Predict Canada Per Capita Income ML Model

In [38]:
```
# Designed by : ALTAF HUSAIN DATA ANALYST
```

Step 1 : Load Important Modules

In [39]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error,mean_squared_error,root_mean_squared_error
import warnings
warnings.filterwarnings('ignore')
print("All module s loaded succesfully")
```

```
All module s loaded succesfully
```

Step 2 : Load Data

In [40]:
```
import kagglehub
path = kagglehub.dataset_download("ananthu19/canada-per-capita-income-prediction")
print("Path to dataset files:", path)
```

```
Path to dataset files: C:\Users\SK COMPUTER\.cache\kagglehub\datasets\ananthu19\canada-per-capita-income-prediction\vers
ions\1
```

In [41]:
```
import os
final_data = path + "/" + os.listdir(path)[0]
```

In [42]:
```
df = pd.read_csv(final_data)
```

In [43]:
```
# step 2.1 :
df.sample()
```

Out[43]:

	year	income
4	1974	5576.514583

In [44]:
```
# step 2.2 :
df.head()
```

Out[44]:

	year	income
0	1970	3399.299037
1	1971	3768.297935
2	1972	4251.175484
3	1973	4804.463248
4	1974	5576.514583

In [45]:
```
# step 2.3 :
df.tail()
```

Out[45]:

	year	income
42	2012	42665.25597
43	2013	42676.46837
44	2014	41039.89360
45	2015	35175.18898
46	2016	34229.19363

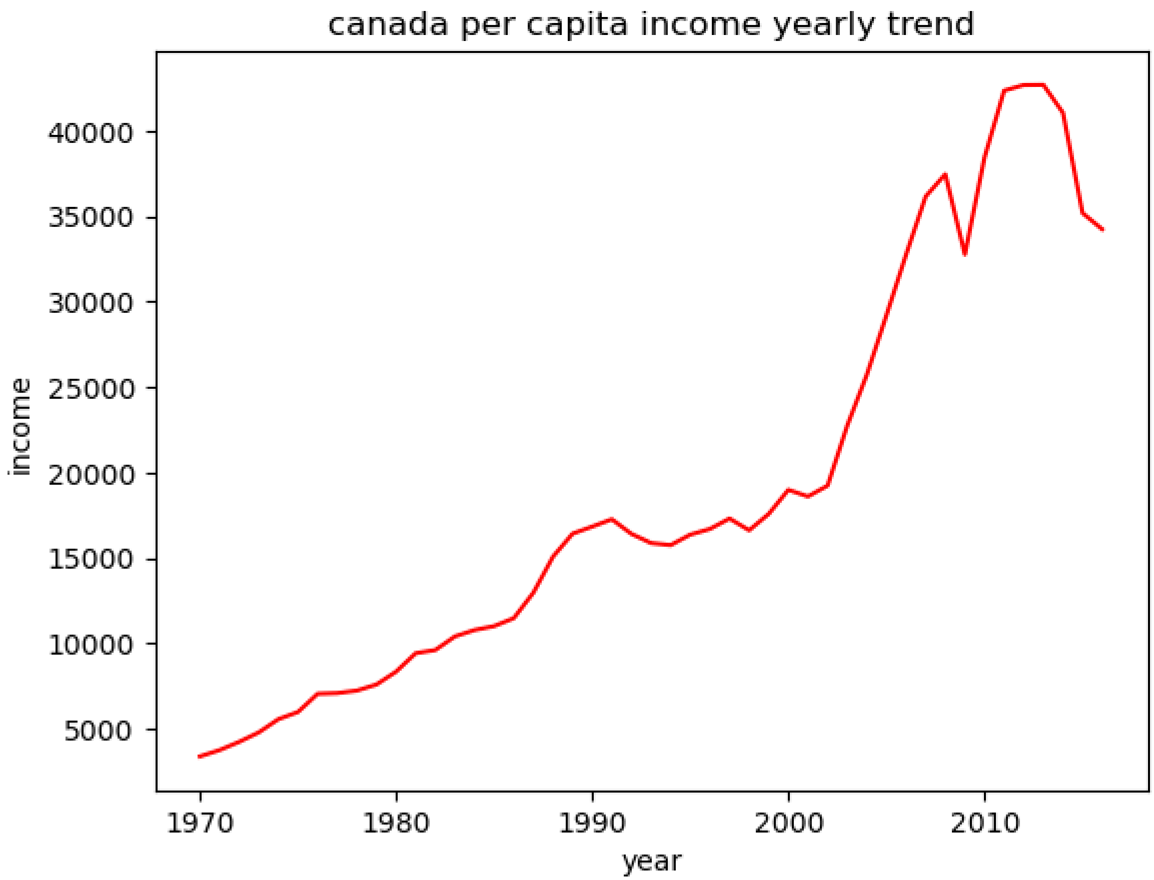
In [46]:
```
# step 2.4:
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 47 entries, 0 to 46
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   year    47 non-null     int64  
 1   income  47 non-null     float64
dtypes: float64(1), int64(1)
memory usage: 884.0 bytes
```

In [47]:
```
# ML only works on numerical data, and here all cols are numerical in nature , we can proceed
```

setp 3: EDA

In [48]:
```
# step 3.1 :
sns.lineplot(data = df,x = 'year',y = 'income',color = 'r')
plt.title('canada per capita income yearly trend')
plt.show()
```



In [49]:
```
# we can use Linear Regression , because  X and y are correlated
```

In [50]:
```
# step 3.2 :
df.describe()
```

Out[50]:

	year	income
count	47.000000	47.000000
mean	1993.000000	18920.137063
std	13.711309	12034.679438
min	1970.000000	3399.299037
25%	1981.500000	9526.914515
50%	1993.000000	16426.725480
75%	2004.500000	27458.601420
max	2016.000000	42676.468370

In [51]:

```
# step 3.3 :
df.corr() # .94 cor value ,which shows high correlation trend is increasing
```

Out[51]:

	year	income
year	1.000000	0.943884
income	0.943884	1.000000

step 4 : Divide data in X and y

- X = features: (year)
- y = Targets: (income)

In [52]:

```
X = df[['year']]
X.shape
```

Out[52]: (47, 1)

In [53]:

```
X.head()
```

Out[53]:

	year
0	1970
1	1971
2	1972
3	1973
4	1974

In [54]:

```
y = df['income']
y.shape
```

Out[54]:

```
(47,)
```

In [55]:

```
y.head()
```

Out[55]:

```
0    3399.299037
1    3768.297935
2    4251.175484
3    4804.463248
4    5576.514583
Name: income, dtype: float64
```

In [56]:

```
# Best line fins :
# Y = m * x +c
# M and C
# we can easily find line
```

Step 5 : Model Buildng

In [57]:

```
# step 5.1 :
lr_model = LinearRegression()
```

In [58]:

```
# step 5.2 :
lr_model.fit(X,y) # this ois for model training
```

Out[58]:

```
▾ LinearRegression
LinearRegression()
```

In [59]:

```
# step 5.3 :
y_pred = lr_model.predict(X)  # model predict value based on  X(year)
```

In [60]:

```
temp_df = df.copy()
temp_df['y_pred_capita'] = y_pred
```

In [61]:

```
temp_df.sample(10)
```

Out[61]:

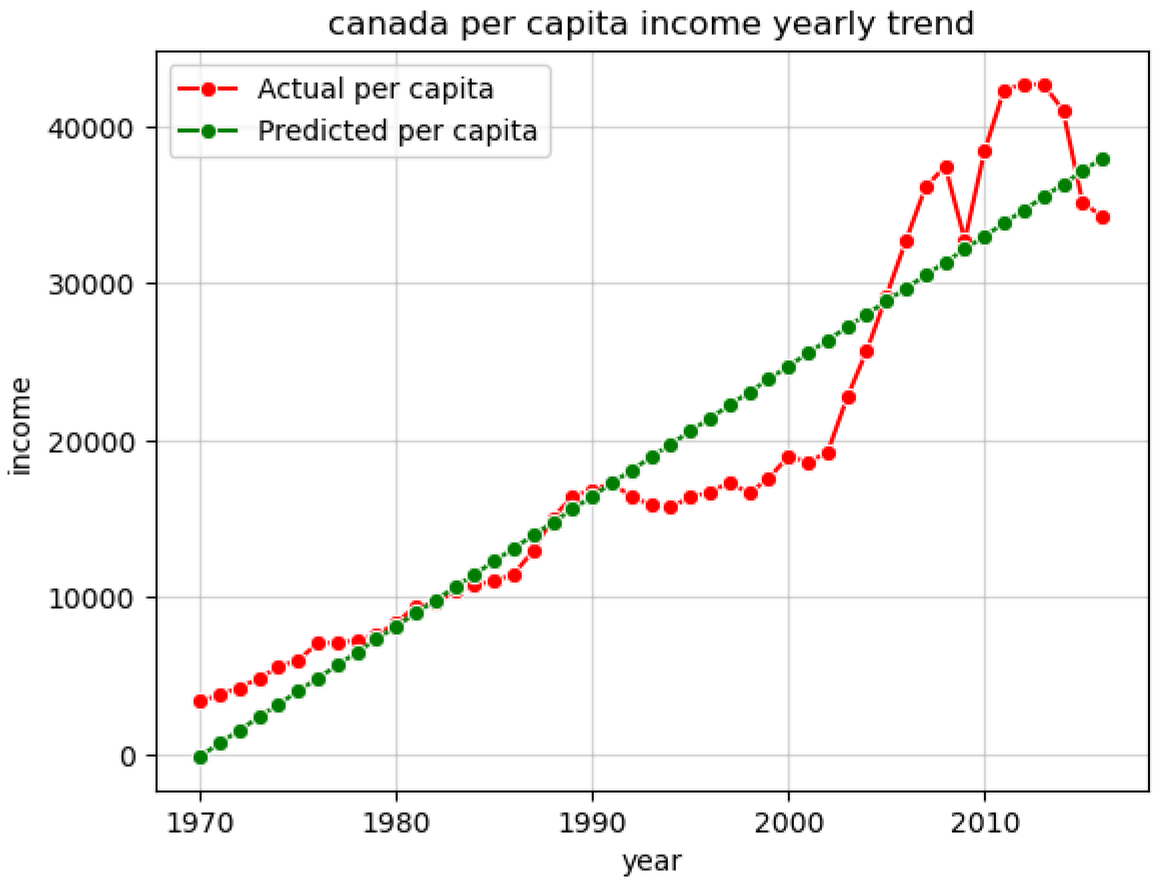
	year	income	y_pred_capita
9	1979	7602.912681	7321.626010
31	2001	18601.397240	25547.857665
30	2000	18987.382410	24719.392590
36	2006	32738.262900	29690.183041
45	2015	35175.188980	37146.368718
6	1976	7062.131392	4836.230785
32	2002	19232.175560	26376.322740
12	1982	9619.438377	9807.021236
1	1971	3768.297935	693.905409
19	1989	16426.725480	15606.276763

Step 6 : Visualize Actual vs Predicted

In [62]:

```
# step 3.1 :
sns.lineplot(data = df,x = 'year',y = 'income',color = 'r',marker= 'o',label = 'Actual per capita')
sns.lineplot(data = temp_df,x = 'year',y = 'y_pred_capita',color = 'g',marker= 'o',label = 'Predicted per capita')
```

```
plt.grid(alpha = 0.5)
plt.legend()
plt.title('canada per capita income yearly trend')
plt.show()
```



Step 7 : checkimg Metrics and Model Evaluation (errors)

In [63]:
```
# step 7.1 :
mae = ((temp_df['income'] - temp_df['y_pred_capita']).abs()).mean()
print('Mean absolute error :',mae)
```

```
Mean absolute error : 3088.866427771443
```

In [64]:
```
# step 7.2 :
mae_sk = mean_absolute_error(y,y_pred)
print('Mean absolute error :',mae_sk)
```

```
Mean absolute error : 3088.866427771443
```

In [65]:
```
# step 7.3:
mse = ((temp_df['income'] - temp_df['y_pred_capita'])** 2).mean()
print('Mean squared error :',mse)
```

```
Mean squared error : 15462739.061504772
```

In [66]:
```
# step 7.4 :
mse_sk = mean_squared_error(y,y_pred)
print('Mean squared error :',mse_sk)
```

```
Mean squared error : 15462739.061504772
```

In [67]:
```
# step 7.5 :
rmse = mse ** 0.5
print('root Mean squared error :',rmse)
```

```
root Mean squared error : 3932.268945723928
```

In [68]:
```
# step 7.6 :
rmse_sk = root_mean_squared_error(y,y_pred)
print('Root Mean squared error :',rmse_sk)
```

```
Root Mean squared error : 3932.268945723928
```

In [69]:
```
# Step 7.7 : model score
model_score = lr_model.score(X,y) # this is model learing score (almost 89 %)
model_score = round(model_score * 100,2)
print('Model has achieved learing score:',model_score)
```

```
Model has achieved learing score: 89.09
```

step 8 : Future per capit predict for the next 7 years

In [70]:
```
next_year  = list(range(2016 ,2026))
next_y = [[i] for i in next_year]
```

```
future_per_capita = lr_model.predict(next_y)
```

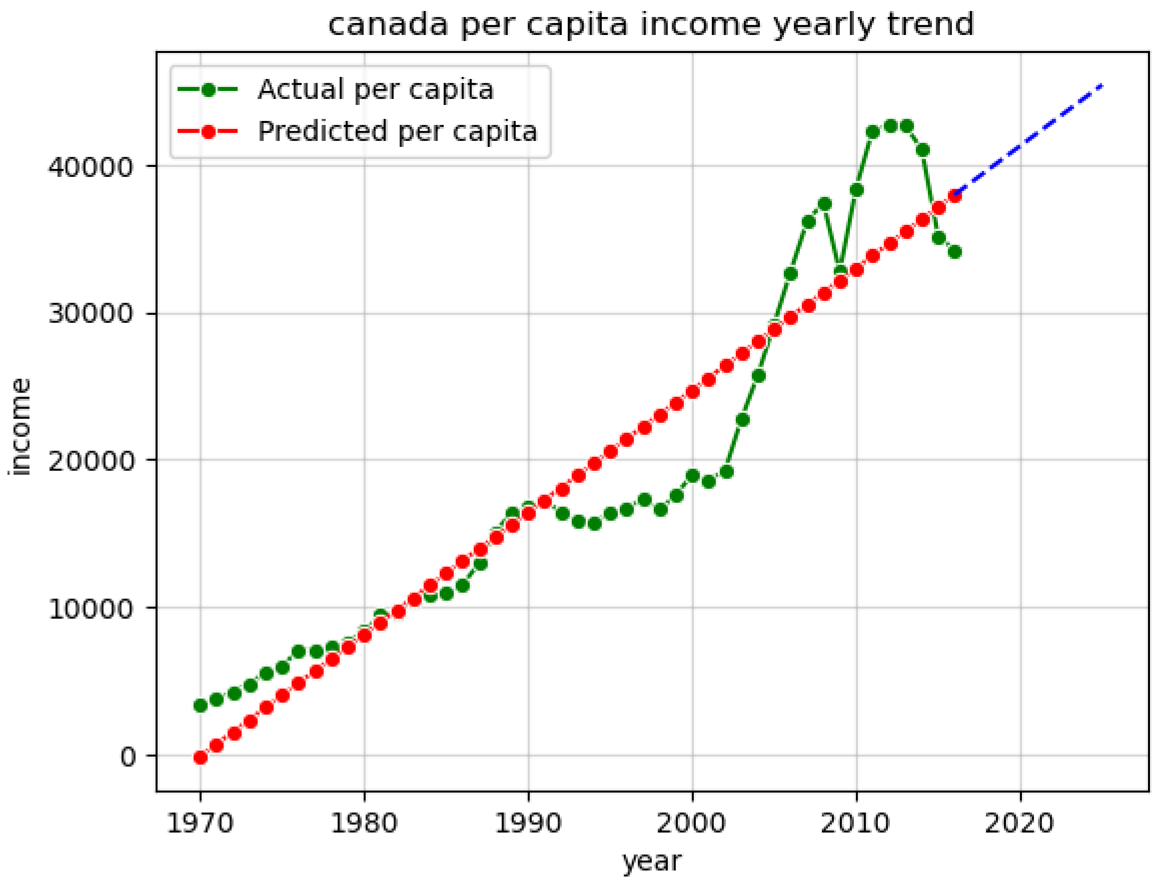
In [71]:
```
future_df = pd.DataFrame({'year' : next_year,'per_capita' : future_per_capita})
future_df
```

Out[71]:

	year	per_capita
0	2016	37974.833794
1	2017	38803.298869
2	2018	39631.763944
3	2019	40460.229019
4	2020	41288.694094
5	2021	42117.159170
6	2022	42945.624245
7	2023	43774.089320
8	2024	44602.554395
9	2025	45431.019471

step 9 : Visualize past and future values

In [72]:
```
# step 3.1 :
sns.lineplot(data = df,x = 'year',y = 'income',color = 'g',marker= 'o',label = 'Actual per capita')
sns.lineplot(data = temp_df,x = 'year',y = 'y_pred_capita',color = 'r',marker= 'o',label = 'Predicted per capita')
sns.lineplot(data = future_df,x = 'year',y = 'per_capita',color = 'b',linestyle = '--')
plt.grid(alpha = 0.5)
plt.legend()
plt.title('canada per capita income yearly trend')
plt.show()
```



step 10 : Input from where user can ask and predict capita based on year

In [77]:

```
year = int(input('Enter year to predict canada per capita : '))
capita = lr_model.predict([[year]])
final_capita = round(capita[0],2)
print(f'Predicted per capita of {year} is : {final_capita} (US$)')
```

```
Predicted per capita of 2035 is : 53715.67 (US$)
```

In [74]:

```
# Designed by : ALTAF HUSAIN DATA ANALYST
```