In [1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import roc_auc_score
import statsmodels.api as sm
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score, cross_validate, train_test_split
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import precision_recall_curve, average_precision_score
%matplotlib inline
```

In [2]:
```
# Считает джини фактора или предсказаний
def gini(y_true, y_score):
    roc_score = roc_auc_score(y_true, y_score)
    return roc_score*2 - 1

def gini_scorrer(clf, X, y):
    y_score= [p[1] for p in clf.predict_proba(X)]
    return gini(y, y_score)


def get_factors_gini(data, target):
    factors_gini = list()
    for c in data.columns:
        g = gini(data[target], data[c])
        factors_gini.append([c,g])
    factors_gini = sorted(factors_gini, key = lambda x: x[1])
    return factors_gini

def get_base_line_score(data, target):
    rf = RandomForestClassifier()
    cv_score = cross_val_score(rf, X = data.drop([target], axis=1), y=data[target], scoring=gini_scorrer, cv=
    return cv_score

def get_feature_importance(data, target):
    rf = RandomForestClassifier()
    rf.fit(X = data.drop([target], axis=1), y= data[target])
    return sorted([[v,i] for v,i in zip(data.drop([target], axis=1).columns, rf.feature_importances_)], key=l

def show_corr(data, th=None):
    if th:
        sns.heatmap(data.corr()>th)
    else:
        sns.heatmap(data.corr())

# Вычисление VIF
def vif(data):
    """
    Calculate VIFs
    :param data: Data
    :return: List of VIFs for each variable in format: Variable - VIF
    """
    res = list()
    for i in range(data.shape[1]):
        res.append([data.columns[i], variance_inflation_factor(data.as_matrix(), i)])
    return res

def rocs(y_true, y_pred, colors, names, name=''):
    ''' Plot several ROC curves

     Keyword arguments:
     y_true -- array of true values arrays
     y_pred -- array of predicted values arrays
     colors -- array of colors for curves
     names -- array of names for curves
     name -- name of graph (default empty string)
     '''
    if (len(y_true) != len(y_pred)) or (len(y_true) != len(colors)):
        print(len(y_true), len(y_pred), len(colors))
        raise BaseException
    plt.figure(figsize=[10, 10])
    ginis = []

    for i in range(0, len(y_true)):
        fpr, tpr, _ = roc_curve(y_true=y_true[i], y_score=y_pred[i], pos_label=None)
        gini_value = gini(y_true=y_true[i], y_score=y_pred[i])
        ginis.append(gini_value)
        plt.plot(fpr, tpr, color=colors[i], label=names[i] + ' (Gini = %0.4f)' % gini_value)

    plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')

    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.0])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic ' + name)
    plt.legend(loc="lower right")
    plt.show()

def pr_curves(y_true, y_pred, colors, names, name=''):
    ''' Plot several PR curves
     Keyword arguments:
     y_true -- array of true values arrays
     y_pred -- array of predicted values arrays
     colors -- array of colors for curves
     names -- array of names for curves
     name -- name of graph (default empty string)
     '''
```

```
    plt.figure(figsize=[10, 10])

    for i in range(0, len(y_true)):
        precision, recall, thresholds = precision_recall_curve(y_true=y_true[i], probas_pred=y_pred[i])
        avg = average_precision_score(y_true[i], y_pred[i])
        plt.plot(recall, precision, lw=1.5, color=colors[i], label=names[i] + ' AUC={0:0.4f}'.format(avg))
    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.ylim([0.0, 1.05])
    plt.xlim([0.0, 1.0])
    plt.legend(loc="upper right")
    plt.show()
```

In [3]:
```
rename_dict = {0: 'prescreaning',
 1:'MA1', 2:'MA2', 3:'MA3', 4:'MA4', 5:'MA5', 6:'MA6',
 7:'MAN1', 8:'MAN2', 9:'MAN3', 10:'MAN4', 11:'MAN5', 12:'MAN6', 13:'MAN7', 14:'MAN8',
 15: 'ED', 16: 'D', 17: 'AMFM', 18: 'label'
}
```

In [4]:
```
retinopathy = pd.read_excel('retinopathy.xlsx', sheet_name=1, header=None)
data = retinopathy.rename(rename_dict, axis=1)
```

In [5]:
```
len(data.columns)
```

Out[5]:
```
19
```

Base line

In [6]:
```
get_base_line_score(data, 'label')
```

```
c:\users\xiaomi\appdata\local\programs\python\python37\lib\site-packages\sklearn\ensemble\forest.py:245: FutureWarning: The default value of n_estimators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
c:\users\xiaomi\appdata\local\programs\python\python37\lib\site-packages\sklearn\ensemble\forest.py:245: FutureWarning: The default value of n_estimators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
c:\users\xiaomi\appdata\local\programs\python\python37\lib\site-packages\sklearn\ensemble\forest.py:245: FutureWarning: The default value of n_estimators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

Out[6]:
```
array([0.42545733, 0.43578158, 0.41600708])
```

In [7]:
```
get_feature_importance(data, 'label')
```

```
c:\users\xiaomi\appdata\local\programs\python\python37\lib\site-packages\sklearn\ensemble\forest.py:245: FutureWarning: The default value of n_estimators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

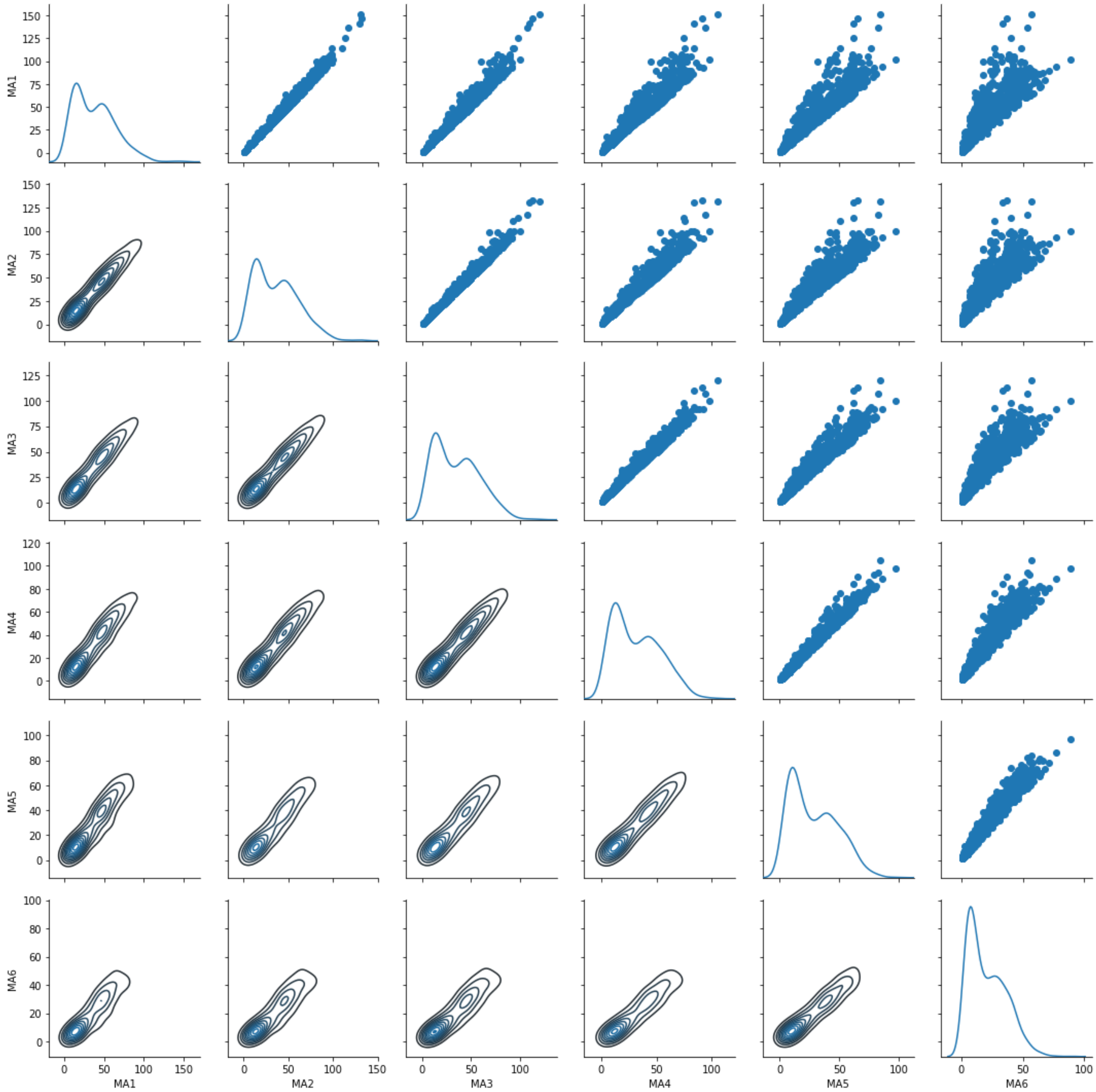
Out[7]:
```
[['MA1', 0.09779023323734454],
 ['MAN1', 0.09035458154793066],
 ['MAN3', 0.07979423015860702],
 ['ED', 0.0719682894638727],
 ['MAN2', 0.06931311572511288],
 ['D', 0.06383256044214967],
 ['MAN4', 0.062322423193816597],
 ['MAN7', 0.06179950175953459],
 ['MA3', 0.05693749767958459],
 ['MA2', 0.05652083100143793],
 ['MAN5', 0.05445902180296812],
 ['MA6', 0.05352262382372688 4],
 ['MA5', 0.04684100424418835],
 ['MA4', 0.04508688549940245],
 ['MAN6', 0.04391757534699079],
 ['MAN8', 0.03131866020755311],
 ['AMFM', 0.008157684571393584],
 ['prescreaning', 0.006063280294385651]]
```

Анализ переменных

Распределение

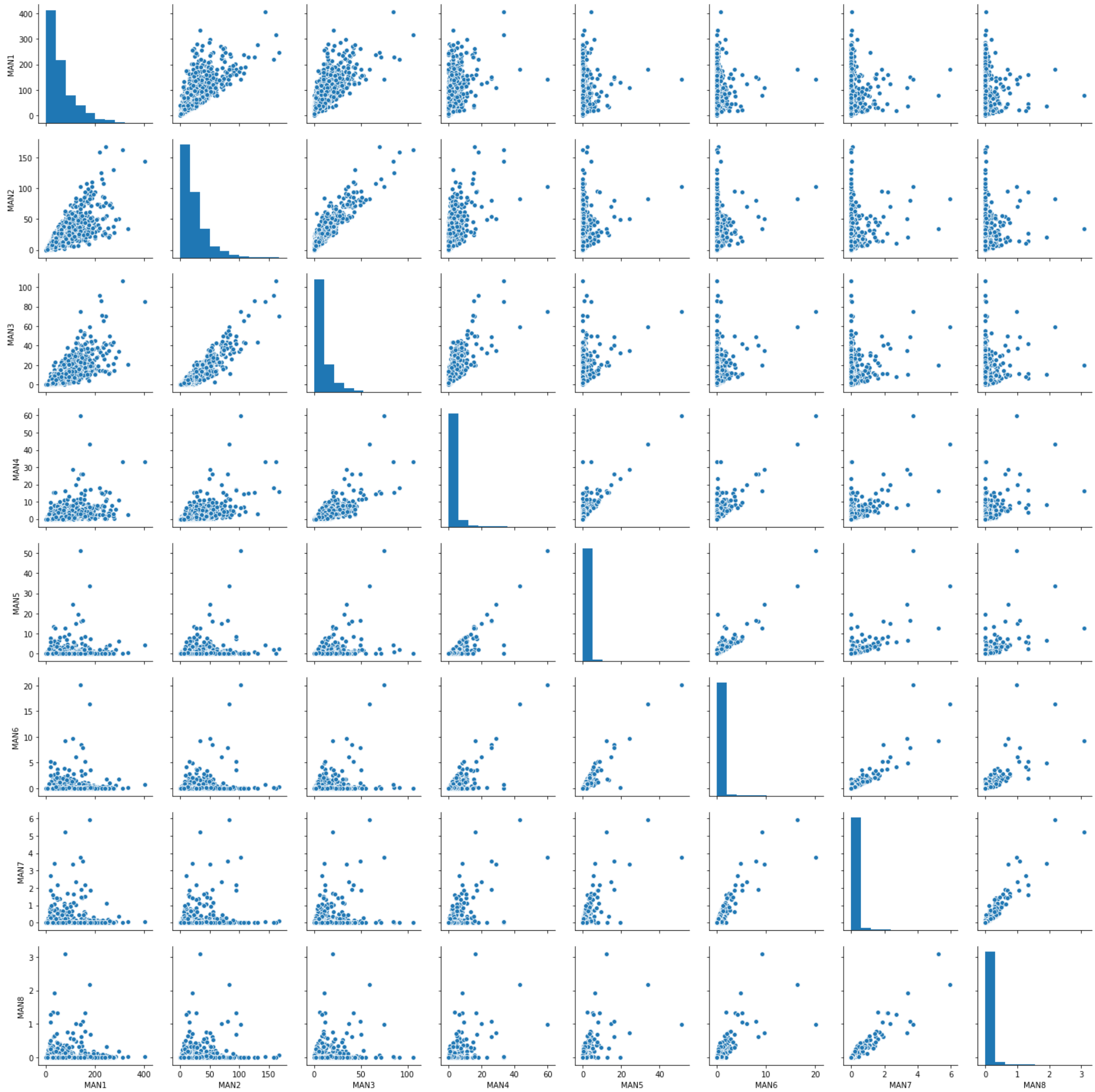
In [8]:
```
g = sns.PairGrid(data[['MA1', 'MA2', 'MA3', 'MA4', 'MA5', 'MA6']])
g.map_diag(sns.kdeplot)
g.map_upper(plt.scatter)
g.map_lower(sns.kdeplot)
```

Out[8]: <seaborn.axisgrid.PairGrid at 0x1750804c9c8>



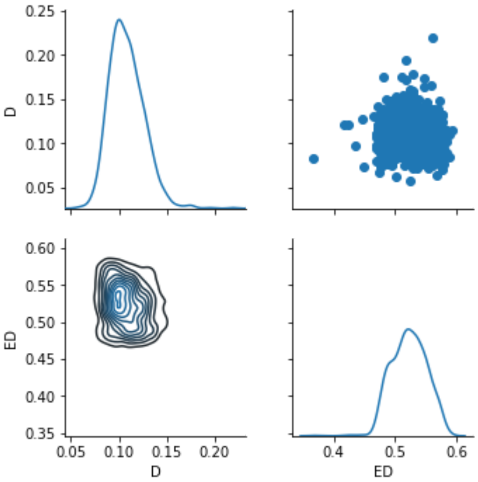
In [9]:
```
sns.pairplot(data[['MAN1', 'MAN2', 'MAN3', 'MAN4', 'MAN5', 'MAN6', 'MAN7', 'MAN8']])
```

Out[9]: <seaborn.axisgrid.PairGrid at 0x1750c3b6b48>



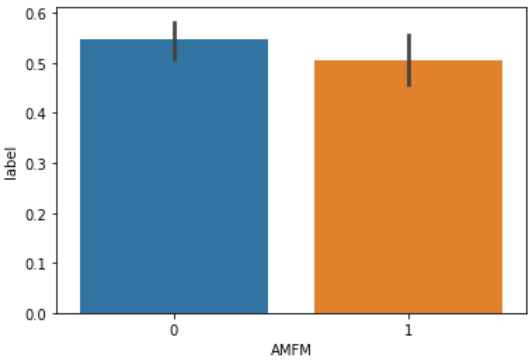
In [10]:
```
g2 = sns.PairGrid(data[['D', 'ED']])
g2.map_diag(sns.kdeplot)
g2.map_upper(plt.scatter)
g2.map_lower(sns.kdeplot)
```

Out[10]: <seaborn.axisgrid.PairGrid at 0x1750e3366c8>



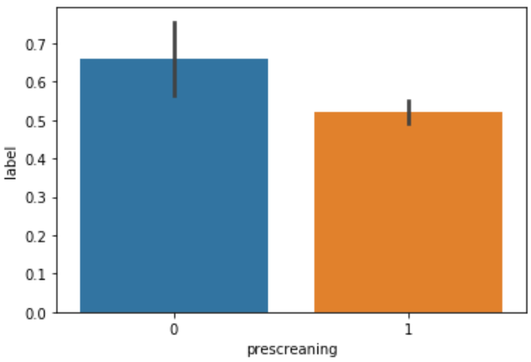
In [11]:
```
# Бинарные переменные
sns.barplot(x='AMFM', y = 'label', data=data)
```

Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x1750e2f7888>



In [12]:
```
sns.barplot(x='prescreaning', y = 'label', data=data)
```

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x175102ef408>

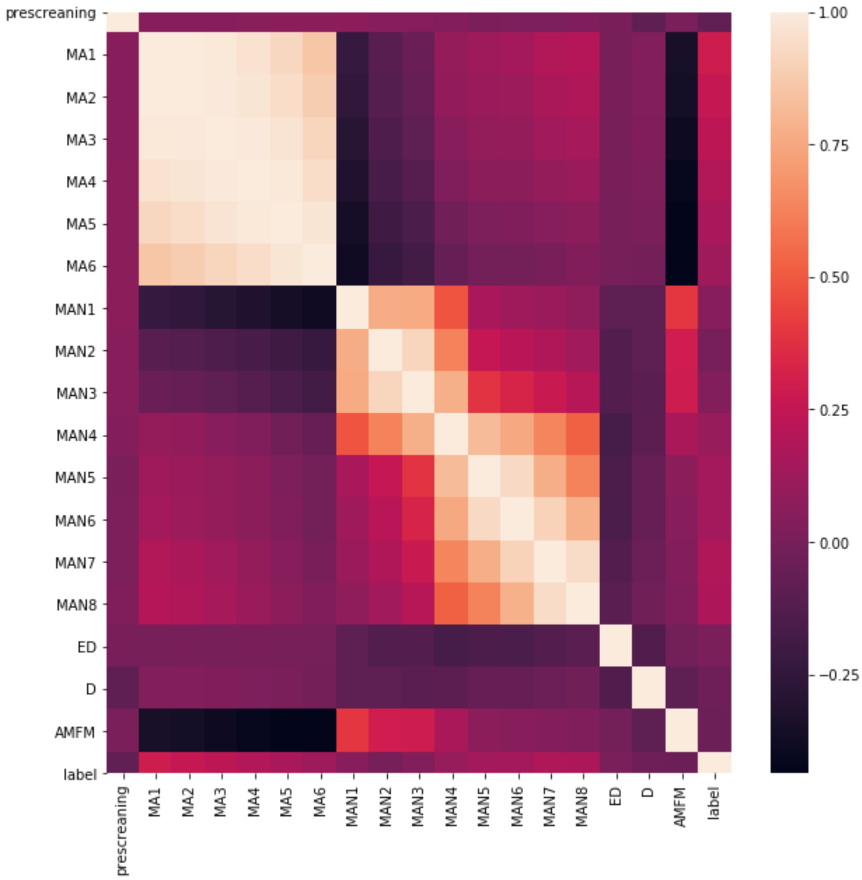


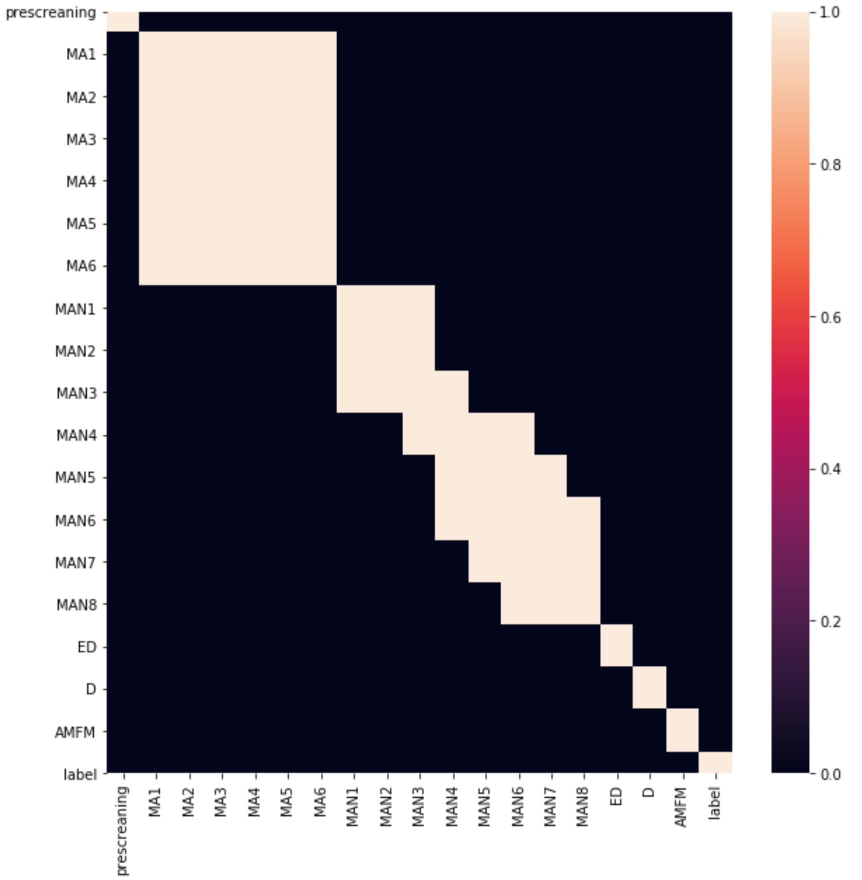
In [13]:
```
original_features = data.columns.values[:-1]
```

Анализ корреляций

In [14]:
```
corrs = data.corr()
plt.figure(figsize=[10,10])
sns.heatmap(corrs)

plt.figure(figsize=[10,10])
sns.heatmap(corrs>0.7)
```

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x1751049ef88>





Новые фичи

In [15]:
```
#хочется логарифмировать всё кроме бинарных признаков и ED, D
to_be_logged = ['MA1', 'MA2', 'MA3', 'MA4', 'MA5', 'MA6', 'MAN1',
       'MAN2', 'MAN3', 'MAN4', 'MAN5', 'MAN6', 'MAN7', 'MAN8']
logged = ['{}_log'.format(c) for c in to_be_logged]

for c in to_be_logged:
    data['{}_log'.format(c)] = np.log1p(data[c])
```

In [16]:
```
# и попробуем ещё все отношения
from itertools import combinations

feature_comb = list(combinations(original_features,2))

for fc in feature_comb:
    data['{}/{}'.format(fc[0],fc[1])] = data[fc[0]]/data[fc[1]]
    #data['{}/{}'.format(fc[1],fc[0])] = data[fc[1]]/data[fc[0]]
```

In [17]:
```
# и произведения
for fc in feature_comb:
    data['{}*{}'.format(fc[0],fc[1])] = data[fc[0]]*data[fc[1]]
    #data['{}/{}'.format(fc[1],fc[0])] = data[fc[1]]/data[fc[0]]
```

In [18]:
```
data.replace(np.inf, np.nan, inplace=True)
clear_data = data.dropna(axis=1)
```

Baseline с новыми фичами

In [19]:
```
get_base_line_score(clear_data, 'label')
```

```
c:\users\xiaomi\appdata\local\programs\python\python37\lib\site-packages\sklearn\ensemble\forest.py:245: Fu
tureWarning: The default value of n_estimators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
c:\users\xiaomi\appdata\local\programs\python\python37\lib\site-packages\sklearn\ensemble\forest.py:245: Fu
tureWarning: The default value of n_estimators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
c:\users\xiaomi\appdata\local\programs\python\python37\lib\site-packages\sklearn\ensemble\forest.py:245: Fu
tureWarning: The default value of n_estimators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

Out[19]:
```
array([0.58771497, 0.67740169, 0.60372502])
```

In [20]:
```
all_features_importance = get_feature_importance(clear_data, 'label')
all_features_importance
```

```
c:\users\xiaomi\appdata\local\programs\python\python37\lib\site-packages\sklearn\ensemble\forest.py:245:
FutureWarning: The default value of n_estimators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

Однофакторный анализ

In [21]:
```
new_features_gini = get_factors_gini(clear_data, 'label')
new_features_gini_df = pd.DataFrame(new_features_gini, columns=['variable', 'gini'])
new_features_gini_df['gini_abs'] = new_features_gini_df['gini'].abs()
new_features_gini_df.sort_values('gini_abs', ascending=False, inplace=True)
```

In [22]:
```
new_features_gini_df.iloc[:40]
```

Out[22]:

	variable	gini	gini_abs
252	label	1.000000	1.000000
251	MA1/MA3	0.577363	0.577363
250	MA1/MA4	0.559989	0.559989
249	MA1/MA2	0.520602	0.520602
248	MA2/MA4	0.467615	0.467615
247	MA1/MA5	0.454296	0.454296
246	MA2/MA3	0.437529	0.437529
245	MA2/MA5	0.382924	0.382924
244	MA3/MA4	0.377559	0.377559
243	MA1/MA6	0.376933	0.376933
0	prescreaning/MA1	-0.332642	0.332642
242	MA1_log	0.324602	0.324602
241	MA1	0.324602	0.324602
240	MA1*ED	0.323607	0.323607
239	MA2/MA6	0.323595	0.323595
238	MA1/D	0.323033	0.323033
237	MA1/ED	0.322538	0.322538
236	MA3/MA5	0.317552	0.317552
235	MA1*MA2	0.308135	0.308135
1	prescreaning/MA2	-0.307442	0.307442
234	MA1*D	0.301024	0.301024
233	MA2_log	0.294920	0.294920
232	MA2	0.294920	0.294920
231	MA2/D	0.294715	0.294715
230	MA2*ED	0.293952	0.293952
229	MA2/ED	0.293750	0.293750
228	MA1*MA3	0.291335	0.291335
2	prescreaning/MA3	-0.278984	0.278984
227	MA3/MA6	0.278626	0.278626
226	MA2*MA3	0.276880	0.276880
225	MA2*D	0.273255	0.273255
224	MA1*MA4	0.272904	0.272904
222	MA3	0.262012	0.262012
223	MA3_log	0.262012	0.262012
221	MA3/D	0.261799	0.261799
220	MA3*ED	0.261567	0.261567
219	MA3/ED	0.261432	0.261432
218	MA2*MA4	0.257960	0.257960
217	MA1*MA5	0.255857	0.255857
216	prescreaning*MA1	0.249099	0.249099

значимость

In [23]:
```
all_features = set(data.columns) - {'label'}
```

In [24]:
```python
import statsmodels.api as sm
import statsmodels.formula.api as smf

one_dim_models_res = []
for feature_name in all_features:
    model = smf.logit(f'label ~ {feature_name}', data).fit()
    model.summary()
    one_dim_models_res.append({
        'feature': feature_name,
        'AIC': model.aic,
        'LLR': model.llr,
        'LLR_pval': model.llr_pvalue
    })

one_dim_models_res = pd.DataFrame(one_dim_models_res).set_index('feature')
```

```
         Iterations 9
Optimization terminated successfully.
         Current function value: 0.654189
         Iterations 5
Optimization terminated successfully.
         Current function value: 0.666627
         Iterations 8
Optimization terminated successfully.
         Current function value: 0.689542
         Iterations 4
Optimization terminated successfully.
         Current function value: 0.646857
         Iterations 11
Optimization terminated successfully.
         Current function value: 0.684393
         Iterations 5
Optimization terminated successfully.
         Current function value: 0.690939
         Iterations 3
```

In [25]:
```python
def get_significance(pval):
    if pval < 0.001:
        return '***'
    elif pval < 0.01:
        return '**'
    elif pval < 0.05:
        return '*'
    elif pval < 0.1:
        return '.'
    else:
        return ''

one_dim_models_res['significance'] =  one_dim_models_res['LLR_pval'].apply(get_significance)
```

In [26]:
```python
one_dim_models_res[one_dim_models_res['significance'] == '***'].shape
```

Out[26]:
```
(282, 4)
```

In [27]:
```
one_dim_models_res.loc[one_dim_models_res['significance'] == '***'].sort_values(by='LLR_pval').head(40)
```

Out[27]:

feature	AIC	LLR	LLR_pval	significance
MA1*MA3	1178.898954	414.273080	1.792138e-89	***
MA1*MA4	1218.432787	374.739247	6.551871e-81	***
MA1*MA2	1248.262139	344.909895	1.887185e-74	***
MA1*MA5	1281.724492	311.447542	3.311661e-67	***
MA2*MA4	1309.669649	283.502385	3.698124e-61	***
MA2*MA3	1311.053141	282.118893	7.367977e-61	***
MA2*MA5	1346.056044	247.115991	2.751578e-53	***
MA1*MA6	1365.792001	227.380033	5.096439e-49	***
MA3*MA4	1395.630717	197.541317	1.433504e-42	***
MA3*MA5	1403.752421	189.419613	8.146689e-41	***
MA2*MA6	1410.371585	182.800449	2.191150e-39	***
MA1/MAN7	1417.604906	173.567128	2.043511e-38	***
MA1*MAN7	1415.359521	177.812513	2.617259e-38	***
MA1/MAN8	1422.994089	168.177945	3.024289e-37	***
MA1*MAN8	1423.591901	169.580133	1.567864e-36	***
MA2*MAN7	1427.637325	165.534709	1.171061e-35	***
MA2/MAN7	1430.451260	160.720774	1.258715e-35	***
MA2/MAN8	1436.474537	154.697497	2.557793e-34	***
MA2*MAN8	1436.639633	156.532401	1.026624e-33	***
MA3*MAN7	1439.191995	153.980040	3.648589e-33	***
MA3/MAN7	1443.803286	147.368748	9.983503e-33	***
MA3/MAN8	1450.115605	141.056429	2.344151e-31	***
MA1/MAN6	1450.189392	140.982642	2.432251e-31	***
MA1*MAN6	1447.791624	145.380410	2.613336e-31	***
MA1*AMFM	1449.054817	144.117217	4.893557e-31	***
MA3*MAN8	1449.207454	143.964580	5.278888e-31	***
MA4*MAN7	1450.201273	142.970762	8.646964e-31	***
MA1/MA6	1453.510784	137.661251	1.280086e-30	***
MA3*MA6	1451.815122	141.356912	1.926973e-30	***
MA1/MA5	1454.522682	136.649352	2.123099e-30	***
MA4/MAN7	1456.321933	134.850101	5.220024e-30	***
MA5*MAN7	1457.101642	136.070392	2.658697e-29	***
MA1/AMFM	1460.130416	131.041618	3.504888e-29	***
MA4/MAN8	1463.242512	127.929522	1.661335e-28	***
MA1/MAN5	1463.446052	127.725982	1.839312e-28	***
MA4*MAN8	1461.218378	131.953656	2.051319e-28	***
MA1/MAN1	1463.677605	127.494429	2.065078e-28	***
MA2*MAN6	1461.385825	131.786209	2.229061e-28	***
MA6*MAN7	1462.225552	130.946482	3.381420e-28	***
MA1*MAN5	1462.546050	130.625984	3.964333e-28	***

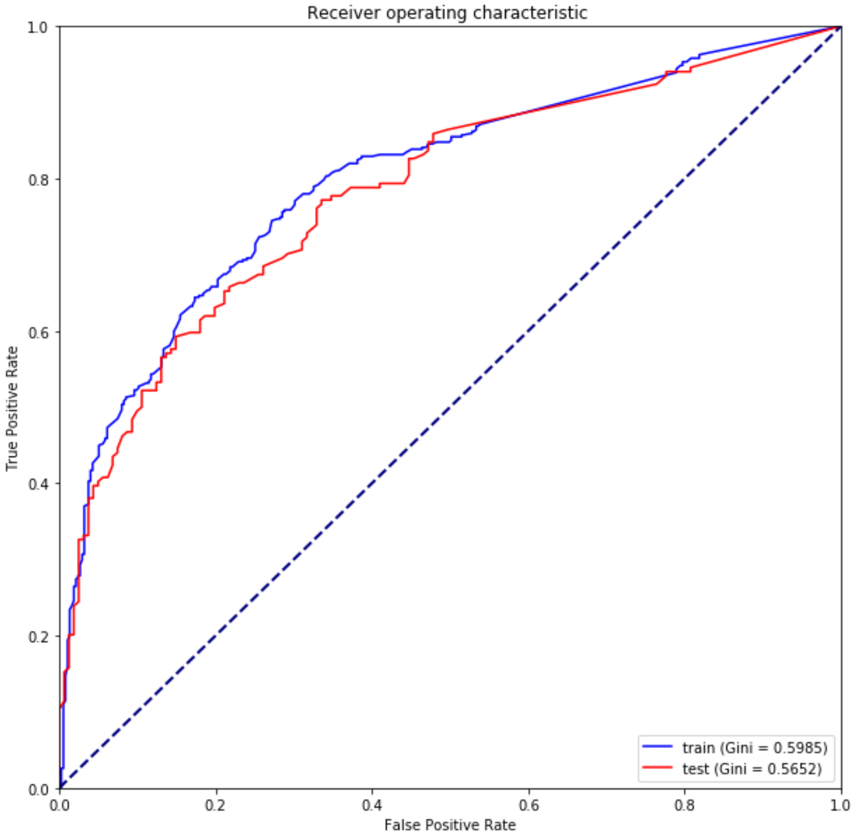
Регрессия

In [28]:
```
def test_model(train, test, model):
    rocs(y_true = [train['label'], test['label']],
     y_pred = [fitted_model.predict(sm.add_constant(train[predictors])), fitted_model.predict(sm.add_constant
     colors = ['blue', 'red'],
     names = ['train', 'test'], name='')
    print('Train gini:', gini(train['label'], fitted_model.predict(sm.add_constant(train[predictors]))))
    print('Test gini:', gini(test['label'], fitted_model.predict(sm.add_constant(test[predictors]))))
    print(fitted_model.summary())
    show_corr(clear_data[predictors])
    vif_df = pd.DataFrame(vif(clear_data[predictors]), columns=['variable', 'vif'])
    print(vif_df.head(10))
```

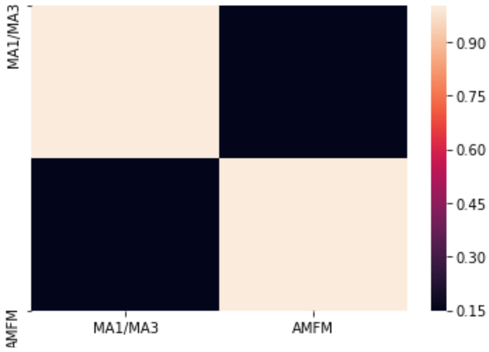
In [29]:
```
train, test = train_test_split(clear_data, test_size=0.3, stratify = clear_data['label'], random_state=42)
```

In [30]:
```
predictors = ['MA1/MA3', 'AMFM']
#predictors = ['MA1/MA4', 'MA1*ED']

model = sm.Logit(train['label'], sm.add_constant(train[predictors]))
fitted_model = model.fit()
test_model(train, test, fitted_model)
```

```
c:\users\xiaomi\appdata\local\programs\python\python37\lib\site-packages\numpy\core\fromnumeric.py:2389: FutureWarning: Method .ptp is deprecated and will be removed in a future version. Use numpy.ptp instead.
  return ptp(axis=axis, out=out, **kwargs)

Optimization terminated successfully.
         Current function value: 0.556833
         Iterations 7
```

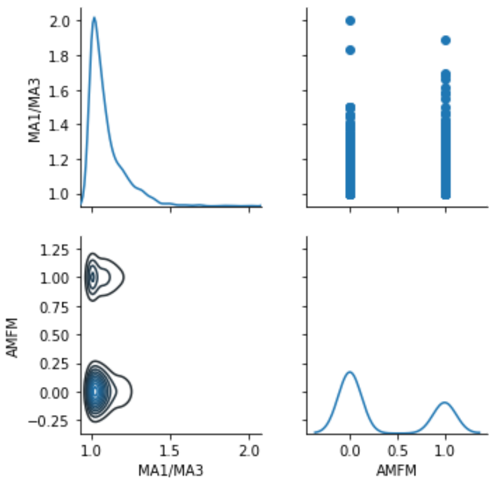



```
c:\users\xiaomi\appdata\local\programs\python\python37\lib\site-packages\numpy\core\fromnumeric.py:2389: FutureWarning: Method .ptp is deprecated and will be removed in a future version. Use numpy.ptp instead.
  return ptp(axis=axis, out=out, **kwargs)
c:\users\xiaomi\appdata\local\programs\python\python37\lib\site-packages\numpy\core\fromnumeric.py:2389: FutureWarning: Method .ptp is deprecated and will be removed in a future version. Use numpy.ptp instead.
  return ptp(axis=axis, out=out, **kwargs)

Train gini: 0.5984699453551914
Test gini: 0.5651836348906294
                           Logit Regression Results
==============================================================================
Dep. Variable:                  label   No. Observations:                  802
Model:                          Logit   Df Residuals:                      799
Method:                           MLE   Df Model:                            2
Date:                Fri, 03 Jan 2020   Pseudo R-squ.:                  0.1942
Time:                        13:27:33   Log-Likelihood:                -446.58
converged:                       True   LL-Null:                       -554.22
Covariance Type:            nonrobust   LLR p-value:                 1.795e-47
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const        -14.9697      1.384    -10.819      0.000     -17.682     -12.258
MA1/MA3       14.2637      1.315     10.848      0.000      11.686      16.841
AMFM          -0.7263      0.183     -3.958      0.000      -1.086      -0.367
==============================================================================
  variable       vif
0  MA1/MA3  1.529027
1     AMFM  1.529027

c:\users\xiaomi\appdata\local\programs\python\python37\lib\site-packages\ipykernel_launcher.py:44: FutureWarning: Method .as_matrix will be removed in a future version. Use .values instead.
```



In [31]:
```
g3 = sns.PairGrid(clear_data[predictors])
g3.map_diag(sns.kdeplot)
g3.map_upper(plt.scatter)
g3.map_lower(sns.kdeplot)
```

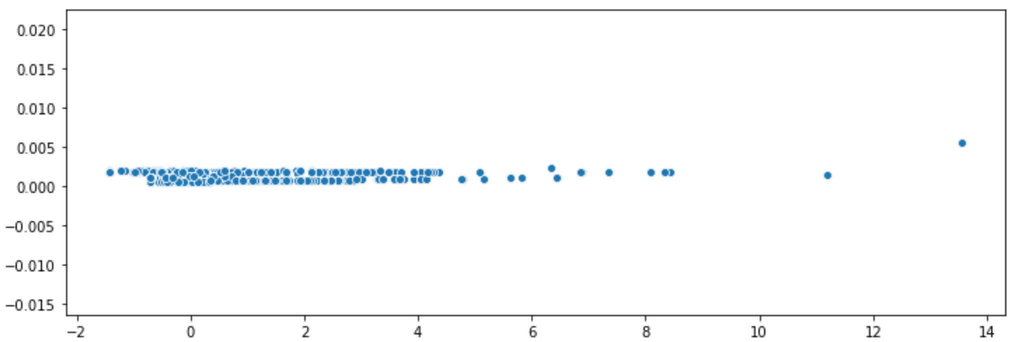
Out[31]: <seaborn.axisgrid.PairGrid at 0x17510bbca88>



Влияние выбросов

In [32]:
```
from statsmodels.genmod.generalized_linear_model import GLM
from statsmodels.genmod import families

final_features = np.array(train[predictors])
cooks_model = GLM(train['label'], final_features, family=families.Binomial()).fit()

infl = cooks_model.get_influence()
plt.figure(figsize=(12, 4))
sns.scatterplot(fitted_model.fittedvalues, infl.cooks_distance[0])
```

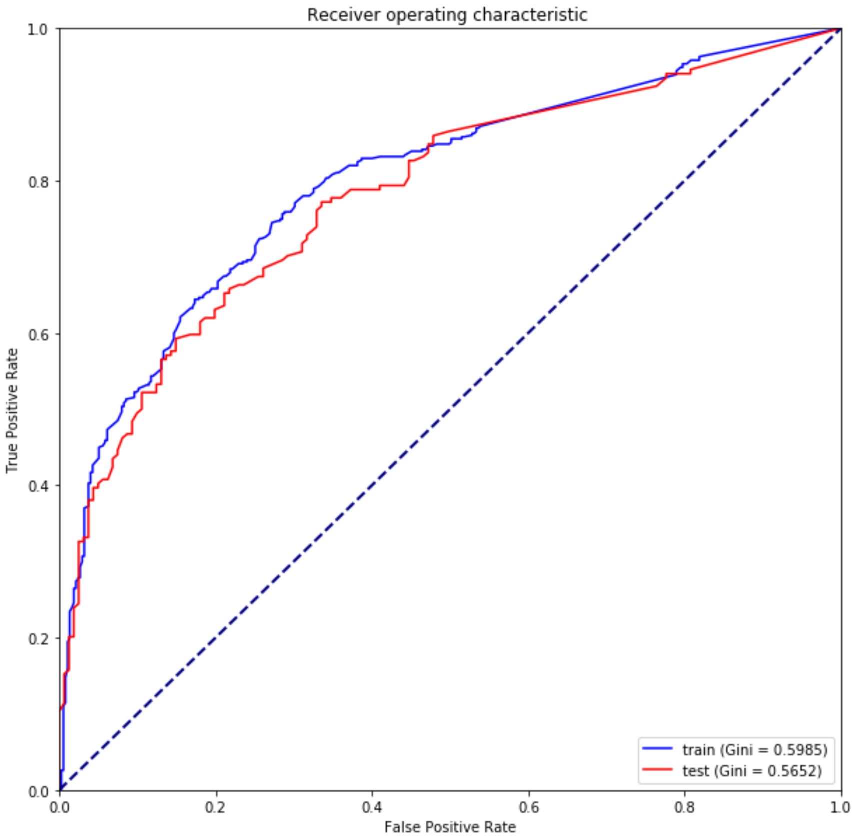
Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x17510ac68c8>



In [33]:
```
new_train = train[infl.cooks_distance[0] < 0.01]
print('Fitting on {} / {} of samples'.format(len(new_train), len(train)))
model_cooks = sm.Logit(new_train['label'], sm.add_constant(new_train[predictors])).fit()
test_model(new_train, test, model_cooks)
```

```
Fitting on 802 / 802 of samples
Optimization terminated successfully.
         Current function value: 0.556833
         Iterations 7
```

```
c:\users\xiaomi\appdata\local\programs\python\python37\lib\site-packages\numpy\core\fromnumeric.py:2389: Fu
tureWarning: Method .ptp is deprecated and will be removed in a future version. Use numpy.ptp instead.
  return ptp(axis=axis, out=out, **kwargs)
```




```
c:\users\xiaomi\appdata\local\programs\python\python37\lib\site-packages\numpy\core\fromnumeric.py:2389: Fu
tureWarning: Method .ptp is deprecated and will be removed in a future version. Use numpy.ptp instead.
  return ptp(axis=axis, out=out, **kwargs)
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  return ptp(axis=axis, out=out, **kwargs)
c:\users\xiaomi\appdata\local\programs\python\python37\lib\site-packages\ipykernel_launcher.py:44: FutureWa
rning: Method .as_matrix will be removed in a future version. Use .values instead.
```

```
Train gini: 0.5984699453551914
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Model:                          Logit   Df Residuals:                      799
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converged:                       True   LL-Null:                       -554.22
Covariance Type:            nonrobust   LLR p-value:                 1.795e-47
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const        -14.9697      1.384    -10.819      0.000     -17.682     -12.258
```
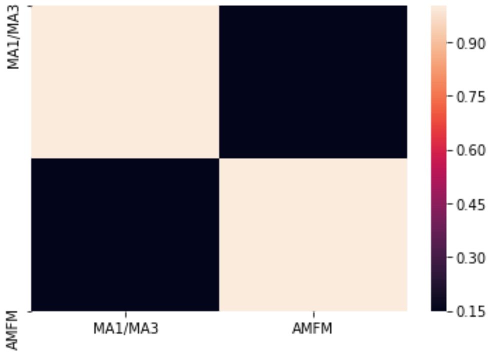

```
MA1/MA3        14.2637       1.315      10.848      0.000      11.686      16.841
AMFM           -0.7263       0.183      -3.958      0.000      -1.086      -0.367
==============================================================================
  variable       vif
0  MA1/MA3  1.529027
1     AMFM  1.529027
```



Выбросы не оказывают большого влияния, удалять их не будем

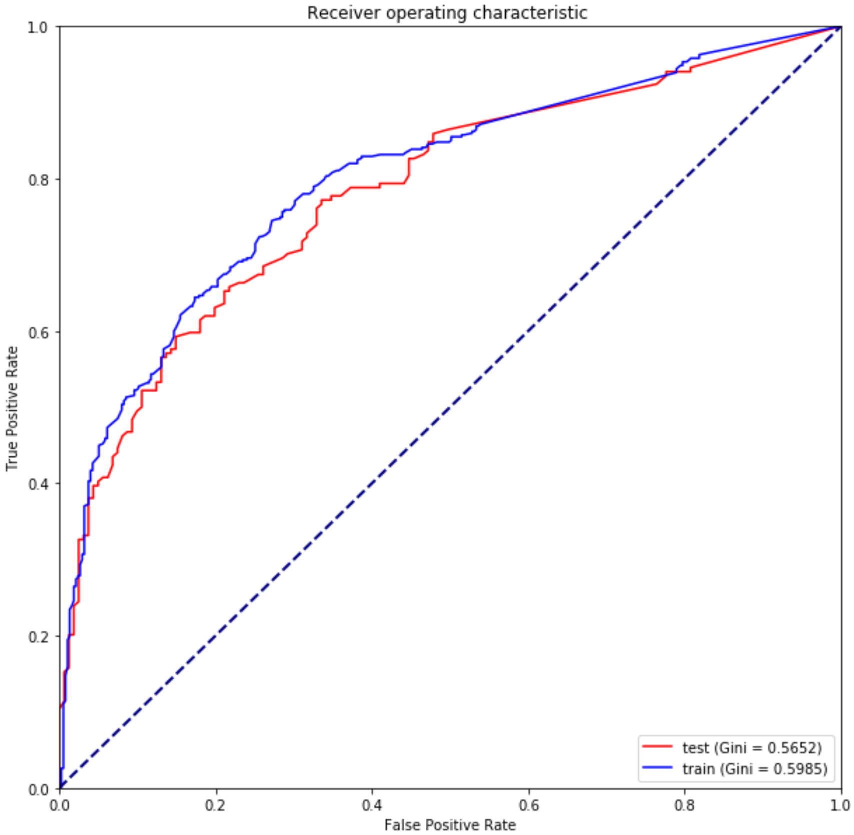
Оценка качества модели

In [34]:
```
test_scores = fitted_model.predict(sm.add_constant(test[predictors]))
train_scores = fitted_model.predict(sm.add_constant(train[predictors]))
```

```
c:\users\xiaomi\appdata\local\programs\python\python37\lib\site-packages\numpy\core\fromnumeric.py:2389: Fu
tureWarning: Method .ptp is deprecated and will be removed in a future version. Use numpy.ptp instead.
  return ptp(axis=axis, out=out, **kwargs)
```

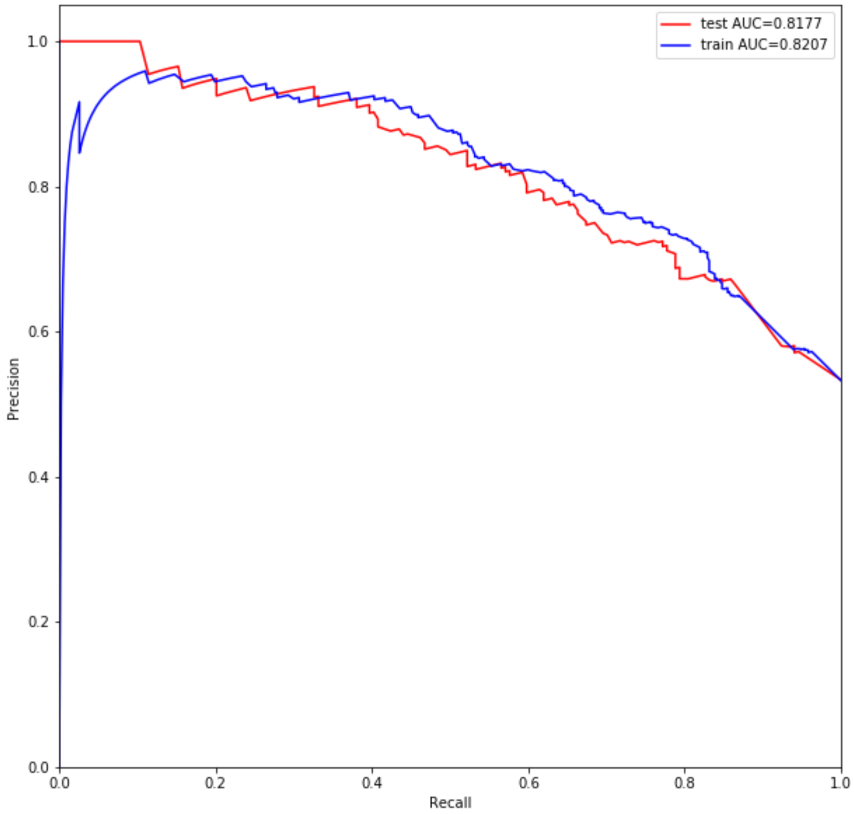
Разделяющая способность

In [35]:
```
rocs(y_true=[test['label'], train['label']], y_pred=[test_scores, train_scores],
    colors=['red', 'blue'], names=['test', 'train'])
```



Средняя точность (PR-кривая)

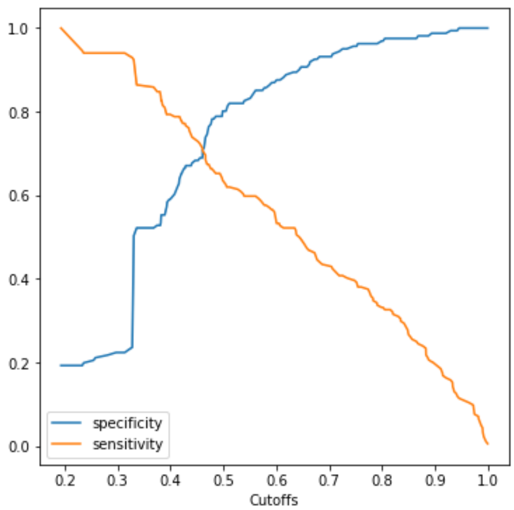
In [36]:
```
pr_curves(y_true=[test['label'], train['label']], y_pred=[test_scores, train_scores],
    colors=['red', 'blue'], names=['test', 'train'])
```



Чувствительность и специфичность

In [37]:
```
n1 = test['label'].sum()
n = len(test['label'])

sensitivity = np.zeros_like(test_scores)
specificity = np.zeros_like(test_scores)
for j, u in enumerate(sorted(test_scores)):
    sensitivity[j] = np.sum((test_scores >= u) * test['label']) / float(n1)
    specificity[j] = np.sum((test_scores <= u) * (1 - test['label'])) / float(n - n1)

plt.figure(figsize=(6, 6))
sns.lineplot(sorted(test_scores), specificity, label='specificity',)
sns.lineplot(sorted(test_scores), sensitivity, label='sensitivity')
plt.xlabel('Cutoffs')
```

Out[37]: Text(0.5, 0, 'Cutoffs')



Порог отсечения

In [38]:
```
sorted_scores = sorted(test_scores)
idx = np.nonzero(np.array(sorted_scores) >= 0.45)[0][0]
print('For cutoff {:.4f}: specificity={:.4f}, sensitivity={:.5f}'.format(
    sorted_scores[idx], specificity[idx], sensitivity[idx]
))
```

```
For cutoff 0.4522: specificity=0.6832, sensitivity=0.72826
```

Выводы и интерпретация

In [39]:
```
confint_results = np.exp(pd.concat((fitted_model.params, fitted_model.conf_int()), axis=1))
confint_results.columns = ['coef', 'confint_2.5', 'confint_97.5']
confint_results
```

Out[39]:

	coef	confint_2.5	confint_97.5
const	3.153142e-07	2.094216e-08	4.747507e-06
MA1/MA3	1.565492e+06	1.189549e+05	2.060247e+07
AMFM	4.836963e-01	3.375911e-01	6.930339e-01

В логистической регрессии

Вероятность наступления события зависит от z: $p = \frac{1}{1+e^{-z}}$, где $z = a_0 + a_1 * x_1 + \ldots + a_n * x_n$
Шанс наступления события зависит от z: $\frac{p}{1-p} = e^z = e^{a_0 + a_1 * x_1 + \ldots + a_n * x_n}$
Таким образом, коэффициент регрессии a_i показывает, что при увеличении значения объясняющей переменной на 1, шанс наступления события увеличивается в e^{a_i} раз

Интерпретация модели

Разберём значения коэффициентов в полученной модели. Переменные вошедшие в модель:

- MA1/MA4 - отношение количества MA, найденных на уровне p-value 0.5, к количеству MA, найденных на уровне p-value 0.7
- MA1*ED - результат AM/FM классификации
  Видим, что:
- увеличение MA1/MA3 на 1 приводит к увеличению шанса возникновения целевого события в $e^{14.2637} = 1565475.23$ раз
- положительный (1) результат AM/FM классификации приводит к уменьшению шанса возникновения целевого события в $e^{0.7263} = 2.07$ раз