Steamlit webapp for Steel plant load Perdiction

Inspiration

Which times of the year is the most energy consumed?

What patterns can we identify in energy usage?

In [2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

from lightgbm import LGBMClassifier
from sklearn.linear_model import RidgeClassifierCV
from xgboost import XGBClassifier
from sklearn.neighbors import NearestCentroid
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.calibration import CalibratedClassifierCV
from sklearn.naive_bayes import BernoulliNB
from sklearn.ensemble import BaggingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.svm import LinearSVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import Perceptron
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neural_network import MLPClassifier
import xgboost as Xgb
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.ensemble import AdaBoostClassifier
import lightgbm as lgb
from sklearn.svm import NuSVC
from sklearn.experimental import enable_hist_gradient_boosting
from sklearn.gaussian_process import GaussianProcessClassifier
from sklearn.gaussian_process.kernels import RBF
from sklearn.linear_model import RidgeClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.linear_model import PassiveAggressiveClassifier


from sklearn.metrics import accuracy_score, classification_report,f1_score,confusion_matrix,precision_score,rec
from sklearn.metrics import confusion_matrix, plot_confusion_matrix, plot_roc_curve, plot_precision_recall_curv

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

```
/opt/conda/lib/python3.7/site-packages/sklearn/experimental/enable_hist_gradient_boosting.py:17: UserWarning: S
ince version 1.0, it is not needed to import enable_hist_gradient_boosting anymore. HistGradientBoostingClassif
ier and HistGradientBoostingRegressor are now stable and can be normally imported from sklearn.ensemble.
  "Since version 1.0, "
```

In [3]:
```
# Color Palettes
colors = ["#bfd3e6", "#9b5b4f", "#4e4151", "#dbba78", "#bb9c55", "#909195","#dc1e1e","#a02933","#716807","#717c
sns.palplot(sns.color_palette(colors))
```

In [4]:
```
#Default theme
sns.set_theme(palette='tab10',
              font='Comic Sans MS',
              font_scale=1.5,
              rc=None)

import matplotlib
matplotlib.rcParams.update({'font.size': 15})
```

```python
plt.style.use('dark_background')
plt.rcParams["axes.grid"] = False
```

In [5]:
```python
df = pd.read_csv("/kaggle/input/steel-industry-energy-consumption/Steel_industry_data.csv")
df.head().style.background_gradient(cmap='copper').set_precision(2)
```

Out[5]:

	date	Usage_kWh	Lagging_Current_Reactive.Power_kVarh	Leading_Current_Reactive_Power_kVarh	CO2(tCO2)	Lagging_Current_Powe
0	01/01/2018 00:15	3.17	2.95	0.00	0.00	
1	01/01/2018 00:30	4.00	4.46	0.00	0.00	
2	01/01/2018 00:45	3.24	3.28	0.00	0.00	
3	01/01/2018 01:00	3.31	3.56	0.00	0.00	
4	01/01/2018 01:15	3.82	4.50	0.00	0.00	

In [6]:
```python
df.describe().T.round(2).sort_values(by='std' , ascending = False)\
                     .style.background_gradient(cmap='GnBu')\
                     .bar(subset=["max"], color='#BB0000')\
                     .bar(subset=["min",], color='green')\
                     .bar(subset=["mean",], color='Orange')\
                     .bar(subset=['std'], color='#716807')\
                     .bar(subset=['50%'], color='#717cb4')
```

Out[6]:

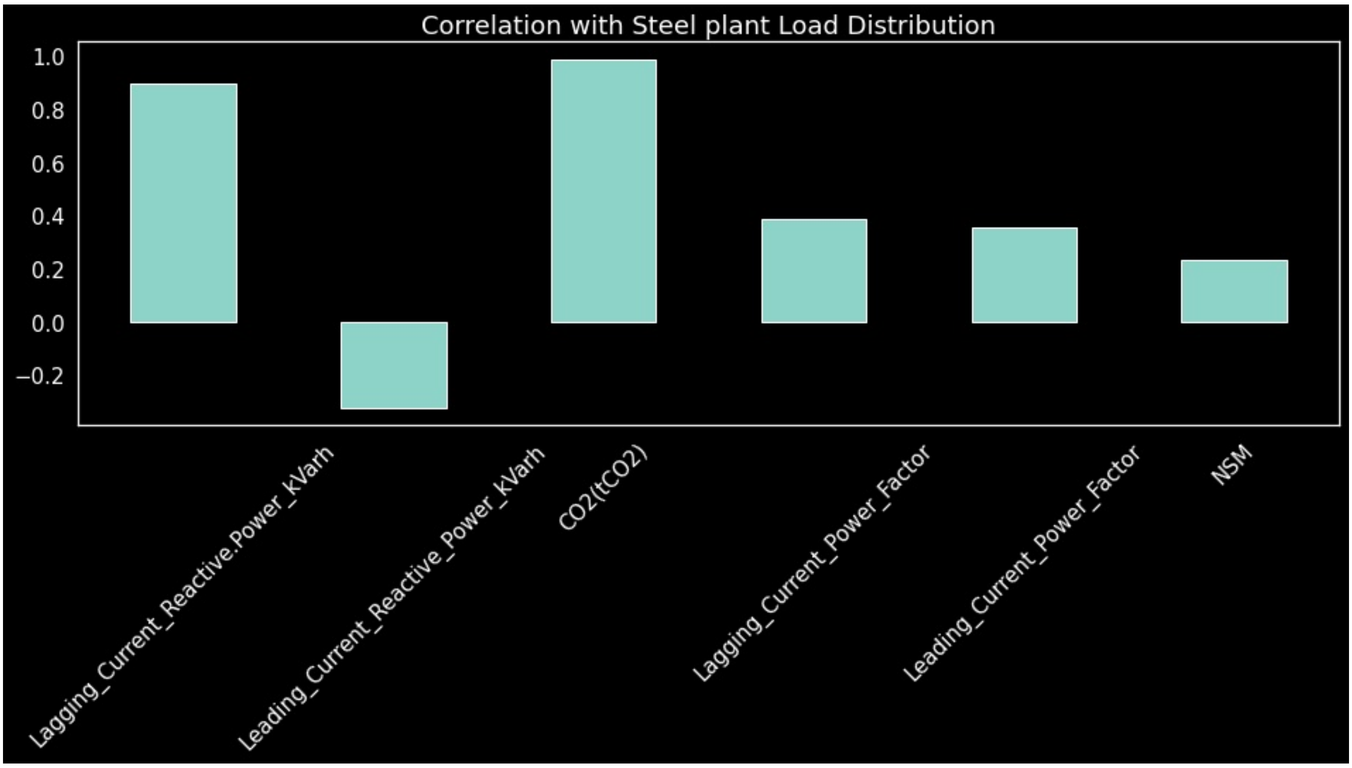
	count	mean	std	min	25%	50%	75%	
NSM	35040.000000	42750.000000	24940.530000	0.000000	21375.000000	42750.000000	64125.000000	8550
Usage_kWh	35040.000000			0.000000	3.200000	4.570000	51.240000	
Leading_Current_Power_Factor	35040.000000			0.000000	99.700000		100.000000	
Lagging_Current_Power_Factor	35040.000000			0.000000	63.320000		99.020000	
Lagging_Current_Reactive.Power_kVarh	35040.000000	13.040000		0.000000	2.300000	5.000000	22.640000	
Leading_Current_Reactive_Power_kVarh	35040.000000	3.870000	7.420000	0.000000	0.000000	0.000000	2.090000	2
CO2(tCO2)	35040.000000	0.010000	0.020000	0.000000	0.000000	0.000000	0.020000	

In [7]:
```python
corr = df.corr()
df.corr().style.background_gradient(cmap='copper').set_precision(2)
```

Out[7]:

	Usage_kWh	Lagging_Current_Reactive.Power_kVarh	Leading_Current_Reactive_Power_kVarh	CO2(tCO
Usage_kWh	1.00	0.90	-0.32	0.9
Lagging_Current_Reactive.Power_kVarh	0.90	1.00	-0.41	0.8
Leading_Current_Reactive_Power_kVarh	-0.32	-0.41	1.00	-0.3
CO2(tCO2)	0.99	0.89	-0.33	1.0
Lagging_Current_Power_Factor	0.39	0.14	0.53	0.3
Leading_Current_Power_Factor	0.35	0.41	-0.94	0.3
NSM	0.23	0.08	0.37	0.2

In [8]:
```python
df1 = df.copy()
#Correlation with Response Variable class
X = df1.drop(['Usage_kWh'],axis=1)
y = df1['Usage_kWh']

X.corrwith(y).plot.bar(
        figsize = (16, 5), title = "Correlation with Steel plant Load Distribution", fontsize = 15,
        rot = 45, grid = False)
plt.show()
```



In [9]:
```python
class color:
    BOLD = '\033[1m'
    END = '\033[0m'
print(f"\033[94m\033[1m")
print(color.BOLD + 'Missing values - Percentage: \n' + color.END)
print(f"\033[91m\033[1m")
print(round(df.isnull().mean() * 100, 2))
```

```
Missing values - Percentage:


date                                    0.0
Usage_kWh                               0.0
Lagging_Current_Reactive.Power_kVarh    0.0
Leading_Current_Reactive_Power_kVarh    0.0
CO2(tCO2)                               0.0
Lagging_Current_Power_Factor            0.0
Leading_Current_Power_Factor            0.0
NSM                                     0.0
WeekStatus                              0.0
Day_of_week                             0.0
Load_Type                               0.0
dtype: float64
```

In [10]:
```python
cat = df.select_dtypes(include='object').columns.tolist()

for col in df[cat]:
    print(f"\033[94m\033[1m")
    print(col,"\n")
    print(f"\033[91m\033[1m")
    print(df[col].value_counts())
    print(f"\033[92m\033[1m")
    print("======="*5)
```

```
date


01/01/2018 00:15    1
01/09/2018 08:45    1
01/09/2018 07:15    1
01/09/2018 07:30    1
01/09/2018 07:45    1
                   ..
02/05/2018 14:45    1
02/05/2018 14:30    1
02/05/2018 14:15    1
02/05/2018 14:00    1
31/12/2018 00:00    1
Name: date, Length: 35040, dtype: int64

===================================

WeekStatus


Weekday    25056
Weekend     9984
Name: WeekStatus, dtype: int64

===================================

Day_of_week


Monday       5088
Tuesday      4992
Wednesday    4992
Thursday     4992
Friday       4992
Saturday     4992
Sunday       4992
Name: Day_of_week, dtype: int64

===================================

Load_Type


Light_Load      18072
Medium_Load      9696
Maximum_Load     7272
Name: Load_Type, dtype: int64

===================================
```

In [11]:

```
#Rename some columns
df = df.rename(columns={'Lagging_Current_Reactive.Power_kVarh': 'Lagging_Reactive_Power_kVarh',
                        'Leading_Current_Reactive_Power_kVarh': 'Leading_Reactive_Power_kVarh',
                        'Lagging_Current_Power_Factor': 'Lagging_Power_Factor',
                        'Leading_Current_Power_Factor': 'Leading_Power_Factor',
                        'CO2(tCO2)':'CO2'})
df.head()
```

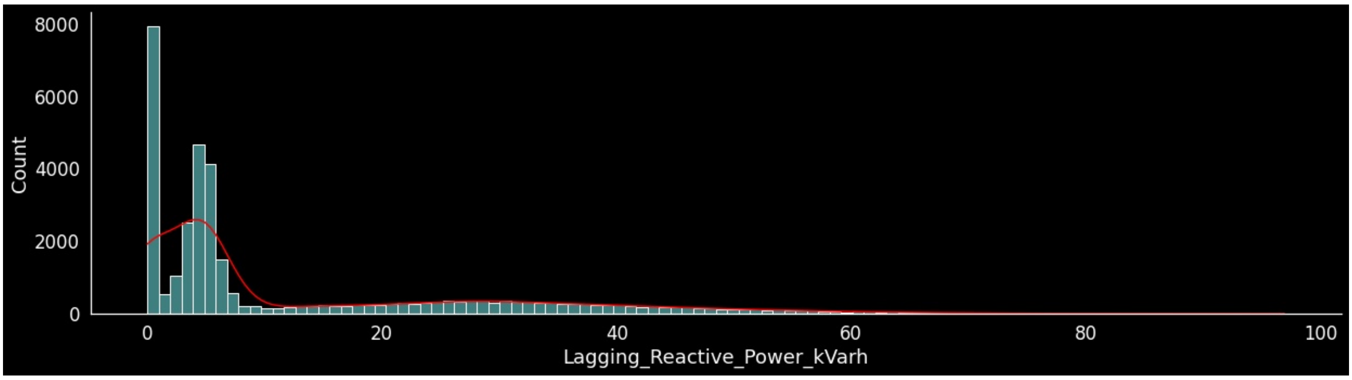
Out[11]:

	date	Usage_kWh	Lagging_Reactive_Power_kVarh	Leading_Reactive_Power_kVarh	CO2	Lagging_Power_Factor	Leading_Power_Facto
0	01/01/2018 00:15	3.17	2.95	0.0	0.0	73.21	100.
1	01/01/2018 00:30	4.00	4.46	0.0	0.0	66.77	100.
2	01/01/2018 00:45	3.24	3.28	0.0	0.0	70.28	100.
3	01/01/2018 01:00	3.31	3.56	0.0	0.0	68.09	100.
4	01/01/2018 01:15	3.82	4.50	0.0	0.0	64.72	100.

In [ ]:

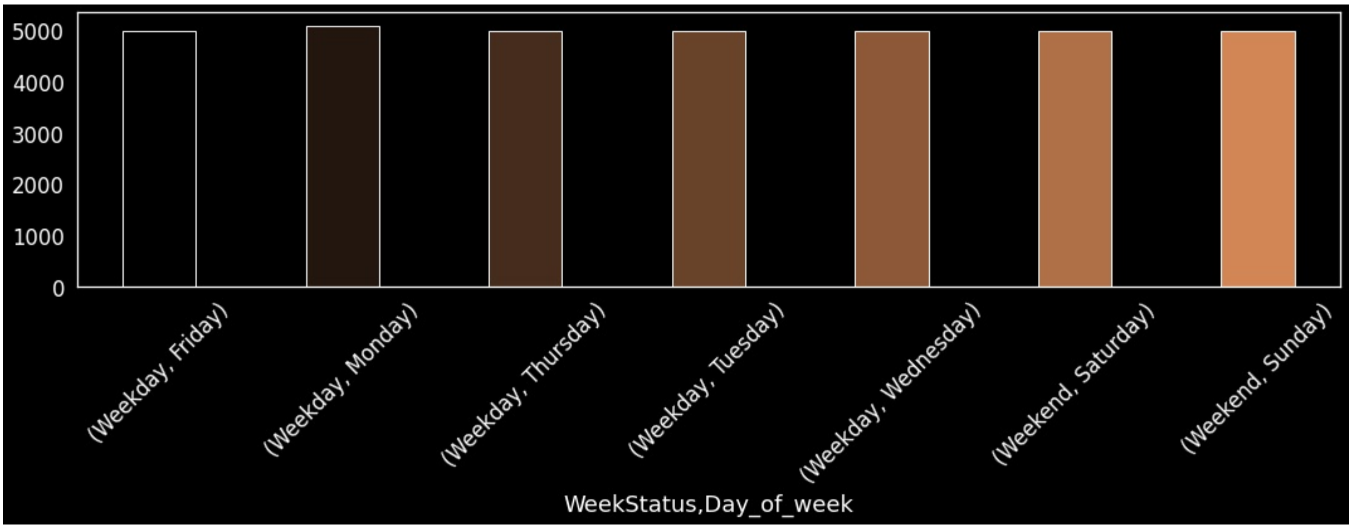
In [12]:

```
sns.displot(data=df, x="Lagging_Reactive_Power_kVarh", kde=True, bins = 100,color = "red", facecolor = "#3F7F7F
```



In [13]:

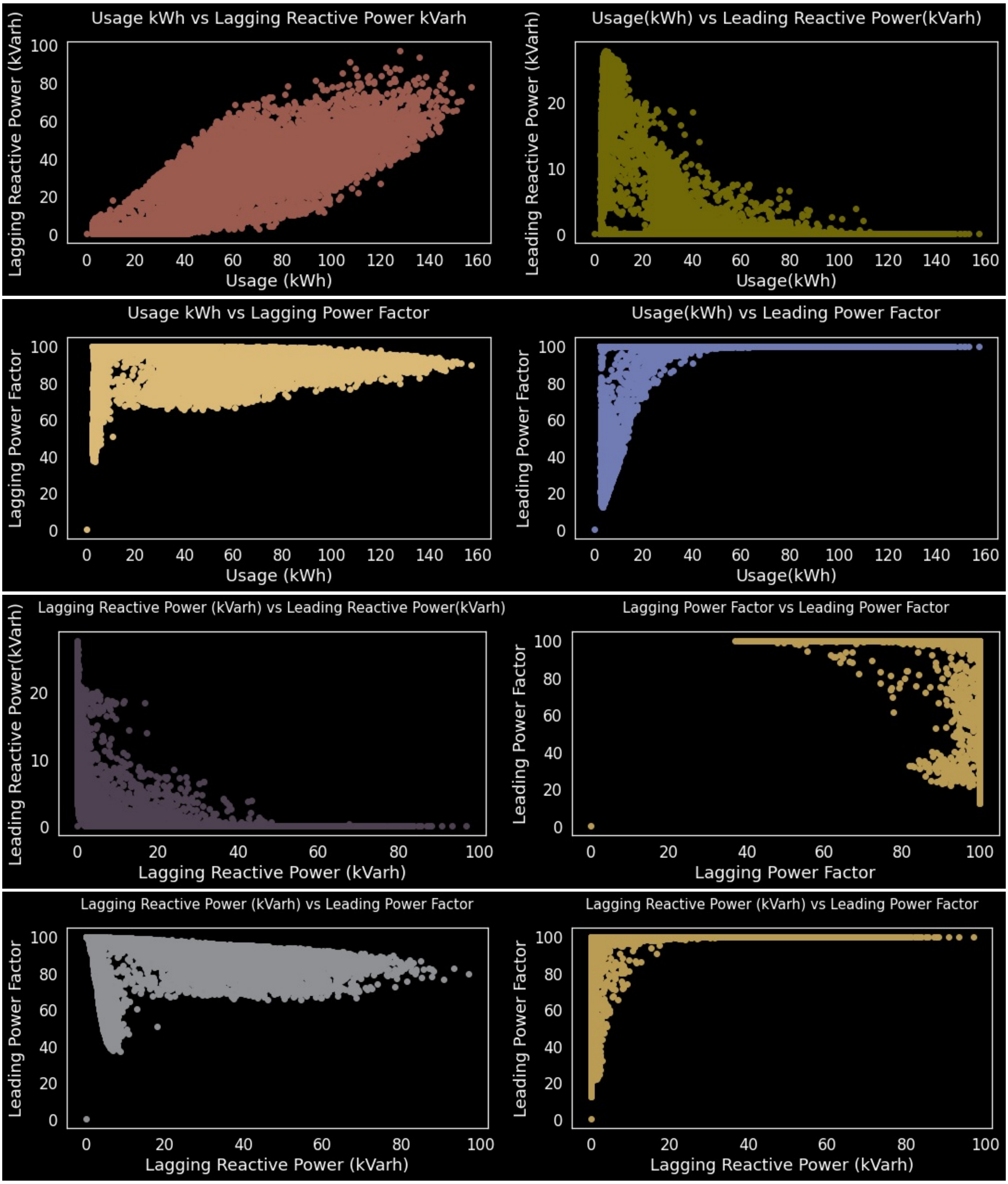
```
plt.figure(figsize=(18,4))
color = plt.cm.copper(np.linspace(0, 1, 10))
df.groupby(['WeekStatus','Day_of_week'])['Usage_kWh'].count().plot(kind='bar', width=.4,color=color);
plt.xticks(rotation=45);
```



In [14]:

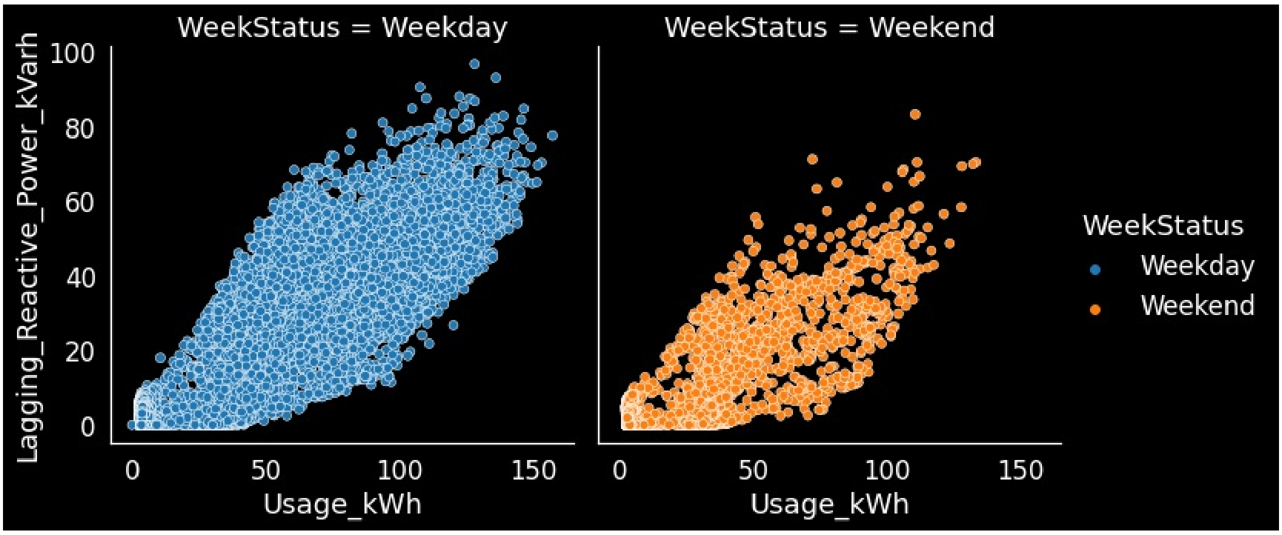
```
fig, (ax1,ax2) =plt.subplots(1,2, figsize=(18,4))
fig, (ax3,ax4) =plt.subplots(1,2, figsize=(18,4))
fig, (ax5,ax6) =plt.subplots(1,2, figsize=(18,4))
fig, (ax7,ax8) =plt.subplots(1,2, figsize=(18,4))

ax1.scatter(data=df,x="Usage_kWh", y="Lagging_Reactive_Power_kVarh", color=colors[1])
ax1.set_title("Usage kWh vs Lagging Reactive Power kVarh",pad=20)
ax1.set_xlabel("Usage (kWh)")
ax1.set_ylabel("Lagging Reactive Power (kVarh)")

ax2.scatter(data=df,x="Usage_kWh",y="Leading_Reactive_Power_kVarh", color=colors[8])
ax2.set_title("Usage(kWh) vs Leading Reactive Power(kVarh)",pad=20)
ax2.set_xlabel("Usage(kWh)")
ax2.set_ylabel("Leading Reactive Power (kVarh)")

ax3.scatter(data=df,x="Usage_kWh", y="Lagging_Power_Factor", color=colors[3])
ax3.set_title("Usage kWh vs Lagging Power Factor",pad=20)
ax3.set_xlabel("Usage (kWh)")
ax3.set_ylabel("Lagging Power Factor")

ax4.scatter(data=df,x="Usage_kWh",y="Leading_Power_Factor", color=colors[9])
ax4.set_title("Usage(kWh) vs Leading Power Factor",pad=20)
ax4.set_xlabel("Usage(kWh)")
ax4.set_ylabel("Leading Power Factor")

ax5.scatter(data=df,x="Lagging_Reactive_Power_kVarh",y="Leading_Reactive_Power_kVarh", color=colors[2])
ax5.set_title("Lagging Reactive Power (kVarh) vs Leading Reactive Power(kVarh)",pad=20,fontsize=15)
ax5.set_xlabel("Lagging Reactive Power (kVarh)")
ax5.set_ylabel("Leading Reactive Power(kVarh)")

ax6.scatter(data=df,x="Lagging_Power_Factor",y="Leading_Power_Factor", color=colors[4])
ax6.set_title("Lagging Power Factor vs Leading Power Factor",pad=20,fontsize=15)
ax6.set_xlabel("Lagging Power Factor")
ax6.set_ylabel("Leading Power Factor")

ax7.scatter(data=df,x="Lagging_Reactive_Power_kVarh",y="Lagging_Power_Factor", color=colors[5])
ax7.set_title("Lagging Reactive Power (kVarh) vs Leading Power Factor",pad=20,fontsize=15)
ax7.set_xlabel("Lagging Reactive Power (kVarh)")
ax7.set_ylabel("Leading Power Factor")

ax8.scatter(data=df,x="Lagging_Reactive_Power_kVarh",y="Leading_Power_Factor", color=colors[4])
ax8.set_title("Lagging Reactive Power (kVarh) vs Leading Power Factor",pad=20,fontsize=15)
ax8.set_xlabel("Lagging Reactive Power (kVarh)")
ax8.set_ylabel("Leading Power Factor")
```

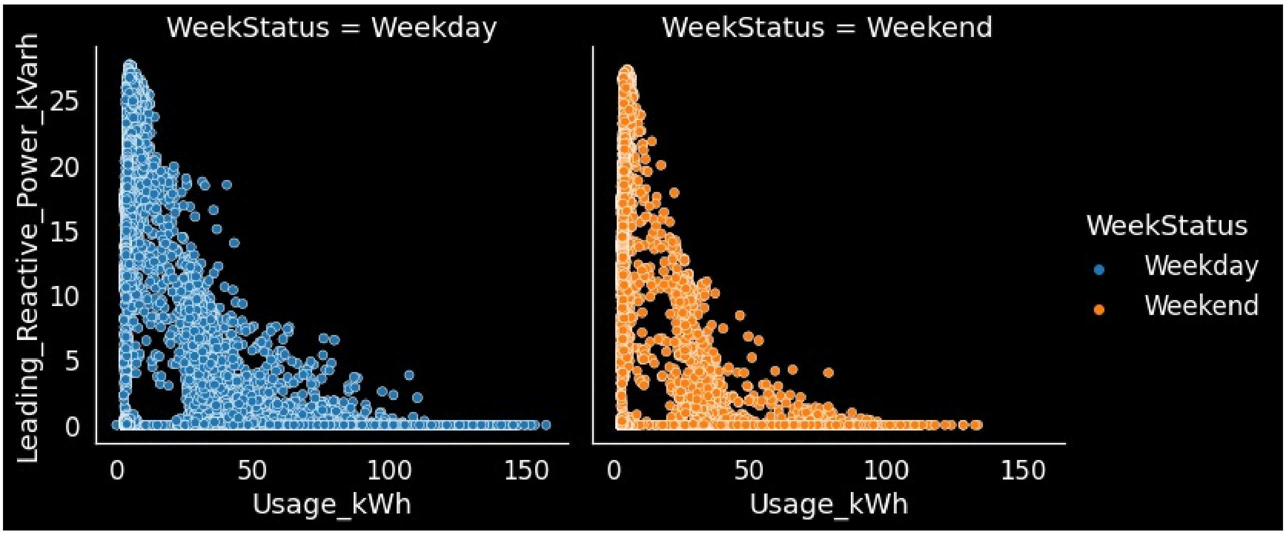
```
plt.show()
```

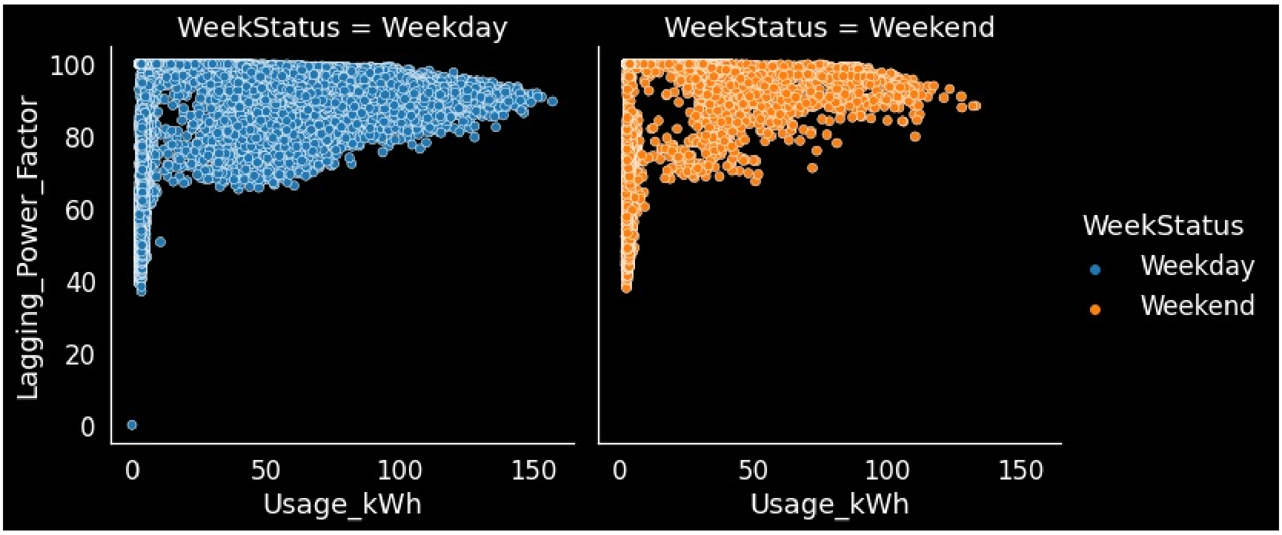


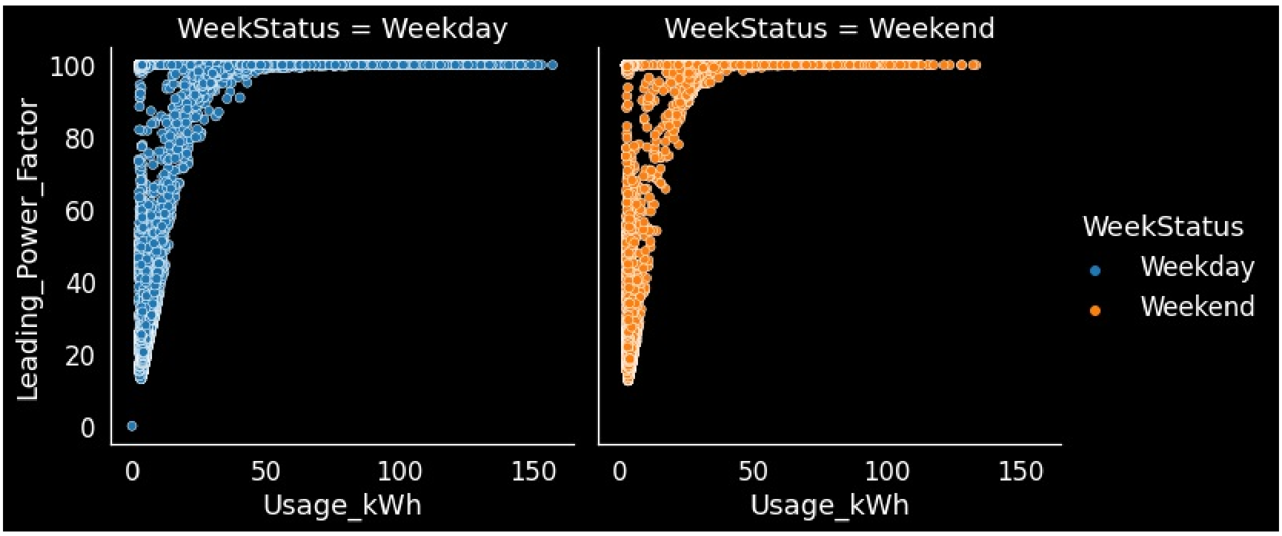
In [15]:

```
sns.relplot(data=df, x="Usage_kWh", y="Lagging_Reactive_Power_kVarh", hue="WeekStatus",col="WeekStatus",palette
sns.relplot(data=df, x="Usage_kWh", y="Leading_Reactive_Power_kVarh", hue="WeekStatus",col="WeekStatus",palette
sns.relplot(data=df, x="Usage_kWh", y="Lagging_Power_Factor", hue="WeekStatus",col="WeekStatus",palette='tab10'
sns.relplot(data=df, x="Usage_kWh", y="Leading_Power_Factor", hue="WeekStatus",col="WeekStatus",palette='tab10'
```



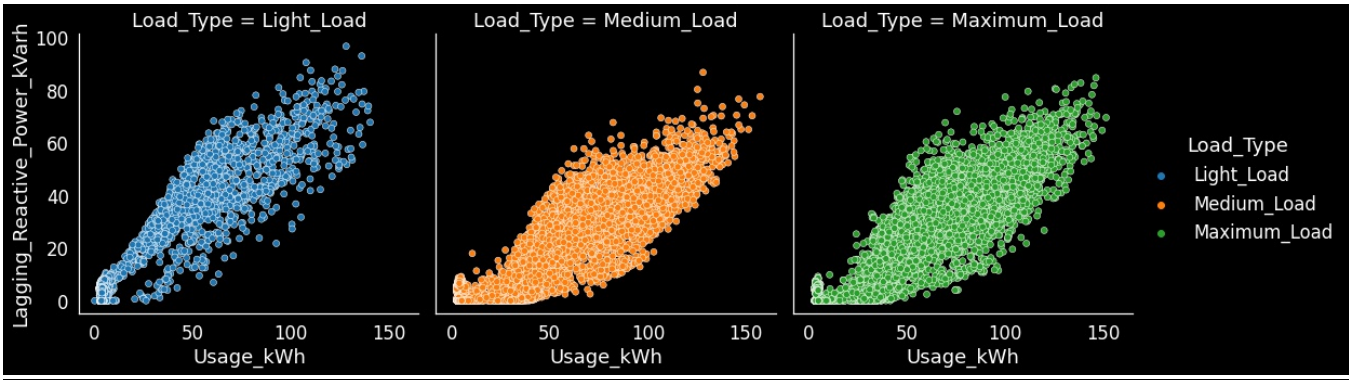


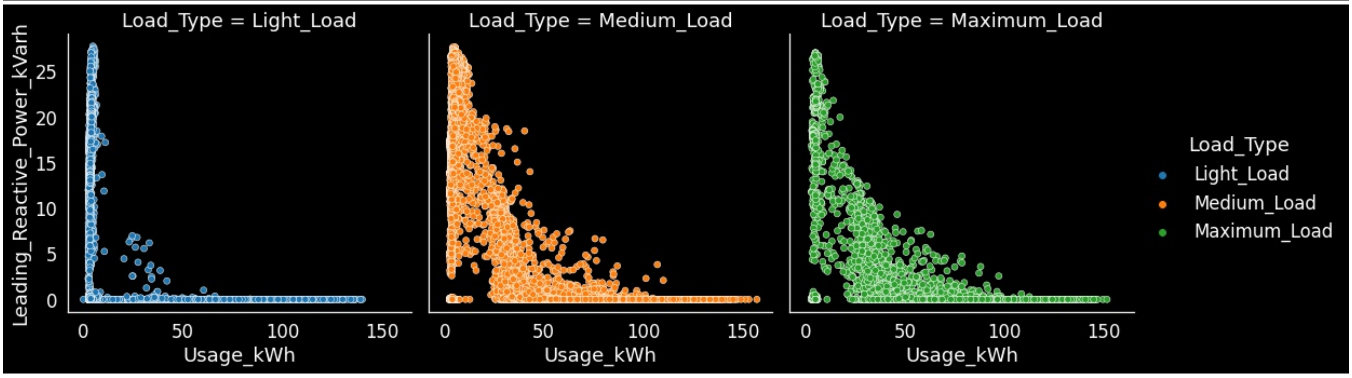


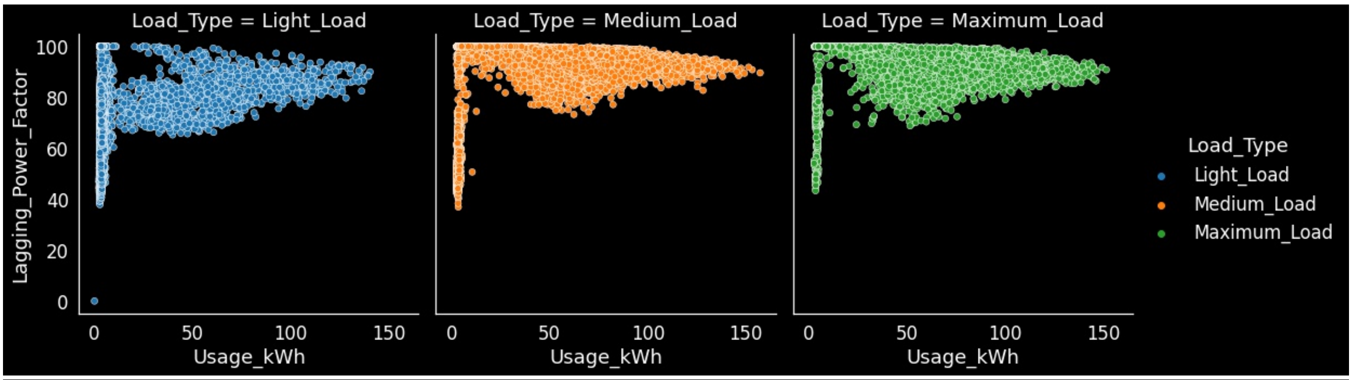


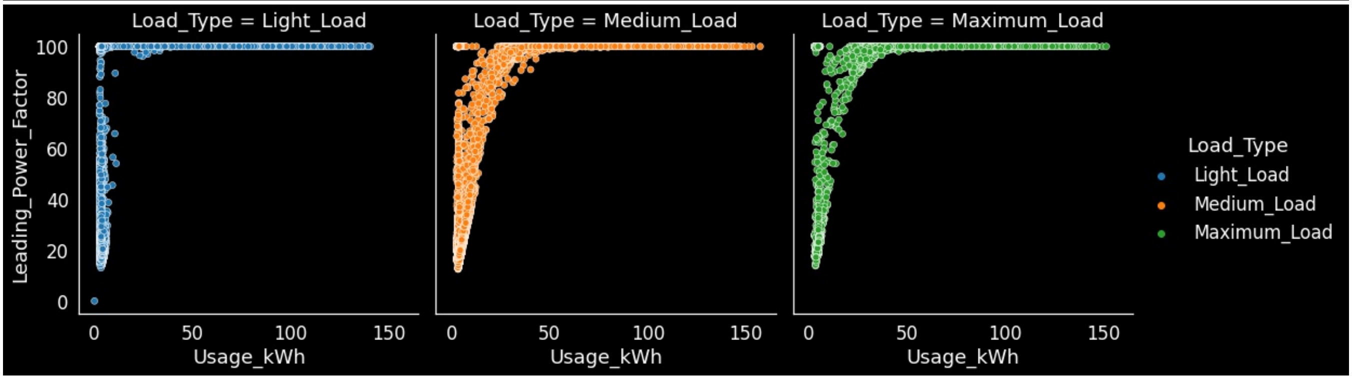
In [16]:
```
sns.relplot(data=df, x="Usage_kWh", y="Lagging_Reactive_Power_kVarh", hue="Load_Type",col="Load_Type",palette='
```

```
sns.relplot(data=df, x="Usage_kWh", y="Leading_Reactive_Power_kVarh", hue="Load_Type",col="Load_Type",palette='
sns.relplot(data=df, x="Usage_kWh", y="Lagging_Power_Factor", hue="Load_Type",col="Load_Type",palette='tab10');
sns.relplot(data=df, x="Usage_kWh", y="Leading_Power_Factor", hue="Load_Type",col="Load_Type",palette='tab10');
```



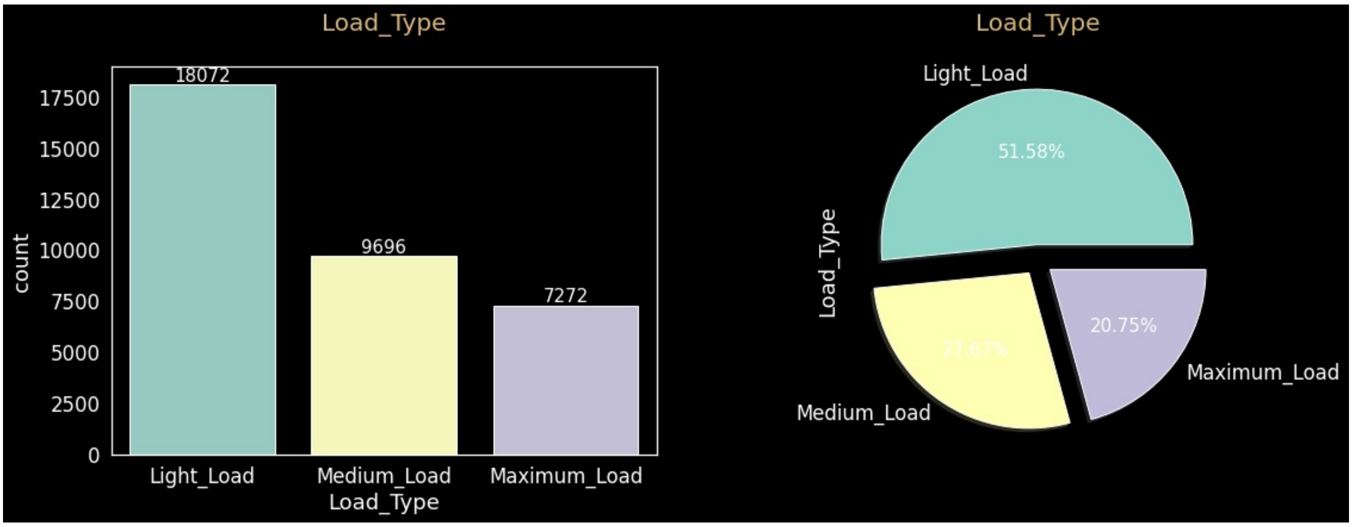






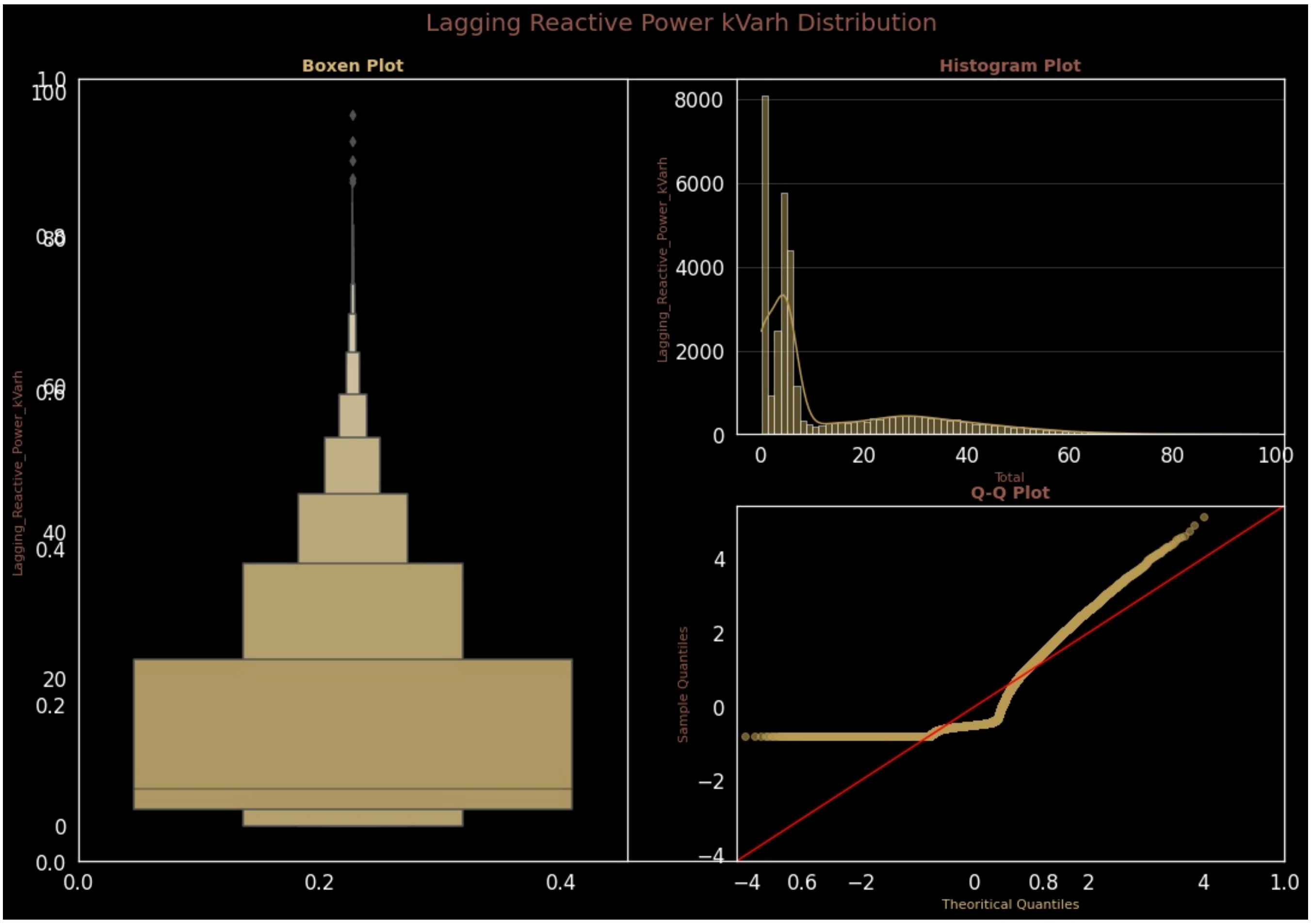
In [17]:

```
ax = plt.figure(figsize=(18,6))
ax = plt.subplot(1,2,1)
ax = sns.countplot(x='Load_Type', data=df)
ax.bar_label(ax.containers[0])
plt.title("Load_Type", fontsize=20,color='#dbba78',font='Times New Roman',pad=30)
ax =plt.subplot(1,2,2)
ax=df['Load_Type'].value_counts().plot.pie(explode=[0.1, 0.1,0.1],autopct='%1.2f%%',shadow=True);
ax.set_title(label = "Load_Type", fontsize = 20,color='#dbba78',font='Times New Roman',pad=30);
```

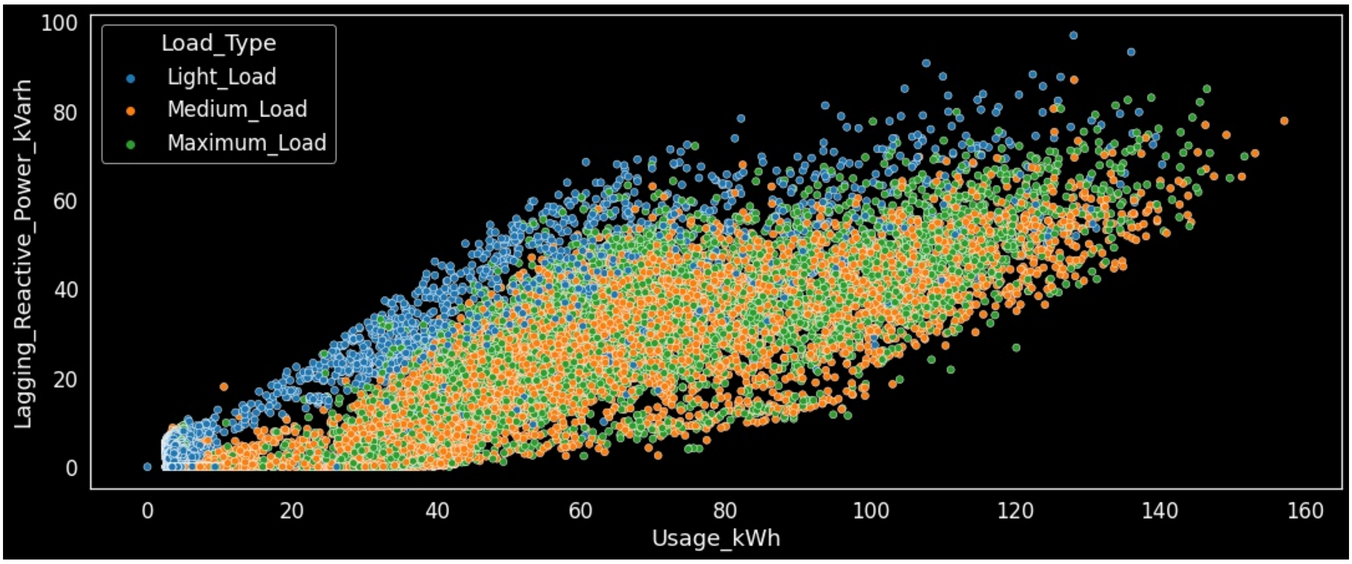


In [18]:

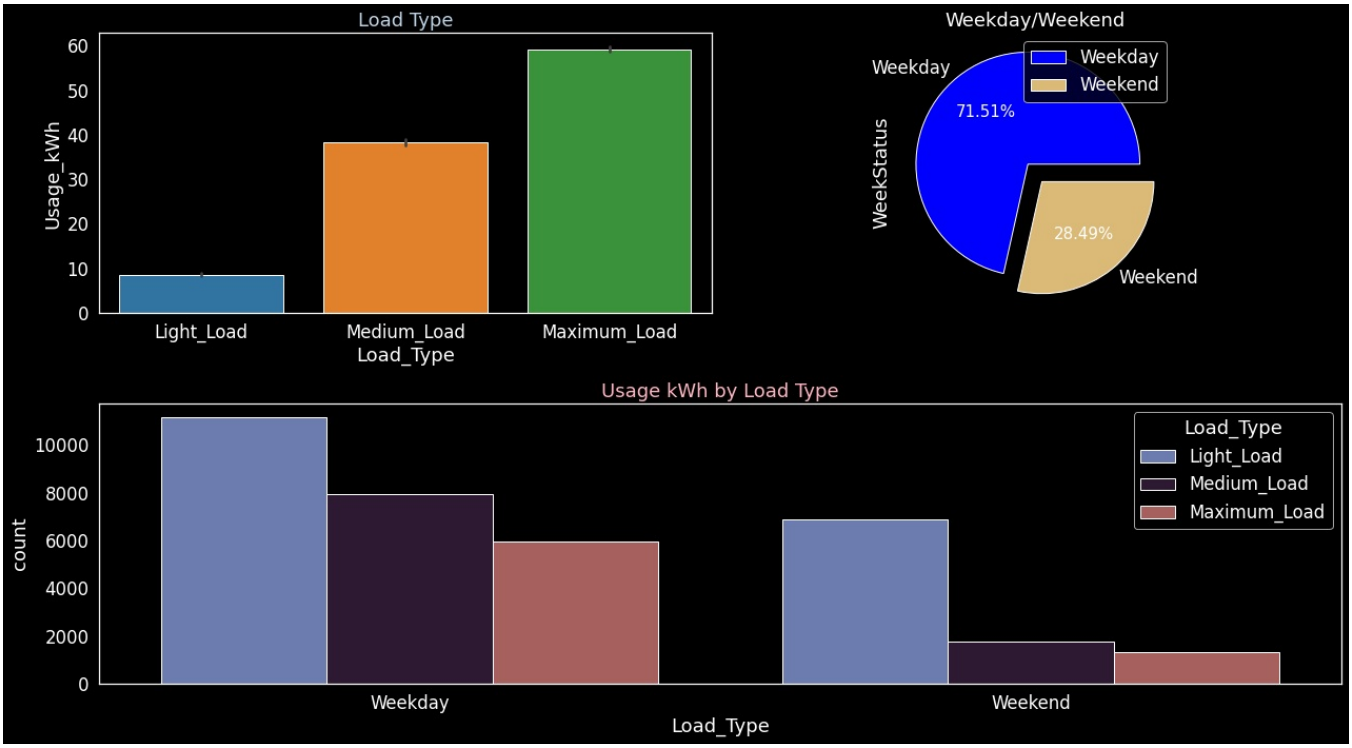
```
from statsmodels.graphics.gofplots import qqplot

var = df['Lagging_Reactive_Power_kVarh']
color = colors[4]
fig = plt.figure(figsize = (18, 12))

# --- Title ---
plt.title("Lagging Reactive Power kVarh Distribution",fontsize=20,font='Comic Sans MS',pad=40,color = colors[1]

# --- Histogram ---
ax_1=fig.add_subplot(2, 2, 2)
plt.title('Histogram Plot', fontweight = 'bold', fontsize = 14, fontfamily = 'Comic Sans MS', color = colors[1]
sns.histplot(data = df, x = var, kde = True, color = color)
plt.xlabel('Total', fontweight = 'regular', fontsize = 11, fontfamily = 'Comic Sans MS', color = colors[1])
plt.ylabel('Lagging_Reactive_Power_kVarh', fontweight = 'regular', fontsize = 11, fontfamily = 'sans-serif', co
plt.grid(axis = 'x', alpha = 0)
plt.grid(axis = 'y', alpha = 0.2)

# --- Q-Q Plot ---
ax_2 = fig.add_subplot(2, 2, 4)
plt.title('Q-Q Plot', fontweight = 'bold', fontsize = 14, fontfamily = 'Comic Sans MS', color = colors[1])
qqplot(var, fit = True, line = '45', ax = ax_2, markerfacecolor = color, markeredgecolor = color, alpha = 0.6)
plt.xlabel('Theoritical Quantiles', fontweight = 'regular', fontsize = 11, fontfamily = 'Comic Sans MS',
           color = colors[3])
plt.ylabel('Sample Quantiles', fontweight = 'regular', fontsize = 11, fontfamily = 'Comic Sans MS', color = col

# --- Boxen Plot ---
ax_3 = fig.add_subplot(1, 2, 1)
plt.title('Boxen Plot', fontweight = 'bold', fontsize = 14, fontfamily = 'Comic Sans MS', color = colors[3])
sns.boxenplot(y = var, data = df, color = color, linewidth = 1.5)
plt.ylabel('Lagging_Reactive_Power_kVarh', fontweight = 'regular', fontsize = 11, fontfamily = 'Comic Sans MS',

plt.show();
```



In [19]:
```
plt.figure(figsize=(18,7))
sns.scatterplot(data=df, x="Usage_kWh", y="Lagging_Reactive_Power_kVarh", hue="Load_Type",palette="tab10");
```

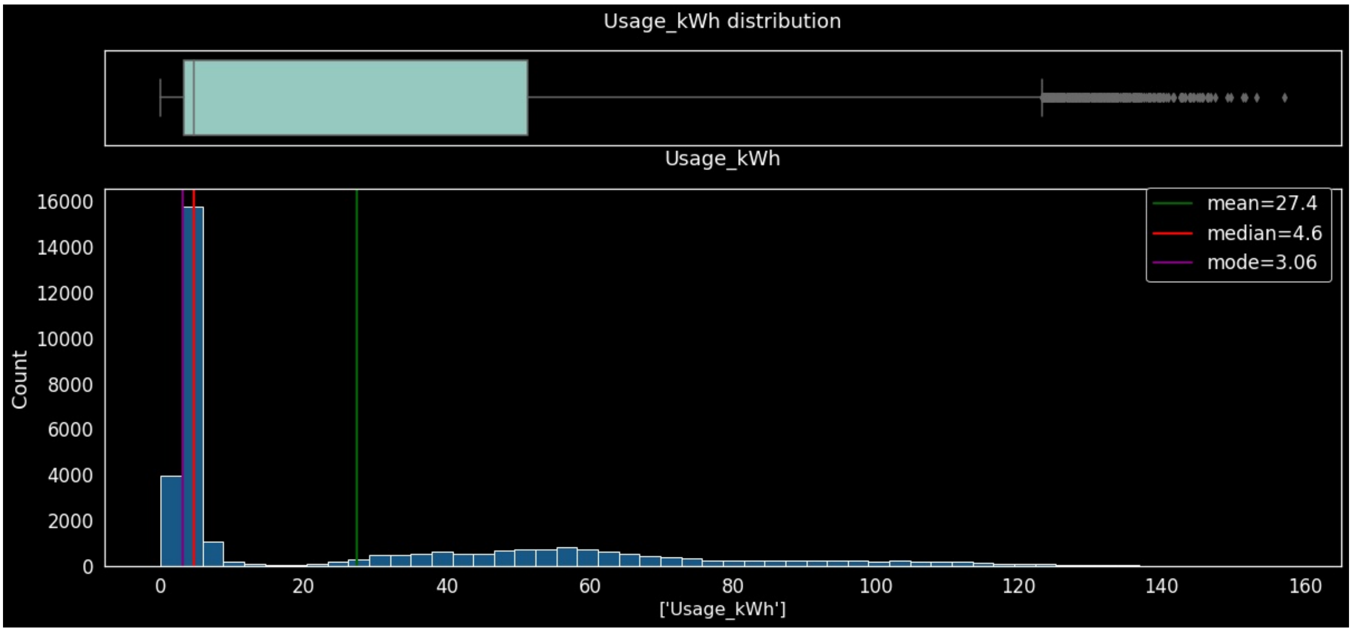


In [20]:
```
plt.figure(figsize=(18,10))

plt.subplot(2,2,1)
sns.barplot(x = 'Load_Type', y = 'Usage_kWh', palette= "tab10",data=df)
plt.title("Load Type", color = "#bfd3e6")
plt.xlabel("Load_Type")
plt.ylabel("Usage_kWh")

plt.subplot(2,2,2)
df["WeekStatus"].value_counts().plot.pie(autopct='%1.2f%%', explode=[0.1, 0.1], colors=['blue','#dbba78'])
p = plt.gcf()
plt.title("Weekday/Weekend")
plt.legend()
plt.subplot(2,2,(3,4))

sns.countplot(x = 'WeekStatus', hue = 'Load_Type', data = df, palette="twilight")
plt.title("Usage kWh by Load Type", color = "Lightpink")
plt.xlabel("Load_Type")
plt.tight_layout()
plt.show()
```



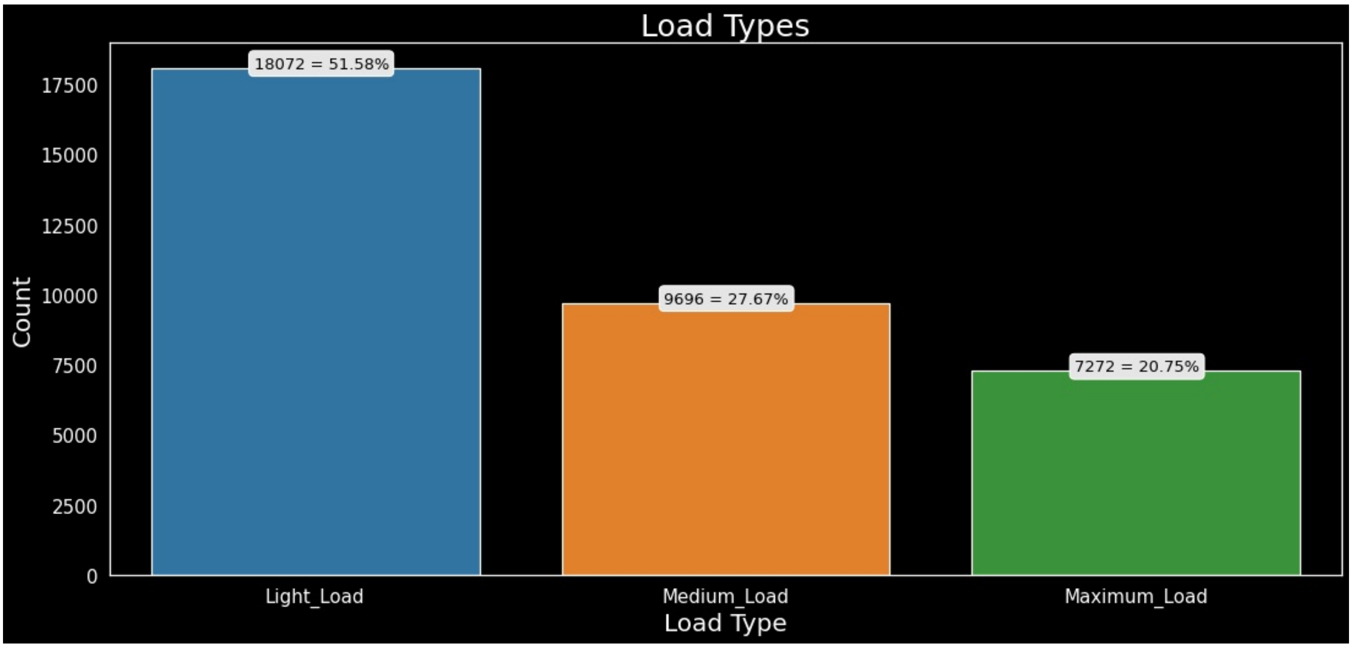
In [21]:

```
col = ['Usage_kWh']
fig, ax = plt.subplots(2, 1, sharex=True, figsize=(17,8),gridspec_kw={"height_ratios": (.2, .8)})
ax[0].set_title('Usage_kWh distribution',fontsize=18,pad=20)
sns.boxplot(x='Usage_kWh', data=df, ax=ax[0])
ax[0].set(yticks=[])
sns.histplot(x='Usage_kWh', data=df, ax=ax[1])
ax[1].set_xlabel(col, fontsize=16)
plt.axvline(df['Usage_kWh'].mean(), color='darkgreen', linewidth=2.2, label='mean=' + str(np.round(df['Usage_kW
plt.axvline(df['Usage_kWh'].median(), color='red', linewidth=2.2, label='median='+ str(np.round(df['Usage_kWh']
plt.axvline(df['Usage_kWh'].mode()[0], color='purple', linewidth=2.2, label='mode='+ str(df['Usage_kWh'].mode()
plt.legend(bbox_to_anchor=(1, 1.03), ncol=1, fontsize=17, fancybox=True, shadow=True, frameon=True)
plt.tight_layout()
plt.show()
```

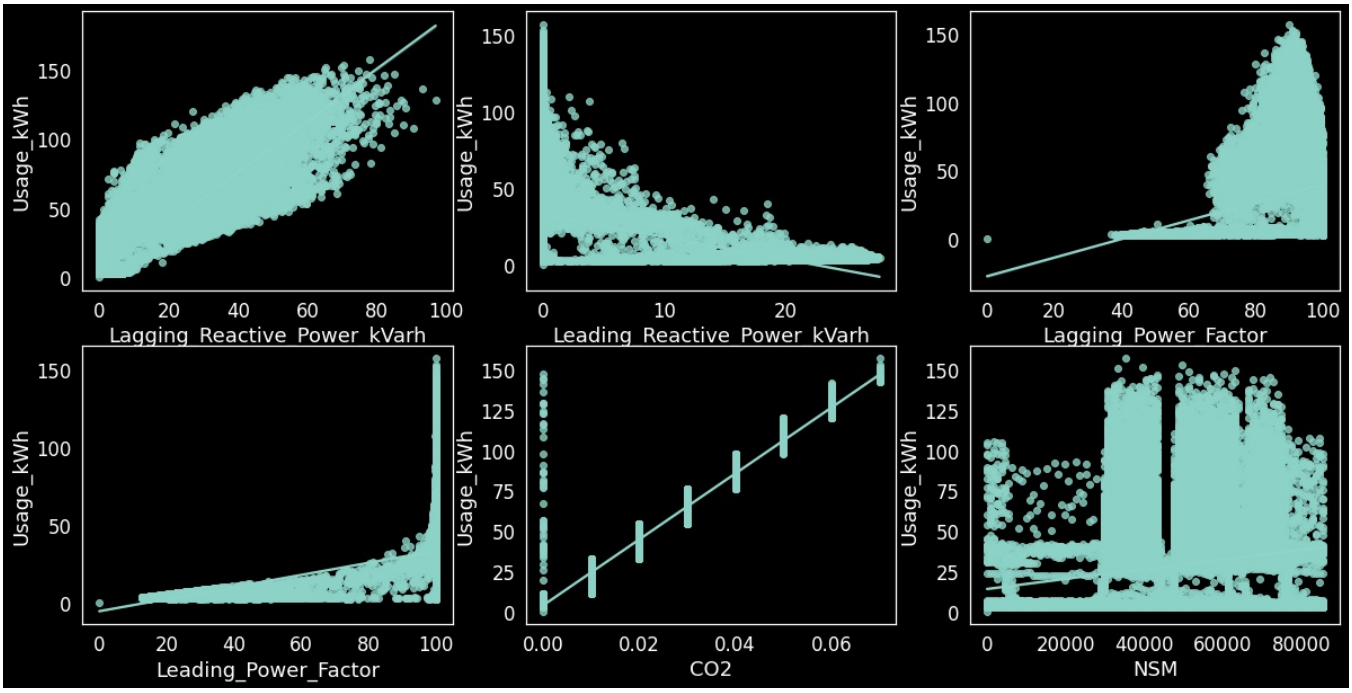


In [22]:

```
#Disaster count(Whether the disaster happened or not )
plt.figure(figsize = (18, 8))
ax = plt.axes()
ax.set_facecolor('black')
ax = sns.countplot(x = 'Load_Type', data = df, palette = 'tab10', edgecolor = 'white', linewidth = 1.2)
plt.title('Load Types', fontsize = 25)
plt.xlabel('Load Type', fontsize = 20)
plt.ylabel('Count', fontsize = 20)
ax.xaxis.set_tick_params(labelsize = 15)
ax.yaxis.set_tick_params(labelsize = 15)
bbox_args = dict(boxstyle = 'round', fc = '0.9')
for p in ax.patches:
        ax.annotate('{:.0f} = {:.2f}%'.format(p.get_height(), (p.get_height() / len(df['Load_Type'])) * 100), (
                    color = 'black',
                    bbox = bbox_args,
                    fontsize = 13)
plt.show()
```

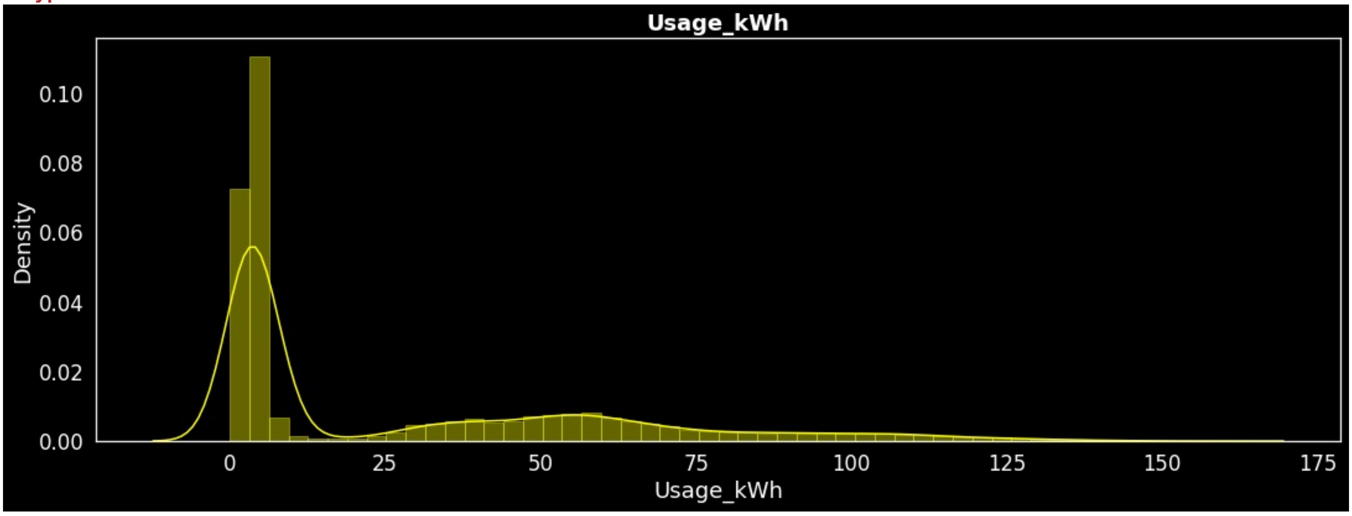


In [23]:
```python
col_names = ['Lagging_Reactive_Power_kVarh','Leading_Reactive_Power_kVarh','Lagging_Power_Factor','Leading_Powe
fig, axs = plt.subplots(nrows=2,ncols=3,figsize=(20,10))
for i in range(0, len(col_names)):
    rows = i // 3
    cols = i % 3
    ax = axs[rows,cols]
    plot = sns.regplot(x = col_names[i], y = 'Usage_kWh', data = df, ax = ax )
```

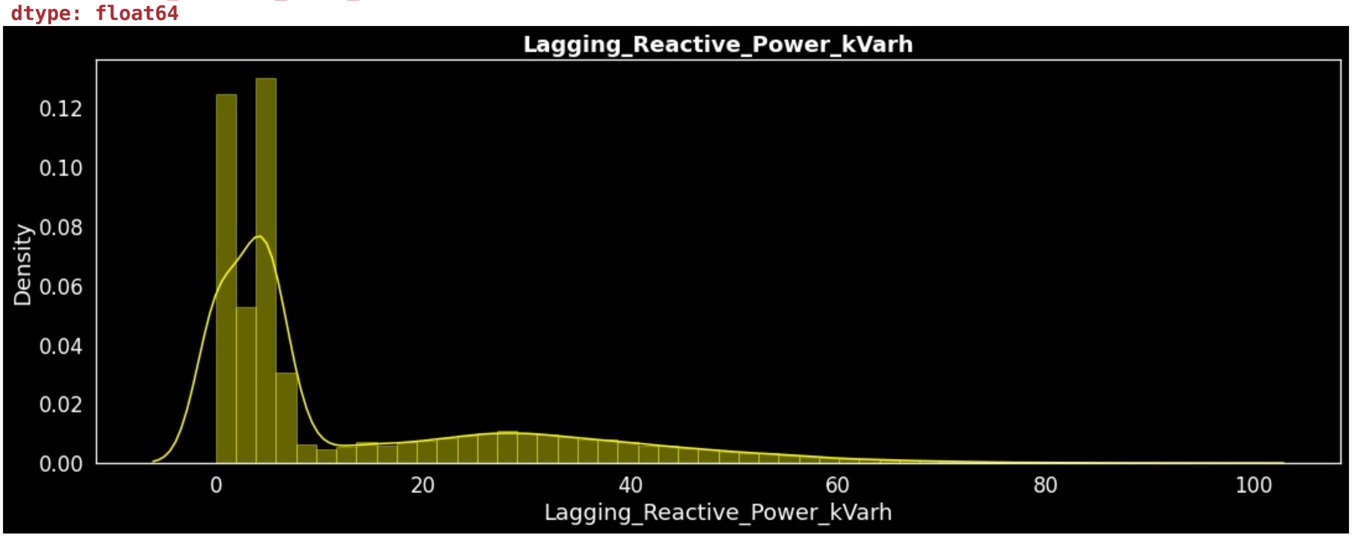


In [24]:
```python
var = ['Usage_kWh', 'Lagging_Reactive_Power_kVarh','Leading_Reactive_Power_kVarh','Lagging_Power_Factor','Leadi

from scipy.stats import skew

for col in df[var]:
    print(f"\033[91m\033[1m")
    print("Skewness:",col,"=",round(skew(df[col]),3))
    print("Kurtosis:",col,    "=",round(df[col].kurt(),2))
    print("Mean:",col,    "=",round(df[col].mean(),2))
    print("Max:",col,     "=",round(df[col].max(),2))
    print("Min:",col,     "=",round(df[col].min(),2))
    print("Median:",col,  "=",round(df[col].median(),2))
    print("Std:",col,     "=",round(df[col].std(),2))
    print("Var:",col,     "=",round(df[col].var(),2))
    print("Mode:",col,    "=",round(df[col].mode(),2))
    plt.figure(figsize=(18,6))
    sns.distplot(df[col],kde=True,bins=50,color="Yellow",hist_kws={"edgecolor": (1,1,0,1)})
    plt.title(col,fontweight="bold")
    plt.show()
    print(f"\033[93m\033[1m")
    print("====="*25)
```

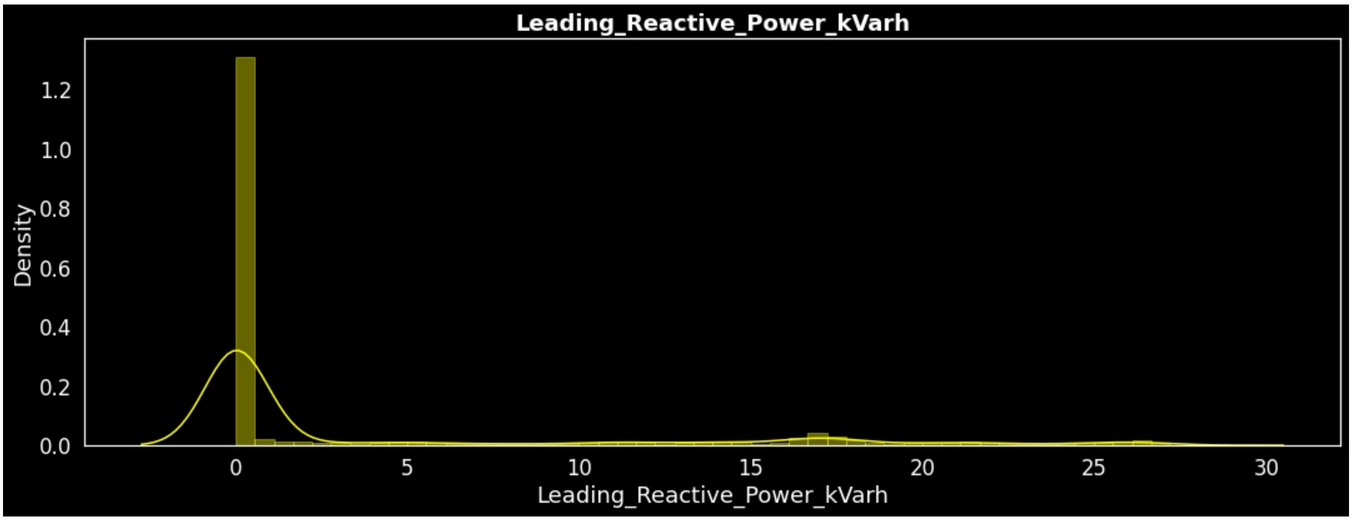
```
Skewness: Usage_kWh = 1.197
Kurtosis: Usage_kWh = 0.39
Mean: Usage_kWh = 27.39
Max: Usage_kWh = 157.18
Min: Usage_kWh = 0.0
Median: Usage_kWh = 4.57
Std: Usage_kWh = 33.44
Var: Usage_kWh = 1118.53
Mode: Usage_kWh = 0    3.06
dtype: float64
```



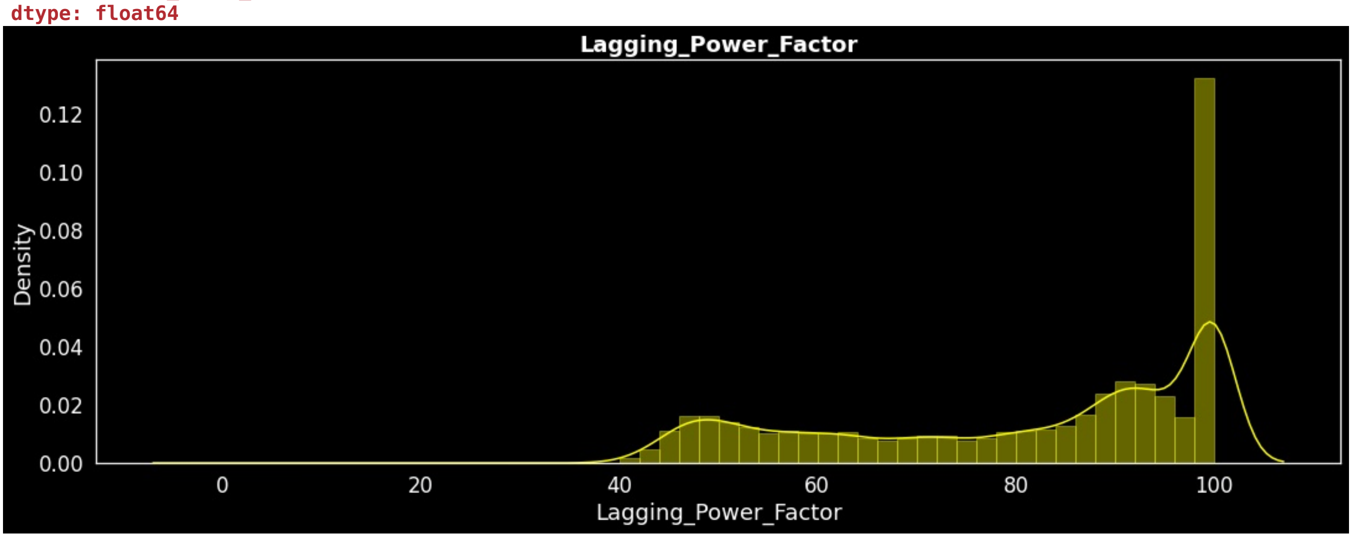

```
================================================================================================================

Skewness: Lagging_Reactive_Power_kVarh = 1.438
Kurtosis: Lagging_Reactive_Power_kVarh = 1.21
Mean: Lagging_Reactive_Power_kVarh = 13.04
Max: Lagging_Reactive_Power_kVarh = 96.91
Min: Lagging_Reactive_Power_kVarh = 0.0
Median: Lagging_Reactive_Power_kVarh = 5.0
Std: Lagging_Reactive_Power_kVarh = 16.31
Var: Lagging_Reactive_Power_kVarh = 265.89
Mode: Lagging_Reactive_Power_kVarh = 0    0.0
dtype: float64
```



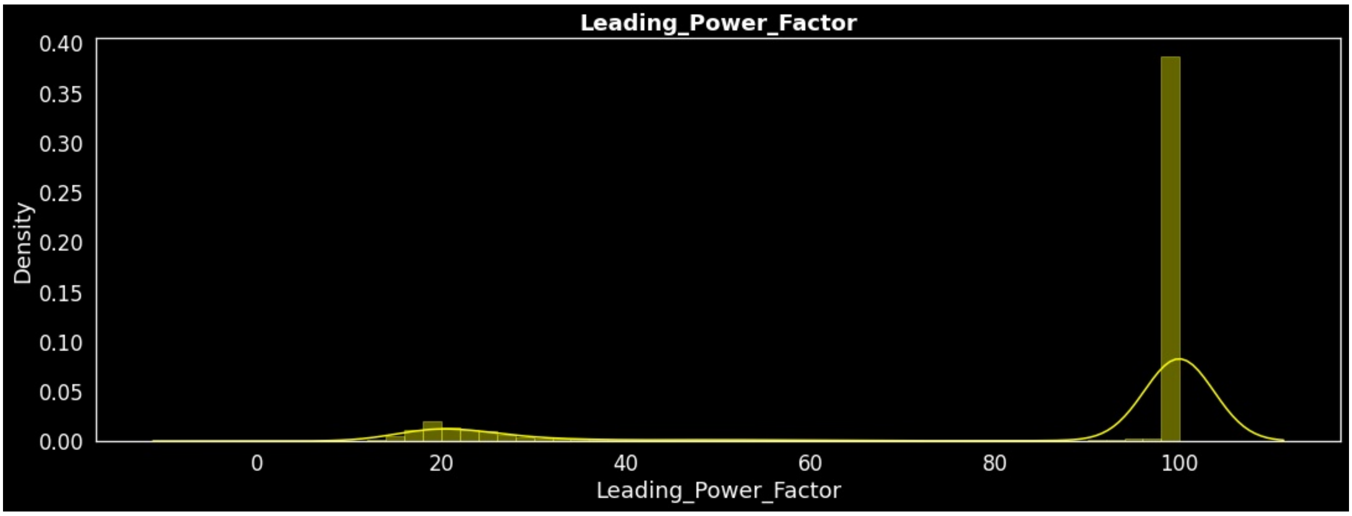

```
================================================================================================================

Skewness: Leading_Reactive_Power_kVarh = 1.734
Kurtosis: Leading_Reactive_Power_kVarh = 1.58
Mean: Leading_Reactive_Power_kVarh = 3.87
Max: Leading_Reactive_Power_kVarh = 27.76
Min: Leading_Reactive_Power_kVarh = 0.0
Median: Leading_Reactive_Power_kVarh = 0.0
Std: Leading_Reactive_Power_kVarh = 7.42
Var: Leading_Reactive_Power_kVarh = 55.12
Mode: Leading_Reactive_Power_kVarh = 0    0.0
dtype: float64
```




```
================================================================================================================

Skewness: Lagging_Power_Factor = -0.606
Kurtosis: Lagging_Power_Factor = -1.1
Mean: Lagging_Power_Factor = 80.58
Max: Lagging_Power_Factor = 100.0
Min: Lagging_Power_Factor = 0.0
Median: Lagging_Power_Factor = 87.96
Std: Lagging_Power_Factor = 18.92
Var: Lagging_Power_Factor = 358.02
Mode: Lagging_Power_Factor = 0    100.0
dtype: float64
```



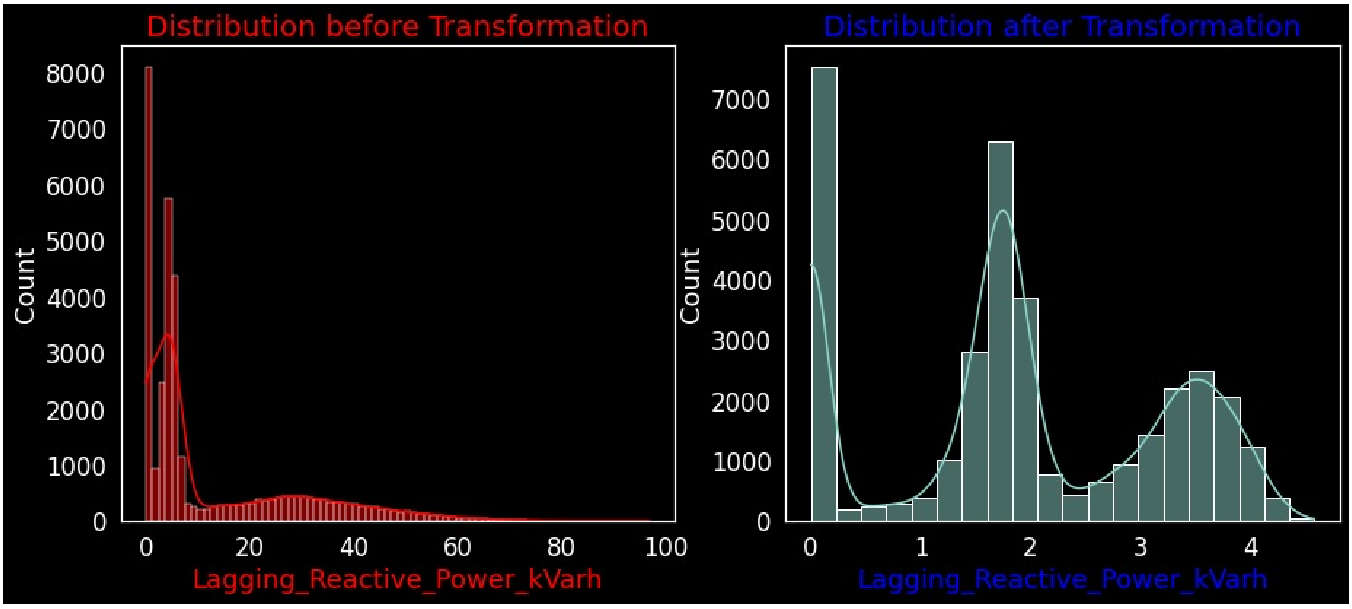

```
================================================================================================================

Skewness: Leading_Power_Factor = -1.512
Kurtosis: Leading_Power_Factor = 0.38
Mean: Leading_Power_Factor = 84.37
Max: Leading_Power_Factor = 100.0
Min: Leading_Power_Factor = 0.0
Median: Leading_Power_Factor = 100.0
Std: Leading_Power_Factor = 30.46
Var: Leading_Power_Factor = 927.6
Mode: Leading_Power_Factor = 0    100.0
dtype: float64
```




```
====================================================================================================
==============
```

In [25]:

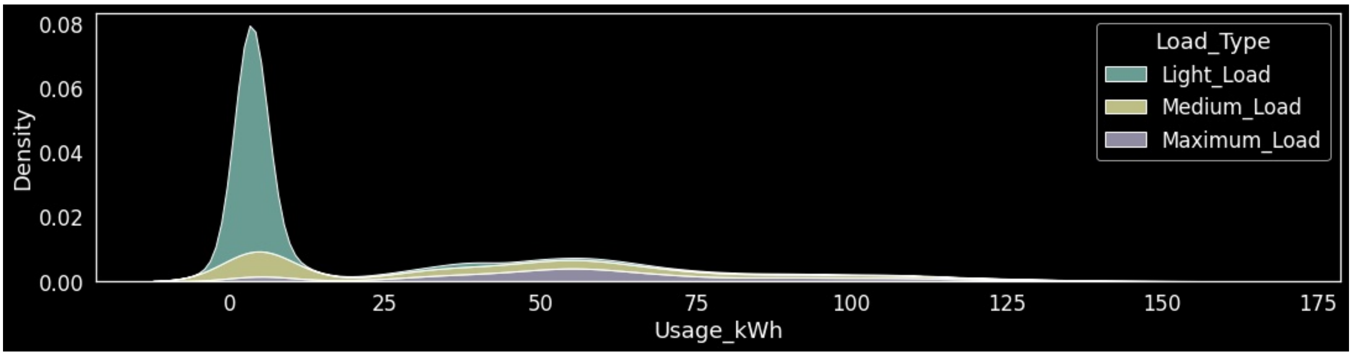
```
from sklearn.preprocessing import FunctionTransformer
from sklearn.compose import ColumnTransformer

old_skew = df.skew().sort_values(ascending=False)
old_skew

def logTrans(feature):   # function to apply transformer and check the distribution with histogram and kdeplot

    logTr = ColumnTransformer(transformers=[("lg", FunctionTransformer(np.log1p), [feature])])

    plt.figure(figsize=(15,6))
    plt.subplot(1,2,1)
    plt.title("Distribution before Transformation", fontsize=20,color='red')
    sns.histplot(df[feature], kde=True, color="red")
    plt.xlabel(feature,color='Red')

    plt.subplot(1,2,2)
    df_log = pd.DataFrame(logTr.fit_transform(df))
    plt.title("Distribution after Transformation", fontsize=20,color='Blue')
    sns.histplot(df_log,bins=20, kde=True , legend=False)
    plt.xlabel(feature,color='Blue')
    plt.show()

    print(f"Skewness was {round(old_skew[feature],2)} before & is {round(df_log.skew()[0],2)} after Log transfo

logTrans(feature="Lagging_Reactive_Power_kVarh")
```




```
Skewness was 1.44 before & is -0.02 after Log transformation.
```

In [26]:

```
plt.figure(figsize=(18,4))
sns.kdeplot(data=df,x="Usage_kWh",hue='Load_Type',multiple="stack");
```



In [27]:

```
# Encode Categorical Columns
from sklearn.preprocessing import LabelEncoder
categ = df.select_dtypes(include = "object").columns

le = LabelEncoder()
df[categ] = df[categ].apply(le.fit_transform)

df.head()
```

Out[27]:

	date	Usage_kWh	Lagging_Reactive_Power_kVarh	Leading_Reactive_Power_kVarh	CO2	Lagging_Power_Factor	Leading_Power_Factor	NS
0	1	3.17	2.95	0.0	0.0	73.21	100.0	9
1	2	4.00	4.46	0.0	0.0	66.77	100.0	18
2	3	3.24	3.28	0.0	0.0	70.28	100.0	27
3	4	3.31	3.56	0.0	0.0	68.09	100.0	36
4	5	3.82	4.50	0.0	0.0	64.72	100.0	45

In [28]:

```
# Split the dataset and prepare some lists to store the models
from sklearn.model_selection import train_test_split
X = df.drop(['Load_Type'], axis=1)
y = df.Load_Type

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state = 42)
```

In [29]:

```
models = []

names = [
    "LGBMClassifier",
    "RidgeClassifierCV",
    "XGBClassifier",
    "QuadraticDiscriminantAnalysis",
    "CalibratedClassifierCV",
    "BernoulliNB",
    "BaggingClassifier",
    "LogisticRegression",
    "NearestCentroid",
    "SVC",
    "LinearSVC",
    "KNeighborsClassifier",
    "GaussianNB",
    "Perceptron",
    "SGDClassifier",
    "DecisionTreeClassifier",
    "RandomForestClassifier",
    "MLPClassifier",
    "ExtraTreesClassifier",
    "AdaBoostClassifier",
    "NuSVC"
]
```

In [30]:

```
scores = []

clf =[
    LGBMClassifier(),
    RidgeClassifierCV(),
    XGBClassifier(),
    QuadraticDiscriminantAnalysis(),
    CalibratedClassifierCV(),
    BernoulliNB(),
    BaggingClassifier(),
    LogisticRegression(),
    NearestCentroid(),
    SVC(),
    LinearSVC(),
    KNeighborsClassifier(),
    GaussianNB(),
    Perceptron(),
```

```
    SGDClassifier(),
    DecisionTreeClassifier(),
    RandomForestClassifier(),
    MLPClassifier(),
    ExtraTreesClassifier(),
    AdaBoostClassifier(),
    NuSVC()

]
```

In [31]:

```
%%time
for model in clf:
    model.fit(X_train, y_train)
    score = model.score(X_test, y_test)
    scores.append(score)

final_scores = pd.DataFrame(zip(names,scores), columns=['Classifier', 'Accuracy'])
```

```
CPU times: user 3min, sys: 2.57 s, total: 3min 3s
Wall time: 2min 55s
```

In [32]:

```
final_scores.sort_values(by='Accuracy',ascending=False).style.background_gradient(cmap="copper").set_properties
            'font-family': 'Comic Sans MS',
            'color': 'Brown',
            'font-size': '15px',"color": "Brown"
        })
```

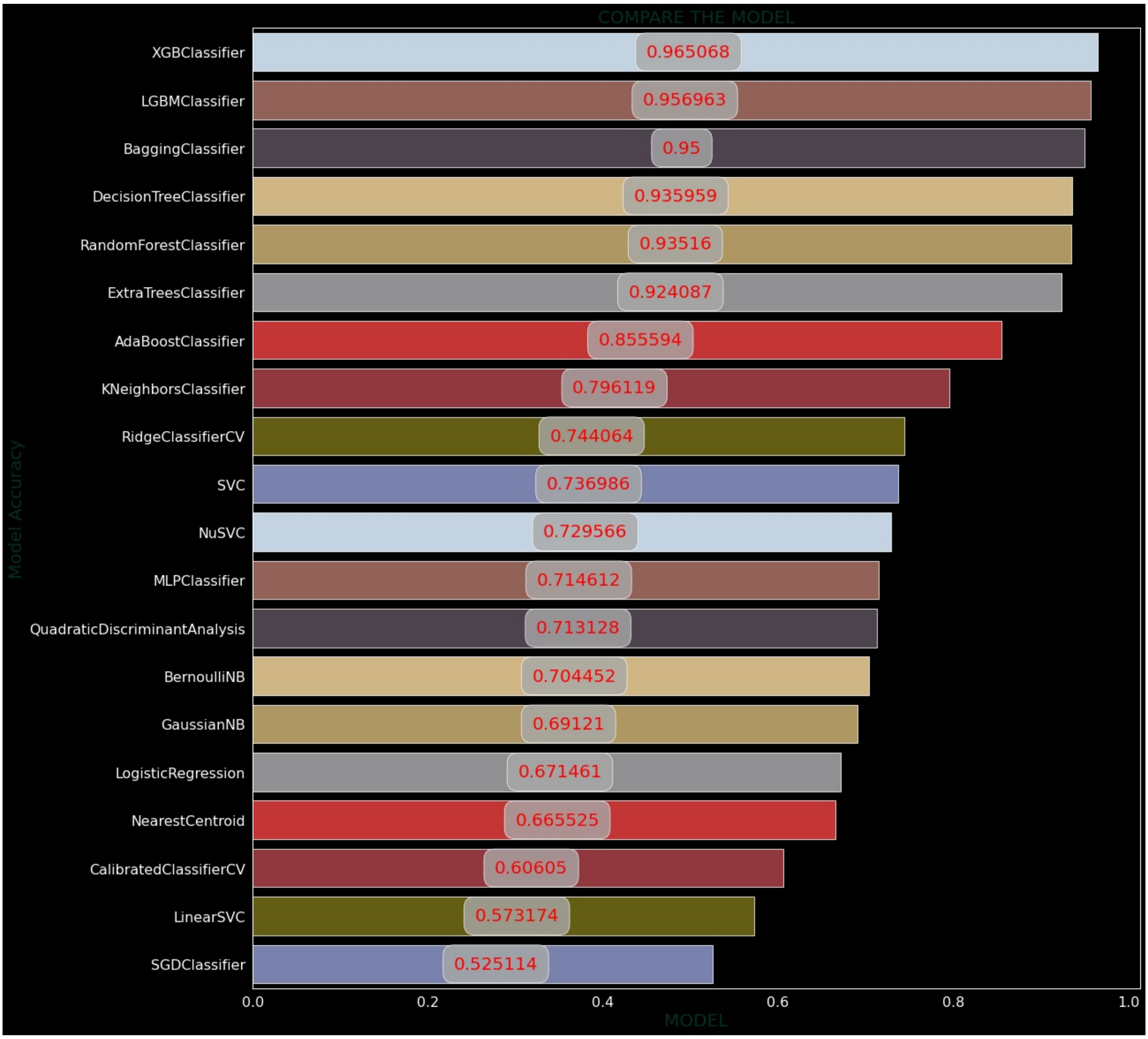
Out[32]:

	Classifier	Accuracy
2	XGBClassifier	0.965068
0	LGBMClassifier	0.956963
6	BaggingClassifier	0.950000
15	DecisionTreeClassifier	0.935959
16	RandomForestClassifier	0.935160
18	ExtraTreesClassifier	0.924087
19	AdaBoostClassifier	0.855594
11	KNeighborsClassifier	0.796119
1	RidgeClassifierCV	0.744064
9	SVC	0.736986
20	NuSVC	0.729566
17	MLPClassifier	0.714612
3	QuadraticDiscriminantAnalysis	0.713128
5	BernoulliNB	0.704452
12	GaussianNB	0.691210
7	LogisticRegression	0.673461
8	NearestCentroid	0.665525
4	CalibratedClassifierCV	0.606050
10	LinearSVC	0.573174
14	SGDClassifier	0.525114
13	Perceptron	0.524087

In [33]:

```
p = plt.figure(figsize=(18,20))
p = sns.set_context('paper', font_scale=1.8)

p = final_scores=final_scores.sort_values(by='Accuracy',ascending=False)[:20]

p = sns.barplot(y= 'Classifier', x= 'Accuracy', data= final_scores,palette=colors[0:10])

for container in p.containers:
    p.bar_label(container,label_type = 'center',padding = 15,size = 20,color = "Red",rotation = 0,
    bbox={"boxstyle": "round", "pad": 0.6, "facecolor": "#a9a9a9", "edgecolor": "white", "alpha": .8})
```

```python
plt.title('COMPARE THE MODEL',fontsize=20,color='#013220')
plt.xlabel('MODEL',fontsize=20,color='#013220')
plt.ylabel('Model Accuracy',fontsize=20,color='#013220');
```



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