

practice

December 27, 2023

```
[2]: import pandas as pd

tomato = pd.read_csv('/Users/thutranghoa/Code/Data_analysis/Data/
↳1666946960_727__tomato-yields.csv')
tomato
```

```
[2]:
```

	Entity	Code	Year	\
0	Africa	NaN	1961	
1	Africa	NaN	1962	
2	Africa	NaN	1963	
3	Africa	NaN	1964	
4	Africa	NaN	1965	
...	
11277	Zimbabwe	ZWE	2016	
11278	Zimbabwe	ZWE	2017	
11279	Zimbabwe	ZWE	2018	
11280	Zimbabwe	ZWE	2019	
11281	Zimbabwe	ZWE	2020	

	Tomatoes	00000388	Yield	005419	tonnes per hectare
0					12.320172
1					12.976988
2					12.867894
3					13.189582
4					13.492712
...					...
11277					7.237900
11278					7.219100
11279					7.225900
11280					7.226900
11281					7.224700


```
[11282 rows x 4 columns]
```

```
[9]: tomato.isna().sum()
```

```
[9]: Entity                                0
      Code                                2489
      Year                                0
      Tomatoes | 00000388 || Yield | 005419 || tonnes per hectare  0
      dtype: int64
```

```
[17]: tomato.describe()
```

```
[17]:
```

	Year	Yields
count	11282.000000	11282.000000
mean	1992.067364	36.514492
std	17.225589	61.719855
min	1961.000000	0.467600
25%	1977.000000	10.140050
50%	1993.000000	18.015349
75%	2007.000000	35.298426
max	2020.000000	523.927795

```
[10]: tomato = tomato.rename(columns={"Tomatoes | 00000388 || Yield | 005419 || \
↳ tonnes per hectare" : "Yields"})
```

```
[11]: tomato.head(5)
```

```
[11]:
```

	Entity Code	Year	Yields
0	Africa NaN	1961	12.320172
1	Africa NaN	1962	12.976988
2	Africa NaN	1963	12.867894
3	Africa NaN	1964	13.189582
4	Africa NaN	1965	13.492712

```
[12]: new_tomato = tomato.copy()
      new_tomato = new_tomato.pivot(index = 'Entity', columns='Year', values='Yields')
      new_tomato
```

```
[12]:
```

Year	1961	1962	1963	1964	1965 \
Entity					
Africa	12.320172	12.976988	12.867894	13.189582	13.492712
Africa (FAO)	12.336499	12.962899	12.888400	13.195300	13.452499
Albania	12.000000	12.000000	12.400000	12.799999	12.799999
Algeria	16.456999	17.500000	17.500000	13.644899	12.285299
Americas (FAO)	18.990599	21.422100	19.558899	20.495800	22.032900
...
World	16.434599	16.976000	16.734600	17.468300	18.143700
Yemen	NaN	NaN	NaN	NaN	NaN
Yugoslavia	12.035399	12.398399	11.910600	12.177400	10.801499
Zambia	10.000000	10.000000	10.000000	10.000000	10.000000
Zimbabwe	7.222200	7.157900	7.368400	7.000000	7.500000

Year	1966	1967	1968	1969	1970	...	\
Entity						...	
Africa	13.327377	12.466840	12.748196	13.281709	12.92659	...	
Africa (FAO)	13.269099	12.445000	12.705600	13.228399	12.89090	...	
Albania	12.500000	13.214299	12.857100	12.000000	12.33330	...	
Algeria	11.177899	9.095799	10.047800	11.190700	9.44960	...	
Americas (FAO)	21.345299	21.999800	24.566200	22.137699	23.05410	...	
...	
World	18.300299	18.771700	19.288700	18.878700	19.32810	...	
Yemen	NaN	NaN	NaN	NaN	NaN	...	
Yugoslavia	11.443299	10.841800	10.419399	10.405499	9.47530	...	
Zambia	10.000000	10.000000	10.000000	11.250000	10.88240	...	
Zimbabwe	7.272700	7.272700	7.272700	7.217400	7.21740	...	

Year	2011	2012	2013	2014	2015	...	\
Entity						...	
Africa	19.040854	16.706995	15.755281	17.457846	17.360165		
Africa (FAO)	18.850000	16.706999	15.755300	17.457800	17.360199		
Albania	32.786900	31.538500	36.022301	37.184399	41.082298		
Algeria	37.502098	36.995800	43.342400	47.055099	48.359299		
Americas (FAO)	53.996197	56.599800	56.908497	60.573200	59.540798		
...	
World	34.805698	33.974800	34.083599	35.511799	36.588100		
Yemen	13.276700	14.154200	11.201500	11.313900	15.515400		
Yugoslavia	NaN	NaN	NaN	NaN	NaN		
Zambia	9.771999	10.000000	9.863000	9.753699	9.770700		
Zimbabwe	7.151900	7.121200	7.121200	7.202100	7.218600		

Year	2016	2017	2018	2019	2020	...	\
Entity						...	
Africa	14.999870	14.249650	13.247025	13.902744	14.087778		
Africa (FAO)	14.999900	14.249599	13.247000	13.902699	14.087800		
Albania	44.014198	44.370499	43.817497	44.975098	45.649399		
Algeria	56.772900	53.646698	58.672398	59.124599	62.164700		
Americas (FAO)	58.476498	57.541199	62.518597	65.266701	67.644997		
...	
World	36.540199	36.509197	36.013500	36.608997	36.979797		
Yemen	13.285000	13.340600	14.188900	13.443900	13.219299		
Yugoslavia	NaN	NaN	NaN	NaN	NaN		
Zambia	9.744699	9.762000	9.787300	9.785000	9.786400		
Zimbabwe	7.237900	7.219100	7.225900	7.226900	7.224700		

[220 rows x 60 columns]

0.0.1 Quốc gia có sản lượng lớn nhất 2000

```
[55]: 'Quốc gia có sản lượng lớn nhất 2000'
year_2000 = tomato.loc[tomato['Year'] == 2000]
df = year_2000.sort_values(by = ['Yields'], ascending=False)
print (df)
print ('Quốc gia có sản lượng cà chua lớn nhất năm 2000 là : ', df.
      ↪iloc[0]['Entity'])
```

	Entity	Code	Year	Yields
6762	Netherlands	NLD	2000	433.333282
2641	Denmark	DNK	2000	392.592590
10555	United Kingdom	GBR	2000	377.000000
9626	Sweden	SWE	2000	353.061188
7391	Norway	NOR	2000	328.032288
...
7743	Papua New Guinea	PNG	2000	4.750000
10046	Togo	TGO	2000	4.046200
339	Angola	AGO	2000	3.714300
9986	Timor	TLS	2000	2.928600
8846	Somalia	SOM	2000	1.532400

[207 rows x 4 columns]

Quốc gia có sản lượng cà chua lớn nhất năm 2000 là : Netherlands

Trong thời 1961 - 2000, quốc gia nào có sản lượng lớn nhất

```
[56]: year_1961_2000 = tomato.loc[(tomato['Year'] >= 1961) & tomato['Year'] <=2000]
temp = year_1961_2000.groupby('Entity', as_index=False).sum()
temp = temp.drop(['Code', 'Year'], axis=1)
temp = temp.sort_values(by = ['Yields'], ascending=False)
print (temp)
print ('Quốc gia có sản lượng cà chua lớn nhất trong thời kì 1961-2000 là : ',
      ↪temp.iloc[0]['Entity'])
```

	Entity	Yields
131	Netherlands	18773.273552
52	Denmark	16433.734818
206	United Kingdom	15035.964096
142	Norway	14902.662529
70	Finland	13949.978889
..
185	Sudan	121.201797
195	Timor	120.913399
167	Serbia and Montenegro	119.856898
23	Bhutan	52.912198
174	Somalia	44.106899

[220 rows x 2 columns]

Quốc gia có sản lượng cà chua lớn nhất trong thời kì 1961-2000 là : Netherlands

```
[58]: df['Entity'].unique()
```

```
[58]: array(['Netherlands', 'Denmark', 'United Kingdom', 'Sweden', 'Norway',  
        'Finland', 'Ireland', 'Belgium', 'Iceland', 'Western Europe (FAO)',  
        'Austria', 'Germany', 'Switzerland', 'France',  
        'Northern Europe (FAO)', 'New Zealand', 'United Arab Emirates',  
        'Israel', 'Cyprus', 'Palestine', 'United States',  
        'Northern America (FAO)', 'Kuwait', 'Portugal', 'Luxembourg',  
        'High-income countries', 'Spain', 'Japan', 'Chile', 'South Korea',  
        'Italy', 'Brazil', 'Oceania (FAO)', 'Oceania', 'Canada', 'Lebanon',  
        'Southern Europe (FAO)', 'Australia', 'Estonia', 'Greece',  
        'European Union (27)', 'European Union (27) (FAO)',  
        'North America', 'Oman', 'Americas (FAO)', 'Jordan', 'Puerto Rico',  
        'Turkey', 'Malta', 'South America (FAO)', 'South America',  
        'Morocco', 'Tunisia', 'Syria', 'Argentina', 'South Africa',  
        'Western Asia (FAO)', 'Egypt', 'Paraguay', 'Hungary',  
        'Eastern Asia (FAO)', 'Southern Africa (FAO)', 'China',  
        'China (FAO)', 'Croatia', 'Peru', 'Turkmenistan', 'Qatar',  
        'Europe', 'Europe (FAO)', 'Northern Africa (FAO)', 'Albania',  
        'French Guiana', 'Taiwan', 'World',  
        'Upper-middle-income countries', 'Dominican Republic',  
        'Cook Islands', 'Asia (FAO)', 'Asia', 'Iran', 'Guatemala',  
        'Costa Rica', 'Armenia', 'El Salvador', 'Saudi Arabia', 'Thailand',  
        'Bahrain', 'Net Food Importing Developing Countries (FAO)',  
        'Belize', 'Reunion', 'Colombia', 'Mexico', 'Central America (FAO)',  
        'Slovenia', 'Ecuador', 'Martinique', 'Algeria', 'Slovakia',  
        'Uzbekistan', 'North Macedonia', 'Polynesia', 'Venezuela',  
        'French Polynesia', 'Malaysia', 'Central Asia (FAO)', 'Africa',  
        'Africa (FAO)', 'Tonga', 'Uruguay', 'Azerbaijan',  
        'Southern Asia (FAO)', 'Jamaica', 'Lower-middle-income countries',  
        'Cameroon', 'Kazakhstan', 'Kenya',  
        'Land Locked Developing Countries (FAO)', 'Belarus', 'Kyrgyzstan',  
        'India', 'Barbados', 'Caribbean (FAO)', 'Guadeloupe',  
        'Small Island Developing States (FAO)', 'Czechia', 'Haiti',  
        'Hong Kong', 'Low-income countries', 'Mali', 'Yemen',  
        'Low Income Food Deficit Countries (FAO)', 'Poland', 'Georgia',  
        'Nicaragua', 'Panama', 'Bulgaria', 'Middle Africa (FAO)',  
        'South-eastern Asia (FAO)', 'Libya', 'Romania', 'Bolivia',  
        'Indonesia', 'Cuba', 'Brunei', 'Iraq', 'Sudan (former)',  
        'Eswatini', 'Trinidad and Tobago', 'Mauritius', 'Suriname',  
        'Eastern Europe (FAO)', 'Senegal', 'Russia', 'Tajikistan',  
        'Honduras', 'Saint Kitts and Nevis', 'Eastern Africa (FAO)',  
        'Latvia', 'Dominica', 'Zambia', 'Burkina Faso', 'Sierra Leone',  
        'Cote d'Ivoire', 'Cape Verde', 'Least Developed Countries (FAO)',  
        'Ukraine', 'Niger', 'Pakistan', 'Ethiopia', 'Madagascar',
```

```

'Comoros', 'Bahamas', 'Antigua and Barbuda', 'Fiji', 'Philippines',
'Malawi', 'Liberia', 'Gabon', 'Moldova', 'Serbia and Montenegro',
'Melanesia', 'North Korea', 'Tanzania', 'Sri Lanka', 'Grenada',
'Mozambique', 'Democratic Republic of Congo', 'Rwanda',
'Bangladesh', 'Uganda', 'Zimbabwe', 'Bosnia and Herzegovina',
'Namibia', 'Western Africa (FAO)', 'Seychelles', 'Guyana',
'Nigeria', 'Lithuania', 'Ghana', 'Benin', 'Congo',
'Papua New Guinea', 'Togo', 'Angola', 'Timor', 'Somalia'],
dtype=object)

```

```

[59]: DNA = ['Timor', 'Indonesia', 'Malaysia', 'Brunei', 'Philippines']
mask = tomato['Entity'].isin(DNA)
tomato[mask]

```

```

[59]:
      Entity Code  Year  Yields
1372  Brunei  BRN  1990  10.5000
1373  Brunei  BRN  1991  10.3333
1374  Brunei  BRN  1992  12.0000
1375  Brunei  BRN  1993  11.2500
1376  Brunei  BRN  1994  12.0000
...
10002  Timor  TLS  2016   5.1818
10003  Timor  TLS  2017   4.9821
10004  Timor  TLS  2018   5.1182
10005  Timor  TLS  2019   5.1182
10006  Timor  TLS  2020   5.1000

```

[242 rows x 4 columns]

```

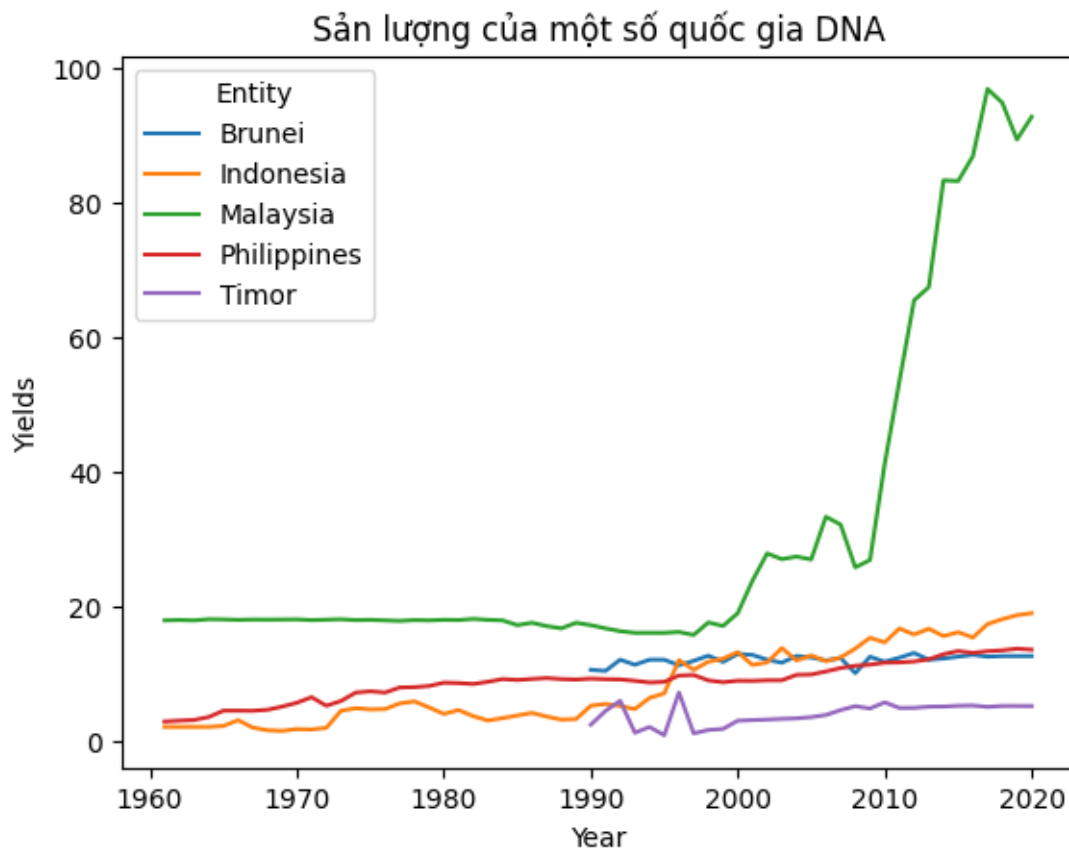
[101]: import seaborn as sns
import matplotlib as plt
sns.lineplot(data=tomato[mask], x="Year", y="Yields", hue="Entity").set(title =
↳ "Sản lượng của một số quốc gia DNA")
# plt.title('Sản lượng của một số quốc gia DNA')

```

```

[101]: [Text(0.5, 1.0, 'Sản lượng của một số quốc gia DNA')]

```



0.1 Phan 2

```
[19]: df2 = pd.read_csv('/Users/thutranghoa/Code/Data_analysis/Data/
↳1667260416_774__Marketing.csv')
df2
```

```
[19]:
```

	Age	Gender	OwnHome	Married	Location	Salary	Children	History	\
0	Old	Female	Own	Single	Far	47500	0	High	
1	Middle	Male	Rent	Single	Close	63600	0	High	
2	Young	Female	Rent	Single	Close	13500	0	Low	
3	Middle	Male	Own	Married	Close	85600	1	High	
4	Middle	Female	Own	Single	Close	68400	0	High	
..	
995	Young	Female	Rent	Single	Close	19400	1	NaN	
996	Middle	Male	Rent	Single	Far	40500	1	NaN	
997	Old	Male	Own	Single	Close	44800	0	Medium	
998	Middle	Male	Own	Married	Close	79000	2	Medium	
999	Young	Male	Rent	Married	Close	53600	1	Medium	

	Catalogs	AmountSpent
0	6	755
1	6	1318
2	18	296
3	18	2436
4	12	1304
..
995	18	384
996	18	1073
997	24	1417
998	18	671
999	24	973

[1000 rows x 10 columns]

```
[21]: df2 = df2.dropna()
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 697 entries, 0 to 999
Data columns (total 10 columns):
#   Column          Non-Null Count  Dtype
---  -
0   Age             697 non-null   object
1   Gender          697 non-null   object
2   OwnHome         697 non-null   object
3   Married         697 non-null   object
4   Location        697 non-null   object
5   Salary          697 non-null   int64
6   Children        697 non-null   int64
7   History         697 non-null   object
8   Catalogs        697 non-null   int64
9   AmountSpent     697 non-null   int64
dtypes: int64(4), object(6)
memory usage: 59.9+ KB
```

```
[26]: from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

df2['Age'] = le.fit_transform(df2['Age'])
```

```
/var/folders/cs/8r3m5sjs0rd7ts526sxt81c0000gn/T/ipykernel_20764/4019742341.py:4
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy


```
df2['Age'] = le.fit_transform(df2['Age'])
```

```
[28]: df2['Gender'] = le.fit_transform(df2['Gender'])
df2['OwnHome'] = le.fit_transform(df2['OwnHome'])
df2['Married'] = le.fit_transform(df2['Married'])
df2['Location'] = le.fit_transform(df2['Location'])
df2['History'] = le.fit_transform(df2['History'])
```

```
/var/folders/cs/8r3m5sjs0rd7ts526sxt81c0000gn/T/ipykernel_20764/3487257344.py:1
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy
df2['Gender'] = le.fit_transform(df2['Gender'])
/var/folders/cs/8r3m5sjs0rd7ts526sxt81c0000gn/T/ipykernel_20764/3487257344.py:2
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy
df2['OwnHome'] = le.fit_transform(df2['OwnHome'])
/var/folders/cs/8r3m5sjs0rd7ts526sxt81c0000gn/T/ipykernel_20764/3487257344.py:3
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy
df2['Married'] = le.fit_transform(df2['Married'])
/var/folders/cs/8r3m5sjs0rd7ts526sxt81c0000gn/T/ipykernel_20764/3487257344.py:4
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy
df2['Location'] = le.fit_transform(df2['Location'])
/var/folders/cs/8r3m5sjs0rd7ts526sxt81c0000gn/T/ipykernel_20764/3487257344.py:5
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy
df2['History'] = le.fit_transform(df2['History'])
```

```
[29]: df2
```

```
[29]:
```

	Age	Gender	OwnHome	Married	Location	Salary	Children	History	\
0	1	0	0	1	1	47500	0	0	
1	0	1	1	1	0	63600	0	0	
2	2	0	1	1	0	13500	0	1	
3	0	1	0	0	0	85600	1	0	
4	0	0	0	1	0	68400	0	0	
..	
991	1	0	1	1	1	11700	0	1	
993	0	0	0	0	1	99200	0	0	
997	1	1	0	1	0	44800	0	2	
998	0	1	0	0	0	79000	2	2	
999	2	1	1	0	0	53600	1	2	

	Catalogs	AmountSpent
0	6	755
1	6	1318
2	18	296
3	18	2436
4	12	1304
..
991	18	540
993	24	5503
997	24	1417
998	18	671
999	24	973

[697 rows x 10 columns]

```
[37]: X = df2.drop(['AmountSpent'], axis=1)
y = df2['AmountSpent']

print (X.shape)
print (y.shape)
```

(697, 9)

(697,)

```
[34]: from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
↳ random_state=44)
```

```
[35]: X_train
```

```
[35]:
```

	Age	Gender	OwnHome	Married	Location	Salary	Children	History	\
345	2	1	0	1	0	31900	0	2	
973	0	0	0	1	1	56200	0	0	

230	1	0	1	1	1	15000	0	1
907	0	1	1	0	1	52800	2	2
960	1	1	0	1	0	71300	0	0
..
116	1	1	0	0	0	58300	0	2
138	2	0	0	0	1	68000	0	0
829	0	1	0	0	1	130600	0	0
245	0	1	0	0	1	120000	3	0
601	2	1	1	1	0	19800	2	1

	Catalogs
345	6
973	18
230	12
907	12
960	18
..	...
116	24
138	24
829	18
245	18
601	12

[487 rows x 9 columns]

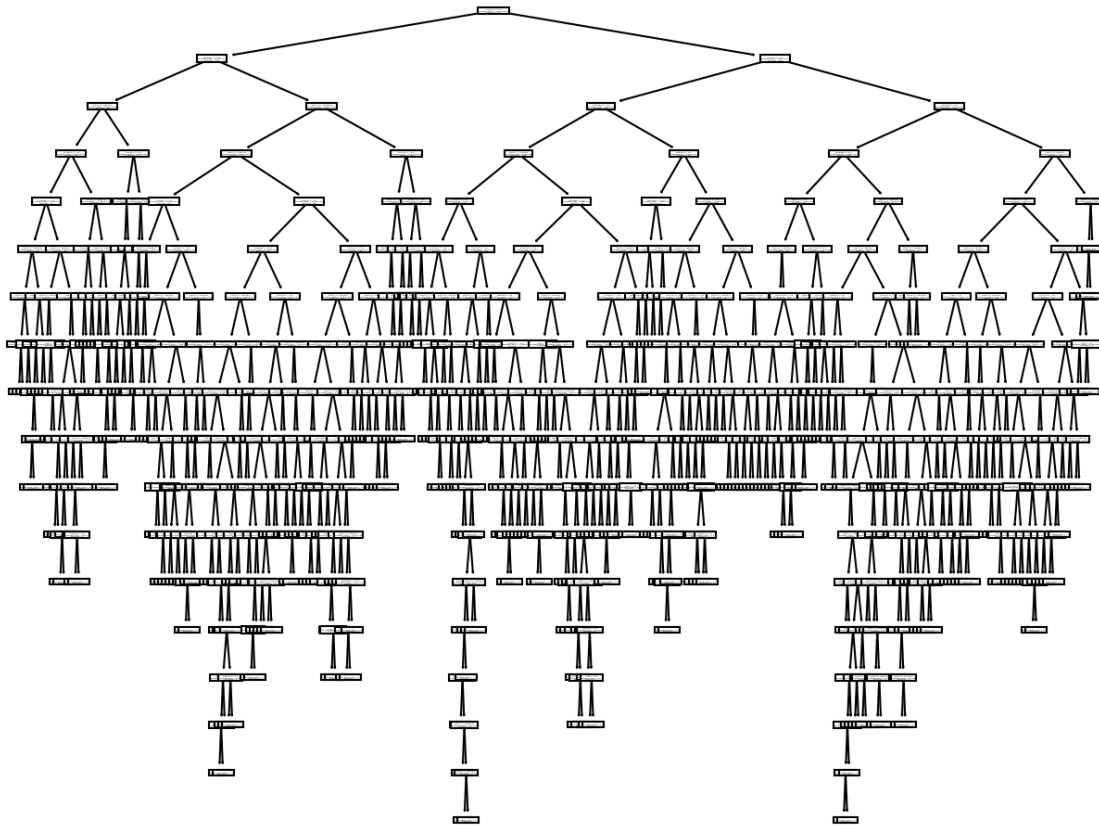
##Decision Tree Regressor

```
[63]: # Import the necessary modules and libraries
import matplotlib.pyplot as plt
import numpy as np

from sklearn.tree import DecisionTreeRegressor

model = DecisionTreeRegressor(random_state=44)
model.fit(X_train, y_train)
predictions = model.predict(X_test)
```

```
[64]: from sklearn.tree import plot_tree
plt.figure(figsize=(10,8), dpi=150)
plot_tree(model, feature_names=X.columns);
```



```
[66]: from sklearn.metrics import mean_squared_error , r2_score
print ('MSE of Decision Tree = ', mean_squared_error(y_test, predictions))
print ('R2_score of Decision Tree = ', r2_score(y_test, predictions))
```

```
MSE of Decision Tree = 338484.38095238095
R2_score of Decision Tree = 0.6578431761813559
```

##Linear Regression

```
[75]: from sklearn.linear_model import LinearRegression

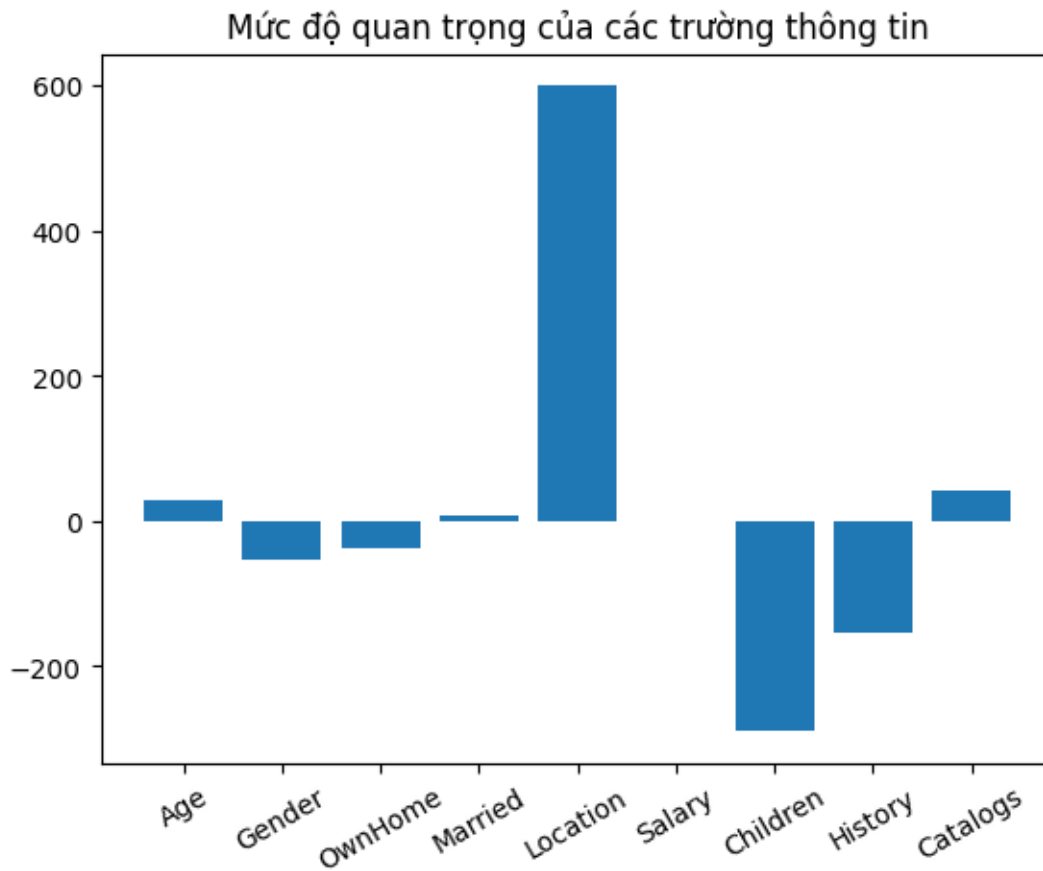
LR = LinearRegression()
LR.fit(X_train, y_train)
predictions = LR.predict(X_test)

print ('MSE of LinearRegression= ', mean_squared_error(y_test, predictions))
print ('R2_score of Linear Regression= ', r2_score(y_test, predictions))
```

```
MSE of LinearRegression= 246144.84279594294
R2_score of Linear Regression= 0.7511845675908819
```

```
[95]: A = list(df2.columns)
A.remove('AmountSpent')
importance = LR.coef_

# plot feature importance
feature = df2.columns
plt.bar(A, importance)
plt.title('Mức độ quan trọng của các trường thông tin')
plt.xticks(rotation = 30)
plt.show()
```



##SVM

```
[72]: from sklearn.svm import SVR
svr = SVR(kernel="linear")
svr.fit(X_train, y_train)

predictions = svr.predict(X_test)
```

```
print ('MSE of SVR = ', mean_squared_error(y_test, predictions))
print ('R2_score of SVR = ', r2_score(y_test, predictions))
```

MSE of SVR = 1043035.9377248775
R2_score of SVR = -0.0543525304668413

```
[73]: from sklearn.svm import SVR
      svr = SVR(kernel="poly")
      svr.fit(X_train, y_train)

      predictions = svr.predict(X_test)

      print ('MSE of SVR = ', mean_squared_error(y_test, predictions))
      print ('R2_score of SVR = ', r2_score(y_test, predictions))
```

MSE of SVR = 711649.5007908453
R2_score of SVR = 0.2806293390034591

```
[74]: from sklearn.svm import SVR
      svr = SVR(kernel="rbf")
      svr.fit(X_train, y_train)

      predictions = svr.predict(X_test)

      print ('MSE of SVR = ', mean_squared_error(y_test, predictions))
      print ('R2_score of SVR = ', r2_score(y_test, predictions))
```

MSE of SVR = 962101.6435287277
R2_score of SVR = 0.027459873881748642

0.2 Nhận xét

Trong 3 model sử dụng thì Linear Regression có R2_score cao nhất, chứng tỏ model này phù hợp nhất. Trong đó, thuộc tính 'Location' có ảnh hưởng lớn nhất đến khoản tiền chi tiêu