Transfer Learning for Visual Scene Understanding

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Ultimate goal
Automatic systems that learn and act autonomously
Medium term goal
Automatic systems that can analyze and interpret data

"Three men sit at a table in a pub, drinking beer. One of them talks while the other two listen."

Image: British Broadcasting Corporation (BBC)
State of the art
Analyze individual aspects of visual data

Scene Classification
- indoors
- in a pub

Action Classification
- drinking
- talking

Object Recognition
- three persons
- one table
- three glasses
State of the art

Task 1

Task 2

Task 3

Tabula Rasa Learning
Future challenge: towards continuously improving systems
Research topics

**Machine Learning**
- Multi-task learning
- Domain adaptation
- Learning to learn
- Learning with weak supervision

**Computer Vision**
- Object recognition
- Object localization
- Semantic segmentation
- Attribute-based classification
Semantic Image Segmentation
State-of-the-art: Convolutional Neural Networks (CNNs)

- deep neural network, all layers convolutional
- predict per-pixel output from per-pixel input
- trained from images with per-pixel ground truth
State-of-the-art: Convolutional Neural Networks (CNNs)

- training set \( \{(x^1, y^1), \ldots, (x^m, y^m)\} \)
- images \( x^i \), ground truth segmentation masks \( y^i \)
- CNN output \( f_{u,c}(x; \theta) \) (probability of class \( c \) at location \( u \))
- measure quality of one prediction by a loss function, e.g.

\[
\text{loss}(f_{u,c}, y) = - \sum_c \sum_u y_{u,c} \log f_{u,c}(x)
\]

- learn CNN parameters by minimizing loss over training set

\[
\min_{\theta} \sum_{i=1}^{m} \text{loss}(f_{u,c}(x^i), y^i)
\]

Problem: creating per-pixel annotation cost a lot of time
Weakly-Supervised Semantic Segmentation

- train from images with per-image class labels (tags)
  - cat
  - sofa
  - table
  - chair
  - horse
  - motorbike
  - ...

- annotation is much weaker, but much easier to generate
Weakly-Supervised Semantic Segmentation

Training:
- training set \( \{(x^1, T^1), \ldots, (x^m, T^m)\} \)
- images \( x^i \), tag annotation \( T^i \), e.g. \( T^i = \{\text{cat, dog}\} \)

how to measure quality of a predicted segmentation mask?
1) pool per-pixel scores \( f_{u;c}(x) \) into per-image scores, \( G_c(x) \)
2) measure if correct classes were predicted, e.g.

\[
\text{loss}(x, T) = - \sum_{c \in T} \log G_c(x) - \sum_{c \in \mathcal{C} \setminus T} \log(1 - G_c(x))
\]

Problem: it doesn’t work very well...

SEC: Seed, Expand and Constrain

VGG-style deep network (16 layers, all convolutional):

- pre-trained classification network
- image dataset to learn from (with per-image class labels)

Main contribution: new, three-part, loss function

$$L_{seed}(x, f(x; \theta), T) + L_{exp.}(f(x; \theta), T) + L_{cnstr.}(x, f(x; \theta))$$
Seed loss:
- network should reproduce weak cues from classification network

Expand loss:
- network should produce reasonable object sizes

Constrain loss:
- network should respect boundaries (image gradients)
Observation:

- Convolutional networks achieve very good results in full-image classification tasks.
  - If we know which part of the image caused the network to make its decision, we can find out where the object is.

SEC: Seed, Expand and Constrain

Multiple possibilities:

1) gradient back-propagation from label to image
   "which change to the image affects the score the most?"

2) mask out different image regions and observe the score

3) use a network with spatial representation until the last layer

Images: adapted from [Zhou, Khosla, Lapedriza, Oliva, Torralba. "Learning Deep Features for Discriminative Localization" CVPR 2016].
SEC: **Seed, Expand and Constrain**

**Observation:**

- Heatmaps, $g_u(x)$, from classification network gives only rough localization, not segmentation mask

- We trust only the most confident core areas $\rightarrow$ **seed regions**

$$S_c(x) = \{ u : g_u(x) \geq 0.2\alpha \} \quad \text{for} \quad \alpha = \max_v g_v(x)$$

(can be precomputed)
Seed loss:

\[ L_{seed}(X, f(X), T) = \frac{-1}{\sum_{c \in T} |S_c|} \sum_{c \in T} \sum_{u \in S_c} \log f_{u,c}(X) \]

The network should produce correct labels where weak cues tell it to.

SEC: Seed, Expand and Constrain
**Observation:** Pooling method influences predicted object sizes

- **max pooling**: class score is maximum of per-pixel scores
  all weight lies on a single pixel → bias towards small objects
- **average pooling**: class score is average of pixel scores
  all pixels have the same weight → bias towards large objects
- **ideal**: all object pixels contribute, but none of the others

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* [Zhou, Khosla, Lapedriza, Oliva, Torralba. "Learning Deep Features for Discriminative Localization" CVPR 2016],
† [Oquab, Bottou, Laptev, Sivic; "Is Object Localization for Free? - Weakly-Supervised Learning With Convolutional Neural Networks", CVPR 2015]
Proposed: global weighted rank pooling (GWRP):

- sort pixels by their activation score, \( i_1, \ldots, i_n \)

\[
f_{i_1, c}(x) \geq f_{i_2, c}(x) \geq \cdots \geq f_{i_n, c}(x)
\]

- pool by linear combination with decreasing weights:

\[
G_c(x; d_c) = \frac{1}{Z(d_c)} \sum_{j=1}^{n} (d_c)^{j-1} f_{i_j, c}(x), \quad \text{for } Z(d_c) = \sum_{j=1}^{n} (d_c)^{j-1}.
\]

- \( d_c \): decay parameter for class \( c \).

Generalizes other poolings:

- \( d_c = 0 \): max pooling \( d_c = 1 \): average pooling
- \( 0 < d_c < 1 \): put more emphasis on locations with high scores
Our choices: (for $n = 41 \times 41$)

- for classes $c$ that are in the image: $d_+ = 0.996$
  $\rightarrow$ 50% of weight on top 10% pixels

- for classes $c$ that are not in the image: $d_- = 1$
  $\rightarrow$ max-pooling, no pixel should have high object score

- for background class: $d_{bg} = 0.999$
  $\rightarrow$ 50% of weight on top 30% pixels

Expresses our prior belief about object sizes.
Loss function:

\[
L_{\text{exp.}}(f(X), T) = -\frac{1}{|T|} \sum_{c \in T} \log G_c(X; d_+) - \log G_{c_{\text{bg}}}(X; d_{\text{bg}}) \\
- \frac{1}{|C \setminus T|} \sum_{c \in C \setminus T} \log(1 - G_c(X; d_-))
\]
Observation:

- applying a fully-connected conditional random field (CRF) to the network output yields crisp segmentation.

Can we make use of this property also at training time?

Images: [Chen, Papandreou, Kokkinos, Murphy, Yuille. "Semantic Image Segmentation with Deep Convolutional Nets and Fully Connected CRFs", ICLR 2015]
SEC: Seed, Expand and Constrain

Main idea:

• learn network such that per-pixel predictions look like CRF predictions (in particular: follow image boundaries)

• $Q_{u,c}(x)$ is output of CRF with CNN outputs $f_{u,c}(x)$ as inputs

• measure difference between CNN output and CRF output (by Kullback-Leibler divergence)

$$\text{KL}(p||q) = \sum_i p_i \frac{\log p_i}{\log q_i}$$
Loss function:

\[
L_{\text{constr.}}(x, f(x)) = \frac{1}{|I|} \sum_{u \in I} \sum_{c \in C} Q_{u,c}(x) \log \frac{Q_{u,c}(x)}{f_{u,c}(x)}
\]
Training

- Continuous in all parameters ("end-to-end differentiable")
- Gradients computed automatically using Theano
- Stochastic gradient descent (backpropagation)
  - Minibatches (size 15)
  - 8000 iterations
  - Dropout rate 0.5
  - Weight decay 0.0005
  - Initial learning rate 0.001, decreased every 2000 iterations
- 7-8 hours on GeForce TITAN-X GPU

Data

- PASCAL VOC 2012 challenge: 20 object classes + background
- Training set: 10,582 weakly annotated images
- Test set: 1456 images (no public labels, uses evaluation server)
- Evaluation by mean intersection-over-union
<table>
<thead>
<tr>
<th>PASCAL VOC 2012 test set</th>
<th>MIL-FCN</th>
<th>CCNN</th>
<th>MIL+ILP+SP-sppxl</th>
<th>SEC (proposed)</th>
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<tbody>
<tr>
<td>background</td>
<td>≈71†</td>
<td>74.7</td>
<td>83.0</td>
<td></td>
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<tr>
<td>aeroplane</td>
<td>24.2</td>
<td>38.8</td>
<td>55.6</td>
<td></td>
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<tr>
<td>bike</td>
<td>19.9</td>
<td>19.8</td>
<td>27.4</td>
<td></td>
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<tr>
<td>bird</td>
<td>26.3</td>
<td>27.5</td>
<td>61.1</td>
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<tr>
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<td>21.7</td>
<td>22.9</td>
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<tr>
<td>bottle</td>
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<td>32.8</td>
<td>52.4</td>
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<tr>
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<td>40.0</td>
<td>70.2</td>
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<tr>
<td>car</td>
<td>42.9</td>
<td>50.1</td>
<td>58.8</td>
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<tr>
<td>cat</td>
<td>48.2</td>
<td>47.1</td>
<td>70.0</td>
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</tr>
<tr>
<td>chair</td>
<td>15.6</td>
<td>7.2</td>
<td>22.1</td>
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<tr>
<td>cow</td>
<td>37.2</td>
<td>44.8</td>
<td>54.3</td>
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<tr>
<td>diningtable</td>
<td>18.3</td>
<td>15.8</td>
<td>27.9</td>
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<tr>
<td>dog</td>
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<td>67.4</td>
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<tr>
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<tr>
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<td>tv/monitor</td>
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<td>41.3</td>
<td>45.2</td>
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<tr>
<td>average</td>
<td>25.7</td>
<td>35.6</td>
<td>35.8</td>
<td>51.5</td>
</tr>
</tbody>
</table>

†: inferred from average
Failure cases (aka, future work):

- consistently co-occurring distractors (trains + tracks, boat + water)
- confusion between objects (chair vs. sofa)
- disconnected object (usually due to occlusion)
Insights from Ablation Study

Most important term in loss function: localization seeds

<table>
<thead>
<tr>
<th>loss function</th>
<th>$L_{\text{expand}}$</th>
<th>$L_{\text{seed}}$</th>
<th>$L_{\text{cnstr.}}$</th>
<th>$L_{\text{seed}} + L_{\text{cnstr.}}$</th>
<th>$L_{\text{expand}} + L_{\text{cnstr.}}$</th>
<th>$L_{\text{seed}} + L_{\text{expand}}$</th>
<th>full SEC loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>mIoU</td>
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<td>49.2</td>
<td>–</td>
<td>49.4</td>
<td>17.2</td>
<td>45.7</td>
<td>50.7</td>
</tr>
</tbody>
</table>

Ground Truth Image $L_{\text{semi}} + L_{\text{bound}}$ $L_{\text{class}} + L_{\text{bound}}$ $L_{\text{class}} + L_{\text{semi}}$ Full Loss
Insights from Ablation Study

Global Weighted Rank Pooling leads to better object sizes than max-pooling or average-pooling

<table>
<thead>
<tr>
<th>Model</th>
<th>foreground fraction</th>
<th>mIoU</th>
</tr>
</thead>
<tbody>
<tr>
<td>GMP</td>
<td>21.0</td>
<td>47.3</td>
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<tr>
<td>GAP</td>
<td>37.5</td>
<td>45.1</td>
</tr>
<tr>
<td>GWRP</td>
<td>26.7</td>
<td>50.7</td>
</tr>
<tr>
<td>ground truth</td>
<td>27.1</td>
<td>–</td>
</tr>
</tbody>
</table>
Summary

Transfer Learning for Visual Scene Understanding
- Transfer information between different learning tasks
  → less training data or less necessary annotation

Weakly-Supervised Image Segmentation
- annotation is weaker (image tags) than the desired system output (segmentation masks)
- requires transfer of information and/or prior knowledge

SEC: Seed, Expand and Constrain [arXiv:1603.06098 [cs.CV]]
- transfer: weak location cues from classification network
- prior knowledge: typical objects sizes
- prior knowledge: objects boundaries align with image gradients
- code and pretrained models will be online
Thanks to...

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