Predicting Backorders using Machine Learning

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a. Abstract

Backorder is a common supply chain problem which can cause many bad effects. Multiple suppliers and limited time that customer are willing to wait make this problem even more difficult to solve. In this paper, two machine learning models are used to build a predictive model for monitoring backorders. They are decision tree and random forest. Sampling and dummy variables are employed in these two models.

b. Introduction

1. Question: Can you predict product backorders?
   In other words, can you predict backorder risk for products based on historical data?
2. Data Source:

- Can you predict product backorders?

https://www.kaggle.com/tiredgeek/predict-bo-trial
This dataset includes training data and test data.
Training dataset contains the descriptive data for the 8 weeks prior to the week we are trying to predict. These data was recorded weekly.

- Columns:
  1) Predictor variables:

sku - Random ID for the product
national_inv - Current inventory level for the part
lead_time - Transit time for product (if available)
in_transit_qty - Amount of product in transit from source
forecast_3_month - Forecast sales for the next 3 months
forecast_6_month - Forecast sales for the next 6 months
forecast_9_month - Forecast sales for the next 9 months
sales_1_month - Sales quantity for the prior 1 month time period
sales_3_month - Sales quantity for the prior 3 month time period
sales_6_month - Sales quantity for the prior 6 month time period
sales_9_month - Sales quantity for the prior 9 month time period
min_bank - Minimum recommend amount to stock
potential_issue - Source issue for part identified
pieces_past_due - Parts overdue from source
perf_6_month_avg - Source performance for prior 6 month period
perf_12_month_avg - Source performance for prior 12 month period
local_bo_qty - Amount of stock orders overdue
deck_risk - Part risk flag
oe_constraint - Part risk flag

ppap_risk - Part risk flag

stop_auto_buy - Part risk flag

rev_stop - Part risk flag

2) Target variable:

went_on_backorder - Product actually went on backorder

3. Backgrounds:

1) What is a backorder?

Backorders are products that are temporarily out of stock, but will ship to customers when it is available.

In other word, a backorder generally indicates that customer demand for a product or service exceeds a company's capacity to supply it.

2) Backorder is a big problem.

- Huge number of sales orders and different suppliers where the out of stock items from increase complexity to the workload.
- Customers may not have the patience to wait for items. It may lead to lost sales and low customer satisfaction.

3) Way to handle it:

In order to monitor backorder, we can use machine learning to identify products at risk of backorders. Sales person can prepare for these products in advance.

Machine learning algorithm: Naive Bayes, Support vector machine, Decision tree, Random forest, K nearest neighbors

c. Code with Documentation

EDA:

1. Load and View my data

Load my data:

```
In [22]: df = pd.read_csv('C:\\Users\\LucyYang\\Juypter\\Kaggle_Training_Dataset_v2.csv')
         df.head()

E:\_LastSemester\2018Spring\DataScience\Tool\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2698: Dtype
Warning: Columns (0) have mixed types. Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)

Out[22]:
```

	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	...
0	1026827	0.0	NaN	0.0	0.0	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	0.0	0.0	...
2	1043696	2.0	NaN	0.0	0.0	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	0.0	0.0	...
4	1044048	8.0	NaN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...

5 rows × 23 columns

View basic info:

In [23]:
```
df.shape
```
Out[23]:
```
(1687861, 23)
```

In [24]:
```
df.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1687861 entries, 0 to 1687860
Data columns (total 23 columns):
sku                  1687861 non-null object
national_inv         1687860 non-null float64
lead_time            1586967 non-null float64
in_transit_qty       1687860 non-null float64
forecast_3_month     1687860 non-null float64
forecast_6_month     1687860 non-null float64
forecast_9_month     1687860 non-null float64
sales_1_month        1687860 non-null float64
sales_3_month        1687860 non-null float64
sales_6_month        1687860 non-null float64
sales_9_month        1687860 non-null float64
min_bank             1687860 non-null float64
potential_issue      1687860 non-null object
pieces_past_due      1687860 non-null float64
perf_6_month_avg     1687860 non-null float64
perf_12_month_avg    1687860 non-null float64
local_bo_qty         1687860 non-null float64
deck_risk            1687860 non-null object
oe_constraint        1687860 non-null object
ppap_risk            1687860 non-null object
stop_auto_buy        1687860 non-null object
rev_stop             1687860 non-null object
went_on_backorder    1687860 non-null object
dtypes: float64(15), object(8)
memory usage: 296.2+ MB
```

View categorical variables:

In [25]:
```
df.deck_risk.value_counts()
df.oe_constraint.value_counts()
df.ppap_risk.value_counts()
df.stop_auto_buy.value_counts()
df.rev_stop.value_counts()
df.went_on_backorder.value_counts()
df.potential_issue.value_counts()
```
Out[25]:
```
No     1686953
Yes        907
Name: potential_issue, dtype: int64
```

2. Data cleaning

Check missing value:

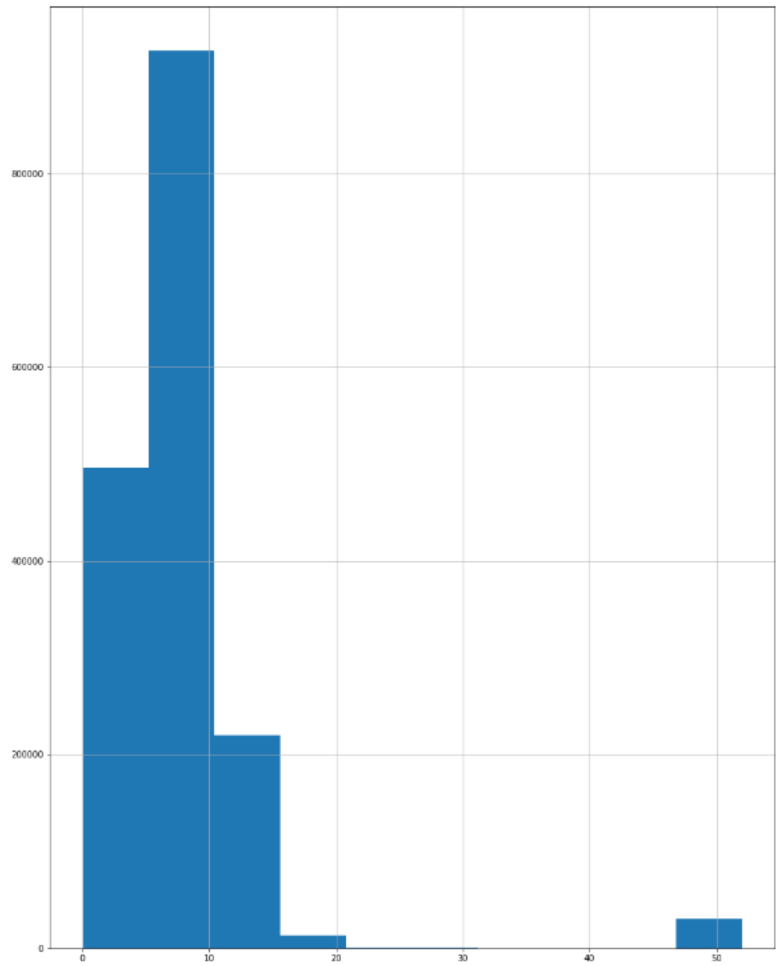
1) Deal with column 'lead_time'

a) deal with column 'lead_time'

the 'lead*time' is a skew right distribution, so we replace the missing value with the mean value*(In practice, for skewed distributions the most commonly reported typical value is the mean)

In [27]:
```
df.lead_time.isnull().sum()/df.shape[0]
```
Out[27]:
```
0.059775692296754473
```

In [28]:
```
plt.show()
df.lead_time.hist(figsize = (15, 20))
```



In [29]:
```
df.lead_time.fillna(df.lead_time.mean(), inplace = True)
```

In [30]:
```
df.lead_time.isnull().sum()
```

Out[30]: 0

2) deal with column 'perf_6_month_avg' (for there missing value is -99)

b) deal with column 'perf_6_month_avg' (for there missing value is -99)

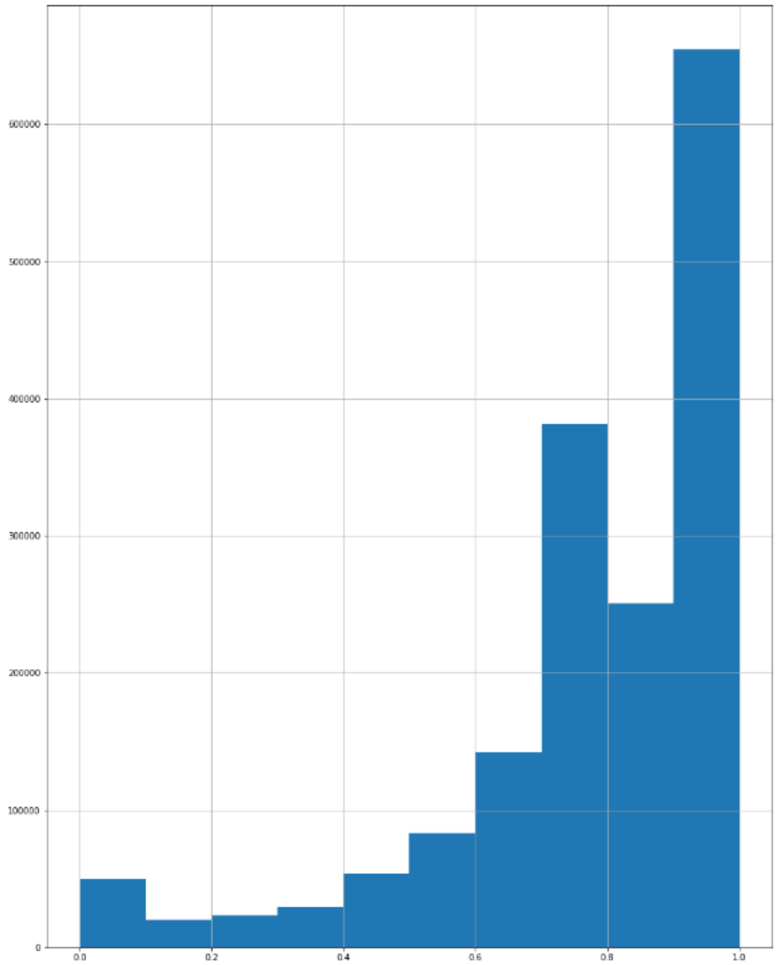
the 'perf_6_month*avg' is a skew left distribution, so we replace the missing value with the mean value*(In practice, for skewed distributions the most commonly reported typical value is the mean)

In [31]:
```
df.perf_6_month_avg.value_counts(dropna = False).values[2]/df.shape[0]
```

Out[31]: 0.07671133861813184l

In [32]:
```
df.perf_6_month_avg.replace(-99.00, np.nan, inplace = True)
```

In [33]:
```
plt.show()
df.perf_6_month_avg.hist(figsize = (15, 20))
```



In [34]:
```
df.perf_6_month_avg.fillna(df.perf_6_month_avg.mean(), inplace = True)
df.perf_6_month_avg.isnull().sum()
```

Out[34]: 0

3) deal with column 'perf_12_month_avg' (for there missing value is -99)

c) deal with column 'perf_12_month_avg' (for there missing value is -99)

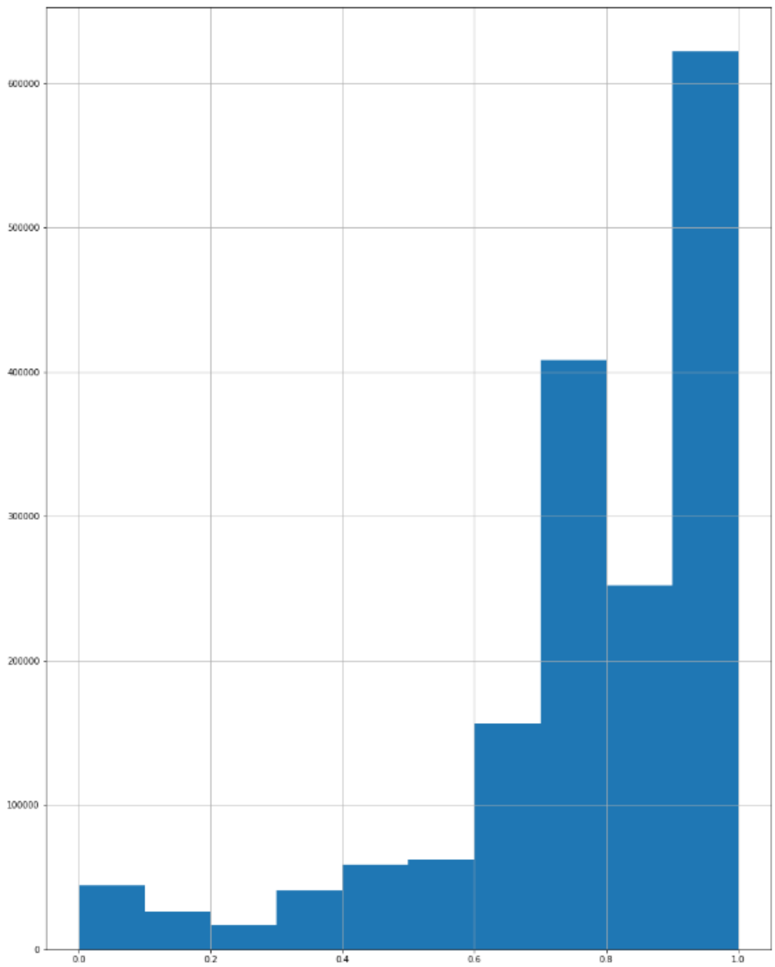
the 'perf_12_month*avg' is a skew left distribution, so we replace the missing value with the mean value*(In practice, for skewed distributions the most commonly reported typical value is the mean)

In [35]:
```
df.perf_12_month_avg.value_counts(dropna = False).values[2]/df.shape[0]
```

Out[35]: 0.069710758001256035

In [36]:
```
df.perf_12_month_avg.replace(-99.00, np.nan, inplace = True)
```

In [81]:
```
plt.show()
df.perf_12_month_avg.hist(figsize = (15, 20))
```




```
Out[81]: <matplotlib.axes._subplots.AxesSubplot at 0x2394c484828>
```

```
In [38]: df.perf_12_month_avg.fillna(df.perf_12_month_avg.mean(), inplace = True)
         df.perf_12_month_avg.isnull().sum()

Out[38]: 0
```

Check inappropriate value

check data type of each column

In [39]:
```
df.dtypes
```

Out[39]:
```
sku                  object
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      object
pieces_past_due     float64
perf_6_month_avg    float64
perf_12_month_avg   float64
local_bo_qty        float64
deck_risk            object
oe_constraint        object
ppap_risk            object
stop_auto_buy        object
rev_stop             object
went_on_backorder    object
dtype: object
```

check each column whether they have inappropraite value

In [40]:
```
df.national_inv.value_counts(dropna = False)
df.in_transit_qty.loc[df['in_transit_qty'] < 0]
df.forecast_3_month.loc[df['forecast_3_month'] < 0]
df.forecast_6_month.loc[df['forecast_6_month'] < 0]
df.forecast_9_month.loc[df['forecast_9_month'] < 0]
df.sales_1_month.loc[df['sales_1_month'] < 0]
df.sales_3_month.loc[df['sales_3_month'] < 0]
df.sales_6_month.loc[df['sales_6_month'] < 0]
df.sales_9_month.loc[df['sales_9_month'] < 0]
df.min_bank.loc[df['min_bank'] < 0]
df.pieces_past_due.loc[df['pieces_past_due'] < 0]
df.local_bo_qty.loc[df['local_bo_qty'] < 0]
```

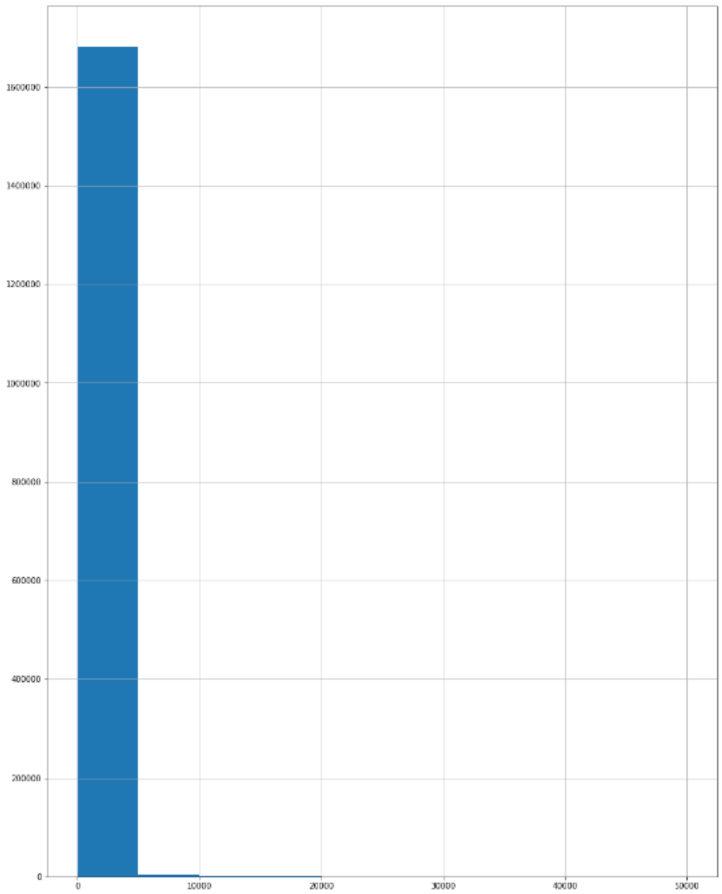
Out[40]:
```
Series([], Name: local_bo_qty, dtype: float64)
```

3. Data distribution

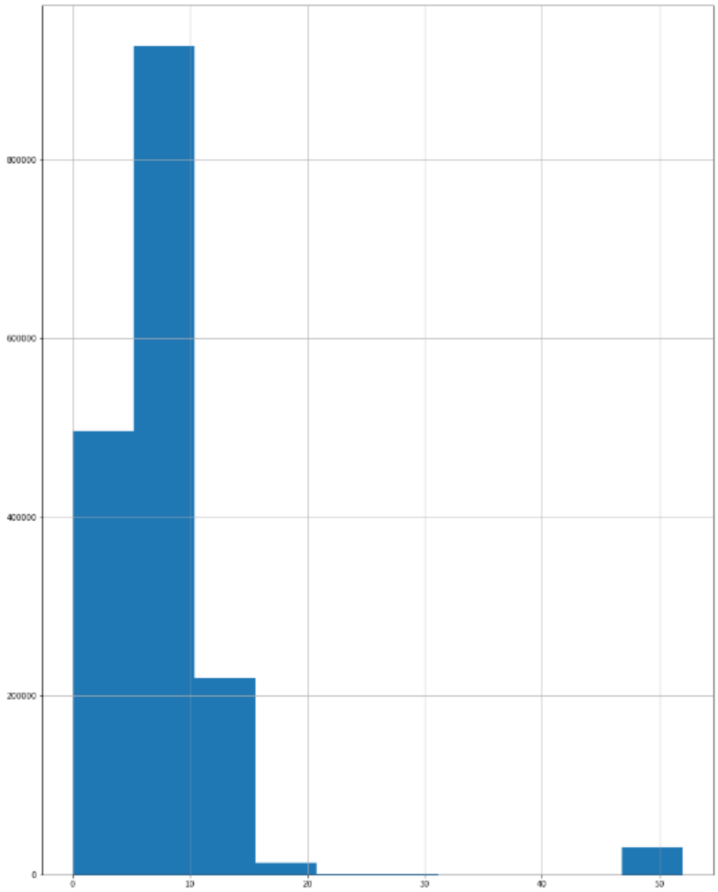
1) Each column distribution

forecast_3_month is a skew right distribution. Most values are gathered in [0, 20000] (the mean is greater than the median.)

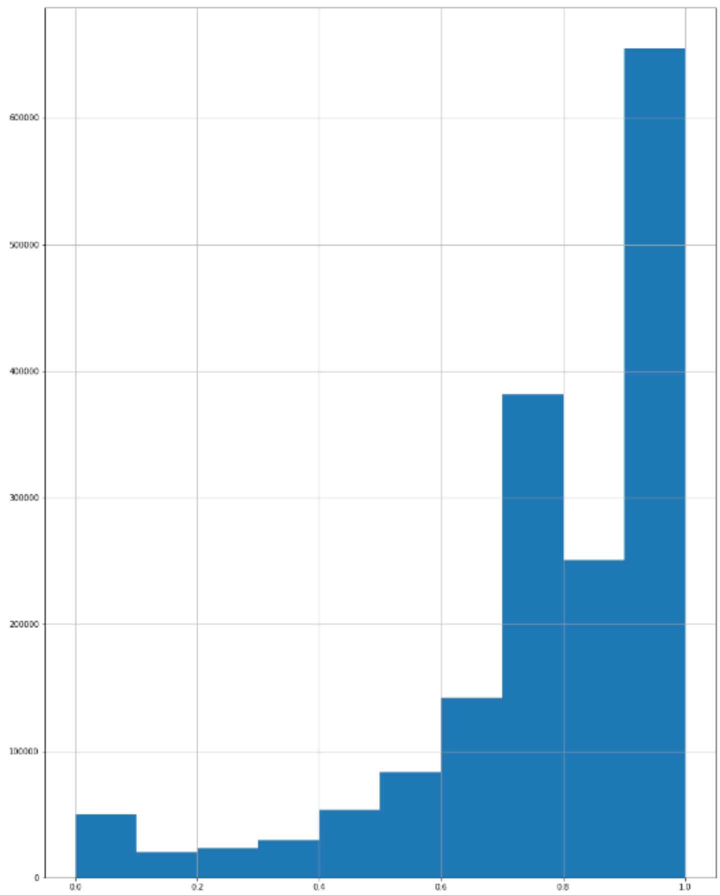
In [85]:
```
plt.show()
df.forecast_3_month.hist(figsize = (15, 20), range = [0, 50000])
```



lead_time is a skew right distribution. Most values are gathered in [0, 60] (the mean is greater than the median.)



perf_6_month_avg is a skew left distribution. The range is [0, 1] (the mean is less than the median.)



2) Summary statistics

Question 3.2: What are the summary statistics?

Answer as follow:

In [50]:
```
df.describe()
```

Out[50]:

	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	sale:
count	1.687860e+06	1.687860e+06	1.687860e+06	1.687860e+06	1.687860e+06	1.687860e+06	1.687860e+06	1.687860e+06	1.687860e+06	1.6
mean	4.961118e+02	7.872267e+00	4.405202e+01	1.781193e+02	3.449867e+02	5.063644e+02	5.592607e+01	1.750259e+02	3.417288e+02	5.2
std	2.961523e+04	6.841885e+00	1.342742e+03	5.026553e+03	9.795152e+03	1.437892e+04	1.928196e+03	5.192378e+03	9.613167e+03	1.4
min	-2.725600e+04	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.0
25%	4.000000e+00	4.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.0
50%	1.500000e+01	8.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00	2.000000e+00	4.0
75%	8.000000e+01	8.000000e+00	0.000000e+00	4.000000e+00	1.200000e+01	2.000000e+01	4.000000e+00	1.500000e+01	3.100000e+01	4.7
max	1.233440e+07	5.200000e+01	4.894080e+05	1.427612e+06	2.461360e+06	3.777304e+06	7.417740e+05	1.105478e+06	2.146625e+06	3.2

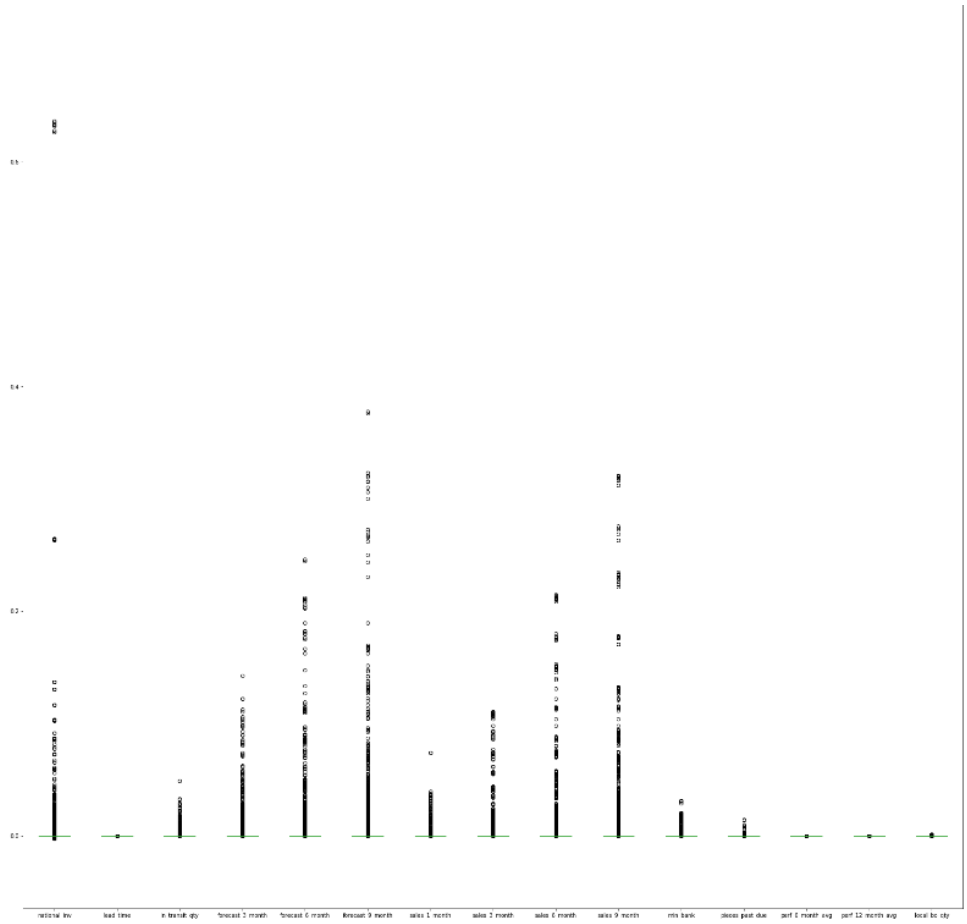
3) Outliers

Question 3.3: Are there anomalies/outliers?

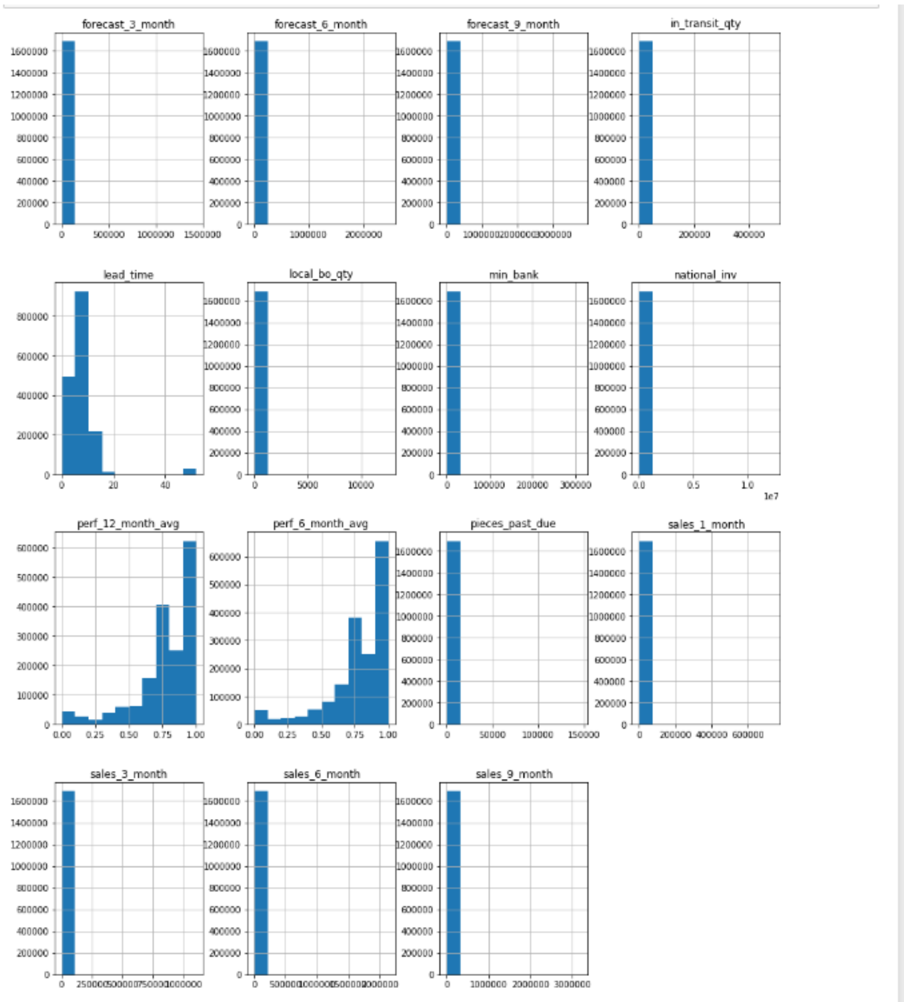
Answer as follow:

1. national_inv has most number of outliers and they are very discrete.
2. (forecast_3_month, forecast_6_month, forecast_9_month), (sales_3_month, sales_6_month, sales_9_month) are two group which outliers are distributed more and more discrete.
3. in_transit_qty, min_bank, pieces_past_due have a few number of outliers
4. leadtime, perf_6_month_avg, perf_12_month_avg, local_bo_qty are gathered.

In [52]:
```
plt.show()
df.plot(kind='box', figsize=(30, 50))
```



4) Plot each column



Summary

- Most columns have a very clustered and representative range.
- Lead time, perf_6_month_avg, perf_12_month_avg cannot find a typical value to represent these columns

5) Columns Correlating

Are any of the columns correlated?

These 3 group are correlated columns:

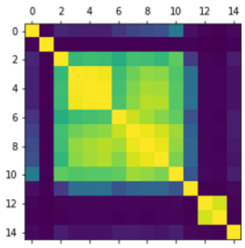
1. forecast_3_month, forecast_6_month, forecast_9_month
2. sales_3_month, sales_6_month, sales_9_month
3. perf_6_month_avg, perf_12_month_avg

In [55]:
```
df.corr()
```

Out[55]:

	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month	sales_1_month	sales_3_month	sales_6_mon
national_inv	1.000000	0.003318	0.098238	0.078199	0.079744	0.078948	0.147449	0.192605	0.22506
lead_time	0.003318	1.000000	-0.006844	-0.008008	-0.008511	-0.008736	-0.005609	-0.006758	-0.00709
in_transit_qty	0.098238	-0.006844	1.000000	0.662648	0.687768	0.679152	0.619270	0.698417	0.68990
forecast_3_month	0.078199	-0.008008	0.662648	1.000000	0.990490	0.977337	0.684494	0.781178	0.83558
forecast_6_month	0.079744	-0.008511	0.687768	0.990490	1.000000	0.994945	0.701770	0.808755	0.86809
forecast_9_month	0.078948	-0.008736	0.679152	0.977337	0.994945	1.000000	0.716367	0.829911	0.89188
sales_1_month	0.147449	-0.005609	0.619270	0.684494	0.701770	0.716367	1.000000	0.918548	0.86747
sales_3_month	0.192605	-0.006758	0.698417	0.781178	0.808755	0.829911	0.918548	1.000000	0.97559
sales_6_month	0.225067	-0.007097	0.689908	0.835585	0.868099	0.891884	0.867479	0.975594	1.00000
sales_9_month	0.239613	-0.007239	0.659372	0.825539	0.858253	0.881894	0.815959	0.929491	0.97183
min_bank	0.399969	-0.007088	0.749974	0.725042	0.738553	0.735891	0.756137	0.856017	0.8371
pieces_past_due	0.030677	-0.001500	0.167460	0.361214	0.363147	0.366001	0.249526	0.304565	0.32355
perf_6_month_avg	0.002869	-0.009766	0.004570	0.006739	0.007503	0.007786	0.006323	0.006938	0.00710
perf_12_month_avg	0.002037	-0.007482	0.001611	0.003357	0.003717	0.003768	0.002058	0.002091	0.0019
local_bo_qty	0.014887	-0.001255	0.066612	0.039419	0.039724	0.039732	0.066188	0.071030	0.0577

In [131]:
```
plt.show()
plt.matshow(df.corr())
```



Out[131]: <matplotlib.image.AxesImage at 0x2398469b780>

Analyze data:

1. Data transform

Converting categorical data into number:

```
In [57]: df_with_dummies = pd.get_dummies(df, columns = ['potential_issue', 'deck_risk', 'oe_constraint', 'ppap_risk', 'stop_auto
         df_with_dummies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1687860 entries, 0 to 1687859
Data columns (total 29 columns):
sku                    1687860 non-null object
national_inv           1687860 non-null float64
lead_time              1687860 non-null float64
in_transit_qty         1687860 non-null float64
forecast_3_month       1687860 non-null float64
forecast_6_month       1687860 non-null float64
forecast_9_month       1687860 non-null float64
sales_1_month          1687860 non-null float64
sales_3_month          1687860 non-null float64
sales_6_month          1687860 non-null float64
sales_9_month          1687860 non-null float64
min_bank               1687860 non-null float64
pieces_past_due        1687860 non-null float64
perf_6_month_avg       1687860 non-null float64
perf_12_month_avg      1687860 non-null float64
local_bo_qty           1687860 non-null float64
went_on_backorder      1687860 non-null object
potential_issue_No     1687860 non-null uint8
potential_issue_Yes    1687860 non-null uint8
deck_risk_No           1687860 non-null uint8
deck_risk_Yes          1687860 non-null uint8
oe_constraint_No       1687860 non-null uint8
oe_constraint_Yes      1687860 non-null uint8
ppap_risk_No           1687860 non-null uint8
ppap_risk_Yes          1687860 non-null uint8
stop_auto_buy_No       1687860 non-null uint8
stop_auto_buy_Yes      1687860 non-null uint8
rev_stop_No            1687860 non-null uint8
rev_stop_Yes           1687860 non-null uint8
dtypes: float64(15), object(2), uint8(12)
memory usage: 251.1+ MB
```

Transform data for model:

```
In [58]: df_with_dummies.shape
Out[58]: (1687860, 29)

In [59]: x_transform = df_with_dummies.drop(['sku', 'went_on_backorder'], axis=1)

In [60]: x_transform.head()
Out[60]:
```

	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_montl
0	0.0	7.872267	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
1	2.0	9.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
2	2.0	7.872267	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
3	7.0	8.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
4	8.0	7.872267	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.(

5 rows × 27 columns

```
In [61]: lb = pre.LabelBinarizer()
         y_transform = lb.fit_transform(df_with_dummies.went_on_backorder)
```

Sampling into train data and test data

```
In [62]: # split dataset into inputs and outputs
         values = df_with_dummies.values
         x = x_transform
         y = y_transform.ravel()
         x = x.astype('int')
         y = y.astype('int')
         x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=6)
```

2. Default decision tree

1) decision tree

```
In [63]: clf_tree = tree.DecisionTreeClassifier()
         clf_tree.fit(x_train, y_train)

Out[63]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
                     max_features=None, max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, presort=False, random_state=None,
                     splitter='best')
```

```
In [64]: y_pred_tree = clf_tree.predict(x_test)
         tree_result = accuracy_score(y_test, y_pred_tree.round())
```

show result

```
In [65]: tree_result

Out[65]: 0.99144775040583932
```

```
show confusion matrix
```

```
In [68]: confusion_matrix(y_test, y_pred_tree.round())

Out[68]: array([[333896,   1366],
                [  1521,    789]], dtype=int64)
```

3. Decision tree(Max Depth = 3)

Build a new model to avoid overfitting

```
In [69]: clf_tree_new = tree.DecisionTreeClassifier(max_depth = 3)
         clf_tree_new.fit(x_train, y_train)
         y_pred_tree_new = clf_tree_new.predict(x_test)
         tree_result_new = accuracy_score(y_test, y_pred_tree_new.round())
```

```
In [70]: tree_result_new

Out[70]: 0.99315701539227186
```

show confusion matrix

```
In [71]: confusion_matrix(y_test, y_pred_tree_new.round())

Out[71]: array([[335262,      0],
                [  2310,      0]], dtype=int64)
```

Draw the decision tree:

Draw the dicision tree

```
In [38]: dot_data = tree.export_graphviz(clf_tree_new, out_file=None)
         graph = graphviz.Source(dot_data)
         graph.render("backorder")
```

```
In [ ]: dot_data = tree.export_graphviz(clf_tree_new, out_file=None,
                                 feature_names=list(x_transform),
                                 class_names="IfBackorder",
                                 filled=True, rounded=True,
                                 special_characters=True)
        graph = graphviz.Source(dot_data)
        graph
```

4. Random forest

2) Random Forest

In [72]:
```
clf = RandomForestClassifier(n_jobs=2, random_state=0)
clf.fit(x_train, y_train)
```

Out[72]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=2,
            oob_score=False, random_state=0, verbose=0, warm_start=False)
```

show result

In [74]:
```
y_pred_clf = clf.predict(x_test)
accuracy_score(y_test, y_pred_clf.round())
```

Out[74]:
```
0.99426196485490503
```

show confusion matrix

In [75]:
```
confusion_matrix(y_test, y_pred_clf.round())
```

Out[75]:
```
array([[335118,    144],
       [  1793,    517]], dtype=int64)
```

d. Results

- ### Summary of EDA:

1. Overall:

1) This dataset is a very big dataset which have 1687861 rows and 23 columns. It means that I need build a large model for this dataset.

2) This dataset has many categorical variables which I need to convert it to numerical variables.

3) The target variable is categorical. So I should choose classification mode to analyse it.

2. Model recommendation:

1) decision tree

2) random forest

3. Data cleaning:

1) This dataset has some missing value: lead_time has NaN; perf_6_month_avg and perf_6_month_avg have -99 as missing value. I use mean to replace the missing value because they are skewed distribution which use mean as typical value.

2) This dataset doesn't have inapproprate values

4. Data distribution:

Most columns are skewd distribution but have a very clusterd and representative range.

1) national_inv has te most number of outliers and are most discrete.

2) (forecast_3_month, forecast_6_month, forecast_9_month), (sales_3_month, sales_6_month, sales_9_month) are two group which are more and more discrete.

3) in_transit_qty, min_bank, pieces_past_due have a few number of outliers and not very discrete.

4) leadtime, perf_6_month_avg, perf_12_month_avg, local_bo_qty are gathered.

5) Lead time, perf_6_month_avg, perf_12_month_avg cannot find a typical value to represent these columns

5. Column correlated:

(forecast_3_month, forecast_6_month, forecast_9_month), (sales_3_month, sales_6_month sales_9_month), (perf_6_month_avg, perf_12_month_avg) are column correlated.

- ### Model results:

1. Accuracy_Score

Model	Accuracy_Score
Default Decision Tree	0.99144775040583932
Decision Tree (max_depth = 3)	0.99315701539227186
Random Forest	0.99426196485490503

2. Confusion Matrix

Default Decision Tree

333896	1366
1521	789

Decision Tree (max_depth = 3)

335262	0
2310	0

Random Forest

335118	144
1793	517

e. Discussion

- To build a predictive model for this classification problem, I try to use SVM model firstly. Support vector machine is a supervised learning model used for classification. However, it runs too slow to build a model with 1687861 records.
- Next model I used is decision tree. Decision tree is a decision support tool that uses a tree-like graph or model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. I used default parameters this time and got a good result. The accuracy score of this prediction is 0.991.
- To avoid overfitting, I set max_depth = 3 to build a new decision tree. This time I got a better accuracy score: 0.993.
- In order to get a better predictive model, I tried random forest at the end. Random forest is an ensemble learning method for classification, regression and other tasks, that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes. I got the best result among these 3 modes: 0.994.
- **Conclusion**
  1) One of the effective way to avoid overfitting is set max depth for the decision tree model.
  2) Random forest is an optimized version of decision tree which can predict the result more accuracy than decision tree.
  3) SVM is not very suitable for a very large dataset.

f. References

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