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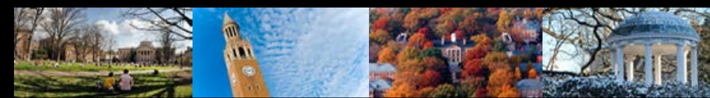

Deep Learning in Medical Imaging Analysis

Dinggang Shen, Ph.D.

IDEA Lab, Department of Radiology, and Biomedical Research Imaging Center (BRIC)
University of North Carolina at Chapel Hill

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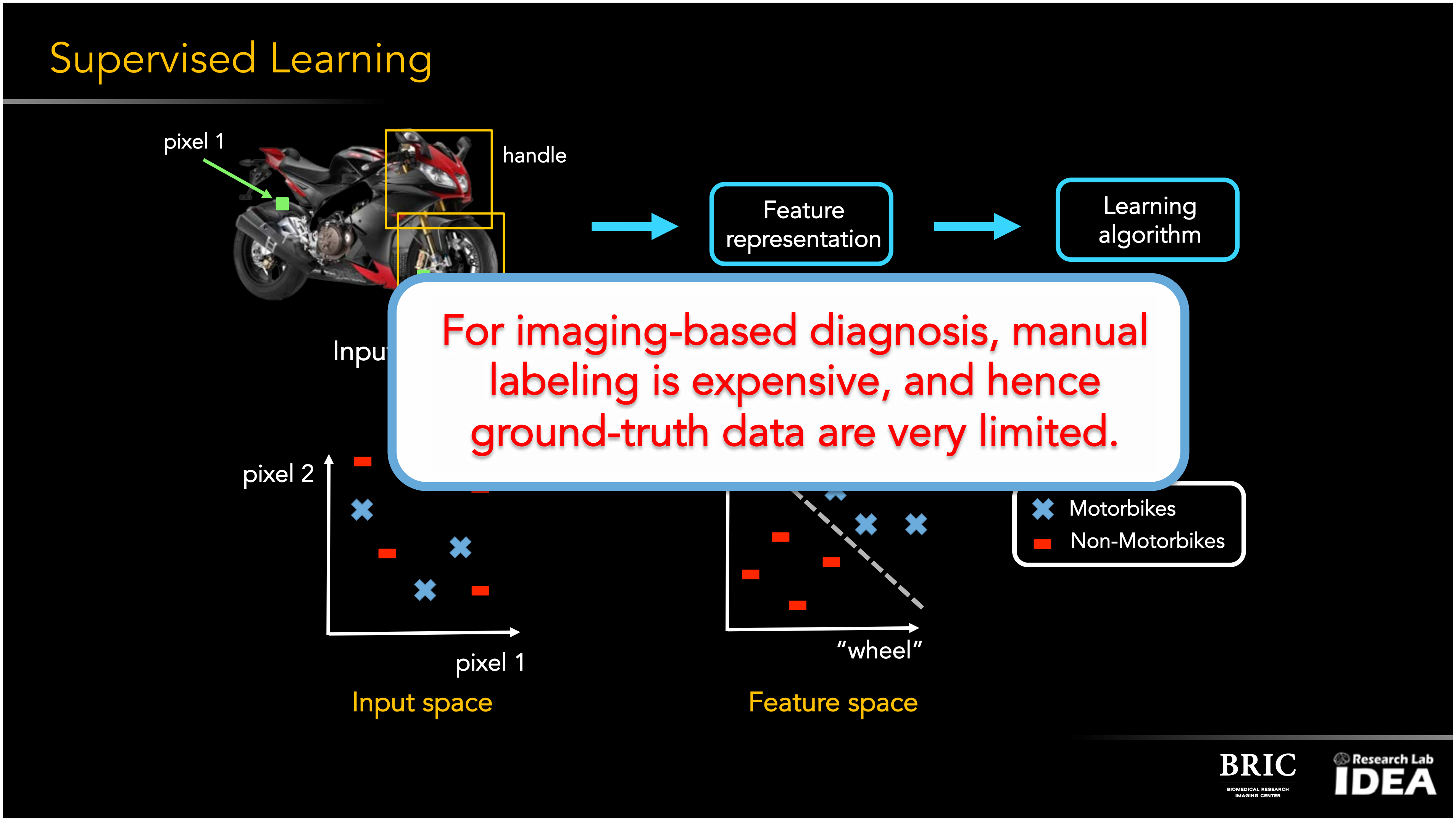
Deep Learning


Supervised Learning
pixel 1
handle
Feature representation
Learning algorithm
Input
For imaging-based diagnosis, manual labeling is expensive, and hence ground-truth data are very limited.
pixel 2
pixel 1
Input space
"wheel"
Feature space
Motorbikes
Non-Motorbikes
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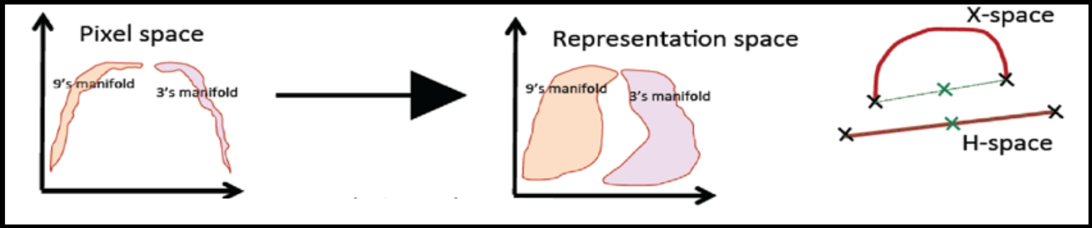
Unsupervised Learning

Method	Limitations
• PCA	✓ Linear ✓ Not optimal for non-Gaussian data
• Gaussian Mixture Models • K-Means	✓ Require knowledge for the number of clusters ✓ Challenging when applied to high-dimensional data
• ICA	✓ Linear model
• Sparse Coding • Non-Linear Embedding	✓ Shallow model (e.g., single-layer representation)

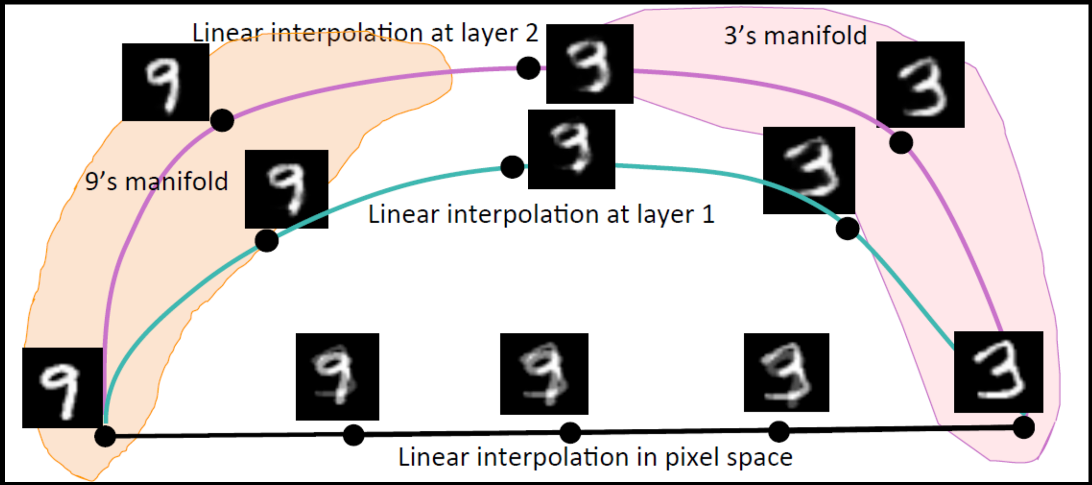
- All these methods involve just one step of mapping!
  → Mapping is shallow, not deep!
  → Thus, not able to represent the complex mapping!

Deep Learning – Why hot?

- Deep mapping and representation



Deeper representations
→ abstractions
→ disentangling



Manifolds are expanded and flattened

The following 5 slides edited from Dr. Yoshua Bengio's tutorial

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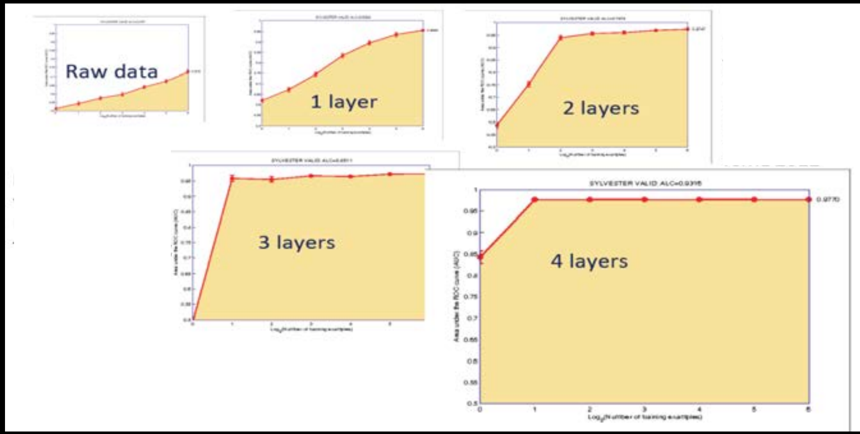
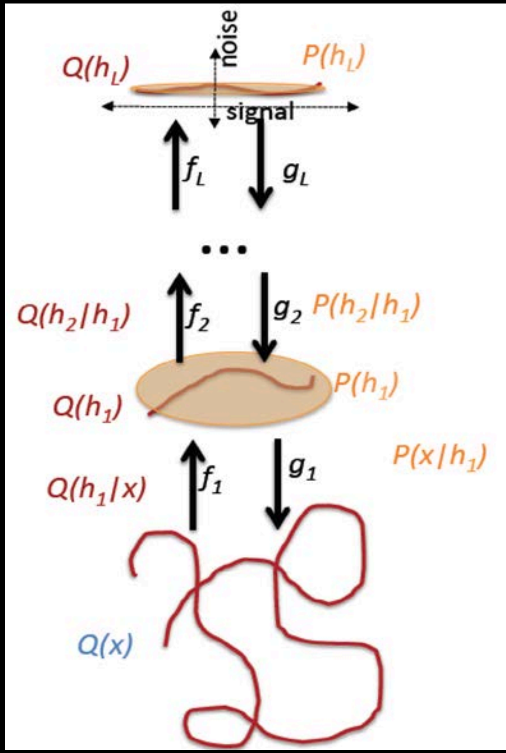
Deep Learning – Why hot?

- Deep mapping and representation
  - Each level transforms the data into a representation, which can be easily modeled
    → Unfolding it more will map the original data to a factorized (uniform-like) distribution

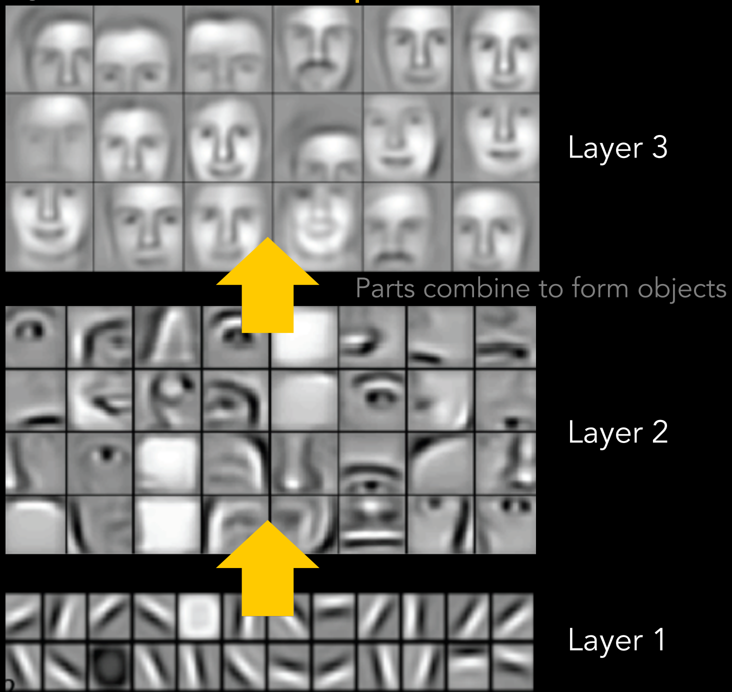


Performance increase with layers



Deep Learning – Why hot?

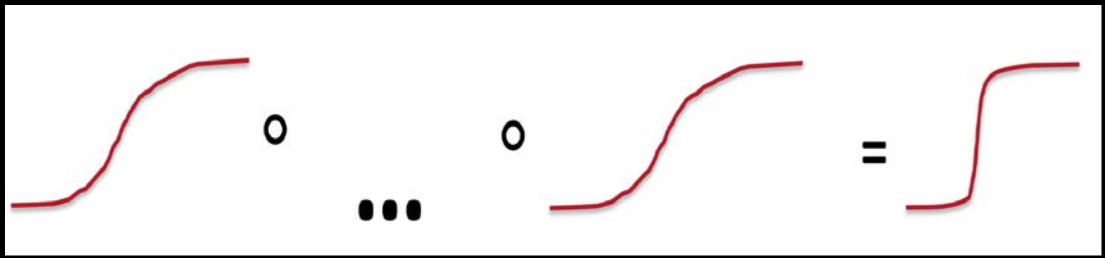
- Successive model layers learn deeper intermediate representations

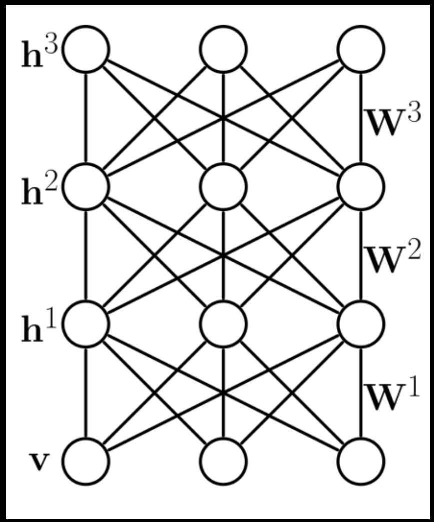


- Prior: Underlying factors and concepts compactly expressed without multiple levels of abstraction

Neural Network – Why not working

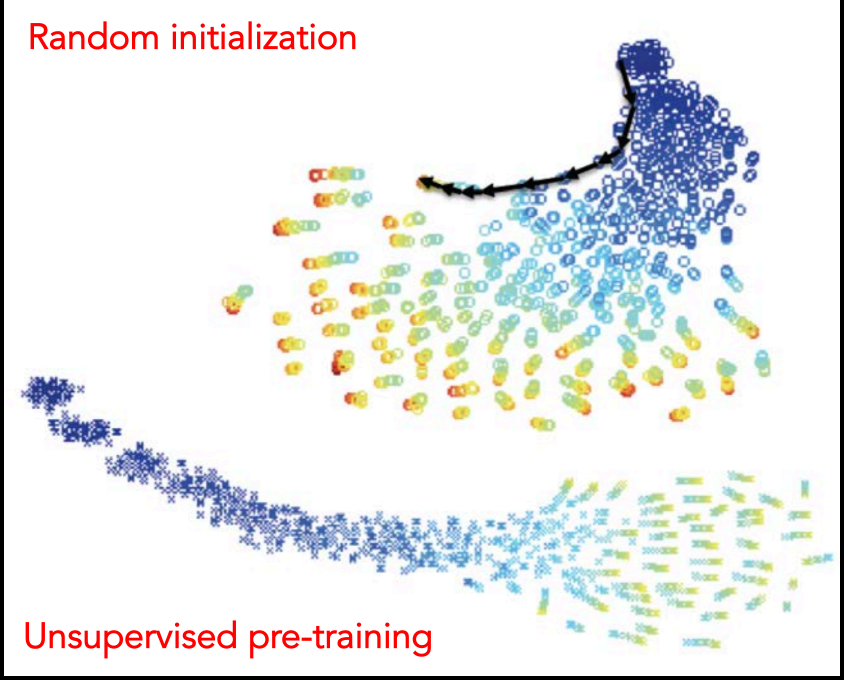
- Issues with previous neural network (NN)
  - Gradient-based method → propagate errors from the last layer to the previous layers
  - Last layer represents high nonlinear function (i.e., a jump function in binary classification) → unstable and large gradient in small range, but zero in most places





Neural Network – Why not working

- Effect of initial conditions in Deep Nets



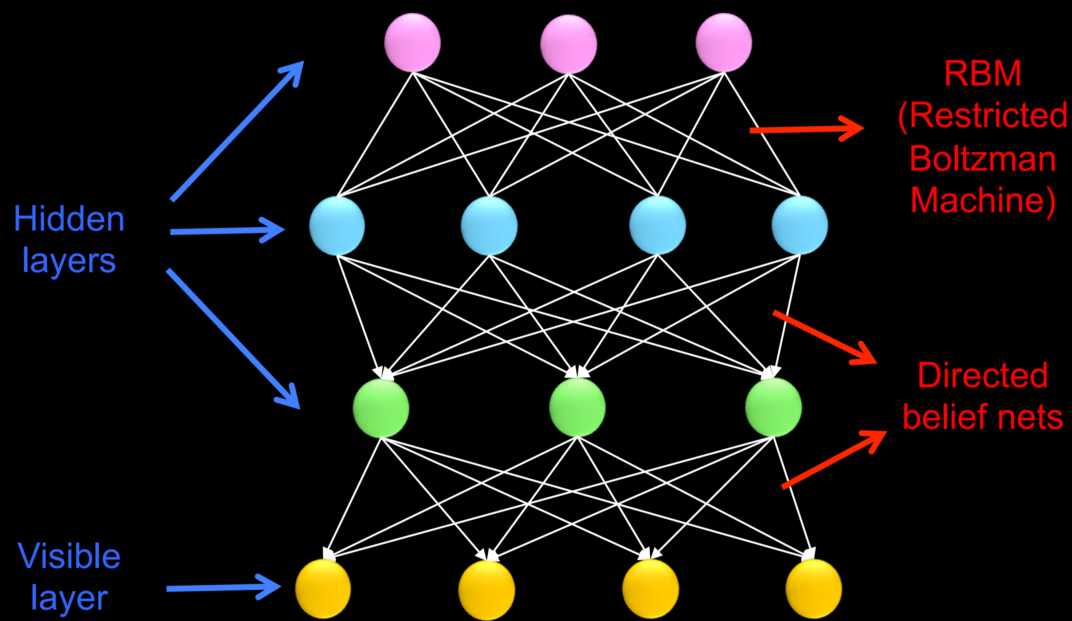
No two training trajectories end up in the same place → huge number of effective local minima

Pre-training: Transfer knowledge from previous learning (representation and explanatory factors) → cases with few examples → shared underlying explanatory factors, between P(X) and P(Y|X)

Deep Learning – Why working now

- Three main reasons
  - New layer-wise training algorithm [Science 2006]
    - Each time, train on simple task
  - Big data, compared to 20 years ago
  - Powerful computers
    - Previous algorithms may be theoretically working, but practically not converged to good local minima with the previous less-powerful computers

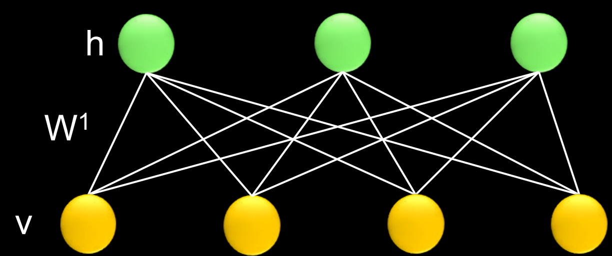
Deep Learning



$$P(v, h^1, h^2, \ldots, h^l) = P(v|h^1)\ P(h^1|h^2) \ldots P(h^{l-2}|h^{l-1})\ P(h^{l-1}, h^l)$$

Deep Learning – Greedy Training

- First step
  - Construct an RBM with an input layer v and a hidden layer h
  - Train the RBM



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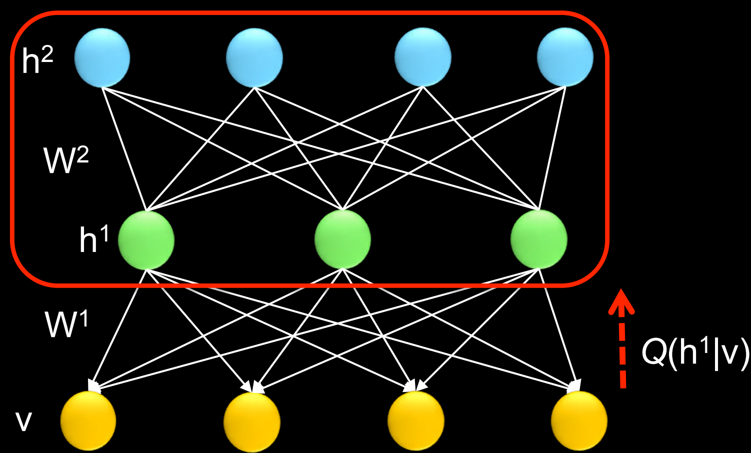
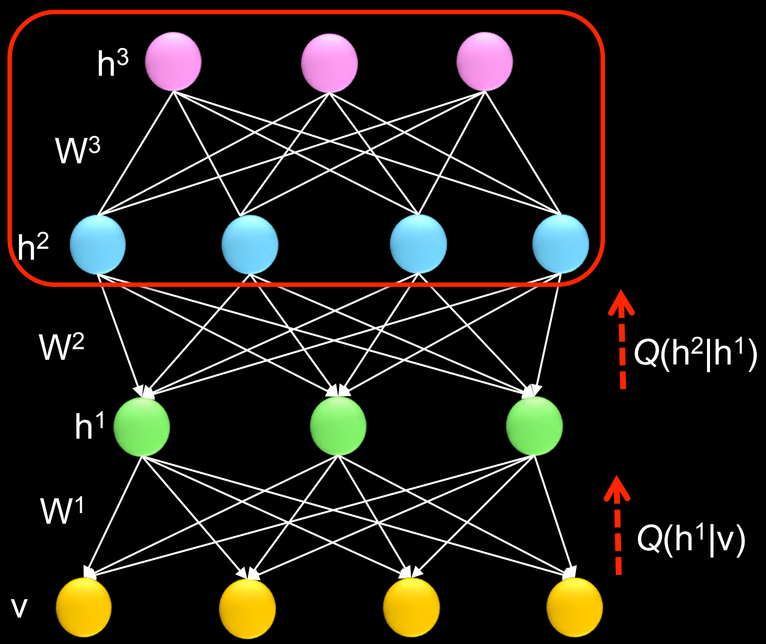
Deep Learning – Greedy Training

- Second step
  - Stack another hidden layer on top of the RBM to form a new RBM
  - Fix W^1, sample h^1 from $Q(h^1|v)$ as input
  - Train W^2 as RBM

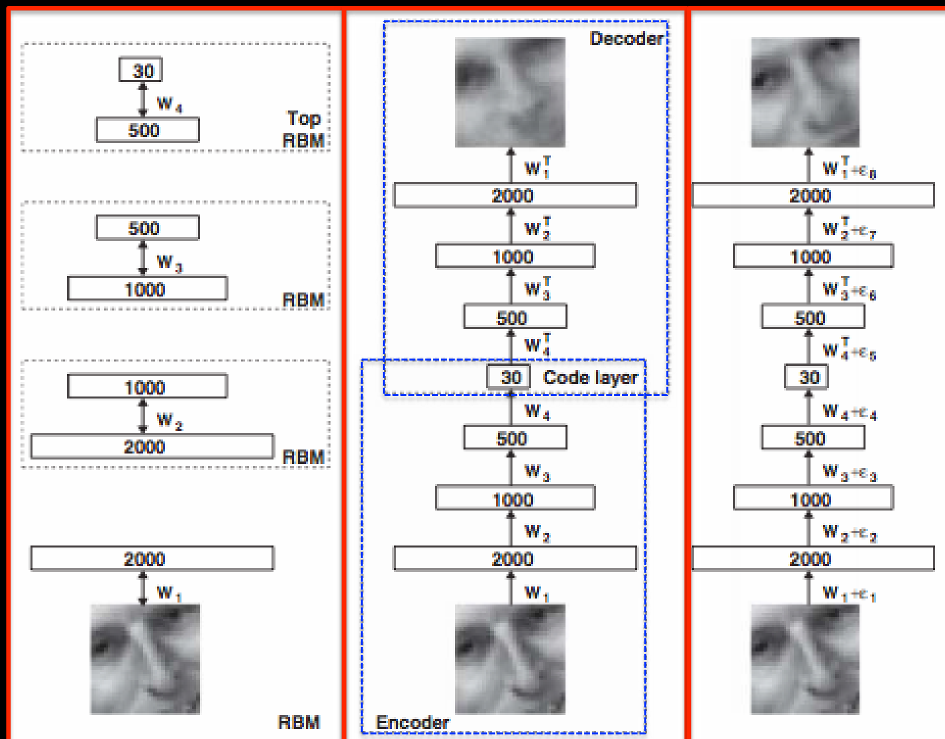


Deep Learning – Greedy Training

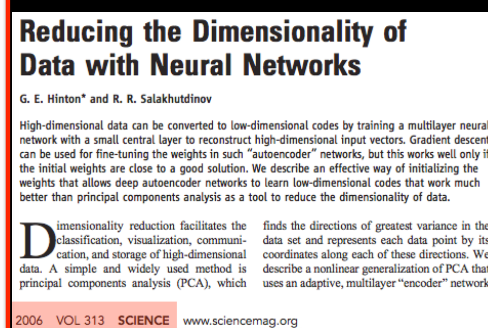
- Third step
  - Continue to stack layers on top of the network, and train it as previous step, with samples sampled from from $Q(h^2|h^1)$
- And so on…



Deep Learning – Stacked Auto-Encoder



Pretraining **Unrolling** **Fine-tuning**



Reducing the Dimensionality of Data with Neural Networks

G. E. Hinton* and R. R. Salakhutdinov

High-dimensional data can be converted to low-dimensional codes by training a multilayer neural network with a small central layer to reconstruct high-dimensional input vectors. Gradient descent can be used for fine-tuning the weights in such "autoencoder" networks, but this works well only if the initial weights are close to a good solution. We describe an effective way of initializing the weights that allows deep autoencoder networks to learn low-dimensional codes that work much better than principal components analysis as a tool to reduce the dimensionality of data.

Dimensionality reduction facilitates the classification, visualization, communication, and storage of high-dimensional data. A simple and widely used method is principal components analysis (PCA), which finds the directions of greatest variance in the data set and represents each data point by its coordinates along each of these directions. We describe a nonlinear generalization of PCA that uses an adaptive, multilayer "encoder" network

2006 VOL 313 SCIENCE www.sciencemag.org

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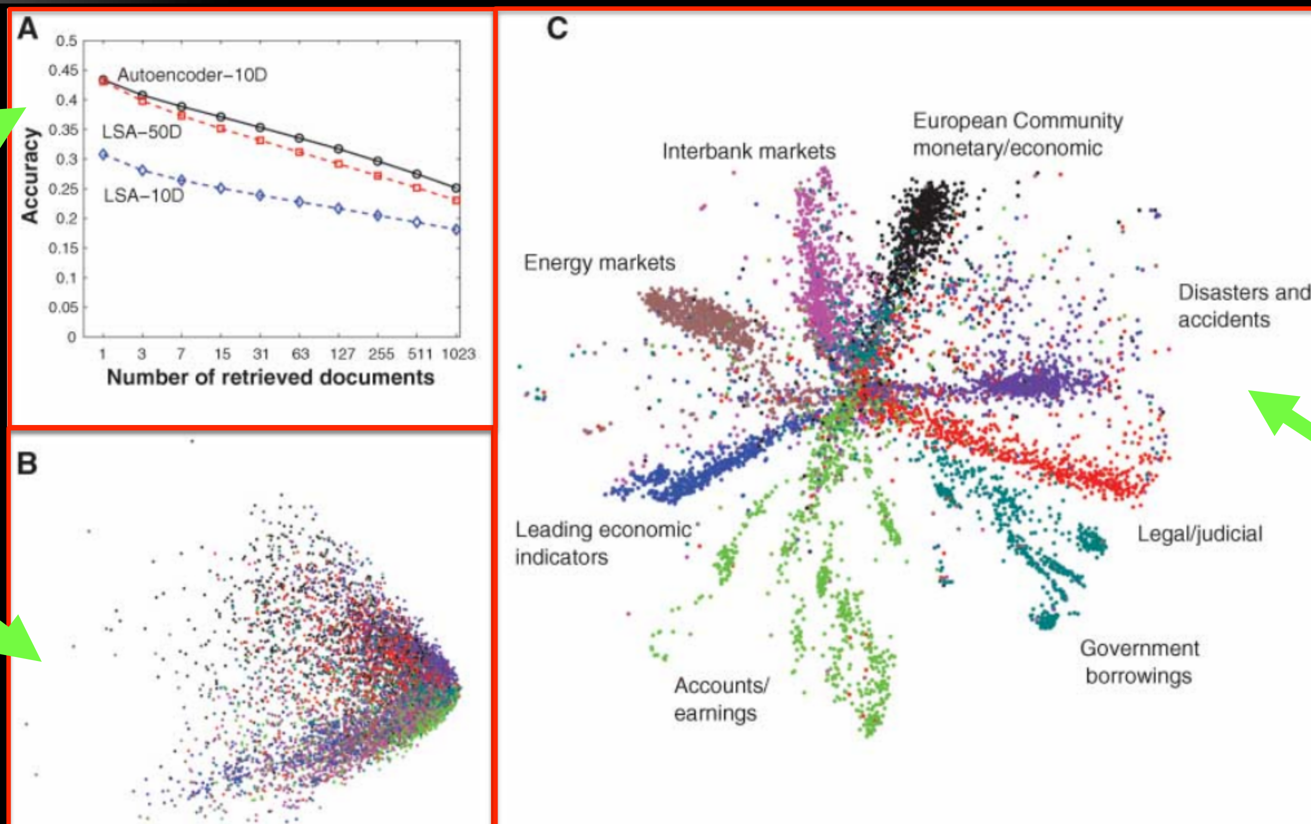
Deep Learning – Stacked Auto-Encoder

The fraction of retrieved documents



The codes produced by 2D LSA

The codes produced by a 500-250-125-2 Auto-Encoder

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Application 1

Segmentation

- Hippocampus Segmentation using 7T MRIs
- Infant Brain Segmentation

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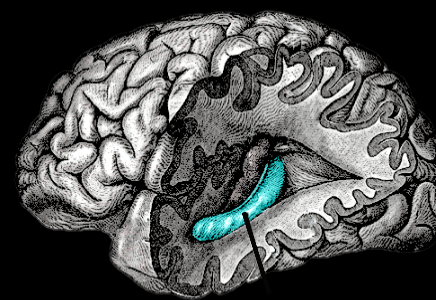
Hippocampus Segmentation

Hippocampus Segmentation Using 7T MR Images

Hippocampus Segmentation

- Challenges in hippocampus segmentation using 1.5T/3T and 7T



1.5T/3T (1 x 1 x 1 mm³)

7.0T (0.35 x 0.35 x 0.35 mm³)

- Low imaging resolution
- Low contrast

- Much richer structural information
- Less partial volume effect
- But, severe intensity inhomogeneity problem

M. Kim, G. Wu, D. Shen, "Unsupervised Deep Learning for Hippocampus Segmentation in 7.0 Tesla MR Images," *MLMI*, 2013.

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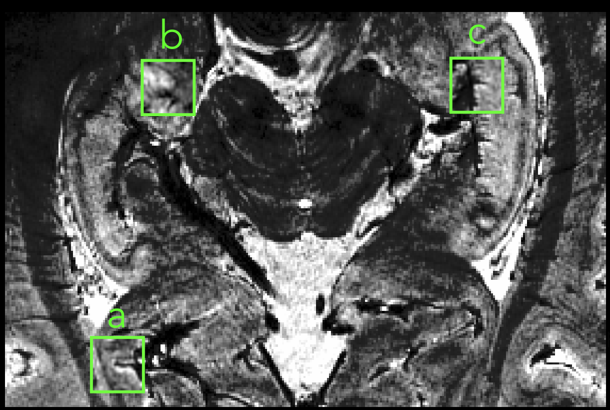
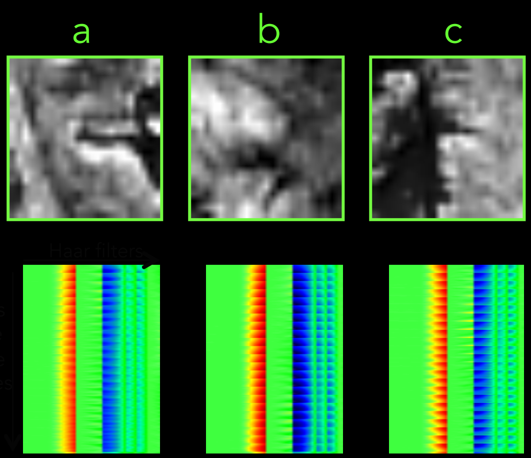
Hand-Crafted Features

- Limited discriminative power of hand-crafted features



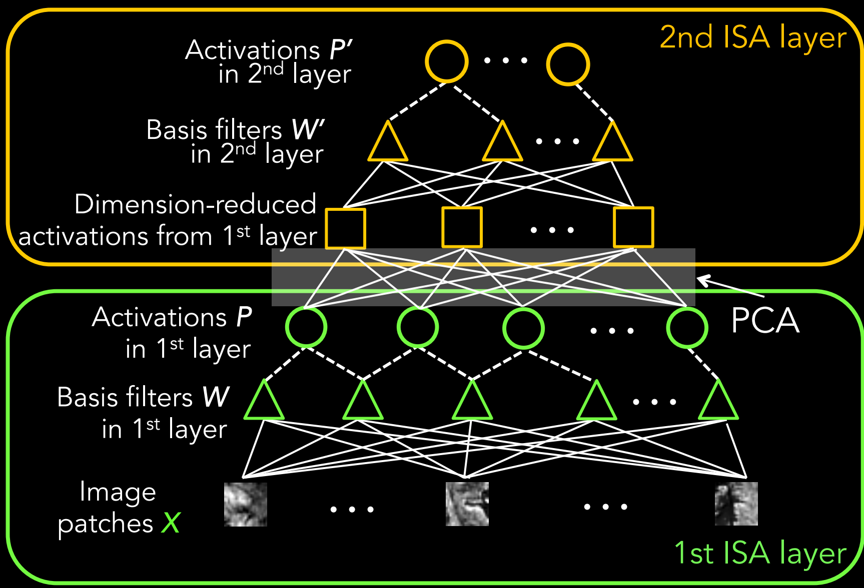
Extracting patches from a 7T MR image

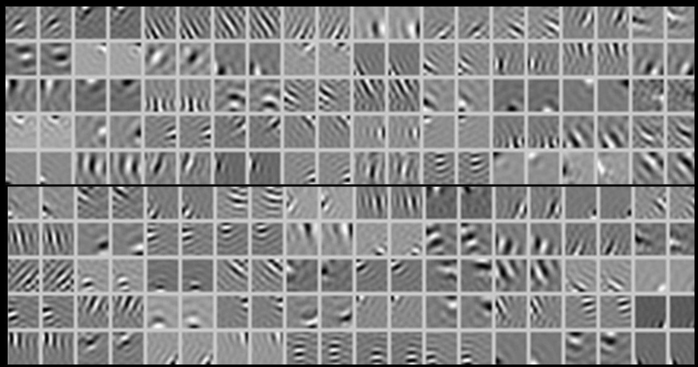


Responses of Haar filters for the image patches

Hierarchical Feature Extraction via Unsupervised Deep Learning

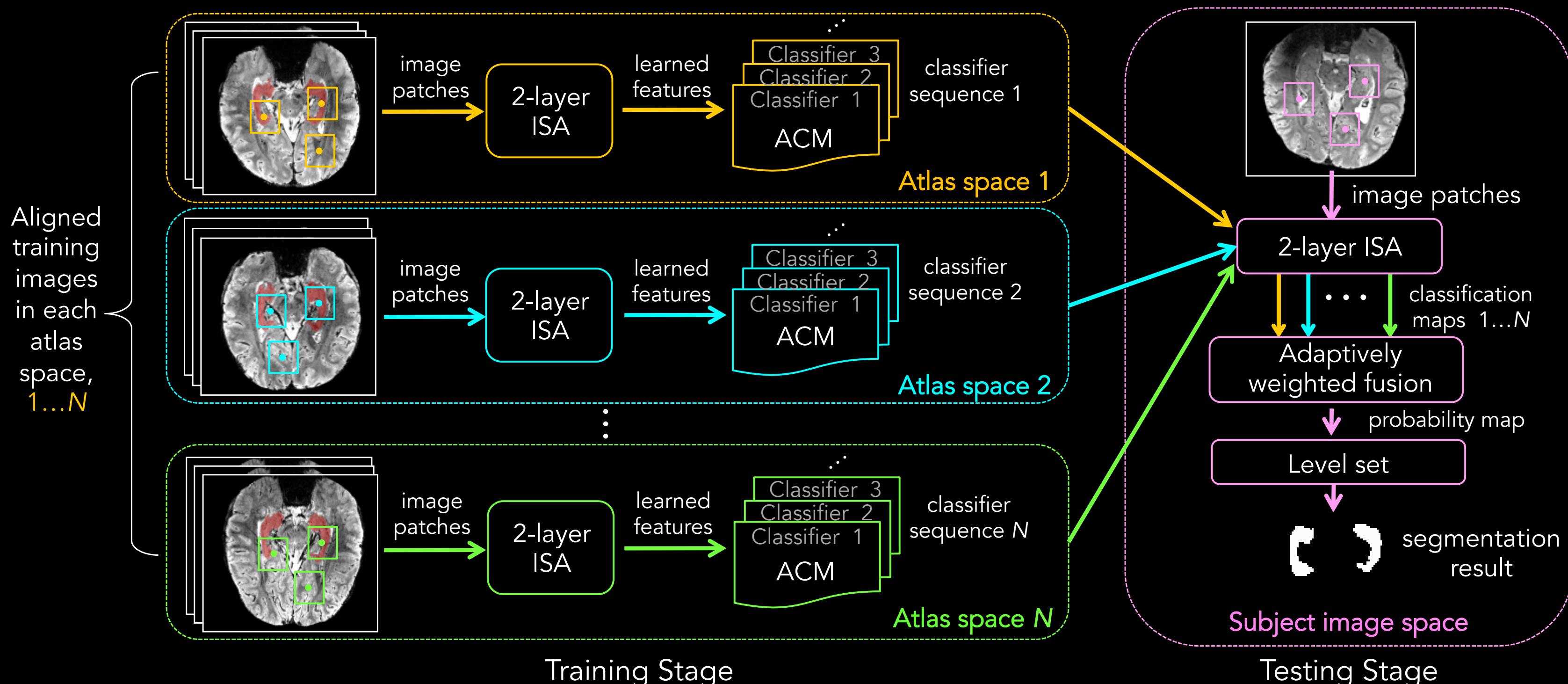
- Stacked two-layer convolutional ISA (Independent Subspace Analysis)





Learned basis filters by the 1st ISA

Multi-Atlas-based Segmentation using Deep Learning Features



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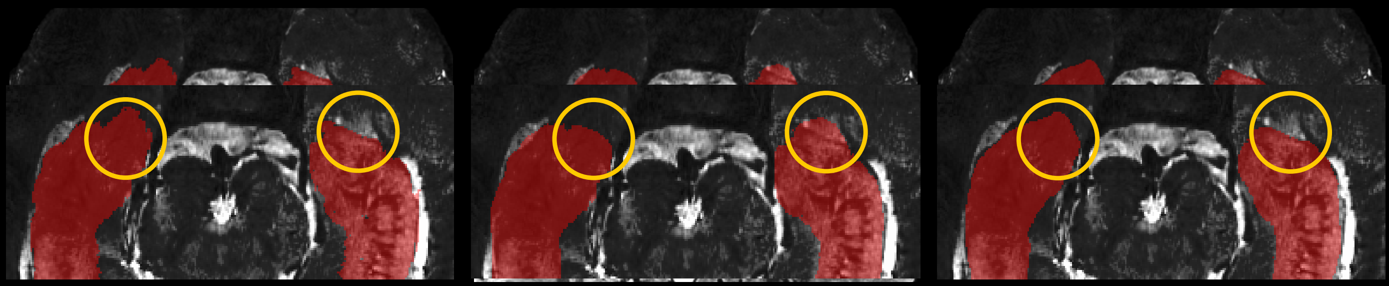
Results



Ground Truth | Haar + Texture Features | Hierarchical Features

Comparison Results Using 20 Leave-One-Out Cases

	P	R	RO	SI
Hand-Crafted Haar + Texture Features	0.843	0.847	0.772	0.865
Hierarchical Patch Representations	0.883	0.881	0.819	0.894

P = Precision; R = Recall; RO = Relative overlap; SI = Similarity index

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Infant Brain Segmentation

Multi-modality Isointense Infant Brain Image Segmentation

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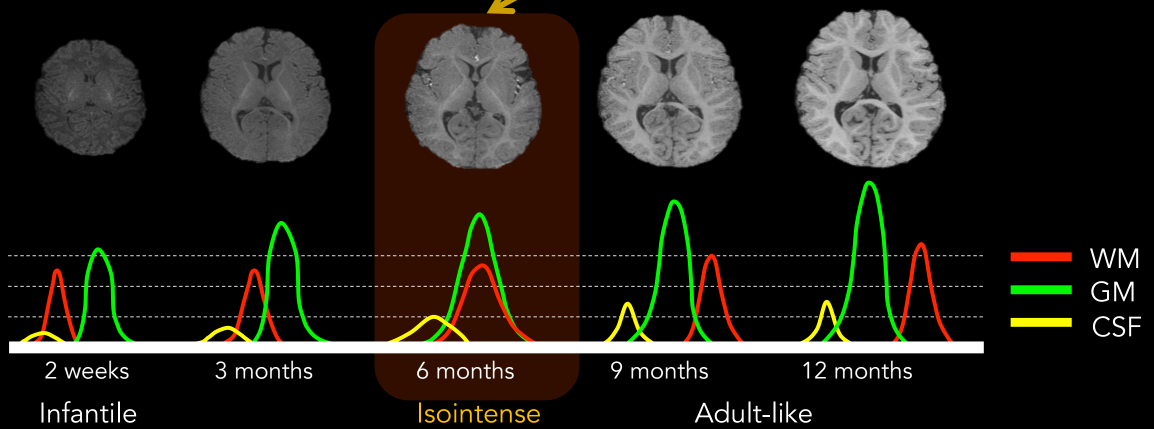
Infant Brain Segmentation

- Challenges in infant brain segmentation
  - Low tissue contrast
  - Low spatial resolution

WM and GM exhibit almost the same level of intensity in both T1 and T2 MR images



W. Zhang, R. Li, H. Deng, L. Wang, W. Lin, S. Ji, D. Shen, "Deep Convolutional neural networks for multi-modality isointense infant brain image segmentation," *Neuroimage*, 2015.

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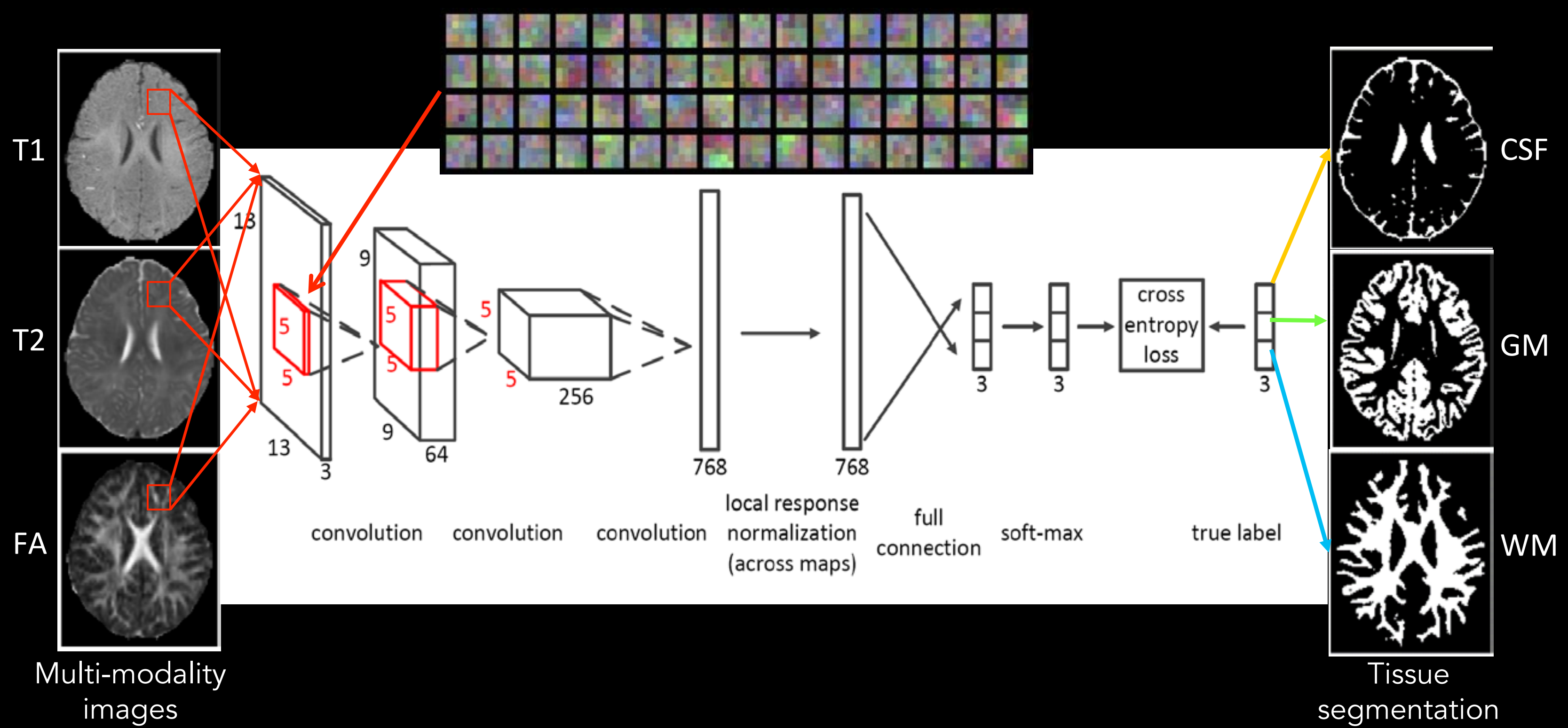
Deep Convolutional Neural Network (CNN)



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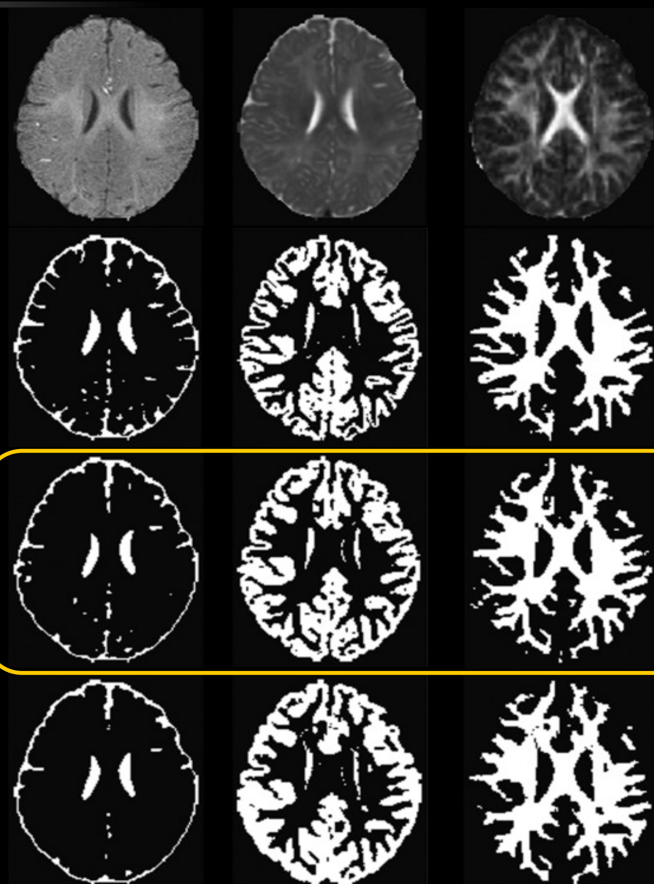
Results

Segmentation performance in terms of Dice ratio achieved by the CNN, RF, SVM, CLS, MV

		Subj. 1	Subj. 2	Subj. 3	Subj. 4	Subj. 5	Subj. 6	Subj. 7	Subj. 8
CSF	CNN	0.83	0.83	0.83	0.84	0.85	0.85	0.82	0.83
	RF	0.82	0.81	0.83	0.81	0.83	0.85	0.79	0.80
	SVM	0.74	0.77	0.77	0.74	0.70	0.78	0.72	0.73
	CLS	0.81	0.82	0.73	0.86	0.84	0.82	0.81	0.83
	MV	0.71	0.69	0.68	0.63	0.63	0.61	0.69	0.69
GM	CNN	0.85	0.86	0.88	0.82	0.81	0.87	0.86	0.86
	RF	0.83	0.85	0.88	0.81	0.80	0.85	0.85	0.84
	SVM	0.79	0.80	0.83	0.75	0.74	0.80	0.80	0.80
	CLS	0.83	0.84	0.85	0.83	0.81	0.87	0.86	0.84
	MV	0.85	0.84	0.85	0.80	0.78	0.80	0.84	0.83
WM	CNN	0.88	0.81	0.88	0.85	0.87	0.87	0.87	0.88
	RF	0.86	0.78	0.87	0.84	0.85	0.86	0.84	0.84
	SVM	0.82	0.74	0.76	0.80	0.80	0.79	0.71	0.76
	CLS	0.84	0.81	0.80	0.82	0.84	0.82	0.83	0.81
	MV	0.86	0.80	0.85	0.82	0.84	0.84	0.84	0.84

CNN: Convolutional Neural Network
RF: Random Forest
SVM: Support Vector Machine
CLS: Coupled Level Sets
MV: Majority Voting

Results



Original multi-modality data (T1, T2 and FA)

Manual segmentations (CSF, GM, and WM)

Segmentation results by CNN

Segmentation results by RF

Application 2

Registration

- Brain MRI Registration

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Brain MRI Registration

Feature-based Symmetric Registration of Brain MR Images

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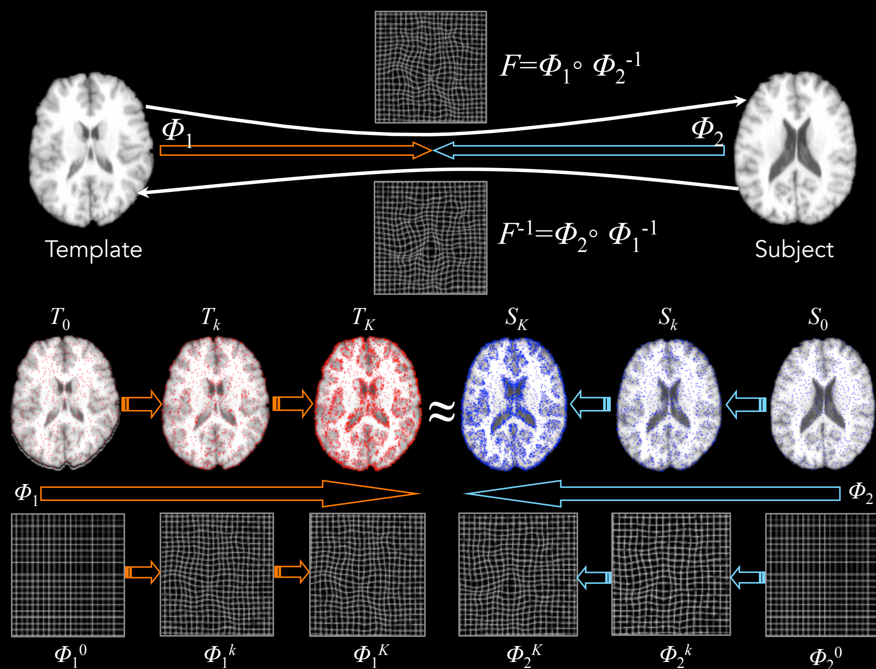
Feature-based Symmetric Image Registration

- S-HAMMER (Symmetric HAMMER)



G. Wu, M. Kim, Q. Wang, B.C. Munsell, D. Shen, "Scalable High Performance Image Registration Framework by Unsupervised Deep Feature Representations Learning", *IEEE TBME*, 2015.

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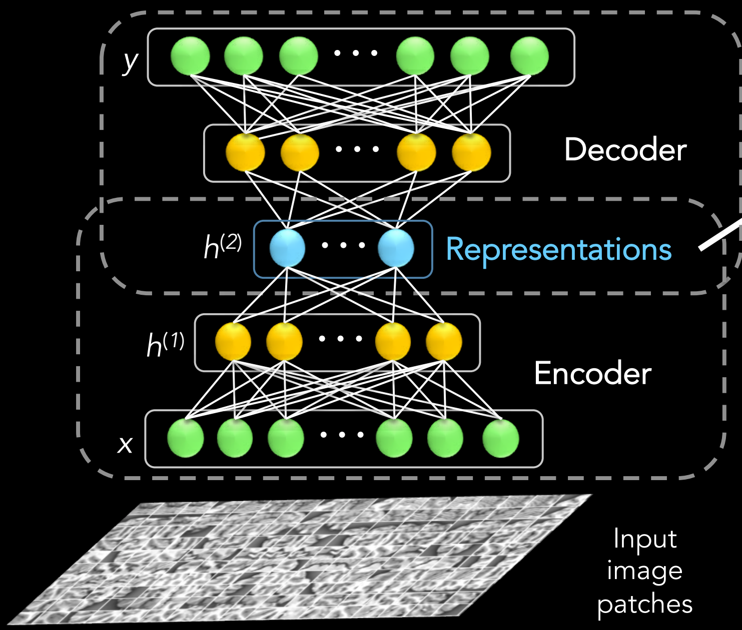
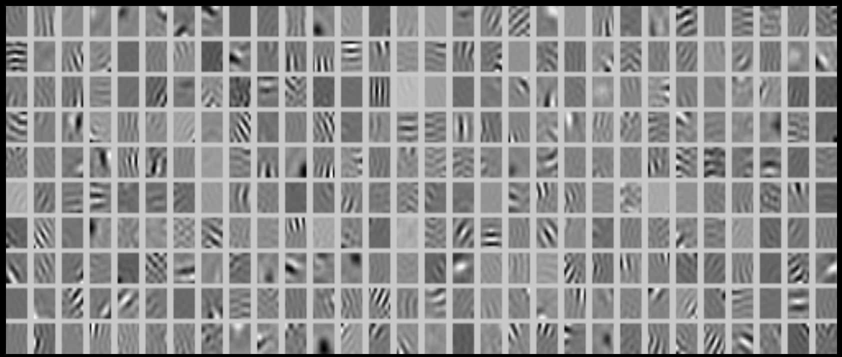
Stacked Auto-Encoder (SAE)

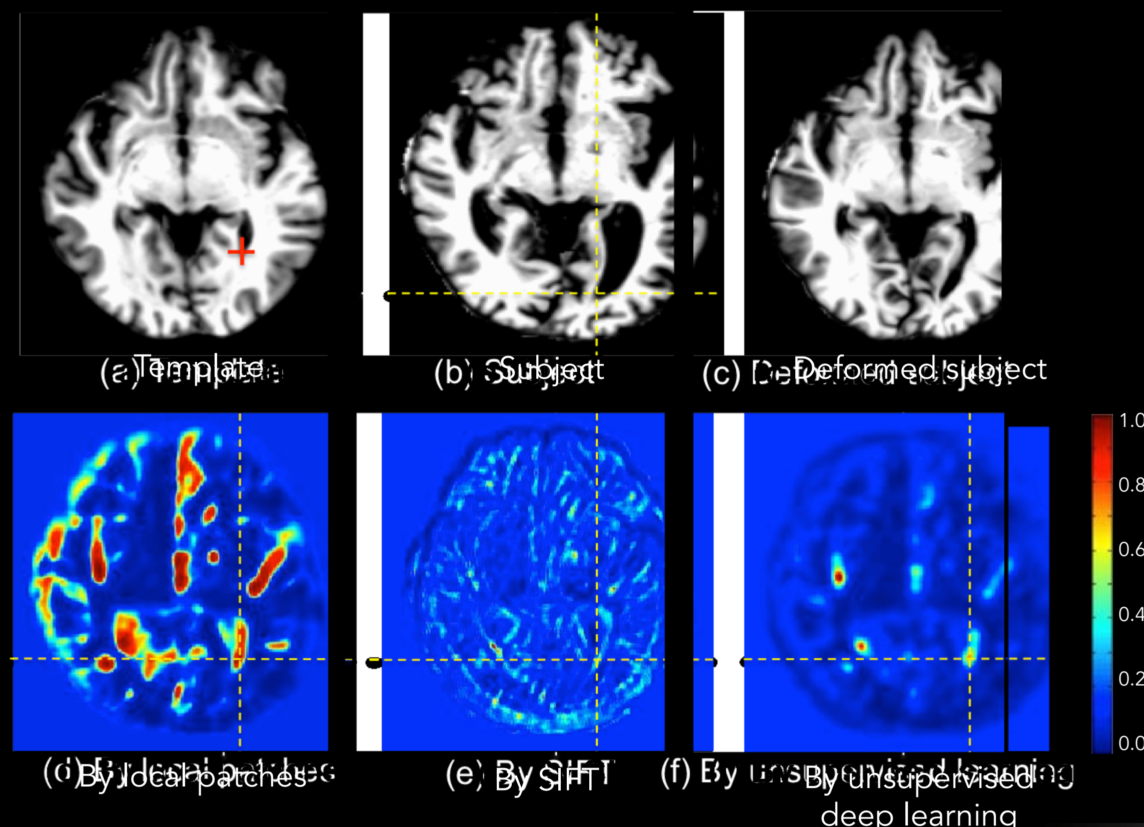


Morphological **signatures** for image registration



Features learned in the first layer

Deep Learning based Intrinsic Features



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Results

Dice ratios of WM, GM, and VN on ADNI dataset (%)

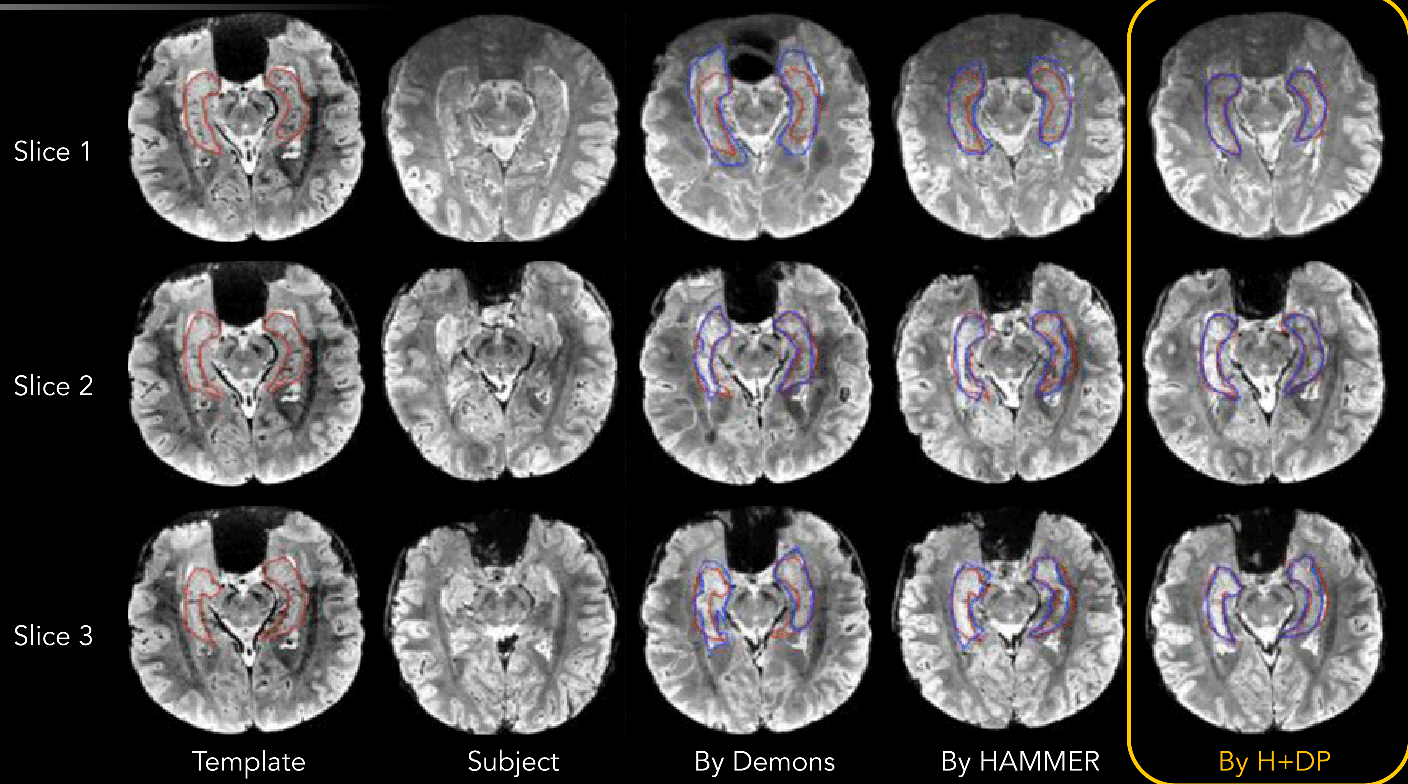
Methods	VN	GM	WM	Overall
Demons	90.2	76.0	85.7	84.0
M+PCA	90.5	76.6	85.5	84.1
M+DP	90.9	76.5	85.8	84.4
HAMMER	91.5	75.5	85.4	84.1
H+PCA	91.7	76.9	86.5	85.0
H+DP	95.0	78.6	88.1	86.6

Averaged Dice ratios of 54 ROIs on LONI LPBA40 dataset (%)

Methods	Average
Demons	68.9
M+PCA	68.9
M+DP	69.2
HAMMER	70.2
H+PCA	70.6
H+DP	72.7

Demons: Diffeomorphic Demons
M+PCA: Multi-channel Demons + PCA
M+DP: Multi-channel Demons + Deep learning
H+PCA: HAMMER + PCA
H+DP: HAMMER + Deep learning

Results



Registration results on 7T MRI brain images

The overlap ratio for hippocampus:
68.5% → 78.4%

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Application 3

Disease Diagnosis

- AD/MCI Diagnosis
- CADx for Lung Nodules and Breast Lesions

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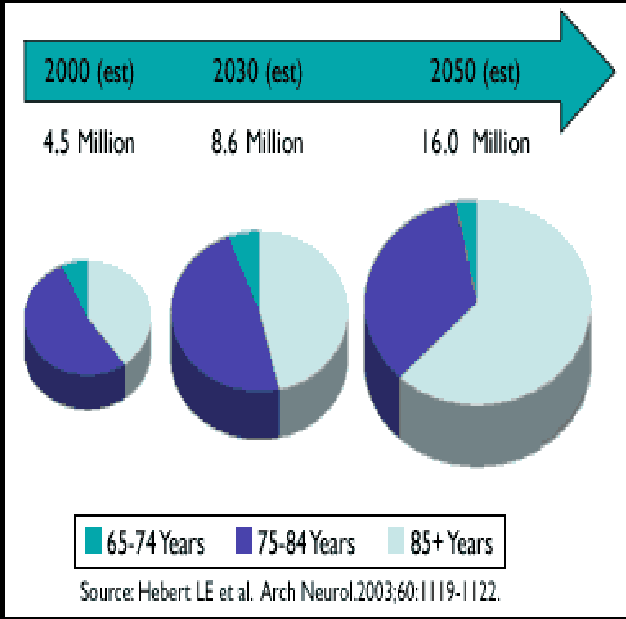
AD/MCI Diagnosis

Classification of Alzheimer's Disease and Mild Cognitive Impairment

Alzheimer's Disease (AD)

- The most common form of dementia
  - An irreversible neurodegenerative disease that causes disruptions in memory, cognition, and eventually death
  - A growing epidemic: Worldwide, nearly 44 million people are living with AD
  - Cannot delay or halt the progression of AD

- Prodromal stage of AD: Mild Cognitive Impairment (MCI)



Forecast of prevalence AD in the US

Computer-Aided Diagnosis for AD

- Neuroimaging modalities for diagnosis
  - MRI, PET, fMRI, …
- Previous works: simple low-level features
  - MRI: gray matter tissue volumes
  - PET: mean signal intensities
  - CSF: biomarker measures

➡ Vulnerable to noises and/or artifacts

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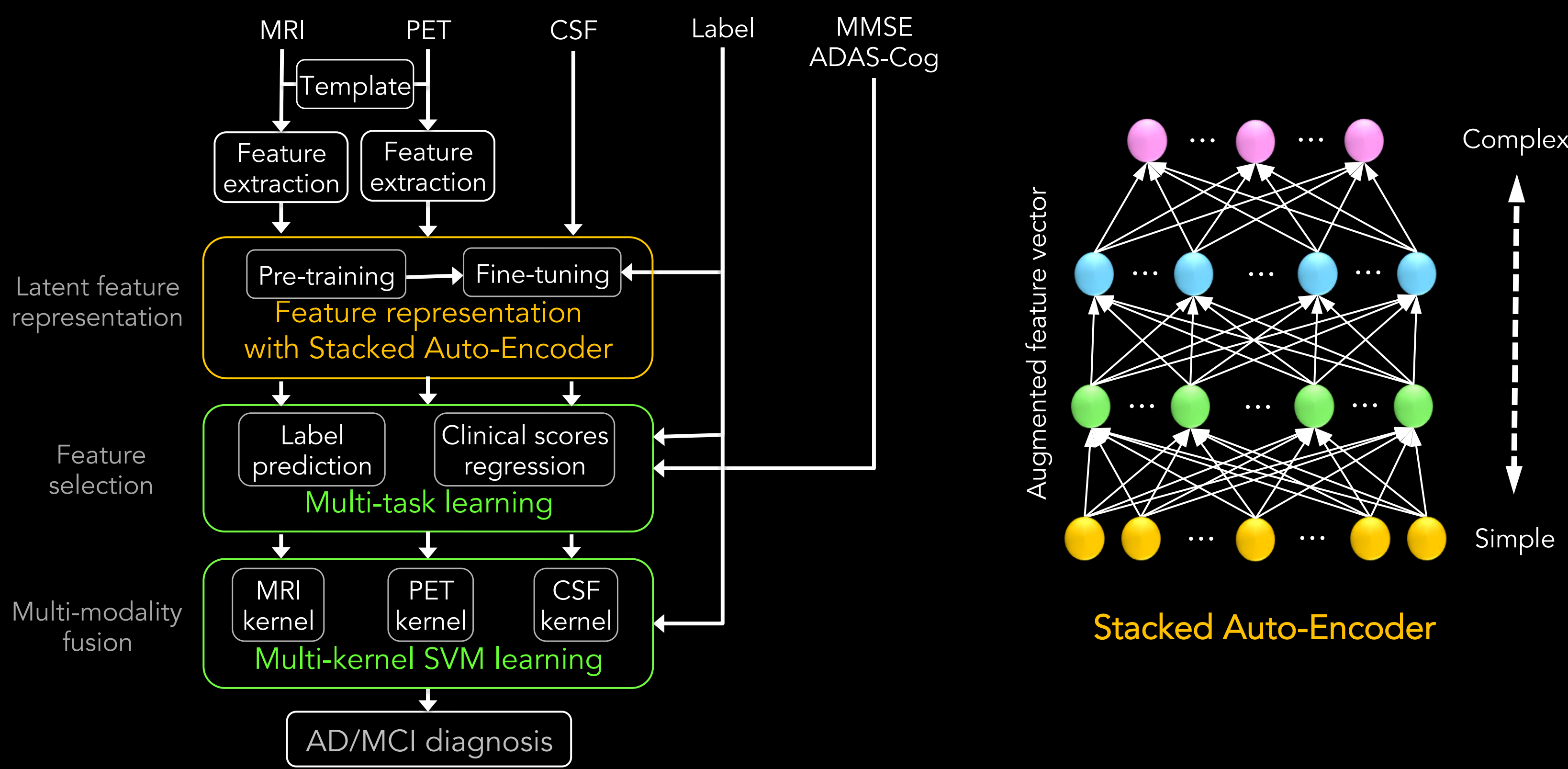
Latent Feature Representation

- Hidden or latent high-level information
  - Deep architecture can be efficiently used to discover latent or hidden representation in self-taught learning
  - Overcome the vulnerability to noise/artifacts in the data by encoding in a hierarchical feature space

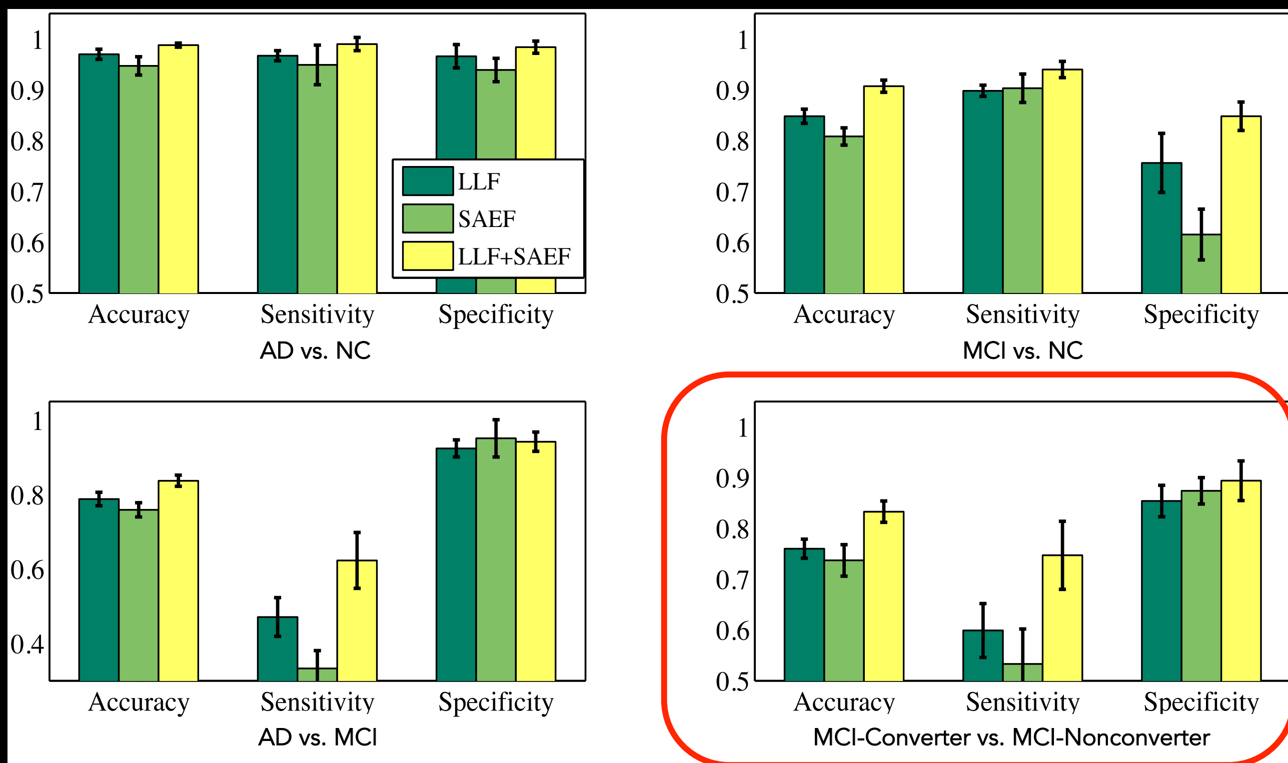
- Unsupervised greedy training
  - Allows us to benefit from the target-unrelated samples to discover general latent feature representations
  - Leverages for enhancement of the accuracy

H.-I. Suk, S.-W. Lee, D. Shen, "Latent Feature Representation with Stacked Auto-Encoder for AD/MCI Diagnosis", *Brain Structure and Function*, 2014.

Latent Feature Representation with SAE



Results



Classification results using ADNI dataset (51 AD, 52 HC, 43 MCI-C, 56 MCI-NC)

LLF: Low-Level Features
SAEF: SAE Features

Multi-Modal Fusion

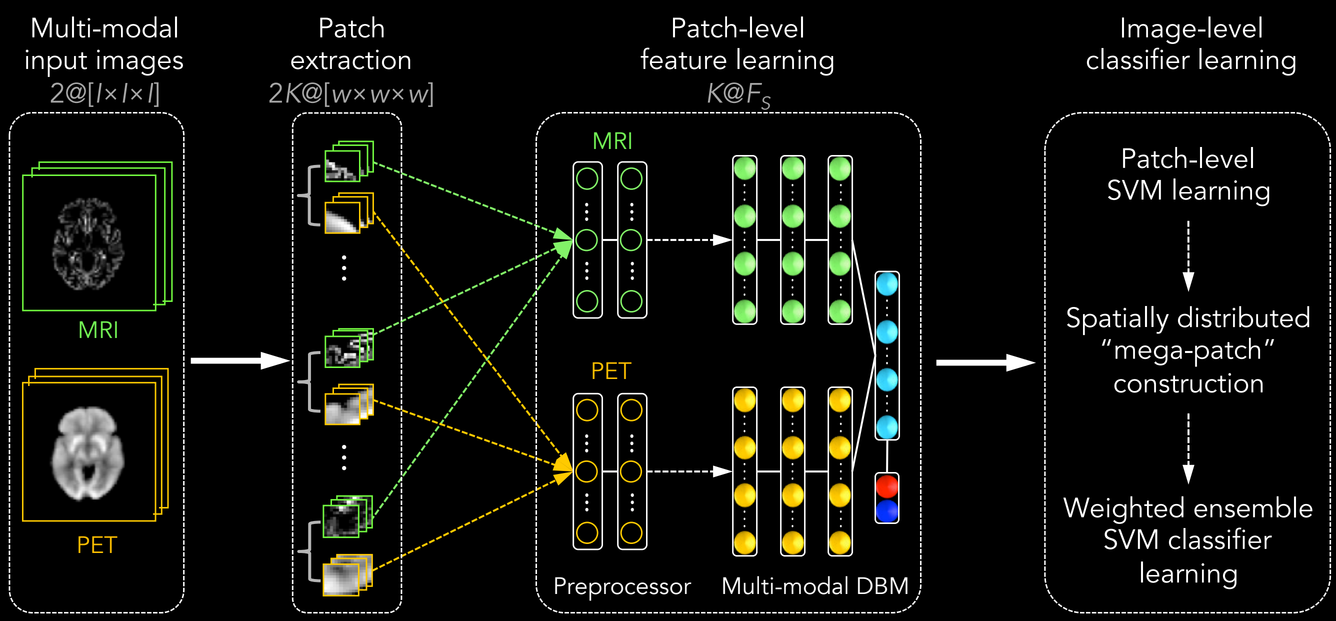
- Fusing complementary information from multiple modalities helps enhance diagnostic accuracy

x Previous approaches
  - Independent steps of feature extraction and modality fusion

✓ Deep Boltzmann Machine (DBM)
  - High-level feature representation via deep learning

✓ Multi-Modal DBM (MM-DBM)
  - Inherent relations between modalities of MRI and PET

Multi-Modal Fusion



l: image size, *w*: patch size, *K*: # of selected patches, *m*: modality index,
F_S: # of hidden units in the top-layer of multi-modal Deep Boltzmann Machine (DBM)

H.-I. Suk, S.-W. Lee, D. Shen, "Hierarchical Feature Representation and Multimodal Fusion with Deep Learning for AD/MCI Diagnosis", *NeuroImage*, 2014.

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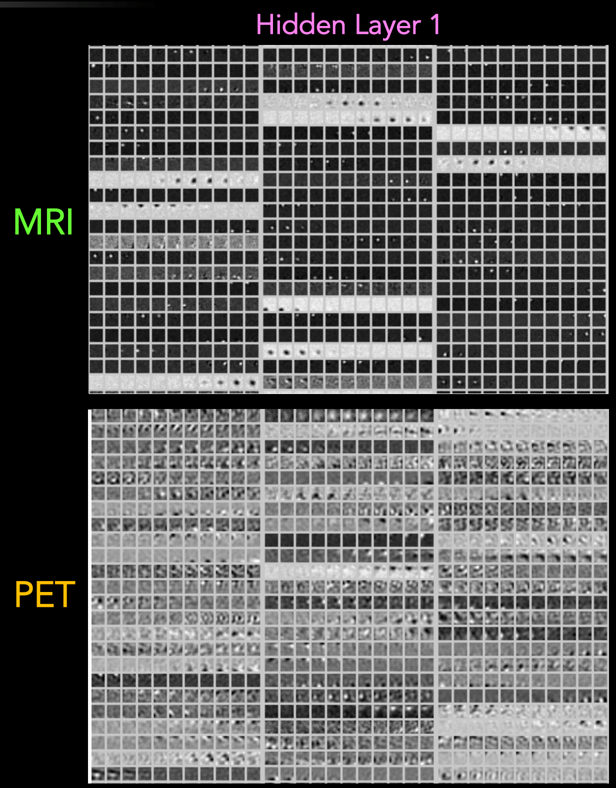
Multi-Modal Fusion



Learned weights

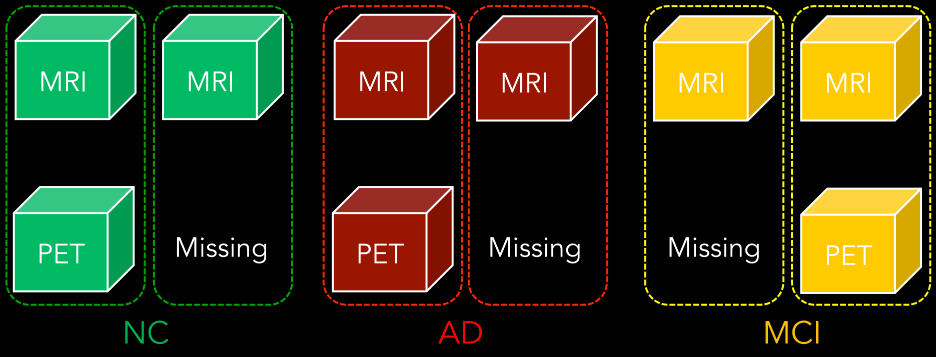
Results

Comparison with state-of-the-art methods

Methods	Dataset (AD/MCI/NC)	AD vs. NC (%)	MCI vs. NC (%)
Kohannim et al., 2010	MRI+PET+CSF (40/83/43)	90.7	75.8
Walhovd et al., 2010	MRI+CSF (38/73/42)	88.8	79.1
Hinrichs et al., 2011	MRI+PET (48/119/66)	92.4	n/a
Westman et al., 2012	MRI+CSF (96/162/111)	91.8	77.6
Zhang and Shen, 2012	MRI+PET+CSF (51/99/52)	93.3	83.2
Proposed method	MRI+PET (93/204/101)	93.5	85.2

Missing Data

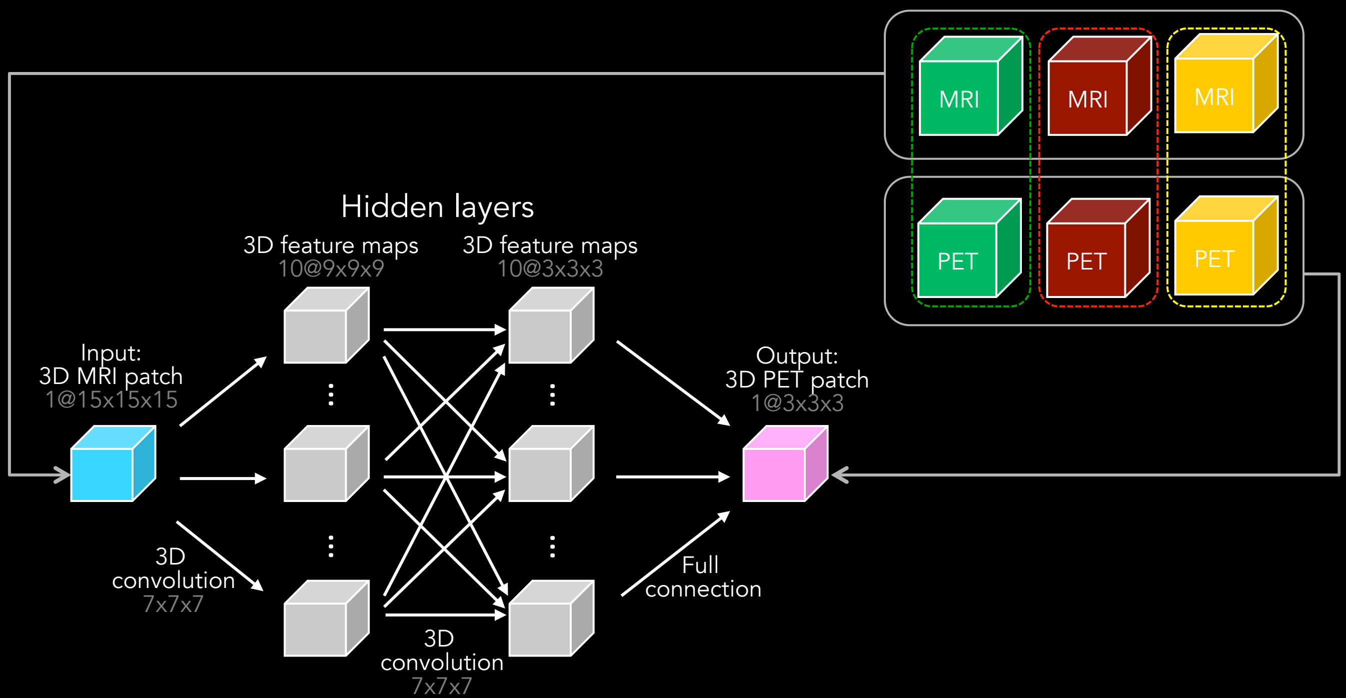
- Incomplete multi-modal neuroimaging data
  - Not all subjects have all data modalities
  - The accuracy of disease diagnosis can be improved if the missing data could be estimated
  - The relationship between different data modalities is complicated and nonlinear



More than 50% of the subjects in ADNI dataset do not have PET data

R. Li, W. Zhang, H. Suk, L. Wang, J. Li, D. Shen, S. Ji, "Deep Learning Based Imaging Data Completion for Improved Brain Disease Diagnosis", *MICCAI*, 2014.

Deep Learning for Multi-modality Data Completion



3D CNN architecture for imaging data completion

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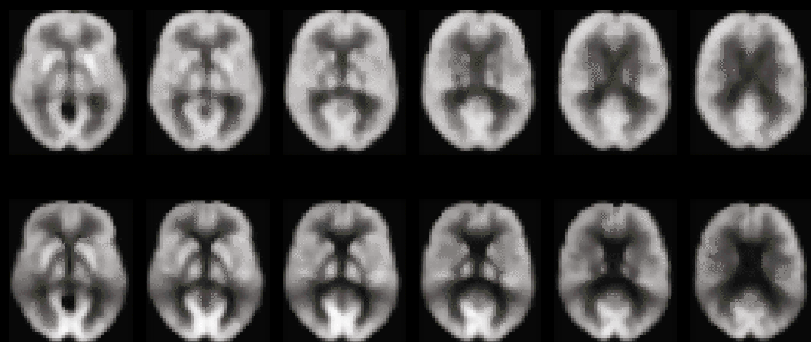
Deep Learning for Multi-modality Data Completion

AD



Predicted PET

Ground truth PET

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Results

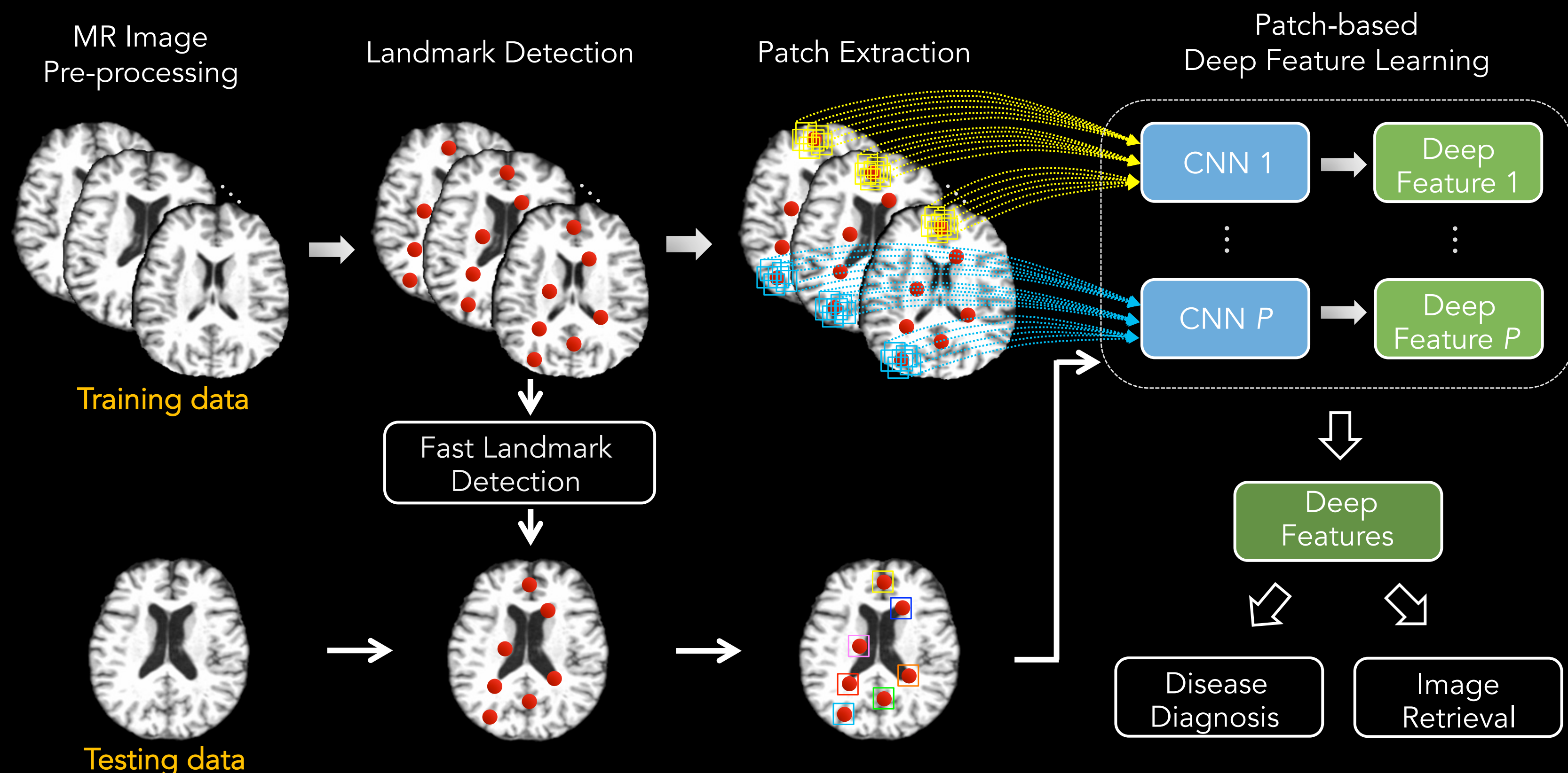
Performance comparison of classification tasks
(308 subjects with both MRI and PET)

		MCI vs. NC	pMCI vs. sMCI	AD vs. NC
PET	True data	0.70±0.02	0.68±0.02	0.90±0.02
	3D CNN	0.69±0.03	0.68±0.02	0.89±0.02
	KNN	0.63±0.02	0.63±0.03	0.74±0.03
	Zero	0.62±0.02	0.61±0.02	0.69±0.02

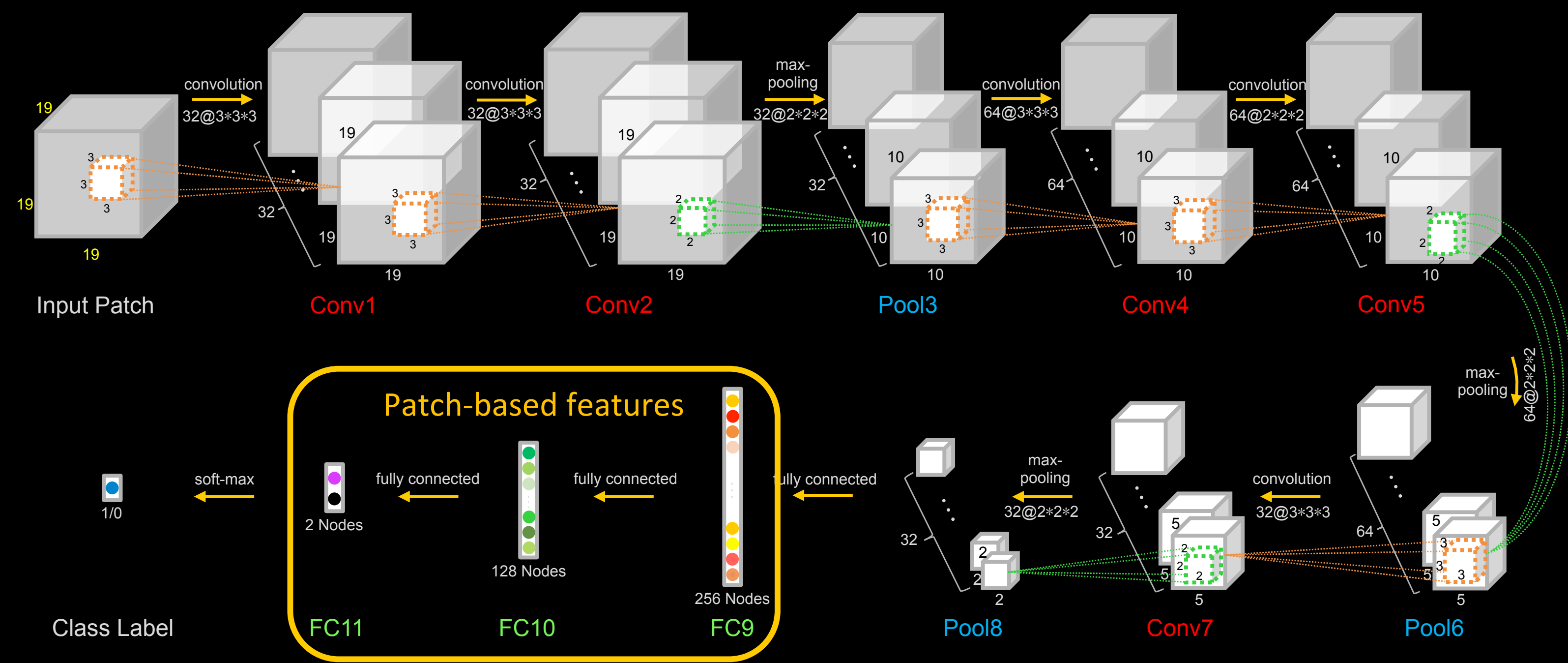
Performance comparison of classification tasks
(830 subjects with MRI and true/estimated PET)

		MCI vs. NC	pMCI vs. sMCI	AD vs. NC
MRI		0.75±0.03	0.72±0.03	0.92±0.02
PET	3D CNN	0.73±0.03	0.70±0.02	0.88±0.02
	KNN	0.64±0.02	0.61±0.03	0.74±0.03
	Zero	0.61±0.02	0.59±0.03	0.70±0.03
MRI+PET	3D CNN	0.76±0.02	0.72±0.02	0.93±0.02
	KNN	0.72±0.02	0.68±0.03	0.77±0.02
	Zero	0.72±0.03	0.63±0.03	0.70±0.02

Landmark-based Deep Feature Learning for AD Diagnosis



Landmark-based Deep Feature Learning for AD Diagnosis



Structure of the 3DCNN model used in this study

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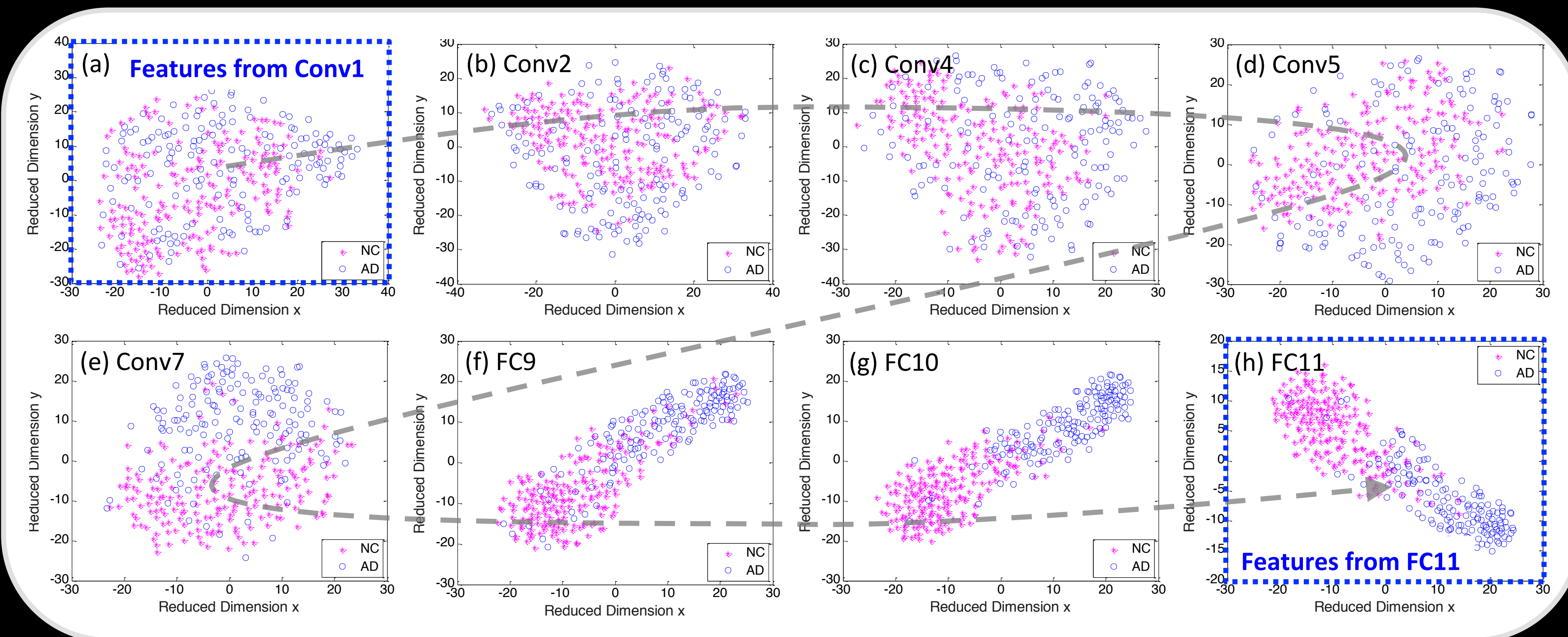
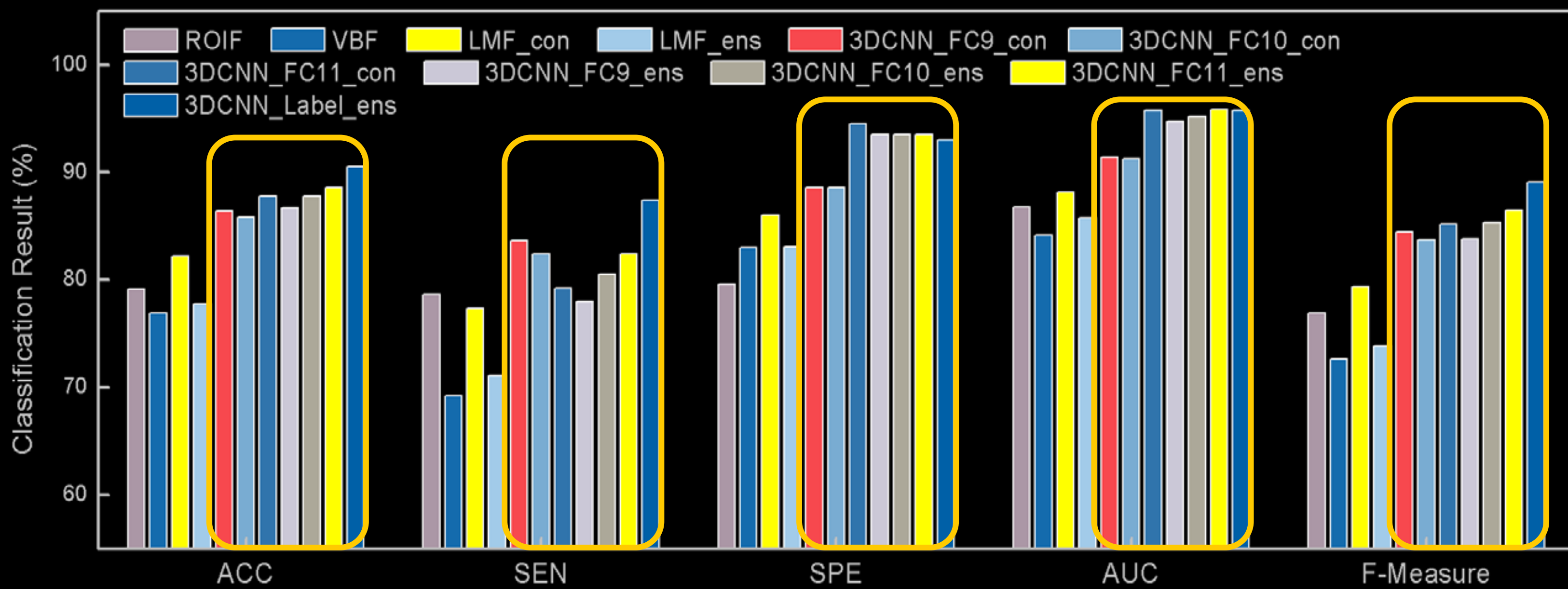
Landmark-based Deep Feature Learning for AD Diagnosis



Manifold visualization of AD and NC subjects in the ADNI-2 dataset, by **t-SNE projection** in learned 3DCNN layers.

Results



Comparison of AD/NC classification results

ROIF: ROI based features; VBF: Voxel based features; LMF: Landmark based morphological features (concatenation/ensemble)
3DCNN_FC9/FC10/FC11: Features from the FC9/FC10/FC11 layer in 3DCNN (concatenation/ensemble)
3DCNN_Label_ens: Ensemble of labels obtained from 3DCNN

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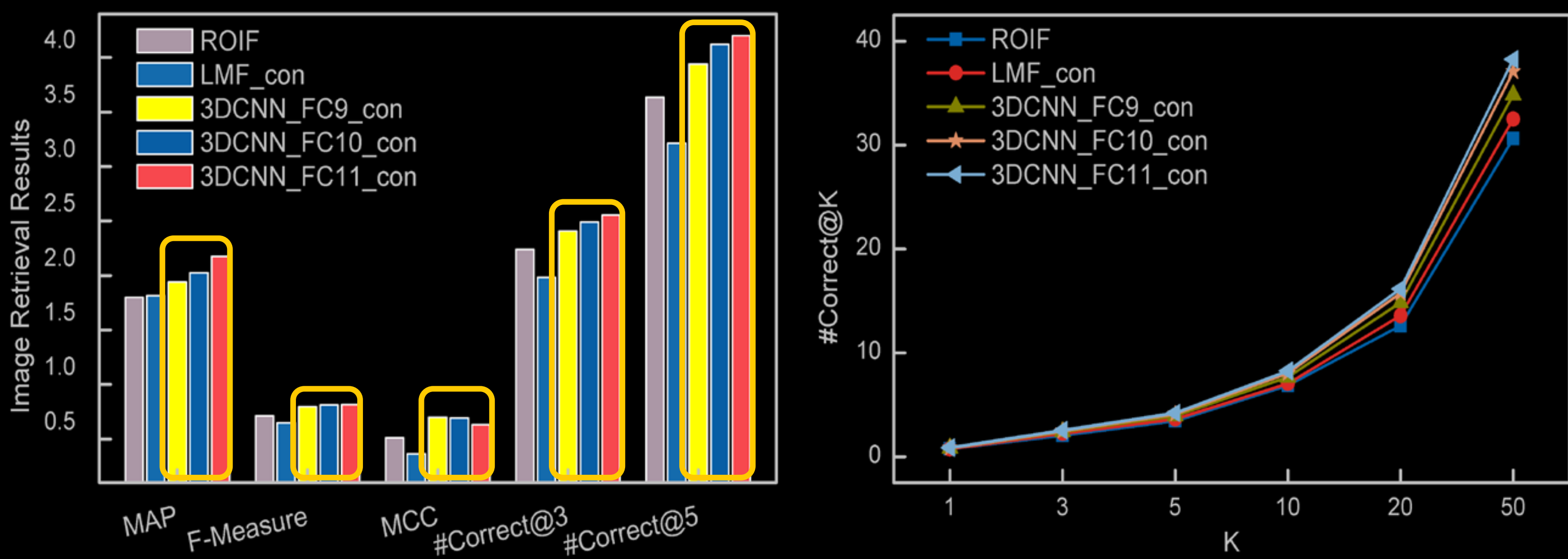
Results



Comparison of AD/NC classification results

MAP: Mean Average Precision
MCC: Matthews Correlation Coefficient
#Correct@K: Number of correct results in top K returned results

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Computer-aided Diagnosis

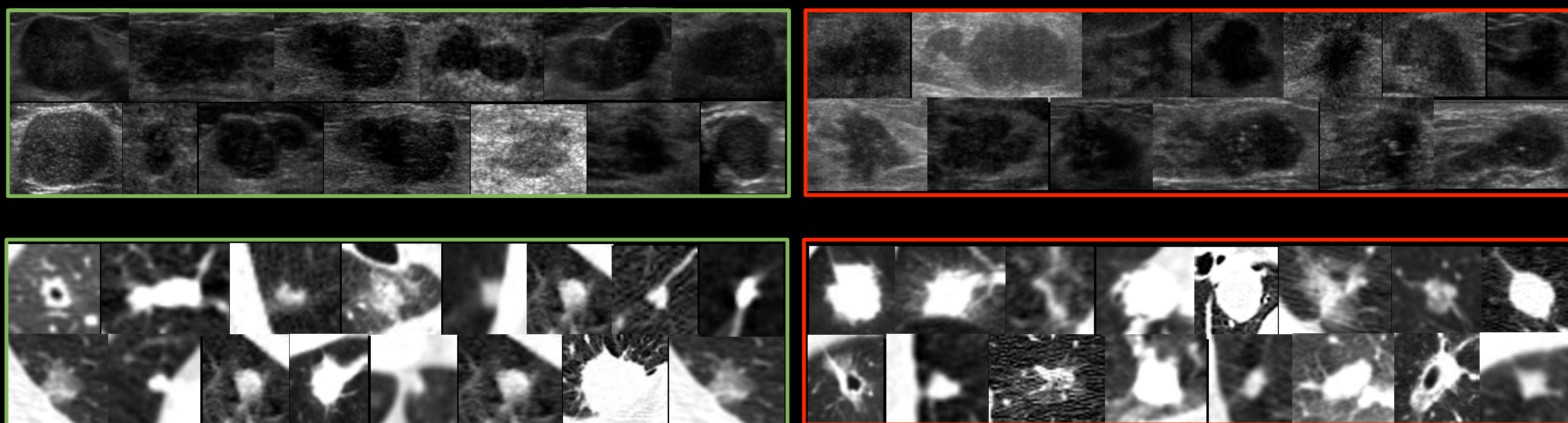
Applications to *Pulmonary Nodules in CT Scans* and *Breast Lesions in Ultrasound Images*

Diagnosis for Lung Nodules and Breast Lesions

Benign | Malignant

Ultrasound Breast Lesions

CT Lung Nodules



Radiologist's Diagnosis

- Inter-observer Variation
- Intra-observer variation
- Dependence on Experience
- Human Error

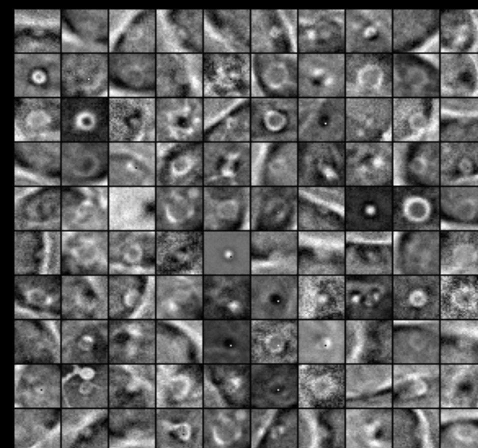
Computer-aided Diagnosis

- Decision Support
- Resolve Intra-observer Variation
- Avoid Unnecessary Biopsy

Deep Learning CADx vs. Conventional CADx

- Deep learning CADx
  - Automatic feature extraction and selection
  - Free of intermediate image processing steps (e.g., image segmentation)

Ultrasound Breast Lesions

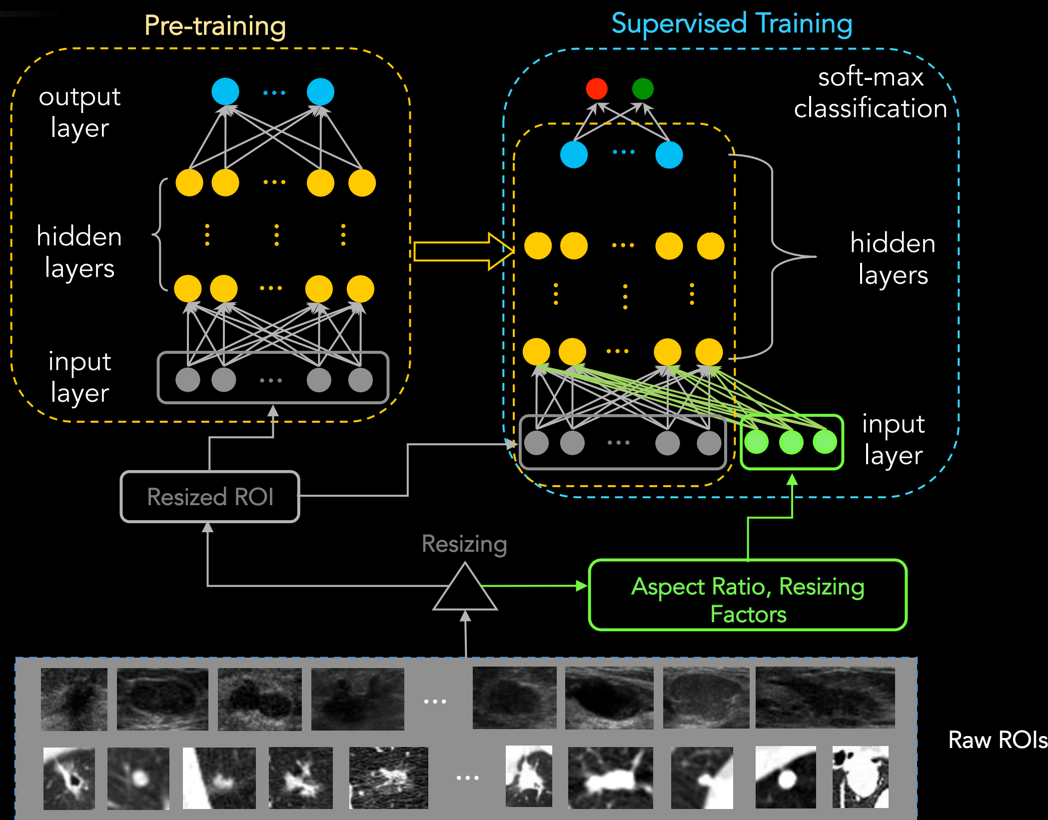


CT Lung Nodules

Learned Patterns with Stacked Denoising Auto-Encoder (SDAE)

J. Cheng, D. Ni, Y. Chou, J. Qin, C. Tiu, Y. Chang, D. Shen, C. Chen, "Computer-Aided Diagnosis with Deep Learning Architecture: Applications to Breast Lesions in US Images and Pulmonary Nodules in CT Scans", *Scientific Reports*, 2016.

SDAE Architecture



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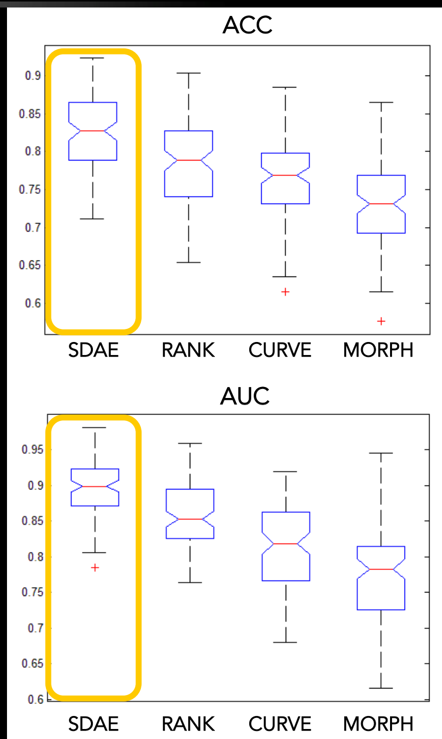
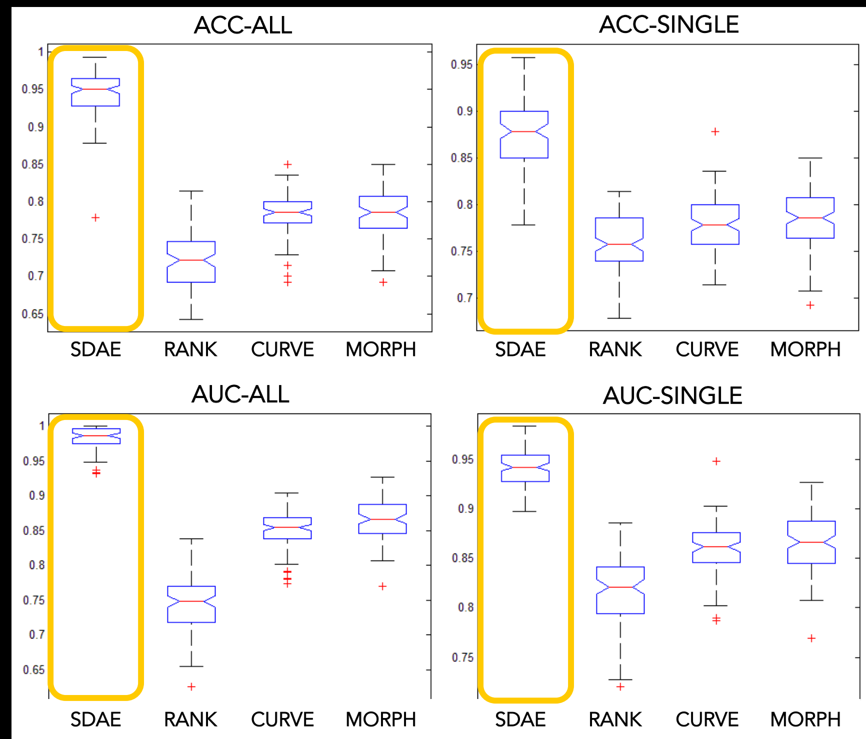
Results

SINGLE: Use ROI of median slice for each nodule
ALL: Use all ROIs for each nodule and vote ROIs at testing

Ultrasound Breast Lesions





CT Lung Nodules

Comparison of classification accuracy

RANK: Ranklet Transform + Grey Level Co-occurrence Matrix (GLCM) Features (Yang et al., 2013)
CURVE: Curvelet Transform + GLCM Features (Sun et al., 2013)
MORPH: Clinical Size and Diameter

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Outcome Prediction

Brain Tumor Patient's Survival Time Prediction

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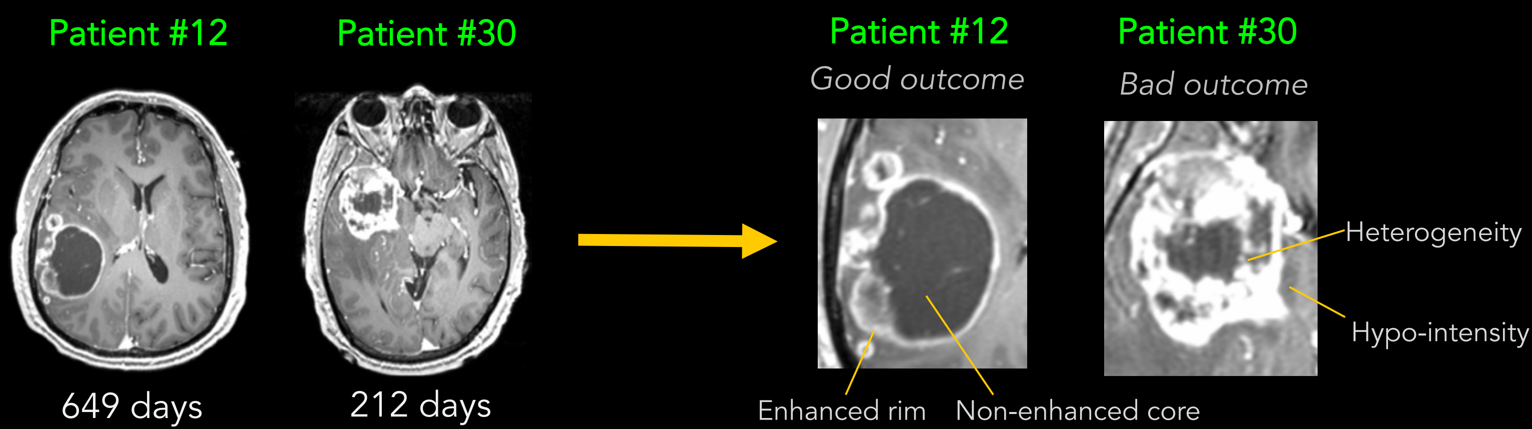
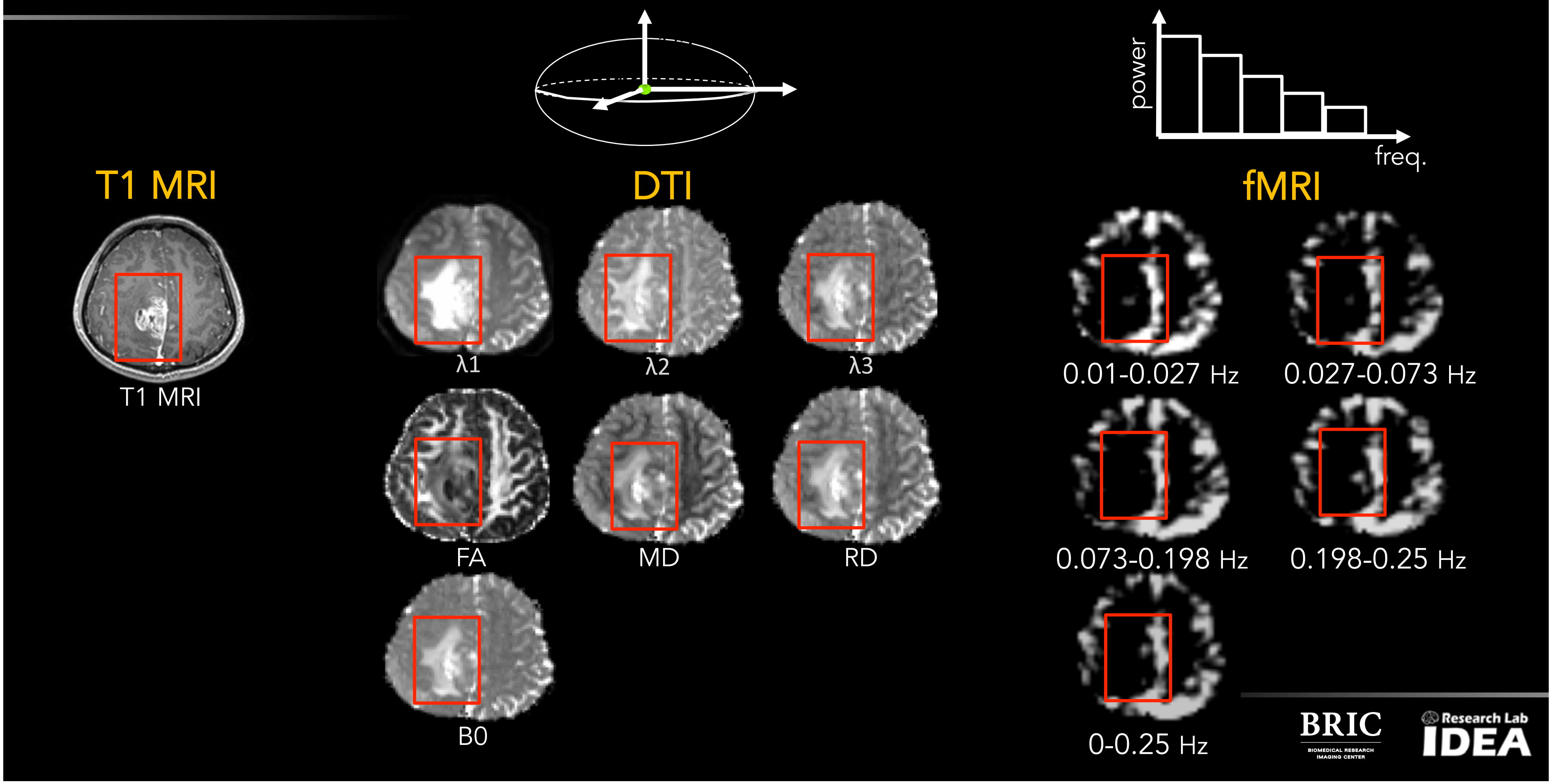
Brain Tumor Patient's Survival Time Prediction

- High-grade gliomas
  - One of most deadly tumors with fast grow rate and poor prognosis
  - Pre-operative outcome prediction with high accuracy is critical for better treatment planning

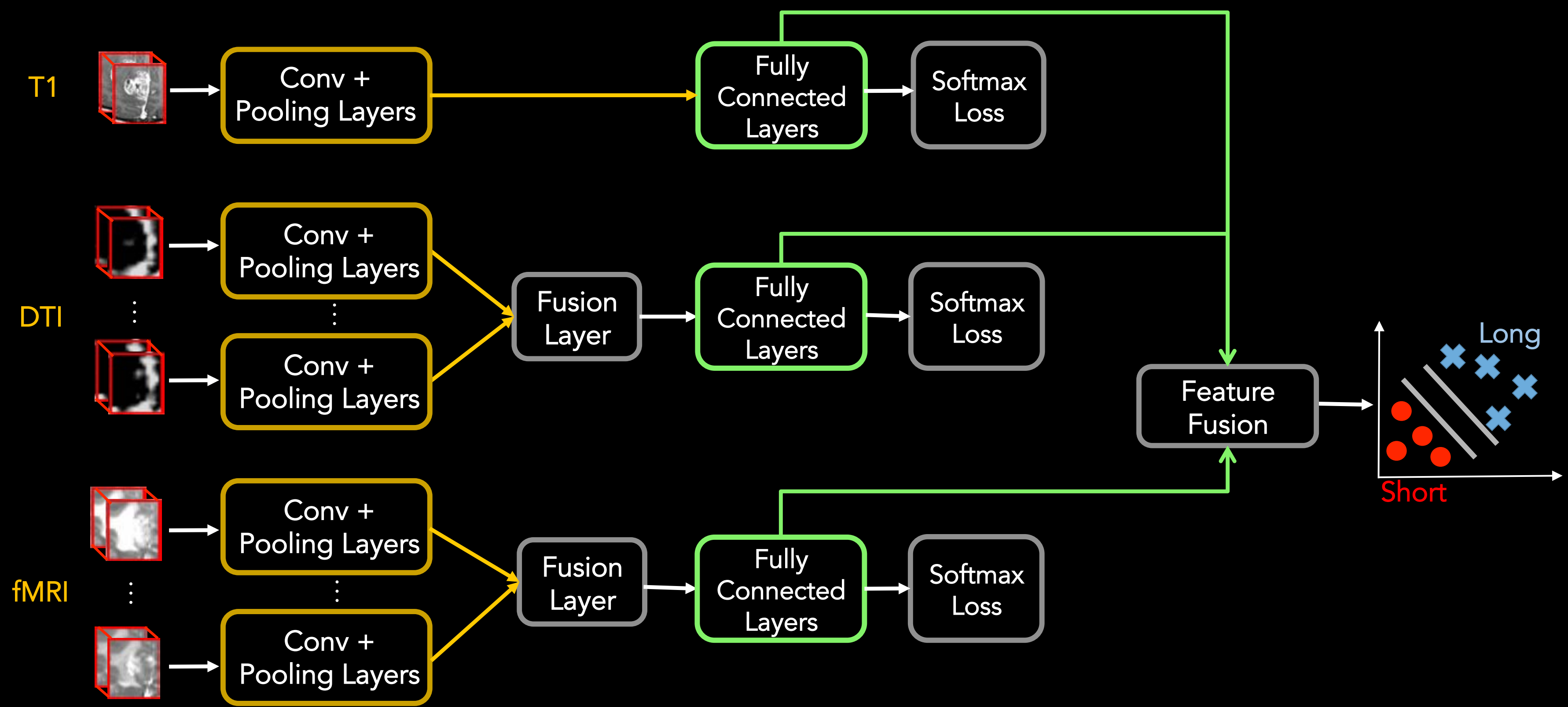


D. Nie, H. Zhang, E. Adeli, L. Liu, D. Shen. "3D Deep Learning for Multi-modal Imaging-guided Survival Time Prediction of Brain Tumor Patients", *MICCAI*, 2016.

Prediction based on Tumor Tissue Appearance



Multi-modal/Multi-channel Deep Learning using 3D-CNN



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Results

Comparison of prediction accuracy

Method	ACC	SEN	SPE	PPR	NPR
Clinical features	62.96	66.39	58.53	63.18	65.28
Haar	69.17	72.81	65.84	65.56	73.14
SIFT	80.56	85.71	77.27	70.59	89.47
2D-CNN	81.25	80.95	81.82	88.35	74.23
Proposed	89.95	96.87	83.90	84.94	93.93

ACC=Accuracy; SEN=Sensitivity; SPE=Specificity; PPR=positive predictive rate; NPR=negative predictive rate

Application 4

Image Synthesis

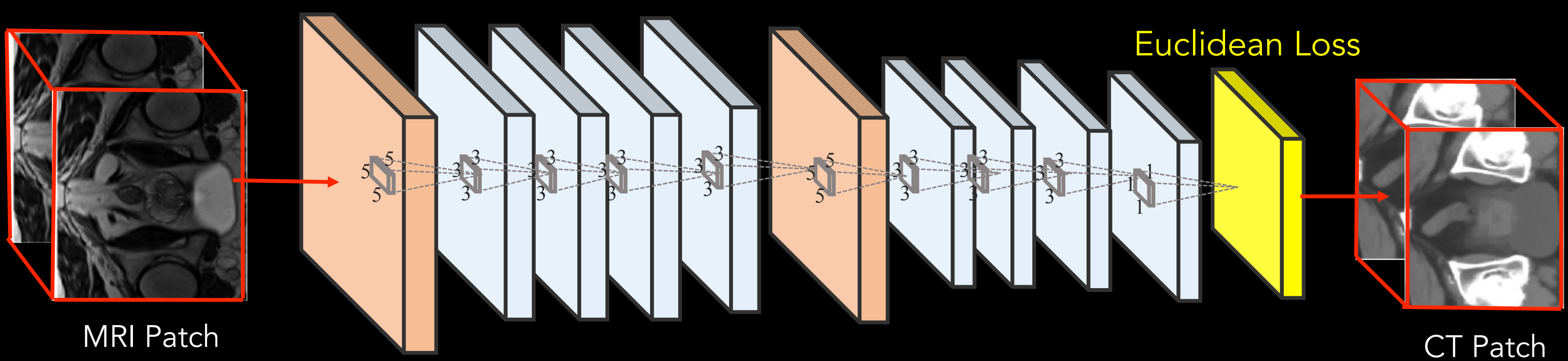
- Estimating CT from MRI
- 7T MRI Construction

Estimating CT from MRI

Estimating CT Images from MRI by Fully Convolutional Networks

Estimating CT from MRI

- CT images
  - (+) Dose planning
  - (+) PET attenuation correction
  - (−) Radiation
- Challenge in estimating CT from MRI
  - Hard to train the networks (3D)



A Basic FCN (Fully Convolutional Network) Architecture

D. Nie, X. Cao, Y. Gao, L. Wang, D. Shen, "Estimating CT Image from MRI Data Using 3D Fully Convolutional Networks", *DLMIA*, 2016.

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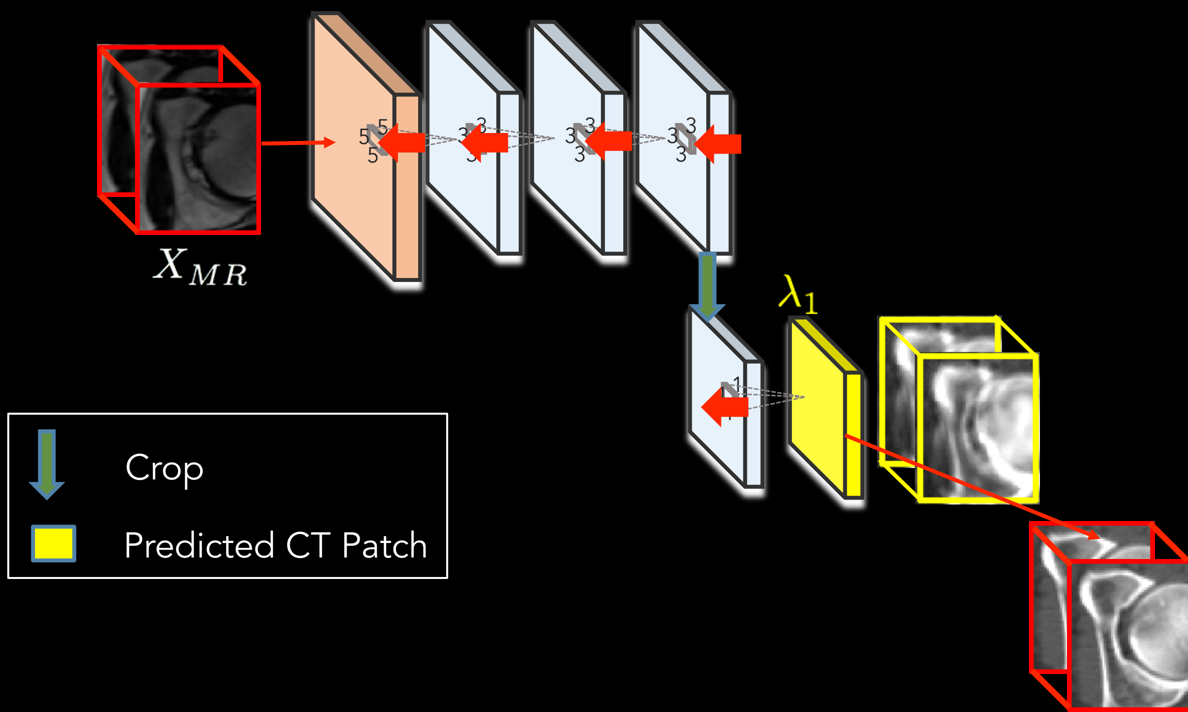
Deeply Supervised Nets (DS-FCN)

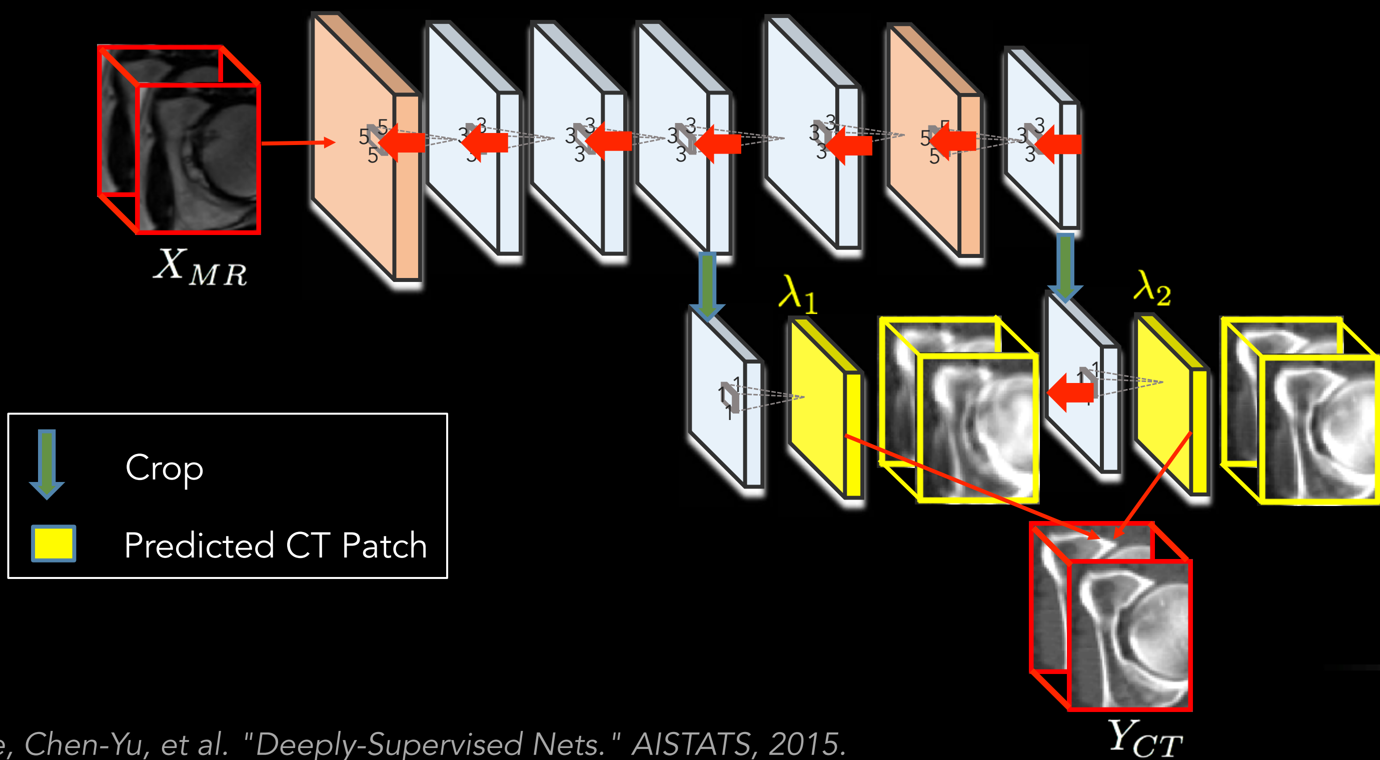
$$J = \underbrace{\gamma R(w_1)}_{\text{Regularizer}} + \underbrace{\lambda_1 L_1(w_1; X_{MR}, Y_{CT})}_{\text{Loss function at level 1}}$$



Lee, Chen-Yu, et al. "Deeply-Supervised Nets." AISTATS, 2015.

Deeply Supervised Nets (DS-FCN)

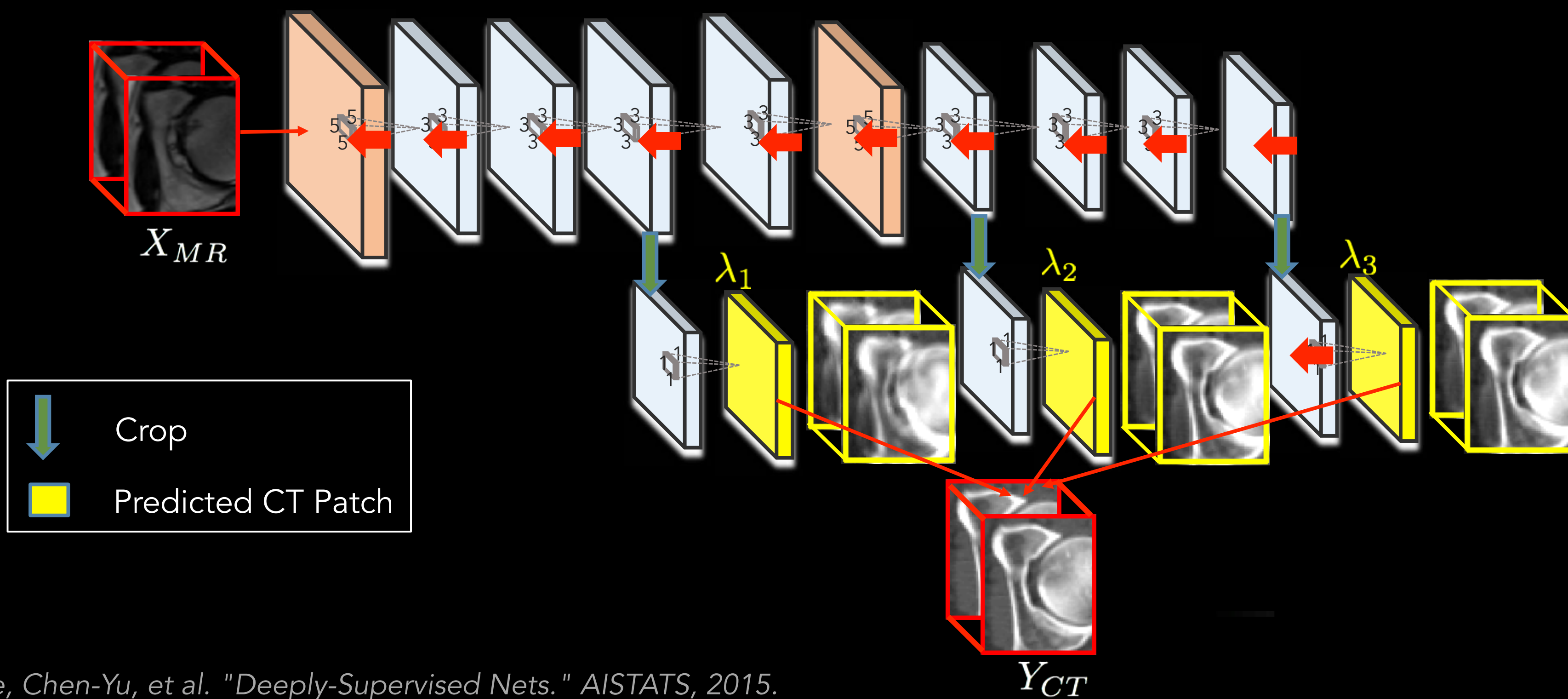
$$J = \gamma R(w_1) + \lambda_1 L_1(w_1; X_{MR}, Y_{CT}) + \gamma R(w_2) + \lambda_2 L_2(w_2; X_{MR}, Y_{CT})$$



Lee, Chen-Yu, et al. "Deeply-Supervised Nets." AISTATS, 2015.

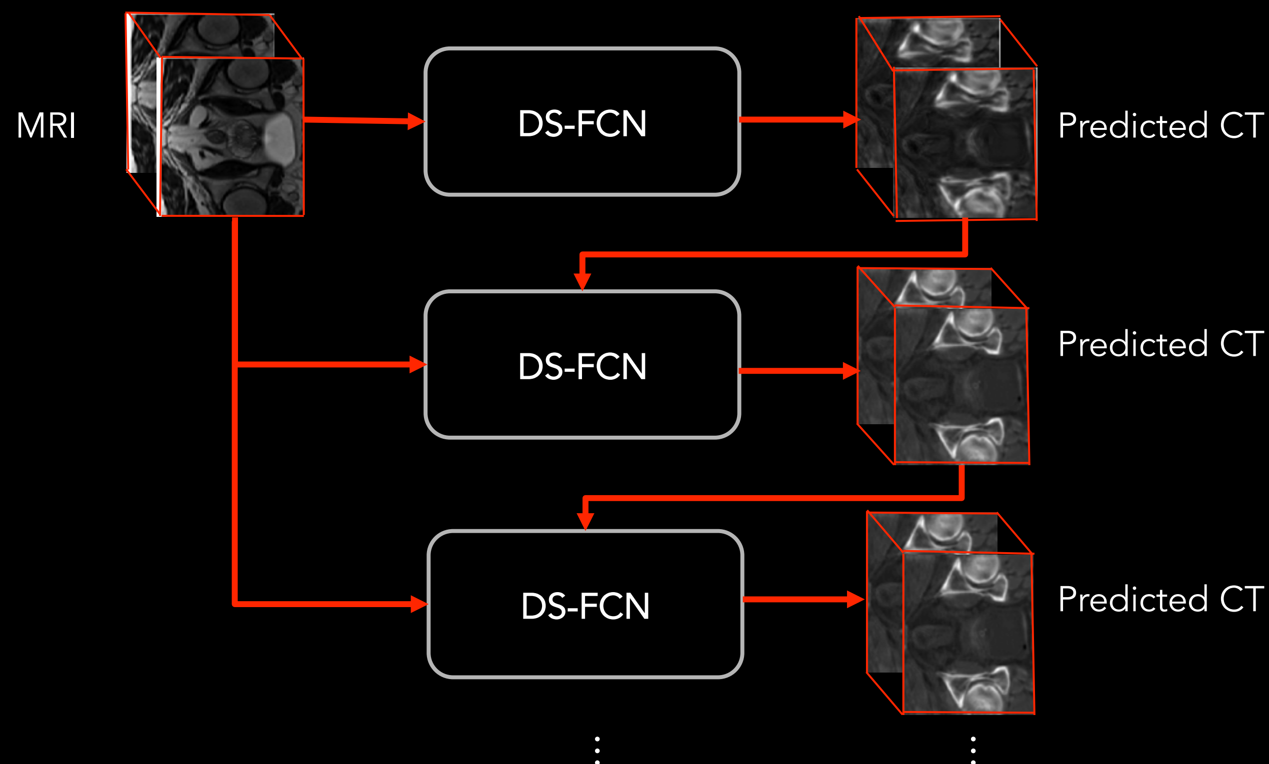
Deeply Supervised Nets (DS-FCN)

$$J = \gamma R(w_1) + \lambda_1 L_1(w_1; X_{MR}, Y_{CT}) + \gamma R(w_2) + \lambda_2 L_2(w_2; X_{MR}, Y_{CT}) + \gamma R(w_3) + \lambda_3 L_3(w_3; X_{MR}, Y_{CT})$$

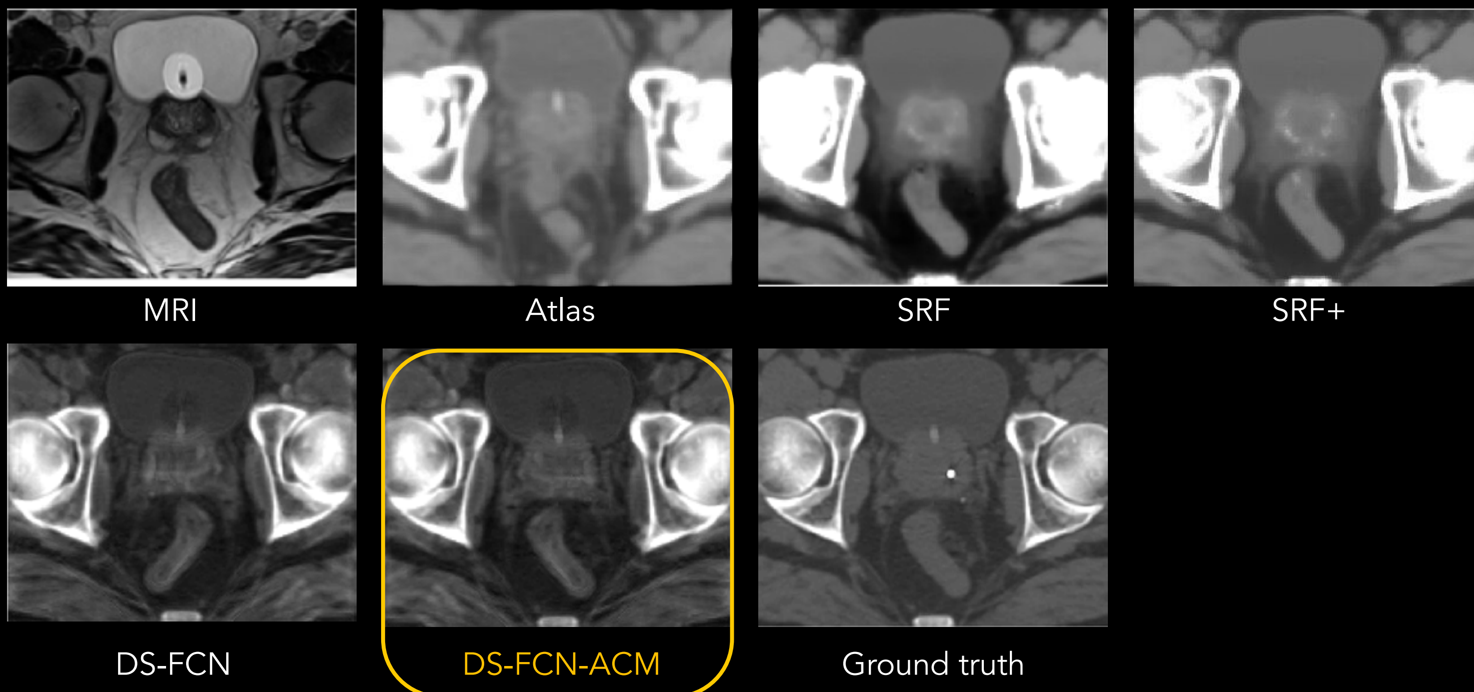


Lee, Chen-Yu, et al. "Deeply-Supervised Nets." AISTATS, 2015.

DS-FCN with Auto-Context Model (ACM)



Results



Comparison of estimated CT images

Atlas: Multi-atlas-based method
SRF: Structure Random Forest
SRF+: Structure Random Forest w/ Auto-context Model Refinement

Results

Performance comparison

Method	MAE		PSNR	
	Mean(std)	Med.	Mean(std)	Med.
Atlas	64.6(6.6)	65.9	29.1(2.0)	29.8
SR	54.3(10.0)	54.0	30.4(2.6)	31.3
SRF+	48.1(4.6)	48.3	32.1(0.9)	31.8
DS-FCN	42.4(5.1)	42.6	33.4(1.3)	33.2
DS-FCN+ACM	38.7(4.6)	38.9	34.2(1.0)	34.1

Atlas: Multi-atlas-based method
SRF: Structure Random Forest
SRF+: Structure Random Forest w/ Auto-context Model Refinement

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7T MRI Reconstruction

Convolutional Neural Network For Reconstruction of 7T-like Images from 3T MRI

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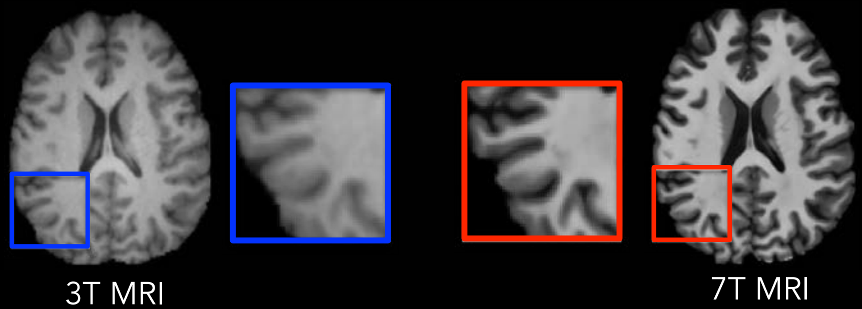
7T vs. 3T MRI

- 7T MRI
  - Higher spatial resolution and better tissue contrast, compared to 3T MRI
  - SNR of 7T MRI ≈ 2.3 * SNR of 3T MRI



- Lower availability and higher price of 7T MRI scanners
  - 20,000 3T scanners vs. 40 7T scanners in the world

➡ Reconstruction of 7T-like images from 3T MRI

K. Bahrami, F. Shi, I. Rekik, D. Shen, "Convolutional Neural Network for Reconstruction of 7T-like Images from 3T MRI Using Appearance and Anatomical Features", *DLMIA*, 2016.

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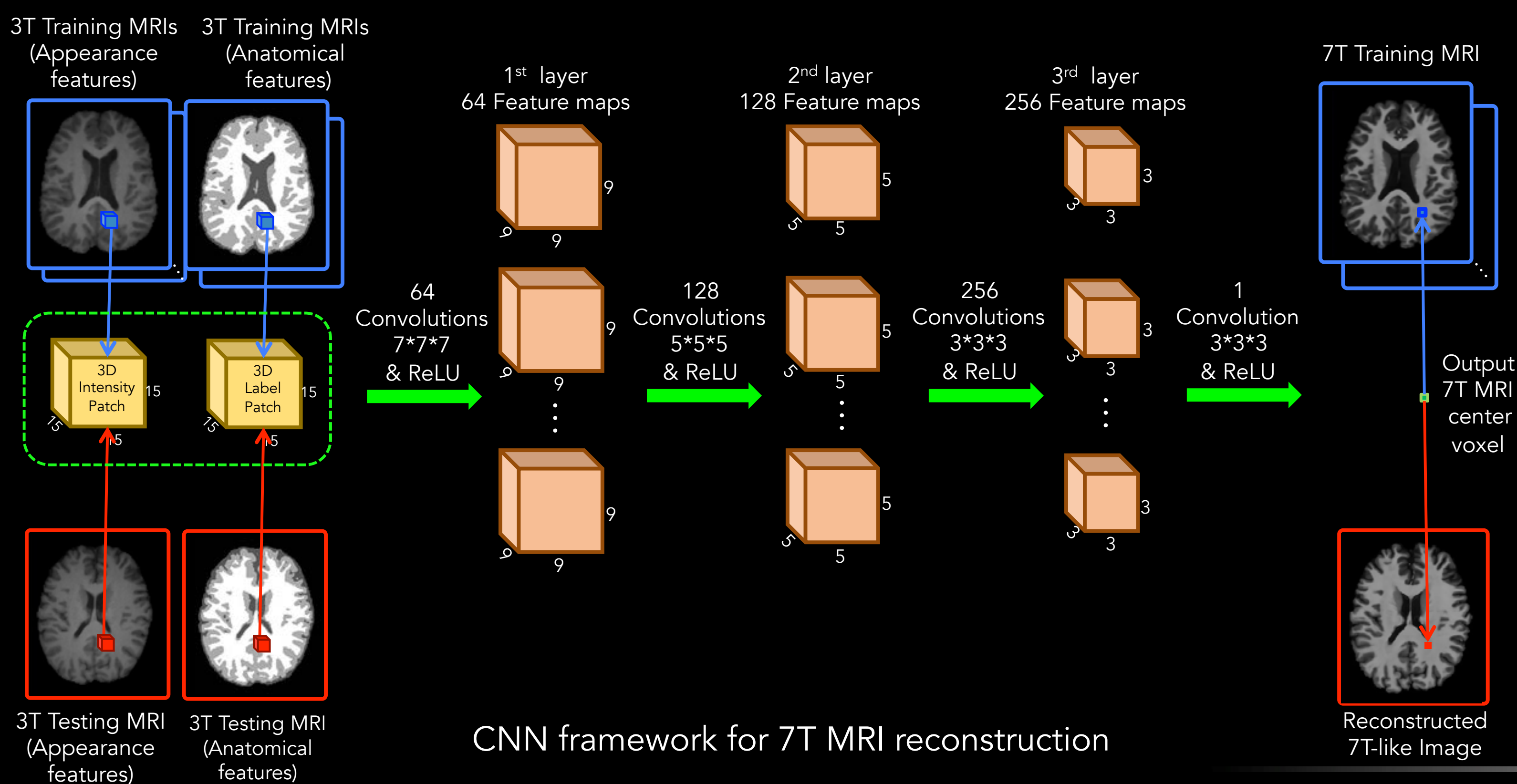
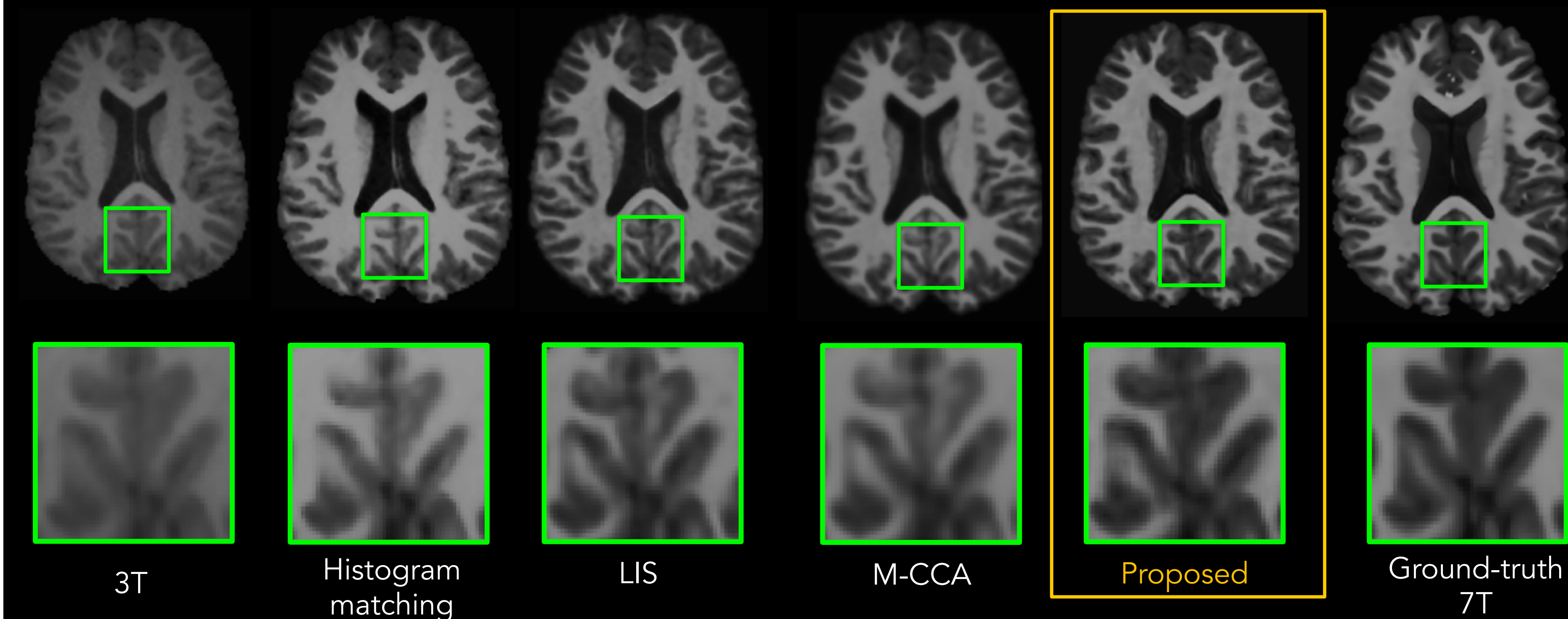
7T MRI Reconstruction



CNN framework for 7T MRI reconstruction

Results



LIS: Local Image Similarity
M-CCA: Multi-level CCA

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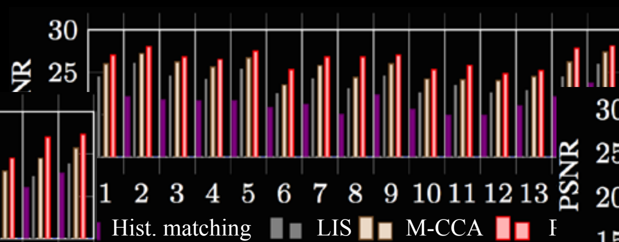
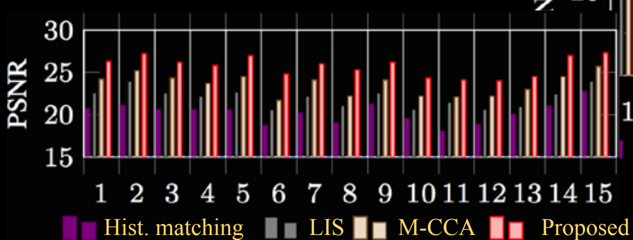
Results

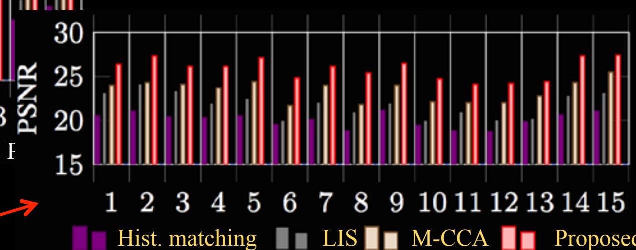


PSNR for 15 subjects

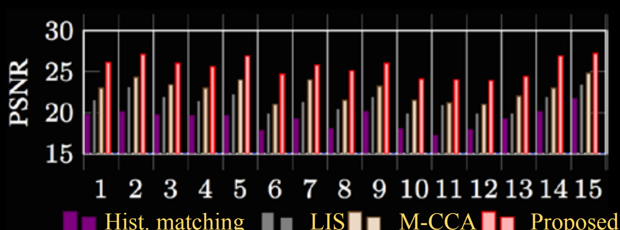


Re-sampling testing images with rate of 2

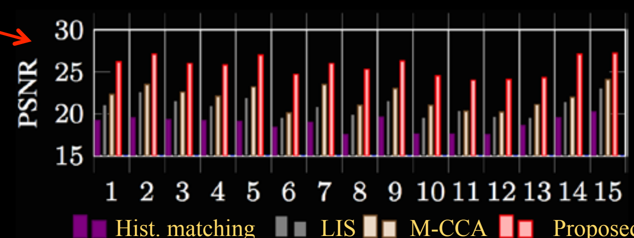
Our results are more reliable than others when the quality of training & testing images are different.



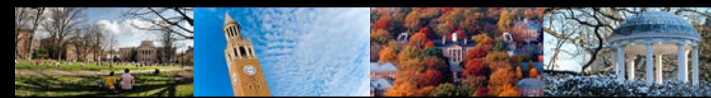
Re-sampling training images with rate of 2



Re-sampling testing images with rate of 3



Re-sampling training images with rate of 3



Thank you!

For more details, please visit:

http://bric.unc.edu/ideagroup

Or google: unc idea

Application 4

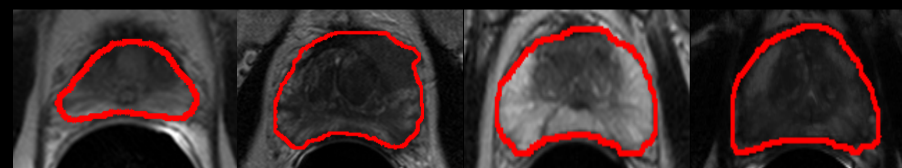
Prostate Labeling

- MRI Prostate Segmentation for Cancer Diagnosis and Treatment

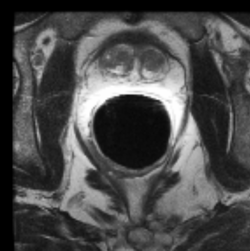
MRI Prostate Segmentation

- MRI prostate images provide good soft tissue contrast
  - MRI-guided transperineal prostate core biospy
  - MRI-guided radiotherapy planning
  - Quantitative analysis using MR images

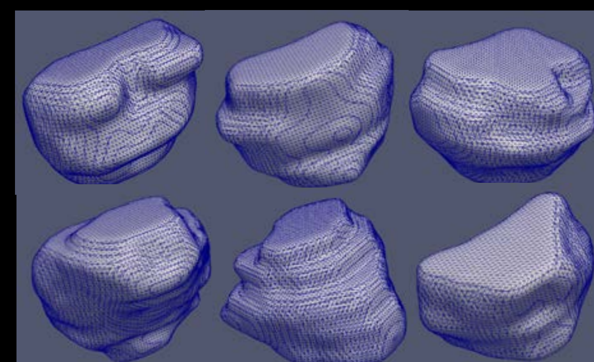
- Challenges



Large inter-subject anatomical appearance variability



Inhomogeneity



Large inter-subject shape variability

S. Liao, Y. Gao, D. Shen, "Representation Learning: A Unified Deep Learning Framework for Automatic Prostate MR Segmentation", *MICCAI*, 2013.

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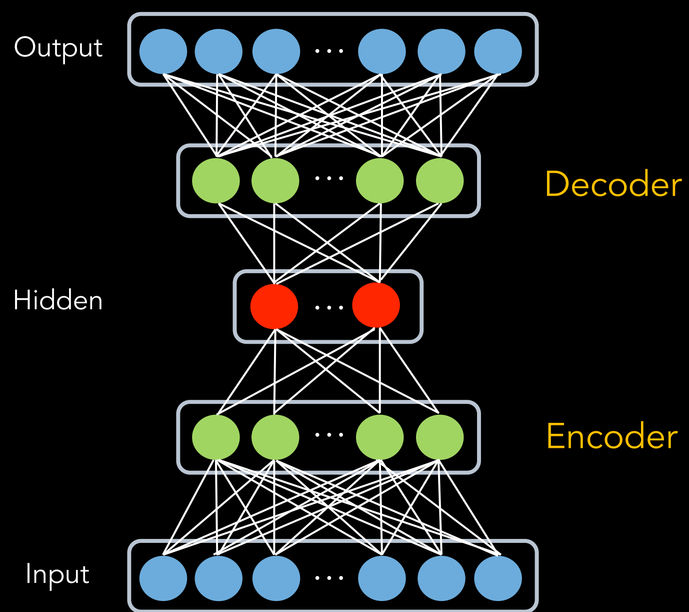
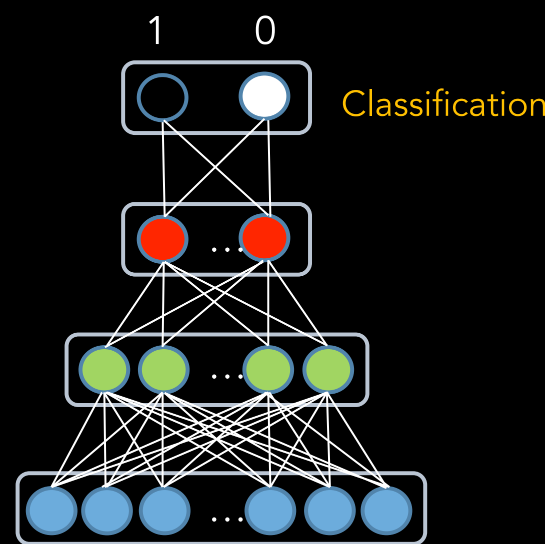
Latent Feature Representation



Discover abstract latent feature representations from the target-unrelated samples through greedy learning



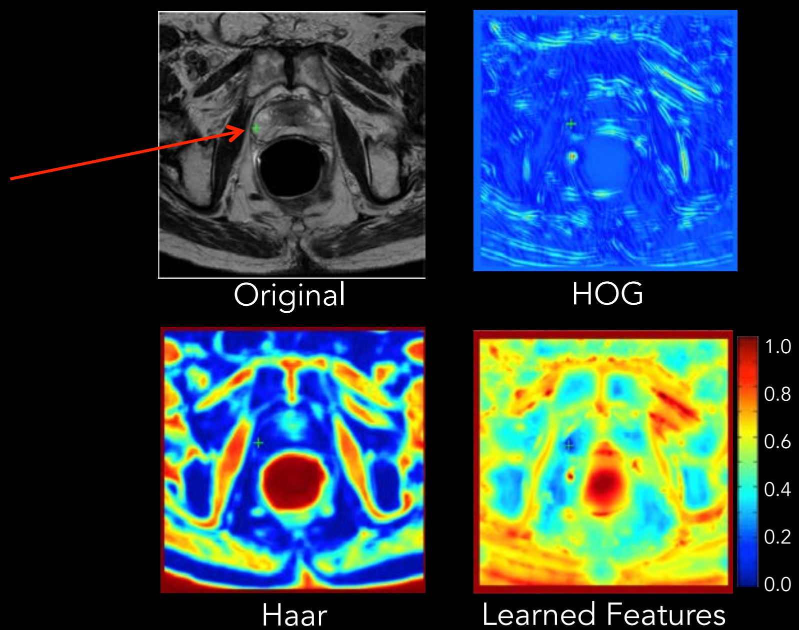
Optimize the deep-learned feature representation for a certain task to enhance accuracy

<u>Pre-training</u>: Unsupervised Stacked Auto-Encoder

<u>Fine-tuning</u>: Supervised Stacked Auto-Encoder

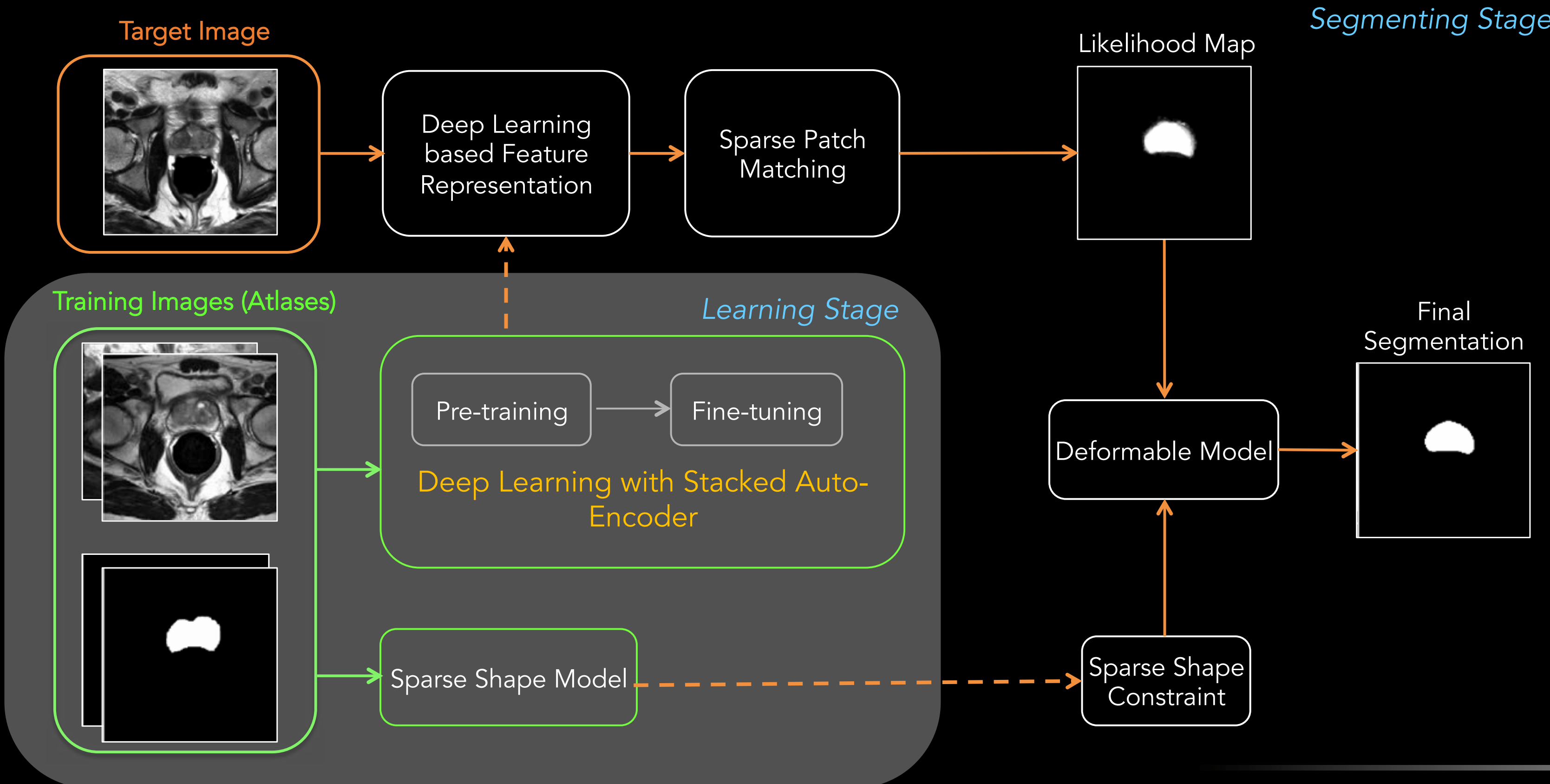
Y. Guo, Y. Gao, <u>D. Shen</u>, "Deformable MR Prostate Segmentation via Deep Feature Learning and Sparse Patch Matching", *IEEE TMI*, 2016.

Latent Feature Representation



Feature Difference Maps

Proposed Framework



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Results

Comparison of segmentation performance

Method	Intensity	Haar	HOG	LBP	Handcraft	Unsupervised SSAE	Supervised SSAE	Supervised SSAE w/ DM
Dice (%)	85.3±6.2	85.6±4.9	85.7±4.9	85.5±4.3	85.9±4.5	86.7±4.4	87.1±4.2	87.8±4.0
Precision (%)	85.1±8.3	85.9±8.5	85.3±8.7	83.7±7.7	87.3±7.4	87.3±7.3	87.1±7.3	91.6±6.5
Hausdorff	8.68±4.24	8.50±2.86	8.51±2.69	8.59±2.38	8.55±2.91	8.65±2.69	8.12±2.89	7.43±2.82
ASD (mm)	1.87±0.93	1.76±0.52	1.74±0.50	1.75±0.44	1.77±0.54	1.68±0.49	1.66±0.49	1.59±0.51

Dice: Dice ratio; Hausdorff: Hausdorff distance; ASD: Average surface distance