Project 87: Predicting Material Backorders in Inventory Management using Machine Learning

In [4]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

#from google.colab import drive
#drive.mount('/gdrive')
#%cd /gdrive
```

In [5]:

```
data_path = 'C:/users/ganesh.chandra/Proj 87- Determinig items for shortage prior occuren
ce- Inventory Mgmt/train_Data.csv'
df = pd.read_csv(data_path)
df
```

```
C:\Users\ganesh.chandra\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3146
: DtypeWarning: Columns (0) have mixed types.Specify dtype option on import or set low_me
mory=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
```

Out[5]:

	sku	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month	sales_1_mor
0	1026827	0.0	NaN	0.0	0.0	0.0	0.0	(
1	1043384	2.0	9.0	0.0	0.0	0.0	0.0	(
2	1043696	2.0	NaN	0.0	0.0	0.0	0.0	(
3	1043852	7.0	8.0	0.0	0.0	0.0	0.0	(
4	1044048	8.0	NaN	0.0	0.0	0.0	0.0	(
...	...	...	...	...	...	...	...	
1687856	1373987	-1.0	NaN	0.0	5.0	7.0	9.0	'
1687857	1524346	-1.0	9.0	0.0	7.0	9.0	11.0	(
1687858	1439563	62.0	9.0	16.0	39.0	87.0	126.0	3
1687859	1502009	19.0	4.0	0.0	0.0	0.0	0.0	:
1687860	(1687860 rows)	NaN	NaN	NaN	NaN	NaN	NaN	N

1687861 rows × 23 columns

In [6]:

```
data_path = 'C:/users/ganesh.chandra/Proj 87- Determinig items for shortage prior occuren
ce- Inventory Mgmt/Kaggle_Test_Dataset_v2.csv'
test = pd.read_csv(data_path)
test
```

```
C:\Users\ganesh.chandra\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3146
: DtypeWarning: Columns (0) have mixed types.Specify dtype option on import or set low_me
mory=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
```

Out[6]:

	sku	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month	sales_1_montl
0	3285085	62.0	NaN	0.0	0.0	0.0	0.0	0.(
1	3285131	9.0	NaN	0.0	0.0	0.0	0.0	0.(
2	3285358	17.0	8.0	0.0	0.0	0.0	0.0	0.(
3	3285517	9.0	2.0	0.0	0.0	0.0	0.0	0.(
4	3285608	2.0	8.0	0.0	0.0	0.0	0.0	0.(
...	...	...	...	...	...	...	...	.
242071	3526988	13.0	12.0	0.0	0.0	0.0	0.0	0.(
242072	3526989	13.0	12.0	0.0	0.0	0.0	0.0	0.(
242073	3526990	10.0	12.0	0.0	0.0	0.0	0.0	0.(
242074	3526991	2913.0	12.0	0.0	0.0	0.0	0.0	0.(
242075	(242075 rows)	NaN	NaN	NaN	NaN	NaN	NaN	NaI

242076 rows × 23 columns

Data Points and features available in data set

In [7]:

```
print(df.shape)
print(test.shape)
```

```
(1687861, 23)
(242076, 23)
```

Sample pre-view of data

In [8]:

```
df.head()
```

Out[8]:

	sku	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month	sales_1_month	sal
0	1026827	0.0	NaN	0.0	0.0	0.0	0.0	0.0	
1	1043384	2.0	9.0	0.0	0.0	0.0	0.0	0.0	
2	1043696	2.0	NaN	0.0	0.0	0.0	0.0	0.0	
3	1043852	7.0	8.0	0.0	0.0	0.0	0.0	0.0	
4	1044048	8.0	NaN	0.0	0.0	0.0	0.0	0.0	

5 rows × 23 columns

Column Names in Data

In [9]:

```
print(df.columns)
print(test.columns)
```

```
Index(['sku', 'national_inv', 'lead_time', 'in_transit_qty',
       'forecast_3_month', 'forecast_6_month', 'forecast_9_month',
       'sales_1_month', 'sales_3_month', 'sales_6_month', 'sales_9_month',
       'min_bank', 'potential_issue', 'pieces_past_due', 'perf_6_month_avg',
       'perf_12_month_avg', 'local_bo_qty', 'deck_risk', 'oe_constraint',
       'ppap_risk', 'stop_auto_buy', 'rev_stop', 'went_on_backorder'],
```

```
      dtype='object')
Index(['sku', 'national_inv', 'lead_time', 'in_transit_qty',
       'forecast_3_month', 'forecast_6_month', 'forecast_9_month',
       'sales_1_month', 'sales_3_month', 'sales_6_month', 'sales_9_month',
       'min_bank', 'potential_issue', 'pieces_past_due', 'perf_6_month_avg',
       'perf_12_month_avg', 'local_bo_qty', 'deck_risk', 'oe_constraint',
       'ppap_risk', 'stop_auto_buy', 'rev_stop', 'went_on_backorder'],
      dtype='object')
```

Col Description Col Name x1 Prduct ID sku x2 Current inventory level of component national_inv x3 Registered transit time lead_time x4 In transit quantity in_transit_qty x5 Forecast sales for the next 3 months forecast_3_month x6 Forecast sales for the next 6 months forecast_6_month x7 Forecast sales for the next 9 months forecast_9_month x8 Sales quantity for the prior 1 month sales_1_month x9 Sales quantity for the prior 3 month sales_3_month x10 Sales quantity for the prior 6 month sales_6_month x11 Sales quantity for the prior 9 month sales_9_month x12 Minimum recommended amount in stock min_bank x13 Parts overdue from source pieces_past_due x14 Source performance in last 6 months perf_6_month_avg x15 Source performance in last 12 months perf_12_month_avg x16 Amount of stock orders overdue local_bo_qty x17 General risk flags deck_risk x18 General risk flags oe_consdft x19 General risk flags ppap_risk x20 General risk flags stop_auto_buy x21 General risk flags rev_stop x22 General risk flags potential_issue x23 Product went on backorder went_on_backorder

In [10]:

```
df.describe()
```

Out[10]:

	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month	sales_1_month	sal
count	1.687860e+06	1.586967e+06	1.687860e+06	1.687860e+06	1.687860e+06	1.687860e+06	1.687860e+06	1.
mean	4.961118e+02	7.872267e+00	4.405202e+01	1.781193e+02	3.449867e+02	5.063644e+02	5.592607e+01	1.
std	2.961523e+04	7.056024e+00	1.342742e+03	5.026553e+03	9.795152e+03	1.437892e+04	1.928196e+03	5.
min	-2.725600e+04	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.
25%	4.000000e+00	4.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.
50%	1.500000e+01	8.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.
75%	8.000000e+01	9.000000e+00	0.000000e+00	4.000000e+00	1.200000e+01	2.000000e+01	4.000000e+00	1.
max	1.233440e+07	5.200000e+01	4.894080e+05	1.427612e+06	2.461360e+06	3.777304e+06	7.417740e+05	1.

Finding Data With Missing Values

In [11]:

```
#Counting Missing Values in Each Column of Data
df.isnull().sum()
```

Out[11]:

```
sku                       0
national_inv              1
lead_time            100894
in_transit_qty            1
forecast_3_month          1
forecast_6_month          1
forecast_9_month          1
sales_1_month             1
sales_3_month             1
sales_6_month             1
sales_9_month             1
min_bank                  1
potential_issue           1
pieces_past_due           1
perf_6_month_avg          1
perf_12_month_avg         1
```

```
perf_12_month_avg            1
local_bo_qty                 1
deck_risk                    1
oe_constraint                1
ppap_risk                    1
stop_auto_buy                1
rev_stop                     1
went_on_backorder            1
dtype: int64
```

In [12]:

```
df[df.went_on_backorder.isnull()]
```

Out[12]:

	sku	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month	sales_1_mor
1687860	(1687860 rows)	NaN	NaN	NaN	NaN	NaN	NaN	N

1 rows × 23 columns

Observation 1: From the above two analysis we can observe that apart from "lead_time" column in the dataset there are only 1 missing values in each column. We also saw using our output column "went_on_backorder" that there is only 1 row where all the values are "NaN". Hence we will be dropping only 1 row from the dataframe.

In [13]:

```
df = df[:-1]
df.shape
```

Out[13]:

```
(1687860, 23)
```

In [14]:

```
test = test[:-1]
test.shape
```

Out[14]:

```
(242075, 23)
```

Count of Data Points for each class which went to backorder and which didn't

In [15]:

```
df["went_on_backorder"].value_counts()
```

Out[15]:

```
No     1676567
Yes      11293
Name: went_on_backorder, dtype: int64
```

Observation 2: The count for the two classes which went to backorder and which didn't clearly indicates we are dealing with imbalanced data set where data points indicating the backorder are very less compared to majority class of items which didn't go in backorder.

Checking for Duplicate Values in Dataset - No Duplicate Values were Found

In [16]:

```
df[df.duplicated(["sku"])]
```

Out[16]:

sku	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month	sales_1_month	sales_3_

0 rows × 23 columns

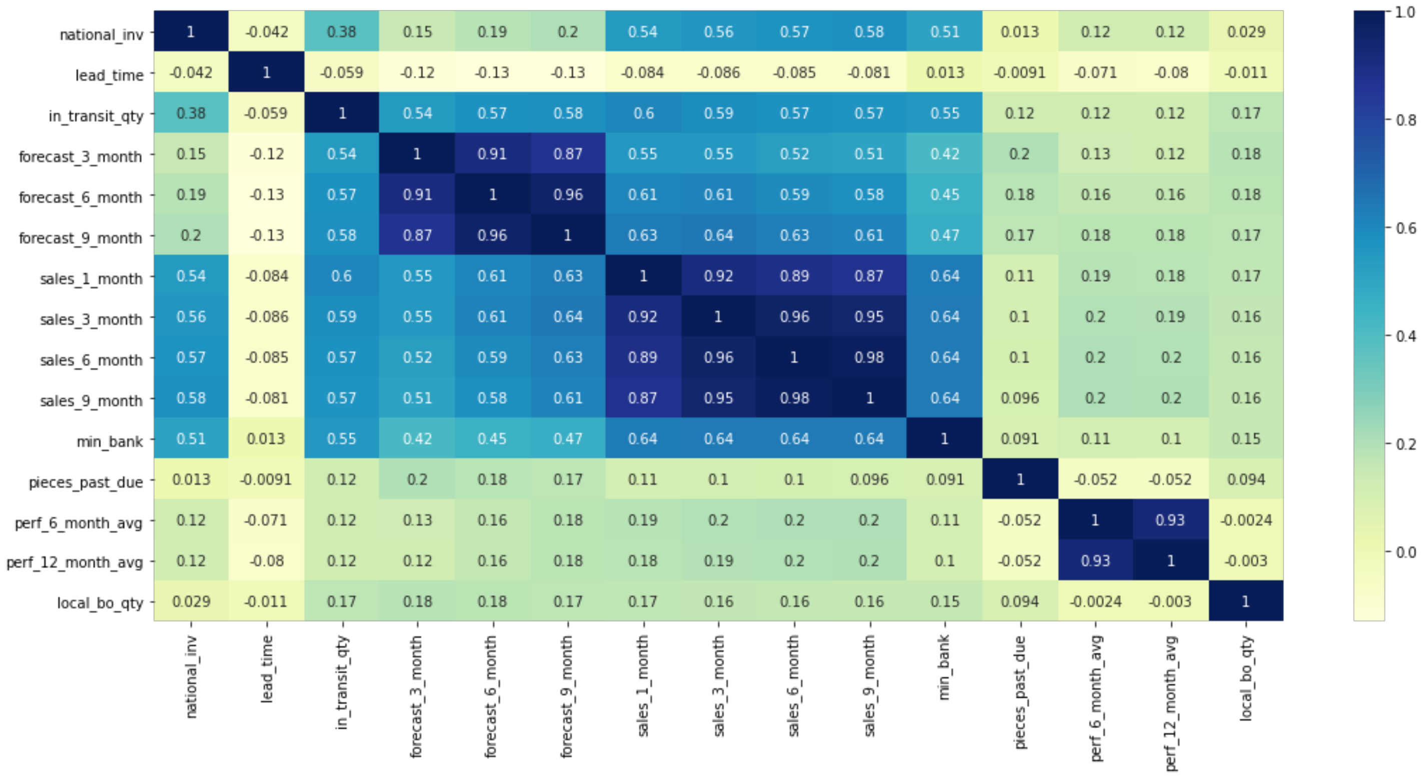
Correlation Analysis

In [17]:

```
cor= df.corr(method='spearman')
plt.figure(figsize=(18,8))
sns.heatmap(cor,xticklabels=cor.columns,yticklabels=cor.columns,annot=True,cmap="YlGnBu"
)
```

Out[17]:

```
<AxesSubplot: >
```



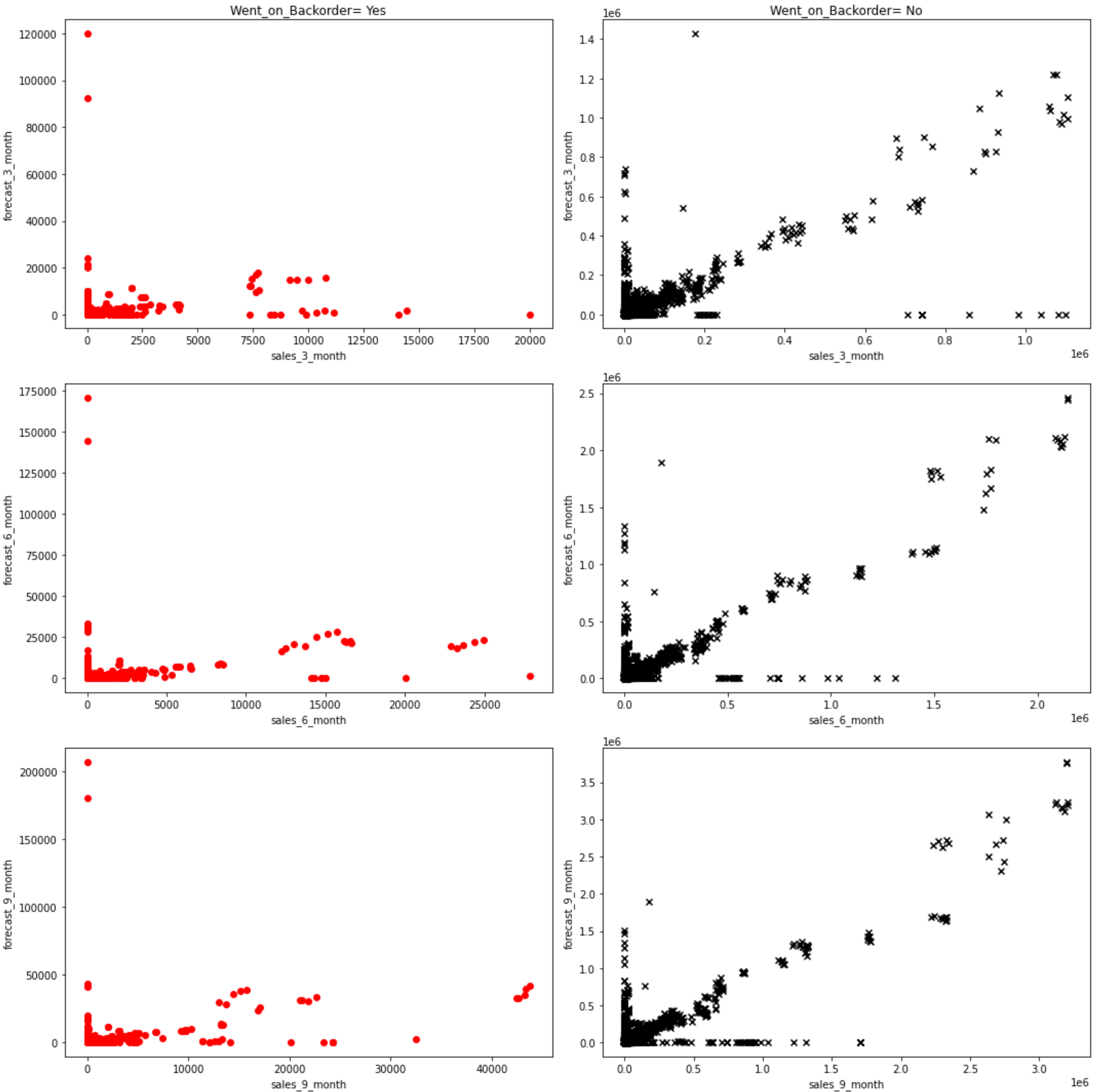
Observation 3: It is observed from the heatmap that "forecast" and "sales" groups have high correlation among themeselves

Plotting Scatter Plot for Sales Vs Forecast vs Went_On_Backorder :

In [18]:

```
#from matplotlib.colorbar import consdfed_layout
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

fig,ax = plt.subplots(3,2,figsize=(15, 15))

ax[0,0].scatter(x='sales_3_month', y='forecast_3_month', data=df[df['went_on_backorder']
=="Yes"],marker="o", color="r")
ax[0,0].set(xlabel='sales_3_month',ylabel='forecast_3_month',title="Went_on_Backorder= Ye
s")

ax[0,1].scatter(x='sales_3_month', y='forecast_3_month', data=df[df['went_on_backorder']
=="No"],marker="x", color="k")
ax[0,1].set(xlabel='sales_3_month',ylabel='forecast_3_month',title="Went_on_Backorder= No
")
```

```
ax[1,0].scatter(x='sales_6_month', y='forecast_6_month', data=df[df['went_on_backorder']
=="Yes"],marker="o", color="r")
ax[1,0].set(xlabel='sales_6_month',ylabel='forecast_6_month')

ax[1,1].scatter(x='sales_6_month', y='forecast_6_month', data=df[df['went_on_backorder']
=="No"],marker="x", color="k")
ax[1,1].set(xlabel='sales_6_month',ylabel='forecast_6_month')

ax[2,0].scatter(x='sales_9_month', y='forecast_9_month', data=df[df['went_on_backorder']
=="Yes"],marker="o", color="r")
ax[2,0].set(xlabel='sales_9_month',ylabel='forecast_9_month')

ax[2,1].scatter(x='sales_9_month', y='forecast_9_month', data=df[df['went_on_backorder']
=="No"],marker="x", color="k")
ax[2,1].set(xlabel='sales_9_month',ylabel='forecast_9_month')

fig.tight_layout()
```



Observation 4:

i.> As observed from corr heatmap, we have plotted separately here sales vs forecast data categorised separately into items which went to backorder and not

ii.> We can observe sales and forecast value approximately vary with each other in sync, however there are

outliers in data.

iii.> Also, we can observe there are products with 0 sales and forecast but still they are in backorder which indicates either they are overdue from past or there is no current inventory level for them

In [19]:

```
#Generating pivot table to check total qty of backorders vs the inventory level (sum of n
ational_inv)
table=pd.pivot_table(df,index="went_on_backorder",values=["national_inv","lead_time","in
_transit_qty","sku"],aggfunc={"national_inv":"sum",
                        "lead_time":"sum","in_transit_qty":"sum","sku":"count"})
table
```

Out[19]:

	in_transit_qty	lead_time	national_inv	sku
went_on_backorder				
No	74304650.0	12423676.0	837125192.0	1676567
Yes	48996.0	69352.0	242040.0	11293

In [20]:

```
#Finding Data points which went to backorder where invoentory level is either less or equ
al to 0 = 890 products
df[(df['went_on_backorder']=="Yes") & (df['national_inv']<0)]
```

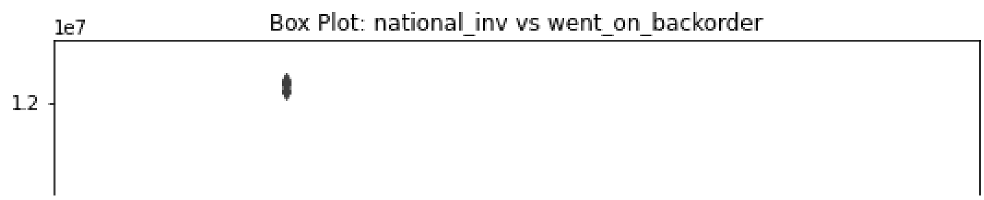
Out[20]:

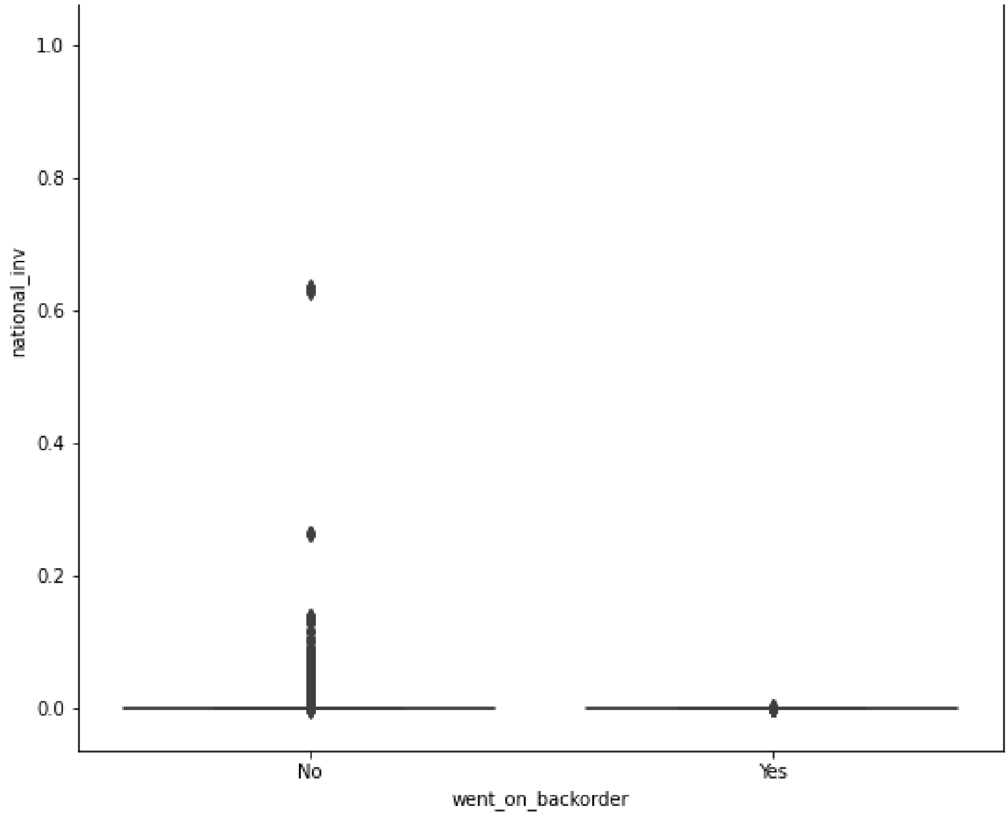
	sku	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month	sales_1_mon
176	1111655	-55.0	8.0	2.0	428.0	526.0	606.0	25
191	1111670	-499.0	12.0	350.0	3452.0	5044.0	7188.0	747
1577	1113057	-4.0	8.0	0.0	24.0	41.0	50.0	3
4141	1115620	-34.0	8.0	0.0	120.0	240.0	240.0	83
5132	1116610	-1.0	0.0	0.0	26.0	36.0	51.0	8
...	...	...	...	...	...	...	...	
1687738	1574269	-3.0	16.0	0.0	13.0	28.0	28.0	4
1687781	1552323	-21.0	2.0	39.0	0.0	0.0	0.0	82
1687826	1569674	-7.0	8.0	0.0	96.0	96.0	144.0	12
1687836	1473147	-94.0	8.0	25.0	786.0	1226.0	1697.0	304
1687857	1524346	-1.0	9.0	0.0	7.0	9.0	11.0	0

890 rows × 23 columns

In [21]:

```
#box-plot for national_inv vs went_on_backorder
plt.figure(figsize=(9, 9))
sns.boxplot(x='went_on_backorder', y='national_inv', data=df)
plt.title('Box Plot: national_inv vs went_on_backorder')
plt.xlabel('went_on_backorder')
plt.ylabel('national_inv')
plt.show()
```





In [22]:

```
#applying log on national_inv and a small epsilon as there are zeros & -ve values. log(0)
= information we don't want inf on our plot.
epsilon = 1e-7
log_national_inv = np.log(df['national_inv'] + epsilon)
df['log_national_inv'] = log_national_inv
df.head(2)
```

```
C:\Users\ganesh.chandra\Anaconda3\lib\site-packages\pandas\core\series.py:726: RuntimeWar
ning: invalid value encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
<ipython-input-22-c85dc3f68496>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  df['log_national_inv'] = log_national_inv
```

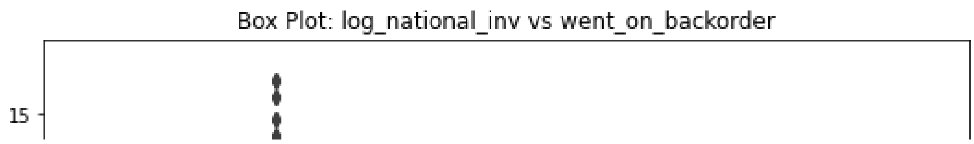
Out[22]:

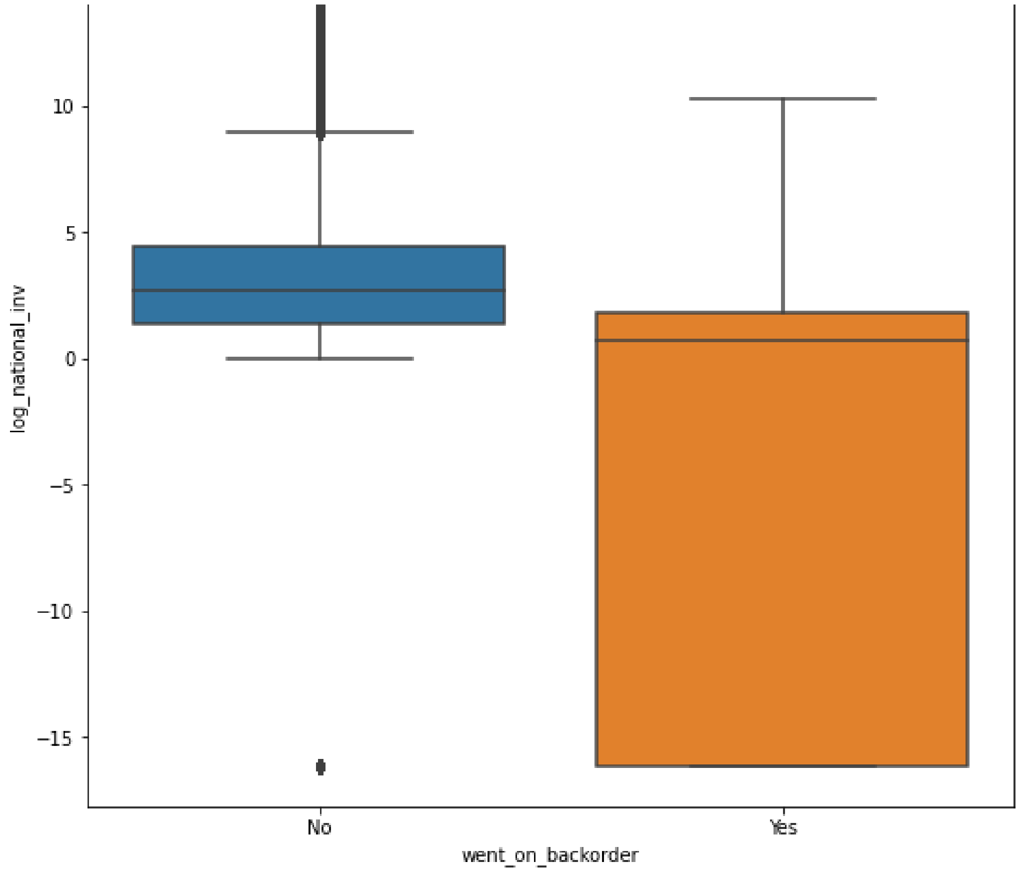
	sku	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month	sales_1_month	sal
0	1026827	0.0	NaN	0.0	0.0	0.0	0.0	0.0	
1	1043384	2.0	9.0	0.0	0.0	0.0	0.0	0.0	

2 rows × 24 columns

In [23]:

```
plt.figure(figsize=(9, 9))
sns.boxplot(x='went_on_backorder', y='log_national_inv', data=df)
plt.title('Box Plot: log_national_inv vs went_on_backorder')
plt.xlabel('went_on_backorder')
plt.ylabel('log_national_inv')
plt.show()
```





In [24]:

```
df.drop('log_national_inv', axis=1, inplace=True) #dropping off the log column as it is n
ot useful for us
```

```
C:\Users\ganesh.chandra\Anaconda3\lib\site-packages\pandas\core\frame.py:4163: SettingWit
hCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  return super().drop(
```

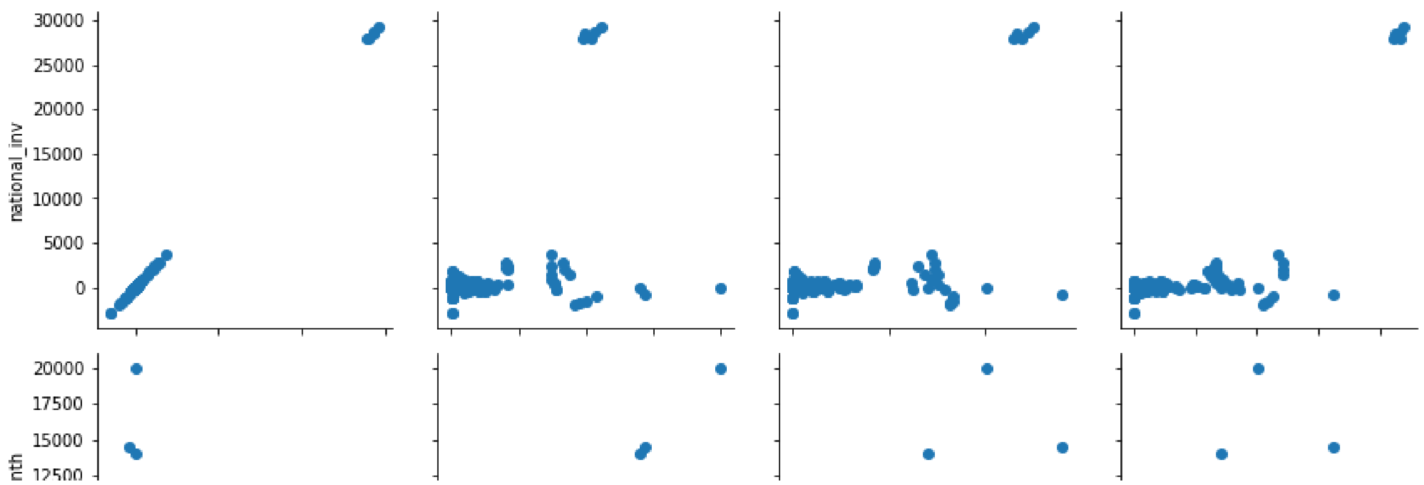
Plotting Pair Plot for Inventory Level vs Sales vs Went_On_Backorder

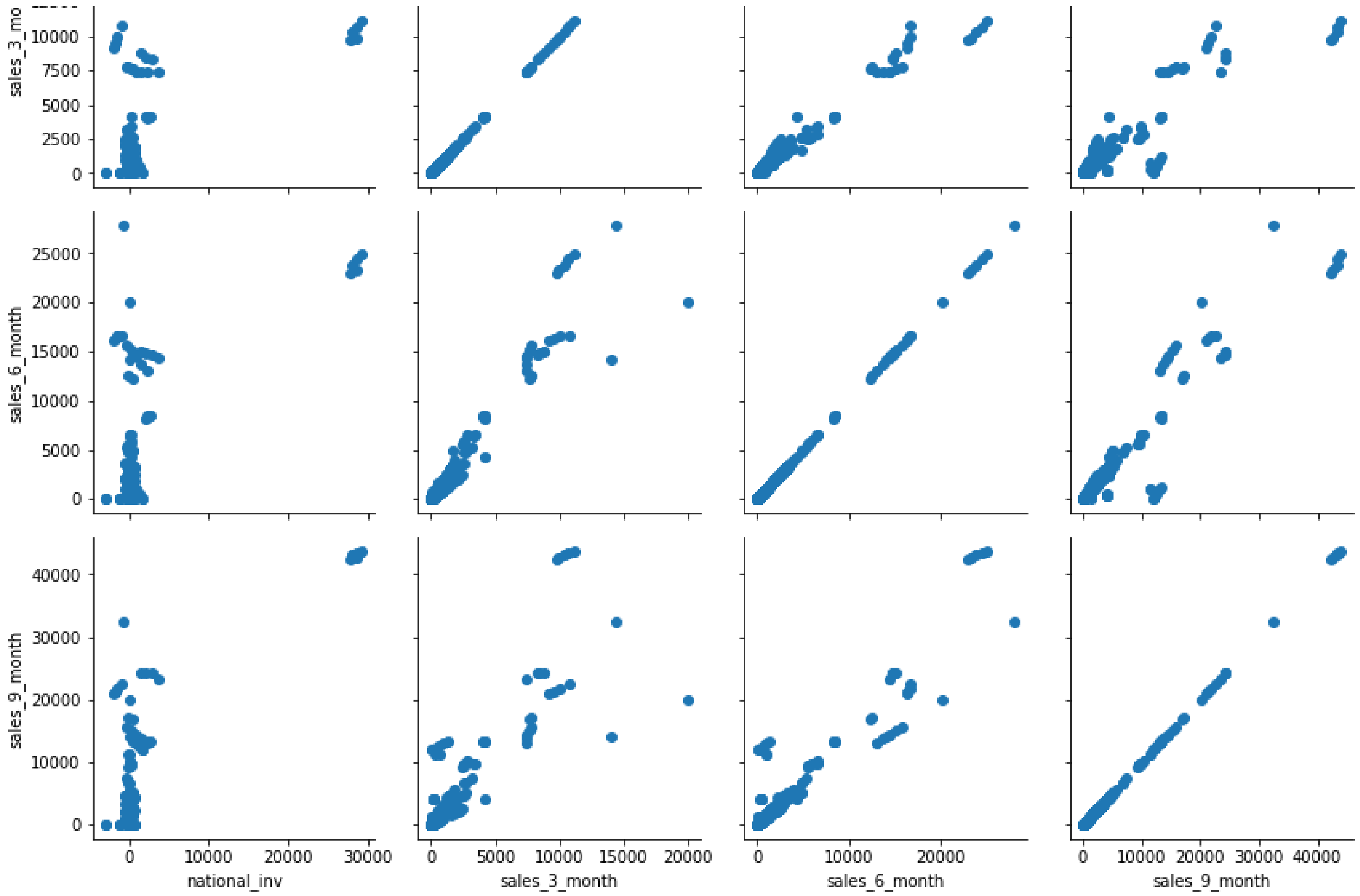
In [25]:

```
cols = ["national_inv",'sales_3_month','sales_6_month','sales_9_month']
g = sns.PairGrid(df[df['went_on_backorder']=="Yes"],vars=cols, hue="went_on_backorder",h
eight=3)

g.map(plt.scatter)
```

Out[25]:

```
<seaborn.axisgrid.PairGrid at 0x29bb36a86a0>
```





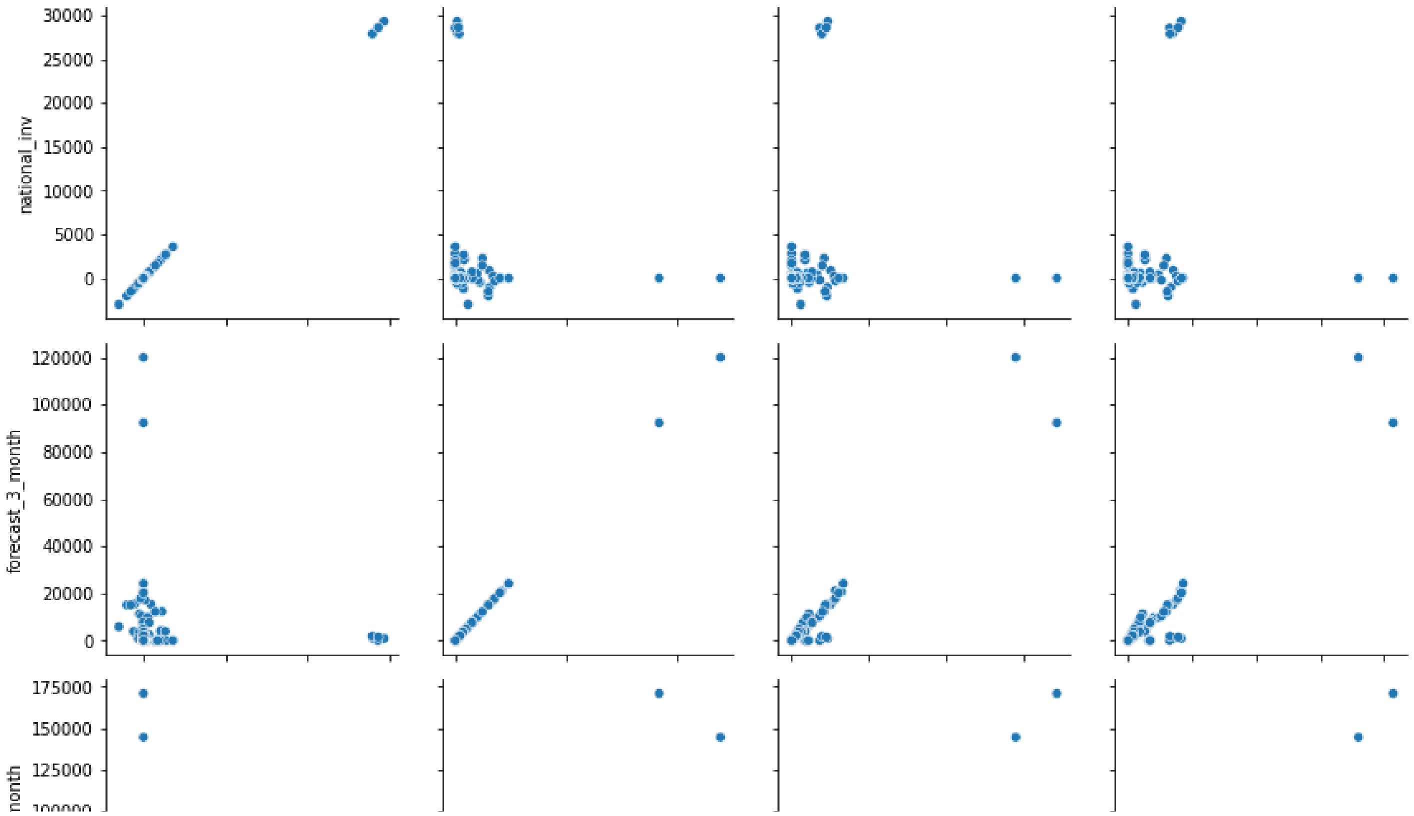
Plotting Pair Plot for Inventory Level vs Forecast vs Went_On_Backorder

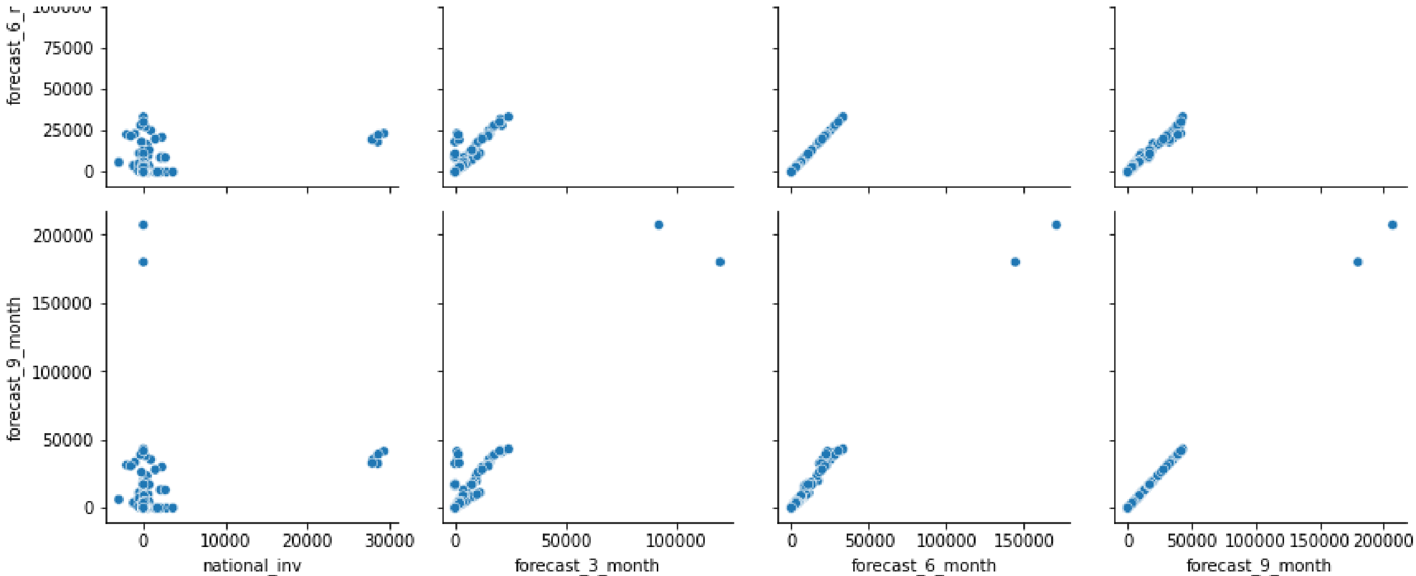
In [26]:

```
cols = ["national_inv",'forecast_3_month','forecast_6_month','forecast_9_month']
g = sns.PairGrid(df[df['went_on_backorder']=="Yes"],vars=cols, hue="went_on_backorder",h
eight=3)

g.map(sns.scatterplot,marker="o", color="r")
```

Out[26]:

```
<seaborn.axisgrid.PairGrid at 0x29bb1411cd0>
```





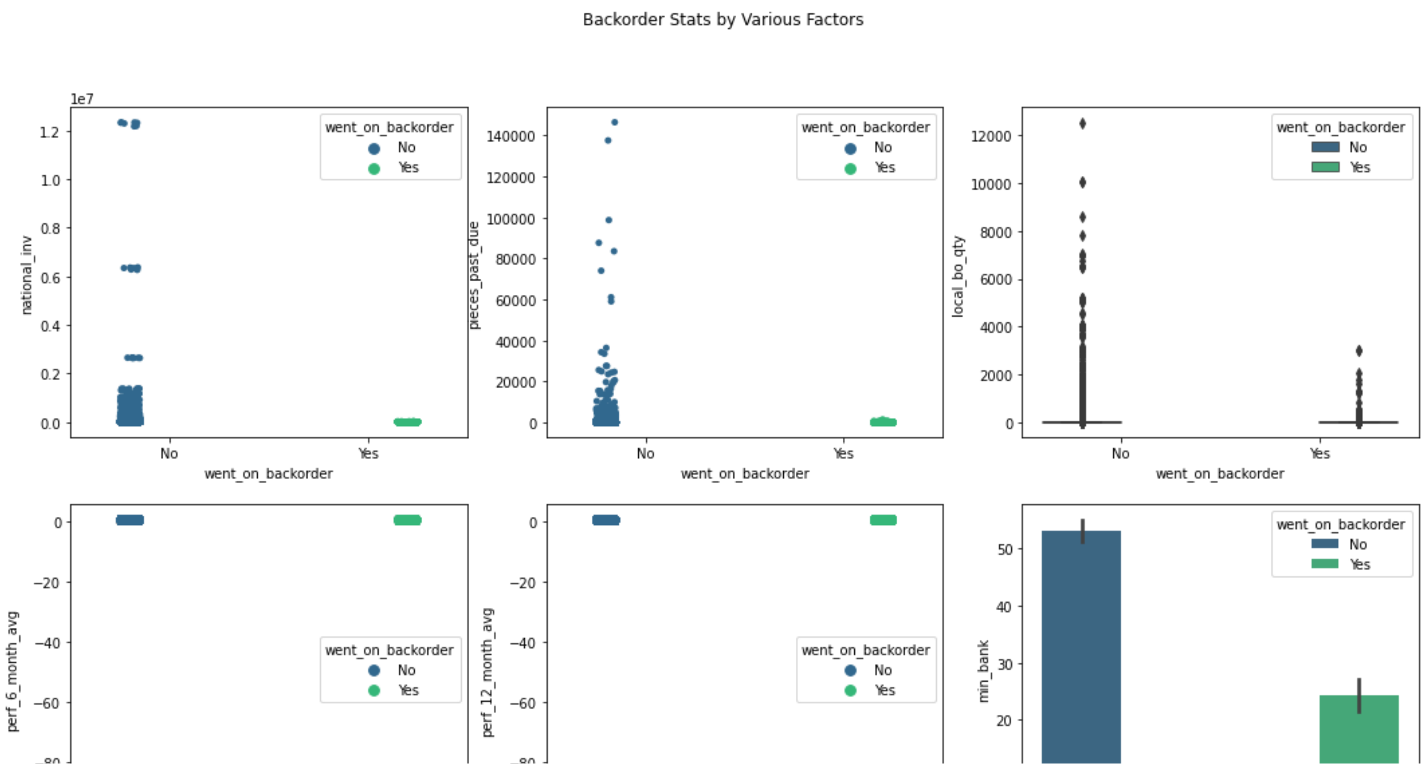
Strip Plot for 'Inventory Level', 'Performance Previous To 6 MOnths', 'Performance Previous To 12 Months', 'Overdue Stock From Source', 'Current Stock Overdue' & 'Minimum Receommended Stock in Inventory' for Products Which Went To backorder

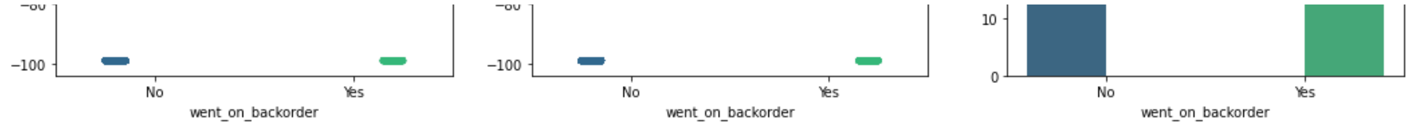
In [27]:

```
fig, axes = plt.subplots(2, 3, figsize=(18, 10))

fig.suptitle('Backorder Stats by Various Factors')

sns.stripplot(ax=axes[0, 0],data=df,x='went_on_backorder', y='national_inv',hue='went_on_backorder',dodge=True, palette='viridis')
sns.stripplot(ax=axes[0, 1],data=df, x='went_on_backorder', y="pieces_past_due",hue='went_on_backorder',dodge=True, palette='viridis')
sns.boxplot(ax=axes[0, 2],data=df, x='went_on_backorder', y="local_bo_qty",hue='went_on_backorder',dodge=True, palette='viridis')
sns.stripplot(ax=axes[1, 0],data=df, x='went_on_backorder', y="perf_6_month_avg",hue='went_on_backorder',dodge=True, palette='viridis')
sns.stripplot(ax=axes[1, 1],data=df, x='went_on_backorder', y="perf_12_month_avg",hue='went_on_backorder',dodge=True, palette='viridis')
sns.barplot(ax=axes[1, 2],data=df, x='went_on_backorder', y="min_bank",hue='went_on_backorder',dodge=True, palette='viridis')
```

Out[27]:

<AxesSubplot: xlabel='went_on_backorder', ylabel='min_bank'>





Observation 5: Observations from above plots are:

1.There are products with 0 or -ve inventory level also which are prone to backorder problems.

2.Previous 6 to 12 months performance is not helpful in determining which products will go to backorder due to approximately equal lower performance averages in both the cases.

3.Most of the values tend to be zero for Minimum Stock Required and there are very less data points with a min_bank value of of 3 or more.

4.Stock overdue from source & Current Stock Overdue could be an important factor in determining which products are going in backorder.

5.Negative Inventory Levels are also responsible for Backorders.

6.Products going in backorder are divided in 2 groups of Inventory Level<-5000 and other outlier group of inventory level>=25000.

Kolmogorov–Smirnov test for numerical features

In [28]:

```
from tqdm import tqdm
from scipy.stats import kstest
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA

'''
we are going to seperate all the features based on the class label. since we have two class labels.
The seperation will result in two distributions.
We will then compare the two distributions to find out how each feature is affecting each class label.
'''
#national_inv
national_inv_vs_went_on_backorder = df.loc[:, ['national_inv', 'went_on_backorder']]
national_inv_0=national_inv_vs_went_on_backorder[national_inv_vs_went_on_backorder['went_on_backorder'] == 'No']['national_inv']
national_inv_1=national_inv_vs_went_on_backorder[national_inv_vs_went_on_backorder['went_on_backorder'] == 'Yes']['national_inv']

#lead_time
lead_time_vs_went_on_backorder = df.loc[:, ['lead_time', 'went_on_backorder']]
lead_time_0 = lead_time_vs_went_on_backorder[lead_time_vs_went_on_backorder['went_on_backorder'] == 'No']['lead_time']
lead_time_1 = lead_time_vs_went_on_backorder[lead_time_vs_went_on_backorder['went_on_backorder'] == 'Yes']['lead_time']

#in_transit_qty
in_transit_qty_vs_went_on_backorder = df.loc[:, ['in_transit_qty', 'went_on_backorder']]
in_transit_qty_0 = in_transit_qty_vs_went_on_backorder[in_transit_qty_vs_went_on_backorder['went_on_backorder'] == 'No']['in_transit_qty']
in_transit_qty_1 = in_transit_qty_vs_went_on_backorder[in_transit_qty_vs_went_on_backorder['went_on_backorder'] == 'Yes']['in_transit_qty']

#forecast_3_month
forecast_3_month_vs_went_on_backorder = df.loc[:, ['forecast_3_month', 'went_on_backorder']]
forecast_3_month_0 = forecast_3_month_vs_went_on_backorder[forecast_3_month_vs_went_on_backorder['went_on_backorder'] == 'No']['forecast_3_month']
forecast_3_month_1 = forecast_3_month_vs_went_on_backorder[forecast_3_month_vs_went_on_backorder['went_on_backorder'] == 'Yes']['forecast_3_month']
```

```
#forecast_6_month
forecast_6_month_vs_went_on_backorder = df.loc[:, ['forecast_6_month', 'went_on_backorder
']]
forecast_6_month_0 = forecast_6_month_vs_went_on_backorder[forecast_6_month_vs_went_on_ba
ckorder['went_on_backorder'] == 'No']['forecast_6_month']
forecast_6_month_1 = forecast_6_month_vs_went_on_backorder[forecast_6_month_vs_went_on_ba
ckorder['went_on_backorder'] == 'Yes']['forecast_6_month']

#forecast_9_month
forecast_9_month_vs_went_on_backorder = df.loc[:, ['forecast_9_month', 'went_on_backorder
']]
forecast_9_month_0 = forecast_9_month_vs_went_on_backorder[forecast_9_month_vs_went_on_ba
ckorder['went_on_backorder'] == 'No']['forecast_9_month']
forecast_9_month_1 = forecast_9_month_vs_went_on_backorder[forecast_9_month_vs_went_on_ba
ckorder['went_on_backorder'] == 'Yes']['forecast_9_month']

#sales_1_month
sales_1_month_vs_went_on_backorder = df.loc[:, ['sales_1_month', 'went_on_backorder']]
sales_1_month_0 = sales_1_month_vs_went_on_backorder[sales_1_month_vs_went_on_backorder['
went_on_backorder'] == 'No']['sales_1_month']
sales_1_month_1 = sales_1_month_vs_went_on_backorder[sales_1_month_vs_went_on_backorder['
went_on_backorder'] == 'Yes']['sales_1_month']

#sales_3_month
sales_3_month_vs_went_on_backorder = df.loc[:, ['sales_3_month', 'went_on_backorder']]
sales_3_month_0 = sales_3_month_vs_went_on_backorder[sales_3_month_vs_went_on_backorder['
went_on_backorder'] == 'No']['sales_3_month']
sales_3_month_1 = sales_3_month_vs_went_on_backorder[sales_3_month_vs_went_on_backorder['
went_on_backorder'] == 'Yes']['sales_3_month']

#sales_6_month
sales_6_month_vs_went_on_backorder = df.loc[:, ['sales_6_month', 'went_on_backorder']]
sales_6_month_0 = sales_6_month_vs_went_on_backorder[sales_6_month_vs_went_on_backorder['
went_on_backorder'] == 'No']['sales_6_month']
sales_6_month_1 = sales_6_month_vs_went_on_backorder[sales_6_month_vs_went_on_backorder['
went_on_backorder'] == 'Yes']['sales_6_month']

#sales_9_month
sales_9_month_vs_went_on_backorder = df.loc[:, ['sales_9_month', 'went_on_backorder']]
sales_9_month_0 = sales_9_month_vs_went_on_backorder[sales_9_month_vs_went_on_backorder['
went_on_backorder'] == 'No']['sales_9_month']
sales_9_month_1 = sales_9_month_vs_went_on_backorder[sales_9_month_vs_went_on_backorder['
went_on_backorder'] == 'Yes']['sales_9_month']

#min_bank
min_bank_vs_went_on_backorder = df.loc[:, ['min_bank', 'went_on_backorder']]
min_bank_0 = min_bank_vs_went_on_backorder[min_bank_vs_went_on_backorder['went_on_backord
er'] == 'No']['min_bank']
min_bank_1 = min_bank_vs_went_on_backorder[min_bank_vs_went_on_backorder['went_on_backord
er'] == 'Yes']['min_bank']

#pieces_past_due
pieces_past_due_vs_went_on_backorder = df.loc[:, ['pieces_past_due', 'went_on_backorder']
]
pieces_past_due_0 = pieces_past_due_vs_went_on_backorder[pieces_past_due_vs_went_on_backo
rder['went_on_backorder'] == 'No']['pieces_past_due']
pieces_past_due_1 = pieces_past_due_vs_went_on_backorder[pieces_past_due_vs_went_on_backo
rder['went_on_backorder'] == 'Yes']['pieces_past_due']

#perf_6_month_avg
perf_6_month_avg_vs_went_on_backorder = df.loc[:, ['perf_6_month_avg', 'went_on_backorder
']]
perf_6_month_avg_0 = perf_6_month_avg_vs_went_on_backorder[perf_6_month_avg_vs_went_on_ba
ckorder['went_on_backorder'] == 'No']['perf_6_month_avg']
perf_6_month_avg_1 = perf_6_month_avg_vs_went_on_backorder[perf_6_month_avg_vs_went_on_ba
ckorder['went_on_backorder'] == 'Yes']['perf_6_month_avg']

#perf_12_month_avg
perf_12_month_avg_vs_went_on_backorder = df.loc[:, ['perf_12_month_avg', 'went_on_backord
er']]
perf_12_month_avg_0 = perf_12_month_avg_vs_went_on_backorder[perf_12_month_avg_vs_went_on
_backorder['went_on_backorder'] == 'No']['perf_12_month_avg']
```

```
perf_12_month_avg_1 = perf_12_month_avg_vs_went_on_backorder[perf_12_month_avg_vs_went_on
_backorder['went_on_backorder'] == 'Yes']['perf_12_month_avg']

#local_bo_qty
local_bo_qty_vs_went_on_backorder = df.loc[:, ['local_bo_qty', 'went_on_backorder']]
local_bo_qty_0 = local_bo_qty_vs_went_on_backorder[local_bo_qty_vs_went_on_backorder['wen
t_on_backorder'] == 'No']['local_bo_qty']
local_bo_qty_1 = local_bo_qty_vs_went_on_backorder[local_bo_qty_vs_went_on_backorder['wen
t_on_backorder'] == 'Yes']['local_bo_qty']
```

In [29]:

```
negative_class = [national_inv_0, lead_time_0, in_transit_qty_0, forecast_3_month_0, fore
cast_6_month_0, forecast_9_month_0, sales_1_month_0,
                 sales_3_month_0, sales_6_month_0, sales_9_month_0, min_bank_0, pieces_p
ast_due_0, perf_6_month_avg_0, perf_12_month_avg_0,
                  local_bo_qty_0]

positive_class = [national_inv_1, lead_time_1, in_transit_qty_1, forecast_3_month_1, fore
cast_6_month_1, forecast_9_month_1, sales_1_month_1,
                 sales_3_month_1, sales_6_month_1, sales_9_month_1, min_bank_1, pieces_p
ast_due_1, perf_6_month_avg_1, perf_12_month_avg_1,
                  local_bo_qty_1]

numerical_feature_names = ['national_inv', 'lead_time', 'in_transit_qty', 'forecast_3_mon
th', 'forecast_6_month', 'forecast_9_month',
                  'sales_1_month', 'sales_3_month', 'sales_6_month', 'sales_9_month', 'm
in_bank', 'pieces_past_due',
                  'perf_6_month_avg', 'perf_12_month_avg', 'local_bo_qty']
```

In [30]:

```
print("KS test results for all the features seperated with respect to went_on_backorder:"
)
for a, b, c in zip(negative_class, positive_class, numerical_feature_names):
    print(f"{c}:   {kstest(a, b)}")
```

```
KS test results for all the features seperated with respect to went_on_backorder:
national_inv:   KstestResult(statistic=0.4593038863202046, pvalue=0.0)
lead_time:   KstestResult(statistic=0.12358668797761088, pvalue=8.871901817096557e-150)
in_transit_qty:   KstestResult(statistic=0.08361356816437004, pvalue=1.1392587380049708e-
68)
forecast_3_month:   KstestResult(statistic=0.5549223474821481, pvalue=0.0)
forecast_6_month:   KstestResult(statistic=0.5380446074846053, pvalue=0.0)
forecast_9_month:   KstestResult(statistic=0.5208074359304866, pvalue=0.0)
sales_1_month:   KstestResult(statistic=0.29399462478309996, pvalue=0.0)
sales_3_month:   KstestResult(statistic=0.3019551028675028, pvalue=0.0)
sales_6_month:   KstestResult(statistic=0.27980928163383156, pvalue=0.0)
sales_9_month:   KstestResult(statistic=0.26490500565360914, pvalue=0.0)
min_bank:   KstestResult(statistic=0.030669661309448926, pvalue=1.3363130686456096e-09)
pieces_past_due:   KstestResult(statistic=0.07816384395447284, pvalue=4.7096180965744114e
-60)
perf_6_month_avg:   KstestResult(statistic=0.09242475354320173, pvalue=7.753365114358343e
-84)
perf_12_month_avg:   KstestResult(statistic=0.10217347973941354, pvalue=2.114564829632489
5e-102)
local_bo_qty:   KstestResult(statistic=0.11079399648833477, pvalue=2.2127554035290613e-12
0)
```

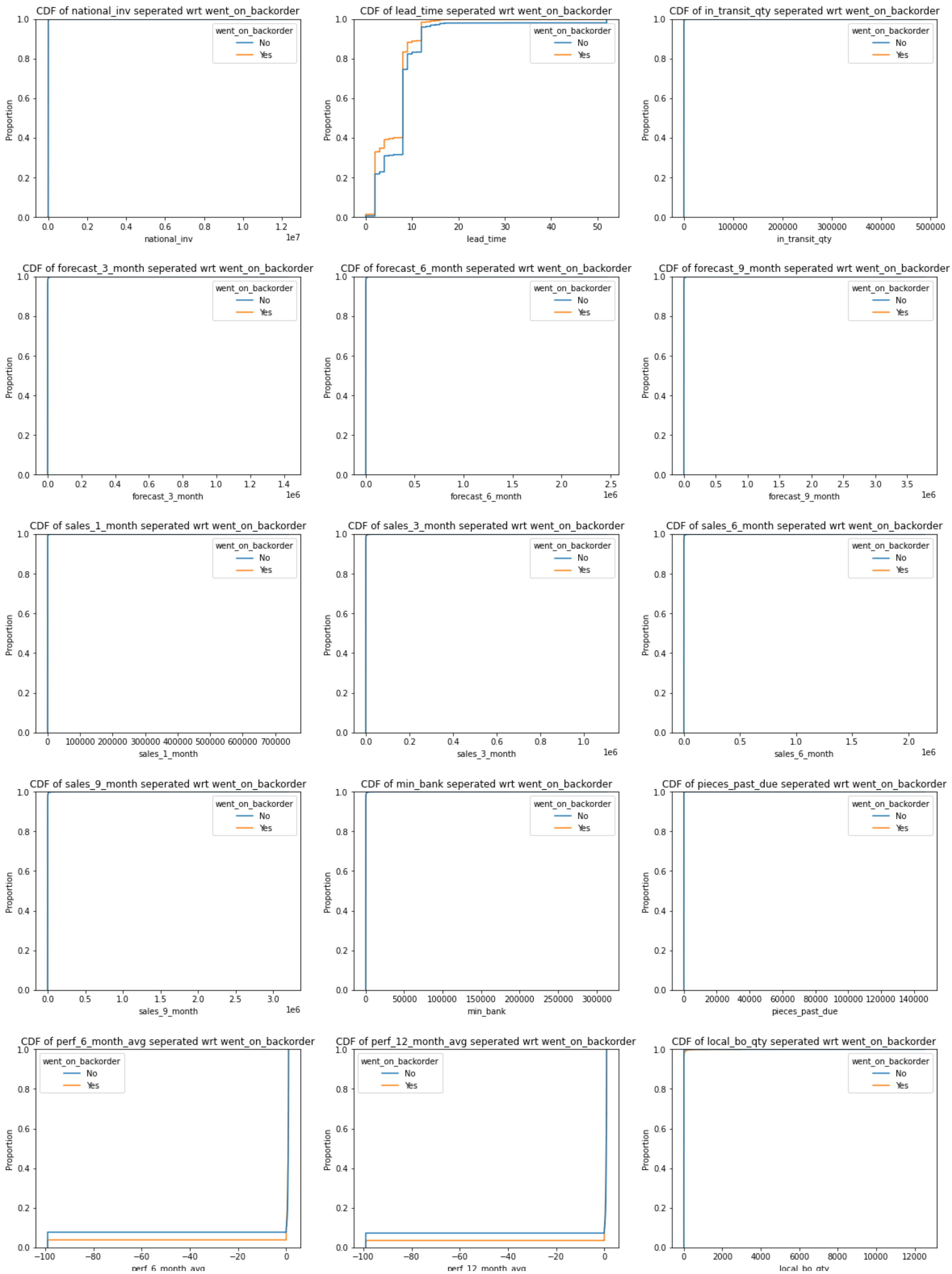
In [31]:

```
seperated_dfs = [national_inv_vs_went_on_backorder, lead_time_vs_went_on_backorder, in_tr
ansit_qty_vs_went_on_backorder, forecast_3_month_vs_went_on_backorder,
forecast_6_month_vs_went_on_backorder, forecast_9_month_vs_went_on_backorder, sales_1_mon
th_vs_went_on_backorder, sales_3_month_vs_went_on_backorder,
sales_6_month_vs_went_on_backorder, sales_9_month_vs_went_on_backorder, min_bank_vs_went_
on_backorder, pieces_past_due_vs_went_on_backorder,
perf_6_month_avg_vs_went_on_backorder, perf_12_month_avg_vs_went_on_backorder, local_bo_q
ty_vs_went_on_backorder]
```

In [32]:

```python
plt.figure(figsize=(20, 28))
for x, y, z in tqdm(zip(range(1,16), numerical_feature_names, seperated_dfs)):
    plt.subplot(5, 3, x)
    plt.subplots_adjust(hspace=0.3)
    sns.ecdfplot(z, x=y, hue='went_on_backorder')
    plt.title(f'CDF of {y} seperated wrt went_on_backorder')
plt.show()
```

```
15it [00:55,  3.72s/it]
```



Observation 6:

We can see that most of the feature have very high number of datapoints at 0. From the ks test for all the numerical feature we can say most of the features do not have a very good p values and thus we will have to reject the null hypothesis. Therefore, these distributions are not similar are do not show much correlation with the target variable.

However, some features like lead_time, perf_6_month_avg, perf_12_month_avg show good enough correlation with the target variable.

Stochastic/Probability Matrix for categorical features

In [33]:

```
df.replace({'Yes': 1, 'No': 0}, inplace=True)

potential_issue_vs_went_on_backorder = df.loc[:, ['potential_issue', 'went_on_backorder']
]
x = np.array(potential_issue_vs_went_on_backorder)

potential_issue_probability_matrix = np.array([[x[np.where((x[:,0] == 0) * (x[:,1] == 0)
)].shape[0] / len(x),
                                                x[np.where((x[:,0] == 0) * (x[:,1] == 1
))].shape[0] / len(x)],
                                               [x[np.where((x[:,0] == 1) * (x[:,1] == 0
))].shape[0] / len(x),
                                                x[np.where((x[:,0] == 1) * (x[:,1] == 1
))].shape[0] / len(x)]])

potential_issue_probability_matrix = pd.DataFrame(potential_issue_probability_matrix, col
umns=['No', 'Yes'], index=['No', 'Yes'])
```

```
C:\Users\ganesh.chandra\Anaconda3\lib\site-packages\pandas\core\frame.py:4379: SettingWit
hCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  return super().replace(
```

In [34]:

```
deck_risk_vs_went_on_backorder = df.loc[:, ['deck_risk', 'went_on_backorder']]
x = np.array(deck_risk_vs_went_on_backorder)

deck_risk_probability_matrix = np.array([[x[np.where((x[:,0] == 0) * (x[:,1] == 0))].sha
pe[0] / len(x),
                                          x[np.where((x[:,0] == 0) * (x[:,1] == 1))].sh
ape[0] / len(x)],
                                         [x[np.where((x[:,0] == 1) * (x[:,1] == 0))].sh
ape[0] / len(x),
                                          x[np.where((x[:,0] == 1) * (x[:,1] == 1))].sh
ape[0] / len(x)]])

deck_risk_probability_matrix = pd.DataFrame(deck_risk_probability_matrix, columns=['No',
'Yes'], index=['No', 'Yes'])
```

In [35]:

```
oe_constraint_vs_went_on_backorder = df.loc[:, ['oe_constraint', 'went_on_backorder']]
x = np.array(oe_constraint_vs_went_on_backorder)

oe_constraint_probability_matrix = np.array([[x[np.where((x[:,0] == 0) * (x[:,1] == 0))]
.shape[0] / len(x),
                                              x[np.where((x[:,0] == 0) * (x[:,1] == 1))
].shape[0] / len(x)],
                                             [x[np.where((x[:,0] == 1) * (x[:,1] == 0))
].shape[0] / len(x),
```

```
                                                x[np.where((x[:,0] == 1) * (x[:,1] == 1))
].shape[0] / len(x)]])

oe_constraint_probability_matrix = pd.DataFrame(oe_constraint_probability_matrix, column
s=['No', 'Yes'], index=['No', 'Yes'])
```

In [36]:

```
ppap_risk_vs_went_on_backorder = df.loc[:, ['ppap_risk', 'went_on_backorder']]
x = np.array(ppap_risk_vs_went_on_backorder)

ppap_risk_probability_matrix = np.array([[x[np.where((x[:,0] == 0) * (x[:,1] == 0))].sha
pe[0] / len(x),
                                        x[np.where((x[:,0] == 0) * (x[:,1] == 1))].sh
ape[0] / len(x)],
                                       [x[np.where((x[:,0] == 1) * (x[:,1] == 0))].sh
ape[0] / len(x),
                                        x[np.where((x[:,0] == 1) * (x[:,1] == 1))].sh
ape[0] / len(x)]])

ppap_risk_probability_matrix = pd.DataFrame(ppap_risk_probability_matrix, columns=['No',
'Yes'], index=['No', 'Yes'])
```

In [37]:

```
stop_auto_buy_vs_went_on_backorder = df.loc[:, ['stop_auto_buy', 'went_on_backorder']]
x = np.array(stop_auto_buy_vs_went_on_backorder)

stop_auto_buy_probability_matrix = np.array([[x[np.where((x[:,0] == 0) * (x[:,1] == 0))]
.shape[0] / len(x),
                                            x[np.where((x[:,0] == 0) * (x[:,1] == 1))
].shape[0] / len(x)],
                                           [x[np.where((x[:,0] == 1) * (x[:,1] == 0))
].shape[0] / len(x),
                                            x[np.where((x[:,0] == 1) * (x[:,1] == 1))
].shape[0] / len(x)]])

stop_auto_buy_probability_matrix = pd.DataFrame(stop_auto_buy_probability_matrix, column
s=['No', 'Yes'], index=['No', 'Yes'])
```

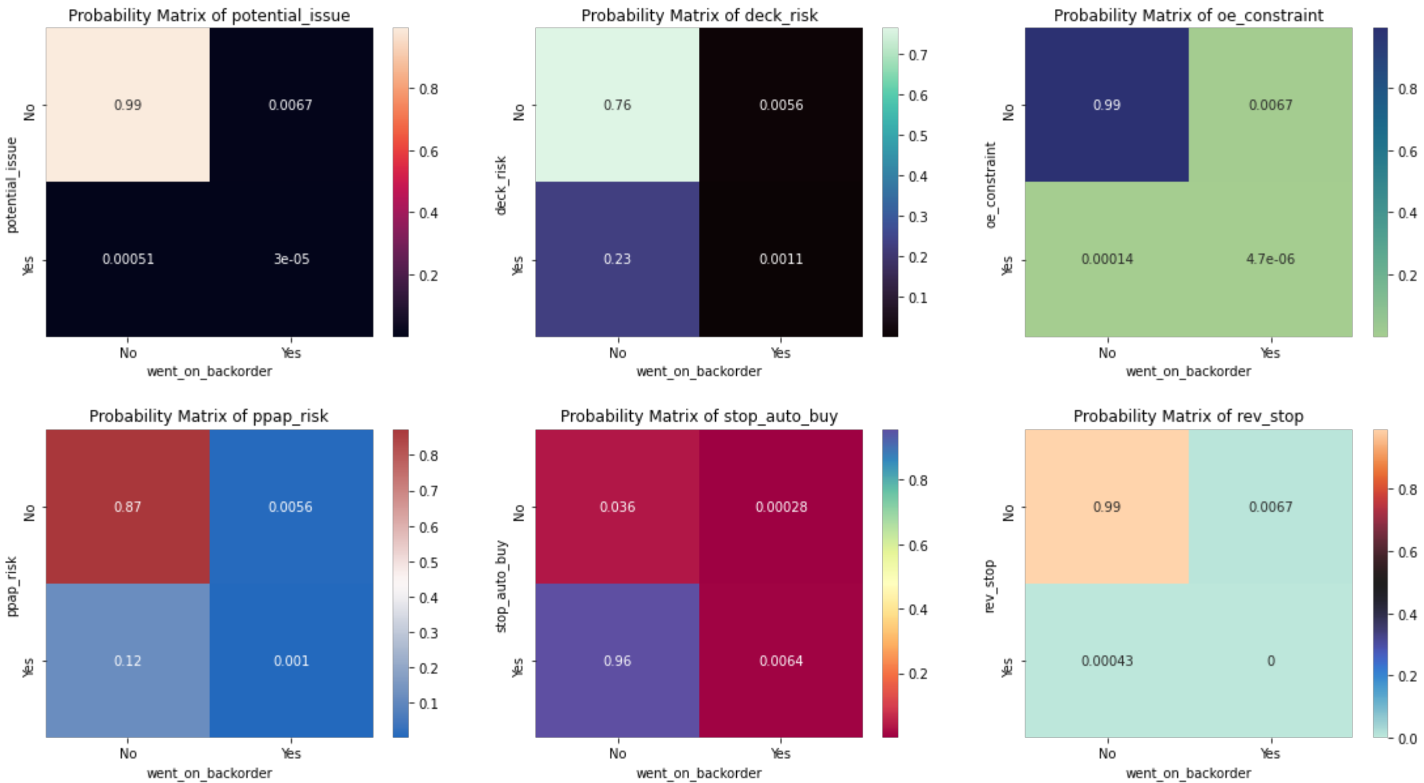
In [38]:

```
rev_stop_vs_went_on_backorder = df.loc[:, ['rev_stop', 'went_on_backorder']]
x = np.array(rev_stop_vs_went_on_backorder)

rev_stop_probability_matrix = np.array([[x[np.where((x[:,0] == 0) * (x[:,1] == 0))].shap
e[0] / len(x),
                                           x[np.where((x[:,0] == 0) * (x[:,1] == 1))]
.shape[0] / len(x)],
                                          [x[np.where((x[:,0] == 1) * (x[:,1] == 0))]
.shape[0] / len(x),
                                           x[np.where((x[:,0] == 1) * (x[:,1] == 1))]
.shape[0] / len(x)]])

rev_stop_probability_matrix = pd.DataFrame(rev_stop_probability_matrix, columns=['No', '
Yes'], index=['No', 'Yes'])
```

In [39]:

```
plt.figure(figsize=(19, 10))
plt.subplot(2, 3, 1)
plt.subplots_adjust(hspace=0.3)
sns.heatmap(potential_issue_probability_matrix, annot=True, cmap='rocket')
plt.title("Probability Matrix of potential_issue")
plt.xlabel('went_on_backorder')
plt.ylabel('potential_issue')

plt.subplot(2, 3, 2)
plt.subplots_adjust(hspace=0.3)
sns.heatmap(deck_risk_probability_matrix, annot=True, cmap='mako')
plt.title("Probability Matrix of deck_risk")
```

```
plt.xlabel('went_on_backorder')
plt.ylabel('deck_risk')

plt.subplot(2, 3, 3)
plt.subplots_adjust(hspace=0.3)
sns.heatmap(oe_constraint_probability_matrix, annot=True, cmap='crest')
plt.title("Probability Matrix of oe_constraint")
plt.xlabel('went_on_backorder')
plt.ylabel('oe_constraint')

plt.subplot(2, 3, 4)
plt.subplots_adjust(hspace=0.3)
sns.heatmap(ppap_risk_probability_matrix, annot=True, cmap='vlag')
plt.title("Probability Matrix of ppap_risk")
plt.xlabel('went_on_backorder')
plt.ylabel('ppap_risk')

plt.subplot(2, 3, 5)
plt.subplots_adjust(hspace=0.3)
sns.heatmap(stop_auto_buy_probability_matrix, annot=True, cmap='Spectral')
plt.title("Probability Matrix of stop_auto_buy")
plt.xlabel('went_on_backorder')
plt.ylabel('stop_auto_buy')

plt.subplot(2, 3, 6)
plt.subplots_adjust(hspace=0.3)
sns.heatmap(rev_stop_probability_matrix, annot=True, cmap='icefire')
plt.title("Probability Matrix of rev_stop")
plt.xlabel('went_on_backorder')
plt.ylabel('rev_stop')

plt.show()
```



In [40]:

```
#saving to csv so we can use it for building the model
import pandas as pd
potential_issue_probability_matrix.to_csv('potential_issue_probability_matrix.csv', index
=False)
deck_risk_probability_matrix.to_csv('deck_risk_probability_matrix.csv', index=False)
oe_constraint_probability_matrix.to_csv('oe_constraint_probability_matrix.csv', index=Fal
se)
ppap_risk_probability_matrix.to_csv('ppap_risk_probability_matrix.csv', index=False)
stop_auto_buy_probability_matrix.to_csv('stop_auto_buy_probability_matrix.csv', index=Fal
se)
```

```
rev_stop_probability_matrix.to_csv('rev_stop_probability_matrix.csv', index=False)
```

Observation 7:

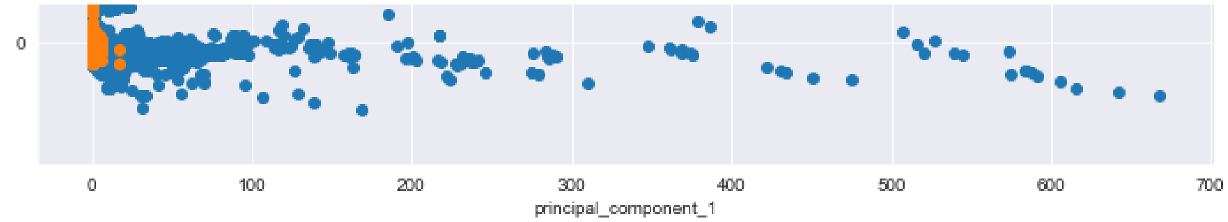
From the above set of probaility matrices for all the categorical features we see that most of these categorical features have a very high probability of having a negetive flag when the product did not go into backorder. Therefore, we can say that when a product does not go into backorder, most of the general risk flag are negative.

Dimensionality Reduction:

Principal Component Analysis

In [42]:

```
#we will perform pca for all the data points which do not have missing values
x_train = df.dropna().drop('went_on_backorder', axis=1)
y_train = df.dropna()['went_on_backorder']

standard_scalar = StandardScaler()

std_x_train = standard_scalar.fit_transform(x_train)

model = PCA(n_components=2, random_state=42)
pca_data = model.fit_transform(std_x_train)
pca_data = np.vstack((pca_data.T, y_train)).T
pca_df = pd.DataFrame(data=pca_data, columns=("principal_component_1", "principal_compone
nt_2", "went_on_backorder"))

sns.set_style("darkgrid")
sns.FacetGrid(pca_df, hue='went_on_backorder', height=10).map(plt.scatter, 'principal_com
ponent_1', 'principal_component_2').add_legend()
plt.title("Principal Component Analysis on train set")
plt.show()
```



Observation 8:

We have used dimensionality reduction techniques, in this case Principal Component Analysis to capture the essence of the data. From the above plot we see that most of the datapoints lie alongside 0. This deduction is true because we have seen many features with mostly 0 values in our EDA. There are outliers in the data but those datapoints does not have to be outlier per se. Furthermore, these potential outliers are more of the negative class compared to the positive class. And, for the positive class, almost all of the datapoints lie alongside 0

Feature Engineering

Imputing Missing values via mean method for continuous data column "Lead_Time"

In [43]:

```
import numpy as np
train = df.fillna(np.mean(df['lead_time']))
```

In [44]:

```
lead_time_mean = np.array(np.mean(train['lead_time']))
```

In [45]:

```
np.save("lead_time_mean.npy",lead_time_mean)
```

In above step mean imputation was done for "lead_time".

In upcoming steps we will focus on categorical columns feature engineering. Two specific columns "Pieces_past_due" & "local_b0_quantity" majority of the values are 0. Hence adding another feature showing if each datapoint in the two features is 0 or non 0 since evry non 0 value is a quantity and we are interested in whether it went to backorder or not.

In [46]:

```
train['pieces_past_due'].value_counts()
```

Out[46]:

```
0.0       1662571
1.0          3917
2.0          2187
4.0          1294
3.0          1217
          ...
2600.0          1
163.0           1
2620.0          1
2628.0          1
2271.0          1
Name: pieces_past_due, Length: 826, dtype: int64
```

In [47]:

```
conditions = [train['pieces_past_due'] == 0, train['pieces_past_due'] > 0]
values = [0, 1]
train['binary_pieces_past_due'] = np.select(conditions, values)
```

```
train['binary_pieces_past_due'].value_counts()
```

Out[47]:

```
0    1662571
1      25289
Name: binary_pieces_past_due, dtype: int64
```

In [48]:

```
train['local_bo_qty'].value_counts()
```

Out[48]:

```
0.0       1664518
1.0          7151
2.0          2982
3.0          1716
4.0          1224
           ...   
1379.0          1
316.0           1
1399.0          1
314.0           1
511.0           1
Name: local_bo_qty, Length: 654, dtype: int64
```

In [49]:

```
conditions = [train['local_bo_qty'] == 0, train['local_bo_qty'] > 0]
values = [0, 1]

train['binary_local_bo_qty'] = np.select(conditions, values)
train['binary_local_bo_qty'].value_counts()
```

Out[49]:

```
0    1664518
1      23342
Name: binary_local_bo_qty, dtype: int64
```

For rest of our categorical features we will impute the 0 values with the respective probability values from the probability matrices.

Potential_issue:

In [50]:

```
conditions = [train['potential_issue'] == 0, train['potential_issue'] == 1]
values = [potential_issue_probability_matrix['No'][0], potential_issue_probability_matrix
['No'][1]]

train['potential_issue'] = np.select(conditions, values)
train['potential_issue'].value_counts()
```

Out[50]:

```
0.992802    1686953
0.000507        907
Name: potential_issue, dtype: int64
```

Deck_Risk:

In [51]:

```
conditions = [train['deck_risk'] == 0, train['deck_risk'] == 1]
values = [deck_risk_probability_matrix['No'][0], deck_risk_probability_matrix['No'][1]]

train['deck_risk'] = np.select(conditions, values)
train['deck_risk'].value_counts()
```

Out[51]:

```
0.764874    1300377
0.228435     387483
Name: deck_risk, dtype: int64
```

Oe_Constraint:

In [52]:

```
conditions = [train['oe_constraint'] == 0, train['oe_constraint'] == 1]
values = [oe_constraint_probability_matrix['No'][0], oe_constraint_probability_matrix['N
o'][1]]

train['oe_constraint'] = np.select(conditions, values)
train['oe_constraint'].value_counts()
```

Out[52]:

```
0.993169    1687615
0.000140        245
Name: oe_constraint, dtype: int64
```

Ppap_Risk:

In [53]:

```
conditions = [train['ppap_risk'] == 0, train['ppap_risk'] == 1]
values = [ppap_risk_probability_matrix['No'][0], ppap_risk_probability_matrix['No'][1]]

train['ppap_risk'] = np.select(conditions, values)
train['ppap_risk'].value_counts()
```

Out[53]:

```
0.873587    1484026
0.119723     203834
Name: ppap_risk, dtype: int64
```

Stop_auto_buy:

In [54]:

```
conditions = [train['stop_auto_buy'] == 0, train['stop_auto_buy'] == 1]
values = [stop_auto_buy_probability_matrix['No'][0], stop_auto_buy_probability_matrix['N
o'][1]]

train['stop_auto_buy'] = np.select(conditions, values)
train['stop_auto_buy'].value_counts()
```

Out[54]:

```
0.957397    1626774
0.035912      61086
Name: stop_auto_buy, dtype: int64
```

Rev_stop:

In [55]:

```
conditions = [train['rev_stop'] == 0, train['rev_stop'] == 1]
values = [rev_stop_probability_matrix['No'][0], rev_stop_probability_matrix['No'][1]]

train['rev_stop'] = np.select(conditions, values)
train['rev_stop'].value_counts()
```

Out[55]:

```
0.992876    1687129
0.000433        731
Name: rev_stop, dtype: int64
```

Same Pre-processing and feature engineering steps from above are applied to test data as well ensuring values imputed in the test set are calculated from train set itself avoiding any data leakage.

In [56]:

```
test.drop('sku', axis=1, inplace=True)

test = test.fillna(np.mean(train['lead_time'])) #train mean imputation

test.replace({'Yes': 1, 'No': 0}, inplace=True) #converting categorical features to bina
ry features

conditions = [test['pieces_past_due'] == 0, test['pieces_past_due'] > 0]
values = [0, 1]

test['binary_pieces_past_due'] = np.select(conditions, values)

conditions = [test['local_bo_qty'] == 0, test['local_bo_qty'] > 0]
values = [0, 1]

test['binary_local_bo_qty'] = np.select(conditions, values)
```

```
C:\Users\ganesh.chandra\Anaconda3\lib\site-packages\pandas\core\frame.py:4163: SettingWit
hCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  return super().drop(
```

In [58]:

```
conditions_pot = [test['potential_issue'] == 0, test['potential_issue'] == 1]
values_pot = [potential_issue_probability_matrix['No'][0], potential_issue_probability_ma
trix['No'][1]]
test['potential_issue'] = np.select(conditions_pot, values_pot)

conditions_de = [test['deck_risk'] == 0, test['deck_risk'] == 1]
values_de = [deck_risk_probability_matrix['No'][0], deck_risk_probability_matrix['No'][1]
]
test['deck_risk'] = np.select(conditions_de, values_de)

conditions_oc = [test['oe_constraint'] == 0, test['oe_constraint'] == 1]
values_oc = [oe_constraint_probability_matrix['No'][0], oe_constraint_probability_matrix
['No'][1]]
test['oe_constraint'] = np.select(conditions_oc, values_oc)

conditions_pr = [test['ppap_risk'] == 0, test['ppap_risk'] == 1]
values_pr = [ppap_risk_probability_matrix['No'][0], ppap_risk_probability_matrix['No'][1]
]
test['ppap_risk'] = np.select(conditions_pr, values_pr)

conditions_stpa = [test['stop_auto_buy'] == 0, test['stop_auto_buy'] == 1]
values_stpa = [stop_auto_buy_probability_matrix['No'][0], stop_auto_buy_probability_matr
ix['No'][1]]
test['stop_auto_buy'] = np.select(conditions_stpa, values_stpa)

conditions_revs = [test['rev_stop'] == 0, test['rev_stop'] == 1]
values_revs = [rev_stop_probability_matrix['No'][0], rev_stop_probability_matrix['No'][1
]]
test['rev_stop'] = np.select(conditions_revs, values_revs)

print("The final dataset that we can use to build a machine learning model is as follows,
where the column 'went_on_backorder' is our target label:\n")
test
```

```
The final dataset that we can use to build a machine learning model is as follows, where
the column 'went_on_backorder' is our target label:
```

Out[58]:

	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month	sales_1_month	sales_3
0	62.0	7.872267	0.0	0.0	0.0	0.0	0.0	
1	9.0	7.872267	0.0	0.0	0.0	0.0	0.0	
2	17.0	8.000000	0.0	0.0	0.0	0.0	0.0	
3	9.0	2.000000	0.0	0.0	0.0	0.0	0.0	
4	2.0	8.000000	0.0	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	...	...	
242070	12.0	12.000000	0.0	0.0	0.0	0.0	0.0	
242071	13.0	12.000000	0.0	0.0	0.0	0.0	0.0	
242072	13.0	12.000000	0.0	0.0	0.0	0.0	0.0	
242073	10.0	12.000000	0.0	0.0	0.0	0.0	0.0	
242074	2913.0	12.000000	0.0	0.0	0.0	0.0	0.0	

242075 rows × 24 columns

Exporting Pre-processed train and test sets:

In [ ]:

```
train.to_csv('preprocessed_train.csv')
```

In [ ]:

```
test.to_csv('preprocessed_test.csv')
```

Plotting for PCA post Feature Engineering:

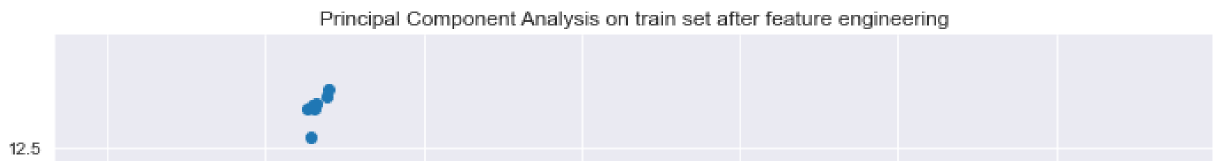
In [60]:

```
# Dropping categorical features
x_train = train.dropna().drop('went_on_backorder', axis=1)
x_train = train.dropna().drop('sku', axis=1)
y_train = train.dropna()['went_on_backorder']
```

In [61]:

```
#PCA Plot
standard_scalar = StandardScaler()
std_x_train = standard_scalar.fit_transform(x_train)
#std_x_train_transform(x_train)
model = PCA(n_components=2, random_state=42)
pca_data = model.fit_transform(std_x_train)
pca_data = np.vstack((pca_data.T, y_train)).T
pca_df = pd.DataFrame(data=pca_data, columns=("principal_component_1", "principal_compone
nt_2", "went_on_backorder"))
sns.set_style("darkgrid")
sns.FacetGrid(pca_df, hue='went_on_backorder', height=10).map(plt.scatter, 'principal_com
ponent_1', 'principal_component_2').add_legend()
plt.title("Principal Component Analysis on train set after feature engineering")
plt.show()
```

```
The history saving thread hit an unexpected error (OperationalError('database or disk is
full')).History will not be written to the database.
```



10.0
7.5
5.0
2.5
0.0
−2.5
principal_component_2
0
100
200
300
400
500
600
principal_component_1
went_on_backorder
0.0
1.0