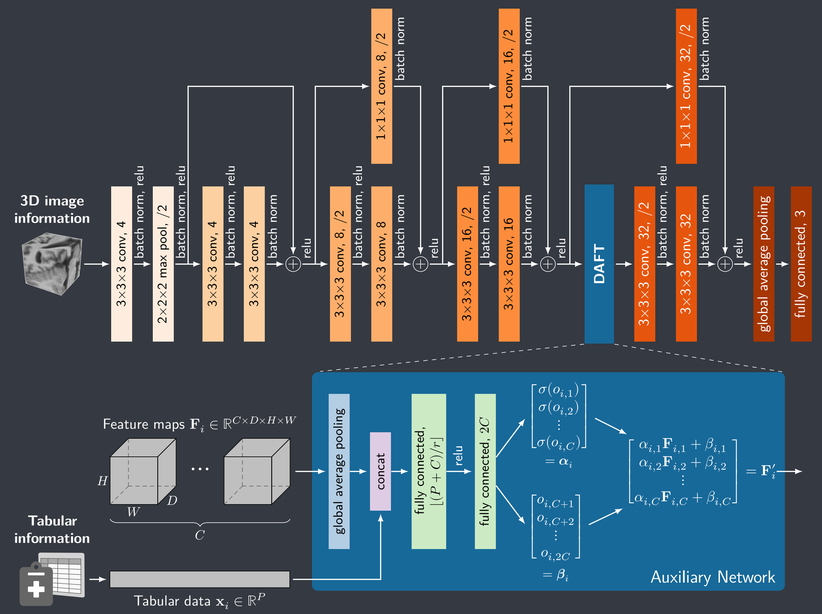
A highly effective module to **integrate tabular and 3D image information** for dementia diagnosis and time-to-dementia prediction.



Combining 3D Image and Tabular Data via the Dynamic Affine Feature Map Transform

Sebastian Pölsterl, Tom Nuno Wolf, and Christian Wachinger

LMU KLINIKUM DER UNIVERSITÄT MÜNCHEN AI med

Background

- CNNs have been shown to be effective for diagnosing Alzheimer's disease from MRI.
- Tabular biomarkers are often required for a **holistic view of the patient's health**: demographics, laboratory measurements, genetics, ...
- How to integrate such data is not well studied.
- *Goal*: **Effective integration** of all sources of information to improve Alzheimer's disease *diagnosis* and *time-to-dementia prediction*.

DAFT: Dynamic Affine Feature Map Transform

- *Idea*: establish a two-way exchange of information between high-level concepts learned from the MRI and the tabular biomarkers.
- *Solution*: an **auxiliary neural network** dynamically incites or represses feature maps of a convolutional layer conditional on both image and tabular information.
- Computationally efficient, because it does not depend on the num. of samples, nor the spatial resolution of feature maps.
- Can be integrated into any type of CNN.

Experiment: Diagnosis

- 1341 subjects from ADNI:
  Dementia (19.6%), MCI (40.1%), CN (40.3%).
- 64^3 ROI around left hippocampus; 9 tabular biomarkers.

	I	T	Balanced Accuracy Validation	Balanced Accuracy Testing
Linear Model	✗	L	0.571 ± 0.024	0.552 ± 0.020
ResNet	✓	–	0.568 ± 0.015	0.504 ± 0.016
Linear Model /w ResNet Features	✓	L	0.585 ± 0.050	0.559 ± 0.053
Concat-1FC	✓	L	0.630 ± 0.043	0.587 ± 0.045
Concat-2FC	✓	NL	0.633 ± 0.036	0.576 ± 0.036
1FC-Concat-1FC	✓	NL	0.632 ± 0.020	0.591 ± 0.024
Duanmu et al. [1]	✓	NL	0.634 ± 0.015	0.578 ± 0.019
FiLM [2]	✓	NL	0.652 ± 0.033	0.601 ± 0.036
DAFT	✓	NL	0.642 ± 0.012	$\mathbf{0.622 \pm 0.044}$

I: Uses images. T: Uses tabular data. L: Linear model. NL: Non-linear model.

Experiment: Time-to-Dementia Prediction

- 755 subjects from ADNI:
  Progressor (37.4%), median follow-up time 2.01 years.
- 64^3 ROI around left hippocampus; 9 tabular biomarkers

	I	T	Concordance Index Validation	Concordance Index Testing
Linear Model	✗	L	0.726 ± 0.040	0.719 ± 0.077
ResNet	✓	–	0.669 ± 0.032	0.599 ± 0.054
Linear Model /w ResNet Features	✓	L	0.743 ± 0.026	0.693 ± 0.044
Concat-1FC	✓	L	0.755 ± 0.025	0.729 ± 0.086
Concat-2FC	✓	NL	0.769 ± 0.026	0.725 ± 0.039
1FC-Concat-1FC	✓	NL	0.759 ± 0.035	0.723 ± 0.056
Duanmu et al. [1]	✓	NL	0.733 ± 0.031	0.706 ± 0.086
FiLM [2]	✓	NL	0.750 ± 0.025	0.712 ± 0.060
DAFT	✓	NL	0.753 ± 0.024	$\mathbf{0.748 \pm 0.045}$

I: Uses images. T: Uses tabular data. L: Linear model. NL: Non-linear model.

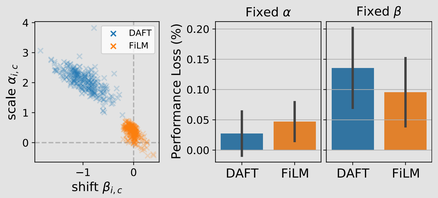
Ablation Study

- DAFT is relatively robust to choice of location.

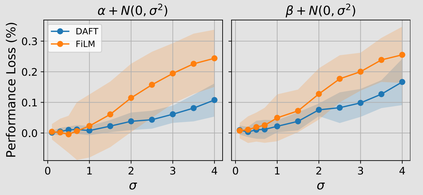
Configuration	Balanced Accuracy	Concordance Index
Before Last ResBlock	0.598 ± 0.038	0.749 ± 0.052
Before Identity-Conv	0.616 ± 0.018	0.745 ± 0.036
Before 1st ReLU	0.622 ± 0.024	0.713 ± 0.085
Before 2nd Conv	0.612 ± 0.034	0.759 ± 0.052
$\boldsymbol{\alpha}_i = \mathbf{1}$	0.581 ± 0.053	0.743 ± 0.015
$\boldsymbol{\beta}_i = \mathbf{0}$	0.609 ± 0.024	0.746 ± 0.057
$\sigma(x) = \text{sigmoid}(x)$	0.600 ± 0.025	0.756 ± 0.064
$\sigma(x) = \tanh(x)$	0.600 ± 0.025	0.770 ± 0.047
Proposed	0.622 ± 0.044	0.748 ± 0.045

DAFT vs FiLM

- Effectiveness of DAFT mostly due to shifting feature maps (β).



- DAFT is more robust to inaccurate α and β.



[1]: Duanmu et al.: Prediction of Pathological Complete Response to Neoadjuvant Chemotherapy in Breast Cancer Using Deep Learning with Integrative Imaging, Molecular and Demographic Data. In: MICCAI (2020)
[2]: Perez et al.: FiLM: Visual Reasoning with a General Conditioning Layer. In: AAAI (2018)