Image-specific Fine-tuning and Uncertainty Estimation for Medical Image Segmentation

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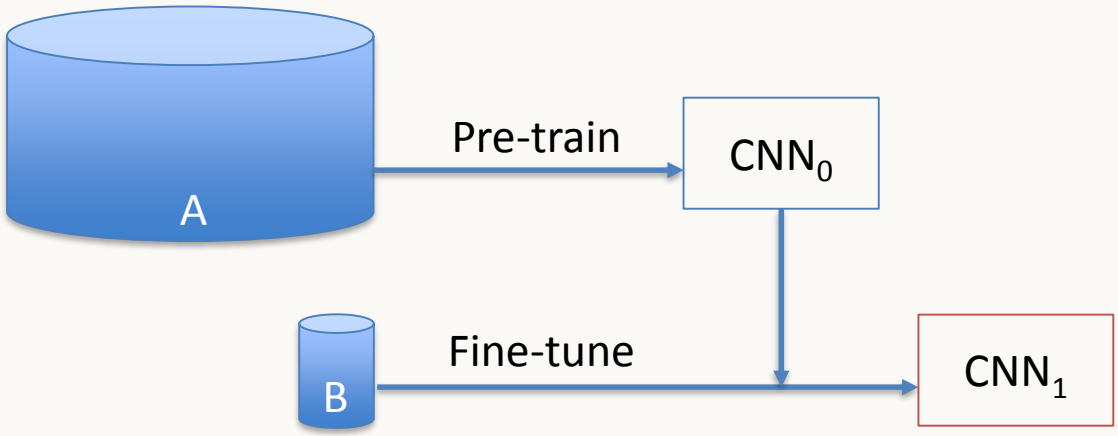
Deep Learning with Convolutional Neural Networks(CNN)

- Advantages and Disadvantages
  - Automatic feature learning, end-to-end
  - Requires large amounts of annotated data

IMAGENET

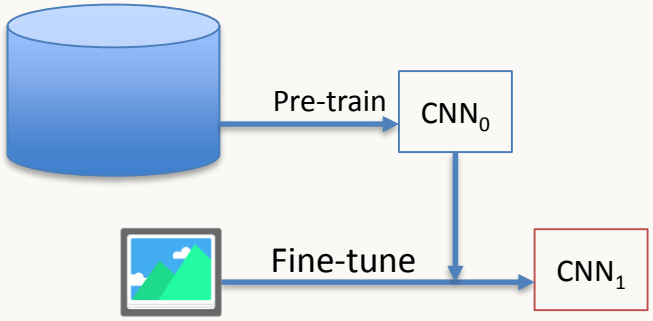
- Fine-tuning of CNNs
  - Adapt a pre-trained model to a given dataset



Fine-tuning and Image-specific Model

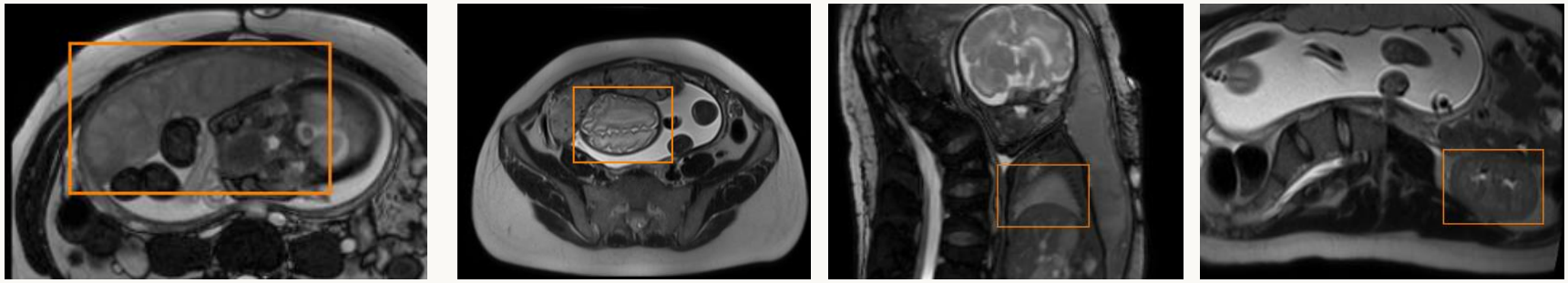
- Fine-tuning of CNNs
  - Adapt a pre-trained model to a given dataset
- Image specific models
  - Self-adaption, e.g. GrabCut

Image-specific CNNs
- Better accuracy?
- Deal with unseen objects?



Fine-tuning and Image-specific Model

- Fetal MR image segmentation
  - Multiple-organs
  - Annotation for all organs ?



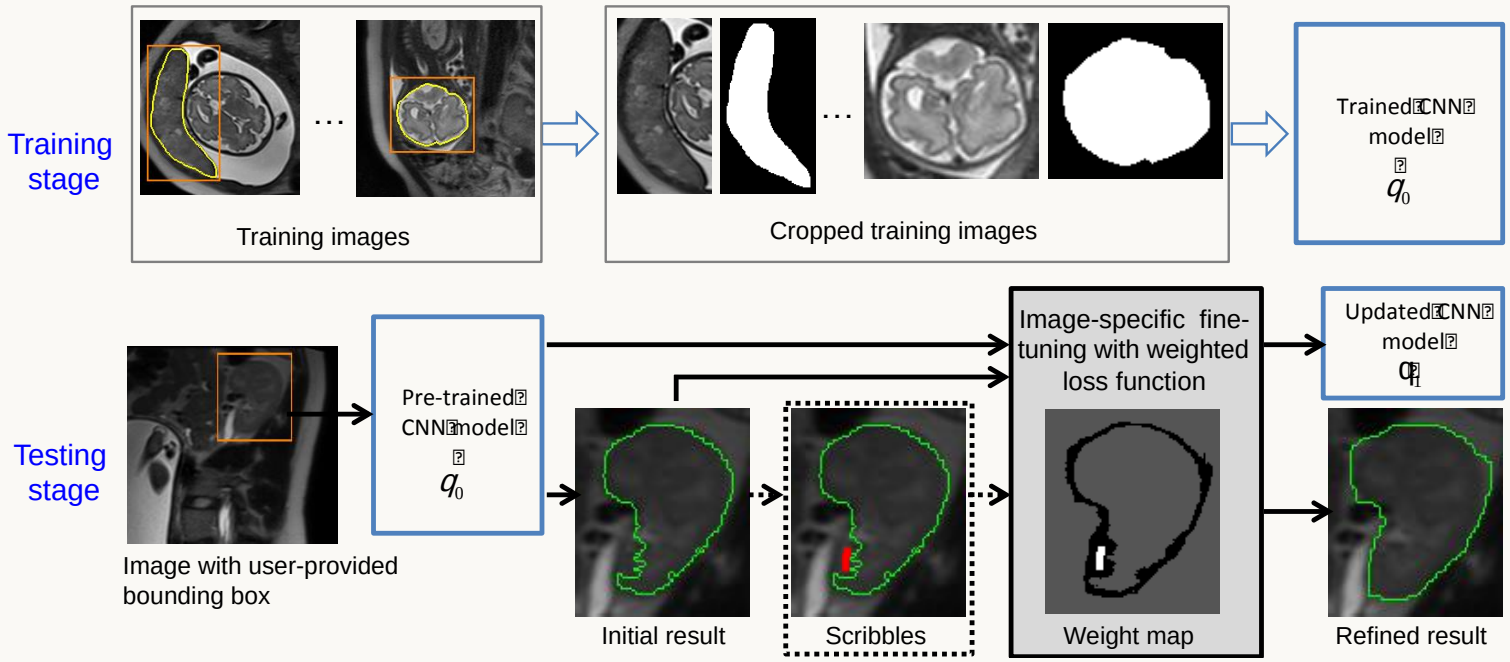
Placenta | Fetal Brain | Fetal Lung | Maternal Kidney

Annotated for training | Unseen during training

Testing

Fine-tuning and Image-specific Model

- Method
  - 1, Use CNN to get an initial segmentation inside a bounding box
  - 2, Fine-tune the CNN with/without scribbles
  - 3, Deal with previously unseen objects



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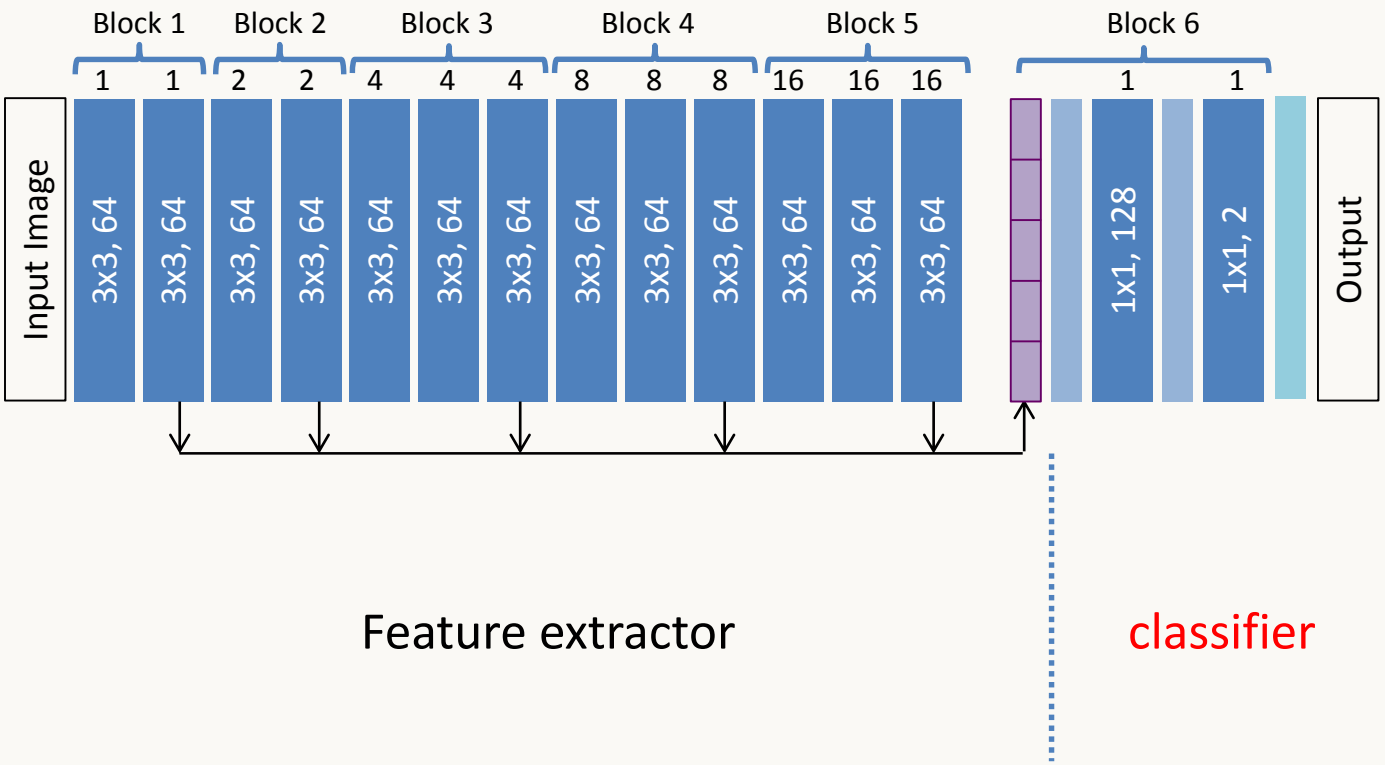
Fine-tuning and Image-specific Model



Only the classifier part is fine-tuned for fast update

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Mathematical Formulation

- Joint optimization:

$$\arg\min_{\hat{Y},\theta}\left\{E(\hat{Y},\theta)=\sum_i \phi(\hat{y}_i|\hat{X},\theta)+\lambda\sum_{i,j}\psi(\hat{y}_i,\hat{y}_j|\hat{X})\right\}$$

$$\text{subject to}: \hat{y}_i = s_i \quad \text{if } i \in S$$

- When θ is fixed

(Graph Cut problem)

$$\arg\min_{\hat{Y}}\left\{\sum_i \phi'(\hat{y}_i|\hat{X},\theta)+\lambda\sum_{i,j}\psi(\hat{y}_i,\hat{y}_j|\hat{X})\right\}$$

$$\phi'(\hat{y}_i|\hat{X},\theta)=\begin{cases}+\infty & \text{if } i\in S \text{ and } \hat{y}_i = s_i\\ 0 & \text{if } i\in S \text{ and } \hat{y}_i \neq s_i\\ -\log P(\hat{y}_i|\hat{X},\theta) & \text{otherwise}\end{cases}$$

- When $\hat{Y}$ is fixed

(Back propagation)

$$\arg\min_{\theta}\left\{-\sum_i\Big(\hat{y}_i\log p_i+(1-\hat{y}_i)\log(1-p_i)\Big)\right\}$$

Iterative update

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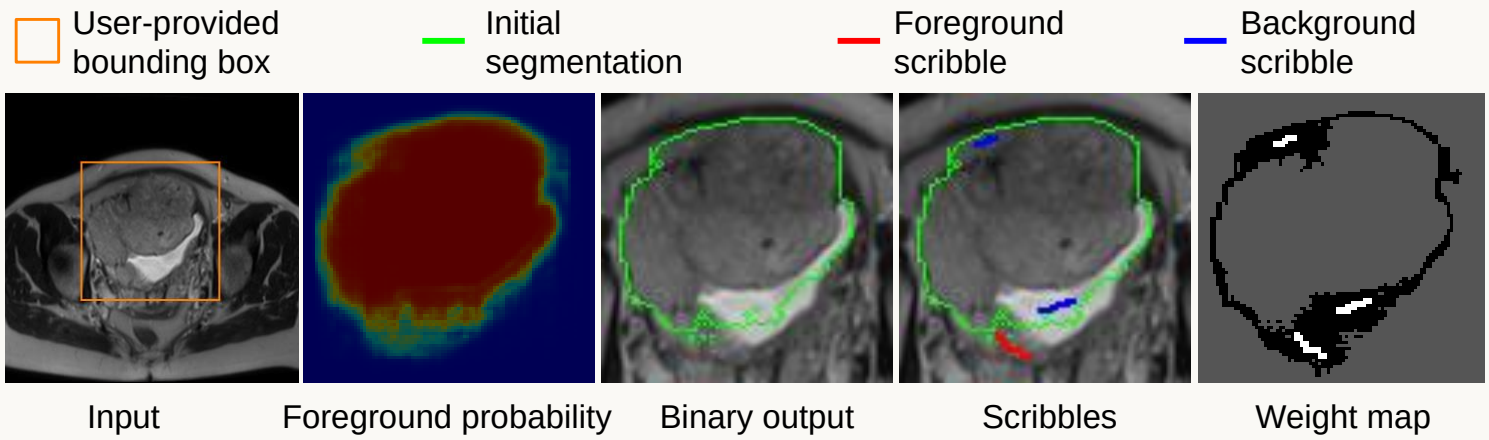
Weighted Loss Function for Fine-tuning

- Pixels with different confidence
  - Network-based confidence
  - Interaction-based confidence



$$\arg\min_{\theta}\left\{-\sum_{i} w(i)\Big(\hat{y}_i \log p_i + (1-\hat{y}_i)\log(1-p_i)\Big)\right\}$$

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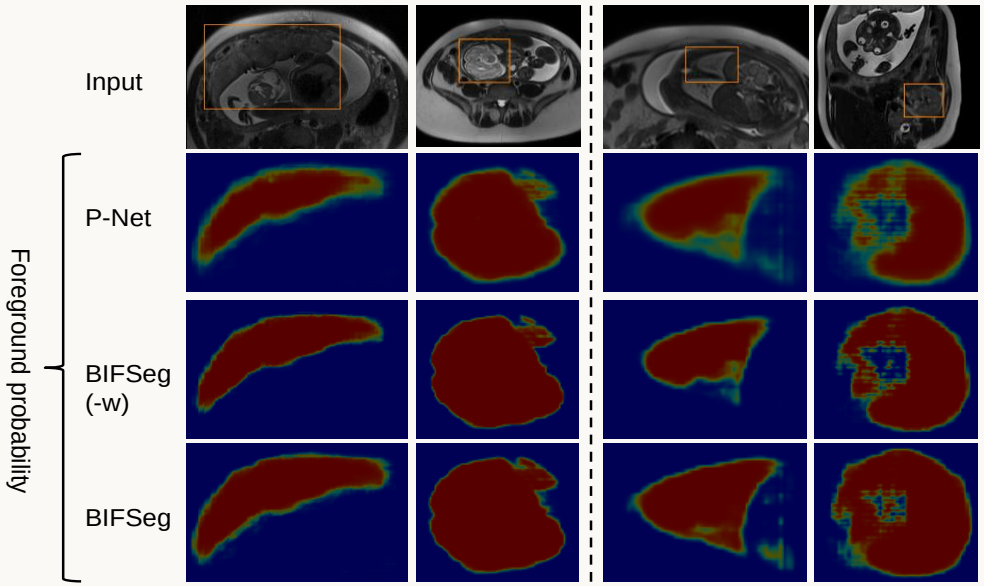
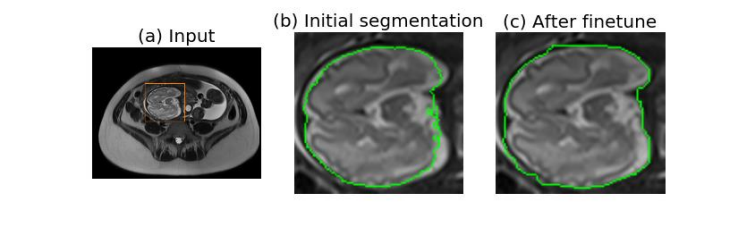
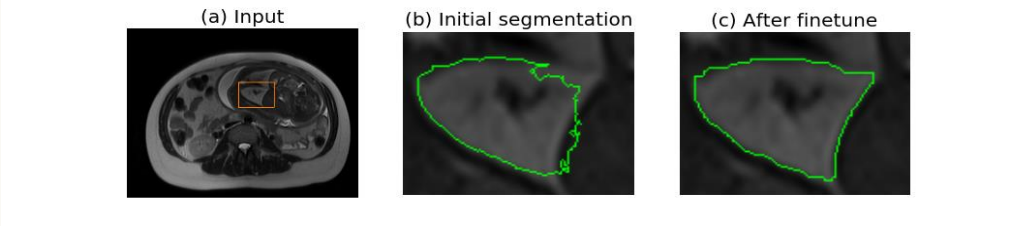
Results with Fetal MR Images

- Unsupervised Fine-tuning

	Train	Test
Placenta	X	X
Fetal Brain	X	X
Fetal Lungs		X
Maternal Kidneys		X
Patient number	10	6







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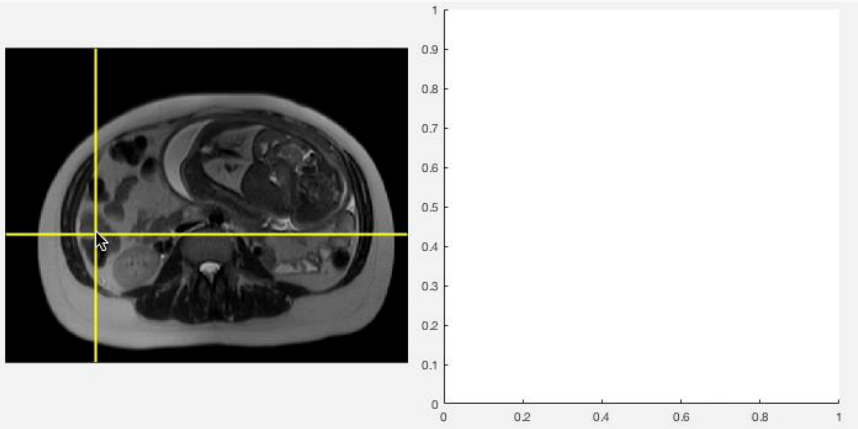
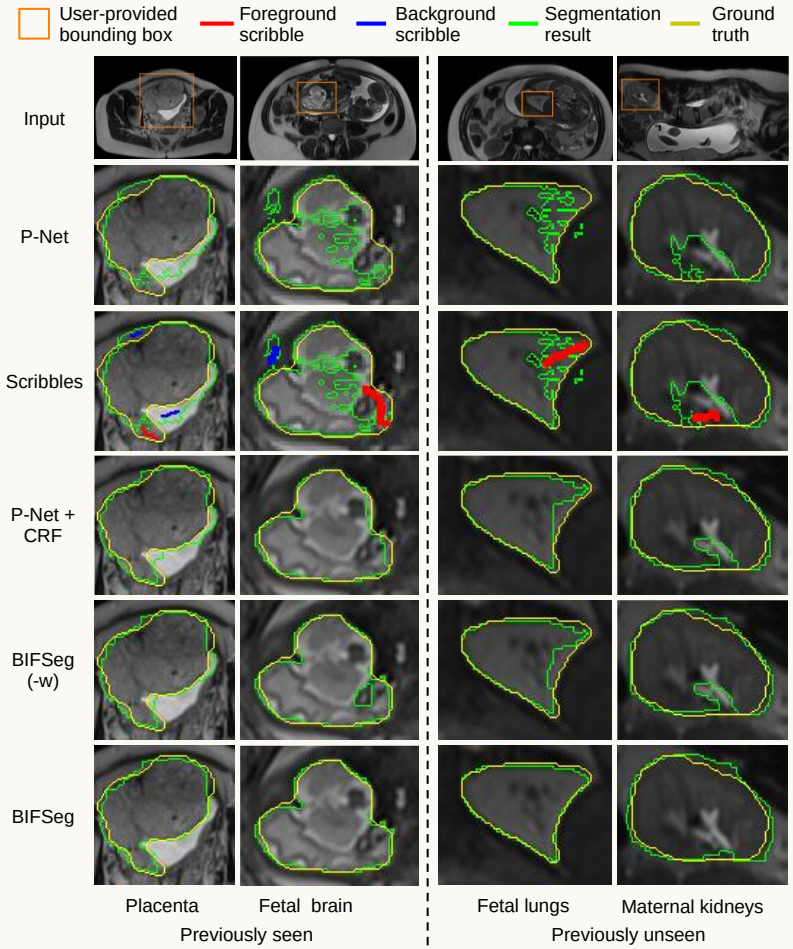
Results with Fetal MR Images

- Supervised Fine-tuning
  - Guided by scribbles
  - Only few interactions
  - Real-time update





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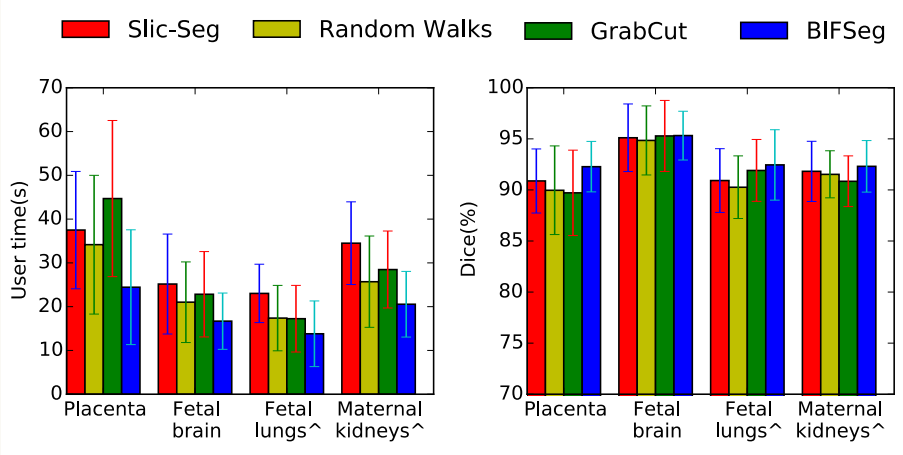
Results with Fetal MR Images

- Quantitative evaluation

TABLE II
QUANTITATIVE COMPARISON OF P-NET AND THREE UNSUPERVISED REFINEMENT METHODS FOR FETAL MRI SEGMENTATION. T_m IS THE MACHINE TIME FOR REFINEMENT. ^ DENOTES PREVIOUSLY UNSEEN OBJECTS. IN EACH ROW, BOLD FONT DENOTES THE BEST VALUE. * DENOTES p-VALUE < 0.05 COMPARED WITH THE OTHERS.

		P-Net	P-Net+CRF	BIFSeg(-w)	BIFSeg
Dice (%)	P	84.57±8.37	84.87±8.14	82.74±10.91	**86.41±7.50***
	FB	89.44±6.45	89.55±6.52	89.09±8.08	**90.39±6.44**
	FL^	83.59±6.42	83.87±6.52	82.17±8.87	**85.35±5.88***
	MK^	85.29±5.08	85.45±5.21	84.61±6.21	**86.33±4.28***
T_m (s)		-	**0.02±0.01***	0.71±0.12	0.72±0.12

P: Placenta, FB: Fetal brain, FL: Fetal lungs, MK: Maternal kidneys.



User time Dice score

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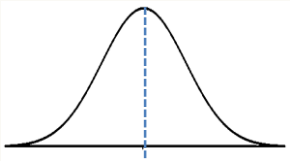
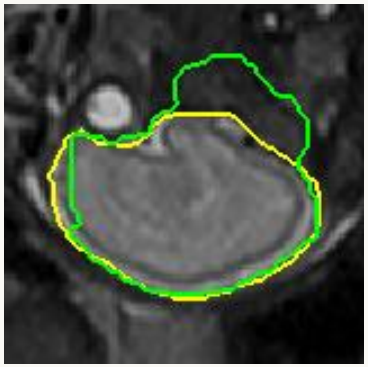
Uncertainty Estimation for CNNs

- Why uncertainty?
  - Consider the distribution of possible predictions
  - Indicate how reliable a prediction is
  - High uncertainty may related to incorrect prediction



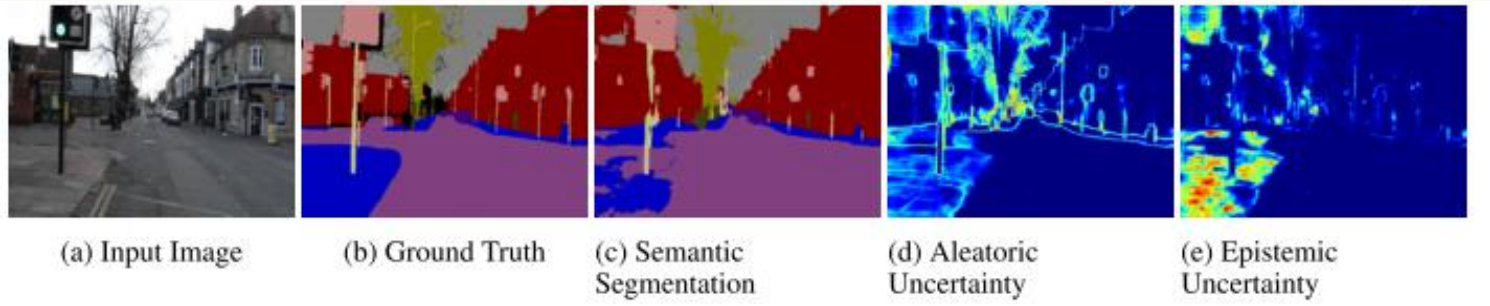
Non-deterministic prediction

Atelectasis ?



Aware of potential incorrect prediction?

Uncertainty Estimation for CNNs



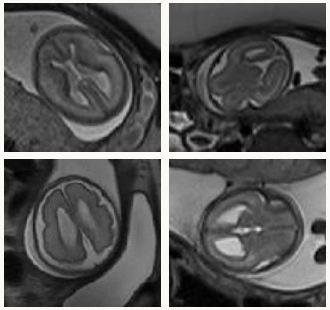
Images from [1]

- Uncertainty types

Epistemic Uncertainty
- Model uncertainty
- Can be explained away given enough data
- Approximated by test-time dropout [2]

Aleatoric Uncertainty
- From image noises
- Inherent in the observations

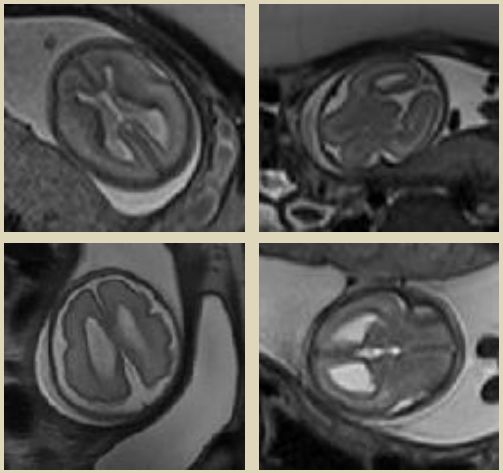
Transformation?



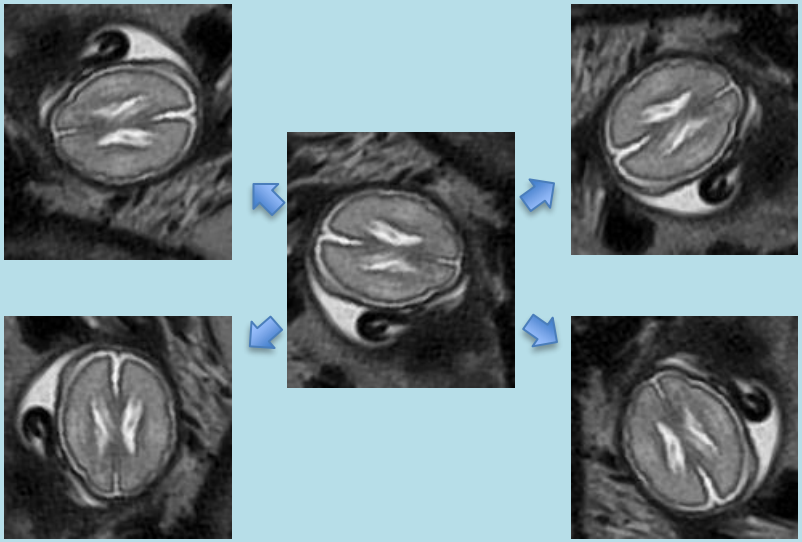
[1] A. Kendall and Y. Gal 2017, What uncertainties do we need in Bayesian deep learning for computer vision?
[2] Y. Gal. and Z. Ghahramani. 2016, Dropout as a Bayesian approximation: representing model uncertainty in deep learning.

Test-time Augmentation and Uncertainty

- Test-time Augmentation
  - Predict multiple transformed version of the input



Variations in training set



More possible observations for a testing image

Not mathematically formulated

Test-time Augmentation and Uncertainty

- A proposed mathematical formulation

Image Acquisition Model $X = \mathcal{T}_\beta(X_0) + e \qquad X_0 = \mathcal{T}_\beta^{-1}(X - e)$

- Assumptions
  1. The transformation is invertible
  2. X and X_0 follow the same distribution → Prior distributions of β and e

CNN prediction $Y = f(\theta, X)$

Monte Carlo Simulation $E(Y) \approx \frac{1}{N}\sum_{n=1}^{N} y_n = \frac{1}{N}\sum_{n=1}^{N} \mathcal{T}_{\beta_n}\left(f\left(\theta, \mathcal{T}_{\beta_n}^{-1}(X - e_n)\right)\right)$, where $\beta_n \sim P_\beta, e_n \sim P_e$

Uncertainty estimation $H(Y^i) \approx -\sum_{m=1}^{M} \hat{p}_m^i \ln(\hat{p}_m^i)$

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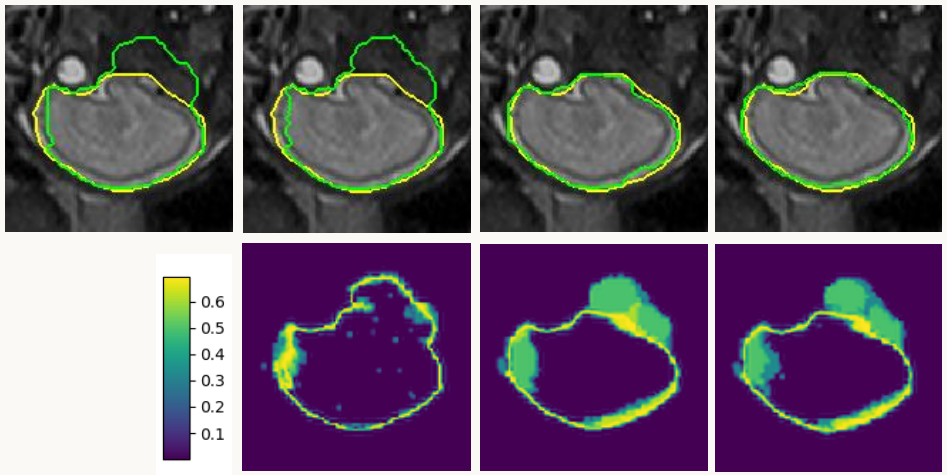
Results on Fetal Brain Segmentation

- Test-time augmentation

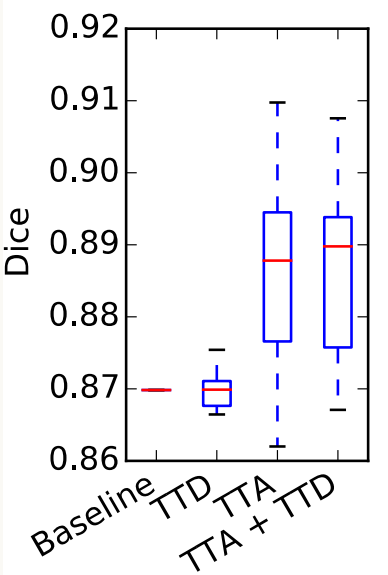
Flipping	rotation	scaling	noise
$p = 0.5$	$r \sim U(0, 2\pi)$	$s \sim U(0.8, 1.2)$	$e \sim \mathcal{N}(0.0, 0.05)$

Dataset (stacks)
- Train: 120
- Valid: 12
- Test: 48

Monte Carlo simul.
- N = 20



Baseline | Test-time dropout (TTD) | Test-time augmentation (TTA) | TTA + TTD



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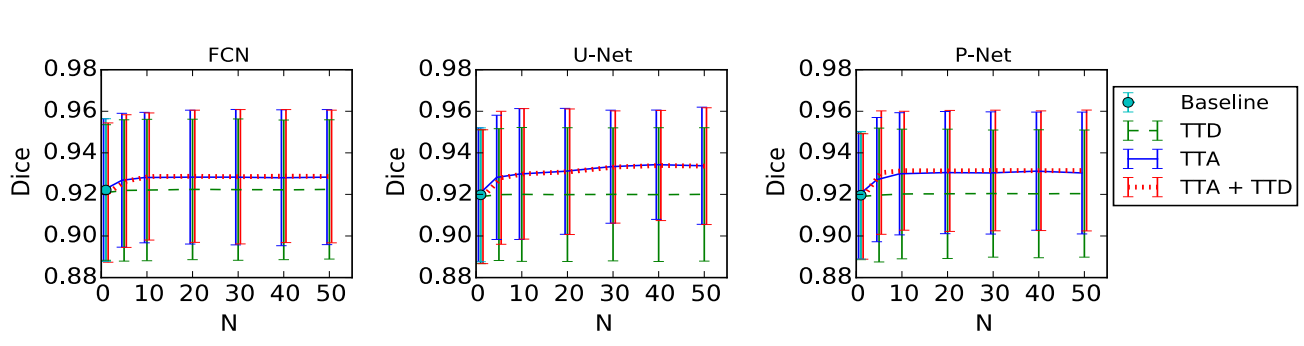
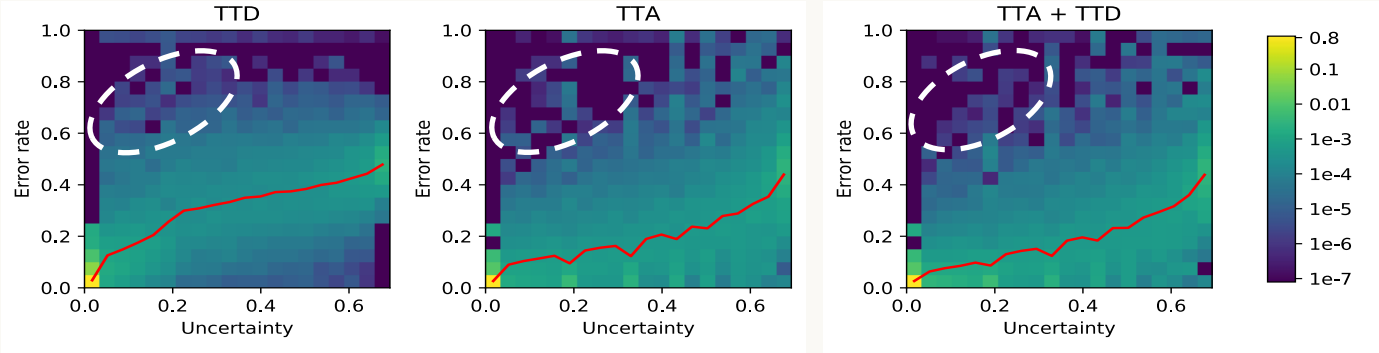
Results on Fetal Brain Segmentation

- Quantitative evaluation



- Error rate as a function of uncertainty



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Results on 3D Brain Tumor Segmentation

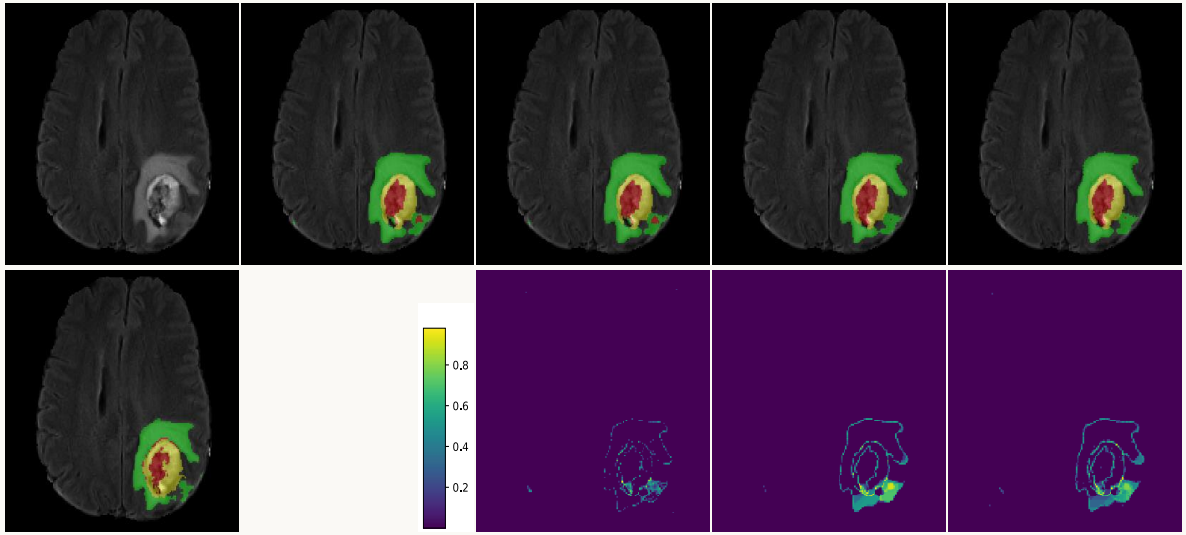
- BraTS dataset

Flipping	rotation	scaling	noise
$p = 0.5$	$r \sim U(0, 2\pi)$	$s \sim U(0.8, 1.2)$	$e \sim \mathcal{N}(0.0, 0.05)$

Multi-modal images
- FLAIR
- T1
- T1C
- T2

Dataset
- Train: 215
- Valid: 20
- Test: 50

Monte Carlo simul.
- N = 40



FLAIR and ground truth | Baseline | TTD | TTA | TTA + TTD

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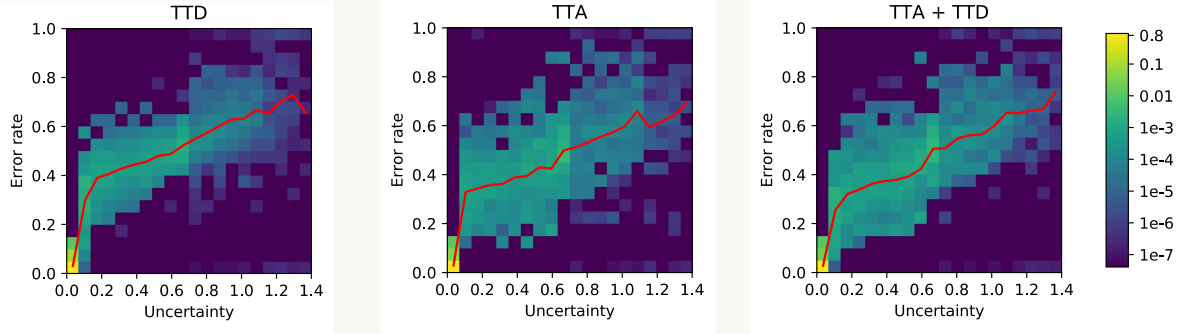
Results on 3D Brain Tumor Segmentation

- Segmentation Accuracy

	3D U-Net			V-Net		
	WT	TC	EC	WT	TC	EC
Baseline	87.69±5.65	78.72±17.96	74.49±20.35	86.92±6.90	76.38±19.15	74.17±26.04
TTD	88.22±5.87	79.25±17.90	75.75±21.03	87.04±6.92	76.61±19.27	74.29±26.01
TTA	88.39±5.74	79.54±17.11	**75.94±20.64**	87.52±6.36	**76.93±19.37**	74.55±26.03
TTA + TTD	**88.52±5.95**	**79.61±17.02**	75.70±20.41	**87.60±6.25**	76.86±19.26	**74.69±25.98**

- Error rate as a function of uncertainty



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Conclusion

- Image-specific fine-tuning
  - Adaptive to a given test image
  - Learn from specific image context
  - Improve segmentation accuracy (supervised or not)
  - Deal with unseen objects

- Uncertainty Estimation
  - Indicate how reliable the result is
  - Model-based and image-based
  - Test-time augmentation and uncertainty

Thanks

Q&A





NiftyNet





http://niftynet.io/