NiftyNet

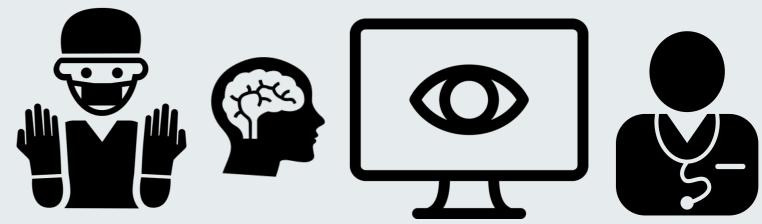
An open-source convolutional neural networks platform for research in medical image analysis and image-guided therapy

MICCAI 2018

Tutorial on Tools Allowing Clinical Translation of Image Computing ALgorithms [T.A.C.T.I.C.AL.]

Presented by Tom Vercauteren

http://niftynet.io https://github.com/NifTK/NiftyNet











NiftyNet: An open consortium for deep learning in medical imaging

NiftyNet: a deep-learning platform for medical imaging

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¹⁰Wellinster, J. & Differ: Centre for International and Recepture Instrument, PRADON, Discontrol (Collapse Leaders, UK ¹⁰Control for Medical Design Of CONTO, Dispersionals of Medical Departure Basematical Dispersioning and Computer Networks, USCalapse Leaders, UK ¹⁰Institute at Housedays, University Collage Leaders, UK II Network Weispitel for Networking ¹⁰Institute at Housedays, University Collage Leaders, UK II Network Weispitel for Networking ¹⁰Institute at Housedays, University Collage Leaders, UK II Network Weispitel for Networking ¹⁰Institute at Housedays, University Collage Leaders, UK II Network Weispitel for Networking ¹⁰Institute at Housedays, University Collage Leaders, UK II Network Weispitel for Networking ¹⁰Institute at Housedays, University Collage Leaders, UK II Networking, ¹⁰Institute at Housedays, ¹⁰Institute at House

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Module The NiDyNe information provides muchine deep-terming problem for a range of model imaging applications including cognitization, regression, image generation and representation harming applications. Components of the NiDyNet priptice harding dash adding, data sugmentation, providu antibirtures, loss functions due to data and and an adding and and and and a the subsystematic or natural image many advances and on data and in the NiDyNet i pricing the shading. The matter of the subsystemic tion, NiDyNe is a built on the TransFlow functional explores sould in a TransFlow I examination of 20 and 3.0 mages and computer stational mapping on TransFlow I examination of 20 and 3.0 mages and computer stational applica-

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Infrastructure paper

Gibson, E., Li, W., Sudre, C., Fidon, L., Shakir, D. I., Wang, G., ... Vercauteren, T. (2018). NiftyNet: a deep-learning platform for medical imaging. *Computer Methods and Programs in Biomedicine*, *158*, 113–122. doi:10.1016/j.cmpb.2018.01.025. arXiv:1709.03485



- Apache-2.0 licensed
- Collection of domain specific knowledge and best practices
- Validated, tested, SOTA network/loss/sampler/aggregator implementations
- Best-practice API usage for data management, multiple-GPU and tensorboard support
- Platform for model evaluation, dissemination and deployment















The need for NiftyNet

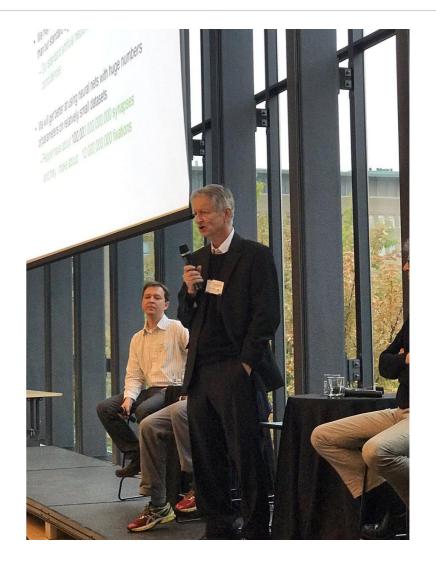
Relevance of deep learning and idiosyncrasies

Radio/patho/dermato/ophtalmo-logists replaced by AI?

"If you work as a radiologist you're like the coyote that's already over the edge of the cliff. **People should stop training radiologists now**, it's just completely obvious that in five years deep learning is going to do better than radiologists.

It might be ten years"

Geoffrey Hinton in 2016



More nuanced opinions

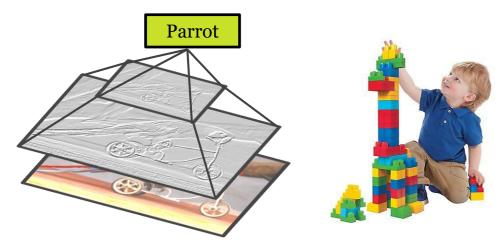


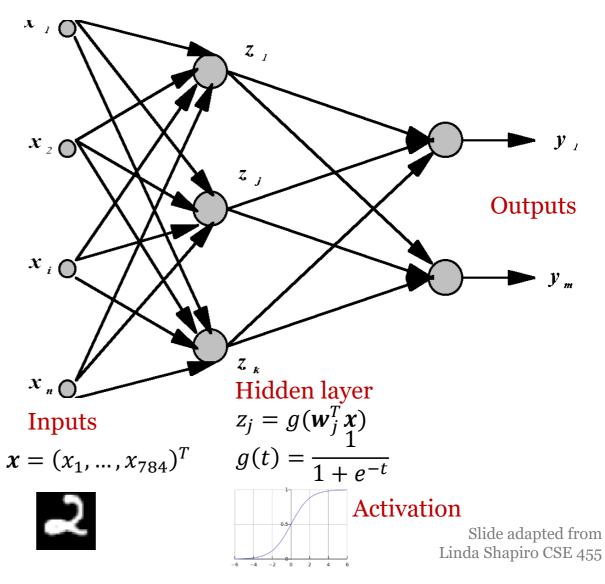
"In the not so far future, machine learning will play a central role in radiology, becoming part of routine workflow and providing daily realtime clinical diagnostic support. I predict that within 10 years **no medical imaging study will be reviewed by a radiologist until it has been preanalyzed** by a machine."

(past RSNA president)

Representation power of neural networks (NN)

- NN with one hidden layer can represent any bounded continuous function
 - Universal approximation theorem (Cybenko 1989)
- Deep neural networks can represent complex functions more efficiently
- Convolutional neural networks allows exploiting image structure





Tangible successes in medical imaging beyond the hype?

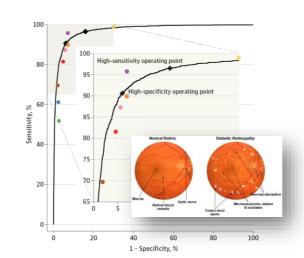


- **As of 2016**, Samsung is using deep learning for breast lesion analysis in its ultrasound product line (S-Detect for Breast)
- Samsung reported using a database of over 10,000 images
- Fair bit of interactivity still involved

Lots of research opportunities to demonstrate impact in medical imaging



- Sep 2018
- 3D U-Net for tissue segmentation
 - Training: 877 OCTs
- 3D DenseNet for classification
 - Input: segmentation results
 - Training: 14,884 3D OCTs
- Testing: 997 patients
- <u>doi:10.1038/s41591-018-0107-6</u>



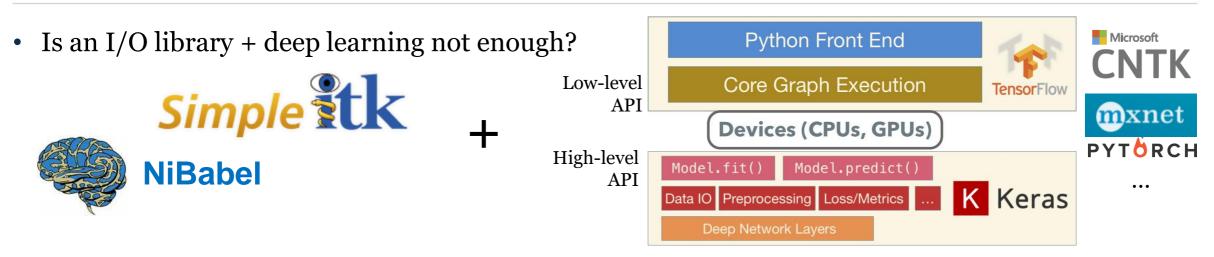
- Dec 2016
- 140,000 retinal images
- Ophtalmologist-level performance to detect diabetic retinopathy
- Inception v3, pre-trained on ImageNet
- <u>doi:10.1001/jama.2016.17216</u>

The role of ConvNet toolkits in medical imaging



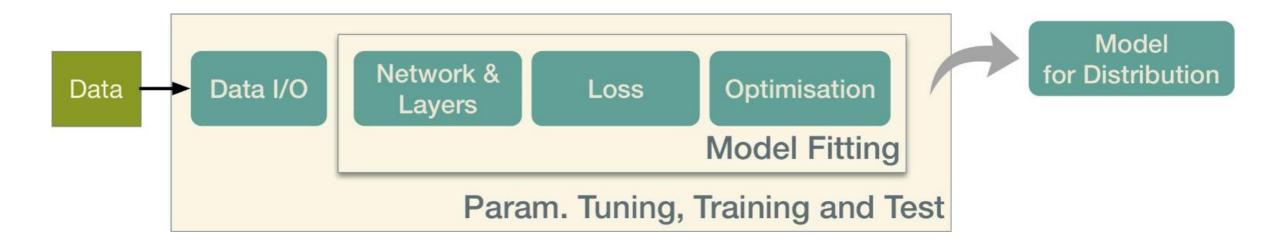
- Many challenges for deep learning in medical imaging
 - 2D+t, 3D, 4D, ...
 - Making use of metadata and prior knowledge: voxel sizes, quantitative intensities, anatomical coordinates, orientationdependence, etc.
 - Interventional applications
 - Efficient use of computational resources
 - Strictly regulated environment for clinical translation
- Resources should be focused on advancing the field while taking advantage of rapidly evolving techniques
- Reproducibility should be a given
- Translation should benefit from validated approaches

Yet another toolkit?

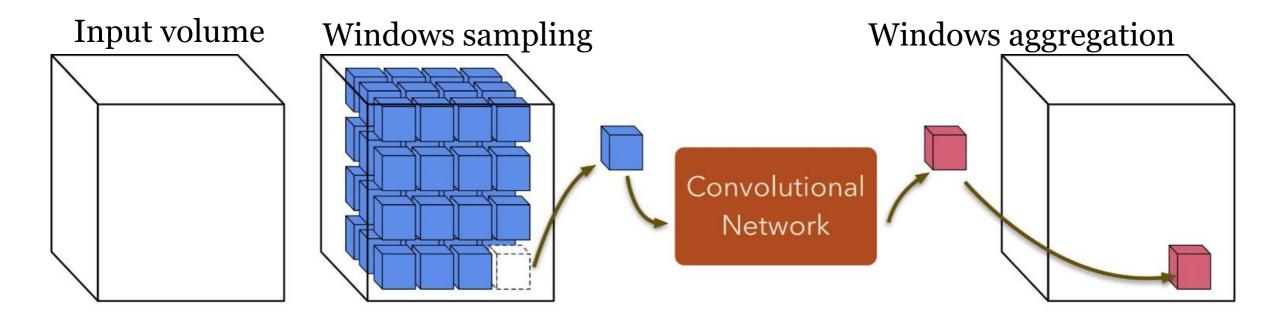


- Need for domain knowledge
 - How to handle 3D, 4D, 5D data and fit it in memory?
 - How to encode voxel-size/scale and coordinate frames intrinsically in deep learning?
 - How to augment medical data in a physics/biology correct manner?
 - Which architectures/loss functions are relevant in medical domain?
 - How to create general best-practice tools that can scale to multiple problems?
 - How do we standardise, compare and share models, and improve their deployability?

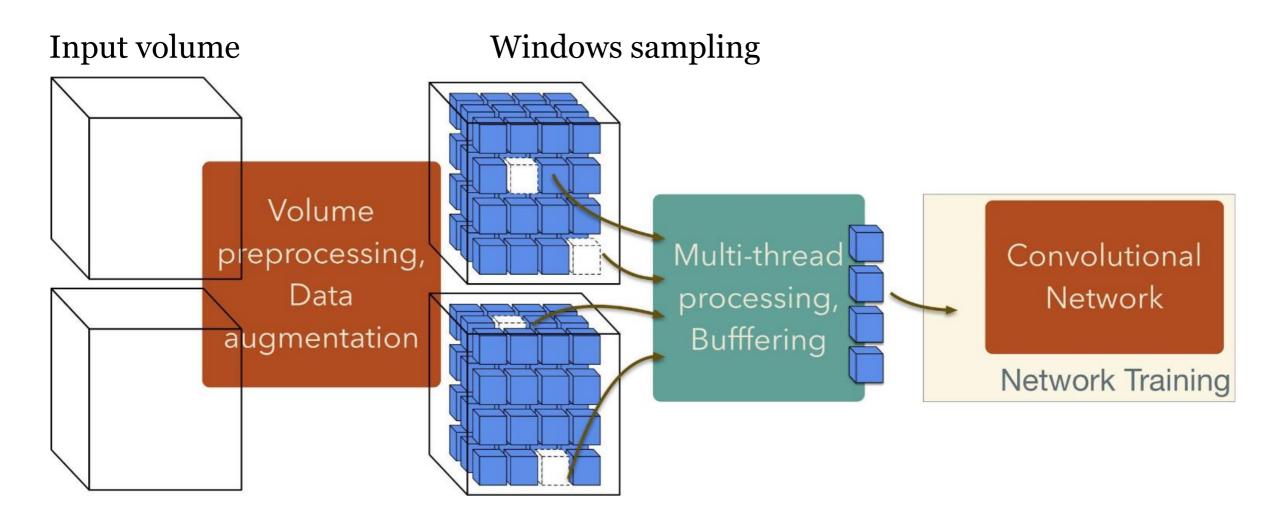
Deep learning project routines



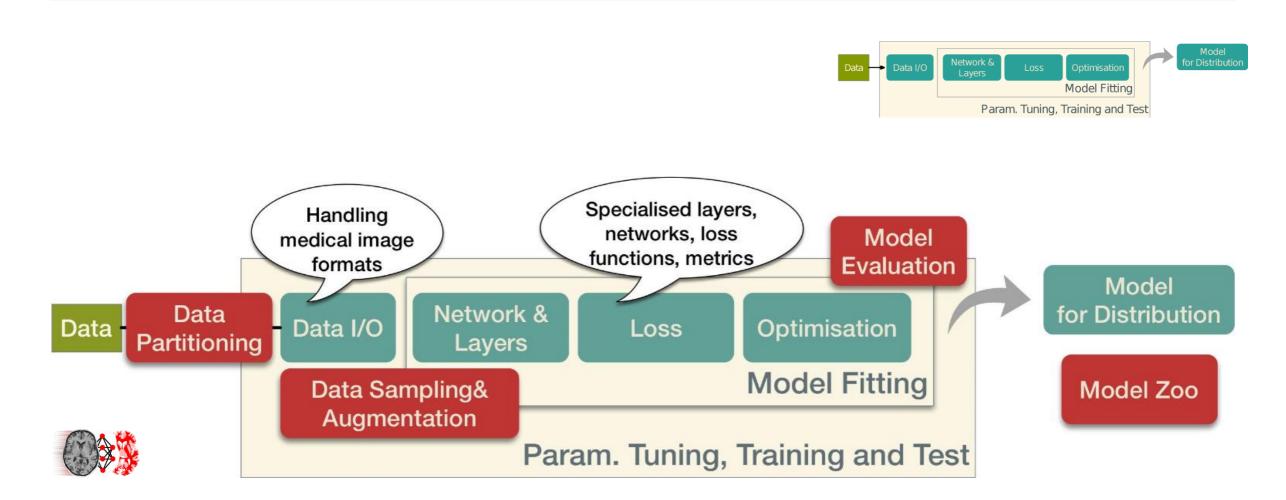
Deep learning in medical imaging – The need for sampling



Deep learning in medical imaging – The need for sampling



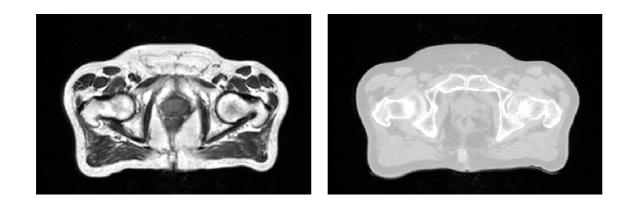
NiftyNet helps fill the gaps

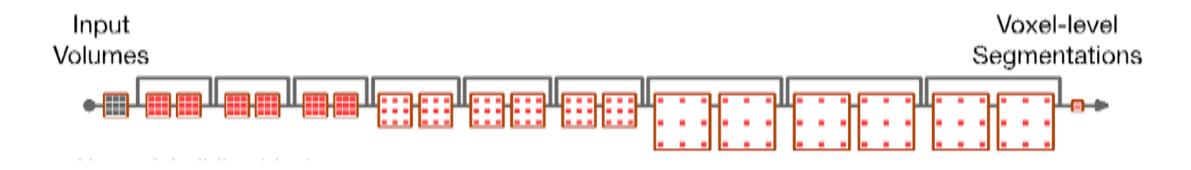


MR to CT synthesis example

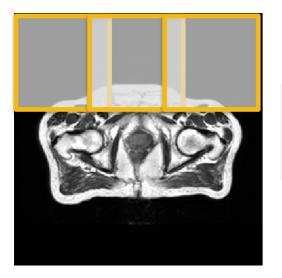
Foregoing the need for CT in PET-MR imaging

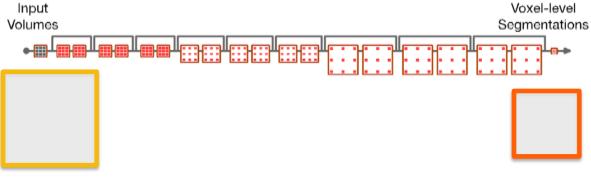
MR to CT synthesis – An image regression example





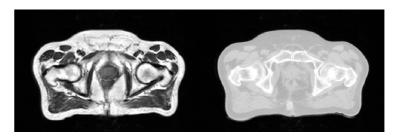
MR to CT synthesis – Sampling at inference

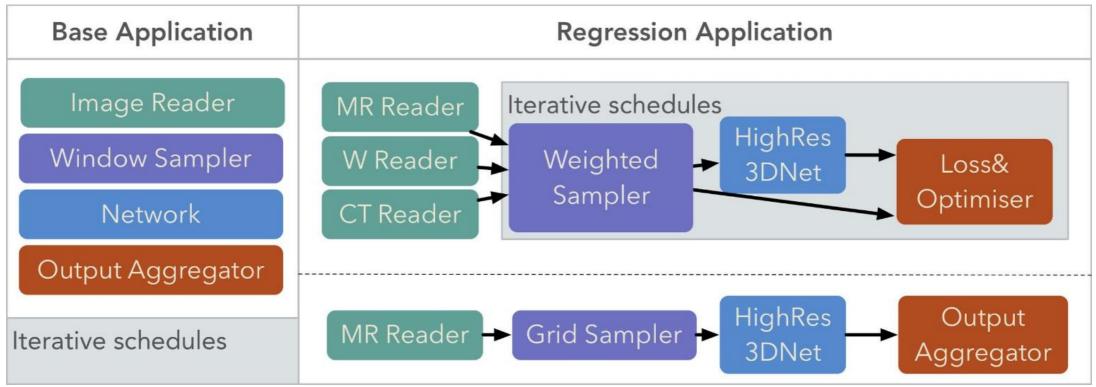




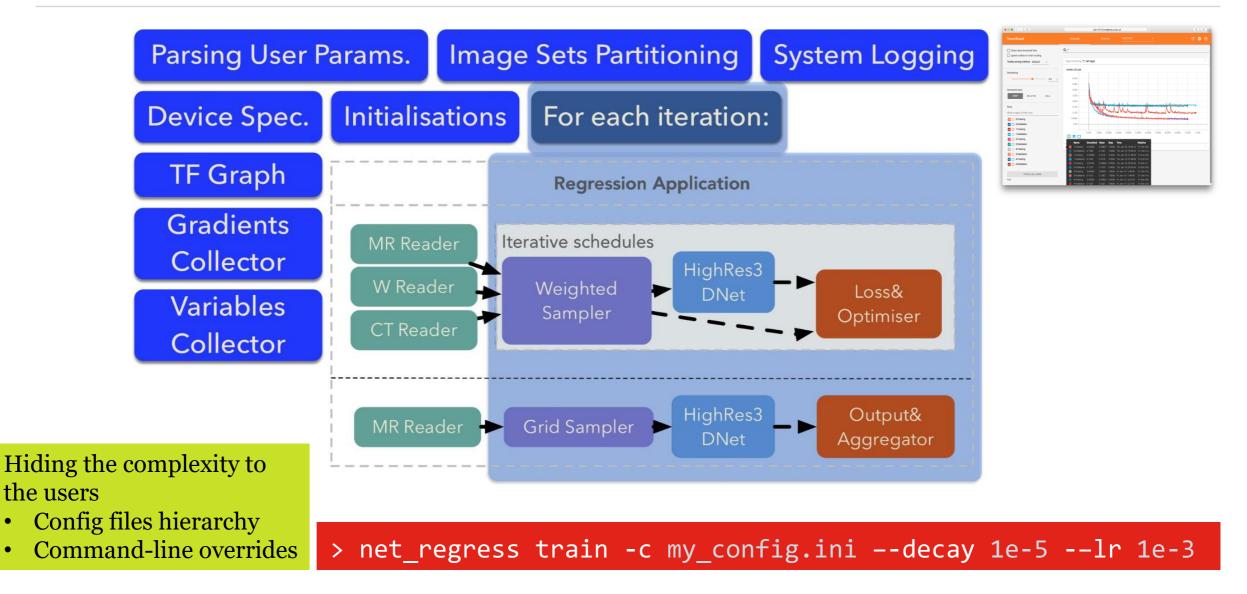
- data augmentation
- window sampling/aggregation
- loss function
- optimisation methods

MR to CT synthesis – Application overview

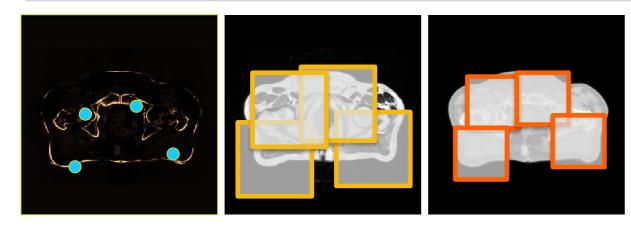




MR to CT synthesis – Added implementation complexity

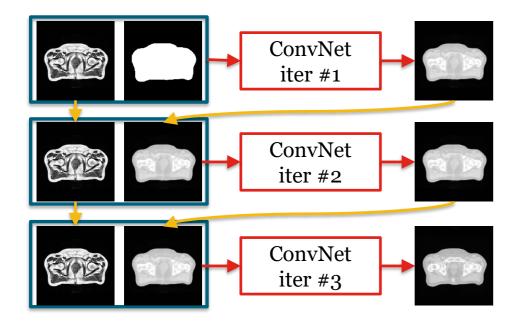


MR to CT synthesis – Advanced algorithms

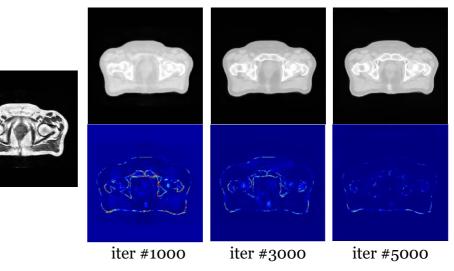


Berger et al., arXiv: 1709.02764

Weighted sampling Error maps from the previous iterations as sampling weights



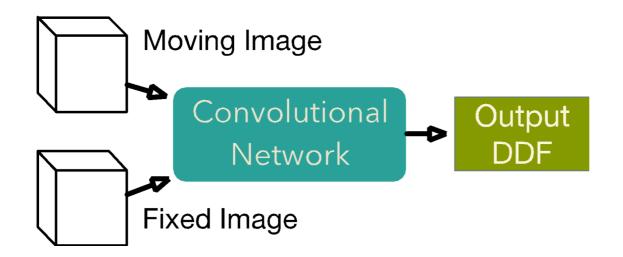
"Autocontext"

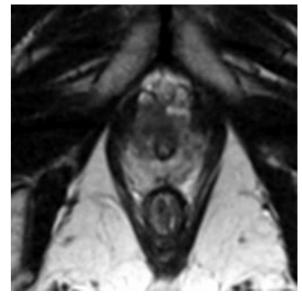


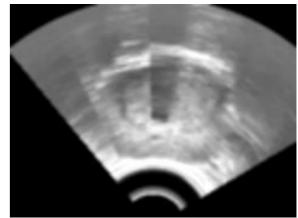


Beyond regression/segmentation/classification – MR to US registration

Hu et al., MedIA 21018 and arXiv: 1711.01666 (2018).

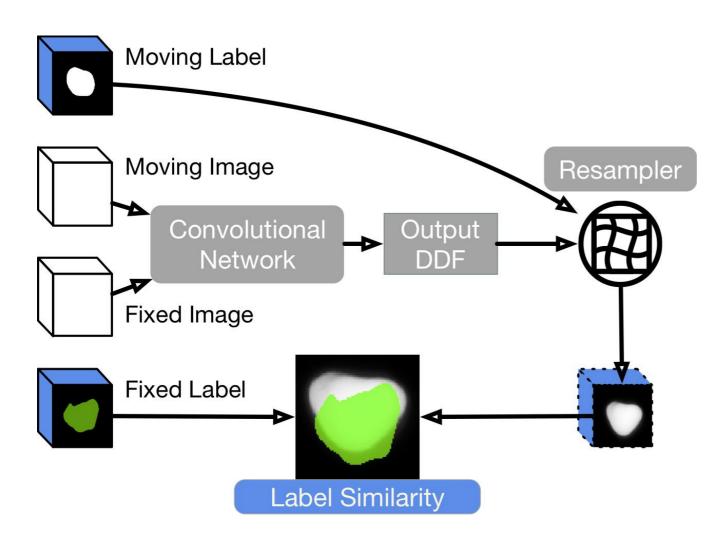


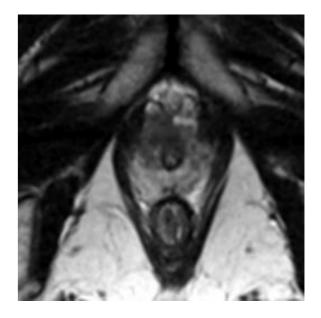


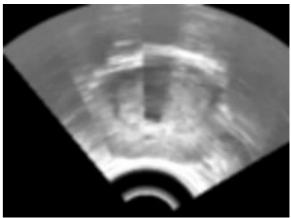


Beyond regression/segmentation/classification – MR to US registration

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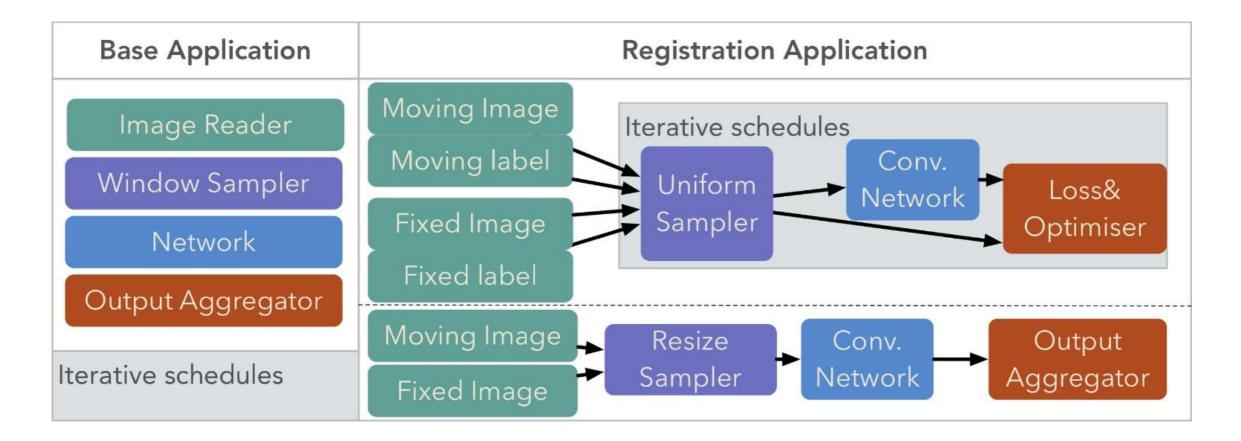




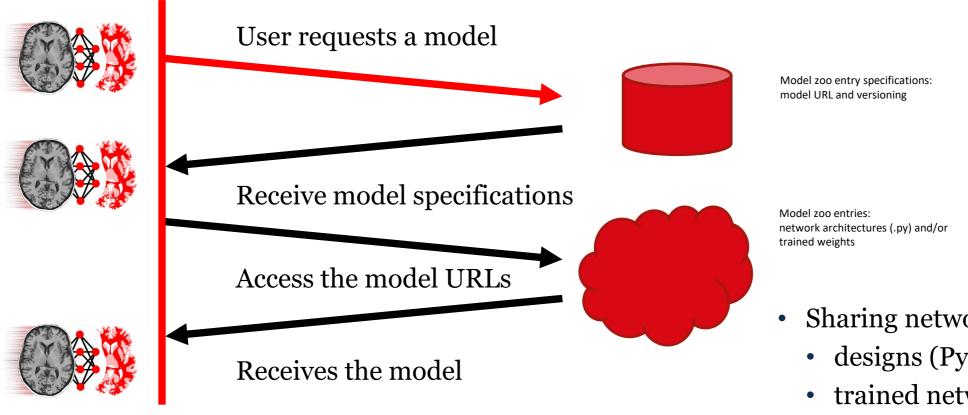


Designing new applications with NiftyNet

> net_run train -c my_config.ini -a registration_app



Model zoo



pip install niftynet tensorflow

net_download dense_vnet_abdominal_ct_model_zoo

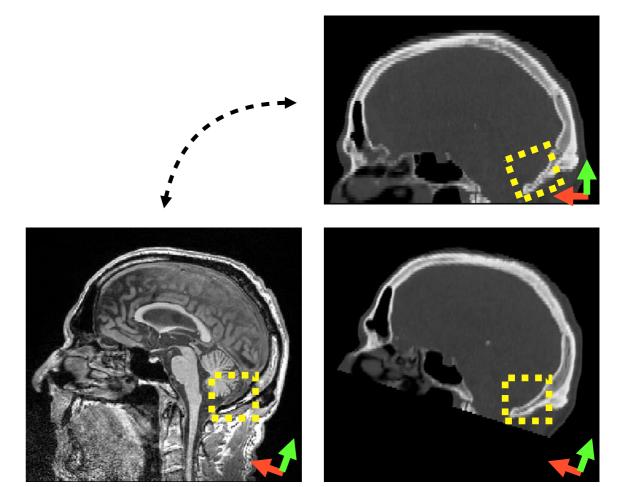
net_segment inference -c ./dense_vnet_abdominal_ct/config.ini

Sharing networks/apps

- designs (Python code)
- trained network weights
- hyperparameters
- demo input data
- Readme file

I/O: Image Loader

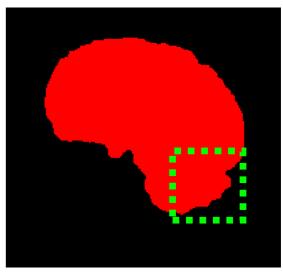
- Multi image-format loader
 - Uses tf.data API
- Supports multimodal inputs
 - Internally or externally
 - Resolution matching
- Handling a set of image volumes
 - Subject or filename grouping
 - Handling missing modalities
- Preprocessing
 - Handling NIfTI/MHD/DICOM file headers
 - Resampling
 - Reorientation
 - Lazy Sampling
 - Intensity normalisation
 - Physics/Model based



I/O: Window sampling and output aggregation

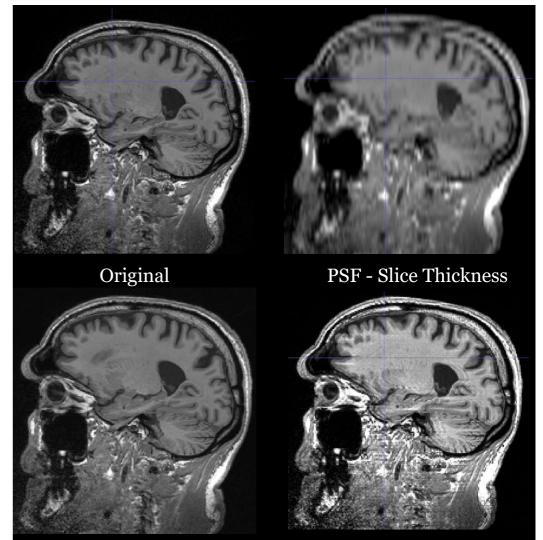
- Window properties
 - Size in "voxels" or "mm"
 - Augmentation by composition
- Sampling
 - Uniform
 - Label Constrained
 - Sample only from areas with specific labels
 - Prescribe certain label sampling rates
 - Frequency Sampler
 - Sample a location given an externally defined map
 - Sample from locations with large errors
- Aggregation
 - Uniform & Overlapping (Effective Receptive Field)
 - Uncertainty Sampling





I/O: Data augmentation

- Training with data augmentation
 - Application-dependent
- Geometrical augmentation
 - Rotation, Translation, Mirror
 - Random elastic deformation
 - Biologically-inspired elastic deformation
- Intensity augmentation
 - Histogram/Physics
 - Noise
 - Point-spread-function
 - Artefacts
 - Pathology/lesions

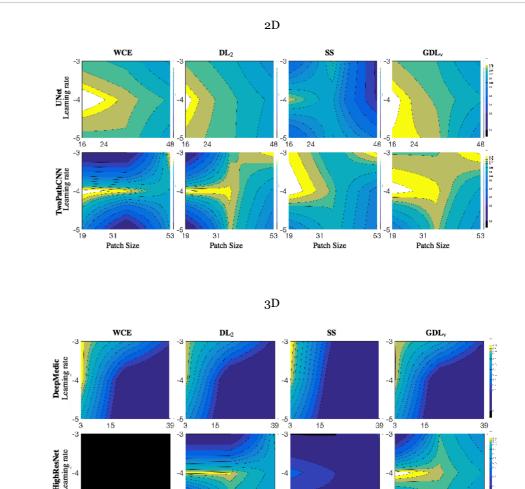


Random Elastic

Movement Artefacts

Network: Designing loss functions

- Losses:
 - Categorical
 - Cross-Entropy
 - Dice (Standard, Generalised, Wasserstein)
 - Sensitivity/Specificity
 - Continuous
 - L2/L1
 - Huber
 - Adversarial
 - Variational
 - KLD
- Loss Types
 - Image-wide (e.g. Classification/GAN)
 - Voxel-wise (e.g. Segmentation/Synthesis)
 - Weighted & probabilistic variants



27

Patch Size

40

27

Patch Size

40

15

49

27

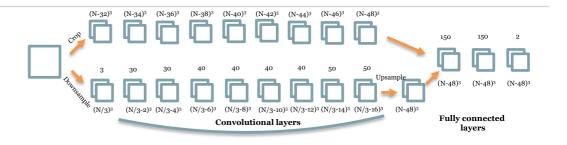
Patch Size

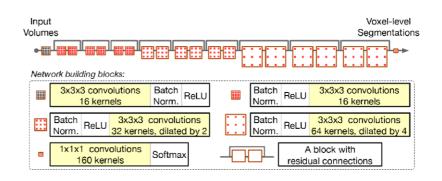
27

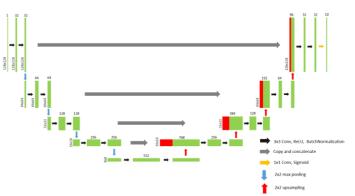
Patch Size

Network: Architectures

- Image-to-image: 2D, 3D, 4D (multimodal)
 - UNet
 - VNet
 - Highway Network
 - DeepMedic
 - HighResNet
- Generative/AutoEncoders
 - AE, dAE, VAE
 - GAN
- Image-to-label
- Multi-task Learning

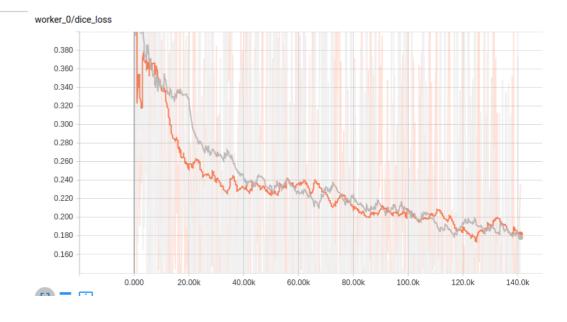


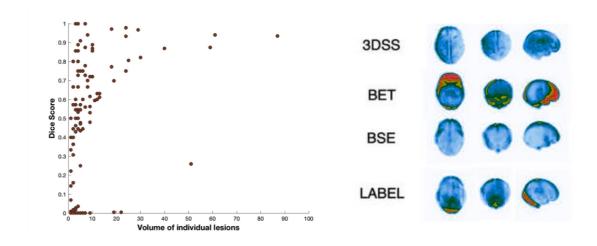




Evaluation: Standardised and validated

- Tensorboard Integration
- Image-level
 - Categorical
 - Overlap: Dice/Jaccard
 - Distance: Hausdorf/MSD
 - Statistical: Sensitivity/Specificity/Recovery
 - Continuous
 - Direct: Mean Absolute Error/L2
 - Perceptual: PSNR/SSIM
- Object Level (Categorical)
 - Volume: Size
 - Overlap, Distance and Statistical metrics
 - F1 stats
- Pixel-level
 - Generation of error maps
- Hyperparameter Optimisation
 - Grid, Random and Divide-and-Conquer Search





What next?

Checkout the repo. Run model zoo entries

Modify config. Run with your data

New networks Contributing to model zoo

New modules/tasks Send us pull requests

Thank you

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http://niftynet.io https://github.com/NifTK/NiftyNet

