Assignment 10

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Assignment 10.1

In the first part of the assignment, you will implement basic text-preprocessing functions in Python. These functions do not need to scale to large text documents and will only need to handle small inputs.

Assignment 10.1.a

Create a tokenize function that splits a sentence into words. Ensure that your tokenizer removes basic punctuation.

```
def tokenize(sentence):
    tokens = []
    # tokenize the sentence
    return tokens
```

In [1]:

```python
import string

def tokenize(sentence):
    # standardize to lowercase
    sentence = sentence.lower()

    # remove punctuation
    sentence = "".join(char for char in sentence if char not in string.punctuation)

    # split words into separate tokens
    return sentence.split()
```

In [2]:

```python
sentence = "Hello World!! This is DSC650 Class"
sentence
```

Out[2]:

```
'Hello World!! This is DSC650 Class'
```

In [3]:
```
tokenized_text = tokenize(sentence)
tokenized_text
```

Out[3]: `['hello', 'world', 'this', 'is', 'dsc650', 'class']`

Assignment 10.1.b

Implement an `ngram` function that splits tokens into N-grams.

```
def ngram(tokens, n):
    ngrams = []
    # Create ngrams
    return ngrams
```

In [4]:
```
def ngram(tokens, n):
    # Zip the tokens into n-grams
    temp = zip(*[tokens[i:] for i in range(0, n)])
    # Join the n-grams
    return [" ".join(ngram) for ngram in temp]
```

In [5]:
```
unigram = ngram(tokenized_text, 1)
unigram
```

Out[5]: `['hello', 'world', 'this', 'is', 'dsc650', 'class']`

In [6]:
```
bigram = ngram(tokenized_text, 2)
bigram
```

Out[6]: `['hello world', 'world this', 'this is', 'is dsc650', 'dsc650 class']`

In [7]:
```
trigram = ngram(tokenized_text, 3)
trigram
```

Out[7]: `['hello world this', 'world this is', 'this is dsc650', 'is dsc650 class']`

Assignment 10.1.c

Implement an one_hot_encode function to create a vector from a numerical vector from a list of tokens.

```
def one_hot_encode(tokens, num_words):
    token_index = {}
    results = ''
    return results
```

In [8]:

```
## Import numpy library
import numpy as np
```

In [9]:

```
def one_hot_encode(tokens, num_words):
    # Build an index of the tokens
    token_index = {}
    for word in tokens:
        if word not in token_index:
            # Assign an index to each unique word
            token_index[word] = len(token_index) + 1
    # Vectorize the tokens
    max_length = 10
    # Create vector of zeros
    results = np.zeros(shape=(max_length,
                              max(token_index.values()) + 1))
    # One-hot-encode the words to the results vector
    for i, word in list(enumerate(tokens))[:max_length]:
        index = token_index.get(word)
        results[i, index] = 1
    return results
```

In [10]:

```
one_hot_text = one_hot_encode(tokenized_text, 1000)
one_hot_text
```

Out[10]:

```
array([[0., 1., 0., 0., 0., 0., 0.],
       [0., 0., 1., 0., 0., 0., 0.],
       [0., 0., 0., 1., 0., 0., 0.],
       [0., 0., 0., 0., 1., 0., 0.],
       [0., 0., 0., 0., 0., 1., 0.],
       [0., 0., 0., 0., 0., 0., 1.],
       [0., 0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0., 0.]])
```

Assignment 10.2

Using listings 6.16, 6.17, and 6.18 in Deep Learning with Python as a guide, train a sequential model with embeddings on the IMDB data found in data/external/imdb/. Produce the model performance metrics and training and validation accuracy curves within the Jupyter notebook.

In [11]:

```
## Import os lib to read the source files
import os
```

In [12]:

```
# Process the labels of the raw IMDB data
imdb_dir = '/home/jovyan/dsc650/data/external/imdb/aclImdb'
train_dir = os.path.join(imdb_dir, 'train')

labels = []
texts = []

for label_type in ['neg', 'pos']:
    dir_name = os.path.join(train_dir, label_type)
    for fname in os.listdir(dir_name):
        if fname[-4:] == '.txt':
            f = open(os.path.join(dir_name, fname))
            texts.append(f.read())
            f.close()
            if label_type == 'neg':
                labels.append(0)
            else:
                labels.append(1)
```

In [13]:

```
# Tokenizing the text and prepare a train/val split
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
import numpy as np

maxlen = 100
training_samples = 200
validation_samples = 10000
max_words = 10000

tokenizer = Tokenizer(num_words=max_words)
tokenizer.fit_on_texts(texts)
```

```
sequences = tokenizer.texts_to_sequences(texts)

word_index = tokenizer.word_index
print('Found %s unique tokens.' % len(word_index))

data = pad_sequences(sequences, maxlen=maxlen)

labels = np.asarray(labels)
print('Shape of data tensor:', data.shape)
print('Shape of label tensor:', labels.shape)

indices = np.arange(data.shape[0])
np.random.shuffle(indices) # shuffle data before splitting
data = data[indices]
labels = labels[indices]

x_train = data[:training_samples]
y_train = labels[:training_samples]
x_val = data[training_samples: training_samples + validation_samples]
y_val = labels[training_samples: training_samples + validation_samples]
```

```
Found 88582 unique tokens.
Shape of data tensor: (25000, 100)
Shape of label tensor: (25000,)
```

In [14]:

```
# Train the model without pretrained word embeddings
from keras.models import Sequential
from keras.layers import Embedding, Flatten, Dense

embedding_dim = 100

model = Sequential()
model.add(Embedding(max_words, embedding_dim, input_length=maxlen))
model.add(Flatten())
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
model.summary()

# Compile and train the model
model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['acc'])
history = model.fit(x_train, y_train,
                    epochs=10,
```

```
                    batch_size=32,
validation_data=(x_val, y_val))
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
embedding (Embedding)        (None, 100, 100)          1000000   
_________________________________________________________________
flatten (Flatten)            (None, 10000)             0         
_________________________________________________________________
dense (Dense)                (None, 32)                320032    
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 33        
=================================================================
Total params: 1,320,065
Trainable params: 1,320,065
Non-trainable params: 0
_________________________________________________________________
Epoch 1/10
7/7 [==============================] - 1s 158ms/step - loss: 0.6882 - acc: 0.4850 - val_loss: 0.6966 - val_acc: 0.5147
Epoch 2/10
7/7 [==============================] - 1s 113ms/step - loss: 0.4924 - acc: 0.9800 - val_loss: 0.6991 - val_acc: 0.5233
Epoch 3/10
7/7 [==============================] - 1s 107ms/step - loss: 0.2739 - acc: 0.9850 - val_loss: 0.6986 - val_acc: 0.5264
Epoch 4/10
7/7 [==============================] - 1s 111ms/step - loss: 0.1183 - acc: 1.0000 - val_loss: 0.7063 - val_acc: 0.5274
Epoch 5/10
7/7 [==============================] - 1s 114ms/step - loss: 0.0560 - acc: 1.0000 - val_loss: 0.7053 - val_acc: 0.5260
Epoch 6/10
7/7 [==============================] - 1s 111ms/step - loss: 0.0290 - acc: 1.0000 - val_loss: 0.7188 - val_acc: 0.5278
Epoch 7/10
7/7 [==============================] - 1s 116ms/step - loss: 0.0161 - acc: 1.0000 - val_loss: 0.7259 - val_acc: 0.5282
Epoch 8/10
7/7 [==============================] - 1s 110ms/step - loss: 0.0094 - acc: 1.0000 - val_loss: 0.7454 - val_acc: 0.5296
Epoch 9/10
7/7 [==============================] - 1s 110ms/step - loss: 0.0057 - acc: 1.0000 - val_loss: 0.7419 - val_acc: 0.5270
Epoch 10/10
7/7 [==============================] - 1s 108ms/step - loss: 0.0034 - acc: 1.0000 - val_loss: 0.7505 - val_acc: 0.5291
```

Evaluate the model on test data

In [15]:

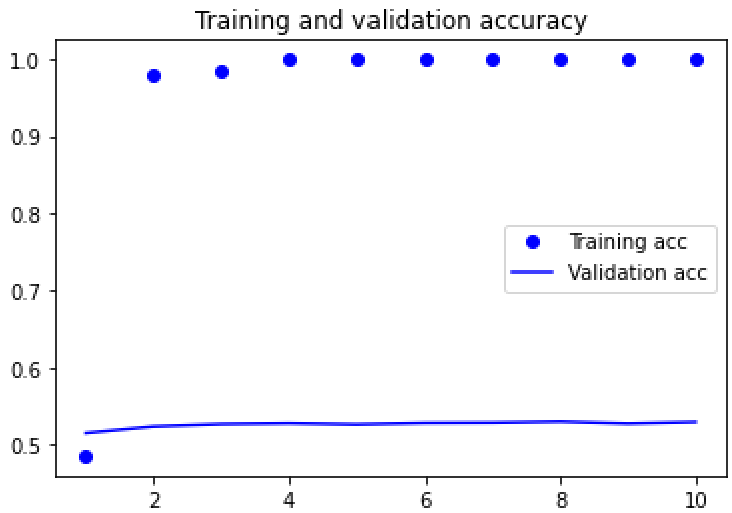
```
# Tokenize the data of the test set
test_dir = os.path.join(imdb_dir, 'test')

labels = []
texts = []
```

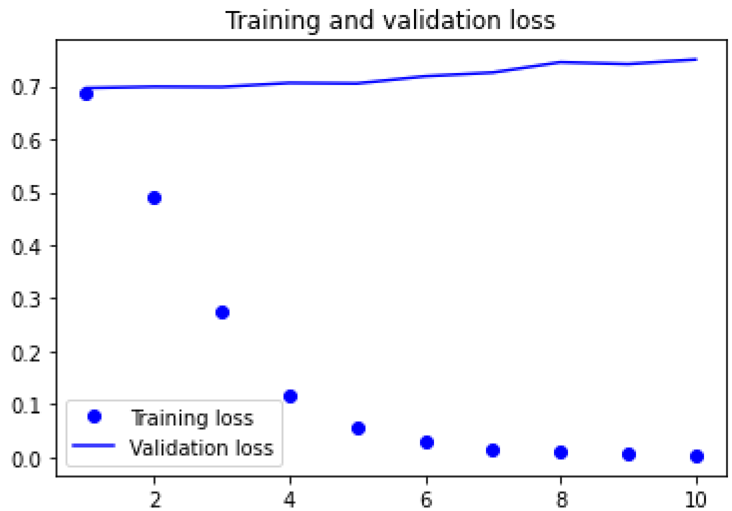
```
for label_type in ['neg', 'pos']:
    dir_name = os.path.join(test_dir, label_type)
    for fname in sorted(os.listdir(dir_name)):
        if fname[-4:] == '.txt':
            f = open(os.path.join(dir_name, fname))
            texts.append(f.read())
            f.close()
            if label_type == 'neg':
                labels.append(0)
            else:
                labels.append(1)

sequences = tokenizer.texts_to_sequences(texts)
x_test = pad_sequences(sequences, maxlen=maxlen)
y_test = np.asarray(labels)
```

Plot the model's performance over time:

In [16]:

```
# Plot the results
import matplotlib.pyplot as plt

acc = history.history['acc']
val_acc = history.history['val_acc']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(1, len(acc) + 1)

plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.legend()

plt.figure()

plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```





Evaluate the model

In [17]:

```
# Evaluate the model on the test set
eval = model.evaluate(x_test, y_test)
print(f"Model Loss:     {eval[0]:.3f}")
print(f"Model Accuracy: {eval[1]*100:.1f}%")
```

```
782/782 [==============================] - 2s 2ms/step - loss: 0.7586 - acc: 0.5310
Model Loss:     0.759
Model Accuracy: 53.1%
```

Assignment 10.3

Using listing 6.27 in Deep Learning with Python as a guide, fit the same data with an LSTM layer. Produce the model performance metrics and training and validation accuracy curves within the Jupyter notebook.

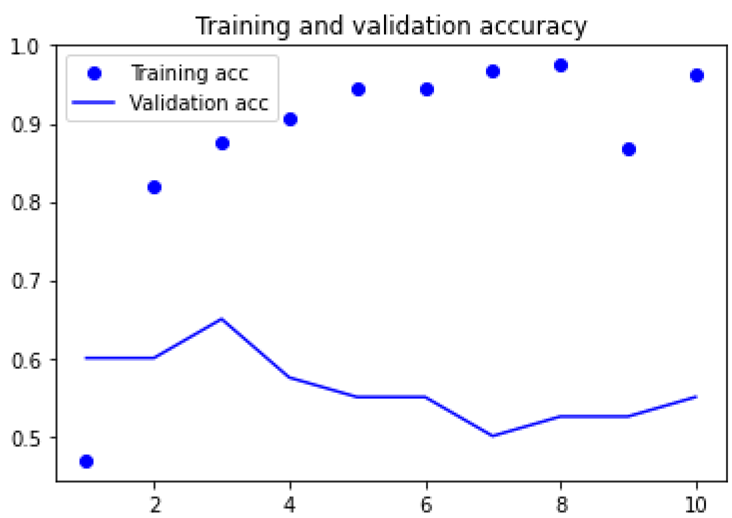
In [18]:

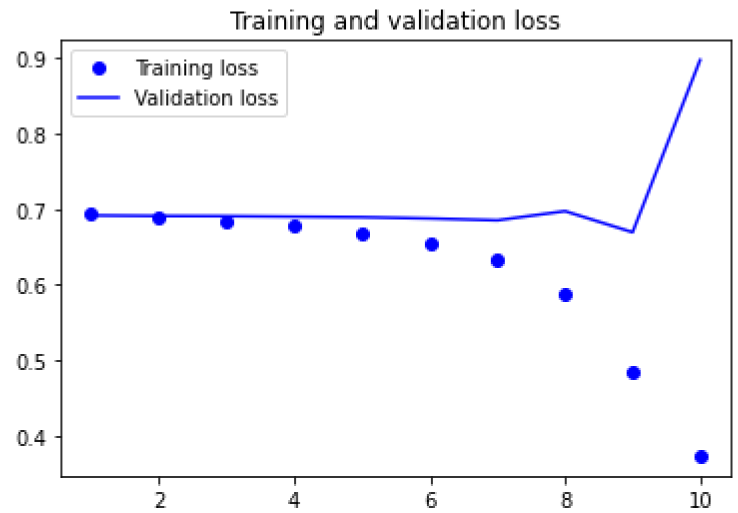
```
# Use the LSTM layer in Keras
from keras.layers import LSTM

max_features = 10000 # Number of words to consider as features

model = Sequential()
model.add(Embedding(max_features, 32))
model.add(LSTM(32))
model.add(Dense(1, activation='sigmoid'))

model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['acc'])
history = model.fit(x_train, y_train,
                    epochs=10,
                    batch_size=128,
                    validation_split=0.2)
```

```
Epoch 1/10
2/2 [==============================] - 1s 255ms/step - loss: 0.6937 - acc: 0.4688 - val_loss: 0.6913 - val_acc: 0.6000
Epoch 2/10
2/2 [==============================] - 0s 90ms/step - loss: 0.6889 - acc: 0.8188 - val_loss: 0.6906 - val_acc: 0.6000
Epoch 3/10
2/2 [==============================] - 0s 70ms/step - loss: 0.6843 - acc: 0.8750 - val_loss: 0.6904 - val_acc: 0.6500
Epoch 4/10
2/2 [==============================] - 0s 74ms/step - loss: 0.6780 - acc: 0.9062 - val_loss: 0.6897 - val_acc: 0.5750
Epoch 5/10
2/2 [==============================] - 0s 81ms/step - loss: 0.6687 - acc: 0.9438 - val_loss: 0.6890 - val_acc: 0.5500
Epoch 6/10
2/2 [==============================] - 0s 75ms/step - loss: 0.6551 - acc: 0.9438 - val_loss: 0.6873 - val_acc: 0.5500
Epoch 7/10
2/2 [==============================] - 0s 78ms/step - loss: 0.6323 - acc: 0.9688 - val_loss: 0.6849 - val_acc: 0.5000
Epoch 8/10
2/2 [==============================] - 0s 75ms/step - loss: 0.5867 - acc: 0.9750 - val_loss: 0.6970 - val_acc: 0.5250
Epoch 9/10
2/2 [==============================] - 0s 74ms/step - loss: 0.4855 - acc: 0.8687 - val_loss: 0.6690 - val_acc: 0.5250
Epoch 10/10
2/2 [==============================] - 0s 76ms/step - loss: 0.3736 - acc: 0.9625 - val_loss: 0.8972 - val_acc: 0.5500
```

Plot the LSTM model's performance over time

In [19]:
```
# Plot the results
import matplotlib.pyplot as plt

acc = history.history['acc']
val_acc = history.history['val_acc']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(1, len(acc) + 1)

plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.legend()

plt.figure()

plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```





Evaluate the LSTM model

In [21]:

```
# Evaluate the model on the test set
eval = model.evaluate(x_test, y_test)
print(f"Model Loss:     {eval[0]:.3f}")
print(f"Model Accuracy: {eval[1]*100:.1f}%")
```

```
782/782 [==============================] - 14s 18ms/step - loss: 0.8248 - acc: 0.5749
Model Loss:     0.825
Model Accuracy: 57.5%
```

Assignment 10.4

Using listing 6.46 in Deep Learning with Python as a guide, fit the same data with a simple 1D convnet. Produce the model performance metrics and training and validation accuracy curves within the Jupyter notebook.

Example 1D convnet for the IMDB dataset

In [22]:

```
# Train and evaluate a simple 1D convnet on the IMDB data
from keras.models import Sequential
from keras import layers
from tensorflow.keras.optimizers import RMSprop

max_len = 100 # set to match dimensions

model = Sequential()
```

```
model.add(layers.Embedding(max_features, 128, input_length=max_len))
model.add(layers.Conv1D(32, 7, activation='relu'))
model.add(layers.MaxPooling1D(5))
model.add(layers.Conv1D(32, 7, activation='relu'))
model.add(layers.GlobalMaxPooling1D())
model.add(layers.Dense(1))

model.summary()

model.compile(optimizer=RMSprop(lr=1e-4),
              loss='binary_crossentropy',
              metrics=['acc'])
history = model.fit(x_train, y_train,
                    epochs=10,
                    batch_size=128,
                    validation_split=0.2)
```

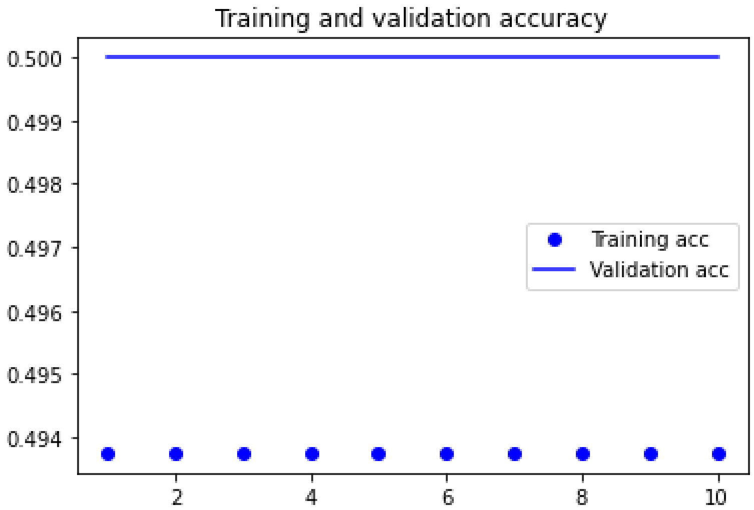
```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_2 (Embedding)      (None, 100, 128)          1280000
_________________________________________________________________
conv1d (Conv1D)              (None, 94, 32)            28704
_________________________________________________________________
max_pooling1d (MaxPooling1D) (None, 18, 32)            0
_________________________________________________________________
conv1d_1 (Conv1D)            (None, 12, 32)            7200
_________________________________________________________________
global_max_pooling1d (Global (None, 32)                0
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 33
=================================================================
Total params: 1,315,937
Trainable params: 1,315,937
Non-trainable params: 0
_________________________________________________________________
Epoch 1/10
2/2 [==============================] - 0s 70ms/step - loss: 3.8011 - acc: 0.4938 - val_loss: 1.7573 - val_acc: 0.5000
Epoch 2/10
2/2 [==============================] - 0s 24ms/step - loss: 1.9258 - acc: 0.4938 - val_loss: 1.6315 - val_acc: 0.5000
Epoch 3/10
2/2 [==============================] - 0s 23ms/step - loss: 1.6121 - acc: 0.4938 - val_loss: 1.5262 - val_acc: 0.5000
Epoch 4/10
2/2 [==============================] - 0s 27ms/step - loss: 1.3692 - acc: 0.4938 - val_loss: 1.3960 - val_acc: 0.5000
Epoch 5/10
2/2 [==============================] - 0s 26ms/step - loss: 1.2292 - acc: 0.4938 - val_loss: 1.3754 - val_acc: 0.5000
```

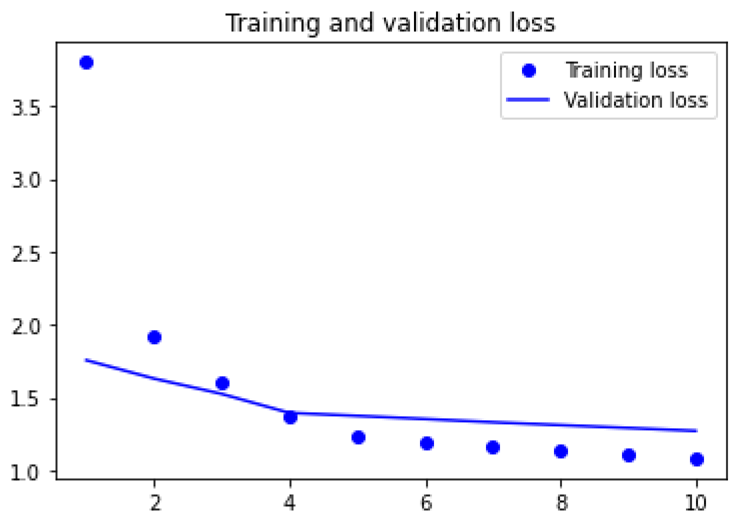
```
Epoch 6/10
2/2 [==============================] - 0s 29ms/step - loss: 1.1972 - acc: 0.4938 - val_loss: 1.3538 - val_acc: 0.5000
Epoch 7/10
2/2 [==============================] - 0s 26ms/step - loss: 1.1655 - acc: 0.4938 - val_loss: 1.3315 - val_acc: 0.5000
Epoch 8/10
2/2 [==============================] - 0s 28ms/step - loss: 1.1356 - acc: 0.4938 - val_loss: 1.3119 - val_acc: 0.5000
Epoch 9/10
2/2 [==============================] - 0s 23ms/step - loss: 1.1095 - acc: 0.4938 - val_loss: 1.2922 - val_acc: 0.5000
Epoch 10/10
2/2 [==============================] - 0s 26ms/step - loss: 1.0841 - acc: 0.4938 - val_loss: 1.2723 - val_acc: 0.5000
```

Plot the 1D convnet model's performance over time

In [23]:

```python
# Plot the results
import matplotlib.pyplot as plt

acc = history.history['acc']
val_acc = history.history['val_acc']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(1, len(acc) + 1)

plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.legend()

plt.figure()

plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```





In [24]:

```
# Evaluate the model on the test set
eval = model.evaluate(x_test, y_test)
print(f"Model Loss:     {eval[0]:.3f}")
print(f"Model Accuracy: {eval[1]*100:.1f}%")
```

```
782/782 [==============================] - 3s 4ms/step - loss: 1.2980 - acc: 0.5000
Model Loss:     1.298
Model Accuracy: 50.0%
```

In [ ]: