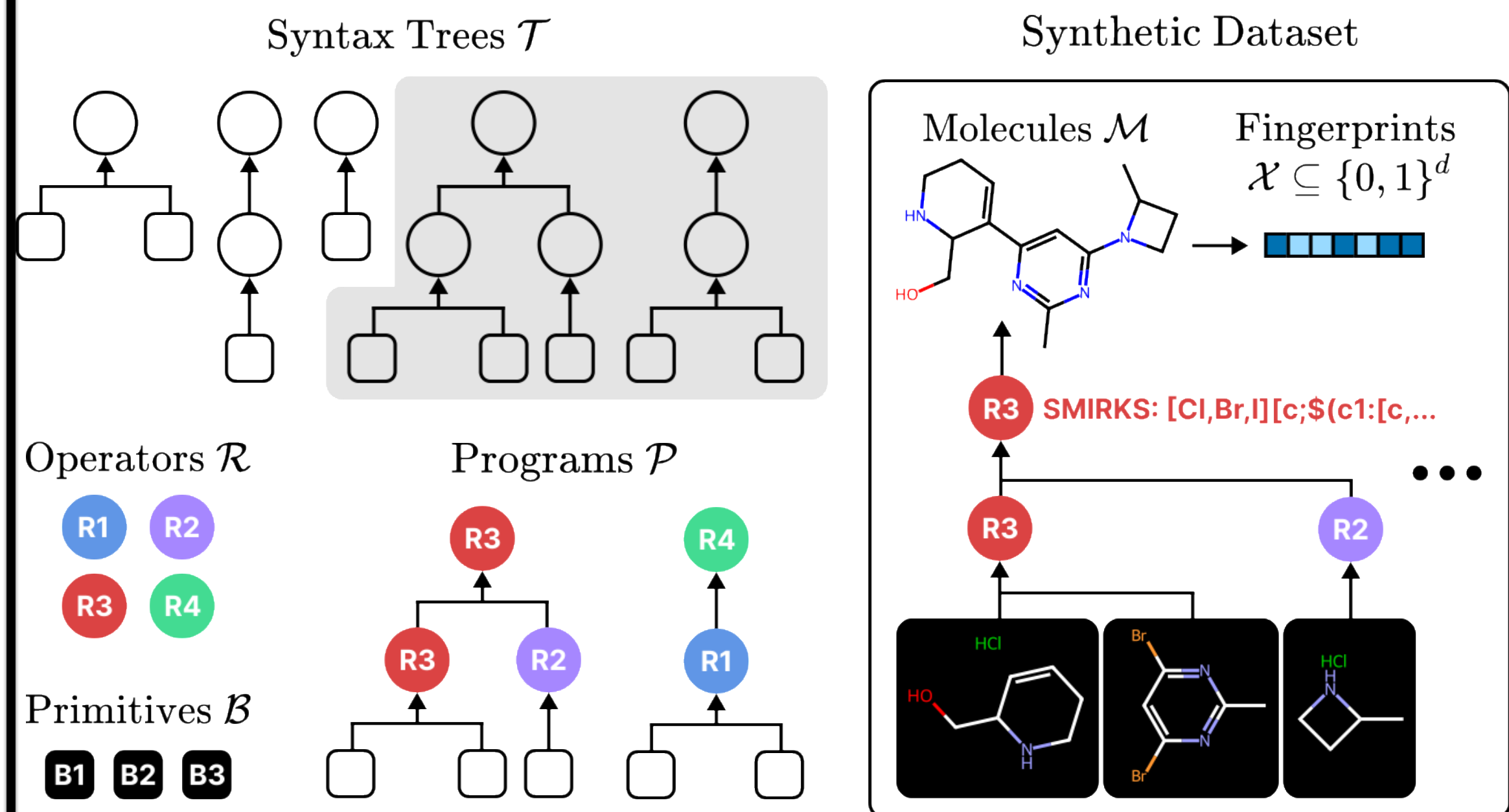


## Preliminaries



### Algorithm 1 Construction of training dataset.

**Require:** A synthetic dataset  $\mathcal{D}_0 \subseteq \mathcal{P} \times \mathcal{B}^*$  of programs (Section 4.1.1).

```

1:  $\mathcal{D} \leftarrow \emptyset$ 
2: for each  $(P, B) \in \mathcal{D}_0$  do
3:   Turn  $(P, B)$  into a fully-filled program  $T \in \partial\mathcal{P}$  whose root is attributed with  $\text{FP}(P, B)$ .
4:   for each  $\Lambda \in 2^T$  containing the root and closed under parent( $\cdot$ ) do
5:      $\text{Frontier}(\Lambda) \leftarrow \{i \in T \mid i \notin \Lambda \text{ and } \text{parent}(i) \in \Lambda\}$ 
6:     Populate node features  $H$  and labels  $Y$  based on  $P$  and  $B$  (App. F)
7:     for  $i \in T - \Lambda$  do
8:       Mask the feature in  $H$  corresponding to node  $i$ 
9:     for  $i \in T - \text{Frontier}(\Lambda)$  do
10:      Mask the label in  $Y$  corresponding to node  $i$ 
11:    $\mathcal{D} \leftarrow \mathcal{D} \cup \{(T, H, Y)\}$ 
return  $\mathcal{D}$ 

```

## Method

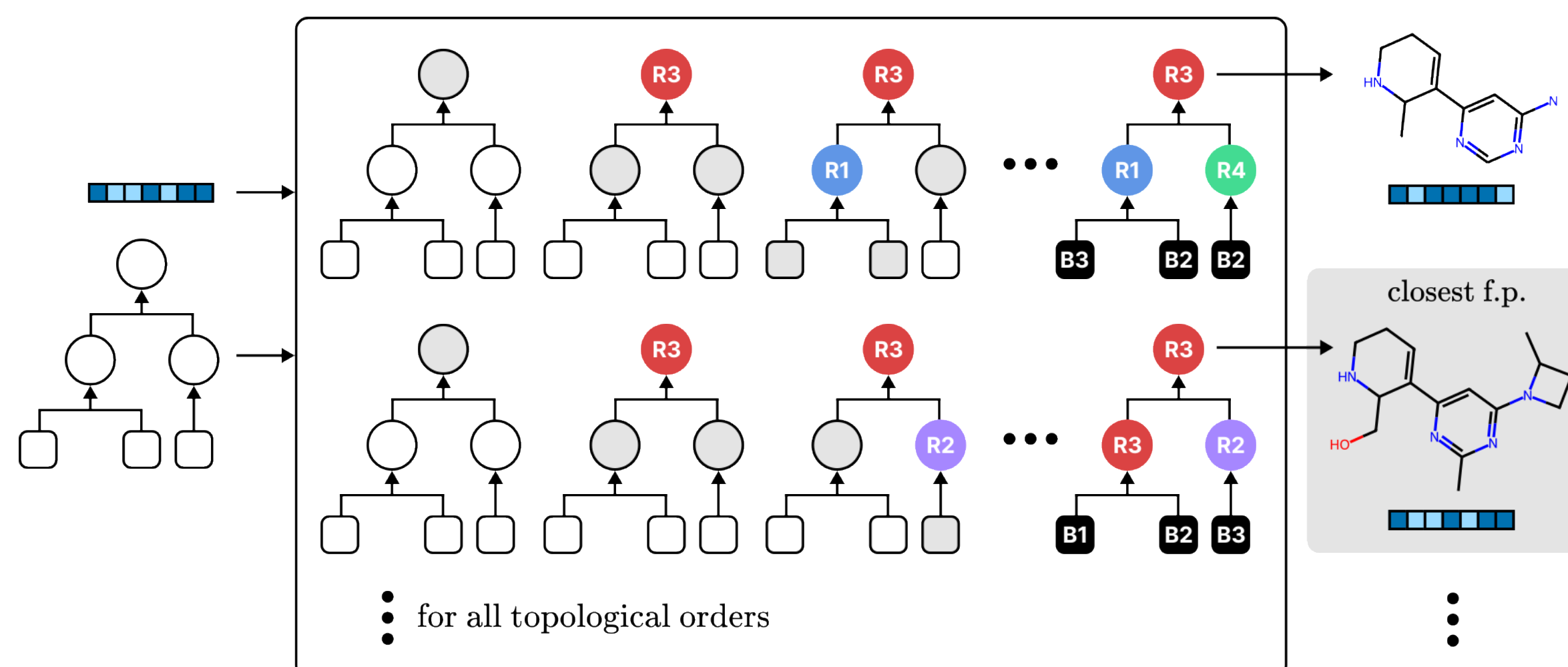


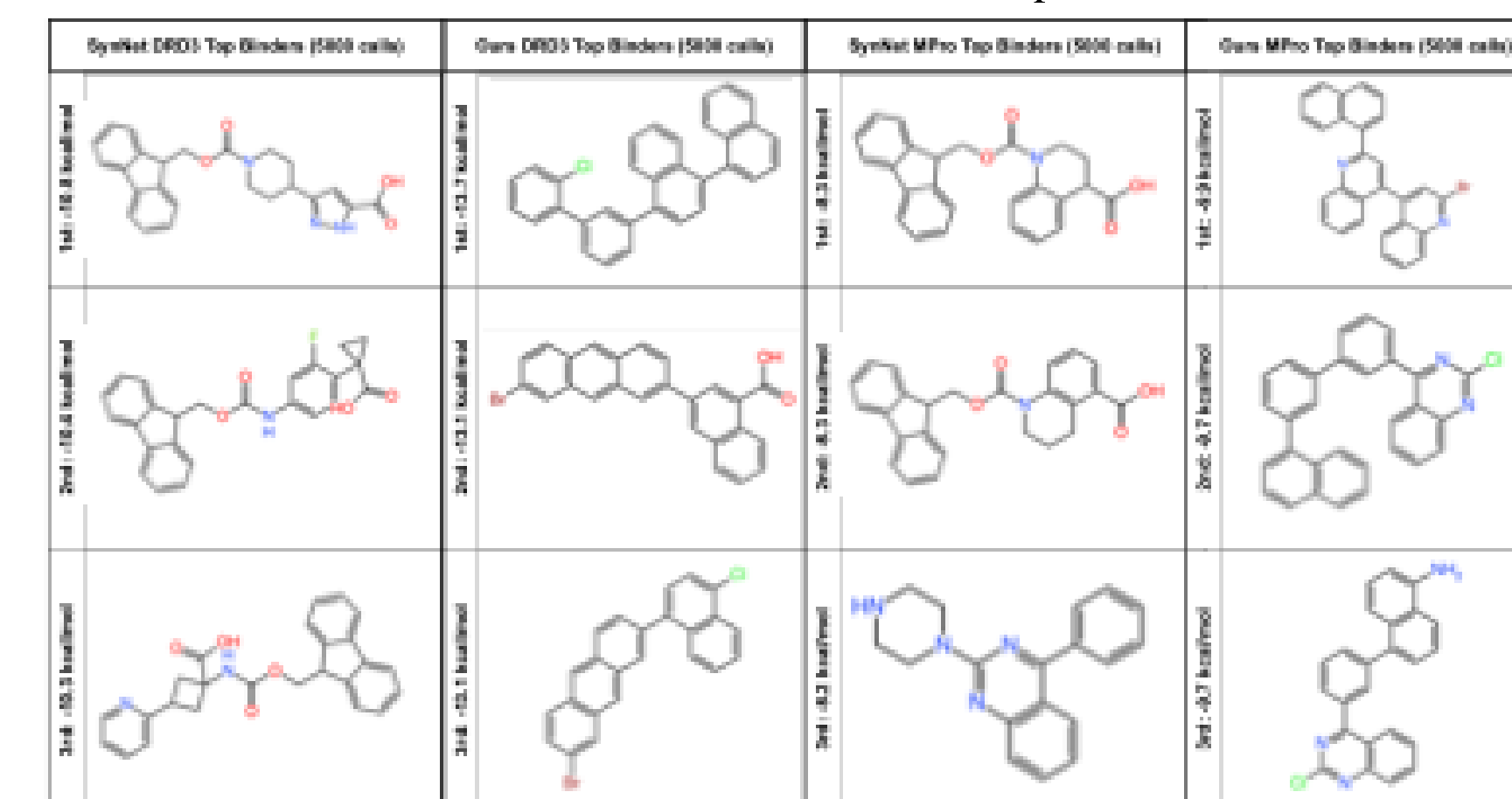
Illustration of our decoding scheme F: (Left) The input is a Morgan fingerprint  $x$  and syntax skeleton  $T$ ; (Middle) Decode once for every topological ordering of the tree, tracking all partial programs with a stack; (Right) Execute all decoded programs, then returning the closest analog which minimizes distance to  $x$ .

# Rxns	$ \hat{\mathcal{T}}_{k \setminus k-1} $	# Rxns	$ \hat{\mathcal{T}}_{k \setminus k-1}  ( \mathcal{T}_{k \setminus k-1} )$	# Topo. Orders (Max, Mean, Std) $_{\hat{\mathcal{T}}_{k \setminus k-1}}$
6	298	1	2 (2)	2, 1.5, 0.5
7	243	2	6 (6)	8, 4.17, 2.79
8	112	3	22 (22)	80, 19.59, 20.55
9	63	4	83 (90)	896, 152.02, 215.53
10	42	5	209 (394)	19200, 2506.25, 3705.77
# Rxns	# Topo. Masks $O_{\hat{\mathcal{T}}_{k \setminus k-1}}$	# Topo. Masks $(\cdot)_{\mathcal{T}_{k \setminus k-1}}$		
1	5, 4, 1	5, 4, 1		
2	11, 7.67, 2.56	11, 7.67, 2.56		
3	26, 14.36, 5.86	26, 14.36, 5.86		
4	56, 27.99, 12.47	56, 26.73, 12.78		
5	131, 65.07, 26.36	131, 49.74, 27.09		
6	287, 165.12, 61.43	287, 92.67, 56.29		

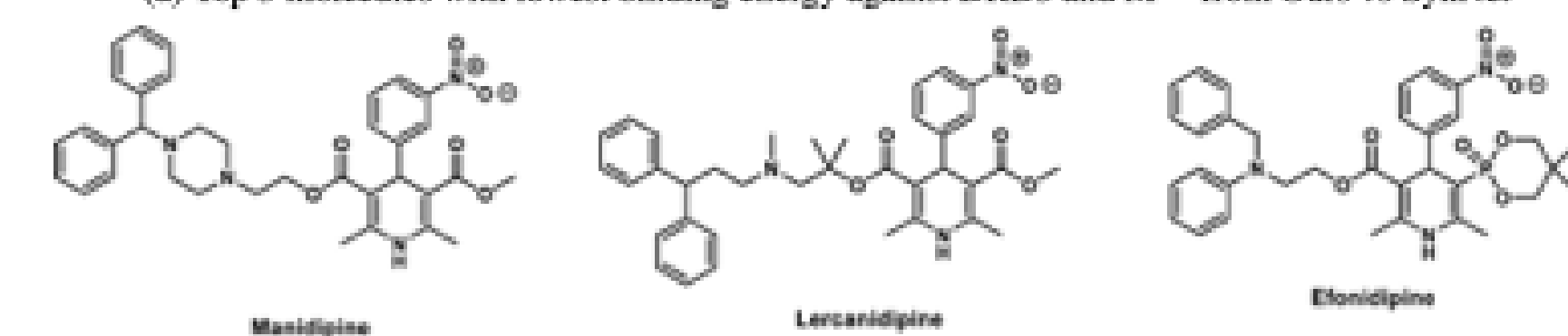
## Results

Category	Method	Score $\uparrow$ Value Rank	AUC $\uparrow$ Value Rank	SA $\downarrow$ Value Rank
Screening	Screening	0.426 20	0.377 20	3.097 8
	MolPAL	0.472 16	0.444 15	3.018 4
String	REINVENT	0.697 2	0.607 2	3.415 9
	REINVENT-SELFIES	0.682 3	0.578 4	3.791 15
	STONED	0.609 8	0.555 6	5.550 24
	smiles_lstm_hc	0.667 5	0.544 8	3.036 5
	smiles_ga	0.548 11	0.503 10	5.422 23
	selfies_lstm_hc	0.539 12	0.431 16	3.743 14
	selfies_vae_bo	0.428 19	0.383 19	3.522 11
	smiles_vae_bo	0.422 21	0.376 21	3.084 7
	selfies_ga	0.48 15	0.337 23	5.709 26
	pasithea	0.338 24	0.326 24	3.66 12
Graph	Graph-GA	<b>0.701</b> 1	0.601 3	3.982 17
	GPBO	0.642 6	0.570 5	3.954 16
	DST	0.555 10	0.479 11	4.146 20
	mars	0.507 14	0.47 12	4.232 21
	mimosa	0.538 13	0.463 13	4.3 22
	gflownet	0.461 17	0.419 17	4.05 19
	gflownet_al	0.417 22	0.387 18	4.005 18
	jt_vae_bo	0.388 23	0.371 22	3.5 10
	graph_mcts	0.317 25	0.28 25	3.732 13
	moldqn	0.213 26	0.187 26	5.604 25
Synthesis	SynNet	0.578 9	0.545 7	3.075 6
	DoG-Gen	0.634 7	0.511 9	2.793 2
	DoG-AE	0.460 18	0.450 14	2.857 3
	Ours	<b>0.670</b> 4	<b>0.608</b> 1	<b>2.739</b> 1

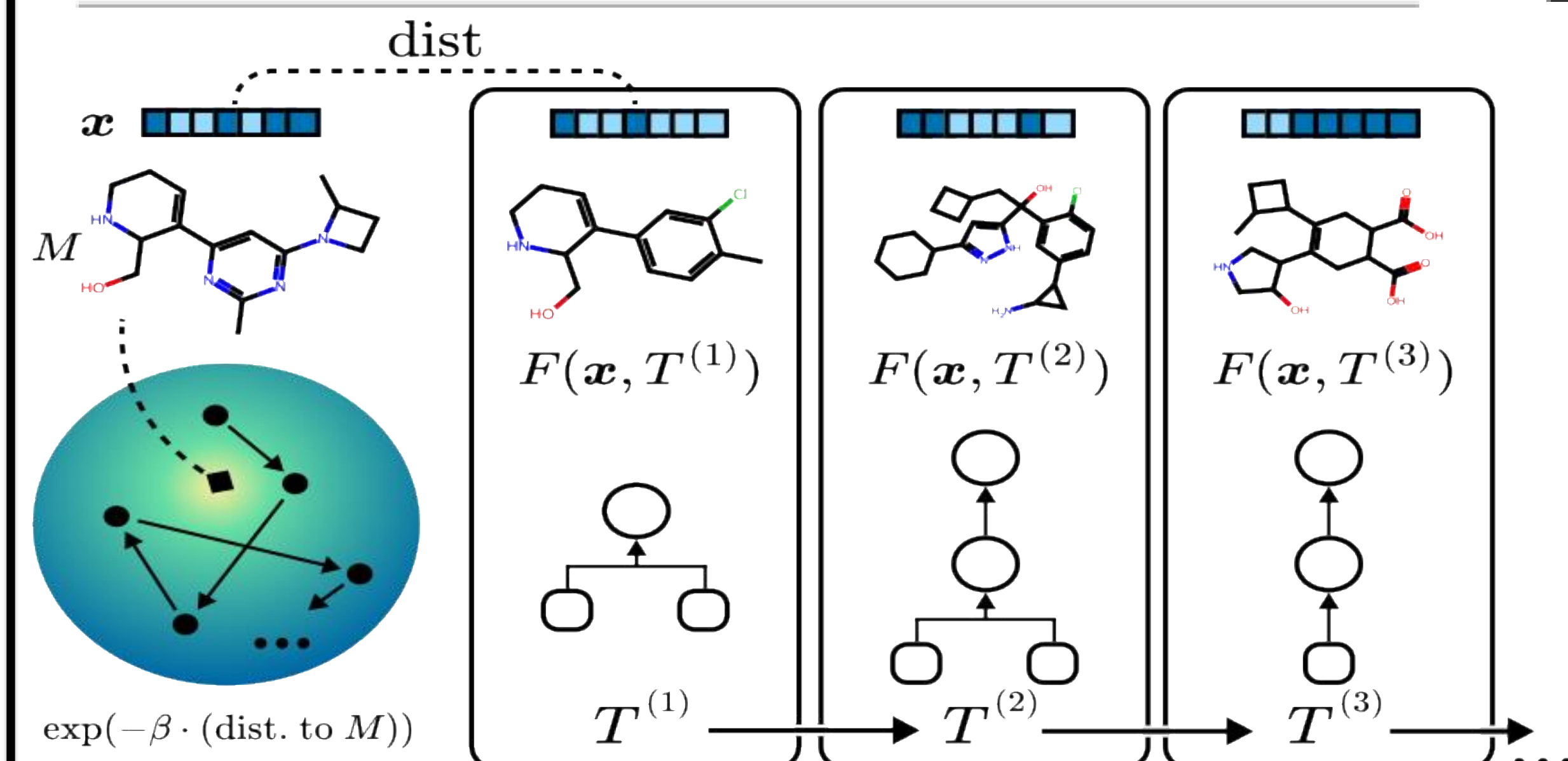
Avg. across GSK3 $\beta$ , JNK3, DRD2, Median1, Median2, Rediscovery, Osimertinib, 6 others  
Baselines from Practical Molecular Optimization.



(a) Top 3 molecules with lowest binding energy against DRD3 and MPP<sup>7</sup> from Ours vs SynNet



(b) Top binders against MPP<sup>7</sup> from literature, based on consensus docking scores (Ghahremanpour et al., 2020)



Our Metropolis-Hastings algorithm iteratively refines the syntax tree skeleton towards the stationary distribution which is proportional to the inverse distance to our target molecule  $M$ .

Our genetic algorithm over the joint design space combines the strategies of semantic crossover ( $\rightarrow$ ) and syntactical mutation ( $\rightarrow$ ) to encourage both global improvement and local exploration.