```
import sys
sys.path.append('../')
from src.models.linear_regression.closed_form import
linear regression closed form
from src.models.linear regression.gradient descent base import
linear regression gradient descent
from src.models.linear regression.lasso gradient descent import
linear regression gradient descent lasso
from src.models.linear regression.ridge gradient descent import
linear regression gradient descent ridge
from src.utils.split data import split train val test
from src.utils.metrics import mean squared error 2,
mean absolute error 2
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn.linear model import LinearRegression, Ridge, Lasso
from sklearn.metrics import mean squared error, mean absolute error
from sklearn.preprocessing import PowerTransformer, StandardScaler
df=pd.read csv('../data/raw/California Houses.csv')
df
      Median House Value Median Income
                                    Median Age Tot Rooms
Tot Bedrooms \
               452600.0
                              8.3252
                                            41
                                                     880
129
                                                    7099
1
               358500.0
                              8.3014
                                            21
1106
2
               352100.0
                              7.2574
                                            52
                                                    1467
190
3
               341300.0
                              5.6431
                                            52
                                                    1274
235
                                            52
                                                    1627
4
               342200.0
                              3.8462
280
. . .
20635
                78100.0
                              1.5603
                                            25
                                                    1665
374
20636
                77100.0
                              2.5568
                                            18
                                                     697
150
                                                    2254
20637
                92300.0
                              1.7000
                                            17
485
```

1.8672

18

1860

20638

84700.0

409 20639 616	89	400.0	2.3886	1	6 2785
	Population H	ouseholds	Latitude	Longitude	Distance_to_coast
0	322	126	37.88	-122.23	9263.040773
1	2401	1138	37.86	-122.22	10225.733072
2	496	177	37.85	-122.24	8259.085109
3	558	219	37.85	-122.25	7768.086571
4	565	259	37.85	-122.25	7768.086571
20635	845	330	39.48	-121.09	162031.481121
20636	356	114	39.49	-121.21	160445.433537
20637	1007	433	39.43	-121.22	153754.341182
20638	741	349	39.43	-121.32	152005.022239
20639	1387	530	39.37	-121.24	146866.196892
0 1 2 3 4 20635 20636 20637 20638	Distance_to_L 556529.15834 554279.85006 554610.71706 555194.26608 555194.26608 654530.18629 659747.06844 654042.21402 657698.00770	2 7 9 7 9 7 6 7 6 7 . 9 8 4 8 9 8	e_to_SanDie /35501.8069 /33236.8843 /33525.6829 /34095.2907 /34095.2907 330631.5430 336245.9152 336699.5731	84 60 37 44 44 47 29 63	ce_to_SanJose \ 67432.517001 65049.908574 64867.289833 65287.138412 65287.138412 248510.058162 246849.888948 240172.220489 238193.865909
20639	648723.33712	6 8	325569.1790	28	233282.769063
0 1 2 3 4 20635 20636	2 1 1 1 22	anFrancisco 1250.213767 0880.600406 8811.487456 8031.047568 8031.047568 2619.890417)) 3 3		

```
20637
                  212097.936232
20638
                  207923.199166
20639
                  205473.376575
[20640 rows x 14 columns]
y=df['Median House Value']
df=df.drop(columns=['Median House Value'])
X_train, X_val, X_test, y_train, y_val, y_test =
split train val test(df,y,random state=42)
print("Train:", X_train.shape, y_train.shape)
print("Validation:", X_val.shape, y_val.shape)
print("Test:", X_test.shape, y_test.shape)
Train: (14447, 13) (14447,)
Validation: (3096, 13) (3096,)
Test: (3097, 13) (3097,)
X train.shape
(14447, 13)
X test.shape
(3097, 13)
X val.shape
(3096, 13)
```

Preprocessing

```
from sklearn.preprocessing import PowerTransformer, StandardScaler
import pandas as pd

cols_to_power = [
    'Distance_to_coast',
    'Median_Income',
    'Tot_Rooms',
    'Tot_Bedrooms',
    'Population',
    'Households'
]

pt = PowerTransformer(method='yeo-johnson')
X_train_pt = X_train.copy()
X_train_pt[cols_to_power] = pt.fit_transform(X_train[cols_to_power])
```

```
X \text{ val pt} = X \text{ val.copy}()
X val pt[cols to power] = pt.transform(X val[cols to power])
X \text{ test pt} = X \text{ test.copy()}
X test pt[cols to power] = pt.transform(X test[cols to power])
from sklearn.preprocessing import RobustScaler
scaler = StandardScaler()
X train scaled = X train pt.copy()
X train scaled[X train scaled.columns] =
scaler.fit transform(X train pt)
X val scaled = X val pt.copy()
X val scaled[X val scaled.columns] = scaler.transform(X val pt)
X test scaled = X test_pt.copy()
X test scaled[X test scaled.columns] = scaler.transform(X test pt)
from sklearn.preprocessing import StandardScaler
import pandas as pd
y_scaler = StandardScaler()
y train = pd.Series(
    y_scaler.fit_transform(y_train.values.reshape(-1, 1)).flatten(),
    index=y train.index,
    name=y train.name
)
y val = pd.Series(
    y scaler.transform(y val.values.reshape(-1, 1)).flatten(),
    index=y val.index,
    name=y val.name
)
y test = pd.Series(
    y scaler.transform(y test.values.reshape(-1, 1)).flatten(),
    index=y_test.index,
    name=y_test.name
)
```

```
y_train
20046
        -1.383333
3024
        -1.399814
15663
         2.539847
20484
         0.099023
9814
         0.614249
15308
        -0.192417
3161
        -1.207255
2630
        -1.293126
         0.295052
18443
3174
        -0.929692
Name: Median House Value, Length: 14447, dtype: float64
X train scaled
                      Median Age Tot Rooms Tot Bedrooms
       Median Income
                                                             Population
20046
           -1.537647
                        -0.292327
                                   -0.493990
                                                  -0.278847
                                                               0.230596
3024
           -0.700725
                         0.104386
                                    0.442045
                                                   0.671771
                                                               0.407974
15663
           -0.014038
                         1.849920
                                    0.849314
                                                   1.501858
                                                               0.140556
20484
            1.089351
                        -0.927066
                                    0.496376
                                                   0.177223
                                                               0.540816
9814
            0.135076
                         0.421756
                                    0.113035
                                                  -0.023637
                                                              -0.159709
15308
            0.392877
                         0.739126
                                  -1.174367
                                                  -0.984907
                                                              -1.162587
3161
           -1.441123
                        -0.212984
                                   -0.382488
                                                  -0.336103
                                                               0.038987
2630
           -1.570950
                         0.263071
                                  -0.761689
                                                  -0.419532
                                                              -0.870014
            0.857422
                        -0.292327
                                    0.927174
18443
                                                   0.522668
                                                               0.935415
3174
           -0.237788
                         0.977153 -1.214804
                                                  -1.403777
                                                              -1.269575
                   Latitude Longitude Distance to coast
       Households
Distance to LA \
20046
        -0.221795
                   0.209041
                               0.274761
                                                   1.843408
0.137450
3024
         0.502607 -0.222522
                               0.049720
                                                   1.145568
```

0.418905					
15663 1.192781	1.341682	1.025257	-1.440556	-2.962798	
20484 0.879629	0.246810	-0.625939	0.419788	0.279046	-
9814	0.030129	0.471731	-1.185509	-1.129066	
0.695681					
1	0 062400	1 127247	1 004012	0 527500	
0.576610	0.902489	-1.137247	1.094913	-0.537500	-
3161 - 0.508667	0.086186	-0.180304	0.354776	1.418868	-
	0.617613	2.409071	-2.325720	-3.099729	
18443	0.673798	0.767257	-1.130499	0.392876	
	1.355059	0.354458	-0.110310	1.649241	
0.102220					
	_	_SanDiego	Distance_to	o_SanJose	
Distance_	_to_SanFra			0.000775	
20046 0.115875		0.044425	•	-0.260775	-
3024 0.030011		-0.182960	-	-0.104978	
15663 1.537317		1.193505	-	-1.286457	-
20484		-0.587086		0.432122	
0.495937 9814		0.758704		-1.245173	_
1.006978					
15308 1.187363		-1.174920		1.228420	
3161		-0.262420		0.042330	
0.156605 2630		2.405411		0.363134	-
0.093045 18443		0.909732	-	-1.558694	_
1.232224					
3174 0.421808		0.262653		-0.615365	-
[14447 ro	ws x 13 c	columns]			
X_val_sca	led				

\	Median_Inco	ome Median	_Age	Tot_Rooms	Tot_Bedrooms	Population
2565	-0.2168	800 0.97	7153	-0.028476	-0.312977	-0.372243
18474	0.2240	052 -0.68	9039	1.102024	1.134551	1.272154
1203	-0.8803	338 -0.13	3642	0.256250	-0.040022	-0.111536
6413	1.3887	68 0.42	1756	0.387188	0.040490	0.178400
17074	-0.3890	004 -0.68	9039	-1.750414	-0.967816	-1.607586
18064	1.7835	80 0.42	1756	0.415848	-0.113903	-0.384161
11950	0.2432	67 0.10	4386	0.466885	0.209198	0.364345
18689	0.6747	′20 -0.76	8381	0.689889	0.522668	1.358130
4214	-1.0838	356 1.45	3208	-0.609821	-0.309152	0.355302
12096	0.7004	34 -1.08	5751	-1.221654	-1.489343	-1.277332
D'ata	Households	Latitude	Longi	tude Dist	cance_to_coast	
2565	ce_to_LA \ -0.261285	2.423144	-2.29	5714	-1.477906	
2.6063 18474	1.164994	0.710967	-1.05	0484	0.263542	
0.7820 1203	-0.035974	1.766418	-1.09	0491	1.626037	
1.6254 6413		-0.705684	0.76	4852	0.575261	-
1.0007 17074	64 -0.892136	0.875148	-1.32	5535	-1.264506	
1.0320	92					
				• • •		
18064 0.9131	-0.198499	0.767257	-1.23	5518	0.162564	
11950 0.7803	0.283236	-0.785430	1.05	9906	0.810660	-
18689	0.563856	0.631221	-1.09	5492	-0.481979	
0.7498 4214	-0.004379	-0.696303	0.64	4830	0.144935	-
1.0482 12096 0.7300	-1.450625	-0.818266	1.11	9917	0.838657	-
	Distance_to	_SanDiego	Dista	nce_to_Sar	nJose	

	SanFrancisco		
2565	2.404068	0.365720	-
0.089462			
18474	0.842694	-1.469922	-
1.154644			
1203	1.561896	-0.563648	-
0.796738			
6413	-0.764890	0.689915	
0.719953			
17074	1.055222	-1.463034	-
1.397277			
18064	0.952847	-1.540713	_
1.277001	01002011	2101012	
11950	-0.890042	0.927014	
0.925185	0.0000.2	0.02.02.	
18689	0.812650	-1.410794	_
1.115112	0.012000	11.12073.	
4214	-0.719292	0.613933	
0.654057	01713232	01013333	
12096	-0.922493	0.988489	
0.978470	0.322433	0.300403	
0.3/04/0			

[3096 rows x 13 columns]

X_test_scaled

	Median_Income	Median_Age	Tot_Rooms	Tot_Bedrooms	Population
15193	1.322107	-1.006409	0.395047	-0.040022	-0.133513
1401	0.595366	0.818468	0.018227	-0.201665	-0.210541
12828	0.283712	-0.371669	-0.007569	-0.271350	-0.059584
3253	-0.979095	-0.847724	-0.816404	-0.407367	-0.087279
19238	0.560099	-0.371669	0.147954	0.053055	-0.236501
11284	1.319999	0.501098	-0.651906	-1.055195	-0.795970
11964	-0.301247	0.342413	0.512678	0.358899	0.584435
5390	-0.384738	0.580441	-0.045644	0.356229	0.587131
860	1.082255	-1.085751	0.740501	0.429648	0.605903
15795	-0.664011	1.849920	1.007597	1.756219	1.247830

	ouseholds	Latitude	Longitude	Distance_to_coast	
Distance ₁	_to_LA \	-1.212301	1.259943	0.076388	_
0.439668	0.097331	-1.212301	1.239943	0.070300	-
	-0.122883	1.095620	-1.255522	-0.530474	
1.156152 12828	-0.237490	1.447437	-0.945464	1.018496	
1.308922	-0.237430	1.44/43/	-0.945404	1.010490	
	-0.432763	0.185586	-0.280342	1.286443	
0.035938 19238	-0.057331	1.372383	-1.530573	0.605795	
1.484850	-0.03/331	1.3/2303	-1.330373	0.003793	
11284	-0 886/07	-0.860484	0.799858	-0.413571	_
0.922535	-0.000407	-0.000404	0.799000	-0.4133/1	-
11964	0.100652	-0.747902	1.064907	0.925358	-
0.780629 5390	0 2/2520	-0.743212	0.589819	-0.491185	
1.032755	0.342320	-0.743212	0.309019	-0.491103	-
860	0.433921	0.922057	-1.200512	-0.351720	
1.004151 15795	1.809035	1.011184	-1.430554	-1.420174	
1.178083	1.009055	1.011104	-1.450554	-1.420174	
		C D'	D:	6 1	
	istance_to to SanFra	_SanDiego	Distance_t	o_SanJose	
15193	_00_54111 10	-1.242355		1.382858	
1.321445		1 164716		1 200072	
1401 1.400417		1.164716		-1.289072	-
12828		1.293006		-0.890911	-
1.014213		0 207021		0.616010	
3253 0.414620		0.207821		-0.616913	-
19238		1.445669		-0.929002	-
1.202754					
				• • •	
11284		-0.886061		0.835355	
0.846215		0.000045		0.001570	
11964 0.902869		-0.860343		0.901579	
5390		-0.729996		0.622398	
0.661233		1 02272		1 400540	
860 1.362556		1.033707		-1.483540	-
15795		1.180854		-1.303150	-

```
1.544933
[3097 rows x 13 columns]
```

Modeling

Baseline models

MODEL 1: MY CLOSED_FORM (all features)

```
model1 my closed form= linear regression closed form()
model1 my closed form.fit(X train scaled,y train)
pred train model1=model1 my closed form.predict(X train scaled)
pred val model1=model1 my closed form.predict(X val scaled)
pred test model1=model1 my closed form.predict(X test scaled)
from sklearn.metrics import mean absolute error, mean squared error
print("##################################")
print("MAE:", mean_absolute_error(y_train, pred_train_model1))
print("MSE:", mean squared error(y train, pred train model1))
print("\n############# VALIDATION ##############")
print("MAE:", mean absolute error(y val, pred val model1))
print("MSE:", mean squared error(y val, pred val model1))
print("\n############## TEST ##############")
print("MAE:", mean absolute error(y test, pred test model1))
print("MSE:", mean squared error(y test, pred test model1))
MAE: 0.4490390201735744
MSE: 0.35783075050647745
MAE: 0.4460110671639358
MSE: 0.34086411026949437
MAE: 0.46286534820987474
MSE: 0.38733770395201156
```

MODEL 2: MY CLOSED_FORM (dropped features)

```
'Distance to SanFrancisco', 'Longitude'
X train scaled droped = X train scaled.drop(columns=cols to drop)
X val scaled droped = X val scaled.drop(columns=cols to drop)
X test scaled droped = X test scaled.drop(columns=cols to drop)
model2 my closed form= linear regression closed form()
model2 my closed form.fit(X train scaled droped, y train)
pred train model2=model2 my closed form.predict(X train scaled droped)
pred_val_model2=model2_my_closed_form.predict(X_val_scaled_droped)
pred test model2=model2 my closed form.predict(X test scaled droped)
print("##################################")
print("MAE:", mean_absolute_error_2(y_train, pred_train_model2))
print("MSE:", mean_squared_error_2(y_train, pred_train_model2))
print("\n############## VALIDATION ################")
print("MAE:", mean absolute error 2(y val, pred val model2))
print("MSE:", mean_squared_error_2(y_val, pred_val_model2))
print("\n############# TEST #############")
print("MAE:", mean_absolute_error_2(y_test, pred_test_model2))
print("MSE:", mean squared error 2(y test, pred test model2))
MAE: 0.4693428009799008
MSE: 0.388385914520206
MAE: 0.46459678002836685
MSE: 0.3718552621398819
MAE: 0.48083893472499756
MSE: 0.4157121474639904
```

MODEL 3: SKLEARN CLOSED_FORM (all features)

```
from sklearn.linear_model import LinearRegression

model3_sklearn_closed_form = LinearRegression()

model3_sklearn_closed_form.fit(X_train_scaled, y_train)

pred_train_model3 = model3_sklearn_closed_form.predict(X_train_scaled)
pred_val_model3 = model3_sklearn_closed_form.predict(X_val_scaled)
pred_test_model3 = model3_sklearn_closed_form.predict(X_test_scaled)

from sklearn.metrics import mean_absolute_error, mean_squared_error
```

```
print("##################################")
print("MAE:", mean absolute error(y train, pred train model3))
print("MSE:", mean squared error(y train, pred train model3))
print("\n############## VALIDATION ##############")
print("MAE:", mean absolute error(y val, pred val model3))
print("MSE:", mean squared error(y val, pred val model3))
print("\n############## TEST #############")
print("MAE:", mean_absolute_error(y_test, pred_test_model3))
print("MSE:", mean_squared_error(y_test, pred_test_model3))
MAE: 0.4490390201735745
MSE: 0.35783075050647745
MAE: 0.4460110671639359
MSE: 0.34086411026949426
MAE: 0.4628653482098747
MSE: 0.38733770395201134
```

MODEL 4: SKLEARN CLOSED_FORM (dropped features)

```
from sklearn.linear model import LinearRegression
from sklearn.metrics import mean absolute error, mean squared error
model4 sklearn closed form = LinearRegression()
model4 sklearn closed form.fit(X train scaled droped, y train)
pred train model4 =
model4 sklearn closed form.predict(X train scaled droped)
pred val model4 =
model4 sklearn closed form.predict(X val scaled droped)
pred test model4 =
model4 sklearn closed form.predict(X test scaled droped)
print("##################################")
print("MAE:", mean absolute error(y train, pred train model4))
print("MSE:", mean squared error(y train, pred train model4))
print("\n############## VALIDATION ##############")
print("MAE:", mean absolute error(y val, pred val model4))
print("MSE:", mean squared error(y val, pred val model4))
print("\n############# TEST #############")
```

MODEL 5: MY Basic GD (all features)

```
model5 my basic gradient descent =
linear regression gradient descent(iterations=1000)
model5 my basic gradient descent.fit(X train scaled, y train)
pred train model5 =
model5 my basic gradient descent.predict(X train scaled)
pred val model5 =
model5 my basic gradient descent.predict(X val scaled)
pred test model5 =
model5 my basic gradient descent.predict(X test scaled)
###########")
print("TRAIN MAE:", mean_absolute_error(y_train, pred_train_model5))
print("TRAIN MSE:", mean_squared_error(y_train, pred_train_model5))
print("VALIDATION MAE:", mean_absolute_error(y_val, pred_val_model5))
print("VALIDATION MSE:", mean_squared_error(y_val, pred_val_model5))
print("TEST MAE:", mean_absolute_error(y_test, pred_test_model5))
print("TEST MSE:", mean squared error(y test, pred test model5))
TRAIN MAE: 0.45814737007116546
TRAIN MSE: 0.3697818138251737
VALIDATION MAE: 0.4568978654930041
VALIDATION MSE: 0.3560298370785626
TEST MAE: 0.47065123886812593
TEST MSE: 0.39591964880872904
```

MODEL 6: MY Basic GD (dropped features)

```
model6_my_basic_gradient_descent =
linear_regression_gradient_descent(iterations=1000)
```

```
model6 my basic gradient descent.fit(X train scaled droped, y train)
pred train model6 =
model6 my basic gradient descent.predict(X train scaled droped)
pred val model6 =
model6 my basic gradient descent.predict(X val scaled droped)
pred test model6 =
model6 my basic gradient descent.predict(X test scaled droped)
print("\n############## MODEL 6: DROPPED COLUMNS
############# ")
print("TRAIN MAE:", mean absolute error(y train, pred train model6))
print("TRAIN MSE:", mean_squared_error(y_train, pred_train_model6))
print("VALIDATION MAE:", mean_absolute_error(y_val, pred_val_model6))
print("VALIDATION MSE:", mean squared error(y val, pred val model6))
print("TEST MAE:", mean_absolute_error(y_test, pred_test_model6))
print("TEST MSE:", mean squared error(y test, pred test model6))
TRAIN MAE: 0.473665481478821
TRAIN MSE: 0.3969199660252751
VALIDATION MAE: 0.4717052431525312
VALIDATION MSE: 0.38363553933798017
TEST MAE: 0.48272596177442856
TEST MSE: 0.4194213379131731
```

MODEL 7: SGDRegressor (all features)

```
from sklearn.linear_model import SGDRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error

model7_sklearn_gradient_descent = SGDRegressor(
    max_iter=1000,
    tol=1e-3,
        alpha=0.0,

    random_state=42
)

model7_sklearn_gradient_descent.fit(X_train_scaled, y_train)

pred_train_model7 =
model7_sklearn_gradient_descent.predict(X_train_scaled)
pred_val_model7 =
model7_sklearn_gradient_descent.predict(X_val_scaled)
pred_test_model7 =
```

```
model7 sklearn gradient descent.predict(X test scaled)
############# ")
print("TRAIN MAE:", mean_absolute_error(y_train, pred_train_model7))
print("TRAIN MSE:", mean_squared_error(y_train, pred_train_model7))
print("VALIDATION MAE:", mean_absolute_error(y_val, pred_val_model7))
print("VALIDATION MSE:", mean_squared_error(y_val, pred_val_model7))
print("TEST MAE:", mean_absolute_error(y_test, pred_test_model7))
print("TEST MSE:", mean_squared_error(y_test, pred_test_model7))
TRAIN MAE: 0.4498276544405565
TRAIN MSE: 0.3597818166385498
VALIDATION MAE: 0.4481324036367169
VALIDATION MSE: 0.3448885016772517
TEST MAE: 0.4632172328143263
TEST MSE: 0.3895115728994916
```

MODEL 8: SGDRegressor (dropped features)

```
model8 sklearn gradient descent = SGDRegressor(
    max iter=1000,
    tol=1e-3,
    penalty='l2',
        alpha=0.0,
    random state=42
model8 sklearn gradient descent.fit(X train scaled droped, y train)
pred train model8 =
model8 sklearn gradient descent.predict(X train scaled droped)
pred val model8 =
model8 sklearn gradient descent.predict(X val scaled droped)
pred test model8 =
model8 sklearn gradient descent.predict(X test scaled droped)
print("\n############# MODEL 8: SGD (DROPPED COLUMNS)
#############")
print("TRAIN MAE:", mean_absolute_error(y_train, pred_train_model8))
print("TRAIN MSE:", mean_squared_error(y_train, pred_train_model8))
print("VALIDATION MAE:", mean_absolute_error(y_val, pred_val_model8))
print("VALIDATION MSE:", mean squared error(y val, pred val model8))
print("TEST MAE:", mean_absolute_error(y_test, pred_test_model8))
print("TEST MSE:", mean squared error(y test, pred test model8))
```

MODEL 9: MY LASSO GD (all features)

```
model9 my lasso gd = linear regression gradient descent lasso(
    iterations=1000,
    learning rate=0.01,
    lambda param=0.1
)
model9_my_lasso_gd.fit(X_train_scaled, y train)
pred train model9 = model9 my lasso gd.predict(X train scaled)
pred_val_model9 = model9_my_lasso_gd.predict(X_val_scaled)
pred test model9 = model9 my lasso gd.predict(X test scaled)
############# ")
print("TRAIN MAE:", mean_absolute_error(y_train, pred_train_model9))
print("TRAIN MSE:", mean_squared_error(y_train, pred_train_model9))
print("VALIDATION MAE:", mean_absolute_error(y_val, pred_val_model9))
print("VALIDATION MSE:", mean_squared_error(y_val, pred_val_model9))
print("TEST MAE:", mean_absolute_error(y_test, pred test model9))
print("TEST MSE:", mean squared error(y test, pred test model9))
################## MODEL 9: LASSO GD (ALL FEATURES)
TRAIN MAE: 0.4581487439058685
TRAIN MSE: 0.36978553457762203
VALIDATION MAE: 0.4568991559554448
VALIDATION MSE: 0.35603363897552276
TEST MAE: 0.47065164238629525
TEST MSE: 0.39592184504328215
```

MODEL 10: MY LASSO GD (dropped features)

```
model10_my_lasso_gd = linear_regression_gradient_descent_lasso(
    iterations=1000,
```

```
learning rate=0.01,
    lambda param=0.1
)
model10 my lasso gd.fit(X train scaled droped, y train)
pred train model10 =
model10_my_lasso_gd.predict(X_train_scaled droped)
pred_val_model10 = model10_my_lasso_gd.predict(X_val_scaled_droped)
pred test model10 = model10 my lasso gd.predict(X test scaled droped)
print("\n############### MODEL 10: LASSO GD (DROPPED COLUMNS)
###########")
print("TRAIN MAE:", mean_absolute_error(y_train, pred_train_model10))
print("TRAIN MSE:", mean_squared_error(y_train, pred_train_model10))
print("VALIDATION MAE:", mean_absolute_error(y_val, pred_val_model10))
print("VALIDATION MSE:", mean_squared_error(y_val, pred_val_model10))
print("TEST MAE:", mean absolute error(y test, pred test model10))
print("TEST MSE:", mean_squared_error(y_test, pred_test_model10))
############################## MODEL 10: LASSO GD (DROPPED COLUMNS)
##############################
TRAIN MAE: 0.4736672520765031
TRAIN MSE: 0.39692341613523013
VALIDATION MAE: 0.4717074154318441
VALIDATION MSE: 0.38363942592246386
TEST MAE: 0.4827268944070502
TEST MSE: 0.4194236388223099
```

MODEL 11: SKLEARN LASSO GD (ALL FEATURES)

```
model11_sklearn_lasso_gd = SGDRegressor(
    max_iter=1000,
    tol=1e-3,
    penalty='l1',
    alpha=0.1,
    learning_rate='constant',
    eta0=0.01,
    random_state=42
)

model11_sklearn_lasso_gd.fit(X_train_scaled, y_train)

pred_train_model11 = model11_sklearn_lasso_gd.predict(X_train_scaled)
pred_val_model11 = model11_sklearn_lasso_gd.predict(X_val_scaled)
pred_test_model11 = model11_sklearn_lasso_gd.predict(X_test_scaled)
```

MODEL 12: SKLEARN LASSO GD (DROPPED COLUMNS)

```
model12 sklearn lasso gd = SGDRegressor(
    max iter=1000,
    tol=1e-3,
    penalty='l1',
    alpha=0.1,
    learning rate='constant',
    eta0=0.01,
    random state=42
)
model12 sklearn lasso gd.fit(X train scaled droped, y train)
pred train model12 =
model12 sklearn lasso gd.predict(X train scaled droped)
pred val model12 =
model12 sklearn lasso gd.predict(X val scaled droped)
pred test model12 =
model12_sklearn_lasso_gd.predict(X_test_scaled_droped)
COLUMNS) ###############")
print("TRAIN MAE:", mean_absolute_error(y_train, pred_train_model12))
print("TRAIN MSE:", mean_squared_error(y_train, pred_train_model12))
print("VALIDATION MAE:", mean_absolute_error(y_val, pred_val_model12))
print("VALIDATION MSE:", mean_squared_error(y_val, pred_val_model12))
```

```
print("TEST MAE:", mean_absolute_error(y_test, pred_test_model12))
print("TEST MSE:", mean_squared_error(y_test, pred_test_model12))

########################

TRAIN MAE: 0.5091589742091546
TRAIN MSE: 0.4987464858799806
VALIDATION MAE: 0.5046967039192498
VALIDATION MSE: 0.4829889911606385
TEST MAE: 0.5137419075674781
TEST MSE: 0.5177886180743421
```

MODEL 13: MY CLOSED-FORM RIDGE (ALL FEATURES)

```
model13 my closed form ridge =
linear regression closed form(lambda param=0.1)
model13 my closed form ridge.fit(X train scaled, y train)
pred train model13 =
model13 my closed form ridge.predict(X train scaled)
pred val model13 = model13 my closed form ridge.predict(X val scaled)
pred test model13 =
model13 my closed form ridge.predict(X test scaled)
print("############## MODEL 13: MY CLOSED-FORM RIDGE (ALL
FEATURES) ##############")
print("TRAIN MAE:", mean_absolute_error(y_train, pred_train_model13))
print("TRAIN MSE:", mean_squared_error(y_train, pred_train_model13))
print("VALIDATION MAE:", mean_absolute_error(y_val, pred_val_model13))
print("VALIDATION MSE:", mean squared error(y val, pred val model13))
print("TEST MAE:", mean_absolute_error(y_test, pred_test_model13))
print("TEST MSE:", mean squared error(y test, pred test model13))
####################### MODEL 13: MY CLOSED-FORM RIDGE (ALL FEATURES)
##############################
TRAIN MAE: 0.4490403975214379
TRAIN MSE: 0.357830764826386
VALIDATION MAE: 0.4460166749869064
VALIDATION MSE: 0.34086940681579275
TEST MAE: 0.4628645635330025
TEST MSE: 0.3873346226459628
```

MODEL 14: MY CLOSED-FORM RIDGE (DROPPED FEATURES)

```
model14 my closed form ridge =
linear regression closed form(lambda param=0.1)
model14 my closed form ridge.fit(X train scaled droped, y train)
pred train model14 =
model14 my closed form ridge.predict(X train scaled droped)
pred val model14 =
model14 my closed form ridge.predict(X val scaled droped)
pred test model14 =
model14 my closed form ridge.predict(X test scaled droped)
print("\n############## MODEL 14: MY CLOSED-FORM RIDGE (DROPPED)
FEATURES) ##############")
print("TRAIN MAE:", mean_absolute_error(y_train, pred_train_model14))
print("TRAIN MSE:", mean_squared_error(y_train, pred_train_model14))
print("VALIDATION MAE:", mean_absolute_error(y_val, pred_val_model14))
print("VALIDATION MSE:", mean_squared_error(y_val, pred_val_model14))
print("TEST MAE:", mean absolute error(y test, pred test model14))
print("TEST MSE:", mean squared error(y test, pred test model14))
######################### MODEL 14: MY CLOSED-FORM RIDGE (DROPPED FEATURES)
TRAIN MAE: 0.4693424231883856
TRAIN MSE: 0.38838591487582674
VALIDATION MAE: 0.4645967176610898
VALIDATION MSE: 0.371856037791626
TEST MAE: 0.4808383353087329
TEST MSE: 0.4157112989434044
```

MODEL 15: SKLEARN RIDGE (ALL FEATURES)

```
from sklearn.linear_model import Ridge
from sklearn.metrics import mean_absolute_error, mean_squared_error

model15_sklearn_closed_form_ridge = Ridge(alpha=0.1, solver='auto', random_state=42)

model15_sklearn_closed_form_ridge.fit(X_train_scaled, y_train)

pred_train_model15 = model15_sklearn_closed_form_ridge.predict(X_train_scaled)
pred_val_model15 = model15_sklearn_closed_form_ridge.predict(X_val_scaled)
pred_test_model15 =
```

```
model15 sklearn closed form ridge.predict(X test scaled)
###############")
print("TRAIN MAE:", mean_absolute_error(y_train, pred_train_model15))
print("TRAIN MSE:", mean_squared_error(y_train, pred_train_model15))
print("VALIDATION MAE:", mean absolute error(y val, pred val model15))
print("VALIDATION MSE:", mean_squared_error(y_val, pred_val_model15))
print("TEST MAE:", mean_absolute_error(y_test, pred test model15))
print("TEST MSE:", mean squared error(y test, pred test model15))
############################## MODEL 15: SKLEARN RIDGE (ALL FEATURES)
TRAIN MAE: 0.44904039752143754
TRAIN MSE: 0.357830764826386
VALIDATION MAE: 0.44601667498690606
VALIDATION MSE: 0.3408694068157927
TEST MAE: 0.46286456353300215
TEST MSE: 0.38733462264596236
```

MODEL 16: SKLEARN RIDGE (DROPPED FEATURES)

```
model16 sklearn closed form ridge = Ridge(alpha=0.1, solver='auto',
random state=42)
model16 sklearn closed form ridge.fit(X train scaled droped, y train)
pred train model16 =
model16 sklearn closed form ridge.predict(X train scaled droped)
pred val model16 =
model16 sklearn closed form ridge.predict(X val scaled droped)
pred test model16 =
model16 sklearn closed form ridge.predict(X test scaled droped)
print("\n############## MODEL 16: SKLEARN RIDGE (DROPPED FEATURES)
###########" )
print("TRAIN MAE:", mean_absolute_error(y_train, pred_train_model16))
print("TRAIN MSE:", mean_squared_error(y_train, pred_train_model16))
print("VALIDATION MAE:", mean_absolute_error(y_val, pred_val_model16))
print("VALIDATION MSE:", mean squared error(y val, pred val model16))
print("TEST MAE:", mean_absolute_error(y_test, pred_test_model16))
print("TEST MSE:", mean squared error(y test, pred test model16))
```

MODEL 17: MY RIDGE GRADIENT DESCENT (ALL FEATURES)

```
from sklearn.metrics import mean absolute error, mean squared error
model17 my gradient descent ridge =
linear regression gradient descent ridge(
   iterations=1000,
   learning rate=0.01,
   lambda param=0.1
)
model17 my gradient descent ridge.fit(X train scaled, y train)
pred train model17 =
model17 my gradient descent ridge.predict(X train scaled)
pred val model17 =
model17 my gradient descent ridge.predict(X val scaled)
pred test model17 =
model17 my gradient descent ridge.predict(X test scaled)
############# ")
print("TRAIN MAE:", mean_absolute_error(y_train, pred_train_model17))
print("TRAIN MSE:", mean_squared_error(y_train, pred_train_model17))
print("VALIDATION MAE:", mean_absolute_error(y_val, pred_val_model17))
print("VALIDATION MSE:", mean squared error(y_val, pred_val_model17))
print("TEST MAE:", mean absolute error(y test, pred test model17))
print("TEST MSE:", mean squared error(y test, pred test model17))
################ MODEL 17: MY RIDGE GD (ALL FEATURES)
##############################
TRAIN MAE: 0.4581477316039109
TRAIN MSE: 0.3697824714738423
VALIDATION MAE: 0.45689821634889355
VALIDATION MSE: 0.3560305741113778
TEST MAE: 0.4706514882306106
TEST MSE: 0.39592005779805267
```

MODEL 18: MY RIDGE GRADIENT DESCENT (DROPPED FEATURES)

```
model18 my gradient descent ridge =
linear regression gradient descent ridge(
   iterations=1000,
   learning rate=0.01,
   lambda param=0.1
)
model18 my gradient descent ridge.fit(X train scaled droped, y train)
pred train model18 =
model18 my gradient descent ridge.predict(X train scaled droped)
pred val model18 =
model18 my gradient descent ridge.predict(X val scaled droped)
pred test model18 =
model18 my gradient descent ridge.predict(X test scaled droped)
###########")
print("TRAIN MAE:", mean_absolute_error(y_train, pred_train_model18))
print("TRAIN MSE:", mean_squared_error(y_train, pred_train_model18))
print("VALIDATION MAE:", mean_absolute_error(y_val, pred_val_model18))
print("VALIDATION MSE:", mean_squared_error(y_val, pred_val_model18))
print("TEST MAE:", mean absolute_error(y_test, pred_test_model18))
print("TEST MSE:", mean squared error(y test, pred test model18))
#################### MODEL 18: MY RIDGE GD (DROPPED FEATURES)
#####################################
TRAIN MAE: 0.4736658066590812
TRAIN MSE: 0.3969205057828532
VALIDATION MAE: 0.4717056101241222
VALIDATION MSE: 0.3836360943400861
TEST MAE: 0.48272616904856624
TEST MSE: 0.4194217361391837
```

MODEL 19: SKLEARN RIDGE (GRADIENT DESCENT, ALL FEATURES)

```
from sklearn.linear_model import SGDRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error

model19_sklearn_ridge_gd = SGDRegressor(
    penalty='l2',
    alpha=0.1,
    max_iter=1000,
    random_state=42
)
```

```
model19 sklearn ridge gd.fit(X train scaled, y train)
pred train model19 = model19 sklearn ridge gd.predict(X train scaled)
pred val model19 = model19 sklearn ridge gd.predict(X val scaled)
pred test model19 = model19 sklearn ridge gd.predict(X test scaled)
############# ")
print("TRAIN MAE:", mean_absolute_error(y_train, pred_train_model19))
print("TRAIN MSE:", mean_squared_error(y_train, pred_train_model19))
print("VALIDATION MAE:", mean absolute error(y val, pred val model19))
print("VALIDATION MSE:", mean squared error(y val, pred val model19))
print("TEST MAE:", mean absolute error(y test, pred test model19))
print("TEST MSE:", mean_squared_error(y_test, pred_test_model19))
#################### MODEL 19: SKLEARN RIDGE (GD, ALL FEATURES)
##############################
TRAIN MAE: 0.4597569439218733
TRAIN MSE: 0.3796024986488221
VALIDATION MAE: 0.45900364722820225
VALIDATION MSE: 0.3664612792603511
TEST MAE: 0.4716110740795363
TEST MSE: 0.40519093291075386
```

MODEL 20: SKLEARN RIDGE (GRADIENT DESCENT, DROPPED FEATURES)

```
model20_sklearn_ridge_gd = SGDRegressor(
    penalty='l2',
    alpha=0.1,
    learning_rate='invscaling',
    max_iter=1000,
    tol=1e-3,
    random_state=42
)

model20_sklearn_ridge_gd.fit(X_train_scaled_droped, y_train)

pred_train_model20 =
    model20_sklearn_ridge_gd.predict(X_train_scaled_droped)
    pred_val_model20 =
    model20_sklearn_ridge_gd.predict(X_val_scaled_droped)
    pred_test_model20 =
    model20_sklearn_ridge_gd.predict(X_test_scaled_droped)

pred_test_model20 =
    model20_sklearn_ridge_gd.predict(X_test_scaled_droped)
```

Evaluate

```
import pandas as pd
from sklearn.metrics import mean absolute error, mean squared error
results = []
for i in range(1, 21):
    mae = mean_absolute_error(y_test, globals()
[f"pred test model{i}"])
    mse = mean squared error(y test, globals()[f"pred test model{i}"])
    results.append({
        "Model #": i,
        "Model Name": [
            "My Closed Form",
            "My Closed Form (Dropped Corr)",
            "Sklearn Closed Form",
            "Sklearn Closed Form (Dropped Corr)",
            "My GD",
            "My GD (Dropped Corr)",
            "Sklearn GD",
            "Sklearn GD (Dropped Corr)",
            "My Lasso GD",
            "My Lasso GD (Dropped Corr)",
            "Sklearn Lasso GD",
            "Sklearn Lasso GD (Dropped Corr)",
            "My Ridge Closed Form",
            "My Ridge Closed Form (Dropped Corr)",
            "Sklearn Ridge Closed Form",
            "Sklearn Ridge Closed Form (Dropped Corr)",
```

```
"My Ridge GD",
            "My Ridge GD (Dropped Corr)",
            "Sklearn Ridge GD",
            "Sklearn Ridge GD (Dropped Corr)"
        ][i-1],
        "Test MAE": mae,
        "Test MSE": mse
    })
comparison_df = pd.DataFrame(results)
comparison df
                                             Model Name Test MAE Test
    Model #
MSE
                                         My Closed Form
                                                         0.462865
0.387338
                         My Closed Form (Dropped Corr)
          2
                                                          0.480839
0.415712
          3
                                   Sklearn Closed Form
                                                         0.462865
0.387338
                    Sklearn Closed Form (Dropped Corr)
                                                          0.480839
0.415712
          5
                                                  My GD
                                                          0.470651
0.395920
                                  My GD (Dropped Corr)
          6
                                                          0.482726
0.419421
          7
                                             Sklearn GD
                                                          0.463217
0.389512
                             Sklearn GD (Dropped Corr)
          8
                                                          0.480315
0.416847
          9
                                            My Lasso GD
                                                          0.470652
0.395922
         10
                            My Lasso GD (Dropped Corr)
                                                          0.482727
0.419424
                                       Sklearn Lasso GD
10
         11
                                                          0.529689
0.493118
11
         12
                       Sklearn Lasso GD (Dropped Corr)
                                                          0.513742
0.517789
                                  My Ridge Closed Form
                                                         0.462865
12
         13
0.387335
                  My Ridge Closed Form (Dropped Corr)
13
                                                          0.480838
         14
0.415711
         15
                             Sklearn Ridge Closed Form
                                                         0.462865
0.387335
```

Sklearn Ridge Closed Form (Dropped Corr)

0.480838

15

16

```
0.415711
                                          My Ridge GD 0.470651
         17
16
0.395920
                           My Ridge GD (Dropped Corr) 0.482726
17
         18
0.419422
         19
                                     Sklearn Ridge GD 0.471611
0.405191
19
         20
                      Sklearn Ridge GD (Dropped Corr) 0.483501
0.427438
```

Hyperparameter Tuning

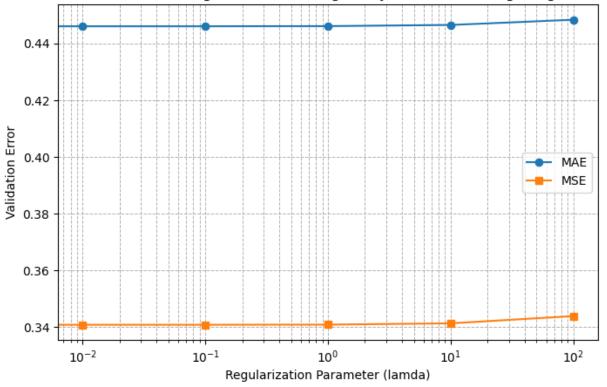
my closed form

```
import numpy as np
from sklearn.metrics import mean_absolute_error, mean squared error
lambda values = [0, 0.01, 0.1, 1, 10, 100]
results = []
for lam in lambda values:
    model = linear regression_closed_form(lambda_param=lam)
    model.fit(X_train_scaled, y_train)
    preds = model.predict(X val scaled)
    mae = mean absolute error(y val, preds)
    mse = mean squared error(y val, preds)
    results.append({
        "lambda": lam,
        "MAE": mae,
        "MSE": mse
    })
import pandas as pd
results df = pd.DataFrame(results)
print(results df.sort values(by="MAE"))
   lambda
                MAE
                          MSE
0
     0.00 0.446011 0.340864
1
     0.01 0.446012 0.340865
2
     0.10 0.446017 0.340869
3
     1.00 0.446066 0.340917
4
   10.00 0.446482 0.341387
5 100.00 0.448314 0.343931
import matplotlib.pyplot as plt
results df = results df.sort values(by="lambda")
```

```
plt.figure(figsize=(8, 5))
plt.plot(results_df["lambda"], results_df["MAE"], marker='o',
label='MAE')
plt.plot(results_df["lambda"], results_df["MSE"], marker='s',
label='MSE')

plt.xscale('log')
plt.xlabel("Regularization Parameter (lamda)")
plt.ylabel("Validation Error")
plt.title("Validation Error vs. Regularization Strength (my closed form ridge Regression)")
plt.legend()
plt.grid(True, which="both", linestyle="--", linewidth=0.7)
plt.show()
```

Validation Error vs. Regularization Strength (my closed form ridge Regression)

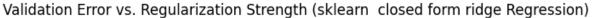


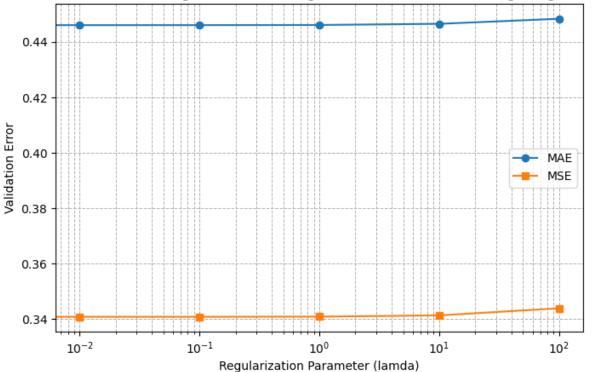
sklearn closed form

```
import numpy as np
from sklearn.metrics import mean_absolute_error, mean_squared_error
lambda_values = [0, 0.01, 0.1, 1, 10, 100]
results = []

for lam in lambda_values:
    model = Ridge(alpha=lam, solver='auto', random_state=42)
```

```
model.fit(X_train_scaled, y_train)
    preds = model.predict(X val scaled)
    mae = mean absolute error(y val, preds)
    mse = mean squared error(y val, preds)
    results.append({
        "lambda": lam,
        "MAE": mae,
        "MSE": mse
    })
import pandas as pd
results df = pd.DataFrame(results)
print(results df.sort values(by="MAE"))
                MAE
   lambda
                          MSE
     0.00 0.446011 0.340864
0
     0.01 0.446012 0.340865
1
2
     0.10 0.446017 0.340869
3
     1.00 0.446066 0.340917
4
   10.00 0.446482 0.341387
5 100.00 0.448314 0.343931
import matplotlib.pyplot as plt
results df = results df.sort values(by="lambda")
plt.figure(figsize=(8, 5))
plt.plot(results df["lambda"], results df["MAE"], marker='o',
label='MAE')
plt.plot(results df["lambda"], results df["MSE"], marker='s',
label='MSE')
plt.xscale('log')
plt.xlabel("Regularization Parameter (lamda)")
plt.vlabel("Validation Error")
plt.title("Validation Error vs. Regularization Strength (sklearn
closed form ridge Regression)")
plt.legend()
plt.grid(True, which="both", linestyle="--", linewidth=0.7)
plt.show()
```

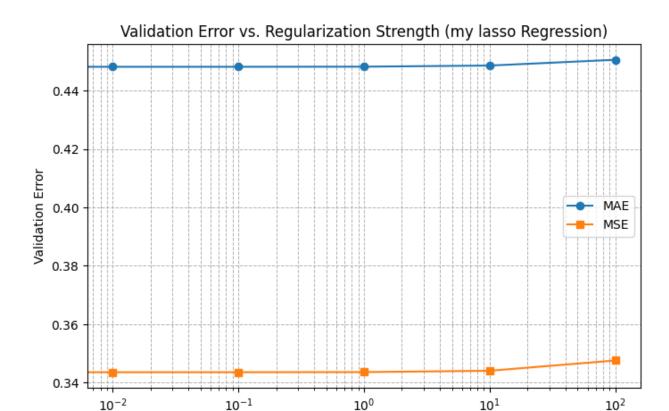




my lasso gd

```
import numpy as np
from sklearn.metrics import mean absolute error, mean squared error
lambda values = [0, 0.01, 0.1, 1, 10, 100]
results = []
for lam in lambda values:
    model = linear regression gradient descent lasso(
    iterations=1000,
    learning rate=0.1,
    lambda param=lam
)
    model.fit(X_train_scaled, y_train)
    preds = model.predict(X_val_scaled)
    mae = mean absolute error(y val, preds)
    mse = mean squared error(y val, preds)
    results.append({
        "lambda": lam,
        "MAE": mae,
        "MSE": mse
```

```
})
import pandas as pd
results df = pd.DataFrame(results)
print(results df.sort values(by="MAE"))
   lambda
               MAE
                         MSE
    0.00 0.448196 0.343543
0
1
    0.01 0.448196 0.343543
2
    0.10 0.448200 0.343547
3
    1.00 0.448235 0.343585
4
   10.00
          0.448628 0.344039
5 100.00 0.450598 0.347565
import matplotlib.pyplot as plt
results df = results df.sort values(by="lambda")
plt.figure(figsize=(8, 5))
plt.plot(results df["lambda"], results df["MAE"], marker='o',
label='MAE')
plt.plot(results_df["lambda"], results_df["MSE"], marker='s',
label='MSE')
plt.xscale('log')
plt.xlabel("Regularization Parameter (lamda)")
plt.ylabel("Validation Error")
plt.title("Validation Error vs. Regularization Strength (my lasso
Regression)")
plt.legend()
plt.grid(True, which="both", linestyle="--", linewidth=0.7)
plt.show()
```



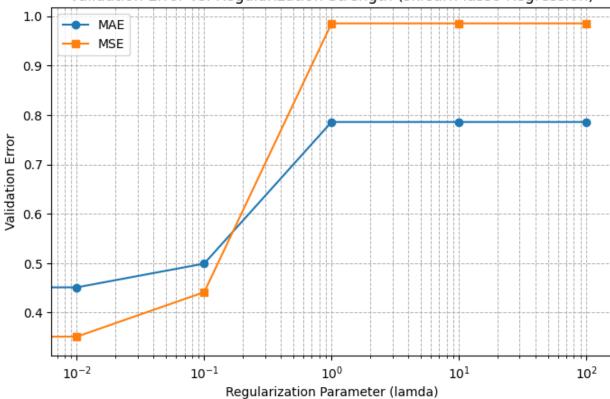
Regularization Parameter (lamda)

sklearn lasso gd

```
import numpy as np
from sklearn.metrics import mean_absolute_error, mean_squared_error
lambda_values = [0, 0.01, 0.1, 1, 10, 100]
results = []
for lam in lambda values:
    model = SGDRegressor(
    max iter=3000,
    tol=1e-3,
    penalty='l1',
    alpha=lam,
    random state=42
)
    model.fit(X_train_scaled, y_train)
    preds = model.predict(X val scaled)
    mae = mean absolute error(y val, preds)
    mse = mean squared error(y val, preds)
    results.append({
```

```
"lambda": lam,
        "MAE": mae,
        "MSE": mse
    })
import pandas as pd
results df = pd.DataFrame(results)
print(results df.sort values(by="MAE"))
   lambda
                MAE
                          MSE
     0.00 0.448132 0.344889
0
1
     0.01 0.451100 0.351372
2
     0.10 0.499110 0.441359
3
     1.00 0.785651 0.985166
4
   10.00
           0.785651
                     0.985166
5 100.00 0.785651 0.985166
import matplotlib.pyplot as plt
results df = results df.sort values(by="lambda")
plt.figure(figsize=(8, 5))
plt.plot(results_df["lambda"], results_df["MAE"], marker='o',
label='MAE')
plt.plot(results df["lambda"], results df["MSE"], marker='s',
label='MSE')
plt.xscale('log')
plt.xlabel("Regularization Parameter (lamda)")
plt.ylabel("Validation Error")
plt.title("Validation Error vs. Regularization Strength (sklearn lasso
Regression)")
plt.legend()
plt.grid(True, which="both", linestyle="--", linewidth=0.7)
plt.show()
```



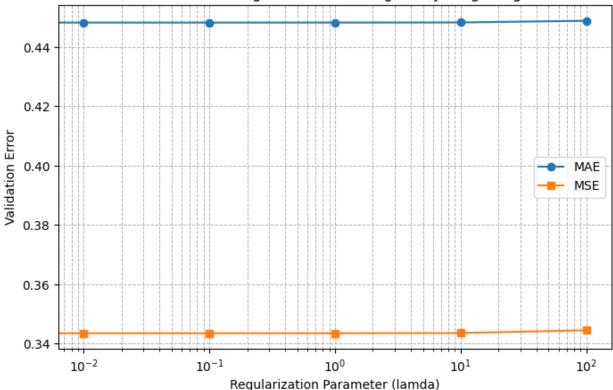


my ridge gd

```
import numpy as np
from sklearn.metrics import mean absolute error, mean squared error
lambda_values = [0, 0.01, 0.1, 1, 10, 100]
results = []
for lam in lambda_values:
    model = linear_regression_gradient_descent_ridge(
    iterations=1000,
    learning rate=0.1,
    lambda param=lam
)
    model.fit(X_train_scaled, y_train)
    preds = model.predict(X val scaled)
    mae = mean absolute error(y val, preds)
    mse = mean_squared_error(y_val, preds)
    results.append({
        "lambda": lam,
        "MAE": mae,
```

```
"MSE": mse
    })
import pandas as pd
results df = pd.DataFrame(results)
print(results df.sort values(by="MAE"))
   lambda
                MAE
                          MSE
0
     0.00 0.448196 0.343543
1
     0.01 0.448196 0.343543
2
     0.10 0.448196 0.343543
3
     1.00 0.448200 0.343550
4
   10.00 0.448239 0.343617
  100.00 0.448799 0.344518
import matplotlib.pyplot as plt
results df = results df.sort values(by="lambda")
plt.figure(figsize=(8, 5))
plt.plot(results df["lambda"], results df["MAE"], marker='o',
label='MAE')
plt.plot(results_df["lambda"], results_df["MSE"], marker='s',
label='MSE')
plt.xscale('log')
plt.xlabel("Regularization Parameter (lamda)")
plt.ylabel("Validation Error")
plt.title("Validation Error vs. Regularization Strength (my Ridge
Regression)")
plt.legend()
plt.grid(True, which="both", linestyle="--", linewidth=0.7)
plt.show()
```



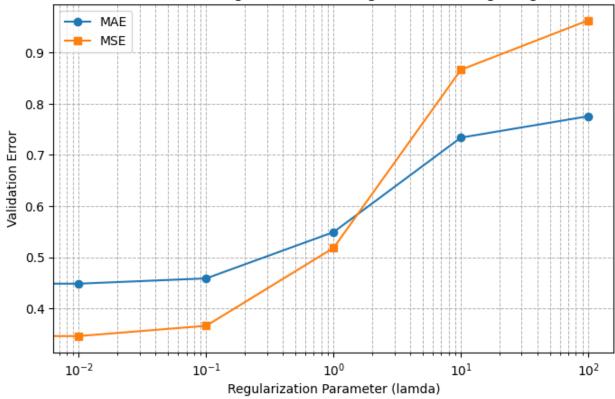


sklearn ridge gd

```
import numpy as np
from sklearn.metrics import mean_absolute_error, mean_squared_error
lambda_values = [0, 0.01, 0.1, 1, 10, 100]
results = []
for lam in lambda values:
    model = SGDRegressor(
    penalty='l2',
    alpha=lam,
    max iter=1000,
    random_state=42,
)
    model.fit(X train scaled, y train)
    preds = model.predict(X_val_scaled)
    mae = mean_absolute_error(y_val, preds)
    mse = mean_squared_error(y_val, preds)
    results.append({
```

```
"lambda": lam,
        "MAE": mae,
        "MSE": mse
    })
import pandas as pd
results df = pd.DataFrame(results)
print(results df.sort values(by="MAE"))
   lambda
                MAE
                          MSE
     0.00 0.448132 0.344889
0
1
     0.01 0.448736 0.346397
2
     0.10 0.459004 0.366461
3
     1.00 0.549406 0.518571
4
    10.00
           0.733879
                     0.866365
5
  100.00
           0.775629 0.962825
import matplotlib.pyplot as plt
results df = results df.sort values(by="lambda")
plt.figure(figsize=(8, 5))
plt.plot(results_df["lambda"], results_df["MAE"], marker='o',
label='MAE')
plt.plot(results df["lambda"], results df["MSE"], marker='s',
label='MSE')
plt.xscale('log')
plt.xlabel("Regularization Parameter (lamda)")
plt.ylabel("Validation Error")
plt.title("Validation Error vs. Regularization Strength (sklearn Ridge
Regression)")
plt.legend()
plt.grid(True, which="both", linestyle="--", linewidth=0.7)
plt.show()
```





Conclusion

Our Pipeline

Data Preprocessing and Model Testing:

• We first performed data preprocessing and then tested our models. We compared the results with the corresponding implementations in scikit-learn.

Feature Selection Impact:

• For each model, we ran experiments twice: once using all features and once after removing highly correlated features. The results were very similar in both cases, indicating that the correlated features did not significantly affect model performance.

Hyperparameter Tuning (Regularization):

• We tuned the regularization parameter to optimize the models. The best performance was achieved with values around 0 or very small, suggesting that heavy regularization is unnecessary. Increasing regularization too much caused underfitting and reduced model performance.

Overfitting and Underfitting Insight:

• The training, validation, and test errors (MAE and MSE) are very close, indicating that the models are not overfitting. The average error of around 0.5 also suggests there is no clear underfitting, though performance could still be improved. We suspect that the data

may contain non-linear patterns, so increasing the polynomial order could help the models capture these relationships and further reduce the error.