# Design of high bulk moduli high entropy alloys using machine learning

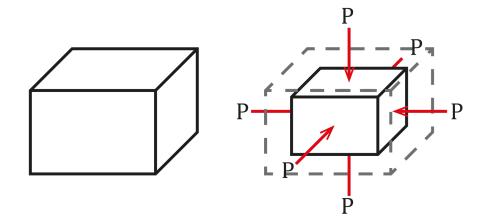
Professor: Dr. Parastar

Presenters: Erfan Nasrollahi – Setayesh Khalili



# High Entropy Alloy

- Composed of 5 or more principal elements in approximately equal atomic percentage
- High entropy due to random distribution stabilize the solid solution phase
- Extraordinary properties (eg. High bulk modulus)



$$k = -Vrac{dP}{dV}$$

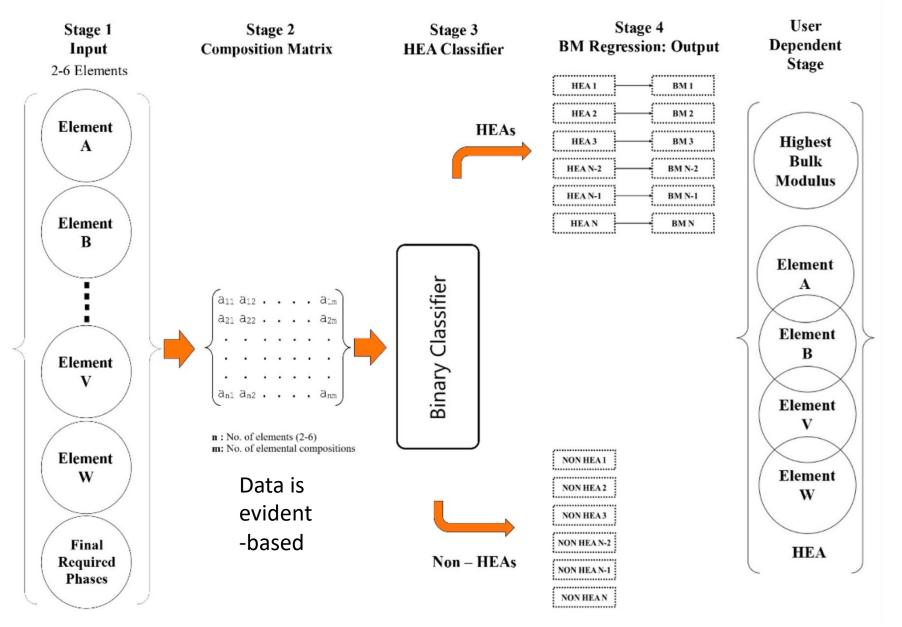
k = bulk modulus

P = pressure

V = initial volume of the substance

ML has been used for optimizing the composition of HEA to achieve enhanced bulk modulus values

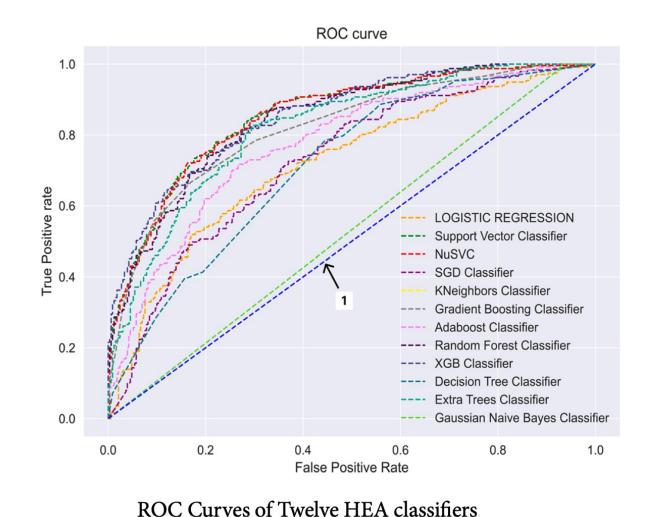
#### Guide line



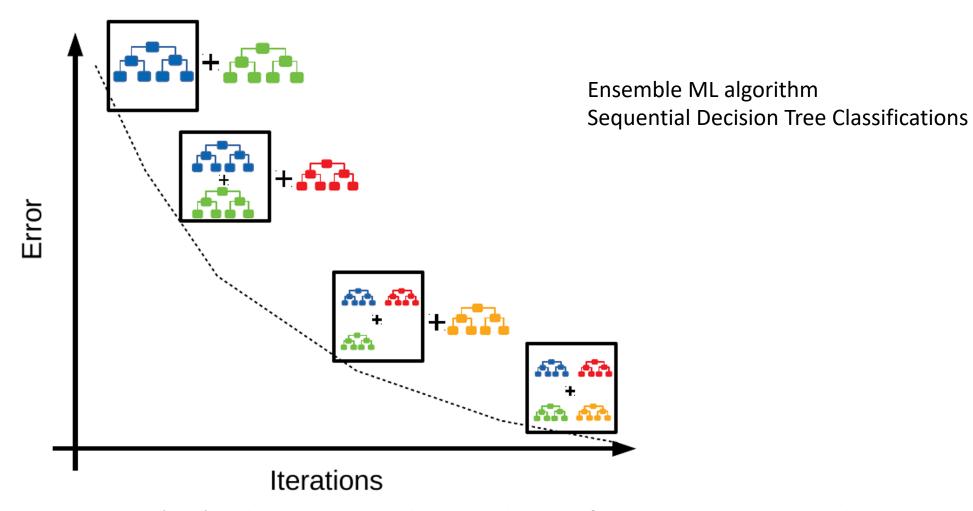
## Binary Classification of HEA & Non-HEA

#### 12 ML algorithms

Linear Regression									
SVC(linear)									
NuSVC									
SGD									
KNC									
Gradient Boosting Classification									
AC									
RFC									
XGB									
Decision Three Classification									
ETC									
Gaussian Naive B									



#### Gradient Boosted Classification



<u>Anshul Saini,(2024)</u> Gradient Boosting Algorithm: A Complete Guide for Beginners, <u>Data Science Blogathon</u>

# Regression

#### seven regression models were trained to predict the bulk modulus of HEAs

RF
XGB
Linear
Lasso
Ridge
ElasticNet
KNN

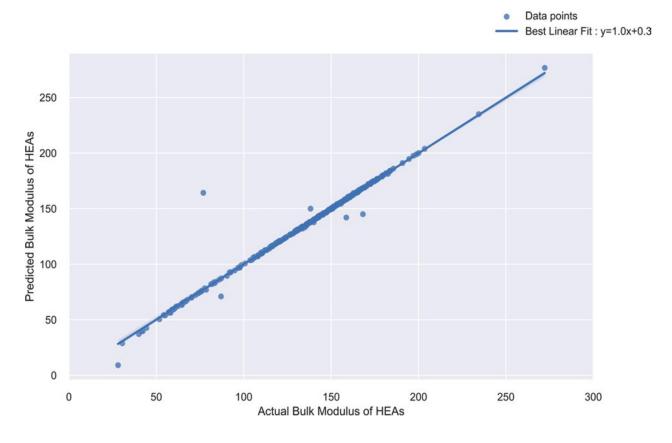


Figure 7. Predicted vs. actual bulk moduli for HEAs.

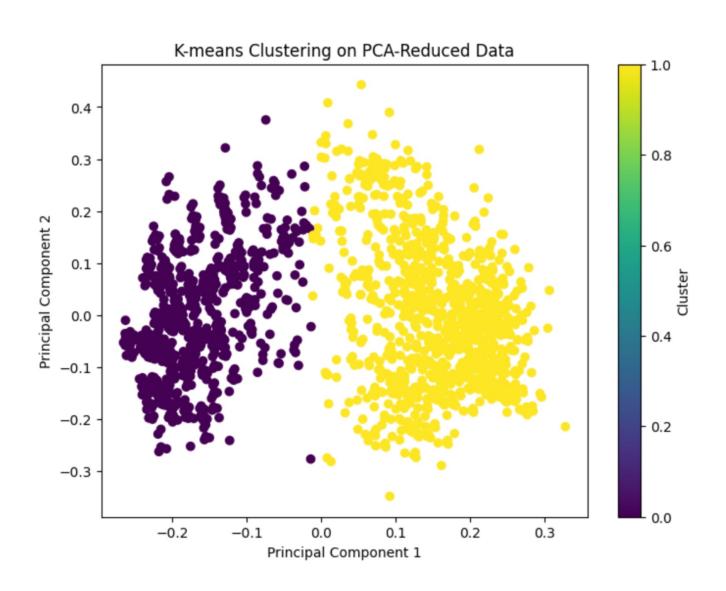
# Our Analysis

## Classification

			Accuracy	,				Precision			Recall					
	trai	train		Test		Tra	in	test			train to			st		
Model	article	us	article	us	cv	article	us	article	us	CV	article	us	article	us	CV	
LR	0.71	0.70	0.69	0.70	0.70	0.73	0.69	0.66	0.68	0.68	0.56	0.60	0.54	0.60	0.58	
SVC(linear)	0.87	0.70	0.78	0.68	0.70	0.87	0.88	0.76	0.92	0.69	0.83	0.88	0.70	0.83	0.58	
NuSVC	0.86	0.90	0.78	0.79	0.78	0.87	0.92	0.76	0.78	0.76	0.82	0.86	0.69	0.72	0.71	
SGD	0.70	0.68	0.66	0.68	0.69	0.66	0.76	0.58	0.78	0.67	0.69	0.38	0.65	0.4	0.62	
KNC	0.80	0.85	0.76	0.72	0.73	0.76	0.82	0.74	0.70	0.69	0.73	0.83	0.67	0.69	0.70	
GBC(Opt)	0.99	0.84	0.77	0.76	0.77	0.77	0.83	0.73	0.73	0.75	0.98	0.79	0.71	0.74	0.69	
AC	0.76	0.72	0.72	0.73	0.72	0.72	0.68	0.67	0.70	0.68	0.68	0.69	0.65	0.73	0.66	
RFC	0.93	1.0	0.76	0.78	0.79	0.76	1.0	0.75	0.79	0.78	0.89	1.0	0.65	0.70	0.71	
XGB	0.99	0.94	0.77	0.78	0.79	0.77	0.94	0.75	0.77	0.78	0.99	0.92	0.70	0.71	0.73	
DTC	0.69	1.0	0.65	0.75	0.75	0.65	1.0	0.56	0.71	0.71	0.80	1.0	0.78	0.73	0.71	
ETC	0.87	1.0	0.74	0.79	0.79	0.74	1.0	0.74	0.77	0.78	0.74	1.0	0.57	0.77	0.72	
GNB	0.48	0.47	0.46	0.47	0.47	0.46	0.45	0.43	0.45	0.45	0.43	1.0	0.99	1.0	1.0	
LDA	-	0.70	-	0.70	0.70	-	0.69	-	0.68	0.66	-	0.63	-	0.63	0.62	
SVM(non-linear)	-	0.86	-	0.78	0.78	-	0.86	-	0.78	0.76	-	0.82	-	0.71	0.70	

		F1_	score			AUC_ROC						
Model	tra	in	test		0.7	tra	in	test		GV.		
	article	us	article	us	CV	article	us	article	us	CV		
LR	0.63	0.63	0.59	0.63	0.62	0.70	0.75	0.67	0.72	0.74		
SVC	0.85	0.88	0.73	0.88	0.62	0.87	0.94	0.77	0.92	0.74		
NuSVC	0.84	0.87	0.72	0.75	0.74	0.86	0.97	0.76	0.87	0.84		
SGD	0.67	0.50	0.61	0.52	0.63	0.79	0.76	0.66	0.73	0.74		
KNC	0.77	0.83	0.70	0.69	0.70	0.79	0.92	0.75	0.80	0.80		
GBC	0.99	0.80	0.72	0.73	0.72	0.99	0.91	0.76	0.83	0.84		
AC	0.71	0.68	0.66	0.71	0.67	0.75	0.82	0.71	0.80	0.79		
RFC	0.92	1.0	0.70	0.74	0.74	0.93	1.0	0.75	0.85	0.87		
XGB	0.99	0.93	0.72	0.72	0.74	0.99	0.99	0.76	0.86	0.87		
DTC	0.70	1.0	0.65	0.72	0.71	0.70	1.0	0.67	0.75	0.74		
ETC	0.84	1.0	0.64	0.77	0.75	0.86	1.0	0.72	0.86	0.87		
GNB	0.63	0.62	0.60	0.62	0.62	0.53	0.52	0.53	0.52	0.52		
LDA	-	0.65	-	0.65	0.64	-	0.77	-	0.75	0.75		
SVM	-	0.84	-	0.74	0.73	-	0.84	-	0.87	0.86		

## PCA and k-means

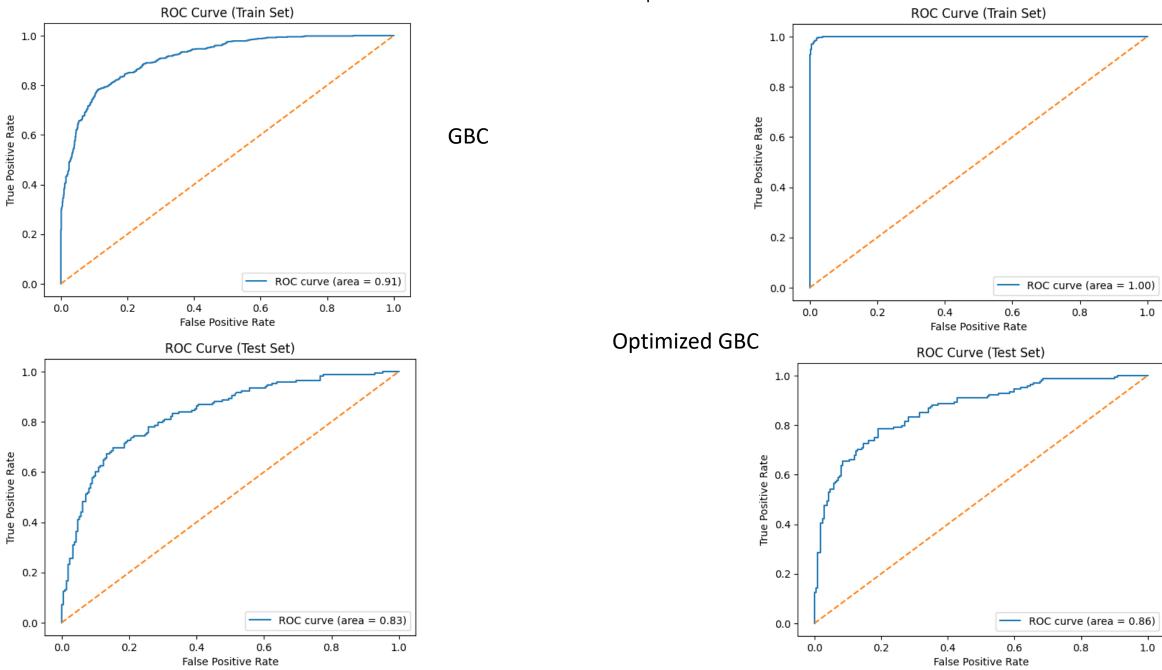


# Gradient Booster Classification model optimization by hyper tunning

The optimization is performed by hyper-parameter tuning using an open-source Python library Hypopt
Hypopt uses a Grid Search algorithm to choose the best combination of hyperparameters after exploring various combinations of hyperparameters

Parameters	Value
Loss	Deviance
n_estimators	100
max_depth	8
random_state	0

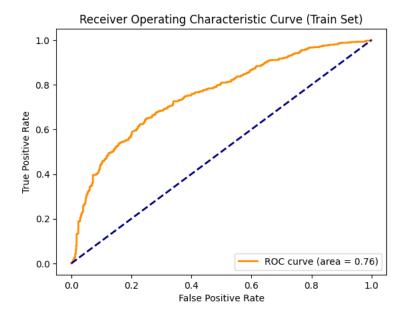
#### Gradient Booster Classification optimization with hyper tunning



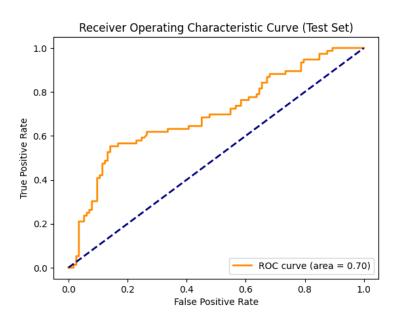
#### Gradient Booster Classification optimization with hyper tunning

model	accuracy				precisio	on		recall			F1_score			AUC_ROC						
	train		test		train		test tra		train	train to		test train		test			train		test	
	artic le	us	articl e	us	articl e	us	articl e	us	artic le	us	artic le	us	artic le	us	articl e	us	articl e	us	articl e	us
GBC	0.99	0.84	0.77	0.76	0.77	0.83	0.73	0.73	0.98	0.79	0.71	0.74	0.99	0.80	0.72	0.73	0.99	0.91	0.76	0.83
GBC opt	0.98	0.98	0.77	0.98		0.98	0.73	0.77		0.98	0.71	0.78		0.98	0.72	0.78		0.99	0.76	0.86

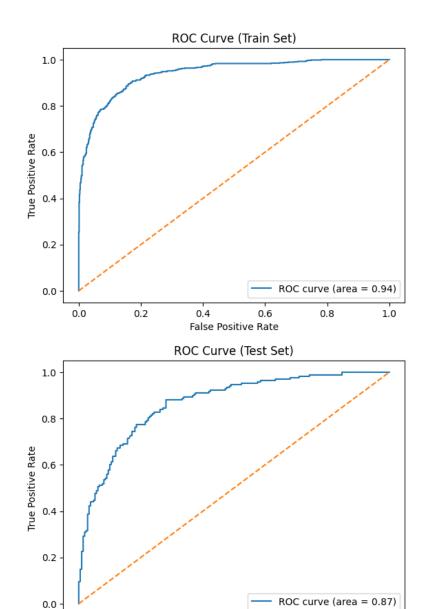
<b>Model</b> Cross validation	accuracy	Precision	Recall	F1_score	AUC_ROC
GCB	0.77	0.75	0.70	0.72	0.84
GCB OPT	0.78	0.76	0.71	0.73	0.86



#### SVC vs SVM



If the hyperplane classifies the dataset linearly then the algorithm we call it as SVC and the algorithm that separates the dataset by non-linear approach then we call it as SVM



0.0

0.2

0.4

False Positive Rate

0.6

0.8

1.0

Premanand S,(2023) The A-Z guide to Support Vector Machine, Data Science Blogathon

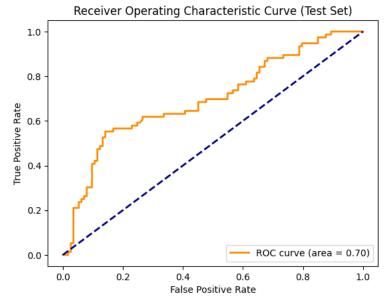
SVC

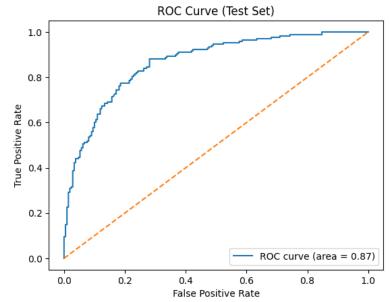
VS

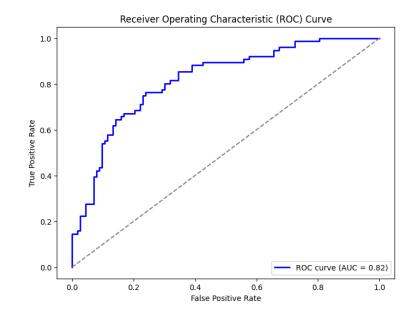
SVCopt VS

**SVM** 

Model Cross validation	accuracy	Precision	Recall	F1_score	AUC_ROC
SVC	0.70	0.68	0.58	0.62	0.73
SVC opt	0.75	0.66	0.76	0.71	0.82
SVM	0.78	0.76	0.70	0.73	0.86







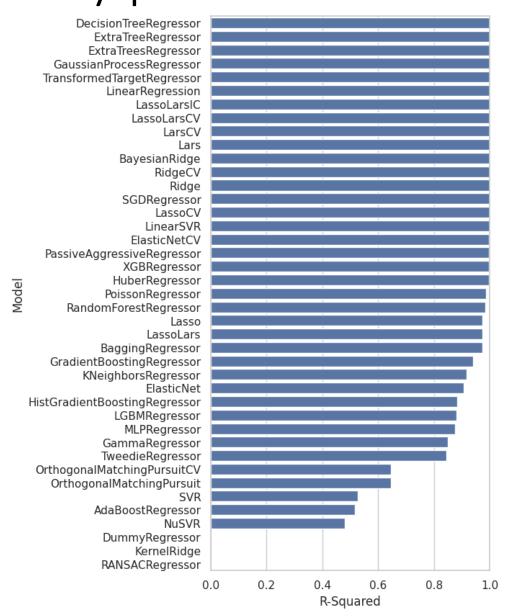
## BM regression

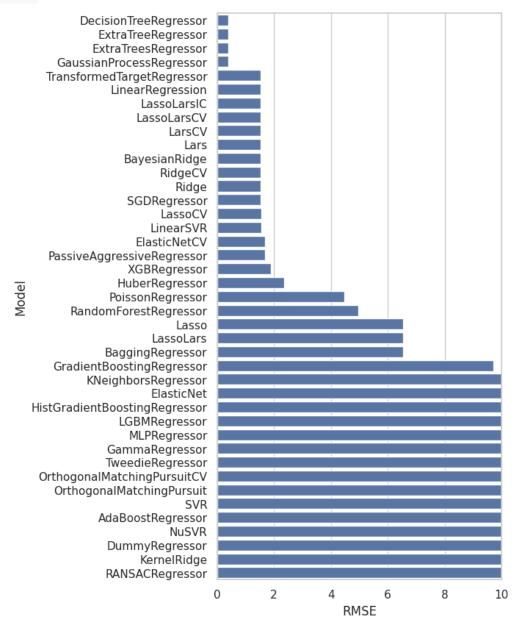
			R-sq	uare		Adj. R-square					
N	Model	Tı	rain	Tes	st	Tra	ain	Test			
		article	us	article	us	article	us	article	us		
	RF	0.99	0.987	0.86	0.888	0.97	0.982	0.83	0.827		
	XGB	0.99	0.997	0.90	0.997	0.99	0.920	0.88	0.876		
L	inear	0.99	0.998	-4e10	-1.8e10	0.99	0.998	-5e10	-2.8e10		
l	Lasso	0.99	0.412	0.98	0.372	0.99	0.358	0.97	0.0482		
F	Ridge	0.99	0.936	0.97	0.917	0.99	0.930	0.97	0.872		
Ela	sticNet	0.99	0.163	0.96	0.082	0.99	0.082	0.95	-0.316		
	KNN	0.96	0.901	0.86	0.837	0.96	0.892	0.82	0.749		
	ra Tree's gressor	-	0.999977	-	0.94506	-	0.99997	-	0.9150		
	sion Tree gressor	-	0.999977	-	0.84066	-	0.99997	-	0.7534		

Model	Me	an Square	d Error (N	1SE)	М	ean Absol	ute Error	(MAE)	Mean Absolute Percentage Error (MAPE)				
	Tra	ain	Te	st	Tra	ain		Test	Tra	ain	Test		
	article	us	article	us	article	us	article	us	article	us	article	us	
RF	29.71	24.58	180.41	166.67	2.43	2.15	6.55	6.35	2.36	43.97	6.95	39.00	
XGB	0.07	3.96	127.42	118.96	0.05	1.45	5.46	5.75	0.03	44.57	5.88	39.36	
Linear	1.54	2.36	6e13	2.75	0.29	0.323	4e5	10938707.4 5	0.24	0.269	5e5	89139 64.09	
Lasso	1.68	925.92 9	26.98	936.06	0.37	21.57	0.84	22.06	0.36	37.12	1.26	32.67	
Ridge	1.56	100.44	30.14	122.55	0.29	4.79	0.79	5.35	0.25	6.034	0.97	5.65	
ElasticNe t	7.58	1319.6 6	49.63	1269.3 8	1.12	27.95	1.93	26.84	1.19		3.22	31.47	
KNN	49.11	155.22	191.70	241.87	3.60	6.66	7.65	8.83	3.37	7.89	8.31	9.34	
ETR	-	0.035	1	81.93	1	0.012	-	4.47	-	44.66	-	39.42	
DTR	-	0.035	-	237.65	-	0.012	-	8.01	-	44.66	-	40.15	

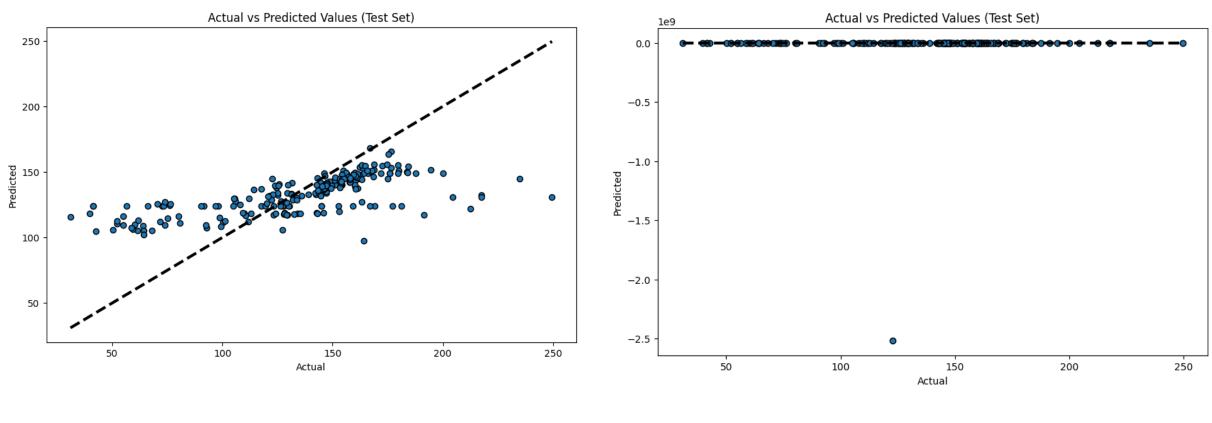
## Lazy predict

pip install lazypredict





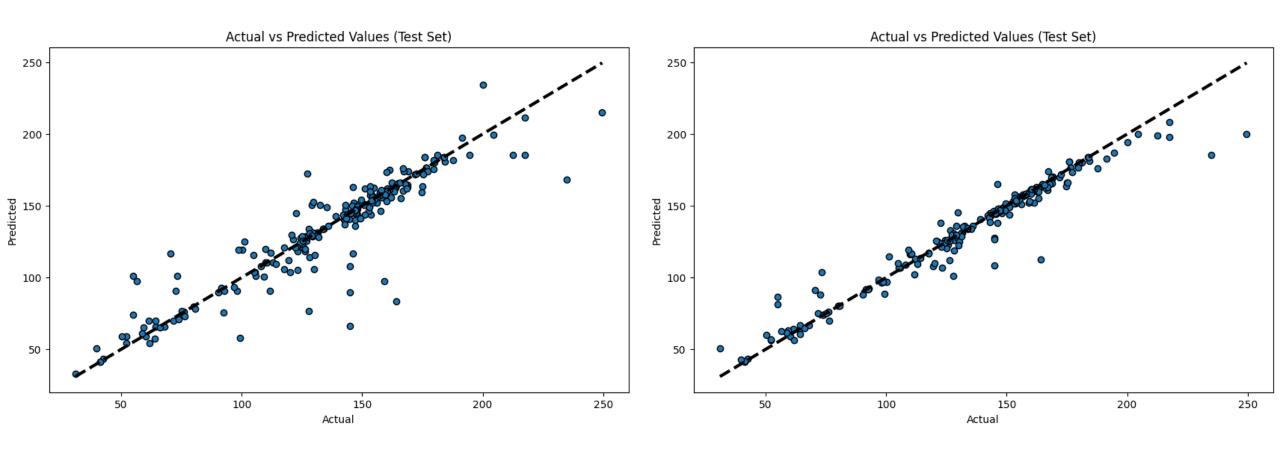
### Lasso & Linear regression did not work for us!



Lasso plot

Linear plot

## DTR & ETR



#### Conclusion

- The Article proposed:
  - GBC as the best model for HEA classification
  - Lasso as the best BM regression model

- Our results:
  - GBC and SVM as the best models for HEA classification
  - ETR as the best BM regression model
  - Data set did not follow any linear attribute

