# 一、数据可视化

图片在experiments/notes/image目录下的各个文件夹下

1.饼图，盒图，直方图，散点图，已经数据降维到3维后的3d分布图。

2.将0类和1类数据分开，做图对比，观察区别。但是并没有什么发现。

# 二、数据特征

## 1.features的数据类型分为两类

**布尔**

```
'users_3w',
'twolow_users',
'roam_users02',
'roam_users01',
'vv_type',
'in16_roam_tag'
```

**数值**

```
'roam_call_duration',
'roam_duration_02',
'mon_use_days',
'is_p_app_wx_times',
'zhujiao_time',
'zhujiao_times',
'mb5',
'mb10',
'mb30',
'mb60',
'ma60',
'total_count',
'beijiao_times',
'use_days',
```

```
'zhujiao',
'beijiao',
'zhujiao_jt',
'open',
'close',
'open_day',
'cell_num'
```

# 2.数据极度不平衡

**总体情况**

label==0 : 299335

label==1: 221

label ==1 vs all : 0.0007 vs 1

**解决办法**

- under sampling
- over sampling
- cost sensitive
- anomaly detection
- 如图

▶ Probability Threshold Moving

▶ Probability Calibration

▶ Ensemble Algorithms

▶ One-Class Classification

# 3.对于数值型特征，数据在低处十分密集。正类、负类的分布差别很小。

**4.布尔型特征分布情况如下。对于所有特征，特征值为0的比例非常高。正类、负类的分布差别很小。**

```
                users_3w
label           0     1
0          251796  47539
1             214      7
############################
                twolow_users
label              0      1
0              279117  20218
1                 214      7
############################
                roam_users02
label              0     1
0              294261  5074
1                 197    24
############################
                roam_users01
label              0      1
0              288157  11178
1                 186     35
############################
                vv_type
label         0      1
0        259488  39847
1           196     25
############################
                in16_roam_tag
label                0      1
0               276510  22825
1                  217      4
############################
```

# 三、降维

## 特征选择

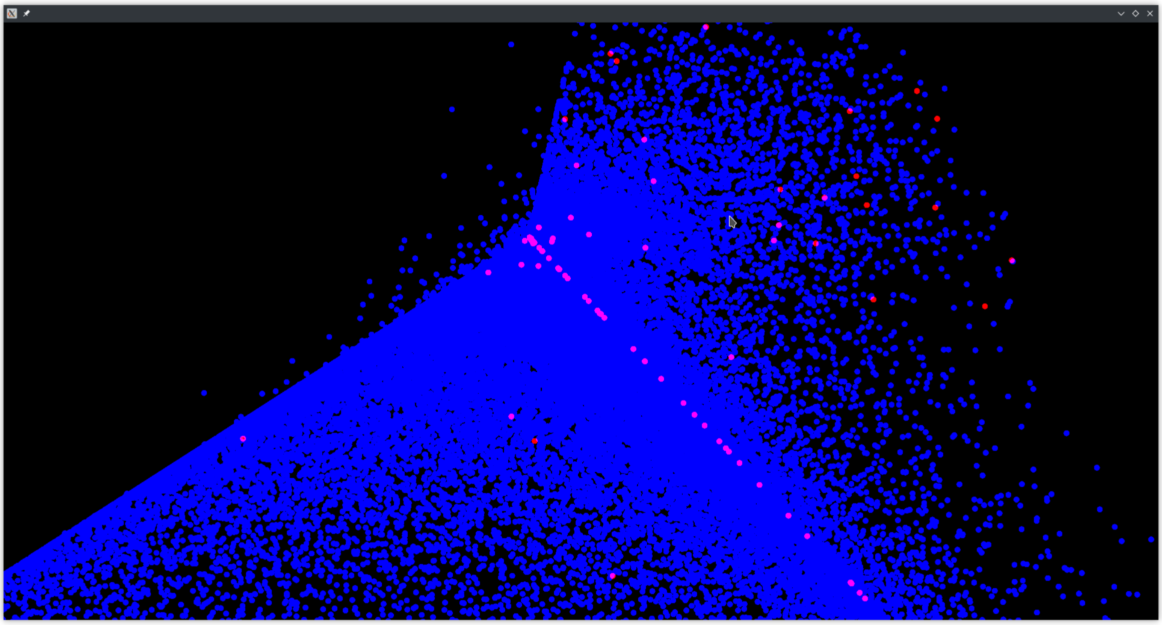
### 1.移除低方差特征

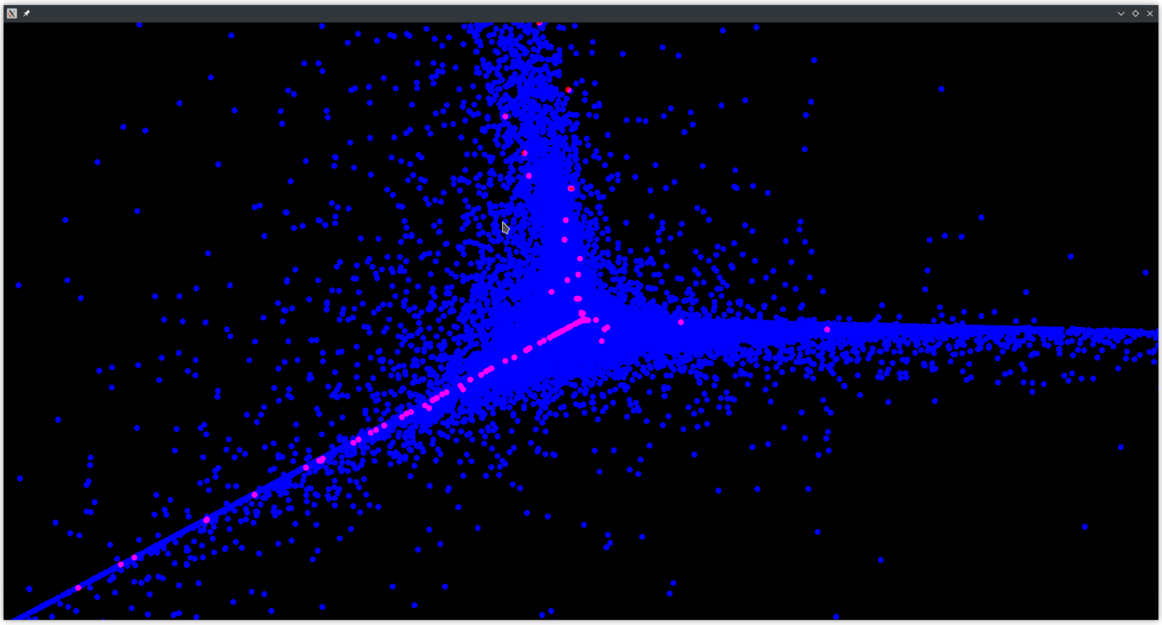
移除那些在整个数据集中特征值为0或者为1的比例超过80%的特征后，只剩下数值型特征。

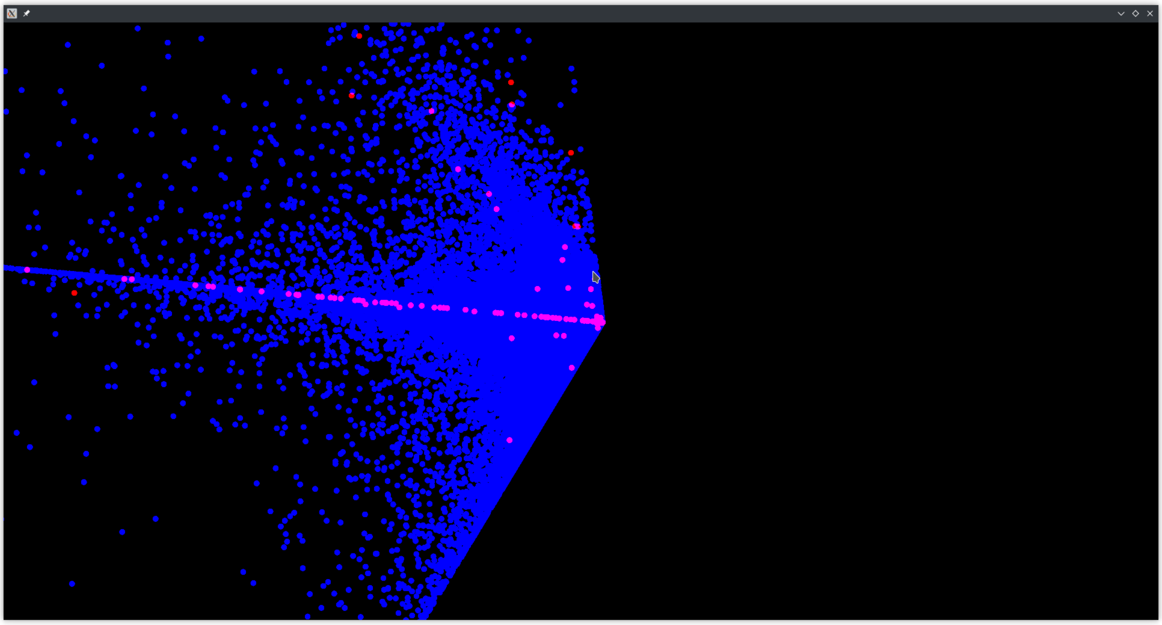
## 特征提取

### 1. PCA

保留99%的variance的情况下，数据可以降到3维







# 四、处理imbalanced data

## 总结：

### 1.采用kfold交叉验证：

使用上采样算法得到的fscore值只有0.66;

使用下采样算法，数据由3万条变成400条;

将两者结合的算法有：SMOTETomek和SMOTEENN，但是耗时非常长。

### 2.使用某月的数据做训练集，另一月数据做测试集，使用随机上采样和sgd classifier：

在训练集上的表现:

```
"precision": 0.8041243531380102,
"recall": 0.3446982964230555,
"f1_score": 0.48254670944182154
```

"true_pos": 103334,
"true_neg": 274262,
"false_pos": 25519,
"false_neg": 196447

模型把很多1类预测成了0类。

在测试集上的表现:

```
"precision": 0.0026360952838607814,
"recall": 0.8067226890756303,
"f1_score": 0.005255018953649091



"true_pos": 190,
"true_neg": 228466,
"false_pos": 71299,
"false_neg": 48
```

模型把很多0类预测成了1类。会出现这种差别，是因为我对训练集进行了上采样，没有对测试集做上采样。

将阈值从默认的0.5调整为其他数值，数值调高，false negative会变得很高，数值调低，false positive 会很高。不能找到一个平衡。

## 3.代价敏感学习

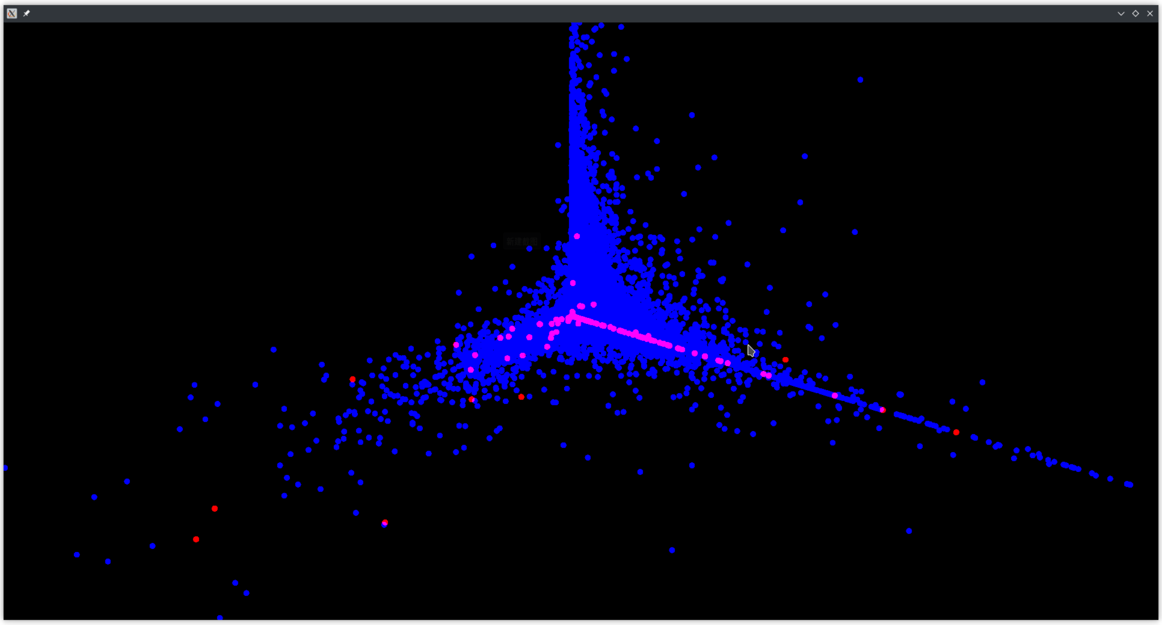
调整sklearn模型的class_weight参数，但是效果也不是很好。

以下是一些试验的记录

**sgd classifier，class_weight={0: 80, 1: 920}，k_fold = KFold(n_splits=5, shuffle=True)**

一、上采样

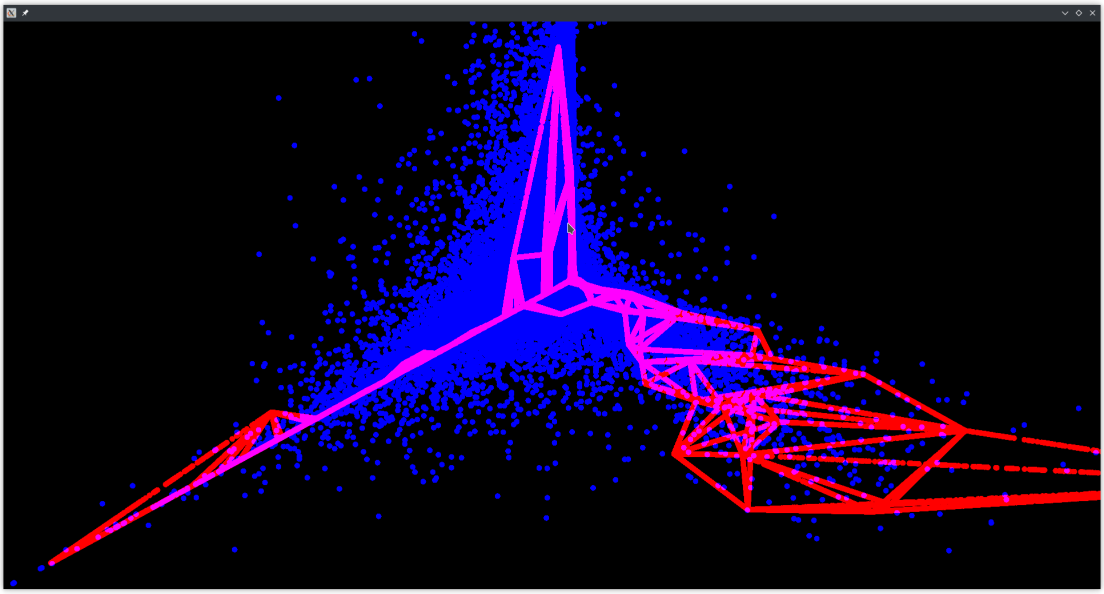
1.随机上采样



```
{
    "precision": 0.5003343475208132,
    "recall": 1.0,
    "f1_score": 0.6669637982328102
}
{
    "precision": 0.5011449133137063,
    "recall": 0.9959161902221926,
    "f1_score": 0.6667708240335685
}
{
    "precision": 0.5025460504862163,
    "recall": 1.0,
    "f1_score": 0.6689259877573734
}
{
    "precision": 0.500822183083896,
    "recall": 1.0,
    "f1_score": 0.6673970957103051
}
{
    "precision": 0.5001797493541564,
    "recall": 1.0,
    "f1_score": 0.6668264247260892
}
```

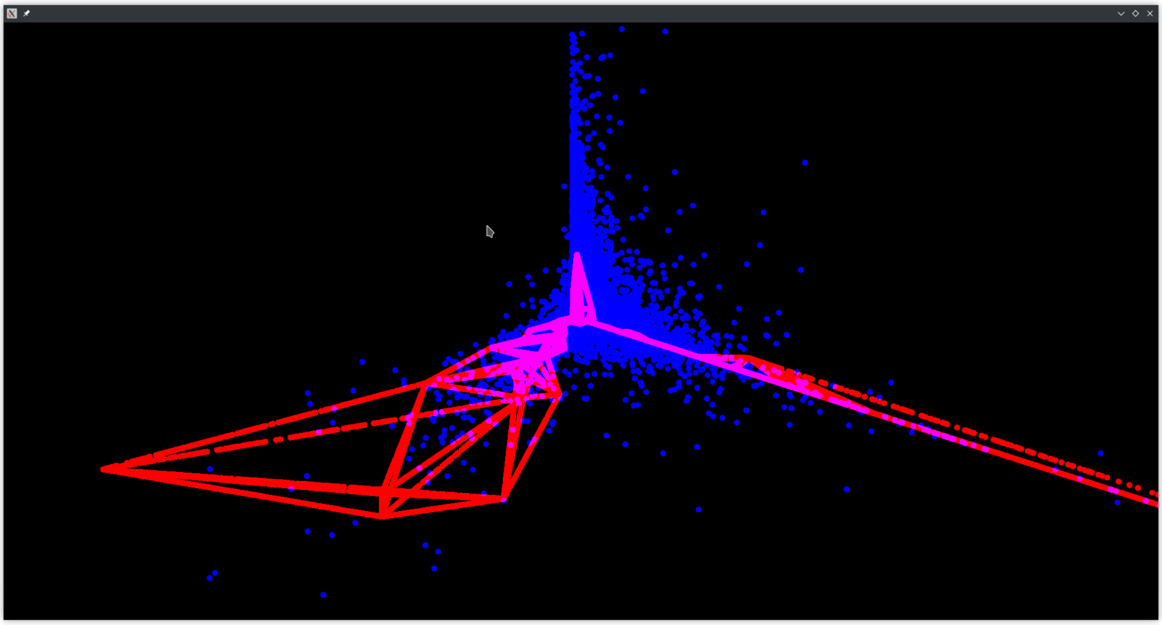
2. SMOTE

kind = regular



```
{
    "precision": 0.503863226239713,
    "recall": 0.9981884660129633,
    "f1_score": 0.6696846201448394
}
{
    "precision": 0.5012154603187955,
    "recall": 0.9974055103612199,
    "f1_score": 0.6671667776987802
}
{
    "precision": 0.5024898220113724,
    "recall": 0.9969127046376183,
    "f1_score": 0.6681841314937335
}
{
    "precision": 0.501532320693427З,
    "recall": 1.0,
    "f1_score": 0.6680273395138282
}
{
    "precision": 0.5001294460544008,
    "recall": 1.0,
    "f1_score": 0.6667817198973429
}
```

3. ADASYN

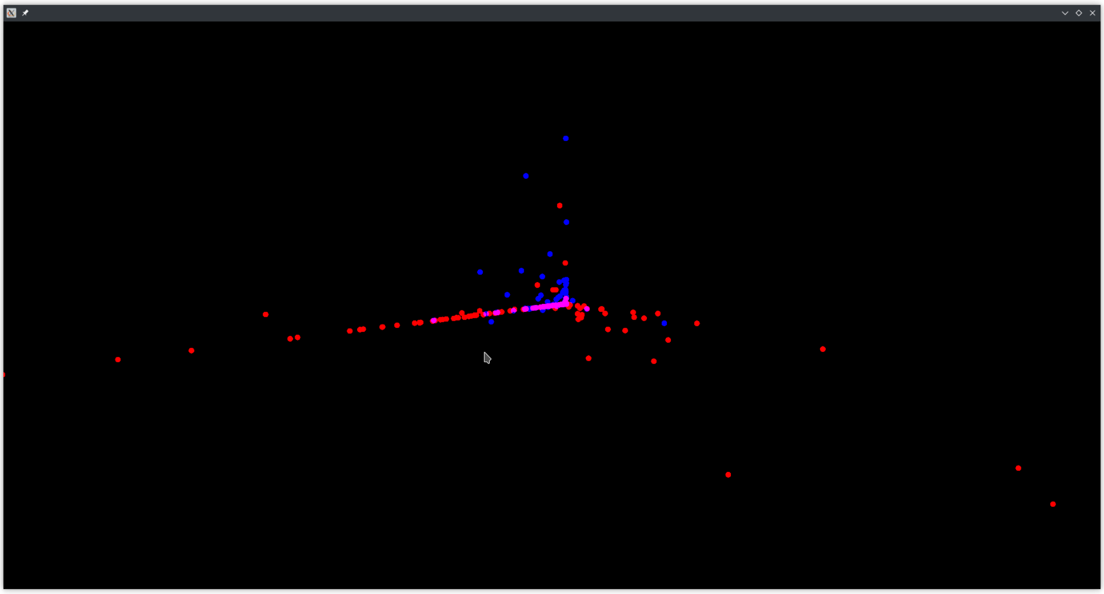


```
{
    "precision": 0.5027217446005452,
    "recall": 0.9988001799730041,
    "f1_score": 0.6688128368501512
}
{
    "precision": 0.5003465582176052,
    "recall": 1.0,
    "f1_score": 0.6669746472601787
}
{
    "precision": 0.4999290347896508,
    "recall": 1.0,
    "f1_score": 0.6666035834952159
}
{
    "precision": 0.5066663318854043,
    "recall": 0.9996532250074309,
    "f1_score": 0.672487627680669
}
{
    "precision": 0.49246358028327847,
    "recall": 0.9843555495744036,
    "f1_score": 0.6564910332138509
```

```
}
```

二、下采样

1. 随机下采样

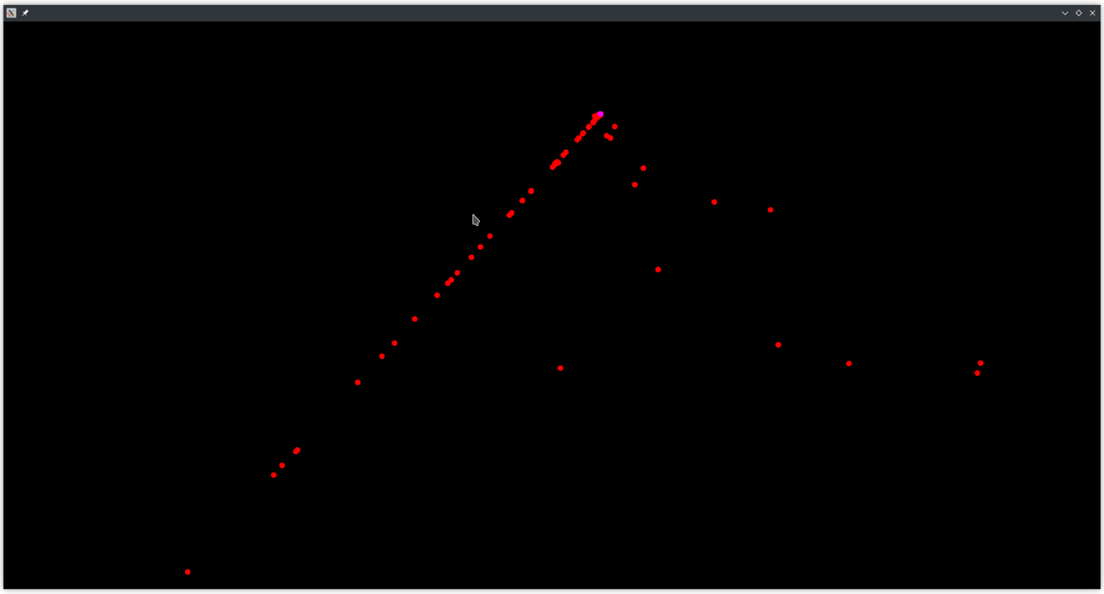


```
{
    "precision": 0.39325842696629215,
    "recall": 1.0,
    "f1_score": 0.564516129032258
}
{
    "precision": 0.6395348837209303,
    "recall": 0.9821428571428571,
    "f1_score": 0.7746478873239436
}
{
    "precision": 0.6,
    "recall": 0.875,
    "f1_score": 0.711864406779661
}
{
    "precision": 0.4186046511627907,
    "recall": 1.0,
    "f1_score": 0.5901639344262295
}
{
    "precision": 0.5131578947368421,
    "recall": 0.8478260869565217,
```

```
    "f1_score": 0.639344262295082
}
```

2. NearMiss

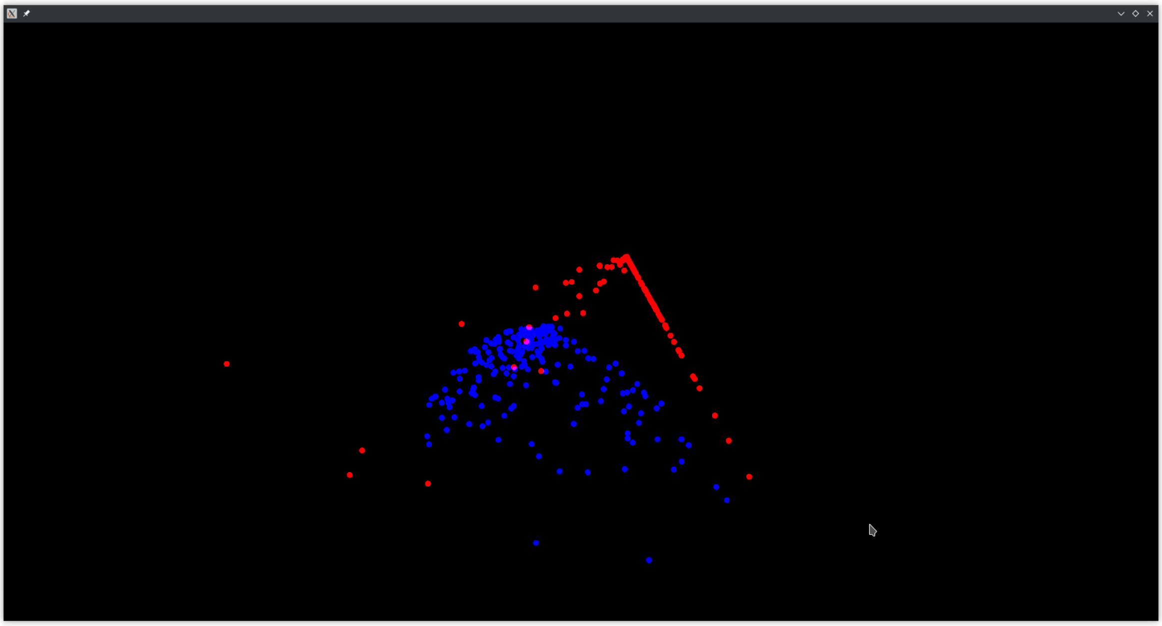
   version=1



```
{
    "precision": 0.5056179775280899,
    "recall": 1.0,
    "f1_score": 0.6716417910447761
}
{
    "precision": 0.4943820224719101,
    "recall": 1.0,
    "f1_score": 0.6616541353383459
}
{
    "precision": 0.4659090909090909,
    "recall": 1.0,
    "f1_score": 0.6356589147286822
}
{
    "precision": 1.0,
    "recall": 0.6304347826086957,
    "f1_score": 0.7733333333333333
}
{
    "precision": 0.5113636363636364,
```

```
    "recall": 1.0,
    "f1_score": 0.6766917293233083
}
```

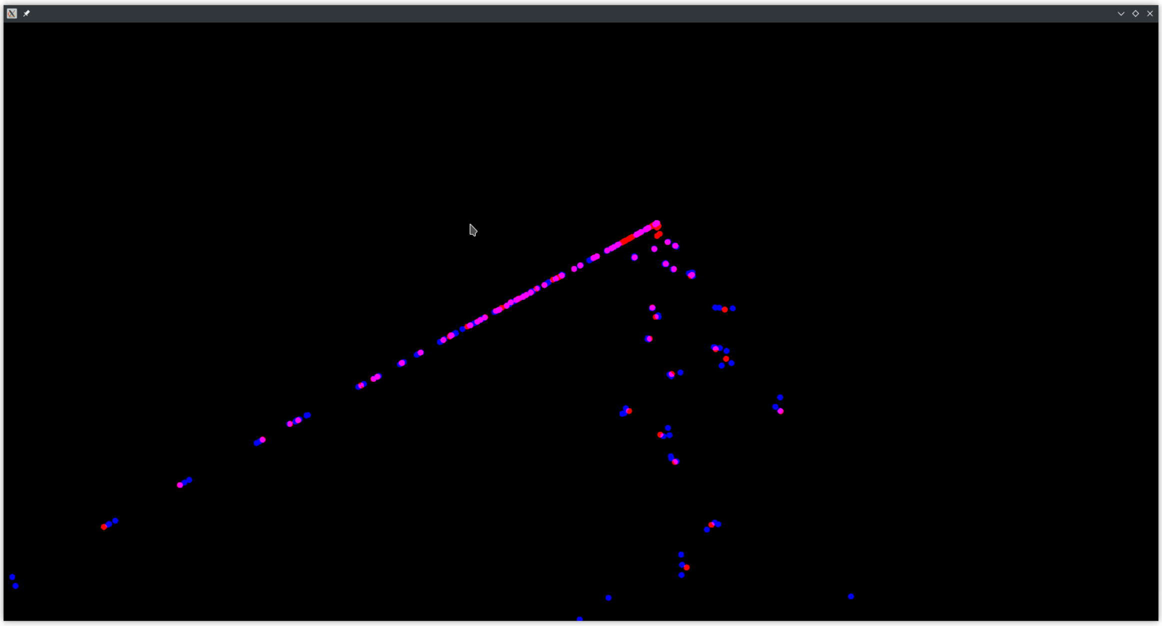
version=2



```
{
    "precision": 0.88,
    "recall": 1.0,
    "f1_score": 0.9361702127659575
}
{
    "precision": 0.9074074074074074,
    "recall": 0.9607843137254902,
    "f1_score": 0.9333333333333333
}
{
    "precision": 0.9512195121951219,
    "recall": 0.975,
    "f1_score": 0.9629629629629629
}
{
    "precision": 0.6612903225806451,
    "recall": 1.0,
    "f1_score": 0.7961165048543689
}
{
    "precision": 0.9777777777777777,
```

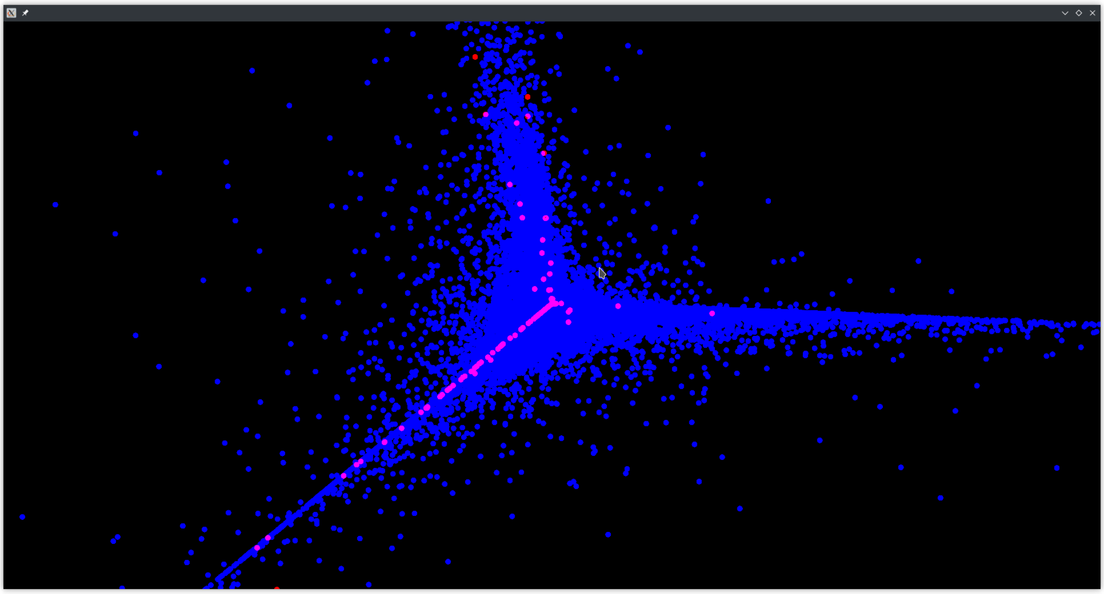
```
    "recall": 0.9777777777777777,
    "f1_score": 0.9777777777777777
}
```

version=3 （耗时较长）



三、上采样和下采样结合

1. TomekLinks (耗时非常长)



# 五、模型选择

使用随机搜索或者网格搜索确定最佳超参数。

需要确定的参数有：class_weight(用于cost-learning)，degree(升维)