1. Problem Statement and Data Description

Problem Statement: Prevent overstocking and understocking of Items by forecasting demand of items for the next week, based on historical data.

Data Description:

Train Data-

- **WEEK_END_DATE** - week ending date
- **STORE_NUM** - store number
- **UPC** - (Universal Product Code) product specific identifier
- **BASE_PRICE** - base price of item
- **DISPLAY** - product was a part of in-store promotional display
- **FEATURE** - product was in in-store circular
- **UNITS** - units sold (target)

Product Data-

- **UPC** - (Universal Product Code) product specific identifier
- **DESCRIPTION** - product description
- **MANUFACTURER** - product manufacturer
- **CATEGORY** - category of product
- **SUB_CATEGORY** - sub-category of product
- **PRODUCT_SIZE** - package size or quantity of product

Store Data-

- **STORE_ID** - store number
- **STORE_NAME** - Name of store
- **ADDRESS_CITY_NAME** - city
- **ADDRESS_STATE_PROV_CODE** - state
- **MSA_CODE** - (Metropolitan Statistical Area) Based on geographic region and population density
- **SEG_VALUE_NAME** - Store Segment Name
- **PARKING_SPACE_QTY** - number of parking spaces in the store parking lot
- **SALES_AREA_SIZE_NUM** - square footage of store
- **AVG_WEEKLY_BASKETS** - average weekly baskets sold in the store

2. Loading Required Libraries and Datasets

In [2]:
```
import seaborn as sns
import pandas as pd
import numpy as np
import random

sns.set_context('notebook',font_scale=1.5)

import matplotlib.pyplot as plt


import warnings
warnings.filterwarnings("ignore")
```

We are provided with three tables containing the required information:

- **product_data**: Consists of details about the product
- **store_data**: Consists of details of various stores associated with the retailer
- **train**: Contains transaction data of products

In [3]:
```
# reading the data files
train = pd.read_csv('train.csv')
product_data = pd.read_csv('product_data.csv')
store_data = pd.read_csv('store_data.csv')
```

In [4]:
```
# checking the size of the dataframes
train.shape, product_data.shape, store_data.shape
```

Out[4]:
```
((232287, 8), (30, 6), (76, 9))
```

3. Understanding and Validating Data

Train Data

In [5]:
```
# printing first 5 rows of the train file
train.head()
```

Out[5]:

	WEEK_END_DATE	STORE_NUM	UPC	PRICE	BASE_PRICE	FEATURE	DISPLAY
0	14-Jan-09	367	1111009477	1.39	1.57	0	0
1	14-Jan-09	367	1111009497	1.39	1.39	0	0
2	14-Jan-09	367	1111085319	1.88	1.88	0	0
3	14-Jan-09	367	1111085345	1.88	1.88	0	0
4	14-Jan-09	367	1111085350	1.98	1.98	0	0

In [6]:
```
# checking datatypes of columns in train file
train.dtypes
```

Out[6]:
```
WEEK_END_DATE     object
STORE_NUM          int64
UPC                int64
PRICE            float64
BASE_PRICE       float64
FEATURE            int64
DISPLAY            int64
UNITS              int64
dtype: object
```

- WEEK_END_DATE has the data type object, but its a datetime variable
- The store number and product codes are read as int, but these are categorical variables.

Datetime variable

- The data is captured for what duration?
- What are the start and end dates?
- Is there any missing data points?

Numerical Variables

- Check the distribution of numerical variables
- Are there any extreme values?
- Are there any missing values in the variables?

Categorical Variables

- Check the unique values for categorical variables
- Are there any missing values in the variables?
- Is there any variable with high cardinality/ sparsity?

WEEK_END_DATE

In [7]:
```
# convert into the date time format
train['WEEK_END_DATE'] = pd.to_datetime(train['WEEK_END_DATE'])
```

In [8]:
```
train['WEEK_END_DATE'].isnull().sum()
```

Out[8]:
```
0
```

In [9]:
```
train['WEEK_END_DATE'].min(), train['WEEK_END_DATE'].max()
```

Out[9]:
```
(Timestamp('2009-01-14 00:00:00'), Timestamp('2011-09-28 00:00:00'
))
```

- The data collected is from January 2009 to September 2011.

Are any dates missing from this period?

In [10]:
```
(train['WEEK_END_DATE'].max() - train['WEEK_END_DATE'].min())/7
```

Out[10]:
```
Timedelta('141 days 00:00:00')
```

In [11]:
```
train['WEEK_END_DATE'].nunique()
```

Out[11]:
```
142
```

- The training data is for 142 weeks, based on the number of unique *weekend dates* in the train file.
- No dates are missing from this period.

Are all dates at a gap of a week?

In [12]:
```
train['WEEK_END_DATE'].dt.day_name().value_counts()
```

Out[12]:
```
Wednesday    232287
Name: WEEK_END_DATE, dtype: int64
```

In [13]:
```
train['WEEK_END_DATE'].dt.day_name().value_counts()
```

Out[13]:
```
Wednesday    232287
Name: WEEK_END_DATE, dtype: int64
```

STORE_NUM and UPC

In [14]:
```
train[['STORE_NUM', 'UPC']].isnull().sum()
```

Out[14]:
```
STORE_NUM    0
UPC          0
dtype: int64
```

In [15]:
```
train['STORE_NUM'].nunique()
```

Out[15]:
```
76
```

In [16]:
```
(train['STORE_NUM'].value_counts()).sort_values()
```

Out[16]:
```
8035     1676
23055    1823
2523     1977
11967    2104
15755    2253
         ...
2277     3824
21237    3950
9825     3955
24991    3967
2513     4098
Name: STORE_NUM, Length: 76, dtype: int64
```

- We have 76 unique stores.
- Every store has minimum of 1676 transactions.

Does each store hold atleast one entry per week?

We have 76 unique stores and 142 weeks of data for the sales. If each store is selling occupies atleast one row in the data, the minimum number of unique rows should be 142*76

In [17]:
```
142*76
```

Out[17]:
```
10792
```

In [18]:
```
train[['WEEK_END_DATE','STORE_NUM']].drop_duplicates().shape
```

Out[18]:
```
(10792, 2)
```

- Implies that each store is atleast selling 1 product each week

In [19]:
```
train['UPC'].nunique()
```

Out[19]:
```
30
```

In [20]:
```
(train['UPC'].value_counts()).sort_values()
```

Out[20]:
```
3700044982       975
3700031613      1664
31254742835     2086
7797508004      2386
1111038080      2797
7797508006      2933
31254742735     3202
7218063052      3641
7797502248      6916
1111038078      7131
2840004770      7636
1111009507      8067
1111087396      8131
1111087395      8155
2840004768      8488
7192100336      9126
1111087398      9989
1111009477     10356
1111009497     10498
```

Is every product sold atleast once, for all 142 weeks?

In [21]:
```
142*30
```

Out[21]:
```
4260
```

In [22]:
```
train[['WEEK_END_DATE','UPC']].drop_duplicates().shape
```

Out[22]:
```
(4260, 2)
```

- We have 30 unique products in the training data
- There are 76 different stores associated with the retailer
- Both the variables do not have any missing values

Is each store selling each product throughout the given period?

Assuming we have information for the sale of every product that is present in the product table (30), against each store associated (76), and for every week (142); we should have 1427630 data rows.

In [23]:
```
142*76*30
```

Out[23]:
```
323760
```

In [24]:
```
train.shape
```

Out[24]:
```
(232287, 8)
```

In [25]:
```
232286/323760
```

Out[25]:
```
0.7174635532493204
```

- We can conclude that all stores are not selling all products each week
- Of all the possible combinations, about 72% of the data is present

For a store selling a particular product, do we have more than one entry?

Each product sold by any store should hold only one row, i.e. a particular store, say 'store A' selling a product 'prod P' should contribute a single row for every week. Let us check that.

In [26]:
```
train.shape
```

Out[26]:
```
(232287, 8)
```

In [27]:
```
train[['WEEK_END_DATE','STORE_NUM','UPC']].drop_duplicates().shape
```

Out[27]:
```
(232287, 3)
```

In [28]:
```
train.groupby(['WEEK_END_DATE','STORE_NUM'])['UPC'].count().mean()
```

Out[28]:
```
21.523999258710155
```

- The shape does not change after using drop duplicates
- Implies that there are unique combinations for week, store and UPC
- On an average, each week we are selling 22 products

Is a store selling a product throughout the period or is there a break?

In [29]:
```
(train.groupby(['STORE_NUM', 'UPC'])['UNITS'].count()).sort_values(
```

Out[29]:
```
STORE_NUM  UPC
4489       1111087396    137
19265      7797508006    137
21221      7797508004    137
6187       1111038080    137
23349      2840004768    137
                        ...
11993      1111085345    142
           1111085319    142
           1111038080    142
           1600027564    142
29159      7797508004    142
Name: UNITS, Length: 1644, dtype: int64
```

- Not all stores sell a product throughout the week
- The minimum number is 137/142

We now have a basic understanding of the number of products and stores we are dealing with in this data.

BASE_PRICE

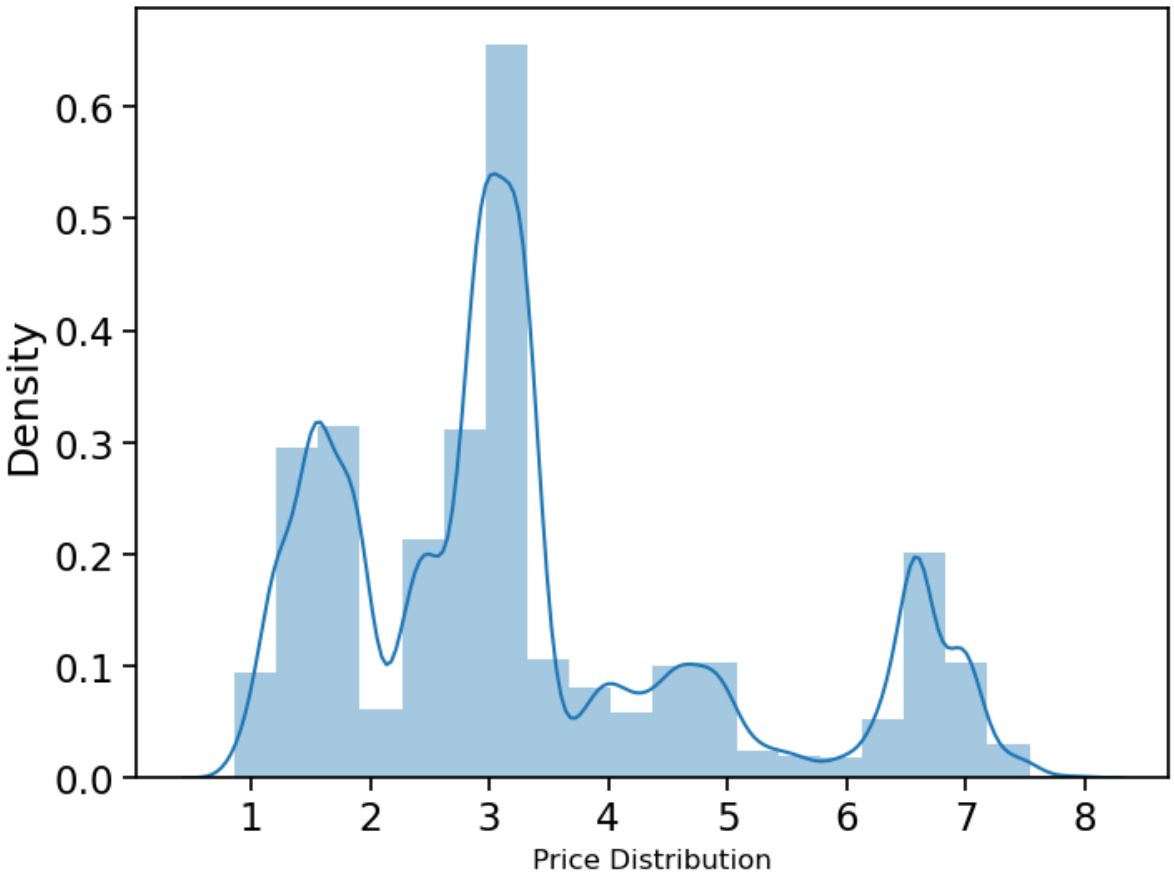
In [30]:
```
train['BASE_PRICE'].isnull().sum()
```

Out[30]:
```
12
```

In [31]:
```
train['BASE_PRICE'].describe()
```

Out[31]:
```
count    232275.000000
mean          3.345204
std           1.678181
min           0.860000
25%           1.950000
50%           2.990000
75%           4.080000
max           7.890000
Name: BASE_PRICE, dtype: float64
```

In [32]:
```
# distribution of Base Price variable
plt.figure(figsize=(8,6))
sns.distplot((train['BASE_PRICE'].values), bins=20, kde=True)
plt.xlabel('Price Distribution', fontsize=12)
plt.show()
```



- No extreme values in the base price variable
- Range for base price is 1 dollar to 8 dollars

FEATURE and DISPLAY

In [33]:
```
train[['FEATURE','DISPLAY']].isnull().sum()
```

Out[33]:
```
FEATURE    0
DISPLAY    0
dtype: int64
```

In [34]:
```
train[['FEATURE','DISPLAY']].dtypes
```

Out[34]:
```
FEATURE    int64
DISPLAY    int64
dtype: object
```

In [35]:
```
train[['FEATURE','DISPLAY']].nunique()
```

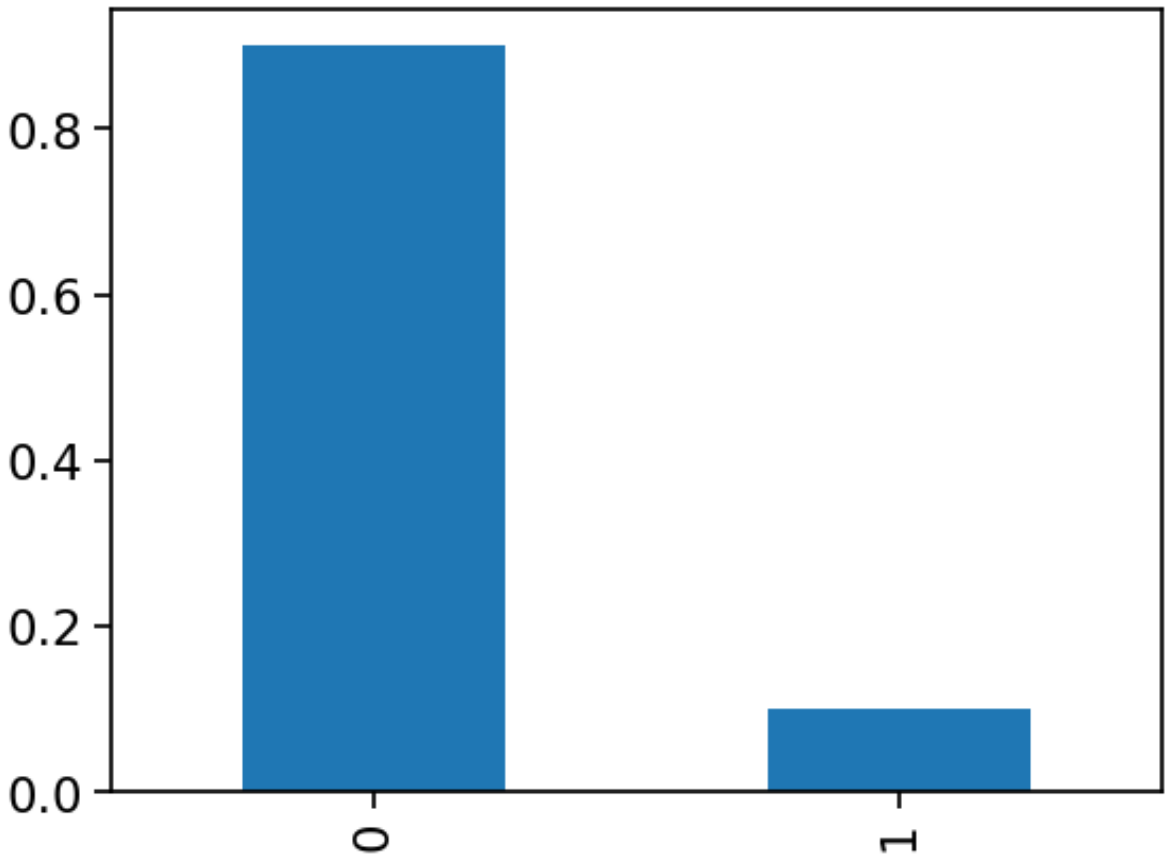
Out[35]:
```
FEATURE    2
DISPLAY    2
dtype: int64
```

In [36]:
```
train['FEATURE'].value_counts(normalize=True)
```

Out[36]:
```
0    0.900111
1    0.099889
Name: FEATURE, dtype: float64
```

In [37]:
```
train['FEATURE'].value_counts(normalize=True).plot(kind='bar')
```

Out[37]: <Axes: >

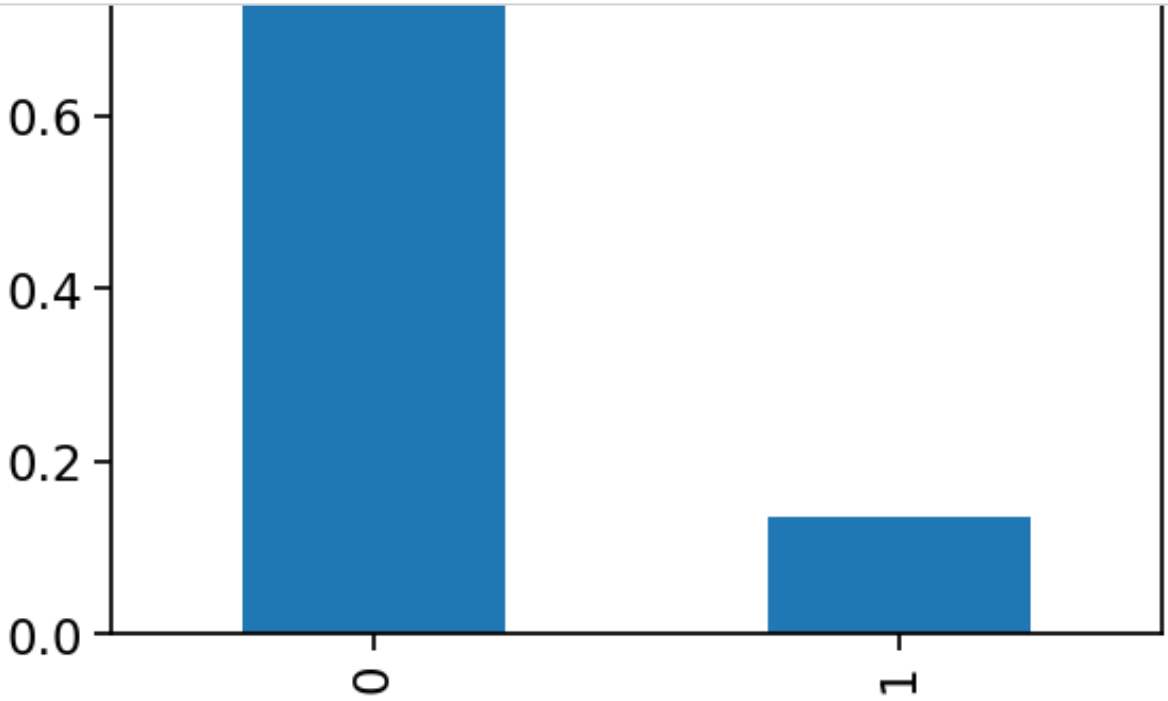


- Approximately 10 percent of product are featured

In [38]:
```
train['DISPLAY'].value_counts(normalize=True)
```

Out[38]:
```
0    0.864999
1    0.135001
Name: DISPLAY, dtype: float64
```

In [39]:
```
train['DISPLAY'].value_counts(normalize=True).plot(kind='bar')
```



- About 13% of products are on display

In [40]:
```
pd.crosstab(train['FEATURE'], train['DISPLAY']).apply(lambda r: r/l
```

Out[40]:

DISPLAY	0	1
FEATURE		
0	0.821824	0.078287
1	0.043175	0.056714

UNITS

In [41]:
```
train['UNITS'].isnull().sum()
```

Out[41]: 0

In [42]:
```
# basic statistical details of UNITS variable
train['UNITS'].describe()
```

Out[42]:
```
count    232287.000000
mean         28.063525
std          35.954341
min           0.000000
25%           9.000000
50%          18.000000
75%          34.000000
max        1800.000000
Name: UNITS, dtype: float64
```

- The Range of values is very high
- Minimum number of units sold is 0 and maximum is 1800
- A huge difference between the 75th percentile and the max value indicates presence of outliers

How many rows in the data have 0 units sold?

Is there only one row with such high sales of 1800?

In [43]:
```
train[train['UNITS'] == 0]
```

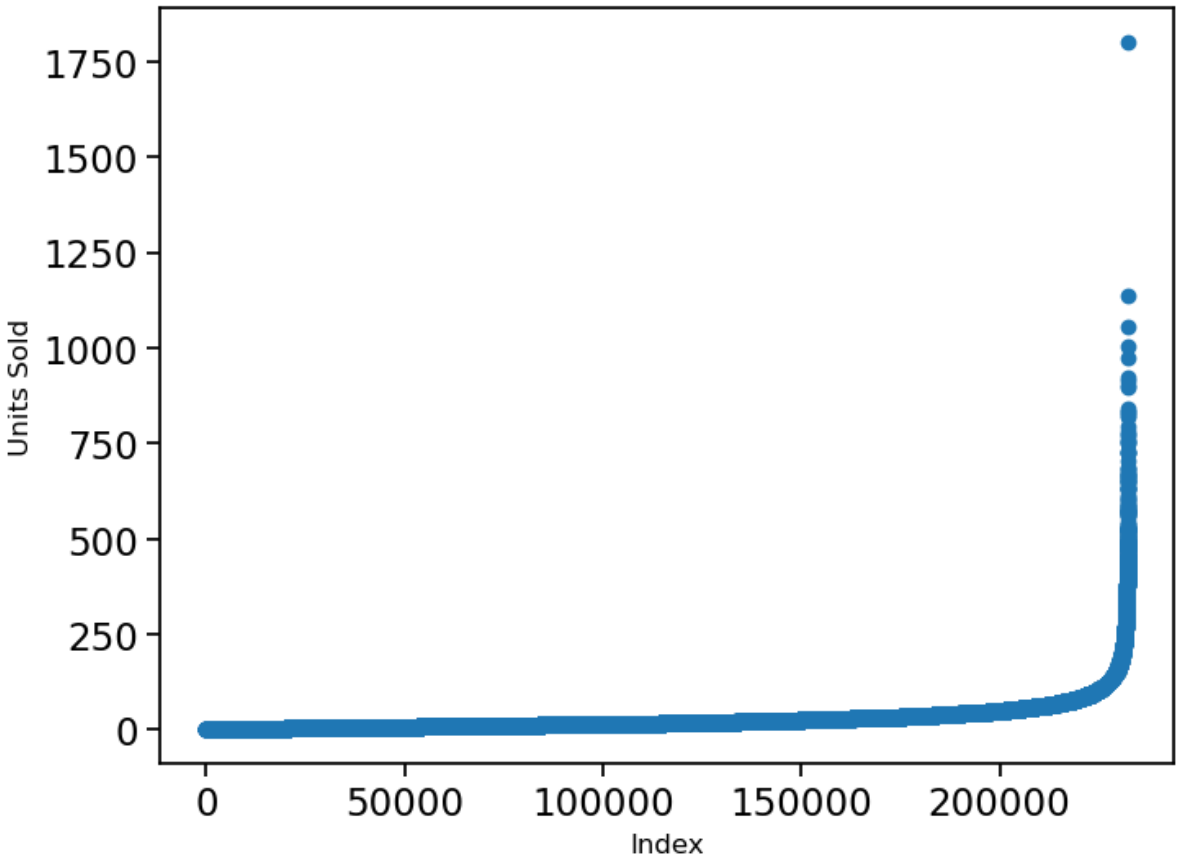
Out[43]:

	WEEK_END_DATE	STORE_NUM	UPC	PRICE	BASE_PRICE	FEATURE	DISI
76752	2009-12-02	28909	31254742735	NaN	4.99	0	

- Only one entry with 0 items sold
- Indicates the given store does not sell the following item
- It's simply a Data Anomaly and will not be useful in model training

In [44]:
```
# keeping rows with UNITS sold not equal to zero
train = train[train['UNITS'] != 0]
```

In [45]:
```
# scatter plot for UNITS variable
plt.figure(figsize=(8,6))
plt.scatter(x = range(train.shape[0]), y = np.sort(train['UNITS'].v
plt.xlabel('Index', fontsize=12)
plt.ylabel('Units Sold', fontsize=12)
plt.show()
```



- Most of the values are less than 250
- There are a few outliers (with 1 outlier way outside the range)

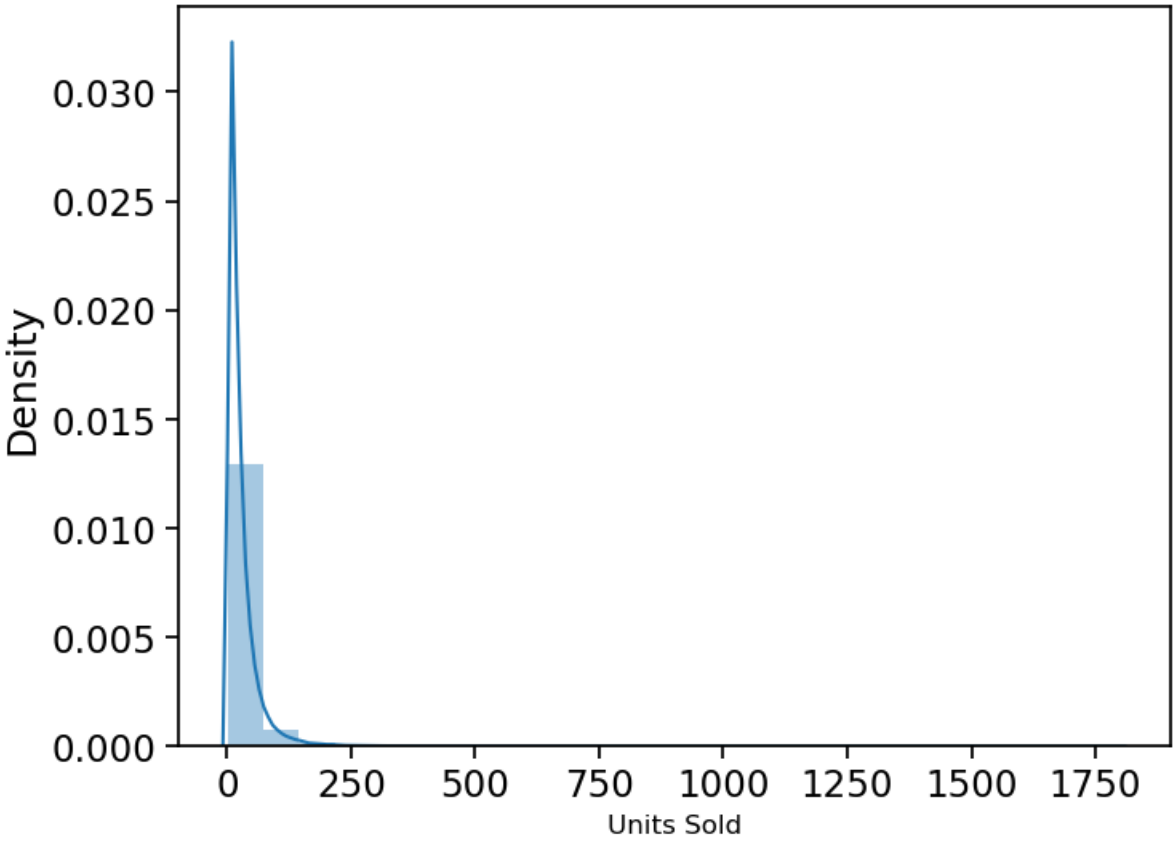
In [46]:
```
train[train['UNITS'] > 1000]
```

Out[46]:

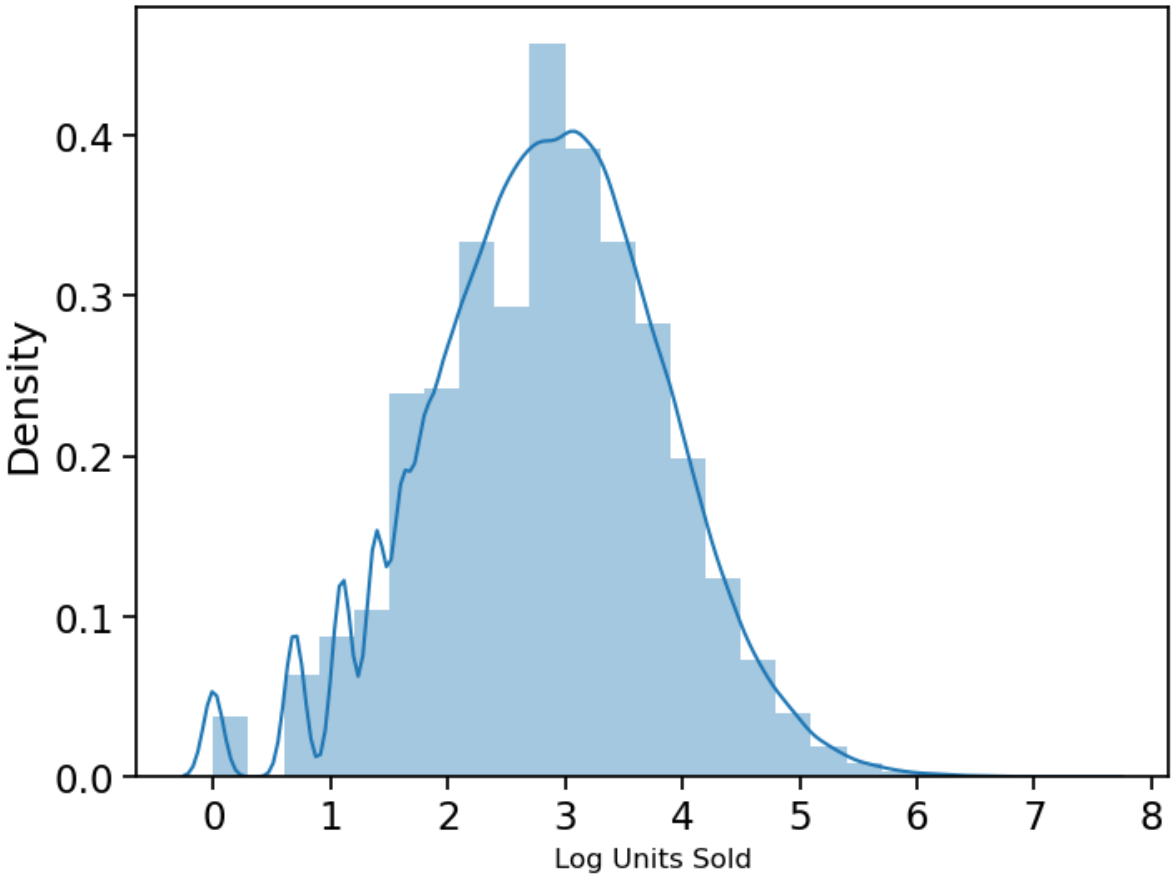
	WEEK_END_DATE	STORE_NUM	UPC	PRICE	BASE_PRICE	FEATURE	DISP
7893	2009-02-11	24991	1600027527	1.67	3.19	1	
7960	2009-02-11	25027	1600027527	1.64	3.19	1	
9597	2009-02-18	25027	1600027527	1.60	3.19	0	
11209	2009-02-25	25027	1600027527	1.64	3.19	1	

To reduce the effect of outliers and for better visualization, here is a log transform of the variable

In [47]:
```
# distribution of UNITS variable
plt.figure(figsize=(8,6))
sns.distplot((train['UNITS'].values), bins=25, kde=True)
plt.xlabel('Units Sold', fontsize=12)
plt.show()
```



In [48]:
```
# log transformed UNITS column
plt.figure(figsize=(8,6))
sns.distplot(np.log(train['UNITS'].values), bins=25, kde=True)
plt.xlabel('Log Units Sold', fontsize=12)
plt.show()
```



- After log transformation, the distribution looks closer to a normal distribution

Understanding Product Data

In [49]:
```
# first five rows of product data
product_data.head()
```

Out[49]:

	UPC	DESCRIPTION	MANUFACTURER	CATEGORY	SUB_CATEGORY	PRODUCT_
0	1111009477	PL MINI TWIST PRETZELS	PRIVATE LABEL	BAG SNACKS	PRETZELS	1
1	1111009497	PL PRETZEL STICKS	PRIVATE LABEL	BAG SNACKS	PRETZELS	1
2	1111009507	PL TWIST PRETZELS	PRIVATE LABEL	BAG SNACKS	PRETZELS	1
3	1111038078	PL BL MINT ANTSPTC RINSE	PRIVATE LABEL	ORAL HYGIENE PRODUCTS	MOUTHWASHES (ANTISEPTIC)	50
4	1111038080	PL ANTSPTC SPG MNT MTHWS	PRIVATE LABEL	ORAL HYGIENE PRODUCTS	MOUTHWASHES (ANTISEPTIC)	50

In [50]:
```
product_data.dtypes
```

Out[50]:
```
UPC             int64
DESCRIPTION    object
MANUFACTURER   object
CATEGORY       object
SUB_CATEGORY   object
PRODUCT_SIZE   object
dtype: object
```

Categorical Variables

- Check the unique values for categorical variables
- Are there any missing values in the variables?
- Is there any variable with high cardinality/ sparsity?

UPC

In [51]:
```
product_data['UPC'].nunique()
```

Out[51]:
```
30
```

- The number is consistent through the train and product data.

Are all the product codes exactly the same?

In [52]:
```
len(set(product_data.UPC).intersection(set(train.UPC)))
```

Out[52]:
```
30
```

CATEGORY

In [53]:
```
# number and list of unique categories in the product data
product_data['CATEGORY'].nunique(), product_data['CATEGORY'].unique
```

Out[53]:
```
(4,
 array(['BAG SNACKS', 'ORAL HYGIENE PRODUCTS', 'COLD CEREAL',
        'FROZEN PIZZA'], dtype=object))
```

In [54]:
```
product_data['CATEGORY'].isnull().sum()
```

Out[54]:
```
0
```

In [55]:
```
product_data['CATEGORY'].value_counts()
```

Out[55]:
```
COLD CEREAL              9
BAG SNACKS               8
FROZEN PIZZA             7
ORAL HYGIENE PRODUCTS    6
Name: CATEGORY, dtype: int64
```

- We have four product categories -
  - BAG SNACKS
  - ORAL HYGIENE PRODUCTS
  - COLD CEREAL
  - FROZEN PIZZA
- There are 9 products with the category 'Cold Cereal'
- Similarly, 8 products labeled 'Bag snacks', 7 with category 'Frozen Pizza' and 6 'Oral Hygiene' Products

Is there any subdivision among the product categories?

SUB_CATEGORY

In [56]:
```
product_data['SUB_CATEGORY'].isnull().sum()
```

Out[56]:
```
0
```

In [57]:
```
product_data['SUB_CATEGORY'].nunique()
```

Out[57]:
```
7
```

In [58]:
```
# displaying subcategories against each category
product_data[['CATEGORY','SUB_CATEGORY']].drop_duplicates().sort_va
```

Out[58]:

	CATEGORY	SUB_CATEGORY
0	BAG SNACKS	PRETZELS
5	COLD CEREAL	ALL FAMILY CEREAL
6	COLD CEREAL	ADULT CEREAL
19	COLD CEREAL	KIDS CEREAL
8	FROZEN PIZZA	PIZZA/PREMIUM
3	ORAL HYGIENE PRODUCTS	MOUTHWASHES (ANTISEPTIC)
16	ORAL HYGIENE PRODUCTS	MOUTHWASH/RINSES AND SPRAYS

The sub-categories give additional detail about the product.

- Cereal has 3 sub categories, differentiating on the age group
- Oral hygiene products have 2 sub categories, antiseptic and rinse/spray
- Bag Snacks & Frozen Pizza have just 1 sub category, no further division

Does the sub category has anything to do with the size of the product?

PRODUCT_SIZE

In [59]:
```
# unique category, sub-category and product size combinations
product_data[['CATEGORY','SUB_CATEGORY','PRODUCT_SIZE']].drop_dupli
```

Out[59]:

	CATEGORY	SUB_CATEGORY	PRODUCT_SIZE
0	BAG SNACKS	PRETZELS	15 OZ
14	BAG SNACKS	PRETZELS	16 OZ
25	BAG SNACKS	PRETZELS	10 OZ
6	COLD CEREAL	ADULT CEREAL	20 OZ
7	COLD CEREAL	ALL FAMILY CEREAL	18 OZ
19	COLD CEREAL	KIDS CEREAL	15 OZ
20	COLD CEREAL	KIDS CEREAL	12.2 OZ
5	COLD CEREAL	ALL FAMILY CEREAL	12.25 OZ
13	COLD CEREAL	ALL FAMILY CEREAL	12 OZ
8	FROZEN PIZZA	PIZZA/PREMIUM	32.7 OZ
9	FROZEN PIZZA	PIZZA/PREMIUM	30.5 OZ
10	FROZEN PIZZA	PIZZA/PREMIUM	29.6 OZ
24	FROZEN PIZZA	PIZZA/PREMIUM	22.7 OZ
21	FROZEN PIZZA	PIZZA/PREMIUM	29.8 OZ
23	FROZEN PIZZA	PIZZA/PREMIUM	28.3 OZ
3	ORAL HYGIENE PRODUCTS	MOUTHWASHES (ANTISEPTIC)	500 ML
16	ORAL HYGIENE PRODUCTS	MOUTHWASH/RINSES AND SPRAYS	1 LT
17	ORAL HYGIENE PRODUCTS	MOUTHWASHES (ANTISEPTIC)	1 LT

The cold cereal for kids is available in two different sizes. Also, the cold cereal for all family has the same size as the cold cereal for kids. Hence subcategory is not an indicator of size.

To summarize

- Bag Snacks has 1 sub category and 3 product size available
- Oral Hygiene product has 2 sub categories and 2 size options
- Frozen Pizza has only 1 sub category and 6 different package size
- cold ceral has 3 sub categoeies, and 6 options in size

DESCRIPTION

In [60]:
```
product_data['DESCRIPTION'].isnull().sum()
```

Out[60]:
```
0
```

In [61]:
```
# number and list of unique descriptions in the prodcut data
product_data['DESCRIPTION'].nunique(), product_data['DESCRIPTION'].
```

Out[61]:
```
(29,
 array(['PL MINI TWIST PRETZELS', 'PL PRETZEL STICKS', 'PL TWIST P
RETZELS',
        'PL BL MINT ANTSPTC RINSE', 'PL ANTSPTC SPG MNT MTHWS',
        'PL HONEY NUT TOASTD OATS', 'PL RAISIN BRAN',
        'PL BT SZ FRSTD SHRD WHT', 'PL SR CRUST SUPRM PIZZA',
        'PL SR CRUST 3 MEAT PIZZA', 'PL SR CRUST PEPPRN PIZZA',
        'GM HONEY NUT CHEERIOS', 'GM CHEERIOS', 'RLDGLD TINY TWIST
S PRTZL',
        'RLDGLD PRETZEL STICKS', 'SCOPE ORIG MINT MOUTHWASH',
        'CREST PH CLN MINT RINSE', 'KELL BITE SIZE MINI WHEAT',
        'KELL FROSTED FLAKES', 'KELL FROOT LOOPS', 'DIGIORNO THREE
MEAT',
        'DIGRN SUPREME PIZZA', 'DIGRN PEPP PIZZA',
        'FRSC BRCK OVN ITL PEP PZ', 'SNYDR PRETZEL RODS',
        'SNYDR SOURDOUGH NIBBLERS', 'SNYDR FF MINI PRETZELS',
        'LSTRNE CL MINT ANTSPTC MW', 'LSTRNE FRS BRST ANTSPC MW'],
       dtype=object))
```

- We have 29 descriptions in the dataset, for 30 products.
- Almost all products have a unique description.

In [62]:
```
(product_data['DESCRIPTION'].value_counts())
```

Out[62]:
```
GM CHEERIOS                  2
PL MINI TWIST PRETZELS       1
SCOPE ORIG MINT MOUTHWASH    1
LSTRNE CL MINT ANTSPTC MW    1
SNYDR FF MINI PRETZELS       1
SNYDR SOURDOUGH NIBBLERS     1
SNYDR PRETZEL RODS           1
FRSC BRCK OVN ITL PEP PZ     1
DIGRN PEPP PIZZA             1
DIGRN SUPREME PIZZA          1
DIGIORNO THREE MEAT          1
KELL FROOT LOOPS             1
KELL FROSTED FLAKES          1
KELL BITE SIZE MINI WHEAT    1
CREST PH CLN MINT RINSE      1
RLDGLD PRETZEL STICKS        1
PL PRETZEL STICKS            1
RLDGLD TINY TWISTS PRTZL     1
GM HONEY NUT CHEERIOS        1
PL SR CRUST PEPPRN PIZZA     1
PL SR CRUST 3 MEAT PIZZA     1
PL SR CRUST SUPRM PIZZA      1
PL BT SZ FRSTD SHRD WHT      1
PL RAISIN BRAN               1
PL HONEY NUT TOASTD OATS     1
PL ANTSPTC SPG MNT MTHWS     1
PL BL MINT ANTSPTC RINSE     1
PL TWIST PRETZELS            1
LSTRNE FRS BRST ANTSPC MW    1
Name: DESCRIPTION, dtype: int64
```

In [63]:
```
product_data.loc[product_data['DESCRIPTION']=='GM CHEERIOS']
```

Out[63]:

	UPC	DESCRIPTION	MANUFACTURER	CATEGORY	SUB_CATEGORY	PRODUCT
12	1600027528	GM CHEERIOS	GENERAL MI	COLD CEREAL	ALL FAMILY CEREAL	
13	1600027564	GM CHEERIOS	GENERAL MI	COLD CEREAL	ALL FAMILY CEREAL	

In [64]:
```
product_data.loc[product_data['UPC'] == 1600027527]
```

Out[64]:

	UPC	DESCRIPTION	MANUFACTURER	CATEGORY	SUB_CATEGORY	PRODUCT
11	1600027527	GM HONEY NUT CHEERIOS	GENERAL MI	COLD CEREAL	ALL FAMILY CEREAL	12.

- More granular description for the product
- Includes the type of product and manufacturer

MANUFACTURER

How many Manufacturers/ suppliers are we associated with?

Are same products created by multiple manufacturers?

In [65]:
```
product_data['MANUFACTURER'].isnull().sum()
```

Out[65]: 0

In [66]:
```
product_data['MANUFACTURER'].nunique()
```

Out[66]: 9

In [67]:
```
# displaying the list of manufacturers against the 4 categories
temp = product_data[['CATEGORY','MANUFACTURER']].drop_duplicates()
pd.crosstab([temp['CATEGORY']], temp['MANUFACTURER'])
```

Out[67]:

MANUFACTURER	FRITO LAY	GENERAL MI	KELLOGG	P & G	PRIVATE LABEL	SNYDER S	TOMBSTONE	TON
CATEGORY								
BAG SNACKS	1	0	0	0	1	1	0	
COLD CEREAL	0	1	1	0	1	0	0	
FROZEN PIZZA	0	0	0	0	1	0	1	
ORAL HYGIENE PRODUCTS	0	0	0	1	1	0	0	

- We have 4 unique categories of Products
- Each category has three manufacturers
- Every category has a manufacturer 'private label' (and 2 other manufacturers)

In [ ]:

In [ ]:

Understanding Store Data

In [68]:
```
store_data.head()
```

Out[68]:

	STORE_ID	STORE_NAME	ADDRESS_CITY_NAME	ADDRESS_STATE_PROV_CODE	MSA_C
0	367	15TH & MADISON	COVINGTON	KY	
1	389	SILVERLAKE	ERLANGER	KY	
2	613	EAST ALLEN	ALLEN	TX	
3	623	HOUSTON	HOUSTON	TX	2
4	2277	ANDERSON TOWNE CTR	CINCINNATI	OH	

In [69]:
```
store_data.dtypes
```

Out[69]:
```
STORE_ID                    int64
STORE_NAME                 object
ADDRESS_CITY_NAME          object
ADDRESS_STATE_PROV_CODE    object
MSA_CODE                    int64
SEG_VALUE_NAME             object
PARKING_SPACE_QTY         float64
SALES_AREA_SIZE_NUM         int64
AVG_WEEKLY_BASKETS          int64
dtype: object
```

Numerical Variables

- Check the distribution of numerical variables
- Are there any extreme values?
- Are there any missing values in the variables?

Categorical Variables

- Check the unique values for categorical variables
- Are there any missing values in the variables?
- Is there any variable with high cardinality/ sparsity?

STORE_ID

In [70]:
```
store_data['STORE_ID'].nunique()
```

Out[70]:
```
76
```

In [71]:
```
len(set(store_data.STORE_ID).intersection(set(train.STORE_NUM)))
```

Out[71]: 76

STORE_NAME

In [72]:
```
store_data['STORE_NAME'].isnull().sum()
```

Out[72]: 0

In [73]:
```
store_data['STORE_NAME'].nunique()
```

Out[73]: 72

- The number of unique store IDs is more than number of unique store names
- There might be stores with same name, located in different city

Which store name is being repeated?

Why do some stores have same name and different ID?

In [74]:
```
# number of store names repeating
store_data['STORE_NAME'].value_counts()
```

Out[74]:
```
HOUSTON            4
MIDDLETOWN         2
15TH & MADISON     1
DUNCANVILLE        1
WOOD FOREST S/C    1
                  ..
AT EASTEX FRWY     1
DENT               1
THE WOODLANDS      1
LANDEN             1
CARROLLTON         1
Name: STORE_NAME, Length: 72, dtype: int64
```

In [75]:
```
store_data.loc[store_data['STORE_NAME'] == 'HOUSTON']
```

Out[75]:

	STORE_ID	STORE_NAME	ADDRESS_CITY_NAME	ADDRESS_STATE_PROV_CODE	MSA_
3	623	HOUSTON	HOUSTON	TX	
9	2513	HOUSTON	HOUSTON	TX	
54	21485	HOUSTON	KATY	TX	
59	23327	HOUSTON	HOUSTON	TX	

In [76]:
```
store_data.loc[store_data['STORE_NAME'] == 'MIDDLETOWN']
```

Out[76]:

	STORE_ID	STORE_NAME	ADDRESS_CITY_NAME	ADDRESS_STATE_PROV_CODE	MSA_
50	21221	MIDDLETOWN	MIDDLETOWN	OH	
74	28909	MIDDLETOWN	MIDDLETOWN	OH	

The store names that are repeated, are actually different stores which either have a different city or different segment (upscale, mainstream, value) or location. Hence they are given a different IDs.

ADDRESS_CITY_NAME and ADDRESS_STATE_PROV_CODE

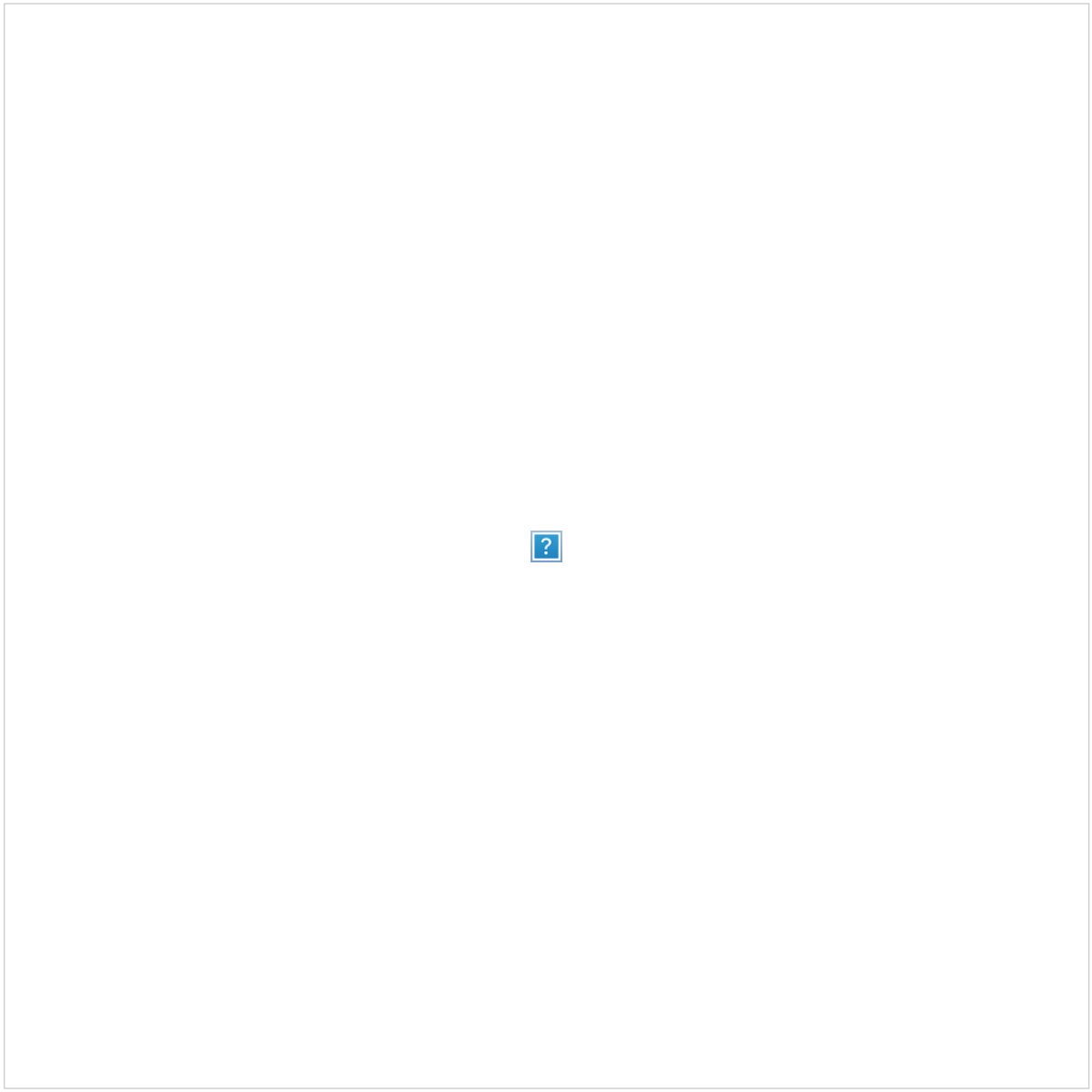
In [77]:
```
store_data[['ADDRESS_STATE_PROV_CODE', 'ADDRESS_CITY_NAME']].isnull
```

Out[77]:
```
ADDRESS_STATE_PROV_CODE    0
ADDRESS_CITY_NAME          0
dtype: int64
```

How many cities and states are the stores located in?

In [78]:
```
store_data[['ADDRESS_STATE_PROV_CODE', 'ADDRESS_CITY_NAME']].nuniqu
```

Out[78]:
```
ADDRESS_STATE_PROV_CODE     4
ADDRESS_CITY_NAME          51
dtype: int64
```



Let's find out the number of stores in each of the state

In [79]:
```
store_data.groupby(['ADDRESS_STATE_PROV_CODE'])['STORE_ID'].count()
```

Out[79]:
```
ADDRESS_STATE_PROV_CODE
IN     1
KY     4
OH    30
TX    41
Name: STORE_ID, dtype: int64
```

- Each store has a unique store ID
- Most stores are from Ohio and Texas ~93%
- Few from Kentucky and Indiana ~7%

In [80]:
```
store_data.groupby(['ADDRESS_STATE_PROV_CODE'])['ADDRESS_CITY_NAME'
```

Out[80]:
```
ADDRESS_STATE_PROV_CODE
IN     1
KY     3
OH    16
TX    31
Name: ADDRESS_CITY_NAME, dtype: int64
```

In [81]:
```
store_data['ADDRESS_CITY_NAME'].value_counts()
```

Out[81]:
```
CINCINNATI         9
HOUSTON            8
MIDDLETOWN         3
COVINGTON          2
SUGAR LAND         2
LOVELAND           2
MAINEVILLE         2
HAMILTON           2
KATY               2
MCKINNEY           2
DAYTON             2
CROWLEY            1
GOSHEN             1
PASADENA           1
WOODLANDS          1
MESQUITE           1
SPRINGFIELD        1
FLOWER MOUND       1
SOUTHLAKE          1
FRISCO             1
WEST CHESTER       1
DENTON             1
CYPRESS            1
LEBANON            1
RICHARDSON         1
GARLAND            1
KETTERING          1
DUNCANVILLE        1
VANDALIA           1
MAGNOLIA           1
BEAUMONT           1
ALLEN              1
MILFORD            1
BLUE ASH           1
CLUTE              1
DICKINSON          1
GRAND PRAIRIE      1
ARLINGTON          1
LAWRENCEBURG       1
ROCKWALL           1
COLLEGE STATION    1
MASON              1
```

```
SAINT MARYS         1
KINGWOOD            1
BAYTOWN             1
THE WOODLANDS       1
INDEPENDENCE        1
DALLAS              1
SHERMAN             1
ERLANGER            1
CARROLLTON          1
Name: ADDRESS_CITY_NAME, dtype: int64
```

MSA_CODE

In [82]:
```
store_data['MSA_CODE'].isnull().sum()
```

Out[82]:
```
0
```

In [83]:
```
store_data['MSA_CODE'].nunique(), store_data['MSA_CODE'].unique()
```

Out[83]:
```
(9, array([17140, 19100, 26420, 17780, 47540, 43300, 19380, 13140,
44220]))
```

In [84]:
```
store_data['MSA_CODE'].value_counts()
```

Out[84]:
```
17140    29
26420    21
19100    17
19380     4
17780     1
47540     1
43300     1
13140     1
44220     1
Name: MSA_CODE, dtype: int64
```

In [85]:
```
(store_data.groupby(['MSA_CODE', 'ADDRESS_STATE_PROV_CODE'])['STORE
```

Out[85]:
```
MSA_CODE  ADDRESS_STATE_PROV_CODE
13140     TX                       1
17140     IN                       1
          KY                       4
          OH                      24
17780     TX                       1
19100     TX                      17
19380     OH                       4
26420     TX                      21
43300     TX                       1
44220     OH                       1
47540     OH                       1
Name: STORE_ID, dtype: int64
```

- These codes are assigned based on the geographical location and population density.
- 17140 is present in all three except Texas (which has a different geographical region)

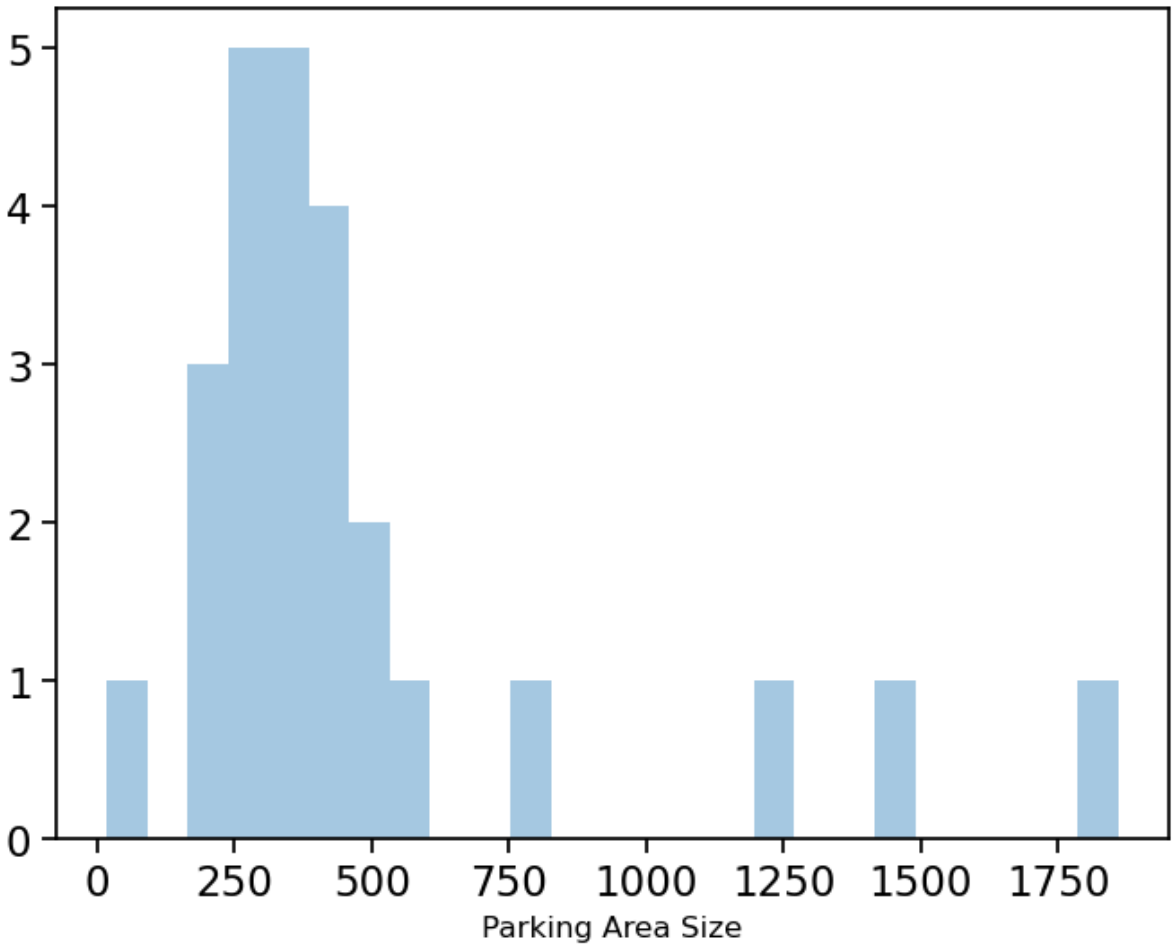
PARKING_SPACE_QTY and SALES_AREA_SIZE_NUM

In [86]:
```
store_data[['PARKING_SPACE_QTY', 'SALES_AREA_SIZE_NUM']].isnull().s
```

Out[86]:
```
PARKING_SPACE_QTY      51
SALES_AREA_SIZE_NUM     0
dtype: int64
```

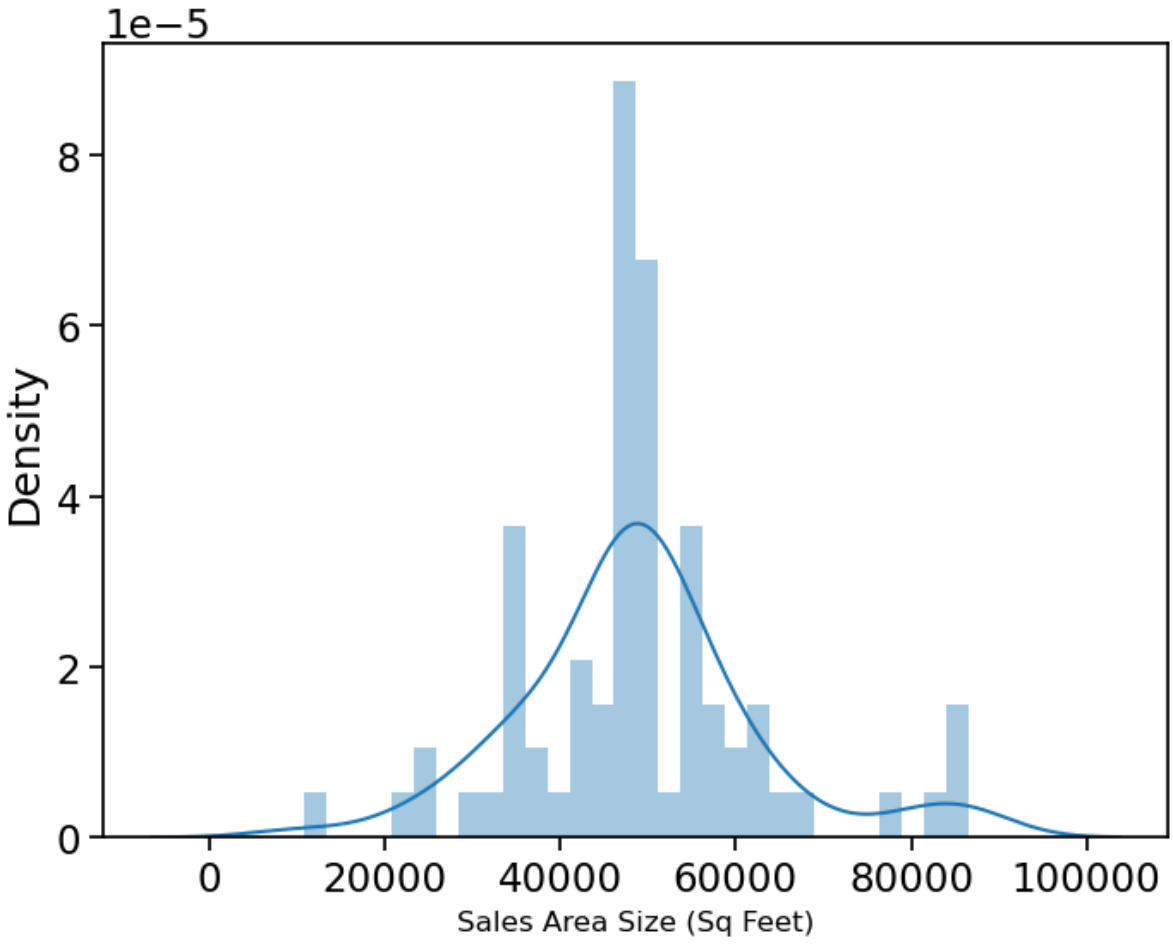
- Of 76 stores, parking area of 51 is missing

In [87]:
```
plt.figure(figsize=(8,6))
sns.distplot(store_data['PARKING_SPACE_QTY'], bins=25, kde=False)
plt.xlabel('Parking Area Size', fontsize=12)
plt.show()
```



- About 15 stores have parking area between 250 - 500 units

In [88]:
```
plt.figure(figsize=(8,6))
sns.distplot(store_data['SALES_AREA_SIZE_NUM'], bins=30, kde=True)
plt.xlabel('Sales Area Size (Sq Feet)', fontsize=12)
plt.show()
```



- Most stores have the area between 30-70 K
- Only a small number of stores have area less than 30k or greater than 90k

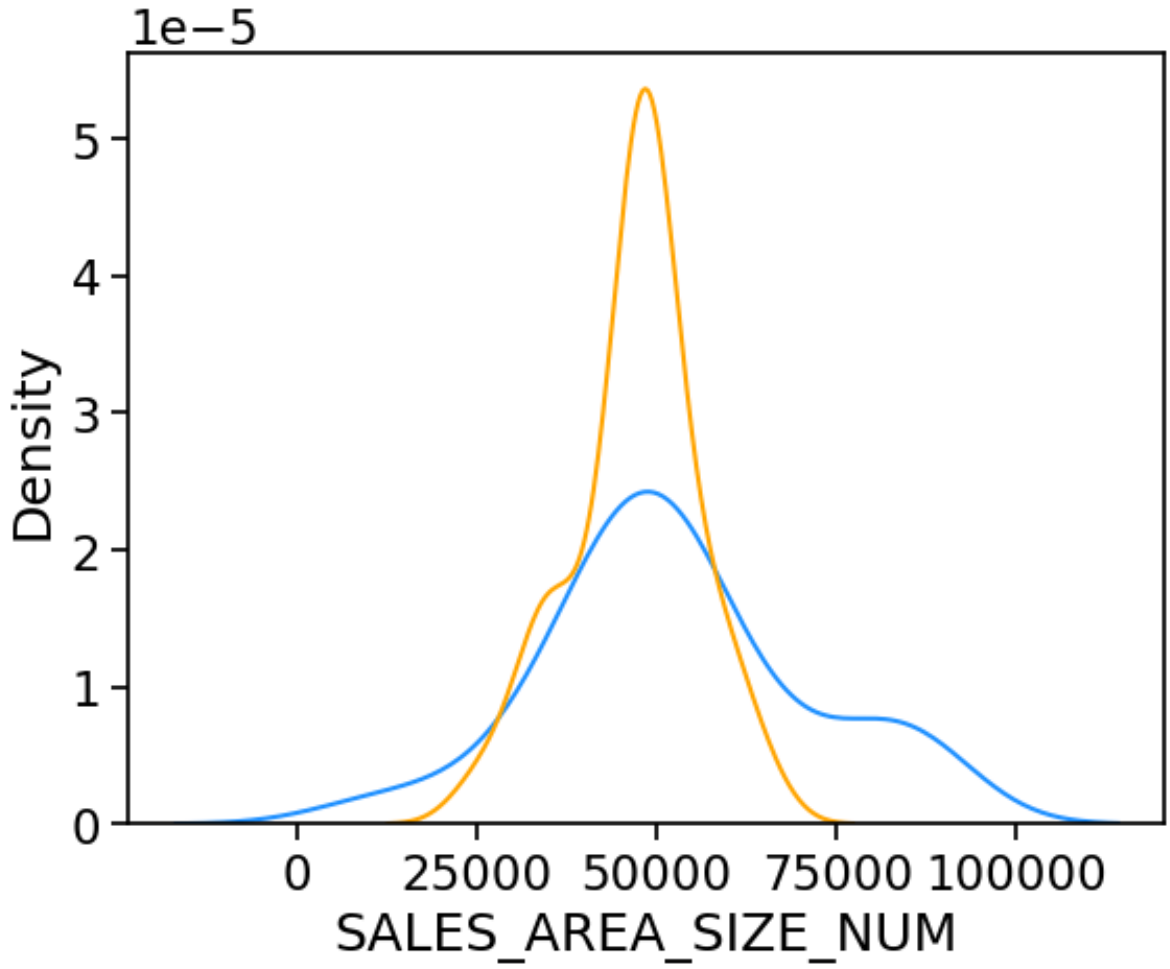
How is Average store size varying for different states?

In [89]:
```
(store_data.groupby(['ADDRESS_STATE_PROV_CODE'])['SALES_AREA_SIZE_N
```

Out[89]:
```
ADDRESS_STATE_PROV_CODE
IN    58563.000000
OH    52691.200000
TX    46920.902439
KY    39855.500000
Name: SALES_AREA_SIZE_NUM, dtype: float64
```

In [90]:
```
state_oh = store_data.loc[store_data['ADDRESS_STATE_PROV_CODE'] ==
state_tx = store_data.loc[store_data['ADDRESS_STATE_PROV_CODE'] ==

sns.distplot(state_oh['SALES_AREA_SIZE_NUM'], hist=False,color= 'do
sns.distplot(state_tx['SALES_AREA_SIZE_NUM'], hist=False,  color= '
```

Out[90]:
```
<Axes: xlabel='SALES_AREA_SIZE_NUM', ylabel='Density'>
```



- Indiana has only one store and the area size is 58,563 sq feet.
- Ohio and Texas have average around 52k and 50k.
- Ohio has stores distributed at all sizes.
- Texas mainly has stores between sales area 30k to 60k

AVG_WEEKLY_BASKETS

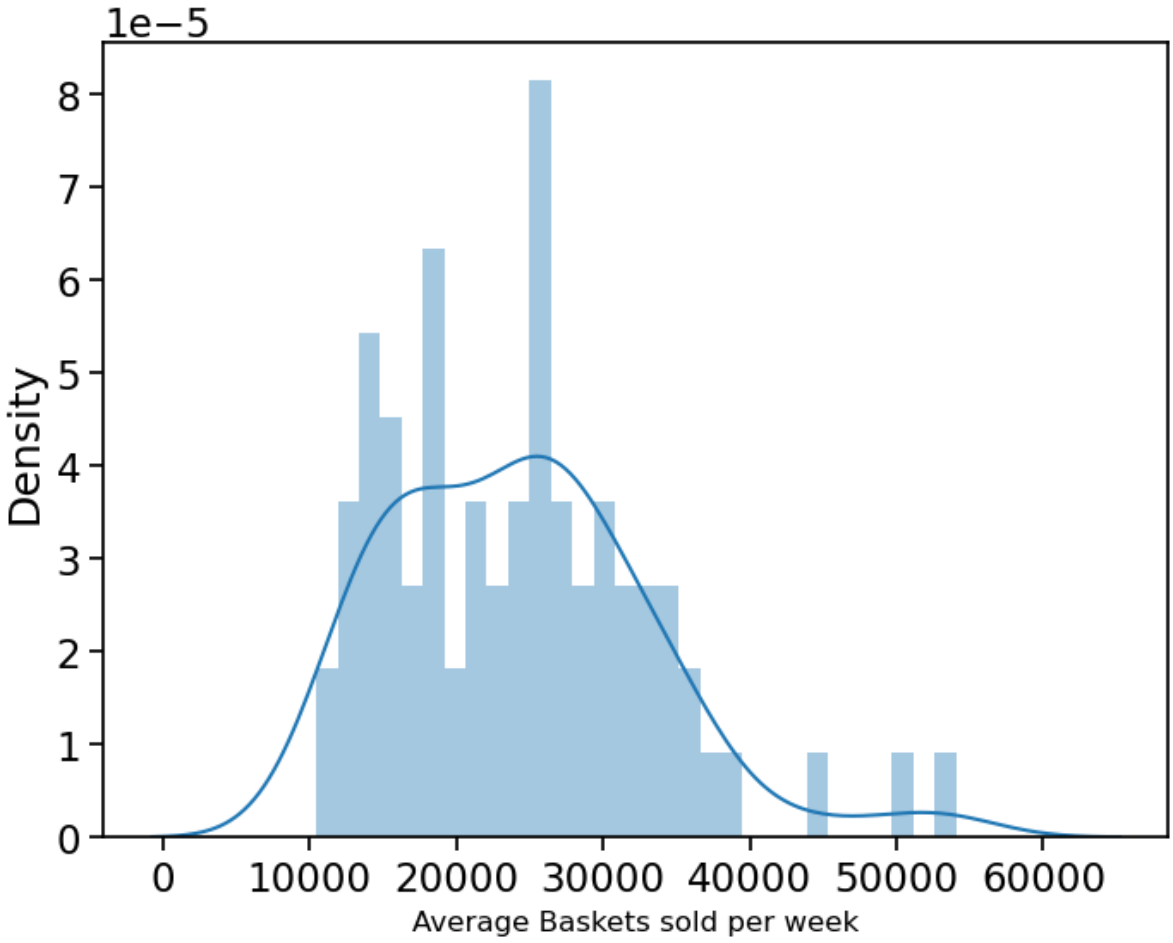
In [91]:
```
store_data['AVG_WEEKLY_BASKETS'].isnull().sum()
```

Out[91]:
```
0
```

In [92]:
```
store_data['AVG_WEEKLY_BASKETS'].describe()
```

Out[92]:
```
count       76.000000
mean     24226.921053
std       8863.939362
min      10435.000000
25%      16983.500000
50%      24667.500000
75%      29398.500000
max      54053.000000
Name: AVG_WEEKLY_BASKETS, dtype: float64
```

In [93]:
```
plt.figure(figsize=(8,6))
sns.distplot(store_data['AVG_WEEKLY_BASKETS'], bins=30, kde=True)
plt.xlabel('Average Baskets sold per week', fontsize=12)
plt.show()
```



What are the average weekly baskets sold for the states?

In [94]:
```
(store_data.groupby(['ADDRESS_STATE_PROV_CODE'])['AVG_WEEKLY_BASKET
```

Out[94]:
```
ADDRESS_STATE_PROV_CODE
OH    26113.766667
TX    23234.195122
KY    21489.000000
IN    19275.000000
Name: AVG_WEEKLY_BASKETS, dtype: float64
```

SEG_VALUE_NAME

In [95]:
```
store_data['SEG_VALUE_NAME'].isnull().sum()
```

Out[95]:
```
0
```

There are certain segments assigned to store, based on the brand and quality of products sold at the store.

- **Upscale stores** : Located in high income neighborhoods and offer more high-end product
- **Mainstream stores** : Located in middle class areas, offering a mix of upscale and value product
- **Value stores** : Focus on low prices products targeting low income customers

Let us look at the distribution of stores in each of these segments

In [96]:
```
store_data['SEG_VALUE_NAME'].value_counts()
```

Out[96]:
```
MAINSTREAM    43
VALUE         19
UPSCALE       14
Name: SEG_VALUE_NAME, dtype: int64
```

Does the segment has any relation with the store area?

Is there a difference in the average sales for each segment?

In [97]:
```
(store_data.groupby(['SEG_VALUE_NAME'])['SALES_AREA_SIZE_NUM'].mean
```

Out[97]:
```
SEG_VALUE_NAME
UPSCALE       59556.428571
MAINSTREAM    50075.976744
VALUE         38706.368421
Name: SALES_AREA_SIZE_NUM, dtype: float64
```

In [98]:
```
(store_data.groupby(['SEG_VALUE_NAME'])['AVG_WEEKLY_BASKETS'].mean(
```

Out[98]:
```
SEG_VALUE_NAME
UPSCALE       28735.928571
MAINSTREAM    24024.093023
VALUE         21363.526316
Name: AVG_WEEKLY_BASKETS, dtype: float64
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

4. Data Exploration - Train, Product, Store

Validating the Hypothesis

During the Hypothesis Generation, we listed down the following hypothesis.

Product Data

- Product type/ Category : Different Product Categories can have significantly varying trends/patterns
- Product Size : Larger products should be more in demand
- Price of Product: Same category products with lower price would have more sales
- Company/ Manufacturer: Well known brands/manufacturers will have higher sales

Train Data

- Offer Applicable: Featured Products with attractive offers will have higher sales
- Product Promotion: Sales will be more for products with in-store promotion

Store Data

- Store Location: Stores in a particular state/city will have a similar trend
- Size of Store: Stores with larger area would have more sales
- Average Wait time: If average baskets sold is higher, wait time would be low. Implies higher sale of units.

Merging the Store and Product Datasets

In [99]:
```
store_product_data = train.merge(product_data, how = 'left', on='UP

store_product_data = store_product_data.merge(store_data, how = 'le
```

In [100]:
```
store_product_data.shape
```

Out[100]:
```
(232286, 22)
```

In [101]:
```
store_product_data.columns
```

Out[101]:
```
Index(['WEEK_END_DATE', 'STORE_NUM', 'UPC', 'PRICE', 'BASE_PRICE',
'FEATURE',
       'DISPLAY', 'UNITS', 'DESCRIPTION', 'MANUFACTURER', 'CATEGOR
Y',
       'SUB_CATEGORY', 'PRODUCT_SIZE', 'STORE_ID', 'STORE_NAME',
       'ADDRESS_CITY_NAME', 'ADDRESS_STATE_PROV_CODE', 'MSA_CODE',
       'SEG_VALUE_NAME', 'PARKING_SPACE_QTY', 'SALES_AREA_SIZE_NUM
',
       'AVG_WEEKLY_BASKETS'],
      dtype='object')
```

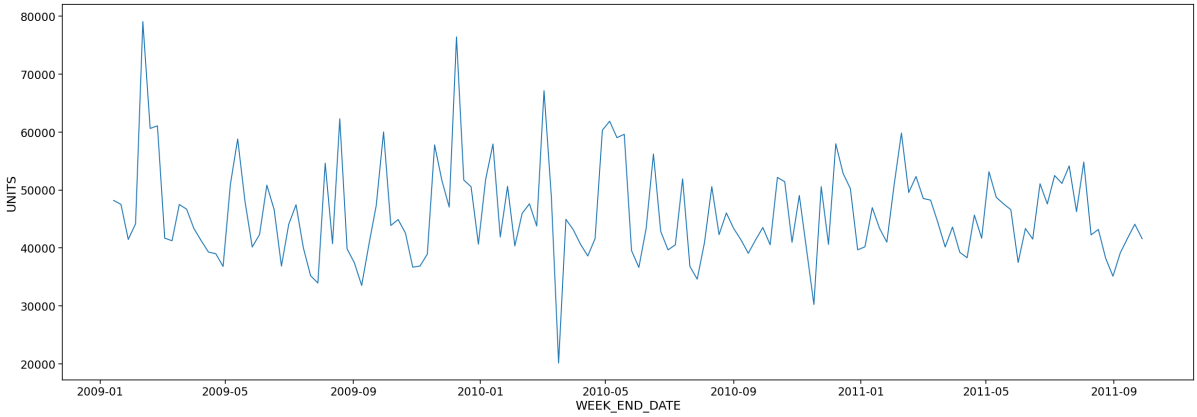
Trend or Seasonal Pattern in Product Sales

- Product type/Category: Different Product Categories can have significantly varying trends/patterns

Units sold per week

In [102]:
```
#sum of units sold per week
weekly_demand = store_product_data.groupby(['WEEK_END_DATE'])['UNIT

plt.figure(figsize=(30,10))
sns.lineplot(x = weekly_demand.index, y = weekly_demand)
```

Out[102]: <Axes: xlabel='WEEK_END_DATE', ylabel='UNITS'>



- Displays the total number of units sold by the retailer (including all products and from all stores)
- The highest number is close to 80,000 and lowest is close to 20,000 units
- There is no evident pattern or trend in the plot
- The spikes can be seen in either direction and at no constant interval

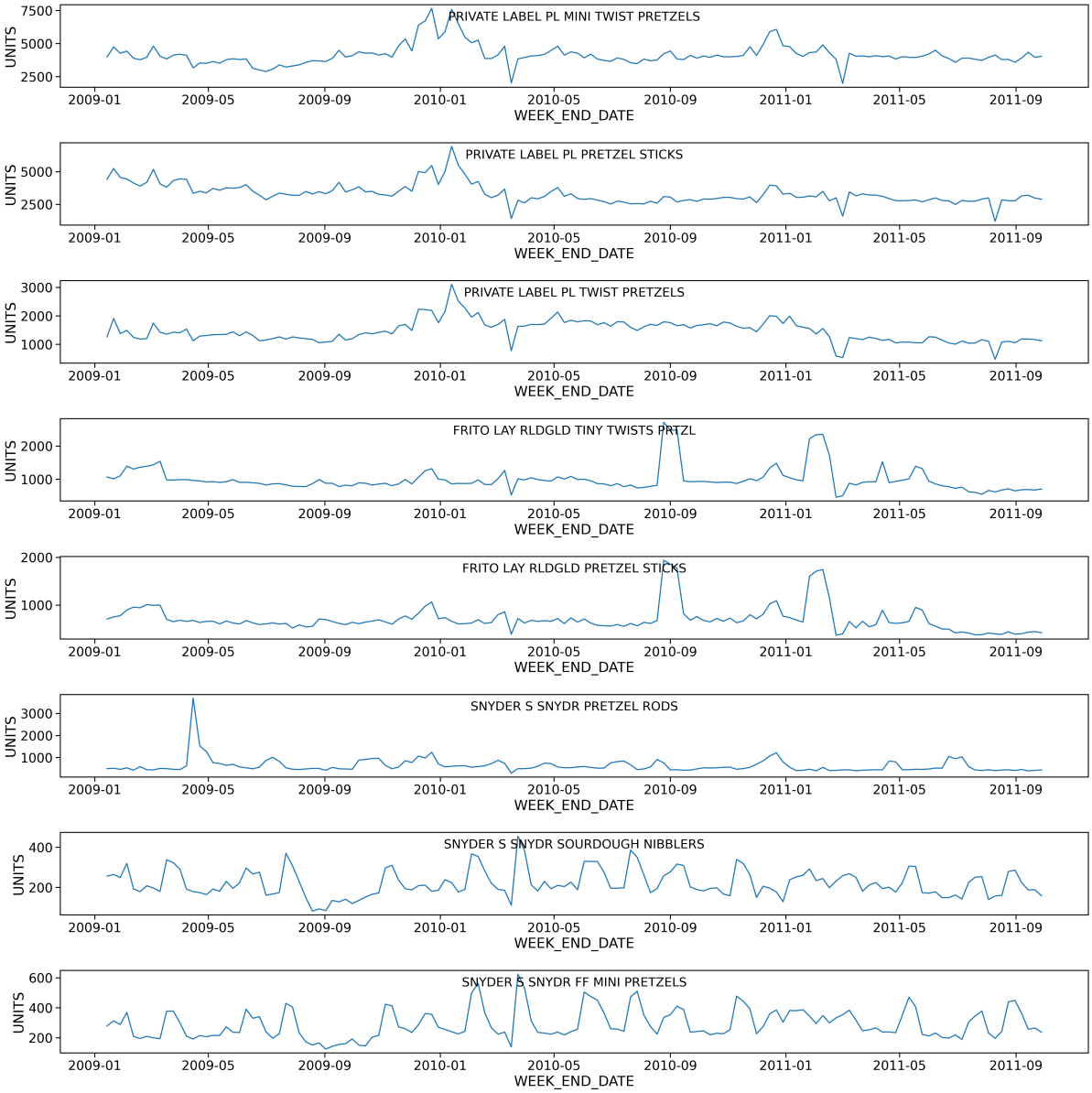
Units sold per week - at product level

Now, we will look at category wise sales or demand patterns to see if there is any similarity within each category

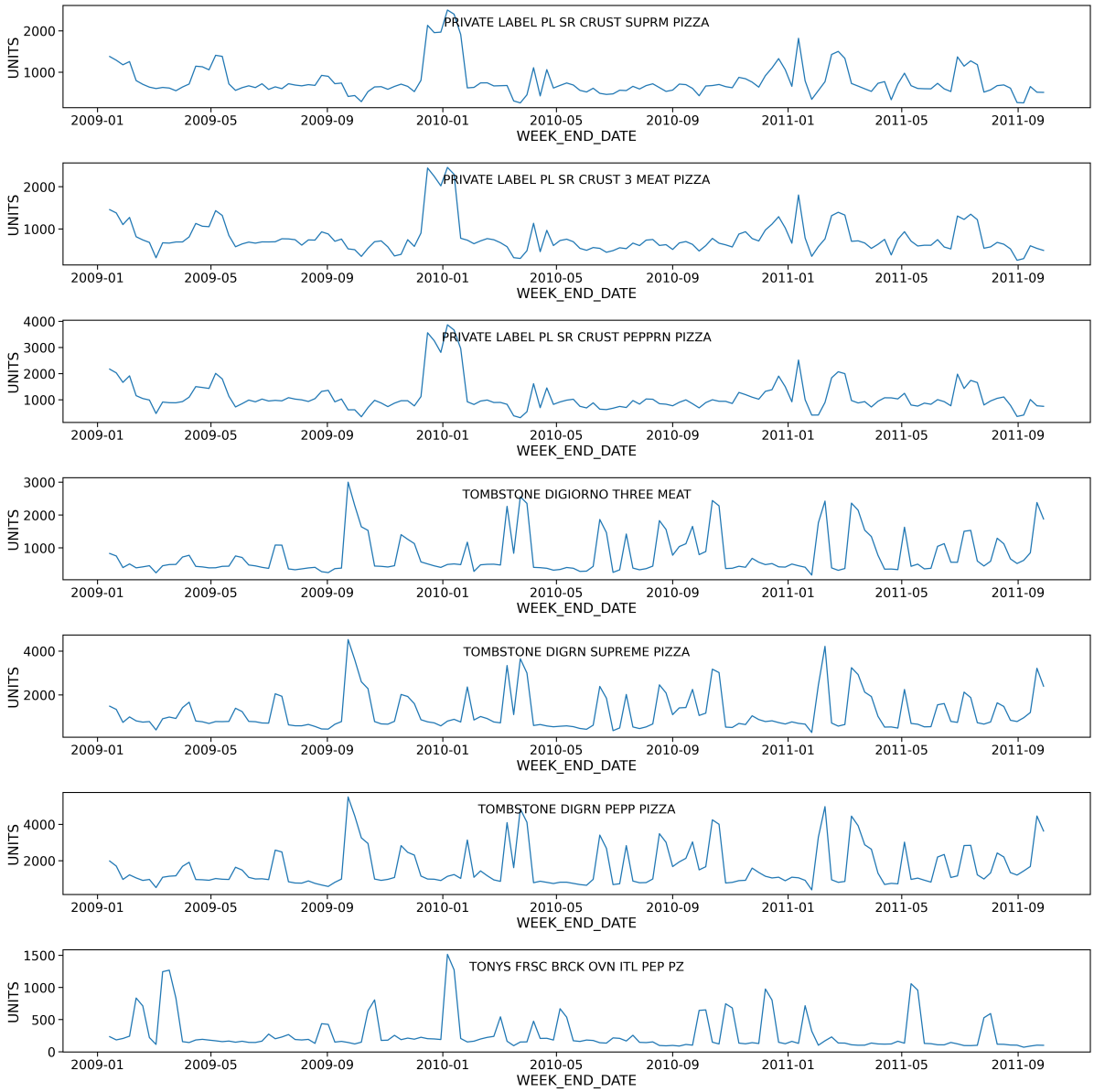
In [103]:
```
# function to plot weekly sales of products
def product_plots(product_list):

    # dictionary storing UPC and weekly sales
    d = {product: store_product_data[store_product_data['UPC'] == pr
    fig, axs = plt.subplots(len(product_list), 1, figsize = (20, 20)
    j = 0

    for product in d.keys():
        # adding manufacturer and descritption in title
        manu = product_data[product_data['UPC'] == product]['MANUFAC
        desc = product_data[product_data['UPC'] == product]['DESCRIP
        # creating the plot
        sns.lineplot(x = d[product].index, y = d[product],ax = axs[j
        j = j+1
    plt.tight_layout()
```

In [104]:
```
# creating list of products based on category
pretzels = list(product_data[product_data['CATEGORY'] == 'BAG SNACK
frozen_pizza = list(product_data[product_data['CATEGORY'] == 'FROZE
oral_hygiene = list(product_data[product_data['CATEGORY'] == 'ORAL
cold_cereal = list(product_data[product_data['CATEGORY'] == 'COLD C
```

In [105]:
```
product_plots(pretzels)
```



In [106]:
```
product_plots(frozen_pizza)
```



- No increasing/decreasing trend for the sale of products over time
- No seasonal patterns seen on individual product sale
- Products by same manufaturer have similar patterns (spikes and drops).

Units sold per week - at store level

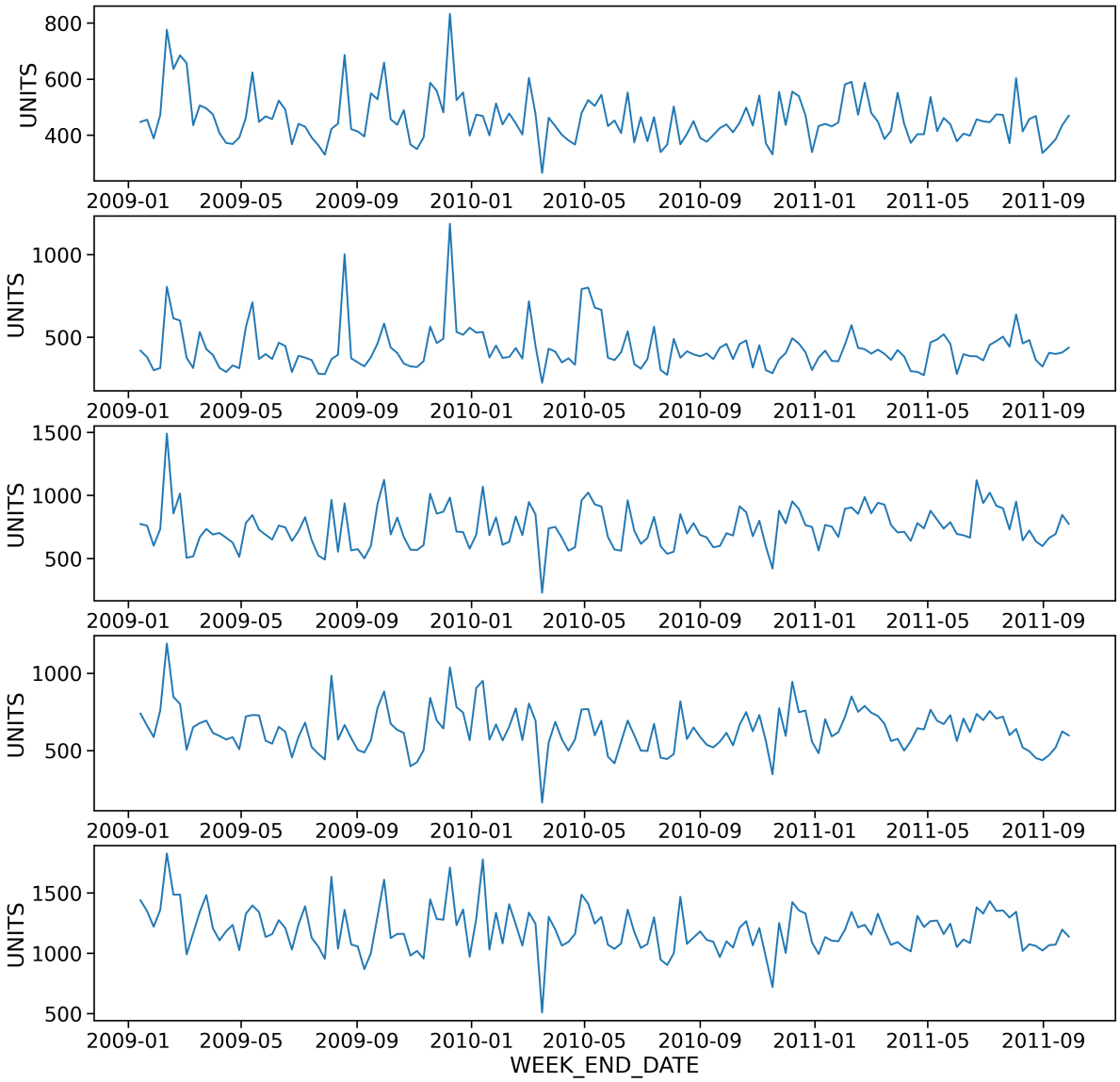
Now, let us look store level demand patterns to see if there are any patterns here.

In [107]:
```
# Randomly selecting 5 store ID
stores_plot = random.sample(list(store_data['STORE_ID']), 5)
```

In [108]:
```
#creating dictionary with store number as keys
# for each store, calculate sum of units sold per week
d = {store: train[train['STORE_NUM'] == store].groupby(['WEEK_END_D
```

In [109]:
```
plt.figure(figsize=(30,10))

fig, axs = plt.subplots(5, 1, figsize = (15, 15), dpi=300)
j = 0
for store in d.keys():
    sns.lineplot(x = d[store].index, y = d[store],ax = axs[j])
    j = j+1
```

```
<Figure size 3000x1000 with 0 Axes>
```



For the randomly selected store numbers, we can see that there is no pattern in the plot. The same was repeated for a number of stores and the data showed no increasing or decreasing trend or seasonality.

Are the sudden increase in sales due to product/in-store promotion?

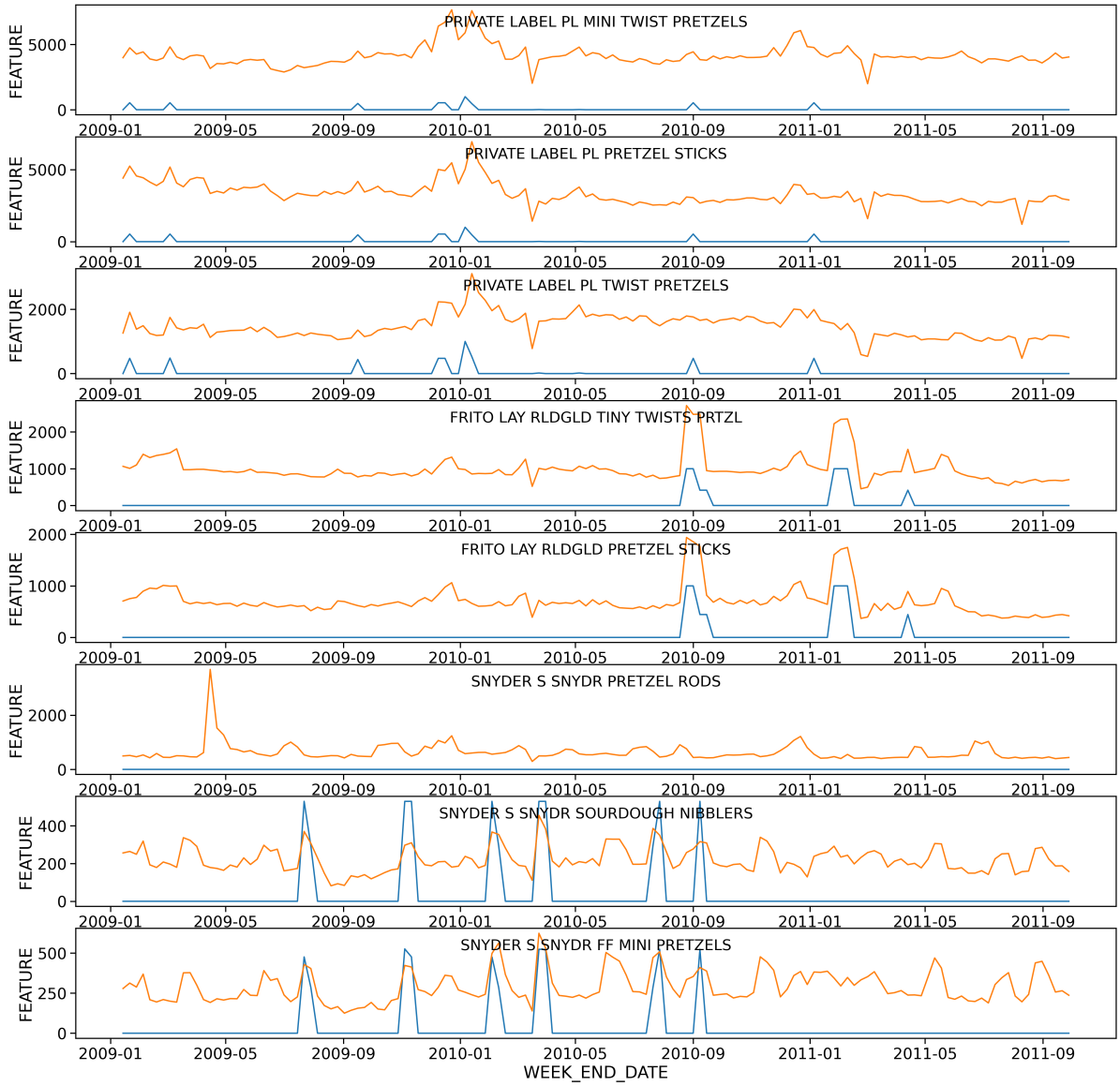
Featured or Displayed Product have higher sale

- Offer Applicable: Featured Products with attractive offers will have higher sales
- Product Promotion: Sales will be more for products with in-store promotion

In [110]:
```
def featured_plots(product_list):
    #dictionary storing UPC and 'Featured' variable
    d_f = {product: 1000*train[train['UPC'] == product].groupby(['W
    #dictionary storing UPC and Product Sales
    d = {product: train[train['UPC'] == product].groupby(['WEEK_END


    fig, axs = plt.subplots(len(product_list), 1, figsize = (20, 20
    j = 0
    for product in d.keys():
        # Manufacturer name and Descritption in title
        manu = product_data[product_data['UPC'] == product]['MANUFA
        desc = product_data[product_data['UPC'] == product]['DESCRI

        # plotting featured and sales values
        sns.lineplot(x = d_f[product].index, y = d_f[product],ax =
        sns.lineplot(x = d[product].index, y = d[product],ax = axs[
        j = j+1
```

In [111]:
```
product_list_f = list(product_data[product_data['CATEGORY'] == 'BAG
```

In [112]:
```
featured_plots(product_list_f)
```

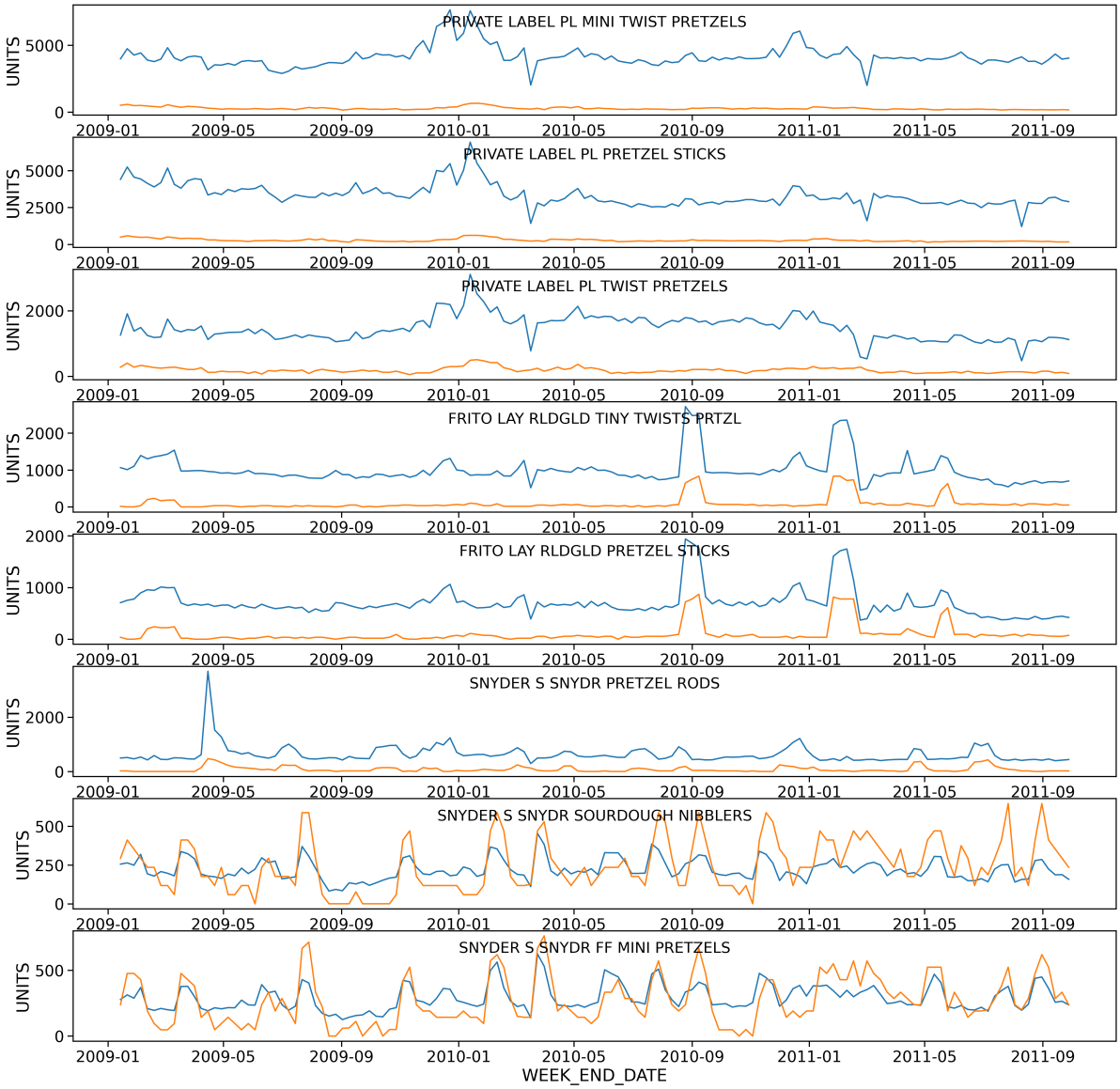


- When the products are featured, the sales increase.

Does the in-store display also have a similar effect?

In [113]:
```
display_plots(product_list):
d_d = {product: 1000*train[train['UPC'] == product].groupby(['WEEK_E
d = {product: train[train['UPC'] == product].groupby(['WEEK_END_DATE
fig, axs = plt.subplots(len(product_list), 1, figsize = (20, 20), dp
j = 0
for product in d.keys():
    manu = product_data[product_data['UPC'] == product]['MANUFACTURE
    desc = product_data[product_data['UPC'] == product]['DESCRIPTION
    sns.lineplot(x = d[product].index, y = d[product],ax = axs[j]).s
    sns.lineplot(x = d_d[product].index, y = d_d[product],ax = axs[j
    j = j+1
```

In [114]:
```
display_plots(product_list_f)
```



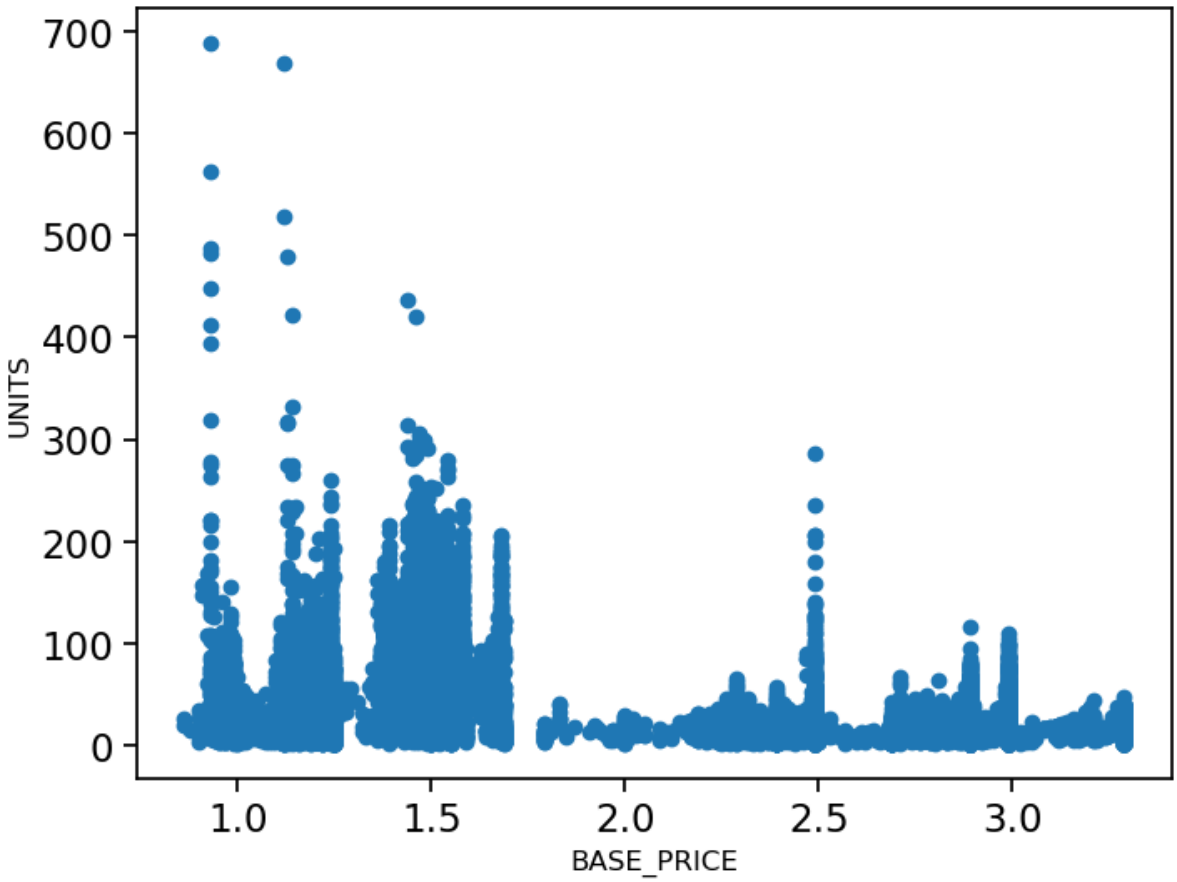
- It is evident that product sales are greatly affected by the display.
- For products on display, the sales are higher.

Product sales higher for lower priced items

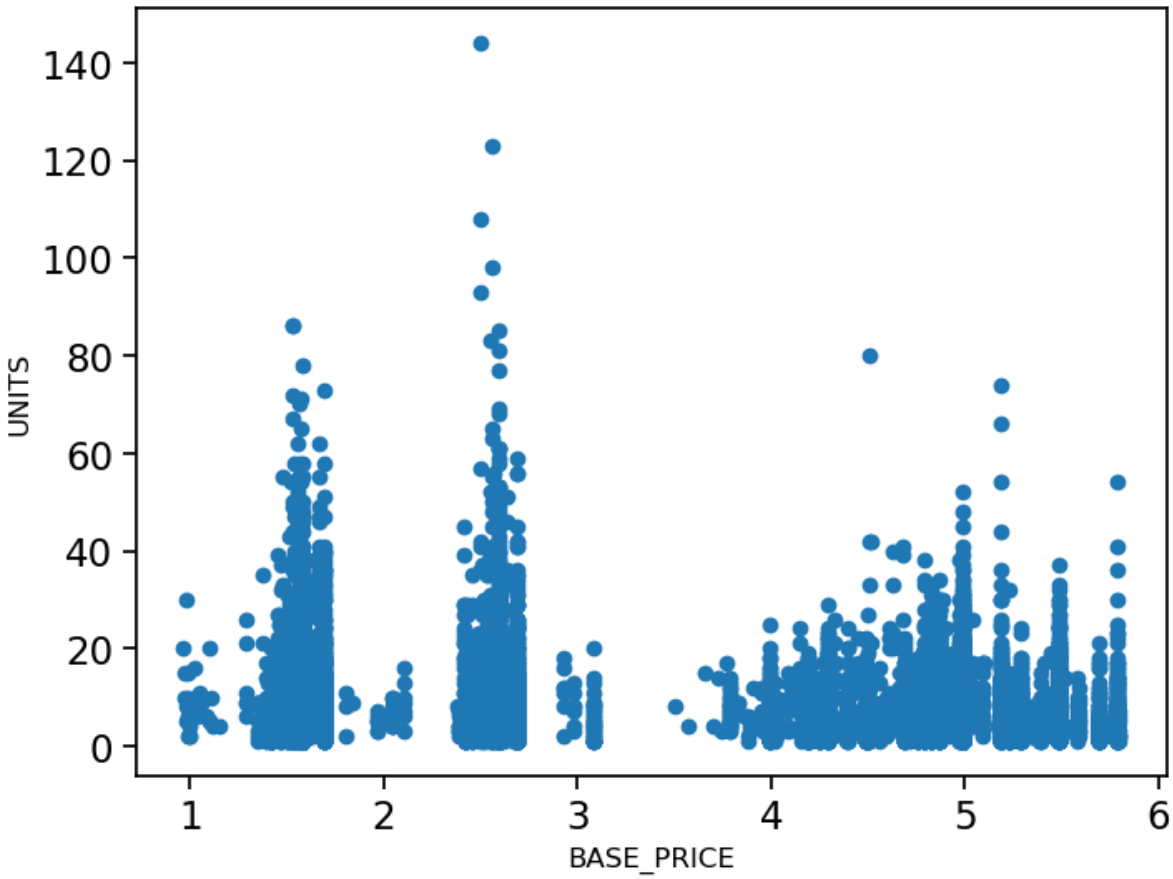
- Price of Product: Same category products with lower price would have more sales

In [115]:
```
product_size_coldcereal = store_product_data.loc[store_product_data
product_size_bagsnacks  = store_product_data.loc[store_product_data
product_size_frozenpizza = store_product_data.loc[store_product_dat
product_size_oralhyiegne = store_product_data.loc[store_product_dat
```

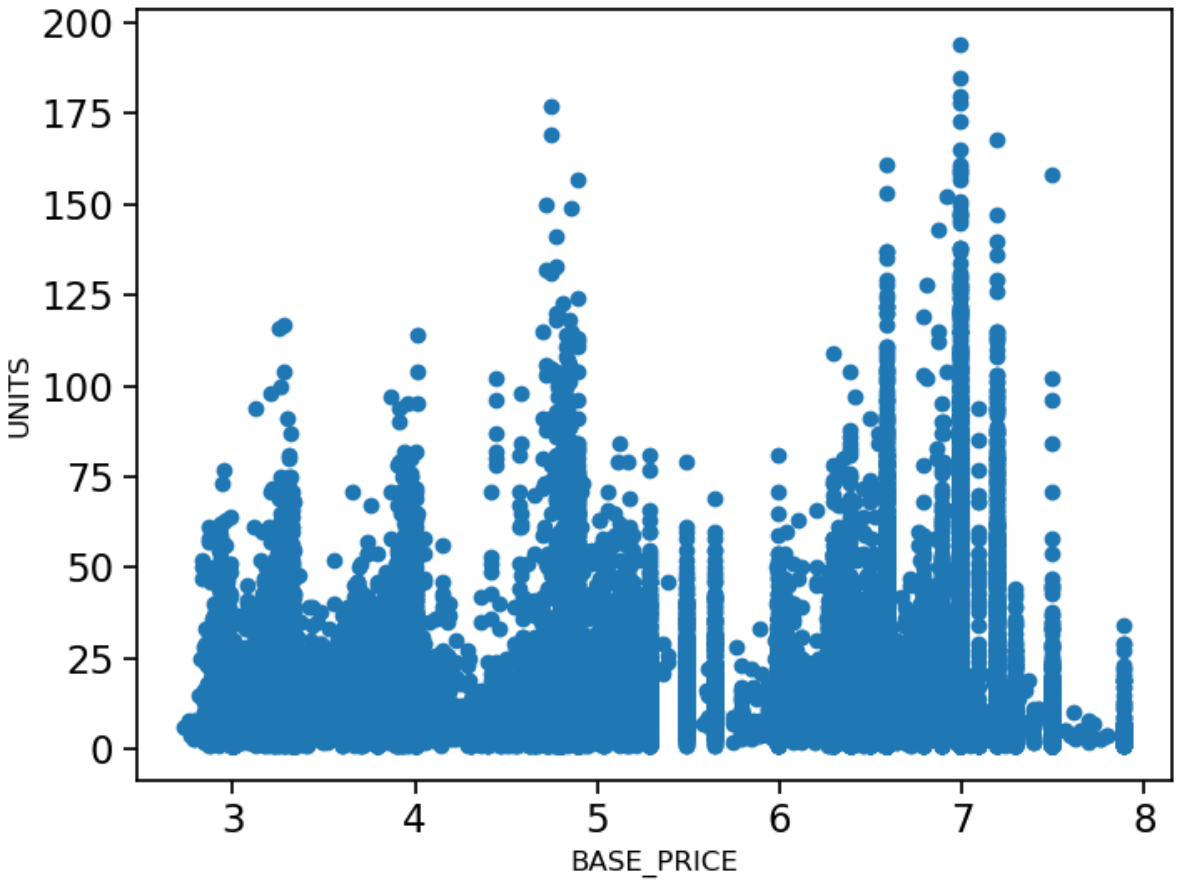
In [116]:
```
# scatter plot for base price and sales
plt.figure(figsize=(8,6))
plt.scatter(x = (product_size_bagsnacks['BASE_PRICE']), y = (produc
plt.xlabel('BASE_PRICE', fontsize=12)
plt.ylabel('UNITS', fontsize=12)
plt.show()
```



In [117]:
```
# scatter plot for base price and sales
plt.figure(figsize=(8,6))
plt.scatter(x = (product_size_oralhyiegne['BASE_PRICE']), y = (prod
plt.xlabel('BASE_PRICE', fontsize=12)
plt.ylabel('UNITS', fontsize=12)
plt.show()
```



In [118]:
```
# scatter plot for base price and sales
plt.figure(figsize=(8,6))
plt.scatter(x = (product_size_frozenpizza['BASE_PRICE']), y = (prod
plt.xlabel('BASE_PRICE', fontsize=12)
plt.ylabel('UNITS', fontsize=12)
plt.show()
```



- For bag snacks and oral hygiene category, items with lower price show a higher sale.
- Frozen pizza items have higher sale for higher price items.

Check the pattern for cold cereal at your end.

Product size versus Product Sales

- Product Size : Larger products should be more in demand

In [119]:
```
pd.crosstab(product_size_coldcereal['CATEGORY'], product_size_coldc
```

Out[119]:

PRODUCT_SIZE	12 OZ	12.2 OZ	12.25 OZ	15 OZ	18 OZ	20 OZ
CATEGORY						
COLD CEREAL	10786	10766	21426	10785	32203	10789

In [120]:
```
pd.crosstab(product_size_bagsnacks['CATEGORY'], product_size_bagsna
```

Out[120]:

PRODUCT_SIZE	10 OZ	15 OZ	16 OZ
CATEGORY			
BAG SNACKS	6916	28921	21443

Is the product sale higher for a particular brand or manufacturer?

Product sales for different manufacturers

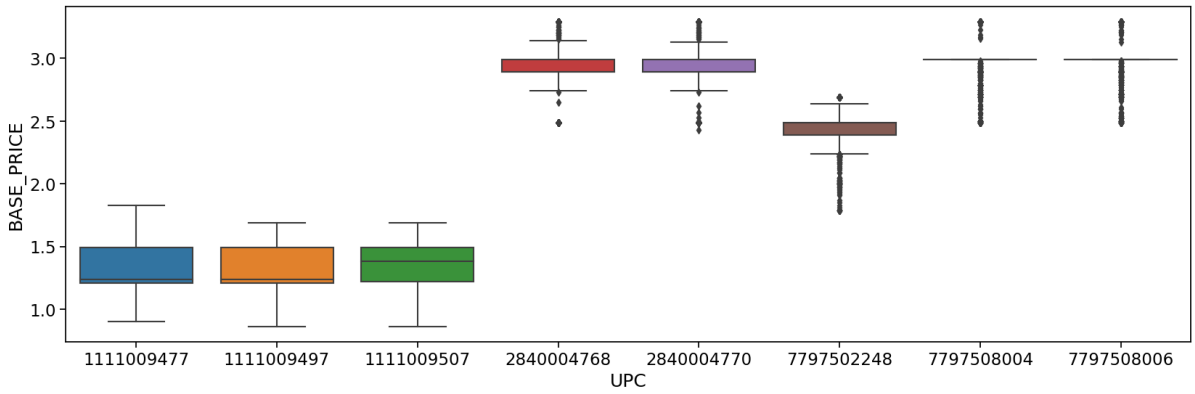
- Company/ Manufacturer: Well known brands/manufacturers will have higher sales

In [121]:
```
pretzels = list(product_data[product_data['CATEGORY'] == 'BAG SNACK
frozen_pizza = list(product_data[product_data['CATEGORY'] == 'FROZE
oral_hygiene = list(product_data[product_data['CATEGORY'] == 'ORAL 
cold_cereal = list(product_data[product_data['CATEGORY'] == 'COLD C
```

In [122]:
```
plt.figure(figsize=(20,6))
ax = sns.boxplot(x="UPC", y="BASE_PRICE", data=train[train['UPC'].i
product_data[product_data['UPC'].isin(pretzels)]
```

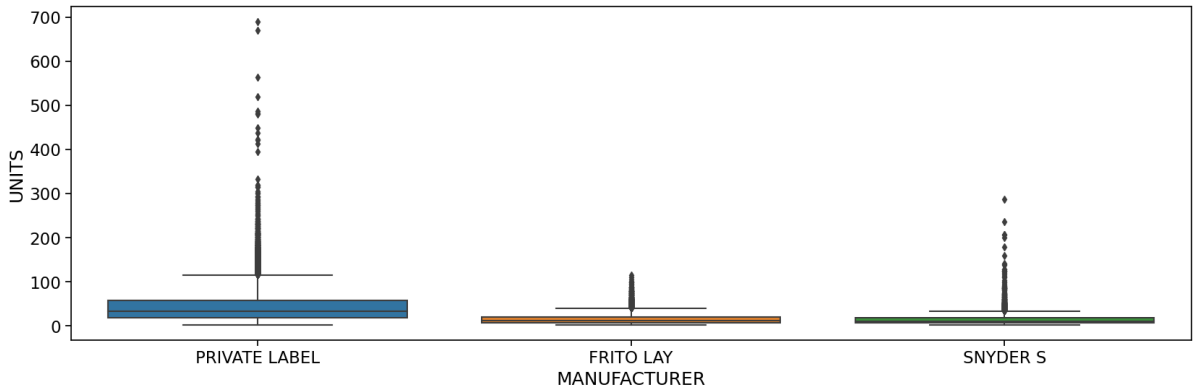
Out[122]:

	UPC	DESCRIPTION	MANUFACTURER	CATEGORY	SUB_CATEGORY	PRODUCT
0	1111009477	PL MINI TWIST PRETZELS	PRIVATE LABEL	BAG SNACKS	PRETZELS	
1	1111009497	PL PRETZEL STICKS	PRIVATE LABEL	BAG SNACKS	PRETZELS	
2	1111009507	PL TWIST PRETZELS	PRIVATE LABEL	BAG SNACKS	PRETZELS	
14	2840004768	RLDGLD TINY TWISTS PRTZL	FRITO LAY	BAG SNACKS	PRETZELS	
15	2840004770	RLDGLD PRETZEL STICKS	FRITO LAY	BAG SNACKS	PRETZELS	
25	7797502248	SNYDR PRETZEL RODS	SNYDER S	BAG SNACKS	PRETZELS	
26	7797508004	SNYDR SOURDOUGH NIBBLERS	SNYDER S	BAG SNACKS	PRETZELS	
27	7797508006	SNYDR FF MINI PRETZELS	SNYDER S	BAG SNACKS	PRETZELS	

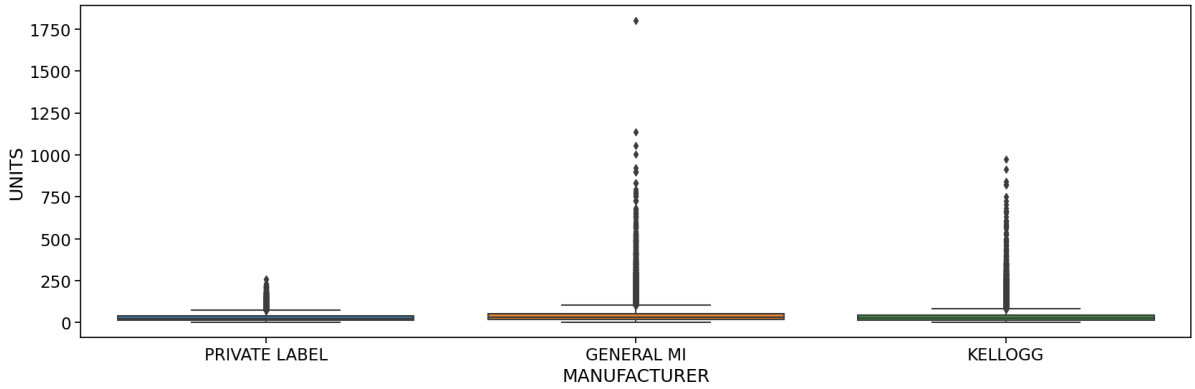


- All Private Label snacks have lower price.
- The Snyder S bag snacks with a smaller size has a lower price.

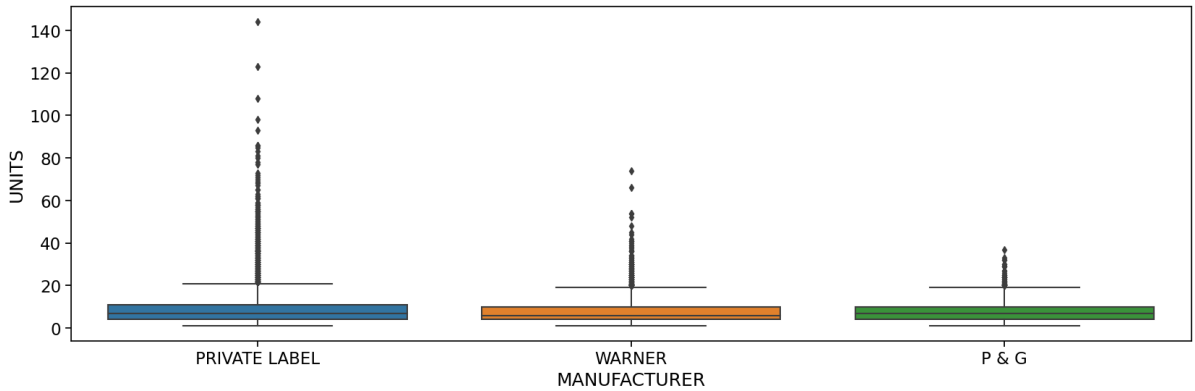
In [123]:
```
plt.figure(figsize=(20,6))
ax = sns.boxplot(x="MANUFACTURER", y="UNITS", data=store_product_da
```



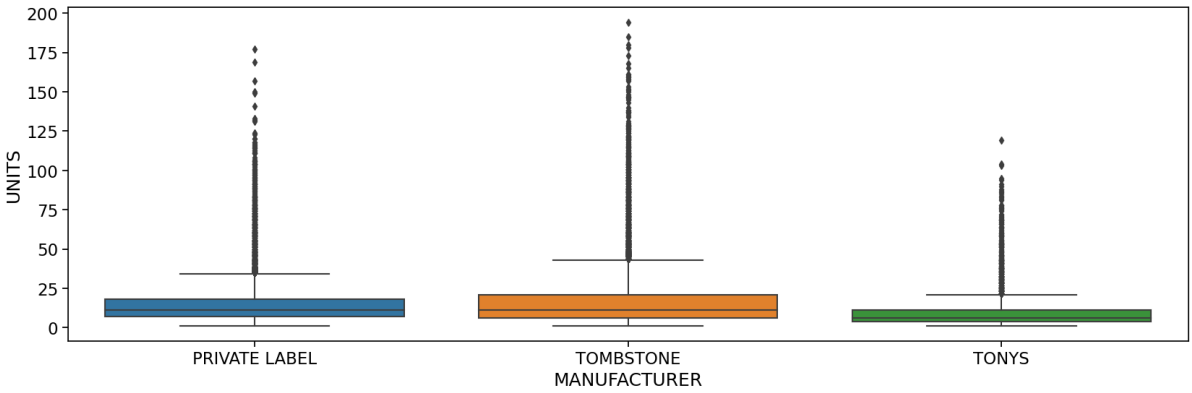
In [124]:
```
plt.figure(figsize=(20,6))
ax = sns.boxplot(x="MANUFACTURER", y="UNITS", data=store_product_da
```



In [125]:
```
plt.figure(figsize=(20,6))
ax = sns.boxplot(x="MANUFACTURER", y="UNITS", data=store_product_da
```



In [126]:
```
plt.figure(figsize=(20,6))
ax = sns.boxplot(x="MANUFACTURER", y="UNITS", data=store_product_da
```



Is there a significant difference in the product sales for different regions?

How are the sales different for stores in different cities?

Unit Sales for Stores in Different States

- Store Location: Stores in a particular state/city will have a similar trend

In [127]:
```
grouped_weekly_sales = store_product_data.groupby(['WEEK_END_DATE',

grouped_weekly_sales = grouped_weekly_sales.merge(store_data, how =

grouped_weekly_sales = grouped_weekly_sales.sort_values(by = 'ADDRE
```

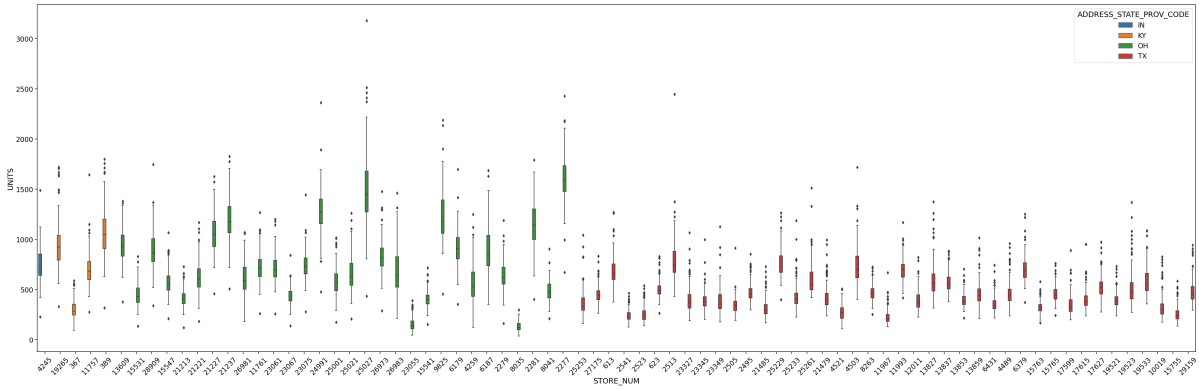
In [128]:
```
state = (store_data[['ADDRESS_STATE_PROV_CODE','STORE_ID']].sort_va
```

In [129]:
```
plt.figure(figsize=(50,15))

ax=sns.boxplot(x="STORE_NUM",y="UNITS",data=grouped_weekly_sales, h
plt.xticks(rotation=45)
```

Out[129]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14
, 15, 16,
        17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31
, 32, 33,
        34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48
, 49, 50,
        51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65
, 66, 67,
        68, 69, 70, 71, 72, 73, 74, 75]),
 [Text(0, 0, '4245'),
  Text(1, 0, '19265'),
  Text(2, 0, '367'),
```

```
Text(3, 0, '11757'),
Text(4, 0, '389'),
Text(5, 0, '13609'),
Text(6, 0, '15531'),
Text(7, 0, '28909'),
Text(8, 0, '15547'),
Text(9, 0, '21213'),
Text(10, 0, '21221'),
Text(11, 0, '21227'),
Text(12, 0, '21237'),
Text(13, 0, '26981'),
Text(14, 0, '11761'),
Text(15, 0, '23061'),
Text(16, 0, '23067'),
Text(17, 0, '23075'),
Text(18, 0, '24991'),
Text(19, 0, '25001'),
Text(20, 0, '25021'),
Text(21, 0, '25027'),
Text(22, 0, '26973'),
Text(23, 0, '26983'),
Text(24, 0, '23055'),
Text(25, 0, '15541'),
Text(26, 0, '9825'),
Text(27, 0, '6179'),
Text(28, 0, '4259'),
Text(29, 0, '6187'),
Text(30, 0, '2279'),
Text(31, 0, '8035'),
Text(32, 0, '2281'),
Text(33, 0, '8041'),
Text(34, 0, '2277'),
Text(35, 0, '25253'),
Text(36, 0, '27175'),
Text(37, 0, '613'),
Text(38, 0, '2541'),
Text(39, 0, '2523'),
Text(40, 0, '623'),
Text(41, 0, '2513'),
Text(42, 0, '23327'),
Text(43, 0, '23345'),
Text(44, 0, '23349'),
Text(45, 0, '2505'),
Text(46, 0, '2495'),
Text(47, 0, '21485'),
Text(48, 0, '25229'),
Text(49, 0, '25233'),
Text(50, 0, '25261'),
Text(51, 0, '21479'),
Text(52, 0, '4521'),
Text(53, 0, '4503'),
Text(54, 0, '8263'),
Text(55, 0, '11967'),
```

```
Text(56, 0, '11993'),
Text(57, 0, '12011'),
Text(58, 0, '13827'),
Text(59, 0, '13837'),
Text(60, 0, '13853'),
Text(61, 0, '13859'),
Text(62, 0, '6431'),
Text(63, 0, '4489'),
Text(64, 0, '6379'),
Text(65, 0, '15763'),
Text(66, 0, '15765'),
Text(67, 0, '17599'),
Text(68, 0, '17615'),
Text(69, 0, '17627'),
Text(70, 0, '19521'),
Text(71, 0, '19523'),
Text(72, 0, '19533'),
Text(73, 0, '10019'),
Text(74, 0, '15755'),
Text(75, 0, '29159')])
```



- The most frequent colors we see are green and orange - Ohio and Texas
- Mostly the number of units is higher for Ohio (considering individual stores)

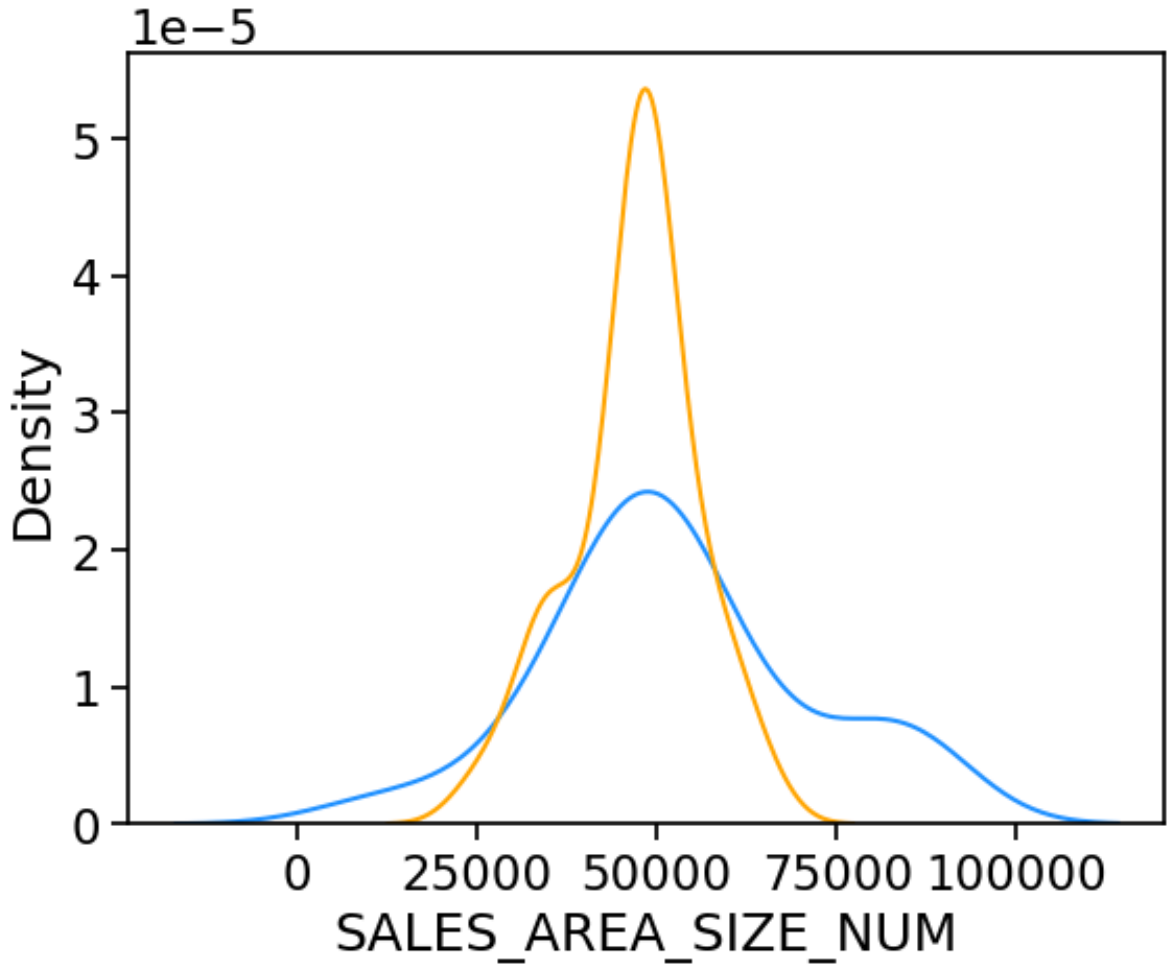
Store Size and unit sales

- Size of Store: Stores with larger area would have more sales

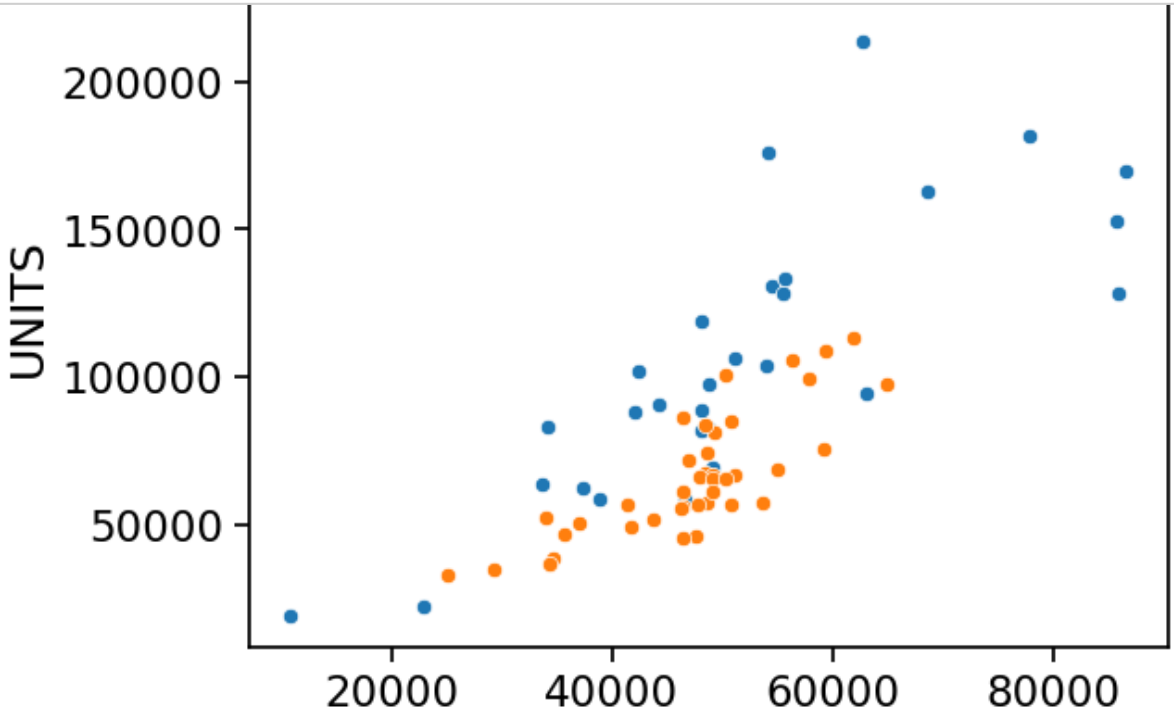
In [130]:
```
store_agg_data = train.groupby(['STORE_NUM'])['UNITS'].sum().reset_
merged_store_data = store_data.merge(store_agg_data, how = 'left',
```

In [131]:
```
state_oh = merged_store_data.loc[merged_store_data['ADDRESS_STATE_P
state_tx = merged_store_data.loc[merged_store_data['ADDRESS_STATE_P

sns.distplot(state_oh['SALES_AREA_SIZE_NUM'], hist=False,color= 'do
sns.distplot(state_tx['SALES_AREA_SIZE_NUM'], hist=False,  color= '
```

Out[131]: <Axes: xlabel='SALES_AREA_SIZE_NUM', ylabel='Density'>



In [132]:
```
sns.scatterplot(x = (state_oh['SALES_AREA_SIZE_NUM']), y = (state_o
sns.scatterplot(x = (state_tx['SALES_AREA_SIZE_NUM']), y = (state_t
```



We will pre-process the categorical features and then the numerical features on all the 3 available tables.

PREPROCESSING: CATEGORICAL FEATURES

- Find out and impute, if we have missing values in the categorical features.
- Remove the features which do not add much information
- Choose an Encoding scheme to convert categorical feature into numeric.

In [133]:
```
# importing required libraries

import pandas as pd
import numpy as np
import category_encoders as ce

import warnings
warnings.filterwarnings('ignore')

import matplotlib.pyplot as plt
%matplotlib inline
```

In [ ]:
```

```

In [ ]:

DATASET 1: Weekly Sales Data contains the following features

- **WEEK_END_DATE** - week date
- **STORE_NUM** - store number
- **UPC** - (Universal Product Code) product specific identifier
- **BASE_PRICE** - base price of item
- **DISPLAY** - product was a part of in-store promotional display
- **FEATURE** - product was in in-store circular
- **UNITS** - units sold (target)

In [134]:
```
# read the train data
data = pd.read_csv('train.csv')
data.head()
```

Out[134]:

	WEEK_END_DATE	STORE_NUM	UPC	PRICE	BASE_PRICE	FEATURE	DISPLAY
0	14-Jan-09	367	1111009477	1.39	1.57	0	0
1	14-Jan-09	367	1111009497	1.39	1.39	0	0
2	14-Jan-09	367	1111085319	1.88	1.88	0	0
3	14-Jan-09	367	1111085345	1.88	1.88	0	0
4	14-Jan-09	367	1111085350	1.98	1.98	0	0

WEEKLY SALES DATA has the following categorical features

- STORE_NUM
- UPC
- FEATURE
- DISPLAY

In [135]:
```
# check for the null values in the categorical features
data[['STORE_NUM', 'UPC', 'FEATURE', 'DISPLAY']].isna().sum()
```

Out[135]:
```
STORE_NUM    0
UPC          0
FEATURE      0
DISPLAY      0
dtype: int64
```

No Null Values

- STORE_NUM - No changes required as it is a key and will be used to merge tables later.
- UPC - No changes required as it is a key and will be used to merge tables later.
- FEATURE - No Preprocessing Required
- DISPLAY - No Preprocessing Required

DATASET 2: PRODUCT DATA contains the details about the products

- **UPC** - (Universal Product Code) product specific identifier
- **DESCRIPTION** - product description
- **MANUFACTURER** - product manufacturer
- **CATEGORY** - category of product
- **SUB_CATEGORY** - sub-category of product
- **PRODUCT_SIZE** - package size or quantity of product

In [136]:
```
# read the product data
product_data = pd.read_csv('product_data.csv')
product_data.head()
```

Out[136]:

	UPC	DESCRIPTION	MANUFACTURER	CATEGORY	SUB_CATEGORY	PRODUCT_
0	1111009477	PL MINI TWIST PRETZELS	PRIVATE LABEL	BAG SNACKS	PRETZELS	1
1	1111009497	PL PRETZEL STICKS	PRIVATE LABEL	BAG SNACKS	PRETZELS	1
2	1111009507	PL TWIST PRETZELS	PRIVATE LABEL	BAG SNACKS	PRETZELS	1
3	1111038078	PL BL MINT ANTSPTC RINSE	PRIVATE LABEL	ORAL HYGIENE PRODUCTS	MOUTHWASHES (ANTISEPTIC)	50
4	1111038080	PL ANTSPTC SPG MNT MTHWS	PRIVATE LABEL	ORAL HYGIENE PRODUCTS	MOUTHWASHES (ANTISEPTIC)	50

PRODUCT DATA has the following categorical features

- UPC
- DESCRIPTION
- MANUFACTURER
- CATEGORY
- SUB_CATEGORY
- PRODUCT_SIZE

In [137]:
```
# shape of the data
product_data.shape
```

Out[137]: (30, 6)

In [138]:
```
# check for the null values in the categorical features
product_data[['UPC', 'DESCRIPTION', 'MANUFACTURER', 'CATEGORY', 'SU
```

Out[138]:
```
UPC             0
DESCRIPTION     0
MANUFACTURER    0
CATEGORY        0
SUB_CATEGORY    0
PRODUCT_SIZE    0
dtype: int64
```

In [139]:
```
# number of unique description
product_data.DESCRIPTION.nunique()
```

Out[139]: 29

In [140]:
```
# number of unique manufacturer
product_data.MANUFACTURER.nunique()
```

Out[140]: 9

In [141]:
```
# number of unique categories
product_data.CATEGORY.nunique()
```

Out[141]: 4

In [142]:
```
# number of unique sub categories
product_data.SUB_CATEGORY.nunique()
```

Out[142]: 7

In [143]:
```
# number of unique product sizes
product_data.PRODUCT_SIZE.nunique()
```

Out[143]: 16

- `DESCRIPTION` - In the description, we have category, subcategory and size of the product and these are already present in the other features as well. So, We will drop this feature as it will not add much value to the model.
- `MANUFACTURER` , `CATEGORY` , `SUB_CATEGORY` - As, there is no order in the given categories, so we will One Hot Encode this features.
- `PRODUCT_SIZE` - The product size units are different for different categories of products. So, here for each category we will do the binning based on different sizes.

In [144]:
```
# drop the DESCRIPTION FEATURE
product_data = product_data.drop(columns= ['DESCRIPTION'])
product_data
```

Out[144]:

	UPC	MANUFACTURER	CATEGORY	SUB_CATEGORY	PRODUCT_SIZE
0	1111009477	PRIVATE LABEL	BAG SNACKS	PRETZELS	15 OZ
1	1111009497	PRIVATE LABEL	BAG SNACKS	PRETZELS	15 OZ
2	1111009507	PRIVATE LABEL	BAG SNACKS	PRETZELS	15 OZ
3	1111038078	PRIVATE LABEL	ORAL HYGIENE PRODUCTS	MOUTHWASHES (ANTISEPTIC)	500 ML
4	1111038080	PRIVATE LABEL	ORAL HYGIENE PRODUCTS	MOUTHWASHES (ANTISEPTIC)	500 ML
5	1111085319	PRIVATE LABEL	COLD CEREAL	ALL FAMILY CEREAL	12.25 OZ
6	1111085345	PRIVATE LABEL	COLD CEREAL	ADULT CEREAL	20 OZ
7	1111085350	PRIVATE LABEL	COLD	ALL FAMILY CEREAL	18 OZ

In [145]:
```
# remove the units from the product size
# we will keep only the values
product_data['PRODUCT_SIZE'] = product_data.PRODUCT_SIZE.apply(lamb
```

In [146]:
```
# change data type of product size from string to float
product_data.PRODUCT_SIZE = product_data.PRODUCT_SIZE.astype(float)
```

In [147]:
```
# Let's see the unique product size values for each category
product_data.groupby(['CATEGORY'])['PRODUCT_SIZE'].unique()
```

Out[147]:
```
CATEGORY
BAG SNACKS                                    [15.0, 16.0, 10.0]
COLD CEREAL                [12.25, 20.0, 18.0, 12.0, 15.0, 12.2]
FROZEN PIZZA                [32.7, 30.5, 29.6, 29.8, 28.3, 22.7]
ORAL HYGIENE PRODUCTS                                [500.0, 1.0]
Name: PRODUCT_SIZE, dtype: object
```

In [148]:
```
# Define 3 bins for category type = "COLD CEREAL"
product_data.loc[product_data.CATEGORY == 'COLD CEREAL', 'PRODUCT_S
    product_data.loc[product_data.CATEGORY == 'COLD CEREAL', 'PRODU
    bins=[10, 13, 16, 21],
    labels=[1, 2, 3]
)
```

In [149]:
```
# Define 2 bins for category type = "ORAL HYGIENE PRODUCTS"
product_data.loc[product_data.CATEGORY == 'ORAL HYGIENE PRODUCTS',
    product_data.loc[product_data.CATEGORY == 'ORAL HYGIENE PRODUCT
```

In [150]:
```
# Define 3 bins for category type = "FROZEN PIZZA"
product_data.loc[product_data.CATEGORY == 'FROZEN PIZZA', 'PRODUCT_
    product_data.loc[product_data.CATEGORY == 'FROZEN PIZZA', 'PROD
    bins=[20, 25, 30, 35],
    labels=[1, 2, 3]
)
```

In [151]:
```
# Define 2 bins for category type = "BAG SNACKS"
product_data.loc[product_data.CATEGORY == 'BAG SNACKS', 'PRODUCT_SI
    product_data.loc[product_data.CATEGORY == 'BAG SNACKS', 'PRODUC
```

In [152]:
```
# value counts of PRODUCT SIZE
product_data.PRODUCT_SIZE.value_counts()
```

Out[152]:
```
15.00     4
16.00     4
1.00      4
18.00     3
500.00    2
12.25     2
32.70     2
20.00     1
30.50     1
29.60     1
12.00     1
12.20     1
29.80     1
28.30     1
22.70     1
10.00     1
Name: PRODUCT_SIZE, dtype: int64
```

In [153]:
```
# One Hot Encode the features
OHE_p = ce.OneHotEncoder(cols= ['MANUFACTURER', 'CATEGORY', 'SUB_CA
```

In [154]:
```
# transform the data
product_data = OHE_p.fit_transform(product_data)
```

In [155]:
```
# updated data
product_data.head()
```

Out[155]:

	UPC	MANUFACTURER_1	MANUFACTURER_2	MANUFACTURER_3	MANUFACTUR
0	1111009477	1	0	0	
1	1111009497	1	0	0	
2	1111009507	1	0	0	
3	1111038078	1	0	0	
4	1111038080	1	0	0	

5 rows × 23 columns

In [156]:
```
# shape of the updated data
product_data.shape
```

Out[156]:
```
(30, 23)
```

In [157]:
```
# columns of the updated data
product_data.columns
```

Out[157]:
```
Index(['UPC', 'MANUFACTURER_1', 'MANUFACTURER_2', 'MANUFACTURER_3'
,
       'MANUFACTURER_4', 'MANUFACTURER_5', 'MANUFACTURER_6', 'MANU
FACTURER_7',
       'MANUFACTURER_8', 'MANUFACTURER_9', 'CATEGORY_1', 'CATEGORY
_2',
       'CATEGORY_3', 'CATEGORY_4', 'SUB_CATEGORY_1', 'SUB_CATEGORY
_2',
       'SUB_CATEGORY_3', 'SUB_CATEGORY_4', 'SUB_CATEGORY_5', 'SUB_
CATEGORY_6',
       'SUB_CATEGORY_7', 'PRODUCT_SIZE', 'PRODUCT_SIZE_BIN'],
      dtype='object')
```

DATASET 3: STORE DATA

- **STORE_ID** - store number
- **STORE_NAME** - Name of store
- **ADDRESS_CITY_NAME** - city
- **ADDRESS_STATE_PROV_CODE** - state
- **MSA_CODE** - (Metropolitan Statistical Area) Based on geographic region and population density
- **SEG_VALUE_NAME** - Store Segment Name
- **PARKING_SPACE_QTY** - number of parking spaces in the store parking lot
- **SALES_AREA_SIZE_NUM** - square footage of store
- **AVG_WEEKLY_BASKETS** - average weekly baskets sold in the store

In [158]:
```
# read the store data
store_data = pd.read_csv('store_data.csv')
store_data.head()
```

Out[158]:

	STORE_ID	STORE_NAME	ADDRESS_CITY_NAME	ADDRESS_STATE_PROV_CODE	MSA_C
0	367	15TH & MADISON	COVINGTON	KY	
1	389	SILVERLAKE	ERLANGER	KY	
2	613	EAST ALLEN	ALLEN	TX	
3	623	HOUSTON	HOUSTON	TX	2
4	2277	ANDERSON TOWNE CTR	CINCINNATI	OH	

STORE DATA has the following categorical features

- STORE_ID
- STORE_NAME
- ADDRESS_CITY_NAME
- ADDRESS_STATE_PROV_CODE
- MSA_CODE
- SEG_VALUE_NAME

In [159]:
```
# shape of the store data
store_data.shape
```

Out[159]:
```
(76, 9)
```

In [160]:
```
# check for the null values

store_data[['STORE_ID', 'STORE_NAME', 'ADDRESS_CITY_NAME', 'ADDRESS
```

Out[160]:
```
STORE_ID                   0
STORE_NAME                 0
ADDRESS_CITY_NAME          0
ADDRESS_STATE_PROV_CODE    0
MSA_CODE                   0
SEG_VALUE_NAME             0
dtype: int64
```

In [161]:
```
# number of unique store names
store_data.STORE_NAME.nunique()
```

Out[161]:
```
72
```

In [162]:
```
# number of unique city names
store_data.ADDRESS_CITY_NAME.nunique()
```

Out[162]:
```
51
```

In [163]:
```
# number of unique state provision code
store_data.ADDRESS_STATE_PROV_CODE.nunique()
```

Out[163]:
```
4
```

In [164]:
```
# number of unique msa code
store_data.MSA_CODE.nunique()
```

Out[164]:
```
9
```

In [165]:
```
# number of unique segment value names
store_data.SEG_VALUE_NAME.nunique()
```

Out[165]:
```
3
```

- `STORE_ID` - No changes required as it is a key and will be used to merge files later.
- `STORE_NAME` - Since, Out of 76 different stores we have 72 unique store names. Store name contains some location information of the store which we have in the form of address city name and state.
- `ADDRESS_CITY_NAME` - Since, Out of 76 different stores we have 51 unique address city names, So we will drop this feature due to high cardinality
- `ADDRESS_STATE_PROV_CODE` , `MSA_CODE` - As, there is no order in the given categories, So, we will One Hot Encode this variable.
- `SEG_VALUE_NAME` - Stores segments are divided into 3 categories: upscale, mainstream and value. Upscale stores are just what they sound like; they are normally located in high income neighborhoods and offer more high-end product. Mainstream is middle of the road, mostly located in middle class areas, offering a mix of upscale and value product. Value stores cater more to low income customers, so there will be more focus on low prices than anything else.

So we will map `VALUE AS 1` , `MAINSTREAM AS 2` and `UPSCALE AS 3` .

In [166]:
```
# drop store name and address
store_data = store_data.drop(columns=['STORE_NAME', 'ADDRESS_CITY_N
```

In [167]:
```
# OneHotEncode the rest of the categorical features
OHE = ce.OneHotEncoder(cols=['ADDRESS_STATE_PROV_CODE', 'MSA_CODE']

store_data.SEG_VALUE_NAME = store_data.SEG_VALUE_NAME.map({'VALUE':
```

In [168]:
```
# transform the data
store_data = OHE.fit_transform(store_data)
```

In [169]:
```
# updated data
store_data.head()
```

Out[169]:

	STORE_ID	ADDRESS_STATE_PROV_CODE_1	ADDRESS_STATE_PROV_CODE_2	ADDRESS
0	367	1	0	
1	389	1	0	
2	613	0	1	
3	623	0	1	
4	2277	0	0	

In [170]:
```
# shape of the updated data
store_data.shape
```

Out[170]:
```
(76, 18)
```

In [171]:
```
# columns of the updated data
store_data.columns
```

Out[171]:
```
Index(['STORE_ID', 'ADDRESS_STATE_PROV_CODE_1', 'ADDRESS_STATE_PRO
V_CODE_2',
       'ADDRESS_STATE_PROV_CODE_3', 'ADDRESS_STATE_PROV_CODE_4', '
MSA_CODE_1',
       'MSA_CODE_2', 'MSA_CODE_3', 'MSA_CODE_4', 'MSA_CODE_5', 'MS
A_CODE_6',
       'MSA_CODE_7', 'MSA_CODE_8', 'MSA_CODE_9', 'SEG_VALUE_NAME',
       'PARKING_SPACE_QTY', 'SALES_AREA_SIZE_NUM', 'AVG_WEEKLY_BAS
KETS'],
      dtype='object')
```

In [172]:
```
store_data.loc[0]
```

Out[172]:
```
STORE_ID                      367.0
ADDRESS_STATE_PROV_CODE_1       1.0
ADDRESS_STATE_PROV_CODE_2       0.0
ADDRESS_STATE_PROV_CODE_3       0.0
ADDRESS_STATE_PROV_CODE_4       0.0
MSA_CODE_1                      1.0
MSA_CODE_2                      0.0
MSA_CODE_3                      0.0
MSA_CODE_4                      0.0
MSA_CODE_5                      0.0
MSA_CODE_6                      0.0
MSA_CODE_7                      0.0
MSA_CODE_8                      0.0
MSA_CODE_9                      0.0
SEG_VALUE_NAME                  1.0
PARKING_SPACE_QTY             196.0
SALES_AREA_SIZE_NUM         24721.0
AVG_WEEKLY_BASKETS          12707.0
Name: 0, dtype: float64
```

PREPROCESSING: NUMERICAL FEATURES

- Check and impute the missing values in the numerical features.
- Check for the outliers and treat them.

DATASET 1: WEEKLY SALES DATA

In [173]:
```
data.head()
```

Out[173]:

	WEEK_END_DATE	STORE_NUM	UPC	PRICE	BASE_PRICE	FEATURE	DISPLAY
0	14-Jan-09	367	1111009477	1.39	1.57	0	0
1	14-Jan-09	367	1111009497	1.39	1.39	0	0
2	14-Jan-09	367	1111085319	1.88	1.88	0	0
3	14-Jan-09	367	1111085345	1.88	1.88	0	0
4	14-Jan-09	367	1111085350	1.98	1.98	0	0

WEEKLY SALES DATA has the following numerical features

- BASE_PRICE
- UNITS (Target)

- BASE_PRICE - Missing Value Imputation

In [174]:
```
# check the null values for the numerical features
data[[ 'BASE_PRICE', 'UNITS']].isna().sum()
```

Out[174]:
```
BASE_PRICE    12
UNITS          0
dtype: int64
```

Imputing the missing values in the Base Price

In [175]:
```
# create a new dataframe which will have "average base price" for t
# we will use this to impute the missing values
avg_price = data.groupby(['STORE_NUM', 'UPC'])['BASE_PRICE'].mean()
```

In [176]:
```
avg_price
```

Out[176]:

	STORE_NUM	UPC	BASE_PRICE
0	367	1111009477	1.489859
1	367	1111009497	1.490634
2	367	1111085319	1.843451
3	367	1111085345	1.827183
4	367	1111085350	2.322113
...	...	...	...
1639	29159	7192100336	6.494965
1640	29159	7192100337	6.496312
1641	29159	7192100339	6.504085
1642	29159	7797502248	2.445634
1643	29159	7797508004	2.952606

1644 rows × 3 columns

In [177]:
```
# null values in BASE PRICE
data.loc[data.BASE_PRICE.isna() == True]
```

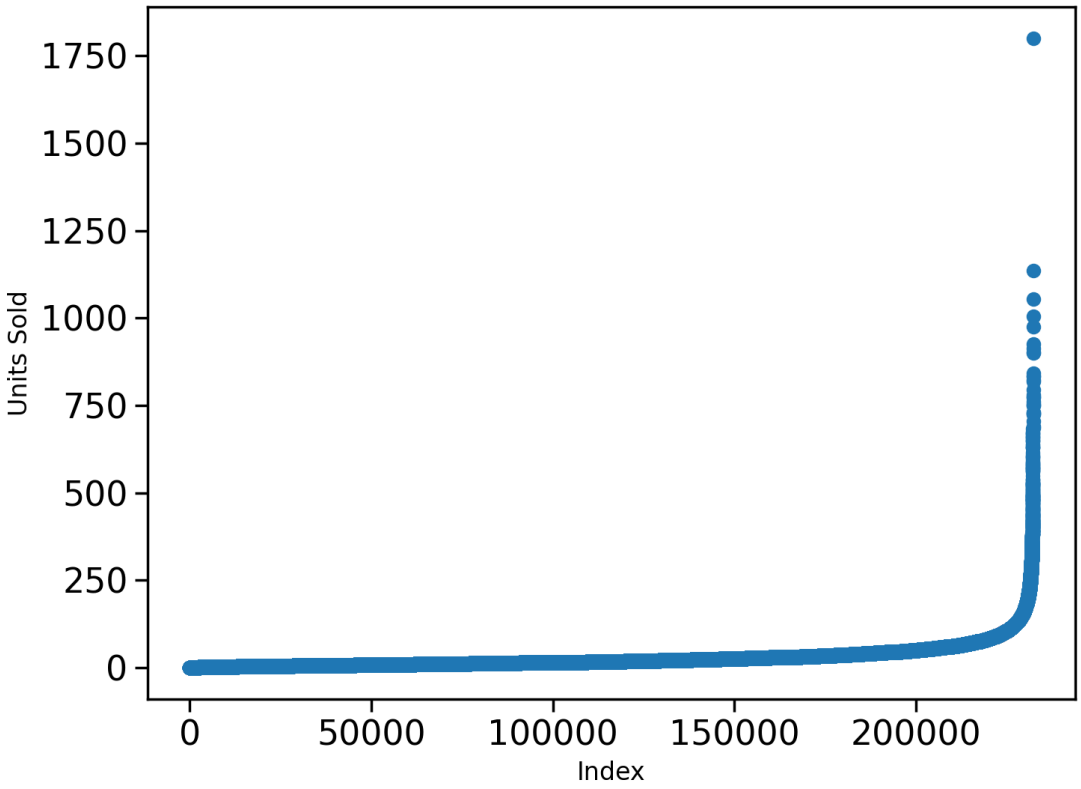
Out[177]:

	WEEK_END_DATE	STORE_NUM	UPC	PRICE	BASE_PRICE	FEATURE	DISPL
279	14-Jan-09	4245	1111087395	3.32	NaN	0	
280	14-Jan-09	4245	1111087398	3.31	NaN	0	
301	14-Jan-09	4259	1111087395	3.33	NaN	0	
303	14-Jan-09	4259	1111087398	3.39	NaN	0	
1918	21-Jan-09	4245	1111087395	3.30	NaN	0	
1919	21-Jan-09	4245	1111087398	3.28	NaN	0	
1940	21-Jan-09	4259	1111087395	3.33	NaN	0	
3555	28-Jan-09	4245	1111087395	3.37	NaN	1	
3556	28-Jan-09	4245	1111087398	3.34	NaN	1	
3577	28-Jan-09	4259	1111087395	3.27	NaN	1	
5191	04-Feb-09	4245	1111087395	3.32	NaN	0	
5192	04-Feb-09	4245	1111087398	3.29	NaN	0	

In [178]:
```
# define function to fill missing base price values
def fill_base_price(x) :
    return avg_price.BASE_PRICE[(avg_price.STORE_NUM == x['STORE_NU
```

In [179]:
```
data.BASE_PRICE[data.BASE_PRICE.isna() == True] = data[data.BASE_PR
```

In [180]:
```
# scatter plot for UNITS variable
# sort the target variable and scatter plot to see if it has some o

%matplotlib notebook
plt.figure(figsize=(8,6))
plt.scatter(x = range(data.shape[0]), y = np.sort(data['UNITS'].val
plt.xlabel('Index', fontsize=12)
plt.ylabel('Units Sold', fontsize=12)
plt.show()
```



In [181]:
```
# number of data points where units are more than 750
data['UNITS'][data.UNITS > 750].shape[0]
```

Out[181]: 21

We can see that, there are a some points above where UNITS are more than 750 and there number is only 21. So, we can remove them as there number is only 21 and will not affect the data and these will act as a noise to our model.

In [182]:
```
data.shape
```

Out[182]: (232287, 8)

In [183]:
```
# remove the values where UNITS are more than 750
data = data[~(data.UNITS > 750)]
```

In [184]:
```
data[data.UNITS > 750].shape[0]
```

Out[184]: 0

DATASET 2: PRODUCT DATA

In [185]:
```
# view the product data
product_data.head()
```

Out[185]:

	UPC	MANUFACTURER_1	MANUFACTURER_2	MANUFACTURER_3	MANUFACTUR
0	1111009477	1	0	0	
1	1111009497	1	0	0	
2	1111009507	1	0	0	
3	1111038078	1	0	0	
4	1111038080	1	0	0	

5 rows × 23 columns

PRODUCT DATA has the following numerical feature

- This dataset has no numerical feature.

DATASET 3: STORE DATA

In [186]:
```
# view the data
store_data.head()
```

Out[186]:

	STORE_ID	ADDRESS_STATE_PROV_CODE_1	ADDRESS_STATE_PROV_CODE_2	ADDRESS
0	367	1	0	
1	389	1	0	
2	613	0	1	
3	623	0	1	
4	2277	0	0	

STORE DATA has the following numerical features

- PARKING_SPACE_QTY
- SALES_AREA_SIZE_NUM
- AVG_WEEKLY_BASKETS

In [187]:
```
# shape of the data
store_data.shape
```

Out[187]: (76, 18)

In [188]:
```
# check for the null values
store_data[['PARKING_SPACE_QTY', 'SALES_AREA_SIZE_NUM', 'AVG_WEEKLY
```

Out[188]:
```
PARKING_SPACE_QTY      51
SALES_AREA_SIZE_NUM     0
AVG_WEEKLY_BASKETS      0
dtype: int64
```

- PARKING_SPACE_QTY - Check its correlation with the SALES_AREA_SIZE_NUM

In [189]:
```
# check correlation
store_data[['PARKING_SPACE_QTY','SALES_AREA_SIZE_NUM']].corr()
```

Out[189]:

	PARKING_SPACE_QTY	SALES_AREA_SIZE_NUM
PARKING_SPACE_QTY	1.000000	0.763274
SALES_AREA_SIZE_NUM	0.763274	1.000000

Note: Since the correlation of the **PARKING_SPACE_QTY** with **SALES_AREA_SIZE_NUM** is high so we can drop this column as it will not add much value to the model.

In [190]:
```
# drop the column
store_data = store_data.drop(columns=['PARKING_SPACE_QTY'])
```

SAVE THE UPDATED FILES

In [191]:
```
data.to_csv('updated_train_data.csv',index=False)
product_data.to_csv('updated_product_data.csv',index=False)
store_data.to_csv('updated_store_data.csv',index=False)
```

Baseline Model

Now that we have done the pre-processing and decided the evaluation metric (RMSLE), we will create baseline models for forecasting demand.

Generally, we create baseline model using very basic techniques like mean prediction and then we try more complex solutions to improve the results that we got from the baseline model. The idea is to spot bugs in our final model as any score which is below baseline is not good enough.

- Predict the target using the mean demand from historical data for that particular store and product
- Use Simple Moving Average (a very basic Time Series Model).
- Train a linear Regression based model and Decision Tree model.

In [192]:
```
# importing the required libraries

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

import warnings
warnings.filterwarnings('ignore')

from sklearn.metrics import mean_squared_log_error as msle

from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
```

In [193]:
```
# reading the pre-processed dataset
train_data = pd.read_csv('updated_train_data.csv')
product_data = pd.read_csv('updated_product_data.csv')
store_data = pd.read_csv('updated_store_data.csv')
```

In [194]:
```
# view the train data
train_data.head(2)
```

Out[194]:

	WEEK_END_DATE	STORE_NUM	UPC	PRICE	BASE_PRICE	FEATURE	DISPLAY
0	14-Jan-09	367	1111009477	1.39	1.57	0	0
1	14-Jan-09	367	1111009497	1.39	1.39	0	0

In [195]:
```
# view the product data
product_data.head(2)
```

Out[195]:

	UPC	MANUFACTURER_1	MANUFACTURER_2	MANUFACTURER_3	MANUFACTUR
0	1111009477	1	0	0	
1	1111009497	1	0	0	

2 rows × 23 columns

In [196]:
```
# view the store data
store_data.head(2)
```

Out[196]:

	STORE_ID	ADDRESS_STATE_PROV_CODE_1	ADDRESS_STATE_PROV_CODE_2	ADDRESS_
0	367	1	0	
1	389	1	0	

Merging Tables

In [197]:
```
# merge the datasets
merge_data = train_data.merge(product_data, how='left', on= 'UPC')
merge_data = merge_data.merge(store_data, how= 'left', left_on= 'ST
```

In [198]:
```
merge_data = merge_data.drop(columns=['STORE_ID'])
```

In [199]:
```
# check if there is any null value in the final merged data set.
merge_data.isna().sum()
```

Out[199]:
```
WEEK_END_DATE                0
STORE_NUM                    0
UPC                          0
PRICE                        3
BASE_PRICE                   0
FEATURE                      0
DISPLAY                      0
UNITS                        0
MANUFACTURER_1               0
MANUFACTURER_2               0
MANUFACTURER_3               0
MANUFACTURER_4               0
MANUFACTURER_5               0
MANUFACTURER_6               0
MANUFACTURER_7               0
MANUFACTURER_8               0
MANUFACTURER_9               0
CATEGORY_1                   0
CATEGORY_2                   0
CATEGORY_3                   0
CATEGORY_4                   0
SUB_CATEGORY_1               0
SUB_CATEGORY_2               0
SUB_CATEGORY_3               0
SUB_CATEGORY_4               0
SUB_CATEGORY_5               0
SUB_CATEGORY_6               0
SUB_CATEGORY_7               0
PRODUCT_SIZE                 0
PRODUCT_SIZE_BIN             0
ADDRESS_STATE_PROV_CODE_1    0
ADDRESS_STATE_PROV_CODE_2    0
ADDRESS_STATE_PROV_CODE_3    0
ADDRESS_STATE_PROV_CODE_4    0
MSA_CODE_1                   0
MSA_CODE_2                   0
MSA_CODE_3                   0
MSA_CODE_4                   0
MSA_CODE_5                   0
MSA_CODE_6                   0
MSA_CODE_7                   0
MSA_CODE_8                   0
MSA_CODE_9                   0
SEG_VALUE_NAME               0
SALES_AREA_SIZE_NUM          0
AVG_WEEKLY_BASKETS           0
dtype: int64
```

In [200]:
```
merge_data['PRICE'].fillna(merge_data['PRICE'].mean(), inplace=True
```

In [201]:
```
# let's look at a row, how data looks in the merged dataset
merge_data.loc[0]
```

Out[201]:

WEEK_END_DATE	14-Jan-09
STORE_NUM	367
UPC	1111009477
PRICE	1.39
BASE_PRICE	1.57
FEATURE	0
DISPLAY	0
UNITS	13
MANUFACTURER_1	1
MANUFACTURER_2	0
MANUFACTURER_3	0
MANUFACTURER_4	0
MANUFACTURER_5	0
MANUFACTURER_6	0
MANUFACTURER_7	0
MANUFACTURER_8	0
MANUFACTURER_9	0
CATEGORY_1	1
CATEGORY_2	0
CATEGORY_3	0
CATEGORY_4	0
SUB_CATEGORY_1	1
SUB_CATEGORY_2	0
SUB_CATEGORY_3	0
SUB_CATEGORY_4	0
SUB_CATEGORY_5	0
SUB_CATEGORY_6	0
SUB_CATEGORY_7	0
PRODUCT_SIZE	15.0
PRODUCT_SIZE_BIN	2
ADDRESS_STATE_PROV_CODE_1	1
ADDRESS_STATE_PROV_CODE_2	0
ADDRESS_STATE_PROV_CODE_3	0
ADDRESS_STATE_PROV_CODE_4	0
MSA_CODE_1	1
MSA_CODE_2	0
MSA_CODE_3	0
MSA_CODE_4	0
MSA_CODE_5	0
MSA_CODE_6	0
MSA_CODE_7	0
MSA_CODE_8	0
MSA_CODE_9	0
SEG_VALUE_NAME	1
SALES_AREA_SIZE_NUM	24721
AVG_WEEKLY_BASKETS	12707

Name: 0, dtype: object

Creating the Validation Set

In [202]:
```
# convert the column WEEK_END_DATE to datetime format
merge_data.WEEK_END_DATE = pd.to_datetime(merge_data.WEEK_END_DATE)
```

- We will store the unique `WEEK_END_DATE` in a list so that it would be easier to split the data based on time. It will be used to create and train and validation split.
- We will keep one week gap between the train and validation set and train set will start from the very begining from where the data is available.

In [203]:
```
# store the unique dates as the dates are already sorted in the ori
weeks = merge_data.WEEK_END_DATE.unique()
```

In [204]:
```
# define the function that will return a dictionary which contains

"""
[
  {
 "validation_set" : ## validation set week,
 "train_set_end_date" : ## last week of trainind set with one gap w
  },
  .
  .
  .
  {
   "validation_set" : ''
   "train_set_end_date" : ''
  }
]

Initially, we will use the same start date of each training data se


The function will take the parameter number which is the number of
"""
def get_train_validation_set(number=1):
    validation_sets = []
    for n in range(number):
        x = {}

        x['validation_set'] = weeks[len(weeks)-n-1]
        x['train_set_end_date'] = weeks[len(weeks)-n-3]
        validation_sets.append(x)

    return validation_sets
```

We could go ahead with just 1 validation set to check the RMSLE score we are getting from different baseline models. However, taking multiple validation sets also allows us to look at the consistency of scores across multiple subsets of data.

Here, we will take 5 validation sets for starters

In [205]:
```
# we will create our baseline model and test it on 5 different sets
validation_sets = get_train_validation_set(number=5)
```

In [206]:
```
# the dictionary that we got from our function
validation_sets
```

Out[206]:
```
[{'validation_set': numpy.datetime64('2011-09-28T00:00:00.000000000'),
  'train_set_end_date': numpy.datetime64('2011-09-14T00:00:00.000000000')},
 {'validation_set': numpy.datetime64('2011-09-21T00:00:00.000000000'),
  'train_set_end_date': numpy.datetime64('2011-09-07T00:00:00.000000000')},
 {'validation_set': numpy.datetime64('2011-09-14T00:00:00.000000000'),
  'train_set_end_date': numpy.datetime64('2011-08-31T00:00:00.000000000')},
 {'validation_set': numpy.datetime64('2011-09-07T00:00:00.000000000'),
  'train_set_end_date': numpy.datetime64('2011-08-24T00:00:00.000000000')},
 {'validation_set': numpy.datetime64('2011-08-31T00:00:00.000000000'),
  'train_set_end_date': numpy.datetime64('2011-08-17T00:00:00.000000000')}]
```

In [207]:
```
# Now, we will use that dictionary and store the train and validati


"""
data_set = [ (train_set_1, valid_set_1), ()..... (train_set_n, va

"""

data_set = []

for data in validation_sets:

    training_data = merge_data[merge_data.WEEK_END_DATE <= data['tr
    validation_data = merge_data[merge_data.WEEK_END_DATE == data['

    data_set.append((training_data, validation_data))
```

MEAN PREDICTION

Now, we will create our first baseline model, `MEAN PREDICTION` . We will use the past data to take average on a group of `STORE_NUM` and `UPC` and use this to predict on the validaion set.

`Evaluation Metric:` **Root Mean Squared Log Error**

In [208]:
```
# define the function to get the RMSLE

def get_msle(true, predicted) :
    return np.sqrt(msle( true, predicted))
```

In [209]:
```

```

```
train_rmsle = []
valid_rmsle = []

for i, data in enumerate(data_set):

    # get the train and validation set
    train, valid = data

    # get the mean prediction dataframe by using a groupby on STORE
    mean_prediction = train.groupby(['STORE_NUM', 'UPC'])['UNITS'].

    # left join the train and validation set with the mean predicti
    train = train.merge(mean_prediction, how='left', on=['STORE_NUM
    valid = valid.merge(mean_prediction, how='left', on=['STORE_NUM

    # In the updated dataframe after the left join,
    # column UNITS_x is the original value of the target variable
    # column UNITS_y is the predicted value of the target variable

    # get the rmsle on train and validation set
    t_rmsle = get_msle(train.UNITS_x, train.UNITS_y)
    v_rmsle = get_msle(valid.UNITS_x, valid.UNITS_y)
    train_rmsle.append(t_rmsle)
    valid_rmsle.append(v_rmsle)

    print('RMSLE ON TRAINING SET: ',i+1, ': ', t_rmsle)
    print('RMSLE ON VALIDATION SET: ',i+1, ': ',v_rmsle)
    print('=============================================================

# get the mean RMSLE on train and validation set.
print('Mean RMSLE on Train: ', np.mean(train_rmsle))
print('Mean RMSLE on Valid: ', np.mean(valid_rmsle))
```

```
RMSLE ON TRAINING SET:  1 :  0.5902592110738579
RMSLE ON VALIDATION SET:  1 :  0.5887804241752373
============================================================
===
RMSLE ON TRAINING SET:  2 :  0.5912639141033686
RMSLE ON VALIDATION SET:  2 :  0.6263169979832923
============================================================
===
RMSLE ON TRAINING SET:  3 :  0.5917964778574165
RMSLE ON VALIDATION SET:  3 :  0.4783767090098456
============================================================
===
RMSLE ON TRAINING SET:  4 :  0.5914356263311358
RMSLE ON VALIDATION SET:  4 :  0.5811810487862565
============================================================
===
RMSLE ON TRAINING SET:  5 :  0.5916390592275275
RMSLE ON VALIDATION SET:  5 :  0.7181642414489362
============================================================
===
Mean RMSLE on Train:  0.5912788577186613
```

```
Mean RMSLE on Valid:  0.5985638842807136
```

Simple Moving Average

- Now, we will use the Simple Moving Average, Like earlier we have used the average over the complete training period. Here, average will be taken on a specified period.
- We will use the predicted value as the average number of UNITS sold in last 8 weeks from a particular store of a particular product.
- As, we have one week gap between the train and validation set.

In [210]:

```
def get_sma(i, train, valid, no_of_weeks=2):

    # create a copy of train and validation set
    train_copy = train.copy()
    valid_copy = valid.copy()

    # group the data by STORE_NUM and UPC and use rolling and mean
    data_copy = train_copy.groupby(['STORE_NUM','UPC'])['UNITS'].ro

    # add the moving average column to the train data
    train_copy['moving_average'] = data_copy['UNITS']

    # the last prediction on train set will be used as prediction o
    # calculate the last_average dataframe by groupby using last fu
    last_average = train_copy.groupby(['STORE_NUM', 'UPC'])['moving

    train_copy = train_copy[['WEEK_END_DATE', 'STORE_NUM', 'UPC', '
    valid_copy = valid_copy[['WEEK_END_DATE','STORE_NUM', 'UPC', 'U

    # drop the null values in the dataframe
    train_copy.dropna(inplace=True)
    # merge the validation data with the last_average by left join
    valid_copy = valid_copy.merge(last_average, how= 'left', on= ['

    # calculate the rmsle on train and validation data
    t_rmsle = get_msle(train_copy['UNITS'], train_copy['moving_aver
    v_rmsle = get_msle(valid_copy['UNITS'], valid_copy['moving_aver


    print('RMSLE ON TRAINING SET: ',i+1, ': ', t_rmsle)
    print('RMSLE ON VALIDATION SET: ',i+1, ': ',v_rmsle)
    print('=========================================================

    return t_rmsle, v_rmsle
```

In [211]:
```
train_rmsle_ma = []
valid_rmsle_ma = []

for i, data in enumerate(data_set):
    train, valid = data

    t_rmsle, v_rmsle = get_sma(i,train, valid, no_of_weeks=8)
    train_rmsle_ma.append(t_rmsle)
    valid_rmsle_ma.append(v_rmsle)

print('Mean RMSLE on Train: ', np.mean(train_rmsle_ma))
print('Mean RMSLE on Valid: ', np.mean(valid_rmsle_ma))
```

```
RMSLE ON TRAINING SET:  1 :  0.532302643351482
RMSLE ON VALIDATION SET:  1 :  0.5469206496913668
================================================================
===
RMSLE ON TRAINING SET:  2 :  0.5332435318948314
RMSLE ON VALIDATION SET:  2 :  0.6421015703332319
================================================================
===
RMSLE ON TRAINING SET:  3 :  0.5335704565359952
RMSLE ON VALIDATION SET:  3 :  0.46149085909723564
================================================================
===
RMSLE ON TRAINING SET:  4 :  0.5324889809038001
RMSLE ON VALIDATION SET:  4 :  0.5878031103068386
================================================================
===
RMSLE ON TRAINING SET:  5 :  0.5318770729185398
RMSLE ON VALIDATION SET:  5 :  0.7558881602487321
================================================================
===
Mean RMSLE on Train:  0.5326965371209298
Mean RMSLE on Valid:  0.598840869935481
```

Linear Regresssion

- Now, we will try one Linear Regression Model and see how it performs on our dataset. We will use the same 5 validation sets and compare the results.
- We will drop the columns like `WEEK_END_DATE` , `STORE_NUM` and `UPC` before training the model.

In [212]:
```
```

```
train_rmsle_lr = []
valid_rmsle_lr = []

for i, data in enumerate(data_set):

    train, valid = data

    # drop the columns that are not required, separate the target a
    train_x = train.drop(columns=['WEEK_END_DATE', 'STORE_NUM', 'UP
    train_y = train['UNITS']

    valid_x = valid.drop(columns=['WEEK_END_DATE', 'STORE_NUM', 'UP
    valid_y = valid['UNITS']

    # create an Object of the Linear Regression model
    model_LR = LinearRegression()
    # fit the model with  the training data
    model_LR.fit(train_x, train_y)

    # predict on the training data
    # the model can predict some negative values also and RMSLE onl
    # So, we will use the clip function. It will convert all the ne
    predict_train = model_LR.predict(train_x).clip(min=0)
    predict_valid = model_LR.predict(valid_x).clip(min=0)

    # get the rmsle on the training and validation data.
    t_rmsle = get_msle(train_y, predict_train)
    v_rmsle = get_msle(valid_y, predict_valid)
    train_rmsle_lr.append(t_rmsle)
    valid_rmsle_lr.append(v_rmsle)

    print('RMSLE ON TRAINING SET: ',i+1, ': ', t_rmsle)
    print('RMSLE ON VALIDATION SET: ',i+1, ': ',v_rmsle)
    print('=========================================================



print('Mean RMSLE on Train: ', np.mean(train_rmsle_lr))
print('Mean RMSLE on Valid: ', np.mean(valid_rmsle_lr))
```

```
RMSLE ON TRAINING SET:  1 :  0.9850085035901924
RMSLE ON VALIDATION SET:  1 :  0.9360090105458742
================================================================
===
RMSLE ON TRAINING SET:  2 :  0.9858832676865847
RMSLE ON VALIDATION SET:  2 :  0.9224889051754708
================================================================
===
RMSLE ON TRAINING SET:  3 :  0.986618725677396
RMSLE ON VALIDATION SET:  3 :  0.9552487380682896
================================================================
---
```

```
---
RMSLE ON TRAINING SET:  4 :  0.9868219574723637
RMSLE ON VALIDATION SET:  4 :  0.9148116305786645
================================================================
===
RMSLE ON TRAINING SET:  5 :  0.987574476499999
RMSLE ON VALIDATION SET:  5 :  0.9609525371424387
================================================================
===
Mean RMSLE on Train:  0.9863813861853071
Mean RMSLE on Valid:  0.9379021643021476
```

We can see that `Linear Regression` has performed really bad. Even predicting the mean vaues would be better model. So, it is clear the target variable has no linear dependency on the avaiable features.

Decision Tree

- Now, we will try one Tree Based Model. We will use the same 5 validation sets and compare the results.
- We will drop the columns like `WEEK_END_DATE` , `STORE_NUM` and `UPC` before training the model.

In [213]:

```
train_rmsle_dtr = []
valid_rmsle_dtr = []

for i, data in enumerate(data_set):

    # get the train and validation set
    train, valid = data

    # drop the columns that are not required, separate the target a
    train_x = train.drop(columns=['WEEK_END_DATE', 'STORE_NUM', 'UP
    train_y = train['UNITS']

    valid_x = valid.drop(columns=['WEEK_END_DATE', 'STORE_NUM', 'UP
    valid_y = valid['UNITS']

    # create an Object of DecisionTree Regressor
    model_DTR = DecisionTreeRegressor()
    # fit the model with the training data
    model_DTR.fit(train_x, train_y)

    # predict the target and set the minimum value of the predicted
    predict_train = model_DTR.predict(train_x).clip(min=0)
    predict_valid = model_DTR.predict(valid_x).clip(min=0)

    # get the rmsle on train and validation set.
    t_rmsle = get_msle(train_y, predict_train)
    v_rmsle = get_msle(valid_y, predict_valid)

    train_rmsle_dtr.append(t_rmsle)
    valid_rmsle_dtr.append(v_rmsle)

    print('RMSLE ON TRAINING SET: ',i+1, ': ', t_rmsle)
    print('RMSLE ON VALIDATION SET: ',i+1, ': ',v_rmsle)
    print('==========================================================



print('Mean RMSLE on Train: ', np.mean(train_rmsle_dtr))
print('Mean RMSLE on Valid: ', np.mean(valid_rmsle_dtr))
```

```
RMSLE ON TRAINING SET:  1 :  0.33490827273781265
RMSLE ON VALIDATION SET:  1 :  0.43942776246715276
================================================================
===
RMSLE ON TRAINING SET:  2 :  0.33462093171092605
RMSLE ON VALIDATION SET:  2 :  0.4734871455424615
================================================================
===
RMSLE ON TRAINING SET:  3 :  0.33418191068253844
RMSLE ON VALIDATION SET:  3 :  0.4616491026128168
================================================================
===
RMSLE ON TRAINING SET:  4 :  0.33367685734780145
RMSLE ON VALIDATION SET:  4 :  0.5002536142851419
```

```
==========================================================================
===
RMSLE ON TRAINING SET:  5 :  0.33369618035935916
RMSLE ON VALIDATION SET:  5 :  0.590307225792689
==========================================================================

===
Mean RMSLE on Train:  0.33421683056768753
Mean RMSLE on Valid:  0.4930249701400524
```

So, we can see that Decision Tree performed way better than the LinearRegression and better than the Mean Prediction.

RandomForest

We just saw that the Decision Tree performed better than the Linear Regression Model. So, we will try one Ensemble Model of Decision Trees like RandomForest and compare the results on the same 5 validation sets.

In [214]:

```
train_rmsle_rfr = []
valid_rmsle_rfr = []

for i, data in enumerate(data_set):
    # get the train and vaidation set
    train, valid = data

    # drop the columns that are not required, separate the target a
    train_x = train.drop(columns=['WEEK_END_DATE', 'STORE_NUM', 'UP
    train_y = train['UNITS']

    valid_x = valid.drop(columns=['WEEK_END_DATE', 'STORE_NUM', 'UP
    valid_y = valid['UNITS']

    # create an object of the Random Forest Regressor
    model_RFR = RandomForestRegressor(random_state=0)

    # fit the model with the training data
    model_RFR.fit(train_x, train_y)

    # predict the target and set the minimum value of the predicted
    predict_train = model_RFR.predict(train_x).clip(min=0)
    predict_valid = model_RFR.predict(valid_x).clip(min=0)

    # get the rmsle on train and validate
    t_rmsle = get_msle(train_y, predict_train)
    v_rmsle = get_msle(valid_y, predict_valid)

    train_rmsle_rfr.append(t_rmsle)
    valid_rmsle_rfr.append(v_rmsle)

    print('RMSLE ON TRAINING SET: ',i+1, ': ', t_rmsle)
    print('RMSLE ON VALIDATION SET: ',i+1, ': ',v_rmsle)
    print('==========================================================

print('Mean RMSLE on Train: ', np.mean(train_rmsle_rfr))
print('Mean RMSLE on Valid: ', np.mean(valid_rmsle_rfr))
```

```
RMSLE ON TRAINING SET:  1 :  0.3492168621997124
RMSLE ON VALIDATION SET:  1 :  0.40810820885472504
============================================================
===
RMSLE ON TRAINING SET:  2 :  0.34901974773801514
RMSLE ON VALIDATION SET:  2 :  0.43529419573400696
============================================================
===
RMSLE ON TRAINING SET:  3 :  0.3486831490932209
RMSLE ON VALIDATION SET:  3 :  0.4261345873171656
============================================================
===
RMSLE ON TRAINING SET:  4 :  0.34818483302639924
RMSLE ON VALIDATION SET:  4 :  0.47354411873189756
============================================================
```

```
===
RMSLE ON TRAINING SET:  5 :  0.34821800563912814
RMSLE ON VALIDATION SET:  5 :  0.5415008997563244
================================================================
===
Mean RMSLE on Train:  0.34866451953929517
Mean RMSLE on Valid:  0.45691640207882395
```

Conclusions

- We have seen that Tree Based Models have a better performance than other models.
- We have a basic idea of what is the baseline.
- But still, we don't know what should be the right number of validation sets required and what should be the size of the training data.
- In the next notebook, we will try performance of model on different sizes of training period and different number of validation sets and choose the right validation startegy.

VALIDATION STRATEGY

- Now, that we have seen Tree based models were giving better results. So, we will use RandomForest Regressor Model in this notebook and we will define our validation strategy to make sure that the model we build is robust.

We need to find out what would be the

- right number of validation sets such that we can get reliable estimates of RMSLE
- right size of the training data to get a robust model

In [215]:
```
# importing the required libraries
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from tqdm import tqdm

from datetime import timedelta

from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_log_error as msle
from sklearn.tree import DecisionTreeRegressor

import warnings
warnings.filterwarnings('ignore')
```

In [216]:
```
# read the updated(preprocessed) train data
train_data = pd.read_csv('updated_train_data.csv')
```

In [217]:
```
# top results of the data
train_data.head()
```

Out[217]:

	WEEK_END_DATE	STORE_NUM	UPC	PRICE	BASE_PRICE	FEATURE	DISPLAY
0	14-Jan-09	367	1111009477	1.39	1.57	0	0
1	14-Jan-09	367	1111009497	1.39	1.39	0	0
2	14-Jan-09	367	1111085319	1.88	1.88	0	0
3	14-Jan-09	367	1111085345	1.88	1.88	0	0
4	14-Jan-09	367	1111085350	1.98	1.98	0	0

In [258]:
```
train_data.isna().sum()
```

Out[258]:
```
WEEK_END_DATE    0
STORE_NUM        0
UPC              0
PRICE            3
BASE_PRICE       0
FEATURE          0
DISPLAY          0
UNITS            0
dtype: int64
```

In [259]:
```
train_data['PRICE'].fillna(train_data['PRICE'].mean(), inplace=True
```

In [260]:
```
# convert the WEEK_END_DATE to datetime
train_data['WEEK_END_DATE'] = pd.to_datetime(train_data['WEEK_END_D
```

In [261]:
```
# first and last week in the dataset
train_data.WEEK_END_DATE.min() , train_data.WEEK_END_DATE.max()
```

Out[261]:
```
(Timestamp('2009-01-14 00:00:00'), Timestamp('2011-09-28 00:00:00'
))
```

In [262]:
```
# number of weeks in the dataset
train_data.WEEK_END_DATE.nunique()
```

Out[262]:
```
142
```

In [263]:
```
# create an array of unique week dates
week = train_data.WEEK_END_DATE.unique()
```

In [264]:
```
# read the other datasets
product_data = pd.read_csv('updated_product_data.csv')
store_data = pd.read_csv('updated_store_data.csv')
```

In [265]:
```
merged_data = train_data.merge(product_data,how='left', on='UPC')
merged_data = merged_data.merge(store_data, how='left', left_on='ST
```

In [266]:
```
merged_data = merged_data.drop(columns=['STORE_ID'])
```

In [267]:
```
# look at data in the first row
merged_data.loc[0]
```

Out[267]:
```
WEEK_END_DATE                 2009-01-14 00:00:00
STORE_NUM                                     367
UPC                                    1111009477
PRICE                                        1.39
BASE_PRICE                                   1.57
FEATURE                                         0
DISPLAY                                         0
UNITS                                          13
MANUFACTURER_1                                  1
MANUFACTURER_2                                  0
MANUFACTURER_3                                  0
MANUFACTURER_4                                  0
MANUFACTURER_5                                  0
MANUFACTURER_6                                  0
MANUFACTURER_7                                  0
MANUFACTURER_8                                  0
MANUFACTURER_9                                  0
CATEGORY_1                                      1
CATEGORY_2                                      0
CATEGORY_3                                      0
CATEGORY_4                                      0
SUB_CATEGORY_1                                  1
SUB_CATEGORY_2                                  0
SUB_CATEGORY_3                                  0
SUB_CATEGORY_4                                  0
SUB_CATEGORY_5                                  0
SUB_CATEGORY_6                                  0
SUB_CATEGORY_7                                  0
PRODUCT_SIZE                                 15.0
PRODUCT_SIZE_BIN                                2
ADDRESS_STATE_PROV_CODE_1                       1
ADDRESS_STATE_PROV_CODE_2                       0
ADDRESS_STATE_PROV_CODE_3                       0
ADDRESS_STATE_PROV_CODE_4                       0
MSA_CODE_1                                      1
MSA_CODE_2                                      0
MSA_CODE_3                                      0
MSA_CODE_4                                      0
MSA_CODE_5                                      0
MSA_CODE_6                                      0
MSA_CODE_7                                      0
MSA_CODE_8                                      0
MSA_CODE_9                                      0
SEG_VALUE_NAME                                  1
SALES_AREA_SIZE_NUM                         24721
AVG_WEEKLY_BASKETS                          12707
Name: 0, dtype: object
```

VALIDATION STRATEGY

For a single iteration, we define a training period on which we will train the model and then we will have `one week gap` and `validate` on the next week and again `one week gap` and `test` on the next week

We discussed during data collection video in Module 1 that the suppliers need 1 week head start for supplying the requested goods to warehouses so we will predict not for the next week but next to the next week as that is the week for which our forecasts would be used in practical scenario.

Now, we need to find out what would be the optimal `number of validation sets` and optimal `number of months` on which we should validate the data.

- Define a function `validation_df` that will take the parameters array of `week` , `no_of_months` , `no_of_validation` and returns a dataframe that contains the imformation like:

- `week` unique week_end_dates array
- `no_of_months` training data duration that needs to be considered
- `no_of_validation` number of validation sets that needs to be created with training period as specified

- `train_start` Data split train set start week
- `train_end` Data split train set end week
- `no_days_train` Number of days we have in the particular validation set
- `validation_week` Data split validation week
- `test_week` Data split test week
- `train_shape` Datapoints available in the train split
- `validation_shape` Datapoints available in the validation week
- `test_shape` Datapoints available in the test week

In [269]:
```
# function to create validation data_frame
def validation_df(data, week, no_of_months, no_of_validation):

    model_set = []
    set_n = 1
    for w in range(len(week)-1,0,-1):
        x_data = {}

        x_data['train_start'] = week[w-3-4*no_of_months]
        x_data['train_end'] = week[w-4]
        x_data['validate_week'] = week[w-2]
        x_data['test_week'] = week[w]
        x_data['no_days_train'] = x_data['train_end'] - x_data['tra
        x_data['set_no'] = 'set'+str(set_n)
        set_n +=1
        model_set.append(x_data)
        if(len(model_set) == no_of_validation):
            break


    datapoints = []

    for s in model_set :
        x = {}
        train_set = data[(data.WEEK_END_DATE >= s['train_start']) &
        x['train_shape'] = train_set.shape[0]
        x['validation_shape']  = data[data.WEEK_END_DATE == s['vali
        x['test_shape'] = data[data.WEEK_END_DATE == s['test_week']
        x.update(s)
        datapoints.append(x)

    df = pd.DataFrame.from_dict(datapoints)
    df['no_days_train'] = df['no_days_train'] + timedelta(days=7)
    return df
```

In [270]:
```
# validation sets for training size = 3 months and number of valida
validation_df(merged_data, week, no_of_months= 3, no_of_validation=
```

Out[270]:

	train_shape	validation_shape	test_shape	train_start	train_end	validate_week	test_wee
0	19647	1640	1642	2011-06-15	2011-08-31	2011-09-14	2011-09 2
1	19657	1632	1638	2011-06-08	2011-08-24	2011-09-07	2011-09 2
2	19654	1629	1640	2011-06-01	2011-08-17	2011-08-31	2011-09 1

In [271]:
```
# validation sets for training size = 6 months and number of valida
validation_df(merged_data, week, no_of_months= 6, no_of_validation=
```

Out[271]:

	train_shape	validation_shape	test_shape	train_start	train_end	validate_week	test_wee
0	39294	1640	1642	2011-03-23	2011-08-31	2011-09-14	2011-09 2
1	39308	1632	1638	2011-03-16	2011-08-24	2011-09-07	2011-09 2
2	39308	1629	1640	2011-03-09	2011-08-17	2011-08-31	2011-09 1
3	39308	1640	1632	2011-03-02	2011-08-10	2011-08-24	2011-09 0

Now, we will calculate `EVALUATION METRIC – RMSLE` for each of the combination of traininig period size from 1 month to 12 months and number of validation sets from 1 to 5. We will use RandomForestRegressor Model

---

In [272]:
```
# function to calculate the root mean squared log error
def get_msle(true, predicted) :
    return np.sqrt(msle( true, predicted))

# function to train the model
# it will calculate and return the RMSLE on train and validation se
def my_model(train_d, validate_d):

    train_x = train_d.drop(columns=['WEEK_END_DATE', 'STORE_NUM', '
    train_y = train_d['UNITS']

    valid_x = validate_d.drop(columns=['WEEK_END_DATE', 'STORE_NUM'
    valid_y = validate_d['UNITS']

    model_RFR = RandomForestRegressor(max_depth=20,random_state=0)
    model_RFR.fit(train_x, train_y)

    predict_validate = model_RFR.predict(valid_x)
    predict_validate = predict_validate.clip(min=0)

    return get_msle(valid_y, predict_validate)


# function will extract the train and validation set using validati
# The defined model will train on each of the set and the average R

def train_model(df,no_of_month):

    model_results = []
    for row in range(df.shape[0]):
        row = df.iloc[row]
        train_set = train_data[(train_data.WEEK_END_DATE >= row['tr
        validate_set = train_data[train_data.WEEK_END_DATE == row['
        train_set['month'] = no_of_month
        validate_set['month'] = no_of_month
        model_results.append(my_model(train_set,validate_set))

    return np.mean(model_results), np.std(model_results)
```

Now, we define a function `get_matrix` that will take parameter `max_months` the number of months of training period and `max_cv` the number of validation sets.

It will return mean rmsle and standard deviation of the rmsle calculated over the different combinations of the months and validation sets.

In [273]:
```
# define get matrix
def get_matrix(max_months=1, max_cv=1):
    final_results_mean = []
    final_results_std = []

    for i in tqdm(range(1,max_months+1,1)):
        for j in range(1,max_cv+1,1):
            #print(i,j,'done')
            x = {}
            y = {}
            x['No_of_months'] = i
            x['validation_sets'] = j
            y['No_of_months'] = i
            y['validation_sets'] = j
            x['Results'] , y['Results'] = train_model(validation_df
            final_results_mean.append(x)
            final_results_std.append(y)


    return pd.DataFrame.from_dict(final_results_mean).pivot_table(i
```

In [274]:
```
# let's first try with the months from range 1 to 12 and validation
final_mean, final_std = get_matrix(max_months=12,max_cv=5)
```

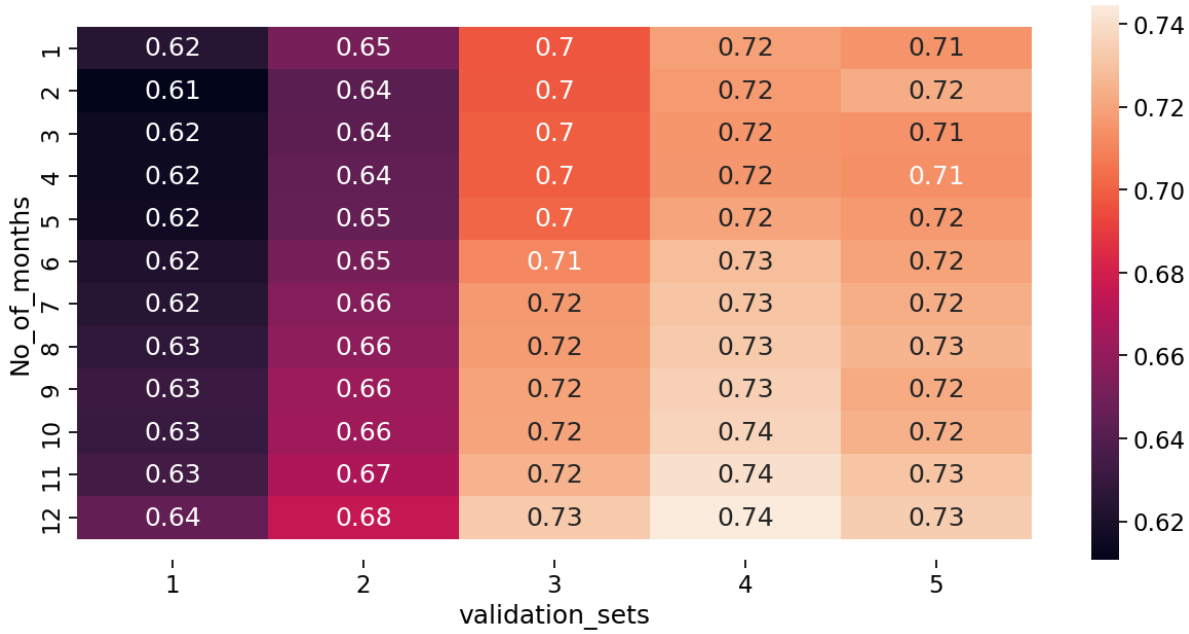
```
100%|██████████| 12/12 [05:28<00:
00, 27.41s/it]
```

Let's see how different combinations of training periods and validation sets give results.

In [275]:
```
# As the returned dataframe has multiindex columns, so drop one lev
final_mean.columns = final_mean.columns.droplevel()
```

In [276]:
```
# correlation plot of the variables in the train data
plot = final_mean[final_mean.columns]
plt.figure(figsize=(15,7))
ax = sns.heatmap(plot,annot=True)
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
```

Out[276]: (12.5, -0.5)



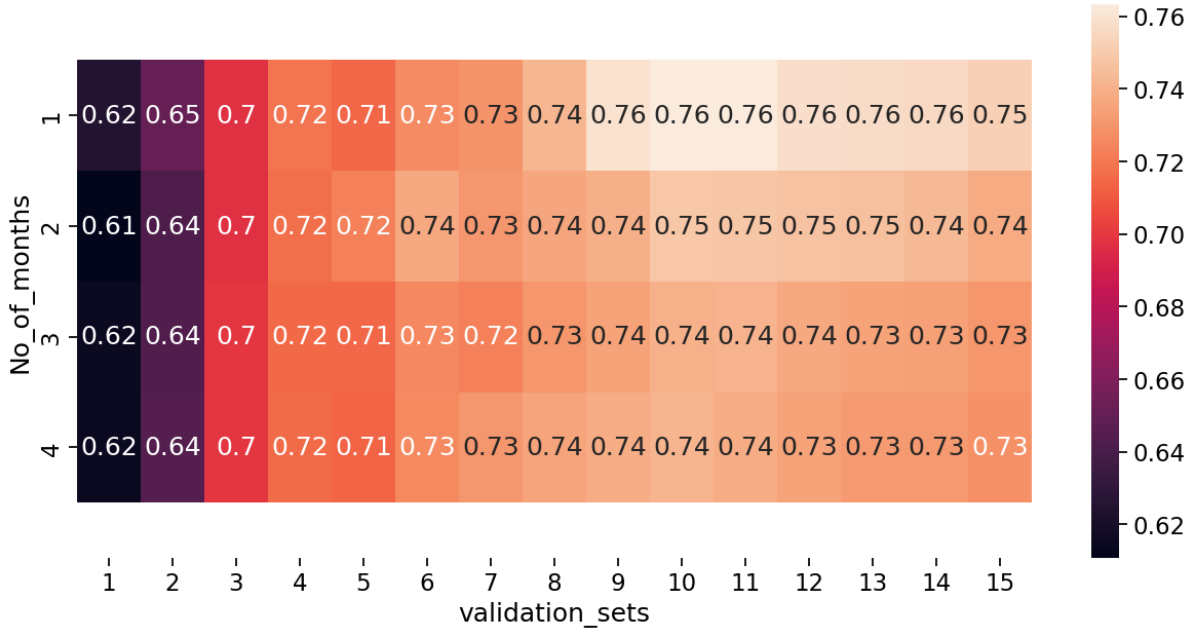
- We can see that, as we increase the size of the training period, the value of RMSLE increases. And for 2 months of train data we are getting the best score here and it keeps on increasing as we go further back. So, Let's calculate the results again by keeping the max training period to be 4 months and no of validation sets to be 15.

In [277]:
```
final_mean2, final_std2 = get_matrix(max_months=4,max_cv=15)
```

```
100%|████████████████████████████████████████| 4/4 [05:52<00:
00, 88.14s/it]
```

In [278]:
```
# correlation plot of the variables in the train data
final_mean2.columns = final_mean2.columns.droplevel()
plot = final_mean2[final_mean2.columns]
plt.figure(figsize=(15,7))
ax = sns.heatmap(plot,annot=True)
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
```

Out[278]: (4.5, -0.5)



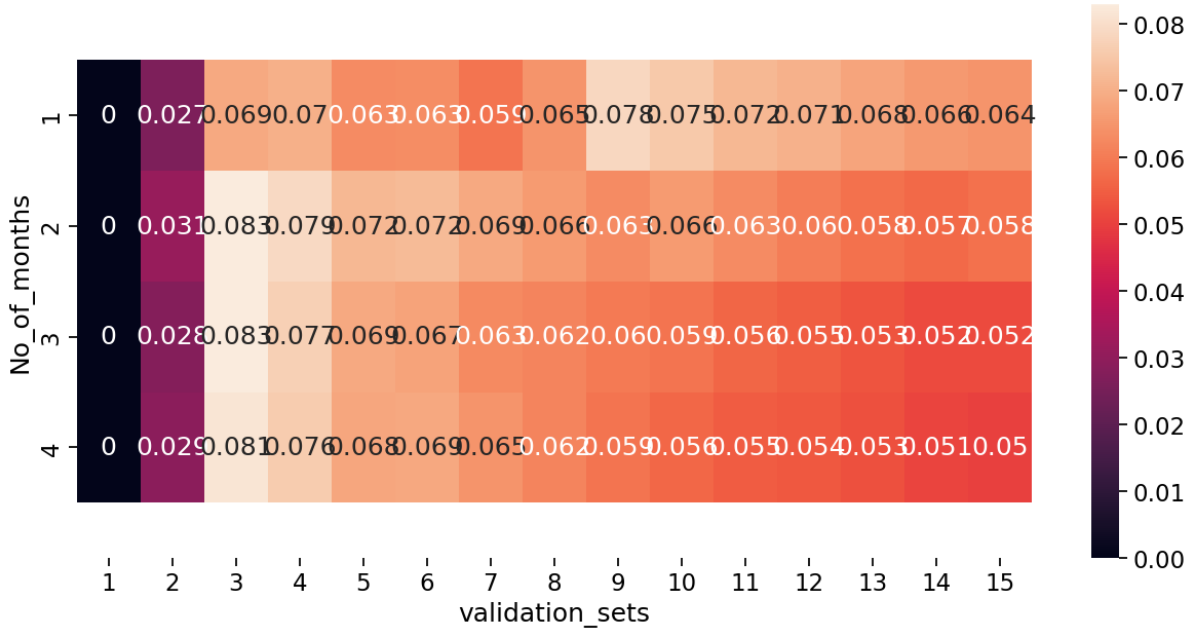
Now, Using the training period of 2 months, the RMSLE value gets stable after the 9 validation sets to value 0.74.

Standard Deviation

Now, Let's see the standard deviation of the results over the validation sets.

In [279]:
```
# correlation plot of the variables in the train data
final_std2.columns = final_std2.columns.droplevel()
plot = final_std2[final_std2.columns]
plt.figure(figsize=(15,7))
ax = sns.heatmap(plot,annot=True)
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
```

Out[279]: (4.5, -0.5)



The lowest standard deviation is with 14 validation sets, and you can also see that the standard deviation increases with 15th validation set in both 2 and 3 months period results.

So, we will validate our model with 2 months of training period and 14 validation sets.

FEATURE ENGINEERING

We will first merge all the datasets that are available to us `train_data` , `product_data` and `store _data` and build a Random Forest model on it. And then, we will engineer some features from the existing datasets and try to improve the performance of the model.

In [280]:
```
# importing required libraries
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
from tqdm import tqdm_notebook
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_log_error as msle
```

Read the pre-processed Datasets

We have already updated the datasets like imputing missing values, convert categorical variables into numerical ones and removed the variables with high cardinality.

You can always try and transform the variables according to your business understanding and try to check if that is working well for you or not.

In [281]:
```
# reading the dataset
train_data = pd.read_csv('updated_train_data.csv')
product_data = pd.read_csv('updated_product_data.csv')
store_data = pd.read_csv('updated_store_data.csv')
```

In [282]:
```
train_data.head(2)
```

Out[282]:

	WEEK_END_DATE	STORE_NUM	UPC	PRICE	BASE_PRICE	FEATURE	DISPLAY
0	14-Jan-09	367	1111009477	1.39	1.57	0	0
1	14-Jan-09	367	1111009497	1.39	1.39	0	0

Train Data:

- **WEEK_END_DATE**: Will be used to divide the data into train, validate and test.
- **STORE_NUM**: Will be used to merge files.
- **UPC**: Will be used to merge files
- **BASE_PRICE**: It was already present in the numeric form.
- **FEATURE**: It was already present in the numeric form.
- **DISPLAY**: It was already present in the numeric form.
- **UNITS**: Target Variable

In [294]:
```
train_data.isna().sum()
```

Out[294]:
```
WEEK_END_DATE    0
STORE_NUM        0
UPC              0
PRICE            3
BASE_PRICE       0
FEATURE          0
DISPLAY          0
UNITS            0
dtype: int64
```

In [295]:
```
train_data['PRICE'].fillna(train_data['PRICE'].mean(), inplace=True
```

In [296]:
```
product_data.head(2)
```

Out[296]:

	UPC	MANUFACTURER_1	MANUFACTURER_2	MANUFACTURER_3	MANUFACTUR
0	1111009477	1	0	0	
1	1111009497	1	0	0	

2 rows × 23 columns

Product Data

- **UPC**: Will be used to merge files.
- **MANUFACTURER**: We have transformed the variable by One Hot Encoding.
- **CATEGORY**: We have transformed the variable by One Hot Encoding.
- **SUB_CATEGORY**: We have transformed the variable the variable by One Hot Encoding.
- **PRODUCT_SIZE**: It was initially available as different size units for different categories of products, like `PRETZELS` were available in `Ounces (OZ)` and `MOUTHWASH` were in `MILI LITRES (ML)`. So we defined the bining according the product category and transformed this feature.

In [297]:
```
store_data.head(2)
```

Out[297]:

	STORE_ID	ADDRESS_STATE_PROV_CODE_1	ADDRESS_STATE_PROV_CODE_2	ADDRESS
0	367	1	0	
1	389	1	0	

Store Data

- **STORE_ID**: Will be used to merge files.
- **ADDRESS_STATE_PROV_CODE**: We have transformed the variable by One Hot Encoding.
- **MSA_CODE**: We have transformed the variable by One Hot Encoding.
- **SEG_VALUE_NAME**: We have transformed the variable by One Hot Encoding.
- **SALES_AREA_SIZE_NUM**: No changes done to this variable, already present in the numeric form.
- **AVG_WEEKLY_BASKETS**: No changes done to this variable, already present in the numeric form.

MERGE ALL THE DATASET

In [298]:
```
merged_data = train_data.merge(product_data, how= 'left', on= 'UPC'
merget_data = merged_data.merge(store_data,how='left', left_on = 'S
merged_data.head(2)
```

Out[298]:

	WEEK_END_DATE	STORE_NUM	UPC	PRICE	BASE_PRICE	FEATURE	DISPLAY
0	14-Jan-09	367	1111009477	1.39	1.57	0	0
1	14-Jan-09	367	1111009497	1.39	1.39	0	0

2 rows × 30 columns

In [299]:
```
merged_data.isna().sum()
```

Out[299]:
```
WEEK_END_DATE       0
STORE_NUM           0
UPC                 0
PRICE               0
BASE_PRICE          0
FEATURE             0
DISPLAY             0
UNITS               0
MANUFACTURER_1      0
MANUFACTURER_2      0
MANUFACTURER_3      0
MANUFACTURER_4      0
MANUFACTURER_5      0
MANUFACTURER_6      0
MANUFACTURER_7      0
MANUFACTURER_8      0
MANUFACTURER_9      0
CATEGORY_1          0
CATEGORY_2          0
CATEGORY_3          0
CATEGORY_4          0
SUB_CATEGORY_1      0
SUB_CATEGORY_2      0
SUB_CATEGORY_3      0
SUB_CATEGORY_4      0
SUB_CATEGORY_5      0
SUB_CATEGORY_6      0
SUB_CATEGORY_7      0
PRODUCT_SIZE        0
PRODUCT_SIZE_BIN    0
dtype: int64
```

In [300]:
```
merged_data.columns
```

Out[300]:
```
Index(['WEEK_END_DATE', 'STORE_NUM', 'UPC', 'PRICE', 'BASE_PRICE',
'FEATURE',
       'DISPLAY', 'UNITS', 'MANUFACTURER_1', 'MANUFACTURER_2',
       'MANUFACTURER_3', 'MANUFACTURER_4', 'MANUFACTURER_5', 'MANU
FACTURER_6',
       'MANUFACTURER_7', 'MANUFACTURER_8', 'MANUFACTURER_9', 'CATE
GORY_1',
       'CATEGORY_2', 'CATEGORY_3', 'CATEGORY_4', 'SUB_CATEGORY_1',
       'SUB_CATEGORY_2', 'SUB_CATEGORY_3', 'SUB_CATEGORY_4', 'SUB_
CATEGORY_5',
       'SUB_CATEGORY_6', 'SUB_CATEGORY_7', 'PRODUCT_SIZE', 'PRODUC
T_SIZE_BIN'],
      dtype='object')
```

So, we have now 28 columns in the merged dataset, We will drop `WEEK_END_DATE` , `STORE_NUM` and `UPC` and train the model on rest of the features with `UNITS` as the target variable.

Initially, we will train and check the performance using the 24 features.

- ***The `WEEK_END_DATE` needs to be converted into datetime format.***
- ***In the validation strategy notebook, we have defined some functions to create the validation sets dataframe. we are going to use the same function here in this notebook also.***

In [301]:
```
# convert to datetime
merged_data.WEEK_END_DATE = pd.to_datetime(merged_data.WEEK_END_DAT

# create an array of unique week dates
week = merged_data.WEEK_END_DATE.unique()
```

In [302]:
```
from datetime import timedelta
def validation_df(data, week, no_of_months, no_of_validation):

    model_set = []
    set_n = 1
    for w in range(len(week)-1,0,-1):
        x_data = {}

        x_data['train_start'] = week[w-3-4*no_of_months]
        x_data['train_end'] = week[w-4]
        x_data['validate_week'] = week[w-2]
        x_data['test_week'] = week[w]
        x_data['no_days_train'] = x_data['train_end'] - x_data['tra
        x_data['set_no'] = 'set'+str(set_n)
        set_n +=1
        model_set.append(x_data)
        if(len(model_set) == no_of_validation):
            break


    datapoints = []

    for s in model_set :
        x = {}
        train_set = data[(data.WEEK_END_DATE >= s['train_start']) &
        x['train_shape'] = train_set.shape[0]
        x['validation_shape']  = data[data.WEEK_END_DATE == s['vali
        x['test_shape'] = data[data.WEEK_END_DATE == s['test_week']
        x.update(s)
        datapoints.append(x)

    df = pd.DataFrame.from_dict(datapoints)
    df['no_days_train'] = df['no_days_train'] + timedelta(days=7)
    return df
```

In [303]:
```
validation_df(merged_data, week, no_of_months=2, no_of_validation=1
```

Out[303]:

	train_shape	validation_shape	test_shape	train_start	train_end	validate_week	test_we
0	13089	1640	1642	2011-07-13	2011-08-31	2011-09-14	2011-0
1	13102	1632	1638	2011-07-06	2011-08-24	2011-09-07	2011-0
2	13101	1629	1640	2011-06-29	2011-08-17	2011-08-31	2011-0
3	13101	1640	1632	2011-06-22	2011-08-10	2011-08-24	2011-0
4	13109	1638	1629	2011-06-15	2011-08-03	2011-08-17	2011-0
5	13108	1631	1640	2011-06-08	2011-07-27	2011-08-10	2011-0
6	13108	1640	1638	2011-06-01	2011-07-20	2011-08-03	2011-0
7	13112	1637	1631	2011-05-25	2011-07-13	2011-07-27	2011-0
8	13104	1635	1640	2011-05-18	2011-07-06	2011-07-20	2011-0
9	13101	1639	1637	2011-05-11	2011-06-29	2011-07-13	2011-0
10	13106	1642	1635	2011-05-04	2011-06-22	2011-07-06	2011-0
11	13102	1639	1639	2011-04-27	2011-06-15	2011-06-29	2011-0
12	13096	1638	1642	2011-04-20	2011-06-08	2011-06-22	2011-0
13	13093	1639	1639	2011-04-13	2011-06-01	2011-06-15	2011-0

In [304]:
```
# function to calculate the root mean squared log error
def get_msle(true, predicted) :
    return np.sqrt(msle(true, predicted))

# function to return the columns on which the model is trained
def get_colums(data):
    print('\n####### The model is trained on Following Columns: ###
    print(data.columns)
    print('=========================================================


# function to train the model
# it will calculate and return the RMSLE on train and validation se
def my_model(train_d, validate_d, model):
    train_x = train_d.drop(columns=['WEEK_END_DATE', 'UNITS'])
    train_y = train_d['UNITS']

    valid_x = validate_d.drop(columns=['WEEK_END_DATE', 'UNITS'])
    valid_y = validate_d['UNITS']

    model.fit(train_x, train_y)

    predict_train = model.predict(train_x)
    predict_train = predict_train.clip(min=0)

    predict_validate = model.predict(valid_x)
    predict_validate = predict_validate.clip(min=0)

    return get_msle(train_y, predict_train), get_msle(valid_y, pred



# function will extract the train and validation set using validati
# The defined model will train on each of the set and the average R
def train_model(df, data, model):

    model_results_train = []
    model_results_valid = []
    for row in tqdm_notebook(range(df.shape[0]),leave=False, desc='

        row = df.iloc[row]
        train_set = data[(data.WEEK_END_DATE >= row['train_start'])
        validate_set = data[data.WEEK_END_DATE == row['validate_wee
        train, valid, data_train = my_model(train_set,validate_set,
        model_results_train.append(train)
        model_results_valid.append(valid)

    return np.mean(model_results_train) , np.mean(model_results_val
```

OPTIMUM VALUE OF N_ESTIMATORS

- First of all, we will calculate the performance of the model using the default features and we will try to tune the parameters to get the best results.
- So, first we will find out the optimal value of n_estimators for the Random Forest Model and we will see the performance of the model on n_estimators value 5, 15, 25..... 245.

In [305]:
```
estimator_results = []
data = merged_data.drop(columns=['STORE_NUM', 'UPC'])


valid_df = validation_df(merged_data, week, no_of_months=2, no_of_v

for estimator in tqdm_notebook(range(5,250,10),leave=True, desc= 'e
    result = {}
    model_RFR = RandomForestRegressor(n_estimators= estimator, rand
    rmsle_train, rmsle_valid, data_train = train_model(valid_df, da
    result['estimator'] = estimator
    result['rmsle_train'] = rmsle_train
    result['rmsle_valid'] = rmsle_valid
    estimator_results.append(result)

get_colums(data_train)
```

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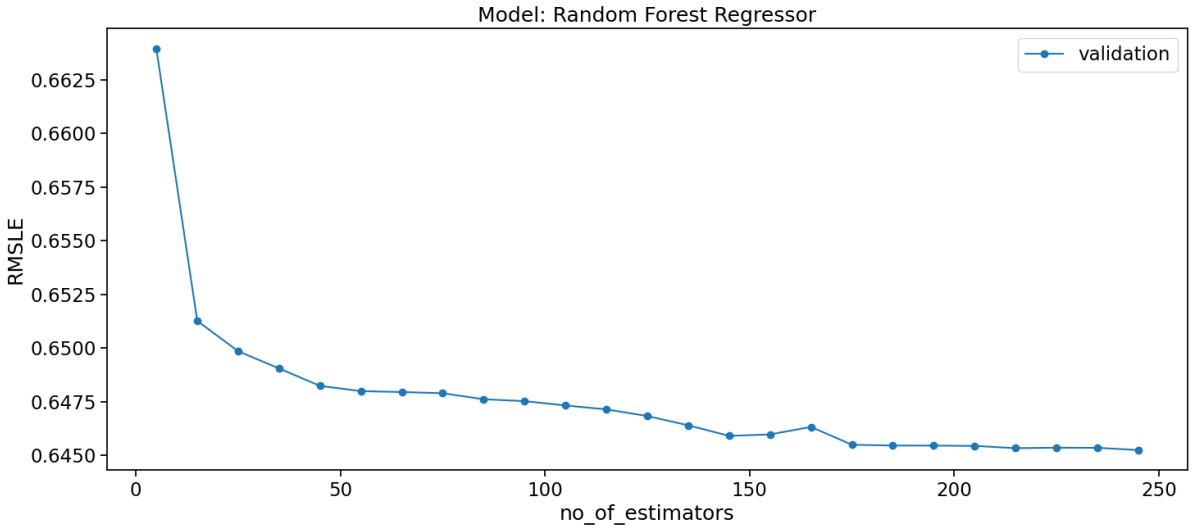
```
####### The model is trained on Following Columns: ###########

Index(['PRICE', 'BASE_PRICE', 'FEATURE', 'DISPLAY', 'MANUFACTURER_
1',
       'MANUFACTURER_2', 'MANUFACTURER_3', 'MANUFACTURER_4', 'MANU
FACTURER_5',
       'MANUFACTURER_6', 'MANUFACTURER_7', 'MANUFACTURER_8', 'MANU
FACTURER_9',
       'CATEGORY_1', 'CATEGORY_2', 'CATEGORY_3', 'CATEGORY_4',
       'SUB_CATEGORY_1', 'SUB_CATEGORY_2', 'SUB_CATEGORY_3', 'SUB_
CATEGORY_4',
       'SUB_CATEGORY_5', 'SUB_CATEGORY_6', 'SUB_CATEGORY_7', 'PROD
UCT_SIZE',
       'PRODUCT_SIZE_BIN'],
      dtype='object')
============================================================
```

In [306]:
```
x = pd.DataFrame.from_dict(estimator_results)
x
```

Out[306]:

	estimator	rmsle_train	rmsle_valid
0	5	0.512508	0.663946
1	15	0.508982	0.651263
2	25	0.507961	0.649851
3	35	0.507538	0.649048
4	45	0.507523	0.648237
5	55	0.507450	0.647991
6	65	0.507247	0.647951
7	75	0.507197	0.647894
8	85	0.507100	0.647614
9	95	0.507077	0.647525
10	105	0.507073	0.647325
11	115	0.507048	0.647141
12	125	0.506981	0.646832
13	135	0.506941	0.646400
14	145	0.506930	0.645909
15	155	0.506919	0.645976
16	165	0.506921	0.646326
17	175	0.506921	0.645494
18	185	0.506916	0.645459
19	195	0.506887	0.645455
20	205	0.506895	0.645441
21	215	0.506899	0.645336
22	225	0.506890	0.645357
23	235	0.506896	0.645352
24	245	0.506886	0.645248

In [307]:
```
plt.figure(figsize=(17,7))
plt.plot(x['estimator'], x['rmsle_valid'], marker='o',label='valida
plt.title('Model: Random Forest Regressor')
plt.ylabel('RMSLE')
plt.xlabel('no_of_estimators')
plt.legend();
```



N_ESTIMATORS = 175

The RMSLE is lowest on n_estimators value 175 is around 0.667 and seems to get stable after that. So, we will keep the value of the n_estimators = 175.

OPTIMUM VALUE OF MAX_DEPTH

Now, we will keep the value of n_estimators fixed as 175 and try different values of max_depth from 1, 2, ...29.

In [308]:
```
```

```
depth_results = []
data = merged_data.drop(columns=['STORE_NUM', 'UPC'])


valid_df = validation_df(merged_data, week, no_of_months=2, no_of_v
for depth in tqdm_notebook(range(1,30,1), leave=True, desc= 'max_de
    result = {}

    model_RFR = RandomForestRegressor(max_depth=depth,n_estimators=

    rmsle_train, rmsle_valid , data_train = train_model(valid_df, d
    result['depth'] = depth
    result['rmsle_train'] = rmsle_train
    result['rmsle_valid'] = rmsle_valid
    depth_results.append(result)

get_colums(data_train)
```

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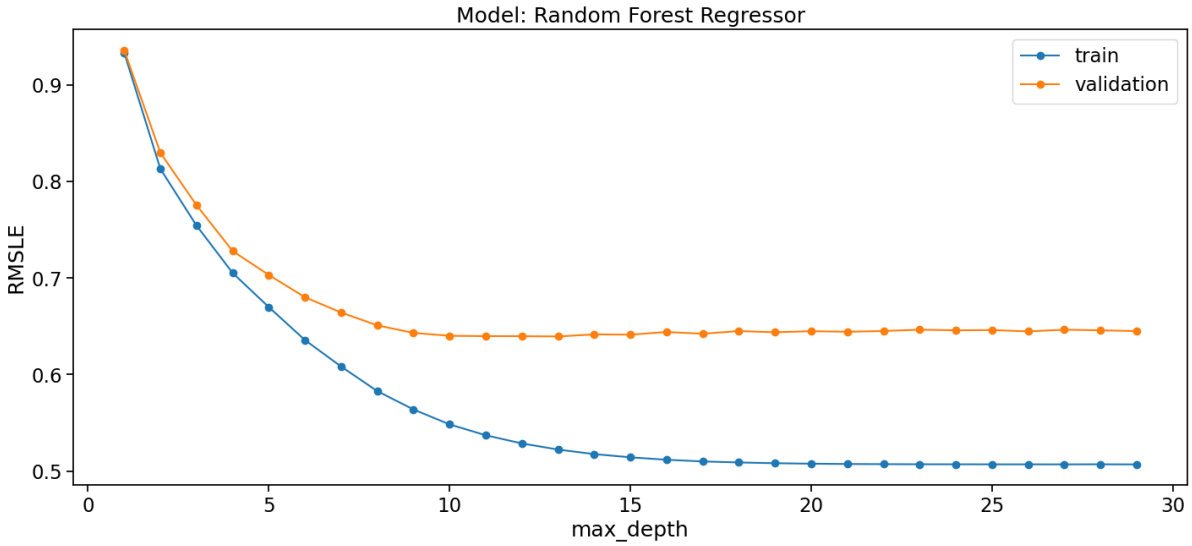
```
####### The model is trained on Following Columns: ###########

Index(['PRICE', 'BASE_PRICE', 'FEATURE', 'DISPLAY', 'MANUFACTURER_
1',
       'MANUFACTURER_2', 'MANUFACTURER_3', 'MANUFACTURER_4', 'MANU
FACTURER_5',
       'MANUFACTURER_6', 'MANUFACTURER_7', 'MANUFACTURER_8', 'MANU
FACTURER_9',
       'CATEGORY_1', 'CATEGORY_2', 'CATEGORY_3', 'CATEGORY_4',
       'SUB_CATEGORY_1', 'SUB_CATEGORY_2', 'SUB_CATEGORY_3', 'SUB_
CATEGORY_4',
       'SUB_CATEGORY_5', 'SUB_CATEGORY_6', 'SUB_CATEGORY_7', 'PROD
UCT_SIZE',
       'PRODUCT_SIZE_BIN'],
      dtype='object')
============================================================
```

In [309]:
```
x = pd.DataFrame.from_dict(depth_results)
x
```

Out[309]:

	depth	rmsle_train	rmsle_valid
0	1	0.933897	0.936389
1	2	0.813392	0.830074
2	3	0.754588	0.775736
3	4	0.705389	0.728126
4	5	0.669968	0.703301
5	6	0.635802	0.680215
6	7	0.608346	0.664374
7	8	0.582848	0.651052
8	9	0.563853	0.643228
9	10	0.548341	0.640244
10	11	0.537086	0.639898
11	12	0.528603	0.639825
12	13	0.522251	0.639530
13	14	0.517535	0.641706
14	15	0.514211	0.641407
15	16	0.511689	0.644191
16	17	0.509927	0.642371
17	18	0.508891	0.645143
18	19	0.508109	0.643901
19	20	0.507617	0.645006
20	21	0.507281	0.644432
21	22	0.507129	0.645183
22	23	0.507009	0.646574
23	24	0.506986	0.645919
24	25	0.506934	0.646192
25	26	0.506928	0.644763
26	27	0.506906	0.646571
27	28	0.506983	0.645901
28	29	0.506860	0.645104

In [310]:
```
plt.figure(figsize=(17,7))
plt.plot(x['depth'], x['rmsle_train'], marker='o',label='train');
plt.plot(x['depth'], x['rmsle_valid'], marker='o',label='validation
plt.title('Model: Random Forest Regressor')
plt.ylabel('RMSLE')
plt.xlabel('max_depth')
plt.legend();
```



MAX_DEPTH = 10

The RMSLE gets stable on both validation and train set after max_depth 10 and the RMSLE is still around 0.67

ADD TIME BASED FEATURES

- Now, we will add some Time based features to the data like year of the transaction, month, day, day_of_year, week, quarter.
- And we will once again check the performace of the model for different max_depth 1 to 29 and will decide whether we have selected the right value of max_depth or not.

In [311]:
```
# year
merged_data['year']  = merged_data['WEEK_END_DATE'].dt.year
# month
merged_data['month'] = merged_data['WEEK_END_DATE'].dt.month
# day
merged_data['day'] = merged_data['WEEK_END_DATE'].dt.day
# day_of year
merged_data['day_of_year'] = merged_data['WEEK_END_DATE'].dt.dayofy
# week
merged_data["week"] = merged_data['WEEK_END_DATE'].dt.week
# quarter
merged_data["quarter"] = merged_data['WEEK_END_DATE'].dt.quarter
```

In [312]:
```
depth_results = []
data = merged_data.drop(columns=['STORE_NUM', 'UPC'])

valid_df = validation_df(merged_data, week, no_of_months=2, no_of_v
for depth in tqdm_notebook(range(1,16,1), desc='max_depth', leave=T
    result = {}

    model_RFR = RandomForestRegressor(max_depth= depth, n_estimator

    rmsle_train, rmsle_valid, data_train = train_model(valid_df, da
    result['depth'] = depth
    result['rmsle_train'] = rmsle_train
    result['rmsle_valid'] = rmsle_valid
    depth_results.append(result)

get_colums(data_train)
```

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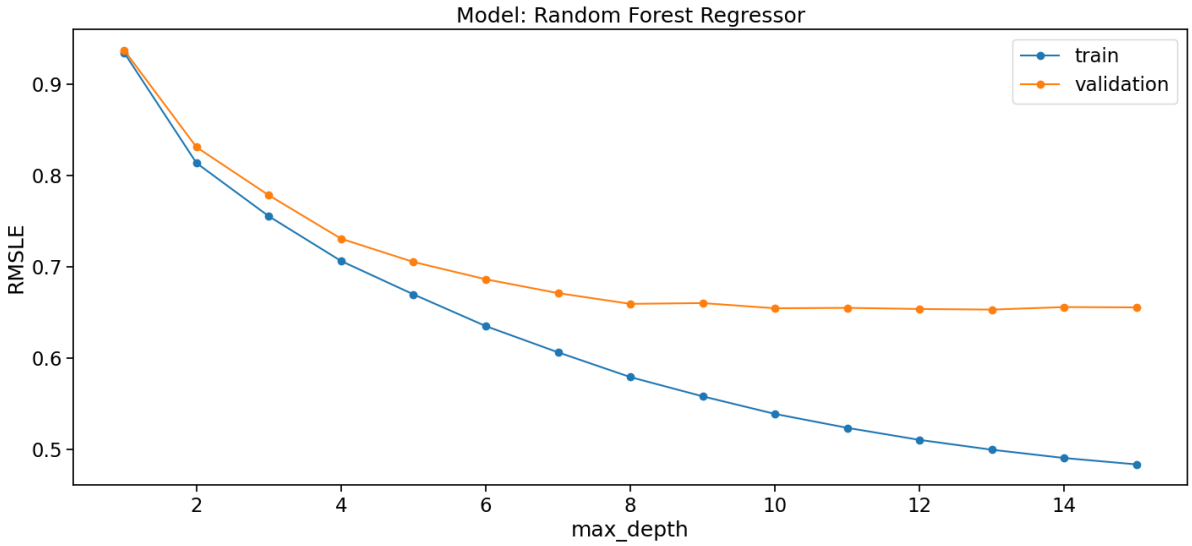
```
####### The model is trained on Following Columns: ###########

Index(['PRICE', 'BASE_PRICE', 'FEATURE', 'DISPLAY', 'MANUFACTURER_
1',
       'MANUFACTURER_2', 'MANUFACTURER_3', 'MANUFACTURER_4', 'MANU
FACTURER_5',
       'MANUFACTURER_6', 'MANUFACTURER_7', 'MANUFACTURER_8', 'MANU
FACTURER_9',
       'CATEGORY_1', 'CATEGORY_2', 'CATEGORY_3', 'CATEGORY_4',
       'SUB_CATEGORY_1', 'SUB_CATEGORY_2', 'SUB_CATEGORY_3', 'SUB_
CATEGORY_4',
       'SUB_CATEGORY_5', 'SUB_CATEGORY_6', 'SUB_CATEGORY_7', 'PROD
UCT_SIZE',
       'PRODUCT_SIZE_BIN', 'year', 'month', 'day', 'day_of_year',
'week',
       'quarter'],
      dtype='object')
============================================================
```

In [313]:
```
x = pd.DataFrame.from_dict(depth_results)
x
```

Out[313]:

	depth	rmsle_train	rmsle_valid
0	1	0.934254	0.936938
1	2	0.813452	0.830857
2	3	0.755247	0.778215
3	4	0.706248	0.730671
4	5	0.669784	0.705234
5	6	0.635063	0.686289
6	7	0.606364	0.671135
7	8	0.579226	0.659390
8	9	0.558194	0.660221
9	10	0.538937	0.654553
10	11	0.523719	0.654998
11	12	0.510511	0.653773
12	13	0.499761	0.653107
13	14	0.490700	0.655884
14	15	0.483720	0.655516

In [314]:
```
x = pd.DataFrame.from_dict(depth_results)
plt.figure(figsize=(17,7))
plt.plot(x['depth'], x['rmsle_train'], marker='o',label='train');
plt.plot(x['depth'], x['rmsle_valid'], marker='o',label='validation
plt.title('Model: Random Forest Regressor')
plt.ylabel('RMSLE')
plt.xlabel('max_depth')
plt.legend();
```



So, we can still see that the value of RMSLE on both train and validation set is getting stable after the max_depth 10. Now, we will keep on adding the new features to the data and check if it is improving the results or not.

- max_depth : 10
- no_of_estimators : 175

NEW FEATURES

- FOR EACH STORE_ID WE WILL FIND
- **UNIQUE NUMBER OF MANUFACTURERS**
  - For, each of the stores we will find out the number of unique number of manufactures as a feature. We are assumuing that more number of manufactures will give more options to the customers and will impact the sales.
  - We will have to use the original `train_data` and `product_data` to calculate this as we have encoded this feature during the pre-processing step.
- **UNIQUE NUMBER OF CATEGORY AND SUB_CATEGORIES THEY HAVE**
  - Similarly, we will find out the unique number of categories and sub categories that a particular store has.

In [315]:
```
# read the columns 'STORE_NUM' and 'UPC' from the train data
original_train_data = pd.read_csv('train.csv', usecols= ['STORE_NUM
```

In [316]:
```
# read the original product_data
original_product_data = pd.read_csv('product_data.csv')
original_product_data.head(5)
```

Out[316]:

	UPC	DESCRIPTION	MANUFACTURER	CATEGORY	SUB_CATEGORY	PRODUCT_
0	1111009477	PL MINI TWIST PRETZELS	PRIVATE LABEL	BAG SNACKS	PRETZELS	1
1	1111009497	PL PRETZEL STICKS	PRIVATE LABEL	BAG SNACKS	PRETZELS	1
2	1111009507	PL TWIST PRETZELS	PRIVATE LABEL	BAG SNACKS	PRETZELS	1
3	1111038078	PL BL MINT ANTSPTC RINSE	PRIVATE LABEL	ORAL HYGIENE PRODUCTS	MOUTHWASHES (ANTISEPTIC)	50
4	1111038080	PL ANTSPTC SPG MNT MTHWS	PRIVATE LABEL	ORAL HYGIENE PRODUCTS	MOUTHWASHES (ANTISEPTIC)	50

In [317]:
```
# merge the train and product data
original_train_data = original_train_data.merge(original_product_da
```

In [318]:
```
# Now, we will create another dataframe unique_store_data
# We will group the data by STORE_NUM and find unique values of the

unique_store_data = original_train_data.groupby(['STORE_NUM'])['MAN
```

In [319]:
```
# rename the columns of the dataframe 'unique_store_data'
unique_store_data.columns = ['STORE_NUM', 'U_MANUFACTURER', 'U_CATE
```

In [320]:
```
# now , merge this new dataframe with the dataframe that has all th
data_with_unique_store = merged_data.merge(unique_store_data, how=
# let's have a look at the data
data_with_unique_store.head()
```

Out[320]:

	WEEK_END_DATE	STORE_NUM	UPC	PRICE	BASE_PRICE	FEATURE	DISPLAY
0	2009-01-14	367	1111009477	1.39	1.57	0	0
1	2009-01-14	367	1111009497	1.39	1.39	0	0
2	2009-01-14	367	1111085319	1.88	1.88	0	0
3	2009-01-14	367	1111085345	1.88	1.88	0	0
4	2009-01-14	367	1111085350	1.98	1.98	0	0

5 rows × 39 columns

In [321]:
```
# train a model with the new features.
model_RFR = RandomForestRegressor(max_depth=10, n_estimators=175)
new_data = data_with_unique_store.drop(columns=['STORE_NUM', 'UPC']

valid_df = validation_df(new_data, week, no_of_months=2, no_of_vali

rmsle_train, rmsle_valid, data_train = train_model(valid_df, new_da
```

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In [322]:
```
print('RMSLE on train set: ', rmsle_train)
print('RMSLE on validation set:', rmsle_valid)
```

```
RMSLE on train set:  0.47815248934614774
RMSLE on validation set: 0.6029966506151875
```

In [323]:
```
data_train.columns
```

Out[323]:
```
Index(['PRICE', 'BASE_PRICE', 'FEATURE', 'DISPLAY', 'MANUFACTURER_
1',
       'MANUFACTURER_2', 'MANUFACTURER_3', 'MANUFACTURER_4', 'MANU
FACTURER_5',
       'MANUFACTURER_6', 'MANUFACTURER_7', 'MANUFACTURER_8', 'MANU
FACTURER_9',
       'CATEGORY_1', 'CATEGORY_2', 'CATEGORY_3', 'CATEGORY_4',
       'SUB_CATEGORY_1', 'SUB_CATEGORY_2', 'SUB_CATEGORY_3', 'SUB_
CATEGORY_4',
       'SUB_CATEGORY_5', 'SUB_CATEGORY_6', 'SUB_CATEGORY_7', 'PROD
UCT_SIZE',
       'PRODUCT_SIZE_BIN', 'year', 'month', 'day', 'day_of_year',
'week',
       'quarter', 'U_MANUFACTURER', 'U_CATEGORY', 'U_SUB_CATEGORY'
],
      dtype='object')
```

Here, we can see that there is significant improvement in the model performance. On the validation set RMSLE is now 0.600

GET LAG FEATURES

Now, we will create the lag features, which will be the number of units ordered of the same product from the same store at exactly one year ago.

In [324]:
```
# define a function that will return calculate the units sold numbe
# We need to calculate this for 52 Weeks or 1 Year

def get_lag_feature(data, no_of_week=1, return_Series= False):
    data_copy = data.copy()
    sample_1 = data_copy[['WEEK_END_DATE', 'STORE_NUM', 'UPC', 'UNI
    data_copy['NEW_DATE'] = data_copy.WEEK_END_DATE + timedelta(day
    data_copy['PAST_DATE'] = data_copy.WEEK_END_DATE

    sample_2 = data_copy[['NEW_DATE','PAST_DATE', 'STORE_NUM', 'UPC
    final = sample_1.merge(sample_2, how = 'left', left_on = ['WEEK
    final = final.drop(columns=['NEW_DATE'])
    final.fillna(0,inplace = True)

    if return_Series:
        return final['UNITS_y']
    else: return final
```

In [325]:
```
# Let's verify the function is correct or not.
# In the following dataframe, We have UNITS_x as the units sold on
# In the following dataframe, We have UNITS_y as the units sold on

get_lag_feature(merged_data, no_of_week = 8)
```

Out[325]:

	WEEK_END_DATE	STORE_NUM	UPC	UNITS_x	PAST_DATE	UNITS_y
0	2009-01-14	367	1111009477	13	0	0.0
1	2009-01-14	367	1111009497	20	0	0.0
2	2009-01-14	367	1111085319	14	0	0.0
3	2009-01-14	367	1111085345	29	0	0.0
4	2009-01-14	367	1111085350	35	0	0.0
...	...	...	...	...	...	...
232261	2011-09-28	29159	7192100336	32	2011-08-03 00:00:00	16.0
232262	2011-09-28	29159	7192100337	31	2011-08-03 00:00:00	10.0
232263	2011-09-28	29159	7192100339	23	2011-08-03 00:00:00	13.0
232264	2011-09-28	29159	7797502248	8	2011-08-03 00:00:00	7.0
232265	2011-09-28	29159	7797508004	7	2011-08-03 00:00:00	7.0

232266 rows × 6 columns

In [326]:
```
# let's see the last third row of the dataframe
merged_data.loc[(merged_data.WEEK_END_DATE == '2011-09-28') & (merg
```

Out[326]:
```
232263    23
Name: UNITS, dtype: int64
```

In [327]:
```
merged_data.loc[(merged_data.WEEK_END_DATE == '2011-08-03') & (merg
```

Out[327]:
```
219173    13
Name: UNITS, dtype: int64
```

In [328]:
```
#  create a feature UNITS BEFORE 52_WEEK
data_with_unique_store['UNITS_BEFORE_52WEEK'] = get_lag_feature(dat
```

In [329]:
```
# train the model with the new feature

model_RFR = RandomForestRegressor(max_depth=10, n_estimators=175)

new_data = data_with_unique_store.drop(columns= ['STORE_NUM', 'UPC'
valid_df = validation_df(new_data, week, no_of_months=2, no_of_vali

rmsle_train, rmsle_valid, data_train = train_model(valid_df, new_da
```

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In [330]:
```
# mean RMSLE on train and validation set
print('RMSLE on train set: ', rmsle_train)
print('RMSLE on validation set:', rmsle_valid)
```

```
RMSLE on train set:  0.4181179694938823
RMSLE on validation set: 0.5744715023401298
```

In [331]:
```
# columns on the updated data.
data_train.columns
```

Out[331]:
```
Index(['PRICE', 'BASE_PRICE', 'FEATURE', 'DISPLAY', 'MANUFACTURER_
1',
       'MANUFACTURER_2', 'MANUFACTURER_3', 'MANUFACTURER_4', 'MANU
FACTURER_5',
       'MANUFACTURER_6', 'MANUFACTURER_7', 'MANUFACTURER_8', 'MANU
FACTURER_9',
       'CATEGORY_1', 'CATEGORY_2', 'CATEGORY_3', 'CATEGORY_4',
       'SUB_CATEGORY_1', 'SUB_CATEGORY_2', 'SUB_CATEGORY_3', 'SUB_
CATEGORY_4',
       'SUB_CATEGORY_5', 'SUB_CATEGORY_6', 'SUB_CATEGORY_7', 'PROD
UCT_SIZE',
       'PRODUCT_SIZE_BIN', 'year', 'month', 'day', 'day_of_year',
'week',
       'quarter', 'U_MANUFACTURER', 'U_CATEGORY', 'U_SUB_CATEGORY'
,
       'UNITS_BEFORE_52WEEK'],
      dtype='object')
```

We can see a slight improvement in the RMSLE on the validaiton set. It is 0.585 now

DIFFERENCE IN PRICE FROM LAST WEEK

This will be our new feature. Whether the increase/decrease in price from the last week makes any difference to the model or not.

In [332]:
```
# get the price difference
data_with_unique_store['price_difference'] = data_with_unique_store
```

In [333]:
```
# let's verify we have calculated the right price difference or not
data_with_unique_store.loc[(data_with_unique_store.STORE_NUM == 367
```

Out[333]:

	STORE_NUM	UPC	BASE_PRICE	price_difference	UNITS
0	367	1111009477	1.57	NaN	13
1640	367	1111009477	1.57	0.00	24
3276	367	1111009477	1.36	-0.21	7
4912	367	1111009477	1.38	0.02	12
6552	367	1111009477	1.50	0.12	16
8179	367	1111009477	1.49	-0.01	21
9814	367	1111009477	1.49	0.00	11
11427	367	1111009477	1.49	0.00	10
13040	367	1111009477	1.39	-0.10	13
14677	367	1111009477	1.48	0.09	13

In [334]:
```
# fill the null values in the price difference with 0
data_with_unique_store.price_difference.fillna(0,inplace=True)
```

In [335]:
```
model_RFR = RandomForestRegressor(max_depth=10, n_estimators=175)

new_data = data_with_unique_store.drop(columns=['STORE_NUM', 'UPC']

valid_df = validation_df(new_data, week, no_of_months= 2, no_of_val

rmsle_train, rmsle_valid, data_train = train_model(valid_df, new_da
```

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In [336]:
```
print('RMSLE on train set: ', rmsle_train)
print('RMSLE on validation set:', rmsle_valid)
```

```
RMSLE on train set:  0.41871157489128424
RMSLE on validation set: 0.5731874606590718
```

In [337]:
```
data_train.columns
```

Out[337]:
```
Index(['PRICE', 'BASE_PRICE', 'FEATURE', 'DISPLAY', 'MANUFACTURER_
1',
       'MANUFACTURER_2', 'MANUFACTURER_3', 'MANUFACTURER_4', 'MANU
FACTURER_5',
       'MANUFACTURER_6', 'MANUFACTURER_7', 'MANUFACTURER_8', 'MANU
FACTURER_9',
       'CATEGORY_1', 'CATEGORY_2', 'CATEGORY_3', 'CATEGORY_4',
       'SUB_CATEGORY_1', 'SUB_CATEGORY_2', 'SUB_CATEGORY_3', 'SUB_
CATEGORY_4',
       'SUB_CATEGORY_5', 'SUB_CATEGORY_6', 'SUB_CATEGORY_7', 'PROD
UCT_SIZE',
       'PRODUCT_SIZE_BIN', 'year', 'month', 'day', 'day_of_year',
'week',
       'quarter', 'U_MANUFACTURER', 'U_CATEGORY', 'U_SUB_CATEGORY'
,
       'UNITS_BEFORE_52WEEK', 'price_difference'],
      dtype='object')
```

The performance of the model has not changed. It is same as before.

AVERAGE BEFORE 2 MONTH

- As we have one week gap between the training period and the validation set so for each store and product combination we will calculate the average units sold in 2 months before 1 week.
- In simple terms, the average number of units sold from 7 days to 63 days ago
- Let's see is this feature useful to us or not.

In [338]:
```
# make 2 columns one with 63 days difference from the week end date
data_with_unique_store['2_MONTH_BEFORE'] = data_with_unique_store.W
data_with_unique_store['1_WEEK_BEFORE'] = data_with_unique_store.WE
```

In [339]:
```
data_with_unique_store[['WEEK_END_DATE', '2_MONTH_BEFORE', '1_WEEK_
```

Out[339]:

	WEEK_END_DATE	2_MONTH_BEFORE	1_WEEK_BEFORE
232261	2011-09-28	2011-07-27	2011-09-21
232262	2011-09-28	2011-07-27	2011-09-21
232263	2011-09-28	2011-07-27	2011-09-21
232264	2011-09-28	2011-07-27	2011-09-21
232265	2011-09-28	2011-07-27	2011-09-21

In [340]:
```
from tqdm._tqdm_notebook import tqdm_notebook
tqdm_notebook.pandas()
# calculate the average units in the period
def get_average_units(x):
    data_2month = data_with_unique_store[(data_with_unique_store.WE
    return data_2month.UNITS.mean()
```

In [341]:
```
data_with_unique_store['AVERAGE_UNITS_IN_2_MONTH'] = data_with_uniq
```

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In [342]:
```
# fill the null values with 0
data_with_unique_store.AVERAGE_UNITS_IN_2_MONTH.fillna(0,inplace=Tr
```

In [343]:
```
# drop the date columns that we have created, as they are of no use
new_data = data_with_unique_store.drop(columns=['2_MONTH_BEFORE','1
```

In [344]:
```
model_RFR = RandomForestRegressor(max_depth=10, n_estimators=175)

valid_df = validation_df(new_data, week, no_of_months=2, no_of_vali

rmsle_train, rmsle_valid, data_train = train_model(valid_df,new_dat
```

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In [345]:
```
print('RMSLE on train set: ', rmsle_train)
print('RMSLE on validation set:', rmsle_valid)
```

```
RMSLE on train set:  0.34044916362092964
RMSLE on validation set: 0.46287787578255796
```

In [346]:
```
data_train.columns
```

Out[346]:
```
Index(['PRICE', 'BASE_PRICE', 'FEATURE', 'DISPLAY', 'MANUFACTURER_
1',
       'MANUFACTURER_2', 'MANUFACTURER_3', 'MANUFACTURER_4', 'MANU
FACTURER_5',
       'MANUFACTURER_6', 'MANUFACTURER_7', 'MANUFACTURER_8', 'MANU
FACTURER_9',
       'CATEGORY_1', 'CATEGORY_2', 'CATEGORY_3', 'CATEGORY_4',
       'SUB_CATEGORY_1', 'SUB_CATEGORY_2', 'SUB_CATEGORY_3', 'SUB_
CATEGORY_4',
       'SUB_CATEGORY_5', 'SUB_CATEGORY_6', 'SUB_CATEGORY_7', 'PROD
UCT_SIZE',
       'PRODUCT_SIZE_BIN', 'year', 'month', 'day', 'day_of_year',
'week',
       'quarter', 'U_MANUFACTURER', 'U_CATEGORY', 'U_SUB_CATEGORY'
,
       'UNITS_BEFORE_52WEEK', 'price_difference', 'AVERAGE_UNITS_I
N_2_MONTH'],
      dtype='object')
```

- The last feature that we added has made significant improvement in the RMSLE score on the validation data.
- The RMSLE is now `0.4677`

In [347]:
```
data_with_unique_store.to_csv('final_data.csv',index=False)
```

Testing Final Models and Feature Importance

In [348]:
```
# importing required libraries

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

import warnings
warnings.filterwarnings('ignore')

from sklearn.ensemble import RandomForestRegressor
from tqdm import tqdm
from datetime import timedelta
from sklearn.metrics import mean_squared_log_error as msle
```

In [349]:
```
# read the dataset
data = pd.read_csv('final_data.csv')
```

In [350]:
```
# check for the null values
data.isna().sum().sum()
```

Out[350]: 0

In [351]:
```
data.loc[0]
```

Out[351]:
```
WEEK_END_DATE                2009-01-14
STORE_NUM                           367
UPC                          1111009477
PRICE                              1.39
BASE_PRICE                         1.57
FEATURE                               0
DISPLAY                               0
UNITS                                13
MANUFACTURER_1                        1
MANUFACTURER_2                        0
MANUFACTURER_3                        0
MANUFACTURER_4                        0
MANUFACTURER_5                        0
MANUFACTURER_6                        0
MANUFACTURER_7                        0
MANUFACTURER_8                        0
MANUFACTURER_9                        0
CATEGORY_1                            1
CATEGORY_2                            0
CATEGORY_3                            0
CATEGORY_4                            0
SUB_CATEGORY_1                        1
SUB_CATEGORY_2                        0
SUB_CATEGORY_3                        0
SUB_CATEGORY_4                        0
SUB_CATEGORY_5                        0
SUB_CATEGORY_6                        0
SUB_CATEGORY_7                        0
PRODUCT_SIZE                       15.0
PRODUCT_SIZE_BIN                      2
year                               2009
month                                 1
day                                  14
day_of_year                          14
week                                  3
quarter                               1
U_MANUFACTURER                        4
U_CATEGORY                            3
U_SUB_CATEGORY                        5
UNITS_BEFORE_52WEEK                 0.0
price_difference                    0.0
2_MONTH_BEFORE               2008-11-12
1_WEEK_BEFORE                2009-01-07
AVERAGE_UNITS_IN_2_MONTH            0.0
Name: 0, dtype: object
```

In [352]:
```
# drop the columns that are not required
data = data.drop(columns= ['2_MONTH_BEFORE', '1_WEEK_BEFORE'])
```

In [353]:
```
data.WEEK_END_DATE = pd.to_datetime(data.WEEK_END_DATE)
```

In [354]:
```
week = data.WEEK_END_DATE.unique()
```

In [355]:
```
def validation_df(data, week, no_of_months, no_of_validation):

    model_set = []
    set_n = 1
    for w in range(len(week)-1,0,-1):
        x_data = {}

        x_data['train_start_1'] = week[w-3-4*no_of_months]
        x_data['train_end_1'] = week[w-4]
        x_data['train_start_2'] = week[w-1-4*no_of_months]
        x_data['validate_week'] = week[w-2]
        x_data['test_week'] = week[w]
        x_data['no_days_train_1'] = x_data['train_end_1'] - x_data[
        x_data['no_days_train_2'] = x_data['validate_week'] - x_dat
        x_data['set_no'] = 'set'+str(set_n)
        set_n +=1
        model_set.append(x_data)
        if(len(model_set) == no_of_validation):
            break


    df = pd.DataFrame.from_dict(model_set)
    df['no_days_train_1'] = df['no_days_train_1'] + timedelta(days=
    df['no_days_train_2'] = df['no_days_train_2'] + timedelta(days=
    return df
```

In [356]:
```
validation_df(data, week, no_of_months=2, no_of_validation = 14)
```

Out[356]:

	train_start_1	train_end_1	train_start_2	validate_week	test_week	no_days_train_1	no_
0	2011-07-13	2011-08-31	2011-07-27	2011-09-14	2011-09-28	56 days	
1	2011-07-06	2011-08-24	2011-07-20	2011-09-07	2011-09-21	56 days	
2	2011-06-29	2011-08-17	2011-07-13	2011-08-31	2011-09-14	56 days	
3	2011-06-22	2011-08-10	2011-07-06	2011-08-24	2011-09-07	56 days	
4	2011-06-15	2011-08-03	2011-06-29	2011-08-17	2011-08-31	56 days	
5	2011-06-08	2011-07-27	2011-06-22	2011-08-10	2011-08-24	56 days	
6	2011-06-01	2011-07-20	2011-06-15	2011-08-03	2011-08-17	56 days	
7	2011-05-25	2011-07-13	2011-06-08	2011-07-27	2011-08-10	56 days	
8	2011-05-18	2011-07-06	2011-06-01	2011-07-20	2011-08-03	56 days	
9	2011-05-11	2011-06-29	2011-05-25	2011-07-13	2011-07-27	56 days	
10	2011-05-04	2011-06-22	2011-05-18	2011-07-06	2011-07-20	56 days	
11	2011-04-27	2011-06-15	2011-05-11	2011-06-29	2011-07-13	56 days	
12	2011-04-20	2011-06-08	2011-05-04	2011-06-22	2011-07-06	56 days	
13	2011-04-13	2011-06-01	2011-04-27	2011-06-15	2011-06-29	56 days	

In [357]:
```
# define a function to calculate the evaluation sets.
# this time we will include test set also
def get_evaluation_sets(data, df):
    evaluation_set = []

    for row in range(df.shape[0]):
        print(df.loc[row]['set_no'])
        # get the train data 1
        train_data_1 = data[(data.WEEK_END_DATE >= df.loc[row]['tra
        # get the validate data
        validation_data = data[data.WEEK_END_DATE == df.loc[row]['v
        # get the train data 2
        train_data_2 = data[(data.WEEK_END_DATE >= df.loc[row]['tra
        # get the test data
        test_data = data[data.WEEK_END_DATE == df.loc[row]['test_we
        evaluation_set.append((train_data_1, validation_data, train
    return evaluation_set
```

In [358]:
```
# get the evaluation sets
evaluation_sets = get_evaluation_sets(data,
                                      validation_df(data,
                                                    week,
                                                    no_of_months= 2
                                                    no_of_validatio
                                     )
```

```
set1
set2
set3
set4
set5
set6
set7
set8
set9
set10
set11
set12
set13
set14
```

In [359]:
```
# function to calculate the root mean squared log error
def get_msle(true, predicted) :
    return np.sqrt(msle(true, predicted))
```

Define function to calculate results on the evaluation sets.

In [360]:
```
def get_results_on_evaluation_set(eval_set, model):
    results = []
    set_n = 1
    for eval_data in tqdm(eval_set):

        x = {}
        train_data_1, validate, train_data_2, test = eval_data

        # separate the independent and target variables from train
        train_data_1_x = train_data_1.drop(columns= ['WEEK_END_DATE
        train_data_1_y = train_data_1['UNITS']

        validate_x = validate.drop(columns= ['WEEK_END_DATE', 'STOR
        validate_y = validate['UNITS']

        train_data_2_x = train_data_2.drop(columns= ['WEEK_END_DATE
        train_data_2_y = train_data_2['UNITS']

        test_x = test.drop(columns= ['WEEK_END_DATE', 'STORE_NUM',
        test_y = test['UNITS']


        # fit the model on the training data
        model_valid = model.fit(train_data_1_x, train_data_1_y)

        # predict the target on train and validate
        predict_train_1 = model_valid.predict(train_data_1_x).clip(
        predict_valid   = model_valid.predict(validate_x).clip(min=


        # fit the model on the training data
        model_test  = model.fit(train_data_2_x, train_data_2_y)

        # predict the target on train and test
        predict_train_2 = model_test.predict(train_data_2_x).clip(m
        predict_test    = model_test.predict(test_x).clip(min=0)


        # calculate the rmsle on train and valid
        rmsle_train_1 = get_msle(train_data_1_y, predict_train_1)
        rmsle_valid   = get_msle(validate_y, predict_valid)

        # calculate the rmsle on train and test
        rmsle_train_2 = get_msle(train_data_2_y, predict_train_2)
        rmsle_test    = get_msle(test_y, predict_test)


        x['set_no'] = set_n
        set_n +=1
        x['rmsle_train_1'] = rmsle_train_1
        x['rmsle_valid'] = rmsle_valid
        x['rmsle_train_2'] = rmsle_train_2
        x['rmsle_test'] = rmsle_test
        results.append(x)
```

```
    return pd.DataFrame.from_dict(results)
```

In [361]:
```
# define function to get the best 10 feature importance plot
def get_feature_importance(eval_set, model):
    train_data_1, validate, train_data_2, test = eval_set

    train_data_x = train_data_2.drop(columns= ['WEEK_END_DATE', 'ST
    train_data_y = train_data_2['UNITS']

    test_x = test.drop(columns= ['WEEK_END_DATE', 'STORE_NUM', 'UPC
    test_y = test['UNITS']

    model.fit(train_data_x, train_data_y)
    (pd.Series(model.feature_importances_, index=train_data_x.colum
```

RANDOM FOREST

In [362]:
```
### define randomforest model
model_rf = RandomForestRegressor(max_depth=10, n_estimators=175, ra

# calculate the results using the random forest
results_RFR = get_results_on_evaluation_set(evaluation_sets, model_
```

```
100%|██████████████████████████████████████| 14/14 [02:22<00:
00, 10.21s/it]
```

In [363]:
```
results_RFR[['rmsle_train_2', 'rmsle_test']]
```

Out[363]:

	rmsle_train_2	rmsle_test
0	0.350602	0.411522
1	0.354616	0.493730
2	0.355195	0.415886
3	0.345287	0.459826
4	0.341424	0.558863
5	0.344649	0.470151
6	0.334453	0.463753
7	0.333277	0.534483
8	0.330174	0.431620
9	0.331476	0.461010
10	0.340073	0.480501
11	0.342064	0.428297
12	0.340506	0.429245
13	0.338532	0.437915

In [364]:
```
# average rmsle
results_RFR[['rmsle_train_2', 'rmsle_test']].mean()
```

Out[364]:
```
rmsle_train_2    0.341595
rmsle_test       0.462629
dtype: float64
```