Transfer Learning

UNIVERSIDADE FEDERAL DO RIO GRANDE DO NORTE

Transfer Learning

Large Dataset → Trained DL Model

IMAGENET

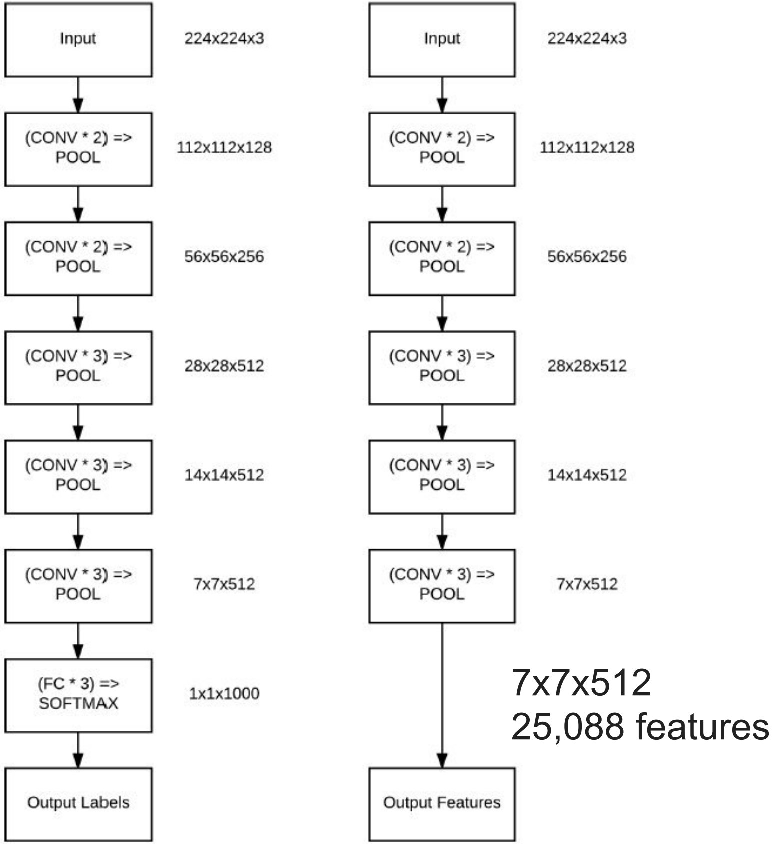
Small Dataset → Transfer Learning → New DL Model

In general, there are **two types of transfer learning** when applied to deep learning for **computer vision**:

1. Treating networks as arbitrary feature extractors.
2. Removing the fully-connected layers of an existing network, placing new FC layer set on top of the CNN, and fine-tuning these weights (and optionally previous layers) to recognize object classes.

Transfer Learning: Extracting features with a pre-trained CNN

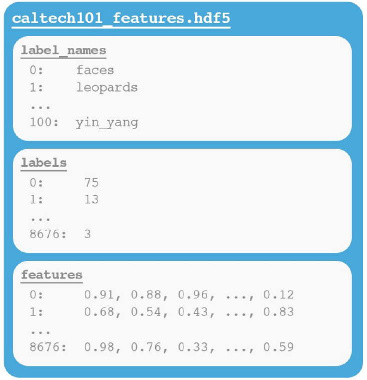
VGG 16




```python
# import the necessary packages
from tensorflow.keras.applications import VGG16

model = VGG16(weights="imagenet", include_top=False)
features = model.predict(batchImages, batch_size=bs)
```

Shallow ML Classifier
(Logistic Regression, RF, Xgboost, etc)

Image	Features 25088 columns	Class
#01		Cat
#02		Cat
#N		Dog



Caltech 101
8677 instances

Animals: Cat, Dog & Panda
3000 instances

Flowers 17
1360 instances

```python
# INPUTS
# path to input dataset
dataset = "animals"

# path to output HDF5 file
output  = "animals/hdf5/features.hdf5"

# size of feature extraction buffer
buffer_size = 1000

# store the batch size in a convenience variable
bs = 32

# feature extraction
feature_extraction(dataset,output,buffer_size,bs)

# train and evaluate
train_and_evaluate(output)
```

```
Database keys ['features', 'label_names', 'labels']
[INFO] tuning hyperparameters...
[INFO] best hyperparameters: {'C': 0.1}
[INFO] evaluating...
              precision    recall  f1-score   support

        cats       0.97      1.00      0.98       264
        dogs       0.99      0.96      0.98       250
       panda       1.00      1.00      1.00       236

    accuracy                           0.99       750
   macro avg       0.99      0.99      0.99       750
weighted avg       0.99      0.99      0.99       750
```

	precision	recall	f1-score	support
Faces	0.98	0.99	0.99	119
Faces_easy	0.99	0.99	0.99	109
Leopards	0.98	1.00	0.99	55
Motorbikes	1.00	1.00	1.00	195
accordion	1.00	1.00	1.00	12
airplanes	1.00	1.00	1.00	214
⋮	⋮		⋮	
watch	1.00	0.98	0.99	63
water_lilly	1.00	0.33	0.50	12
wheelchair	1.00	1.00	1.00	14
wild_cat	0.90	0.90	0.90	10
windsor_chair	1.00	1.00	1.00	15
wrench	1.00	0.89	0.94	9
yin_yang	0.88	0.88	0.88	16
accuracy			0.95	2170
macro avg	0.94	0.93	0.93	2170
weighted avg	0.96	0.95	0.95	2170

Caltech 101

	precision	recall	f1-score	support
bluebell	0.95	1.00	0.97	19
buttercup	1.00	0.87	0.93	23
coltsfoot	1.00	0.96	0.98	23
cowslip	0.67	0.80	0.73	25
crocus	1.00	0.90	0.95	20
daffodil	0.78	0.95	0.86	19
daisy	0.94	1.00	0.97	15
dandelion	1.00	0.89	0.94	19
fritillary	0.91	1.00	0.95	20
iris	1.00	0.86	0.92	21
lilyvalley	0.86	0.95	0.90	20
pansy	0.88	1.00	0.93	14
snowdrop	0.90	0.95	0.93	20
sunflower	1.00	1.00	1.00	18
tigerlily	1.00	0.94	0.97	18
tulip	0.89	0.65	0.76	26
windflower	0.95	1.00	0.98	20
accuracy			0.91	340
macro avg	0.93	0.92	0.92	340
weighted avg	0.92	0.91	0.91	340

Flowers 17

Large Dataset

Trained DL Model

IMAGENET

Small Dataset

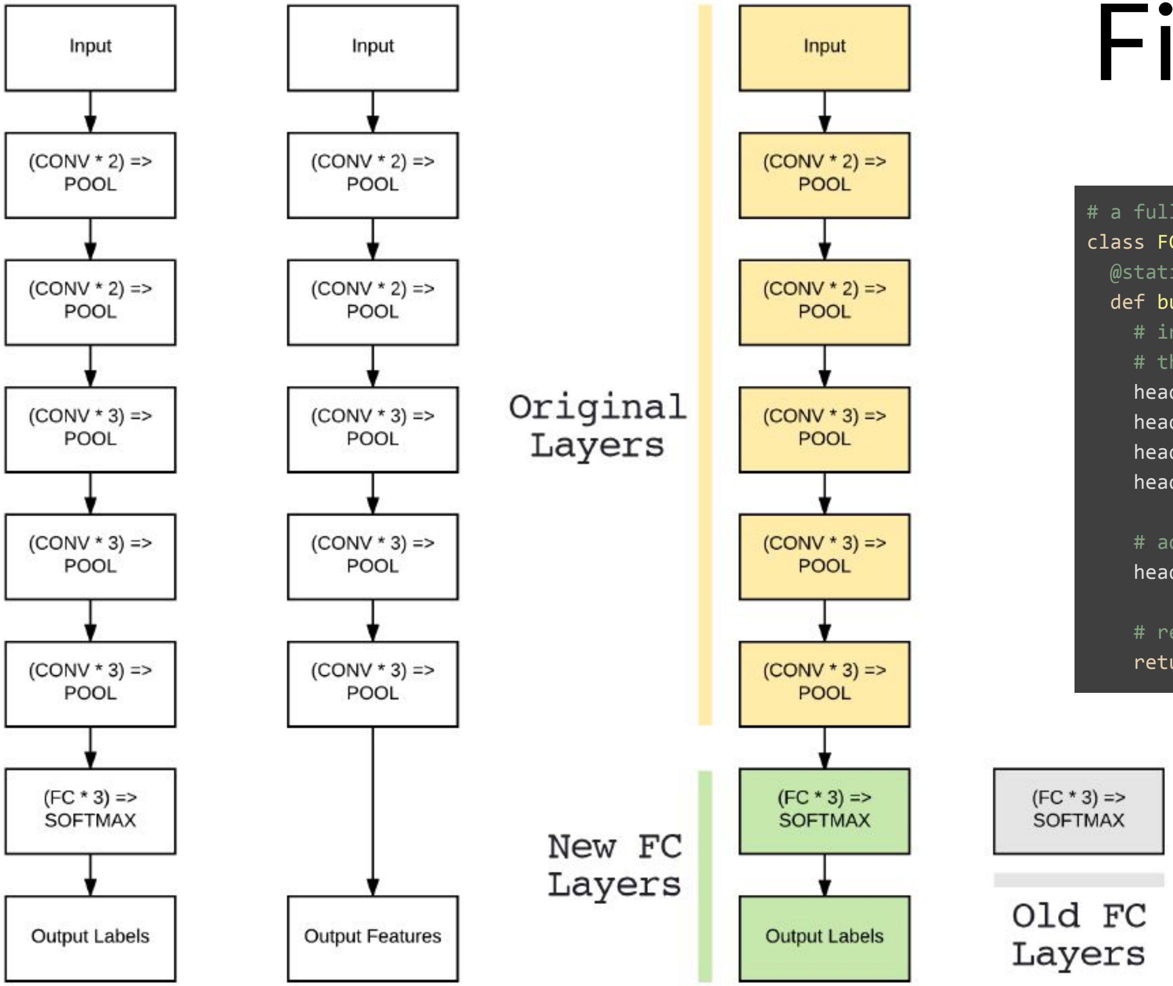
Transfer Learning

New DL Model

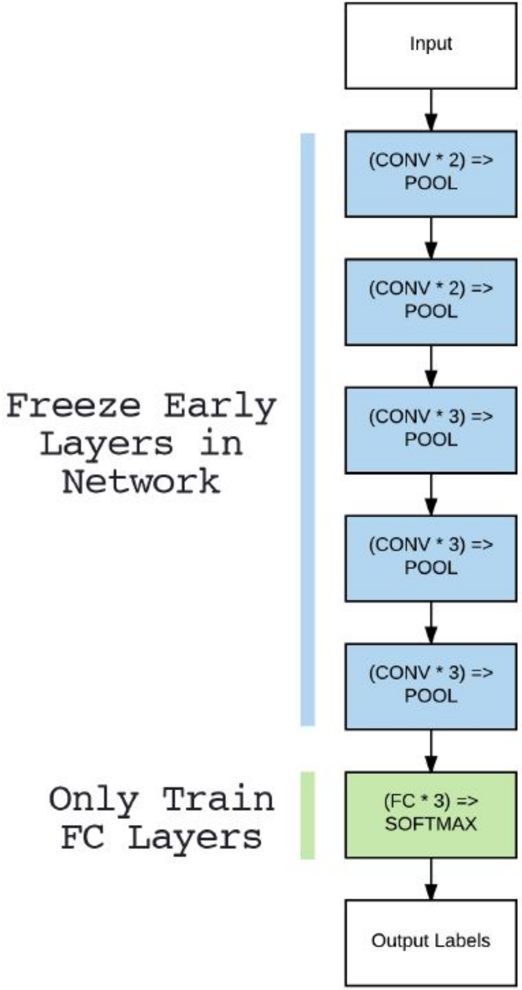
In general, there are **two types of transfer learning** when applied to deep learning for **computer vision**:

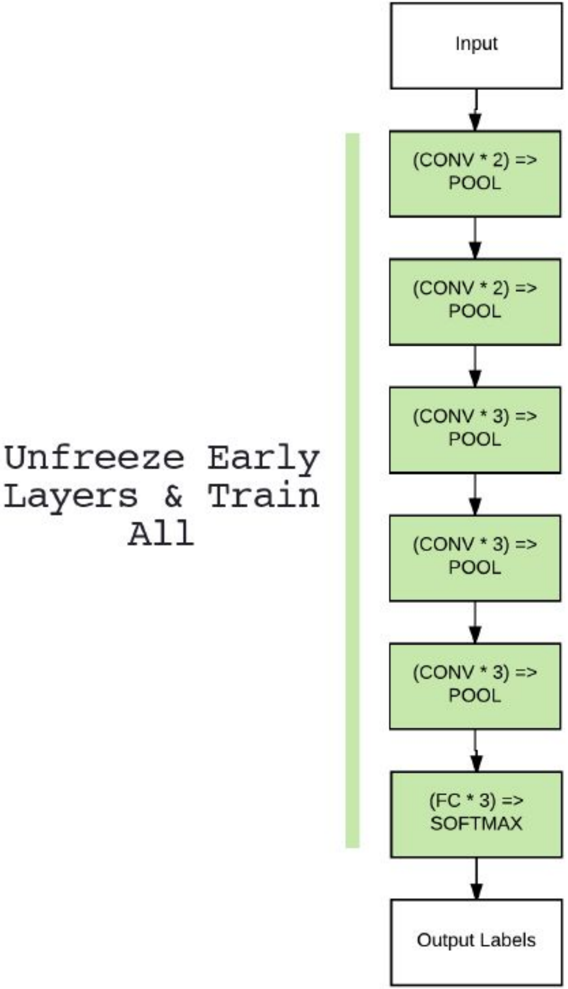
1. ~~Treating networks as arbitrary feature extractors.~~
2. Removing the fully-connected layers of an existing network, placing new FC layer set on top of the CNN, and **fine-tuning** these weights (and optionally previous layers) to recognize object classes.

Fine-Tuning




```python
# a fully connect network
class FCHeadNet:
  @staticmethod
  def build(baseModel, classes, D):
    # initialize the head model that will be placed on top of
    # the base, then add a FC layer
    headModel = baseModel.output
    headModel = Flatten(name="flatten")(headModel)
    headModel = Dense(D, activation="relu")(headModel)
    headModel = Dropout(0.5)(headModel)

    # add a softmax layer
    headModel = Dense(classes,activation="softmax")(headModel)

    # return the model
    return headModel
```





RMSprop is frequently used in situations where we need to quickly obtain reasonable performance (first stage - left image).
SGD using a very small learning rate (second stage - right image)

Tip!

```python
# loop over all layers in the base model and freeze them so they
# will *not* be updated during the training process
for layer in baseModel.layers:
  layer.trainable = False
```

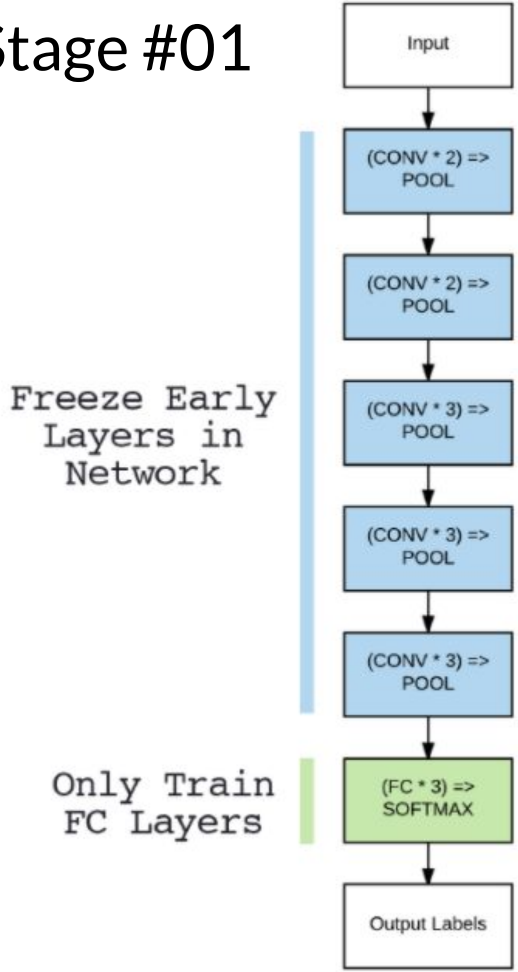
Let's do a fine tuning using VGG 16 over Flowers 17

Flowers 17
1360 instances

Previous result using feature extraction

	precision	recall	f1-score	support
bluebell	0.95	1.00	0.97	19
buttercup	1.00	0.87	0.93	23
coltsfoot	1.00	0.96	0.98	23
cowslip	0.67	0.80	0.73	25
crocus	1.00	0.90	0.95	20
daffodil	0.78	0.95	0.86	19
daisy	0.94	1.00	0.97	15
dandelion	1.00	0.89	0.94	19
fritillary	0.91	1.00	0.95	20
iris	1.00	0.86	0.92	21
lilyvalley	0.86	0.95	0.90	20
pansy	0.88	1.00	0.93	14
snowdrop	0.90	0.95	0.93	20
sunflower	1.00	1.00	1.00	18
tigerlily	1.00	0.94	0.97	18
tulip	0.89	0.65	0.76	26
windflower	0.95	1.00	0.98	20
accuracy			0.91	340
macro avg	0.93	0.92	0.92	340
weighted avg	0.92	0.91	0.91	340

Stage #01



Epochs: 25, RMSProp (0.001), FC (256)

```
[INFO] evaluating after initialization...
```

	precision	recall	f1-score	support
bluebell	0.94	0.79	0.86	19
buttercup	0.90	0.95	0.92	19
coltsfoot	0.79	0.94	0.86	16
cowslip	0.77	0.85	0.81	20
crocus	0.73	0.89	0.80	18
daffodil	0.78	0.78	0.78	23
daisy	1.00	0.95	0.97	20
dandelion	0.94	0.80	0.86	20
fritillary	1.00	0.86	0.92	21
iris	1.00	1.00	1.00	16
lilyvalley	0.95	0.95	0.95	22
pansy	1.00	0.91	0.95	23
snowdrop	0.95	0.83	0.88	23
sunflower	0.95	0.95	0.95	20
tigerlily	0.82	0.93	0.87	15
tulip	0.69	0.74	0.71	27
windflower	0.95	1.00	0.97	18
accuracy			0.88	340
macro avg	0.89	0.89	0.89	340
weighted avg	0.89	0.88	0.88	340

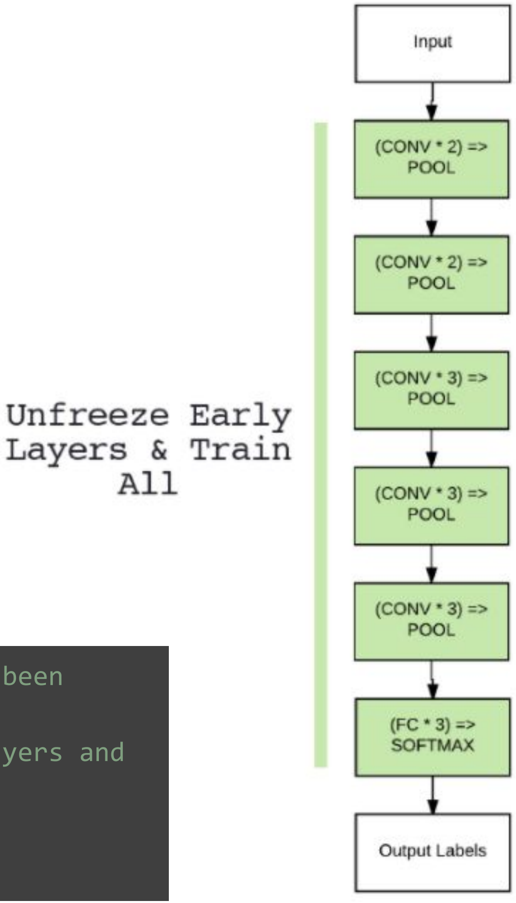
Stage #02

```
# import the necessary packages
from tensorflow.keras.applications import VGG16

# whether or not to include top of CNN
include_top = 0

# load the VGG16 network
print("[INFO] loading network...")
model = VGG16(weights="imagenet", include_top= include_top > 0)
print("[INFO] showing layers...")

# loop over the layers in the network and display them to the
# console
for (i, layer) in enumerate(model.layers):
  print("[INFO] {}\t{}".format(i, layer.__class__.__name__))
```

VGG-16 without FC

```
[INFO] loading network...
[INFO] showing layers...
[INFO] 0        InputLayer
[INFO] 1        Conv2D
[INFO] 2        Conv2D
[INFO] 3        MaxPooling2D
[INFO] 4        Conv2D
[INFO] 5        Conv2D
[INFO] 6        MaxPooling2D
[INFO] 7        Conv2D
[INFO] 8        Conv2D
[INFO] 9        Conv2D
[INFO] 10       MaxPooling2D
[INFO] 11       Conv2D
[INFO] 12       Conv2D
[INFO] 13       Conv2D
[INFO] 14       MaxPooling2D
[INFO] 15       Conv2D
[INFO] 16       Conv2D
[INFO] 17       Conv2D
[INFO] 18       MaxPooling2D
```

Stage #02



VGG-16 without FC

```
[INFO] loading network...
[INFO] showing layers...
[INFO] 0        InputLayer
[INFO] 1        Conv2D
[INFO] 2        Conv2D
[INFO] 3        MaxPooling2D
[INFO] 4        Conv2D
[INFO] 5        Conv2D
[INFO] 6        MaxPooling2D
[INFO] 7        Conv2D
[INFO] 8        Conv2D
[INFO] 9        Conv2D
[INFO] 10       MaxPooling2D
[INFO] 11       Conv2D
[INFO] 12       Conv2D
[INFO] 13       Conv2D
[INFO] 14       MaxPooling2D
[INFO] 15       Conv2D
[INFO] 16       Conv2D
[INFO] 17       Conv2D
[INFO] 18       MaxPooling2D
```

```
# now that the head FC layers have been trained/initialized, lets
# unfreeze the final set of CONV layers and make them trainable
for layer in baseModel.layers[15:]:
  layer.trainable = True
```

Feature extraction

	precision	recall	f1-score	support
bluebell	0.95	1.00	0.97	19
buttercup	1.00	0.87	0.93	23
coltsfoot	1.00	0.96	0.98	23
cowslip	0.67	0.80	0.73	25
crocus	1.00	0.90	0.95	20
daffodil	0.78	0.95	0.86	19
daisy	0.94	1.00	0.97	15
dandelion	1.00	0.89	0.94	19
fritillary	0.91	1.00	0.95	20
iris	1.00	0.86	0.92	21
lilyvalley	0.86	0.95	0.90	20
pansy	0.88	1.00	0.93	14
snowdrop	0.90	0.95	0.93	20
sunflower	1.00	1.00	1.00	18
tigerlily	1.00	0.94	0.97	18
tulip	0.89	0.65	0.76	26
windflower	0.95	1.00	0.98	20
accuracy			0.91	340
macro avg	0.93	0.92	0.92	340
weighted avg	0.92	0.91	0.91	340

Stage #02 fine tuning
SGD (0.001), epochs = 100

	precision	recall	f1-score	support
bluebell	0.90	0.95	0.92	19
buttercup	1.00	0.95	0.97	19
coltsfoot	0.83	0.94	0.88	16
cowslip	0.90	0.90	0.90	20
crocus	0.85	0.94	0.89	18
daffodil	0.91	0.87	0.89	23
daisy	1.00	0.95	0.97	20
dandelion	0.89	0.85	0.87	20
fritillary	1.00	0.90	0.95	21
iris	1.00	1.00	1.00	16
lilyvalley	1.00	0.95	0.98	22
pansy	1.00	0.91	0.95	23
snowdrop	0.92	1.00	0.96	23
sunflower	1.00	0.90	0.95	20
tigerlily	1.00	1.00	1.00	15
tulip	0.81	0.93	0.86	27
windflower	1.00	1.00	1.00	18
accuracy			0.94	340
macro avg	0.94	0.94	0.94	340
weighted avg	0.94	0.94	0.94	340

Playground Prediction Competition

Dogs vs. Cats

Create an algorithm to distinguish dogs from cats

Kaggle · 213 teams · 7 years ago

Overview Data Notebooks Discussion Leaderboard Rules Team

Overview

- Description
- Prizes
- Evaluation
- Winners

In this competition, you'll write an algorithm to classify whether images contain either a dog or a cat. This is easy for humans, dogs, and cats. Your computer will find it a bit more difficult.

HDF5
AlexNet
ResNet50
Transfer Learning

http://bit.do/alexnet_epoch45