

# Q1. Assumptions of ANOVA and violations

ANOVA requires the following assumptions:

## 1. Independence of observations

- Observations are independent of each other
- **Violation example:** Measuring the same subject multiple times in one-way ANOVA

## 2. Normality

- Data in each group is approximately normally distributed
- **Violation example:** Strongly skewed data or heavy outliers

## 3. Homogeneity of variances (equal variances)

- Variances across groups are equal
- **Violation example:** One group has much larger variance than others

● Violations can lead to **inflated Type I errors** or **loss of power**.

✓ Remedies: data transformation, Welch's ANOVA, or non-parametric tests.

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# Q2. Types of ANOVA

## 1. One-way ANOVA

- One independent variable (factor)
- Example: Comparing test scores across 3 teaching methods

## 2. Two-way ANOVA

- Two independent variables

- Example: Teaching method × gender

### 3. Repeated Measures ANOVA

- Same subjects measured multiple times
- Example: Blood pressure before, during, and after treatment

## Q3. Partitioning of variance in ANOVA

Total variation in data is divided as:

$SST = SSB \text{ (Between)} + SSW \text{ (Within)}$   
 $SST = SSB \text{ (Between)} + SSW \text{ (Within)}$

- **Between-group variance:** due to treatment/factor
- **Within-group variance:** due to random error

📌 Important because the **F-statistic** is based on this ratio:

$F = \frac{\text{Between variance}}{\text{Within variance}}$   
 $F = \frac{\text{Between variance}}{\text{Within variance}}$

## Q4. Calculating SST, SSB, SSW in one-way ANOVA (Python)

```
import numpy as np
```

```
groups = {
    'A': np.array([5, 6, 7]),
    'B': np.array([8, 9, 6]),
    'C': np.array([4, 5, 3])
}
```

```
all_data = np.concatenate(list(groups.values()))
grand_mean = np.mean(all_data)
```

```

# SST
SST = np.sum((all_data - grand_mean)**2)

# SSB
SSB = sum(len(v) * (np.mean(v) - grand_mean)**2 for v in
groups.values())

# SSW
SSW = sum(np.sum((v - np.mean(v))**2) for v in groups.values())

SST, SSB, SSW

```

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## Q5. Two-way ANOVA main & interaction effects (Python)

```

import pandas as pd
import statsmodels.api as sm
from statsmodels.formula.api import ols

df = pd.DataFrame({
    'score': [80, 82, 78, 85, 88, 90, 75, 77, 74, 79],
    'method': ['A', 'A', 'A', 'B', 'B', 'B', 'A', 'A', 'B', 'B'],
    'gender': ['M', 'F', 'M', 'F', 'M', 'F', 'F', 'M', 'F', 'M']
})

model = ols('score ~ C(method) * C(gender)', data=df).fit()
anova_table = sm.stats.anova_lm(model, typ=2)
anova_table

```

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## Q6. Interpretation of $F = 5.23$ , $p = 0.02$

- $p\text{-value} < 0.05 \rightarrow$  **Reject null hypothesis**
- There is a **statistically significant difference** between group means

- ANOVA does **not** tell which groups differ → post-hoc test required
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## Q7. Missing data in repeated measures ANOVA

### Common methods:

1. **Listwise deletion** – remove subjects with missing data  
✗ Reduces sample size
  2. **Mean/Last observation imputation**  
✗ Underestimates variability
  3. **Mixed-effects models (preferred)**  
✓ Handles missing data appropriately
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## Q8. Post-hoc tests after ANOVA

| Test       | When to use                               |
|------------|---|
| Tukey HSD  | Equal variances, all pairwise comparisons |
| Bonferroni | Conservative, many comparisons            |
| Scheffé    | Unequal sample sizes                      |
| Dunnett    | Compare groups to a control               |

📌 Example: ANOVA shows diet differences → use Tukey HSD to find which diets differ.

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## Q9. One-way ANOVA: Diet weight loss (Python)

```
from scipy.stats import f_oneway
```

```
diet_A = [5, 6, 7, 8]  
diet_B = [3, 4, 5, 4]
```

```
diet_C = [6, 7, 8, 9]
```

```
F, p = f_oneway(diet_A, diet_B, diet_C)
```

```
F, p
```

### Interpretation

- If  $p < 0.05 \rightarrow$  Significant difference in mean weight loss among diets
- 

## Q10. Two-way ANOVA: Software $\times$ Experience (Python)

```
df = pd.DataFrame({  
    'time': [30,28,35,40,38,42,25,27,29,34,36,33],  
    'software': ['A','A','A','B','B','B','C','C','C','A','B','C'],  
    'experience': ['N','E','N','E','N','E','N','E','N','E','N','E']  
})
```

```
model = ols('time ~ C(software) * C(experience)', data=df).fit()  
sm.stats.anova_lm(model, typ=2)
```

### Interpretation

- Main effect: software or experience affects time
  - Interaction: software effectiveness depends on experience
- 

## Q11. Two-sample t-test & post-hoc

```
from scipy.stats import ttest_ind
```

```
control = [70,72,68,75,71]
```

```
experimental = [78,80,82,79,81]
```

```
t, p = ttest_ind(control, experimental)
```

t, p

- If  $p < 0.05 \rightarrow$  significant difference
- Since only two groups  $\rightarrow$  **no post-hoc needed**  
(Post-hoc is for  $\geq 3$  groups)

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## Q12. Repeated Measures ANOVA: Retail store sales

```
from statsmodels.stats.anova import AnovaRM
```

```
df = pd.DataFrame({  
    'day': list(range(1,31))*3,  
    'store': ['A']*30 + ['B']*30 + ['C']*30,  
    'sales': np.random.normal(100, 10, 90),  
    'subject': list(range(1,31))*3  
})
```

```
anova = AnovaRM(df, 'sales', 'subject', within=['store'])  
anova.fit()
```

### If significant:

- Conduct **pairwise comparisons** with Bonferroni correction
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