

# 1 第二题

用VGG16进行特征提取，进行cifar-10的分类

In [59]:

```
# 导入预训练模型VGG16模型的卷积基
from tensorflow.keras.applications import VGG16
conv_base = VGG16(weights='imagenet', include_top=False, input_shape=(32, 32, 3))
```

In [60]:

```
# 数据及准备
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.utils import to_categorical
import numpy as np
# 从keras中读取cifar10数据集
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
# 数据预处理, 标准化处理
x_train = x_train.reshape((50000, 32, 32, 3))
x_train = x_train.astype('float32')/255
x_test = x_test.reshape((10000, 32, 32, 3))
x_test = x_test.astype('float32')/255
# 训练数据划分为训练集和验证集
x_val = x_train[:1000]                                ## 前1000个样本作验证集Validation
partial_x_train = x_train[1000:]                      ## 其余样本作训练集
```

In [61]:

```
y_train.shape
```

Out[61]:

```
(50000, 1)
```

In [62]:

```
partial_x_train.shape
```

Out[62]:

```
(49000, 32, 32, 3)
```

In [63]:

```
# 提取数据特征: 调用卷积基输出函数分别提取训练集、验证集、测试集的特征(samples, 4, 4, 512), 并将其展
train_features = np.reshape(conv_base.predict(partial_x_train), (49000, 1 * 1 * 512))
validation_features = np.reshape(conv_base.predict(x_val), (1000, 1 * 1 * 512))
test_features = np.reshape(conv_base.predict(x_test), (10000, 1 * 1 * 512))
```

WARNING:tensorflow:AutoGraph could not transform <function Model.make\_predict\_function.<locals>.predict\_function at 0x168909820> and will run it as-is.

Please report this to the TensorFlow team. When filing the bug, set the verbosity to 10 (on Linux, `export AUTOGRAPH\_VERBOSITY=10`) and attach the full output.

Cause: unsupported operand type(s) for -: 'NoneType' and 'int'

To silence this warning, decorate the function with @tf.autograph.experimental.do\_not\_convert

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In [64]:

```
# 将类别标签转化为独热矩阵表示
```

```
y_train = to_categorical(y_train)
```

```
y_test = to_categorical(y_test)
```

In [65]:

```
# 将类别标签也相应划分为训练集、验证集、测试集
```

```
y_val = y_train[:1000] ## 前1000个验证集样本标签
```

```
partial_y_train = y_train[1000:] ## 训练集样本标签
```

```
train_labels = partial_y_train
```

```
validation_labels = y_val
```

```
test_labels = y_test
```

In [66]:

```
# 定义全连接分类器
```

```
from tensorflow.keras import models
```

```
from tensorflow.keras import layers
```

```
from tensorflow.keras import optimizers
```

```
model = models.Sequential()
```

```
##model.add(layers.Flatten(input_shape=conv_base.output_shape[1:]))
```

```
model.add(layers.Dense(256, activation='relu', input_dim=1 * 1 * 512))
```

```
model.add(layers.Dropout(0.5))
```

```
# model.add(layers.Dense(64, activation='relu'))
```

```
# model.add(layers.Dropout(0.25))
```

```
model.add(layers.Dense(10, activation='softmax'))
```

In [67]:

# 编译和训练全连接分类器

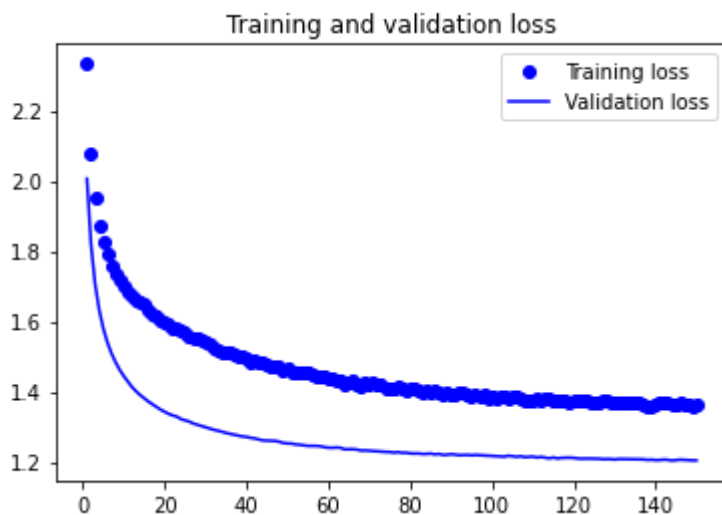
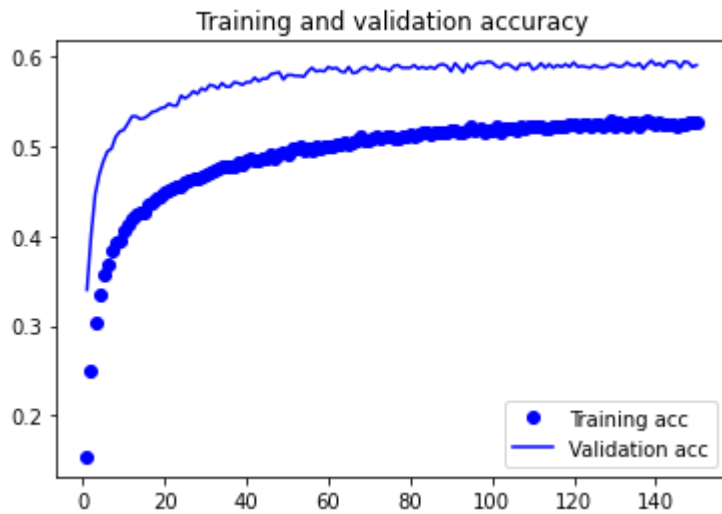
```
model.compile(optimizer=optimizers.RMSprop(lr=2e-5), loss='categorical_crossentropy',  
history = model.fit(train_features, train_labels, epochs=150, batch_size=64, validation_data=(val_features, val_labels))  
##history = model.fit(train_features, train_labels, epochs=30, batch_size=256, validation_data=(val_features, val_labels))
```

0 - accuracy: 0.5212 - val\_loss: 1.2012 - val\_accuracy: 0.5910  
Epoch 145/150  
766/766 [=====] - 1s 801us/step - loss: 1.363  
6 - accuracy: 0.5225 - val\_loss: 1.2052 - val\_accuracy: 0.5930  
Epoch 146/150  
766/766 [=====] - 1s 858us/step - loss: 1.361  
6 - accuracy: 0.5257 - val\_loss: 1.2068 - val\_accuracy: 0.5870  
Epoch 147/150  
766/766 [=====] - 1s 786us/step - loss: 1.363  
0 - accuracy: 0.5245 - val\_loss: 1.2060 - val\_accuracy: 0.5940  
Epoch 148/150  
766/766 [=====] - 1s 800us/step - loss: 1.359  
0 - accuracy: 0.5296 - val\_loss: 1.2051 - val\_accuracy: 0.5930  
Epoch 149/150  
766/766 [=====] - 1s 774us/step - loss: 1.360  
5 - accuracy: 0.5274 - val\_loss: 1.2047 - val\_accuracy: 0.5880  
Epoch 150/150  
766/766 [=====] - 1s 775us/step - loss: 1.357  
2 - accuracy: 0.5282 - val\_loss: 1.2047 - val\_accuracy: 0.5900

In [68]:

# 绘制训练过程中的损失曲线和精度曲线

```
import matplotlib.pyplot as plt
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
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 [69]:

```
# 在测试集上评估模型性能
test_loss, test_acc = model.evaluate(test_features, test_labels)
print('loss = {}, accuracy = {}'.format(test_loss, test_acc))
# 实验结论
# loss = 1.2414, accuracy = 0.5653    ## epochs=150, batch_size=64

313/313 [=====] - 0s 271us/step - loss: 1.241
4 - accuracy: 0.5653
loss = 1.241441249847412, accuracy = 0.5652999877929688
```

## 2 第三题

微调最后一个卷积层，进行cifar-10的分类

In [70]:

```
# 数据及准备
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.utils import to_categorical
# 从keras中读取cifar10数据集
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
# 数据预处理，标准化处理
x_train = x_train.reshape((50000, 32, 32, 3))
x_train = x_train.astype('float32')/255
x_test = x_test.reshape((10000, 32, 32, 3))
x_test = x_test.astype('float32')/255
# 训练数据划分为训练集和验证集
x_val = x_train[:1000]                                ## 前1000个样本作验证集Validation
partial_x_train = x_train[1000:]                      ## 其余样本作训练集
train_x = partial_x_train
# 将类别标签转化为独热矩阵表示
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
# 将类别标签也相应划分为训练集、验证集、测试集
y_val = y_train[:1000]                                ## 前1000个验证集样本标签
partial_y_train = y_train[1000:]                      ## 训练集样本标签
train_y = partial_y_train
```

In [71]:

```
# 第一次训练
# 定义全连接分类器
from tensorflow.keras import models
from tensorflow.keras import layers
from tensorflow.keras import optimizers
model = models.Sequential()
# 添加卷积基并冻结
model.add(conv_base)
conv_base.trainable = False      ## 卷积基冻结, 不参加训练, 否则网络参数太多!
# 添加Dense层
model.add(layers.Flatten())
model.add(layers.Dense(256, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))
print(model.summary())          ## 查看模型
```

Model: "sequential\_9"

Layer (type)	Output Shape	Param #
=====		
vgg16 (Functional)	(None, 1, 1, 512)	14714688
flatten_2 (Flatten)	(None, 512)	0
dense_19 (Dense)	(None, 256)	131328
dense_20 (Dense)	(None, 10)	2570
=====		
Total params: 14,848,586		
Trainable params: 133,898		
Non-trainable params: 14,714,688		
=====		
None		

In [72]:

# 编译和训练全连接分类器

```
model.compile(optimizer=optimizers.RMSprop(lr=2e-5), loss='categorical_crossentropy',
              history = model.fit(train_x, train_y, epochs=30, batch_size=256, validation_data=(x_
```

Epoch 1/30

WARNING:tensorflow:AutoGraph could not transform <function Model.make\_train\_function.<locals>.train\_function at 0x2c77b41f0> and will run it as-is.

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192/192 [=====] - ETA: 0s - loss: 2.4064 - ac

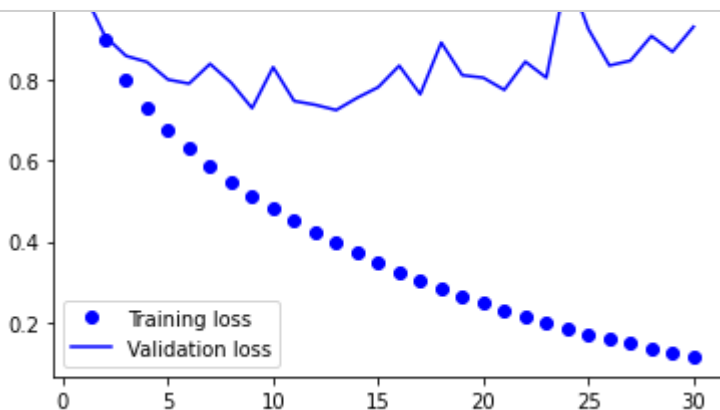
In [73]:

```

# 第二次训练
# 从顶层开始解冻直到'block5_conv1'
conv_base.trainable = True      ## 解冻卷积基
set_trainable = False          ## 逻辑变量赋初值
# 循环从block1_conv1开始, 直到block5_conv1将set_trainable 设为true, 此后各层均layer.trainable=True
for layer in conv_base.layers:
    if layer.name == 'block5_conv1':
        set_trainable = True
    if set_trainable:
        layer.trainable = True  ## 设置该层解冻
    else:
        layer.trainable = False ## 设置该层冻结
# 编译和训练全连接分类器
model.compile(optimizer=optimizers.RMSprop(lr=2e-5), loss='categorical_crossentropy')
history = model.fit(train_x, train_y, epochs=30, batch_size=256, validation_data=(x_test, y_test))
# 绘制训练过程中的损失曲线和精度曲线
import matplotlib.pyplot as plt
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
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()

# 在测试集上评估模型性能
test_loss, test_acc = model.evaluate(x_test, y_test)
print('loss = {}, accuracy = {}'.format(test_loss, test_acc))
#出现了一定的过拟合现象

```





In [74]:

```
# 在测试集上评估模型性能
```

```
test_loss, test_acc = model.evaluate(x_test, y_test)
```

```
print('loss = {}, accuracy = {}'.format(test_loss, test_acc))
```

```
#loss = 0.9345357418060303, accuracy = 0.7401000261306763
```

```
313/313 [=====] - 10s 31ms/step - loss: 0.934
```

```
5 - accuracy: 0.7401
```

```
loss = 0.9345357418060303, accuracy = 0.7401000261306763
```