In [24]:
```
# Basic Libraries
import numpy as np
import pandas as pd
import seaborn as sb
import matplotlib.pyplot as plt # we only need pyplot
from plotnine import *
sb.set() # set the default Seaborn style for graphics
```

Titanic Dataset

In [25]:
```
titanic_data=pd.read_csv('train.csv')
```

In [26]:
```
print('Dimensions of training data: ',titanic_data.shape)
titanic_data.head(3)
```

```
Dimensions of training data:  (891, 12)
```

Out[26]:

	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	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	

- Summary:
  - 10 predictors/features
  - 1 response variable
  - 1 ID column

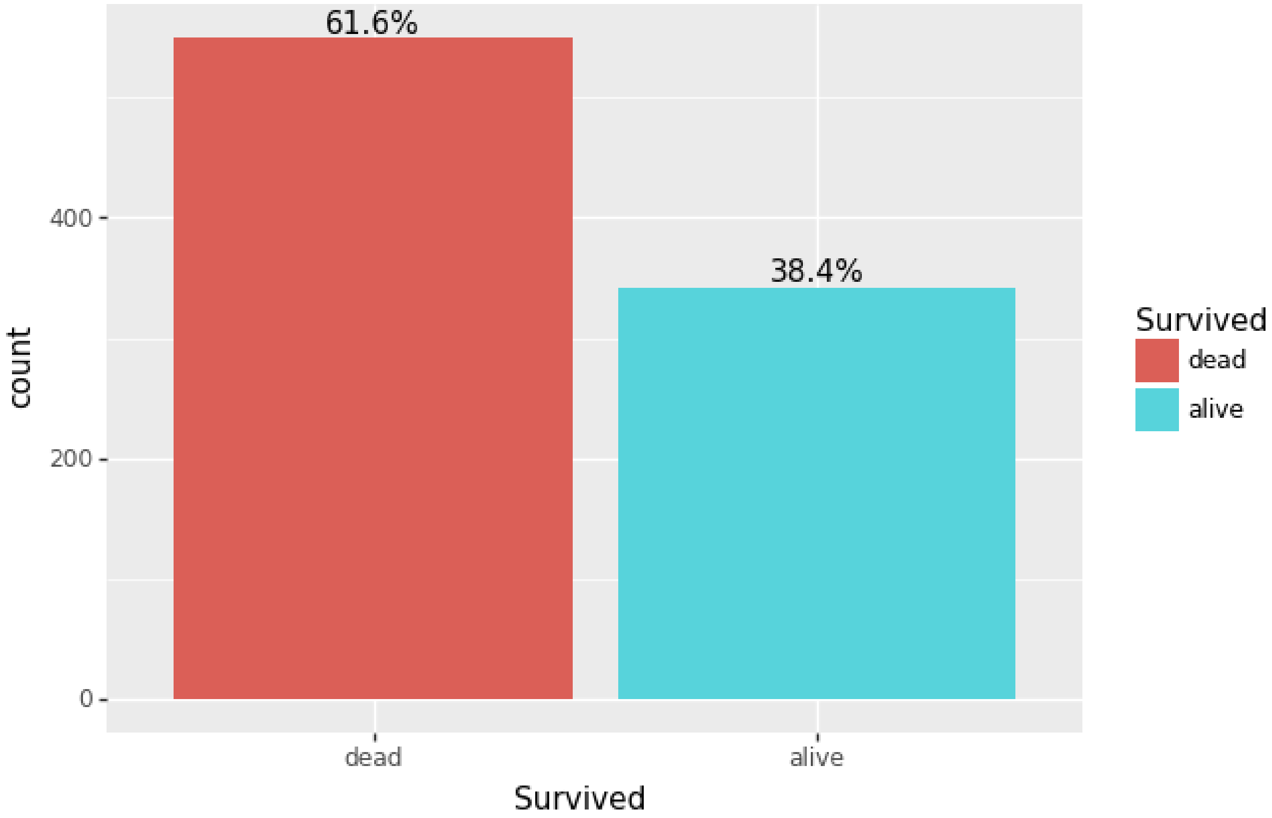
Response Variable: Survived

In [27]:
```
# convert the response categorical
response_copy=titanic_data['Survived'].copy()
titanic_data['Survived']=pd.Categorical(titanic_data['Survived'])

# rename response categories to more meaningful ones
titanic_data['Survived']=titanic_data['Survived'].cat.rename_categories({0:'dead',1:'al
```

- Steps:
  - Converted response to categorical
  - renamed to more meaningful categories

- kept a copy of the original for certain visualizations

In [28]:
```
ggplot(titanic_data,aes(x='Survived',fill='Survived'))+geom_bar()+geom_text(
    aes(label='stat(prop)*100', group=1),
     stat='count',
     nudge_y=0.125,
     va='bottom',
     format_string='{:.1f}%'
 )
```



Out[28]: <ggplot: (-9223371946262305424)>

- Observation:
    - slightly imbalanced

Basic Exploratory data analysis

In [29]:
```
titanic_data.dtypes
```

Out[29]:
```
PassengerId       int64
Survived       category
Pclass            int64
Name             object
Sex              object
Age             float64
SibSp             int64
Parch             int64
Ticket           object
Fare            float64
Cabin            object
Embarked         object
dtype: object
```

In [30]:
```
print("Number of levels:")
print()
for var in titanic_data.columns:
    print("{:<20}:{}".format(var,len(titanic_data[var].unique())))
```

```
Number of levels:

PassengerId         :891
Survived            :2
Pclass              :3
Name                :891
Sex                 :2
Age                 :89
SibSp               :7
Parch               :7
Ticket              :681
Fare                :248
Cabin               :148
Embarked            :4
```

- Obersvation:
  - all names are unique, though i won't assume it's completely useless
  - similarly, there are a **lot of levels for Ticket and Cabin variable**, but it may hold some patterens and information

dealing with the NAs (temporarily)

In [31]:
```
titanic_data.isna().sum()
```

Out[31]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

In [32]:
```
    # fill Age variable with random integers between mean and max
from random import randint
titanic_data['Age'].fillna(randint(int(titanic_data['Age'].min()),titanic_data['Age'].m
    # fill Cabin NAs with 'Missing' because there are too many
titanic_data['Cabin'].fillna('Missing',inplace=True)
    # fill embarked NAs with its mode
titanic_data['Embarked'].fillna(titanic_data['Embarked'].mode()[0],inplace=True)
```

- Steps:
  - dealt with NAs temporarily to make visualizations
- Observation:
  - there are newborns who's Age's are in decimals and less than 1

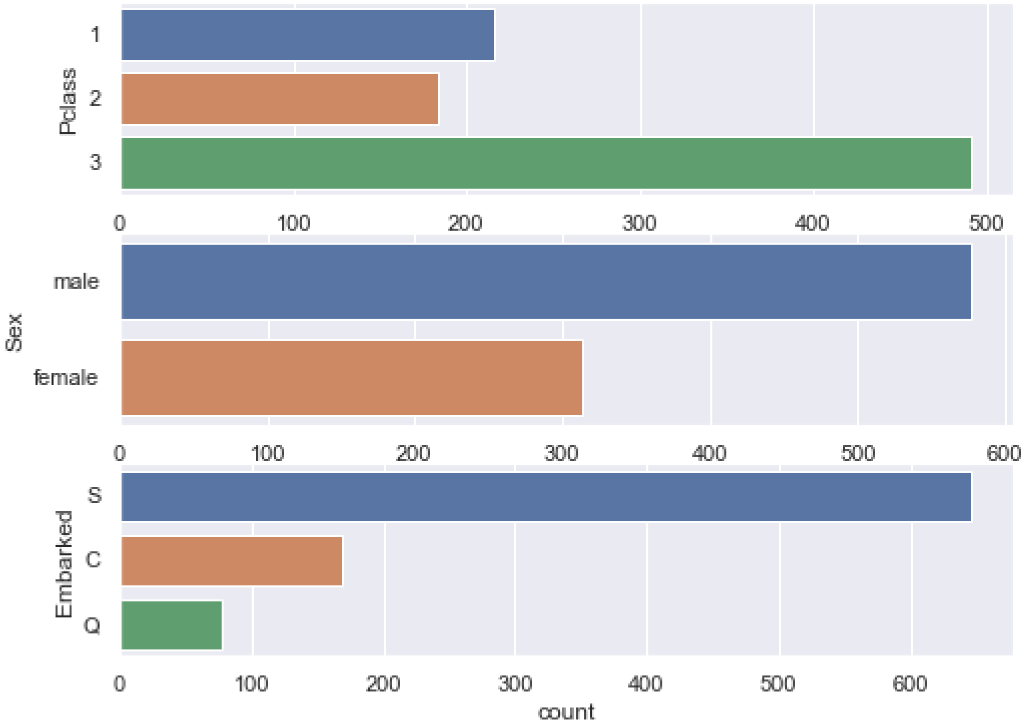
In [33]:
```
print("Newborns:",list(titanic_data[titanic_data['Age']<1]['Age']))
```

```
Newborns: [0.83, 0.92, 0.75, 0.75, 0.67, 0.42, 0.83]
```

- will leave them as they are

Visualizing Pclass, Sex, Embarked

In [34]:
```
# uni-variate visuals
f, axes = plt.subplots(3,1 , figsize=(8, 6))
for i,var in enumerate(['Pclass','Sex','Embarked']):
    sb.countplot(data=titanic_data,y=var,ax=axes[i])
```

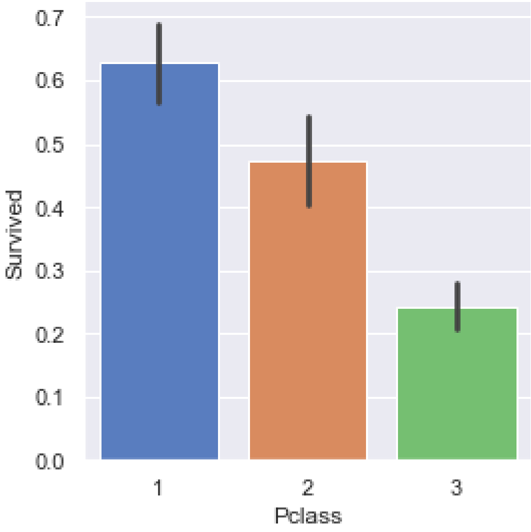


- Observation:
    - most passengers are from Pclass 3, are male and came from Southhampton

In [35]:
```
for var in ['Pclass','Sex','Embarked']:
    titanic_data[var]=pd.Categorical(titanic_data[var])
```

- converted 'Pclass','Sex','Embarked' into categorical types

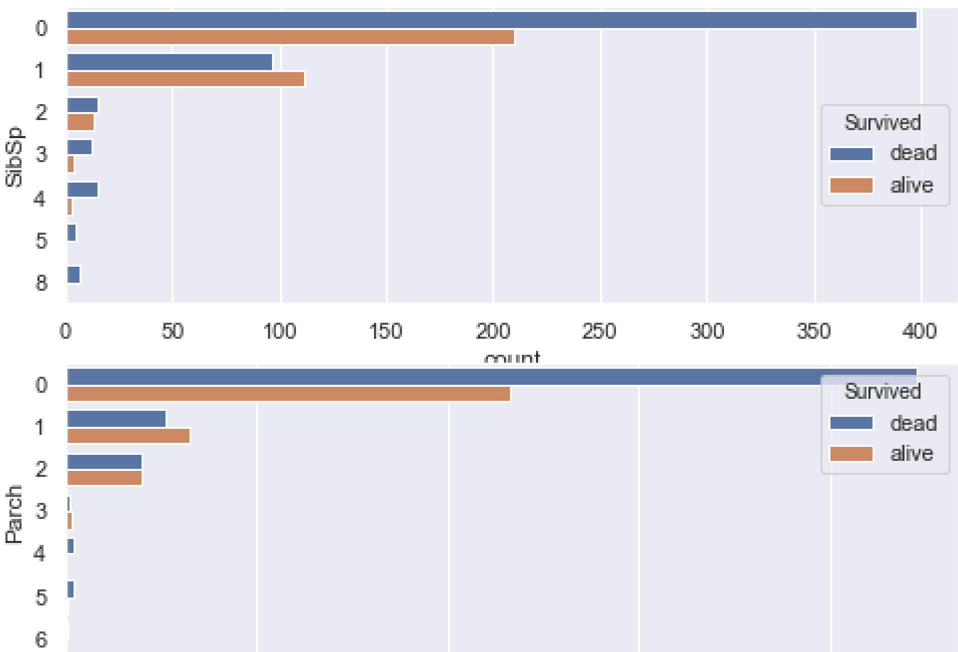
In [36]:
```
temp_data=pd.concat([titanic_data[['Pclass','Sex','Embarked']],response_copy],axis=1)
for i,var in enumerate(['Pclass','Sex','Embarked']):
    sb.catplot(x=var,y='Survived',data=temp_data,kind='bar',palette='muted',height=4, a
```



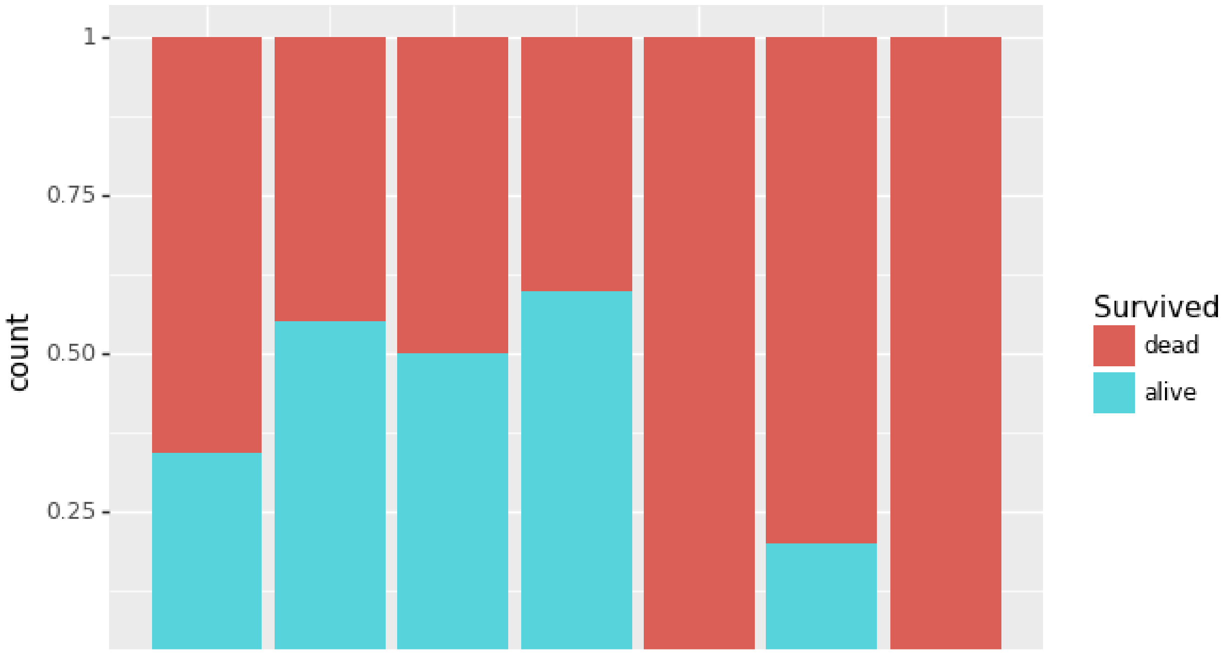
- Observations:
  - people from class 3, males and from Southampton are more likely to die
  - people from class 1 and females are more likely to live

Visualising SibSp and Parch

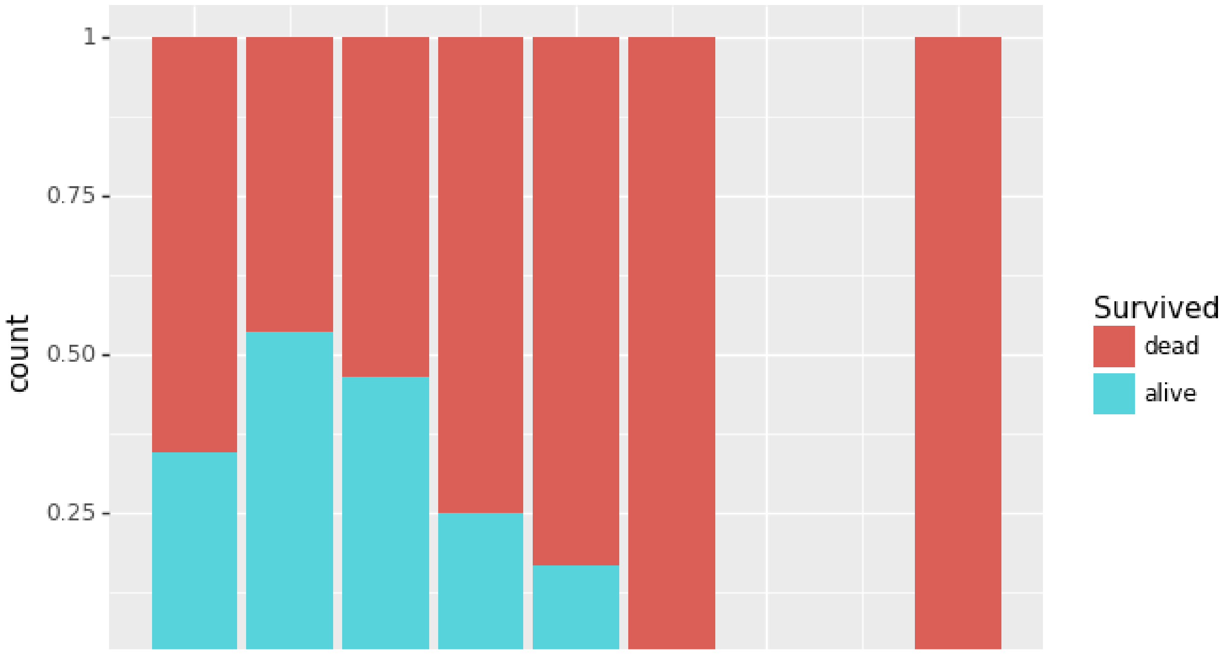
In [37]:
```
f, axes = plt.subplots(2,1 , figsize=(8, 6))
for i,var in enumerate(['SibSp','Parch']):
    sb.countplot(data=titanic_data,y=var,hue='Survived',ax=axes[i])
```



In [38]:
```
ggplot(titanic_data,aes(x='Parch',fill='Survived'))+geom_bar(position='fill')
```



In [39]:
```
ggplot(titanic_data,aes(x='SibSp',fill='Survived'))+geom_bar(position='fill')
```



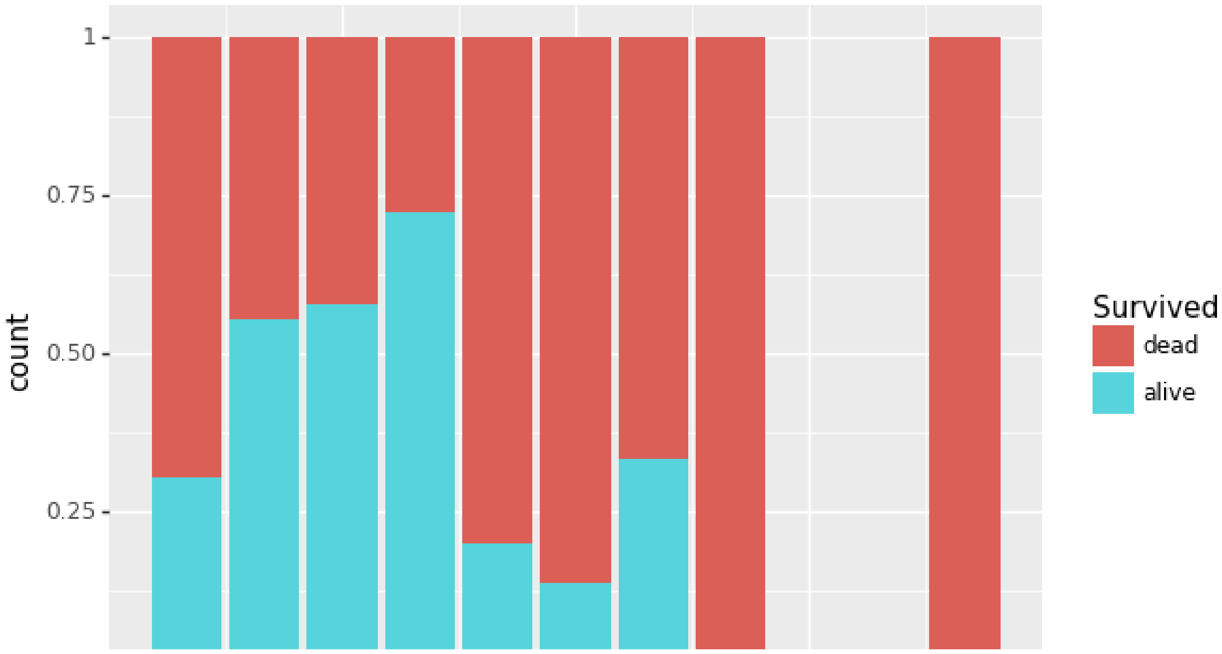
- Observation:
  - people who have one to two children are more likely to survive
  - people who are alone, or have too big of a family are more likely to die

new feature: family_size

- Sums SibSp and Parch and includes the target passenger

In [40]:
```
titanic_data['family_size']=titanic_data['SibSp']+titanic_data['Parch']+1
```

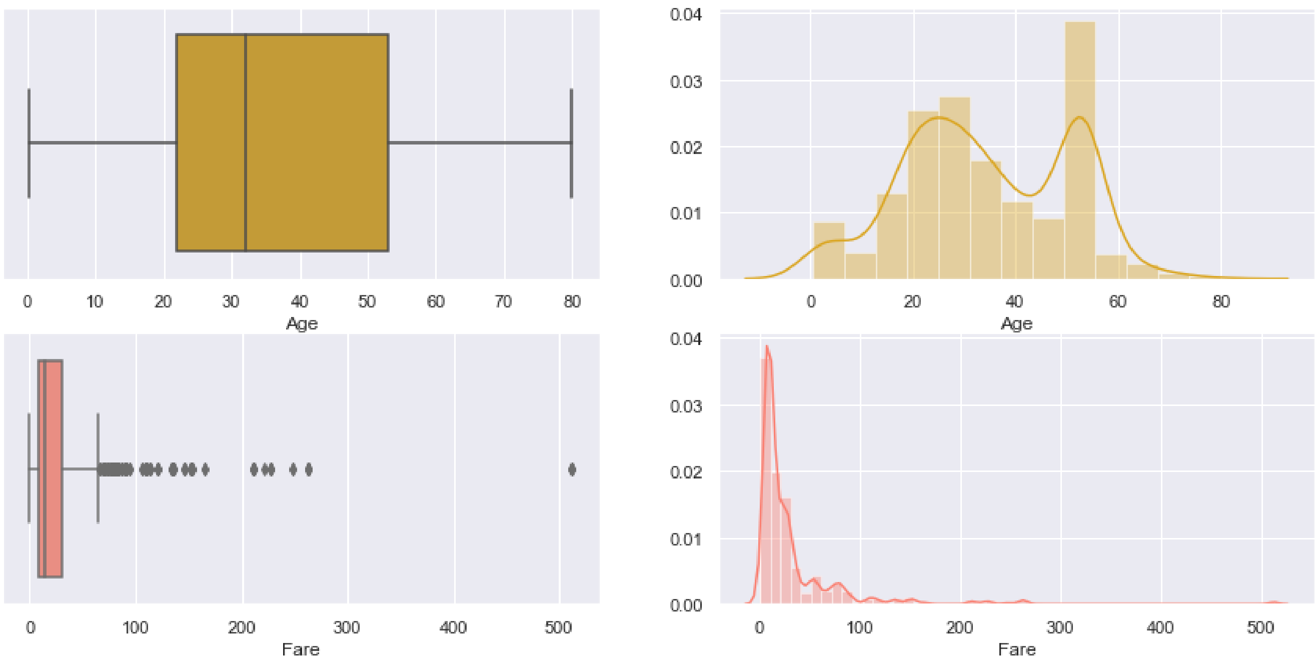
In [41]:
```
ggplot(titanic_data,aes(x='family_size',fill='Survived'))+geom_bar(position='fill')
```



- Observation:
  - smaller families a more likely to survive than larger ones
  - however, being alone indicates smaller chance of survival

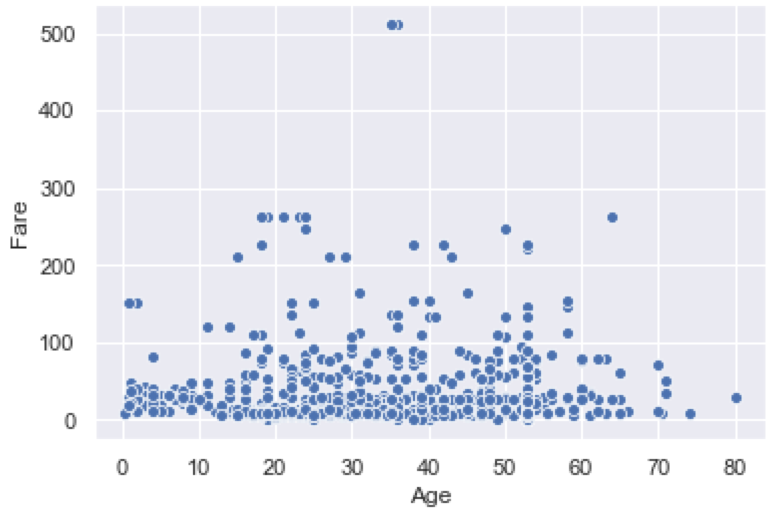
Visualising Age and Fare

In [42]:
```
f, axes = plt.subplots(2,2 , figsize=(15, 7))
color_list=['goldenrod','salmon']
for i,var in enumerate(['Age','Fare']):
    sb.boxplot(titanic_data[var],ax=axes[i,0],color=color_list[i])
    sb.distplot(titanic_data[var],ax=axes[i,1],color=color_list[i])
```



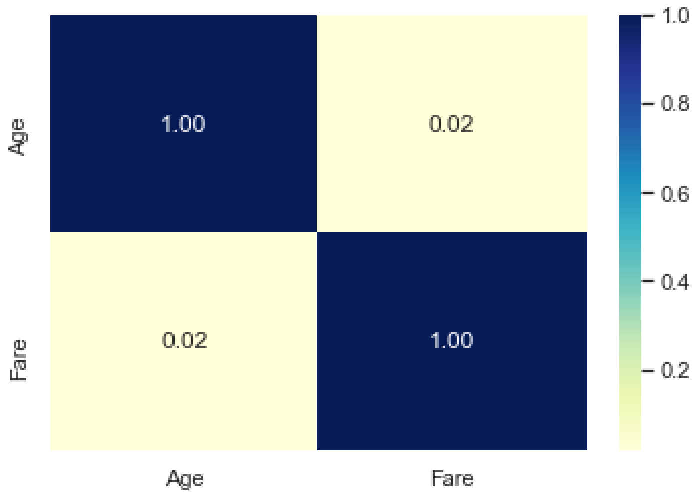
In [43]:
```python
sb.scatterplot(x='Age', y='Fare',data=titanic_data)
```

Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x1517b7437c8>



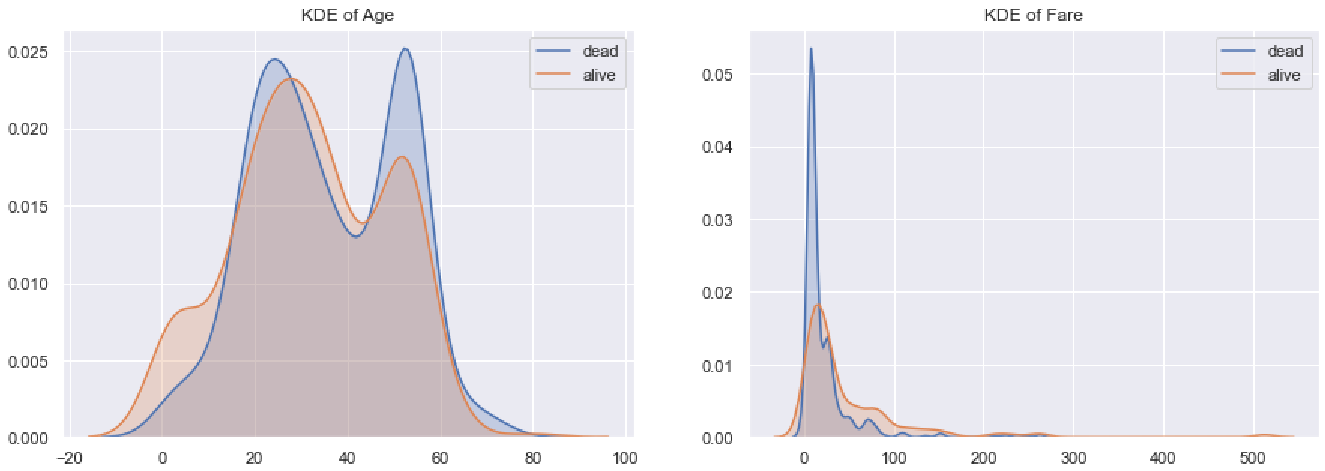
In [44]:
```python
sb.heatmap(titanic_data[['Age','Fare']].corr(),annot=True,cmap="YlGnBu",fmt='.2f')
```

Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x1517b3aa2c8>



- Observation:
  - most people are aged between 22 and 35
  - most people pay between 10 and 30
  - there is no correlation between Age and Fare

In [45]:
```
f, axes = plt.subplots(1,2 , figsize=(15, 5))
for i,var in enumerate(['Age','Fare']):
    for level in titanic_data['Survived'].unique():
        sb.kdeplot(titanic_data[titanic_data['Survived']==level][var],shade=True,label=
```



- Obersvation:
  - children under the age of 10 are more likely to survive
  - people who paid more for their fare are more likely to survive

Visualising Cabin variable

In [46]:
```
titanic_data['Cabin'].unique()
```

Out[46]:
```
array(['Missing', 'C85', 'C123', 'E46', 'G6', 'C103', 'D56', 'A6',
       'C23 C25 C27', 'B78', 'D33', 'B30', 'C52', 'B28', 'C83', 'F33',
       'F G73', 'E31', 'A5', 'D10 D12', 'D26', 'C110', 'B58 B60', 'E101',
       'F E69', 'D47', 'B86', 'F2', 'C2', 'E33', 'B19', 'A7', 'C49', 'F4',
       'A32', 'B4', 'B80', 'A31', 'D36', 'D15', 'C93', 'C78', 'D35',
       'C87', 'B77', 'E67', 'B94', 'C125', 'C99', 'C118', 'D7', 'A19',
       'B49', 'D', 'C22 C26', 'C106', 'C65', 'E36', 'C54',
       'B57 B59 B63 B66', 'C7', 'E34', 'C32', 'B18', 'C124', 'C91', 'E40',
       'T', 'C128', 'D37', 'B35', 'E50', 'C82', 'B96 B98', 'E10', 'E44',
       'A34', 'C104', 'C111', 'C92', 'E38', 'D21', 'E12', 'E63', 'A14',
       'B37', 'C30', 'D20', 'B79', 'E25', 'D46', 'B73', 'C95', 'B38',
       'B39', 'B22', 'C86', 'C70', 'A16', 'C101', 'C68', 'A10', 'E68',
       'B41', 'A20', 'D19', 'D50', 'D9', 'A23', 'B50', 'A26', 'D48',
       'E58', 'C126', 'B71', 'B51 B53 B55', 'D49', 'B5', 'B20', 'F G63',
       'C62 C64', 'E24', 'C90', 'C45', 'E8', 'B101', 'D45', 'C46', 'D30',
       'E121', 'D11', 'E77', 'F38', 'B3', 'D6', 'B82 B84', 'D17', 'A36',
       'B102', 'B69', 'E49', 'C47', 'D28', 'E17', 'A24', 'C50', 'B42',
       'C148'], dtype=object)
```

In [47]:
```
def multiple_cabins(target):
    if target=='Missing':
        return False
    elif len(target)>4:
        return True
    else:
        return False
```

In [48]:
```
titanic_data[titanic_data['Cabin'].apply(lambda x: multiple_cabins(x))].sort_values(['C
```

Out[48]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cab
872	873	dead	1	Carlsson, Mr. Frans Olof	male	33.00	0	0	695	5.0000	B B B
679	680	alive	1	Cardeza, Mr. Thomas Drake Martinez	male	36.00	0	1	PC 17755	512.3292	B B B
742	743	alive	1	Ryerson, Miss. Susan Parker "Suzette"	female	21.00	2	2	PC 17608	262.3750	B B B B
311	312	alive	1	Ryerson, Miss. Emily Borie	female	18.00	2	2	PC 17608	262.3750	B B B B
				Baxter, Mr.					PC		B

- Observation:
  - there are passengers that have the same combination of cabins but pay drastically different fares. those are likely erroneous

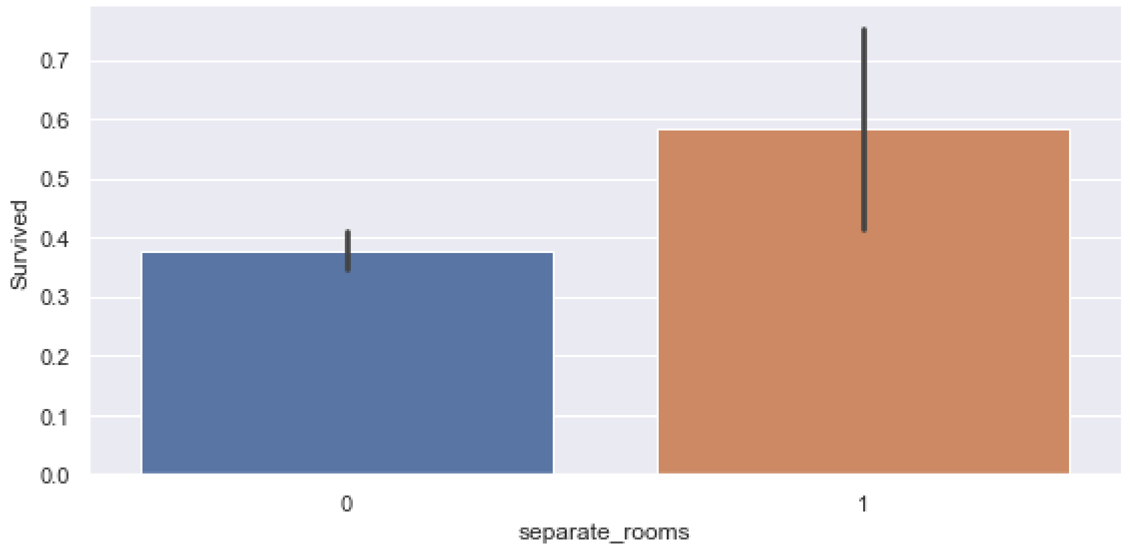
In [31]:
```
titanic_data['separate_rooms']=titanic_data['Cabin'].apply(lambda x: 1 if multiple_cabi
titanic_data['separate_rooms']=pd.Categorical(titanic_data['separate_rooms'])
```

In [32]:
```
titanic_data['separate_rooms'].value_counts()
```

Out[32]:
```
0    867
1     24
Name: separate_rooms, dtype: int64
```

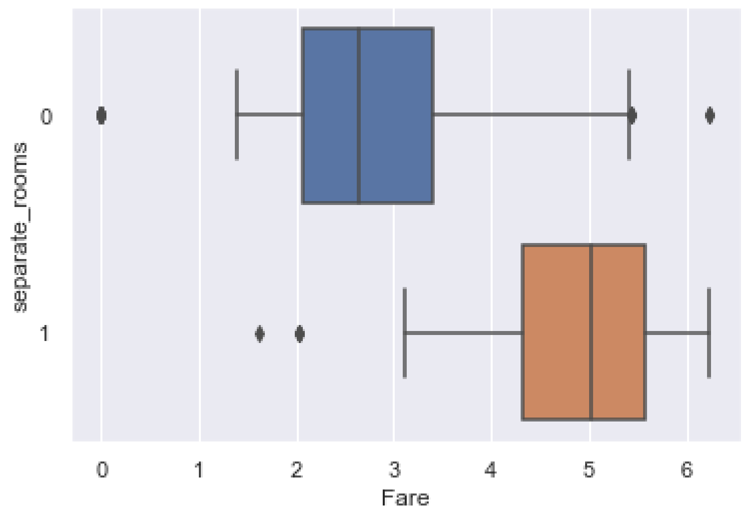
In [33]:
```
temp_data=pd.concat([titanic_data['separate_rooms'],response_copy],axis=1)
sb.catplot(x='separate_rooms',y='Survived',data=temp_data,kind='bar',height=4, aspect=2
```

Out[33]: <seaborn.axisgrid.FacetGrid at 0x2df5e65c448>



In [34]:
```
sb.boxplot(data=titanic_data,y='separate_rooms',x='Fare')
```

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x2df5e7ab688>



- Observation:
  - interestingly people who had multiple rooms had higher change of survival
  - but that could be due to the fact that they tended to pay more if they had multiple rooms

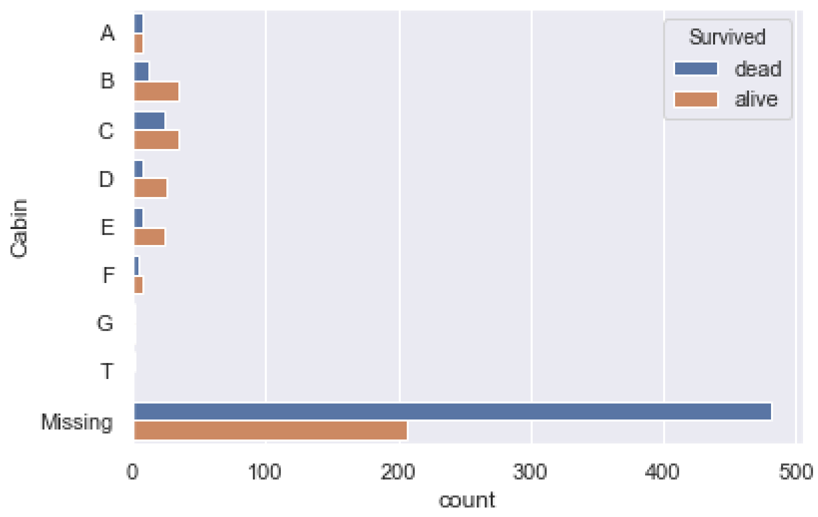
- likely **not a useful feature** because Fare variable already captures this information and the levels here is too imbalanced

In [35]:
```
titanic_data['Cabin']=titanic_data['Cabin'].apply(lambda x: x if x=='Missing' else x[0]
```

- Cabin Variable:
  - reduced its cardinality by grouping alphabets together
  - levels have 2 alphebets; will just take the first occuring one

In [36]:
```
sb.countplot(data=titanic_data,y='Cabin',hue='Survived',order=['A','B','C','D','E','F',
```

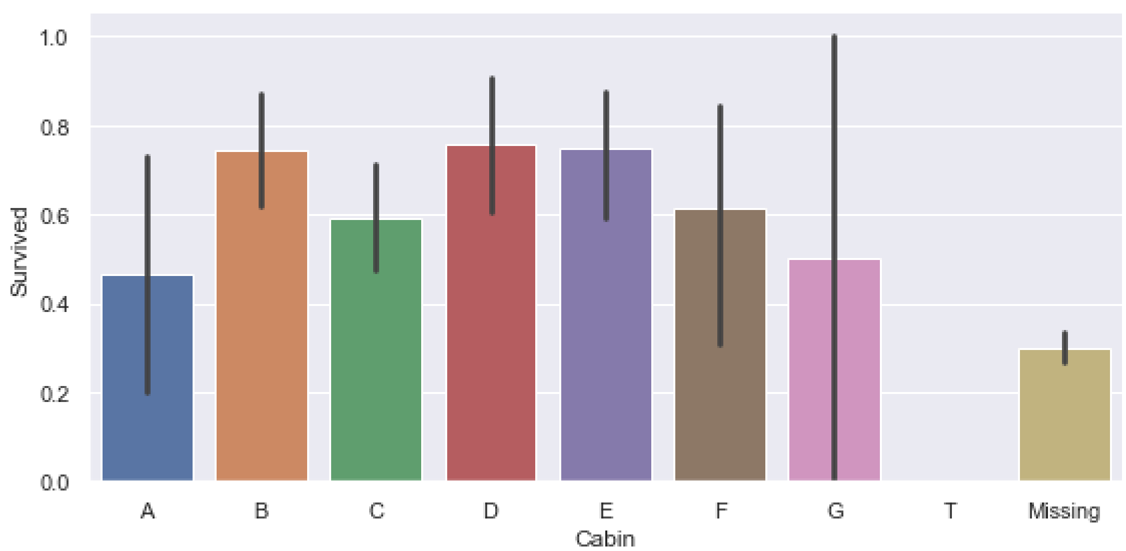
Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x2df5e4caf48>



- Observation:
  - some levels are quite rare

In [37]:
```
temp_data=pd.concat([titanic_data['Cabin'],response_copy],axis=1)
sb.catplot(x='Cabin',y='Survived',data=temp_data,kind='bar',height=4, aspect=2,order=['
```

Out[37]: <seaborn.axisgrid.FacetGrid at 0x2df5f9d1688>



- Observation:

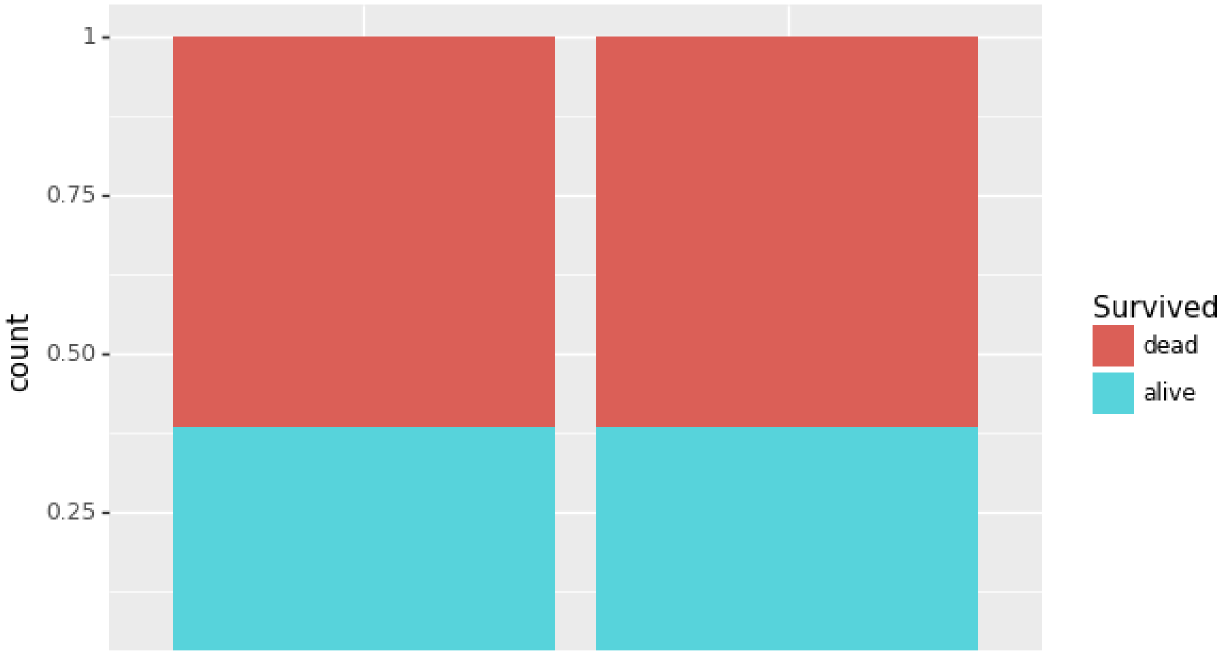
- people with no cabin tagged are more likely to die
- Cabins B,C,D,E are more likely to survive

Visualising Ticket variable

In [38]:
```
def letters_present(target):
    for i in target:
        if i.isalpha():
            return True
    return False

def extract_letters(target):
    result=''
    for i in target:
        if i.isalpha():
            result+=i
    return result
```

In [39]:
```
titanic_data['ticket_letters']=titanic_data['Ticket'].apply(lambda x: 'present' if lett
```

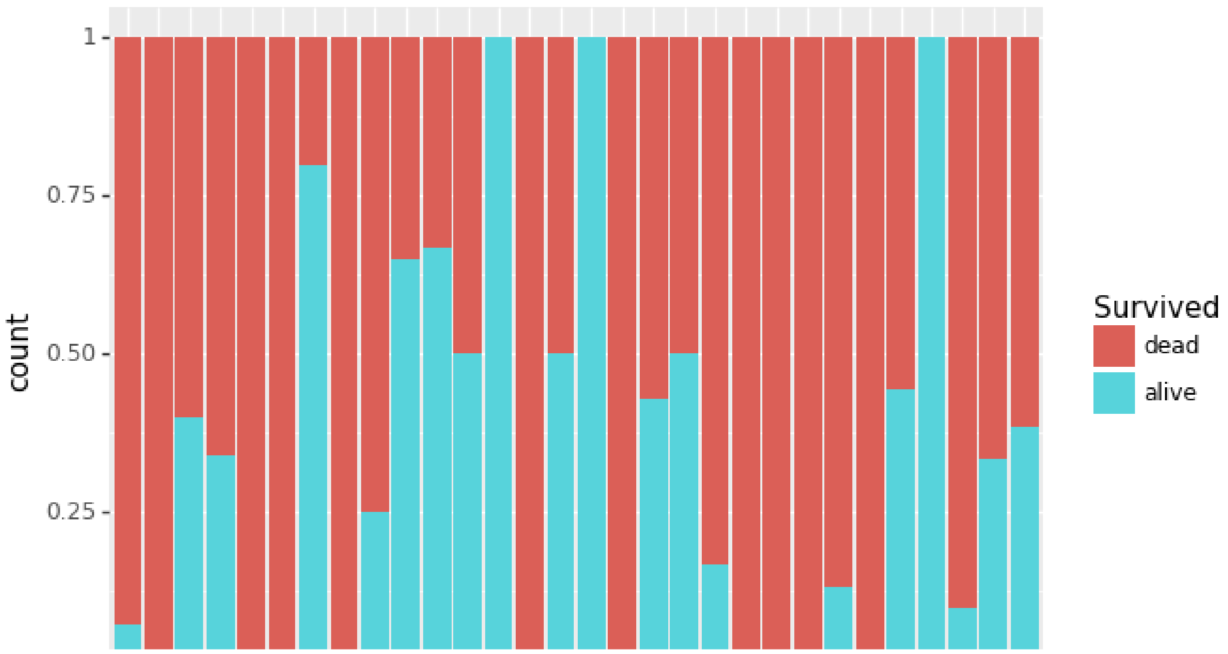
In [40]:
```
ggplot(titanic_data,aes(x='ticket_letters',fill='Survived'))+geom_bar(position='fill')
```



- Observation:
  - whether letters were present or not in the ticket didn't matter

In [41]:
```
titanic_data['test']=titanic_data['Ticket'].apply(lambda x: extract_letters(x) if lette
```

In [42]:
```
ggplot(titanic_data,aes(x='test',fill='Survived'))+geom_bar(position='fill')+  theme(ax
```



In [43]:
```
titanic_data['test'].value_counts()
```

Out[43]:
```
absent      661
PC           60
CA           41
A            28
STONO        18
SOTONOQ      15
WC           10
SCPARIS       7
SOC           6
FCC           5
C             5
LINE          4
SCParis       4
WEP           3
PP            3
SOPP          3
SOTONO        2
SWPP          2
PPP           2
```

- Observations:
  - looking at the levels like 'absent', 'PC' and 'CA', where the sample size are largest, their dead/alive ratio are very close to that of the population
  - other levels likely had varying proportions by chance due to small sample size
  - this variable likely has close to **no effect on survival**

Visualising Name variable

In [44]:
```
print("Number of unique names: ",len(titanic_data['Name'].unique()))
```

```
Number of unique names:  891
```

In [45]:
```python
titanic_data['Name'].unique()
```

Out[45]:
```
array(['Braund, Mr. Owen Harris',
       'Cumings, Mrs. John Bradley (Florence Briggs Thayer)',
       'Heikkinen, Miss. Laina',
       'Futrelle, Mrs. Jacques Heath (Lily May Peel)',
       'Allen, Mr. William Henry', 'Moran, Mr. James',
       'McCarthy, Mr. Timothy J', 'Palsson, Master. Gosta Leonard',
       'Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)',
       'Nasser, Mrs. Nicholas (Adele Achem)',
       'Sandstrom, Miss. Marguerite Rut', 'Bonnell, Miss. Elizabeth',
       'Saundercock, Mr. William Henry', 'Andersson, Mr. Anders Johan',
       'Vestrom, Miss. Hulda Amanda Adolfina',
       'Hewlett, Mrs. (Mary D Kingcome) ', 'Rice, Master. Eugene',
       'Williams, Mr. Charles Eugene',
       'Vander Planke, Mrs. Julius (Emelia Maria Vandemoortele)',
       'Masselmani, Mrs. Fatima', 'Fynney, Mr. Joseph J',
       'Beesley, Mr. Lawrence', 'McGowan, Miss. Anna "Annie"',
       'Sloper, Mr. William Thompson', 'Palsson, Miss. Torborg Danira',
       'Asplund, Mrs. Carl Oscar (Selma Augusta Emilia Johansson)',
       'Emir, Mr. Farred Chehab', 'Fortune, Mr. Charles Alexander',
```

- insight:
  - looking at the Name column, there seems to be a some prefixes:
    - Master
    - Mr
    - Miss (and etc.)
  - they always end with a fullstop and begin with a space

In [46]:
```python
def extract_prefixes(target):
    temp=target.split('.')[0]
    return temp.split(' ')[-1]
```

In [47]:
```python
titanic_data['Name'].apply(lambda x: extract_prefixes(x)).value_counts()
```

Out[47]:
```
Mr          517
Miss        182
Mrs         125
Master       40
Dr            7
Rev           6
Col           2
Mlle          2
Major         2
Ms            1
Countess      1
Capt          1
Don           1
Lady          1
Mme           1
Jonkheer      1
Sir           1
Name: Name, dtype: int64
```

- Observation:
  - the rare levels can be classified with the majority based on their prefix:
    - Dr,Rev,Col, Major, Capt, Sir, Don; Mr (Mode)

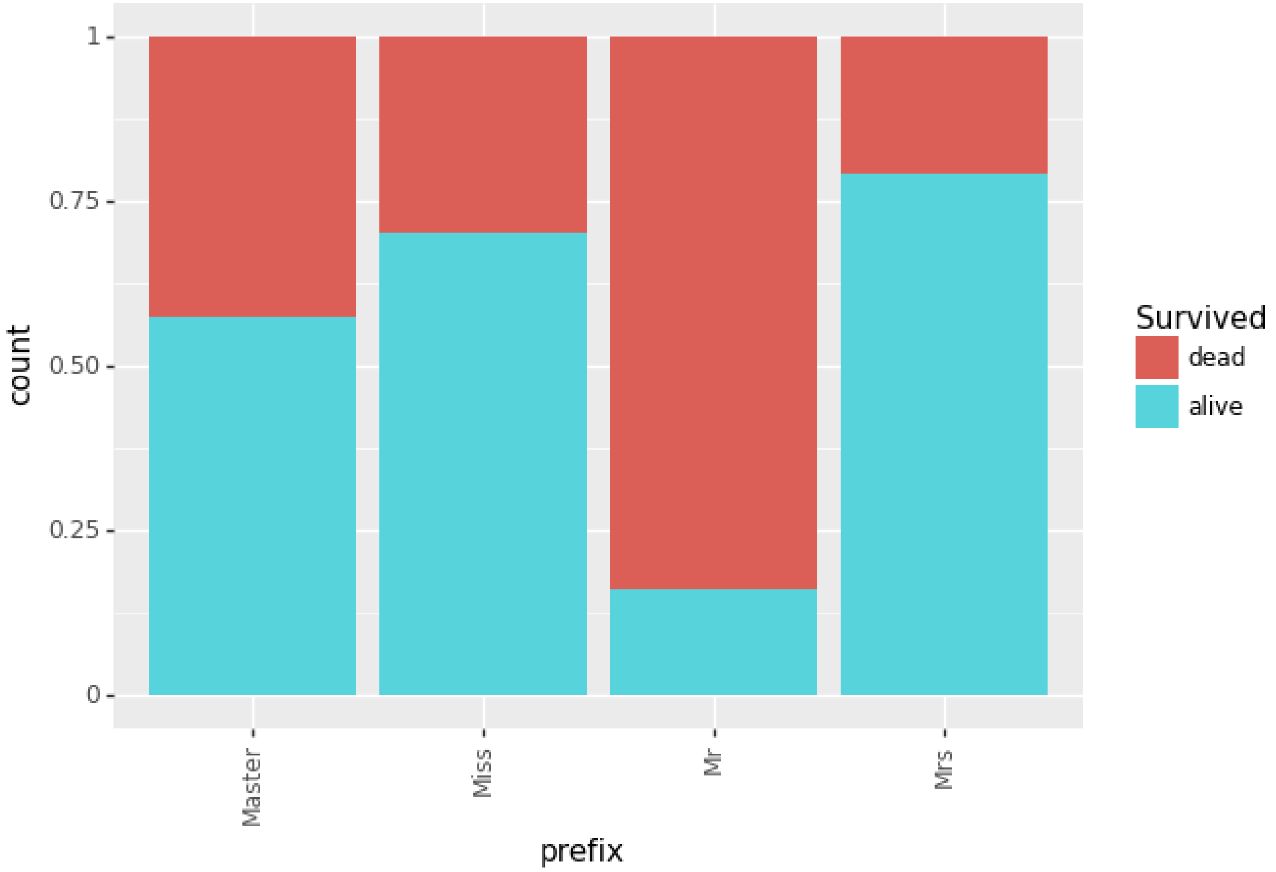
- Mlle, Ms, Countess, Jonkheer, MMe,Lady;Miss (Mode)

In [48]:
```
titanic_data['prefix']=titanic_data['Name'].apply(lambda x: extract_prefixes(x))
```

In [49]:
```
def reclassify_prefix_by_gender(target):
    if target in ['Mlle', 'Ms', 'Countess', 'Jonkheer', 'Mme','Lady']:
        return 'Miss'
    elif target in ['Miss','Mr','Master', 'Mrs']:
        return target
    else:
        return 'Mr'
```

In [50]:
```
titanic_data['prefix']=titanic_data['prefix'].apply(lambda x: reclassify_prefix_by_gend
```

In [51]:
```
ggplot(titanic_data,aes(x='prefix',fill='Survived'))+geom_bar(position='fill')+  theme(
```

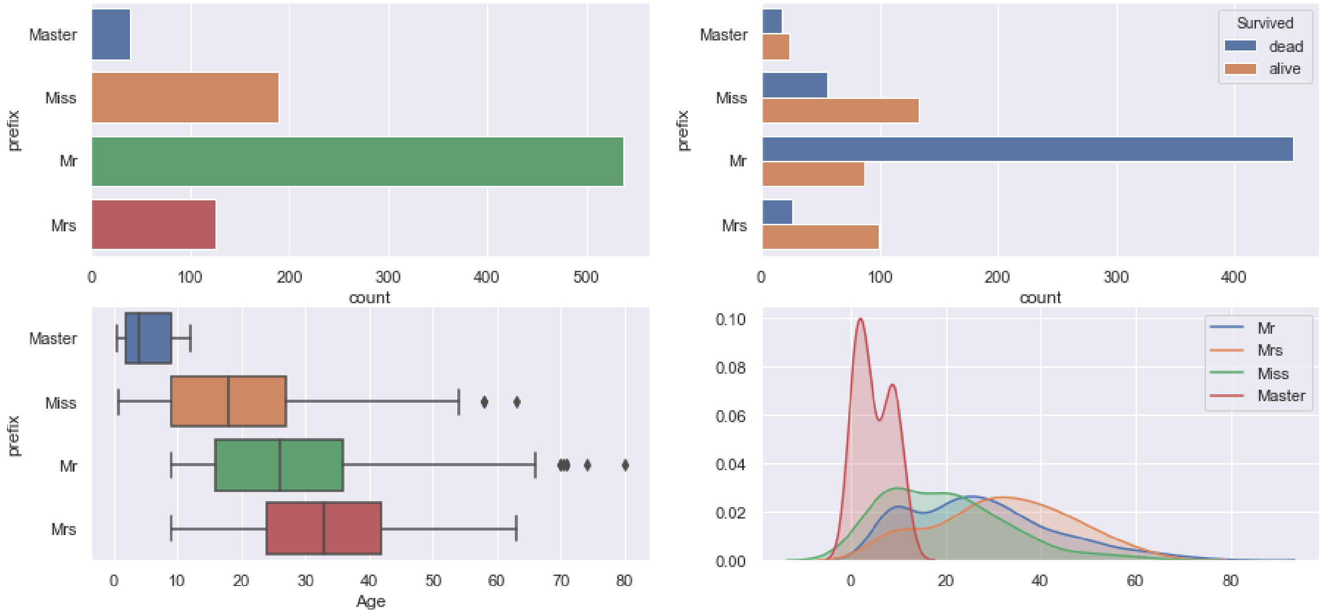


Out[51]: <ggplot: (-9223371839454181724)>

- Observations:
  - there are way too many levels, some of which are quite rare and will not have impact
- Decision:
  - group rare levels together to reduce noise and cardinality

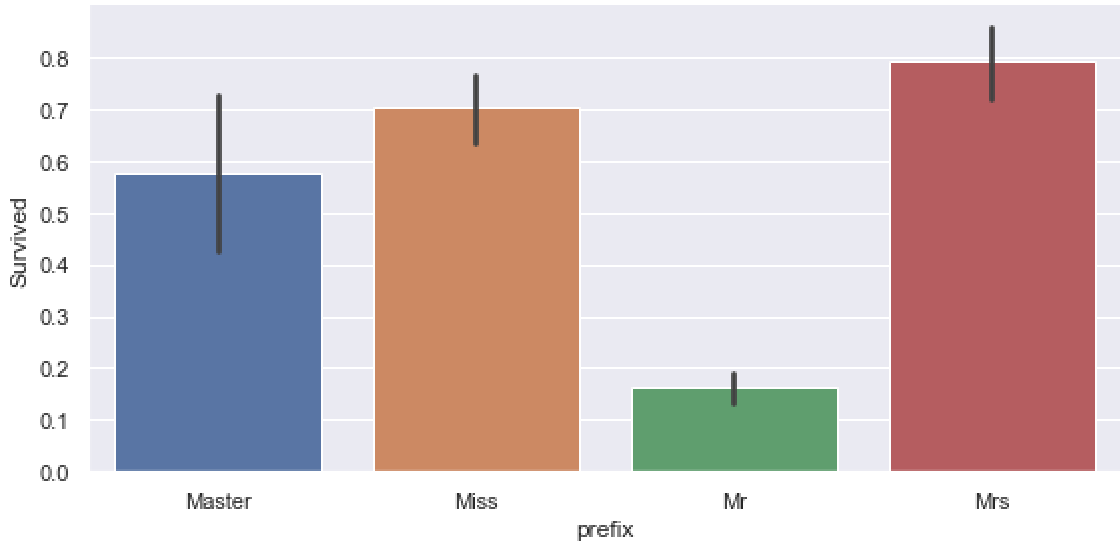
In [52]:
```
titanic_data['prefix']=pd.Categorical(titanic_data['prefix'])
```

In [53]:
```
f, axes = plt.subplots(2,2 , figsize=(15, 7))
sb.countplot(data=titanic_data,y='prefix',ax=axes[0,0])
sb.countplot(data=titanic_data,y='prefix',hue='Survived',ax=axes[0,1])
sb.boxplot(data=titanic_data,x='Age',y='prefix',ax=axes[1,0])
for level in titanic_data['prefix'].unique():
    sb.kdeplot(titanic_data[titanic_data['prefix']==level]['Age'],ax=axes[1,1],shade=Tr
```



In [54]:
```
temp_data=pd.concat([titanic_data['prefix'],response_copy],axis=1)
sb.catplot(x='prefix',y='Survived',data=temp_data,kind='bar',height=4, aspect=2)
```

Out[54]: <seaborn.axisgrid.FacetGrid at 0x2df5fa43288>



- Observation:
  - prefix is not only a good predictor for survival('Mr' are more likely to die)
  - it also **predicts well for age** as well

Data Preparation

In [52]:
```python
# Basic Libraries
import numpy as np
import pandas as pd
import seaborn as sb
import matplotlib.pyplot as plt # we only need pyplot
from plotnine import *
sb.set() # set the default Seaborn style for graphics
```

In [53]:
```python
# read data
titanic_train=pd.read_csv('train.csv')
titanic_test=pd.read_csv('test.csv')
print('Training set dimensions:',titanic_train.shape)
print('Test set dimensions:',titanic_test.shape)
```

```
Training set dimensions: (891, 12)
Test set dimensions: (418, 11)
```

In [54]:
```python
# combine training and test set to do processing together
titanic_processing=pd.concat([titanic_train,titanic_test],axis=0,sort=True).reset_index
```

In [55]:
```python
titanic_processing.isna().sum()
```

Out[55]:
```
Age             263
Cabin          1014
Embarked          2
Fare              1
Name              0
Parch             0
PassengerId       0
Pclass            0
Sex               0
SibSp             0
Survived        418
Ticket            0
dtype: int64
```

- Observation:
  - NAs present in 4 features
  - NAs in Survived refer to the test set

In [56]:
```python
titanic_processing.dtypes
```

Out[56]:
```
Age             float64
Cabin            object
Embarked         object
Fare            float64
Name             object
Parch             int64
PassengerId       int64
Pclass            int64
Sex              object
SibSp             int64
Survived        float64
Ticket           object
dtype: object
```

variable: Survived

In [57]:
```
titanic_processing['Survived']=pd.Categorical(titanic_processing['Survived'])
```

- Step:
  - Response converted to categorical
  - 0 is dead, 1 is alive

variable: Pclass

In [58]:
```
# titanic_processing=pd.get_dummies(titanic_processing,columns=['Pclass'],prefix='Pclas
titanic_processing['Pclass']=pd.Categorical(titanic_processing['Pclass'])
```

variable: Name , engineered feature: prefix

In [59]:
```
def extract_prefixes(target):
    temp=target.split('.')[0]
    return temp.split(' ')[-1]
def reclassify_prefix_by_gender(target):
    if target in ['Miss','Mlle', 'Ms', 'Countess', 'Jonkheer', 'Mme','Lady']:
        return 'Mrs'
    elif target in ['Mr','Master', 'Mrs']:
        return target
    else:
        return 'Mr'
titanic_processing['prefix']=titanic_processing['Name'].apply(lambda x: extract_prefixe
titanic_processing['prefix']=titanic_processing['prefix'].apply(lambda x: reclassify_pr
titanic_processing.drop(['Name'],axis=1,inplace=True)
```

- Steps:
  - engineered categorical feature; prefix, from name variable:
    - classes: Mr, Mrs, Master
    - since Miss and Mrs have very similar survival rate i will group them
    - the remaining prefixes are quite rare so i will group they to Mr and Mrs respectively(by gender)
  - drop original feature

variable: Sex

In [60]:
```
titanic_processing['Sex']=pd.Categorical(titanic_processing['Sex'])
titanic_processing['Sex']=titanic_processing['Sex'].cat.rename_categories({'male':1,'fe
```

- Steps:
  - converted to categorical
  - label encode male as 1 and female as 0

variable: SibSp and Parch , engineered feature: family_size

In [61]:
```
titanic_processing['family_size']=titanic_processing['SibSp']+titanic_processing['Parch
```

- Steps:
  - SibSp and Parch kept as integer rather than binning or categorizing which may cause bias and loss of information
  - having a family member around could aid in survival while having too many may lead to death, so family_size could capture this information
  - add one to include the target passenger themselve

variable: Ticket

In [62]:
```
titanic_processing.drop(['Ticket'],axis=1,inplace=True)
```

- Steps:
  - ticket dropped because it is not predictive of survival

variable: Cabin

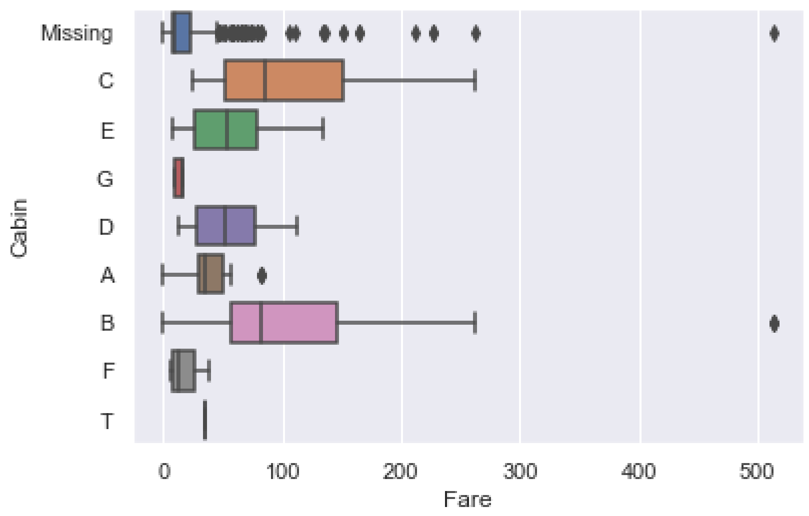
In [63]:
```
titanic_processing['Cabin'].fillna('Missing',inplace=True)
titanic_processing['Cabin']=titanic_processing['Cabin'].apply(lambda x: x if x=='Missin
#titanic_processing=pd.get_dummies(titanic_processing,columns=['Cabin'])
from sklearn.preprocessing import LabelEncoder
labelencoder = LabelEncoder()
titanic_processing['Cabin_encoded']=labelencoder.fit_transform(titanic_processing['Cabi
cabin_mapping=titanic_processing.groupby(['Cabin_encoded','Cabin'])
```

- Steps:
  - NAs assigned as 'Missing'
  - the others are assigned theri first occuring letter cabin
  - treated as categorical
  - ONE HOT ENCODED

variable: fare

In [64]:
```
sb.boxplot(data=titanic_processing,y='Cabin',x='Fare')
```

Out[64]: <matplotlib.axes._subplots.AxesSubplot at 0x1517b7e8548>



- Observations:
  - Cabin does seem to be a strong indicator of Fare

In [65]:
```
titanic_processing[titanic_processing['Fare'].isna()]
```

Out[65]:

	Age	Cabin	Embarked	Fare	Parch	PassengerId	Pclass	Sex	SibSp	Survived	prefix	family_siz
1043	60.5	Missing	S	NaN	0	1044	3	1	0	NaN	Mr	

In [66]:
```
titanic_processing.loc[titanic_processing['Fare'].isna(),'Fare']=titanic_processing.loc
```

- Steps:
  - Replace Fare NAs with median based on Cabin

In [67]:
```
titanic_processing['Fare']=titanic_processing['Fare'].apply( lambda x: np.log1p(x))
```

- steps:
  - log of fare taken to reduce skew

variable: Embarked

In [68]:
```
titanic_processing[titanic_processing['Embarked'].isna()]
```

Out[68]:

	Age	Cabin	Embarked	Fare	Parch	PassengerId	Pclass	Sex	SibSp	Survived	prefix	family_s
61	38.0	B	NaN	4.394449	0	62	1	0	0	1.0	Mrs	
829	62.0	B	NaN	4.394449	0	830	1	0	0	1.0	Mrs	

In [69]:
```
titanic_processing['Embarked'].fillna(titanic_processing['Embarked'].mode()[0],inplace=
#titanic_processing=pd.get_dummies(titanic_processing,columns=['Embarked'])
labelencoder = LabelEncoder()
titanic_processing['Embarked_encoded']=labelencoder.fit_transform(titanic_processing['E
embarked_mapping=titanic_processing.groupby(['Embarked_encoded','Embarked'])
```

- Steps:
  - there are only 2 NAs, of which will be filled with the mode; Southampton, 'S'
  - one hot encoded

variable: Age

In [70]:
```
for level in titanic_processing['prefix'].unique():
    median_age=titanic_processing[titanic_processing['prefix']==level]['Age'].median()
    titanic_processing.loc[titanic_processing['prefix']==level,'Age']=titanic_processin
```

- Steps:
  - replaced NAs with median age based on their respective prefixes
  - kepted as float
- IMPT note:
  - titanic_processing.loc[titanic_processing['prefix']==level,'Age'] works because it's a single operation -titanic_processing[titanic_processing['prefix']==level]['Age'] will not because it's a chained operation which will give a warning

variable: prefix

In [71]:
```
#titanic_processing=pd.get_dummies(titanic_processing,columns=['prefix'])
from sklearn.preprocessing import LabelEncoder
labelencoder = LabelEncoder()
titanic_processing['prefix_encoded']=labelencoder.fit_transform(titanic_processing['pre
prefix_mapping=titanic_processing.groupby(['prefix_encoded','prefix'])
```

- Steps:
  - one hot encode

variable: PassengerID

In [72]:
```
titanic_processing.drop(['PassengerId'],axis=1,inplace=True)
```

- Steps:
    - dropped

consolidating cleaned data

In [73]:
```
titanic_processing.columns
```

Out[73]:
```
Index(['Age', 'Cabin', 'Embarked', 'Fare', 'Parch', 'Pclass', 'Sex', 'SibSp',
       'Survived', 'prefix', 'family_size', 'Cabin_encoded',
       'Embarked_encoded', 'prefix_encoded'],
      dtype='object')
```

In [74]:
```
titanic_processing.dtypes
```

Out[74]:
```
Age                  float64
Cabin                 object
Embarked              object
Fare                 float64
Parch                  int64
Pclass              category
Sex                 category
SibSp                  int64
Survived            category
prefix                object
family_size            int64
Cabin_encoded          int32
Embarked_encoded       int32
prefix_encoded         int32
dtype: object
```

In [75]:
```
# treat every feature as categorical except fare and age
for var in ['Parch','SibSp','family_size','Cabin_encoded','Embarked_encoded','prefix_en
    titanic_processing[var]=pd.Categorical(titanic_processing[var])
```

In [76]:
```
# scale the numeric variables to speed up modelling
from sklearn.preprocessing import MinMaxScaler
MMscaler = MinMaxScaler()
titanic_processing[['Age', 'Fare']]=MMscaler.fit_transform(titanic_processing[['Age', '
```

In [77]:
```
titanic_cleaned=titanic_processing[['Age', 'Fare', 'Parch', 'Pclass','Sex', 'SibSp',
       'Survived', 'family_size', 'Cabin_encoded',
       'Embarked_encoded', 'prefix_encoded']].copy()
```

```
In [78]: # check data types
         titanic_cleaned.dtypes
```

```
Out[78]: Age                  float64
         Fare                 float64
         Parch               category
         Pclass              category
         Sex                 category
         SibSp               category
         Survived            category
         family_size         category
         Cabin_encoded       category
         Embarked_encoded    category
         prefix_encoded      category
         dtype: object
```

```
In [79]: titanic_test_cleaned=titanic_cleaned[titanic_cleaned['Survived'].isna()]
         titanic_train_cleaned=titanic_cleaned[~titanic_cleaned['Survived'].isna()]
```

- Steps:
  - split to the original training and test sets given

```
In [80]: y_titanic_train_cleaned=titanic_train_cleaned['Survived']
         X_titanic_train_cleaned=titanic_train_cleaned.drop(['Survived'],axis=1)
         X_titanic_test_cleaned=titanic_test_cleaned.drop(['Survived'],axis=1)
```

- Steps:
  - separate predictor from response variable

Training the models

- Observation:
  - taking the log of fare actually caused the test set to perform worse which is an indication of overfitting
  - label encoding performed better than one hot encoding

```
In [132]: from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, ExtraT
          from sklearn.svm import SVC
          from sklearn.model_selection import StratifiedKFold, cross_val_score,GridSearchCV,learn
```

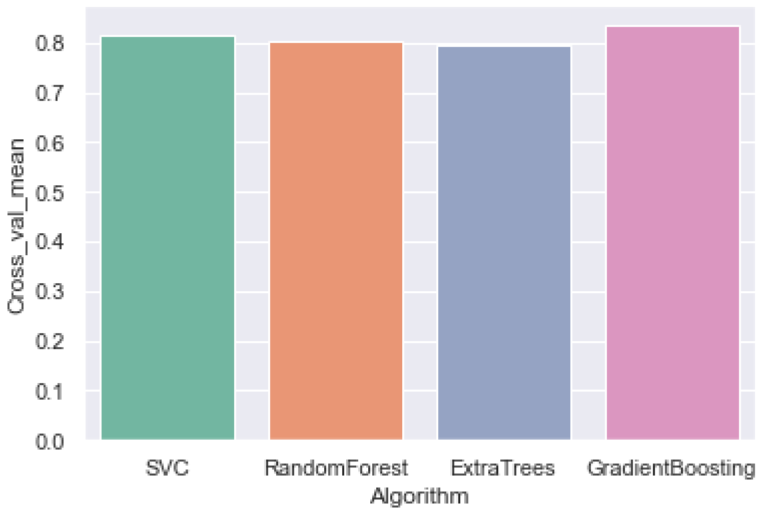
```
In [133]: kfold=StratifiedKFold(n_splits=10)
```

- Steps:
  - since there is a class imabalance(more people are dead than alive), we use stratified k fold so that the **proportion of each class in each fold is preserved**

In [134]:
```
random_state=2
classifiers=[]
classifiers.append(SVC(random_state=random_state))
classifiers.append(RandomForestClassifier(random_state=random_state))
classifiers.append(ExtraTreesClassifier(random_state=random_state))
classifiers.append(GradientBoostingClassifier(random_state=random_state))

cv_results=[]
for classifier in classifiers:
    cv_results.append(cross_val_score(classifier,X_titanic_train_cleaned,y_titanic_trai

cv_means=[]
cv_std=[]
for cv_result in cv_results:
    cv_means.append(cv_result.mean())
    cv_std.append(cv_result.std())

result_table=pd.DataFrame({'Algorithm':['SVC','RandomForest','ExtraTrees','GradientBoos
                          'Cross_val_mean':cv_means,
                          'Cross_val_std':cv_std})
```

In [135]:
```
sb.barplot(x='Algorithm',y='Cross_val_mean',data=result_table,palette='Set2')
```

Out[135]: <matplotlib.axes._subplots.AxesSubplot at 0x176cc969088>



- Observation:
    - Gradient boosting outperforms the other models

Hyperparameter tuning

load tuned models with pickle

In [41]:
```
# !pip install joblib
import joblib
GS_ranFor=joblib.load('GS_ranFor.pkl')
GS_graBoo=joblib.load('GS_graBoo.pkl')
GS_SVM=joblib.load('GS_SVM.pkl')
GS_exTrees=joblib.load('GS_exTrees.pkl')
```

Random Forest

ranFor=RandomForestClassifier()

ranFor_paramgrid={"max_depth":[None, 8,15], "max_features":[4,6,8], "min_samples_split":[2,3,4], "min_samples_leaf":[3,5], "n_estimators":[300,500,1000], "criterion":["gini"]}

GS_ranFor=GridSearchCV(ranFor,param_grid=ranFor_paramgrid,cv=kfold,scoring='accuracy',n_jobs=-1)

GS_ranFor.fit(X_titanic_train_cleaned,y_titanic_train_cleaned)

- Best parameters and best score:

In [140]:
```
best_ranFor=GS_ranFor.best_estimator_
print(best_ranFor)
print("Score: {:.5f}".format(GS_ranFor.best_score_))
```

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=8, max_features=6, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=3, min_samples_split=4,
                       min_weight_fraction_leaf=0.0, n_estimators=500,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
Score: 0.84287
```

Gradient Boosting

graBoo=GradientBoostingClassifier()

graBoo_paramgrid={'loss':['deviance'], 'n_estimators':[300,500,1000], 'learning_rate':[0.05,0.1,0.3], 'max_depth':[None, 8,15], 'min_samples_leaf':[100,150], 'max_features':[4,6,8]}

GS_graBoo=GridSearchCV(graBoo,param_grid=graBoo_paramgrid,scoring='accuracy',n_jobs=-1,cv=kfold)

GS_graBoo.fit(X_titanic_train_cleaned,y_titanic_train_cleaned)

- Best parameters and best score:

In [141]:
```
best_graBoo=GS_graBoo.best_estimator_
print(best_graBoo)
print("Score: {:.5f}".format(GS_graBoo.best_score_))
```

```
GradientBoostingClassifier(criterion='friedman_mse', init=None,
                           learning_rate=0.3, loss='deviance', max_depth=8,
                           max_features=6, max_leaf_nodes=None,
                           min_impurity_decrease=0.0, min_impurity_split=None,
                           min_samples_leaf=100, min_samples_split=2,
                           min_weight_fraction_leaf=0.0, n_estimators=300,
                           n_iter_no_change=None, presort='auto',
                           random_state=None, subsample=1.0, tol=0.0001,
                           validation_fraction=0.1, verbose=0,
                           warm_start=False)
Score: 0.83502
```

Support Vector Machine

SVM=SVC(probability=True)

SVM_paramgrid={'kernel':['rbf'], 'gamma':[0.001,0.01,0.1,1], 'C':[1,10,50,100,200,300,1000]}

GS_SVM=GridSearchCV(SVM,param_grid=SVM_paramgrid,scoring='accuracy',n_jobs=-1,cv=kfold)

GS_SVM.fit(X_titanic_train_cleaned,y_titanic_train_cleaned)

- Best parameters and best score:

In [142]:
```
best_SVM=GS_SVM.best_estimator_
print(best_SVM)
print("Score: {:.5f}".format(GS_SVM.best_score_))
```

```
SVC(C=50, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma=0.01, kernel='rbf',
    max_iter=-1, probability=True, random_state=None, shrinking=True, tol=0.001,
    verbose=False)
Score: 0.83389
```

Extra Trees

exTrees=ExtraTreesClassifier()

exTrees_paramgrid={"max_depth":[None, 8,15], "max_features":[4,6,8], "min_samples_split":[2,3,4], "min_samples_leaf":[3,5], "n_estimators":[300,500,1000], "criterion":["gini"]}

GS_exTrees=GridSearchCV(exTrees,param_grid=exTrees_paramgrid,scoring='accuracy',n_jobs=-1,cv=kfold

GS_exTrees.fit(X_titanic_train_cleaned,y_titanic_train_cleaned)

- Best parameters and best score:

In [143]:
```
best_exTrees=GS_exTrees.best_estimator_
print("Best parameters:")
print(best_exTrees)
print("Score: {:.5f}".format(GS_exTrees.best_score_))
```

```
Best parameters:
ExtraTreesClassifier(bootstrap=False, class_weight=None, criterion='gini',
                     max_depth=None, max_features=8, max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=3, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, n_estimators=300,
                     n_jobs=None, oob_score=False, random_state=None, verbose=0,
                     warm_start=False)
Score: 0.83502
```

Saving the models- executed

import joblib joblib.dump(GS_ranFor,'GS_ranFor.pkl') joblib.dump(GS_SVM,'GS_SVM.pkl') joblib.dump(GS_graBoo,'GS_graBoo.pkl') joblib.dump(GS_exTrees,'GS_exTrees.pkl')

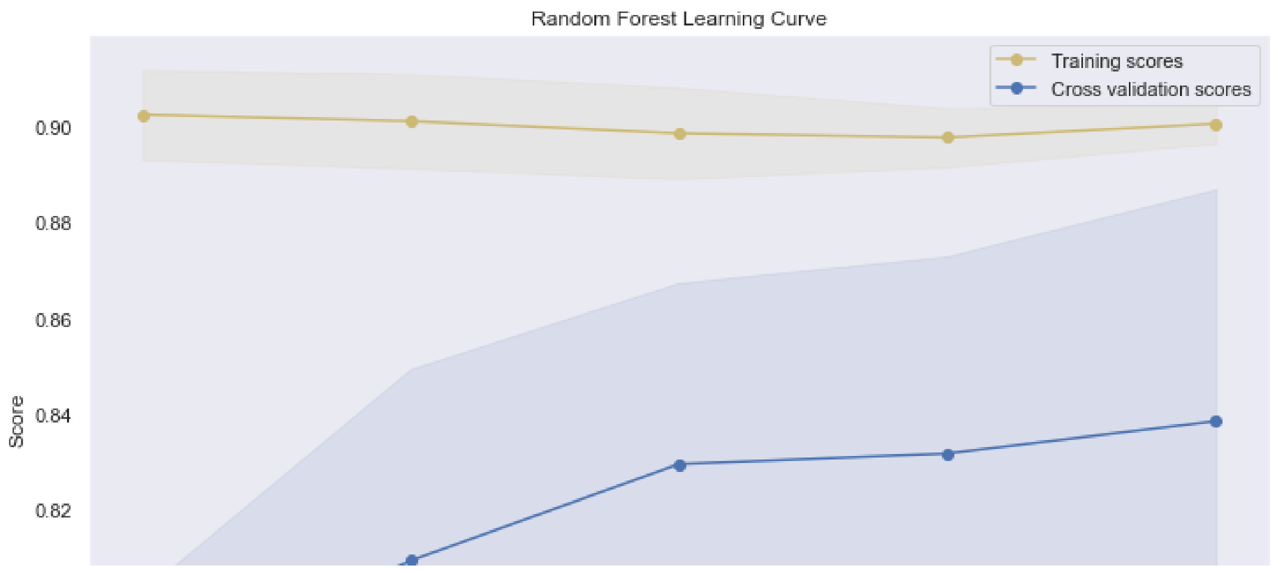
Plot Learning curve

- the difference in accuracy between training and test can indicate the degree of overfitting

In [46]:
```
def plot_learning_curve(estimator,title,X,y,ylim=None,cv=None,n_jobs=-1,train_sizes=np.

    plt.figure(figsize=(12, 8))
    plt.title(title)
    plt.xlabel('Training Examples')
    plt.ylabel('Score')

    train_sizes,train_scores,test_scores=learning_curve(estimator ,X , y,
                                                          cv=cv,
                                                          n_jobs=n_jobs,
                                                          train_sizes=train_sizes)

    train_scores_mean=np.mean(train_scores,axis=1)
    train_scores_std=np.std(train_scores,axis=1)
    test_scores_mean=np.mean(test_scores,axis=1)
    test_scores_std=np.std(test_scores,axis=1)

    plt.grid()

    plt.fill_between(train_sizes,
                     train_scores_mean-train_scores_std,
                     train_scores_mean+train_scores_std, alpha= 0.1 ,color='y')
    plt.fill_between(train_sizes,
                     test_scores_mean-test_scores_std,
                     test_scores_mean+test_scores_std, alpha= 0.1 ,color='b')

    plt.plot(train_sizes,train_scores_mean,'o-',color='y',
             label='Training scores')
    plt.plot(train_sizes,test_scores_mean,'o-',color='b',
             label='Cross validation scores')

    plt.legend(loc='best')
    return plt
```

In [145]:
```
plot_learning_curve(best_ranFor,'Random Forest Learning Curve',
                    X_titanic_train_cleaned,y_titanic_train_cleaned,
                    cv=kfold)
plot_learning_curve(best_graBoo,'Gradient Boosting Learning Curve',
                    X_titanic_train_cleaned,y_titanic_train_cleaned,
                    cv=kfold)
plot_learning_curve(best_SVM,'SVM Learning Curve',
                    X_titanic_train_cleaned,y_titanic_train_cleaned,
                    cv=kfold)
plot_learning_curve(best_exTrees,'Extra Trees Learning Curve',
                    X_titanic_train_cleaned,y_titanic_train_cleaned,
                    cv=kfold)
```

Out[145]:
```
<module 'matplotlib.pyplot' from 'C:\\Users\\tanch\\AppData\\Roaming\\Python\\Pytho
n37\\site-packages\\matplotlib\\pyplot.py'>
```

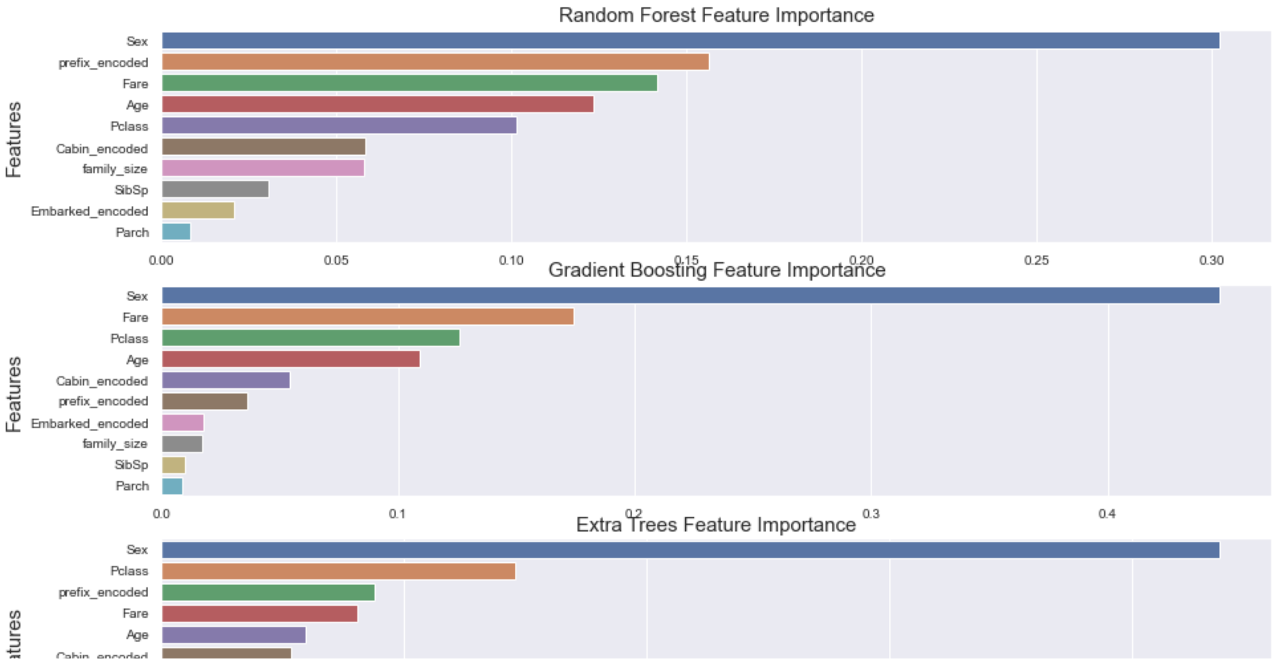


- Observation:
  - overfitting in the gradiant boosting classifier seems to be consistently lower, even with very few training examples
  - although random forest has the best accuracy, its standard deviation is also the greatest
  - at 800 training examples, difference in accuracy between training and test sets are around the same

Feature importance

In [146]:
```
names_classifiers=[('Random Forest',best_ranFor),
                   ('Gradient Boosting',best_graBoo),
                   ('Extra Trees',best_exTrees)]
```

In [147]:
```
f, axes = plt.subplots(3,1 , figsize=(15, 10))
for i,classifier in enumerate(names_classifiers):
    indices=np.argsort(classifier[1].feature_importances_)[::-1]
    g=sb.barplot(y=X_titanic_train_cleaned.columns[indices],x=classifier[1].feature_imp
    g.set_ylabel('Features',fontsize=15)
    g.tick_params(labelsize=10)
    g.set_title(classifier[0]+' Feature Importance',fontsize=15)
```



- Obervation:
    - Sex and prefix looks to be one of the top features in all three models (SVM doesn't allow feature importance)
    - family_size indeed was a stronger predictor compared to Parch and SibSp

Ensemble modelling

- combining the predictions from the best models

In [148]:
```
VotingClassifier=VotingClassifier(estimators=[('Random Forest',best_ranFor),
                                              ('Gradient Boosting',best_graBoo),
                                              ('Extra Trees',best_exTrees),
                                               ('SVM',best_SVM)],
                                  voting='soft',
                                  n_jobs=-1)
VotingClassifier.fit(X_titanic_train_cleaned,y_titanic_train_cleaned)
```

Out[148]:
```
VotingClassifier(estimators=[('Random Forest',
                              RandomForestClassifier(bootstrap=True,
                                                     class_weight=None,
                                                     criterion='gini',
                                                     max_depth=8,
                                                     max_features=6,
                                                     max_leaf_nodes=None,
                                                     min_impurity_decrease=0.0,
                                                     min_impurity_split=None,
                                                     min_samples_leaf=3,
                                                     min_samples_split=4,
                                                     min_weight_fraction_leaf=0.0,
                                                     n_estimators=500,
                                                     n_jobs=None,
                                                     oob_score=False,
                                                     random_state=None,
                                                     verb...
                                                   n_estimators=300,
                                                   n_jobs=None, oob_score=False,
```

Predicting on the test set and submission

ensemble model

In [149]:
```
test_predictions=pd.Series(VotingClassifier.predict(X_titanic_test_cleaned),name='Survi
results=pd.concat([titanic_test['PassengerId'],test_predictions],axis=1)
results['Survived']=results['Survived'].astype(int)
results.to_csv('ensemble_results.csv',index=False)
```

random forest

In [150]:
```
test_predictions=pd.Series(best_ranFor.predict(X_titanic_test_cleaned),name='Survived')
results=pd.concat([titanic_test['PassengerId'],test_predictions],axis=1)
results['Survived']=results['Survived'].astype(int)
results.to_csv('ranFor_results.csv',index=False)
```

gradient boosting

In [151]:
```
test_predictions=pd.Series(best_graBoo.predict(X_titanic_test_cleaned),name='Survived')
results=pd.concat([titanic_test['PassengerId'],test_predictions],axis=1)
results['Survived']=results['Survived'].astype(int)
results.to_csv('graBoo_results.csv',index=False)
```

SVM

In [152]:
```
test_predictions=pd.Series(best_SVM.predict(X_titanic_test_cleaned),name='Survived')
results=pd.concat([titanic_test['PassengerId'],test_predictions],axis=1)
results['Survived']=results['Survived'].astype(int)
results.to_csv('SVM_results.csv',index=False)
```

extra Trees

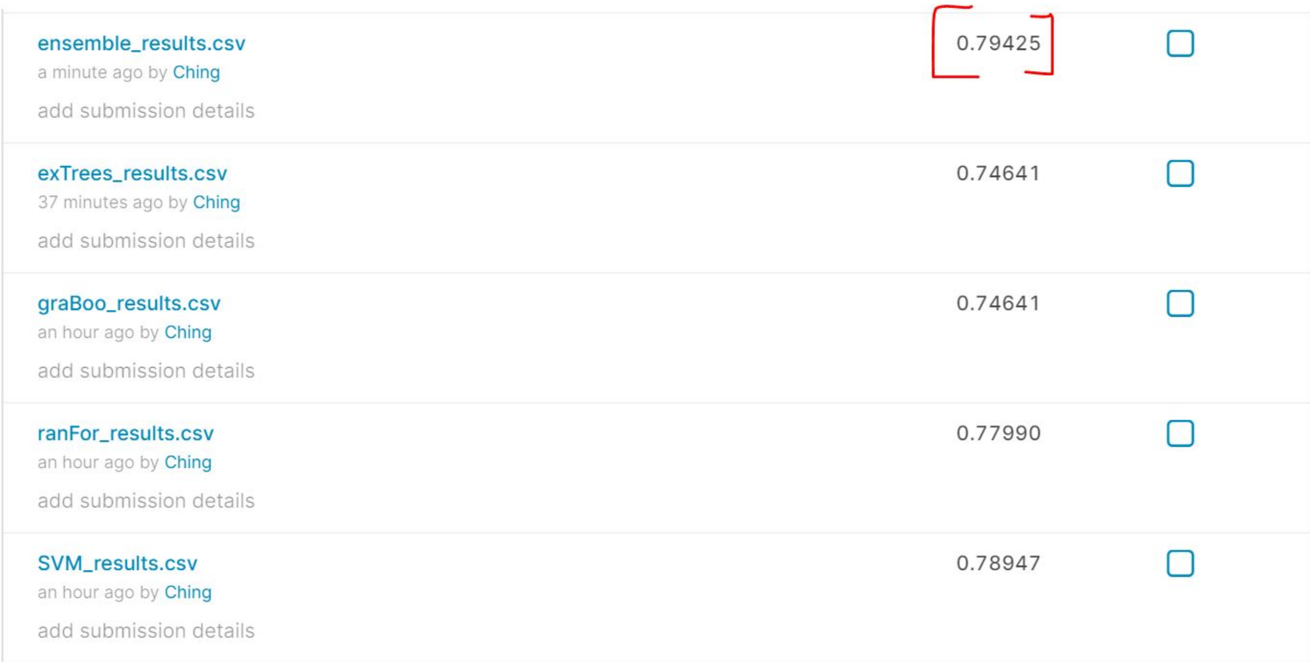
In [153]:
```
test_predictions=pd.Series(best_exTrees.predict(X_titanic_test_cleaned),name='Survived'
results=pd.concat([titanic_test['PassengerId'],test_predictions],axis=1)
results['Survived']=results['Survived'].astype(int)
results.to_csv('exTrees_results.csv',index=False)
```

RESULTS

In [123]:
```
from IPython.display import Image
```

In [2]:
```
Image(filename='kaggle_scores.JPG')
```

Out[2]:



- looks like different model need different input data to perform well:
  - after scaling the data and adjusting the data types, tree based models saw a significant drop in performance while SVM improved significantly

catBoost

- much faster training time
- provides categoric support
- performs better with less preprocessing required
- good default parameters, so performs well even without hypertuning

In [82]:
```
titanic_cleaned.head()
```

Out[82]:

	Age	Fare	Parch	Pclass	Sex	SibSp	Survived	family_size	Cabin_encoded	Embarked_encod
0	0.273456	0.338125	0	3	1	1	0.0	2	7	
1	0.473882	0.685892	0	1	0	1	1.0	2	2	
2	0.323563	0.350727	0	3	0	0	1.0	1	7	
3	0.436302	0.639463	0	1	0	1	1.0	2	2	
4	0.436302	0.352955	0	3	1	0	0.0	1	7	

- for catboost, i will keep variables: sex, pclass, cabin, embarked and prefix as categoric
- the remaining will be numeric

In [84]:
```
# convert to int type
for var in ['Parch','SibSp','family_size']:
    titanic_cleaned[var]=titanic_cleaned[var].astype(int)

# scale the numeric variables to speed up modelling
from sklearn.preprocessing import MinMaxScaler
MMscaler = MinMaxScaler()
titanic_processing[['Parch','SibSp','family_size']]=MMscaler.fit_transform(titanic_proc
```

In [93]:
```
# specifying categoric features for catboost
categoric_features=['Pclass', 'Sex', 'Cabin_encoded', 'Embarked_encoded', 'prefix_encod
```

In [85]:
```
titanic_cleaned.dtypes
```

Out[85]:
```
Age                  float64
Fare                 float64
Parch                  int32
Pclass              category
Sex                 category
SibSp                  int32
Survived            category
family_size            int32
Cabin_encoded       category
Embarked_encoded    category
prefix_encoded      category
dtype: object
```

In [87]:
```
titanic_test_cleaned=titanic_cleaned[titanic_cleaned['Survived'].isna()]
titanic_train_cleaned=titanic_cleaned[~titanic_cleaned['Survived'].isna()]
```

- Steps:
  - split to the original training and test sets given

In [88]:
```
y_titanic_train_cleaned=titanic_train_cleaned['Survived']
X_titanic_train_cleaned=titanic_train_cleaned.drop(['Survived'],axis=1)
X_titanic_test_cleaned=titanic_test_cleaned.drop(['Survived'],axis=1)
```

- Steps:
  - separate predictor from response variable

In [94]:
```
%%time
from catboost import CatBoostClassifier,cv,Pool
params = {'loss_function':'Logloss',
          'eval_metric':'Accuracy',
          'verbose': 200,
          'random_seed': 1
         }

all_train_data = Pool(data=X_titanic_train_cleaned,
                      label=y_titanic_train_cleaned,
                      cat_features=categoric_features
                     )

scores = cv(pool=all_train_data,
            params=params,
            fold_count=5,
            seed=1,
            shuffle=True,
            stratified=True, # if True the folds are made by preserving the percentage 
            plot=True
           )
```

```
MetricVisualizer(layout=Layout(align_self='stretch', height='500px'))

0:	learn: 0.8252027	test: 0.8181954 best: 0.8181954 (0)	total: 403ms
remaining: 6m 42s
200:	learn: 0.8790786	test: 0.8272157 best: 0.8339572 (28)	total: 53.1s
remaining: 3m 30s
400:	learn: 0.9119021	test: 0.8238638 best: 0.8339572 (28)	total: 1m 59s
remaining: 2m 58s
600:	learn: 0.9318215	test: 0.8272409 best: 0.8339572 (28)	total: 3m 17s
remaining: 2m 11s
800:	learn: 0.9475353	test: 0.8272346 best: 0.8339572 (28)	total: 4m 44s
remaining: 1m 10s
999:	learn: 0.9593169	test: 0.8317417 best: 0.8339572 (28)	total: 6m 14s
remaining: 0us
Wall time: 6min 15s
```

In [100]:
```
scores.tail()
```

Out[100]:

	iterations	test-Accuracy-mean	test-Accuracy-std	train-Accuracy-mean	train-Accuracy-std	test-Logloss-mean	test-Logloss-std	train-Logloss-mean	train-Logloss-std
995	995	0.831742	0.031244	0.959317	0.007807	0.429848	0.069382	0.152494	0.012211
996	996	0.831742	0.031244	0.959317	0.007807	0.429865	0.069257	0.152375	0.012176
997	997	0.831742	0.031244	0.959317	0.007807	0.429973	0.069274	0.152242	0.012188
998	998	0.831742	0.031244	0.959317	0.007807	0.429941	0.069264	0.152188	0.012181
999	999	0.831742	0.031244	0.959317	0.007807	0.429936	0.069199	0.152073	0.012148

- cross validation accuracy is 0.8317

In [121]:
```python
test_predictions=pd.Series(cbc.predict(X_titanic_test_cleaned).astype(int),name='Surviv
results=pd.concat([titanic_test['PassengerId'],test_predictions],axis=1)
results.to_csv('catboost_results.csv',index=False)
```

In [117]:
```python
cbc = CatBoostClassifier()
cbc.fit(all_train_data,
          use_best_model=True,
         )
```

```
You should provide test set for use best model. use_best_model parameter has been s
witched to false value.
```

In [124]:
```python
Image(filename='catboost_scores.JPG')
```

Out[124]: