Lab#3

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0.1 Lab 3: Wide data and linear models

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[131]:
```
## Import libraries
import numpy as np
import pandas as pd
import seaborn as sns
import os
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn import manifold
from matplotlib import pyplot

from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import␣
↪LogisticRegression,LinearRegression,Lasso,Ridge,ElasticNet
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.metrics import precision_score, recall_score, f1_score
from sklearn.model_selection import train_test_split
```

[132]:
```
testX=pd.read_csv('/Users/aliceqichaowu/Desktop/38615/test_X.csv')
trainX=pd.read_csv('/Users/aliceqichaowu/Desktop/38615/train_X.csv')
trainY=pd.read_csv('/Users/aliceqichaowu/Desktop/38615/train_y.csv')
```

[133]:
```
print(testX.info())
print(trainX.info())
print(trainY.info())
testX.head(5)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110 entries, 0 to 109
Columns: 17971 entries, Unnamed: 0 to ENSG00000283697
dtypes: float64(17970), object(1)
memory usage: 15.1+ MB
None
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 444 entries, 0 to 443
Columns: 17971 entries, Unnamed: 0 to ENSG00000283697
dtypes: float64(17970), object(1)
memory usage: 60.9+ MB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 444 entries, 0 to 443
Data columns (total 2 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   Unnamed: 0                    444 non-null    object
 1   xml_neoplasm_histologic_grade 444 non-null    int64
dtypes: int64(1), object(1)
memory usage: 7.1+ KB
None
```

[133]:

```
                             Unnamed: 0  ENSG00000000003  ENSG00000000005  \
0  1576BB97-F8EA-48FF-9494-EBC7A0C97312         7.503849         1.685440
1  63F4281A-4D90-4589-879E-549097FB3459         6.112919        -5.425877
2  74CF740D-201D-4070-99B9-F007E7C4D472         6.183846         1.217355
3  1329E1C1-743E-4541-9081-165572D4BF47         6.325535        -0.197432
4  88BBA1BF-44E0-416E-A028-04F410A3FE5D         7.162383        -5.539710

   ENSG00000000419  ENSG00000000457  ENSG00000000938  ENSG00000000971  \
0         8.090089         5.546588         3.412025         5.871539
1         5.604743         4.248246         3.374033         3.370075
2         6.093903         4.403216         5.722867         6.123209
3         6.722632         4.509093         4.941256         3.700171
4         6.186110         5.270282         5.412103         3.781568

   ENSG00000001036  ENSG00000001084  ENSG00000001167  …  ENSG00000282651  \
0         8.395029         5.894996         6.313896  …         3.626396
1         6.804015         4.646287         6.236134  …        -5.425877
2         7.680258         4.983386         5.626569  …        11.317818
3         7.492606         5.031053         5.859242  …         3.536141
4         7.285779         4.847552         6.337205  …         5.112772

   ENSG00000282815  ENSG00000282939  ENSG00000283063  ENSG00000283439  \
0        -2.640463        -7.278265         0.721287        -7.278265
1        -2.143410         1.956699         1.377768        -5.425877
2        -5.259782         5.093316         3.800607        -5.259782
3        -1.362703         3.480703         0.776383        -0.999629
4        -5.539710         4.369268         2.927849         0.791397

   ENSG00000283463  ENSG00000283526  ENSG00000283586  ENSG00000283632  \
0         4.672536         5.153675        -7.278265         4.843800
```

```
1          4.560829         3.735085        -5.425877         4.105789
2          4.966710         2.829487        -5.259782         5.118704
3          4.794226        -5.399485        -5.399485         4.660878
4          4.542333         4.628775        -5.539710         4.812787

   ENSG00000283697
0          4.302864
1          4.803357
2          5.024979
3          4.684343
4          4.524834

[5 rows x 17971 columns]
```

[231]:
```
# Check missing values
print('There are %i nan in the dataframe' % trainY.isna().sum().sum())
```

```
There are 0 nan in the dataframe
```

[134]:
```
# Set up X_test, X_train, and y
y = trainY.iloc[:,1:]
X_train = trainX.iloc[:,1:]
X_test= testX.iloc[:,1:]
```

[135]:
```
# Normalization
scaler = StandardScaler()  # normalization: zero mean, unit variance
scaler.fit(X_train)  # scaling factor determined from the training set

X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)  # apply the same scaling to the test set
```

0.1.2 1. Try different linear models: linear regression, logistic regression, Ridge regression, LASSO

[51]:
```
## Linear regression:
# accruacy: 0.91666 (private), 0.84375 (public)
mdl_lar= LinearRegression()
mdl_lar.fit(X_train, y)
y_pred_LaR_temp = np.squeeze(mdl_lar.predict(X_test))
y_pred_LaR=[]
for i in y_pred_LaR_temp:
    if i>0.5:
        y_pred_LaR.append(1)
    else:
        y_pred_LaR.append(0)
# [ x for x in y_pred_LaR if x != 0 ]
```

[75]:
```python
## Logistic regression
# accruacy: 0.88888 (private), 0.83870 (public)
mdl_lr = LogisticRegression('none')
mdl_lr.fit(X_train, y)
y_pred_lr_temp = np.squeeze(mdl_lr.predict(X_test))
y_pred_LR=[]
for i in y_pred_lr_temp:
    if i>0.5:
        y_pred_LR.append(1)
    else:
        y_pred_LR.append(0)
```

```
/Users/aliceqichaowu/opt/anaconda3/lib/python3.8/site-
packages/sklearn/utils/validation.py:63: DataConversionWarning: A column-vector
y was passed when a 1d array was expected. Please change the shape of y to
(n_samples, ), for example using ravel().
  return f(*args, **kwargs)
```

[65]:
```python
## Ridge regression
# accruacy: 0.91666 (private), 0.84375 (public)
mdl_rr = Ridge(alpha=0.1)
mdl_rr.fit(X_train, y)
y_pred_rr_temp = np.squeeze(mdl_rr.predict(X_test))
y_pred_RR=[]
for i in y_pred_rr_temp:
    if i>0.5:
        y_pred_RR.append(1)
    else:
        y_pred_RR.append(0)
```

[66]:
```python
## Lasso regression:
# accruacy: 0.87671 (private), 0.86567 (public)
mdl_las = Lasso(alpha=0.1)
mdl_las.fit(X_train, y)
y_pred_las_temp = np.squeeze(mdl_las.predict(X_test))
y_pred_Las=[]
for i in y_pred_las_temp:
    if i>0.5:
        y_pred_Las.append(1)
    else:
        y_pred_Las.append(0)
```

[73]:
```python
## Elastic Net
# accruacy: 0.87323 (private), 0.84848 (public)
mdl_en = ElasticNet(alpha=0.1)
mdl_en.fit(X_train, y)
y_pred_en_temp = np.squeeze(mdl_en.predict(X_test))
y_pred_EN=[]
```

```
for i in y_pred_en_temp:
    if i>0.5:
        y_pred_EN.append(1)
    else:
        y_pred_EN.append(0)
```

0.1.3 2. Test regularization parameters:

- Try L1 (lasso) and L2 (ridge) on logistic regression; Try lasso and ridge regression models with with different alpha values
- After trying different models, I found out the logistic model wirh penalty='elasticnet',solver='saga',l1_ratio=0.5 has the highest accuracy 0.90140 (private score) and 0.88888 (public score).

[165]:
```
## Logistic regression
# LR1 (logitstic, penalty='l1',solver='liblinear'): 0.85714 (private), 0.81967␣
↪(public)
# LR2 (logitstic, penalty='elasticnet',solver='saga',l1_ratio=0.5): 0.90140, 0.
↪88888
# LR2, alpha=100: 0.79120, 0.76404

mdl_lr1 = LogisticRegression(penalty='l1',solver='liblinear')
mdl_lr2 = LogisticRegression(penalty='elasticnet',solver='saga',l1_ratio=0.5)
mdl_en_a1 = ElasticNet(alpha=1)
mdl_en_a100 = ElasticNet(alpha=100)

mdl_lr1.fit(X_train, y)
mdl_lr2.fit(X_train, y)
mdl_en_a1.fit(X_train, y)
mdl_en_a100.fit(X_train, y)

y_pred_lr_temp1 = np.squeeze(mdl_lr1.predict(X_test))
y_pred_lr_temp2 = np.squeeze(mdl_lr2.predict(X_test))
y_pred_en_a1_temp=np.squeeze(mdl_en_a1.predict(X_test))
y_pred_en_a100_temp=np.squeeze(mdl_en_a100.predict(X_test))

y_pred_LR1=[]
y_pred_LR2=[]
y_pred_en_a1=[]
y_pred_en_a100=[]

for i in y_pred_en_a100_temp:
    if i>0.5:
        y_pred_en_a100.append(1)
    else:
        y_pred_en_a100.append(0)
```

```
/Users/aliceqichaowu/opt/anaconda3/lib/python3.8/site-
packages/sklearn/utils/validation.py:63: DataConversionWarning: A column-vector
y was passed when a 1d array was expected. Please change the shape of y to
(n_samples, ), for example using ravel().
  return f(*args, **kwargs)
/Users/aliceqichaowu/opt/anaconda3/lib/python3.8/site-
packages/sklearn/utils/validation.py:63: DataConversionWarning: A column-vector
y was passed when a 1d array was expected. Please change the shape of y to
(n_samples, ), for example using ravel().
  return f(*args, **kwargs)
/Users/aliceqichaowu/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_sag.py:328: ConvergenceWarning: The max_iter was
reached which means the coef_ did not converge
  warnings.warn("The max_iter was reached which means "
```

0.1.4 3. Random shuffle

- Model accuracy: 0.67605 (private), 0.65671 (public)

We can see that the random model will have a random chance level

[130]:
```
from sklearn.utils import shuffle
X_ran, y_ran = shuffle(X_train, y)

reg = LinearRegression()
reg.fit(X_ran,y_ran)

y_pred_ran_temp = reg.predict(X_test)
y_pred_ran=[]
for i in y_pred_ran_temp:
    if i>0.5:
        y_pred_ran.append(1)
    else:
        y_pred_ran.append(0)
# y_pred_ran
```

[152]:
```
## export the y_pred data file
y_pred_col=pd.DataFrame(data={'ID':testX.iloc[:
 ↪,0],'xml_neoplasm_histologic_grade':y_pred_en_a100})
os.makedirs('/Users/aliceqichaowu/Desktop/38615/', exist_ok=True)
y_pred_col.to_csv('/Users/aliceqichaowu/Desktop/38615/pred_en_a100.
 ↪csv',index=False)
```

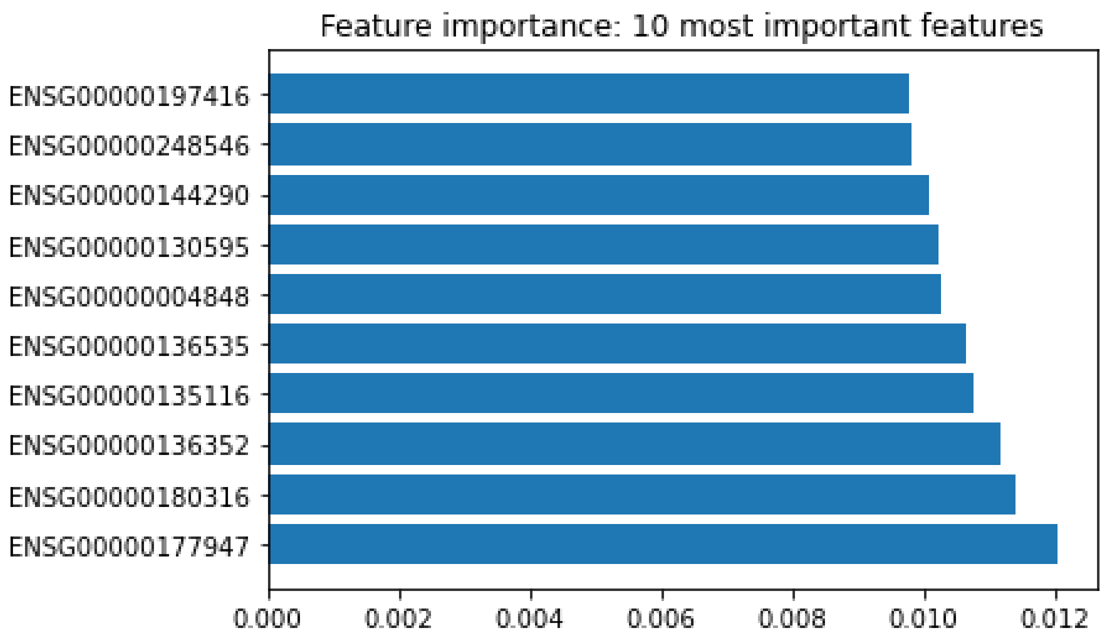
0.1.5 4. Feature importance: find out the 10 most important features

[224]:
```
importance = np.flip(np.argsort(mdl_lr2.coef_[0]))
importance10=importance[0:10]
all_feat=testX.columns[1:]
```

```python
all_arr=np.array(all_feat)
print(all_arr[importance10])
plt.barh(all_arr[importance10], np.flip(np.sort(mdl_lr2.coef_[0]))[0:10])
plt.title('Feature importance: 10 most important features')
```

```
['ENSG00000177947' 'ENSG00000180316' 'ENSG00000136352' 'ENSG00000135116'
 'ENSG00000136535' 'ENSG00000004848' 'ENSG00000130595' 'ENSG00000144290'
 'ENSG00000248546' 'ENSG00000197416']
```

[224]: Text(0.5, 1.0, 'Feature importance: 10 most important features')

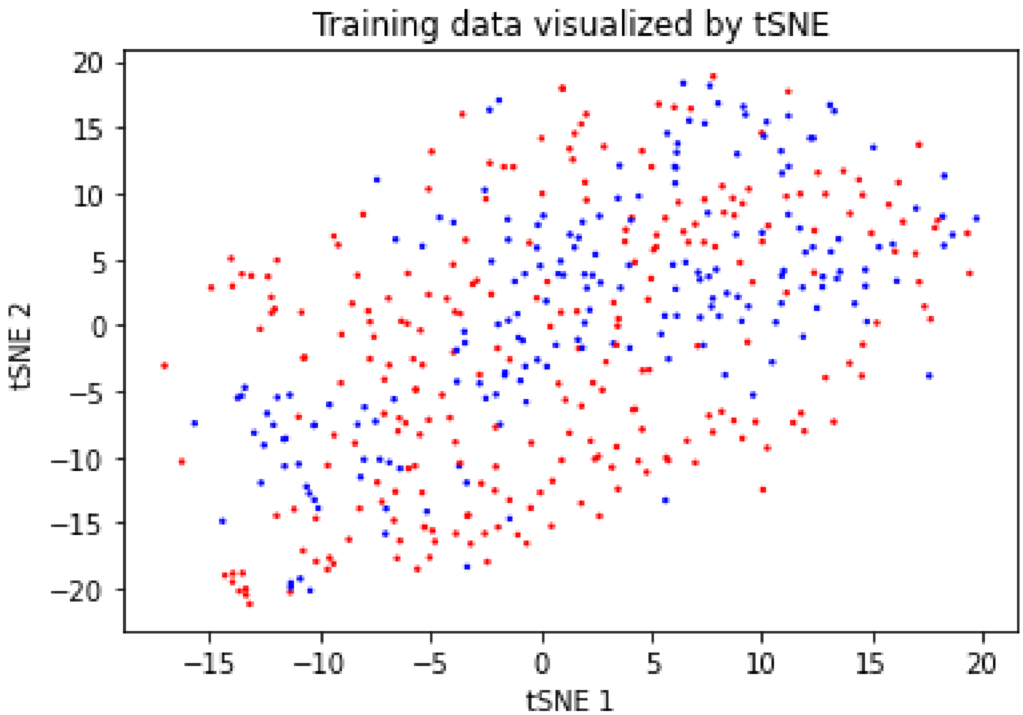


0.1.6 5. Visualize the dataset: implement tSNE to visualize the clusters

- Here, we can see it is hard to differentiate two classes with tSNE

[234]:
```python
tsne = manifold.TSNE(random_state=42,n_components=2)
X_tsne = tsne.fit_transform(X_train)
colors = {0:'b', 1:'r'}
fig1,ax = plt.subplots()
ax.scatter(X_tsne[:,0], X_tsne[:,1],c=trainY.iloc[:,-1].map(colors), s=2)
ax.set_xlabel('tSNE 1')
ax.set_ylabel('tSNE 2')
plt.title('Training data visualized by tSNE')
```

[234]: Text(0.5, 1.0, 'Training data visualized by tSNE')


Training data visualized by tSNE
tSNE 1
tSNE 2
20
15
10
5
0
−5
−10
−15
−20
20
15
10
5
0
−5
−10
−15

```
[ ]:
```