Data Analysis ¶

In this notebook, our goal is to perform a comprehensive analysis of our dataset to extract valuable information and gain insights from the data. Through this analysis, we hope to identify trends, patterns, and relationships in the data that can help us understand a little more from roller coasters.

In [114]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
import geopandas as gpd
```

In [115]:

```
df = pd.read_csv('coaster_db_clean.csv')
```

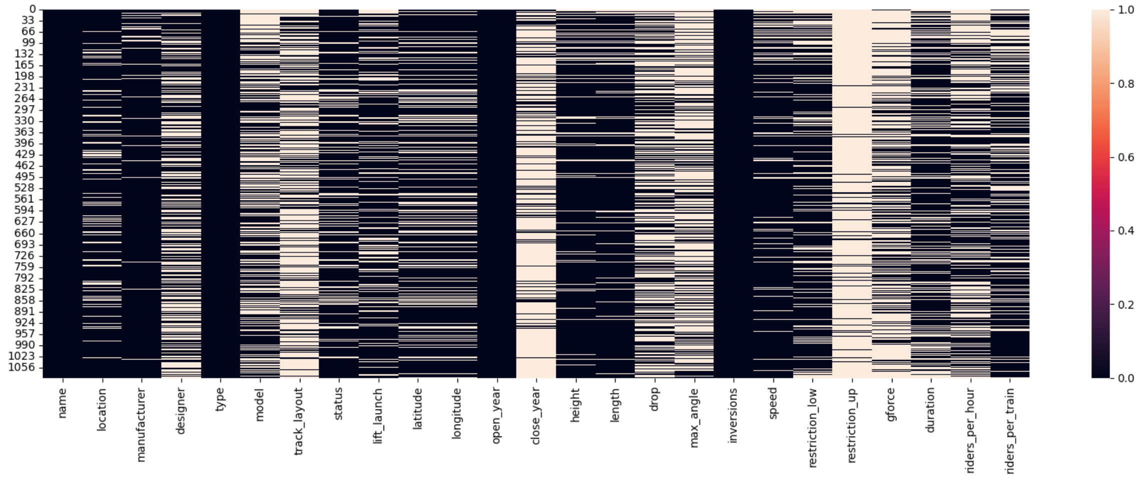
In [116]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1087 entries, 0 to 1086
Data columns (total 25 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   name               1087 non-null   object 
 1   location           915 non-null    object 
 2   manufacturer       1028 non-null   object 
 3   designer           578 non-null    object 
 4   type               1087 non-null   object 
 5   model              629 non-null    object 
 6   track_layout       366 non-null    object 
 7   status             874 non-null    object 
 8   lift_launch        804 non-null    object 
 9   latitude           812 non-null    float64
 10  longitude          812 non-null    float64
 11  open_year          1087 non-null   int64  
 12  close_year         236 non-null    float64
 13  height             965 non-null    float64
 14  length             953 non-null    float64
 15  drop               494 non-null    float64
 16  max_angle          357 non-null    float64
 17  inversions         1087 non-null   int64  
 18  speed              937 non-null    float64
 19  restriction_low    831 non-null    float64
 20  restriction_up     96 non-null     float64
 21  gforce             362 non-null    float64
 22  duration           763 non-null    float64
 23  riders_per_hour    575 non-null    float64
 24  riders_per_train   716 non-null    float64
dtypes: float64(14), int64(2), object(9)
memory usage: 212.4+ KB
```

In [117]:

```
plt.figure(figsize=(20, 6))
sns.heatmap(df.isnull());
```



As we can see from our dataset, there are numerous missing values, which can pose a challenge to our data analysis. Missing data can lead to biased or incomplete results, and can limit the scope of our analysis. The upper restriction has a lot of missing values, we are dropping it.

In [118]:

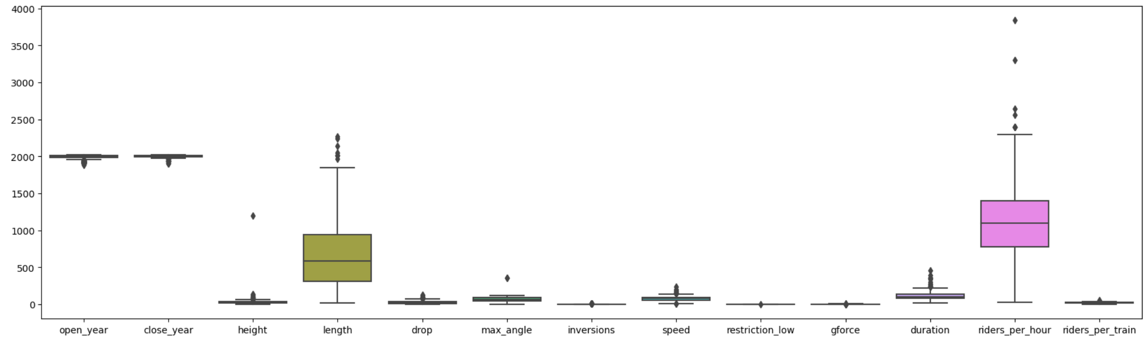
```
df = df.drop('restriction_up', axis = 1)
```

1. Identifying Outliers

Outliers have a significant impact on data analysis, as they can skew results and prevent an accurate representation of the majority of the data. This can lead to misleading insights and inferences, and can even invalidate statistical analyses and models. Our approach to identifying them are boxplots.

In [119]:

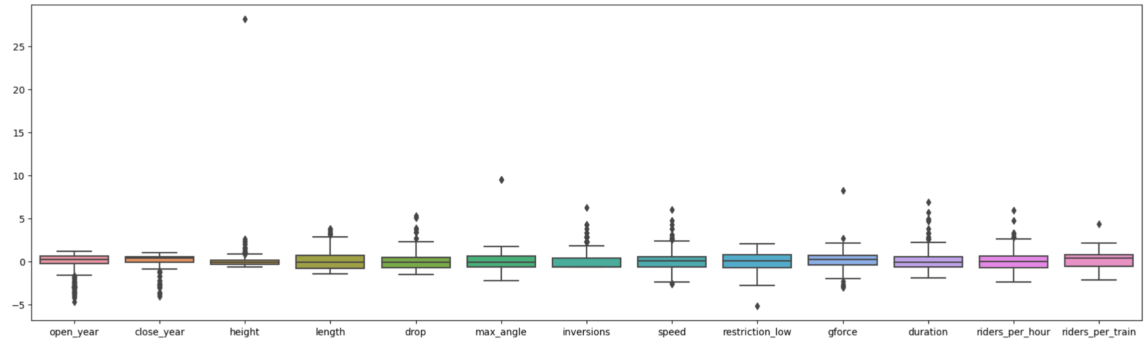
```
cat = range(1, 9)
geo = [9, 10]
num = range(11,24)
var = range(13, 18)
target = range(18, 24)

df_aux = df.iloc[:, num]

plt.figure(figsize=(21, 6))
sns.boxplot(df_aux);
```



Since we are trying to identify outliers for features with different ranges, we have some distortions, making difficult to address outliers properly. In order to solve this problem, it is recommended to scale the features to the same mean and standard deviation. By doing so, we can obtain a more accurate visual analysis that is not biased towards features with a larger range.

In [120]:

```
df_aux = df.iloc[:, num]
scaler = StandardScaler()
df_scaled = scaler.fit_transform(df_aux)
df_scaled = pd.DataFrame(df_scaled, columns=df_aux.columns)

plt.figure(figsize=(21, 6))
sns.boxplot(df_scaled);
```



Let's investigate the outliers for the following features: `height` , `max_angle` , `gforce` , `restriction_low` , `riders_per_train` .

In [121]:

```
df.query('height > 1000').transpose()
```

Out[121]:

	905
name	Smoky Mountain Alpine Coaster
location	NaN
manufacturer	Wiegand
designer	NaN
type	Steel
model	custom
track_layout	NaN
status	operating
lift_launch	lift
latitude	35.7934
longitude	-83.5965
open_year	2013
close_year	NaN
height	1199.9976
length	NaN
drop	NaN
max_angle	NaN
inversions	0
speed	43.2
restriction_low	1.4224
gforce	NaN
duration	NaN
riders_per_hour	NaN
riders_per_train	2.0

The Smoky Mountain Alpine Coaster is actually a type of roller coaster known as a mountain coaster, which uses the natural terrain of a mountain to create a unique and thrilling ride experience. It's true that the coaster's location on a mountain contributes to its height. The coaster uses magnetic braking systems to maintain a slower speed despite its height, which can impact the overall ride experience for riders.

In [122]:

```
df.query('restriction_low < 0.8').transpose()
```

Out[122]:

	132
name	Lil' Thunder
location	Six Flags Great Adventure
manufacturer	Molina & Sons
designer	NaN
type	Steel
model	little dipper
track_layout	NaN
status	closed
lift_launch	NaN
latitude	40.138
longitude	-74.44
open_year	1976
close_year	1983.0
height	2.7432
length	60.6552
drop	0.9144
max_angle	NaN
inversions	0
speed	8.0
restriction_low	0.508
gforce	NaN
duration	27.0
riders_per_hour	NaN
riders_per_train	NaN

Lil' Thunder have the lowest height restriction, but also have the slowest speed, which justifies this particular characteristic, ensuring a safer and more enjoyable experience for riders.

In [123]:

```
df.query('gforce > 6.5').transpose()
```

Out[123]:

	1
name	Flip Flap Railway
location	Sea Lion Park
manufacturer	Lina Beecher
designer	Lina Beecher
type	Wood
model	NaN
track_layout	NaN
status	closed
lift_launch	NaN
latitude	40.578
longitude	-73.979
open_year	1895
close_year	1902.0
height	NaN
length	NaN
drop	NaN
max_angle	NaN
inversions	1
speed	NaN
restriction_low	NaN
gforce	12.0
duration	NaN
riders_per_hour	NaN
riders_per_train	2.0

Flip Flap Railway was notorious for the extreme g-forces that it produced in its riders. The circular nature of the coaster's loop, as well as its relatively small diameter of 25 feet, meant that it could produce forces of approximately 12 g. This caused riders to often experience discomfort and neck injuries from whiplash.

In [124]:

```
df.query('max_angle > 130').transpose()
```

Out[124]:

	679	833
name	G Force	BuzzSaw
location	Drayton Manor Theme Park	Dreamworld
manufacturer	Maurer AG	Maurer AG
designer	NaN	NaN
type	Other	Steel
model	custom	custom
track_layout	NaN	NaN
status	closed	closed
lift_launch	NaN	lift
latitude	52.6128	-27.8623
longitude	-1.7147	153.3149
open_year	2005	2011
close_year	2018.0	2021.0
height	24.9936	46.20768
length	384.9624	45.72
drop	NaN	NaN
max_angle	360.0	360.0
inversions	3	2
speed	69.6	104.32
restriction_low	1.3462	1.3
gforce	4.3	5.0
duration	45.0	50.0
riders_per_hour	1100.0	600.0
riders_per_train	12.0	12.0

BuzzSaw and GForce are twisted roller coasters, which justified the max angle being 360º.

In [125]:

```
df.loc[905, 'height'] = np.nan
df.loc[1, 'gforce'] = np.nan
df.loc[[679, 833], 'max_angle'] = np.nan

df.loc[df['type'] == 'other', 'type'] = np.nan
```

2. Top 5 locations, manufacturers and designers analysis

In [126]:

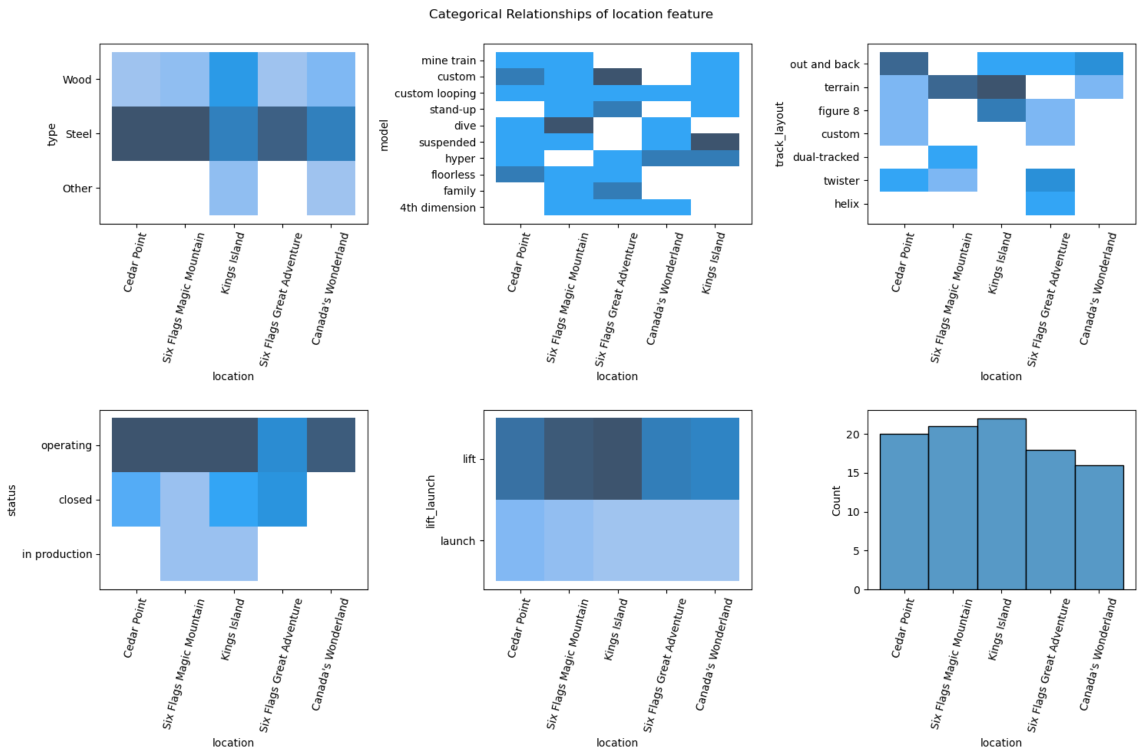
```
for col in df.iloc[:, cat].columns:
    n = len(df[col].value_counts())
    print(f'{col:12s}:  {n:3d}')
```

```
location    :  298
manufacturer:  102
designer    :  153
type        :    3
model       :   50
track_layout:   14
status      :    3
lift_launch :    2
```

`location` , `manufacturer` , `designer` , `model` and `track_layout` exhibit a high cardinality, posing challenges in analyzing the dataset. Consequently, our focus will be on investigating the top five most frequently occurring values within these variables.

In [127]:

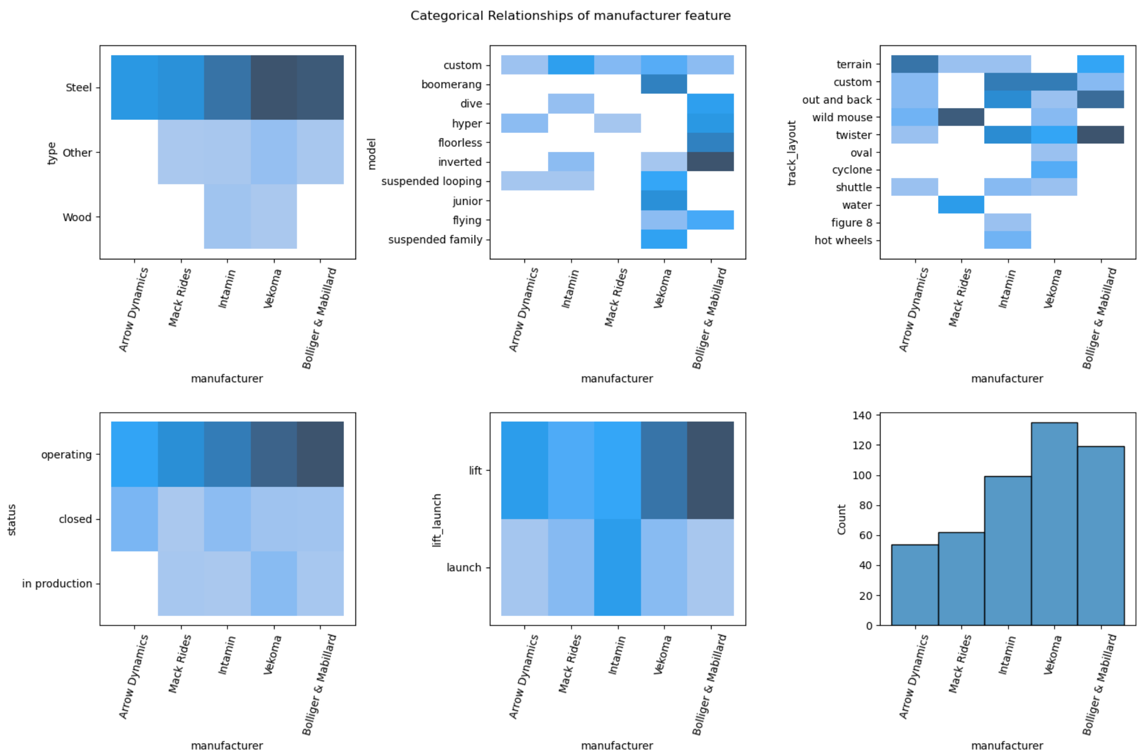
```
df_aux = df.iloc[:, cat]

cols = df.iloc[:, cat].columns

cc = ['location', 'manufacturer', 'designer']

col_drop = cols.to_list()
col_drop = [cd for cd in col_drop if cd not in cc]


def plot_categorical(df, c):

    series = df.loc[:, c].value_counts(
    ).sort_values(ascending = False)

    series = series.iloc[:5].index
    ind = df.loc[:, c].isin(series)
    df_ = df.loc[ind, :]

    fig, ax = plt.subplots(2, 3, figsize = (15, 10))

    fig.suptitle(f'Categorical Relationships of {c} feature')
    for i, col in enumerate(col_drop):

        if col == 'model':
            series = df_.loc[:, col].value_counts(
            ).sort_values(ascending = False)

            series = series.iloc[:10].index
            ind = df_.loc[:, col].isin(series)
            df_2 = df_.loc[ind, :]

            sns.histplot(data=df_2, x = c, y = col, ax = ax[i//3, i%3])
            ax[i//3, i%3].tick_params(axis='x', rotation=75)
            ax[i//3, i%3].set_title(' ')

        else:
            sns.histplot(data=df_, x = c, y = col, ax = ax[i//3, i%3])
            ax[i//3, i%3].tick_params(axis='x', rotation=75)
            ax[i//3, i%3].set_title(' ')

    sns.histplot(data=df_, x = c, ax = ax[1, 2])
    ax[1, 2].tick_params(axis='x', rotation=75)
    ax[1, 2].set_title('')

    fig.tight_layout()

    return None

plot_categorical(df_aux, 'location')
```



- Custom models are more presented in Six Flags Great Adventure.
- Suspended models are predominant in Kings Island.
- Terrain track layout are predominant in Six Flags Magic Mountain and Kings Island.

In [128]:

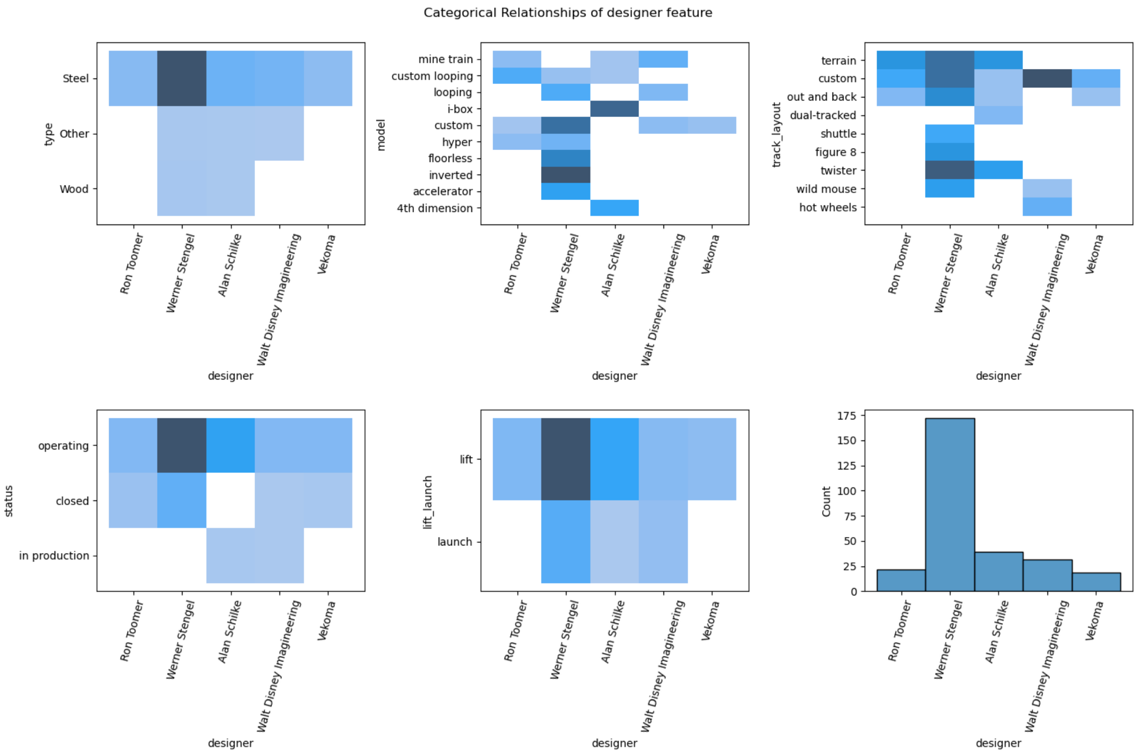
```
plot_categorical(df_aux, 'manufacturer')
```



- Inverted models are predominant in Bolliger & Mabillard.
- Wild Mouse track layouts are predominant in Mack Rides.
- Twister track layouts are predominant in Bolliger & Mabillard.
- Vekoma produces the most roller coasters, with a wide variety in model and track layout types.

In [129]:

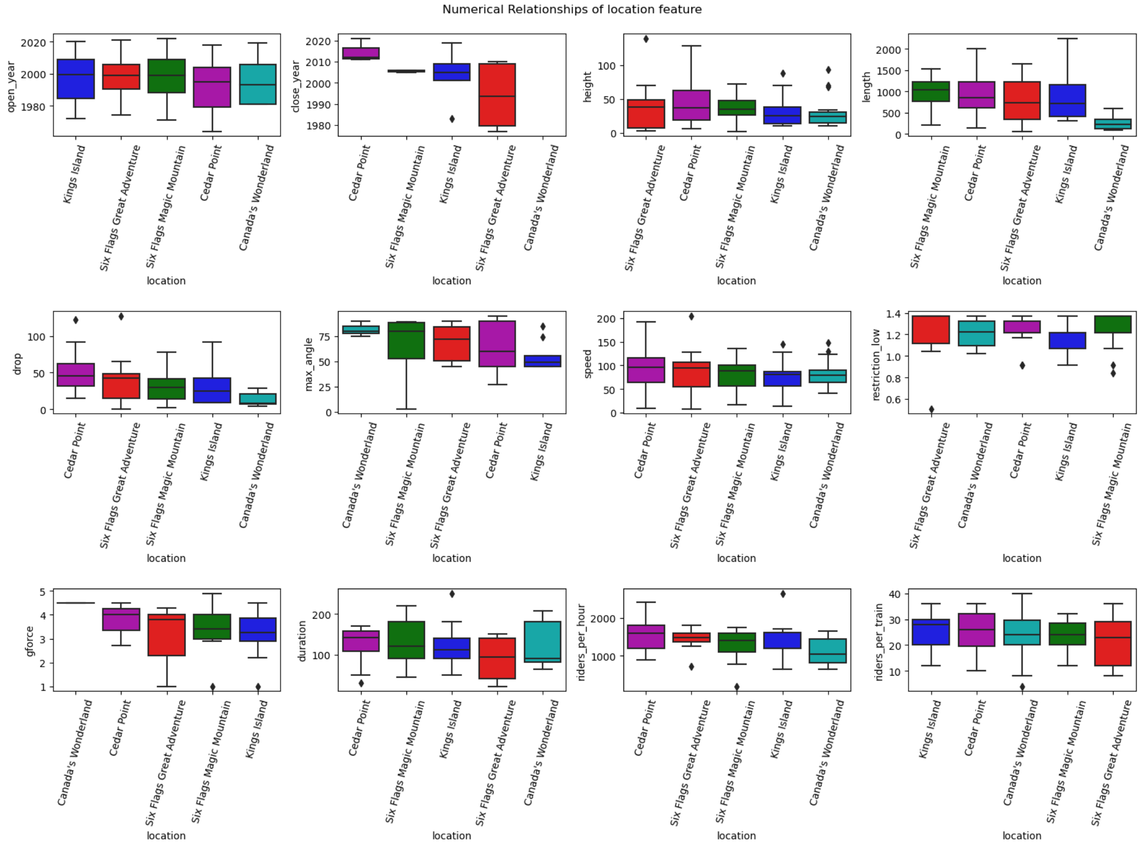
```
plot_categorical(df_aux, 'designer')
```



- Werner Stengel is responsible for the largest amount of roller coasters designed, with wide variety in model and track layout types.
- i-box seems to be only produced by Alan Schlike, how mostly produced this type of roller coaster model.
- Walk Disney Imagineening highly focus in custom track layouts.

In [130]:

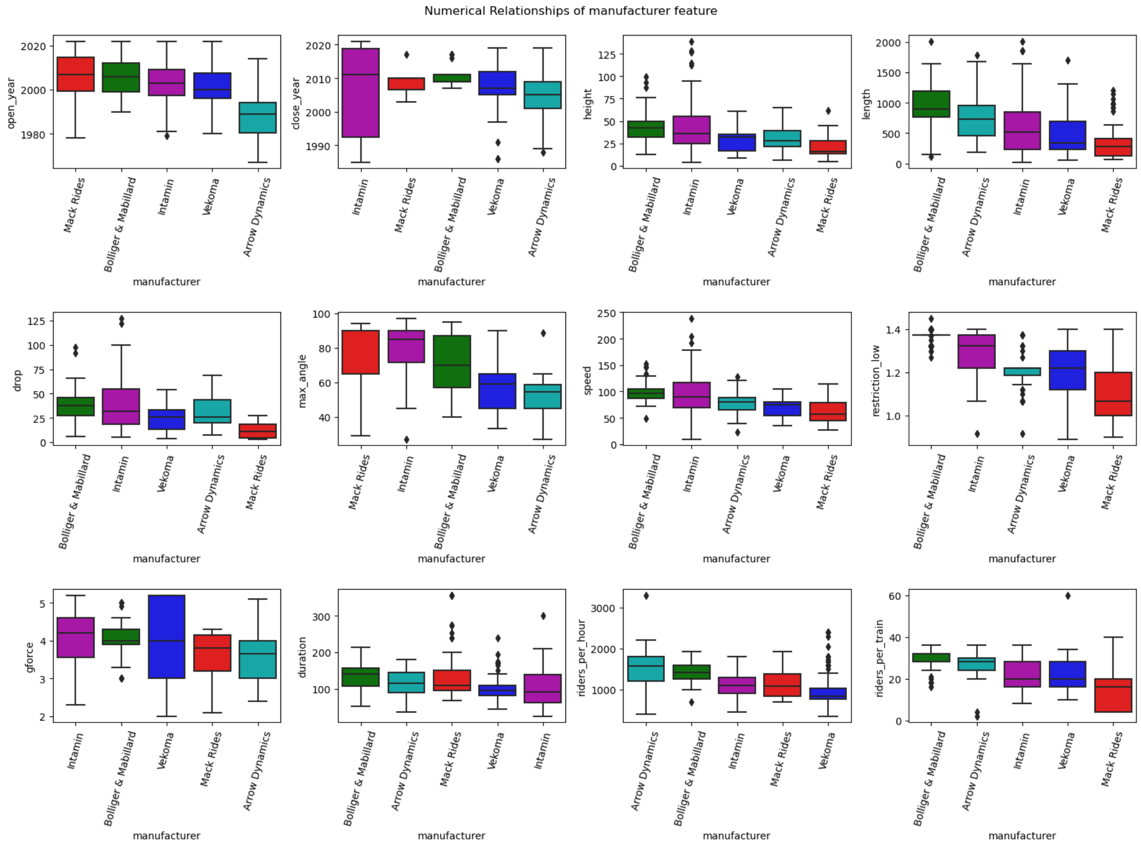
```
cc = ['location', 'manufacturer', 'designer']
drops = ['inversions']

num_cols = df.iloc[:, num].columns
total_cols = list(num_cols) + cc

df_aux = df.loc[:, total_cols]

col_drop = num_cols.to_list()
col_drop = [cd for cd in col_drop if cd not in drops]

def plot_numeric(df_aux, c):

    series = df_aux.loc[:, c].value_counts(
    ).sort_values(ascending = False)

    series = series.iloc[:5].index
    ind = df_aux.loc[:, c].isin(series)
    df_aux1 = df_aux.loc[ind, :]

    sc = 0.8

    color = ['b', 'g', 'm', 'r', 'c']

    my_pal = {s:cr for s, cr  in zip(series, color)}

    fig, ax = plt.subplots(3, 4, figsize = (20 * sc, 15 * sc))

    fig.suptitle(f'Numerical Relationships of {c} feature')

    for i, col in enumerate(col_drop):

        my_order = df_aux1.groupby(
            by=[c])[col].median(
        ).sort_values(ascending=False)

        sns.boxplot(data=df_aux1, x = c, y = col, ax = ax[i//4, i%4],
                    order = my_order.index, palette=my_pal);
        ax[i//4, i%4].tick_params(axis='x', rotation=75)

        ax[i//4, i%4].set_title(' ')

    fig.tight_layout()

plot_numeric(df_aux, 'location')
```



- Six Flags Magic Mountain roller coaster were closed in proximate dates.
- Canada's Wonderland have a small length distribuition, as well as drop.
- Canada's Wonderland max angle are predominaly large.
- Canada's Wonderland have a unique g-force.

In [131]:

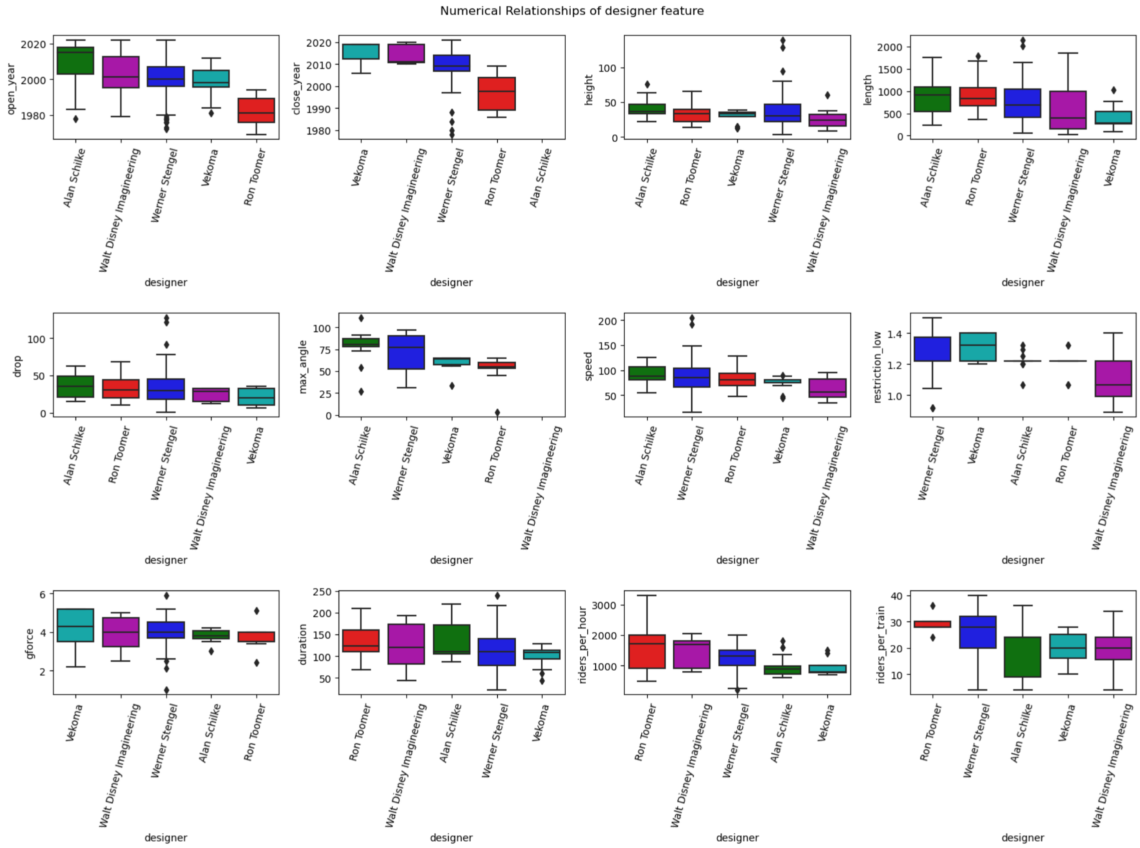
```
plot_numeric(df_aux, 'manufacturer')
```



- Mack Rides drop have a small drop distribuition.
- Boilinger & Mabillard have a high height restriction.
- Boilinger & Mabillard rides per train are considerable values.

In [132]:

```
plot_numeric(df_aux, 'designer')
```



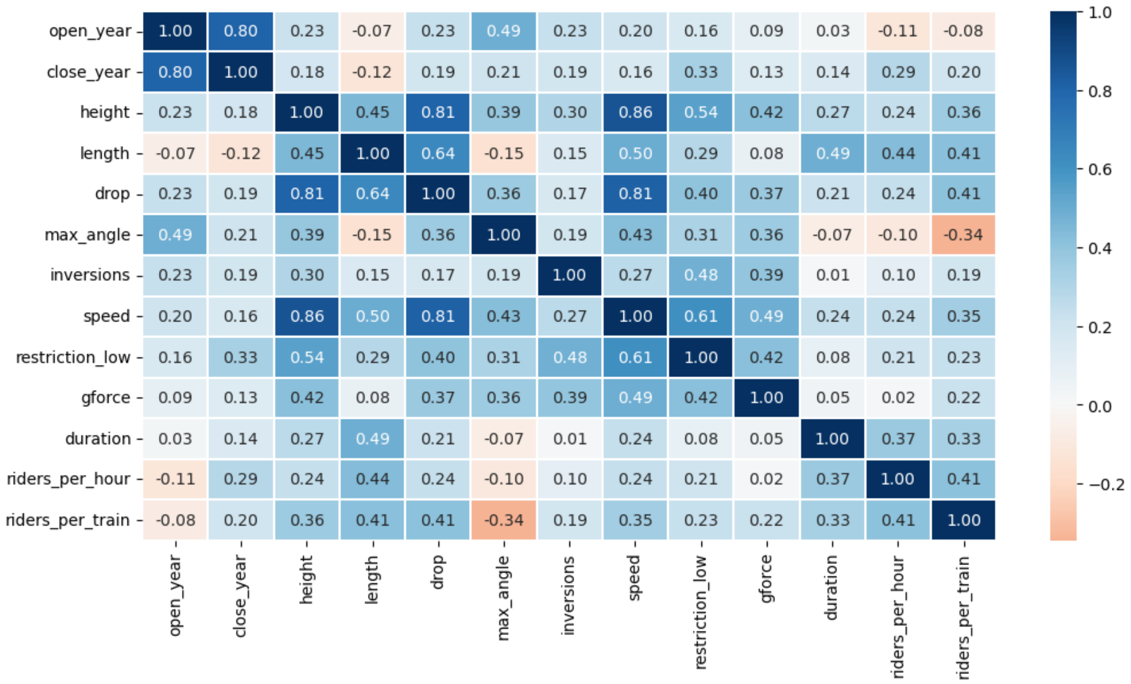
- Vekoma roller coasters speed values have low variance.
- Ron Toomer have designed riders per train have a low variance.

3. Numerical Features

Next, let's explore the correlation matrix of the roller coaster, focusing solely on its numerical features. Then, the most notable correlation are going to be further explored.

In [133]:

```
plt.figure(figsize=(12, 6))
sns.heatmap(df.iloc[:, num].corr(),
            center=0, linewidth=0.1,
            annot = True, fmt = '.2f', cmap = 'RdBu');
```



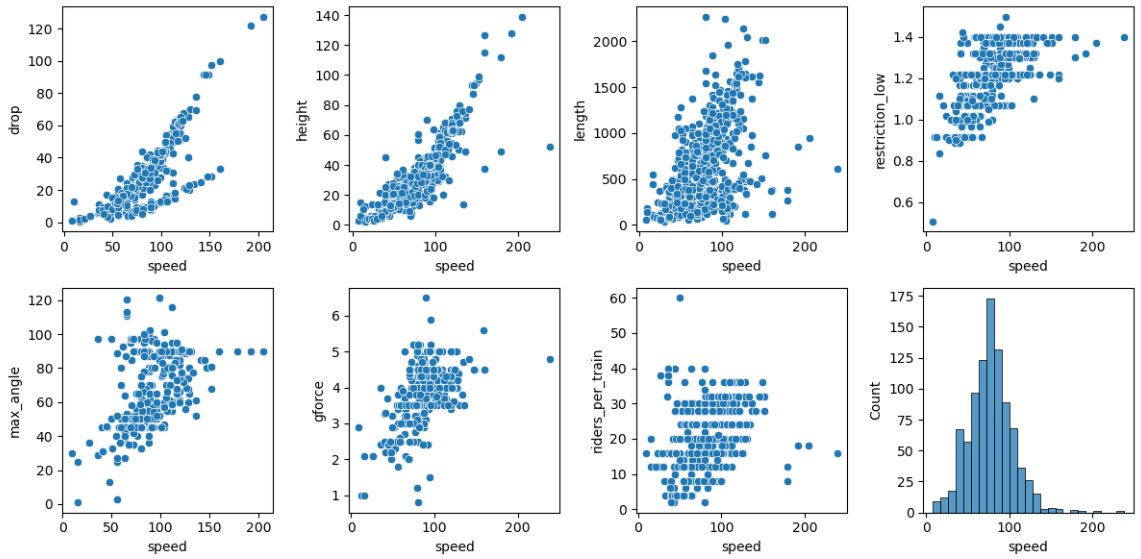
Some relations to highlight:

- Speed is strongly correlated with drop and height, and moderately with max angle, restriction height, length, gforce and riders per train.
- Height is strongly correlated with drop, and moderately with length, height restriction, max angle, inversions, gforce and riders per train.
- Length is moderately correlated with drop, duration, riders per hour and riders per train.
- GForce is moderately correlated with max angle, drop, inversions and height restriction.
- Height restriction is moderately with max angle, drop, inversions and close year.
- Riders per train is moderately correlated with duration, drop, riders per hour, max angle.
- Open year is strongly correlated with close year and max angle.
- Duration is moderately correlated with riders per hour.
- Drop is moderately correlated with max angle.

3.1. Speed

In [134]:

```
fig, ax = plt.subplots(2, 4, figsize = (12, 6))

feats = ['drop', 'height', 'length', 'restriction_low', 'max_angle', 'gforce', 'riders_p

for i, f in enumerate(feats):
    sns.scatterplot(data = df, x = 'speed', y=f, ax = ax[i//4, i%4])

bin_number = 25 #int((sum(df['speed'].notnull()))**0.5)

sns.histplot(data = df, x = 'speed', ax = ax[1, 3], bins = bin_number)

fig.tight_layout()
```



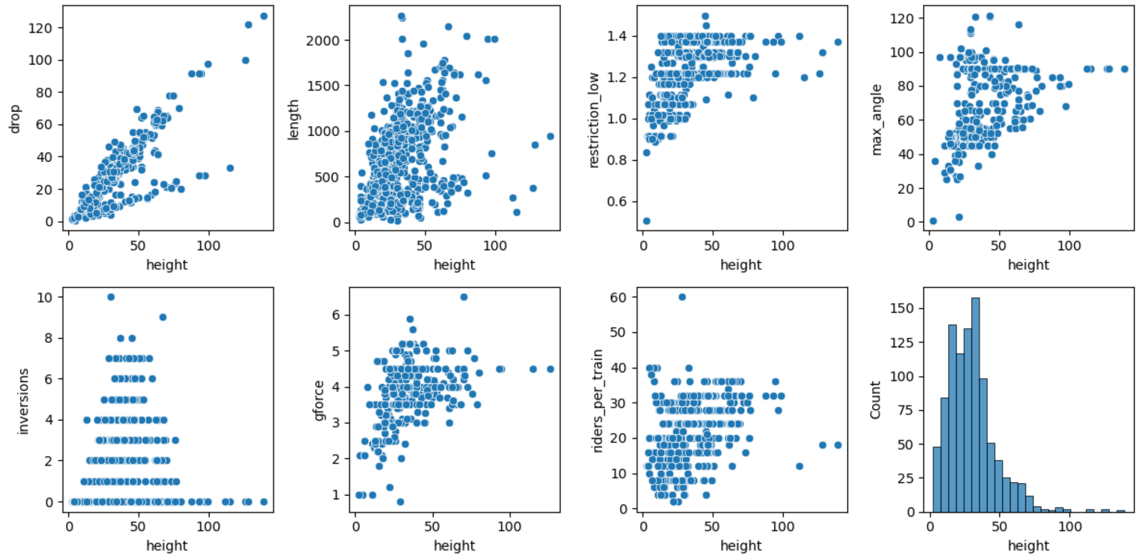
Conclusions:

- A roller coaster's speed is directly influenced by the height and drop it possesses. The higher the drop and height, the faster the train will ride.
- Roller coasters with longer lengths provide ample space for the train to gather speed, enhancing the overall experience.
- Higher speeds necessitate stricter restrictions for riders due to the increased intensity and potential risks.
- The maximum angle of a roller coaster impacts its speed since the gravitational force becomes more prominent, affecting the overall velocity.
- Generally, as speed increases, the g-force experienced by riders also tends to increase.
- There is a positive correlation between the number of riders per train and speed. This relationship can be explained by the additional weight that riders contribute to the train, thereby increasing the gravitational force experienced during the ride.

3.2. Height

In [135]:

```
fig, ax = plt.subplots(2, 4, figsize = (12, 6))

feats = ['drop', 'length', 'restriction_low', 'max_angle', 'inversions', 'gforce', 'ride

xx = 'height'

for i, f in enumerate(feats):
    sns.scatterplot(data = df, x = xx, y=f, ax = ax[i//4, i%4])

bin_number = 25

sns.histplot(data = df, x = xx, ax = ax[1, 3], bins = bin_number)

fig.tight_layout()
```



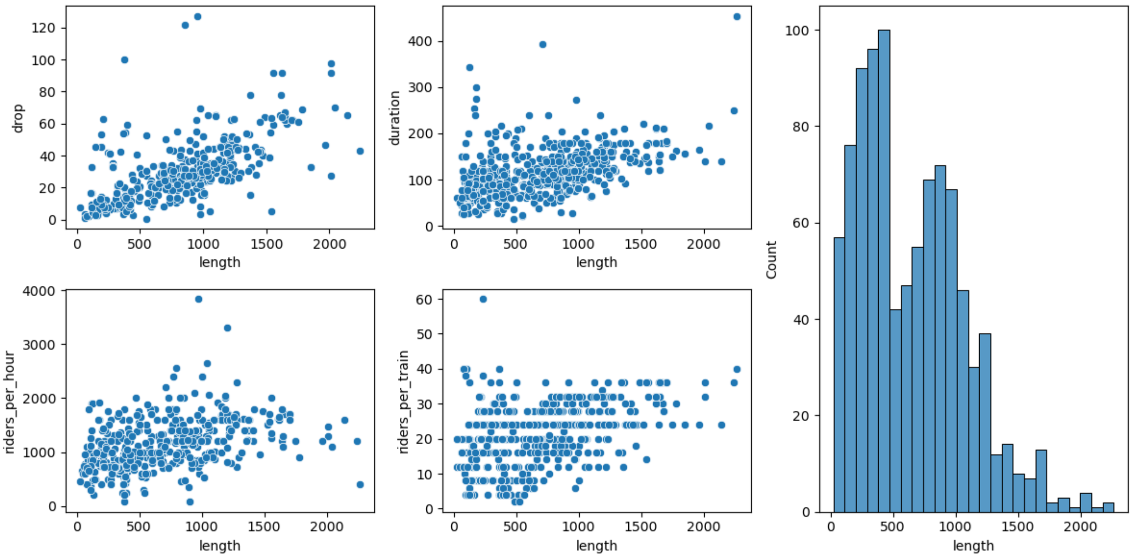
Conclusions:

- Higher heights allow for the setting of more significant drops in a roller coaster.
- Roller coasters with greater heights require a longer track length to accommodate the thrilling ride experience.
- Large height values necessitate more stringent height restrictions for riders.
- Increasing the height of a roller coaster leads to higher costs and increased track usage, which may not always justify the additional expenses associated with incorporating inversion systems.
- As height influences speed, it indirectly affects the experienced g-force during the ride.
- There is a positive correlation between the maximum angle and the number of riders per train with the height of the roller coaster.

3.3. Length

In [136]:

```
fig, ax = plt.subplots(2, 3, figsize = (12, 6))

feats = ['drop', 'duration', 'riders_per_hour', 'riders_per_train']

xx = 'length'

for i, f in enumerate(feats):
    sns.scatterplot(data = df, x = xx, y=f, ax = ax[i//2, i%2])

gs = ax[0, 2].get_gridspec()

ax[0, 2].remove()
ax[1, 2].remove()

bin_number = 25

axbig = fig.add_subplot(gs[:, 2])
sns.histplot(data = df, x = xx, bins = bin_number)


fig.tight_layout()
```



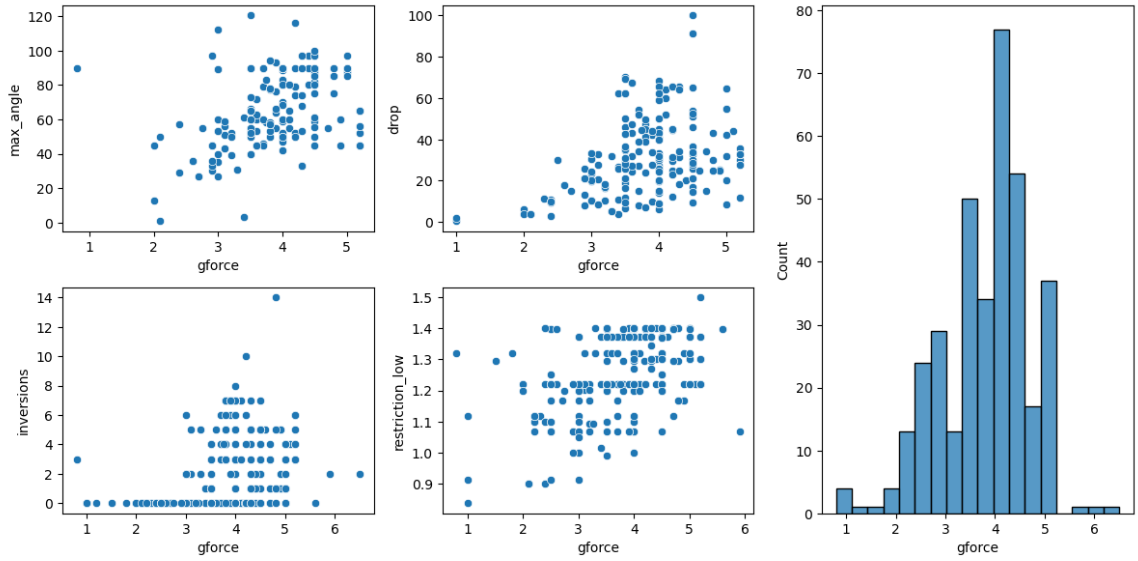
Conclusions:

- When examining the relationship between length and height, it becomes evident that length indirectly influences the value of the drop in a roller coaster.
- Roller coaster rides tend to last longer when the length of the track is increased.
- One might expect that longer rides would result in a decrease in the number of riders per hour. However, the increase in the number of riders per train as the length of the roller coaster increases leads to an overall increase in riders per hour. This phenomenon can be attributed to the careful consideration of ride duration by designers. They take into account how long the ride will last and the willingness of people to wait, leading them to carefully select the number of riders per train.

3.4. G-force

In [137]:

```
fig, ax = plt.subplots(2, 3, figsize = (12, 6))

feats = ['max_angle', 'drop', 'inversions', 'restriction_low']

xx = 'gforce'

for i, f in enumerate(feats):
    sns.scatterplot(data = df, x = xx, y=f, ax = ax[i//2, i%2])

gs = ax[0, 2].get_gridspec()

ax[0, 2].remove()
ax[1, 2].remove()

bin_number = 18

axbig = fig.add_subplot(gs[:, 2])
sns.histplot(data = df, x = xx, bins = bin_number)

fig.tight_layout()
```



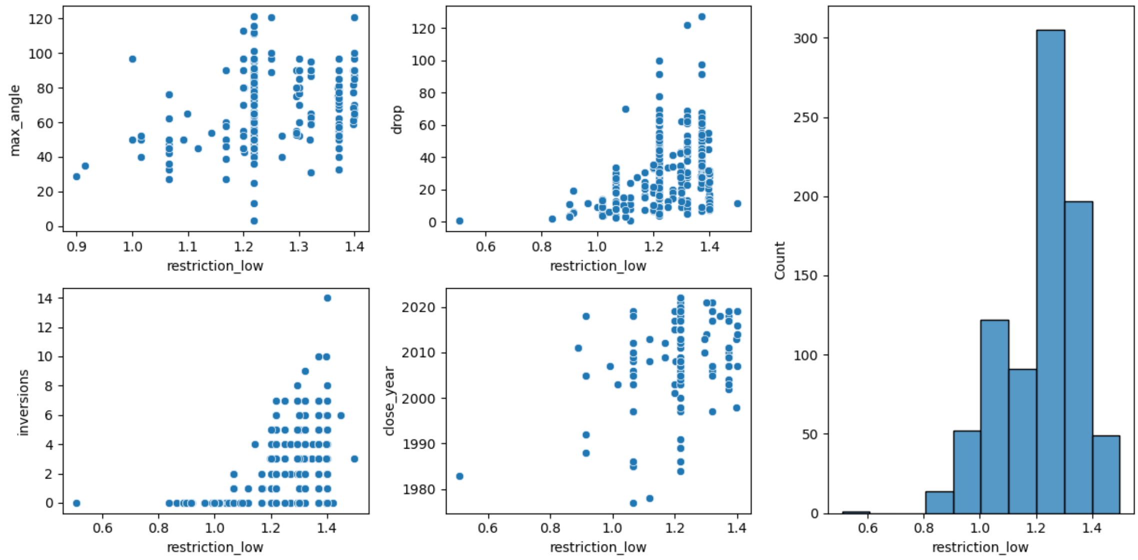
Conclusions:

- The maximum angle and drop of a roller coaster directly impact the experienced g-force during the ride.
- G-forces smaller than 3 can only be achieved when the roller coaster does not have any inversions.
- The level of g-force experienced on a roller coaster affects the height restrictions for riders.

3.5. Height restriction

In [138]:

```
fig, ax = plt.subplots(2, 3, figsize = (12, 6))

feats = ['max_angle', 'drop', 'inversions', 'close_year']

xx = 'restriction_low'

for i, f in enumerate(feats):
    sns.scatterplot(data = df, x = xx, y=f, ax = ax[i//2, i%2])

gs = ax[0, 2].get_gridspec()

ax[0, 2].remove()
ax[1, 2].remove()

bin_number = 10

axbig = fig.add_subplot(gs[:, 2])
sns.histplot(data = df, x = xx, bins = bin_number)

fig.tight_layout()
```



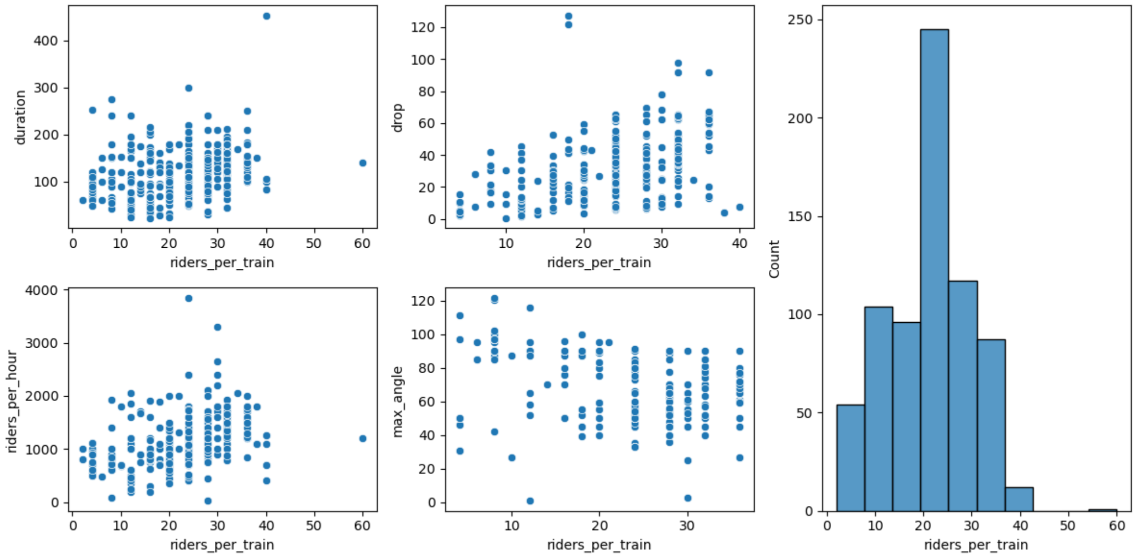
Conclusions:

- To accommodate smaller children in the roller coaster, it is necessary for the ride to exclude inversions. This design choice ensures a safer and more accessible experience for young riders.

3.6. Riders per train

In [139]:

```
fig, ax = plt.subplots(2, 3, figsize = (12, 6))

feats = ['duration', 'drop', 'riders_per_hour', 'max_angle']

xx = 'riders_per_train'

for i, f in enumerate(feats):
    sns.scatterplot(data = df, x = xx, y=f, ax = ax[i//2, i%2])

gs = ax[0, 2].get_gridspec()

ax[0, 2].remove()
ax[1, 2].remove()

bin_number = 10

axbig = fig.add_subplot(gs[:, 2])
sns.histplot(data = df, x = xx, bins = bin_number)

fig.tight_layout()
```



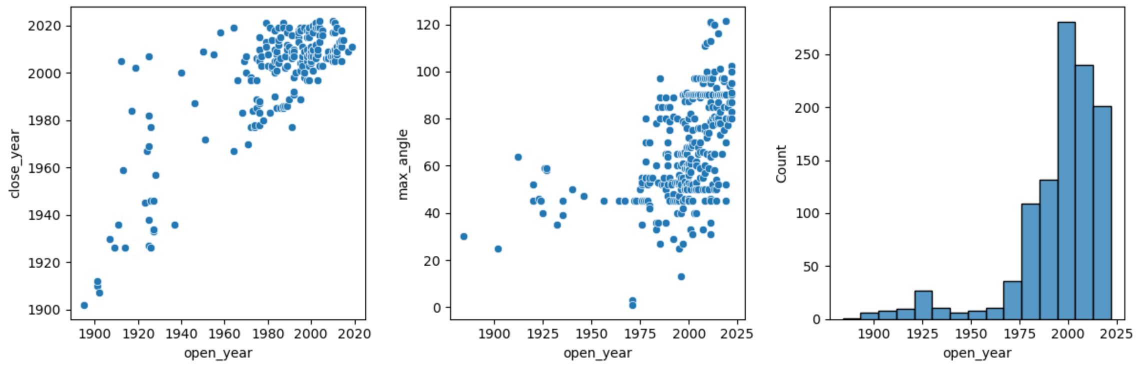
Conclusions:

- The number of riders per train is indirectly related to the drop of the roller coaster due to the relationship with the length of the ride. Longer rides often allow for more riders per train, as there is ample track to accommodate multiple passengers.
- There is a positive correlation between the number of riders per train and the number of riders per hour. When the roller coaster can accommodate more passengers in each train, it increases the overall capacity of the ride, resulting in a higher number of riders per hour.

3.7. Open Year

In [140]:

```
fig, ax = plt.subplots(1, 3, figsize = (12, 4))

feats = ['close_year', 'max_angle']

xx = 'open_year'

for i, f in enumerate(feats):
    sns.scatterplot(data = df, x = xx, y=f, ax = ax[i ])

bin_number = 15

sns.histplot(data = df, x = xx, ax = ax[2], bins = bin_number)

fig.tight_layout()
```



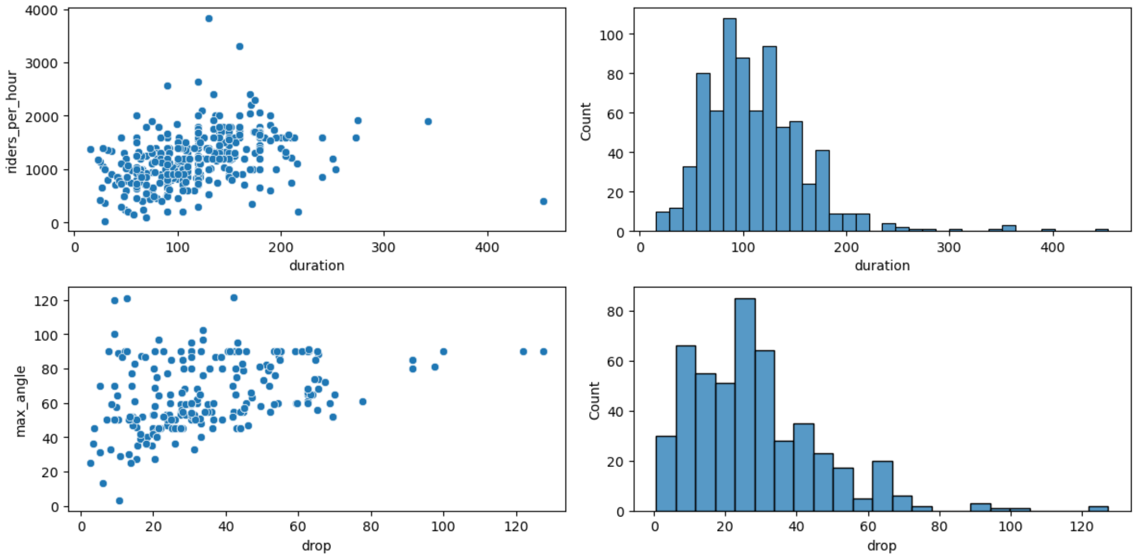
Conclusions:

- The difference between the close date and the open date is not significantly large.
- High max angles started to be considered past 1975.
- Most of the roller coaster were built recently.

3.8. Duration and Drop

In [141]:

```
fig, ax = plt.subplots(2, 2, figsize = (12, 6))

feats = ['riders_per_hour', 'max_angle']

xx = ['duration', 'drop']

sns.scatterplot(data = df, x = xx[0], y=feats[0], ax = ax[0, 0])
sns.scatterplot(data = df, x = xx[1], y=feats[1], ax = ax[1, 0])

sns.histplot(data = df, x = xx[0], ax = ax[0, 1])
sns.histplot(data = df, x = xx[1], ax = ax[1, 1])

fig.tight_layout()
```



Conclusions:

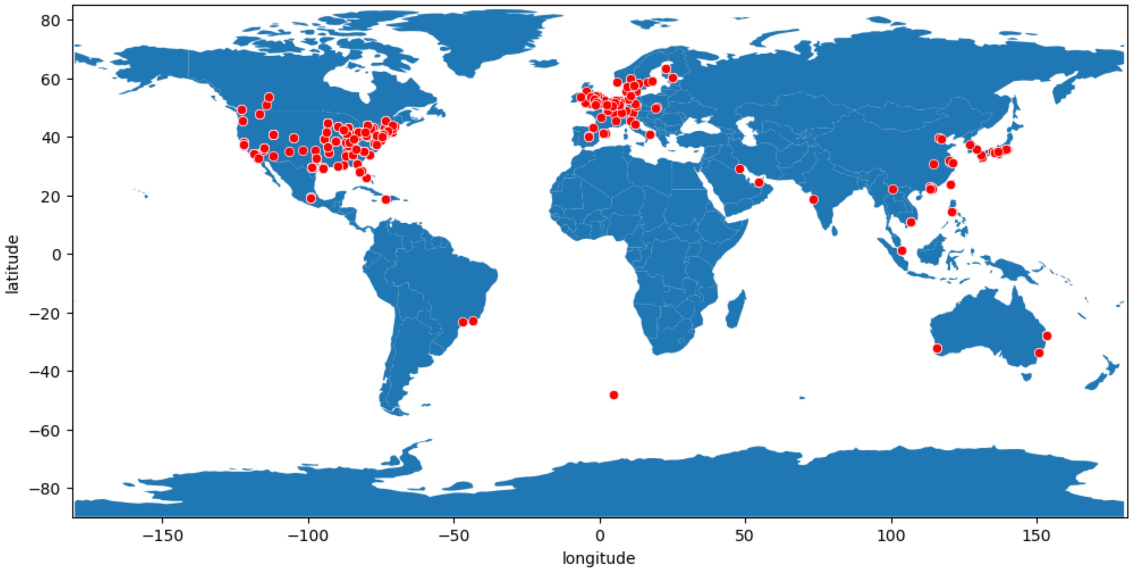
- Similarly, we can observe the same relationship between riders per hour and the duration of the ride, as we did with riders per hour and the length of the roller coaster.
- A steeper maximum angle often corresponds to a larger drop, adding to the excitement and intensity of the ride.

4. Geospatial Information

Since we have access to the locations of our roller coasters, let's explore the possibility of extracting geospatial information.

In [142]:

```
fig, ax = plt.subplots(1, 1, figsize = (12, 6))
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))

world.plot(ax = ax);
sns.scatterplot(data = df, x = 'longitude', y = 'latitude', color = 'r');
ax.set_xlim(-181, 181);
ax.set_ylim(-90, 85);
```



We have a point in the middle of nowhere, the only one below -40º latitude.

In [143]:

```
df.query('latitude < -40').transpose()
```

Out[143]:

	1062
name	Krampus Expédition
location	Nigloland
manufacturer	Mack Rides
designer	NaN
type	Steel
model	NaN
track_layout	water
status	operating
lift_launch	lift
latitude	-48.2617
longitude	4.6142
open_year	2021
close_year	NaN
height	28.01112
length	599.9988
drop	NaN
max_angle	NaN
inversions	0
speed	78.4
restriction_low	1.1
gforce	3.5
duration	240.0
riders_per_hour	850.0
riders_per_train	8.0

The roller coaster is located in France. It was supposed to be positive latitude (+48.2617). Let's give a correction.

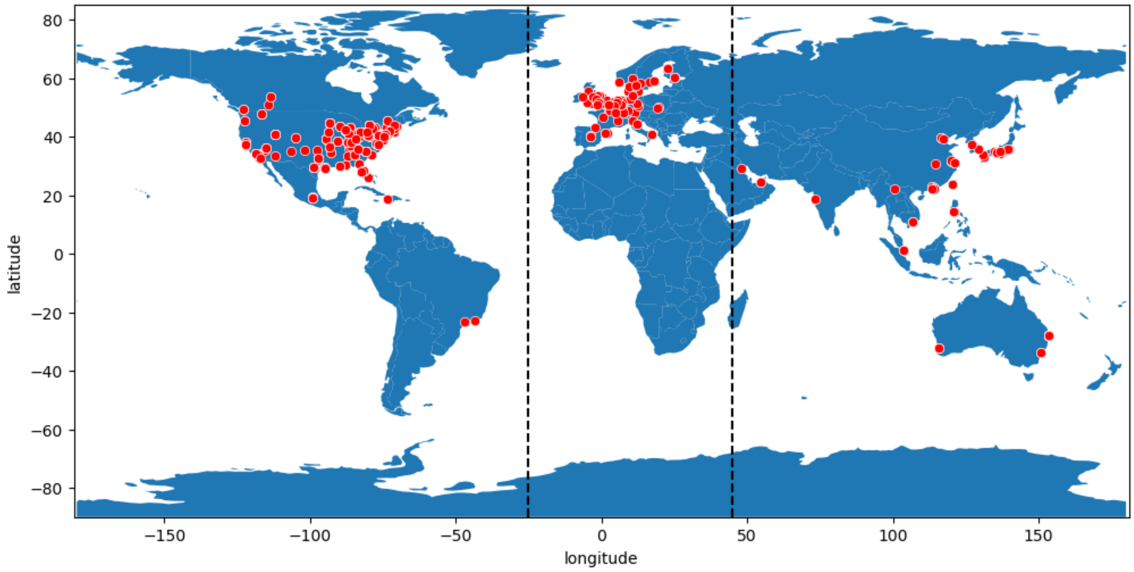
In [144]:

```
df.loc[1062, 'latitude'] *= (-1)
```

The majority of roller coasters are concentrated in two main regions: the United States and Europe, while Asia and Oceania have fewer instances. Let's categorize the roller coasters into three main groups based on their locations: America, Europe, and Asia/Oceania.

In [145]:

```
fig, ax = plt.subplots(1, 1, figsize = (12, 8))
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))

world.plot(ax = ax);
sns.scatterplot(data = df, x = 'longitude', y = 'latitude', color = 'r');
ax.axvline(45, color= 'k', ls = '--')
ax.axvline(-25, color= 'k', ls = '--');
ax.set_xlim(-181, 181);
ax.set_ylim(-90, 85);
```

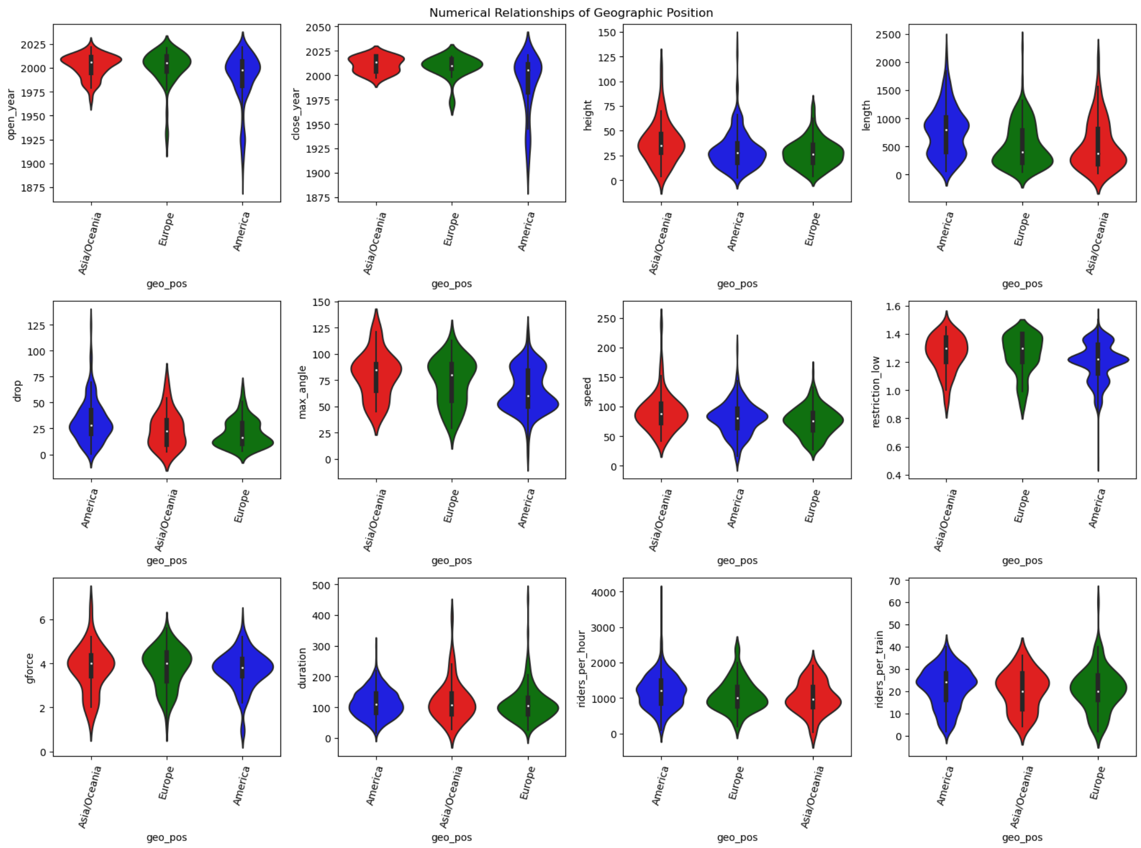


In [146]:

```
mask1 = (df.loc[:, 'longitude'] <= - 25)
mask2 = (df.loc[:, 'longitude'] > - 25) & (df.loc[:, 'longitude'] < 48)
mask3 = (df.loc[:, 'longitude'] >= 48)

df['geo_pos'] = np.nan
df.loc[mask1, 'geo_pos'] = 'America'
df.loc[mask2, 'geo_pos'] = 'Europe'
df.loc[mask3, 'geo_pos'] = 'Asia/Oceania'
```

In [149]:

```
num_cols = df.iloc[:, num].columns
total_cols = list(num_cols) + ['geo_pos']

df_aux = df.loc[:, total_cols]

series = df_aux.loc[:, 'geo_pos'].value_counts().index

col_drop = num_cols.to_list()
col_drop.remove('inversions')

sc = 0.8

color = ['b', 'g', 'r']

my_pal = {s:cr for s, cr  in zip(series, color)}

fig, ax = plt.subplots(3, 4, figsize = (20 * sc, 15 * sc))

fig.suptitle(f'Numerical Relationships of Geographic Position')

for i, col in enumerate(col_drop):

        my_order = df_aux.groupby(
            by=['geo_pos'])[col].median(
        ).sort_values(ascending=False)

        sns.violinplot(data=df_aux, x = 'geo_pos', y = col, ax = ax[i//4, i%4],
                       order = my_order.index, palette=my_pal);
        ax[i//4, i%4].tick_params(axis='x', rotation=75)

fig.tight_layout()
```



Conclusions:

- One might supposed that the roller coasters started in America. But the dataset did not considered the previous initiatives in Russia and France, leading to wrong conclusions.
- The large drops roller coasters are concentrated in America.
- Max angles are located in Asia/Oceania on average, followed by Europe and America, the last one having a
- Asia/Oceania have the fastest roller coasters, followed by America and Europe.

In [150]:

```
df_aux.loc[:, ['geo_pos', 'speed']].groupby('geo_pos').describe()
```

Out[150]:

	speed							
	count	mean	std	min	25%	50%	75%	max
geo_pos								
America	439.0	80.001458	27.555190	8.00	63.84	80.00	96.00	204.80
Asia/Oceania	74.0	90.125405	31.541243	41.60	71.52	87.52	104.32	238.56
Europe	186.0	75.443441	24.018277	26.88	59.68	75.84	89.44	159.04

In [151]:

```
df_aux.loc[:, ['geo_pos', 'max_angle']].groupby('geo_pos').describe()
```

Out[151]:

	max_angle							
	count	mean	std	min	25%	50%	75%	max
geo_pos								
America	190.0	65.375789	20.350233	3.0	50.00	60.0	84.0	121.5
Asia/Oceania	29.0	79.931034	21.655057	45.0	65.00	85.0	90.0	121.0
Europe	58.0	73.737931	21.786354	29.0	55.25	80.0	90.0	113.1

5. Conclusion

By analyzing these various aspects, we can gain insights into the design, safety considerations, and rider experience of roller coasters. These findings can be valuable for park operators, ride designers, and enthusiasts seeking to understand the dynamics and characteristics of roller coasters worldwide.

In [36]:

```
#df_ml = df.loc[:, ['type',
#            'geo_pos',
#            'lift_launch',
#            'height',
#            'length',
#            'drop',
#            'max_angle',
#            'inversions',
#            'speed',
#            'restriction_low',
#            'gforce',
#            'duration',
#            'riders_per_hour',
#            'riders_per_train']]
```