Collision Severity Predicton: A Case study of Seattle

1. Introduction

Road accidents are an important issue of our modern societies, responsible for millions of deaths and injuries every year in the world. Seattle, a city on Puget Sound in the Pacific Northwest., Washington State's largest city, is a home to a large tech industry, with Microsoft and Amazon headquartered in its metropolitan area. The city is of high socio-economic value and is rapidly changing with time. The rapid economic growth that the city has developed in the past has resulted in improving the lifestyle of the people living over there. With the raised standard of living in the city, and greater purchasing power of its inhabitants, the number of automobiles on the roads has increased rapidly. With so many people owning and operating vehicles on the roads, problems like traffic jams, congestion on roads, and road accidents are becoming a common sight. Now, wouldn't it be great if there is something in place that could warn the road users, given the weather and the road conditions about the possibility of them getting into a car accident and how severe it would be, so that they would drive more carefully or even change their travel if they are able to? Well, this is exactly what this project addresses. The data for this work was taken from open data platform hosted by the city of Seattle found here. This includes all types of collisions from 2004 to Present. This data is updated weekly, so the presented analysis is based on the data collected at that time (Wednesday, 07 October 2020). This dataset also provides information regarding the cause and type of the collisions.

2. Data

In this section, we will be importing the dataset, exploring it and understanding it to select relevant data with the appropriate features as per the needs and wants of the problem.

Firstly, importing some important python libraries:

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib as mlp
import matplotlib.pyplot as plt
```

Now importing the data set from the remote source are taking a perfunctory look at it:

In [2]:

```
df= pd.read_csv("http://data-seattlecitygis.opendata.arcgis.com/datasets/5b5c745e0f1f48e7
a53acec63a0022ab_0.csv?outSR=%7B%22latestWkid%22%3A2926%2C%22wkid%22%3A2926%7D")
df.head()
```

```
/opt/conda/envs/Python36/lib/python3.6/site-packages/IPython/core/interactiveshell.py:302
0: DtypeWarning: Columns (35) have mixed types. Specify dtype option on import or set low
_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

Out[2]:

	X	Y	OBJECTID	INCKEY	COLDETKEY	REPORTNO	STATUS	ADDRTYPE	INTKEY	LOCATION
0	1.268354e+06	265256.609668	1	1003	1003	3503158	Matched	Block	NaN	AURORA AVE N BETWEEN N 117TH PL AND N 125TH ST
1	1.259316e+06	202173.388163	2	56200	56200	1795087	Matched	Block	NaN	35TH AVE SW BETWEEN SW MORGAN ST AND SW HOLLY ST
2	1.264342e+06	259613.000382	3	327037	328537	E979380	Matched	Intersection	37122.0	3RD AVE NW AND NW 100TH ST
3	1.279221e+06	222017.872023	4	327278	328778	E996362	Unmatched	Intersection	30602.0	M L KING JR WAY S AND S JACKSON ST
4	1.262205e+06	242179.124204	5	1248	1248	3645424	Unmatched	Block	NaN	W EWING ST BETWEEN 6TH AVE W AND W EWING PL

5 rows × 40 columns

In [3]:

```
df.size
```

Out[3]:

```
8861000
```

In [4]:

```
df.shape
```

```
df.shape
```

Out[4]:

```
(221525, 40)
```

In [5]:

```
df.columns
```

Out[5]:

```
Index(['X', 'Y', 'OBJECTID', 'INCKEY', 'COLDETKEY', 'REPORTNO', 'STATUS',
       'ADDRTYPE', 'INTKEY', 'LOCATION', 'EXCEPTRSNCODE', 'EXCEPTRSNDESC',
       'SEVERITYCODE', 'SEVERITYDESC', 'COLLISIONTYPE', 'PERSONCOUNT',
       'PEDCOUNT', 'PEDCYLCOUNT', 'VEHCOUNT', 'INJURIES', 'SERIOUSINJURIES',
       'FATALITIES', 'INCDATE', 'INCDTTM', 'JUNCTIONTYPE', 'SDOT_COLCODE',
       'SDOT_COLDESC', 'INATTENTIONIND', 'UNDERINFL', 'WEATHER', 'ROADCOND',
       'LIGHTCOND', 'PEDROWNOTGRNT', 'SDOTCOLNUM', 'SPEEDING', 'ST_COLCODE',
       'ST_COLDESC', 'SEGLANEKEY', 'CROSSWALKKEY', 'HITPARKEDCAR'],
      dtype='object')
```

So there are 40 columns with different names. The description of these names can be found here. A brief summary of the dataframe along with the datatype of the columns can be found below.

Let us rename these column names to make it more convenient for

In [6]:

```
df.rename(columns={'SEVERITYCODE': 'severity_code', 'X':'longitude', 'Y': 'latitude',
                   'ADDRTYPE':'addr_type', 'LOCATION': 'location','SEVERITYDESC':'severi
ty_desc', 'COLLISIONTYPE':'collision_type',
                   'PERSONCOUNT':'person_count', 'PEDCOUNT': 'ped_count', 'PEDCYLCOUNT':
'ped_cycle_count', 'VEHCOUNT': 'veh_count',
                   'INCDTTM': 'incident_date&time', 'JUNCTIONTYPE': 'junc_type', 'SDOT_C
OLCODE': 'case_code', 'SDOT_COLDESC': 'case_desc',
                   'UNDERINFL':'under_infl', 'WEATHER': 'weather', 'ROADCOND': 'roadcond
', 'LIGHTCOND': 'light_cond',
                   'ST_COLCODE': 'st_code', 'ST_COLDESC': 'st_desc', 'HITPARKEDCAR':'hit
_parked_car', 'SPEEDING':'speeding',
                   'FATALITIES':'fatalities', 'INJURIES':'injuries', 'SERIOUSINJURIES':'
serious_injuries', 'INCDATE':'incident_date',
                   'INATTENTIONIND':'inattention_involved', 'PEDROWNOTGRNT':'ped_row_not
_granted', 'SDOTCOLNUM':'sdot_collision_num'}, inplace=True)
```

In [7]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 221525 entries, 0 to 221524
Data columns (total 40 columns):
longitude                214050 non-null float64
latitude                 214050 non-null float64
OBJECTID                 221525 non-null int64
INCKEY                   221525 non-null int64
COLDETKEY                221525 non-null int64
REPORTNO                 221525 non-null object
STATUS                   221525 non-null object
addr_type                217813 non-null object
INTKEY                   71936 non-null float64
location                 216935 non-null object
EXCEPTRSNCODE            101122 non-null object
EXCEPTRSNDESC            11779 non-null object
severity_code            221524 non-null object
severity_desc            221525 non-null object
collision_type           195212 non-null object
person_count             221525 non-null int64
ped_count                221525 non-null int64
ped_cycle_count          221525 non-null int64
veh_count                221525 non-null int64
injuries                 221525 non-null int64
```

```
injuries                 221525 non-null int64
serious_injuries         221525 non-null int64
fatalities               221525 non-null int64
incident_date            221525 non-null object
incident_date&time       221525 non-null object
junc_type                209551 non-null object
case_code                221524 non-null float64
case_desc                221524 non-null object
inattention_involved     30188 non-null object
under_infl               195232 non-null object
weather                  195022 non-null object
roadcond                 195103 non-null object
light_cond               194933 non-null object
ped_row_not_granted      5195 non-null object
sdot_collision_num       127205 non-null float64
speeding                 9929 non-null object
st_code                  212112 non-null object
st_desc                  195212 non-null object
SEGLANEKEY               221525 non-null int64
CROSSWALKKEY             221525 non-null int64
hit_parked_car           221525 non-null object
dtypes: float64(5), int64(12), object(23)
memory usage: 67.6+ MB
```

Now that we have acquired the data, let us try to comprehend it to get some idea on which attributes or features should be selected for the modelling.

3. Data Understanding

The aim of this work is to predict the severity of a car accident based on various attributes. The columns 'severity_code and 'severity_desc' depict the code that corresponds to the level of severity as classified by SDOT and the description of the severity of the collision respectively. Let us have a look at the data distribution according to the severity of the incident.

Collision Severity

In [8]:

```
df.groupby(['severity_code', 'severity_desc']).size().to_frame('counts')
```

Out[8]:

		counts
severity_code	**severity_desc**	
0	**Unknown**	21615
1	**Property Damage Only Collision**	137671
2	**Injury Collision**	58783
2b	**Serious Injury Collision**	3105
3	**Fatality Collision**	350

The severity codes are a little confusing because of alphanumeric label 2b. Let us replace 2b with 3 and 3 with 4 in the severity_code column.

In [9]:

```
df['severity_code'].replace(to_replace={'3':'4', '2b': '3'}, inplace=True)
df['severity_code'].value_counts().to_frame('Counts')
```

Out[9]:

	Counts
1	137671

	Counts
1	[illegible]
2	58783
0	21615
3	3105
4	350

We can see that majority of collisions are non-fatal in nature, with most collisions only leading to property damage an injuries. Now, let us have a look at the various collision types recorded in the dataset.

Collision Type

In [10]:

```
df['collision_type'].value_counts().to_frame('Counts').sort_values(by='Counts',ascending
=False)
```

Out[10]:

	Counts
Parked Car	48551
Angles	35573
Rear Ended	34691
Other	24588
Sideswipe	18891
Left Turn	14115
Pedestrian	7666
Cycles	5932
Right Turn	3017
Head On	2188

We see that collision with parked cars was the most frequent collision type while head on Collisions were the least common. These collisions happened at different locations as shown in the following section.

Collision Address type and Junction Type

In [11]:

```
df.groupby(['addr_type', 'junc_type']).size().to_frame('Counts')
```

Out[11]:

		Counts
addr_type	junc_type	
Alley	At Intersection (but not related to intersection)	1
	Driveway Junction	66
	Mid-Block (not related to intersection)	195
Block	At Intersection (but not related to intersection)	1
	At Intersection (intersection related)	4
	Driveway Junction	11426
	Mid-Block (but intersection related)	24388
	Mid-Block (not related to intersection)	100976
	Ramp Junction	153

		Counts
	Ramp Junction	153
	Unknown	12
addr_type	**junc_type**	
Intersection	**At Intersection (but not related to intersection)**	2491
	At Intersection (intersection related)	69189
	Mid-Block (but intersection related)	1
	Mid-Block (not related to intersection)	15
	Ramp Junction	35
	Unknown	6

We see that most collisions occured at the Blocks and Intersections. This may be due to the fact that these locations are the points where traffic merges and therefore are much prone to conflicts. Now let us see the description of the weather conditions during the time of the collision.

Weather

In [12]:

```
df['weather'].value_counts().to_frame('Counts')
```

Out[12]:

	Counts
Clear	114738
Raining	34036
Overcast	28552
Unknown	15131
Snowing	919
Other	860
Fog/Smog/Smoke	577
Sleet/Hail/Freezing Rain	116
Blowing Sand/Dirt	56
Severe Crosswind	26
Partly Cloudy	10
Blowing Snow	1

We find that most collisions occur during clear weather condition followed by raining and overcast conditions. This might be because the drivers tend to avoid driving when the weather condition is worse. Next, let us see the road conditons at the spot of collisions.

Road Condition

In [13]:

```
df['roadcond'].value_counts().to_frame('Counts')
```

Out[13]:

	Counts
Dry	128588
Wet	48734
Unknown	15139
Ice	1232

	counts
Snow/Slush	1014
Other	136
Standing Water	119
Sand/Mud/Dirt	77
Oil	64

Most collisions seem to have happened on dry and wet roads.

Light Condition

We can see the light conditions during the collision in the table below.

In [14]:

```
df['light_cond'].value_counts().to_frame('counts')
```

Out[14]:

	counts
Daylight	119492
Dark - Street Lights On	50133
Unknown	13532
Dusk	6082
Dawn	2609
Dark - No Street Lights	1579
Dark - Street Lights Off	1239
Other	244
Dark - Unknown Lighting	23

So most collisions occurred during good lighting conditions during daytime and at night with street lights on. Another factor that can cause accidents is the condition of the road user being intoxicated i.e. under the influence of alcohol and drugs. The next section shows the distibution of whether the driver involved was under the influence of drugs or alcohol.

Under the Influence of alcohol/drugs

In [15]:

```
df['under_infl'].value_counts().to_frame('counts')
```

Out[15]:

	counts
N	103927
0	81676
Y	5399
1	4230

We see that this column has different entries used, which are just the duplicate of themselves .Hence changing them to a unique numeric data which will be good for processing the data.

In [16]:

```
df['under_infl'].replace(to_replace={'Y':1, 'N':0, '1':1, '0':0}, inplace=True)
```

```
df['under_infl'].value_counts().to_frame('counts')
```

Out[16]:

	counts
0.0	185603
1.0	9629

So we can see that in most cases people were not intoxicated. Now let us have a look at the distribution of various road users involved in these collisions.

Collisions by Road User

In [17]:

```
df[['person_count', 'ped_count', 'ped_cycle_count', 'veh_count']].describe()
```

Out[17]:

	person_count	ped_count	ped_cycle_count	veh_count
count	221525.000000	221525.000000	221525.000000	221525.000000
mean	2.226941	0.038118	0.027360	1.730482
std	1.470050	0.201766	0.164537	0.829754
min	0.000000	0.000000	0.000000	0.000000
25%	2.000000	0.000000	0.000000	2.000000
50%	2.000000	0.000000	0.000000	2.000000
75%	3.000000	0.000000	0.000000	2.000000
max	93.000000	6.000000	2.000000	15.000000

We see that mostly vehicle owners were involved in these accidents, with an average of 2.23 people and 1.73 vehicle involved in each collision. Now let us move to the Data Cleaning and Preprocessing stage.

2. Data Cleaning & Preprocessing

The first step in this would be to take care of the missing or Nan values in the dataframe. If Nan values are present, we would either delete the entire row/column or replace the null value to some other suitable value, depending on the requirement. Let us find ut how many null values are present in each column.

In [18]:

```
df.isnull().sum()
```

Out[18]:

```
longitude             7475
latitude              7475
OBJECTID                 0
INCKEY                   0
COLDETKEY                0
REPORTNO                 0
STATUS                   0
addr_type             3712
INTKEY              149589
location              4590
EXCEPTRSNCODE       120403
EXCEPTRSNDESC       209746
severity_code            1
severity_desc            0
collision_type       26313
person_count             0
ped_count                0
```

```
ped_cycle_count              0
veh_count                    0
injuries                     0
serious_injuries             0
fatalities                   0
incident_date                0
incident_date&time           0
junc_type                11974
case_code                    1
case_desc                    1
inattention_involved    191337
under_infl               26293
weather                  26503
roadcond                 26422
light_cond               26592
ped_row_not_granted     216330
sdot_collision_num       94320
speeding                211596
st_code                   9413
st_desc                  26313
SEGLANEKEY                   0
CROSSWALKKEY                 0
hit_parked_car               0
dtype: int64
```

STATUS, INTKEY,OBJECTID, INCKEY, COLDETKEY, REPORTNO, EXCEPTRSNCODE, EXCEPTRSNDESC, incident_date, inattention_involved, ped_row_not_granted, sdot_collision_num, SEGLANEKEY, CROSSWALKKEY, addr_type, location, st_code, st_desc, case_code, case_desc has a lot of missing values and they are not useful and irrelevant for this dataset. So they are dropped.

In [19]:

```
df.drop(['STATUS', 'INTKEY', 'OBJECTID', 'INCKEY', 'COLDETKEY', 'REPORTNO', 'EXCEPTRSNCODE', 'EXCEPTRSNDESC', 'incident_date', 'inattention_involved', 'ped_row_not_granted', 'sdot_collision_num', 'SEGLANEKEY', 'CROSSWALKKEY', 'addr_type', 'location', 'st_code', 'st_desc', 'case_code', 'case_desc'], axis=1, inplace=True)
```

In [20]:

```
df.shape
```

Out[20]:

```
(221525, 20)
```

In [21]:

```
df.isnull().sum()
```

Out[21]:

```
longitude              7475
latitude               7475
severity_code             1
severity_desc             0
collision_type        26313
person_count              0
ped_count                 0
ped_cycle_count           0
veh_count                 0
injuries                  0
serious_injuries          0
fatalities                0
incident_date&time        0
junc_type             11974
under_infl            26293
weather               26503
roadcond              26422
light_cond            26592
speeding             211596
hit_parked_car            0
```

```
dtype: int64
```

The speeding column has a lot of missing values and consists of only 'y' in cases that involved speeding. So, converting Y->1 and nan->0 to make the speeding column consistent and get rid of all Nan values.

In [22]:

```
df['speeding'].replace(to_replace={'Y':1, np.nan:0, '1':1, '0':0}, inplace=True)
df['speeding'].value_counts().to_frame('counts')
```

Out[22]:

	counts
0	211596
1	9929

The dataset has some columns with useless data like unknown and others which won't fall under any of the category and they are a kind of outliers which ruin the dataset .Hence they are all converted to nan, thereby, paving way to group them under the category of missing values.

In [23]:

```
df.replace(to_replace={'Unknown':np.nan, 'Other':np.nan}, inplace=True)
```

Now dropping all rows with missing data in the dataset.

In [24]:

```
df.dropna(axis=0, inplace=True)
```

In [25]:

```
df.shape
```

Out[25]:

```
(148112, 20)
```

In [26]:

```
df.isnull().sum()
```

Out[26]:

```
longitude              0
latitude               0
severity_code          0
severity_desc          0
collision_type         0
person_count           0
ped_count              0
ped_cycle_count        0
veh_count              0
injuries               0
serious_injuries       0
fatalities             0
incident_date&time     0
junc_type              0
under_infl             0
weather                0
roadcond               0
light_cond             0
speeding               0
hit_parked_car         0
dtype: int64
```

So, as we can see, we are only left with 20 columns in our dataset, with each column being devoid of missing

values. Let us now extract year, month, weekday and time details from 'incident_date&time' column.

In [27]:

```
# Convert incident_date&time to date type.
df['incident_date&time'] = pd.to_datetime(df['incident_date&time'], errors='coerce')

# Extract month, weekday, hour information
df['Year']=df['incident_date&time'].dt.year
df['Month']=df['incident_date&time'].dt.month
df['Weekday']=df['incident_date&time'].dt.weekday
df['Hour']=df['incident_date&time'].dt.hour
```

In [28]:

```
# Dropping the incident_date&time colum now:
df.drop('incident_date&time', axis =1, inplace= True)
```

In [29]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 148112 entries, 0 to 221523
Data columns (total 23 columns):
longitude            148112 non-null float64
latitude             148112 non-null float64
severity_code        148112 non-null object
severity_desc        148112 non-null object
collision_type       148112 non-null object
person_count         148112 non-null int64
ped_count            148112 non-null int64
ped_cycle_count      148112 non-null int64
veh_count            148112 non-null int64
injuries             148112 non-null int64
serious_injuries     148112 non-null int64
fatalities           148112 non-null int64
junc_type            148112 non-null object
under_infl           148112 non-null float64
weather              148112 non-null object
roadcond             148112 non-null object
light_cond           148112 non-null object
speeding             148112 non-null int64
hit_parked_car       148112 non-null object
Year                 148112 non-null int64
Month                148112 non-null int64
Weekday              148112 non-null int64
Hour                 148112 non-null int64
dtypes: float64(3), int64(12), object(8)
memory usage: 27.1+ MB
```

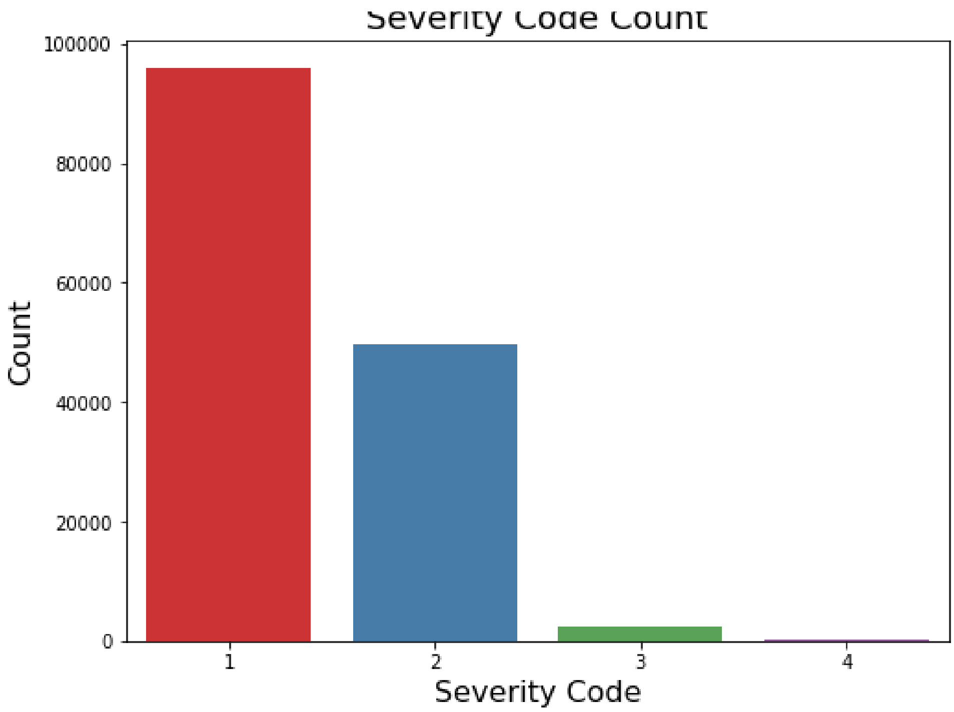
This concludes the data cleaning part of our work. Now let us begin exploratory data analysis before we move to modelling.

5. Exploratory Data Analysis

We will start by visualizing the distribution of accident severity.

In [30]:

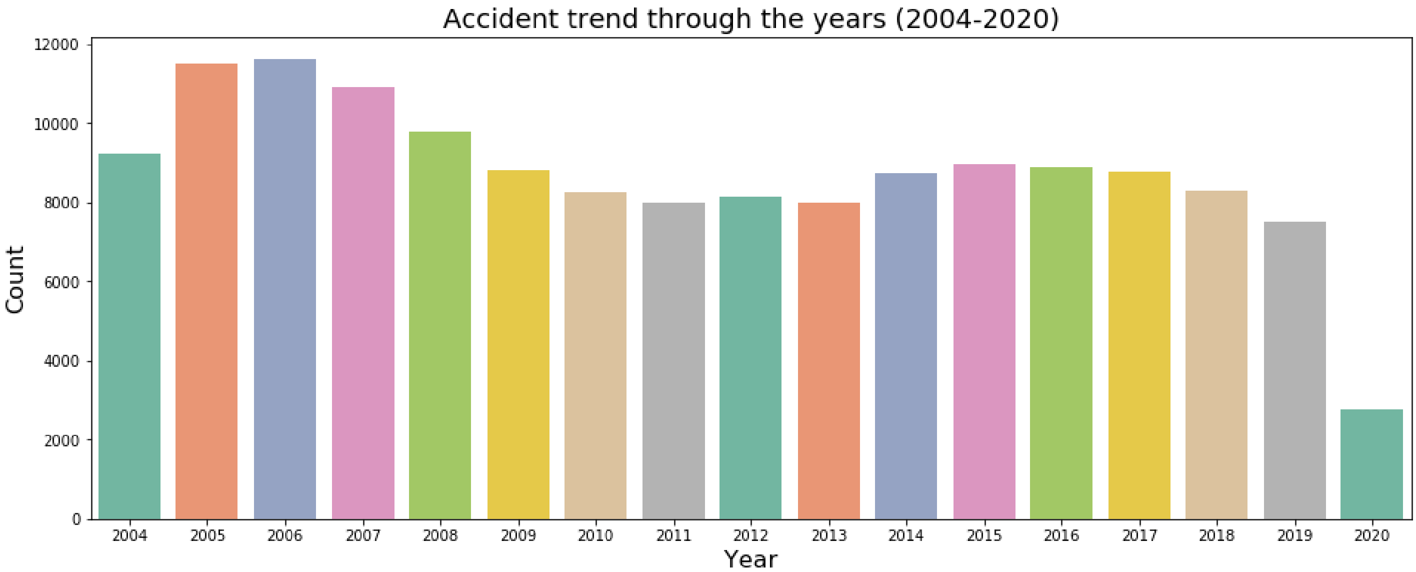
```
import seaborn as sns

plt.figure(figsize=(8,6))
sns.countplot(x ='severity_code', palette='Set1', data = df)
plt.title('Severity Code Count', fontsize=18)
plt.xlabel('Severity Code', fontsize=16)
plt.ylabel('Count', fontsize=16)
plt.show()
```



Again we see that most accidents cause only property damage or minor injuries. Next, let us see the trend of collisions on roads through the years.

In [31]:

```
plt.figure(figsize=(16,6))
sns.countplot(x ='Year', palette='Set2', data = df)
plt.title('Accident trend through the years (2004-2020)', fontsize=18)
plt.xlabel('Year', fontsize=16)
plt.ylabel('Count', fontsize=16)
plt.show()
```

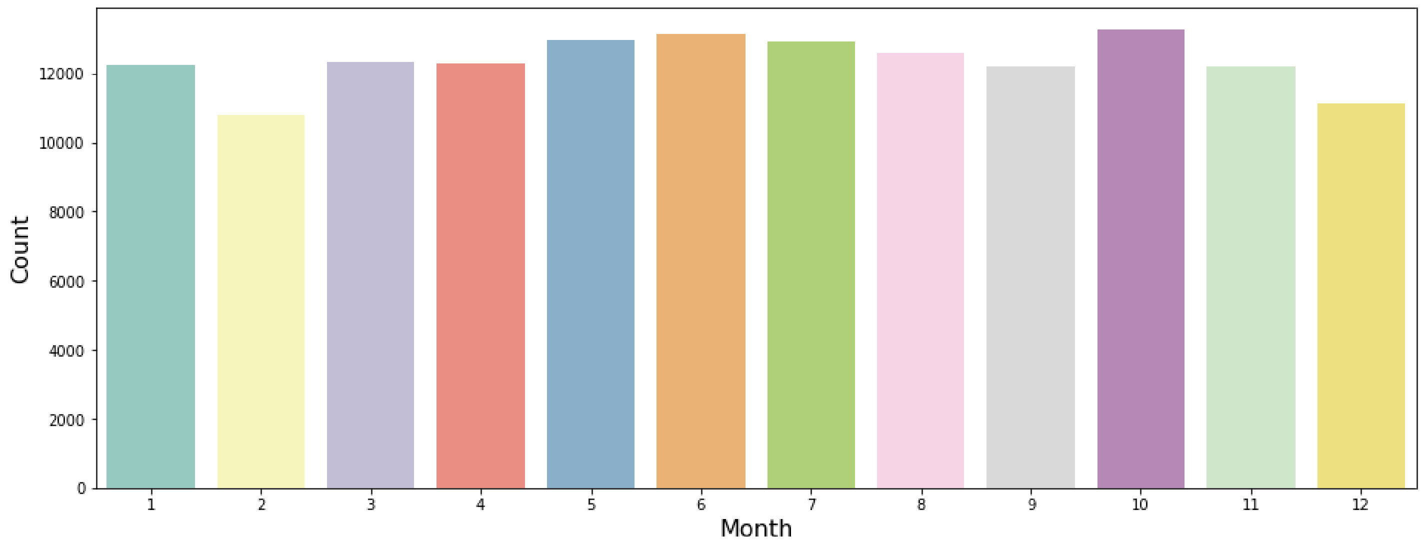


So we can see that the number of road accidents have somewhat decreased over the last decade which is a good sign. The data for the year 2020 is incomplete and should not be seen in comparison with previus years. Next let us have a look at the accident trends through the Months.

In [32]:

```
plt.figure(figsize=(16,6))
sns.countplot(x ='Month', palette='Set3', data = df)
plt.title('Accident trend through the months (2004-2020)', fontsize=18)
plt.xlabel('Month', fontsize=16)
plt.ylabel('Count', fontsize=16)
plt.show()
```

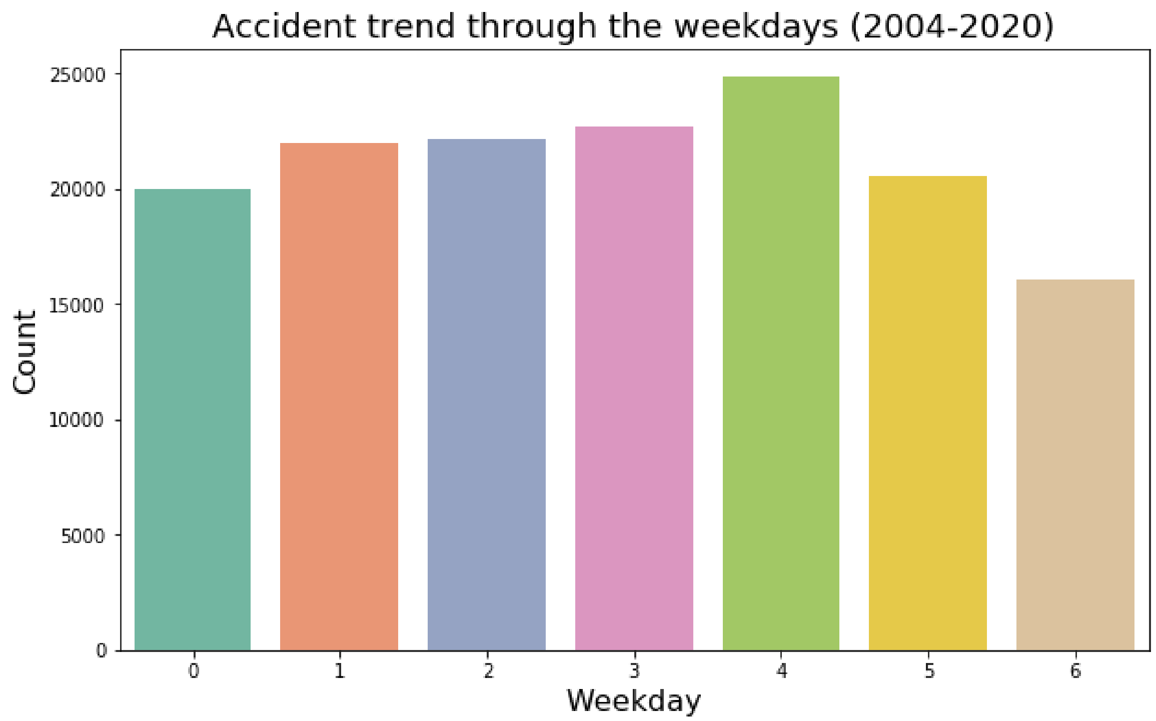
Accident trend through the months (2004-2020)



There is no clear trend in number of collisions and month of the year. How about the collision trend through the weekdays?

In [33]:

```
plt.figure(figsize=(10,6))
sns.countplot(x ='Weekday', palette='Set2', data = df)
plt.title('Accident trend through the weekdays (2004-2020)', fontsize=18)
plt.xlabel('Weekday', fontsize=16)
plt.ylabel('Count', fontsize=16)
plt.show()
```



In the plot above weekday 0 corresponds to Monday and so on. We see that the number of accidents peak on friday then start decreasing again. Now let us have a look at the hourly distribution of collisions in a day. But before that let us divide the day into different times such as morning, noon, night etc.

In [34]:

```
bins = [0,4,8,12,16,20,24]
labels = ['Late Night', 'Early Morning','Morning','Noon','Eve','Night']
df['Time'] = pd.cut(df['Hour'], bins=bins, labels=labels, include_lowest=True)
df[['Time', 'Hour']].sample(5)
```

Out[34]:

	Time	Hour

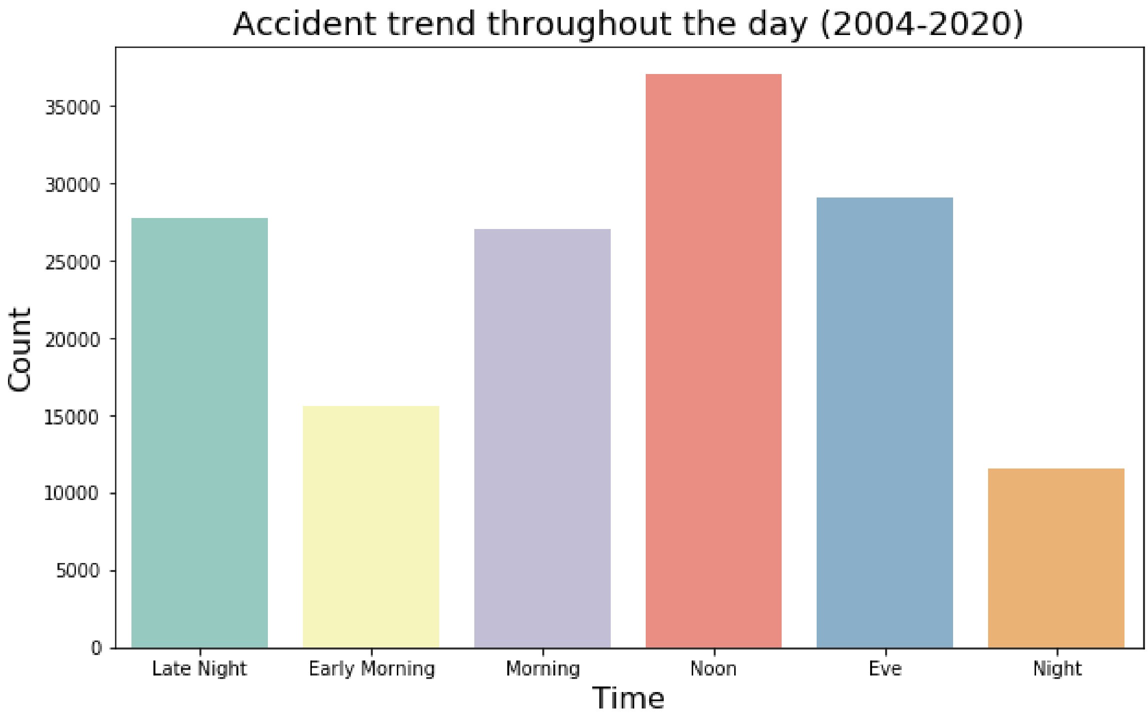
	Time	Hour
161380	Night	22
145744	Early Morning	8
78266	Morning	9
218917	Night	21
218878	Morning	12

In [35]:

```
df.drop('Hour', axis=1, inplace=True) #Dropping Hour column as it is no longer needed
```

In [36]:

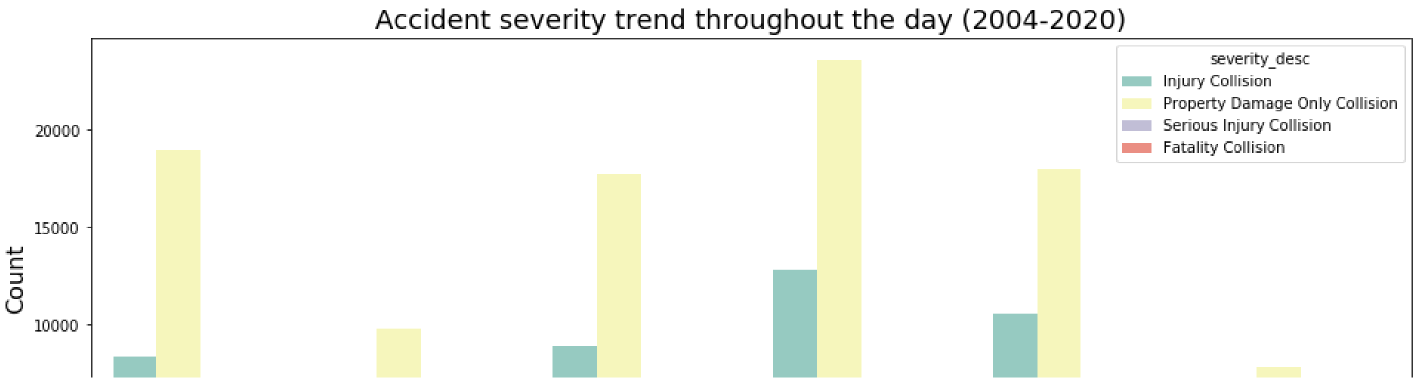
```
plt.figure(figsize=(10,6))
sns.countplot(x ='Time', palette='Set3', data = df)
plt.title('Accident trend throughout the day (2004-2020)', fontsize=18)
plt.xlabel('Time', fontsize=16)
plt.ylabel('Count', fontsize=16)
plt.show()
```

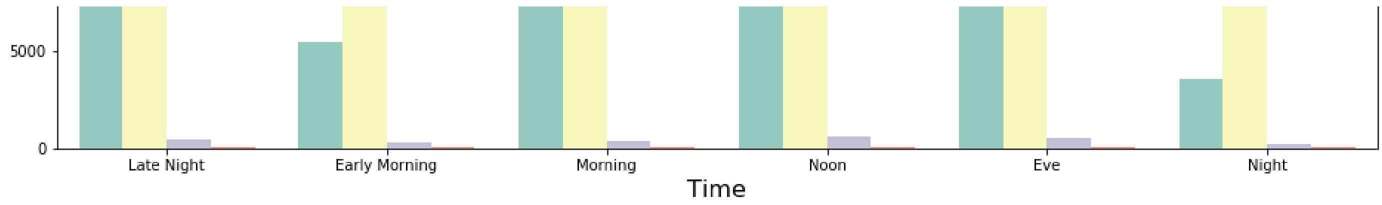


We can see that most accidents happen at noon followed by evening and late night repectively. Let us also see how the severity of accidents vary through different times of the day.

In [37]:

```
plt.figure(figsize=(16,6))
sns.countplot(x ='Time', palette='Set3', hue= 'severity_desc', data = df)
plt.title('Accident severity trend throughout the day (2004-2020)', fontsize=18)
plt.xlabel('Time', fontsize=16)
plt.ylabel('Count', fontsize=16)
plt.show()
```





In [38]:

```
pd.crosstab(df.Time, df.severity_code)
```

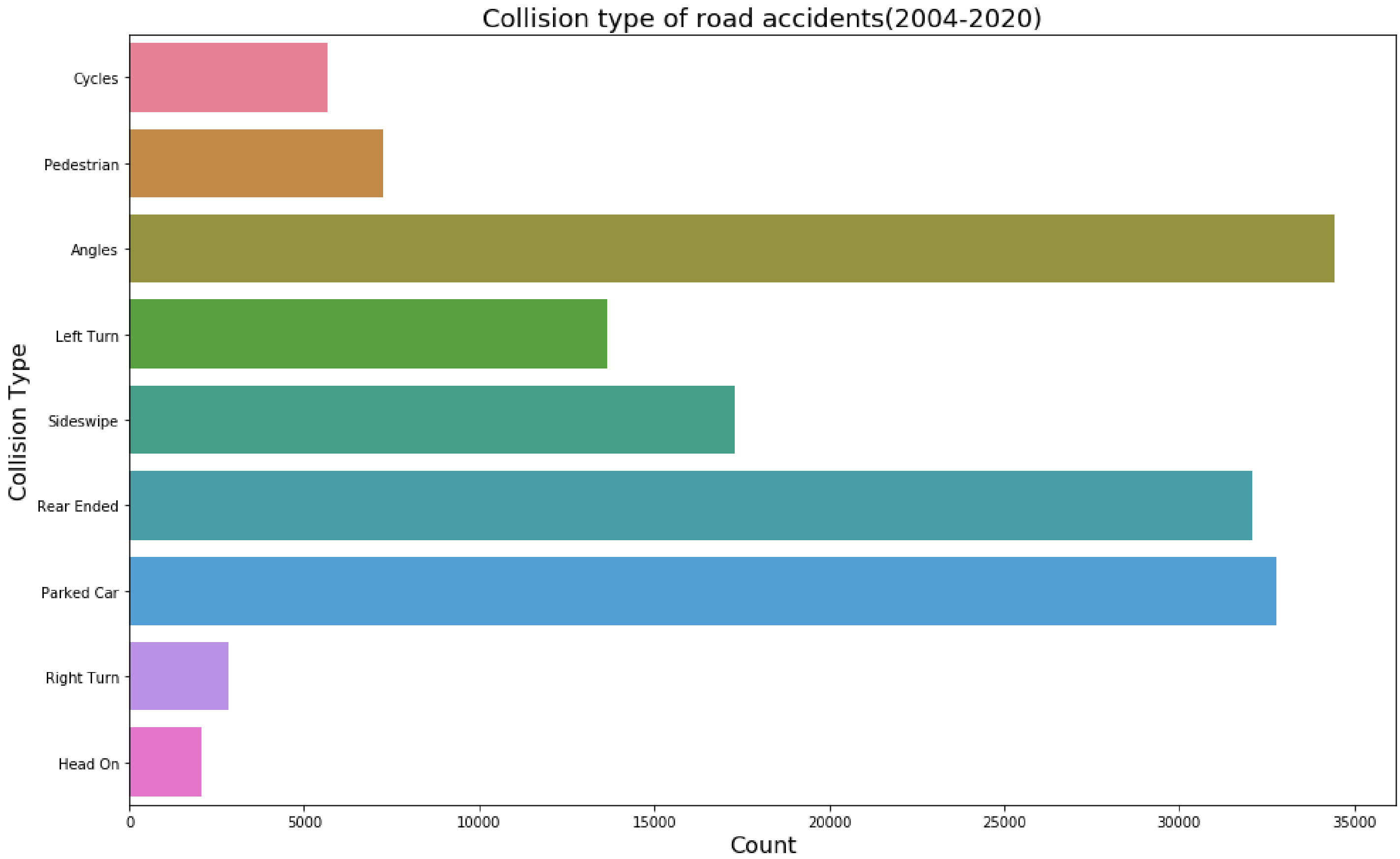
Out[38]:

severity_code	1	2	3	4
Time				
Late Night	18941	8323	477	55
Early Morning	9796	5438	282	30
Morning	17778	8892	359	33
Noon	23574	12838	568	53
Eve	17988	10520	543	45
Night	7802	3534	219	24

We see that most fatal accidents happen at late might and noon, but we cannot establish anything concrete from this distribution. Next, let us look at the distribution of collision type.

In [39]:

```
plt.figure(figsize=(16,10))
sns.countplot(y ='collision_type', palette='husl', data = df)
plt.title('Collision type of road accidents(2004-2020)', fontsize=18)
plt.xlabel('Count', fontsize=16)
plt.ylabel('Collision Type', fontsize=16)
plt.show()
```

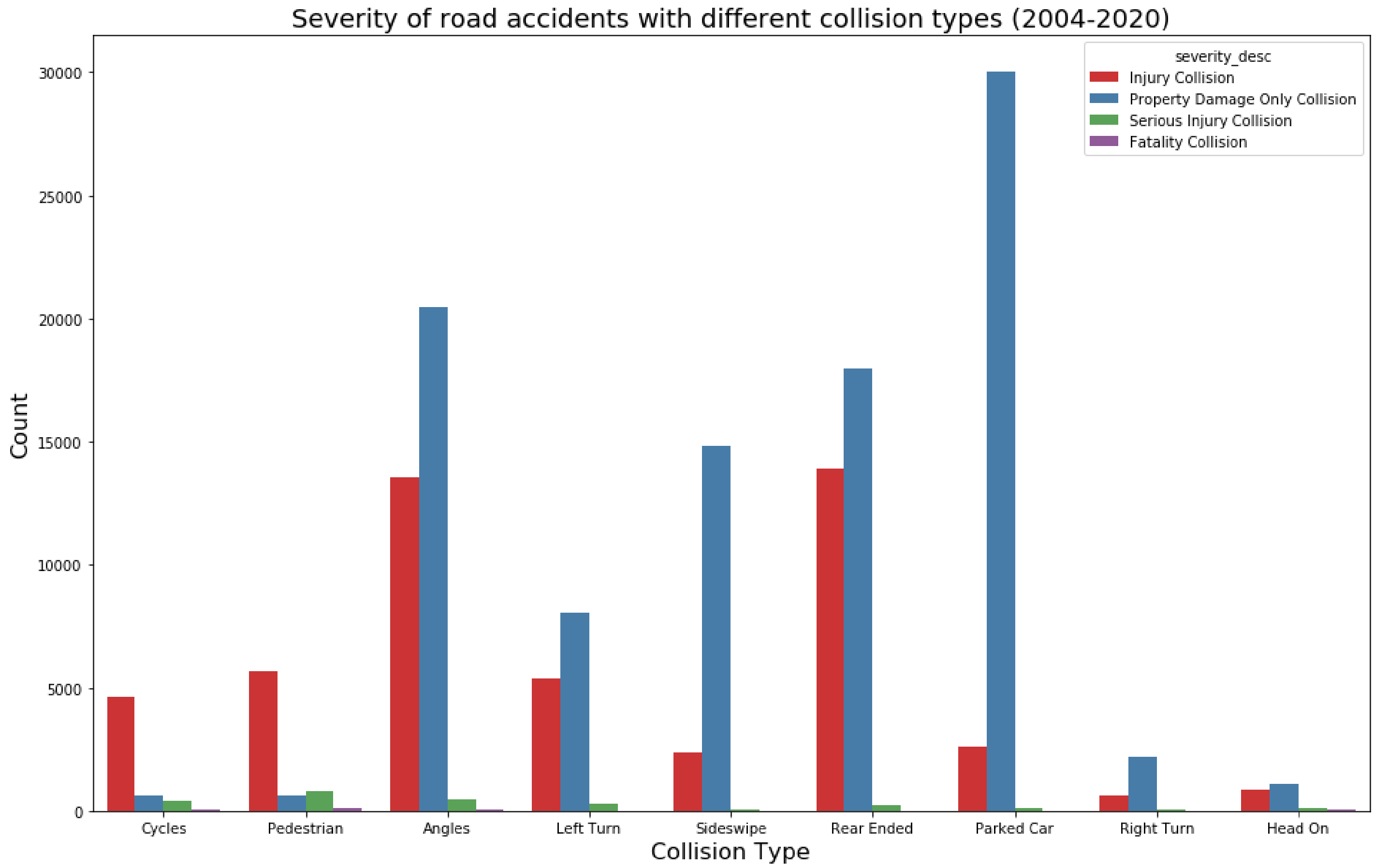


We see that most accidents are angled crashes followed by parked car and rear end crashes. Let us see the

severity distribution of these collision types.

In [40]:

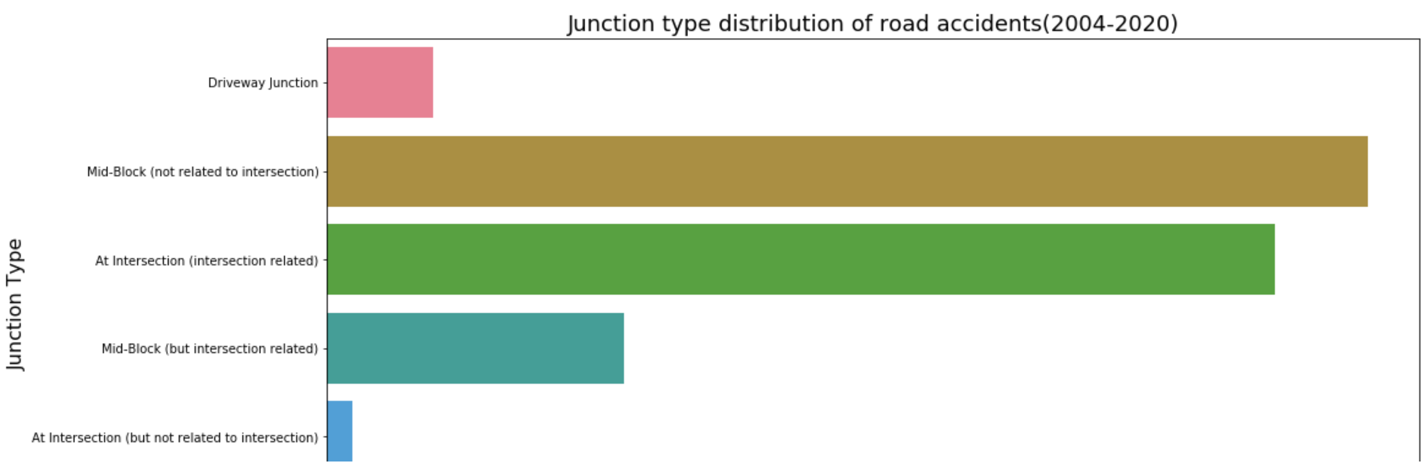
```
plt.figure(figsize=(16,10))

sns.countplot(hue ='severity_desc', palette='Set1', x= 'collision_type', data = df)
plt.title('Severity of road accidents with different collision types (2004-2020)', fontsi
ze=18)
plt.xlabel('Collision Type', fontsize=16)
plt.ylabel('Count', fontsize=16)
plt.show()
```

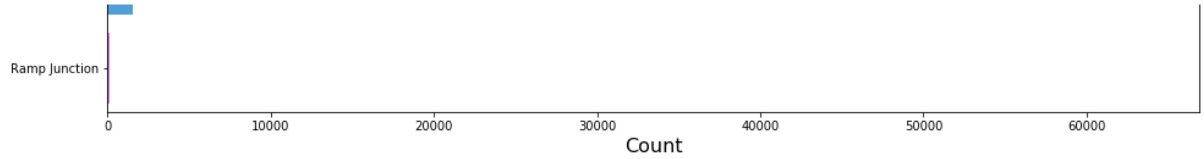


As expected, we can see that most property damage only collisions are caused by parked car collisions. And most serious injuries and fatalities are caused by collisions with pedestrians. As such special attantion should be paid towards pedestrian safety. We can also see the collision distribution as per junction type.

In [41]:

```
plt.figure(figsize=(16,8))
sns.countplot(y ='junc_type', palette='husl', data = df)
plt.title('Junction type distribution of road accidents(2004-2020)', fontsize=18)
plt.xlabel('Count', fontsize=16)
plt.ylabel('Junction Type', fontsize=16)
plt.show()
```

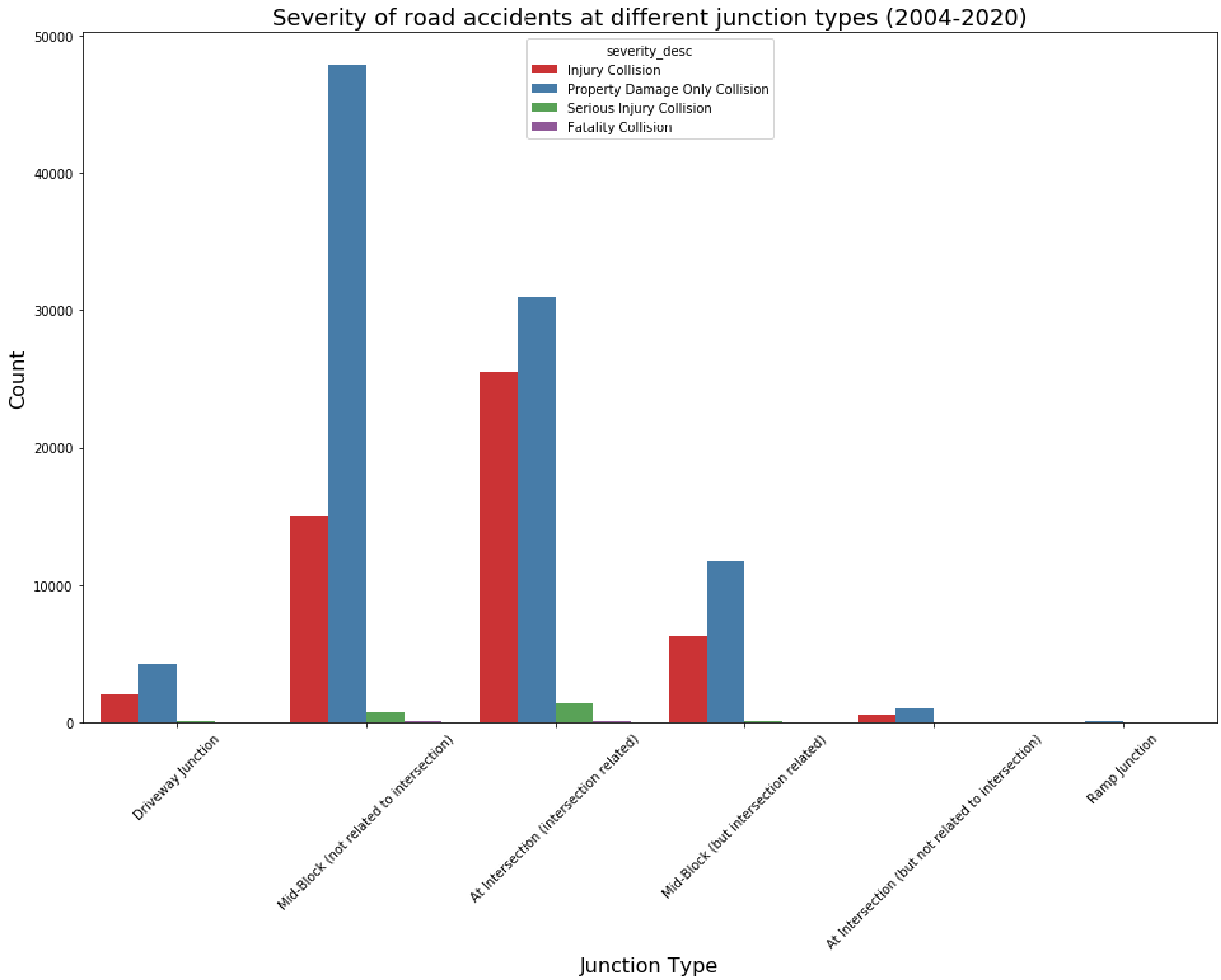




We fins that most collisions occur at midblock and intersections as expected, given that they are points where the traffic merges. Now let us see the severity distribution of collisions at these locations.

In [42]:

```
plt.figure(figsize=(16,10))

sns.countplot(hue ='severity_desc', palette='Set1', x= 'junc_type', data = df)
plt.title('Severity of road accidents at different junction types (2004-2020)', fontsize=
18)
plt.xlabel('Junction Type', fontsize=16)
plt.ylabel('Count', fontsize=16)
plt.xticks(rotation= 45)
plt.show()
```



We find that most property damage only collisions occur at midblocks while most injury collisions happen at intersections. Now let us see how weather, road conditions and light conditions affect collision count.

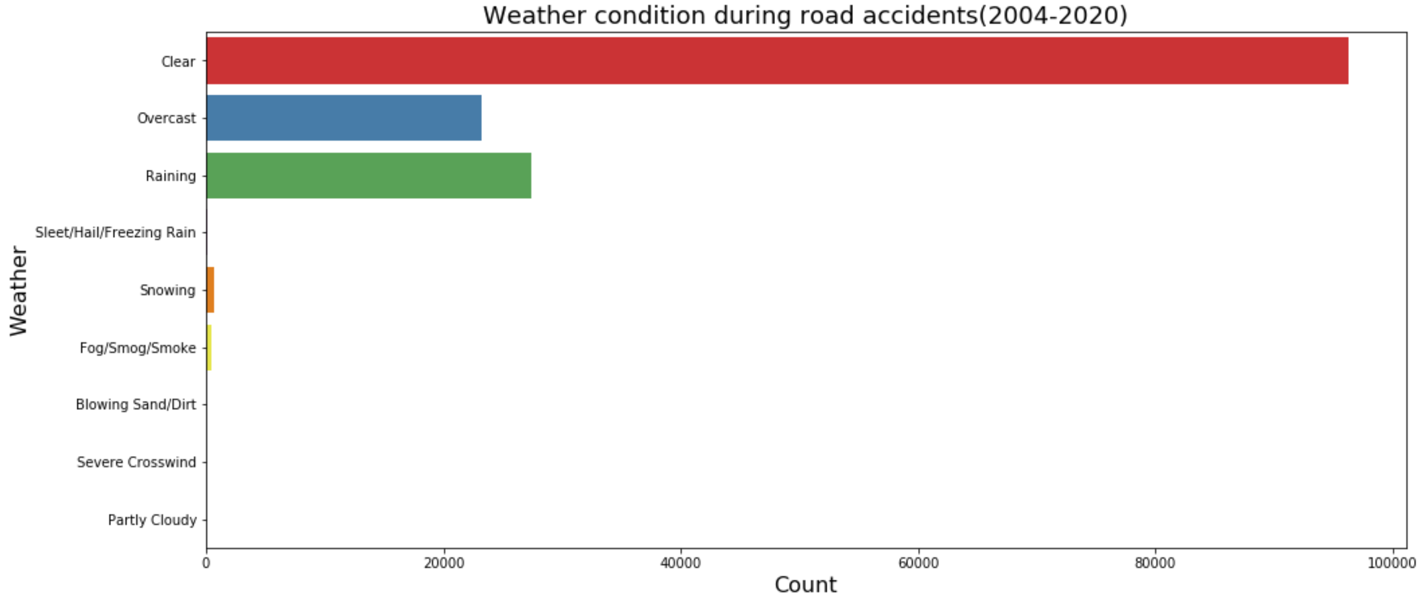
In [43]:

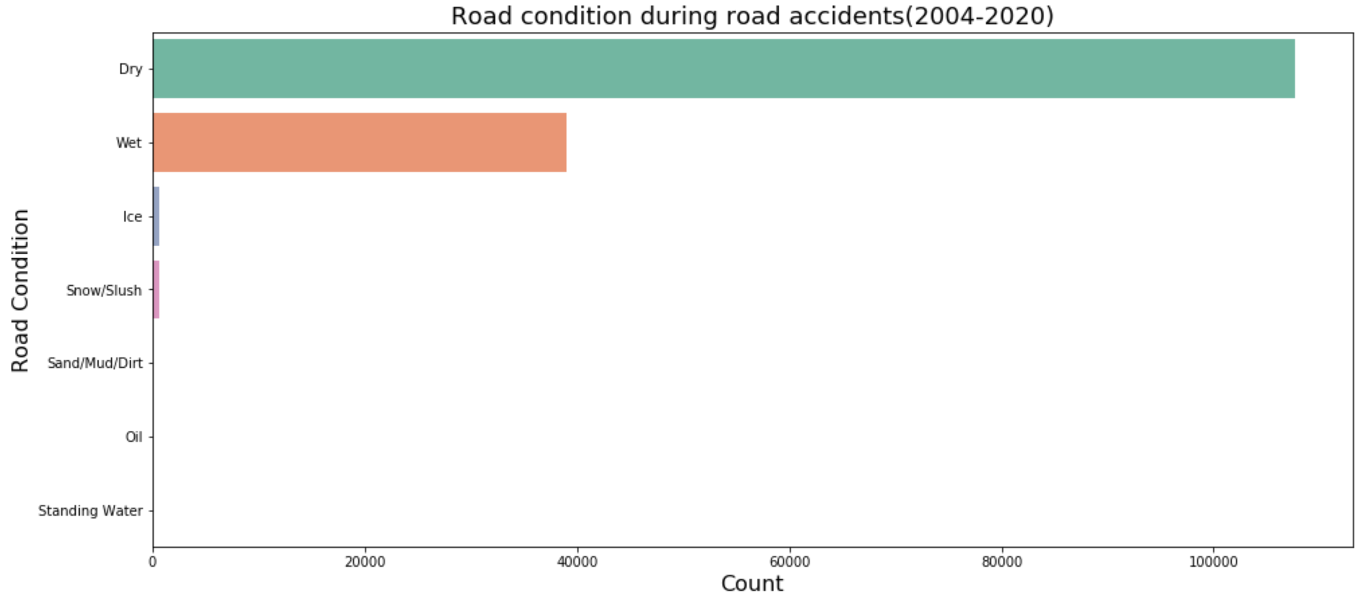
```
fig= plt.figure(figsize=(16,24))
ax1= fig.add_subplot(3,1,1)
ax2= fig.add_subplot(3,1,2)
ax3= fig.add_subplot(3,1,3)
sns.countplot(y ='weather', palette='Set1', data = df, ax=ax1)
```

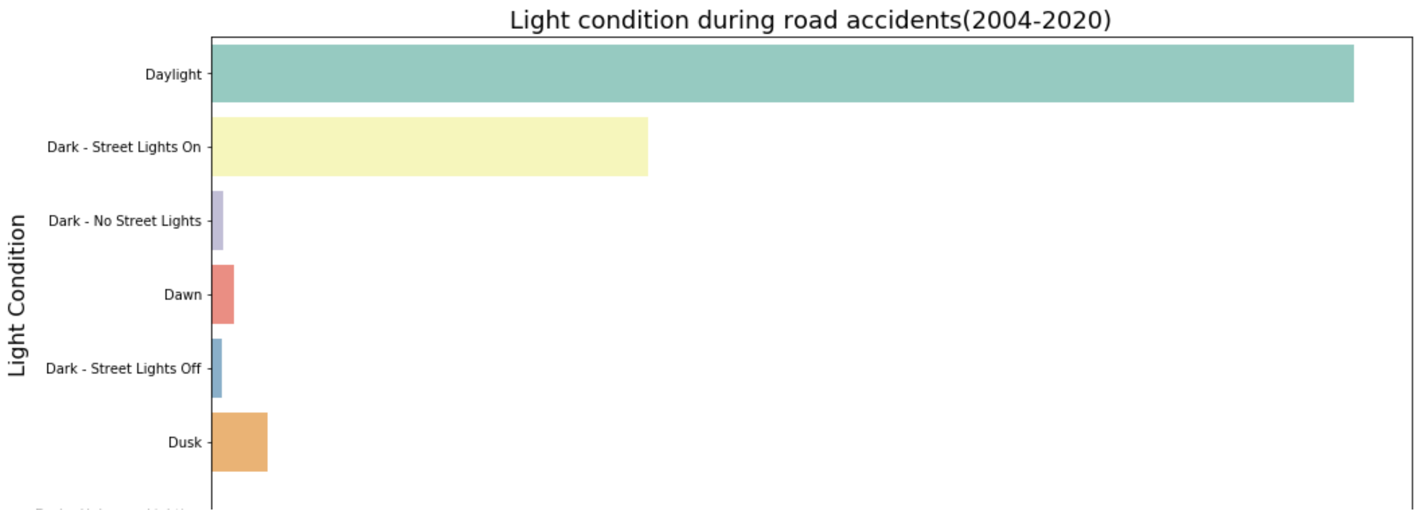
```
sns.countplot(y ='roadcond', palette='Set2', data = df, ax=ax2)
sns.countplot(y ='light_cond', palette='Set3', data = df, ax=ax3)
ax1.set_title('Weather condition during road accidents(2004-2020)', fontsize=18)
ax1.set_xlabel('Count', fontsize=16)
ax1.set_ylabel('Weather', fontsize=16)
ax2.set_title('Road condition during road accidents(2004-2020)', fontsize=18)
ax2.set_xlabel('Count', fontsize=16)
ax2.set_ylabel('Road Condition', fontsize=16)
ax3.set_title('Light condition during road accidents(2004-2020)', fontsize=18)
ax3.set_xlabel('Count', fontsize=16)
ax3.set_ylabel('Light Condition', fontsize=16)
```

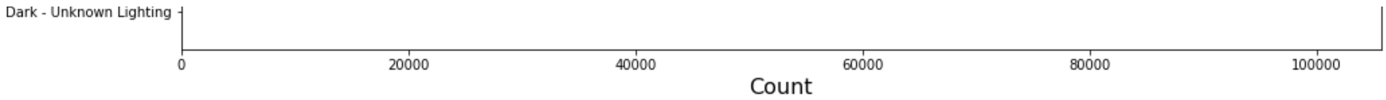
Out[43]:

```
Text(0, 0.5, 'Light Condition')
```









Unexpectedly, most collisions happened during clear days on dry roads in daylight. This might be because of greater traffic volume during the day time and clear weather.

Now let us see how many accidents happened under the influence of alcohol/drugs and the severity of these accidents.

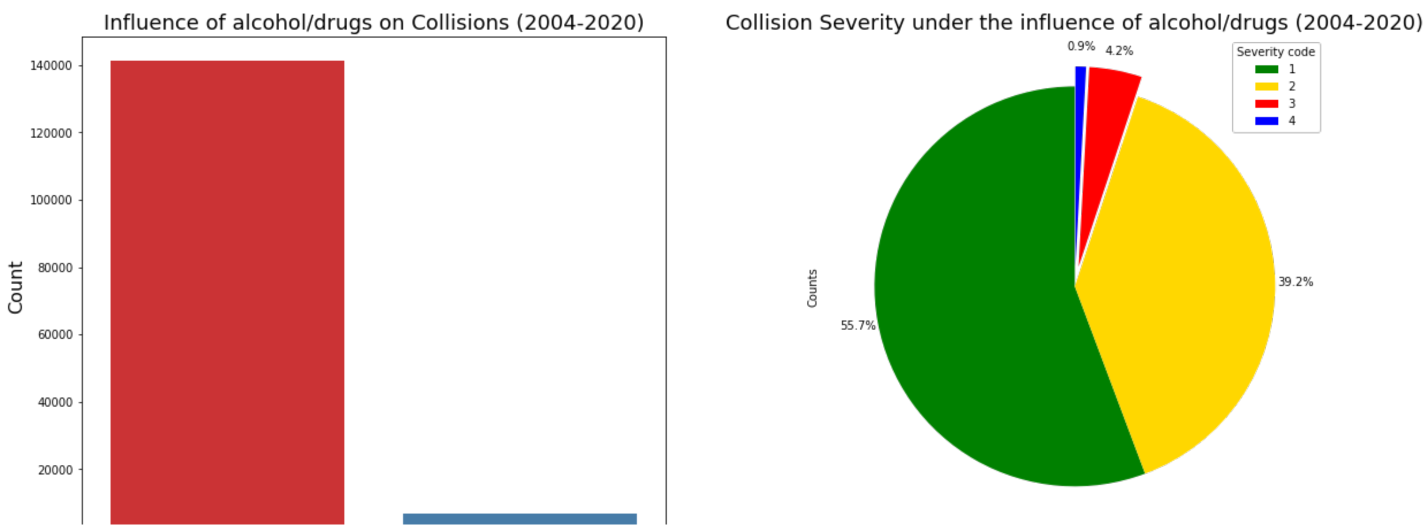
In [44]:

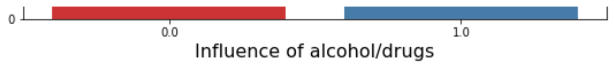
```
fig= plt.figure(figsize=(20,8))
ax1= fig.add_subplot(1,2,1)
ax2= fig.add_subplot(1,2,2)

sns.countplot(x ='under_infl', palette='Set1', data = df, ax=ax1)
color_list= ['green', 'gold', 'red', 'blue']
explode_list=[0, 0, 0.1, 0.1]
df[df.under_infl==1].groupby('severity_code').size().to_frame('Counts').Counts.plot(kind
='pie', autopct= '%1.1f%%', startangle= 90, shadow= False,
                                                    pctdistance =1.1, color
s= color_list, explode=explode_list, labels=None, ax=ax2)


ax1.set_title('Influence of alcohol/drugs on Collisions (2004-2020)', fontsize=18)
ax1.set_xlabel('Influence of alcohol/drugs', fontsize=16)
ax1.set_ylabel('Count', fontsize=16)

ax2.set_title('Collision Severity under the influence of alcohol/drugs (2004-2020)', font
size=18)
ax2.legend(title= 'Severity code',labels= df[df.under_infl==1].groupby('severity_code').
size().to_frame().index, loc= 'upperright')
```

```
/opt/conda/envs/Python36/lib/python3.6/site-packages/matplotlib/legend.py:497: UserWarnin
g: Unrecognized location "upperright". Falling back on "best"; valid locations are
 best
 upper right
 upper left
 lower left
 lower right
 right
 center left
 center right
 lower center
 upper center
 center

  % (loc, '\n\t'.join(self.codes)))
```

Out[44]:

```
<matplotlib.legend.Legend at 0x7fb054453c88>
```





We see that in the majority of the collisions that occur, the drivers where not under the influence of alcohol/drugs. Among those that do, 44.3% collisions lead to injuries with some even serious or fatal. Now let us see how speeding affects the collision count and severity.

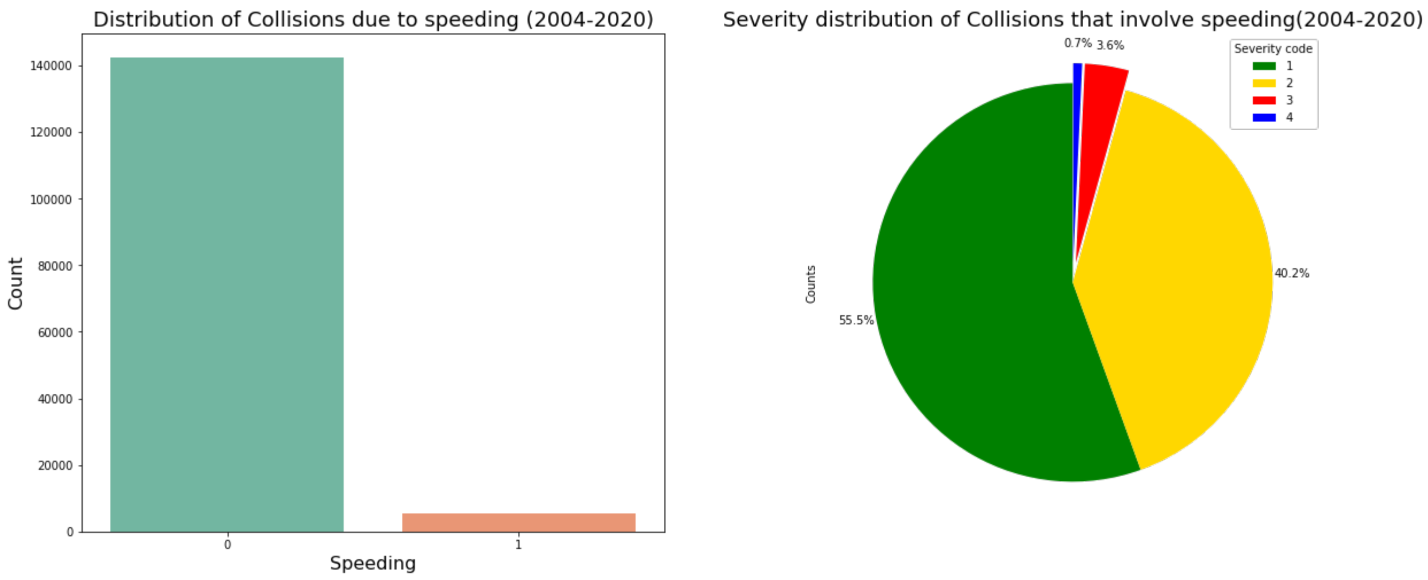
In [45]:

```
fig= plt.figure(figsize=(20,8))
ax1= fig.add_subplot(1,2,1)
ax2= fig.add_subplot(1,2,2)

sns.countplot(x ='speeding', palette='Set2', data = df, ax=ax1)

color_list= ['green', 'gold', 'red', 'blue']
explode_list=[0, 0, 0.1, 0.1]
df[df.speeding==1].groupby('severity_code').size().to_frame('Counts').Counts.plot(kind='
pie', autopct= '%1.1f%%', startangle= 90, shadow= False,
                                                   pctdistance =1.1, color
s= color_list, explode=explode_list, labels=None, ax=ax2)


ax1.set_title('Distribution of Collisions due to speeding (2004-2020)', fontsize=18)
ax1.set_xlabel('Speeding', fontsize=16)
ax1.set_ylabel('Count', fontsize=16)

ax2.set_title('Severity distribution of Collisions that involve speeding(2004-2020)', fon
tsize=18)
ax2.legend(title= 'Severity code',labels= df[df.speeding==1].groupby('severity_code').si
ze().to_frame().index, loc= 'upperright')
```

```
/opt/conda/envs/Python36/lib/python3.6/site-packages/matplotlib/legend.py:497: UserWarnin
g: Unrecognized location "upperright". Falling back on "best"; valid locations are
 best
 upper right
 upper left
 lower left
 lower right
 right
 center left
 center right
 lower center
 upper center
 center

  % (loc, '\n\t'.join(self.codes)))
```

Out[45]:

```
<matplotlib.legend.Legend at 0x7fb05423a940>
```



Again we see that most collisions do not involve speeding which is a good thing. Amongst those that involve speeding, 44.5% of collisions result in injuries with some even serious and fatal. Now let us see how many collisions involve hitting of a parked car and how severe these collisions are.

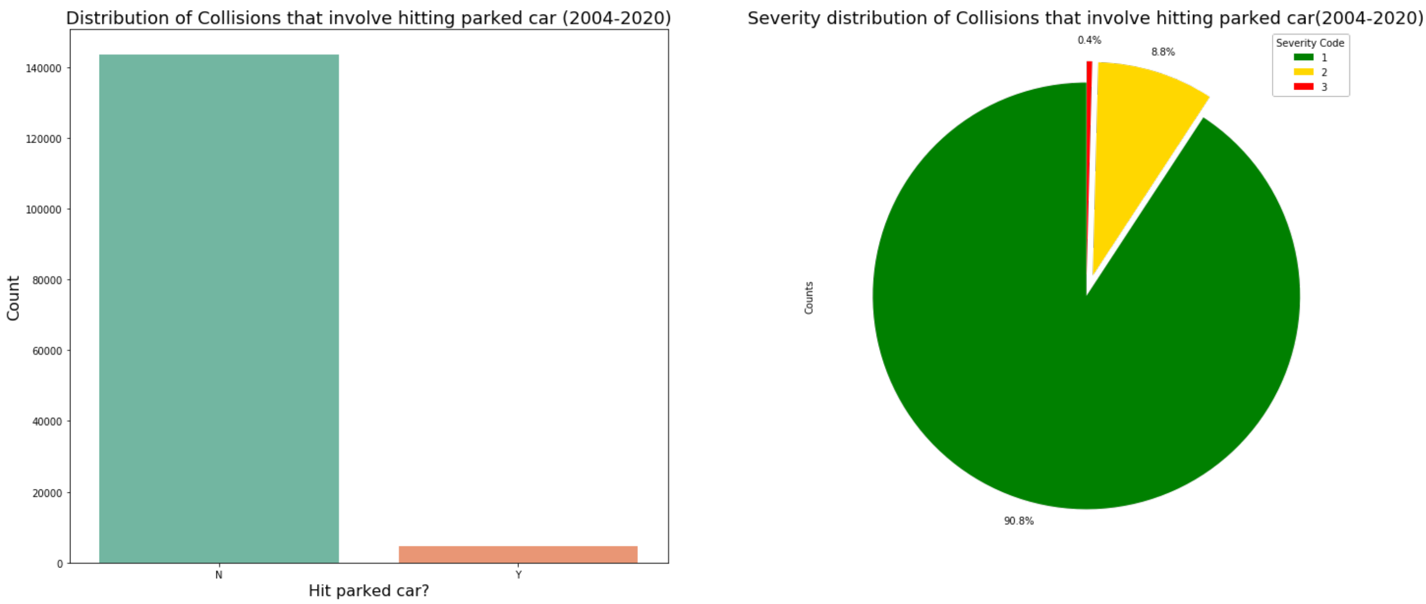
In [46]:

```
fig= plt.figure(figsize=(24,10))
ax1= fig.add_subplot(1,2,1)
ax2= fig.add_subplot(1,2,2)

sns.countplot(x ='hit_parked_car', palette='Set2', data = df, ax=ax1)

color_list= ['green', 'gold', 'red']
explode_list=[0, 0.1, 0.1]
df[df.hit_parked_car=='Y'].groupby('severity_code').size().to_frame('Counts').Counts.plo
t(kind='pie', autopct= '%1.1f%%', startangle= 90, shadow= False,
                                                                  pctdistance =1.1, color
s= color_list, explode=explode_list, labels=None, ax=ax2)

ax1.set_title('Distribution of Collisions that involve hitting parked car (2004-2020)', f
ontsize=18)
ax1.set_xlabel('Hit parked car?', fontsize=16)
ax1.set_ylabel('Count', fontsize=16)

ax2.set_title('Severity distribution of Collisions that involve hitting parked car(2004-2
020)', fontsize=18)
ax2.legend(title= 'Severity Code',labels= df[df.hit_parked_car=='Y'].groupby('severity_c
ode').size().to_frame().index, loc= 'upperright')
```

```
/opt/conda/envs/Python36/lib/python3.6/site-packages/matplotlib/legend.py:497: UserWarnin
g: Unrecognized location "upperright". Falling back on "best"; valid locations are
 best
 upper right
 upper left
 lower left
 lower right
 right
 center left
 center right
 lower center
 upper center
 center

  % (loc, '\n\t'.join(self.codes)))
```

Out[46]:

```
<matplotlib.legend.Legend at 0x7fb054183898>
```



We see that most collisions do not involve hitiing parked cars. And even amongst those that do, there are no fatalities and very few resulted in serious injuries amongst the people involved. Now let us see the correlation

fatalities and very few resulted in serious injuries amongst the people involved. Now let us see the correlation between the severity_code and injuries, serious_injuries and fatalities columns, as they seem to indicate the same thing superficially.

In [47]:

```
df_temp= df[['severity_code','injuries', 'serious_injuries', 'fatalities' ]].groupby('se
verity_code', as_index= False).sum()
df_temp
```

Out[47]:

	severity_code	injuries	serious_injuries	fatalities
0	1	0	0	0
1	2	66586	0	0
2	3	3493	2607	0
3	4	225	84	248

So the matrix indicates very strong correlation with severity. Let us check the correlation coefficient between severity_code and these features.

Since, apart from Severity Code = 1 ("Property Damage Only Collision"), Severity code is assigned based on the injury level, the former is a direct reflection of the latter. If we use injury features as predictors, it is easily seen that those will overwhelm the other features, and the prediction will be based on the after-effects of a collision. Therefore, these three features will be ignored.

In [48]:

```
df.drop(['injuries', 'serious_injuries', 'fatalities'], axis= 1, inplace=True)
```

In [49]:

```
df.columns
```

Out[49]:

```
Index(['longitude', 'latitude', 'severity_code', 'severity_desc',
       'collision_type', 'person_count', 'ped_count', 'ped_cycle_count',
       'veh_count', 'junc_type', 'under_infl', 'weather', 'roadcond',
       'light_cond', 'speeding', 'hit_parked_car', 'Year', 'Month', 'Weekday',
       'Time'],
      dtype='object')
```

Superficially it appears that 'severity_code', 'collision_type', 'person_count', 'ped_count', 'ped_cycle_count', 'veh_count', 'junc_type', 'under_infl', 'weather', 'roadcond', 'light_cond', 'speeding', 'hit_parked_car' are the only columns that are relevant to the problem. The column hit_parked_car seem to have object variables 'Y' and 'N', thus replacing them with '1' and '0' respectively to make the dataset more uniform.

In [50]:

```
df['hit_parked_car'].replace(to_replace={'Y':1, 'N':0 }, inplace=True)
```

In [51]:

```
df= df[[ 'severity_code', 'collision_type', 'person_count', 'ped_count', 'ped_cycle_coun
t', 'veh_count', 'junc_type', 'under_infl',
        'weather', 'roadcond', 'light_cond', 'speeding', 'hit_parked_car']]
```

In [52]:

```
df.dtypes
```

Out[52]:

```
severity_code        object
collision_type       object
```

```
collision_type        object
person_count           int64
ped_count              int64
ped_cycle_count        int64
veh_count              int64
junc_type             object
under_infl           float64
weather               object
roadcond              object
light_cond            object
speeding               int64
hit_parked_car         int64
dtype: object
```

The features 'collision_type', 'junc_type', 'weather', 'roadcond', 'light_cond' are object type and need to be converted into int type for modelling as they are going to be the independent variables or predictors. So, employing one-hot encoding to add dummy variables to the dataframe in their place.

In [53]:

```
df = pd.concat([df.drop(['junc_type', 'collision_type', 'weather', 'roadcond', 'light_co
nd' ], axis=1),
                 pd.get_dummies(df['weather']),
                 pd.get_dummies(df['roadcond']),
                 pd.get_dummies(df['light_cond']),
               pd.get_dummies(df['junc_type']),
               pd.get_dummies(df['collision_type'])], axis=1)
df.reset_index(drop=True, inplace=True)
```

In [54]:

```
df.head().T
```

Out[54]:

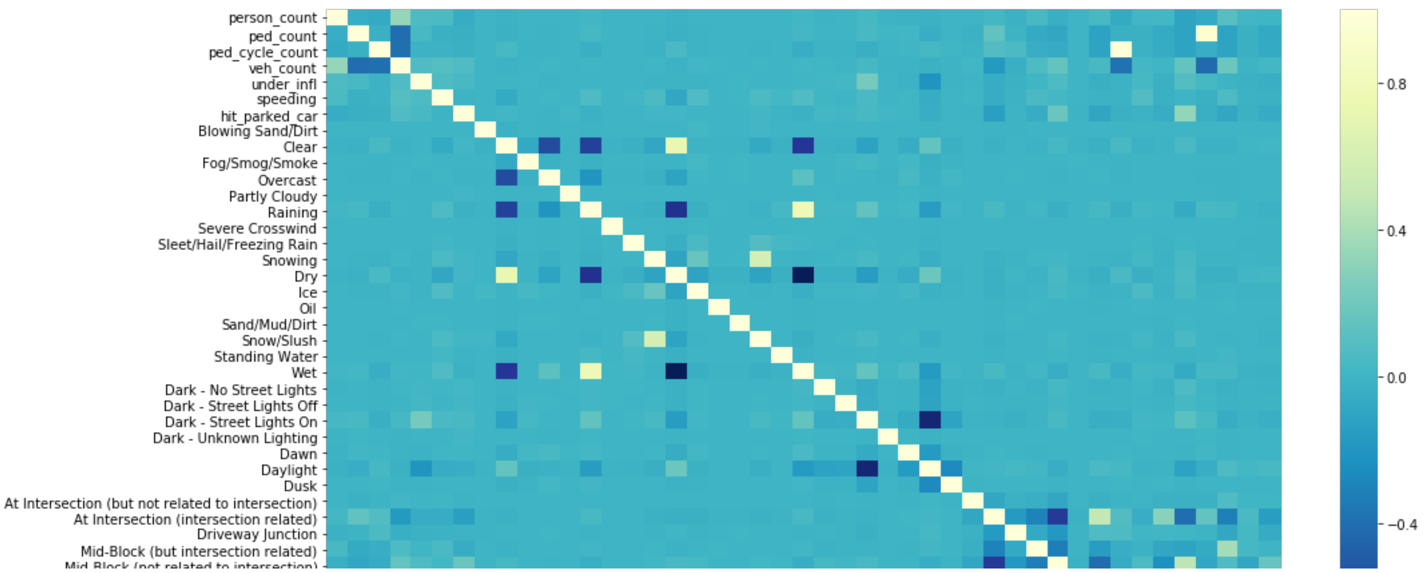
	0	1	2	3	4
severity_code	2	2	1	2	1
person_count	2	7	2	5	3
ped_count	0	1	0	0	0
ped_cycle_count	1	0	0	0	0
veh_count	1	1	2	2	2
under_infl	0	0	0	0	0
speeding	0	0	0	0	0
hit_parked_car	0	0	0	0	0
Blowing Sand/Dirt	0	0	0	0	0
Clear	1	0	0	1	1
Fog/Smog/Smoke	0	0	0	0	0
Overcast	0	1	1	0	0
Partly Cloudy	0	0	0	0	0
Raining	0	0	0	0	0
Severe Crosswind	0	0	0	0	0
Sleet/Hail/Freezing Rain	0	0	0	0	0
Snowing	0	0	0	0	0
Dry	1	1	0	1	1
Ice	0	0	0	0	0
Oil	0	0	0	0	0
Sand/Mud/Dirt	0	0	0	0	0
Snow/Slush	0	0	0	0	0

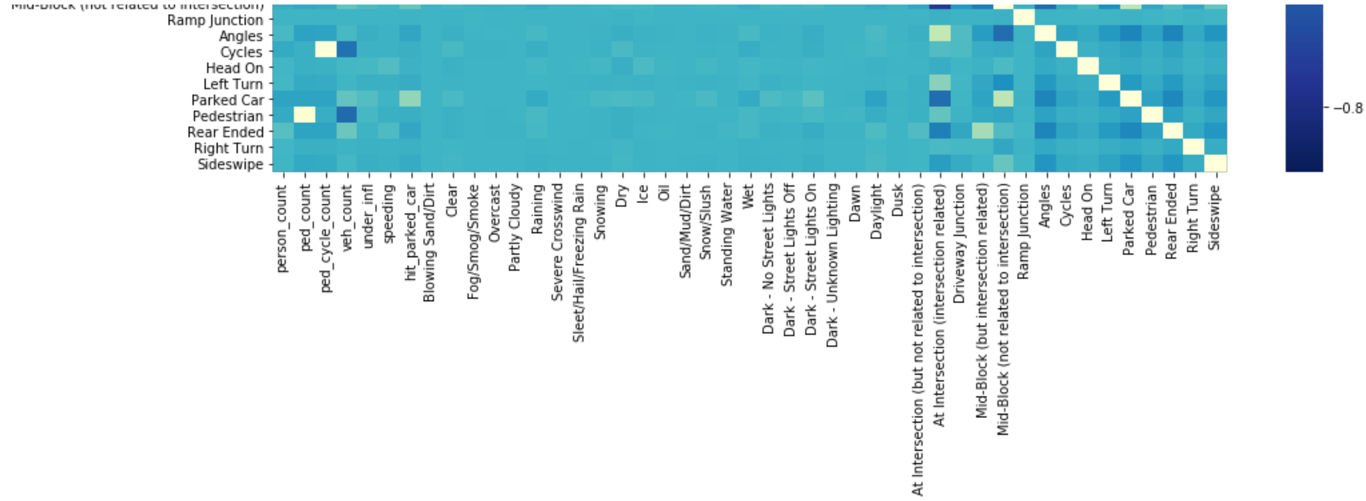
	0	1	2	3	4
Snow/Slush	0	0	0	0	0
Standing Water	0	0	0	0	0
Wet	0	0	1	0	0
Dark - No Street Lights	0	0	0	0	0
Dark - Street Lights Off	0	0	0	0	0
Dark - Street Lights On	0	1	0	0	0
Dark - Unknown Lighting	0	0	0	0	0
Dawn	0	0	0	0	0
Daylight	1	0	1	1	1
Dusk	0	0	0	0	0
At Intersection (but not related to intersection)	0	0	0	0	0
At Intersection (intersection related)	0	0	1	1	1
Driveway Junction	1	0	0	0	0
Mid-Block (but intersection related)	0	0	0	0	0
Mid-Block (not related to intersection)	0	1	0	0	0
Ramp Junction	0	0	0	0	0
Angles	0	0	1	0	0
Cycles	1	0	0	0	0
Head On	0	0	0	0	0
Left Turn	0	0	0	1	0
Parked Car	0	0	0	0	0
Pedestrian	0	1	0	0	0
Rear Ended	0	0	0	0	0
Right Turn	0	0	0	0	0
Sideswipe	0	0	0	0	1

Now let us find the correlation between our variables. Correlation is a statistical technique that can show whether and how strongly pairs of variables are interdependent. Finding the correlation among the features of the dataset helps understand the data better. For example, in the heatmap shown below, it can be observed that some features have a strong positive / negative correlation while most of them have weak / no correlation.

In [55]:

```
plt.figure(figsize=(16,10))
sns.heatmap(df.corr(), cmap='YlGnBu_r')
plt.show()
```





We are going to take all features other than severity_code, which is our target variable, as predictors. Now before we begin modelling, let us split the dataset into train and test sets using train_test_split() after standardizing the input features.

In [56]:

```
import itertools
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler

#Setting target variable
target='severity_code'

# set X and y
y = df[target]
X = df.drop(target, axis=1)

X = StandardScaler().fit(X).transform(X)

# Split the data set into training and testing data sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=21
, stratify=y)
```

Balancing

Let us take a look at how balanced the data set is by counting and normalizing the number of instances of each class of the severity_code.

In [57]:

```
df['severity_code'].value_counts(normalize=True).to_frame('Counts')
```

Out[57]:

	Counts
1	0.647341
2	0.334510
3	0.016528
4	0.001620

We see that the data is heavily skewed towards severity_code 1 and 2, with severity_code 3 and 4 acounting for less than even 2% of the data. This shows that there is a need to balance the data.

Multi-Class to binary-Class

Often times, the skewed multi-class classification problem is converted to the two-class problem by taking the minority classes versus the addition of the rest of the classes. We first begin by turning the muli-class problem

into a binary class problem by aggregating severity_code 1, 2 that represent minor or no injuries into one class and severity_code 3, 4 that represent serious cases into another class.

In [58]:

```
df['severity_code'].replace(to_replace={'1':0, '2':0, '3':1, '4':1}, inplace=True)
```

In [59]:

```
df.severity_code.value_counts()
```

Out[59]:

```
0    145424
1      2688
Name: severity_code, dtype: int64
```

As seen above, severity_code 1 is extremely rare, or in other words, the data is highly skewed. The main challenge of dealing with this type of data is that the machine learning algorithms train with almost 100% accuracy and fails to classify the minority class. This is intuitive since when the occurrence of the majority class is 99% per cent, even if the classifier is hard-coded to predict majority class always, the accuracy will still be 99%. We appreciate that false negative is very costly here, that is actual severity code 4 is not predicted. The situation is just like the detection of fraudulent transactions or diagnosing diseases. There are many ways to deal with this situation by balancing the data synthetically by exploration method before training. We might

(1) under-sample the majority class

(2) over-sample the minority class or

(3) have a combination of (1) and (2), i.e. over- and under-sample simultaneously.

The combination of over- and under-sampling will be used since the data is large enough. level 1 will be randomly over-sampled to 10000 and other levels will be randomly under-sampled to 10000.

In [60]:

```
df = pd.concat([df[df['severity_code']==1].sample(10000, replace = True), df[df['severit
y_code']==0].sample(10000)], axis=0)
print('Resampled data:', df['severity_code'].value_counts())
```

```
Resampled data: 1    10000
0    10000
Name: severity_code, dtype: int64
```

Now the data has been balanced with both classes having the same counts. Finally we can move to the next stage i.e. Modelling. But before that, let us split the dataset again.

In [61]:

```
target='severity_code'

# set X and y
y = df[target]
X = df.drop(target, axis=1)

X = StandardScaler().fit(X).transform(X)

# Split the data set into training and testing data sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=21
, stratify=y)
```

6. Modelling

In this section, we will apply four machine learning classification techniques on the data set available to train the model. These classification techniques are K-Nearest Neighbour, Decision Tree, Logistic Regression and Support Vector Machines. We will then test and compare the accuracy of these models on the test dataset using

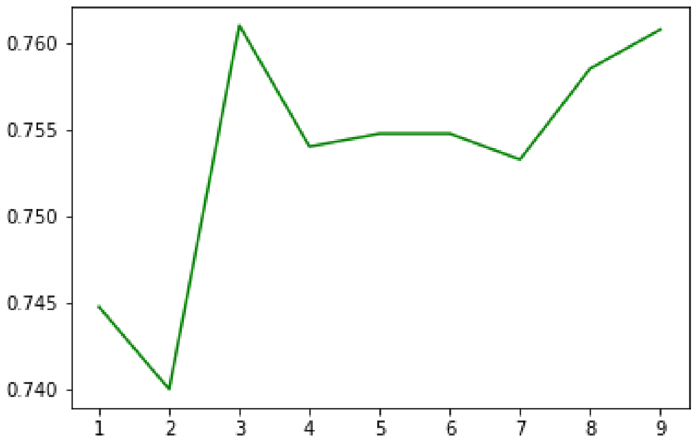
Jaccard index, F1 score and Log loss.

K-Nearest Neighbor

In [62]:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics

Ks=10
mean_acc= np.zeros((Ks-1))

for n in range(1,Ks):
    neigh= KNeighborsClassifier(n_neighbors=n).fit(X_train, y_train)
    yhat= neigh.predict(X_test)
    mean_acc[n-1]= metrics.accuracy_score(y_test, yhat)
    mean_acc

plt.plot(range(1,Ks), mean_acc, 'g')

print("Best Accuracy was with", mean_acc.max(), "with K= ", mean_acc.argmax() +1)
```

```
Best Accuracy was with 0.761 with K=  3
```



In [63]:

```
k=5
neigh_=KNeighborsClassifier(n_neighbors=k).fit(X_train, y_train)
neigh_
yhat=neigh_.predict(X_test)
yhat[0:5]
```

Out[63]:

```
array([0, 0, 1, 0, 1])
```

In [64]:

```
#Accuracy Evaluation using Jaccard Index

print("Train set accuracy:", metrics.accuracy_score(y_train, neigh_.predict(X_train)))


print("Test set accuracy:", metrics.accuracy_score(y_test, yhat))
```

```
Train set accuracy: 0.7936875
Test set accuracy: 0.75475
```

Decision Tree

In [65]:

```
from sklearn import tree
```

```
from sklearn.tree import DecisionTreeClassifier as DTC
dt= DTC(min_samples_split = 5, max_features = 'log2', class_weight='balanced', random_st
ate=42)
dt.fit(X_train, y_train)
pdt= dt.predict(X_test)
print(pdt[0:5])
print(y_test[0:5])
```

```
[0 0 1 0 1]
30759     0
136583    0
122344    1
132843    0
21491     1
Name: severity_code, dtype: int64
```

In [66]:

```
#Evaluation

print("Decision Tree's Accuracy: ", metrics.accuracy_score(y_test, pdt))
```

```
Decision Tree's Accuracy:  0.78425
```

Logistic Regression

In [85]:

```
# Logistic Regression using default setting
from sklearn.linear_model import LogisticRegression
LR= LogisticRegression(max_iter=10000, random_state=42)
LR.fit(X_train, y_train)
yhat= LR.predict(X_test)
yhat[0:5]
```

Out[85]:

```
array([0, 0, 1, 0, 1])
```

In [86]:

```
yhat_prob= LR.predict_proba(X_test)
yhat_prob[0:5]
```

Out[86]:

```
array([[0.87557657, 0.12442343],
       [0.86605987, 0.13394013],
       [0.1135206 , 0.8864794 ],
       [0.92232072, 0.07767928],
       [0.12281697, 0.87718303]])
```

In [87]:

```
#Evaluation using Logloss
from sklearn.metrics import log_loss
log_loss(y_test, yhat_prob)
```

Out[87]:

```
0.5032449012020984
```

In [88]:

```
#Grid Search
from sklearn.model_selection import GridSearchCV

LR_grid = {
           'C':         [0.001, 0.009, 0.01, 0.09, 1, 5, 10, 25],
           'max_iter': [1000, 10000, 100000]
          }
```

```
lr_cv = GridSearchCV(estimator=LogisticRegression(random_state=42), param_grid = LR_grid
, scoring = 'accuracy', cv = 5)

lr_cv.fit(X_train, y_train)
print('Best Parameters: ', lr_cv.best_params_)
```

```
Best Parameters:  {'C': 5, 'max_iter': 1000}
```

In [89]:

```
# Logistic Regression using C=5 and max_iter=1000
from sklearn.linear_model import LogisticRegression
LR= LogisticRegression(C=5, max_iter=1000, penalty='l2')
LR.fit(X_train, y_train)
yhat= LR.predict(X_test)
yhat[0:5]
```

Out[89]:

```
array([0, 0, 1, 0, 1])
```

In [90]:

```
yhat_prob= LR.predict_proba(X_test)
yhat_prob[0:5]
```

Out[90]:

```
array([[0.87567767, 0.12432233],
       [0.86613879, 0.13386121],
       [0.11346369, 0.88653631],
       [0.92238833, 0.07761167],
       [0.12279089, 0.87720911]])
```

In [91]:

```
#Evaluation using Logloss
from sklearn.metrics import log_loss
log_loss(y_test, yhat_prob)
```

Out[91]:

```
0.5032405234579438
```

SVM

In [92]:

```
from sklearn import svm
clf= svm.SVC(kernel= 'rbf')
clf.fit(X_train, y_train)

yhat= clf.predict(X_test)
yhat[0:5]
```

Out[92]:

```
array([0, 0, 1, 0, 1])
```

In [93]:

```
#Evaluation using f1 score
from sklearn.metrics import f1_score
f1_score(y_test, yhat, average='weighted')
```

Out[93]:

```
0.7670176683278558
```

That concludes our modelling part. Now let us move to the evaluation of these models and select the best.

7. Evaluation

In [97]:

```
from sklearn.metrics import f1_score
from sklearn.metrics import log_loss
from sklearn.metrics import jaccard_score
```

In [99]:

```
knn_pred=neigh_.predict(X_test)
jc1=jaccard_score(y_test, knn_pred)
fs1=f1_score(y_test, knn_pred, average='weighted')

tree_pred=dt.predict(X_test)
jc2=jaccard_score(y_test, tree_pred)
fs2=f1_score(y_test, tree_pred, average='weighted')

svm_pred=clf.predict(X_test)
jc3=jaccard_score(y_test, svm_pred)
fs3=f1_score(y_test, svm_pred, average='weighted')

log_pred=LR.predict(X_test)
proba=LR.predict_proba(X_test)
jc4=jaccard_score(y_test, log_pred)
fs4=f1_score(y_test, log_pred, average='weighted')
ll4=log_loss(y_test, proba)

list_jc = [jc1, jc2, jc3, jc4]
list_fs = [fs1, fs2, fs3, fs4]
list_ll = ['NA', 'NA', 'NA', ll4]


import pandas as pd

# fomulate the report format
df = pd.DataFrame(list_jc, index=['KNN','Decision Tree','SVM','Logistic Regression'])
df.columns = ['Jaccard']
df.insert(loc=1, column='F1-score', value=list_fs)
df.insert(loc=2, column='LogLoss', value=list_ll)
df.columns.name = 'Algorithm'
df
```

Out[99]:

Algorithm	Jaccard	F1-score	LogLoss
KNN	0.613170	0.754623	NA
Decision Tree	0.641760	0.784223	NA
SVM	0.608256	0.767018	NA
Logistic Regression	0.600420	0.761707	0.503241

8. Conclusion

We can conclude that the Decision Tree is the best model in this scenario an KNN is the second best. While Logistic Regression appears to be the worst of the four techniques. The initial data had a lot of missing values and was unbalanced, so we had to ensure proper cleaning and balancing of the data in order to prevent a skewed model. From the exploratory analysis, we see that most accidents cause only property damage or minor injuries.Most accidents are angled crashes followed by parked car and rear end crashes. We also see that most accidents happen during clear days on dry roads in daylight. Most property damage only collisions occur at midblocks while most injury collisions happen at intersections. And most serious injuries and fatalities are caused by collisions with pedestrians. As such special attention should be paid towards pedestrian safety. Further, we find that most property damage only collisions occur at midblocks while most injury collisions happen at intersections. Finally, influence of alcohol/drugs and speeding appear to increase the severity of accidents.

``` 
******************************************************
***************
```

In [ ]:

```

```