


```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score
```

```
inv_data = pd.read_csv('Training_BOP.csv')
inv_data.head()
```

 <ipython-input-4-e4a784c923cc>:1: DtypeWarning: Columns (0) have mixed types. Specify dtype option on im
inv_data = pd.read_csv('Training_BOP.csv')

	sku	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month
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

5 rows × 23 columns

```
# Calculate the total number of rows in the lead_time column
```

```
total_rows = inv_data['lead_time'].shape[0]
```

```
# Calculate the number of empty (NaN) cells in the lead_time column
```

```
empty_cells = inv_data['lead_time'].isna().sum()
```

```
# Calculate the percentage of empty cells
```

```
percentage_empty = (empty_cells / total_rows) * 100
```

```
# Print the result
```

```
print(f"Percentage of empty cells in 'lead_time': {percentage_empty:.2f}%")
```

 Percentage of empty cells in 'lead_time': 5.98%

```
# Remove rows where 'lead_time' is NaN
```

```
inv_data_cleaned = inv_data.dropna(subset=['lead_time'])
```

```
# Drop the 'sku' column
```


```
inv_data_cleaned = inv_data_cleaned.drop(columns=['sku'])
```

```
# Optionally, you can reset the index if needed
```

```
inv_data_cleaned.reset_index(drop=True, inplace=True)
```

```
# Display the cleaned DataFrame
```

```
print(inv_data_cleaned)
```

 1586963 0.0 2.0 0.0 10.0
1586964 -1.0 9.0 0.0 7.0
1586965 62.0 9.0 16.0 39.0
1586966 19.0 4.0 0.0 0.0

	forecast_6_month	forecast_9_month	sales_1_month	sales_3_month	\
0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	

0	0.0	0.0	...	0.0	0.99
1	0.0	0.0	...	0.0	0.10
2	0.0	0.0	...	0.0	0.82
3	0.0	0.0	...	0.0	0.00
4	0.0	0.0	...	0.0	0.82
...
1586962	849.0	1074.0	...	0.0	0.85
1586963	7.0	7.0	...	0.0	0.69
1586964	11.0	12.0	...	0.0	0.86
1586965	153.0	205.0	...	0.0	0.86
1586966	12.0	20.0	...	0.0	0.73

	perf_12_month_avg	local_bo_qty	deck_risk	oe_constraint	ppap_risk	\
0	0.99	0.0	No	No	No	
1	0.13	0.0	No	No	No	
2	0.87	0.0	No	No	No	
3	0.00	0.0	Yes	No	Yes	
4	0.87	0.0	No	No	No	
...	
1586962	0.90	1.0	No	No	No	
1586963	0.69	5.0	Yes	No	No	
1586964	0.84	1.0	Yes	No	No	
1586965	0.84	6.0	No	No	No	
1586966	0.78	1.0	No	No	No	

	stop_auto_buy	rev_stop	went_on_backorder
0	Yes	No	No
1	Yes	No	No
2	Yes	No	No
3	Yes	No	No
4	Yes	No	No
...
1586962	Yes	No	No
1586963	Yes	No	No
1586964	No	No	Yes
1586965	Yes	No	No
1586966	Yes	No	No

[1586967 rows x 22 columns]

```
inv_data_cleaned.to_csv('modified_training_bop.csv', index=False)
```



```
-----
KeyboardInterrupt                                Traceback (most recent call last)
<ipython-input-7-133279b27e33> in <cell line: 0>()
----> 1 inv_data_cleaned.to_csv('modified_training_bop.csv', index=False)

----- 11 frames -----
/usr/local/lib/python3.11/dist-packages/pandas/core/indexes/base.py in get_values_for_csv(values,
date_format, na_rep, quoting, float_format, decimal)
    7832
    7833         if not quoting:
-> 7834             values = values.astype(str)
    7835     else:
    7836         values = np.array(values, dtype="object")

KeyboardInterrupt:
```

Using the modified file hereforth

```
mod_inv_data = pd.read_csv('modified_training_bop.csv')
mod_inv_data.head()
```

	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month	sales_1_
0	2.0	9.0	0.0	0.0	0.0	0.0	
1	7.0	8.0	0.0	0.0	0.0	0.0	
2	13.0	8.0	0.0	0.0	0.0	0.0	
3	6.0	2.0	0.0	0.0	0.0	0.0	
4	4.0	8.0	0.0	0.0	0.0	0.0	

5 rows × 22 columns

```
mod_inv_data.shape
```

```
(349965, 22)
```

```
mod_inv_data.describe()
```

	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month	sa
count	3.499650e+05	349965.000000	349965.000000	3.499650e+05	3.499650e+05	3.499650e+05	3
mean	4.576183e+02	7.865724	42.446185	1.906193e+02	3.714684e+02	5.433477e+02	
std	2.513422e+04	7.077886	1059.243965	5.147186e+03	1.022631e+04	1.507274e+04	
min	-1.349100e+04	0.000000	0.000000	0.000000e+00	0.000000e+00	0.000000e+00	
25%	4.000000e+00	4.000000	0.000000	0.000000e+00	0.000000e+00	0.000000e+00	
50%	1.400000e+01	8.000000	0.000000	0.000000e+00	0.000000e+00	0.000000e+00	
75%	7.900000e+01	9.000000	0.000000	5.000000e+00	1.600000e+01	2.600000e+01	
max	1.233440e+07	52.000000	288960.000000	1.218328e+06	2.446072e+06	3.760840e+06	7

```
# Get the value counts for the 'went_on_backorder' column
number_of_values = mod_inv_data['went_on_backorder'].value_counts()
```

```
# Print the results
print(number_of_values)
```

```
went_on_backorder
No      346496
Yes      3469
Name: count, dtype: int64
```

There is a severe imbalance between No and Yes Values which is not ideal for a binary classification based model. Therefore, I will sample only some of the 'No' values in order to achieve a 60-40 distribution

```
# Separate the "yes" and "no" values
yes_values = mod_inv_data[mod_inv_data['went_on_backorder'] == 'Yes']
no_values = mod_inv_data[mod_inv_data['went_on_backorder'] == 'No']

# Randomly sample the "no" values to get 11,305 entries
no_values_sampled = no_values.sample(n=3000, random_state= 1)

# Randomly sample the "yes" values to get 11,305 entries
yes_values_sampled = yes_values.sample(n=3000, random_state= 1)

# Concatenate the "yes" values with the sampled "no" values
modified_data = pd.concat([yes_values_sampled, no_values_sampled])

# Optionally shuffle the resulting DataFrame
modified_data = modified_data.sample(frac=1, random_state= 1).reset_index(drop=True)

eq_data = modified_data['went_on_backorder'].value_counts()
```

```
# Check the new distribution
print(modified_data)
```

```

national_inv lead_time in_transit_qty forecast_3_month \
0 -2.0 8.0 0.0 38.0
1 1.0 8.0 0.0 10.0
2 0.0 2.0 0.0 5.0
3 5.0 2.0 0.0 0.0
4 685.0 8.0 0.0 0.0
...
5995 -1.0 8.0 5.0 70.0
5996 8.0 8.0 0.0 0.0
5997 568.0 12.0 164.0 564.0
5998 8.0 8.0 0.0 0.0
5999 220.0 12.0 0.0 0.0

forecast_6_month forecast_9_month sales_1_month sales_3_month \
0 56.0 80.0 8.0 22.0
1 10.0 10.0 3.0 8.0
2 5.0 5.0 0.0 0.0
3 0.0 0.0 0.0 0.0
4 0.0 0.0 0.0 0.0
...
5995 91.0 126.0 6.0 24.0
5996 0.0 0.0 0.0 0.0
5997 993.0 1460.0 264.0 754.0
5998 3.0 6.0 1.0 5.0
5999 0.0 0.0 0.0 2.0

sales_6_month sales_9_month ... pieces_past_due perf_6_month_avg \
0 36.0 42.0 ... 0.0 0.74
1 9.0 9.0 ... 0.0 1.00
2 0.0 0.0 ... 0.0 0.00
3 0.0 0.0 ... 0.0 0.55
4 0.0 0.0 ... 0.0 1.00
...
5995 51.0 88.0 ... 0.0 0.00
5996 0.0 1.0 ... 0.0 -99.00
5997 1558.0 2479.0 ... 0.0 0.89
5998 9.0 11.0 ... 0.0 0.99
5999 6.0 19.0 ... 0.0 0.05

perf_12_month_avg local_bo_qty deck_risk oe_constraint ppap_risk \
0 0.76 2.0 No No No
1 0.94 0.0 No No No
2 0.00 0.0 Yes No No
3 0.77 0.0 No No No
4 1.00 0.0 No No No
...
5995 0.27 1.0 No No No
5996 -99.00 0.0 No No No
5997 0.71 0.0 No No No
5998 0.97 0.0 No No No
5999 0.06 0.0 No No No

stop_auto_buy rev_stop went_on_backorder
0 Yes No Yes
1 Yes No Yes
2 Yes No Yes
3 Yes No No
4 Yes No No

```

```
# List of columns to replace "Yes" and "No" with 1 and 0
columns_to_replace = ['deck_risk', 'oe_constraint', 'ppap_risk', 'stop_auto_buy', 'rev_stop', 'potential_iss
```

```
# Create a copy of the original DataFrame
super_mod_file = modified_data.copy()
```

```
# Replace "Yes" with 1 and "No" with 0 in the specified columns
super_mod_file[columns_to_replace] = super_mod_file[columns_to_replace].replace({'Yes': 1, 'No': 0})
```

```

<ipython-input-55-7ebc93aacb91>:8: FutureWarning: Downcasting behavior in `replace` is deprecated and wi
super_mod_file[columns_to_replace] = super_mod_file[columns_to_replace].replace({'Yes': 1, 'No': 0})

```

```
super_mod_file.head()
```



```
print(super_mod_file.head()) # Display the first few rows
print(super_mod_file.dtypes) # Display the data types of each column
```



```
0      -2.0      8.0      0.0      38.0
1       1.0      8.0      0.0     10.0
2       0.0      2.0      0.0      5.0
3       5.0      2.0      0.0      0.0
4     685.0      8.0      0.0      0.0
```

```
      forecast_6_month  forecast_9_month  sales_1_month  sales_3_month  \
0                56.0             80.0             8.0             22.0
1                10.0             10.0             3.0             8.0
2                 5.0              5.0             0.0             0.0
3                 0.0              0.0             0.0             0.0
4                 0.0              0.0             0.0             0.0
```

```
      sales_6_month  sales_9_month  ...  pieces_past_due  perf_6_month_avg  \
0                36.0             42.0  ...              0.0             0.74
1                 9.0              9.0  ...              0.0             1.00
2                 0.0              0.0  ...              0.0             0.00
3                 0.0              0.0  ...              0.0             0.55
4                 0.0              0.0  ...              0.0             1.00
```

```
      perf_12_month_avg  local_bo_qty  deck_risk  oe_constraint  ppap_risk  \
0                 0.76             2.0         0              0          0
1                 0.94             0.0         0              0          0
2                 0.00             0.0         1              0          0
3                 0.77             0.0         0              0          0
4                 1.00             0.0         0              0          0
```

```
      stop_auto_buy  rev_stop  went_on_backorder
0                 1         0              Yes
1                 1         0              Yes
2                 1         0              Yes
3                 1         0              No
4                 1         0              No
```

```
[5 rows x 22 columns]
```

```
national_inv      float64
lead_time         float64
in_transit_qty    float64
forecast_3_month  float64
forecast_6_month  float64
forecast_9_month  float64
sales_1_month     float64
sales_3_month     float64
sales_6_month     float64
sales_9_month     float64
min_bank         float64
potential_issue    int64
pieces_past_due   float64
perf_6_month_avg  float64
perf_12_month_avg float64
local_bo_qty      float64
deck_risk         int64
oe_constraint     int64
ppap_risk        int64
stop_auto_buy     int64
rev_stop         int64
went_on_backorder object
dtype: object
```

```
super_mod_file.groupby('went_on_backorder').mean()
```

```
super_mod_file.groupby('went_on_backorder').mean()
```



	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month
went_on_backorder						

No	359.114000	7.664000	26.550333	140.307000	281.522667	419.114000
Yes	10.747667	6.372333	4.258333	144.151333	218.062333	297.151333

2 rows × 7 columns

```
import pandas as pd
```

```
# Specify the columns to check for NaN values
```

```
columns_to_check = [  
    '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'  
]
```

```
# Remove rows with NaN values in the specified columns
```

```
super_mod_file_cleaned = super_mod_file.dropna(subset=columns_to_check)
```

```
X = super_mod_file_cleaned.drop(columns='went_on_backorder')
```

```
Y = super_mod_file_cleaned['went_on_backorder']
```

```
X = X.dropna()
```

```
Y = Y[X.index]
```

Double-click (or enter) to edit

```
print(X)
```

```
print(Y)
```



5995	91.0	126.0	6.0	24.0
5996	0.0	0.0	0.0	0.0
5997	993.0	1460.0	264.0	754.0
5998	3.0	6.0	1.0	5.0
5999	0.0	0.0	0.0	2.0

	sales_6_month	sales_9_month	...	potential_issue	pieces_past_due	\
0	36.0	42.0	...	0	0.0	
1	9.0	9.0	...	0	0.0	
2	0.0	0.0	...	0	0.0	
3	0.0	0.0	...	0	0.0	
4	0.0	0.0	...	0	0.0	
...	
5995	51.0	88.0	...	0	0.0	

1	0	0	1	0
2	0	0	1	0
3	0	0	1	0
4	0	0	1	0
...
5995	0	0	1	0
5996	0	0	1	0
5997	0	0	1	0
5998	0	0	1	0
5999	0	0	1	0

[6000 rows x 21 columns]

0 Yes
1 Yes
2 Yes
3 No
4 No

...
5995 Yes
5996 No
5997 No
5998 Yes
5999 No

Name: went_on_backorder, Length: 6000, dtype: object

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.1, stratify=Y, random_state=1)

print(X_train)

print(Y_train)

	national_inv	lead_time	in_transit_qty	forecast_3_month	\
3960	13.0	12.0	0.0	2.0	
4780	6.0	2.0	0.0	40.0	
157	24.0	2.0	0.0	0.0	
315	3.0	8.0	0.0	4.0	
3336	4565.0	12.0	0.0	0.0	
...	
2726	-152.0	12.0	0.0	626.0	
5797	0.0	2.0	0.0	0.0	
2384	374.0	12.0	0.0	320.0	
5831	47.0	12.0	0.0	623.0	
436	7.0	8.0	0.0	0.0	

	forecast_6_month	forecast_9_month	sales_1_month	sales_3_month	\
3960	4.0	6.0	4.0	7.0	
4780	40.0	40.0	0.0	0.0	
157	0.0	0.0	0.0	0.0	
315	9.0	14.0	1.0	4.0	
3336	0.0	0.0	5.0	65.0	
...	
2726	791.0	901.0	153.0	299.0	
5797	0.0	0.0	1.0	3.0	
2384	960.0	960.0	94.0	339.0	
5831	1063.0	1503.0	112.0	387.0	
436	8.0	12.0	1.0	5.0	

	sales_6_month	sales_9_month	...	potential_issue	pieces_past_due	\
3960	17.0	24.0	...	0	0.0	
4780	0.0	0.0	...	0	0.0	
157	0.0	0.0	...	0	0.0	
315	10.0	14.0	...	0	0.0	
3336	99.0	107.0	...	0	0.0	
...	
2726	513.0	712.0	...	0	0.0	
5797	5.0	6.0	...	0	0.0	
2384	728.0	1153.0	...	0	0.0	
5831	787.0	1205.0	...	0	0.0	
436	10.0	16.0	...	0	0.0	

	perf_6_month_avg	perf_12_month_avg	local_bo_qty	deck_risk	\
3960	0.76	0.73	0.0	0	
4780	0.98	0.97	0.0	1	
157	0.80	0.60	0.0	1	
315	0.78	0.74	0.0	0	
3336	0.96	0.86	0.0	0	
...	
2726	0.00	0.02	69.0	0	
5797	0.99	0.99	0.0	0	

2384	0.88	0.81	0.0	0
5831	0.88	0.86	4.0	0
436	0.89	0.78	0.0	0

	oe_constraint	ppap_risk	stop_auto_buy	rev_stop
3960	0	0	1	0
4780	0	0	1	0
157	0	0	1	0
315	0	0	1	0
3336	0	0	1	0

```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
model = LogisticRegression(solver='lbfgs', max_iter=1000)
```

```
model.fit(X_train_scaled, Y_train)
```

```
LogisticRegression
LogisticRegression(max_iter=1000)
```

Accuracy on Training Data

```
X_train_prediction = model.predict(X_train)
training_data_accuracy = accuracy_score(X_train_prediction, Y_train)
print('Accuracy on training data : ', training_data_accuracy)
```

```
Accuracy on training data : 0.7409259259259259
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2732: UserWarning: X has feature names with non-string labels (e.g. int64).
warnings.warn(
```

```
X_test_prediction = model.predict(X_test)
test_data_accuracy = accuracy_score(X_test_prediction, Y_test)
print('Accuracy on test data : ', test_data_accuracy)
```

```
Accuracy on test data : 0.7366666666666667
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2732: UserWarning: X has feature names with non-string labels (e.g. int64).
warnings.warn(
```

Test on Random Data from the Dataset

```
# Original input data
input_data = [-1, 0, 0, 26, 36, 51, 8, 18, 42, 52, 1, 'No', 0, 0, 0, 1, 'No', 'No', 'No', 'No', 'No']
# Replace 'No' with 0 and 'Yes' with 1
mod_input_data = [0 if x == 'No' else 1 if x == 'Yes' else x for x in input_data]

mod_input_data_as_numpy_array = np.asarray(mod_input_data)

reshaped_mod_input_data = mod_input_data_as_numpy_array.reshape(1, -1)

predict = model.predict(reshaped_mod_input_data)

print(predict)

if predict == 'Yes':
    print('There will be a shortage')
else:
    print('There will not be a shortage')
```

```
['Yes']
There will be a shortage
```


Start coding or generate with AI.