

Supplementary Information for "Minimizing the training dataset for efficient crystal structure prediction by graph neural network"

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Here we estimate the maximum efficiency improvement of graph neural network (GNN)¹ when applied to the direct-space asymmetric unit (DAU) instead of unit cell. We consider the situation in which N atoms are uniformly dispersed in unit cell. We can determine the value of N by summing the product of the number of atoms in DAU and its corresponding multiplicity, i.e., $N = \sum_i^K \text{num}_i * \text{mul}_i$, where the multiplicity is the number of equivalent positions in the unit cell. Since the inner area of the DAU generally contains most of the atoms (num_K) and has the highest multiplicity (mul_K), we can approximate N as $\text{num}_K * \text{mul}_K$. Meanwhile, the computational cost of GNN is nearly linear depend on the number of input atoms, the maximum efficiency improvement thus can be estimated by the highest multiplicity of each space group. The results are listed in Tables S1–S5.

TABLE S1. Maximum efficiency improvement of GNN applied in 2D materials.

Space Group	Maximum Improvement	Space Group	Maximum Improvement
1 ($P1$)	1	10 ($P4$)	4
2 ($P211$)	2	11 ($P4mm$)	8
3 ($P1m1$)	2	12 ($P4gm$)	8
4 ($P1g1$)	2	13 ($P3$)	3
5 ($C1m1$)	4	14 ($P3m1$)	6
6 ($P2mm$)	4	15 ($P31m$)	6
7 ($P2mg$)	4	16 ($P6$)	6
8 ($P2gg$)	4	17 ($P6mm$)	12
9 ($C2mm$)	8		

TABLE S2. Maximum efficiency improvement of GNN applied in 3D materials.

Space Group	Maximum Improvement	Space Group	Maximum Improvement
1 ($P1$)	1	12 ($C2/m$)	8
2 ($P-1$)	2	13 ($P2/c$)	4
3 ($P2$)	2	14 ($P21/c$)	4
4 ($P21$)	2	15 ($C2/c$)	8
5 ($C2$)	4	16 ($P222$)	4
6 (Pm)	2	17 ($P2221$)	4
7 (Pc)	2	18 ($P21212$)	4
8 (Cm)	4	19 ($P212121$)	4
9 (Cc)	4	20 ($C2221$)	8
10 ($P2/m$)	4	21 ($C222$)	8
11 ($P21/m$)	4	22 ($F222$)	16

TABLE S3. Maximum efficiency improvement of GNN applied in 3D materials.

Space Group	Maximum Improvement	Space Group	Maximum Improvement
23 (<i>I222</i>)	8	57 (<i>Pbcm</i>)	8
24 (<i>I212121</i>)	8	58 (<i>Pnnm</i>)	8
25 (<i>Pmm2</i>)	4	59 (<i>Pmmn</i>)	8
26 (<i>Pmc21</i>)	4	60 (<i>Pbcn</i>)	8
27 (<i>Pcc2</i>)	4	61 (<i>Pbca</i>)	8
28 (<i>Pma2</i>)	4	62 (<i>Pnma</i>)	8
29 (<i>Pca21</i>)	4	63 (<i>Cmcm</i>)	16
30 (<i>Pnc2</i>)	4	64 (<i>Cmca</i>)	16
31 (<i>Pmn21</i>)	4	65 (<i>Cmmm</i>)	16
32 (<i>Pba2</i>)	4	66 (<i>Cccm</i>)	16
33 (<i>Pna21</i>)	4	67 (<i>Cmma</i>)	16
34 (<i>Pnn2</i>)	4	68 (<i>Ccca</i>)	16
35 (<i>Cmm2</i>)	8	69 (<i>Fmmm</i>)	32
36 (<i>Cmc21</i>)	8	70 (<i>Fddd</i>)	32
37 (<i>Ccc2</i>)	8	71 (<i>Immm</i>)	16
38 (<i>Amm2</i>)	8	72 (<i>Ibam</i>)	16
39 (<i>Abm2</i>)	8	73 (<i>Ibca</i>)	16
40 (<i>Ama2</i>)	8	74 (<i>Imma</i>)	16
41 (<i>Aba2</i>)	8	75 (<i>P₄</i>)	4
42 (<i>Fmm2</i>)	16	76 (<i>P₄1</i>)	4
43 (<i>Fdd2</i>)	16	77 (<i>P₄2</i>)	4
44 (<i>Imm2</i>)	8	78 (<i>P₄3</i>)	4
45 (<i>Iba2</i>)	8	79 (<i>I₄</i>)	8
46 (<i>Ima2</i>)	8	80 (<i>I₄1</i>)	8
47 (<i>Pmmm</i>)	8	81 (<i>P-4</i>)	4
48 (<i>Pnnn</i>)	8	82 (<i>I-4</i>)	8
49 (<i>Pccm</i>)	8	83 (<i>P₄/m</i>)	8
50 (<i>Pban</i>)	8	84 (<i>P₄2/m</i>)	8
51 (<i>Pmma</i>)	8	85 (<i>P₄/n</i>)	8
52 (<i>Pnna</i>)	8	86 (<i>P₄2/n</i>)	8
53 (<i>Pmna</i>)	8	87 (<i>I₄/m</i>)	16
54 (<i>Pcca</i>)	8	88 (<i>I₄1/a</i>)	16
55 (<i>Pbam</i>)	8	89 (<i>P₄22</i>)	8
56 (<i>Pccn</i>)	8	90 (<i>P₄212</i>)	8

TABLE S4. Maximum efficiency improvement of GNN applied in 3D materials.

Space Group	Maximum Improvement	Space Group	Maximum Improvement
91 ($P4122$)	8	125 ($P4/nbm$)	16
92 ($P41212$)	8	126 ($P4/nnc$)	16
93 ($P4222$)	8	127 ($P4/mbm$)	16
94 ($P42212$)	8	128 ($P4/mnc$)	16
95 ($P4322$)	8	129 ($P4/nmm$)	16
96 ($P43212$)	8	130 ($P4/ncc$)	16
97 ($I422$)	16	131 ($P42/mmc$)	16
98 ($I4122$)	16	132 ($P42/mcm$)	16
99 ($P4mm$)	8	133 ($P42/nbc$)	16
100 ($P4bm$)	8	134 ($P42/nnm$)	16
101 ($P42cm$)	8	135 ($P42/mbc$)	16
102 ($P42nm$)	8	136 ($P42/mnm$)	16
103 ($P4cc$)	8	137 ($P42/nmc$)	16
104 ($P4nc$)	8	138 ($P42/ncm$)	16
105 ($P42mc$)	8	139 ($I4/mmm$)	32
106 ($P42bc$)	8	140 ($I4/mcm$)	32
107 ($I4mm$)	16	141 ($I41/amd$)	32
108 ($I4cm$)	16	142 ($I41/acd$)	32
109 ($I41md$)	16	143 ($P3$)	3
110 ($I41cd$)	16	144 ($P31$)	3
111 ($P-42m$)	8	145 ($P32$)	3
112 ($P-42c$)	8	146 ($R3$)	9
113 ($P-421m$)	8	147 ($P-3$)	6
114 ($P-421c$)	8	148 ($R-3$)	18
115 ($P-4m2$)	8	149 ($P312$)	6
116 ($P-4c2$)	8	150 ($P321$)	6
117 ($P-4b2$)	8	151 ($P3112$)	6
118 ($P-4n2$)	8	152 ($P3121$)	6
119 ($I-4m2$)	16	153 ($P3212$)	6
120 ($I-4c2$)	16	154 ($P3221$)	6
121 ($I-42m$)	16	155 ($R32$)	18
122 ($I-42d$)	16	156 ($P3m1$)	6
123 ($P4/mmm$)	16	157 ($P31m$)	6
124 ($P4/mcc$)	16	158 ($P3c1$)	6

TABLE S5. Maximum efficiency improvement of GNN applied in 3D materials.

Space Group	Maximum Improvement	Space Group	Maximum Improvement
159 (<i>P31c</i>)	6	195 (<i>P23</i>)	12
160 (<i>R3m</i>)	18	196 (<i>F23</i>)	48
161 (<i>R3c</i>)	18	197 (<i>I23</i>)	24
162 (<i>P-31m</i>)	12	198 (<i>P213</i>)	12
163 (<i>P-31c</i>)	12	199 (<i>I213</i>)	24
164 (<i>P-3m1</i>)	12	200 (<i>Pm-3</i>)	24
165 (<i>P-3c1</i>)	12	201 (<i>Pn-3</i>)	24
166 (<i>R-3m</i>)	36	202 (<i>Fm-3</i>)	96
167 (<i>R-3c</i>)	36	203 (<i>Fd-3</i>)	96
168 (<i>P6</i>)	6	204 (<i>Im-3</i>)	48
169 (<i>P61</i>)	6	205 (<i>Pa-3</i>)	24
170 (<i>P65</i>)	6	206 (<i>Ia-3</i>)	48
171 (<i>P62</i>)	6	207 (<i>P432</i>)	24
172 (<i>P64</i>)	6	208 (<i>P4232</i>)	24
173 (<i>P63</i>)	6	209 (<i>F432</i>)	96
174 (<i>P-6</i>)	6	210 (<i>F4132</i>)	96
175 (<i>P6/m</i>)	12	211 (<i>I432</i>)	48
176 (<i>P63/m</i>)	12	212 (<i>P4332</i>)	24
177 (<i>P622</i>)	12	213 (<i>P4132</i>)	24
178 (<i>P6122</i>)	12	214 (<i>I4132</i>)	48
179 (<i>P6522</i>)	12	215 (<i>P-43m</i>)	24
180 (<i>P6222</i>)	12	216 (<i>F-43m</i>)	96
181 (<i>P6422</i>)	12	217 (<i>I-43m</i>)	48
182 (<i>P6322</i>)	12	218 (<i>P-43n</i>)	24
183 (<i>P6mm</i>)	12	219 (<i>F-43c</i>)	96
184 (<i>P6cc</i>)	12	220 (<i>I-43d</i>)	48
185 (<i>P63cm</i>)	12	221 (<i>Pm-3m</i>)	48
186 (<i>P63mc</i>)	12	222 (<i>Pn-3n</i>)	48
187 (<i>P-6m2</i>)	12	223 (<i>Pm-3n</i>)	48
188 (<i>P-6c2</i>)	12	224 (<i>Pn-3m</i>)	48
189 (<i>P-62m</i>)	12	225 (<i>Fm-3m</i>)	192
190 (<i>P-62c</i>)	12	226 (<i>Fm-3c</i>)	192
191 (<i>P6/mmm</i>)	24	227 (<i>Fd-3m</i>)	192
192 (<i>P6/mcc</i>)	24	228 (<i>Fd-3c</i>)	192
193 (<i>P63/mcm</i>)	24	229 (<i>Im-3m</i>)	96
194 (<i>P63/mmc</i>)	24	230 (<i>Ia-3d</i>)	96

TABLE S6. The structural validity and average energy of initial structures of four different methods (ML-PSO, ML-DFT, DFT-GA, and SCCOP) on 27 typical compounds. Each method has repeated 5 times to generate initial samples. The solid line means that the average energy is greater than zero. The DAUGNN of SCCOP is randomly initialized.

Compounds	Dimension	Structural Validity (%)			Average Energy (eV/atom)		
		ML-PSO(DFT)	DFT-GA	SCCOP	ML-PSO(DFT)	DFT-GA	SCCOP
BN	2	89.5	100.0	100.0	-5.0038	-0.3862	-4.5068
C	2	67.2	100.0	100.0	-4.2315	-0.6811	-5.0535
FeSe	2	93.9	100.0	100.0	-0.2252	-0.0009	-2.5340
MoTe ₂	2	85.3	100.0	100.0	-0.0057	0.0000	-2.6888
Mo ₂ C	2	100.0	100.0	100.0	0.0000	-0.0360	-3.7200
SiC	2	65.4	100.0	100.0	-1.8279	-0.0580	-4.1524
Ti ₂ C	2	100.0	100.0	100.0	0.0000	-0.1611	-4.0651
BaO	3	100.0	100.0	100.0	-2.5802	-2.0223	-3.5338
BeS	3	100.0	100.0	100.0	-2.7016	-1.3387	-3.1908
C	3	100.0	100.0	100.0	-5.0743	-4.2250	-5.2224
CaO	3	100.0	100.0	100.0	-2.7499	-2.3678	-3.6545
CaTiO ₃	3	100.0	100.0	100.0	-4.7407	-3.4935	-4.5581
CdO	3	99.6	100.0	100.0	-1.7696	-0.8799	-2.3478
CdS	3	100.0	100.0	100.0	-1.3625	-0.6330	-1.9324
CsCl	3	100.0	100.0	100.0	-1.4466	-1.1234	-2.4130
GaAs	3	99.7	100.0	100.0	-2.3411	-1.2963	-3.2288
KF	3	100.0	100.0	100.0	-2.0759	-1.8304	-2.7469
LiF	3	100.0	100.0	100.0	-3.0137	-2.5299	-3.0642
MgO	3	100.0	100.0	100.0	-2.7630	-2.1304	-3.1916
MgS	3	99.6	100.0	100.0	-1.7695	-1.1438	-2.6839
NaCl	3	100.0	100.0	100.0	-2.0633	-1.1435	-2.3143
PbMoO ₃	3	100.0	100.0	100.0	-2.4754	-2.2387	-4.3484
PbZrO ₃	3	100.0	100.0	100.0	-1.8184	-2.4638	-4.6649
RbCl	3	100.0	100.0	100.0	-2.5289	-1.0804	-2.3926
SrS	3	100.0	100.0	100.0	-3.1306	-1.2857	-3.1246
TiB ₂	3	100.0	100.0	100.0	-2.7240	-2.9971	-4.9640
ZnO	3	87.2	100.0	100.0	-1.2925	-1.1868	-2.6299
Rate	—	18/27	27/27	27/27	4/27	0/27	23/27

TABLE S7. The structural validity and average energy of initial structures of four different methods (ML-PSO, ML-DFT, DFT-GA, and SCCOP) on 27 typical compounds. Each method has repeated 5 times to generate initial samples. The solid line means that the average energy is greater than zero. The DAUGNN of SCCOP is pretrained by database.

Compounds	Dimension	Structural Validity (%)			Average Energy (eV/atom)		
		ML-PSO(DFT)	DFT-GA	SCCOP	ML-PSO(DFT)	DFT-GA	SCCOP
BN	2	89.5	100.0	100.0	-5.0038	-0.3862	-6.1222
C	2	67.2	100.0	100.0	-4.2315	-0.6811	-6.3948
FeSe	2	93.9	100.0	100.0	-0.2252	-0.0009	-2.7905
MoTe ₂	2	85.3	100.0	100.0	-0.0057	0.0000	-2.1225
Mo ₂ C	2	100.0	100.0	100.0	0.0000	-0.0360	-5.2784
SiC	2	65.4	100.0	100.0	-1.8279	-0.0580	-5.4964
Ti ₂ C	2	100.0	100.0	100.0	0.0000	-0.1611	-5.0393
BaO	3	100.0	100.0	100.0	-2.5802	-2.0223	-4.1975
BeS	3	100.0	100.0	100.0	-2.7016	-1.3387	-3.7173
C	3	100.0	100.0	100.0	-5.0743	-4.2250	-6.1803
CaO	3	100.0	100.0	100.0	-2.7499	-2.3678	-4.5083
CaTiO ₃	3	100.0	100.0	100.0	-4.7407	-3.4935	-5.3116
CdO	3	99.6	100.0	100.0	-1.7696	-0.8799	-2.9449
CdS	3	100.0	100.0	100.0	-1.3625	-0.6330	-2.2391
CsCl	3	100.0	100.0	100.0	-1.4466	-1.1234	-2.5226
GaAs	3	99.7	100.0	100.0	-2.3411	-1.2963	-3.3658
KF	3	100.0	100.0	100.0	-2.0759	-1.8304	-3.1067
LiF	3	100.0	100.0	100.0	-3.0137	-2.5299	-3.8424
MgO	3	100.0	100.0	100.0	-2.7630	-2.1304	-4.1469
MgS	3	99.6	100.0	100.0	-1.7695	-1.1438	-3.2129
NaCl	3	100.0	100.0	100.0	-2.0633	-1.1435	-2.7214
PbMoO ₃	3	100.0	100.0	100.0	-2.4754	-2.2387	-5.0351
PbZrO ₃	3	100.0	100.0	100.0	-1.8184	-2.4638	-5.3016
RbCl	3	100.0	100.0	100.0	-2.5289	-1.0804	-2.5808
SrS	3	100.0	100.0	100.0	-3.1306	-1.2857	-3.6581
TiB ₂	3	100.0	100.0	100.0	-2.7240	-2.9971	-5.6665
ZnO	3	87.2	100.0	100.0	-1.2925	-1.1868	-3.3529
Rate	—	18/27	27/27	27/27	0/27	0/27	27/27

TABLE S8. Comparison of the time cost and search accuracy of four CSP methods for 27 typical compounds.

Methods	Dimension	Accuracy	Time (min)
ML-PSO	2	0/7	8.09
ML-DFT	2	7/7	12.47
DFT-GA	2	7/7	95.19
SCCOP	2	7/7	7.06
ML-PSO	3	6/20	2.04
ML-DFT	3	16/20	12.43
DFT-GA	3	20/20	115.69
SCCOP	3	20/20	4.14

Figs. S1 and S2 illustrate the search process for 27 compositions. For each composition, the left figure shows the energy descent process, and the right figure displays its density of states (DOS).

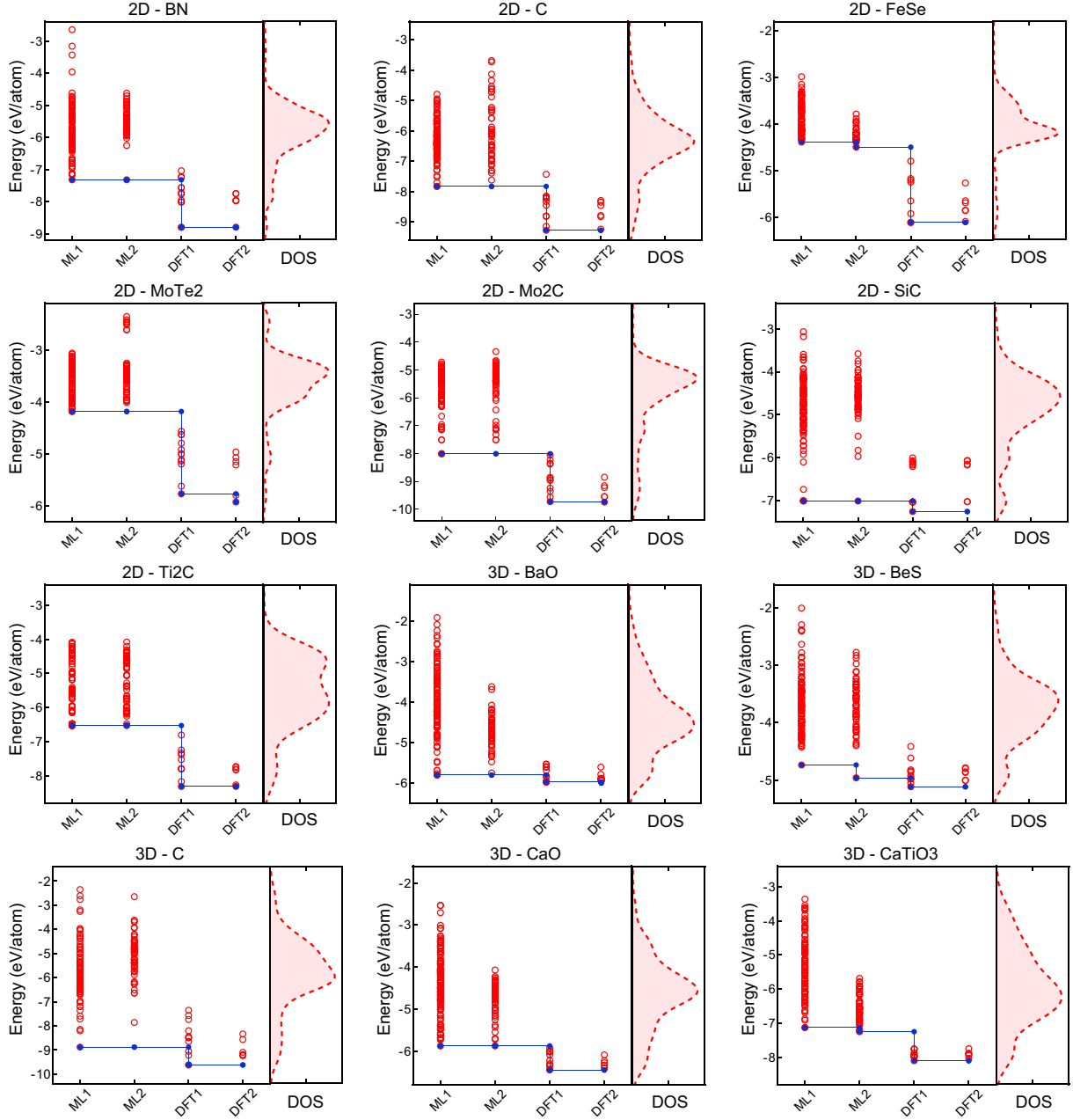


Fig. S1. Structure search process of SCCOP on 2D and 3D materials. ML1 and ML2 are the machine learning (ML) structure search and optimization, respectively, DFT1 and DFT2 are the structure optimization by VASP.

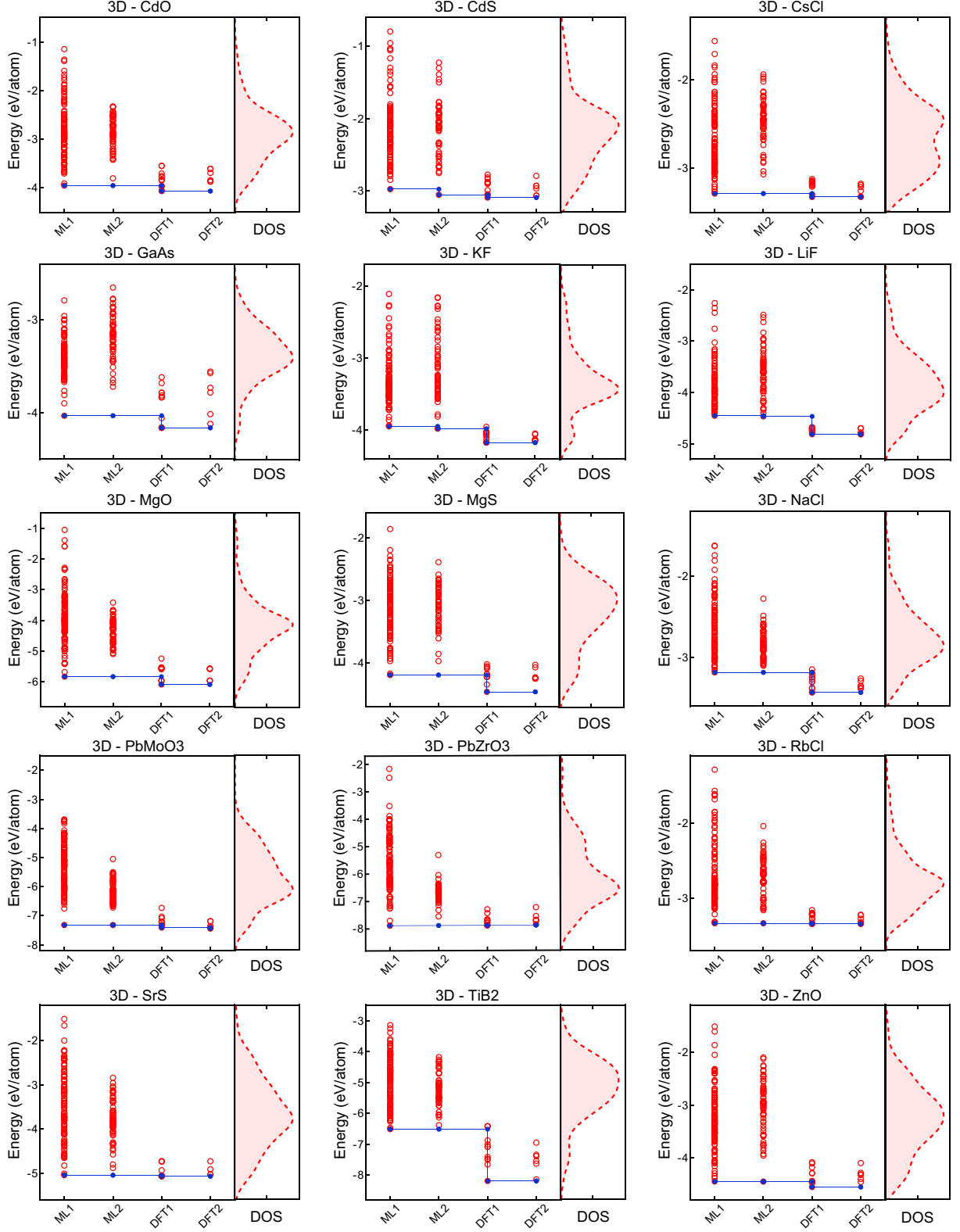


Fig. S2. Structure search process of SCCOP on 2D and 3D materials. ML1 and ML2 are the machine learning (ML) structure search and optimization, respectively, DFT1 and DFT2 are the structure optimization by VASP.

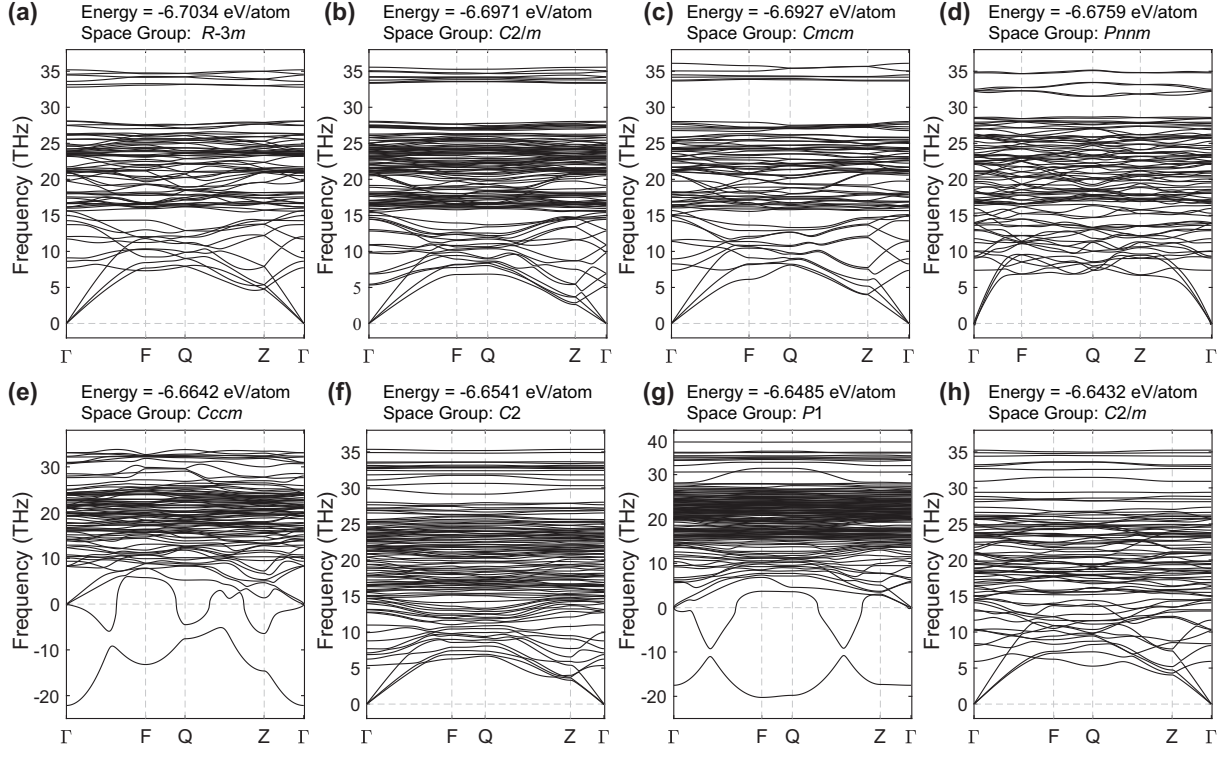


Fig. S3. Phonon spectrum of boron allotropes discovered by SCCOP.

To generate the lattice parameters $\mathbf{L}$, which include the lengths of three lattice vectors and the angles between them, we fit the values $(a, b, c, \alpha, \beta, \gamma)$ using statistical distributions obtained from databases. In most cases, we use the Gamma distribution $\Gamma(\alpha, \beta)$, where α is the shape parameter and β is the scale parameter. This distribution is suitable for generating lattice parameters due to its non-negative nature. However, in some cases, fitting with a Gamma distribution is challenging, and we use a normal distribution $\mathcal{N}(\mu, \sigma^2)$ instead, where μ and σ are the mean and standard deviation of the normal distribution, respectively. Additionally, we also employ a mixture of two distributions, such as $p_1 \cdot \mathcal{N}(\mu_1, \sigma_1^2)$, $p_2 \cdot \mathcal{N}(\mu_2, \sigma_2^2)$, or $p_1 \cdot \Gamma(\alpha_1, \beta_1)$, $p_2 \cdot \Gamma(\alpha_2, \beta_2)$. This means that each distribution is selected with a probability of p_1 and p_2 , respectively, and the total probability density is the sum of the probabilities of each individual distribution. For 2D materials, we utilize three databases: JARVIS-DFT², C2DB³, and 2DMATPedia⁴. The distributions of lattice parameters for 2D materials are presented in Table S9, taking into consideration that the value of c depends on the thickness of the vacuum layer. For 3D materials, we utilize the OQMD⁵ database, and the distributions of lattice parameters for 3D materials are shown in Table S10.

TABLE S9. Distribution of $(a, b, c, \alpha, \beta, \gamma)$ for different space groups in 2D materials.

Space Group	a	b	c	α	β	γ
1–2	$\Gamma(9.21, 0.53)$	$\Gamma(7.04, 1.06)$	—	90°	90°	$\begin{cases} 0.58 \cdot \mathcal{N}(107.12, 8.59) \\ 0.42 \cdot \mathcal{N}(73.34, 6.21) \end{cases}$
3–9	$\Gamma(10.23, 0.43)$	$\Gamma(8.51, 0.88)$	—	90°	90°	90°
10–12	$\Gamma(12.72, 0.35)$	$b = a$	—	90°	90°	90°
13–17	$\begin{cases} 0.4 \cdot \Gamma(24.82, 0.26) \\ 0.6 \cdot \Gamma(57.08, 0.06) \end{cases}$	$b = a$	—	90°	90°	120°

TABLE S10. Distribution of $(a, b, c, \alpha, \beta, \gamma)$ for different space groups in 3D materials.

Space Group	a	b	c	α	β	γ
1–2	$\Gamma(11.14, 0.54)$	$\Gamma(14.91, 0.42)$	$\Gamma(9.31, 0.75)$	$\Gamma(19.67, 5.48)$	$\Gamma(21.63, 4.76)$	$\Gamma(6.80, 12.82)$
3–15	$\Gamma(8.93, 0.73)$	$\Gamma(7.51, 0.90)$	$\Gamma(9.99, 0.83)$	90°	$\begin{cases} 0.85 \cdot \mathcal{N}(108.24, 8.77) \\ 0.15 \cdot \mathcal{N}(74.80, 4.97) \end{cases}$	90°
16–74	$\Gamma(5.84, 1.05)$	$\Gamma(6.95, 0.93)$	$\Gamma(6.40, 1.09)$	90°	90°	90°
75–142	$\Gamma(17.21, 0.27)$	$b = a$	$\Gamma(11.64, 0.69)$	90°	90°	90°
143–194	$\Gamma(35.58, 0.13)$	$b = a$	$\Gamma(20.78, 0.24)$	90°	90°	120°
195–230	$\Gamma(17.24, 0.27)$	$b = a$	$c = a$	90°	90°	90°

For the prediction of area calculated by lattice parameters (a, b, γ) , the formula⁶ $\hat{S}_{\text{opt}} = A \sum_i r_i + B \sum_i X_i + C \sum_i E a_i + D$ is used, where $A = 3.19$, $B = -0.01$, $C = 0.25$ and $D = 1.18$. The relative error is fitted by a normal distribution $\mathcal{N}(\mu, \sigma^2)$, the $\mu = -0.10$ and $\sigma = 0.28$, $\hat{S}_{\text{min}} \leq S_{\text{opt}} \leq \hat{S}_{\text{max}}$ holds in 95% of cases, where $\hat{S}_{\text{min}} = \frac{1}{1+\mu+2\sigma} \cdot \hat{S}_{\text{opt}}$ and $\hat{S}_{\text{max}} = \frac{1}{1+\mu-2\sigma} \cdot \hat{S}_{\text{opt}}$.

For the space utilization rate, which is defined as $\sum_i S_i / S_{\text{opt}} \cdot 100\%$. We collect structures from databases: JARVIS-DFT, C2DB, and 2DMATPedia, and only keep the structures with thickness less than 4Å. The distribution of space utilization rate of 2D materials is shown in Fig. S4, and the $\mu = 0.56$ and $\sigma = 0.18$, This means that the volume inequality $\tilde{S}_{\text{min}} \leq S_{\text{opt}} \leq \tilde{S}_{\text{max}}$ holds with 95% probability, where $\tilde{S}_{\text{min}} = \frac{1}{\mu+2\sigma} \cdot \sum_i S_i$ and $\tilde{S}_{\text{max}} = \frac{1}{\mu-2\sigma} \cdot \sum_i S_i$.

Therefore, by combining the two bounds from distribution of relative error and space utilization rate, we obtain the tighter bounds for constraining area of 2D materials,

$$\max(\hat{S}_{\text{min}}, \tilde{S}_{\text{min}}) \leq S_{\text{opt}} \leq \min(\hat{S}_{\text{max}}, \tilde{S}_{\text{max}})$$

Finally, the lattice parameters (a, b, γ) are generated repeatedly by the statistical distribution until the area constraint is satisfied.

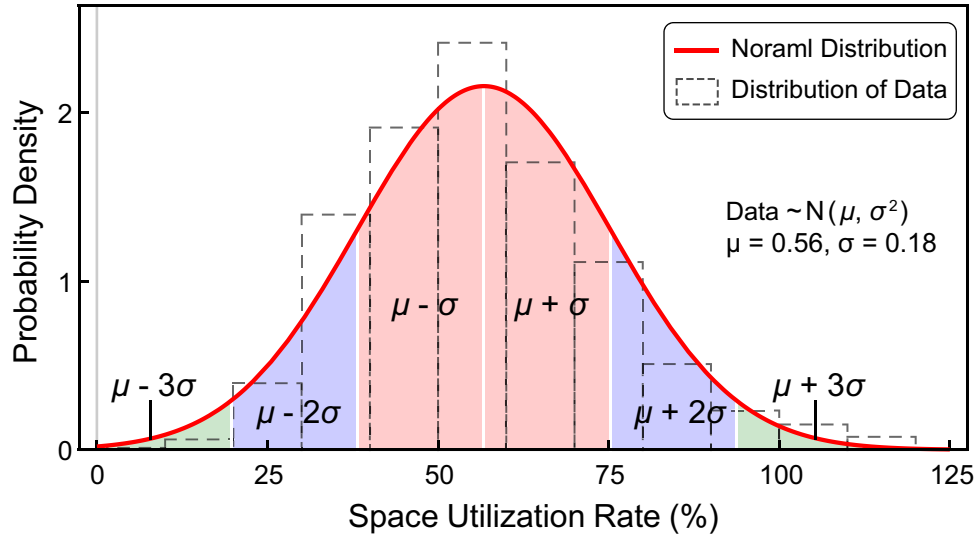


Fig. S4. Distribution of space utilization for 2D materials.

For 2D materials, we collected structures from three databases: JARVIS-DFT, C2DB, and 2DMATPedia. After removing ill-converged crystals, the full database contains 10,751 materials. For 3D materials, we collected structures from the OQMD database. After removing ill-converged crystals, the full database contains 817,133 materials.

To pre-train the GNN model, we used batchsize of 128 and 512 for 2D and 3D materials, respectively, with the Adam optimizer⁷. Each model was trained with 60% of the data, validated with 20% of the data, and the best-performing model in the validation set was selected. The remaining 20% of the data was used to test the generalization ability of the selected model. The pretrain model was trained for 120 epochs in a multi-learning rate style, with a learning rate of 0.01 for the first 100 epochs and a learning rate of 0.001 for the last 20 epochs. The performance of the model in the test set and the mean square error (MAE) of the validation set during training are shown in Fig. S5.

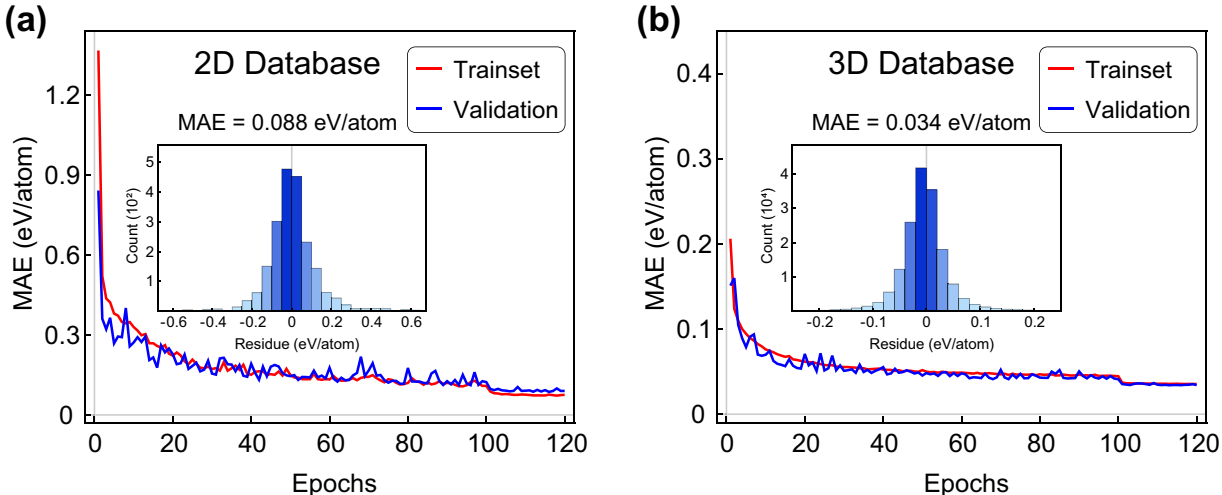


Fig. S5. The MAE of the GNN model during training and the MAE of the best-performing model on the test set for (a) 2D materials and (b) 3D materials.

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