딥러닝/클라우드

Chapter 14

Transfer Learning

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1. Summary

- Transfer learning (전이학습)
  - Transfer learning (TL) is a research problem in machine learning (ML) that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem.

  - For example, knowledge gained while learning to recognize cars could apply when trying to recognize trucks.
  - imageNet 문제를 해결하는데 사용한 DNN 모델을 다른 image 분류 문제에 활용
    - Neural network architecture
    - weights

1. Summary

- Keras Applications are deep learning models that are made available alongside pre-trained weights.
- These models can be used for prediction, feature extraction, and fine-tuning

Keras Applications

- Xception
- EfficientNet B0 to B7
- VGG16 and VGG19
- ResNet and ResNetV2
- MobileNet and MobileNetV2
- DenseNet
- NasNetLarge and NasNetMobile
- InceptionV3
- InceptionResNetV2

1. Summary

Available models

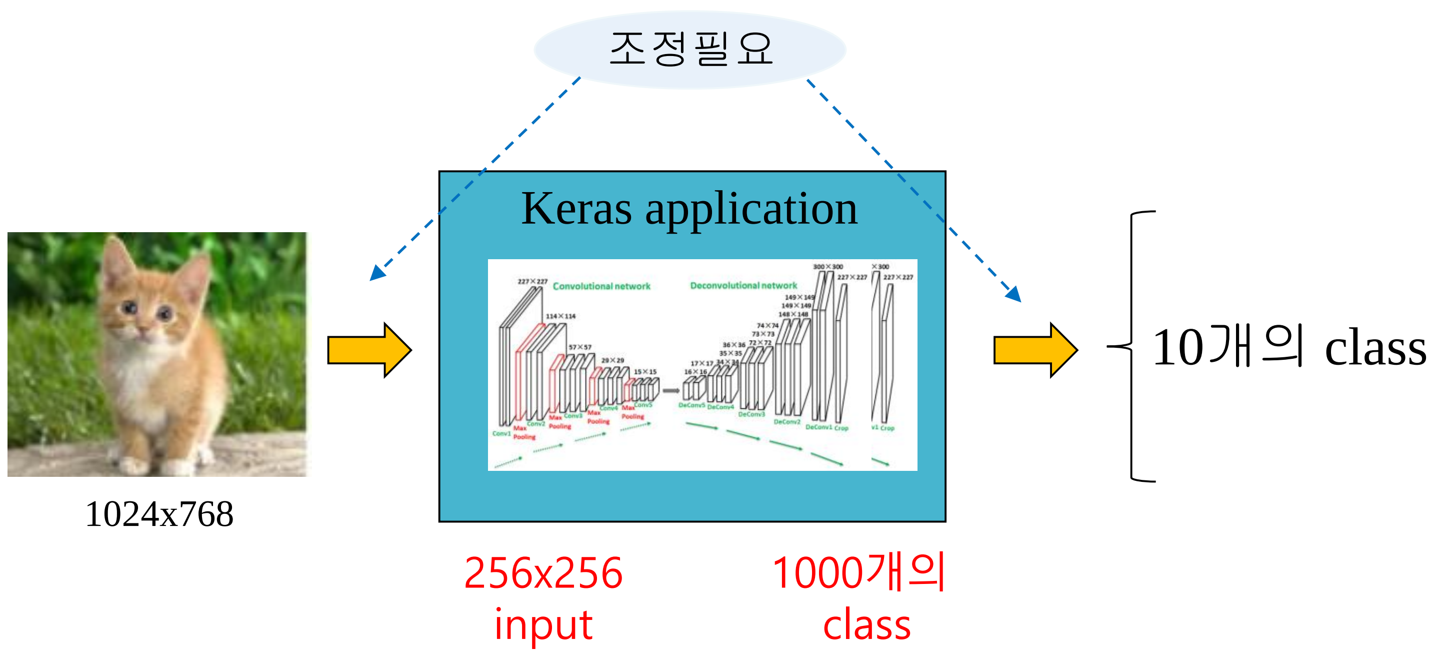
Model	Size	Top-1 Accuracy	Top-5 Accuracy	Parameters	Depth
Xception	88 MB	0.790	0.945	22,910,480	126
VGG16	528 MB	0.713	0.901	138,357,544	23
VGG19	549 MB	0.713	0.900	143,667,240	26
ResNet50	98 MB	0.749	0.921	25,636,712	-
ResNet101	171 MB	0.764	0.928	44,707,176	-
ResNet152	232 MB	0.766	0.931	60,419,944	-
ResNet50V2	98 MB	0.760	0.930	25,613,800	-
ResNet101V2	171 MB	0.772	0.938	44,675,560	-
ResNet152V2	232 MB	0.780	0.942	60,380,648	-
InceptionV3	92 MB	0.779	0.937	23,851,784	159
InceptionResNetV2	215 MB	0.803	0.953	55,873,736	572
MobileNet	16 MB	0.704	0.895	4,253,864	88
MobileNetV2	14 MB	0.713	0.901	3,538,984	88
DenseNet121	33 MB	0.750	0.923	8,062,504	121
DenseNet169	57 MB	0.762	0.932	14,307,880	169
DenseNet201	80 MB	0.773	0.936	20,242,984	201

1. Summary

NASNetMobile	23 MB	0.744	0.919	5,326,716	-
NASNetLarge	343 MB	0.825	0.960	88,949,818	-
EfficientNetB0	29 MB	-	-	5,330,571	-
EfficientNetB1	31 MB	-	-	7,856,239	-
EfficientNetB2	36 MB	-	-	9,177,569	-
EfficientNetB3	48 MB	-	-	12,320,535	-
EfficientNetB4	75 MB	-	-	19,466,823	-
EfficientNetB5	118 MB	-	-	30,562,527	-
EfficientNetB6	166 MB	-	-	43,265,143	-
EfficientNetB7	256 MB	-	-	66,658,687	-

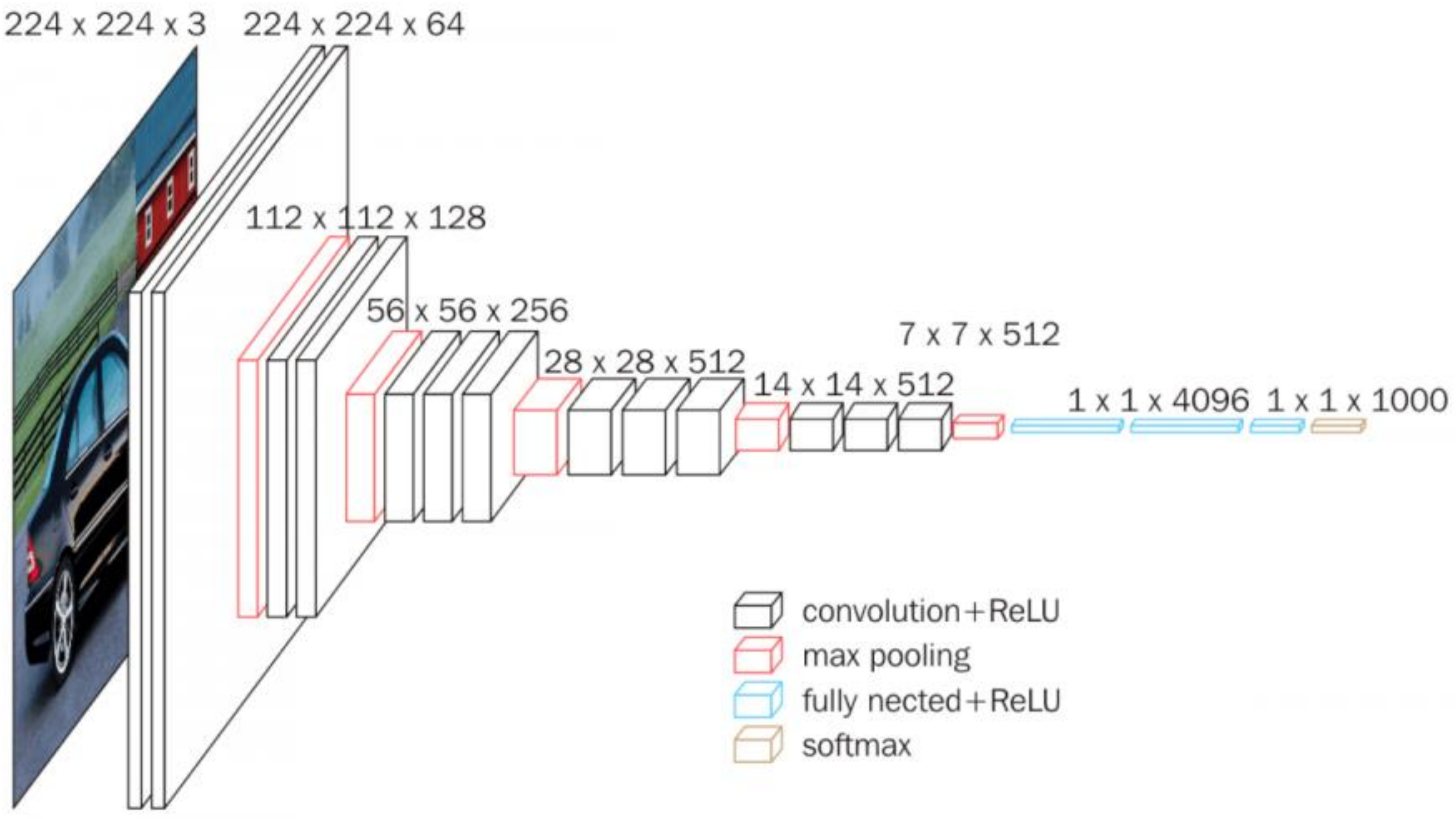
1. Summary

- 이 모델들은 imagenet 의 데이터에 맞추어 구조가 만들어짐
- 다른 작업에 사용하려면 입력과 출력의 dimension 이 다를 수 있다.
- Keras 에서는 이런 부분을 조정할 수 있도록 지원한다



2. VGG16 example

- VGG16 architecture



https://bskyvision.com/504

2. VGG16 example

- Case 1. Predict a random image

  - Load VGG16 model
  - Prepare a image
  - Predict the image

2. VGG16 example

```
from keras.preprocessing.image import load_img
from keras.preprocessing.image import img_to_array
from keras.applications.vgg16 import preprocess_input
from keras.applications.vgg16 import decode_predictions
from keras.applications.vgg16 import VGG16

# load the model
model = VGG16()        # take a long time

# load an image from file
image = load_img('D:/data/sample_img_1.jpg', target_size=(224, 224))

# convert the image pixels to a numpy array
image = img_to_array(image)

# reshape data for the model
image = image.reshape((1, image.shape[0], image.shape[1], image.shape[2]))
```

2. VGG16 example

```
# prepare the image for the VGG model
image = preprocess_input(image)


# predict the probability across all output classes
pred = model.predict(image)
```

```
In [35]: image.shape
Out[35]: (1, 224, 224, 3)
```

```
In [37]: pred
Out[37]:
array([[2.02823500e-08, 2.36752442e-07, 4.87318896e-09, 1.45811576e-08,
        2.95860527e-08, 6.06516650e-08, 8.11169087e-09, 1.99178729e-07,
        1.34378226e-07, 2.45495016e-07, 1.73777636e-07, 4.73473506e-07,
        4.38422518e-07, 9.14644076e-08, 3.74206678e-07, 1.15517921e-07,
        2.07582545e-07, 1.64247808e-07, 1.92927331e-07, 3.33448384e-07,
        8.47046966e-09, 4.27838813e-08, 4.27860840e-08, 1.17808099e-07,
        1.19830617e-07, 2.76811019e-08, 4.42640697e-08, 2.22004218e-07,
        6.31745465e-08, 3.23924428e-06, 4.34751257e-08, 2.62859260e-07,
        1.53438549e-07, 5.41724745e-08, 2.16927365e-08, 1.60927467e-08,
        1.78756821e-07, 3.80799996e-08, 1.06899286e-07, 1.05639970e-07,
        7.63831949e-08, 6.99591993e-08, 5.16803986e-08, 6.35227693e-08,
```

```
In [38]: pred.shape
Out[38]: (1, 1000)
```

2. VGG16 example

```
# convert the probabilities to class labels
label = decode_predictions(pred)
```

```
In [40]: label
Out[40]:
[[('n03063599', 'coffee_mug', 0.7272259),
  ('n03063689', 'coffeepot', 0.10312535),
  ('n07930864', 'cup', 0.06428892),
  ('n04398044', 'teapot', 0.032623097),
  ('n03950228', 'pitcher', 0.025435064)]]
```

```
# retrieve the most likely result, e.g. highest probability
label = label[0][0]

# print the classification
print('%s (%.2f%%)' % (label[1], label[2]*100))
```

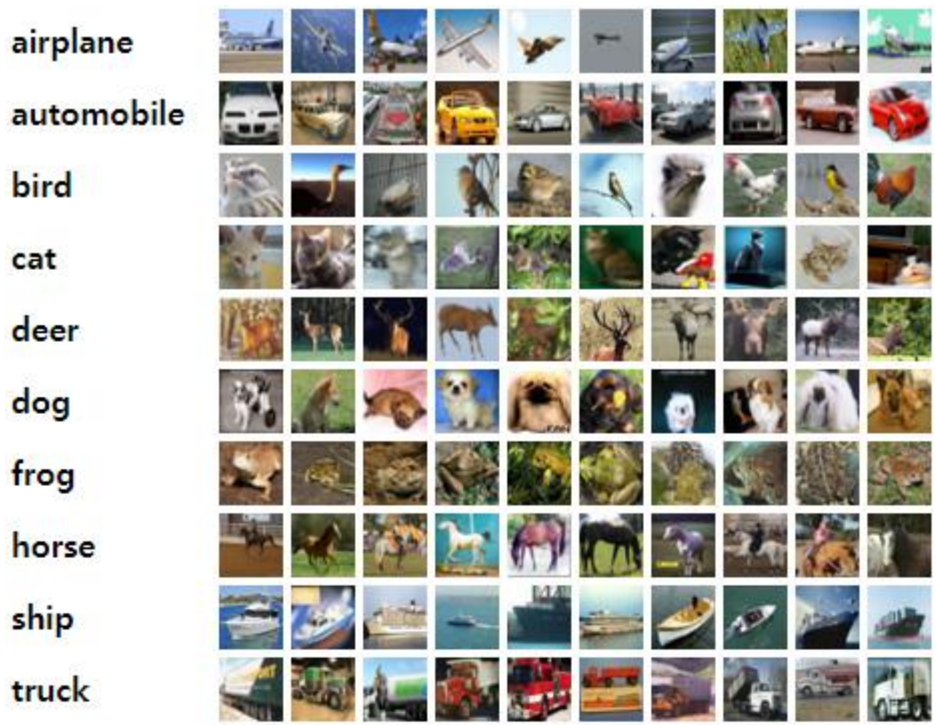
```
In [42]: print('%s (%.2f%%)' % (label[1], label[2]*100))
coffee_mug (72.72%)
```

```
In [22]: model.summary()
Model: "vgg16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_3 (InputLayer)         (None, 224, 224, 3)       0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 224, 224, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 224, 224, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 112, 112, 64)      0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 112, 112, 128)     73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 112, 112, 128)     147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 56, 56, 128)
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 56, 56, 256)
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 56, 56, 256)
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 56, 56, 256)
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 28, 28, 256)
_________________________________________________________________
```

```
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 28, 28, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 14, 14, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 7, 7, 512)         0
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0
_________________________________________________________________
fc1 (Dense)                  (None, 4096)              102764544
_________________________________________________________________
fc2 (Dense)                  (None, 4096)              16781312
_________________________________________________________________
predictions (Dense)          (None, 1000)              4097000
=================================================================
```

2. VGG16 example

- Case 2. CIFAR-10 classification
  - The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes, with 6000 images per class.
  - There are 50000 training images and 10000 test images.



http://www.cs.utoronto.ca/~kriz/cifar.html

2. VGG16 example

```
from keras import optimizers
from keras.datasets import cifar10
from keras.engine import Model
from keras.layers import Dropout, Flatten, Dense
from keras.utils import np_utils
from keras.applications.vgg16 import VGG16

# set up base model
img_width, img_height = 32, 32
base_model = VGG16(weights='imagenet',
                   include_top=False,        # output 부분 사용x
                   input_shape=(32, 32, 3))

nb_epoch = 2      # try 50
nb_classes = 10
```

```
In [15]: base_model.summary()
Model: "vgg16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_2 (InputLayer)         (None, 32, 32, 3)         0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 32, 32, 64)        1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 32, 32, 64)        36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 16, 16, 64)        0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 16, 16, 128)       73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 16, 16, 128)       147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 8, 8, 128)         0
_________________________________________________________________
block3 conv1 (Conv2D)        (None, 8, 8, 256)         295168
```

```
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 2, 2, 512)         0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 2, 2, 512)         2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 2, 2, 512)         2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 2, 2, 512)         2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 1, 1, 512)         0
=================================================================
Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0
```

Fully connect layers 가 제거됨

2. VGG16 example

```
# load dataset
(X_train, y_train), (X_test, y_test) = cifar10.load_data()
y_train = np_utils.to_categorical(y_train, nb_classes)
y_test = np_utils.to_categorical(y_test, nb_classes)


# Extract the last layer from third block of vgg16 model
last = base_model.get_layer('block5_pool').output

# Add classification layers on top of it
x = Flatten()(last)
x = Dense(256, activation='relu')(x)
x = Dropout(0.5)(x)
output = Dense(10, activation='softmax')(x)

model = Model(base_model.input, output)
model.summary()
```

2. VGG16 example

```
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 2, 2, 512)         2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 2, 2, 512)         2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 2, 2, 512)         2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 1, 1, 512)         0
_________________________________________________________________
flatten_3 (Flatten)          (None, 512)               0
_________________________________________________________________
dense_5 (Dense)              (None, 256)               131328
_________________________________________________________________
dropout_3 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_6 (Dense)              (None, 10)                2570
=================================================================
Total params: 14,848,586
Trainable params: 14,848,586
Non-trainable params: 0
_________________________________________________________________
```

추가된 부분

2. VGG16 example

```
model.compile(loss='binary_crossentropy',
              optimizer=optimizers.SGD(lr=1e-3, momentum=0.9),
              metrics=['accuracy'])

model.fit(X_train, y_train,
          validation_data=(X_test, y_test),
          nb_epoch=nb_epoch,
          batch_size=200,
          verbose=1)

# Final evaluation of the model
scores = model.evaluate(X_test, y_test, verbose=0)
print("loss: %.2f" % scores[0])
print("acc: %.2f" % scores[1])
```

2. VGG16 example

```
Train on 50000 samples, validate on 10000 samples
Epoch 1/2
50000/50000 [==============================] - 1566s 31ms/step - loss: 0.3772 -
accuracy: 0.8973 - val_loss: 0.3251 - val_accuracy: 0.9000
Epoch 2/2
50000/50000 [==============================] - 1568s 31ms/step - loss: 0.3251 -
accuracy: 0.9000 - val_loss: 0.3251 - val_accuracy: 0.9000
loss: 0.33
acc: 0.90
```

26분

3. EfficientNet

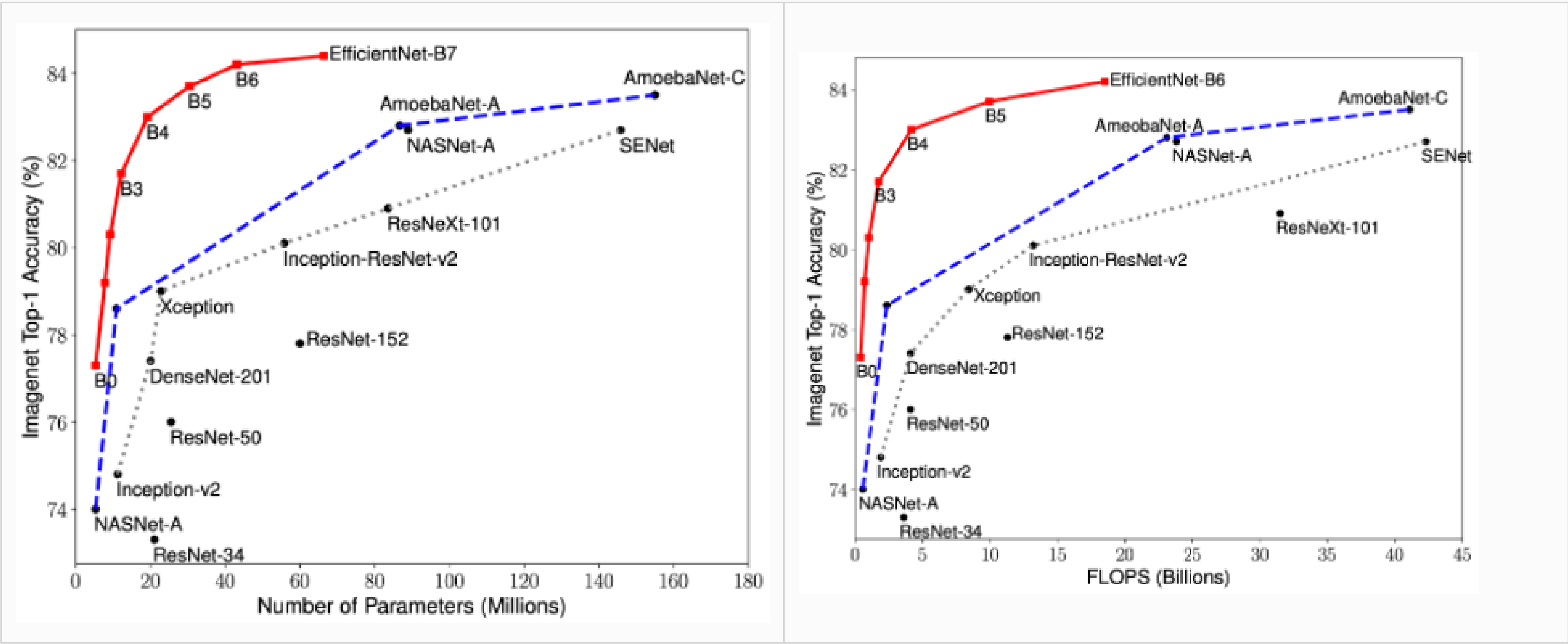
- EfficientNet, first introduced in Tan and Le, 2019 is among the most efficient models (i.e. requiring least FLOPS for inference) that reaches State-of-the-Art accuracy on both imagenet and common image classification transfer learning tasks.

- EfficientNet provides a family of models (B0 to B7) that represents a good combination of efficiency and accuracy on a variety of scales.

- efficiency-oriented base model (B0) to surpass models at every scale

https://keras.io/examples/vision/image_classification_efficientnet_fine_tuning/

3. EfficientNet



https://pypi.org/project/efficientnet/#installation

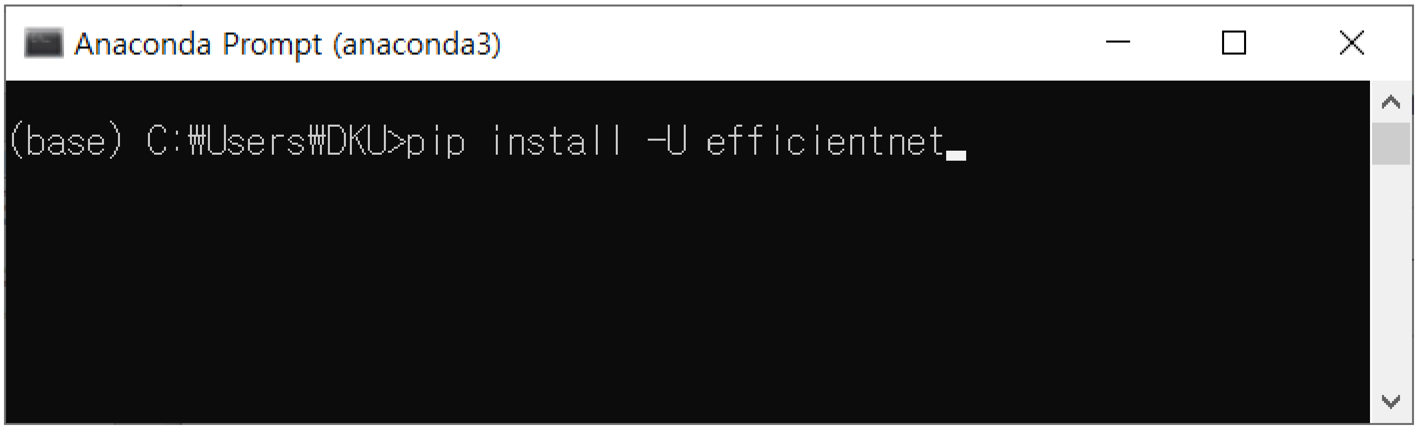
3. EfficientNet

- B0 to B7 variants of EfficientNet
  - Resolution: Resolutions not divisible by 8, 16, etc. cause zero-padding near boundaries of some layers which wastes computational resources.
  - Depth and width: The building blocks of EfficientNet demands channel size to be multiples of 8.

Base model	**resolution**
EfficientNetB0	224
EfficientNetB1	240
EfficientNetB2	260
EfficientNetB3	300
EfficientNetB4	380
EfficientNetB5	456
EfficientNetB6	528
EfficientNetB7	600

3. EfficientNet

- Install efficientnet



  - `pip install -U efficientnet`

3. EfficientNet

```
from keras import optimizers
from keras.datasets import cifar10
from keras.engine import Model
from keras.layers import Dropout, Flatten, Dense
from keras.utils import np_utils

import efficientnet.keras as efn

img_width, img_height = 32, 32
base_model = efn.EfficientNetB0(weights='imagenet',
                   include_top=False,
                   input_shape=(32, 32, 3))

nb_epoch = 2    # 50 is good
nb_classes = 10
```

3. EfficientNet

```
In [3]: base_model.summary()
Model: "efficientnet-b0"

______________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==============================================================================================
input_1 (InputLayer)            (None, 32, 32, 3)    0
______________________________________________________________________________________________
stem_conv (Conv2D)              (None, 16, 16, 32)   864         input_1[0][0]
______________________________________________________________________________________________
stem_bn (BatchNormalization)    (None, 16, 16, 32)   128         stem_conv[0][0]
```

```
______________________________________________________________________________________________
block7a_project_conv (Conv2D)   (None, 1, 1, 320)    368640      block7a_se_excite[0][0]
______________________________________________________________________________________________
block7a_project_bn (BatchNormal (None, 1, 1, 320)    1280        block7a_project_conv[0][0]
______________________________________________________________________________________________
top_conv (Conv2D)               (None, 1, 1, 1280)   409600      block7a_project_bn[0][0]
______________________________________________________________________________________________
top_bn (BatchNormalization)     (None, 1, 1, 1280)   5120        top_conv[0][0]
______________________________________________________________________________________________
top_activation (Activation)     (None, 1, 1, 1280)   0           top_bn[0][0]
==============================================================================================
Total params: 4,049,564
Trainable params: 4,007,548
Non-trainable params: 42,016
______________________________________________________________________________________________
```

3. EfficientNet

```
# load dataset
(X_train, y_train), (X_test, y_test) = cifar10.load_data()
y_train = np_utils.to_categorical(y_train, nb_classes)
y_test = np_utils.to_categorical(y_test, nb_classes)


# Extract the last layer from third block of model
last = base_model.get_layer('top_activation').output

# Add classification layers on top of it
x = Flatten()(last)
x = Dense(256, activation='relu')(x)
x = Dropout(0.5)(x)
output = Dense(10, activation='softmax')(x)

model = Model(base_model.input, output)
```

3. EfficientNet

```
_____________________________________________________________________________________________
block7a_se_excite (Multiply)     (None, 1, 1, 1152)   0           block7a_activation[0][0]
                                                                  block7a_se_expand[0][0]
_____________________________________________________________________________________________
block7a_project_conv (Conv2D)    (None, 1, 1, 320)    368640      block7a_se_excite[0][0]
_____________________________________________________________________________________________
block7a_project_bn (BatchNormal (None, 1, 1, 320)    1280        block7a_project_conv[0][0]
_____________________________________________________________________________________________
top_conv (Conv2D)                (None, 1, 1, 1280)   409600      block7a_project_bn[0][0]
_____________________________________________________________________________________________
top_bn (BatchNormalization)      (None, 1, 1, 1280)   5120        top_conv[0][0]
_____________________________________________________________________________________________
top_activation (Activation)      (None, 1, 1, 1280)   0           top_bn[0][0]
_____________________________________________________________________________________________
flatten_1 (Flatten)              (None, 1280)         0           top_activation[0][0]
_____________________________________________________________________________________________
dense_1 (Dense)                  (None, 256)          327936      flatten_1[0][0]
_____________________________________________________________________________________________
dropout_1 (Dropout)              (None, 256)          0           dense_1[0][0]
_____________________________________________________________________________________________
dense_2 (Dense)                  (None, 10)           2570        dropout_1[0][0]
=============================================================================================
Total params: 4,380,070
Trainable params: 4,338,054
Non-trainable params: 42,016
_____________________________________________________________________________________________
```

3. EfficientNet

```
model.compile(loss='binary_crossentropy',
              optimizer=optimizers.SGD(lr=1e-3, momentum=0.9),
              metrics=['accuracy'])

model.summary()


model.fit(X_train, y_train,
          validation_data=(X_test, y_test),
          nb_epoch=nb_epoch,
          batch_size=200,
          verbose=1)

# Final evaluation of the model
scores = model.evaluate(X_test, y_test, verbose=0)
print("loss: %.2f" % scores[0])
print("acc: %.2f" % scores[1])
```

3. EfficientNet

```
Train on 50000 samples, validate on 10000 samples
Epoch 1/2
50000/50000 [==============================] - 535s 11ms/step - loss: 0.3907 - accuracy: 0.8875 -
val_loss: 0.3351 - val_accuracy: 0.8995
Epoch 2/2
50000/50000 [==============================] - 513s 10ms/step - loss: 0.3658 - accuracy: 0.8915 -
val_loss: 0.3219 - val_accuracy: 0.8996
Out[11]: <keras.callbacks.callbacks.History at 0x11b75170c48>
```

```
loss: 0.32
acc: 0.90
```

3. EfficientNet

- This parameter serves as a toggle for extra regularization in finetuning, but does not affect loaded weights.

```
base_model = efn.EfficientNetB0(weights='imagenet’,
                                 drop_connect_rate=0.4)
```

4. Keras Regression

- Regression 은 출력 값이 1개, one-hot encoding 불필요
- Boston housing dataset

BostonHousing 데이터 설명

[01]	CRIM	자치시(town) 별 1인당 범죄율
[02]	ZN	25,000 평방피트를 초과하는 거주지역의 비율
[03]	INDUS	비소매상업지역이 점유하고 있는 토지의 비율
[04]	CHAS	찰스강에 대한 더미변수(강의 경계에 위치한 경우는 1, 아니면 0)
[05]	NOX	10ppm 당 농축 일산화질소
[06]	RM	주택 1가구당 평균 방의 개수
[07]	AGE	1940년 이전에 건축된 소유주택의 비율
[08]	DIS	5개의 보스턴 직업센터까지의 접근성 지수
[09]	RAD	방사형 도로까지의 접근성 지수
[10]	TAX	10,000 달러 당 재산세율
[11]	PTRATIO	자치시(town)별 학생/교사 비율
[12]	B	1000(Bk-0.63)^2, 여기서 Bk는 자치시별 흑인의 비율을 말함.
[13]	LSTAT	모집단의 하위계층의 비율(%)
[14]	MEDV	본인 소유의 주택가격(중앙값) (단위: $1,000)

http://dator.co.kr/?vid=ctg258&mid=textyle&document_srl=1721307

4. Keras Regression

```
from keras.models import Sequential
from keras.layers import Dense
from sklearn.model_selection import train_test_split
from keras.datasets import boston_housing

# load dataset
(X_train, y_train), (X_test, y_test) = boston_housing.load_data()

model = Sequential()
model.add(Dense(16, input_dim=13, activation='relu'))
model.add(Dense(8, activation='relu'))
model.add(Dense(1))                                 # output

model.compile(loss='mean_squared_error', optimizer='adam')

model.fit(X_train, y_train, epochs=200, batch_size=10)
```

```
Epoch 1/200
404/404 [==============================] - 1s 2ms/step - loss: 271.7087
Epoch 2/200
404/404 [==============================] - 0s 116us/step - loss: 132.0523
Epoch 3/200
404/404 [==============================] - 0s 109us/step - loss: 91.2605
Epoch 4/200
404/404 [==============================] - 0s 111us/step - loss: 80.1819
Epoch 5/200
404/404 [==============================] - 0s 106us/step - loss: 76.2772
Epoch 6/200
404/404 [==============================] - 0s 116us/step - loss: 75.0198
Epoch 7/200
404/404 [==============================] - 0s 116us/step - loss: 79.4039
Epoch 8/200
404/404 [==============================] - 0s 109us/step - loss: 74.7349
Epoch 9/200
404/404 [==============================] - 0s 116us/step - loss: 70.2591
Epoch 10/200
```

```
Epoch 194/200
404/404 [==============================] - 0s 111us/step - loss: 28.7584
Epoch 195/200
404/404 [==============================] - 0s 113us/step - loss: 28.9097
Epoch 196/200
404/404 [==============================] - 0s 116us/step - loss: 29.4230
Epoch 197/200
404/404 [==============================] - 0s 109us/step - loss: 28.9272
Epoch 198/200
404/404 [==============================] - 0s 111us/step - loss: 27.5968
Epoch 199/200
404/404 [==============================] - 0s 106us/step - loss: 27.4105
Epoch 200/200
404/404 [==============================] - 0s 165us/step - loss: 26.2822
Out[56]: <keras.callbacks.callbacks.History at 0x25c289dbd08>
```

4. Keras Regression

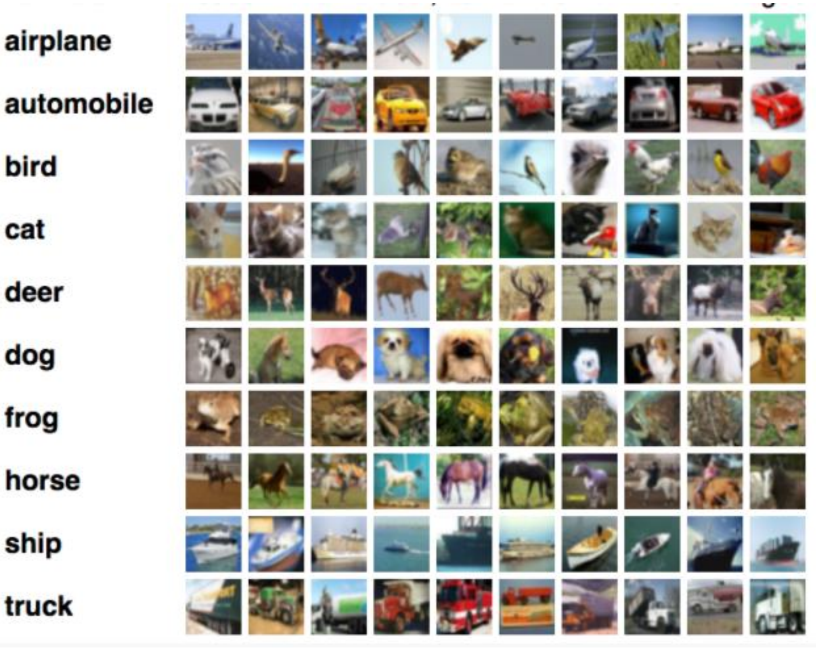
```
Y_prediction = model.predict(X_test).flatten()

for i in range(10):
  real_price = y_test[i]
  predicted_price = Y_prediction[i]
  print('Real Price: {:.3f}, Predicted Price: {:.3f}'.format(real_price,
                                                           predicted_price))
```

```
Real Price: 7.200, Predicted Price: 9.471
Real Price: 18.800, Predicted Price: 21.751
Real Price: 19.000, Predicted Price: 23.354
Real Price: 27.000, Predicted Price: 31.055
Real Price: 22.200, Predicted Price: 25.802
Real Price: 24.500, Predicted Price: 21.640
Real Price: 31.200, Predicted Price: 29.827
Real Price: 22.900, Predicted Price: 26.122
Real Price: 20.500, Predicted Price: 19.287
Real Price: 23.200, Predicted Price: 21.618
```

5. Deep learning application for computer vision

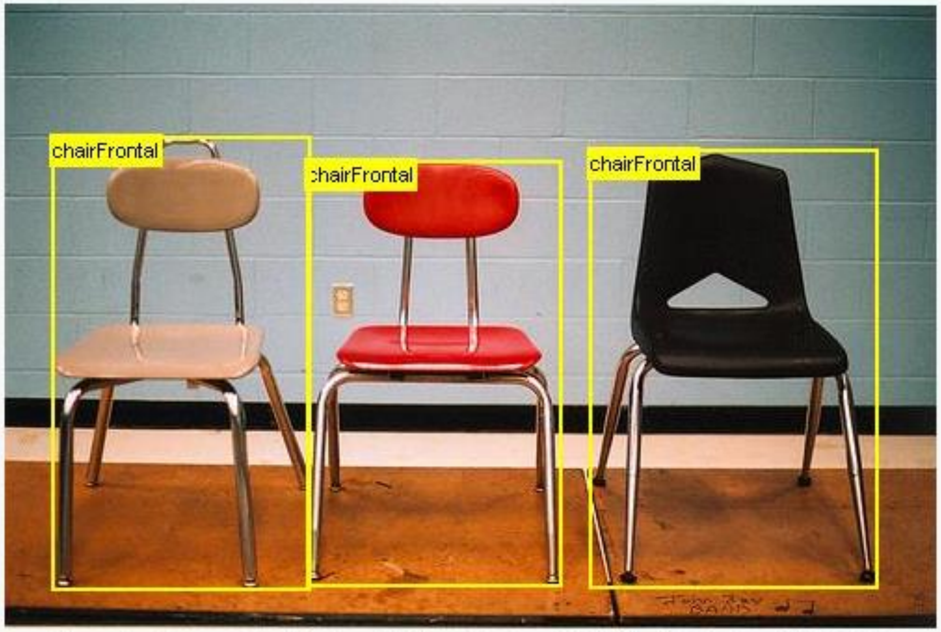
- https://machinelearningmastery.com/applications-of-deep-learning-for-computer-vision/
- (1) Image Classification



5. Deep learning application for computer vision

- (2) Image Classification With Localization

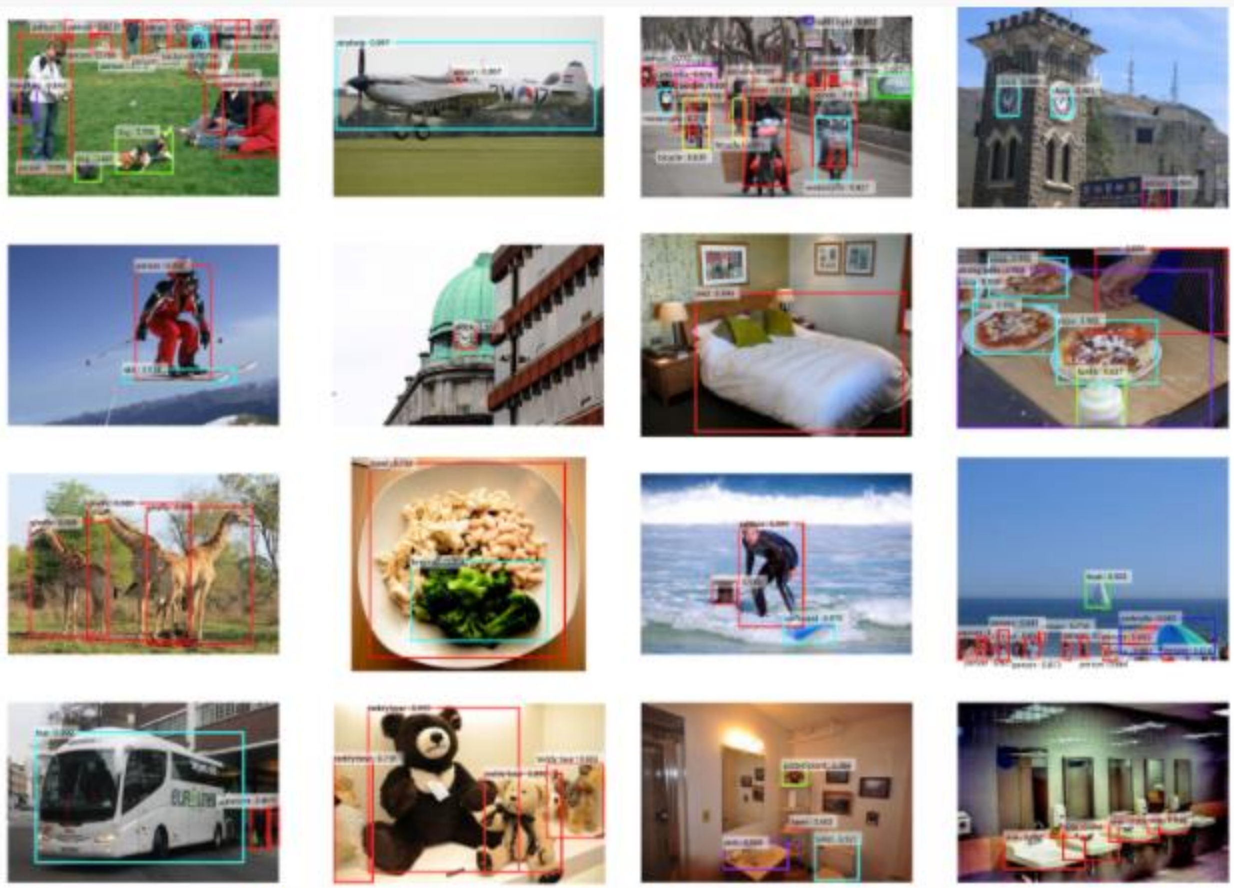
Example of Image Classification With Localization of a Dog from VOC 2012



Example of Image Classification With Localization of Multiple Chairs From VOC 2012

5. Deep learning application for computer vision

- (3) Object Detection



Example of Object Detection With Faster R-CNN on the MS COCO Dataset

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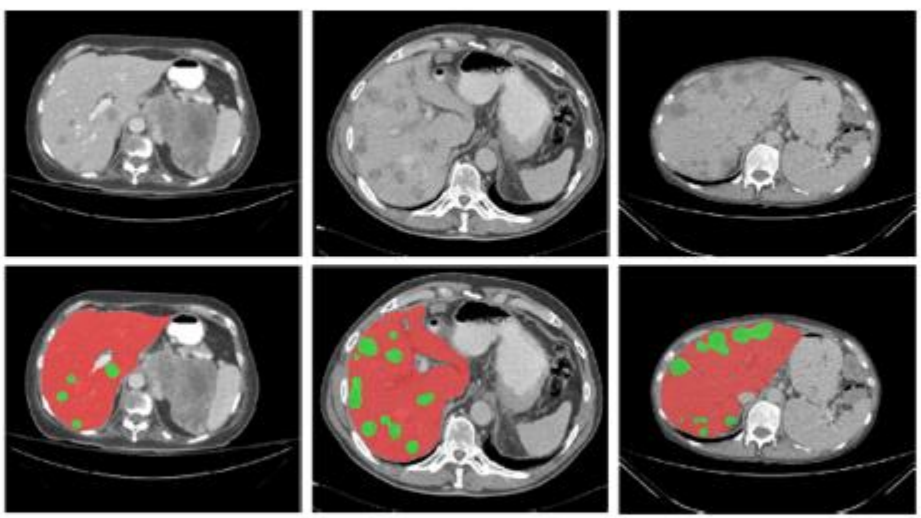
- (4) Object Segmentation

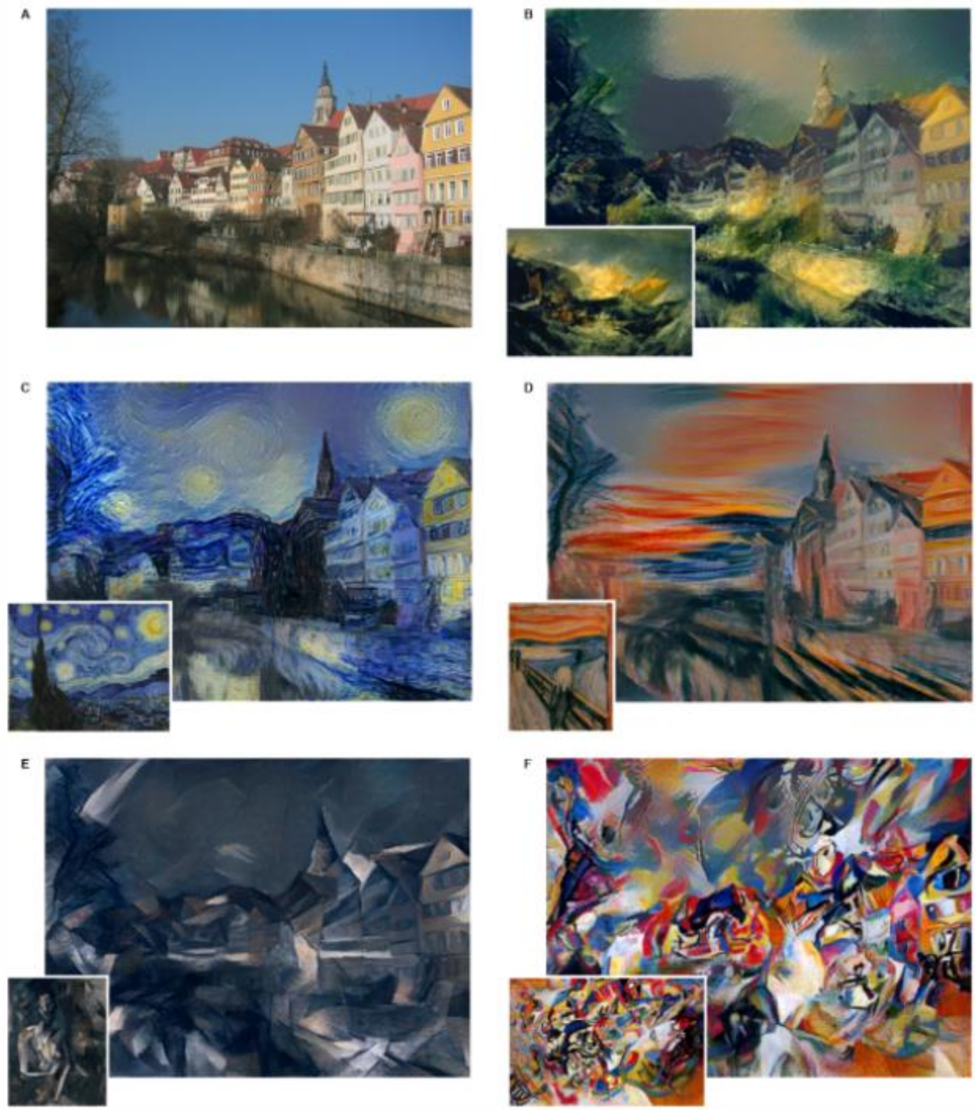
Example of Object Segmentation on the COCO Dataset
Taken from "Mask R-CNN".



https://www.kakaobrain.com/blog/48

5. Deep learning application for computer vision

- (5) Style Transfer



Example of Neural Style Transfer From Famous Artworks to a Photograph
Taken from "A Neural Algorithm of Artistic Style"

5. Deep learning application for computer vision

- (6) Image Colorization

Examples of Photo Colorization
Taken from "Colorful Image Colorization"

5. Deep learning application for computer vision

- (7) Image Reconstruction

Example of Photo Inpainting.
Taken from "Image Inpainting for Irregular Holes Using Partial Convolutions"

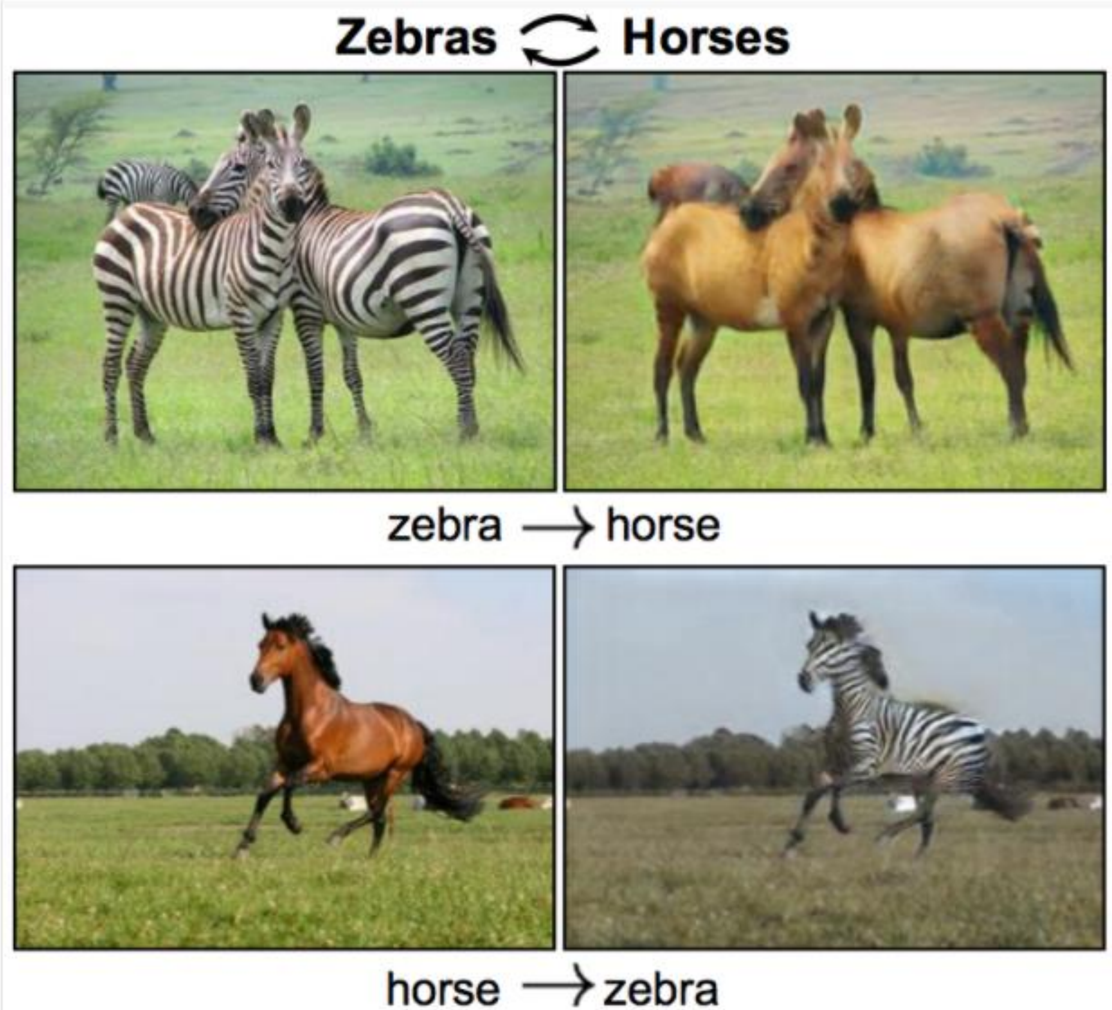
5. Deep learning application for computer vision

- (8) Image Super-Resolution

Example of the Results From Different Super-Resolution Techniques.
Taken from "Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network"

5. Deep learning application for computer vision

- (9) Image Synthesis



Example of Styling Zebras and Horses.
Taken from "Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks"


수고 했어요
ⓒ 손글씨쓰는김쌤