# Deep Learning (CS324)

# Visualizing and Understanding Convolutional Networks

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# Content

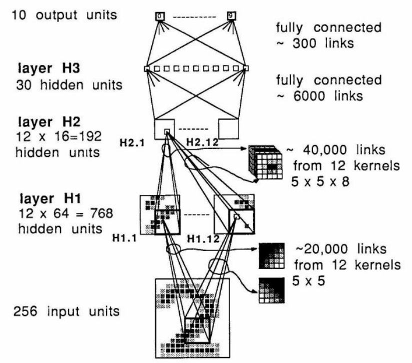
- Background
- Motivation
- Methodology
- Convnet Visualization
- Experiments
- Q&A

# Part I Background

# Previous Research — CNN

- Introduction of CNN LeCun *et al.*

  LeCun, Y., Boser, B., Denker, J.S., Henderson, D., Howard, R.E., Hubbard, W.,Jackel, L.D.: Backpropagation applied to handwritten zip code recognition. NeuralComput. 1(4), 541–551 (1989)




- Good Performance on NORB, CIFAAR-10 Data Sets Ciresan *et al.*

  Ciresan, D.C., Meier, J., Schmidhuber, J.: Multi-column deep neural networks for image classification. In: CVPR (2012)

- Good Performance on ImageNet2012 Krizhevsky *et al.*

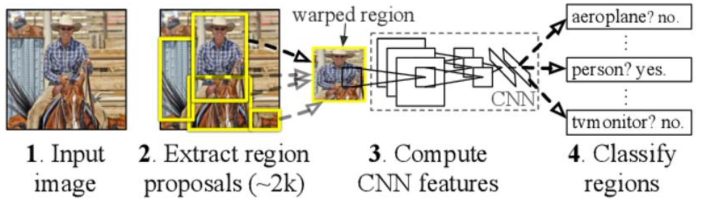
  Krizhevsky, A., Sutskever, I., Hinton, G.: Imagenet classification with deep convolutional neural networks. In: NIPS (2012)

IMAGENET

Error Rate 16.4%

- Good Performance on PASCAL VOC Data Sets Girshick *et al.*

  Girshick, R., Donahue, J., Darrell, T., Malik, J.: Rich feature hierarchies for accurate object detection and semantic segmentation. arXiv:1311.2524 (2014)



# Related Work — Visualization

- Mostly limited to the 1st Layer
- Performing gradient descent in image space to minimize the unit's activation Erhan *et a*l.

  Erhan, D., Bengio, Y., Courville, A., Vincent, P.: Visualizing higher-layer features of a deep network. Technical report, University of Montreal (2009)
- Projecting back from the fully connected layers  Simonyan *et al.*

  Le, Q.V., Ngiam, J., Chen, Z., Chia, D., Koh, P., Ng, A.Y.: Tiled convolutional neural networks. In: NIPS (2010)
- Visualization that identify patches that are responsible for strong activations at higher layer Girshick *et al.*

  Girshick, R., Donahue, J., Darrell, T., Malik, J.: Rich feature hierarchies for accurate object detection and semantic segmentation. arXiv:1311.2524 (2014)

# Related Work — Feature Generalization

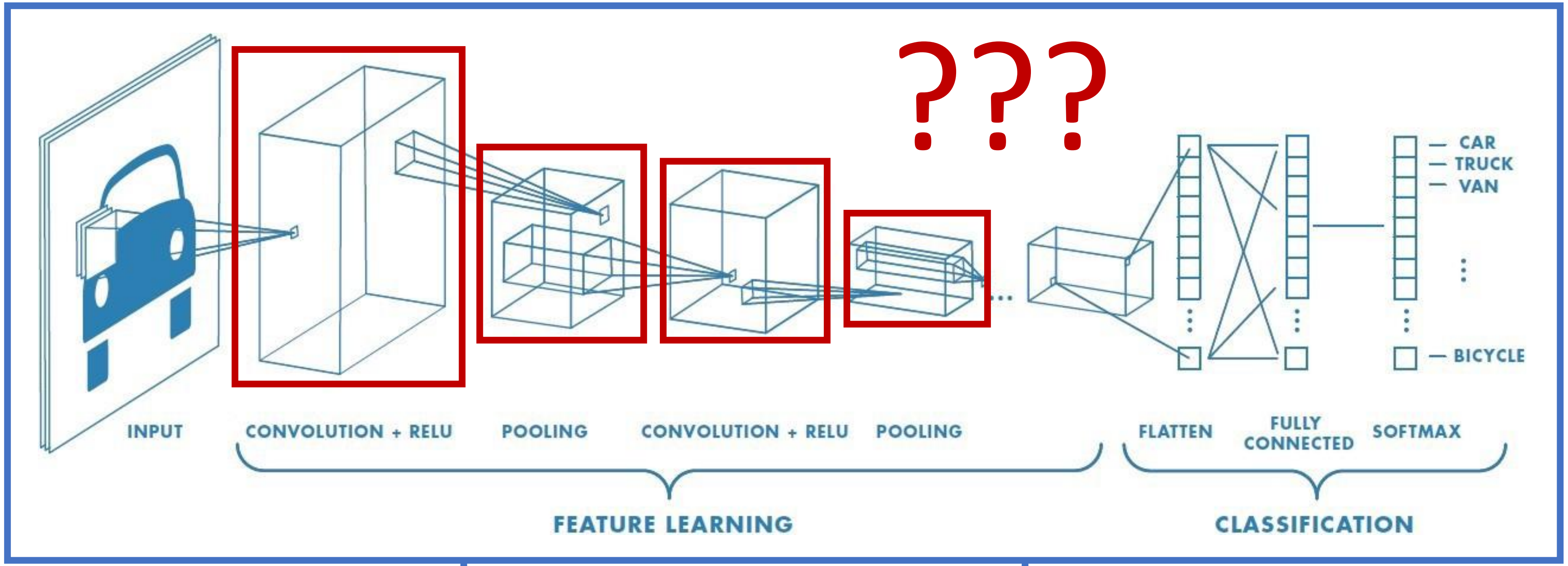
- Generalization Ability of CNN features Donahue & Girshick *et al.*

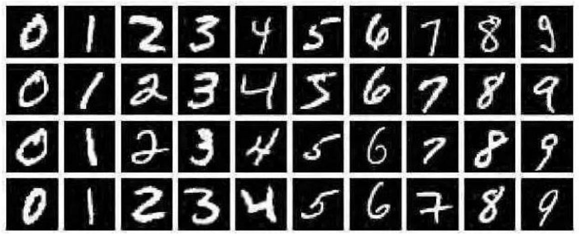
  Donahue, J., Jia, Y., Vinyals, O., Hoffman, J., Zhang, N., Tzeng, E., Darrell, T.:DeCAF: A deep convolutional activation feature for generic visual recognition.arXiv:1310.1531 (2013)

  Girshick, R., Donahue, J., Darrell, T., Malik, J.: Rich feature hierarchies for accurate object detection and semantic segmentation. arXiv:1311.2524 (2014)

# Part II Motivation

# What's Inside CNN?



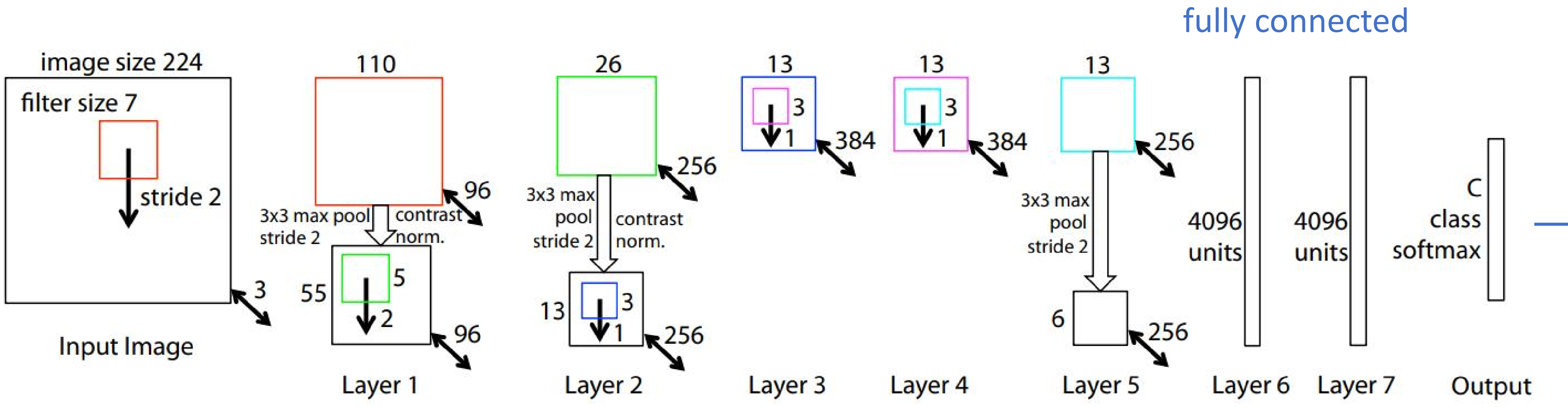



https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

# Part III Methodology

# Architecture of Convnet

Similar to Krizhevsky ImageNet




Loss Function

Cross-Entropy

Input: 224 x 224 x 3(RGB) → Filter: 7 x 7 x 96(channel) Stride: 2 both x and y → Passed through a rectified a liner function (ReLU) → Max Pool: 3 x 3 Stride: 2 for both x and y → contrast normalized across feature maps

← Update Parameters: Back Propogation + SGD ←

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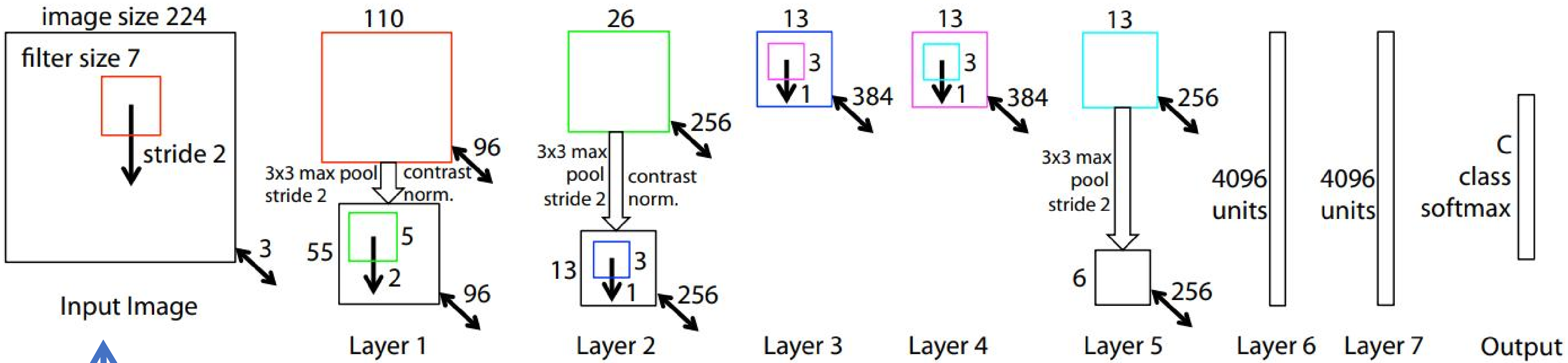
# Training Details

SGD batch size: 128
Learning Rate: $10^{-2}$
Momentum Term: 0.9
Dropout rate: 0.5

All weights are initialized to $10^{-2}$ and biases are set to 0




IMAGENET
2012 training set
1.3 million images
1000 different classes

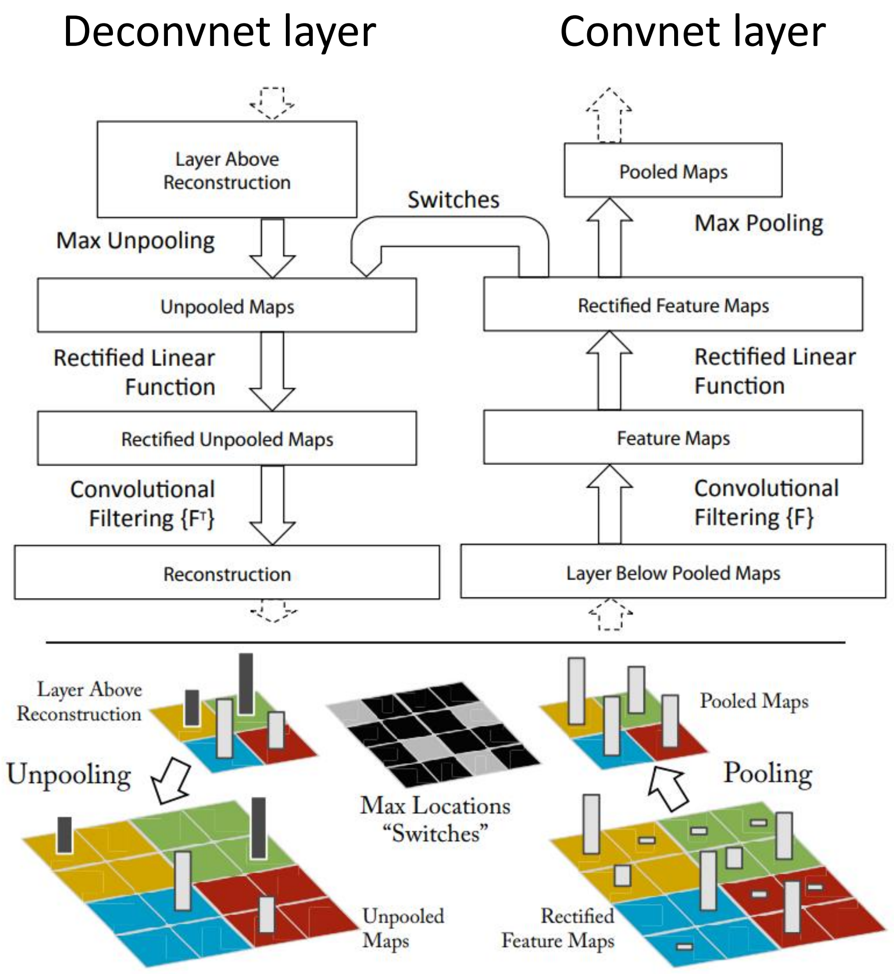
Renormalize each filter in the convolutional layers whose RMS value exceeds a fixed radius of $10^{-1}$ to this fixed radius

70 epochs
12 days
single GTX580 GPU

# Architecture of Deconvnet

The deconvnet will reconstruct an approximate version of the convnet features from the layer beneath.

- Unpooling
  recording the locations of the maxima within each pooling region in a set of switch variables
- Rectification
  pass the reconstructed signal through ReLU
- Filtering
  transposed version of the same filters
  filpping each filter vertically and horizontally

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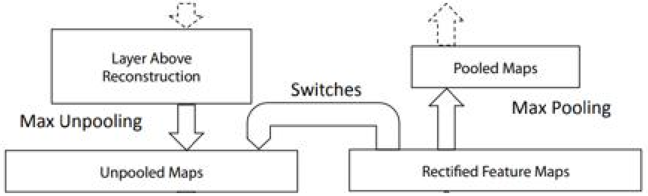
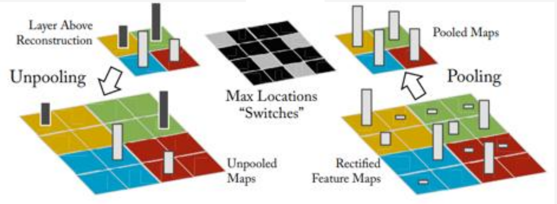
# Deconvnet: Unpooling



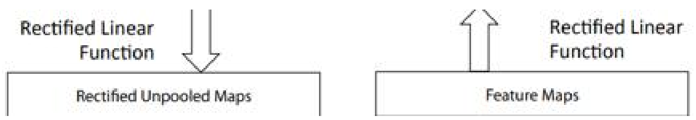

```python
class DPooling(object):

    def __init__(self, layer):

        self.layer = layer
        self.poolsize = layer.pool_size


    def up(self, data, learning_phase = 0):

        [self.up_data, self.switch] = \
                self.__max_pooling_with_switch(data, self.poolsize)
        return self.up_data

    def down(self, data, learning_phase = 0):

        self.down_data = self.__max_unpooling_with_switch(data, self.switch)
        return self.down_data
  # Compute unpooled output using pooled data and switch
  def __max_unpooling_with_switch(self, input, switch):

      print('switch '+str(switch.shape))
      print('input  '+str(input.shape))
      tile = np.ones((math.floor(switch.shape[1] / input.shape[1]),
          math.floor( switch.shape[2] / input.shape[2])))
      print('tile '+str(tile.shape))
      tile=numpy.expand_dims(tile,axis=3)
      input=numpy.squeeze(input,axis=0)
      out = np.kron(input, tile)
      print('out '+str(out.shape))
      unpooled = out * switch
      unpooled=numpy.expand_dims(unpooled,axis=0)
      return unpooled
```




```python
def __max_pooling_with_switch(self, input, poolsize):

    switch = np.zeros(input.shape)
    out_shape = list(input.shape)
    row_poolsize = int(poolsize[0])
    col_poolsize = int(poolsize[1])
    print(row_poolsize)
    print(col_poolsize)
    out_shape[1] = math.floor(out_shape[1] / poolsize[0])
    out_shape[2] = math.floor(out_shape[2] / poolsize[1])
    print(out_shape)
    pooled = np.zeros(out_shape)

    for sample in range(input.shape[0]):
        for dim in range(input.shape[3]):
            for row in range(out_shape[1]):
                for col in range(out_shape[2]):
                    patch = input[sample,
                            row * row_poolsize : (row + 1) * row_poolsize,
                            col * col_poolsize : (col + 1) * col_poolsize,dim]
                    max_value = patch.max()
                    pooled[sample, row, col,dim] = max_value
                    max_col_index = patch.argmax(axis = 1)
                    max_cols = patch.max(axis = 1)
                    max_row = max_cols.argmax()
                    max_col = max_col_index[max_row]
                    switch[sample,
                            row * row_poolsize + max_row,
                            col * col_poolsize + max_col,
                          dim]  = 1
    return [pooled, switch]
```

https://github.com/saketd403/Visualizing-and-Understanding-Convolutional-neural-networks

# Deconvnet: Rectification



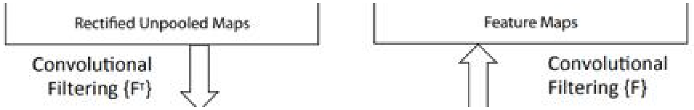

```python
class DActivation(object):
    def __init__(self, layer, linear = False):

        self.layer = layer
        self.linear = linear
        self.activation = layer.activation
        input = K.placeholder(shape = layer.output_shape)

        output = self.activation(input)
        # According to the original paper,
        # In forward pass and backward pass, do the same activation(relu)
        # Up method
        self.up_func = K.function(
                [input, K.learning_phase()], [output])
        # Down method
        self.down_func = K.function(
                [input, K.learning_phase()], [output])
```

```python
def up(self, data, learning_phase = 0):

    self.up_data = self.up_func([data, learning_phase])
    self.up_data=np.squeeze(self.up_data,axis=0)
    self.up_data=numpy.expand_dims(self.up_data,axis=0)
    print(self.up_data.shape)
    return self.up_data

def down(self, data, learning_phase = 0):

    self.down_data = self.down_func([data, learning_phase])
    self.down_data=np.squeeze(self.down_data,axis=0)
    self.down_data=numpy.expand_dims(self.down_data,axis=0)
    print(self.down_data.shape)
    return self.down_data
```

https://github.com/saketd403/Visualizing-and-Understanding-Convolutional-neural-networks

# Deconvnet: Filtering

```python
class DConvolution2D(object):

    def __init__(self, layer):
        self.layer = layer

        weights = layer.get_weights()
        W = weights[0]
        b = weights[1]

        filters = W.shape[3]
        up_row = W.shape[0]
        up_col = W.shape[1]
        input_img = keras.layers.Input(shape = layer.input_shape[1:])

        output=keras.layers.Conv2D(filters,(up_row,up_col),kernel_initializer=tf.constant_initializer(W),
                                   bias_initializer=tf.constant_initializer(b),padding='same')(input_img)
        self.up_func = K.function([input_img, K.learning_phase()], [output])
        # Deconv filter (exchange no of filters and depth of each filter)
        W = np.transpose(W, (0,1,3,2))
        # Reverse columns and rows
        W = W[::-1, ::-1,:,:]
        down_filters = W.shape[3]
        down_row = W.shape[0]
        down_col = W.shape[1]
        b = np.zeros(down_filters)
        input_d = keras.layers.Input(shape = layer.output_shape[1:])

        output=keras.layers.Conv2D(down_filters,(down_row,down_col),kernel_initializer=tf.constant_initializer(W),
                                   bias_initializer=tf.constant_initializer(b),padding='same')(input_d)
        self.down_func = K.function([input_d, K.learning_phase()], [output])
```

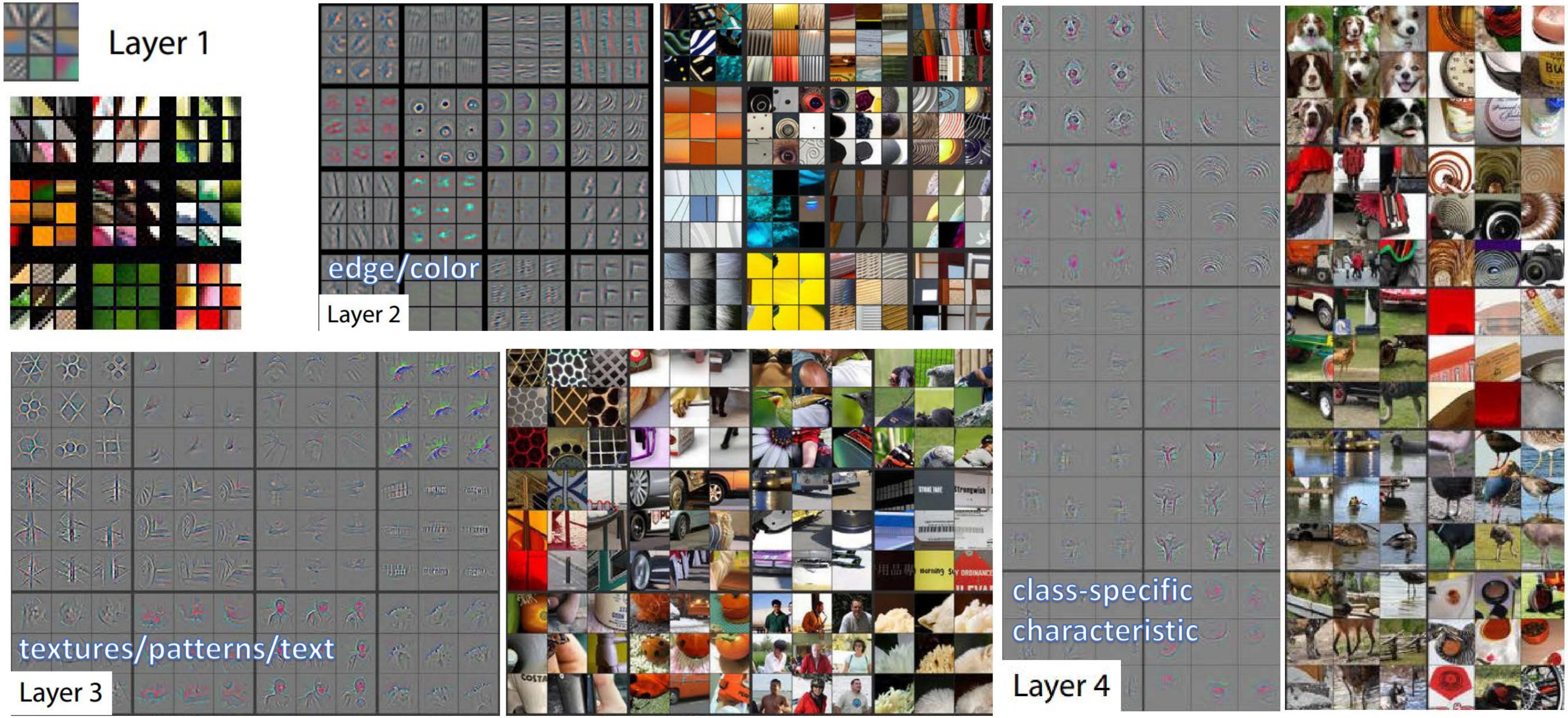



```python
def up(self, data, learning_phase = 0):
    #Forward pass
    self.up_data = self.up_func([data, learning_phase])
    self.up_data=np.squeeze(self.up_data,axis=0)
    self.up_data=numpy.expand_dims(self.up_data,axis=0)
    #print(self.up_data.shape)
    return self.up_data

def down(self, data, learning_phase = 0):
    # Backward pass
    self.down_data= self.down_func([data, learning_phase])
    self.down_data=np.squeeze(self.down_data,axis=0)
    self.down_data=numpy.expand_dims(self.down_data,axis=0)
    #print(self.down_data.shape)
    return self.down_data
```

https://github.com/saketd403/Visualizing-and-Understanding-Convolutional-neural-networks

# Part IV Convnet Visualization

# Convnet Visualization

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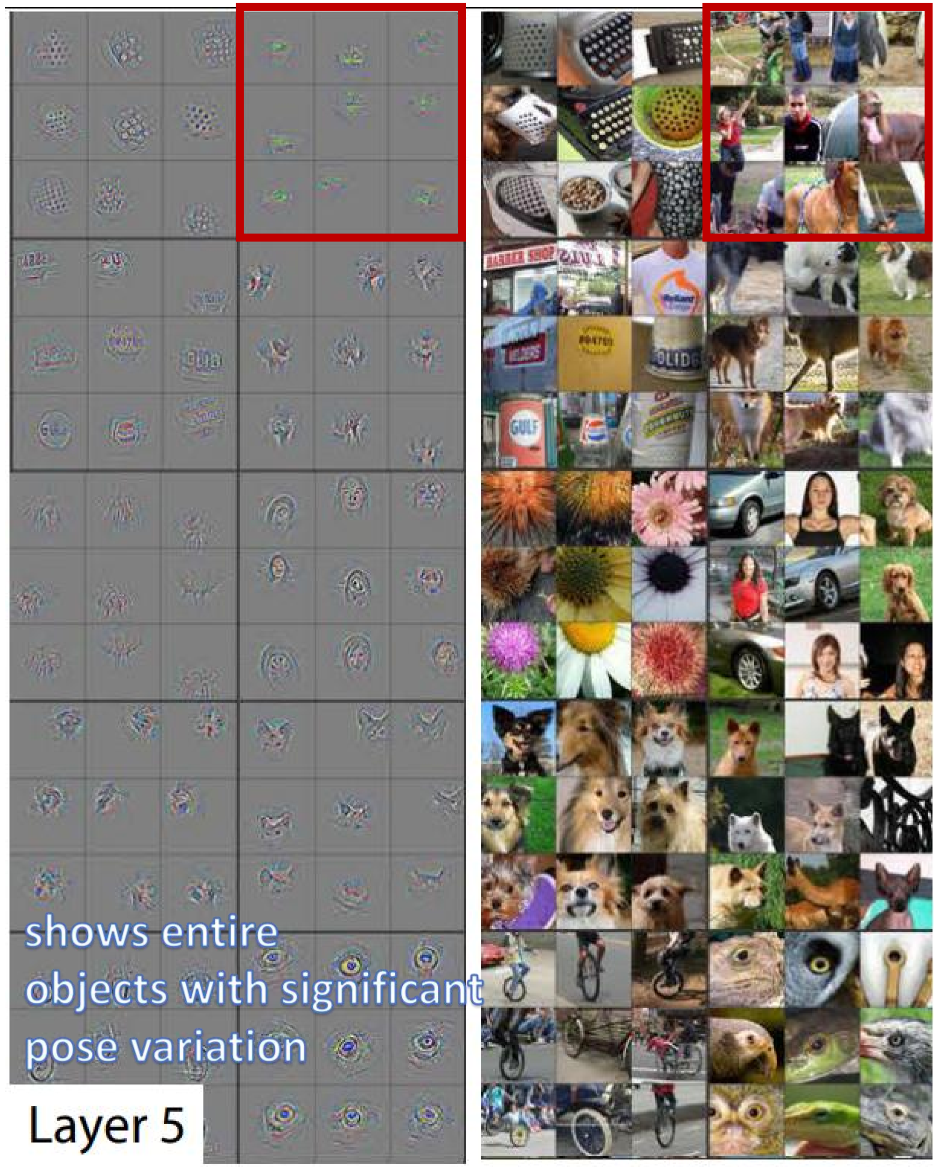
# Convnet Visualization

Original image

Features detected in feature map 127 of convolutional layer 3 of block 3 of VGG16 model

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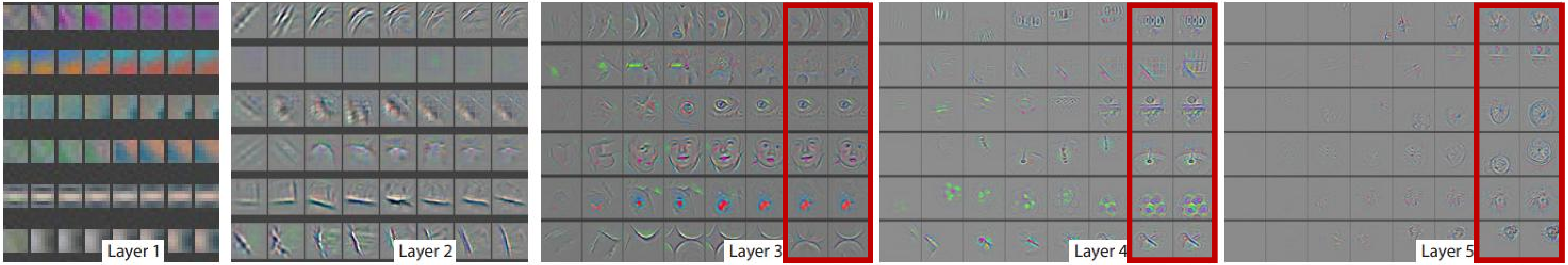
https://github.com/saketd403/Visualizing-and-Understanding-Convolutional-neural-networks

# Feature Evolution

The strongest activation (across all training examples) for a given feature map, projected down to pixel space using the deconvnet approach




A randomly chosen subset of features at epochs [1,2,5,10,20,30,40,64]

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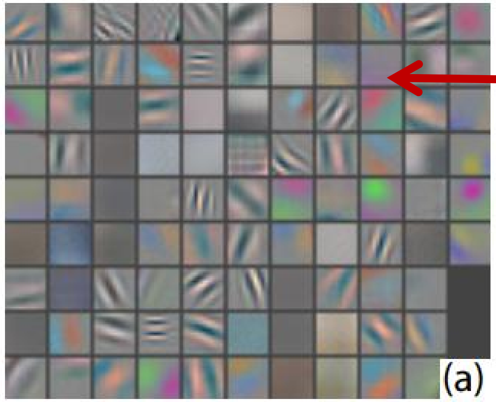
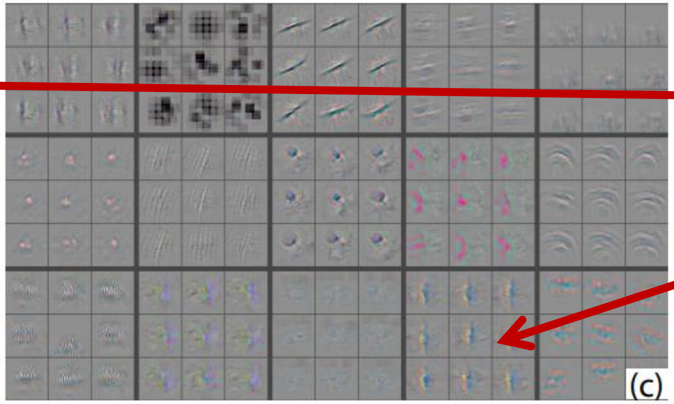
# Architecture Selection

Krizhevsky *et al.*



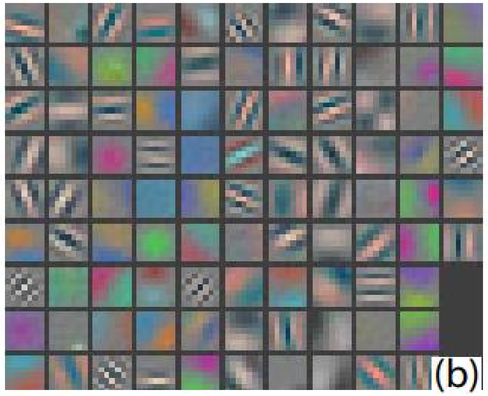



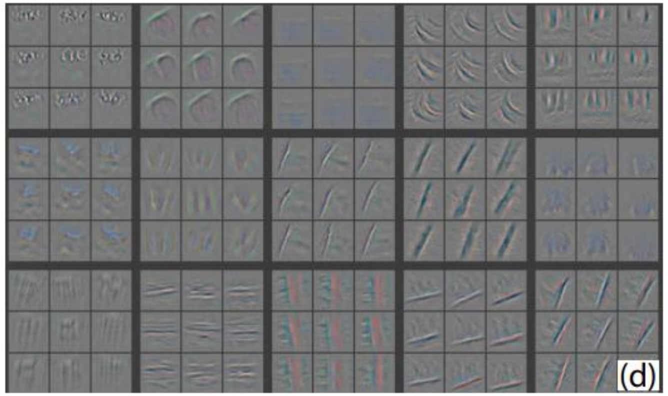

little coverage of the mid frequencies

aliasing artifacts

(i) reduced the 1st layer filter size from 11x11 to 7x7
(ii) made the stride of the convolution 2, rather than 4

Adjust



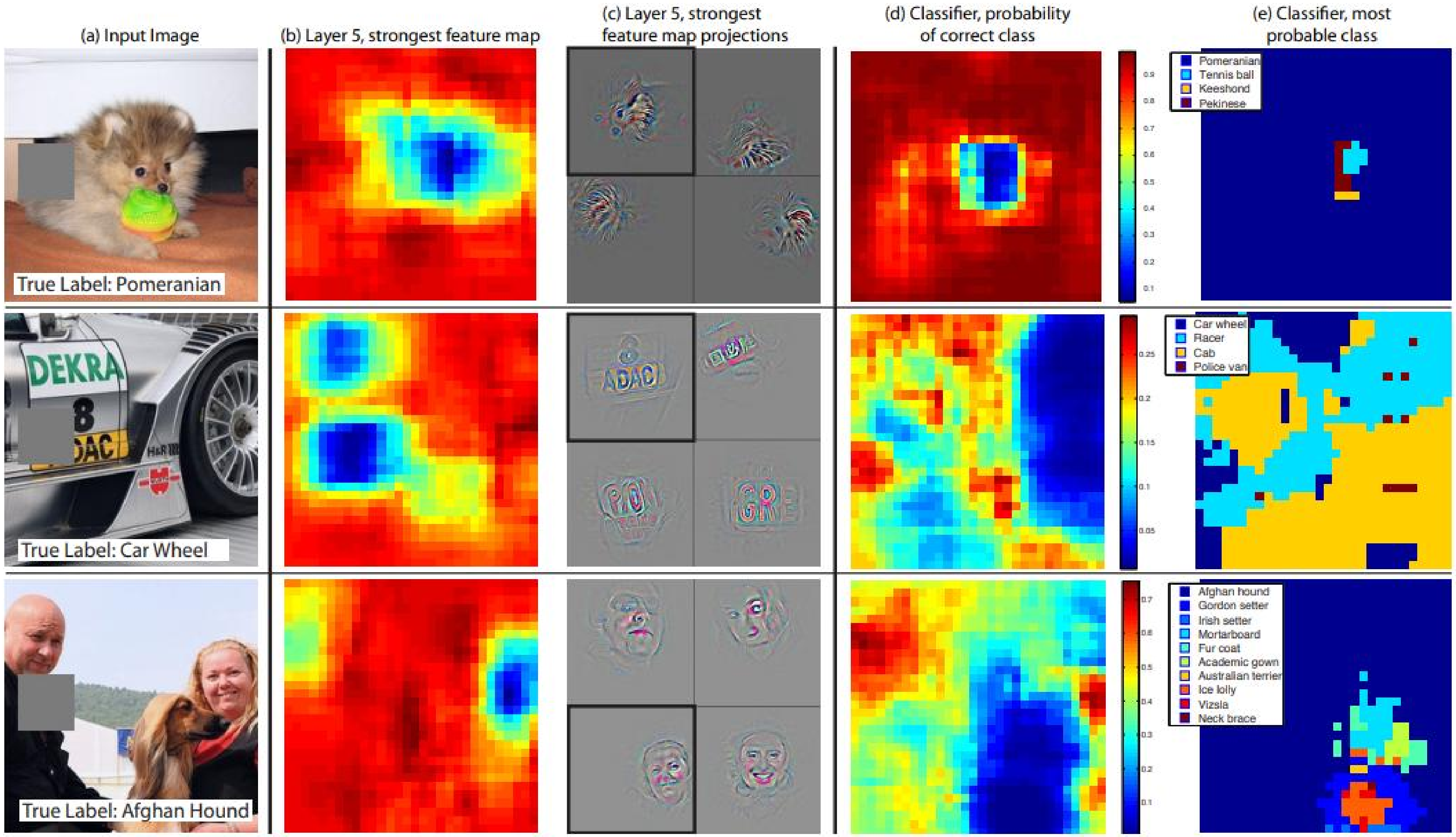




improves the classification performance

# Occlusion Sensitivity

the probability of the correct class drops significantly when the object is occluded

the visualization genuinely corresponds to the image structure that stimulates that feature map

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# Part V Experiments

# Experiement Result - ImageNet2012

Change the Srchitecture

(i) reduced the 1st layer filter size from 11x11 to 7x7

(ii) made the stride of the convolution 2, rather than 4

| Error % | Val Top-1 | Val Top-5 | Test Top-5 |
|---|---|---|---|
| Gunji *et al.* [12] | - | - | 26.2 |
| DeCAF [7] | - | - | 19.2 |
| Krizhevsky *et al.* [18], 1 convnet | 40.7 | 18.2 | −− |
| Krizhevsky *et al.* [18], 5 convnets | 38.1 | 16.4 | 16.4 |
| Krizhevsky *et al.* *[18], 1 convnets | 39.0 | 16.6 | −− |
| Krizhevsky *et al.* *[18], 7 convnets | 36.7 | 15.4 | 15.3 |
| Our replication of Krizhevsky *et al.* , 1 convnet | 40.5 | 18.1 | −− |
| 1 convnet as per Fig. 3 | 38.4 | 16.5 | −− |
| 5 convnets as per Fig. 3 – (a) | 36.7 | 15.3 | 15.3 |
| 1 convnet as per Fig. 3 but with layers 3,4,5: 512,1024,512 maps – (b) | 37.5 | 16.0 | 16.1 |
| 6 convnets, (a) & (b) combined | 36.0 | 14.7 | 14.8 |
| Howard [15] | - | - | 13.5 |
| Clarifai [28] | - | - | 11.7 |

Data Augmentation

Weak

# Experiement Result - ImageNet2012

## Varying ImageNet Model Sizes

- overall depth of the model is important for obtaining good performance

A slight increase in error when only remove the fully connected layers/convolutionallayers

dramatically worse

- increase the size of CNN layer will give a good performance

Changing the size of the fully connected layers makes little difference to performance

Increasing the size of the middle convolution layers goes give a useful gain in performance

| Error % | Train Top-1 | Val Top-1 | Val Top-5 |
|---|---|---|---|
| Our replication of Krizhevsky *et al.* [18], 1 convnet | 35.1 | 40.5 | 18.1 |
| Removed layers 3,4 | 41.8 | 45.4 | 22.1 |
| Removed layer 7 | 27.4 | 40.0 | 18.4 |
| Removed layers 6,7 | 27.4 | 44.8 | 22.4 |
| Removed layer 3,4,6,7 | 71.1 | 71.3 | 50.1 |
| Adjust layers 6,7: 2048 units | 40.3 | 41.7 | 18.8 |
| Adjust layers 6,7: 8192 units | 26.8 | 40.0 | 18.1 |
| Our Model (as per Fig. 3) | 33.1 | 38.4 | 16.5 |
| Adjust layers 6,7: 2048 units | 38.2 | 40.2 | 17.6 |
| Adjust layers 6,7: 8192 units | 22.0 | 38.8 | 17.0 |
| Adjust layers 3,4,5: 512,1024,512 maps | 18.8 | **37.5** | **16.0** |
| Adjust layers 6,7: 8192 units and Layers 3,4,5: 512,1024,512 maps | **10.0** | 38.3 | 16.9 |

# Feature Generalization

| # Train | Acc % 15/class | Acc % 30/class |
|---|---|---|
| Bo *et al.* [3] | – | $81.4 \pm 0.33$ |
| Yang *et al.* [17] | 73.2 | 84.3 |
| Non-pretrained convnet | $22.8 \pm 1.5$ | $46.5 \pm 1.7$ |
| ImageNet-pretrained convnet | $\mathbf{83.8 \pm 0.5}$ | $\mathbf{86.5 \pm 0.5}$ |

Caltech-101

| # Train | Acc % 15/class | Acc % 30/class | Acc % 45/class | Acc % 60/class |
|---|---|---|---|---|
| Sohn *et al.* [24] | 35.1 | 42.1 | 45.7 | 47.9 |
| Bo *et al.* [3] | $40.5 \pm 0.4$ | $48.0 \pm 0.2$ | $51.9 \pm 0.2$ | $55.2 \pm 0.3$ |
| Non-pretr. | $9.0 \pm 1.4$ | $22.5 \pm 0.7$ | $31.2 \pm 0.5$ | $38.8 \pm 1.4$ |
| ImageNet-pretr. | $\mathbf{65.7 \pm 0.2}$ | $\mathbf{70.6 \pm 0.2}$ | $\mathbf{72.7 \pm 0.4}$ | $\mathbf{74.2 \pm 0.3}$ |

Caltech-256

| Acc % | [22] | [27] | [21] | Ours | Acc % | [22] | [27] | [21] | Ours |
|---|---|---|---|---|---|---|---|---|---|
| Airplane | 92.0 | **97.3** | 94.6 | 96.0 | Dining table | 63.2 | **77.8** | 69.0 | 67.7 |
| Bicycle | 74.2 | **84.2** | 82.9 | 77.1 | Dog | 68.9 | 83.0 | **92.1** | 87.8 |
| Bird | 73.0 | 80.8 | 88.2 | **88.4** | Horse | 78.2 | 87.5 | **93.4** | 86.0 |
| Boat | 77.5 | 85.3 | 60.3 | **85.5** | Motorbike | 81.0 | **90.1** | 88.6 | 85.1 |
| Bottle | 54.3 | **60.8** | 60.3 | 55.8 | Person | 91.6 | 95.0 | **96.1** | 90.9 |
| Bus | 85.2 | **89.9** | 89.0 | 85.8 | Potted plant | 55.9 | 57.8 | **64.3** | 52.2 |
| Car | 81.9 | **86.8** | 84.4 | 78.6 | Sheep | 69.4 | 79.2 | **86.6** | 83.6 |
| Cat | 76.4 | 89.3 | 90.7 | **91.2** | Sofa | 65.4 | **73.4** | 62.3 | 61.1 |
| Chair | 65.2 | **75.4** | 72.1 | 65.0 | Train | 86.7 | **94.5** | 91.1 | 91.8 |
| Cow | 63.2 | 77.8 | **86.8** | 74.4 | Tv | 77.4 | **80.7** | 79.8 | 76.1 |
| Mean | 74.3 | 82.2 | **82.8** | 79.0 | # won | 0 | **11** | 6 | 3 |

PASCAL 2012

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# Part VI Q&A

# Thank You!