

#### Structural Bioinformatics GENOME 541 Spring 2023

**Lecture 4**: Nucleic Acids Frank DiMaio (dimaio@uw.edu)

## DNA structure

- B-form DNA
  - right-handed anti-parallel double helix
  - ~10 base pairs per turn
  - 3.4 Å rise per base pair
  - C2' endo sugar pucker
  - A:T and G:C base pairs
  - wide major groove, narrow minor groove



#### DNA structure: a single nucleotide



#### DNA structure: Watson-Crick base-pairing



major groove

# **DNA** structure

- A-form DNA
  - right-handed anti-parallel double helix
  - ~11 base pairs per turn
  - 2.56 Å rise per base pair
  - C3' endo sugar pucker
  - A:T and G:C base pairs
  - narrow and deep major groove, wide and shallow minor groove



## DNA structure

- Z-form DNA
  - left-handed anti-parallel double helix
  - alternating C:G and G:C base pairs
  - found under high salt conditions
  - rare in nature



# Factors Stabilizing the DNA Duplex

- 1. "Hydrophobic interactions," base stacking
  - vertical base stacking interactions make duplex formation enthalpically favored



#### 2. Ionic interactions

- duplex becomes more stable as ionic strength increases
- presence of positive counterions partially neutralizes negative charges of backbone phosphates
- 3. Hydrogen bonding between base pairs

# **DNA** bending

- B-form DNA bends in three major modes:
  - major kinking (CAP)
  - writhe (TBP)
  - smooth continuous bending (Mat a1/alpha2 homeodomain)
- Different base steps have different intrinsic bending propensities
  - pyrimidine-purine base steps can form sharp kinks (e.g. T-A steps)



# DNA bending: kinking in CAP:DNA





Kink at C-A step (pyrimidine-purine)

#### DNA bending: writhing in TBP:DNA



## DNA bending: smooth bending in MAT a1-alpha2:DNA



# **DNA hydration**

- DNA is highly hydrated under physiological conditions
- Specific ordered water locations have been identified through analysis of highresolution DNA crystal structures
  - major groove base waters
  - minor groove spine of hydration



#### DNA hydration: major groove waters



#### DNA hydration: minor groove waters



**1BNA** 

# **DNA recognition**

- Direct readout
  - protein recognizes specific pattern of hydrogen bond donors/acceptors, packing sites
  - major groove usually targeted due to uniqueness of hbond pattern
- Indirect readout
  - protein recognizes DNA shape
  - sequence-specific DNA bending
  - phosphate backbone contacts often important

#### DNA recognition: direct readout



Arg-Gua hbonds

Asn-Ade hbonds

### DNA recognition: indirect readout



Kink at pyrimidine-purine base step

### **DNA recognition: major families**

Helix-turn-helix (1cgp)
Homeodomain (1b72)
Zinc finger (1aay)
bZIP (1ysa)
bHLH (1mdy)

### C2H2 zinc finger: Zif268



1AAY



# Water-mediated interactions: Trp repressor



#### DNA is wrapped around nucleosomes



DNA bending leads to sequence preferences for nucleosome positioning

#### Protein-DNA interfaces require new sampling moves

Double-helical DNA fragment insertions preserve basepairing outside the region of fragment insertion

![](_page_22_Figure_2.jpeg)

Interface moves sample the protein-DNA rigid body orientation using homologous structures as templates

Protein fragment insertions sample backbone conformation without perturbing DNA or binding mode

![](_page_22_Picture_5.jpeg)

![](_page_22_Figure_6.jpeg)

Kinematic structure for DNA allows torsionspace (internal coordinate) sampling while maintaining the DNA duplex

### RNA structures are highly diverse

![](_page_23_Picture_1.jpeg)

**RNA duplex** 

transfer RNA

#### Examples of RNA structural motifs

![](_page_24_Figure_1.jpeg)

Figure 6–94. Molecular Biology of the Cell, 4th Edition.

![](_page_24_Figure_3.jpeg)

![](_page_24_Figure_4.jpeg)

#### Secondary structure of yeast Phe tRNA

![](_page_25_Figure_1.jpeg)

#### Free energy computation predicts RNA secondary structure (mfold)

![](_page_26_Figure_1.jpeg)

#### Mfold algorithm (Zuker & Stiegler, NAR 1981 9(1):133)

W(i,j) – min free energy formed from subsequence [i...j] V(i,j) – min free energy from all substructures where I and j pair

$$\begin{split} W(i,j) &= \min \left\{ \begin{array}{ll} E(FH(i,j)) & (1) \\ \min_{i < k < m < j} E(FL(i,j;k,m)) + V(k,m) & (2) \\ \min_{i+1 < k < j-2} W(i+1,k) + W(k+1,j-1) & (3) \\ \end{array} \right. \\ W(i,j) &= \min \left\{ \begin{array}{ll} W(i+1,j) & (4)a \\ W(i,j-1) & (4)b \\ W(i,j-1) & (4)b \\ V(i,j) & (1-3) \\ \min_{i < k < j-1} (W(i,k) + W(k+1,j) & (5) \\ \end{array} \right. \\ \end{split}$$

![](_page_28_Picture_0.jpeg)

#### ARTICLE

https://doi.org/10.1038/s41467-021-21194-4 OPEN

RNA secondary structure prediction using deep learning with thermodynamic integration

Check for updates

Kengo Sato⊚ <sup>1⊠</sup>, Manato Akiyama<sup>1</sup> & Yasubumi Sakakibara<sup>1</sup>

![](_page_28_Figure_5.jpeg)

#### 3D structure of yeast Phe tRNA fold

![](_page_29_Figure_1.jpeg)

Non-WC base pairs and base triples in yeast tRNA Phe

![](_page_30_Figure_1.jpeg)

A9 intercalates between adjacent G45 and m<sup>7</sup>G46 in yeast tRNA Phe

![](_page_31_Figure_1.jpeg)

# Six backbone dihedral angles $(\alpha - \zeta)$ per nucleotide

![](_page_32_Figure_1.jpeg)

## Prediction of RNA tertiary structure

![](_page_33_Figure_1.jpeg)

#### *De Novo* RNA Tertiary Structure Prediction at Atomic Resolution Using Geometric Potentials from Deep Learning

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#### ABSTRACT

Experimental characterization of RNA structure remains difficult, especially for non-coding RNAs that are critical to many cellular activities. We developed DeepFoldRNA to predict RNA structures from sequence alone by coupling deep self-attention neural networks with gradient-based folding simulations. The method was tested on two independent benchmark datasets from Rfam families and RNA-Puzzle experiments, where DeepFoldRNA constructed models with an average RMSD=2.69 Å and TM-score=0.743, which outperformed state-of-the-art methods and the best models submitted from the RNA-Puzzles community by a large margin. On average, DeepFoldRNA required ~1 minute to fold medium-sized RNAs, which was ~350-4000 times faster than the leading Monte Carlo simulation approaches. These results demonstrate the major advantage of advanced deep learning techniques to learn more accurate information from evolutionary profiles than knowledge-based potentials derived from simple statistics of the PDB library. The high speed and accuracy of the developed method should enable large-scale atomic-level RNA structure modeling applications.