02PreProcessing

November 10, 2018

1 前處理-資料清理

- 1. missing data
 - 平均值、標準差、屆在平均值與標準差之間的亂數
- 2. range 差異過大的資料
 - 偵測 (identity): PCA
 - 處理: 取 log e.g. 10^1 => 1, 10^6 => 6
- 3. 資料不一致的問題
 - domain knowledge e.g. 年紀為負的
- 4. 正規化 (Normalize)
 - L1 Norm(穩定: 水平調整較少):

$$- \| \|_1 = \sum \| \|_1$$

• L2 Norm(強健: 較能對抗 outlier):

$$- \| \|_2 = \frac{1}{\sqrt{(\sum^2)}}$$

- 5. 類別型資料的處理
 - 自然語言 (NLP): 先轉成類別型資料
 - · onehot encoding

0	1	2
[1,0,0]	[0,1,0]	[0,0,1]

- 7. Feature 產生工具
 - PolynomialFeatures: (_1, _2)=> (1, _1, _2, _1^2, _1 _2, _2^2)
- 8. 議題:
 - 請問取 log 與 normalize 有什麼差別?

2 IMPORT & DATA

```
In [1]: import pandas as pd
       import numpy as np
       from collections import Counter
       import re
       import numpy as np
       from sklearn import preprocessing
       import matplotlib.pyplot as plt
       from mpl toolkits.mplot3d import Axes3D
       from sklearn.decomposition import PCA
       import os
       import random
       import math
In [2]: df = pd.read_csv('train.csv')
       # 請查看 df.info()
       # 並找出共有幾種型別,以及哪一些欄位有 null 值
       #=======your works starts========#
       df_info =
       <class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
PassengerId
             891 non-null int64
Survived
             891 non-null int64
Pclass
             891 non-null int64
Name
             891 non-null object
Sex
             891 non-null object
             714 non-null float64
Age
             891 non-null int64
SibSp
Parch
             891 non-null int64
Ticket
             891 non-null object
Fare
             891 non-null float64
Cabin
             204 non-null object
Embarked
             889 non-null object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.6+ KB
In [3]: # 請查看 df.describe()
       # 請透過 mean 關注每一個變數的 scale
       #=======your works starts=======#
       df_describe =
```

```
df_describe
Out[3]:
               PassengerId
                               Survived
                                             Pclass
                                                             Age
                                                                       SibSp \
                891.000000
                            891.000000
                                         891.000000
                                                     714.000000
                                                                  891.000000
        count
                446.000000
                               0.383838
                                           2.308642
                                                       29.699118
                                                                    0.523008
        mean
        std
                257.353842
                               0.486592
                                           0.836071
                                                       14.526497
                                                                    1.102743
        min
                  1.000000
                               0.000000
                                           1.000000
                                                        0.420000
                                                                    0.000000
        25%
                               0.000000
                                           2.000000
                223.500000
                                                       20.125000
                                                                    0.000000
        50%
                446.000000
                               0.000000
                                           3.000000
                                                       28.000000
                                                                    0.000000
        75%
                668.500000
                               1.000000
                                           3.000000
                                                       38.000000
                                                                    1.000000
        max
                891.000000
                               1.000000
                                           3.000000
                                                       80.000000
                                                                    8.000000
                    Parch
                                  Fare
               891.000000
                            891.000000
        count
                 0.381594
                             32.204208
        mean
        std
                 0.806057
                             49.693429
        min
                 0.000000
                             0.000000
        25%
                 0.000000
                             7.910400
        50%
                 0.000000
                             14.454200
        75%
                 0.000000
                             31.000000
                 6.000000
                           512.329200
        max
In [4]: # 請透過 head() 查看 df 的頭 5 行
        #=======your works starts=========#
        df head =
        #========your works ends=========#
        df_head
Out [4]:
           PassengerId Survived Pclass
        0
                     1
                                0
                                        3
                     2
        1
                                1
                                        1
        2
                     3
                                        3
                                1
        3
                     4
                                1
                                        1
        4
                     5
                                        3
                                                          Name
                                                                   Sex
                                                                         Age
                                                                              SibSp
        0
                                      Braund, Mr. Owen Harris
                                                                  male
                                                                        22.0
                                                                                   1
        1
           Cumings, Mrs. John Bradley (Florence Briggs Th...
                                                                female
                                                                        38.0
                                                                                   1
        2
                                       Heikkinen, Miss. Laina
                                                                female
                                                                        26.0
                                                                                   0
                Futrelle, Mrs. Jacques Heath (Lily May Peel)
        3
                                                                female
                                                                        35.0
                                                                                   1
                                     Allen, Mr. William Henry
        4
                                                                  male
                                                                        35.0
           Parch
                             Ticket
                                        Fare Cabin Embarked
        0
               0
                                      7.2500
                         A/5 21171
                                               NaN
                                                           S
        1
                          PC 17599
                                               C85
                                                           C
               0
                                     71.2833
```

7.9250

NaN

S

STON/02. 3101282

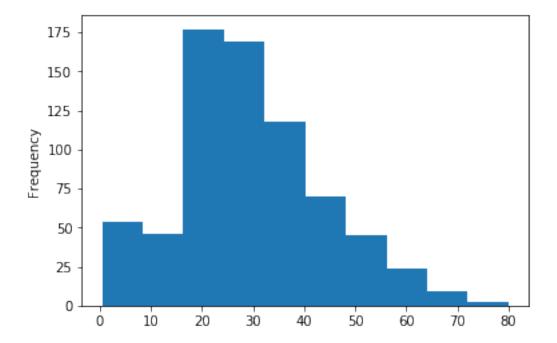
2

3	0	113803	53.1000	C123	S
4	0	373450	8.0500	NaN	S

3 PREPROCESSING

3.1 Age - Fill in missing values

```
In [5]: # 查看 Age 的分布狀況 (hint: df['Age'].plot('hist'))
#=======your works starts======#
age_ax =
#======your works ends======#
plt.show()
```



```
In [6]: # 作法一: 取平均值

#=======your works starts======#

avg_age =

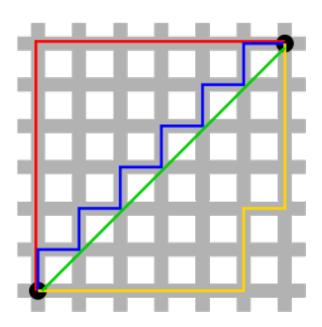
#=======your works ends=======#

print("avg_age", avg_age)

# avg_age 29.69911764705882
```

avg_age 29.69911764705882

```
In [7]: # 作法二: 取中位數
       #=======your works starts========#
       median_age =
       print("median_age", median_age)
       # median age 28.0
median_age 28.0
In [8]: # 作法三: 用相同的分布產生亂數塞入 (hint: 使用 np.random.randint)
       std = df['Age'].std()
       mean = df['Age'].mean()
       size = len(df[pd.isnull(df['Age'])])
       np.random.seed(1212)
       #=======your works starts========#
       random_age =
       #=======your works ends========#
       print("random_age", random_age)
       print("len(random_age)", len(random_age))
       # random_age [23 41 37 17 31 20 28 24 16 42 33 19 22 20 29 15 32 16 35 40 35 34 26 27
       # len(random_age) 177
random_age [23 41 37 17 31 20 28 24 16 42 33 19 22 20 29 15 32 16 35 40 35 34 26 27
37 28 30 23 31 33 42 30 25 21 29 15 21 16 39 39 21 31 31 37 31 30 23 41
30 35 33 21 31 28 39 37 31 29 29 40 16 43 20 29 36 22 27 41 32 24 35 23
29 43 33 43 31 34 34 28 27 40 29 35 27 20 40 37 16 29 29 39 20 17 20 35
24 42 34 33 26 38 42 31 30 40 34 16 35 16 34 24 43 29 22 29 20 43 29 38
37 39 35 42 40 19 32 17 25 36 15 26 31 23 19 24 34 39 39 19 17 28 16 35
20 16 29 18 34 43 16 28 30 42 27 25 36 19 22 43 37 38 30 15 32 38 41 21
26 33 20 19 21 29 40 30 28]
len(random_age) 177
In [9]: df['avg_age'] = df['Age']
       df.loc[pd.isnull(df['Age']), 'avg_age'] = avg_age
       df['median_age'] = df['Age']
       df.loc[pd.isnull(df['Age']), 'median_age'] = median_age
       df['random_age'] = df['Age']
       df.loc[pd.isnull(df['Age']), 'random_age'] = random_age
       df.loc[pd.isnull(df['Age']), ['avg_age', 'median_age', 'random_age']].head()
Out [9]:
             avg_age median_age random_age
       5
           29.699118
                           28.0
                                      23.0
```



11_12_norm

17	29.699118	28.0	41.0
19	29.699118	28.0	37.0
26	29.699118	28.0	17.0
28	29.699118	28.0	31.0

3.2 Age - Normalize

- L1 Normalization: $||x||_2 = \sqrt{(\sum_i x_i^2)} = \sqrt{x_1^2 + x_2^2 + \ldots + x_i^2}$ L2 Normalization: $||x||_1 = \sum_i |x_i| = |x_1| + |x_2| + \ldots + |x_i|$
- difference

```
In [10]: #請寫出 L1 Normaliaze 的 function
        def normalize_l1(X):
            """if type(X) == np.array, and X has two dimensiions"""
           #=======your works starts=======#
           11_x =
           X =
           #======your works ends======#
           return X
        X = [[1., -1., 2.],
            [2., 0., 0.],
            [ 0., 1., -1.]]
        X_normalized = normalize_l1(X)
        print(X_normalized)
        # [[ 0.25 -0.25 0.5 ]
```

```
# [ 0.5 O. O. ]
        # [ 0. 0.25 -0.25]]
[[ 0.25 -0.25 0.5 ]
Γ 0.5
       0.
             0. 1
ΓΟ.
       0.25 - 0.25]
In [11]: #請寫出 L2 Normaliaze 的 function
        def normalize_12(X):
           """if type(X) == np.array, and X has two dimensiions"""
           #=======your works starts=======#
           12_x =
           X =
           #=======your works ends========#
           return X
        X_normalized = normalize_12(X)
        print(X_normalized)
        # [[ 0.28867513 -0.28867513 0.57735027]
        # [ 0.57735027 0.
                                  0.
        # \( \int 0 \).
                       0.28867513 -0.28867513]]
[[ 0.28867513 -0.28867513  0.57735027]
[ 0.57735027 0.
                        0.
ΓΟ.
             0.28867513 -0.28867513]]
In [12]: X = [[1., -1., 2.],
            [2., 0., 0.],
            [ 0., 1., -1.]]
        # 請使用 preprocessing.normalize(X, norm='l1') 比較,與我們自己寫的 normalize function
        #=======your works starts======#
        X_normalized =
        #=======your works ends=======#
        print(X_normalized)
        # sklearn l1_norm
        # [[ 0.25 -0.25 0.5 ]
        # [ 1. O. O. ]
        # [ 0. 0.5 -0.5 ]]
[[ 0.25 -0.25 0.5 ]
Г1.
       0. 0. ]
[ 0.
       0.5 -0.5]]
In [13]: avg_age_l1 = normalize_l1(df['avg_age'].values)
        avg_age_12 = normalize_12(df['avg_age'].values)
```

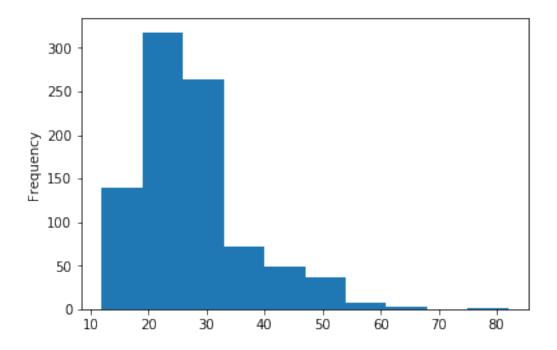
```
df['avg_age_l1'] = avg_age_l1
        df['avg_age_12'] = avg_age_12
        df[['avg_age', 'avg_age_l1', 'avg_age_l2']].head()
Out[13]:
           avg_age avg_age_11 avg_age_12
        0
              22.0
                     0.000831
                                 0.022735
              38.0
                     0.001436
        1
                                0.039270
        2
              26.0
                     0.000983
                                0.026869
        3
              35.0
                     0.001323
                                0.036170
                     0.001323
        4
              35.0
                                0.036170
3.3 Cabin - NLP category
In [14]: #整理出每一個 Cabin 的個數並排序 (hint:Counter(), sorted())
        #=======your works starts=======#
        sorted_cabin_counter =
        #=======your works ends=======#
        print(sorted_cabin_counter[:10])
        # [('A10', 1), ('A14', 1), ('A16', 1), ('A19', 1), ('A20', 1), ('A23', 1), ('A24', 1)
[('A10', 1), ('A14', 1), ('A16', 1), ('A19', 1), ('A20', 1), ('A23', 1), ('A24', 1), ('A26', 1
In [15]: # 抓出第一個 char 出來分類·並轉成 int 類別 (hint:Counter(), sorted())
        #=======your works starts=======#
        new_Cabin =
        mapping_dict =
        new_Cabin_int =
        #=======your works ends=======#
        print(new_Cabin.values[:10])
        print(mapping_dict)
        print(new_Cabin_int[:10])
        # ['n' 'C' 'n' 'C' 'n' 'n' 'E' 'n' 'n' 'n']
        # {'n': 0, 'B': 1, 'T': 2, 'E': 3, 'C': 4, 'F': 5, 'G': 6, 'D': 7, 'A': 8}
        # [0, 4, 0, 4, 0, 0, 3, 0, 0, 0]
['n' 'C' 'n' 'C' 'n' 'n' 'E' 'n' 'n' 'n']
{'T': 0, 'A': 1, 'F': 2, 'G': 3, 'n': 4, 'C': 5, 'E': 6, 'D': 7, 'B': 8}
[4, 5, 4, 5, 4, 4, 6, 4, 4, 4]
In [16]: df['cabin_cat'] = new_Cabin_int
        df[['Cabin', 'cabin_cat']].head()
```

```
Out[16]: Cabin cabin_cat
           NaN
                      5
        1
           C85
        2
           NaN
                       4
        3 C123
                      5
           NaN
3.4 Sex - Category
In [17]: # 請算出 Sex 共有幾個類別,每一個類別共出現幾次 (hint:Counter)
        #=======your works starts=======#
        #========your works ends========#
       print(counter)
        #Counter({'male': 577, 'female': 314})
Counter({'male': 577, 'female': 314})
In [18]: # 創造出一個與 df['Sex'] 等長的 array, 並將 df['Sex'] 中的 male 換成 1, female 換成 0
        #======your works starts=======#
        sex_mapping =
        sex_cat =
        #======your works ends=======#
       print("Counter(sex_cat)", Counter(sex_cat))
        #Counter(sex_cat) Counter({1: 577, 0: 314})
Counter(sex_cat) Counter({1: 577, 0: 314})
In [19]: df['sex_cat'] = sex_cat
       Counter(df['sex_cat'])
Out[19]: Counter({1: 577, 0: 314})
   Ticket - Category
3.5
In [20]: #整理出每一個 Ticket 的個數並排序 (hint:Counter(), sorted())
        #=======your works starts=======#
        sorted_ticket_counter =
        #=======your works ends=======#
       print(sorted_ticket_counter)
        # [('110152', 3), ('110413', 3), ('110465', 2), ('110564', 1), ('110813', 1), ('11124
```

```
[('110152', 3), ('110413', 3), ('110465', 2), ('110564', 1), ('110813', 1), ('111240', 1), ('1
In [21]: # ticket
        ticket_cat = {}
        for ticket in df['Ticket']:
           if ticket.isdigit():
               ticket_cat[ticket] = 1
           elif ticket.startswith('A'):
               ticket_cat[ticket] = 2
           elif ticket.startswith('C'):
               ticket_cat[ticket] = 3
           elif ticket.startswith('F'):
               ticket_cat[ticket] = 4
           elif ticket.startswith('P'):
               ticket_cat[ticket] = 5
           elif ticket.startswith('SOTON'):
               ticket_cat[ticket] = 6
           elif ticket.startswith('STON'):
               ticket_cat[ticket] = 7
           elif ticket.startswith('S'):
               ticket_cat[ticket] = 8
           elif ticket.startswith('W'):
               ticket_cat[ticket] = 9
           else:
               ticket_cat[ticket] = 0
        df['ticket_cat'] = df['Ticket'].apply(ticket_cat.get)
        print(Counter(df['ticket_cat']))
Counter({1: 661, 5: 65, 3: 47, 8: 30, 2: 29, 7: 18, 6: 17, 9: 13, 4: 7, 0: 4})
3.6 Embarked - Category
In [22]: #整理出每一個 Embarked 的個數並排序 (hint:Counter(), sorted())
        sorted_embarked_counter =
        #=======your works ends=======#
        print(sorted_embarked_counter)
        # [('C', 168), ('Q', 77), ('S', 644), ('nan', 2)]
[('C', 168), ('Q', 77), ('S', 644), ('nan', 2)]
In [23]: # 創造 embarked 的類別對應 dict
        #=======your works starts=======#
        embarked_cat =
```

```
print(embarked_cat)
        #{nan: 0, 'S': 1, 'Q': 2, 'C': 3}
{nan: 0, 'C': 1, 'S': 2, 'Q': 3}
In [24]: # 轉換 embarked 為數字類別
        #=======your works starts=======#
        df['embarked cat'] =
        #======your works ends======#
        print(Counter(df['embarked_cat']))
        #Counter({1: 644, 3: 168, 2: 77, 0: 2})
Counter({2: 644, 1: 168, 3: 77, 0: 2})
3.7 Title - NLP category
In [25]: #請找到位在","以及"."的所有字並將"", ".", "," 去掉 (hint: re.findall(), str.replace
        def find_call(name):
           #=======your works starts=======#
           return name
        title_cat_series = df['Name'].apply(find_call)
        print(title_cat_series.values[:10])
        #['Mr' 'Mrs' 'Miss' 'Mrs' 'Mr' 'Mr' 'Mr' 'Master' 'Mrs' 'Mrs']
['Mr' 'Mrs' 'Miss' 'Mrs' 'Mr' 'Mr' 'Mr' 'Master' 'Mrs' 'Mrs']
In [26]: title_mapping= {
            'Ms':"Miss",
            'Mlle': "Miss",
            'Miss':"Miss",
            'Mrs':"Mrs",
            'Mme': "Mrs",
            'MrsMartin(ElizabethL':"Mrs",
            'Mr':"Mr"
           }
        title_cat = {"Mr": 1, "Miss": 2, "Mrs": 3, "Master": 4, "Rare": 5}
        def process_title(call):
           if title_cat.get(call):
```

```
return title_cat.get(call)
           else:
              return title_cat.get(title_mapping.get(call, "Rare"))
       df['title_cat'] = title_cat_series.apply(process_title)
       print(Counter(df['title_cat']))
Counter({1: 517, 2: 185, 3: 126, 4: 40, 5: 23})
3.8 Title - Length
In [27]: # 算出 df['Name'] 中每一個名字的長度並放進一個 array
       #======your works starts======#
       name length =
       #=======your works ends=======#
       print(Counter(pd.cut(name_length, bins=10, labels=range(10))))
       # Counter({1: 303, 2: 237, 0: 204, 3: 57, 4: 53, 5: 26, 6: 8, 7: 2, 9: 1})
Counter({1: 303, 2: 237, 0: 204, 3: 57, 4: 53, 5: 26, 6: 8, 7: 2, 9: 1})
In [28]: df['name_length'] = name_length
In [29]: # 劃出每一長度區間次數的長條分布圖 (如長度界在 10~20 之間的有出現約 150 次)(hint: df[col
       #=======your works starts======#
       df['name_length'].plot('hist')
       plt.show()
```



3.9 Fare - PCA, smooth noisy data, feature generation

```
In [30]: # 請找出 dtype 是 np.int64 或 np.float64 且名稱不以'_cat' 結尾的欄位。
#=========your works starts======#

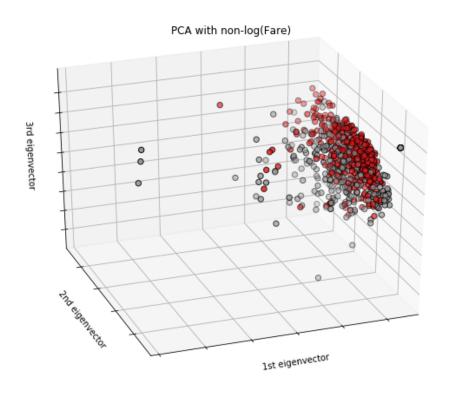
number_cols =
#========your works ends======#

print(number_cols)
# ['PassengerId', 'Survived', 'Pclass', 'Age', 'SibSp', 'Parch', 'Fare', 'avg_age', 'E'PassengerId', 'Survived', 'Pclass', 'Age', 'SibSp', 'Parch', 'Fare', 'avg_age', 'median_age'

請參照這個連結・劃出以下這張 PCA 圖

In [31]: X = df[['Pclass', 'Parch', 'SibSp', 'Fare', 'avg_age', 'name_length']].values
Y = np.array(df['Survived'])
```

#!=========!#



PCA_chart

```
#!======!#
plt.show()
```

```
In [32]: # 請找出標準差最大的欄位 ['Pclass', 'Parch', 'SibSp', 'Fare', 'avg_age', 'name_length']
#!=======your works starts======!#
#!=====your works ends======!#
```

```
Out [32]:
                   Pclass
                               Parch
                                           SibSp
                                                       Fare
                                                                        name_length
                                                                avg_age
              891.000000
                         891.000000
                                      891.000000
                                                 891.000000
                                                                         891.000000
        count
                                                             891.000000
                 2.308642
                            0.381594
                                        0.523008
                                                  32.204208
                                                              29.699118
                                                                          26.965208
        mean
                                        1.102743
                                                  49.693429
                                                              13.002015
        std
                 0.836071
                            0.806057
                                                                           9.281607
        min
                 1.000000
                            0.000000
                                        0.000000
                                                   0.000000
                                                              0.420000
                                                                          12.000000
        25%
                            0.000000
                 2.000000
                                        0.000000
                                                   7.910400
                                                              22.000000
                                                                          20.000000
        50%
                 3.000000
                            0.000000
                                        0.000000
                                                  14.454200
                                                              29.699118
                                                                          25.000000
        75%
                 3.000000
                            0.000000
                                        1.000000
                                                  31.000000
                                                              35.000000
                                                                          30.000000
                 3.000000
                            6.000000
                                        8.000000 512.329200
                                                              80.000000
                                                                          82.000000
        max
In [33]: # 請找出 Fare 的平均值 (mean), 並填入 df['Fare'] 中
        #=======your works starts=======#
        avg_fare =
        df[pd.isnull(df['Fare'])] =
        #=======your works ends=======#
        # df['Fare'].fillna(avg_fare)
        print("avg_fare", avg_fare)
        # 32.204207968574636
        print("number of null of Fare:", len(df[pd.isnull(df['Fare'])]))
        # number of null of Fare: 0
avg fare 32.204207968574636
number of null of Fare: 0
In [34]: df['Fare'].describe()
Out[34]: count
                 891.000000
        mean
                  32.204208
        std
                  49.693429
        min
                   0.000000
        25%
                   7.910400
        50%
                  14.454200
        75%
                  31.000000
        max
                 512.329200
        Name: Fare, dtype: float64
In [35]: # 找出 Fare==0 的 row, 補上 Fare=1
        df[df['Fare']=
        #=======your works ends=======#
        print("number of Fare equals zero:", len(df[df['Fare']==0]))
        # number of Fare equals zero: 0
number of Fare equals zero: 0
```

```
In [36]: # 請算出 Fare 以 10 為底的 log 值
        #=======your works starts=======#
        fare_log10 =
        #======your works ends=======#
        print(fare_log10[:5])
        # [0.86033801 1.8529878 0.89899927 1.72509452 0.90579588]
[0.86033801 1.8529878  0.89899927 1.72509452 0.90579588]
In [37]: df['fare_log10'] = fare_log10
        df[['Fare', 'fare_log10']].head()
Out [37]:
              Fare fare_log10
            7.2500
                     0.860338
        0
        1 71.2833
                     1.852988
        2 7.9250 0.898999
        3 53.1000 1.725095
            8.0500
                     0.905796
In [38]: X = np.matrix(df[['Parch', 'SibSp', 'avg_age', 'fare_log10']])
        Y = np.array(df['Survived'])
        fig = plt.figure(1, figsize=(8, 6))
        ax = Axes3D(fig, elev=-150, azim=110)
        X_reduced = PCA(n_components=3).fit_transform(X)
        ax.scatter(X_reduced[:, 0], X_reduced[:, 1], X_reduced[:, 2], c=Y,
                   cmap=plt.cm.Set1, edgecolor='k', s=40)
        ax.set_title("PCA with non-log(Fare)")
        ax.set_xlabel("1st eigenvector")
        ax.w_xaxis.set_ticklabels([])
        ax.set_ylabel("2nd eigenvector")
        ax.w_yaxis.set_ticklabels([])
        ax.set_zlabel("3rd eigenvector")
        ax.w_zaxis.set_ticklabels([])
        plt.show()
```

4 類別型變數 onehot encode

If you want the future behaviour and silence this warning, you can specify "categories='auto'" In case you used a LabelEncoder before this OneHotEncoder to convert the categories to integer warnings.warn(msg, FutureWarning)

```
In [40]: enc = preprocessing.OneHotEncoder()
    # 請使用 enc.fit_transform 兩個步驟 · onehot encode embarked_cat
    #=========your works starts======#
    embarked_cat_onehot =
    #=========#

embarked_cat_onehot[:3]
# array([[0., 0., 1., 0.],
# [0., 1., 0., 0.],
# [0., 0., 1., 0.]])
```

If you want the future behaviour and silence this warning, you can specify "categories='auto'" In case you used a LabelEncoder before this OneHotEncoder to convert the categories to integer warnings.warn(msg, FutureWarning)

5 PolynomialFeatures

```
In [41]: poly = preprocessing.PolynomialFeatures(degree=2)
# 請利用 poly.fit_transform 製造出 fare_log10 的 0 次項、1 次項、2 次項,並把 0 次項拿掉
```

```
fare_log10_poly =
        print(fare_log10_poly[:2])
        # [[1.
                     0.86033801 0.74018149]
        # [1.
                     1.8529878 3.43356378]]
[[0.86033801 0.74018149]
 [1.8529878 3.43356378]]
In [42]: # 請利用 poly.fit_transform 製造出'fare_log10', 'random_age' 的二項次及其一次交成項
        #=======your works starts=======#
        age_fare_ploy =
        #=======your works ends=======#
        print(age_fare_ploy[:2])
        # [[8.60338007e-01 8.31383556e-04 7.40181486e-01 7.15270871e-04 6.91198616e-07]
        # [1.85298780e+00 1.43602614e-03 3.43356378e+00 2.66093892e-03 2.06217108e-06]]
[[8.60338007e-01 8.31383556e-04 7.40181486e-01 7.15270871e-04
 6.91198616e-07]
 [1.85298780e+00 1.43602614e-03 3.43356378e+00 2.66093892e-03
 2.06217108e-06]]
5.1 Preprocessing Conclude
In [43]: df.columns
Out[43]: Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
              'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked', 'avg_age', 'median_age',
              'random_age', 'avg_age_l1', 'avg_age_l2', 'cabin_cat', 'sex_cat',
              'ticket_cat', 'embarked_cat', 'title_cat', 'name_length', 'fare_log10'],
             dtype='object')
In [44]: X = df[['SibSp', 'Parch', 'avg_age_12', 'sex_cat', 'name_length', 'fare_log10']].value
        X = np.concatenate([X, title_cat_onehot, embarked_cat_onehot, age_fare_ploy], axis=1)
        Y = df[['Survived']].values
        print(X.shape)
        print(Y.shape)
(891, 20)
(891, 1)
```

Accuracy: 0.8026905829596412