Tesla_Sales_Performance

December 26, 2024

[294]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import warnings
warnings.filterwarnings('ignore')
sns.set_style('white')
```

[43]:
```
df = pd.read_excel("Tesla sales data.xlsx")
```

[44]:
```
df.head()
```

[44]:

	Model	Period	Country	Purchase type	Version	Price	Gross Profit
0	Model S	201601	US	Deposit	75D AWD	75700	22407.268985
1	Model S	201601	US	Cash purchase	75D AWD	75700	22407.268985
2	Model S	201601	US	Cash purchase	75 RWD	70700	20927.264428
3	Model S	201601	US	Cash purchase	75 RWD	70700	20927.264428
4	Model S	201601	US	Cash purchase	75 RWD	70700	20927.264428

[45]:
```
for i in [col for col in df.columns if df[col].dtype == 'object' and␣
 ↪len(df[col].unique())<= 10]:
    print(i)
    print(df[i].unique())
    print('_'*100)
```

```
Model
['Model S' 'Model X']
----------------------------------------------------------------------------------------------------
Country
['US' 'Germany' 'Australia']
----------------------------------------------------------------------------------------------------
Purchase type
['Deposit' 'Cash purchase']
----------------------------------------------------------------------------------------------------
Version
```

```
['75D AWD' '75 RWD' '90D AWD' '60D AWD' '90D' 'P90D']
--------------------------------------------------------------------------------
--------------------
```

[46]:
```
df.shape
```

[46]:
```
(85592, 7)
```

[47]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 85592 entries, 0 to 85591
Data columns (total 7 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Model          85592 non-null  object
 1   Period         85592 non-null  int64
 2   Country        85592 non-null  object
 3   Purchase type  85592 non-null  object
 4   Version        85592 non-null  object
 5   Price          85592 non-null  int64
 6   Gross Profit   85592 non-null  float64
dtypes: float64(1), int64(2), object(4)
memory usage: 4.6+ MB
```

- **first we need to perfom some data cleaning on Period feature so that we can extract the Year feature**
- **second we will create a new feature profitability ratio and Cost ratio**

[48]:
```
import re
```

[49]:
```
df.head()
```

[49]:

	Model	Period	Country	Purchase type	Version	Price	Gross Profit
0	Model S	201601	US	Deposit	75D AWD	75700	22407.268985
1	Model S	201601	US	Cash purchase	75D AWD	75700	22407.268985
2	Model S	201601	US	Cash purchase	75 RWD	70700	20927.264428
3	Model S	201601	US	Cash purchase	75 RWD	70700	20927.264428
4	Model S	201601	US	Cash purchase	75 RWD	70700	20927.264428

[50]:
```
df['date'] = pd.to_datetime(df['Period'],format='%Y%m')
df['year'] = df['date'].dt.year
```

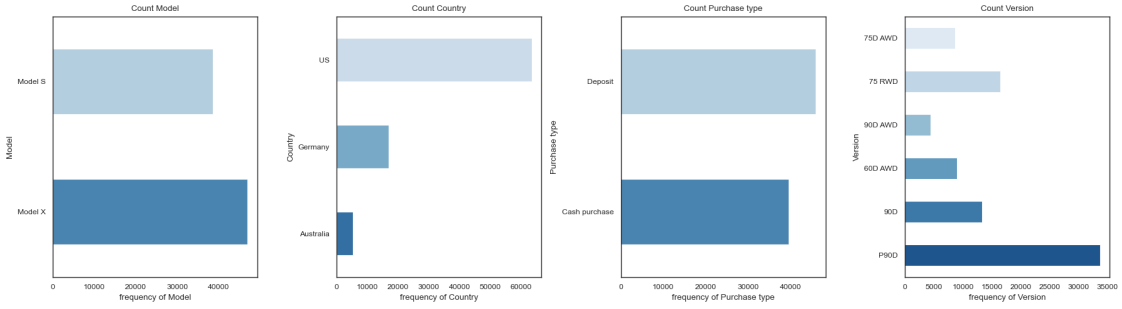
[52]:
```
df.drop('Period',axis=1,inplace=True)
```

[98]:
```
# Profitability Ratio
df['Profitability Ratio'] = df['Gross Profit']/df['Price']
df['Cost Ratio'] = 1-df['Profitability Ratio']
df.head(5)
```

[98]:
```
    Model Country  Purchase type  Version  Price  Gross Profit       date  \
0  Model S      US        Deposit  75D AWD  75700  22407.268985 2016-01-01
1  Model S      US  Cash purchase  75D AWD  75700  22407.268985 2016-01-01
2  Model S      US  Cash purchase   75 RWD  70700  20927.264428 2016-01-01
3  Model S      US  Cash purchase   75 RWD  70700  20927.264428 2016-01-01
4  Model S      US  Cash purchase   75 RWD  70700  20927.264428 2016-01-01

   year  Profitability Ratio  Cost Ratio
0  2016             0.296001    0.703999
1  2016             0.296001    0.703999
2  2016             0.296001    0.703999
3  2016             0.296001    0.703999
4  2016             0.296001    0.703999
```

frequency of Categorical data

[295]:
```
cols = [col for col in df.columns if df[col].dtype == 'object' and len(df[col].
 ↪unique())<= 10]
fig,ax = plt.subplots(1,4,figsize=(18,5))
ax=ax.flatten()
for i, c in enumerate(cols):
    sns.countplot(df,y=c,palette='Blues',ax=ax[i],hue=c,legend=False,width=0.5)
    ax[i].set_title(f'Count {c}')
    ax[i].set_xlabel(f'frequency of {c}')
plt.tight_layout()
```



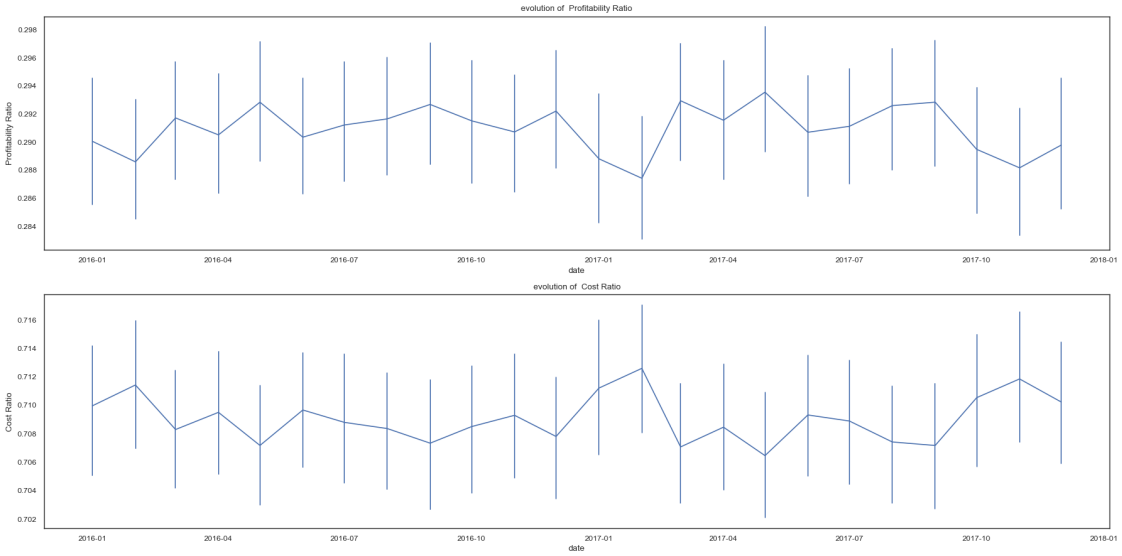
Sales and profit evolution

[310]:
```
df.columns
```

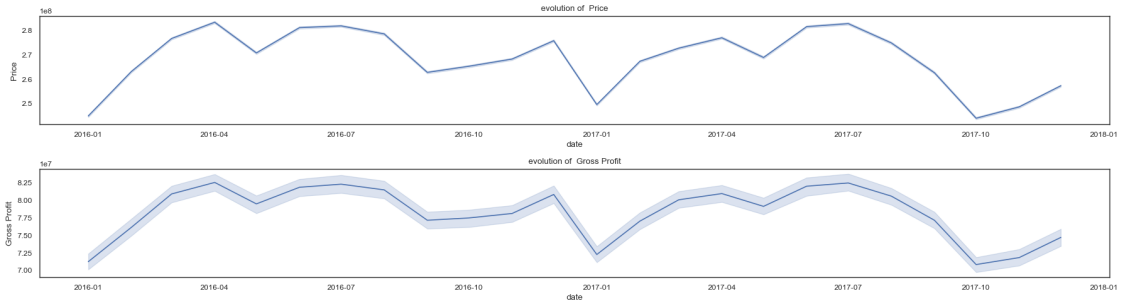
[310]:
```
Index(['Model', 'Country', 'Purchase type', 'Version', 'Price', 'Gross Profit',
       'date', 'year', 'Profitability Ratio', 'Cost Ratio'],
      dtype='object')
```

profitability Ratio and cost Ratio evolution

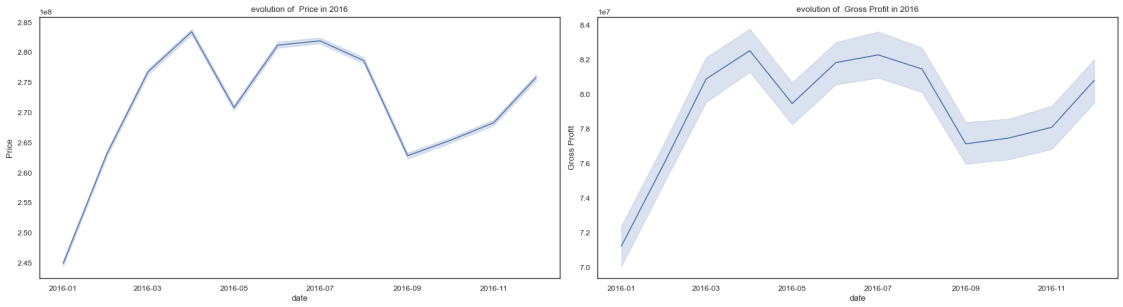
[314]:
```
fig,ax = plt.subplots(2,1,figsize=(18,9))
ax=ax.flatten()
for i, c in enumerate(['Profitability Ratio', 'Cost Ratio']):
    sns.lineplot(df,x='date',y=c,ax=ax[i],estimator=np.mean,err_style='bars')
    ax[i].set_title(f'evolution of  {c}')
plt.tight_layout()
```



[296]:
```
fig,ax = plt.subplots(2,1,figsize=(18,5))
ax=ax.flatten()
for i, c in enumerate(['Price','Gross Profit']):
    sns.lineplot(df,x='date',y=c,ax=ax[i],estimator=sum)
    ax[i].set_title(f'evolution of  {c}')
plt.tight_layout()
```

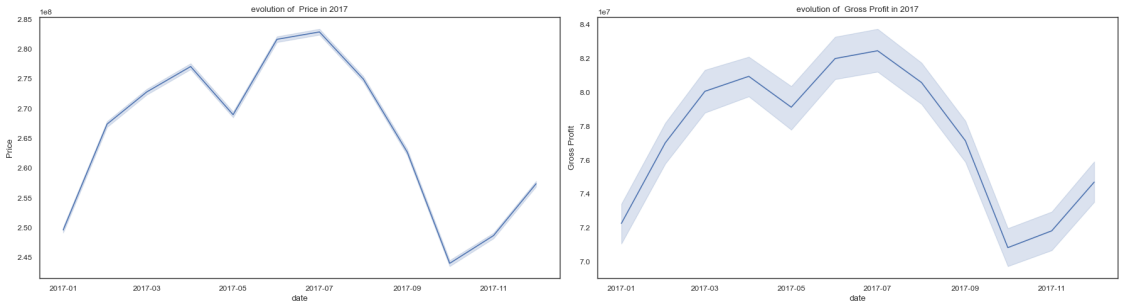


[298]:
```
fig,ax = plt.subplots(1,2,figsize=(18,5))
ax=ax.flatten()
for i, c in enumerate(['Price','Gross Profit']):
    data = df.query('year == 2016')
    sns.lineplot(data,x='date',y=c,ax=ax[i],estimator=sum)
    ax[i].set_title(f'evolution of  {c} in 2016')
plt.tight_layout()
```



Sales and profit evolution in 2017

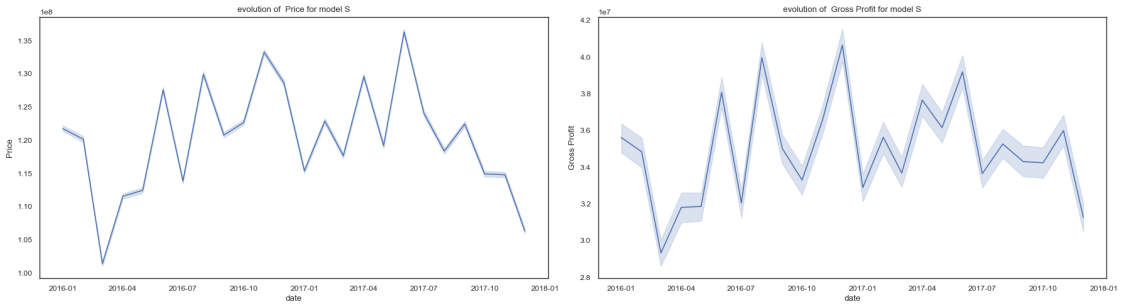
[299]:
```
fig,ax = plt.subplots(1,2,figsize=(18,5))
ax=ax.flatten()
for i, c in enumerate(['Price','Gross Profit']):
    data = df.query('year == 2017')
    sns.lineplot(data,x='date',y=c,ax=ax[i],estimator=sum)
    ax[i].set_title(f'evolution of  {c} in 2017')
plt.tight_layout()
```



Sales and profit evolution of model S

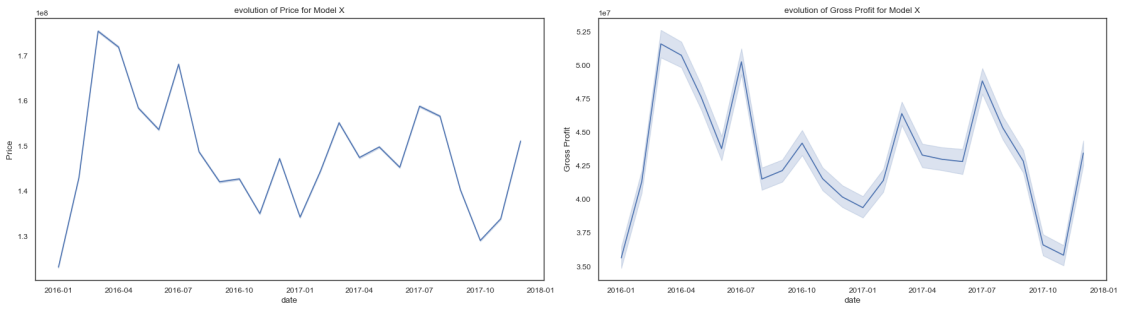
[300]:
```
fig,ax = plt.subplots(1,2,figsize=(18,5))
ax=ax.flatten()
```

```
for i, c in enumerate(['Price','Gross Profit']):
    data = df.query('Model == "Model S"')
    sns.lineplot(data,x='date',y=c,ax=ax[i],estimator=sum)
    ax[i].set_title(f'evolution of  {c} for model S')
plt.tight_layout()
```



Sales and profit evolution of model M

[301]:
```
fig,ax = plt.subplots(1,2,figsize=(18,5))
ax=ax.flatten()
for i, c in enumerate(['Price','Gross Profit']):
    data = df.query('Model == "Model X"')
    sns.lineplot(data,x='date',y=c,ax=ax[i],estimator=sum,err_style='band')
    ax[i].set_title(f'evolution of {c} for Model X')
plt.tight_layout()
```

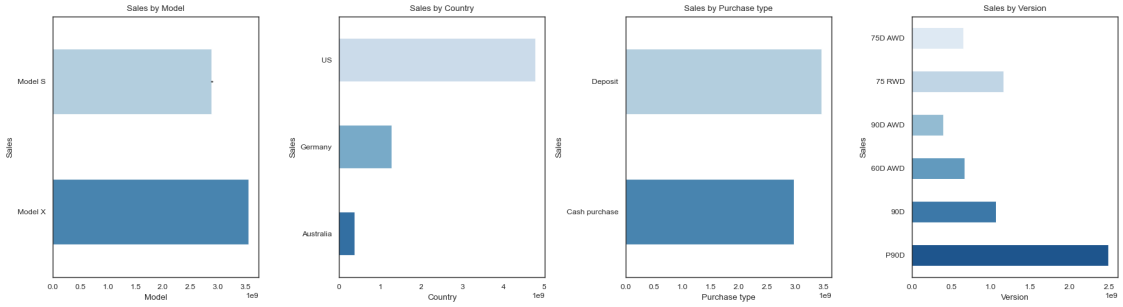


[302]:
```
from markdown import markdown
from IPython.display import display, Markdown
```

[303]:
```
cols = [col for col in df.columns if df[col].dtype == 'object' and len(df[col].
 ↪unique())<= 10]
fig,ax = plt.subplots(1,4,figsize=(18,5))
ax=ax.flatten()
```

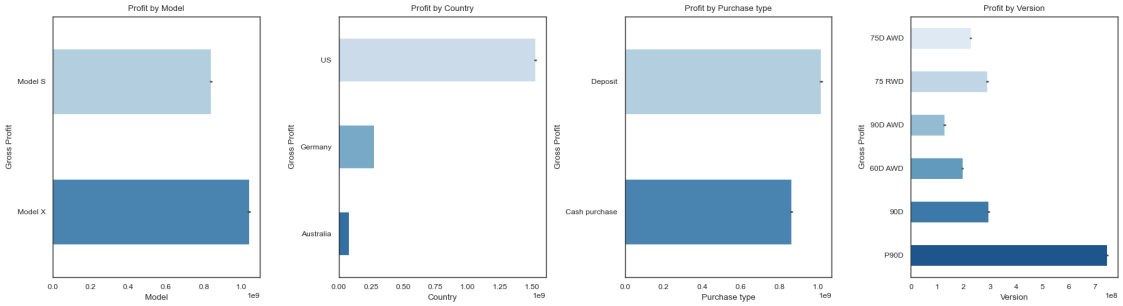
```
text = " ### **Total sales by ``model`` ,``Country``, ``Version`` and␣
 ↪``Purshase Type``**"
display(Markdown(text))
for i, c in enumerate(cols):
    sns.
 ↪barplot(df,y=c,x='Price',palette='Blues',ax=ax[i],hue=c,legend=False,width=0.
 ↪5,estimator=sum)
    ax[i].set_title(f'Sales by {c}')
    ax[i].set_xlabel(f'{c}')
    ax[i].set_ylabel('Sales')
plt.tight_layout()
```

Total sales by model ,Country, Version and Purshase Type



[308]:
```
cols = [col for col in df.columns if df[col].dtype == 'object' and len(df[col].
 ↪unique())<= 10]
fig,ax = plt.subplots(1,4,figsize=(18,5))
ax=ax.flatten()
text = " ### **Total Gross Profit by ``model`` ,``Country``, ``Version`` and␣
 ↪``Purshase Type``**"
display(Markdown(text))
for i, c in enumerate(cols):
    sns.barplot(df,y=c,x='Gross␣
 ↪Profit',palette='Blues',ax=ax[i],hue=c,legend=False,width=0.5,estimator=sum)
    ax[i].set_title(f'Profit by {c}')
    ax[i].set_xlabel(f'{c}')
    ax[i].set_ylabel('Gross Profit')
plt.tight_layout()
```

Total Gross Profit by model ,Country, Version and Purshase Type



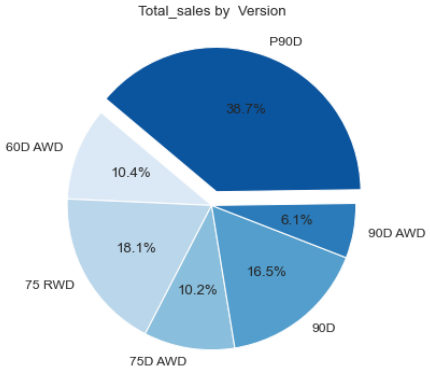
Sales Performance by car version

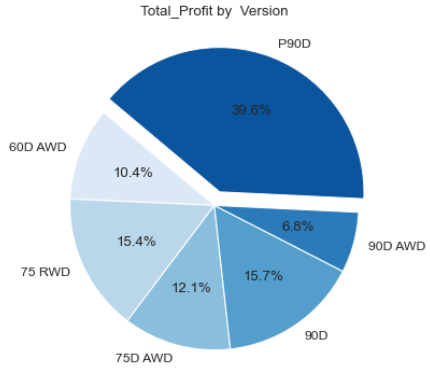
[304]:
```
def agg_table(name,flt):
    result = df.groupby(flt).agg(
        Total_sales = ('Price','sum'),
        Total_Profit = ('Gross Profit','sum'),
        Volume_sold = ('Model','count'),
        avg_profitability = ('Profitability Ratio','mean'))
    globals()[name]=result


agg_table('SP_Version','Version')
SP_Version.reset_index(inplace=True)
```

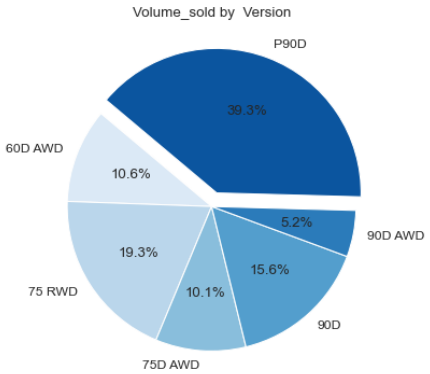
[305]:
```
SP_Version_1
```

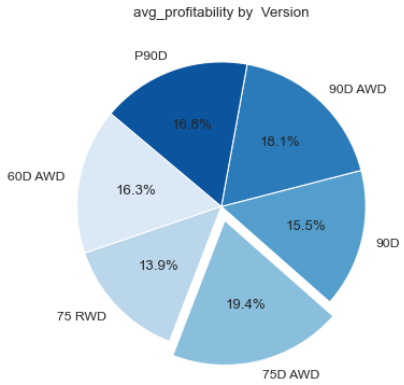
[305]:
```
<pandas.io.formats.style.Styler at 0x1d027ee9150>
```

[306]:
```
def plot_summary(data,flt):
    fig,ax = plt.subplots(2,2,figsize=(20,7.5))
    ax=ax.flatten()
    colors = sns.color_palette("Blues", len(data))
    for i , c in enumerate(data.iloc[:,1:].columns):
        explode = [0.1 if val == data[c].max() else 0 for val in data[c]]

        ax[i].pie(data[c],labels=data[flt],autopct='%1.1f%%',␣
 ↪startangle=140,explode=explode,colors=colors)
        ax[i].set_title(f'{c} by  {flt}')
        plt.tight_layout()
plot_summary(SP_Version,'Version')
```







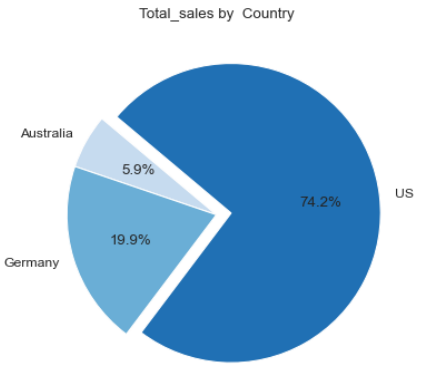


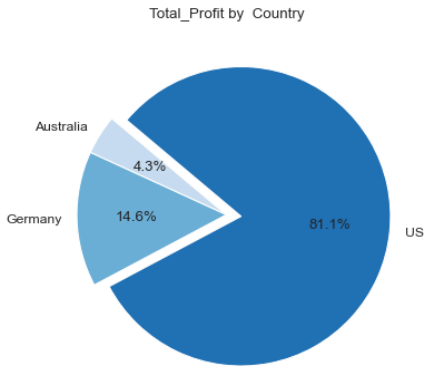
Sales Performance by car Country

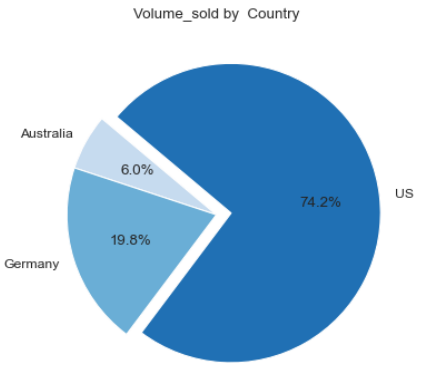
[261]:
```
agg_table('SP_Country','Country')
SP_Country.reset_index(inplace=True)
SP_Country_1 = SP_Country.style.background_gradient(cmap='Blues')
SP_Country_1
```

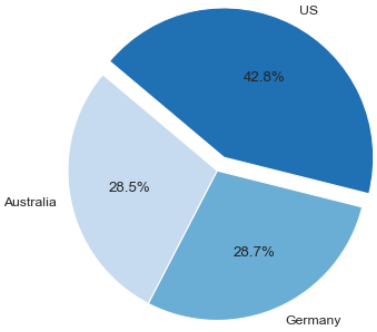
[261]: <pandas.io.formats.style.Styler at 0x1d043c29790>

[307]:
```
plot_summary(SP_Country,'Country')
```









[315]:
```
df.head()
```

[315]:

	Model	Country	Purchase type	Version	Price	Gross Profit	date	year	Profitability Ratio	Cost Ratio
0	Model S	US	Deposit	75D AWD	75700	22407.268985	2016-01-01	2016	0.296001	0.703999
1	Model S	US	Cash purchase	75D AWD	75700	22407.268985	2016-01-01	2016	0.296001	0.703999
2	Model S	US	Cash purchase	75 RWD	70700	20927.264428	2016-01-01	2016	0.296001	0.703999
3	Model S	US	Cash purchase	75 RWD	70700	20927.264428	2016-01-01	2016	0.296001	0.703999
4	Model S	US	Cash purchase	75 RWD	70700	20927.264428	2016-01-01	2016	0.296001	0.703999

1 Analysis of Tesla Sales Performance Visualizations

1.1 1. Categorical Data Frequency

- **Count Plots:**

- **Model**: Shows the frequency of sales across models (e.g., Model S vs. Model X), indicating popularity.

- **Country**: Displays sales distribution across countries (e.g., US, Germany, Australia), identifying key markets.

- **Purchase Type**: Differentiates between deposits and cash purchases, reflecting customer preferences.

- **Version**: Shows popularity of different versions (e.g., 75D AWD, 90D AWD), informing production and marketing strategies.

1.2 2. Sales and Profit Evolution

- **Line Plots for Price and Gross Profit**:
  - **Overall Trends**: A rising trend in both price and gross profit suggests increasing sales volume or price adjustments over time.

  - **Yearly Breakdown**: Focused analysis of sales performance for 2016 and 2017, potentially highlighting seasonal trends or the impact of new model releases.

1.3 3. Profitability and Cost Ratios

- **Evolution of Profitability and Cost Ratios**:
  - **Profitability Ratio**: A stable or increasing ratio indicates effective cost management and pricing strategies.

  - **Cost Ratio**: A decreasing cost ratio suggests improved efficiency in production or sales processes.

1.4 4. Sales Performance by Model

- **Model-Specific Sales and Profit Plots**:
  - **Model S**: Higher sales and profits suggest strong consumer preference.

  - **Model X**: Comparatively lower sales or profits may indicate a need for marketing adjustments or product improvements.

1.5 5. Total Sales and Gross Profit by Categories

- **Bar Plots**:
  - **Sales by Model/Country**: Identifies high-performing models in specific countries, guiding regional marketing strategies.

  - **Profit by Version/Purchase Type**: Highlights which versions or purchase types yield the highest profits, informing inventory and pricing decisions.

1.6 6. Aggregated Tables and Summary Visualizations

- **Aggregated Sales Performance**:
  - Tables summarizing total sales, total profit, volume sold, and average profitability by version and country provide a comprehensive overview.

  - **Pie Charts**: Help in understanding the proportion of total sales and profits contributed by each category, identifying key drivers of revenue.

1.7 Conclusion

The visualizations collectively provide a detailed view of Tesla's sales performance, revealing trends, consumer preferences, and profitability insights. This analysis can guide strategic decisions regarding marketing, production, and pricing.

[ ]:
```
Tesla_Sales_Performance
jupyter nbconvert --to pdf Tesla_Sales_Performance.ipynb
```