INSAID
INTERNATIONAL SCHOOL OF AI AND DATA SCIENCE

Sales Forecasting

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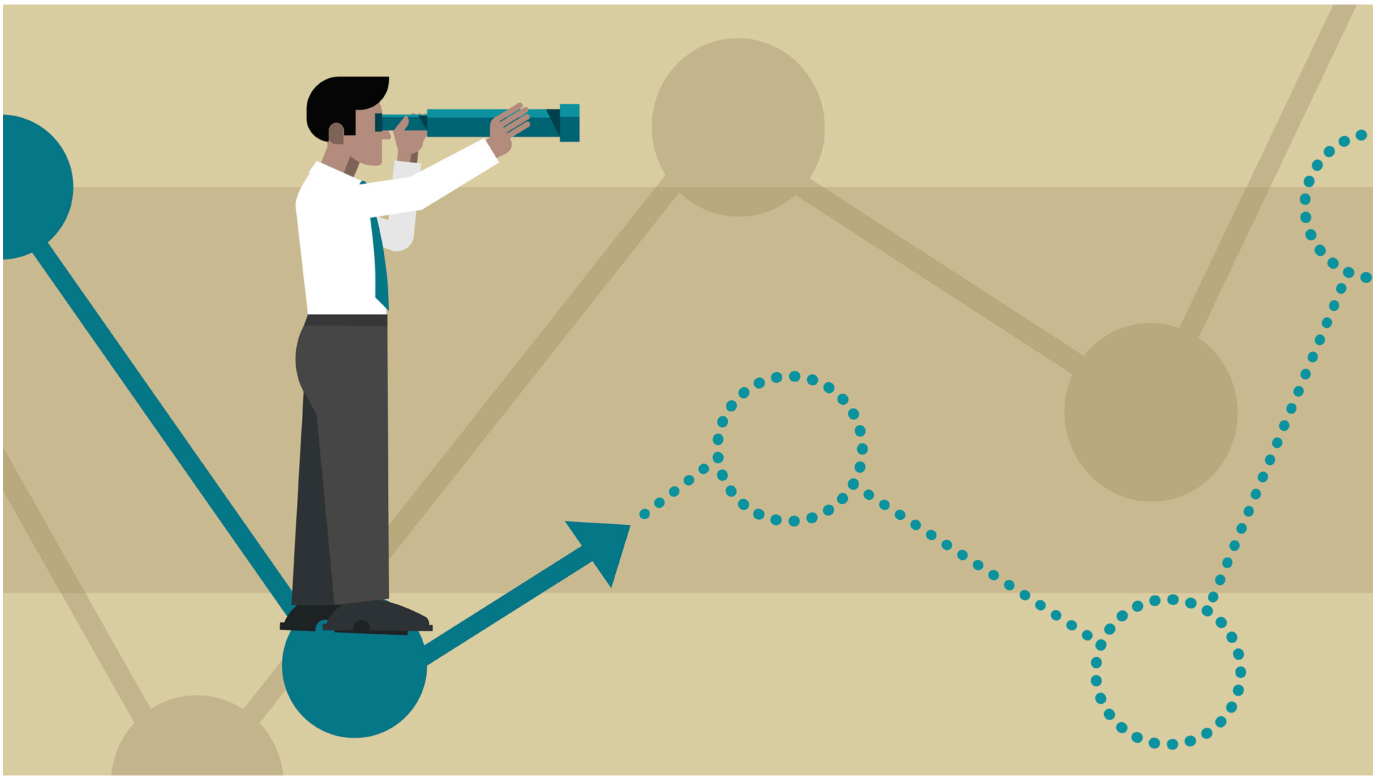
1. Introduction

- Forecasting means the **estimation** of quantity, type, and quality of future work e.g. sales.
- Any forecast can be termed as an **indicator** of what is likely to happen in a specified **future** time frame in a particular field.
- Therefore, the sales forecast indicates as to how much of a particular **product** is likely to be **sold** in a specified future period in a specified market at specified price.
- For any manufacturing concern, it is very necessary to assess the **market trends** sufficiently in advance.
- This forecast helps the management in determining as to how much **revenue** can be expected to be realized, how much to manufacture, and what shall be the **requirement** of men, machines, and money.

2. Problem Statement

- The **demand** for a product or service keeps **changing** from time to time.
- No business can improve its financial performance without **estimating customer demand** and future sales of products/services accurately.



Business Scenario:

- A multinational retail corporation named **Shopper's Depot** operates a chain of hypermarkets, discount department stores, and grocery stores all around the world.
- The company is planning to open some additional stores in different regions and the management wants to **predict** the **future sales** of these stores and the **factors affecting** the sales numbers.
- This will help them in allocating a **budget** to each store according to the amount of mechanical and human resources required in the stores and setting up the **supply chain** and **inventory** systems.
- One challenge of modeling retail data is the need to make decisions based on **limited history**.
- As a result, the company has assigned its Data Science division the task to make the **department-wide sales forecast** for each store.
- The **target feature** is the **Weekly_Sales** column which shows the **sales** for the given department in the given store for a particular week.

3. Importing Libraries

3.1 Installing Libraries

Note: After installing, you need to restart the runtime. Make sure not to execute the cell again after restarting the runtime.

```
!pip install -q pandas-profiling --upgrade
```

3.2 Importing Libraries

```
# For Numerical Python
import numpy as np

# For Panel Data Analysis
import pandas as pd
pd.set_option('display.max_columns', None)
pd.set_option('mode.chained_assignment', None)
pd.set_option('display.precision', 4)

from pandas_profiling import ProfileReport

# For Data Visualization
import matplotlib.pyplot as plt
%matplotlib inline

import seaborn as sns

# To Disable Warnings
import warnings
warnings.filterwarnings("ignore")


# For Data Model Development
from sklearn.model_selection import train_test_split, cross_val_score, GridSear
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR


# For Machine Learning Model Evaluation
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

4. Data Loading and Dataset Description

- We are provided with historical sales data for **45 The Shopper's Depot** stores located in different regions from **2010-02-05 to 2012-11-01**.
- Each store contains about **99** different **departments**, and we are tasked with predicting the department-wide sales for each store.

- In addition to the stores basic operations, *The Shopper's Depot* runs several **promotional markdown events** throughout the year.
  - These markdowns are known to **affect sales**, but it is challenging to predict which departments are affected and the extent of the impact.

Records	Features	Dataset Size
421,570	16	37 MB

Column	Description
Store	The store number.
Dept	The department number.
Date	The week
Weekly_Sales	Sales for the given department in the given store.
IsHoliday	Whether the week is a special holiday week.
Temperature	Average temperature in the region.
Fuel_Price	Cost of fuel in the region.
MarkDown1	Anonymized data related to promotional markdowns that **The Shopper's Depot** is running.
MarkDown2	Anonymized data related to promotional markdown.
MarkDown3	Anonymized data related to promotional markdowns.
MarkDown4	Anonymized data related to promotional markdowns.
MarkDown5	Anonymized data related to promotional markdowns.
CPI	The consumer price index.
Unemployment	The unemployment rate.
Type	Type of the store.
Size	Size of the store.

4.1 Data Loading

```
sales_df = pd.read_csv('https://storage.googleapis.com/retail-analytics-data/week
sales_df.head()
```

	Store	Dept	Date	Weekly_Sales	IsHoliday	Temperature	Fuel_Price	MarkDow
0	1	1	2010-02-05	24924.50	False	42.31	2.572	N
1	1	2	2010-02-05	50605.27	False	42.31	2.572	N
2	1	3	2010-02-05	13740.12	False	42.31	2.572	N
3	1	4	2010-02-05	39954.04	False	42.31	2.572	N
4	1	5	2010-02-05	32229.38	False	42.31	2.572	N

4.2 Pre Profiling Report

- Using **pandas-profiling** to quickly *analyse* our data.

```
profile = ProfileReport(sales_df, progress_bar=False, minimal=True)
```

```
profile.to_file(output_file="Pre_Profiling_Report.html")
print('Pre-Profiling Accomplished!')
```

```
Pre-Profiling Accomplished!
```

Observations:

- There are **16 variables** and **421570 observations** in the dataset.
- There are **1422431 missing** cells (**21.1%** of all cells) in the data.
- Of all the 16 variables **13** are **numerical**, **2** are **categorical** and **1** is **boolean**.
- `Date` column has a high cardinality with 143 distinct values.
- `Date` only contains **datetime** values, but is having a **categorical** dtype.
- All the MarkDown columns have more than **64% missing** values:
    - `MarkDown1` has **270889** (**64.3%**) missing values
    - `MarkDown2` has **310322** (**73.6%**) missing values
    - `MarkDown3` has **284479** (**67.5%**) missing values
    - `MarkDown4` has **286603** (**68.0%**) missing values
    - `MarkDown5` has **270138** (**64.1%**) missing values

- All the MarkDown columns have a **positive skewness** values and very **high kurtosis** value suggesting presence of **outliers**.
- `IsHoliday` contains only **two unique** values True and False.
- `Type` has **3** distinct values: **A**, **B**, and **C**.
- `Weekly_Sales` has a mean of 15981.25 and a median of 7612.03
    - The **skewness** is **3.26**, meaning the distribution if positive (right) skewed.
    - Also, it has a very high **kurtosis** value at **21.49**, suggesting presence of outliers in the distribution.
    - The maximimum value in this column is **693099.36** which is very far away from the **95-th percentile** value of **61201.95**, meaning that it's an **outlier**.

5. Data Pre-Processing

5.1 Dealing with Missing Values

- First, we will check the **number** of missing values in each column.

```
# Checking number of missing values
sales_df.isnull().sum()
```

```
Store                0
Dept                 0
Date                 0
Weekly_Sales         0
IsHoliday            0
Temperature          0
Fuel_Price           0
MarkDown1       270889
MarkDown2       310322
MarkDown3       284479
MarkDown4       286603
MarkDown5       270138
CPI                  0
Unemployment         0
Type                 0
Size                 0
dtype: int64
```

- We know that each Markdown column has more than **64% missing values** from the Profiling Report.
- But, we don't know for sure whether these **markdown events** were even *organized prior to November 2011*, so we should not just fill these values with the median value.

- Instead we will **fill** the missing values with **0**, in order to maintain the integrity of the dataset.

```
# Filling the missing values with 0
sales_df.fillna(0, inplace=True)
```

```
# Rechecking for missing values
sales_df.isnull().sum()
```

```
Store           0
Dept            0
Date            0
Weekly_Sales    0
IsHoliday       0
Temperature     0
Fuel_Price      0
MarkDown1       0
MarkDown2       0
MarkDown3       0
MarkDown4       0
MarkDown5       0
CPI             0
Unemployment    0
Type            0
Size            0
dtype: int64
```

- All the missing values in the data have been **filled**.
- There are **no missing values** in the data now.

5.2 Feature (Month) Extraction from Date

- We will **change** the **datatype** of the `Date` column from *Object* to *DateTime*.

```
# Changing the Date column's dtype from Object to DateTime
sales_df['Date'] = pd.to_datetime(sales_df['Date'])
```

- We can now use this `Date` column to extract **day**, **month** and **year** information as features.
- But, we are **aggregating** the *sales on a weekly basis*, so there's no point in extracting the Day from the Date.
- Also, the Year will only have **3 distinct** values 2010, 2011 and 2012.
  - Sales can only be affected by Year due to some **rare phenomenon** like Stock Market Crashes, Disease Outbreaks, or Natual Disasters.

  - Since, these can't be predicted in advance we can say that the **Year won't affect** the **weekly sales** of the stores.
- As a result, we will only extract the **Month** information from the `Date` column.

```
# Creating Month column in the sales_df after extracting the information from Dat
sales_df['Month'] = sales_df['Date'].dt.month
```

```
sales_df.head()
```

	Store	Dept	Date	Weekly_Sales	IsHoliday	Temperature	Fuel_Price	MarkDow
0	1	1	2010-02-05	24924.50	False	42.31	2.572	(
1	1	2	2010-02-05	50605.27	False	42.31	2.572	(
2	1	3	2010-02-05	13740.12	False	42.31	2.572	(
3	1	4	2010-02-05	39954.04	False	42.31	2.572	(
4	1	5	2010-02-05	32229.38	False	42.31	2.572	(

- `Month` column is added to the sales_df containing the **month** from the weekly sales date.
- We can still see that we have two columns having **categorical / textual** data: `IsHoliday`, and `Type`.
- We will **encode** these columns *after performing* the **analysis** on the data, so that they car be used in the model for prediction.

6. Exploratory Data Analysis

Question 1: How are the stores distributed based on their Type?

```
# Checking the count of each type of store
sales_df.groupby(['Type'])['Store'].nunique()
```

```
Type
A    22
B    17
C     6
Name: Store, dtype: int64
```

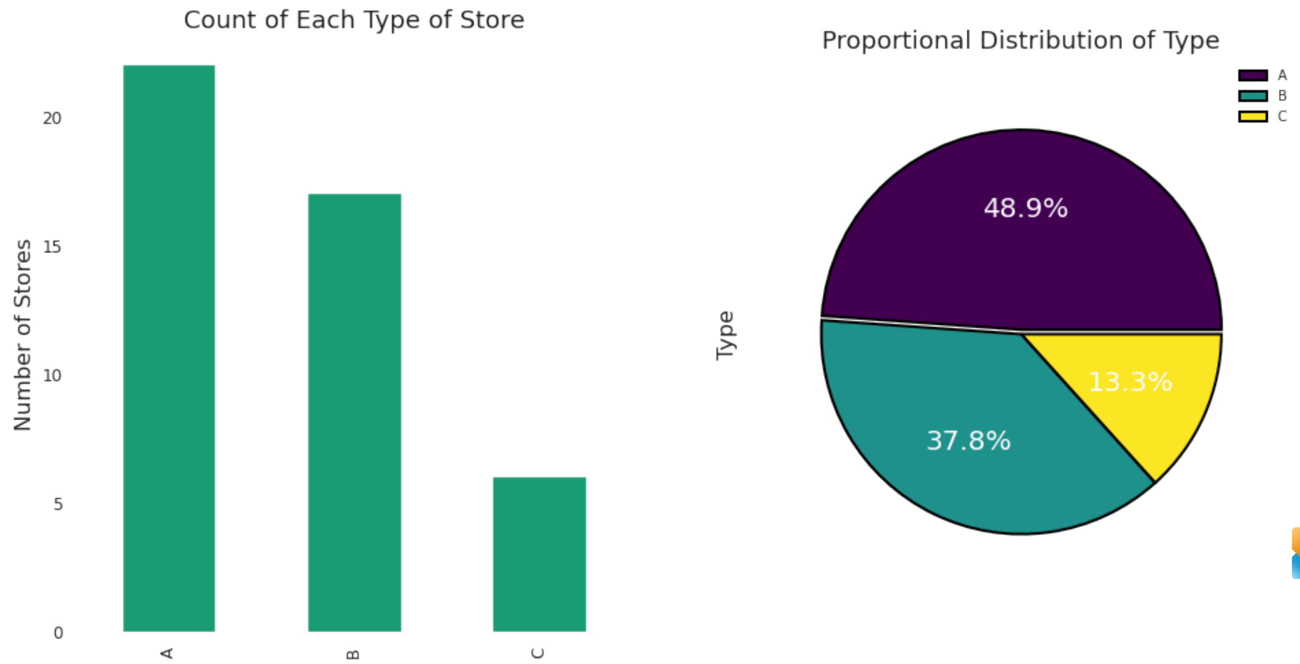
```
# Plotting the Count and Proportional Distribution of Stores based on Type
plt.figure(figsize=(16, 8))
plt.subplot(1, 2, 1)

# Plotting the count of each type of store
sales_df.groupby(['Type'])['Store'].nunique().plot(kind='bar', colormap='Dark2',
plt.xlabel('')
plt.ylabel('Number of Stores', fontsize=16)
plt.title('Count of Each Type of Store', fontsize=18)

plt.subplot(1, 2, 2)

# Plotting the proportional distribution stores
sales_df.groupby(['Type'])['Store'].nunique().plot(kind='pie', autopct='%1.1f%%',
                                                   colormap='viridis', legend=Tru
                                                   textprops={'fontsize':20, 'col
plt.ylabel('Type', fontsize=16)
plt.title('Proportional Distribution of Type', fontsize=18)
```

```
Text(0.5, 1.0, 'Proportional Distribution of Type')
```



Observations:

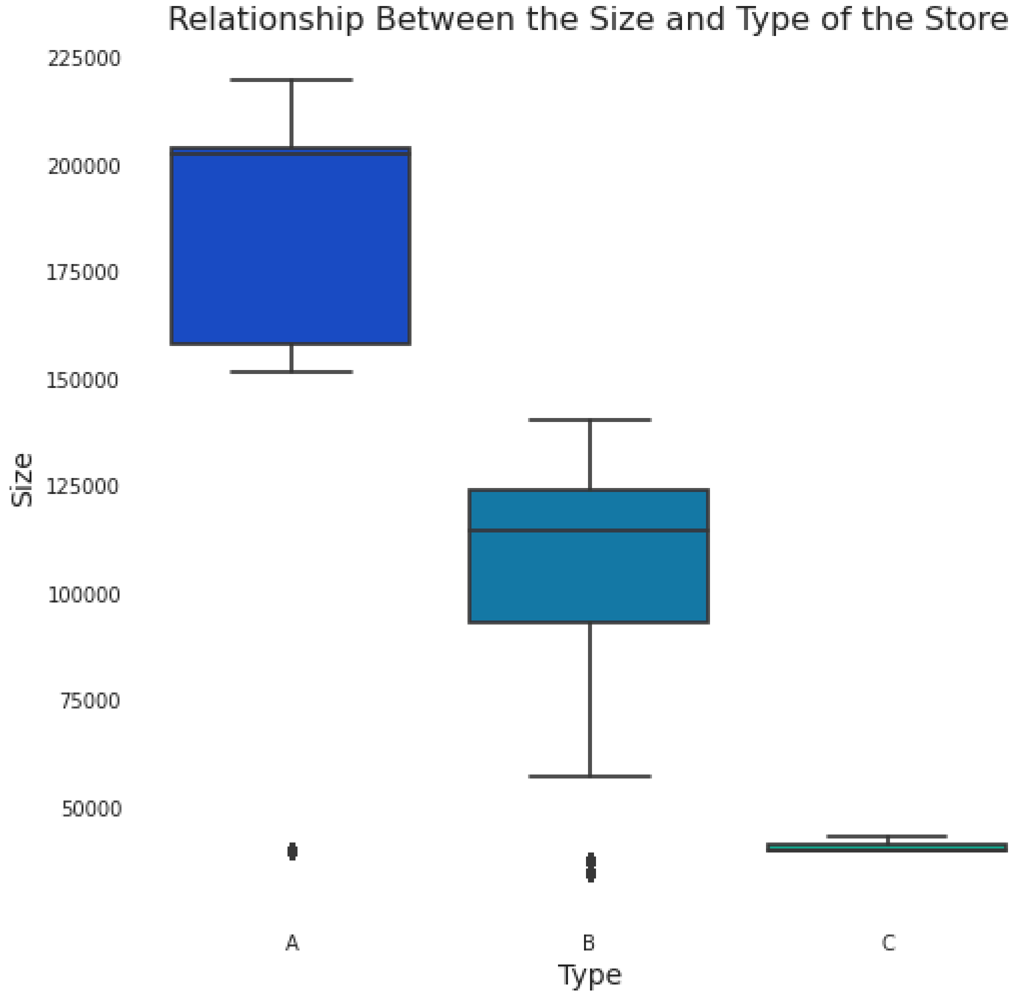
- Stores belonging to **Type A** have the highest number of counts with **22**, accounting for **48.9%** of all stores in the data.
- **Type B** stores have **17** counts followed by **Type C** stores with **6** counts.
  - **37.8%** stores belong to type **B** and the remaining **13.3%** stores belong to the type **C**.

- We now know the proportional distribution of stores based on their type, but can we find some other relationship between the other features.

Question 2: Is the Size of the Store related to the Type of the Store?

```
plt.figure(figsize=(8, 8))
sns.boxplot(data=sales_df, x='Type', y='Size', palette='winter', width=0.8)
plt.xlabel('Type', fontsize=14)
plt.ylabel('Size', fontsize=14)
plt.title('Relationship Between the Size and Type of the Store', fontsize=16)
```

```
Text(0.5, 1.0, 'Relationship Between the Size and Type of the Store')
```



Observations:

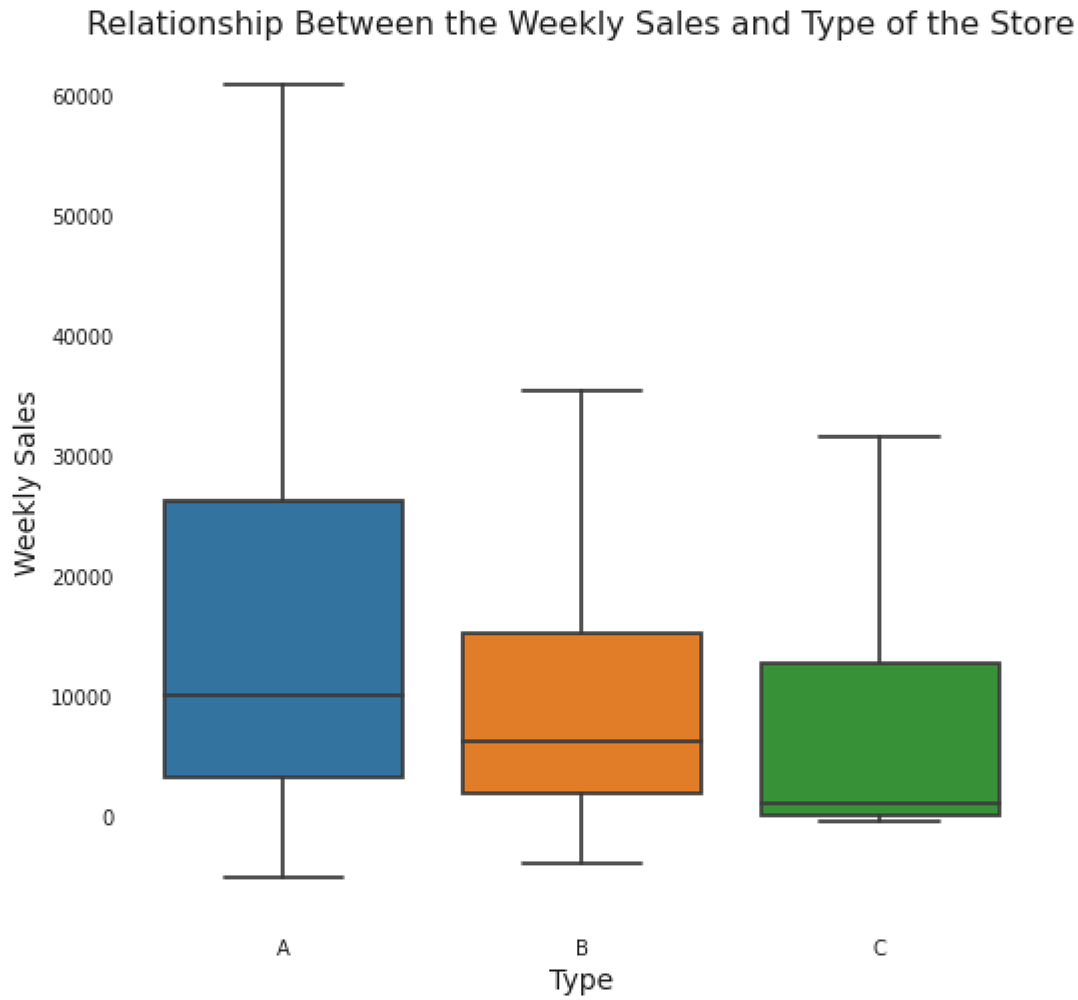
- **Type A** stores have the **largest** size, followed by Type B stores.
- **Type C** stores have the **smallest** size.
- There is **no overlapped area** in *size among A, B, and C* which means that *Type* is the **best predictor** for the *Size* of the store.
- We infer that Type might just be a **proxy** or **alias** for the Size of the store.

- **Larger stores** might have **higher weekly sales**.
- Can we see a relationship between the `Type` and `Weekly_Sales` of a store.

Question 3: Does the Larger Sized Stores have Higher Weekly Sales?

```
plt.figure(figsize=(8, 8))
sns.boxplot(data=sales_df, x='Type', y='Weekly_Sales', width=0.8, showfliers=Fals
plt.xlabel('Type', fontsize=14)
plt.ylabel('Weekly Sales', fontsize=14)
plt.title('Relationship Between the Weekly Sales and Type of the Store', fontsize
```

```
Text(0.5, 1.0, 'Relationship Between the Weekly Sales and Type of the Store')
```



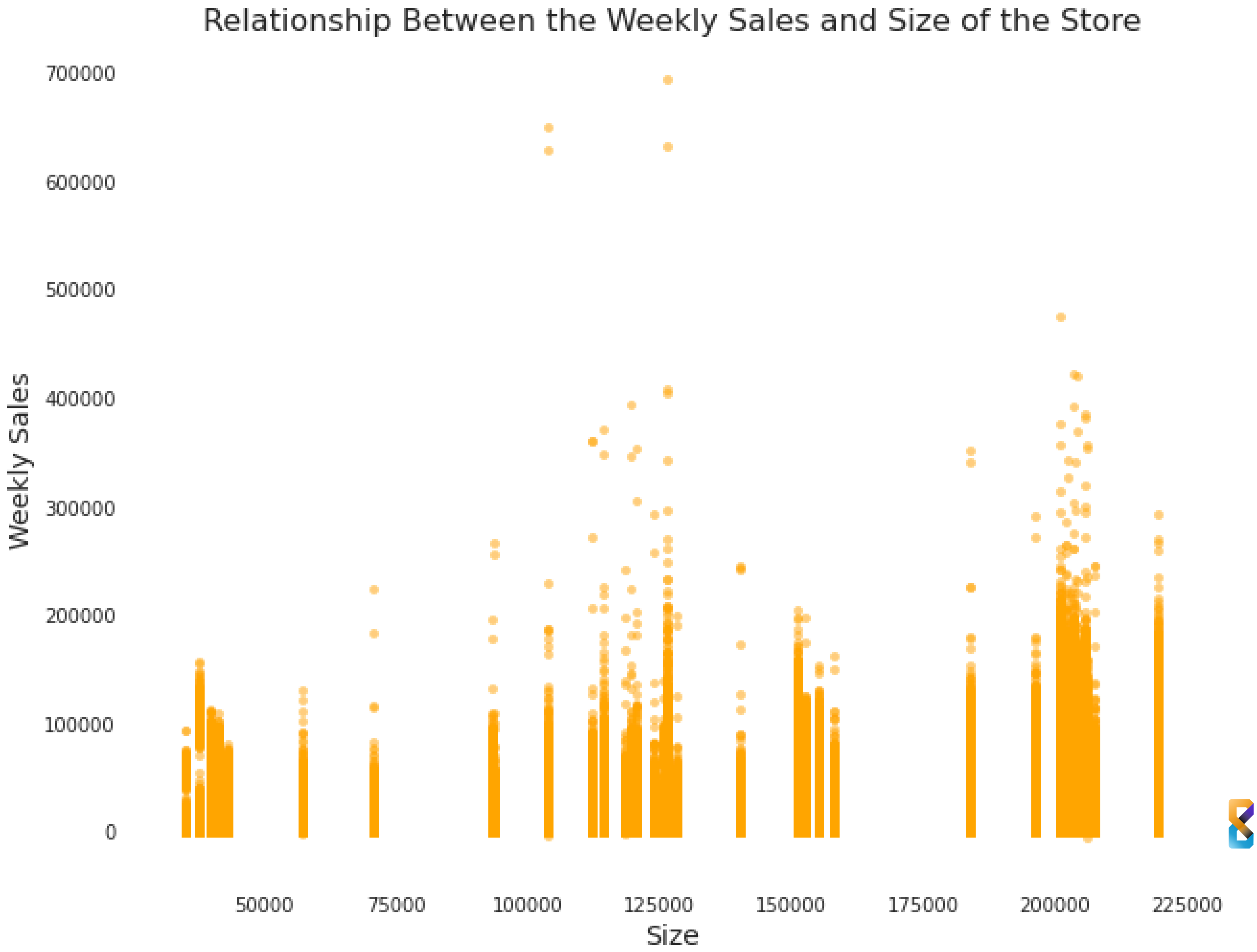
Observations:

- The **median** of **A** is the **highest** and **C** is the **lowest**.
- Also, the order of median of size and median of sales is the same.
- That means the stores with **larger sizes** have **higher sales** record.

Question 4: Is there a Strong Positive Correlation between the Size and the Weekly Sales of a Store?

```
sales_df.plot(kind='scatter', x='Size', y='Weekly_Sales', alpha=0.5, figsize=(10,
plt.xlabel('Size', fontsize=14)
plt.ylabel('Weekly Sales', fontsize=14)
plt.title('Relationship Between the Weekly Sales and Size of the Store', fontsize
```

```
Text(0.5, 1.0, 'Relationship Between the Weekly Sales and Size of the Store')
```



Observations:

- Based on this plot, the results don't look so good.
- We **can't infer** any **distinct relationship** between *size* and *sales*.
- It seems a bit **linear**.

Question 5: How does each Store perform on the basis of Weekly Sales?

```
plt.figure(figsize=(19, 7))
sns.boxplot(data=sales_df, x='Store', y='Weekly_Sales', hue='Type', showfliers=Fa
plt.xlabel('Store', fontsize=14)
plt.ylabel('Weekly Sales', fontsize=14)
plt.title('Weekly Sales of Each Store with respect to the Type of the Store', fon
```

```
Text(0.5, 1.0, 'Weekly Sales of Each Store with respect to the Type of the Store')
```

Observations:

- Each store has a **distinct distribution** of weekly sales throughout the dataset.
- Most of the **Type A** stores have **higher weekly sales record** than other type stores.

- `Store` can be the variable giving **important information** on weekly sales.
- But it is including so much **intrinsic information** of *Type*, *Size*, and *Department*.
- We need to segment this information into distinct plots.

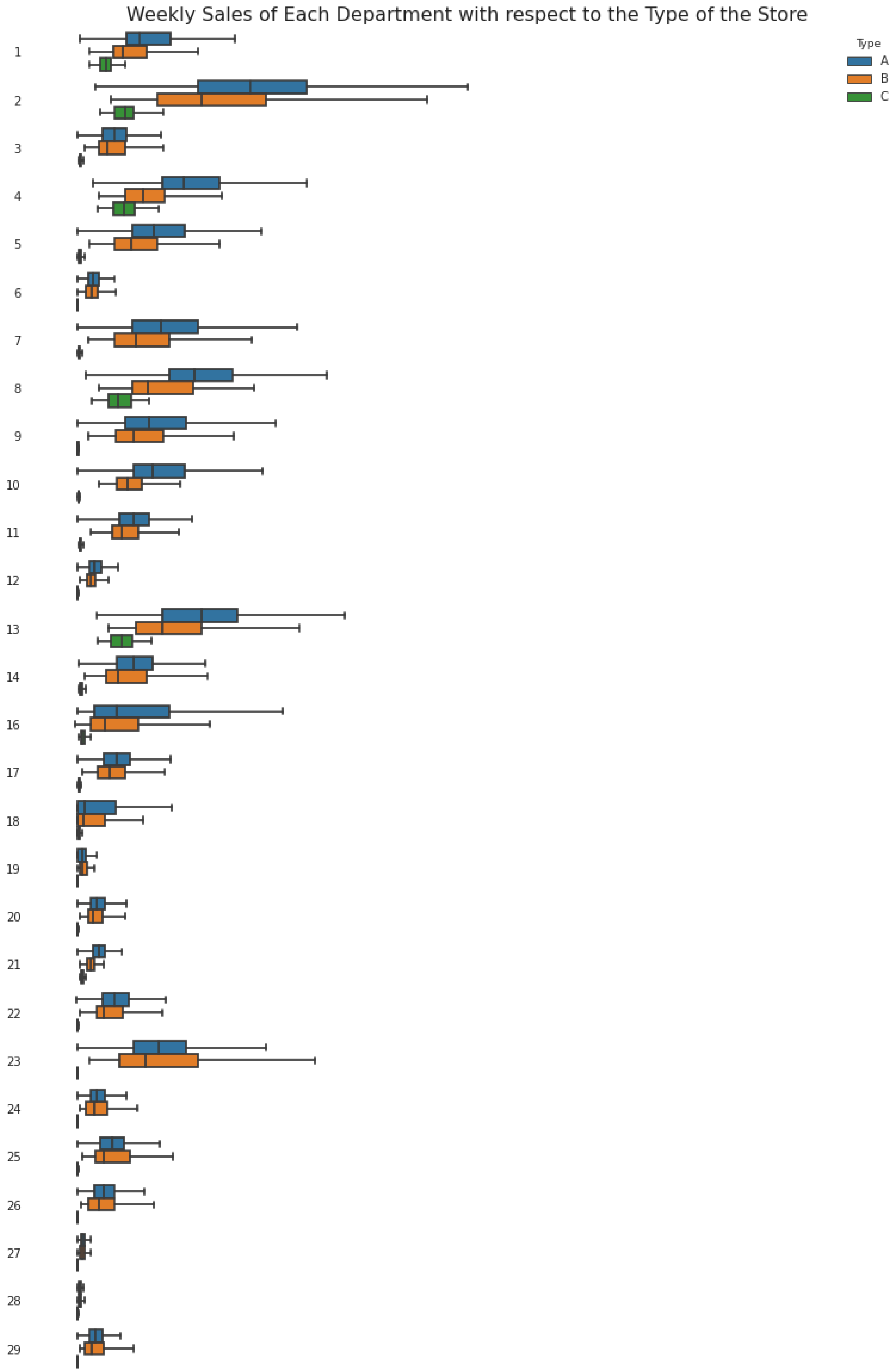
Observation:

- There **isn't a significant relationship** between the weekly sales of the stores for holidays and non-holidays.
- But, we do see **higher weekly sales** soaring during the **holiday weeks**.

Question 6: Does the Weekly Sales for each Department vary with the Size of the Store?

```
plt.figure(figsize=(13, 60))
sns.boxplot(data=sales_df, x='Weekly_Sales', y='Dept', hue='Type', orient='h', sh
plt.xlabel('Weekly Sales', fontsize=14)
plt.ylabel('Department', fontsize=14)
plt.title('Weekly Sales of Each Department with respect to the Type of the Store'
```

```
Text(0.5, 1.0, 'Weekly Sales of Each Department with respect to the Type of the Store')
```



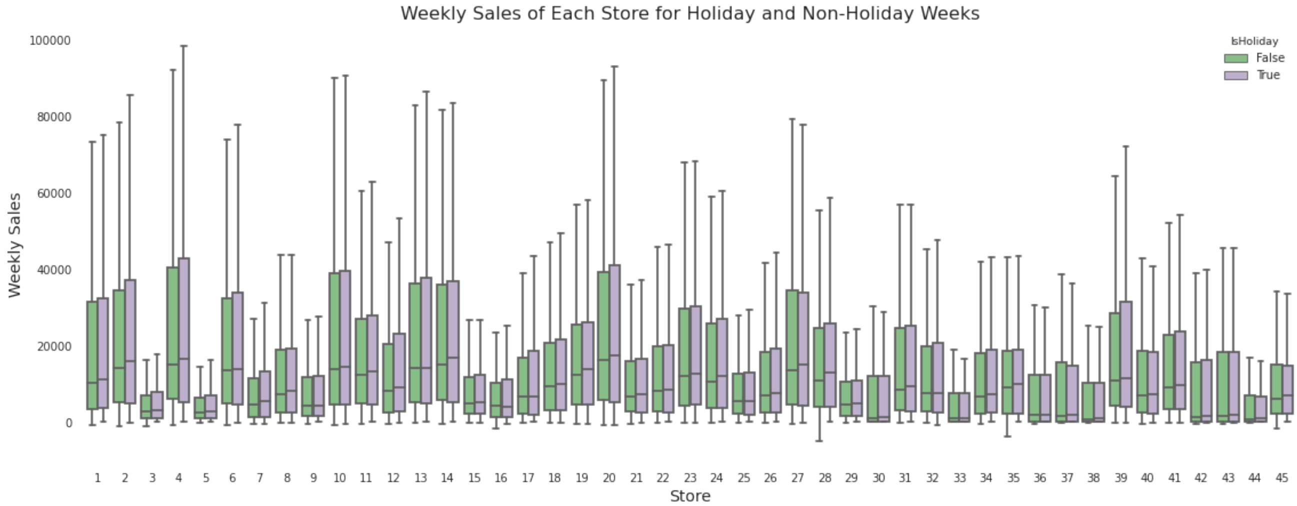
Observations:

- We can clearly observe that the Departments belonging to **Type A** stores have the **highest sales record**.
- This can imply that *departments at* the **larger stores** have **higher weekly sales record** than those at the *smaller stores*.

Question 7: Do the Holidays impact the Weekly Sales of the Stores?

```
plt.figure(figsize=(19, 7))
sns.boxplot(data=sales_df, x='Store', y='Weekly_Sales', hue='IsHoliday', showflie
plt.xlabel('Store', fontsize=14)
plt.ylabel('Weekly Sales', fontsize=14)
plt.title('Weekly Sales of Each Store for Holiday and Non-Holiday Weeks', fontsiz
```

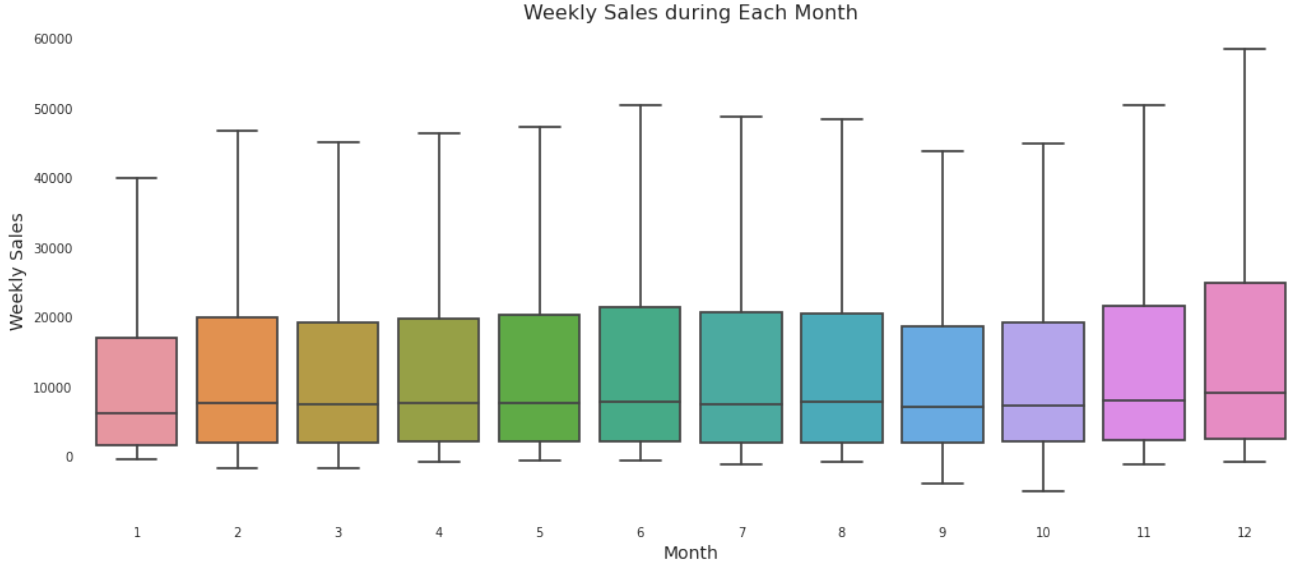
```
Text(0.5, 1.0, 'Weekly Sales of Each Store for Holiday and Non-Holiday
Weeks')
```



Question 8: How does the Weekly Sales vary for each Month?

```
plt.figure(figsize=(17, 7))
sns.boxplot(data=sales_df, x='Month', y='Weekly_Sales', showfliers=False)
plt.xlabel('Month', fontsize=14)
plt.ylabel('Weekly Sales', fontsize=14)
plt.title('Weekly Sales during Each Month', fontsize=16)
```

```
Text(0.5, 1.0, 'Weekly Sales during Each Month')
```



Observations:

- Month **12** i. e. **December** has the **highest sales record** than any other month.
  - This might be due to the fact that most people do their **Christmas shopping** during this time.
- Also, Month **1** i. e. **January** has the lowest median weekly sales compared to other montl
  - This might be because of the **New Year Resolutions** made by people, which prevent them from buying certain things in January.

Question 9: Does the Store Size have an effect on the Weekly Sales of each Month?

```
plt.figure(figsize=(19, 7))
sns.boxplot(data=sales_df, x='Month', y='Weekly_Sales', hue='Type', showfliers=Fa
plt.xlabel('Month', fontsize=14)
plt.ylabel('Weekly Sales', fontsize=14)
plt.title('Weekly Sales during Each Month with respect to the Type of the Store',
```

```
Text(0.5, 1.0, 'Weekly Sales during Each Month with respect to the Type of the Store')
```

Observations:

- Again, we can see that the **Type A** stores have the **highest weekly sales record** for **each month**.
- This means that the **larger stores** have **higher sales record** each month than the smaller stores.

7. Post Data Processing & Analysis

7.1 Encoding Categorical Data

- The `Type` column in the dataset contains **categorical** data.
- It has **3** distinct values: **A**, **B**, and **C**.
- We will use **dummy encoding** to achieve this.

```
# Creating dummy variable of the Type column
sales_df = pd.get_dummies(sales_df, columns=['Type'])
sales_df.head()
```

	Store	Dept	Date	Weekly_Sales	IsHoliday	Temperature	Fuel_Price	MarkDow
0	1	1	2010-02-05	24924.50	False	42.31	2.572	(
1	1	2	2010-02-05	50605.27	False	42.31	2.572	(
2	1	3	2010-02-05	13740.12	False	42.31	2.572	(
3	1	4	2010-02-05	39954.04	False	42.31	2.572	(
4	1	5	2010-02-05	32229.38	False	42.31	2.572	(

7.2 Feature (Day) Extraction from Date

- During Data Preprocessing we **didn't extracted** the **day** information from the `Date` because it wouldn't have helped us during the analysis.
- But, the ML *models can't process* **DateTime** format features and hence we need to **remove** the *Date column* from the dataset *before training* our models.
- So, in order to conserve the weekly date information, we will create a **Day** column by **extracting** the *day information* from the date.

```
# Creating Day column in the sales_df after extracting the information from Date
sales_df['Day'] = sales_df['Date'].dt.day
sales_df.head()
```

	Store	Dept	Date	Weekly_Sales	IsHoliday	Temperature	Fuel_Price	MarkDow
0	1	1	2010-02-05	24924.50	False	42.31	2.572	(
1	1	2	2010-02-05	50605.27	False	42.31	2.572	(
2	1	3	2010-02-05	13740.12	False	42.31	2.572	(
3	1	4	2010-02-05	39954.04	False	42.31	2.572	(
4	1	5	2010-02-05	32229.38	False	42.31	2.572	(

- `Day` column is created in the dataframe containing the **day** value from the `Date` column.

```
# Removing Date column from sales_df
sales_df.drop(['Date'], axis=1, inplace=True)
```

```
sales_df.head()
```

	Store	Dept	Weekly_Sales	IsHoliday	Temperature	Fuel_Price	MarkDown1	Ma
0	1	1	24924.50	False	42.31	2.572	0.0	
1	1	2	50605.27	False	42.31	2.572	0.0	
2	1	3	13740.12	False	42.31	2.572	0.0	
3	1	4	39954.04	False	42.31	2.572	0.0	
4	1	5	32229.38	False	42.31	2.572	0.0	

- `Date` is removed from the **sales_df**.

7.3 Data Splitting

- Now, we will **split** the dataset into **Train** and **Test** subsets.
- We will use **80%** data for **training** and the remaining **20%** data for **testing** our models.

- First, we will **separate** the **dependent** and **independent** variable from the data *by creating* a **feature matrix** and a **target vector**.

```
# Creating the feature matrix by removing the target variable
X = sales_df.drop(['Weekly_Sales'], axis=1)
X.head()
```

	Store	Dept	IsHoliday	Temperature	Fuel_Price	MarkDown1	MarkDown2	MarkD
0	1	1	False	42.31	2.572	0.0	0.0	
1	1	2	False	42.31	2.572	0.0	0.0	
2	1	3	False	42.31	2.572	0.0	0.0	
3	1	4	False	42.31	2.572	0.0	0.0	
4	1	5	False	42.31	2.572	0.0	0.0	

```
# Creating the target vector
y = sales_df['Weekly_Sales']
y.head()
```

```
0    24924.50
1    50605.27
2    13740.12
3    39954.04
4    32229.38
Name: Weekly_Sales, dtype: float64
```

```
# Using scikit-learn's train_test_split function to split the dataset into train
# 80% of the data will be in the train set and 20% in the test set, as specified
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_s
```

```
# Checking the shapes of the training and test sets.
print('Training Data Shape:', X_train.shape, y_train.shape)
print('Testing Data Shape:', X_test.shape, y_test.shape)
```

```
Training Data Shape: (337256, 18) (337256,)
Testing Data Shape: (84314, 18) (84314,)
```

8. Model Development & Evaluation

- In this section, we will be **building** our Machine Learning models and fitting them with the training data.
- We will be building models using:
  - **All** the **features** of the training set.
  - The most **important features** of the training set, according to the Random Forest algorithm.
- We will use **K-fold Cross Validation** to validate our models and select the best one.

- We are creating a **helper function** `display_scores` that will help us in **displaying** our *K-fold cross validation* **scores**.

```
# A helper function to display the scores along with the mean and standard deviat
def display_scores(scores):
    scores_rmse = np.sqrt(-scores)
    print('Scores:', scores_rmse)
    print('Mean:', scores_rmse.mean())
    print('Standard Deviation:', scores_rmse.std())
```

8.1 Baseline Models

- In the baseline models, we will be using **all** the **features** of the dataset in our models.

- We will be performing **5-fold** cross-validation to **validate** our models.

8.1.1 Linear Regression Model

```
base_lr = LinearRegression()

# Performing K-fold Cross-validation for 5 folds.
scores = cross_val_score(estimator=base_lr, X=X_train, y=y_train, cv=5, scoring='

# Displaying the RMSE scores with display_score helper function.
display_scores(scores)
```

```
Scores: [21979.65938525 21608.2746695  21404.32551374 21509.42372403
 21560.27891321]
Mean: 21612.392441145716
Standard Deviation: 195.71008510269482
```

Observations:

- After perfoming **5-fold** cross-validation on our Baseline Linear Regression model, we get a mean **RMSE** score of **21612.39**
- This is not a good score at all, and we can't use this model in production.
- The **standard deviation** of **195** means that our model is performing almost similarly on each fold it was tested on, and is **generalizing** well on unseen data.

8.1.2 Decision Tree Model

```
base_dt = DecisionTreeRegressor(random_state=0)

# Performing K-fold Cross-validation for 5 folds.
scores = cross_val_score(estimator=base_dt, X=X_train, y=y_train, cv=5, scoring='

# Displaying the RMSE scores with display_score helper function.
display_scores(scores)
```

```
Scores: [5720.92847526 5119.94975833 5488.43259412 4896.45625268 5387.6484672
Mean: 5322.683109524694
Standard Deviation: 287.42404417975183
```

Observations:

- We get a mean **RMSE** score of **5322.68** for our Baseline Decision Tree model.
- This is **4 times lower** than the Linear Regression model.

- The Decision Tree model is performing much **better** than the Linear Regression model.
- Standard Deviation at **287** is slightly **higher** than the Linear Regression model, meaning that the model is **slightly overfitting** on some folds but it won't affect the performance of the model that much.

8.1.3 Random Forest Model

```
# Creating a Random Forest model.
base_rf = RandomForestRegressor(n_estimators=10, random_state=0, n_jobs=-1)
```

```
%%time
# Performing K-fold Cross-validation for 5 folds.
scores = cross_val_score(estimator=base_rf, X=X_train, y=y_train, cv=5, scoring='
```

```
CPU times: user 5.51 s, sys: 1.25 s, total: 6.76 s
Wall time: 1min 53s
```

```
# Displaying the RMSE scores with display_score helper function.
display_scores(scores)
```

```
Scores: [4319.99875092 4066.30575485 4051.58900922 3742.37212307 3806.3770273
Mean: 3997.3285330754197
Standard Deviation: 206.5349241335799
```

Observations:

- The mean **RMSE** score for the Baseline Random Forest Model is **3997.32**
- This is significantly **lower** than the Decision Tree model.
- It took **1 minute and 53 seconds** to perform 5-fold cross-validation on our Random Fores model having 10 trees.
- Random Forest is the best performing baseline model with the lowest RMSE score.
- Also, the standard deviation at **206** is **lower** than the Decision Tree model and almost equal to the Linear Regression model, meaning it is **generalizing** well on unseen data.

Checking Feature Importances

- Now, we will check the **feature importance** of each feature using the **Random Forest** model.

```
# Fitting the baseline Random Forest model on the entire train set to obtain the
base_rf.fit(X_train, y_train)
```

```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=None, max_features='auto',
max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=10, n_jobs=-1, oob_score=False,
                      random_state=0, verbose=0, warm_start=False)
```

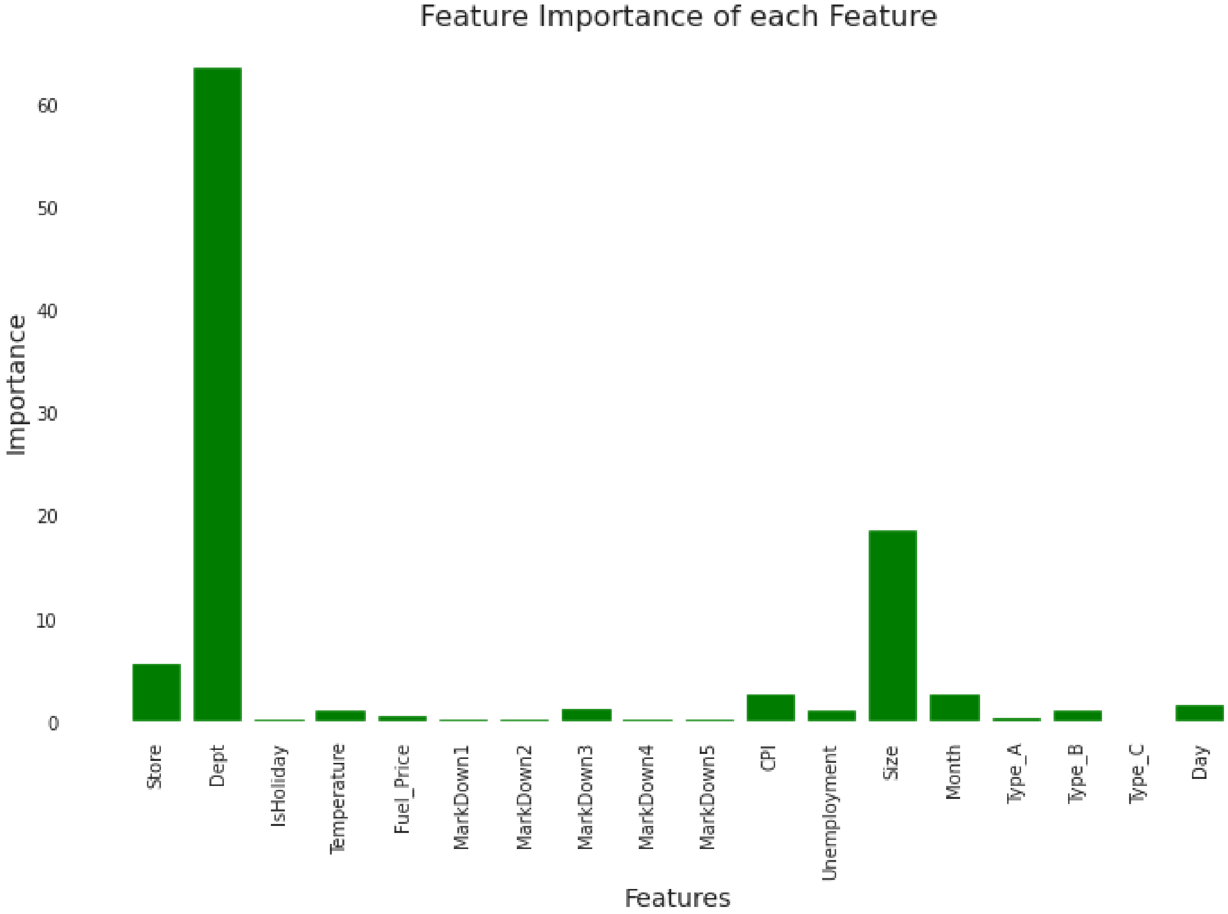
```
# Checking the feature importances of various features.
# Sorting the importances by descending order (lowest importance at the bottom).
for score, name in sorted(zip(base_rf.feature_importances_, X_train.columns), rev
    print('Feature importance of', name, ':', score*100, '%')
```

```
Feature importance of Dept : 63.35810299763713 %
Feature importance of Size : 18.569980351886365 %
Feature importance of Store : 5.573725706913679 %
Feature importance of CPI : 2.618559255198255 %
Feature importance of Month : 2.559015020219087 %
Feature importance of Day : 1.5469516159062249 %
Feature importance of MarkDown3 : 1.1309550707319727 %
Feature importance of Temperature : 1.0773925158979962 %
Feature importance of Unemployment : 1.06655871240621 %
Feature importance of Type_B : 1.0414267506149872 %
Feature importance of Fuel_Price : 0.4511742700747896 %
Feature importance of Type_A : 0.3384028827577717 %
Feature importance of IsHoliday : 0.1998231830044261 %
Feature importance of MarkDown4 : 0.12507571080904759 %
Feature importance of MarkDown2 : 0.10784629584368607 %
Feature importance of MarkDown5 : 0.10035897765823766 %
Feature importance of MarkDown1 : 0.09489185759088627 %
Feature importance of Type_C : 0.03975882484923432 %
```

- The feature importances are organized in a **descending** order, meaning the **most important** features are at the **top** and least important at the bottom.
- Let's **plot** the feature importances on a bar chart for a better visual look.

```
# Plotting the Feature Importance of each feature.
plt.figure(figsize=(12, 7))
plt.bar(X_train.columns, base_rf.feature_importances_*100, color='green')
plt.xlabel('Features', fontsize=14)
plt.ylabel('Importance', fontsize=14)
plt.xticks(rotation=90)
plt.title('Feature Importance of each Feature', fontsize=16)
```

```
Text(0.5, 1.0, 'Feature Importance of each Feature')
```



- The *feature importance* of columns tells us which **features** are **most important** to the model while making predictions.
- Here we can see that the `Dept` column has the highest feature importance with **63.35 %**, followed by `Size` column having **18.56 %** importance.
- **Top 6** most **important** features are: `Dept`, `Size`, `Store`, `CPI`, `Month`, and `Day`.
- We will use only these features in our Essential Feature Models.

8.2 Essential Feature Models

- In the essential feature models, we will be using only the **most important features** of the dataset in our models.
- The features are selected on the basis of the **feature importance** obtained from the Random Forest model.
- We will be performing **5-fold** cross-validation to **validate** our models.

```
X_train_essential = X_train[['Dept', 'Size', 'Store', 'CPI', 'Month', 'Day']]
X_train_essential.head()
```

	Dept	Size	Store	CPI	Month	Day
138466	96	123737	15	131.7350	3	5
289214	10	42988	30	212.9033	2	18
52351	10	202505	6	213.3400	1	21
203504	27	140167	21	217.1650	10	21
233606	25	203819	24	136.4788	11	25

8.2.1 Linear Regression Model

```
essential_lr = LinearRegression()


# Performing K-fold Cross-validation for 5 folds.
scores = cross_val_score(estimator=essential_lr, X=X_train_essential, y=y_train,


# Displaying the RMSE scores with display_score helper function.
display_scores(scores)
```

```
Scores: [22040.66751093 21675.93363968 21460.984622   21564.3695183
 21607.5399267 ]
Mean: 21669.8990435237
Standard Deviation: 198.07879666498823
```

Observations:

- After perfoming **5-fold** cross-validation on our Essential Feature Linear Regression mode we get a mean **RMSE** score of **21669.89**
- The RMSE value has increased a little because we are only using 6 features, but the change is very small.
- Still the **error** is very **large**, and hence this model can't be used to make predictions on the test set.

8.2.2 Decision Tree Model

```
essential_dt = DecisionTreeRegressor(random_state=0)


# Performing K-fold Cross-validation for 5 folds.
scores = cross_val_score(estimator=essential_dt, X=X_train_essential, y=y_train,
```

```
# Displaying the RMSE scores with display_score helper function.
display_scores(scores)
```

```
Scores: [4610.05869919 4651.93730874 4900.27942032 4498.63060733 4564.0302572
Mean: 4644.9872585609555
Standard Deviation: 137.4166661941294
```

Observations:

- We get a mean **RMSE** score of **4644.98** for our Essential Feature Decision Tree model.
- The RMSE has **decreased** by a lot even though we are only using 6 features.
- The standard deviation at **137** has also decreased meaning the model is **generalizing** well on unseen data.

8.2.3 Random Forest Model

```
# Creating a Random Forest model.
essential_rf = RandomForestRegressor(n_estimators=10, random_state=0, n_jobs=-1)
```

```
%%time
# Performing K-fold Cross-validation for 5 folds.
scores = cross_val_score(estimator=essential_rf, X=X_train_essential, y=y_train,
```

```
CPU times: user 5.13 s, sys: 1.05 s, total: 6.18 s
Wall time: 52.6 s
```

```
# Displaying the RMSE scores with display_score helper function.
display_scores(scores)
```

```
Scores: [3863.71427227 3765.26075202 3876.94027072 3458.74011555 3466.58863
Mean: 3686.2488085858436
Standard Deviation: 186.60702567666544
```

Observations:

- The mean **RMSE** score for the Essential Feature Random Forest Model is **3686.24**
- Our model has improved even though we are using only a **subset** (i. e. 6 features) of the features from the entire dataset.
- It took **53 seconds** to perform 5-fold cross-validation on our Random Forest model having 10 trees.
- The **training time** has **reduced** significantly and the **performance** has **improved**.
- The RMSE is still significantly **lower** than the Decision Tree model.

Model Comparision

Baseline Models

Model	RMSE Score
Linear Regression	21612.39
Decision Tree	5322.68
Random Forest	3997.32

Essential Feature Models

Model	RMSE Score
Linear Regression	21669.89
Decision Tree	4644.98
Random Forest	3686.24

Observations:

- Essential Feature Random Forest is the **best performing model** with the **lowest RMSE** score.
- It **outperforms** all the baseline and essential feature models.

8.3 Hyperparameter Tuning of Model

Creating the Parameter Grid

- The parameter grid will contain all the **values** for each hyperparameter to be used while **searching** for the best hyperparameter combinations.

```
param_grid = [{'n_estimators': [10, 20, 30], 'max_depth': [None, 2, 3, 5], 'max_f
```

```
temp_rf = RandomForestRegressor(random_state=0, n_jobs=-1)
```

Creating Grid Search

- We will input the **model**, **parameter grid**, **scoring method** and **number of folds** to use for cross-validation into the grid search object.
- We are using **5-fold** cross-validation here.

```
grid_search = GridSearchCV(estimator=temp_rf, param_grid=param_grid, scoring='neg
```

Performing Grid Search

- Here, we will supply the **dataset** to be used in grid search and **initialize** our search.

```
%%time
grid_search.fit(X_train_essential, y_train)
```

```
CPU times: user 1min 6s, sys: 3.11 s, total: 1min 9s
Wall time: 16min 27s
GridSearchCV(cv=5, error_score=nan,
             estimator=RandomForestRegressor(bootstrap=True, ccp_alpha=0.0,
                                             criterion='mse', max_depth=None,
                                             max_features='auto',
                                             max_leaf_nodes=None,
                                             max_samples=None,
                                             min_impurity_decrease=0.0,
                                             min_impurity_split=None,
                                             min_samples_leaf=1,
                                             min_samples_split=2,
                                             min_weight_fraction_leaf=0.0,
                                             n_estimators=100, n_jobs=-1,
                                             oob_score=False, random_state=0,
                                             verbose=0, warm_start=False),
             iid='deprecated', n_jobs=-1,
             param_grid=[{'max_depth': [None, 2, 3, 5],
                          'max_features': ['auto', 2, 4],
                          'n_estimators': [10, 20, 30]}],
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='neg_mean_squared_error', verbose=0)
```

- Now, we will calculate the **best RMSE** score found by Grid Search.

```
# Calculating the best RMSE score found by Grid Search
np.sqrt(-grid_search.best_score_)
```

```
3562.015451656953
```

- We get an RMSE score of **3562.01** which is **lower** than our Essential Feature Random Forest model.
- This means that we have **improved** our **model performance** after tuning the hyperparameters.

- Let's find out the **hyperparameter values** which provide us the best RMSE score.

```
# The hyperparameter values which provide us the best RMSE score
grid_search.best_params_
```

```
{'max_depth': None, 'max_features': 'auto', 'n_estimators': 30}
```

- We're gonna **use** these hyperparameter **values** in our final model.

8.4 Final Model

- We found out the **best hyperparameter combinations** for our Random Forest model.
- Now, we will use the model with those hyperparameters as our **final model**.
- Using this final model, we will make **predictions** on our test set.

Creating the Final Model

- We will create the final random forest model using the **grid_search**'s `best_estimator_` attribute.

```
# Creating the final random forest model from the grid search's best estimator.
final_rf = grid_search.best_estimator_
```

Fitting the Final Model

```
# Fitting the final model with training set
final_rf.fit(X_train_essential, y_train)
```

```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=None, max_features='auto',
max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=30, n_jobs=-1, oob_score=False,
                      random_state=0, verbose=0, warm_start=False)
```

- After fitting the final model with the training data, we are ready to make **predictions** on the test set.

Removing Non-Essential Features from the Test Set

- We trained our model on only the most important features of the dataset.
- So, we need to **remove** the **non-important features** from our test set as well.
- If we don't remove the non-essential features our model will give an **error** while making predictions due to the **difference in shapes** of training and testing sets.

```
# Creating the test set with only the essential features
X_test_essential = X_test[['Dept', 'Size', 'Store', 'CPI', 'Month', 'Day']]
X_test_essential.head()
```

	Dept	Size	Store	CPI	Month	Day
272342	97	206302	28	129.1338	7	15
176581	20	120653	18	138.3772	8	31
354212	98	39690	38	126.6019	4	9
281444	90	93638	29	134.5144	5	6
124208	4	219622	13	129.7937	10	28

Making Predictions

- Now, we will make **predictions** on both our training and testing sets.

```
# Making predictions on the train set
y_train_pred = final_rf.predict(X_train_essential)
```

```
# Making predictions on the test set
y_test_pred = final_rf.predict(X_test_essential)
```

```
pd.DataFrame({'Actual Test Set Values': y_test[0:5].values, 'Predicted Test Set V
```

	Actual Test Set Values	Predicted Test Set Values
0	21577.44	21197.2510
1	8370.28	7449.3907
2	4985.05	4698.7330
3	10512.26	10789.3463
4	40924.39	40338.0643

- Our model is making very **good predictions** on the test set.
- It is **performing well** on unseen data.

Calculating the RMSE Score

- Here we will **calculate** the **RMSE** score for both the training and testing datasets.

```
# Estimating RMSE on Train & Test Data
print('RMSE for Train Set:', np.round(np.sqrt(mean_squared_error(y_train, y_train
print('RMSE for Test Set:', np.round(np.sqrt(mean_squared_error(y_test, y_test_pr
```

```
RMSE for Train Set: 1287.97
RMSE for Test Set: 3261.2
```

Observations:

- We are getting a **RMSE** score of **3261.2**, which is significantly **lower** than the one we obtained on the validation set during cross-validation.
- We can't judge our model's performace on the basis of RMSE score alone.
- We need some additional evaluation metric to evaluate our model performace.

Calculating R-Squared Value

- Now, we will **calculate** the **R-Squared** value for both our train and test sets.

```
# Estimating R-Squared on Train & Test Data
print('R-Squared for Train Set:', np.round(r2_score(y_train, y_train_pred), decim
print('R-Squared for Test Set:', np.round(r2_score(y_test, y_test_pred), decimals
```

```
R-Squared for Train Set: 1.0
R-Squared for Test Set: 0.98
```

Observations:

- The **R-Squared** value for the **train** set is **1.0,** and for the **test** set is **0.98**
- This is a very **high R-Squared** value, that means our model is a **very good model**.
- This model can be **deployed to production** servers to make real-time predictions on unseen data.

Plotting Actual vs Predicted Values

- Creating a helper function `plot_score` which will help us in plotting the **actual** and **predicted** values.

```
# Creating a helper function to plot the actual and predicted values for train an
def plot_score(y_train, y_train_pred, y_test, y_test_pred):
  '''
  Plot acutal and predicted values for train & test data
  y_train: actual y_train values
  y_train_pred: predicted values of y_train
  y_test: actual y_test values
  y_test_pred: predicted values of y_test
```