DETERMINING LVH

Our aim in this project is to build a model for predicting a person whether he/she has LVH or not. We will choose one of the classification algorithms in supervised machine learning.

DATA WRANGLING

In [1]:
```
#Loading libraries

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

In [2]:
```
data = pd.read_csv('data_problem_A.data')
data.head()
```

Out[2]:

	5.70	?	3.70	58.00	?.1	?.2	249.30	456.47	Normal.
0	7.70	6.60	?	20.00	?	?	260.92	443.43	LVH.
1	6.20	4.30	4.60	59.00	?	?	255.63	478.96	LVH.
2	5.70	4.40	3.80	49.00	?	?	195.28	381.94	Normal.
3	9.10	?	4.60	17.00	?	?	259.55	395.67	LVH.
4	6.60	5.60	5.20	28.00	?	?	343.32	630.72	LVH.

In [3]:
```
names = pd.read_csv('data_problem_A.names')
names
```

Out[3]:

	LVH	Normal. | class names
0	LVIDD: continuous. | LV end-diastolic dim	NaN
1	LVIDS: continuous. | LV end-systolic dim	NaN
2	LA: continuous. | left atrial size	NaN
3	EF: continuous. | ejection fraction	NaN
4	MA_DEC: continuous. | mitral inflow dece...	NaN
5	EA_RATIO: continuous. | mitral E to A ratio	NaN
6	MWS: continuous. | meridional wall st...	NaN
7	CWS: continuous. | circumferential wa...	NaN

DATA PREPROCESSING METHODS

In [4]:
```
# Column names should be assigned in this order below:
# ['LVIDD','LVIDS','LA','EF','MA_DEC','EA_RATIO','MWS','CWS','class_na
mes']

data = pd.read_csv('data_problem_A.data',names=['LVIDD','LVIDS','LA','
EF','MA_DEC',
                                                 'EA_RATIO','MWS','CWS'
,'class_names'])
data.head()
```

Out[4]:

	LVIDD	LVIDS	LA	EF	MA_DEC	EA_RATIO	MWS	CWS	class_names
0	5.70	?	3.70	58.00	?	?	249.30	456.47	Normal.
1	7.70	6.60	?	20.00	?	?	260.92	443.43	LVH.
2	6.20	4.30	4.60	59.00	?	?	255.63	478.96	LVH.
3	5.70	4.40	3.80	49.00	?	?	195.28	381.94	Normal.
4	9.10	?	4.60	17.00	?	?	259.55	395.67	LVH.

In [5]:
```
print('Number of row in data:{}\nNumber of row in names:{}'.format(len
(data),len(names)))
```

```
Number of row in data:778
Number of row in names:8
```

In [6]:
```
#VARIABLES NEED TO BE CONVERTED TO CORRECT DATA TYPE(FLOAT)
data.dtypes.value_counts()
```

Out[6]:
```
object    9
dtype: int64
```

MISSING VALUES AND COLUMNS

In [7]:
```
def unknown(x):
    return sum(x=='?')
data.apply(unknown)
```

Out[7]:
```
LVIDD          182
LVIDS          213
LA             250
EF              10
MA_DEC         504
EA_RATIO       503
MWS             16
CWS             20
class_names      0
dtype: int64
```

In [8]:
```
data[data=='?'] = np.nan
data = data.fillna('NaN')
data.head()
```

Out[8]:

	LVIDD	LVIDS	LA	EF	MA_DEC	EA_RATIO	MWS	CWS	class_names
0	5.70	NaN	3.70	58.00	NaN	NaN	249.30	456.47	Normal.
1	7.70	6.60	NaN	20.00	NaN	NaN	260.92	443.43	LVH.
2	6.20	4.30	4.60	59.00	NaN	NaN	255.63	478.96	LVH.
3	5.70	4.40	3.80	49.00	NaN	NaN	195.28	381.94	Normal.
4	9.10	NaN	4.60	17.00	NaN	NaN	259.55	395.67	LVH.

In [9]:
```
data['LVH_normal'] = data['class_names'].map({'LVH.': 1, 'Normal.': 0}
)
data.head(10)
```

Out[9]:

	LVIDD	LVIDS	LA	EF	MA_DEC	EA_RATIO	MWS	CWS	class_names	LVH_normal
0	5.70	NaN	3.70	58.00	NaN	NaN	249.30	456.47	Normal.	0
1	7.70	6.60	NaN	20.00	NaN	NaN	260.92	443.43	LVH.	1
2	6.20	4.30	4.60	59.00	NaN	NaN	255.63	478.96	LVH.	1
3	5.70	4.40	3.80	49.00	NaN	NaN	195.28	381.94	Normal.	0
4	9.10	NaN	4.60	17.00	NaN	NaN	259.55	395.67	LVH.	1
5	6.60	5.60	5.20	28.00	NaN	NaN	343.32	630.72	LVH.	1
6	4.30	2.80	3.70	60.00	NaN	NaN	128.20	276.00	Normal.	0
7	NaN	NaN	NaN	46.00	NaN	NaN	190.98	381.41	Normal.	0
8	6.70	5.70	NaN	31.00	NaN	NaN	NaN	NaN	LVH.	1
9	5.90	NaN	NaN	18.00	NaN	NaN	136.40	271.91	LVH.	1

In [10]:
```
data.dtypes.value_counts()
```

Out[10]:
```
object    9
int64     1
dtype: int64
```

In [11]:
```
#It is time to convert object data types to float.

data['LVIDD'] = data['LVIDD'].astype(float)
data['LVIDS'] = data['LVIDS'].astype(float)
data['LA'] = data['LA'].astype(float)
data['EF'] = data['EF'].astype(float)
data['MA_DEC'] = data['MA_DEC'].astype(float)
data['EA_RATIO'] = data['EA_RATIO'].astype(float)
data['MWS'] = data['MWS'].astype(float)
data['CWS'] = data['CWS'].astype(float)
```

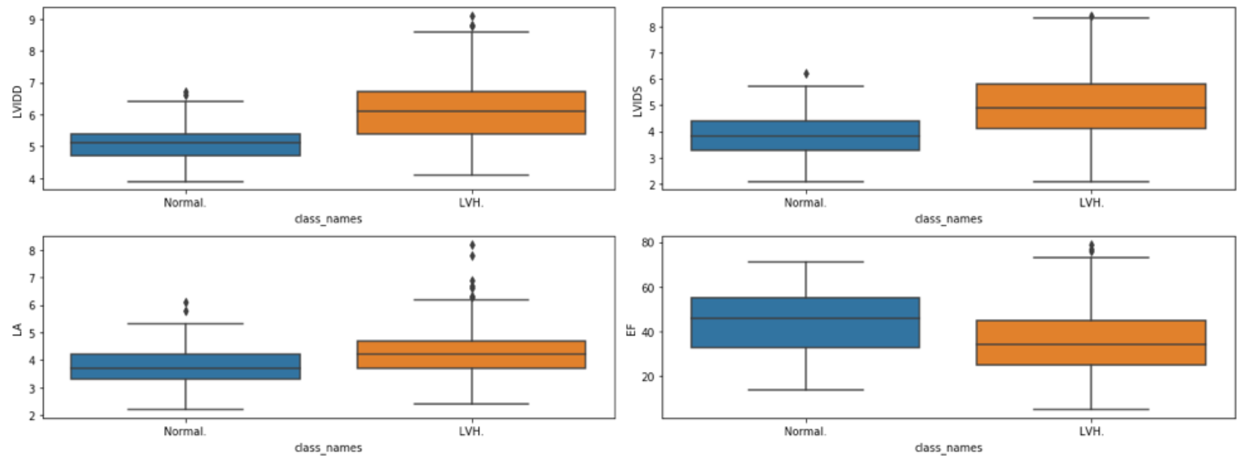
In [12]:
```
#Let`s check it out now.

data.dtypes.value_counts()
```

Out[12]:
```
float64    8
object     1
int64      1
dtype: int64
```

EXPLORATORY DATA ANALYSIS (EDA)

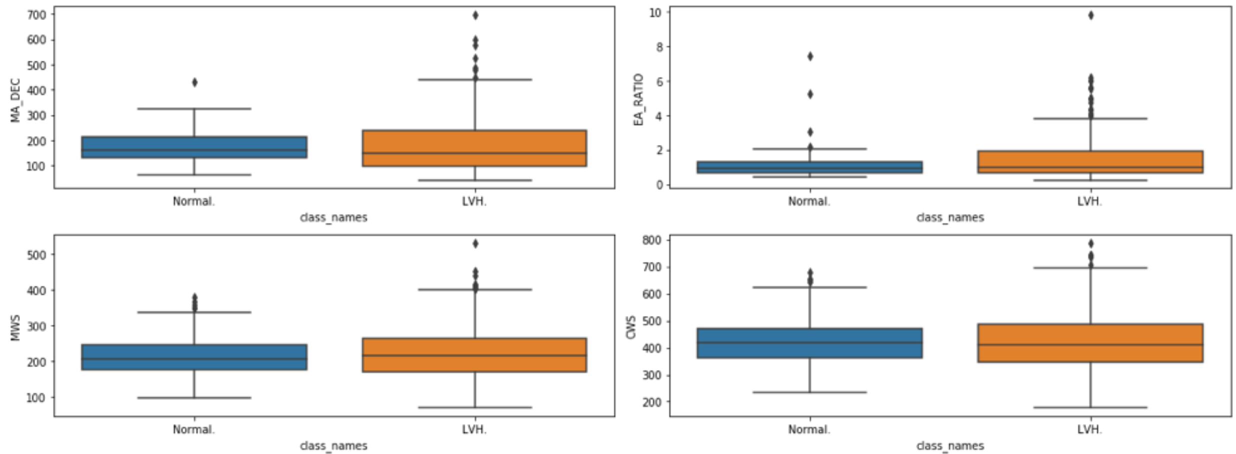
In [13]:

```
fig, ((a,b),(c,d))= plt.subplots(2,2,figsize=(16,6))
sns.boxplot(y='LVIDD',x='class_names',data=data,ax=a)
sns.boxplot(y='LVIDS',x='class_names',data=data,ax=b)
sns.boxplot(y='LA',x='class_names',data=data,ax=c)
sns.boxplot(y='EF',x='class_names',data=data,ax=d)
plt.tight_layout()
```



Graph above shows some dominant dependent variables in determining LVH or not. There is a clear difference(distinction) between normal and LVH when we compare LVIDD values so that LVIDD is a definetly significant feature whether a person has LVH or not. LVIDS is another factor we can not ignore. We also should consider by checking EF.We actually see that the EF of the patients with LVH are low. However,there is an inverse impact on LHV.

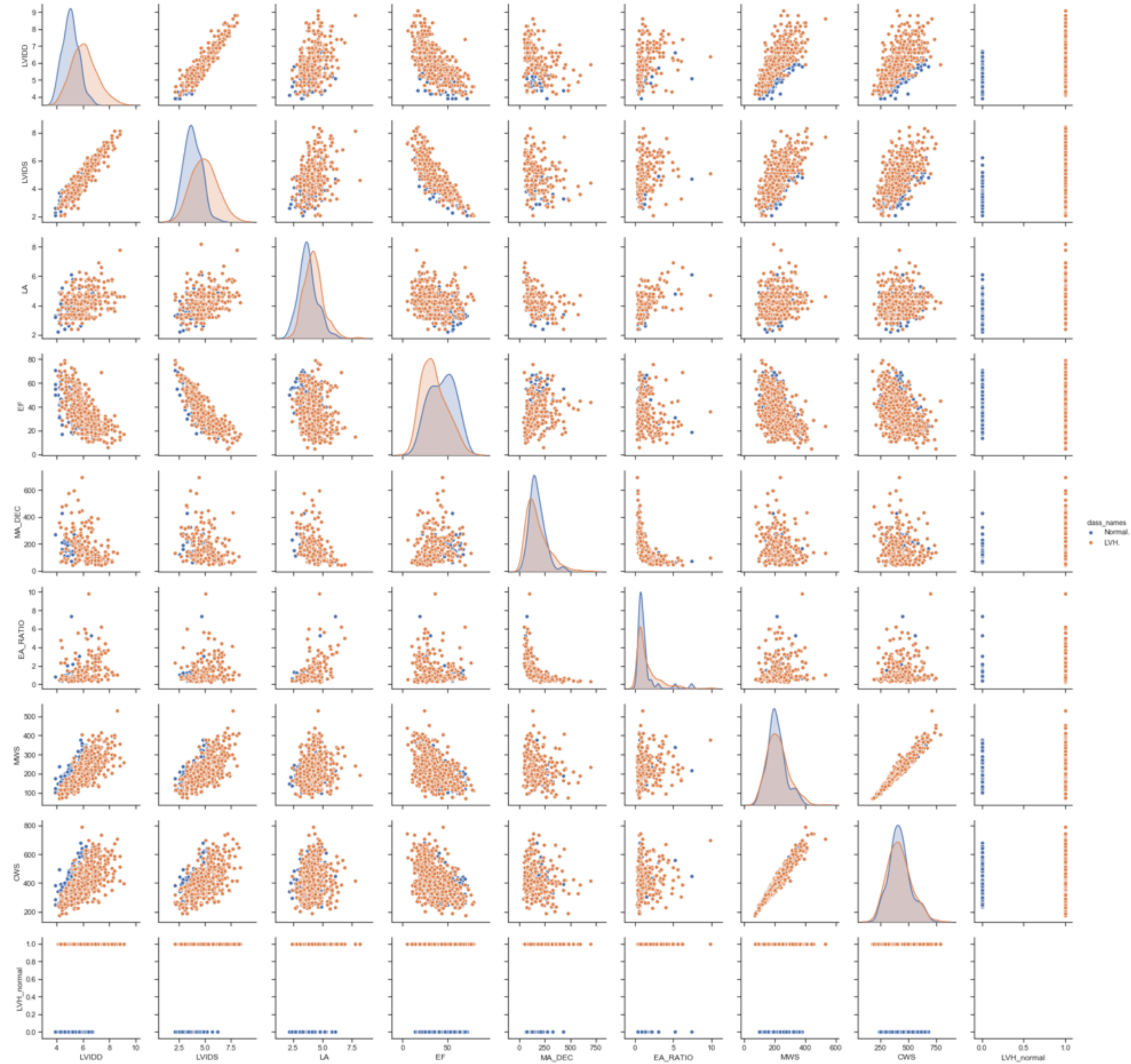
In [14]:
```
fig, ((a,b),(c,d))= plt.subplots(2,2,figsize=(16,6))
sns.boxplot(y='MA_DEC',x='class_names',data=data,ax=a)
sns.boxplot(y='EA_RATIO',x='class_names',data=data,ax=b)
sns.boxplot(y='MWS',x='class_names',data=data,ax=c)
sns.boxplot(y='CWS',x='class_names',data=data,ax=d)
plt.tight_layout()
```



Values of normal and LHV are overlapping in terms of MA-DEC. I will ignore MA-DEC values since most of them are missing and overlapping values.

In [15]:
```
import warnings
warnings.filterwarnings('ignore')
#I want to check pair relationships depend on class names.
sns.set_context('poster')
sns.set(style="ticks", color_codes=True)
sns.pairplot(data,hue='class_names')
```

Out[15]: <seaborn.axisgrid.PairGrid at 0x7f8a392affd0>



REMARKABLE OUTCOMES FROM PAIRPLOT GRAPH

A graph showing the distribution of normal(blue) and LHV(orange) values depending on variables.

There are some features especially LVIDD and LVIDS that really cause having LVH in a positive way. There is a strong positive linearship between LVIDD and LVIDS that make an impact in same way.

I also realize that there is an inverse ratio between ejection fraction (EF) and patiologic(LHV). This is being supported by strong negative linearship between EF and LVIDS.

Another statistical result is the lower the ea ratio, the higher the risk of disease.

In [16]:
```
# Let`s see the correlation table below.
# It helps us to understand mathematically what kind of relationship b
etween features.
correlation = data.corr()
correlation
```

Out[16]:

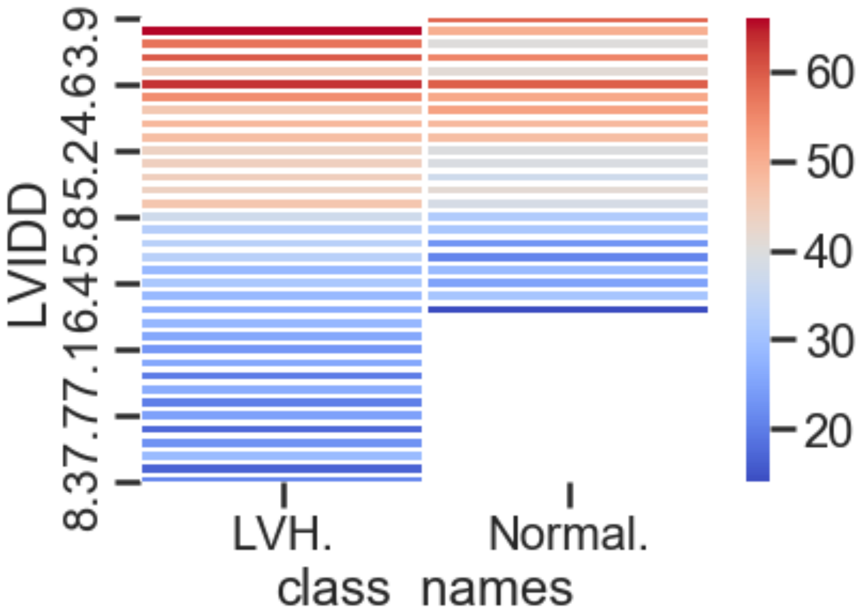
	LVIDD	LVIDS	LA	EF	MA_DEC	EA_RATIO	MWS	(
LVIDD	1.000000	0.927745	0.381542	-0.662069	-0.326368	0.246252	0.689533	0.56
LVIDS	0.927745	1.000000	0.378561	-0.847876	-0.259162	0.176615	0.672509	0.56
LA	0.381542	0.378561	1.000000	-0.287708	-0.416758	0.500338	0.160760	0.12
EF	-0.662069	-0.847876	-0.287708	1.000000	0.196010	-0.171842	-0.499491	-0.43
MA_DEC	-0.326368	-0.259162	-0.416758	0.196010	1.000000	-0.566762	-0.176236	-0.14
EA_RATIO	0.246252	0.176615	0.500338	-0.171842	-0.566762	1.000000	0.142137	0.13
MWS	0.689533	0.672509	0.160760	-0.499491	-0.176236	0.142137	1.000000	0.96
CWS	0.568410	0.562676	0.121076	-0.437495	-0.146997	0.137155	0.969209	1.00
LVH_normal	0.411677	0.364705	0.224251	-0.233383	0.011854	0.075852	0.054171	-0.01

In [17]:
```
#How do the columns affect LVH?
top_cor_features = correlation.index
plt.figure(figsize=(24,24))
sns.set_context('poster')
sns.heatmap(data[top_cor_features].corr(),annot=True,cmap='RdYlGn')
plt.tight_layout()
```

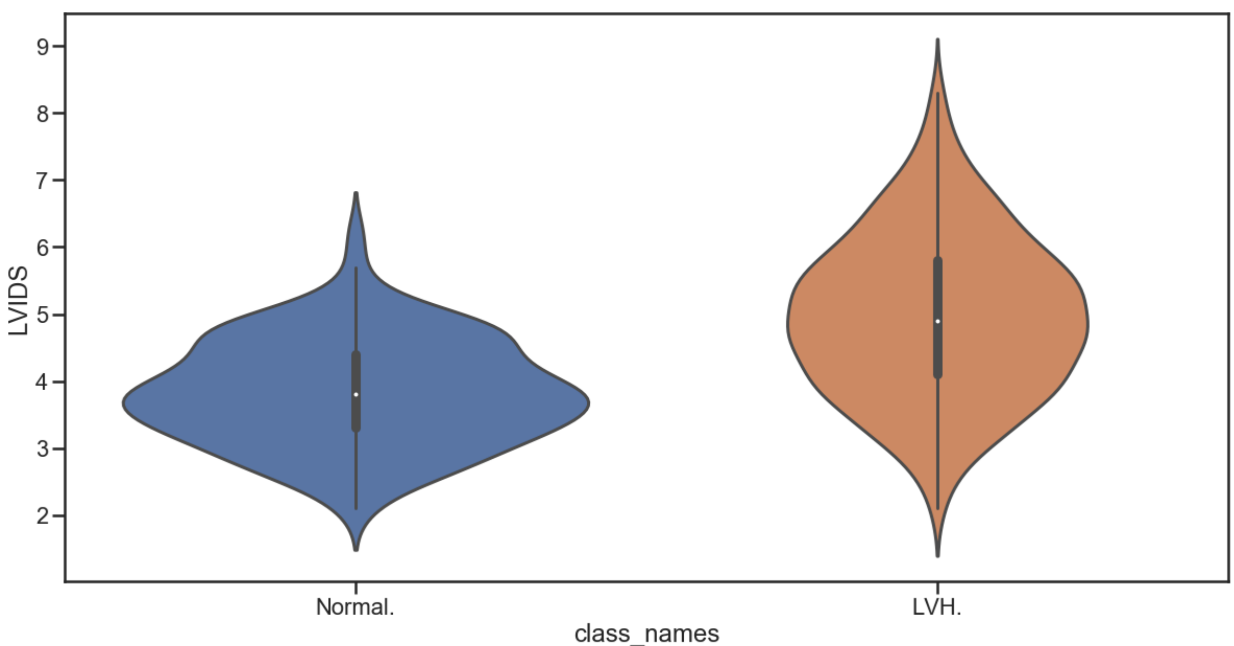
The heatmap above shows clearly correlation among the features. LVIDD-LVIDS-LA are independent values that affect LVH in positive direction. On the other hand,EF has an inverse impact on the patologic situation. Beside,we can ignore MA-DEC column due to less impact in addition %65 missing values.

In [18]:
```
df1 = data.pivot_table(index='LVIDD',columns='class_names',values='EF'
)
sns.heatmap(df1,cmap='coolwarm',linewidths=1.5)
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8a09241b00>



In [19]:
```
fig,ax = plt.subplots(figsize=(20,10))
sns.set_context('poster')
fig = sns.violinplot(x='class_names',y='LVIDS',data=data)
```



Values of people with LVH are higher than normal people. Value range in LVH is way wider than normal people. There might be different factors on it later on to be analyzed. LVH has more outliers or marjinal values since upper and lower edges are sharper.

STATISTICAL INFERENCES

In [20]:
```
data.describe()
```

Out[20]:

	LVIDD	LVIDS	LA	EF	MA_DEC	EA_RATIO	MWS	
count	596.000000	565.000000	528.000000	768.000000	274.000000	275.000000	762.000000	7
mean	5.913423	4.753097	4.174432	36.881510	179.394161	1.497818	220.332808	4
std	0.980767	1.223359	0.837119	14.372681	107.244362	1.366011	69.137602	1
min	3.900000	2.100000	2.200000	5.000000	42.000000	0.250000	69.520000	1
25%	5.200000	3.800000	3.600000	25.000000	107.000000	0.655000	172.402500	3
50%	5.800000	4.700000	4.100000	35.000000	151.000000	0.970000	210.815000	4
75%	6.450000	5.600000	4.700000	47.000000	228.000000	1.820000	258.280000	4
max	9.100000	8.400000	8.200000	79.000000	696.000000	9.800000	531.710000	7

In [21]:
```
# Let`s see the correlation table below.
# It helps us to understand mathematically what kind of relationship b
etween features.
correlation = data.corr()
correlation
```

Out[21]:

	LVIDD	LVIDS	LA	EF	MA_DEC	EA_RATIO	MWS	(
LVIDD	1.000000	0.927745	0.381542	-0.662069	-0.326368	0.246252	0.689533	0.56
LVIDS	0.927745	1.000000	0.378561	-0.847876	-0.259162	0.176615	0.672509	0.56
LA	0.381542	0.378561	1.000000	-0.287708	-0.416758	0.500338	0.160760	0.12
EF	-0.662069	-0.847876	-0.287708	1.000000	0.196010	-0.171842	-0.499491	-0.43
MA_DEC	-0.326368	-0.259162	-0.416758	0.196010	1.000000	-0.566762	-0.176236	-0.14
EA_RATIO	0.246252	0.176615	0.500338	-0.171842	-0.566762	1.000000	0.142137	0.13
MWS	0.689533	0.672509	0.160760	-0.499491	-0.176236	0.142137	1.000000	0.96
CWS	0.568410	0.562676	0.121076	-0.437495	-0.146997	0.137155	0.969209	1.00
LVH_normal	0.411677	0.364705	0.224251	-0.233383	0.011854	0.075852	0.054171	-0.01

LVIDD,LVIDS and LA are the features that most affect LVH and directly proportionals. EF and having LVH is inversely related to each other generally. These numbers and all graps above prove each other.

In [22]:
```
lvh = data[data['class_names']== 'LVH.']
normal = data[data['class_names']== 'Normal.']
```

In [23]:
```
lvh.sort_values(by=['LVIDD'], axis=0, ascending=False).head(10)
```

Out[23]:

	LVIDD	LVIDS	LA	EF	MA_DEC	EA_RATIO	MWS	CWS	class_names	LVH_normal
4	9.1	NaN	4.6	17.0	NaN	NaN	259.55	395.67	LVH.	1
417	8.8	8.1	7.8	15.0	NaN	NaN	240.32	416.95	LVH.	1
11	8.8	NaN	NaN	13.0	NaN	NaN	283.73	512.30	LVH.	1
501	8.8	7.9	4.6	19.0	NaN	NaN	355.39	584.27	LVH.	1
367	8.6	7.7	4.6	24.0	134.0	1.02	531.71	708.06	LVH.	1
740	8.4	NaN	3.6	20.0	NaN	NaN	349.42	585.49	LVH.	1
652	8.4	8.1	4.9	12.0	NaN	NaN	403.41	674.43	LVH.	1
714	8.4	6.9	4.2	33.0	NaN	NaN	295.82	486.05	LVH.	1
489	8.4	NaN	4.8	24.0	NaN	NaN	392.42	568.49	LVH.	1
447	8.3	6.8	4.8	21.0	NaN	NaN	239.79	465.62	LVH.	1

In [24]:
```
lvh.sort_values(by=['EF'], axis=0, ascending=False).head(10)
```

Out[24]:

	LVIDD	LVIDS	LA	EF	MA_DEC	EA_RATIO	MWS	CWS	class_names	LVH_normal
31	4.6	2.1	4.4	79.0	NaN	NaN	113.87	270.48	LVH.	1
734	4.6	2.2	4.6	77.0	NaN	NaN	117.04	253.90	LVH.	1
765	4.3	2.1	4.8	76.0	132.0	2.36	139.73	319.02	LVH.	1
196	5.1	2.6	NaN	73.0	NaN	NaN	173.27	357.65	LVH.	1
88	5.3	2.8	4.6	72.0	NaN	NaN	177.96	363.67	LVH.	1
250	4.2	NaN	NaN	70.0	NaN	NaN	69.52	176.88	LVH.	1
160	4.6	NaN	4.1	70.0	NaN	NaN	140.45	309.99	LVH.	1
28	5.4	NaN	NaN	69.0	203.0	0.64	146.90	276.47	LVH.	1
681	7.4	NaN	6.6	69.0	44.0	6.20	231.82	388.37	LVH.	1
684	4.7	2.7	3.1	67.0	273.0	0.83	141.12	296.58	LVH.	1

In [25]:
```
normal.sort_values(by=['LVIDD'], axis=0, ascending=False).head(10)
```

Out[25]:

	LVIDD	LVIDS	LA	EF	MA_DEC	EA_RATIO	MWS	CWS	class_names	LVH_normal
163	6.7	6.2	4.9	14.0	NaN	NaN	368.04	652.14	Normal.	0
572	6.6	NaN	4.8	31.0	61.0	5.26	338.08	560.94	Normal.	0
774	6.4	5.7	NaN	25.0	NaN	NaN	273.42	496.82	Normal.	0
756	6.3	4.8	4.8	29.0	NaN	NaN	323.19	614.09	Normal.	0
211	6.2	NaN	NaN	21.0	NaN	NaN	349.30	655.69	Normal.	0
278	6.1	NaN	3.1	23.0	NaN	NaN	337.90	566.36	Normal.	0
68	5.9	4.9	3.7	34.0	NaN	NaN	348.10	624.61	Normal.	0
530	5.9	5.2	NaN	21.0	NaN	NaN	358.85	642.55	Normal.	0
497	5.9	4.6	NaN	39.0	NaN	NaN	326.23	584.14	Normal.	0
50	5.8	4.8	NaN	24.0	168.0	0.64	378.67	678.42	Normal.	0

In [26]:
```
normal.sort_values(by=['EF'], axis=0, ascending=False).head(10)
```

Out[26]:

	LVIDD	LVIDS	LA	EF	MA_DEC	EA_RATIO	MWS	CWS	class_names	LVH_normal
178	3.9	2.1	3.3	71.0	NaN	NaN	176.92	382.82	Normal.	0
667	NaN	NaN	3.2	69.0	NaN	NaN	198.32	429.20	Normal.	0
207	4.3	2.4	3.4	69.0	NaN	NaN	120.39	264.79	Normal.	0
666	NaN	NaN	NaN	69.0	NaN	NaN	153.45	323.15	Normal.	0
331	4.8	NaN	3.6	67.0	163.0	1.53	142.65	304.16	Normal.	0
356	NaN	2.6	3.8	67.0	125.0	1.00	209.62	441.36	Normal.	0
116	4.8	2.8	NaN	66.0	NaN	NaN	194.13	414.49	Normal.	0
529	4.3	2.7	3.8	66.0	NaN	NaN	184.90	392.31	Normal.	0
515	4.8	3.1	NaN	65.0	NaN	NaN	154.27	314.06	Normal.	0
709	NaN	2.9	2.8	64.0	275.0	1.27	199.77	425.01	Normal.	0

These four datasets above make me think 4 values(LVIDD-LVIDS-LA-EF) play a decisive role in LHV detection. I am not of the opinion that the others have contributed a lot. After all these four values are taken into account, EA ratio may also help.

MACHINE LEARNING PART

In [27]:
```
data.head()
```

Out[27]:

	LVIDD	LVIDS	LA	EF	MA_DEC	EA_RATIO	MWS	CWS	class_names	LVH_normal
0	5.7	NaN	3.7	58.0	NaN	NaN	249.30	456.47	Normal.	0
1	7.7	6.6	NaN	20.0	NaN	NaN	260.92	443.43	LVH.	1
2	6.2	4.3	4.6	59.0	NaN	NaN	255.63	478.96	LVH.	1
3	5.7	4.4	3.8	49.0	NaN	NaN	195.28	381.94	Normal.	0
4	9.1	NaN	4.6	17.0	NaN	NaN	259.55	395.67	LVH.	1

In [28]:
```
#Let`s check missing value rate
total = data.isnull().sum().sort_values(ascending=False)
percent = (data.isnull().sum()/data.isnull().count()).sort_values(asce
nding=False)
missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Per
cent'])
missing_data.head(9)
```

Out[28]:

	Total	Percent
MA_DEC	504	0.647815
EA_RATIO	503	0.646530
LA	250	0.321337
LVIDS	213	0.273779
LVIDD	182	0.233933
CWS	20	0.025707
MWS	16	0.020566
EF	10	0.012853
LVH_normal	0	0.000000

In [29]:
```
#Fill in missing values with median due to limited time.
#I would probably use Regression imputation or Stochastic regression i
mputation but it takes time.
data['LVIDD'] = data['LVIDD'].fillna(data['LVIDD'].median())
data['LVIDS'] = data['LVIDS'].fillna(data['LVIDS'].median())
data['LA'] = data['LA'].fillna(data['LA'].median())
data['EF'] = data['EF'].fillna(data['EF'].median())
data['EA_RATIO'] = data['EA_RATIO'].fillna(data['EA_RATIO'].median())
data['CWS'] = data['CWS'].fillna(data['CWS'].median())
data['MWS'] = data['MWS'].fillna(data['MWS'].median())
data['MA_DEC'] = data['MA_DEC'].fillna(data['MA_DEC'].median())
```

In [30]:
```
total = data.isnull().sum().sort_values(ascending=False)
percent = (data.isnull().sum()/data.isnull().count()).sort_values(asce
nding=False)
missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Per
cent'])
missing_data.head(9)
```

Out[30]:

	Total	Percent
LVH_normal	0	0.0
class_names	0	0.0
CWS	0	0.0
MWS	0	0.0
EA_RATIO	0	0.0
MA_DEC	0	0.0
EF	0	0.0
LA	0	0.0
LVIDS	0	0.0

In [31]:
```
data.head()
```

Out[31]:

	LVIDD	LVIDS	LA	EF	MA_DEC	EA_RATIO	MWS	CWS	class_names	LVH_normal
0	5.7	4.7	3.7	58.0	151.0	0.97	249.30	456.47	Normal.	0
1	7.7	6.6	4.1	20.0	151.0	0.97	260.92	443.43	LVH.	1
2	6.2	4.3	4.6	59.0	151.0	0.97	255.63	478.96	LVH.	1
3	5.7	4.4	3.8	49.0	151.0	0.97	195.28	381.94	Normal.	0
4	9.1	4.7	4.6	17.0	151.0	0.97	259.55	395.67	LVH.	1

BUILDING BASELINE MODEL

In [32]:
```
#Importing required libraries for ML
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegressionCV
from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier
```

In [33]:
```
num_cal = data[['LVIDD','LVIDS','LA','EF','MA_DEC','EA_RATIO','MWS','C
WS']]
target_col = data[['LVH_normal']]
```

In [34]:
```
new_data = data.drop(['class_names'], axis=1)
new_data.head()
```

Out[34]:

	LVIDD	LVIDS	LA	EF	MA_DEC	EA_RATIO	MWS	CWS	LVH_normal
0	5.7	4.7	3.7	58.0	151.0	0.97	249.30	456.47	0
1	7.7	6.6	4.1	20.0	151.0	0.97	260.92	443.43	1
2	6.2	4.3	4.6	59.0	151.0	0.97	255.63	478.96	1
3	5.7	4.4	3.8	49.0	151.0	0.97	195.28	381.94	0
4	9.1	4.7	4.6	17.0	151.0	0.97	259.55	395.67	1

In [35]:
```
#Seting feature and target columns

x = num_cal.values
y = target_col.values
x.shape[0]== y.shape[0]
```
Out[35]:
```
True
```

In [92]:
```
#Split data as train and test set

X_train, X_test, y_train, y_test = train_test_split(x, y, test_size =
0.3, random_state = 38)
```

DECISION TREE

In [93]:
```
dtc = DecisionTreeClassifier(criterion='entropy',random_state=38)
dtc.fit(X_train,y_train)

y_pred = dtc.predict(X_test)

cm = confusion_matrix(y_test,y_pred)
cm
```
Out[93]:
```
array([[ 23,  17],
       [ 19, 175]])
```

In [94]:
```
round(accuracy_score(y_test,y_pred),2)
```
Out[94]:
```
0.85
```

KNN

In [95]:
```
import warnings
warnings.filterwarnings('ignore')

knn = KNeighborsClassifier(n_neighbors=5,metric='minkowski')
knn.fit(X_train,y_train)

y_pred = knn.predict(X_test)

cm = confusion_matrix(y_test,y_pred)
cm
```

Out[95]:
```
array([[  4,  36],
       [  5, 189]])
```

In [96]:
```
round(accuracy_score(y_test,y_pred),2)
```

Out[96]:
```
0.82
```

RANDOM FOREST

In [97]:
```
import warnings
warnings.filterwarnings('ignore')

rfc = RandomForestClassifier(random_state=38)
rfc.fit(X_train,y_train)

y_pred = rfc.predict(X_test)

cm = confusion_matrix(y_test,y_pred)
cm
```

Out[97]:
```
array([[ 18,  22],
       [ 12, 182]])
```

In [98]:
```
round(accuracy_score(y_test,y_pred),2)
```

Out[98]:
```
0.85
```

LOGISTIC REGRESSION

In [99]:
```
import warnings
warnings.filterwarnings('ignore')

logr = LogisticRegressionCV(random_state=38)
logr.fit(X_train,y_train)

y_pred = logr.predict(X_test)

cm = confusion_matrix(y_test,y_pred)
cm
```

Out[99]:
```
array([[ 17,  23],
       [ 12, 182]])
```

In [100]:
```
round(accuracy_score(y_test,y_pred),3)
```

Out[100]:
```
0.85
```

GRADIENT BOOSTING

In [101]:
```
gbc = GradientBoostingClassifier(random_state=38)
gbc.fit(X_train,y_train)

y_pred = gbc.predict(X_test)

cm = confusion_matrix(y_test,y_pred)
cm
```

Out[101]:
```
array([[ 20,  20],
       [ 11, 183]])
```

In [102]:
```
round(accuracy_score(y_test,y_pred),2)
```

Out[102]:
```
0.87
```

XGBOOST

In [116]:
```
xgb = XGBClassifier()
xgb.fit(X_train,y_train)

y_predxgb = xgb.predict(X_test)

cm = confusion_matrix(y_test,y_predxgb)
cm
```

Out[116]:
```
array([[ 19,  21],
       [  8, 186]])
```

In [117]:
```
round(accuracy_score(y_test,y_predxgb),2)
```

Out[117]:
```
0.88
```

I decide to finalize my model with XGBoost that predicts 88% correctly because sum of false positive and false negative is low in comparasion with other models.(21+8=29)

MODEL TUNNING

In [118]:
```
#Import necessary modules
from sklearn.model_selection import RandomizedSearchCV

# Setup the hyperparameter grid

p = {'n_estimators':[50,100,150],
          'min_child_weight': [1, 5, 10],
          'learning_rate':[0.05,0.1,0.15,0.2],
          'gamma': [0.5, 1, 1.5, 2, 5],
          'max_depth': [3, 4, 5]
        }

# Instantiate a XGBoosting classifier
xgb = XGBClassifier(random_state=38)

# Instantiate the RandomizedSearchCV object
gs = RandomizedSearchCV(estimator = xgb,param_distributions= p,scoring
='accuracy',cv=5,random_state=38)

# Fit it to the data
gs.fit(X_train,y_train)

# Print the tuned parameters and score
print('Tuned XGboosting Parameters: {}'.format(gs.best_params_))
print("Best score is {}".format(gs.best_score_))
```

```
Tuned XGboosting Parameters: {'n_estimators': 150, 'min_child_weight
': 1, 'max_depth': 3, 'learning_rate': 0.2, 'gamma': 2}
Best score is 0.8731617647058824
```

In [121]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test,y_predxgb))
```

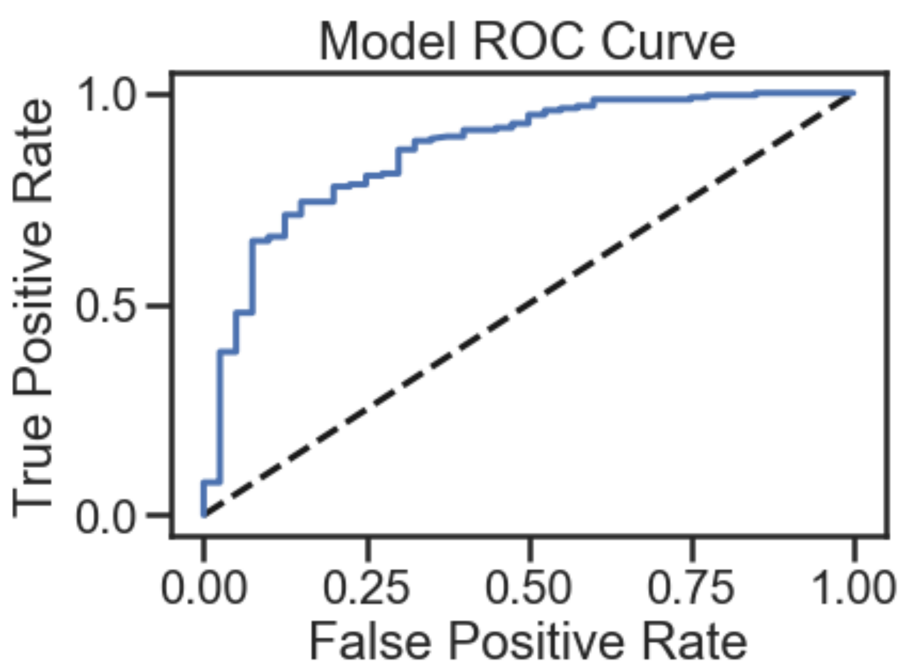
```
              precision    recall  f1-score   support

           0       0.70      0.47      0.57        40
           1       0.90      0.96      0.93       194

    accuracy                           0.88       234
   macro avg       0.80      0.72      0.75       234
weighted avg       0.87      0.88      0.87       234
```

The model`s accuracy that I build is 88%.It seems very satisfying but we also should consider other metrics. Sensivity and specificty in other words TP rate and FP rates are really significant. We need to check ROC and AUC.We have seen actually 90% precision in determining LVH. This is really fantastic result that gives us hope that we can improve the model. The reason of 0.57 at f1-score for normal people is imbalanced data that we had before lots of missing values. Naturally, this imbalanced data(0.57) is affecting recall value for normal people. Overall,our model is very good in terms of sensivity but it needs to be improved for specificity.

ROC

In [129]:
```
#Receiver Operator Characteristic(ROC) provides a simple way to summar
ize confusion matrix.
from sklearn.metrics import roc_curve
```

In [142]:
```
y_pred_prob = xgb.predict_proba(X_test)[:,1]
fpr,tpr,thresholds = roc_curve(y_test,y_pred_prob)
plt.plot([0,1],[0,1],'k--')
plt.plot(fpr,tpr,label='Model')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Model ROC Curve')
plt.show()
```



AUC using Cross-Validation

In [144]:
```
from sklearn.model_selection import cross_val_score
cv_scores = cross_val_score(logr,X_test,y_test,cv=5,scoring='roc_auc')
cv_scores
```

Out[144]:
```
array([0.81410256, 0.93910256, 0.67628205, 0.88782051, 0.79934211])
```

If the AUC is greater than 0.5, the model is better than random guessing. Always a good sign! Luckily we do not have any value is less than 0.5.This makes our model more meaningful in labelling correctly.

RESULT

--- I reached almost 90% accuracy with a dataset that had lots of missing data.

--- There are especially some features such as LVIDD,LVIDS,LA directly proportional with LHV.

--- Enjection Fraction (EF) is also a critic value to decide whether a person has LHV or not.

--- EF is inversely proportional with LHV.

--- Some features (MA-DEC,CWS) in the dataset have a little effect.

--- I found out some outcomes from graphs after than confirmed with a SME.

In [ ]:
```
```