数据预处理

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

1. 数据加载与粗略查看

- 数据加载
- 数据粗略查看

1.1 数据加载

```
# csv文件
df = pd.read_csv('titanic.csv')
# 但有时数据不是简单的csv，它按照文本保存，如“ID||texttexttexttext”这样的一条数据需要将中间的“||”当作分隔符，读取方式如下：
# train = pd.read_csv('../input/training_text', sep="\|\|", engine='python', header=None, skiprows=1, names=
["ID","Text"])
# 更多参数应查阅pandas文档
```

1.2 数据粗略查看

```
df.head(5)      #显示前5行数据
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Emba
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

```
df.tail(5)      #显示后5行数据
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.00	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.00	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.45	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.00	C148	C
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.75	NaN	Q

```
df.columns     #查看列名
```

```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

```
df.info()     #查看各字段的信息
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

```
df.shape      #查看数据集行列分布，几行几列
```

```
(891, 12)
```

```
df.describe() #查看数据的大体情况
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

2. 处理丢失的数据

- 处理丢失值
    - 找到丢失位置
    - 处理
        - 填补
        - 忽略
- 处理重复值
- 处理偏离值
    - 查找偏离值
    - 处理
        - 删除
        - 标准化/归一化

2.1 处理丢失值

2.1.1 找到丢失位置

```
# 输出每个列丢失值也即值为NaN的数据和，并从多到少排序
total = df.isnull().sum().sort_values(ascending=False)
print(total)
```

```
Cabin          687
Age            177
Embarked         2
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
SibSp            0
Parch            0
Ticket           0
Fare             0
dtype: int64
```

```
# 也可以输出百分比
percent =(df.isnull().sum()/df.isnull().count()).sort_values(ascending=False)
missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
print(missing_data)
```

```
             Total   Percent
Cabin          687  0.771044
Age            177  0.198653
Embarked         2  0.002245
PassengerId      0  0.000000
Survived         0  0.000000
Pclass           0  0.000000
Name             0  0.000000
Sex              0  0.000000
SibSp            0  0.000000
Parch            0  0.000000
Ticket           0  0.000000
Fare             0  0.000000
```

2.1.2 处理-填补

```
# 使用中位数填补
df['Age'] = df['Age'].fillna(df['Age'].median())
```

```
# 使用平均数填补
df['Age'] = df['Age'].fillna(df['Age'].mean())
```

2.1.3 处理-忽略

```
# 去掉一列：当缺失行数比较多或该特征不重要的时候
df = df.drop(['Cabin'], axis = 1)
```

```
#去掉这个特征为空的行：当缺失行数比较少的时候
#当然后面可以加上inplace=True表示直接就在内存中替换了不用再赋值个train_new，但是本人多次删除掉几个行，发现有问题时又需要重新建立已经分析好的train，很浪费时间，个人认为还是重新开辟一个比较好
df_new = df.drop(df[df['Embarked'].isnull()].index)
```

2.2 处理重复值

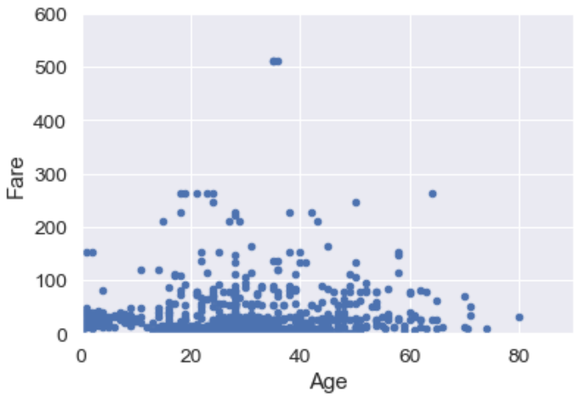
```
df_new = df_new.drop_duplicates()
```

2.3 处理偏离值

2.3.1 寻找偏离值

```
#bivariate analysis saleprice/grlivarea
var = 'Age'
data = pd.concat([df['Fare'], df[var]], axis=1)
data.plot.scatter(x=var, y='Fare', xlim=(0,90), ylim=(0,600));
```

```
*c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its length matches with *x* & *y*.  Please use the *color* keyword-argument or provide a 2D array with a single row if you intend to specify the same RGB or RGBA value for all points.
```



2.3.2 处理-删除

```
df.sort_values(by = 'Fare', ascending = False)[:2]
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
258	259	1	1	Ward, Miss. Anna	female	35.0	0	0	PC 17755	512.3292	C
737	738	1	1	Lesurer, Mr. Gustave J	male	35.0	0	0	PC 17755	512.3292	C

```
df = df.drop(df[df['PassengerId'] == 259].index)
df = df.drop(df[df['PassengerId'] == 738].index)
```

2.3.3 处理-保留

当然并不是所有的偏离值都需要删除，具体需要在分析之后选择处理方式。这里将偏离值保留下来并不是原封不动保留，而需要做标准化或归一化处理，具体的处理方式可查看最后一节数据转换、标准化、归一化

3. 数据统计

```
# 统计某一列中各个元素值出现的次数
df['Pclass'].value_counts()
```

```
3    491
1    214
2    184
Name: Pclass, dtype: int64
```

```
# 数据的偏斜度
df['Pclass'].skew()
```

```
-0.6369977585999191
```

```
# 数据的峰度
df['Pclass'].kurt()
```

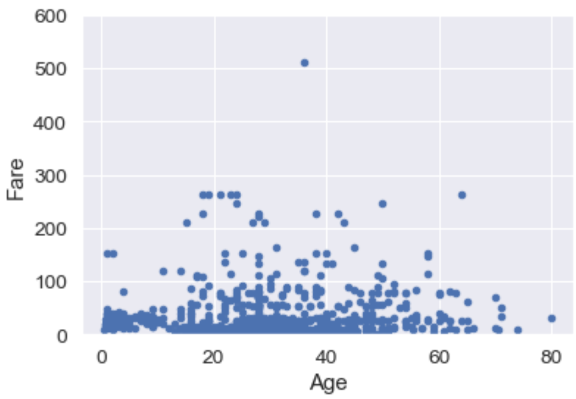
```
-1.2694374832322646
```

```
# 计算两个列的相关度
df['Age'].corr(df['Fare'])
```

```
0.09821633399014416
```

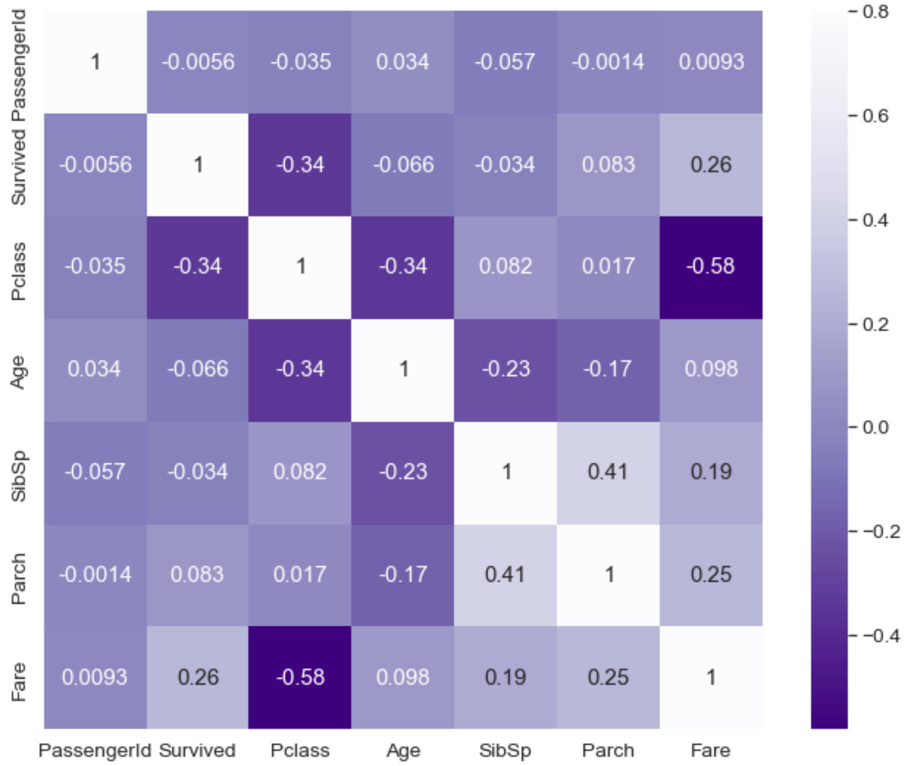
```
# 观察两个列的值的二维图
x = 'Age'; y = 'Fare'
data = pd.concat([df[y], df[x]], axis=1)
data.plot.scatter(x=x, y=y, ylim=(0,600));
```

```
*c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its length matches with *x* & *y*.  Please use the *color* keyword-argument or provide a 2D array with a single row if you intend to specify the same RGB or RGBA value for all points.
```



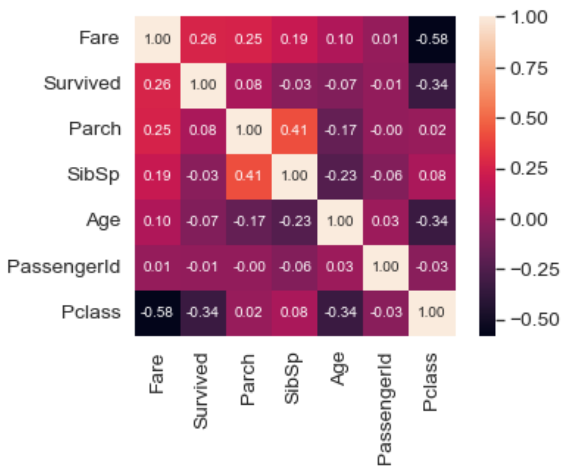

```
# 计算所有特征值每两个之间的相关系数，并做热力图
corrmat = df.corr() # 得到相关系数
f,ax = plt.subplots(figsize = (12,9))
sns.heatmap(corrmat, vmax = .8, square = True, annot=True, cmap = 'Purples_r') # 热力图
```

```
<AxesSubplot:>
```




```
#取出相关性最大的前十个，做出热点图表示
k = 7 #number of variables for heatmap
cols = corrmat.nlargest(k, 'Fare')['Fare'].index
cm = np.corrcoef(df[cols].values.T)
sns.set(font_scale=1.25)
sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'size': 10}, yticklabels=cols.values,
 xticklabels=cols.values)
```

```
<AxesSubplot:>
```



4. 特征值的合并、连接

- 分组
- 合并
- 连接

4.1 分组

```
# 按照船舱等级分组----------------------一个特征值
df.groupby('Pclass',as_index=False)
# 按照船舱等级与船费分组---------------两个特征值
df.groupby(['Pclass','Fare'],as_index=False)
# 船舱等级、船费、年龄-----------------三个特征值
df.groupby(['Pclass','Fare','Age'],as_index=False)
# 跟MSSubClass进行分组，并求分组后的平均值
test = df[['Pclass', 'Fare']].groupby(['Pclass'], as_index=False).mean()
# 选取特定的属性的某个值然后进行分类
df[df['Age']==22].groupby(['Pclass'],as_index=False)
print(test)
```

```
   Pclass       Fare
0       1  80.153057
1       2  20.662183
2       3  13.675550
```

4.2 合并

```
# 获得分组后，统计分组中'end_loc'的数量返回为一列由‘userid’和‘user_count’组成的新的DataFrame
age_count = df.groupby('Pclass',as_index=False)['Age'].agg({'age_count':'count'})
# 将获得的新的DataFrame合并到train，更多的merge参数请查阅文档
new_df = pd.merge(df, age_count, on=['Pclass'], how='left')
print(age_count)
```

```
   Pclass  age_count
0       1        214
1       2        184
2       3        491
```

4.3 连接

```
# 将训练数据与测试数据连接起来，以便一起进行数据清洗。
# 这里需要注意的是，如果没有后面的ignore_index=True，那么index的值在连接后的这个新数据中是不连续的，如果要按照index删除一行数据，可能会发现多删一条。
train = df[:600]
test = df[600:]
merge_data = pd.concat([train, test], ignore_index=True)

# 另一种合并方式，按列名字进行合并。
all_data = pd.concat((df.loc[:,'Pclass':'Age'], test.loc[:,'Pclass':'Age']))
all_data.head()
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	Pclass	Name	Sex	Age
0	3	Braund, Mr. Owen Harris	male	22.0
1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0
2	3	Heikkinen, Miss. Laina	female	26.0
3	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0
4	3	Allen, Mr. William Henry	male	35.0

5. 数据转换、标准化、归一化

- 数据转换
- 标准化
- 归一化

5.1 数据转换

```
# 浮点型数值转换为整型
df['Age'] = df['Age'].astype(int)
```

```
# 字符串的替换--映射
df['Sex'] = df['Sex'].map({'female':0,'male':1}).astype(int)
# 一般建议将map拿出来
# sex_mapping = {"female": 0, "male": 1}
# df['Sex'] = df['Sex'].map(sex_mapping)
```

```
# one-hot独热编码
df = pd.get_dummies(df)
```

```
# 将连续型特征值分块，每一块用数字标识
df.loc[ df['Fare'] <= 7.91, 'Fare'] = 0
df.loc[(df['Fare'] > 7.91) & (df['Fare'] <= 14.454), 'Fare'] = 1
df.loc[(df['Fare'] > 14.454) & (df['Fare'] <= 31), 'Fare']   = 2
df.loc[ df['Fare'] > 31, 'Fare'] = 3
df['Fare'] = df['Fare'].astype(int)
```

```
# df['Age'] = np.log(df['Age'])
# 而有时这样的log不可行，就需要使用log（x+1）来 处理
# 原因：https://blog.csdn.net/liyuanbhu/article/details/8544644
df['Age'] = np.log1p(df['Age'])
```

```
# 将偏斜度大于0.75的数值列log转换，使之尽量符合正态分布
# numeric_feats = ['Age', 'Fare']
# skewed_feats = df[numeric_feats].apply(lambda x: skew(x.dropna())) #compute skewness
# skewed_feats = skewed_feats[skewed_feats > 0.75]
# skewed_feats = skewed_feats.index
# df[skewed_feats] = np.log1p(df[skewed_feats])
```

5.2 标准化

见**数据预处理-标准化与归一化**

5.3 归一化

见**数据预处理-标准化与归一化**

6. 参考资料

1. 数据预处理
2. 唐宇迪数据分析


```

```