Main_with_outputs

June 20, 2021

0.0.1 Introduction

In this Milestone(3), we are concerned with the efficiency of differend Neural Networks; fit_time, prediction_time, accuracy, etc. Although the structure of this MS is like the previous MS, but we have done a thorogh and comprehensive study on the performance of the models. Five models has been tested deeply; please note that if you have completely random NN, the accuracy should be around 4%. While our models can easily provide more than 50%.

Group members: Hamid Pour Mohammad, Mehdi Naghi Lou, Saeid Entezari.

[1]:
```
import tensorflow as tf
from tensorflow import keras as ks
import numpy as np
from pandas import read_csv, concat, DataFrame
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
from time import time
```

[2]:
```
from pandas import read_csv
df=read_csv('data_clean.csv') # importing the data

def sampler(df, n): # It chooses n samples from df (encoding and cleaning are␣
 ↪considered)
    df_s=df.sample(n)
    encoder=LabelEncoder() # encoding the labels
    encoder.fit(df_s['target_tag'])
    global encoder_classes # saving the order of the classes
    encoder_classes=encoder.classes_
    df_s['target_tag']=encoder.transform(df_s['target_tag'])
    # we have a reason to delete the 164th feature! Explanation is too long;␣
 ↪but in short, it's because of
    # the intercurrent variables. So, let's get rid of it:
    df_s= concat([df_s.iloc[:,1:164], df_s.iloc[:,165:]], axis=1)
    return df_s

# converting probabilities to classes, and make confusion matrix:
def confusion_matrix_func(model, X_test, Y_test):
```

```
    def probability_to_class(Y_pred_probabilities):
        Y_pred=[np.argmax(i) for i in Y_pred_probabilities]
        return Y_pred

    Y_pred=probability_to_class(model.predict(X_test))
    conf_matrix=DataFrame(encoder_classes, columns=[''])
    conf_matrix=concat([conf_matrix,
                        DataFrame(confusion_matrix(Y_test, Y_pred),␣
↪columns=list(encoder_classes))], axis=1)
    return conf_matrix
```

0.0.2 Evaluating the models:

As the metrics, we want to use confusion matrix first. Because it shows us how many predictions are correct, without considering the importance of each class; no class is superior in our research. On the other hand, some of wrong predictions are important. because some of them show the better choice to classify a Tweet; and some of them show the correlations and overlapping of different classes. For example, 'gym' and 'bodybuilding' are overlapping according to the confusion matrix, and you can find correlations and overlapping very well. Also, almost all the classes have the same number of samples, so we consider the accuracy of prediction, as another metric. Please note that our metric is sparse_categorical_accuracy, because we have 27 classes. Neural network models can find the correlations between various words in the texture of tweets; so they can provide accurate predictions if they have been trained well.

0.0.3 Changing the complexity:

In the below link: https://www.innoarchitech.com/blog/machine-learning-an-in-depth-non-technical-guide-part-3 you can read:

"In machine learning, model complexity often refers to the number of features or terms included in a given predictive model, as well as whether the chosen model is linear, nonlinear, and so on. It can also refer to the algorithmic learning complexity or computational complexity."

Thus, we will change the number of features (kept features) in each model, and explore optimal value. Also, we change the structure of the model (it means the comlexity of the structure of the model will change too).

[5]:
```
# These lists will be utlized for comparing the models:
fit_time_list=[]
predict_time_list=[]
best_accuracy_list=[]
best_val_accuracy_list=[]
min_loss_list=[]
min_val_loss_list=[]
bias_list=[]
variance_list=[]
```

==

0.0.4 Model 1:

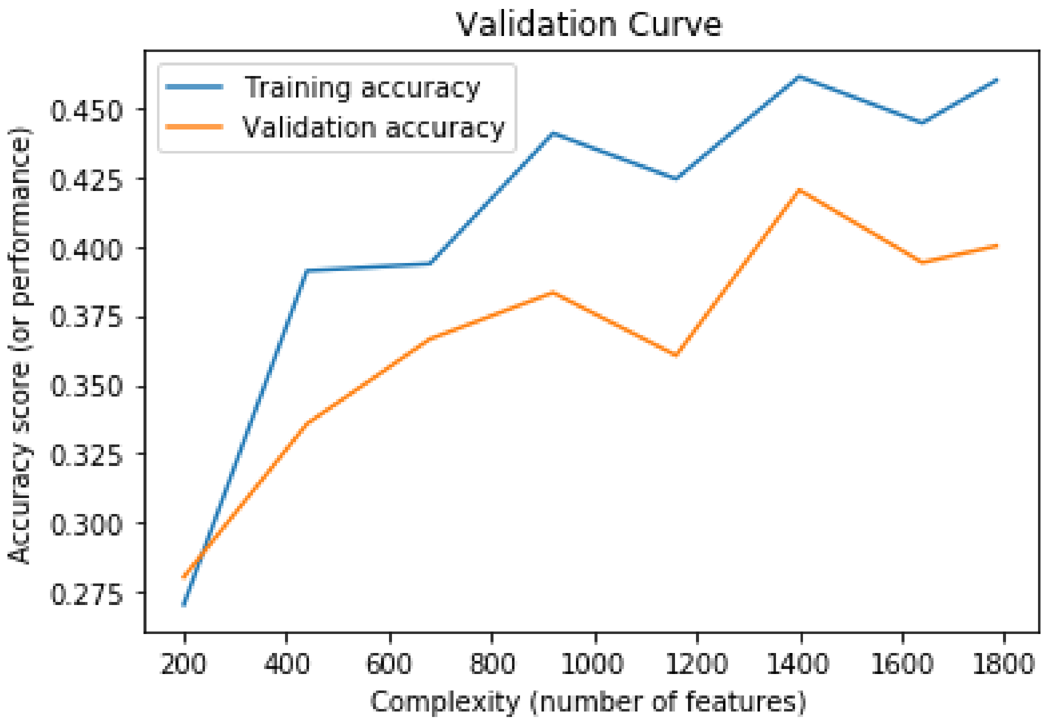
In this model, we are utlizing a NN with two hidden layers; 400 nodes for each hidden layer. The activation function is relu (it's sigmoid for output layer). The optimizing algorithm is SGD with lr=0.1. Also, we have considered regularization to have 0.01 impact coefficient. About loss function and metric, they are sparse_categorical_crossentropy and sparse_categorical_accuracy.

[6]:
```
# model_1:
# Let's train some different forms of model_1:
# different number of features; changing the complexity:
n_kept_features = list(range(200, df.shape[1]+1, 240)) + [df.shape[1]-3]
accuracy_list=[]
val_accuracy_list=[]

print('Validation Curve process for model_1:')
print('(Please note that our metric is acuuracy: sparse_categorical_accuracy)')
start_time=time() # time for fitting
for n in n_kept_features:
    acc=[] # calculate the accuracy for a few times
    val_acc=[] # calculate the validation accuracy for a few times
    for i in range(3): # training a few times, to find the average
        df_sample=sampler(df, 3000) # choose some samples
        X_train, X_test, Y_train, Y_test = train_test_split( df_sample.iloc[:,1:
↪n], df_sample['target_tag'])

        reg_coef_1=0.01 # impact coefficient of regularization
        model_1=ks.models.Sequential()
        model_1.add(ks.layers.Dense(units=400, activation=ks.activations.relu,␣
↪input_dim=X_train.shape[1],
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_1)))
        model_1.add(ks.layers.Dense(units=400, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_1)))
        model_1.add(ks.layers.Dense(units=27, activation=ks.activations.
↪sigmoid))

        model_1.compile(optimizer=ks.optimizers.SGD(0.1), loss=ks.losses.
↪sparse_categorical_crossentropy,
                        metrics=ks.metrics.sparse_categorical_accuracy)
        history=model_1.fit(X_train, Y_train, validation_split=0.1, epochs=7,␣
↪batch_size=30, verbose=0)
        acc.append( np.mean( np.sort(history.
↪history['sparse_categorical_accuracy'])[-3:] ) )
        val_acc.append( np.mean( np.sort(history.
↪history['val_sparse_categorical_accuracy'])[-3:] ) )
```

```
    accuracy_list.append(np.mean(acc))
    val_accuracy_list.append(np.mean( val_acc ))
    print(f'{n} features: done')

end_time=time()

print(f'\nThe optimal value for the Complexity (n_f) is: {n_kept_features[np.
 ↪argmax(val_accuracy_list)]}')
plt.plot(n_kept_features, accuracy_list, label='Training accuracy')
plt.plot(n_kept_features, val_accuracy_list, label='Validation accuracy')
plt.xlabel('Complexity (number of features)'), plt.ylabel('Accuracy score (or␣
 ↪performance)')
plt.title('Validation Curve')
plt.legend()
```

```
Validation Curve process for model_1:
(Please note that our metric is acuuracy: sparse_categorical_accuracy)
200 features: done
440 features: done
680 features: done
920 features: done
1160 features: done
1400 features: done
1640 features: done
1784 features: done

The optimal value for the Complexity (n_f) is: 1400
```

[6]:
```
<matplotlib.legend.Legend at 0x7f82c9ab1810>
```



[7]:
```python
# model_1:
# average fitting time (for various n_kept_features):
fit_time_list.append( (end_time-start_time)/len(n_kept_features) )
best_accuracy_list.append(max(accuracy_list))
best_val_accuracy_list.append(max(val_accuracy_list))

print('Confusion Matrix for model_1:')
# Please note that there are 27 classes; so it's quiet fair to have a large␣
↪confusion matrix
start_time=time()
c_m=confusion_matrix_func(model_1, X_test, Y_test)
end_time=time()
predict_time_list.append(end_time-start_time)

c_m
```

```
Confusion Matrix for model_1:
```

[7]:

		animal	architecture	art	biology	bodybuilding	business	\
0	animal	20	0	2	0	0	0	
1	architecture	0	6	0	0	0	0	
2	art	1	0	16	0	0	0	
3	biology	0	0	0	7	0	0	
4	bodybuilding	0	0	0	0	0	0	

5	business	0	0	0	1	0	0
6	covid	0	0	0	0	0	0
7	culture	0	0	0	0	0	0
8	election	0	0	0	0	0	0
9	engineering	0	0	0	1	0	0
10	fashion	0	0	1	0	0	0
11	food	0	0	0	0	0	0
12	government	0	0	0	0	0	0
13	gym	0	0	0	0	0	0
14	innovation	0	0	0	0	0	0
15	job	0	0	0	0	0	0
16	love	0	0	1	0	0	0
17	marketing	0	0	0	0	0	0
18	medical	0	0	0	0	0	0
19	pet	11	0	0	0	0	0
20	pharmacy	0	0	0	0	0	0
21	physics	0	0	0	1	0	0
22	political	0	0	0	0	0	0
23	science	0	0	1	0	0	0
24	solar	0	0	0	0	0	0
25	technology	0	0	0	0	0	0
26	travel	0	1	0	0	0	0

	covid	culture	election	…	marketing	medical	pet	pharmacy	physics	\
0	0	0	0	…	3	0	0	0	0	
1	0	0	0	…	6	0	0	0	0	
2	0	0	0	…	1	0	0	0	0	
3	0	0	0	…	0	0	0	0	19	
4	0	0	0	…	0	0	0	0	0	
5	3	0	0	…	14	0	0	0	5	
6	12	0	0	…	3	0	0	0	0	
7	1	16	0	…	5	0	0	0	0	
8	0	0	0	…	0	0	0	0	0	
9	1	0	0	…	0	0	0	0	0	
10	0	0	0	…	0	0	0	0	0	
11	0	0	0	…	9	0	0	0	0	
12	1	0	0	…	5	0	0	0	0	
13	0	0	0	…	1	0	0	0	0	
14	0	0	0	…	5	0	0	0	0	
15	0	0	0	…	2	0	0	0	0	
16	1	0	0	…	4	0	0	0	0	
17	0	0	0	…	21	0	0	0	2	
18	0	0	0	…	5	0	0	0	0	
19	0	0	0	…	3	0	3	0	0	
20	0	0	0	…	4	0	0	0	0	
21	0	0	0	…	4	0	0	0	18	
22	0	0	0	…	3	0	0	0	1	

```
23      0         0          0  ...           3          0    0          0          0
24      0         0          0  ...           0          0    0          0          0
25      0         0          0  ...           5          0    0          0          0
26      3         0          0  ...           4          0    0          0          0

    political  science  solar  technology  travel
0           0        0      0           7       0
1           0        0      0          14       0
2           0        0      0           8       0
3           0        0      0           2       0
4           0        0      0           4       0
5           0        0      0           9       0
6           0        0      0          11       0
7           0        0      0          13       0
8           0        0      0          11       0
9           0        0      0          19       0
10          0        0      0           7       0
11          0        0      0          15       0
12          0        0      0          10       0
13          0        0      0          10       0
14          0        1      0          22       0
15          0        1      0           0       0
16          0        0      0          16       0
17          0        0      0           6       0
18          0        0      0          20       0
19          0        0      0           4       0
20          0        0      0           8       0
21          0        0      0           5       0
22          0        0      0           8       0
23          0        5      0          19       0
24          0        0     18           0       0
25          0        1      0          25       0
26          0        0      0          11      14

[27 rows x 28 columns]
```

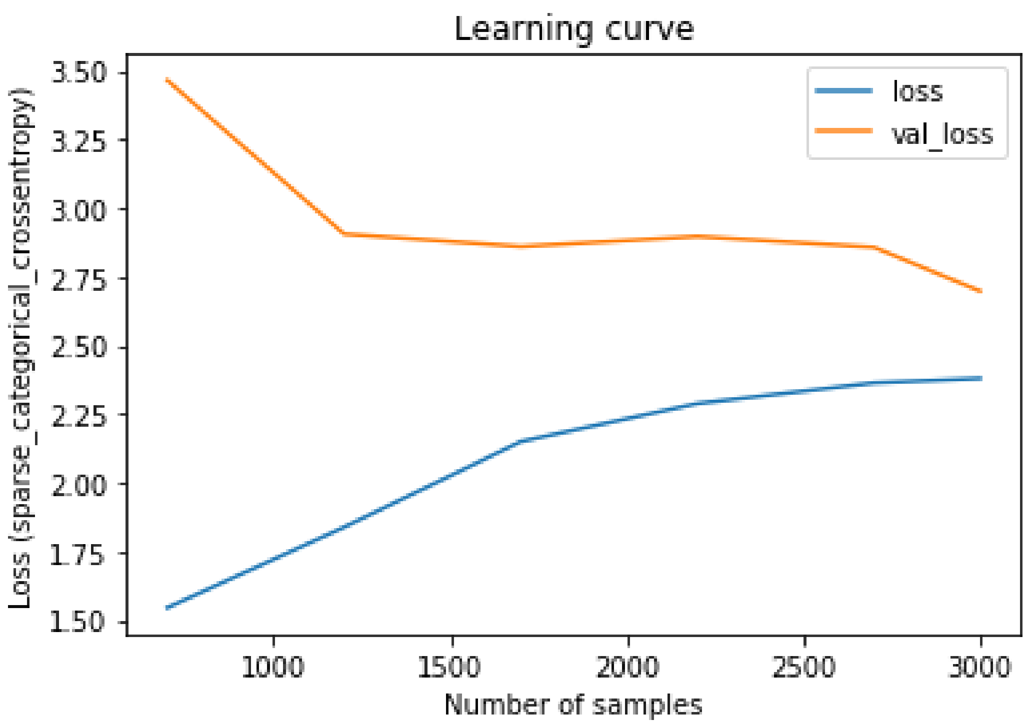
[8]:

```python
# model_1:
# Now, we are exploring the Learning Curve process:
n_f=600 # let's set the number of features to be 600 for here (we are still in␣
 ↪model_1):
n_samples=[700, 1200, 1700, 2200, 2700, 3000] # number of data samples we are␣
 ↪using here
loss_list=[]
val_loss_list=[]

print('Learning Curve process for model_1:')
for n_s in n_samples:
```

```
    loss=[]
    val_loss=[]
    for i in range(2): # training a few times, to find the average
        df_sample=sampler(df, n_s)
        X_train, X_test, Y_train, Y_test = train_test_split( df_sample.iloc[:,1:
↪n_f], df_sample['target_tag'])

        reg_coef_1=0.01
        model_1=ks.models.Sequential()
        model_1.add(ks.layers.Dense(units=400, activation=ks.activations.relu,␣
↪input_dim=X_train.shape[1],
                                        kernel_regularizer=ks.regularizers.
↪l2(reg_coef_1)))
        model_1.add(ks.layers.Dense(units=400, activation=ks.activations.relu,
                                        kernel_regularizer=ks.regularizers.
↪l2(reg_coef_1)))
        model_1.add(ks.layers.Dense(units=27, activation=ks.activations.
↪sigmoid))

        model_1.compile(optimizer=ks.optimizers.SGD(0.1), loss=ks.losses.
↪sparse_categorical_crossentropy,
                          metrics=ks.metrics.sparse_categorical_accuracy)
        history=model_1.fit(X_train, Y_train, validation_split=0.1, epochs=17,␣
↪batch_size=5, verbose=0)
        loss.append( np.mean( np.sort(history.history['loss'])[:3] ) )
        val_loss.append( np.mean( np.sort(history.history['val_loss'])[:3] ) )

    loss_list.append(np.mean( loss ))
    val_loss_list.append(np.mean( val_loss ))
    print(f'{n_s} samples: done')

min_loss_list.append(min(loss_list))
min_val_loss_list.append(min(val_loss_list))

print(f'\nBias: {np.mean(loss_list[-2:]+val_loss_list[-2:])}')
print(f'Variance: {np.mean(np.array(val_loss_list[-2:])-np.array(loss_list[-2:
↪]))/2}')
print("""According to the amount of bias and variance, it seems that we have␣
↪enough data. Please
note that we have 100,000 samples (in total). And it is almost a good model.""")
plt.plot(n_samples, loss_list, label='loss')
plt.plot(n_samples, val_loss_list, label='val_loss')
plt.xlabel('Number of samples'), plt.ylabel('Loss␣
↪(sparse_categorical_crossentropy)')
plt.title('Learning curve')
plt.legend()
```

```
Learning Curve process for model_1:
700 samples: done
1200 samples: done
1700 samples: done
2200 samples: done
2700 samples: done
3000 samples: done

Bias: 2.575176378091176
Variance: 0.20309215784072887
According to the amount of bias and variance, it seems that we have enough data.
Please
note that we have 100,000 samples (in total). And it is almost a good model.
```

[8]: <matplotlib.legend.Legend at 0x7f82d83ab3d0>



Please note that we are using regularization with 0.01 impact coefficient. Without regularization, we have to deal with overfitting.

[9]:
```
bias_list.append( np.mean(loss_list[-2:]+val_loss_list[-2:]) )
variance_list.append( np.mean(np.array(val_loss_list[-2:])-np.
↪array(loss_list[-2:]))/2 )
```

0.0.5 Fine tunning other hyper-parameter of the model:

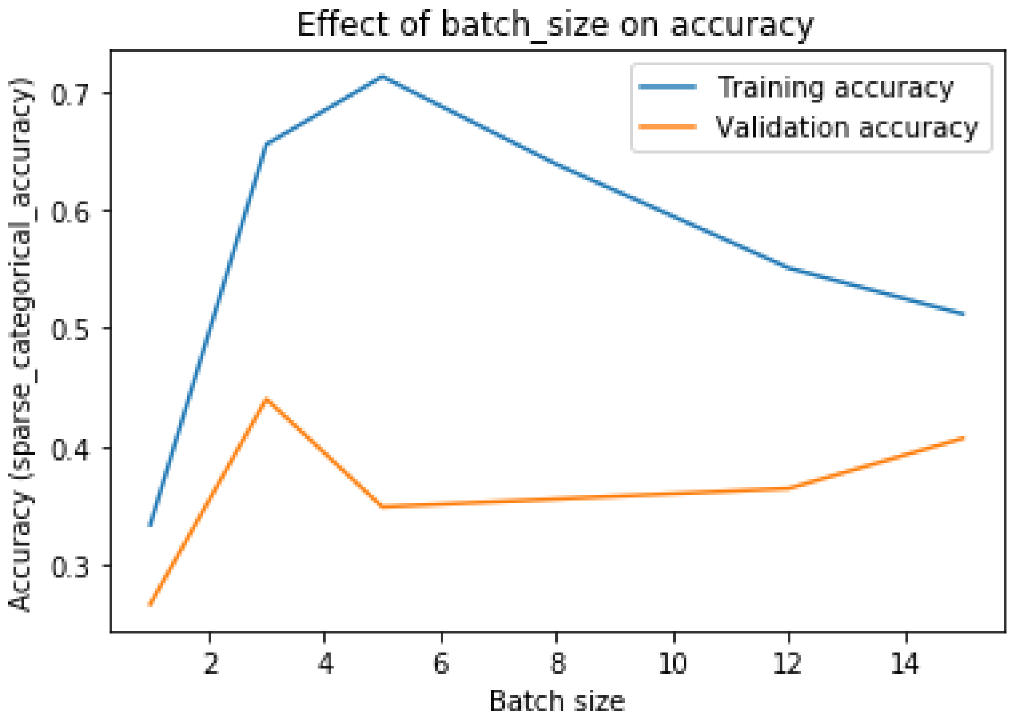
Now, we like to fine tune other hyper-parameter of the model; it's batch_size. Because we have understood that it is very important to have a good batch_size.

[16]:
```
# model_1:
# Fine tunning another hyper-model of model_1; batch_size or learning rate can␣
↪be tunned.
# Here, we go for the batch_size:
n_f=600
n_batch_sizes=[1, 3, 5, 8, 12, 15] # different number of batch_size
accuracy_list=[]
val_accuracy_list=[]

print('Fine tunning another hyper-parameter of model_1:')
for n_b_s in n_batch_sizes:
    accuracy=[]
    val_accuracy=[]
    for i in range(2): # training a few times, to find the average
        df_sample=sampler(df, 1000)
        X_train, X_test, Y_train, Y_test = train_test_split( df_sample.iloc[:,1:
↪n_f], df_sample['target_tag'])

        reg_coef_1=0.01
        model_1=ks.models.Sequential()
        model_1.add(ks.layers.Dense(units=400, activation=ks.activations.relu,␣
↪input_dim=X_train.shape[1],
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_1)))
        model_1.add(ks.layers.Dense(units=400, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_1)))
        model_1.add(ks.layers.Dense(units=27, activation=ks.activations.
↪sigmoid))

        model_1.compile(optimizer=ks.optimizers.SGD(0.1), loss=ks.losses.
↪sparse_categorical_crossentropy,
                        metrics=ks.metrics.sparse_categorical_accuracy)
        history=model_1.fit(X_train, Y_train, validation_split=0.1, epochs=10,␣
↪batch_size=n_b_s, verbose=0)
        accuracy.append( np.mean( np.sort(history.
↪history['sparse_categorical_accuracy'])[-3:] ) )
        val_accuracy.append( np.mean( np.sort(history.
↪history['val_sparse_categorical_accuracy'])[-3:] ) )

    accuracy_list.append(np.mean( accuracy ))
    val_accuracy_list.append(np.mean( val_accuracy ))
```

```
    print(f'Batch_size = {n_b_s} : done')

print(f'\nBest Batch_size: {n_batch_sizes[ np.argmax(val_accuracy_list) ]}')
plt.plot(n_batch_sizes, accuracy_list, label='Training accuracy')
plt.plot(n_batch_sizes, val_accuracy_list, label='Validation accuracy')
plt.xlabel('Batch size'), plt.ylabel('Accuracy (sparse_categorical_accuracy)')
plt.title('Effect of batch_size on accuracy')
plt.legend()
```

```
Fine tunning another hyper-parameter of model_1:
Batch_size = 1 : done
Batch_size = 3 : done
Batch_size = 5 : done
Batch_size = 8 : done
Batch_size = 12 : done
Batch_size = 15 : done

Best Batch_size: 3
```

[16]: <matplotlib.legend.Legend at 0x7f82f34fb290>



===

0.0.6 Model 2:

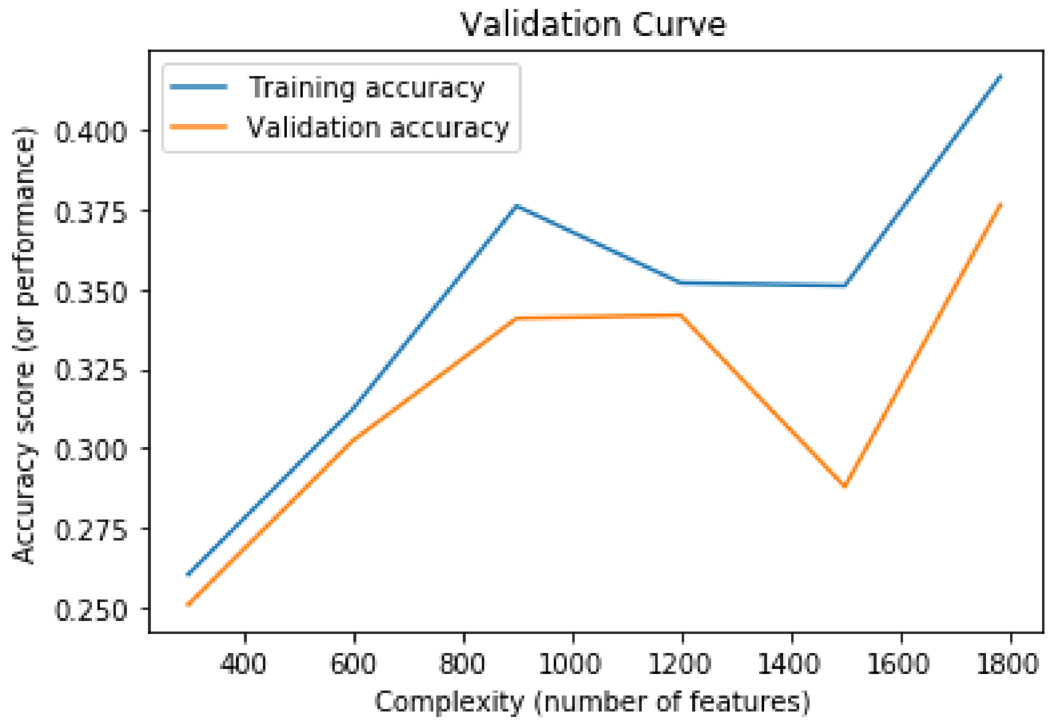
In the second model, we are utlizing a NN with 3 hidden layers; 350, 400, 100 nodes for hidden layers. Actually, we are making the NN deeper. The activation function is relu (it's sigmoid for output layer). The optimizing algorithm is SGD with lr=0.1 and batch_size=5. Also, we have considered regularization to have 0.01 impact coefficient. About loss function and metric, they are sparse_categorical_crossentropy and sparse_categorical_accuracy.

[17]:
```
# model_2:
# Let's train some different forms of model_2:
# different number of features; changing the complexity:
n_kept_features = list(range(300, df.shape[1]+1, 300)) + [df.shape[1]-3]
accuracy_list=[]
val_accuracy_list=[]

print('Validation Curve process for model_2:')
print('(Please note that our metric is acuuracy: sparse_categorical_accuracy)')
start_time=time() # time for fitting
for n in n_kept_features:
    acc=[] # calculate the accuracy for a few times
    val_acc=[] # calculate the validation accuracy for a few times
    for i in range(3): # training a few times, to find the average
        df_sample=sampler(df, 3000) # choose some samples
        X_train, X_test, Y_train, Y_test = train_test_split( df_sample.iloc[:,1:
↪n], df_sample['target_tag'])

        reg_coef_2=0.01 # impact coefficient of regularization
        model_2=ks.models.Sequential()
        model_2.add(ks.layers.Dense(units=350, activation=ks.activations.relu,␣
↪input_dim=X_train.shape[1],
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_2)))
        model_2.add(ks.layers.Dense(units=400, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_2)))
        model_2.add(ks.layers.Dense(units=100, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_2)))
        model_2.add(ks.layers.Dense(units=27, activation=ks.activations.
↪sigmoid))

        model_2.compile(optimizer=ks.optimizers.SGD(0.1), loss=ks.losses.
↪sparse_categorical_crossentropy,
                        metrics=ks.metrics.sparse_categorical_accuracy)
        history=model_2.fit(X_train, Y_train, validation_split=0.1, epochs=7,␣
↪batch_size=5, verbose=0)
```

```
        acc.append( np.mean( np.sort(history.
↪history['sparse_categorical_accuracy'])[-3:] ) )
        val_acc.append( np.mean( np.sort(history.
↪history['val_sparse_categorical_accuracy'])[-3:] ) )

    accuracy_list.append(np.mean(acc))
    val_accuracy_list.append(np.mean( val_acc ))
    print(f'{n} features: done')

end_time=time()

print(f'\nThe optimal value for the Complexity (n_f) is: {n_kept_features[np.
↪argmax(val_accuracy_list)]}')
plt.plot(n_kept_features, accuracy_list, label='Training accuracy')
plt.plot(n_kept_features, val_accuracy_list, label='Validation accuracy')
plt.xlabel('Complexity (number of features)'), plt.ylabel('Accuracy score (or␣
↪performance)')
plt.title('Validation Curve')
plt.legend()
```

```
Validation Curve process for model_2:
(Please note that our metric is acuuracy: sparse_categorical_accuracy)
300 features: done
600 features: done
900 features: done
1200 features: done
1500 features: done
1784 features: done

The optimal value for the Complexity (n_f) is: 1784
```

[17]:
```
<matplotlib.legend.Legend at 0x7f8304301910>
```



[18]:
```
# model_2:
# average fitting time (for various n_kept_features):
fit_time_list.append( (end_time-start_time)/len(n_kept_features) )
best_accuracy_list.append(max(accuracy_list))
best_val_accuracy_list.append(max(val_accuracy_list))

print('Confusion Matrix for model_2:')
# Please note that there are 27 classes; so it's quiet fair to have a large␣
↪confusion matrix
start_time=time()
c_m=confusion_matrix_func(model_2, X_test, Y_test)
end_time=time()
predict_time_list.append(end_time-start_time)

c_m
```

Confusion Matrix for model_2:

[18]:

		animal	architecture	art	biology	bodybuilding	business	\
0	animal	7	0	3	0	0	0	
1	architecture	0	17	2	0	0	0	
2	art	2	0	22	0	0	3	
3	biology	0	0	0	18	0	0	
4	bodybuilding	0	0	1	0	0	0	

5	business	0	1	0	3	0	5
6	covid	1	0	0	0	0	0
7	culture	0	1	1	0	0	1
8	election	0	0	0	0	0	2
9	engineering	0	2	0	0	0	0
10	fashion	0	0	2	0	0	0
11	food	0	0	1	0	0	1
12	government	0	0	0	0	0	4
13	gym	0	0	0	0	0	0
14	innovation	0	1	0	1	0	3
15	job	0	0	0	0	0	1
16	love	1	0	0	0	0	0
17	marketing	0	0	0	1	0	0
18	medical	0	0	1	0	0	0
19	pet	3	0	0	0	0	0
20	pharmacy	0	0	0	0	0	0
21	physics	1	0	1	14	0	0
22	political	0	0	0	1	0	0
23	science	0	2	0	1	0	0
24	solar	0	1	0	0	0	0
25	technology	0	0	0	0	0	2
26	travel	0	2	1	0	0	2

	covid	culture	election	…	marketing	medical	pet	pharmacy	physics	\
0	1	0	0	…	1	1	3	0	0	
1	0	1	0	…	0	2	0	0	0	
2	0	1	0	…	3	2	0	0	0	
3	0	0	0	…	0	0	0	0	7	
4	0	0	0	…	2	1	0	0	0	
5	0	1	0	…	10	5	0	0	1	
6	10	1	0	…	2	6	0	0	0	
7	0	8	0	…	4	3	0	0	0	
8	0	1	0	…	2	0	0	0	0	
9	0	0	0	…	2	2	0	0	1	
10	0	0	0	…	0	1	0	0	0	
11	0	0	0	…	5	5	0	0	0	
12	1	0	0	…	5	3	0	0	0	
13	0	0	0	…	3	1	0	0	0	
14	0	1	0	…	4	3	0	0	0	
15	0	1	0	…	0	0	0	0	0	
16	0	0	0	…	2	0	1	0	0	
17	0	2	0	…	12	1	0	0	1	
18	0	1	0	…	3	22	0	0	0	
19	0	0	0	…	0	0	13	0	0	
20	0	2	0	…	0	4	0	0	0	
21	0	0	0	…	0	1	0	0	25	
22	0	1	0	…	0	3	0	0	0	

```
23      0      0      0  ...       1      6   0       0       0
24      0      0      0  ...       0      0   0       0       0
25      0      0      0  ...       2      3   0       0       0
26      0      0      0  ...       5      2   0       0       0

    political  science  solar  technology  travel
0           0        0      0           1       3
1           0        2      0           1       5
2           0        0      0           2       0
3           0        1      0           0       0
4           0        0      0           0       0
5           0        5      0           3       2
6           0        2      0           2       1
7           0        0      0           2       2
8           0        1      0           1       1
9           0        5      0           4       0
10          0        1      0           0       1
11          0        3      0           0       3
12          0        3      0           4       0
13          0        0      0           1       1
14          0        6      0           9       1
15          0        2      0           0       0
16          0        0      0           0       2
17          0        3      0           0       2
18          0        0      0           1       0
19          0        0      0           0       0
20          0        0      0           1       0
21          0        4      0           1       0
22          0        4      0           4       0
23          0       10      0           1       1
24          0        1     18           1       0
25          0        2      0          11       0
26          0        1      0           0      10

[27 rows x 28 columns]
```

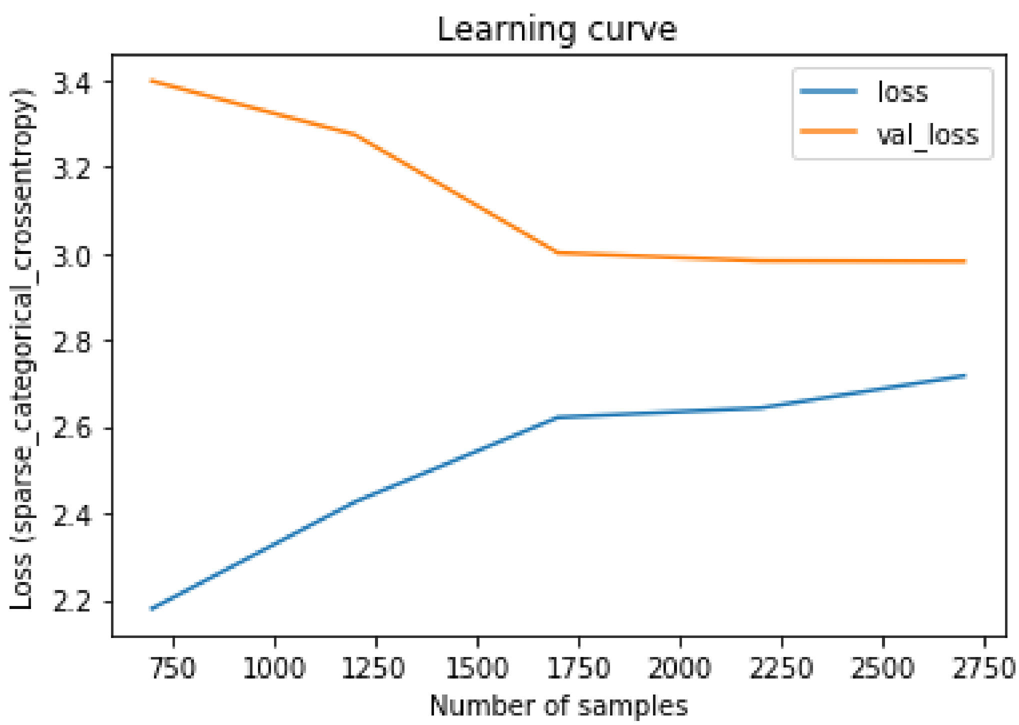
[19]:
```
# model_2:
# Now, we are exploring the Learning Curve process:
n_f=600 # let's set the number of features to be 600 for here (we are still in␣
 ↪model_2):
n_samples=[700, 1200, 1700, 2200, 2700] # number of data samples we are using␣
 ↪here
loss_list=[]
val_loss_list=[]

print('Learning Curve process for model_2:')
for n_s in n_samples:
```

```
    loss=[]
    val_loss=[]
    for i in range(2): # training a few times, to find the average
        df_sample=sampler(df, n_s)
        X_train, X_test, Y_train, Y_test = train_test_split( df_sample.iloc[:,1:
↪n_f], df_sample['target_tag'])

        reg_coef_2=0.01
        model_2=ks.models.Sequential()
        model_2.add(ks.layers.Dense(units=350, activation=ks.activations.relu,␣
↪input_dim=X_train.shape[1],
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_2)))
        model_2.add(ks.layers.Dense(units=400, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_2)))
        model_2.add(ks.layers.Dense(units=100, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_2)))
        model_2.add(ks.layers.Dense(units=27, activation=ks.activations.
↪sigmoid))

        model_2.compile(optimizer=ks.optimizers.SGD(0.1), loss=ks.losses.
↪sparse_categorical_crossentropy,
                    metrics=ks.metrics.sparse_categorical_accuracy)
        history=model_2.fit(X_train, Y_train, validation_split=0.1, epochs=15,␣
↪batch_size=5, verbose=0)
        loss.append( np.mean( np.sort(history.history['loss'])[:3] ) )
        val_loss.append( np.mean( np.sort(history.history['val_loss'])[:3] ) )

    loss_list.append(np.mean( loss ))
    val_loss_list.append(np.mean( val_loss ))
    print(f'{n_s} samples: done')

min_loss_list.append(min(loss_list))
min_val_loss_list.append(min(val_loss_list))

print(f'\nBias: {np.mean(loss_list[-2:]+val_loss_list[-2:])}')
print(f'Variance: {np.mean(np.array(val_loss_list[-2:])-np.array(loss_list[-2:
↪]))/2}')
print("""According to the amount of bias and variance, it seems that we have␣
↪enough data. Please
note that we have 100,000 samples (in total). And it is almost a good model.""")
plt.plot(n_samples, loss_list, label='loss')
plt.plot(n_samples, val_loss_list, label='val_loss')
```

```
plt.xlabel('Number of samples'), plt.ylabel('Loss␣
 ↪(sparse_categorical_crossentropy)')
plt.title('Learning curve')
plt.legend()
```

```
Learning Curve process for model_2:
700 samples: done
1200 samples: done
1700 samples: done
2200 samples: done
2700 samples: done

Bias: 2.830942004919052
Variance: 0.15106539924939455
According to the amount of bias and variance, it seems that we have enough data.
Please
note that we have 100,000 samples (in total). And it is almost a good model.
```

[19]: <matplotlib.legend.Legend at 0x7f830421a410>



Please note that we are using regularization with 0.01 impact coefficient. Without regularization, we have to deal with overfitting.

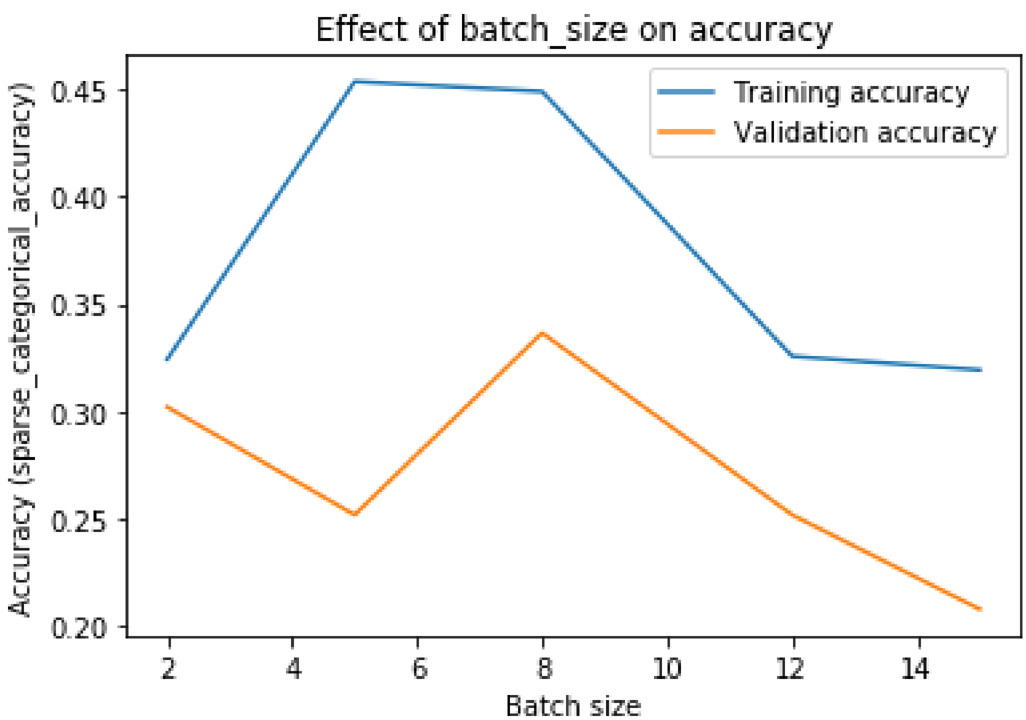
[20]:
```
bias_list.append( np.mean(loss_list[-2:]+val_loss_list[-2:]) )
variance_list.append( np.mean(np.array(val_loss_list[-2:])-np.
 ↪array(loss_list[-2:]))/2 )
```

[21]:
```
# model_2:
# Fine tunning another hyper-model of model_2; batch_size or learning rate can␣
 ↪be tunned.
# Here, we go for the batch_size:
n_f=600
n_batch_sizes=[2, 5, 8, 12, 15] # different number of batch_size
accuracy_list=[]
val_accuracy_list=[]

print('Fine tunning another hyper-parameter of model_2:')
for n_b_s in n_batch_sizes:
    accuracy=[]
    val_accuracy=[]
    for i in range(2): # training a few times, to find the average
        df_sample=sampler(df, 700)
        X_train, X_test, Y_train, Y_test = train_test_split( df_sample.iloc[:,1:
 ↪n_f], df_sample['target_tag'])

        reg_coef_2=0.01
        model_2=ks.models.Sequential()
        model_2.add(ks.layers.Dense(units=350, activation=ks.activations.relu,␣
 ↪input_dim=X_train.shape[1],
                                    kernel_regularizer=ks.regularizers.
 ↪l2(reg_coef_2)))
        model_2.add(ks.layers.Dense(units=400, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
 ↪l2(reg_coef_2)))
        model_2.add(ks.layers.Dense(units=100, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
 ↪l2(reg_coef_2)))
        model_2.add(ks.layers.Dense(units=27, activation=ks.activations.
 ↪sigmoid))

        model_2.compile(optimizer=ks.optimizers.SGD(0.1), loss=ks.losses.
 ↪sparse_categorical_crossentropy,
                        metrics=ks.metrics.sparse_categorical_accuracy)
        history=model_2.fit(X_train, Y_train, validation_split=0.1, epochs=10,␣
 ↪batch_size=n_b_s, verbose=0)
        accuracy.append( np.mean( np.sort(history.
 ↪history['sparse_categorical_accuracy'])[-3:] ) )
        val_accuracy.append( np.mean( np.sort(history.
 ↪history['val_sparse_categorical_accuracy'])[-3:] ) )
```

```python
    accuracy_list.append(np.mean( accuracy ))
    val_accuracy_list.append(np.mean( val_accuracy ))
    print(f'Batch_size = {n_b_s} : done')

print(f'\nBest Batch_size: {n_batch_sizes[ np.argmax(val_accuracy_list) ]}')
plt.plot(n_batch_sizes, accuracy_list, label='Training accuracy')
plt.plot(n_batch_sizes, val_accuracy_list, label='Validation accuracy')
plt.xlabel('Batch size'), plt.ylabel('Accuracy (sparse_categorical_accuracy)')
plt.title('Effect of batch_size on accuracy')
plt.legend()
```

```
Fine tunning another hyper-parameter of model_2:
Batch_size = 2 : done
Batch_size = 5 : done
Batch_size = 8 : done
Batch_size = 12 : done
Batch_size = 15 : done

Best Batch_size: 8
```

[21]: <matplotlib.legend.Legend at 0x7f82d81a0dd0>



==

0.0.7 Model 3:

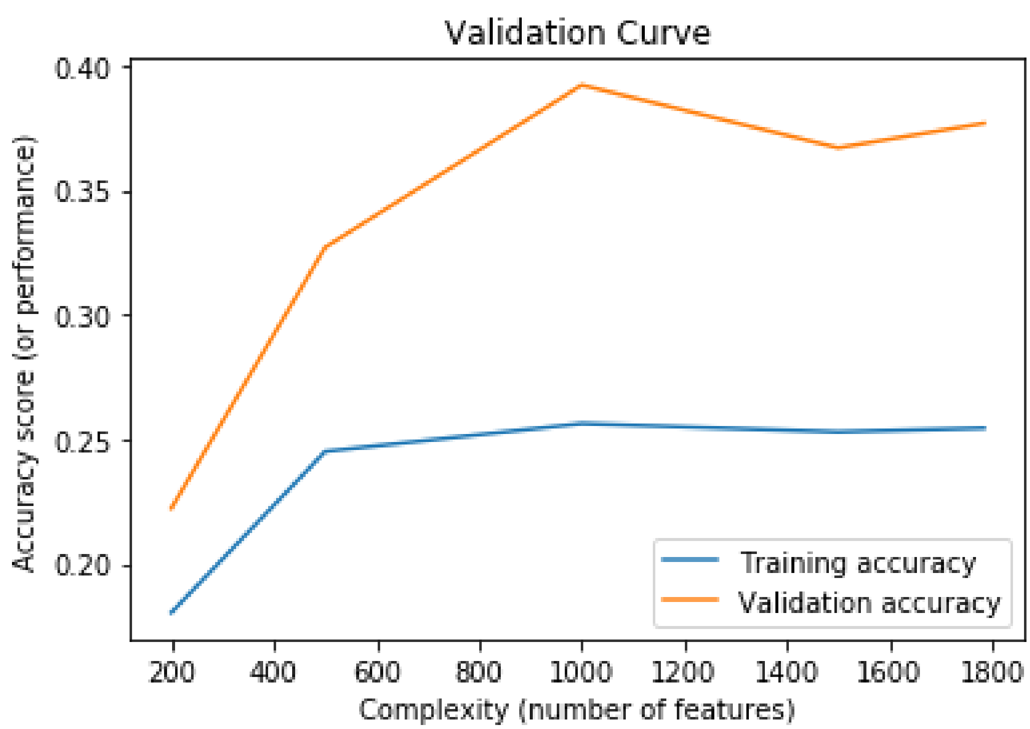
In the third model, we are utlizing a NN with 2 hidden layers; 350 and 350 nodes for hidden layers. The activation function is still relu (it's sigmoid for output layer). But now, the optimizing algorithm is ADAM with batch_size=10, and starting learning_rate=0.005. Also, we have considered Dropout layers after each layers of nodes, with 0.8 probability. About loss function and metric, they are sparse_categorical_crossentropy and sparse_categorical_accuracy.

[30]:
```
# model_3:
# Let's train some different forms of model_3:
# different number of features; changing the complexity:
n_kept_features=[200, 500, 1000, 1500, df.shape[1]-3]
accuracy_list=[]
val_accuracy_list=[]

print('Validation Curve process for model_3:')
print('(Please note that our metric is acuuracy: sparse_categorical_accuracy)')
start_time=time() # time for fitting
for n in n_kept_features:
    acc=[] # calculate the accuracy for a few times
    val_acc=[] # calculate the validation accuracy for a few times
    for i in range(3): # training a few times, to find the average
        df_sample=sampler(df, 3000) # choose some samples
        X_train, X_test, Y_train, Y_test = train_test_split( df_sample.iloc[:,1:
↪n], df_sample['target_tag'])

        model_3=ks.models.Sequential()
        model_3.add(ks.layers.Dense(units=350, activation=ks.activations.relu,␣
↪input_dim=X_train.shape[1]))
        model_3.add(ks.layers.Dropout(0.8))
        model_3.add(ks.layers.Dense(units=350, activation=ks.activations.relu))
        model_3.add(ks.layers.Dropout(0.8))
        model_3.add(ks.layers.Dense(units=27, activation=ks.activations.
↪sigmoid))

        model_3.compile(optimizer=ks.optimizers.Adam(0.005), loss=ks.losses.
↪sparse_categorical_crossentropy,
                        metrics=ks.metrics.sparse_categorical_accuracy)
        history=model_3.fit(X_train, Y_train, validation_split=0.1, epochs=7,␣
↪batch_size=10, verbose=0)

        acc.append( np.mean( np.sort(history.
↪history['sparse_categorical_accuracy'])[-3:] ) )
        val_acc.append( np.mean( np.sort(history.
↪history['val_sparse_categorical_accuracy'])[-3:] ) )

    accuracy_list.append(np.mean(acc))
```

```
    val_accuracy_list.append(np.mean( val_acc ))
    print(f'{n} features: done')

end_time=time()

print(f'\nThe optimal value for the Complexity (n_f) is: {n_kept_features[np.
 ↪argmax(val_accuracy_list)]}')
plt.plot(n_kept_features, accuracy_list, label='Training accuracy')
plt.plot(n_kept_features, val_accuracy_list, label='Validation accuracy')
plt.xlabel('Complexity (number of features)'), plt.ylabel('Accuracy score (or␣
 ↪performance)')
plt.title('Validation Curve')
plt.legend()
```

```
Validation Curve process for model_3:
(Please note that our metric is acuuracy: sparse_categorical_accuracy)
200 features: done
500 features: done
1000 features: done
1500 features: done
1784 features: done

The optimal value for the Complexity (n_f) is: 1000
```

[30]:
```
<matplotlib.legend.Legend at 0x7f82f370f450>
```



Plese note that we are utlizing Dropout; this is why Validation accuracy is greater than Training accuracy.

[31]:
```python
# model_3:
# average fitting time (for various n_kept_features):
fit_time_list.append( (end_time-start_time)/len(n_kept_features) )
best_accuracy_list.append(max(accuracy_list))
best_val_accuracy_list.append(max(val_accuracy_list))

print('Confusion Matrix for model_3:')
# Please note that there are 27 classes; so it's quiet fair to have a large␣
↪confusion matrix
start_time=time()
c_m=confusion_matrix_func(model_3, X_test, Y_test)
end_time=time()
predict_time_list.append(end_time-start_time)

c_m
```

```
Confusion Matrix for model_3:
```

[31]:

		animal	architecture	art	biology	bodybuilding	business	\
0	animal	7	0	0	0	0	0	
1	architecture	0	16	1	0	0	0	
2	art	0	1	14	0	0	0	
3	biology	0	0	0	22	0	0	
4	bodybuilding	0	0	0	0	2	0	
5	business	0	0	0	3	0	0	
6	covid	0	0	0	0	0	0	
7	culture	0	0	0	0	0	0	
8	election	0	0	0	0	0	0	
9	engineering	0	0	0	1	0	0	
10	fashion	0	0	1	0	0	0	
11	food	0	0	0	0	0	0	
12	government	0	0	0	0	0	0	
13	gym	0	0	0	0	1	0	
14	innovation	0	0	0	0	0	0	
15	job	0	0	0	0	0	0	
16	love	1	0	2	0	0	0	
17	marketing	0	0	0	1	0	0	
18	medical	0	0	0	0	0	0	
19	pet	1	0	0	0	0	0	
20	pharmacy	0	0	0	1	0	0	
21	physics	0	0	0	11	0	0	
22	political	0	0	0	0	0	0	

23	science	2	0	0	3	0	1
24	solar	0	0	0	0	0	0
25	technology	0	0	0	0	0	0
26	travel	0	0	1	0	0	0

	covid	culture	election	…	marketing	medical	pet	pharmacy	physics	\
0	0	0	0	…	0	0	0	0	0	
1	0	1	0	…	0	0	0	0	0	
2	0	0	0	…	0	0	0	0	0	
3	0	0	0	…	2	0	0	0	1	
4	0	0	0	…	0	0	0	0	0	
5	0	0	0	…	2	0	0	0	0	
6	0	0	0	…	0	0	0	0	0	
7	0	6	0	…	0	0	0	0	0	
8	0	0	0	…	0	0	0	0	0	
9	0	0	0	…	0	0	0	0	0	
10	0	0	0	…	0	0	0	0	0	
11	0	0	0	…	0	0	0	0	0	
12	0	0	0	…	0	0	0	0	0	
13	0	0	0	…	0	0	0	0	0	
14	0	0	0	…	0	0	0	0	0	
15	0	0	0	…	0	0	0	0	0	
16	0	0	0	…	0	0	0	0	0	
17	0	0	0	…	2	0	0	0	0	
18	0	0	0	…	0	5	0	0	0	
19	0	0	0	…	0	0	4	0	0	
20	0	0	0	…	0	0	0	0	0	
21	0	0	0	…	5	0	0	0	9	
22	0	0	0	…	0	0	0	0	0	
23	0	0	0	…	0	0	0	0	0	
24	0	0	0	…	0	0	0	0	0	
25	0	0	0	…	1	0	0	0	0	
26	0	0	0	…	0	0	0	0	0	

	political	science	solar	technology	travel
0	0	0	0	0	2
1	0	1	0	1	4
2	0	0	0	0	3
3	0	1	0	0	0
4	0	2	0	2	5
5	0	0	0	1	1
6	0	0	0	0	9
7	0	1	0	0	2
8	0	0	0	0	0
9	0	0	0	3	5
10	0	0	0	0	1
11	0	2	0	0	0

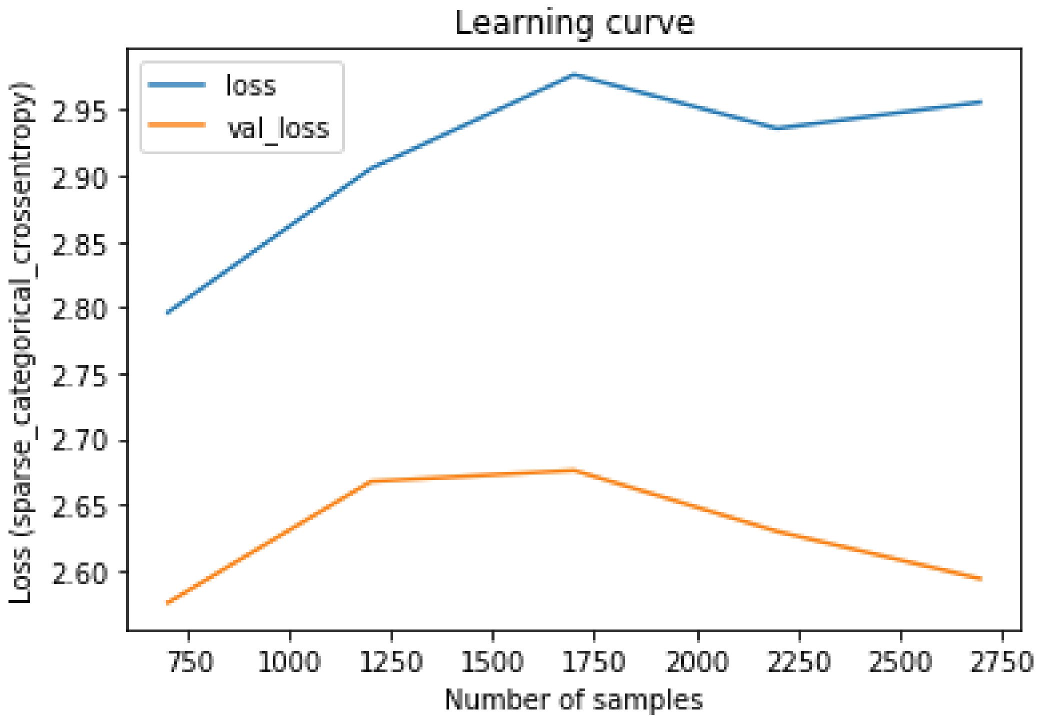
```
12          0       0    0        0     0
13          0       1    0        1     0
14          0       0    0        0     3
15          0       2    0        1     0
16          0       0    0        0     3
17          0       0    0        1     2
18          0       0    0        0     1
19          0       0    0        1     1
20          0       0    0        0     2
21          0       0    0        0     1
22          0       0    0        0     1
23          0       1    0        0     4
24          0       0   33        0     0
25          0       0    0        6     1
26          0       0    0        0    12

[27 rows x 28 columns]
```

[32]:
```python
# model_3:
# Now, we are exploring the Learning Curve process:
n_f=600 # let's set the number of features to be 600 for here (we are still in␣
↪model_3):
n_samples=[700, 1200, 1700, 2200, 2700] # number of data samples we are using␣
↪here
loss_list=[]
val_loss_list=[]

print('Learning Curve process for model_3:')
for n_s in n_samples:
    loss=[]
    val_loss=[]
    for i in range(2): # training a few times, to find the average
        df_sample=sampler(df, n_s)
        X_train, X_test, Y_train, Y_test = train_test_split( df_sample.iloc[:,1:
↪n_f], df_sample['target_tag'])

        model_3=ks.models.Sequential()
        model_3.add(ks.layers.Dense(units=350, activation=ks.activations.relu,␣
↪input_dim=X_train.shape[1]))
        model_3.add(ks.layers.Dropout(0.8))
        model_3.add(ks.layers.Dense(units=350, activation=ks.activations.relu))
        model_3.add(ks.layers.Dropout(0.8))
        model_3.add(ks.layers.Dense(units=27, activation=ks.activations.
↪sigmoid))

        model_3.compile(optimizer=ks.optimizers.Adam(0.005), loss=ks.losses.
↪sparse_categorical_crossentropy,
```

```
                    metrics=ks.metrics.sparse_categorical_accuracy)
        history=model_3.fit(X_train, Y_train, validation_split=0.1, epochs=10,␣
↪batch_size=10, verbose=0)
        loss.append( np.mean( np.sort(history.history['loss'])[:3] ) )
        val_loss.append( np.mean( np.sort(history.history['val_loss'])[:3] ) )

    loss_list.append(np.mean( loss ))
    val_loss_list.append(np.mean( val_loss ))
    print(f'{n_s} samples: done')

min_loss_list.append(min(loss_list))
min_val_loss_list.append(min(val_loss_list))

print(f'\nBias: {np.mean(loss_list[-2:]+val_loss_list[-2:])}')
print(f'Variance: {np.mean(np.array(val_loss_list[-2:])-np.array(loss_list[-2:
↪]))/2}')
print("""According to the bias and variance, it is not obvious if the data is␣
↪enough or not, for this
model. It seems tha the model is not performing well (maybe, Dropout is not␣
↪suitable for this model.)""")
plt.plot(n_samples, loss_list, label='loss')
plt.plot(n_samples, val_loss_list, label='val_loss')
plt.xlabel('Number of samples'), plt.ylabel('Loss␣
↪(sparse_categorical_crossentropy)')
plt.title('Learning curve')
plt.legend()
```

```
Learning Curve process for model_3:
700 samples: done
1200 samples: done
1700 samples: done
2200 samples: done
2700 samples: done

Bias: 2.7787423829237623
Variance: -0.16706370313962293
According to the bias and variance, it is not obvious if the data is enough or
not, for this
model. It seems tha the model is not performing well (maybe, Dropout is not
suitable for this model.)
```

[32]:
```
<matplotlib.legend.Legend at 0x7f82e9129650>
```



As we know, since we are using Dropout, the Training Loss is not comprehensive. Also, the learning curve does not seems to be very helpful.

On the other hand, we shoud note that we have 100,000 samples (in total). Anyway we are not sure model_3 can be useful for these data.')

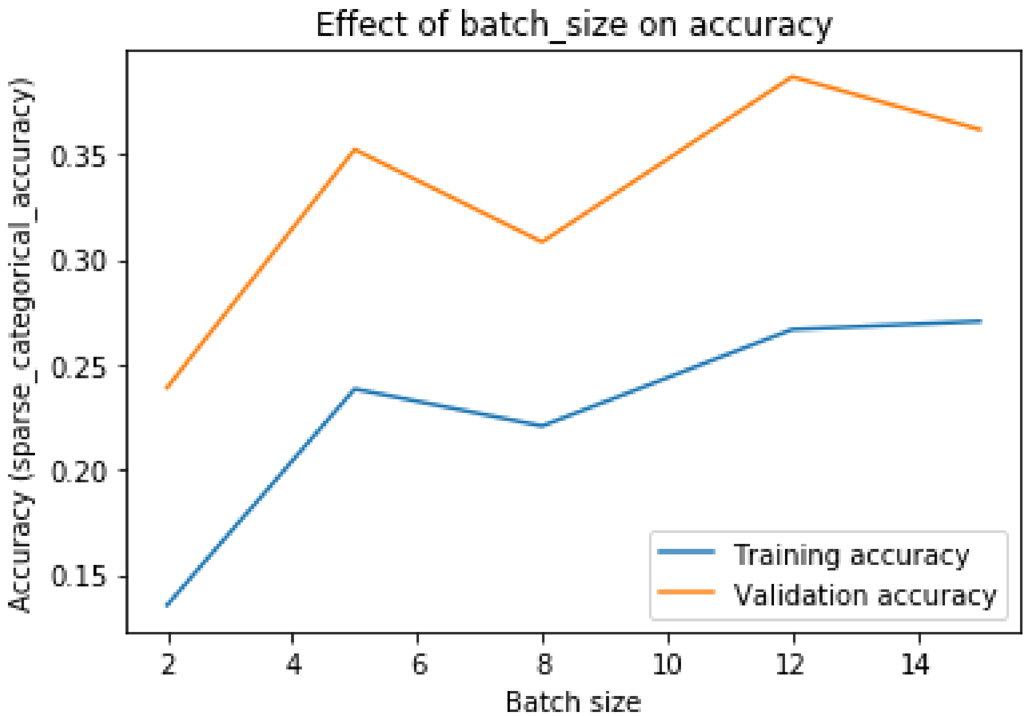
[33]:
```
bias_list.append( np.mean(loss_list[-2:]+val_loss_list[-2:]) )
variance_list.append( np.mean(np.array(val_loss_list[-2:])-np.
↪array(loss_list[-2:]))/2 )
```

[34]:
```
# model_3:
# Fine tunning another hyper-model of model_3; batch_size or the probability of␣
↪the Dropout can be tunned.
# Here, we go for the batch_size:
n_f=600
n_batch_sizes=[2, 5, 8, 12, 15] # different number of batch_size
accuracy_list=[]
val_accuracy_list=[]

print('Fine tunning another hyper-parameter of model_3:')
for n_b_s in n_batch_sizes:
    accuracy=[]
    val_accuracy=[]
    for i in range(2): # training a few times, to find the average
```

```
        df_sample=sampler(df, 700)
        X_train, X_test, Y_train, Y_test = train_test_split( df_sample.iloc[:,1:
↪n_f], df_sample['target_tag'])

        model_3=ks.models.Sequential()
        model_3.add(ks.layers.Dense(units=350, activation=ks.activations.relu,␣
↪input_dim=X_train.shape[1]))
        model_3.add(ks.layers.Dropout(0.8))
        model_3.add(ks.layers.Dense(units=350, activation=ks.activations.relu))
        model_3.add(ks.layers.Dropout(0.8))
        model_3.add(ks.layers.Dense(units=27, activation=ks.activations.
↪sigmoid))

        model_3.compile(optimizer=ks.optimizers.Adam(0.005), loss=ks.losses.
↪sparse_categorical_crossentropy,
                        metrics=ks.metrics.sparse_categorical_accuracy)
        history=model_3.fit(X_train, Y_train, validation_split=0.1, epochs=8,␣
↪batch_size=n_b_s, verbose=0)
        accuracy.append( np.mean( np.sort(history.
↪history['sparse_categorical_accuracy'])[-3:] ) )
        val_accuracy.append( np.mean( np.sort(history.
↪history['val_sparse_categorical_accuracy'])[-3:] ) )

    accuracy_list.append(np.mean( accuracy ))
    val_accuracy_list.append(np.mean( val_accuracy ))
    print(f'Batch_size = {n_b_s} : done')

print(f'\nBest Batch_size: {n_batch_sizes[ np.argmax(val_accuracy_list) ]}')
plt.plot(n_batch_sizes, accuracy_list, label='Training accuracy')
plt.plot(n_batch_sizes, val_accuracy_list, label='Validation accuracy')
plt.xlabel('Batch size'), plt.ylabel('Accuracy (sparse_categorical_accuracy)')
plt.title('Effect of batch_size on accuracy')
plt.legend()
```

```
Fine tunning another hyper-parameter of model_3:
Batch_size = 2 : done
Batch_size = 5 : done
Batch_size = 8 : done
Batch_size = 12 : done
Batch_size = 15 : done

Best Batch_size: 12
```

[34]:
```
<matplotlib.legend.Legend at 0x7f82d87d9850>
```



==

0.0.8 Model 4:

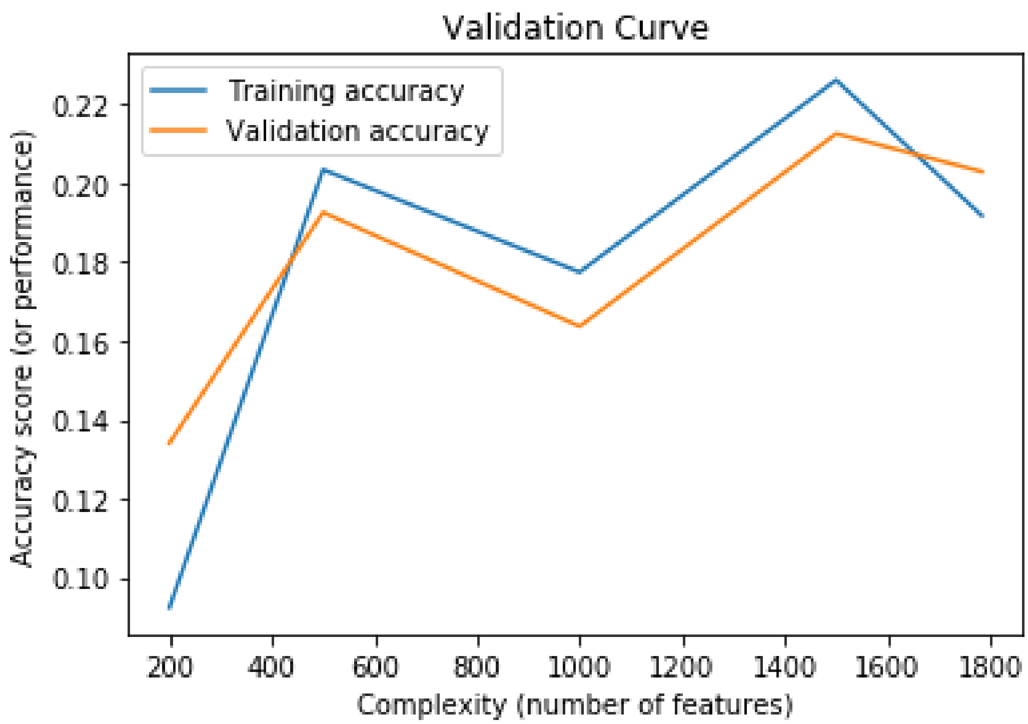
In the forth model, we are utlizing a NN with 4 hidden layers; 400, 300, 150, 150 nodes for hidden layers. Actually, we are making the NN deeper. The activation function is relu (it's sigmoid for output layer). The optimizing algorithm is SGD with lr=0.1 and batch_size=5. Also, we have considered regularization to have 0.01 impact coefficient. About loss function and metric, they are sparse_categorical_crossentropy and sparse_categorical_accuracy.

[35]:
```
# model_4:
# Let's train some different forms of model_4:
# different number of features; changing the complexity:
n_kept_features=[200, 500, 1000, 1500, df.shape[1]-3]
accuracy_list=[]
val_accuracy_list=[]

print('Validation Curve process for model_4:')
print('(Please note that our metric is acuuracy: sparse_categorical_accuracy)')
start_time=time() # time for fitting
for n in n_kept_features:
    acc=[] # calculate the accuracy for a few times
    val_acc=[] # calculate the validation accuracy for a few times
    for i in range(2): # training a few times, to find the average
```

```
        df_sample=sampler(df, 3000) # choose some samples
        X_train, X_test, Y_train, Y_test = train_test_split( df_sample.iloc[:,1:
↪n], df_sample['target_tag'])

        reg_coef_4=0.01 # impact coefficient of regularization
        model_4=ks.models.Sequential()
        model_4.add(ks.layers.Dense(units=400, activation=ks.activations.relu,␣
↪input_dim=X_train.shape[1],
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_4)))
        model_4.add(ks.layers.Dense(units=300, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_4)))
        model_4.add(ks.layers.Dense(units=150, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_4)))
        model_4.add(ks.layers.Dense(units=150, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_4)))
        model_4.add(ks.layers.Dense(units=27, activation=ks.activations.
↪sigmoid))

        model_4.compile(optimizer=ks.optimizers.SGD(0.1), loss=ks.losses.
↪sparse_categorical_crossentropy,
                        metrics=ks.metrics.sparse_categorical_accuracy)
        history=model_4.fit(X_train, Y_train, validation_split=0.1, epochs=7,␣
↪batch_size=5, verbose=0)
        acc.append( np.mean( np.sort(history.
↪history['sparse_categorical_accuracy'])[-3:] ) )
        val_acc.append( np.mean( np.sort(history.
↪history['val_sparse_categorical_accuracy'])[-3:] ) )

    accuracy_list.append(np.mean(acc))
    val_accuracy_list.append(np.mean( val_acc ))
    print(f'{n} features: done')

end_time=time()

print(f'\nThe optimal value for the Complexity (n_f) is: {n_kept_features[np.
↪argmax(val_accuracy_list)]}')
plt.plot(n_kept_features, accuracy_list, label='Training accuracy')
plt.plot(n_kept_features, val_accuracy_list, label='Validation accuracy')
plt.xlabel('Complexity (number of features)'), plt.ylabel('Accuracy score (or␣
↪performance)')
plt.title('Validation Curve')
plt.legend()
```

```
Validation Curve process for model_4:
(Please note that our metric is acuuracy: sparse_categorical_accuracy)
200 features: done
500 features: done
1000 features: done
1500 features: done
1784 features: done

The optimal value for the Complexity (n_f) is: 1500
```

[35]: <matplotlib.legend.Legend at 0x7f8304077950>



[36]:
```
# model_4:
# average fitting time (for various n_kept_features):
fit_time_list.append( (end_time-start_time)/len(n_kept_features) )
best_accuracy_list.append(max(accuracy_list))
best_val_accuracy_list.append(max(val_accuracy_list))

print('Confusion Matrix for model_4:')
# Please note that there are 27 classes; so it's quiet fair to have a large␣
↪confusion matrix
start_time=time()
c_m=confusion_matrix_func(model_4, X_test, Y_test)
end_time=time()
```

```
predict_time_list.append(end_time-start_time)

c_m
```

Confusion Matrix for model_4:

[36]:

		animal	architecture	art	biology	bodybuilding	business	\
0	animal	0	0	0	0	0	6	
1	architecture	0	0	0	0	0	4	
2	art	0	0	0	0	0	9	
3	biology	0	0	0	0	0	2	
4	bodybuilding	0	0	0	0	0	0	
5	business	0	0	0	0	0	3	
6	covid	0	0	0	0	0	7	
7	culture	0	0	0	0	0	7	
8	election	0	0	0	0	0	1	
9	engineering	0	0	0	0	0	3	
10	fashion	0	0	0	0	0	4	
11	food	0	0	0	0	0	2	
12	government	0	0	0	0	0	9	
13	gym	0	0	0	0	0	4	
14	innovation	0	0	0	0	0	4	
15	job	0	0	0	0	0	0	
16	love	0	0	0	0	0	9	
17	marketing	0	0	0	0	0	5	
18	medical	0	0	0	0	0	11	
19	pet	0	0	0	0	0	1	
20	pharmacy	0	0	0	0	0	3	
21	physics	0	0	0	0	0	1	
22	political	0	0	0	0	0	3	
23	science	0	0	0	0	0	5	
24	solar	0	0	0	0	0	0	
25	technology	0	0	0	0	0	6	
26	travel	0	0	0	0	0	1	

	covid	culture	election	…	marketing	medical	pet	pharmacy	physics	\
0	13	0	0	…	0	0	0	0	0	
1	10	0	0	…	0	0	0	0	0	
2	15	0	0	…	0	0	0	0	0	
3	2	0	0	…	0	0	0	0	16	
4	2	0	0	…	0	0	0	0	0	
5	8	0	0	…	0	0	0	0	1	
6	20	0	0	…	0	0	0	0	0	
7	21	0	0	…	0	0	0	0	0	
8	9	0	0	…	0	0	0	0	0	
9	12	0	0	…	0	0	0	0	0	
10	3	0	0	…	0	0	0	0	0	

11	7	0	0	…	0	0	0	0	0
12	22	0	0	…	0	0	0	0	0
13	10	0	0	…	0	0	0	0	0
14	18	0	0	…	0	0	0	0	0
15	4	0	0	…	0	0	0	0	0
16	26	0	0	…	0	0	0	0	0
17	4	0	0	…	0	0	0	0	1
18	11	0	0	…	0	0	0	0	0
19	8	0	0	…	0	0	0	0	0
20	7	0	0	…	0	0	0	0	2
21	1	0	0	…	0	0	0	0	19
22	6	0	0	…	0	0	0	0	2
23	7	0	0	…	0	0	0	0	4
24	1	0	0	…	0	0	0	0	2
25	13	0	0	…	0	0	0	0	0
26	13	0	0	…	0	0	0	0	0

	political	science	solar	technology	travel
0	0	1	0	0	7
1	0	1	0	0	7
2	0	3	0	0	1
3	0	8	0	0	0
4	0	0	0	0	8
5	0	12	0	0	0
6	0	1	0	0	3
7	0	2	0	0	2
8	0	1	0	0	2
9	0	4	0	0	7
10	0	23	0	0	2
11	0	3	0	0	8
12	0	2	0	0	2
13	0	0	0	0	11
14	0	6	0	0	1
15	0	0	0	0	13
16	0	4	0	0	0
17	0	16	0	0	2
18	0	11	0	0	2
19	0	0	0	0	14
20	0	2	0	0	3
21	0	6	0	0	0
22	0	4	0	0	0
23	0	10	0	0	2
24	0	5	21	0	0
25	0	4	0	0	2
26	0	1	0	0	9

[27 rows x 28 columns]

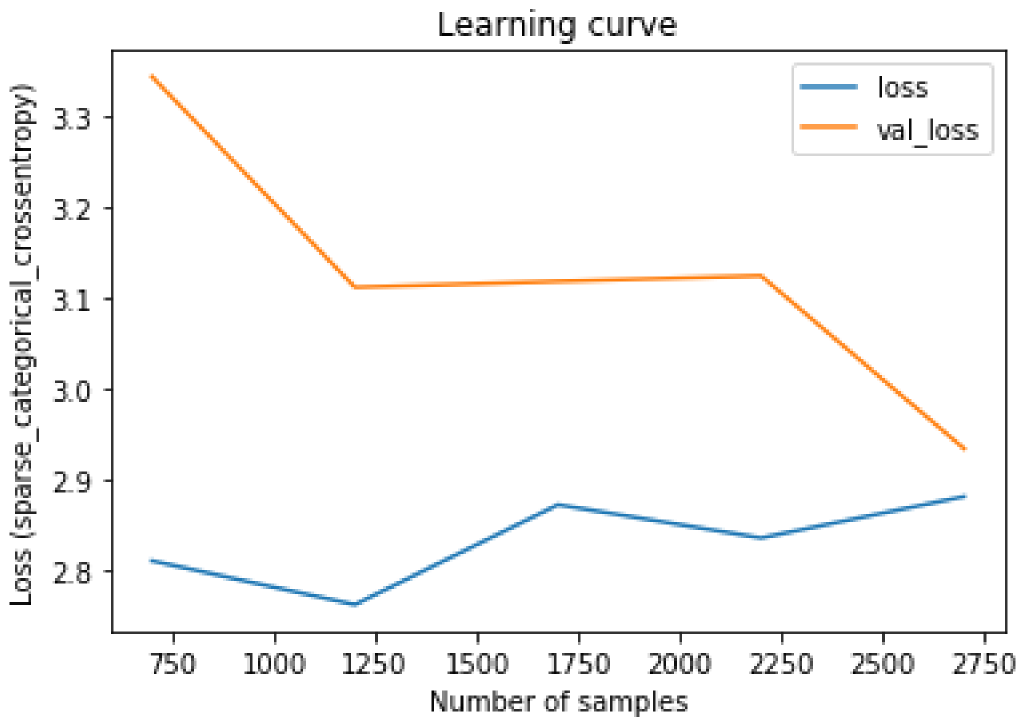
[37]:

```
# model_4:
# Now, we are exploring the Learning Curve process:
n_f=600 # let's set the number of features to be 600 for here (we are still in␣
↪model_4):
n_samples=[700, 1200, 1700, 2200, 2700] # number of data samples we are using␣
↪here
loss_list=[]
val_loss_list=[]

print('Learning Curve process for model_4:')
for n_s in n_samples:
    loss=[]
    val_loss=[]
    for i in range(2): # training a few times, to find the average
        df_sample=sampler(df, n_s)
        X_train, X_test, Y_train, Y_test = train_test_split( df_sample.iloc[:,1:
↪n_f], df_sample['target_tag'])

        reg_coef_4=0.01 # impact coefficient of regularization
        model_4=ks.models.Sequential()
        model_4.add(ks.layers.Dense(units=400, activation=ks.activations.relu,␣
↪input_dim=X_train.shape[1],
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_4)))
        model_4.add(ks.layers.Dense(units=300, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_4)))
        model_4.add(ks.layers.Dense(units=150, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_4)))
        model_4.add(ks.layers.Dense(units=150, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_4)))
        model_4.add(ks.layers.Dense(units=27, activation=ks.activations.
↪sigmoid))

        model_4.compile(optimizer=ks.optimizers.SGD(0.1), loss=ks.losses.
↪sparse_categorical_crossentropy,
                        metrics=ks.metrics.sparse_categorical_accuracy)
        history=model_4.fit(X_train, Y_train, validation_split=0.1, epochs=15,␣
↪batch_size=5, verbose=0)
        loss.append( np.mean( np.sort(history.history['loss'])[:3] ) )
        val_loss.append( np.mean( np.sort(history.history['val_loss'])[:3] ) )

    loss_list.append(np.mean( loss ))
    val_loss_list.append(np.mean( val_loss ))
```

```
    print(f'{n_s} samples: done')

min_loss_list.append(min(loss_list))
min_val_loss_list.append(min(val_loss_list))

print(f'\nBias: {np.mean(loss_list[-2:]+val_loss_list[-2:])}')
print(f'Variance: {np.mean(np.array(val_loss_list[-2:])-np.array(loss_list[-2:
→]))/2}')
print("""According to the amount of bias and variance, it seems that we have␣
→enough data. Please
note that we have 100,000 samples (in total). And it is almost a good model.""")
plt.plot(n_samples, loss_list, label='loss')
plt.plot(n_samples, val_loss_list, label='val_loss')
plt.xlabel('Number of samples'), plt.ylabel('Loss␣
→(sparse_categorical_crossentropy)')
plt.title('Learning curve')
plt.legend()
```

```
Learning Curve process for model_4:
700 samples: done
1200 samples: done
1700 samples: done
2200 samples: done
2700 samples: done

Bias: 2.9437675972779593
Variance: 0.08559971054395055
According to the amount of bias and variance, it seems that we have enough data.
Please
note that we have 100,000 samples (in total). And it is almost a good model.
```

[37]:
```
<matplotlib.legend.Legend at 0x7f82b81adb50>
```



Please note that we are using regularization with 0.01 impact coefficient. Without regularization, we have to deal with overfitting.

[38]:
```
bias_list.append( np.mean(loss_list[-2:]+val_loss_list[-2:]) )
variance_list.append( np.mean(np.array(val_loss_list[-2:])-np.
 ↪array(loss_list[-2:]))/2 )
```

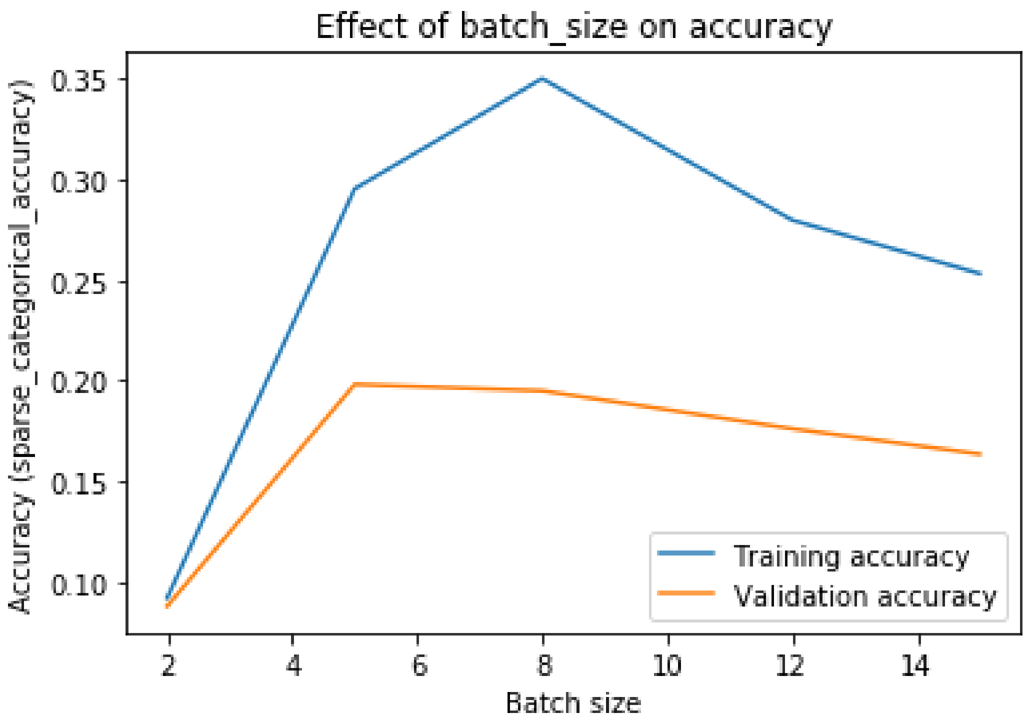
[39]:
```
# model_4:
# Fine tunning another hyper-model of model_4; batch_size or learning rate can␣
 ↪be tunned.
# Here, we go for the batch_size:
n_f=600
n_batch_sizes=[2, 5, 8, 12, 15] # different number of batch_size
accuracy_list=[]
val_accuracy_list=[]

print('Fine tunning another hyper-parameter of model_4:')
for n_b_s in n_batch_sizes:
    accuracy=[]
    val_accuracy=[]
    for i in range(2): # training a few times, to find the average
        df_sample=sampler(df, 700)
        X_train, X_test, Y_train, Y_test = train_test_split( df_sample.iloc[:,1:
 ↪n_f], df_sample['target_tag'])
```

```
        reg_coef_4=0.01 # impact coefficient of regularization
        model_4=ks.models.Sequential()
        model_4.add(ks.layers.Dense(units=400, activation=ks.activations. relu,␣
 ↪input_dim=X_train.shape[1],
                                    kernel_regularizer=ks.regularizers.
 ↪l2(reg_coef_4)))
        model_4.add(ks.layers.Dense(units=300, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
 ↪l2(reg_coef_4)))
        model_4.add(ks.layers.Dense(units=150, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
 ↪l2(reg_coef_4)))
        model_4.add(ks.layers.Dense(units=150, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
 ↪l2(reg_coef_4)))
        model_4.add(ks.layers.Dense(units=27, activation=ks.activations.
 ↪sigmoid))

        model_4.compile(optimizer=ks.optimizers.SGD(0.1), loss=ks.losses.
 ↪sparse_categorical_crossentropy,
                        metrics=ks.metrics.sparse_categorical_accuracy)
        history=model_4.fit(X_train, Y_train, validation_split=0.1, epochs=15,␣
 ↪batch_size=n_b_s, verbose=0)
        accuracy.append( np.mean( np.sort(history.
 ↪history['sparse_categorical_accuracy'])[-3:] ) )
        val_accuracy.append( np.mean( np.sort(history.
 ↪history['val_sparse_categorical_accuracy'])[-3:] ) )

    accuracy_list.append(np.mean( accuracy ))
    val_accuracy_list.append(np.mean( val_accuracy ))
    print(f'Batch_size = {n_b_s} : done')

print(f'\nBest Batch_size: {n_batch_sizes[ np.argmax(val_accuracy_list) ]}')
plt.plot(n_batch_sizes, accuracy_list, label='Training accuracy')
plt.plot(n_batch_sizes, val_accuracy_list, label='Validation accuracy')
plt.xlabel('Batch size'), plt.ylabel('Accuracy (sparse_categorical_accuracy)')
plt.title('Effect of batch_size on accuracy')
plt.legend()
```

```
Fine tunning another hyper-parameter of model_4:
Batch_size = 2 : done
Batch_size = 5 : done
Batch_size = 8 : done
Batch_size = 12 : done
Batch_size = 15 : done
```

```
Best Batch_size: 5
```

[39]: <matplotlib.legend.Legend at 0x7f82e361d2d0>




```
==========================================================================
```

0.0.9 Model 5:

In the fifth model, we are utlizing a NN with 4 hidden layers; 350, 350, 500, 150 nodes for hidden layers. Actually, we are not changing the depth, but increasing the number of nodes. The activation function is relu (it's sigmoid for output layer). The optimizing algorithm is SGD with lr=0.1 and batch_size=15. Also, we have considered regularization to have 0.01 impact coefficient. About loss function and metric, they are sparse_categorical_crossentropy and sparse_categorical_accuracy.

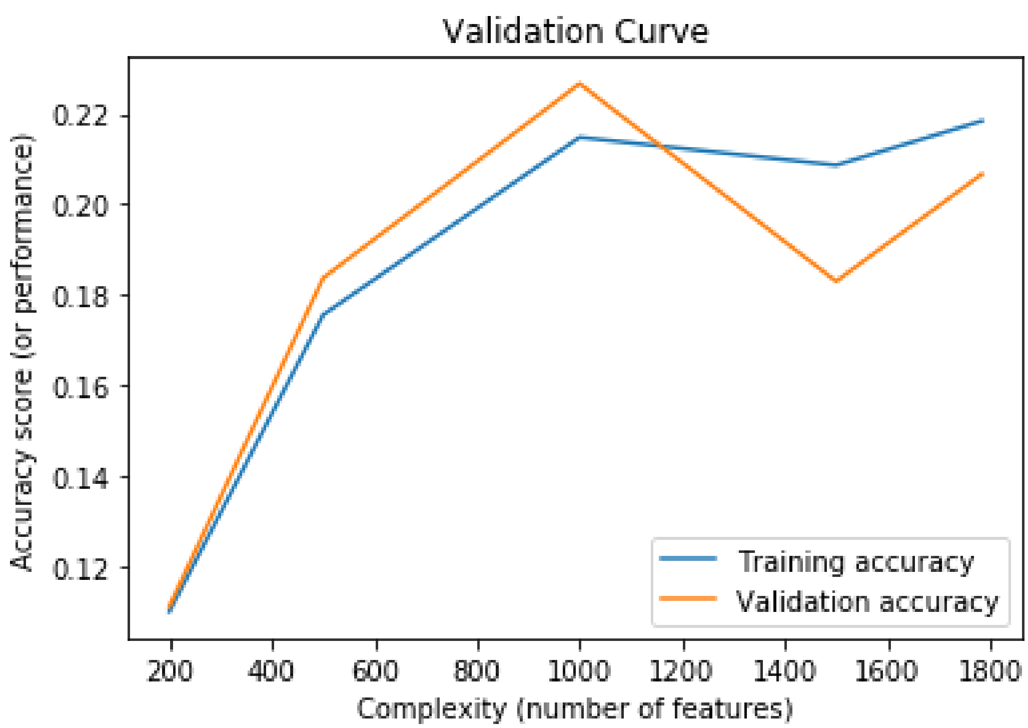
[41]:
```
# model_5:
# Let's train some different forms of model_5:
# different number of features; changing the complexity:
n_kept_features=[200, 500, 1000, 1500, df.shape[1]-3]
accuracy_list=[]
val_accuracy_list=[]

print('Validation Curve process for model_5:')
print('(Please note that our metric is acuuracy: sparse_categorical_accuracy)')
start_time=time() # time for fitting
```

```
for n in n_kept_features:
    acc=[] # calculate the accuracy for a few times
    val_acc=[] # calculate the validation accuracy for a few times
    for i in range(2): # training a few times, to find the average
        df_sample=sampler(df, 3000) # choose some samples
        X_train, X_test, Y_train, Y_test = train_test_split( df_sample.iloc[:,1:
↪n], df_sample['target_tag'])

        reg_coef_5=0.01 # impact coefficient of regularization
        model_5=ks.models.Sequential()
        model_5.add(ks.layers.Dense(units=350, activation=ks.activations.relu,␣
↪input_dim=X_train.shape[1],
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_5)))
        model_5.add(ks.layers.Dense(units=350, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_5)))
        model_5.add(ks.layers.Dense(units=500, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_5)))
        model_5.add(ks.layers.Dense(units=150, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_5)))
        model_5.add(ks.layers.Dense(units=27, activation=ks.activations.
↪sigmoid))

        model_5.compile(optimizer=ks.optimizers.SGD(0.1), loss=ks.losses.
↪sparse_categorical_crossentropy,
                        metrics=ks.metrics.sparse_categorical_accuracy)
        history=model_5.fit(X_train, Y_train, validation_split=0.1, epochs=7,␣
↪batch_size=15, verbose=0)
        acc.append( np.mean( np.sort(history.
↪history['sparse_categorical_accuracy'])[-3:] ) )
        val_acc.append( np.mean( np.sort(history.
↪history['val_sparse_categorical_accuracy'])[-3:] ) )

    accuracy_list.append(np.mean(acc))
    val_accuracy_list.append(np.mean( val_acc ))
    print(f'{n} features: done')

end_time=time()

print(f'\nThe optimal value for the Complexity (n_f) is: {n_kept_features[np.
↪argmax(val_accuracy_list)]}')
plt.plot(n_kept_features, accuracy_list, label='Training accuracy')
plt.plot(n_kept_features, val_accuracy_list, label='Validation accuracy')
```

```
plt.xlabel('Complexity (number of features)'), plt.ylabel('Accuracy score (or␣
 ↪performance)')
plt.title('Validation Curve')
plt.legend()
```

```
Validation Curve process for model_5:
(Please note that our metric is acuuracy: sparse_categorical_accuracy)
200 features: done
500 features: done
1000 features: done
1500 features: done
1784 features: done

The optimal value for the Complexity (n_f) is: 1000
```

[41]:
```
<matplotlib.legend.Legend at 0x7f82b82c50d0>
```



[42]:
```
# model_5:
# average fitting time (for various n_kept_features):
fit_time_list.append( (end_time-start_time)/len(n_kept_features) )
best_accuracy_list.append(max(accuracy_list))
best_val_accuracy_list.append(max(val_accuracy_list))
```

```
print('Confusion Matrix for model_5:')
# Please note that there are 27 classes; so it's quiet fair to have a large␣
↪confusion matrix
start_time=time()
c_m=confusion_matrix_func(model_5, X_test, Y_test)
end_time=time()
predict_time_list.append(end_time-start_time)

c_m
```

Confusion Matrix for model_5:

[42]:

```
                   animal  architecture  art  biology  bodybuilding  business  \
0          animal       0             0    0        0             0         0
1    architecture       0             0    3        0             0         0
2             art       0             0   13        0             0         0
3         biology       0             0    0        0             0         0
4    bodybuilding       0             0    0        0             0         0
5        business       0             0    0        0             0         0
6           covid       0             0    1        0             0         0
7         culture       0             0    1        0             0         0
8        election       0             0    0        0             0         0
9     engineering       0             0    0        0             0         0
10        fashion       0             0    4        0             0         0
11           food       0             0    0        0             0         0
12     government       0             0    0        0             0         0
13            gym       0             0    0        0             0         0
14     innovation       0             0    0        0             0         0
15            job       0             0    0        0             0         0
16           love       0             0    0        0             0         0
17      marketing       0             0    0        0             0         0
18        medical       0             0    0        0             0         0
19            pet       0             0    0        0             0         0
20       pharmacy       0             0    0        0             0         0
21        physics       0             0    0        0             0         0
22      political       0             0    2        0             0         0
23        science       0             0    0        0             0         0
24          solar       0             0    0        0             0         0
25     technology       0             0    0        0             0         0
26         travel       0             0    0        0             0         0

    covid  culture  election  …  marketing  medical  pet  pharmacy  physics  \
0       2        0         0  …          2        3   13         0        0
1       0        0         0  …         14       13    1         0        0
2       0        0         0  …         10        2    1         0        0
3       0        0         0  …          3        0    0         0       32
4       0        0         0  …          0        3    2         0        0
```

5	0	0	0	…	9	6	0	0	2
6	3	0	0	…	13	11	1	0	1
7	0	0	0	…	9	10	1	0	0
8	0	0	0	…	4	6	0	0	0
9	0	0	0	…	10	5	0	0	1
10	0	0	0	…	2	2	1	0	0
11	0	0	0	…	3	0	2	0	0
12	0	0	0	…	3	11	1	0	0
13	0	0	0	…	3	6	4	0	0
14	0	0	0	…	8	10	0	0	0
15	0	0	0	…	4	2	0	0	0
16	1	0	0	…	5	3	4	0	0
17	0	0	0	…	12	12	2	0	4
18	0	0	0	…	10	14	2	0	0
19	0	0	0	…	2	2	14	0	0
20	0	0	0	…	7	15	0	0	0
21	0	0	0	…	0	0	0	0	28
22	0	0	0	…	6	8	0	0	2
23	0	0	0	…	13	2	2	0	2
24	0	0	0	…	0	1	0	0	0
25	0	0	0	…	8	16	0	0	1
26	0	0	0	…	6	2	16	0	0

	political	science	solar	technology	travel
0	0	0	0	0	0
1	0	0	0	0	1
2	0	0	0	0	1
3	0	0	0	0	0
4	0	0	0	0	0
5	0	0	0	0	0
6	0	0	0	0	2
7	0	0	0	0	0
8	0	0	0	0	0
9	0	0	0	0	0
10	0	0	0	0	0
11	0	0	0	0	0
12	0	0	0	0	0
13	0	0	0	0	0
14	0	0	0	0	0
15	0	0	0	0	0
16	0	0	0	0	1
17	0	0	0	0	0
18	0	0	0	0	0
19	0	0	0	0	0
20	0	0	0	0	1
21	0	0	0	0	0
22	0	0	0	0	0

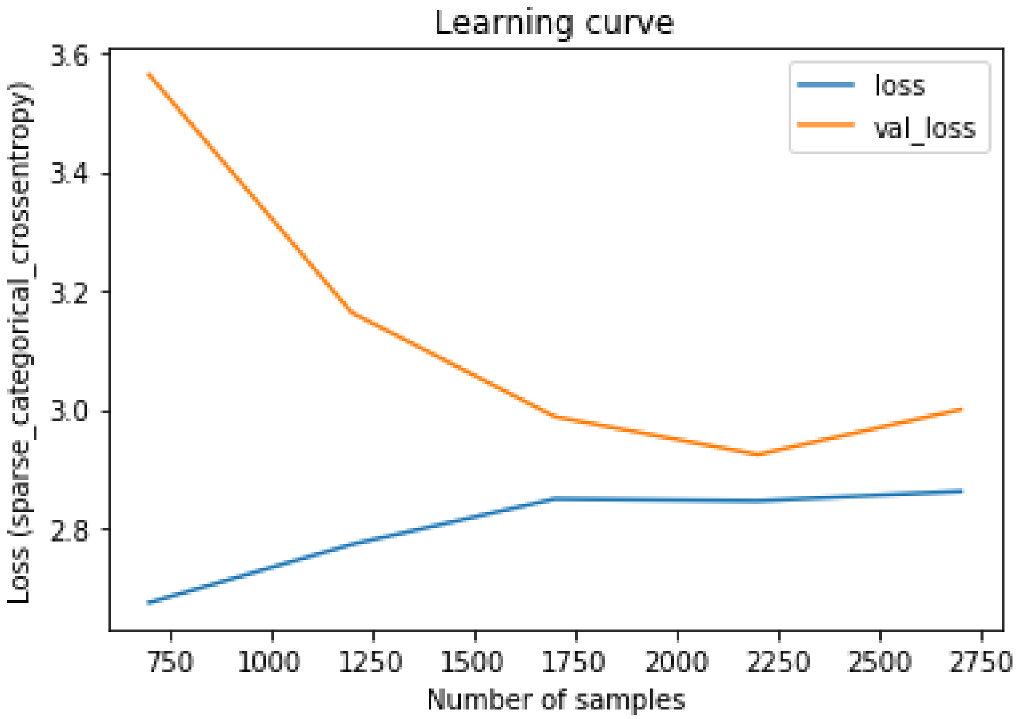
```
23            0            0        0              0          0
24            0            0       20              0          0
25            0            0        0              0          1
26            0            0        0              0          0

[27 rows x 28 columns]
```

[43]:
```
# model_5:
# Now, we are exploring the Learning Curve process:
n_f=600 # let's set the number of features to be 600 for here (we are still in␣
↪model_5):
n_samples=[700, 1200, 1700, 2200, 2700] # number of data samples we are using␣
↪here
loss_list=[]
val_loss_list=[]

print('Learning Curve process for model_5:')
for n_s in n_samples:
    loss=[]
    val_loss=[]
    for i in range(2): # training a few times, to find the average
        df_sample=sampler(df, n_s)
        X_train, X_test, Y_train, Y_test = train_test_split( df_sample.iloc[:,1:
↪n_f], df_sample['target_tag'])

        reg_coef_5=0.01 # impact coefficient of regularization
        model_5=ks.models.Sequential()
        model_5.add(ks.layers.Dense(units=350, activation=ks.activations.relu,␣
↪input_dim=X_train.shape[1],
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_5)))
        model_5.add(ks.layers.Dense(units=350, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_5)))
        model_5.add(ks.layers.Dense(units=500, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_5)))
        model_5.add(ks.layers.Dense(units=150, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_5)))
        model_5.add(ks.layers.Dense(units=27, activation=ks.activations.
↪sigmoid))

        model_5.compile(optimizer=ks.optimizers.SGD(0.1), loss=ks.losses.
↪sparse_categorical_crossentropy,
                        metrics=ks.metrics.sparse_categorical_accuracy)
```

```
        history=model_5.fit(X_train, Y_train, validation_split=0.1, epochs=15,␣
 ↪batch_size=5, verbose=0)
        loss.append( np.mean( np.sort(history.history['loss'])[:3] ) )
        val_loss.append( np.mean( np.sort(history.history['val_loss'])[:3] ) )

    loss_list.append(np.mean( loss ))
    val_loss_list.append(np.mean( val_loss ))
    print(f'{n_s} samples: done')

min_loss_list.append(min(loss_list))
min_val_loss_list.append(min(val_loss_list))

print(f'\nBias: {np.mean(loss_list[-2:]+val_loss_list[-2:])}')
print(f'Variance: {np.mean(np.array(val_loss_list[-2:])-np.array(loss_list[-2:
 ↪]))/2}')
print("""According to the amount of bias and variance, it seems that we have␣
 ↪enough
data. Please note that we have 100,000 samples (in total)""")
plt.plot(n_samples, loss_list, label='loss')
plt.plot(n_samples, val_loss_list, label='val_loss')
plt.xlabel('Number of samples'), plt.ylabel('Loss␣
 ↪(sparse_categorical_crossentropy)')
plt.title('Learning curve')
plt.legend()
```

```
Learning Curve process for model_5:
700 samples: done
1200 samples: done
1700 samples: done
2200 samples: done
2700 samples: done

Bias: 2.908160348733266
Variance: 0.05389159917831432
According to the amount of bias and variance, it seems that we have enough
data. Please note that we have 100,000 samples (in total)
```

[43]:
```
<matplotlib.legend.Legend at 0x7f82b839aa10>
```



Please note that we are using regularization with 0.01 impact coefficient. Without regularization, we have to deal with overfitting.

[44]:
```
bias_list.append( np.mean(loss_list[-2:]+val_loss_list[-2:]) )
variance_list.append( np.mean(np.array(val_loss_list[-2:])-np.
 ↪array(loss_list[-2:]))/2 )
```

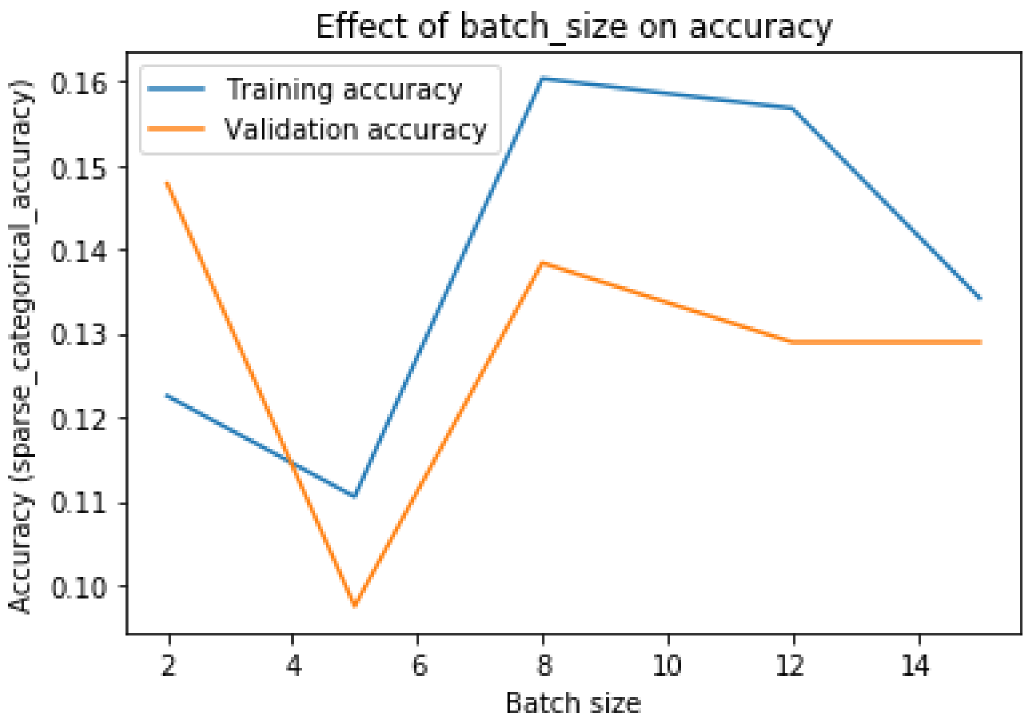
[46]:
```
# model_5:
# Fine tunning another hyper-model of model_5; batch_size or learning rate can␣
 ↪be tunned.
# Here, we go for the batch_size:
n_f=600
n_batch_sizes=[2, 5, 8, 12, 15] # different number of batch_size
# n_batch_sizes=[2,5]
accuracy_list=[]
val_accuracy_list=[]

print('Fine tunning another hyper-parameter of model_5:')
for n_b_s in n_batch_sizes:
    accuracy=[]
    val_accuracy=[]
    for i in range(2): # training a few times, to find the average
        df_sample=sampler(df, 700)
```

```
        X_train, X_test, Y_train, Y_test = train_test_split( df_sample.iloc[:,1:
↪n_f], df_sample['target_tag'])

        reg_coef_5=0.01 # impact coefficient of regularization
        model_5=ks.models.Sequential()
        model_5.add(ks.layers.Dense(units=350, activation=ks.activations.relu,␣
↪input_dim=X_train.shape[1],
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_5)))
        model_5.add(ks.layers.Dense(units=350, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_5)))
        model_5.add(ks.layers.Dense(units=500, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_5)))
        model_5.add(ks.layers.Dense(units=150, activation=ks.activations.relu,
                                    kernel_regularizer=ks.regularizers.
↪l2(reg_coef_5)))
        model_5.add(ks.layers.Dense(units=27, activation=ks.activations.
↪sigmoid))

        model_5.compile(optimizer=ks.optimizers.SGD(0.1), loss=ks.losses.
↪sparse_categorical_crossentropy,
                     metrics=ks.metrics.sparse_categorical_accuracy)
        history=model_5.fit(X_train, Y_train, validation_split=0.1, epochs=5,␣
↪batch_size=n_b_s, verbose=0)
        accuracy.append( np.mean( np.sort(history.
↪history['sparse_categorical_accuracy'])[-3:] ) )
        val_accuracy.append( np.mean( np.sort(history.
↪history['val_sparse_categorical_accuracy'])[-3:] ) )

    accuracy_list.append(np.mean( accuracy ))
    val_accuracy_list.append(np.mean( val_accuracy ))
    print(f'Batch_size = {n_b_s} : done')

print(f'\nBest Batch_size: {n_batch_sizes[ np.argmax(val_accuracy_list) ]}')
plt.plot(n_batch_sizes, accuracy_list, label='Training accuracy')
plt.plot(n_batch_sizes, val_accuracy_list, label='Validation accuracy')
plt.xlabel('Batch size'), plt.ylabel('Accuracy (sparse_categorical_accuracy)')
plt.title('Effect of batch_size on accuracy')
plt.legend()
```

```
Fine tunning another hyper-parameter of model_5:
Batch_size = 2 : done
Batch_size = 5 : done
Batch_size = 8 : done
Batch_size = 12 : done
```

```
Batch_size = 15 : done

Best Batch_size: 2
```

[46]: <matplotlib.legend.Legend at 0x7f82c9e56f50>



[56]:
```
# For Comparing:
model_list=['model_1', 'model_2', 'model_3', 'model_4', 'model_5']
total_number_of_layers_list=[4, 5, 6, 6, 6]
number_of_hidden_nodes_list=[800, 850, 700, 1000, 1350]
overfit_controling=['Regularization', 'Regularization', 'Dropout',␣
 ↪'Regularization', 'Regularization']
variance_list=np.abs(variance_list)
```

[58]:
```
print('Comparing the models:')
DataFrame(zip(model_list,
          total_number_of_layers_list,
          number_of_hidden_nodes_list,
          fit_time_list,
          predict_time_list,
          best_accuracy_list,
          best_val_accuracy_list,
          min_loss_list,
          min_val_loss_list,
```

```
            bias_list,
            variance_list,
            overfit_controling),
            columns=['', 'total_number_of_layers', 'number_of_hidden_nodes',␣
↪'fit_time', 'prediction_time',
                     'best_accuracy', 'best_val_accuracy', 'min_loss',␣
↪'min_val_loss', 'bias', 'variance',
                     'overfit_controling'])
```

Comparing the models:

[58]:

		total_number_of_layers	number_of_hidden_nodes	fit_time
0	model_1	4	800	13.065566
1	model_2	5	850	43.287993
2	model_3	6	700	23.715857
3	model_4	6	1000	30.815356
4	model_5	6	1350	15.592041

	prediction_time	best_accuracy	best_val_accuracy	min_loss	min_val_loss
0	0.294317	0.461180	0.420247	1.545587	2.698786
1	0.222327	0.416626	0.376296	2.179018	2.981330
2	0.213158	0.256187	0.392099	2.796139	2.575549
3	0.230614	0.226173	0.212593	2.761690	2.933845
4	0.240349	0.218436	0.226667	2.675062	2.924040

	bias	variance	overfit_controling
0	2.575176	0.203092	Regularization
1	2.830942	0.151065	Regularization
2	2.778742	0.167064	Dropout
3	2.943768	0.085600	Regularization
4	2.908160	0.053892	Regularization

0.0.10 Important results:

1. Four or five layers should be enough for our task.
2. We need about 1000 nodes to creat a good model.
3. Regularization is beter than Dropout for this task.
4. It's better to increase the number of nodes at the primary layers, and then decrease them.