Data Analysis

Miguel Alejandro Salas Reyna (2022), Data Science and Mathematics Student.

Instituto Tecnológico y de Estudios Superiores de Monterrey (ITESM).

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import date
import numpy as np
import seaborn as sn
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
import plotly.express as px
```

In [2]:
```
df = pd.read_csv("Automotive_2_clean_data.csv")
```

In [3]:
```
df
```

Out[3]:

	offerType	price	abtest	vehicleType	yearOfRegistration	gearbox	powerPS	model
0	Angebot	10499	control	limousine	2006	manual	163	3er
1	Angebot	2750	test	kleinwagen	1999	manual	50	lupo
2	Angebot	3500	control	kombi	2004	manual	125	astra
3	Angebot	7500	control	kombi	2012	manual	116	focus
4	Angebot	1050	test	kleinwagen	2002	manual	105	147
...	...	...	...	...	...	...	...	...
116926	Angebot	7900	test	limousine	2010	manual	140	golf
116927	Angebot	3200	control	limousine	2004	manual	225	leon
116928	Angebot	1199	test	cabrio	2000	automatik	101	fortwo
116929	Angebot	9200	test	bus	1996	manual	102	transporter
116930	Angebot	3400	test	kombi	2002	manual	100	golf

116931 rows × 14 columns

In [4]:
```
df = df.drop(columns=['monthOfRegistration'])
```

In [5]:
```
df['notRepairedDamage'] = df['notRepairedDamage'].map({0: "no", 1: "yes"})
```

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 116931 entries, 0 to 116930
Data columns (total 13 columns):
 #   Column              Non-Null Count   Dtype 
---  ------              --------------   ----- 
 0   offerType           116931 non-null  object
 1   price               116931 non-null  int64 
 2   abtest              116931 non-null  object
 3   vehicleType         116931 non-null  object
 4   yearOfRegistration  116931 non-null  int64 
 5   gearbox             116931 non-null  object
 6   powerPS             116931 non-null  int64 
 7   model               116931 non-null  object
 8   kilometer           116931 non-null  int64 
 9   fuelType            116931 non-null  object
 10  brand               116931 non-null  object
 11  notRepairedDamage   116931 non-null  object
 12  status              116931 non-null  int64 
dtypes: int64(5), object(8)
memory usage: 11.6+ MB
```

In [7]:
```
string_col = df.select_dtypes(include="object").columns
df[string_col]=df[string_col].astype("string")
```

In [8]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 116931 entries, 0 to 116930
Data columns (total 13 columns):
 #   Column              Non-Null Count   Dtype 
---  ------              --------------   ----- 
 0   offerType           116931 non-null  string
 1   price               116931 non-null  int64 
 2   abtest              116931 non-null  string
 3   vehicleType         116931 non-null  string
 4   yearOfRegistration  116931 non-null  int64 
 5   gearbox             116931 non-null  string
 6   powerPS             116931 non-null  int64 
 7   model               116931 non-null  string
 8   kilometer           116931 non-null  int64 
 9   fuelType            116931 non-null  string
 10  brand               116931 non-null  string
 11  notRepairedDamage   116931 non-null  string
 12  status              116931 non-null  int64 
dtypes: int64(5), string(8)
memory usage: 11.6 MB
```

In [9]:
```
string_col=df.select_dtypes("string").columns.to_list()
```

In [10]:
```
num_col=df.columns.to_list()
#print(num_col)
for col in string_col:
    num_col.remove(col)
num_col.remove("status")
```

In [11]:
```
df.describe().T
```

Out[11]:

	count	mean	std	min	25%	50%	75%	
price	116931.0	4728.572620	4333.565384	0.0	1399.0	3200.0	6900.0	
yearOfRegistration	116931.0	2003.035577	5.359477	1986.0	1999.0	2003.0	2007.0	
powerPS	116931.0	118.587817	44.888983	50.0	80.0	114.0	147.0	
kilometer	116931.0	128653.949765	36147.280310	5000.0	125000.0	150000.0	150000.0	1
status	116931.0	0.174009	0.379119	0.0	0.0	0.0	0.0	

In [12]:
```
px.imshow(df.corr(),title="Correlation Plot of the Sold Car Prediction")
```

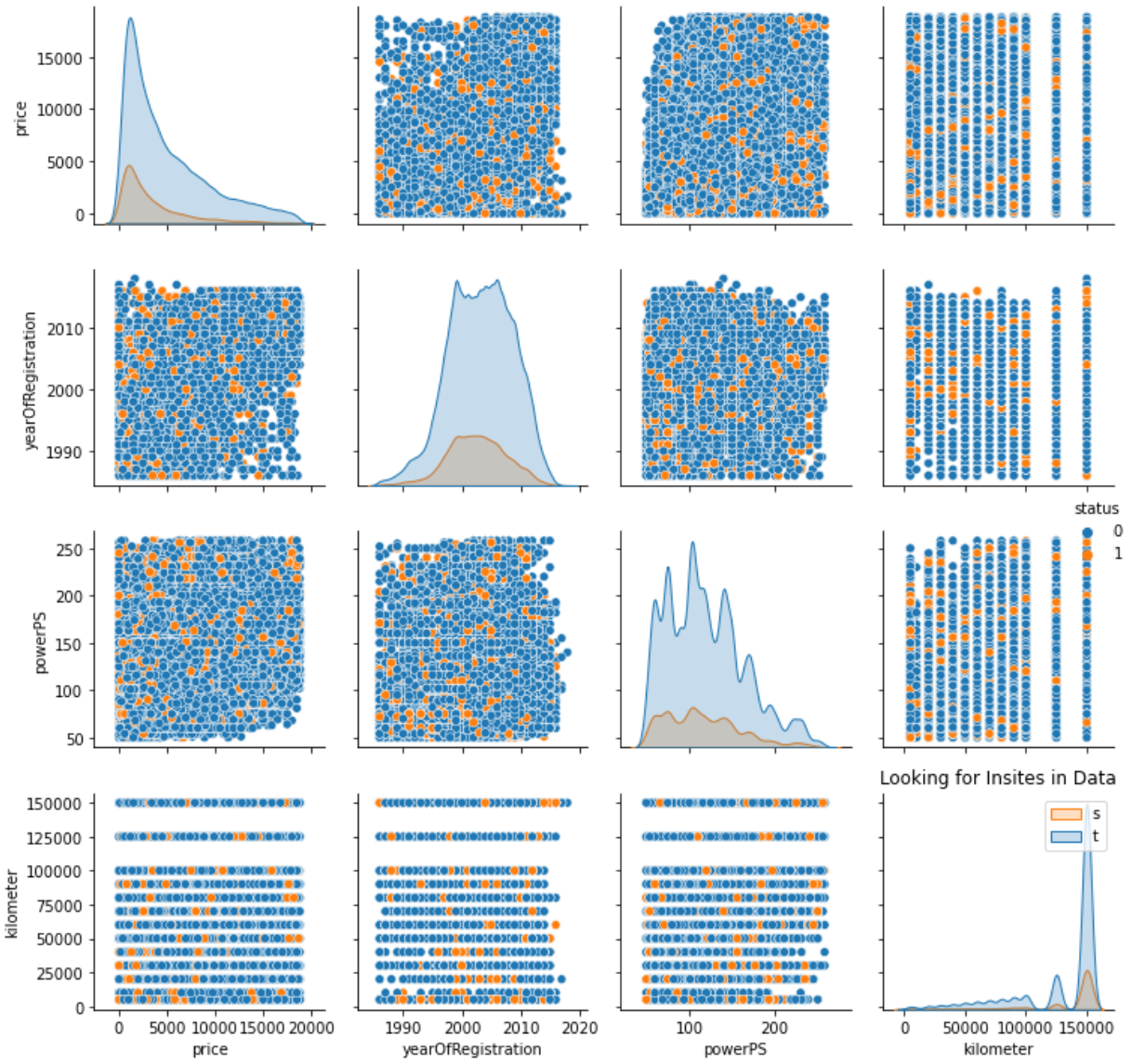
In [13]:
```
# Shows the Distribution of Sold Cars with respect to male and female
fig=px.histogram(df,
                 x="status",
                 color="brand",
                 hover_data=df.columns,
                 title="Distribution of Sold Cars by brand",
                 barmode="group")
fig.show()
```

In [14]:
```
fig=px.histogram(df,
                 x="status",
                 color="gearbox",
                 hover_data=df.columns,
                 title="Sold Cars by Gearbox"
                )
fig.show()
```

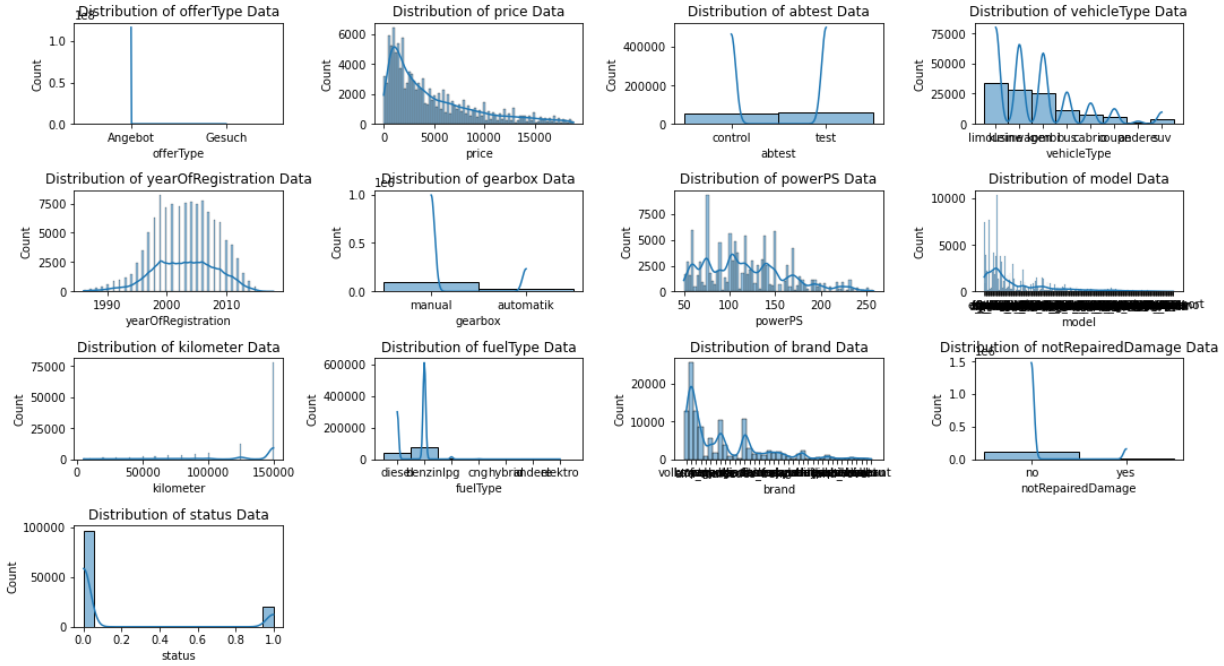
In [15]:
```
plt.figure(figsize=(15,10))
sns.pairplot(df,hue="status")
plt.title("Looking for Insites in Data")
plt.legend("status")
plt.tight_layout()
plt.plot()
```

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

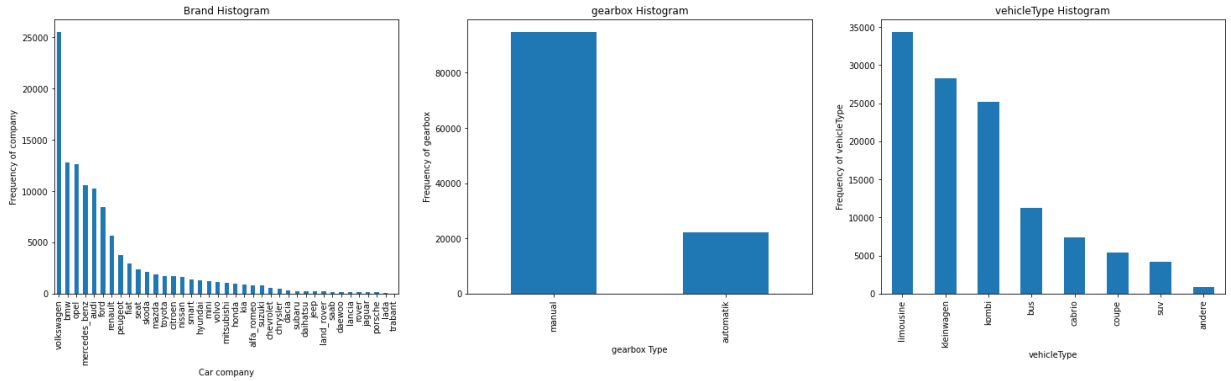
```
<Figure size 1080x720 with 0 Axes>
```



In [16]:
```
plt.figure(figsize=(15,10))
for i,col in enumerate(df.columns,1):
    plt.subplot(5,4,i)
    plt.title(f"Distribution of {col} Data")
    sns.histplot(df[col],kde=True)
    plt.tight_layout()
    plt.plot()
```

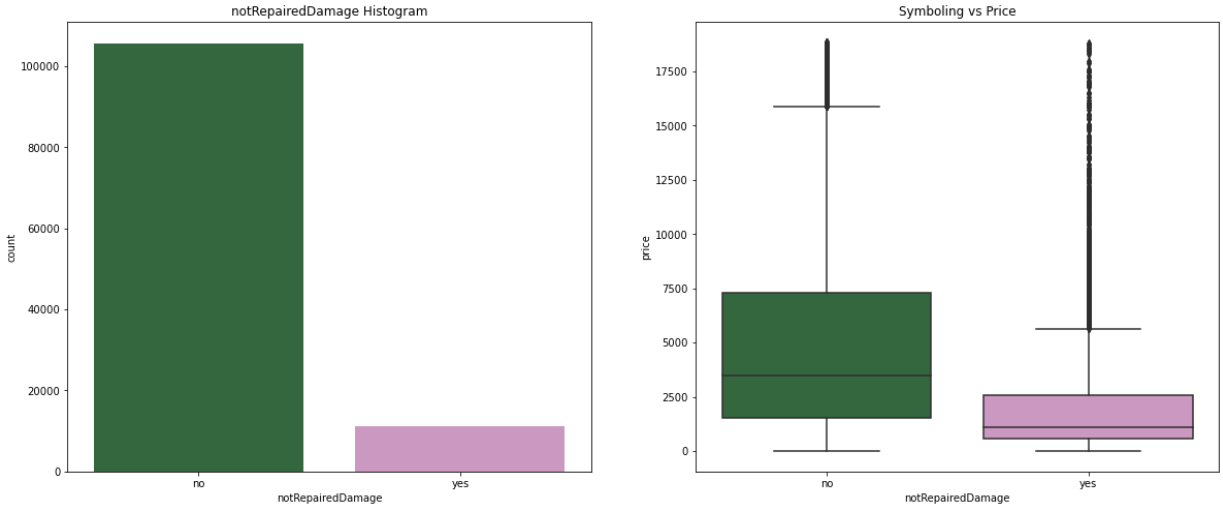


In [17]:
```
plt.figure(figsize=(25, 6))

plt.subplot(1,3,1)
plt1 = df.brand.value_counts().plot(kind = 'bar')
plt.title('Brand Histogram')
plt1.set(xlabel = 'Car company', ylabel='Frequency of company')

plt.subplot(1,3,2)
plt1 = df.gearbox.value_counts().plot(kind = 'bar')
plt.title('gearbox Histogram')
plt1.set(xlabel = 'gearbox Type', ylabel='Frequency of gearbox')

plt.subplot(1,3,3)
plt1 = df.vehicleType.value_counts().plot(kind = 'bar')
plt.title('vehicleType Histogram')
plt1.set(xlabel = 'vehicleType', ylabel='Frequency of vehicleType')

plt.show()
```



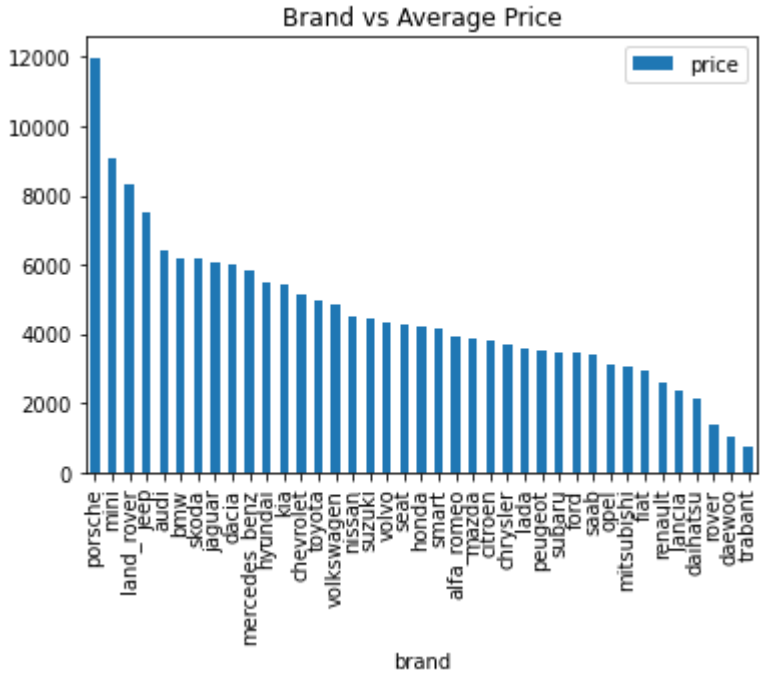
In [18]:
```
plt.figure(figsize=(20,8))

plt.subplot(1,2,1)
plt.title('notRepairedDamage Histogram')
sns.countplot(df.notRepairedDamage, palette=("cubehelix"))

plt.subplot(1,2,2)
plt.title('Symboling vs Price')
sns.boxplot(x=df.notRepairedDamage, y=df.price, palette=("cubehelix"))

plt.show()
```

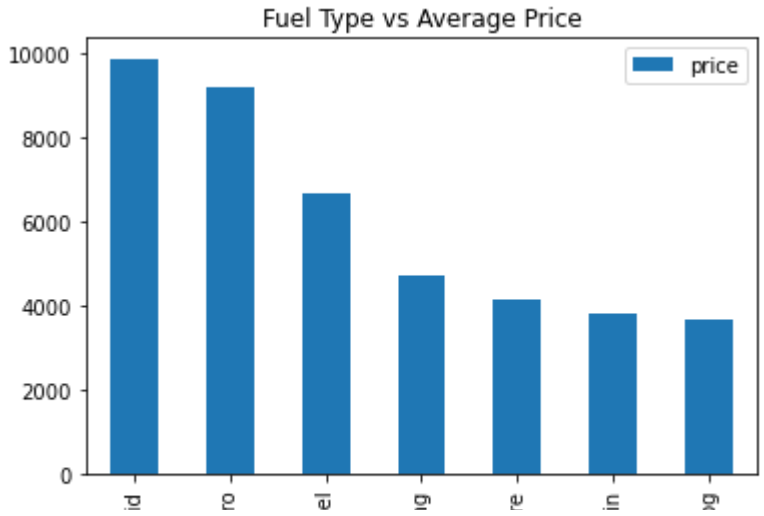
```
D:\conda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:

Pass the following variable as a keyword arg: x. From version 0.12, the only va
lid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
```

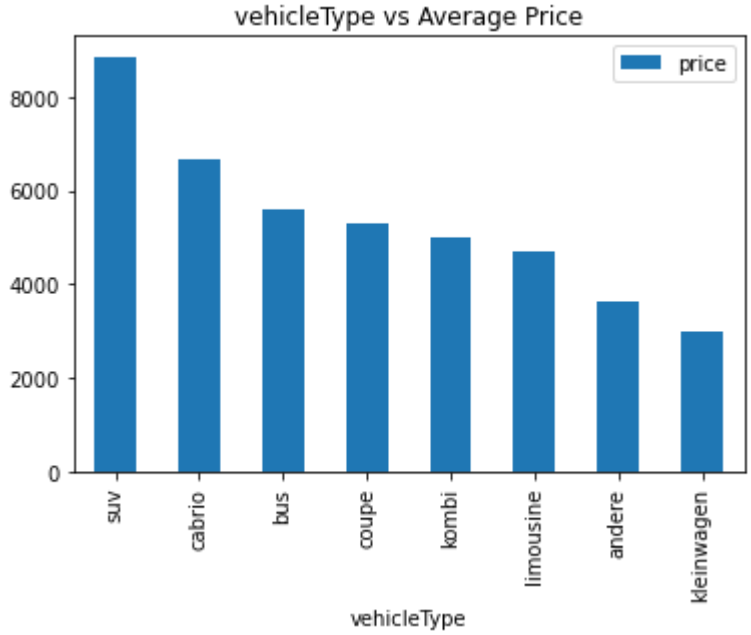


In [19]:
```
plt.figure(figsize=(25, 6))

df2 = pd.DataFrame(df.groupby(['brand'])['price'].mean().sort_values(ascending =
df2.plot.bar()
plt.title('Brand vs Average Price')
plt.show()

df3 = pd.DataFrame(df.groupby(['fuelType'])['price'].mean().sort_values(ascending
df3.plot.bar()
plt.title('Fuel Type vs Average Price')
plt.show()

df4 = pd.DataFrame(df.groupby(['vehicleType'])['price'].mean().sort_values(ascend
df4.plot.bar()
plt.title('vehicleType vs Average Price')
plt.show()
```

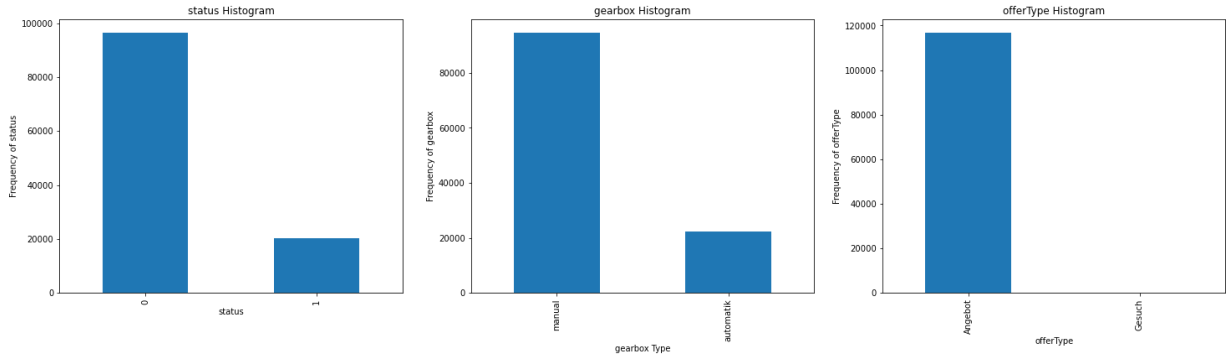
```
<Figure size 1800x432 with 0 Axes>
```




Fuel Type vs Average Price
price
10000
8000
6000
4000
2000
0


vehicleType vs Average Price
price
8000
6000
4000
2000
0
suv
cabrio
bus
coupe
kombi
limousine
andere
kleinwagen
vehicleType

In [20]:
```
plt.figure(figsize=(25, 6))

plt.subplot(1,3,1)
plt1 = df.status.value_counts().plot(kind = 'bar')
plt.title('status Histogram')
plt1.set(xlabel = 'status', ylabel='Frequency of status')

plt.subplot(1,3,2)
plt1 = df.gearbox.value_counts().plot(kind = 'bar')
plt.title('gearbox Histogram')
plt1.set(xlabel = 'gearbox Type', ylabel='Frequency of gearbox')

plt.subplot(1,3,3)
plt1 = df.offerType.value_counts().plot(kind = 'bar')
plt.title('offerType Histogram')
plt1.set(xlabel = 'offerType', ylabel='Frequency of offerType')

plt.show()
```



In [21]:
```
df_tree = df.apply(LabelEncoder().fit_transform)
df_tree.head()
```

Out[21]:

	offerType	price	abtest	vehicleType	yearOfRegistration	gearbox	powerPS	model	kilometer
0	0	1771	0	6	20	1	113	11	9
1	0	711	1	4	13	1	0	143	4
2	0	856	0	5	18	1	75	42	12
3	0	1450	0	5	26	1	66	103	12
4	0	334	1	4	16	1	55	2	12

In [22]:
```
df_nontree=pd.get_dummies(df,columns=string_col,drop_first=False)
df_nontree.head()
```

Out[22]:

	price	yearOfRegistration	powerPS	kilometer	status	offerType_Angebot	offerType_Gesuch	ab
0	10499	2006	163	90000	0	1	0	
1	2750	1999	50	40000	0	1	0	
2	3500	2004	125	150000	0	1	0	
3	7500	2012	116	150000	0	1	0	
4	1050	2002	105	150000	0	1	0	

5 rows × 311 columns

Non Tree Based Algorithms

In [23]:
```
X = df_nontree.iloc[:,df_nontree.columns != 'status']
y = df_nontree.status
```

In [24]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_
```

In [25]:
```
from sklearn.model_selection import train_test_split

from sklearn.linear_model import LogisticRegression

from sklearn import preprocessing

from sklearn.metrics import accuracy_score, classification_report, confusion_matr
```

In [26]:
```
scaler = preprocessing.StandardScaler().fit(X_train)
X_train_scaled = scaler.transform(X_train)
```

Logistic Regression

In [27]:
```
model = LogisticRegression()
```

In [28]:
```
model.fit(X_train_scaled, y_train)
```

```
D:\conda\lib\site-packages\sklearn\linear_model\_logistic.py:763: ConvergenceWa
rning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-
learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on)
```

Out[28]:
```
LogisticRegression()
```

In [29]:
```
train_acc = model.score(X_train_scaled, y_train)
print("The Accuracy for Training Set is {}".format(train_acc*100))
```

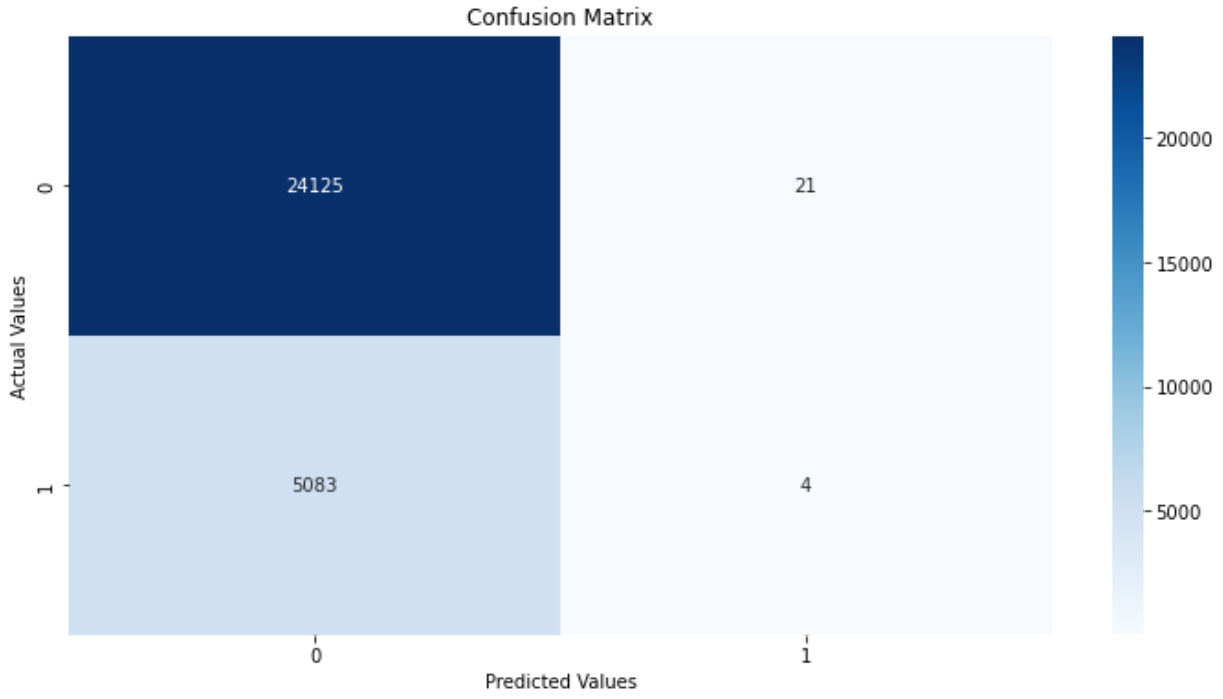
```
The Accuracy for Training Set is 82.55034322333462
```

In [30]:
```
y_pred = model.predict(X_test)
test_acc = accuracy_score(y_test, y_pred)
print("The Accuracy for Test Set is {}".format(test_acc*100))
```

```
The Accuracy for Test Set is 82.54027982075051
```

In [31]:
```
cm=confusion_matrix(y_test,y_pred)
plt.figure(figsize=(12,6))
plt.title("Confusion Matrix")
sns.heatmap(cm, annot=True,fmt='d', cmap='Blues')
plt.ylabel("Actual Values")
plt.xlabel("Predicted Values")
#plt.savefig('confusion_matrix.png')
```

Out[31]: Text(0.5, 33.0, 'Predicted Values')



In [32]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.83      1.00      0.90     24146
           1       0.16      0.00      0.00      5087

    accuracy                           0.83     29233
   macro avg       0.49      0.50      0.45     29233
weighted avg       0.71      0.83      0.75     29233
```

Naive Bayes

In [33]:
```
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train, y_train)
```

Out[33]: GaussianNB()

In [34]:
```
y_pred  =  classifier.predict(X_test)
```

In [35]:
```
y_pred
```

Out[35]:
```
array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
```

In [36]:
```
y_test
```

Out[36]:
```
48608    0
75149    0
33386    0
75488    0
64879    0
        ..
4115     0
21239    1
94376    0
70536    1
27906    0
Name: status, Length: 29233, dtype: int64
```

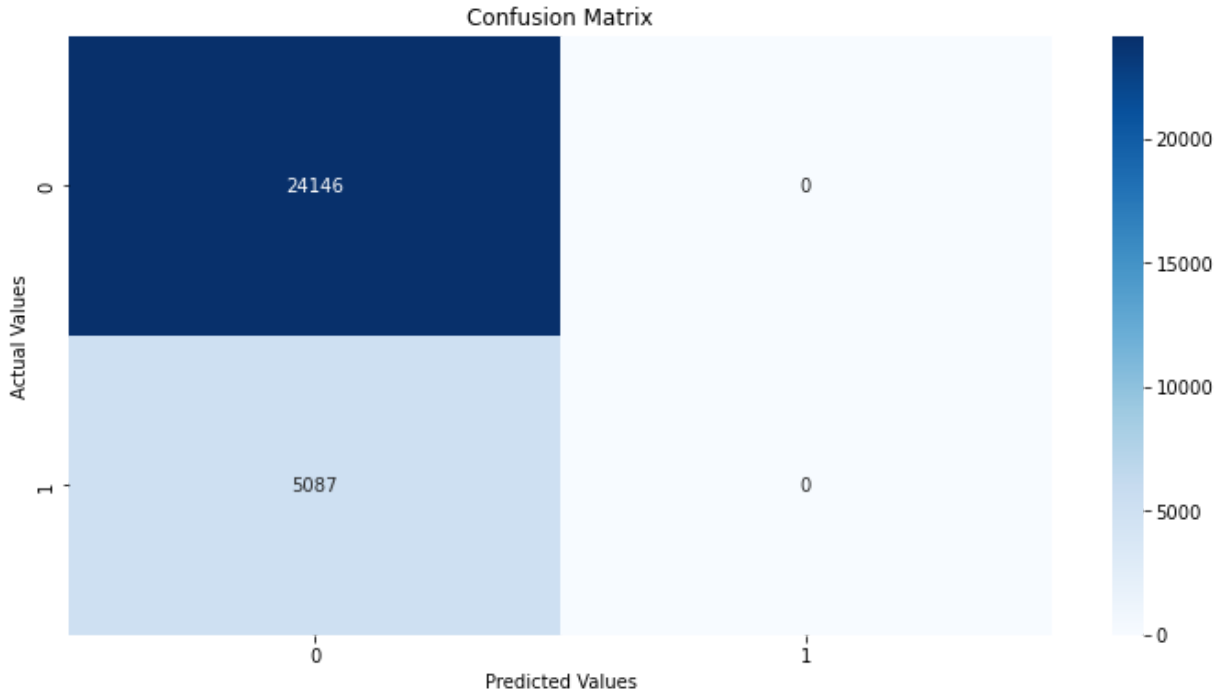
In [37]:
```
cm = confusion_matrix(y_test, y_pred)
ac = accuracy_score(y_test,y_pred)
```

In [38]:
```
print(cm)
print(ac)
print(classification_report(y_test,y_pred))
```

```
[[24146     0]
 [ 5087     0]]
0.825984332774604
              precision    recall  f1-score   support

           0       0.83      1.00      0.90     24146
           1       0.00      0.00      0.00      5087

    accuracy                           0.83     29233
   macro avg       0.41      0.50      0.45     29233
weighted avg       0.68      0.83      0.75     29233


D:\conda\lib\site-packages\sklearn\metrics\_classification.py:1248: UndefinedMe
tricWarning:

Precision and F-score are ill-defined and being set to 0.0 in labels with no pr
edicted samples. Use `zero_division` parameter to control this behavior.

D:\conda\lib\site-packages\sklearn\metrics\_classification.py:1248: UndefinedMe
tricWarning:

Precision and F-score are ill-defined and being set to 0.0 in labels with no pr
edicted samples. Use `zero_division` parameter to control this behavior.

D:\conda\lib\site-packages\sklearn\metrics\_classification.py:1248: UndefinedMe
tricWarning:

Precision and F-score are ill-defined and being set to 0.0 in labels with no pr
edicted samples. Use `zero_division` parameter to control this behavior.
```

In [39]:
```
plt.figure(figsize=(12,6))
plt.title("Confusion Matrix")
sns.heatmap(cm, annot=True,fmt='d', cmap='Blues')
plt.ylabel("Actual Values")
plt.xlabel("Predicted Values")
#plt.savefig('confusion_matrix.png')
```

Out[39]: Text(0.5, 33.0, 'Predicted Values')



SVM

In [40]:
```
from sklearn.svm import SVC
```

In [41]:
```
#clf=SVC(kernel="linear")
#clf.fit(X_train,y_train)
#y_pred=clf.predict(X_test)
```

In [42]:
```
#cm = confusion_matrix(y_test, y_pred)
#ac = accuracy_score(y_test,y_pred)
```

In [43]:
```
#clf=SVC(kernel="sigmoid")
#clf.fit(X_train,y_train)
#y_pred=clf.predict(X_test)
```

In [44]:
```
#cm = confusion_matrix(y_test, y_pred)
#ac = accuracy_score(y_test,y_pred)
```

In [45]:
```
#clf=SVC(kernel="rfb")
#clf.fit(X_train,y_train)
#y_pred=clf.predict(X_test)
```

In [46]:
```
#cm = confusion_matrix(y_test, y_pred)
#ac = accuracy_score(y_test,y_pred)
```

In [47]:
```
#clf=SVC(kernel="poly")
#clf.fit(X_train,y_train)
#y_pred=clf.predict(X_test)
```

In [48]:
```
#cm = confusion_matrix(y_test, y_pred)
#ac = accuracy_score(y_test,y_pred)
```

KNN

In [49]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [50]:
```
clf=KNeighborsClassifier(n_neighbors=32)
clf.fit(X_train,y_train)
y_pred=clf.predict(X_test)
```

In [51]:
```
cm = confusion_matrix(y_test, y_pred)
ac = accuracy_score(y_test,y_pred)
```

In [52]:
```
print(cm)
print(ac)
print(classification_report(y_test,y_pred))
```

```
[[24105    41]
 [ 5042    45]]
0.8261211644374509
              precision    recall  f1-score   support

           0       0.83      1.00      0.90     24146
           1       0.52      0.01      0.02      5087

    accuracy                           0.83     29233
   macro avg       0.68      0.50      0.46     29233
weighted avg       0.77      0.83      0.75     29233
```

Tree Based Algorithm

In [53]:
```
target = "status"
feature_col_tree=df_tree.columns.to_list()
feature_col_tree.remove(target)
```

In [54]:
```
X = df_tree.iloc[:,df_tree.columns != 'status']
y = df_tree.status
```

In [55]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_
```

Desicion Tree

In [56]:
```
from sklearn.tree import DecisionTreeClassifier
clf=DecisionTreeClassifier(criterion="entropy")
clf.fit(X_train,y_train)
y_pred=clf.predict(X_test)
```

In [57]:
```
cm = confusion_matrix(y_test, y_pred)
ac = accuracy_score(y_test,y_pred)
```

In [58]:
```
print(cm)
print(ac)
print(classification_report(y_test,y_pred))
```

```
[[20366  3780]
 [ 3608  1479]]
0.7472719187219923
              precision    recall  f1-score   support

           0       0.85      0.84      0.85     24146
           1       0.28      0.29      0.29      5087

    accuracy                           0.75     29233
   macro avg       0.57      0.57      0.57     29233
weighted avg       0.75      0.75      0.75     29233
```

In [60]:
```
from sklearn import tree
text_representation = tree.export_text(clf)
print(text_representation)
```

```
|--- feature_1 <= 1032.50
|   |--- feature_9 <= 1.50
|   |   |--- feature_1 <= 501.50
|   |   |   |--- feature_4 <= 12.50
|   |   |   |   |--- feature_1 <= 264.50
|   |   |   |   |   |--- feature_11 <= 0.50
|   |   |   |   |   |   |--- feature_1 <= 210.50
|   |   |   |   |   |   |   |--- feature_7 <= 21.50
|   |   |   |   |   |   |   |   |--- feature_6 <= 97.50
|   |   |   |   |   |   |   |   |   |--- feature_1 <= 142.50
|   |   |   |   |   |   |   |   |   |   |--- feature_1 <= 49.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |   |   |   |   |   |--- feature_1 >  49.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 13
|   |   |   |   |   |   |   |   |   |--- feature_1 >  142.50
|   |   |   |   |   |   |   |   |   |   |--- feature_4 <= 11.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 16
|   |   |   |   |   |   |   |   |   |   |--- feature_4 >  11.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 14
```

In [61]:
```
#import graphviz
#from sklearn import tree

#dot_data = tree.export_graphviz(clf, out_file=None, feature_names=feature_col_tr

#graph = graphviz.Source(dot_data, format="png")
#graph
```

In [62]:
```
#from dtreeviz.trees import dtreeviz # remember to load the package

#viz = dtreeviz(clf, X, y,target_name= target, feature_names=feature_col_tree, cl

#viz
```

Random Forest

In [63]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [64]:
```
clf=RandomForestClassifier(n_estimators=200,criterion="entropy")
clf.fit(X_train,y_train)
y_pred=clf.predict(X_test)
```

In [65]:
```
cm = confusion_matrix(y_test, y_pred)
ac = accuracy_score(y_test,y_pred)
```

In [66]:
```
print(cm)
print(ac)
print(classification_report(y_test,y_pred))
```

```
[[23304   842]
 [ 4320   767]]
0.8234187390962269
              precision    recall  f1-score   support

           0       0.84      0.97      0.90     24146
           1       0.48      0.15      0.23      5087

    accuracy                           0.82     29233
   macro avg       0.66      0.56      0.56     29233
weighted avg       0.78      0.82      0.78     29233
```

XGBoost

In [67]:
```
from xgboost import XGBClassifier
```

In [68]:
```
clf=XGBClassifier(use_label_encoder=False)
clf.fit(X_train,y_train)
y_pred=clf.predict(X_test)
```

```
[21:30:15] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.5.
1/src/learner.cc:1115: Starting in XGBoost 1.3.0, the default evaluation metric
used with the objective 'binary:logistic' was changed from 'error' to 'loglos
s'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

In [69]:
```
cm = confusion_matrix(y_test, y_pred)
ac = accuracy_score(y_test,y_pred)
```

In [71]:
```
print(cm)
print(ac)
print(classification_report(y_test,y_pred))
```

```
[[23933   213]
 [ 4694   393]]
0.8321417576027093
              precision    recall  f1-score   support

           0       0.84      0.99      0.91     24146
           1       0.65      0.08      0.14      5087

    accuracy                           0.83     29233
   macro avg       0.74      0.53      0.52     29233
weighted avg       0.80      0.83      0.77     29233
```

Conclusion: If the intention is identifiying if a car will be sold (True Positives) I would choose between Random Forest an Desicion Tree Algorithm.