supply-chain-shipment-price-data

November 8, 2019

1 Supply Chain Shipment Pricing Data - Data Analysis and Modeling

Dataset Description: This data set provides supply chain health commodity shipment and pricing data.

File Descriptions

Item	Description
File Name :	SCMS_Delivery_History_Dataset.csv
File Size :	Approx. 570kb
Total Records :	10,324
File Updated :	February 24, 2016

1.1 Following are steps for Data Analysis and Modeling

- Import Packages
- Import CSV file
- Check Total Records in CSV file
- Check DataType of CSV file
- Rename columns
- Print first 5 and last 5 recods from DataSet
- Total 16 Country wise count with graph
- Shipment Mode percentage wise Pie Chart
- Conclusion

2 Import Packages

[83]:
```
import os

import pandas as pd
import numpy as np
from decimal import Decimal
from IPython.display import Image
```

```
import re

import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sn

import plotly.graph_objs as go
import plotly.offline as py
py.init_notebook_mode(connected=True)
pd.options.mode.chained_assignment = None
pd.options.display.max_columns = 9999
pd.options.display.float_format = '{:20,.2f}'.format

from sklearn import metrics
from sklearn import tree
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor

export_flag = True
if export_flag:
    import chart_studio
    chart_studio.tools.set_credentials_file(username='jr.cinco5',␣
 ↪api_key='9197r3roMkAbXG3iwTy3')
```

3 Import CSV file

[74]:
```
DataSet = pd.read_csv('SCMS_Delivery_History_Dataset.csv').fillna('no_value')
```

4 Check Total Records in CSV file

[75]:
```
TotalRowCount = len(DataSet)
print("Total Number of Data Count :", TotalRowCount)
```

```
Total Number of Data Count : 10324
```

5 Check DataType of CSV file

[47]:
```
DataSet.dtypes
```

[47]:
```
ID                                int64
Project Code                     object
PQ #                             object
PO / SO #                        object
ASN/DN #                         object
Country                          object
Managed By                       object
Fulfill Via                      object
Vendor INCO Term                 object
Shipment Mode                    object
PQ First Sent to Client Date     object
PO Sent to Vendor Date           object
Scheduled Delivery Date          object
Delivered to Client Date         object
Delivery Recorded Date           object
Product Group                    object
Sub Classification               object
Vendor                           object
Item Description                 object
Molecule/Test Type               object
Brand                            object
Dosage                           object
Dosage Form                      object
Unit of Measure (Per Pack)        int64
Line Item Quantity                int64
Line Item Value                 float64
Pack Price                      float64
Unit Price                      float64
Manufacturing Site               object
First Line Designation           object
Weight (Kilograms)               object
Freight Cost (USD)               object
Line Item Insurance (USD)        object
dtype: object
```

6 Rename columns

[76]:
```
DataSet.rename(columns={"Freight Cost (USD)": "Freight_Cost_USD"}, inplace=True)
```

7 Print first 5 and last 5 recods from DataSet

[77]:
```
DataSet[['Unit of Measure (Per Pack)', 'Line Item Quantity', 'Pack Price',␣
↪'Unit Price', 'Weight (Kilograms)',
                          'Country', 'Shipment Mode', 'Freight_Cost_USD']]
```

[77]:

	Unit of Measure (Per Pack)	Line Item Quantity	Pack Price	Unit Price	Weight (Kilograms)	Country	Shipment Mode	Freight_Cost_USD
0	30	19	29.00	0.97	13	Côte d'Ivoire	Air	780.34
1	240	1000	6.20	0.03	358	Vietnam	Air	4521.5
2	100	500	80.00	0.80	171	Côte d'Ivoire	Air	1653.78
3	60	31920	3.99	0.07	1855	Vietnam	Air	16007.06
4	60	38000	3.20	0.05	7590	Vietnam	Air	45450.08
…	…	…	…	…	…	…	…	…
10319	60	166571	3.60	0.06	See DN-4307 (ID#:83920)	Zimbabwe	Truck	See DN-4307 (ID#:83920)
10320	60	21072	6.52	0.11	See DN-4313 (ID#:83921)	Côte d'Ivoire	Truck	See DN-4313 (ID#:83921)
10321	30	514526	9.99	0.33	Weight Captured Separately	Zambia	Truck	Freight Included in Commodity Cost
10322	60	17465	6.52	0.11	1392	Zimbabwe	Truck	Freight Included in Commodity Cost
10323	60	36639	1.99	0.03	Weight Captured Separately	Zimbabwe	Truck	Freight Included in Commodity Cost

[10324 rows x 8 columns]

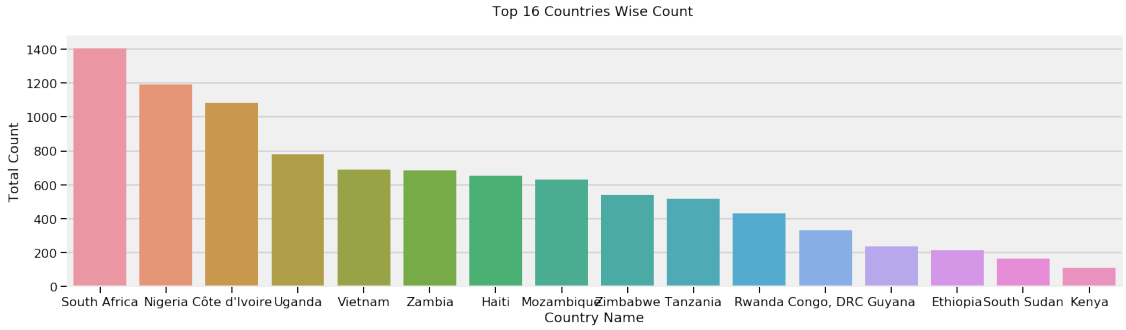
8 Total 16 Country wise count with graph

[78]:
```
DataSet = DataSet.dropna()
ItemCount = DataSet["Country"].value_counts().nlargest(43)
print("Top 43 Countries Wise Count \n")
print(ItemCount)
sn.set_context("talk",font_scale=1)
plt.figure(figsize=(22,6))
sn.countplot(DataSet['Country'],order = DataSet['Country'].value_counts().
 ↪nlargest(16).index)
plt.title('Top 16 Countries Wise Count \n')
plt.ylabel('Total Count')
plt.xlabel('Country Name')
```

```
Top 43 Countries Wise Count

South Africa          1406
Nigeria               1194
Côte d'Ivoire         1083
Uganda                 779
Vietnam                688
Zambia                 683
Haiti                  655
Mozambique             631
Zimbabwe               538
Tanzania               519
Rwanda                 430
Congo, DRC             333
Guyana                 237
Ethiopia               216
South Sudan            164
Kenya                  111
Burundi                 98
Namibia                 95
Cameroon                75
Botswana                70
Ghana                   58
Dominican Republic      52
Sudan                   46
Swaziland               35
Mali                    17
Pakistan                15
Guatemala               15
Malawi                  14
Benin                   13
Lebanon                  8
Libya                    8
```

```
Angola                    7
Liberia                   6
Lesotho                   4
Sierra Leone              4
Afghanistan               3
Togo                      3
Senegal                   3
Kazakhstan                2
Kyrgyzstan                2
Burkina Faso              2
Belize                    1
Guinea                    1
Name: Country, dtype: int64
```

[78]: Text(0.5, 0, 'Country Name')

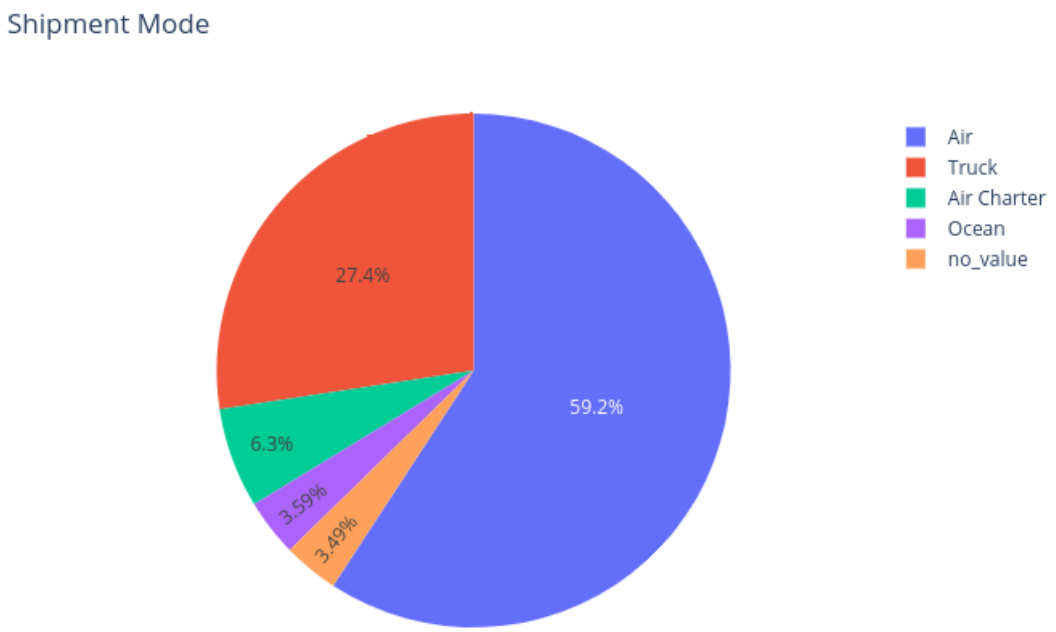


9 Shipment Mode percentage wise Pie Chart

[103]:
```
ShippingMode = DataSet["Shipment Mode"].value_counts()
labels = (np.array(ShippingMode.index))
sizes = (np.array((ShippingMode / ShippingMode.sum())*100))

trace = go.Pie(labels=labels, values=sizes)
layout = go.Layout(title="Shipment Mode")
dat = [trace]
fig = go.Figure(data=dat, layout=layout)

show_image = None
if export_flag:
    chart_studio.plotly.image.save_as(fig, filename='shipment-mode-plot.png')
    show_image = Image('shipment-mode-plot.png')
else:
    py.iplot(fig, filename="Shipment Mode")
```

```
show_image
```

[103]:



10 ETL

[86]:

```
regex = {
    "id_number": ":\d*"
}

def change_to_number(freight_cost_usd):
    match = re.search(regex['id_number'], freight_cost_usd, re.IGNORECASE)
    if match:
        id = match.group(0).replace(':','')
        filtered = DataSet.query("ID == "+id)
        return filtered['Freight_Cost_USD'].item()
    else:
        return freight_cost_usd

def convert_to_number(weight):
    match = re.search(regex['id_number'], weight, re.IGNORECASE)
```

```
    if match:
        id = match.group(0).replace(':','')
        filtered = DataSet.query("ID == "+id)
        return filtered['Weight (Kilograms)'].item()
    else:
        return weight
```

[53]:
```
DataSet['Freight_Cost_USD_Clean'] = DataSet['Freight_Cost_USD'].
↪apply(change_to_number)
DataSet['Weight_Kilograms_Clean'] = DataSet['Weight (Kilograms)'].
↪apply(convert_to_number)
```

```
/home/jhonny/anaconda3/envs/supply-chain/lib/python3.7/site-
packages/ipykernel_launcher.py:10: FutureWarning:

`item` has been deprecated and will be removed in a future version

/home/jhonny/anaconda3/envs/supply-chain/lib/python3.7/site-
packages/ipykernel_launcher.py:19: FutureWarning:

`item` has been deprecated and will be removed in a future version
```

[54]:
```
freight_cost_indexes = DataSet.index[(DataSet['Freight_Cost_USD_Clean'] ==␣
↪'Freight Included in Commodity Cost')
                        | (DataSet['Freight_Cost_USD_Clean'] == 'Invoiced␣
↪Separately')].tolist()
weight_indexes = DataSet.index[DataSet['Weight_Kilograms_Clean'] == 'Weight␣
↪Captured Separately'].tolist()
shipment_indexes = DataSet.index[DataSet['Shipment Mode'] == 'no_value'].
↪tolist()
print("Freight_Cost_USD_Clean indexes:",len(freight_cost_indexes))
print("Weight_Kilograms_Clean indexes:",len(weight_indexes))
print("Shipment Mode indexes:         ",len(shipment_indexes))

indexes = list(set(freight_cost_indexes + weight_indexes + shipment_indexes))
print("Indexes:",len(indexes))
DataSetClean = DataSet.drop(indexes)

print("Size:", DataSetClean.shape)

DataSetClean[['Unit of Measure (Per Pack)', 'Line Item Quantity', 'Pack Price',␣
↪'Unit Price', 'Weight (Kilograms)',
                        'Country', 'Shipment Mode', 'Freight_Cost_USD']]
```

```
Freight_Cost_USD_Clean indexes: 1786
Weight_Kilograms_Clean indexes: 1633
```

```
Shipment Mode indexes:          360
Indexes: 2142
Size: (8182, 35)
```

[54]:
```
       Unit of Measure (Per Pack)  Line Item Quantity           Pack Price  \
0                              30                   19                29.00
1                             240                 1000                 6.20
2                             100                  500                80.00
3                              60                31920                 3.99
4                              60                38000                 3.20
…                             …                    …                    …
10316                          60                15000                 6.52
10317                          30                 6724                 3.12
10318                          60               205243                 3.60
10319                          60               166571                 3.60
10320                          60                21072                 6.52

                Unit Price       Weight (Kilograms)        Country  \
0                     0.97                       13  Côte d'Ivoire
1                     0.03                      358        Vietnam
2                     0.80                      171  Côte d'Ivoire
3                     0.07                     1855        Vietnam
4                     0.05                     7590        Vietnam
…                    …                          …            …
10316                 0.11                     1547        Nigeria
10317                 0.10  See DN-4282 (ID#:83919)        Nigeria
10318                 0.06  See DN-4307 (ID#:83920)       Zimbabwe
10319                 0.06  See DN-4307 (ID#:83920)       Zimbabwe
10320                 0.11  See DN-4313 (ID#:83921)  Côte d'Ivoire

      Shipment Mode         Freight_Cost_USD
0               Air                   780.34
1               Air                   4521.5
2               Air                  1653.78
3               Air                 16007.06
4               Air                 45450.08
…              …                      …
10316   Air Charter                     3410
10317           Air  See DN-4282 (ID#:83919)
10318         Truck  See DN-4307 (ID#:83920)
10319         Truck  See DN-4307 (ID#:83920)
10320         Truck  See DN-4313 (ID#:83921)

[8182 rows x 8 columns]
```

[55]:
```
shipment_mode = DataSetClean['Shipment Mode'].unique()
print('shipment mode', shipment_mode, '\n')
```

```
countries = DataSetClean['Country'].unique()
print('countries', countries, '\n')

manufacturing = DataSetClean['Manufacturing Site'].unique()
print('manufacturing', manufacturing)
```

```
shipment mode ['Air' 'Truck' 'Air Charter' 'Ocean']

countries ["Côte d'Ivoire" 'Vietnam' 'Nigeria' 'Tanzania' 'Zambia' 'Rwanda'
'Haiti'
 'Ethiopia' 'Guyana' 'Zimbabwe' 'Namibia' 'Botswana' 'Mozambique' 'Kenya'
 'Uganda' 'Senegal' 'Benin' 'Lesotho' 'Swaziland' 'Angola' 'Pakistan'
 'Sierra Leone' 'Cameroon' 'South Sudan' 'Burundi' 'South Africa' 'Malawi'
 'Congo, DRC' 'Dominican Republic' 'Sudan' 'Mali' 'Ghana' 'Togo'
 'Afghanistan' 'Guatemala' 'Liberia' 'Guinea' 'Libya']

manufacturing ['Ranbaxy Fine Chemicals LTD' 'Aurobindo Unit III, India'
 'ABBVIE GmbH & Co.KG Wiesbaden' 'Ranbaxy, Paonta Shahib, India'
 'Trinity Biotech, Plc' 'Cipla, Goa, India' 'Premier Med. Corp Ltd. India'
 'BMS Meymac, France' 'Chembio Diagnostics Sys. Inc.'
 'ABBVIE Ludwigshafen Germany' 'Inverness Japan'
 'Pacific Biotech, Thailand' 'Standard Diagnostics, Korea'
 'Gilead(Nycomed) Oranienburg DE' 'Bio-Rad Laboratories'
 'Mylan (formerly Matrix) Nashik' 'Novartis Pharma AG, Switzerland'
 'Not Applicable' 'Ipca Dadra/Nagar Haveli IN' 'MSD, Haarlem, NL'
 'Gland Pharma Ltd Pally Factory' 'ABBVIE (Abbott) Logis. UK'
 'Hetero Unit III Hyderabad IN' 'ABBVIE (Abbott) France'
 'Strides, Bangalore, India.' 'Cipla, Patalganga, India'
 'Aspen-OSD, Port Elizabeth, SA' 'KHB Test Kit Facility, Shanghai China'
 'Inverness USA' 'OMEGA Diagnostics, UK' 'Roche Madrid'
 'INVERNESS ORGENICS LINE' 'Novartis Pharma Suffern, USA' 'Roche Basel'
 "ABBVIE (Abbott) St. P'burg USA" 'GSK Mississauga (Canada)'
 'Micro Labs Ltd. (Brown & Burk), India' 'Meditab (for Cipla) Daman IN'
 'Medopharm Malur Factory, INDIA' 'Orasure Technologies, Inc USA'
 'Weifa A.S., Hausmanngt. 6, P.O. Box 9113 GrÃ¸nland, 0133, Oslo, Norway'
 'MSD Manati, Puerto Rico, (USA)' 'MSD Elkton USA' 'GSK Ware (UK)'
 'Emcure Plot No.P-2, I.T-B.T. Park, Phase II, MIDC, Hinjwadi, Pune, India'
 'Alere Medical Co., Ltd.' 'Premier Medical Corporation'
 'Janssen-Cilag, Latina, IT' 'Aurobindo Unit VII, IN'
 'Micro labs, Verna, Goa, India' 'Orasure Technologies, Inc'
 'Mylan,  H-12 & H-13, India' 'Hetero, Jadcherla, unit 5, IN'
 'Bristol-Myers Squibb Anagni IT' 'Medochemie Factory A, CY'
 'Cipla Ltd A-42 MIDC Mahar. IN' 'bioLytical Laboratories'
 'EY Laboratories, USA' 'Micro Labs, Hosur, India'
 'Remedica, Limassol, Cyprus' 'INVERNESS ANY'
 'Guilin OSD site, No 17, China' 'Cipla, Kurkumbh, India'
```

```
'GSK Barnard Castle UK' 'Janssen Ortho LLC, Puerto Rico'
'Gland Pharma, Hyderabad, IN' 'MSD Patheon, Canada' 'Access BIO, L.C.'
'Human Diagnostic' 'BMS Evansville, US' 'Mepro Pharm Wadhwan Unit II'
'Ranbaxy per Shasun Pharma Ltd' 'Ranbaxy per Shasun Pharma'
'Macleods Daman Plant INDIA']
```

[56]:
```
DataSetClean['country_encoded'] = DataSetClean['Country'].map( {
    'South Africa': 1,
    'Nigeria': 2,
    "Côte d'Ivoire": 3,
    'Uganda': 4,
    'Vietnam': 5,
    'Zambia': 6,
    'Haiti': 7,
    'Mozambique': 8,
    'Zimbabwe': 9,
    'Tanzania': 10,
    'Rwanda': 11,
    'Congo, DRC': 12,
    'Guyana': 13,
    'Ethiopia': 14,
    'South Sudan': 15,
    'Kenya': 16,
    'Burundi': 17,
    'Namibia': 18,
    'Cameroon': 19,
    'Botswana': 20,
    'Ghana': 21,
    'Dominican Republic': 22,
    'Sudan': 23,
    'Swaziland': 24,
    'Mali': 25,
    'Pakistan': 26,
    'Guatemala': 27,
    'Malawi': 28,
    'Benin': 29,
    'Lebanon': 30,
    'Libya': 31,
    'Angola': 32,
    'Liberia': 33,
    'Lesotho': 34,
    'Sierra Leone': 35,
    'Togo': 36,
    'Afghanistan': 37,
    'Senegal': 38,
    'Kyrgyzstan': 39,
    'Burkina Faso': 40,
```

```
    'Kazakhstan': 41,
    'Guinea': 42,
    'Belize': 43 } ).astype(int)
DataSetClean['shipment_mode_encoded'] = DataSetClean['Shipment Mode'].map({
    'Air': 1,
    'Truck': 2,
    'Air Charter': 3,
    'Ocean': 4 }).astype(int)

DataSetClean['manufacturing_site_encoded'] = DataSetClean['Manufacturing Site'].
 ↪map({
    'Ranbaxy Fine Chemicals LTD': 1,
    'Aurobindo Unit III, India': 2,
    'ABBVIE GmbH & Co.KG Wiesbaden': 3,
    'Ranbaxy, Paonta Shahib, India': 4,
    'Trinity Biotech, Plc': 5,
    'Cipla, Goa, India': 6,
    'Premier Med. Corp Ltd. India': 7,
    'BMS Meymac, France': 8,
    'Chembio Diagnostics Sys. Inc.': 9,
    'ABBVIE Ludwigshafen Germany': 10,
    'Inverness Japan': 11,
    'Pacific Biotech, Thailand': 12,
    'Standard Diagnostics, Korea': 13,
    'Gilead(Nycomed) Oranienburg DE': 14,
    'Bio-Rad Laboratories': 15,
    'Mylan (formerly Matrix) Nashik': 16,
    'Novartis Pharma AG, Switzerland': 17,
    'Not Applicable': 18,
    'Ipca Dadra/Nagar Haveli IN': 19,
    'MSD, Haarlem, NL': 20,
    'Gland Pharma Ltd Pally Factory': 21,
    'ABBVIE (Abbott) Logis. UK': 22,
    'Hetero Unit III Hyderabad IN': 23,
    'ABBVIE (Abbott) France': 24,
    'Strides, Bangalore, India.': 25,
    'Cipla, Patalganga, India': 26,
    'Aspen-OSD, Port Elizabeth, SA': 27,
    'KHB Test Kit Facility, Shanghai China': 28,
    'Inverness USA': 29,
    "MSD Midrand, J'burg, SA": 30,
    'OMEGA Diagnostics, UK': 31,
    'Roche Madrid': 32,
    'INVERNESS ORGENICS LINE': 33,
    'GSK Aranda': 34,
    'Novartis Pharma Suffern, USA': 35,
    'Roche Basel': 36,
```

```
    "ABBVIE (Abbott) St. P'burg USA": 37,
    'GSK Mississauga (Canada)': 38,
    'Micro Labs Ltd. (Brown & Burk), India': 39,
    'Meditab (for Cipla) Daman IN': 40,
    'Medopharm Malur Factory, INDIA': 41,
    'Orasure Technologies, Inc USA': 42,
    'Weifa A.S., Hausmanngt. 6, P.O. Box 9113 GrÃ¸nland, 0133, Oslo, Norway':␣
↪43,
    'GSK Cape Town Factory (South Africa)': 44,
    'MSD Manati, Puerto Rico, (USA)': 45,
    'MSD Elkton USA': 46,
    'GSK Ware (UK)': 47,
    'MSD Patheon, Canada': 48,
    'GSK Crawley': 49,
    'Emcure Plot No.P-2, I.T-B.T. Park, Phase II, MIDC, Hinjwadi, Pune, India':␣
↪50,
    'MSD South Granville Australia': 51,
    'Alere Medical Co., Ltd.': 52,
    'Premier Medical Corporation': 53,
    'Janssen-Cilag, Latina, IT': 54,
    'Aurobindo Unit VII, IN': 55,
    'Micro labs, Verna, Goa, India': 56,
    'Orasure Technologies, Inc': 57,
    'Mylan,  H-12 & H-13, India': 58,
    'Hetero, Jadcherla, unit 5, IN': 59,
    'Bristol-Myers Squibb Anagni IT': 60,
    'Medochemie Factory A, CY': 61,
    'Cipla Ltd A-42 MIDC Mahar. IN': 62,
    'bioLytical Laboratories': 63,
    'EY Laboratories, USA': 64,
    'Micro Labs, Hosur, India': 65,
    'Remedica, Limassol, Cyprus': 66,
    'INVERNESS ANY': 67,
    'Guilin OSD site, No 17, China': 68,
    'Cipla, Kurkumbh, India': 69,
    'GSK Barnard Castle UK': 70,
    'Janssen Ortho LLC, Puerto Rico': 71,
    'Gland Pharma, Hyderabad, IN': 72,
    'Access BIO, L.C.': 73,
    'Human Diagnostic': 74,
    'BMS Evansville, US': 75,
    'Mepro Pharm Wadhwan Unit II': 76,
    'Ranbaxy per Shasun Pharma Ltd': 77,
    'Ranbaxy per Shasun Pharma': 78,
    'Macleods Daman Plant INDIA': 79
}).astype(int)
```

11 Change data type of columns

[57]:
```
DataSetClean['Freight_Cost_USD_Clean'] = pd.
 ↪to_numeric(DataSetClean['Freight_Cost_USD_Clean'])
DataSetClean['Weight_Kilograms_Clean'] = pd.
 ↪to_numeric(DataSetClean['Weight_Kilograms_Clean'])
DataSetClean.dtypes
```

[57]:
```
ID                                int64
Project Code                     object
PQ #                             object
PO / SO #                        object
ASN/DN #                         object
Country                          object
Managed By                       object
Fulfill Via                      object
Vendor INCO Term                 object
Shipment Mode                    object
PQ First Sent to Client Date     object
PO Sent to Vendor Date           object
Scheduled Delivery Date          object
Delivered to Client Date         object
Delivery Recorded Date           object
Product Group                    object
Sub Classification               object
Vendor                           object
Item Description                 object
Molecule/Test Type               object
Brand                            object
Dosage                           object
Dosage Form                      object
Unit of Measure (Per Pack)        int64
Line Item Quantity                int64
Line Item Value                 float64
Pack Price                      float64
Unit Price                      float64
Manufacturing Site               object
First Line Designation           object
Weight (Kilograms)               object
Freight_Cost_USD                 object
Line Item Insurance (USD)        object
Freight_Cost_USD_Clean          float64
Weight_Kilograms_Clean            int64
country_encoded                   int64
shipment_mode_encoded             int64
manufacturing_site_encoded        int64
```

```
dtype: object
```

12 Machine Learning Modeling

[58]:
```
predictors = DataSetClean[['Unit of Measure (Per Pack)', 'Line Item Quantity',␣
↪'Pack Price', 'Unit Price', 'Weight_Kilograms_Clean',
                           'country_encoded', 'shipment_mode_encoded',␣
↪'manufacturing_site_encoded']]
predictors
```

[58]:

	Unit of Measure (Per Pack)	Line Item Quantity	Pack Price	\
0	30	19	29.00	
1	240	1000	6.20	
2	100	500	80.00	
3	60	31920	3.99	
4	60	38000	3.20	
…	…	…	…	
10316	60	15000	6.52	
10317	30	6724	3.12	
10318	60	205243	3.60	
10319	60	166571	3.60	
10320	60	21072	6.52	

	Unit Price	Weight_Kilograms_Clean	country_encoded	\
0	0.97	13	3	
1	0.03	358	5	
2	0.80	171	3	
3	0.07	1855	5	
4	0.05	7590	5	
…	…	…	…	
10316	0.11	1547	2	
10317	0.10	6183	2	
10318	0.06	25880	9	
10319	0.06	25880	9	
10320	0.11	4426	3	

	shipment_mode_encoded	manufacturing_site_encoded
0	1	1
1	1	2
2	1	3
3	1	4
4	1	2
…	…	…
10316	3	2
10317	1	25

```
10318                      2                         6
10319                      2                        58
10320                      2                        23

[8182 rows x 8 columns]
```

[59]:
```
predictors.describe()
```

[59]:
```
       Unit of Measure (Per Pack)   Line Item Quantity           Pack Price  \
count                    8,182.00             8,182.00             8,182.00
mean                        75.33            21,201.81                20.68
std                         76.55            42,549.60                41.77
min                          1.00                 1.00                 0.00
25%                         30.00               847.25                 3.78
50%                         60.00             4,449.50                 8.26
75%                         90.00            21,505.50                20.50
max                      1,000.00           619,999.00             1,250.00

                Unit Price  Weight_Kilograms_Clean      country_encoded  \
count             8,182.00                8,182.00             8,182.00
mean                  0.60                4,545.52                 7.52
std                   2.35               13,661.93                 5.41
min                   0.00                    0.00                 1.00
25%                   0.07                  283.00                 3.00
50%                   0.15                1,351.50                 6.00
75%                   0.41                4,481.25                10.00
max                  30.00              857,354.00                42.00

       shipment_mode_encoded  manufacturing_site_encoded
count               8,182.00                    8,182.00
mean                    1.48                       15.84
std                     0.79                       15.85
min                     1.00                        1.00
25%                     1.00                        2.00
50%                     1.00                       11.00
75%                     2.00                       23.00
max                     4.00                       79.00
```

[60]:
```
targets = DataSetClean.Freight_Cost_USD_Clean
targets
```

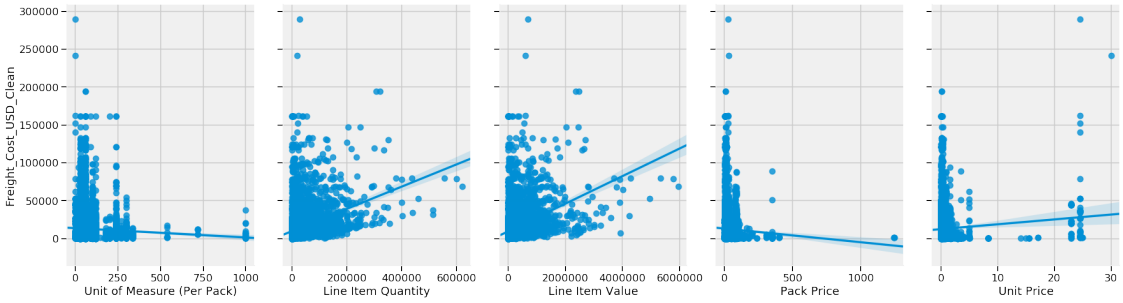
[60]:
```
0                    780.34
1                  4,521.50
2                  1,653.78
3                 16,007.06
4                 45,450.08
                  ...
```

```
10316                3,410.00
10317               47,281.56
10318               46,111.55
10319               46,111.55
10320               14,734.92
Name: Freight_Cost_USD_Clean, Length: 8182, dtype: float64
```

13 Correlations

[61]:
```
sn.pairplot(DataSetClean,
            x_vars=['Unit of Measure (Per Pack)', 'Line Item Quantity', 'Line␣
 ↪Item Value', 'Pack Price', 'Unit Price'],
            y_vars='Freight_Cost_USD_Clean', height=7, aspect=0.7, kind='reg')
```

[61]:
```
<seaborn.axisgrid.PairGrid at 0x7f197b6c8550>
```



14 Test and Training Data

[62]:
```
train_features, test_features, train_targets, test_targets =␣
 ↪train_test_split(predictors, targets, test_size=0.2, random_state=3)

print('test features shape: ', test_features.shape)
print('test targets shape: ', test_targets.shape)

print('train features shape: ', train_features.shape)
print('train targets shape: ', train_targets.shape)
```

```
test features shape:  (1637, 8)
test targets shape:  (1637,)
train features shape:  (6545, 8)
train targets shape:  (6545,)
```

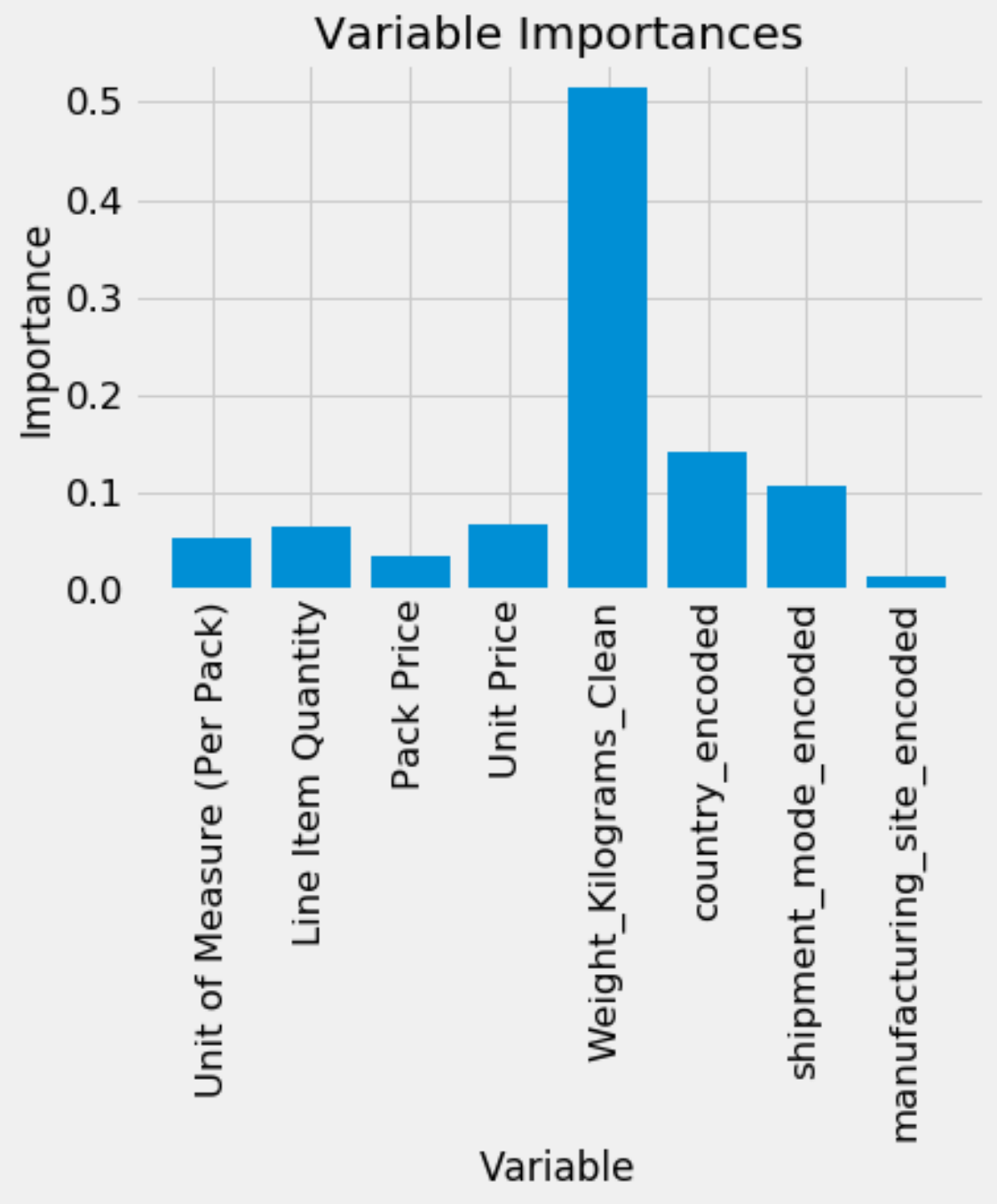
15 Decision Tree Regressor

[63]:
```
tree_regressor = DecisionTreeRegressor(max_depth=15) # MAE 6.08 minutes, R2 -1.
↪20

tree_regressor = tree_regressor.fit(train_features, train_targets)

print('node_count => ', tree_regressor.tree_.node_count)

tree_regressor.get_params()
```

```
node_count =>  4349
```

[63]:
```
{'criterion': 'mse',
 'max_depth': 15,
 'max_features': None,
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'presort': False,
 'random_state': None,
 'splitter': 'best'}
```

[64]:
```
# Saving feature names for later use
feature_list = list(predictors.columns)
importances = list(tree_regressor.feature_importances_)

# Set the style
plt.style.use('fivethirtyeight')

# list of x locations for plotting
x_values = list(range(len(importances)))

# Make a bar chart
plt.bar(x_values, importances, orientation = 'vertical')

# Tick labels for x axis
plt.xticks(x_values, feature_list, rotation='vertical')

# Axis labels and title
plt.ylabel('Importance'); plt.xlabel('Variable'); plt.title('Variable␣
↪Importances');
```


Variable Importances
Importance
0.5
0.4
0.3
0.2
0.1
0.0
Unit of Measure (Per Pack)
Line Item Quantity
Pack Price
Unit Price
Weight_Kilograms_Clean
country_encoded
shipment_mode_encoded
manufacturing_site_encoded
Variable

16 Verify model using Test Data

[65]:
```
#Predecimos para los valores del grupo Test
tree_predictions = tree_regressor.predict(test_features)
df = pd.DataFrame({'Actual':test_targets, 'Predicted':tree_predictions})
df
```

[65]:

	Actual	Predicted
10026	3,526.27	3,651.01
5425	1,400.91	1,599.22
2860	11,314.20	13,731.60
7063	6,036.96	5,056.74
1750	2,989.45	3,651.01
…	…	…
9356	2,528.69	3,651.01
1400	1,053.86	734.66
317	12,770.05	14,829.77
3440	365.48	350.02
7550	12,648.36	14,893.07

[1637 rows x 2 columns]

17 Metrics

[66]:
```
results = pd.DataFrame({'Score':['Mean Absolute Error', 'Root Mean Squared␣
 ↪Error', 'Mean Squared Error', 'R Square']})
tree_score = [metrics.mean_absolute_error(test_targets, tree_predictions),
              np.sqrt(metrics.mean_squared_error(test_targets,␣
 ↪tree_predictions)),
              metrics.mean_squared_error(test_targets, tree_predictions)/10000,
              metrics.r2_score(test_targets, tree_predictions)*10000]
results['Tree Desicion'] = tree_score

print('Mean Absolute Error:     {} [$]'.format(results.iloc[0, 1]))
print('Root Mean Squared Error: {} [$]'.format(results.iloc[1, 1]))
print('Mean Squared Error:      {} [$]'.format(results.iloc[2, 1]))
print('R Square:                {} [%]'.format(results.iloc[3, 1])) # 1 is␣
 ↪better
results
```

```
Mean Absolute Error:     5095.493314582138 [$]
Root Mean Squared Error: 11750.808786409198 [$]
Mean Squared Error:      13808.150713475161 [$]
R Square:                6154.946623278115 [%]
```

[66]:

	Score	Tree Desicion
0	Mean Absolute Error	5,095.49
1	Root Mean Squared Error	11,750.81
2	Mean Squared Error	13,808.15
3	R Square	6,154.95

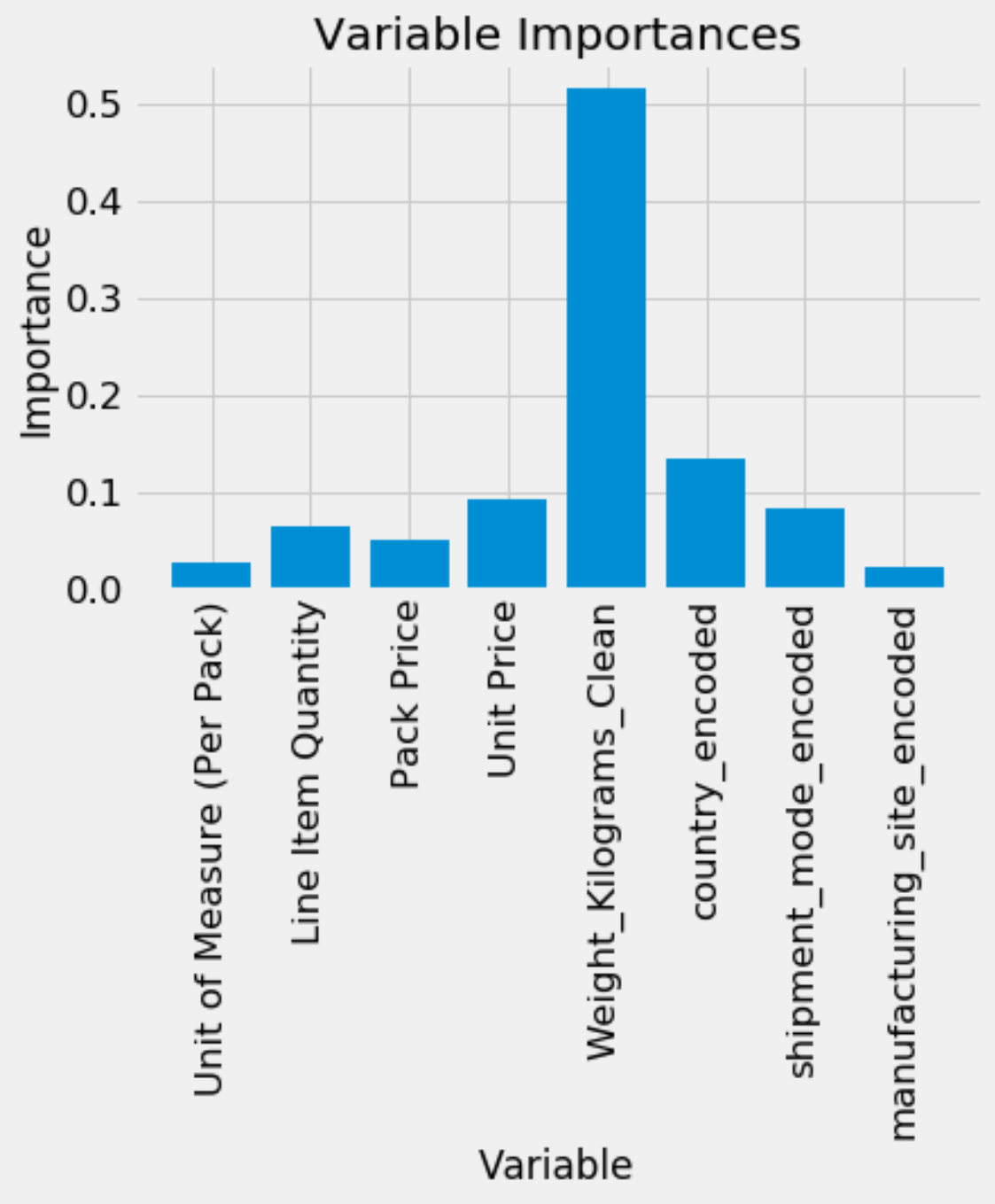
18 Random Forest Regressor

[67]:
```
rand_forest_regressor = RandomForestRegressor(n_estimators=500, random_state=3)

rand_forest_regressor = rand_forest_regressor.fit(train_features, train_targets)

rand_forest_regressor.get_params()
```

[67]:
```
{'bootstrap': True,
 'criterion': 'mse',
 'max_depth': None,
 'max_features': 'auto',
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 500,
 'n_jobs': None,
 'oob_score': False,
 'random_state': 3,
 'verbose': 0,
 'warm_start': False}
```

[68]:
```
# Saving feature names for later use
feature_list = list(predictors.columns)
importances = list(rand_forest_regressor.feature_importances_)

# Set the style
plt.style.use('fivethirtyeight')

# list of x locations for plotting
x_values = list(range(len(importances)))

# Make a bar chart
plt.bar(x_values, importances, orientation='vertical')

# Tick labels for x axis
```

```
plt.xticks(x_values, feature_list, rotation='vertical')

# Axis labels and title
plt.ylabel('Importance'); plt.xlabel('Variable'); plt.title('Variable␣
 ↪Importances');
```



19 Verify Model using Test Data

[69]:
```
rf_predictions = rand_forest_regressor.predict(test_features)
df = pd.DataFrame({'Actual':test_targets, 'Predicted':rf_predictions})
df
```

[69]:

	Actual	Predicted
10026	3,526.27	3,832.25
5425	1,400.91	1,468.25
2860	11,314.20	13,243.27
7063	6,036.96	5,802.95
1750	2,989.45	3,964.51
…	…	…
9356	2,528.69	3,675.51
1400	1,053.86	1,513.39
317	12,770.05	14,292.23
3440	365.48	1,623.07
7550	12,648.36	15,952.38

[1637 rows x 2 columns]

20 Metrics

[70]:
```
rf_score = [metrics.mean_absolute_error(test_targets, rf_predictions),
            np.sqrt(metrics.mean_squared_error(test_targets, rf_predictions)),
            metrics.mean_squared_error(test_targets, rf_predictions)/10000,
            metrics.r2_score(test_targets, rf_predictions)*10000]
results['Random Forest'] = rf_score

print('Mean Absolute Error:     {} [$]'.format(results.iloc[0, 2]))
print('Root Mean Squared Error: {} [$]'.format(results.iloc[1, 2]))
print('Mean Squared Error:      {} [$]'.format(results.iloc[2, 2]))
print('R Square:                {} [%]'.format(results.iloc[3, 2])) # 1 is␣
 ↪better
results
```

```
Mean Absolute Error:     4416.38844743828 [$]
Root Mean Squared Error: 9219.642342163452 [$]
Mean Squared Error:      8500.180491741317 [$]
R Square:                7633.017745770982 [%]
```

[70]:

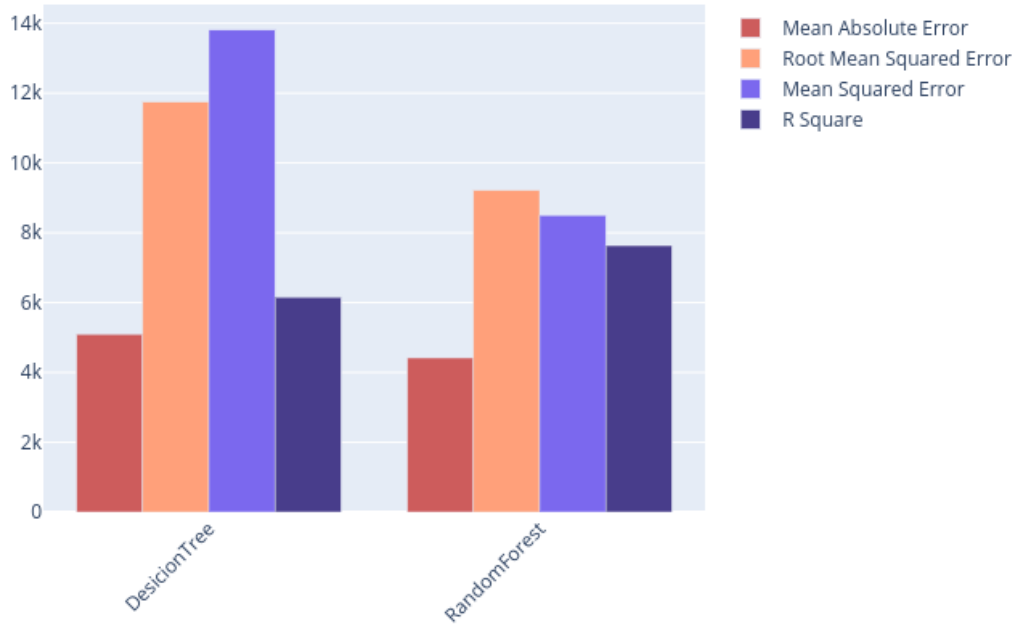
	Score	Tree Desicion	Random Forest
0	Mean Absolute Error	5,095.49	4,416.39
1	Root Mean Squared Error	11,750.81	9,219.64
2	Mean Squared Error	13,808.15	8,500.18

```
3                R Square          6,154.95          7,633.02
```

21 Comparison

[102]:
```
model_name = ['DesicionTree', 'RandomForest']

fig = go.Figure()
fig.add_trace(go.Bar(
    x=model_name,
    y=results.iloc[0,1:],
    name='Mean Absolute Error',
    marker_color='indianred'
))
fig.add_trace(go.Bar(
    x=model_name,
    y=results.iloc[1,1:],
    name='Root Mean Squared Error',
    marker_color='lightsalmon'
))
fig.add_trace(go.Bar(
    x=model_name,
    y=results.iloc[2,1:],
    name='Mean Squared Error',
    marker_color='mediumslateblue'
))
fig.add_trace(go.Bar(
    x=model_name,
    y=results.iloc[3,1:],
    name='R Square',
    marker_color='darkslateblue'
))

# Here we modify the tickangle of the xaxis, resulting in rotated labels.
fig.layout.update(barmode='group', xaxis_tickangle=-45)

show_image = None
if export_flag:
    chart_studio.plotly.image.save_as(fig, filename='comparison-plot.png')
    show_image = Image('comparison-plot.png')
else:
    fig.show()

show_image
```

[102]:



22 Conclusion

- Los features seleccionados fueron tratados para eliminar todos los datos nulos.
- Los features seleccionados fueron tratados para transformar con valores validos.
- Los features los features claves fueron **el Peso, el modo de envio y el pais destino**.
- Se eligieron los algoritmos de Arbol de Desición y Random Forest para la predicción del precio de envio, donde el mejor resultado fue obtenido por el Random Forest.