

EQUIVARIANT ENERGY-GUIDED SDE FOR INVERSE MOLECULAR DESIGN

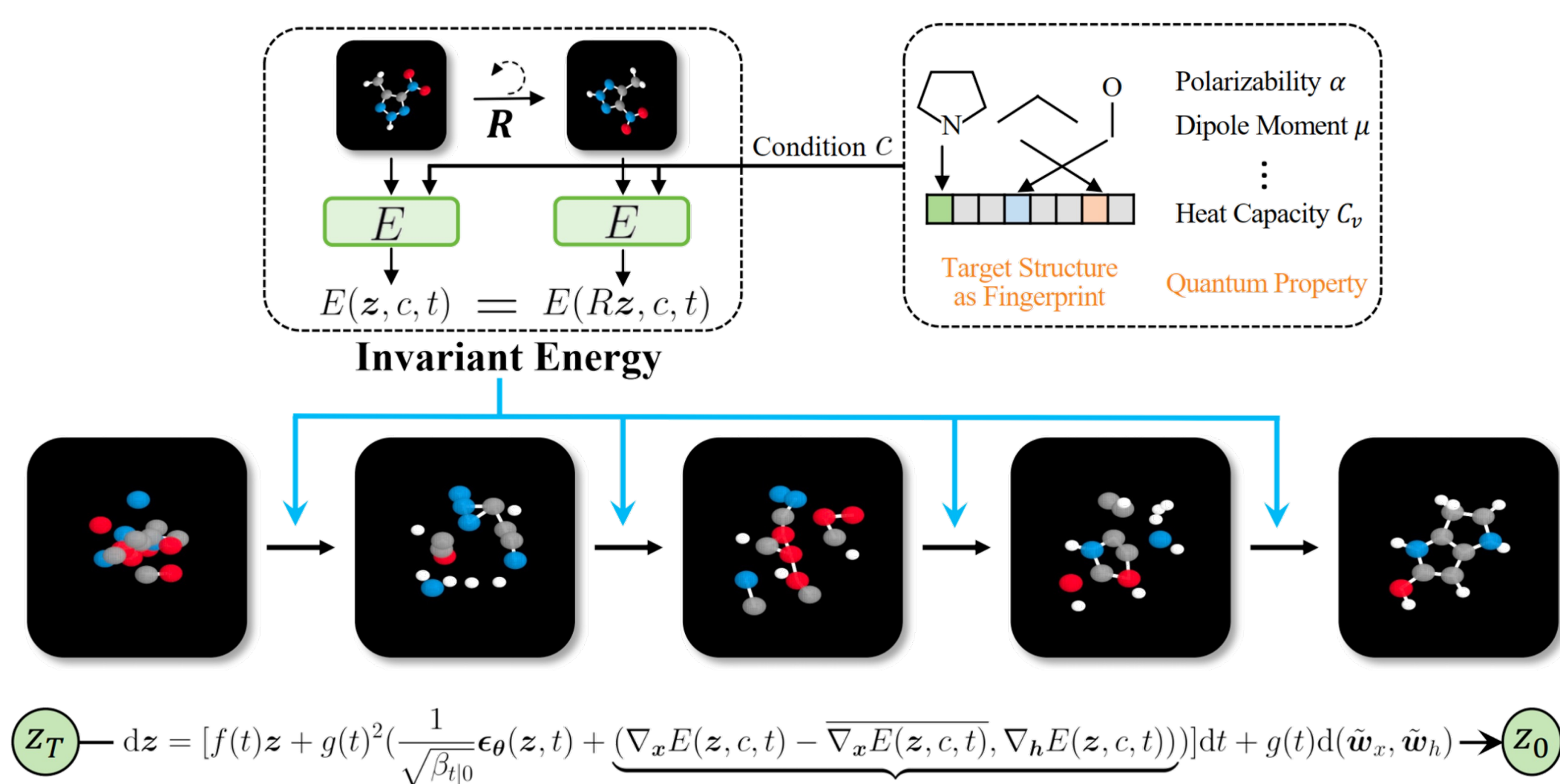
<https://github.com/gracezhao1997/EEGSDE> ICLR 2023

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Motivation

- we propose equivariant energy-guided stochastic differential equations (EEGSDE), a flexible framework for controllable 3D molecule generation under the guidance of an energy function in diffusion models.



- Guide generated molecules towards desired properties c via a time-dependent energy function $E(z, c, t)$:

$$dz = [f(t)z + g(t)^2 \left(\frac{1}{\sqrt{\beta_{t|0}}} \epsilon_{\theta}(z, t) + (\nabla_x E(z, c, t) - \nabla_x E(z, c, t), \nabla_h E(z, c, t)) \right)] dt + g(t) d(\tilde{w}_x, \tilde{w}_h), z_T \sim p_T(z_T)$$

energy gradient taken in the product space

Rotation invariance:

Theorem 2. Suppose the assumptions in Theorem 1 hold and $E(z, c, t)$ is invariant to any orthogonal transformation R , i.e., $E(Rz, h, c, t) = E(z, h, c, t)$. Then $p_{\theta}(z_0|c)$ is invariant to any rotational transformation.

The EEGSDE defines a distribution $p(z_0|c)$ conditioned on the property c , which is invariant to translational and rotational transformations

Choice of Energy

- Generating molecules with desired quantum property :

- The energy function is defined as the squared error between the predicted property and the desired property:

time-dependent property prediction model the desired property

$$E(z_t, c, t) = s |g(z_t, t) - c|^2$$

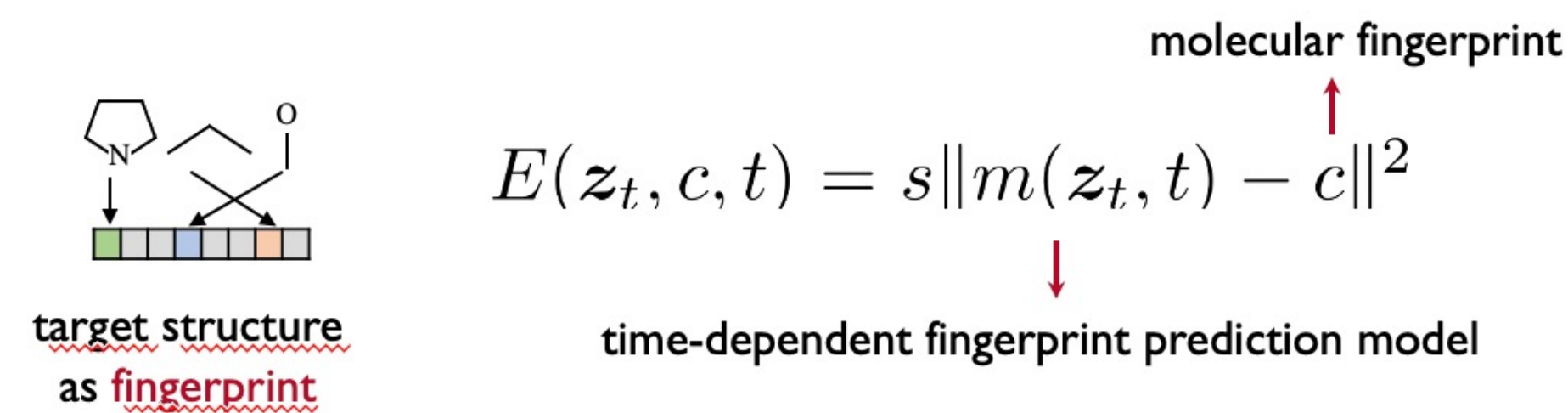
- Implementation of property prediction model :

$$g(z_t, t) = \text{Dec}(\text{EGNN}^h(x_t, h'_t)), \quad h'_t = \text{concatenate}(h_t, t)$$

the second component (h feature part) in the output of EGNN
invariant to orthogonal transformations

- Generating molecules with target structure :

- The energy function is defined as the squared error between the predicted fingerprint and the molecule fingerprint :



- Implementation of fingerprint prediction model :

multi-label classifier

$$m(z_t, t) = \sigma(\text{Dec}(\text{EGNN}^h(x_t, h'_t))), \quad h'_t = \text{concatenate}(h_t, t)$$

- Generating molecules with multiple target properties:

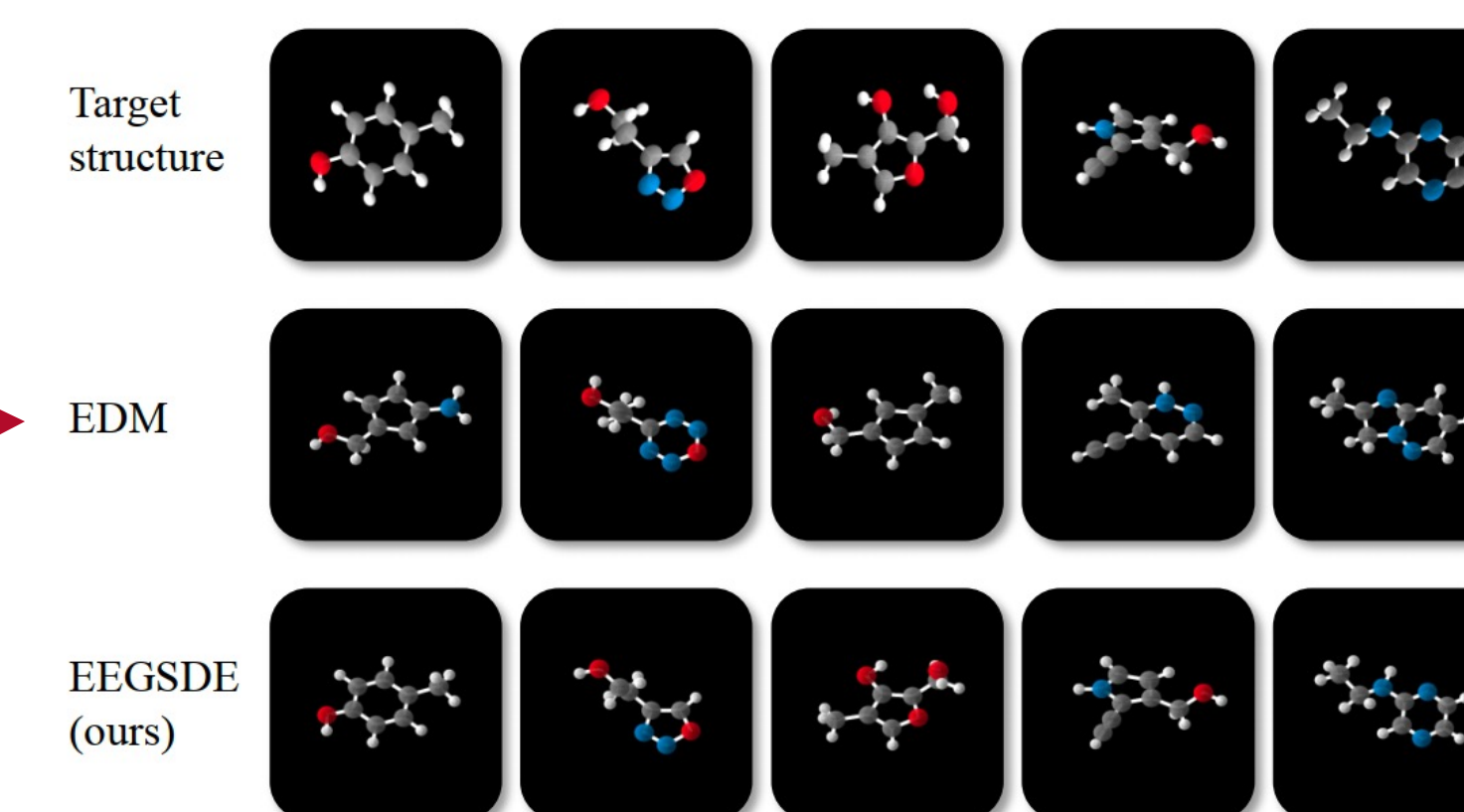
- EEGSDE is able to generate molecules targeted to multiple properties by combining the corresponding energy functions linearly:

$$E(z_t, c, t) = \sum_{k=1}^K E_k(z_t, c_k, t)$$

EEGSDE is able to generate more accurate molecules than EDM

Method	MAE↓	Method	MAE↓
C_v ($\frac{\text{cal}}{\text{mol}}\text{K}$)		μ (D)	
U-bound	6.879±0.015	U-bound	1.613±0.003
#Atoms	1.971	#Atoms	1.053
Conditional EDM	1.065±0.010	Conditional EDM	1.123±0.013
EEGSDE (s=1)	1.037±0.010	EEGSDE (s=0.5)	0.930±0.005
EEGSDE (s=5)	0.981±0.002	EEGSDE (s=1)	0.858±0.006
EEGSDE (s=10)	0.941±0.005	EEGSDE (s=2)	0.777±0.007
L-bound	0.040	L-bound	0.043
$\Delta\epsilon$ (meV)		ϵ_{HOMO} (meV)	
U-bound	1464±4	U-bound	645±41
#Atoms	866	#Atoms	426
Conditional EDM	671±5	Conditional EDM	371±2
EEGSDE (s=0.5)	574±4	EEGSDE (s=0.1)	357±4
EEGSDE (s=1)	542	EEGSDE (s=0.5)	320±1
EEGSDE (s=3)	487±3	EEGSDE (s=1)	302±2
L-bound	65	L-bound	39

EEGSDE better capture the structure information in molecules than EDM



EEGSDE has significantly better MAE on both properties than the conditional EDM

Method	MAE1↓	MAE2↓
C_v ($\frac{\text{cal}}{\text{mol}}\text{K}$), μ (D)		
Conditional EDM	1.079±0.007	1.156±0.011
EEGSDE (s ₁ =10, s ₂ =1)	0.981±0.008	0.912±0.006
$\Delta\epsilon$ (meV), μ (D)		
Conditional EDM	683±1	1.130±0.007
EEGSDE (s ₁ =s ₂ =1)	563±3	0.866±0.003
α (Bohr ³), μ (D)		
Conditional EDM	2.76±0.01	1.158±0.002
EEGSDE (s ₁ =s ₂ =1.5)	2.61±0.01	0.855±0.007