Semantic Segmentation with Incomplete Annotations

Medical Computer Vision and Health Informatics Workshop

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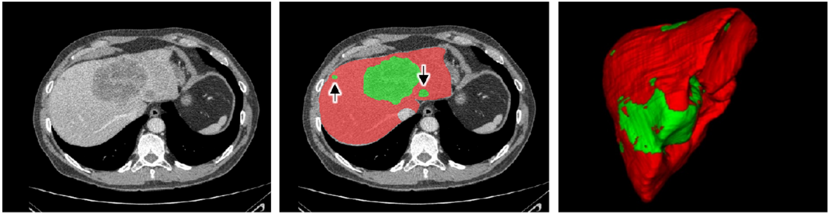
Outline

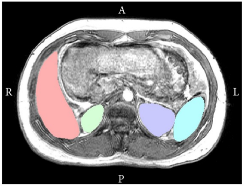
Context: Semantic Segmentation of Medical Images

- Semantic Segmentation: class label for each image pixel / voxel
- Deep ConvNets: tremendous sucess for visual recognition
- Semantic Segmentation of natural images: Fully Convolutional Networks (FCN), *e.g.* DeepLab [Chen et al., 2018]
    - Adpated FCN architectures for medical images, *e.g.* U-Net [Ronneberger et al., 2015]
    - FCN: base architecture for leading approaches in recent medical segmentation challenges, *e.g.* LITS'17 [Han, 2017, Li et al., 2017]

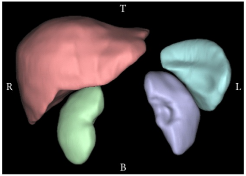


Datasets for Medical Image Semantic Segmentation

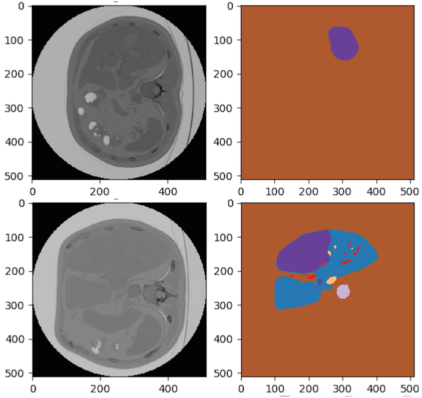
- ConvNets: large amount of data with clean annotations
- Annotation very costly for semantic segmentation: pixel-level labeling
    - Exacerbated in medical images: 3D data, highly qualified professionals needed, *e.g.* tumors (extreme appearance variations)



(a)

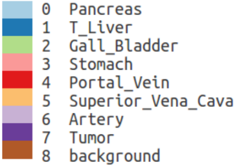


(b)



Semantic Segmentation of 3D CT-scans

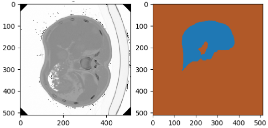
- Internal dataset[1]: ~ 1000 patients of $100 \times 512 \times 512$ images



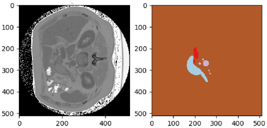
🟦	0	Pancreas
🟦	1	T_Liver
🟩	2	Gall_Bladder
🟥	3	Stomach
🟥	4	Portal_Vein
🟧	5	Superior_Vena_Cava
🟪	6	Artery
🟪	7	Tumor
🟫	8	background

- 3D segmentation: focusing on 2D slices
  $\Rightarrow$ independent training in each image

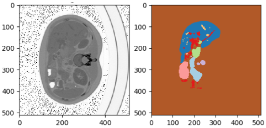
Liver

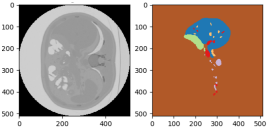


Pancreas

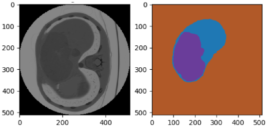


Stomach





Gall blader



Tumor

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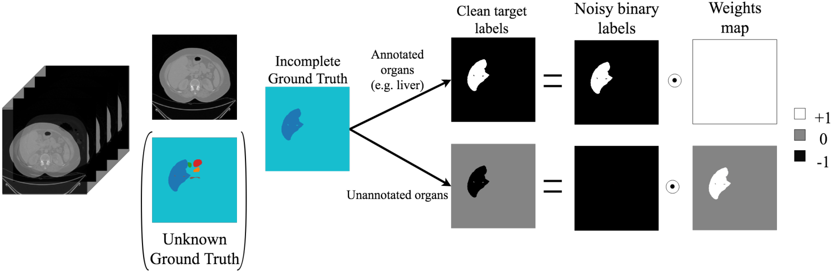
[1] IRCAD: `https://www.ircad.fr/fr/`

Semantic Segmentation with Incomplete Annotations

- Large scale dataset, BUT:
  - Clinical experts: focus on a subset of organs
    ⇒ **Incomplete annotations** wrt full Ground Truth



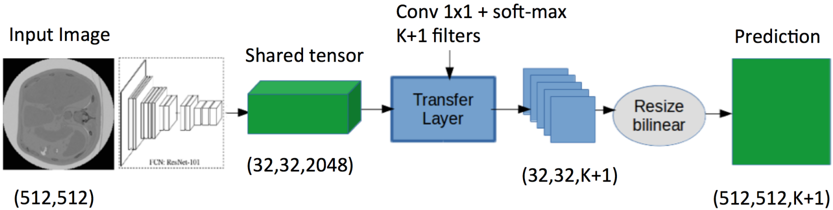
- **How to train deep ConvNets in this context ?**
  - Organ(s) missing the whole volumes, but: organ segmented in volume ⇒ complete annotation for that class
  - **Core idea:** generating clean target labels from noisy input labels
    - Binary mask w_k for each class ⇒ ambiguous *vs* non-ambiguous pixels

Outline

1. Context
2. **Semantic Segmentation with Incomplete Annotations**
3. Experiments

Semantic Segmentation with Incomplete Annotations

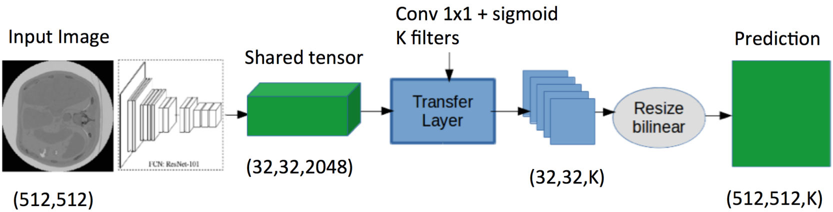
- Standard FCN not adapted to this context, *e.g.* DeepLab [Chen et al., 2018]



  - Shared Fully Convolutional Layers, ResNet [He et al., 2016]
  - Last tensor: 1×1 conv + soft-max $\Rightarrow$ single class prediction
  - **Incomplete annotation: "background" $\Leftrightarrow$ missing organ**
    $\Rightarrow$ conflict with pixels with proper organ annotations during training

Semantic Segmentation with Incomplete Annotations

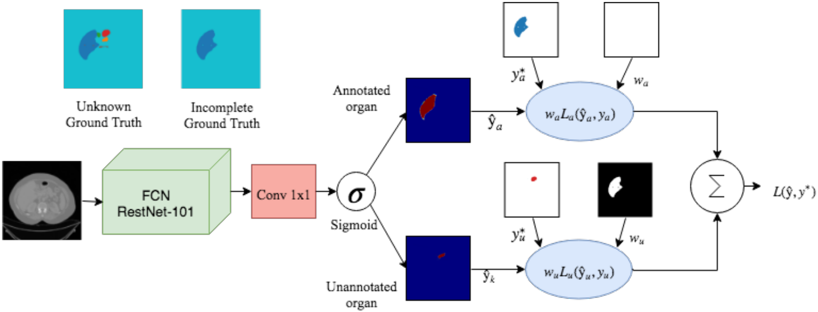
- Our approach for **S**emantic segmentation with **MI**ssing **L**abels and convn**E**ts (SMILE)
- Depart from the $(K+1)$ multi-class classification formulation, classify each organ independently using K binary classifiers



SMILE Training

- Binary CE loss at each pixel: $L_k(\hat{y}_k, y_k^*) = -\ (y_k^*\ log(\hat{y}_k) + (1 - y_k^*)\ log(1 - \hat{y}_k))$
- Final loss: weighted sum of binary losses:

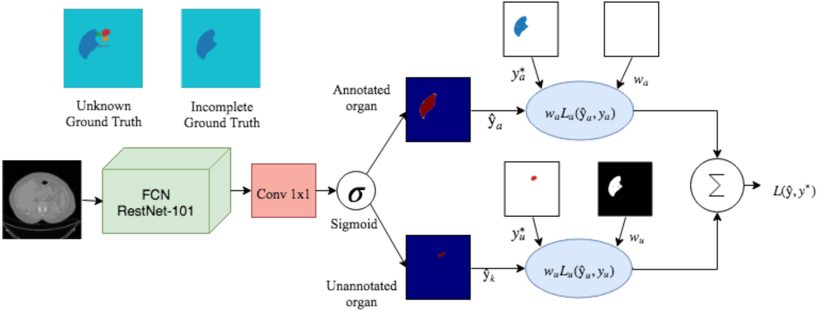
$$L(\hat{y}, y^*) = \sum_{k=1}^{K} w_k\ L_k(\hat{y}_k, y_k^*)$$



SMILE Training

- **Core SMILE component: binary weight maps $\mathbf{w_k} \in \{0; 1\}$**
  - Selecting or ignoring each pixel for class k
    - Class k present in volume: $w_k = 1 \ \forall$ pixel in volume
    - Class k absent:

$$w_k = \begin{cases} 1 \text{ if } \exists k' \neq k \text{s.t.} w_{k'} = 1 \ (\Rightarrow y_k^* = -1), \\ 0 \text{ otherwise (pixel ignored)} \end{cases}$$



SMILE Training

- **Analysis of labels used by FCN baseline and SMILE *vs* Ground Truth (GT)**
- For class k:
  - β_k ratio of voxels in a volume
  - α the ratio of missing labels for this organ in the dataset.

Baseline FCN

Used GT	Pos	Neg
Pos	$(1-\alpha)\cdot\beta_k$	$\alpha\cdot\beta_k$
Neg	0	$1-\beta_k$

SMILE

Used GT	Pos	Neg
Pos	$(1-\alpha)\cdot\beta_k$	0
Neg	0	$(1-\alpha)\cdot(1-\beta_k)+\epsilon$

$$\epsilon = \sum_{k'\neq k} \beta_{k'}$$

- **Both baseline and SMILE: only true positive**
  - **BUT only use $(1-\alpha)\cdot\beta_k$ vs β_k**

SMILE Training

Baseline FCN

Used GT	Pos	Neg
Pos	$(1-\alpha)\cdot\beta_k$	$\alpha\cdot\beta_k$
Neg	0	$1-\beta_k$

SMILE

Used GT	Pos	Neg
Pos	$(1-\alpha)\cdot\beta_k$	0
Neg	0	$(1-\alpha)\cdot(1-\beta_k)+\epsilon$

$$\epsilon = \sum_{k' \neq k} \beta_{k'}$$

- **Baseline:**
  - **False Negatives (FN)**: $\alpha \cdot \beta_k$, *i.e.* unannotated pixels indeed belonging to the organ
  - $\boxed{\frac{\textbf{TP}}{\textbf{FN}} = \frac{1-\alpha}{\alpha} : \ \alpha > \mathbf{0.5} \Rightarrow \frac{\textbf{TP}}{\textbf{FN}} < \mathbf{1}}$
- **SMILE:**
  - **Only true positives and true negatives**
  - **Less true negatives than baseline:** $(1-\alpha)\cdot(1-\beta_k)+\epsilon$ *vs* $(1-\beta_k)$
    - $\approx \alpha$ less negatives, but as $\beta << 1$, *e.g.* $\beta = 0.05$[2]
      $\Rightarrow$ **in practice, largely enough negative to train**

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[2] organs ⇔ small volume portion

SMILEr Training

Incremental self-supervision and relabeling

- SMILE True Positives (TP) labels $\propto (1-\alpha)$
- **<u>Motovation:</u> automatically increasing number of TP labels**
  - Compensate for incomplete annotations
- Auto-supervision: create target positive labels
  $\Rightarrow$ **SMILEr** (re-labeling)
- Using a curriculum strategy [Bengio et al., 2009]
  1. Train ConvNet with SMILE: certain labels only, *i.e.* true positives and negatives $\Rightarrow$ **"easy samples"**
  2. Seek for new true positives with current model
     - **"Harder samples"**, automatic labeling
     - Use this new labels as target to train a new model with more positives
     - Iterate
- $\frac{TP}{FP}$: key indicator of SMILEr sucess

SMILEr Training

- SMILEr algorithm: applied for each binary organ classifier independently[a]

Algorithm 1 Algorithm for training SMILEr for class k

```
Require: Training set $\{(\mathbf{x}_i, \mathbf{y}_i^*)\}$, $\gamma_{max}$, $T$, SMILE model $m_0$ for class $k$.
Initialize $\mathbf{y}_{i,0}^* = \mathbf{y}_i^*$, $N_u \leftarrow$ number of unannotated images for class $k$
for t=1 to T do
    $\gamma_t = \frac{t}{T}\gamma_{max}$
    for i=1 to $N_u$ do
        $\hat{y}_i{}^{+} \leftarrow (m_t, \mathbf{x}_i)$ // Find predicted positive pixels by $m_t$ in image $\mathbf{x}_i$
        $y_{i,t}^{*,+} \leftarrow (m_t, \mathbf{x}_i, \gamma_t, \hat{y}_k{}^{+})$ // Assign new ⊕ taget labels
        $y_{i,t}^* = y_{i,t-1}^* \cup y_{i,t}^{*,+}$ // Augment training set
    end for
    $m_t = train(\{(\mathbf{x}_i, \mathbf{y}_{i,t}^*)\},)$ // Re-train model with augmented training set
end for
Ensure: SMILEr Model $m_T$
```

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[a] Ignoring the dependence on class k for the sake of clarity.

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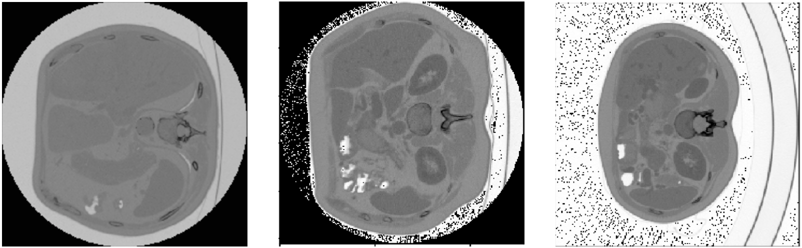
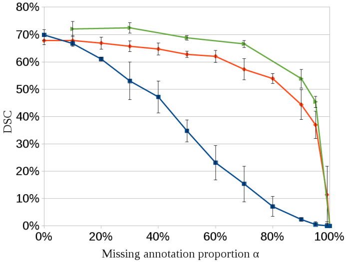
3. Experiments

Dataset and setup

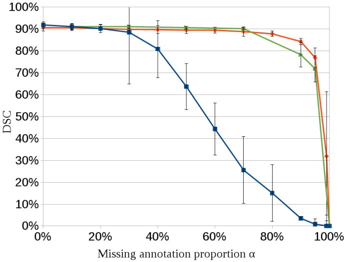
- Experiments on sub-set of our dataset with complete ground truth annotations
- 72 3D CT-scan volumes (~ 100 512×512 images) for three organs: liver, pancreas and stomach
- Partially annotated dataset generated: randomly removing $\alpha\%$ of organs in the volumes independently
- Comparison of our methods (SMILE, SMILEr) wrt DeepLab baseline
  - Train 80% / Test (20%), $K = 5$ datasplits



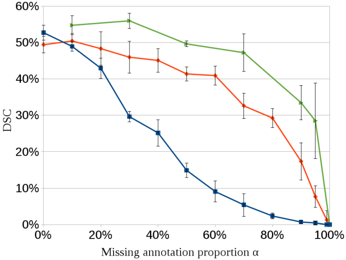
Quantitative results



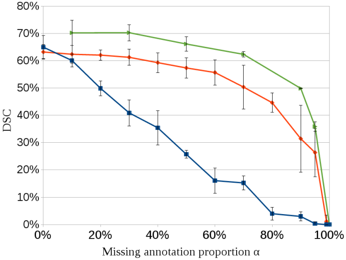
Mean



Liver



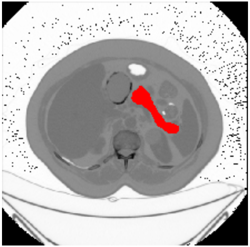
Pancreas



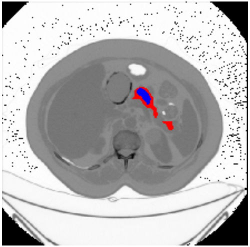
Stomach

SMILEr re-labeling, $\alpha = 50\%$

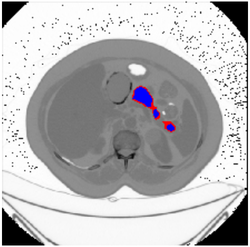
GT



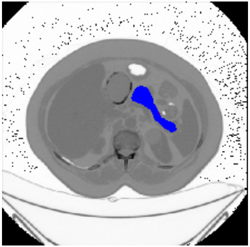
SMILEr $t = 1$



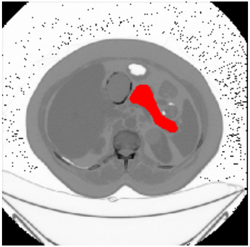
SMILEr $t = 2$



$T = 3$, $\gamma_{max} = 1.0$

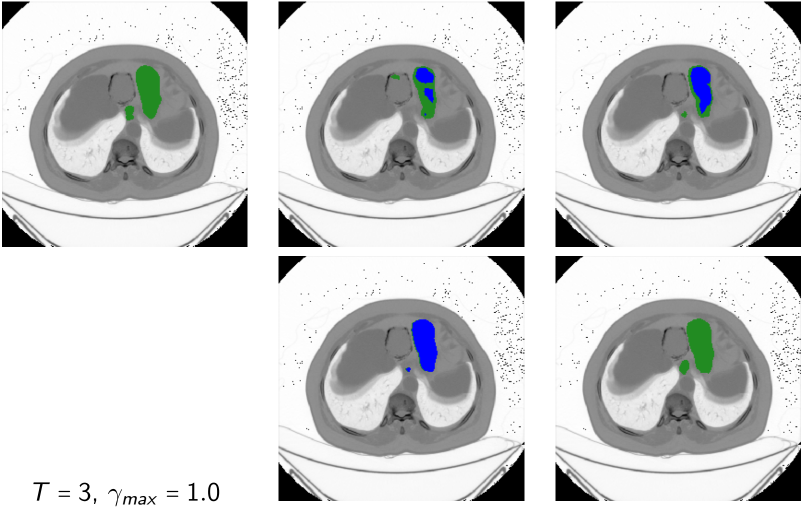


SMILEr $t = 3$



Final prediction

SMILEr re-labeling, $\alpha = 70\%$



GT

SMILEr $t = 1$

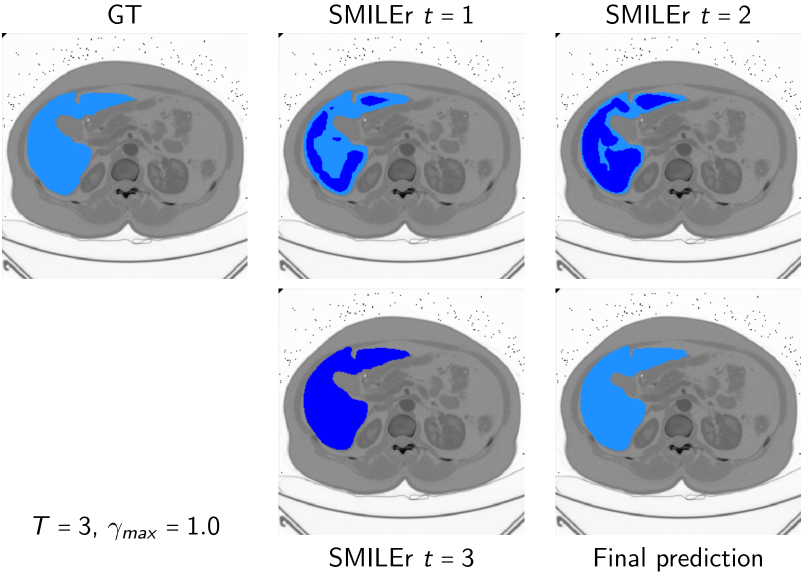
SMILEr $t = 2$

SMILEr $t = 3$

Final prediction

$T = 3$, $\gamma_{max} = 1.0$

SMILEr re-labeling, $\alpha = 70\%$



GT

SMILEr $t = 1$

SMILEr $t = 2$

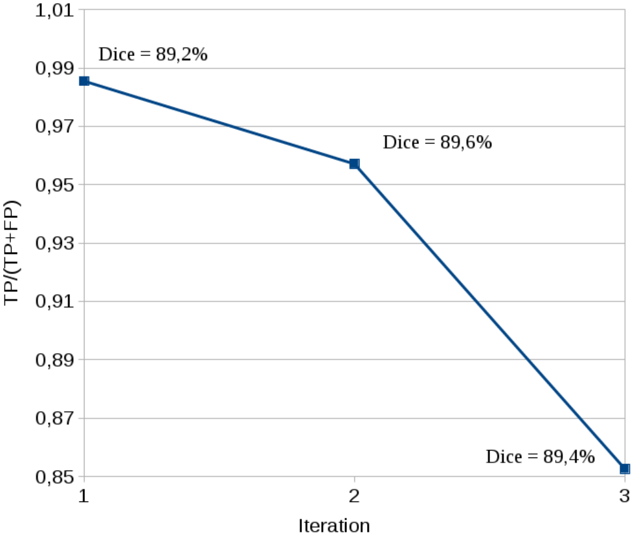
SMILEr $t = 3$

Final prediction

$T = 3$, $\gamma_{max} = 1.0$

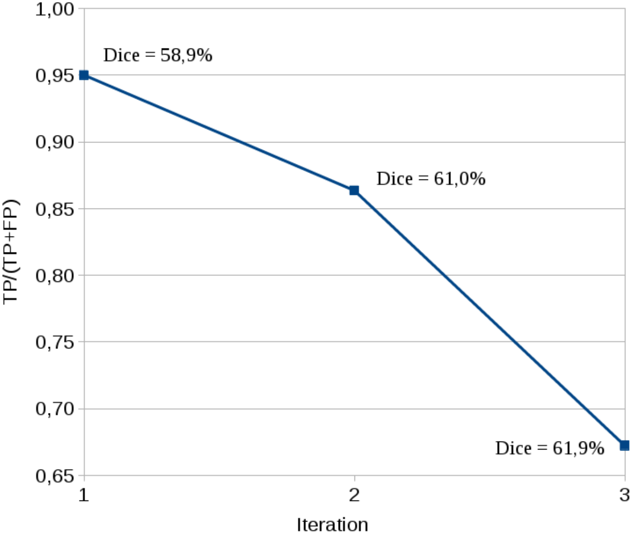
Re-labeling method

- $\frac{TP}{TP+FP}$ vs Curriculum iterations for Liver (α = 70%)



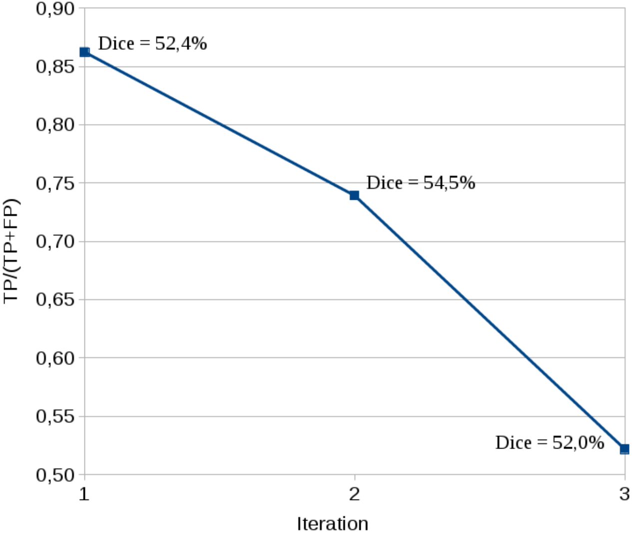
Re-labeling method

- $\frac{TP}{TP+FP}$ vs Curriculum iterations for Stomach (α = 70%)

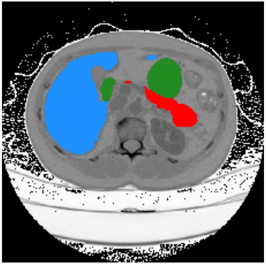


Re-labeling method

- $\frac{TP}{TP+FP}$ vs Curriculum iterations for Pancreas (α = 70%)

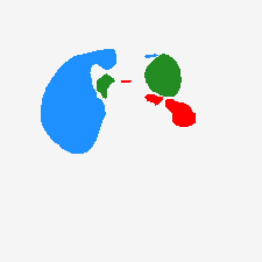


Segmentation results, $\alpha = 70\%$

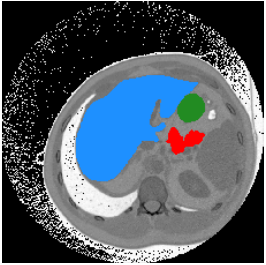


GT

baseline

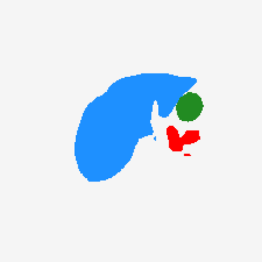


SMILEr



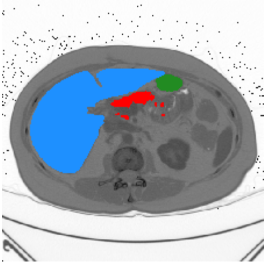
GT

baseline

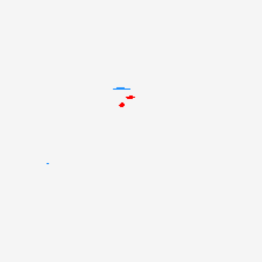


SMILEr

Segmentation results, $\alpha = 70\%$

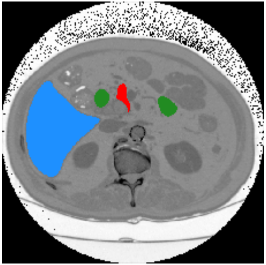


GT



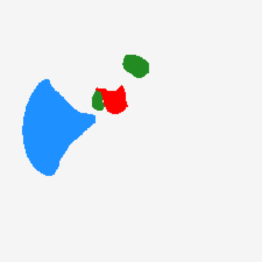
baseline

SMILEr



GT

baseline



SMILEr

Conclusion

- Method for learning with incomplete ground truth annotations
- First stage: train only with correct label
- Second stage: re-label positives
- Future works:
  - Evaluation in larger datasets with more classes
  - Using 3D conv backbones models
  - Using uncertainty estimate [Kendall and Gal, 2017] for selecting target auto-supervision labels

GT SMILEr

Thank you for your attention!

Joint work with:

- Olivier Petit, PhD Student
- Luc Soler, Prof. at IRCAD, Visible Patient CEO

Questions?

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