Weakly Supervised Learning

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July 04, 2018

Outline

From 2D Annotation to 3D Annotation

From Labels to Localization

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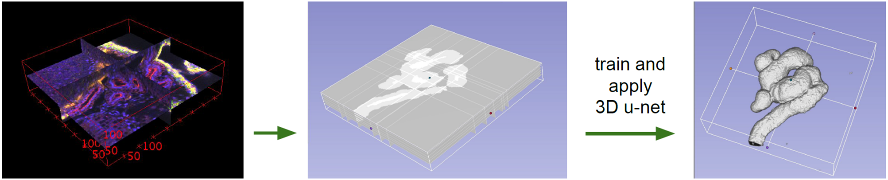
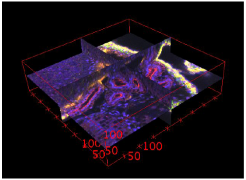
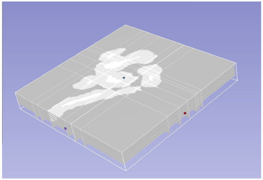


- Only few labeled 2D slices

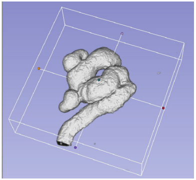
Source: [1]

From 2D Annotation to 3D Annotation





train and apply 3D u-net



- Only few labeled 2D slices
- Generalize to the 3D case

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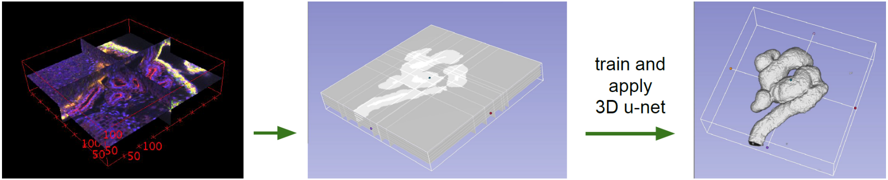
From 2D Annotation to 3D Annotation



- Only few labeled 2D slices
- Generalize to the 3D case
- Interactive segmentation

Source: [1]

Training with Sparse Labels

"One hot" labels *y* with element *i* being 1

$$L = -\log\left(\frac{e^{s_i}}{\sum_{k=1}^{K} e^{s_k}}\right)$$

Source: [1]

Training with Sparse Labels

"One hot" labels y with element i being 1

$$L = -\log\left(\frac{\mathrm{e}^{s_i}}{\sum_{k=1}^{K}\mathrm{e}^{s_k}}\right)$$

Sparse

➔ Add a label y_{k+1}

$$L' = L \cdot \mathrm{w}(\mathbf{y})$$

Where $\mathrm{w}(\mathbf{y}) = \begin{cases} 0 & \text{if } y_{k+1} = 1 \\ w_i > 0 & \text{otherwise} \end{cases}$

Source: [1]

From Bounding Boxes to Segmentation

Expensively annotated

Fully supervised

- Manual segmentation is tedious

Source: [2]

From Bounding Boxes to Segmentation

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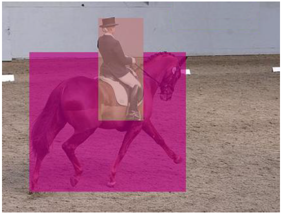
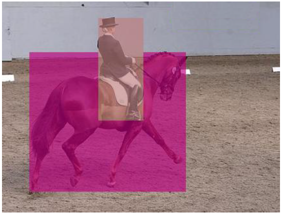
Cheaply annotated



- Manual segmentation is tedious
- Bounding boxes are less tedious

Source: [2]

From Bounding Boxes to Segmentation

Expensively annotated Fully supervised	Cheaply annotated	Cheaply annotated Weakly supervised
		

- Manual segmentation is tedious
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→ Learn segmentation from boxes

Source: [2]

Naive Recursive Training

Observation: Bounding boxes as target lead to basic segmentations.

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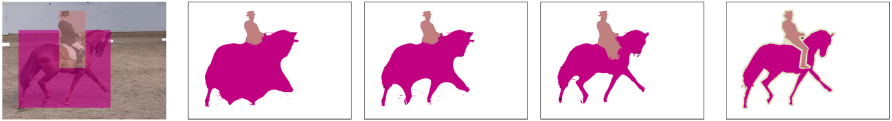

Example input rectangles	Output after 1 training round	After 5 rounds	After 10 rounds	Ground truth

→ Smaller box is foreground

Source: [2]

Naive Recursive Training

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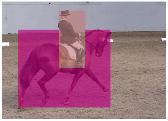
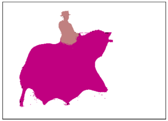


Example
input rectangles



Output after
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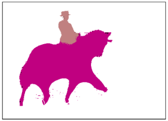
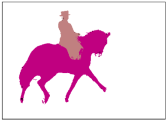
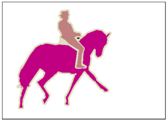


After
5 rounds



After
10 rounds



Ground
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- **Suppress** detections

  ...of wrong class

  ...outside of box

  ...<% box area

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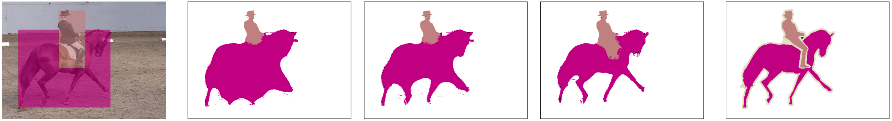

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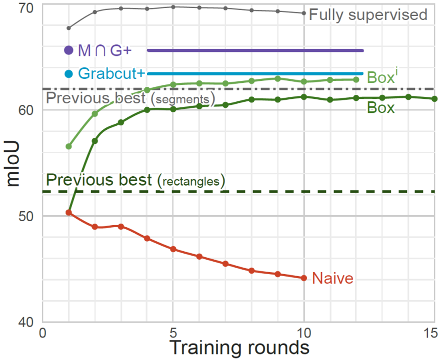
- Apply CRF on output

Source: [2]

Improved Recursive Training



➔ Shrink box - beats state of the art

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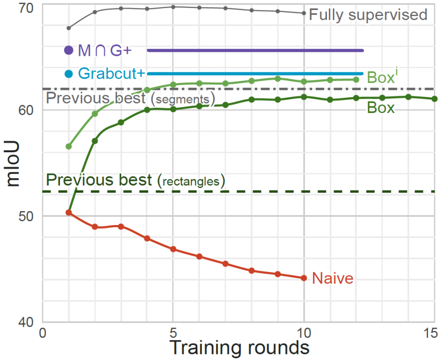
Improved Recursive Training



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- Use Grabcut

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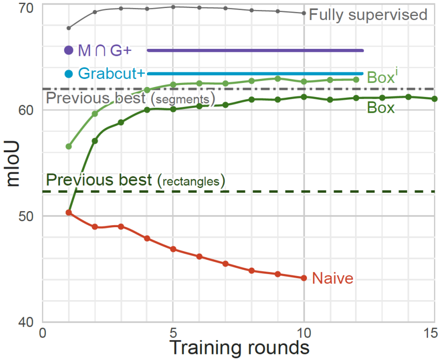

→ Shrink box - beats state of the art

- Use Grabcut
- Combine Grabcut and MCG

Source: [2]

From Labels to Localization

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Four ingredients:

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- **Pretrained** filters

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From Labels to Localization

Four ingredients:

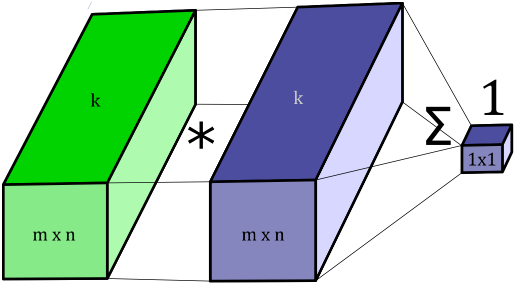
- **Pretrained** filters
- Whole **arbitrary size** image as input
- **Localize** class
- Classify **individually**

Arbitrary input size

➔ **Fully connected** layer fixes the size

Arbitrary input size

- ➔ **Fully connected** layer fixes the size
- ➔ Replace by **convolutional** layer



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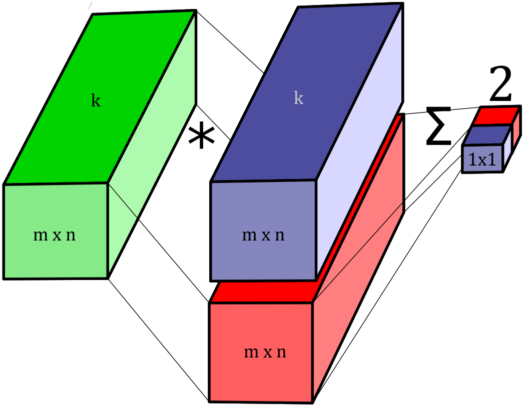

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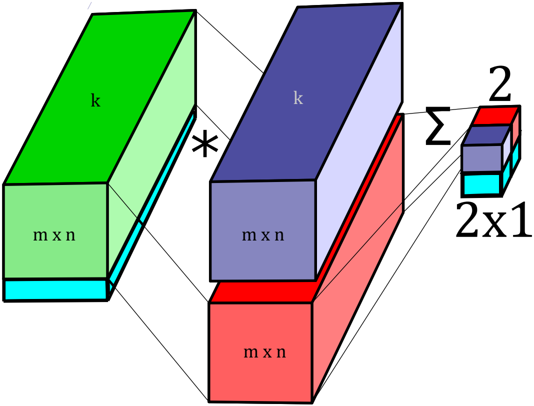
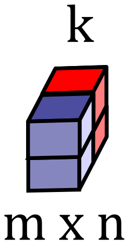


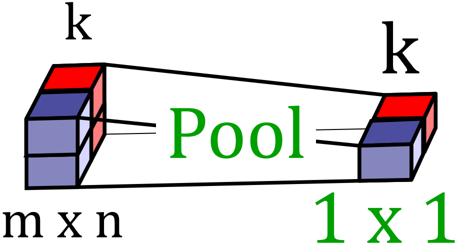
Arbitrary input size

- How to localize?



Arbitrary input size

- How to localize?
- Global pooling
- Oquab et al., 2015: Max pooling; Bolei et al., 2016: Average pooling



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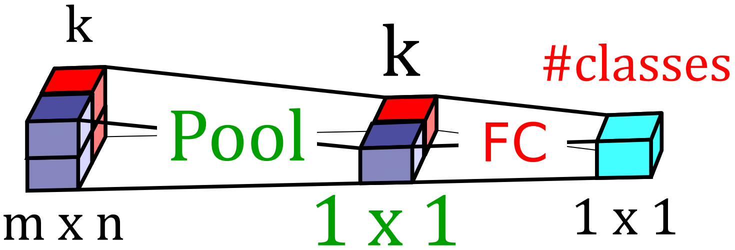

Individual Classification

➔ **Multiple objects** could be visible

$$L_i = -\log\left(\frac{\mathrm{e}^{s_i}}{\sum_{k=1}^{K} \mathrm{e}^{s_k}}\right)$$

Individual Classification

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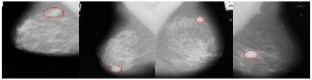
$$L_i = -\log\left(\frac{e^{s_i}}{\sum_{k=1}^{K} e^{s_k}}\right)$$

Change "one-hot" labels y_k from 0 to -1 indicating "absence"

$$\begin{aligned} L_i &= \sum_{k}^{K} -\log\left(\frac{1}{1+e^{-y_k s_k(\mathbf{x})}}\right) \\ &= \sum_{k}^{K} \log\left(1+e^{-y_k s_k(\mathbf{x})}\right) \end{aligned}$$

What if we can't get an appropriate pretrained net?



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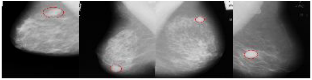
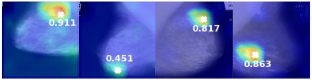
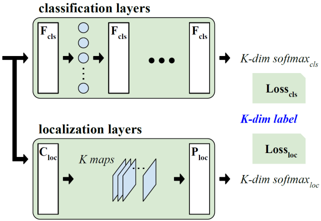




→ Multi-task learning



$$\text{Loss}_{total} = (1 - \alpha)\,\text{Loss}_{cls} + \alpha\,\text{Loss}_{loc}$$

Also significantly **boosts** the **localization**!

Source: Hwang et al., Self-Transfer Learning for Fully Weakly Supervised Object Localization, 2016

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References

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[1] Özgün Çiçek, Ahmed Abdulkadir, Soeren S Lienkamp, et al. "3d u-net: learning dense volumetric segmentation from sparse annotation". In: International Conference on Medical Image Computing and Computer-Assisted Springer. 2016, pp. 424–432.

[2] Anna Khoreva, Rodrigo Benenson, Jan Hosang, et al. "Simple Does It: Weakly Supervised Instance and Semantic Segmentation". In: arXiv preprint arXiv:1603.07485 (2016).

[3] Maxime Oquab, Léon Bottou, Ivan Laptev, et al. "Is object localization for free?-weakly-supervised learning with convolutional neural networks". In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recogniti 2015, pp. 685–694.

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[5] Sangheum Hwang and Hyo-Eun Kim. "Self-Transfer Learning for Weakly Supervised Lesion Localization". In: International Conference on Medical Image Computing and Computer-Assisted Springer. 2016, pp. 239–246.

[6] Richard O. Duda, Peter E. Hart, and David G. Stork. Pattern classification. 2nd ed. New York: Wiley-Interscience, Nov. 2000.