bagging 减小方差； boosting 减小偏差；stacking 改进预测

In [1]:
```
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
import numpy as np
# 集成模型
from sklearn.ensemble import BaggingClassifier,RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier,GradientBoostingClassifier
from sklearn.ensemble import VotingClassifier
# 单个模型
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
# 数据集划分
from sklearn.model_selection import train_test_split
# 预处理 缺失值填充
from sklearn.impute import SimpleImputer
# 模型评价
from sklearn.metrics import accuracy_score,precision_score,\
recall_score,f1_score,fbeta_score,auc
from sklearn.metrics import precision_recall_curve, \
roc_auc_score,roc_curve,classification_report
# 可视化
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
data=pd.read_csv("d:/datasets/loan_data_set.csv")
```

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            614 non-null    object 
 1   Gender             601 non-null    object 
 2   Married            611 non-null    object 
 3   Dependents         599 non-null    object 
 4   Education          614 non-null    object 
 5   Self_Employed      582 non-null    object 
 6   ApplicantIncome    614 non-null    int64  
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         592 non-null    float64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object 
 12  Loan_Status        614 non-null    object 
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
```

In [4]:
```
data.describe()
```

Out[4]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	592.000000	600.00000	564.000000
mean	5403.459283	1621.245798	146.412162	342.00000	0.842199
std	6109.041673	2926.248369	85.587325	65.12041	0.364878
min	150.000000	0.000000	9.000000	12.00000	0.000000
25%	2877.500000	0.000000	100.000000	360.00000	1.000000
50%	3812.500000	1188.500000	128.000000	360.00000	1.000000
75%	5795.000000	2297.250000	168.000000	360.00000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000

In [5]:
```
data.isnull().sum()
```

Out[5]:
```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

In [6]:
```
data.head()
```

Out[6]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area	Loan_Status
0	LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	360.0	1.0	Urban	Y
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	360.0	1.0	Rural	N
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	360.0	1.0	Urban	Y
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	360.0	1.0	Urban	Y
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	360.0	1.0	Urban	Y

```
'Loan_ID', 'Gender', 'Married', 'Dependents', 'Education', 'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'
```

In [7]:
```
#实例化 SimpleImputer, 分别是众数与均值填充
imp_mean=SimpleImputer(missing_values=np.nan,strategy="mean")
imp_most=SimpleImputer(missing_values=np.nan,strategy="most_frequent")
#特征标签分离 (X, Y)
Y=data.Loan_Status
X=data.drop(["Loan_ID","Loan_Status"],axis=1)
#数值型特征用均值填充
X[['LoanAmount','Loan_Amount_Term', 'Credit_History']]=\
imp_mean.fit_transform(X[['LoanAmount','Loan_Amount_Term', 'Credit_History']])
#非数值型数据用众数填充
X[['Gender', 'Married', 'Dependents','Self_Employed']]=\
imp_most.fit_transform(data[['Gender','Married', 'Dependents', 'Self_Employed']])
```

```
X.info()
```

In [8]:
```
X=pd.get_dummies(X)
```

```
X
```

```
X.info()
```

In [9]:
```
Y=Y.map({"Y":1,"N":0})
X_train,X_test, y_train, y_test=train_test_split(X,Y,test_size=0.25,random_state=10)
```

In [10]:
```
model_DF=DecisionTreeClassifier(random_state=10)
model_DF.fit(X_train,y_train)
model_DF.score(X_test,y_test)
```

Out[10]: 0.7207792207792207

In [11]:
```
model_LR=LogisticRegression(random_state=2)
model_LR.fit(X_train,y_train)
model_LR.score(X_test,y_test)
```

Out[11]: 0.7922077922077922

In [12]:
```
model_svc=SVC(random_state=10)
model_svc.fit(X_train,y_train)
model_svc.score(X_test,y_test)
```

Out[12]: 0.7337662337662337

In [13]:
```
model_KNN=KNeighborsClassifier(n_neighbors=7)
model_KNN.fit(X_train,y_train)
model_KNN.score(X_test,y_test)
```

Out[13]: 0.6688311688311688

Bagging

In [14]:
```
%%time
bag_DF=BaggingClassifier(n_estimators=100,\
                         base_estimator=DecisionTreeClassifier(random_state=10),\
                         oob_score=True,random_state=10,bootstrap=True)
bag_DF.fit(X_train,y_train)
```

```
Wall time: 626 ms
```

Out[14]:
```
BaggingClassifier(base_estimator=DecisionTreeClassifier(random_state=10),
                  n_estimators=100, oob_score=True, random_state=10)
```

In [15]:
```
bag_DF.score(X_test,y_test)
```

Out[15]: 0.7597402597402597

In [16]:
```
X_pred1=bag_DF.predict(X_test)
print(classification_report(y_test,X_pred1))
```

```
              precision    recall  f1-score   support

           0       0.58      0.37      0.45        41
           1       0.80      0.90      0.85       113

    accuracy                           0.76       154
   macro avg       0.69      0.63      0.65       154
weighted avg       0.74      0.76      0.74       154
```

In [17]:
```
%%time
bag_DF.oob_score_
```

```
Wall time: 0 ns
```

Out[17]: 0.7847826086956522

In [18]:
```
y_pred_Bag=bag_DF.predict(X_test)
```

In [19]:
```
f1_score(y_test,y_pred_Bag,pos_label=0)
```

Out[19]: 0.44776119402985076

In [20]:
```
fbeta_score(y_test,y_pred_Bag,beta=100,pos_label=0)  #fbeta=1+beta*beta/(beta*beta/recall+1/precision) ,考虑哪一个指标更重要
```

Out[20]: 0.3658670425777877 4

In [ ]:
```

```

In [21]:
```
model_LR=LogisticRegression(random_state=10)
bag_LR=BaggingClassifier(n_estimators=100,base_estimator=model_LR,\
                         oob_score=True,random_state=10)
bag_LR.fit(X_train,y_train).score(X_test,y_test)
```

Out[21]: 0.7987012987012987

In [22]:
```
model_LR=LogisticRegression(class_weight="balanced",random_state=10)
bag_LR=BaggingClassifier(n_estimators=100,base_estimator=model_LR,\
                         oob_score=True,random_state=10)
bag_LR.fit(X_train,y_train)
```

Out[22]:
```
BaggingClassifier(base_estimator=LogisticRegression(class_weight='balanced',
                                                    random_state=10),
                  n_estimators=100, oob_score=True, random_state=10)
```

In [23]:
```
bag_LR.score(X_test,y_test)
```

Out[23]: 0.7792207792207793

In [24]:
```
y_pred_LR=bag_LR.predict(X_test)
```

In [25]:
```
print(classification_report(y_test,y_pred_LR))
```

```
              precision    recall  f1-score   support

           0       0.59      0.56      0.57        41
           1       0.84      0.86      0.85       113

    accuracy                           0.78       154
   macro avg       0.72      0.71      0.71       154
weighted avg       0.78      0.78      0.78       154
```

In [26]:
```
bag_svc=BaggingClassifier(n_estimators=100,\
                          base_estimator=SVC(),\
                          oob_score=True,random_state=10)
bag_svc.fit(X_train,y_train).score(X_test,y_test)
```

Out[26]: 0.7337662337662337

In [27]:
```
bag_KNN=BaggingClassifier(n_estimators=100,\
                          base_estimator=KNeighborsClassifier(),\
                          oob_score=True,random_state=10)
bag_KNN.fit(X_train,y_train).score(X_test,y_test)
```

Out[27]: 0.6493506493506493

In [ ]:
```

```

随机森林

In [28]:
```
bag_RFC=RandomForestClassifier(n_estimators=100,\
                          oob_score=True,random_state=10)
bag_RFC.fit(X_train,y_train).score(X_test,y_test)
```

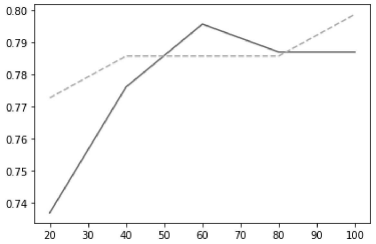
Out[28]: 0.7987012987012987

In [29]:
```
grid_n=list(range(20,101,20))
```

In [30]:
```
oob_score=[]
accuracy_score=[]
for item in grid_n:
    model=RandomForestClassifier(n_estimators=item,random_state=10,oob_score=True)
    model.fit(X_train,y_train)
    oob_score.append(model.oob_score_)
    accuracy_score.append(model.score(X_test,y_test))
    #auc_s.append(roc_auc_score(y_test, model.predict_proba(X_test)[:,1]))
```

In [31]:
```
plt.plot(grid_n,oob_score)
plt.plot(grid_n,accuracy_score,"y--")
```

Out[31]: [<matplotlib.lines.Line2D at 0x21992a04040>]



boosting

In [32]:
```
from sklearn.ensemble import AdaBoostClassifier
model_ada=AdaBoostClassifier(n_estimators=100,random_state=10,algorithm="SAMME")
model_ada.fit(X_train,y_train)
```

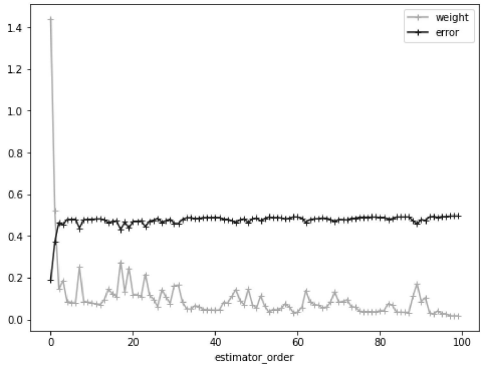
Out[32]: AdaBoostClassifier(algorithm='SAMME', n_estimators=100, random_state=10)

In [33]:
```
model_ada.score(X_test,y_test)
```

Out[33]: 0.8181818181818182

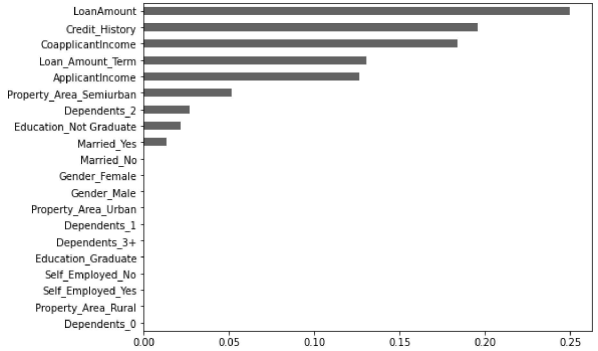
In [34]:
```
plt.figure(figsize=(8,6))
plt.plot(model_ada.estimator_weights_,"y-+",label="weight")
plt.plot(model_ada.estimator_errors_,"b-+",label="error")
plt.xlabel("estimator_order")
plt.legend()
```

Out[34]: <matplotlib.legend.Legend at 0x21992ac95b0>



In [35]:
```
plt.figure(figsize=(8,6))
pd.Series(model_ada.feature_importances_,index=X_train.columns).sort_values().plot(kind="barh")
```

Out[35]: <AxesSubplot:>

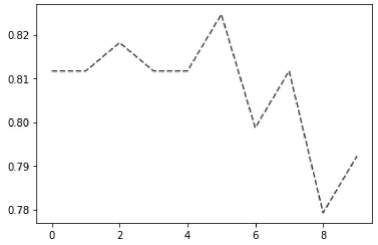


In [36]:
```
grid_rate=np.linspace(0.01,1,10)
```

In [37]:
```
error=[]
for item in grid_rate:
    model=AdaBoostClassifier(random_state=10,learning_rate=item)
    model.fit(X_train,y_train)
    error.append(model.score(X_test,y_test))
```

In [38]:
```
plt.plot(error,"r--",label="rate")
```

Out[38]:
```
[<matplotlib.lines.Line2D at 0x21992c9da30>]
```



Gradient Boosting Decision Tree

In [39]:
```
from sklearn.ensemble import GradientBoostingClassifier
```

In [40]:
```
model_gbdt=GradientBoostingClassifier(random_state=10,subsample=.7)
model_gbdt.fit(X_train,y_train)
```

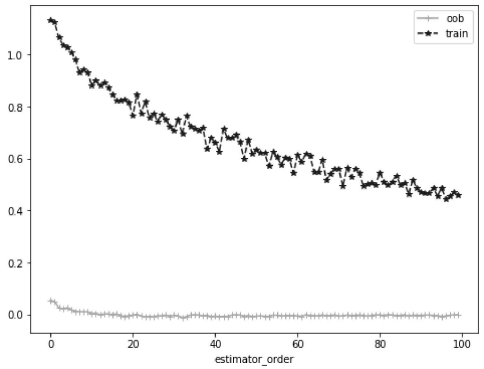
Out[40]:
```
GradientBoostingClassifier(random_state=10, subsample=0.7)
```

In [41]:
```
model_gbdt.score(X_test,y_test)
```

Out[41]:
```
0.7987012987012987
```

In [42]:
```
plt.figure(figsize=(8,6))
plt.plot(model_gbdt.oob_improvement_,"y+-",label="oob")
plt.plot(model_gbdt.train_score_,"b--*",label="train")
plt.xlabel("estimator_order")
plt.legend()
```

Out[42]:
```
<matplotlib.legend.Legend at 0x21992ce0b20>
```



VoltingClassifier 硬投票 软投票

In [43]:
```
from sklearn.ensemble import VotingClassifier
```

In [44]:
```
model_vote_hard=VotingClassifier(estimators=[("DF",model_DF),("LR",model_LR)])
model_vote_hard.fit(X_train,y_train)
```

Out[44]:
```
VotingClassifier(estimators=[('DF', DecisionTreeClassifier(random_state=10)),
                             ('LR',
                              LogisticRegression(class_weight='balanced',
                                                 random_state=10))])
```

In [45]:
```
y_pred_v_h=model_vote_hard.predict(X_test)
```

In [46]:
```
print(classification_report(y_test,y_pred_v_h))
```

```
              precision    recall  f1-score   support

           0       0.45      0.71      0.55        41
           1       0.87      0.68      0.76       113

    accuracy                           0.69       154
   macro avg       0.66      0.69      0.65       154
weighted avg       0.75      0.69      0.71       154
```

In [47]:
```
model_vote_soft=VotingClassifier(estimators=[("DF",model_DF),("LR",model_LR)],voting="soft")
model_vote_soft.fit(X_train,y_train)
```

Out[47]:
```
VotingClassifier(estimators=[('DF', DecisionTreeClassifier(random_state=10)),
                             ('LR',
                              LogisticRegression(class_weight='balanced',
                                                 random_state=10))],
                 voting='soft')
```

In [48]:
```
model_vote_soft.score(X_test,y_test)
```

Out[48]:
```
0.7207792207792207
```

In [49]:
```
best_rf=RandomForestClassifier(max_features=6,n_estimators=500,random_state=10)
best_gbdt=GradientBoostingClassifier(n_estimators=200,learning_rate=0.01,subsample=0.3,random_state=10)
model_vote_hard=VotingClassifier(estimators=[("RF",best_rf),("gbdt",best_gbdt)])
model_vote_hard.fit(X_train,y_train)
```

Out[49]:
```
VotingClassifier(estimators=[('RF',
                              RandomForestClassifier(max_features=6,
                                                     n_estimators=500,
                                                     random_state=10)),
                             ('gbdt',
                              GradientBoostingClassifier(learning_rate=0.01,
                                                         n_estimators=200,
                                                         random_state=10,
                                                         subsample=0.3))])
```

In [50]:
```
model_vote_soft.score(X_test,y_test)
```

Out[50]:
```
0.7207792207792207
```

In [51]:
```
best_rf=RandomForestClassifier(max_features=6,n_estimators=500,random_state=10)
best_gbdt=GradientBoostingClassifier(n_estimators=200,learning_rate=0.01,subsample=0.3,random_state=10)
model_vote_soft_w=VotingClassifier(estimators=[("RF",best_rf),("gbdt",best_gbdt)],voting="soft",weights=[0.76,0.73])
model_vote_soft_w.fit(X_train,y_train)
model_vote_soft_w.score(X_test,y_test)
```

Out[51]:
```
0.8116883116883117
```