Randomized complete block design

Table of Contents

In [1]:
```
print('\nEnabling interactive shell outputs ...')
print('   Use command pass; to disable cell text outputs')
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"

import warnings
warnings.filterwarnings('ignore')
warnings.simplefilter(action="ignore",category=UserWarning)
warnings.simplefilter(action="ignore",category=FutureWarning)

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import statsmodels.api as sm



%matplotlib inline
%config InlineBackend.figure_formats = {'png', 'retina'}
```

```
Enabling interactive shell outputs ...
   Use command pass; to disable cell text outputs
```

RCBD Analysis

In [3]:
```
df = pd.read_excel('lect04-blocking.xlsx', sheet_name='StrengthData1',header=None)
df

a = df.shape[0]
b = df.shape[1]
strength_data = pd.DataFrame({'Strength': df.stack().values,
                              'ChemType': np.repeat(['C1','C2','C3','C4'],b),
                              'Fabric': ['F1','F2','F3','F4','F5']*a})
strength_data
```

Out[3]:

	0	1	2	3	4
0	1.3	1.6	0.5	1.2	1.1

	0	1	2	3	4
1	2.2	2.4	0.4	2.0	1.8
2	1.8	1.7	0.6	1.5	1.3
3	3.9	4.4	2.0	4.1	3.4

Out[3]:

	Strength	ChemType	Fabric
0	1.3	C1	F1
1	1.6	C1	F2
2	0.5	C1	F3
3	1.2	C1	F4
4	1.1	C1	F5
5	2.2	C2	F1
6	2.4	C2	F2
7	0.4	C2	F3
8	2.0	C2	F4
9	1.8	C2	F5
10	1.8	C3	F1
11	1.7	C3	F2
12	0.6	C3	F3
13	1.5	C3	F4
14	1.3	C3	F5
15	3.9	C4	F1
16	4.4	C4	F2
17	2.0	C4	F3
18	4.1	C4	F4
19	3.4	C4	F5

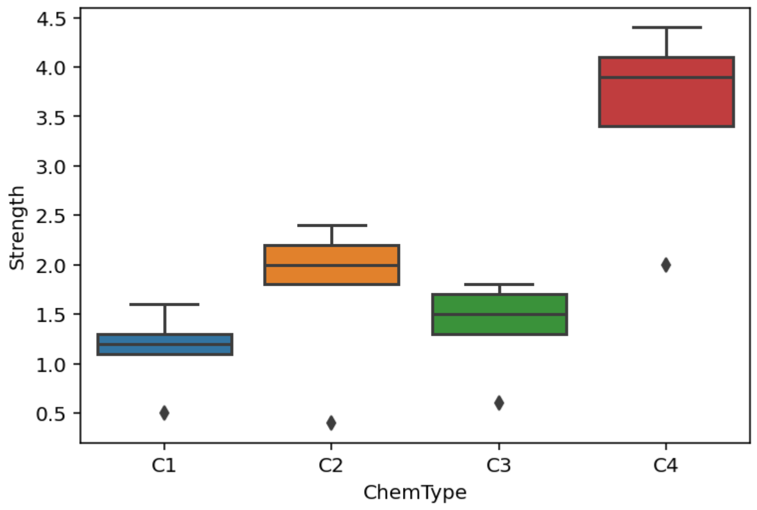
In [5]:

```python
### Load table and convert to dataframe
df = pd.read_excel('lect04-blocking.xlsx', sheet_name='StrengthData2',header=0)
strength_data = pd.melt(df, id_vars='ChemType', value_vars=df.columns[1:],
                        var_name='Fabric', value_name='Strength')
print(strength_data)
```

```
  ChemType Fabric  Strength
0       C1     F1       1.3
1       C2     F1       2.2
2       C3     F1       1.8
3       C4     F1       3.9
4       C1     F2       1.6
5       C2     F2       2.4
6       C3     F2       1.7
7       C4     F2       4.4
```

```
8         C1     F3       0.5
9         C2     F3       0.4
10        C3     F3       0.6
11        C4     F3       2.0
12        C1     F4       1.2
13        C2     F4       2.0
14        C3     F4       1.5
15        C4     F4       4.1
16        C1     F5       1.1
17        C2     F5       1.8
18        C3     F5       1.3
19        C4     F5       3.4
```

In [6]:
```
sns.boxplot(x='ChemType',y='Strength',data=strength_data);
```



Manual calculations for RCBD analysis

In [7]:
```
# Compute variables
a = len(strength_data.ChemType.unique())
b = len(strength_data.Fabric.unique())
total_y = sum(strength_data.Strength)
SST = sum(strength_data.Strength**2) - (total_y**2)/(a*b)

# Compute SS terms
yi_dot = strength_data.groupby('ChemType').aggregate({'Strength':'sum'}).Strength
SSTr = sum(yi_dot**2)/b - (total_y**2)/(a*b)
ydot_j = strength_data.groupby('Fabric').aggregate({'Strength':'sum'}).Strength
SSB = sum(ydot_j**2)/a - (total_y**2)/(a*b)
SSE = SST - SSB - SSTr
print("SST = {:.3f}, SSTr = {:.3f}, SSB = {:.3f}, SSE = {:.3f}".format(SST, SSTr, SSB,

# Compute MS Terms
MSTr = SSTr/(a-1)
MSB = SSB/(b-1)
MSE = SSE/((a-1)*(b-1))
F0 = MSTr/MSE
p_value = stats.f.sf(F0, a-1,(a-1)*(b-1))
print("MSTr = {0:.3f}, MSE = {1:.3f}, F0 = {2:.3f}, P-value = {3:.3f}".format(MSTr, MSE
```

```
SST = 25.688, SSTr = 18.044, SSB = 6.693, SSE = 0.951
MSTr = 6.015, MSE = 0.079, F0 = 75.895, P-value = 0.000
```

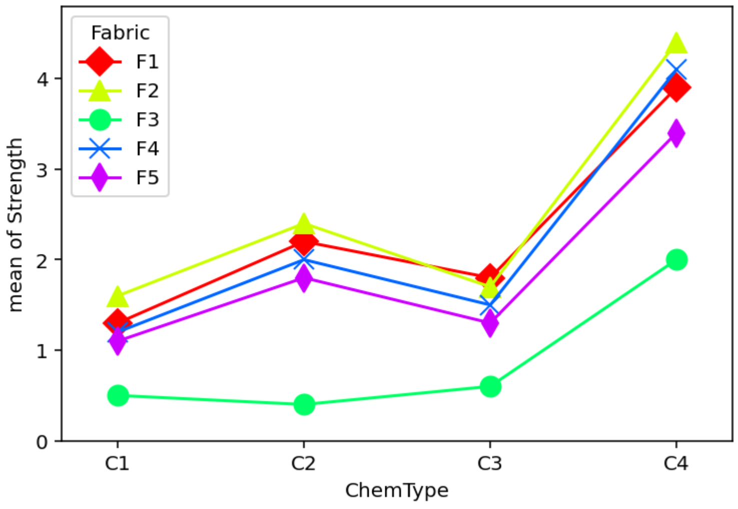
RCBD Calculation from Statsmodel

In [8]:
```
from statsmodels.formula.api import ols # Require patsy version 5.0.1+
from statsmodels.stats.anova import anova_lm

mod = ols('Strength ~ ChemType + Fabric', strength_data).fit()
anova_table = sm.stats.anova_lm(mod)
print(anova_table)
```

```
            df  sum_sq   mean_sq          F        PR(>F)
ChemType   3.0  18.044  6.014667  75.894848  4.518310e-08
Fabric     4.0   6.693  1.673250  21.113565  2.318913e-05
Residual  12.0   0.951  0.079250        NaN           NaN
```

Visualizing Interaction Assumption

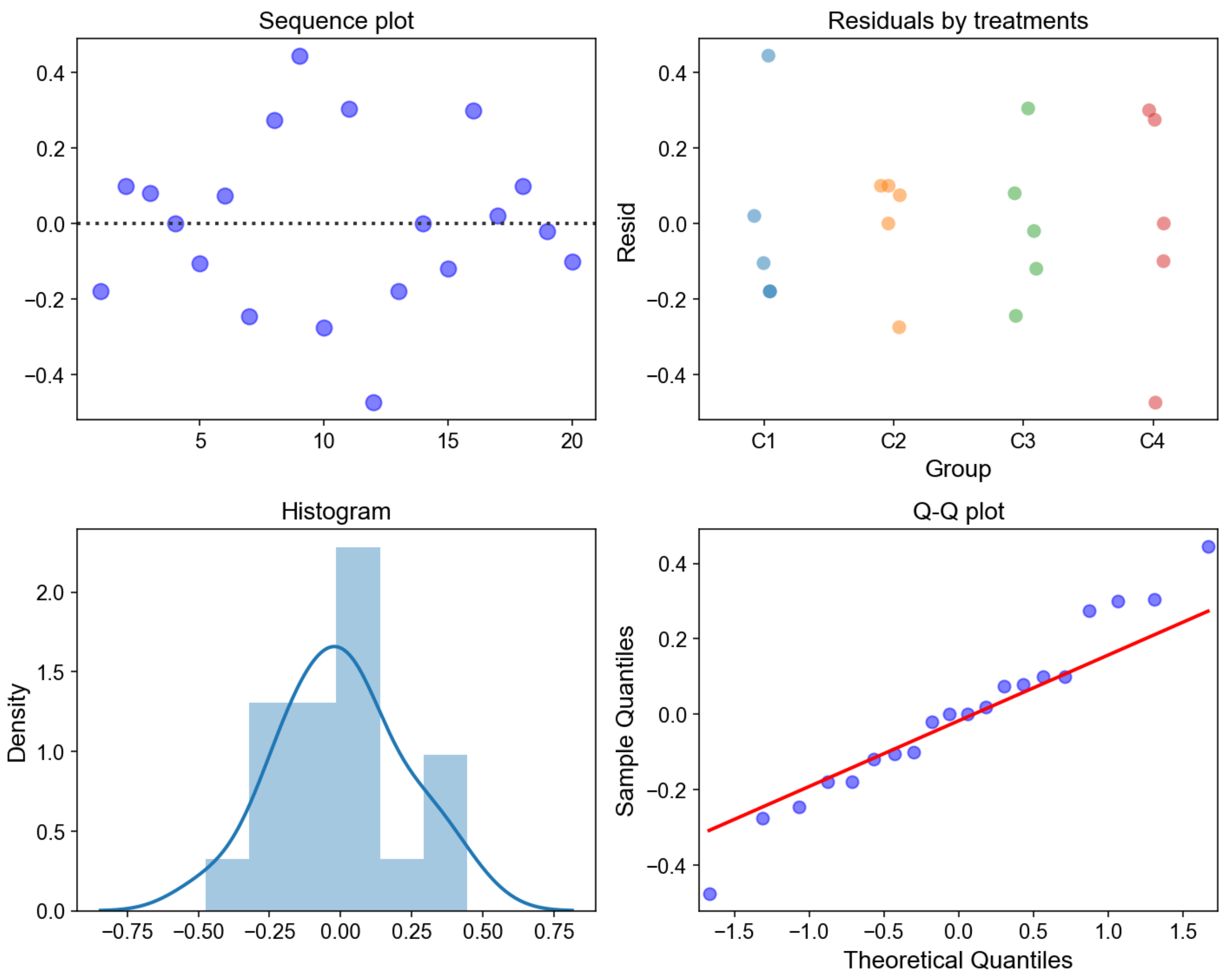
In [9]:
```
from statsmodels.graphics.factorplots import interaction_plot

fig = interaction_plot(strength_data.ChemType,
                       strength_data.Fabric,
                       strength_data.Strength,
                       markers=['D','^','o','x','d'], ms=10)
```



Normality Check Plotting function

In [10]:
```
def check_anova_normality(group, x):

    kws = dict(color='blue', marker='o', markersize=7, alpha=0.5)
    sns1_kws = dict(color='blue', marker='o', s=80, alpha=0.5)
    sns2_kws = dict(marker='o', s=8, alpha=0.5)

    T = len(x)

    fig = plt.figure(figsize=(10,8))

    ax1 = fig.add_subplot(221)
    ax2 = fig.add_subplot(222)
    ax3 = fig.add_subplot(223)
    ax4 = fig.add_subplot(224)

    #ax1.plot(x, color='blue', alpha=0.5, linestyle='--', marker='o', ms=4)
    n=len(x)
    sns.residplot(np.linspace(1,n,n), x, ax=ax1, scatter_kws=sns1_kws) # color='blue',
    #sns.scatterplot(np.linspace(1,n,n), x, ax=ax1, **sns1_kws)
    ax1.set_title('Sequence plot')
    # Scatter plot
    #ax2.scatter(x, x.shift(), alpha=0.5, color='red')
    #ax2.set_title(r'Scatter plot of $e_n$ vs $e_{n+1}$')

    # Residual groupplot
    resid_df = pd.DataFrame({'Group':group, 'Resid':x})
    sns.stripplot(x='Group', y='Resid', data=resid_df, ax=ax2, **sns2_kws)
    ax2.set_title('Residuals by treatments')

    # Box plot
    #ax2.boxplot(x,showmeans=True)
    #ax2.set_title('Boxplot')

    # histogram plot
    sns.distplot(x, hist=True, kde=True, ax=ax3)
    ax3.set_title('Histogram')


    # qq plot
    sm.graphics.qqplot(x,line='q',ax=ax4, **kws)
    ax4.set_title('Q-Q plot')
    plt.tight_layout()
```

In [9]:
```
check_anova_normality(strength_data['ChemType'], mod.resid)
```



Friedman Test

In [11]:

```
from scipy.stats import friedmanchisquare

y1=[1.3, 1.6, 0.5, 1.2, 1.1]
y2=[2.2, 2.4, 0.4, 2.0, 1.8]
y3=[1.8, 1.7, 0.6, 1.5, 1.3]
y4=[3.9, 4.4, 2.0, 4.1, 3.4]

stat, p = friedmanchisquare(y1, y2, y3, y4)
print('Test statistics = {:.2f}, p-value = {:.4f}'.format(stat, p))
# interpret
alpha = 0.05
if p > alpha:
  print('No effect (fail to reject H0)')
else:
  print('Effect observed (reject H0)')
```

```
Test statistics = 12.12, p-value = 0.0070
Effect observed (reject H0)
```

Your Turn -- Activity I: RCBD Analysis

In [15]:

```
### Load dataset as dataframe
df = pd.read_excel('lect04-blocking.xlsx', sheet_name='Algorithm Running Time',header=N
print(df)

a = df.shape[0]
b = df.shape[1]
algor_data = pd.DataFrame({'Algorithm': df.stack().values,
                            'Type': np.repeat(['A1','A2','A3','A4'],b),
                            'DataSet': ['D1','D2','D3','D4','D5', 'D6']*a})

algor_data
```

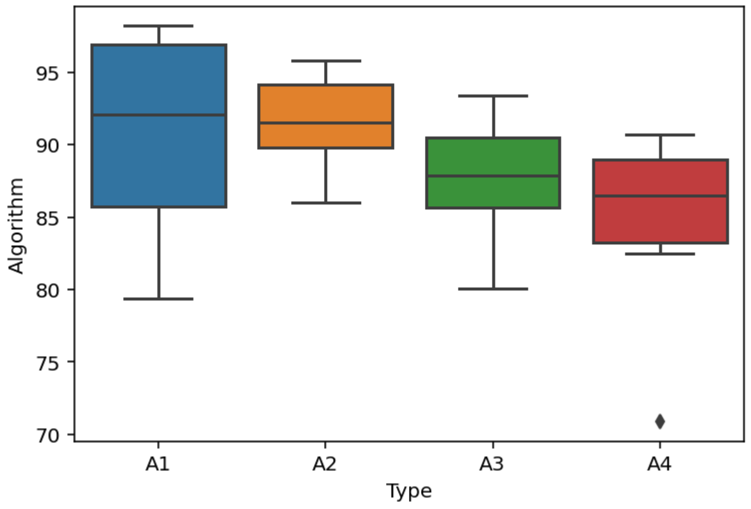
```
      0     1     2     3     4     5
0  90.3  84.2  98.2  93.9  79.4  97.9
1  92.5  89.5  90.6  94.7  86.0  95.8
2  85.5  90.8  89.6  86.2  80.1  93.4
3  82.5  89.5  85.6  87.4  70.9  90.7
```

Out[15]:

	Algorithm	Type	DataSet
0	90.3	A1	D1
1	84.2	A1	D2
2	98.2	A1	D3
3	93.9	A1	D4
4	79.4	A1	D5
5	97.9	A1	D6
6	92.5	A2	D1
7	89.5	A2	D2
8	90.6	A2	D3
9	94.7	A2	D4
10	86.0	A2	D5
11	95.8	A2	D6

	Algorithm	Type	DataSet
12	85.5	A3	D1
13	90.8	A3	D2
14	89.6	A3	D3
15	86.2	A3	D4
16	80.1	A3	D5
17	93.4	A3	D6
18	82.5	A4	D1
19	89.5	A4	D2
20	85.6	A4	D3
21	87.4	A4	D4
22	70.9	A4	D5
23	90.7	A4	D6

In [16]:
```
sns.boxplot(x='Type',y='Algorithm',data=algor_data);
```



RCBD Analysis

In [17]:
```
# Compute variables
a = len(algor_data.Type.unique())
b = len(algor_data.DataSet.unique())
total_y = sum(algor_data.Algorithm)
SST = sum(algor_data.Algorithm**2) - (total_y**2)/(a*b)

# Compute SS terms
yi_dot = algor_data.groupby('Type').aggregate({'Algorithm':'sum'}).Algorithm
SSTr = sum(yi_dot**2)/b - (total_y**2)/(a*b)
ydot_j = algor_data.groupby('DataSet').aggregate({'Algorithm':'sum'}).Algorithm
SSB = sum(ydot_j**2)/a - (total_y**2)/(a*b)
SSE = SST - SSB - SSTr
print("SST = {:.3f}, SSTr = {:.3f}, SSB = {:.3f}, SSE = {:.3f}".format(SST, SSTr, SSB,

# Compute MS Terms
```

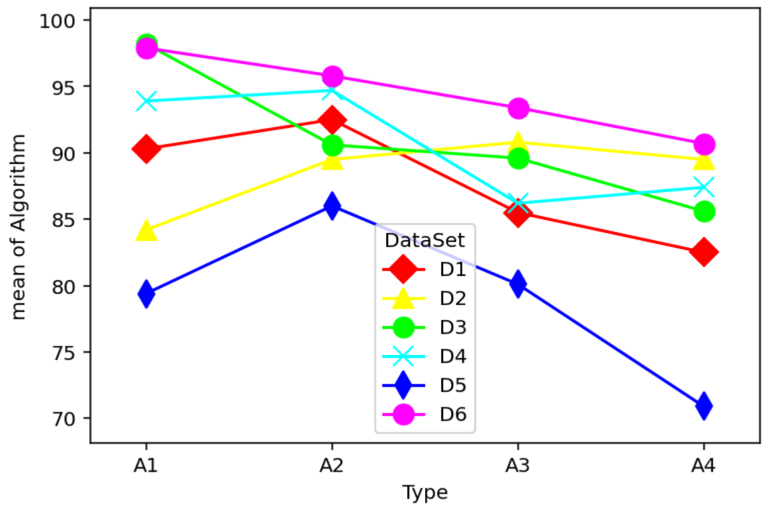
```
MSTr = SSTr/(a-1)
MSB = SSB/(b-1)
MSE = SSE/((a-1)*(b-1))
F0 = MSTr/MSE
p_value = stats.f.sf(F0, a-1,(a-1)*(b-1))
print("MSTr = {0:.3f}, MSE = {1:.3f}, F0 = {2:.3f}, P-value = {3:.3f}".format(MSTr, MSE
```

```
SST = 912.060, SSTr = 186.363, SSB = 539.360, SSE = 186.337
MSTr = 62.121, MSE = 12.422, F0 = 5.001, P-value = 0.013
```

In [18]:
```
from statsmodels.formula.api import ols # Require patsy version 5.0.1+
from statsmodels.stats.anova import anova_lm

mod = ols('Algorithm ~ Type + DataSet', algor_data).fit()
anova_table = sm.stats.anova_lm(mod)
print(anova_table)
```

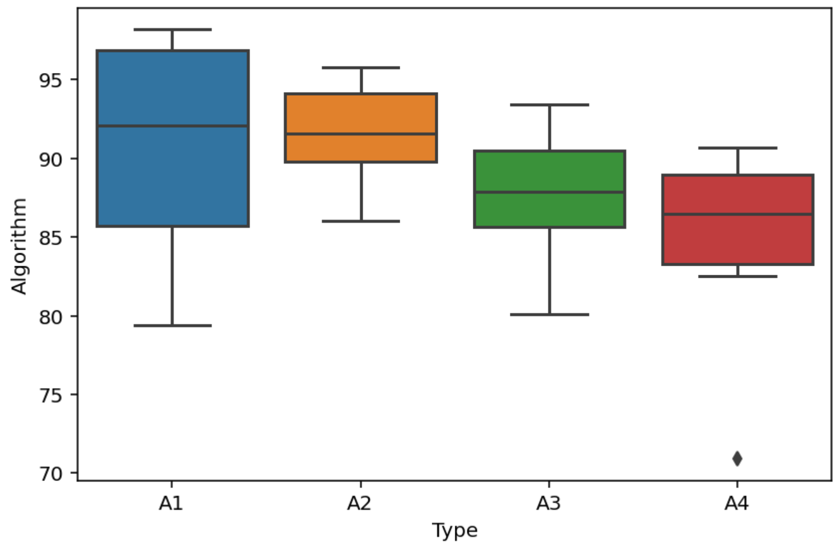
```
            df      sum_sq     mean_sq         F    PR(>F)
Type       3.0  186.363333   62.121111  5.000716  0.013367
DataSet    5.0  539.360000  107.872000  8.683637  0.000494
Residual  15.0  186.336667   12.422444       NaN       NaN
```

In [22]:
```
from statsmodels.graphics.factorplots import interaction_plot

fig = interaction_plot(algor_data.Type,
                       algor_data.DataSet,
                       algor_data.Algorithm,
                       markers=['D','^','o','x','d', 'o'], ms=10)
```



CRD Analysis

In [23]:
```
from statsmodels.formula.api import ols # Require patsy version 5.0.1+
from statsmodels.stats.anova import anova_lm
import statsmodels.api as sm
import matplotlib.pyplot as plt
import seaborn as sns

fig = plt.figure(figsize=(6,4));
sns.boxplot(x='Type',y='Algorithm',data=algor_data);
plt.tight_layout()
pass;
```



In [24]:
```
### Generate ANOVA table
algor_app_model = ols('Algorithm ~ Type', data=algor_data).fit()
df['resid'] = algor_app_model.resid
aov_table = sm.stats.anova_lm(algor_app_model, typ=1)
aov_table
```

Out[24]:

	df	sum_sq	mean_sq	F	PR(>F)
Type	3.0	186.363333	62.121111	1.712041	0.196681
Residual	20.0	725.696667	36.284833	NaN	NaN

จากการทำ RCBD และ CRD จะพบว่า การ blocking ทำให้โมเดลมีผลที่ถูกต้องมากขึ้นและ p-value ตกในช่วงที่ reject H0 ทำให้สรุปได้ว่า ค่าเฉลี่ยของ running time ต่างกัน