#### In [1]:

```
import pandas as pd
from sklearn.model selection import train test split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.metrics import fl_score, precision_score, recall_score, roc_auc_score, accuracy_sco
re, roc curve, confusion matrix
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from xgboost.sklearn import XGBClassifier
import lightgbm as lgb
from sklearn.preprocessing import MinMaxScaler
import os
import pandas as pd
import lightgbm as lgb
from sklearn. preprocessing import Imputer
import math
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
%matplotlib inline
from sklearn.preprocessing import Imputer
from sklearn import preprocessing
import numpy as np
```

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\ensemble\weight\_boosting.py:29:
DeprecationWarning: numpy.core.umath\_tests is an internal NumPy module and should not be imported. It will be removed in a future NumPy release.

from numpy.core.umath\_tests import innerld

### In [2]:

```
f = 'pocd.csv'
pocd = pd.read_csv(f, encoding = 'gb18030')
pocd.describe()
```

#### Out[2]:

	Sex	Age	Location	Tumor size	Grade	Sta
count	1330.000000	1330.000000	1330.000000	1330.000000	1330.000000	1330.0000
mean	1.680451	57.630827	2.022556	4.651053	1.830827	2.418045
std	0.466477	11.934602	0.889417	2.608218	0.375046	0.757986
min	1.000000	19.000000	1.000000	0.500000	1.000000	1.000000
25%	1.000000	50.000000	1.000000	3.000000	2.000000	2.000000
50%	2.000000	59.000000	2.000000	4.000000	2.000000	3.000000
75%	2.000000	66.000000	3.000000	6.000000	2.000000	3.000000
max	2.000000	89.000000	3.000000	30.000000	2.000000	3.000000

## In [3]:

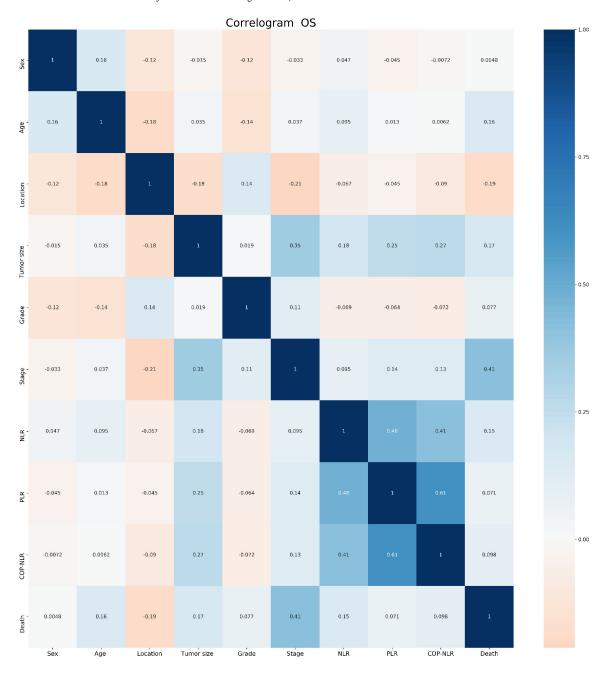
```
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns

plt.figure(figsize=(22,23), dpi= 600)
sns.heatmap(pocd.corr(), xticklabels=pocd.corr().columns, yticklabels=pocd.corr().columns,
cmap='RdBu', center=0, annot=True)

plt.title('Correlogram OS', fontsize=22)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
```

## Out[3]:

(array([0.5, 1.5, 2.5, 3.5, 4.5, 5.5, 6.5, 7.5, 8.5, 9.5]), (a list of 10 Text yticklabel objects))



```
In [4]:
```

```
X= pocd.iloc[:, 0:-1]
y = pocd.iloc[:, -1:]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=2018, stratif
y=y)
print(X_train)
print(y_train)
```

	Sex	Age	Location	Tumor size	Grade	Stage	NLR	PLR	\
1003	1	59	2	8.0	2	3	1.307692	72. 527473	
180	2	46	3	1.0	2	1	1.500000	106.666667	
1096	1	51	3	8.0	2	3	1. 280488	119. 512195	
1050	2	38	2	1.0	2	3	1. 205279	70. 381232	
155	2	57	3	1.0	2	1	1.068421	69. 473684	
1064	2	74	2	6.0	2	3	3. 133333	130.666667	
879	2	57	1	11.0	2	3	3. 208861	232. 911392	
1022	2	69	2	2.0	2	3	1.004348	111. 304348	
1211	2	43	3	5. 0	2	3	2.742105	214. 210526	
970	1	59	2	6. 0	2	3	2.058824	272. 764706	

	COP-NLR
1003	0
180	0
1096	0
1050	0
155	0
1064	1
879	2
1022	0
1211	1
970	1

[1064 rows x 9 columns]

	Death	
1003	1	
180	0	
1096	1	
1050	0	
155	0	
1064	1	
879	1	
1022	1	
1211	1	
970	0	

[1064 rows x 1 columns]

```
In [5]:
```

```
xy_train = pd.concat([X_train, y_train], axis=1)
xy_test = pd.concat([X_test, y_test], axis=1)

f_xy_train = os.path.splitext(f)[0] + '_train.csv'
f_xy_test = os.path.splitext(f)[0] + '_test.csv'
xy_train.to_csv(f_xy_train, index=False, encoding = 'gb18030')
xy_test.to_csv(f_xy_test, index=False, encoding = 'gb18030')

xy_train = pd.read_csv(f_xy_train, encoding = 'gb18030')
xy_test = pd.read_csv(f_xy_test, encoding = 'gb18030')
```

## In [6]:

```
X_train = xy_train.iloc[:, 0:-1]
y_train = xy_train.iloc[:, -1:]
X_test = xy_test.iloc[:, 0:-1]
y_test = xy_test.iloc[:, -1:]
```

# In [7]:

```
import numpy as np

X_train = np. array(X_train)

X_test = np. array(X_test)
y_train = np. array(y_train)

ya, yb = y_train. shape
y_train = y_train. reshape(ya,)
y_test = np. array(y_test)
ya, yb = y_test. shape
y_test = y_test. reshape(ya,)
```

#### In [8]:

```
from sklearn.preprocessing import MinMaxScaler
ss = MinMaxScaler()
xy_train = ss.fit_transform(xy_train, y_train)
xy_test = ss.transform(xy_test)
print(xy_train)
[[0. 0.57142857 0.5 ... 0.05973563 0 1
```

[1.   0.38571429   1.     0.09140097			J
[0. 0.45714286 1 0.10331566	0.	1.	]
[1.       0.71428571 0.5       0.09570258         [1.       0.34285714 1.       0.19115179	0. 5	1. 1.	]
[0. 0.57142857 0.5 0.24546292	0. 5	0.	

### In [9]:

```
xy_train. shape
```

#### Out[9]:

(1064, 10)

### In [11]:

```
1r = LogisticRegression(penalty='12', tol=0.0001, C=0.1, fit intercept=True, intercept scaling=1, cl
ass_weight=None, max_iter=100, multi_class='ovr', verbose=0, warm_start=False, n_jobs=1)
模型
lr.fit(X train, y train)
lr y proba=lr.predict proba(X train)
lr_y_pre=lr.predict(X_train)
lr score = lr. score(X train, y train)
lr_accuracy_score=accuracy_score(y_train, lr_y_pre)
lr_preci_score=precision_score(y_train, lr_y_pre)
lr recall score=recall score(y train, lr y pre)
lr_f1_score=f1_score(y_train, lr_y_pre)
lr auc=roc auc score(y train, lr y proba[:, 1])
print ('lr accuracy score: %. 3f, lr preci score: %. 3f, lr recall score: %. 3f, lr fl score: %. 3f, lr au
c:%. 3f'
      %(lr accuracy score, lr preci score, lr recall score, lr f1 score, lr auc))
lr accuracy score: 0.657, lr preci score: 0.575, lr recall score: 0.496, lr f1 score: 0.5
33, 1r auc: 0.737
In [12]:
tr = DecisionTreeClassifier(splitter='best', max_depth=5, min_samples_split=80, min_samples_leaf
=65, min_weight_fraction_leaf=0.01, max_features=None, random_state=None,
max_leaf_nodes=None, class_weight=None, presort=False)
tr.fit(X_train, y_train)
tr y pre=tr.predict(X train)
tr y proba=tr.predict proba(X train)
tr_score = tr. score(X_train, y_train)
tr_accuracy_score=accuracy_score(y_train, tr_y_pre)
tr_preci_score=precision_score(y_train, tr_y_pre)
tr_recall_score=recall_score(y_train, tr_y_pre)
tr f1 score=f1 score(y train, tr y pre)
tr auc=roc auc score(y train, tr y proba[:, 1])
print ('tr_accuracy_score: %. 3f, tr_preci_score: %. 3f, tr_recall_score: %. 3f, tr_fl_score: %. 3f, tr_au
c:%. 3f'
```

tr\_accuracy\_score: 0. 698, tr\_preci\_score: 0. 659, tr\_recall\_score: 0. 484, tr\_f1\_score: 0. 5 58, tr\_auc: 0.767

%(tr\_accuracy\_score, tr\_preci\_score, tr\_recall\_score, tr\_fl\_score, tr\_auc))

### In [13]:

forest\_accuracy\_score:0.885, forest\_preci\_score:0.878, forest\_recall\_score:0.823, for est f1 score:0.850, forest auc:0.943

### In [14]:

Gbdt\_accuracy\_score:0.756, Gbdt\_preci\_score:0.675, Gbdt\_recall\_score:0.730, Gbdt\_f1\_s core:0.702, Gbdt\_auc:0.846

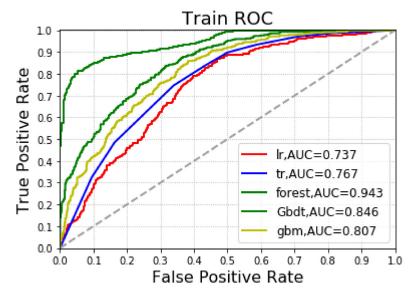
### In [18]:

gbm\_accuracy\_score:0.725, gbm\_preci\_score: 0.641, gbm\_recall\_score:0.685, gbm\_f1\_score:0.662, gbm\_auc:0.807

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\preprocessing\label.py:151: Dep recationWarning: The truth value of an empty array is ambiguous. Returning False, but in future this will result in an error. Use `array.size > 0` to check that an array is not empty.

if diff:

```
#机器学习算法图集合 plt. figure (figsize=(8, 6), facecolor='w')
lr_fpr, lr_tpr, lr_threasholds=roc_curve(y_train, lr_y_proba[:, 1]) # 计算ROC的值, lr_threasholds为阈
tr fpr, tr tpr, tr threasholds=roc curve(y train, tr y proba[:,1]) # 计算ROC的值, 1r threasholds为阈
盾
forest_fpr, forest_tpr, forest_threasholds=roc_curve(y_train, forest_y_proba[:,1]) # 计算ROC的值, sv
m threasholds为阈值
Gbdt_fpr,Gbdt_tpr,Gbdt_threasholds=roc_curve(y_train,Gbdt_y_proba[:,1]) # 计算ROC的值,svm_threas
holds为阈值
#Xgbc fpr, Xgbc tpr, Xgbc threasholds=roc curve(y train, Xgbc y pre) # 计算ROC的值, svm threasholds
gbm_fpr,gbm_tpr,gbm_threasholds=roc_curve(y_train,gbm_y_proba[:,1]) # 计算ROC的值,svm_threashold
s为阈值
plt.plot(lr_fpr, lr_tpr, c='r', lw=2, label=u'lr, AUC=%.3f'% lr_auc)
plt.plot(tr_fpr, tr_tpr, c='b', lw=2, label=u'tr, AUC=%.3f' % tr_auc)
plt.plot(forest fpr, forest tpr, c='g', lw=2, label=u' forest, AUC=%. 3f' % forest auc)
plt.plot(Gbdt_fpr,Gbdt_tpr,c='g',lw=2,label=u'Gbdt,AUC=%.3f' % Gbdt_auc)
#plt. plot (Xgbc_fpr, Xgbc_tpr, c='g', lw=2, label=u'Xgbc, AUC=%. 3f' % svm_auc)
plt.plot(gbm_fpr, gbm_tpr, c='y', lw=2, label=u'gbm, AUC=%.3f' % gbm auc)
plt. plot ((0, 1), (0, 1), c=' #a0a0a0', lw=2, ls='--')
plt.xlim(-0.001, 1.001)
plt.ylim(-0.001, 1.001)
plt. xticks (np. arange (0, 1.1, 0.1))
plt. yticks (np. arange (0, 1.1, 0.1))
plt.xlabel('False Positive Rate', fontsize=16)
plt.ylabel('True Positive Rate', fontsize=16)
plt.grid(b=True, ls=':')
plt.legend(loc='lower right', fancybox=True, framealpha=0.8, fontsize=12)
plt.title(u'Train ROC', fontsize=18)
fig = plt.figure(figsize=(8, 15), dpi= 600)
plt.show()
```



⟨Figure size 4800x9000 with 0 Axes⟩

```
In [21]:
1r = LogisticRegression(tol=0.000001, C=1, max iter=1000, n jobs=-1)
lr.fit(X_train, y_train)
lr y proba=lr.predict proba(X test)
lr y pre=lr.predict(X test)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear model\logistic.py:1228:
UserWarning: 'n_jobs' > 1 does not have any effect when 'solver' is set to 'libli
near'. Got 'n_jobs' = -1.
  " = \{\}. ". format(self. n jobs))
In [22]:
lr score = lr.score(X test, y test)
lr accuracy score=accuracy score(y test, lr y pre)
lr_preci_score=precision_score(y_test, lr_y_pre)
lr_recall_score=recall_score(y_test, lr_y_pre)
lr f1 score=f1 score(y test, lr y pre)
lr auc=roc auc score(y test, lr y proba[:, 1])
print ('lr accuracy score: %. 3f, lr preci score: %. 3f, lr recall score: %. 3f, lr fl score: %. 3f, lr au
c:%. 3f'
      %(lr_accuracy_score, lr_preci_score, lr_recall_score, lr_f1_score, lr_auc))
```

 $lr\_accuracy\_score: 0.\ 763, lr\_preci\_score: 0.\ 719, lr\_recall\_score: 0.\ 657, lr\_f1\_score: 0.\ 687, lr\_auc: 0.\ 830$ 

## In [23]:

```
tr = DecisionTreeClassifier(splitter='best', max_depth=5, min_samples_split=80, min_samples_leaf =65, min_weight_fraction_leaf=0.01, max_features=None, random_state=None, max_leaf_nodes=None, class_weight=None, presort=False) # 決策材模型 tr.fit(X_train, y_train) tr_y_pre=tr.predict(X_test) tr_y_proba=tr.predict_proba(X_test)
```

### In [24]:

```
tr_score = tr. score(X_test, y_test)
tr_accuracy_score=accuracy_score(y_test, tr_y_pre)
tr_preci_score=precision_score(y_test, tr_y_pre)
tr_recall_score=recall_score(y_test, tr_y_pre)
tr_fl_score=fl_score(y_test, tr_y_pre)
tr_auc=roc_auc_score(y_test, tr_y_proba[:,1])
print('tr_accuracy_score:%.3f, tr_preci_score:%.3f, tr_recall_score:%.3f, tr_fl_score:%.3f, tr_auc:%.3f'
    %(tr_accuracy_score, tr_preci_score, tr_recall_score, tr_fl_score, tr_auc))
```

tr\_accuracy\_score:0.684, tr\_preci\_score:0.644, tr\_recall\_score:0.448, tr\_f1\_score:0.528, tr\_auc:0.765

#### In [25]:

```
forest=RandomForestClassifier(n_estimators=500, max_features = "auto", min_samples_leaf = 5 , rando m_state = 41) # 随机森林 forest.fit(X_train, y_train) forest_y_pre=forest.predict(X_test) forest_y_proba=forest.predict_proba(X_test)
```

```
In [26]:
```

```
forest_accuracy_score=accuracy_score(y_test, forest_y_pre)
forest_preci_score=precision_score(y_test, forest_y_pre)
forest_recall_score=recall_score(y_test, forest_y_pre)
forest_fl_score=fl_score(y_test, forest_y_pre)
forest_auc=roc_auc_score(y_test, forest_y_proba[:,1])
print('forest_accuracy_score:%.3f, forest_preci_score:%.3f, forest_recall_score:%.3f, forest_fl_s
core:%.3f, forest_auc:%.3f'
%
(forest_accuracy_score, forest_preci_score, forest_recall_score, forest_fl_score, forest_auc))
```

forest\_accuracy\_score:0.680, forest\_preci\_score:0.596, forest\_recall\_score:0.590, for est f1 score:0.593, forest auc:0.781

## In [27]:

```
\label{lem:contingClassifier} Gbdt=GradientBoostingClassifier (learning_rate=0.2, n_estimators=60, max_depth=2, max_features='auto', min_samples_split=20, min_samples_leaf=3, random_state=1) \#CBDT Gbdt. fit (X_train, y_train) Gbdt_y_pre=Gbdt. predict (X_test) Gbdt_y_proba=Gbdt. predict_proba (X_test)
```

### In [28]:

```
Gbdt_accuracy_score=accuracy_score(y_test, Gbdt_y_pre)
Gbdt_preci_score=precision_score(y_test, Gbdt_y_pre)
Gbdt_recall_score=recall_score(y_test, Gbdt_y_pre)
Gbdt_f1_score=f1_score(y_test, Gbdt_y_pre)
Gbdt_auc=roc_auc_score(y_test, Gbdt_y_proba[:,1])
print('Gbdt_accuracy_score:%.3f, Gbdt_preci_score:%.3f, Gbdt_recall_score:%.3f, Gbdt_f1_score:%.3
f, Gbdt_auc:%.3f'
    %(Gbdt_accuracy_score, Gbdt_preci_score, Gbdt_recall_score, Gbdt_f1_score, Gbdt_auc))
```

Gbdt\_accuracy\_score:0.718, Gbdt\_preci\_score:0.642, Gbdt\_recall\_score:0.648, Gbdt\_f1\_s core:0.645, Gbdt\_auc:0.802

### In [31]:

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\preprocessing\label.py:151: Dep recationWarning: The truth value of an empty array is ambiguous. Returning False, but in future this will result in an error. Use `array.size > 0` to check that an array is not empty.

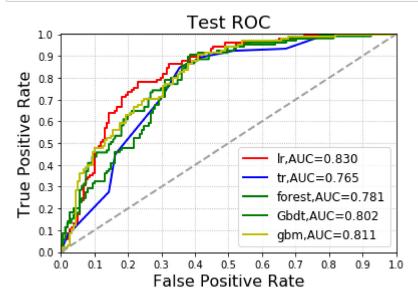
if diff:

#### In [32]:

gbm\_accuracy\_score:0.733, gbm\_preci\_score: 0.660, gbm\_recall\_score:0.667, gbm\_f1\_score:0.664, gbm\_auc:0.811

### In [34]:

```
tr_fpr, tr_tpr, tr_threasholds=roc_curve(y_test, tr_y_proba[:, 1])
lr_fpr, lr_tpr, lr_threasholds=roc_curve(y_test, lr_y_proba[:, 1])
forest fpr, forest tpr, forest threasholds=roc curve(y test, forest y proba[:, 1])
Gbdt fpr, Gbdt tpr, Gbdt threasholds=roc curve(y test, Gbdt y proba[:, 1])
gbm fpr, gbm tpr, gbm threasholds=roc curve(y test, gbm y proba[:, 1])
plt.plot(lr_fpr, lr_tpr, c='r', lw=2, label=u'lr, AUC=%.3\,f'\,\%lr_auc)
plt.plot(tr_fpr, tr_tpr, c='b', lw=2, label=u'tr, AUC=%.3f' % tr_auc)
plt.plot(forest fpr, forest tpr, c='g', lw=2, label=u' forest, AUC=%. 3f' % forest auc)
plt.plot(Gbdt fpr, Gbdt tpr, c='g', lw=2, label=u'Gbdt, AUC=%. 3f' % Gbdt auc)
plt.plot(gbm_fpr, gbm_tpr, c='y', lw=2, label=u'gbm, AUC=%.3f' % gbm_auc)
plt. plot ((0, 1), (0, 1), c=' \#a0a0a0', 1w=2, 1s='--')
plt.xlim(-0.001, 1.001)
plt.ylim(-0.001, 1.001)
plt. xticks (np. arange (0, 1.1, 0.1))
plt. yticks (np. arange (0, 1.1, 0.1))
plt.xlabel('False Positive Rate', fontsize=16)
plt.ylabel('True Positive Rate', fontsize=16)
plt.grid(b=True, ls=':')
plt.legend(loc='lower right', fancybox=True, framealpha=0.8, fontsize=12)
plt.title(u'Test ROC', fontsize=18)
fig = plt. figure (figsize=(8, 15), dpi= 600)
plt. show()
```



⟨Figure size 4800x9000 with 0 Axes⟩

## In [35]:

```
import numpy as np

cols = pocd.iloc[:, 0:-1].columns
feature_importance = gbm.feature_importances_
feature_importance = 100.0 * (feature_importance / feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5

fig = plt.figure(figsize=(2, 3), dpi= 300)

plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, cols[sorted_idx], fontsize=5)
plt.xlabel('Relative Importance', fontsize=6)
plt.title('gbm Variable Importance', fontsize=5)
plt.show();
```