

Self Supervised Learning

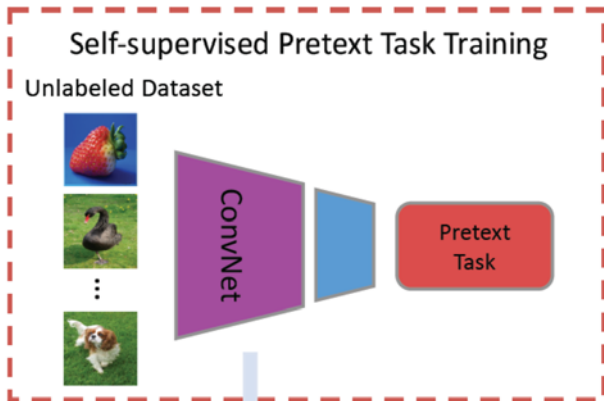
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Gwangju Institute of Science and Technology

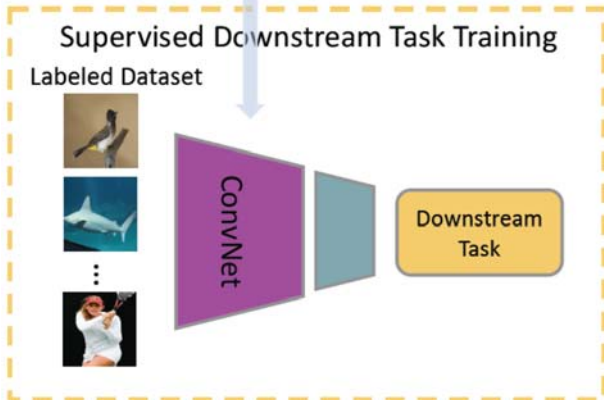
Self-supervised Learning

- Supervised learning is powerful. However, it requires a “large” amount of “labeled” data. To relieve the burden,
 - Transfer learning
 - Semi-supervised learning
 - Weakly-supervised
 - Unsupervised learning
- Self-supervised learning (SSL) is
 - Sub-class of unsupervised learning
 - To define pretext tasks which can be formulated using only unlabeled data. It requires higher-level semantic understanding in order to solve.
 - The features obtained from pretext tasks can be successfully transferred to classification, object detection, and segmentation tasks.

General Pipeline of SSL



Knowledge Transfer



- Visual Features are learned by pretext tasks.
- The learned parameters serve as a pre-trained model.
- They are transferred to other downstream. Then, fine-tuned.
- The performance of downstream tasks is used to evaluate the quality of learned features.

Pretext Task

Unlabeled Dataset

( , P_1)

( , P_2)

\vdots

( , P_N)



Output

O_1

O_2

\vdots

O_N



Objective Function

$loss(P_1, O_1)$

$loss(P_2, O_2)$

\vdots

$loss(P_N, O_N)$

Pretext Task: Generation-based Methods

- “Colorful image colorization”, ECCV, 2016.

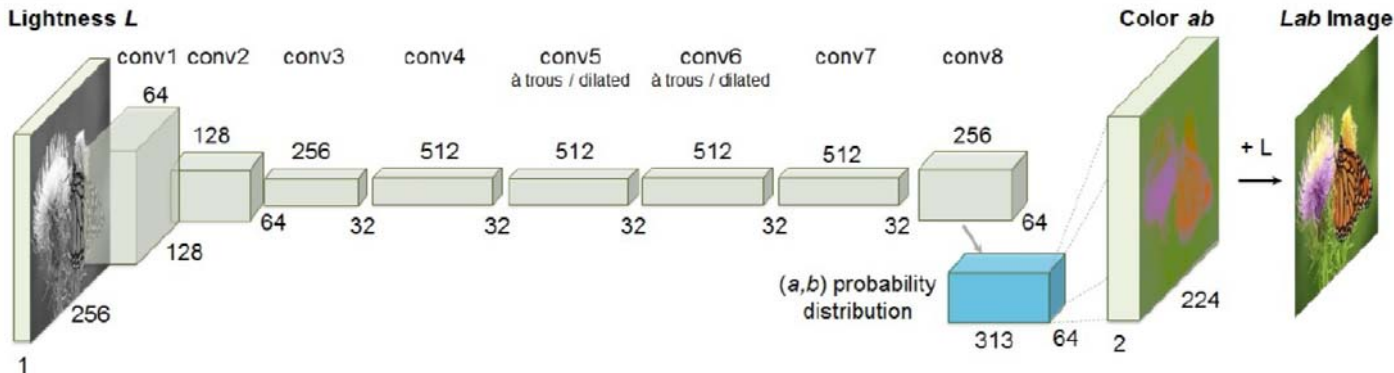


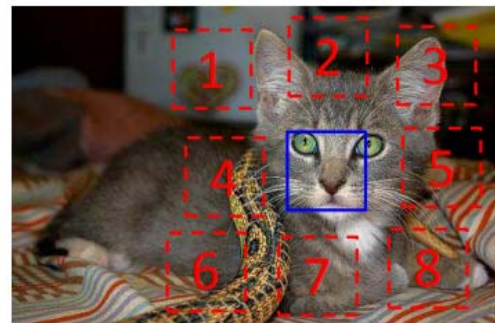
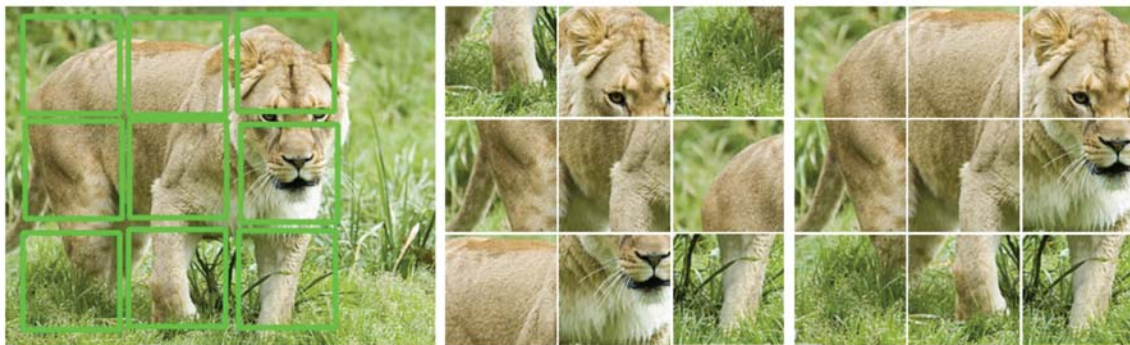
Image colorization



Super-resolution

Pretext Task: Context-based Methods

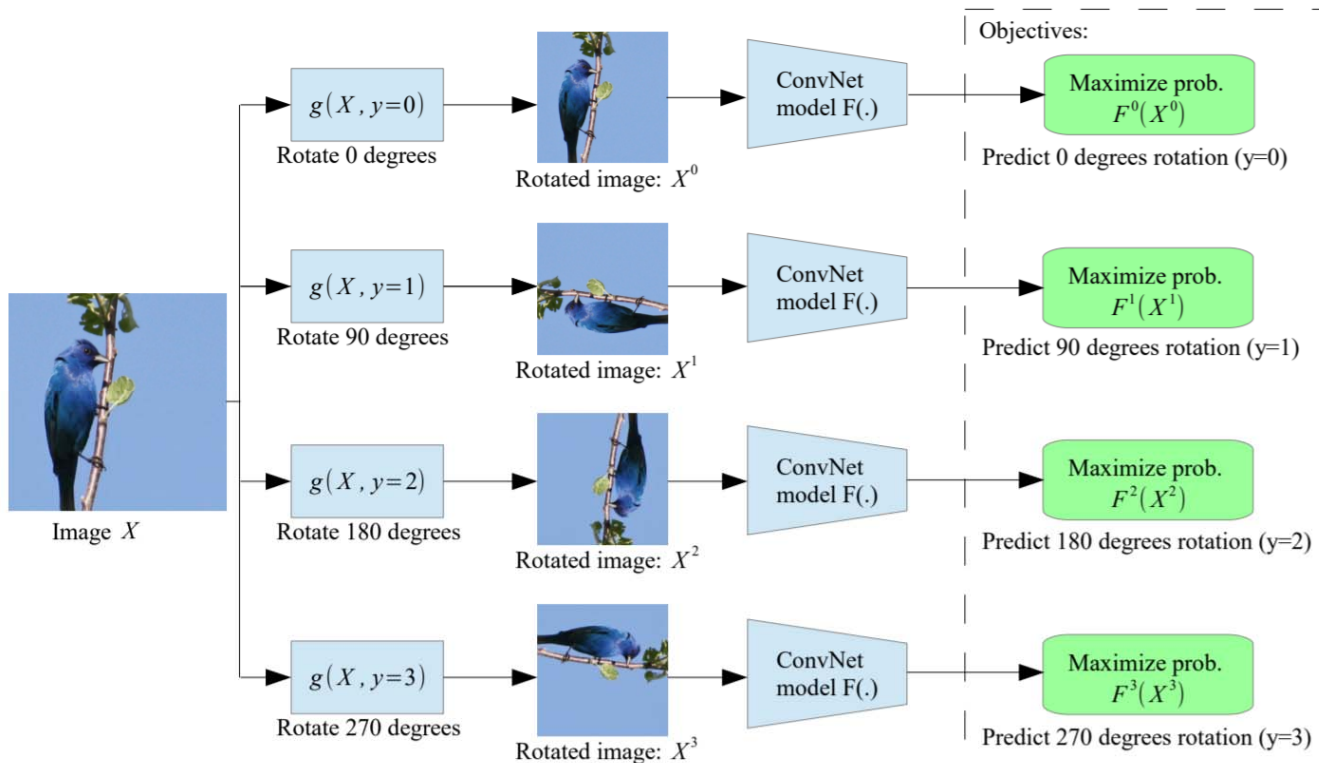
- “Unsupervised learning of visual representations by solving jigsaw puzzles,” ECCV, 2016.
 - Generate image patches
 - Shuffled image patches
 - Correct order of the sampled 9 patches



$$X = \left(\begin{array}{c} \text{cat face} \\ \text{cat ear} \end{array} \right); Y = 3$$

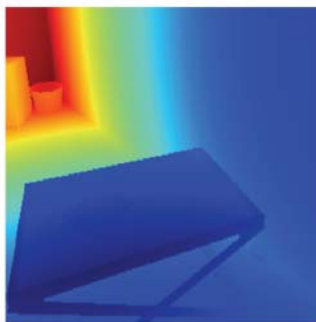
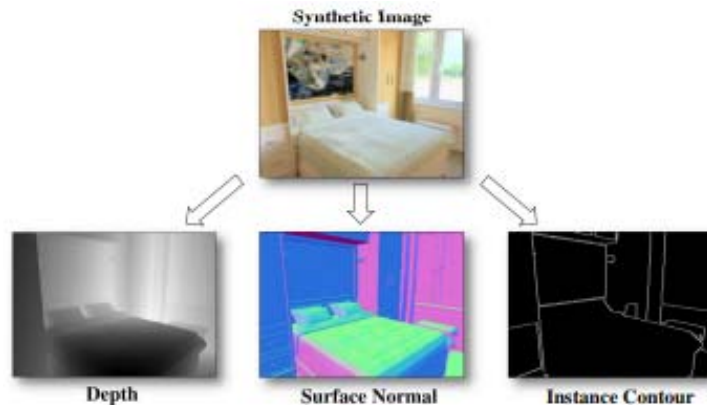
Pretext Task: Context-based Methods

- “Unsupervised representation learning by predicting image rotation”, ICLR, 2018.



Pretext Task: Free Semantic Label-based Methods

- Learning with labels generated by game engines.



Synthetic Image

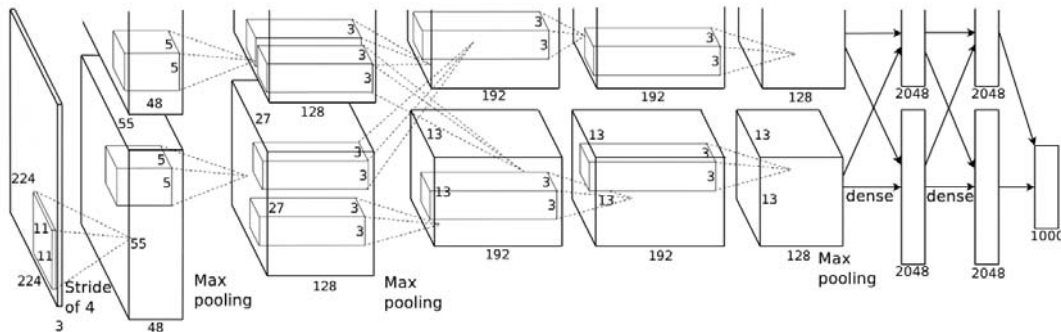
Depth

Instance Segmentation Optical Flow

Performance Evaluation (1/2)

- Classification problems on ImageNet and Places datasets.
- The linear classifier is trained based on the n^{th} convolutional layer of AlexNet.

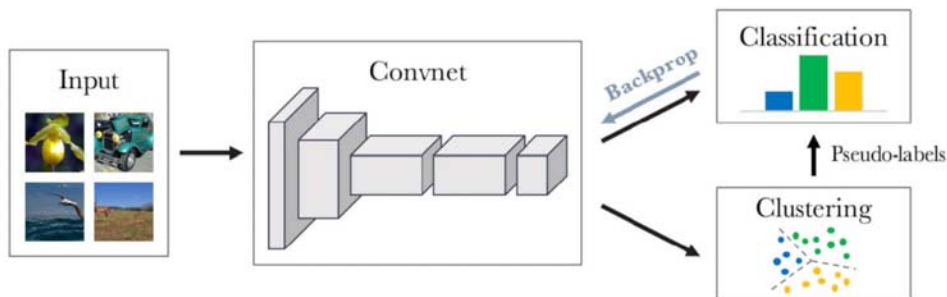
Method	Pretext Tasks	ImageNet					Places				
		conv1	conv2	conv3	conv4	conv5	conv1	conv2	conv3	conv4	conv5
Places labels [8]	—	—	—	—	—	—	22.1	35.1	40.2	43.3	44.6
ImageNet labels [8]	—	19.3	36.3	44.2	48.3	50.5	22.7	34.8	38.4	39.4	38.7
Random(Scratch) [8]	—	11.6	17.1	16.9	16.3	14.1	15.7	20.3	19.8	19.1	17.5
ColorfulColorization [18]	Generation	12.5	24.5	30.4	31.5	30.3	16.0	25.7	29.6	30.3	29.7
BiGAN [122]	Generation	17.7	24.5	31.0	29.9	28.0	21.4	26.2	27.1	26.1	24.0
SplitBrain [42]	Generation	17.7	29.3	35.4	35.2	32.8	21.3	30.7	34.0	34.1	32.5
ContextEncoder [19]	Context	14.1	20.7	21.0	19.8	15.5	18.2	23.2	23.4	21.9	18.4
ContextPrediction [41]	Context	16.2	23.3	30.2	31.7	29.6	19.7	26.7	31.9	32.7	30.9
Jigsaw [20]	Context	18.2	28.8	34.0	33.9	27.1	23.0	32.1	35.5	34.8	31.3
Learning2Count [130]	Context	18.0	30.6	34.3	32.5	25.7	23.3	33.9	36.3	34.7	29.6
DeepClustering [44]	Context	13.4	32.3	41.0	39.6	38.2	19.6	33.2	39.2	39.8	34.7



AlexNet
(2012)

Performance Evaluation (2/2)

Method	Pretext Tasks	Classification	Detection	Segmentation
ImageNet Labels [8]	—	79.9	56.8	48.0
Random(Scratch) [8]	—	57.0	44.5	30.1
ContextEncoder [19]	Generation	56.5	44.5	29.7
BiGAN [122]	Generation	60.1	46.9	35.2
ColorfulColorization [18]	Generation	65.9	46.9	35.6
SplitBrain [42]	Generation	67.1	46.7	36.0
RankVideo [38]	Context	63.1	47.2	35.4 [†]
PredictNoise [46]	Context	65.3	49.4	37.1 [†]
JigsawPuzzle [20]	Context	67.6	53.2	37.6
ContextPrediction [41]	Context	65.3	51.1	—
Learning2Count [130]	Context	67.7	51.4	36.6
DeepClustering [44]	Context	73.7	55.4	45.1
WatchingVideo [81]	Free Semantic Label	61.0	52.2	—
CrossDomain [30]	Free Semantic Label	68.0	52.6	—
AmbientSound [154]	Cross Modal	61.3	—	—
TiedToEgoMotion [95]	Cross Modal	—	41.7	—
EgoMotion [94]	Cross Modal	54.2	43.9	—

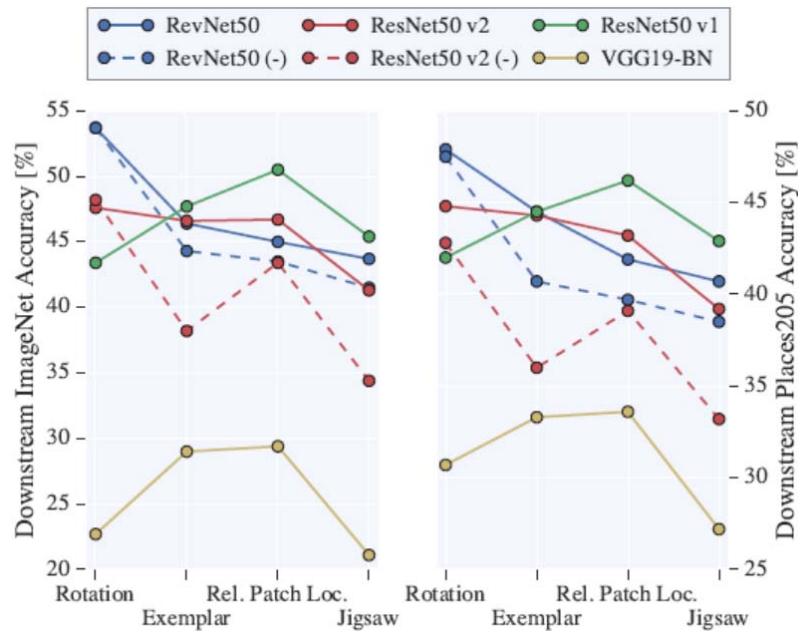


Deep
clustering
(2018)

Revisiting Self-supervised Learning

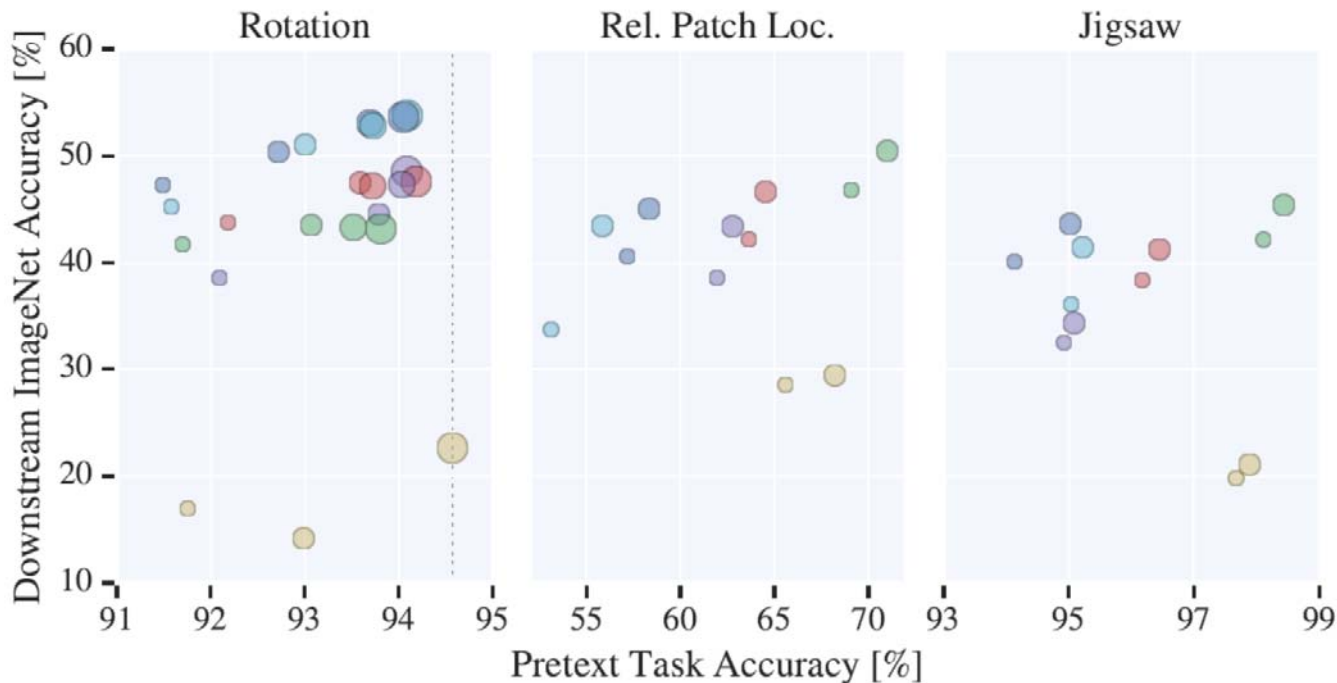
- “Revisiting self-supervised visual representation learning”, CVPR, 2019.

Family	ImageNet		Places205	
	Prev.	Ours	Prev.	Ours
A Rotation[11]	38.7	55.4	35.1	48.0
R Exemplar[8]	31.5	46.0	-	42.7
R Rel. Patch Loc.[8]	36.2	51.4	-	45.3
A Jigsaw[34, 51]	34.7	44.6	35.5	42.2
V CC+vgg-Jigsaw++[36]	37.3	-	37.5	-
A Counting[35]	34.3	-	36.3	-
A Split-Brain[51]	35.4	-	34.1	-
V DeepClustering[3]	41.0	-	39.8	-
R CPC[37]	48.7 [†]	-	-	-
R Supervised RevNet50	74.8	74.4	-	58.9
R Supervised ResNet50 v2	76.0	75.8	-	61.6
V Supervised VGG19	72.7	75.0	58.9	61.5



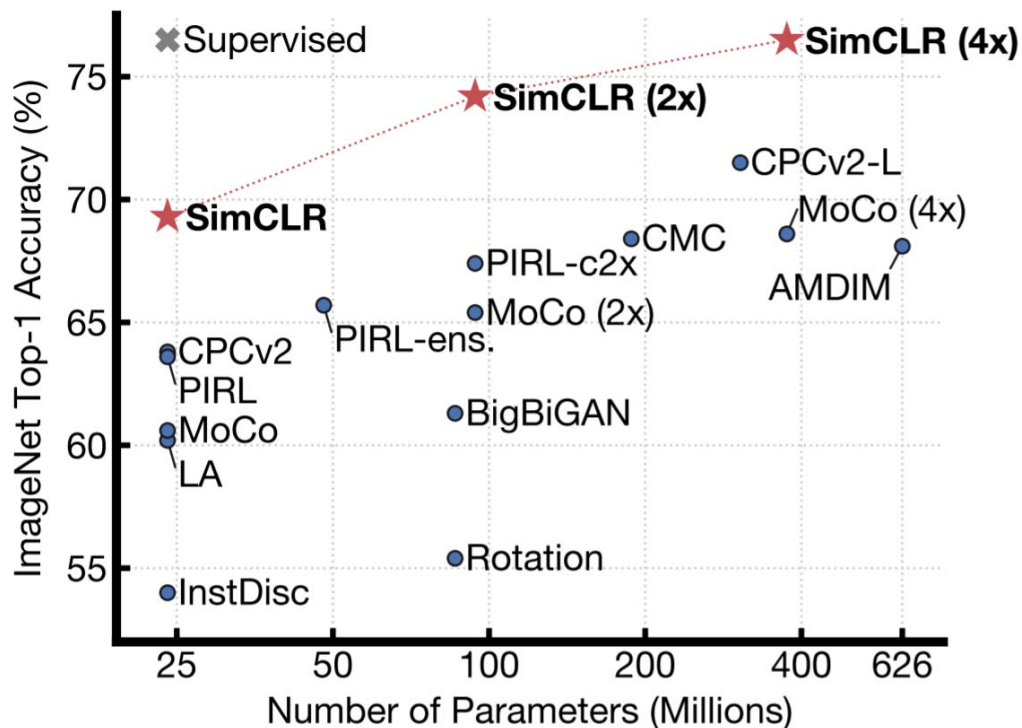
Revisiting Self-supervised Learning

- “Revisiting self-supervised visual representation learning”, CVPR, 2019.
 - According to pretext accuracy, the widest VGG model is the best one for Rotation, but it performs poorly on the downstream task.



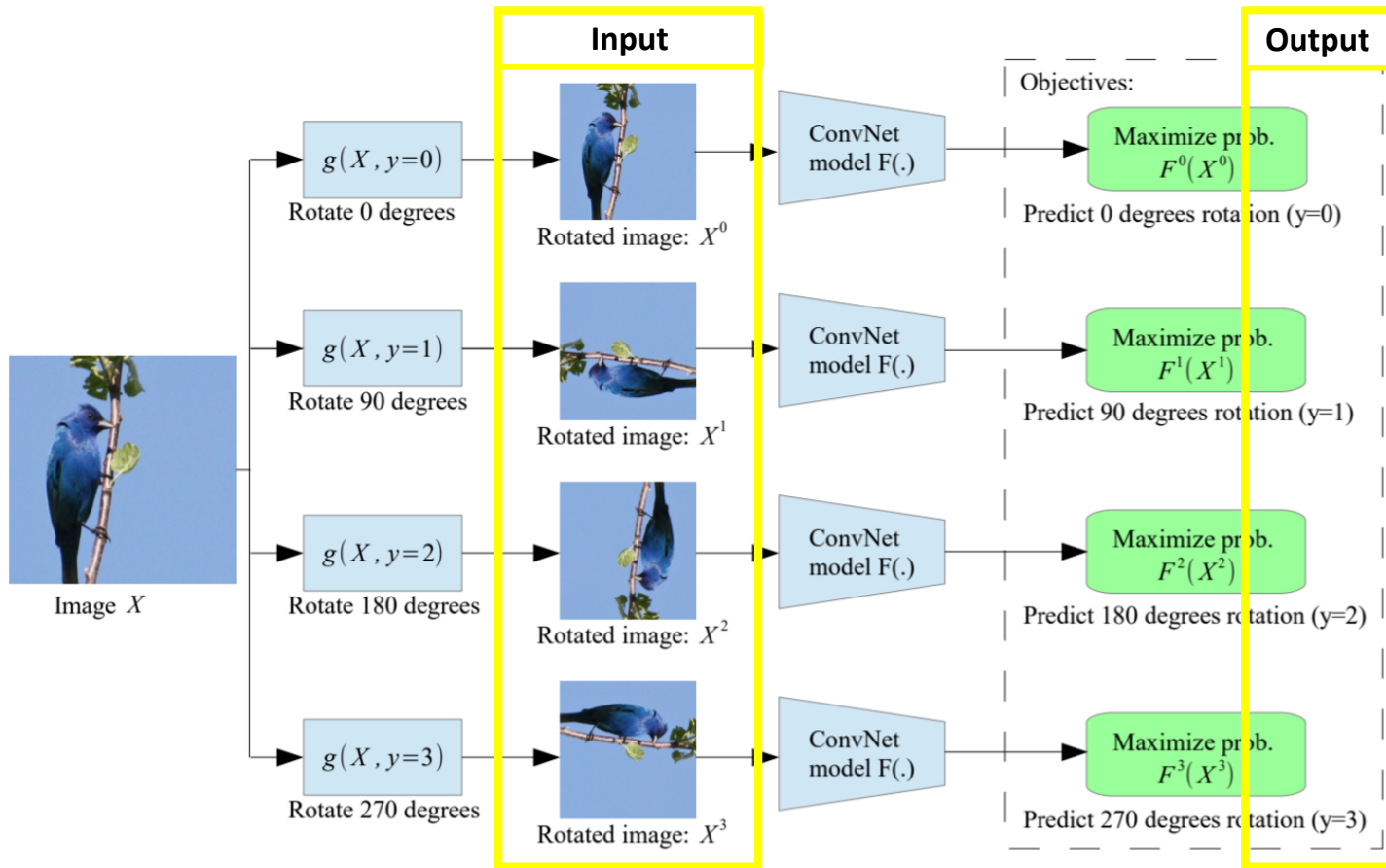
SimCLR

- “Simple framework for contrastive learning of visual representations (SimCLR)”, 2020.



Demo

RotNet



Dataset

1. Import library

```
1 import tensorflow as tf
2 import numpy as np
3
4 from tensorflow import keras
5 from tensorflow.keras import Sequential
6 from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
7
8 import matplotlib.pyplot as plt
```

2. Load MNIST dataset ¶

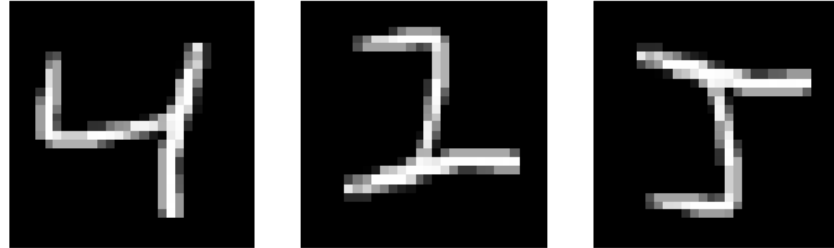
```
1 #Load MNIST dataset
2 (X_train, Y_train), (X_test, Y_test) = keras.datasets.mnist.load_data()
3
4 # using 1000 data for test
5 X_train=X_train[:1000]
6 Y_train=Y_train[:1000]
7
8 # using 300 data for test
9 X_test=X_test[:300]
10 Y_test=Y_test[:300]
11
12 print(X_train.shape)
```

Rotation

- Rotation can be implemented by flip and transpose

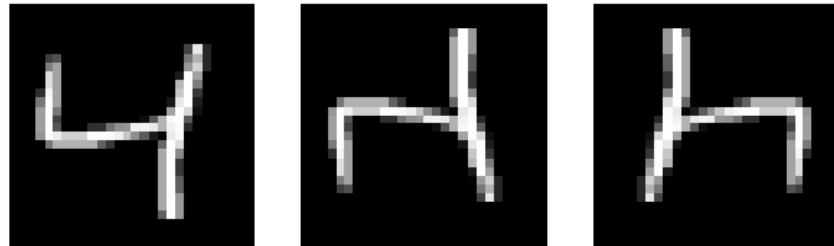
90 degrees

→ Transpose + Vertical flip



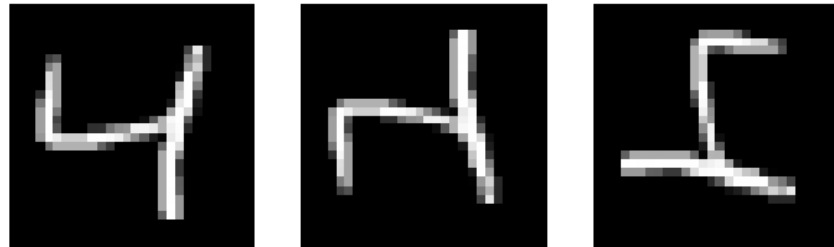
180 degrees

→ Vertical flip + Horizontal flip



270 degrees

→ Vertical flip + Transpose



Pretext Task Model

- ConvNet model for rotation detection
 - Model : 3 Conv layer + 1 FC layer
 - Optimizer : Stochastic Gradient Descent(SGD)

3 Pretext-task Model

```

1
2 layer1 = Conv2D(64, kernel_size=(3, 3), strides=(2, 2), padding='same',
3               activation='relu', kernel_initializer='random_normal')
4 layer2 = MaxPooling2D(pool_size=(2, 2), strides=(2, 2))
5 layer3 = Conv2D(32, kernel_size=(3, 3), strides=(1, 1), padding='same',
6               activation='relu', kernel_initializer='random_normal')
7 layer4 = MaxPooling2D(pool_size=(2, 2), strides=(2, 2))
8 layer5 = Conv2D(16, kernel_size=(3, 3), strides=(2, 2), padding='same',
9               activation='relu', kernel_initializer='random_normal')
10
11 layer6 = Flatten()
12 layer7 = Dense(4, activation='softmax', kernel_initializer='random_normal')
13
14 model = keras.Sequential([keras.Input(shape=(28, 28, 1)),
15                           layer1, layer2, layer3, layer4, layer5,
16                           layer6, layer7])
17 model.summary()
  
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 14, 14, 64)	640
max_pooling2d (MaxPooling2D)	(None, 7, 7, 64)	0
conv2d_1 (Conv2D)	(None, 7, 7, 32)	18464
max_pooling2d_1 (MaxPooling2D)	(None, 3, 3, 32)	0
conv2d_2 (Conv2D)	(None, 2, 2, 16)	4624
flatten (Flatten)	(None, 64)	0
dense (Dense)	(None, 4)	260
Total params: 23,988		
Trainable params: 23,988		
Non-trainable params: 0		

Pretext Task Training

```

1 sgd = keras.optimizers.SGD(learning_rate = 0.001, momentum = 0.9)
2 model.compile(loss = 'categorical_crossentropy', optimizer = sgd, metrics = ['accuracy'])
3 hist = model.fit(X_rotate, Y_rotate, batch_size = 192, epochs = 50, verbose = 2, shuffle=False)

```

```

1 # Freeze the pretext model
2 model.trainable=False

```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 14, 14, 64)	640
max_pooling2d (MaxPooling2D)	(None, 7, 7, 64)	0
conv2d_1 (Conv2D)	(None, 7, 7, 32)	18464
max_pooling2d_1 (MaxPooling2D)	(None, 3, 3, 32)	0
conv2d_2 (Conv2D)	(None, 2, 2, 16)	4624
flatten (Flatten)	(None, 64)	0
dense (Dense)	(None, 4)	260

Total params: 23,988
 Trainable params: 23,988
 Non-trainable params: 0



Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 14, 14, 64)	640
max_pooling2d (MaxPooling2D)	(None, 7, 7, 64)	0
conv2d_1 (Conv2D)	(None, 7, 7, 32)	18464
max_pooling2d_1 (MaxPooling2D)	(None, 3, 3, 32)	0
conv2d_2 (Conv2D)	(None, 2, 2, 16)	4624
flatten (Flatten)	(None, 64)	0
dense (Dense)	(None, 4)	260

Total params: 23,988
 Trainable params: 0
 Non-trainable params: 23,988

Transfer

- Deep layers are specified only for pretext task

Model	ConvB1	ConvB2	ConvB3	ConvB4	ConvB5
RotNet with 3 conv. blocks	85.45	88.26	62.09	-	-
RotNet with 4 conv. blocks	85.07	89.06	86.21	61.73	-
RotNet with 5 conv. blocks	85.04	89.76	86.82	74.50	50.37

Downstream Task

- ConvNet model for digit classification
 - Model: 2 Conv layer + 1 FC layer
 - Optimizer : Stochastic Gradient Descent(SGD)
 - Since pretext task model freezes and transfers, It has only 2,890 trainable parameters

```

1 layer9=Flatten()
2 layer10 = Dense(10,activation = 'softmax',kernel_initializer='random_normal')
3 # new layer to classify 10 numbers
4
5 model2 = keras.Sequential([keras.Input(shape=(28,28,1)),
6                             layer1, layer2, layer3, layer4, layer9, layer10,])
7 model2.summary()
  
```



3 Pretext-task Model

```

1
2 layer1 = Conv2D(64, kernel_size=(3, 3), strides=(2, 2), padding='same',
3               activation='relu',kernel_initializer='random_normal')
4 layer2 = MaxPooling2D(pool_size=(2, 2), strides=(2, 2))
5 layer3 = Conv2D(32, kernel_size=(3, 3), strides=(1, 1), padding='same',
6               activation='relu',kernel_initializer='random_normal')
7 layer4 = MaxPooling2D(pool_size=(2, 2), strides=(2, 2))
8 layer5 = Conv2D(16, kernel_size=(3, 3), strides=(2, 2), padding='same',
9               activation='relu',kernel_initializer='random_normal')
10
11 layer6 = Flatten()
12 layer7 = Dense(4, activation='softmax',kernel_initializer='random_normal')
13
14 model = keras.Sequential([keras.Input(shape=(28,28,1)),
15                             layer1, layer2, layer3, layer4, layer5,
16                             layer6, layer7])
17 model.summary()
  
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 14, 14, 64)	640
max_pooling2d (MaxPooling2D)	(None, 7, 7, 64)	0
conv2d_1 (Conv2D)	(None, 7, 7, 32)	18464
max_pooling2d_1 (MaxPooling2D)	(None, 3, 3, 32)	0
flatten_1 (Flatten)	(None, 288)	0
dense_1 (Dense)	(None, 10)	2890
Total params: 21,994		
Trainable params: 2,890		
Non-trainable params: 19,104		

Supervised Model

- ConvNet model for digit classification
 - It has same model architecture with downstream model
 - Optimizer : Stochastic Gradient Descent(SGD)
 - The number of total parameter is same with down stream model, but it has 0 Non-trainable parameters

5 Supervised Model

```

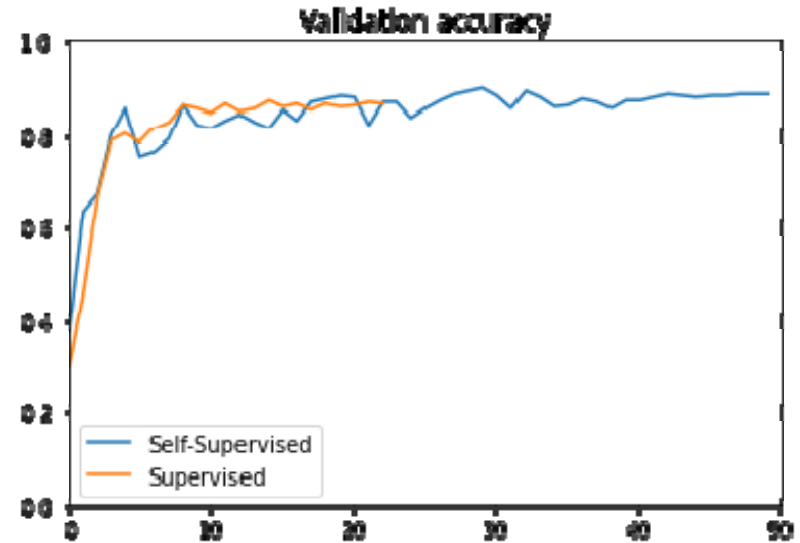
1 #supervised model
2 model3 = Sequential()
3
4 model3.add(Conv2D(64, kernel_size=(3, 3), strides=(2, 2), activation='relu', padding='same',
5                 kernel_initializer='random_normal', input_shape=(28, 28, 1)))
6 model3.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
7 model3.add(Conv2D(32, kernel_size=(3, 3), strides=(1, 1), activation='relu', padding='same',
8                 kernel_initializer='random_normal'))
9 model3.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
10
11 model3.add(Flatten())
12 model3.add(Dense(10, activation='softmax', kernel_initializer='random_normal'))
13
14 model3.summary()
  
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 14, 14, 64)	640
max_pooling2d_2 (MaxPooling2D)	(None, 7, 7, 64)	0
conv2d_4 (Conv2D)	(None, 7, 7, 32)	18464
max_pooling2d_3 (MaxPooling2D)	(None, 3, 3, 32)	0
flatten_2 (Flatten)	(None, 288)	0
dense_2 (Dense)	(None, 10)	2890

Total params: 21,994
 Trainable params: 21,994
 Non-trainable params: 0

Training Result



Test Result

```
1 eval_self = model_down.evaluate(X_test,Y_test,batch_size = 64,steps =10,verbose = 2)
```

10/10 - 0s - loss: 1.8287 - accuracy: 0.8967

```
1 eval_super = model_super.evaluate(X_test,Y_test,batch_size = 64,steps =10, verbose = 2)
```

10/10 - 0s - loss: 0.4288 - accuracy: 0.8933