Homework 02 - Exploratory Data Analysis in Python

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3. Assess relationships within a novel data set

a) Describe and visualize correlations between numerical variables

b) Visualize correlations of all numerical variables within groups

c) Describe and visualize relationships based on target variables

3.1. Required Setup

In [1]:
```
# Import all required libraries
# Data analysis and manipulation
import pandas as pd
# Working with arrays
import numpy as np
# Statistical visualization
import seaborn as sns
# Matlab plotting for Python
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
# Data analysis
import statistics as stat
import scipy.stats as stats
# Two-sample Chi-Square test
from scipy.stats import chi2_contingency
# Predictive data analysis: process data
from sklearn import preprocessing as pproc
# Predictive data analysis: linear models
from sklearn.model_selection import cross_val_predict
# Predictive data analysis: linear models
from sklearn.linear_model import LinearRegression
# Visualizing missing values
import missingno as msno
# Statistical modeling
import statsmodels.api as sm
# Statistical modeling: ANOVA
from statsmodels.formula.api import ols
# Mosaic plot
from statsmodels.graphics.mosaicplot import mosaic
from itertools import product

# Increase font and figure size of all seaborn plot elements
sns.set(font_scale = 1.5, rc = {'figure.figsize':(8, 8)})

# Change theme to "white"
sns.set_style("white")
```

3.2 Loading a data set

In [2]:
```python
tornadosData = pd.read_csv('C:/Users/sanja/OneDrive/Desktop/University of Arizona Classes/INFO 523 - Data Mining/HW/hw-02-SanjaySiddi/data/tornados.csv')
```

3.3 Examining the data set and trimming the data

In [3]:
```python
tornadosData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 68693 entries, 0 to 68692
Data columns (total 27 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   om            68693 non-null  int64
 1   yr            68693 non-null  int64
 2   mo            68693 non-null  int64
 3   dy            68693 non-null  int64
 4   date          68693 non-null  object
 5   time          68693 non-null  object
 6   tz            68693 non-null  object
 7   datetime_utc  68693 non-null  object
 8   st            68693 non-null  object
 9   stf           68693 non-null  int64
 10  mag           67937 non-null  float64
 11  inj           68693 non-null  int64
 12  fat           68693 non-null  int64
 13  loss          41523 non-null  float64
 14  slat          68693 non-null  float64
 15  slon          68693 non-null  float64
 16  elat          68693 non-null  float64
 17  elon          68693 non-null  float64
 18  len           68693 non-null  float64
 19  wid           68693 non-null  int64
 20  ns            68693 non-null  int64
 21  sn            68693 non-null  int64
 22  f1            68693 non-null  int64
 23  f2            68693 non-null  int64
 24  f3            68693 non-null  int64
 25  f4            68693 non-null  int64
 26  fc            68693 non-null  bool
dtypes: bool(1), float64(7), int64(14), object(5)
memory usage: 13.7+ MB
```

In [4]:
```python
# creating a copy of the tornados data set
data = tornadosData.copy()

# renaming columns for readability
data = data.rename(columns={'om':'Tornado ID','yr':'Year','mo':'Month','dy':'Day','date':'Date','time':'Time','tz':'Timezone','st':'State','mag':'Magnitude','inj':'Injuries','fat':'Fatality','lo

# removing non-important columns
data = data.drop(columns=['Tornado ID','Time','Timezone','Month','Day','datetime_utc','stf','slat','slon','elat','elon','f1','f2','f3','f4','sn','fc'])

# filling NaN with 0
data = data.fillna(0)
```

Creating a sub group

In [5]:
```python
def loss_group_data(data):
  if data.Loss >= 0 and data.Loss <= 10000: return "Low loss"
  elif data.Loss > 10000 and data.Loss <= 100000: return "Medium loss"
  else: return "Huge loss"

# Apply the function to data
```

```
data['Loss_group'] = data.apply(loss_group_data, axis = 1)

# What does the data look like
data.head(1000)
```

Out[5]:

	Year	Date	State	Magnitude	Injuries	Fatality	Loss	Length	Width	States Affected	Loss_group
0	1950	1950-10-01	OK	1.0	0	0	50000.0	15.8	10	1	Medium loss
1	1950	1950-10-09	NC	3.0	3	0	500000.0	2.0	880	1	Huge loss
2	1950	1950-11-20	KY	2.0	0	0	500000.0	0.1	10	1	Huge loss
3	1950	1950-11-20	KY	1.0	0	0	500000.0	0.1	10	1	Huge loss
4	1950	1950-11-20	MS	1.0	3	0	50000.0	2.0	37	1	Medium loss
...	...	...	...	...	...	...	...	...	...	...	...
995	1953	1953-06-04	FL	1.0	0	0	50.0	0.1	10	1	Low loss
996	1953	1953-06-05	FL	0.0	0	0	50.0	0.1	10	1	Low loss
997	1953	1953-06-05	UT	0.0	0	0	0.0	8.0	147	1	Low loss
998	1953	1953-06-05	TX	0.0	0	0	0.0	0.1	10	1	Low loss
999	1953	1953-06-05	MI	0.0	0	0	500.0	1.0	50	1	Low loss

1000 rows × 11 columns

3.4. Describe and Visualize Correlations

In [6]:

```
# subset dataframe to include only numeric columns
numData = data.select_dtypes(include='number')

# Table of correlations between numerical variables
numData.corr()
```

Out[6]:

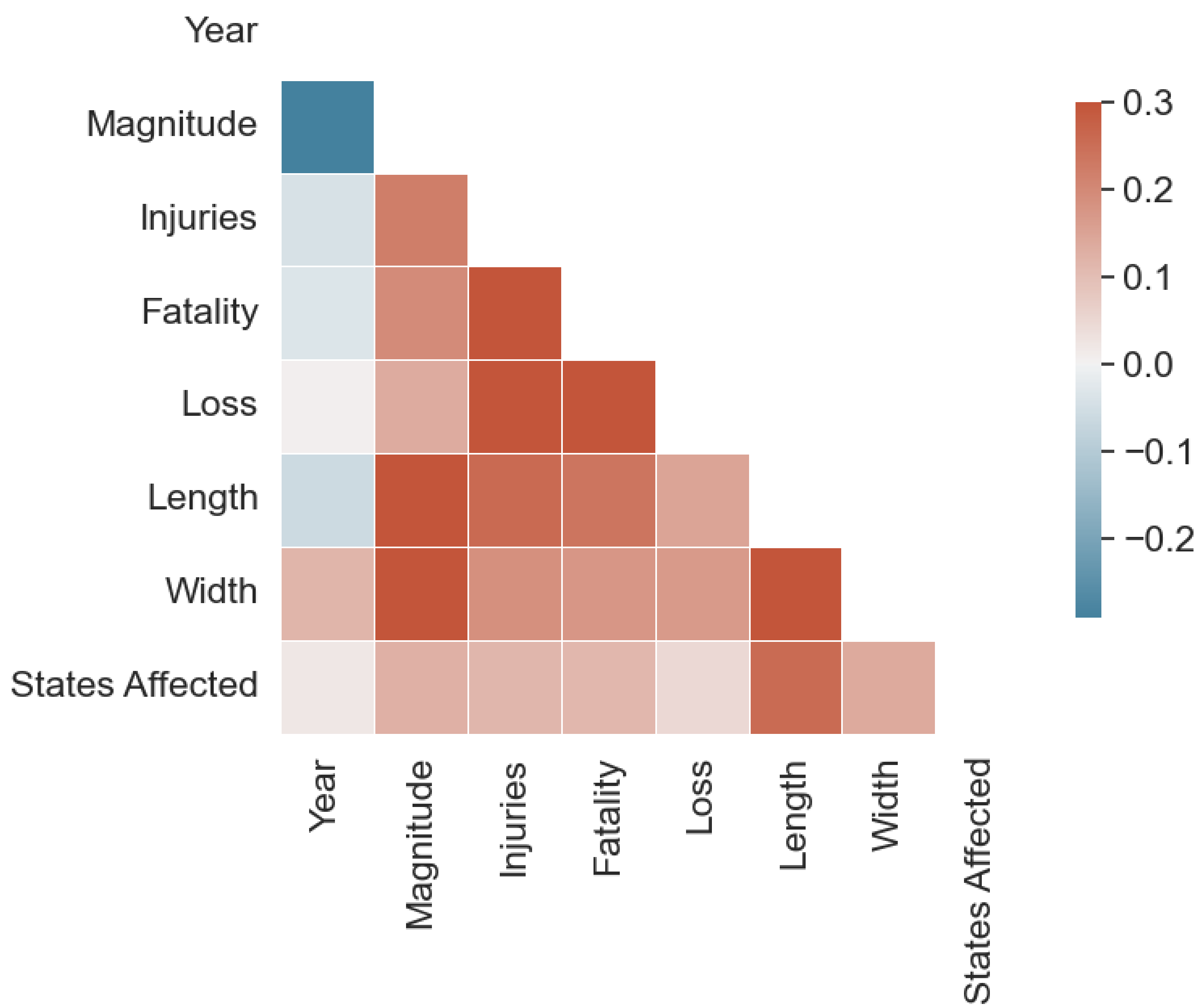
	Year	Magnitude	Injuries	Fatality	Loss	Length	Width	States Affected
Year	1.000000	-0.291051	-0.042735	-0.033557	0.006165	-0.060327	0.116627	0.019638
Magnitude	-0.291051	1.000000	0.220586	0.195350	0.134760	0.441320	0.420711	0.126749
Injuries	-0.042735	0.220586	1.000000	0.761659	0.518769	0.256337	0.185440	0.113673
Fatality	-0.033557	0.195350	0.761659	1.000000	0.462200	0.237266	0.174050	0.112272
Loss	0.006165	0.134760	0.518769	0.462200	1.000000	0.148073	0.167963	0.048318
Length	-0.060327	0.441320	0.256337	0.237266	0.148073	1.000000	0.378556	0.254201
Width	0.116627	0.420711	0.185440	0.174050	0.167963	0.378556	1.000000	0.136645
States Affected	0.019638	0.126749	0.113673	0.112272	0.048318	0.254201	0.136645	1.000000

To read heatmaps - Darker colors indicate stronger correlations, while lighter colors indicate weaker correlations. Positive correlations (when one variable increases, the other variable tends to increase) are usually represented by warm colors, such as red or orange. Negative correlations (when one variable increases, the other variable tends to decrease) are usually represented by cool colors, such as blue or green.

In [7]:

```
# Heatmap correlation matrix of numerical variables
# Correlation matrix
corr = numData.corr()

# Generating a mask for the upper triangle
mask = np.triu(np.ones_like(corr, dtype = bool))
```

```python
# Generating a custom diverging colormap
cmap = sns.diverging_palette(230, 20, as_cmap = True)

# Heatmap of the correlation matrix
sns.heatmap(corr, cmap = cmap, mask = mask, vmax = 0.3, center = 0,
            square = True, linewidths = 0.5, cbar_kws = {"shrink": .5})

# Tight margins for plot
plt.tight_layout()

# Show plot
plt.show()
```



There is a strong positive correlation between the Magnitude and length, magnitude and width - as the length increases, the magnitude also increases, similarly with the width as represented by the color and darkness of the blocks.

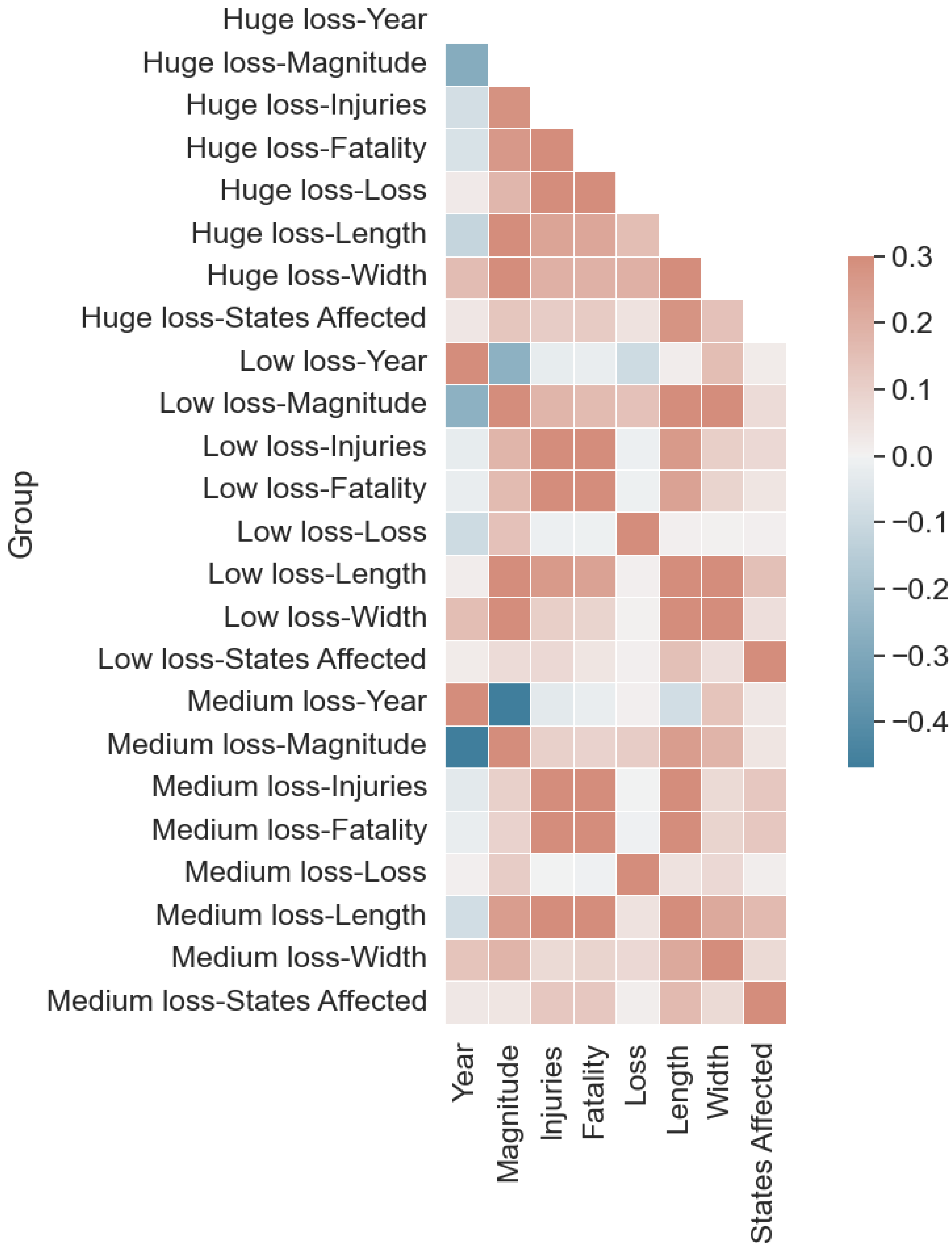
3.5. Visualize Correlations within Groups

In [8]:

```python
# Increase font and figure size of all seaborn plot elements
sns.set(font_scale = 1.5, rc = {'figure.figsize':(10, 10)})
```

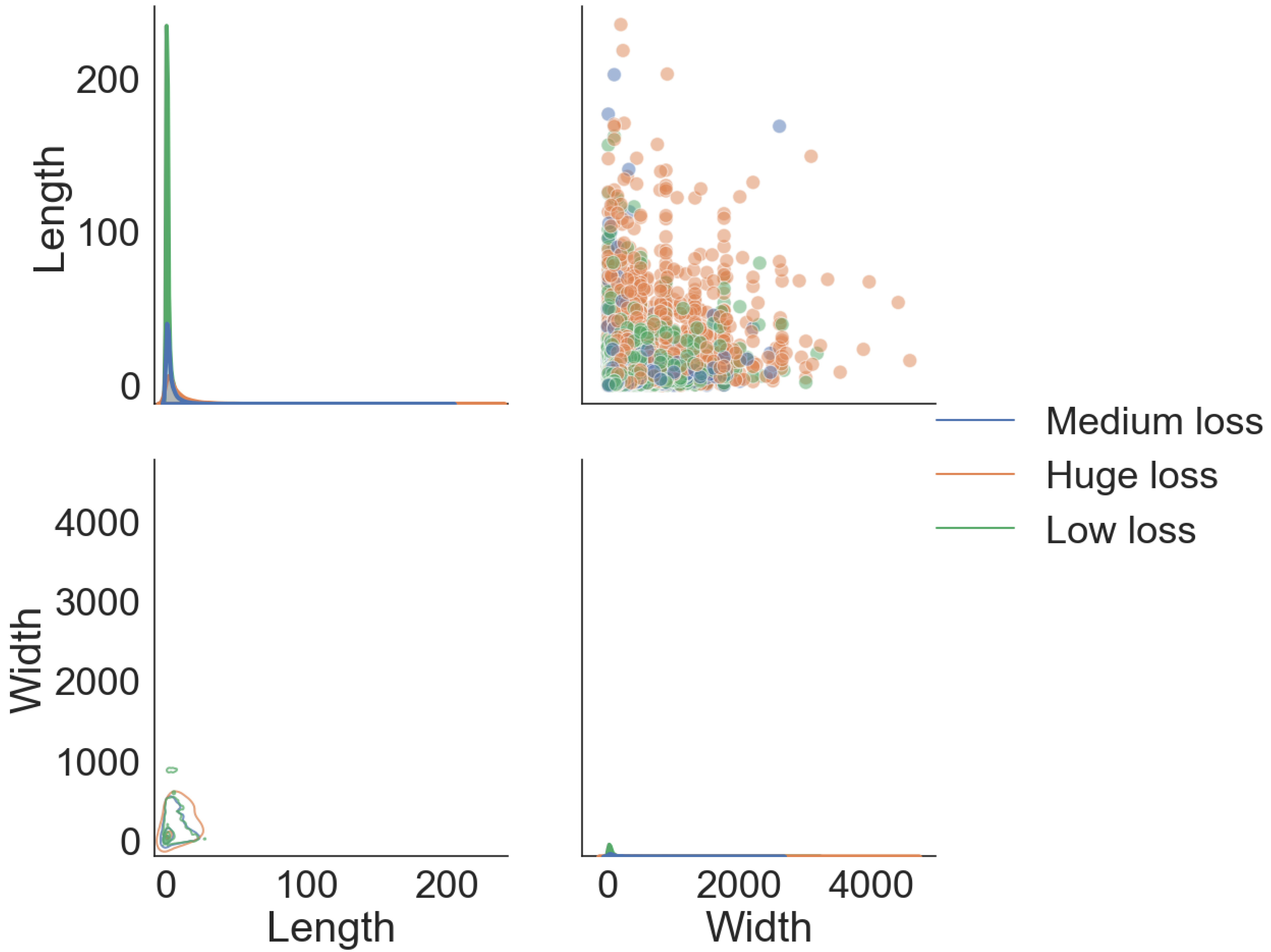
```python
# Change theme to "white"
sns.set_style("white")

# Heatmap correlation matrix of numerical variables
# Correlation matrix
corr = data.groupby('Loss_group').corr()

# Generating a mask for the upper triangle
mask = np.triu(np.ones_like(corr, dtype = bool))

# Generaing a custom diverging colormap
cmap = sns.diverging_palette(230, 20, as_cmap = True)

# Heatmap of the correlation matrix
ax = sns.heatmap(corr, cmap = cmap, mask = mask, vmax = 0.3, center = 0,
            square = True, linewidths = 0.5, cbar_kws = {"shrink": .5})

# Change y-axis label
ax.set(ylabel = 'Group')

# Tight margins for plot
plt.tight_layout()

# Show plot
plt.show()
```

```
C:\Users\sanja\AppData\Local\Temp\ipykernel_16324\1357174802.py:9: FutureWarning: The default value of numeric_only in DataFrameGroupBy.corr is deprecated. In a future version, numeric_only wil
l default to False. Either specify numeric_only or select only columns which should be valid for the function.
  corr = data.groupby('Loss_group').corr()
```



There is a strong negative correlation between the Medium loss-Year and the magnitude, we can also observe a weak positive correlation between Low loss - Injuries and States affected

In [9]:
```
dataplot = data[["Loss_group", "Length", "Width"]]

# Increase font and figure size of all seaborn plot elements
sns.set(font_scale = 2.5, rc = {'figure.figsize':(10, 10)})

# Change seaborn plot theme to white
sns.set_style("white")

# Empty subplot grid for pairwise relationships
g = sns.PairGrid(dataplot, hue = "Loss_group", height = 5)

# Adding scatterplots to the upper portion of the grid
g1 = g.map_upper(sns.scatterplot, alpha = 0.5, s = 100)

# Adding a kernal density plot to the diagonal of the grid
g2 = g1.map_diag(sns.kdeplot, fill = True, linewidth = 3)

# Adding a kernal density plot to the lower portion of the grid
g3 = g2.map_lower(sns.kdeplot, levels = 5, alpha = 0.75)

# Remove legend title
g4 = g3.add_legend(title = "", adjust_subtitles = True)

# Show plot
plt.show()
```



The first plot has a right skewed, unimodal distribution

For the second plot - as the length and width increases, the huge loss is scattered

3rd plot - I couldn't figure out anything from this plot

The fourth plot is a tiny unimodal right skewed plot

3.6. Describe and Visualize Relationships Based on Target Variables

Numerical Target Variables: Numerical Variable of Interest

In [10]:
```
# The numerical predictor variable
X = data[["Year"]]

# The numerical target variable
Y = data[["Magnitude"]]

# Defining the linear model, drop NAs
model = sm.OLS(Y, X, missing = 'drop')

# Fitting the model
model_result = model.fit()

# Summary of the linear model
model_result.summary()
```

Out[10]:

OLS Regression Results

Dep. Variable:	Magnitude	**R-squared (uncentered):**	0.423
Model:	OLS	**Adj. R-squared (uncentered):**	0.423
Method:	Least Squares	**F-statistic:**	5.032e+04
Date:	Fri, 06 Oct 2023	**Prob (F-statistic):**	0.00
Time:	19:18:08	**Log-Likelihood:**	-89986.
No. Observations:	68693	**AIC:**	1.800e+05
Df Residuals:	68692	**BIC:**	1.800e+05
Df Model:	1		
Covariance Type:	nonrobust		

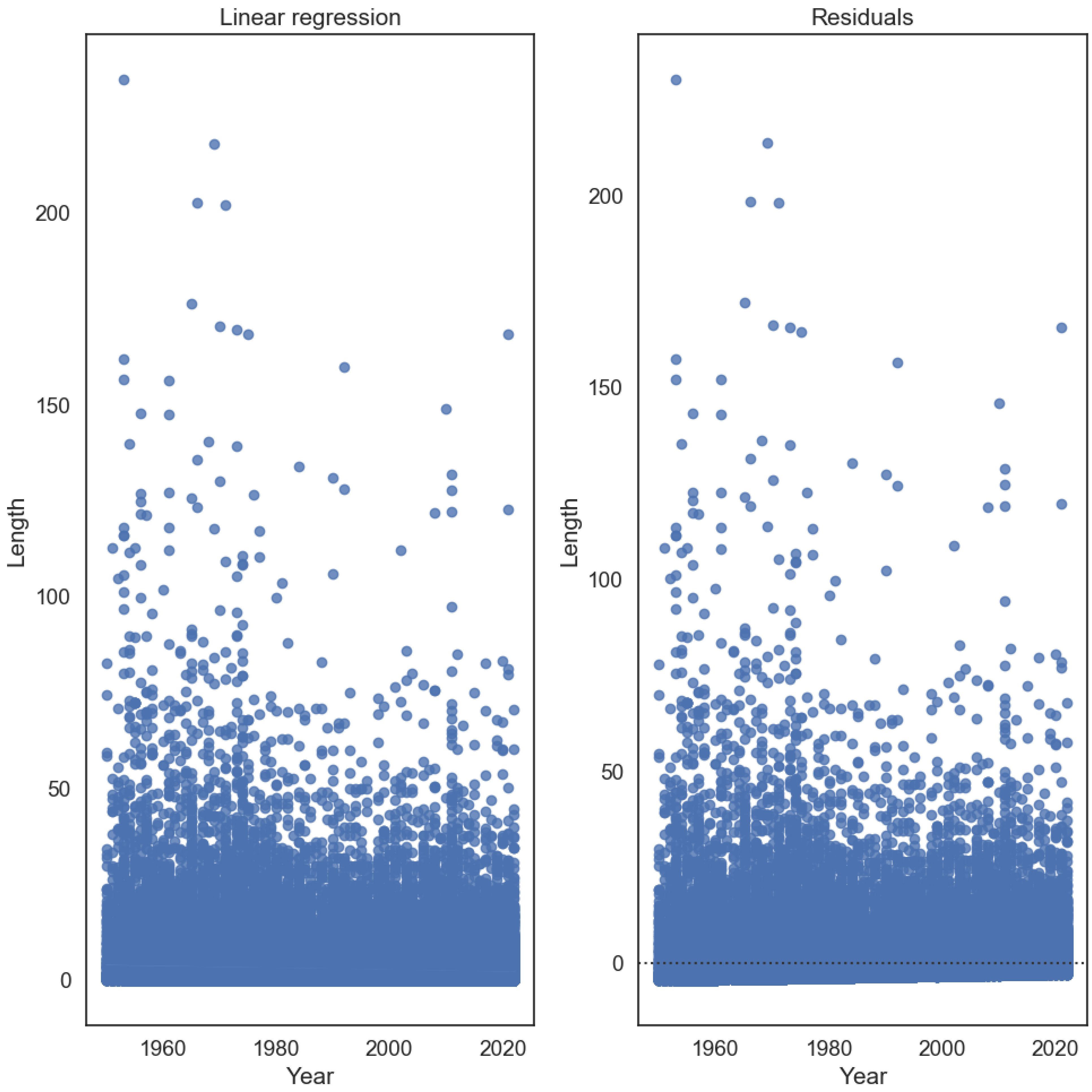
	coef	std err	t	P>|t|	[0.025	0.975]
Year	0.0004	1.72e-06	224.329	0.000	0.000	0.000

Omnibus:	11222.689	**Durbin-Watson:**	1.376
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	17969.269
Skew:	1.134	**Prob(JB):**	0.00
Kurtosis:	4.066	**Cond. No.**	1.00

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [11]:
```
# Plotting the linear relationship
```

```python
# Increase font and figure size of all seaborn plot elements
sns.set(font_scale = 1.25, rc = {'figure.figsize':(10,10)})

# Change seaborn plot theme to white
sns.set_style("white")

# Subplots
fig, (ax1, ax2) = plt.subplots(ncols = 2, nrows = 1)

# Regression plot between Length and Width
sns.regplot(data = data, x = "Year", y = "Length", ax = ax1)

# Setting regression plot title
ax1.set_title("Linear regression")

# Regression plot between Length and Width
sns.residplot(data = data, x = "Year",
              y = "Length", ax = ax2)

# Setting residual plot title
ax2.set_title("Residuals")

# Tight margins
plt.tight_layout()

# Show plot
plt.show()
```



Cannot make out any best fit line from the above plot

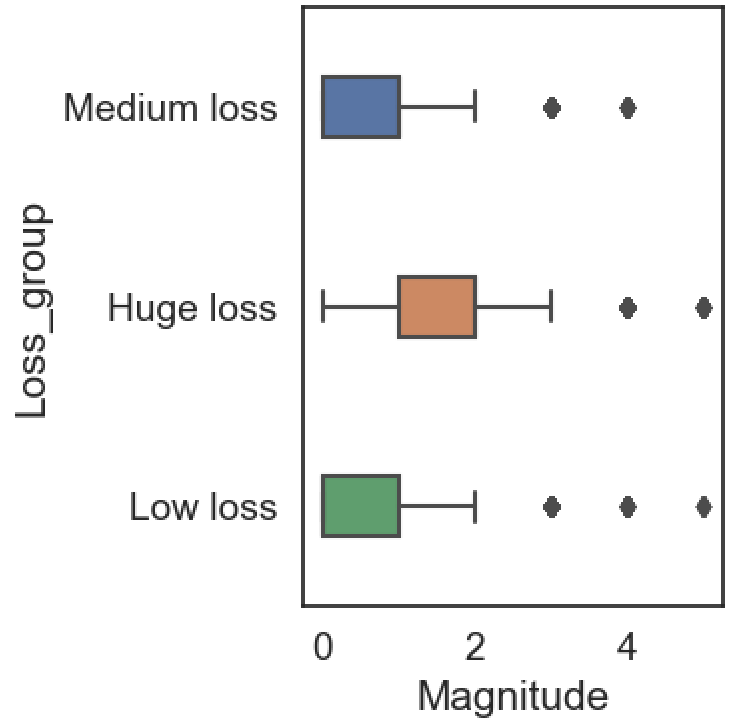
Numerical Target Variables: Categorical Variable of Interest

In [12]:
```
model = ols('Magnitude ~ C(Loss_group)', data = data).fit()

sm.stats.anova_lm(model, typ = 2)
```

Out[12]:

	sum_sq	df	F	PR(>F)
C(Loss_group)	16892.277498	2.0	15237.176868	0.0
Residual	38075.640631	68690.0	NaN	NaN

In [13]:
```
# Increasing font and figure size of all seaborn plot elements
sns.set(font_scale = 1.25, rc = {'figure.figsize':(4, 4)})

# Changing seaborn plot theme to white
sns.set_style("white")

# Box plot
Group_Box = sns.boxplot(data = data, x = "Magnitude", y = "Loss_group", width = 0.3)

# Tweaking the visual presentation
Group_Box.set(ylabel = "Loss_group")

# Tight margins
plt.tight_layout()

# Show plot
plt.show()
```



Categorical Target Variables: Numerical Variable of Interest

In [14]:
```
# Grouped describe by one column, stacked
Groups = data.groupby('Loss_group').describe().unstack(1)

# Printing all rows
print(Groups.to_string())
```

```
                     Loss_group
Year          count  Huge loss      1.369700e+04
                     Low loss       3.942300e+04
                     Medium loss    1.557300e+04
              mean   Huge loss      1.990799e+03
                     Low loss       1.993182e+03
                     Medium loss    1.989421e+03
              std    Huge loss      1.820398e+01
                     Low loss       1.941247e+01
                     Medium loss    2.077901e+01
              min    Huge loss      1.950000e+03
                     Low loss       1.950000e+03
                     Medium loss    1.950000e+03
              25%    Huge loss      1.977000e+03
                     Low loss       1.978000e+03
                     Medium loss    1.972000e+03
              50%    Huge loss      1.991000e+03
                     Low loss       1.997000e+03
                     Medium loss    1.991000e+03
              75%    Huge loss      2.006000e+03
                     Low loss       2.009000e+03
                     Medium loss    2.008000e+03
              max    Huge loss      2.022000e+03
                     Low loss       2.022000e+03
                     Medium loss    2.022000e+03
Magnitude     count  Huge loss      1.369700e+04
                     Low loss       3.942300e+04
                     Medium loss    1.557300e+04
              mean   Huge loss      1.655545e+00
                     Low loss       3.915227e-01
                     Medium loss    9.499133e-01
              std    Huge loss      9.477771e-01
                     Low loss       6.529991e-01
                     Medium loss    7.586699e-01
              min    Huge loss      0.000000e+00
                     Low loss       0.000000e+00
                     Medium loss    0.000000e+00
              25%    Huge loss      1.000000e+00
                     Low loss       0.000000e+00
                     Medium loss    0.000000e+00
              50%    Huge loss      2.000000e+00
                     Low loss       0.000000e+00
                     Medium loss    1.000000e+00
              75%    Huge loss      2.000000e+00
                     Low loss       1.000000e+00
                     Medium loss    1.000000e+00
              max    Huge loss      5.000000e+00
                     Low loss       5.000000e+00
                     Medium loss    4.000000e+00
Injuries      count  Huge loss      1.369700e+04
                     Low loss       3.942300e+04
                     Medium loss    1.557300e+04
              mean   Huge loss      5.997737e+00
                     Low loss       2.091165e-01
                     Medium loss    4.532845e-01
              std    Huge loss      3.824353e+01
                     Low loss       4.902696e+00
                     Medium loss    8.787993e+00
              min    Huge loss      0.000000e+00
                     Low loss       0.000000e+00
                     Medium loss    0.000000e+00
              25%    Huge loss      0.000000e+00
                     Low loss       0.000000e+00
                     Medium loss    0.000000e+00
```

	50%	Huge loss	0.000000e+00
		Low loss	0.000000e+00
		Medium loss	0.000000e+00
	75%	Huge loss	2.000000e+00
		Low loss	0.000000e+00
		Medium loss	0.000000e+00
	max	Huge loss	1.740000e+03
		Low loss	3.790000e+02
		Medium loss	7.950000e+02
Fatality	count	Huge loss	1.369700e+04
		Low loss	3.942300e+04
		Medium loss	1.557300e+04
	mean	Huge loss	3.773819e-01
		Low loss	1.367222e-02
		Medium loss	2.741925e-02
	std	Huge loss	3.109803e+00
		Low loss	4.030989e-01
		Medium loss	7.425152e-01
	min	Huge loss	0.000000e+00
		Low loss	0.000000e+00
		Medium loss	0.000000e+00
	25%	Huge loss	0.000000e+00
		Low loss	0.000000e+00
		Medium loss	0.000000e+00
	50%	Huge loss	0.000000e+00
		Low loss	0.000000e+00
		Medium loss	0.000000e+00
	75%	Huge loss	0.000000e+00
		Low loss	0.000000e+00
		Medium loss	0.000000e+00
	max	Huge loss	1.580000e+02
		Low loss	3.600000e+01
		Medium loss	5.800000e+01
Loss	count	Huge loss	1.369700e+04
		Low loss	3.942300e+04
		Medium loss	1.557300e+04
	mean	Huge loss	6.065210e+06
		Low loss	1.326724e+03
		Medium loss	5.048957e+04
	std	Huge loss	5.269340e+07
		Low loss	2.674777e+03
		Medium loss	1.898780e+04
	min	Huge loss	1.020000e+05
		Low loss	0.000000e+00
		Medium loss	1.010000e+04
	25%	Huge loss	5.000000e+05
		Low loss	0.000000e+00
		Medium loss	5.000000e+04
	50%	Huge loss	5.000000e+05
		Low loss	0.000000e+00
		Medium loss	5.000000e+04
	75%	Huge loss	1.277000e+06
		Low loss	5.000000e+02
		Medium loss	5.000000e+04
	max	Huge loss	2.800100e+09
		Low loss	1.000000e+04
		Medium loss	1.000000e+05
Length	count	Huge loss	1.369700e+04
		Low loss	3.942300e+04
		Medium loss	1.557300e+04
	mean	Huge loss	8.775156e+00
		Low loss	1.732077e+00
		Medium loss	3.288476e+00
	std	Huge loss	1.381718e+01

```
                           Low loss       4.714724e+00
                           Medium loss    6.588536e+00
                    min    Huge loss      0.000000e+00
                           Low loss       0.000000e+00
                           Medium loss    0.000000e+00
                    25%    Huge loss      1.100000e+00
                           Low loss       1.000000e-01
                           Medium loss    3.000000e-01
                    50%    Huge loss      4.100000e+00
                           Low loss       3.000000e-01
                           Medium loss    1.000000e+00
                    75%    Huge loss      1.040000e+01
                           Low loss       1.400000e+00
                           Medium loss    3.750000e+00
                    max    Huge loss      2.347000e+02
                           Low loss       1.620000e+02
                           Medium loss    2.021000e+02
Width               count  Huge loss      1.369700e+04
                           Low loss       3.942300e+04
                           Medium loss    1.557300e+04
                    mean   Huge loss      2.303130e+02
                           Low loss       6.596304e+01
                           Medium loss    1.058129e+02
                    std    Huge loss      3.288138e+02
                           Low loss       1.360737e+02
                           Medium loss    1.707058e+02
                    min    Huge loss      0.000000e+00
                           Low loss       0.000000e+00
                           Medium loss    0.000000e+00
                    25%    Huge loss      5.000000e+01
                           Low loss       1.000000e+01
                           Medium loss    2.300000e+01
                    50%    Huge loss      1.000000e+02
                           Low loss       3.000000e+01
                           Medium loss    5.000000e+01
                    75%    Huge loss      3.000000e+02
                           Low loss       5.000000e+01
                           Medium loss    1.000000e+02
                    max    Huge loss      4.576000e+03
                           Low loss       3.170000e+03
                           Medium loss    2.600000e+03
States Affected     count  Huge loss      1.369700e+04
                           Low loss       3.942300e+04
                           Medium loss    1.557300e+04
                    mean   Huge loss      1.028473e+00
                           Low loss       1.002892e+00
                           Medium loss    1.006293e+00
                    std    Huge loss      1.702320e-01
                           Low loss       5.509649e-02
                           Medium loss    7.908061e-02
                    min    Huge loss      1.000000e+00
                           Low loss       1.000000e+00
                           Medium loss    1.000000e+00
                    25%    Huge loss      1.000000e+00
                           Low loss       1.000000e+00
                           Medium loss    1.000000e+00
                    50%    Huge loss      1.000000e+00
                           Low loss       1.000000e+00
                           Medium loss    1.000000e+00
                    75%    Huge loss      1.000000e+00
                           Low loss       1.000000e+00
                           Medium loss    1.000000e+00
                    max    Huge loss      3.000000e+00
```

```
Low loss       3.000000e+00
Medium loss    2.000000e+00
```

Categorical Target Variables: Categorical Variable of Interest

In [15]:

```
data1 = data.dropna()
Qual = stat.mean(data1.Magnitude + stat.stdev(data1.Magnitude))
print(Qual)
# Create HighMagnitude from the Magnitude column
def HighMagnitude_data(data):
  if data.Magnitude >= Qual: return "Yes"
  else: return "No"

# Apply the function to data and create a dataframe
HighMagnitude = pd.DataFrame(data1.apply(HighMagnitude_data, axis = 1))

# Name new column
HighMagnitude.columns = ['HighMagnitude']

# Concatenate the two dataframes
data1 = pd.concat([data1, HighMagnitude], axis = 1)

# First six rows of new dataset
data1.head()
```

```
1.664694957327893
```

Out[15]:

	Year	Date	State	Magnitude	Injuries	Fatality	Loss	Length	Width	States Affected	Loss_group	HighMagnitude
0	1950	1950-10-01	OK	1.0	0	0	50000.0	15.8	10	1	Medium loss	No
1	1950	1950-10-09	NC	3.0	3	0	500000.0	2.0	880	1	Huge loss	Yes
2	1950	1950-11-20	KY	2.0	0	0	500000.0	0.1	10	1	Huge loss	Yes
3	1950	1950-11-20	KY	1.0	0	0	500000.0	0.1	10	1	Huge loss	No
4	1950	1950-11-20	MS	1.0	3	0	50000.0	2.0	37	1	Medium loss	No

In [16]:

```
obs = pd.crosstab(data1.Loss_group, data1.HighMagnitude)
print(obs)
```

```
HighMagnitude     No   Yes
Loss_group
Huge loss       6666  7031
Low loss       36784  2639
Medium loss    12407  3166
```

In [17]:

```
# Chi-square test
chi2, p, dof, ex = chi2_contingency(obs, correction = False)

# Interpret
alpha = 0.05

# Printing the interpretation
print('Statistic = %.3f, p = %.3f' % (chi2, p))
```

```
Statistic = 13366.460, p = 0.000
```

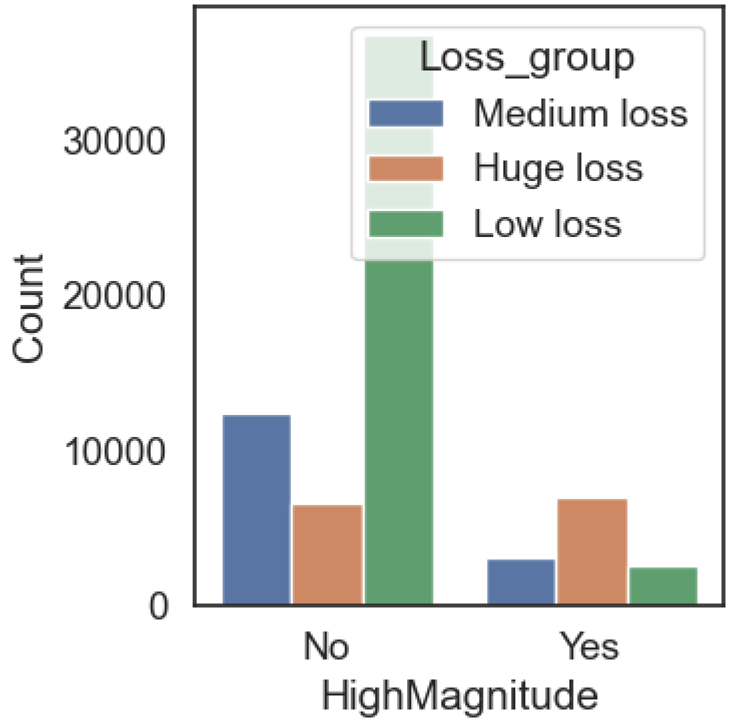
In [18]:

```
if p > alpha:
  print('Chi-square value is not greater than critical value (fail to reject H0)')
else:
    print('Chi-square value is greater than critical value (reject H0)')
```

```
Chi-square value is greater than critical value (reject H0)
```

In [19]:

```
# Increasing font and figure size of all seaborn plot elements
sns.set(font_scale = 1.25)

# Changing seaborn plot theme to white
sns.set_style("white")

# Counting plot of HighMagnitude grouped by Loss_Group
counts = sns.countplot(data = data1, x = "HighMagnitude", hue = "Loss_group")

# Tweaking the visual presentation
counts.set(ylabel = "Count")

# Tight margins
plt.tight_layout()

# Show plot
plt.show()
```



In [ ]: