Take home Assignment

We have solved before a problem, where we had implemented linear regression with one feature and one target.

However, in the real world, most machine learning problems require us to work with more than one feature.

We will now consider the home loan approval dataset, where we will calculate an individual's home loan eligibility, depending not only on the age of the person but also on the credit rating and other features.

Therefore in order to determine whether or not a person should be eligible for a home loan, you'll have to collect multiple features, such as age, income, credit rating, number of dependents, etc.

You have to work on this multiple regression

Step 1: Import necessary libraries

In [3]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn import datasets, linear_model
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
```

Step 2: Reading the dataset

In [4]:
```
df = pd.read_csv("https://raw.githubusercontent.com/mona-patra/FDP-5days/main/Day%202/loan-approval-dataset.csv")
df
```

Out[4]:

	age	credit-rating	children	loan-approval
0	19	27.900	0	16884.92400
1	18	42.130	1	1725.55230
2	28	33.000	3	4449.46200
3	33	22.705	0	21984.47061
4	32	28.880	0	3866.85520
...	...	...	...	...
1333	50	30.970	3	10600.54830
1334	18	31.920	0	2205.98080
1335	18	36.850	0	1629.83350
1336	21	25.800	0	2007.94500
1337	61	29.070	0	29141.36030

1338 rows × 4 columns

Step 3: Understanding the dataset, finding shape of the dataset, info on the dataset, correlation among the variables etc.

In [5]:
```
df.head()
```

Out[5]:

	age	credit-rating	children	loan-approval
0	19	27.900	0	16884.92400
1	18	42.130	1	1725.55230
2	28	33.000	3	4449.46200
3	33	22.705	0	21984.47061
4	32	28.880	0	3866.85520

In [6]:
```
df.columns
```

Out[6]: Index(['age', 'credit-rating', 'children', 'loan-approval'], dtype='object')

In [7]:
```
df.shape
```

Out[7]: (1338, 4)

In [8]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   age            1338 non-null   int64  
 1   credit-rating  1338 non-null   float64
 2   children       1338 non-null   int64  
 3   loan-approval  1338 non-null   float64
dtypes: float64(2), int64(2)
memory usage: 41.9 KB
```

In [9]:
```
df.describe()
```

Out[9]:

	age	credit-rating	children	loan-approval
count	1338.000000	1338.000000	1338.000000	1338.000000
mean	39.207025	30.669645	1.094918	13270.422265
std	14.049960	6.105650	1.205493	12110.011237
min	18.000000	15.960000	0.000000	1121.873900
25%	27.000000	26.296250	0.000000	4740.287150
50%	39.000000	30.400000	1.000000	9382.033000
75%	51.000000	34.700000	2.000000	16639.912515
max	64.000000	53.130000	5.000000	63770.428010

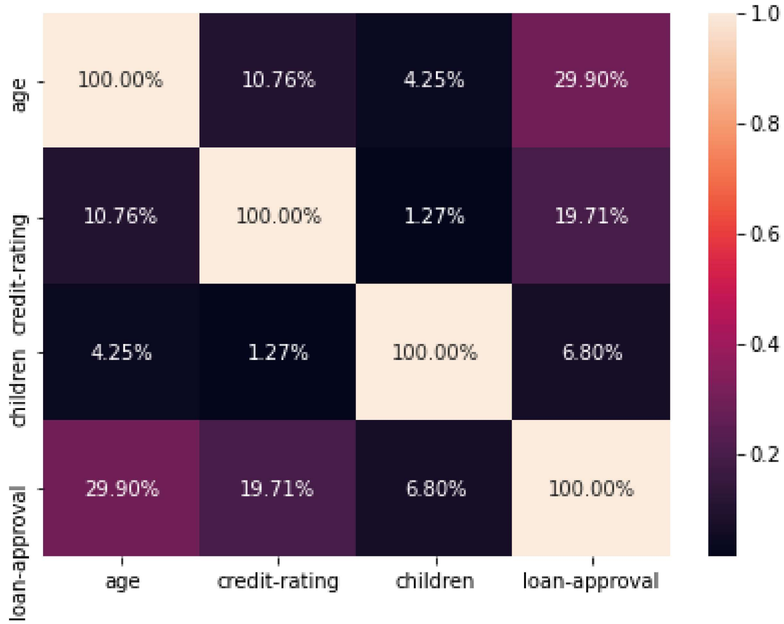
In [10]:
```
corr = df.corr()
corr.style.background_gradient(cmap='plasma')
```

Out[10]:

	age	credit-rating	children	loan-approval
age	1.000000	0.107593	0.042469	0.299008
credit-rating	0.107593	1.000000	0.012663	0.197122
children	0.042469	0.012663	1.000000	0.067998
loan-approval	0.299008	0.197122	0.067998	1.000000

In [11]:
```python
import seaborn as sns
plt.figure(figsize = (7,5))
sns.heatmap(corr,annot = True,fmt='.2%')
```

Out[11]:
```
<AxesSubplot:>
```



In [ ]:

Step 4: Defining the feature and the target variable, X and y, where

In [12]:
```python
X = df[['age','credit-rating','children']]
y = df['loan-approval']
```

In [13]:
```
X.head()
```

Out[13]:

	age	credit-rating	children
0	19	27.900	0
1	18	42.130	1
2	28	33.000	3
3	33	22.705	0
4	32	28.880	0

In [14]:
```
y.head()
```

Out[14]:
```
0    16884.92400
1     1725.55230
2     4449.46200
3    21984.47061
4     3866.85520
Name: loan-approval, dtype: float64
```

Step 5: Create Train and Test set

In [35]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size = 0.7, test_size = 0.3, random_state = 100)
```

In [36]:
```
# Take a look at the splittted dataset
print(X.shape)
print(y.shape)
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(1338, 3)
(1338,)
(936, 3)
(402, 3)
(936,)
(402,)
```

Step 6: Train your model

In [37]:
```
regr = linear_model.LinearRegression()
regr.fit(X_train,y_train)
```

Out[37]:
```
LinearRegression()
```

In [38]:
```
regr.coef_
```

Out[38]:
```
array([250.20504314, 301.42340575, 520.34313128])
```

In [39]:
```
regr.intercept_
```

Out[39]:
```
-6466.22119199591
```

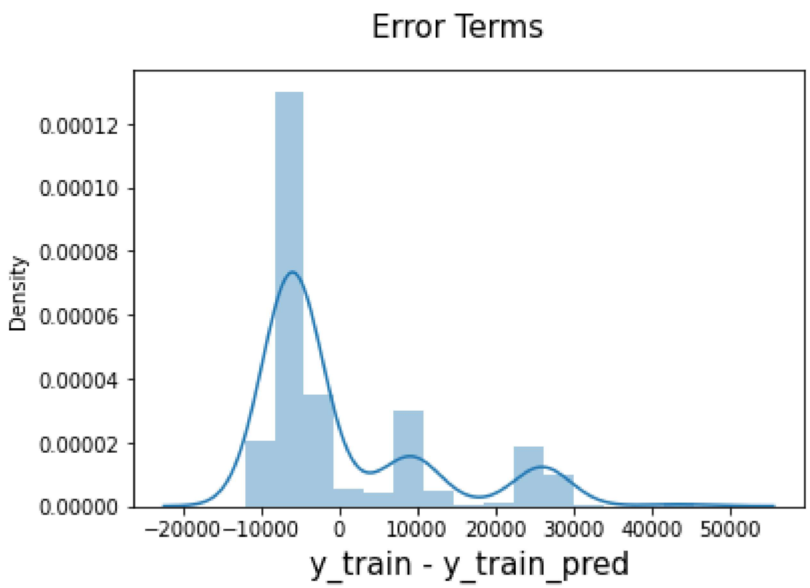
In [40]:
```
# Predicting y_value using teting data of X
y_pred = regr.predict(X_test)

# Creating residuals from the y_train and y_pred
res = (y_test - y_pred)
```

Step 7: Evaluate the model

In [41]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [42]:
```
import seaborn as sns
fig = plt.figure()
sns.distplot(res, bins = 15)
fig.suptitle('Error Terms', fontsize = 15)
plt.xlabel('y_train - y_train_pred', fontsize = 15)        # X-label
plt.show()
```



In [43]:
```
# Checking the R-squared value
r_squared = r2_score(y_test, y_pred)
r_squared
```

Out[43]: 0.10995726547136453

In [44]:

```
# Mean square error
print('Mean squared error: %.2f'% mean_squared_error(y_test, y_pred))
# The mean absolute error
print('Mean Absolute Error: %.2f'% mean_absolute_error(y_test, y_pred))
```

```
Mean squared error: 129232148.96
Mean Absolute Error: 8899.63
```

In [ ]:

```

```