Heart Disease

Context

This database contains 76 attributes, but all published experiments refer to using a subset of 14 of them. In particular, the is the only one that has been used by ML researchers to this date. The "goal" field refers to the presence of heart disease represented by a binary value: 0 (no disease) and 1 (presence of disease).

Content

Attribute Information:

- 1. age
- 2. **sex**
- 3. cp: chest pain type (4 values)
- 4. trestbps:resting blood pressure
- 5. chol:serum cholesterol in mg/dl
- 6. **fbs**:fasting blood sugar > 120 mg/dl
- 7. restecg:resting electrocardiographic results (values 0,1,2)
- 8. thalach:maximum heart rate achieved
- 9. exang:exercise induced angina
- 10. **oldpeak** = ST depression induced by exercise relative to rest
- 11. slope:the slope of the peak exercise ST segment
- 12. ca:number of major vessels (0-3) colored by fluorosopy
- 13. thal: 1 = normal; 2 = fixed defect; 3 = reversable defect

The names and social security numbers of the patients were recently removed from the database, replaced with dummy

Acknowledgements

Creators:

- 1. Hungarian Institute of Cardiology. Budapest: Andras Janosi, M.D.
- 2. University Hospital, Zurich, Switzerland: William Steinbrunn, M.D.
- 3. University Hospital, Basel, Switzerland: Matthias Pfisterer, M.D.
- 4. V.A. Medical Center, Long Beach and Cleveland Clinic Foundation: Robert Detrano, M.D., Ph.D.

Donor: David W. Aha (aha '@' ics.uci.edu) (714) 856-8779

Get the data

Create kaggle folder and import json

```
!mkdir -p ~/.kaggle
!echo '{"username":"user","key":"key"}' > /root/.kaggle/kaggle.json
!chmod 600 ~/.kaggle/kaggle.json
!ls ~/.kaggle
L> kaggle.json
```

▼ Download kaggle dataset

Ikaggle datasets download ronitf/heart-disease-uci

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Downloading heart-disease-uci.zip to /content
 0% 0.00/3.40k [00:00<?, ?B/s]
100% 3.40k/3.40k [00:00<00:00, 2.93MB/s]</pre>

Move to directory and unzip files

42 cells hidden

Load libraries

```
import matplotlib.pyplot as plt
import matplotlib
matplotlib.rcParams.update({'font.size': 12})
import pandas as pd
import numpy as np
```

Preliminary exploratory data analysis

load into pandas dataframe and have a quick look at the data

```
df = pd.read_csv('heart.csv')
df.describe()
```

С→		200	504	c n	tnosthns	cho]	£hc	nostosa	thalach	0.44
_		age sex c		ср	trestbps chol		fbs	restecg	спатасп	ex
	count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000
	mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.528053	149.646865	0.326
	std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	22.905161	0.469
	min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000
	25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	133.500000	0.000
	50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	153.000000	0.000
	75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	166.000000	1.000
	max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.000000	1.000

df.head()

₽		age	sex	ср	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
	0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
	1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
	2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
	3	56	1	1	120	236	0	1	178	0	8.0	2	0	2	1
	4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

Check for missing data

no missing data

df isnull() sum()

```
C→ age
             0
   sex
             0
   ср
   trestbps 0
             0
   chol
             0
   fbs
            0
   restecg
            0
   thalach
   exang
            0
   oldpeak 0
   slope
   ca
   thal
             0
   target
             0
   dtype: int64
```

▼ Check data type

All attributes are integers or floats. The dataset can be used as is. No pre-processing is required

```
df.dtypes
```

```
int64
C→ age
                 int64
   sex
                 int64
   ср
   trestbps
               int64
   chol
                int64
              int64
int64
   fbs
                int64
   restecg
   thalach
                int64
   exang
   oldpeak float64
              int64
   slope
   ca
                int64
   int64
target int64
   dtype: object
```

▼ Split the data into train and test

Now split the dataset into a training set and a test set.

We will use the test set in the final evaluation of our model.

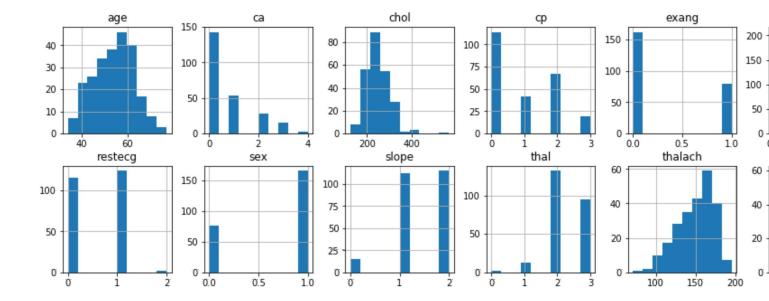
```
train_dataset = df.sample(frac=0.8,random_state=0)
test_dataset = df.drop(train_dataset.index)
```

Inspect the data

C→

Have a quick look at the joint distribution of a few pairs of columns from the training set.

```
train_dataset.loc[:,train_dataset.columns != 'target'].hist(figsize=(19,5), layout=(2,7));
```



Also look at the overall statistics:

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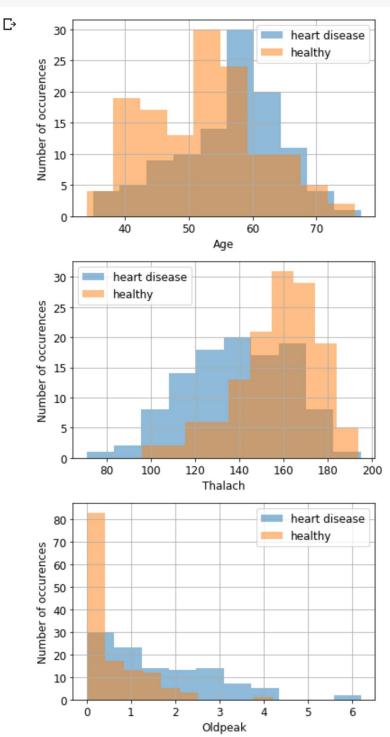
```
train_stats = train_dataset.describe()
train_stats.pop("target")
train_stats = train_stats.transpose()
train_stats
```

	count	mean	std	min	25%	50%	75%	max
age	242.0	54.128099	8.904992	34.0	48.0	54.5	60.75	77.0
sex	242.0	0.685950	0.465098	0.0	0.0	1.0	1.00	1.0
ср	242.0	0.962810	1.031989	0.0	0.0	1.0	2.00	3.0
trestbps	242.0	131.396694	17.352331	94.0	120.0	130.0	140.00	200.0
chol	242.0	247.181818	51.235037	126.0	212.0	241.5	274.00	564.0
fbs	242.0	0.144628	0.352454	0.0	0.0	0.0	0.00	1.0
restecg	242.0	0.528926	0.516522	0.0	0.0	1.0	1.00	2.0
thalach	242.0	149.797521	22.935873	71.0	134.5	153.0	167.75	195.0
exang	242.0	0.330579	0.471396	0.0	0.0	0.0	1.00	1.0
oldpeak	242.0	0.991322	1.162148	0.0	0.0	0.6	1.60	6.2
slope	242.0	1.413223	0.606595	0.0	1.0	1.0	2.00	2.0
ca	242.0	0.685950	0.985649	0.0	0.0	0.0	1.00	4.0
thal	242.0	2.322314	0.614012	0.0	2.0	2.0	3.00	3.0

```
def quick_plot(x,y,z):
    groups=train_dataset.groupby(by=z)
    fig, ax = plt.subplots()
    for name, group in groups:
        ax.plot(group[x], group[y], marker='.', linestyle='', ms=12, label=name)
    ax.legend()
    ax.grid()
    plt.xlabel(x);
    plt.ylabel(y);

def plot_hist(var):
    plt.figure()
    train_dataset.groupby(by='target')[var].hist(alpha=.5);
    plt.legend(['heart disease','healthy']);
    plt.xlabel(var.capitalize());
    plt.ylabel('Number of occurences');
```

```
plot_hist('age')
plot_hist('thalach')
plot_hist('oldpeak')
```



▼ Split features from labels

Separate the target value, or "label", from the features. This label is the value that you will train the model to predict.

```
train_labels = train_dataset.pop('target')
test_labels = test_dataset.pop('target')
```

Normalize the data

```
def norm(x):
    return (x - train_stats['mean']) / train_stats['std']
normed_train_data = norm(train_dataset)
normed_test_data = norm(test_dataset)
```

Forecasting model for classification problem

Build the model

Let's build our model. We will compare the accuracy on the testing set of different classifiers from sckit-learn library.

```
from sklearn.feature_selection import SelectKBest

from sklearn.feature_selection import chi2

from sklearn.metrics import accuracy_score

from sklearn.neural_network import MLPClassifier

from sklearn.neighbors import KNeighborsClassifier

from sklearn.svm import SVC

from sklearn.gaussian_process import GaussianProcessClassifier

from sklearn.gaussian_process.kernels import RBF

from sklearn.tree import DecisionTreeClassifier

from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier

from sklearn.naive_bayes import GaussianNB

from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
```

The classifiers used and compared are presented below.

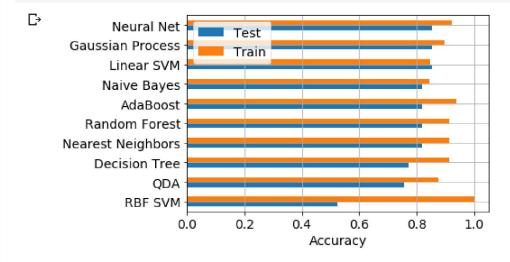
Comparison of classifiers

The results in terms of accuracy on the testing set are presented below. The three best performing classifiers are the Line process and Neural net with an accuracy of 85.2%.

```
results=pd.DataFrame(columns=names,index=['score','main_attr','train_score'])
for name, clf in zip(names, classifiers):
    clf.fit(normed_train_data, train_labels)
    results.loc['train_score',name]=clf.score(normed_train_data, train_labels)
    results.loc['score',name]=clf.score(normed_test_data, test_labels)
    if hasattr(clf, "feature_importances_"):
        results.loc['main_attr',name]=normed_train_data.columns[clf.feature_importances_>0]
    else:
        results.loc['main_attr',name]=np.nan
#results.transpose().sort_values(by='score',ascending=False)
results.loc['score',:].sort_values(ascending=False)
```

```
Neural Net
                     0.852459
Gaussian Process
                     0.852459
Linear SVM
                     0.852459
Naive Bayes
                     0.819672
AdaBoost
                     0.819672
Random Forest
                     0.819672
Nearest Neighbors
                     0.819672
Decision Tree
                     0.770492
QDA
                     0.754098
RBF SVM
                      0.52459
Name: score, dtype: object
```

```
results.loc[['score','train_score'],:].transpose().sort_values(by='score').plot.barh();
plt.xlabel('Accuracy');
plt.grid();
plt.legend(['Test','Train'],loc='upper left');
```



Main features

Identification and Analysis of the most important features.

```
ft_imp=pd.DataFrame(columns=normed_test_data.columns,index=['coef'])
clf=AdaBoostClassifier()
clf.fit(normed_train_data, train_labels)
for i,j in zip(normed_test_data.columns,clf.feature_importances_):
    ft_imp[i]=j
ft_imp.transpose().sort_values(by='coef',ascending=False).head(6)
```

```
C→ coef

oldpeak 0.16

age 0.14

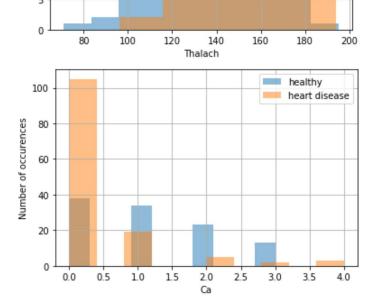
chol 0.14

trestbps 0.12

thalach 0.10

ca 0.10
```

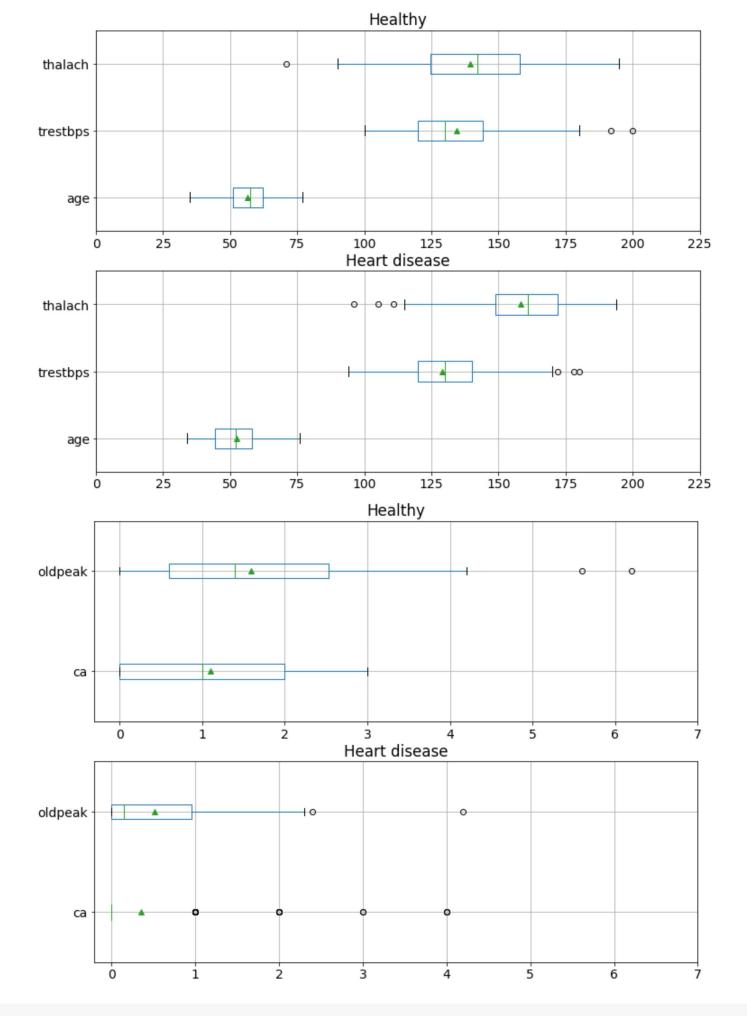
```
plot_hist('oldpeak')
plot_hist('age')
plot_hist('chol')
plot_hist('trestbps')
plot_hist('thalach')
plot_hist('ca')
```



```
def sh_boxplot(ft,trange):
   plt.figure(figsize=(12,9))
   plt.subplot(2,1,1)
   train_dataset.loc[train_dataset.target==0,ft].boxplot(vert=False,showmeans=True);
   plt.xticks(trange)
   plt.title('Healthy');
   plt.subplot(2,1,2)
   train_dataset.loc[train_dataset.target==1,ft].boxplot(vert=False,showmeans=True);
   plt.xticks(trange)
   plt.title('Heart disease');

sh_boxplot(['age','trestbps','thalach'],range(0,230,25))
   sh_boxplot(['ca','oldpeak'],range(0,8))
```

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quick_plot('age','thalach','target')

