Vfold Modeling of RNA Targets in CASP16

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AF3-assisted physics-based modeling



ITScore for docking: Zou lab

Vfold toolbox – Physics-based models

To predict 2D structure from the sequence Free energy modeling: **Vfold2D** (monomer) **VfoldMCPX** (multimer)

The distribution of β_p vs. θ 100 200 150 250 300 350 (f)backbone virtual bond base/sugar virtual bond 160-160 N1(9 140 -140 120 120 80 -80 60. -60 (a) 200 250 350 100 150 300 50

A virtual bond (4 beads) representation of RNA conformations

MC sampling guided by know structures

Free energy parameters for motifs

To predict long-range kissing interactions Vfold2D-MD (unpublished)



To generate (initial) 3D from 2D **Template-based modeling: Vfold3D & VfoldLA:**



2D structure

To predict the (final) 3D from (2D+initial 3D) MD simulation: IsRNA



A Bayesian FF derived from known structures

IsRNA: Coarse-grained molecular dynamics simulation



Group II intron (412 nts)

To predict the (final) 3D from (2D+initial 3D) RNAJP: MC/MD hybrid simulation



Li, J., & Chen, S. J., (2022) Nucleic Acids Research

AlphaFold 3

If AF3 models agree with the Vfold predictions We are happy!

□ If AF3 models are different from the Vfold predictions We are also happy: AF3 model + 2D → MD simulation

We are always happy with AF3!

Vfold performance in CASP16 – an overview



- Strong performance on small RNAs and natural RNAs due to the availability of (some) templates and/or the computationally efficient simulations capable of generating extensive structural ensembles for analysis.
 - Poor performance on IncRNAs, as template information and additional structural information is not readily available, resulting in computationally challenging simulations.
 - **Mixed performance** on **RNA-protein targets**. Without template or literature information, RNAprotein docking presents a significant challenge.

Five representative targets



Four representative targets:

The Good:

- Two RRE SL2 targets (our best models: 6.68 Å and 3.40 Å)
- RNA Origami dimer (our best model: 19.17 Å)

The Bad:

- raiA RNA (our best model: 15.84 Å)
- GOLLD IncRNA (our best model: 48.18 Å)

(1) RRE SLII (R1203): Importance of template refinement



Rev response element (**RRE**)+**Rev** protein \rightarrow transport viral mRNA out of nucleus

AF3 → different T-shaped topologies- w/wt tRNA scaffold





SLII with the tRNA scaffold (R1203): Good

SLII without the tRNA scaffold (R1203): Bad

(1) RRE SLII (R1203): Importance of template refinement



The native structure

Our best model: 6.68 Å

The template we used: RRE SLIIB with Rev peptide (PDB 1ETG)

The good: Vfold correctly predicted the coaxial stacking between SLIIA and SLIIB, as well as the T-shape of the 3WJ.

The bad: A66 and C67 form base pairs within SLIIB (following the template), but in the native structure, they flip out and stack with A68 and G69.

(2) RRE SLII (R1296): AF3-assisted sampling

A single mutation \rightarrow Similar 2D but dramatically different 3D

The predicted 2D structure

Vfold suggests a highly dynamic 3WJ



AF3 → Y-shaped topologies (Fab-free)



(2) RRE SLII (R1296): AF3-assisted sampling





The native structure

Our best model: 3.4 Å

The good: Vfold correctly modeled the 3WJ conformation, in which the three arms do not exhibit coaxial stacking.

The bad: Vfold incorrectly predicts that A38 flip out to form base triples; additionally, we missed the A-minor interaction between A31 and SLIIA.



Low-barrier dimerization:

(A1-B1) + (A2-B2) → (A1-B2) + (A2-B1)

AF3 fails to generate a viable structure





(3) RNA origami dimer (R1281)

helix6-helix6 kissing

helix1-helix1 kissing



The native structure (dimer) Mode 2 but for helix 6



Monomer from our best model (red) against the native structure (green): 19.17 Å

(4) raiA RNA (R1242): good 2D \rightarrow bad 3D

Structure information and in-line probing experiment on raiA motif from literature[1].

Α G pk' C. acetobutylicum ATCC 824 raiA motif RNA N ≥97% conservation of the specific nucleotide depicted N ≥97% conservation of P1a G-C either a purine or pyrimidine Sites of spontaneous RNA strand scission 5'99U-A

The 2D structure was predicted by combining literature info with our models.



The good: Vfold predicts good 2D structure

Specificity: 0.88 (ppv) Sensitivity: 0.94 (recall) F1-score: 0.91

The three pseudoknots are all correctly predicted.

[1] Soares, Lucas W., Christopher G. King, Chrishan M. Fernando, Adam Roth, and Ronald R. Breaker. (2024). *PNAS*

(4) raiA RNA (R1242): Good 2D \rightarrow bad 3D



The native structure

The bad: the kink turn-like junction and the large 3WJ

Vfold fails to generate the initial 3D structure → the predicted model

(5) GOLLD lncRNA (R1250): Structural rearrangement upon R-R binding



The bad: 2D structure prediction accuracy

Specificity: 0.55 (many false positives) Sensitivity: 0.85 F1-score: 0.67 The formation of pseudoknots are correctly predicted, but with low specificity.



(5) GOLLD lncRNA (R1250): Structural rearrangement upon R-R binding



The native structure (6-mer)

The bad: We first modeled the monomer structure and subsequently assembled the 6-mer structure through RNA-RNA docking. This resulted in overly compact monomer and 6-mer structures.

This target highlights the significant challenges in predicting large and multimeric RNA structures at both the 2D and 3D levels.

Our best model (6-mer): 67.2 Å

Perspectives

What we did right:

- Natural and small RNAs
- Conformation sampling using CGMD simulations
- Prediction of dimerization modes

What went wrong:

- Large RNA, both at 2D and 3D levels
- Multimeric RNAs: docking of monomeric RNA doesn't work
- RNA-Protein complexes

Future directions:

- New models for the simulations of large/multimeric RNAs
- Integration of machine learning-base models with simulation methods
- Improving RNA-protein docking, accounting for RNA flexibility

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