Don't over fit II competition

This is my EE551 individual project. It is a playground prediction competition on Kaggle.

Exploratory Data Analysis(EDA)

Datacollection

In [5]:

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
train = pd.read_csv('dataset/train.csv')
test = pd.read_csv('dataset/test.csv')
```

In [6]:

```
train.shape
```

Out[6]:

```
(250, 302)
```

In [7]:

```
train.head()
```

Out[7]:

	id	target	0	1	2	3	4	5	6	7	...	290	291
0	0	1.0	-0.098	2.165	0.681	-0.614	1.309	-0.455	-0.236	0.276	...	0.867	1.347
1	1	0.0	1.081	-0.973	-0.383	0.326	-0.428	0.317	1.172	0.352	...	-0.165	-1.695
2	2	1.0	-0.523	-0.089	-0.348	0.148	-0.022	0.404	-0.023	-0.172	...	0.013	0.263
3	3	1.0	0.067	-0.021	0.392	-1.637	-0.446	-0.725	-1.035	0.834	...	-0.404	0.640
4	4	1.0	2.347	-0.831	0.511	-0.021	1.225	1.594	0.585	1.509	...	0.898	0.134

5 rows × 302 columns

In [8]:

```
sample_submission = pd.read_csv('sample_submission.csv')
sample_submission.head()
```

Out[8]:

	id	target
0	250	0
1	251	0
2	252	0
3	253	0
4	254	0

In [9]:

```
test.head()
```

Out[9]:

	id	0	1	2	3	4	5	6	7	8	...	290	291
0	250	0.500	-1.033	-1.595	0.309	-0.714	0.502	0.535	-0.129	-0.687	...	-0.088	-2.628
1	251	0.776	0.914	-0.494	1.347	-0.867	0.480	0.578	-0.313	0.203	...	-0.683	-0.066
2	252	1.750	0.509	-0.057	0.835	-0.476	1.428	-0.701	-2.009	-1.378	...	-0.094	0.351
3	253	-0.556	-1.855	-0.682	0.578	1.592	0.512	-1.419	0.722	0.511	...	-0.336	-0.787
4	254	0.754	-0.245	1.173	-1.623	0.009	0.370	0.781	-1.763	-1.432	...	2.184	-1.090

5 rows × 301 columns

In [10]:

```
train.tail()
```

Out[10]:

	id	target	0	1	2	3	4	5	6	7	...	290	2
245	245	0.0	-1.199	0.466	-0.908	2.771	1.631	0.931	0.182	-0.652	...	0.724	0.1
246	246	0.0	0.237	0.233	-0.380	-1.748	0.839	-0.721	-0.114	0.005	...	0.857	0.1
247	247	0.0	1.411	-1.465	0.119	0.583	1.634	-0.207	1.173	1.622	...	-0.499	-0.4
248	248	1.0	0.620	1.040	0.184	-0.570	-0.087	-0.748	-1.559	-0.553	...	0.557	-1.4
249	249	0.0	0.489	0.403	0.139	-2.046	1.345	0.122	1.255	0.647	...	-0.025	1.3

5 rows × 302 columns

In [11]:

```
train.columns
```

Out[11]:

```
Index(['id', 'target', '0', '1', '2', '3', '4', '5', '6', '7',
       ...
       '290', '291', '292', '293', '294', '295', '296', '297', '29
8', '299'],
      dtype='object', length=302)
```

In [12]:

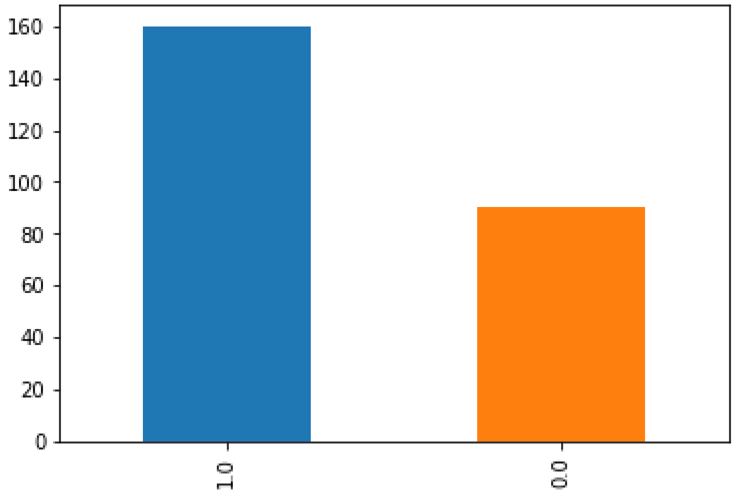
```
print(train.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 250 entries, 0 to 249
Columns: 302 entries, id to 299
dtypes: float64(301), int64(1)
memory usage: 589.9 KB
None
```

Visualization

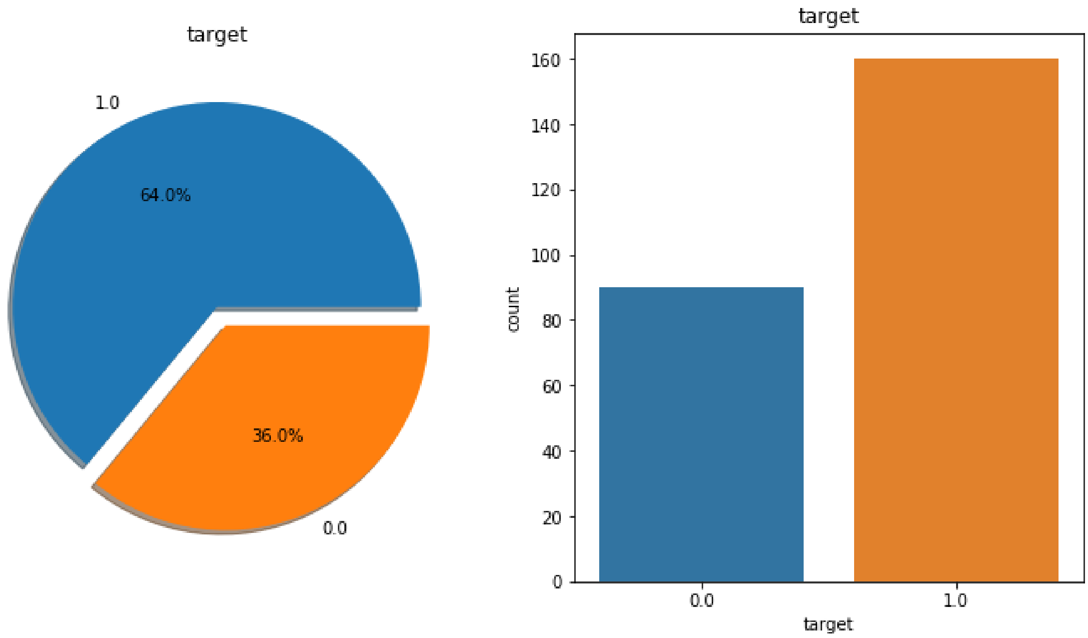
In [13]:

```
train['target'].value_counts().plot.bar();
```



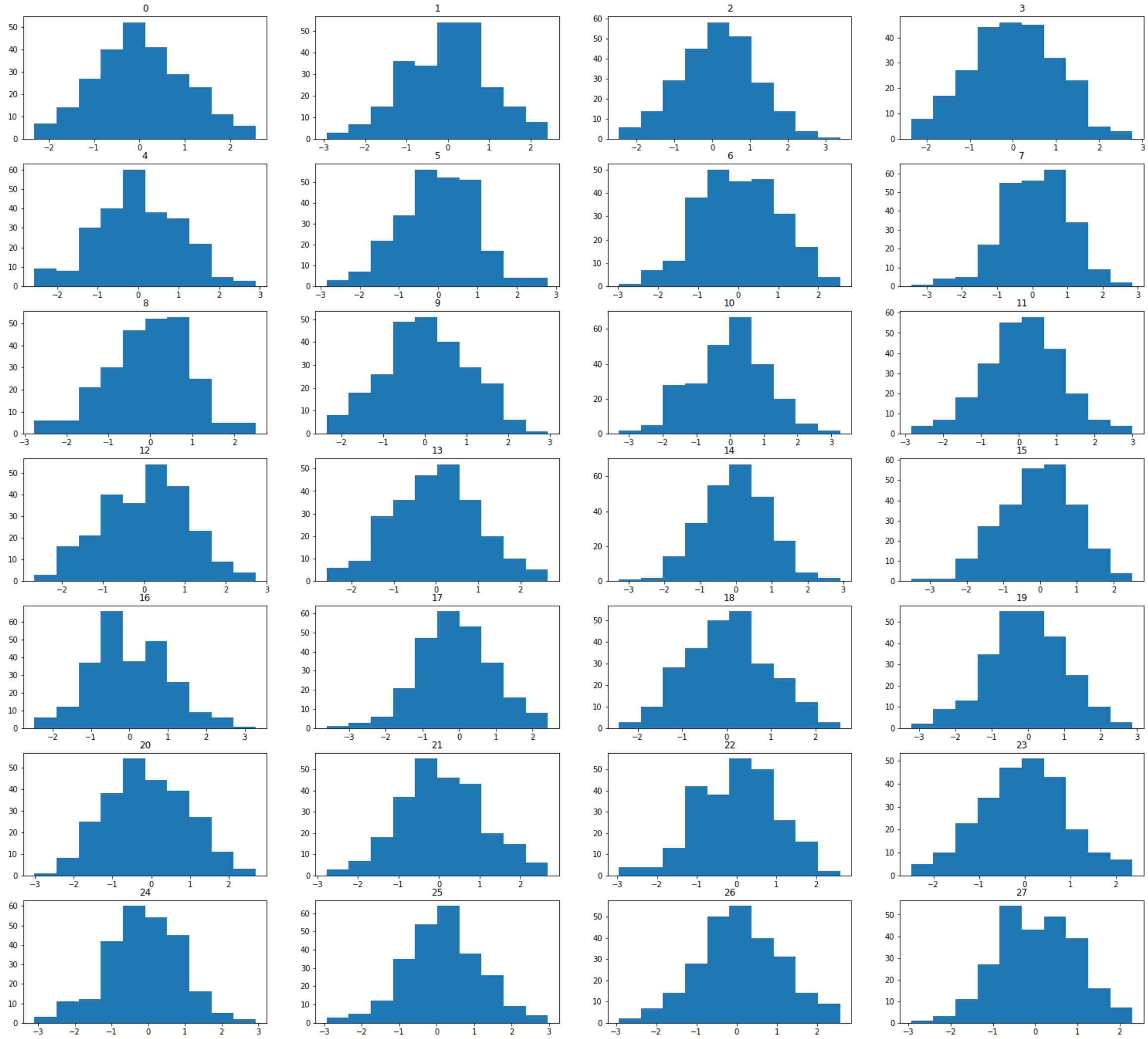
In [14]:

```
import seaborn as sns
f,ax = plt.subplots(1,2,figsize=(12,6))
train['target'].value_counts().plot.pie(explode=[0,0.1],autopct ='%1.1f%%',ax=ax
[0],shadow = True)
ax[0].set_title('target')
ax[0].set_ylabel('')
sns.countplot('target', data = train, ax = ax[1])
ax[1].set_title('target')
plt.show()
```



In [15]:

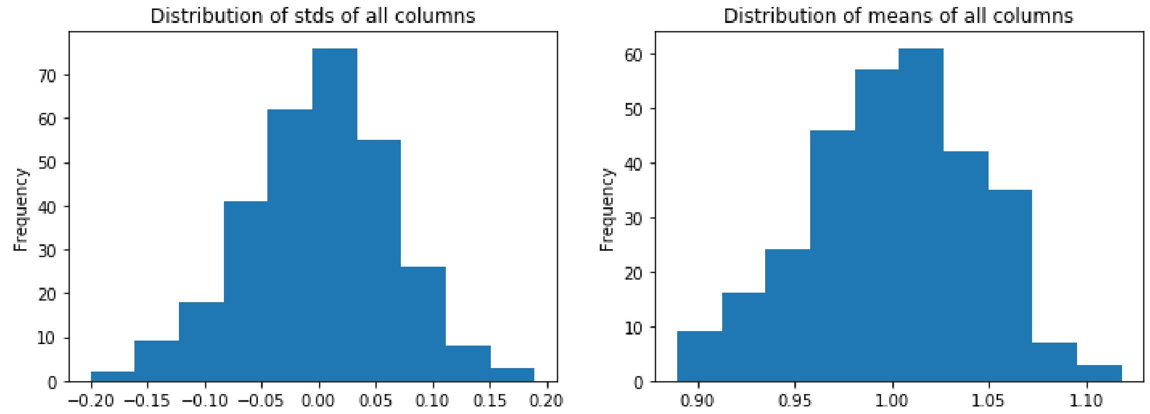
```
plt.figure(figsize = (26,24))
for i, col in enumerate(list(train.columns)[2:30]):
    plt.subplot(7, 4, i+1)
    plt.hist(train[col])
    plt.title(col)
```



Values in columns are more or less similar.

In [16]:

```
plt.figure(figsize = (12,4))
plt.subplot(1,2,1)
train[train.columns[2:]].mean().plot('hist')
plt.title('Distribution of stds of all columns')
plt.subplot(1,2,2)
train[train.columns[2:]].std().plot('hist')
plt.title('Distribution of means of all columns')
plt.show()
```



Columns have mean of 0 +/- 0.15 and std of 1 +/- 0.1.

In [17]:

```
corr = train.corr()['target'].sort_values(ascending = False)
```

In [18]:

```
corr.head(10)
```

Out[18]:

```
target    1.000000
33        0.373608
65        0.293846
24        0.173096
183       0.164146
199       0.159442
201       0.142238
30        0.132705
289       0.127213
114       0.124792
Name: target, dtype: float64
```

In [19]:

```
corr.tail(10)
```

Out[19]:

```
16    -0.144267
194   -0.150384
id    -0.151498
189   -0.155956
80    -0.162558
73    -0.167557
295   -0.170501
91    -0.192536
117   -0.197496
217   -0.207215
Name: target, dtype: float64
```

Logistic regression

In [20]:

```
from sklearn.model_selection import train_test_split, learning_curve, Stratified
KFold, KFold, cross_val_score, GridSearchCV, RepeatedStratifiedKFold
from sklearn.preprocessing import StandardScaler
X_train = train.drop(['id', 'target'], axis = 1)
y_train = train['target']
X_test = test.drop(['id'], axis = 1)
```

Find the best parameters for function 'LogisticRegression'.

In [21]:

```
from sklearn.linear_model import LogisticRegression
log = LogisticRegression(penalty = 'l1', random_state = 42)
params = {'solver': ['liblinear', 'saga'],
         'C': [0.001, 0.1, 1, 10, 50],
         'tol': [0.00001,  0.0001, 0.001, 0.005],
         'class_weight': ['balanced', None]}
log_gs = GridSearchCV(log, params, cv = StratifiedKFold(n_splits = 5), verbose =
1, n_jobs = -1, scoring = 'roc_auc')

log_gs.fit(X_train, y_train)

log_best = log_gs.best_estimator_

print(log_best)
print(log_gs.best_score_)
```

```
Fitting 5 folds for each of 80 candidates, totalling 400 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent w
orkers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    2.4s

LogisticRegression(C=1, class_weight=None, dual=False, fit_intercept
=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l1', random_state=42, solver='liblin
ear',
          tol=1e-05, verbose=0, warm_start=False)
0.8177083333333334

[Parallel(n_jobs=-1)]: Done 400 out of 400 | elapsed:    5.4s finish
ed
```

Define a function to plot learning curve.

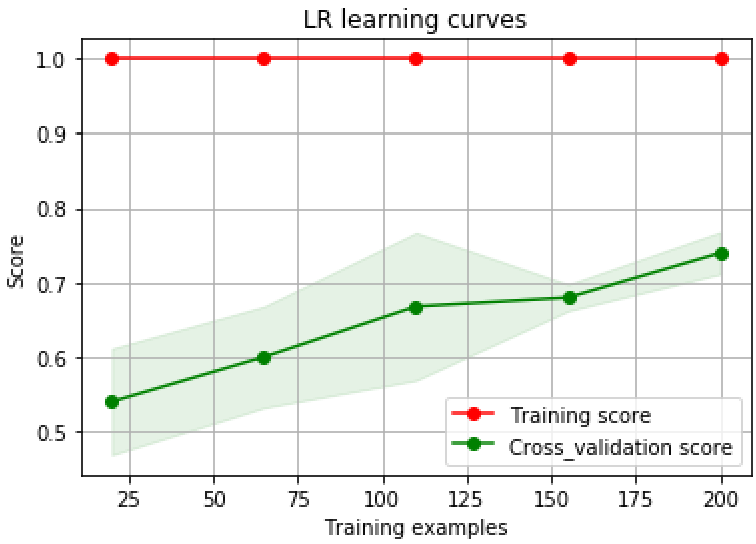
In [22]:

```
def plot_learning_curve(estimator, title, X, y, ylim = None, cv = None, n_jobs =
-1, train_sizes = np.linspace(.1, 1.0, 5)):
    plt.figure()
    plt.title(title)
    if ylim is not None:
        plt.ylim(*ylim)
    plt.xlabel("Training examples")
    plt.ylabel("Score")
    train_sizes, train_scores, test_scores = learning_curve(estimator, X_train,
y_train, cv = cv, n_jobs = -1, train_sizes = np.linspace(.1, 1.0, 5))
    train_scores_mean = np.mean(train_scores, axis = 1)
    train_scores_std = np.std(train_scores, axis = 1)
    test_scores_mean = np.mean(test_scores, axis = 1)
    test_scores_std = np.std(test_scores, axis = 1)
    plt.grid()
    plt.fill_between(train_sizes, train_scores_mean-train_scores_std, train_scor
es_mean+train_scores_std, alpha = 0.1,color = 'r')
    plt.fill_between(train_sizes, test_scores_mean-test_scores_std, test_scores_
mean+test_scores_std, alpha = 0.1,color = 'g')
    plt.plot(train_sizes, train_scores_mean, 'o-', color = 'r',label = "Training
score")
    plt.plot(train_sizes, test_scores_mean, 'o-', color = 'g',label = "Cross_val
idation score")
    plt.legend(loc = 'best')
    return plt
```

Plot the learning curve of log_best.

In [23]:

```
learningCurve = plot_learning_curve(log_best, "LR learning curves",X_train, y_tr
ain, cv = StratifiedKFold(n_splits = 5))
```



Define a function to draw roc curve.

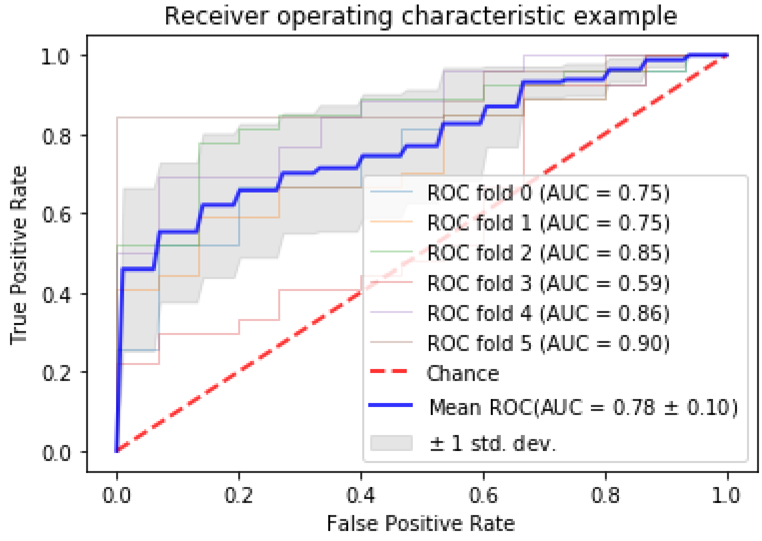
In [24]:

```
from sklearn.metrics import confusion_matrix, classification_report, roc_curve,
auc
from scipy import interp
def plot_roc(clf, X = X_train, y = y_train, n = 6):
    tprs = []
    aucs = []
    mean_fpr = np.linspace(0,1,100)
    i = 0
    classifier = clf
    cv = StratifiedKFold(n_splits = n)
    for train, test in cv.split(X,y):
        probas_ = classifier.fit(X.iloc[train], y.iloc[train]).predict_proba(X.i
loc[test])
        fpr, tpr, thresholds = roc_curve(y[test], probas_[:, 1])
        tprs.append(interp(mean_fpr, fpr, tpr))
        tprs[-1][0] = 0.0
        roc_auc = auc(fpr,tpr)
        aucs.append(roc_auc)
        plt.plot(fpr, tpr, lw = 1, alpha = 0.3, label = 'ROC fold %d (AUC = %0.2
f)' % (i, roc_auc))
        i += 1
    plt.plot([0, 1], [0, 1], linestyle = '--', lw =2, color = 'r', label = 'Chan
ce', alpha =.8)
    mean_tpr = np.mean(tprs, axis = 0)
    mean_tpr[-1] = 1.0
    mean_auc = auc(mean_fpr, mean_tpr)
    std_auc = np.std(aucs)
    plt.plot(mean_fpr, mean_tpr, color = 'b', label = r'Mean ROC(AUC = %0.2f $\p
m$ %0.2f)' % (mean_auc, std_auc), lw =2, alpha = .8)
    std_tpr = np.std(tprs, axis = 0)
    tprs_upper = np.minimum(mean_tpr + std_tpr,1)
    tprs_lower = np.maximum(mean_tpr - std_tpr,0)
    plt.fill_between(mean_fpr, tprs_lower, tprs_upper, color ='grey', alpha = 0.
2, label = r'$\pm$ 1 std. dev.')
    plt.xlim([-0.05, 1.05])
    plt.ylim([-0.05, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic example')
    plt.legend(loc = 'lower right')
    plt.show()
```

Plot the roc curve of log_best.

In [25]:

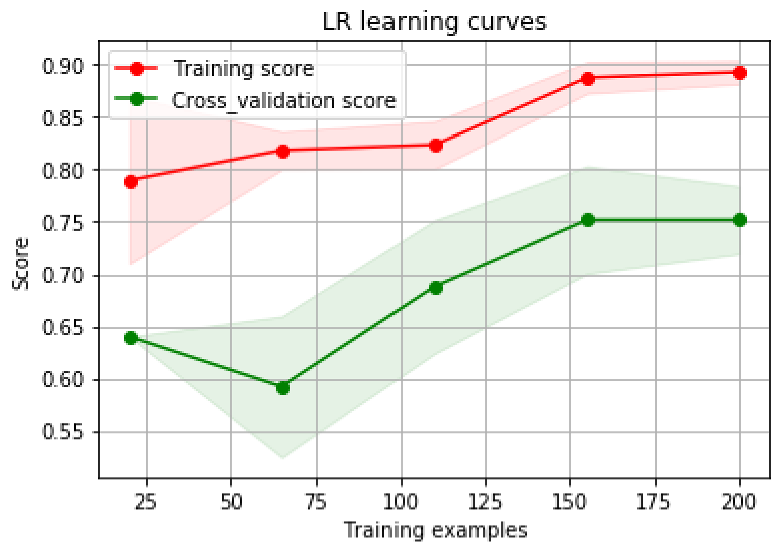
```
roc = plot_roc(log_best)
```



cv_score is far away from training score. It is overfitting. C is responsible for level of regularization and the smaller it is, the bigger the level of regularization it is. First try C = 0.1

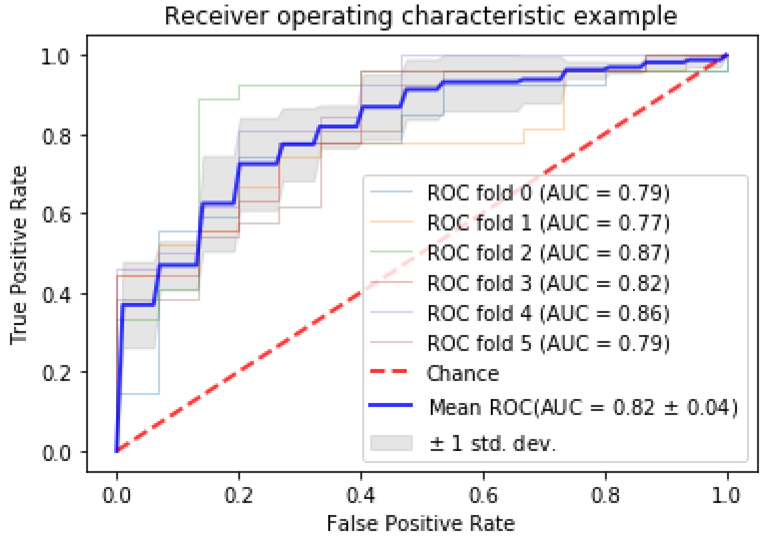
In [26]:

```
log_p0 = LogisticRegression(class_weight = 'balanced', penalty = 'l1', C = 0.1,
solver = 'saga', random_state = 42)
learningCurve0 = plot_learning_curve(log_p0, "LR learning curves", X_train, y_tr
ain, cv = StratifiedKFold(n_splits = 5))
```



In [27]:

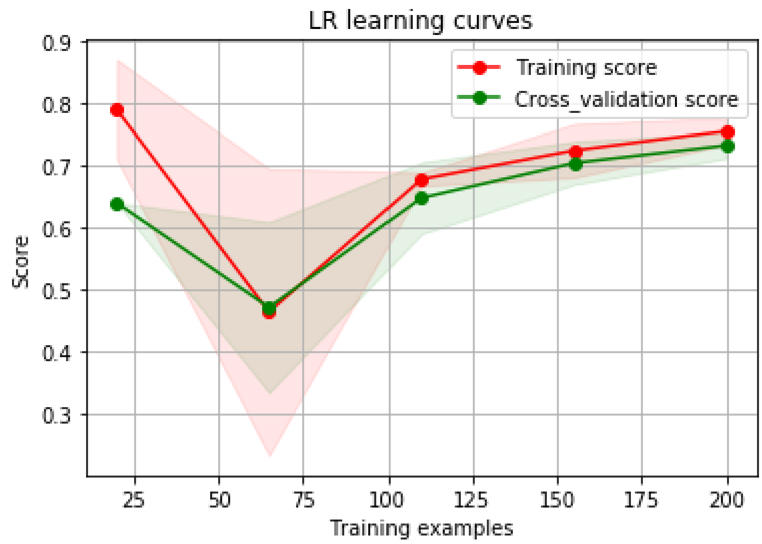
```
roc0 = plot_roc(log_p0)
```



Try C = 0.05.

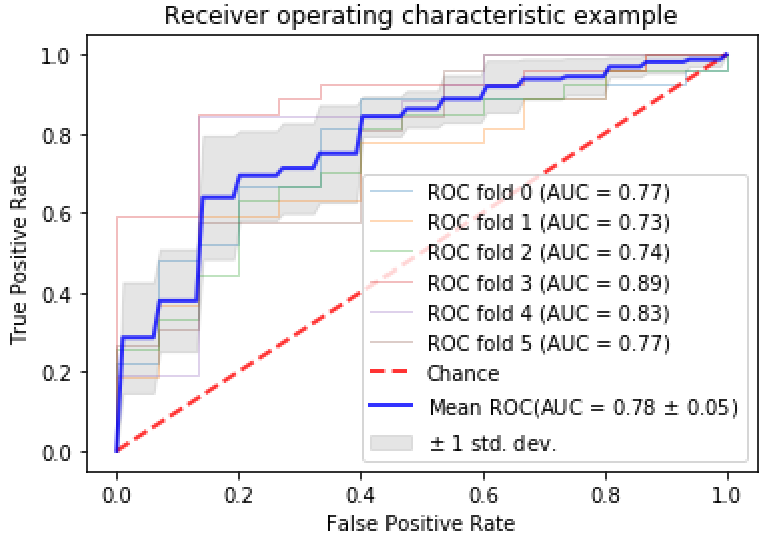
In [28]:

```
log_p1 = LogisticRegression(class_weight = 'balanced', penalty = 'l1', C = 0.05,
solver = 'saga', random_state = 42)
learningCurve1 = plot_learning_curve(log_p1, "LR learning curves", X_train, y_tr
ain, cv = StratifiedKFold(n_splits = 5))
```



In [29]:

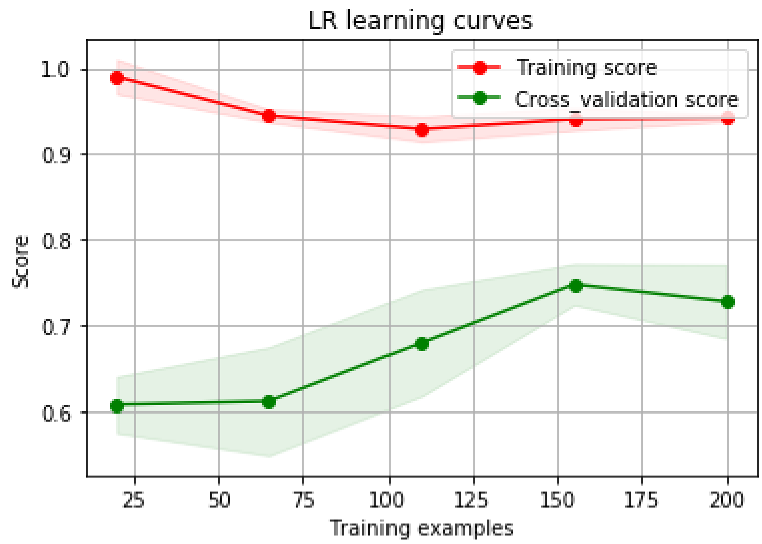
```
roc1 = plot_roc(log_p1)
```



Try C = 0.15.

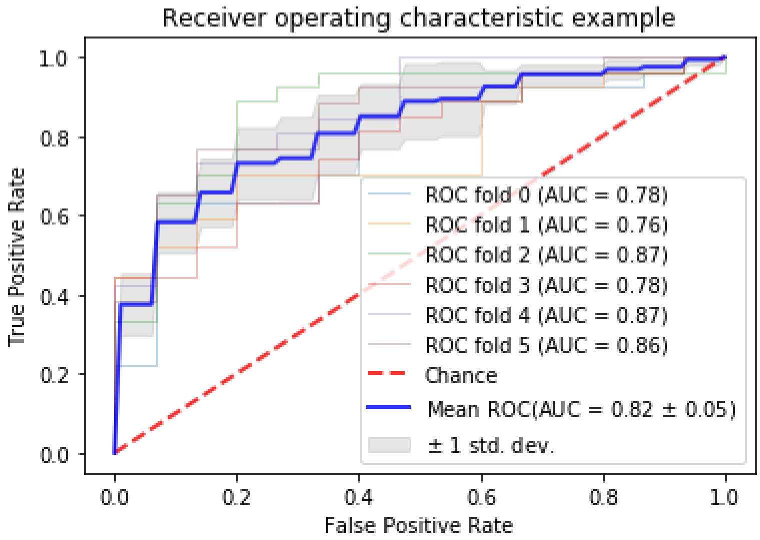
In [30]:

```
log_p2 = LogisticRegression(class_weight = 'balanced', penalty = 'l1', C = 0.15,
solver = 'saga', random_state = 42)
learningCurve2 = plot_learning_curve(log_p2, "LR learning curves", X_train, y_tr
ain, cv = StratifiedKFold(n_splits = 5))
```



In [31]:

```
roc2 = plot_roc(log_p2)
```



It seems like that when C = 0.1, the model performs best.

Output the first submission file.

In [32]:

```
log_p0.fit(X_train, y_train)
log_pred0 = log_p0.predict_proba(X_test)[:,1]
submission0 = pd.DataFrame({'id':test['id'],
                           'target':log_pred0})
submission0.to_csv('submissions/submission0.csv', index = False)
```

Feature Selection

Use eli5 to do the feature selection.

In [33]:

```
import eli5
eli5.show_weights(log_p0,top = 50)
```

Out[33]:

y=1.0 top features

Weight?	Feature
+0.713	x33
+0.491	x65
+0.370	<BIAS>
+0.229	x199
+0.070	x101
+0.032	x226
+0.028	x24
+0.026	x176
+0.015	x30
+0.014	x17
+0.013	x201
+0.006	x183
-0.001	x209
-0.008	x156
-0.020	x239
-0.022	x180
-0.024	x252
-0.030	x4
-0.030	x237
-0.034	x288
-0.037	x276
-0.039	x127
-0.050	x90
-0.055	x227
-0.055	x165
-0.065	x134
-0.069	x82
-0.076	x298
-0.084	x43
-0.096	x16
-0.096	x133
-0.108	x80
-0.109	x108
-0.109	x194
-0.115	x189
-0.117	x258
-0.165	x295
-0.196	x73
-0.196	x117
-0.281	x91
-0.304	x217

In [34]:

```
(log_p0.coef_ != 0).sum()
```

Out[34]:

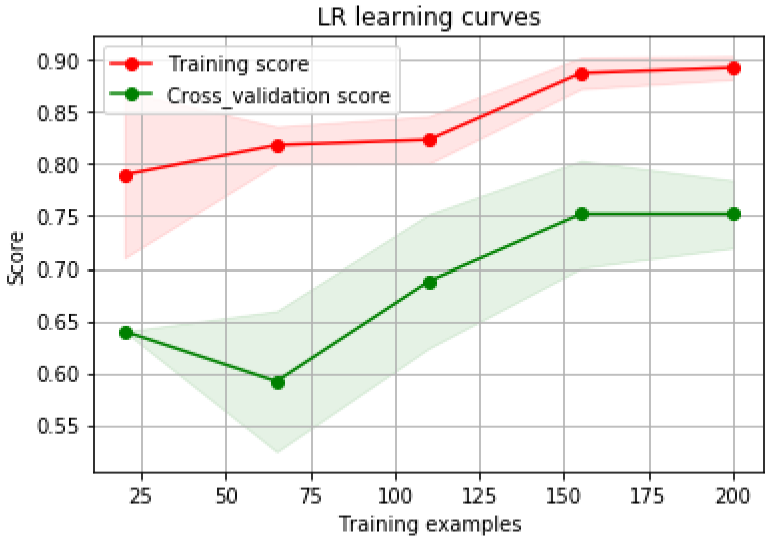
```
40
```

In [35]:

```
top_features = [i[1:] for i in eli5.formatters.as_dataframe.explain_weights_df(l
og_p0).feature if 'BIAS' not in i]
X_train_new = train[top_features]
```

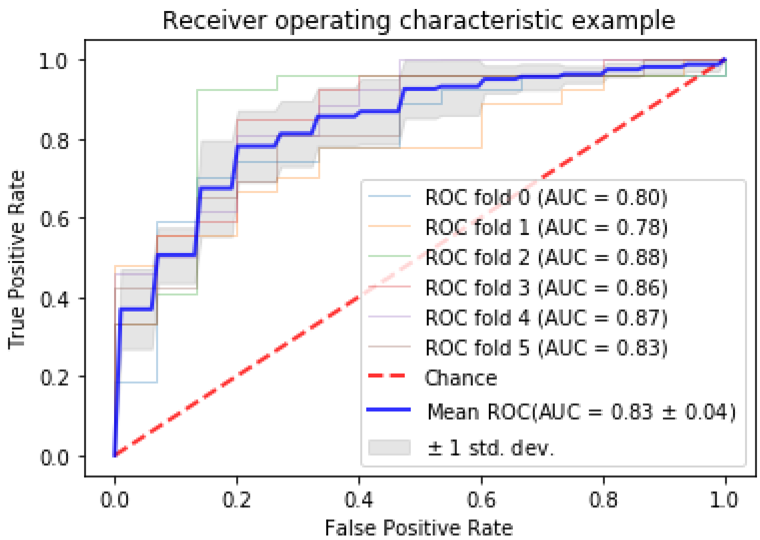
In [36]:

```
learningCurve3 = plot_learning_curve(log_p0, "LR learning curves", X_train_new,
y_train, cv = StratifiedKFold(n_splits = 5))
```



In [37]:

```
roc3 = plot_roc(log_p0,X_train_new)
```



In [38]:

```
log_p0.fit(X_train_new, y_train)
X_test_new = test[top_features]
log_pred3 = log_p0.predict_proba(X_test_new)[:,1]
submission1 = pd.DataFrame({'id':test['id'],
                            'target':log_pred3})
submission1.to_csv('submissions/submission1.csv', index = False)
```

In [39]:

```
X_test_new.head()
```

Out[39]:

	33	65	199	101	226	24	176	30	17	201	...	80	10
0	1.988	-1.010	-0.298	1.464	0.540	0.183	-1.283	-1.003	0.764	-0.488	...	1.198	-0.63
1	0.543	-0.781	0.961	-0.981	0.476	0.475	-0.670	1.077	-2.107	-0.426	...	-0.421	0.64
2	-1.191	-0.529	0.329	0.266	-0.751	0.427	-1.331	-0.036	-1.039	-0.847	...	-1.030	1.1
3	0.542	0.754	-0.336	0.321	-1.386	0.173	-1.506	-0.374	0.857	-1.032	...	0.560	-1.87
4	0.635	-1.210	-2.235	-0.174	-1.592	1.130	2.212	0.794	0.006	1.718	...	-3.389	0.39

5 rows × 40 columns

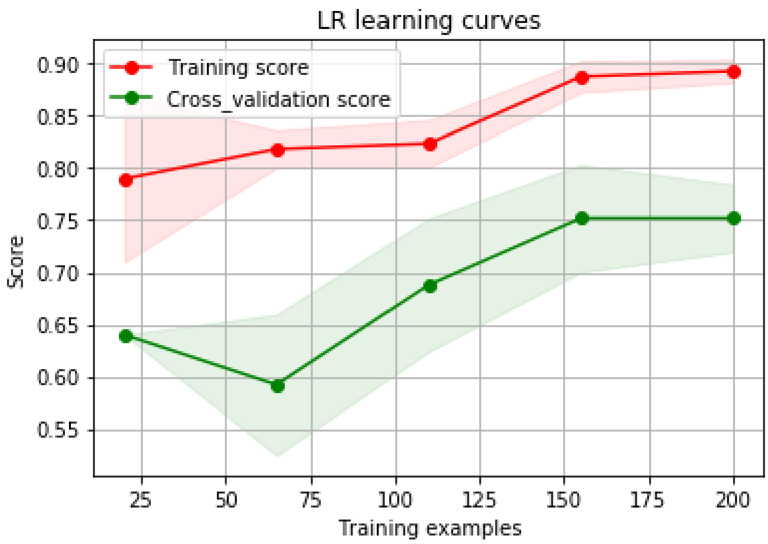
Add new statistics.

In [40]:

```
train['mean'] = train.mean(1)
train['std'] = train.std(1)
test['mean'] = test.mean(1)
test['std'] = test.std(1)
X_train_add = train[top_features + ['mean']]
X_test_add = test[top_features + ['mean']]
```

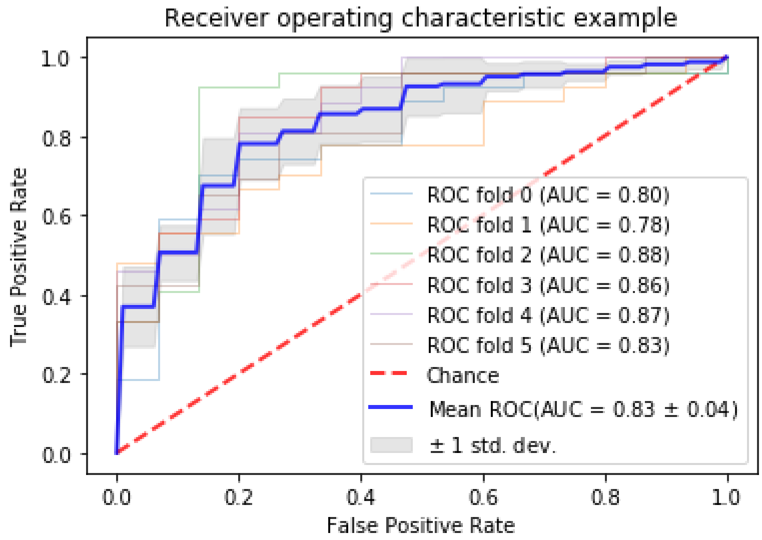
In [41]:

```
learningCurve4 = plot_learning_curve(log_p0, "LR learning curves", X_train_add,
y_train, cv = StratifiedKFold(n_splits = 5))
```



In [42]:

```
roc4 = plot_roc(log_p0,X_train_add)
```



In [43]:

```
log_p0.fit(X_train_add, y_train)
log_pred4 = log_p0.predict_proba(X_test_add)[:,1]
submission2 = pd.DataFrame({'id':test['id'],
                            'target':log_pred4})
submission2.to_csv('submissions/submission2.csv', index = False)
```

Decison Tree

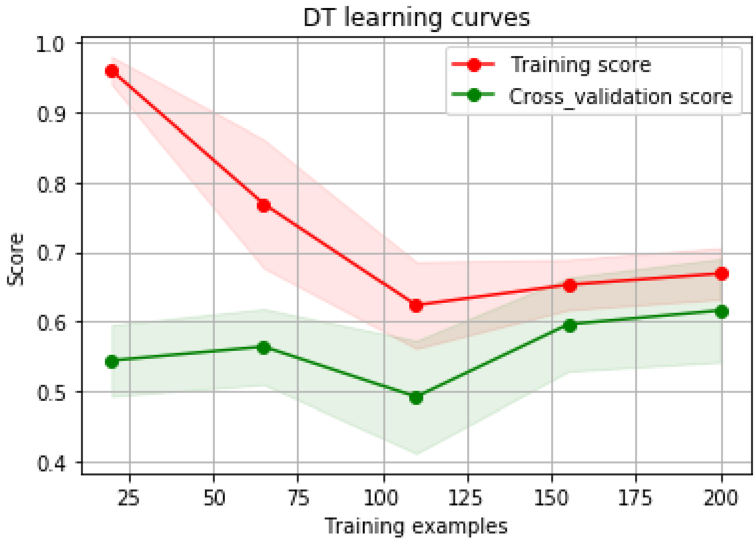
In [44]:

```
from sklearn.tree import DecisionTreeClassifier
X_train = train.drop(['id', 'target'], axis = 1)
y_train = train['target']
X_test = test.drop(['id'], axis = 1)
tree = DecisionTreeClassifier()
params = {'criterion':['gini','entropy'],
          'max_depth':[1,3,5,7,10],
         'class_weight': ['balanced', None]}
trees = GridSearchCV(tree, params, cv = StratifiedKFold(n_splits = 5), verbose = 
1, n_jobs = -1, scoring = 'roc_auc')

trees.fit(X_train, y_train)

tree_best = trees.best_estimator_

print(tree_best)
print(trees.best_score_)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent w
orkers.

DecisionTreeClassifier(class_weight='balanced', criterion='gini', ma
x_depth=1,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_stat
e=None,
            splitter='best')
0.634375

[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:    0.6s finish
ed
```

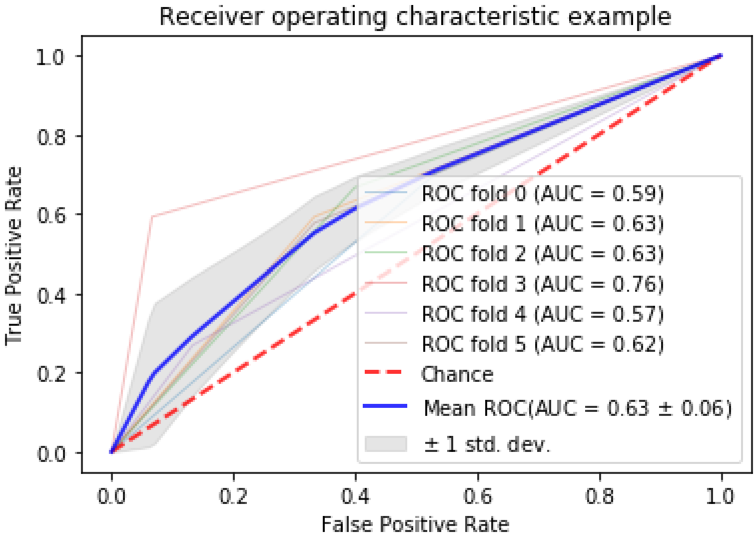
In [45]:

```
learningCurve5 = plot_learning_curve(tree_best, "DT learning curves", X_train_ad
d, y_train, cv = StratifiedKFold(n_splits = 5))
```



In [46]:

```
roc5 = plot_roc(tree_best,X_train_add)
```



Decision tree is not suitable for this dataset.

Lasso Regression

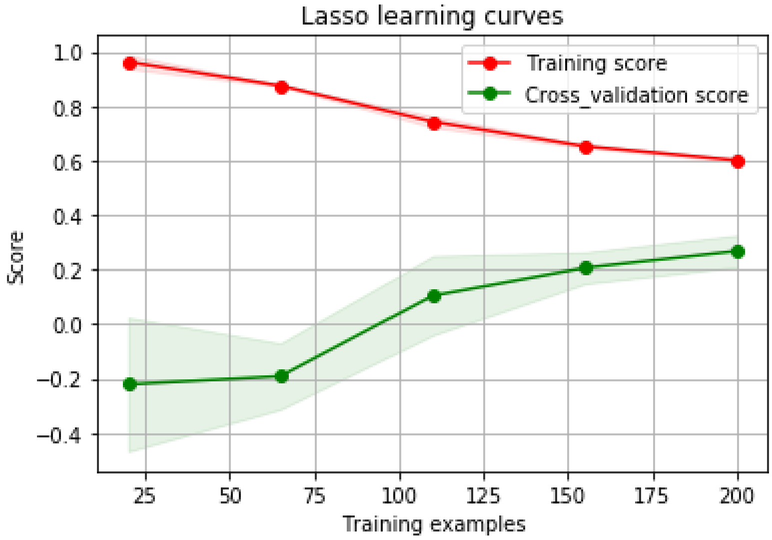
In [47]:

```
from sklearn.linear_model import Lasso
X_train = train.drop(['id', 'target'], axis = 1)
y_train = train['target']
X_test = test.drop(['id'], axis = 1)
las = Lasso(alpha=0.031, tol=0.01, random_state=42, selection='random')

params = {
            'alpha' : [0.022, 0.021, 0.02, 0.019, 0.023, 0.024, 0.025, 0.026, 0.
027, 0.029, 0.031],
            'tol'   : [0.0013, 0.0014, 0.001, 0.0015, 0.0011, 0.0012, 0.0016, 0.
0017]
        }
las_ss = GridSearchCV(las, params, cv = StratifiedKFold(n_splits = 5), verbose =
1, n_jobs = -1, scoring = 'roc_auc')

las_ss.fit(X_train, y_train)

las_best = las_ss.best_estimator_

print(las_ss)
print(las_ss.best_score_)
```

```
Fitting 5 folds for each of 88 candidates, totalling 440 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent w
orkers.

GridSearchCV(cv=StratifiedKFold(n_splits=5, random_state=None, shuff
le=False),
       error_score='raise-deprecating',
       estimator=Lasso(alpha=0.031, copy_X=True, fit_intercept=True,
max_iter=1000,
   normalize=False, positive=False, precompute=False, random_state=4
2,
   selection='random', tol=0.01, warm_start=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid={'alpha': [0.022, 0.021, 0.02, 0.019, 0.023, 0.02
4, 0.025, 0.026, 0.027, 0.029, 0.031], 'tol': [0.0013, 0.0014, 0.00
1, 0.0015, 0.0011, 0.0012, 0.0016, 0.0017]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='war
n',
       scoring='roc_auc', verbose=1)
0.8350694444444444

[Parallel(n_jobs=-1)]: Done 440 out of 440 | elapsed:    0.6s finish
ed
```

In [48]:

```
learningCurve6 = plot_learning_curve(las_best, "Lasso learning curves", X_train,
y_train, cv = StratifiedKFold(n_splits = 5))
```

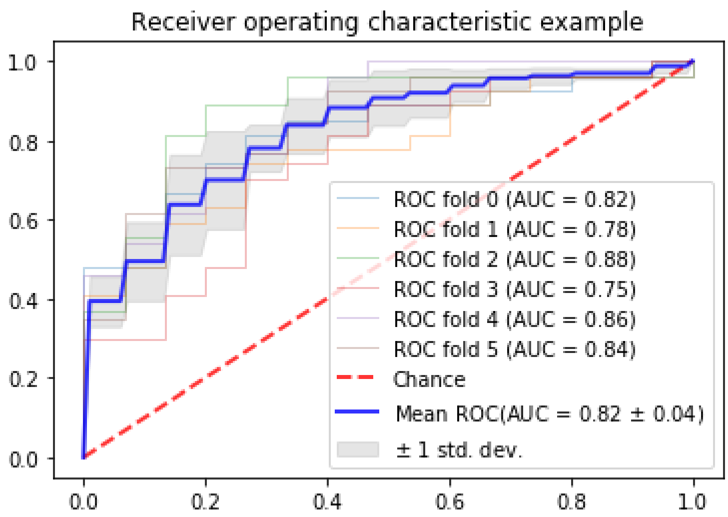


In [49]:

```
def plot_roc0(clf, X = X_train, y = y_train, n = 6):
    tprs = []
    aucs = []
    mean_fpr = np.linspace(0, 1, 100)
    i = 0
    classifier = clf
    cv = StratifiedKFold(n_splits = n)
    for train, test in cv.split(X,y):
        probas_ = classifier.fit(X.iloc[train], y.iloc[train]).predict(X.iloc[te
st])
        fpr, tpr, thresholds = roc_curve(y[test], probas_)
        tprs.append(interp(mean_fpr, fpr, tpr))
        tprs[-1][0] = 0.0
        roc_auc = auc(fpr,tpr)
        aucs.append(roc_auc)
        plt.plot(fpr, tpr, lw = 1, alpha = 0.3, label = 'ROC fold %d (AUC = %0.2
f)' % (i, roc_auc))
        i += 1
    plt.plot([0, 1], [0, 1], linestyle = '--', lw =2, color = 'r', label = 'Chan
ce', alpha =.8)
    mean_tpr = np.mean(tprs, axis = 0)
    mean_tpr[-1] = 1.0
    mean_auc = auc(mean_fpr, mean_tpr)
    std_auc = np.std(aucs)
    plt.plot(mean_fpr, mean_tpr, color = 'b', label = r'Mean ROC(AUC = %0.2f $\p
m$ %0.2f)' % (mean_auc, std_auc), lw =2, alpha = .8)
    std_tpr = np.std(tprs, axis = 0)
    tprs_upper = np.minimum(mean_tpr + std_tpr,1)
    tprs_lower = np.maximum(mean_tpr - std_tpr,0)
    plt.fill_between(mean_fpr, tprs_lower, tprs_upper, color ='grey', alpha = 0.
2, label = r'$\pm$ 1 std. dev.')
    plt.title('Receiver operating characteristic example')
    plt.legend(loc = 'lower right')
    plt.show()
```

In [50]:

```
roc6 = plot_roc0(las_best,X_train)
```



In [51]:

```
las_best.fit(X_train_add, y_train)
las_best_pred = las_best.predict(X_test_add)
submission3 = pd.DataFrame({'id':test['id'],
                           'target':las_best_pred})
submission3.to_csv('submissions/submission3.csv', index = False)
```

In [ ]:

```

```