Project Cardiovascular Disease Dataset

أمراض القلب والأوعية الدموية

Design & Data:

the purpose is prediction if a patient has cardiovascular disease or not, beside of patients medical information such as height, weight, age, blood pressure, glucose levels, and cholesterol levels.

the dataset is https://www.kaggle.com/sulianova/cardiovascular-disease-dataset

Features:

- Age | Objective Feature | age | int (days)
- Height | Objective Feature | height | int (cm) |
- Weight | Objective Feature | weight | float (kg) |
- Gender | Objective Feature | gender | categorical code |
- Systolic blood pressure | Examination Feature | ap_hi | int |
- Diastolic blood pressure | Examination Feature | ap_lo | int |
- Cholesterol | Examination Feature | cholesterol | 1: normal, 2: above normal, 3: well above normal |
- Glucose | Examination Feature | gluc | 1: normal, 2: above normal, 3: well above normal |
- Smoking | Subjective Feature | smoke | binary |
- Alcohol intake | Subjective Feature | alco | binary |
- Physical activity | Subjective Feature | active | binary |
- Presence or absence of cardiovascular disease | Target Variable | cardio | binary |

import the tools that we will need

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import precision_score, recall_score, accuracy_score, roc_auc_scor
from sklearn.metrics import classification_report, confusion_matrix

%matplotlib inline
```

read the dataset file witch was separated semicolon

In [2]:
```
df = pd.read_csv("cardio_train.csv", sep = ';') #the data semicolon (not comma) separat
df.head(5)
```

Out[2]:

	id	age	gender	height	weight	ap_hi	ap_lo	cholesterol	gluc	smoke	alco	active	cardio
0	0	18393	2	168	62.0	110	80	1	1	0	0	1	0
1	1	20228	1	156	85.0	140	90	3	1	0	0	1	1
2	2	18857	1	165	64.0	130	70	3	1	0	0	0	1
3	3	17623	2	169	82.0	150	100	1	1	0	0	1	1
4	4	17474	1	156	56.0	100	60	1	1	0	0	0	0

check the columns names

In [3]:
```
df.columns
```

Out[3]:
```
Index(['id', 'age', 'gender', 'height', 'weight', 'ap_hi', 'ap_lo',
       'cholesterol', 'gluc', 'smoke', 'alco', 'active', 'cardio'],
      dtype='object')
```

and check the the number of records and features

In [4]:
```
df.shape
```

Out[4]:
```
(70000, 13)
```

In [5]:
```
#check for null
df.isnull().sum().any()
```

Out[5]:
```
False
```

see descriptive statistics of the features

In [6]:
```
df.describe()
```

Out[6]:

	id	age	gender	height	weight	ap_hi	ap_l
count	70000.000000	70000.000000	70000.000000	70000.000000	70000.000000	70000.000000	70000.00000
mean	49972.419900	19468.865814	1.349571	164.359229	74.205690	128.817286	96.63041
std	28851.302323	2467.251667	0.476838	8.210126	14.395757	154.011419	188.47253

	id	age	gender	height	weight	ap_hi	ap_l
min	0.000000	10798.000000	1.000000	55.000000	10.000000	-150.000000	-70.00000
25%	25006.750000	17664.000000	1.000000	159.000000	65.000000	120.000000	80.00000
50%	50001.500000	19703.000000	1.000000	165.000000	72.000000	120.000000	80.00000
75%	74889.250000	21327.000000	2.000000	170.000000	82.000000	140.000000	90.00000
max	99999.000000	23713.000000	2.000000	250.000000	200.000000	16020.000000	11000.00000

EDA:

cleaning:

- 1 drop column `id` as it is irrelevant to target variable.
- 2 Transform `age` column into years instead of days.
- 3 clean the unrealistic values in `ap_hi` and `ap_lo`
- 4 clean the unrealistic values in `height` and `weight`
- 5 add **Body Mass Index (BMI)** column
- 6 change the encode for `gender` from 1-2 to F-M
- 7 check for **duplicated** data

1 drop column `id` as it is irrelevant to target variable.

In [7]:
```
#1 columns before drop id
df.shape
```
Out[7]:
```
(70000, 13)
```

In [8]:
```
#1 drop id
df=df.drop('id',axis=1)
```

In [9]:
```
#1  columns after drop id
df.shape
```
Out[9]:
```
(70000, 12)
```

2 Transform `age` column into years instead of days.

In [10]:
```
#2 before
df.age[:3]
```
Out[10]:
```
0    18393
1    20228
```

```
2    18857
Name: age, dtype: int64
```

In [11]:

```
#2 age from days to years
df.age = np.round(df.age/365.25,decimals=1)
```

use round function from numpy for rounding decimals

In [12]:

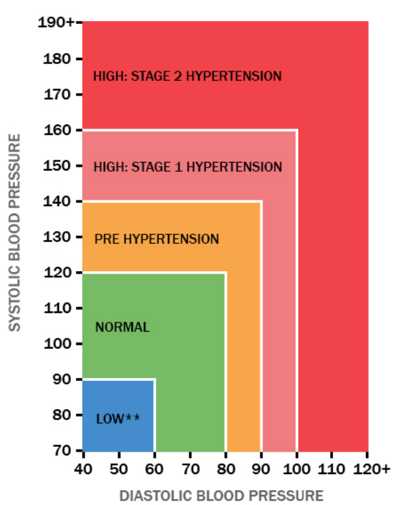
```
#2  after
df[['age']].sort_values(by=['age'],ascending=True)
```

Out[12]:

	age
22343	29.6
30666	29.7
6219	29.8
55905	30.0
44857	39.1
...	...
57191	64.9
50714	64.9
20931	64.9
36603	64.9
68005	64.9

70000 rows × 1 columns

3 clean the unrealistic values in `ap_hi` and `ap_lo`



the normal human blood pressure in Systolic blood pressure (ap_hi) between 70-190 and in Diastolic blood pressure (ap_lo) between 40-120 we have unreal readings in our data and we will drop them

In [13]:

```
#3 before
df[['ap_hi']].sort_values(by=['ap_hi'],ascending=True)
```

Out[13]:

	ap_hi
35040	-150
23988	-140
46627	-120
25240	-120
16021	-115
...	...
47253	14020
25464	14020
25519	14020
46912	14020
40852	16020

70000 rows × 1 columns

In [14]:

```
#3 before
df[['ap_lo']].sort_values(by=['ap_lo'],ascending=True)
```

Out[14]:

	ap_lo
60106	-70
40330	0
42397	0
56950	0
63787	0
...	...
43434	9800
68538	10000
23849	10000
2381	10000
43326	11000

70000 rows × 1 columns

test if the record want to drop is less than 5% of the data

In [15]:
```
df.shape[0:1] #number of raws
```
Out[15]:
```
(70000,)
```

5% of 70000 is 3500

so, more than 66500 is ok

In [16]:
```
# check the raws numbers if we drop
#(ap_hi) between 70-190
#(ap_lo) between 40-120
del_df= df[(df['ap_lo']<=120) & (df['ap_hi']<=190)]
del_df= df[(df['ap_lo']>=40) & (df['ap_hi']>=70)]
del_df.shape[0:1]
```
Out[16]:
```
(69757,)
```

its ok

In [17]:
```
#3 drop unreal readings
#(ap_hi) between 70-190
#(ap_lo) between 40-120
df= df[(df['ap_lo']<=120) & (df['ap_hi']<=190)]
df= df[(df['ap_lo']>=40) & (df['ap_hi']>=70)]
```

now the max and min realiztic

In [18]:
```
df[['ap_lo','ap_hi']].describe()
```
Out[18]:

	ap_lo	ap_hi
count	68548.000000	68548.000000
mean	81.247593	126.452179
std	9.313123	16.301674
min	40.000000	70.000000
25%	80.000000	120.000000
50%	80.000000	120.000000
75%	90.000000	140.000000
max	120.000000	190.000000

4 clean the unrealistic values in `height` and `weight`

Adults Weight to Height Ratio Chart		
Height - Ft. In. (cms)	Female	Male
4' 6" - (137 cm)	63 - 77 lb - (28.5 - 34.9 kg)	63 - 77 lb - (28.5 - 34.9 kg)
4' 7" - (140 cm)	68 - 83 lb - (30.8 - 37.6 kg)	68 - 84 lb - (30.8 - 38.1 kg)
4' 8" - (142 cm)	72 - 88 lb - (32.6 - 39.9 kg)	74 - 90 lb - (33.5 - 40.8 kg)
4' 9" - (145 cm)	77 - 94 lb - (34.9 - 42.6 kg)	79 - 97 lb - (35.8 - 43.9 kg)
4' 10" - (147 cm)	81 - 99 lb - (36.4 - 44.9 kg)	85 - 103 lb - (38.5 - 46.7 kg)
4' 11" - (150 cm)	86 - 105 lb - (39 - 47.6 kg)	90 - 110 lb - (40.8 - 49.9 kg)
5' 0" - (152 cm)	90 - 110 lb - (40.8 - 49.9 kg)	95 - 117 lb - (43.1 - 53 kg)
5' 1" - (155 cm)	95 - 116 lb - (43.1 - 52.6 kg)	101 - 123 lb - (45.8 - 55.8 kg)
5' 2" - (157 cm)	99 - 121 lb - (44.9 - 54.9 kg)	106 - 130 lb - (48.1 - 58.9 kg)
5' 3" - (160 cm)	104 - 127 lb - (47.2 - 57.6 kg)	112 - 136 lb - (50.8 - 61.6 kg)
5' 4" - (163 cm)	108 - 132 lb - (49 - 59.9 kg)	117 - 143 lb - (53 - 64.8 kg)
5' 5" - (165 cm)	113 - 138 lb - (51.2 - 62.6 kg)	122 - 150 lb - (55.3 - 68 kg)
5' 6" - (168 cm)	117 - 143 lb - (53 - 64.8 kg)	128 - 156 lb - (58 - 70.7 kg)
5' 7" - (170 cm)	122 - 149 lb - (55.3 - 67.6 kg)	133 - 163 lb - (60.3 - 73.9 kg)
5' 8" - (173 cm)	126 - 154 lb - (57.1 - 69.8 kg)	139 - 169 lb - (63 - 76.6 kg)
5' 9" - (175 cm)	131 - 160 lb - (59.4 - 72.6 kg)	144 - 176 lb - (65.3 - 79.8 kg)
5' 10" - (178 cm)	135 - 165 lb - (61.2 - 74.8 kg)	149 - 183 lb - (67.6 - 83 kg)
5' 11" - (180 cm)	140 - 171 lb - (63.5 - 77.5 kg)	155 - 189 lb - (70.3 - 85.7 kg)
6' 0" - (183 cm)	144 - 176 lb - (65.3 - 79.8 kg)	160 - 196 lb - (72.6 - 88.9 kg)
6' 1" - (185 cm)	149 - 182 lb - (67.6 - 82.5 kg)	166 - 202 lb - (75.3 - 91.6 kg)
6' 2" - (188 cm)	153 - 187 lb - (69.4 - 84.8 kg)	171 - 209 lb - (77.5 - 94.8 kg)
6' 3" - (191 cm)	158 - 193 lb - (71.6 - 87.5 kg)	176 - 216 lb - (79.8 - 98 kg)
6' 4" - (193 cm)	162 - 198 lb - (73.5 - 89.8 kg)	182 - 222 lb - (82.5 - 100.6 kg)
6' 5" - (195 cm)	167 - 204 lb - (75.7 - 92.5 kg)	187 - 229 lb - (84.8 - 103.8 kg)
6' 6" - (198 cm)	171 - 209 lb - (77.5 - 94.8 kg)	193 - 235 lb - (87.5 - 106.5 kg)
6' 7" - (201 cm)	176 - 215 lb - (79.8 - 97.5 kg)	198 - 242 lb - (89.8 - 109.7 kg)
6' 8" - (203 cm)	180 - 220 lb - (81.6 - 99.8 kg)	203 - 249 lb - (92 - 112.9 kg)
6' 9" - (205 cm)	185 - 226 lb - (83.9 - 102.5 kg)	209 - 255 lb - (94.8 - 115.6 kg)
6' 10" - (208 cm)	189 - 231 lb - (85.7 - 104.8 kg)	214 - 262 lb - (97 - 118.8 kg)
6' 11" - (210 cm)	194 - 237 lb - (88 - 107.5 kg)	220 - 268 lb - (99.8 - 121.5 kg)
7' 0" - (213 cm)	198 - 242 lb - (89.8 - 109.7 kg)	225 - 275 lb - (102 - 124.7 kg)

adlut height between 137-213

adlut weight between 28.5-124.7

In [19]:

```
# the max and min not realiztic
df[['height','weight']].describe()
```

Out[19]:

	height	weight
count	68548.000000	68548.000000
mean	164.362111	74.089397
std	8.179812	14.304198
min	55.000000	11.000000
25%	159.000000	65.000000
50%	165.000000	72.000000
75%	170.000000	82.000000
max	250.000000	200.000000

In [20]:

```python
# check the raws numbers if we drop
del_df = df[(df['height']<=213.0) & (df['height']>=137.0)]
del_df = df[(df['weight']<=124.7) & (df['weight']>=28.5)]
del_df.shape[0:1]
```

Out[20]:

```
(68185,)
```

its less than 5% so its ok

In [21]:

```python
#4 drop the unreals
#adlut height between 137-213
#adlut weight between 28.5-124.7
df = df[(df['height']<=213.0) & (df['height']>=137.0)]
df = df[(df['weight']<=124.7) & (df['weight']>=28.5)]
```

In [22]:

```python
# the max and min realiztic
df[['height','weight']].describe()
```

Out[22]:

	height	weight
count	68072.000000	68072.000000
mean	164.427562	73.766033
std	7.799930	13.536602
min	137.000000	29.000000
25%	159.000000	65.000000
50%	165.000000	72.000000
75%	170.000000	82.000000
max	207.000000	124.000000

5 add **Body Mass Index (BMI)** column

Let's create a new feature - Body Mass Index (BMI):

$$BMI = \frac{mass_{kg}}{height^2_m},$$

it's easier to compute BMI instead of height and weight

BMI	Weight status
Below 18.5	Underweight
18.5-24.9	Normal weight
25.0-29.9	Overweight
30.0-34.9	Obesity class I
35.0-39.9	Obesity class II
Above 40	Obesity class III

BMI btween 18.5-40

In [23]:

```
# add the feature
df['BMI'] = df['weight']/((df['height']/100)**2)
```

In [24]:

```
# not realiztic
df[['BMI']].sort_values(by=['BMI'],ascending=True)
```

Out[24]:

	BMI
60699	9.917581
16906	10.726644
18559	11.718750
58200	12.254473
16322	12.855831
...	...
66997	54.666667
69708	55.459105
15319	56.295740
49377	57.870370
28448	58.024202

68072 rows × 1 columns

In [25]:

```
# check the raws numbers if we drop
del_df = df[(df['BMI']<40.0) & (df['BMI']>18.5)]
del_df.shape[0:1]
```

Out[25]:

```
(66054,)
```

its less than 5% so its ok

In [26]:

```
# cant be less than 18.5 and more than 40, so drop unreals
df = df[(df['BMI']<40.0) & (df['BMI']>18.5)]
```

In [27]:

```
# realiztic
df[['BMI']].sort_values(by=['BMI'],ascending=True)
```

Out[27]:

	BMI
46646	18.507766
25855	18.507766
16208	18.507766

	BMI
60844	18.507766
10612	18.507766
...	...
8959	39.958377
65510	39.958377
35444	39.959508
56331	39.965649
52820	39.965649

66054 rows × 1 columns

6 change the encode for `gender` from 1-2 to F-M

In [28]:
```
df["gender"].unique()
```

Out[28]:
```
array([2, 1], dtype=int64)
```

we dont have info who is 1 or 2

so this next cell can know besided on info that the height avg. of male is more than female

In [29]:
```
#take the mean of both 1 and 2
a = df[df["gender"]==1]["height"].mean()
b = df[df["gender"]==2]["height"].mean()

# compare
if a > b:
    gender = "male"
    gender1 = "female"
else:
    gender = "female"
    gender1 = "male"

print("Gender:1 is "+ gender +" & Gender:2 is " + gender1)
```

```
Gender:1 is female & Gender:2 is male
```

In [30]:
```
# use lambda fun. to change the 1,2 to f.m
df['gender'] = df['gender'].apply(lambda x: 'F' if x == 1 else 'M')
```

In [31]:
```
df.gender.value_counts()
```

Out[31]:
```
F    42665
M    23389
Name: gender, dtype: int64
```

7 check for **duplicated** data

In [32]:
```
# check the rows and columns
df.shape
```

Out[32]:
```
(66054, 13)
```

In [33]:
```
# see how much duplicated rows
df.duplicated().sum()
```

Out[33]:
```
673
```

In [34]:
```
#drpp the 673 duplicated raw
df.drop_duplicates(inplace=True)
```

In [35]:
```
# now we should have 0
df.duplicated().sum()
```

Out[35]:
```
0
```

In [36]:
```
# check the rows and columns
df.shape
```

Out[36]:
```
(65381, 13)
```

EDA:

Questions:

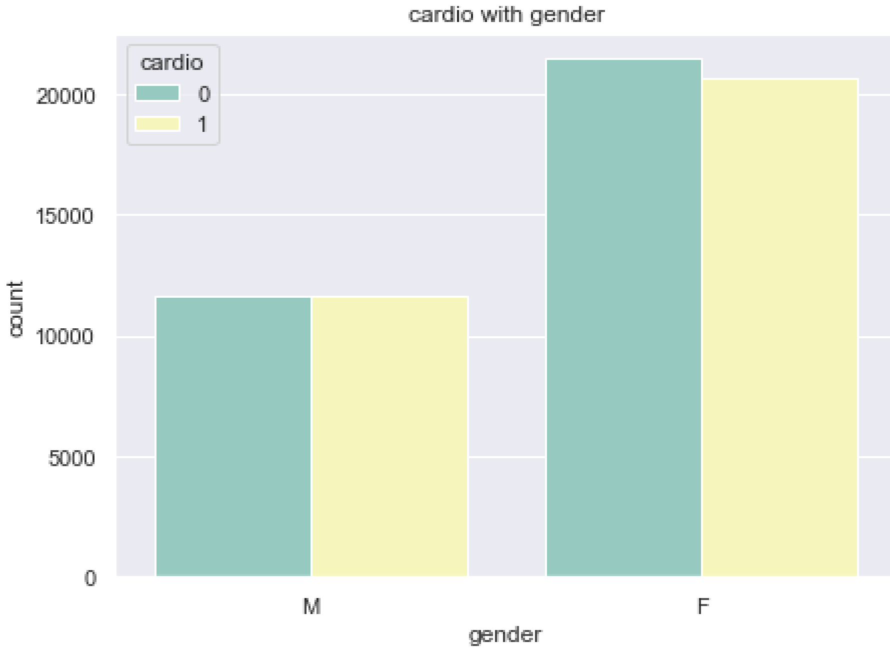
- 1 Which gender has more has cardiovascular disease?
- 2 Which age group has more has cardiovascular disease?
- 3 Blood pressure effect the cardiovascular disease?

1 Which gender has more cardiovascular disease?

In [67]:
```
sns.set_style('whitegrid') #to make white grid in the graph
sns.set(rc={'figure.figsize':(7,5)}) # for edit size
sns.countplot(df.gender,hue=df.cardio, palette="Set3"); #make the graph
plt.title('cardio with gender'); # add title
```

```
C:\Users\ichra\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pas
s the following variable as a keyword arg: x. From version 0.12, the only valid position
al argument will be `data`, and passing other arguments without an explicit keyword will
```

```
result in an error or misinterpretation.
  warnings.warn(
```



In [39]:

```python
# show count of cardio in every gender
df.groupby(['gender', 'cardio']).agg({'cardio': 'count'})
```

Out[39]:

gender	cardio	cardio
F	**0**	21467
	1	20640
M	**0**	11657
	1	11617

the females is more than males so lets try another way with percent (%)

In [40]:

```python
# show count of cardio in every gender in percent
gender_cardio = df.groupby(['gender', 'cardio']).agg({'cardio': 'count'})
gender = df.groupby(['gender']).agg({'cardio': 'count'})
gender_cardio.div(gender, level='gender')* 100
```

Out[40]:

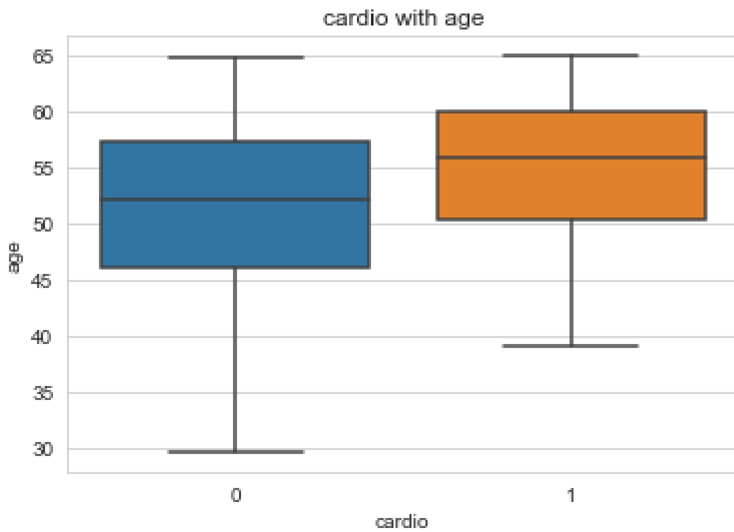
gender	cardio	cardio
F	**0**	50.982022
	1	49.017978
M	**0**	50.085933
	1	49.914067

the females more than males in this dataset but when it come with percent they almost **50/50** to have cardiovascular disease

2 Which age group has more has cardiovascular disease?

most the ages that has cardio btween 50-60

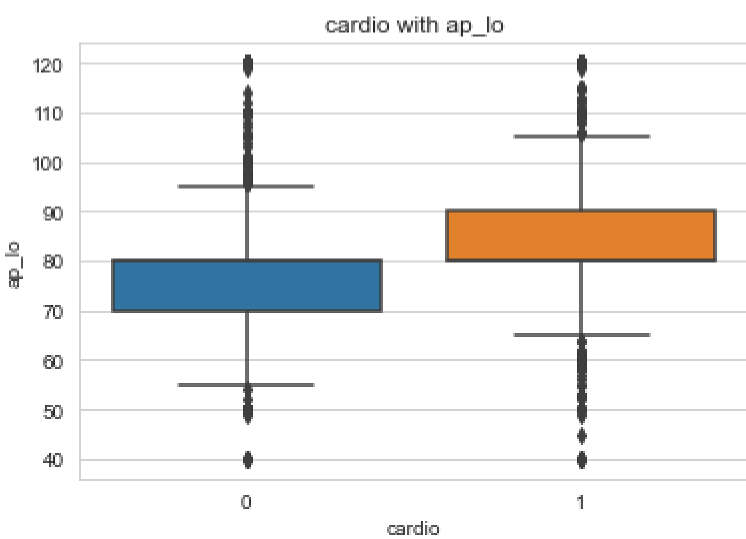
In [41]:
```
sns.boxplot( x="cardio", y="age", data=df); # make boxplot
plt.title('cardio with age'); #set title
```



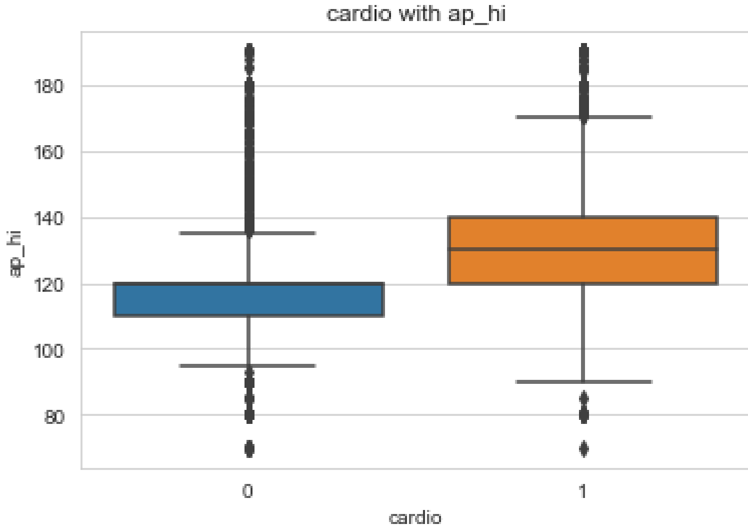
3 Patients with cardiovascular disease have high Blood pressure?

Yes, they have higher than patients they dont

In [42]:
```
sns.boxplot( x="cardio", y="ap_lo", data=df); # make boxplot
plt.title('cardio with ap_lo'); #set title
```



In [43]:
```
sns.boxplot( x="cardio", y="ap_hi", data=df); # make boxplot
plt.title('cardio with ap_hi'); #set title
```



Model :

we will use **Logistic Regression** for predictions if a patient has cardiovascular disease or not

- Step 1: Feature selection
- Step 2: Split the data
- Step 3: Scale the train data
- Step 4: Use Logistic Regression

Step 1: Feature selection

In [45]:
```
df.corr()['cardio'].sort_values(ascending=False) #show correlation for cardio with othe
```

Out[45]:
```
cardio         1.000000
ap_hi          0.429374
ap_lo          0.336169
age            0.239377
cholesterol    0.218216
BMI            0.183562
weight         0.167538
gluc           0.086210
height        -0.007635
alco          -0.010798
smoke         -0.017629
active        -0.034054
Name: cardio, dtype: float64
```

Features `ap_hi, ap_lo` are higher (moderate positive correlation) correlation with `cardio`

Feature `cardio` is the predict target to predict the patient have cardiovascular disease or not

Step 2 : Split the data

In [46]:
```
X = df[['ap_hi', 'ap_lo']] #seleced feature
y = df['cardio'] #target feature
```

In [47]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4
```

Step 3: Scale the train data and test data

In [48]:
```
sc = StandardScaler() # use StandardScaler
lr = LogisticRegression() # use LogisticRegression
```

In [49]:
```
X_train_sc = sc.fit_transform(X_train) # Scale train
```

In [50]:
```
X_test_sc = sc.transform(X_test)  # Scale test
```

Step 4: Use Logistic Regression

In [51]:
```
lr.fit(X_train_sc,y_train) # use LogisticRegression
```

Out[51]:
```
LogisticRegression()
```

In [52]:
```
lr.score(X_train_sc,y_train) #show the train score
```

Out[52]:
```
0.7125458855919241
```

train score = 0.71

In [53]:
```
y_pred=lr.predict(X_test_sc) # Estimated target
```

In [54]:
```
accuracy_score(y_test,y_pred) #test result
```

Out[54]:
```
0.7056664372562514
```

the train score is 0.71

and the test score was 0.705 almost 0.71

In [55]:
```
df['cardio'].value_counts() #  balanced data
```

Out[55]:
```
0    33124
1    32257
Name: cardio, dtype: int64
```

we have balanced data

Classification report

to measure the quality of predictions

In [57]:

```
print(classification_report(y_test,y_pred))
```

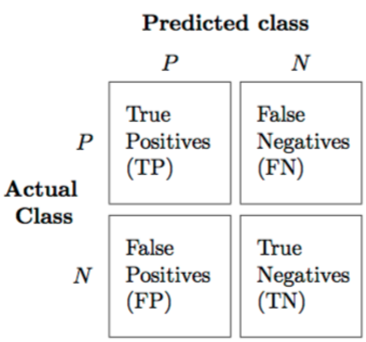
```
              precision    recall  f1-score   support

           0       0.67      0.81      0.73      6517
           1       0.76      0.61      0.67      6560

    accuracy                           0.71     13077
   macro avg       0.71      0.71      0.70     13077
weighted avg       0.71      0.71      0.70     13077
```

Precision is Accuracy of positive predictions.

In [58]:

```
print(confusion_matrix(y_test, y_pred))
```

```
[[5255 1262]
 [2587 3973]]
```



In [ ]: