In [19]:
```python
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
import math
```

Task One

To figure out the values of alpha and beta in y = alpha(x) + beta:

1. Find the mean values of x[i] and y[i]
2. To find alpha, sum each value of x[i] - x_mean, then multiply this by the sum of each value of y[i] - y_mean
3. Divide this result by the sum of (x[i] - x_mean)squared. This results in alpha.
4. To find beta, minus alpha*(x_mean) from the mean of y.
5. You now have both alpha and beta for the equation y = alpha*(x) + beta

Task Two

In [2]:
```python
df = pd.DataFrame({
    'x': [5,6,8],
    'y': [20,22,33]
})
df
```

Out[2]:

	x	y
0	5	20
1	6	22
2	8	33

In [3]:
```python
mean_of_x = (5+6+8)/3
mean_of_y = (20+22+33)/3
print(mean_of_x)
print(mean_of_y)
```

```
6.333333333333333
25.0
```

Now to find alpha using step 2

In [4]:
```python
x_y_sums = ((5 - mean_of_x)*(20 - mean_of_y)) + ((6 - mean_of_x)*(22 - mean_of_y)) + ((8 - mean_of_x)*(
33 - mean_of_y))
print(x_y_sums)

xs_squared = ((5 - mean_of_x)**2 + (6 - mean_of_x)**2 + (8 - mean_of_x)**2)
print(xs_squared)

alpha = x_y_sums/xs_squared
print(alpha)
```

```
21.0
4.666666666666666
4.500000000000001
```

Here is a more automated version of above

In [5]:
```python
x = df['x']
y = df['y']

top = 0
bot = 0

for i in range(len(df['x'])):
    top += (x[i] - mean_of_x)*(y[i] - mean_of_y)
    bot += (x[i] - mean_of_x)**2
print(top)
print(bot)
print(top/bot)
```

```
21.0
4.666666666666666
4.500000000000001
```

To find beta, we multiply alpha by mean_of_x and take the result away from mean_of_y

In [6]:
```python
beta = mean_of_y - (alpha*mean_of_x)
print(beta)
```

```
-3.5000000000000036
```

Now we have both alpha and beta, we can put them into our linear equation:\ y = 4.50*(x) + (-3.50)

Here, 4.50 is the slope of the line and -3.50 is the y-intercept. If x is 0, y = -3.50 and for every value that x increases, y increases by 4.50.

Task Three and Four

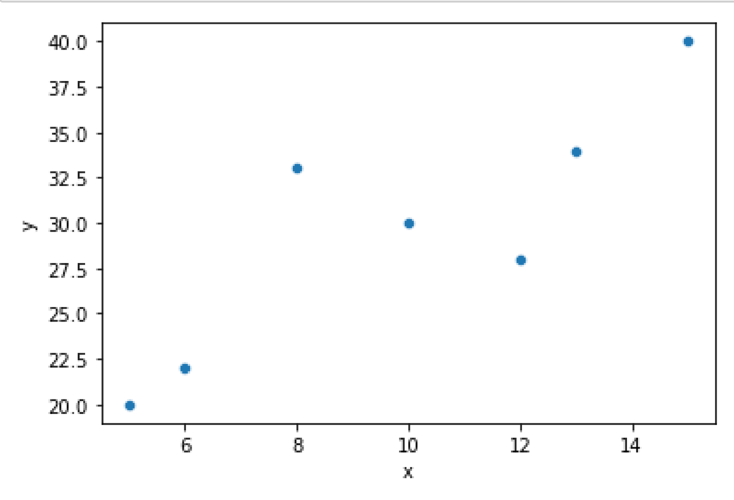
Now I will use a larger dataset and follow the same method but with more python-like language and then try and plot the results on a graph with the line.

In [7]:
```python
df = pd.DataFrame({
    'x': [5,6,8,10,12,13,15],
    'y': [20,22,33,30,28,34,40]
})
df
```

Out[7]:

	x	y
0	5	20
1	6	22
2	8	33
3	10	30
4	12	28
5	13	34
6	15	40

In [8]:
```python
sns.scatterplot(data=df, x='x', y='y')
plt.show()
```



In [9]:
```python
x = df.x
y = df.y
```

In [10]:
```python
x_mean = np.mean(x)
y_mean = np.mean(y)
print(x_mean, y_mean)
```

```
9.857142857142858 29.571428571428573
```

In [11]:
```python
top = 0
bot = 0

for i in range(len(x)):
    top += (x[i] - x_mean)*(y[i] - y_mean)
    bot += (x[i] - x_mean)**2

alpha = top/bot
alpha
```

Out[11]: 1.612068965517241

beta = y_mean - alpha*(x_mean)

In [12]:
```python
beta = y_mean - alpha*x_mean
beta
```

Out[12]: 13.681034482758625

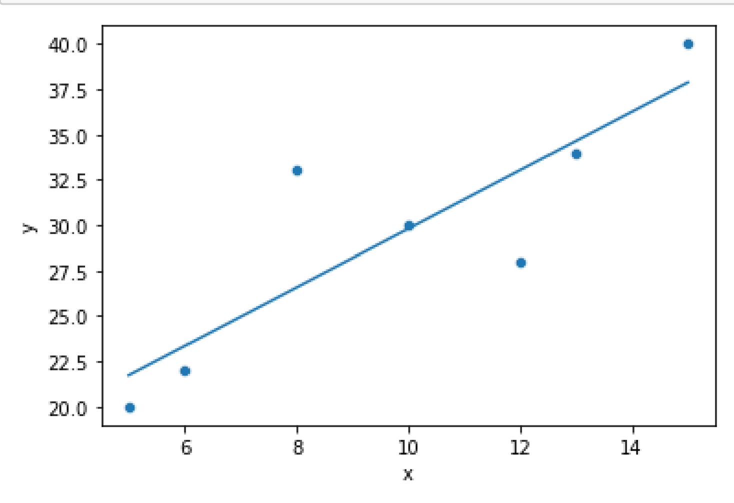
y = alpha*(x) + beta\ Here I insert the minimum and maximum x values from my data into the equation to get the corresponding y values.

In [13]:
```python
five = (alpha*5) + beta
fifteen = (alpha*15) + beta
print(five)
print(fifteen)
```

```
21.741379310344833
37.86206896551724
```

The resulting graph with the line of best fit. Using this we can now estimate values along the line.

In [14]:
```python
sns.scatterplot(data=df, x='x', y='y')
plt.plot([5,15],[21.741, 37.862])
plt.show()
```



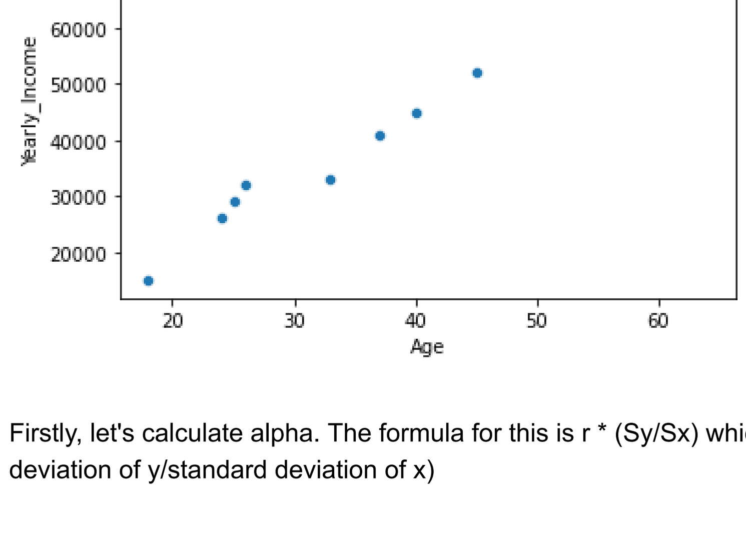
From below I will demonstrate a more complex method, using Pearson's correlation coefficient

In [15]:
```python
df = pd.DataFrame({'Age': [18,25,57,45,26,64,37,40,24,33], 'Yearly_Income':
                   [15000, 29000,68000,52000,32000,80000,41000,45000,26000,33000]})
df
```

Out[15]:

	Age	Yearly_Income
0	18	15000
1	25	29000
2	57	68000
3	45	52000
4	26	32000
5	64	80000
6	37	41000
7	40	45000
8	24	26000
9	33	33000

In [16]:
```python
sns.scatterplot(data=df, x='Age', y='Yearly_Income')
plt.show()
```



Firstly, let's calculate alpha. The formula for this is r * (Sy/Sx) which stands for Pearson's correlation coefficient multiplying (standard deviation of y/standard deviation of x)

This is the formula for Pearson's correlation coefficient:
alt text
\ It looks daunting but we will fill this in bit by bit. If the image doesn't load, the link is:
https://editor.analyticsvidhya.com/uploads/39170Formula.JPG

In [39]:
```python
x = df.Age
y = df.Yearly_Income

top = 0
bot = 0

for i in range(len(x)):
    top += (x[i] - np.mean(x))*(y[i] - np.mean(y))
    bot += math.sqrt(((x[i] - np.mean(x))**2)*((y[i] - np.mean(y))**2))

r = top/bot
print(r)
```

```
0.999917240964218
```

Now we have r we can return to our formula for alpha which is r * (Sy/Sx).

In [40]:
```python
Sy = np.std(df.Yearly_Income)
Sx = np.std(df.Age)
print(Sy, Sx)
```

```
18880.942773071478 14.187670703818863
```

Slotting these into our formula gives:

In [47]:
```python
alpha = r*(Sy/Sx)
print(alpha)
```

```
1330.6892018131773
```

So our slope is equal to 1330.689. For every 1 value that Age moves along, Yearly Income moves by 1330.689.\ To figure out beta is easier now we have this value. The formula for beta is (mean of y) - (alpha * mean of x).

In [48]:
```python
beta = (np.mean(df.Yearly_Income)) - (alpha * np.mean(df.Age))
print(beta)
```

```
-7002.431546906242
```

Now that we have all the values, we can input them into our formula:\ y = -7002.431 + (1330.689 * x)

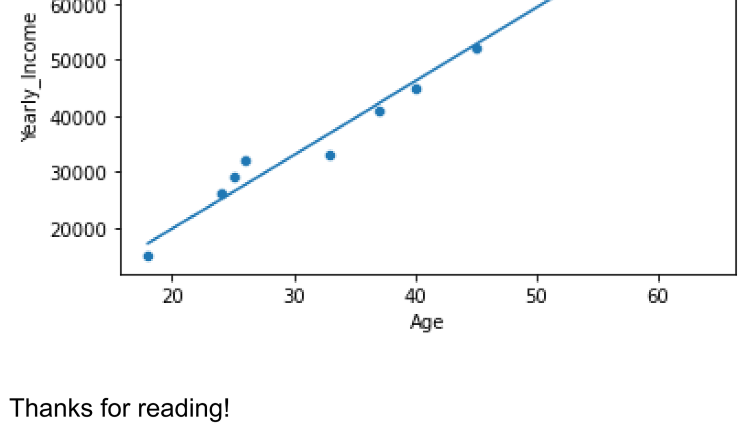
Our maximum age is 64, but we can now predict values above this value using the formula. However, let's say the retirement age is 65 in this scenario and we're only interested in this populations active working income. Let's also set our lower boundary as 18 due to it being the youngest working age in this population.\ We can calculate the Y values by inputting 64 and 18 into our formula:

In [49]:
```python
print(-7002.431 + 1330.689*18)
print(-7002.431 + 1330.689*64)
```

```
16949.971
78161.66500000001
```

In [51]:
```python
#plotting the scatter plot
sns.scatterplot(data=df, x='Age', y='Yearly_Income')

plt.plot([18,64], [17141.924, 77886.397])
plt.show()
```



Thanks for reading!

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