Problem 1 A research laboratory was developing a new compound for the relief of severe cases of hay fever. In an experiment with 36 volunteers, the amounts of the two active ingredients (A & B) in the compound were varied at three levels each. Randomization was used in assigning four volunteers to each of the nine treatments. The data on hours of relief can be found in the following .csv file: Fever.csv

In [2]:
```
import numpy as np
import pandas as pd
import seaborn as sns
from statsmodels.formula.api import ols      # For n-way ANOVA
from statsmodels.stats.anova import _get_covariance,anova_lm # For n-way ANO
%matplotlib inline
```

1.1) State the Null and Alternate Hypothesis for conducting one-way ANOVA for both the variables ‘A’ and ‘B’ individually. [both statement and statistical form like Ho=mu, Ha>mu]

1. Null hypothesis (Ho): There is no difference in average relief for any of the active level in A HoA: Mu1 = Mu2 = Mu3 Alternative hypothesis (Ha): There is a difference in average relief for any of the active level in A HaA: Mu1 not equal to Mu2 not equal to Mu3
2. Null hypothesis (Ho): There is no difference in average relief for any of the active level in B HoB: Mu1 = Mu2 = Mu3 Alternative hypothesis (Ha): There is a difference in average relief for any of the active level in B HaB: Mu1 not equal to Mu2 not equal to Mu3
3. Null hypothesis (Ho): The effect of one independent variable A on average relief does not depend on the effect of the other independent variable B. Alternative hypothesis (Ha): There is an interaction effect between A and B

1.2) Perform one-way ANOVA for variable ‘A’ with respect to the variable ‘Relief’. State whether the Null Hypothesis is accepted or rejected based on the ANOVA results.

In [3]:
```
DF = pd.read_csv('Fever-1.csv')
```

In [6]:
```
DF.head()
```

Out[6]:

	A	B	Volunteer	Relief
0	1	1	1	2.4
1	1	1	2	2.7
2	1	1	3	2.3
3	1	1	4	2.5
4	1	2	1	4.6

In [8]:
```
DF.describe()
```

Out[8]:

	A	B	Volunteer	Relief
count	36.000000	36.000000	36.000000	36.000000
mean	2.000000	2.000000	2.500000	7.183333
std	0.828079	0.828079	1.133893	3.272090
min	1.000000	1.000000	1.000000	2.300000
25%	1.000000	1.000000	1.750000	4.675000
50%	2.000000	2.000000	2.500000	6.000000
75%	3.000000	3.000000	3.250000	9.325000
max	3.000000	3.000000	4.000000	13.500000

In [5]:
```
DF.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 36 entries, 0 to 35
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   A          36 non-null     int64  
 1   B          36 non-null     int64  
 2   Volunteer  36 non-null     int64  
 3   Relief     36 non-null     float64
dtypes: float64(1), int64(3)
memory usage: 1.2 KB
```

In [9]:
```
DF.groupby(['A','Volunteer'])['Relief'].agg(['mean','std']).round(2)
```

Out[9]:

A	Volunteer	mean	std
1	**1**	3.93	1.33
	2	3.80	0.96
	3	3.87	1.38
	4	3.93	1.24
2	**1**	7.93	1.85
	2	7.87	2.31
	3	7.63	1.85
	4	7.90	2.26
3	**1**	9.83	3.70
	2	9.73	3.71
	3	9.93	3.74
	4	9.83	3.51

The mean relief of 1 active level ranges from 3.80 to 3.93 The mean relief of 2 active level ranges from 7.63 to 7.93 The mean relief of 3 active level ranges from 9.73 to 9.93

In [16]:
```
DF.groupby(['A'])['Relief'].agg(['mean','std']).round(2)
```

Out[16]:

A	mean	std
1	3.88	1.06
2	7.83	1.78
3	9.83	3.13

In [20]:
```
DF.A = pd.Categorical(DF.A)
```

In [21]:
```
DF.A.value_counts
```

Out[21]:
```
<bound method IndexOpsMixin.value_counts of 0     1
1     1
2     1
3     1
4     1
5     1
6     1
7     1
8     1
9     1
10    1
11    1
12    2
13    2
14    2
15    2
16    2
17    2
18    2
19    2
20    2
21    2
22    2
23    2
24    3
25    3
26    3
27    3
28    3
29    3
30    3
31    3
32    3
33    3
34    3
35    3
Name: A, dtype: category
Categories (3, int64): [1, 2, 3]>
```

Average alone is not good enough description of the data, though there is quite some variation in relief. For example, the original data show that the minimum relief time of 3 active level is in the range of maximum relief time of 2 active level in A

The ANOVA model helps in estimating the total amount of variation that exists in the relief time. Hence split the total variation into two: Between and Within Group variation for A

ANOVA: Hypothesis test Is one active component has higher relief time, or it is random noise due to sampling effect

One way ANOVA F test using Statsmodels

In [27]:
```
formula = 'Relief ~ C(A)'
model = ols(formula, DF).fit()
aov_table = anova_lm(model)
print(aov_table)
```

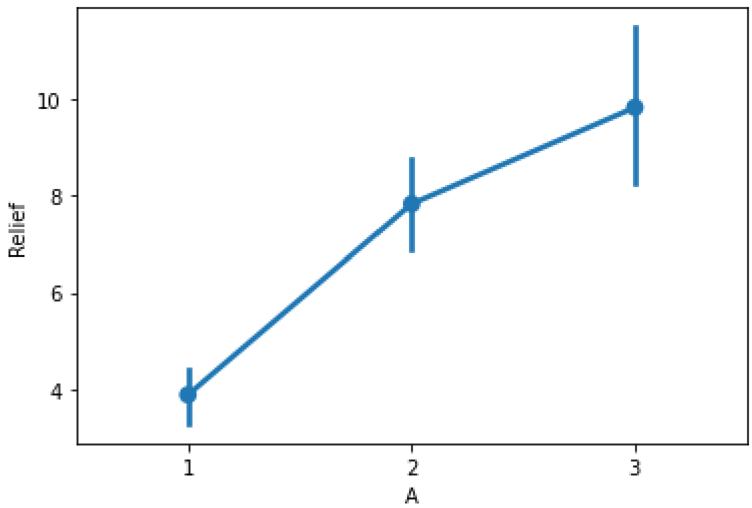
```
            df   sum_sq     mean_sq          F        PR(>F)
C(A)       2.0   220.02  110.010000  23.465387  4.578242e-07
Residual  33.0   154.71    4.688182        NaN           NaN
```

-Df shows the degrees of freedom for each variable (number of levels in the variable minus 1). -Sum sq is the sum of squares (a.k.a. the variation between the group means created by the levels of the independent variable and the overall mean). -Mean sq shows the mean sum of squares (the sum of squares divided by the degrees of freedom). -F value is the test statistic from the F-test (the mean square of the variable divided by the mean square of each parameter). -Pr(>F) is the p-value of the F statistic, and shows how likely it is that the F-value calculated from the F-test would have occurred if the null hypothesis of no difference was true.

From this output we can see that 1.Amount of active ingredients explain a significant amount of variation in average relief (p-values < 0.05). Hence reject the null hypothesis. This means that with the observed data, there is enough evidence to assume a general difference in the relief time of the active ingredients(1,2,3) in A

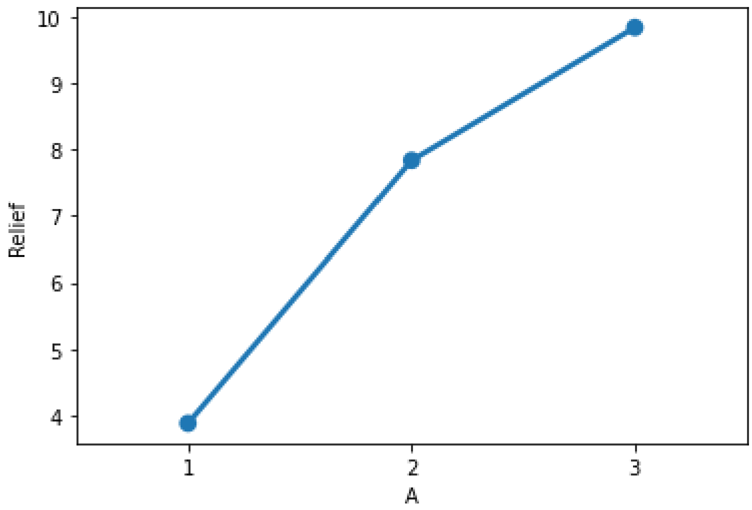
In [28]:
```
sns.pointplot(x='A', y='Relief', data=DF)
```

Out[28]: <AxesSubplot:xlabel='A', ylabel='Relief'>



In [29]:
```
sns.pointplot(x='A', y='Relief', data=DF, ci=None)
```

Out[29]:
```
<AxesSubplot:xlabel='A', ylabel='Relief'>
```



1.3) Perform one-way ANOVA for variable ‘B’ with respect to the variable ‘Relief’. State whether the Null Hypothesis is accepted or rejected based on the ANOVA results.

In [4]:
```
DF.groupby(['B','Volunteer'])['Relief'].agg(['mean','std']).round(2)
```

Out[4]:

B	Volunteer	mean	std
1	1	4.77	2.06
	2	4.53	1.61
	3	4.57	1.97
	4	4.67	1.93
2	1	7.80	2.82
	2	7.93	3.31
	3	8.07	2.90
	4	7.93	2.85
3	1	9.13	4.35
	2	8.93	4.26
	3	8.80	4.45
	4	9.07	4.31

In [9]:
```
DF.groupby(['B'])['Relief'].agg(['mean','std']).round(2)
```

Out[9]:

B	mean	std
1	4.63	1.62
2	7.93	2.54
3	8.98	3.71

In [6]:
```
DF.B = pd.Categorical(DF.B)
```

In [8]:
```
DF.B.value_counts()
```

Out[8]:
```
3    12
2    12
1    12
Name: B, dtype: int64
```

One way ANOVA F test using Statsmodels

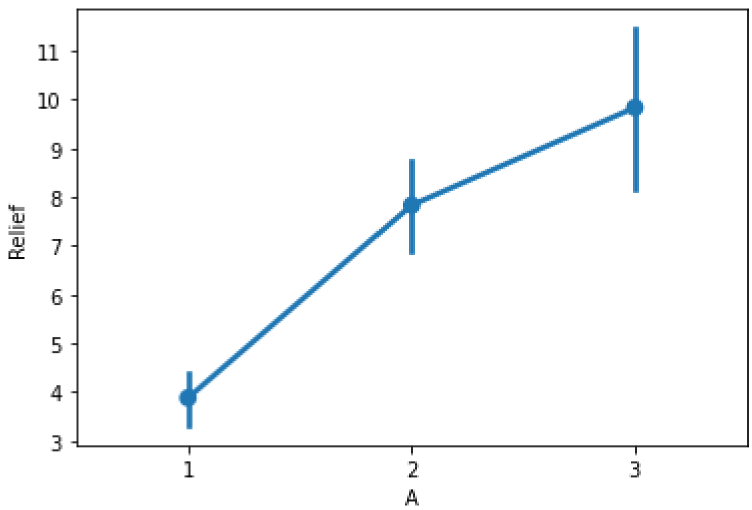
In [10]:
```
formula = 'Relief ~ C(B)'
model = ols(formula, DF).fit()
aov_table = anova_lm(model)
print(aov_table)
```

```
            df  sum_sq    mean_sq         F   PR(>F)
C(B)       2.0  123.66  61.830000  8.126777  0.00135
Residual  33.0  251.07   7.608182       NaN      NaN
```

From this output we can see that 1.Amount of active ingredients explain a significant amount of variation in average relief (p-values < 0.05). Hence reject the null hypothesis. This means that with the observed data, there is enough evidence to assume a general difference in the relief time of the active ingredients(1,2,3) in B

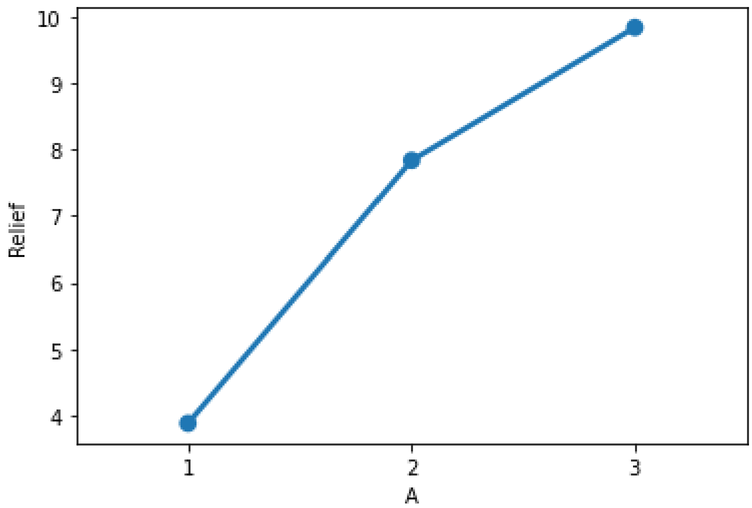
In [11]:
```
sns.pointplot(x='A', y='Relief', data=DF)
```

Out[11]:
```
<AxesSubplot:xlabel='A', ylabel='Relief'>
```



In [12]:
```
sns.pointplot(x='A', y='Relief', data=DF, ci=None)
```

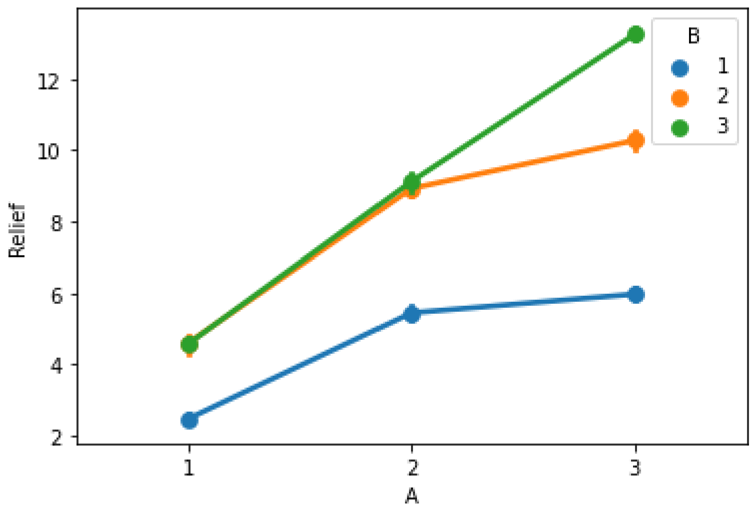
Out[12]: <AxesSubplot:xlabel='A', ylabel='Relief'>



1.4) Analyse the effects of one variable on another with the help of an interaction plot. What is the interaction between the two treatments? [hint: use the 'pointplot' function from the 'seaborn' function]

In [18]:
```
sns.pointplot(x='A', y='Relief', data=DF, hue = 'B')
```

Out[18]: <AxesSubplot:xlabel='A', ylabel='Relief'>



In [19]:
```
formula = 'Relief ~ C(A) + C(B) + C(A):C(B)'
model = ols(formula, DF).fit()
aov_table = anova_lm(model)
print(aov_table)
```

```
             df   sum_sq     mean_sq            F        PR(>F)
C(A)        2.0  220.020  110.010000  1827.858462  1.514043e-29
C(B)        2.0  123.660   61.830000  1027.329231  3.348751e-26
C(A):C(B)   4.0   29.425    7.356250   122.226923  6.972083e-17
Residual   27.0    1.625    0.060185          NaN           NaN
```

From this output we can see that 1.Amount of active ingredients explain a significant amount of variation in average relief (p-values < 0.05). Hence reject the null hypothesis. This means that with the observed data, there is enough evidence to assume a general difference in the relief time of the active ingredients(1,2,3) when there is influence of A on B

Hence it shows that there is an interaction between the two ingredients

1.5) Perform a two-way ANOVA based on the different ingredients (variable 'A' & 'B' along with their interaction **'AB') with the variable 'Relief' and state your results.***

In [30]:
```
formula = 'Relief ~ C(A) + C(B) + C(A):C(B)'
model = ols(formula, DF).fit()
aov_table = anova_lm(model)
print(aov_table)
```

```
             df   sum_sq     mean_sq            F        PR(>F)
C(A)        2.0  220.020  110.010000  1827.858462  1.514043e-29
C(B)        2.0  123.660   61.830000  1027.329231  3.348751e-26
C(A):C(B)   4.0   29.425    7.356250   122.226923  6.972083e-17
Residual   27.0    1.625    0.060185          NaN           NaN
```

From this output we can see that 1.Amount of active ingredients explain a significant amount of variation in average relief (p-values < 0.05). Hence reject the null hypothesis. This means that with the observed data, there is enough evidence to assume a general difference in the relief time of the active ingredients(1,2,3) when there is influence of A on B

1.6) Mention the business implications of performing ANOVA for this particular case study.

Analysis of variance (ANOVA) is an analysis tool used in statistics that splits an observed aggregate variability found inside a data set into two parts: systematic factors and random factors. The systematic factors have a statistical influence on the given data set, while the random factors do not. Analysts use the ANOVA test to determine the influence that independent variables have on the dependent variable in a regression study.

1. ANOVA test in this case study helped to compare A and B group
2. To determine whether a relationship exists between them and also if there is any variabilty between the groups

In [ ]:
```

```