import all the necessary libraries:

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler

from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier
from sklearn.neighbors import KNeighborsClassifier

from sklearn.metrics import accuracy_score
from sklearn.model_selection import GridSearchCV
```

Pass the warnings:

In [2]:
```
import warnings
warnings.filterwarnings('ignore')
```

Read the dataset and store it into pandas dataframe:

In [3]:
```
df = pd.read_csv('dft-road-casualty-statistics-accident-2021.csv', low_memory=False)
```

Exploratory Data Analysis:

Displayt the shape of the dataset:

In [4]:
```
df.shape
```

Out[4]:
```
(101087, 36)
```

Display the data types of all columns in the data frame:

In [5]:
```
df.dtypes
```

Out[5]:
```
accident_index                                  object
accident_year                                    int64
accident_reference                              object
location_easting_osgr                          float64
location_northing_osgr                         float64
longitude                                      float64
latitude                                       float64
police_force                                     int64
accident_severity                                int64
number_of_vehicles                               int64
number_of_casualties                             int64
date                                            object
day_of_week                                      int64
time                                            object
local_authority_district                         int64
local_authority_ons_district                    object
local_authority_highway                         object
first_road_class                                 int64
first_road_number                                int64
road_type                                        int64
speed_limit                                      int64
junction_detail                                  int64
junction_control                                 int64
second_road_class                                int64
second_road_number                               int64
pedestrian_crossing_human_control                int64
pedestrian_crossing_physical_facilities          int64
light_conditions                                 int64
weather_conditions                               int64
road_surface_conditions                          int64
special_conditions_at_site                       int64
carriageway_hazards                              int64
urban_or_rural_area                              int64
did_police_officer_attend_scene_of_accident      int64
trunk_road_flag                                  int64
lsoa_of_accident_location                       object
dtype: object
```

Display the column names in the data frame:

Display the column names in the data frame:

In [6]:
```
df.columns
```

Out[6]:
```
Index(['accident_index', 'accident_year', 'accident_reference',
       'location_easting_osgr', 'location_northing_osgr', 'longitude',
       'latitude', 'police_force', 'accident_severity', 'number_of_vehicles',
       'number_of_casualties', 'date', 'day_of_week', 'time',
       'local_authority_district', 'local_authority_ons_district',
       'local_authority_highway', 'first_road_class', 'first_road_number',
       'road_type', 'speed_limit', 'junction_detail', 'junction_control',
       'second_road_class', 'second_road_number',
       'pedestrian_crossing_human_control',
       'pedestrian_crossing_physical_facilities', 'light_conditions',
       'weather_conditions', 'road_surface_conditions',
       'special_conditions_at_site', 'carriageway_hazards',
       'urban_or_rural_area', 'did_police_officer_attend_scene_of_accident',
       'trunk_road_flag', 'lsoa_of_accident_location'],
      dtype='object')
```

display the general information about the dataset:

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 101087 entries, 0 to 101086
Data columns (total 36 columns):
 #   Column                                       Non-Null Count   Dtype  
---  ------                                       --------------   -----  
 0   accident_index                               101087 non-null  object 
 1   accident_year                                101087 non-null  int64  
 2   accident_reference                           101087 non-null  object 
 3   location_easting_osgr                        101070 non-null  float64
 4   location_northing_osgr                       101070 non-null  float64
 5   longitude                                    101070 non-null  float64
 6   latitude                                     101070 non-null  float64
 7   police_force                                 101087 non-null  int64  
 8   accident_severity                            101087 non-null  int64  
 9   number_of_vehicles                           101087 non-null  int64  
 10  number_of_casualties                         101087 non-null  int64  
 11  date                                         101087 non-null  object 
 12  day_of_week                                  101087 non-null  int64  
 13  time                                         101087 non-null  object 
 14  local_authority_district                     101087 non-null  int64  
 15  local_authority_ons_district                 101087 non-null  object 
 16  local_authority_highway                      101087 non-null  object 
 17  first_road_class                             101087 non-null  int64  
 18  first_road_number                            101087 non-null  int64  
 19  road_type                                    101087 non-null  int64  
 20  speed_limit                                  101087 non-null  int64  
 21  junction_detail                              101087 non-null  int64  
 22  junction_control                             101087 non-null  int64  
 23  second_road_class                            101087 non-null  int64  
 24  second_road_number                           101087 non-null  int64  
 25  pedestrian_crossing_human_control            101087 non-null  int64  
 26  pedestrian_crossing_physical_facilities      101087 non-null  int64  
 27  light_conditions                             101087 non-null  int64  
 28  weather_conditions                           101087 non-null  int64  
 29  road_surface_conditions                      101087 non-null  int64  
 30  special_conditions_at_site                   101087 non-null  int64  
 31  carriageway_hazards                          101087 non-null  int64  
 32  urban_or_rural_area                          101087 non-null  int64  
 33  did_police_officer_attend_scene_of_accident  101087 non-null  int64  
 34  trunk_road_flag                              101087 non-null  int64  
 35  lsoa_of_accident_location                    101087 non-null  object 
dtypes: float64(4), int64(25), object(7)
memory usage: 27.8+ MB
```

Print the first 10 rows of the dataset:

In [8]:
```
df.head(10)
```

Out[8]:

	accident_index	accident_year	accident_reference	location_easting_osgr	location_northing_osgr	longitude	latitude	police_force	accide
0	2021010287148	2021	010287148	521508.0	193079.0	-0.246102	51.623425	1	
1	2021010287149	2021	010287149	535379.0	180783.0	-0.050574	51.509767	1	
2	2021010287151	2021	010287151	529701.0	170398.0	-0.136152	51.417769	1	
3	2021010287155	2021	010287155	525312.0	178385.0	-0.196411	51.490536	1	
4	2021010287157	2021	010287157	512144.0	171526.0	-0.388169	51.431649	1	
5	2021010287163	2021	010287163	536569.0	183334.0	-0.032448	51.532404	1	
6	2021010287167	2021	010287167	531818.0	188393.0	-0.099009	51.578996	1	
7	2021010287168	2021	010287168	541068.0	190017.0	0.035049	51.591350	1	
8	2021010287185	2021	010287185	530553.0	162637.0	-0.126757	51.347826	1	
9	2021010287189	2021	010287189	543401.0	186128.0	0.067118	51.555817	1	

10 rows × 36 columns

Convert date into pandas datetime object:

In [9]:
```
df['date'] = pd.to_datetime(df['date'],)
```

Extract day, month and week some useful features from 'date' column:

In [10]:
```
df['day'] = df['date'].dt.day
df['month'] = df['date'].dt.month
df['week'] = df['date'].dt.isocalendar().week
```

accident_severity is out target variable, display the unique values in accident_severity column:

1 = Satal, 2= Serious and 3 = Slight

In [11]:
```
df['accident_severity'].unique()
```

Out[11]:
```
array([3, 2, 1], dtype=int64)
```

display the value count for the accident_severity (target) variable:

In [12]:
```
df['accident_severity'].value_counts()
```

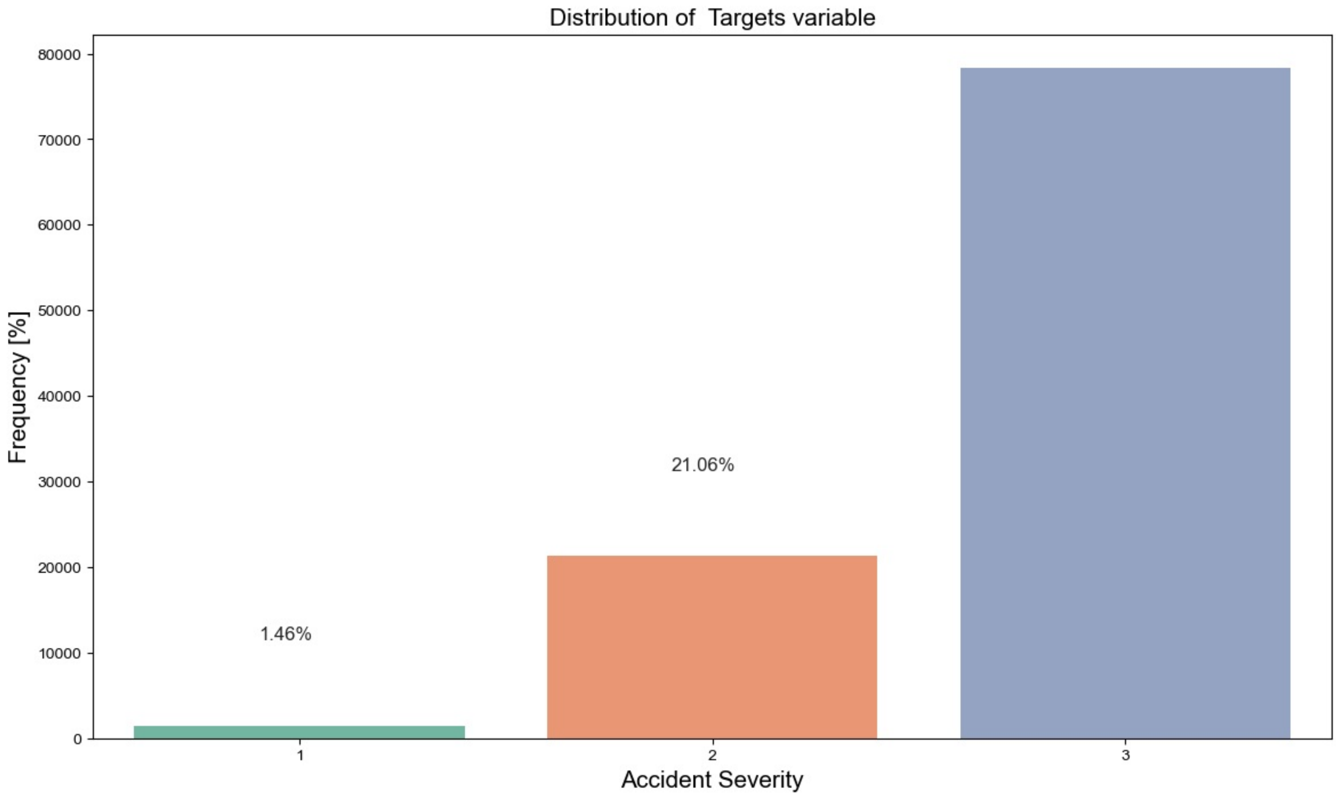
Out[12]:
```
3    78329
2    21284
1     1474
Name: accident_severity, dtype: int64
```

Univariate Analysis:

Distribution of original data by target (accident_severity):

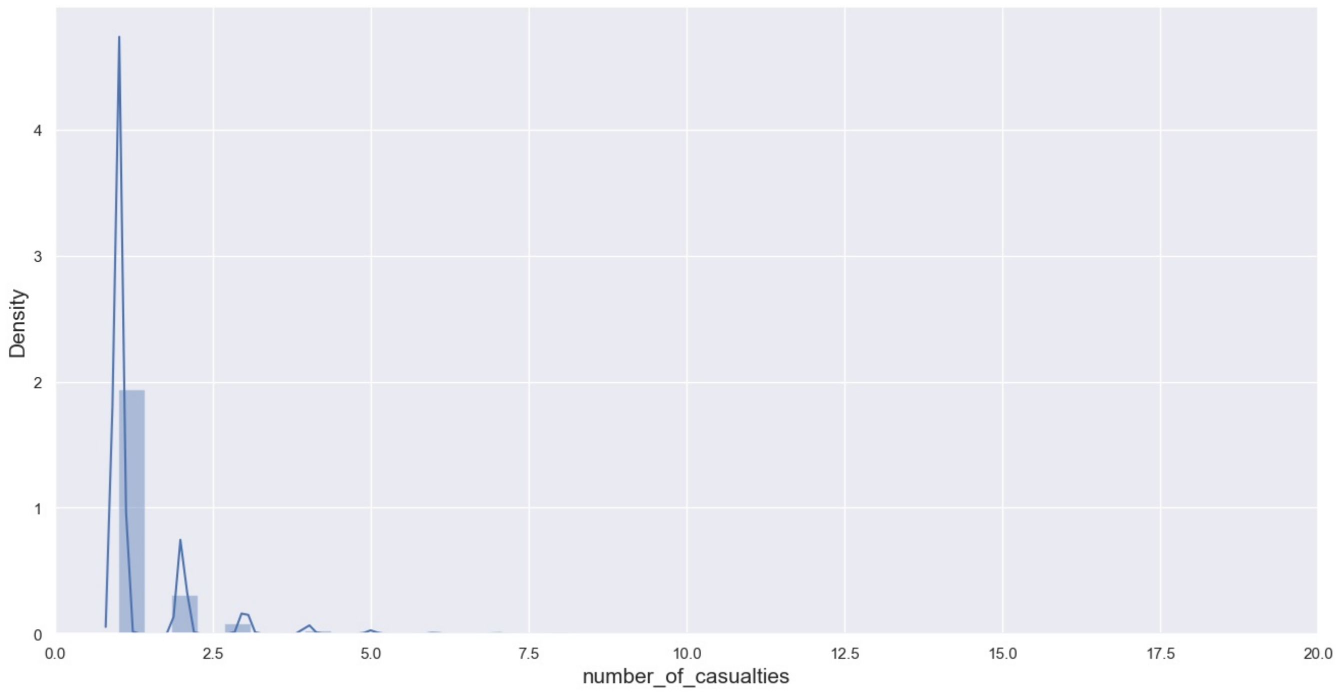
In [13]:
```
ax = sns.countplot(x = df.accident_severity ,palette="Set2")
sns.set(font_scale=1)
ax.set_xlabel(' ')
ax.set_ylabel(' ')
fig = plt.gcf()
fig.set_size_inches(14,8)
for p in ax.patches:
    ax.annotate('{:.2f}%'.format(100*p.get_height()/len(df.accident_severity)), (p.get_x()+ 0.3, p.get_height()

plt.title('Distribution of  Targets variable',fontsize = 15)
plt.xlabel('Accident Severity',fontsize = 15)
plt.ylabel('Frequency [%]',fontsize = 15)
plt.show()
```



Number of casualties distribution

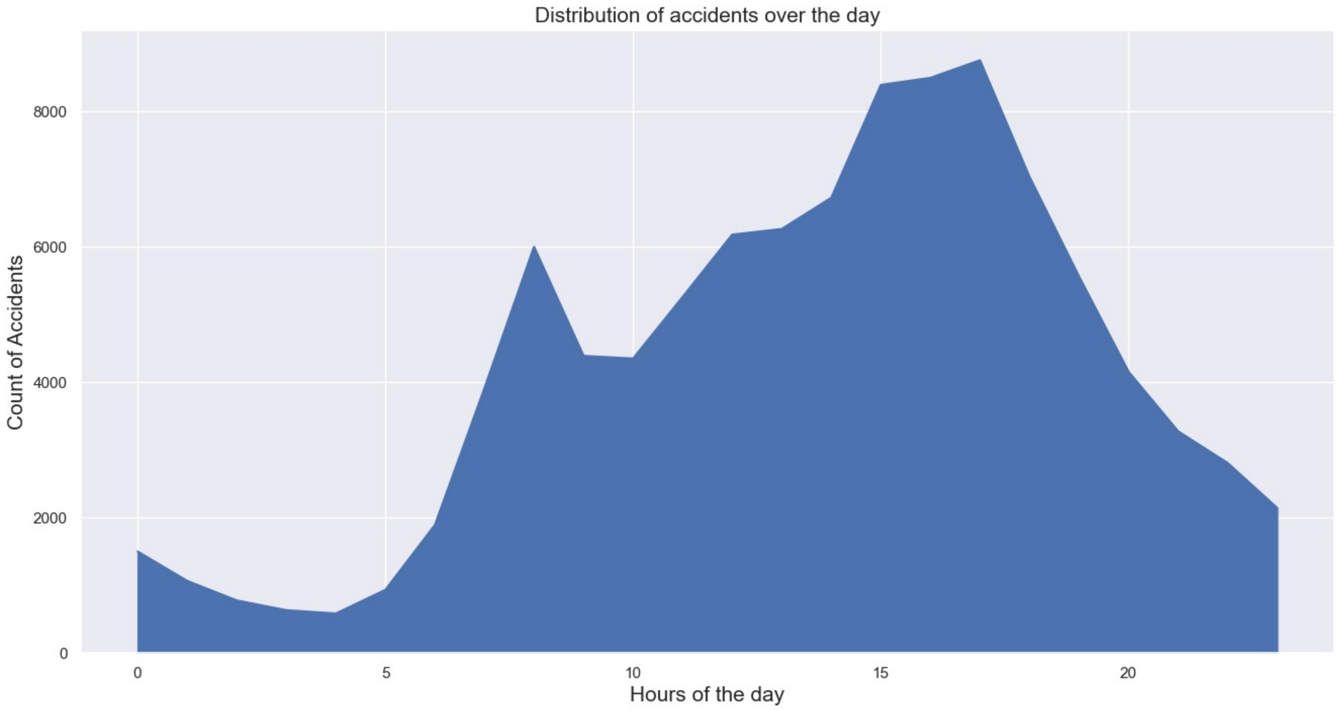
In [14]:
```
plt.figure(figsize=(16,8))
sns.distplot(df.number_of_casualties).set_xlim(0,20)
plt.xlabel('number_of_casualties' ,fontsize = 15)
plt.ylabel('Density',fontsize = 15)
plt.show()
print('Min:',    df.number_of_casualties.min(), '\n'
      'Max:',    df.number_of_casualties.max(), '\n'
      'Median:', df.number_of_casualties.median())
```




```
Min: 1
Max: 22
Median: 1.0
```

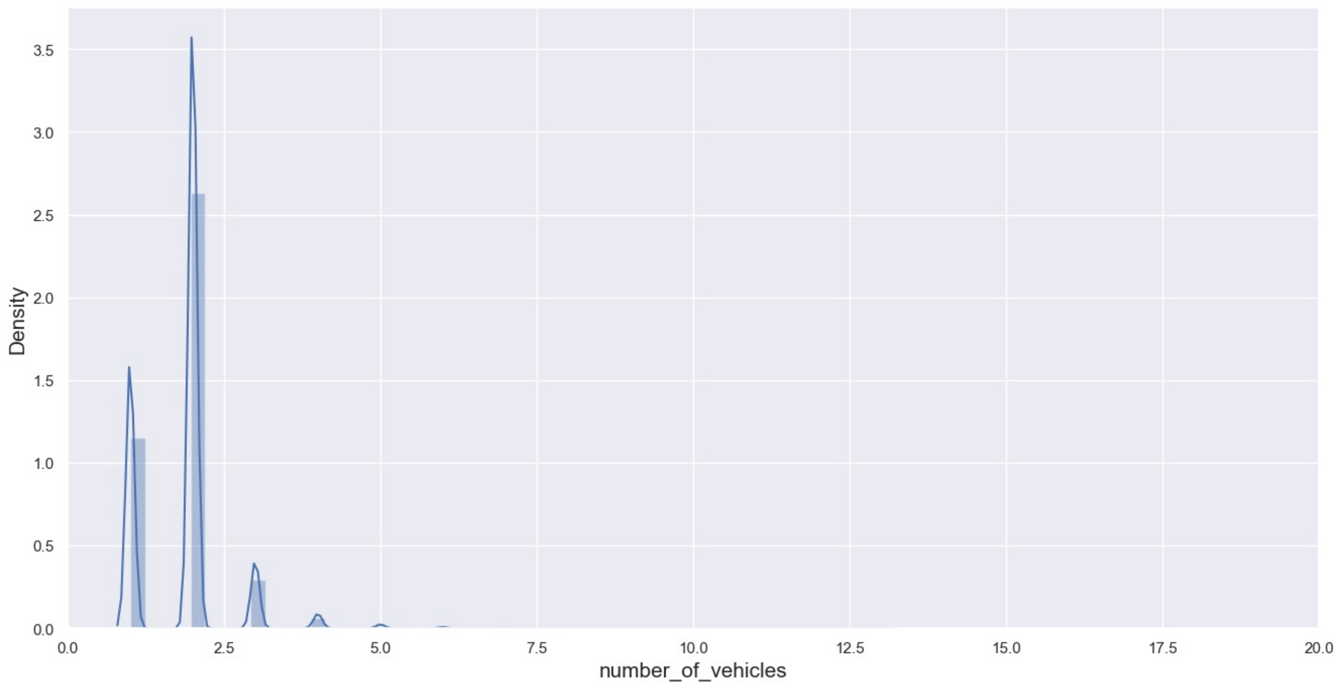
Distribution of accidents over the day

In [15]:
```
time_x = pd.to_datetime(df['time'], format='%H:%M').dt.hour
plt.figure(figsize=(16,8))
ax = time_x.value_counts().sort_index().plot(kind = 'area')
ax.set_xlabel('Hours of the day', fontsize = 15)
ax.set_ylabel('Count of Accidents', fontsize = 15)
ax.set_title('Distribution of accidents over the day', fontsize = 15)
plt.show()
```



Number of vehicles distribution

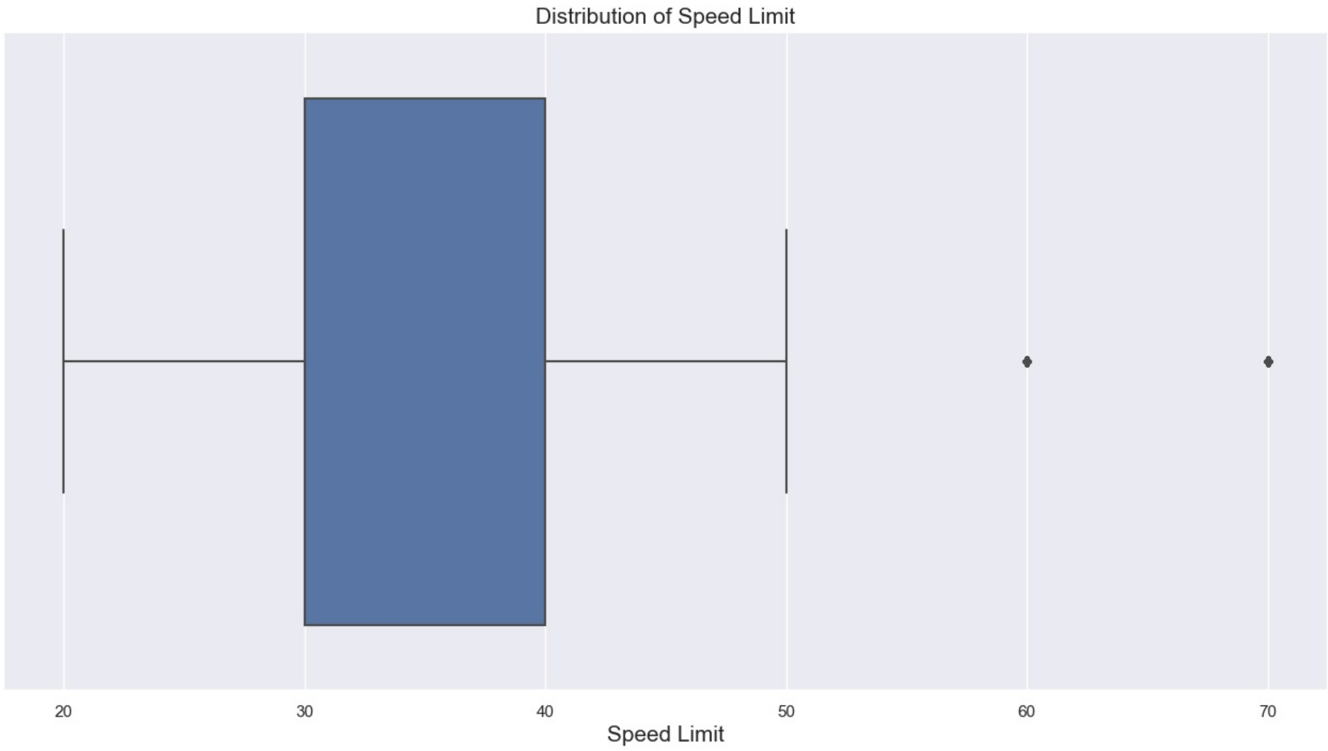
In [16]:
```
plt.figure(figsize=(16,8))
sns.distplot(df.number_of_vehicles).set_xlim(0,20)
plt.xlabel('number_of_vehicles',fontsize = 15)
plt.ylabel('Density',fontsize = 15)
plt.show()
print('Min:',    df.number_of_vehicles.min(), '\n'
      'Max:',    df.number_of_vehicles.max(), '\n'
      'Median:', df.number_of_vehicles.median())
```




```
Min: 1
Max: 13
Median: 2.0
```

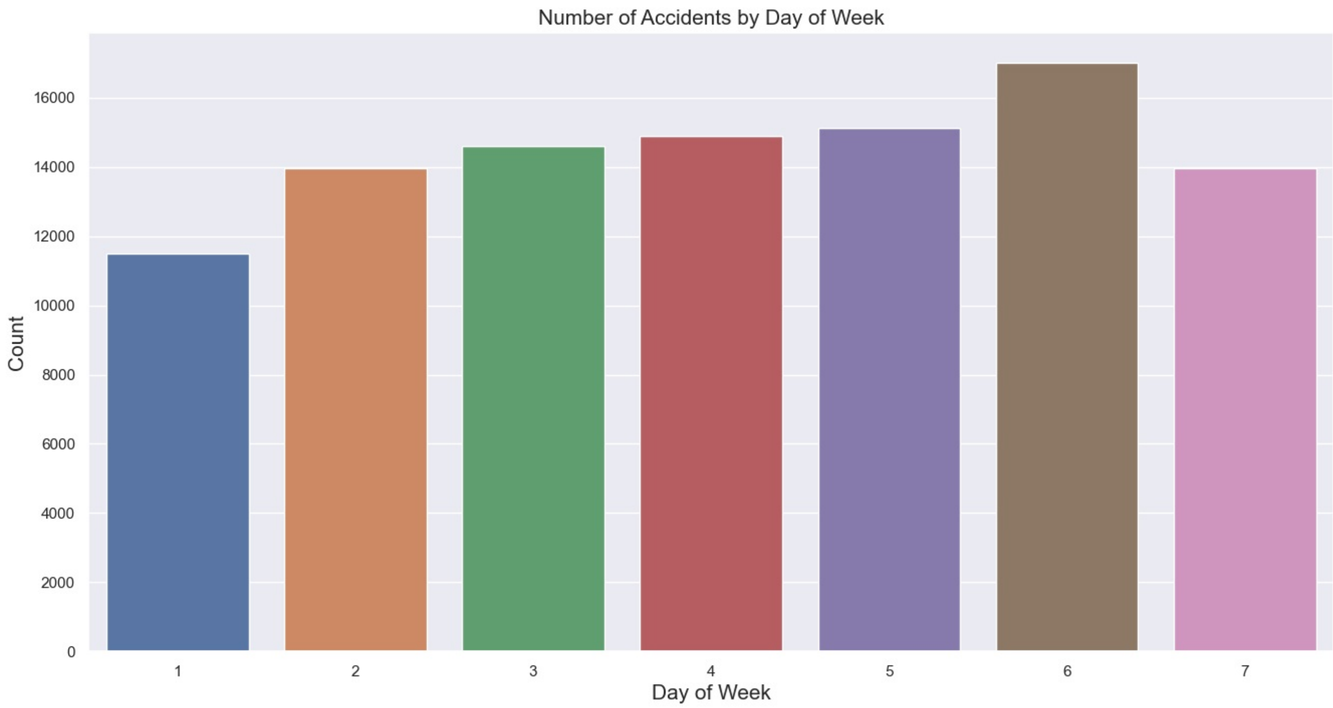
A boxplot to show Distribution of Speed Limit:

In [17]:
```
import seaborn as sns
plt.figure(figsize = (16, 8))
sns.boxplot(x=df["speed_limit"])
plt.title("Distribution of Speed Limit",fontsize = 15)
plt.xlabel("Speed Limit",fontsize = 15)
plt.show()
```



Bar chart of "day_of_week"

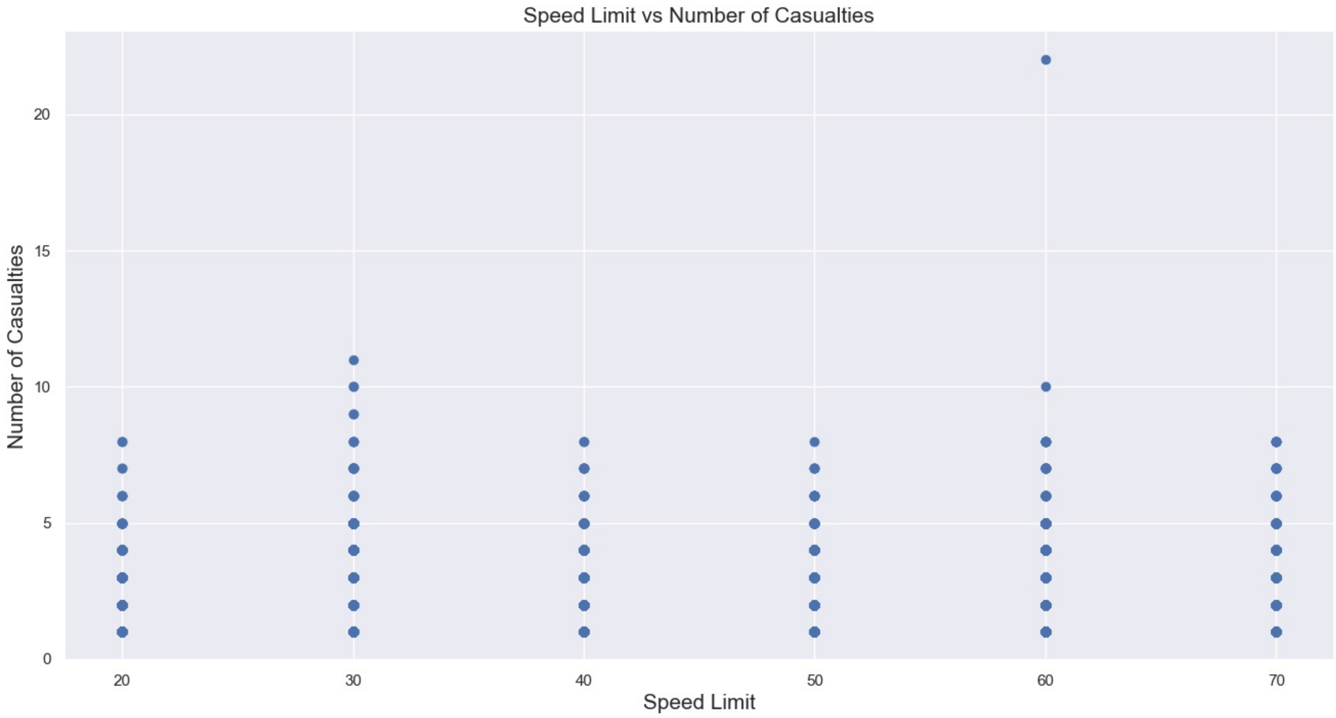
In [18]:
```
plt.figure(figsize = (16, 8))
sns.countplot(x=df["day_of_week"])
plt.title("Number of Accidents by Day of Week",fontsize = 15)
plt.xlabel("Day of Week",fontsize = 15)
plt.ylabel("Count",fontsize = 15)
plt.show()
```



Multivariate Analysis:

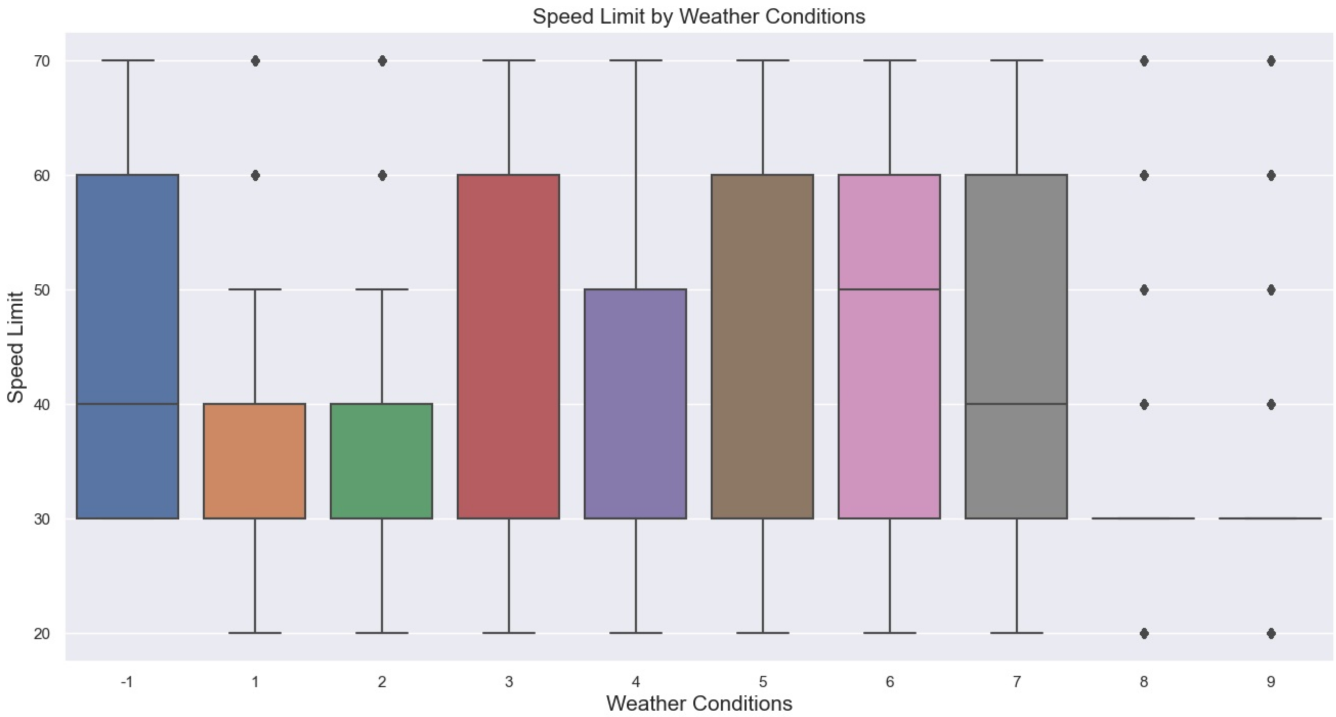
Scatter plot of "speed_limit" vs "number_of_casualties"

In [19]:
```
plt.figure(figsize = (16, 8))
plt.scatter(x=df["speed_limit"], y=df["number_of_casualties"])
plt.title("Speed Limit vs Number of Casualties",fontsize = 15)
plt.xlabel("Speed Limit",fontsize = 15)
plt.ylabel("Number of Casualties",fontsize = 15)
plt.show()
```



Box plot of "speed_limit" by "weather_conditions"

```
In [20]: plt.figure(figsize = (16, 8))
sns.boxplot(x=df["weather_conditions"], y=df["speed_limit"])
plt.title("Speed Limit by Weather Conditions",fontsize = 15)
plt.xlabel("Weather Conditions",fontsize = 15)
plt.ylabel("Speed Limit",fontsize = 15)
plt.show()
```



Drop the unnecessary columns:

```
In [21]: df.drop(['accident_index', 'accident_reference', 'local_authority_ons_district', 'local_authority_highway','tim
```

Check are there any missing values in the data frame:

```
In [22]: df.isnull().any()
```

Out[22]:
```
location_easting_osgr                          True
location_northing_osgr                         True
longitude                                      True
latitude                                       True
police_force                                  False
accident_severity                             False
number_of_vehicles                            False
number_of_casualties                          False
day_of_week                                   False
local_authority_district                      False
first_road_class                              False
first_road_number                             False
road_type                                     False
speed_limit                                   False
junction_detail                               False
junction_control                              False
second_road_class                             False
second_road_number                            False
pedestrian_crossing_human_control             False
pedestrian_crossing_physical_facilities       False
light_conditions                              False
weather_conditions                            False
road_surface_conditions                       False
special_conditions_at_site                    False
carriageway_hazards                           False
urban_or_rural_area                           False
did_police_officer_attend_scene_of_accident   False
trunk_road_flag                               False
day                                           False
month                                         False
week                                          False
dtype: bool
```

Count the number of missing values in each column of the data frame:

In [23]:
```
df.isnull().sum()
```

Out[23]:
```
location_easting_osgr                         17
location_northing_osgr                        17
longitude                                     17
latitude                                      17
police_force                                   0
accident_severity                              0
number_of_vehicles                             0
number_of_casualties                           0
day_of_week                                    0
local_authority_district                       0
first_road_class                               0
first_road_number                              0
road_type                                      0
speed_limit                                    0
junction_detail                                0
junction_control                               0
second_road_class                              0
second_road_number                             0
pedestrian_crossing_human_control              0
pedestrian_crossing_physical_facilities        0
light_conditions                               0
weather_conditions                             0
road_surface_conditions                        0
special_conditions_at_site                     0
carriageway_hazards                            0
urban_or_rural_area                            0
did_police_officer_attend_scene_of_accident    0
trunk_road_flag                                0
day                                            0
month                                          0
week                                           0
dtype: int64
```

Fill the missing values in location_easting_osgr, location_northing_osgr, longitude and latitude columns:

In [24]:
```
df['location_easting_osgr'] = df['location_easting_osgr'].fillna(df['location_easting_osgr'].mean())
df['location_northing_osgr'] = df['location_northing_osgr'].fillna(df['location_northing_osgr'].mean())
df['longitude'] = df['longitude'].fillna(df['longitude'].mode()[0])
df['latitude'] = df['latitude'].fillna(df['latitude'].mode()[0])
```

Convert (1 = Satal, 2= Serious and 3 = Slight) to binary values (0 = Slight, 1 = Serious):

Now we have binary classification problem

In [25]:
```
df['accident_severity'] = df['accident_severity'].replace([2 , 1], 0)
df['accident_severity'] = df['accident_severity'].replace(3, 1)
```

Value counts of the accident_severity again:

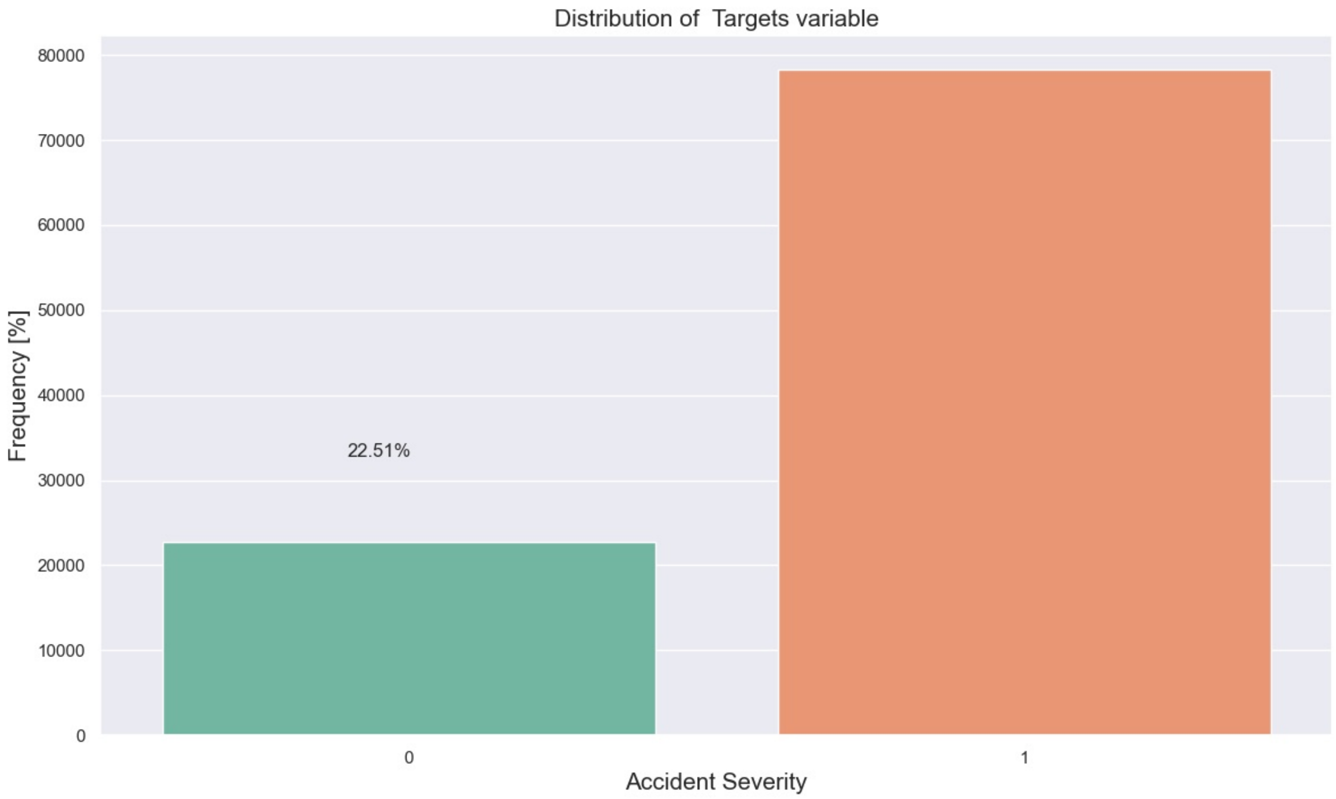
In [26]:
```
df['accident_severity'].value_counts()
```

Out[26]:
```
1    78329
0    22758
Name: accident_severity, dtype: int64
```

Distribution of original data by targets

In [27]:
```
ax = sns.countplot(x = df.accident_severity ,palette="Set2")
sns.set(font_scale=1)
ax.set_xlabel(' ')
ax.set_ylabel(' ')
fig = plt.gcf()
fig.set_size_inches(14,8)
for p in ax.patches:
    ax.annotate('{:.2f}%'.format(100*p.get_height()/len(df.accident_severity)), (p.get_x()+ 0.3, p.get_height()

plt.title('Distribution of  Targets variable',fontsize = 15)
plt.xlabel('Accident Severity',fontsize = 15)
plt.ylabel('Frequency [%]',fontsize = 15)
plt.show()
```



Store features into feature matrix X and target into vector y:

In [28]:
```
# Features
X = df.loc[:,df.columns != 'accident_severity']
#Target
y = df['accident_severity']
```

Feature Selection using SelectKbest method:

import SelectKBest and f_classif from sklear for feature seletion:

In [29]:
```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_classif
```

Initialized SelectKBest with f_classif test and k= 15

In [30]:
```
test = SelectKBest(score_func=f_classif, k=15)
```

Fit the SelectKBest model:

In [31]:
```
fit = test.fit(X, y)
```

Transform the features:

In [32]:
```
filtered_features= fit.transform(X)
```

Show the supporting variables given by SelectKBest (True/false):

In [33]:
```
test.get_support()
```

Out[33]:
```
array([ True,  True,  True,  True,  True,  True,  True, False, False,
       False, False, False,  True,  True,  True, False, False,  True,
        True, False, False, False, False, False,  True,  True,  True,
       False, False, False])
```

Display the scores of the features assigned by the SelectkBest:

In [34]:
```
test.scores_
```

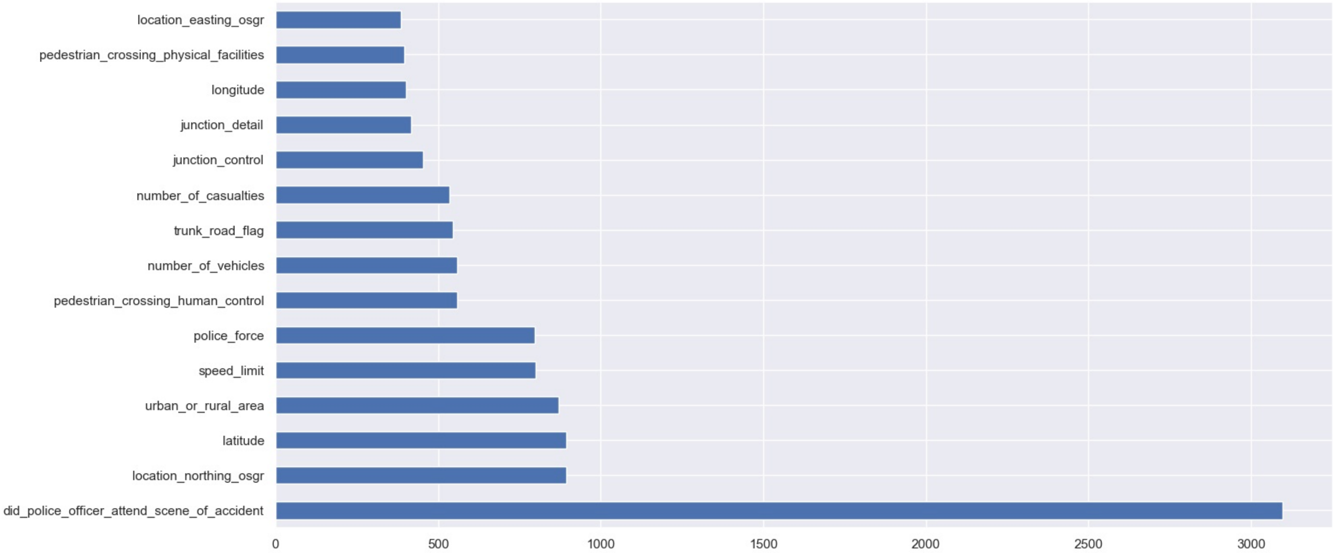
Out[34]:
```
array([3.84971810e+02, 8.95087532e+02, 4.02284280e+02, 8.93272967e+02,
       7.97990970e+02, 5.59635947e+02, 5.34741889e+02, 3.50200756e+00,
       5.35788886e-01, 5.79057112e+00, 1.32390689e+01, 7.51023189e+01,
       8.00915704e+02, 4.16713322e+02, 4.52602180e+02, 2.40140360e+02,
       2.98832159e+01, 5.59677285e+02, 3.95078409e+02, 2.19327845e+02,
       1.63862236e+02, 6.92030265e+01, 1.76458734e+02, 1.03446956e+02,
       8.70096249e+02, 3.09693189e+03, 5.46305865e+02, 2.45257733e+00,
       5.42266011e+00, 5.26975474e+00])
```

Find the Feature importance for each feature:

In [35]:
```
feat_importances = pd.Series(test.scores_, index=X.columns)
```

Display the feature importance using a bar chart

In [36]:
```
feat_importances.nlargest(15).plot(kind='barh',figsize = (16,8))
plt.show()
```



Getting the column names:

In [37]:
```
column_names = X.columns[test.get_support()]
column_names
```

Out[37]:
```
Index(['location_easting_osgr', 'location_northing_osgr', 'longitude',
       'latitude', 'police_force', 'number_of_vehicles',
       'number_of_casualties', 'speed_limit', 'junction_detail',
       'junction_control', 'pedestrian_crossing_human_control',
       'pedestrian_crossing_physical_facilities', 'urban_or_rural_area',
       'did_police_officer_attend_scene_of_accident', 'trunk_road_flag'],
      dtype='object')
```

Selecting the relevant columns given by SelectKbest only:

In [38]:
```
X_Selectkbest = X[column_names]
X_Selectkbest.head()
```

Out[38]:

	location_easting_osgr	location_northing_osgr	longitude	latitude	police_force	number_of_vehicles	number_of_casualties	speed_limit	j
0	521508.0	193079.0	-0.246102	51.623425	1	3	1	30	
1	535379.0	180783.0	-0.050574	51.509767	1	2	3	30	
2	529701.0	170398.0	-0.136152	51.417769	1	2	4	30	
3	525312.0	178385.0	-0.196411	51.490536	1	1	1	30	
4	512144.0	171526.0	-0.388169	51.431649	1	4	1	20	

Divide the data set into training and Testing sets (training set 80%, Testing set 20%):

In [39]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_Selectkbest, y, test_size=0.20, random_state=0)
```

Use StandardScaler to scale the values of the dataset:

In [40]:
```
SC = StandardScaler()
X_train_scaled = SC.fit_transform(X_train)
X_test_scaled = SC.fit_transform(X_test)
```

Experimental Design:

Logistic Regression Model

In [41]:
```
#Initialize the LogisticRegression Model
Lg_classifier = LogisticRegression()
# Train the model on training set
Lg_classifier.fit(X_train_scaled, y_train)
```

Out[41]:
```
LogisticRegression()
```

Make prediction and evaluation on seen data:

In [42]:
```
# Make prediction on seen data
y_pred = Lg_classifier.predict(X_train_scaled)
#he Accuracy score for Logistic Regresson on seen data :
Lg_score_seen = accuracy_score(y_train, y_pred)
print('The Accuracy score for Logistic Regresson on seen data : ', Lg_score_seen)
```

```
The Accuracy score for Logistic Regresson on seen data :  0.774870469524787
```

Make prediction and evaluation on unseen data:

In [43]:
```
# Make prediction on unseen data
y_pred = Lg_classifier.predict(X_test_scaled)
#he Accuracy score for Logistic Regresson on unseen data :
Lg_score_unseen = accuracy_score(y_test, y_pred)
print('The Accuracy score for Logistic Regresson on unseen data : ', Lg_score_unseen)
```

```
The Accuracy score for Logistic Regresson on unseen data :  0.7803442477000693
```

Decision Tree Classifier Model

In [44]:
```
#Initialize the DecisionTreeClassifier Model
Dt_classifier = DecisionTreeClassifier()
# Train the model on training set
Dt_classifier.fit(X_train_scaled, y_train)
```

Out[44]:
```
DecisionTreeClassifier()
```

Make prediction and evaluation on seen data:

In [45]:
```
# Make prediction on seen data
y_pred = Dt_classifier.predict(X_train_scaled)
#he Accuracy score for decision tree on seen data :
Dt_score_seen = accuracy_score(y_train, y_pred)
print('The Accuracy score for decision tree on seen data : ', Dt_score_seen)
```

```
The Accuracy score for decision tree on seen data :  0.9999381716108768
```

Make prediction and evaluation on unseen data:

In [46]:
```
# Make prediction on unseen data
```

```
y_pred = Dt_classifier.predict(X_test_scaled)
#he Accuracy score for decision tree on unseen data :
Dt_score_unseen = accuracy_score(y_test, y_pred)
print('The Accuracy score for decision tree on unseen data : ', Dt_score_unseen)
```

```
The Accuracy score for decision tree on unseen data :  0.6771688594321892
```

RandomForest Classifier Model

In [47]:
```
#Initialize the RandomForestClassifier Model
Rf_Classifier = RandomForestClassifier(n_estimators = 100, )
# Train the model on training set
Rf_Classifier.fit(X_train_scaled, y_train)
```

Out[47]:
```
RandomForestClassifier()
```

Make prediction and evaluation on seen data:

In [48]:
```
# Make prediction on seen data
y_pred = Rf_Classifier.predict(X_train_scaled)
#he Accuracy score for Random Forest on seen data :
Rf_score_seen = accuracy_score(y_train, y_pred)
print('The Accuracy score for Random Forest on seen data : ', Rf_score_seen)
```

```
The Accuracy score for Random Forest on seen data :  0.9999381716108768
```

Make prediction and evaluation on unseen data:

In [49]:
```
# Make prediction on unseen data
y_pred = Rf_Classifier.predict(X_test_scaled)
#he Accuracy score for Random Forest on unseen data :
Rf_score_unseen = accuracy_score(y_test, y_pred)
print('The Accuracy score for Random Forest on unseen data : ', Rf_score_unseen)
```

```
The Accuracy score for Random Forest on unseen data :  0.7588782273221881
```

Gradient Boosting Classifier Model

In [50]:
```
#Initialize the GradientBoostingClassifier Model
Gb_Classifier = GradientBoostingClassifier()
# Train the model on training set
Gb_Classifier.fit(X_train_scaled, y_train)
```

Out[50]:
```
GradientBoostingClassifier()
```

Make prediction and evaluation on seen data:

In [51]:
```
# Make prediction on seen data
y_pred = Gb_Classifier.predict(X_train_scaled)
#he Accuracy score for Gradient Boosting on seen data :
Gb_score_seen = accuracy_score(y_train, y_pred)
print('The Accuracy score for Gradient Boosting on seen data : ', Gb_score_seen)
```

```
The Accuracy score for Gradient Boosting on seen data :  0.7768489779767278
```

Make prediction and evaluation on unseen data:

In [52]:
```
# Make prediction on unseen data
y_pred = Gb_Classifier.predict(X_test_scaled)
#he Accuracy score for  Gradient Boosting on unseen data :
Gb_score_unseen = accuracy_score(y_test, y_pred)
print('The Accuracy score for  Gradient Boosting on unseen data : ', Gb_score_unseen)
```

```
The Accuracy score for  Gradient Boosting on unseen data :  0.781679691364131
```

XGB Classifier Model

In [53]:
```
#Initialize the XGBClassifier Model
XGB_Classifier = XGBClassifier()
# Train the model on training set
XGB_Classifier.fit(X_train_scaled, y_train)
```

Out[53]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, ...)
```

Make prediction and evaluation on seen data:

In [54]:
```
# Make prediction on seen data
y_pred = XGB_Classifier.predict(X_train_scaled)
#he Accuracy score for XGB_Classifier on seen data :
XGB_score_seen = accuracy_score(y_train, y_pred)
print('The Accuracy score for XGB_Classifier on seen data : ', XGB_score_seen)
```

```
The Accuracy score for XGB_Classifier on seen data :  0.7921947841570935
```

Make prediction and evaluation on unseen data:

In [55]:
```
# Make prediction on unseen data
y_pred = XGB_Classifier.predict(X_test_scaled)
#he Accuracy score for  XGB_Classifier on unseen data :
XGB_score_unseen = accuracy_score(y_test, y_pred)
print('The Accuracy score for XGB_Classifier on unseen data : ', XGB_score_unseen)
```

```
The Accuracy score for XGB_Classifier on unseen data :  0.7806410129587497
```

KNeighbors Classifier Model

In [56]:
```
#Initialize the KNeighborsClassifier Model
KNN_Classifier = KNeighborsClassifier()
# Train the model on KNeighborsClassifier set
KNN_Classifier.fit(X_train_scaled, y_train)
```

Out[56]:
```
KNeighborsClassifier()
```

Make prediction and evaluation on seen data:

In [57]:
```
# Make prediction on seen data
y_pred = KNN_Classifier.predict(X_train_scaled)
#he Accuracy score for KNN classifier on seen data :
KNN_score_seen = accuracy_score(y_train, y_pred)
print('The Accuracy score for KNN_Classifier on seen data : ', KNN_score_seen)
```

```
The Accuracy score for KNN_Classifier on seen data :  0.8085793072747283
```

Make prediction and evaluation on unseen data:

In [58]:
```
# Make prediction on unseen data
y_pred = KNN_Classifier.predict(X_test_scaled)
#he Accuracy score for  KNN classifier on unseen data :
KNN_score_unseen = accuracy_score(y_test, y_pred)
print('The Accuracy score for KNN_Classifier on unseen data : ', KNN_score_unseen)
```

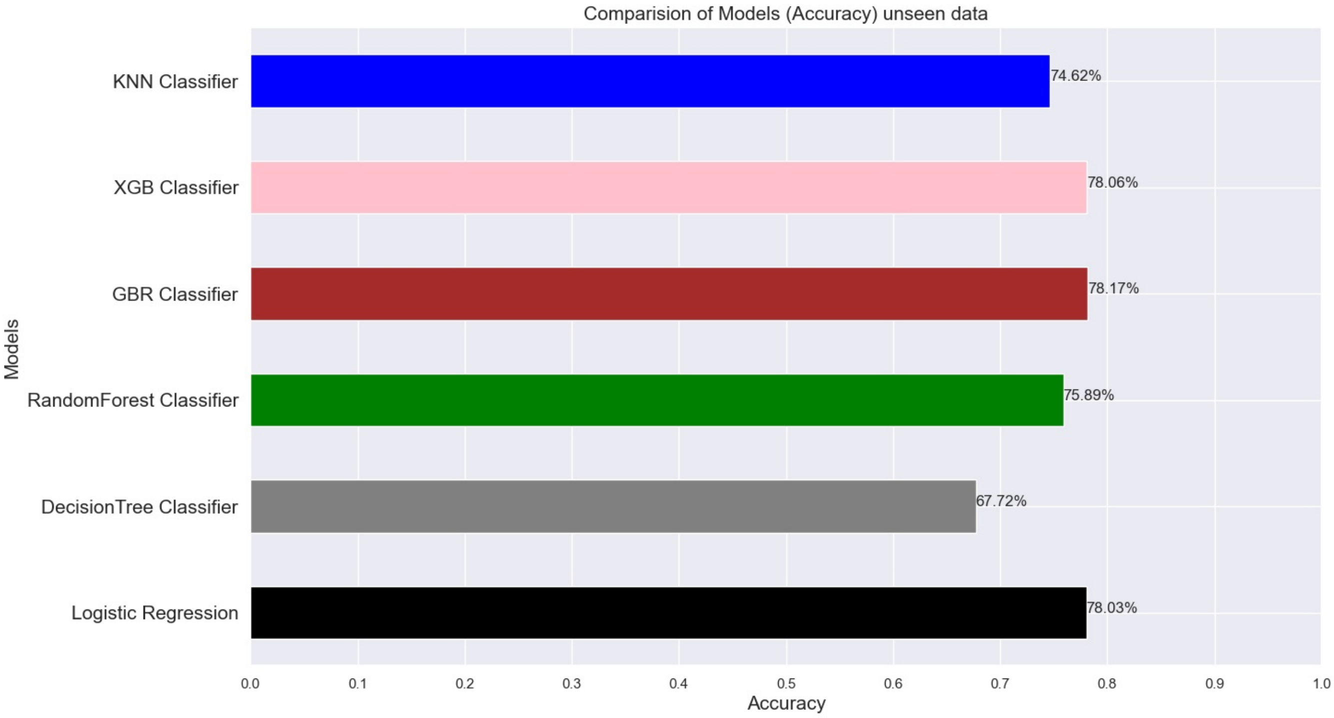
```
The Accuracy score for KNN_Classifier on unseen data :  0.7462162429518251
```

Create two lists of model name and respective Accuracies:

In [59]:
```
scores = pd.Series([Lg_score_unseen, Dt_score_unseen, Rf_score_unseen, Gb_score_unseen, XGB_score_unseen, KNN_s
Model_Names = ['Logistic Regression','DecisionTree Classifier','RandomForest Classifier', 'GBR Classifier' ,'XG
```

Comparision of Models in terms evaluation metric (accuracy Score):

In [60]:
```
ax = scores.plot(kind = 'barh',figsize=(15,9),color=['black','gray','green','brown','pink','blue','red'])
ax.set_title('Comparision of Models (Accuracy) unseen data',fontsize=15)
ax.set_xticks([0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0])
ax.set_yticklabels(Model_Names,fontsize=15,)
ax.set_ylabel("Models",fontsize=15)
ax.set_xlabel("Accuracy",fontsize=15)
[ax.text(v, i, '{:.2f}%'.format(100*v)) for i, v in enumerate(scores)];
plt.show()
```



Evaluation and further modelling improvements

Hyper parameter Tuning for Highest performing Model (Logistic Regression)

In [61]:
```
# Create logistic regression object
lr = LogisticRegression()

# Set hyperparameters to tune
hyperparameters = {
    'penalty': ['l1', 'l2'],
    'C': [0.01, 0.1, 1, 10, 100],
    'solver': ['liblinear']
}
```

Create GridSearchCV object and fit it on training data:

In [62]:
```
# Create GridSearchCV object
clf = GridSearchCV(lr, hyperparameters, cv=5)

# Fit GridSearchCV object to training data
clf.fit(X_train_scaled, y_train)
```

Out[62]:
```
GridSearchCV(cv=5, estimator=LogisticRegression(),
             param_grid={'C': [0.01, 0.1, 1, 10, 100], 'penalty': ['l1', 'l2'],
                         'solver': ['liblinear']})
```

Print best hyperparameters and best score

In [63]:
```
# Print best hyperparameters and best score
print('Best parameters:', clf.best_params_)
print('Best score:', clf.best_score_)
```

```
Best parameters: {'C': 10, 'penalty': 'l2', 'solver': 'liblinear'}
Best score: 0.7748951929440493
```

In [ ]:

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js