Projeto - Acidente de Trabalho

The database is basically records of accidents from 12 different plants in 03 different countries which every line in the data is an occurrence ofan accident

In [1]:

```
!pip3 install bnlearn
```

```
Requirement already satisfied: bnlearn in c:\users\ooliv\anaconda3\lib\site-
packages (0.3.11)
Requirement already satisfied: pandas in c:\users\ooliv\anaconda3\lib\site-p
ackages (from bnlearn) (1.0.5)
Requirement already satisfied: community in c:\users\ooliv\anaconda3\lib\sit
e-packages (from bnlearn) (1.0.0b1)
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e-packages (from bnlearn) (20.4)
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ite-packages (from bnlearn) (0.11.1)
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ckages (from bnlearn) (1.18.5)
Requirement already satisfied: networkx>=2.5 in c:\users\ooliv\anaconda3\lib
\site-packages (from bnlearn) (2.5)
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-packages (from bnlearn) (1.0.2)
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Requirement already satisfied: df2onehot in c:\users\ooliv\anaconda3\lib\sit
e-packages (from bnlearn) (0.2.14)
Requirement already satisfied: matplotlib>=3.3.2 in c:\users\ooliv\anaconda3
\lib\site-packages (from bnlearn) (3.3.3)
Requirement already satisfied: ismember in c:\users\ooliv\anaconda3\lib\site
-packages (from bnlearn) (0.1.3)
Requirement already satisfied: python-dateutil>=2.6.1 in c:\users\ooliv\anac
onda3\lib\site-packages (from pandas->bnlearn) (2.8.1)
Requirement already satisfied: pytz>=2017.2 in c:\users\ooliv\anaconda3\lib
\site-packages (from pandas->bnlearn) (2020.1)
Requirement already satisfied: Flask in c:\users\ooliv\anaconda3\lib\site-pa
ckages (from community->bnlearn) (1.1.2)
Requirement already satisfied: requests in c:\users\ooliv\anaconda3\lib\site
-packages (from community->bnlearn) (2.24.0)
Requirement already satisfied: six in c:\users\ooliv\anaconda3\lib\site-pack
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Requirement already satisfied: pyparsing>=2.0.2 in c:\users\ooliv\anaconda3
\lib\site-packages (from packaging->bnlearn) (2.4.7)
Requirement already satisfied: scipy>=1.0 in c:\users\ooliv\anaconda3\lib\si
te-packages (from statsmodels->bnlearn) (1.5.0)
Requirement already satisfied: patsy>=0.5 in c:\users\ooliv\anaconda3\lib\si
te-packages (from statsmodels->bnlearn) (0.5.1)
Requirement already satisfied: decorator>=4.3.0 in c:\users\ooliv\anaconda3
\lib\site-packages (from networkx>=2.5->bnlearn) (4.4.2)
Requirement already satisfied: scikit-learn in c:\users\ooliv\anaconda3\lib
\site-packages (from sklearn->bnlearn) (0.23.1)
Requirement already satisfied: cycler>=0.10 in c:\users\ooliv\anaconda3\lib
\site-packages (from matplotlib>=3.3.2->bnlearn) (0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\ooliv\anaconda3
\lib\site-packages (from matplotlib>=3.3.2->bnlearn) (1.2.0)
Requirement already satisfied: pillow>=6.2.0 in c:\users\ooliv\anaconda3\lib
\site-packages (from matplotlib>=3.3.2->bnlearn) (7.2.0)
Requirement already satisfied: Werkzeug>=0.15 in c:\users\ooliv\anaconda3\li
b\site-packages (from Flask->community->bnlearn) (1.0.1)
Requirement already satisfied: click>=5.1 in c:\users\ooliv\anaconda3\lib\si
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te-packages (from Flask->community->bnlearn) (7.1.2)
Requirement already satisfied: itsdangerous>=0.24 in c:\users\ooliv\anaconda
3\lib\site-packages (from Flask->community->bnlearn) (1.1.0)
Requirement already satisfied: Jinja2>=2.10.1 in c:\users\ooliv\anaconda3\li
b\site-packages (from Flask->community->bnlearn) (2.11.2)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in
c:\users\ooliv\anaconda3\lib\site-packages (from requests->community->bnlear
n) (1.25.9)
Requirement already satisfied: chardet<4,>=3.0.2 in c:\users\ooliv\anaconda3
\lib\site-packages (from requests->community->bnlearn) (3.0.4)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\ooliv\anaconda
3\lib\site-packages (from requests->community->bnlearn) (2020.11.8)
Requirement already satisfied: idna<3,>=2.5 in c:\users\ooliv\anaconda3\lib
\site-packages (from requests->community->bnlearn) (2.10)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\ooliv\anacon
da3\lib\site-packages (from scikit-learn->sklearn->bnlearn) (2.1.0)
Requirement already satisfied: joblib>=0.11 in c:\users\ooliv\anaconda3\lib
\site-packages (from scikit-learn->sklearn->bnlearn) (0.16.0)
Requirement already satisfied: MarkupSafe>=0.23 in c:\users\ooliv\anaconda3
\lib\site-packages (from Jinja2>=2.10.1->Flask->community->bnlearn) (1.1.1)
```

In [2]:

```
!pip3 install category_encoders
```

```
Requirement already satisfied: category_encoders in c:\users\ooliv\anaconda3
\lib\site-packages (2.2.2)
Requirement already satisfied: patsy>=0.5.1 in c:\users\ooliv\anaconda3\lib
\site-packages (from category_encoders) (0.5.1)
Requirement already satisfied: scikit-learn>=0.20.0 in c:\users\ooliv\anacon
da3\lib\site-packages (from category_encoders) (0.23.1)
Requirement already satisfied: numpy>=1.14.0 in c:\users\ooliv\anaconda3\lib
\site-packages (from category_encoders) (1.18.5)
Requirement already satisfied: pandas>=0.21.1 in c:\users\ooliv\anaconda3\li
b\site-packages (from category_encoders) (1.0.5)
Requirement already satisfied: scipy>=1.0.0 in c:\users\ooliv\anaconda3\lib
\site-packages (from category_encoders) (1.5.0)
Requirement already satisfied: statsmodels>=0.9.0 in c:\users\ooliv\anaconda
3\lib\site-packages (from category_encoders) (0.11.1)
Requirement already satisfied: six in c:\users\ooliv\anaconda3\lib\site-pack
ages (from patsy>=0.5.1->category_encoders) (1.15.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\ooliv\anacon
da3\lib\site-packages (from scikit-learn>=0.20.0->category_encoders) (2.1.0)
Requirement already satisfied: joblib>=0.11 in c:\users\ooliv\anaconda3\lib
\site-packages (from scikit-learn>=0.20.0->category_encoders) (0.16.0)
Requirement already satisfied: pytz>=2017.2 in c:\users\ooliv\anaconda3\lib
\site-packages (from pandas>=0.21.1->category_encoders) (2020.1)
Requirement already satisfied: python-dateutil>=2.6.1 in c:\users\ooliv\anac
onda3\lib\site-packages (from pandas>=0.21.1->category_encoders) (2.8.1)
```

In [3]:

```
# Importar bibliotecas
import os
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import pgmpy
import bnlearn
from sklearn.preprocessing import StandardScaler, LabelEncoder, OneHotEncoder, minmax_s
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB, MultinomialNB, BernoulliNB, CategoricalNB
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import accuracy_score, confusion_matrix, plot_confusion_matrix, cl
from sklearn.utils import shuffle
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
import category_encoders as ce
from math import sqrt
import warnings
warnings.filterwarnings('ignore');
import plotly.express as px
import random
```

In [4]:

```
url = 'https://raw.githubusercontent.com/paulo-al-castro/datafiles/master/accident_data
db = pd.read_csv(url)
```

In [5]:

```
db.head()
```

Out[5]:

	Data	Countries	Local	Industry Sector	Accident Level	Potential Accident Level	Genre	Employee ou Terceiro	Risco Critico
0	2016-01-01 00:00:00	Country_01	Local_01	Mining	I	IV	Male	Third Party	Pressed
1	2016-01-02 00:00:00	Country_02	Local_02	Mining	I	IV	Male	Employee	Pressurized Systems
2	2016-01-06 00:00:00	Country_01	Local_03	Mining	I	III	Male	Third Party (Remote)	Manual Tools
3	2016-01-08 00:00:00	Country_01	Local_04	Mining	I	I	Male	Third Party	Others
4	2016-01-10 00:00:00	Country_01	Local_04	Mining	IV	IV	Male	Third Party	Others

In [6]:

```python
db.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 439 entries, 0 to 438
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype 
---  ------                    --------------  ----- 
 0   Data                      439 non-null    object
 1   Countries                 439 non-null    object
 2   Local                     439 non-null    object
 3   Industry Sector           439 non-null    object
 4   Accident Level            439 non-null    object
 5   Potential Accident Level  439 non-null    object
 6   Genre                     439 non-null    object
 7   Employee ou Terceiro      439 non-null    object
 8   Risco Critico             439 non-null    object
dtypes: object(9)
memory usage: 31.0+ KB
```

In [7]:

```python
# Verificar se existe alguma coluna sem valor atribuído
categorial = [var for var in db.columns]
db[categorial].isnull().sum()
```

Out[7]:

```
Data                        0
Countries                   0
Local                       0
Industry Sector             0
Accident Level              0
Potential Accident Level    0
Genre                       0
Employee ou Terceiro        0
Risco Critico               0
dtype: int64
```

Columns description

Data: timestamp or time/date information

Countries: which country the accident occurred (anonymized)

Local: the city where the manufacturing plant is located (anonymized)

Industry sector: which sector the plant belongs to (Mining, metals,Others)

Accident level: from I to VI, it registers how severe was the accident (I means not severe ...VI most severe)

Potential Accident Level: Depending on the Accident Level, the database also registers how severe the accident could have been (due to other factors involved in the accident)

Genre: ifthe person is male offemale

Employee or Third Party: if the injured person is an employee or a third party

Critical Risk: some description ofthe risk involved in the accident

Verificar quantidade de itens diferentes em cada coluna

In [8]:

```
db['Countries'].value_counts()
```

Out[8]:

```
Country_01    263
Country_02    132
Country_03     44
Name: Countries, dtype: int64
```

In [9]:

```
db['Local'].value_counts()
```

Out[9]:

```
Local_03    90
Local_05    59
Local_06    58
Local_01    57
Local_04    56
Local_10    44
Local_08    29
Local_02    24
Local_07    14
Local_12     4
Local_09     2
Local_11     2
Name: Local, dtype: int64
```

In [10]:

```
db['Industry Sector'].value_counts()
```

Out[10]:

```
Mining    241
Metals    148
Others     50
Name: Industry Sector, dtype: int64
```

Percebe-se que poderemos ter problemas com a quantidade de 'Accident Level' (nível do acidente), pois os acidentes de maior nível são de menor quantidade.

In [11]:

```
db['Accident Level'].value_counts().sort_index()
```

Out[11]:

```
I      328
II      40
III     31
IV      31
V        9
Name: Accident Level, dtype: int64
```

In [12]:

```
db['Potential Accident Level'].value_counts().sort_index()
```

Out[12]:

```
I       49
II      95
III    106
IV     155
V       33
VI       1
Name: Potential Accident Level, dtype: int64
```

In [13]:

```
db['Genre'].value_counts()
```

Out[13]:

```
Male      417
Female     22
Name: Genre, dtype: int64
```

In [14]:

```
db['Employee ou Terceiro'].value_counts()
```

Out[14]:

```
Third Party             189
Employee                181
Third Party (Remote)     69
Name: Employee ou Terceiro, dtype: int64
```

In [15]:

```
print('Quantidade de itens diferentes em Risco Crítico: {}'.format(len(db['Risco Critic

db['Risco Critico'].value_counts()
```

```
Quantidade de itens diferentes em Risco Crítico: 34
```

Out[15]:

```
Others                                     232
Pressed                                     24
Manual Tools                                20
Chemical substances                         17
Venomous Animals                            16
Pressurized Systems / Chemical Substances   15
Cut                                         14
Projection                                  13
Bees                                        10
Fall                                         9
Vehicles and Mobile Equipment                8
Fall prevention (same level)                 7
remains of choco                             7
Pressurized Systems                          7
Fall prevention                              6
Suspended Loads                              6
Blocking and isolation of energies           3
Power lock                                   3
Liquid Metal                                 3
Projection of fragments                      2
Machine Protection                           2
Electrical Shock                             2
Not applicable                               2
Projection/Manual Tools                      1
Plates                                       1
Projection/Burning                           1
Individual protection equipment              1
Poll                                         1
Burn                                         1
Confined space                               1
Electrical installation                      1
Projection/Choco                             1
\nNot applicable                             1
Traffic                                      1
Name: Risco Critico, dtype: int64
```

Possivelmente existem alguns Riscos Críticos que são identicos ou de certa forma parecidas. O ideal é juntar os riscos iguais com nomes diferentes. A coluna 'Risco Critico' possui dois itens, diferentes, de 'Not applicable', iremos colocá-los juntos.

In [16]:

```
db.loc[(db['Risco Critico'] == '\nNot applicable'), 'Risco Critico'] = 'Not applicable'
db.loc[(db['Risco Critico'] == 'Fall prevention (same level)') | (db['Risco Critico'] =
db.loc[(db['Risco Critico'] == 'Projection of fragments') | (db['Risco Critico'] == 'Pr
db.loc[(db['Risco Critico'] == 'Projection/Manual Tools'), 'Risco Critico'] = 'Manual T
db.loc[(db['Risco Critico'] == 'Projection/Burning') , 'Risco Critico'] = 'Burn'
db.loc[(db['Risco Critico'] == 'Electrical Shock'), 'Risco Critico'] = 'Blocking and is
db.loc[(db['Risco Critico'] == 'Electrical installation'), 'Risco Critico'] = 'Power lo
db.loc[(db['Risco Critico'] == 'Pressurized Systems') | (db['Risco Critico'] == 'Chemic

# Os novos valores atribuídos para o 'Risco Critico' ficaram assim:
print('Quantidade de itens diferentes em Risco Crítico: {}'.format(len(db['Risco Critic

db['Risco Critico'].value_counts()
```

```
Quantidade de itens diferentes em Risco Crítico: 23
```

Out[16]:

```
Others                                      232
Pressurized Systems / Chemical Substances    39
Pressed                                      24
Fall                                         22
Manual Tools                                 21
Venomous Animals                             16
Projection                                   16
Cut                                          14
Bees                                         10
Vehicles and Mobile Equipment                 8
remains of choco                              7
Suspended Loads                               6
Blocking and isolation of energies            5
Power lock                                    4
Not applicable                                3
Liquid Metal                                  3
Burn                                          2
Machine Protection                            2
Poll                                          1
Confined space                                1
Plates                                        1
Individual protection equipment               1
Traffic                                       1
Name: Risco Critico, dtype: int64
```

Tipos dos dados nas colunas

In [17]:

```
db.dtypes
```

Out[17]:

```
Data                         object
Countries                    object
Local                        object
Industry Sector              object
Accident Level               object
Potential Accident Level     object
Genre                        object
Employee ou Terceiro         object
Risco Critico                object
dtype: object
```

Vamos dividir a coluna 'Data' em quatro colunas de interesse: day (dia), month (mês), year (ano) e week_day (dia da semana).

In [18]:

```
db['Data'] = db['Data'].astype(str).str.split(' ', expand=True)[0]
db['Data'] = pd.to_datetime(db['Data'].astype(str), format='%Y-%m-%d').dt.date
db["Day"] = db['Data'].map(lambda x: x.day)
db["Month"] = db['Data'].map(lambda x: x.month)
db["Year"] = db['Data'].map(lambda x: x.year)
db['Week_day'] = db['Data'].map(lambda x: x.weekday())
db.drop(columns='Data', inplace=True)
```

In [19]:

```
# Reorganizar ordens das colunas
# Passar as colunas 'Day', 'Month', 'Year' e 'Week_day' para as primeiras posições do d
cols = db.columns.to_list()
cols = [cols[-2]] + [cols[-3]] + [cols[-4]] + [cols[-1]] + cols[:3] + cols[4:8] + [cols
db = db[cols]
db.head()

```

Out[19]:

	Year	Month	Day	Week_day	Countries	Local	Industry Sector	Potential Accident Level	Genre	Employee ou Terceiro
0	2016	1	1	4	Country_01	Local_01	Mining	IV	Male	Third Party
1	2016	1	2	5	Country_02	Local_02	Mining	IV	Male	Employee
2	2016	1	6	2	Country_01	Local_03	Mining	III	Male	Third Party (Remote)
3	2016	1	8	4	Country_01	Local_04	Mining	I	Male	Third Party
4	2016	1	10	6	Country_01	Local_04	Mining	IV	Male	Third Party

Análise dos dados

In [20]:

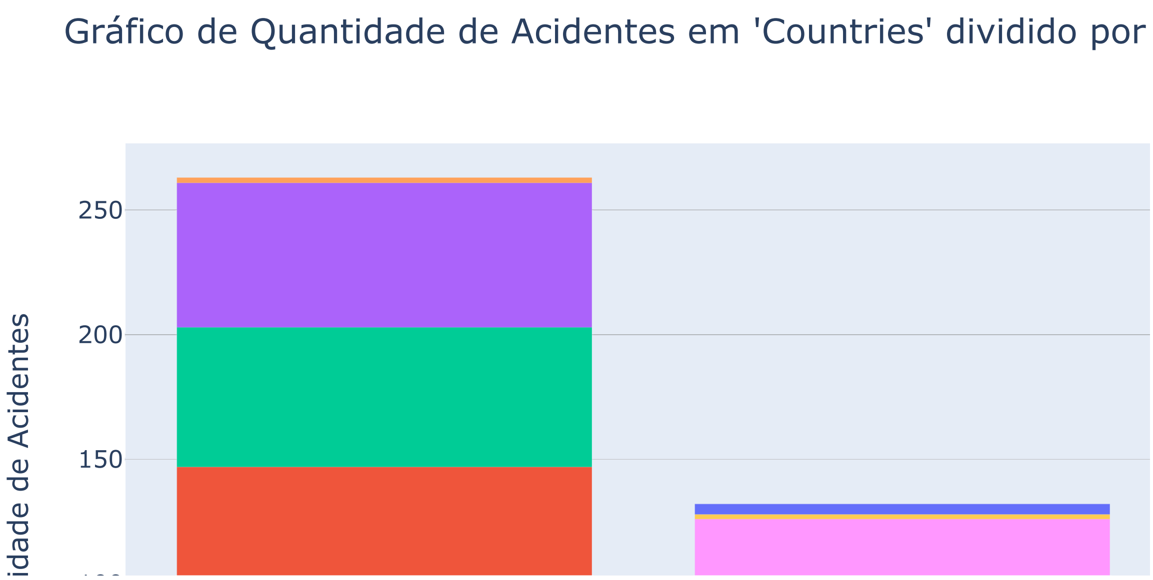
```
def img_barplot(dataset, eixo_x, especie):
    '''Função para transformar os dados de interesse em gráfico de barras em modo stack
    dataset -> banco de dados
    eixo_x -> coluna do dataset que ficará no eixo x do gráfico de barras
    especie -> coluna do dataset que divide o resultado em especies

    saída -> gráfico de barras mostrando a quantidade de acidentes pelo eixo_x dividido
    '''
    eixo_y = 'Year'
    title = f'Gráfico de Quantidade de Acidentes em \'{eixo_x}\' dividido por \'{especi
    dataset_dados = dataset.groupby(by=[eixo_x, especie])[eixo_y].count().reset_index()
    fig = px.bar(dataset_dados, x=eixo_x, y=eixo_y, color=especie,
                 barmode = 'stack', title=title, labels={'Year':'Quantidade de Acidente
    fig.show()
```

Não existe a mesma variável 'Local' para 'Countries' diferentes. Logo a coluna

'Countries' poderá ser descartada:

In [21]:

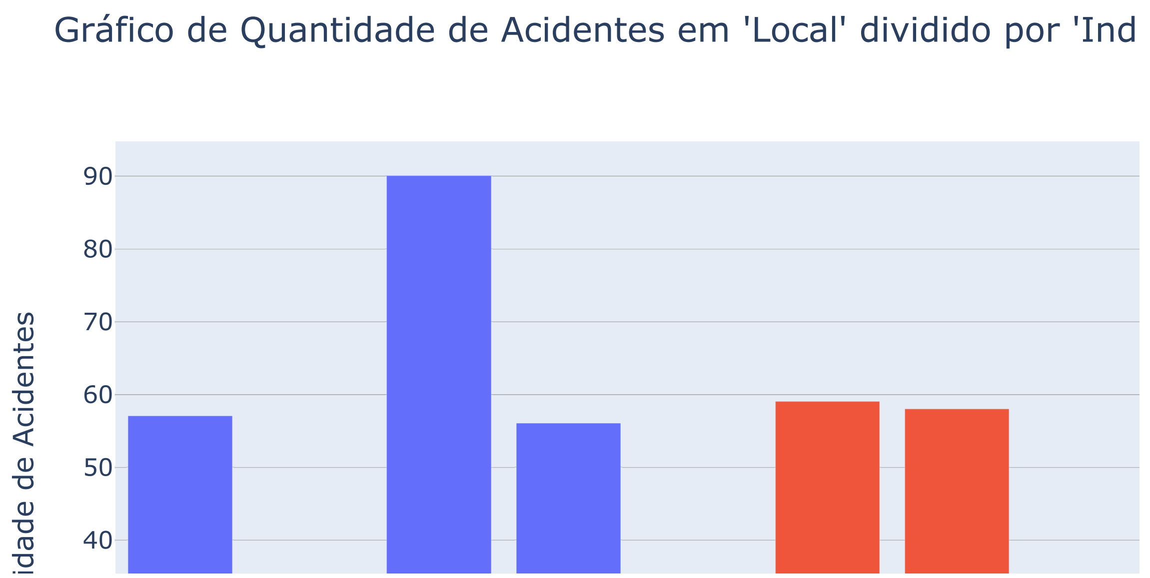
```
x, species = 'Countries', 'Local'
img_barplot(db, x, species)
```



Cada 'Local' tem somente um tipo de setor industrial ('Industry Sector'):

In [22]:

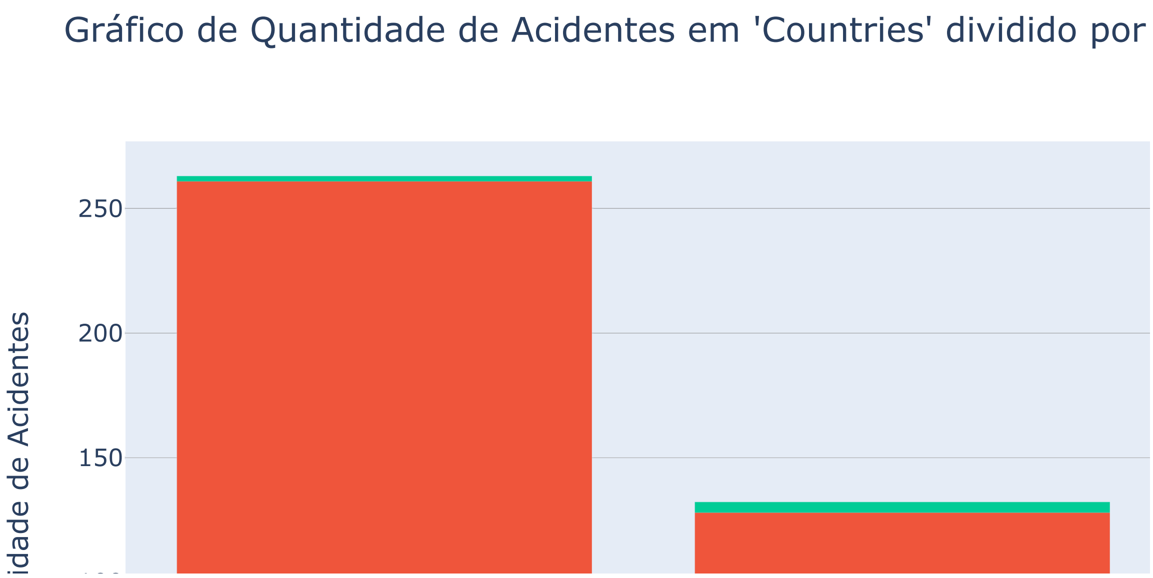
```
x, species = 'Local', 'Industry Sector'
img_barplot(db, x, species)
```



Relação de setor industrial em cada país:

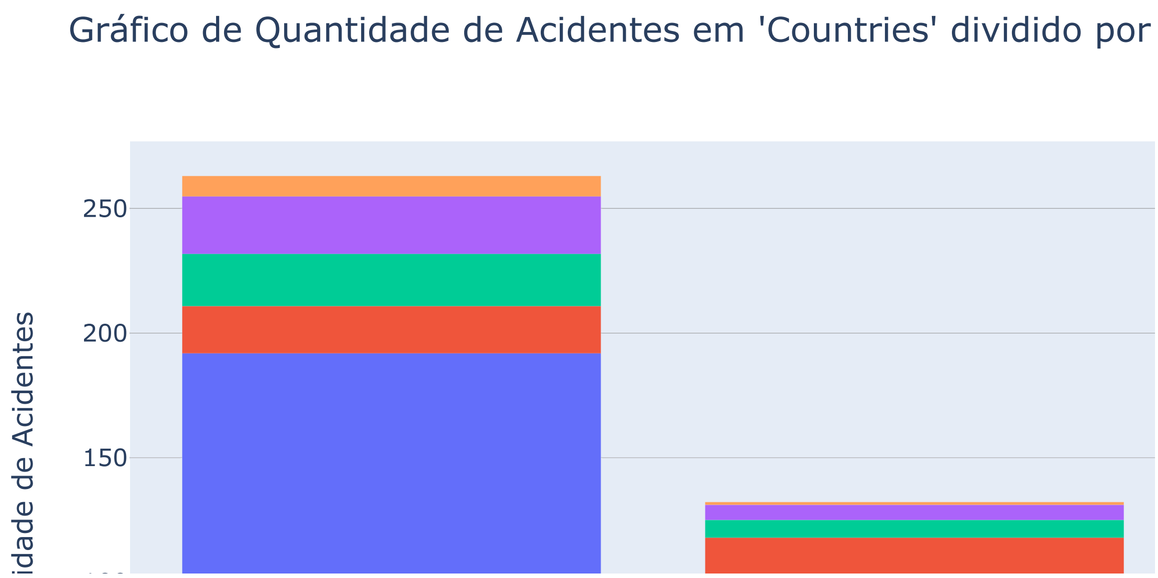
In [23]:

```
x, species = 'Countries', 'Industry Sector'
img_barplot(db, x, species)
```



In [24]:

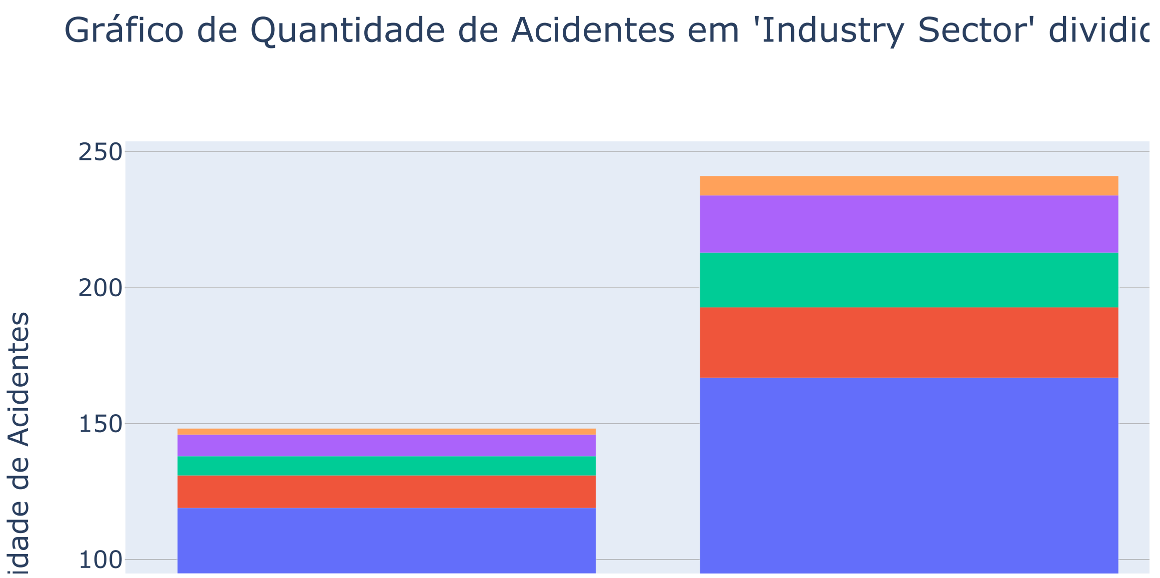
```
x, species = 'Countries', 'Accident Level'
img_barplot(db, x, species)
```




```
Quantidade de Nível de acidentes (Accident Level) por 'Industry Sector':
```

In [25]:

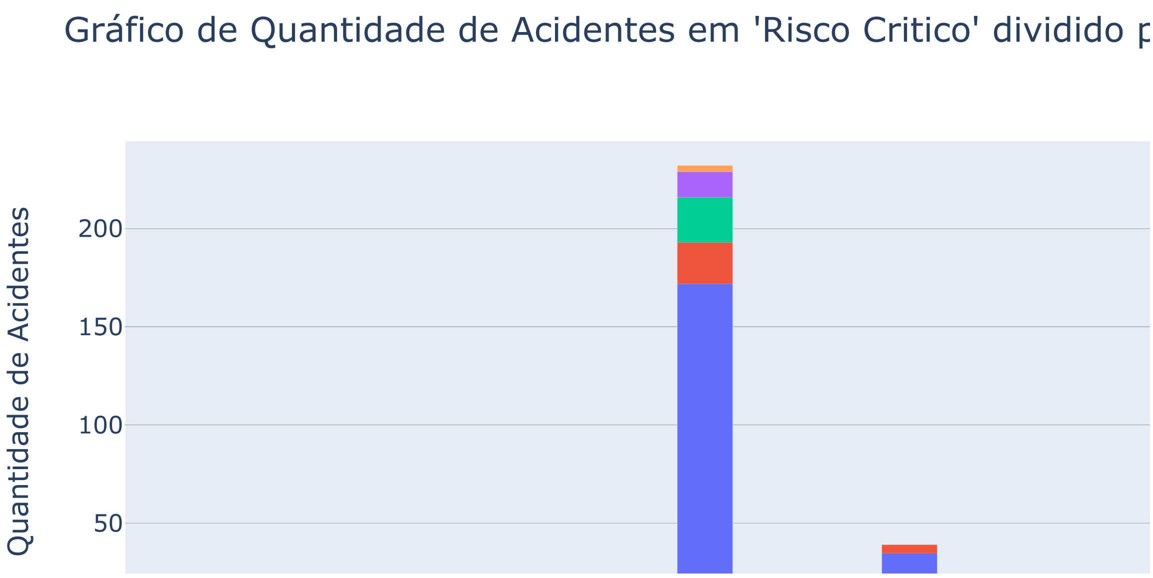
```
x, species = 'Industry Sector', 'Accident Level'
img_barplot(db, x, species)
```




```
Quantidade de Nível de acidentes (Accident Level) por 'Risco Critico':
```

In [26]:

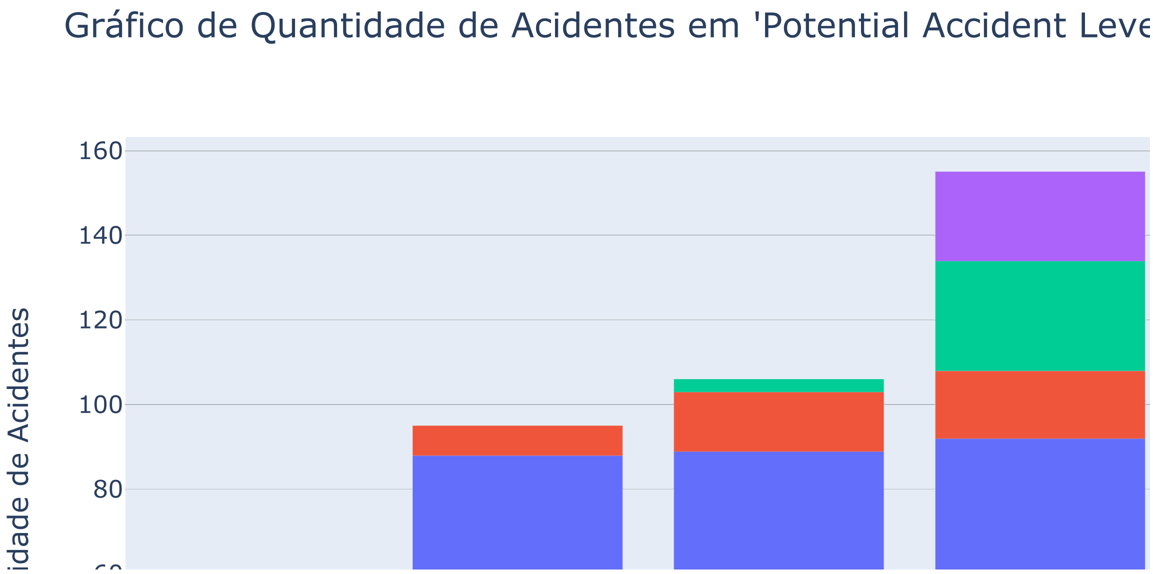
```
x, species = 'Risco Critico', 'Accident Level'
img_barplot(db, x, species)
```



Quantidade de Nível de acidentes (Accident Level) por 'Potential Accident Level':
Percebe-se que há uma relação de casualidade entre eles. O 'Potential Accident Level' não pode ser mais baixo que o 'Accident Level'.

In [27]:

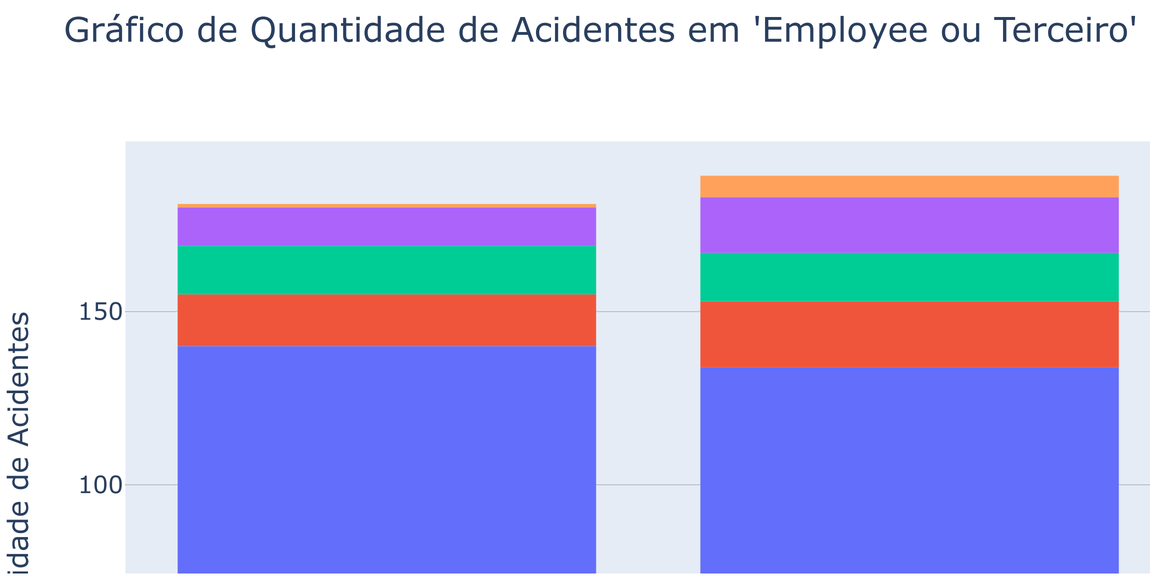
```
x, species = 'Potential Accident Level', 'Accident Level'
img_barplot(db, x, species)
```



Há uma relação no nível de acidente causados por 'Third Party':

In [28]:

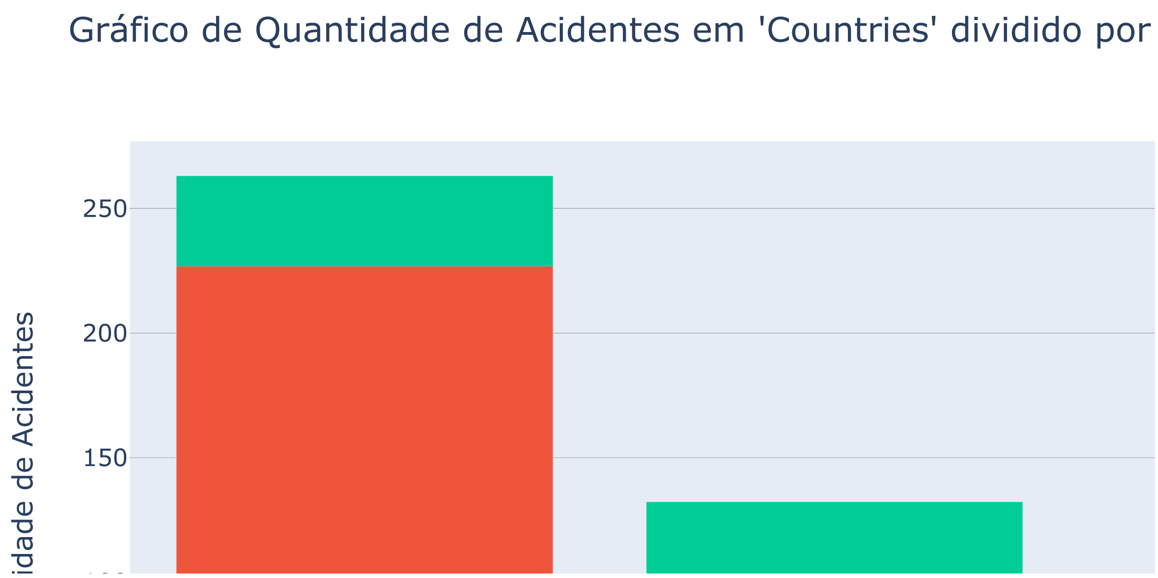
```
x, species = 'Employee ou Terceiro', 'Accident Level'
img_barplot(db, x, species)
```



Há uma relação entre país e tipo de empregado:

In [29]:

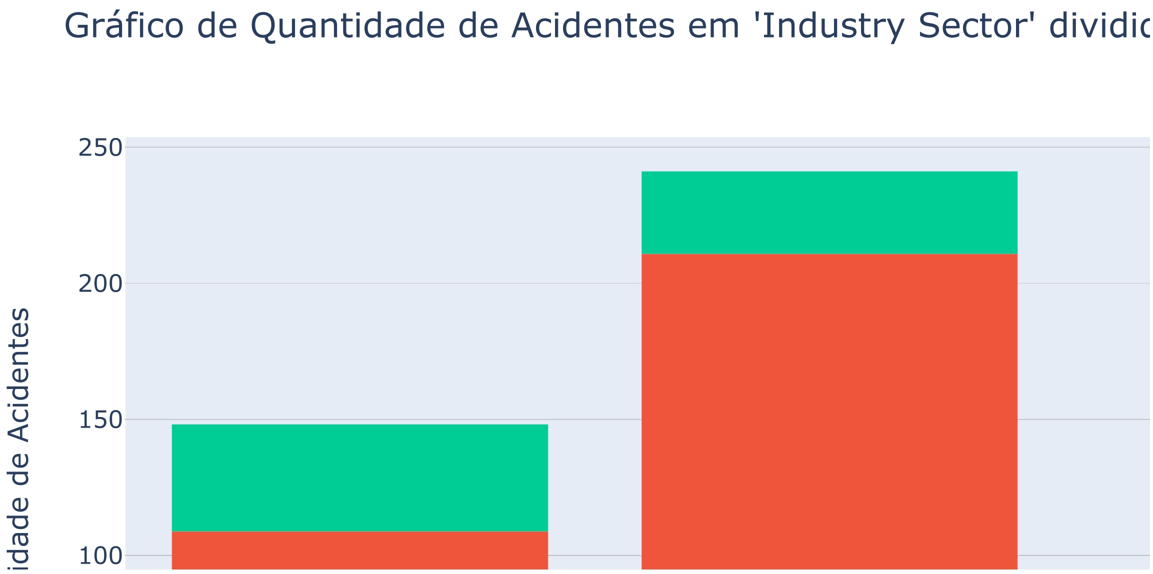
```
x, species = 'Countries', 'Employee ou Terceiro'
img_barplot(db, x, species)
```



Há uma relação entre setor industrial e tipo de empregado:

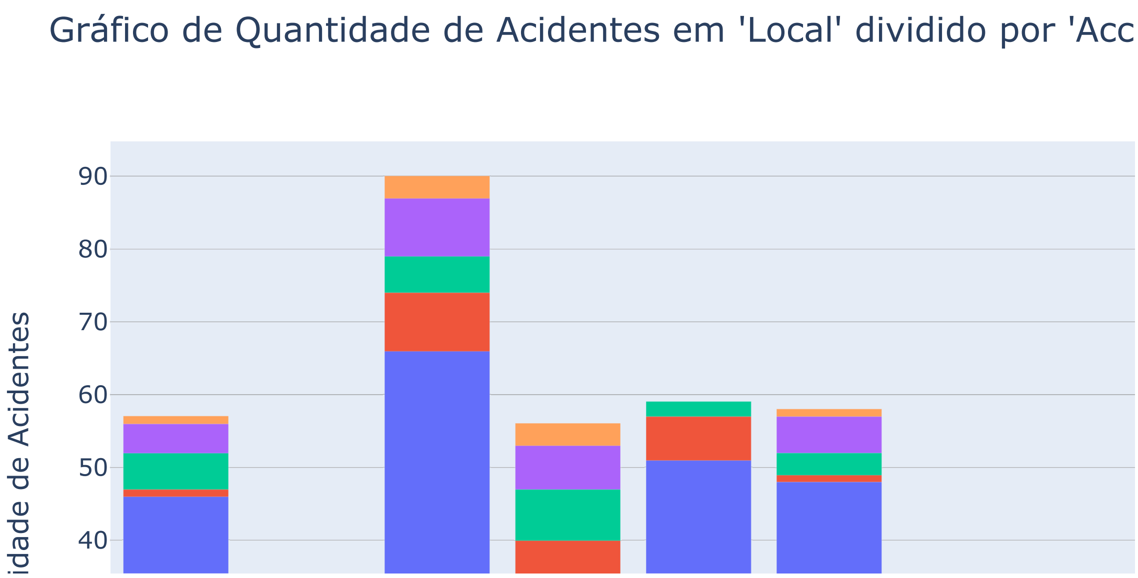
In [30]:

```
x, species = 'Industry Sector', 'Employee ou Terceiro'
img_barplot(db, x, species)
```



In [31]:

```
x, species = 'Local', 'Accident Level'
img_barplot(db, x, species)
```

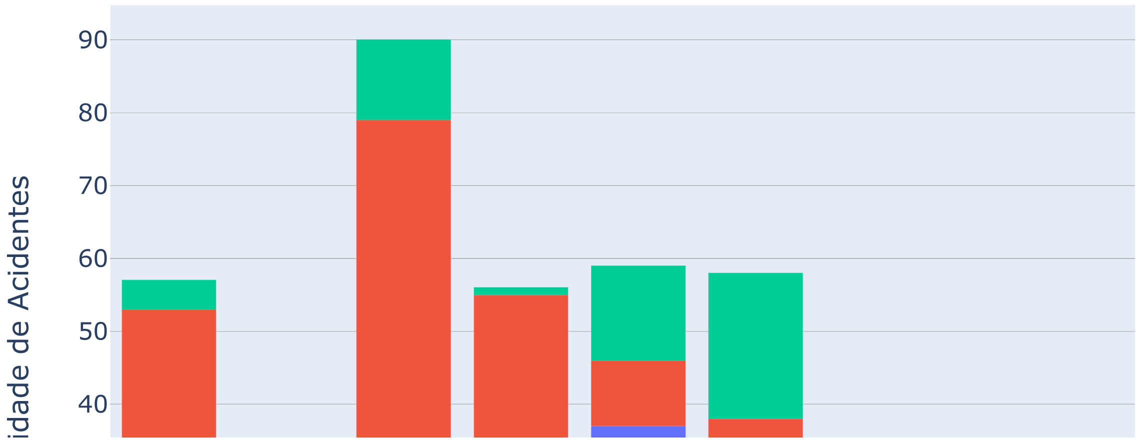


Há uma relação entre local e tipo de empregado:

In [32]:

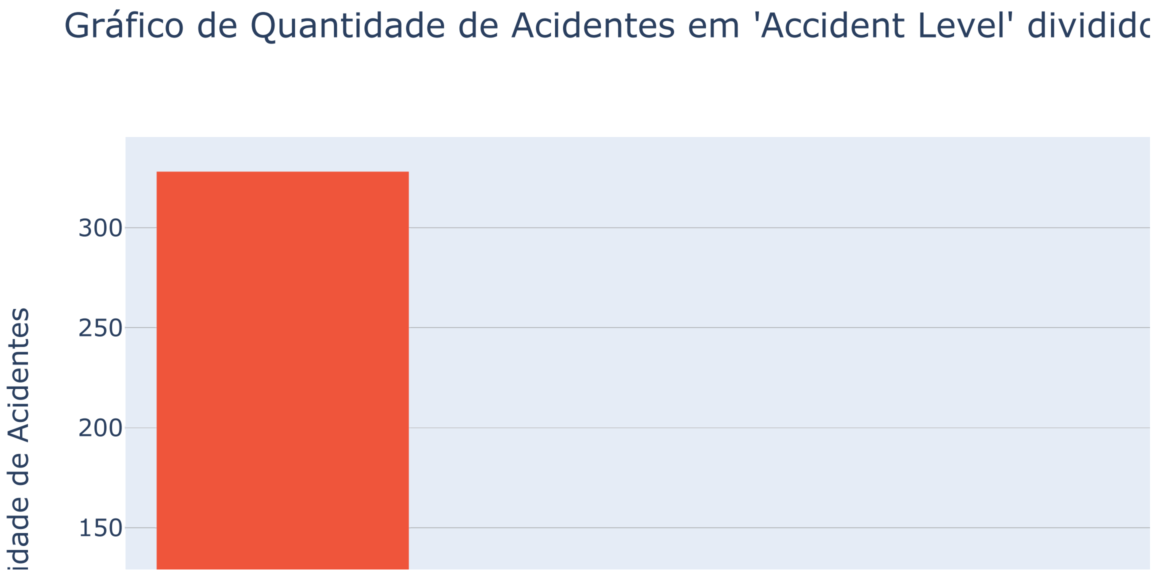
```
x, species = 'Local', 'Employee ou Terceiro'
img_barplot(db, x, species)
```

Gráfico de Quantidade de Acidentes em 'Local' dividido por 'Em



In [33]:

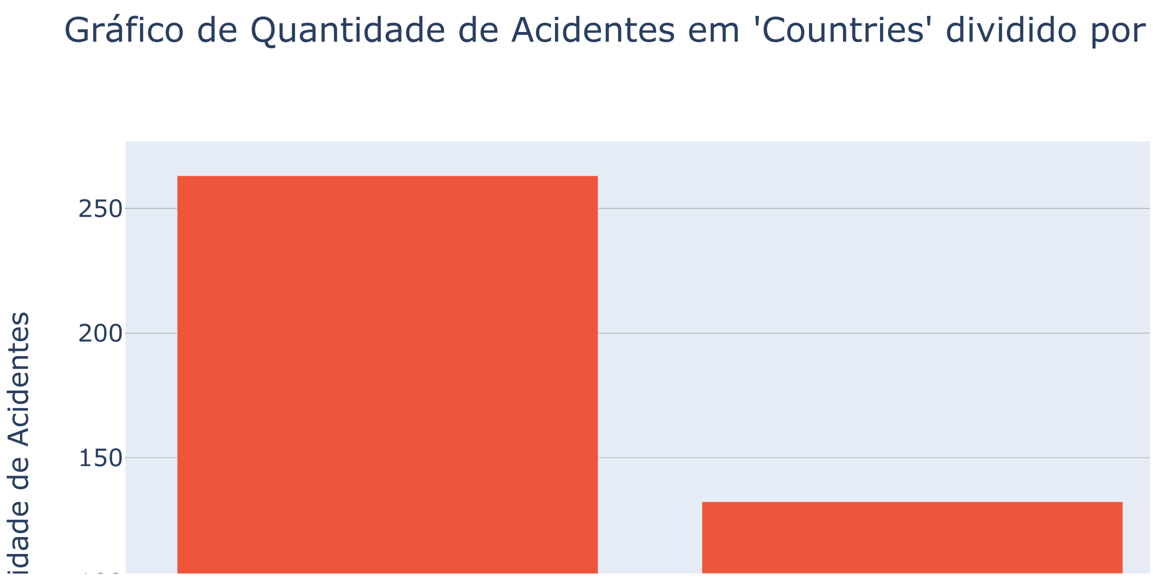
```
x, species = 'Accident Level', 'Genre'
img_barplot(db, x, species)
```



Há relação entre gênero e países:

In [34]:

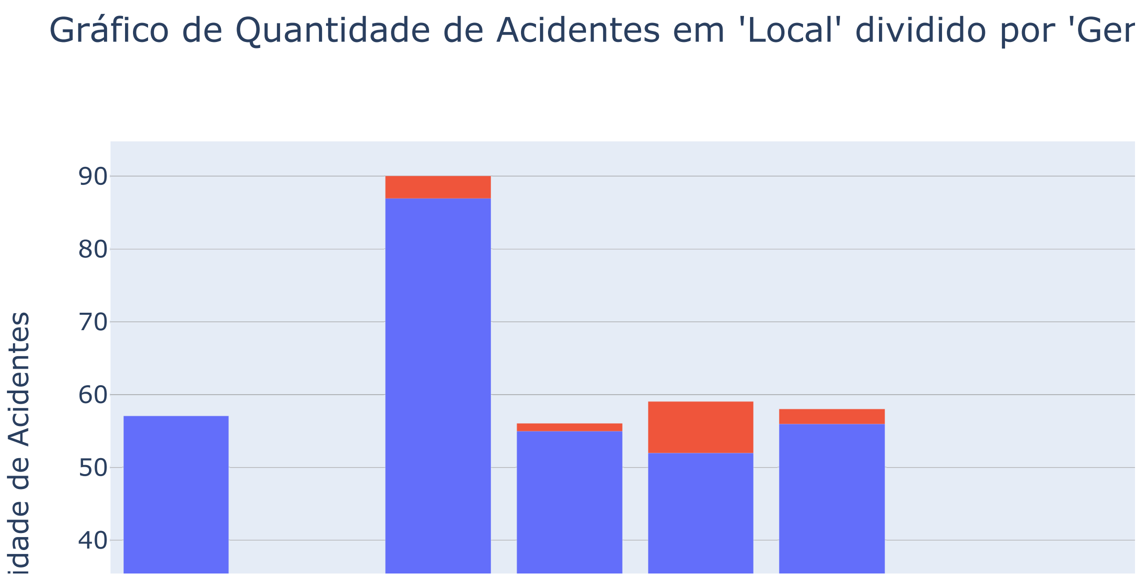
```
x, species = 'Countries', 'Genre'
img_barplot(db, x, species)
```



Há relação entre local e gênero:

In [35]:

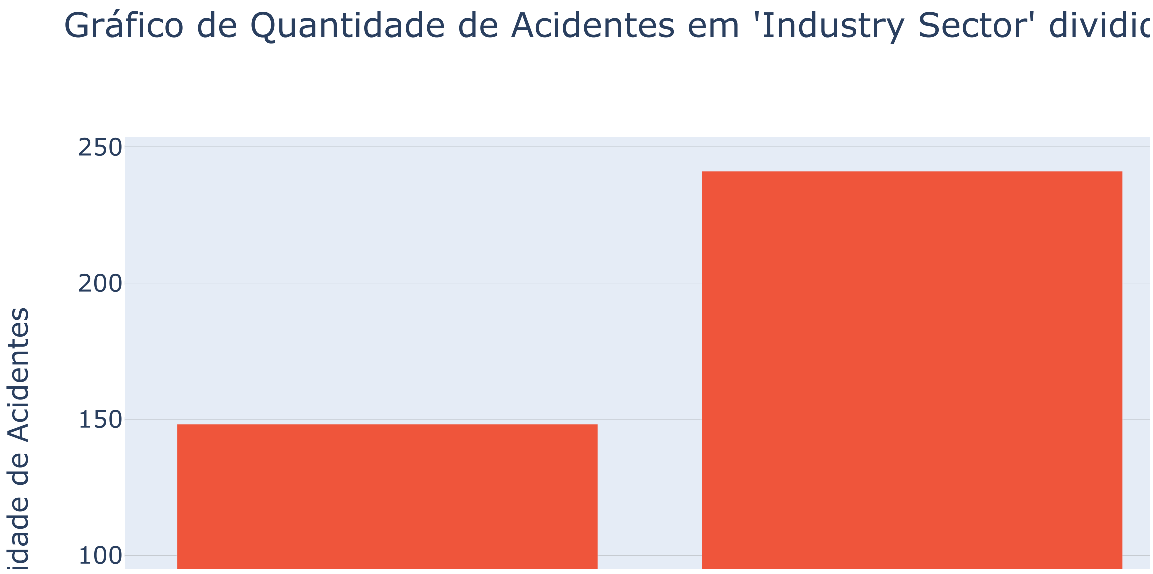
```
x, species = 'Local', 'Genre'
img_barplot(db, x, species)
```



Existe uma relação de proporção entre gênero no setor da industria:
Exemplo: Existem mais homens trabalhando em mining.

In [36]:

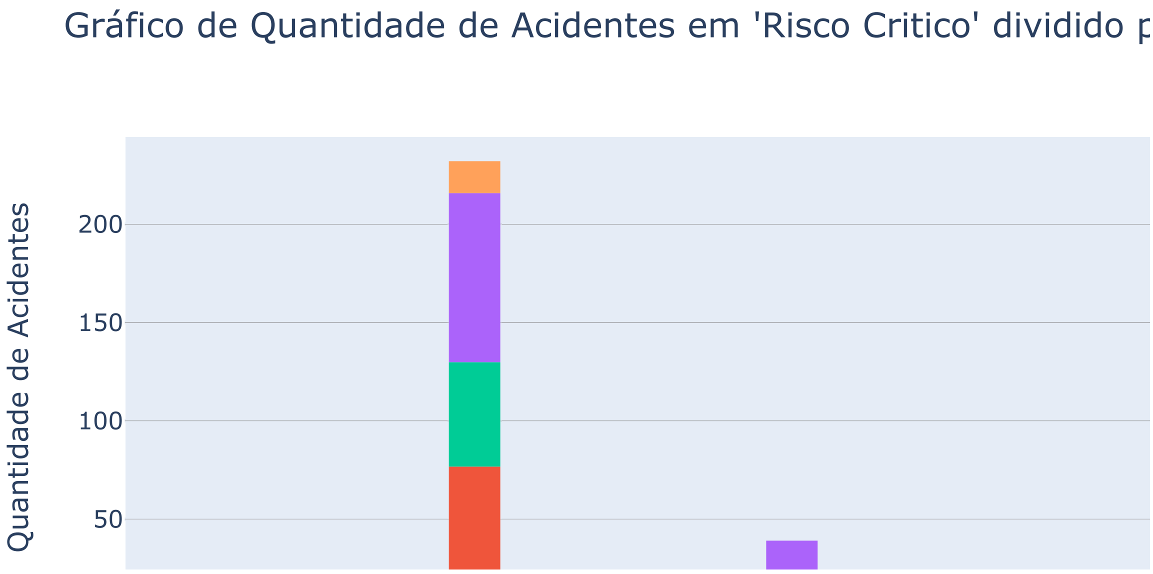
```
x, species = 'Industry Sector', 'Genre'
img_barplot(db, x, species)
```



Há uma relação entre risco crítico e Potential Accident Level:

In [37]:

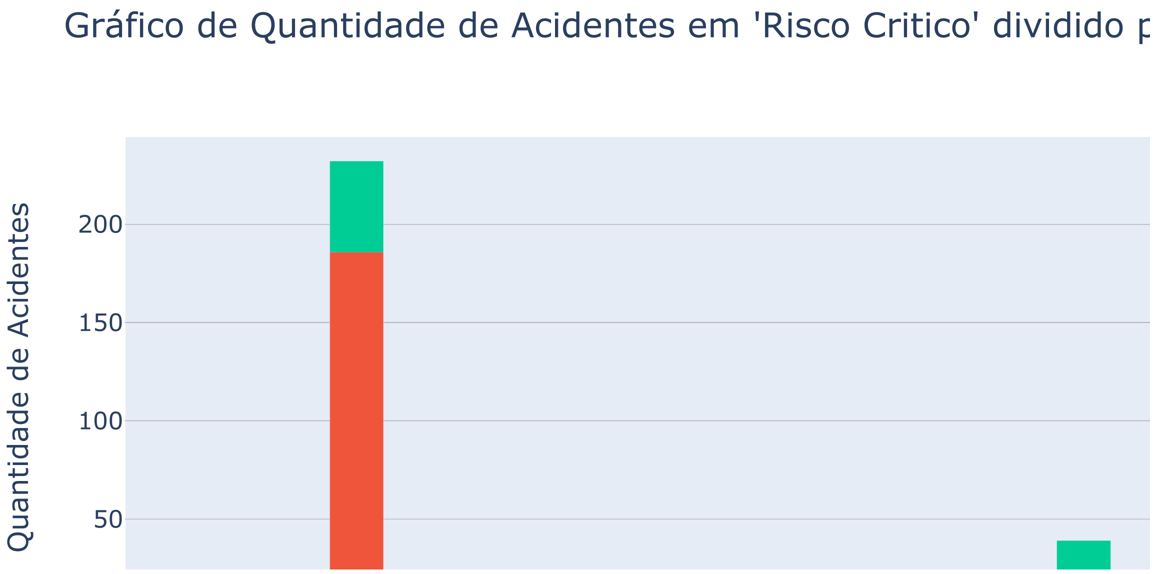
```
x, species = 'Risco Critico', 'Potential Accident Level'
img_barplot(db, x, species)
```



Há relação entre país e risco crítico:

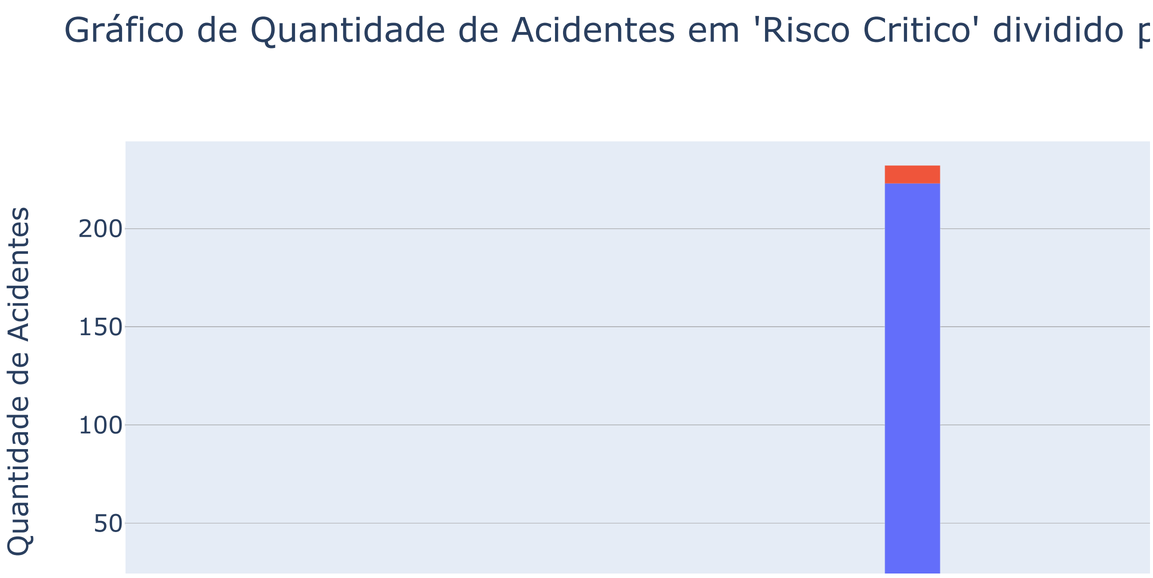
In [38]:

```
x, species = 'Risco Critico', 'Countries'
img_barplot(db, x, species)
```



In [39]:

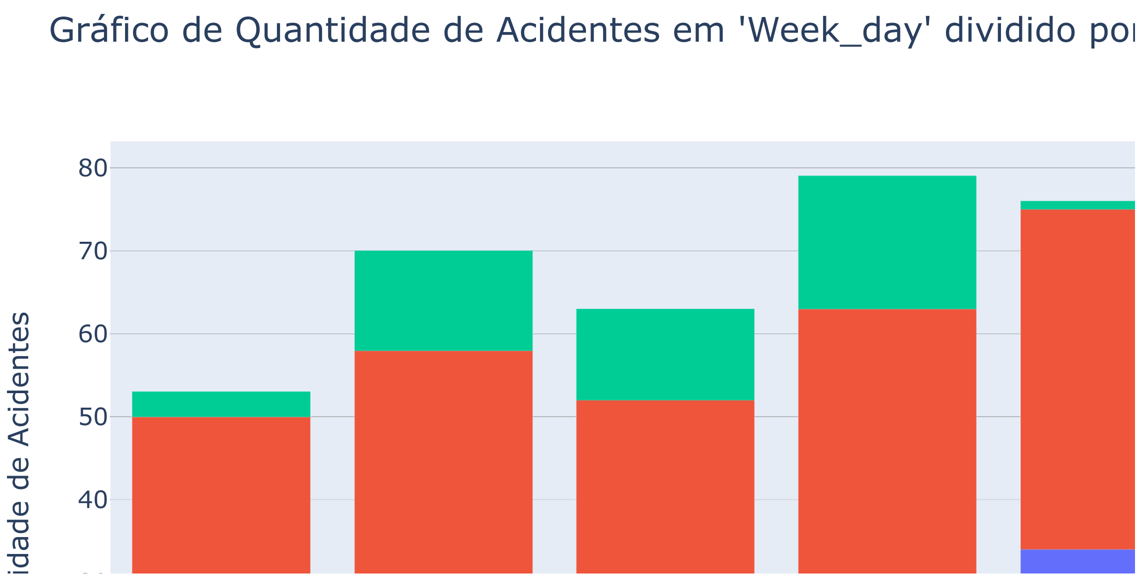
```
x, species = 'Risco Critico', 'Genre'
img_barplot(db, x, species)
```



Relação de acidente no dia da semana pelo setor industrial:

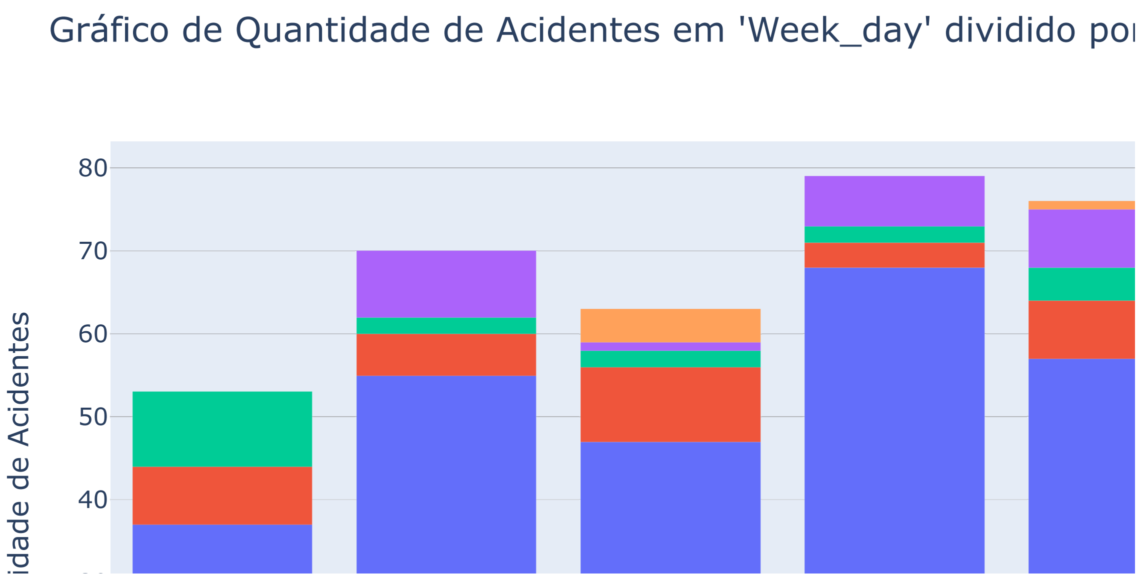
In [40]:

```
x, species = 'Week_day', 'Industry Sector'
img_barplot(db, x, species)
```



In [41]:

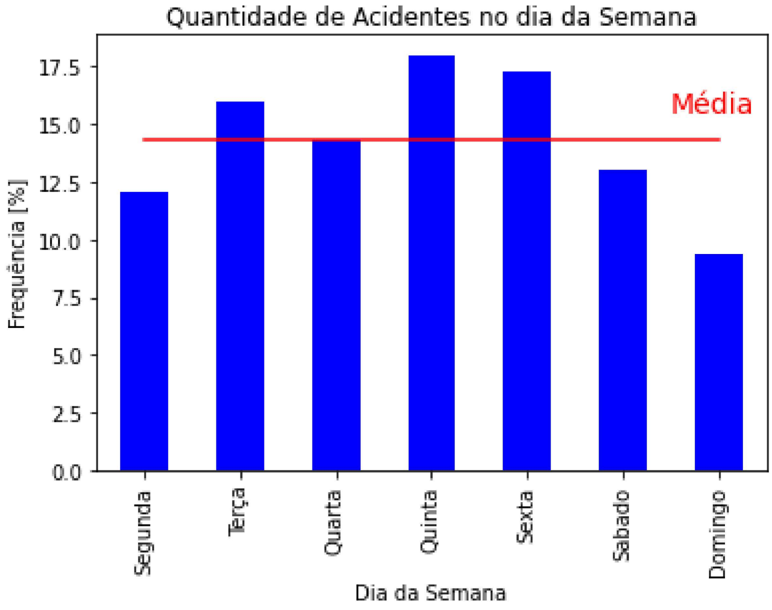
```
x, species = 'Week_day', 'Accident Level'
img_barplot(db, x, species)
```




```
Quantidade de acidentes no dia da semana:
```

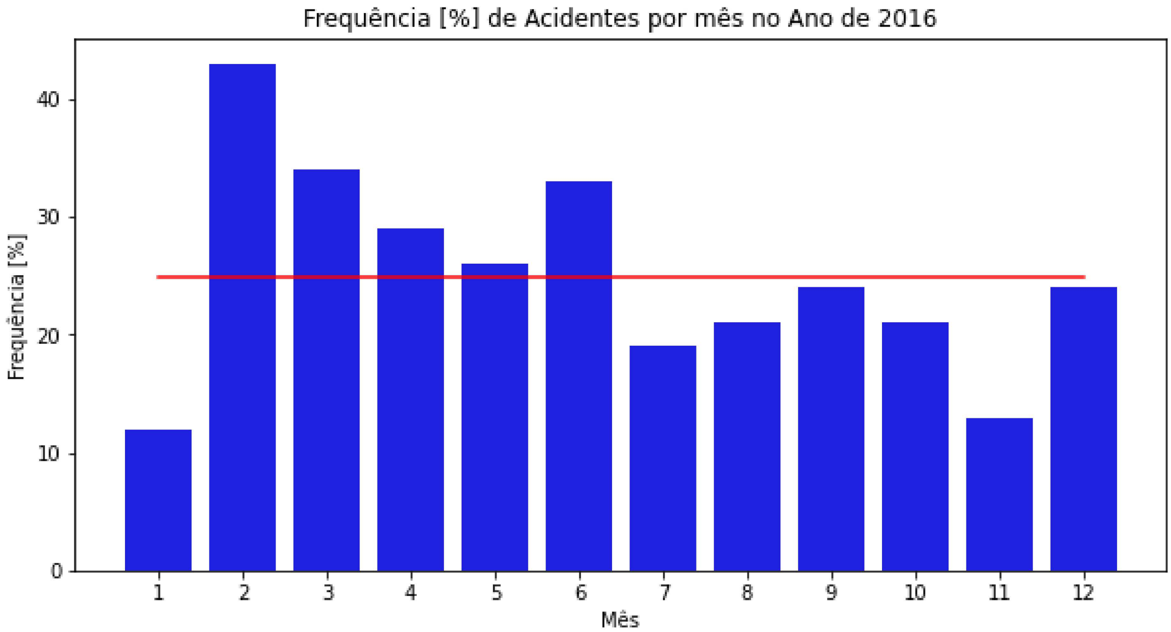
In [42]:

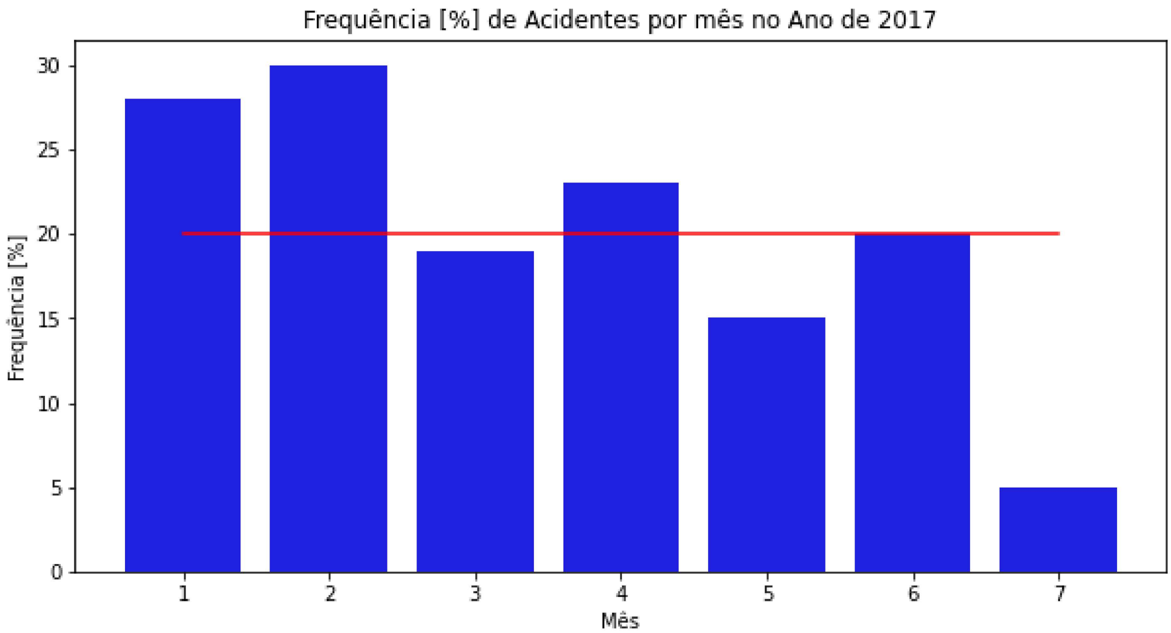
```

db_week = db['Week_day'].value_counts(normalize=True).sort_index()
db_week.index = ['Segunda', 'Terça', 'Quarta', 'Quinta', 'Sexta', 'Sabado', 'Domingo']

round(db_week*100, 2).plot.bar(color='Blue')
plt.plot([round((db_week*100).mean(), 2)]*7, 'red')
plt.text(5.5, 15.5, 'Média', color='red',fontsize=14)
plt.title('Quantidade de Acidentes no dia da Semana')
plt.xlabel('Dia da Semana')
plt.ylabel('Frequência [%]')
plt.show()
```



In [43]:

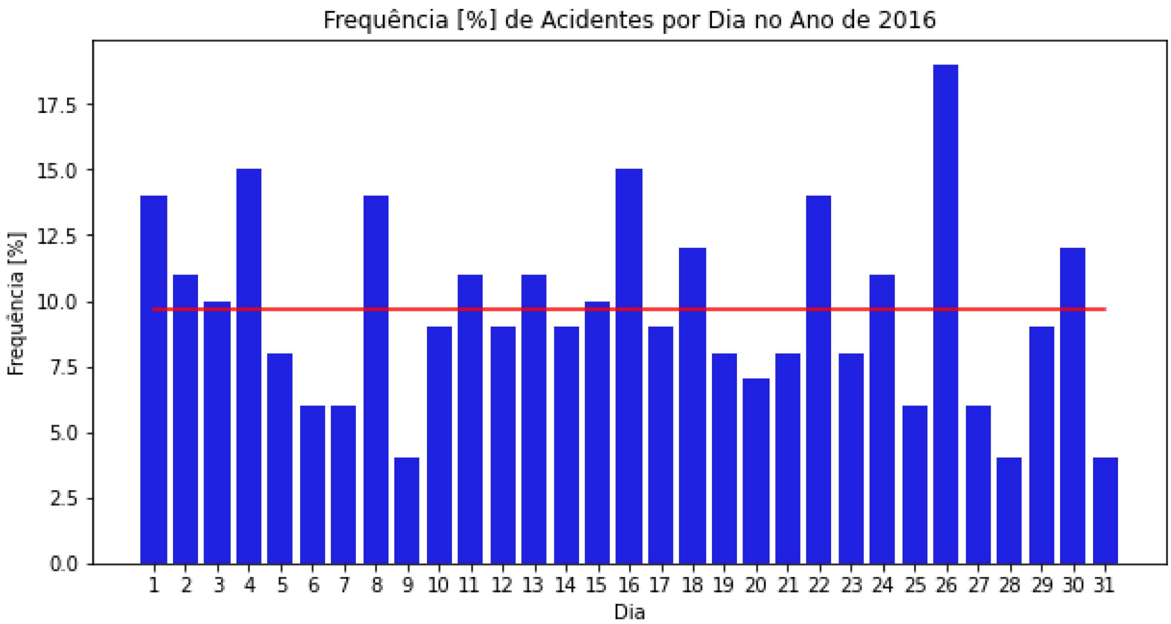
```
valor_2016 = db.loc[(db['Year'] == 2016), ['Month', 'Day']].groupby(by='Month').count()
valor_2017 = db.loc[(db['Year'] == 2017), ['Month', 'Day']].groupby(by='Month').count()

plt.figure(figsize=(10, 5))
sns.barplot(x='Month', y='Day', data=valor_2016, color='Blue')
plt.plot([valor_2016['Day'].mean()]*12, 'red')
plt.title('Frequência [%] de Acidentes por mês no Ano de 2016')
plt.xlabel('Mês')
plt.ylabel('Frequência [%]')
plt.show()

plt.figure(figsize=(10, 5))
sns.barplot(x='Month', y='Day', data=valor_2017, color='Blue')
plt.plot([valor_2017['Day'].mean()]*7, 'red')
plt.title('Frequência [%] de Acidentes por mês no Ano de 2017')
plt.xlabel('Mês')
plt.ylabel('Frequência [%]')
plt.show()
```

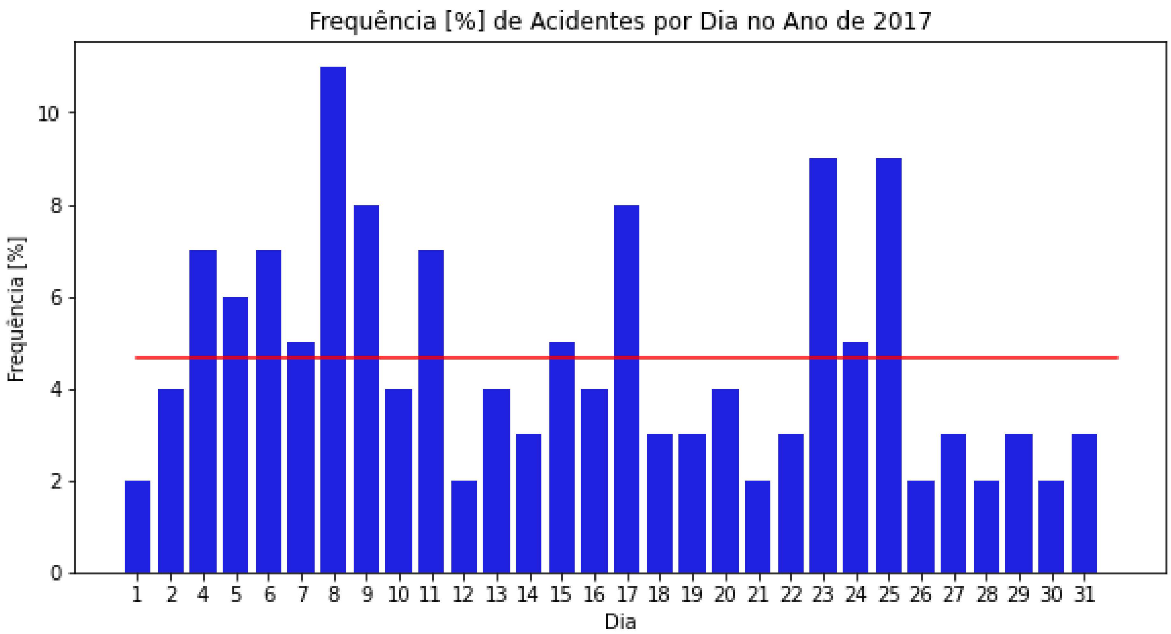




In [44]:

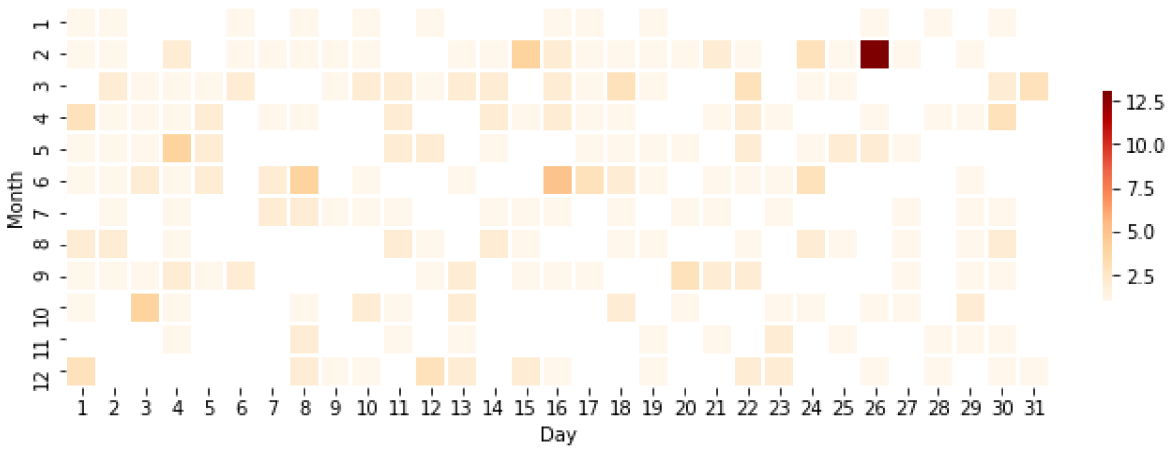
```
valor_2016 = db.loc[(db['Year'] == 2016), ['Month', 'Day']].groupby(by='Day').count().r
valor_2017 = db.loc[(db['Year'] == 2017), ['Month', 'Day']].groupby(by='Day').count().r

plt.figure(figsize=(10, 5))
sns.barplot(x='Day', y='Month', data=valor_2016, color='Blue')
plt.plot([valor_2016['Month'].mean()]*31, 'red')
plt.title('Frequência [%] de Acidentes por Dia no Ano de 2016')
plt.xlabel('Dia')
plt.ylabel('Frequência [%]')
plt.show()

plt.figure(figsize=(10, 5))
sns.barplot(x='Day', y='Month', data=valor_2017, color='Blue')
plt.plot([valor_2017['Month'].mean()]*31, 'red')
plt.title('Frequência [%] de Acidentes por Dia no Ano de 2017')
plt.xlabel('Dia')
plt.ylabel('Frequência [%]')
plt.show()
```





In [45]:

```
# db2 = db.loc[(db['Year'] == 2016), ['Month', 'Day']]
gp = pd.pivot_table(db.loc[(db['Year'] == 2016), ['Month', 'Day']], index='Month', colu
plt.figure(figsize=(10,10))
g = sns.heatmap(
    gp,
    square=True, # make cells square
    cbar_kws={'fraction' : 0.01}, # shrink colour bar
    cmap='OrRd', # use orange/red colour map
    linewidth=1 # space between cells
)
```



In [46]:

```python
# Converter os valores da colunas 'Potential Accident Level' e 'Accident Level' para de
def mudar_valor(database, coluna, buscar, saida):
    '''Função para mudar valor de determinada coluna no dataframe'''
    database.loc[database[coluna] == buscar, coluna] = saida
    return database

db = mudar_valor(db, coluna='Potential Accident Level', buscar='I', saida=1)
db = mudar_valor(db, coluna='Potential Accident Level', buscar='II', saida=2)
db = mudar_valor(db, coluna='Potential Accident Level', buscar='III', saida=3)
db = mudar_valor(db, coluna='Potential Accident Level', buscar='IV', saida=4)
db = mudar_valor(db, coluna='Potential Accident Level', buscar='V', saida=5)
db = mudar_valor(db, coluna='Potential Accident Level', buscar='VI', saida=6)
db = mudar_valor(db, coluna='Accident Level', buscar='I', saida=1)
db = mudar_valor(db, coluna='Accident Level', buscar='II', saida=2)
db = mudar_valor(db, coluna='Accident Level', buscar='III', saida=3)
db = mudar_valor(db, coluna='Accident Level', buscar='IV', saida=4)
db = mudar_valor(db, coluna='Accident Level', buscar='V', saida=5)

db.head()
```

Out[46]:

	Year	Month	Day	Week_day	Countries	Local	Industry Sector	Potential Accident Level	Genre	Employee ou Terceiro
0	2016	1	1	4	Country_01	Local_01	Mining	4	Male	Third Party
1	2016	1	2	5	Country_02	Local_02	Mining	4	Male	Employee
2	2016	1	6	2	Country_01	Local_03	Mining	3	Male	Third Party (Remote)
3	2016	1	8	4	Country_01	Local_04	Mining	1	Male	Third Party
4	2016	1	10	6	Country_01	Local_04	Mining	4	Male	Third Party

Ajuste de Labels

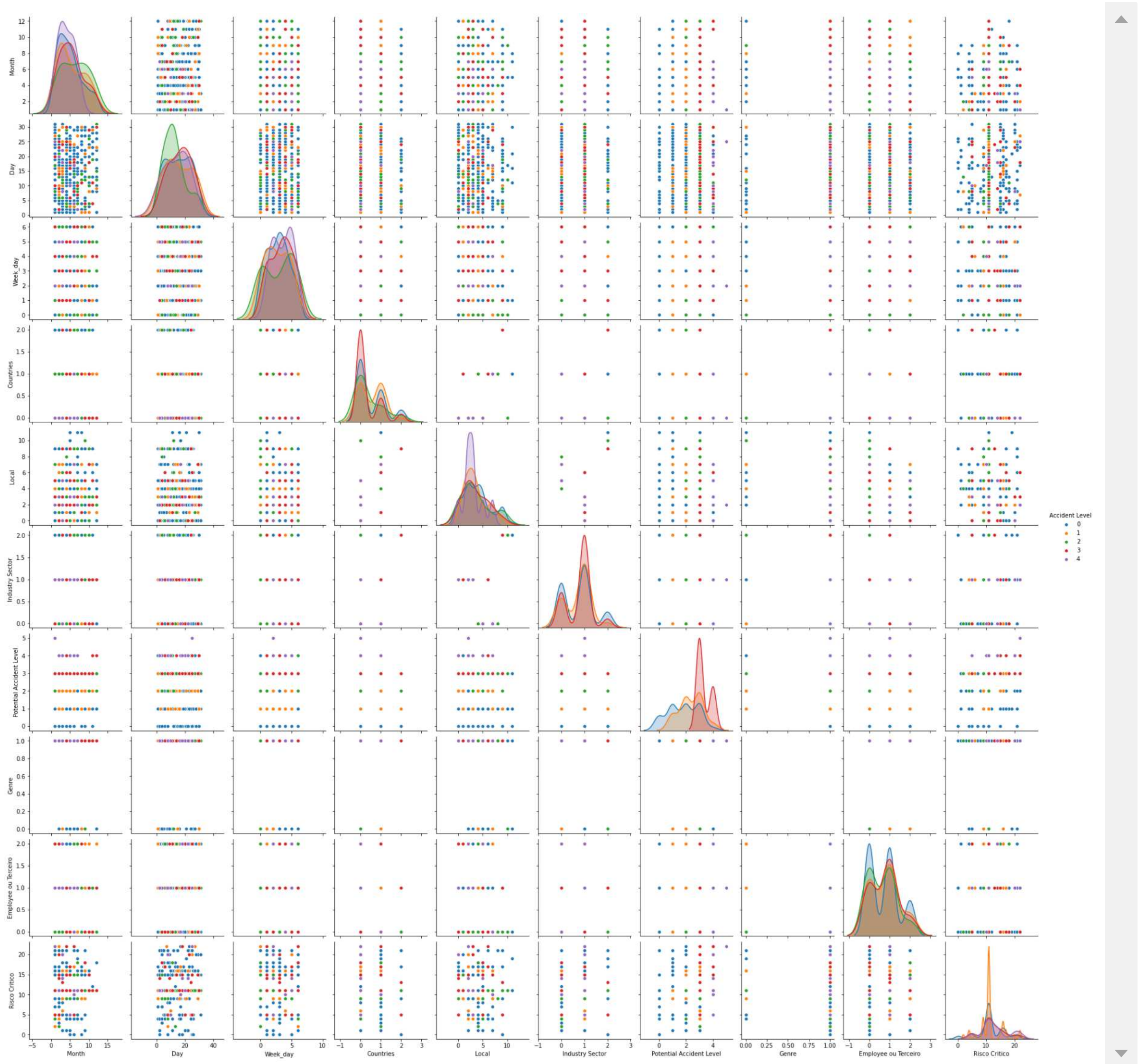
É preciso rotular as colunas com formato strings para fazer uma análise de correlação.

In [47]:

```
db1 = db.copy() # Cópia do dataset para rotular as categorias

# Função para transformar os rótulos de cada coluna para a função matrix plot
transform_dict = {col: LabelEncoder() for col in db1.iloc[:,4:]}
for col in db1.iloc[:,4:]:
    transform_dict[col].fit_transform(db1[col])

db1['Countries'] = transform_dict['Countries'].transform(db1['Countries'])
db1['Local'] = transform_dict['Local'].transform(db1['Local'])
db1['Industry Sector'] = transform_dict['Industry Sector'].transform(db1['Industry Sect
db1['Accident Level'] = transform_dict['Accident Level'].transform(db1['Accident Level'
db1['Potential Accident Level'] = transform_dict['Potential Accident Level'].transform(
db1['Genre'] = transform_dict['Genre'].transform(db1['Genre'])
db1['Employee ou Terceiro'] = transform_dict['Employee ou Terceiro'].transform(db1['Emp
db1['Risco Critico'] = transform_dict['Risco Critico'].transform(db1['Risco Critico'])
db1['Year'] = db1['Year'].astype(int)
db1['Month'] = db1['Month'].astype(int)
db1['Day'] = db1['Day'].astype(int)
db1['Week_day'] = db1['Week_day'].astype(int)

# Plot Matrix
sns.pairplot(db1.iloc[:,1:], hue='Accident Level')
```

Out[47]:

<seaborn.axisgrid.PairGrid at 0x1afc914e8b0>



Após a análise será descartado algumas colunas do dataset

```
As colunas: 'Year', 'Month', 'Day' não são significativas para o processo
```

In [48]:

```
db.drop(columns=['Year', 'Month', 'Day'], inplace=True)
db.head()
```

Out[48]:

	Week_day	Countries	Local	Industry Sector	Potential Accident Level	Genre	Employee ou Terceiro	Risco Critico	Accident Level
0	4	Country_01	Local_01	Mining	4	Male	Third Party	Pressed	1
1	5	Country_02	Local_02	Mining	4	Male	Employee	Pressurized Systems / Chemical Substances	1
2	2	Country_01	Local_03	Mining	3	Male	Third Party (Remote)	Manual Tools	1
3	4	Country_01	Local_04	Mining	1	Male	Third Party	Others	1
4	6	Country_01	Local_04	Mining	4	Male	Third Party	Others	4

Separar conjunto de treinamento e teste

In [49]:

```
# Copiar dataset
db_modelo = db.copy()

prop = 0.2 # Valor utilizado para o conjunto de testes
randon_state = 20 # Valor aleatório para embaralhar as linhas do dataset

# Ajustar coluna 'Accident Level' e 'Potential Accident Level' para valores numericos
db_modelo['Accident Level'] = db_modelo['Accident Level'].astype(int)
db_modelo['Potential Accident Level'] = db_modelo['Potential Accident Level'].astype(ir
db_modelo['Week_day'] = db_modelo['Week_day'].astype(int)

# Função para transformar os rótulos de cada coluna
colunas_transformar = ['Countries', 'Local', 'Industry Sector', 'Genre', 'Employee ou T
transform_dict = {col: LabelEncoder() for col in db_modelo.loc[:,colunas_transformar]}
for col in db_modelo.loc[:,colunas_transformar]:
    transform_dict[col].fit_transform(db_modelo[col])
for coluna in colunas_transformar:
    db_modelo[coluna] = transform_dict[coluna].transform(db_modelo[coluna])

# Separar dados de entrada e rótulos (saída)
X = db_modelo.iloc[:,:-1]
y = db_modelo.iloc[:,-1]

# Separar dados de treinamento
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=prop, random_state=
```

Classificador Naive Bayes

Utilizando a base de dados fornecida, criar um classificador baseado em Näive Bayes que classifique o nível do acidente dadas as demais informações. Discuta quais variáveis são mais ou menos relevantes para o processo de decisão.

In [50]:

```
# Função para apresentar os resultados:

def resultado_modelo(modelo, X_treino, X_teste, y_treino, y_teste, modelo_nome='Naive E
    '''Está função cria os resultados de interesse apresentado pelo Naive Bayes'''

    print('Resultado do modelo utilizando validação cruzada com k-fold de 10')
    print()
    # Acurácia
    scores_acc = cross_val_score(modelo, X_treino, y_treino, cv = 10, scoring='accuracy
    print('Cross-validation scores accurancy: {}'.format(scores_acc))
    print('Average cross-validation score accurancy: {}'.format(scores_acc.mean()))
    print()

    # Root Mean Square Error (RMSE)
    scores_rmse = cross_val_score(modelo, X_treino, y_treino, cv = 10, scoring='neg_roc
    print('Cross-validation Root Mean Square Error (RMSE):{}'.format(scores_rmse))
    print('Average cross-validation Root Mean Square Error (RMSE): {}'.format(scores_rm
    print()

    # KAPPA (RMSE)
    scores_kappa = cross_val_score(modelo, X_treino, y_treino, cv = 10, scoring=make_sc
    print('Cross-validation kappa Score:{}'.format(scores_kappa))
    print('Average cross-validation kappa Score: {}'.format(scores_kappa.mean()))

    print()
    print('#'*100)
    print()

    print('Resultado do modelo no conjunto de treinamento e teste')
    print()
    # Acurácia treinamento e teste
    pred_treino = model.predict(X_treino)
    print('Test set Score: ', accuracy_score(y_teste, predicted))
    print('Training set score: ', accuracy_score(y_treino, pred_treino))
    # Estatística Kappa
    kappa = cohen_kappa_score(y_teste, predicted)
    print('Kappa Score do conjunto de teste: {}'.format(kappa))
    # RMSE
    rmse = mean_squared_error(y_teste, predicted)
    print('RMSE do conjunto de teste: {}'.format(rmse))
    print()
    # Relatorio de Classificação
    print('Relatório do conjunto de teste')
    print(classification_report(y_teste, predicted, target_names=['I', 'II', 'III', 'IV
    print()

    # Matriz de Confusão
    print('Matriz de Confusão do conjunto de teste')
    print()

    fig, ax = plt.subplots(dpi=100)
    disp = plot_confusion_matrix(modelo, X_teste, y_teste, cmap=plt.cm.Blues,
                                 display_labels=['I', 'II', 'III', 'IV', 'V'], ax=ax)
    plt.title('Matriz de Confusão do ' + str(modelo_nome))
    plt.xlabel("Valor Predito")
    plt.ylabel("Valor Real")
    plt.show()
```

Naive Bayes

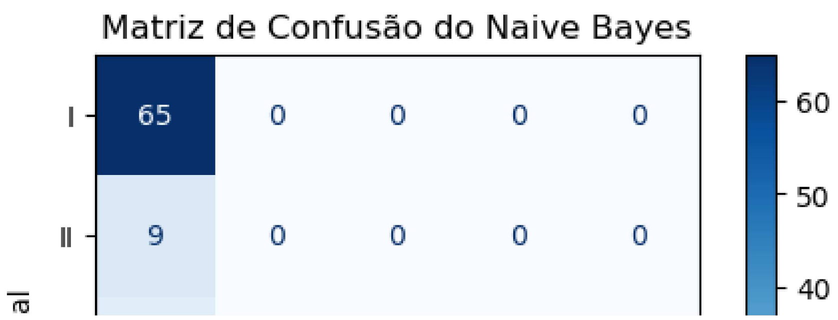
In [51]:

```
#Create a MultinomialNB Classifier
model = MultinomialNB()

# # Train the model using the training sets
model.fit(X_train,y_train)

# #Predict Output
predicted= model.predict(X_test)
```

In [52]:

```
1 resultado_modelo(model, X_train, X_test, y_train, y_test)
```

```
Resultado do modelo utilizando validação cruzada com k-fold de 10

Cross-validation scores accurancy: [0.75       0.77142857 0.77142857 0.74285
714 0.74285714 0.74285714
 0.74285714 0.74285714 0.74285714 0.74285714]
Average cross-validation score accurancy: 0.7492857142857143

Cross-validation Root Mean Square Error (RMSE):[1.22474487 1.13389342 1.1338
9342 1.18321596 1.18321596 1.05559733
 1.09544512 1.05559733 1.24211801 1.24211801]
Average cross-validation Root Mean Square Error (RMSE): 1.1549839402976598

Cross-validation kappa Score:[-0.         -0.         -0.         -0.
-0.         -0.06804734
 -0.         -0.         -0.         -0.        ]
Average cross-validation kappa Score: -0.006804733727810641

############################################################################
########################

Resultado do modelo no conjunto de treinamento e teste

Test set Score:  0.7386363636363636
Training set score:  0.7492877492877493
Kappa Score do conjunto de teste: 0.0
RMSE do conjunto de teste: 1.2954545454545454

Relatório do conjunto de teste
              precision    recall  f1-score   support

           I       0.74      1.00      0.85        65
          II       0.00      0.00      0.00         9
         III       0.00      0.00      0.00         7
          IV       0.00      0.00      0.00         5
           V       0.00      0.00      0.00         2

    accuracy                           0.74        88
   macro avg       0.15      0.20      0.17        88
weighted avg       0.55      0.74      0.63        88


Matriz de Confusão do conjunto de teste
```



Análise dos parâmetros mais importantes do Naive Bayes

In [53]:

```
pd.DataFrame(model.coef_, columns=X_train.columns.values.tolist(), index=model.classes_
```

Out[53]:

	Week_day	Countries	Local	Industry Sector	Potential Accident Level	Genre	Employee ou Terceiro	Risco Critico
1	-2.142283	-3.817159	-1.820161	-3.458328	-2.164083	-3.238204	-3.488943	-0.728736
2	-2.330200	-3.875100	-2.052569	-3.556646	-1.929190	-3.280393	-3.351852	-0.678981
3	-2.089663	-4.182898	-1.998096	-3.202069	-1.826246	-3.202069	-3.607534	-0.785411
4	-2.038791	-4.470209	-2.072314	-3.458608	-1.831152	-3.253814	-3.553918	-0.747532
5	-2.045208	-4.610158	-2.084429	-3.511545	-1.692387	-3.223863	-3.106080	-0.825968

In [54]:

```
pd.DataFrame(model.feature_count_, columns=X_train.columns.values.tolist(), index=mode]
```

Out[54]:

	Week_day	Countries	Local	Industry Sector	Potential Accident Level	Genre	Employee ou Terceiro	Risco Critico
1	741.0	138.0	1023.0	198.0	725.0	247.0	192.0	3049.0
2	74.0	15.0	98.0	21.0	111.0	28.0	26.0	390.0
3	72.0	8.0	79.0	23.0	94.0	23.0	15.0	268.0
4	90.0	7.0	87.0	21.0	111.0	26.0	19.0	330.0
5	25.0	1.0	24.0	5.0	36.0	7.0	8.0	87.0

In [55]:

```
pd.DataFrame(np.e**model.feature_log_prob_*100, columns=X_train.columns.values.tolist()
```

Out[55]:

	Week_day	Countries	Local	Industry Sector	Potential Accident Level	Genre	Employee ou Terceiro	Risco Critico
1	11.738649	2.199019	16.199968	3.148236	11.485524	3.923430	3.053314	48.251859
2	9.727626	2.075227	12.840467	2.853437	14.526589	3.761349	3.501946	50.713359
3	12.372881	1.525424	13.559322	4.067797	16.101695	4.067797	2.711864	45.593220
4	13.018598	1.144492	12.589413	3.147353	16.022890	3.862661	2.861230	47.353362
5	12.935323	0.995025	12.437811	2.985075	18.407960	3.980100	4.477612	43.781095

In [56]:

```
np.e**(model.class_log_prior_)
```

Out[56]:

```
array([0.74928775, 0.08831909, 0.06837607, 0.07407407, 0.01994302])
```

In [57]:

```
prob = np.e**(model.feature_log_prob_[4, :])
pd.DataFrame(np.round(prob*100, 2),
             index=X_train.columns.values.tolist()).sort_values(by=0, ascending=False).
```

Out[57]:

	Importância
Risco Critico	43.78
Potential Accident Level	18.41
Week_day	12.94
Local	12.44
Employee ou Terceiro	4.48
Genre	3.98
Industry Sector	2.99
Countries	1.00

Classificador Bayesiano com estrutura determinada a partir dos dados

Utilizando a base de dados fornecida, criar um classificador bayesiano com estrutura determinada a partir dos dados, teste diferentes parâmetros de treinamento de modo a tentar encontrar um modelo que supere o modelo Näive Bayes. Discuta quais variáveis são mais ou menos relevantes para o processo de decisão

In [58]:

```
def pred_bayes(data, modelo_treinado):
    '''Função para predição dos valores em um modelo Bayesiano

    data -> dataset em formato pandas (valor de saida ou rótulo terá que estar na últi
    modelo -> modelo da rede Bayesiana treinada pelo bnlearn.parameter_learning.fit

    saída -> pandas series com os valores da predição da rede bayesiana
    '''

    pred_list = []
    saida = data.columns.values[-1]

    for row in range(len(data)):
        evidencia = {}
        for column in data.columns.values[:-1]:
            valor = data.iloc[row].loc[column]
            evidencia[column] = valor

        # Realizar inferência no modelo treinado
        prob_row = bnlearn.inference.fit(modelo_treinado, variables=[saida], evidence=

        prob_to_list = prob_row.values.tolist() # transformar saída da inferência em l
        max_value = max(prob_to_list) # Pegar valor máximo da lista
        pred = int(prob_to_list.index(max_value)) + 1 # Valor de saída (index + 1)

        pred_list.append(pred)

    return pd.Series(np.array(pred_list))

def kfoldcv(indices, k = 10, seed = randon_state):
    '''Função kfold'''

    size = len(indices)
    subset_size = round(size / k)
    random.Random(seed).shuffle(indices)

    subsets = [indices[x:x+subset_size] for x in range(0, len(indices), subset_size)]

    kfolds = []
    for i in range(k):
        test = subsets[i]
        train = []
        for subset in subsets:
            if subset != test:
                train.append(subset)
        kfolds.append((train,test))

    return kfolds

def dictSplitTrainTest(dataset_treino, k=10, seed=20):
    '''Retorna um dicionário contendo os indíces de treinamento e teste em kfolds'''
    db_treino = dataset_treino.reset_index(drop=True)
    indice = [x for x in range(len(db_treino))]
    divisao = kfoldcv(indice, k=k, seed=seed)

    cv = {}
    for j in range(len(divisao)):
        treino = 'treino' + str(j)
        teste = 'teste' + str(j)
```

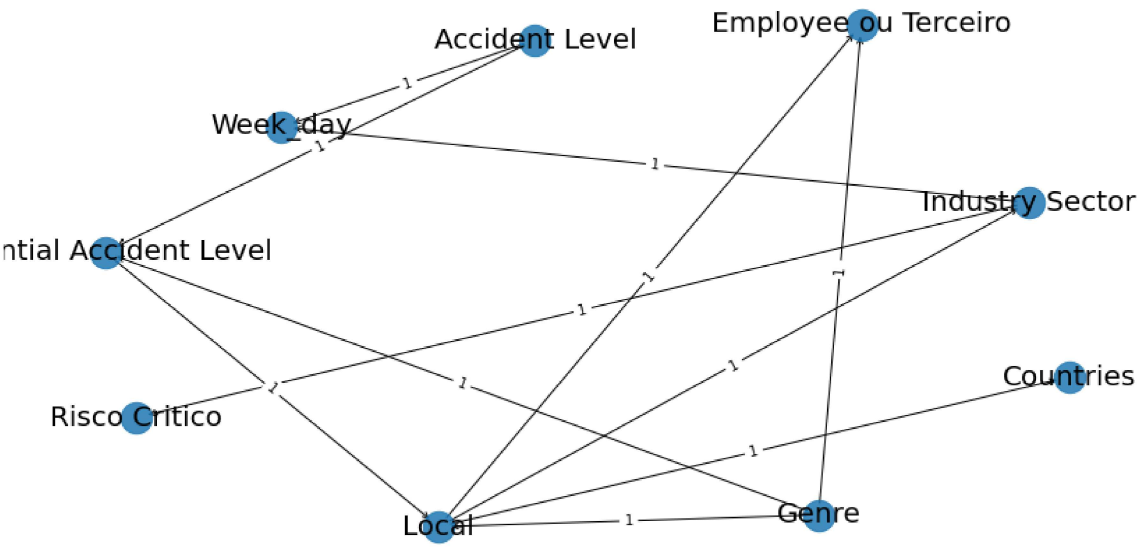
```
        cv[treino] = []
        cv[teste] = []
        cv[teste] += divisao[j][1]

        for lista in divisao[j][0]:
            cv[treino] += lista

    return cv

def cvBayes(data_treino, modelo_bayes, k=10, seed=20):
    '''Realizar validação cruzada kfold

    Retorna 3 listas com k resultados, sendo:
        primeira lista de acuracidade;
        segunda lista o de kappa score;
        terceira lista o de rmse;
    '''

    lista_cv_acc = []
    lista_cv_kappa = []
    lista_cv_rmse = []

    dicSplit = dictSplitTrainTest(data_treino, k=k, seed=seed) #Chamar função para div

    for i in range(int(len(dicSplit)/2)):

        # Separar indices do conjunto de treinamento
        nome_treino = 'treino' + str(i)
        nome_teste = 'teste' + str(i)
        df_treino = data_treino.iloc[dicSplit[nome_treino]]
        df_teste = data_treino.iloc[dicSplit[nome_teste]]
        df_inteiro = data_treino.iloc[dicSplit[nome_treino]+dicSplit[nome_teste]]

        # Treinar o modelo bayesiano
        modelo_treinado = bnlearn.parameter_learning.fit(modelo_bayes, df_inteiro, ver

        # Predição no conjunto de teste
        predicao = pred_bayes(data=df_teste, modelo_treinado=modelo_treinado)

        y_teste = df_teste.iloc[:,-1].astype(int)
        acc = accuracy_score(y_teste, predicao)
        kappa = cohen_kappa_score(y_teste, predicao)
        rmse = mean_squared_error(y_teste, predicao)

        lista_cv_acc.append(acc)
        lista_cv_kappa.append(kappa)
        lista_cv_rmse.append(rmse)

    return lista_cv_acc, lista_cv_kappa, lista_cv_rmse
```

Achar modelo ótimo da rede Bayesiana Estruturada para o conjunto do dataset

In [59]:

```
#Buscar modelo otimo hill climbing search and metric function 'K2'
modelo_bayes_otimo = bnlearn.structure_learning.fit(db_modelo, methodtype='hc', scorety

# Gráfico do modelo
G = bnlearn.plot(modelo_bayes_otimo)
```

```
[bnlearn] >Computing best DAG using [hc]
[bnlearn] >Set scoring type at [k2]
[bnlearn] >Plot based on BayesianModel
```



In [60]:

```
edges = [('Local', 'Industry Sector'), ('Local', 'Countries'), ('Local', 'Employee ou T
         ('Industry Sector', 'Risco Critico'), ('Industry Sector', 'Week_day'),
         ('Potential Accident Level', 'Local'), ('Genre', 'Local'), ('Genre', 'Employee
         ('Genre', 'Potential Accident Level'), ('Accident Level', 'Potential Accident
         ('Accident Level', 'Week_day')]
```

Treinar e testar o modelo Bayesiano

In [61]:

```
# Juntar data de treinamento X com y (entrada e saída)
db_b_treino = X_train.copy() # Será utilizado na validação cruzada kfold
db_b_treino['Accident Level'] = y_train

# Juntar data de teste X com y (entrada e saída)
db_b_teste = X_test.copy()
db_b_teste['Accident Level'] = y_test

# Treinar o modelo bayesiano
modelo_treinado = bnlearn.parameter_learning.fit(modelo_bayes_otimo, db_modelo, verbose

#Create a Bayes Classifier no conjunto de teste
pred_test = pred_bayes(data=db_b_teste, modelo_treinado=modelo_treinado)

#Create a Bayes Classifier no conjunto de treinamento
pred_train = pred_bayes(data=db_b_treino, modelo_treinado=modelo_treinado)
```

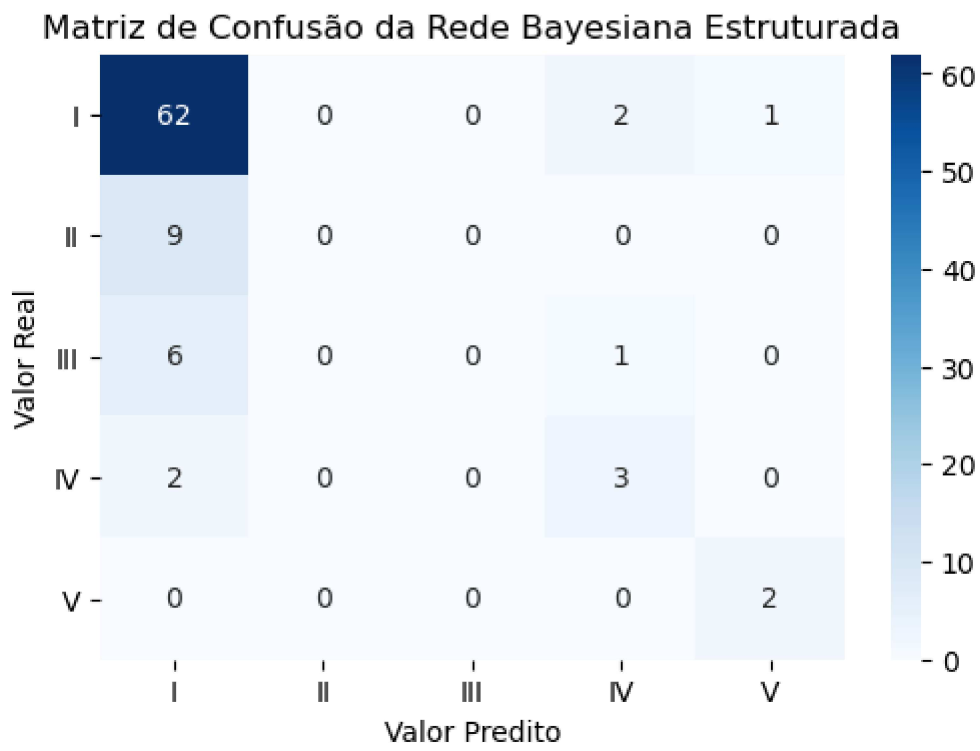
In [62]:

```
print('Resultado do modelo utilizando validação cruzada com k-fold de 10')
print()

lista_cv_acc, lista_cv_kappa, lista_cv_rmse = cvBayes(data_treino=db_b_treino,
                                                      modelo_bayes=modelo_bayes_otimo,

# Acurácia
print('Cross-validation scores accurancy:{}'.format(lista_cv_acc))
print('Average cross-validation score accurancy: {}'.format(np.mean(lista_cv_acc)))
print()

# KAPPA (RMSE)
print('Cross-validation kappa Score:{}'.format(lista_cv_kappa))
print('Average cross-validation kappa Score: {}'.format(np.mean(lista_cv_kappa)))
print()

# RMSE
print('Cross-validation RMSE:{}'.format(lista_cv_rmse))
print('Average cross-validation RMSE: {}'.format(np.mean(lista_cv_rmse)))

print()
print('#'*100)
print()

print('Resultado do modelo no conjunto de treinamento e teste')
print()
y_teste = db_b_teste.iloc[:,-1].astype(int)
y_treino = db_b_treino.iloc[:,-1].astype(int)

# Acurácia treinamento e teste
print('Test set Score: ', accuracy_score(y_teste, pred_test))
print('Training set score: ', accuracy_score(y_treino,pred_train))
print()

# Estatística Kappa
kappa = cohen_kappa_score(y_teste, pred_test)
print('Kappa Score do conjunto de teste:{}'.format(kappa))
print()

# Estatística RMSE
rmse = mean_squared_error(y_teste, pred_test)
print('RMSE conjunto de teste:{}'.format(rmse))
print()

# Relatorio de Classificação
print('Relatório do conjunto de teste')
print(classification_report(y_teste, pred_test, target_names=['I', 'II', 'III', 'IV', '
print()

#Get the confusion matrix
cf_matrix = confusion_matrix(y_teste, pred_test)
fig, ax = plt.subplots(dpi=100)
sns.heatmap(cf_matrix, xticklabels=['I', 'II', 'III', 'IV', 'V'],
            yticklabels=['I', 'II', 'III', 'IV', 'V'], annot=True, cmap='Blues' , ax=a
plt.title('Matriz de Confusão da Rede Bayesiana Estruturada')
plt.xlabel("Valor Predito")
plt.ylabel("Valor Real")
plt.yticks(rotation=0)
```

```
Resultado do modelo utilizando validação cruzada com k-fold de 10

Cross-validation scores accurancy:[0.8571428571428571, 0.7142857142857143,
0.8, 0.7428571428571429, 0.7714285714285715, 0.8, 0.7142857142857143, 0.6,
0.7714285714285715, 0.8571428571428571]
Average cross-validation score accurancy: 0.7628571428571428

Cross-validation kappa Score:[0.5084269662921348, 0.18414918414918413, -0.04
2553191489361764, 0.1964285714285714, 0.0572390572390572, 0.262048192771084
4, 0.10025706940874035, 0.0, 0.23287671232876717, 0.5635910224438903]
Average cross-validation kappa Score: 0.20624635845720682

Cross-validation RMSE:[0.22857142857142856, 0.8571428571428571, 1.6, 1.28571
42857142858, 1.7428571428571429, 0.2857142857142857, 1.6571428571428573, 2.1
142857142857143, 0.8571428571428571, 0.9714285714285714]
Average cross-validation RMSE: 1.1600000000000001

############################################################################
########################

Resultado do modelo no conjunto de treinamento e teste

Test set Score:  0.7613636363636364
Training set score:  0.7663817663817664

Kappa Score do conjunto de teste:0.28177225029148856

RMSE conjunto de teste:0.9772727272727273

Relatório do conjunto de teste
              precision    recall  f1-score   support

           I       0.78      0.95      0.86        65
          II       0.00      0.00      0.00         9
         III       0.00      0.00      0.00         7
          IV       0.50      0.60      0.55         5
           V       0.67      1.00      0.80         2

    accuracy                           0.76        88
   macro avg       0.39      0.51      0.44        88
weighted avg       0.62      0.76      0.69        88
```

Out[62]:

```
(array([0.5, 1.5, 2.5, 3.5, 4.5]),
 [Text(0, 0.5, 'I'),
  Text(0, 1.5, 'II'),
  Text(0, 2.5, 'III'),
  Text(0, 3.5, 'IV'),
  Text(0, 4.5, 'V')])
```



Decision Tree

Teste com o método de Árvore de Decisão

In [63]:

```
#Create a MultinomialNB Classifier
model = DecisionTreeClassifier()

# # Train the model using the training sets
model.fit(X_train,y_train)

# #Predict Output
predicted= model.predict(X_test)
```

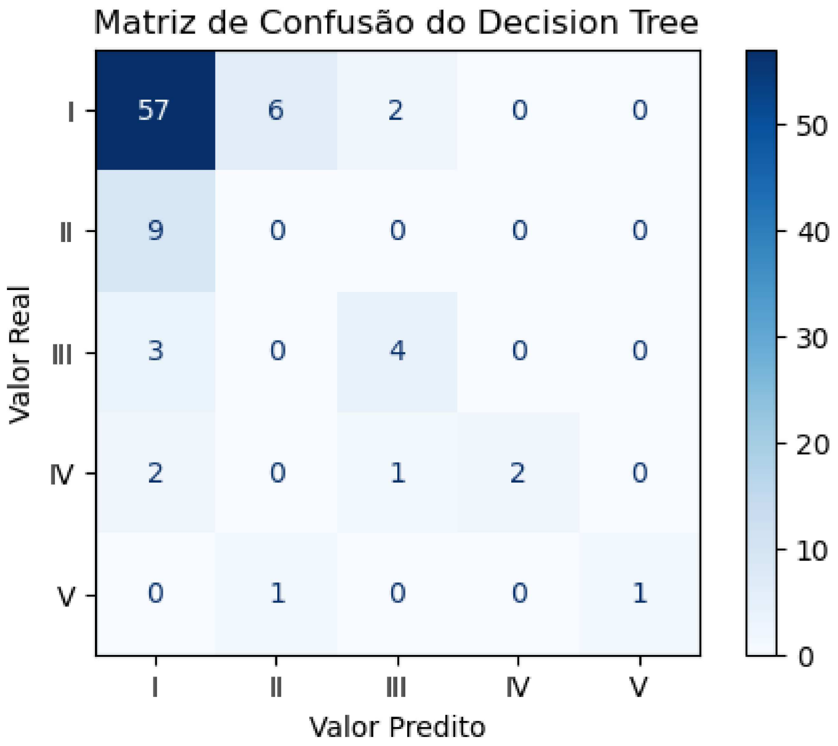
In [66]:

```
import graphviz
dot_data = tree.export_graphviz(model, out_file=None,
                                feature_names=X_train.columns.values.tolist(),
                                class_names='Accidente Level',
                                filled=True, rounded=True,
                                special_characters=True)
graph = graphviz.Source(dot_data)
```

In [65]:

```
1 resultado_modelo(model, X_train, X_test, y_train, y_test, modelo_nome='Decision Tree')
```

```
Resultado do modelo utilizando validação cruzada com k-fold de 10

Cross-validation scores accurancy: [0.77777778 0.71428571 0.74285714 0.6
0.62857143 0.68571429
 0.62857143 0.77142857 0.71428571 0.68571429]
Average cross-validation score accurancy: 0.6949206349206349

Cross-validation Root Mean Square Error (RMSE):[0.94280904 0.77459667 1.1832
1596 1.15881713 1.30930734 1.12122382
 1.01418511 1.01418511 1.10840941 1.10840941]
Average cross-validation Root Mean Square Error (RMSE): 1.0735158999840064

Cross-validation kappa Score:[-0.44401544 -0.39130435 -0.44664032 -0.1493055
6 -0.09181637 -0.11764706
 -0.07284768 -0.3        -0.03314917 -0.26931106]
Average cross-validation kappa Score: -0.2316037007799705

############################################################################
########################

Resultado do modelo no conjunto de treinamento e teste

Test set Score:  0.7272727272727273
Training set score:  0.9401709401709402
Kappa Score do conjunto de teste: 0.297171381031614
RMSE do conjunto de teste: 0.7159090909090909

Relatório do conjunto de teste
              precision    recall  f1-score   support

           I       0.80      0.88      0.84        65
          II       0.00      0.00      0.00         9
         III       0.57      0.57      0.57         7
          IV       1.00      0.40      0.57         5
           V       1.00      0.50      0.67         2

    accuracy                           0.73        88
   macro avg       0.67      0.47      0.53        88
weighted avg       0.72      0.73      0.71        88


Matriz de Confusão do conjunto de teste
```


Matriz de Confusão do Decision Tree
Valor Real
Valor Predito
I
II
III
IV
V
57 6 2 0 0
9 0 0 0 0
3 0 4 0 0
2 0 1 2 0
0 1 0 0 1
0
10
20
30
40
50