heart failure

September 23, 2020

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```
df = pd.
 ↪read_csv('datasets_727551_1263738_heart_failure_clinical_records_dataset.
 ↪csv')
df.head()
```

[2]:
```
    age  anaemia  creatinine_phosphokinase  diabetes  ejection_fraction  \
0  75.0        0                       582         0                 20
1  55.0        0                      7861         0                 38
2  65.0        0                       146         0                 20
3  50.0        1                       111         0                 20
4  65.0        1                       160         1                 20

   high_blood_pressure  platelets  serum_creatinine  serum_sodium  sex  \
0                    1  265000.00               1.9           130    1
1                    0  263358.03               1.1           136    1
2                    0  162000.00               1.3           129    1
3                    0  210000.00               1.9           137    1
4                    0  327000.00               2.7           116    0

   smoking  time  DEATH_EVENT
0        0     4            1
1        0     6            1
2        1     7            1
3        0     7            1
4        0     8            1
```

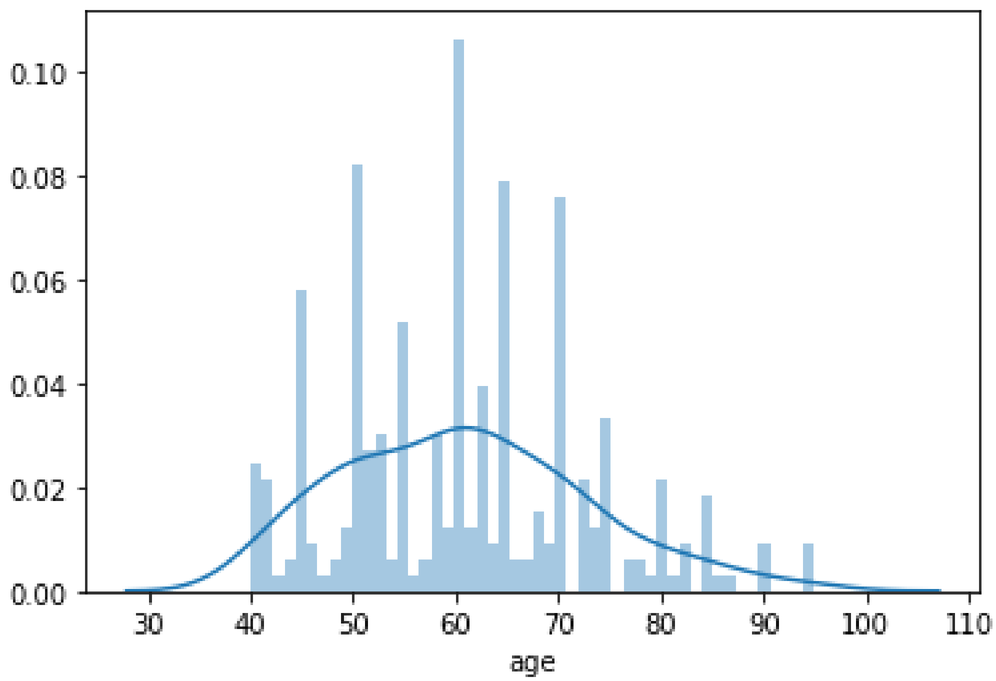
[3]:
```
df.isnull().sum()
```

[3]:
```
age                         0
anaemia                     0
creatinine_phosphokinase    0
diabetes                    0
ejection_fraction           0
high_blood_pressure         0
```

```
platelets                   0
serum_creatinine            0
serum_sodium                0
sex                         0
smoking                     0
time                        0
DEATH_EVENT                 0
dtype: int64
```

[4]:
```
sns.distplot(df['age'], bins = 50)
```

[4]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f95eee19b70>
```



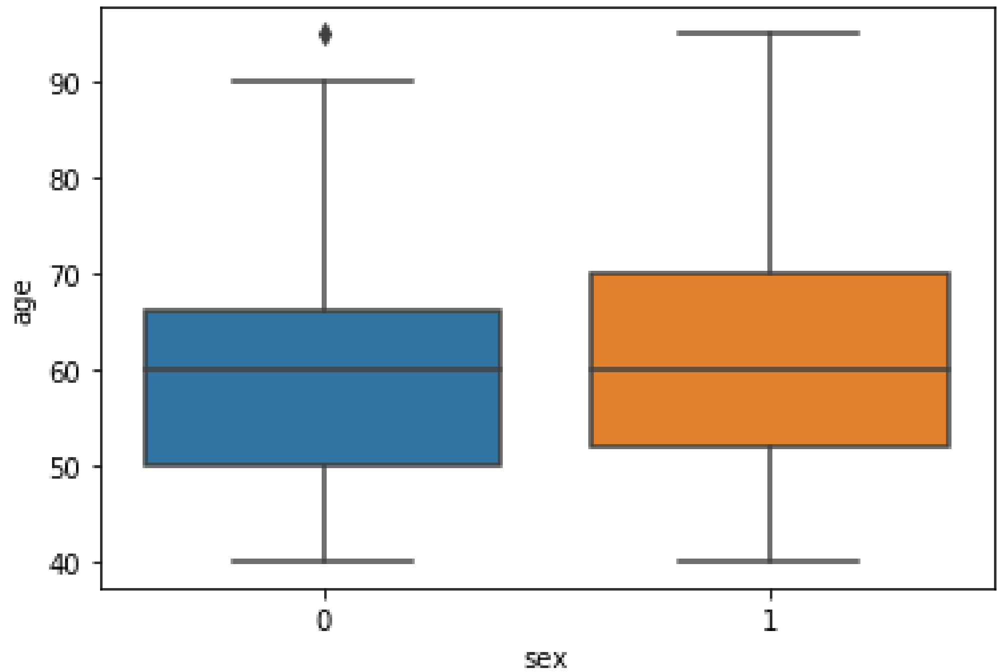
[5]:
```
df.describe()
```

[5]:
```
              age     anaemia  creatinine_phosphokinase    diabetes  \
count  299.000000  299.000000                299.000000  299.000000
mean    60.833893    0.431438                581.839465    0.418060
std     11.894809    0.496107                970.287881    0.494067
min     40.000000    0.000000                 23.000000    0.000000
25%     51.000000    0.000000                116.500000    0.000000
50%     60.000000    0.000000                250.000000    0.000000
75%     70.000000    1.000000                582.000000    1.000000
max     95.000000    1.000000               7861.000000    1.000000

       ejection_fraction  high_blood_pressure      platelets  \
count         299.000000           299.000000     299.000000
```

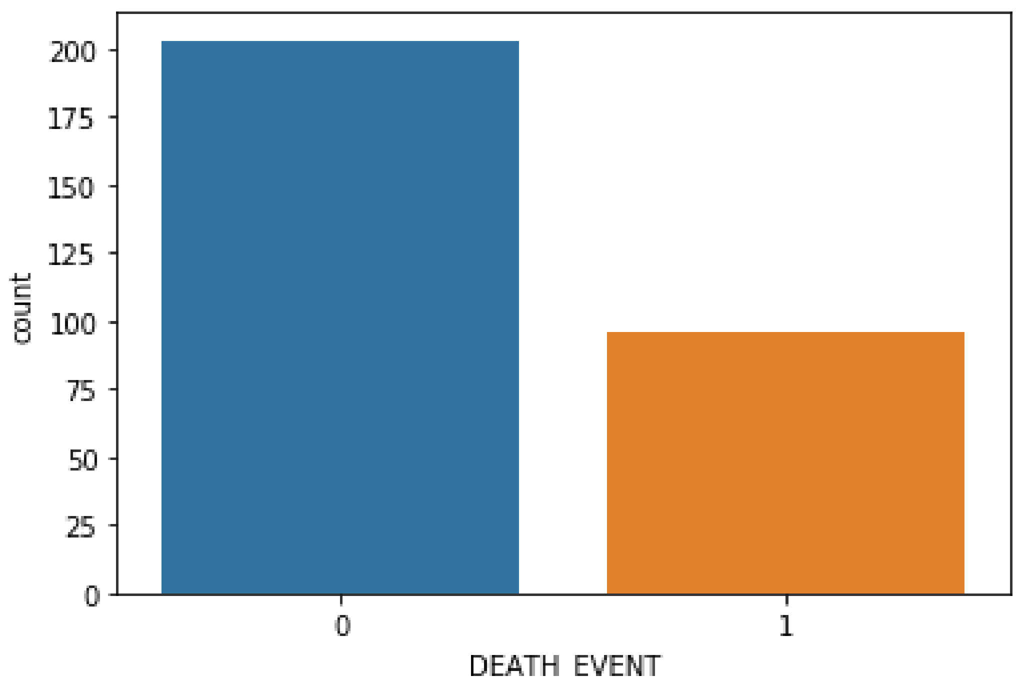
```
mean          38.083612            0.351171  263358.029264
std           11.834841            0.478136   97804.236869
min           14.000000            0.000000   25100.000000
25%           30.000000            0.000000  212500.000000
50%           38.000000            0.000000  262000.000000
75%           45.000000            1.000000  303500.000000
max           80.000000            1.000000  850000.000000

       serum_creatinine  serum_sodium         sex    smoking        time  \
count         299.00000    299.000000  299.000000  299.00000  299.000000
mean            1.39388    136.625418    0.648829    0.32107  130.260870
std             1.03451      4.412477    0.478136    0.46767   77.614208
min             0.50000    113.000000    0.000000    0.00000    4.000000
25%             0.90000    134.000000    0.000000    0.00000   73.000000
50%             1.10000    137.000000    1.000000    0.00000  115.000000
75%             1.40000    140.000000    1.000000    1.00000  203.000000
max             9.40000    148.000000    1.000000    1.00000  285.000000

       DEATH_EVENT
count    299.00000
mean       0.32107
std        0.46767
min        0.00000
25%        0.00000
50%        0.00000
75%        1.00000
max        1.00000
```

[6]:
```python
# age ~ sex
sns.boxplot(x = 'sex', y = 'age', data = df)
```

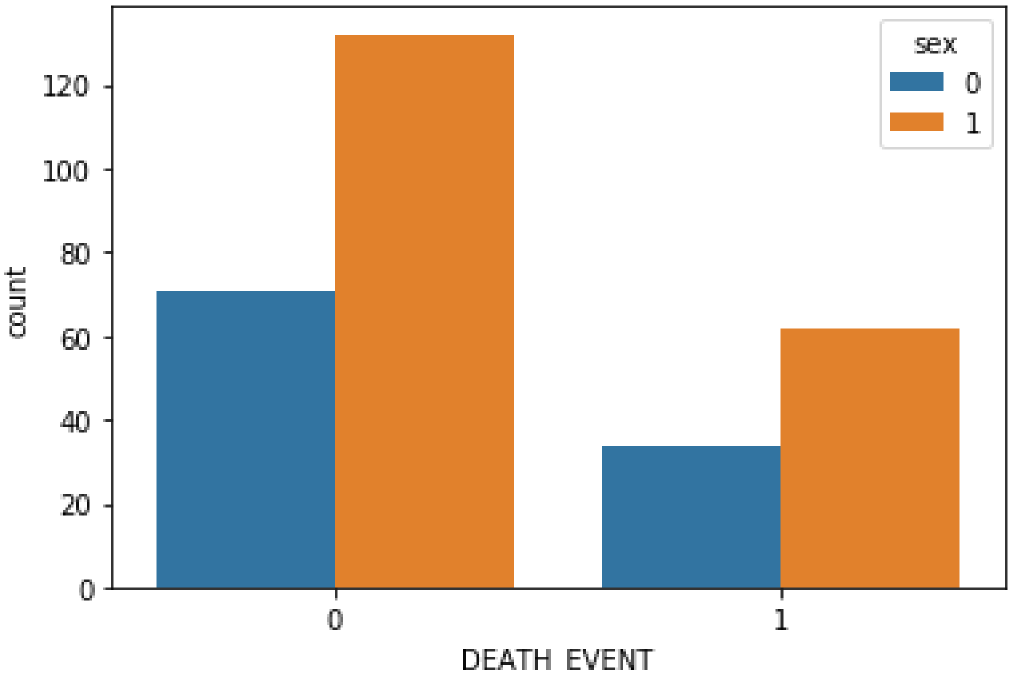
[6]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f95ef8538d0>
```



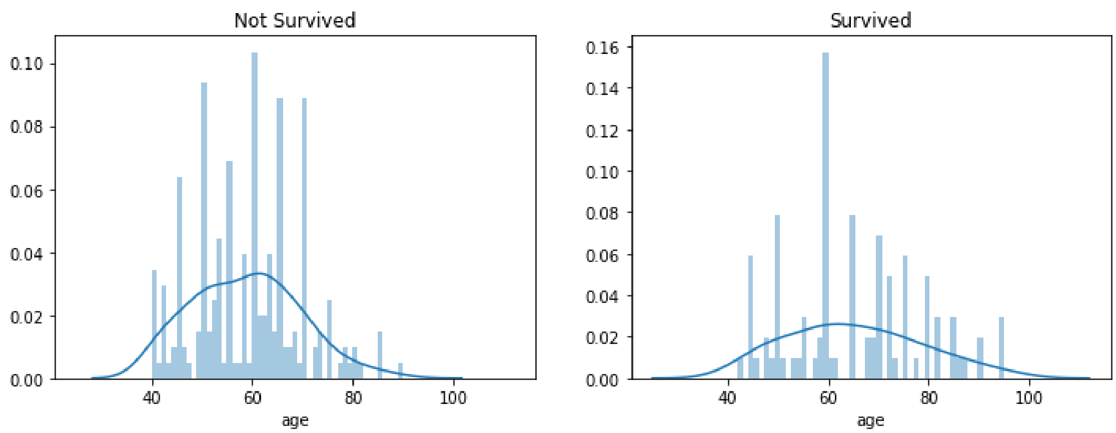
[7]:
```
# death event
sns.countplot(df['DEATH_EVENT'])
plt.show()
```



[8]:
```
# death event ~ gender
sns.countplot(x ='DEATH_EVENT', hue = 'sex', data = df)
plt.show()
```

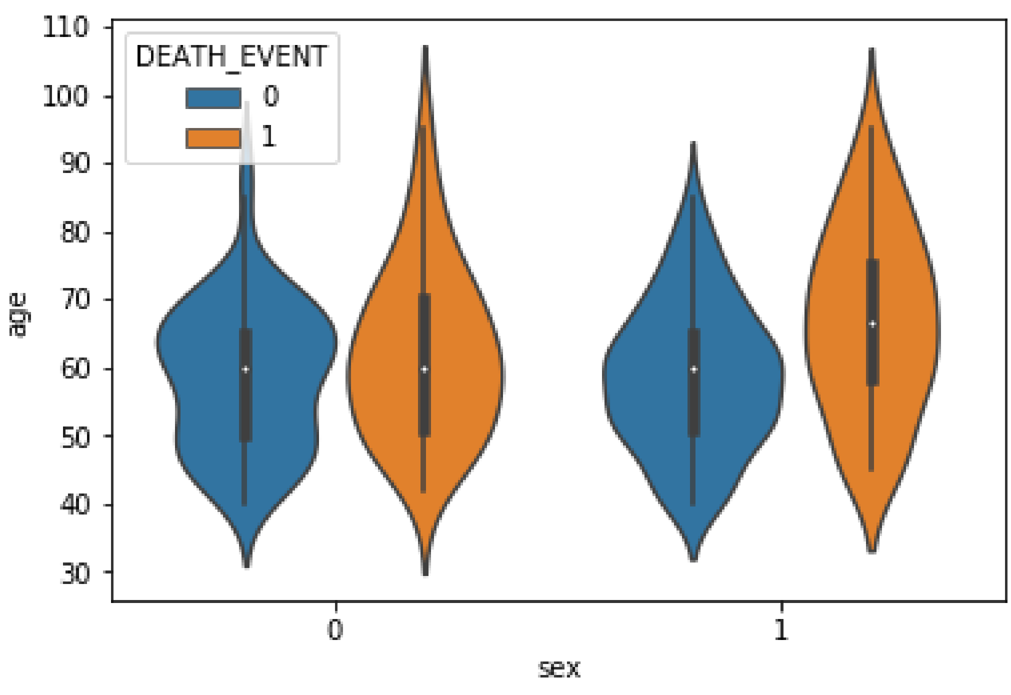


[9]:
```
# Gender factor Analysis ~ survived or not

f, axes = plt.subplots(1, 2, figsize = (12, 4), sharex = True)
sns.distplot(df[df['DEATH_EVENT'] == 0]['age'], ax = axes[0], bins = 50)
axes[0].set_title('Not Survived')

sns.distplot(df[df['DEATH_EVENT'] == 1]['age'], ax = axes[1], bins = 50)
axes[1].set_title('Survived')
plt.show()
```



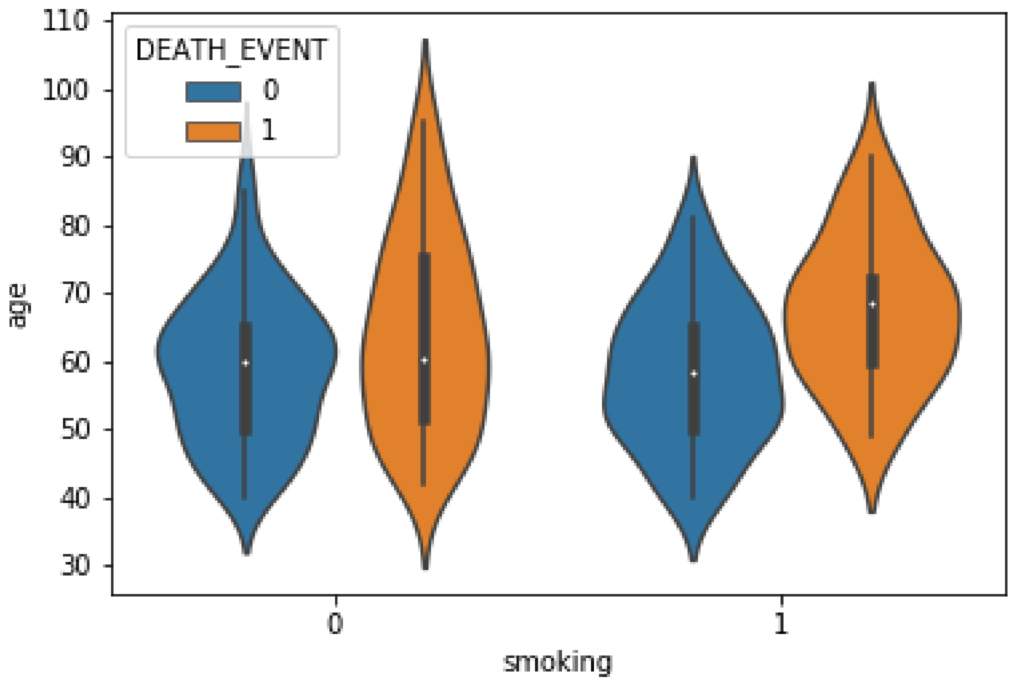
[10]:
```
# Gender factor Analysis ~ survived vs gender
sns.violinplot(x = 'sex', y = 'age', hue = 'DEATH_EVENT', data = df)
```

[10]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f95efd6fac8>`



[11]:
```
# Gender factor Analysis ~ survived vs smoking
sns.violinplot(x = 'smoking', y = 'age', hue = 'DEATH_EVENT', data = df)
```

[11]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f95efecd5c0>`

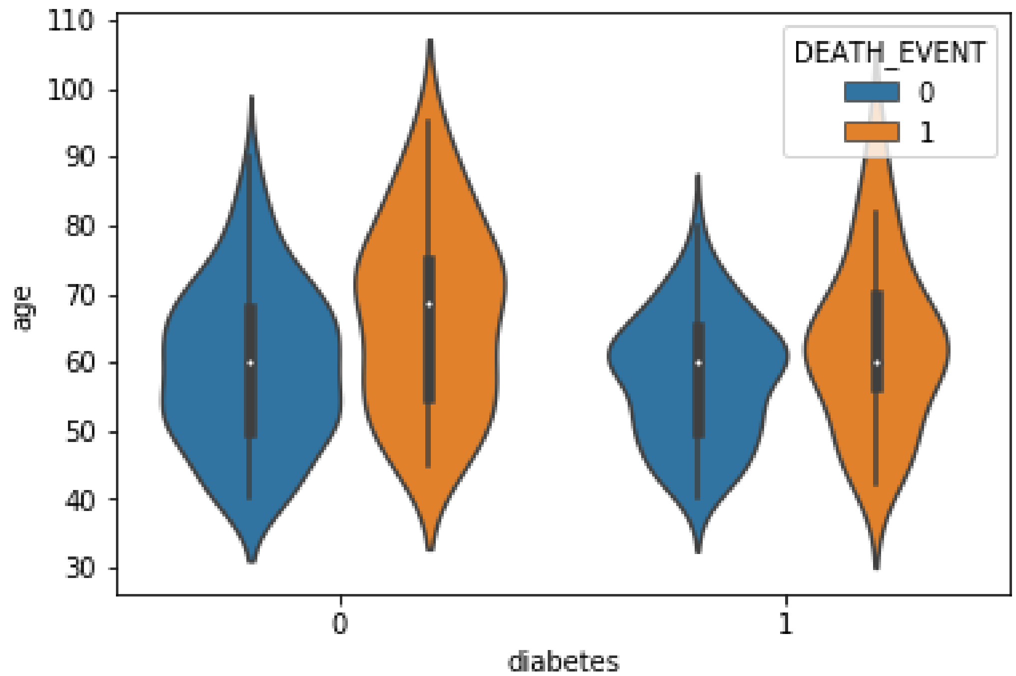


[12]:
```
print('The Survival is high for not smoking person 55 to 65, while for smoking␣
↪person it is between 50 to 60')
print('Death event for smoking person is high than not smoking person')
```

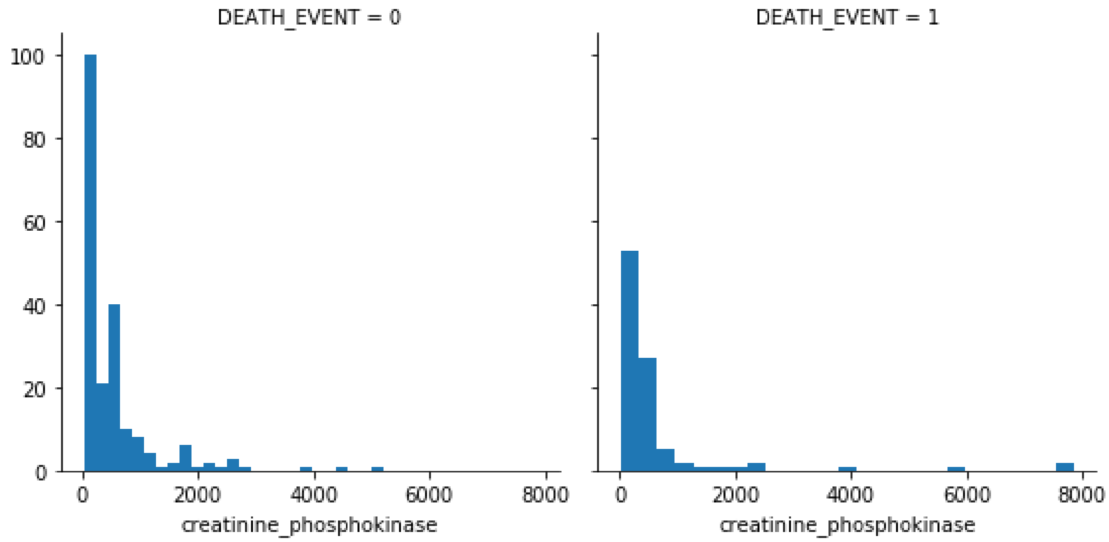
```
The Survival is high for not smoking person 55 to 65, while for smoking person
it is between 50 to 60
Death event for smoking person is high than not smoking person
```

[13]:
```
# Analysis in Age and Diabetes on Survival Status
sns.violinplot(x = 'diabetes', y = 'age', hue = 'DEATH_EVENT', data = df)
```

[13]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f95effcda58>`

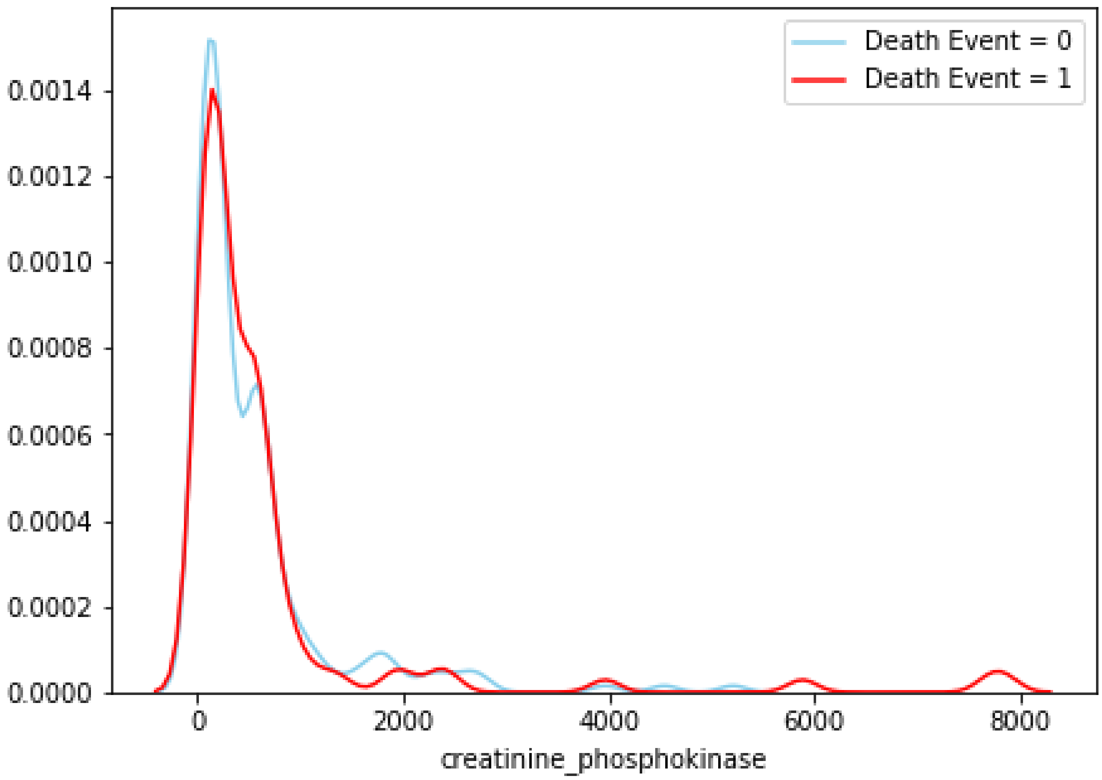


[14]:
```
### other variables on survival status
### creatinine_phosphokinase
g = sns.FacetGrid(df, col="DEATH_EVENT", height=4, aspect=1)
g = g.map(plt.hist, "creatinine_phosphokinase", bins = 25)
```

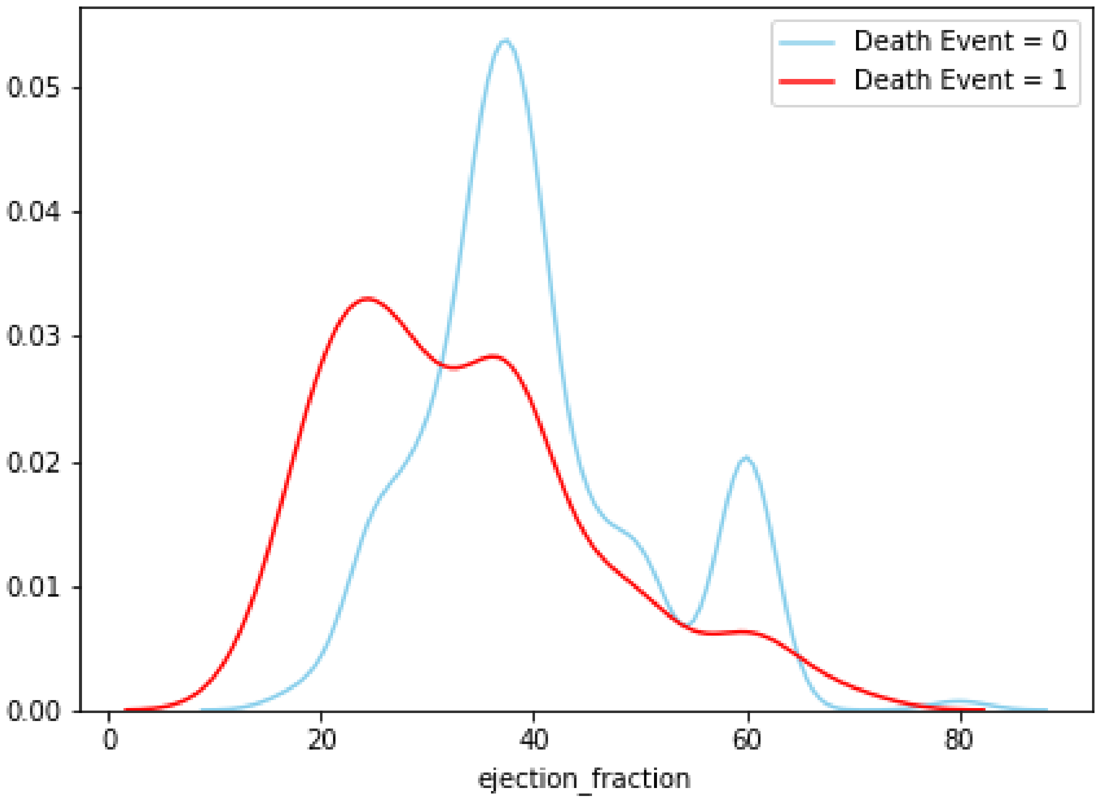


[15]:
```
## or on the same axis
plt.figure(figsize=(7, 5))
```

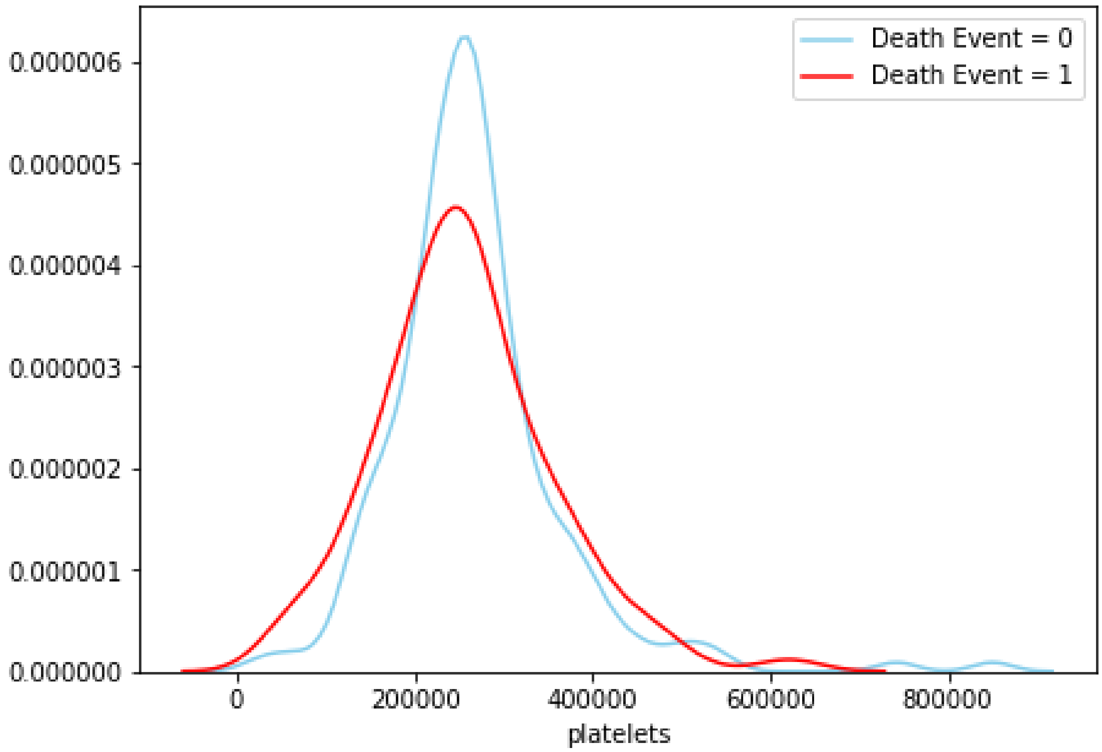
```
sns.distplot( df[df['DEATH_EVENT'] == 0]["creatinine_phosphokinase"] ,␣
 ↪color="skyblue", label="Death Event = 0",hist=False)
sns.distplot( df[df['DEATH_EVENT'] == 1]["creatinine_phosphokinase"] ,␣
 ↪color="red", label="Death Event = 1",hist=False)
plt.legend()
plt.show()
```



[16]:
```
### ejection_fraction on survival status

plt.figure(figsize=(7, 5))
sns.distplot( df[df['DEATH_EVENT'] == 0]["ejection_fraction"] ,␣
 ↪color="skyblue", label="Death Event = 0",hist=False)
sns.distplot( df[df['DEATH_EVENT'] == 1]["ejection_fraction"] , color="red",␣
 ↪label="Death Event = 1",hist=False)
plt.legend()
plt.show()
```



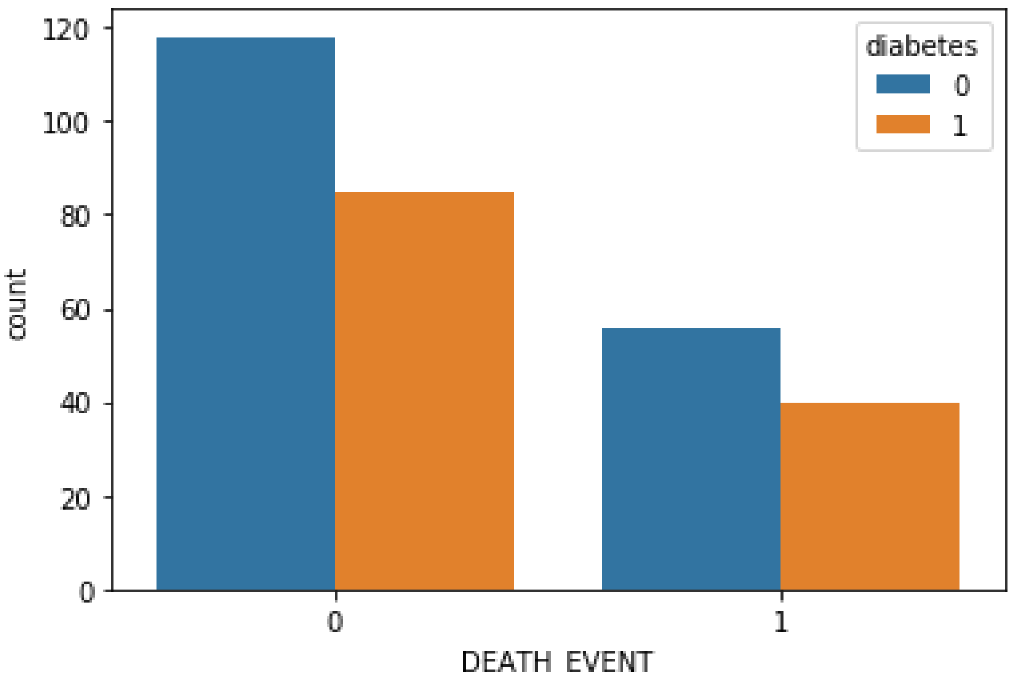
[17]:
```
### platelets on survival status

plt.figure(figsize=(7, 5))
sns.distplot( df[df['DEATH_EVENT'] == 0]["platelets"] , color="skyblue",␣
 ↪label="Death Event = 0",hist=False)
sns.distplot( df[df['DEATH_EVENT'] == 1]["platelets"] , color="red",␣
 ↪label="Death Event = 1",hist=False)
plt.legend()
plt.show()
```



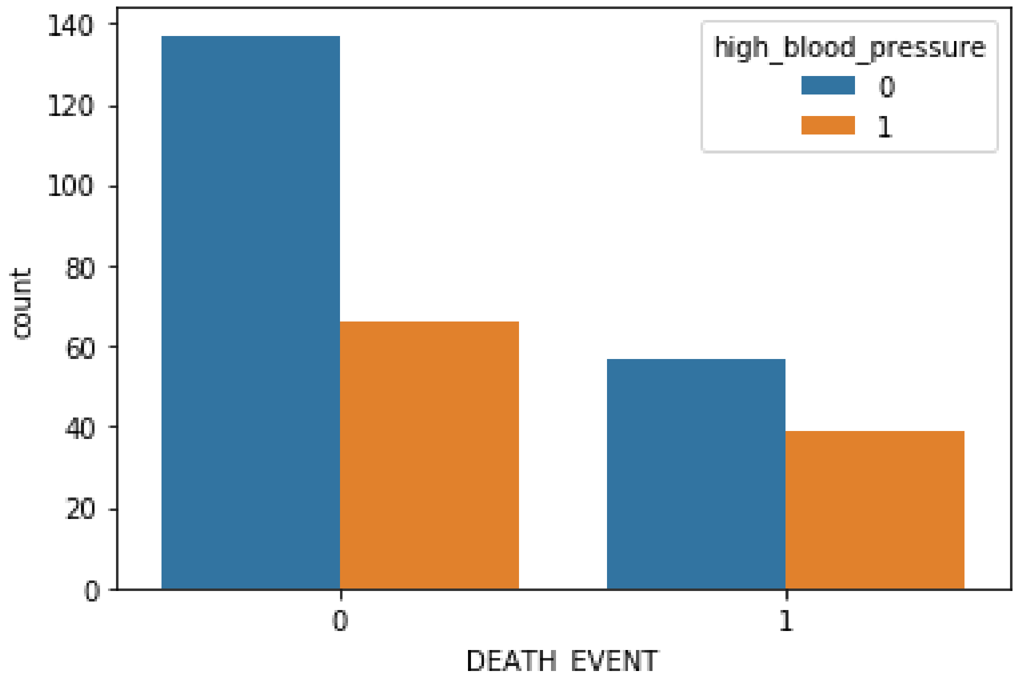
[18]:
```
df.head()
```

[18]:
```
    age  anaemia  creatinine_phosphokinase  diabetes  ejection_fraction  \
0  75.0        0                       582         0                 20
1  55.0        0                      7861         0                 38
2  65.0        0                       146         0                 20
3  50.0        1                       111         0                 20
4  65.0        1                       160         1                 20

   high_blood_pressure  platelets  serum_creatinine  serum_sodium  sex  \
0                    1  265000.00               1.9           130    1
1                    0  263358.03               1.1           136    1
2                    0  162000.00               1.3           129    1
3                    0  210000.00               1.9           137    1
4                    0  327000.00               2.7           116    0

   smoking  time  DEATH_EVENT
0        0     4            1
1        0     6            1
2        1     7            1
3        0     7            1
4        0     8            1
```

[19]:
```
#diabetes
sns.countplot(x ='DEATH_EVENT', hue = 'diabetes', data = df)
plt.show()
```

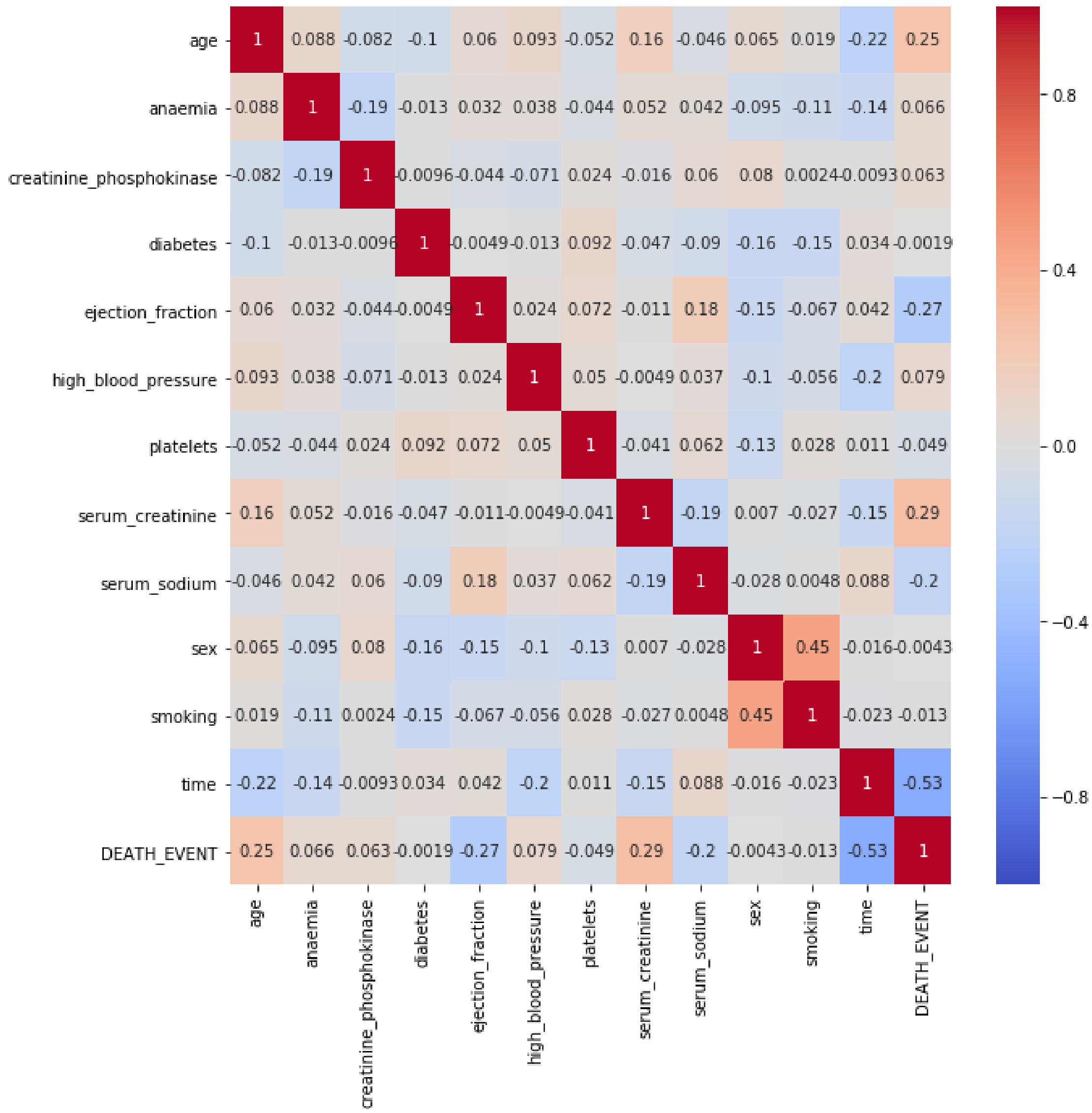


[20]:
```
#high_blood_pressure
sns.countplot(x ='DEATH_EVENT', hue = 'high_blood_pressure', data = df)
plt.show()
```



[21]:
```
plt.figure(figsize=(10,10))
sns.heatmap(df.corr(), vmin=-1, cmap='coolwarm', annot=True)
```

[21]: <matplotlib.axes._subplots.AxesSubplot at 0x7f95f0699240>



[22]:
```
### modeling
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import␣
↪confusion_matrix,accuracy_score,classification_report
```

[23]:
```
y = df['DEATH_EVENT']
X = df.drop('DEATH_EVENT', axis = 1)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,␣
↪random_state = 1)
```

[24]:
```
knn = KNeighborsClassifier()

param = dict(n_neighbors = [2, 5, 10, 20, 50])
knn_grid = GridSearchCV(estimator=knn, param_grid = param, cv = 5, scoring =␣
↪'accuracy')
knn_grid.fit(X_train, y_train)
```

[24]:
```
GridSearchCV(cv=5, estimator=KNeighborsClassifier(),
             param_grid={'n_neighbors': [2, 5, 10, 20, 50]},
             scoring='accuracy')
```

[25]:
```
knn_grid.best_params_
```

[25]:
```
{'n_neighbors': 50}
```

[26]:
```
knn = KNeighborsClassifier(n_neighbors=50)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.71      1.00      0.83        64
           1       0.00      0.00      0.00        26

    accuracy                           0.71        90
   macro avg       0.36      0.50      0.42        90
weighted avg       0.51      0.71      0.59        90


/Users/shijiecai/anaconda3/lib/python3.7/site-
packages/sklearn/metrics/_classification.py:1221: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

[27]:
```
rf = RandomForestClassifier()
n_estimators = [100, 200, 300]
max_depth = [3, 4, 5, 6]
min_samples_split = [3, 4, 5]
max_features = ['auto', 'sqrt']
params = dict(n_estimators = n_estimators, max_depth=max_depth,␣
↪max_features=max_features, min_samples_split=min_samples_split)

rf_grid = GridSearchCV(estimator=rf, param_grid=params, n_jobs=-1, cv=5,␣
↪scoring = 'accuracy')
rf_grid.fit(X_train, y_train)
```

[27]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid={'max_depth': [3, 4, 5, 6],
```

```
                              'max_features': ['auto', 'sqrt'],
                              'min_samples_split': [3, 4, 5],
                              'n_estimators': [100, 200, 300]},
                 scoring='accuracy')
```

[28]:
```
rf_grid.best_params_
```

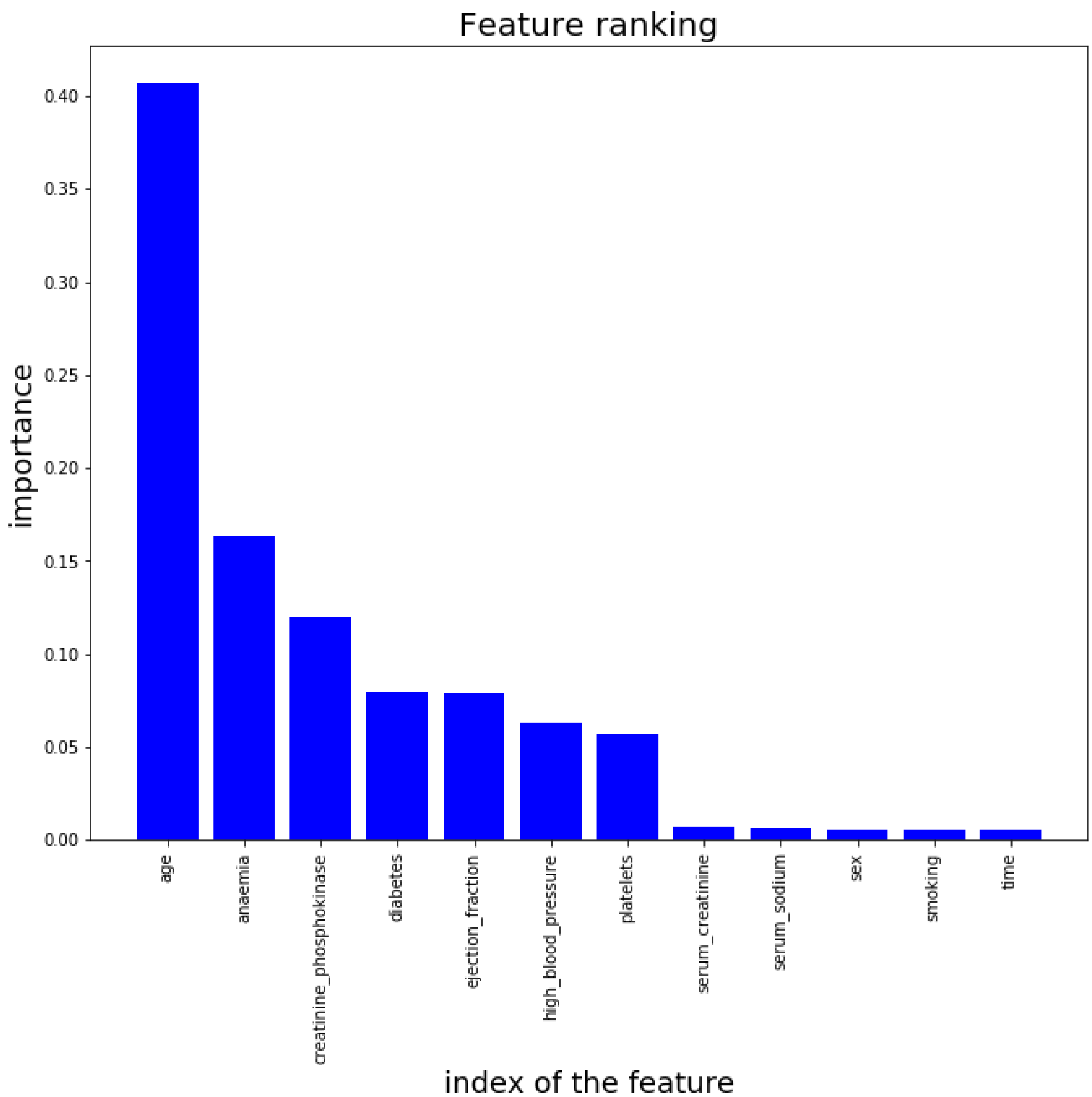
[28]:
```
{'max_depth': 5,
 'max_features': 'sqrt',
 'min_samples_split': 5,
 'n_estimators': 300}
```

[29]:
```
params = {'max_depth': 4,
 'max_features': 'auto',
 'min_samples_split': 4,
 'n_estimators': 200}

rf = RandomForestClassifier(**params)
rf.fit(X_train, y_train)
y_pred = rf.predict(X_test)

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

```
              precision    recall  f1-score   support

           0       0.89      0.98      0.93        64
           1       0.95      0.69      0.80        26

    accuracy                           0.90        90
   macro avg       0.92      0.84      0.87        90
weighted avg       0.90      0.90      0.89        90
```

[30]:
```
importance = rf.feature_importances_
indices = np.argsort(importance)[::-1]
feature_names = X.columns

f, ax = plt.subplots(figsize=(11, 9))
plt.title("Feature ranking", fontsize = 20)
plt.bar(range(X.shape[1]), importance[indices],
    color="b",
    align="center")
plt.xticks(range(X.shape[1]), feature_names, rotation = 90)
plt.xlim([-1, X.shape[1]])
plt.ylabel("importance", fontsize = 18)
plt.xlabel("index of the feature", fontsize = 18)
```

[30]:
```
Text(0.5, 0, 'index of the feature')
```



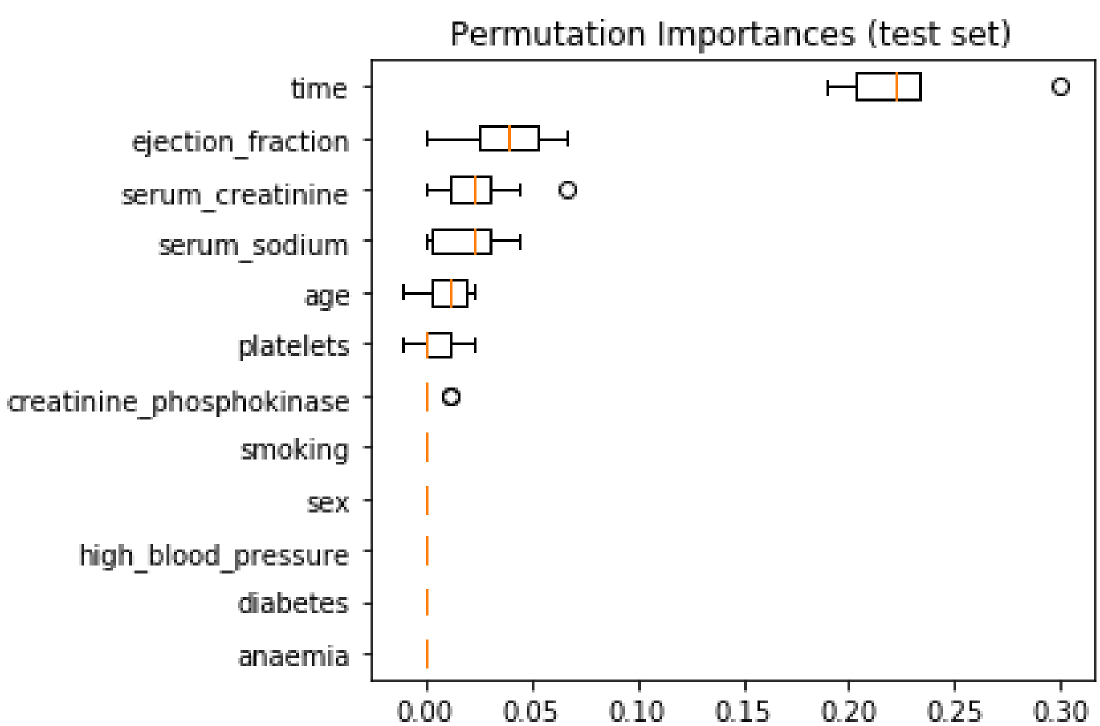
[31]:
```
### since we have tried feature importance for rf, let's try another one:␣
 ↪permutation importance.
import eli5
from eli5.sklearn import PermutationImportance
my_model = rf.fit(X_train, y_train)
perm = PermutationImportance(my_model, random_state=10).fit(X_test, y_test)
eli5.show_weights(perm, feature_names = X_train.columns.tolist())
```

```
/Users/shijiecai/anaconda3/lib/python3.7/site-
packages/sklearn/utils/deprecation.py:143: FutureWarning: The
sklearn.metrics.scorer module is  deprecated in version 0.22 and will be removed
in version 0.24. The corresponding classes / functions should instead be
imported from sklearn.metrics. Anything that cannot be imported from
```

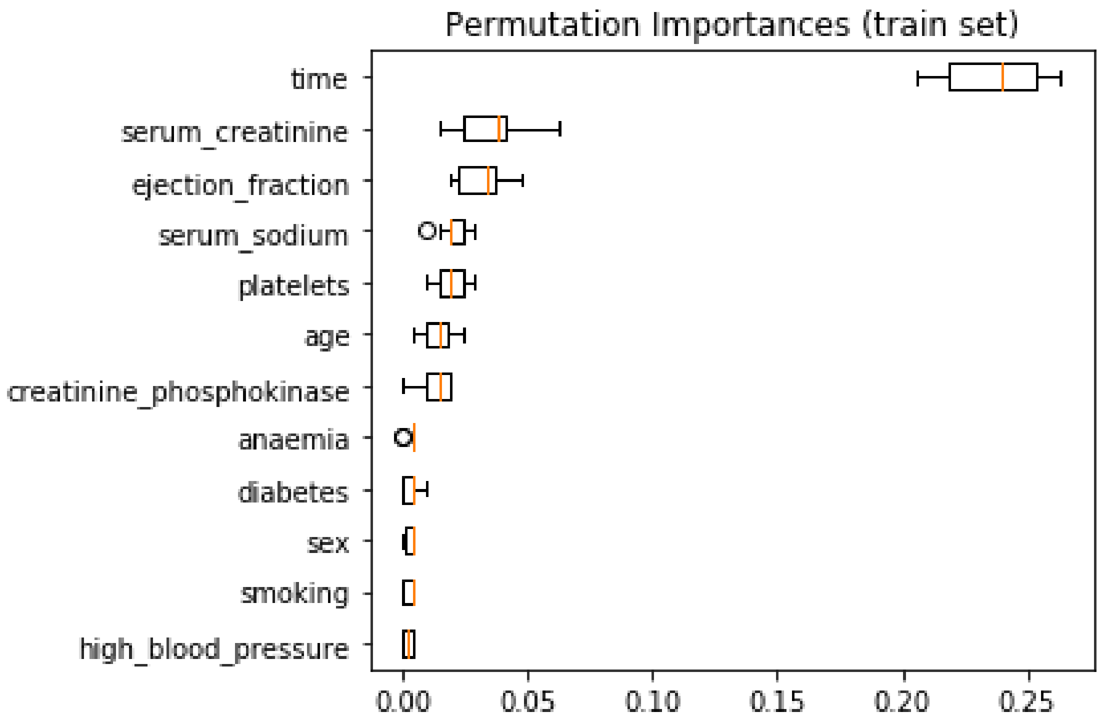
```
sklearn.metrics is now part of the private API.
  warnings.warn(message, FutureWarning)
/Users/shijiecai/anaconda3/lib/python3.7/site-
packages/sklearn/utils/deprecation.py:143: FutureWarning: The
sklearn.feature_selection.base module is  deprecated in version 0.22 and will be
removed in version 0.24. The corresponding classes / functions should instead be
imported from sklearn.feature_selection. Anything that cannot be imported from
sklearn.feature_selection is now part of the private API.
  warnings.warn(message, FutureWarning)
Using TensorFlow backend.
```

[31]:
```
<IPython.core.display.HTML object>
```

[32]:
```
from sklearn.inspection import permutation_importance
result = permutation_importance(rf, X_test, y_test,␣
 ↪n_repeats=10,random_state=42, n_jobs=2)
sorted_idx = result.importances_mean.argsort()

fig, ax = plt.subplots()
ax.boxplot(result.importances[sorted_idx].T,
           vert=False, labels=X_test.columns[sorted_idx])
ax.set_title("Permutation Importances (test set)")
fig.tight_layout()
plt.show()
```



[33]:
```
result = permutation_importance(rf, X_train, y_train, n_repeats=10,
                                random_state=42, n_jobs=2)
sorted_idx = result.importances_mean.argsort()

fig, ax = plt.subplots()
ax.boxplot(result.importances[sorted_idx].T,
           vert=False, labels=X_train.columns[sorted_idx])
ax.set_title("Permutation Importances (train set)")
fig.tight_layout()
plt.show()
```



[34]:
```
### maybe this is the reason why we have low accuracy, only a fall fraction of␣
↪variables are important
```

[35]:
```
Features = ['time','ejection_fraction','serum_creatinine','age',␣
↪'serum_sodium','creatinine_phosphokinase']
y = df['DEATH_EVENT']
X = df[Features]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,␣
↪random_state = 1)
```

[36]:
```
knn = KNeighborsClassifier()

param = dict(n_neighbors = list(range(1, 10)))
```

```
knn_grid = GridSearchCV(estimator=knn, param_grid = param, cv = 5, scoring =␣
 ↪'accuracy')
knn_grid.fit(X_train, y_train)
knn_grid.best_params_
```

[36]: {'n_neighbors': 9}

[37]:
```
knn = KNeighborsClassifier(n_neighbors=9)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.82      0.98      0.89        64
           1       0.92      0.46      0.62        26

    accuracy                           0.83        90
   macro avg       0.87      0.72      0.75        90
weighted avg       0.85      0.83      0.81        90
```

[38]:
```
rf = RandomForestClassifier()
n_estimators = [100, 200, 300]
max_depth = [3, 4, 5, 6]
min_samples_split = [3, 4, 5]
max_features = ['auto', 'sqrt']
params = dict(n_estimators = n_estimators, max_depth=max_depth,␣
 ↪max_features=max_features, min_samples_split=min_samples_split)

rf_grid = GridSearchCV(estimator=rf, param_grid=params, n_jobs=-1, cv=5,␣
 ↪scoring = 'accuracy')
rf_grid.fit(X_train, y_train)
rf_grid.best_params_
```

[38]:
```
{'max_depth': 5,
 'max_features': 'sqrt',
 'min_samples_split': 4,
 'n_estimators': 100}
```

[39]:
```
params = {'max_depth': 5,
 'max_features': 'sqrt',
 'min_samples_split': 3,
 'n_estimators': 100}

rf = RandomForestClassifier(**params)
rf.fit(X_train, y_train)
y_pred = rf.predict(X_test)
```

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

```
              precision    recall  f1-score   support

           0       0.90      0.95      0.92        64
           1       0.86      0.73      0.79        26

    accuracy                           0.89        90
   macro avg       0.88      0.84      0.86        90
weighted avg       0.89      0.89      0.89        90
```

[40]:
```
### knn is improved, however, rf is worse.
```

[41]:
```
from xgboost import XGBClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
```

[42]:
```
dt = DecisionTreeClassifier()
max_leaf = list(range(5, 11))
criterion = ['gini', 'entropy']
params = dict(max_leaf_nodes=max_leaf, criterion=criterion)

dt_grid = GridSearchCV(estimator=dt, param_grid=params, n_jobs=-1, cv=5,␣
 ↪scoring = 'accuracy')
dt_grid.fit(X_train, y_train)
```

[42]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(), n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_leaf_nodes': [5, 6, 7, 8, 9, 10]},
             scoring='accuracy')
```

[43]:
```
dt_grid.best_params_
```

[43]:
```
{'criterion': 'entropy', 'max_leaf_nodes': 5}
```

[44]:
```
dt = DecisionTreeClassifier(max_leaf_nodes=5, random_state=30,␣
 ↪criterion='entropy')
dt.fit(X_train, y_train)
y_pred = dt.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.86      0.94      0.90        64
           1       0.80      0.62      0.70        26

    accuracy                           0.84        90
   macro avg       0.83      0.78      0.80        90
```

```
weighted avg       0.84      0.84      0.84        90
```

[45]:
```
#### lets try gradient boosting
# first try: no pruning
```

[46]:
```
from sklearn import metrics
```

[47]:
```
gbm = GradientBoostingClassifier(random_state=4)
gbm.fit(X_train,y_train)
y_pred = gbm.predict(X_test)
y_predprob = gbm.predict_proba(X_test)[:,1]
print("Accuracy : %.4g (test)" % metrics.accuracy_score(y_test, y_pred))
print("AUC Score : %f" % metrics.roc_auc_score(y_test, y_predprob))
```

```
Accuracy : 0.8444 (test)
AUC Score : 0.916466
```

[48]:
```
### lets prune the tree
```

[49]:
```
gbm = GradientBoostingClassifier()
learning_rate = [0.01, 0.05, 0.1, 0.5, 1]
n_estimators = [100, 200, 300]
criterion = ['friedman_mse', 'mse', 'mae']
max_depth = range(3,14,2)

params = dict(learning_rate = learning_rate, n_estimators = n_estimators,␣
 ↪criterion = criterion, max_depth = max_depth)
gbm_grid = GridSearchCV(estimator=gbm, param_grid=params, n_jobs=-1, cv=5,␣
 ↪scoring = 'accuracy')
gbm_grid.fit(X_train, y_train)
```

[49]:
```
GridSearchCV(cv=5, estimator=GradientBoostingClassifier(), n_jobs=-1,
             param_grid={'criterion': ['friedman_mse', 'mse', 'mae'],
                         'learning_rate': [0.01, 0.05, 0.1, 0.5, 1],
                         'max_depth': range(3, 14, 2),
                         'n_estimators': [100, 200, 300]},
             scoring='accuracy')
```

[50]:
```
gbm_grid.best_params_
```

[50]:
```
{'criterion': 'mae',
 'learning_rate': 0.01,
 'max_depth': 3,
 'n_estimators': 200}
```

[51]:
```
params = {'criterion': 'mse',
 'learning_rate': 0.01,
 'max_depth': 3,
 'n_estimators': 100}
```

```
gbm = GradientBoostingClassifier(**params)
gbm.fit(X_train, y_train)
y_pred = gbm.predict(X_test)
y_predprob = gbm.predict_proba(X_test)[:,1]
print("Accuracy : %.4g" % metrics.accuracy_score(y_test, y_pred))
print("AUC Score : %f" % metrics.roc_auc_score(y_test, y_predprob))
```

```
Accuracy : 0.8222
AUC Score : 0.905349
```

[72]:
```
xgb = XGBClassifier()
eta = list(np.arange(0.1,1,0.2))
max_depth = list(range(2,9,2))
subsample = list(np.arange(0.3, 1, 0.2))
n_estimators = list(range(100, 600, 100))
colsample_bytree = list(np.arange(0.3, 1, 0.2))

params = dict(eta = eta, n_estimators = n_estimators, subsample = subsample,␣
 ↪max_depth = max_depth, colsample_bytree=colsample_bytree)
xgb_grid = GridSearchCV(estimator=xgb, param_grid=params, n_jobs=-1, cv=5,␣
 ↪scoring = 'accuracy')
xgb_grid.fit(X_train, y_train)
```

[72]:
```
GridSearchCV(cv=5,
             estimator=XGBClassifier(base_score=None, booster=None,
                                     colsample_bylevel=None,
                                     colsample_bynode=None,
                                     colsample_bytree=None, gamma=None,
                                     gpu_id=None, importance_type='gain',
                                     interaction_constraints=None,
                                     learning_rate=None, max_delta_step=None,
                                     max_depth=None, min_child_weight=None,
                                     missing=nan, monotone_constraints=None,
                                     n_estimators=100, n_jobs...
                                     scale_pos_weight=None, subsample=None,
                                     tree_method=None, validate_parameters=None,
                                     verbosity=None),
             n_jobs=-1,
             param_grid={'colsample_bytree': [0.3, 0.5, 0.7,
                                              0.9000000000000001],
                         'eta': [0.1, 0.30000000000000004, 0.5000000000000001,
                                 0.7000000000000001, 0.9000000000000001],
                         'max_depth': [2, 4, 6, 8],
                         'n_estimators': [100, 200, 300, 400, 500],
                         'subsample': [0.3, 0.5, 0.7, 0.9000000000000001]},
             scoring='accuracy')
```

[74]:
```
gbm_grid.best_params_
```

[74]: {'eta': 0.1, 'max_depth': 2, 'n_estimators': 100, 'subsample': 0.3}

[87]:
```
params = {'eta': 0.1, 'max_depth': 2, 'n_estimators': 100, 'subsample': 0.3,␣
↪'colsample_bytree':0.7}

xgb = XGBClassifier(**params)
xgb.fit(X_train, y_train)
y_pred = xgb.predict(X_test)
y_predprob = xgb.predict_proba(X_test)[:,1]
print("Accuracy : %.4g" % metrics.accuracy_score(y_test, y_pred))
print("AUC Score : %f" % metrics.roc_auc_score(y_test, y_predprob))
```

```
Accuracy : 0.8778
AUC Score : 0.913462
```

[ ]: