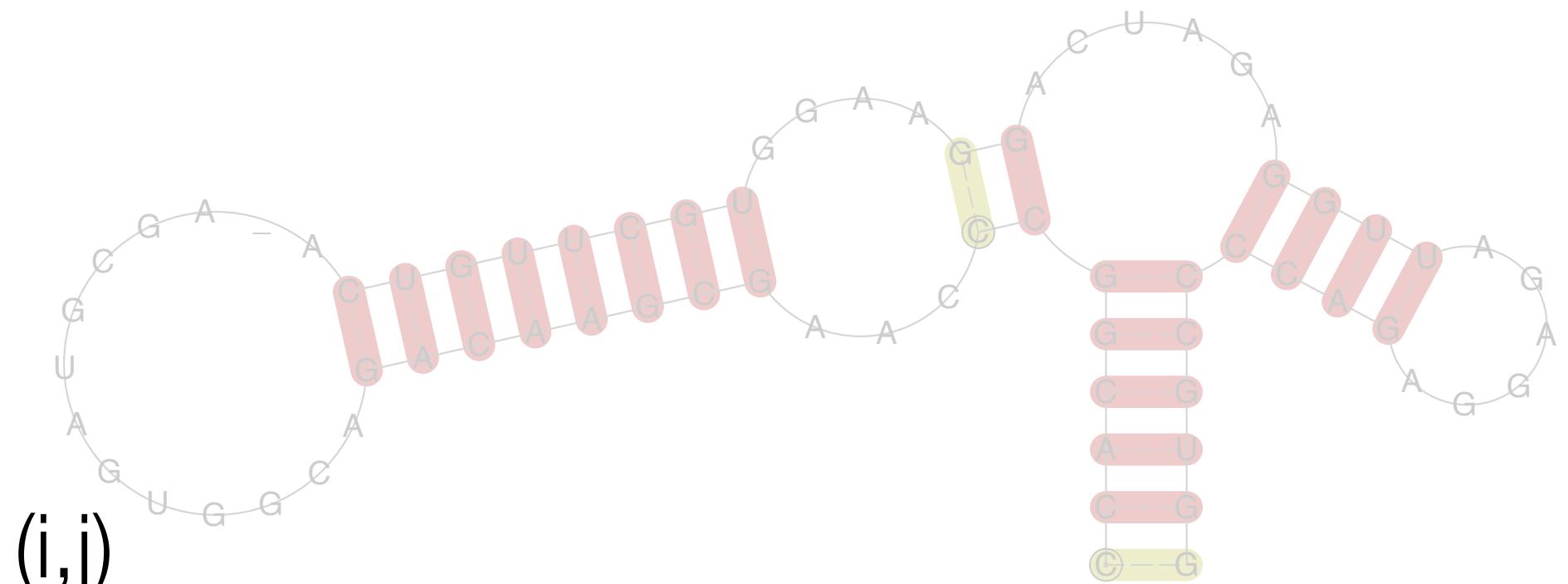


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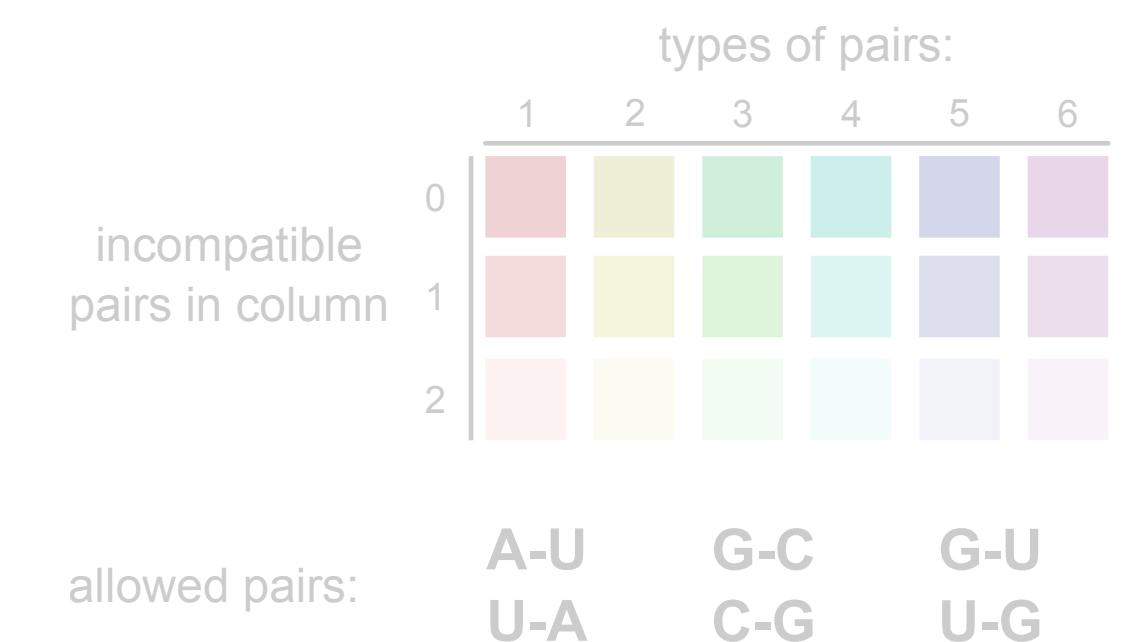


RNA Covariation as Evolutionary Trait

- High mutation rate in RNA viruses due to error-prone RdRP
- For base pair (i,j): GC/CG/AU/UA/GU/UG
- Consistent mutation: different standard combinations
- Compensatory mutation: both positions are mutated
- Presence of both strongly supports predicted base pair (i,j)

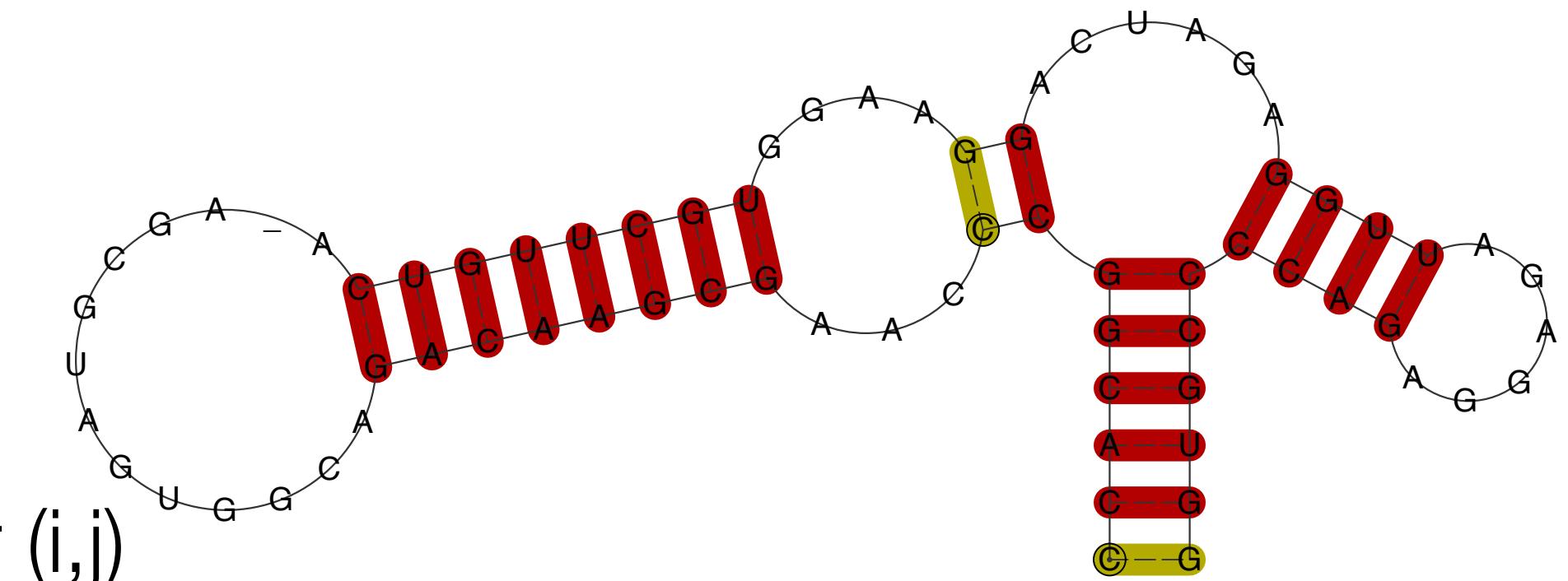


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USUV.11 CCACGGCUCAA GCGAACAGACGGUGAUGCAG-A CUGUUCGU GGAAAG GACUAGA GGUUAGAGGA GACCCCGUGG 72
UCACGGCCCAAGCGAACAGACGGUGAUGCAG-A CUGUUCGU GGAAAG GACUAGA GGUUAGAGGA GACCCCGUGG 72
.....10.....20.....30.....40.....50.....60.....70..



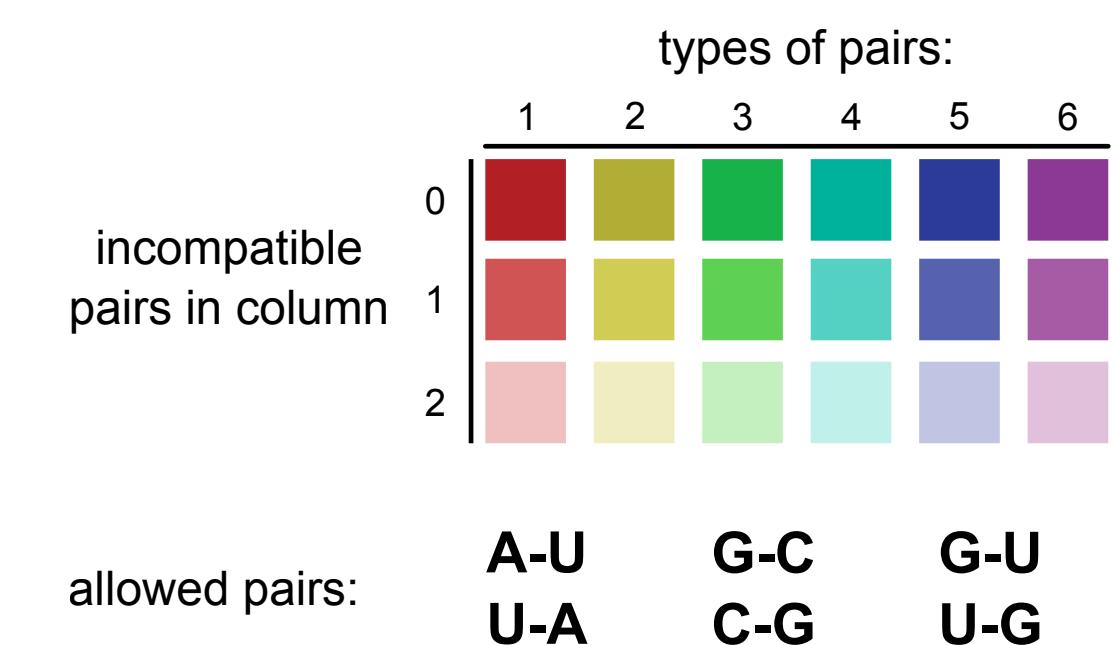
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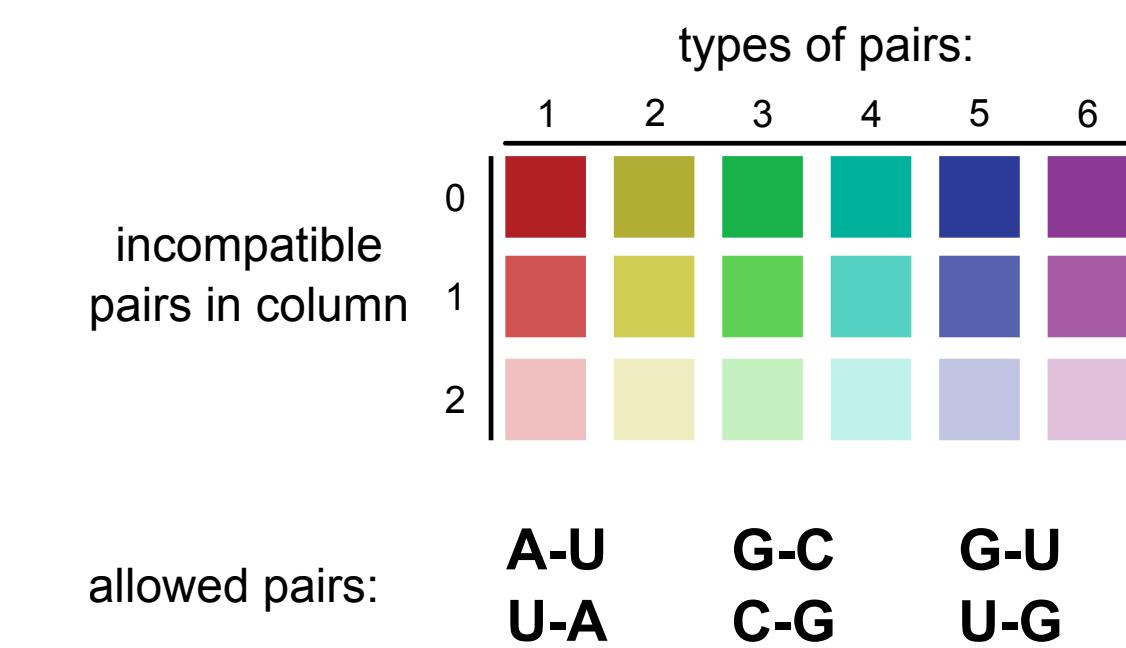
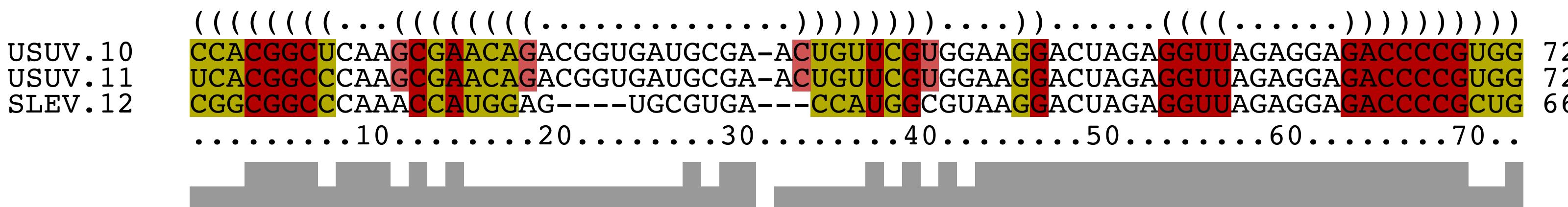
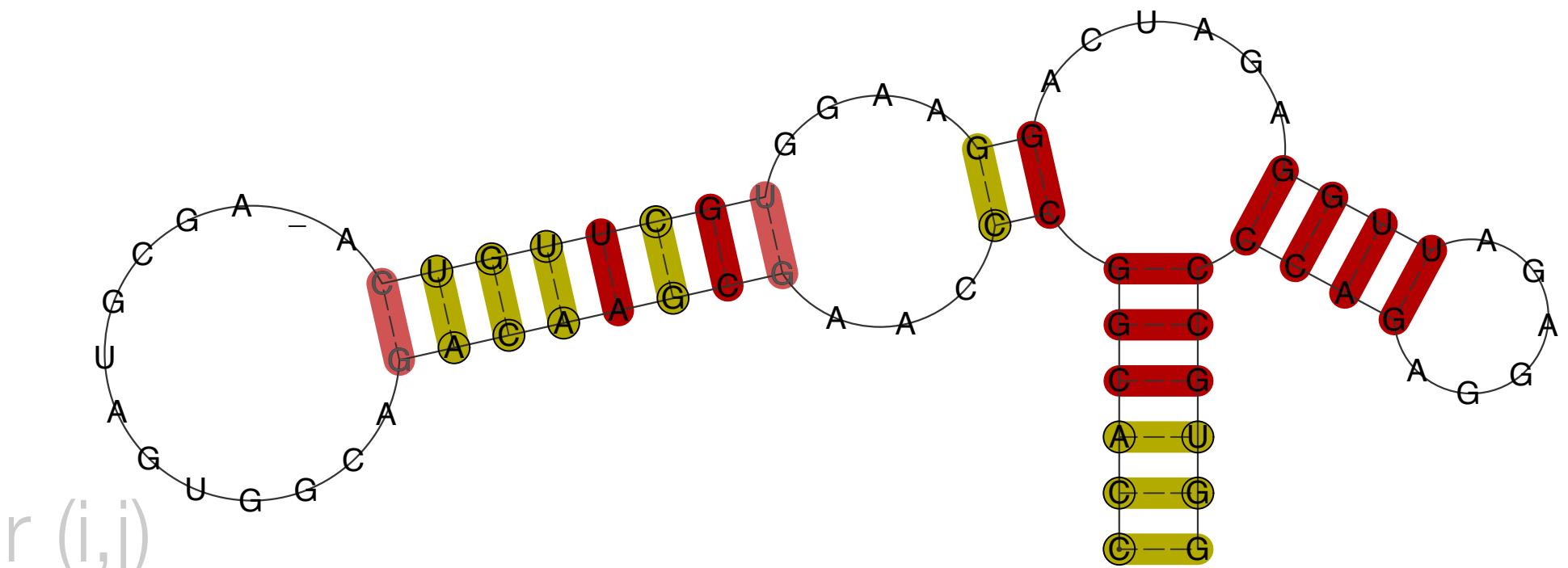
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|---------|---|----|
| USUV.10 | <code>(((((.....((((.....))))))).....((.....))))))</code> | |
| | <code>CCACGGCUCAA</code> | 72 |
| USUV.11 | <code>GC</code> | 72 |
| | <code>GAACAGACGGUGAUGC</code> | |
| | <code>GA</code> | |
| | <code>GUUCGUGGA</code> | |
| | <code>GG</code> | |
| | <code>ACUAGA</code> | |
| | <code>GU</code> | |
| | <code>AGAGGA</code> | |
| | <code>AC</code> | |
| | <code>CCCGUGG</code> | |
| | <code>CC</code> | |

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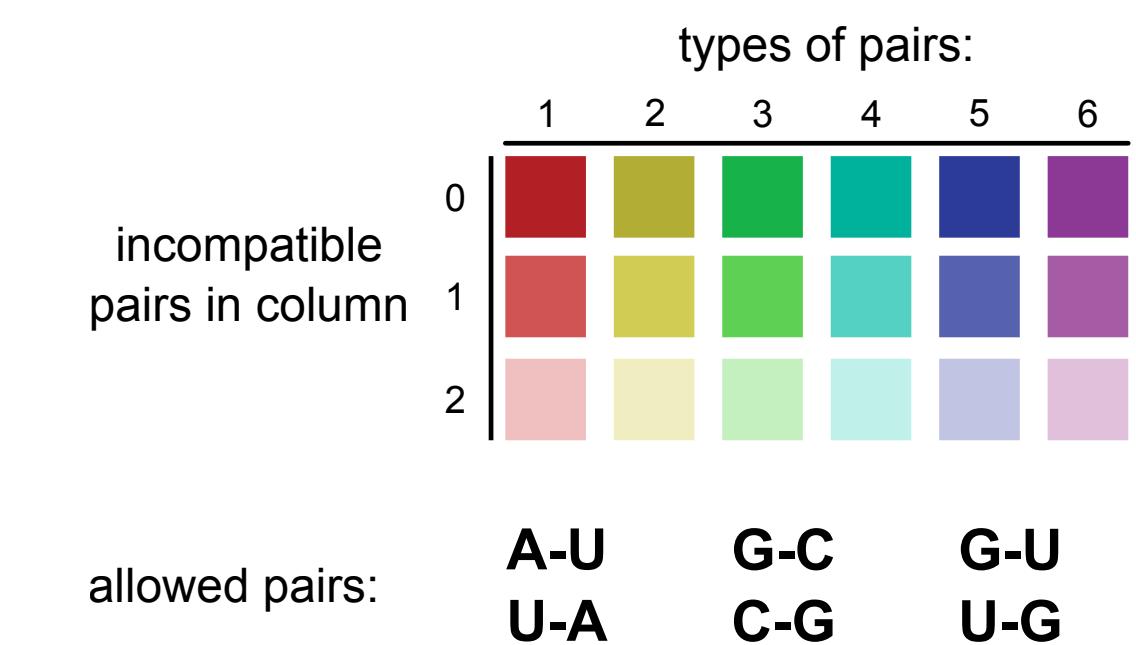
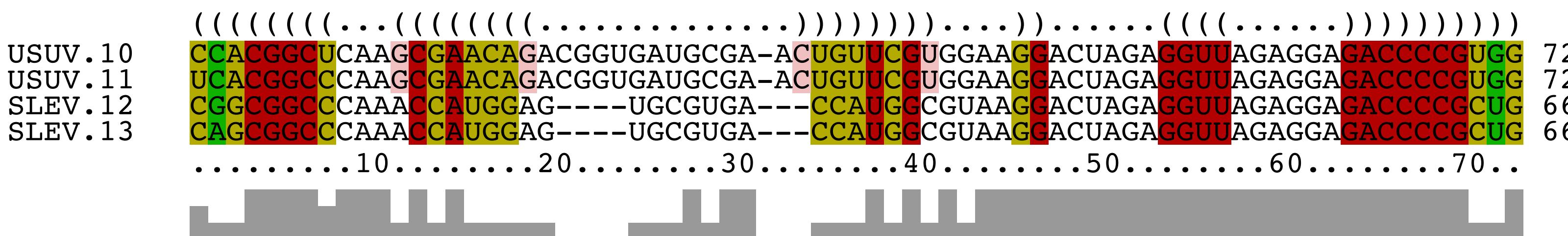
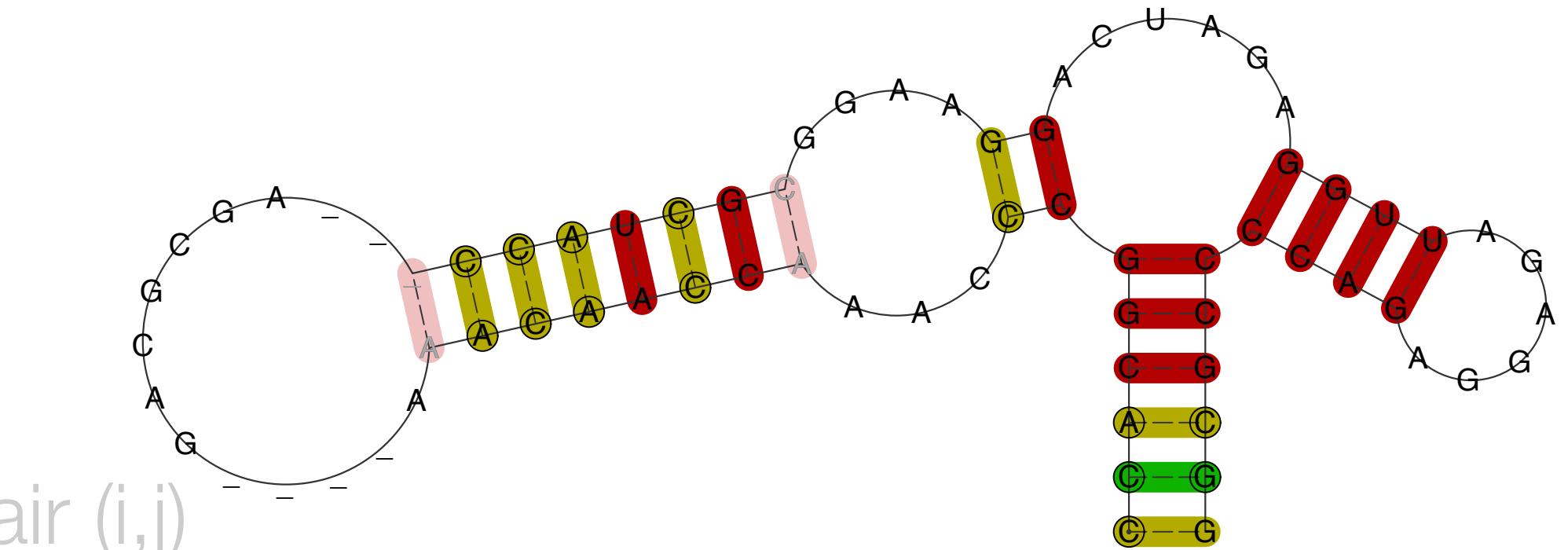
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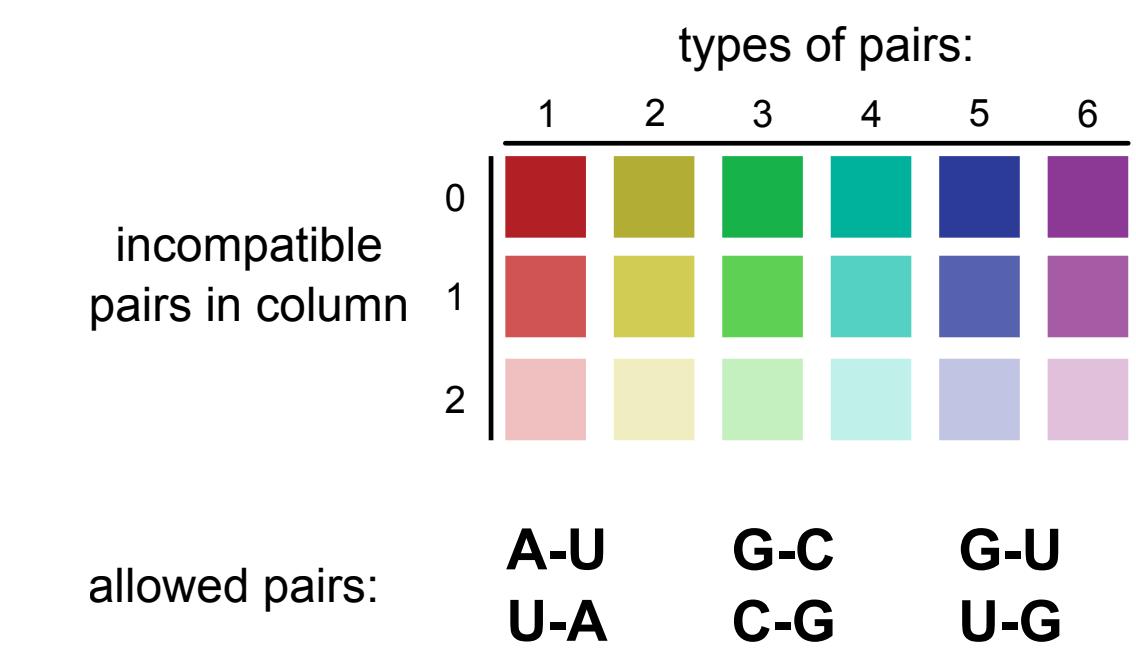
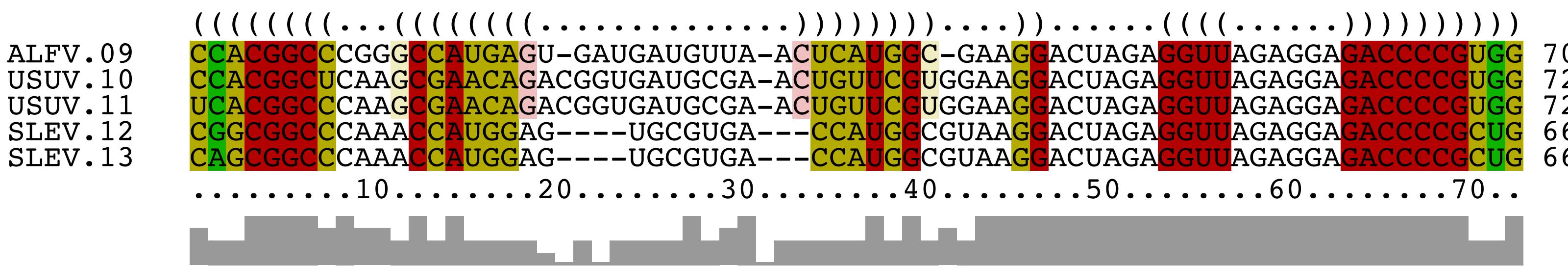
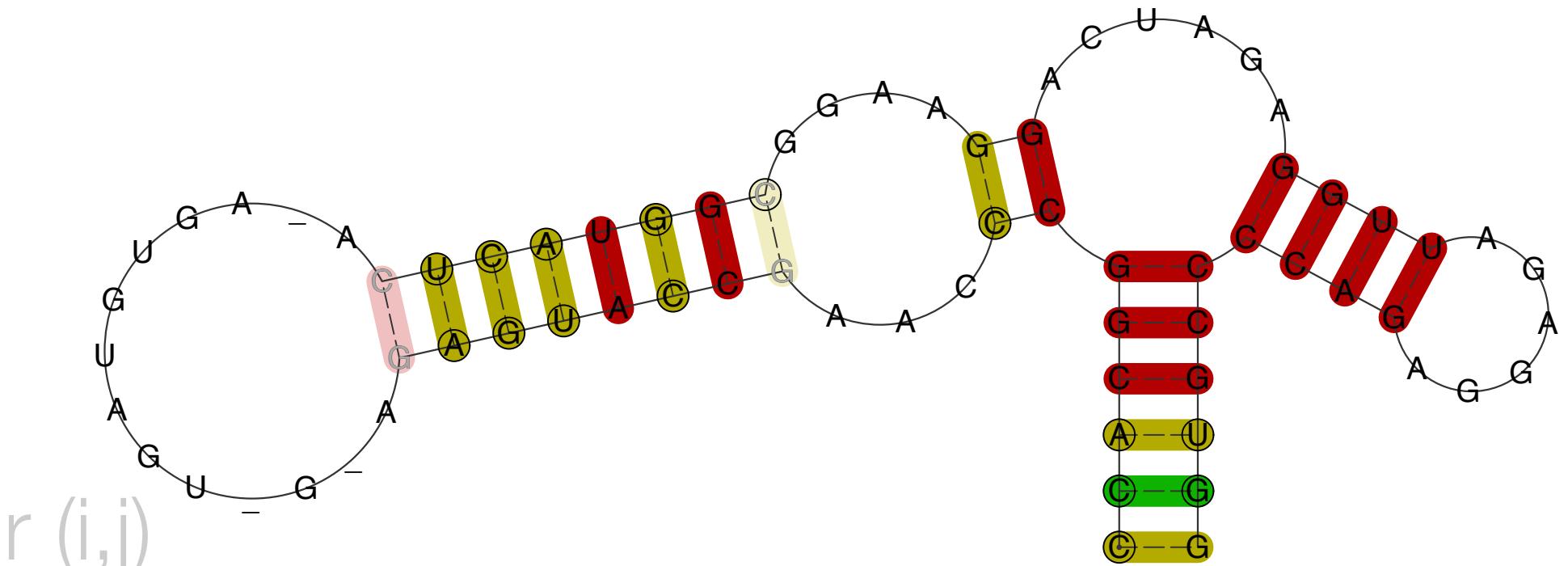
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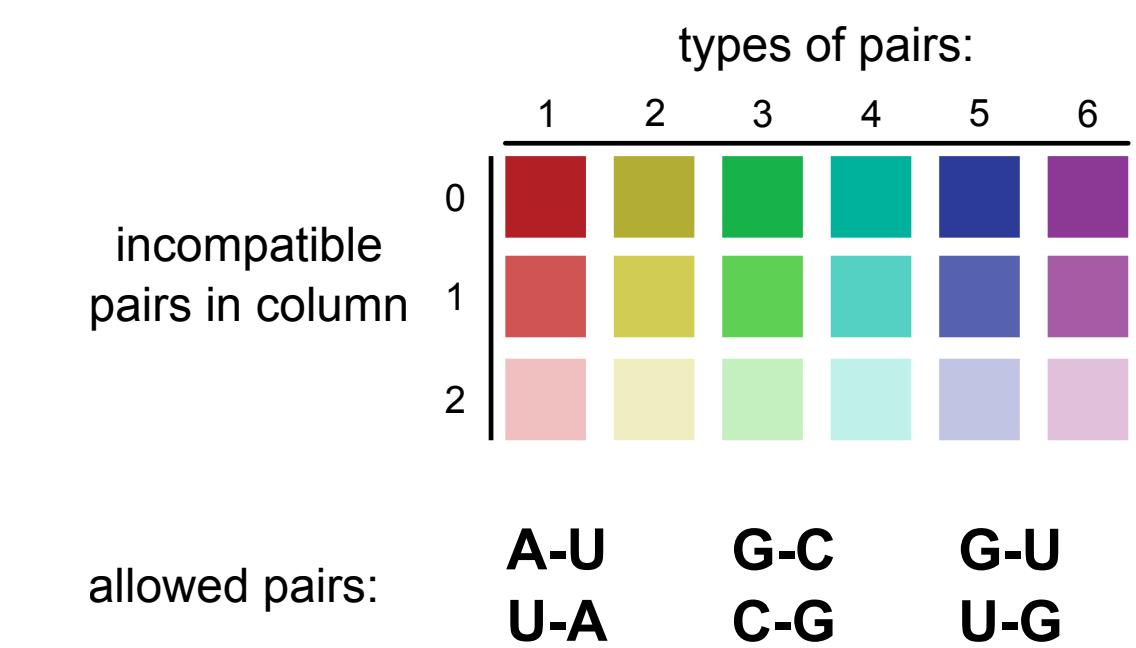
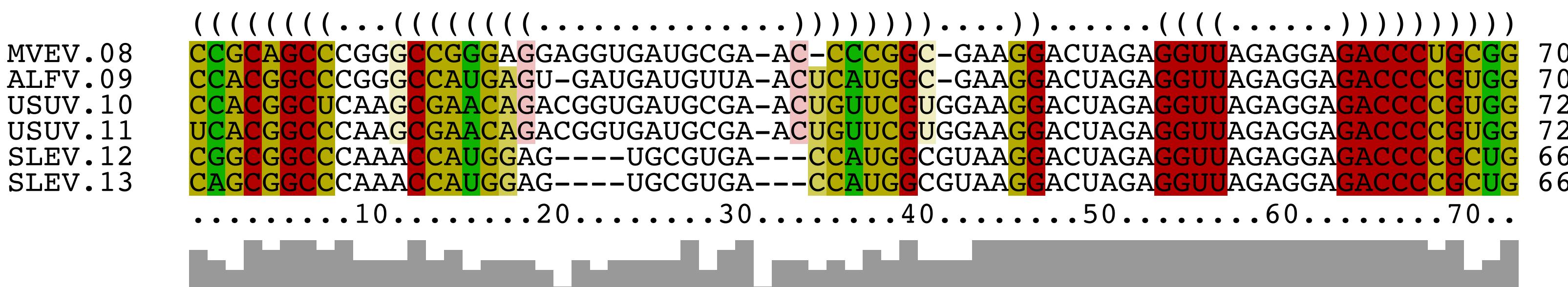
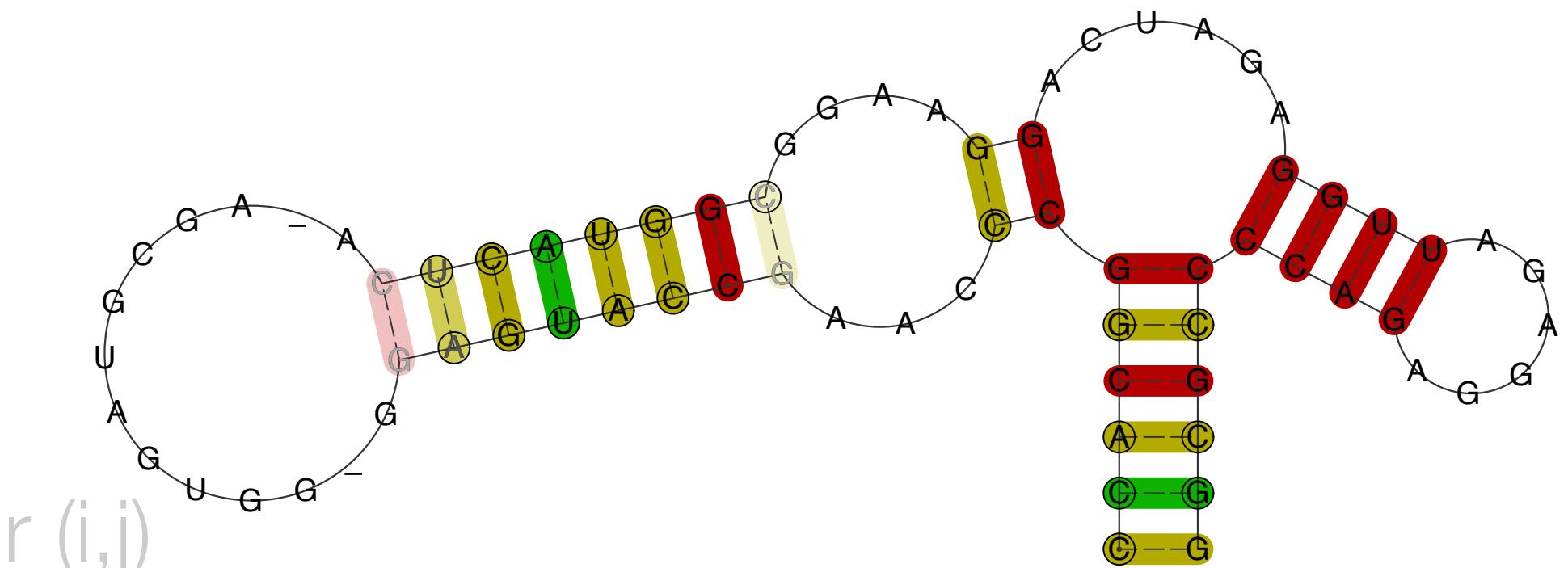
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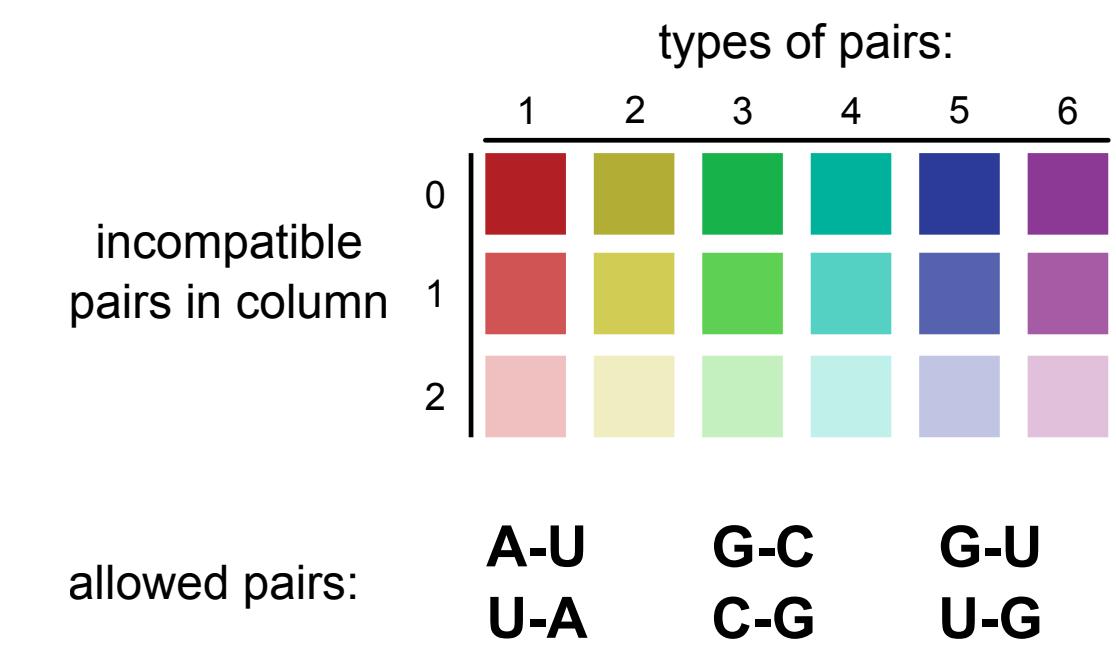
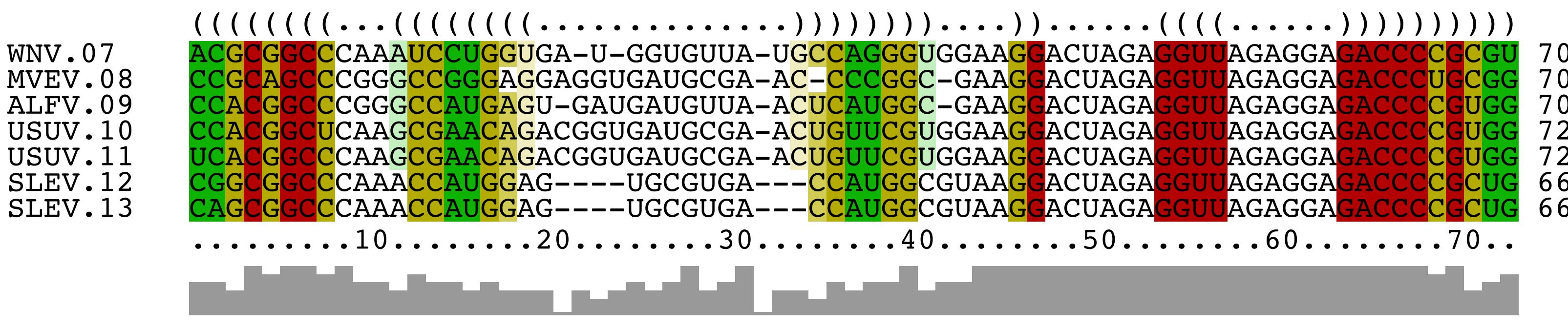
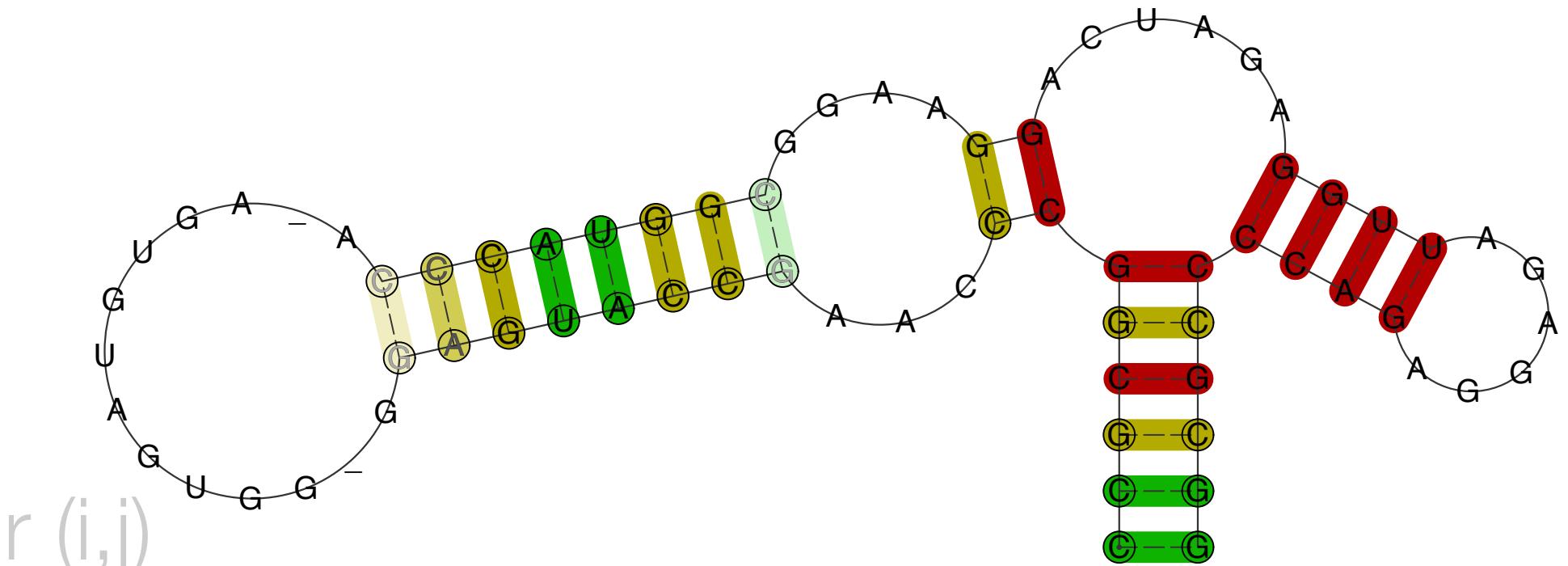
RNA Covariation as Evolutionary Trait

- High mutation rate in RNA viruses due to error-prone RdRP
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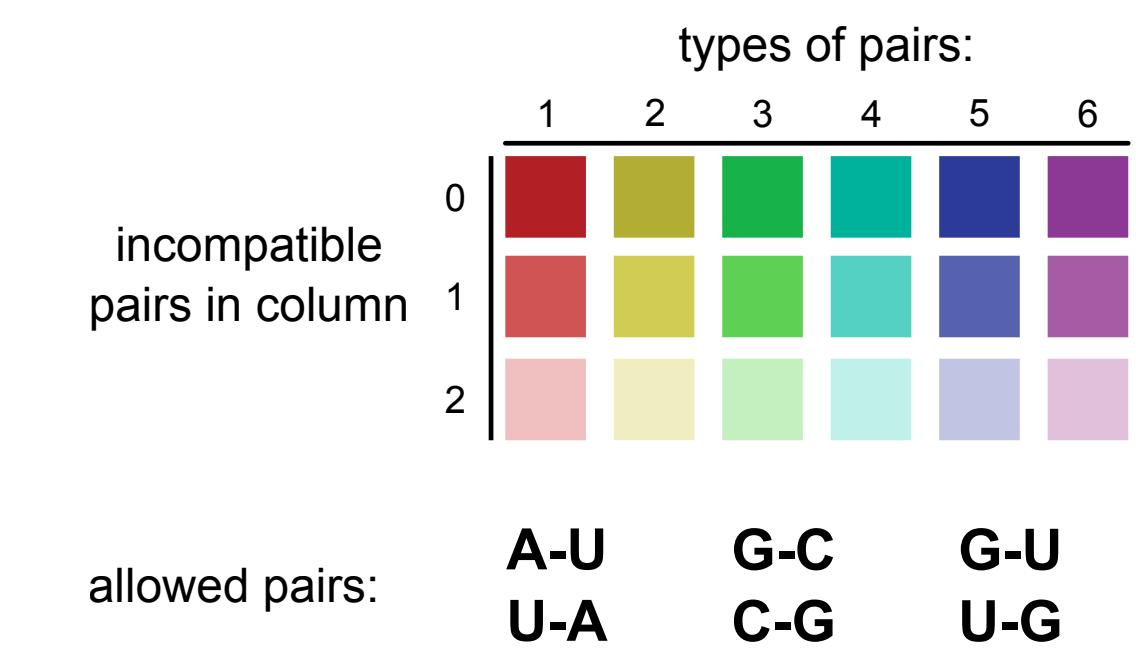
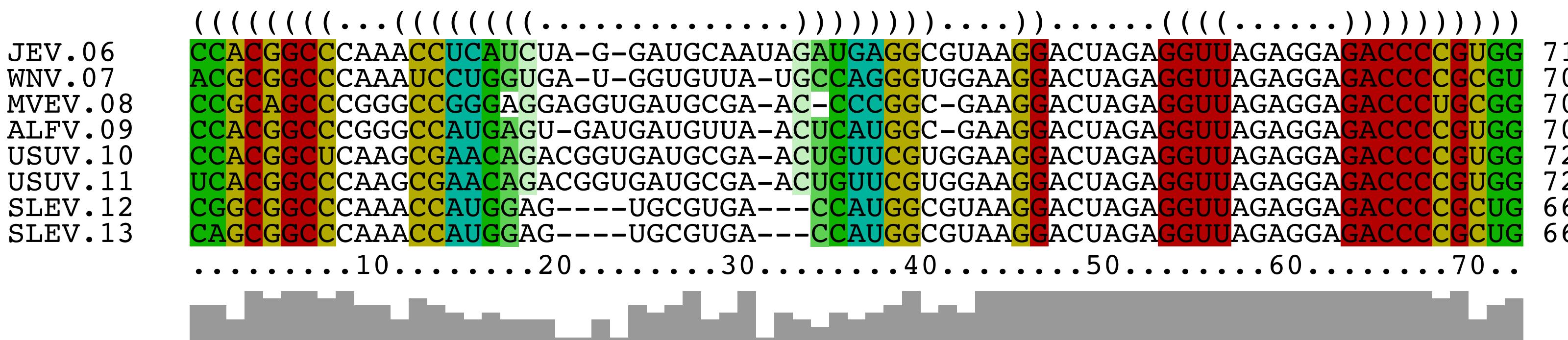
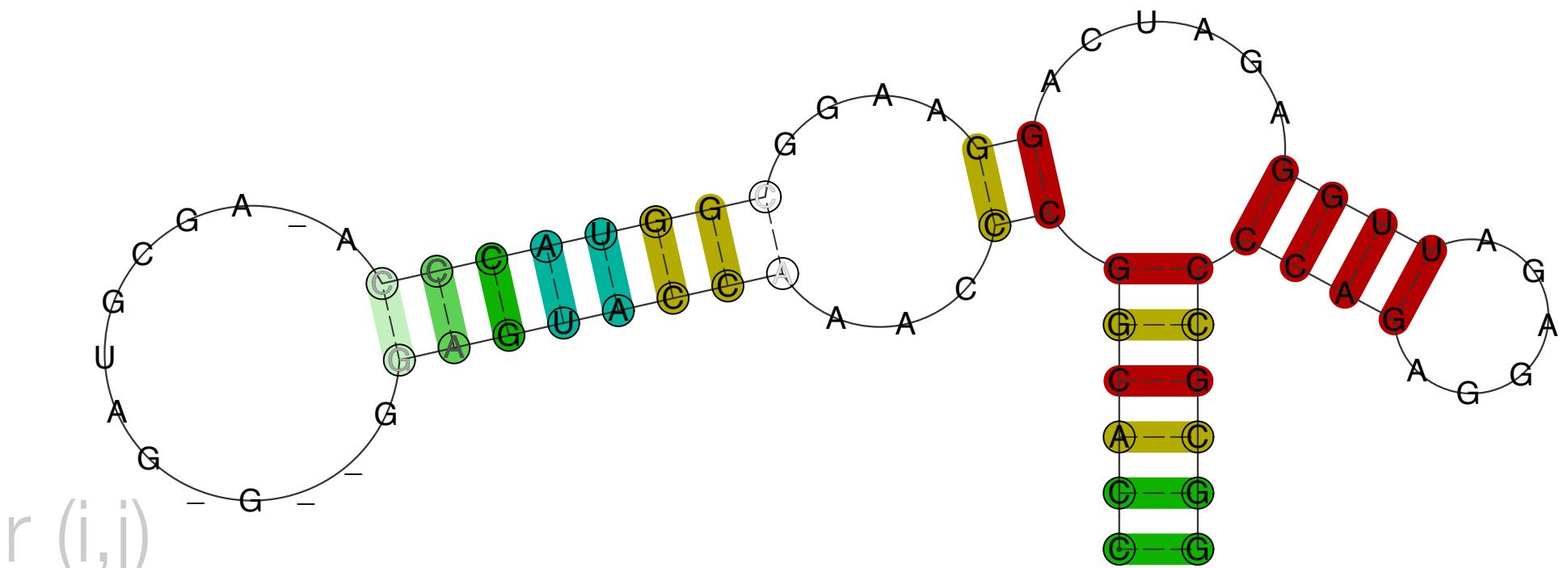
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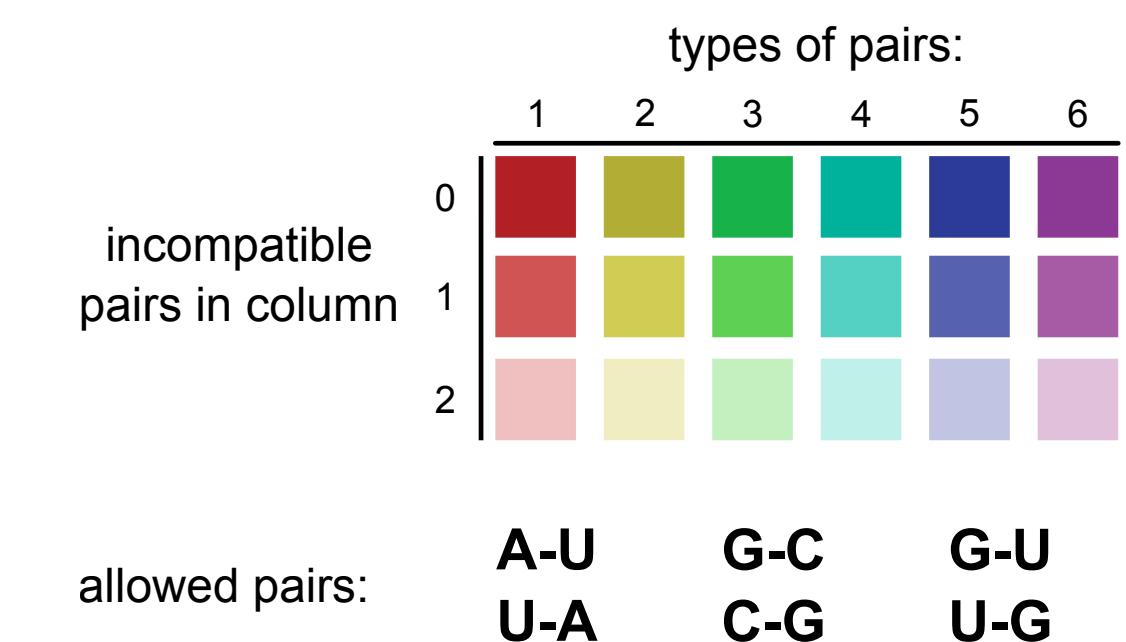
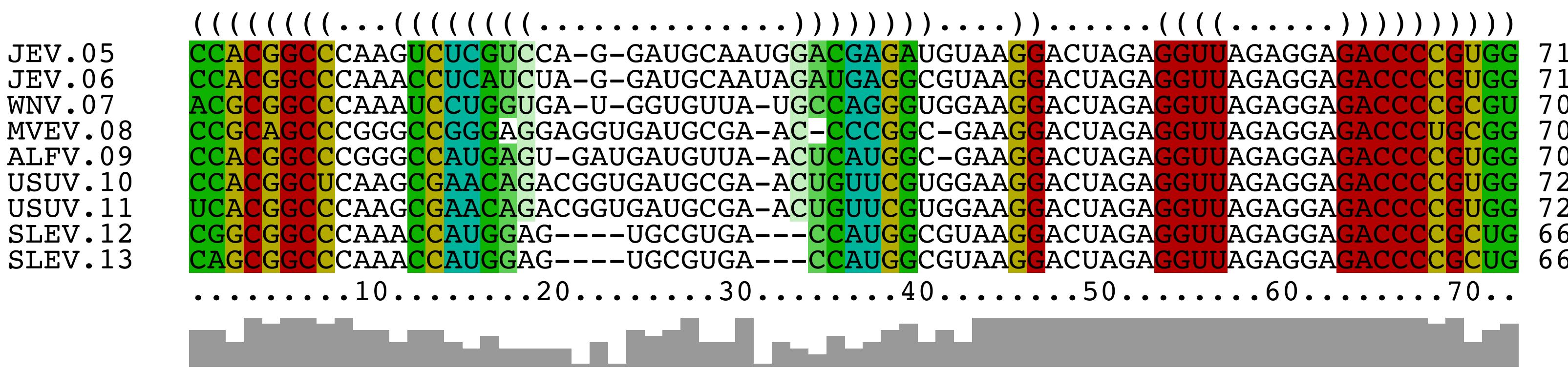
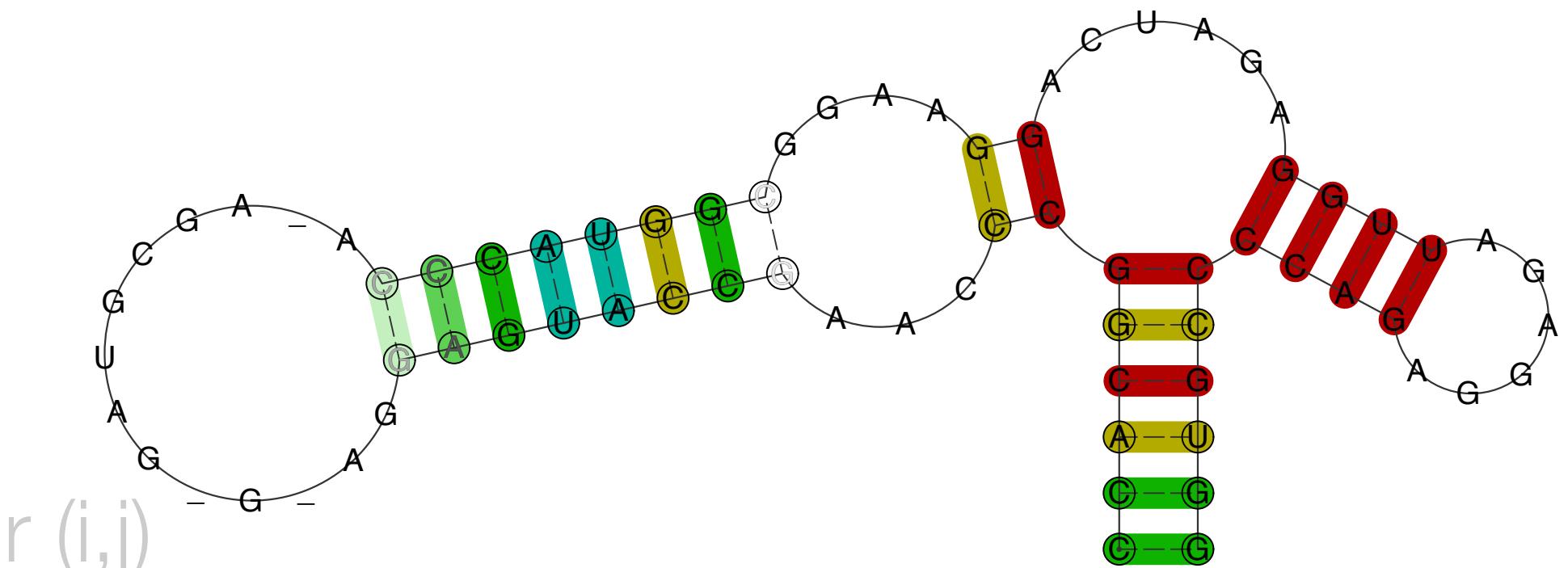
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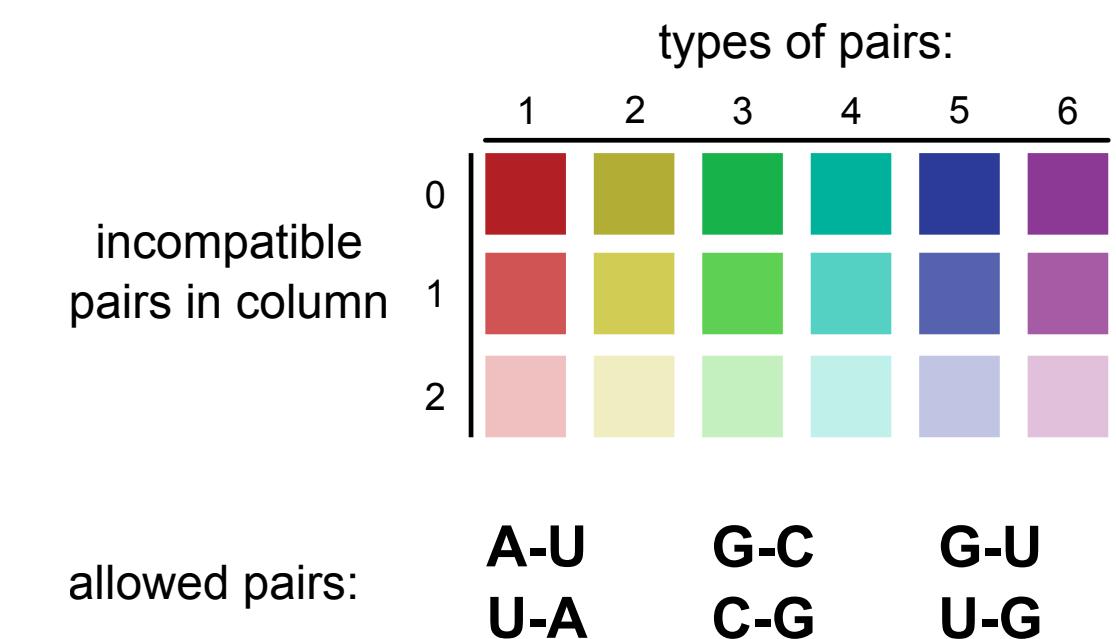
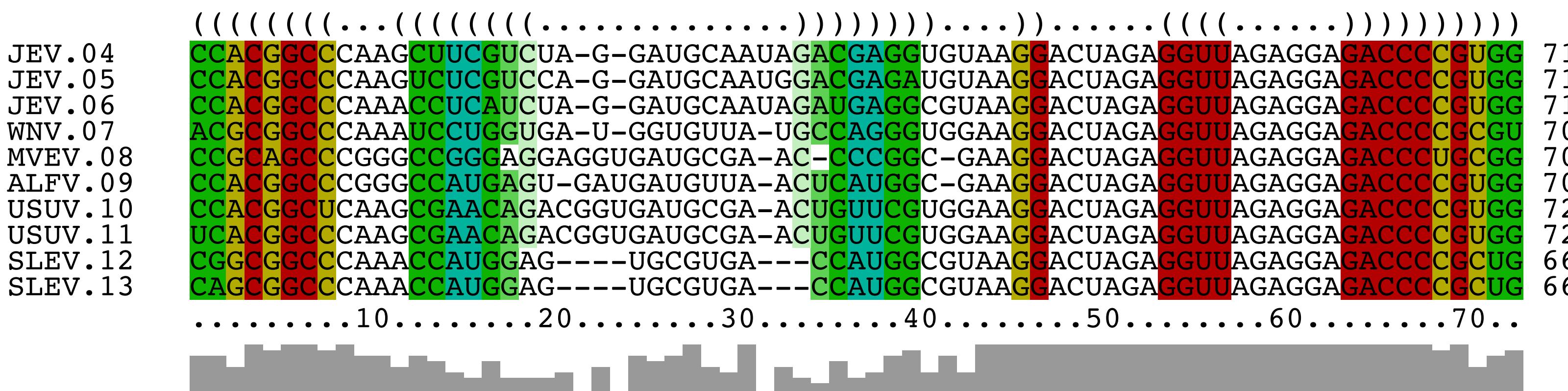
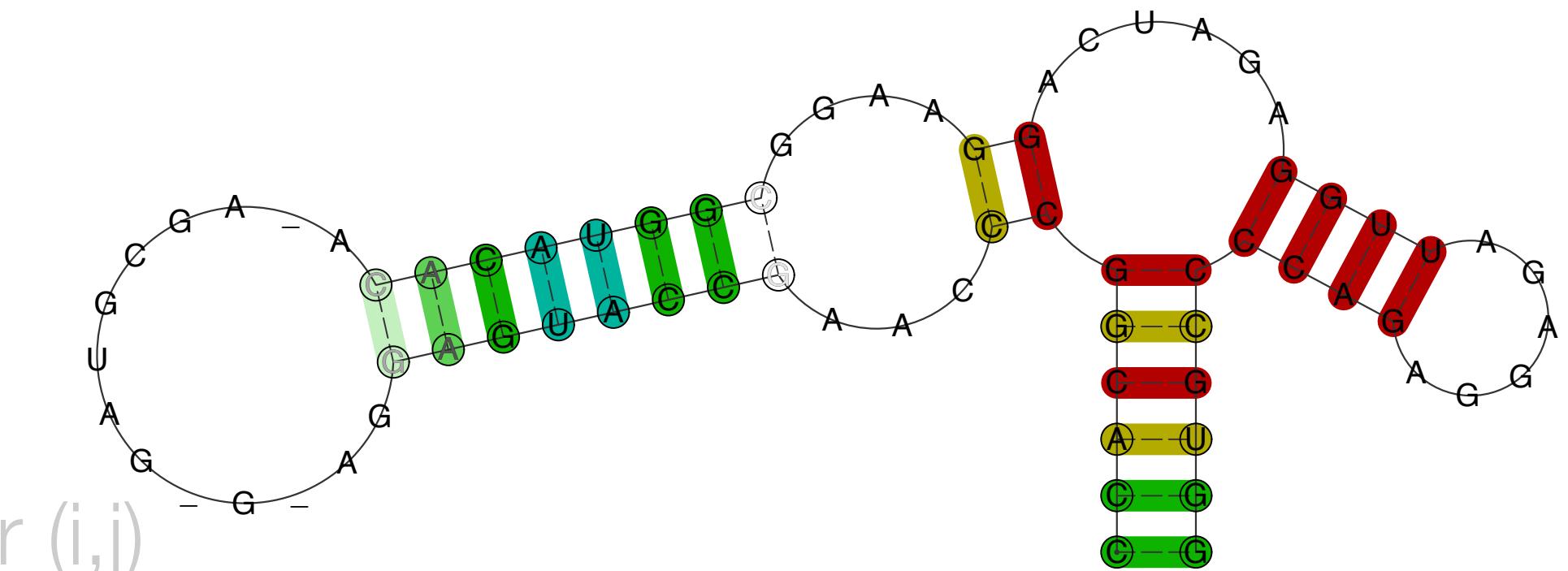
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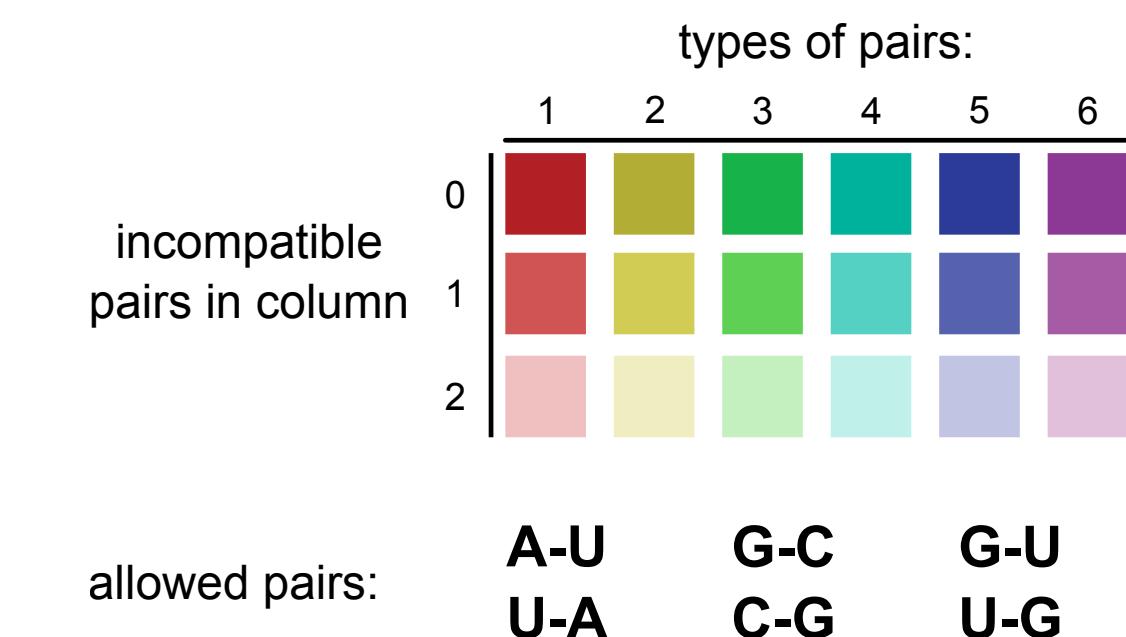
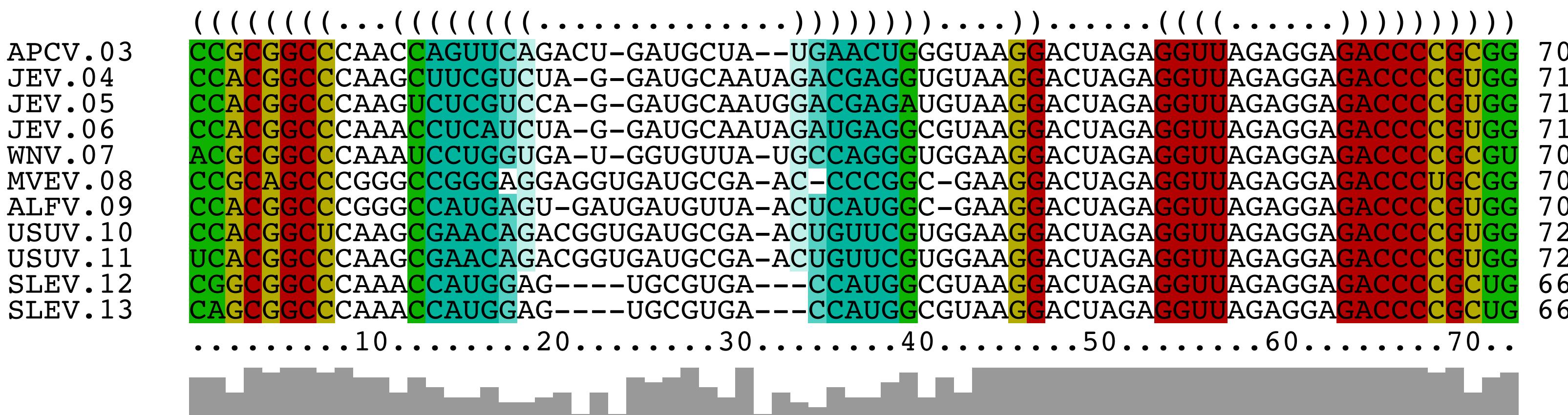
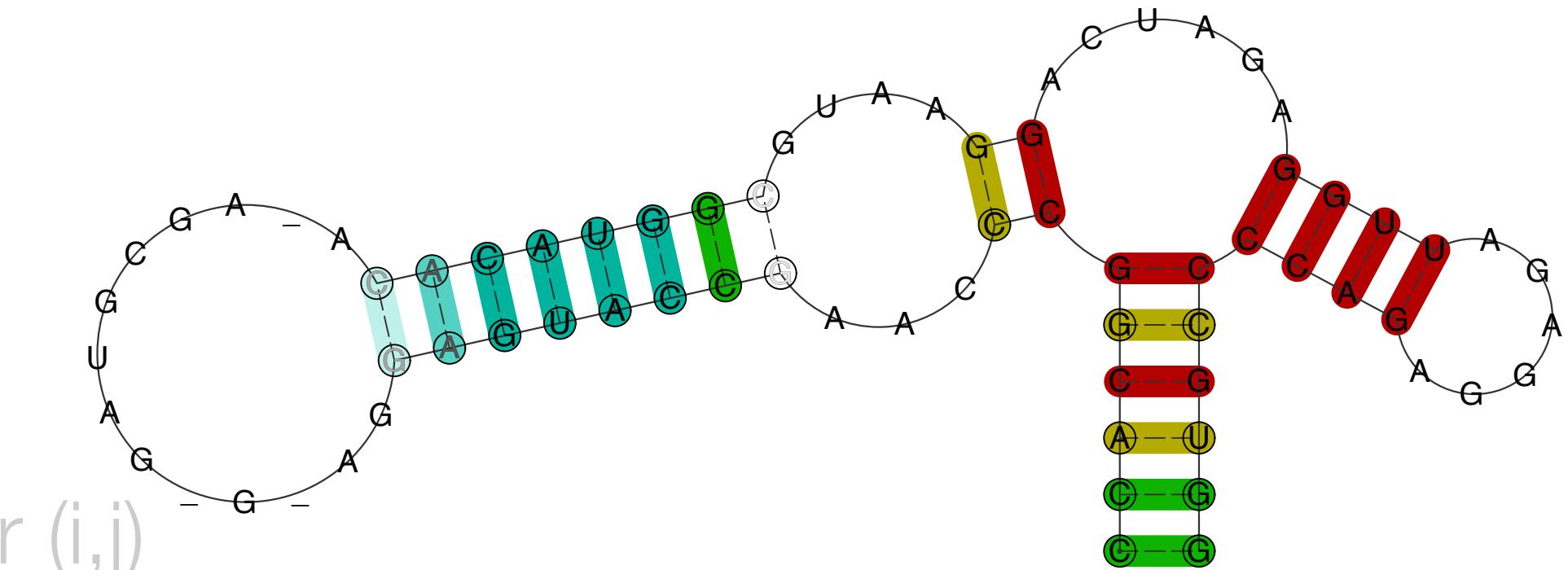
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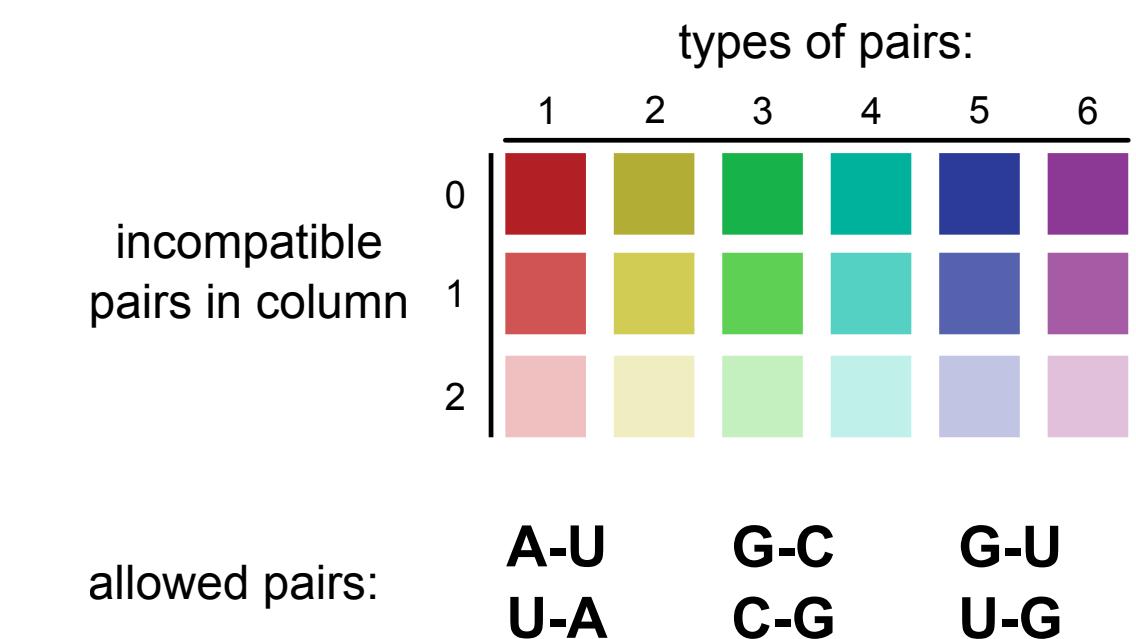
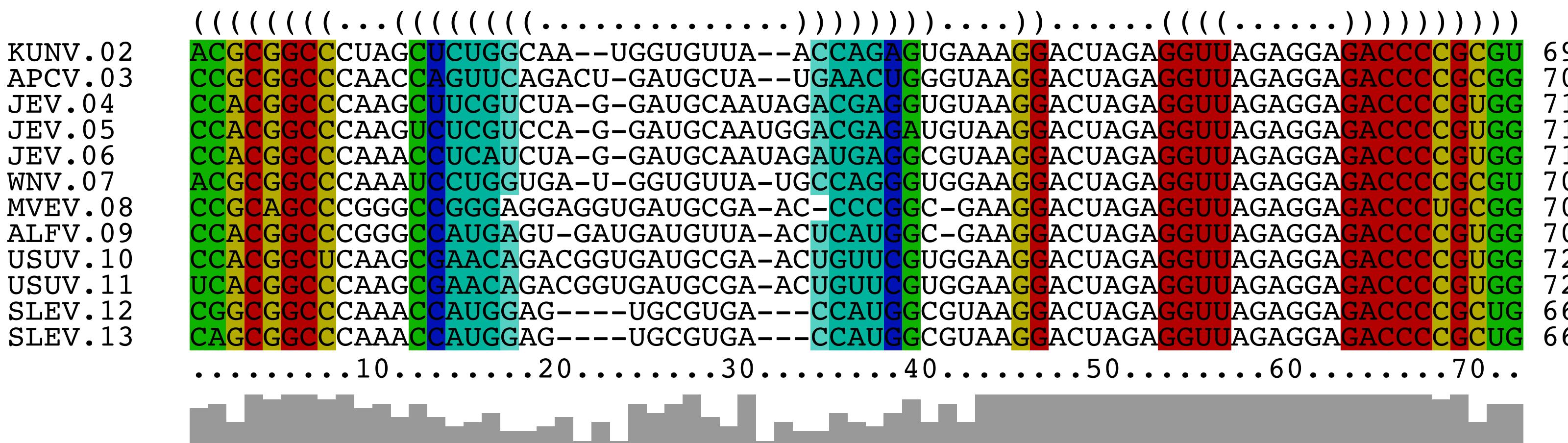
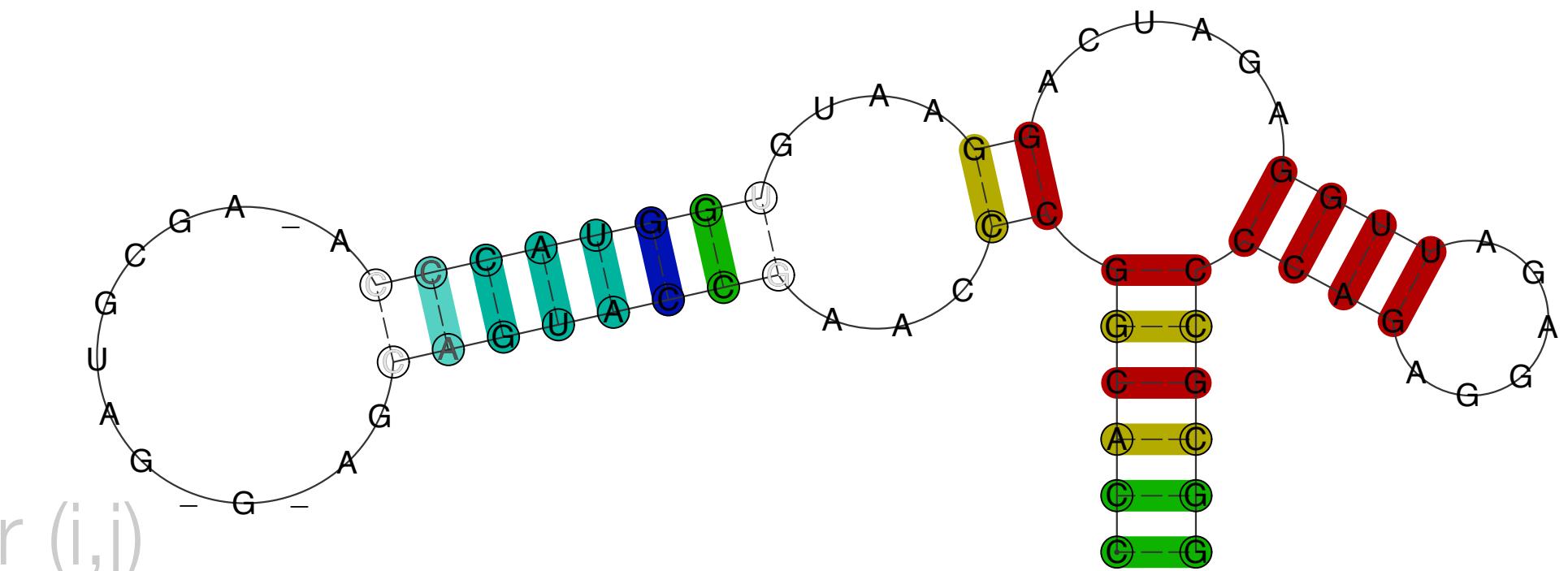
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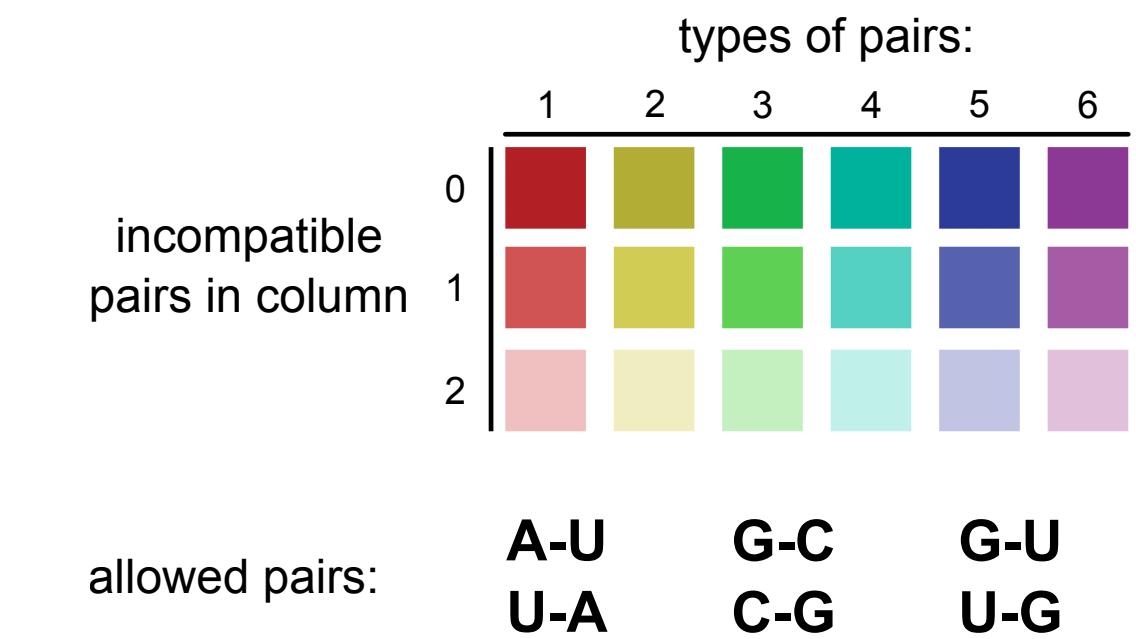
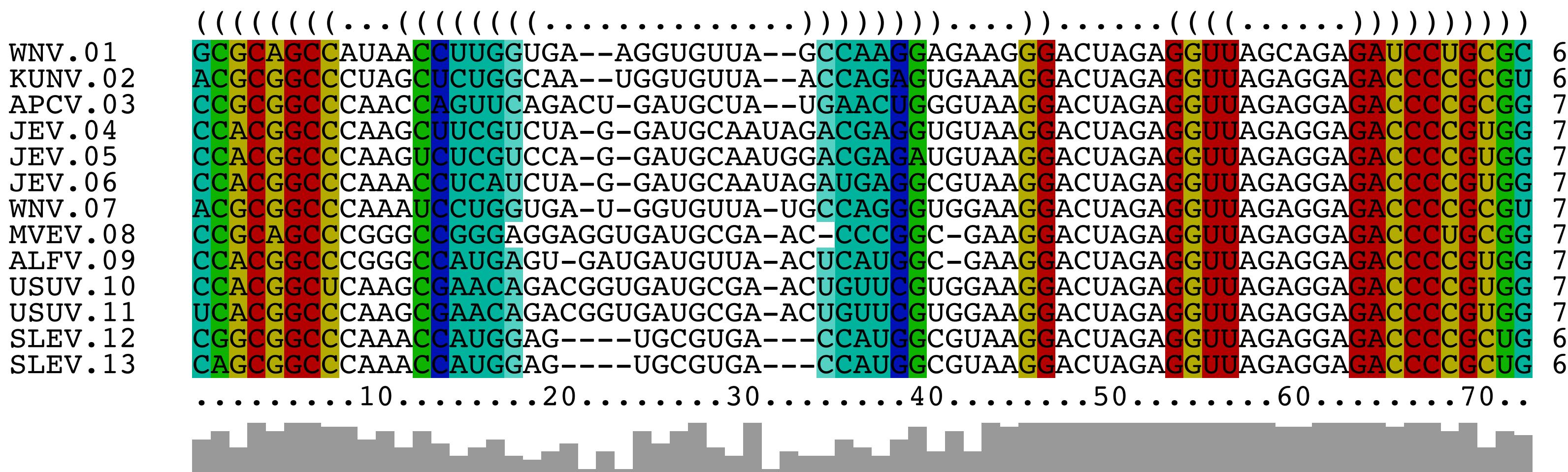
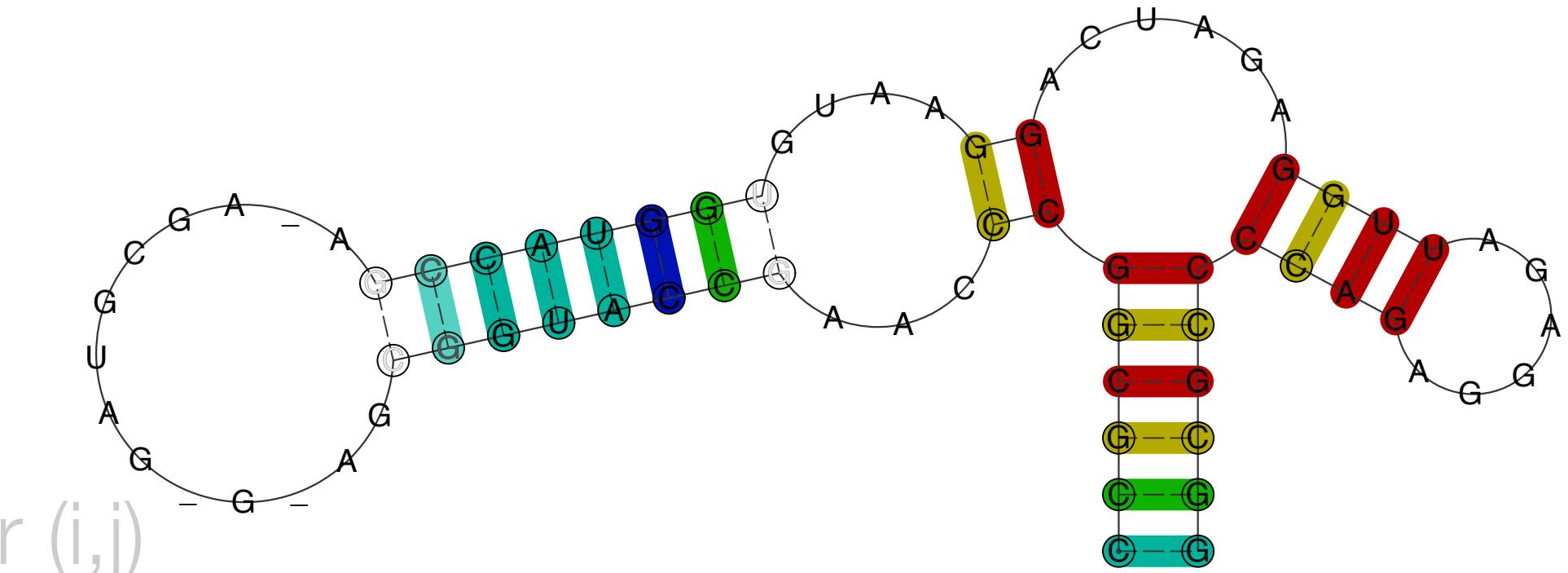
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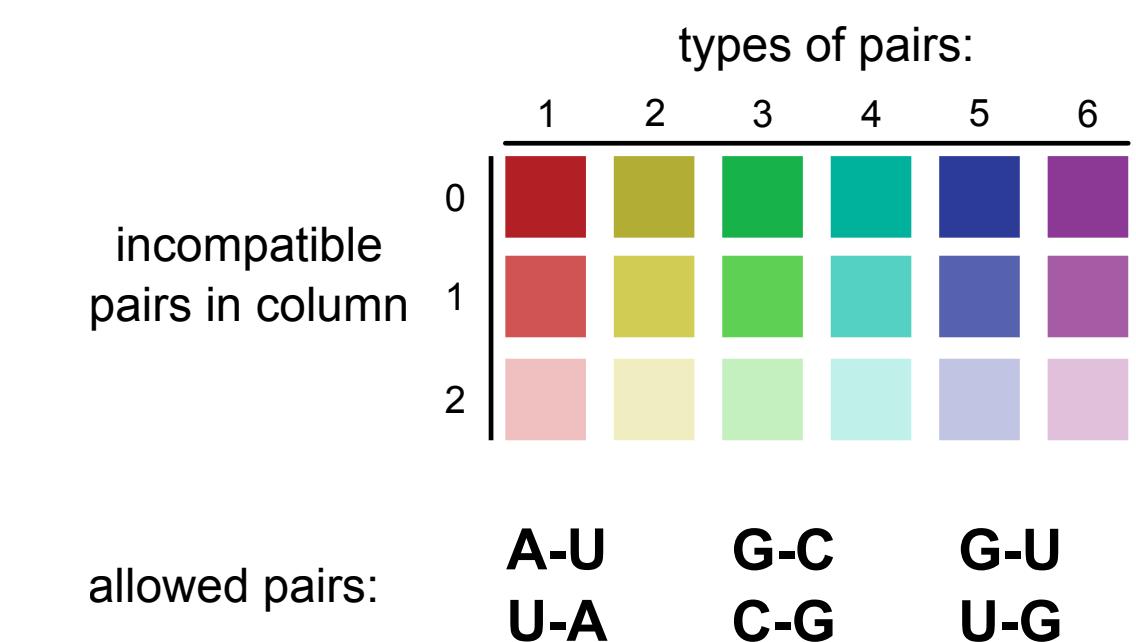
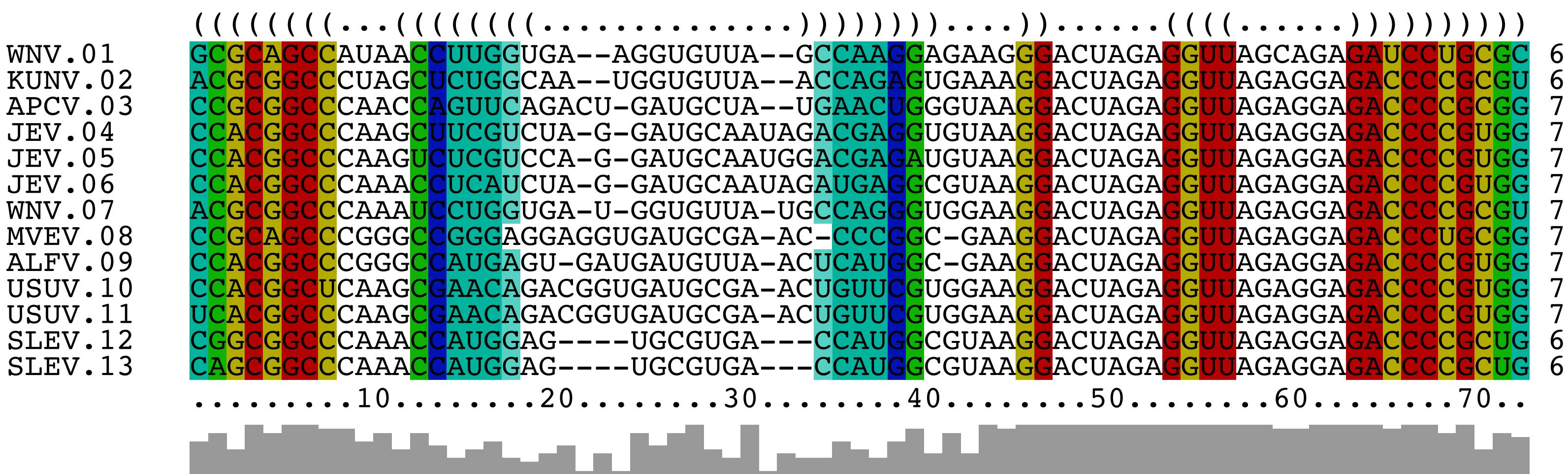
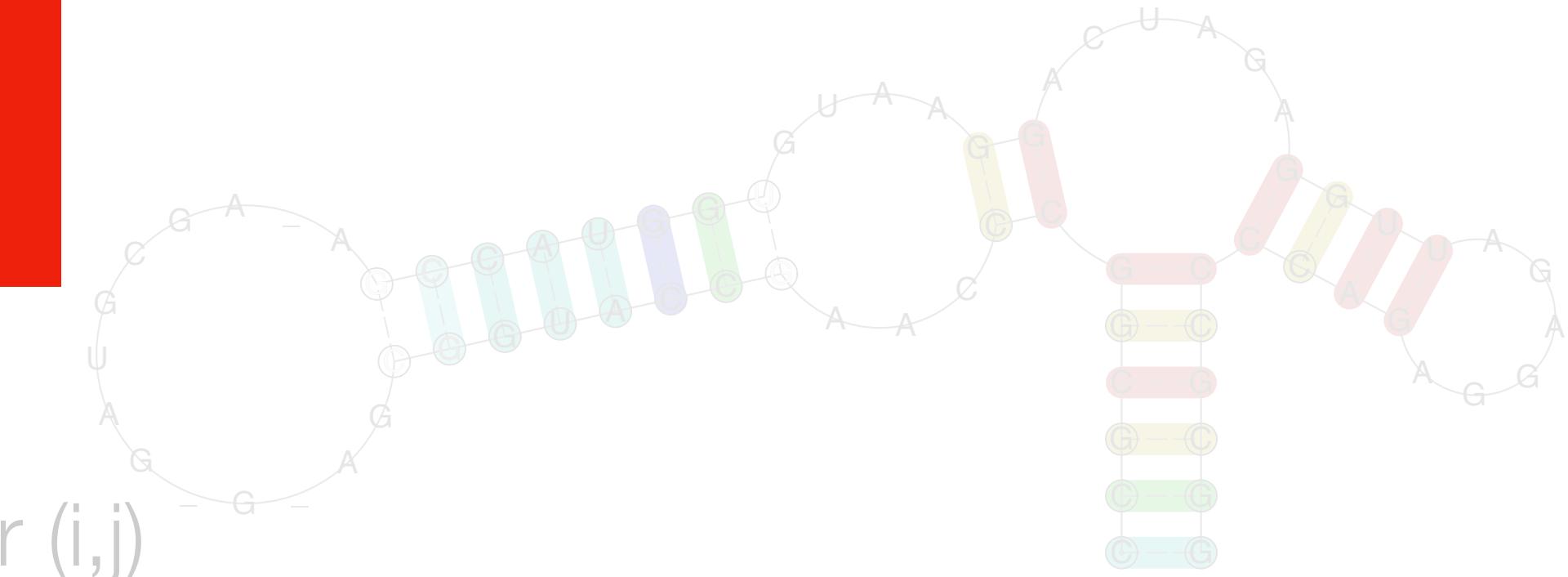
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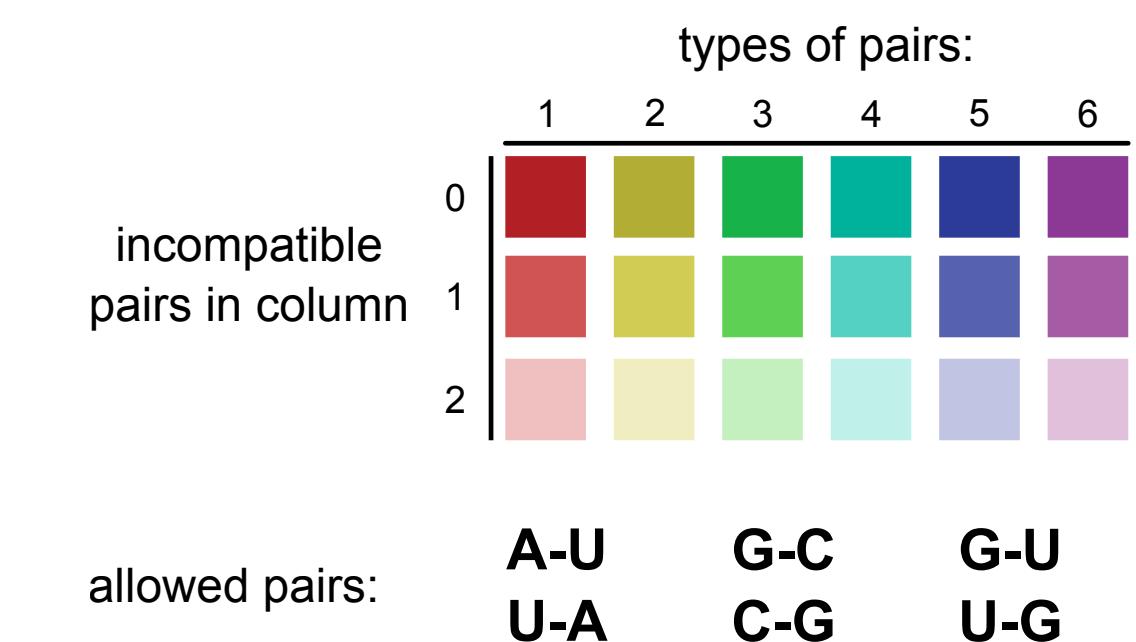
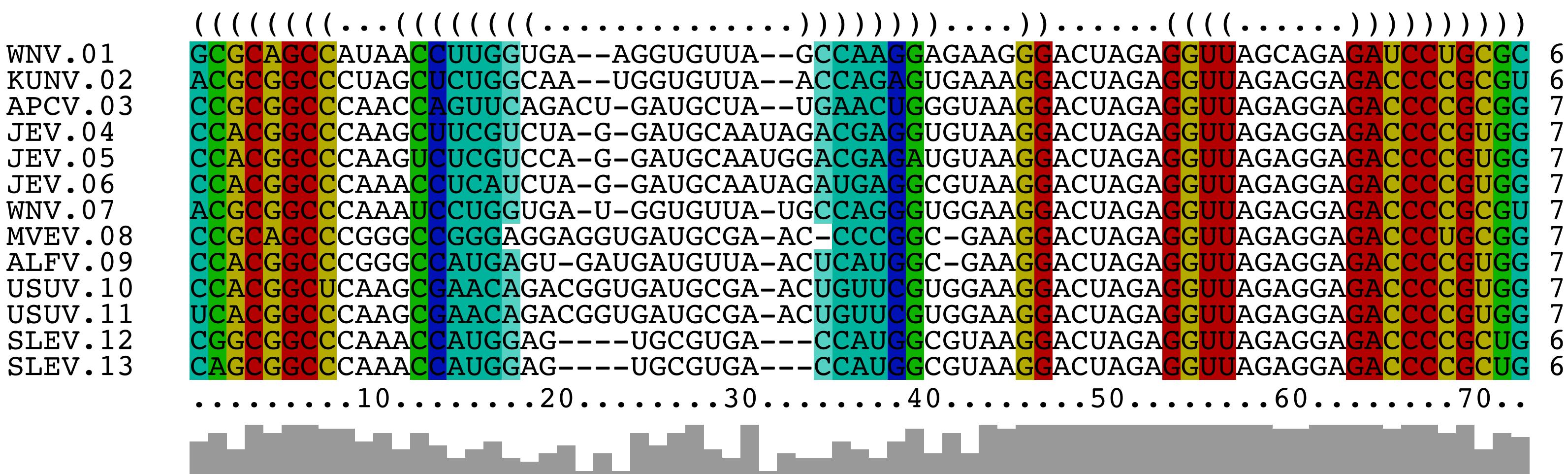
RNA Covariation as Evolutionary Trait

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- We use structural RNA alignments and Covariance Models to find conserved elements
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RNA Covariation as Evolutionary Trait

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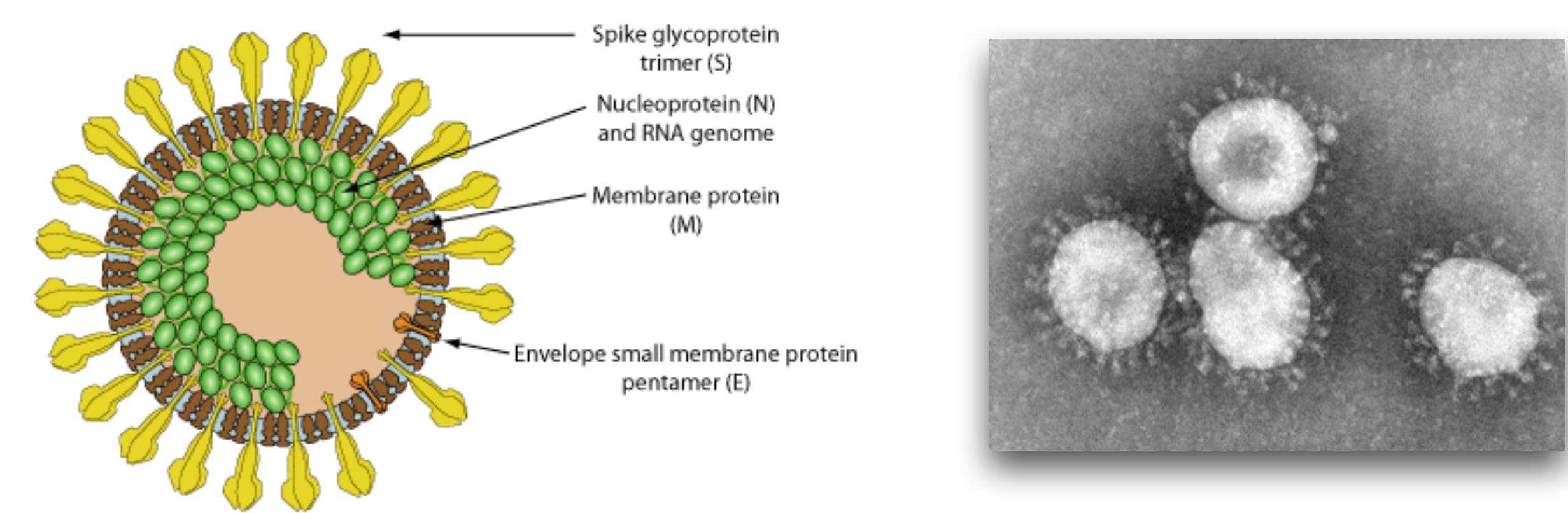


Part II:

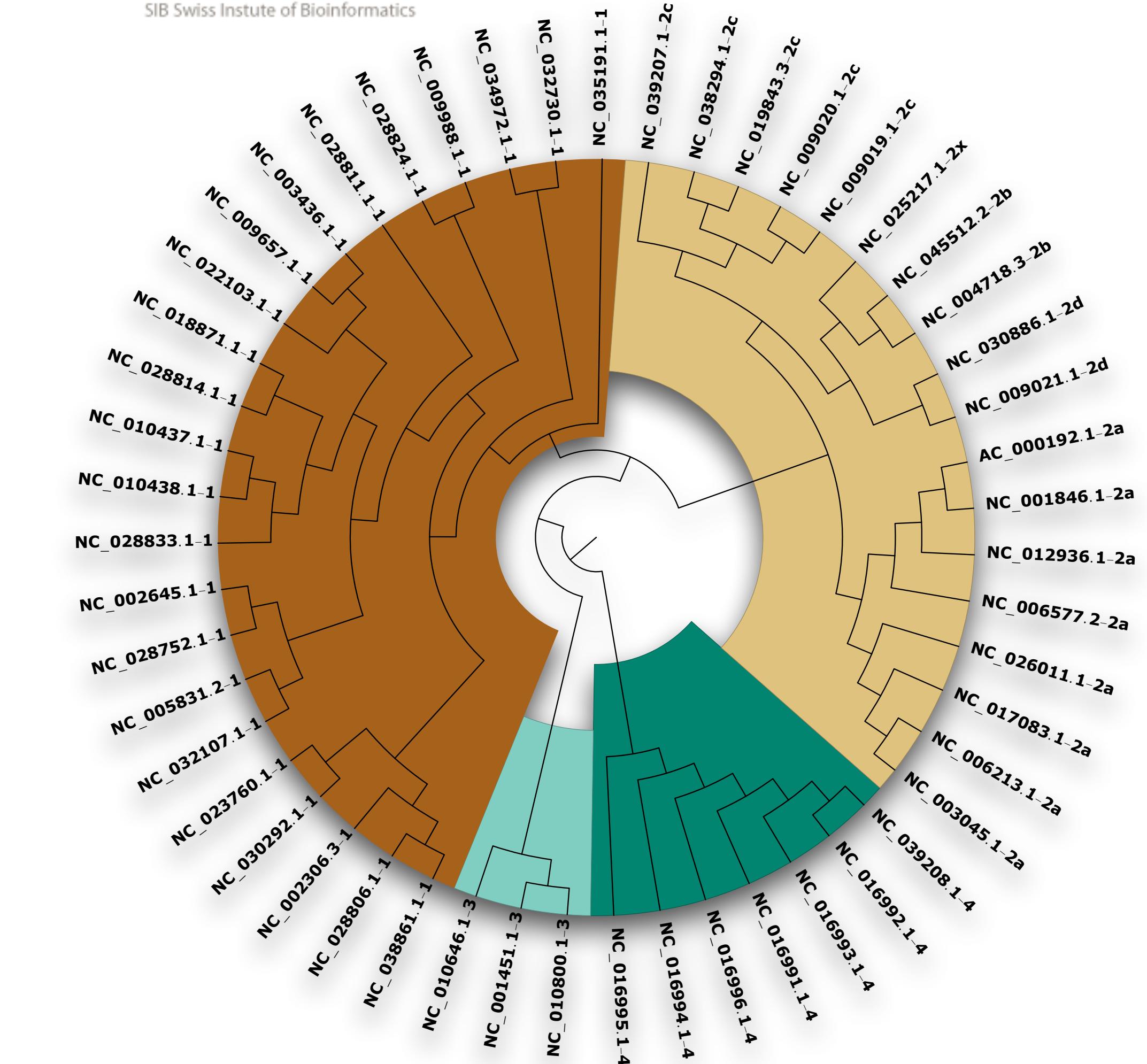
Coronaviruses

Coronaviruses (CoV)

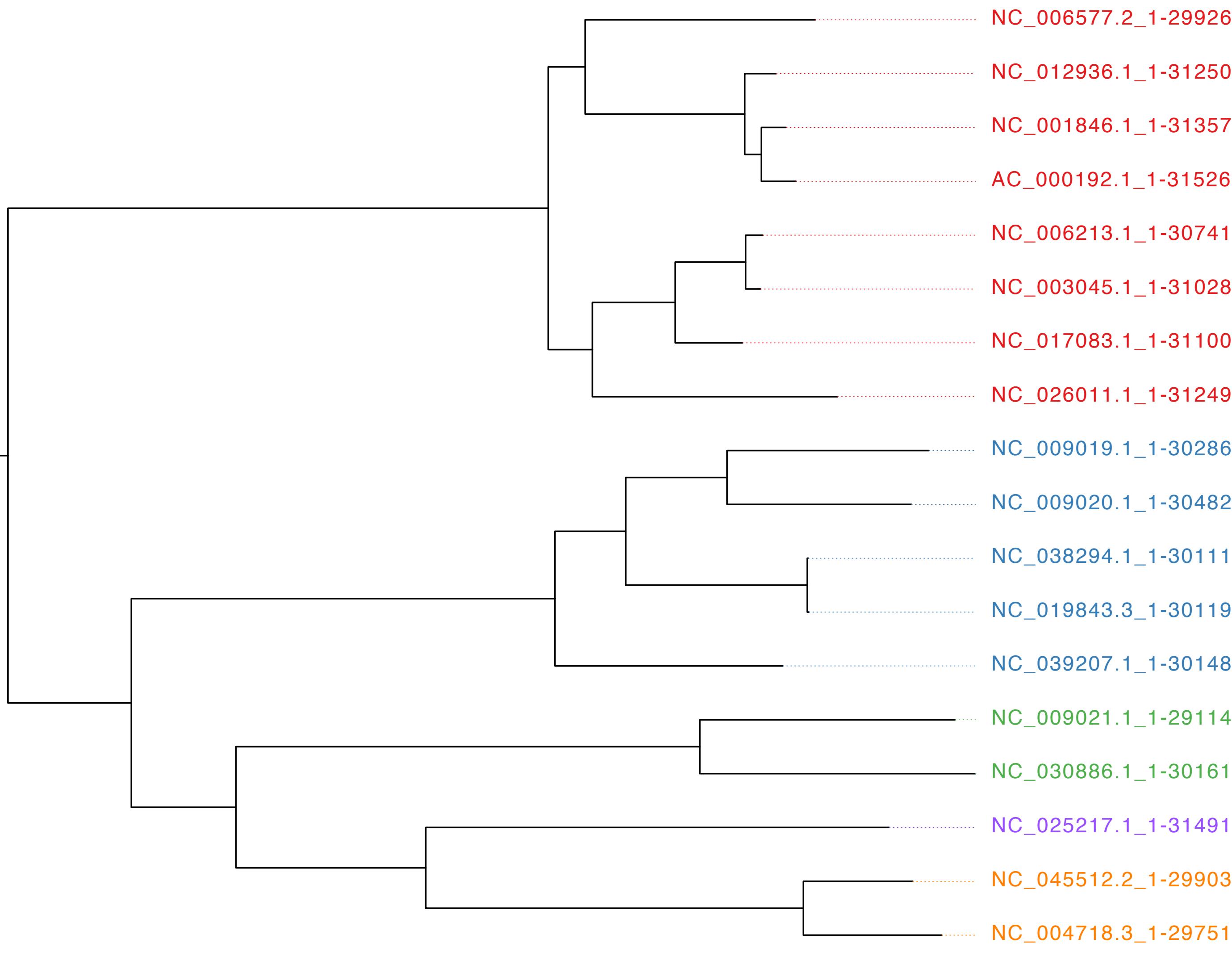
- ▶ Order *Nidovirales* / family *Coronaviridae* / genus *Alpha|Beta|Gamma|Deltacoronavirus*
- ▶ Cause respiratory infections in humans
- ▶ Some CoVs cause outbreaks and are a global health concern (SARS, MERS)
- ▶ Others circulate continuously, causing influenza-like illness or common cold
- ▶ CoVs infect animals; outbreaks result from spillover events
- ▶ Human-to-human transmission
- ▶ Only experimental vaccines



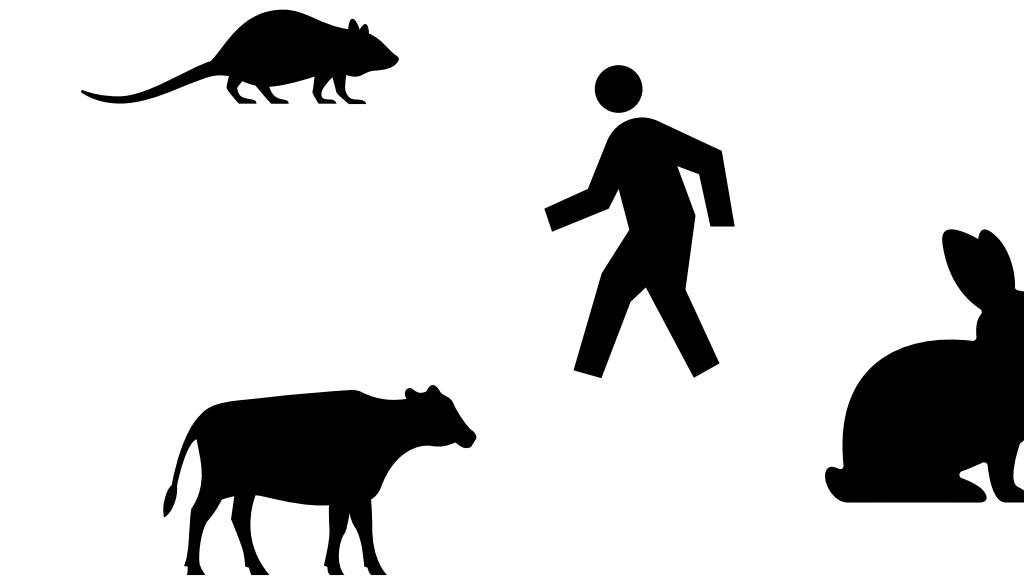
© ViralZone 2020
SIB Swiss Institute of Bioinformatics



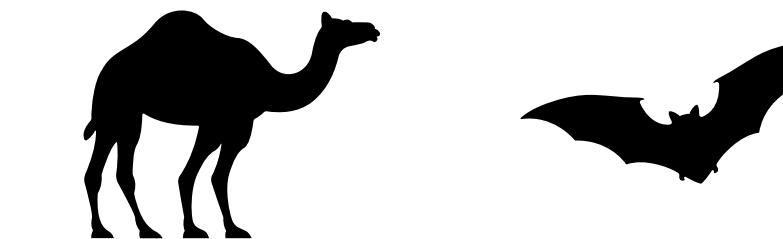
Betacoronavirus phylogeny



Embecovirus (group 2a)



Merbecovirus (group 2c)



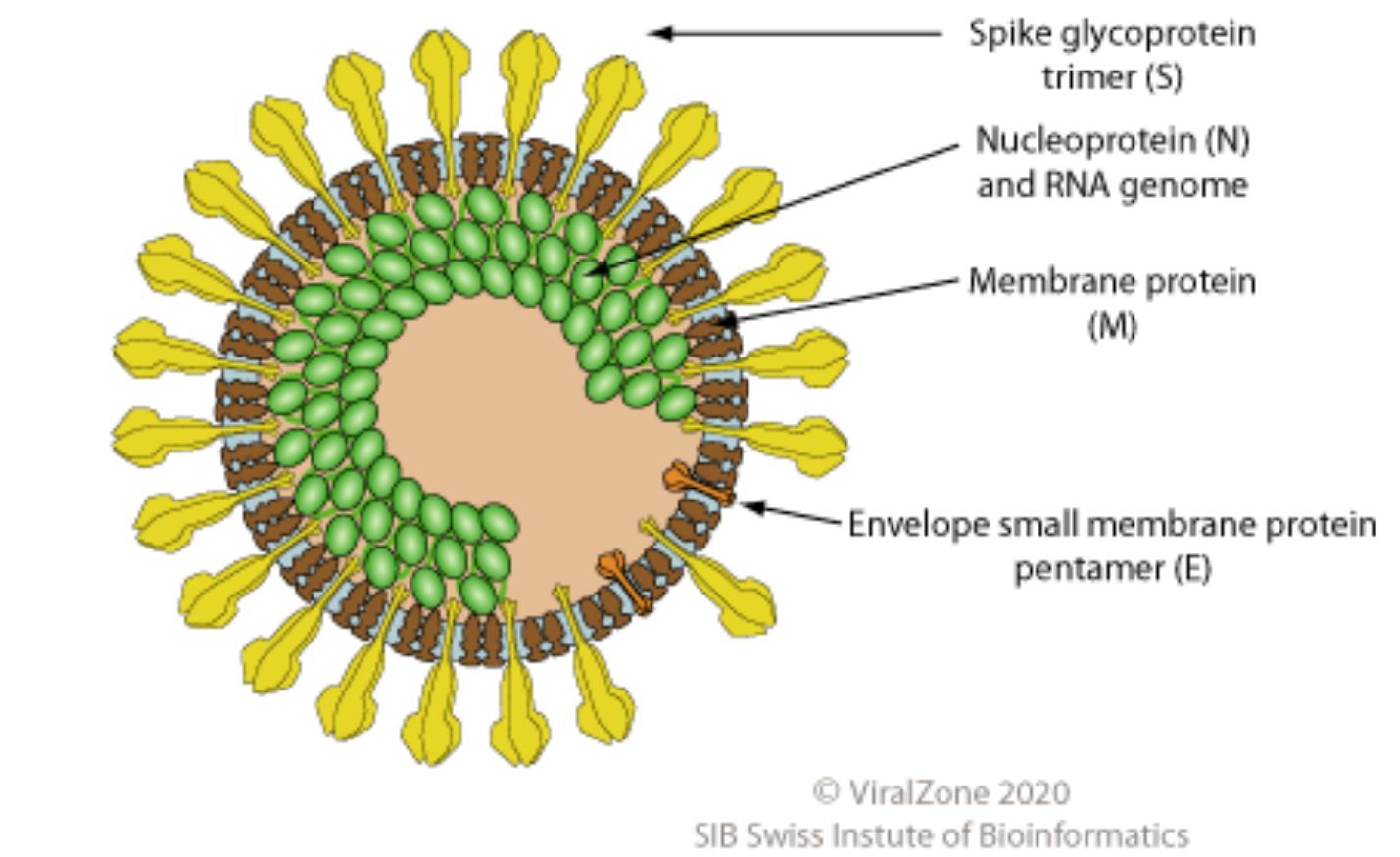
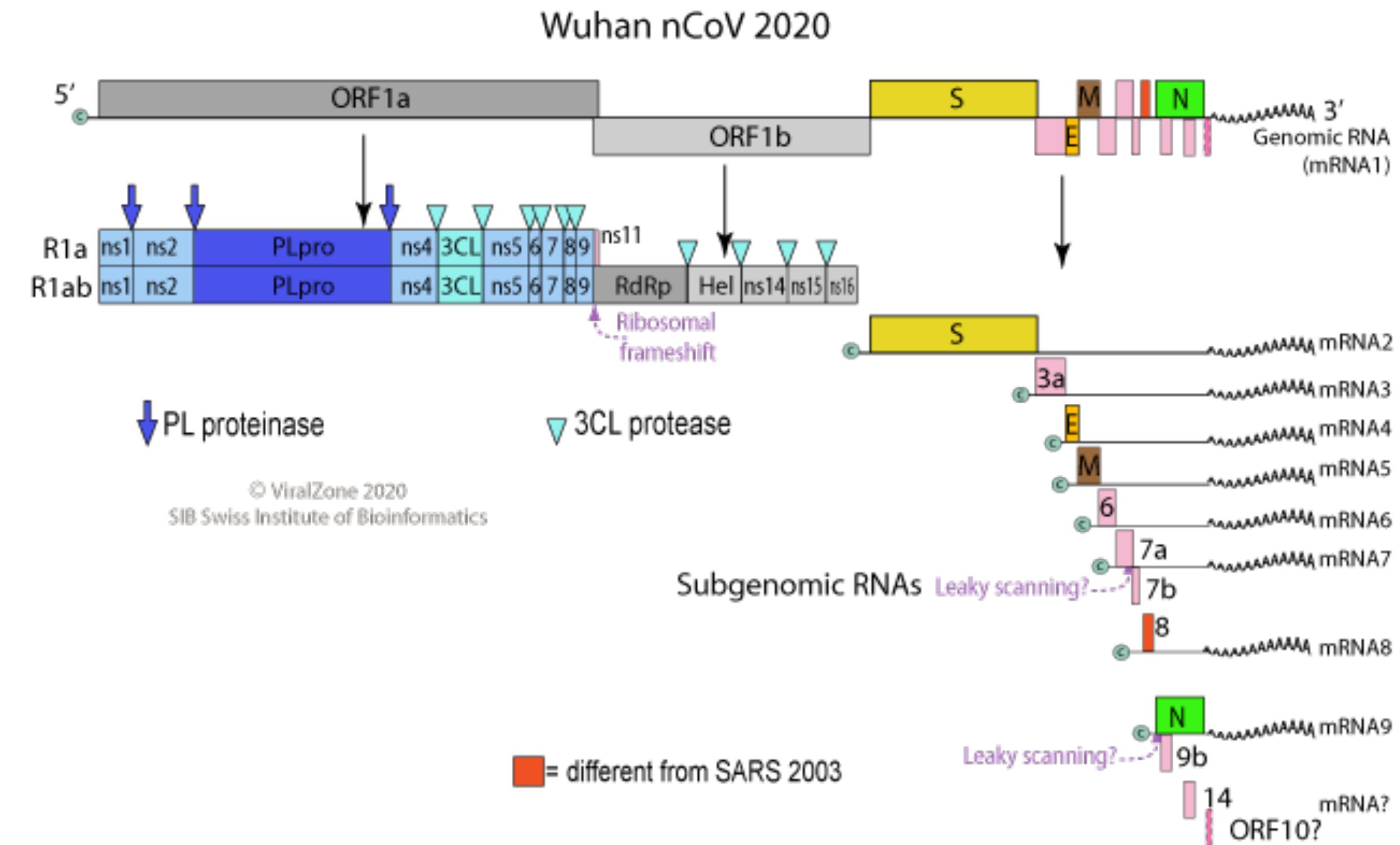
Nobecovirus (group 2d)

Hibecovirus

Sarbecovirus (group 2b)

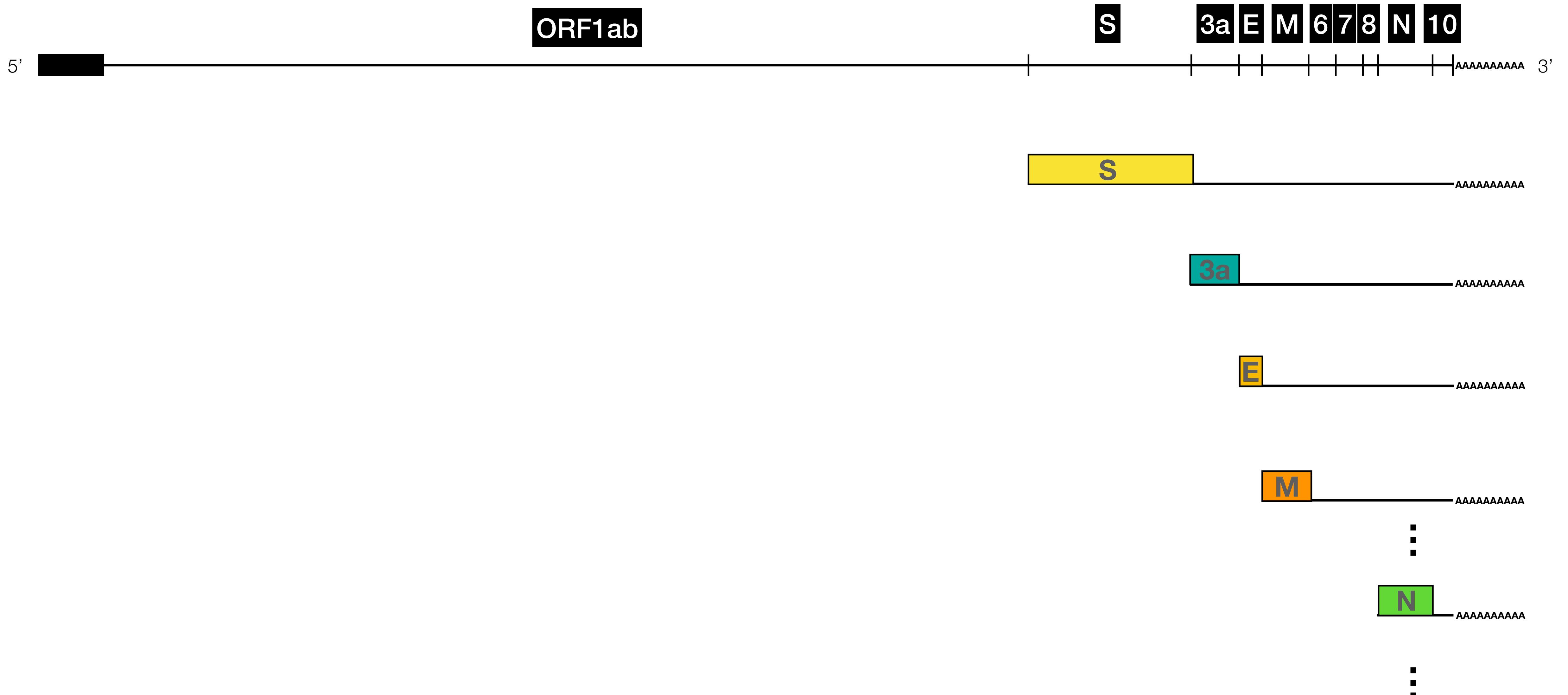


CoV Genome Organization

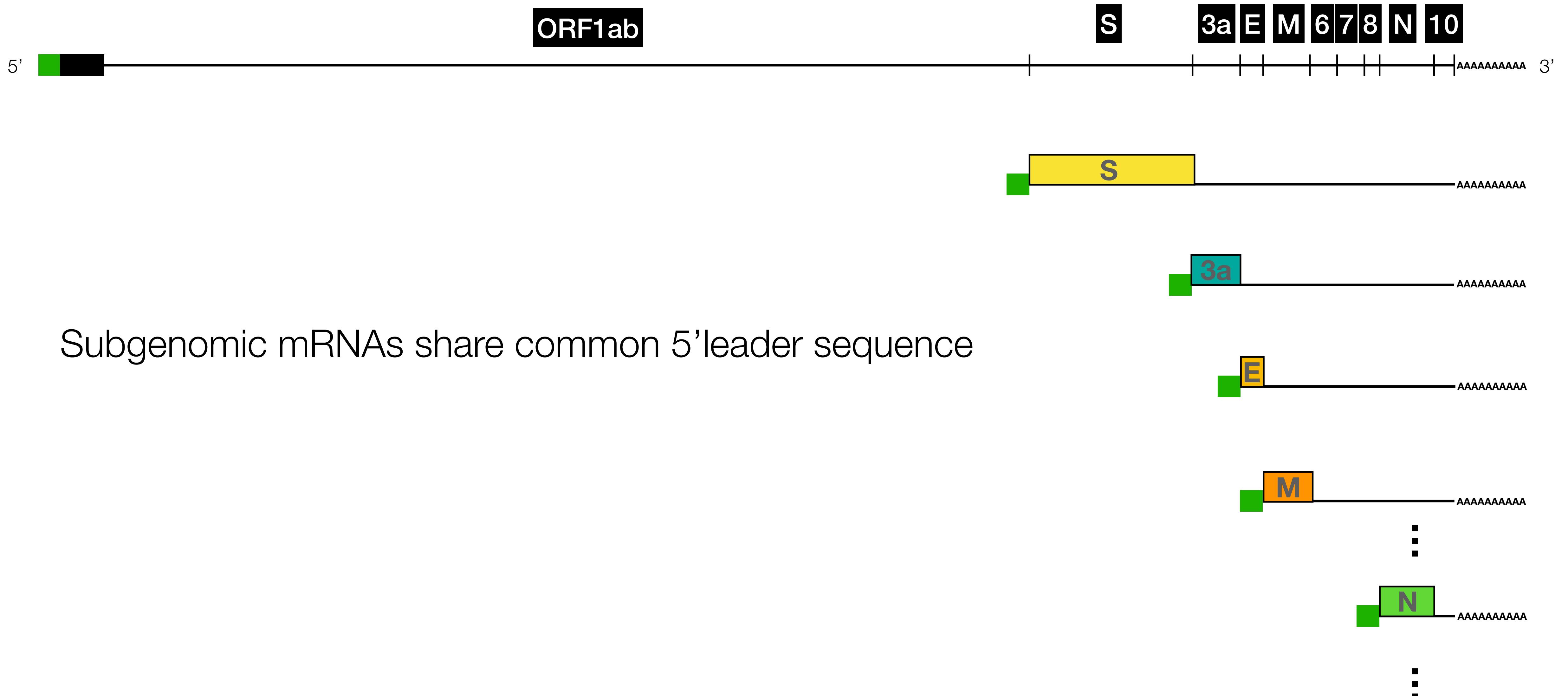


- Non-segmented, linear ssRNA(+) genomes of 27-32kb length (largest RNA viruses)
- Capped and polyadenylated
- Genomic RNA encodes ORF1a & ORF1b, yielding RdRp & non-structural proteins
- Subgenomic RNAs encode structural proteins

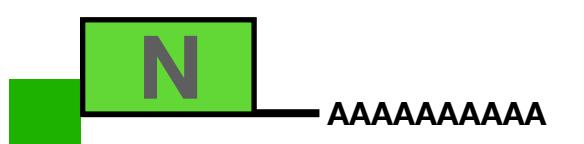
CoV RNA species



CoV Subgenomic mRNAs



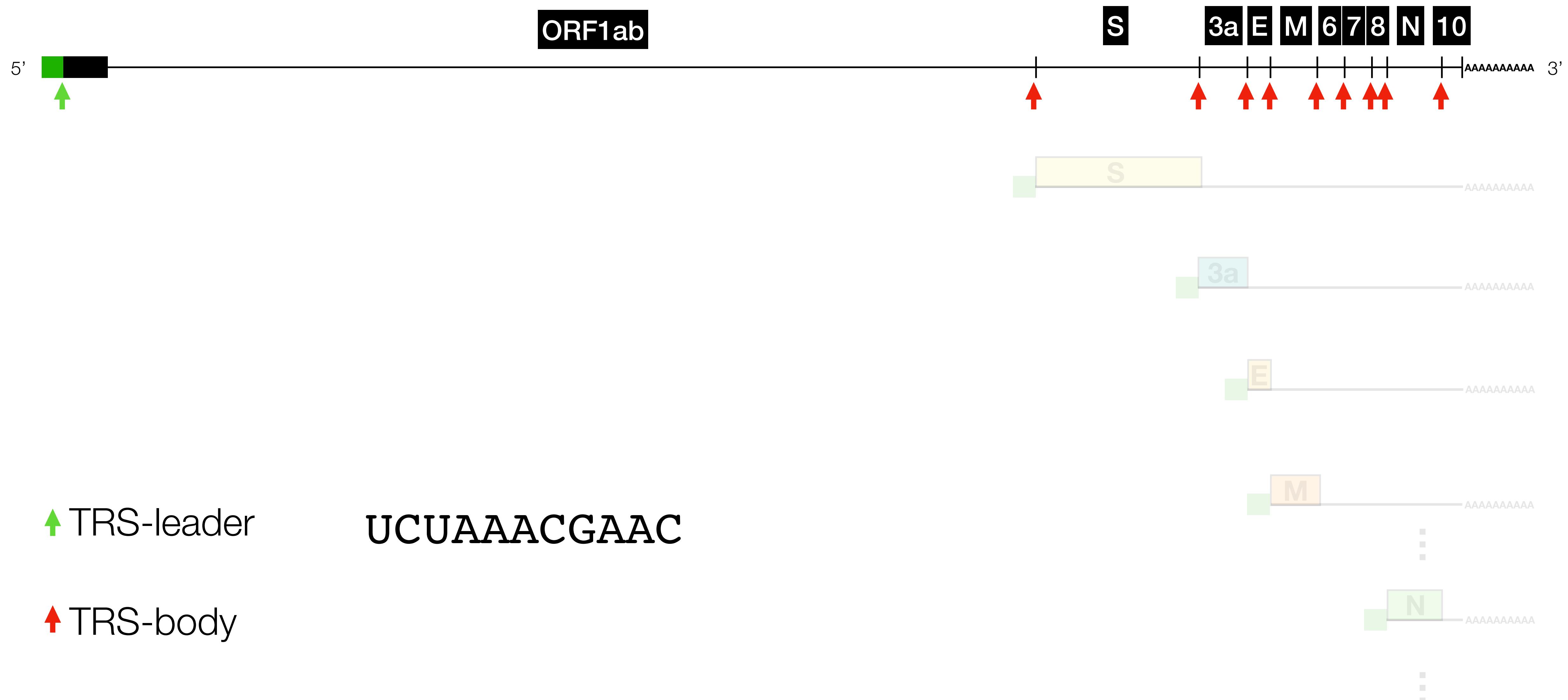
CoV Subgenomic mRNAs



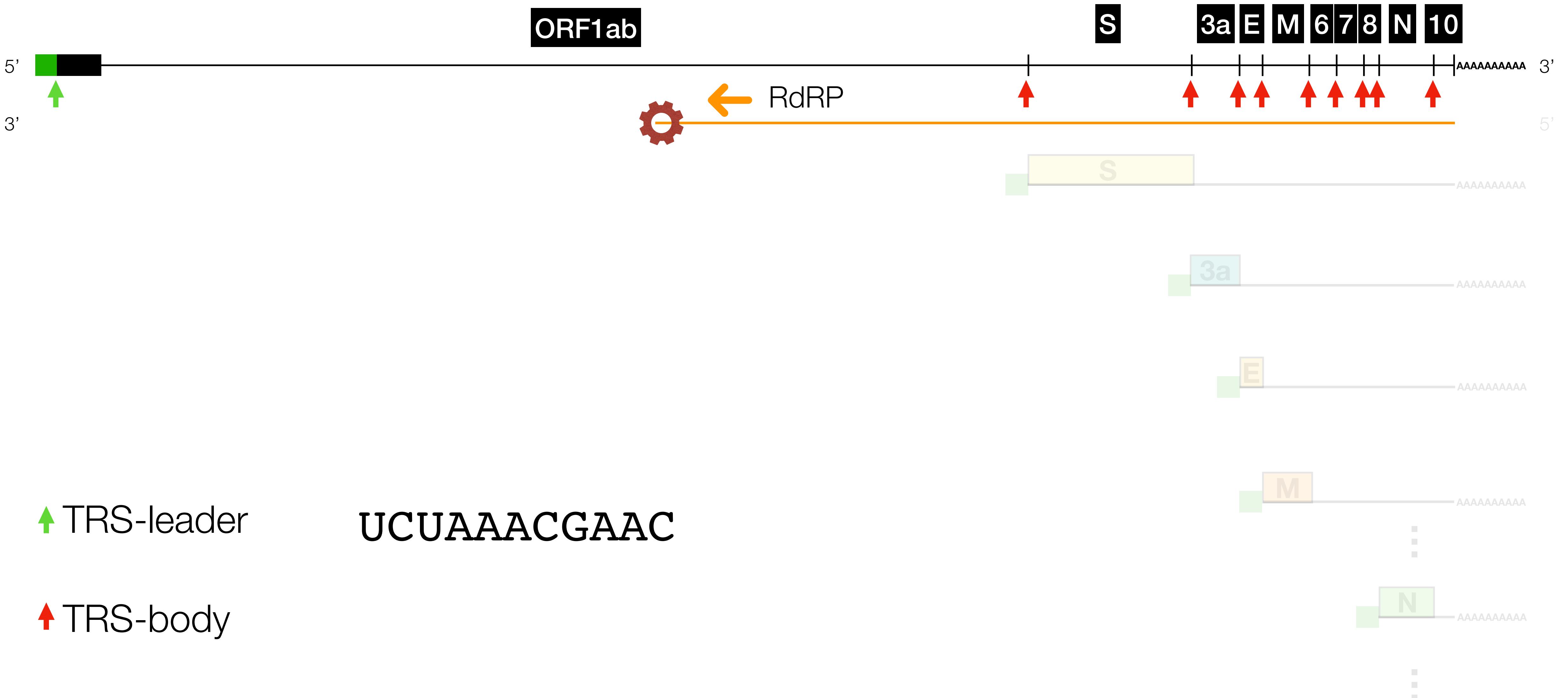
Subgenomic mRNAs share common 5'leader sequence

How are they built?

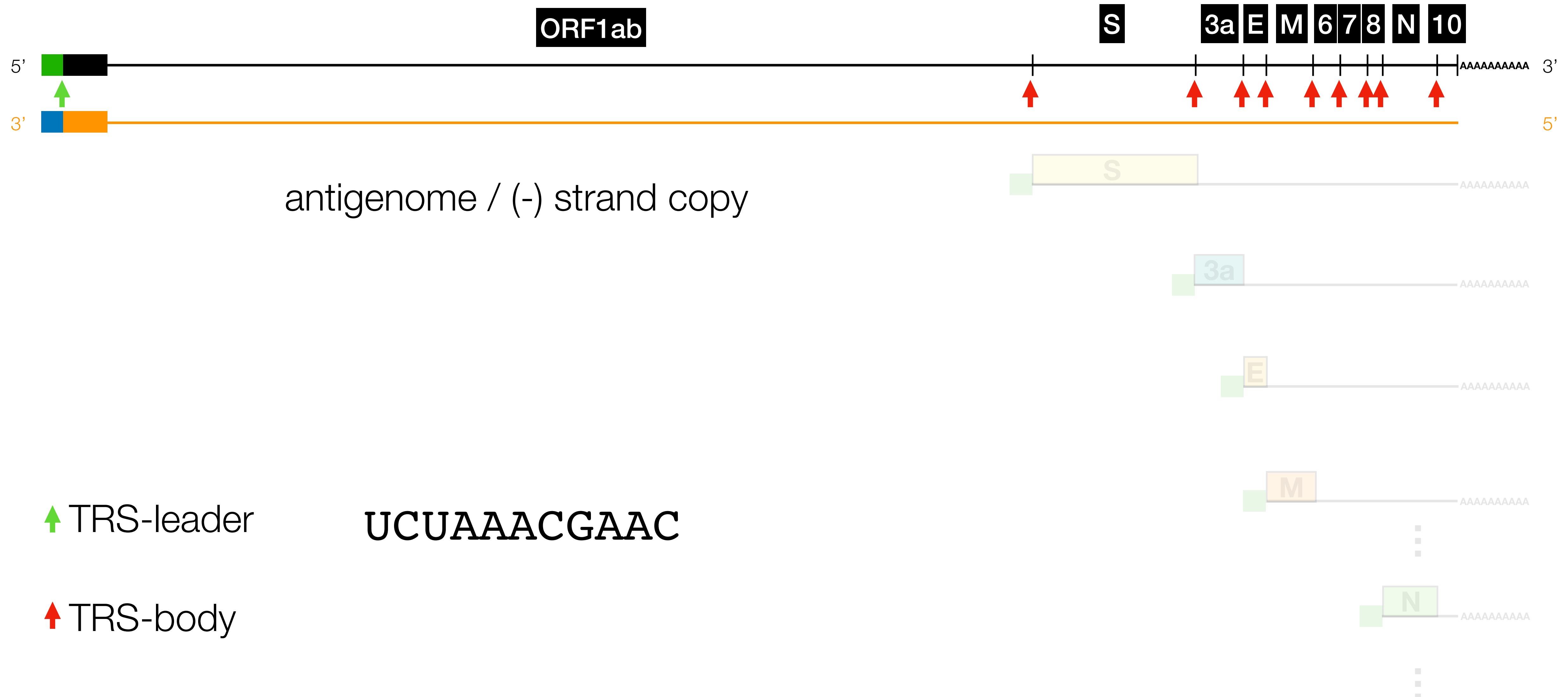
CoV Discontinuous Transcription



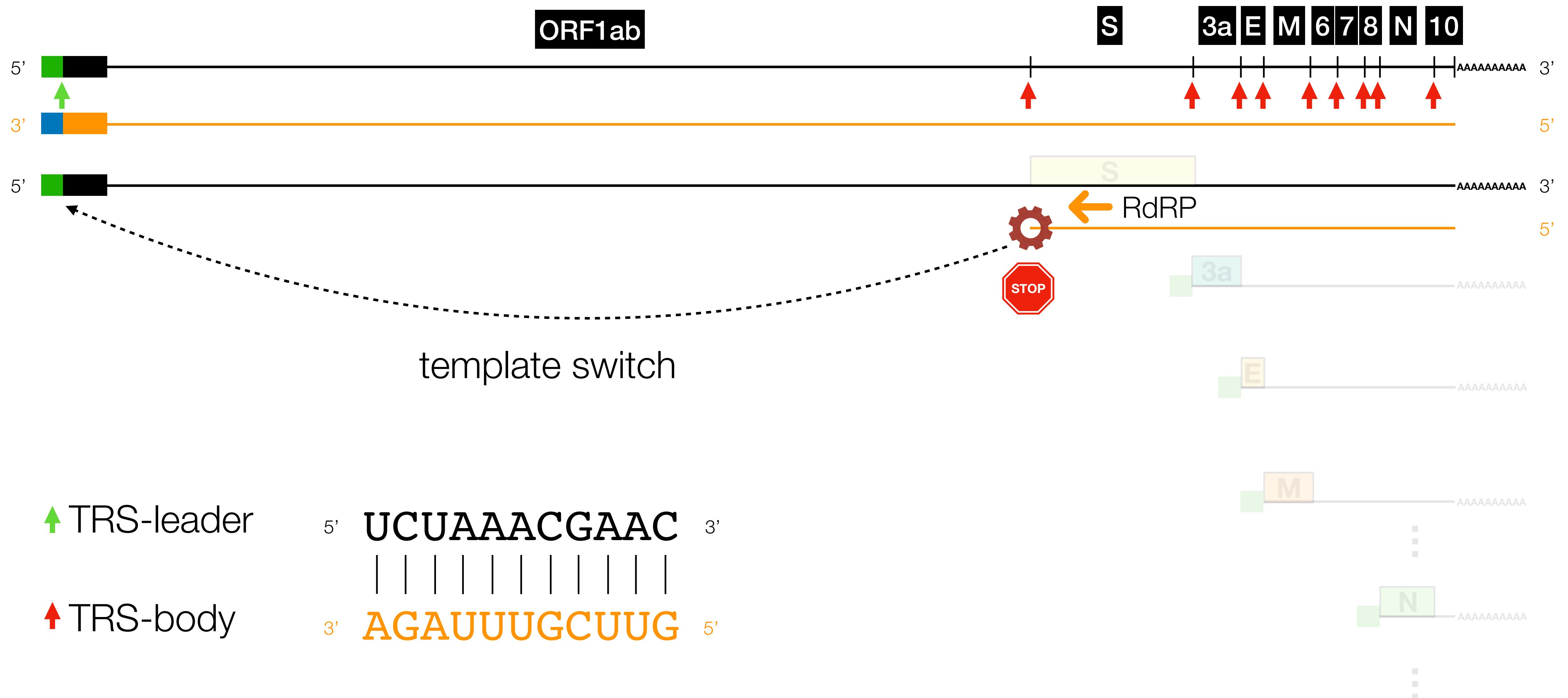
CoV Discontinuous Transcription



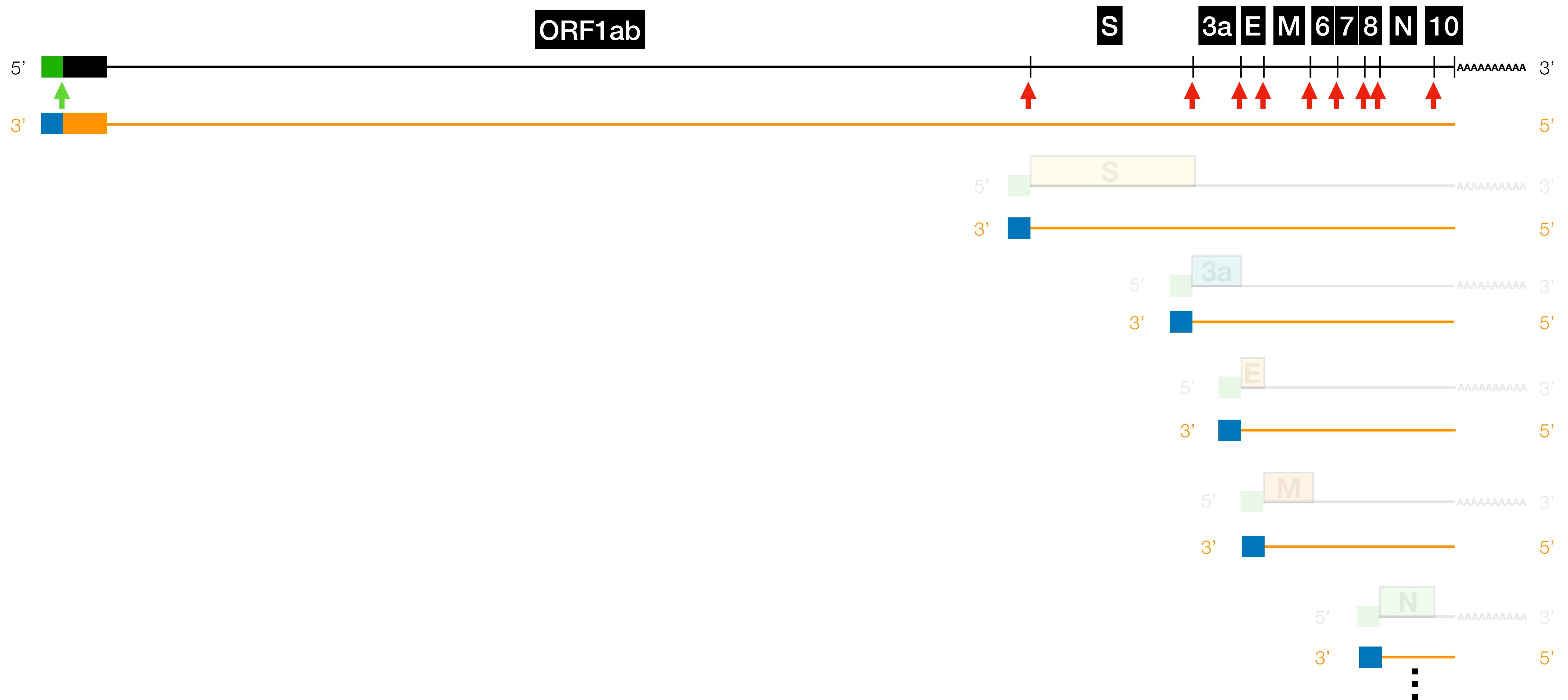
CoV Discontinuous Transcription



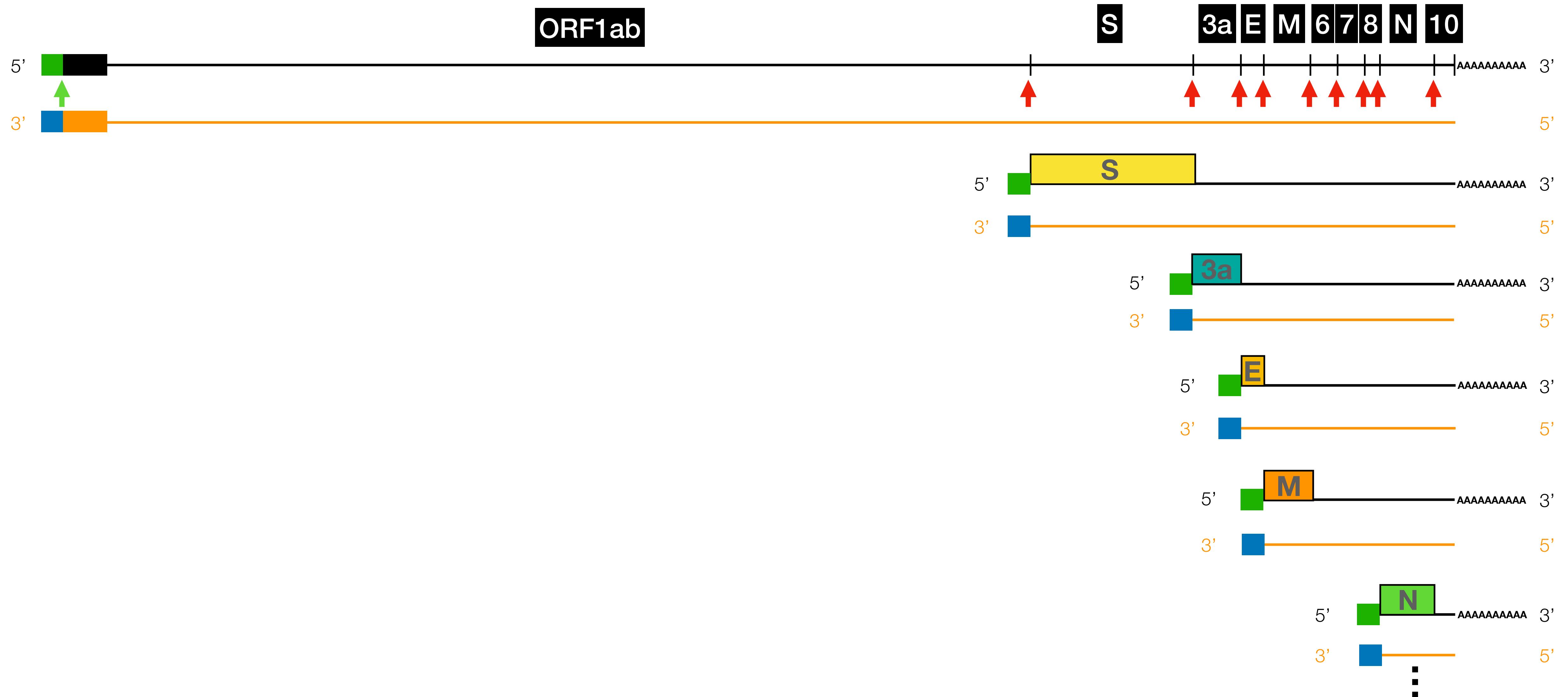
CoV Discontinuous Transcription



CoV Discontinuous Transcription



CoV Discontinuous Transcription

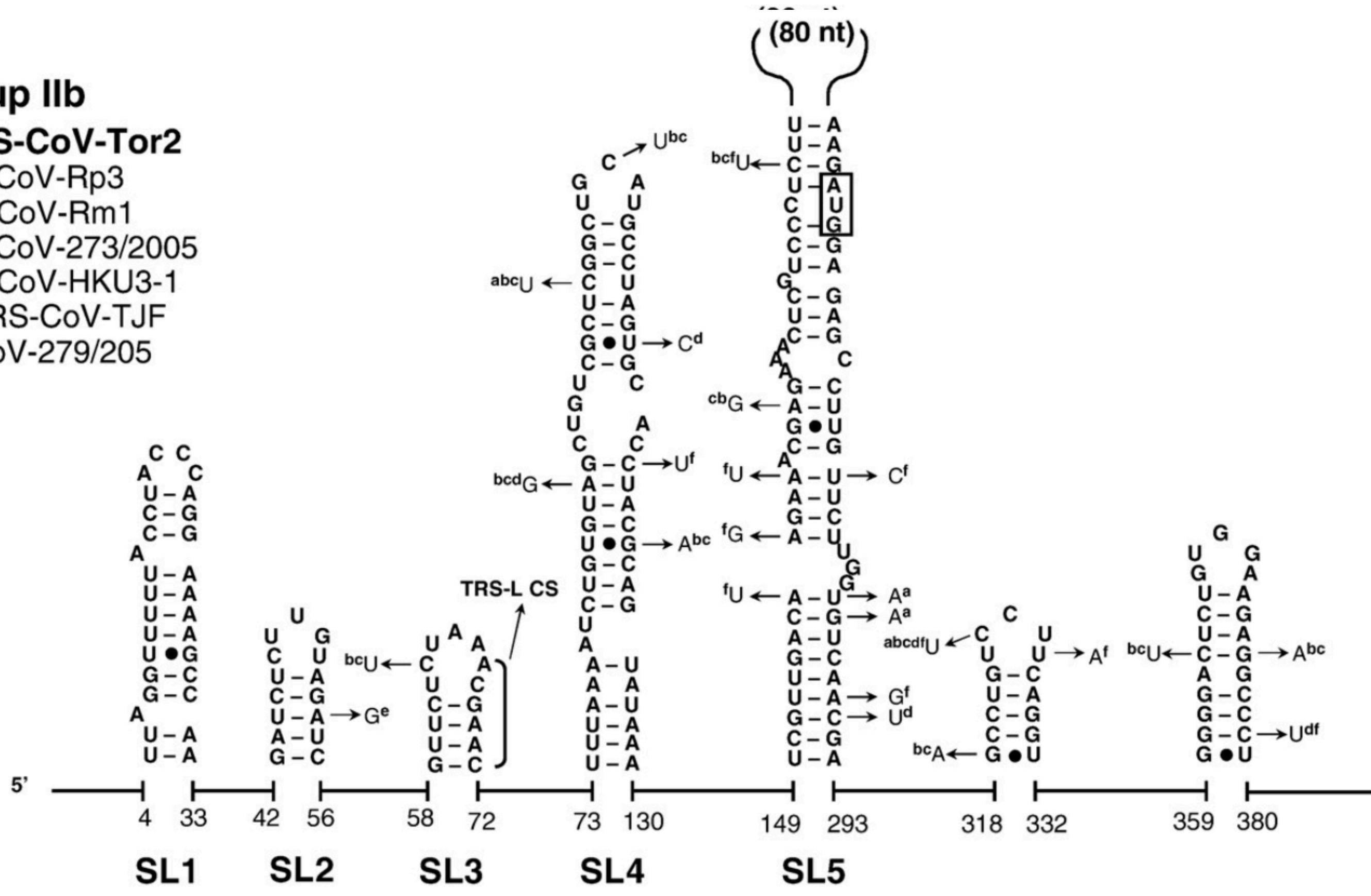


CoV 5'UTR & Leader Region

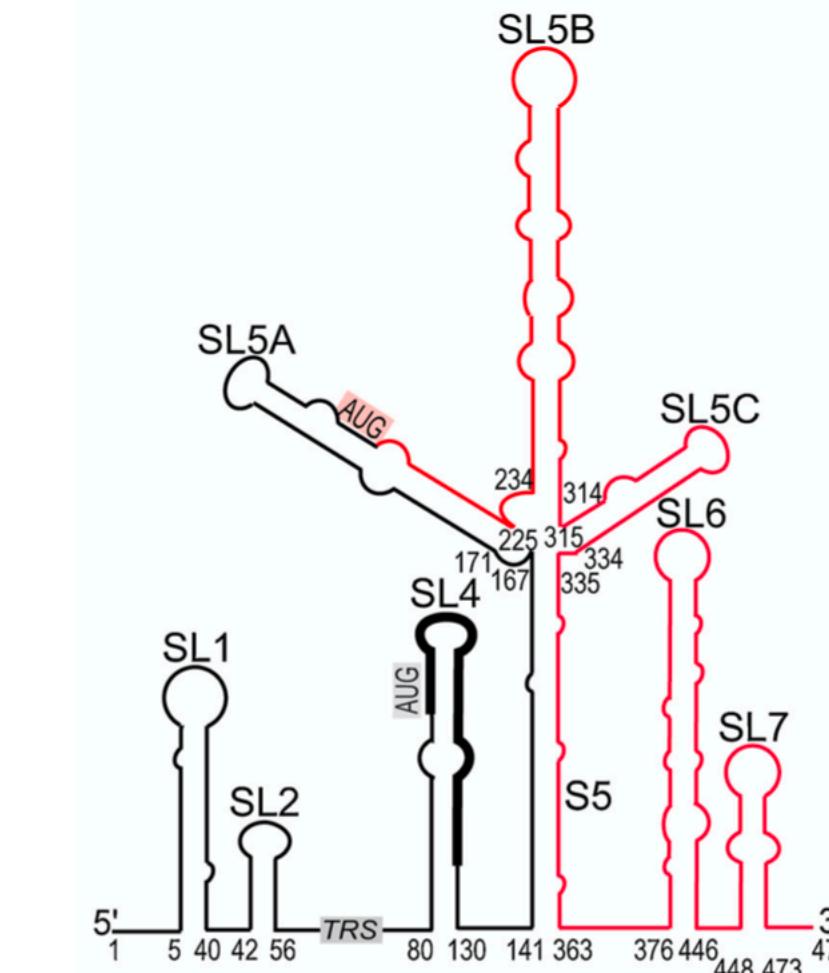
B) Group IIb

SARS-CoV-Tor2

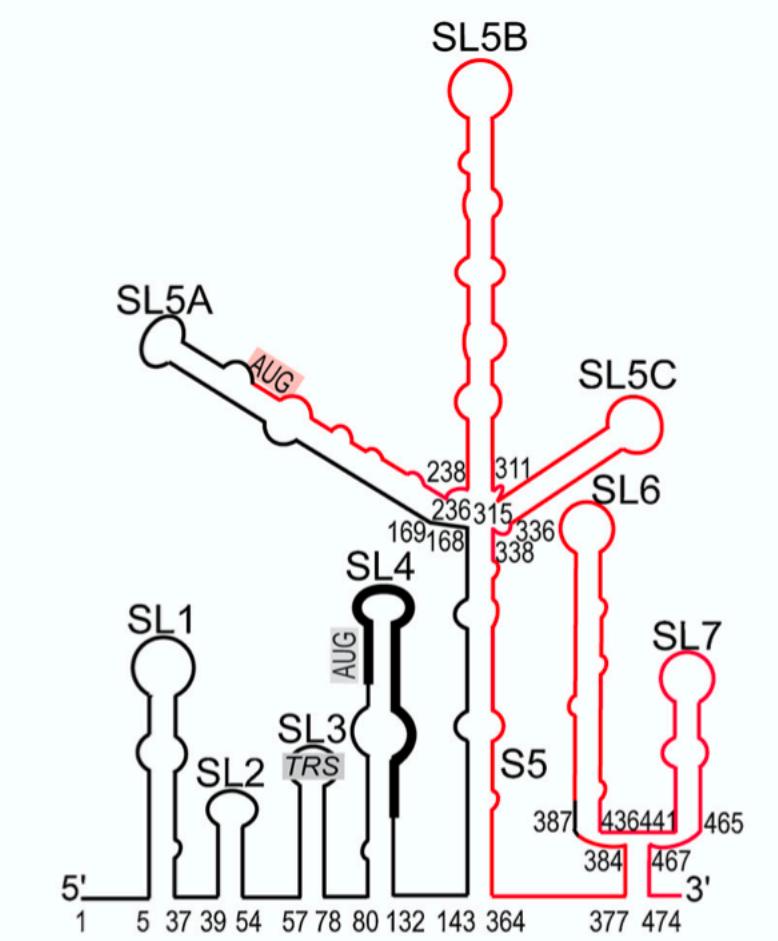
- a:BtSCoV-Rp3
- b:BtSCoV-Rm1
- c:BtSCoV-273/2005
- d:BtSCoV-HKU3-1
- e:SARS-CoV-TJF
- f:BtCoV-279/205



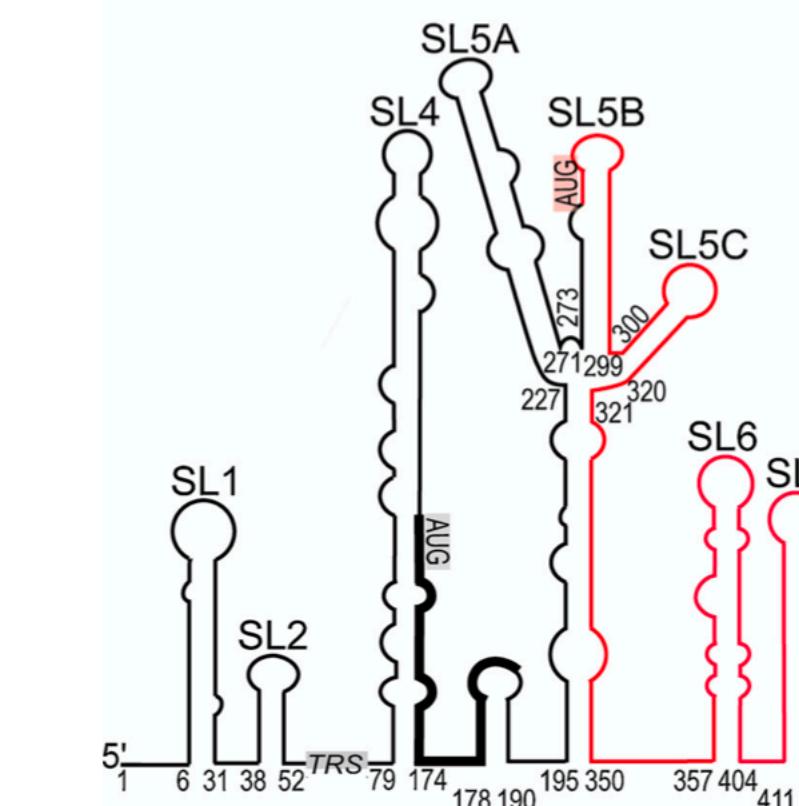
(A) MHV-A59



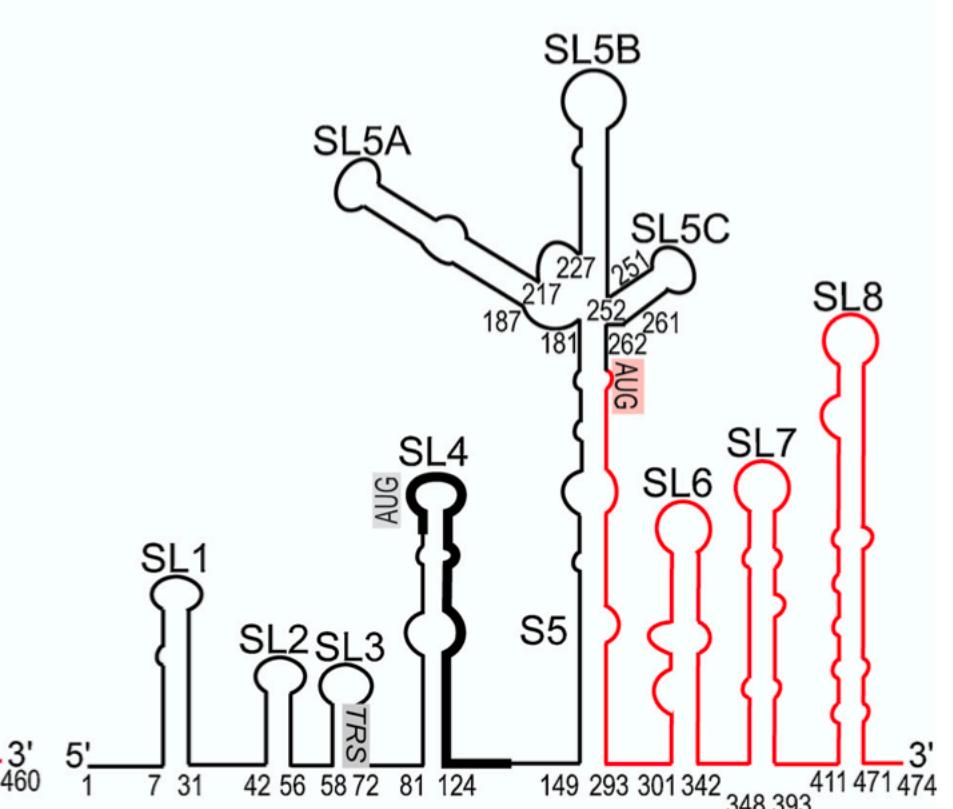
(B) BCoV



(C) MERS-CoV



(D) SARS-CoV

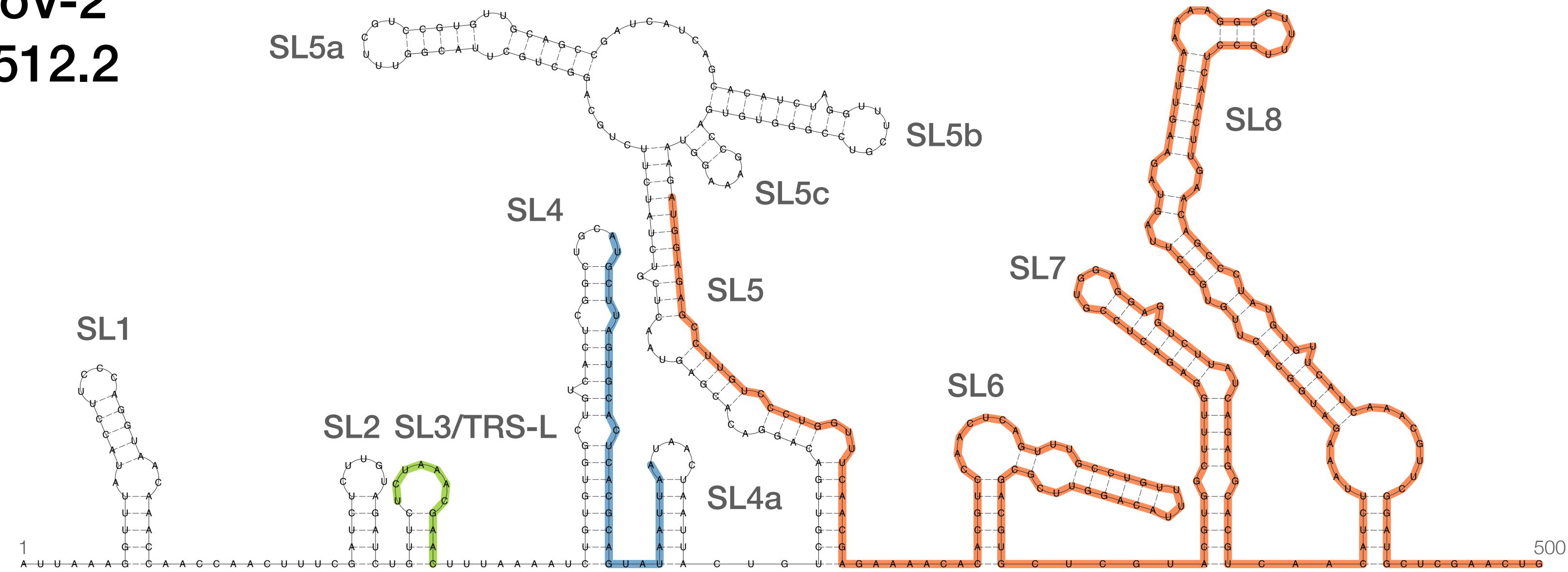


Chen, S. C., & Olshtoorn, R. C. (2010)
Virology, 401(1), 29-41.

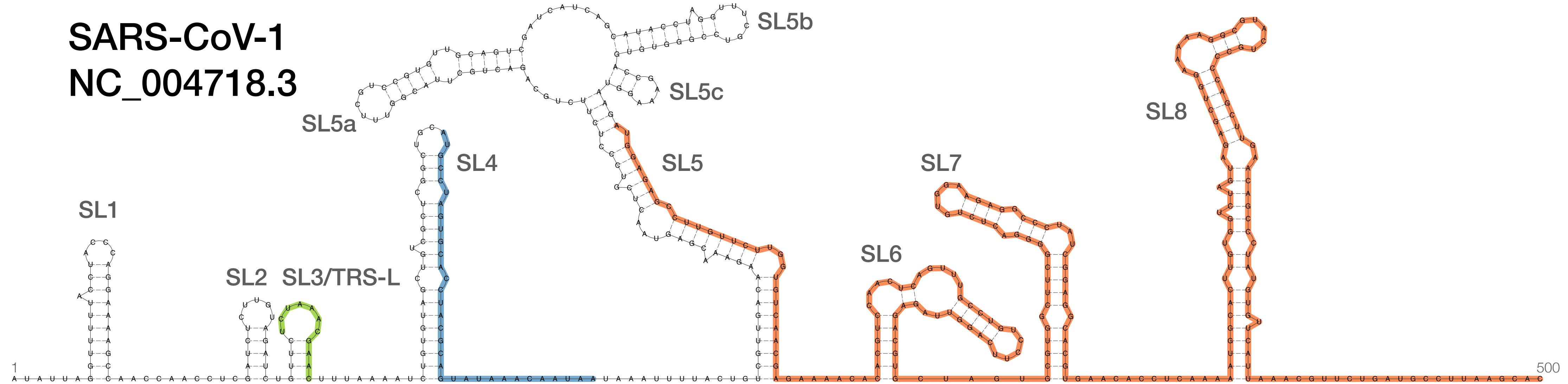
Yang, D., & Leibowitz, J. L. (2015)
Virus research, 206, 120-133.

SARS-CoV-1/2 Leader Region

SARS-CoV-2
NC_045512.2



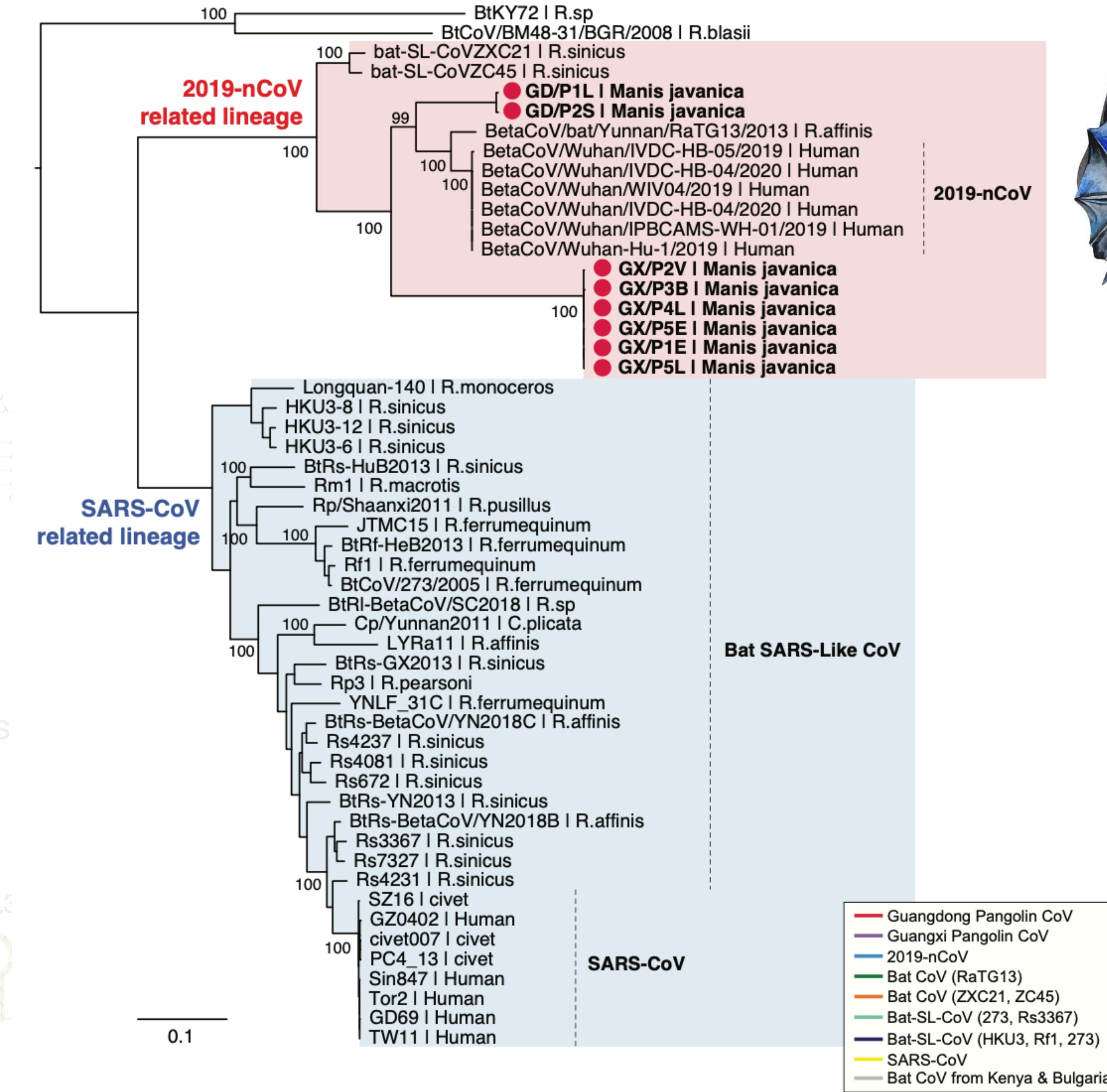
SARS-CoV-1
NC_004718.3



SARS-CoV-1/2 Leader Region

SARS-CoV-2
NC_045512.2

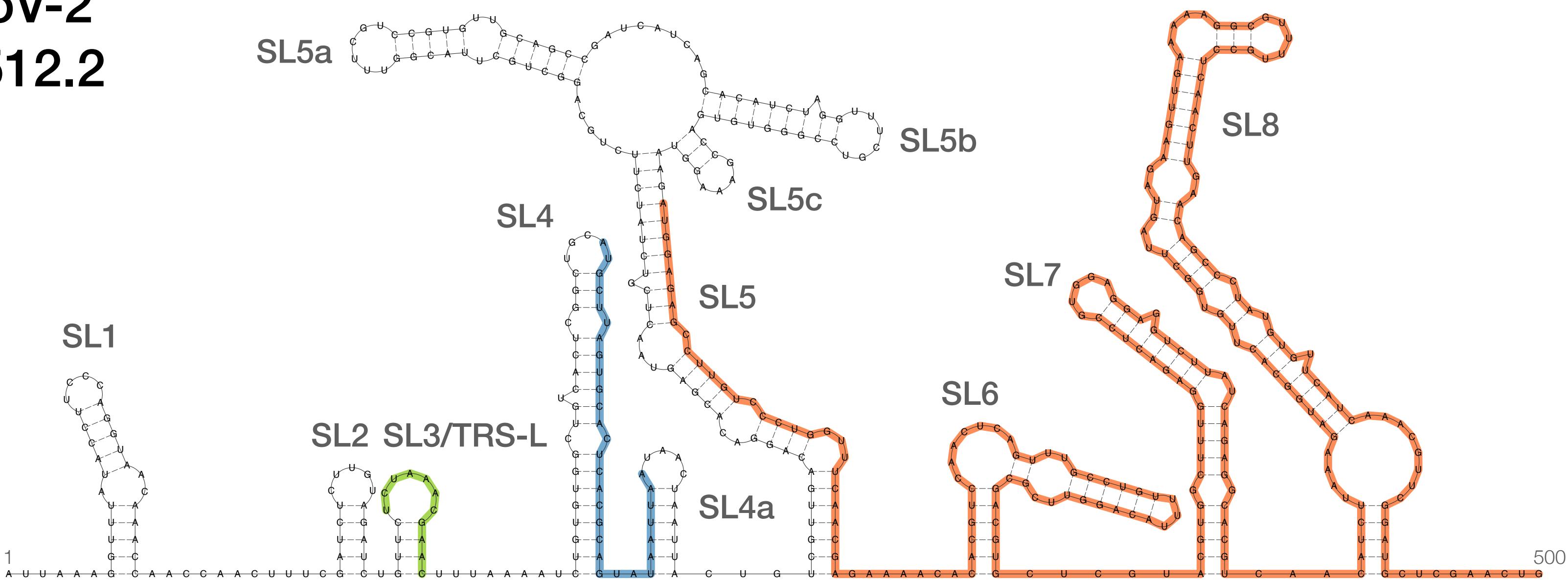
SARS-CoV-1
NC_004718.3



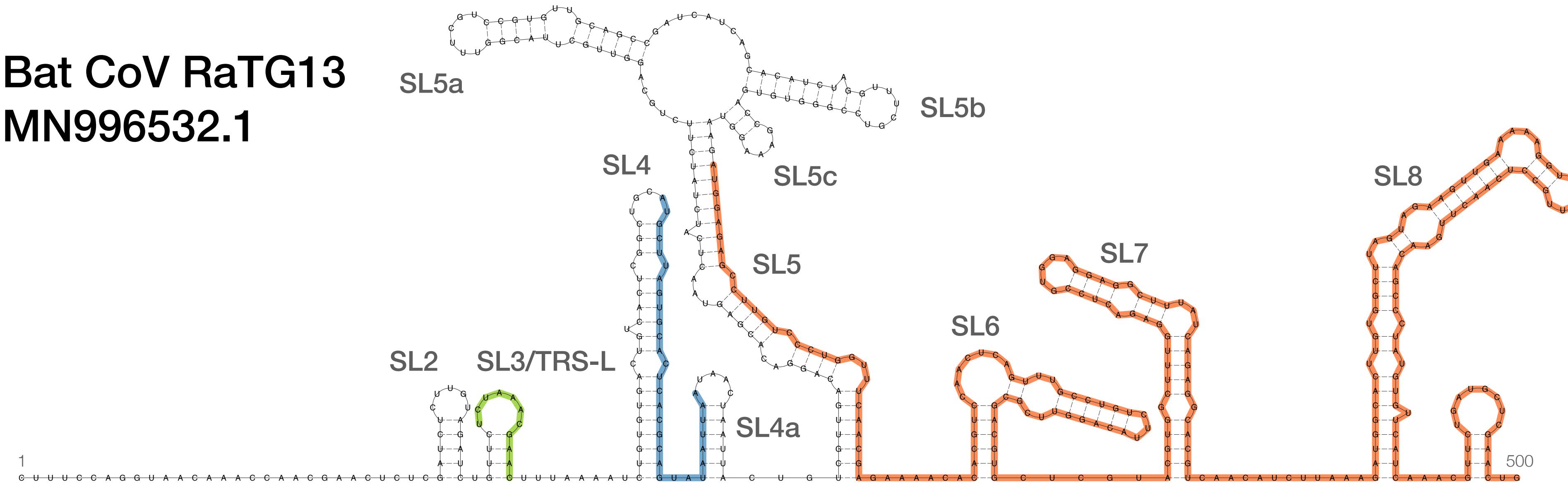
Lam et al. (2020)
bioRxiv 2020.02.13.945485.

Sarbecovirus Leader Region

SARS-CoV-2
NC_045512.2

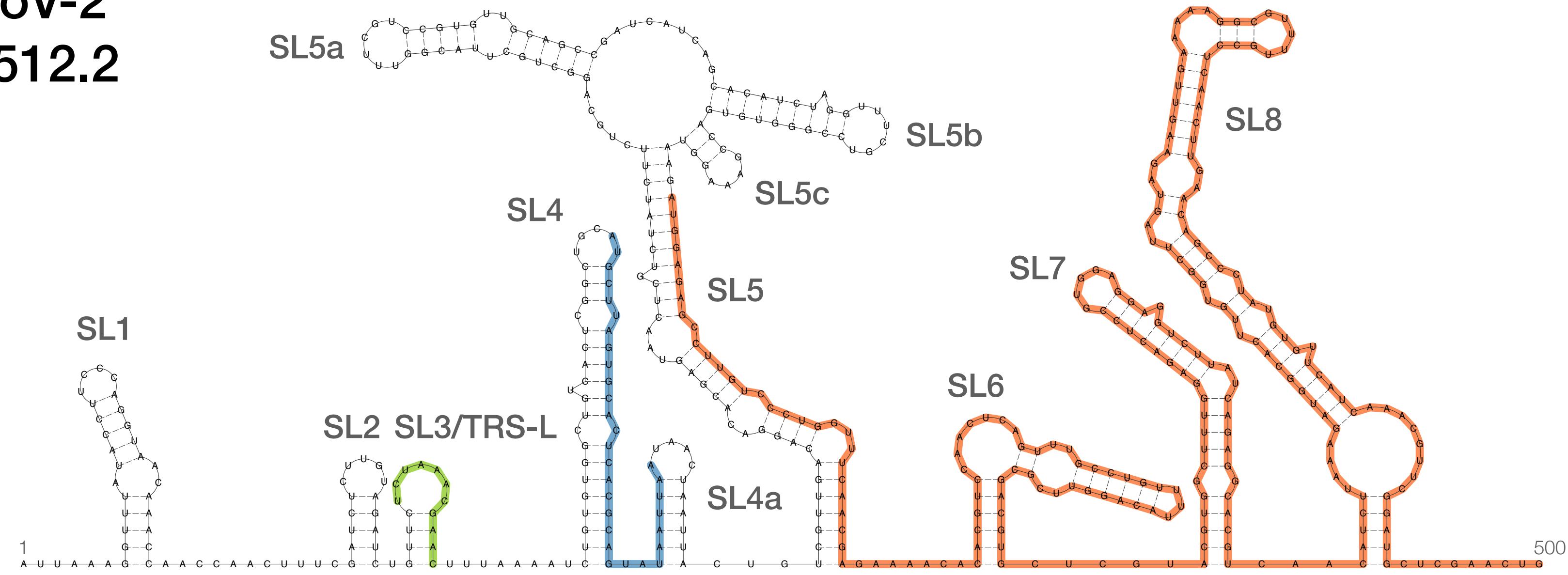


Bat CoV RaTG13
MN996532.1

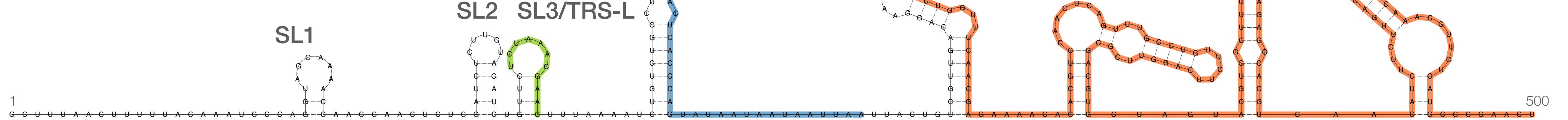


Sarbecovirus Leader Region

SARS-CoV-2
NC_045512.2



Pangolin CoV
EPI_ISL_410541



Sarbecovirus Leader Region

SARS-CoV-2
NC_045512.2

Structural multiple sequence alignment (MSA) of four Sarbecovirus leader regions

NC_045512.2-2b_SARS-CoV-2
MN996532.1-2b_RatG13
EPI_ISL_410541-2b_Pangolin-BetaCoV
NC_004718.3-2b_SARS-CoV

NC_045512.2-2b_SARS-CoV-2
MN996532.1-2b_RatG13
EPI_ISL_410541-2b_Pangolin-BetaCoV
NC_004718.3-2b_SARS-CoV

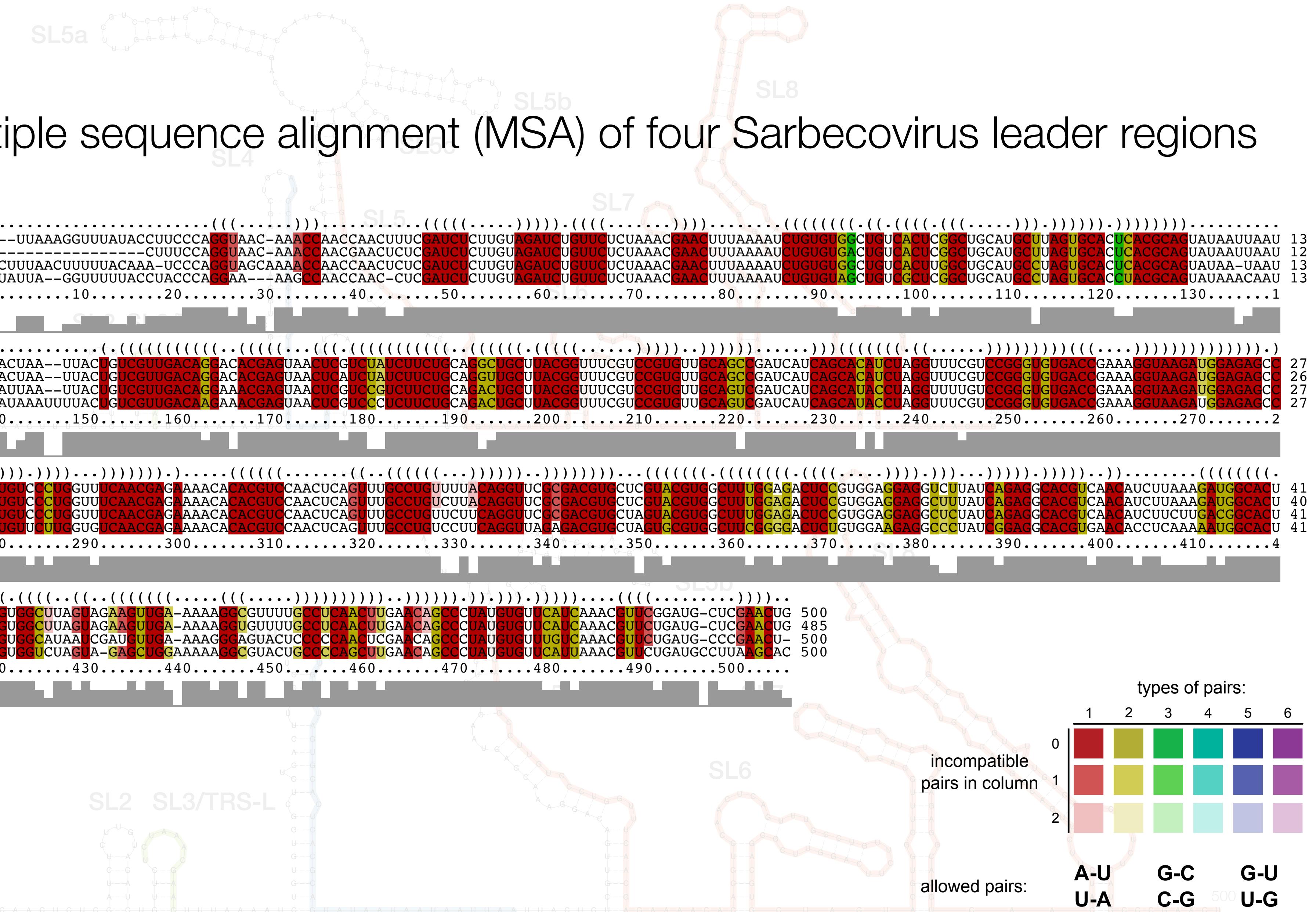
NC_045512.2-2b_SARS-CoV-2
MN996532.1-2b_RatG13
EPI_ISL_410541-2b_Pangolin-BetaCoV
NC_004718.3-2b_SARS-CoV

NC_045512.2-2b_SARS-CoV-2
MN996532.1-2b_RatG13
EPI_ISL_410541-2b_Pangolin-BetaCoV
NC_004718.3-2b_SARS-CoV

Pangolin CoV

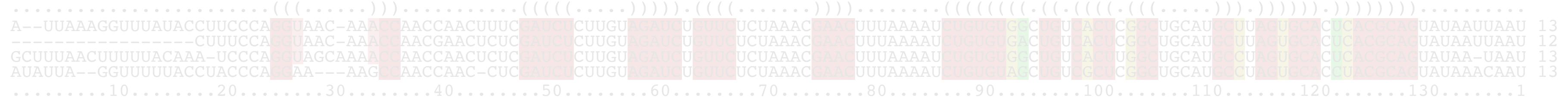
EPI_ISL_410541

SL1 SL2 SL3/TRS-L



Sarbecovirus Leader Region

NC_045512.2-2b SARS-CoV-2
MN996532.1-2b RatG13
EPI_ISL_410541-2b Pangolin-BetaCoV
NC_004718.3-2b SARS-CoV

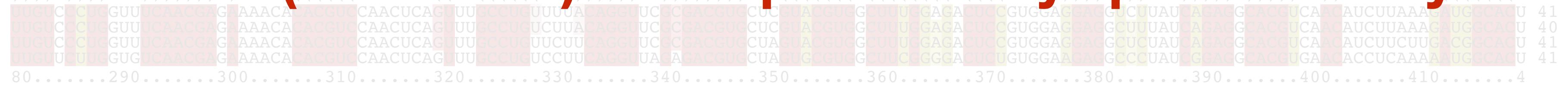


NC_045512.2-2b SARS-CoV-2
MN996532.1-2b RatG13
EPI_ISL_410541-2b Pangolin-BetaCoV
NC_004718.3-2b SARS-CoV



How to characterise a (structural) MSA qualitatively/quantitatively?

NC_045512.2-2b SARS-CoV-2
MN996532.1-2b RatG13
EPI_ISL_410541-2b Pangolin-BetaCoV
NC_004718.3-2b SARS-CoV



Can we use this information to classify novel conserved RNAs?

NC_045512.2-2b SARS-CoV-2
MN996532.1-2b RatG13
EPI_ISL_410541-2b Pangolin-BetaCoV
NC_004718.3-2b SARS-CoV



Using structure prediction for gene finding

Two traits: Thermodynamic stability and structure conservation

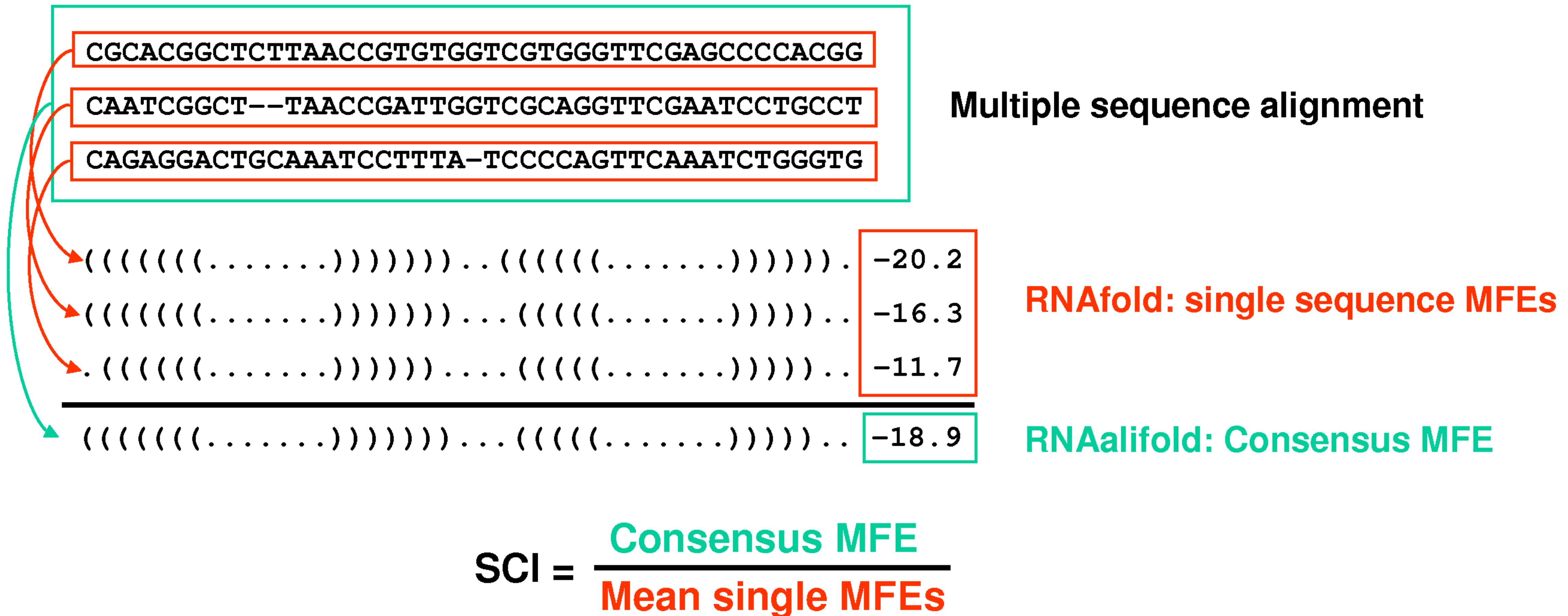
Naturally occurring structured RNAs have a lower folding energy compared to random sequences of the same size and sequence composition.

1. Calculate native MFE m
2. Calculate mean μ and standard deviation σ of MFEs of a large number of shuffled random sequences
3. Express significance in standard deviations from the means as

$$z = \frac{m - \mu}{\sigma}$$

Negative z-scores indicate that the native RNA is more stable than random RNAs

Structure Conservation Index (SCI)



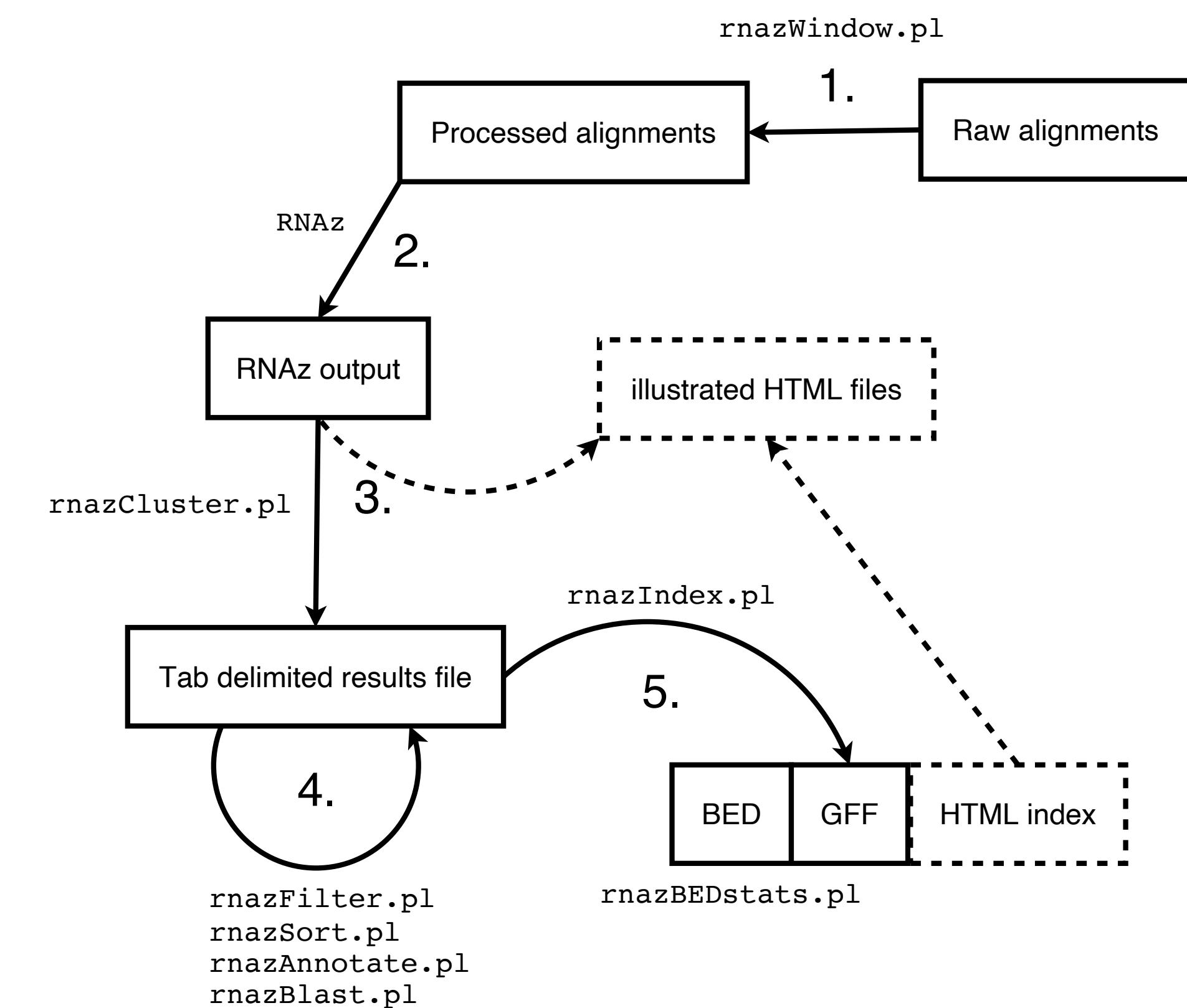
The SCI is an efficient and convenient measure for secondary structure conservation

RNAz: Classification of Conserved RNAs

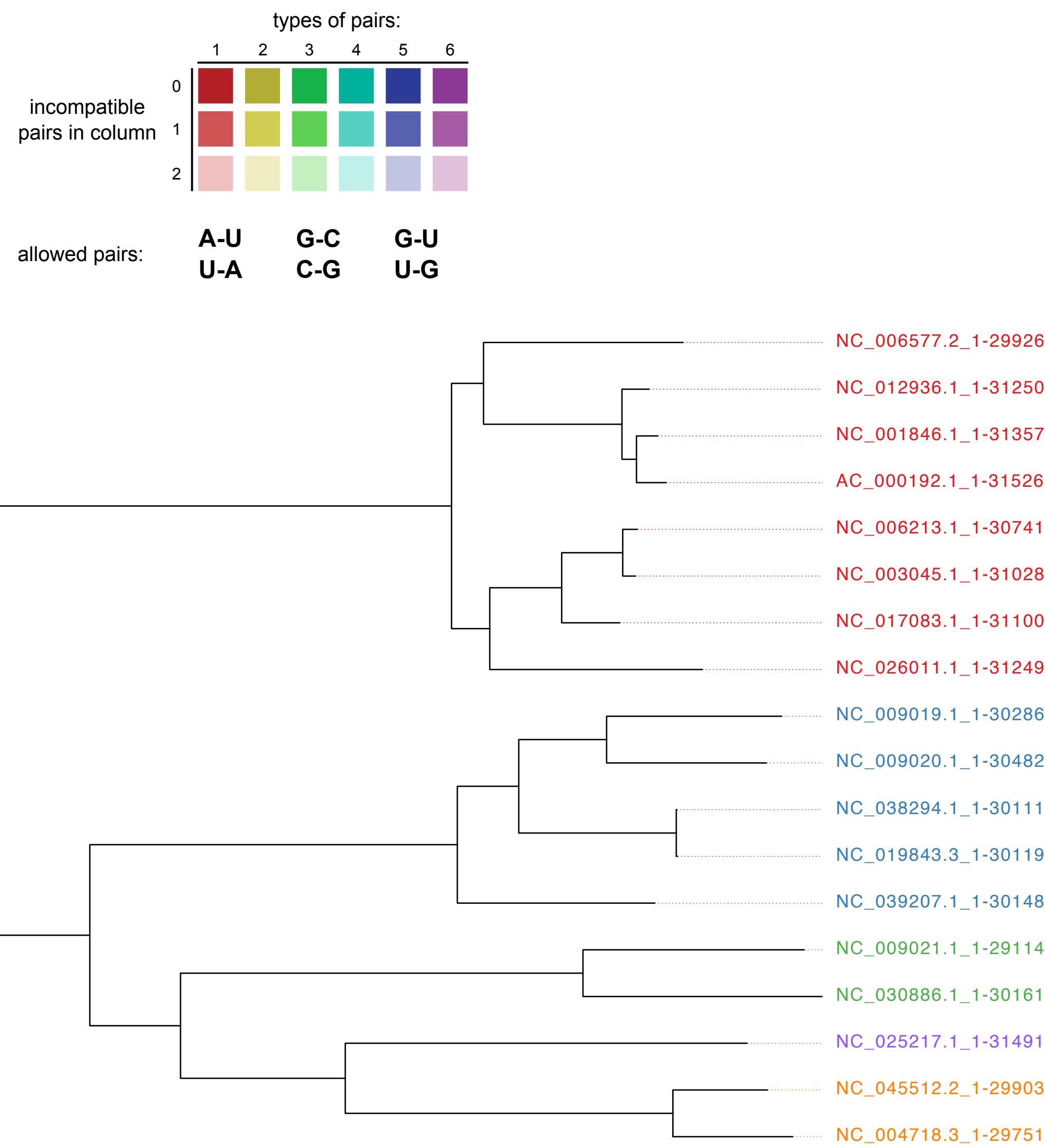
- RNAz detects conserved RNAs by screening MSA for secondary structures that are
 1. Thermodynamically stable
 2. Evolutionarily conserved, by SCI
- Uses a Support Vector Machine (SVM) to classify based on these (and a few other) measures

→ “RNA class probability”

Washietl, S. Hofacker I.L., Stadler, P.F. (2005)
Proc Natl Acad Sci USA, 102:2454-2459.

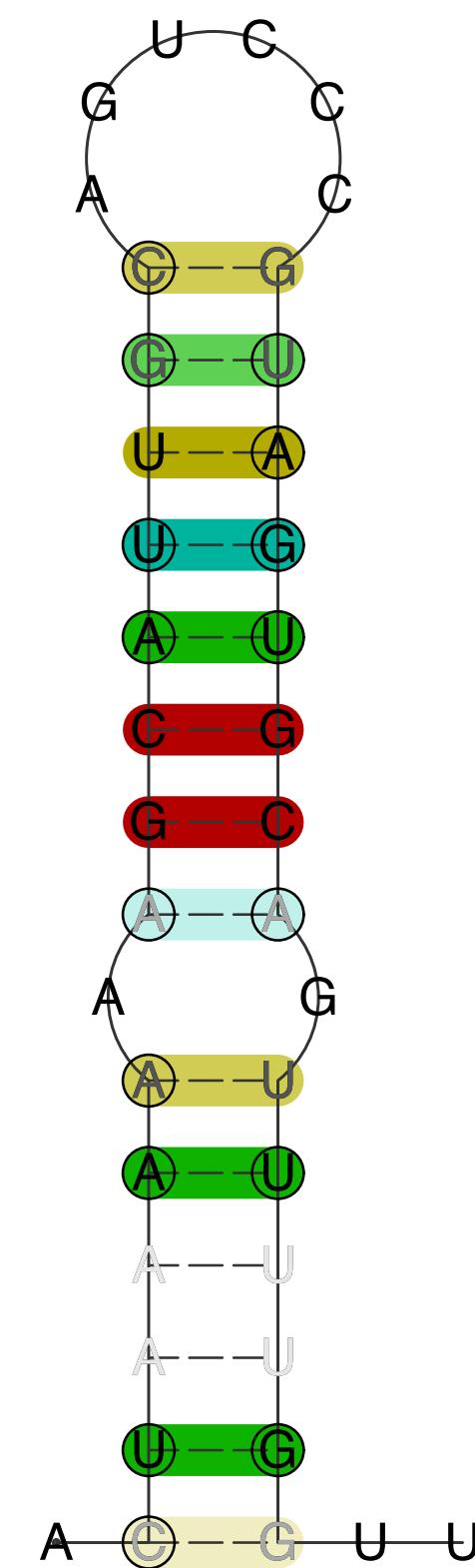


Conserved RNAs in CoV Coding Regions



Found in Embecovirus species:

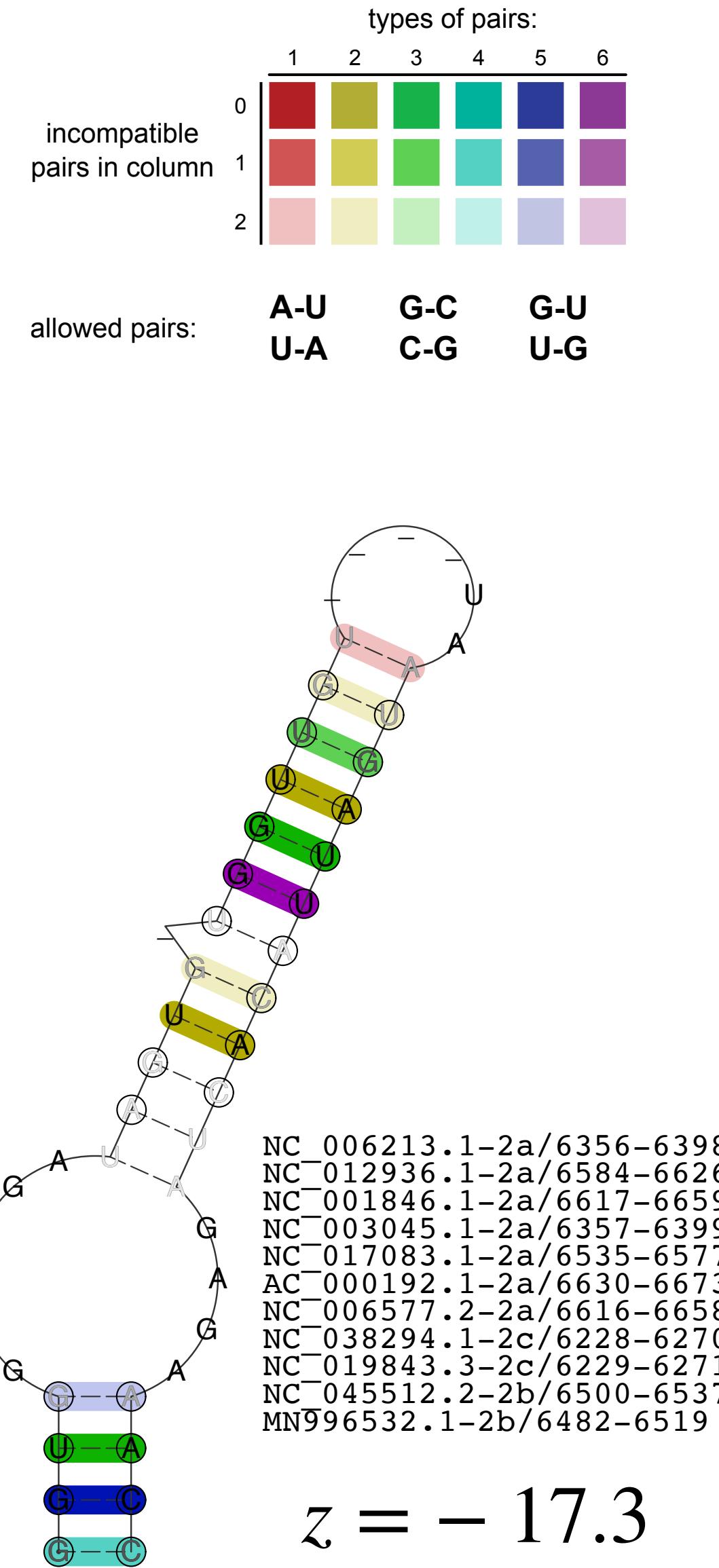
- *Bovine coronavirus*
 - *Human coronavirus OC43*
 - *Mouse hepatitis virus*
 - *Rat coronavirus Parker*
 - *Rabbit coronavirus HKU14*
 - *Human coronavirus HKU1*
 - *Betacoronavirus HKU24*



$$z = -5.0$$

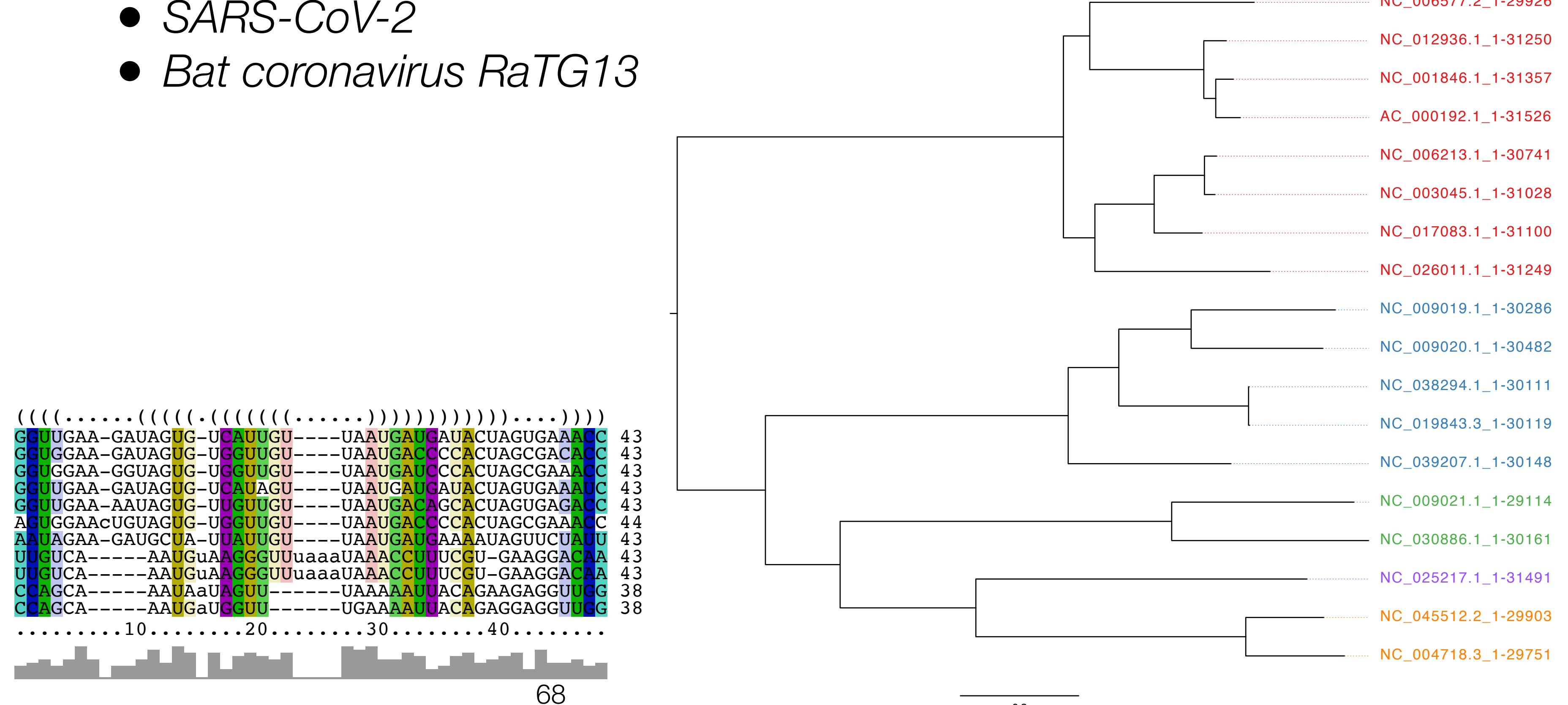
0.2

Conserved RNAs in CoV Coding Regions

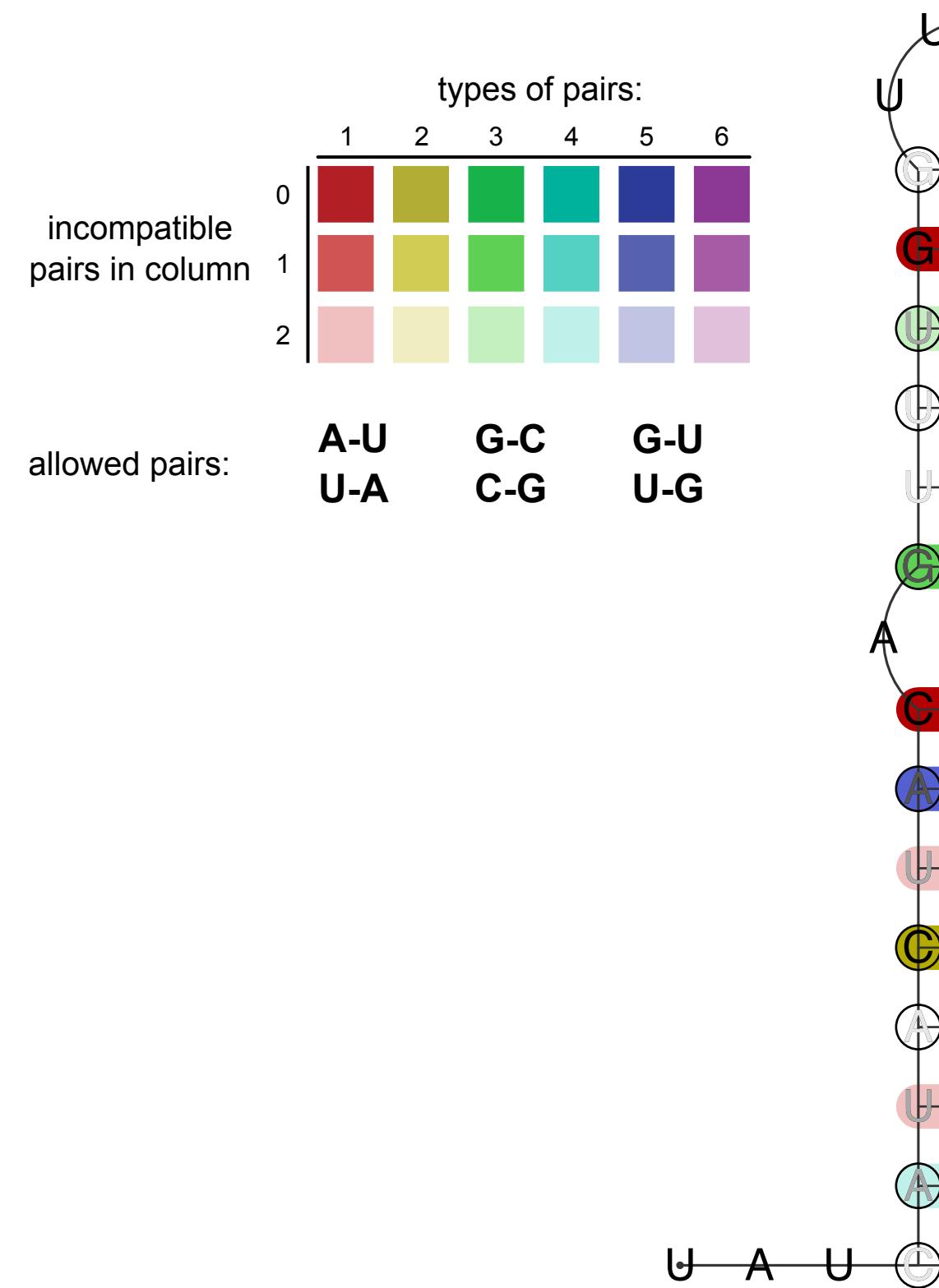


Found in Embecovirus species as well as

- *Betacoronavirus England 1* (Merbecovirus)
 - *Middle East respiratory syndrome coronavirus* (*MERS*)
 - SARS-CoV-2
 - *Bat coronavirus RaTG13*

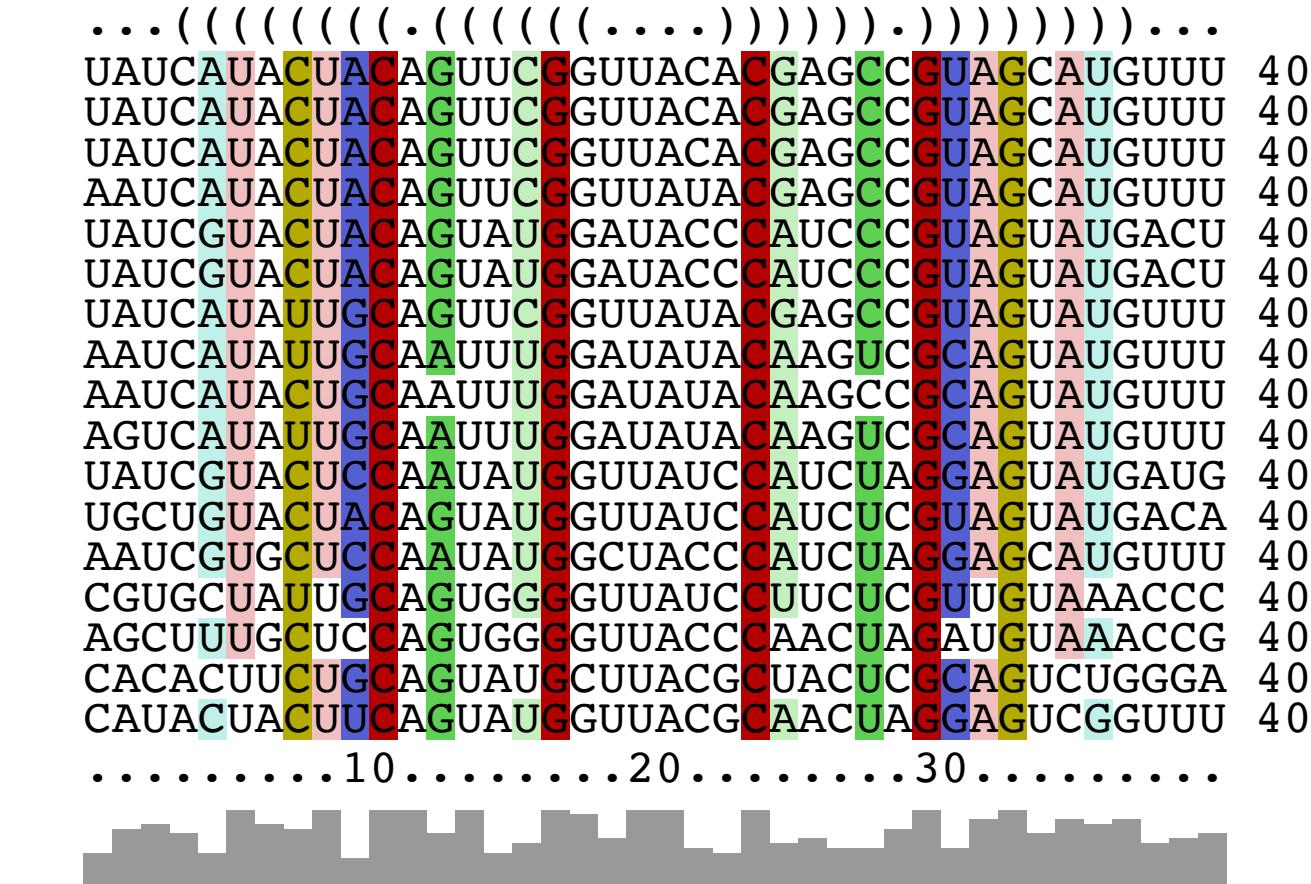


Conserved RNAs in CoV Coding Regions



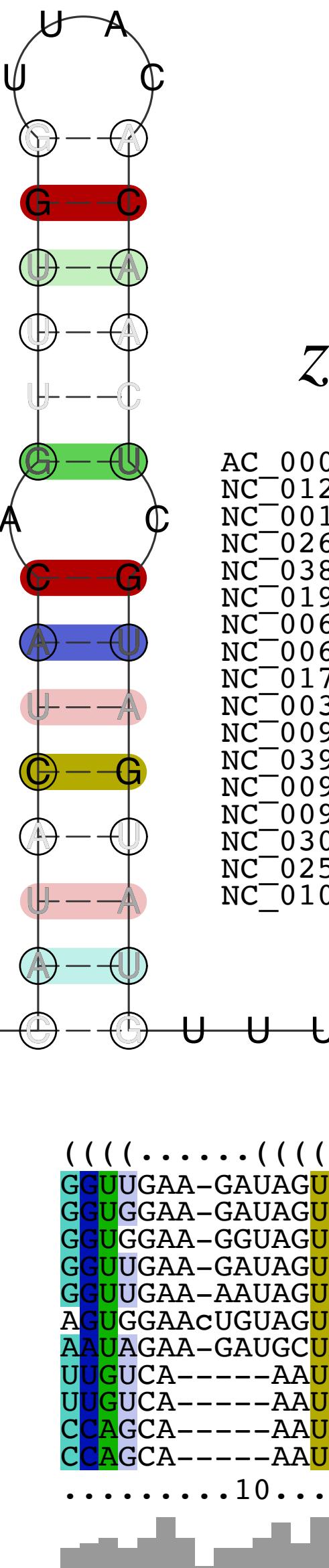
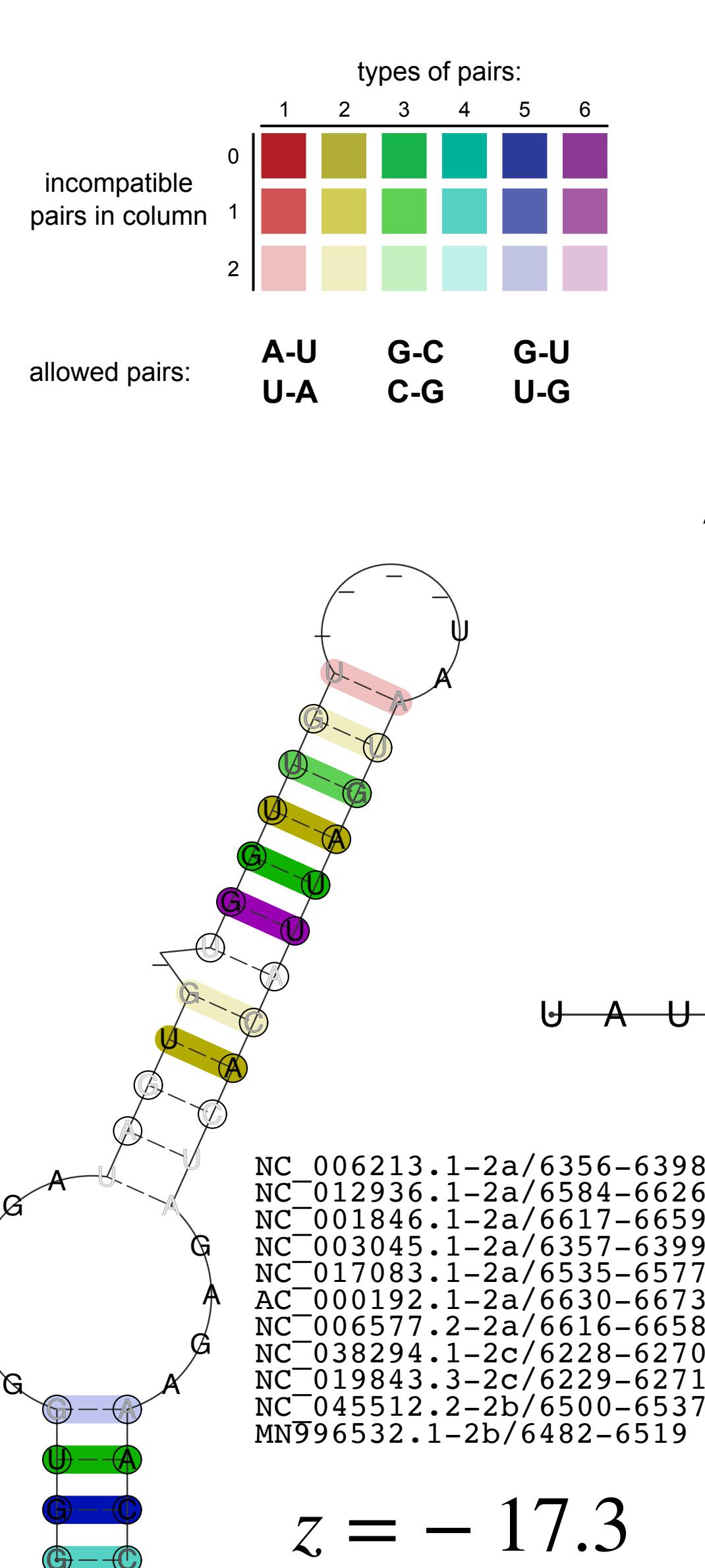
$$z = -9.3$$

AC_000192.1-2a/29255-29294
 NC_012936.1-2a/29015-29054
 NC_001846.1-2a/29081-29120
 NC_026011.1-2a/29021-29060
 NC_038294.1-2c/27944-27983
 NC_019843.3-2c/27945-27984
 NC_006577.2-2a/27731-27770
 NC_006213.1-2a/28487-28526
 NC_017083.1-2a/28870-28909
 NC_003045.1-2a/28801-28840
 NC_009019.1-2c/28092-28131
 NC_039207.1-2c/27931-27970
 NC_009020.1-2c/28261-28300
 NC_009021.1-2d/25787-25826
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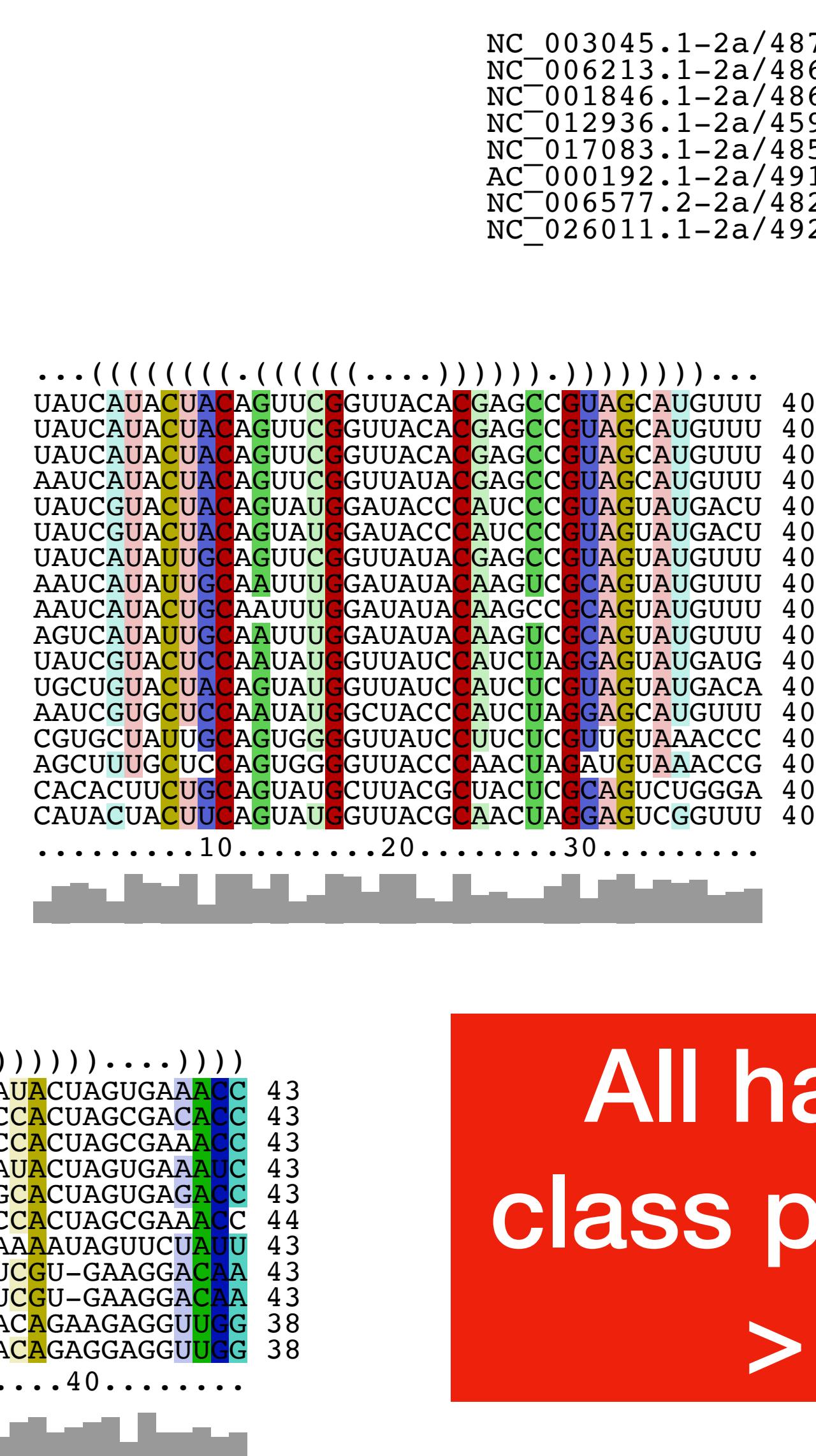


- Found in Embecovirus & Merbecovirus species plus
 - *Bat coronavirus HKU9-1* (Nobecovirus)
 - *Rousettus bat coronavirus* (Nobecovirus)
 - *Bat Hp-betacoronavirus* (Hibecovirus)
 - *Turkey coronavirus* (Gammacoronavirus)

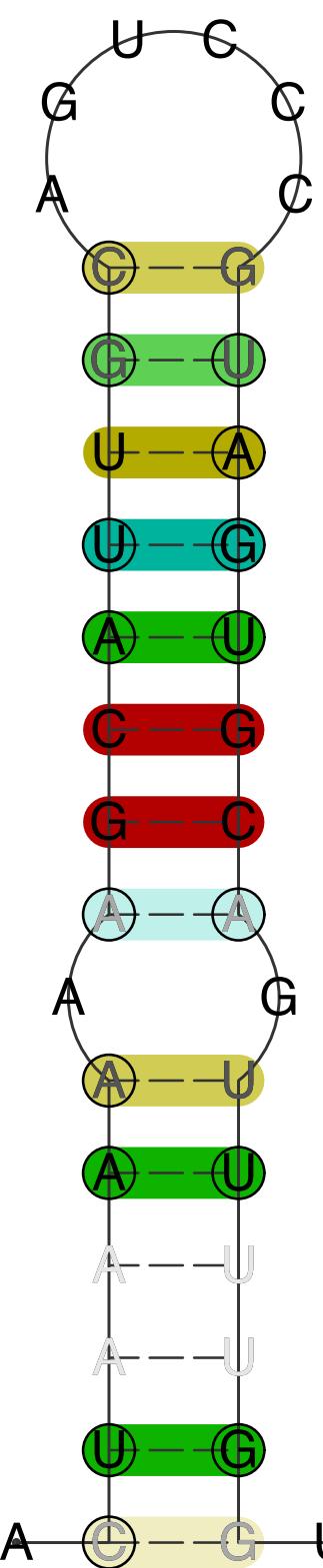
Conserved RNAs in CoV Coding Regions



$$z = -9.3$$



$z = -5.0$

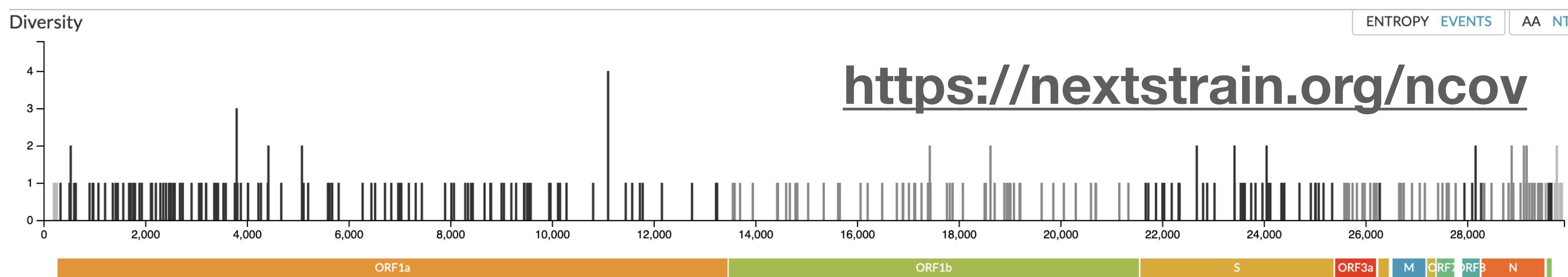
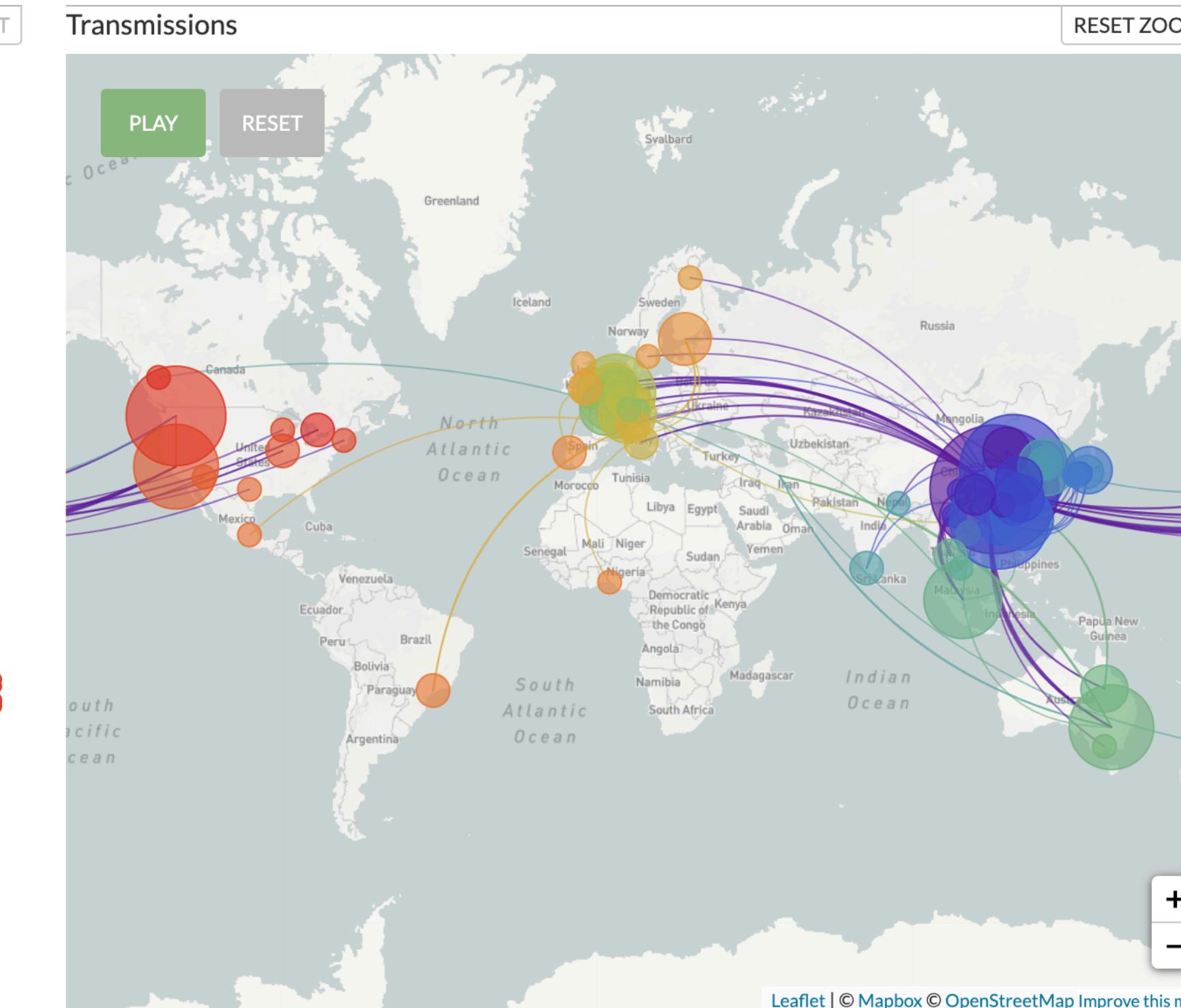
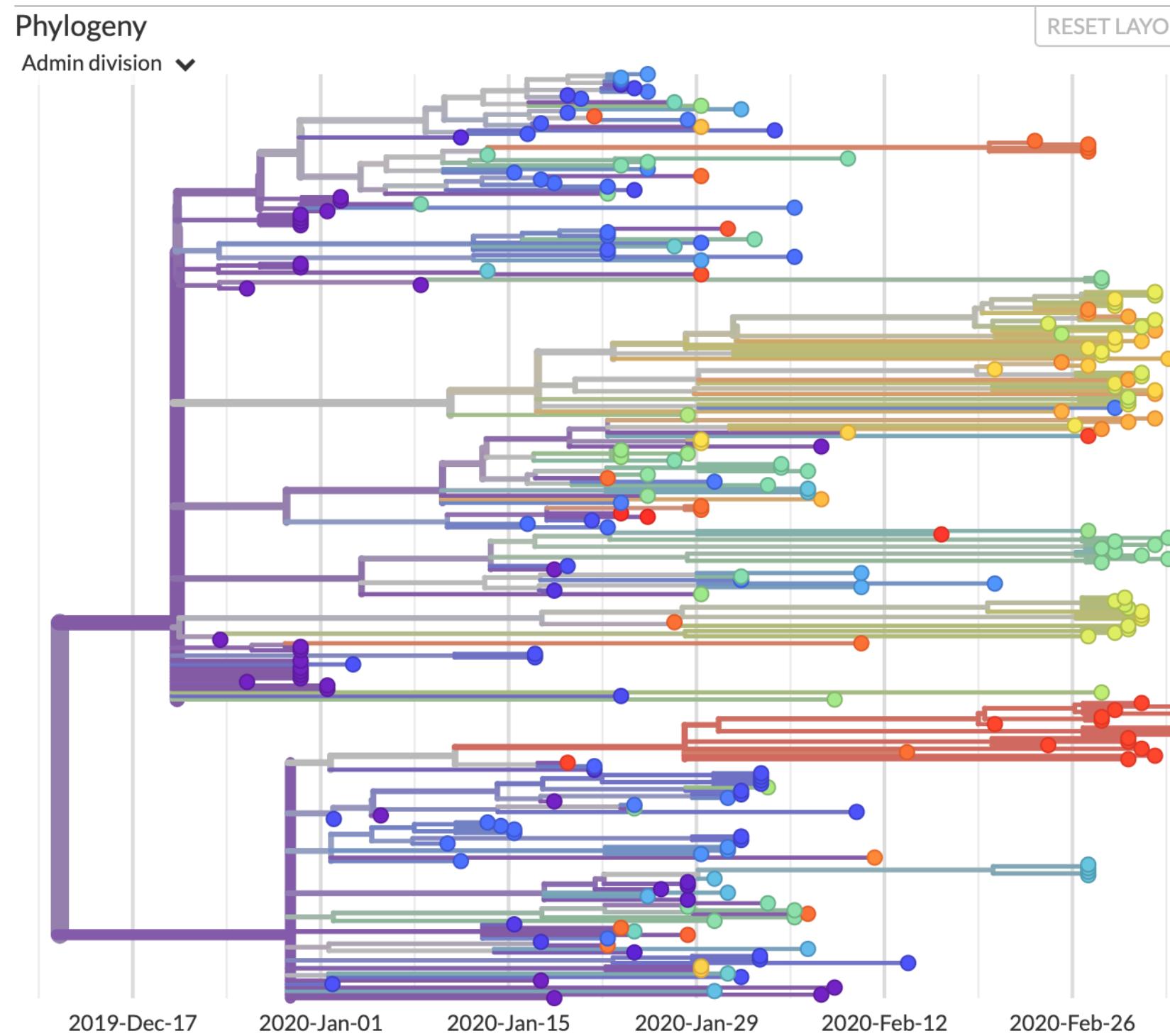


All have RNAz
class probabilities
 > 0.999

SARS-CoV-2 Molecular Epidemiology

Built with github.com/nextstrain/ncov using data from [GISaid](#).

Showing 264 of 264 genomes sampled between Dec 2019 and Mar 2020.



<https://nextstrain.org/ncov>

Summary

- RNA secondary structure prediction via dynamic programming algorithms
- Functional RNA structures are evolutionarily conserved in coding and non-coding regions
- Structural alignments and covariance models are used to find conserved RNAs
- SARS-CoV-2 shares ancestral roots with bat and pangolin CoVs
- ViennaRNA Web Services are available at

<http://rna.tbi.univie.ac.at/>

Acknowledgements

TBI Vienna

Ivo L. Hofacker
Ronny Lorenz
Roman Ochsenreiter
Peter Wolschann

University San Diego

Adriano de Bernardi Schneider

Chulalongkorn University Bangkok

Thanyada Rungrotmongkol
Nitchakan Darai



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University of Kent

Martin Michaelis
Mark Wass

Hokkaido University

Hirofumi Sawa
Yasuko Orba
Christida Wastika



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