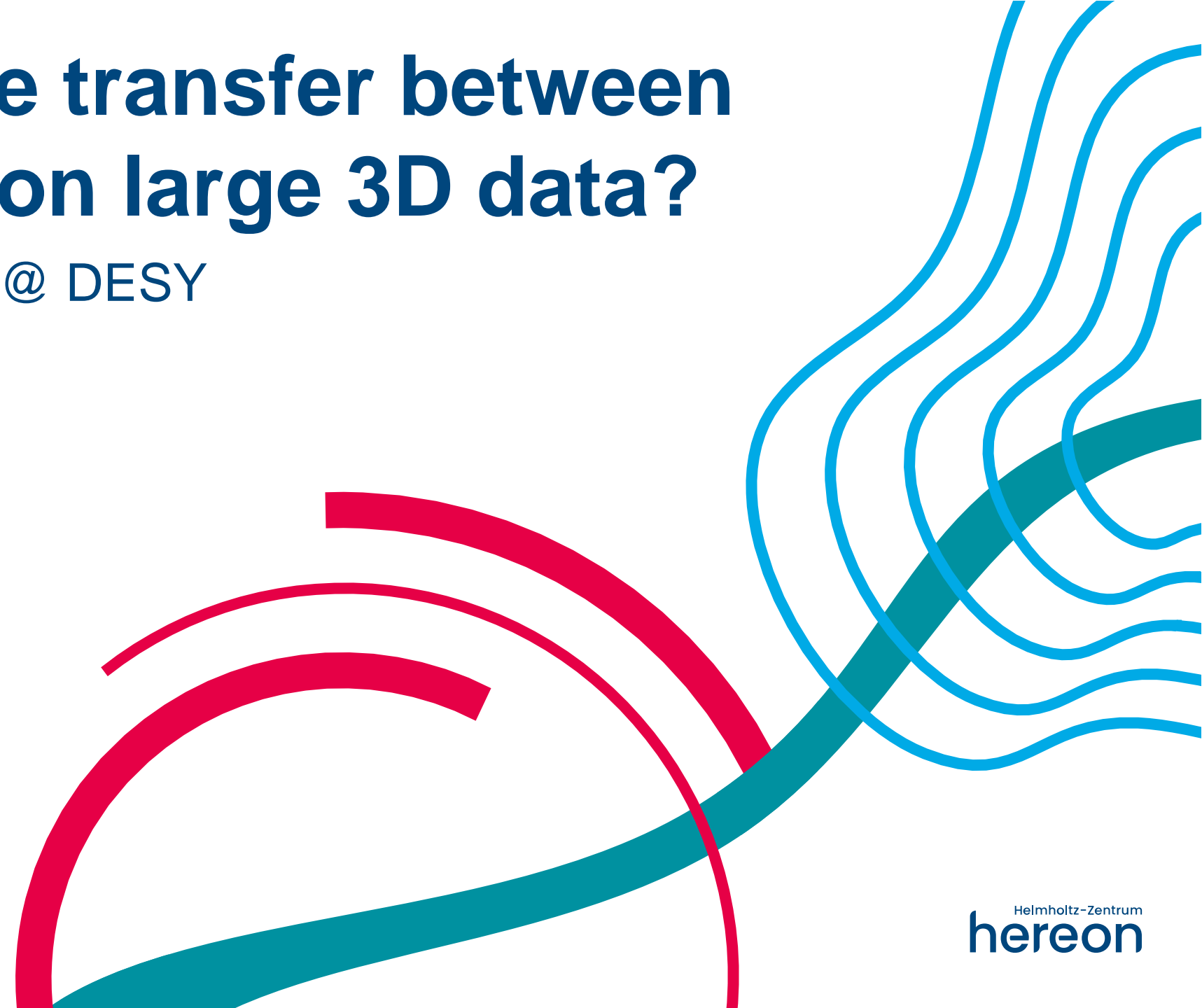


How to enable transfer between DL networks on large 3D data?

4th Round Table on AI @ DESY

Christian Lucas

Hamburg, 3 Dec 2021



Metallic Biomaterials, Imaging and Data Science

Who? Where? What?

Helmholtz-Zentrum Hereon, Geesthacht

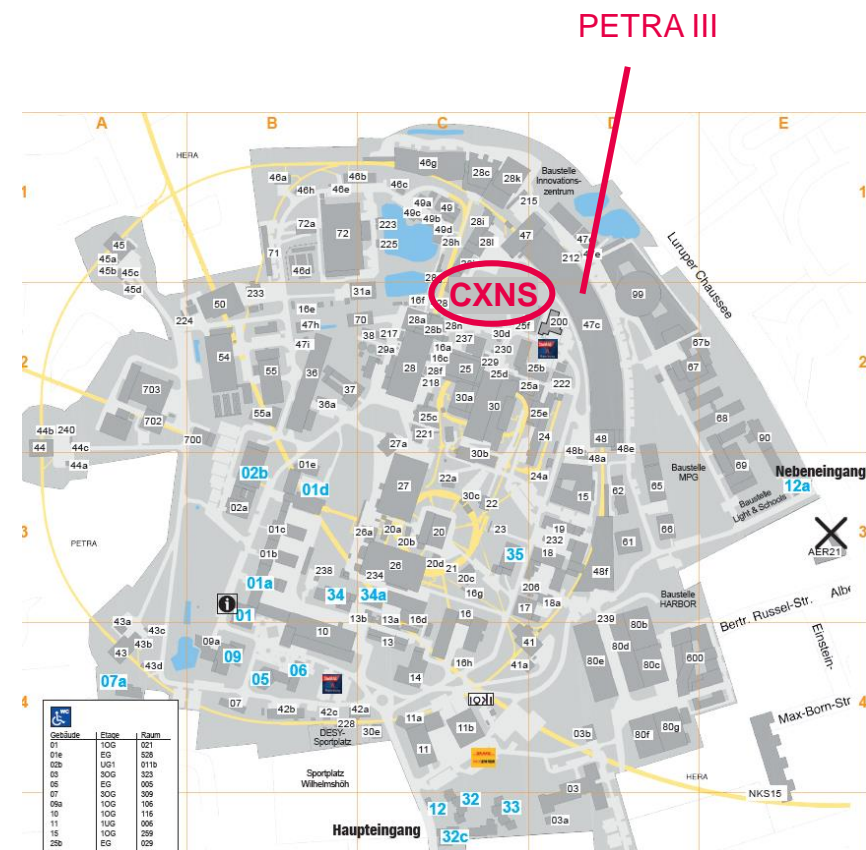
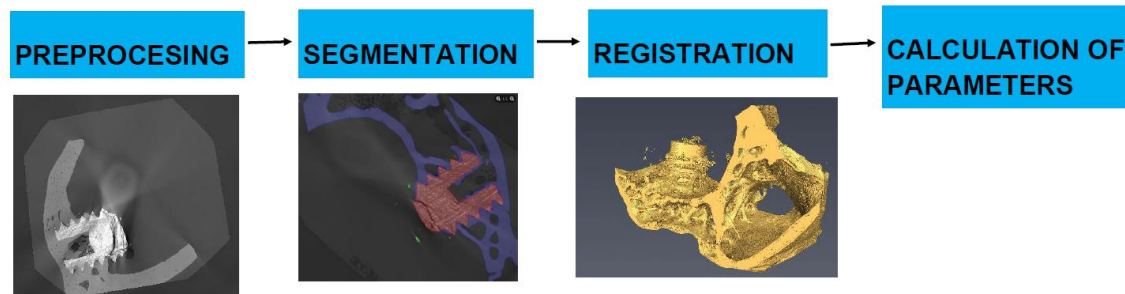
- at PETRA III (e.g. IBL @ P05) using X-ray micro/nano tomography for materials
- outstation on DESY campus (CXNS building)

Institute of Metallic Biomaterials (Prof. Regine Willumeit-Römer)

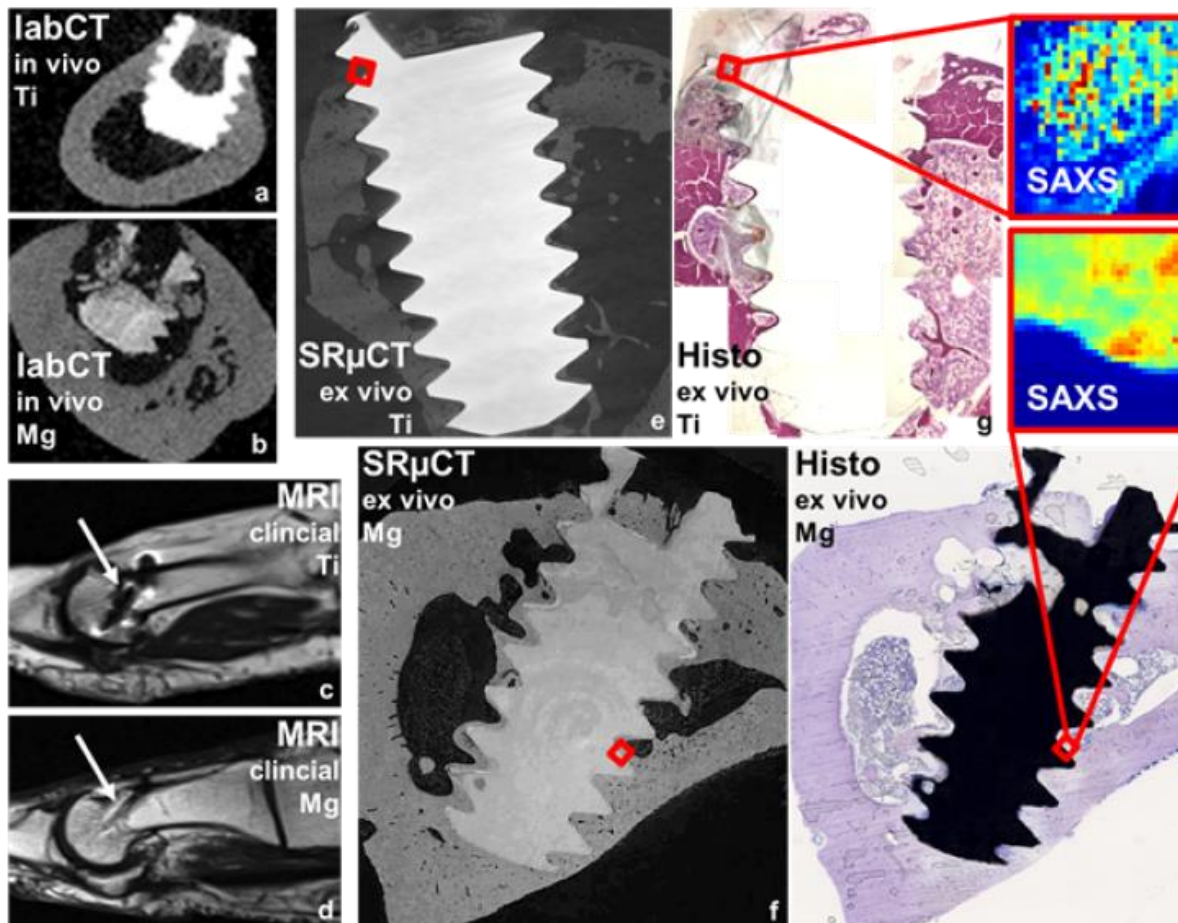
- medical implant materials: based on titanium/magnesium
 - improve biocompatibility, adapt to mechanical bone properties
 - alloys that degrade over time in human body
 - add pharmaceutically active elements for therapeutic effects

Imaging and Data Science Department

- image processing for analysis of degradation samples



Multi-task Deep Learning for Large-scale Multimodal Biomedical Image Analysis (MDLMA)



Yet another beamtime/project...

Artifact reduction?

Segmentation?

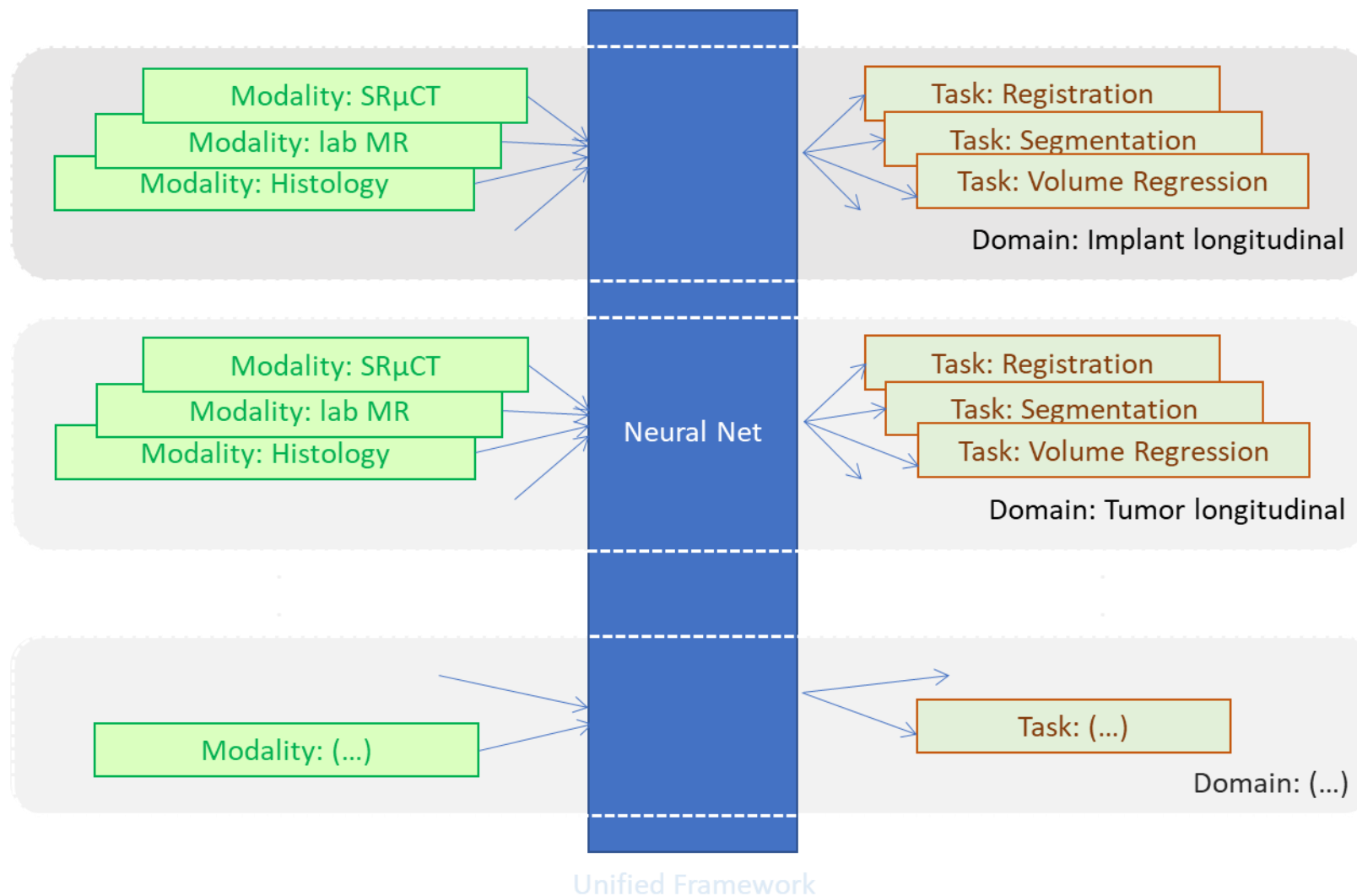
Registration?

Do not reinvent the wheel each time!
(i.e. reduce ML training)

→ **Need a common/generic foundation...**

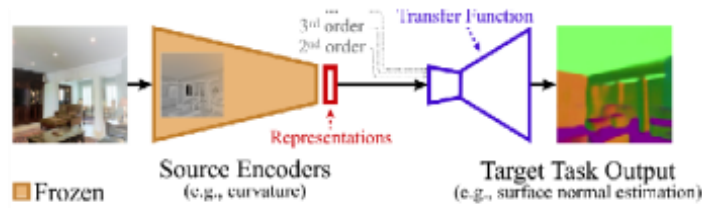
Handle a selection of multiple modalities/tasks/domains

Common/Generic unified approach?



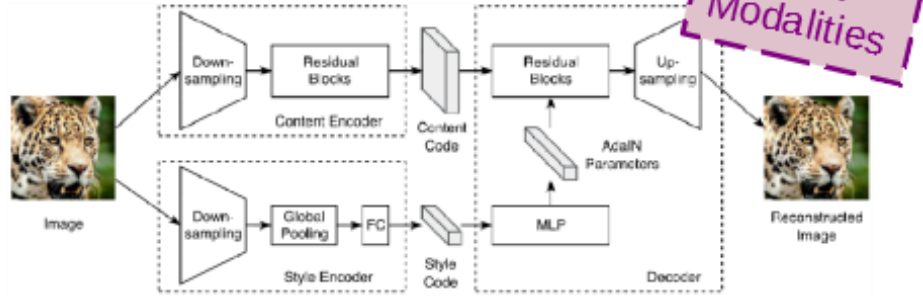
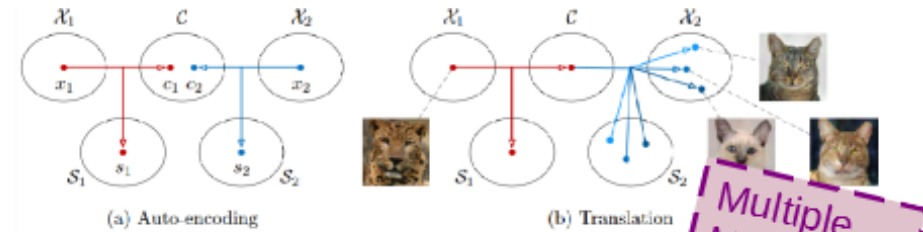
Disentangled representations

Basis for many transfers between modalities, tasks, etc.



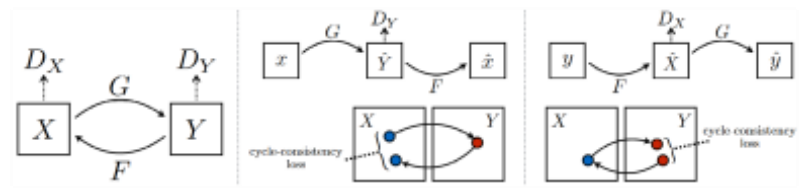
Transfer Function. We use one or multiple source tasks to predict a target task's output.

Zamir et al. (2018) **Taskonomy: Disentangling Task Transfer Learning**

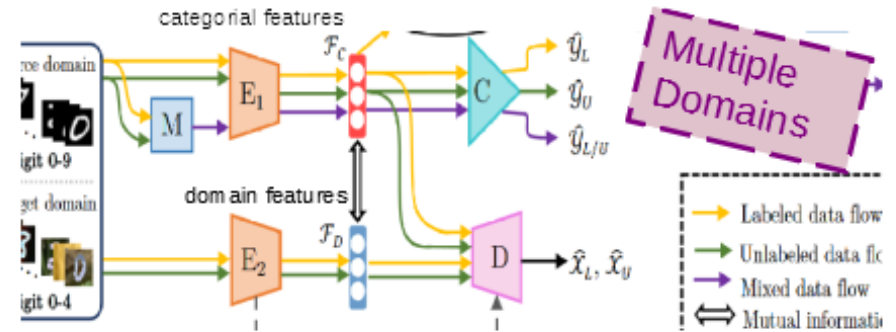


Huang et al (2018) **Multimodal Unsupervised Image-to-Image Translation (MUNIT)**

General disentanglement trick:



Zhu et al (2017) **Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks**



Meng et al. (2020) **Learning Cross-domain Generalizable Features by Representation Disentanglement**

Disentangled representations

Challenges for a unified network

Goal: Training end-to-end to benefit from all available information

“It’s the *memory*, stupid!”

Disentangling representations: many encoders/decoders, complex nets
→ increasing dependency graph (e.g. store many intermediate results)

Synchrotron tomography: HIGH resolution!
→ 2048x2048x2048 32-bit image exceeds Nvidia V100’s 32GB RAM

Registration tasks require full image information (find correspondences)
→ full image representation (not patches)

... sums up to a **HUGE** memory demand



Parallelization and precision reduction are – by far – not enough!

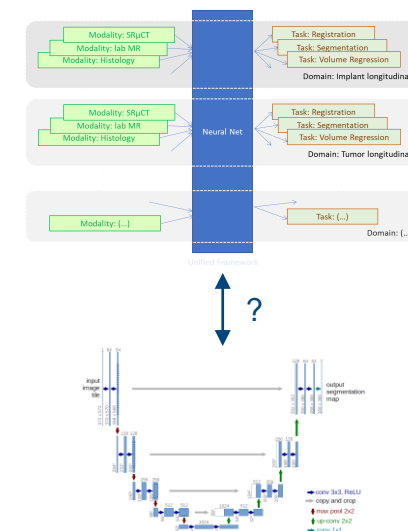
Exploit high resolution information & multi-modal/multiple task information

Idea: Separation between

low-resolution but complex unified network (3D full representation) trained on all modality and task

and

high-resolution specialized but less complex networks (2D patch) trained specific modality and task (e.g. SR μ CT segmentation)



How to transfer between both (model-agnostic) to fine-tune?

- Ensemble Fusion
- Knowledge Distillation transfer
- Cross-resolutional attention

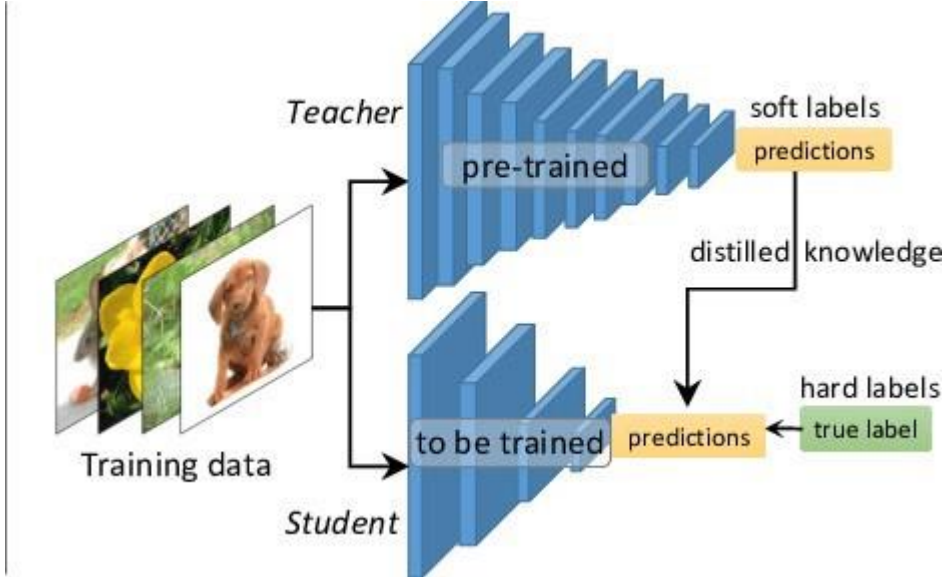
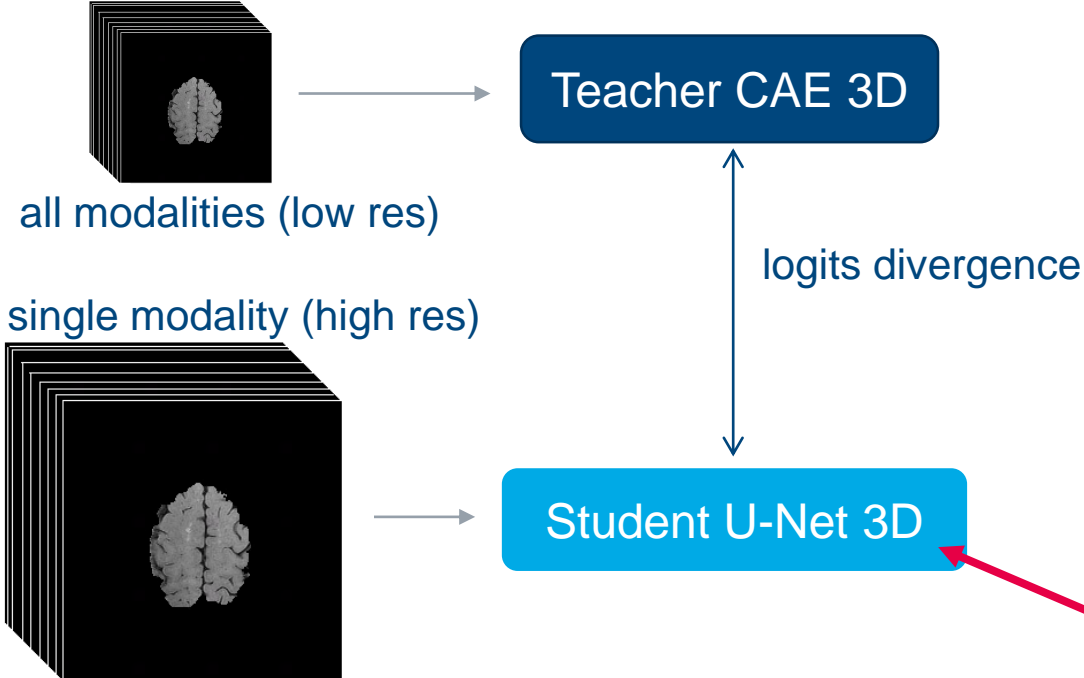
...

Knowledge Distillation

Transfer *soft* target knowledge

Exploit information about soft target (logits) of a teacher network

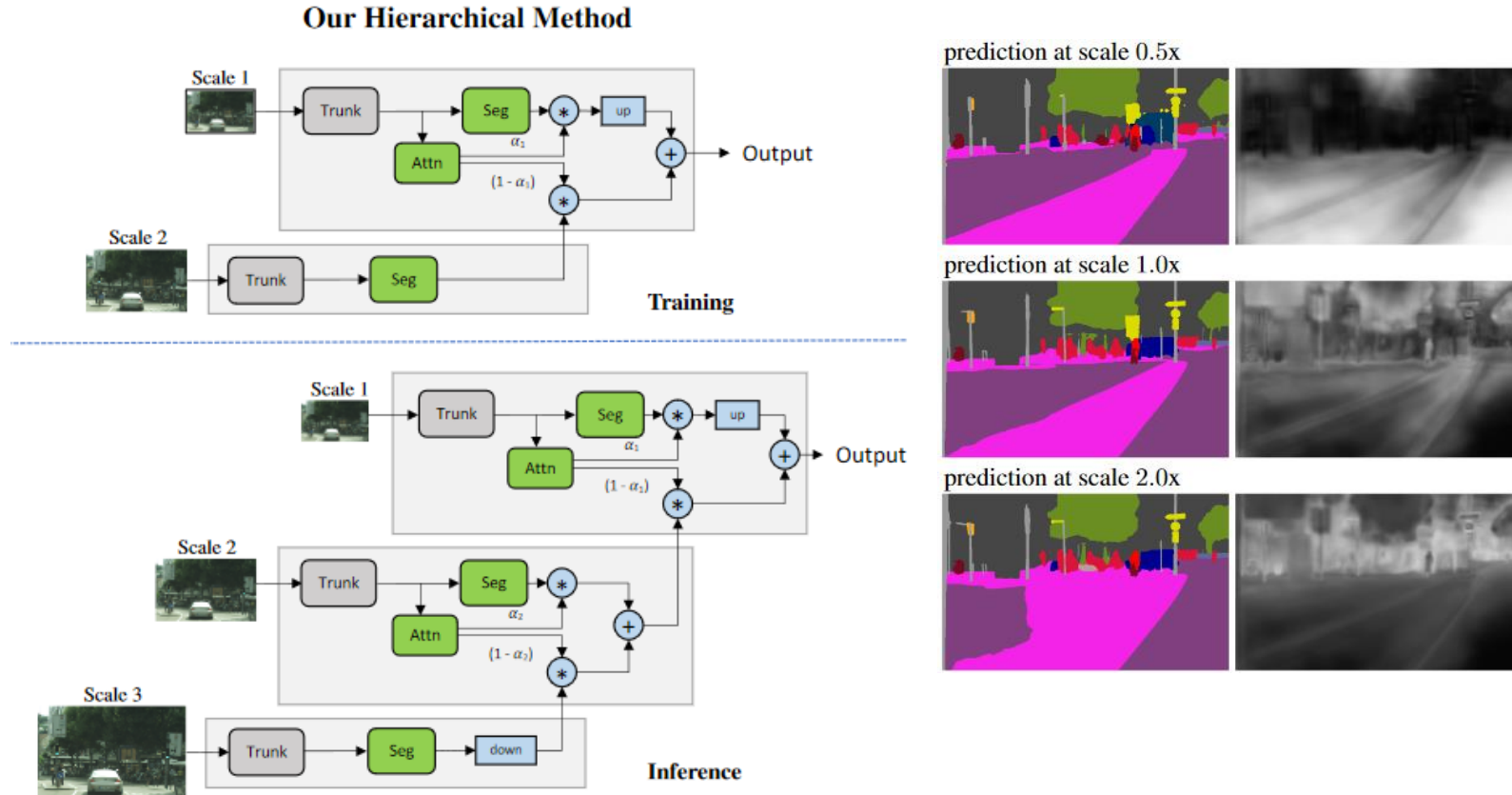
First experiments on a public 3D brain tumor dataset:



Results on 3D ok, but not sufficient for 3D to 2D transfer!

Current work-in-progress

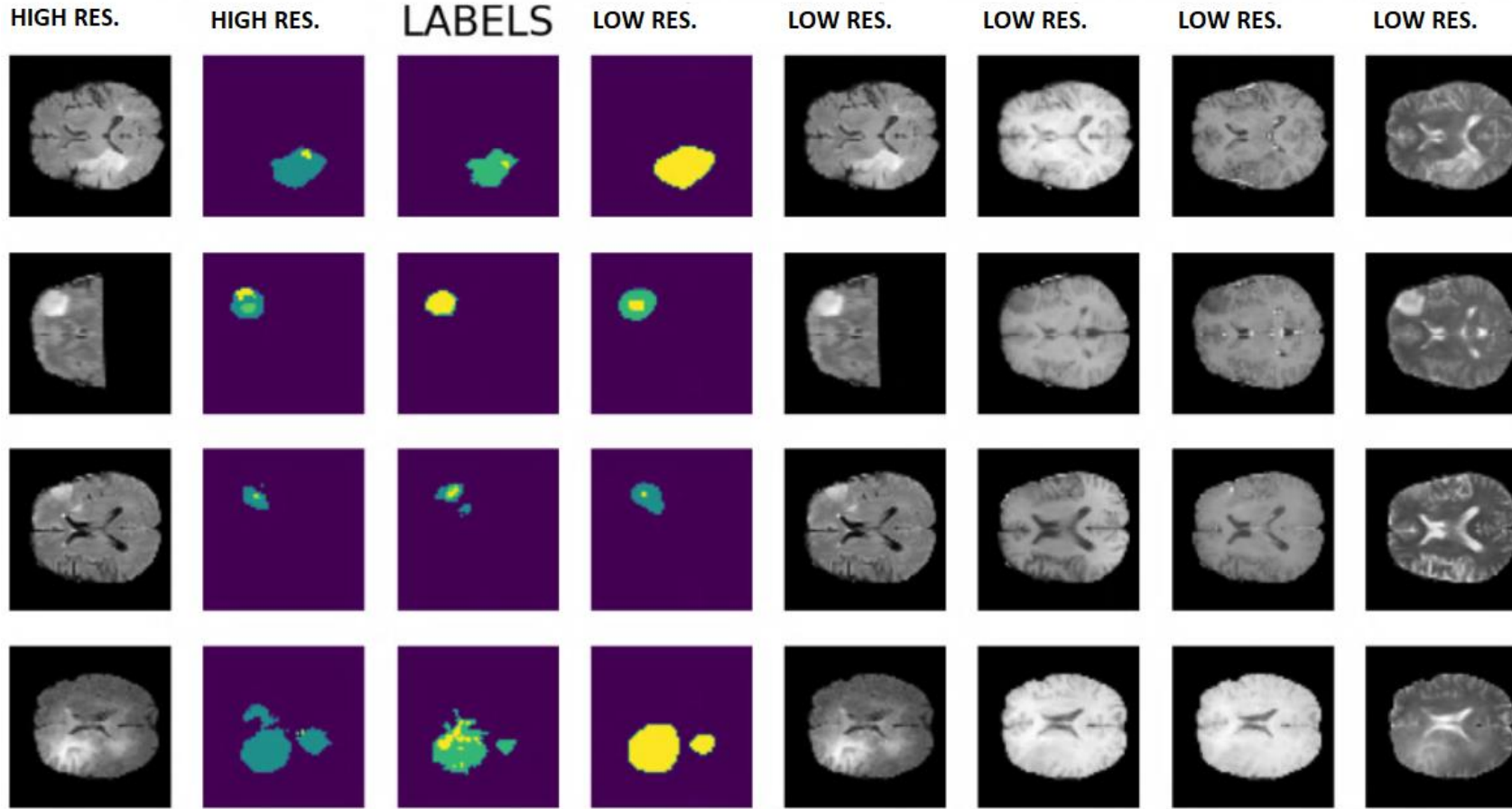
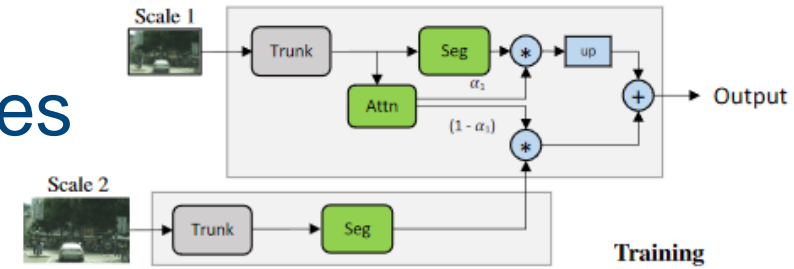
Attention fusion approaches across resolution scales



Tao, Sapra, Catanzaro (Nvidia, 2020): HIERARCHICAL MULTI-SCALE ATTENTION FOR SEMANTIC SEGMENTATION

Current work-in-progress

Attention fusion approaches across resolution scales



Scale 2

Scale 1

No sufficient methodology/results yet...

Similar problems? Facing same constraints with CV?

If you like to exchange experience, I am pleased to hear from you:

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