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A Heteroscedastic Uncertainty Model for Decoupling Sources of MRI Image Quality

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Outline

Motivation / Context
- MRI Artefacts
- Quality Control
- Types of Uncertainty

Proposed Methodology
- Segmentation Uncertainty
- Decoupled Uncertainty Model
- Network / Training
- k-Space Augmentation

Experiments / Results
- Simulated
- Real-world

Summary / Limitations / Ongoing Research

MRI Artefacts

Patient motion

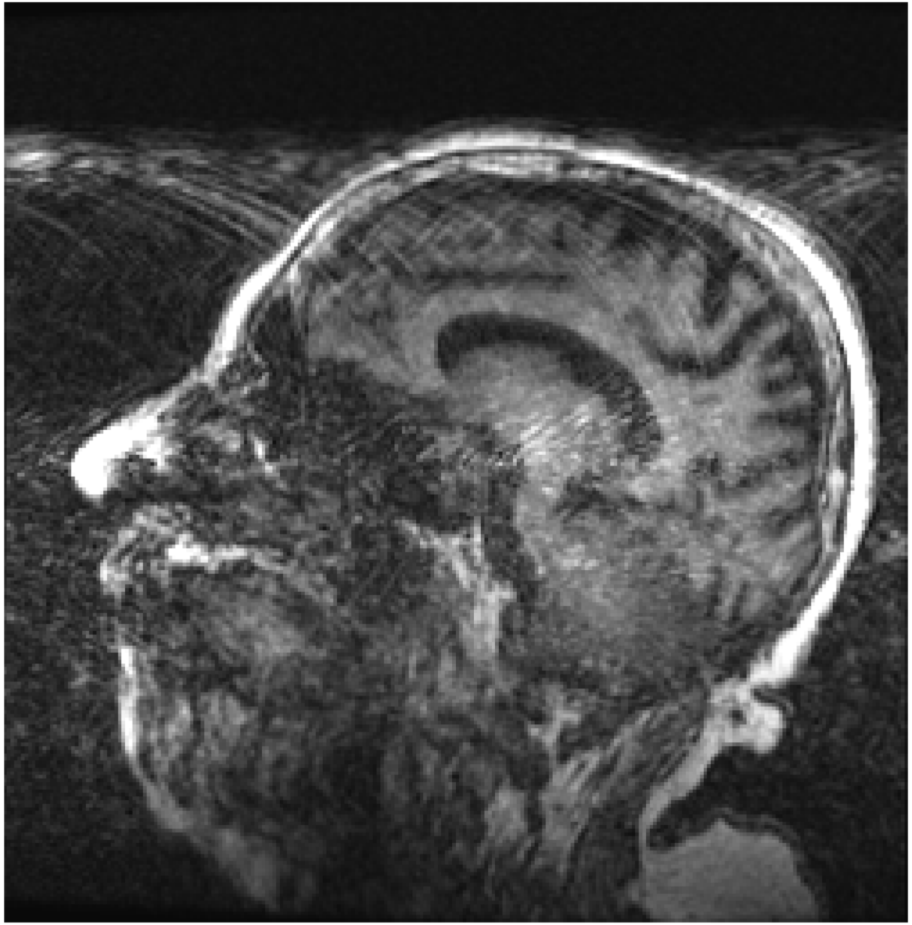
Acquisition noise

Blurring

Aliasing / wraparound

Radio-frequency spikes

And more...



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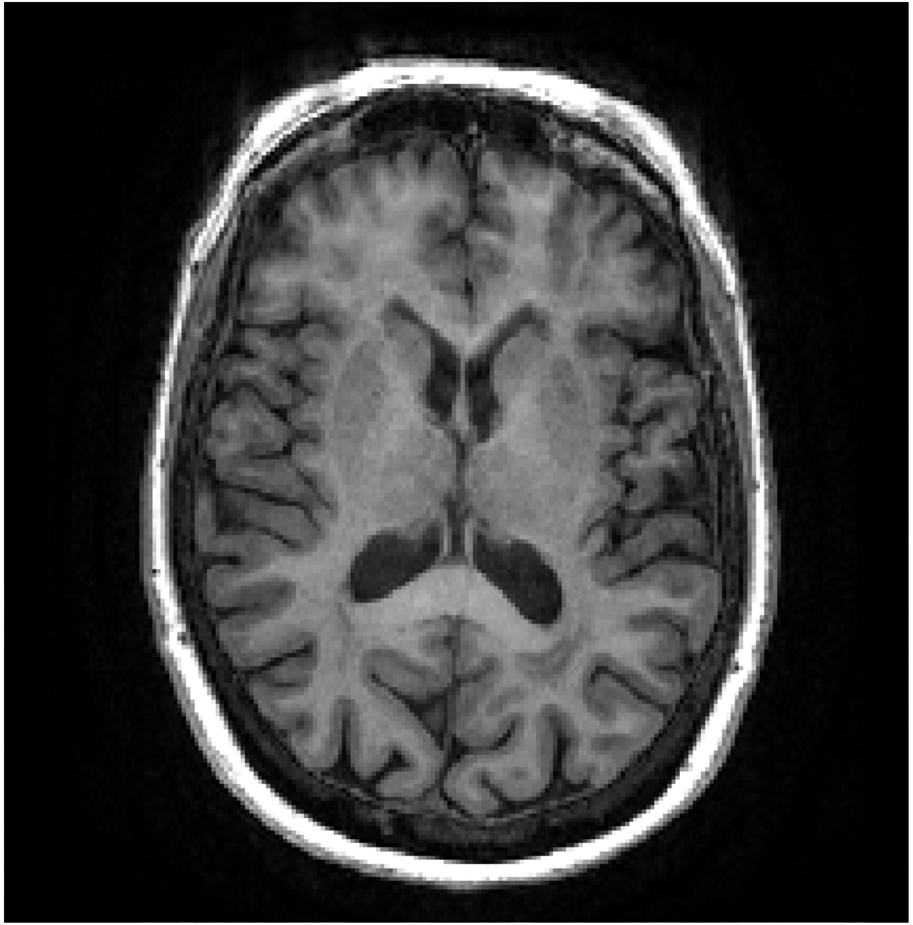

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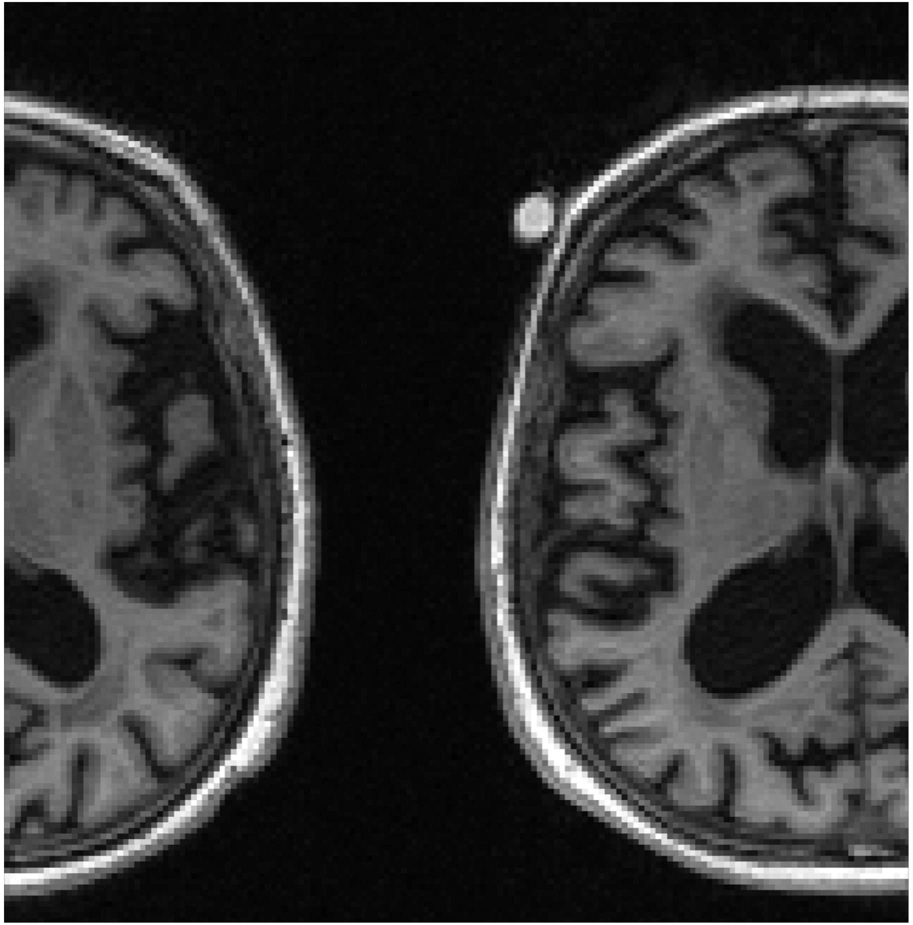

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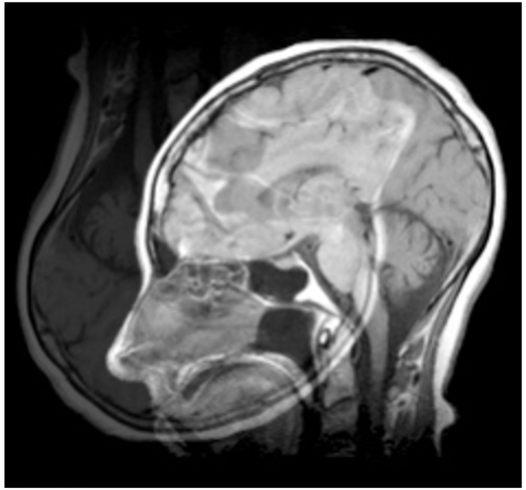
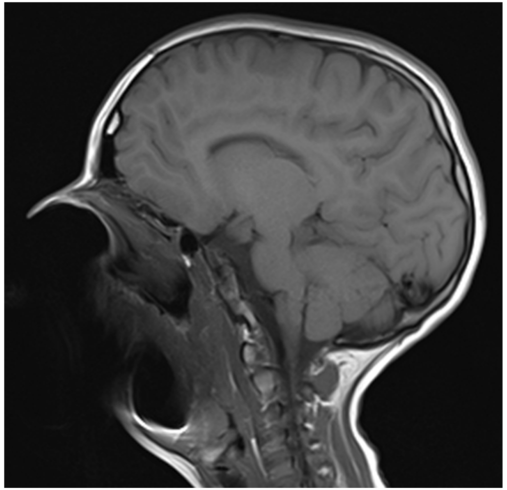
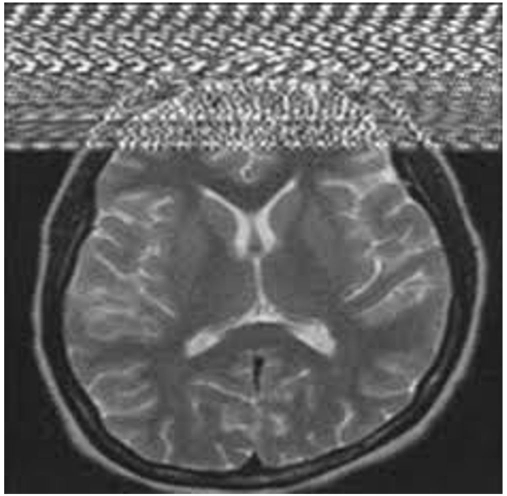





MRI Quality Control (QC)

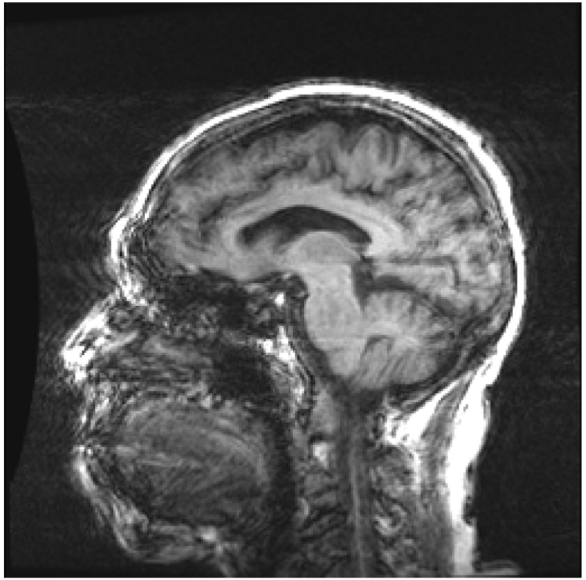
Manual QC:

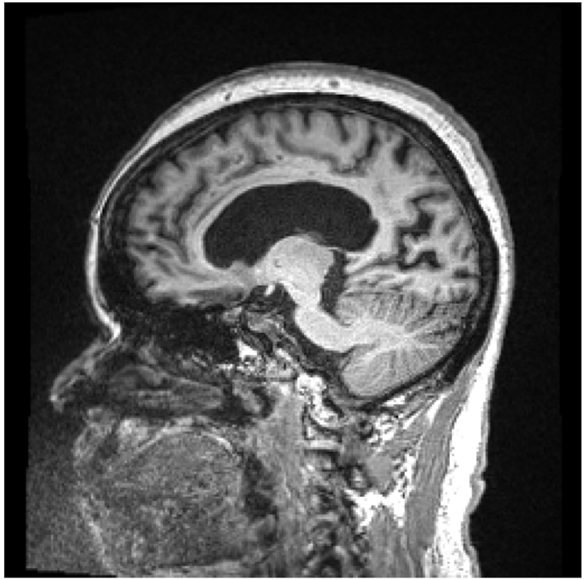
+ Gold standard
- Time-consuming / labour-intensive
- Inter- and intra-rater variability
- Subjective / protocol dependent
- Some artefacts difficult to detect (e.g. motion)

Automatic QC:

+ Faster / consistent
- Currently limited methods (e.g. slice SNR / Mean Abs Motion)
- Definition of image quality?
- “Visual” vs “algorithmic” QC
- Task dependent

What do we mean by quality?





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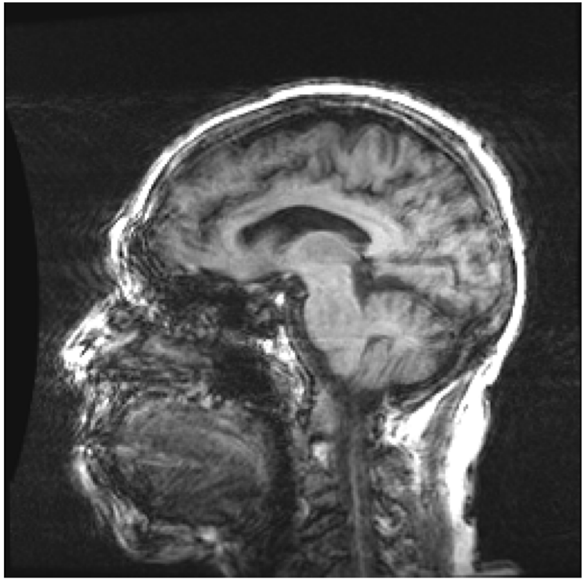

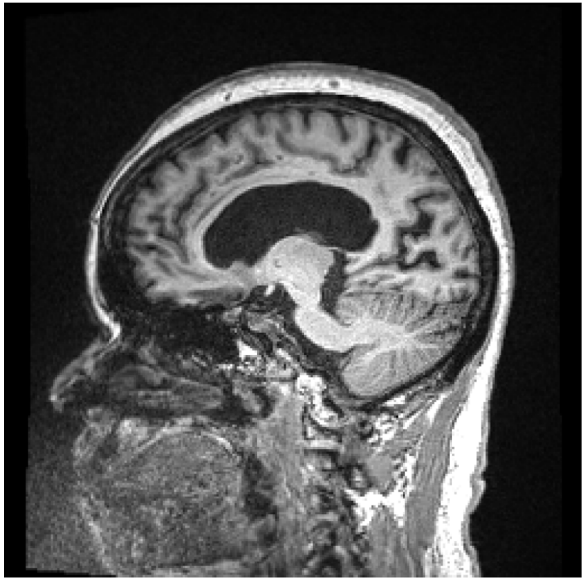

Affects our ability to reach a conclusion
— represented by uncertainty!

Modelling Uncertainty

Bayesian neural networks model uncertainty

Two main types of uncertainty:

Modelling Uncertainty

Bayesian neural networks model uncertainty

Two main types of uncertainty:

Epistemic

Uncertainty in the model

Aleatoric

Homoscedastic - Task uncertainty

Heteroscedastic - Data uncertainty

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Homoscedastic - Task uncertainty

Heteroscedastic - Data uncertainty

Heteroscedastic uncertainty is a natural way of capturing data quality!

Segmentation Uncertainty

As in [1], for segmentation we model:

$$p(\mathbf{y}|\mathbf{x}) = \mathrm{Softmax}\left(\mathbf{f}^{\mathbf{W}}(\mathbf{x})/\sigma^2\right)$$

Maximising the log-likelihood:

$$L = \frac{1}{\sigma^2}\mathrm{CE}\left(\mathbf{y}, \mathbf{f}^{\mathbf{W}}(\mathbf{x})\right) + \frac{1}{2}\log\sigma^2$$

[1] A. Kendall, Y. Gal, and R. Cipolla, “Multi-task learning using uncertainty to weigh losses for scene geometry and semantics.” CVPR, pp. 7482–7491, 2017.

Uncertainty Decomposition Model

Assumption: causes of uncertainty are independent (e.g. noise / motion)

Total variance can be decomposed:

$$\sigma^2 = \sigma_t^2 + \sum_i^N \sigma_i^2$$

for N possible augmentations

σ_t^2 task uncertainty given clean data

σ_i^2 variance due to the i^{th} augmentation

Loss Functions

Task Loss:

$$L_{task} = \frac{1}{\sigma_t^2}\mathrm{CE}\left(\mathbf{y}, \mathbf{f}^{\mathbf{W}}(\mathbf{x})\right) + \frac{1}{2}\log\sigma_t^2$$

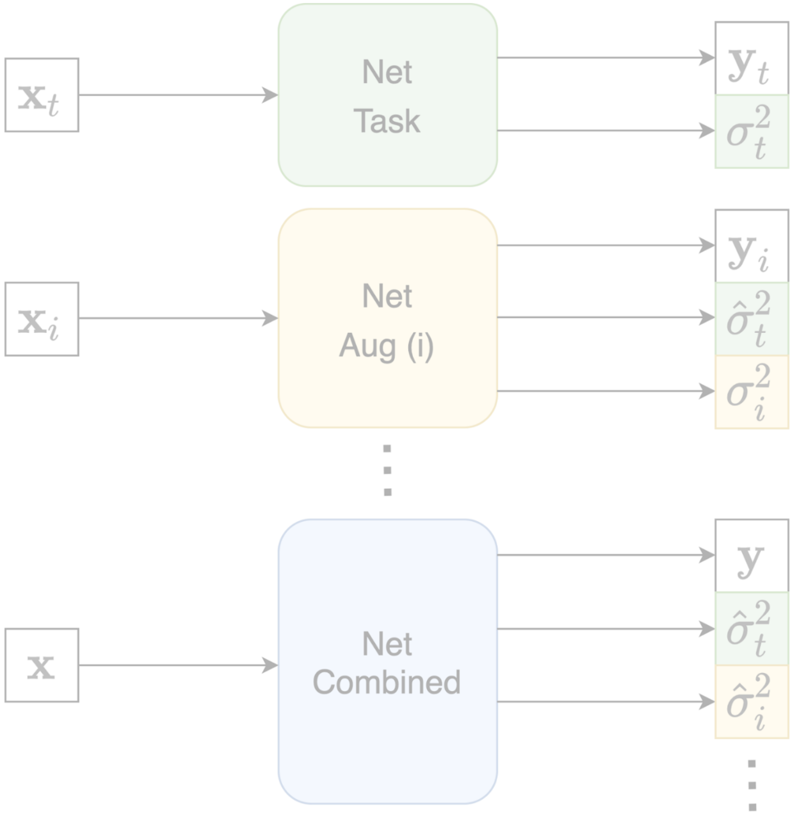
Augmentation Loss:

$$L_{aug_i} = \frac{\mathrm{CE}\left(\mathbf{y},\mathbf{f}^{\mathbf{W}}(\mathbf{x})\right)}{\sigma_t^2+\sigma_i^2} + \frac{1}{2}\log\left(\sigma_t^2 + \sigma_i^2\right)$$

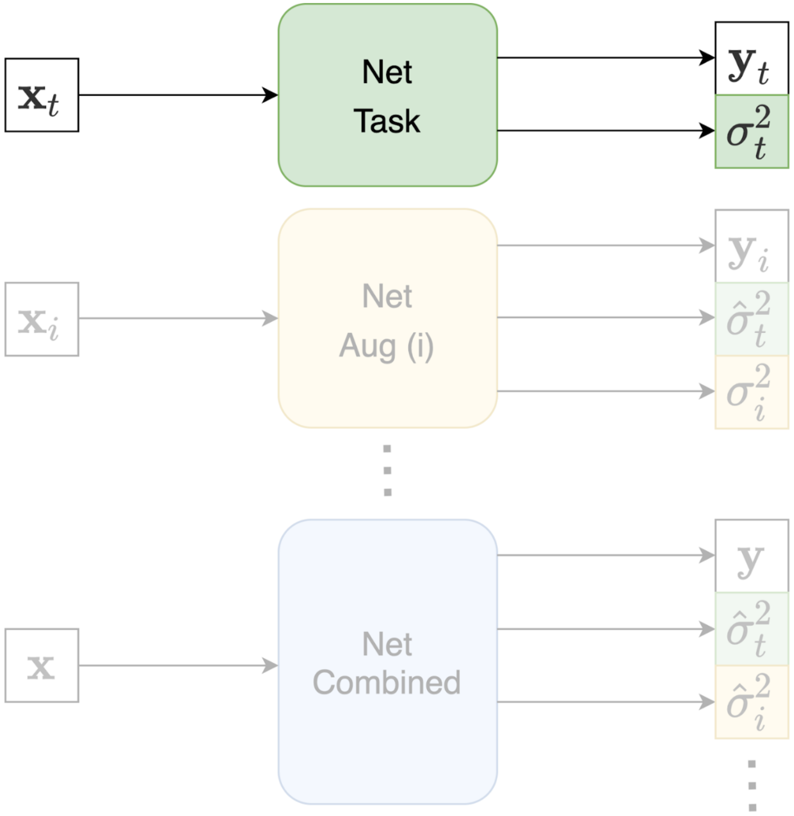
Total Loss:

$$L_{total} = \frac{\mathrm{CE}\left(\mathbf{y},\mathbf{f}^{\mathbf{W}}(\mathbf{x})\right)}{\sigma_t^2+\sum_i^N \sigma_i^2} + \frac{1}{2}\log\left(\sigma_t^2 + \sum_i^N \sigma_i^2\right)$$

Training Strategy

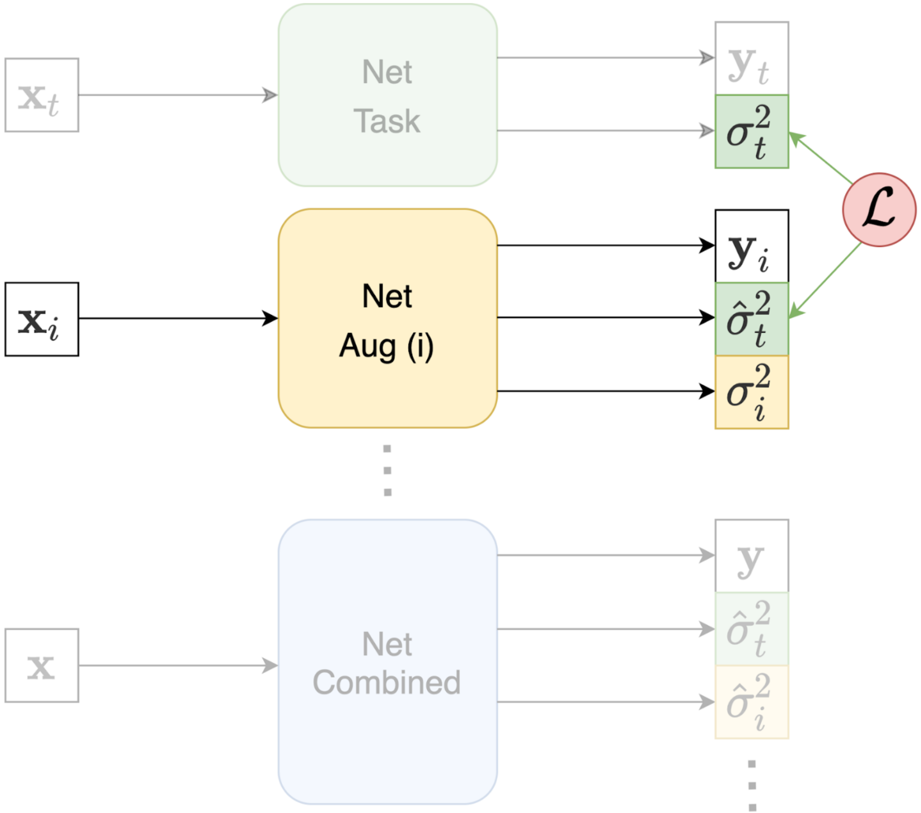


Training Strategy - Step 1



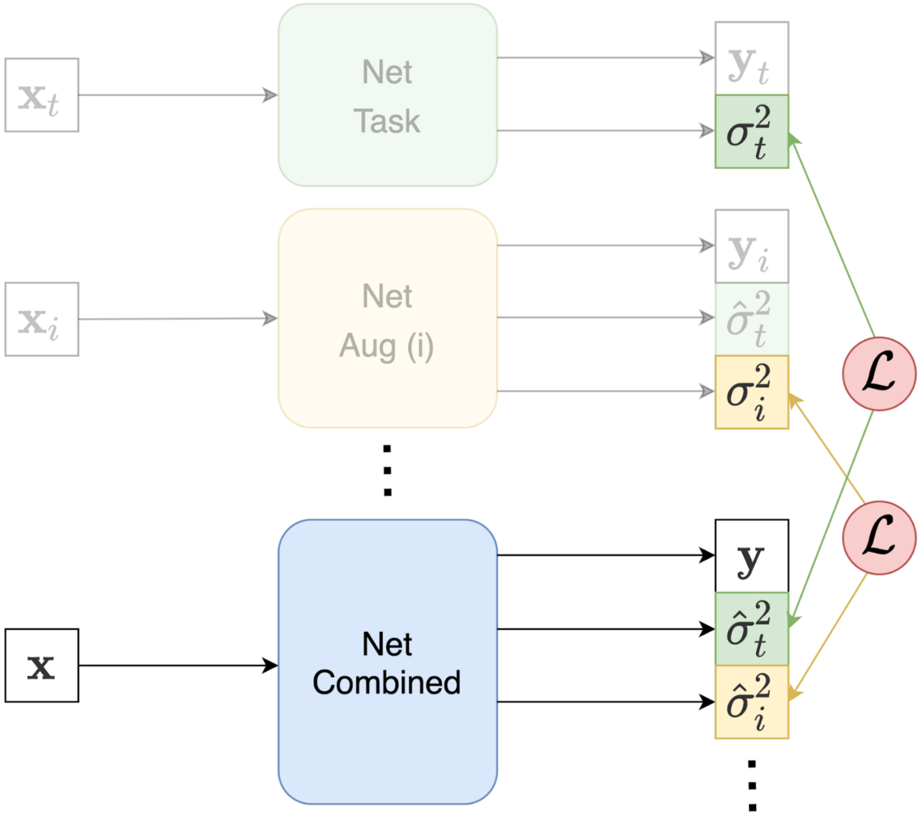
$$L_{task} = \frac{\text{CE}}{\sigma_t^2} + \frac{1}{2}\log\sigma_t^2$$

Training Strategy - Step 2



$$L_{aug_i} = \frac{\text{CE}}{\hat{\sigma}_t^2 + \sigma_i^2} + \frac{1}{2}\log\left(\hat{\sigma}_t^2 + \sigma_i^2\right) + L\left(\hat{\sigma}_t^2, \sigma_t^2\right)$$

Training Strategy - Step 3



$$
\begin{aligned}
L_{combined} = & \frac{\mathrm{CE}}{\hat{\sigma}_t^2 + \sum_i \hat{\sigma}_i^2} \\
& + \frac{1}{2}\log\left(\hat{\sigma}_t^2 + \sum_i \hat{\sigma}_i^2\right) \\
& + L\left(\hat{\sigma}_t^2, \sigma_t^2\right) \\
& + \sum_i L\left(\hat{\sigma}_i^2, \sigma_i^2\right)
\end{aligned}
$$

Consistency Loss

Enforce consistency between network uncertainty outputs:

$$L(\sigma^2, \hat{\sigma}^2) = L_1(\sigma^2, \hat{\sigma}^2) + L_{grad}(\sigma^2, \hat{\sigma}^2) + \lambda L_{SSIM}(\sigma^2, \hat{\sigma}^2)$$

Gradients / SSIM preserve uncertainty structure as image degrades

Severe artefacts — segmentation position / shape / visibility changes causing SSIM to breakdown — SSIM loss down-weighted by $\lambda = 0.1$

k-Space Augmentation

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R. Shaw, C. H. Sudre, T. Varsavsky, S. Ourselin and M. J. Cardoso, “A k-Space Model of Movement Artefacts: Application to Segmentation Augmentation and Artefact Removal,” in IEEE Transactions on Medical Imaging, 2020

Implementation Details

All networks use 3D U-Net [2]

Each network has 2 outputs: segmentation y and vector of variances

One network per augmentation to be decoupled

[2] F. Isensee, J. Petersen, A. Klein, D. Zimmerer, P.F. Jaeger, et al. “nnu-net: Self-adapting framework for u-net-based medical image segmentation,” Bildverarbeitung fur die Medizin, 2019.

Data

272 ADNI scans passed manual QC — Assumed artefact-free

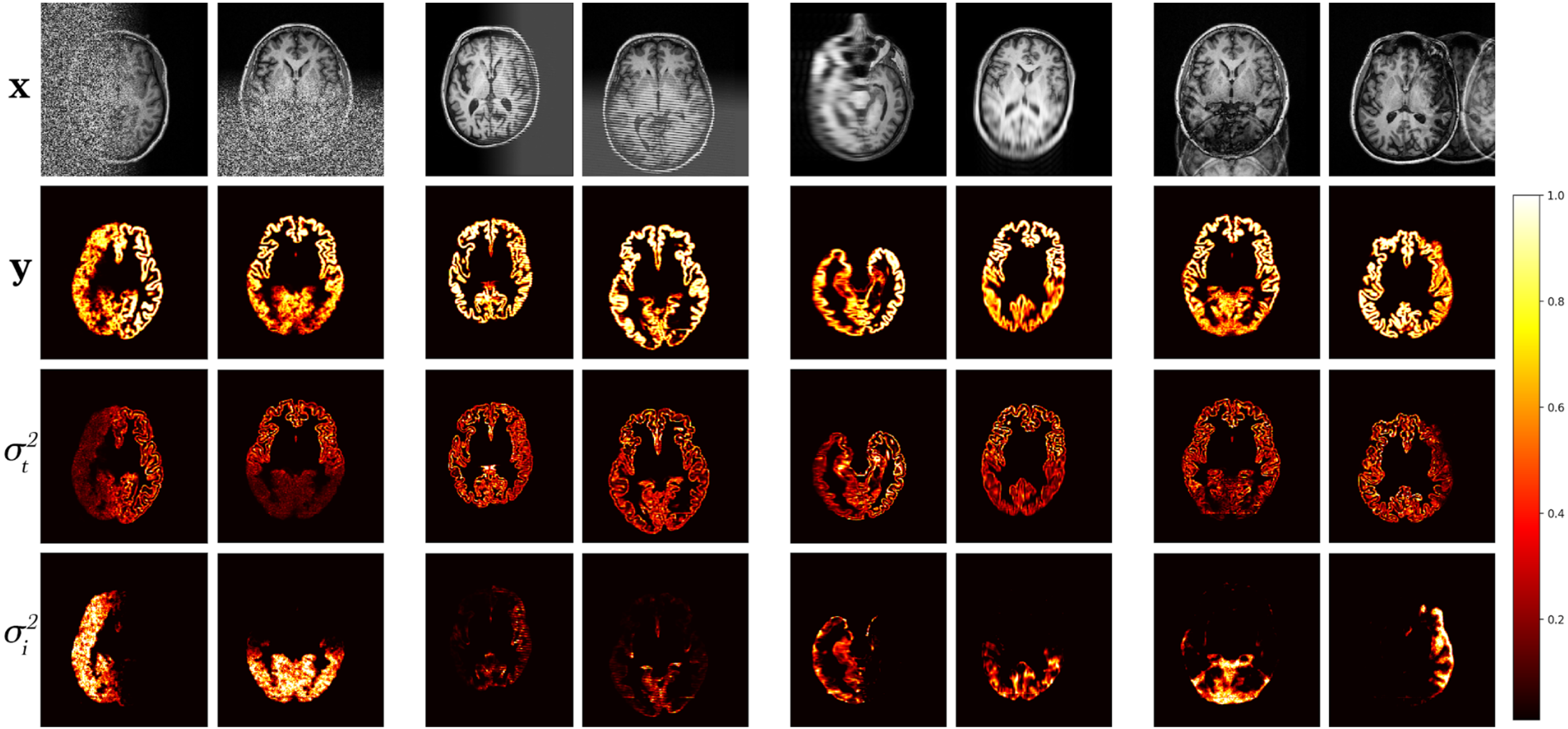
80% train / 10% val / 10% test

Gray matter segmentation maps generated by [3]

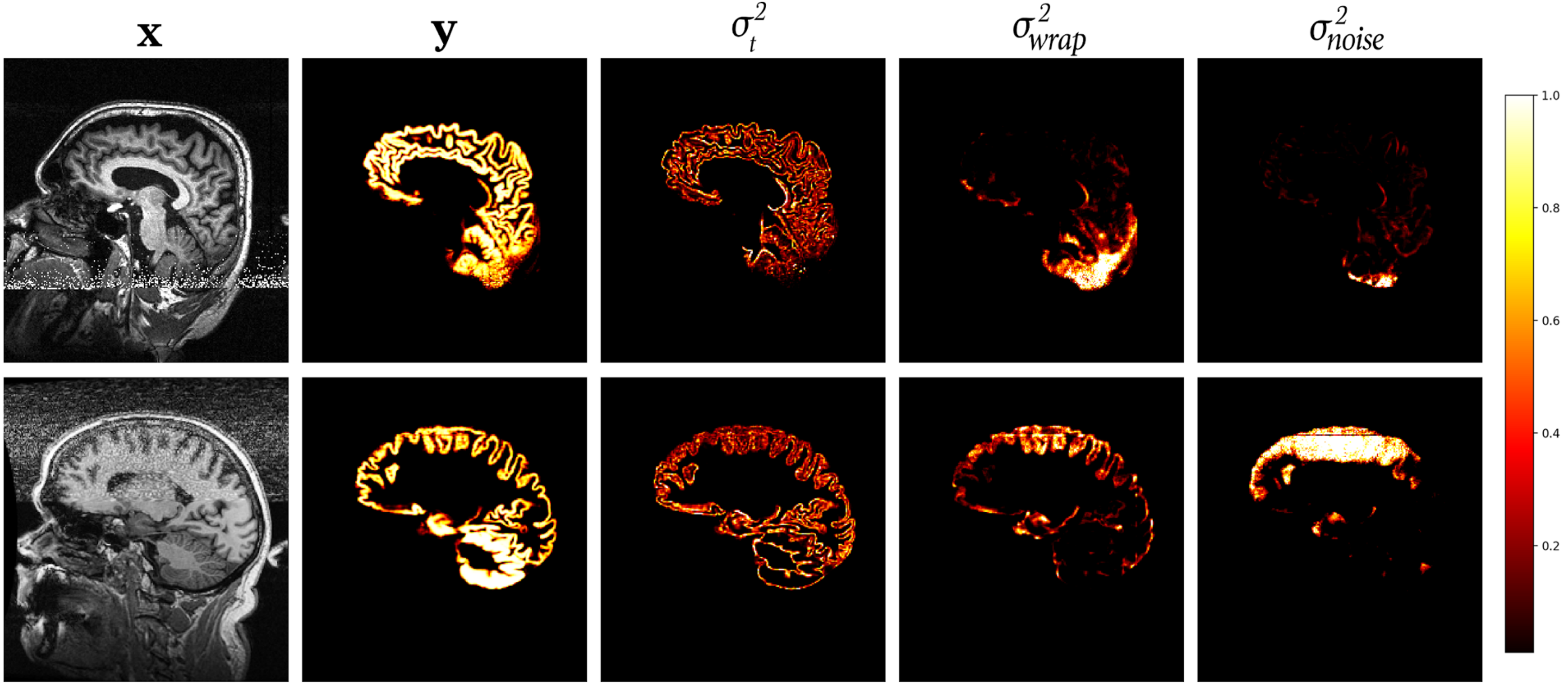
Random k-Space augmentations generated on-the-fly (p=0.5)

[3] M. J. Cardoso, M. Modat, R. Wolz et al. “Geodesic Information Flows: Spatially-Variant Graphs and Their Application to Segmentation and Fusion,” IEEE Trans Med Imaging, 2015.

Results - Simulated



Results - Real-world



Limitations

Data assumed artefact-free

Interactions of sources of uncertainty not modelled (e.g. noise / blur)

Segmentation uncertainty only / not “visual” quality

Ability to decouple artefacts depends on:

- Network size / capacity
- Severity of artefacts
- Artefact appearance variability
- Training / augmentation procedure

How generalisable are artefact augmentations?

Summary

Task uncertainty as a measure of image quality

A method of decoupling uncertainty to identify MRI artefacts

Ongoing research

- Validation against human-based QC ratings
- “Visual” vs “algorithmic” QC
- Generalisability?
- Decouple-ability of artefact subtypes?

Thank you