MIE1624 assignment 2

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In [1]:
```
import numpy as np
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.metrics import make_scorer, confusion_matrix
from sklearn.model_selection import learning_curve
import matplotlib.pyplot as plt
import seaborn as sns
```

Read in Data

In [2]:
```
df = pd.read_csv('clean_kaggle_data_2022 2.csv')
```

```
/usr/local/lib/python3.7/dist-packages/IPython/core/interactiveshell
.py:3326: DtypeWarning: Columns (0) have mixed types.Specify dtype o
ption on import or set low_memory=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

In [ ]:
```
df.head(5)
```

Out[ ]:

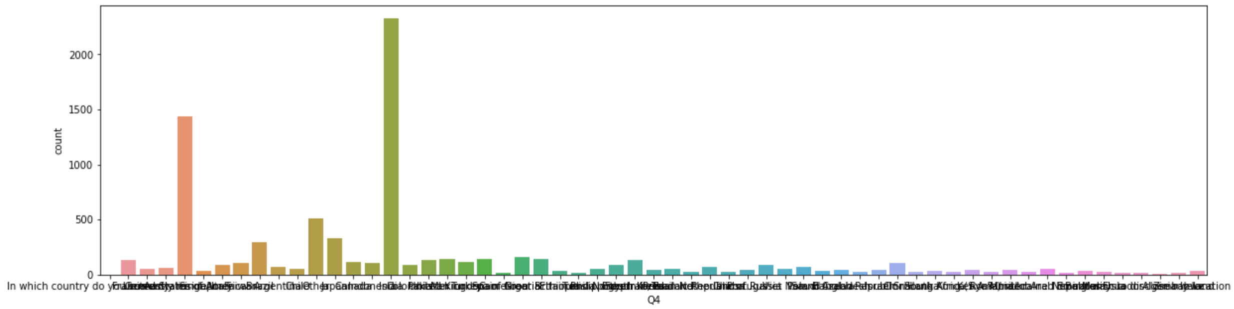
	Duration (in seconds)	Q2	Q3	Q4	Q5	Q6_1	Q6_2	Q6_3	
0	Duration (in seconds)	What is your age (# years)?	What is your gender? - Selected Choice	In which country do you currently reside?	Are you currently a student? (high school, uni...	On which platforms have you begun or completed...	On which platforms have you begun or completed...	On which platforms have you begun or completed...	On pla ha be comp
1	851	55-59	Man	France	No	Coursera	NaN	Kaggle Learn Courses	
2	501	30-34	Man	Germany	No	Coursera	edX	NaN	
3	787	70+	Man	Australia	No	Coursera	NaN	Kaggle Learn Courses	
4	1132	40-44	Man	United States of America	No	Coursera	NaN	Kaggle Learn Courses	

5 rows × 298 columns

Data cleaning

In [ ]:
```
# Show the distribution of Q3
Q4_cates = [v for v in df['Q4'].unique() if type(v) == str]
fig, ax = plt.subplots(figsize=(20,5))
sns.countplot(x='Q4', data=df, ax=ax, order=Q4_cates)
```

Out[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb799df41d0>
```



In [ ]:
```
print ("Countries currently reside:")
df['Q4'].value_counts().head(10)
```

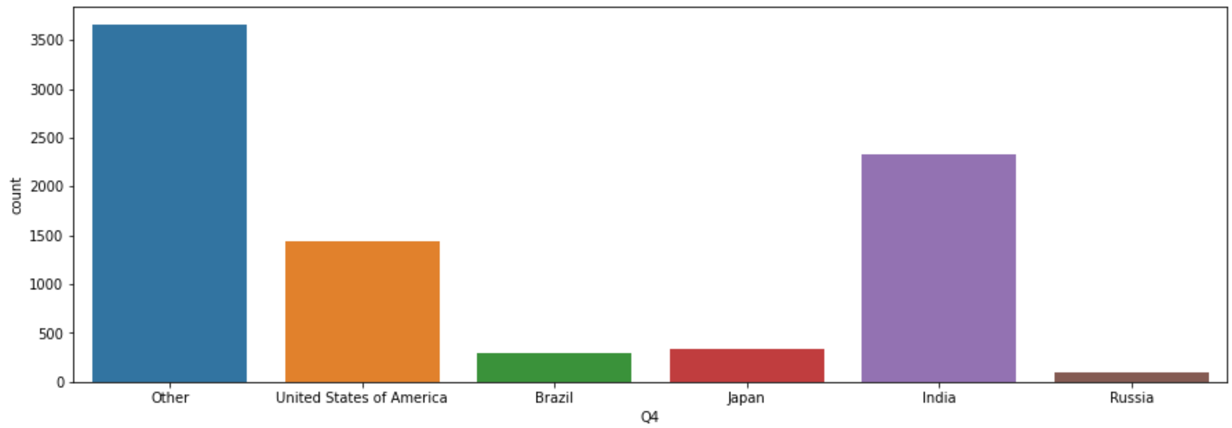
```
Countries currently reside:
```

Out[ ]:
```
India                                                   2328
United States of America                                1434
Other                                                    511
Japan                                                    333
Brazil                                                   292
Nigeria                                                  159
Spain                                                    140
Mexico                                                   139
United Kingdom of Great Britain and Northern Ireland     139
France                                                   137
Name: Q4, dtype: int64
```

Since there is a large number of countries that has too few people, we merge the category into "India", "United States of America", "Brazil", "Japan" and "Russia", which are the 6 countries with the largest number of people. The other people are merged to the category "other".

In [3]:
```
# Change the rest of the countries as Other
countries_selected = ["India", "United States of America", "Brazil", "
Japan", "Russia"]
df["Q4"]=df["Q4"].apply(lambda x: x if x in countries_selected else "O
ther")
fig, ax = plt.subplots(figsize=(15,5))
sns.countplot(x='Q4', ax=ax, data=df)
```

Out[3]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4b6577be50>
```



Convert Categorical Variables

In [4]:
```
# remove the description row
df1 = df.iloc[1:]
```

In [5]:
```
# since we use encoded Q29 as output, we drop Q29_buckets.
df1.drop(["Q29_buckets"], axis=1, inplace=True)
```

```
/usr/local/lib/python3.7/dist-packages/pandas/core/frame.py:4913: Se
ttingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pand
as-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-co
py
  errors=errors,
```

We convert all the categorical features into dummies.

In [6]:
```
# Find the categorical variables
for col in df1.columns:
  if "_" in col and col != "Q29_Encoded":
    # Create dummy features for each categorical feature
    # Drop the first dummy variables because its value is implied
    # by the other dummy variable columns
    dummies = pd.get_dummies(df1[col], prefix=col)

    # Add the new features to the dataframe via concating
    df1 = pd.concat([df1, dummies], axis=1)

    # Drop the original categorical feature columns
    df1.drop(col, axis=1, inplace=True)
```

In [7]:
```
# convert Q3, Q4, Q23, Q24 into categorical variables
cate_cols = ['Q3', 'Q4', 'Q23', 'Q24']
for col in cate_cols:
    # Create dummy features for each categorical feature
    # Drop the first dummy variables because its value is implied
    # by the other dummy variable columns
    dummies1 = pd.get_dummies(df1[col], prefix=col)

    # Add the new features to the dataframe via concating
    df1 = pd.concat([df1, dummies1], axis=1)

    # Drop the original categorical feature columns
    df1.drop(col, axis=1, inplace=True)
```

Handle NA values

In [ ]:
```
# Find the columns with NaN

for col in df1.columns:
    if "_" not in col or col == 'Q29_Encoded':
      print(col, df1[df1[col].isnull()].shape[0]/df1.shape[0])
```

```
Duration (in seconds) 0.0
Q2 0.0
Q5 0.0
Q8 0.0
Q9 0.3614798426745329
Q11 0.0
Q16 0.084070796460177
Q22 0.801622418879056
Q25 0.0
Q26 0.0
Q27 0.0
Q29 0.0
Q30 0.006145526057030482
Q32 0.7712635201573255
Q43 0.4575958702064897
Q29_Encoded 0.0
```

We drop the variable Q22 and Q32 since they have huge proportions of missing values. We keep Duration (in seconds) now since the longer time people answer the question.

In [8]:
```
df1.drop(["Q22", "Q32", "Q9","Q43"], axis=1, inplace=True)
```

We drop the rows that Q16 or Q30 have na.

In [9]:
```
df1 = df1.dropna(subset=['Q16', 'Q30'])
df1.shape
```

Out[9]:
```
(7409, 329)
```

Convert Integer Variables

We select the features that need to be converted into integer variables.

In [ ]:
```
int_cols = []
for col in df1.columns:
    us = list(df1[col].unique())
    if us != [0,1] and us != [1,0] and col != "Q29_Encoded":
        int_cols.append(col)
        print(col, df1[col].unique())    #Q2 8 11 16 25 26 27 30
```

```
Duration (in seconds) ['851' '501' '787' ... 8570 38795 1651]
Q2 ['55-59' '30-34' '70+' '40-44' '50-54' '25-29' '60-69' '35-39' '2
2-24'
 '45-49' '18-21']
Q5 ['No']
Q8 ['Some college/university study without earning a bachelor’s degr
ee'
 'Bachelor’s degree' 'Doctoral degree' 'Master’s degree'
 'I prefer not to answer' 'No formal education past high school'
 'Professional doctorate']
Q11 ['10-20 years' '20+ years' '5-10 years' '3-5 years' '< 1 years'
 '1-3 years']
Q16 ['1-2 years' '4-5 years' '5-10 years' '2-3 years' 'Under 1 year'
 '3-4 years' '10-20 years' 'I do not use machine learning methods']
Q25 ['0-49 employees' '250-999 employees' '1000-9,999 employees'
 '50-249 employees' '10,000 or more employees']
Q26 ['1-2' '20+' '3-4' '5-9' '0' '10-14' '15-19']
Q27 ['We recently started using ML methods (i.e., models in producti
on for less than 2 years)'
 'We have well established ML methods (i.e., models in production fo
r more than 2 years)'
 'We are exploring ML methods (and may one day put a model into prod
uction)'
 'I do not know'
 'We use ML methods for generating insights (but do not put working
models into production)'
 'No (we do not use ML methods)']
Q29 ['25,000-29,999' '100,000-124,999' '200,000-249,999' '150,000-19
9,999'
 '90,000-99,999' '30,000-39,999' '3,000-3,999' '50,000-59,999'
 '125,000-149,999' '15,000-19,999' '5,000-7,499' '10,000-14,999'
 '20,000-24,999' '$0-999' '7,500-9,999' '4,000-4,999' '2,000-2,999'
 '80,000-89,999' '250,000-299,999' '$500,000-999,999' '70,000-79,999
'
 '1,000-1,999' '60,000-69,999' '40,000-49,999' '>$1,000,000'
 '300,000-499,999']
Q30 ['$1000-$9,999' '$0 ($USD)' '$100-$999' '$100,000 or more ($USD)
' '$1-$99'
 '$10,000-$99,999']
```

In [10]:
```
# drop Q5 since there is only 1 answer
df1.drop(["Q5"], axis=1, inplace=True)
```

In [11]:
```
# Q2
Q2_dt = {'18-21':0, '22-24':1, '25-29':2, '30-34':3, '35-39':4, '40-44
':5, '45-49':6, '50-54':7, '55-59':8,
         '60-69':9, '70+':10}
df1['Q2'] = df1['Q2'].map(Q2_dt)
print("Q2: ", df1['Q2'].unique())
```

```
Q2:  [ 8  3 10  5  7  2  9  4  1  6  0]
```

In [12]:
```
df2 = df1.copy()
```

In [13]:
```
# Q8
Q8_dt = {'I prefer not to answer':0, 'No formal education past high sc
hool':1,
         'Some college/university study without earning a bachelor’s d
egree':2,
         'Bachelor’s degree':3, 'Master’s degree':4, 'Professional doc
torate':5,
         'Doctoral degree':5}
df2['Q8'] = df2['Q8'].map(Q8_dt)
print("Q8: ", df2['Q8'].unique())
```

```
Q8:  [2 3 5 4 0 1]
```

In [14]:
```
# Q25
Q25_dt = {'0-49 employees':1, '50-249 employees':5, '250-999 employees
':25,
         '1000-9,999 employees':250, '10,000 or more employees':500}
df2['Q25'] = df2['Q25'].map(Q25_dt)
print("Q25: ", df2['Q25'].unique())
```

```
Q25:  [  1  25 250   5 500]
```

In [15]:
```
#Q26
Q26_dt = {'0':0, '1-2':1, '3-4':2, '5-9':3, '10-14':4, '15-19':5, '20+
':6}
df2['Q26'] = df2['Q26'].map(Q26_dt)
print("Q26: ", df2['Q26'].unique())
```

```
Q26:  [1 6 2 3 0 4 5]
```

In [16]:
```
# Q27
Q27_dt = {'I do not know':0,
          'No (we do not use ML methods)': 1,
          'We use ML methods for generating insights (but do not put wo
rking models into production)':3,
          'We are exploring ML methods (and may one day put a model int
o production)':2,
          'We recently started using ML methods (i.e., models in produc
tion for less than 2 years)':4,
          'We have well established ML methods (i.e., models in product
ion for more than 2 years)':5}
df2['Q27'] = df2['Q27'].map(Q27_dt)
print("Q27: ", df2['Q27'].unique())
```

```
Q27:  [4 5 2 0 3 1]
```

In [17]:
```
# Q16
Q16_dt = {'Under 1 year':1, '1-2 years':2, '2-3 years':3, '3-4 years':
4, '4-5 years':5, '5-10 years':6,
           '10-20 years':7, 'I do not use machine learning methods':0}
df2['Q16'] = df2['Q16'].map(Q16_dt)
print("Q16: ", df2["Q16"].unique())
```

```
Q16:  [2 5 6 3 1 4 7 0]
```

In [18]:
```
# Q11
Q11_dt = {'< 1 years':0, '1-3 years':1, '3-5 years':2,
           '5-10 years':4, '10-20 years':8,'20+ years':16}

df2['Q11'] = df2['Q11'].map(Q11_dt)
print("Q11: ", df2["Q11"].unique())
```

```
Q11:  [ 8 16  4  2  0  1]
```

In [19]:
```
# Q30
Q30_dt = {'$0 ($USD)':0, '$1-$99':1, '$100-$999':10, '$1000-$9,999':10
0, '$10,000-$99,999':1000,
           '$100,000 or more ($USD)':1000}
df2['Q30'] = df2['Q30'].map(Q30_dt)
print("Q30: ", df2['Q30'].unique())
```

```
Q30:  [ 100    0   10 1000    1]
```

In [20]:
```
# drop Q29
df2.drop(["Q29"], axis=1, inplace=True)
```

In [25]:
```
len(list(df2.columns))
```

Out[25]:
```
327
```

After performing data cleaning and convert categorical data into numerical data, we have 326 features for predicting the Q29, which is the current yearly compensation of the participants.

3.1 Exploratory data analysis

We are going to visualize the order of feature importance and pick the variables that are most related to Q29_encoded from over 300 features for fitting logistic regression model.

In [ ]:
```
# show the top 10 features that have the highest correlation
corr = df2.corr()
corr_Q29 = corr['Q29_Encoded']
print(corr_Q29.nlargest(11))
```

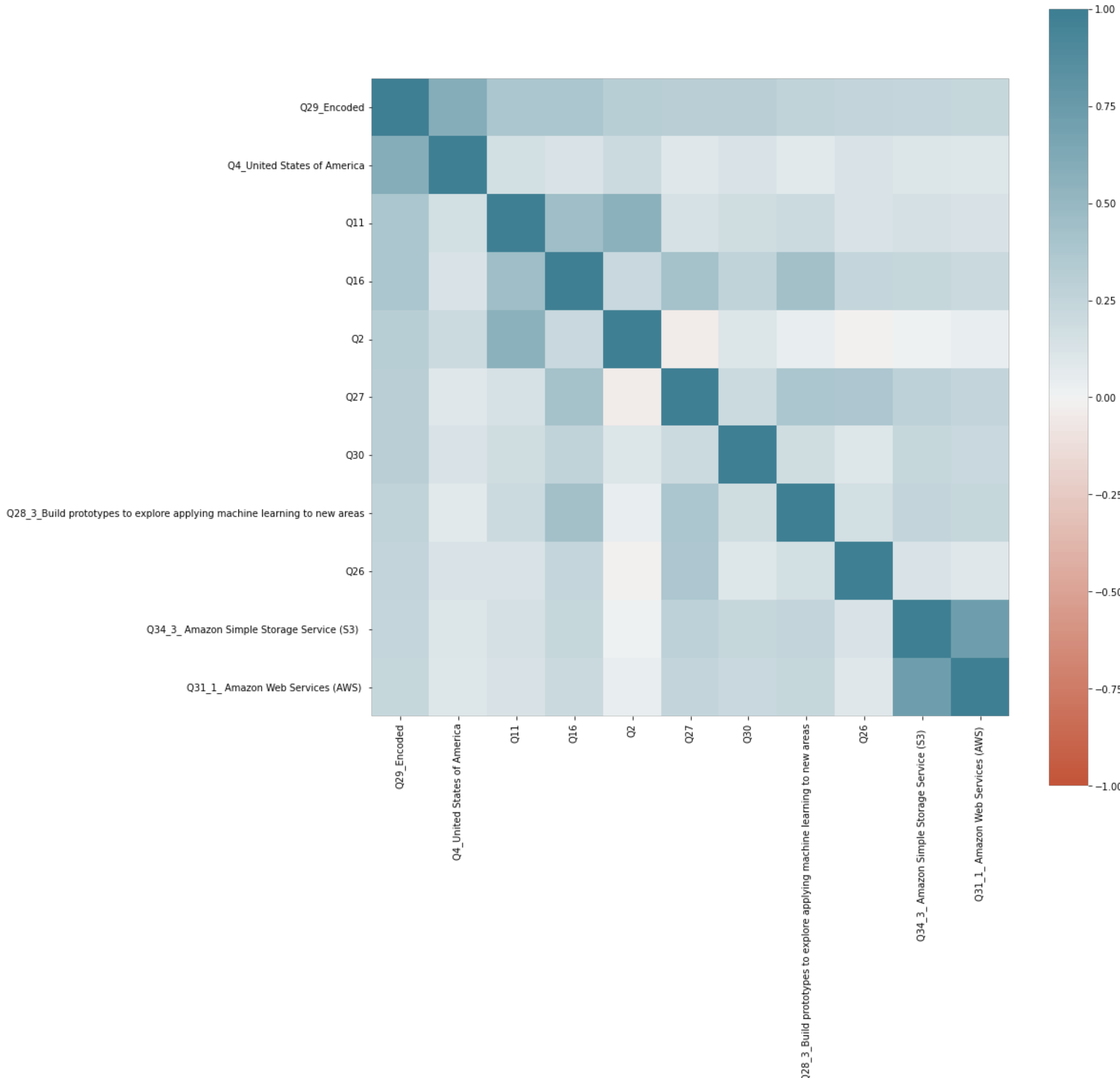
```
Q29_Encoded
1.000000
Q4_United States of America
0.593737
Q11
0.379169
Q16
0.375654
Q2
0.316067
Q27
0.302316
Q30
0.298588
Q28_3_Build prototypes to explore applying machine learning to new a
reas    0.262150
Q26
0.256761
Q34_3_ Amazon Simple Storage Service (S3)
0.247301
Q31_1_ Amazon Web Services (AWS)
0.228119
Name: Q29_Encoded, dtype: float64
```

In [ ]:
```
# visualize the corr plot
fig, ax = plt.subplots(1,1,figsize=(15,15))

top10 = list(corr_Q29.nlargest(11).index)
corr = corr.loc[top10, top10]

sns.heatmap(
    corr,
    vmin=-1, vmax=1, center=0,
    cmap=sns.diverging_palette(20, 220, n=200),
    ax = ax,
    square=True
)
```

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fa745cb4390>



Based on the graph above, we can see that the most correlated feature is whether the participant lives in the US.

The most related 5 questions are:

1. In which country do you currently reside? - United States of America
2. For how many years have you been writing code and/or programming?
3. For how many years have you used machine learning methods?
4. What is your age (# years)?
5. Does your current employer incorporate machine learning methods into their business?

3.2 Feature selection

The features are selected from training data using Lasso regression. The idea of the regularized regression is to optimize the cost function and reduce the absolute values of the coefficients. It will automatically select the useful features and discard the useless or redundant features. Discarding a feature will make its coefficient equal to 0. In our case, we are selecting the features with coefficient larger than 0.1 for reducing the number of features selected. We also tune α hyperparameter in order to make Lasso regression work properly.

In [21]:
```
from sklearn.model_selection import train_test_split
# Separating the data into training and tests set (7:3)

X_train, X_test, y_train, y_test = train_test_split(
    df2.drop(labels=['Q29_Encoded'], axis=1),
    df2['Q29_Encoded'],
    test_size=0.3,
    random_state=0)
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[21]:
```
((5186, 326), (2223, 326), (5186,), (2223,))
```

In [22]:
```
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import Lasso
```

In [23]:
```
pipeline = Pipeline([
                     ('scaler',StandardScaler()),
                     ('model',Lasso())
])
```

In this step, we optimize the α hyperparameter. The tested values are from 0.1 to 10 with 0.1 step. We apply GridSearchCV for this task.

In [24]:
```
search = GridSearchCV(pipeline,
                      {'model__alpha':np.arange(0.1,10,0.1)},
                      cv = 5, scoring="neg_mean_squared_error",verbose
=3
                      )
```

In [25]:
```
search.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 99 candidates, totalling 495 fits
[CV 1/5] END ................model__alpha=0.1;, score=-7.533 total
time=   0.3s
[CV 2/5] END ................model__alpha=0.1;, score=-8.606 total
time=   0.3s
[CV 3/5] END ................model__alpha=0.1;, score=-8.118 total
time=   0.3s
[CV 4/5] END ................model__alpha=0.1;, score=-8.855 total
time=   0.3s
[CV 5/5] END ................model__alpha=0.1;, score=-8.752 total
time=   0.4s
[CV 1/5] END ................model__alpha=0.2;, score=-7.735 total
time=   0.3s
[CV 2/5] END ................model__alpha=0.2;, score=-8.915 total
time=   0.3s
[CV 3/5] END ................model__alpha=0.2;, score=-8.494 total
time=   0.3s
[CV 4/5] END ................model__alpha=0.2;, score=-9.267 total
time=   0.3s
[CV 5/5] END ................model__alpha=0.2;, score=-9.009 total
time=   0.3s
[CV 1/5] END .model__alpha=0.30000000000000004;, score=-7.949 total
time=   0.3s
[CV 2/5] END .model__alpha=0.30000000000000004;, score=-9.273 total
time=   0.3s
[CV 3/5] END .model__alpha=0.30000000000000004;, score=-8.905 total
time=   0.3s
[CV 4/5] END .model__alpha=0.30000000000000004;, score=-9.645 total
time=   0.3s
[CV 5/5] END .model__alpha=0.30000000000000004;, score=-9.302 total
time=   0.3s
```

```
[CV 1/5] END ................model__alpha=0.4;, score=-8.226 total
time=   0.3s
[CV 2/5] END ................model__alpha=0.4;, score=-9.688 total
time=   0.3s
[CV 3/5] END ................model__alpha=0.4;, score=-9.376 total
time=   0.3s
[CV 4/5] END ...............model__alpha=0.4;, score=-10.066 total
time=   0.3s
[CV 5/5] END ................model__alpha=0.4;, score=-9.666 total
time=   0.3s
[CV 1/5] END ................model__alpha=0.5;, score=-8.601 total
time=   0.3s
[CV 2/5] END ...............model__alpha=0.5;, score=-10.180 total
time=   0.3s
[CV 3/5] END ................model__alpha=0.5;, score=-9.913 total
time=   0.3s
[CV 4/5] END ...............model__alpha=0.5;, score=-10.507 total
time=   0.3s
[CV 5/5] END ...............model__alpha=0.5;, score=-10.135 total
time=   0.3s
[CV 1/5] END ................model__alpha=0.6;, score=-9.005 total
time=   0.3s
[CV 2/5] END ...............model__alpha=0.6;, score=-10.690 total
time=   0.3s
[CV 3/5] END ...............model__alpha=0.6;, score=-10.470 total
time=   0.3s
[CV 4/5] END ...............model__alpha=0.6;, score=-10.940 total
time=   0.3s
[CV 5/5] END ...............model__alpha=0.6;, score=-10.656 total
time=   0.3s
[CV 1/5] END ..model__alpha=0.7000000000000001;, score=-9.402 total
time=   0.3s
[CV 2/5] END .model__alpha=0.7000000000000001;, score=-11.172 total
time=   0.3s
[CV 3/5] END .model__alpha=0.7000000000000001;, score=-10.994 total
time=   0.3s
[CV 4/5] END .model__alpha=0.7000000000000001;, score=-11.360 total
time=   0.3s
[CV 5/5] END .model__alpha=0.7000000000000001;, score=-11.131 total
time=   0.3s
[CV 1/5] END ................model__alpha=0.8;, score=-9.834 total
time=   0.3s
[CV 2/5] END ...............model__alpha=0.8;, score=-11.680 total
time=   0.3s
[CV 3/5] END ...............model__alpha=0.8;, score=-11.520 total
time=   0.3s
[CV 4/5] END ...............model__alpha=0.8;, score=-11.801 total
time=   0.3s
[CV 5/5] END ...............model__alpha=0.8;, score=-11.619 total
time=   0.3s
```

```
[CV 1/5] END ...............model__alpha=0.9;, score=-10.309 total
time=   0.3s
[CV 2/5] END ...............model__alpha=0.9;, score=-12.230 total
time=   0.3s
[CV 3/5] END ...............model__alpha=0.9;, score=-12.075 total
time=   0.3s
[CV 4/5] END ...............model__alpha=0.9;, score=-12.260 total
time=   0.3s
[CV 5/5] END ...............model__alpha=0.9;, score=-12.106 total
time=   0.3s
[CV 1/5] END ...............model__alpha=1.0;, score=-10.758 total
time=   0.3s
[CV 2/5] END ...............model__alpha=1.0;, score=-12.771 total
time=   0.3s
[CV 3/5] END ...............model__alpha=1.0;, score=-12.634 total
time=   0.3s
[CV 4/5] END ...............model__alpha=1.0;, score=-12.741 total
time=   0.3s
[CV 5/5] END ...............model__alpha=1.0;, score=-12.531 total
time=   0.3s
[CV 1/5] END ...............model__alpha=1.1;, score=-11.221 total
time=   0.3s
[CV 2/5] END ...............model__alpha=1.1;, score=-13.223 total
time=   0.3s
[CV 3/5] END ...............model__alpha=1.1;, score=-13.130 total
time=   0.3s
[CV 4/5] END ...............model__alpha=1.1;, score=-13.230 total
time=   0.3s
[CV 5/5] END ...............model__alpha=1.1;, score=-12.929 total
time=   0.3s
[CV 1/5] END .model__alpha=1.2000000000000002;, score=-11.704 total
time=   0.3s
[CV 2/5] END .model__alpha=1.2000000000000002;, score=-13.714 total
time=   0.3s
[CV 3/5] END .model__alpha=1.2000000000000002;, score=-13.651 total
time=   0.3s
[CV 4/5] END .model__alpha=1.2000000000000002;, score=-13.691 total
time=   0.3s
[CV 5/5] END .model__alpha=1.2000000000000002;, score=-13.372 total
time=   0.3s
[CV 1/5] END .model__alpha=1.3000000000000003;, score=-12.206 total
time=   0.3s
[CV 2/5] END .model__alpha=1.3000000000000003;, score=-14.246 total
time=   0.3s
[CV 3/5] END .model__alpha=1.3000000000000003;, score=-14.213 total
time=   0.3s
[CV 4/5] END .model__alpha=1.3000000000000003;, score=-14.192 total
time=   0.3s
[CV 5/5] END .model__alpha=1.3000000000000003;, score=-13.858 total
time=   0.3s
```

```
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time=   0.3s
[CV 5/5] END .model__alpha=2.8000000000000003;, score=-19.655 total
time=   0.3s
```

```
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time=   0.3s
[CV 5/5] END ...............model__alpha=9.9;, score=-19.655 total
time=   0.3s
```

Out[25]:
```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('scaler', StandardScaler()),
                                       ('model', Lasso())]),
             param_grid={'model__alpha': array([0.1, 0.2, 0.3, 0.4,
0.5, 0.6, 0.7, 0.8, 0.9, 1. , 1.1, 1.2, 1.3,
       1.4, 1.5, 1.6, 1.7, 1.8, 1.9, 2. , 2.1, 2.2, 2.3, 2.4, 2.5, 2
.6,
       2.7, 2.8, 2.9, 3. , 3.1, 3.2, 3.3, 3.4, 3.5, 3.6, 3.7, 3.8, 3
.9,
       4. , 4.1, 4.2, 4.3, 4.4, 4.5, 4.6, 4.7, 4.8, 4.9, 5. , 5.1, 5
.2,
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       7.9, 8. , 8.1, 8.2, 8.3, 8.4, 8.5, 8.6, 8.7, 8.8, 8.9, 9. , 9
.1,
       9.2, 9.3, 9.4, 9.5, 9.6, 9.7, 9.8, 9.9])},
             scoring='neg_mean_squared_error', verbose=3)
```

We find the best value for α 0.1.

In [26]:
```
search.best_params_
# {'model__alpha': 0.1}
```

Out[26]:
```
{'model__alpha': 0.1}
```

We get the values of the coefficients of Lasso regression. And calculate the importance of the features, which are the absolute values of the importance.

In [27]:
```
coefficients = search.best_estimator_.named_steps['model'].coef_
```

In [28]:
```
importance = np.abs(coefficients)
```

In [29]:
```
list_coeff = importance.tolist()
```

In [30]:
```
data = {'feature': X_train.columns, 'importance': list_coeff}
```

In [31]:
```
lasso_df = pd.DataFrame(data=data)
```

In [32]:
```
feature_selected = lasso_df.loc[lasso_df['importance'] > 0.1]
```

The selected features are displayed below. The features roughly match the results of the correlation. Which the participants currently live in the U.S. is the most important selected feature.

In [33]:
```
feature_selected.sort_values(by=['importance'], ascending=False)
```

Out[33]:

	feature	importance
296	Q4_United States of America	1.917392
4	Q16	0.475760
292	Q4_India	0.461307
3	Q11	0.452736
8	Q30	0.402439
1	Q2	0.355494
305	Q23_Manager (Program, Project, Operations, Exe...	0.316032
7	Q27	0.311769
311	Q24_Academics/Education	0.305348
6	Q26	0.298401
5	Q25	0.205203
152	Q31_1_ Amazon Web Services (AWS)	0.172359
141	Q21_8_ Kaggle datasets	0.134619
146	Q28_3_Build prototypes to explore applying mac...	0.127739
171	Q34_3_ Amazon Simple Storage Service (S3)	0.106091

3.Model implementation

In [33]:
```
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, make_scorer
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
```

We define the function below to fit one logistic regression among the 14 regressions, which return the probability of the person from the Q29_encoded >= num. We scale the X training set and test set using MinMaxScaler separately, which subtracts the minimum value in the feature and then divides by the range. It helps to keep the data into range of 0 and 1 and preserve the shape of the original distribution. We didn't choose StandardScaler since it is useful for features follow a Normal distribution.

In [34]:
```
def one_log_regression(X_train, y_train, X_test, y_test, num, solver,
C):

  X_train_y = X_train.copy()

  X_train_y['Q29_Encoded'] = y_train

  df34 = X_train_y.copy()
  for i in range (0,X_train.shape[0]):
    if (X_train_y['Q29_Encoded'].iloc[i]>=num):
      df34['Q29_Encoded'].iloc[i]=1

    else:
      df34['Q29_Encoded'].iloc[i]=0


  X34=df34.drop(labels=['Q29_Encoded'], axis=1)
  y34=df34['Q29_Encoded']


  scaler = MinMaxScaler()
  X_train_scaled = scaler.fit_transform(X34)
  X_test_scaled = scaler.fit_transform(X_test)

  model = LogisticRegression(solver=solver, C = C)
  model.fit(X_train_scaled, y34)

  # prob of array([0., 1.]).  predict x_test
  prob = model.predict_proba(X_test_scaled)

  return prob # shape(2223, 2)
```

We define the function below to merge the 14 probabilities derived from the 14 logistic regressions. The ordinal logistic model can compute the probability of every class and make classifications by choosing the class with the largest probability among the 14 classes. It return the predicted labels for each observations in the testing data.

In [35]:
```
def ordinal_logistic_regression(X_train, y_train, X_test, y_test, solv
er, C):

  prob_list = []

  for n in range(1,15): #num 1-14
    prob = one_log_regression(X_train, y_train, X_test, y_test, n, sol
ver, C)

    prob_list.append(prob) # 15*[2223, 2]


    # merge 14 classes probability to 15*2223
  prob_14_list = []

  for i in range(0, X_test.shape[0]): #2223 test observations

      # prob(class0)
    prob0 = prob_list[0][i][0]
      # prob 1 = prob(y>=1) - prob(y>=2)
    prob1 = prob_list[0][i][1] - prob_list[1][i][1]
      # prob 2 = prob(y>=2) - prob(y>=3)
    prob2 = prob_list[1][i][1] - prob_list[2][i][1]

    prob3 = prob_list[2][i][1] - prob_list[3][i][1]

    prob4 = prob_list[3][i][1] - prob_list[4][i][1]

    prob5 = prob_list[4][i][1] - prob_list[5][i][1]

    prob6 = prob_list[5][i][1] - prob_list[6][i][1]

    prob7 = prob_list[6][i][1] - prob_list[7][i][1]

    prob8 = prob_list[7][i][1] - prob_list[8][i][1]

    prob9 = prob_list[8][i][1] - prob_list[9][i][1]

    prob10 = prob_list[9][i][1] - prob_list[10][i][1]

    prob11 = prob_list[10][i][1] - prob_list[11][i][1]
```

```
    prob12 = prob_list[11][i][1] - prob_list[12][i][1]

    prob13 = prob_list[12][i][1] - prob_list[13][i][1]

    prob14 = prob_list[13][i][1]

    prob_14_list.append([prob0, prob1, prob2, prob3,\
                         prob4, prob5, prob6,prob7,\
                         prob8, prob9, prob10,prob11,\
                         prob12, prob13, prob14])


      # merge 15*2223 prob list to 1*2223 predicted label
  prediction_list = []

  for i in range(0, X_test.shape[0]): #2223 test observations
    class_prob14 =  prob_14_list[i]

    max_value = max(class_prob14)
    index = class_prob14.index(max_value)
    prediction_list.append(index)


  return prediction_list
```

In [ ]:
```
from sklearn.metrics import classification_report
```

For question 3, we compute the accuracy of the model output by using the number of the correct predictions divided by the total number of the predictions. The predicted labels are compared with the actual y values to determine whether the model have corrent predictions.

In [45]:
```
def get_accuracy(y_test, prediction_list):


  acc = 0
  #from series to list
  y_test_list = y_test.iloc[:,0].tolist()

  for i in range(0, len(y_test_list)):
    if y_test_list[i] == prediction_list[i]:
      acc += 1


  return round(acc/len(y_test_list),3)
```

Below is the repetitative work as the same data split in the previous part for convenience.

In [103]:
```
X = df2.drop(['Q29_Encoded'],axis=1)
y = df2['Q29_Encoded']

X = X[feature_selected.feature]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=0)
```

We define the function for splitting the data into 10 folds for cross validation. The model fits training data X_train and y_train, and make predictions based on X_test. The predicted labels are compared with y_test for computing accuracy. The hyperparameter are defined as solver and C, which can be used for tuning later.

In [55]:
```
import warnings
#warnings.filterwarnings("ignore", category=ConvergenceWarning)
warnings.filterwarnings("ignore")
import statistics as st

def cross_validation(X_train, X_test, y_train, y_test, solver, C):

  kfold = KFold(n_splits=10)
  kfold.get_n_splits(X_train)

  accuracy = np.zeros(10)
  np_idx = 0
  acc_all = []

  for train_idx, test_idx in kfold.split(X_train):
      X_train_cv, X_test_cv = X_train.values[train_idx], X_train.value
s[test_idx]
      y_train_cv, y_test_cv = y_train.values[train_idx], y_train.value
s[test_idx]

      X_train_cv = pd.DataFrame(X_train_cv)
      X_test_cv = pd.DataFrame(X_test_cv)
      y_train_cv = pd.DataFrame(y_train_cv)
      y_test_cv = pd.DataFrame(y_test_cv)
      # print(X_train_cv.shape, type(X_train_cv), X_test_cv.shape, typ
e(X_test_cv))
      prediction_list = ordinal_logistic_regression(X_train_cv, y_trai
n_cv, X_test_cv, y_test_cv, solver = solver, C=C)

      accu = get_accuracy(y_test_cv, prediction_list)
      acc_all.append(accu)
      np_idx += 1
      print ("Fold {}: Accuracy: {}%".format(np_idx, round(accu,3)*100
))

  print('solover =', solver, 'C=', C, 'average accuracy =', st.mean(ac
c_all), 'accuracy std =', st.stdev(acc_all),)
```

We tune the hyperparameter C for the selected values 1, 0.5, 0.1, 0.05, 0.01 and 0.001. The other hyperparameter solver is assigned to be 'newton-cg' in this case. Based on the results below, we have the accuracy between 30% to 40%. The model with solover = newton-cg and C= 0.05 has the highest average accuracy for the 10 folds, which is around 0.387. The corresponding standard deviation for the accuracy is around 0.026.

In [41]:
```
C=[1, 0.5, 0.1, 0.05, 0.01, 0.001]
for c in C:
  cross_validation(X_train, X_test, y_train, y_test, solver = 'newton-cg', C = c)
```

```
Fold 1: Accuracy: 35.3%
Fold 2: Accuracy: 39.1%
Fold 3: Accuracy: 39.5%
Fold 4: Accuracy: 38.3%
Fold 5: Accuracy: 42.0%
Fold 6: Accuracy: 36.0%
Fold 7: Accuracy: 35.3%
Fold 8: Accuracy: 41.3%
Fold 9: Accuracy: 37.3%
Fold 10: Accuracy: 40.300000000000004%
solover = newton-cg C= 1 average accuracy = 0.3844 accuracy std = 0.024235877904003767
Fold 1: Accuracy: 35.3%
Fold 2: Accuracy: 39.5%
Fold 3: Accuracy: 40.1%
Fold 4: Accuracy: 38.0%
Fold 5: Accuracy: 41.8%
Fold 6: Accuracy: 36.199999999999996%
Fold 7: Accuracy: 34.9%
Fold 8: Accuracy: 41.3%
Fold 9: Accuracy: 37.3%
Fold 10: Accuracy: 40.2%
solover = newton-cg C= 0.5 average accuracy = 0.3846 accuracy std = 0.024797849369115332
Fold 1: Accuracy: 35.6%
Fold 2: Accuracy: 40.1%
Fold 3: Accuracy: 40.1%
Fold 4: Accuracy: 38.3%
Fold 5: Accuracy: 41.4%
Fold 6: Accuracy: 35.5%
Fold 7: Accuracy: 35.099999999999994%
Fold 8: Accuracy: 41.3%
Fold 9: Accuracy: 38.0%
Fold 10: Accuracy: 40.0%
solover = newton-cg C= 0.1 average accuracy = 0.3854 accuracy std = 0.024235877904003767
Fold 1: Accuracy: 35.8%
Fold 2: Accuracy: 40.300000000000004%
Fold 3: Accuracy: 39.900000000000006%
Fold 4: Accuracy: 39.1%
Fold 5: Accuracy: 41.4%
Fold 6: Accuracy: 35.5%
Fold 7: Accuracy: 34.599999999999994%
Fold 8: Accuracy: 42.1%
```

```
Fold 9: Accuracy: 38.4%
Fold 10: Accuracy: 40.0%
solover = newton-cg C= 0.05 average accuracy = 0.3871 accuracy std =
0.02587340977400029
Fold 1: Accuracy: 35.8%
Fold 2: Accuracy: 38.7%
Fold 3: Accuracy: 38.5%
Fold 4: Accuracy: 37.6%
Fold 5: Accuracy: 40.1%
Fold 6: Accuracy: 35.099999999999994%
Fold 7: Accuracy: 33.0%
Fold 8: Accuracy: 41.099999999999994%
Fold 9: Accuracy: 37.8%
Fold 10: Accuracy: 39.4%
solover = newton-cg C= 0.01 average accuracy = 0.3771 accuracy std =
0.0245694028327014
Fold 1: Accuracy: 32.800000000000004%
Fold 2: Accuracy: 35.6%
Fold 3: Accuracy: 36.0%
Fold 4: Accuracy: 34.699999999999996%
Fold 5: Accuracy: 37.8%
Fold 6: Accuracy: 32.800000000000004%
Fold 7: Accuracy: 30.3%
Fold 8: Accuracy: 37.5%
Fold 9: Accuracy: 34.2%
Fold 10: Accuracy: 36.9%
solover = newton-cg C= 0.001 average accuracy = 0.3486 accuracy std
= 0.02388956071406737
```

Bias-variance trade-off

The bias-variance trade-off for the model is analyzed below. For the multiclass classification problem, the bias is defined as the deviation of the average estimate from the target value, which is the mean of the squared error between the average of the predictions and the true value (bias = np.mean((np.mean(prediction) - y_test)**2). The variance is the variance of the accuray in each fold. Then we compute the average bias and variance for the 10 folds to find the bias and variance of the model with the certain C values.

In [76]:
```
import warnings
#warnings.filterwarnings("ignore", category=ConvergenceWarning)
warnings.filterwarnings("ignore")
import statistics as st

def cross_validation_bias_var(X_train, X_test, y_train, y_test, solver
, C):
  # return bias and var for these hyperparameters
  kfold = KFold(n_splits=10)
  kfold.get_n_splits(X_train)

  np_idx = 0

  biaslist=[]
  varslist=[]

  for train_idx, test_idx in kfold.split(X_train):
      X_train_cv, X_test_cv = X_train.values[train_idx], X_train.value
s[test_idx]
      y_train_cv, y_test_cv = y_train.values[train_idx], y_train.value
s[test_idx]

      X_train_cv = pd.DataFrame(X_train_cv)
      X_test_cv = pd.DataFrame(X_test_cv)
      y_train_cv = pd.DataFrame(y_train_cv)
      y_test_cv = pd.DataFrame(y_test_cv)

      # print(X_train_cv.shape, type(X_train_cv), X_test_cv.shape, typ
e(X_test_cv))
      prediction_list = ordinal_logistic_regression(X_train_cv, y_trai
n_cv, X_test_cv, y_test_cv, solver = solver, C=C)


      #find bias and var for each fold
      bias, var = get_bias_var(y_test_cv, prediction_list)

      biaslist.append(bias)
      varslist.append(var)

      np_idx += 1

  return st.mean(biaslist), st.mean(varslist)
```

In [46]:
```
def get_bias_var(y_test_cv, prediction_list):

  y_test_list = y_test_cv.squeeze()

  bias = np.mean((np.mean(prediction_list) - y_test_list)**2)

  var = np.var(prediction_list)

  return bias, var
```

In [77]:
```
###Create bias and variance lists.
bias_hyper = []
var_hyper = []
C=[1, 0.5, 0.1, 0.05, 0.01, 0.001]

for c in C:
  bias, var = cross_validation_bias_var(X_train, X_test, y_train, y_te
st, solver = 'newton-cg', C = c)

  bias_hyper.append(bias)
  var_hyper.append(var)
```

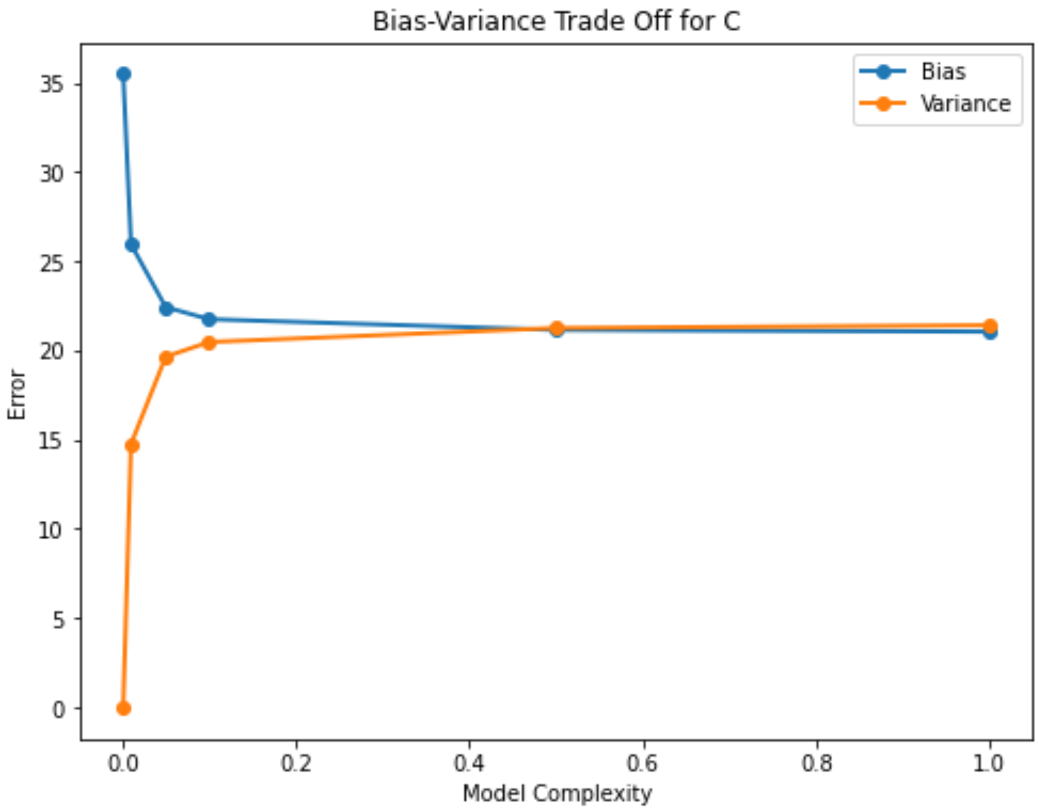
The 6 biases and variances corresponding to the value C are displayed below.

In [78]:
```
print(bias_hyper)
print(var_hyper)
```

```
[21.0523858162569, 21.149091783708837, 21.747833306194625, 22.426251
11438751, 25.946448301874174, 35.491045297981714]
[21.411291391489392, 21.253680973722012, 20.469530570480675, 19.6466
00189646268, 14.7507816040375, 0.0]
```

Based on the graph below, we can see that as the model complexity increases, the variance of the model increases and the bias of the model decreases. When the model complexity is too much, the model may try to overfit the training data and have high variance. The Model with high variance captures lots of noice from training data and can not generalize on the testing data which it hasn’t seen before. In this way, as the complexity of the model increases, it may get lower accuarcy score for the test data.

In [79]:
```
Bias = pd.DataFrame(bias_hyper,index=C)
Variance = pd.DataFrame(var_hyper,index=C)
plt.figure(figsize=(8,6))
plt.plot(Bias, label="Bias",linewidth = 2, marker='o')
plt.plot(Variance, label="Variance", linewidth = 2,marker='o')
plt.legend()
plt.title("Bias-Variance Trade Off for C")
plt.xlabel('Model Complexity')
plt.ylabel('Error')
plt.show()
```



4. Model tuning

In [37]:
```
from sklearn.metrics import make_scorer, confusion_matrix
```

In the net step, the hyperparameters C and solver are tuned by applying grid search based on the f1 scores.

In [39]:
```
def get_f1_score(y_test, prediction_list):

  #from series to list
  y_test_list = y_test.squeeze()

  TN = confusion_matrix(y_test_list, prediction_list)[0][0]
  FP = confusion_matrix(y_test_list, prediction_list)[0][1]
  FN = confusion_matrix(y_test_list, prediction_list)[1][0]
  TP = confusion_matrix(y_test_list, prediction_list)[1][1]


  if (TP == 0):
    Precision = 0
  else:
    Precision = TP/(TP+FP)

  if (TP == 0):
    Recall = 0
  else:
    Recall = TP/(TP+FN)


  if (Recall == 0) or (Precision == 0):

    f1 = 0
  else:
    f1 = 2*Precision*Recall/(Precision + Recall)

  return f1
```

In [40]:
```
import warnings
#warnings.filterwarnings("ignore", category=ConvergenceWarning)
warnings.filterwarnings("ignore")
import statistics as st

def cross_validation_f1(X_train, X_test, y_train, y_test, solver, C):

  kfold = KFold(n_splits=10)
  kfold.get_n_splits(X_train)

  accuracy = np.zeros(10)
  np_idx = 0
  acc_all = []


  for train_idx, test_idx in kfold.split(X_train):
      X_train_cv, X_test_cv = X_train.values[train_idx], X_train.value
s[test_idx]
      y_train_cv, y_test_cv = y_train.values[train_idx], y_train.value
s[test_idx]

      X_train_cv = pd.DataFrame(X_train_cv)
      X_test_cv = pd.DataFrame(X_test_cv)
      y_train_cv = pd.DataFrame(y_train_cv)
      y_test_cv = pd.DataFrame(y_test_cv)
      # print(X_train_cv.shape, type(X_train_cv), X_test_cv.shape, typ
e(X_test_cv))
      prediction_list = ordinal_logistic_regression(X_train_cv, y_trai
n_cv, X_test_cv, y_test_cv, solver = solver, C=C)

      f1 = get_f1_score(y_test_cv, prediction_list)
      acc_all.append(f1)
      np_idx += 1
      print ("Fold {}: f1 score: {}".format(np_idx, f1))

  print('solover =', solver, 'C=', C, 'average f1 score =', st.mean(ac
c_all), 'accuracy std =', st.stdev(acc_all))
  return st.mean(acc_all), st.stdev(acc_all)
```

In [41]:
```
best_params = {}
best_accuracy = 0
best_std = 0

for C in [1, 0.1, 0.01, 0.001]:
  for solver in ['newton-cg','lbfgs','liblinear','sag']:
        avg_acc, std = cross_validation_f1(X_train, X_test, y_train, y
_test, solver = solver, C = C)

        #print('solover =', solver, 'C=', C, 'average accuracy =', avg
_acc, 'accuracy std =', std)


        if avg_acc > best_accuracy:
            best_params = {'C':C, 'solver':solver}
            best_accuracy = avg_acc
            best_std = std

print (best_params)
print ("Best Score: {}({})".format(best_accuracy,best_std,3))

print ("\nThe optimal log model uses C={}, and a {} solver, and has a
cross validation f1 score of {} with a standard deviation of {}".forma
t(best_params['C'],best_params['solver'],best_accuracy,best_std))
```

```
Fold 1: f1 score: 0
Fold 2: f1 score: 0
Fold 3: f1 score: 0
Fold 4: f1 score: 0.0909090909090909
Fold 5: f1 score: 0
Fold 6: f1 score: 0
Fold 7: f1 score: 0.046511627906976744
Fold 8: f1 score: 0.03636363636363636
Fold 9: f1 score: 0
Fold 10: f1 score: 0.0851063829787234 2
solover = newton-cg C= 1 average f1 score = 0.025889073815842743 acc
uracy std = 0.03695457178657299
Fold 1: f1 score: 0
Fold 2: f1 score: 0
Fold 3: f1 score: 0
Fold 4: f1 score: 0.0909090909090909
Fold 5: f1 score: 0
Fold 6: f1 score: 0
Fold 7: f1 score: 0.046511627906976744
Fold 8: f1 score: 0.03636363636363636
Fold 9: f1 score: 0
Fold 10: f1 score: 0.0851063829787234 2
solover = lbfgs C= 1 average f1 score = 0.025889073815842743 accurac
y std = 0.03695457178657299
```

```
Fold 1: f1 score: 0
Fold 2: f1 score: 0
Fold 3: f1 score: 0
Fold 4: f1 score: 0.0909090909090909
Fold 5: f1 score: 0
Fold 6: f1 score: 0
Fold 7: f1 score: 0
Fold 8: f1 score: 0.03571428571428571
Fold 9: f1 score: 0
Fold 10: f1 score: 0.08510638297872342
solover = liblinear C= 1 average f1 score = 0.021172975960210002 acc
uracy std = 0.03696863584716678
Fold 1: f1 score: 0
Fold 2: f1 score: 0
Fold 3: f1 score: 0
Fold 4: f1 score: 0.0909090909090909
Fold 5: f1 score: 0
Fold 6: f1 score: 0
Fold 7: f1 score: 0.046511627906976744
Fold 8: f1 score: 0.03636363636363636
Fold 9: f1 score: 0
Fold 10: f1 score: 0.08510638297872342
solover = sag C= 1 average f1 score = 0.025889073815842743 accuracy
std = 0.03695457178657299
Fold 1: f1 score: 0
Fold 2: f1 score: 0
Fold 3: f1 score: 0
Fold 4: f1 score: 0.044444444444444446
Fold 5: f1 score: 0
Fold 6: f1 score: 0
Fold 7: f1 score: 0
Fold 8: f1 score: 0
Fold 9: f1 score: 0
Fold 10: f1 score: 0.04347826086956522
solover = newton-cg C= 0.1 average f1 score = 0.008792270531400966 a
ccuracy std = 0.018537132701819694
Fold 1: f1 score: 0
Fold 2: f1 score: 0
Fold 3: f1 score: 0
Fold 4: f1 score: 0.044444444444444446
Fold 5: f1 score: 0
Fold 6: f1 score: 0
Fold 7: f1 score: 0
Fold 8: f1 score: 0
Fold 9: f1 score: 0
Fold 10: f1 score: 0.04347826086956522
solover = lbfgs C= 0.1 average f1 score = 0.008792270531400966 accur
acy std = 0.018537132701819694
Fold 1: f1 score: 0
Fold 2: f1 score: 0
```

```
Fold 3: f1 score: 0
Fold 4: f1 score: 0.044444444444444446
Fold 5: f1 score: 0
Fold 6: f1 score: 0
Fold 7: f1 score: 0.045454545454545456
Fold 8: f1 score: 0
Fold 9: f1 score: 0
Fold 10: f1 score: 0.043478260869565216
solover = liblinear C= 0.1 average f1 score = 0.013337725076855511 a
ccuracy std = 0.021480829723367584
Fold 1: f1 score: 0
Fold 2: f1 score: 0
Fold 3: f1 score: 0
Fold 4: f1 score: 0.044444444444444446
Fold 5: f1 score: 0
Fold 6: f1 score: 0
Fold 7: f1 score: 0
Fold 8: f1 score: 0
Fold 9: f1 score: 0
Fold 10: f1 score: 0.043478260869565216
solover = sag C= 0.1 average f1 score = 0.008792270531400966 accurac
y std = 0.018537132701819694
Fold 1: f1 score: 0
Fold 2: f1 score: 0
Fold 3: f1 score: 0
Fold 4: f1 score: 0
Fold 5: f1 score: 0
Fold 6: f1 score: 0
Fold 7: f1 score: 0
Fold 8: f1 score: 0
Fold 9: f1 score: 0
Fold 10: f1 score: 0
solover = newton-cg C= 0.01 average f1 score = 0 accuracy std = 0.0
Fold 1: f1 score: 0
Fold 2: f1 score: 0
Fold 3: f1 score: 0
Fold 4: f1 score: 0
Fold 5: f1 score: 0
Fold 6: f1 score: 0
Fold 7: f1 score: 0
Fold 8: f1 score: 0
Fold 9: f1 score: 0
Fold 10: f1 score: 0
solover = lbfgs C= 0.01 average f1 score = 0 accuracy std = 0.0
Fold 1: f1 score: 0
Fold 2: f1 score: 0
Fold 3: f1 score: 0
Fold 4: f1 score: 0
Fold 5: f1 score: 0
Fold 6: f1 score: 0
```

```
Fold 7: f1 score: 0
Fold 8: f1 score: 0
Fold 9: f1 score: 0
Fold 10: f1 score: 0
solover = liblinear C= 0.01 average f1 score = 0 accuracy std = 0.0
Fold 1: f1 score: 0
Fold 2: f1 score: 0
Fold 3: f1 score: 0
Fold 4: f1 score: 0
Fold 5: f1 score: 0
Fold 6: f1 score: 0
Fold 7: f1 score: 0
Fold 8: f1 score: 0
Fold 9: f1 score: 0
Fold 10: f1 score: 0
solover = sag C= 0.01 average f1 score = 0 accuracy std = 0.0
Fold 1: f1 score: 0
Fold 2: f1 score: 0
Fold 3: f1 score: 0
Fold 4: f1 score: 0
Fold 5: f1 score: 0
Fold 6: f1 score: 0
Fold 7: f1 score: 0
Fold 8: f1 score: 0
Fold 9: f1 score: 0
Fold 10: f1 score: 0
solover = newton-cg C= 0.001 average f1 score = 0 accuracy std = 0.0
Fold 1: f1 score: 0
Fold 2: f1 score: 0
Fold 3: f1 score: 0
Fold 4: f1 score: 0
Fold 5: f1 score: 0
Fold 6: f1 score: 0
Fold 7: f1 score: 0
Fold 8: f1 score: 0
Fold 9: f1 score: 0
Fold 10: f1 score: 0
solover = lbfgs C= 0.001 average f1 score = 0 accuracy std = 0.0
Fold 1: f1 score: 0
Fold 2: f1 score: 0
Fold 3: f1 score: 0
Fold 4: f1 score: 0
Fold 5: f1 score: 0
Fold 6: f1 score: 0
Fold 7: f1 score: 0
Fold 8: f1 score: 0
Fold 9: f1 score: 0
Fold 10: f1 score: 0
solover = liblinear C= 0.001 average f1 score = 0 accuracy std = 0.0
Fold 1: f1 score: 0
```

```
Fold 2: f1 score: 0
Fold 3: f1 score: 0
Fold 4: f1 score: 0
Fold 5: f1 score: 0
Fold 6: f1 score: 0
Fold 7: f1 score: 0
Fold 8: f1 score: 0
Fold 9: f1 score: 0
Fold 10: f1 score: 0
solover = sag C= 0.001 average f1 score = 0 accuracy std = 0.0
{'C': 1, 'solver': 'newton-cg'}
Best Score: 0.025889073815842743(0.03695457178657299)

The optimal log model uses C=1, and a newton-cg solver, and has a cr
oss validation f1 score of 0.025889073815842743 with a standard devi
ation of 0.03695457178657299
```

Apply computing the 16 combinations of the hyperparameters, we find the optimal model with C = 1 and solver = newton-cg.

feature importance

We extract the 15 coefficients for all the 14 logistic regression models below, and compute means of coefficients the 14 models for the 15 features.

In [101]:
```
def one_log_regression_feature(X_train, y_train, X_test, y_test, num,
solver, C):

  X_train_y = X_train.copy()

  X_train_y['Q29_Encoded'] = y_train

  df34 = X_train_y.copy()
  for i in range (0,X_train.shape[0]):
    if (X_train_y['Q29_Encoded'].iloc[i]>=num):
      df34['Q29_Encoded'].iloc[i]=1

    else:
      df34['Q29_Encoded'].iloc[i]=0


  X34=df34.drop(labels=['Q29_Encoded'], axis=1)
  y34=df34['Q29_Encoded']


  scaler = MinMaxScaler()
  X_train_scaled = scaler.fit_transform(X34)
  X_test_scaled = scaler.fit_transform(X_test)

  model = LogisticRegression(solver=solver, C = C)
  model.fit(X_train_scaled, y34)

  w = model.coef_[0]

  return w
```

In [114]:
```
def ordinal_logistic_regression_feature(X_train, y_train, X_test, y_te
st, solver, C):

  w_list = []

  for n in range(1,15): #num 1-14
    w = one_log_regression_feature(X_train, y_train, X_test, y_test, n
, solver, C)

    w_list.append(w) # 15*[2223, 2]


  return w_list
```

In [115]:
```
w_list = ordinal_logistic_regression_feature(X_train, y_train, X_test,
y_test, solver = 'newton-cg', C = 1)
```

In [125]:
```
def get_feature_weight(w_list, feature_num):

  weight = []

  for i in range(0, 14):
    weight.append(w_list[i][feature_num])

  return st.mean(weight)
```

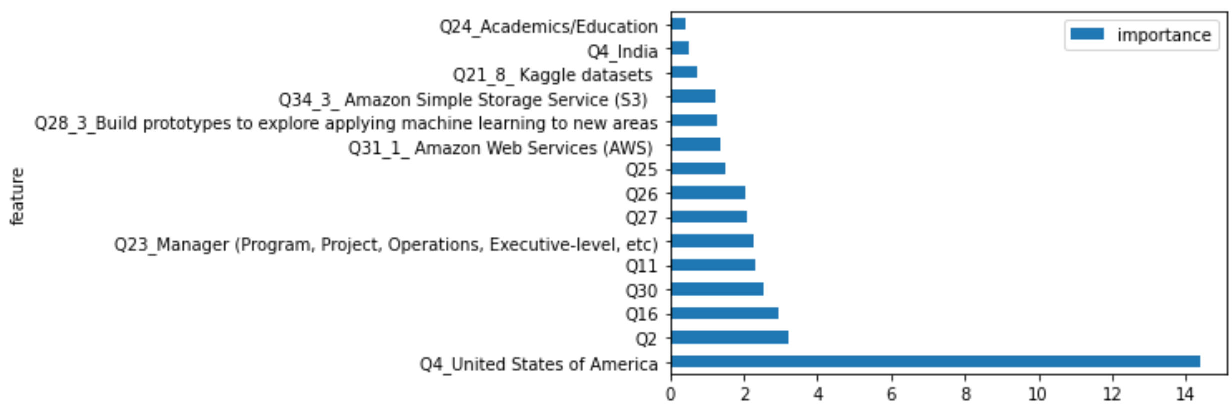
In [126]:
```
weight_list = []
for n in range(0,15):
  weight_list.append(get_feature_weight(w_list, n))
```

In [142]:
```
weight_list_e = []
for w in weight_list:
  weight = pow(math.e,w)
  weight_list_e.append(weight)
```

In [143]:
```
import math
feature_importance = pd.DataFrame(feature_selected.feature, columns =
["feature"])

feature_importance["importance"] = weight_list_e
feature_importance = feature_importance.sort_values(by =['importance']
, ascending = False)
```

In [144]:
```
ax = feature_importance.plot.barh(x = 'feature', y = 'importance')
plt.show()
```



Based on the graph above, the question Q4_USA has the largest coefficient in the regression, meaning that it is the most important feature, followed by Q2, Q16 and Q30 respectively. The results are pretty similar for the correlation plots in the previous part, where Q4_USA, Q2, Q16 are the features that have larger correlation with the target variable y.

5.Testing & Discussion

We use the optimal model (C=1, solver = newton-cg) to make classifications on the test set. The model is fitted with the training data.

In [50]:
```
prediction_list = ordinal_logistic_regression(X_train, y_train, X_test
, y_test, solver = 'newton-cg', C = 1)
```

In [55]:
```
y_test = pd.DataFrame(y_test)

accu = get_accuracy(y_test, prediction_list)

f1 = get_f1_score(y_test, prediction_list)

bias, var = get_bias_var(y_test, prediction_list)

print('Apply the optimal model for test data: test accuracy:', accu, '
test f1 score:', f1, 'bias:', bias, 'variance:', var)
```

```
Apply the optimal model for test data: test accuracy: 0.394 test f1
score: 0.03980099502487562 bias: 20.364903053162163 variance: 21.535
831689677842
```

In [65]:
```
y_test = y_test.tolist()
```

In [78]:
```
pred_count = []
actual_count = []
for i in range(0,15):

  pred_count.append(prediction_list.count(i))
  actual_count.append(y_test.count(i))
```

In [79]:
```
print('pred_count', pred_count)
print('actual_count', actual_count)
```

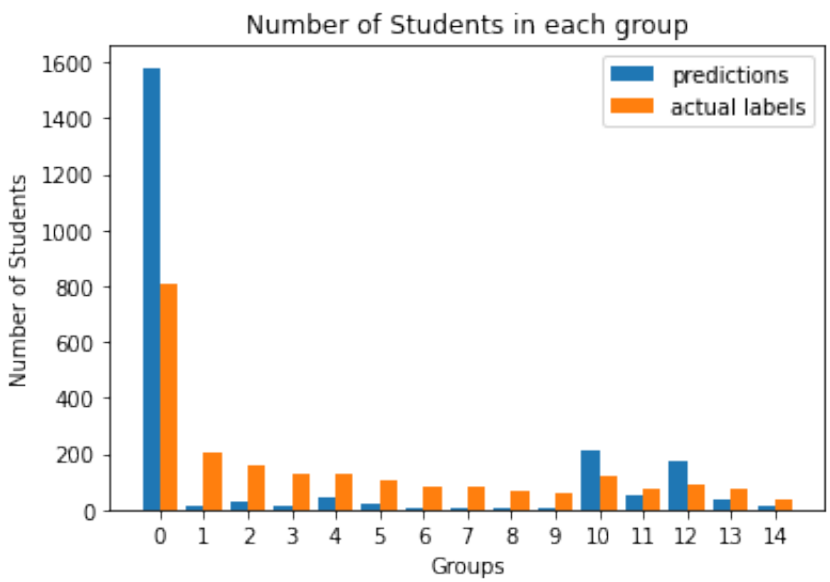
```
pred_count [1581, 16, 30, 15, 47, 22, 7, 7, 3, 3, 215, 54, 173, 39,
11]
actual_count [808, 207, 156, 132, 130, 108, 84, 80, 71, 56, 117, 76,
92, 73, 33]
```

In [83]:
```
X = ['0','1','2','3','4','5','6','7','8','9','10','11','12','13','14']
prd = pred_count
act = actual_count

X_axis = np.arange(len(X))

plt.bar(X_axis - 0.2, prd, 0.4, label = 'predictions')
plt.bar(X_axis + 0.2, act, 0.4, label = 'actual labels')

plt.xticks(X_axis, X)
plt.xlabel("Groups")
plt.ylabel("Number of Students")
plt.title("Number of Students in each group")
plt.legend()
plt.show()
```



We want to compute training accuracy by prediting the X_train and compare the predictions with the actual X_test. Then we plot the distribution of true target variable values and the predictions.

In [84]:
```
prediction_list = ordinal_logistic_regression(X_train, y_train, X_trai
n, y_train, solver = 'newton-cg', C = 1)
```

In [100]:
```
y_train = pd.DataFrame(y_train)

accu = get_accuracy(y_train, prediction_list)

f1 = get_f1_score(y_train, prediction_list)

bias, var = get_bias_var(y_train, prediction_list)

print('Apply the optimal model for train data: train accuracy:', accu,
'train f1 score:', f1, 'bias:', bias, 'variance:', var)
```

```
Apply the optimal model for train data: train accuracy: 0.393 train
f1 score: 0.016563146997929604 bias: 21.049503773918005 variance: 21
.51778892681638
```

In [96]:
```
y_train.squeeze()
y_train = y_train.tolist()
```

In [97]:
```
pred_count = []
actual_count = []
for i in range(0,15):

  pred_count.append(prediction_list.count(i))
  actual_count.append(y_train.count(i))
```

In [98]:
```
print('pred_count', pred_count)
print('actual_count', actual_count)
```

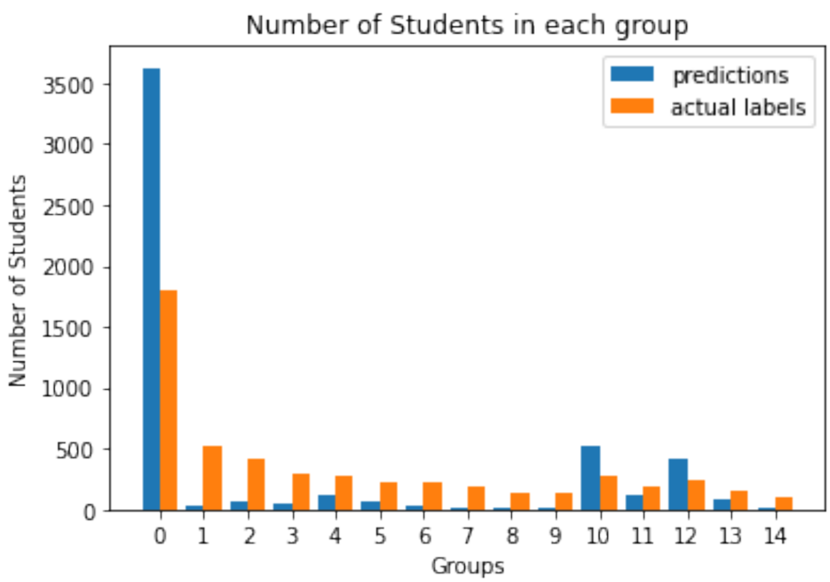
```
pred_count [3624, 35, 72, 54, 119, 58, 23, 22, 6, 15, 524, 112, 423,
80, 19]
actual_count [1807, 519, 408, 301, 270, 228, 220, 194, 141, 137, 273
, 183, 242, 156, 107]
```

In [99]:
```
X = ['0','1','2','3','4','5','6','7','8','9','10','11','12','13','14']
prd = pred_count
act = actual_count

X_axis = np.arange(len(X))

plt.bar(X_axis - 0.2, prd, 0.4, label = 'predictions')
plt.bar(X_axis + 0.2, act, 0.4, label = 'actual labels')

plt.xticks(X_axis, X)
plt.xlabel("Groups")
plt.ylabel("Number of Students")
plt.title("Number of Students in each group")
plt.legend()
plt.show()
```



Based on the analysis above, the test accuracy is slightly above the training accuracy, which is around 0.394 (compared to 0.393 of the training). The test f1 score is also slightly above the training score (0.0398 vs 0.0166). The bias and variance are around 20 and 22 for the test data respectively. For training data, the model has the scores of 21 and 22. The accuracy of the model is similar for training and test data, indicating that the performance of the model is not bad. When predicting the test labels, the variance and bias does not change too much compared to the predictions for the training labels, meaning that the model does not overfit or underfit. However, the model still have a low performance since the accuracy is below 50 percent and it can not even predict half of the samples right. The higher test accuracy might be because that the test data is similar to the training ones and have some easier points. We may try n-fold cross validation and try more n for this problem. The low accuracy of the model also indicates that the model is not complex enough for this problem. We may try other complex machine learning algorithm such as neuron network, random forest, etc,

In [140]:
```
%%shell
jupyter nbconvert --to html /content/FFFFinalMIE1624_assignment_2.ipyn
b
```

```
[NbConvertApp] Converting notebook /content/FFFFinalMIE1624_assignme
nt_2.ipynb to html
[NbConvertApp] Writing 675121 bytes to /content/FFFFinalMIE1624_assi
gnment_2.html
```

Out[140]: