In [1]:

```
import os

data_dir = './jena_climate'
fname = os.path.join(data_dir, 'jena_climate_2009_2016.csv')

f = open(fname)
data = f.read()
f.close()
lines = data.split('\n')
header = lines[0].split(',')
lines = lines[1:]

print(header)
print(len(lines))
```

['"Date Time"', '"p (mbar)"', '"T (degC)"', '"Tpot (K)"', '"Tdew (degC)"', '"rh (%)"', '"VPmax (mbar)"', '"VPact (mbar)"', '"VPdef (mbar)"', '"sh (g/kg)"', '"H20C (mmol/mol)"', '"rho (g/m**3)"', '"wv (m/s)"', '"max. wv (m/s)"', '"wd (deg)"'] 420551

In [2]:

```
import numpy as np
float_data = np.zeros((len(lines), len(header) - 1))
for i, line in enumerate(lines):
   values = [float(x) for x in line.split(',')[1:]]
   float_data[i, :] = values
```

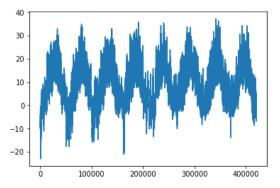
In [5]:

```
from matplotlib import pyplot as plt

temp = float_data[:, 1]
plt.plot(range(len(temp)), temp)
```

Out[5]:

[<matplotlib.lines.Line2D at 0x255e747e898>]

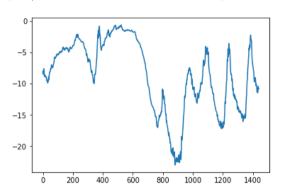


In [6]:

```
plt.plot(range(1440), temp[:1440])
```

Out[6]:

[<matplotlib.lines.Line2D at 0x255e7f334a8>]



In [3]:

```
mean = float_data[:200000].mean(axis=0)
float_data -= mean
std = float_data[:200000].std(axis=0)
float_data /= std
```

In [4]:

```
def generator(data, lookback, delay, min_index, max_index, shuffle=False, batch_size=128, step=6
   if max index is None:
       max index = len(data) - delay - 1
   i = min index + lookback
    while 1:
        if shuffle:
            rows = np.random.randint(min_index + lookback, max_index, size=batch_size)
        else:
            if i + batch_size >= max_index:
               i = min index + lookback
            rows = np.arange(i, min(i + batch_size, max_index))
           i += len(rows)
        samples = np.zeros((len(rows), lookback // step, data.shape[-1]))
        targets = np.zeros((len(rows),))
        for i, row in enumerate(rows):
           indices = range(rows[i] - lookback, rows[i], step)
           samples[j] = data[indices]
           targets[j] = data[rows[j] + delay][1]
        yield samples, targets
```

In [5]:

In [21]:

```
def evaluate_naive_method():
    batch_maes = []
    for step in range(val_steps):
        samples, targets = next(val_gen)
        preds = samples[:, -1, 1]
        mae = np.mean(np.abs(preds - targets))
        batch_maes.append(mae)
    print(np.mean(batch_maes))
```

0.28706624352615373

In [22]:

```
celsius_mae = 0.29 * std[1]
celsius_mae
```

Out[22]:

2.5672247338393395

In [24]:

```
from keras.models import Sequential
from keras import layers
from keras.optimizers import RMSprop

model = Sequential()
model.add(layers.Flatten(input_shape=(lookback // step, float_data.shape[-1])))
model.add(layers.Dense(32, activation='relu'))
model.add(layers.Dense(1))
model.compile(optimizer=RMSprop(), loss='mae')

history = model.fit_generator(
    train_gen,
    steps_per_epoch=500,
    epochs=20,
    validation_data = val_gen,
    validation_steps = val_steps)
```

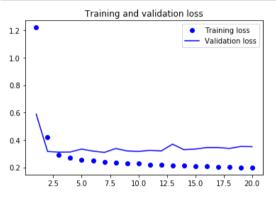
Epoch 1/20	
500/500 [======] - 15s 31ms/step - loss: 1.2200 - val_los	3
s: 0.5875	
Epoch 2/20 E00/E00 [
500/500 [===================================	3
s: 0.3158	
Epoch 3/20 500/500 [===================================	,
s: 0.3108)
Epoch 4/20	
500/500 [===================================	2
s: 0.3119	,
Epoch 5/20	
500/500 [===================================	3
s: 0.3330	
Epoch 6/20	
500/500 [=======] - 13s 27ms/step - loss: 0.2486 - val_los	3
s: 0.3184	
Epoch 7/20	
500/500 [=======] - 13s 27ms/step - loss: 0.2415 - val_los	3
s: 0.3090	
Epoch 8/20	
500/500 [======] - 13s 27ms/step - loss: 0.2353 - val_los	3
s: 0.3375	
Epoch 9/20	
500/500 [======] - 13s 27ms/step - loss: 0.2291 - val_los	3
s: 0.3196	
Epoch 10/20	
500/500 [======] - 14s 27ms/step - loss: 0.2268 - val_los	3
s: 0.3159	
Epoch 11/20	
500/500 [=======] - 13s 27ms/step - loss: 0.2209 - val_los	3
s: 0.3242 Epoch 12/20	
500/500 [===================================	,
s: 0.3194	,
Epoch 13/20	
500/500 [===================================	3
s: 0.3690	,
Epoch 14/20	
500/500 [===================================	3
s: 0.3287	
Epoch 15/20	
500/500 [===================================	3
s: 0.3336	
Epoch 16/20	
500/500 [======] - 13s 27ms/step - loss: 0.2059 - val_los	3
s: 0.3443	
Epoch 17/20	
500/500 [===================================	3
s: 0.3445	
Epoch 18/20	
500/500 [=======] - 14s 27ms/step - loss: 0.2030 - val_los	i
s: 0.3380	
Epoch 19/20 500/500 [===================================	,
s: 0.3522)
Epoch 20/20	
500/500 [=======] - 14s 27ms/step - loss: 0.1982 - val_los	3
s: 0.3508	•

In [27]:

```
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(loss) + 1)

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()
```



GRU를 사용한 모델을 훈련하고 평가하기

In [30]:

```
model = Sequential()
model.add(layers.GRU(32, input_shape=(None, float_data.shape[-1])))
model.add(layers.Dense(1))

model.compile(optimizer=RMSprop(), loss='mae')
history = model.fit_generator(
    train_gen,
    steps_per_epoch=500,
    epochs=20,
    validation_data = val_gen,
    validation_steps = val_steps)
```

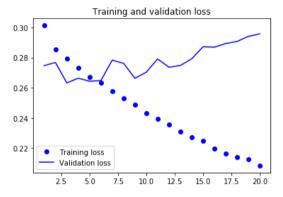
F 1 1/00		
Epoch 1/20		
	- 1/6	6s 352ms/step - loss: 0.3013 - val_lo
ss: 0.2747		
Epoch 2/20		
500/500 [=======] -	- 172	2s 344ms/step - loss: 0.2854 - val_lo
ss: 0.2768		
Epoch 3/20		
	_ 176	6s 352ms/step - loss: 0.2795 - val_lo
	- 170	05 0021115/51ep - 1055. 0.2790 - Val_10
ss: 0.2632		
Epoch 4/20		
500/500 [========] -	- 172	2s 344ms/step - loss: 0.2734 - val_lo
ss: 0.2664		
Epoch 5/20		
500/500 [======] -	- 171	1s 342ms/sten = loss: 0 2671 = val lo
ss: 0.2644	17 1	13 042113/31CP 1033: 0.20/1 Val_10
Epoch 6/20		
500/500 [======]	- 1/3	3s 346ms/step - loss: 0.2635 - val_lo
ss: 0.2647		
Epoch 7/20		
500/500 [======] -	- 173	3s 346ms/step - loss: 0.2577 - val lo
ss: 0.2783		
Epoch 8/20		
· ·	170	20 242mg/oton loop: 0 2520 walle
500/500 [=======]	- 1/2	28 343118/81ep = 1088. 0.2330 = Val_10
ss: 0.2762		
Epoch 9/20		
500/500 [======] -	- 172	2s 344ms/step - loss: 0.2486 - val_lo
ss: 0.2663		
Epoch 10/20		
500/500 [======]	- 172	2s 345ms/sten = loss: 0 2433 = val lo
ss: 0.2704	112	23 043m3/310p 1033 0.2400 Val_10
Epoch 11/20		
· ·	474	4 040 / 1 1 1 0 0005
500/500 [======]	- 174	4s 348ms/step - loss: 0.2395 - val_lo
· ·	- 174	4s 348ms/step - loss: 0.2395 - val_lo
500/500 [======]	- 174	4s 348ms/step - loss: 0.2395 - val_lo
500/500 [=====] ss: 0.2791		- · ·
500/500 [=====] ss: 0.2791 Epoch 12/20 500/500 [=====] .		- · ·
500/500 [======] ss: 0.2791 Epoch 12/20 500/500 [=====] ss: 0.2737		- · ·
500/500 [======] · ss: 0.2791 Epoch 12/20 500/500 [=====] · ss: 0.2737 Epoch 13/20	- 174	4s 349ms/step - loss: 0.2356 - val_lo
500/500 [======] · ss: 0.2791 Epoch 12/20 500/500 [=====] · ss: 0.2737 Epoch 13/20 500/500 [=====] ·	- 174	4s 349ms/step - loss: 0.2356 - val_lo
500/500 [======] · ss: 0.2791 Epoch 12/20 500/500 [=====] · ss: 0.2737 Epoch 13/20 500/500 [======] · ss: 0.2748	- 174	4s 349ms/step - loss: 0.2356 - val_lo
500/500 [===================================	- 174 - 173	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo
500/500 [===================================	- 174 - 173	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo
500/500 [===================================	- 174 - 173	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo
500/500 [===================================	- 174 - 173 - 172	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo
500/500 [===================================	- 174 - 173 - 172	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo
500/500 [===================================	- 174 - 173 - 172	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo
500/500 [===================================	- 174 - 173 - 172	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo
500/500 [===================================	- 174 - 173 - 172 - 170	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo 0s 340ms/step - loss: 0.2247 - val_lo
500/500 [===================================	- 174 - 173 - 172 - 170	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo
500/500 [===================================	- 174 - 173 - 172 - 170	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo 0s 340ms/step - loss: 0.2247 - val_lo
500/500 [===================================	- 174 - 173 - 172 - 170	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo Os 340ms/step - loss: 0.2247 - val_lo Os 341ms/step - loss: 0.2196 - val_lo
500/500 [===================================	- 174 - 173 - 172 - 170	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo 0s 340ms/step - loss: 0.2247 - val_lo
500/500 [===================================	- 174 - 173 - 172 - 170	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo Os 340ms/step - loss: 0.2247 - val_lo Os 341ms/step - loss: 0.2196 - val_lo
500/500 [===================================	- 174 - 173 - 172 - 170	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo Os 340ms/step - loss: 0.2247 - val_lo Os 341ms/step - loss: 0.2196 - val_lo
500/500 [===================================	- 174 - 173 - 172 - 170 - 170	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo 0s 340ms/step - loss: 0.2247 - val_lo 0s 341ms/step - loss: 0.2196 - val_lo 9s 338ms/step - loss: 0.2163 - val_lo
500/500 [===================================	- 174 - 173 - 172 - 170 - 170	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo 0s 340ms/step - loss: 0.2247 - val_lo 0s 341ms/step - loss: 0.2196 - val_lo 9s 338ms/step - loss: 0.2163 - val_lo
500/500 [===================================	- 174 - 173 - 172 - 170 - 170	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo 0s 340ms/step - loss: 0.2247 - val_lo 0s 341ms/step - loss: 0.2196 - val_lo 9s 338ms/step - loss: 0.2163 - val_lo
500/500 [===================================	- 174 - 173 - 172 - 170 - 170 - 169	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo 0s 340ms/step - loss: 0.2247 - val_lo 0s 341ms/step - loss: 0.2196 - val_lo 0s 338ms/step - loss: 0.2163 - val_lo 0s 339ms/step - loss: 0.2142 - val_lo
500/500 [===================================	- 174 - 173 - 172 - 170 - 170 - 169	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo 0s 340ms/step - loss: 0.2247 - val_lo 0s 341ms/step - loss: 0.2196 - val_lo 0s 338ms/step - loss: 0.2163 - val_lo 0s 339ms/step - loss: 0.2142 - val_lo
500/500 [===================================	- 174 - 173 - 172 - 170 - 170 - 169	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo 0s 340ms/step - loss: 0.2247 - val_lo 0s 341ms/step - loss: 0.2196 - val_lo 0s 338ms/step - loss: 0.2163 - val_lo 0s 339ms/step - loss: 0.2142 - val_lo
500/500 [===================================	- 174 - 173 - 172 - 170 - 170 - 169 - 170	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo 0s 340ms/step - loss: 0.2247 - val_lo 0s 341ms/step - loss: 0.2196 - val_lo 9s 338ms/step - loss: 0.2163 - val_lo 9s 339ms/step - loss: 0.2142 - val_lo 0s 340ms/step - loss: 0.2126 - val_lo
500/500 [===================================	- 174 - 173 - 172 - 170 - 170 - 169 - 170	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo 0s 340ms/step - loss: 0.2247 - val_lo 0s 341ms/step - loss: 0.2196 - val_lo 9s 338ms/step - loss: 0.2163 - val_lo 9s 339ms/step - loss: 0.2142 - val_lo 0s 340ms/step - loss: 0.2126 - val_lo
500/500 [===================================	- 174 - 173 - 172 - 170 - 170 - 169 - 170	4s 349ms/step - loss: 0.2356 - val_lo 3s 347ms/step - loss: 0.2307 - val_lo 2s 344ms/step - loss: 0.2270 - val_lo 0s 340ms/step - loss: 0.2247 - val_lo 0s 341ms/step - loss: 0.2196 - val_lo 9s 338ms/step - loss: 0.2163 - val_lo 9s 339ms/step - loss: 0.2142 - val_lo 0s 340ms/step - loss: 0.2126 - val_lo

In [31]:

```
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(loss) + 1)

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()
```



드롭아웃 규제된 GRU

In [32]:

```
model = Sequential()
model.add(layers.GRU(32, dropout=0.2, recurrent_dropout=0.2, input_shape=(None, float_data.shape
[-1])))
model.add(layers.Dense(1))

model.compile(optimizer=RMSprop(), loss='mae')
history = model.fit_generator(
    train_gen,
    steps_per_epoch=500,
    epochs=40,
    validation_data = val_gen,
    validation_steps = val_steps)
```

WARNING:tensorflow:From C:WProgramDataWAnaconda3WlibWsite-packagesWkerasWbackendWt ensorflow backend.pv:3445: calling dropout (from tensorflow.pvthon.ops.nn ops) wit h keep prob is deprecated and will be removed in a future version. Instructions for updating: Please use 'rate' instead of 'keep_prob'. Rate should be set to 'rate = 1 - keep_p rob`. Epoch 1/40 ss: 0.2877 Epoch 2/40 ss: 0.2738 Epoch 3/40 500/500 [== ss: 0.2756 Fnoch 4/40 500/500 [== ss: 0.2734 Fnoch 5/40 500/500 [=== ss: 0.2714 Epoch 6/40 ss: 0.2704 Epoch 7/40 500/500 [== ss: 0.2668 Epoch 8/40 500/500 [== ss: 0.2692 Epoch 9/40 500/500 [=== ss: 0.2631 Epoch 10/40 ss: 0.2681 Epoch 11/40 ss: 0.2633 Epoch 12/40 500/500 [=============] - 192s 384ms/step - loss: 0.2878 - val_lo ss: 0.2656 Epoch 13/40 500/500 [=== ss: 0.2670 Epoch 14/40 500/500 [=== ss: 0.2614 Epoch 15/40 500/500 [=== ss: 0.2645 Epoch 16/40 ss: 0.2654 Epoch 17/40 500/500 [=== ss: 0.2682 Epoch 18/40 ss: 0.2650 Epoch 19/40

500/500 [=======]	-	195s	390ms/step -	loss:	0.2788 - val_lo
ss: 0.2643					
Epoch 20/40					
500/500 [=======]	-	194s	388ms/step -	loss:	0.2793 - val_lo
ss: 0.2726					
Epoch 21/40					
500/500 [======]	-	194s	387ms/step -	loss:	0.2772 - val_lo
ss: 0.2666					
Epoch 22/40					
500/500 [=======]	_	192s	385ms/step -	loss:	0.2778 - val_lo
ss: 0.2672					
Epoch 23/40					
500/500 [======]	-	193s	385ms/step -	loss:	0.2772 - val_lo
ss: 0.2677					
Epoch 24/40					
500/500 [=======]	_	193s	387ms/step -	loss:	0.2762 - val_lo
ss: 0.2658					
Epoch 25/40					
500/500 [======]	-	193s	385ms/step -	loss:	0.2732 - val_lo
ss: 0.2661					
Epoch 26/40					
500/500 [=======]	_	192s	385ms/step -	loss:	0.2752 - val_lo
ss: 0.2654					
Epoch 27/40					
500/500 [=======]	-	200s	400ms/step -	loss:	0.2733 - val_lo
ss: 0.2662					
Epoch 28/40					
500/500 [=======]	_	198s	396ms/step -	loss:	0.2730 - val_lo
ss: 0.2670					
Epoch 29/40					
500/500 [======]	-	192s	383ms/step -	loss:	0.2726 - val_lo
ss: 0.2667					
Epoch 30/40					
500/500 [========]					
	_	192s	384ms/step -	loss:	0.2724 - val_lo
ss: 0.2675	_	192s	384ms/step -	loss:	0.2724 - val_lo
ss: 0.2675 Epoch 31/40					
ss: 0.2675 Epoch 31/40 500/500 []					
ss: 0.2675 Epoch 31/40					
ss: 0.2675 Epoch 31/40 500/500 [======] ss: 0.2669 Epoch 32/40	-	193s	386ms/step -	loss:	0.2706 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [===================================	-	193s	386ms/step -	loss:	0.2706 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [===================================	-	193s	386ms/step -	loss:	0.2706 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [===================================	_	193s 194s	386ms/step - 388ms/step -	loss:	0.2706 - val_lo 0.2703 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [] ss: 0.2669 Epoch 32/40 500/500 [] ss: 0.2714 Epoch 33/40 500/500 []	_	193s 194s	386ms/step - 388ms/step -	loss:	0.2706 - val_lo 0.2703 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [===================================	_	193s 194s	386ms/step - 388ms/step -	loss:	0.2706 - val_lo 0.2703 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [===================================	-	193s 194s 194s	386ms/step - 388ms/step - 387ms/step -	loss:	0.2706 - val_lo 0.2703 - val_lo 0.2707 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [===================================	-	193s 194s 194s	386ms/step - 388ms/step - 387ms/step -	loss:	0.2706 - val_lo 0.2703 - val_lo 0.2707 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [] ss: 0.2669 Epoch 32/40 500/500 [] ss: 0.2714 Epoch 33/40 500/500 [] ss: 0.2656 Epoch 34/40 500/500 [] ss: 0.2670	-	193s 194s 194s	386ms/step - 388ms/step - 387ms/step -	loss:	0.2706 - val_lo 0.2703 - val_lo 0.2707 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [] ss: 0.2669 Epoch 32/40 500/500 [] ss: 0.2714 Epoch 33/40 500/500 [] ss: 0.2656 Epoch 34/40 500/500 [] ss: 0.2670 Epoch 35/40		193s 194s 194s 191s	386ms/step - 388ms/step - 387ms/step - 381ms/step -	loss: loss: loss:	0.2706 - val_lo 0.2703 - val_lo 0.2707 - val_lo 0.2696 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [] ss: 0.2669 Epoch 32/40 500/500 [] ss: 0.2714 Epoch 33/40 500/500 [] ss: 0.2656 Epoch 34/40 500/500 [] ss: 0.2670 Epoch 35/40 500/500 []		193s 194s 194s 191s	386ms/step - 388ms/step - 387ms/step - 381ms/step -	loss: loss: loss:	0.2706 - val_lo 0.2703 - val_lo 0.2707 - val_lo 0.2696 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [] ss: 0.2669 Epoch 32/40 500/500 [] ss: 0.2714 Epoch 33/40 500/500 [] ss: 0.2656 Epoch 34/40 500/500 [] ss: 0.2670 Epoch 35/40 500/500 []		193s 194s 194s 191s	386ms/step - 388ms/step - 387ms/step - 381ms/step -	loss: loss: loss:	0.2706 - val_lo 0.2703 - val_lo 0.2707 - val_lo 0.2696 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [===================================		193s 194s 194s 191s	386ms/step - 388ms/step - 387ms/step - 381ms/step - 380ms/step -	loss: loss: loss: loss:	0.2706 - val_lo 0.2703 - val_lo 0.2707 - val_lo 0.2696 - val_lo 0.2686 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [===================================		193s 194s 194s 191s	386ms/step - 388ms/step - 387ms/step - 381ms/step - 380ms/step -	loss: loss: loss: loss:	0.2706 - val_lo 0.2703 - val_lo 0.2707 - val_lo 0.2696 - val_lo 0.2686 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [===================================		193s 194s 194s 191s	386ms/step - 388ms/step - 387ms/step - 381ms/step - 380ms/step -	loss: loss: loss: loss:	0.2706 - val_lo 0.2703 - val_lo 0.2707 - val_lo 0.2696 - val_lo 0.2686 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [===================================		193s 194s 194s 191s 190s	386ms/step - 388ms/step - 387ms/step - 380ms/step - 387ms/step -	loss: loss: loss: loss:	0.2706 - val_lo 0.2703 - val_lo 0.2707 - val_lo 0.2696 - val_lo 0.2686 - val_lo 0.2681 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [===================================		193s 194s 194s 191s 190s	386ms/step - 388ms/step - 387ms/step - 380ms/step - 387ms/step -	loss: loss: loss: loss:	0.2706 - val_lo 0.2703 - val_lo 0.2707 - val_lo 0.2696 - val_lo 0.2686 - val_lo 0.2681 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [===================================		193s 194s 194s 191s 190s	386ms/step - 388ms/step - 387ms/step - 380ms/step - 387ms/step -	loss: loss: loss: loss:	0.2706 - val_lo 0.2703 - val_lo 0.2707 - val_lo 0.2696 - val_lo 0.2686 - val_lo 0.2681 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [===================================		193s 194s 194s 191s 190s 194s	386ms/step - 388ms/step - 387ms/step - 381ms/step - 380ms/step - 387ms/step -	loss: loss: loss: loss: loss:	0.2706 - val_lo 0.2703 - val_lo 0.2707 - val_lo 0.2696 - val_lo 0.2686 - val_lo 0.2691 - val_lo 0.2685 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [===================================		193s 194s 194s 191s 190s 194s	386ms/step - 388ms/step - 387ms/step - 381ms/step - 380ms/step - 387ms/step -	loss: loss: loss: loss: loss:	0.2706 - val_lo 0.2703 - val_lo 0.2707 - val_lo 0.2696 - val_lo 0.2686 - val_lo 0.2691 - val_lo 0.2685 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [=] ss: 0.2669 Epoch 32/40 500/500 [=] ss: 0.2714 Epoch 33/40 500/500 [=] ss: 0.2656 Epoch 34/40 500/500 [=] ss: 0.2670 Epoch 35/40 500/500 [=] ss: 0.2707 Epoch 36/40 500/500 [=] ss: 0.2675 Epoch 37/40 500/500 [=] ss: 0.2678 Epoch 37/40 500/500 [=] ss: 0.2678 Epoch 37/40 500/500 [=] ss: 0.2698 Epoch 38/40 500/500 [=		193s 194s 194s 191s 190s 194s	386ms/step - 388ms/step - 387ms/step - 381ms/step - 380ms/step - 387ms/step -	loss: loss: loss: loss: loss:	0.2706 - val_lo 0.2703 - val_lo 0.2707 - val_lo 0.2696 - val_lo 0.2686 - val_lo 0.2691 - val_lo 0.2685 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [=] ss: 0.2669 Epoch 32/40 500/500 [=] ss: 0.2714 Epoch 33/40 500/500 [=] ss: 0.2656 Epoch 34/40 500/500 [=] ss: 0.2670 Epoch 35/40 500/500 [=] ss: 0.2670 Epoch 36/40 500/500 [=] ss: 0.2675 Epoch 37/40 500/500 [=] ss: 0.2698 Epoch 38/40 500/500 [=] ss: 0.2694 Epoch 39/40	- - - -	193s 194s 194s 191s 190s 194s 194s	386ms/step - 388ms/step - 387ms/step - 381ms/step - 380ms/step - 387ms/step - 388ms/step -	loss: loss: loss: loss: loss: loss:	0.2706 - val_lo 0.2703 - val_lo 0.2707 - val_lo 0.2696 - val_lo 0.2686 - val_lo 0.2691 - val_lo 0.2685 - val_lo 0.2680 - val_lo
ss: 0.2675 Epoch 31/40 500/500 [=] ss: 0.2669 Epoch 32/40 500/500 [=] ss: 0.2714 Epoch 33/40 500/500 [=] ss: 0.2656 Epoch 34/40 500/500 [=] ss: 0.2670 Epoch 35/40 500/500 [=] ss: 0.2707 Epoch 36/40 500/500 [=] ss: 0.2675 Epoch 37/40 500/500 [=] ss: 0.2678 Epoch 37/40 500/500 [=] ss: 0.2678 Epoch 37/40 500/500 [=] ss: 0.2698 Epoch 38/40 500/500 [=	- - - -	193s 194s 194s 191s 190s 194s 194s	386ms/step - 388ms/step - 387ms/step - 381ms/step - 380ms/step - 387ms/step - 388ms/step -	loss: loss: loss: loss: loss: loss:	0.2706 - val_lo 0.2703 - val_lo 0.2707 - val_lo 0.2696 - val_lo 0.2686 - val_lo 0.2691 - val_lo 0.2685 - val_lo 0.2680 - val_lo

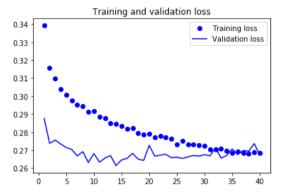
```
ss: 0.2736
Epoch 40/40
500/500 [------] - 194s 387ms/step - loss: 0.2683 - val_lo
ss: 0.2672
```

In [33]:

```
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(loss) + 1)

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()
```



드롭아웃 규제 및 스태킹(stacking, 적재)한 GRU 모델

In [6]:

```
from keras.models import Sequential
from keras import layers
from keras.optimizers import RMSprop

model = Sequential()
model.add(layers.GRU(32, dropout=0.1, recurrent_dropout=0.5, return_sequences=True, input_shape=
(None, float_data.shape[-1])))
model.add(layers.GRU(64, activation='relu', dropout=0.1, recurrent_dropout=0.5))
model.add(layers.Dense(1))

model.compile(optimizer=RMSprop(), loss='mae')
history = model.fit_generator(
    train_gen,
    steps_per_epoch=500,
    epochs=40,
    validation_data = val_gen,
    validation_steps = val_steps)
```

Using TensorFlow backend.

WARNING:tensorflow:From C:\programData\pro

Instructions for updating:

Colocations handled automatically by placer.

WARNING:tensorflow:From C:WProgramDataWAnaconda3WlibWsite-packagesWkerasWbackendWtensorflow_backend.py:3445: calling dropout (from tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed in a future version.

Instructions for updating:

Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_p rob`.

WARNING:tensorflow:From C:\(\text{WProgramDataWAnaconda3WIibWsite-packagesWtensorflowWpythonWopsWmath_ops.py:3066: to_int32 (from tensorflow.python.ops.math_ops) is deprecated and will be removed in a future version.

Instructions for updating:

ss: 0.2652

```
Use tf.cast instead.
```

instead.						
	 	- 384s	768ms/step	- loss:	0.3344	- val_lo
	 =====]	- 381s	762ms/step	- loss:	0.3134	- val_lo
	 ======]	- 384s	768ms/step	- loss:	0.3072	- val_lo
]	- 387s	773ms/step	- loss:	0.3005	- val_lo
]	- 389s	778ms/step	- loss:	0.2988	- val_lo
	_					_
	 1	- 388s	775ms/step	- loss:	0.2953	- val lo
	,					
	 1	- 385s	770ms/sten	- loss:	0 2930	- val lo
	,	0000	77011070100	1000	0.2000	va1_10
	 1	- 388s	776ms/sten	- loss:	0 2902	- val lo
	J	0003	77011373100	1000	0.2002	Va1_10
	 1	- 387c	77/me/etan	- Ince	0 2868	- val lo
	J	0073	//-HIIS/310p	1033	0.2000	Va1_10
)						
	 1	- 3880	777me/eton	- loce:	0 2866	- val la
	J	0003	7771113731CP	1033	0.2000	Va1_10
)						
	 1	- 387c	77/me/eton	- loce:	0.0848	- val lo
		0075	//4IIIS/316p	1055	0.2040	Va1_10
`						
	 1	200-	770 /		0 0007	
]	- 3008	//oilis/step	- 1088	0.2021	- vai_10
	1	005-	770/		0 0000	
	 j	- 3858	//Ullis/step	- 1088	0.2800	- vai_10
`						
	1	007	774		0.0700	
]	- 38/s	//4ms/step	- Ioss:	0.2798	- vai_lo

500/500 [======] - 385s 771ms/step - loss: 0.2789 - val_lo

Epoch 16/40	
	86s 773ms/step - loss: 0.2772 - val_lo
ss: 0.2658	
Epoch 17/40	
500/500 [=======] - 3	89s 777ms/step - loss: 0.2757 - val_lo
ss: 0.2705	
Epoch 18/40	
500/500 [======] - 3	83s 766ms/step - loss: 0.2764 - val_lo
ss: 0.2662	
Epoch 19/40	
·	87s 774ms/step - loss: 0.2725 - val_lo
ss: 0.2646	0/3 // HII3/310p 1033. 0.2/23 Val_10
Epoch 20/40	04 700 / 1 1 1 0 0747 1 1
	81s 763ms/step - loss: 0.2717 - val_lo
ss: 0.2672	
Epoch 21/40	
	77s 755ms/step - loss: 0.2729 - val_lo
ss: 0.2692	
Epoch 22/40	
500/500 [======] - 3	76s 752ms/step - loss: 0.2719 - val_lo
ss: 0.2641	
Epoch 23/40	
500/500 [=======] - 3	84s 768ms/step - loss: 0.2709 - val_lo
ss: 0.2655	
Epoch 24/40	
500/500 [=======] - 3	84s 768ms/step - Loss: 0 2692 - val lo
ss: 0.2652	0.10 70011107 0100
Epoch 25/40	
·	85s 770ms/step - loss: 0.2684 - val_lo
ss: 0.2644	035 7701115/51Ep 1055: 0.2004 Val_10
Epoch 26/40	01- 700/
	81s 762ms/step - loss: 0.2670 - val_lo
ss: 0.2683	
Epoch 27/40	
	82s 764ms/step - loss: 0.2675 - val_lo
ss: 0.2765	
Epoch 28/40	
500/500 [=======] - 3	81s 761ms/step - loss: 0.2667 - val_lo
ss: 0.2706	
Epoch 29/40	
500/500 [======] - 3	81s 763ms/step - loss: 0.2647 - val_lo
ss: 0.2703	
Epoch 30/40	
500/500 [=======] - 3	83s 767ms/step - loss: 0.2649 - val_lo
ss: 0.2691	
Epoch 31/40	
	86s 773ms/step - loss: 0.2643 - val_lo
ss: 0.2681	000 770m070top 1000 0.2010 Val_10
Epoch 32/40	
	87s 774ms/step - loss: 0.2646 - val_lo
ss: 0.2665	0/3 //41113/3(ep 1033: 0.2040 Val_10
Epoch 33/40	04- 700/
500/500 [=====] - 3	848 /091118/Step - 1088. U.2008 - Val_10
ss: 0.2674	
Epoch 34/40	
500/500 [======] - 3	/8s /5/ms/step - loss: 0.2620 - val_lo
ss: 0.2729	
Epoch 35/40	
500/500 [======] - 36	84s 768ms/step - loss: 0.2618 - val_lo
ss: 0.2765	
Epoch 36/40	

```
500/500 [=======] - 380s 760ms/step - loss: 0.2611 - val_lo ss: 0.2747

Epoch 37/40

500/500 [======] - 381s 762ms/step - loss: 0.2607 - val_lo ss: 0.2655

Epoch 38/40

500/500 [======] - 375s 751ms/step - loss: 0.2590 - val_lo ss: 0.2697

Epoch 39/40

500/500 [======] - 373s 745ms/step - loss: 0.2581 - val_lo ss: 0.2648

Epoch 40/40

500/500 [======] - 376s 752ms/step - loss: 0.2582 - val_lo ss: 0.2654
```

In [9]:

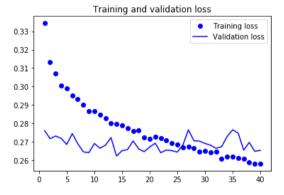
```
from matplotlib import pyplot as plt

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

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

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()
```



거꾸로 된 시퀸스 사용한 LSTM

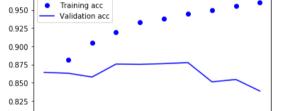
In [13]:

```
from keras.datasets import imdb
from keras.preprocessing import sequence
max features = 10000
maxlen = 500
(x train, v train), (x test, v test) = imdb.load data(num words = max features)
x_{train} = [x[::-1] \text{ for } x \text{ in } x_{train}]
x_{test} = [x[::-1] \text{ for } x \text{ in } x_{test}]
x train = sequence.pad sequences(x train, maxlen=maxlen)
x_test = sequence.pad_sequences(x_test, maxlen=maxlen)
model = Sequential()
model.add(lavers.Embedding(max features, 128))
model.add(layers.LSTM(32))
model.add(lavers.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)
```

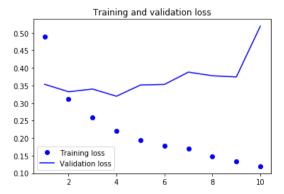
```
Train on 20000 samples, validate on 5000 samples
Epoch 1/10
20000/20000 [===========] - 121s 6ms/step - loss: 0.4890 - acc:
0.7677 - val loss: 0.3535 - val acc: 0.8642
Epoch 2/10
0.8811 - val_loss: 0.3322 - val_acc: 0.8630
Epoch 3/10
20000/20000 [=======] - 120s 6ms/step - loss: 0.2588 - acc:
0.9046 - val loss: 0.3399 - val acc: 0.8578
Epoch 4/10
0.9191 - val_loss: 0.3195 - val_acc: 0.8756
Fnoch 5/10
20000/20000 [============] - 118s 6ms/step - loss: 0.1947 - acc:
0.9326 - val_loss: 0.3515 - val_acc: 0.8752
Epoch 6/10
0.9376 - val loss: 0.3531 - val acc: 0.8762
Epoch 7/10
0.9443 - val_loss: 0.3882 - val_acc: 0.8776
20000/20000 [=======] - 119s 6ms/step - loss: 0.1469 - acc:
0.9500 - val_loss: 0.3779 - val_acc: 0.8512
Fpoch 9/10
0.9553 - val_loss: 0.3745 - val_acc: 0.8544
Epoch 10/10
0.9601 - val_loss: 0.5192 - val_acc: 0.8386
```

In [14]:

```
import matplotlib.pvplot 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()
```



Training and validation accuracy



양방향 LSTM

0.800

0.775

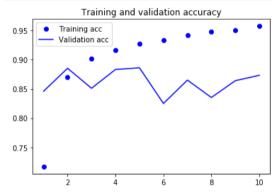
In [16]:

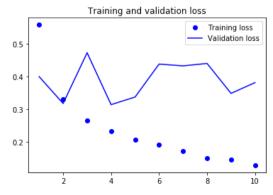
```
model = Sequential()
model.add(layers.Embedding(max_features, 32))
model.add(layers.Bidirectional(layers.LSTM(32)))
model.add(layers.Dense(1, activation='sigmoid'))
model.compile(optimizer=RMSprop(), loss='binary_crossentropy', metrics=['acc'])
history = model.fit(
    x_train, y_train,
    epochs=10,
    batch_size = 128,
    validation_split = 0.2)
```

```
Train on 20000 samples, validate on 5000 samples
Epoch 1/10
20000/20000 [=======] - 230s 12ms/step - loss: 0.5586 - ac
c: 0.7169 - val loss: 0.3998 - val acc: 0.8460
Epoch 2/10
c: 0.8706 - val_loss: 0.3175 - val_acc: 0.8852
Epoch 3/10
20000/20000 [=======] - 228s 11ms/step - loss: 0.2645 - ac
c: 0.9020 - val loss: 0.4729 - val acc: 0.8510
Epoch 4/10
20000/20000 [==========] - 224s 11ms/step - loss: 0.2325 - ac
c: 0.9158 - val_loss: 0.3140 - val_acc: 0.8832
20000/20000 [======] - 227s 11ms/step - loss: 0.2064 - ac
c: 0.9271 - val_loss: 0.3373 - val_acc: 0.8860
Epoch 6/10
20000/20000 [=========== ] - 228s 11ms/step - loss: 0.1909 - ac
c: 0.9331 - val loss: 0.4382 - val acc: 0.8250
Fnoch 7/10
20000/20000 [=========== ] - 233s 12ms/step - loss: 0.1714 - ac
c: 0.9421 - val_loss: 0.4327 - val_acc: 0.8650
20000/20000 [============] - 226s 11ms/step - loss: 0.1501 - ac
c: 0.9476 - val_loss: 0.4402 - val_acc: 0.8352
Fpoch 9/10
20000/20000 [============= ] - 226s 11ms/step - loss: 0.1458 - ac
c: 0.9503 - val_loss: 0.3486 - val_acc: 0.8640
Epoch 10/10
20000/20000 [==========] - 226s 11ms/step - loss: 0.1285 - ac
c: 0.9574 - val_loss: 0.3815 - val_acc: 0.8732
```

In [17]:

```
import matplotlib.pvplot 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.leaend()
plt.show()
```





양방향 GRU

In [19]:

```
model = Sequential()
model.add(layers.Bidirectional(layers.GRU(32), input_shape=(None, float_data.shape[-1])))
model.add(layers.Dense(1))

model.compile(optimizer=RMSprop(), loss='mae')
history = model.fit_generator(
    train_gen,
    steps_per_epoch=500,
    epochs=40,
    validation_data = val_gen,
    validation_steps = val_steps)
```

```
Epoch 1/40
ss: 0.2860
Epoch 2/40
ss: 0.2725
Epoch 3/40
500/500 [=======] - 516s 1s/step - loss: 0.2654 - val_loss:
0.2773
Epoch 4/40
500/500 [=====] - 517s 1s/step - loss: 0.2617 - val loss:
0.2696
Epoch 5/40
500/500 [===
           0.2705
Epoch 6/40
500/500 [===
             ======== ] - 517s 1s/step - loss: 0.2505 - val_loss:
0.2904
Epoch 7/40
500/500 [========== ] - 517s 1s/step - loss: 0.2443 - val_loss:
0.2851
Epoch 8/40
500/500 [========= ] - 517s 1s/step - loss: 0.2377 - val_loss:
0.2811
Epoch 9/40
500/500 [===
            0.2917
Epoch 10/40
500/500 [====
        0.2877
Epoch 11/40
500/500 [============= ] - 517s 1s/step - loss: 0.2209 - val_loss:
0.2970
Epoch 12/40
500/500 [========== ] - 517s 1s/step - loss: 0.2151 - val_loss:
0.3061
Epoch 13/40
500/500 [======== ] - 517s 1s/step - loss: 0.2104 - val_loss:
0.3042
Epoch 14/40
0.3077
Epoch 15/40
500/500 [======] - 518s 1s/step - loss: 0.2019 - val loss:
0.3154
Epoch 16/40
500/500 [=======] - 517s 1s/step - loss: 0.1962 - val_loss:
0.3123
Epoch 17/40
500/500 [====
         0.3218
Epoch 18/40
0.3204
Epoch 19/40
500/500 [====
           0.3272
Epoch 20/40
500/500 [========== ] - 518s 1s/step - loss: 0.1808 - val_loss:
0.3267
Epoch 21/40
```

```
500/500 [======] - 517s 1s/step - loss: 0.1766 - val_loss:
0.3284
Epoch 22/40
500/500 [======] - 517s 1s/step - loss: 0.1750 - val_loss:
0.3291
Epoch 23/40
500/500 [======] - 516s 1s/step - loss: 0.1713 - val loss:
0.3325
Epoch 24/40
500/500 [======] - 516s 1s/step - loss: 0.1687 - val_loss:
0.3292
Epoch 25/40
500/500 [====
     0.3273
Fpoch 26/40
0.3320
Epoch 27/40
500/500 [=======] - 516s 1s/step - loss: 0.1613 - val_loss:
0.3284
Epoch 28/40
500/500 [===
      0.3346
Epoch 29/40
500/500 [====
      0.3312
Epoch 30/40
500/500 [=======] - 516s 1s/step - loss: 0.1547 - val_loss:
0.3368
Epoch 31/40
0.3374
Epoch 32/40
500/500 [=======] - 515s 1s/step - loss: 0.1516 - val_loss:
0.3442
Epoch 33/40
0.3402
Epoch 34/40
0.3440
Epoch 35/40
500/500 [=======] - 518s 1s/step - loss: 0.1464 - val_loss:
0.3477
Epoch 36/40
0.3421
Epoch 37/40
0.3455
Epoch 38/40
0.3465
Epoch 39/40
500/500 [===
      0.3474
Epoch 40/40
0.3423
```

In [20]:

```
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(loss) + 1)

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()
```

Training and validation loss 0.35 Training loss Validation loss 0.25 0.20 0.15 0 5 10 15 20 25 30 35 40