Multi-Scale Context Aggregation by Dilated Convolutions

Yi-An Lai
2018.03.07

http://goo.gl/XLtqZB
Outline

● Situations and Results (4)
● Dilated, Explained (3)
● Context Module and the Front End (6)
● Show and Justify (8)
● Extensions (2)
S1: Dense Prediction?

- One pixel, one prediction: **Pixel-wise**
  - Segmentation, surface normal, depth estimation, style transfer

- Common ConvNets **NOT** tailored for this
  - LeNet, AlexNet, VGG: **image-wise** classifications

“—”: Redundant components?
“+”: Better networks?

S2: What we want

- Customized architecture, tailored module
  - Full-resolution output

- **Multiscale** contexts: receptive field (RF)
  - LeNet, et al. — Stacking + Pooling / Sub-sampling — RF↑
  - Conflicts: **multiscale** vs **dense prediction**

https://guillaumebrg.wordpress.com/2016/02/13/adopting-the-vgg-net-approach-more-layers-smaller-filters/
S3: What others did

- Noh et al. — Encoder-Decoder
  - Heavy downsampling necessary?

- Farabet et al. — Rescaled images
  - Separate handling necessary?
S4: What we’ve done

- Why not modify architecture
  - Replace Fully-connected with Conv (previous works)
  - Remove redundant components — last 2 pooling

- Why not invent new module
  - Multiscale-capable, resolution-preserving

D1: Dilated Conv

- Vanilla Conv:
  \[(F \ast k)(p) = \sum_{s+t=p} F(s) k(t).\]

- \(l\)-Dilated Conv: filter element spacing
  \[(F \ast_l k)(p) = \sum_{s+l|t=p} F(s) k(t).\]

Q1: What’s the RF here?
D2: Dilated C

- Red: receptive field
- F1: dilation = 1
- F2: dilation = 2
- F3: dilation = 4
- **Exponential RF** as stacking with dilations 1, 2, 4, 8, ...
  \[ F_{i+1} = F_i \ast_{2^i} k_i \quad \text{for} \quad i = 0, 1, \ldots, n - 2. \]
- (i+1)th layer RF:
  \[ (2^{i+2} - 1) \times (2^{i+2} - 1) \]
  (Whiteboard explain)
- **Multiscale + full resolution!**
D3: WaveNet - 1D Dilated Conv

- Causal/Online version

Receptive field

http://goo.gl/XLtqZB

https://deepmind.com/blog/wavenet-generative-model-raw-audio/
So Far, So Good?
C1: The Module

- **Goal:** performance↑ using multiscale contexts
- **All Dilated Conv = Multiscale + Full-resolution**
- **(W, H, C) in, (W, H, C) out → Plug into any layer!**
  - Equip feature maps with multiscale contextual info
- **Module:**
  - 1 - 7: + ReLU
  - Equal #channel

Q2: Why stop RF expansion at layer 6?

![Image](https://leonardoaraujosantos.gitbooks.io/artificial-intelligence/content/convolutional_neural_networks.html)
C2: Initializations - inspiration

- RNN initialized with **identity** matrix + ReLU (Red) → Beat LSTM

"A Simple Way to Initialize Recurrent Networks of Rectified Linear Units." QV Le, et al

Image: [http://speech.ee.ntu.edu.tw/~tlkagk/courses_ML17_2.html](http://speech.ee.ntu.edu.tw/~tlkagk/courses_ML17_2.html)
C3: Initializations

- Basic: #channel the same
  - Identity initializations → "copy & paste"

- Large: #channel double
  - Copy & paste but with scaling
  - All other zeros → break symmetry
    → Randomly initialized and small (<< 0.5)

C4: Front End - Modified VGG 16

1. Input 900 x 900 x 3 (reflection padding)
C4: Front End - Modified VGG 16

1. Input 900 x 900 x 3 (reflection padding)

2. No padding in the middle at all
C4: Front End - Modified VGG 16

1. Input 900 x 900 x 3 (reflection padding)

2. No padding in the middle at all

3. Last 2 pooling $\rightarrow$ dilated
1. Input 900 x 900 x 3 (reflection padding)

2. No padding in the middle at all

3. Last 2 pooling → dilated

4. Fully Connected → Conv

Dilation: 2
Kernal: 7 x 7

Dilation: 4

C=4096
C=4096
C=21
C=21
C4: Front End - Modified VGG 16

1. Input 900 x 900 x 3 (reflection padding)

2. No padding in the middle at all

3. Last 2 pooling → dilated

4. Fully Connected → Conv

5. Softmax: 21 classes → 64 x 64 x 21

Prediction: upsample to original size (500 x 500)
C4: Front End - VGG 16

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2. No padding in the middle at all

3. Last 2 pooling → dilated

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Prediction: upsample to original size (500 x 500)

Q3: Where did authors plug in the module?
   A. after blue 1
   B. after blue 2
   C. after blue 3
   D. after brown
C5: Front End Performance

Table 2: Our front-end prediction module is simpler and more accurate than prior models. This table reports accuracy on the VOC-2012 test set.

<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
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<td>Our front end</td>
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→ Modified architecture performs good!
C6: Front Line

More accurate

More details
S1: Training

- **VOC 2012 + COCO**
  - COCO: images with at least 1 class in VOC
  - 2-stage: (VOC + COCO) → VOC
  - Front End **only**: 71.3% test → Our modifications justified

- **Module: context aggre.**
  - Add padding for inputs (64 x 64 x C), why? → RF 67 x 67, to output 64 x 64 x C
  - Train Front End → Fixed → Train module (Joint ~ the same)
  - Goal: Testing the module + Pairing with **structured prediction** (Could be jointly learned)
Warning of New Stuff!
S2: Wait, structured prediction?

- Inputs and outputs: objects with **structures**
  - Object: sequence, boxes, images, list, tree…
  - Need more powerful $F$ to define “compatibility” of $(X, Y)$
S2: Wait, structured prediction?

- Inputs and outputs: objects with **structures**
  - *Object*: sequence, boxes, images, list, tree…
  - Need more powerful $F$ to define “compatibility” of $(X, Y)$

\[ f: X \rightarrow Y \]

- Retrieval

  "Machine learning" (keyword)

  ![A list of web pages (Search Result)](image)

[http://speech.ee.ntu.edu.tw/~tlkagk/courses_MLSD_15_2.html](http://speech.ee.ntu.edu.tw/~tlkagk/courses_MLSD_15_2.html)
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Retrieval

```
X:  "Machine learning" (keyword)  Y:  A list of web pages (Search Result)
```

Speech

```
X:  (One kind of sequence)  Y:  “大家好，歡迎大家來修
  機器學習及其結構化” (Another kind of sequence)
```

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- Inputs and outputs: objects with **structures**
  - **Object**: sequence, boxes, images, list, tree…
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- **Retrieval**
  - $X$: "Machine learning" (keyword)
  - $Y$: A list of web pages (Search Result)

- **Detection**
  - $X$: Image
  - $Y$: Object Positions

- **Speech**
  - $X$: (One kind of sequence)
  - $Y$: “大家好，歡迎大家來修機器學習及其深層與結構化” (Another kind of sequence)

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- **Pose**
  - $X$: Image
  - $Y$: Pose

http://speech.ee.ntu.edu.tw/~tlkagk/courses_MLSD_15_2.html
S3: How?

- Structured prediction in only 3 steps
- As easy as putting an elephant into a refrigerator
S4: 3 Steps

1. **Evaluation**: how does “compatibility” $F(X, Y)$ look like?

   - **Object Detection**: $F(x=\text{人物图}, y=\text{框})$
   - **Summarization**: $F(x=\text{一篇长文}, y=\text{一篇短文})$

   [http://speech.ee.ntu.edu.tw/~tlkagk/courses_MLSD15_2.html](http://speech.ee.ntu.edu.tw/~tlkagk/courses_MLSD15_2.html)

   Energy-based model: [https://cs.nyu.edu/~yann/research/ebm/](https://cs.nyu.edu/~yann/research/ebm/)
S4: 3 Steps

1. **Evaluation**: how does “compatibility” $F(X, Y)$ look like?

   - **Object Detection**: $F(x=\text{[image]}, y=\text{[object]})$
   - **Summarization**: $F(x=\text{[long document]}, y=\text{[summary]})$  

2. **Inference**: Solve “arg max” problem
   - Detection $Y$: all possible bounding boxes
   - Summarization $Y$: all combinations of sentences in a doc

http://speech.ee.ntu.edu.tw/~tlkagk/courses_MLSD15_2.html  
**Energy-based model**: https://cs.nyu.edu/~yann/research/ebm/
S4: 3 Steps

1. **Evaluation**: how does “compatibility” $F(X, Y)$ look like?

   - **Object Detection**: $F(x=\text{}, y=\text{})$
   - **Summarization**: $F(x=\text{}, y=\text{})$

2. **Inference**: Solve “arg max” problem
   - Detection $Y$: all possible bounding boxes
   - Summarization $Y$: all combinations of sentences in a doc

3. **Training**: Given data $(x_i, y_i)$, learn $F$ such that

   - $F(x^1, y^1)$ for all $y \neq \hat{y}^1$
   - $F(x^2, y)$ for all $y \neq \hat{y}^2$
   - $F(x^r, y)$ for all $y \neq \hat{y}^r$

   ![Diagram](http://speech.ee.ntu.edu.tw/~tlkagk/courses_MLSD15_2.html)

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S5: Structured predictions used

- **Goal**: refine details to improve performance

- **CRF**: [Efficient Inference in Fully Connected CRFs with Gaussian Edge Potentials, Krähenbühl, et al. (2011)]
  - Pairwise links between pixels
  - Capture fine edge details with long range dependencies

- **RNN-CRF**: [Conditional Random Fields as Recurrent Neural Networks, Zheng, et al. (2015)]
  - Interpret CRFs as RNN
  - Can be plug into CNNs and jointly learned

- **Q4**: What are our inputs and outputs for structured prediction here?

- More about Conditional Random Fields (CRFs)
  - Machine Learning: A Probabilistic Perspective
  - [http://dontloo.github.io/blog/CRF/](http://dontloo.github.io/blog/CRF/)
S6: Evaluate Module

Effective & Synergistic

<table>
<thead>
<tr>
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<td><strong>Front end</strong></td>
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</tbody>
</table>

Table 3: Controlled evaluation of the effect of the context module on the accuracy of three different architectures for semantic segmentation. Experiments performed on the VOC-2012 validation set.
S7: Now the real test

- Yellow: **off** by a margin
- Green: **over** by a margin

Table 4: Evaluation on the VOC-2012 test set.

<table>
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</table>

→ Context module boost performance
S8: Other datasets

- Urban Scenes: CamVid, KITTI, Cityscapes
- Adjust #layer in the module w.r.t. input size
- Outperform all prior works
- Code: https://github.com/fyu/dilation
E1: Strength & Weakness

- **Strength**
  - *Multiscale* contextual information
  - Full-resolution context module can be **plugged** into any layer
  - Architecture from classification tasks is modified and justified for segmentation
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  - Multiscale contextual information
  - Full-resolution context module can be plugged into any layer
  - Architecture from classification tasks is modified and justified for segmentation

- **Weakness**
  - Only 64 * 64 output size: lose details → Helped by CRF
  - Full-resolution requires more memory usage
  - Performance $\uparrow$ $\phi \pi$ more parameters rather than multiscale info?
    → No experiment to compare with another module with all vanilla conv
E2: Got ideas?

1. Multi-head **self-attention** rather than dilated conv for multiscale info?

https://pythonmachinelearning.pro/introduction-to-convolutional-neural-networks-for-vision-tasks/
E2: Got ideas?

1. Multi-head **self-attention** rather than dilated conv for multiscale info?

2. Striding as “**learnable**” pooling
   → replace all pooling layers

https://pythonmachinelearning.pro/introduction-to-convolutional-neural-networks-for-vision-tasks/
E2: Got ideas?

1. Multi-head **self-attention** rather than dilated conv for multiscale info?

2. Striding as “**learnable**” pooling
   → replace all pooling layers

3. Other variants:

https://pythonmachinelearning.pro/introduction-to-convolutional-neural-networks-for-vision-tasks/
Than