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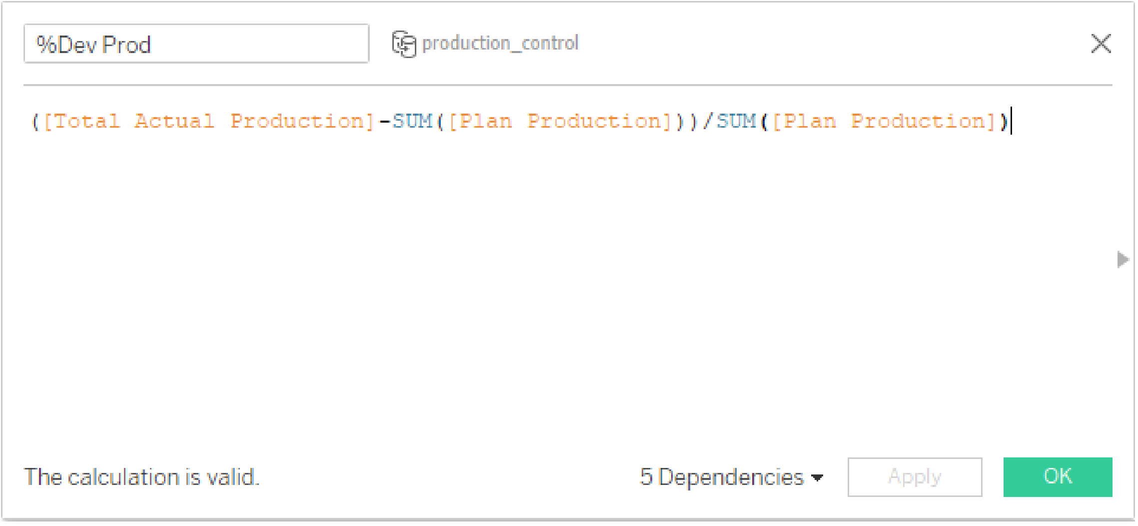
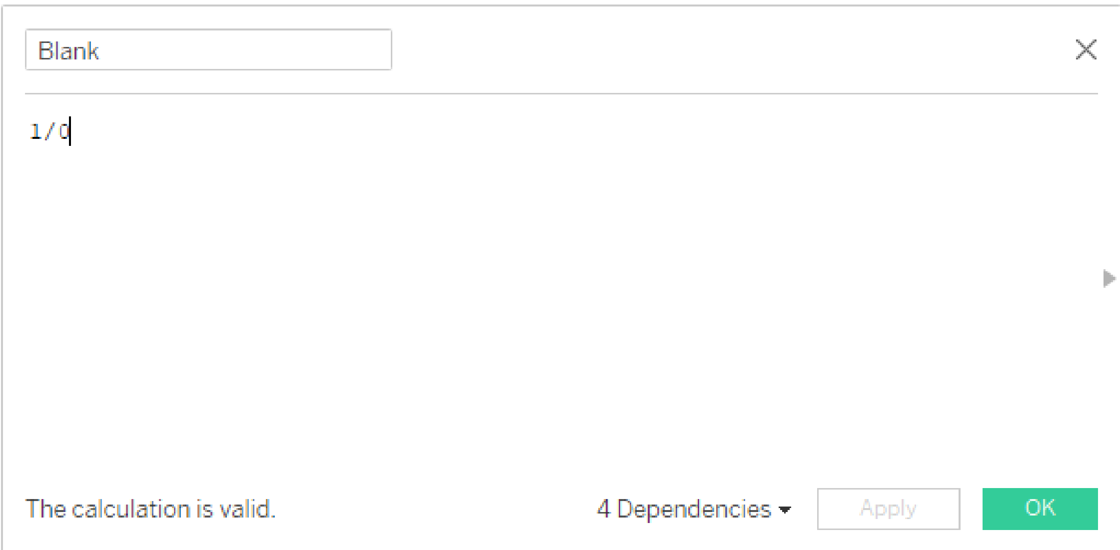
APPENDIX A

CALCULATED FIELDS IN TABLEAU


%Dev Prod
production_control
([Total Actual Production]-SUM([Plan Production]))/SUM([Plan Production])
The calculation is valid.
5 Dependencies
Apply
OK


Actual Production
production_control
IF SUM([Hauler Production])<SUM([Loader Production])
THEN SUM([Hauler Production])
ELSE SUM([Loader Production])
END
The calculation is valid.
16 Dependencies
Apply
OK


Blank
1/0
The calculation is valid.
4 Dependencies
Apply
OK


Clustering
production_control
Results are computed along Table (across).
SCRIPT_INT("return tabpy.query('cluster_predictor',_arg1,_arg2,_arg3)['response']
[Con Dev Pa],[Con Dev Ua],[Con Dev Pdty])
Default Table Calculation
The calculation is valid.
3 Dependencies
Apply
OK

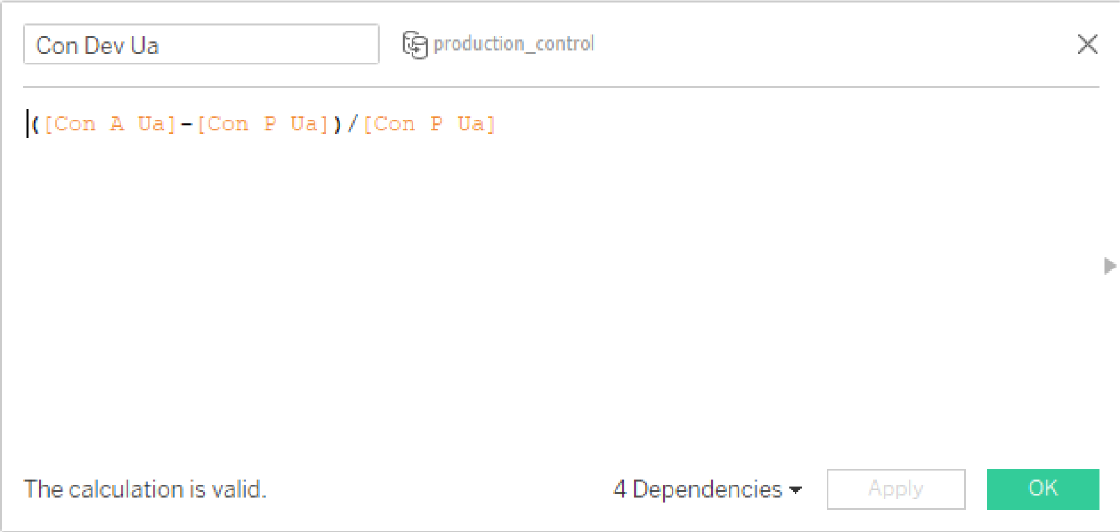

Con A Pa
production_control
SUM([A Pa]*[A Qty])/SUM([A Qty])
The calculation is valid.
10 Dependencies
Apply
OK


Con A Pdty
production_control
SUM([A Pdty]*[A Qty])/SUM([A Qty])
The calculation is valid.
7 Dependencies
Apply
OK


Con A Ua
production_control
SUM([A Ua]*[A Qty])/SUM([A Qty])
The calculation is valid.
10 Dependencies
Apply
OK


Con Dev Pa
production_control
([Con A Pa]-[Con P Pa])/[Con P Pa]
The calculation is valid.
4 Dependencies
Apply
OK

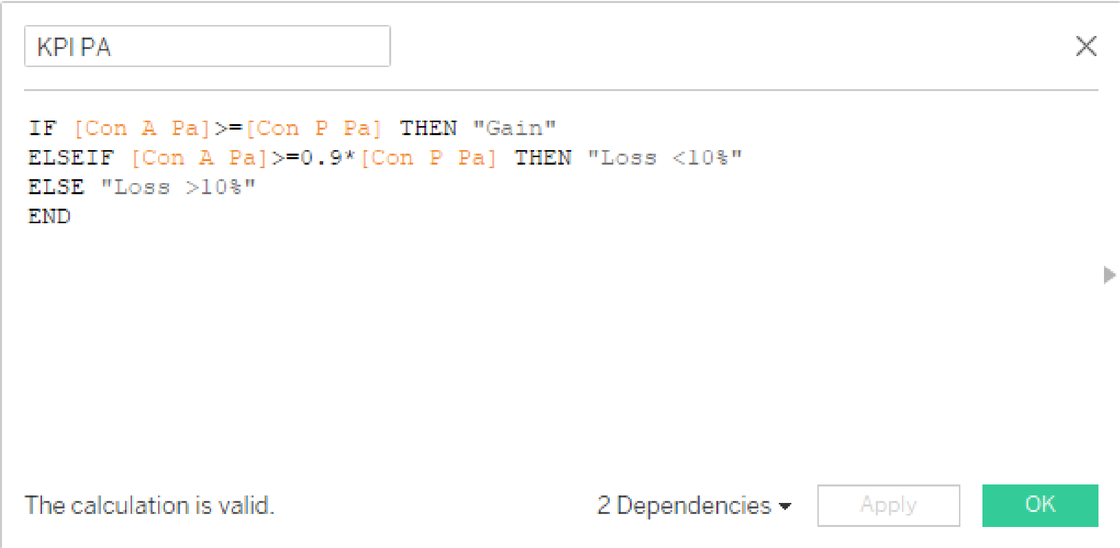

Con Dev Pdty
production_control
([Con A Pdty]-[Con P Pdty])/[Con P Pdty]
The calculation is valid.
4 Dependencies
Apply
OK


Con Dev Ua
production_control
([Con A Ua]-[Con P Ua])/[Con P Ua]
The calculation is valid.
4 Dependencies
Apply
OK


Con P Pa
production_control
SUM([P Pa]*[P Qty])/SUM([P Qty])
The calculation is valid.
10 Dependencies
Apply
OK


Con P Pdty
production_control
SUM([P Pdty]*[P Qty])/SUM([P Qty])
The calculation is valid.
7 Dependencies
Apply
OK


Con P Ua
production_control
SUM([P Ua]*[P Qty])/SUM([P Qty])
The calculation is valid.
10 Dependencies
Apply
OK


KPI PA
IF [Con A Pa]>=[Con P Pa] THEN "Gain"
ELSEIF [Con A Pa]>=0.9*[Con P Pa] THEN "Loss <10%"
ELSE "Loss >10%"
END
The calculation is valid.
2 Dependencies
Apply
OK


KPI Pdty
production_control
IF ([Con A Pdty])>=[Con P Pdty] THEN "Gain"
ELSE "Loss"
END
The calculation is valid.
2 Dependencies
Apply
OK

KPI Production — production_control

```
IF ([Actual Production])>=SUM([Plan Production]) THEN "Gain"
ELSEIF ([Actual Production])>=0.9*SUM([Plan Production]) THEN "Loss <10%"
ELSE "Loss >10%"
END
```

The calculation is valid. 6 Dependencies Apply OK

KPI UA

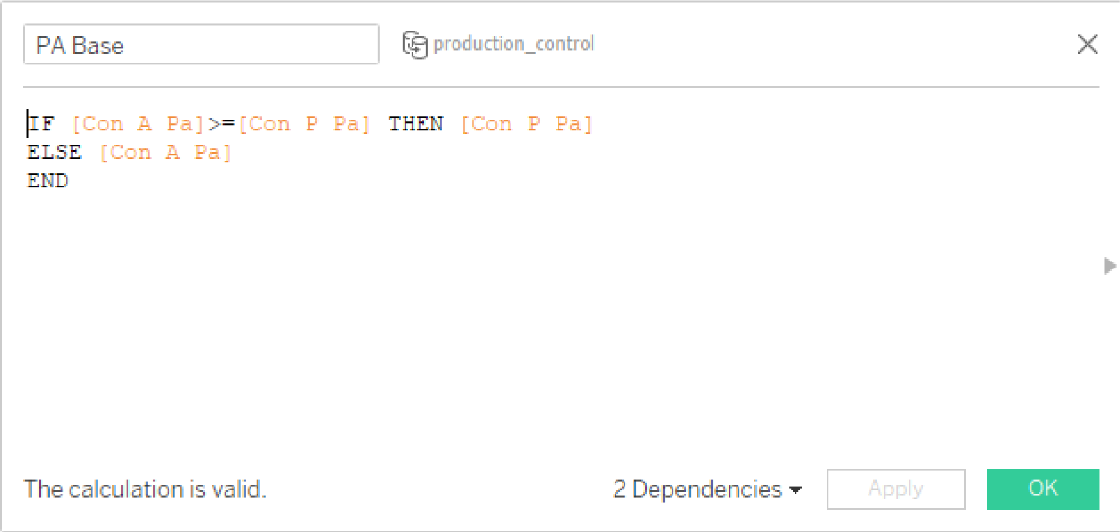
```
IF [Con A Ua]>=[Con P Ua] THEN "Gain"
ELSEIF [Con A Ua]>=0.9*[Con P Ua] THEN "Loss <10%"
ELSE "Loss >10%"
END
```

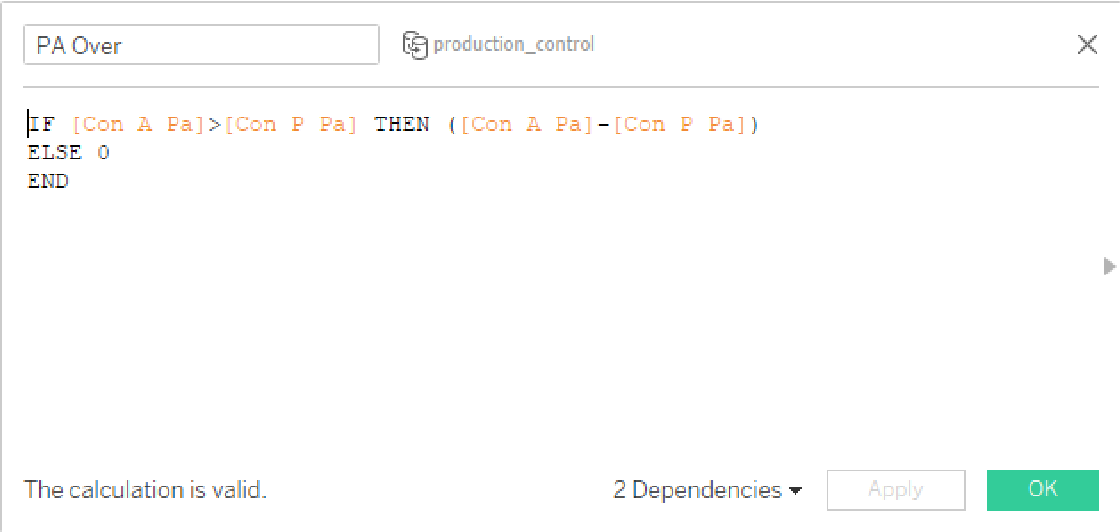
The calculation is valid. 2 Dependencies Apply OK

KPI Time Usage — production_control

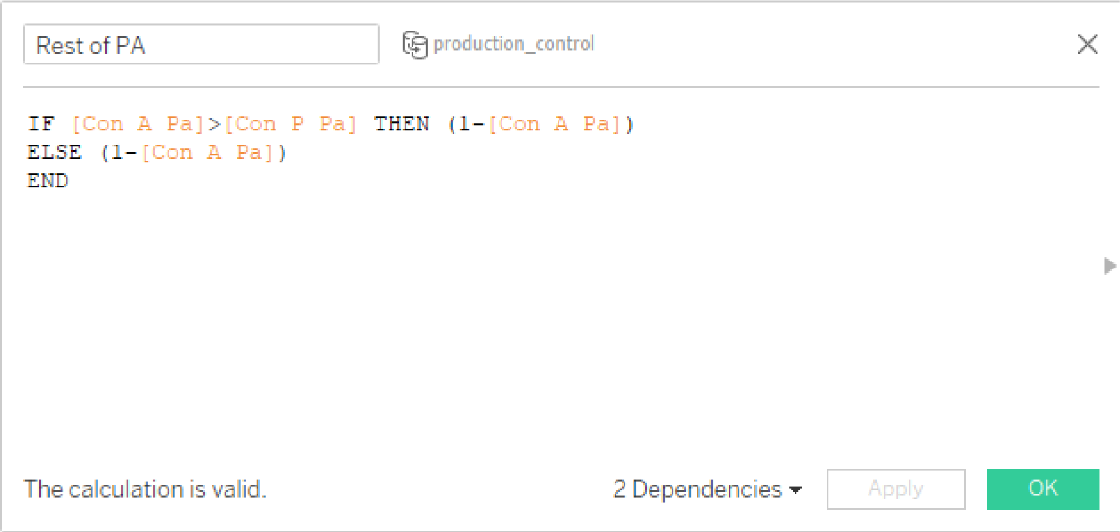
```
IF AVG([A Hr])<=AVG([P Hr]) THEN "Gain"
ELSE "Loss"
END
```

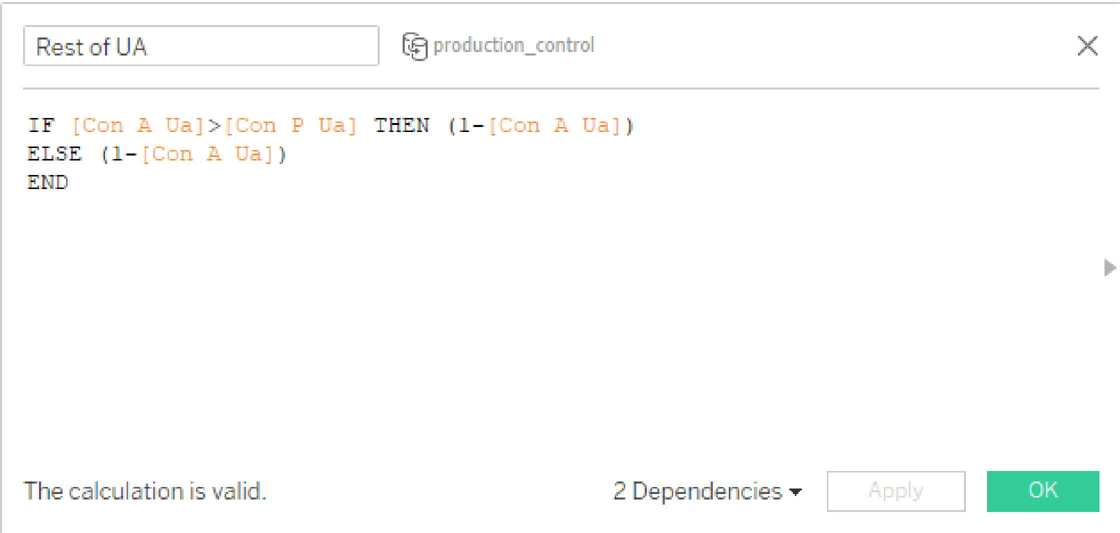
The calculation is valid. 2 Dependencies Apply OK


PA Base
production_control
IF [Con A Pa]>=[Con P Pa] THEN [Con P Pa]
ELSE [Con A Pa]
END
The calculation is valid.
2 Dependencies
Apply
OK


PA Over
production_control
IF [Con A Pa]>[Con P Pa] THEN ([Con A Pa]-[Con P Pa])
ELSE 0
END
The calculation is valid.
2 Dependencies
Apply
OK

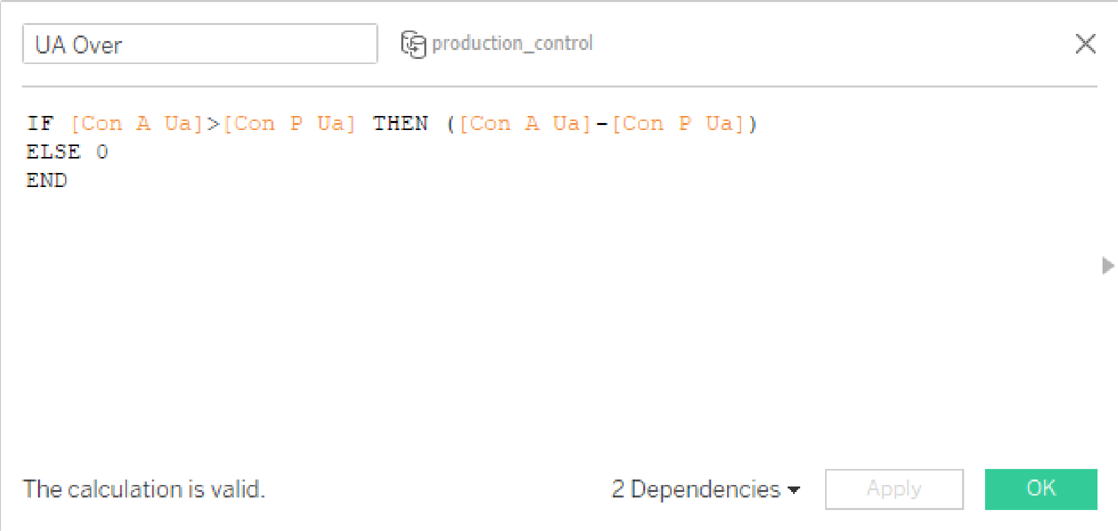

PA Under
production_control
IF [Con A Pa]>[Con P Pa] THEN 0
ELSE ([Con P Pa]-[Con A Pa])
END
The calculation is valid.
2 Dependencies
Apply
OK


Rest of PA
production_control
IF [Con A Pa]>[Con P Pa] THEN (1-[Con A Pa])
ELSE (1-[Con A Pa])
END
The calculation is valid.
2 Dependencies
Apply
OK


Rest of UA
production_control
IF [Con A Ua]>[Con P Ua] THEN (1-[Con A Ua])
ELSE (1-[Con A Ua])
END
The calculation is valid.
2 Dependencies
Apply
OK


Total Actual Production
production_control
SUM({FIXED [Date],[Class],[Con Code] : [Actual Production]})
The calculation is valid.
9 Dependencies
Apply
OK


UA Base
production_control
IF [Con A Ua]>=[Con P Ua] THEN [Con P Ua]
ELSE [Con A Ua]
END
The calculation is valid.
2 Dependencies
Apply
OK


UA Over
production_control
IF [Con A Ua]>[Con P Ua] THEN ([Con A Ua]-[Con P Ua])
ELSE 0
END
The calculation is valid.
2 Dependencies
Apply
OK


UA Under
production_control
IF [Con A Ua]>[Con P Ua] THEN 0
ELSE ([Con P Ua]-[Con A Ua])
END
The calculation is valid.
2 Dependencies
Apply
OK

Class-Extend production_control

```
IF [Class]="OB" THEN "Overburden"
ELSEIF [Class]="CG" THEN "Coal Getting"
END
```

The calculation is valid. 5 Dependencies Apply OK

Filter Daily production_control

```
[Date] = [Param Date]
```

The calculation is valid. 11 Dependencies Apply OK

Filter MTD production_control

```
[Date] <= [Param Date] AND
DATETRUNC( 'month', [Date]) = DATETRUNC('month', [Param Date])
```

The calculation is valid. 3 Dependencies Apply OK

Filter WTD — production_control

```
[Date] <= [Param Date] AND
DATETRUNC( 'week', [Date]) = DATETRUNC('week', [Param Date])
```

The calculation is valid. 3 Dependencies Apply OK

Filter YTD — production_control

```
[Date] <= [Param Date] AND
DATETRUNC( 'year', [Date]) = DATETRUNC('year', [Param Date])
```

The calculation is valid. 3 Dependencies Apply OK

Hauler Production — production_control

```
IF [Sub Class]="Hauling OB"
THEN [A Pa]*[A Ua]*[A Pdty]*[A Qty]*24
END
```

The calculation is valid. 17 Dependencies Apply OK


Loader Production
production_control
IF [Sub Class]="Loading OB"
THEN [A Pa]*[A Ua]*[A Pdty]*[A Qty]*24
ELSE NULL
END
The calculation is valid.
17 Dependencies
Apply
OK


Plan Production
production_control
IF [Sub Class]="Loading OB" OR [Sub Class]="Loading CG"
THEN [P Pa]*[P Ua]*[P Pdty]*[P Qty]*24
END
The calculation is valid.
12 Dependencies
Apply
OK

APPENDIX B

PYTHON CODE FOR DATA MINING

```python
#importing library
import pandas as pd
import numpy as np
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
import seaborn as sns
import matplotlib.pyplot as plt
get_ipython().run_line_magic('matplotlib', 'inline')


#importing dataset
df = pd.read_excel('data_parameter_prod.xlsx')
df.tail(5)

#check if there are any null values
df.isnull().sum()

#check data type for each column
df.info()

#descriptive statistic of numeric data
df.describe()

#Boxplot Visualization
num = ['p_pa','p_ua','p_pdty','p_qty','a_pa','a_ua','a_pdty','a_qty']
def plotBox():
    fig, ax =plt.subplots(2,4, figsize=(16,8))
    i=0;j=0;k=0
    while i<=1:
        while j<=3:
            sns.boxplot(df[num[k]], ax=ax[i, j])
            j+=1;k+=1
        j=0;i+=1;
    plt.show()
plotBox()

# check the anomaly data where actual UA > 1
df_anomaly = df.loc[df['a_ua']>1]
# show anomaly data
df_anomaly

# replace the value of actual UA>1 into plan UA
df_anomaly.loc[:,'a_ua'] = df_anomaly.loc[:,'p_ua']
# show anomaly data (after cleaning)
df_anomaly

# check descriptive statistic of anomaly data (after cleaning)
df_anomaly.describe()
```

```
# replace anomaly (UA>1) in source data with cleaned data
df.loc[df_anomaly.index] = df_anomaly

# descriptive statistic of numeric data
df.describe()

# check the anomaly data where actual PA, UA and Qty < 0
df_anomaly2 = df[(df['a_pa']<0) | (df['a_ua']<0) | (df['a_qty']<0)]
df_anomaly2

# replace the value of actual PA, UA, and Qty < 0 into absolute value (po
sitive)
df_anomaly2[['a_pa','a_ua','a_qty']]= df_anomaly2[['a_pa','a_ua','a_qty']
].abs()
# show anomaly data (after cleaning)
df_anomaly2

# replace anomaly (PA, UA, and Qty < 1) in source data with cleaned data
df.loc[df_anomaly2.index] = df_anomaly2

# final check descriptive statistic of numeric data
df.describe()

plotBox()

# save clean dataset
df.to_excel("data_parameter_cleaned.xlsx", index=False)

# create new columns containing the multiplication of the PA, UA, and Pdt
y parameters with Quantity

df['p_pa_x_qty'] = df['p_pa']*df['p_qty']
df['p_ua_x_qty'] = df['p_ua']*df['p_qty']
df['p_pdty_x_qty'] = df['p_pdty']*df['p_qty']

df['a_pa_x_qty'] = df['a_pa']*df['a_qty']
df['a_ua_x_qty'] = df['a_ua']*df['a_qty']
df['a_pdty_x_qty'] = df['a_pdty']*df['a_qty']

# show data (last rows)
df.tail()

# group data by date, contractor, and class (OB/CG) with sum aggregation
data_by_con = df.groupby(['date','con_code','class']).sum()

# repair the structure of data
data_by_con.columns.name = None
```

```
data_by_con = data_by_con.reset_index()
# show data (after grouping)
data_by_con.tail()


# create new columns containing the division of the (parameter x quantity
) column with total quantity
# this new columns is the average parameter (PA, UA, and Pdty) of each co
ntractor in a daily date

data_by_con['con_p_pa'] = data_by_con['p_pa_x_qty']/data_by_con['p_qty']
data_by_con['con_p_ua'] = data_by_con['p_ua_x_qty']/data_by_con['p_qty']
data_by_con['con_p_pdty'] = data_by_con['p_pdty_x_qty']/data_by_con['p_qt
y']

data_by_con['con_a_pa'] = data_by_con['a_pa_x_qty']/data_by_con['a_qty']
data_by_con['con_a_ua'] = data_by_con['a_ua_x_qty']/data_by_con['a_qty']
data_by_con['con_a_pdty'] = data_by_con['a_pdty_x_qty']/data_by_con['a_qt
y']

data_by_con.tail()

# create new columns containing the deviation of actual parameter with it
s plan parameter

data_by_con['dev_pa'] = (data_by_con['con_a_pa']-
data_by_con['con_p_pa'])/data_by_con['con_p_pa']*100
data_by_con['dev_ua'] = (data_by_con['con_a_ua']-
data_by_con['con_p_ua'])/data_by_con['con_p_ua']*100
data_by_con['dev_pdty'] = (data_by_con['con_a_pdty']-
data_by_con['con_p_pdty'])/data_by_con['con_p_pdty']*100

# create new dataset containing only the columns used for the modelling s
tages
df_new = data_by_con[['date','con_code','class','dev_pa','dev_ua','dev_pd
ty']]
df_new

# check if there is null value
df_new.isna().sum()

# replace null value with 0
df_new = df_new.fillna(0)

# final check descriptive statistic of numeric data
df_new.describe()
```

```
# create X that only contain 3 parameters (PA, UA, Pdty) as input data to
 model
X = df_new[['dev_pa','dev_ua','dev_pdty']].values

# iteration to get SSE and Silhouette Score for each k
clusters_inertia = []
clusters_silhouette = []
df_evaluation = []
for i in range(2,11):
    km = KMeans(n_clusters=i).fit(X)
    clusters_inertia.append(km.inertia_)
    sscore = silhouette_score(X, km.labels_, metric='euclidean')
    clusters_silhouette.append(sscore)
    df_evaluation.append([i, km.inertia_, sscore])

df_evaluation

# Visualize SSE for each k
fig, ax = plt.subplots(figsize=(8, 4))
sns.lineplot(x=list(range(2, 11)), y=clusters_inertia, ax=ax)
ax.set_title('Finding Elbow')
ax.set_xlabel('N Clusters')
ax.set_ylabel('Inertia/SSE')

# Visualize Silhouette Score for each k
fig, ax = plt.subplots(figsize=(8, 4))
sns.lineplot(x=list(range(2, 11)), y=clusters_silhouette, ax=ax)
ax.set_title('Silhouette Score')
ax.set_xlabel('N Clusters')
ax.set_ylabel('Score')

# Training KMeans model with n_clusters (k)=4

model_km = KMeans(n_clusters=4)
y_clusters = model_km.fit_predict(X)

# Save the model to file named "model_kmeans.sav"
# to use in deployment stage

import pickle

filename = 'model_kmeans.sav'
pickle.dump(model_km, open(filename, 'wb'))

get_ipython().run_line_magic('matplotlib', 'qt')

fig = plt.figure(figsize = (15,15))
ax = fig.add_subplot(111, projection='3d')
```

```
val = [100,0,0]
labels = ['x', 'y', 'z']
colors = ['r', 'g', 'b']
for v in range(3):
    x = [val[v-0], -val[v-0]]
    y = [val[v-1], -val[v-1]]
    z = [val[v-2], -val[v-2]]
    ax.plot(x,y,z,'k-', linewidth=1)
    ax.text(val[v-0], val[v-1], val[v-2],
            labels[v], color=colors[v], fontsize=20)

a = np.array(y_clusters==0)
b = np.array(y_clusters==1)
c = np.array(y_clusters==2)
d = np.array(y_clusters==3)

ax.scatter(X[a,0],X[a,1],X[a,2], s=40, color='blue', label="cluster 0")
ax.scatter(X[b,0],X[b,1],X[b,2], s=40, color='orange', label="cluster 1")
ax.scatter(X[c,0],X[c,1],X[c,2], s=40, color='green', label="cluster 2")
ax.scatter(X[d,0],X[d,1],X[d,2], s=40, color='#D12B60', label="cluster 3"
)

ax.set_xlabel('%Dev PA')
ax.set_ylabel('%Dev UA')
ax.set_zlabel('%Dev Pdty')

ax.legend()
plt.show()


# check the centroid point of each cluster
centroids = model_km.cluster_centers_
centroids

# create new column called 'label' in data containing the clusters
df_new['label'] = y_clusters


# check the contractors labelled as cluster 0
df_cluster0 = df_new[df_new['label']==0]
df_cluster0['con_code'].value_counts()


df_new[df_new['label']==0].describe()


# check the contractors labelled as cluster 1
```

```
df_cluster1 = df_new[df_new['label']==1]
df_cluster1['con_code'].value_counts()


df_new[df_new['label']==1].describe()


# check the contractors labelled as cluster 2
df_cluster1 = df_new[df_new['label']==2]
df_cluster1['con_code'].value_counts()


df_new[df_new['label']==2].describe()


# check the contractors labelled as cluster 3
df_cluster1 = df_new[df_new['label']==3]
df_cluster1['con_code'].value_counts()


df_new[df_new['label']==3].describe()
```

APPENDIX C

PYTHON CODE FOR MODEL DEPLOYMENT

```python
# import tabpy library and connect to localhost
import tabpy_client
from tabpy.tabpy_tools.client import Client
client = tabpy_client.Client('http://localhost:9004/')


# load model
import pickle
filename = 'model_kmeans.sav'
model_km = pickle.load(open(filename, 'rb'))


# function to using cluster prediction in Tableau
def cluster_predictor( _arg1, _arg2, _arg3):
    import pandas as pd
    row = {'dev_pa': _arg1[0],
           'dev_ua': _arg2[0],
           'dev_pdty': _arg3[0]}
    #Convert it into a dataframe
    x_data = pd.DataFrame(data=row,index=[0])
    #Predict the cluster
    return int(model_km.predict(x_data)[0])

 model deployment to Tableau
client.deploy('cluster_predictor', cluster_predictor,'Clustering',overrid
e = True)
```

APPENDIX D

SAMPLE DATASET PARAMETER

Table D. Sample Dataset Parameter

Index	date	con_code	site_code	class	sub_class	equipment	p_pa	p_ua	p_pdty	p_qty	a_pa	a_ua	a_pdty	a_qty
0	01/01/2022	A	P	OB	Loading OB	EX2500	0.8549	0.476662	924	2	0.75	0	0	4
1	01/01/2022	A	P	OB	Loading OB	PC2000	0.8749	0.488626	711	18	1	0	0	18
2	01/01/2022	A	P	OB	Loading OB	PC1250	0.8749	0.488626	350	2	1	0	0	0
3	01/01/2022	A	P	OB	Hauling OB	HD785	0.890905	0	101.0492	168	0.950311	0	0	167
4	01/01/2022	A	P	CG	Loading CG	PC400	0.901961	0	190	0.75	1	0	0	5
......	......	......	......	......	......	......	......	......	......	......	......	......	......	......
8877	31/05/2022	D	R	CG	Hauling CG	Scania P360	0.85	0.5	25	5	0.62	0.34	20	4
8878	31/05/2022	D	R	CG	Hauling CG	Scania P460	0.89	0.56	34	10	0.94	0.35	30	9
8879	31/05/2022	G	S	OB	Loading OB	PC2000	0.92	0.58	734	1	1	0.65125	783.7797	1
8880	31/05/2022	G	S	OB	Loading OB	EX1200	0.92	0.58	525	6	1	0.624444	441.9505	6
8881	31/05/2022	G	S	OB	Loading OB	PC800	0.92	0.58	260	2	0.9325	0.742627	186.0923	2

APPENDIX E

SAMPLE DATASET TUM (TIME USAGE MANAGEMENT)

Table E. Sample Dataset TUM (Time Usage Management)

Index	date	con_code	site_code	lag_indicator	sublead_indicator	p_hr	a_hr
1	02/01/2022	C	O	OB	Holiday	0	0
2	02/01/2022	C	O	OB	Rain	3.870968	0.457504
3	02/01/2022	C	O	OB	Slippery	0.851613	0
4	02/01/2022	C	O	OB	Shift Change	0.333333	0.417062
5	02/01/2022	C	O	OB	Safety Talk	0	0
6	02/01/2022	C	O	OB	Meal & Rest	2	1.921011
7	02/01/2022	C	O	OB	Praying	0	0.032859
8	02/01/2022	C	O	OB	Friday Praying	0	0
9	02/01/2022	C	O	OB	Blasting	0	0
10	02/01/2022	C	O	OB	Refueling	0.333333	0
11	02/01/2022	C	O	OB	Fasting	0	0
12	02/01/2022	C	O	OB	Front & Disposal Repair	0.333333	2.466983
13	02/01/2022	C	O	OB	Equipment Travel	0.166667	0.154186
14	02/01/2022	C	O	OB	Road Repair	0	0
15	02/01/2022	C	O	OB	No Work Location	0	0
…..	…..	…..	…..	…..	…..	…..	…..
67454	29/05/2022	G	S	OB	Road Repair	0	1.414444
67455	29/05/2022	G	S	OB	No Work Location	0	0
67456	29/05/2022	G	S	OB	No Operator (EXC)	0	0
67457	29/05/2022	G	S	OB	Wait Operator (EXC)	0	0.092222
67458	29/05/2022	G	S	OB	No Hauler/Truck	0	0
67459	29/05/2022	G	S	OB	Wait Hauler/Truck	0	1.414444
67460	29/05/2022	G	S	OB	Wait Support	0	0
67461	29/05/2022	G	S	OB	Internal Problem	0	0
67462	29/05/2022	G	S	OB	Customer Problem	0	0
67463	29/05/2022	G	S	OB	No Material	0	0
67464	29/05/2022	G	S	OB	Relocation	0	0
67465	29/05/2022	G	S	OB	Safety	0	0.008888
67466	29/05/2022	G	S	OB	Hazard	0	0
67467	29/05/2022	G	S	OB	Bad Visibility	0.008333	0
67468	29/05/2022	G	S	OB	External Issues	0	0.277777