Supplementary materials

Performance of Nitrogen Reduction Reaction on Metal Bound g-C₆N₆: Combined Approach of Machine Learning and DFT

Moumita Mukherjee^a, Sayan Dutta^a, Madhusudan Ghosh^b, Partha Basuchowdhuri^{b*},

Ayan Datta^{a*}

^aSchool of Chemical Sciences, Indian Association for the Cultivation of Science, Kolkata.

^bSchool of Mathematical and Computational Science, Indian Association for the Cultivation of

Science, Kolkata

 Table S1: List of Hyperparameters for the Regression Model and Classification

 model.

Models		Hyperparameters		
Regression	GBR	n_estimators = 100		
model		$learning_rate = 0.1$		
		$max_depth = 3$		
		min_sample_split = 2		
		min_sample_leaf = 1		
	RFR	n_estimators = 100		
		min_sample_split = 2		
		min_sample_leaf = 1		
Classification	Logistic Regression	regularization parameter = $0.01, 0.1,$		
Model		1.0, 10.0, 100.0		

Support Vector Machine	regularization parameter = 2, 3, 4, 5		
	Kernal = rbf, linear		
Random Forest Classifier	Number of trees = 10, 50, 100, 200		
	Max_depth = 2, 3, 4, 5		

Here, n_estimators determine the maximum number of trees; max_depth estimates the depth of each individual trees in the forest; min_sample_splits is the representative of minimum number of samples required to split an internal node; min_samples_leaf is the minimum number of samples required to be at a leaf node.

In this study, we have used two different strategies, namely, Bootstrap aggregating or bagging and boosting for machine learning.

Bagging: Given a training set, bagging generates a number of new training subsets, by sampling from the original training set uniformly and with replacement. Suppose m training subsets are generated. Then m models are fitted using these m samples, and the final prediction is done by averaging the results. Consider the case of Random Forest (RF). Decision trees that are very deep often overfit the training set, *i.e.* they have low bias, but high variance (i.e., they are flexible). An RF averages multiple (decorrelated) deep decision trees, trained on different parts of the same training set. This should lead to decreased variance because some of the variance should cancel out (at least in theory). This can come at the cost of a slight increase in bias.

Boosting: In case of boosting, we build a strong classifier by combining multiple "weak learners" that have high bias but low variance (i.e., they are inflexible). The weak learners are added sequentially to the strong classifier. After a weak learner is added, the misclassified data in the training set are given higher weights and the correctly classified data are given smaller weights so that future weak learners can concentrate on the misclassified data in the training set. Boosting, thus, reduces bias without increasing the variance. In fact, it has been observed that boosting can also reduce the variance.

Catalyst	Metal adsorption energy (eV)			
	Position_1	Position_2		
Sc-C ₆ N ₆	-416.426	-417.928		
Ti-C ₆ N ₆	-414.603	-417.779		
Cr-C ₆ N ₆	-414.273	-418.342		
Mn-C ₆ N ₆	-414.435	-417.860		
Co-C ₆ N ₆	-414.667	-414.678		
Ni-C ₆ N ₆	-413.577	-413.581		
Cu-C ₆ N ₆	-411.760	-411.761		
Nb-C ₆ N ₆	-415.012	-419.126		
Mo-C ₆ N ₆	-414.452	-418.375		
Tc-C ₆ N ₆	-416.824	-417.319		
Ru-C ₆ N ₆	-412.561	-416.149		
Hf-C ₆ N ₆	-415.954	-420.643		
Ta-C ₆ N ₆	-416.143	-420.345		
$W-C_6N_6$	-415.973	-419.483		
Re-C ₆ N ₆	-415.524	-418.317		
Ir-C ₆ N ₆	-415.745	-415.933		
Pt-C ₆ N ₆	-413.454	-413.497		
Au-C ₆ N ₆	-410.916	-410.920		

Table S2: Adsorption energy of Metals in C₆N₆ substrate at different position.

There are four possible binding sites available on M@C6N6. After optimization, the metal atoms on position_3 and 4 coincide with position_2. Therefore, comparing the energy values obtained for position_1 and position_2, we find that the adsorption energy is higher in position_2 than position_1.

Table S3: Adsorption energy of Nitrogen on metal catalyst in two modes.

Catalyst	N ₂ adsorption e	ergy (eV) (E _{ads})	
	End-On	Side-On	
Sc-C ₆ N ₆	-0.80	-0.48	
Ti-C ₆ N ₆	-1.05	-0.61	
Cr-C ₆ N ₆	-0.47	Not stable	
Mn-C ₆ N ₆	-0.43	-0.09	
Co-C ₆ N ₆	-0.98	-0.42	
Ni-C ₆ N ₆	-0.67	-0.64	
Cu-C ₆ N ₆	-0.74	-0.73	
Nb-C ₆ N ₆	-1.31	-0.82	
Mo-C ₆ N ₆	-0.92	-0.40	
Tc-C ₆ N ₆	-0.90	-0.40	
Ru-C ₆ N ₆	-1.05	-0.33	
Hf-C ₆ N ₆	-1.33	-0.88	
Ta-C ₆ N ₆	-1.36	-0.84	
W-C ₆ N ₆	-1.33	-0.71	
Re-C ₆ N ₆	-0.96	-0.21	
Ir-C ₆ N ₆	-1.07	-0.90	
Pt-C ₆ N ₆	-0.70	-0.61	
Au-C ₆ N ₆	-0.21	-0.21	



Figure S1: The relation between d-band center and adsorption energy of N_2 .



Figure S2: Optimized structures of different intermediates on Ta@C₆N₆.

 Table S4:
 Feature statistics of the dataset used for machine learning method.

Metals doped in Substrate	r _{cov}	d _{M-N}	$\mathcal{E}_{ ext{d}}$	q	EA	IE	EN	dz	θ_d
Sc	1.7	2.13	1.50	1.33	0.188	6.54	1.36	0.31	1
Ti	1.6	2.06	0.95	2.6	0.075	6.82	1.54	0.28	2
Cr	1.39	1.93	-1.13	4.75	0.675	6.76	1.66	0.25	5
Mn	1.39	2.08	-1.29	5.72	0.500	7.435	1.55	0.23	5
Со	1.26	1.94	-0.46	8.13	0.662	7.86	1.88	0.21	7
Ni	1.24	1.93	-0.90	9.21	1.157	7.635	1.91	0.195	8
Cu	1.32	2.04	-0.92	10.25	1.24	7.73	1.9	0.19	10
Nb	1.64	2.12	0.85	11.33	0.917	6.31	1.6	0.51	4
Mo	1.54	2.01	0.42	4.77	0.747	7.099	2.16	0.49	5
Tc	1.47	0.83	-0.62	5.9	0.55	7.28	1.99	0.455	5
Ru	1.42	1.88	-0.89	7.24	1.046	7.37	2.22	0.45	7
Hf	1.75	2.16	0.55	2.35	0.178	6.824	1.3	0.63	2
Та	1.7	2.077	0.56	3.42	0.323	7.887	1.5	0.605	3
W	1.62	1.99	0.58	4.63	0.816	7.98	2.36	0.59	5
Re	1.51	1.95	-0.08	5.79	0.06	7.877	1.9	0.565	5
Ir	1.41	1.87	-0.85	8.32	1.564	9.121	2.22	0.526	7
Pt	1.36	1.96	-1.64	9.39	2.125	9.0	2.28	0.51	8
Au	1.36	2.53	-2.07	10.49	2.308	9.225	2.54	0.488	10



Figure S3. Comparison of Training and Test RMSE over average of 50 cross

validations

LR: Linear regression

Lasso: Lasso regression

Ridge: Ridge regression

KNN: K-nearest neighbor regression

SVR: Support vector regression

RFR: Random Forest regression

GBR: Gradient boost regression



Figure S4. Schematic diagram of work-flow for the classification model.

No. of	Metals	Predicted probability by				
Distribution		Voting Logistic		Support	Random	
		Classifier	Regression	Vector	Forest	
				Machine	Classifier	
1	Ta	0.710	0.419	0.810	0.900	
	Ti	0.357	0.416	0.254	0.400	
	Ni	0.243	0.431	0.198	0.100	
	Pt	0.361	0.415	0.270	0.400	
2	Та	0.713	0.335	0.904	0.900	
	Nb	0.643	0.334	0.695	0.900	
	Pt	0.217	0.242	0.209	0.200	
	Ni	0.146	0.430	0.105	0.100	
3	Ta	0.520	0.251	0.609	0.700	
	Со	0.127	0.248	0.134	0.100	
	W	0.506	0.251	0.367	0.900	
	Hf	0.426	0.252	0.526	0.500	
4	Cr	0.243	0.332	0.099	0.300	
	Pt	0.227	0.332	0.149	0.200	
	Та	0.587	0.335	0.826	0.600	
	Re	0.417	0.334	0.519	0.400	
5	Ti	0.327	0.417	0.064	0.500	
	Nb	0.691	0.419	0.754	0.900	
	Tc	0.554	0.398	0.747	0.500	
	Ru	0.404	0.416	0.598	0.200	
6	Re	0.505	0.417	0.597	0.500	
	Co	0.197	0.411	0.082	0.100	
	Ni	0.206	0.410	0.107	0.100	
	Sc	0.442	0.419	0.309	0.600	

Table S5: Cross validation result for different classification models.

7	Re	0.526	0.334	0.545	0.700
	Sc	0.336	0.336	0.174	0.500
	Nb	0.557	0.336	0.735	0.600
	Mn	0.106	0.172	0.046	0.100
8	Мо	0.323	0.334	0.437	0.200
	W	0.461	0.335	0.549	0.500
	Pt	0.205	0.332	0.185	0.100
	Ru	0.183	0.317	0.217	0.100
9	Tc	0.331	0.333	0.361	0.300
	W	0.597	0.334	0.555	0.900
	Re	0.520	0.344	0.516	0.700
	Ti	0.328	0.364	0.120	0.500
10	Nb	0.587	0.335	0.626	0.800
	Re	0.477	0.334	0.597	0.500
	Cr	0.156	0.325	0.043	0.100
	Pt	0.274	0.332	0.091	0.400
11	Со	0.277	0.468	0.037	0.300
	Ru	0.453	0.480	0.410	0.400
	Mn	0.281	0.498	0.047	0.300
	Cr	0.315	0.480	0.047	0.400
12	Hf	0.726	0.420	0.657	0.900
	Mn	0.157	0.414	0.030	0.100
	Ni	0.570	0.412	0.029	0.000
	Cr	0.258	0.414	0.022	0.100
13	Ni	0.134	0.365	0.056	0.100
	Ti	0.625	0.462	0.837	0.700
	Мо	0.586	0.423	0.732	0.600
	Cr	0.413	0.434	0.726	0.100
14	Tc	0.486	0.415	0.445	0.600
	Ni	0.300	0.383	0.516	0.100
	Hf	0.458	0.446	0.429	0.500
	Cr	0.386	0.424	0.436	0.300
15	Tc	0.394	0.334	0.556	0.500
	Mn	0.262	0.331	0.076	0.100
	Nb	0.466	0.335	0.651	0.700
	Hf	0.437	0.336	0.621	0.600
16	Mn	0.237	0.414	0.096	0.200
	Pt	0.294	0.413	0.168	0.300

	Mo	0.411	0.417	0.417	0.400
	Cr	0.193	0.414	0.414	0.100
17	Mo	0.463	0.417	0.472	0.500
	Pt	0.266	0.415	0.183	0.200
	Со	0.170	0.412	0.097	0.100
	Ti	0.391	0.416	0.157	0.600
18	Ni	0.163	0.411	0.077	0.100
	Ti	0.408	0.417	0.108	0.700
	Mo	0.491	0.417	0.457	0.600
	Cr	0.191	0.414	0.060	0.100
19	Re	0.331	0.251	0.441	0.300
	Au	0.182	0.248	0.298	0.100
	Nb	0.343	0.251	0.484	0.300
	Mo	0.181	0.250	0.293	0.100
20	Tc	0.586	0.416	0.744	0.600
	Ni	0.157	0.412	0.059	0.100
	Nb	0.570	0.420	0.789	0.500
	Cr	0.258	0.414	0.059	0.300