In [778]:
```
import scipy.stats as sps
import pandas as pd
import numpy as np
```

Task3

In [153]:
```
train3 = pd.read_csv('./hw11t3v0_train.txt', '\t', header=None)
test3 = pd.read_csv('./hw11t3v0_test.txt', '\t', header=None)
target3 = pd.read_csv('./hw11t3v0_target.txt', '\t', header=None)
```

In [779]:
```
train3.head()
```

Out[779]:

	0	1	2	3	4	5	6
0	61.493	22.774	-31.684	1.864	0.716	-0.809	-0.511
1	60.472	35.267	-40.022	2.306	-3.104	-1.770	-2.169
2	-75.192	-3.148	21.730	1.021	4.874	0.138	2.262
3	-3.592	-31.405	22.565	-0.350	-0.155	-0.646	-3.618
4	-96.133	-2.158	26.496	-0.154	1.581	1.577	1.988

In [13]:
```
test3.head()
```

Out[13]:

	0	1	2	3	4	5	6
0	-71.330	2.211	17.034	1.842	1.858	-0.117	2.152
1	-63.588	-4.953	19.954	3.100	-1.069	-0.132	2.692
2	38.756	24.093	-26.677	0.372	0.641	-0.157	-0.010
3	-14.522	-33.612	26.929	3.177	-4.449	-0.561	1.284
4	-11.235	-34.898	26.959	0.665	-2.671	-0.199	-0.337

In [14]:
```
target3.head()
```

Out[14]:

	0
0	-79.404
1	-87.106
2	-458.711
3	100.090
4	-583.253

In [15]:
```
len(target3)
```
Out[15]: 500

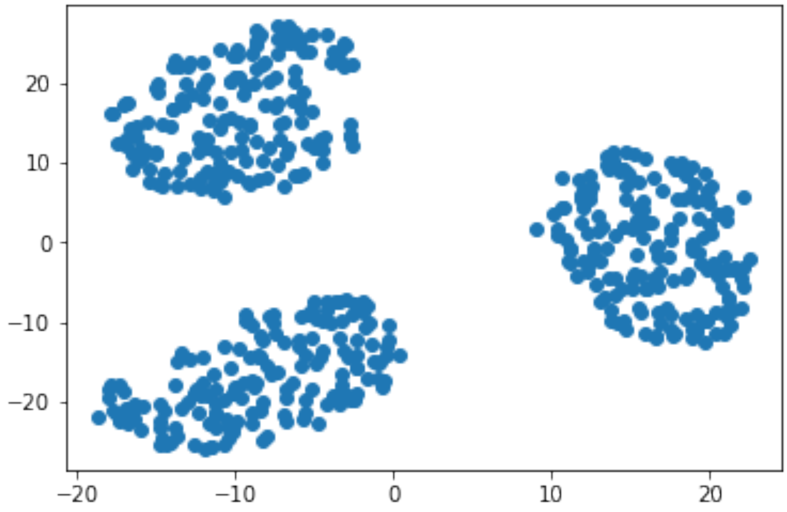
In [17]:
```
len(train3)
```
Out[17]: 500

In [20]:
```
from sklearn.manifold import TSNE
```

In [21]:
```
tsne = TSNE(n_components=2, n_iter=200)

X_tsne = tsne.fit_transform(np.concatenate((train3, test3)))
X_train_tsne, X_test_tsne = X_tsne[:len(train3)], X_tsne[len(train3
):]
```

In [22]:
```
import matplotlib.pyplot as plt
%matplotlib inline
```

In [26]:
```
plt.scatter(X_train_tsne[:,0], X_train_tsne[:,1])
```
Out[26]:
```
<matplotlib.collections.PathCollection at 0x10f6822b0>
```



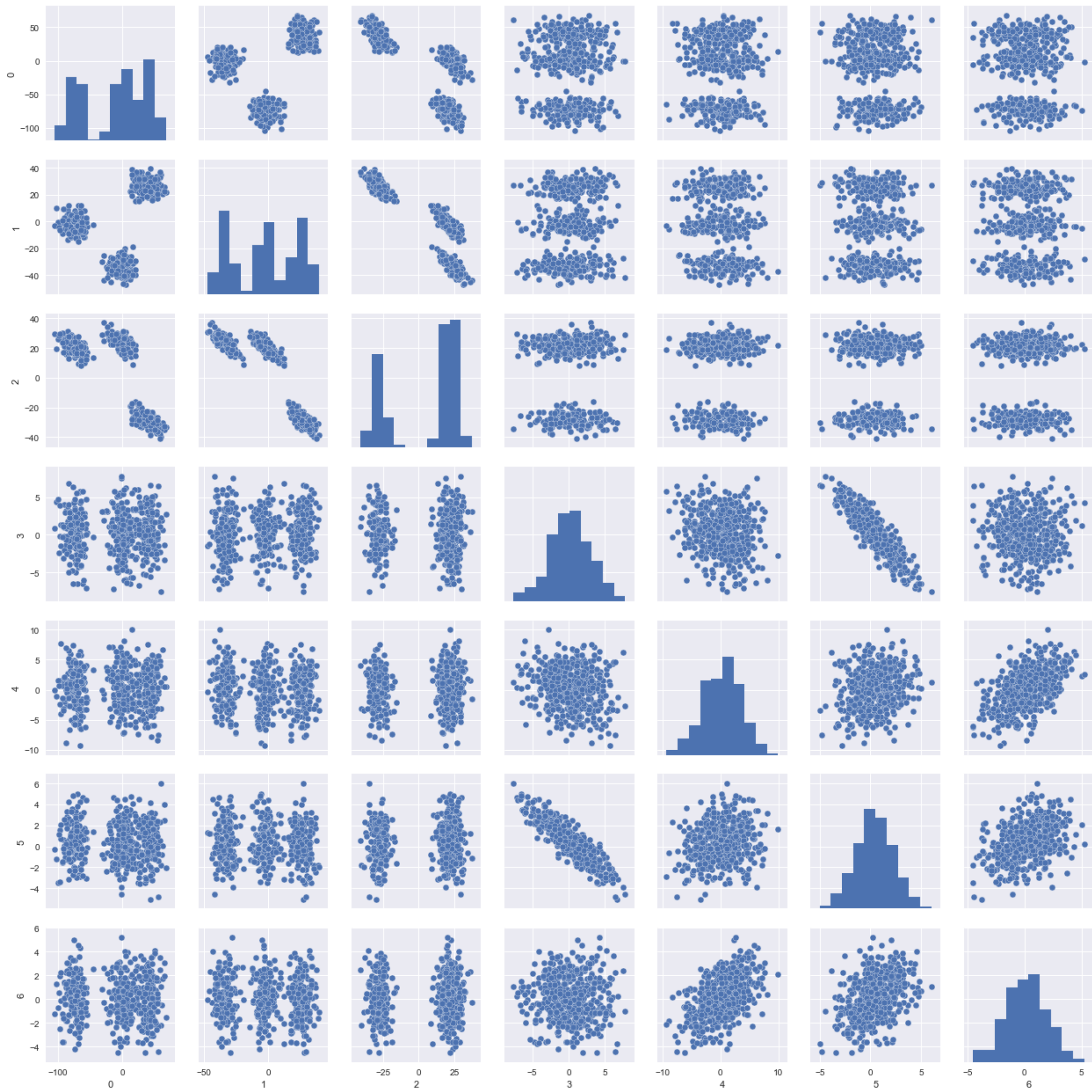
После применения T-SNE отчетливо видны 3 кластера

In [27]:
```
import seaborn as sns
```

Взглянем на попарные зависимости признаков

```
In [29]: sns.pairplot(train3)
```

```
Out[29]: <seaborn.axisgrid.PairGrid at 0x10f94a128>
```



видно, что данные вообще линейно разделимы, если спроецировать на 2 признака

```
In [36]: from sklearn.linear_model import LinearRegression
         from sklearn.metrics import mean_squared_error
         from sklearn.cross_validation import train_test_split
         from sklearn.cross_validation import cross_val_score
```

```
In [34]: X_train, X_test, y_train, y_test = train_test_split(train3, target3
         )
```

```
In [92]: cross_val_score(estimator=LinearRegression(), X=train3, y=target3,
         scoring='mean_squared_error').mean()
```

```
Out[92]: -3249.294337623202
```

Получаем очень большую ошибку, скорее всего данные не линейные

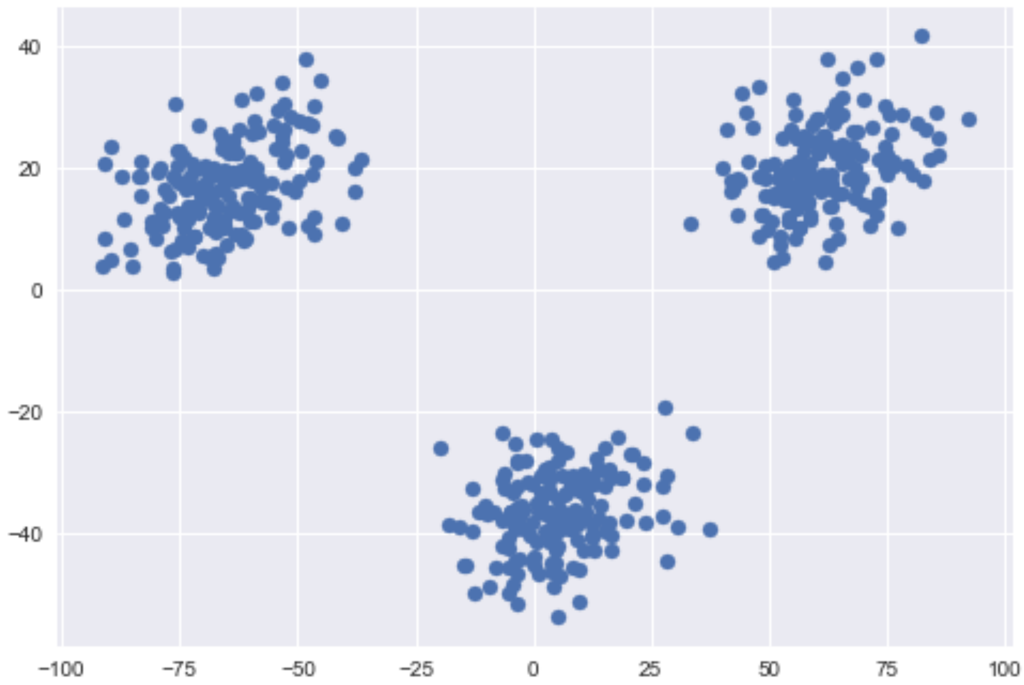
Попробуем понизить размерность, кластеризовать там данные и внутри каждого кластера запустить свою линейную модель

In [780]:
```
from sklearn.decomposition import PCA
```

In [98]:
```
pca = PCA(n_components=2)

X_pca = pca.fit_transform(np.concatenate((train3, test3)))
X_train_pca, X_test_pca = X_pca[:len(train3)], X_pca[len(train3):]
```

In [99]:
```
plt.scatter(X_train_pca[:,0], X_train_pca[:,1])
```

Out[99]:
```
<matplotlib.collections.PathCollection at 0x10f4b00f0>
```



PCA отработал очень хорошо

In [101]:
```
from sklearn.cluster import KMeans
```

In [102]:
```
kmen = KMeans(n_clusters=3)
```

In [103]:
```
kmen.fit(X_train_pca)
```

Out[103]:
```
KMeans(copy_x=True, init='k-means++', max_iter=300, n_clusters=3,
n_init=10,
    n_jobs=1, precompute_distances='auto', random_state=None, tol=
0.0001,
    verbose=0)
```

In [104]:
```
kmen.labels_
```

Out[104]:
```
array([0, 0, 1, 2, 1, 2, 0, 1, 0, 2, 2, 2, 2, 2, 2, 1, 1, 0, 2, 0,
2, 1, 0,
       1, 0, 0, 2, 0, 1, 2, 1, 0, 2, 1, 1, 0, 1, 1, 0, 2, 0, 0, 1,
1, 2, 1,
       2, 2, 2, 2, 1, 0, 1, 1, 0, 0, 2, 2, 0, 1, 2, 1, 1, 2, 2, 0,
2, 0, 0,
       2, 0, 2, 1, 1, 0, 0, 0, 2, 2, 1, 0, 0, 0, 2, 0, 0, 1, 0, 2,
2, 2, 0,
       2, 1, 2, 2, 0, 0, 0, 1, 0, 0, 0, 2, 1, 2, 0, 1, 2, 2, 0, 0,
2, 1, 1,
       2, 1, 2, 2, 0, 1, 1, 2, 1, 1, 0, 2, 0, 1, 0, 2, 0, 2, 0, 2,
0, 0, 0,
       0, 2, 1, 1, 1, 0, 1, 2, 2, 2, 2, 1, 2, 0, 2, 0, 0, 1, 1, 0,
1, 0, 1,
       0, 2, 2, 1, 2, 1, 2, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 2, 1,
1, 2, 2,
       1, 1, 2, 1, 2, 0, 2, 2, 2, 0, 0, 2, 2, 2, 0, 0, 2, 0, 2, 2,
1, 2, 1,
       1, 1, 1, 0, 0, 0, 1, 2, 0, 2, 1, 2, 0, 2, 1, 0, 2, 2, 2, 1,
0, 1, 2,
       0, 1, 1, 1, 2, 2, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 1,
0, 2, 2,
       1, 2, 0, 1, 1, 0, 1, 0, 0, 2, 2, 2, 1, 2, 2, 1, 1, 2, 1, 1,
1, 1, 2,
       0, 0, 1, 1, 1, 2, 1, 2, 1, 2, 0, 1, 2, 1, 0, 0, 2, 2, 0, 0,
0, 1, 0,
       0, 1, 1, 0, 1, 2, 0, 0, 1, 0, 0, 2, 2, 1, 0, 0, 2, 2, 2, 0,
1, 0, 2,
       1, 0, 2, 1, 2, 1, 2, 1, 2, 0, 2, 1, 0, 0, 2, 1, 0, 0, 0, 2,
2, 0, 1,
       1, 2, 0, 1, 2, 1, 2, 2, 1, 0, 2, 2, 1, 1, 2, 0, 1, 1, 2, 2,
1, 2, 0,
       0, 0, 0, 2, 2, 2, 2, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 2, 2, 1,
0, 0, 0,
       0, 1, 2, 0, 0, 0, 2, 0, 2, 2, 0, 1, 1, 2, 0, 0, 1, 1, 2, 0,
1, 2, 0,
       1, 0, 1, 2, 1, 2, 0, 0, 1, 0, 0, 0, 0, 1, 1, 2, 0, 0, 1, 0,
2, 0, 0,
       2, 1, 2, 1, 1, 2, 2, 1, 0, 0, 1, 2, 2, 0, 2, 1, 2, 2, 1, 1,
2, 2, 1,
       0, 0, 1, 1, 0, 0, 2, 2, 1, 1, 1, 1, 0, 2, 1, 0, 2, 1, 0, 0,
2, 0, 1,
       2, 2, 1, 1, 2, 1, 2, 1, 0, 0, 1, 1, 0, 0, 2, 1, 2], dtype=i
nt32)
```

In [110]:
```
predicted_for_test = kmen.predict(X_test_pca)
predicted_for_test
```

Out[110]:
```
array([1, 1, 0, 2, 2, 1, 2, 1, 1, 0, 1, 2, 2, 2, 1, 1, 1, 0, 0, 0,
1, 0, 0,
       1, 1, 2, 2, 0, 2, 1, 0, 2, 0, 2, 2, 2, 1, 0, 2, 1, 0, 1, 2,
2, 2, 1,
       2, 1, 1, 1], dtype=int32)
```

In [113]:
```
XX_tr, XX_te, yy_tr, yy_te = train_test_split(X_train_pca, target3)
```

In [114]:
```
def split_to_three(data, trgts):
    clus = kmen.predict(data)
    nol = data[clus == 0]
    odin = data[clus == 1]
    dva = data[clus == 2]
    tar_0 = trgts[clus == 0]
    tar_1 = trgts[clus == 1]
    tar_2 = trgts[clus == 2]
    return nol, odin, dva, tar_0, tar_1, tar_2
```

In [115]:
```
train_splitted = split_to_three(XX_tr, yy_tr)
test_splitted = split_to_three(XX_te, yy_te)
```

In [112]:
```
# train_0 = X_train_pca[kmen.labels_ == 0]
# train_1 = X_train_pca[kmen.labels_ == 1]
# train_2 = X_train_pca[kmen.labels_ == 2]
# #-----------------------------------------#
# target_0 = target3[kmen.labels_ == 0]
# target_1 = target3[kmen.labels_ == 1]
# target_2 = target3[kmen.labels_ == 2]
# #-----------------------------------------#
# test_0 = X_test_pca[predicted_for_test == 0]
# test_1 = X_test_pca[predicted_for_test == 1]
# test_2 = X_test_pca[predicted_for_test == 2]
```

In [117]:
```
lr = LinearRegression()
```

In [136]:
```
preds = []
```

In [137]:
```
lr.fit(train_splitted[0], train_splitted[3])
preds += list(lr.predict(test_splitted[0])[:,0])
```

In [139]:
```
lr.fit(train_splitted[1], train_splitted[4])
preds += list(lr.predict(test_splitted[1])[:,0])
```

In [140]:
```
lr.fit(train_splitted[2], train_splitted[5])
preds += list(lr.predict(test_splitted[2])[:,0])
```

In [141]:
```
len(preds)
```

Out[141]: 125

In [143]:
```
len(XX_te)
```

Out[143]: 125

In [107]:
```
len(train_0)
```

Out[107]: 172

In [ ]:
```
y_tteeeeest = test_splitted[]
```

In [151]:
```
mean_squared_error(preds, np.concatenate(test_splitted[3:]))
```

Out[151]:
```
71.623309201026117
```

Получили намного более вменяемое значение, нежели в самом начале!

In [781]:
```
preds[:10]
```

Out[781]:
```
[-53.839236159807491,
 -38.434303294556173,
 -58.954994772090934,
 -43.608146099782481,
 -84.071014184801157,
 -61.755494825681573,
 -61.034684344794407,
 -54.466166526112211,
 -49.161351311794654,
 -57.087385109901199]
```

Task4 то же самое, что и в предыдущем задании

In [154]:
```
train4 = pd.read_csv('./hw11t4v0_train.txt', '\t', header=None)
test4 = pd.read_csv('./hw11t4v0_test.txt', '\t', header=None)
target4 = pd.read_csv('./hw11t4v0_target.txt', '\t', header=None)
```

In [157]:
```
len(train4)
```

Out[157]:
```
500
```

In [176]:
```
from sklearn.svm import SVR
```

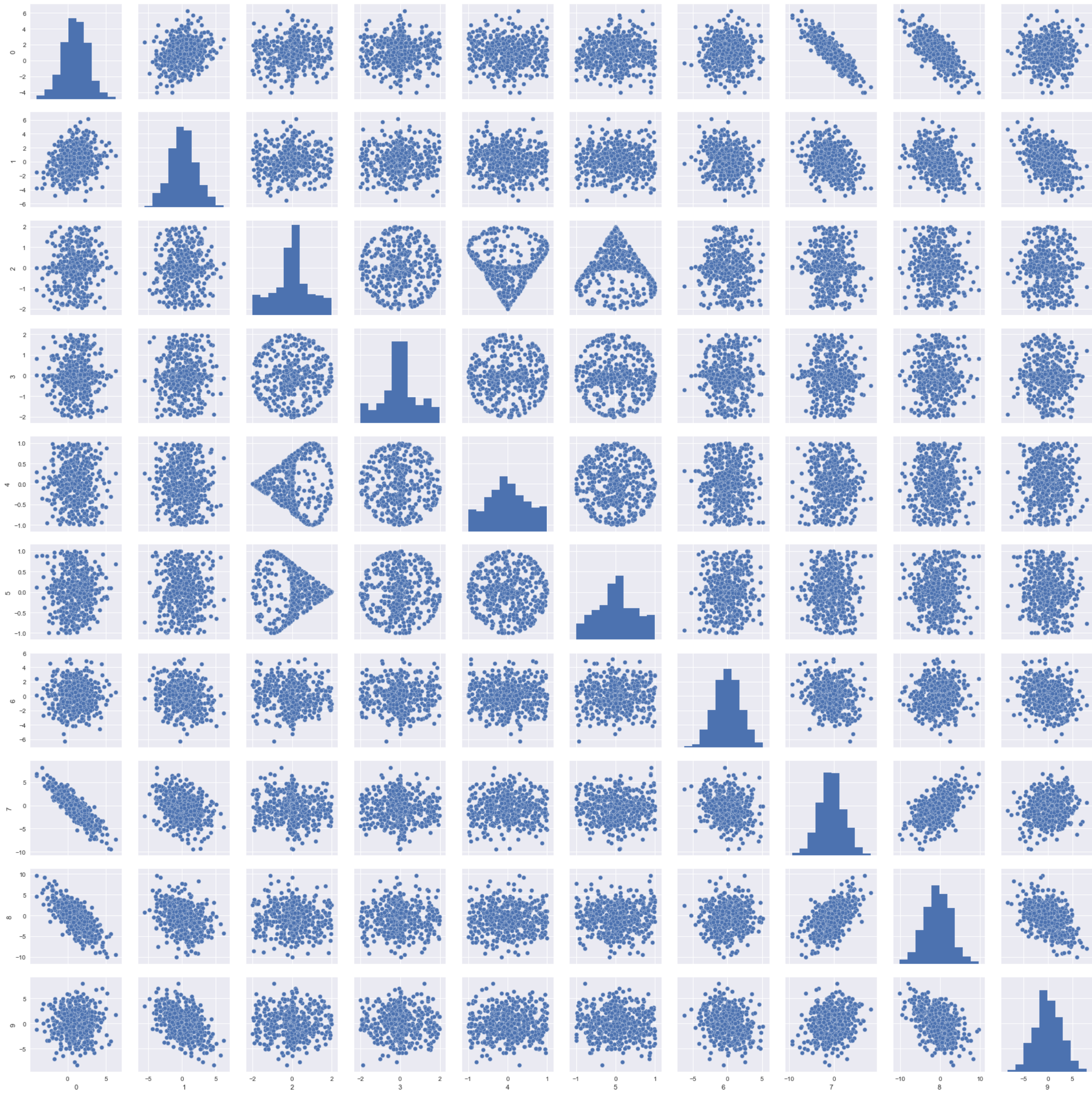
In [182]:
```
cross_val_score(estimator=SVR(), X=train4, y=target4.values.ravel()
, scoring='mean_squared_error').mean()
```

Out[182]:
```
-361215.73056817154
```

Получаем просто гигантскую ошибку

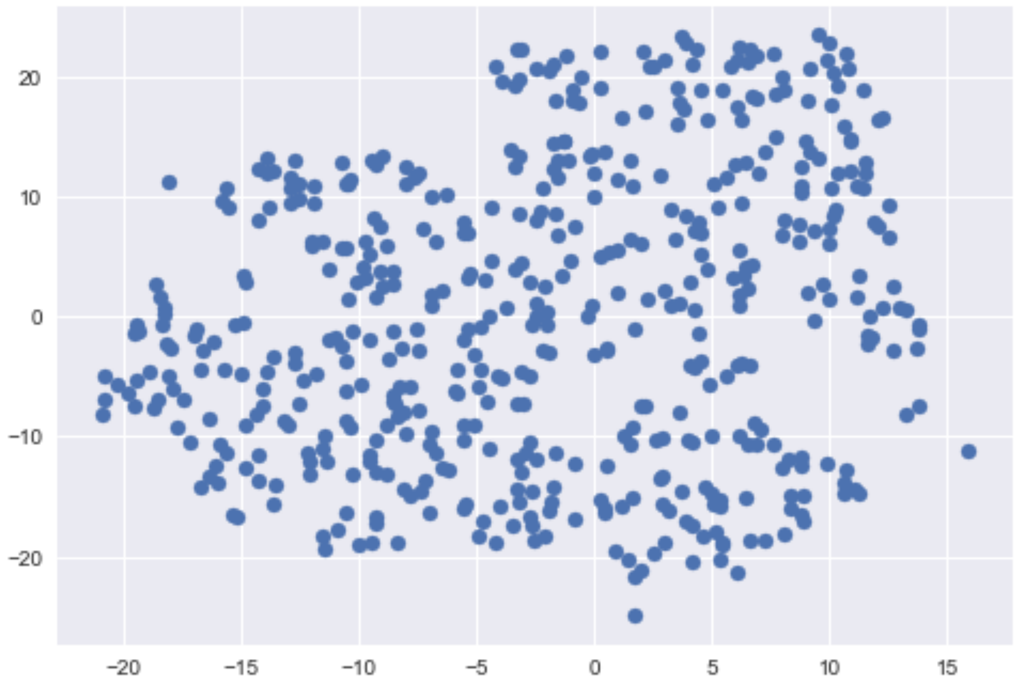
In [156]:
```
sns.pairplot(train4)
```

Out[156]: <seaborn.axisgrid.PairGrid at 0x112323f28>



кажется, наши данные похожина обычный шум(

```
In [782]: tsne = TSNE(n_components=2, n_iter=200)

          X_tsne = tsne.fit_transform(np.concatenate((train4, test4)))
          X_train_tsne, X_test_tsne = X_tsne[:len(train3)], X_tsne[len(train3
          ):]
          plt.scatter(X_train_tsne[:,0], X_train_tsne[:,1])

Out[782]: <matplotlib.collections.PathCollection at 0x1210d3f28>
```



Как из pairplot-a, так и из результатов работы t-sne, не выходит получить нормальную визуализацию в двумерном пр-ве. Посмотрим, как работает линейная регрессия на исходных признаках, а далее попробуем уменьшить размерность

```
In [165]: cross_val_score(estimator=LinearRegression(), X=train4, y=target4,
          scoring='mean_squared_error').mean()

Out[165]: -372146.59386070567
```

Воспользуемся Робастной Линейной Регрессией

```
In [166]: cross_val_score(estimator=RANSACRegressor(LinearRegression()), X=tr
          ain4, y=target4, scoring='mean_squared_error').mean()

Out[166]: -365065.35907338286
```

Тоже не помогла

In [163]:
```
target4[:10]
```

Out[163]:

	0
0	9.873
1	-1.530
2	8.508
3	6.963
4	49.940
5	-0.500
6	540.809
7	403.464
8	41.071
9	13.461

In [167]:
```
from sklearn.cluster import MeanShift
```

In [783]:
```
pca = PCA(n_components='mle')

X_pca = pca.fit_transform(np.concatenate((train4, test4)))
X_train_pca, X_test_pca = X_pca[:len(train4)], X_pca[len(train4):]
```

In [785]:
```
X_train_pca.shape
```

Out[785]:
```
(500, 9)
```

Методом Максимальеного правдоподобия получается, что лучше вообще не выкидывать признаки

In [168]:
```
from tqdm import tqdm
```

Воспользуемся нами пройденной ядерной регрессией, быть может, она нам поможет

In [238]:
```
dims = range(2, 9)
ansas = []
for dim in tqdm(dims):
    pca = PCA(n_components=dim)

    X_pca = pca.fit_transform(np.concatenate((train4, test4)))
    X_train_pca, X_test_pca = X_pca[:len(train4)], X_pca[len(train4
):]
    ansas.append(cross_val_score(estimator=kernel_regression.Kernel
Regression(), X=X_train_pca, y=target4.values.ravel(), scoring='mea
n_squared_error', cv=5))
```

```
100%|██████████| 7/7 [00:00<00:00, 84.36it/s]
```

In [239]:
```
ansas
```

Out[239]:
```
[array([  -55604.12893692,  -112289.91619638,  -168425.12668202,
          -82265.49715863, -1431944.03861944]),
 array([  -55323.63340705,   -79778.59355673,  -146824.15780479,
         -148337.28019332, -1385012.74557578]),
 array([  -57463.87608721,   -77123.19188435,  -141055.07322855,
          -75950.1320367 , -1442641.70404021]),
 array([  -58814.99680759,   -83301.15842256,  -141766.84609072,
          -73428.29858537, -1451160.26153275]),
 array([  -61782.49250037,   -82346.87966883,  -141480.78690932,
          -70118.06368102, -1463035.28643482]),
 array([  -61506.36850335,   -82511.12723661,  -142509.80962115,
          -69215.60737002, -1466009.96510083]),
 array([  -59560.01969514,   -79396.58486618,  -143076.52828576,
          -71366.68789475, -1467578.07286856])]
```

Стало получше, но все же все очень плохо еще

In [229]:
```
import kernel_regression
```

In [230]:
```
qwe = kernel_regression.KernelRegression()
```

In [ ]:
```
qwe.fit(X_train_pca, )
```

In [201]:
```
len(X_train_pca)
```

Out[201]:
```
500
```

In [231]:
```
cross_val_score(kernel_regression.KernelRegression(), X_train_pca,
target4.values.ravel(), scoring='mean_squared_error')
```

Out[231]:
```
array([ -78489.51576325, -160882.81273417, -929284.2929403 ])
```

Стало лучше, может стоит взять другое число компонент?

In [213]:
```
XX_tr, XX_te, yy_tr, yy_te = train_test_split(X_train_pca, target4.
values.ravel())
```

In [214]:
```
yy_tr.ravel().shape
```

Out[214]: (375,)

In [215]:
```
qwe.fit(XX_tr, yy_tr)
```

Out[215]: KernelRegression(gamma=None, kernel='rbf')

In [216]:
```
list(XX_te[0])
```

Out[216]: [4.0811149129003059, -5.7517575232752005]

In [217]:
```
len(qwe.predict(list(XX_te[0])))
```

```
/usr/local/lib/python3.6/site-packages/sklearn/utils/validation.py
:386: DeprecationWarning: Passing 1d arrays as data is deprecated
in 0.17 and willraise ValueError in 0.19. Reshape your data either
using X.reshape(-1, 1) if your data has a single feature or X.resh
ape(1, -1) if it contains a single sample.
  DeprecationWarning)
```

Out[217]: 1

In [218]:
```
qwe.predict(list(XX_te[0]))
```

```
/usr/local/lib/python3.6/site-packages/sklearn/utils/validation.py
:386: DeprecationWarning: Passing 1d arrays as data is deprecated
in 0.17 and willraise ValueError in 0.19. Reshape your data either
using X.reshape(-1, 1) if your data has a single feature or X.resh
ape(1, -1) if it contains a single sample.
  DeprecationWarning)
```

Out[218]: array([21.33802497])

Task 5

In [409]:
```
train5 = pd.read_csv('./hw11t5v3_train.txt', '\t', header=None)
test5 = pd.read_csv('./hw11t5v3_test.txt', '\t', header=None)
target5 = pd.read_csv('./hw11t5v3_target.txt', '\t', header=None)
target5_test = pd.read_csv('./hw11t5v3_target_test.txt', '\t', head
er=None)
```

In [410]:
```
train5.head()
```

Out[410]:

	0	1	2
0	0.895	-2.873	0.504
1	2.856	0.168	1.951
2	-0.576	-0.238	-0.437
3	-0.277	0.205	-0.218
4	3.494	-0.137	1.955

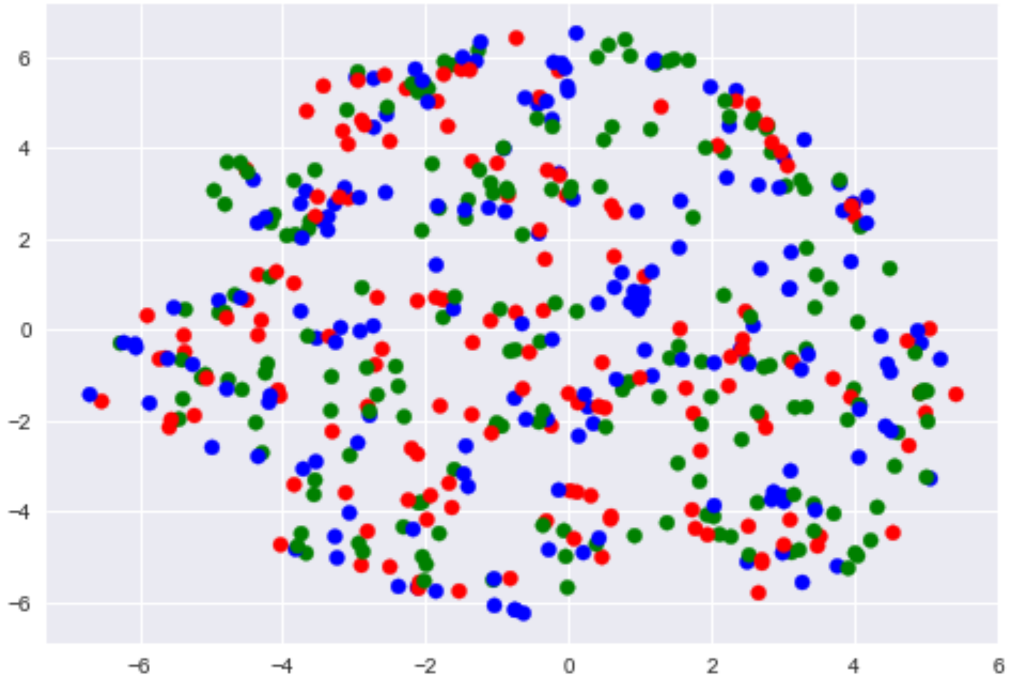
In [ ]:
```

```

In [411]:
```
sns.pairplot(train5)
```

Out[411]: <seaborn.axisgrid.PairGrid at 0x11a2d8a90>

In [749]:
```
tsne = TSNE(n_components=2, n_iter=100000, learning_rate=50)

X_tsne = tsne.fit_transform(np.concatenate((train4, test4)))
X_train_tsne, X_test_tsne = X_tsne[:len(train3)], X_tsne[len(train3
):]
plt.scatter(X_train_tsne[:,0], X_train_tsne[:,1], c=[clrs[targ[0]]
for targ in target5.values])
```

Out[749]: <matplotlib.collections.PathCollection at 0x11e82a748>



С виду сразу не понять, сколько тут будет кластеров, используем алго, окоторый сам определяет их число

In [750]:
```
ms = MeanShift()
ms_preds = ms.fit_predict(X_train_tsne)
```

In [751]:
```
ms_preds
```

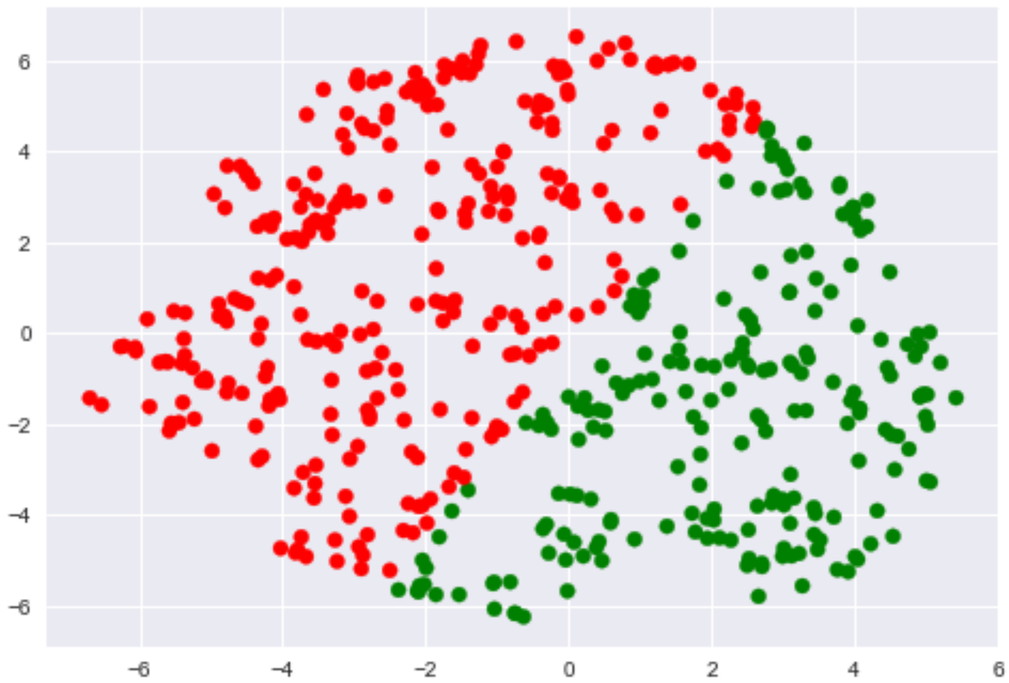
```
Out[751]: array([1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0,
          0, 1, 1,
                 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0,
          0, 0, 0,
                 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0,
          0, 0, 0,
                 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1,
          1, 1, 0,
                 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0,
          1, 0, 0,
                 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0,
          0, 0, 0,
                 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1,
          0, 0, 1,
                 1, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1,
          0, 1, 0,
                 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 0, 0,
          0, 1, 0,
                 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0,
          0, 0, 0,
                 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1,
          1, 0, 0,
                 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1,
          0, 0, 0,
                 0, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1,
          1, 0, 1,
                 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1,
          1, 0, 1,
                 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 1,
          1, 0, 0,
                 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0,
          0, 0, 1,
                 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0,
          0, 1, 1,
                 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0,
          0, 0, 0,
                 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0,
          0, 0, 1,
                 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0,
          1, 0, 1,
                 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1,
          1, 1, 0,
                 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1])
```

Нарисуем новые кластера и в каждом из них запустим свой KNN

```
In [752]: test_ms_preds = ms.predict(X_test_tsne)
```

In [753]:
```
plt.scatter(X_train_tsne[:,0], X_train_tsne[:,1], c=[clrs[targ + 1]
for targ in ms_preds])
```

Out[753]: <matplotlib.collections.PathCollection at 0x120edc390>



In [754]:
```
X_tr_0 = X_train_tsne[ms_preds == 0]
X_tr_1 = X_train_tsne[ms_preds == 1]
trgt_tr_0 = target5[ms_preds == 0].values.ravel()
trgt_tr_1 = target5[ms_preds == 1].values.ravel()
#-------------------------
X_te_0 = X_test_tsne[test_ms_preds == 0]
X_te_1 = X_test_tsne[test_ms_preds == 1]
trgt_te_0 = target5_test[test_ms_preds == 0].values.ravel()
trgt_te_1 = target5_test[test_ms_preds == 1].values.ravel()
```

In [761]:
```
knn_0 = KNeighborsClassifier(2)
knn_0.fit(X_tr_0, trgt_tr_0)
knn_1 = KNeighborsClassifier(2)
knn_1.fit(X_tr_1, trgt_tr_1)
```

Out[761]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minko
wski',
           metric_params=None, n_jobs=1, n_neighbors=2, p=2,
           weights='uniform')
```

In [762]:
```
preds_0 = knn_0.predict(X_te_0)
preds_1 = knn_1.predict(X_te_1)
```

In [763]:
```
accuracy_score(np.concatenate((preds_0, preds_1)), np.concatenate((
trgt_te_0, trgt_te_1)))
```

Out[763]: 0.46000000000000002

T-SNE дает более-менее результат, воспользуемся PCA и проделаем для него то же самое

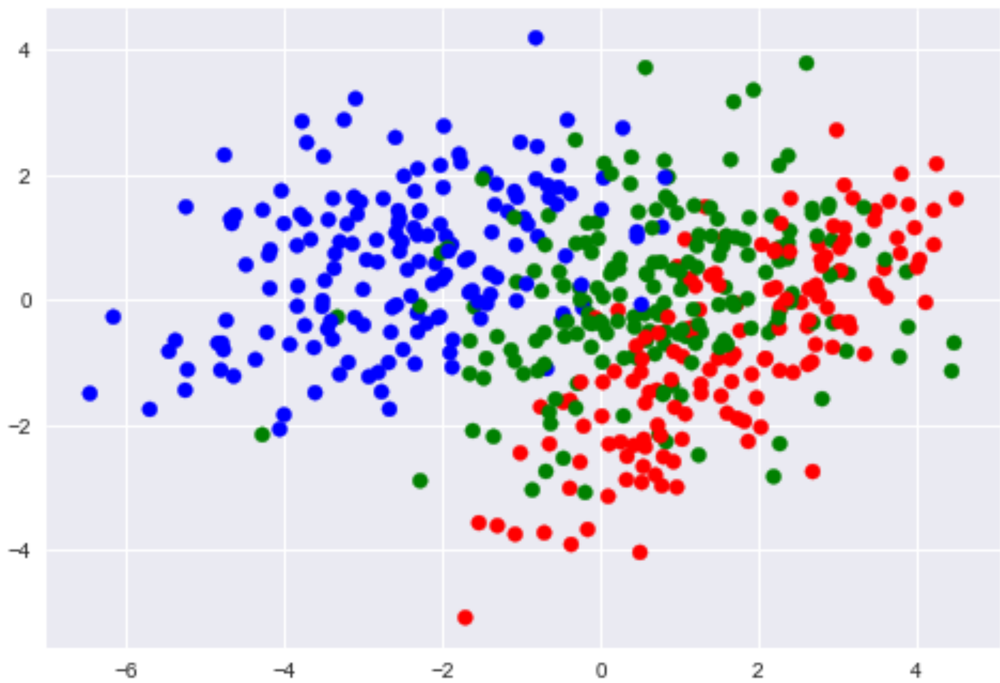
In [768]:
```
pca = PCA(n_components='mle')

X_pca = pca.fit_transform(np.concatenate((train5, test5)))
X_train_pca, X_test_pca = X_pca[:len(train5)], X_pca[len(train5):]
```

In [769]:
```
clrs = {1:'red', 2:'green', 3:'blue'}
```

In [770]:
```
colorrrs = [clrs]
```

In [777]:
```
plt.scatter(X_train_pca[:,0], X_train_pca[:,1], c=[clrs[targ[0]] fo
r targ in target5.values])
```

Out[777]: <matplotlib.collections.PathCollection at 0x1203ca7b8>



In [772]:
```
ms = MeanShift()
ms_preds = ms.fit_predict(X_train_pca)
```

In [774]:
```
len(np.unique(ms_preds))
```

Out[774]: 1

Всего один кластер

In [278]:
```
from sklearn.metrics import accuracy_score
```

In [775]:
```
knn_pca = KNeighborsClassifier()
knn_pca.fit(X_train_pca, target5.values.ravel())
predictions_knn_pca = knn_pca.predict(X_test_pca)
```

In [776]:
```
accuracy_score(predictions_knn_pca, target5_test.values.ravel())
```

Out[776]:
```
0.64000000000000001
```

Task6

In [526]:
```
from sklearn.datasets import fetch_olivetti_faces
```

In [546]:
```
dataset = fetch_olivetti_faces()
faces = dataset.images
```

In [540]:
```
faces[0]
```

Out[540]:
```
array([ 0.30991736,  0.36776859,  0.41735536, ...,  0.15289256,
        0.16115703,  0.1570248 ], dtype=float32)
```

In [545]:
```
dataset.images[0].shape
```

Out[545]:
```
(64, 64)
```

In [550]:
```
# set up the figure
fig = plt.figure(figsize=(6, 6))  # figure size in inches
fig.subplots_adjust(left=0, right=1, bottom=0, top=1, hspace=0.05,
wspace=0.05)

# plot the faces: each image is 64x64 pixels
for i in range(64):
    ax = fig.add_subplot(8, 8, i + 1, xticks=[], yticks=[])
    ax.imshow(faces[i], cmap=plt.cm.bone)
```

In [537]:
```
len((faces['data'])[0])
```

Out[537]: 4096

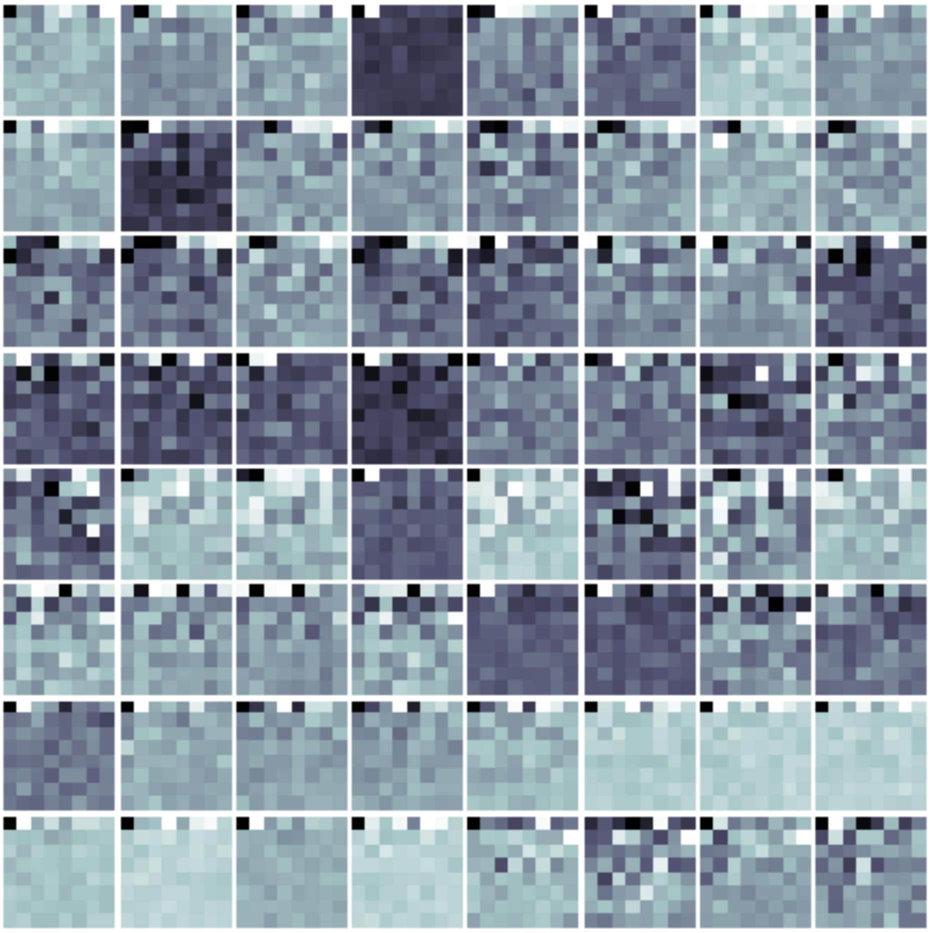
In [553]:
```
X,y=dataset.data, dataset.target
pca_oliv = PCA(64)
X_proj = pca_oliv.fit_transform(X)
print(X_proj.shape)
```

```
(400, 64)
```

Вот так выглядят данные 8x8

In [562]:

```
# set up the figure
fig = plt.figure(figsize=(6, 6))  # figure size in inches
fig.subplots_adjust(left=0, right=1, bottom=0, top=1, hspace=0.05,
wspace=0.05)

# plot the faces: each image is 64x64 pixels
for i in range(64):
    ax = fig.add_subplot(8, 8, i + 1, xticks=[], yticks=[])
    ax.imshow(X_proj[i].reshape((8,8)), cmap=plt.cm.bone)
```



In [554]:
```
print(np.cumsum(pca_oliv.explained_variance_ratio_))
```

```
[ 0.23812743  0.37806708  0.45775321  0.50773644  0.54383487  0.57
540423
  0.59967256  0.62003654  0.63961768  0.65633893  0.67229116  0.68
666095
  0.69912833  0.71059966  0.72122842  0.73100561  0.74019623  0.74
835199
  0.75589073  0.76336056  0.77034634  0.77649266  0.78233194  0.78
802919
  0.79349113  0.79880971  0.80394787  0.80890626  0.81348288  0.81
78947
  0.82191473  0.82575661  0.8293761   0.83272153  0.83592534  0.83
908576
  0.84213722  0.84512359  0.84794497  0.85068506  0.85328281  0.85
582274
  0.8582682   0.86066657  0.86297548  0.86523968  0.86746252  0.86
966693
  0.87175614  0.87380594  0.87577438  0.87768877  0.87953925  0.88
132864
  0.88310474  0.88482958  0.88651544  0.88815713  0.88977599  0.89
135993
  0.89291424  0.89443654  0.89593613  0.89741325]
```

In [555]:
```
len(pca_oliv.explained_variance_ratio_)
```

Out[555]:
```
64
```

Круто, сжав в 64 раза изображения сохряняется почти 90% дисперсии

Посмотрим на 8 главных компонент, как они выглядят

In [557]:

```
fig = plt.figure(figsize=(8,8))
fig.subplots_adjust(left=0, right=1, bottom=0, top=1, hspace=0.05,
wspace=0.05)
# plot the faces, each image is 64 by 64 pixels
for i in range(10):
    ax = fig.add_subplot(5, 5, i+1, xticks=[], yticks=[])
    ax.imshow(np.reshape(pca_oliv.components_[i,:], (64,64)), cmap=
plt.cm.bone, interpolation='nearest')
```

А теперь перейдем от 8x8 обратно в 64x64

In [563]:

```
X_inv_proj = pca_oliv.inverse_transform(X_proj)
X_proj_img = np.reshape(X_inv_proj,(400,64,64))
fig = plt.figure(figsize=(6,6))
fig.subplots_adjust(left=0, right=1, bottom=0, top=1, hspace=0.05,
wspace=0.05)
for i in range(64):
    ax = fig.add_subplot(8, 8, i+1, xticks=[], yticks=[])
    ax.imshow(X_proj_img[i], cmap=plt.cm.bone, interpolation='neare
st')
```

In [566]:
```
pca_oliv.components_.shape
```
Out[566]: (64, 4096)

In [ ]:
```
faces[0].dot(pca_oliv.components_)
```

In [630]:
```
def draw_projected(rooted):
    X,y=dataset.data, dataset.target
    pca_oliv = PCA(n_components=rooted ** 2)
    X_proj = pca_oliv.fit_transform(X)
    print(X_proj.shape)
    # set up the figure
    fig = plt.figure(figsize=(6, 6))  # figure size in inches
    fig.subplots_adjust(left=0, right=1, bottom=0, top=1, hspace=0.
05, wspace=0.05)

    # plot the faces: each image is 64x64 pixels
    for i in range(64):
        ax = fig.add_subplot(8, 8, i + 1, xticks=[], yticks=[])
        ax.imshow(X_proj[i].reshape((rooted,rooted)), cmap=plt.cm.b
one)
```

In [625]:
```
datka[0].shape
```
Out[625]: (4096,)

In [ ]:
```

```

In [626]:
```
ooo = PCA(n_components=4096)
```

In [627]:
```
prj = ooo.fit_transform(datka)
```

In [628]:
```
ooo.components_.shape
```

Out[628]: (400, 4096)

In [629]:
```
prj.shape
```

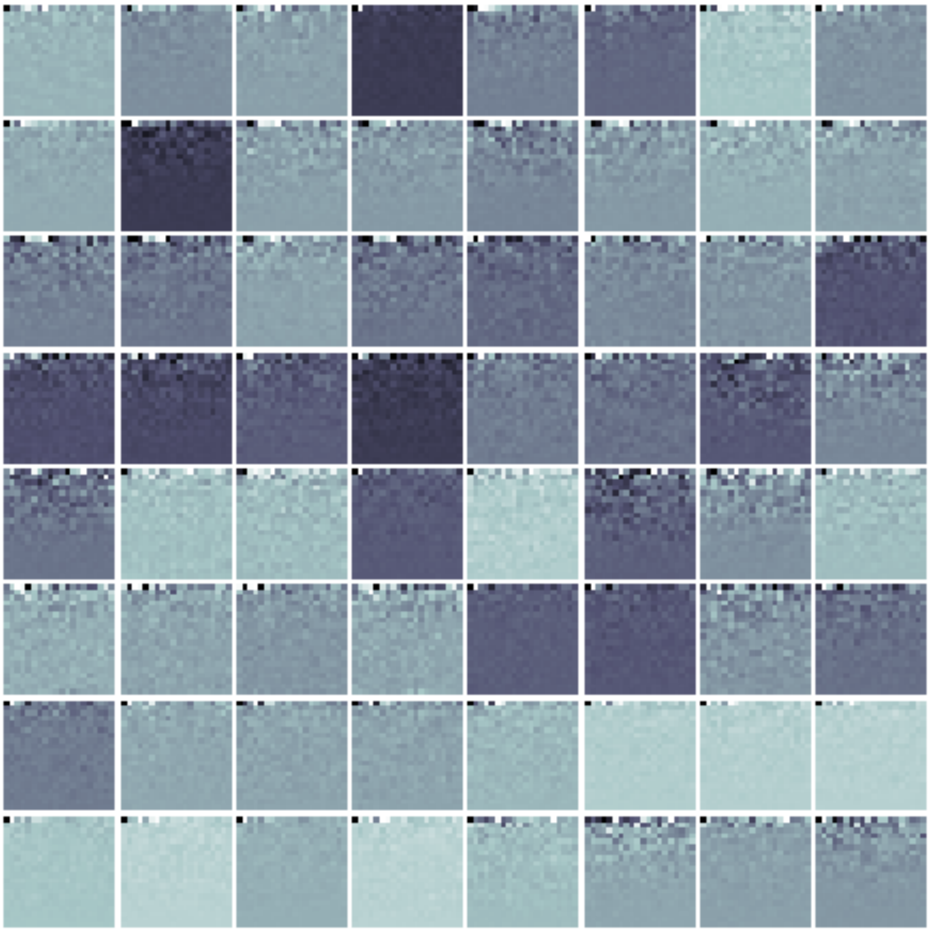
Out[629]: (400, 400)

In [604]:
```
np.sqrt(4096)
```

Out[604]: 64.0

In [658]:
```
draw_projected(20)
```

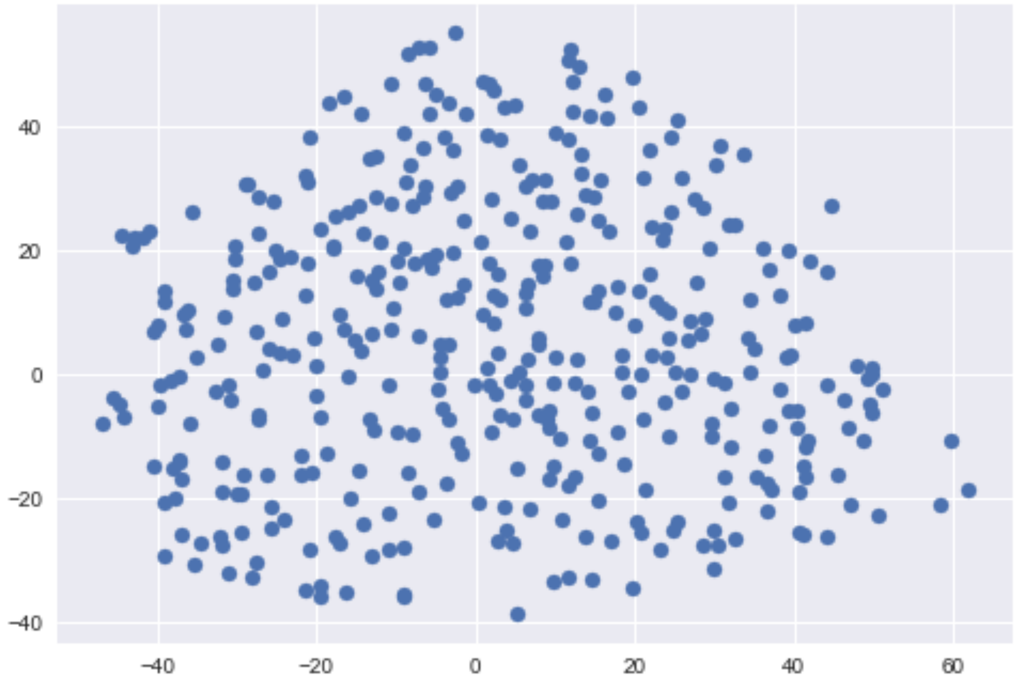
```
(400, 400)
```



Теперь применим T-SNE и PCA для размерности 2 и посмотрим, появились ли кластера

In [656]:
```
tsne = TSNE(n_components=2, n_iter=10000)

X_tsne = tsne.fit_transform(datka)
plt.scatter(X_tsne[:,0], X_tsne[:,1])
```

Out[656]: <matplotlib.collections.PathCollection at 0x1209e1390>



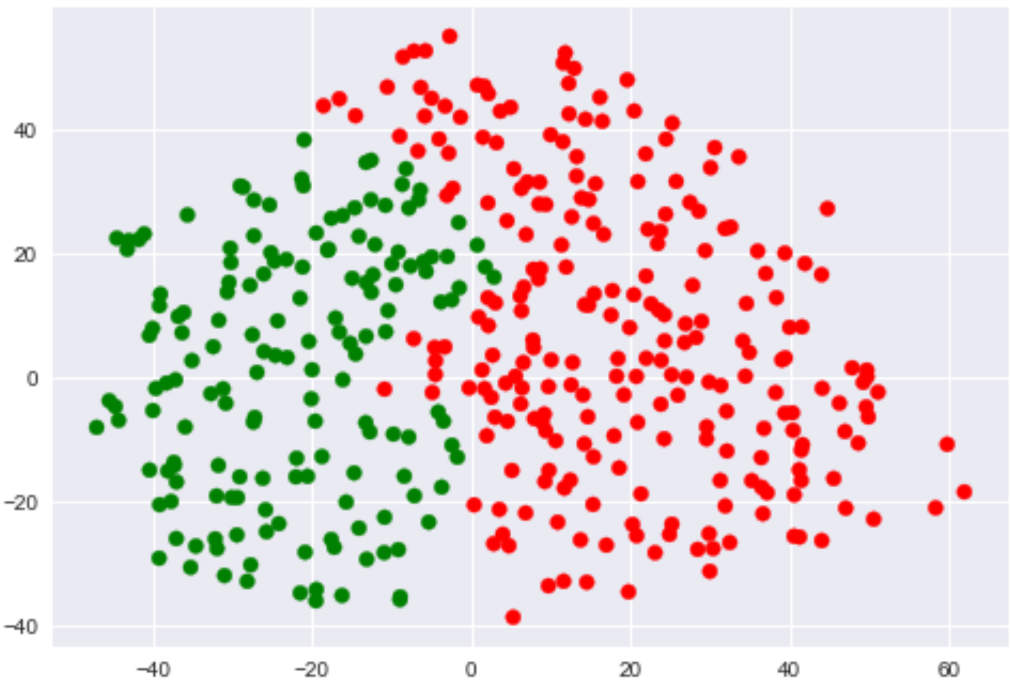
In [675]:
```
ac = AgglomerativeClustering()
clustered_tsne = ac.fit_predict(X_tsne)
```

In [676]:
```
clustered_tsne
```

```
Out[676]: array([1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
          0, 0, 0,
                 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0,
          0, 0, 0,
                 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0,
          0, 1, 0,
                 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
          0, 0, 0,
                 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0,
          0, 0, 0,
                 1, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0,
          0, 0, 0,
                 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0,
          1, 1, 0,
                 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1,
          1, 1, 1,
                 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0,
          0, 0, 0,
                 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
          0, 0, 0,
                 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
          1, 0, 0,
                 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
          1, 1, 1,
                 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
          0, 0, 0,
                 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
          1, 0, 0,
                 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
          0, 0, 0,
                 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0,
          0, 0, 0,
                 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
          0, 0, 0,
                 1, 1, 0, 1, 0, 0, 0, 0, 0])
```

In [678]:
```
plt.scatter(X_tsne[:,0], X_tsne[:,1], c=[clrs[elem + 1] for elem in clustered_tsne])
```

Out[678]: <matplotlib.collections.PathCollection at 0x1263dda90>



Вот что дал нам T-SNE, вовсе тяжело найти тут какие-либо кластера

Взглянем, что нам дает PCA

In [ ]:

In [659]:
```
pca = PCA(n_components=2)

X_pca = pca.fit_transform(datka)
plt.scatter(X_pca[:,0], X_pca[:,1])
```

Out[659]: <matplotlib.collections.PathCollection at 0x12056b4a8>

In [665]:
```
from sklearn.cluster import AgglomerativeClustering
```

In [672]:
```
ac = AgglomerativeClustering(3)
clustered_pca = ac.fit_predict(X_pca)
```

In [673]:
```
clustered_pca
```

```
Out[673]: array([2, 2, 2, 0, 2, 0, 2, 0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2,
          2, 2, 2,
                 0, 0, 0, 0, 0, 2, 2, 0, 2, 0, 2, 2, 0, 0, 0, 2, 2, 0, 2, 2,
          0, 0, 0,
                 0, 0, 0, 0, 2, 2, 2, 0, 0, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0, 0,
          2, 2, 0,
                 0, 2, 2, 2, 2, 2, 2, 2, 2, 0, 2, 0, 2, 0, 0, 0, 0, 0, 0, 0,
          0, 0, 2,
                 2, 2, 2, 2, 2, 2, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0, 0,
          0, 2, 0,
                 0, 0, 0, 2, 0, 0, 2, 0, 0, 0, 2, 0, 0, 0, 0, 2, 2, 2, 0, 0,
          2, 0, 0,
                 2, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 2, 0, 2, 0,
          0, 0, 0,
                 0, 2, 2, 0, 0, 0, 0, 0, 0, 2, 2, 0, 0, 0, 0, 2, 0, 2, 0, 0,
          0, 0, 2,
                 2, 0, 2, 2, 2, 0, 2, 2, 2, 0, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0,
          0, 0, 0,
                 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 0, 2, 0, 0,
          2, 0, 0,
                 0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 2, 2, 0, 2, 0, 2, 0, 0, 2, 2,
          2, 0, 2,
                 2, 2, 0, 2, 2, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0, 2, 0,
          0, 2, 0,
                 2, 2, 2, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 2, 2, 2, 0, 0, 0,
          0, 0, 0,
                 0, 0, 2, 2, 2, 2, 0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
          2, 1, 1,
                 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 2,
          0, 2, 0,
                 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1,
          1, 0, 1,
                 0, 0, 0, 2, 2, 0, 2, 0, 2, 2, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1,
          1, 1, 2,
                 0, 0, 0, 0, 2, 0, 2, 0, 0])
```

In [674]:
```
plt.scatter(X_pca[:,0], X_pca[:,1], c=[clrs[elem + 1] for elem in c
lustered_pca])
```

Out[674]: <matplotlib.collections.PathCollection at 0x1204bdb70>

В случае с PCA получилось более-менее отделить кластера. Мы смотрели ранее на главные 8 компонент, например, и они хорошо были похожи на те лица, а их можно разделить на кластера

In [ ]: