```
In [90]:
           import pandas as pd
           import requests
           from zipfile import ZipFile
           from io import BytesIO
           import numpy as np
           pd.set_option('display.max_columns', None)
In [105...
           response = requests.get("https://archive.ics.uci.edu/ml/machine-learning-databases/0
           files = ZipFile(BytesIO(response.content))
           df = pd.read_csv(files.open("dataset_diabetes/diabetic_data.csv"))
In [106...
           #variavel para pegar as colunas do df em fomra de lista
           cols = df.columns
           #variavel para selecionar colunas numéricas do df
           num_cols = df._get_numeric_data().columns
           #variavel que diminui as colunas numéricas das colunas, obtendo-se as colunas categó
           cat_col = list(set(cols) - set(num_cols))
In [107...
           #laço for para valores únicos categóricos
           for coluna in cat_col:
               print(coluna + str(df[coluna].unique()) + '\n')
           #laço for para valores únicos numéricos
           for col in num_cols:
               print( str(type(col)) + col + str(df[col].unique()) + '\n')
          readmitted['NO' '>30' '<30']
          glipizide-metformin['No' 'Steady']
          troglitazone['No' 'Steady']
          glyburide['No' 'Steady' 'Up' 'Down']
          glimepiride['No' 'Steady' 'Down' 'Up']
          chlorpropamide['No' 'Steady' 'Down' 'Up']
          tolazamide['No' 'Steady' 'Up']
          max_glu_serum['None' '>300' 'Norm' '>200']
          payer_code['?' 'MC' 'MD' 'HM' 'UN' 'BC' 'SP' 'CP' 'SI' 'DM' 'CM' 'CH' 'PO' 'WC' 'OT'
           'OG' 'MP' 'FR']
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          citoglipton['No']
          change['No' 'Ch']
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'594' '501' '810' '643' '430' '528' '205' '791' '983' '992' '490' '172'
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    'Orthopedics-Reconstructive' 'Psychiatry' 'Emergency/Trauma'
    'Pulmonology' 'Surgery-Neuro' 'Obsterics&Gynecology-GynecologicOnco'
    'ObstetricsandGynecology' 'Pediatrics' 'Hematology/Oncology'
    'Otolaryngology' 'Surgery-Colon&Rectal' 'Pediatrics-CriticalCare'
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 'Surgery-Pediatric' 'Pediatrics-EmergencyMedicine'
 'PhysicalMedicineandRehabilitation' 'InfectiousDiseases' 'Anesthesiology'
 'Rheumatology' 'AllergyandImmunology' 'Surgery-Maxillofacial'
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 'Dentistry' 'Surgeon' 'Surgery-Vascular' 'Osteopath'
 'Psychiatry-Addictive' 'Surgery-Cardiovascular' 'PhysicianNotFound'
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 'Pathology' 'Dermatology' 'SportsMedicine' 'Speech' 'Hospitalist'
 'OutreachServices' 'Cardiology-Pediatric' 'Perinatology'
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#valores a serem excluídos
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df

Out[109...

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1	149190	55629189	Caucasian	Female	[10- 20)	?	1	
2	64410	86047875	AfricanAmerican	Female	[20- 30)	?	1	
3	500364	82442376	Caucasian	Male	[30- 40)	?	1	
4	16680	42519267	Caucasian	Male	[40- 50)	?	1	
•••								
101761	443847548	100162476	AfricanAmerican	Male	[70- 80)	?	1	
101762	443847782	74694222	AfricanAmerican	Female	[80- 90)	?	1	
101763	443854148	41088789	Caucasian	Male	[70- 80)	?	1	
101764	443857166	31693671	Caucasian	Female	[80- 90)	?	2	

race gender age weight admission_type_id dischar

encounter_id patient_nbr

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                    443867222
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                                                                                         1
                                              Caucasian
                                                         Male
          101766 rows × 50 columns
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           df = df[~df.isin(drop_values).any(axis=1)]
           cols = df.columns
In [111...
           #variavel para selecionar colunas numéricas do df
           num_cols = df._get_numeric_data().columns
           #variavel que diminui as colunas numéricas das colunas, obtendo-se as colunas categó
           cat_col = list(set(cols) - set(num_cols))
           #laço for para valores únicos categóricos
           for coluna in cat_col:
               print(coluna + str(df[coluna].unique()) + '\n')
           #laço for para valores únicos numéricos
           for col in num_cols:
               print( str(type(col)) + col + str(df[col].unique()) + '\n')
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          troglitazone['No']
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          glimepiride['No' 'Steady' 'Down' 'Up']
          chlorpropamide['No']
          tolazamide['No']
          max_glu_serum['None']
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            '707' 'E885' '196' '295' '410' '997' '250.13' 'E935' '518' '517' '412'
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  920619 57623949 92960091 21834369 88544232 82325961 56220255
22999122 97243407 109829538 34776900 14359797 72877500 102299175
110949183
         7315353 77912109 61204185 84774825 81509751 96133068
 31004532 51516873 32021208 80895078 76092336 51609195 73997415
 60401475 113993721 102420747
                            23170572 113272641 55028079 72075951
                            54387162 94593078 21938337 69187482
39067056 104832666 21645018
                           20434689 78156405 51748416 78590844
111136032 21653595 61094367
```

```
47343420 80882010 92330604 65228292 63937845 108826011 85268259
                                                          21739896
 69870915 84140199 115179624 106584858
                                       4945113 54955197
 21148866 51672447 81362061 85663323 49094244 108000405
                                                          79480854
101754036 83724669 81529380 34511220 101447406 23441985
                                                          80096418
 98935092 109806192 98229618 66612906 32890041 80133525
                                                          21620106
 109926063 108520641 106598295 60092856 94270959 108470223 89231274
107610858
          5732190 84448305 81850653 55143027 111055230 114691221
 85440906 10397718 83292120 61983675 52109901 110116746 108612801
106000974 88476876 66544470 62916849 52809273
                                                  1840977
                                                         62416152
101634570 91231434 49884534 92525355 91551195 108462762 78516324
 29666772 88422057 108963711 18505530
                                       3157407 51079491
 89952723 60914322 100616103 68391864 62795961 88981110 36627768
 75949227 105455421 36102690 94901697 85736007 60001884 11528595
 109931175 83082510 88996941 102998124 100983141 21011481 104920191
103333095 75976587 104516208 73237077 91563588 55275210 85354254
 80147826 86280867 25770735 16528968 82766511 80913897 63822510
 97787358 66578481 109575621 27465723 103397130 80966655 70095411
 20256345 41290605 87170643 93890061 58963203 42517854 72267075
 82970667 65705580 88125012 111711870 30840552 48648636 107450397
 29121129 21642084 78660819 83628900 22325814 83669193 104844231
  2836278 97074369 22724991 65952252 28022877 45296928 126247874
 96392187 91541142 102961089 68660595 88603146 73590318 100178811
103321521 69640065 80873244 104956029 61696620 60750342 14612832
 53482221 62917911 81850140 66569706 86580594 96867576 98183286
 89244846 73798299 98225649 77498496 7959330 42846687 108074322
 48911328 85662477 94843530 75455487 113431365 106407477 36184986
 51543576 45149013 88646436 64296630 94783464 96584418 67659543
 92317950 117405302 182408828 65099880 67372344 18843498 88298091
184274798 65858589 54222390 94037994 91383840 75760884 166875089
 40593096 82133919 100694196 110778327 57186270 51354945 112982949
114986772 47543940 26106084 104922396 51168771 80256915 111222522
 44945478 72144513 94573413 90853668 123812618 117516146
 97708986 113392368]
<class 'str'>admission_type_id[3 1 2 5]
<class 'str'>discharge_disposition_id[ 3 11 1 6 5 7 13 4 2 18]
<class 'str'>admission_source_id[ 1 5 7 4 6 17]
<class 'str'>time_in_hospital[10 6 2 3 4 1 5 11 8
                                                     7 14 9 12 13]
                                                              1 50 45 41 47
<class 'str'>num_lab_procedures[ 65  73  58  33
                                               5 63
                                                    75
                                                         46
61 52 70 54 59
 71 69
                               72
                                   32
                                       79
                                                          49
                                                              21
                                                                  42
          4 66 76
                    53
                        23
                            44
                                           84
                                               62
                                                   67
                                                       60
                            68
                               43
                                   55
                                       12
                                               40
                                                   77
                                                              22
                                                                  78
         27
                10
                    51
                        64
                                           56
                                                       35
                        81
                             8
                               29
                                    39
                                       31
                                               74
                                                   28
                                                              37
 57
             48
                    24
                                          34
                                                       87
                                                          18
                                                                  16
 85
         14
             20
                83
                     2
                        93
                            15
                               92
                                    19
                                       11 105
                                                   88
      7
                                               13
                                                       26
<class 'str'>num procedures[1 0 3 4 2 6 5]
<class 'str'>num medications[28 16 12 7 11 20 15 10 21 23 17 9 18 8 26 25 31 13 1
4 5 22 44 4 27
24 3 6 19 32 40 33 39 41 29 30 42 43 36 58 34 55 1 2 52 57 46]
<class 'str'>number outpatient[ 1 0 4 2 3 5 6 14 10 9 8 7 11 13 15]
<class 'str'>number emergency[ 1 0 3 2 6 4
<class 'str'>number inpatient[ 3 0 6 1 5 2 4 9 10 7]
<class 'str'>number diagnoses[9 7 6 8 5 3 4]
```

```
Out[112... (1043, 50)
```

df.shape

In [112...

```
In [113...
           #lista para colunas a serem excluídas
           colunas_excluidas = ['payer_code'
           ,'medical_specialty'
           ,'admission_type_id'
           ,'admission_source_id'
           ,'discharge_disposition_id'
           ,'patient_nbr']
           df = df.drop(colunas_excluidas, axis = 1)
In [114...
           #colunas diagnoticos para o tipo string
           df['diag_1'] = df['diag_1'].astype(pd.StringDtype())
           df['diag_2'] = df['diag_2'].astype(pd.StringDtype())
           df['diag_3'] = df['diag_3'].astype(pd.StringDtype())
In [115...
           #atribuição do diconarioa de valores para equalizar numericamente as variaveis
           df['glipizide-metformin'] = df['glipizide-metformin'].map({'No': 0}) #['No']
           df['change'] = df['change'].map({'No': 0, 'Ch': 1}) #['Ch' 'No']
           df['tolbutamide'] = df['tolbutamide'].map({'No': 0}) #['No']
           df['examide'] = df['examide'].map({'No': 0}) #['No']
           df['pioglitazone'] = df['pioglitazone'].map({'No': 0, 'Steady': 1,'Up': 2, 'Down': 3
           df['diabetesMed'] = df['diabetesMed'].map({'No': 0, 'Yes': 1}) #['Yes' 'No']
           df['citoglipton'] = df['citoglipton'].map({'No': 0}) #['No']
           df['insulin'] = df['insulin'].map({'Steady': 0, 'No': 1, 'Down': 2, 'Up': 3}) #['Steady': 0, 'No': 1, 'Down': 2, 'Up': 3})
           df['troglitazone'] = df['troglitazone'].map({'No': 0}) #['No']
           df['glimepiride-pioglitazone'] = df['glimepiride-pioglitazone'].map({'No': 0}) #['No
           df['glyburide-metformin'] = df['glyburide-metformin'].map({'No': 0}) #['No']
           df['metformin-pioglitazone'] = df['metformin-pioglitazone'].map({'No': 0}) #['No']
           df['miglitol'] = df['miglitol'].map({'No': 0}) #['No']
           df['glyburide'] = df['glyburide'].map({'No': 0, 'Steady': 1,'Up': 2, 'Down':3}) #['No': 0, 'Steady': 1,'Up': 2, 'Down':3})
           df['tolazamide'] = df['tolazamide'].map({'No': 0}) #['No']
           df['max_glu_serum'] = df['max_glu_serum'].map({'None': 0, 'Norm': 1,'>200': 2, '>300
           df['nateglinide'] = df['nateglinide'].map({'No': 0, 'Steady': 1}) #['No' 'Steady']
           df['metformin-rosiglitazone'] = df['metformin-rosiglitazone'].map({'No': 0}) #['No']
           df['glimepiride'] = df['glimepiride'].map({'No': 0, 'Steady': 1,'Down': 2, 'Up': 3})
           df['metformin'] = df['metformin'].map({'No': 0, 'Steady': 1,'Up': 2, 'Down': 3}) #['
           df['A1Cresult'] = df['A1Cresult'].map({'None': 0, 'Norm': 1,'>8': 2, '>7': 3}) #['No
           df['chlorpropamide'] = df['chlorpropamide'].map({'No': 0}) #['No']
           df['acetohexamide'] = df['acetohexamide'].map({'No': 0}) #['No']
           df['rosiglitazone'] = df['rosiglitazone'].map({'No': 0, 'Steady': 1})
           df['glipizide'] = df['glipizide'].map({'Steady': 0, 'No': 1, 'Up': 2, 'Down': 3})
           df['acarbose'] = df['acarbose'].map({'No': 0, 'Steady': 1})
           df['repaglinide'] = df['repaglinide'].map({'No': 0, 'Steady': 1,'Up': 2})
           df['readmitted'] = df['readmitted'].map({'NO': 0, '<30': 1,'>30': 1})
           df["gender"] = df['gender'].map({'Male': 0, 'Female': 1})
           df["age"] = df['age'].map({'[0-10)': 0, '[10-20)': 1, '[20-30)': 2, '[30-40)': 3, '[
           df['race'] = df['race'].map({'Caucasian': 0, 'AfricanAmerican': 1, 'Asian': 2, 'Hispa
           df["weight"] = df['weight'].map({'[0-25)': 0, '[25-50)': 1, '[50-75)': 2, '[75-100)'}
In [117...
           df = df.dropna()
In [121...
           #lista de atribuição das patologias
           Circulatory = np.arange(390,460).tolist() + [785]
           Circulatory_str = [str(elemento) for elemento in Circulatory]
           Respiratory = np.arange(460,520).tolist() + [786]
           Respiratory_str = [str(elemento) for elemento in Respiratory]
```

```
Digestive = np.arange(520,580).tolist() + [787]
Digestive_str = [str(elemento) for elemento in Digestive]

Injury = np.arange(800,1000).tolist() + [786]
Injury_str = [str(elemento) for elemento in Injury]

Musculoskeletal = np.arange(710,740).tolist() + [786]
Musculoskeletal_str = [str(elemento) for elemento in Musculoskeletal]

Genitourinary = np.arange(580,630).tolist() + [788]
Genitourinary_str = [str(elemento) for elemento in Genitourinary]

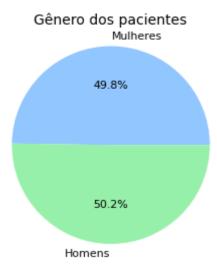
Neoplasms = np.arange(140,240).tolist()
Neoplasms_str = [str(elemento) for elemento in Neoplasms]

Other = np.arange(240,250).tolist() + np.arange(251,280).tolist() + [780,781,784,790)
Other_str = [str(elemento) for elemento in Other]
```

```
In [122...
            #atribuição das patologias dentre as colunas de diagnostico
            df.loc[df['diag_1'].str.startswith('250'), 'diag_1'] = 'Diabetes'
            df.loc[df['diag_2'].str.startswith('250'), 'diag_2'] = 'Diabetes'
            df.loc[df['diag_3'].str.startswith('250'), 'diag_3'] = 'Diabetes'
            df.loc[df['diag_1'].isin(Circulatory_str), 'diag_1'] = 'Circulatory'
            df.loc[df['diag_1'].isin(Respiratory_str), 'diag_1'] = 'Respiratory'
            df.loc[df['diag_1'].isin(Digestive_str), 'diag_1'] = 'Digestive'
            df.loc[df['diag_1'].isin(Injury_str), 'diag_1'] = 'Injury'
            df.loc[df['diag_1'].isin(Musculoskeletal_str), 'diag_1'] = 'Musculoskeletal'
df.loc[df['diag_1'].isin(Genitourinary_str), 'diag_1'] = 'Genitourinary'
            df.loc[df['diag_1'].isin(Neoplasms_str), 'diag_1'] = 'Neoplasms'
            df.loc[df['diag_2'].isin(Circulatory_str), 'diag_2'] = 'Circulatory'
            df.loc[df['diag_2'].isin(Respiratory_str), 'diag_2'] = 'Respiratory'
            df.loc[df['diag_2'].isin(Digestive_str), 'diag_2'] = 'Digestive'
            df.loc[df['diag_2'].isin(Injury_str), 'diag_2'] = 'Injury'
            df.loc[df['diag_2'].isin(Musculoskeletal_str), 'diag_2'] = 'Musculoskeletal'
            df.loc[df['diag_2'].isin(Genitourinary_str), 'diag_2'] = 'Genitourinary'
            df.loc[df['diag_2'].isin(Neoplasms_str), 'diag_2'] = 'Neoplasms'
            df.loc[df['diag_3'].isin(Circulatory_str), 'diag_3'] = 'Circulatory'
            df.loc[df['diag_3'].isin(Respiratory_str), 'diag_3'] = 'Respiratory'
            df.loc[df['diag_3'].isin(Digestive_str), 'diag_3'] = 'Digestive'
            df.loc[df['diag_3'].isin(Injury_str), 'diag_3'] = 'Injury'
            df.loc[df['diag_3'].isin(Musculoskeletal_str), 'diag_3'] = 'Musculoskeletal'
            df.loc[df['diag_3'].isin(Genitourinary_str), 'diag_3'] = 'Genitourinary'
            df.loc[df['diag 3'].isin(Neoplasms str), 'diag 3'] = 'Neoplasms'
            patology = ["Circulatory", "Respiratory", "Digestive", "Injury", "Musculoskeletal", "Geni
            df.loc[~df['diag_1'].isin(patology), 'diag_1'] = 'Other'
            df.loc[~df['diag_2'].isin(patology), 'diag_2'] = 'Other'
df.loc[~df['diag_3'].isin(patology), 'diag_3'] = 'Other'
```

```
#verificação da atribuiçãode valores
colunas_excluidas_2 = ['encounter_id']
df = df.drop(colunas_excluidas_2, axis = 1)
len(df["diag_1"].unique()) == len(df["diag_2"].unique()) == len(df["diag_3"].unique()
#laço for para atribuição
diags = ['diag 1','diag 2','diag 3']
```

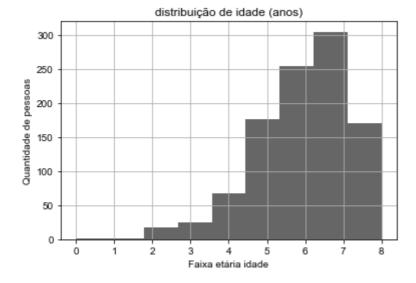
```
for diag in diags:
                df[diag] = df[diag].map({'Circulatory': 0, 'Respiratory': 1, 'Digestive': 2, 'Inj
                            , 'Musculoskeletal': 4, 'Genitourinary': 5, 'Neoplasms': 6, 'Other':
           df['age'] = df['age'].astype(int)
In [126...
           #importação da biblioteca para plotagem e exploração
           from collections import Counter
           import matplotlib.pyplot as plt
           #slice das variaveis
           gender = Counter(df["gender"])
           gender
          Counter({1: 508, 0: 513})
Out[126...
In [127...
           age = Counter(df["age"])
           age
           Counter({7: 305, 8: 171, 6: 255, 4: 68, 5: 177, 2: 18, 3: 25, 0: 1, 1: 1})
Out[127...
In [128...
           weight = Counter(df["weight"])
           weight
           Counter({3: 431, 2: 270, 4: 220, 5: 46, 1: 26, 6: 16, 7: 6, 0: 6})
Out[128...
In [129...
           race = Counter(df["race"])
           race
          Counter({0: 977, 1: 30, 4: 13, 2: 1})
Out[129...
In [130...
           race = Counter(df["race"])
           race
          Counter({0: 977, 1: 30, 4: 13, 2: 1})
Out[130...
In [131...
           plt.style.use('seaborn-pastel')
           plt.pie(gender.values(), labels = ["Mulheres", "Homens"],
           autopct = '%1.1f%%', textprops={'fontsize': 11})
           plt.axis("image")
           plt.title("Gênero dos pacientes", fontsize=14,pad =12)
           plt.show()
```

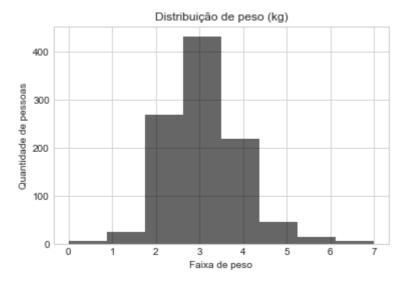


```
In [132...

df.age.hist(bins=9, color = 'black', alpha = 0.6)
plt.style.use('seaborn-whitegrid')
plt.xlabel("Faixa etária idade")
plt.ylabel("Quantidade de pessoas")
plt.title("distribuição de idade (anos)")
plt.show()

df.weight.hist(bins=8, color = 'black', alpha = 0.6)
plt.style.use('seaborn-whitegrid')
plt.xlabel("Faixa de peso")
plt.ylabel("Quantidade de pessoas")
plt.title("Distribuição de peso (kg)")
plt.show()
```

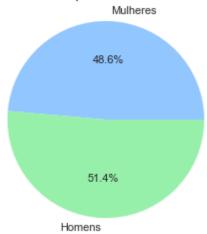




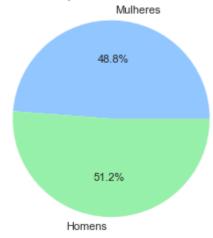
```
In [133...
           #slice dataframe pela variavel target
           df readmitted = df.loc[df['readmitted'] == 1 ]
           df not readmitted = df.loc[df['readmitted'] == 0]
           #slice do genero nos dataframes
           gender_not_readmitted = Counter(df_not_readmitted["gender"])
           gender_not_readmitted
           gender_readmitted = Counter(df_readmitted["gender"])
           gender readmitted
           plt.style.use('seaborn-pastel')
           plt.pie(gender_readmitted.values(), labels = ["Mulheres", "Homens"],
           autopct = '%1.1f%%', textprops={'fontsize': 11})
           plt.axis("image")
           plt.title("Gênero dos pacientes readmitidos", fontsize=14,pad =12)
           plt.show()
           plt.style.use('seaborn-pastel')
           plt.pie(gender_not_readmitted.values(), labels = ["Mulheres", "Homens"],
           autopct = '%1.1f%%', textprops={'fontsize': 11})
           plt.axis("image")
           plt.title("Gênero dos pacientes não readmitidos", fontsize=14,pad =12)
           plt.show()
           race_readmitted = Counter(df_readmitted["race"])
           race readmitted
           race not readmitted = Counter(df not readmitted["race"])
           race not readmitted
           weight readmitted = Counter(df not readmitted["weight"])
           weight_readmitted
           weight not readmitted = Counter(df not readmitted["weight"])
           weight_not_readmitted
           plt.style.use('seaborn-whitegrid')
           plt.bar(['M','F'], gender_readmitted.values())
           plt.ylabel('Número de pacientes')
           plt.xlabel('Raça')
           plt.title('pacientes por sexo - readmitidos')
           plt.show()
           plt.style.use('seaborn-whitegrid')
           plt.bar(['M','F'], gender_not_readmitted.values())
           plt.ylabel('Número de pacientes')
           plt.xlabel('Raça')
           plt.title('pacientes por sexo - não readmitidos')
```

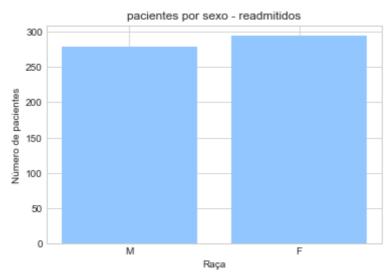
```
plt.show()
plt.style.use('seaborn-whitegrid')
plt.bar(list(race_readmitted.keys()), race_readmitted.values())
plt.ylabel('Número de pacientes')
plt.xlabel('Raça')
plt.title('pacientes por raça - readmitidos')
plt.show()
plt.style.use('seaborn-whitegrid')
plt.bar(list(race_not_readmitted.keys()), race_not_readmitted.values())
plt.ylabel('Número de pacientes')
plt.xlabel('Raça')
plt.title('pacientes por raça - não readmitidos')
plt.show()
plt.style.use('seaborn-whitegrid')
plt.bar(['M','F'], gender_readmitted.values())
plt.ylabel('Número de pacientes')
plt.xlabel('Raça')
plt.title('pacientes por sexo - readmitidos')
plt.show()
plt.style.use('seaborn-whitegrid')
plt.bar(['M','F'], gender_not_readmitted.values())
plt.ylabel('Número de pacientes')
plt.xlabel('Raça')
plt.title('pacientes por sexo - não readmitidos')
plt.show()
plt.style.use('seaborn-whitegrid')
plt.bar(list(weight_readmitted.keys()), weight_readmitted.values())
plt.ylabel('Número de pacientes')
plt.xlabel('Peso (kg)')
plt.title('Pacientes por peso (kg) - readmitidos')
plt.show()
plt.style.use('seaborn-whitegrid')
plt.bar(list(weight not readmitted.keys()), weight not readmitted.values())
plt.ylabel('Número de pacientes')
plt.xlabel('Peso (kg)')
plt.title('Pacientes por peso (kg) - não readmitidos')
plt.show()
```

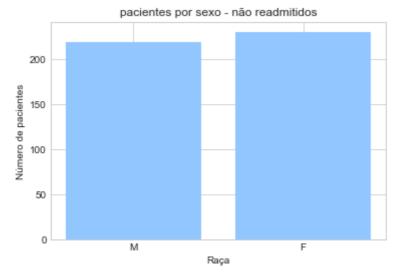
Gênero dos pacientes readmitidos

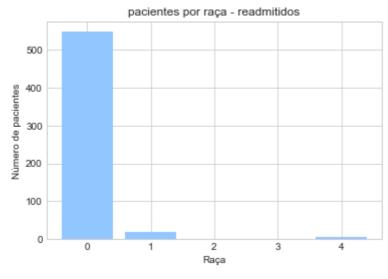


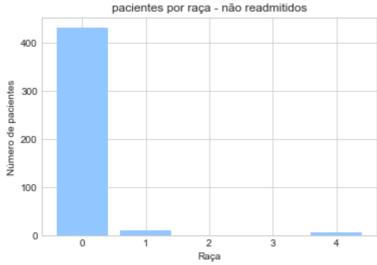
Gênero dos pacientes não readmitidos

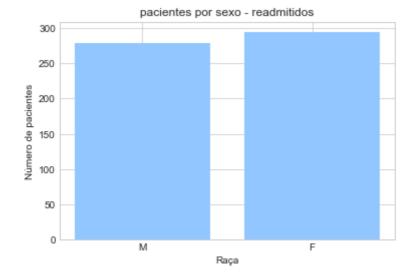


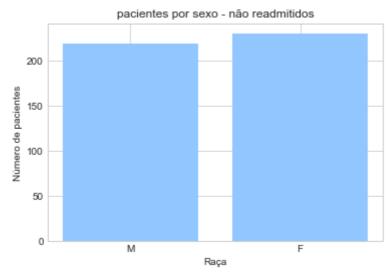


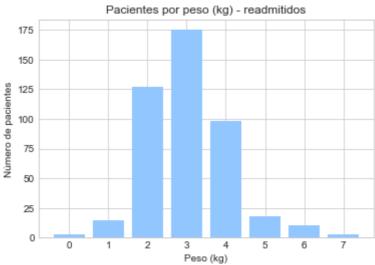


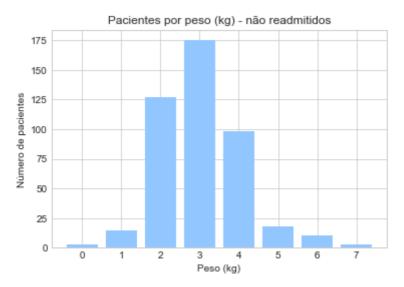












```
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score

#separação dados de treinno e teste
X = df.drop('readmitted',axis=1).values
y = df['readmitted'].values
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=0)
```

```
In [135... #aplicação algoritmo KNN from sklearn.neighbors import KNeighborsClassifier
```

knn = KNeighborsClassifier()

```
knn = knn.fit(X_train, y_train)
           print("Acurácia: ", knn.score(X_train, y_train))
           tp_knn = knn.predict(X_test)
           print("Acurácia de previsão: ", accuracy score(y test, tp knn))
           print(classification_report(y_test, tp_knn))
           from sklearn.metrics import precision_score, accuracy_score, recall_score, f1_score
           print(f"Accuracy: {round(accuracy_score(y_test, tp_knn), 2)}")
           print(f"Precision: {round(precision_score(y_test, tp_knn), 2)}")
           print(f"Recall: {round(recall_score(y_test, tp_knn), 2)}")
           print(f"F1_score: {round(f1_score(y_test, tp_knn), 2)}")
          Acurácia: 0.7058823529411765
          Acurácia de previsão: 0.46579804560260585
                        precision
                                     recall f1-score
                                                         support
                     0
                             0.41
                                        0.44
                                                  0.42
                                                             136
                     1
                              0.52
                                        0.49
                                                  0.50
                                                             171
                                                  0.47
                                                             307
              accuracy
                             0.46
                                        0.46
                                                  0.46
                                                             307
             macro avg
                             0.47
                                        0.47
                                                  0.47
                                                             307
          weighted avg
          Accuracy: 0.47
          Precision: 0.52
          Recall: 0.49
          F1_score: 0.5
In [136...
           #aplicação algoritmo Naive Bayes
           from sklearn.naive_bayes import GaussianNB
           from sklearn.metrics import accuracy_score, classification_report
           nb = GaussianNB()
           nb = nb.fit(X_train, y_train)
           print("Acurácia: ", nb.score(X_train, y_train))
           tp_nb = nb.predict(X_test)
           print(classification_report(y_test, tp_nb))
           from sklearn.metrics import precision_score, accuracy_score, recall_score, f1_score
           print(f"Accuracy: {round(accuracy_score(y_test, tp_nb), 2)}")
           print(f"Precision: {round(precision_score(y_test, tp_nb), 2)}")
           print(f"Recall: {round(recall score(y test, tp nb), 2)}")
           print(f"F1 score: {round(f1 score(y test, tp nb), 2)}")
          Acurácia: 0.6386554621848739
                                    recall f1-score
                        precision
                                                         support
                                                  0.55
                     a
                              0.48
                                        0.63
                                                             136
                             0.61
                                        0.46
                                                  0.53
                     1
                                                             171
                                                  0.54
                                                             307
              accuracy
                             0.55
                                        0.55
                                                  0.54
                                                             307
             macro avg
          weighted avg
                             0.56
                                        0.54
                                                  0.54
                                                             307
          Accuracy: 0.54
          Precision: 0.61
          Recall: 0.46
          F1_score: 0.53
In [137...
           #aplicação algoritmo gradiente descendente
           from sklearn.linear_model import SGDClassifier
           sgd = SGDClassifier()
           sgd = sgd.fit(X_train, y_train)
           print("Acurácia: ", sgd.score(X_train, y_train))
           tp_sgd = sgd.predict(X_test)
           print(classification_report(y_test, tp_sgd))
           from sklearn.metrics import precision_score, accuracy_score, recall_score, f1_score
```

```
print(f"Accuracy: {round(accuracy_score(y_test, tp_sgd), 2)}")
print(f"Precision: {round(precision_score(y_test, tp_sgd), 2)}")
print(f"Recall: {round(recall_score(y_test, tp_sgd), 2)}")
print(f"F1_score: {round(f1_score(y_test, tp_sgd), 2)}")
```

Acurácia: 0.5700280112044818 recall f1-score precision support 0 0.57 0.03 0.06 136 1 0.56 0.98 0.71 171 0.56 307 accuracy 0.57 0.51 0.38 macro avg 307 weighted avg 0.42 0.57 0.56 307

Accuracy: 0.56 Precision: 0.56 Recall: 0.98 F1_score: 0.71

In []: