

## Code

### Notebook\_Regresi\_B\_Ridge\_VS\_SupportVektor\_Bernard

```
[56] import pandas as pd
import numpy as np

df_dataset = pd.read_csv('D:\1 tugas kuliah\sems\ML\project uts\Dataset UTS_Gasal 2425.csv')
df_dataset
```

	squaremeters	numberofrooms	hasyard	haspool	floors	citycode	citypartrange	numprevowners	made	isnewbuilt	hasstormprotector	basement	attic	garage	hasstorageroom	hasguestroom
0	75523	3	no	yes	63	9373	3	8	2005	old	yes	4313	9005	956	no	
1	55712	58	no	yes	19	34457	6	8	2021	old	no	2937	8852	135	yes	
2	86929	100	yes	no	11	98155	3	4	2003	new	no	6326	4748	654	no	
3	51522	3	no	no	61	9047	8	3	2012	new	yes	632	5792	807	yes	
4	96470	74	yes	no	21	92029	4	2	2011	new	yes	5414	1172	716	yes	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	341	83	no	no	8	1960	4	4	1993	new	yes	2366	4016	229	yes	
9996	21514	5	no	yes	11	91373	1	1	1999	old	no	2584	5266	787	no	
9997	1726	89	no	yes	5	73133	7	6	2009	old	yes	9311	1698	218	no	
9998	44403	29	yes	yes	12	34606	9	4	1990	old	yes	9061	1742	230	no	
9999	1440	84	no	no	49	18412	6	10	1994	new	no	8485	2024	278	yes	

10000 rows x 18 columns

```
[57] df_dataset2 = df_dataset.drop(['category'], axis=1)
df_dataset2
```

	squaremeters	numberofrooms	hasyard	haspool	floors	citycode	citypartrange	numprevowners	made	isnewbuilt	hasstormprotector	basement	attic	garage	hasstorageroom	hasguestroom
0	75523	3	no	yes	63	9373	3	8	2005	old	yes	4313	9005	956	no	
1	55712	58	no	yes	19	34457	6	8	2021	old	no	2937	8852	135	yes	
2	86929	100	yes	no	11	98155	3	4	2003	new	no	6326	4748	654	no	
3	51522	3	no	no	61	9047	8	3	2012	new	yes	632	5792	807	yes	
4	96470	74	yes	no	21	92029	4	2	2011	new	yes	5414	1172	716	yes	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	341	83	no	no	8	1960	4	4	1993	new	yes	2366	4016	229	yes	
9996	21514	5	no	yes	11	91373	1	1	1999	old	no	2584	5266	787	no	
9997	1726	89	no	yes	5	73133	7	6	2009	old	yes	9311	1698	218	no	
9998	44403	29	yes	yes	12	34606	9	4	1990	old	yes	9061	1742	230	no	
9999	1440	84	no	no	49	18412	6	10	1994	new	no	8485	2024	278	yes	

10000 rows x 17 columns

```
[58] df_dataset2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 17 columns):
 #   Column              Non-Null Count  Dtype  
---  -
 0   squaremeters        10000 non-null  int64  
 1   numberofrooms       10000 non-null  int64  
 2   hasyard             10000 non-null  object  
 3   haspool             10000 non-null  object  
 4   floors              10000 non-null  int64  
 5   citycode            10000 non-null  int64  
 6   citypartrange       10000 non-null  int64  
 7   numprevowners       10000 non-null  int64  
 8   made                10000 non-null  int64  
 9   isnewbuilt          10000 non-null  object  
10   hasstormprotector   10000 non-null  object  
11   basement            10000 non-null  int64  
12   attic               10000 non-null  int64  
13   garage              10000 non-null  int64  
14   hasstorageroom      10000 non-null  object  
15   hasguestroom        10000 non-null  int64  
16   price               10000 non-null  float64
dtypes: float64(1), int64(11), object(5)
memory usage: 1.3+ MB
```

```
[59] df_dataset2.describe()
```

	squaremeters	numberofrooms	floors	citycode	citypartrange	numprevowners	made	basement	attic	garage	hasguestroom	price
count	10000.00000	10000.00000	10000.00000	10000.00000	10000.00000	10000.00000	10000.00000	10000.00000	10000.00000	10000.00000	10000.00000	1.000000e+04
mean	49870.13120	50.358400	50.276300	50225.486100	5.510100	5.521700	2005.48850	5033.103900	5028.01060	553.12120	4.99460	4.993448e+06
std	28774.37535	28.816696	28.889171	29006.675799	2.872024	2.856667	9.30809	2876.729545	2894.33221	262.05017	3.17641	2.877424e+06
min	89.00000	1.000000	1.000000	3.000000	1.000000	1.000000	1990.00000	0.000000	1.00000	100.00000	0.00000	1.031350e+04
25%	25098.50000	25.000000	25.000000	24693.750000	3.000000	3.000000	1997.00000	2559.750000	2512.00000	327.75000	2.00000	2.516402e+06
50%	50105.50000	50.000000	50.000000	50693.000000	5.000000	5.000000	2005.50000	5092.500000	5045.00000	554.00000	5.00000	5.016180e+06
75%	74609.75000	75.000000	76.000000	75683.250000	8.000000	8.000000	2014.00000	7511.250000	7540.50000	777.25000	8.00000	7.469092e+06
max	99999.00000	100.000000	100.000000	99953.000000	10.000000	10.000000	2021.00000	10000.000000	10000.00000	1000.00000	10.00000	1.000677e+07

```
print("Data null \n", df_dataset2.isnull().sum())
print("\nData kosong \n", df_dataset2.empty)
print("\nData NaN \n", df_dataset2.isna().sum())
```

Data null

squaremeters	0
numberofrooms	0
hasyard	0
haspool	0
floors	0
citycode	0
citypartrange	0
numprevowners	0
made	0
isnewbuilt	0
hasstormprotector	0
basement	0
attic	0
garage	0
hasstorageroom	0
hasguestroom	0
price	0

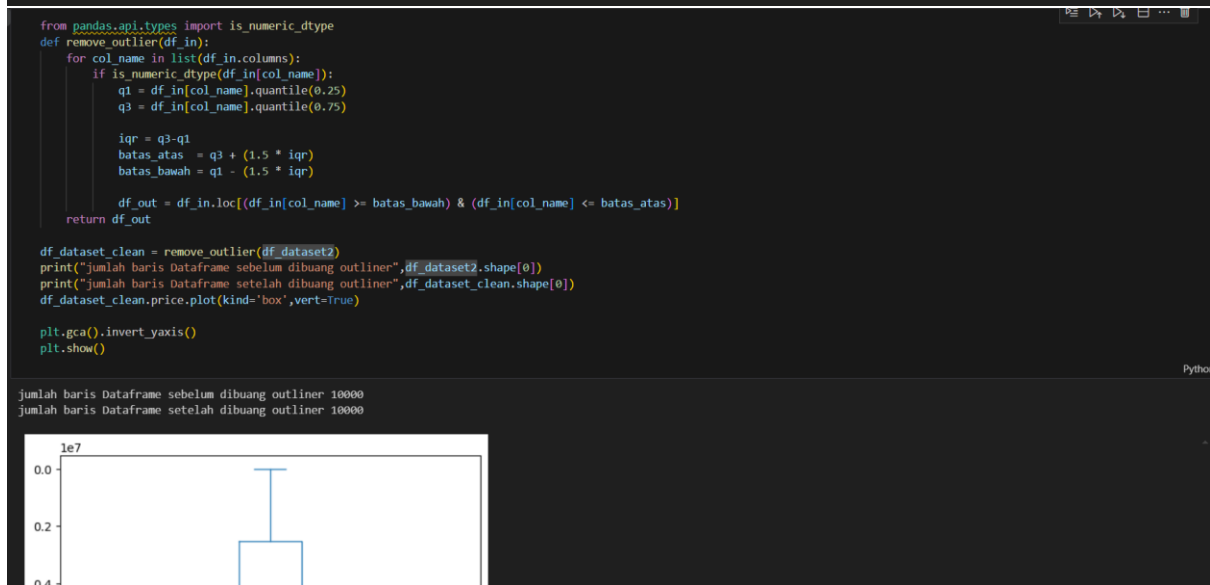
dtype: int64

Data kosong

False

Data NaN

squaremeters	0
...	
hasstorageroom	0
hasguestroom	0
price	0



```

from sklearn.model_selection import train_test_split
X_regress = df_dataset_clean.drop('price',axis=1)
Y_regress = df_dataset_clean.price

```

```

X_train, X_test, y_train, y_test = train_test_split(X_regress, Y_regress, \
                                                    test_size = 0.25,
                                                    random_state=20)

```

+ Code + Markdown

Python

```

from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import make_column_transformer

```

```

kolom_kategori=['hasyard','haspool','isnewbuilt','hasstormprotector', 'hasstorageroom']

```

```

transform = make_column_transformer(
    (OneHotEncoder(),kolom_kategori),remainder='passthrough'
)

```

Python

```

x_train_enc = transform.fit_transform(X_train)
X_test_enc = transform.fit_transform(X_test)

df_train_enc = pd.DataFrame(x_train_enc,columns=transform.get_feature_names_out())
df_test_enc = pd.DataFrame(X_test_enc,columns=transform.get_feature_names_out())

df_train_enc
df_test_enc

```

Python

	onehotencoder_hasyard_no	onehotencoder_hasyard_yes	onehotencoder_haspool_no	onehotencoder_haspool_yes	onehotencoder_isnewbuilt_new	onehotencoder_isnewbuilt_old	onehotencoder
0	0.0	1.0	0.0	1.0	0.0	1.0	
1	1.0	0.0	1.0	0.0	0.0	1.0	
2	1.0	0.0	0.0	1.0	1.0	0.0	
3	0.0	1.0	1.0	0.0	0.0	1.0	
4	1.0	0.0	0.0	1.0	1.0	0.0	
...	...	...	...	...	...	...	
2495	1.0	0.0	0.0	1.0	1.0	0.0	
2496	0.0	1.0	0.0	1.0	1.0	0.0	
2497	0.0	1.0	0.0	1.0	0.0	1.0	
2498	1.0	0.0	1.0	0.0	0.0	1.0	
2499	1.0	0.0	1.0	0.0	0.0	1.0	

2500 rows × 21 columns

```

from sklearn.linear_model import Ridge
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.feature_selection import SelectKBest, f_regression
from sklearn.metrics import mean_absolute_error, mean_squared_error

pipe_Ridge = Pipeline(steps=[
    ('scale', StandardScaler()),
    ('feature_selection', SelectKBest(score_func=f_regression)),
    ('reg', Ridge())
])

```

```

param_grid_Ridge = {
    'reg__alpha':[0.01,0.1,1,10,100,1000],
    'feature_selection__k':np.arange(1,20),
}

```

```

GSCV_RR = GridSearchCV(pipe_Ridge, param_grid_Ridge, cv = 5,
                        scoring='neg_mean_squared_error', error_score='raise')

```

```

GSCV_RR.fit(x_train_enc, y_train)

```

```

print("best Model:{}".format(GSCV_RR.best_estimator_))

```

```

print("Ridge best parameters:{}".format(GSCV_RR.best_params_))

```

```

print("Koeffisien/bobot:{}".format(GSCV_RR.best_estimator_.named_steps['reg'].coef_))

```

```

print("Intercept/bias:{}".format(GSCV_RR.best_estimator_.named_steps['reg'].intercept_))

```

```

Ridge_predict = GSCV_RR.predict(X_test_enc)

```

```

mse_Ridge = mean_squared_error(y_test, Ridge_predict)

```

```

mae_Ridge = mean_absolute_error(y_test, Ridge_predict)

```

```

print("Ridge mean Squared Error (MSE): {}".format(mse_Ridge))

```

```

print("Ridge Mean Absolute Error (MAE): {}".format(mae_Ridge))

```

```

print("Ridge Root Mean Squared Error: {}".format(np.sqrt(mse_Ridge)))

```

Python

```

best Model:Pipeline(steps=[('scale', StandardScaler()),
    ('feature_selection',
    SelectKBest(k=19,
    score_func=<function f_regression at 0x00002797E4A7E20>)),
    ('reg', Ridge(alpha=0.01))])
Ridge best parameters: {'feature_selection__k': 19, 'reg__alpha': 0.01}

```

Spaces: 4 Cell: 11 of 21 Go Live

```
df_results = pd.DataFrame(y_test, columns=["price"])
df_results = pd.DataFrame(y_test)
df_results['Ridge prediction'] = Ridge_predict

df_results['Selisih_price_RR'] = df_results['Ridge prediction'] - df_results['price']

df_results

2500 rows x 3 columns

df_results.describe()

price Ridge prediction Selisih IPK RR
9957 3055190.2 3.051666e+06 -3524.193541
1687 7719488.8 7.719265e+06 -224.272822
2116 9265884.1 9.266680e+06 796.068579
231 6126371.1 6.126390e+06 18.889707
2780 9720521.5 9.722524e+06 2002.449403
... ... ... ...
8514 1349726.5 1.347881e+06 -1845.591504
5190 7578283.3 7.577291e+06 -992.486931
6766 2437565.3 2.435221e+06 -2344.283798
347 9086961.1 9.086326e+06 -634.693933
6961 3933732.6 3.934429e+06 696.320979

from sklearn.svm import SVR
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.feature_selection import SelectKBest, f_regression
from sklearn.metrics import mean_absolute_error, mean_squared_error

pipe_SVR = Pipeline(steps=[
    ('scale', StandardScaler()),
    ('feature_selection', SelectKBest(score_func=f_regression)),
    ('reg', SVR(kernel='linear'))
])

param_grid_SVR = (
    'reg_C': [0.01, 0.1, 1, 10, 100],
    'reg_epsilon': [0.1, 0.2, 0.5, 1],
    'feature_selection_k': np.arange(1, 20)
)

gscv_SVR = GridSearchCV(pipe_SVR, param_grid_SVR, cv=5, scoring='neg_mean_squared_error')

gscv_SVR.fit(x_train_enc, y_train)

print("best Model: {}".format(gscv_SVR.best_estimator_))
print("SVR best parameters: {}".format(gscv_SVR.best_params_))

print("Koefisien/bobot: {}".format(gscv_SVR.best_estimator_.named_steps['reg'].coef_))
print("Intercept/bias: {}".format(gscv_SVR.best_estimator_.named_steps['reg'].intercept_))

SVR_predict = gscv_SVR.predict(X_test_enc)

mse_SVR = mean_squared_error(y_test, SVR_predict)
mae_SVR = mean_absolute_error(y_test, SVR_predict)

print("SVR Mean Squared Error (MSE): {}".format(mse_SVR))
print("SVR Mean Absolute Error (MAE): {}".format(mae_SVR))
print("SVR Root Mean Squared Error: {}".format(np.sqrt(mse_SVR)))

best Model: Pipeline(steps=[('scale', StandardScaler()),
                             ('feature_selection',
                              SelectKBest(k=1,
                                             score_func=<function f_regression at 0x000002797E4A7E20>)),
                             ('reg', SVR(C=100, kernel='linear'))])
SVR best parameters: {'feature_selection_k': 1, 'reg_C': 100, 'reg_epsilon': 0.1}
Koefisien/bobot: [[648847.92251728]]
Intercept/bias: [5021559.39311446]
SVR Mean Squared Error (MSE): 4920673080582.885
SVR Mean Absolute Error (MAE): 1909730.1031783433
SVR Root Mean Squared Error: 2218239.028155871

df_results['SVR prediction'] = SVR_predict
df_results = pd.DataFrame(y_test)
df_results['SVR prediction'] = SVR_predict

df_results['Selisih_price_SVR'] = df_results['SVR prediction'] - df_results['price']

df_results.head()

price SVR prediction Selisih_price_SVR
9957 3055190.2 4.582547e+06 1.527356e+06
1687 7719488.8 5.635386e+06 -2.084103e+06
2116 9265884.1 5.982655e+06 -3.283229e+06
231 6126371.1 5.276162e+06 -8.502087e+05
2780 9720521.5 6.085625e+06 -3.634897e+06

df_results.describe()

price SVR prediction Selisih_price_SVR
9957 3055190.2 4.582547e+06 1.527356e+06
1687 7719488.8 5.635386e+06 -2.084103e+06
2116 9265884.1 5.982655e+06 -3.283229e+06
231 6126371.1 5.276162e+06 -8.502087e+05
2780 9720521.5 6.085625e+06 -3.634897e+06
```

```
df_results = pd.DataFrame({'price':y_test})

df_results['Ridge Prediction'] = Ridge_predict
df_results['Selisih_price_RR'] = df_results['price'] - df_results['Ridge Prediction']

df_results['SVR Prediction'] = SVR_predict
df_results['Selisih_price_SVR'] = df_results['price'] - df_results['SVR Prediction']

df_results.head()
```

	price	Ridge Prediction	Selisih_price_RR	SVR Prediction	Selisih_price_SVR
9957	3055190.2	3.051666e+06	3524.193541	4.582547e+06	-1.527356e+06
1687	7719488.8	7.719265e+06	224.272822	5.635386e+06	2.084103e+06
2116	9265884.1	9.266680e+06	-796.068579	5.982655e+06	3.283229e+06
231	6126371.1	6.126390e+06	-18.889707	5.276162e+06	8.502087e+05
2780	9720521.5	9.722524e+06	-2002.449403	6.085625e+06	3.634897e+06

```
df_results.describe()
```

	price	Ridge Prediction	Selisih_price_RR	SVR Prediction	Selisih_price_SVR
count	2.500000e+03	2.500000e+03	2500.000000	2.500000e+03	2.500000e+03
mean	4.984921e+06	4.984926e+06	-5.190951	5.019020e+06	-3.409985e+04
std	2.862950e+06	2.862962e+06	1881.424864	6.445100e+05	2.218441e+06
min	1.548800e+04	1.666434e+04	-6265.641829	3.901132e+06	-3.885644e+06
25%	2.531105e+06	2.533338e+06	-1178.857910	4.466953e+06	-1.935848e+06
50%	4.986667e+06	4.987591e+06	-2.898140	5.019965e+06	-3.354598e+04
75%	7.302733e+06	7.302944e+06	-4.610247e+02	5.570391e+06	-4.870433e+05
max	1.548800e+07	1.666434e+07	-6265.641829	6.445100e+06	-3.885644e+06

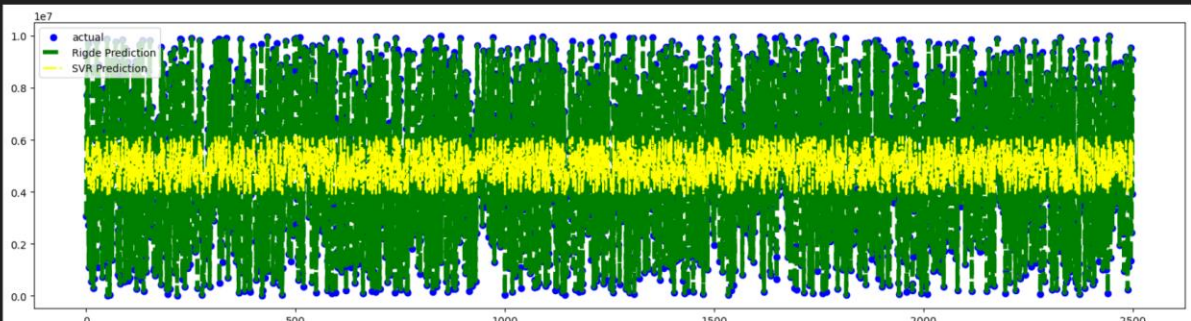
```
import matplotlib.pyplot as plt

plt.figure(figsize=(20,5))

data_len = range(len(y_test))

plt.scatter(data_len, df_results.price, label="actual", color="blue")
plt.plot(data_len, df_results['Ridge Prediction'], label="Ridge Prediction", color="green", linewidth=4, linestyle="dashed")
plt.plot(data_len, df_results['SVR Prediction'], label="SVR Prediction", color="yellow", linewidth=2, linestyle="-.")
plt.legend()
plt.show
```

<function matplotlib.pyplot.show(close=None, block=None)>



```
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np

mae_ridge = mean_absolute_error(df_results['price'], df_results['Ridge Prediction'])
rmse_ridge = np.sqrt(mean_squared_error(df_results['price'], df_results['Ridge Prediction']))
ridge_feature_count = GSCV_RR.best_params_['feature_selection_k']

mae_svr = mean_absolute_error(df_results['price'], df_results['SVR Prediction'])
rmse_svr = np.sqrt(mean_squared_error(df_results['price'], df_results['SVR Prediction']))
svr_feature_count = GSCV_SVR.best_params_['feature_selection_k']

print(f'Ridge MAE: {mae_ridge}, Ridge RMSE: {rmse_ridge}, Ridge Feature Count: {ridge_feature_count}')
print(f'SVR MAE: {mae_svr}, SVR RMSE: {rmse_svr}, SVR Feature Count: {svr_feature_count}')
```

Ridge MAE: 1466.0025565480937, Ridge RMSE: 1881.0557034890273, Ridge Feature Count: 19  
SVR MAE: 1909730.1031783433, SVR RMSE: 2218259.020155871, SVR Feature Count: 1

```
import pickle

best_model = GSCV_SVR.best_estimator_

with open('BestModel REG SVR SciPy.pkl', 'wb') as f:
    pickle.dump(best_model, f)

print("Model terbaik berhasil disimpan ke BestModel REG SVR SciPy.pkl")
```