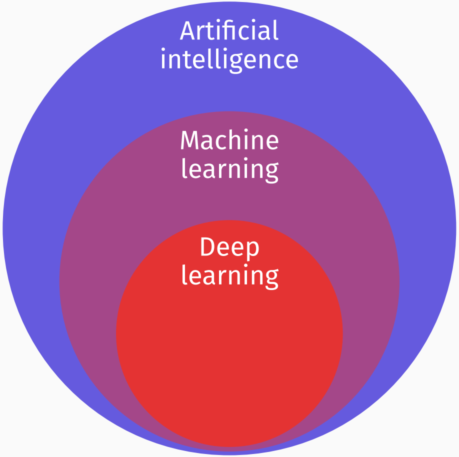
Enabling deep learning in small MRI datasets with transfer learning

UNIVERSITY OF OSLO

Deep learning on MRI data



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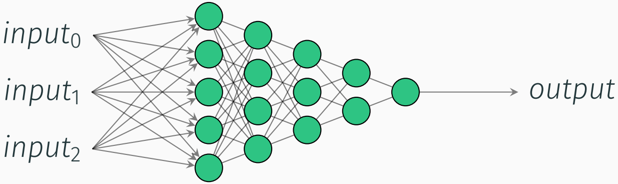

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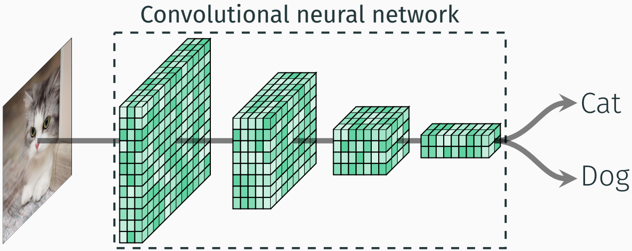

Deep learning on MRI data

Model	Year	Imagenet top-1 accuracy	Parameters
InceptionV3	2016	77.9%	23.9M
ResNet152V2	2016	78.0%	60.4M
DenseNet201	2017	77.3%	20.2M
NASNetLarge	2017	82.5%	88.9M
MobileNetV2	2018	71.3%	3.5M
EfficientNetB7	2019	84.3%	66.7M
EfficientNetV2L	2021	85.7%	119.0M
Vision Transformer L/16	2021	85.2%	307M
ConvNeXtXLarge	2022	86.3%	350.1M

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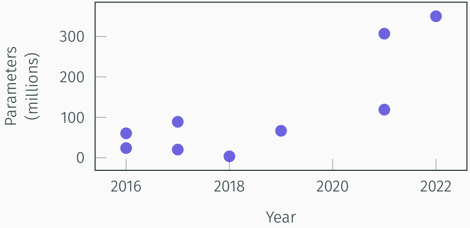

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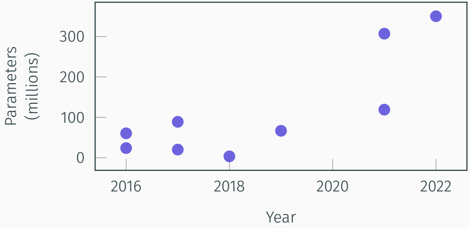
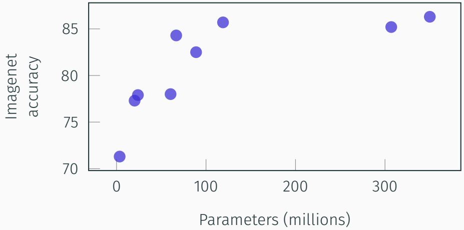
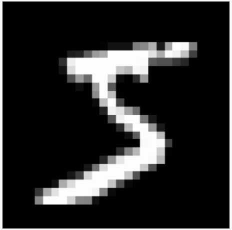




Deep learning on MRI data

Dataset	Size	Dimensionality
MNIST	∼70K	28x28 pixels



Deep learning on MRI data

Dataset	Size	Dimensionality
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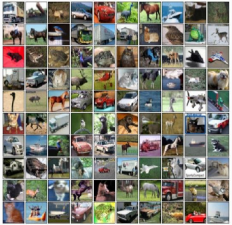
CIFAR	∼60K	32x32 pixels



Deep learning on MRI data

Dataset	Size	Dimensionality
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COCO	∼330K	640x640 pixels
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UK Biobank	45,891	256x256x256 voxels
ABCD	11,660	256x256x256 voxels
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TOP	2,222	256x256x256 voxels
HBN	1,365	256x256x256 voxels
QTIM	1,201	256x256x256 voxels
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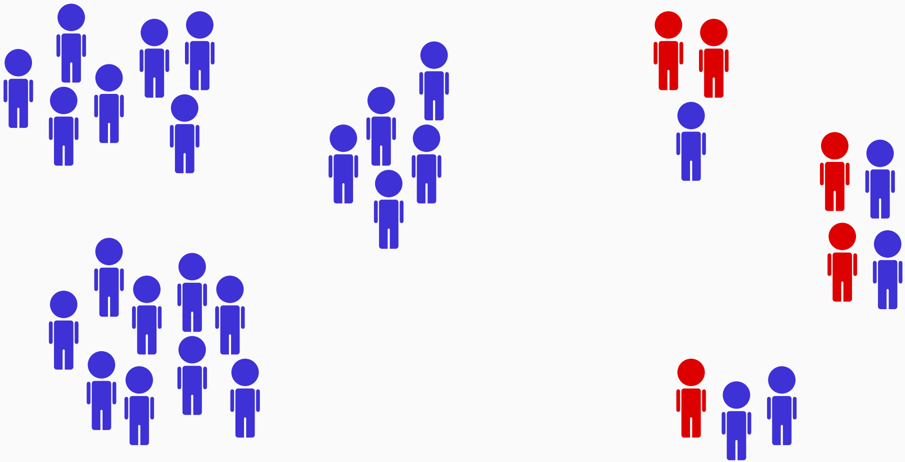

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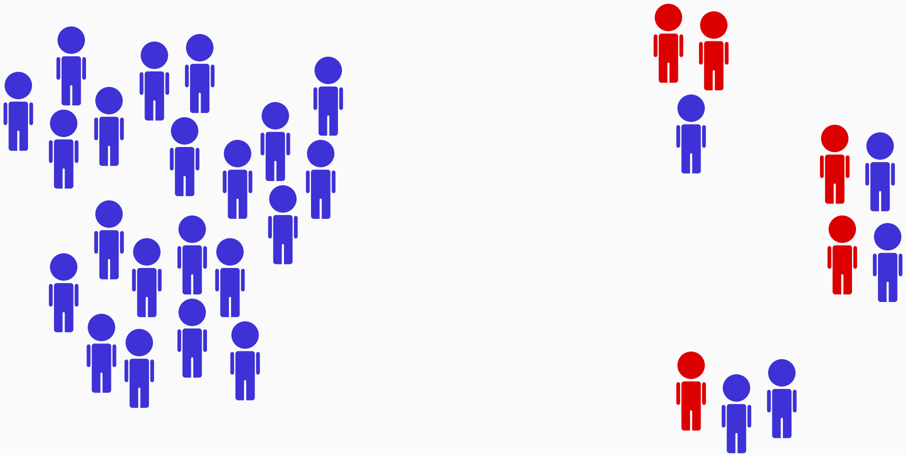

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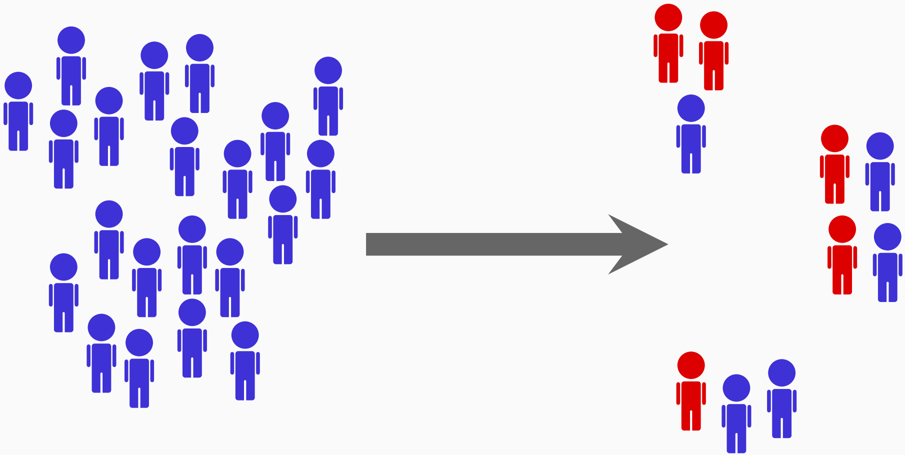

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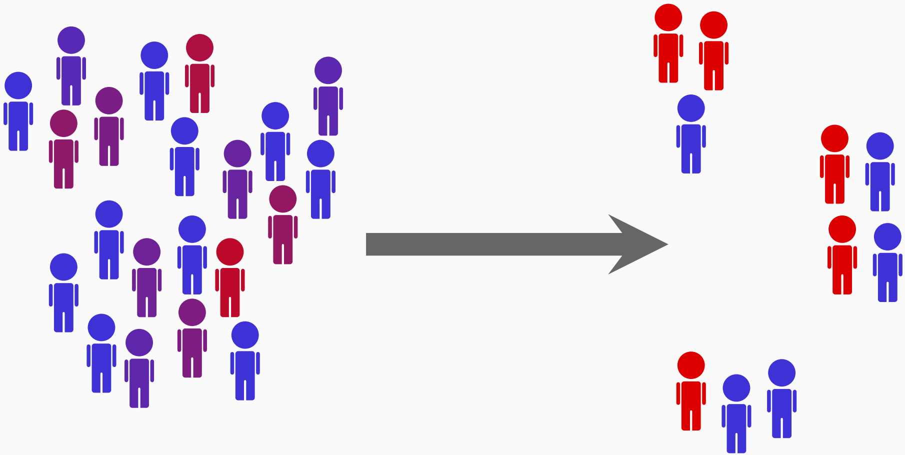
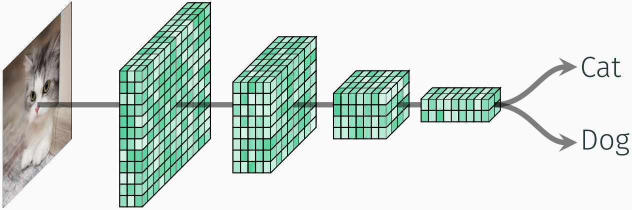


Transfer learning

How does CNNs work



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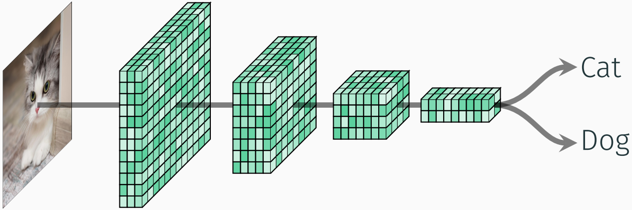

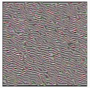

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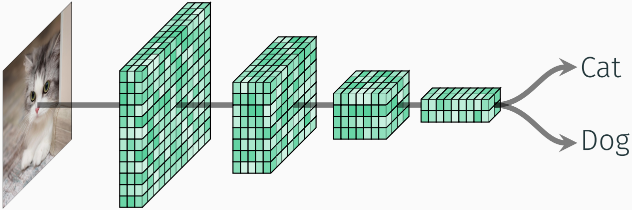

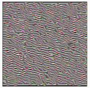

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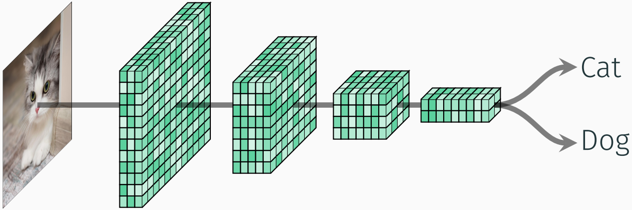

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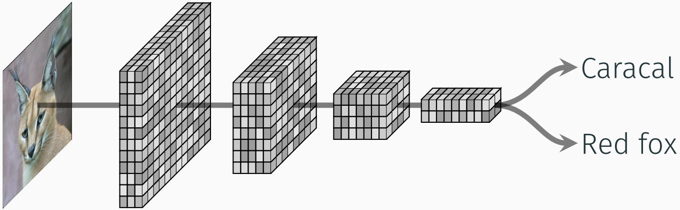

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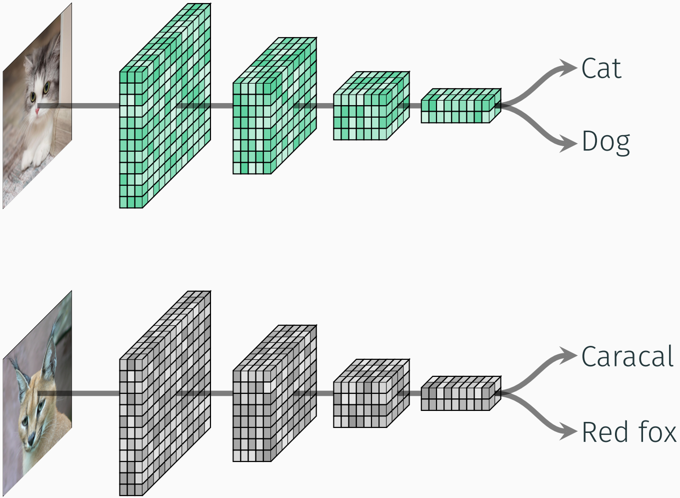

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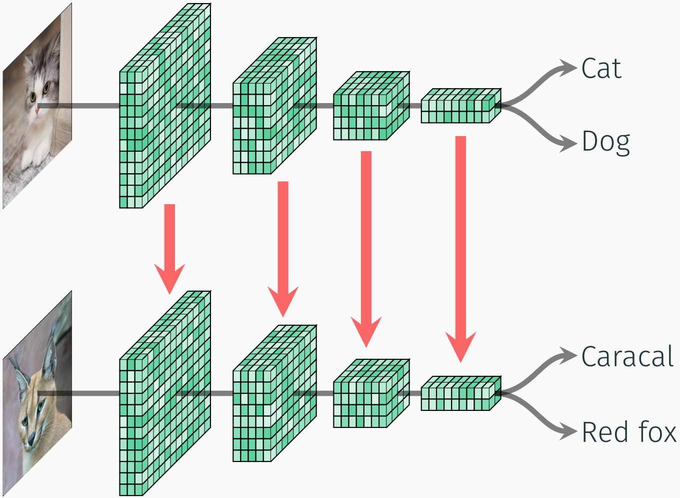

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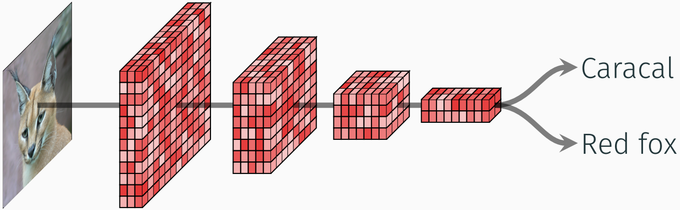

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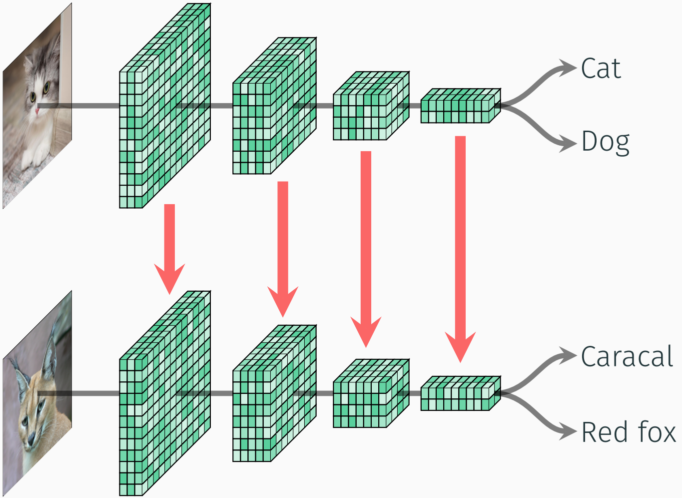

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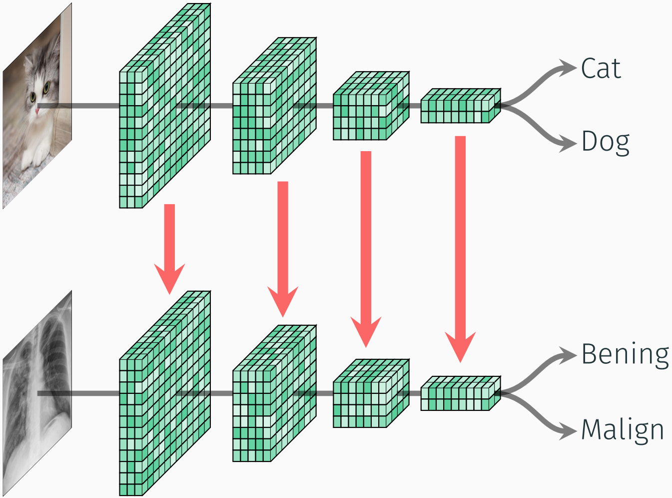
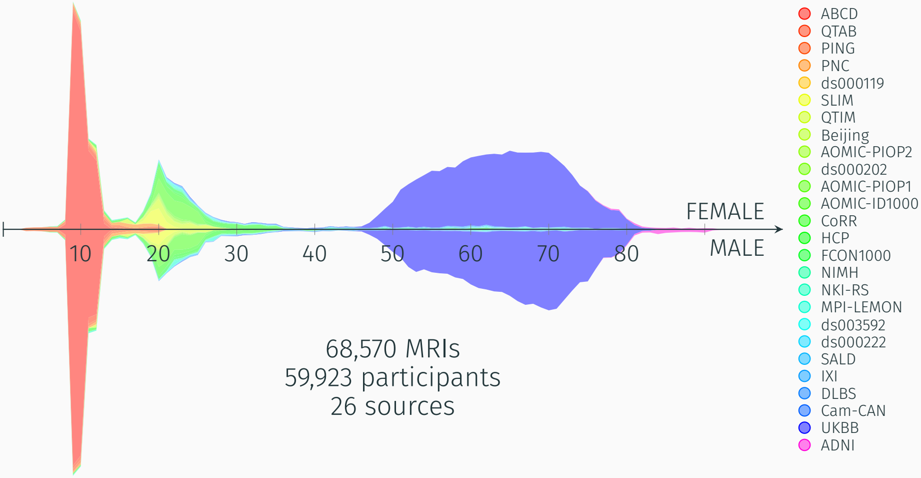


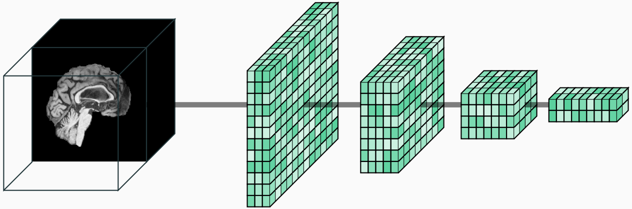
Our work

Methods: Training dataset



68,570 MRIs
59,923 participants
26 sources

Methods: Modelling



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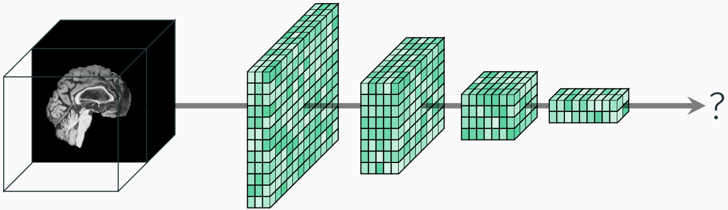

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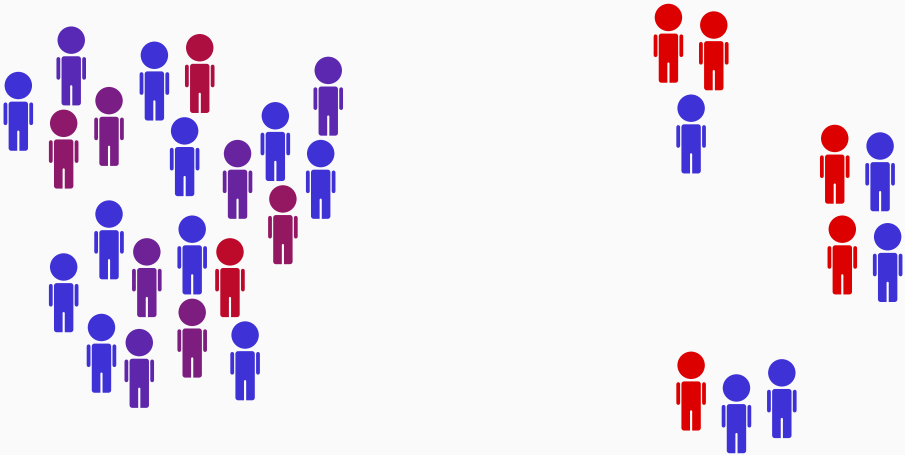

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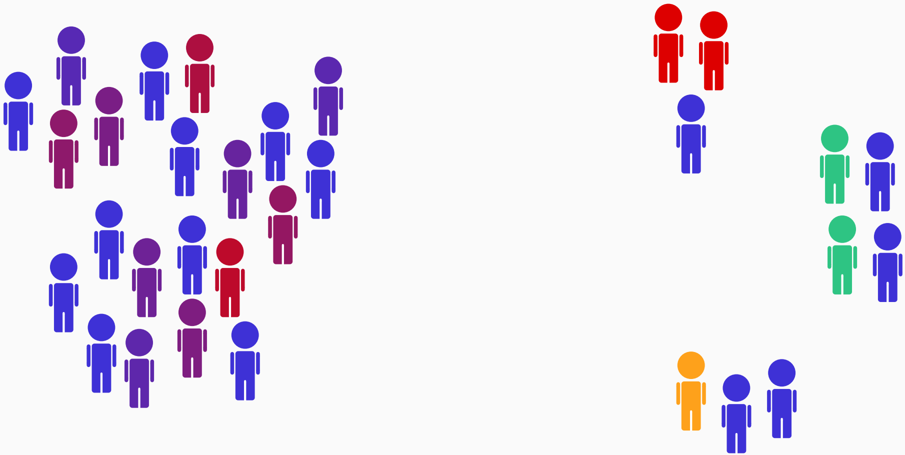
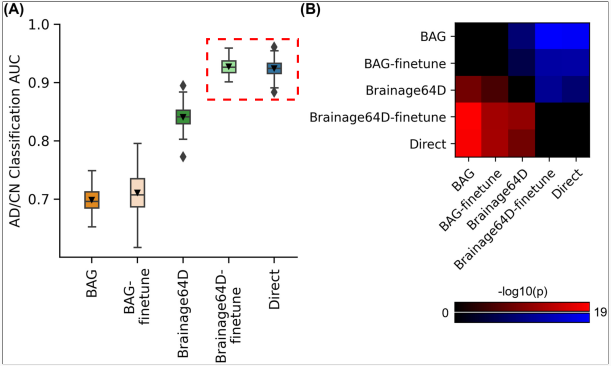


Methods: Modelling

> Furthermore, we see this result as evidence that deep learning models trained to predict age in large multisite datasets constitute excellent starting points for transfer learning, which can subsequently be fine-tuned to a variety of tasks.

Leonardsen, E. H., Peng, H., Kaufmann, T., Agartz, I., Andreassen, O. A., Celius, E. G., ... & Wang, Y. (2022). Deep neural networks learn general and clinically relevant representations of the ageing brain. *NeuroImage*, *256*, 119210.

Methods: Modelling



Tan, T. W. K., Nguyen, K. N., Zhang, C., Kong, R., Cheng, S. F., Ji, F., ... & Australian Imaging Biomarkers and Lifestyle Study of Aging. (2025). Mind the gap: Does brain age improve Alzheimer's disease prediction?. *Human Brain Mapping*, *46*(12), e70276.

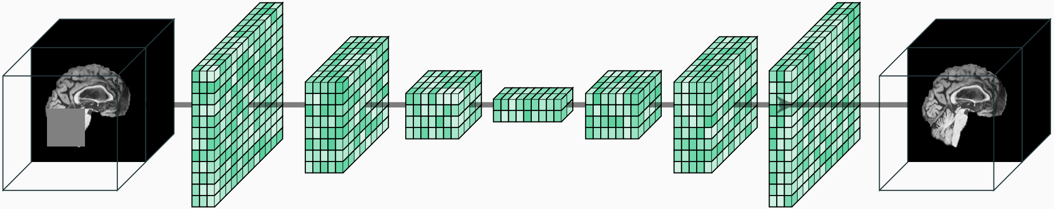
Methods: Modelling

Brain age

Brain age

Self-supervised approaches

Methods: Modelling

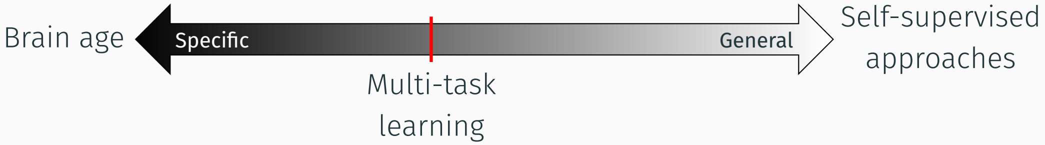


Methods: Modelling

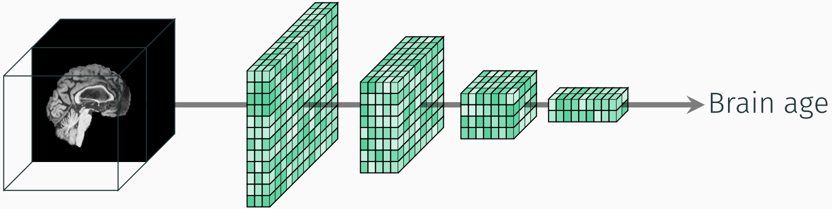
Brain age

Self-supervised approaches

Methods: Modelling



Methods: Multi-task learning



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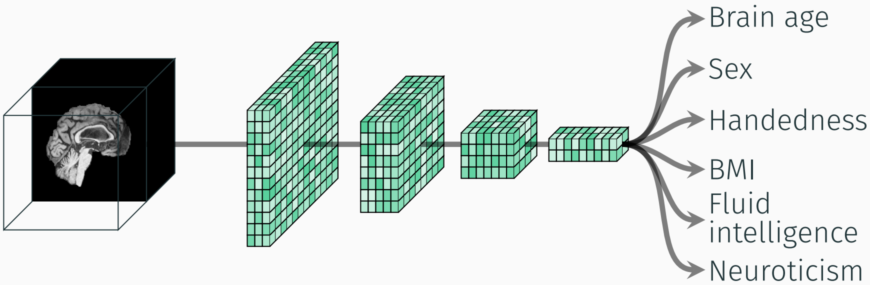

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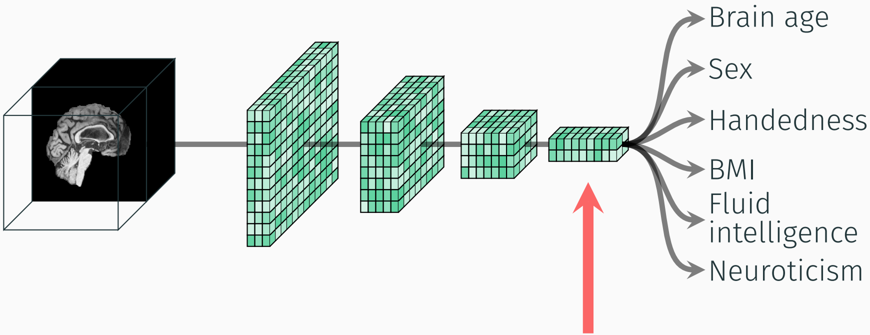
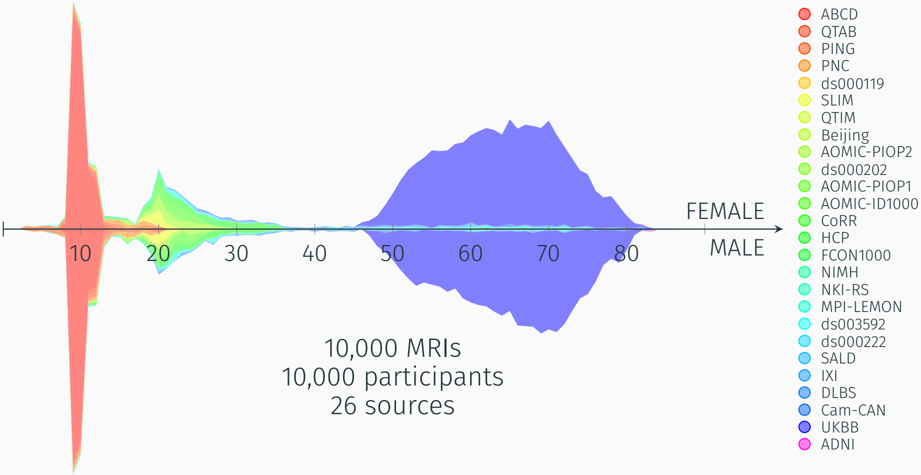


Methods: Multi-task learning

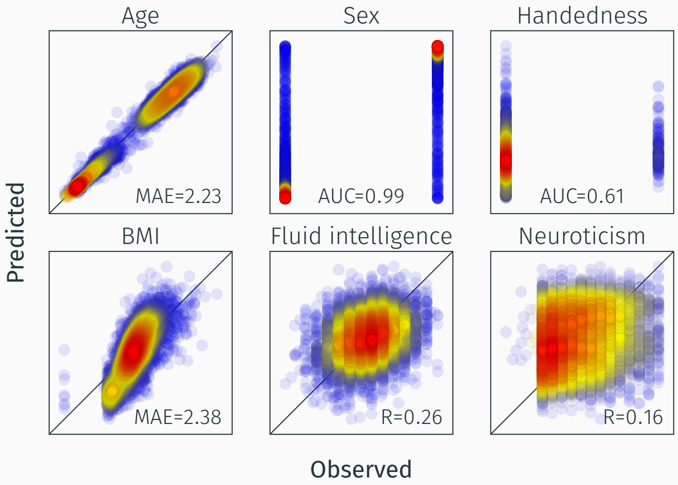
	Age	Sex	Handedness	BMI	Fluid intelligence	Neuroticism
Age	1	0	0.02	0.52	-0.1	-0.04
Sex	0	1	0.03	0.04	-0.15	0.04
Handedness	-0.02	0.03	1	0	0.03	-0.03
BMI	0.52	0.04	0	1	-0.03	-0.05
Fluid intelligence	-0.1	-0.15	0.03	-0.03	1	-0.04
Neuroticism	-0.04	0.04	-0.03	-0.05	-0.04	1

Results: Validation

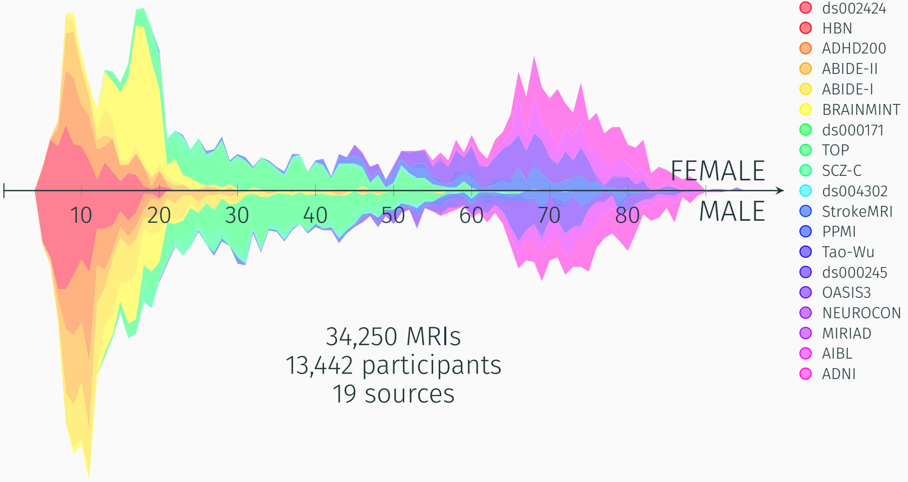


10,000 MRIs
10,000 participants
26 sources

Results: Validation

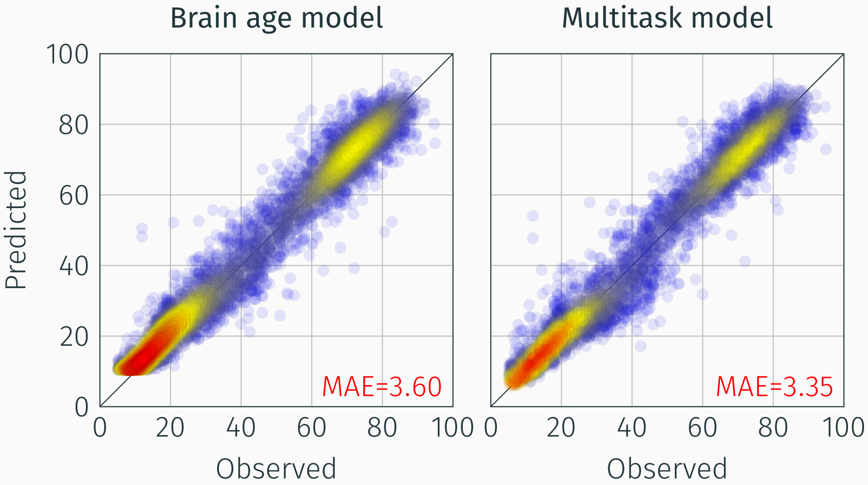


Results: Brain age

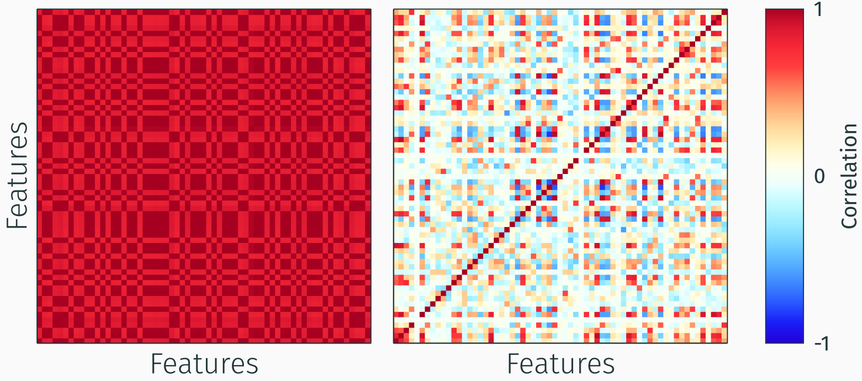


34,250 MRIs
13,442 participants
19 sources

Results: Brain age



Results: Feature spaces



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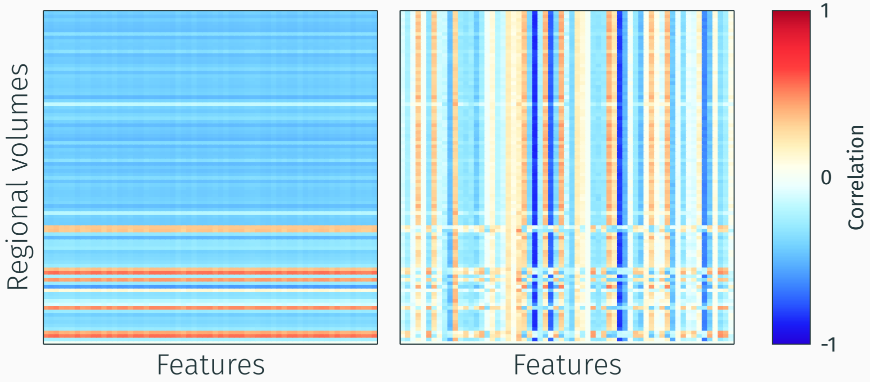


Transfer learning: Motivation

Will transfer learning from the pretrained multi-task model result in better predictive performance in downstream prediction tasks relying on small datasets for training?

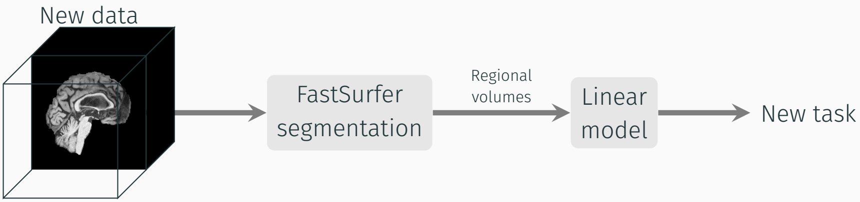
Transfer learning: Prediction tasks

Four prediction tasks:

1. Heterogeneous brain age prediction
   - 6,750 images from 20 sources
2. Homogeneous brain age prediction
   - 1,072 images from TOP
3. Classification of patients with Alzheimer's disease and healthy controls
   - 10,660 images from ADNI
4. Classification of patients with schizophrenia and bipolar disorder
   - 1,037 images from TOP

Transfer learning: Modelling approaches

Linear model | Baseline | Direct transfer | Finetuned multi-task model | Finetuned brain age model | Partially fine-tuned multi-task model



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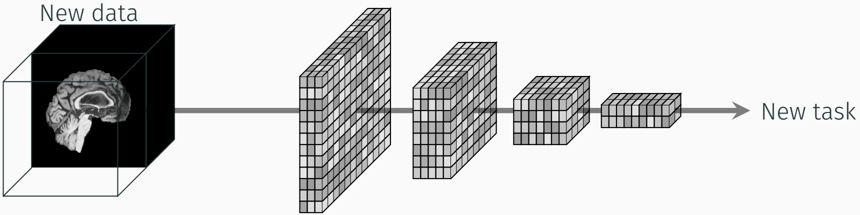

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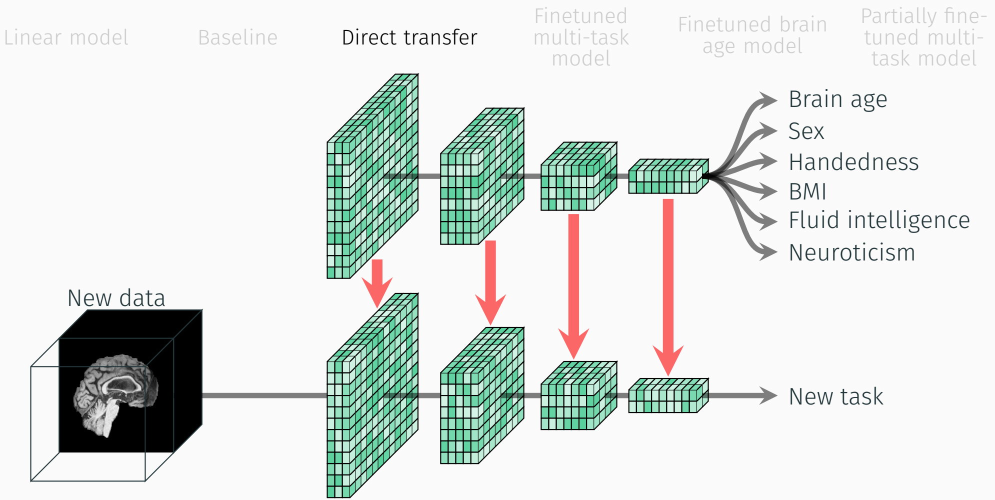


Transfer learning: Modelling approaches

Linear model

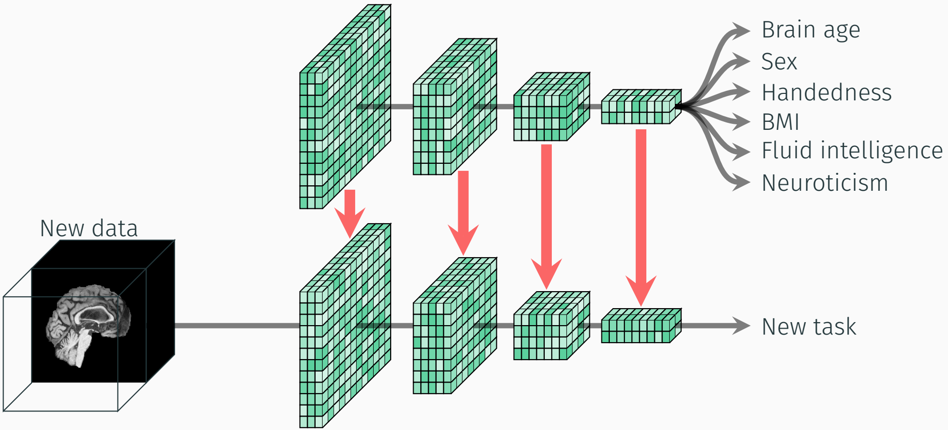
Baseline

Direct transfer

Finetuned multi-task model

Finetuned brain age model

Partially fine-tuned multi-task model



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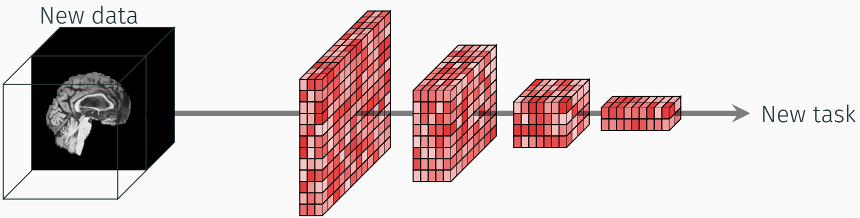

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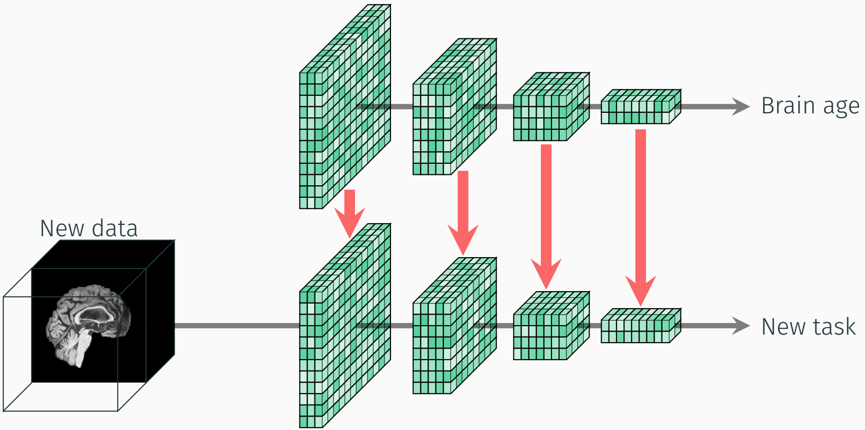

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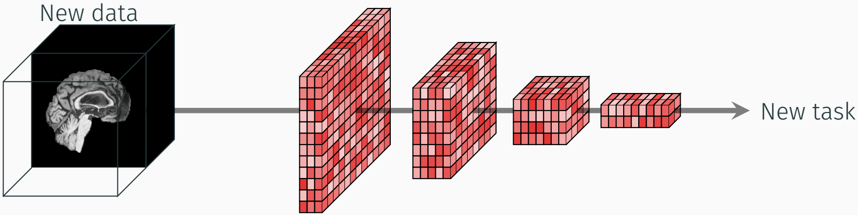

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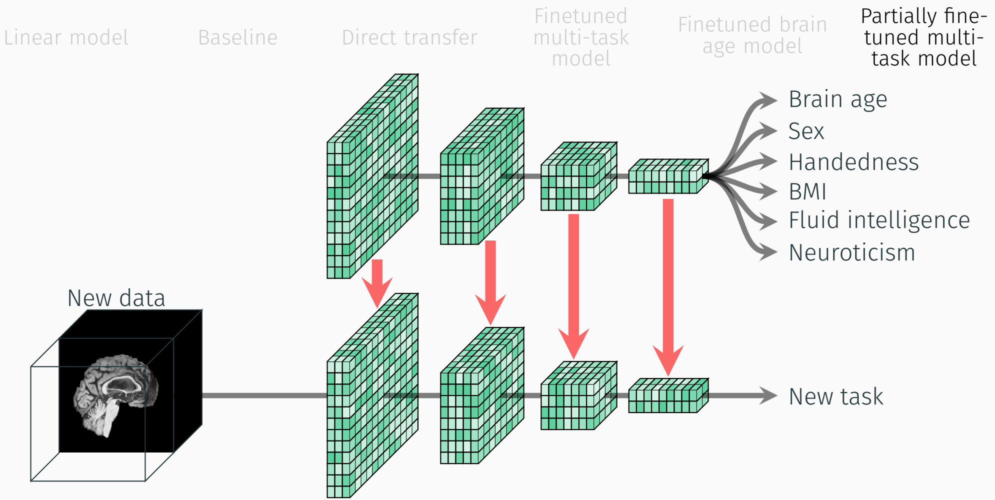

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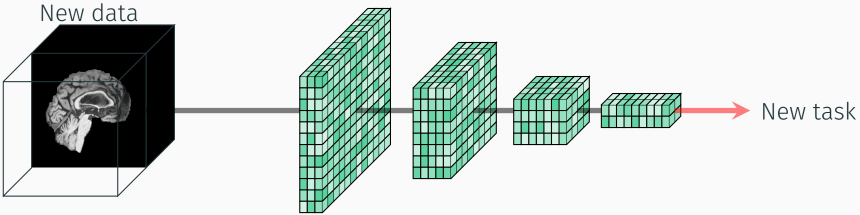
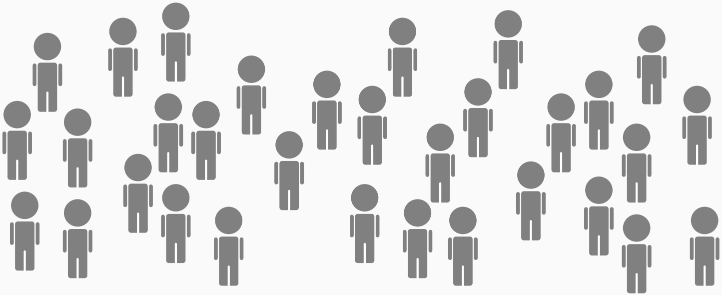
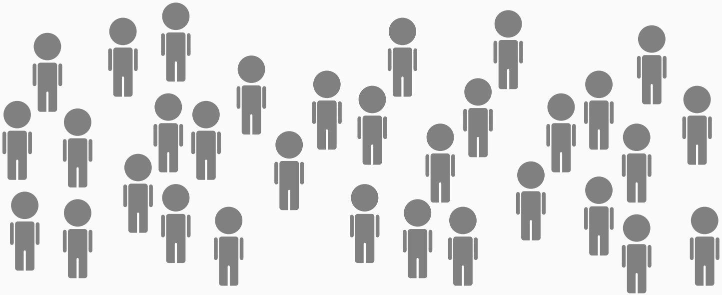


Transfer learning: Sampling



Transfer learning: Sampling

n=100



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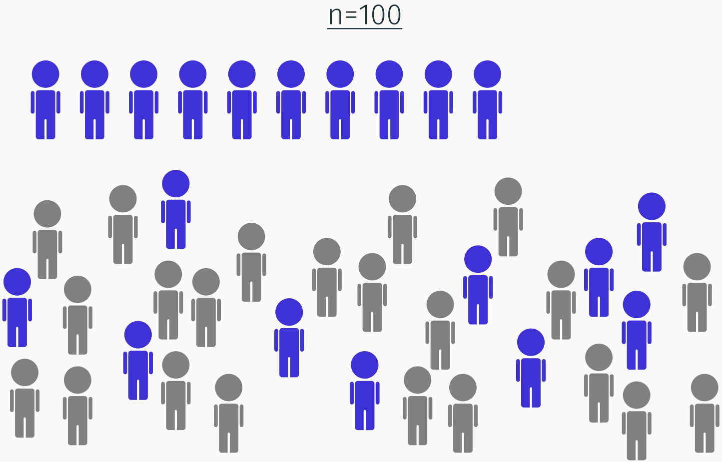
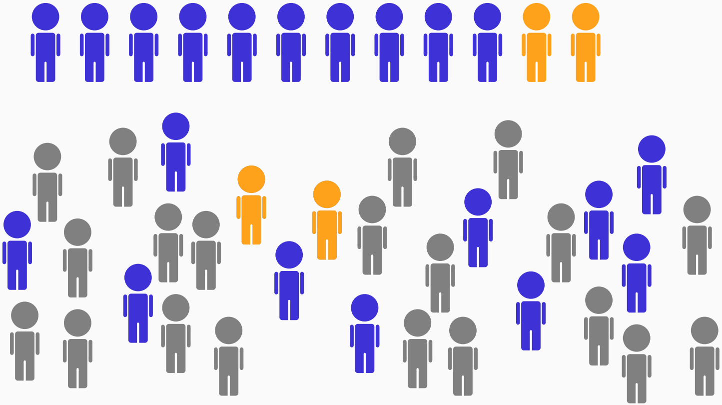


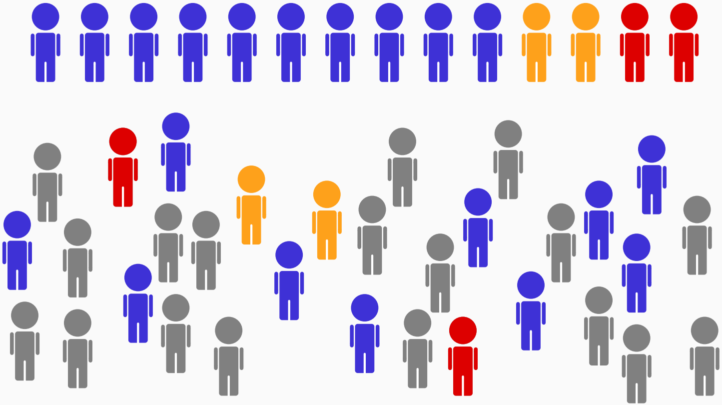
Transfer learning: Sampling

n=100

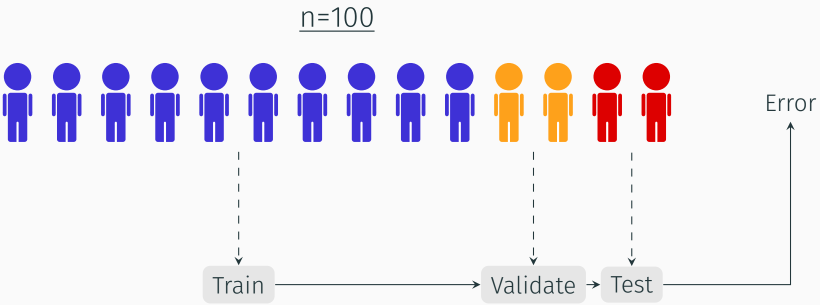


Transfer learning: Sampling

n=100

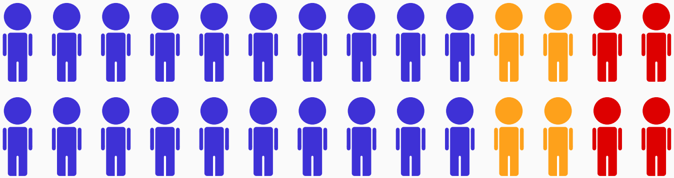


Transfer learning: Sampling



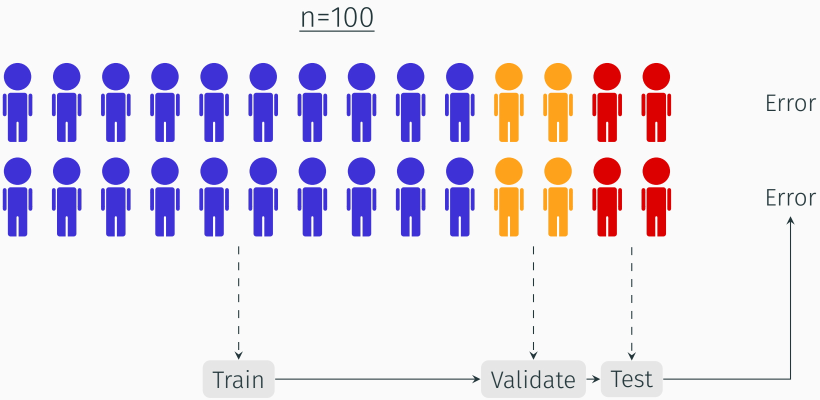
Transfer learning: Sampling

n=100

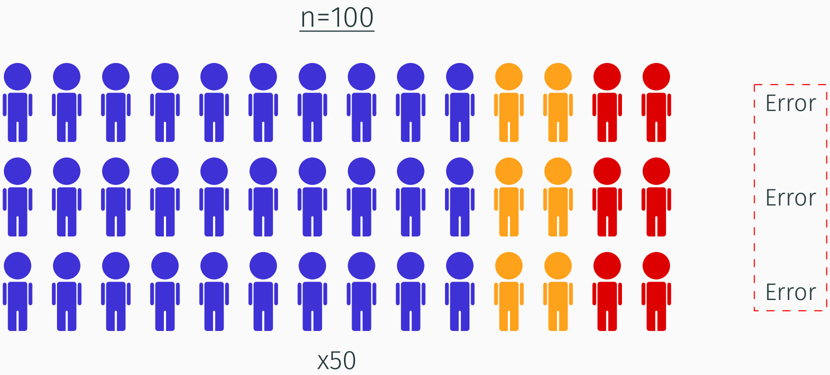


Error

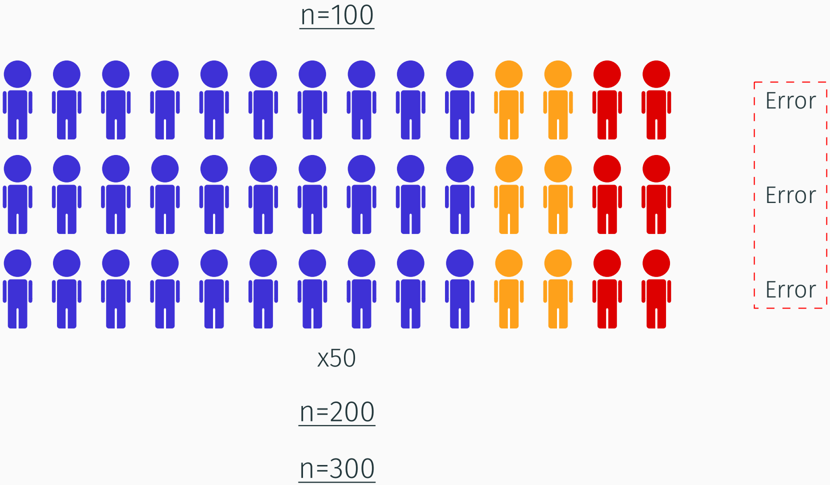
Transfer learning: Sampling



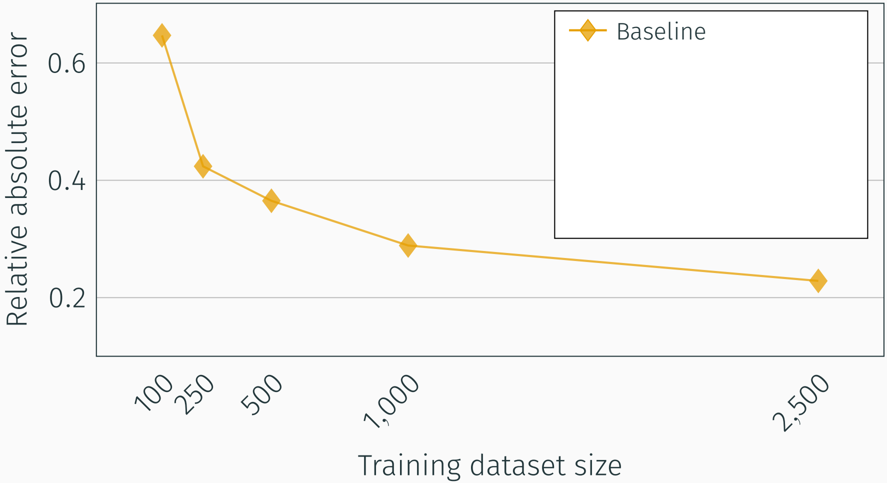
Transfer learning: Sampling



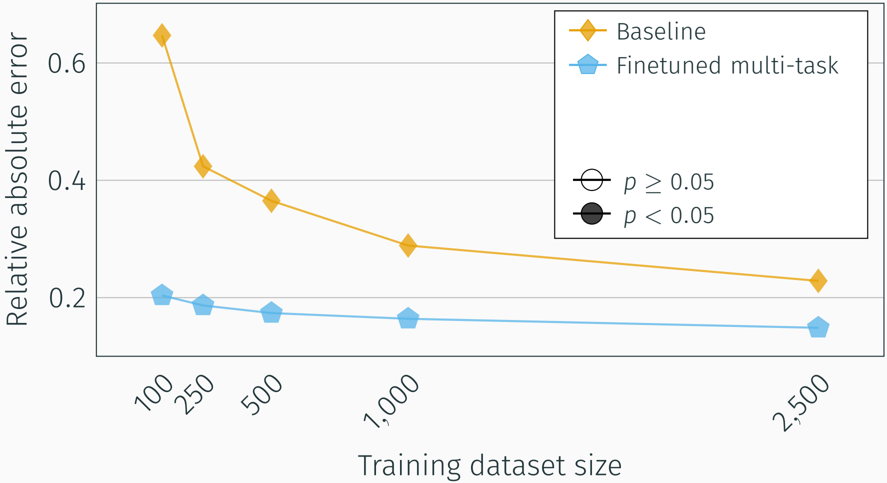
Transfer learning: Sampling



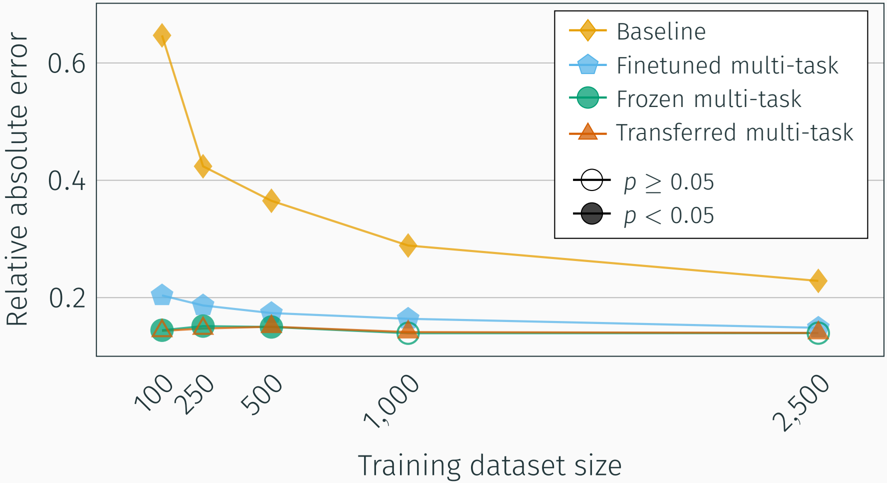
Results: Heterogeneous brain age predictions



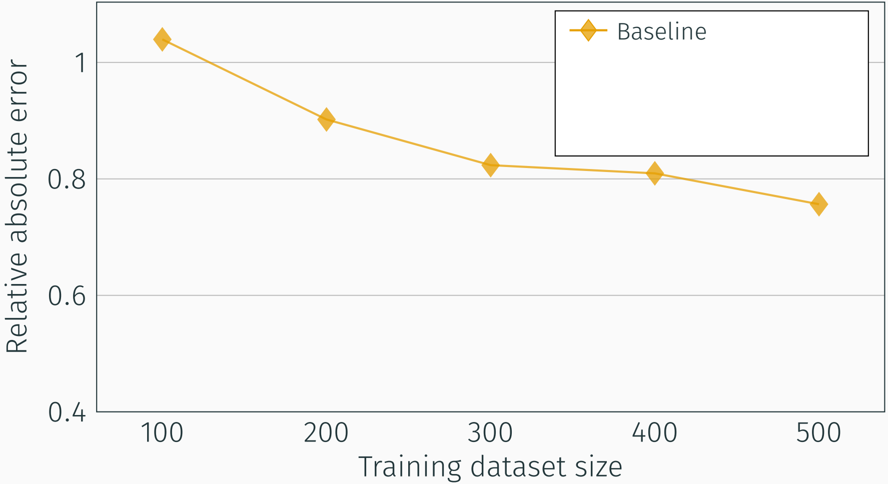
Results: Heterogeneous brain age predictions



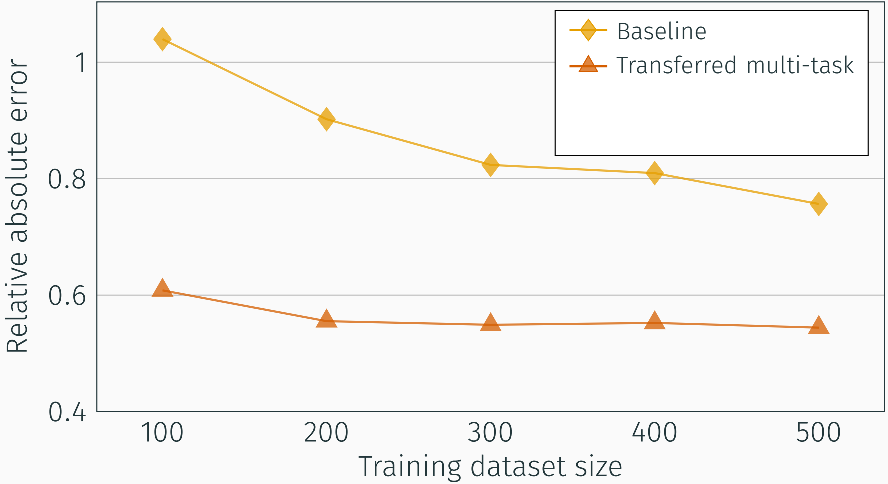
Results: Heterogeneous brain age predictions



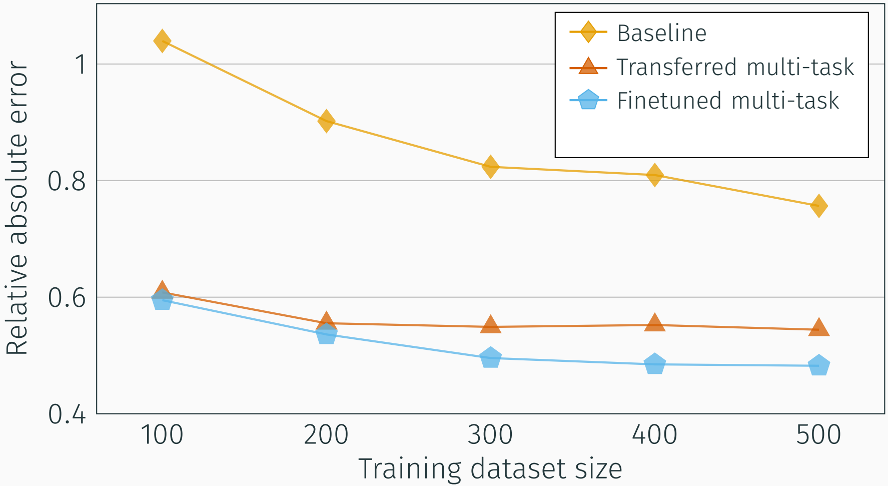
Results: Homogeneous brain age predictions



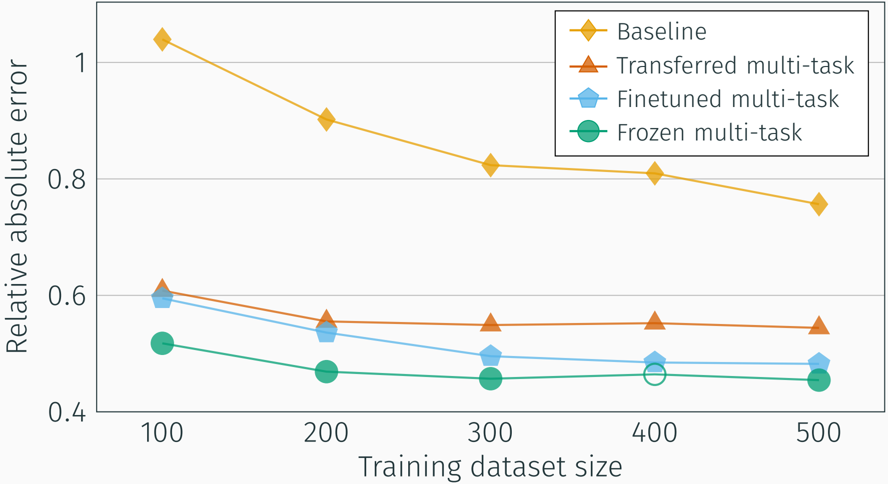
Results: Homogeneous brain age predictions



Results: Homogeneous brain age predictions



Results: Homogeneous brain age predictions

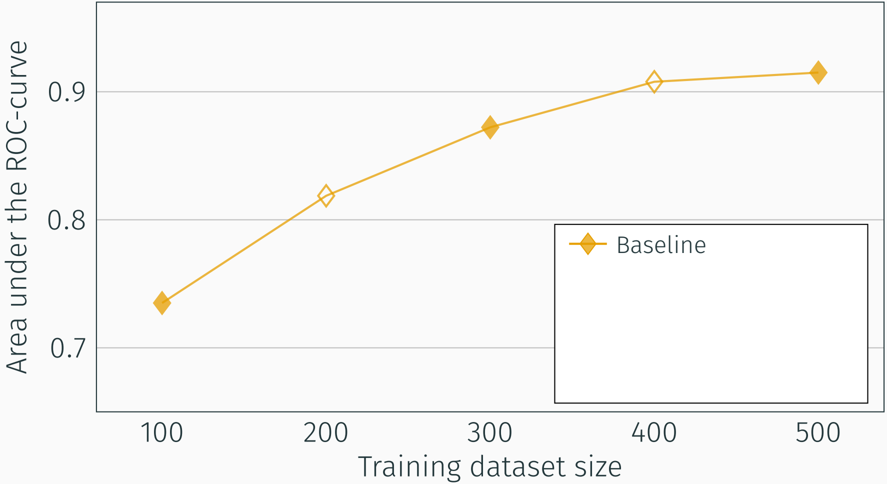


Results: Brain age

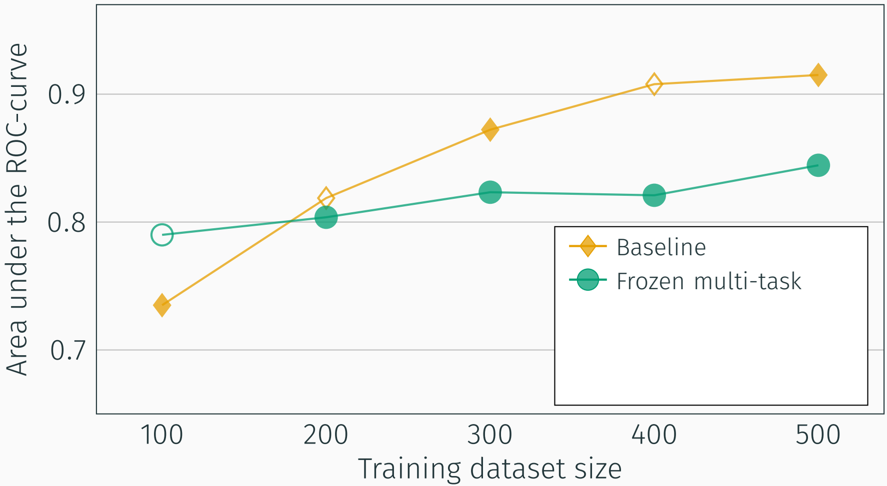
If you want to accurately predict brain age in new samples:

- You should *always* use a pretrained model
- In smaller, homogeneous, samples the model should ideally be finetuned, but using a pretrained model off-the-shelf works reasonably well

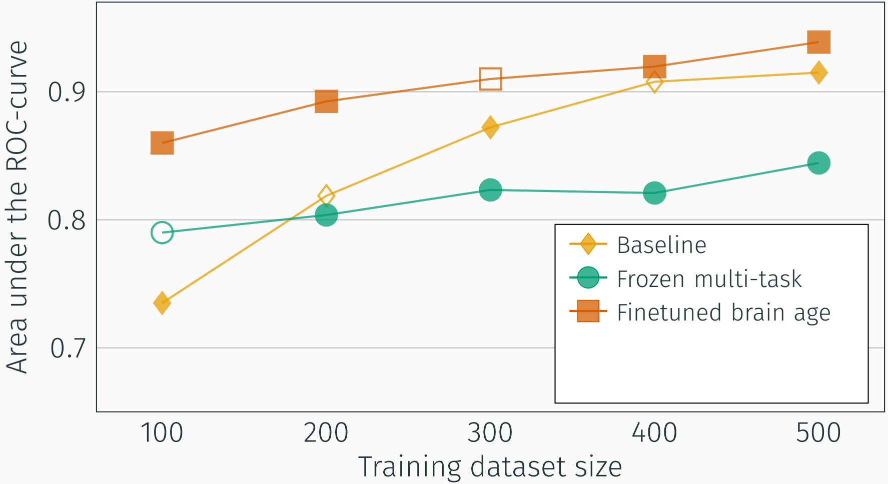
Results: AD vs HC classification



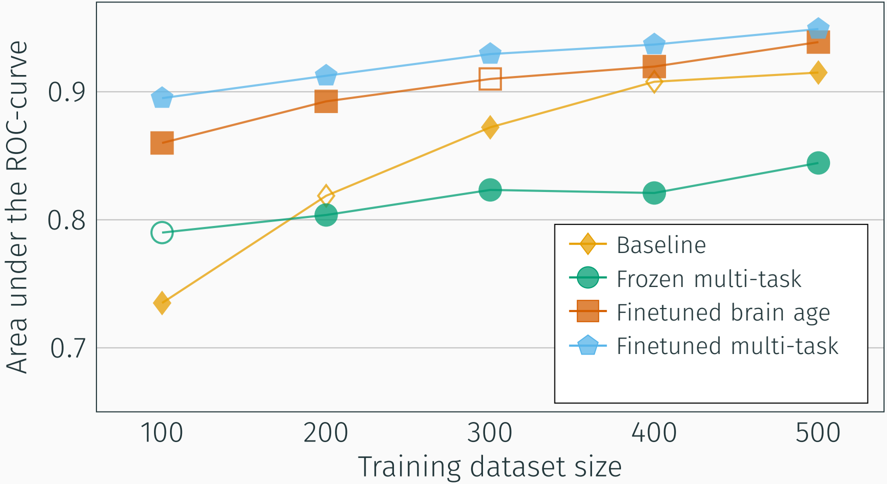
Results: AD vs HC classification



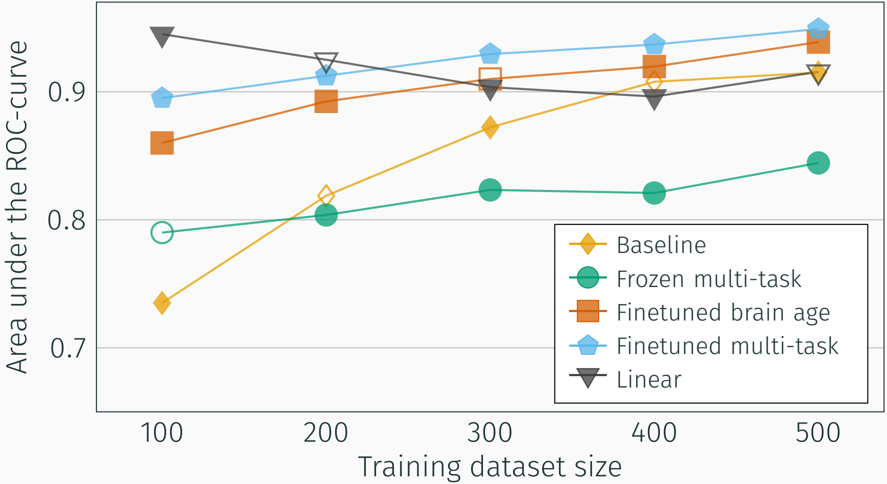
Results: AD vs HC classification



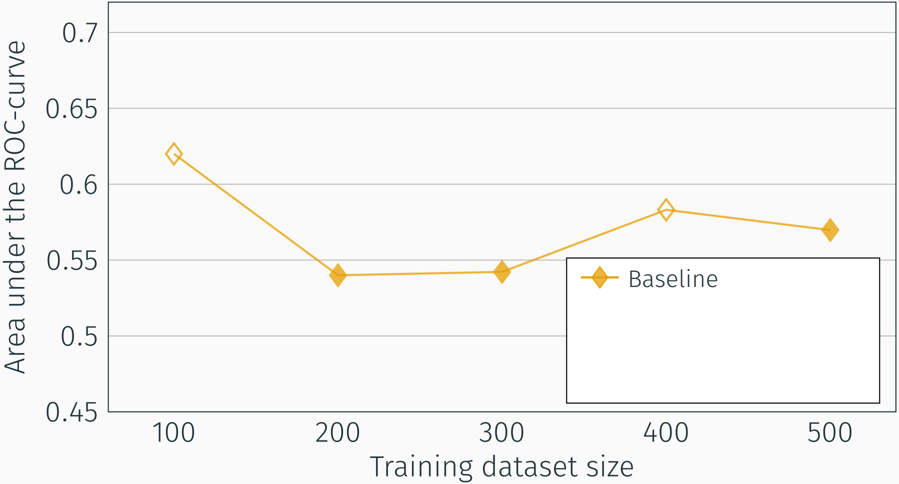
Results: AD vs HC classification



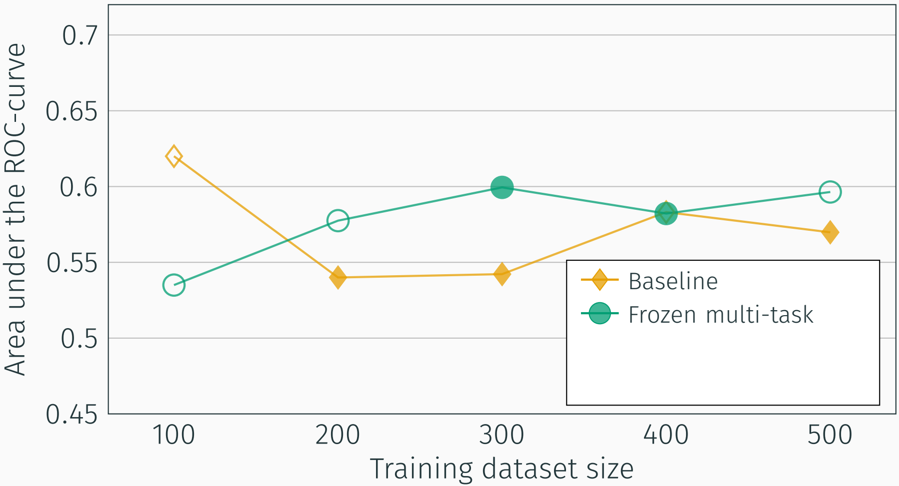
Results: AD vs HC classification



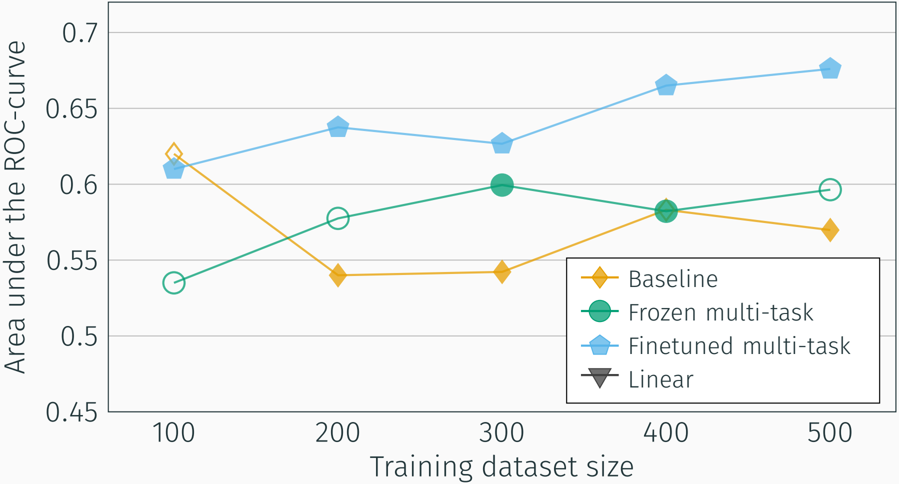
Results: SCZ vs BD classification



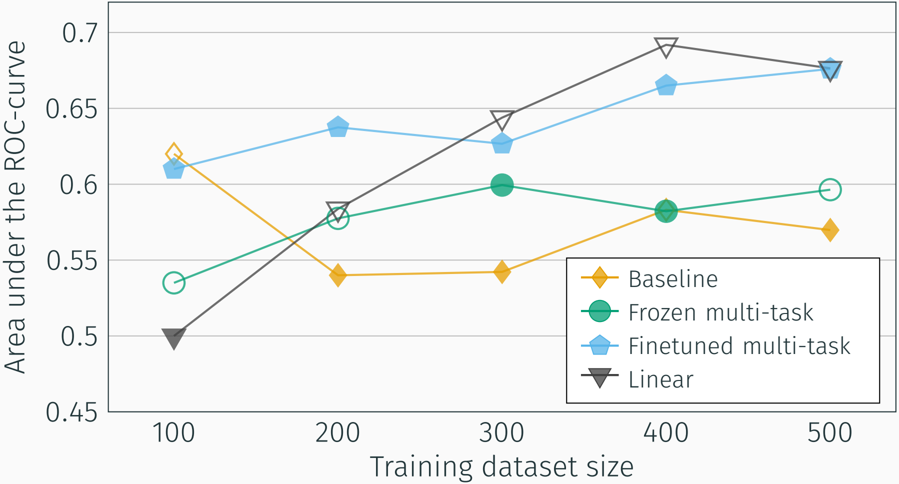
Results: SCZ vs BD classification



Results: SCZ vs BD classification



Results: SCZ vs BD classification



Results: Brain age

If you want to accurately predict anything[1] in new samples:

- If you are using a CNN, you should *always*[2] use a pretrained model, and a multi-task model outperforms a single-task model even when the pretraining task is closely related to the downstream task
- However, apparently[3], you can get quite far with simple linear models

1. At least clinical binary classification problems
2. Unless you are training a classifier for SCZ vs BD with 100 samples
3. It seems quite complicated to determine when the linear model is best

Thank you for your attention!

estenhl@uio.no