AML_HW1_Questions

September 23, 2024

0.1 Homework 1: Applied Machine Learning

This assignment covers contents of the first three lectures.

The emphasis for this assignment would be on the following: 1. Data Visualization and Analysis 2. Linear Models for Regression and Classification 3. Support Vector Machines

[83]:
```python
import warnings

def fxn():
    warnings.warn("deprecated", DeprecationWarning)

with warnings.catch_warnings():
    warnings.simplefilter("ignore")
    fxn()
```

[84]:
```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from numpy.linalg import inv
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder, OrdinalEncoder
from sklearn.metrics import r2_score
from sklearn.svm import LinearSVC, SVC
```

0.2 Part 1: Data Visualization and Analysis

Understanding data characteristics and patterns is crucial for building effective models. In this part, we will visualize and analyze the `insurance.csv` dataset.

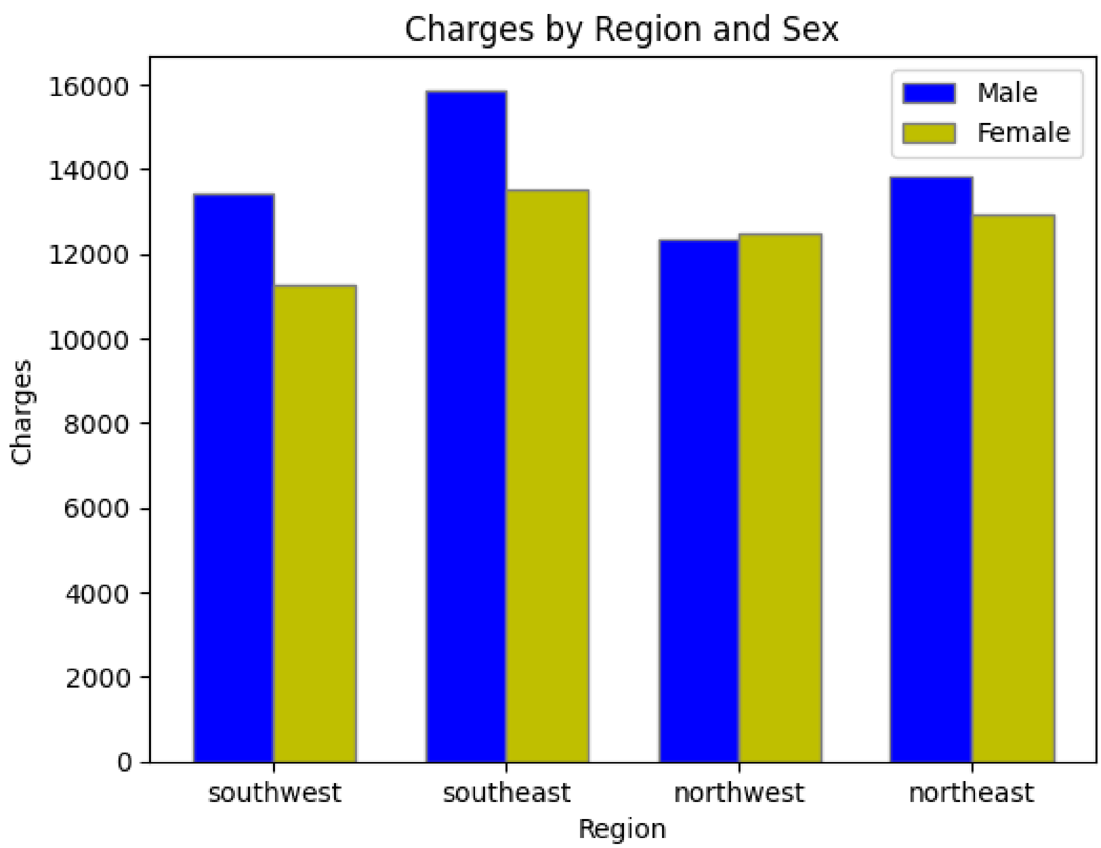
Note: Remember to label plot axes while plotting.

[85]:
```python
# Load the dataset
insurance_df = pd.read_csv('insurance.csv')
```

1.1 Create a bar chart to compare the average insurance charges by sex and region.

[86]:

```
regions = insurance_df['region'].unique()

mean_charges_male = [insurance_df[(insurance_df['region'] == region) &␣
 ↪(insurance_df['sex'] == 'male')]['charges'].mean() for region in regions]
mean_charges_female = [insurance_df[(insurance_df['region'] == region) &␣
 ↪(insurance_df['sex'] == 'female')]['charges'].mean() for region in regions]

bar_width = 0.35

r1 = np.arange(len(regions))
r2 = [x + bar_width for x in r1]

plt.bar(r1, mean_charges_male, color='b', width=bar_width, edgecolor='grey',␣
 ↪label='Male')
plt.bar(r2, mean_charges_female, color='y', width=bar_width, edgecolor='grey',␣
 ↪label='Female')


plt.title('Charges by Region and Sex')
plt.xlabel('Region')
plt.ylabel('Charges')
plt.xticks([r + bar_width/2 for r in range(len(regions))], regions)

plt.legend()
plt.show()
```

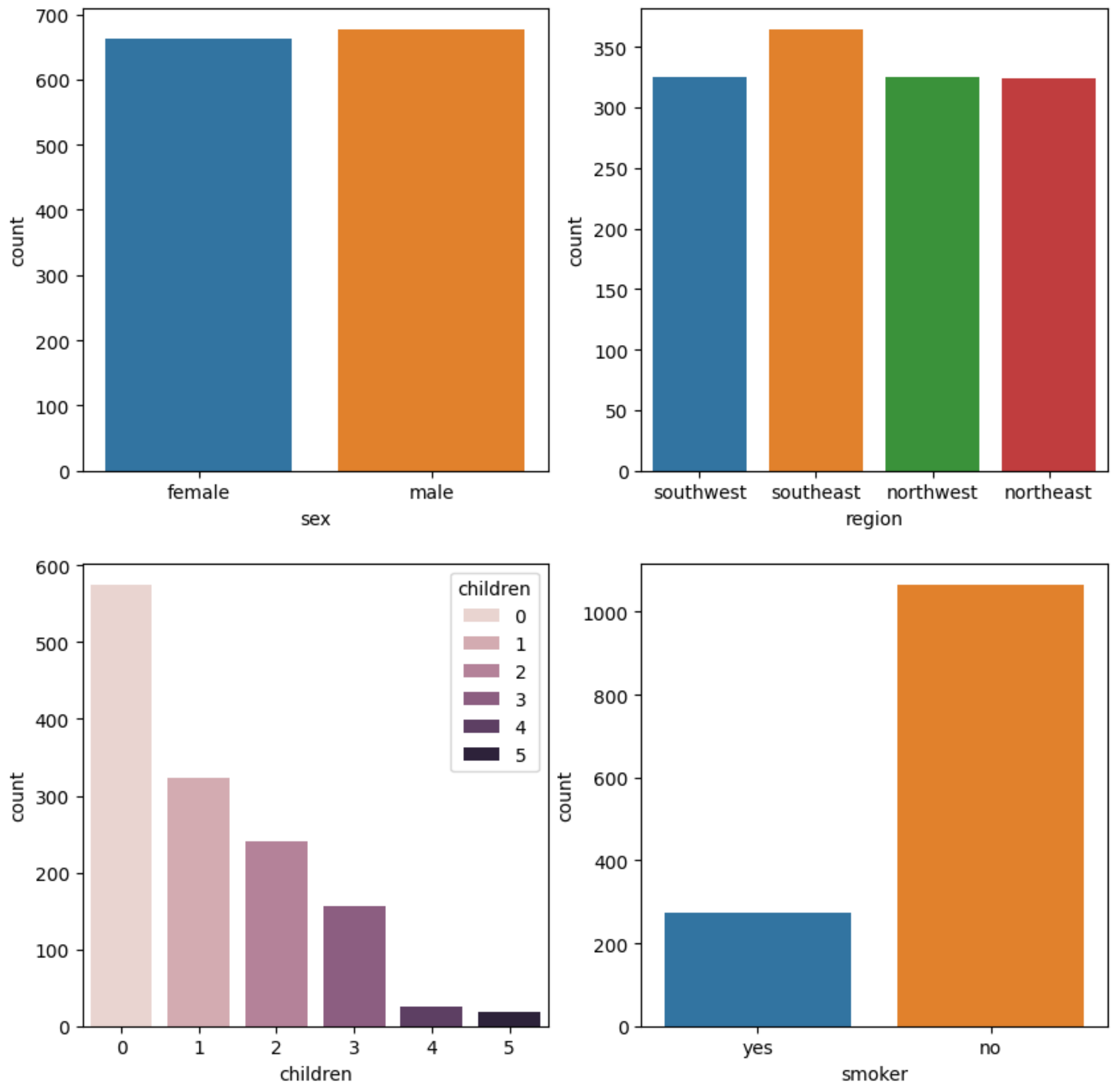


The plot shows the average charges varies by region but it shows that the charges for female-identified individuals are lower than for male identified individuals in all regions.

1.2 Plot a small multiple of bar charts to visualize the data distribution for the following categorical variables: 1. **sex** 2. **region** 3. **children** 4. **smoker**

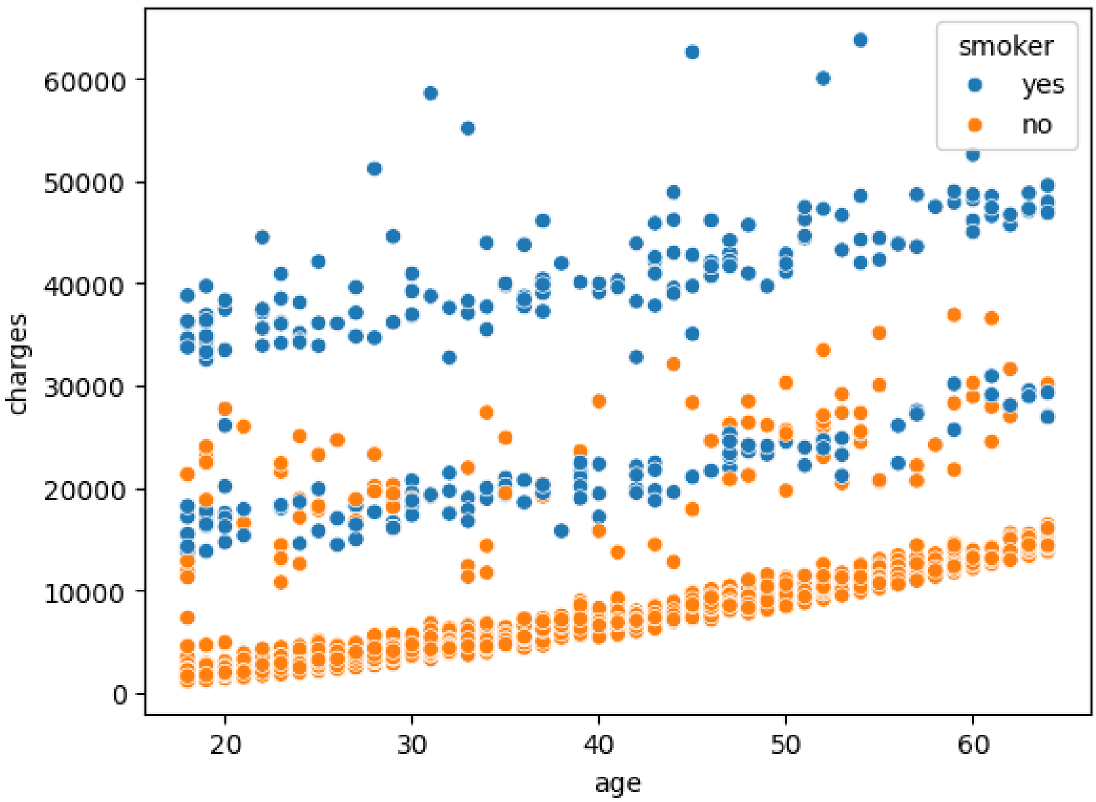
Make subplots in the same graph

[87]:
```
variables = ["sex",'region','children','smoker']
fig, ax = plt.subplots(2,2,figsize=(10,10))

for var, subplot in zip(variables, ax.flatten()):
    sns.countplot(x=var, data=insurance_df, ax=subplot,hue = var)
```



1.3 Compare the insurance charges by age and smoker. Create a Scatter plot for age vs insurance charges categorize them by smoker type.

[88]:
```
sns.scatterplot(x='age',y='charges',data=insurance_df,hue='smoker')
plt.show()
```



0.3 Part 2: Linear Models for Regression and Classification

In this section, we will be implementing three linear models **linear regression, logistic regression, and SVM**.

0.3.1 2.1 Linear Regression

We will now proceed with splitting the dataset and implementing linear regression to predict `insurance charges`.

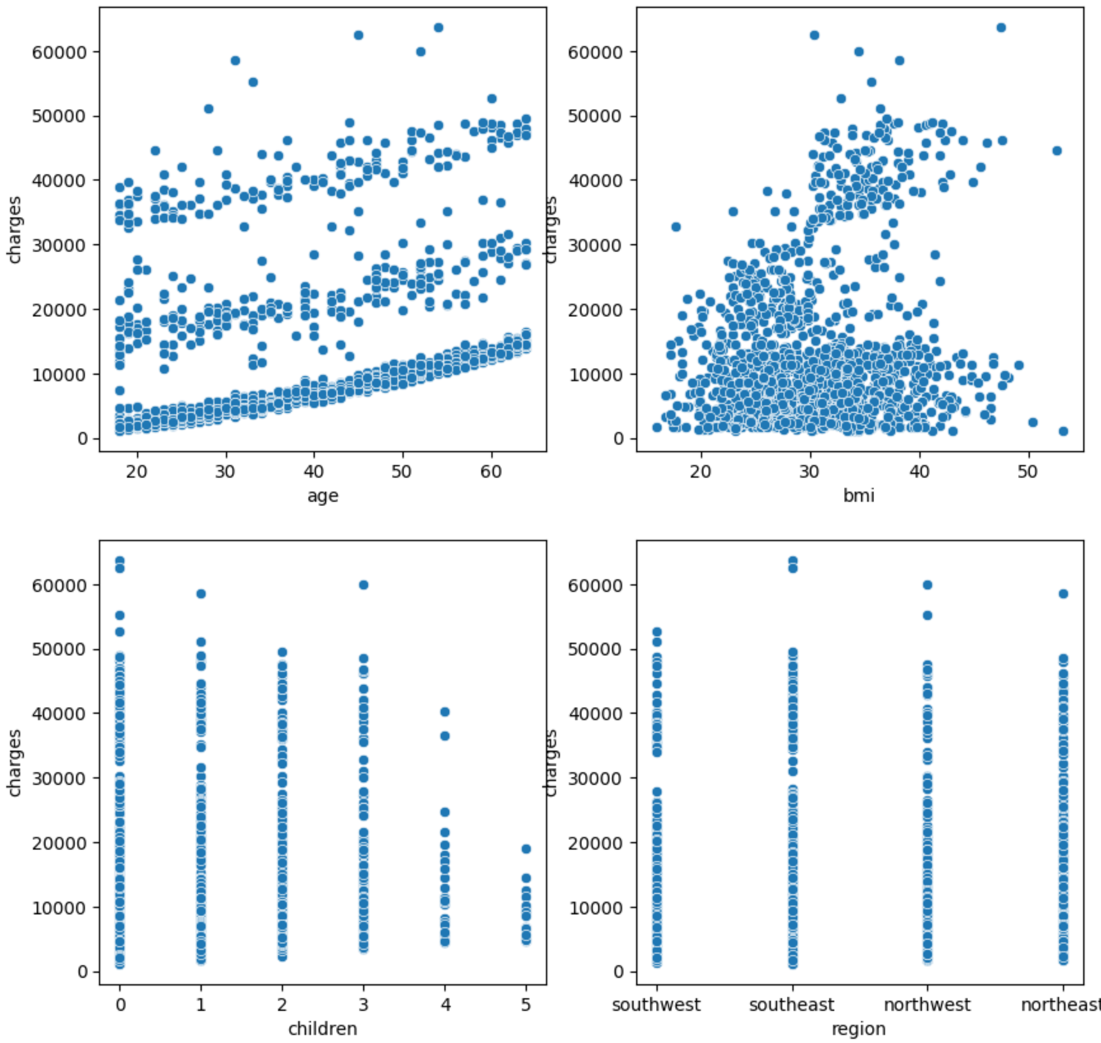
[89]:
```
# Split the dataset into features and labels
insurance_X = insurance_df.drop(columns=['charges'])
insurance_y = insurance_df['charges']
```

2.1.1 Plot relationships between features (age, bmi, children, region) and the target variable `charges` as a small multiple of scatter plots. 1. age 2. bmi 3. children 4. region

Make sure to label the axes.

[90]:
```
variables = ["age",'bmi','children','region']
fig, ax = plt.subplots(2,2,figsize=(10,10))

for var, subplot in zip(variables, ax.flatten()):
```

```
    sns.scatterplot(x=var, y ='charges', data=insurance_df, ax=subplot)
```



2.1.2 From the visualizations above, do you think linear regression is a good model for this problem? Why and/or why not? Please explain.

Linear regression could be a good model if we take all the categorical data into consideration - as some of the features shows linear relationship within certain clusters. If these cluster can be modeled using categorical features, then linear regression could work. Linear regression is good because we want to predict the final charges, which is a numerical value. However, it is important to note that these variables do not show a straightforward continuous relationship with the target variables.

0.3.2 Data Preprocessing

Before we can fit a linear regression model, several pre-processing steps should be applied to the dataset:

1. **Encode categorical features appropriately** (e.g., `sex`, `smoker`, `region`).
2. **Check for multicollinearity** by analyzing the correlation matrix and removing any highly collinear features.
3. **Split the dataset** into training (60%), validation (20%), and test (20%) sets.
4. **Standardize the feature matrices** (`X_train`, `X_val`, and `X_test`) to have zero mean and unit variance. Ensure that the standardization parameters (mean, variance) are learned from `X_train` and then applied to all sets to avoid information leakage.
5. **Add a column of ones** to `X_train`, `X_val`, and `X_test` for learning the bias term in the linear model.

2.1.3 Encode the categorical variables of the Insurance dataset.

[91]:
```
### Code here
from sklearn.compose import make_column_transformer



ohe_features=["sex",'smoker','region']
encoder = OneHotEncoder()

encoded_features = encoder.fit_transform(insurance_X[ohe_features])

encoded_df = pd.DataFrame(encoded_features.toarray(), columns=encoder.
 ↪get_feature_names_out(ohe_features))
insurance_X = insurance_X.drop(columns=ohe_features).reset_index(drop=True)
insurance_X = pd.concat([insurance_X, encoded_df], axis=1)
```

2.1.4 Plot the correlation matrix, and check if there is high correlation between the given numerical features (Threshold >= 0.8). If yes, drop one from each pair of highly correlated features from the dataframe. It is fine if you do not find any highly correlated features. Why could this be necessary before proceeding further?

[92]:
```
insurance_X.corr()
```

[92]:
```
                       age       bmi  children  sex_female  sex_male  \
age               1.000000  0.109272  0.042469    0.020856 -0.020856
bmi               0.109272  1.000000  0.012759   -0.046371  0.046371
children          0.042469  0.012759  1.000000   -0.017163  0.017163
sex_female        0.020856 -0.046371 -0.017163    1.000000 -1.000000
sex_male         -0.020856  0.046371  0.017163   -1.000000  1.000000
smoker_no         0.025019 -0.003750 -0.007673    0.076185 -0.076185
smoker_yes       -0.025019  0.003750  0.007673   -0.076185  0.076185
region_northeast  0.002475 -0.138156 -0.022808    0.002425 -0.002425
region_northwest -0.000407 -0.135996  0.024806    0.011156 -0.011156
region_southeast -0.011642  0.270025 -0.023066   -0.017117  0.017117
region_southwest  0.010016 -0.006205  0.021914    0.004184 -0.004184

                  smoker_no  smoker_yes  region_northeast  region_northwest  \
age                0.025019   -0.025019          0.002475         -0.000407
```

```
bmi                -0.003750   0.003750         -0.138156         -0.135996
children           -0.007673   0.007673         -0.022808          0.024806
sex_female          0.076185  -0.076185          0.002425          0.011156
sex_male           -0.076185   0.076185         -0.002425         -0.011156
smoker_no           1.000000  -1.000000         -0.002811          0.036945
smoker_yes         -1.000000   1.000000          0.002811         -0.036945
region_northeast   -0.002811   0.002811          1.000000         -0.320177
region_northwest    0.036945  -0.036945         -0.320177          1.000000
region_southeast   -0.068498   0.068498         -0.345561         -0.346265
region_southwest    0.036945  -0.036945         -0.320177         -0.320829

                  region_southeast  region_southwest
age                      -0.011642          0.010016
bmi                       0.270025         -0.006205
children                 -0.023066          0.021914
sex_female               -0.017117          0.004184
sex_male                  0.017117         -0.004184
smoker_no                -0.068498          0.036945
smoker_yes                0.068498         -0.036945
region_northeast         -0.345561         -0.320177
region_northwest         -0.346265         -0.320829
region_southeast          1.000000         -0.346265
region_southwest         -0.346265          1.000000
```

[93]:
```
insurance_X.drop(columns=['sex_female','smoker_no','region_northeast'], inplace=True)
```

We want to avoid multicolinearity because we are seeking a close formed solution, and you can not find the inverse of the X matrix if it is not full rank.

2.1.5 Split the dataset into training (60%), validation (20%), and test (20%) sets.

[94]:
```
insurance_X_dev, insurance_X_test, insurance_y_dev, insurance_y_test = train_test_split(insurance_X, insurance_y, test_size=0.2, random_state=0)
insurance_X_train, insurance_X_val, insurance_y_train, insurance_y_val = train_test_split(insurance_X_dev, insurance_y_dev, test_size=0.25, random_state=0)
```

2.1.6 Standardize the columns in the feature matrices.

[95]:
```
### Code here
numerical_features = ['age', 'bmi', 'children']

scaler = StandardScaler()
scaler.fit(insurance_X_train[numerical_features])

insurance_X_train[numerical_features] = scaler.transform(insurance_X_train[numerical_features])
```

```
insurance_X_val[numerical_features] = scaler.
  ↪transform(insurance_X_val[numerical_features])
insurance_X_test[numerical_features] = scaler.
  ↪transform(insurance_X_test[numerical_features])
```

[96]:
```
# Adding a column of ones to include the bias term
columns = insurance_X_train.columns
insurance_X_train = np.hstack([np.ones((insurance_X_train.shape[0], 1)),␣
  ↪insurance_X_train])
insurance_X_val = np.hstack([np.ones((insurance_X_val.shape[0], 1)),␣
  ↪insurance_X_val])
insurance_X_test = np.hstack([np.ones((insurance_X_test.shape[0], 1)),␣
  ↪insurance_X_test])
```

At the end of this pre-processing, you should have the following vectors and matrices:

- **insurance_X_train**: Training set feature matrix.
- **insurance_X_val**: Validation set feature matrix.
- **insurance_X_test**: Test set feature matrix.
- **insurance_y_train**: Training set labels (insurance charges).
- **insurance_y_val**: Validation set labels.
- **insurance_y_test**: Test set labels.

0.3.3 Implement Linear Regression

Now that the data is preprocessed, we can implement a linear regression model, specifically Ridge Regression, which incorporates L2 regularization.

Given a feature matrix (X), a label vector (y), and a weight vector (w), the hypothesis function for linear regression is:

$$y = Xw$$

The objective is to find the optimal weight vector (w) that minimizes the following loss function:

$$\min_w \|Xw - y\|_2^2 + \alpha \|w\|_2^2$$

Where: - $\|Xw - y\|_2^2$ penalizes predictions that differ from actual labels. - $\alpha \|w\|_2^2$ is the regularization term, helping reduce overfitting by penalizing large weights. - α is the regularization parameter.

The closed-form solution for Ridge Regression is given by the Normal Equations:

$$w = (X^T X + \alpha I)^{-1} X^T y$$

2.1.7 Implement a `LinearRegression` class with `train` and `predict` methods

We will now implement a custom `LinearRegression` class with L2 regularization (Ridge Regression).

Note: You may NOT use sklearn for this implementation. You may, however, use `np.linalg.solve` to find the closed-form solution. It is highly recommended that you vectorize your code.

[97]:
```
class LinearRegression():
    '''
    Linear regression model with L2-regularization (i.e. ridge regression).

    Attributes
    ----------
    alpha: regularization parameter
    w: (n x 1) weight vector
    '''
    def __init__(self, alpha=0):
        self.alpha = alpha
        self.w = None

    def train(self, X, y):
        '''Trains model using ridge regression closed-form solution.
        Parameters:
        X : (m x n) feature matrix
        y: (m x 1) label vector
        '''
        if type(y) == pd.Series:
            y = y.values
        if type(X) == pd.DataFrame:
            X = X.values
        self.w = np.linalg.solve(X.T @ X + self.alpha * np.eye(X.shape[1]), X.T␣
↪@ y)


    def predict(self, X):
        '''Predicts on X using trained model.
        Parameters:
        X : (m x n) feature matrix
        Returns:
        y_pred: (m x 1) prediction vector
        '''
        y_predict = X @ self.w
        return y_predict
```

2.1.8 Train, Evaluate, and Interpret Linear Regression Model

Train a linear regression model ($\alpha = 0$) on the insurance dataset. Make predictions and report the R^2 score on the training, validation, and test sets. Report the first 3 and last 3 predictions on the test set, along with the actual labels.

[98]:
```python
def get_report(y_pred, y_test):
    """
    Report the first 3 and last 3 predictions on X_test,
    along with the actual labels in y_test.

    Returns:
        A dataframe with 6 rows comparing predictions and actuals.
    """
    preds = np.concatenate([y_pred[:3], y_pred[-3:]])
    actuals = np.concatenate([y_test[:3], y_test[-3:]])
    df_compare = pd.DataFrame({'Prediction': preds,
                               'Actual': actuals})
    df_compare['Position'] = [1, 2, 3, len(y_pred) - 2, len(y_pred) - 1,␣
 ↪len(y_pred)]
    df_compare = df_compare.set_index('Position')
    return df_compare
```

[99]:
```python
model = LinearRegression()
model.train(insurance_X_train, insurance_y_train)
y_pred = model.predict(insurance_X_test)
get_report(y_pred, insurance_y_test)
```

[99]:

Position	Prediction	Actual
1	11351.075203	9724.53000
2	9700.882215	8547.69130
3	38235.614552	45702.02235
266	16352.480222	20709.02034
267	32989.621066	40932.42950
268	9542.694645	9500.57305

[100]:
```python
model.train(insurance_X_train, insurance_y_train)
y_train_pred = model.predict(insurance_X_train)
r2_train = r2_score(insurance_y_train, y_train_pred)
print(f"R^2 on training set is: {r2_train:.4f}")

y_val_pred = model.predict(insurance_X_val)
r2_val = r2_score(insurance_y_val, y_val_pred)
print(f"R^2 on validation set is: {r2_val:.4f}")

y_test_pred = model.predict(insurance_X_test)
r2_test = r2_score(insurance_y_test, y_test_pred)
print(f"R^2 on test set is: {r2_test:.4f}")
```

```
R^2 on training set is: 0.7410
R^2 on validation set is: 0.7242
R^2 on test set is: 0.7998
```

2.1.9 Use the mean of the training labels (insurance_y_train) as the prediction for all instances. Report the R^2 on the training, validation, and test sets using this baseline.

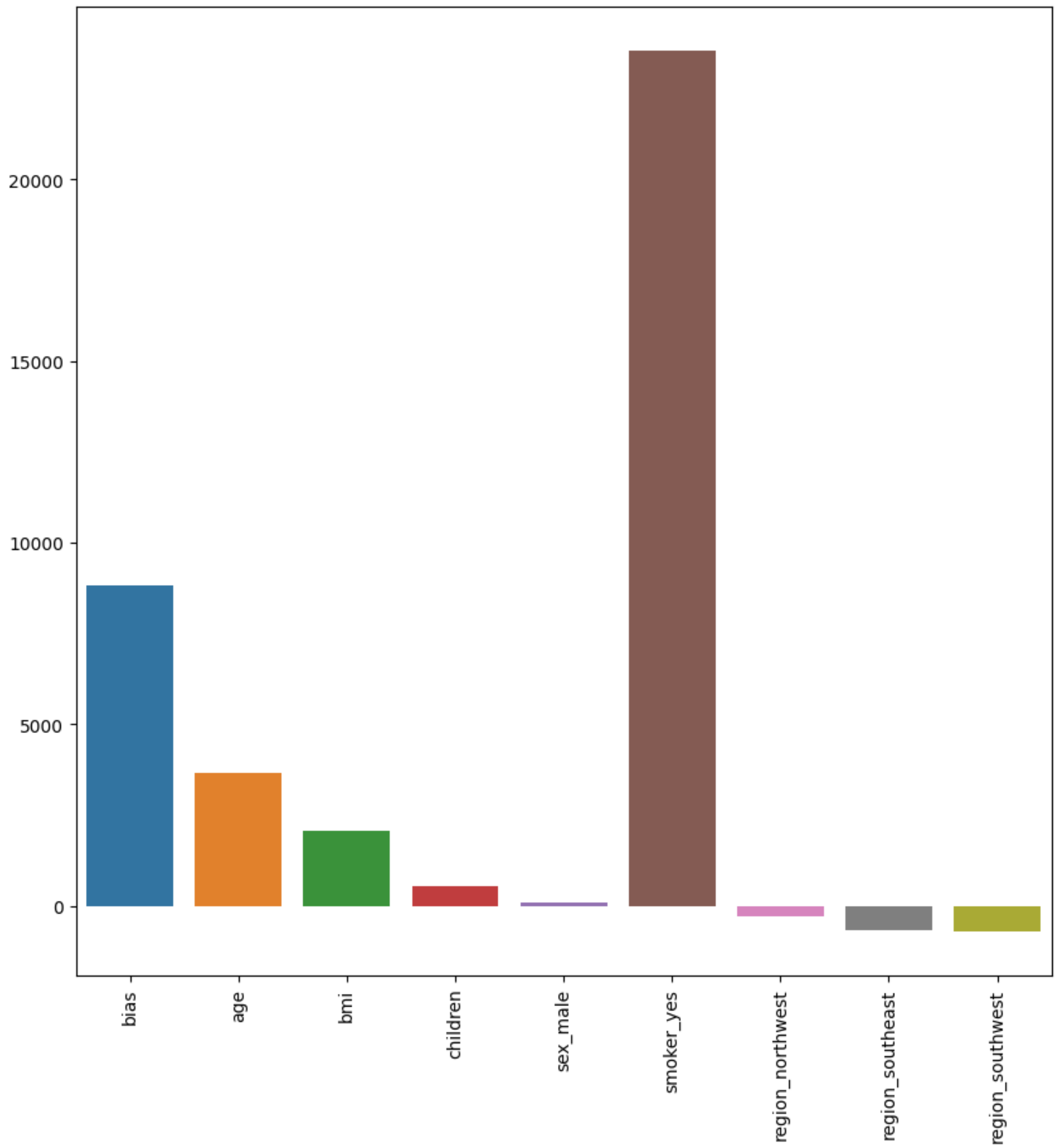
This is a common baseline used in regression problems and tells you if your model is any good. Your linear regression R^2 should be much higher than these baseline R^2.

[101]:
```
### Code here
y_pred_baseline = np.mean(insurance_y_train)
training_r2 = r2_score(insurance_y_train, np.full(insurance_y_train.shape,␣
 ↪y_pred_baseline))
validation_r2 = r2_score(insurance_y_val, np.full(insurance_y_val.shape,␣
 ↪y_pred_baseline))
test_r2 = r2_score(insurance_y_test, np.full(insurance_y_test.shape,␣
 ↪y_pred_baseline))
print(f"Baseline R^2: Training = {training_r2:.4f}, Validation = {validation_r2:
 ↪.4f}, Test = {test_r2:.4f}")
```

```
Baseline R^2: Training = 0.0000, Validation = -0.0008, Test = -0.0004
```

2.1.10 Interpret your model trained on the insurance dataset using a bar chart of the model weights. Make sure to label the bars (x-axis) and don't forget the bias term!

[102]:
```
weights = model.w
names = ['bias'] + list(columns)

fig = plt.figure(figsize=(10,10))
ax = sns.barplot(x=names,y = weights, hue = names)
ax.tick_params(axis='x', rotation=90)
```



2.1.11 According to your model, which features are the greatest contributors to insurance charges?

Smoker status and the age are the greatest contributor to insurance charges

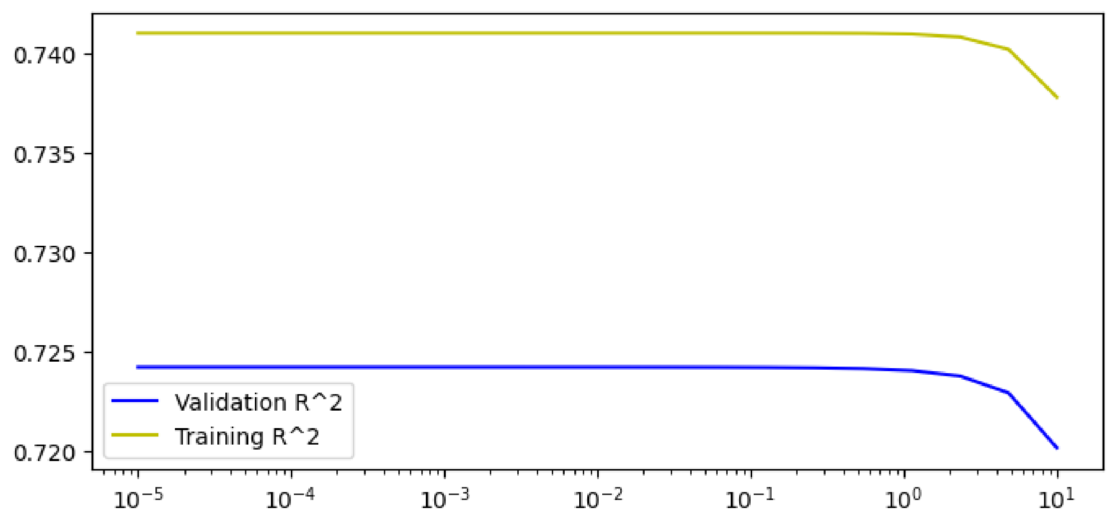
0.3.4 Hyperparameter Tuning (α)

Now, let's tune the α regularization parameter for ridge regression on the insurance dataset.

2.1.12 Sweep out values for α using `alphas = np.logspace(-5, 1, 20)`. Perform a grid search over these α values, recording the training and validation R^2 for each α. Plot the results with a log scale for α. A simple grid search is fine, no need for k-fold cross

validation. Plot the training and validation R^2 as a function of α on a single figure. Make sure to label the axes and the training and validation R^2 curves. Use a log scale for the x-axis.**

[103]:
```
### Code here

alphas= np.logspace(-5,1,20)

val_scores = []
train_scores = []
for alpha in alphas:
    model = LinearRegression(alpha=alpha)
    model.train(insurance_X_train, insurance_y_train)
    y_pred_train = model.predict(insurance_X_train)
    y_pred_val = model.predict(insurance_X_val)
    validation_r2 = r2_score(insurance_y_val, y_pred_val)
    train_r2 = r2_score(insurance_y_train, y_pred_train)
    val_scores.append(validation_r2)
    train_scores.append(train_r2)

fig = plt.figure(figsize=(8,8))
ax = fig.add_subplot(2, 1, 1)
plt.plot(alphas, val_scores, label='Validation R^2',color = 'b')
plt.plot(alphas, train_scores, label='Training R^2',color='y')
ax.set_xscale('log')
plt.legend()
plt.show()
```



2.1.13 Explain your plot above. How do training and validation R^2 behave with increasing α?

The model's performance decreases while increasing alpha

0.3.5 2.2 Logistic Regression

2.2.1 Load the dataset, the dataset to be used is loan_data.csv

[104]:
```
loan_data_df = pd.read_csv('loan_data.csv')
```

[105]:
```
loan_data_df = loan_data_df.drop(columns=['Loan_ID'])
```

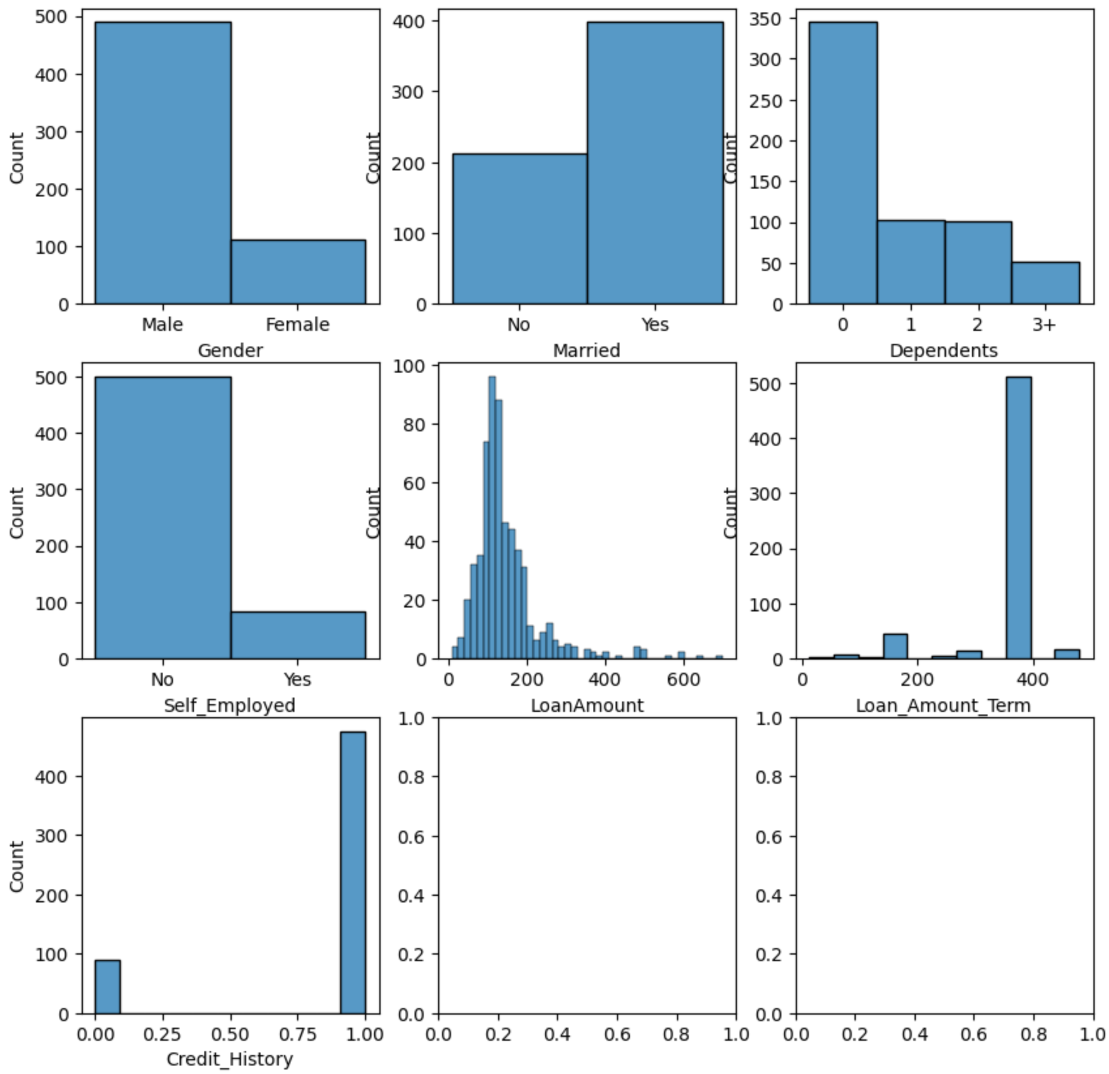
2.2.2 Are there any missing values in the dataset? If so, what is the best way to deal with it and why?

[106]:
```
print("There are %.2f%% rows with missing values." %␣
↪(len(loan_data_df[loan_data_df.isnull().any(axis=1)]) / len(loan_data_df) *␣
↪100))
```

```
There are 21.82% rows with missing values.
```

There are a lot of missing data - about 22% rows have them. We can't simply drop the rows because that will greatly reduce our dataset size. For the columns with missing values, I want to examine the distribution of the data. If the distribution centers around some mode, I will use the mode to backfill the missing data.

[107]:
```
columns_with_missing_values = loan_data_df.columns[loan_data_df.isnull().any()]
fig, ax = plt.subplots(3,3,figsize=(10,10))
for var, subplot in zip(columns_with_missing_values, ax.flatten()):
    sns.histplot(x=var, data=loan_data_df, ax=subplot)
```



[108]:
```
columns_to_back_fill =␣
↪["Gender",'Dependents','Married','Self_Employed','Credit_History','Loan_Amount_Term']
for column in columns_to_back_fill:
    loan_data_df[column] = loan_data_df[column].fillna(loan_data_df[column].
↪mode()[0])


loan_data_df['LoanAmount'] = loan_data_df[column].fillna(loan_data_df[column].
↪median())

print("Now there are %.2f%% rows with missing values. We will drop these rows."␣
↪% (len(loan_data_df[loan_data_df.isnull().any(axis=1)]) / len(loan_data_df)␣
↪* 100))
```

```
loan_data_df = loan_data_df.dropna(axis=0)
```

Now there are 0.00% rows with missing values. We will drop these rows.

2.2.3 Encode the categorical variables.

[109]:
```
ohe_features=["Education",'Gender','Married','Dependents','Self_Employed','Property_Area','Cre

loan_data_X = loan_data_df.drop(columns=['Loan_Status'])
loan_data_X = pd.get_dummies(loan_data_X, columns=ohe_features,drop_first=True)

loan_data_y = loan_data_df['Loan_Status']

features = loan_data_X.columns
```

2.2.4 Do you think that the distribution of labels is balanced? Why/why not? Hint: Find the probability of the different categories.

[110]:
```
p_yes = len(loan_data_df[loan_data_df['Loan_Status'] == 'Y']) /␣
↪len(loan_data_df)
p_no = 1 - p_yes

print("the probability of loan status being yes is %.2f%% and being no is %.
↪2f%%, which is very loopsised to yes" % (p_yes,p_no))
```

```
the probability of loan status being yes is 0.69% and being no is 0.31%, which
is very loopsised to yes
```

the probability of loan status being yes is 0.69% and being no is 0.31%, which is very loopsised to yes

2.2.5 Plot the correlation matrix (first separate features and Y variable), and check if there is high correlation between the given numerical features (Threshold >=0.9). If yes, drop those highly correlated features from the dataframe.

[111]:
```
loan_data_X.corr()
```

[111]:
```
                         ApplicantIncome  CoapplicantIncome  LoanAmount  \
ApplicantIncome                 1.000000          -0.116605   -0.046531
CoapplicantIncome              -0.116605           1.000000   -0.059383
LoanAmount                     -0.046531          -0.059383    1.000000
Education_Not Graduate         -0.140760          -0.062290   -0.073928
Gender_Male                     0.058809           0.082912   -0.074030
Married_Yes                     0.051708           0.075948   -0.100912
Dependents_1                    0.040861          -0.029769   -0.088492
Dependents_2                   -0.034650           0.010016   -0.010609
Dependents_3+                   0.156687           0.041491   -0.077273
Self_Employed_Yes               0.127180          -0.016100   -0.033739
Property_Area_Semiurban        -0.014246          -0.027044    0.059141
Property_Area_Urban            -0.000598           0.022776   -0.094279
```

```
Credit_History_1.0            -0.018615          0.011134  -0.004705
Loan_Amount_Term_36.0         -0.018580         -0.031698  -0.272093
Loan_Amount_Term_60.0         -0.003474          0.024034  -0.250781
Loan_Amount_Term_84.0         -0.016914         -0.014616  -0.325050
Loan_Amount_Term_120.0        -0.029970         -0.030178  -0.242086
Loan_Amount_Term_180.0         0.069387          0.088838  -0.700935
Loan_Amount_Term_240.0         0.006690         -0.044901  -0.128820
Loan_Amount_Term_300.0         0.067018          0.033155  -0.096891
Loan_Amount_Term_360.0        -0.054644         -0.045559   0.668008
Loan_Amount_Term_480.0        -0.026042         -0.032920   0.338215

                         Education_Not Graduate  Gender_Male  Married_Yes  \
ApplicantIncome                       -0.140760     0.058809     0.051708
CoapplicantIncome                     -0.062290     0.082912     0.075948
LoanAmount                            -0.073928    -0.074030    -0.100912
Education_Not Graduate                 1.000000     0.045364     0.012304
Gender_Male                            0.045364     1.000000     0.364569
Married_Yes                            0.012304     0.364569     1.000000
Dependents_1                          -0.013355    -0.004466     0.113853
Dependents_2                           0.020822     0.129953     0.249547
Dependents_3+                          0.055288     0.096319     0.132566
Self_Employed_Yes                     -0.010383    -0.000525     0.004489
Property_Area_Semiurban               -0.039410    -0.108623     0.005845
Property_Area_Urban                   -0.034279     0.034530     0.000546
Credit_History_1.0                    -0.073658     0.009170     0.010938
Loan_Amount_Term_36.0                  0.038995    -0.047012    -0.078437
Loan_Amount_Term_60.0                  0.038995     0.027002    -0.018387
Loan_Amount_Term_84.0                 -0.042786    -0.014173     0.059018
Loan_Amount_Term_120.0                 0.019525     0.033098     0.001998
Loan_Amount_Term_180.0                 0.097799     0.082181     0.096363
Loan_Amount_Term_240.0                 0.006226    -0.014173     0.016486
Loan_Amount_Term_300.0                 0.004461     0.040174     0.035885
Loan_Amount_Term_360.0                -0.087713    -0.060806    -0.053978
Loan_Amount_Term_480.0                 0.018553    -0.034526    -0.084144

                         Dependents_1  Dependents_2  Dependents_3+  \
ApplicantIncome              0.040861     -0.034650       0.156687
CoapplicantIncome           -0.029769      0.010016       0.041491
LoanAmount                  -0.088492     -0.010609      -0.077273
Education_Not Graduate      -0.013355      0.020822       0.055288
Gender_Male                 -0.004466      0.129953       0.096319
Married_Yes                  0.113853      0.249547       0.132566
Dependents_1                 1.000000     -0.198046      -0.134337
Dependents_2                -0.198046      1.000000      -0.133547
Dependents_3+               -0.134337     -0.133547       1.000000
Self_Employed_Yes            0.082044      0.032434       0.003278
Property_Area_Semiurban      0.011661     -0.012017       0.007863
```

```
Property_Area_Urban          0.069320      0.016569      -0.047460
Credit_History_1.0           0.009757      0.007987      -0.060473
Loan_Amount_Term_36.0        0.051281     -0.025365      -0.017206
Loan_Amount_Term_60.0       -0.025516     -0.025365       0.086365
Loan_Amount_Term_84.0        0.072641      0.073285      -0.024372
Loan_Amount_Term_120.0      -0.031276      0.031912      -0.021090
Loan_Amount_Term_180.0       0.062613     -0.021083       0.099422
Loan_Amount_Term_240.0       0.072641      0.018677      -0.024372
Loan_Amount_Term_300.0      -0.004852      0.026292       0.037722
Loan_Amount_Term_360.0      -0.054712     -0.006575      -0.078999
Loan_Amount_Term_480.0      -0.042286     -0.013302      -0.009401

                         Self_Employed_Yes  …  Credit_History_1.0  \
ApplicantIncome                   0.127180  …           -0.018615
CoapplicantIncome                -0.016100  …            0.011134
LoanAmount                       -0.033739  …           -0.004705
Education_Not Graduate           -0.010383  …           -0.073658
Gender_Male                      -0.000525  …            0.009170
Married_Yes                       0.004489  …            0.010938
Dependents_1                      0.082044  …            0.009757
Dependents_2                      0.032434  …            0.007987
Dependents_3+                     0.003278  …           -0.060473
Self_Employed_Yes                 1.000000  …           -0.001550
Property_Area_Semiurban           0.008710  …            0.035976
Property_Area_Urban              -0.030338  …           -0.016934
Credit_History_1.0               -0.001550  …            1.000000
Loan_Amount_Term_36.0            -0.022443  …            0.023537
Loan_Amount_Term_60.0             0.061583  …            0.023537
Loan_Amount_Term_84.0             0.027721  …            0.033341
Loan_Amount_Term_120.0            0.041153  …            0.028851
Loan_Amount_Term_180.0           -0.016265  …           -0.064968
Loan_Amount_Term_240.0            0.027721  …            0.033341
Loan_Amount_Term_300.0            0.042033  …           -0.035851
Loan_Amount_Term_360.0           -0.017046  …            0.056036
Loan_Amount_Term_480.0           -0.031114  …           -0.054711

                         Loan_Amount_Term_36.0  Loan_Amount_Term_60.0  \
ApplicantIncome                      -0.018580              -0.003474
CoapplicantIncome                    -0.031698               0.024034
LoanAmount                           -0.272093              -0.250781
Education_Not Graduate                0.038995               0.038995
Gender_Male                          -0.047012               0.027002
Married_Yes                          -0.078437              -0.018387
Dependents_1                          0.051281              -0.025516
Dependents_2                         -0.025365              -0.025365
Dependents_3+                        -0.017206               0.086365
Self_Employed_Yes                    -0.022443               0.061583
```

Property_Area_Semiurban	0.073101	-0.044705
Property_Area_Urban	-0.040028	0.081642
Credit_History_1.0	0.023537	0.023537
Loan_Amount_Term_36.0	1.000000	-0.003268
Loan_Amount_Term_60.0	-0.003268	1.000000
Loan_Amount_Term_84.0	-0.004629	-0.004629
Loan_Amount_Term_120.0	-0.004006	-0.004006
Loan_Amount_Term_180.0	-0.015883	-0.015883
Loan_Amount_Term_240.0	-0.004629	-0.004629
Loan_Amount_Term_300.0	-0.008408	-0.008408
Loan_Amount_Term_360.0	-0.139763	-0.139763
Loan_Amount_Term_480.0	-0.009046	-0.009046

	Loan_Amount_Term_84.0	Loan_Amount_Term_120.0 \
ApplicantIncome	-0.016914	-0.029970
CoapplicantIncome	-0.014616	-0.030178
LoanAmount	-0.325050	-0.242086
Education_Not Graduate	-0.042786	0.019525
Gender_Male	-0.014173	0.033098
Married_Yes	0.059018	0.001998
Dependents_1	0.072641	-0.031276
Dependents_2	0.073285	0.031912
Dependents_3+	-0.024372	-0.021090
Self_Employed_Yes	0.027721	0.041153
Property_Area_Semiurban	-0.021607	0.041470
Property_Area_Urban	-0.013614	0.000648
Credit_History_1.0	0.033341	0.028851
Loan_Amount_Term_36.0	-0.004629	-0.004006
Loan_Amount_Term_60.0	-0.004629	-0.004006
Loan_Amount_Term_84.0	1.000000	-0.005674
Loan_Amount_Term_120.0	-0.005674	1.000000
Loan_Amount_Term_180.0	-0.022499	-0.019468
Loan_Amount_Term_240.0	-0.006557	-0.005674
Loan_Amount_Term_300.0	-0.011910	-0.010306
Loan_Amount_Term_360.0	-0.197978	-0.171313
Loan_Amount_Term_480.0	-0.012814	-0.011088

	Loan_Amount_Term_180.0	Loan_Amount_Term_240.0 \
ApplicantIncome	0.069387	0.006690
CoapplicantIncome	0.088838	-0.044901
LoanAmount	-0.700935	-0.128820
Education_Not Graduate	0.097799	0.006226
Gender_Male	0.082181	-0.014173
Married_Yes	0.096363	0.016486
Dependents_1	0.062613	0.072641
Dependents_2	-0.021083	0.018677
Dependents_3+	0.099422	-0.024372

```
Self_Employed_Yes                 -0.016265               0.027721
Property_Area_Semiurban           -0.087146               0.020112
Property_Area_Urban                0.114563               0.029473
Credit_History_1.0                -0.064968               0.033341
Loan_Amount_Term_36.0             -0.015883              -0.004629
Loan_Amount_Term_60.0             -0.015883              -0.004629
Loan_Amount_Term_84.0             -0.022499              -0.006557
Loan_Amount_Term_120.0            -0.019468              -0.005674
Loan_Amount_Term_180.0             1.000000              -0.022499
Loan_Amount_Term_240.0            -0.022499               1.000000
Loan_Amount_Term_300.0            -0.040862              -0.011910
Loan_Amount_Term_360.0            -0.679267              -0.197978
Loan_Amount_Term_480.0            -0.043966              -0.012814

                         Loan_Amount_Term_300.0  Loan_Amount_Term_360.0  \
ApplicantIncome                        0.067018               -0.054644
CoapplicantIncome                      0.033155               -0.045559
LoanAmount                            -0.096891                0.668008
Education_Not Graduate                 0.004461               -0.087713
Gender_Male                            0.040174               -0.060806
Married_Yes                            0.035885               -0.053978
Dependents_1                          -0.004852               -0.054712
Dependents_2                           0.026292               -0.006575
Dependents_3+                          0.037722               -0.078999
Self_Employed_Yes                      0.042033               -0.017046
Property_Area_Semiurban                0.024871                0.032510
Property_Area_Urban                   -0.030746               -0.099409
Credit_History_1.0                    -0.035851                0.056036
Loan_Amount_Term_36.0                 -0.008408               -0.139763
Loan_Amount_Term_60.0                 -0.008408               -0.139763
Loan_Amount_Term_84.0                 -0.011910               -0.197978
Loan_Amount_Term_120.0                -0.010306               -0.171313
Loan_Amount_Term_180.0                -0.040862               -0.679267
Loan_Amount_Term_240.0                -0.011910               -0.197978
Loan_Amount_Term_300.0                 1.000000               -0.359572
Loan_Amount_Term_360.0                -0.359572                1.000000
Loan_Amount_Term_480.0                -0.023274               -0.386887

                         Loan_Amount_Term_480.0
ApplicantIncome                       -0.026042
CoapplicantIncome                     -0.032920
LoanAmount                             0.338215
Education_Not Graduate                 0.018553
Gender_Male                           -0.034526
Married_Yes                           -0.084144
Dependents_1                          -0.042286
Dependents_2                          -0.013302
```

```
Dependents_3+                        -0.009401
Self_Employed_Yes                    -0.031114
Property_Area_Semiurban               0.028433
Property_Area_Urban                   0.023916
Credit_History_1.0                   -0.054711
Loan_Amount_Term_36.0                -0.009046
Loan_Amount_Term_60.0                -0.009046
Loan_Amount_Term_84.0                -0.012814
Loan_Amount_Term_120.0               -0.011088
Loan_Amount_Term_180.0               -0.043966
Loan_Amount_Term_240.0               -0.012814
Loan_Amount_Term_300.0               -0.023274
Loan_Amount_Term_360.0               -0.386887
Loan_Amount_Term_480.0                1.000000

[22 rows x 22 columns]
```

2.2.6 Apply the following pre-processing steps:

1. Convert the label from a Pandas series to a Numpy (m x 1) vector. If you don't do this, it may cause problems when implementing the logistic regression model.
2. Split the dataset into training (60%), validation (20%), and test (20%) sets.
3. Standardize the columns in the feature matrices. To avoid information leakage, learn the standardization parameters from training, and then apply training, validation and test dataset.
4. Add a column of ones to the feature matrices of train, validation and test dataset. This is a common trick so that we can learn a coefficient for the bias term of a linear model.

[112]:
```
loan_data_y = np.where(loan_data_y == 'Y', 1, 0)
loan_data_y=loan_data_y.reshape(-1,1)

loan_X_dev, loan_X_test, loan_y_dev, loan_y_test =␣
↪train_test_split(loan_data_X, loan_data_y, test_size=0.2, random_state=0)
loan_X_train, loan_X_val, loan_y_train, loan_y_val =␣
↪train_test_split(loan_X_dev, loan_y_dev, test_size=0.25, random_state=0)

numerical_features= ['ApplicantIncome','CoapplicantIncome','LoanAmount']
preprocessor = make_column_transformer((StandardScaler(),␣
↪numerical_features),remainder='passthrough')
preprocessor.fit(loan_X_train)

loan_X_train = preprocessor.transform(loan_X_train)
loan_X_val = preprocessor.transform(loan_X_val)
loan_X_test = preprocessor.transform(loan_X_test)

loan_X_train = np.hstack([np.ones((loan_X_train.shape[0], 1)), loan_X_train])
loan_X_val = np.hstack([np.ones((loan_X_val.shape[0], 1)), loan_X_val])
loan_X_test = np.hstack([np.ones((loan_X_test.shape[0], 1)), loan_X_test])
```

0.3.6 Implement Logisitc Regression

We will now implement logistic regression with L2 regularization. Given an (m x n) feature matrix X, an (m x 1) label vector y, and an (n x 1) weight vector w, the hypothesis function for logistic regression is:

$$y = \sigma(Xw)$$

where $\sigma(x) = \frac{1}{1+e^{-x}}$, i.e. the sigmoid function. This function scales the prediction to be a probability between 0 and 1, and can then be thresholded to get a discrete class prediction.

Just as with linear regression, our objective in logistic regression is to learn the weights w which best fit the data. For L2-regularized logistic regression, we find an optimal w to minimize the following loss function:

$$\min_w \; -y^T \, \log(\sigma(Xw)) \; - \; (\mathbf{1} - y)^T \, \log(\mathbf{1} - \sigma(Xw)) \; + \; \alpha \|w\|_2^2$$

Unlike linear regression, however, logistic regression has no closed-form solution for the optimal w. So, we will use gradient descent to find the optimal w. The (n x 1) gradient vector g for the loss function above is:

$$g = X^T \Big(\sigma(Xw) - y \Big) + 2\alpha w$$

Below is pseudocode for gradient descent to find the optimal w. You should first initialize w (e.g. to a (n x 1) zero vector). Then, for some number of epochs t, you should update w with $w - g $, where η is the learning rate and g is the gradient. You can learn more about gradient descent here.

$w = \mathbf{0}$

for $i = 1, 2, ..., t$

$ w = w - g $

A LogisticRegression class with five methods: train, predict, calculate_loss, calculate_gradient, and calculate_sigmoid has been implemented for you below.

[113]:
```
class LogisticRegression():
    '''
    Logistic regression model with L2 regularization.

    Attributes
    ----------
    alpha: regularization parameter
    t: number of epochs to run gradient descent
    eta: learning rate for gradient descent
    w: (n x 1) weight vector
    '''

    def __init__(self, alpha=0, t=100, eta=1e-3):
```

```
        self.alpha = alpha
        self.t = t
        self.eta = eta
        self.w = None

    def train(self, X, y):
        '''Trains logistic regression model using gradient descent
        (sets w to its optimal value).

        Parameters
        ----------
        X : (m x n) feature matrix
        y: (m x 1) label vector

        Returns
        -------
        losses: (t x 1) vector of losses at each epoch of gradient descent
        '''

        loss = list()
        self.w = np.zeros((X.shape[1],1))
        for i in range(self.t):
            self.w = self.w - (self.eta * self.calculate_gradient(X, y))
            loss.append(self.calculate_loss(X, y))
        return loss

    def predict(self, X):
        '''Predicts on X using trained model. Make sure to threshold
        the predicted probability to return a 0 or 1 prediction.

        Parameters
        ----------
        X : (m x n) feature matrix

        Returns
        -------
        y_pred: (m x 1) 0/1 prediction vector
        '''
        y_pred = self.calculate_sigmoid(X.dot(self.w))
        y_pred[y_pred >= 0.5] = 1
        y_pred[y_pred < 0.5] = 0
        return y_pred

    def calculate_loss(self, X, y):
        '''Calculates the logistic regression loss using X, y, w,
        and alpha. Useful as a helper function for train().
```

```
        Parameters
        ----------
        X : (m x n) feature matrix
        y: (m x 1) label vector

        Returns
        -------
        loss: (scalar) logistic regression loss
        '''
        loss= -y.T.dot(np.log(self.calculate_sigmoid(X.dot(self.w)))) - (1-y).T.
↪dot(np.log(1-self.calculate_sigmoid(X.dot(self.w)))) + self.alpha*np.linalg.
↪norm(self.w, ord=2)**2
        return loss.item()

    def calculate_gradient(self, X, y):
        '''Calculates the gradient of the logistic regression loss
        using X, y, w, and alpha. Useful as a helper function
        for train().

        Parameters
        ----------
        X : (m x n) feature matrix
        y: (m x 1) label vector

        Returns
        -------
        gradient: (n x 1) gradient vector for logistic regression loss
        '''
        return X.T.dot(self.calculate_sigmoid( X.dot(self.w)) - y) + 2*self.
↪alpha*self.w


    def calculate_sigmoid(self, x):
        '''Calculates the sigmoid function on each element in vector x.
        Useful as a helper function for predict(), calculate_loss(),
        and calculate_gradient().

        Parameters
        ----------
        x: (m x 1) vector

        Returns
        -------
        sigmoid_x: (m x 1) vector of sigmoid on each element in x
        '''
        return (1)/(1 + np.exp(-x.astype('float')))
```

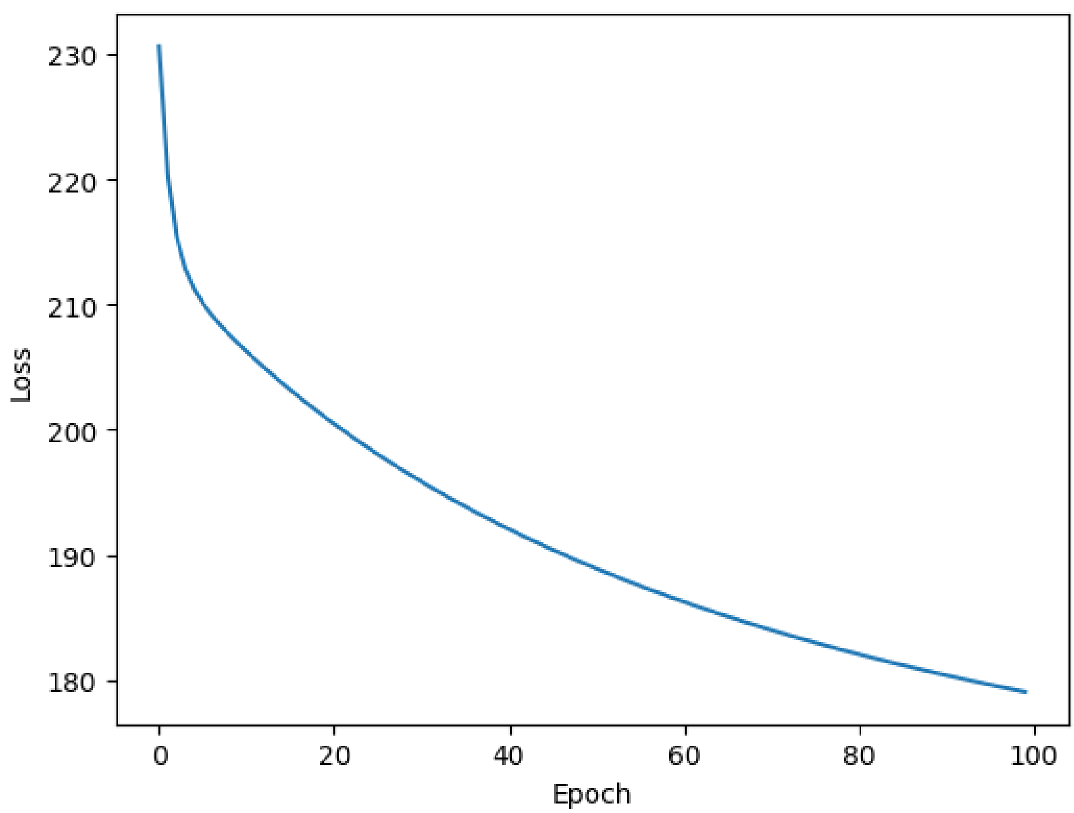
2.2.7 Plot Loss over Epoch and Search the space randomly to find best hyperparameters.

i) Using your implementation above, train a logistic regression model **(alpha=0, t=100, eta=1e-3)** on the loan training data. Plot the training loss over epochs. Make sure to label your axes. You should see the loss decreasing and start to converge.

ii) Using **alpha between (0,1), eta between(0, 0.001) and t between (0, 100)**, find the best hyperparameters for LogisticRegression. You can randomly search the space 20 times to find the best hyperparameters.

iii) Compare accuracy on the test dataset for both the scenarios.

[114]:
```
### Code here
model = LogisticRegression(alpha=0, t=100, eta=1e-3)
epoch = np.array(list(range(100)))
loan_X_train= loan_X_train.astype('float')
loss = model.train(loan_X_train, loan_y_train)

fig = sns.lineplot(x=epoch, y=loss)
fig.set(xlabel='Epoch', ylabel='Loss')
plt.show()
```



[115]:
```
val_scores = []
alpha_random = np.random.sample(20)
eta_random = np.random.sample(20)*0.001
t_random = np.random.randint(0,100,20)

for alpha in alpha_random:
    for eta in eta_random:
        for t in t_random:
            model = LogisticRegression(alpha=alpha, t= int(t), eta=eta)
            model.train(loan_X_train, loan_y_train)
            y_pred = model.predict(loan_X_val)
            val_score = r2_score(loan_y_val, y_pred)
            val_scores.append((val_score, (alpha, eta, t)))
```

[116]:
```
best_params = max(val_scores, key=lambda x: x[0])[1]
print(f"Best hyperparameters: alpha={best_params[0]}, eta={best_params[1]},␣
 ↪t={best_params[2]}")
```

```
Best hyperparameters: alpha=0.019199302177164368, eta=0.000850652766303771, t=91
```

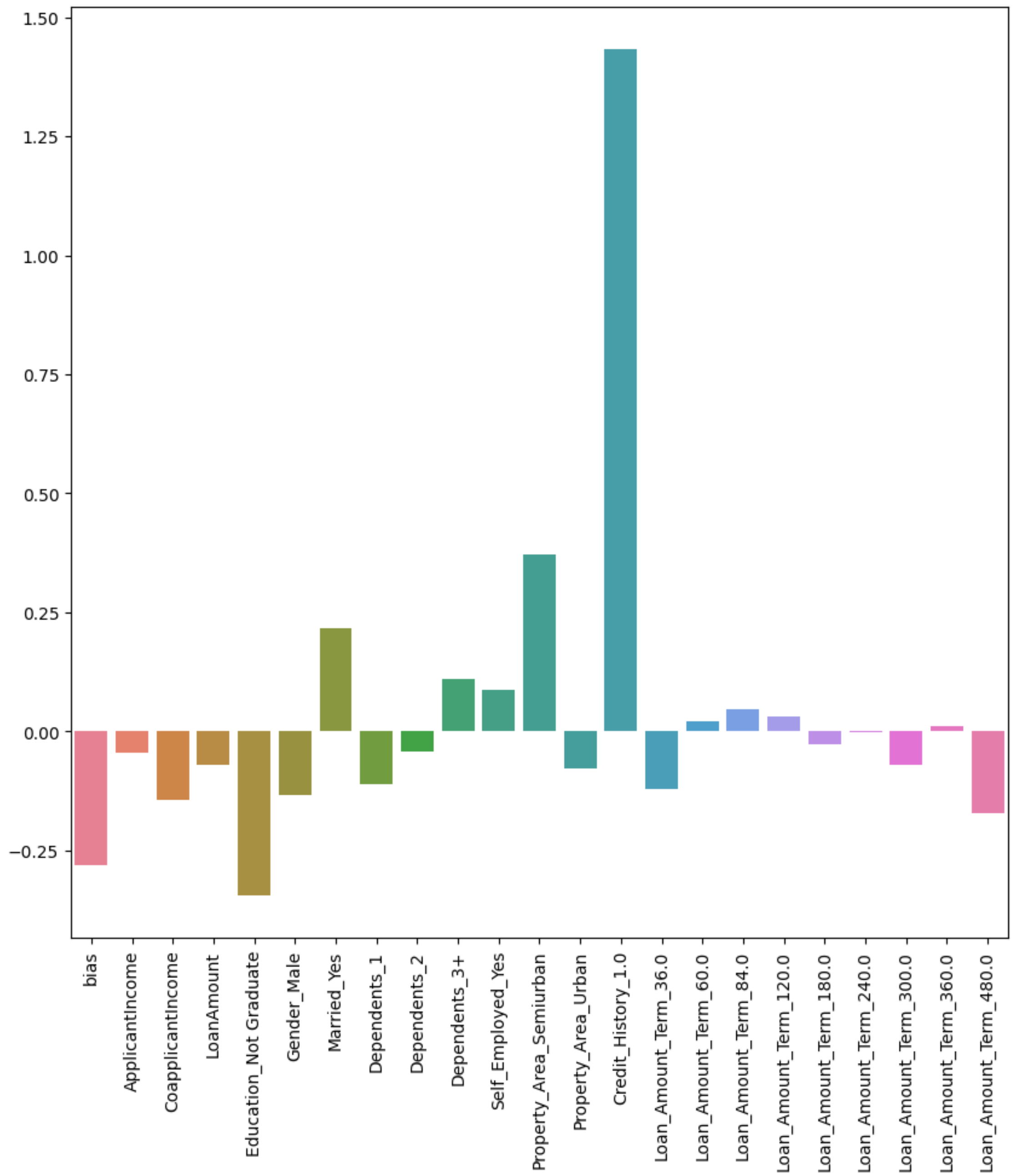
[117]:
```
model_scenario_1 = LogisticRegression(alpha=0, t=100, eta=1e-3)
model_scenario_2= LogisticRegression(alpha=best_params[0], t=best_params[2],␣
 ↪eta=best_params[1])
model_scenario_1.train(loan_X_train, loan_y_train)
model_scenario_2.train(loan_X_train, loan_y_train)

y_pred_scenario_1 = model_scenario_1.predict(loan_X_test)
y_pred_scenario_2 = model_scenario_2.predict(loan_X_test)

print("Scenario 1 R^2: %.3f and Scenario 2 R^2: %.3f" % (r2_score(loan_y_test,␣
 ↪y_pred_scenario_1), r2_score(loan_y_test, y_pred_scenario_2)))
```

```
Scenario 1 R^2: 0.006 and Scenario 2 R^2: 0.006
```

0.3.7 Feature Importance

2.2.8 Interpret your trained model using a bar chart of the model weights. Make sure to label the bars (x-axis) and don't forget the bias term!

[118]:
```
weights = model_scenario_2.w.reshape(-1)
feature_names = ['bias'] + list(features)

fig = plt.figure(figsize=(10,10))
ax = sns.barplot(x=feature_names,y = weights, hue = feature_names)
ax.tick_params(axis='x', rotation=90)
```



No credit history severly negatively impacts the loan decision. Aside from credit history, other factors can impact loan decisions include property area. Semi-urban property owners are more likely to obtain a positive loan decision. Loan applicants with “graduate” education label are more likely to obtain a positive loan decision

0.3.8 2.3 Support Vector Machines

In this part, we will be using support vector machines for classification on the loan dataset.

0.3.9 Train Primal SVM

2.3.1 Train a primal SVM (with default parameters) on the loan dataset. Make predictions and report the accuracy on the training, validation, and test sets.

[119]:
```
primal_svm_model = LinearSVC(dual=False)
primal_svm_model.fit(loan_X_train, loan_y_train.reshape(-1))
primal_y_pred_train = primal_svm_model.predict(loan_X_train)
primal_y_pred_val = primal_svm_model.predict(loan_X_val)
primal_y_pred_test = primal_svm_model.predict(loan_X_test)

print("Primal SVM R^2 for training data: %.3f, for validation data %.3f, for␣
 ↪test data %.3f" % (r2_score(loan_y_train, primal_y_pred_train ),␣
 ↪r2_score(loan_y_val, primal_y_pred_val), r2_score(loan_y_test,␣
 ↪primal_y_pred_test)))
```

```
Primal SVM R^2 for training data: 0.161, for validation data 0.062, for test
data 0.130
```

0.3.10 Train Dual SVM

2.3.2 Train a dual SVM (with default parameters) on the heart disease dataset. Make predictions and report the accuracy on the training, validation, and test sets.

[120]:
```
from sklearn.datasets import load_iris


dual_svm_model = SVC(kernel='linear')
dual_svm_model.fit(loan_X_train, loan_y_train.reshape(-1))
dual_y_pred_train = dual_svm_model.predict(loan_X_train)
dual_y_pred_val = dual_svm_model.predict(loan_X_val)
dual_y_pred_test = dual_svm_model.predict(loan_X_test)

print("Dual SVM R^2 for training data: %.3f, for validation data %.3f, for test␣
 ↪data %.3f" % (r2_score(loan_y_train, dual_y_pred_train ),␣
 ↪r2_score(loan_y_val, dual_y_pred_val), r2_score(loan_y_test,␣
 ↪dual_y_pred_test)))
```

```
Dual SVM R^2 for training data: 0.135, for validation data 0.062, for test data
0.130
```