# titanic

2019 年 5 月 30 日

In [274]:
```
# 泰坦尼克预测

import numpy as np
import pandas as pd

import os
print(os.listdir("./input"))

# 展示输入文件
```

```
['train.csv']
```

## 0.1 输入想要的文件，trian.csv

In [275]:
```
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier

# 导入机器学习包
```

In [276]:
```
titanic = pd.read_csv("./input/train.csv")

titanic.head()

# PassengerId         旅客 ID，这条数据应该没啥用
# Survived: 是否活下来了 1:yes  0:no
```

```
# Pclass 旅客等级 1 2 3 分别代表不同的等级
# Name          名字
# Sex           性别
# Age           年龄
# SibSp          有多少兄弟姐妹/配偶同船
# Parch          有多少父母/子女同船
# Ticket          船票号码，无用数据
# Fare           船票收费
# Cabin           所在小屋
# Embarked          登船城市 C Q S 分别代表不同的城市
# # 数据展开
```

Out[276]:

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       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
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

In [277]:

```
type(test)
```

Out[277]:

```
pandas.core.frame.DataFrame
```

In [278]:

```
titanic[['Pclass', 'Survived']].groupby(['Pclass'], as_index=False).mean()
```

```
# 不同等级旅客生还概率
```

Out[278]:

| | Pclass | Survived |
|---|---|---|
| 0 | 1 | 0.629630 |
| 1 | 2 | 0.472826 |
| 2 | 3 | 0.242363 |

In [279]:
```
titanic[["Sex", "Survived"]].groupby(['Sex'], as_index=False).mean()

# 不同性别旅客生还概率，女性高于男性
```

Out[279]:

| | Sex | Survived |
|---|---|---|
| 0 | female | 0.742038 |
| 1 | male | 0.188908 |

In [280]:
```
    # 填补 age 缺失

titanic["Age"]= titanic["Age"].fillna(titanic["Age"].mean())
```

In [281]:
```
titanic['Age'].mean()

# 乘客年龄均值
```

Out[281]: 29.69911764705882

In [282]:
```
titanic.info()
# 训练集文件信息，891 个数据
```

```
<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
Age            891 non-null float64
SibSp          891 non-null int64
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 [283]: y = titanic['Survived']

          y.head()

          # 设置分类指标
```

```
Out[283]: 0    0
          1    1
          2    1
          3    1
          4    0
          Name: Survived, dtype: int64
```

```
In [284]: titanic["Embarked"] = titanic["Embarked"].fillna(titanic["Embarked"].mode()[0])
          titanic['Cabin'] = titanic['Cabin'].fillna('Unknown')
```

```
In [285]: x = titanic[['Pclass', 'Age', 'Sex','SibSp','Parch','Ticket','Fare','Embarked']]

          # 船舱，年龄，性别等等，892 条数据，删除小屋数据与搭乘港口数据，因为数据缺失又很难插值
          # 设置需要考虑的特征，查看是否具有缺失值

          x.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 8 columns):
Pclass      891 non-null int64
Age         891 non-null float64
Sex         891 non-null object
SibSp       891 non-null int64
Parch       891 non-null int64
Ticket      891 non-null object
```

```
Fare        891 non-null float64
Embarked    891 non-null object
dtypes: float64(2), int64(3), object(3)
memory usage: 55.8+ KB
```

In [286]:
```python
type(x)
```

Out[286]:
```
pandas.core.frame.DataFrame
```

In [287]:
```python
titanic.isnull().sum()
```

Out[287]:
```
PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Cabin          0
Embarked       0
dtype: int64
```

In [288]:
```python
titanic["Embarked"] = titanic["Embarked"].fillna(titanic["Embarked"].mode()[0])
titanic['Cabin'] = titanic['Cabin'].fillna('Unknown')
```

## 0.2 检查数据空缺情况

In [289]:
```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.feature_extraction import DictVectorizer
import pandas as pd
```

In [290]:
```python
x = titanic[['Pclass', 'Age', 'Sex','SibSp','Parch','Ticket','Fare','Embarked']]

# 船舱，年龄，性别等等，892 条数据，删除小屋数据与搭乘港口数据，因为数据缺失又很难插值
# 设置需要考虑的特征，查看是否具有缺失值
```

```
x.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 8 columns):
Pclass      891 non-null int64
Age         891 non-null float64
Sex         891 non-null object
SibSp       891 non-null int64
Parch       891 non-null int64
Ticket      891 non-null object
Fare        891 non-null float64
Embarked    891 non-null object
dtypes: float64(2), int64(3), object(3)
memory usage: 55.8+ KB
```

```
In [291]: type(x)
```

```
Out[291]: pandas.core.frame.DataFrame
```

## 0.3 独热编码

```
In [292]: from sklearn.feature_extraction import DictVectorizer
          x_dict_list = x.to_dict(orient='records')
          print("*" * 30 + " train_dict " + "*" * 30)
          print(pd.Series(x_dict_list[:5]))

          dict_vec = DictVectorizer(sparse=False)
          x = dict_vec.fit_transform(x_dict_list)
          print("*" * 30 + " onehot 编码 " + "*" * 30)
          print(dict_vec.get_feature_names())
          #print(x[:5])
          # 特征抽取 - onehot 编码

          #x.head()

          # 方便进行属性值的选择，特征投影
```

```
#DictVectorizer 的处理对象是符号化（非数字化）的但是具有一定结构的特征数据，如字典等，将
```

```
****************************** train_dict ******************************
0    {'Pclass': 3, 'Age': 22.0, 'Sex': 'male', 'Sib...
1    {'Pclass': 1, 'Age': 38.0, 'Sex': 'female', 'S...
2    {'Pclass': 3, 'Age': 26.0, 'Sex': 'female', 'S...
3    {'Pclass': 1, 'Age': 35.0, 'Sex': 'female', 'S...
4    {'Pclass': 3, 'Age': 35.0, 'Sex': 'male', 'Sib...
dtype: object
****************************** onehot 编码 ******************************
['Age', 'Embarked=C', 'Embarked=Q', 'Embarked=S', 'Fare', 'Parch', 'Pclass', 'Sex=female', 'Se
```

```
In [293]: x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2)
```

## 0.4 划分训练集和测试集

```
In [294]: type(y)
```

```
Out[294]: pandas.core.series.Series
```

## 0.5 划分结果后，开始进行决策树预测与随机森林的参数选择

```
In [295]: dec_tree = DecisionTreeClassifier()
          dec_tree.fit(x_train, y_train)

          print("*" * 30 + " 准确率 " + "*" * 30)
          print(dec_tree.score(x_test, y_test))
```

```
****************************** 准确率 ******************************
0.8156424581005587
```

```
In [247]: import time
          #from sklearn.grid_search import GridSearchCV
```

```python
#gridsearchcv 自动调参


# n_jobs: -1 表示设置为核心数量
# n_estimators: 决策树数目
# max_depth: 树最大深度

rf = RandomForestClassifier(n_jobs=-1)
param = {
    "n_estimators": [120, 200, 300, 500, 800, 1200],
    "max_depth": [5, 8, 15, 25, 30]
}
# 2 折交叉验证
search = sklearn.model_selection.GridSearchCV(rf, param_grid=param, cv=2)
print("*" * 30 + " 超参数网格搜索 " + "*" * 30)

start_time = time.time()
search.fit(x_train, y_train)
print("耗时: {}".format(time.time() - start_time))


print("最优参数: {}".format(search.best_params_))

print("*" * 30 + " 准确率 " + "*" * 30)
print(search.score(x_test, y_test))
```

```
****************************** 超参数网格搜索 ******************************
耗时: 125.43527293205261
最优参数: {'max_depth': 30, 'n_estimators': 300}
****************************** 准确率 ******************************
0.8212290502793296
```

### 0.6 1 超参数网格搜索的最优参数

## 1 2 在 2，8 划分的测试数据集中，准确率达到了 82%

## 2 3 相较于单个决策树的 78% 准确率有了较大提升

## 3 4 下面进行数据可视化的一些工作

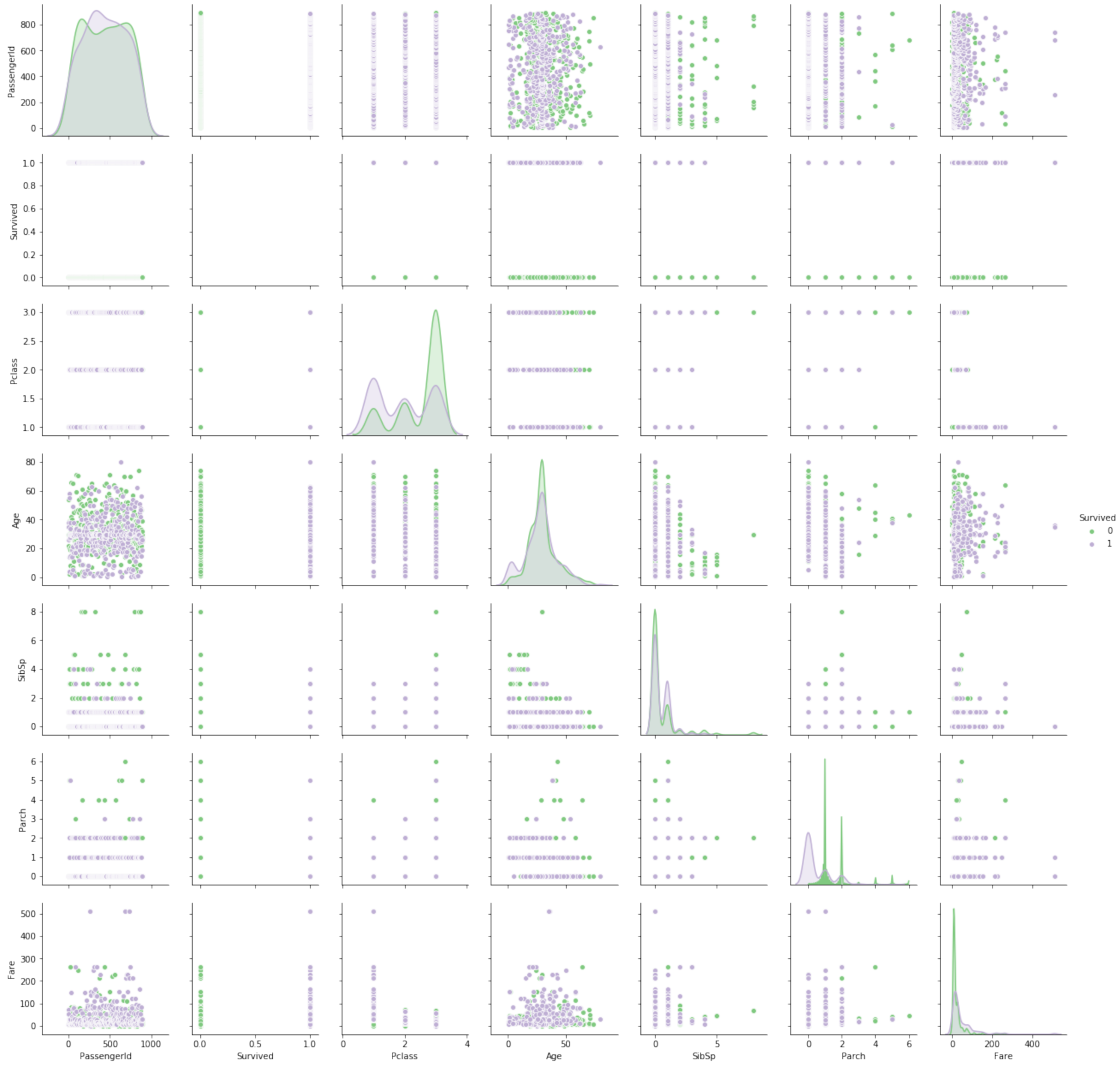
```
In [296]: # 数据的一些可视化操作
          import matplotlib.pyplot as plt
          %matplotlib inline



          import seaborn as sns
          sns.pairplot(titanic, hue = "Survived", diag_kind = "auto", kind = "scatter", palett
```

```
g:\ProgramData\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
g:\ProgramData\Anaconda3\lib\site-packages\statsmodels\nonparametric\kde.py:488: RuntimeWarning
  binned = fast_linbin(X, a, b, gridsize) / (delta * nobs)
g:\ProgramData\Anaconda3\lib\site-packages\statsmodels\nonparametric\kdetools.py:34: RuntimeWa
  FAC1 = 2*(np.pi*bw/RANGE)**2
g:\ProgramData\Anaconda3\lib\site-packages\numpy\core\fromnumeric.py:83: RuntimeWarning: inval
  return ufunc.reduce(obj, axis, dtype, out, **passkwargs)
```

```
Out[296]: <seaborn.axisgrid.PairGrid at 0x1e91ef15e10>
```



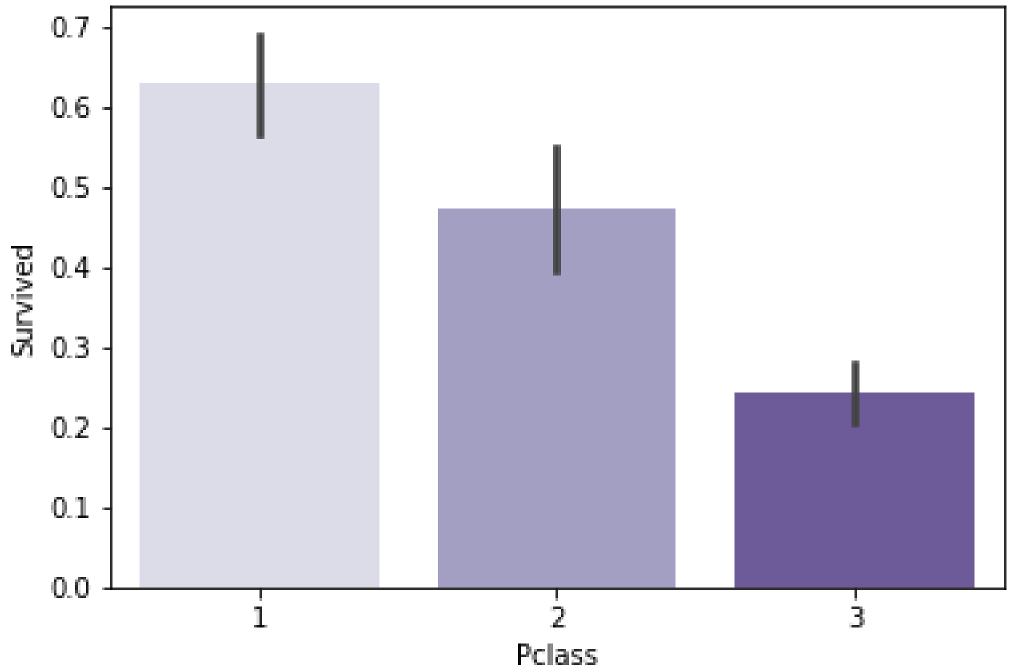

## 3.1 生成 7 个属性的对比属性图

In [297]:

```
sns.barplot("Pclass","Survived",data=titanic,palette="Purples")
```

```
g:\ProgramData\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

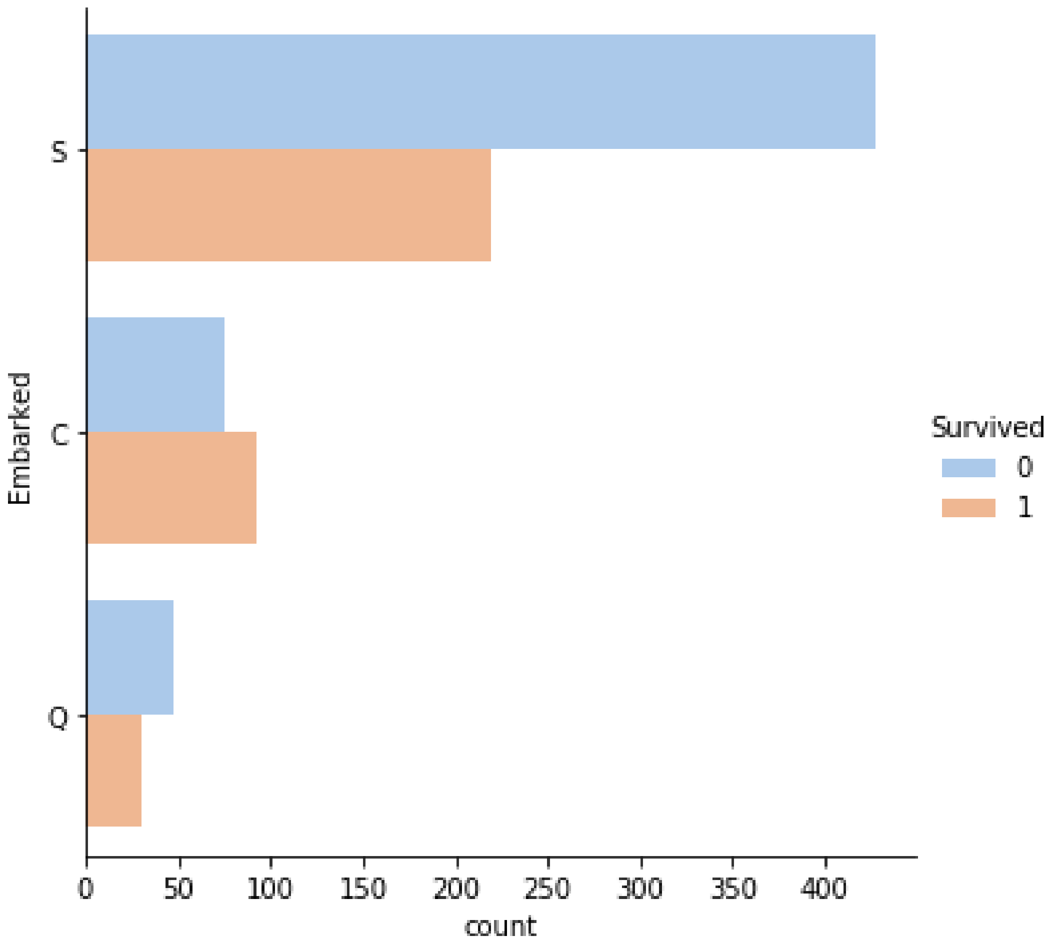
Out[297]: <matplotlib.axes._subplots.AxesSubplot at 0x1e9209cdeb8>




In [298]:

```
sns.catplot(y ="Embarked", hue = "Survived", kind = "count", palette = "pastel",
```

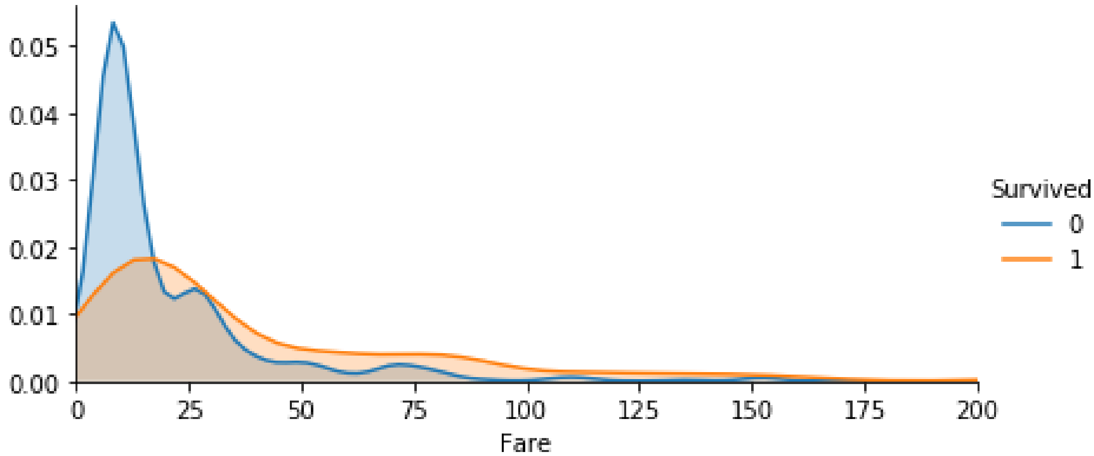
Out[298]: <seaborn.axisgrid.FacetGrid at 0x1e91eee5ef0>




```
In [299]: facet = sns.FacetGrid(titanic, hue="Survived",aspect=2)
          facet.map(sns.kdeplot,'Fare',shade= True)
          facet.set(xlim=(0, 200))
          facet.add_legend()
```

```
g:\ProgramData\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
Out[299]: <seaborn.axisgrid.FacetGrid at 0x1e92111d588>
```

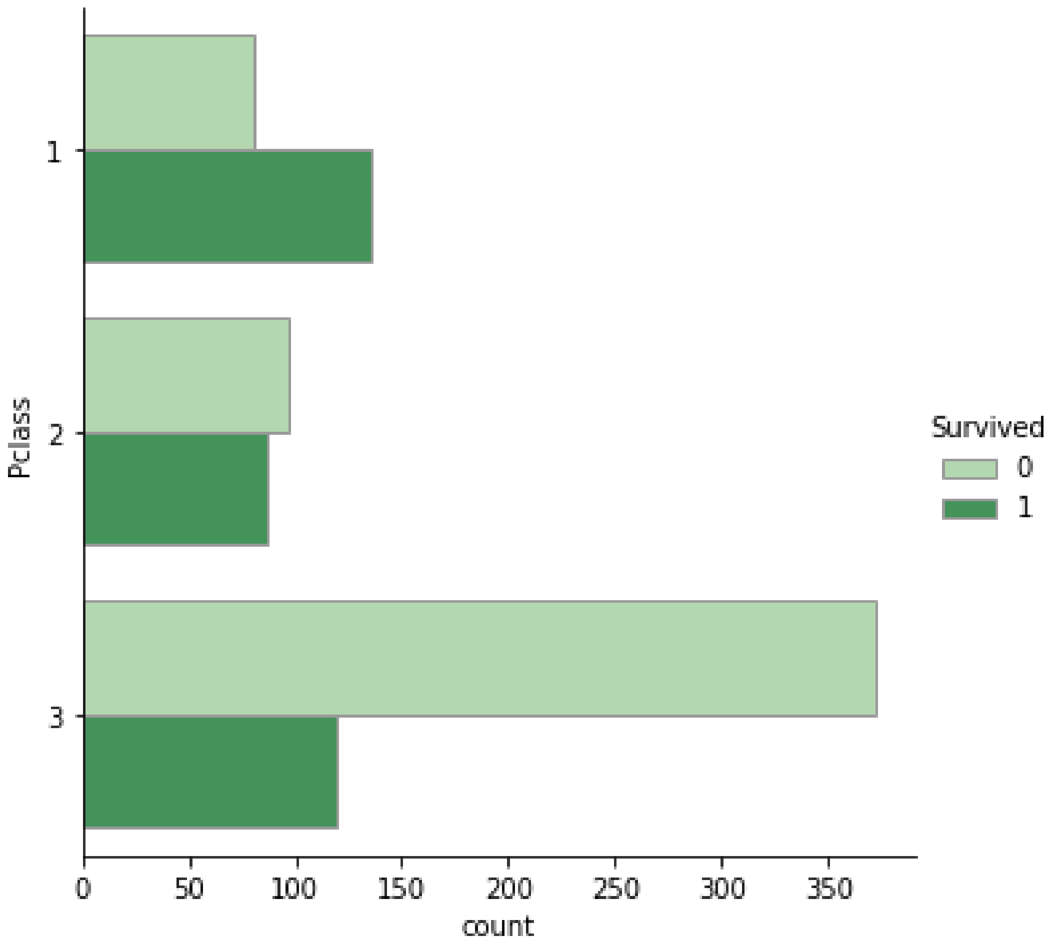



### 3.2 票价与生存率关系

In [300]:
```
# 不同舱位的生存情况


sns.catplot(y="Pclass", hue="Survived", kind="count",palette="Greens", edgecolor=".6
```

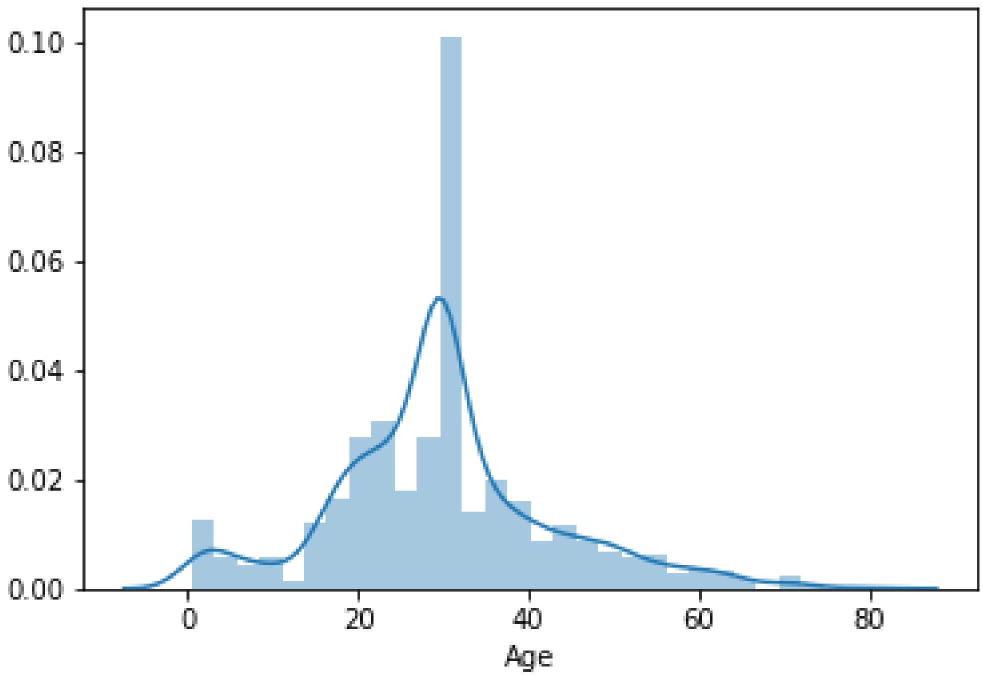
Out[300]: <seaborn.axisgrid.FacetGrid at 0x1e921139a90>




In [301]: sns.distplot(titanic['Age'])

```
g:\ProgramData\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

Out[301]: <matplotlib.axes._subplots.AxesSubplot at 0x1e921229f98>



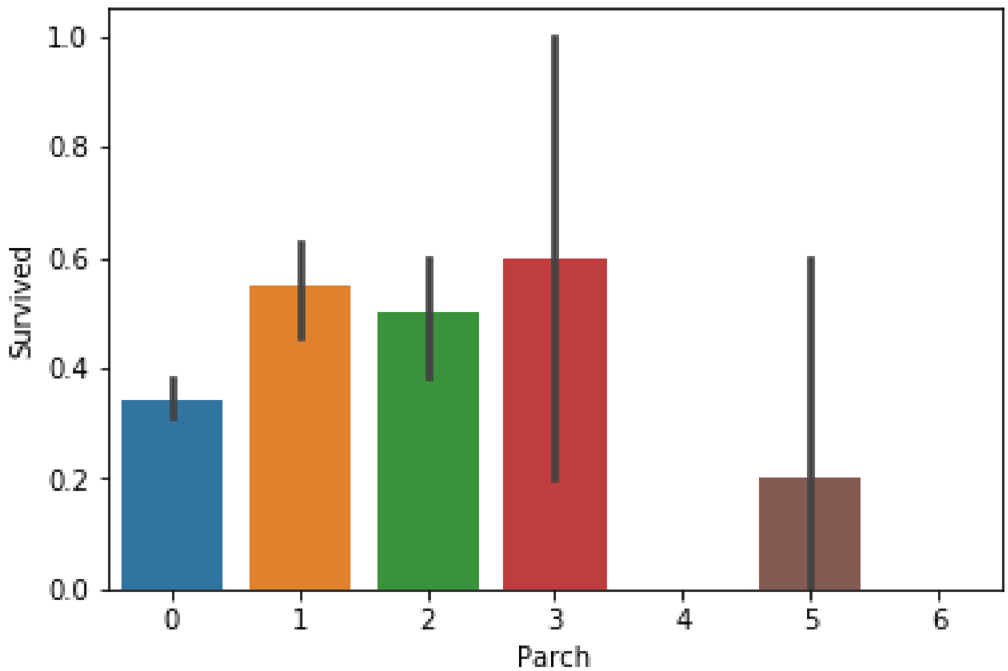

### 3.3 进行年龄的 distplot 展示

直方图又称质量分布图，它是表示资料变化情况的一种主要工具。用直方图可以解析出资料的规则性，比较直观地看出产品质量特性的分布状态，对于资料分布状况一目了然，便于判断其总体质量分布情况。直方图表示通过沿数据范围形成分箱，然后绘制条以显示落入每个分箱的观测次数的数据分布。

```
In [302]: sns.barplot(x="Parch",y="Survived",data=titanic)
```

```
g:\ProgramData\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
Out[302]: <matplotlib.axes._subplots.AxesSubplot at 0x1e921229be0>
```

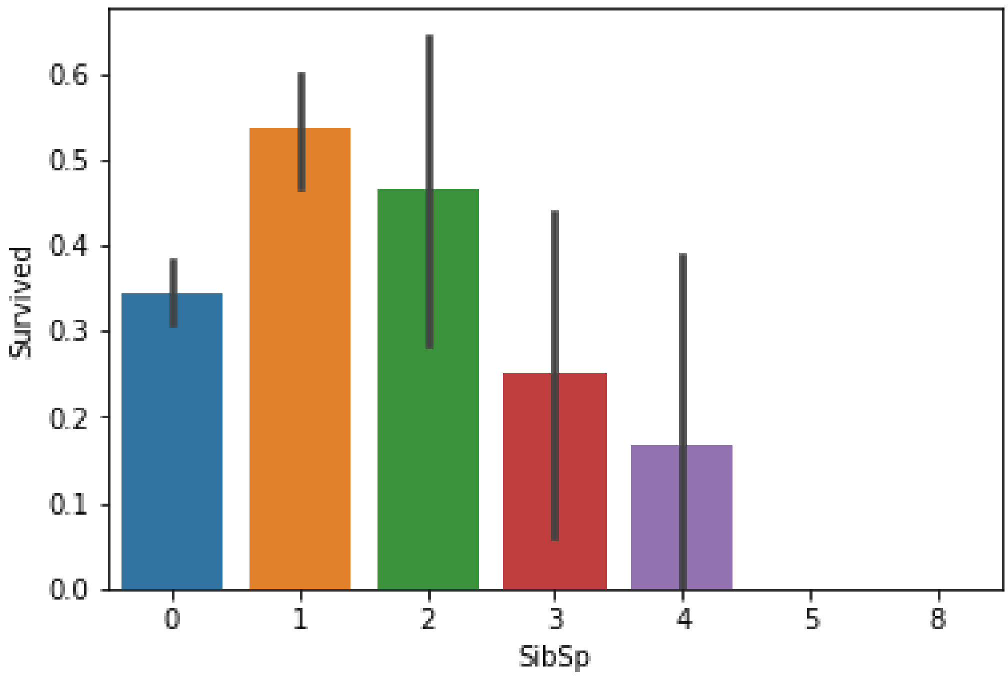



### 3.4 展示携带家庭成员的生存概率

```
In [257]: sns.barplot(x="SibSp",y="Survived",data=titanic)
```

```
g:\ProgramData\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
Out[257]: <matplotlib.axes._subplots.AxesSubplot at 0x1e91b0cc2e8>
```



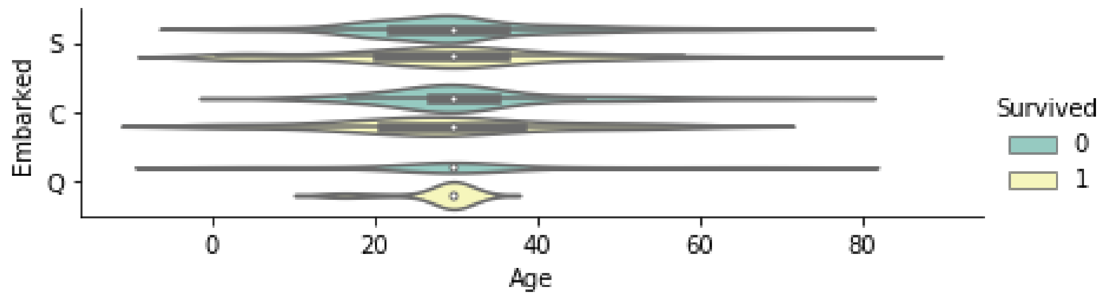

### 3.5 不同兄弟姐妹个数的生存概率

展示

```
In [303]: sns.catplot(x="Age", y="Embarked",hue="Survived", data= titanic, orient="h", height=
                     palette="Set3",
                     kind="violin")
```

```
g:\ProgramData\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
Out[303]: <seaborn.axisgrid.FacetGrid at 0x1e9212ebcf8>
```



```
In [304]: from sklearn. pipeline import make_pipeline
          from sklearn. pipeline import Pipeline
          from sklearn.ensemble import RandomForestClassifier
          #from sklearn.model_selection import GridsearchCV
          from sklearn.feature_selection import SelectKBest
```

```
In [305]: from sklearn.feature_selection import SelectKBest
          select = SelectKBest(k = 20)
          clf = RandomForestClassifier(random_state = 10, warm_start = True,
                                       n_estimators = 300,
                                       max_depth = 30,
                                       max_features = 'sqrt')
          pipeline = make_pipeline(select, clf)
```

### 3.6 训练过程

```
In [306]: pipeline.fit(x_test, y_test)
```

```
g:\ProgramData\Anaconda3\lib\site-packages\sklearn\feature_selection\univariate_selection.py:1
  33  34  35  36  37  38  40  41  42  43  44  46  48  49  51  52  54  55
  56  58  60  61  63  66  67  68  70  71  73  75  76  77  78  80  81  82
  83  85  86  87  88  89  96  98  99 100 103 104 106 107 108 109 110 111
 112 113 114 116 117 119 120 122 124 125 126 129 130 131 132 133 134 136
 137 138 139 140 141 144 145 146 147 148 149 150 151 152 153 155 157 158
 159 160 162 163 164 165 166 168 169 170 171 172 173 174 175 177 178 179
 181 182 183 184 185 188 190 191 192 193 194 195 196 197 198 199 200 201
 202 203 205 206 207 208 210 212 213 214 215 216 217 218 219 220 221 222
 223 224 225 226 227 228 229 231 232 233 234 235 237 238 239 240 241 244
 245 246 247 248 249 250 252 253 254 255 256 257 258 260 261 263 264 265
 267 269 270 271 272 273 274 275 276 277 278 279 280 282 283 284 285 286
 287 288 290 291 293 295 296 297 298 299 301 302 303 304 305 306 307 308
 309 310 311 313 314 317 319 320 321 322 323 324 325 326 327 328 330 331
 332 334 335 337 338 340 342 344 345 346 349 352 353 354 355 356 357 358
 359 360 361 362 363 364 366 367 369 370 371 373 374 375 376 377 378 379
 382 384 386 387 388 389 390 392 393 395 396 397 398 399 400 402 403 404
 405 406 407 408 410 411 413 414 415 416 417 418 419 420 421 422 423 425
```

```
 426 428 429 430 431 432 433 434 435 436 438 439 440 441 442 443 444 446
 447 448 449 450 451 452 453 454 455 457 458 459 461 462 463 464 465 473
 475 476 478 480 481 482 483 484 485 486 487 488 489 490 491 492 494 495
 496 499 501 502 503 504 505 507 508 509 510 511 513 514 515 516 518 520
 521 522 523 525 526 527 528 529 530 531 532 533 534 537 539 541 542 545
 546 548 549 550 551 552 553 554 555 556 557 560 562 564 565 566 568 569
 570 571 572 573 574 575 577 579 580 582 584 585 586 587 588 590 592 594
 595 600 601 603 605 607 608 609 611 613 615 616 617 618 619 622 623 624
 625 626 628 629 630 632 633 634 635 637 638 640 641 642 643 645 646 647
 648 650 651 652 653 654 656 658 659 660 661 662 663 664 665 666 667 668
 670 671 672 673 674 675 676 677 678 680 681 685 687 688 689 690] are constant.
  UserWarning)
g:\ProgramData\Anaconda3\lib\site-packages\sklearn\feature_selection\univariate_selection.py:1
  f = msb / msw
```

```
Out[306]: Pipeline(memory=None,
               steps=[('selectkbest', SelectKBest(k=20, score_func=<function f_classif at 0x00
                      max_depth=30, max_features='sqrt', max_leaf_nodes=None,
                      min_impurity_decrea...mators=300, n_jobs=None,
                      oob_score=False, random_state=10, verbose=0, warm_start=True))])
```

```
In [309]: x
```

```
Out[309]: array([[22.        ,  0.        ,  0.        , ...,  0.        ,
                   0.        ,  0.        ],
                 [38.        ,  1.        ,  0.        , ...,  0.        ,
                   0.        ,  0.        ],
                 [26.        ,  0.        ,  0.        , ...,  0.        ,
                   0.        ,  0.        ],
                 ...,
                 [29.69911765,  0.        ,  0.        , ...,  0.        ,
                   0.        ,  0.        ],
                 [26.        ,  1.        ,  0.        , ...,  0.        ,
                   0.        ,  0.        ],
                 [32.        ,  0.        ,  1.        , ...,  0.        ,
                   0.        ,  0.        ]])
```

```
In [310]: predictions = pipeline.predict(x)
```

```
submission = pd.DataFrame({"Survived": predictions.astype(np.int32)})
submission.to_csv("submission.csv", index=False)
```

### 3.7 对 train.csv 所有数据进行预测，并输出为 submission 文件

对比与原数据预测的准确率

统计结果为 150 个数据预测失败

741 个数据预测成功

### 3.8 百分比

$$\alpha = \frac{150}{891} = 0.8318$$

Pipeline 可以将许多算法模型串联起来，可以用于把多个 estamitors 级联成一个 estamitor, 比如将特征提取、归一化、分类组织在一起形成一个典型的机器学习问题工作流。Pipleline 中最后一个之外的所有 estimators 都必须是变换器（transformers），最后一个 estimator 可以是任意类型（transformer，classifier，regresser）, 如果最后一个 estimator 是个分类器，则整个 pipeline 就可以作为分类器使用，如果最后一个 estimator 是个聚类器，则整个 pipeline 就可以作为聚类器使用。

```
主要带来两点好处：

1.直接调用fit和predict方法来对pipeline中的所有算法模型进行训练和预测。

2.可以结合grid search对参数进行选择.
```