Deep CNN for Segmentation of Myocardial ASL Short-Axis Data: Accuracy, Uncertainty, and Adaptability

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Declaration of Financial Interests or Relationships

Speaker Name: Hung Do

Company Name: Canon Medical Systems USA, Inc. (formerly Toshiba Medical)

Type of Relationship: Employee

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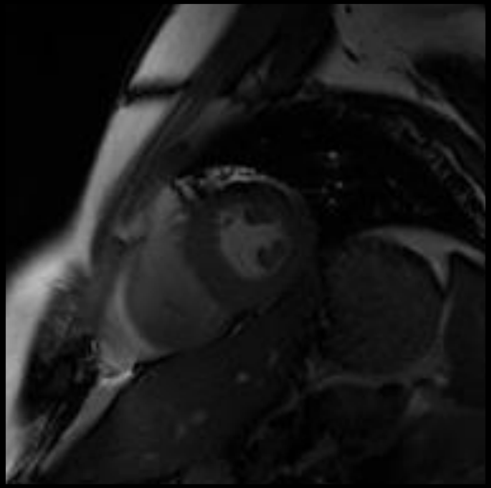
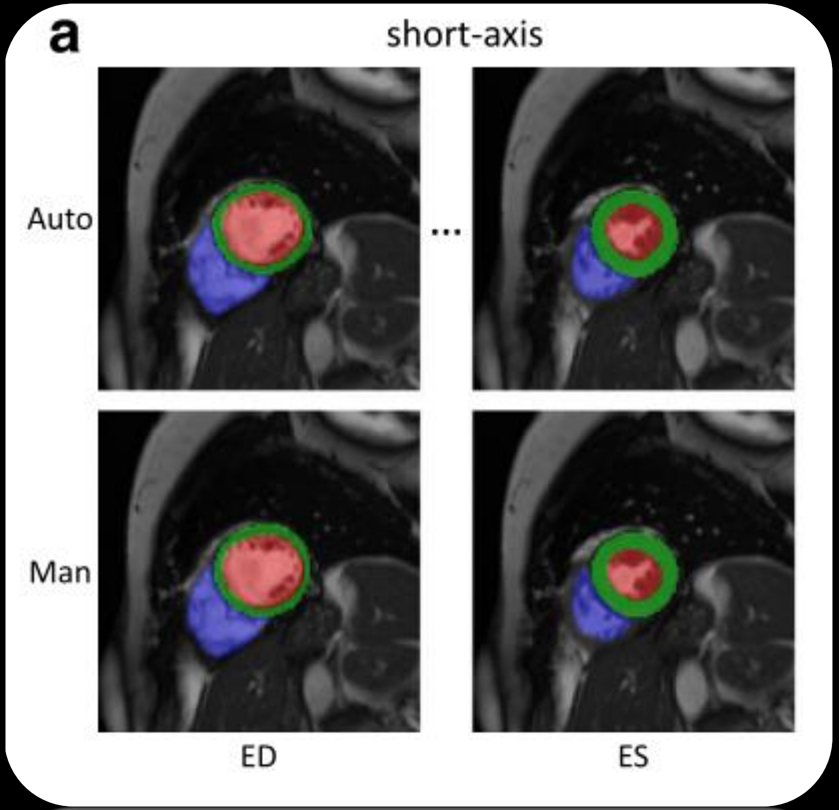
Intro(1): CNN for segmentation

- Comparable to human experts in analyzing cardiac CINE data[1]
  - Dice Coef. of 0.94 for LV blood pool
  - Dice Coef. of 0.88 for LV myocardium
  - Dice Coef. of 0.90 for RV blood pool





1. **Bai, Wenjia** et al. "*Automated CMR image analysis with fully convolutional networks.*" Journal of Cardiovascular Magnetic Resonance 20.1 (2018): 65.

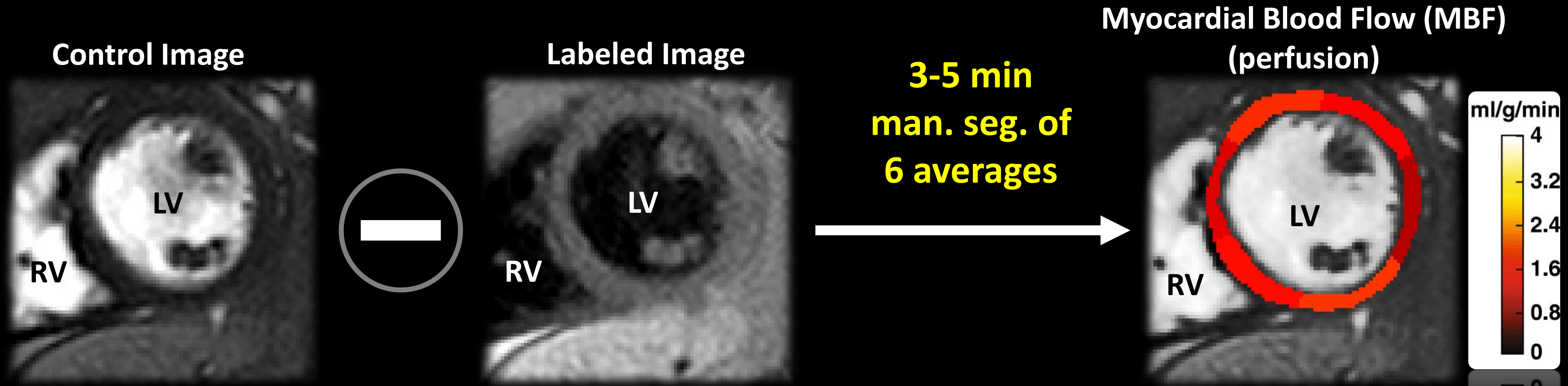
Goals

1. To apply CNN for segmentation of myocardial Arterial Spin Labeled (ASL) data

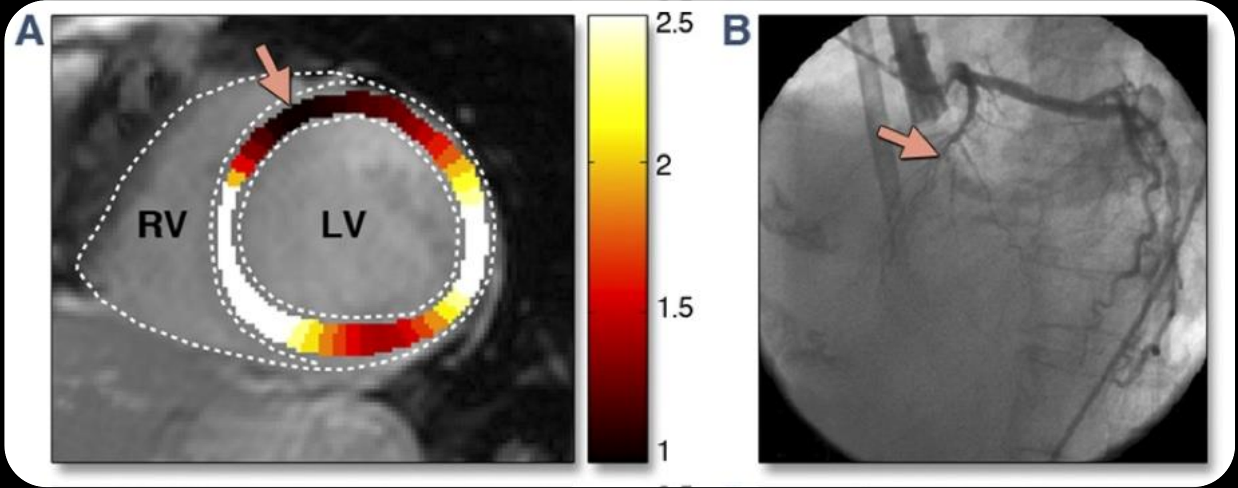
2. To measure model uncertainty using Monte Carlo dropout

3. To adapt the CNN model to the desired trade-off between false positive (FP) and false negative (FN) using Tversky loss function

Intro(2): Myocardial Arterial Spin Labeling (ASL)



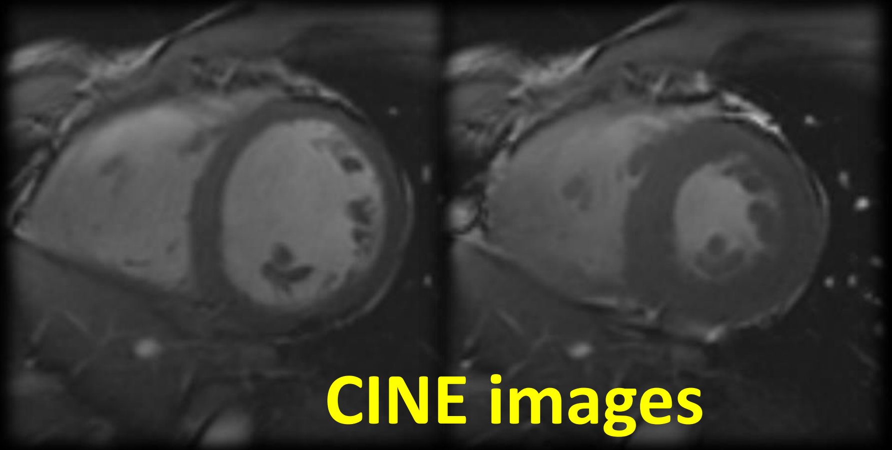
Coronary artery disease (CAD)

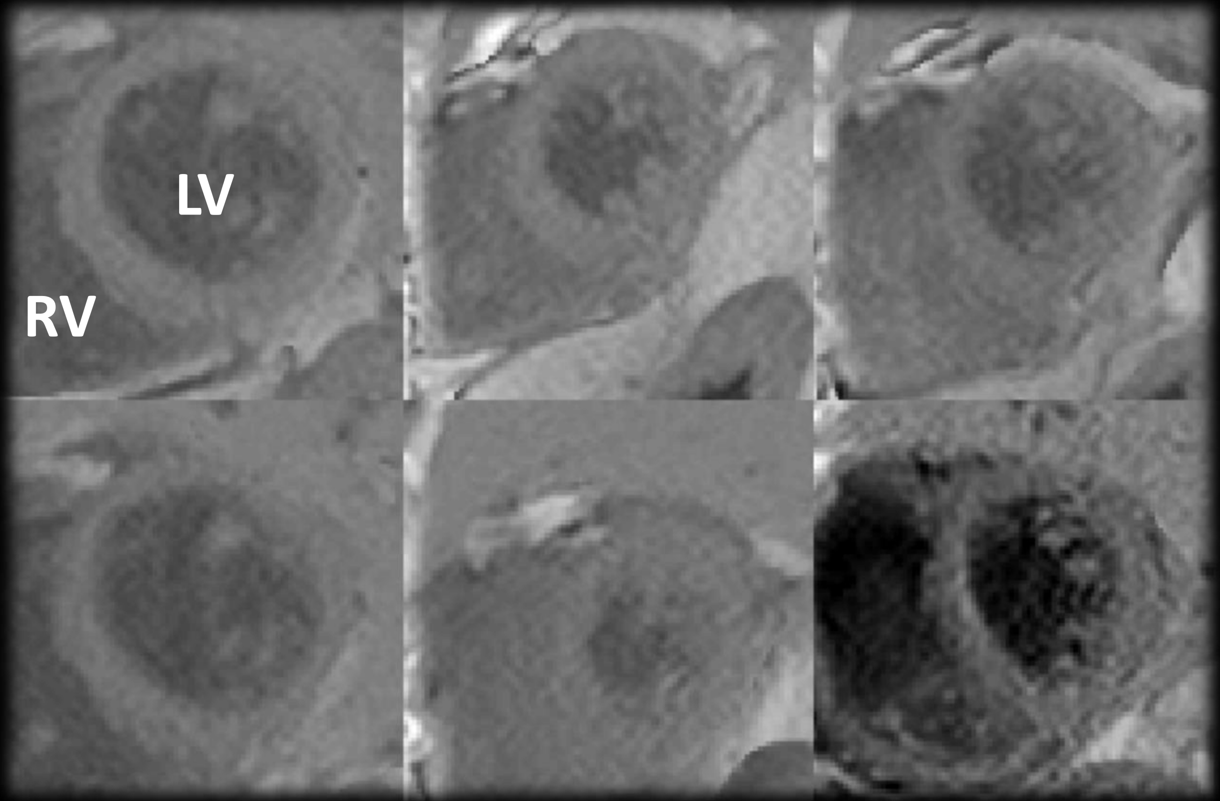


1. **Kober, Frank** et al. "*Myocardial arterial spin labeling.*" Journal of Cardiovascular Magnetic Resonance 2016; 18:22.
2. **Zun, Zungho** et al., " *ASL-CMR Detects Clinically Relevant Increases in Myocardial Blood Flow With Vasodilation.*" iJACC 2011; 4(12):1253-1261.

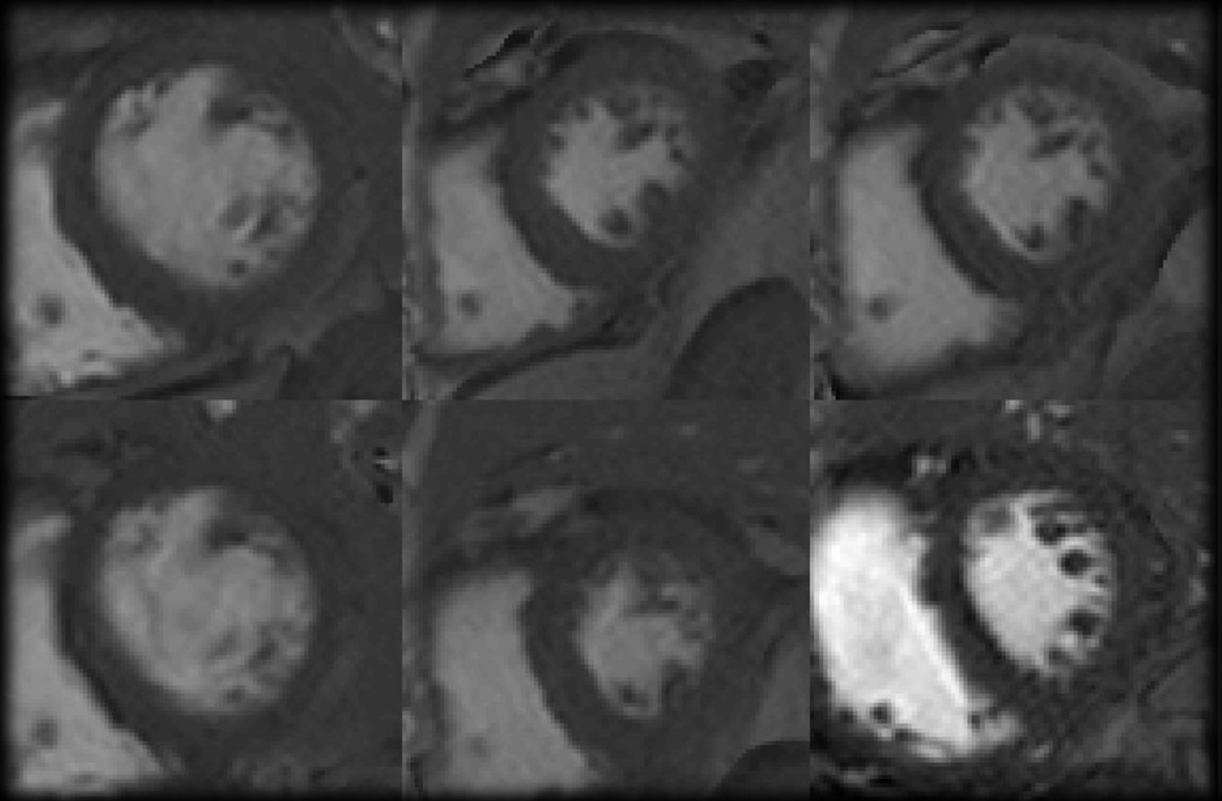
Intro(3): Characteristics of ASL data

- Low resolution
- Low SNR and CNR
- Varying SNR and CNR





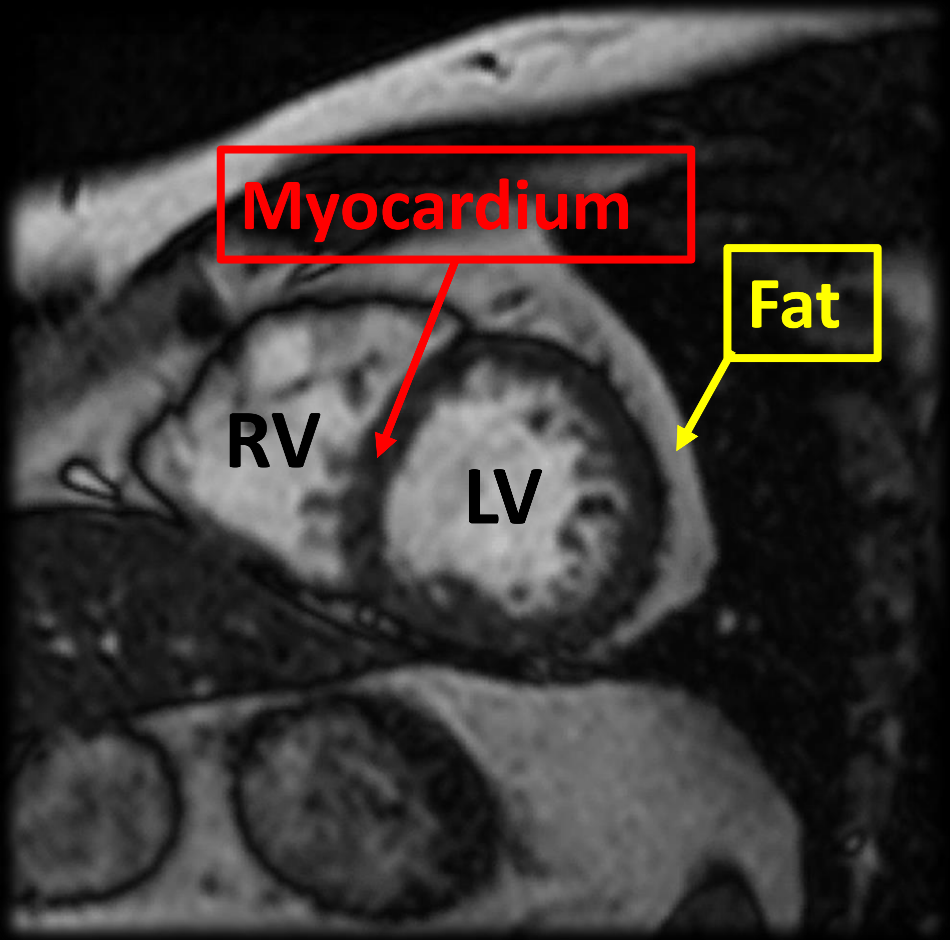
Labeled images

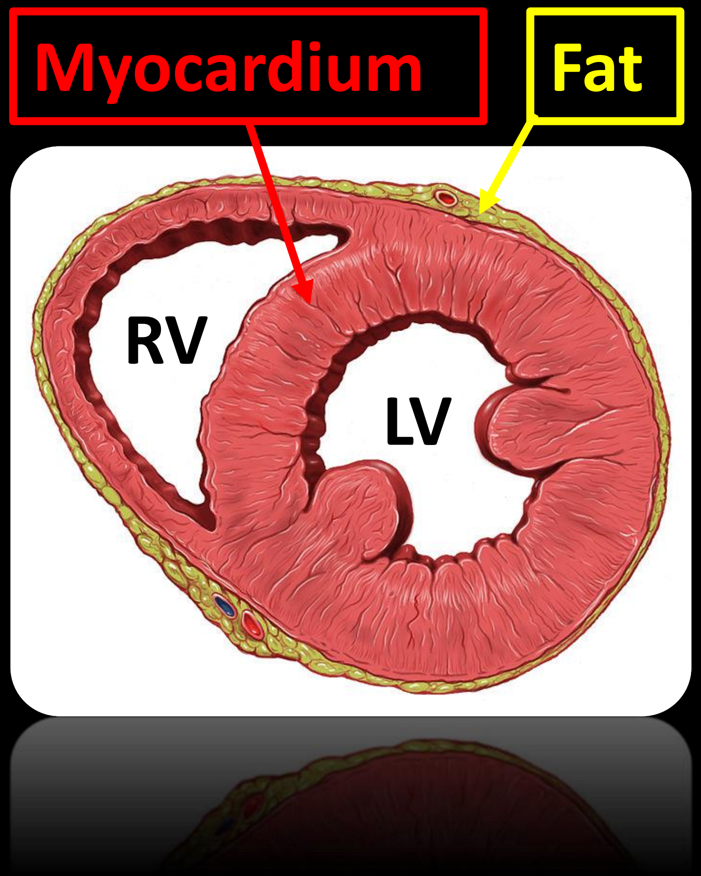


Control images

Intro(4): Partial volume effects

- Ventricular blood and epicardial fat have different physical properties and spin history compared to myocardium.

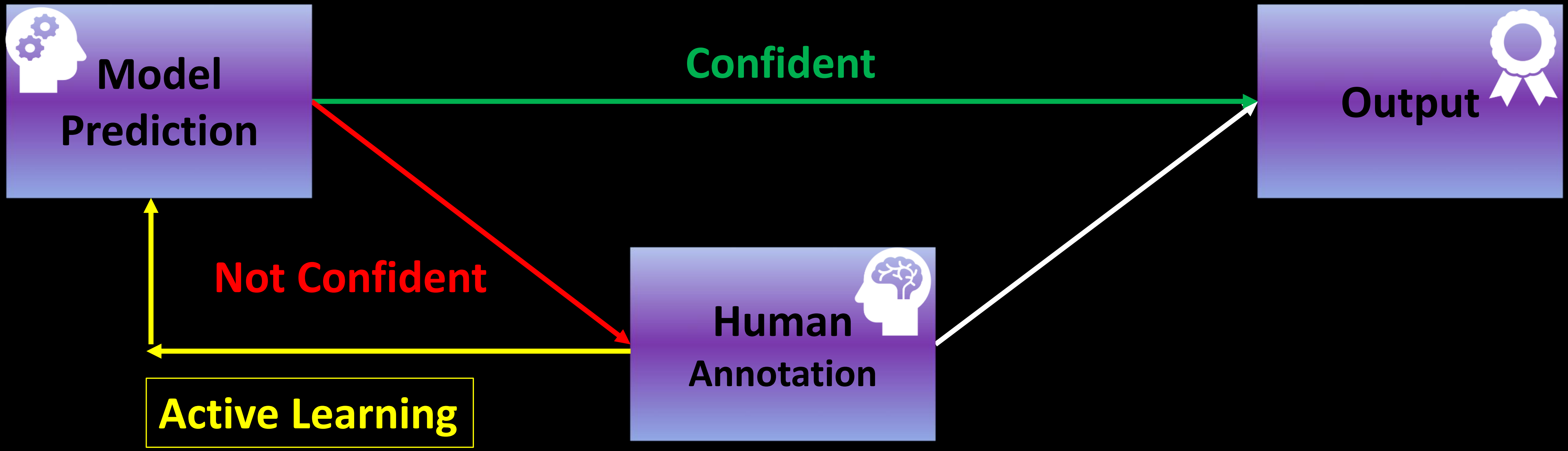




1. Wikimedia Commons contributors, "File:Heart normal short axis section.jpg," *Wikimedia Commons, the free media repository,* (accessed October 11, 2018).

Intro(5): Why model uncertainty?

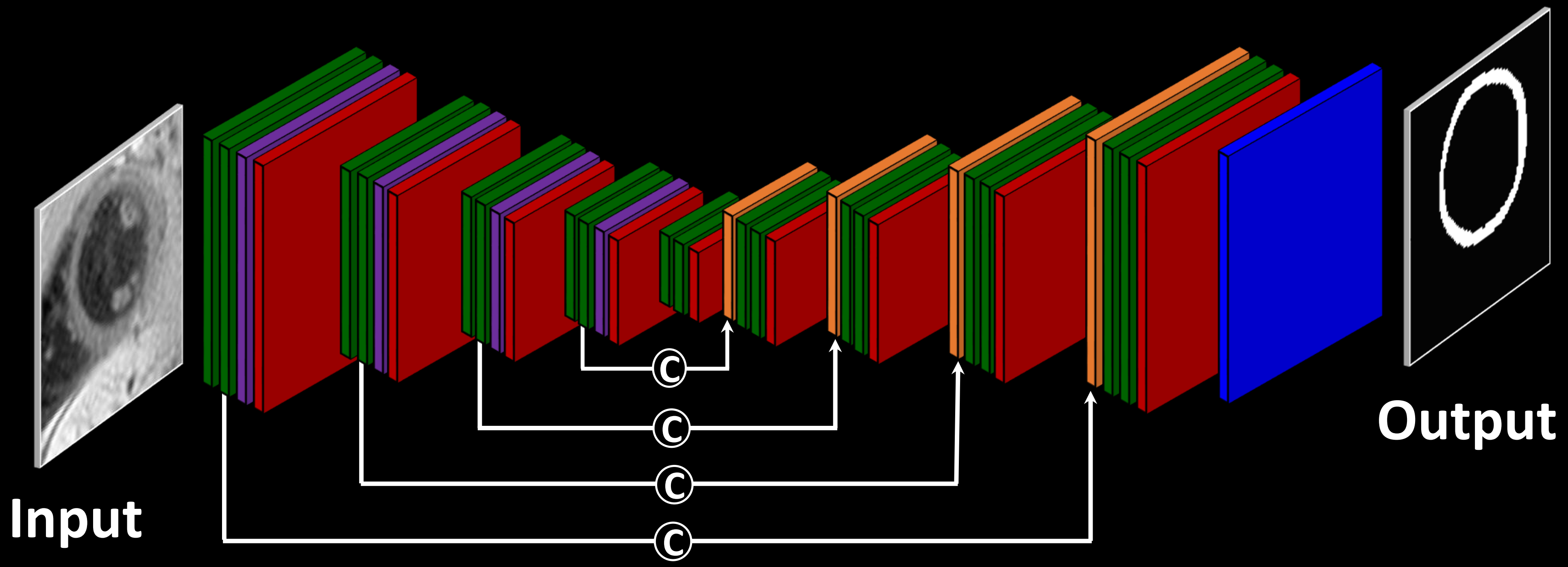
- Quality control during production/deployment
- Model improvement via active learning



1. Diagram adapted from https://www.oreilly.com/ideas/data-preparation-in-the-age-of-deep-learning.

Methods(1): Network Architecture[1]

loss = Binary Cross-Entropy or (1 – Soft-Dice) or (1 – Tversky Index)



5x5 Conv+ReLU+BN   Max Pooling   Monte Carlo Dropout   Upsampling   1x1 Conv+Sigmoid

Ⓒ Channel Concatenation

1. Ronneberger O et al., "*U-net: Convolutional networks for biomedical image segmentation.*" 2015; arXiv:1505.04597.

Methods(2): Dataset and training parameters

- Training and validation data[1]:
  - From 22 subjects: 478 images – 438/40 images for training/validation
- Test data[1]:
  - From 6 "un-seen" heart transplant patients: 144 images (rest and during Adenosine stress)

- Training parameters:
  - 150 epochs
  - Learning rate: 1e-4
  - Dropout rate: 0.5
  - Batch size = 12
  - Adam optimizer

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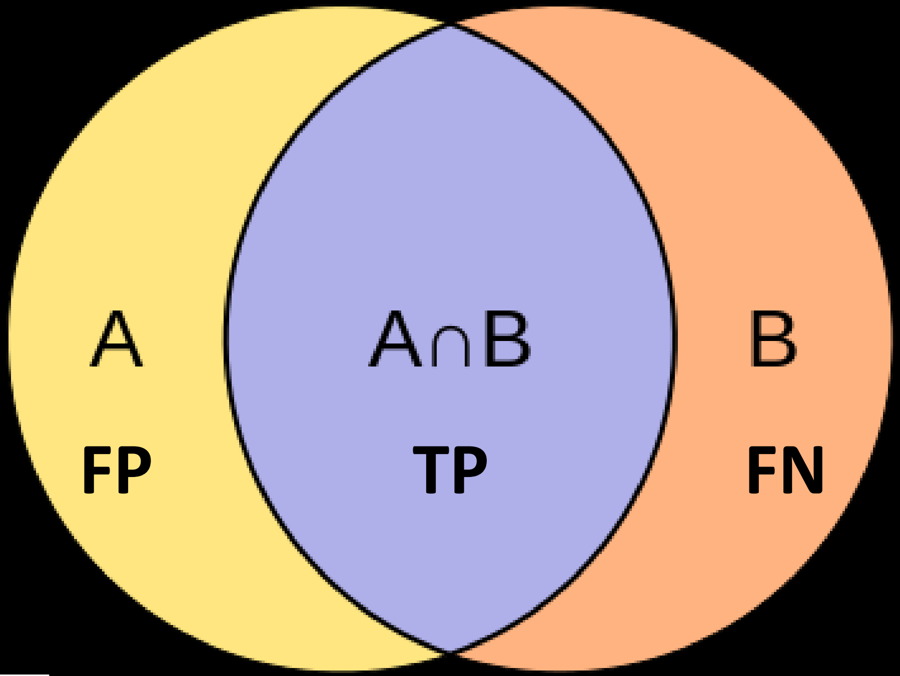
1. **Do, Hung** et al, *"Double-gated Myocardial ASL Perfusion Imaging is Robust to Heart Rate Variation."* Magn Reson Med 2017; 77(5):1975-1980.

Methods(4): Adaptability using Tversky loss

$$Dice = \frac{2 \cdot |A \cap B|}{|A| + |B|}$$

A: Predicted Mask

B: Reference Mask



$$Dice = \frac{2 \cdot TP}{2 \cdot TP + FP + FN} = \frac{TP}{TP + 0.5 \cdot FP + 0.5 \cdot FN}$$

$$Tversky\ Index = \frac{TP}{TP + (1 - \beta) \cdot FP + \beta \cdot FN}$$

Tversky loss = 1- Tversky Index[1]

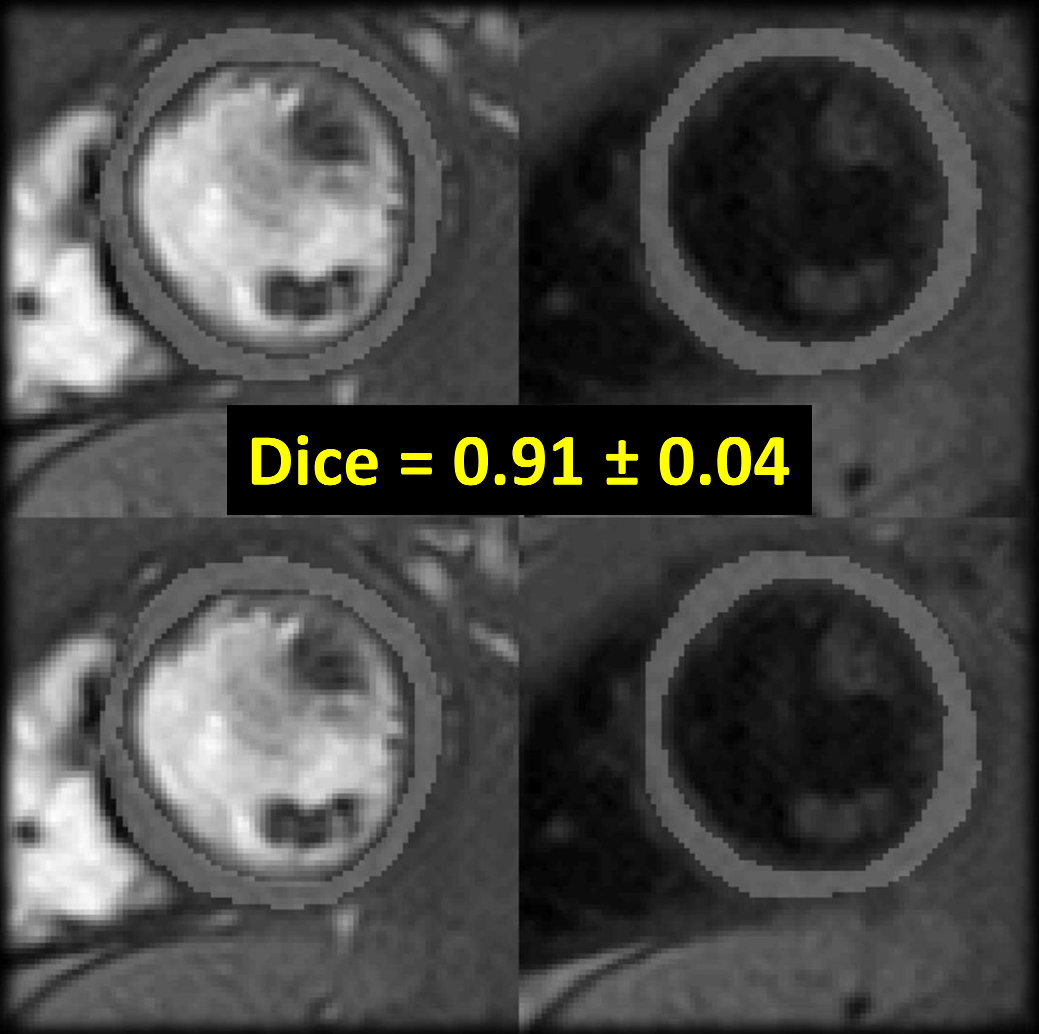
1. **Tversky, Amos**. "*Features of similarity*." Psychological Review 1977;84(4): 327-52.
2. Wikipedia contributors. "Jaccard index." *Wikipedia, The Free Encyclopedia*. Wikipedia, The Free Encyclopedia, 20 Sep. 2018. Web. 5 Oct. 2018.

Results(1): Accuracy – Dice Coefficient

Control Image | Label Image

Auto

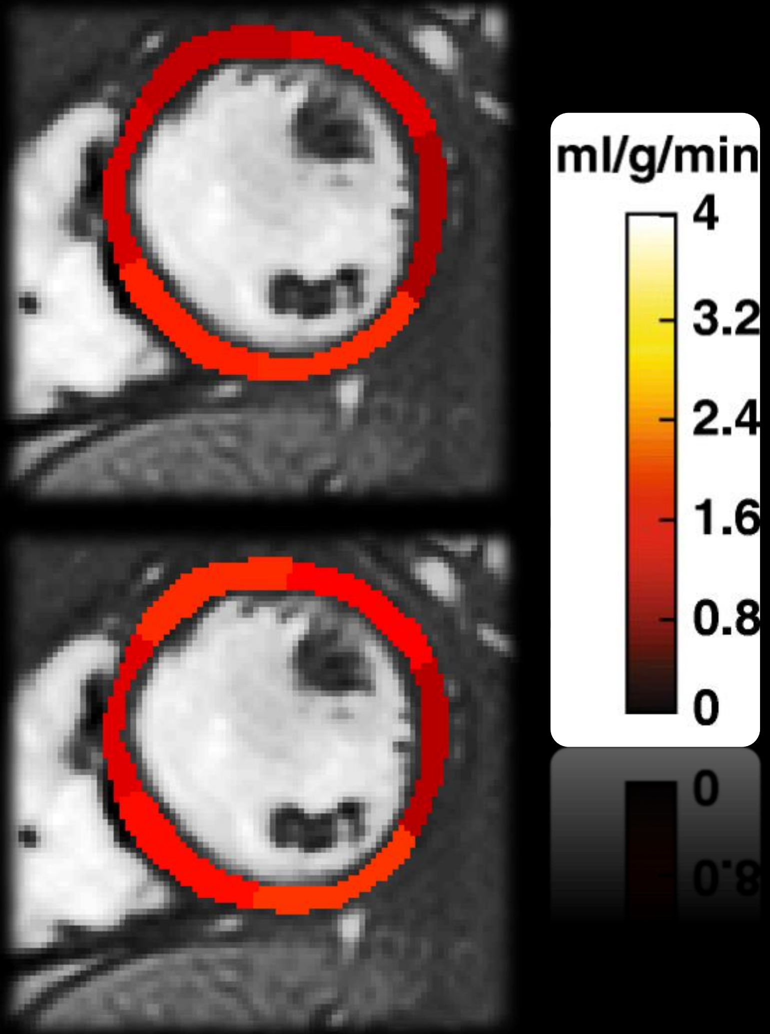
Man



Myocardial Blood Flow (MBF) (perfusion)

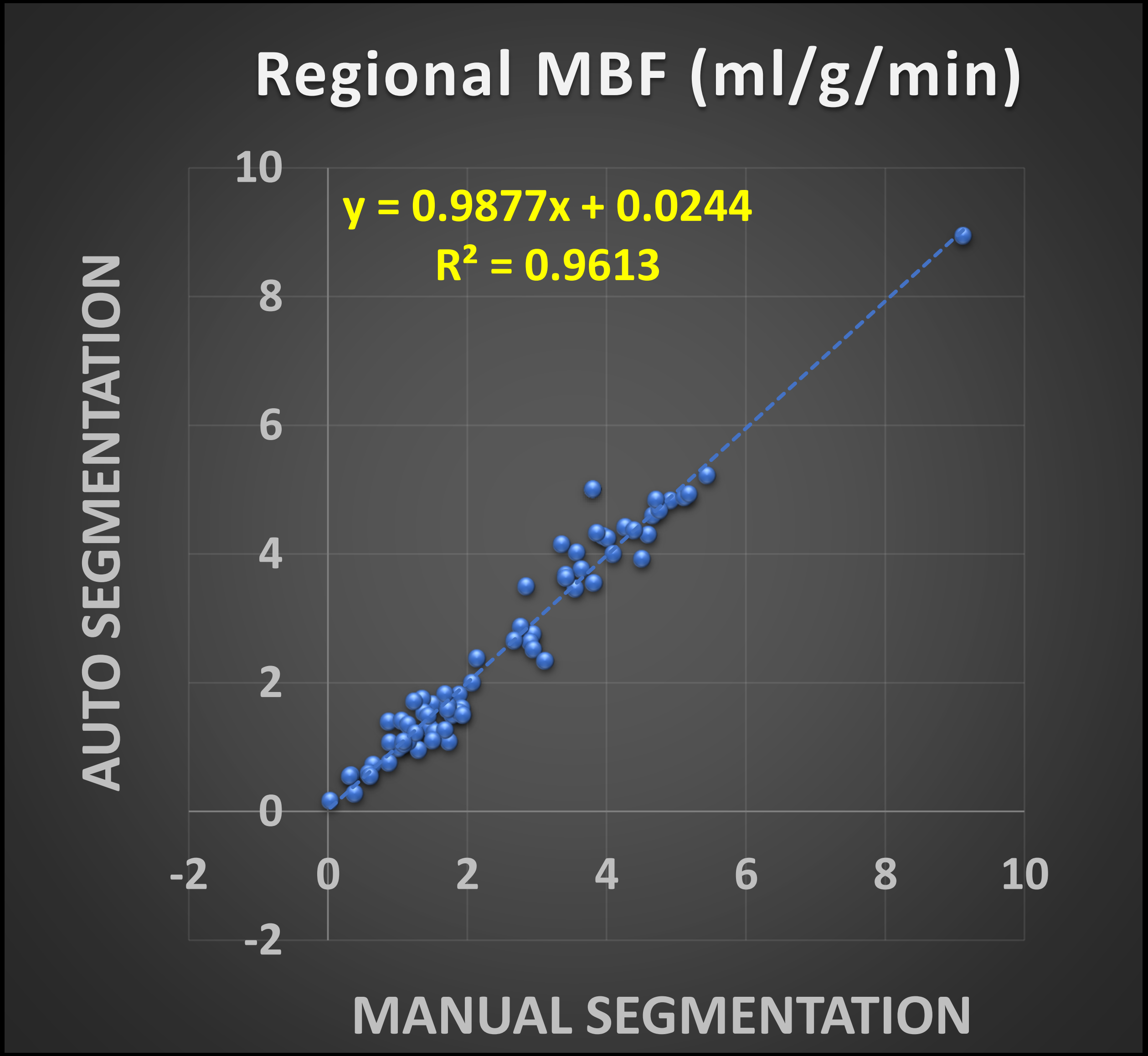
Auto

Man



Results(1): Accuracy – Myocardial Blood Flow (MBF)

MBF measured using automatic segmentation is highly correlated to that measured using manual segmentation



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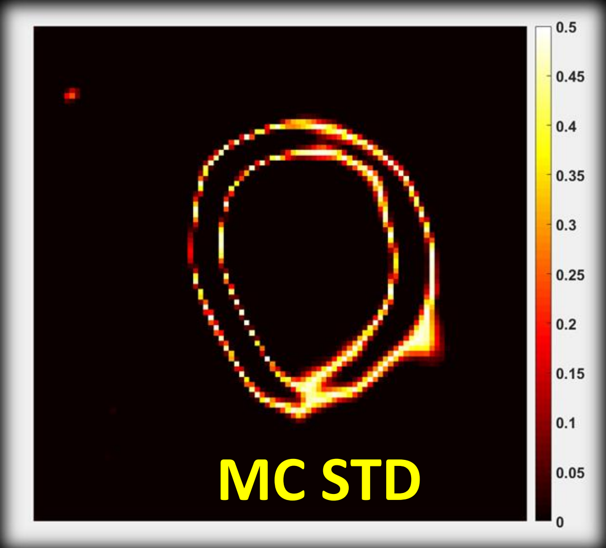
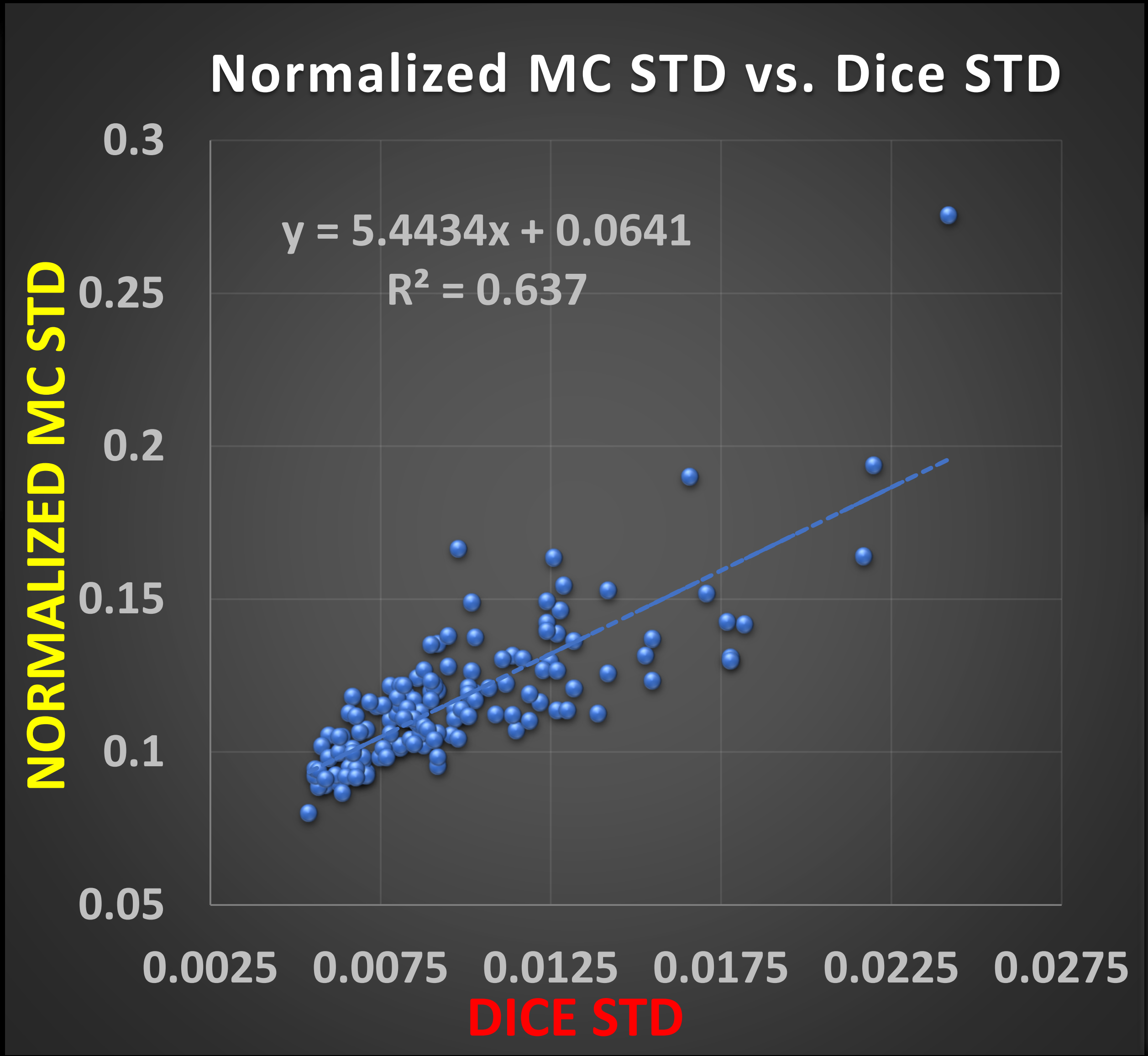
Results(2): Uncertainty

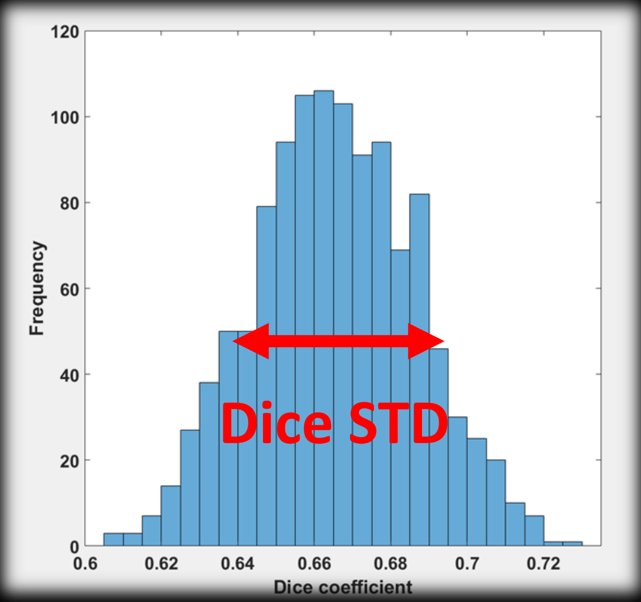
Without manual segmentation

1115 MC trials



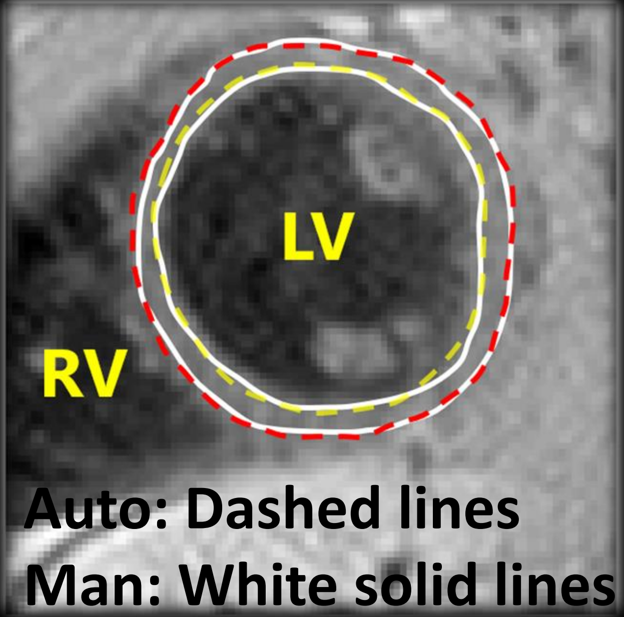


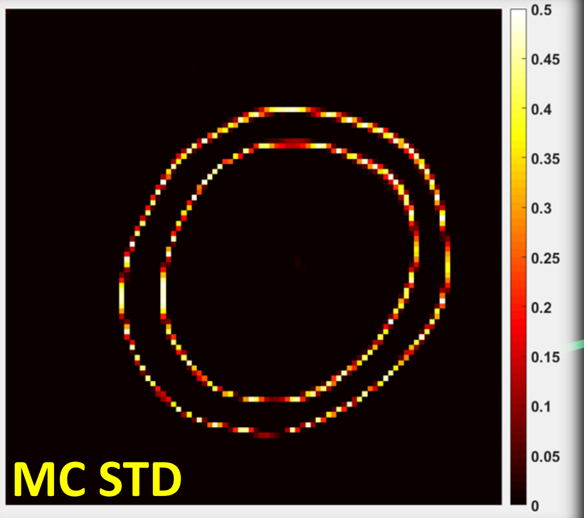
Given man. segmentation

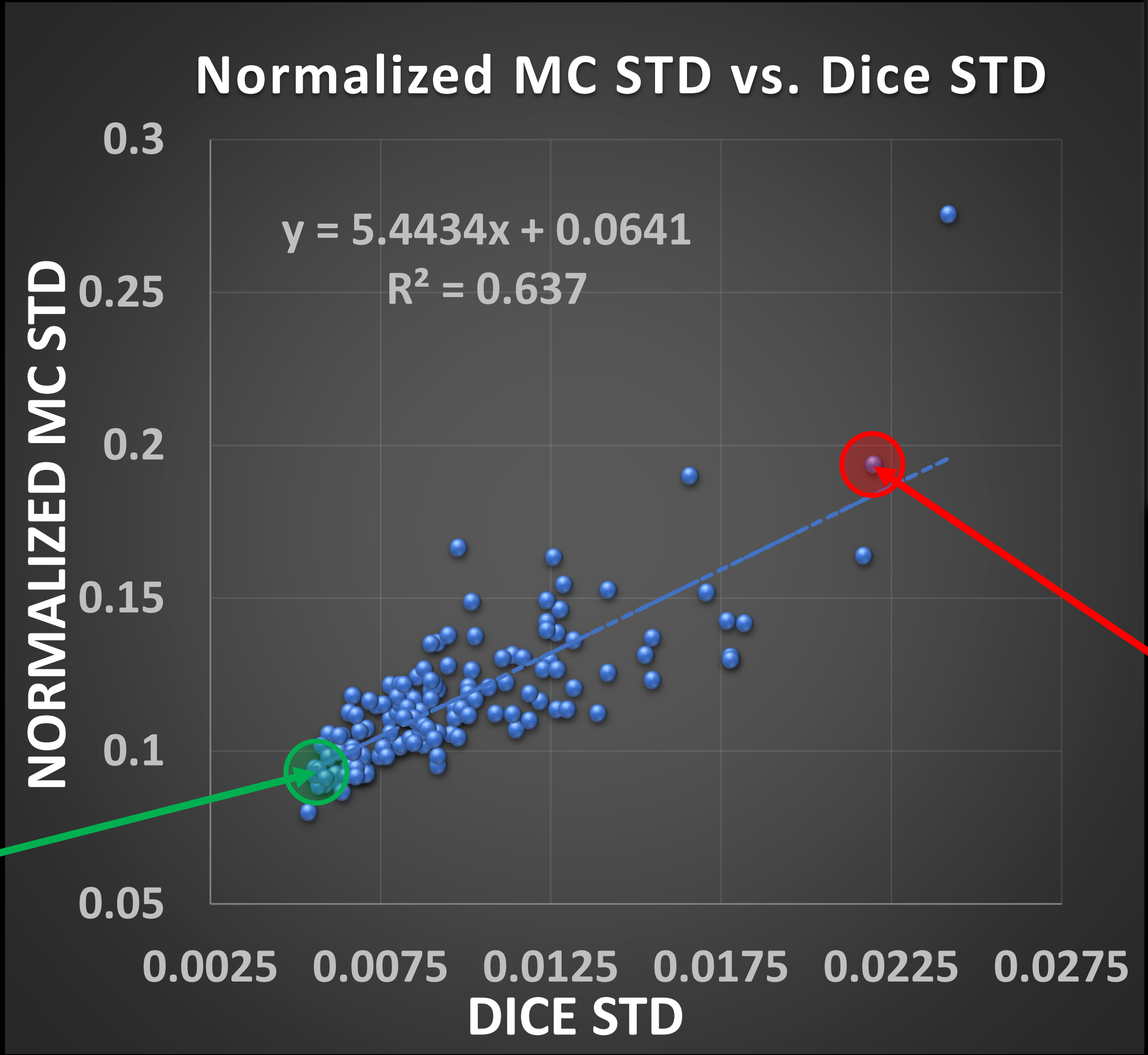


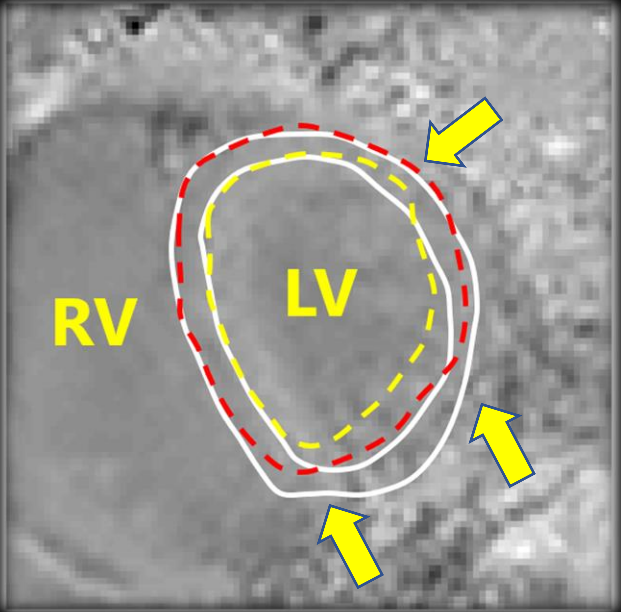
Results(2): Uncertainty

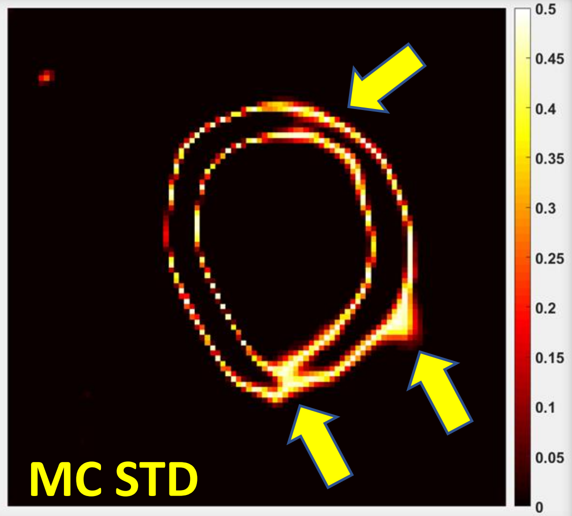
1115 MC trials



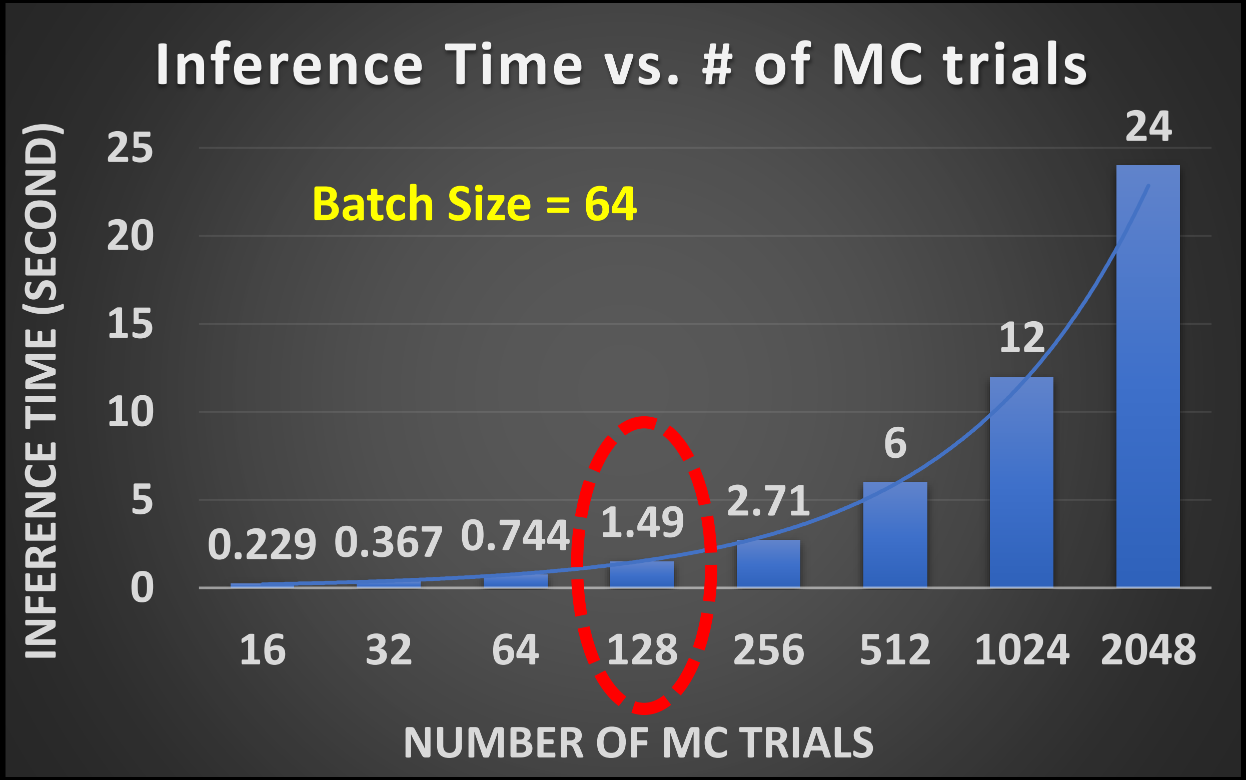


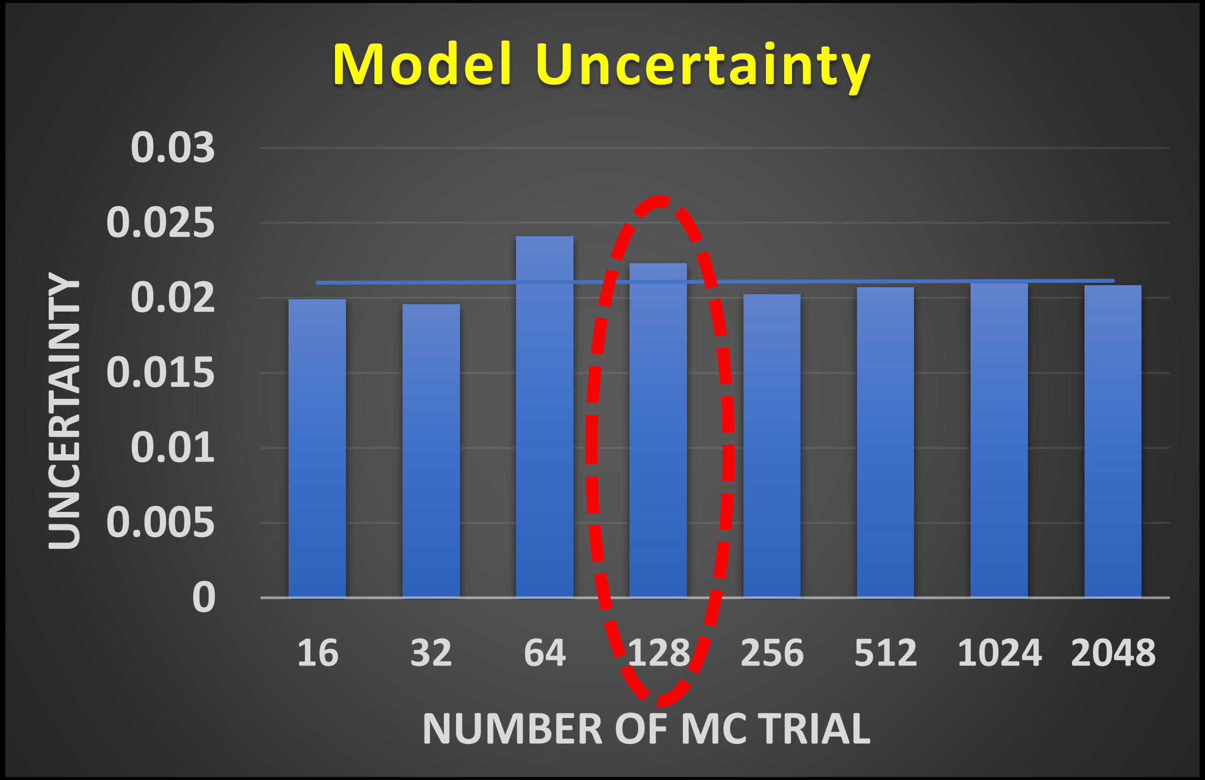






Results(2): Uncertainty – Time penalty per image





~1.5s/image with 128 MC trials

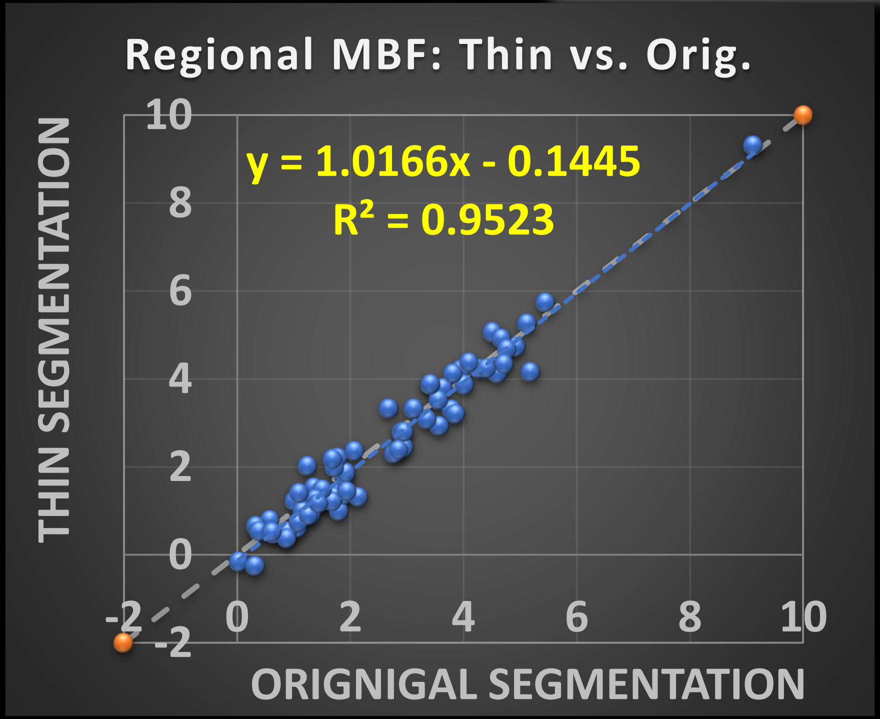
Results(3): Adaptability – Partial volume effects

FP = 0
FN ~300 pixels/im

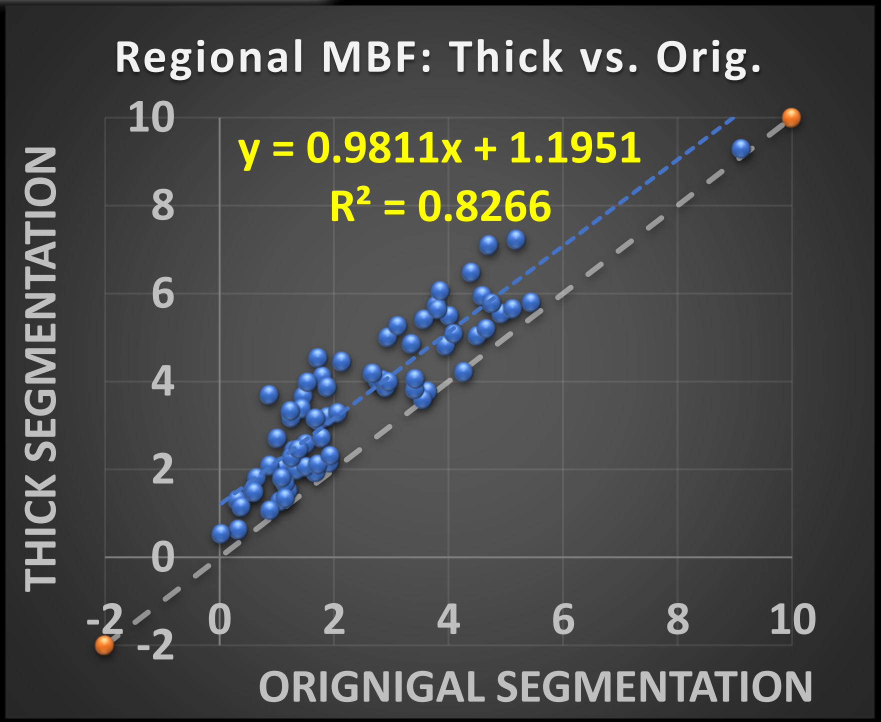
Dice = 0.80 ± 0.04

FP ~400 pixels/im
FN = 0

Dice = 0.81 ± 0.02



Significant overestimation due to partial volume effects



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Results(3): Adaptability – desired FP and FN trade-off

Diamonds: Thick masks

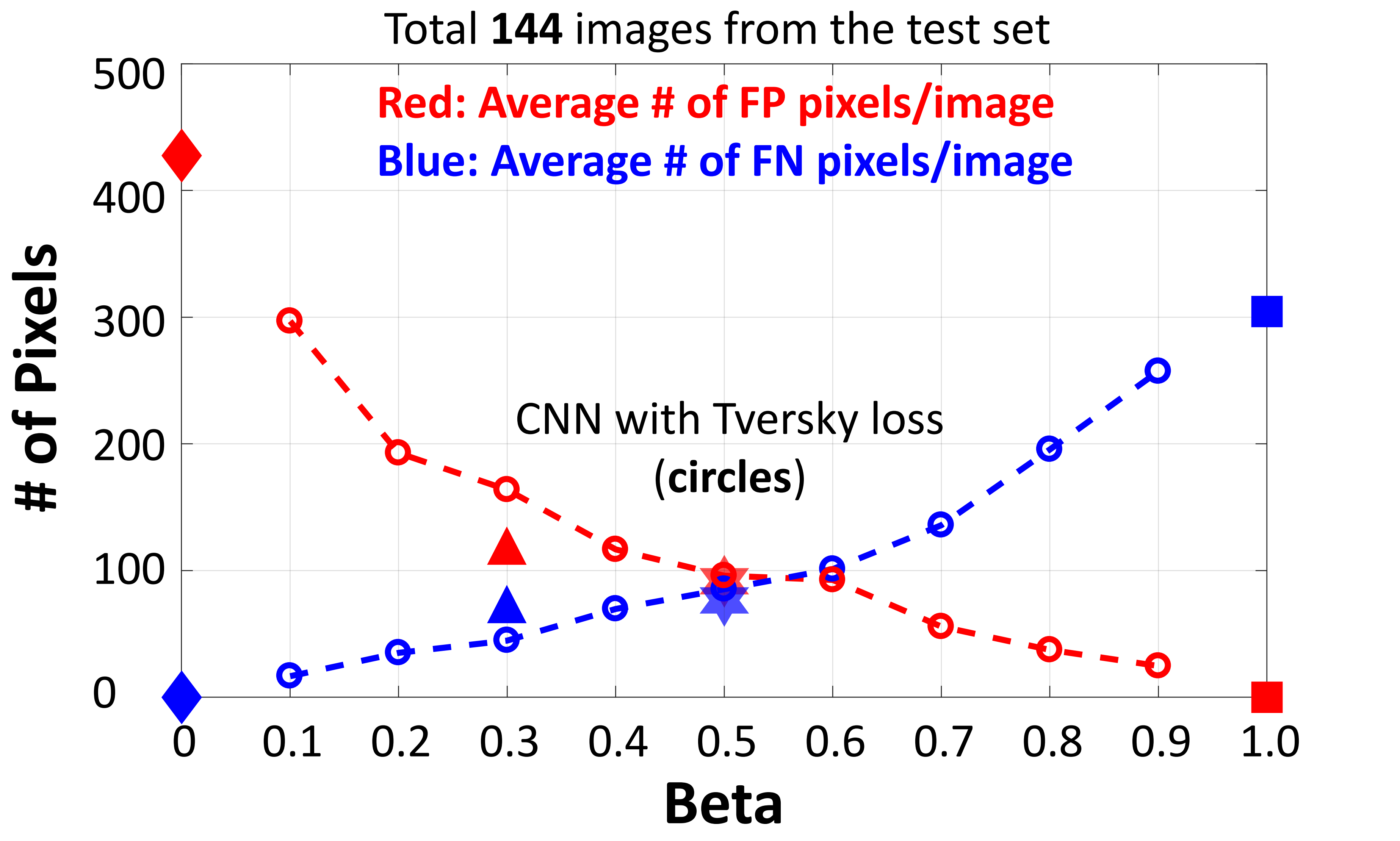
FP ~400pixles/image
FN = 0

Triangles: CNN with Binary Cross-Entropy loss

Stars: CNN with soft-Dice loss

Squares: Thin masks

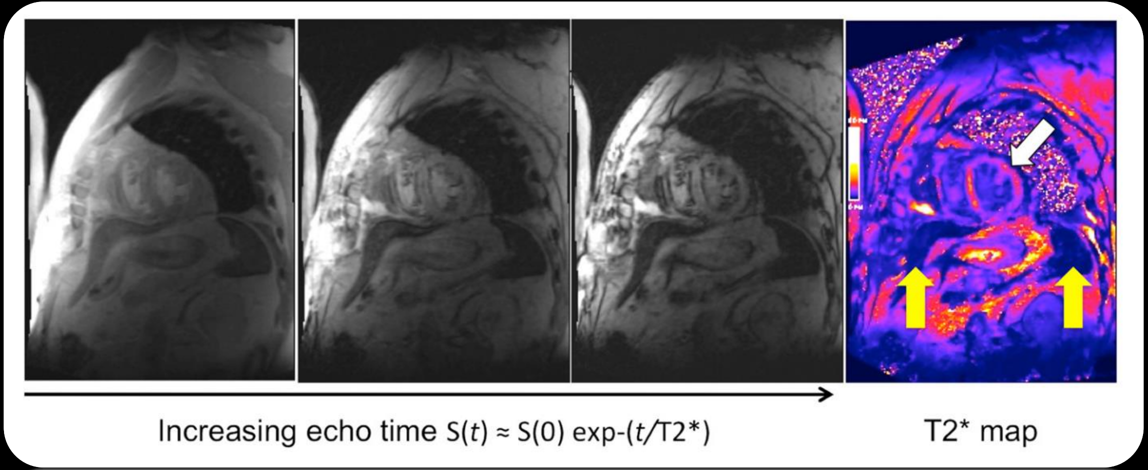
FP = 0
FN ~300pixels/image

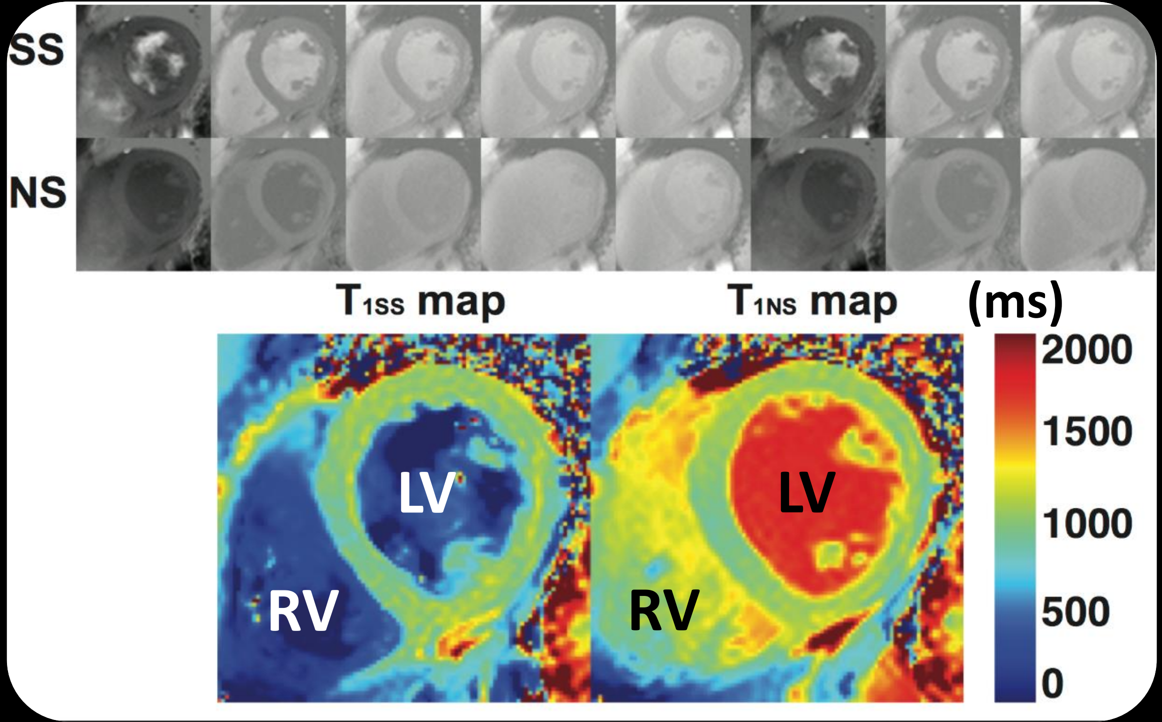


Discussion and Conclusions

- Feasibility to train the CNN model on data with low and varying SNR and CNR
- Ability to estimate model uncertainty for quality control and active learning
- Ability to adapt the network to the desired False Positive and False Negative tradeoff

→ Applicable to other quantitative CMR:
  - First-pass, T1, T2, T2*, T1rho, DTI, MTR, MRE, etc.





1. **Do, Hung** et al. "*Myocardial ASL Perfusion Imaging using MOLLI.*" Proc. ISMRM 24th Scientific Sessions, Singapore, May 2016, p3142.
2. **Alam, Shirjel** et al. "Vascular and plaque imaging with USPIO." *Journal of Cardiovascular Magnetic Resonance* 17.1 (2015): 83.

Acknowledgements

- Funding:
  - Whittier Foundation
  - NIH/NHLBI, #1R01HL130494-01A1

MREL - USC

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Thank you for your attention!

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For over 100 years, the Canon Medical Systems `Made for Life’ philosophy prevails as our ongoing commitment to humanity. Generations of inherited passion creates a legacy of medical innovation and service that continues to evolve as we do. By engaging the brilliant minds of many, we continue to set the benchmark, because we believe quality of life should be a given, not the exception.

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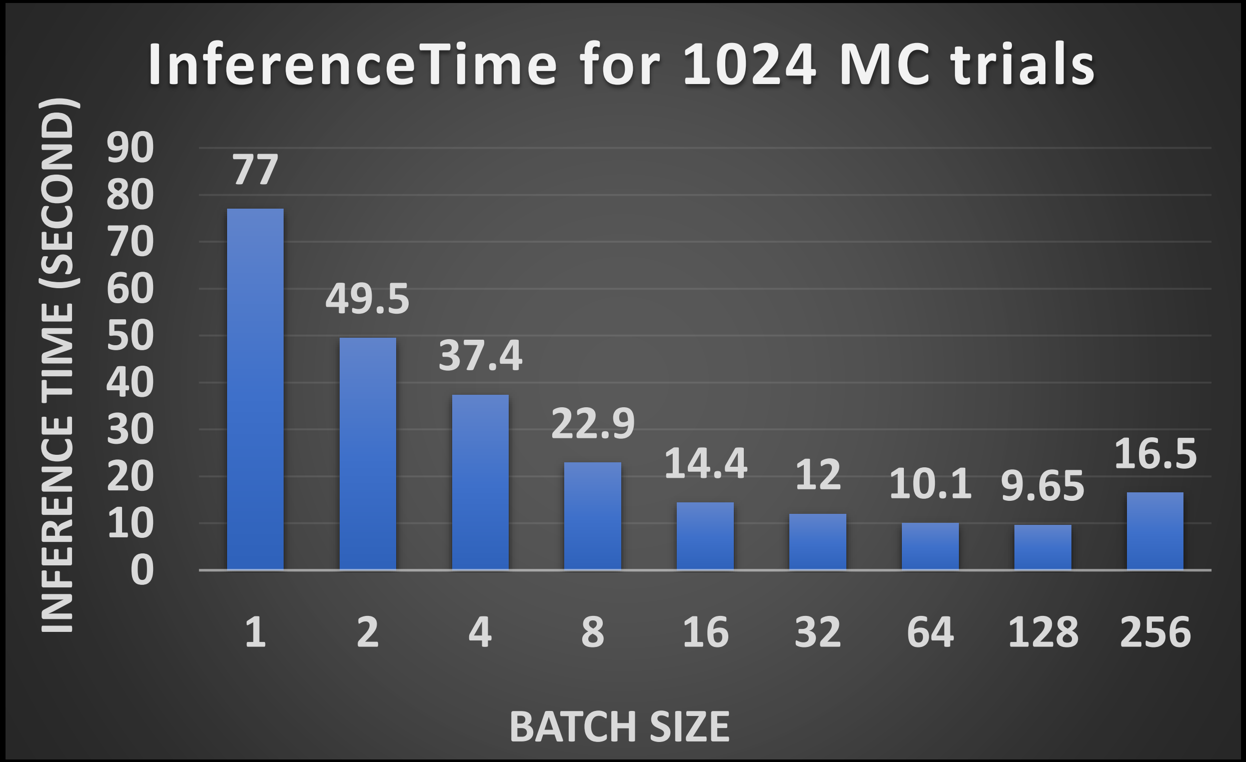
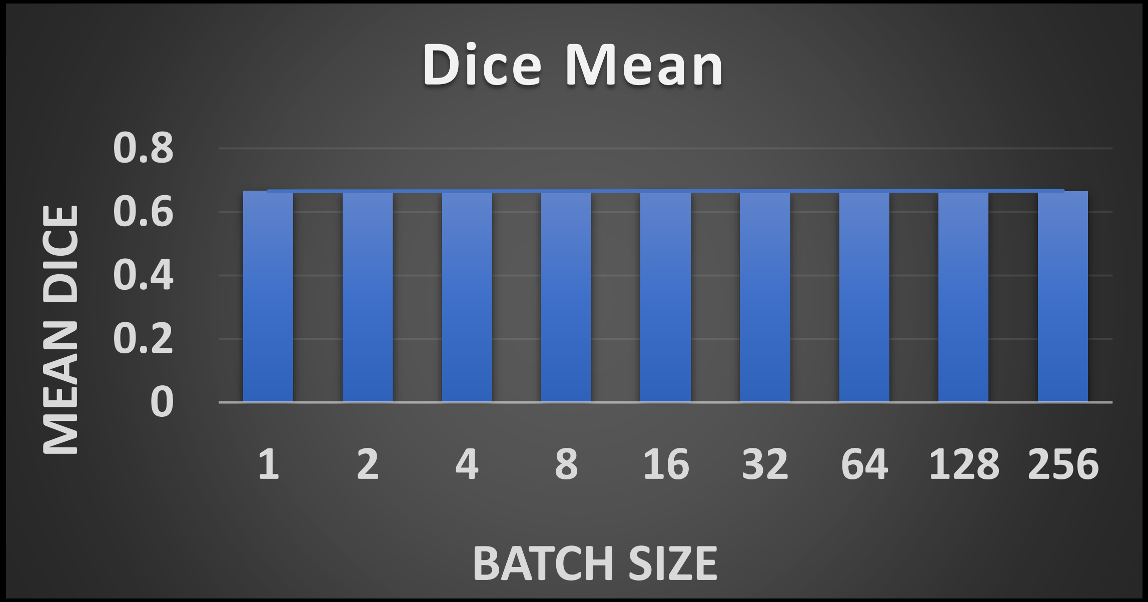
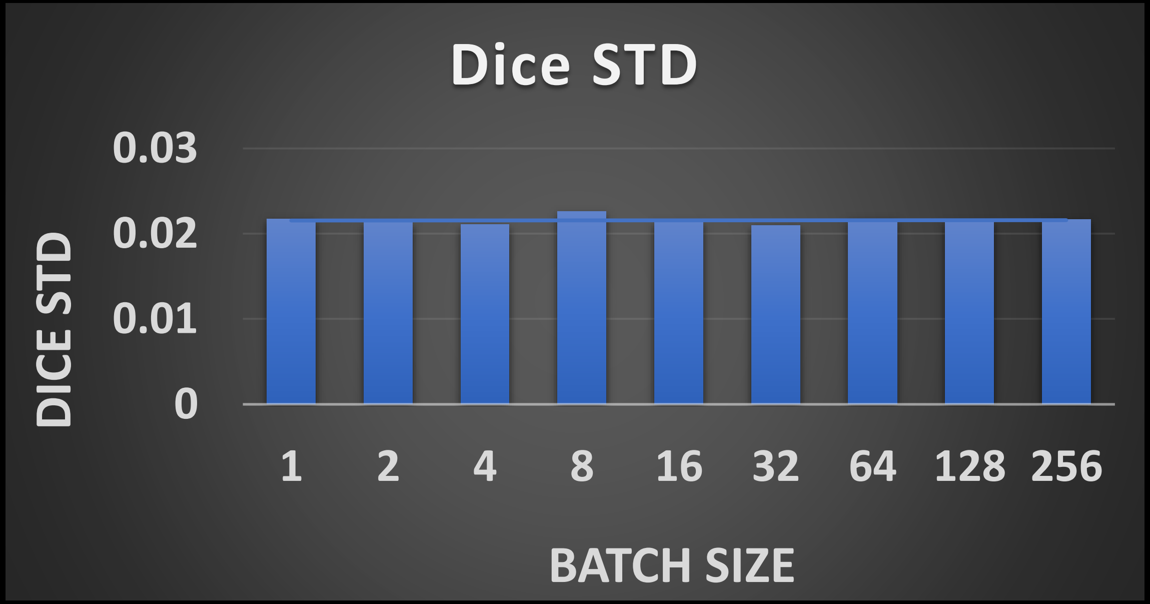
Backup slides

Results(2): Uncertainty – Batch Size







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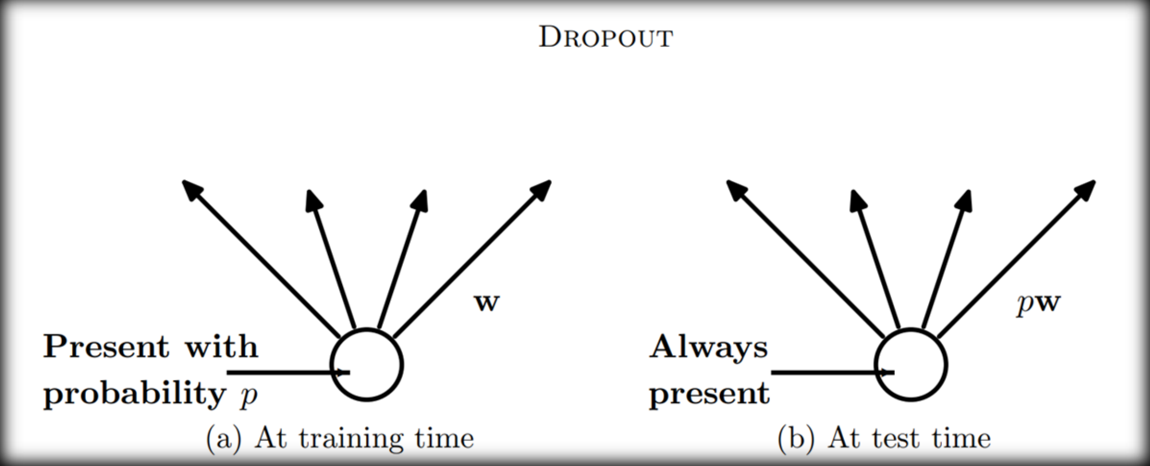
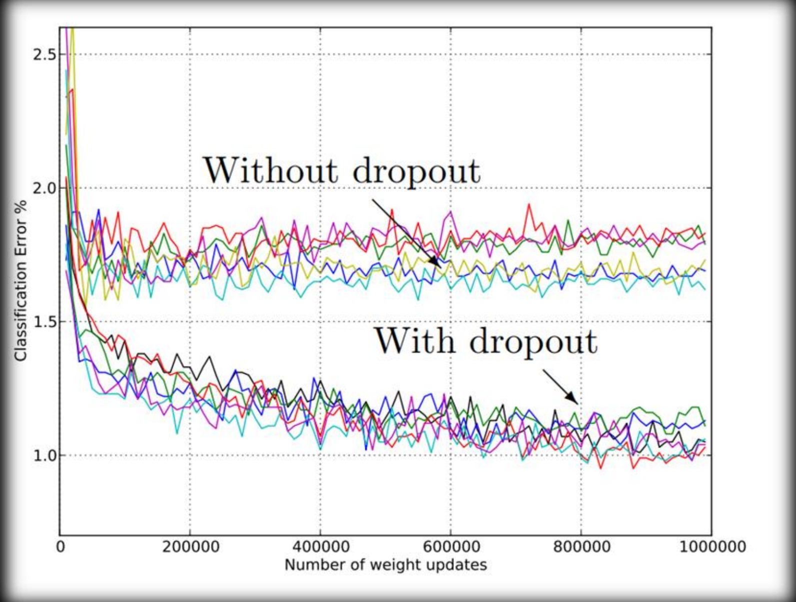
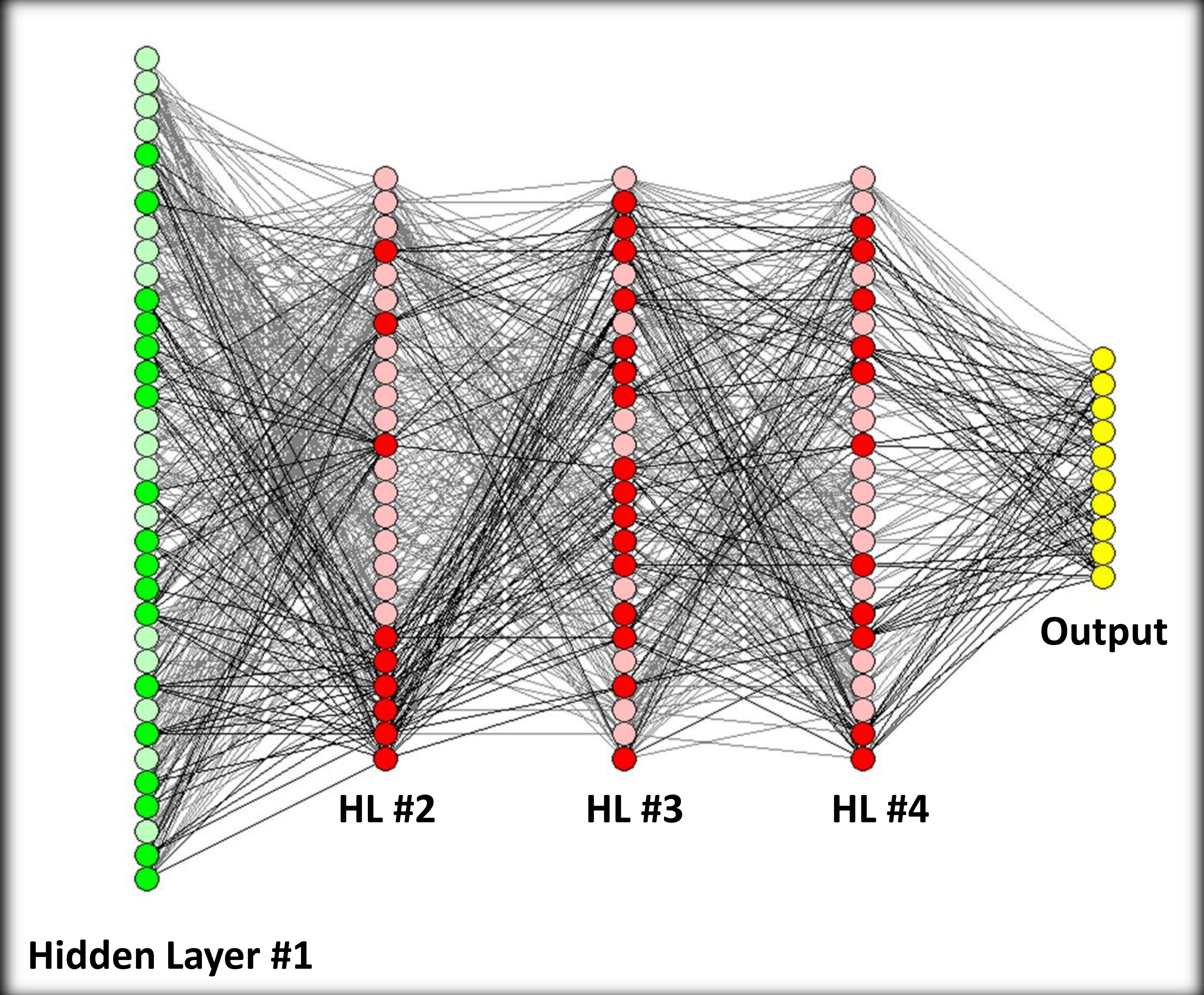
Methods(3): dropout[1]



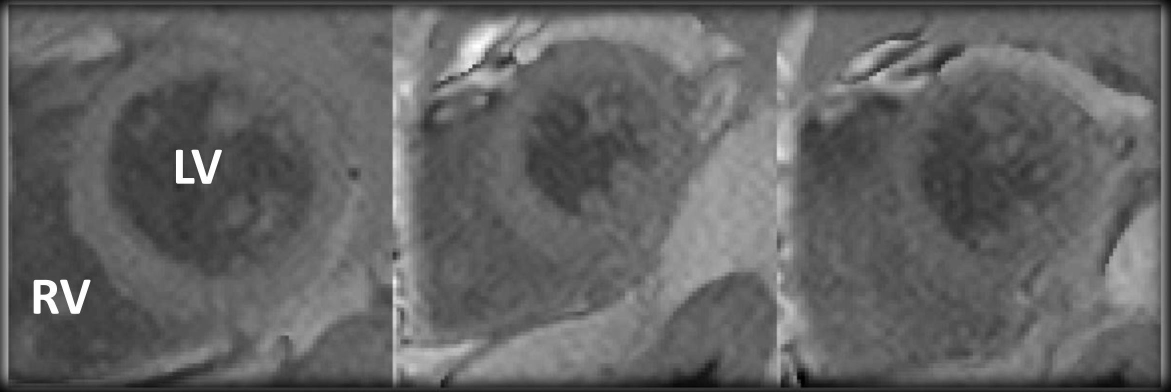


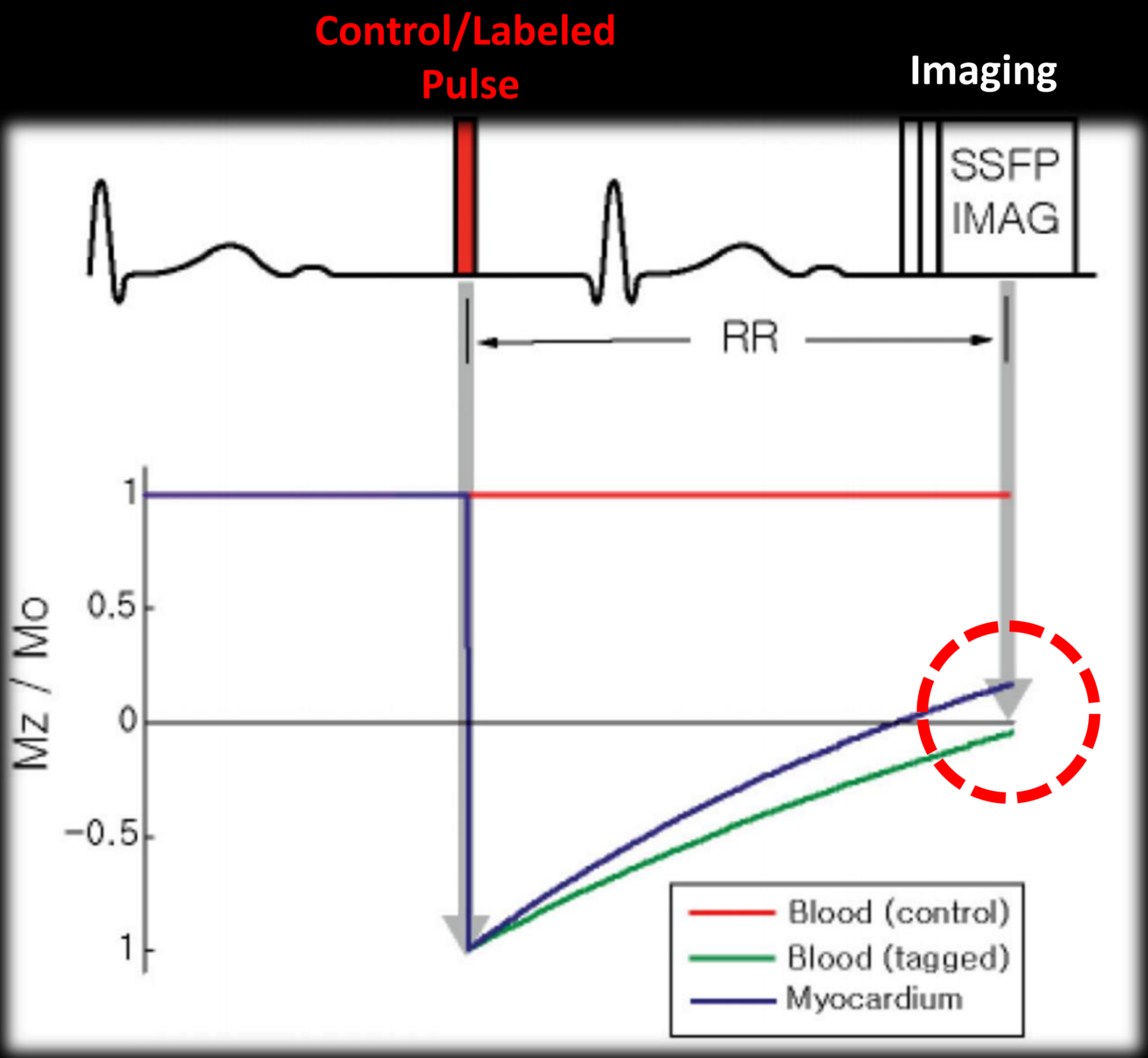


1. Srivastava et al., "*Dropout: A simple way to prevent NN from overfitting.*" JMLR 2014.
2. Animation is adapted from https://www.techemergence.com/what-is-machine-learning/

Intro(3): Data characteristics of ASL

- Low SNR and contrast





1. Zungho Zun et al. "*Assessment of myocardial blood flow in humans using arterial spin labeling: feasibility and SNR requirements.*" *MRM2009;62(4):975-83.*

Methods(3): Uncertainty measure using MC dropout[1]

Dropout as a Bayesian Approximation:
Representing Model Uncertainty in Deep Learning

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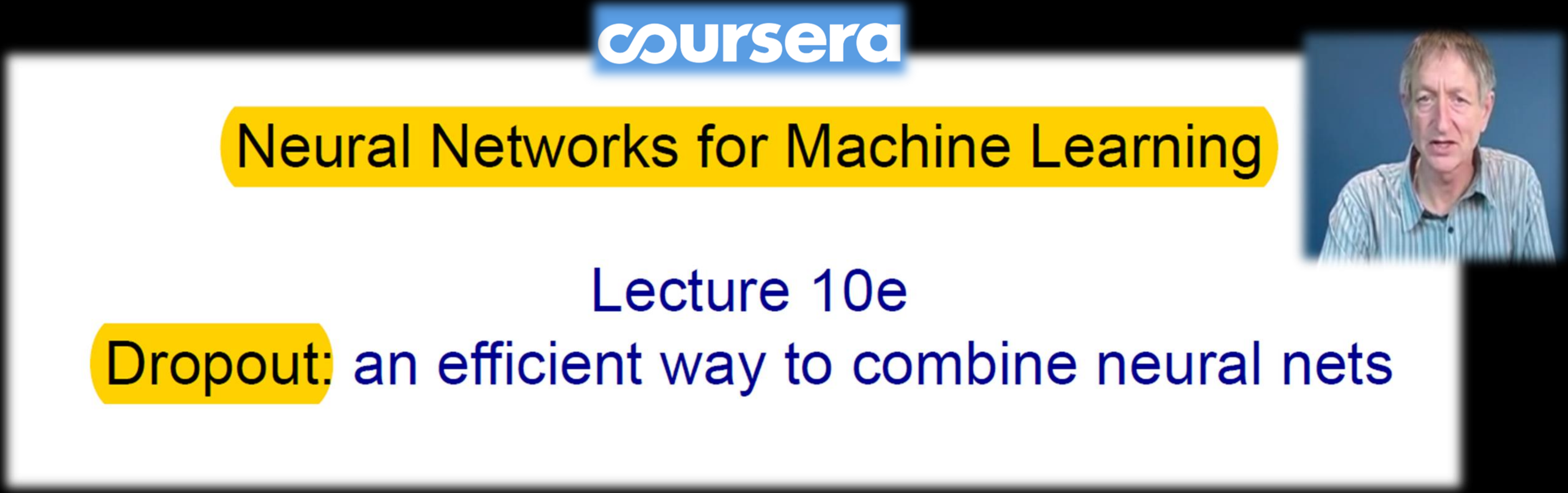
Zoubin Ghahramani ZG201@CAM.AC.UK
University of Cambridge

- Any NN, with dropout applied before every weight layer, is mathematically equivalent to an approximation of the Bayesian model.
- Model uncertainty can be estimated given the posterior distribution of the trained weights

1. **Gal, Yarin** et al. "*Dropout as a Bayesian approximation: Representing model uncertainty in deep learning.*" International conference on ML 2016; 1050-1059.

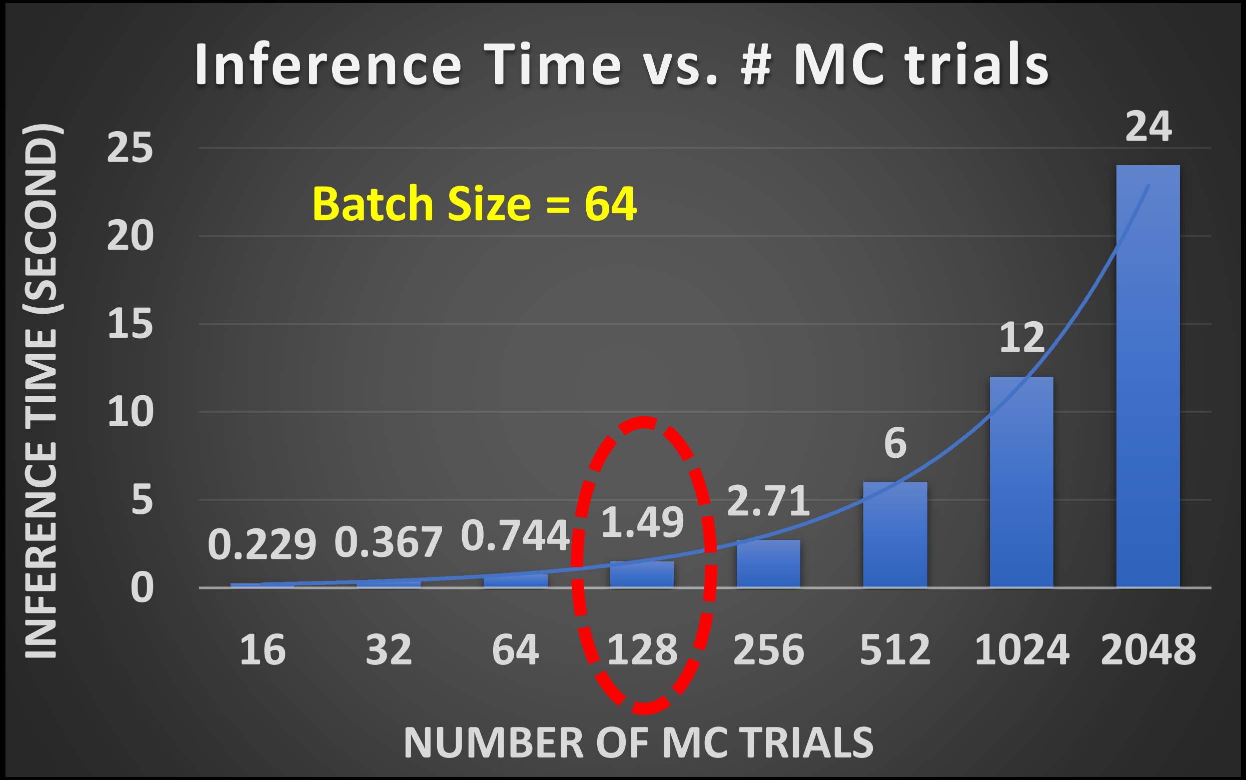
Methods(3): Uncertainty measure using MC dropout[1]

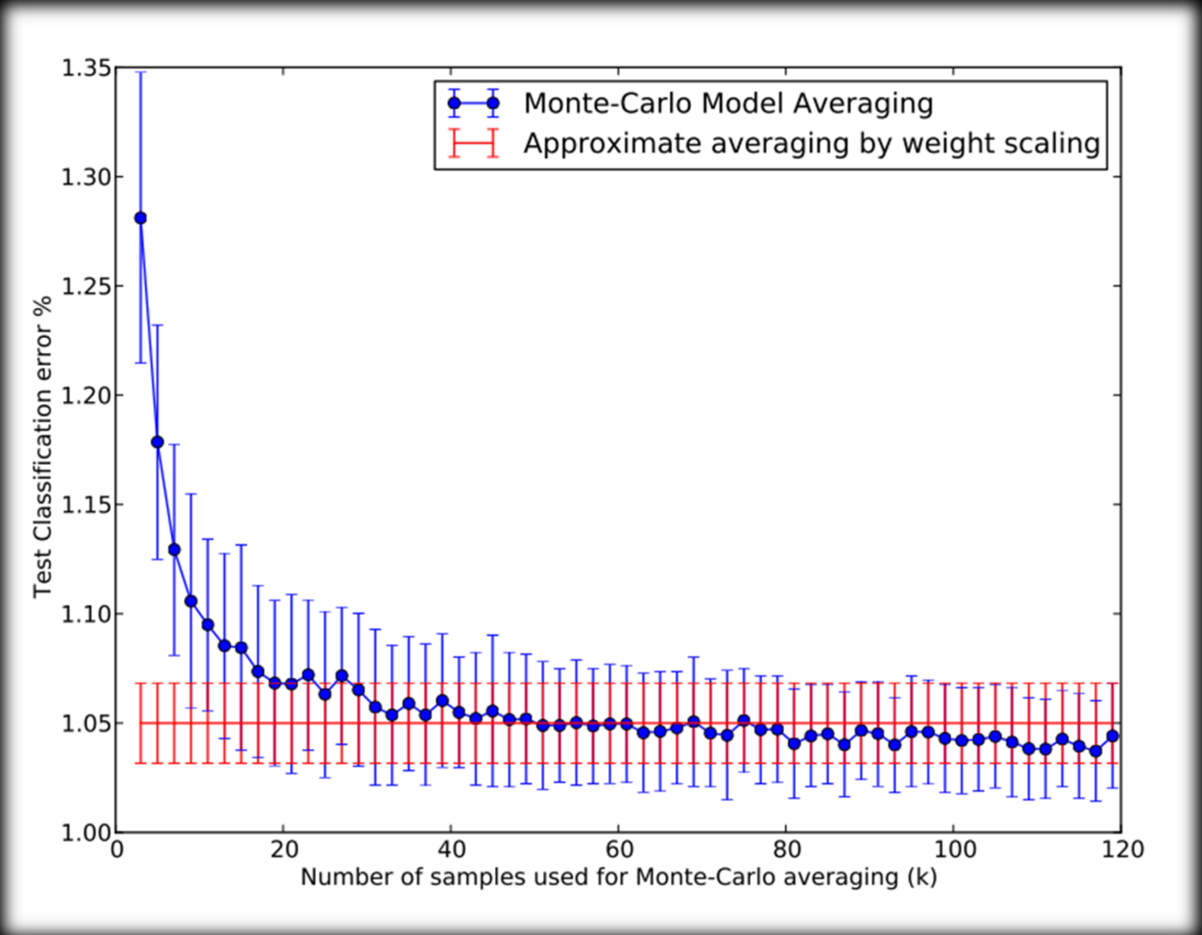


- *"Use dropout of 0.5 in every hidden layer"*
- *"At test time, run the stochastic model several times on the same input"*

1. **Srivastava** et al., *"Dropout: A simple way to prevent NN from overfitting."* JMLR 2014.
2. **Hinton, Geoffrey**, *"Lecture 10.5 – Dropout: An efficient way to combine neural nets."* COURSERA: Neural Networks for Machine Learning 2012: 33-41.

Results(2): Uncertainty – Time penalty

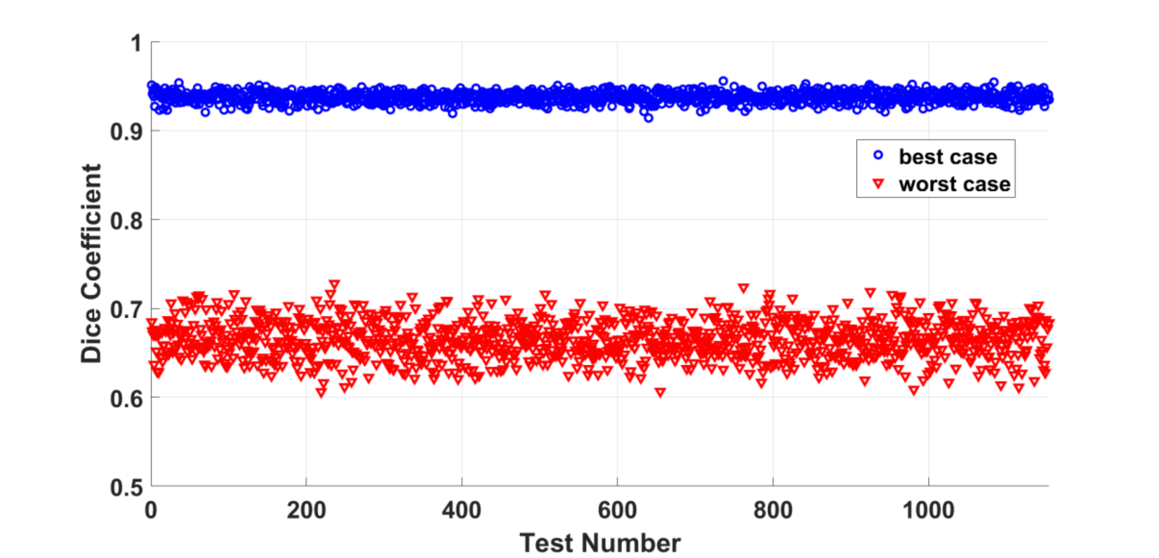


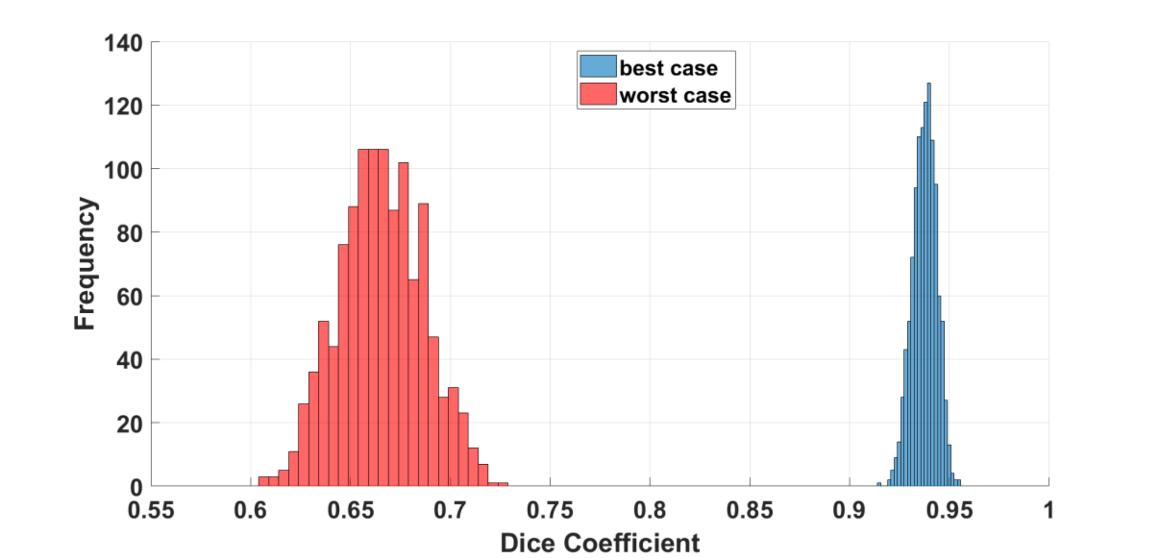


~1.5s/image with 128 MC trials

1. **Srivastava** et al., *"Dropout: A simple way to prevent NN from overfitting."* JMLR 2014.

Figure 2: worst and best





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