## Illuminating protein space with a programmable generative model

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#### Proteins – the chief actors in cells



## Structure – the key component of function



#### **Protein Structure Prediction**



## Protein Sequence prediction



## Structure first – Protein Design



## Generative diffusion process

Forward SDE. **Training**. Data to Noise.



Reverse SDE. Generation. Noise to Data

## Whitening transformation

Correlated diffusion as uncorrelated diffusion in whitened space



$$z = R(x-\mu)$$

## Correlated forward SDE process

$$d\boldsymbol{x} = \boldsymbol{R}d\boldsymbol{z} = -\frac{\boldsymbol{\beta}_t}{2}\boldsymbol{R}\boldsymbol{z}dt + \sqrt{\boldsymbol{\beta}_t}\boldsymbol{R}dw$$

![](_page_8_Figure_2.jpeg)

#### Constraints as a de-whitening transform

![](_page_9_Figure_1.jpeg)

$$F(x) = \sum_{i,j} A_{i,j} x_i x_j$$

 $\mathbb{E}_{p(\boldsymbol{x}_t|\boldsymbol{x}_o)}[F(\boldsymbol{x})] = \alpha_t F(\boldsymbol{x}_0) + (1 - \alpha_t) \mathbb{E}_{p_{model(\boldsymbol{x})}}[F(\boldsymbol{x})]$ 

## Constraint – Chain Structure <sup>b</sup>2 $b_1$ <sup>b</sup>N r<sub>0</sub> $\mathbf{r}_{N}$ r $r_{i,j} \sim \mathcal{N}(0, \gamma^2 |i - j|)$ $\mathbb{E}_{p(\boldsymbol{x_t}|\boldsymbol{x_0})} \left[ D_{ij}^2(\boldsymbol{x_t}) \right] = \alpha_t D_{ij}^2(\boldsymbol{x_0}) + (1 - \alpha_t) 3\gamma^2 |\mathbf{i} - \mathbf{j}|$

### Constraint - Radius of Gyration

![](_page_11_Figure_1.jpeg)

![](_page_11_Figure_2.jpeg)

#### Reverse-time SDE

![](_page_12_Figure_1.jpeg)

t

## Correlated Reverse-time SDE

![](_page_13_Figure_1.jpeg)

$$d\boldsymbol{x} = \left(-\frac{1}{2}\boldsymbol{x} - \boldsymbol{R}\boldsymbol{R}^{T}\boldsymbol{\nabla}_{x}\log\boldsymbol{p}_{t}(\boldsymbol{x})\right)\beta_{t}dt + \sqrt{\beta_{t}}\boldsymbol{R}d\widetilde{\boldsymbol{w}}$$

## Score Estimation

![](_page_14_Figure_1.jpeg)

 $p_{data}(x)$ 

![](_page_14_Figure_3.jpeg)

 $\nabla_x \log p_{data}(x)$ 

 $\sim \nabla_x \log p(x)$ 

## Optimized denoiser

$$\nabla_{\mathbf{x}} \log p_t(\mathbf{x}) = \left( (1 - \alpha_t) \mathbf{R} \mathbf{R}^T \right)^{-1} \left( \sqrt{\alpha_t} \hat{\mathbf{x}}_{\theta}(\mathbf{x}, t) - \mathbf{x} \right)$$

$$\mathcal{L}_{\mathbf{x}}^{\text{reg}}(\mathbf{x}; \theta) = -\mathbb{E}_{\mathbf{x}_t \sim p(\mathbf{x}_t | \mathbf{x}), t \sim \text{Unif}(0, 1)} \left[ \frac{\alpha_t \beta_t}{2(1 - \alpha_t)^2} \left\| \left( \mathbf{R}^{-1} + \omega \mathbf{I} \right) \left( \hat{\mathbf{x}}_{\theta}(\mathbf{x}_t, t) - \mathbf{x} \right) \right\|_2^2 \right]$$

## Optimized denoiser

![](_page_16_Figure_1.jpeg)

## Reduced computational complexity

Random Graph Neural Network

> O(NlogN) or O(N) edges

![](_page_17_Picture_3.jpeg)

## Sub- $\mathcal{O}(N^2)$ scaling - Random edge sampling

![](_page_18_Figure_1.jpeg)

## Backbone graph neural network

![](_page_19_Figure_1.jpeg)

## Equivariant geometry solver

![](_page_20_Figure_1.jpeg)

#### Invariant local frame relations

![](_page_21_Figure_1.jpeg)

## Equivariant geometry solver

![](_page_22_Figure_1.jpeg)

## Sampling of the backbone - overdispersion

![](_page_23_Picture_1.jpeg)

## Low temperature sampling – reweight and concentrate

![](_page_24_Figure_1.jpeg)

#### Annealed reverse-time SDE

![](_page_25_Figure_1.jpeg)

#### Score evolution

![](_page_26_Figure_1.jpeg)

## Score evolution

![](_page_27_Figure_1.jpeg)

## Annealed Langevin dynamics

![](_page_28_Picture_2.jpeg)

![](_page_28_Picture_3.jpeg)

![](_page_29_Figure_0.jpeg)

# From backbone to sequence and heavy atom position

![](_page_30_Picture_1.jpeg)

## Design Network

![](_page_31_Figure_1.jpeg)

## Conditional modeling

![](_page_32_Figure_1.jpeg)

## Conditional modeling

Bayes' rule

$$p(x|y) = \frac{p(x)p(y|x)}{p(y)}$$

Bayes' rule for score functions

![](_page_33_Figure_4.jpeg)

score

## Conditional modeling

![](_page_34_Picture_1.jpeg)

## Symmetry and substructure guided diffusion

![](_page_35_Picture_1.jpeg)

![](_page_35_Picture_2.jpeg)

![](_page_35_Picture_3.jpeg)

![](_page_35_Picture_4.jpeg)

![](_page_35_Picture_5.jpeg)

![](_page_35_Picture_6.jpeg)

![](_page_35_Picture_7.jpeg)

![](_page_35_Picture_8.jpeg)

![](_page_35_Picture_9.jpeg)

![](_page_35_Picture_10.jpeg)

![](_page_35_Picture_11.jpeg)

![](_page_35_Picture_12.jpeg)

![](_page_35_Picture_13.jpeg)

![](_page_35_Picture_14.jpeg)

## Evaluation

- 50,000 single chains, 10,000 complexes qualitative
- 10,000 single chain proteins quantitative
- $\lambda_0 = 10$
- ψ = 2
- 200 steps
- Single chain lengths N: p(N) = 1/N
- Complex # chain and N = # chain and N of random complex from PDB

#### Evaluation – Secondary structurs

![](_page_37_Figure_1.jpeg)

#### Evaluation – Residue interactions

![](_page_38_Figure_1.jpeg)

# Evaluating Chroma by structure prediction with OmegaFold

![](_page_39_Figure_1.jpeg)

## Evaluation - TM-scores

![](_page_40_Figure_1.jpeg)

### Evaluation - TM-scores

![](_page_41_Figure_1.jpeg)

## Evaluation - Novelty and structural homology

![](_page_42_Figure_1.jpeg)

#### **Evaluation - TERMs**

![](_page_43_Figure_1.jpeg)

## Evaluation - Closest-match RMSD for TERMs

![](_page_44_Figure_1.jpeg)

## Limitations

- + combination of promising maturities in GDMs
- + elegant way they implement empirical knowledge
- missing experimental characterization
- no quantitative evaluations for many designs and design choices
- no benchmarking
- sequential generation of backbone, sequence and rotamers
- choice of model to evaluate folding

## Illuminating chroma?!

![](_page_46_Picture_1.jpeg)