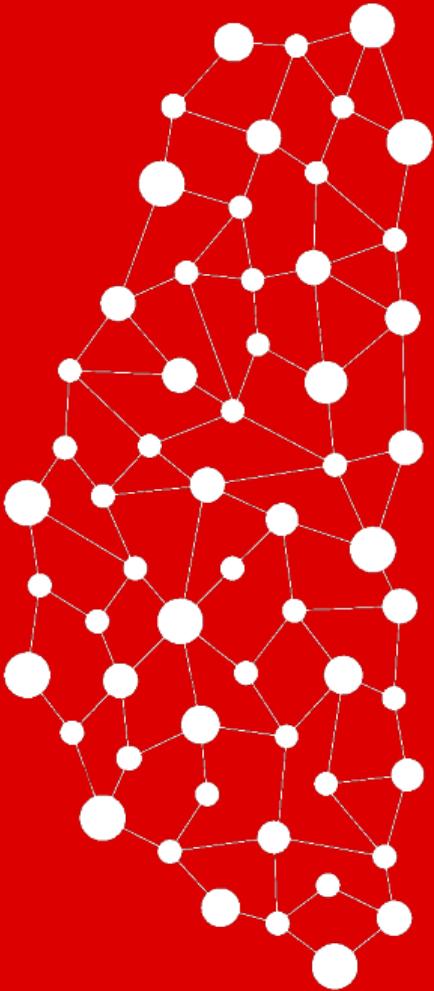
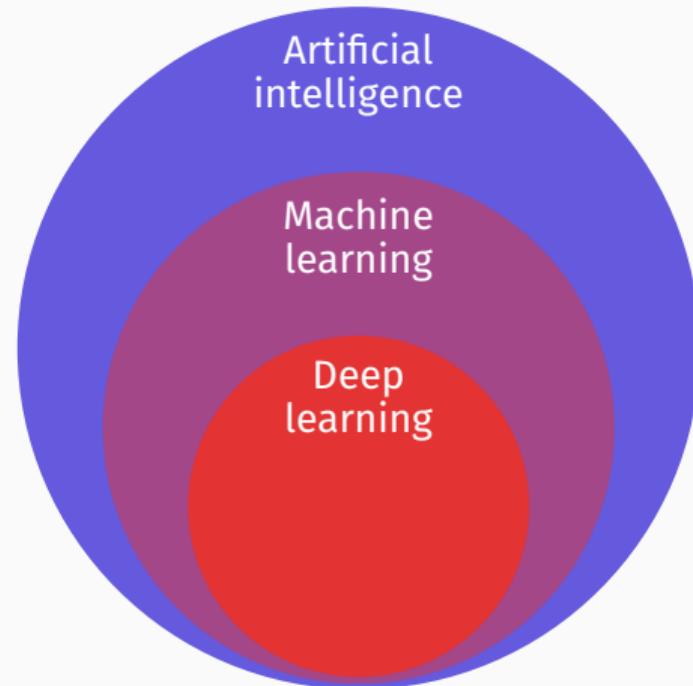


# Enabling deep learning in small MRI datasets with transfer learning

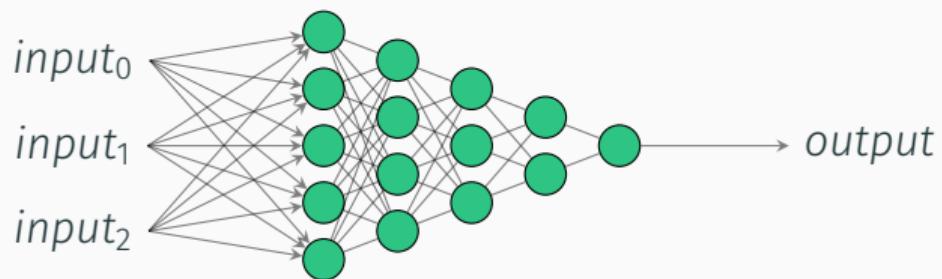


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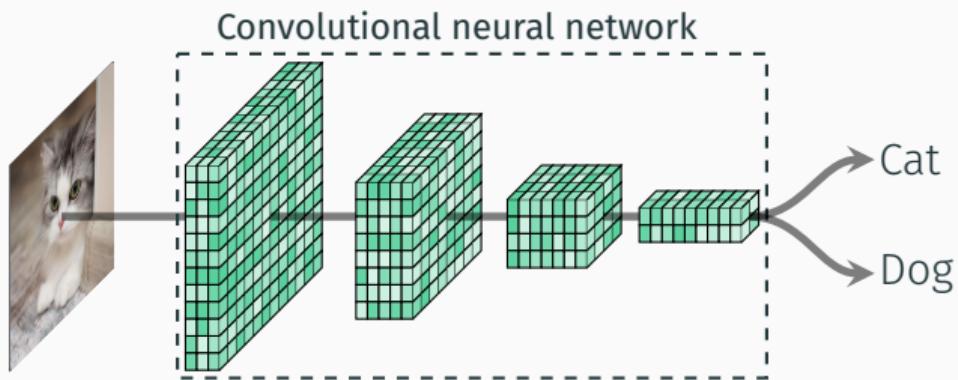
# Deep learning on MRI data



# Deep learning on MRI data



# Deep learning on MRI data



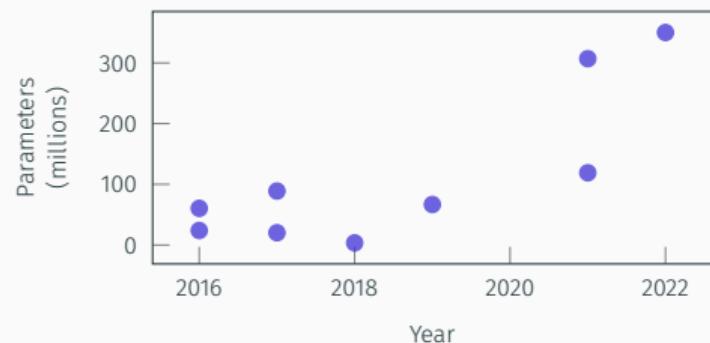
# Deep learning on MRI data

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



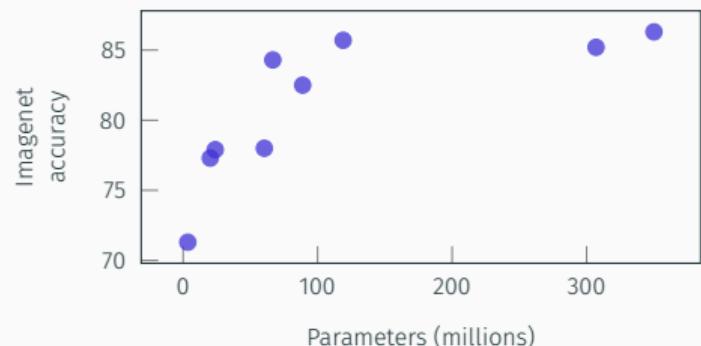
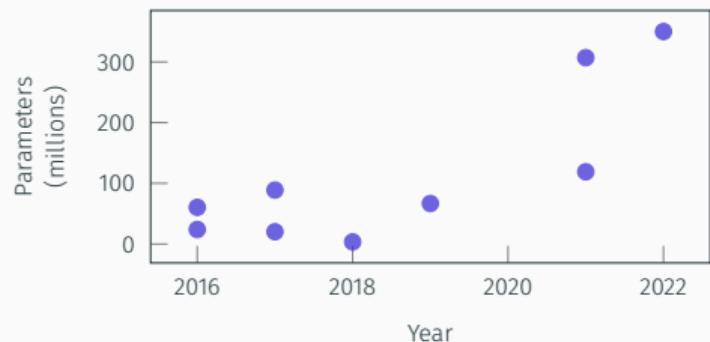
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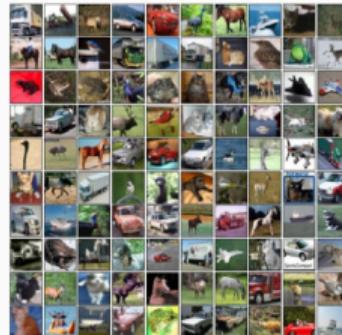
# Deep learning on MRI data

Dataset	Size	Dimensionality
MNIST	~70K	28x28 pixels



# Deep learning on MRI data

Dataset	Size	Dimensionality
MNIST	~70K	28x28 pixels
CIFAR	~60K	32x32 pixels



# Deep learning on MRI data

Dataset	Size	Dimensionality
MNIST	~70K	28x28 pixels
CIFAR	~60K	32x32 pixels
COCO	~330K	640x640 pixels
ImageNet (21k)	~14M	224x224 pixels



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MNIST	~70K	28x28 pixels
CIFAR	~60K	32x32 pixels
COCO	~330K	640x640 pixels
ImageNet (21k)	~14M	224x224 pixels
CLIP	~400M	224x224 pixels
JFT-3B	~3B	256x256 pixels
LAION-5B	~2.3B	336x336 pixels



C: Green Apple Chair



C: sun snow dog



C: Color Palettes



C: pink, japan, aesthetic image



# Deep learning on MRI data

Dataset	Size	Dimensionality
MNIST	~70K	28x28 pixels
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UK Biobank	45,891	256x256x256 voxels
ABCD	11,660	256x256x256 voxels
ADNI	2,729	256x256x256 voxels
TOP	2,222	256x256x256 voxels
HBN	1,365	256x256x256 voxels
QTIM	1,201	256x256x256 voxels
PING	1,176	256x256x256 voxels
CoRR	1,156	256x256x256 voxels
HCP	1,113	256x256x256 voxels
OASIS3	1,062	256x256x256 voxels



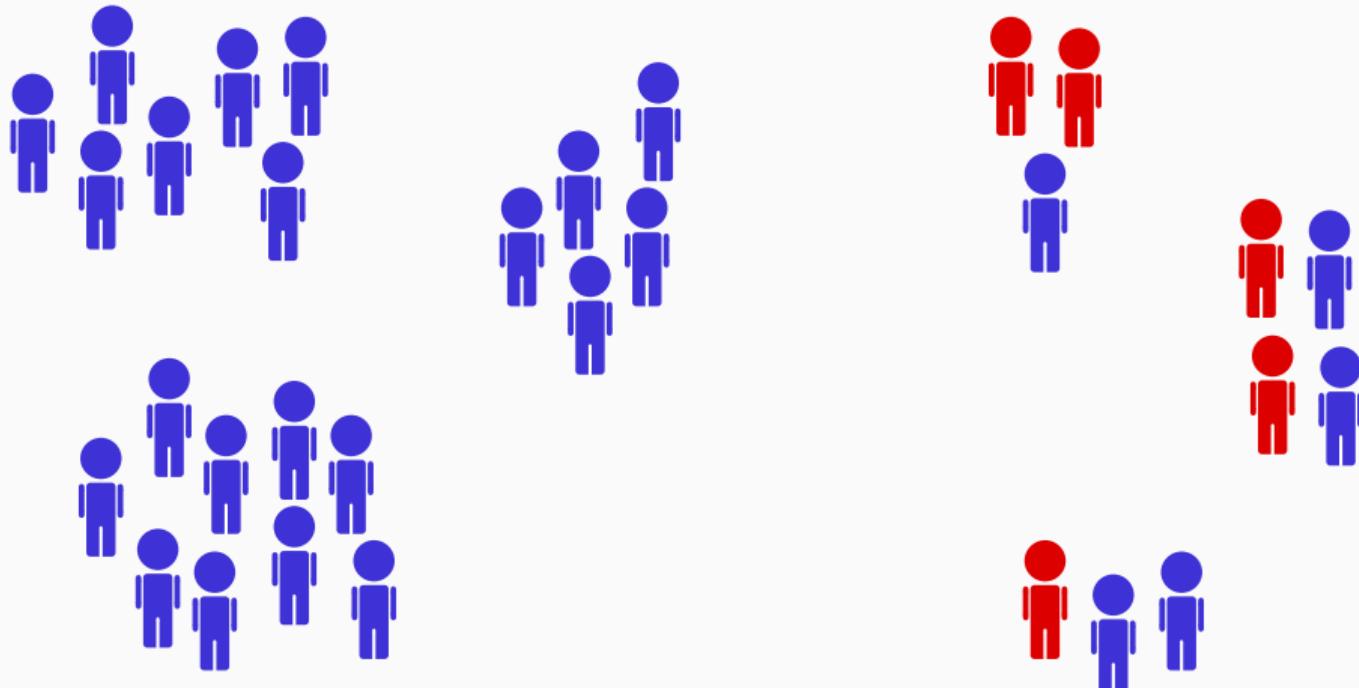
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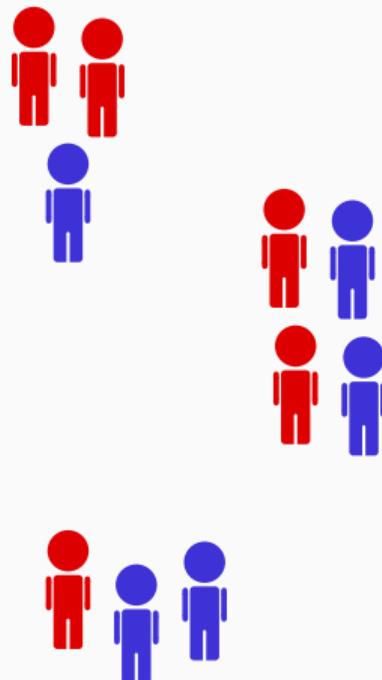
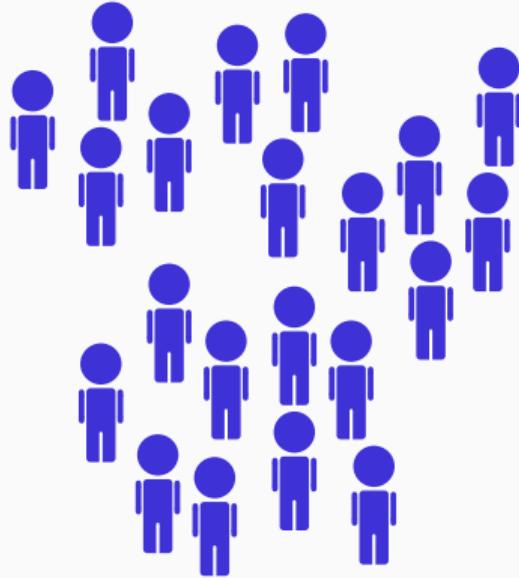
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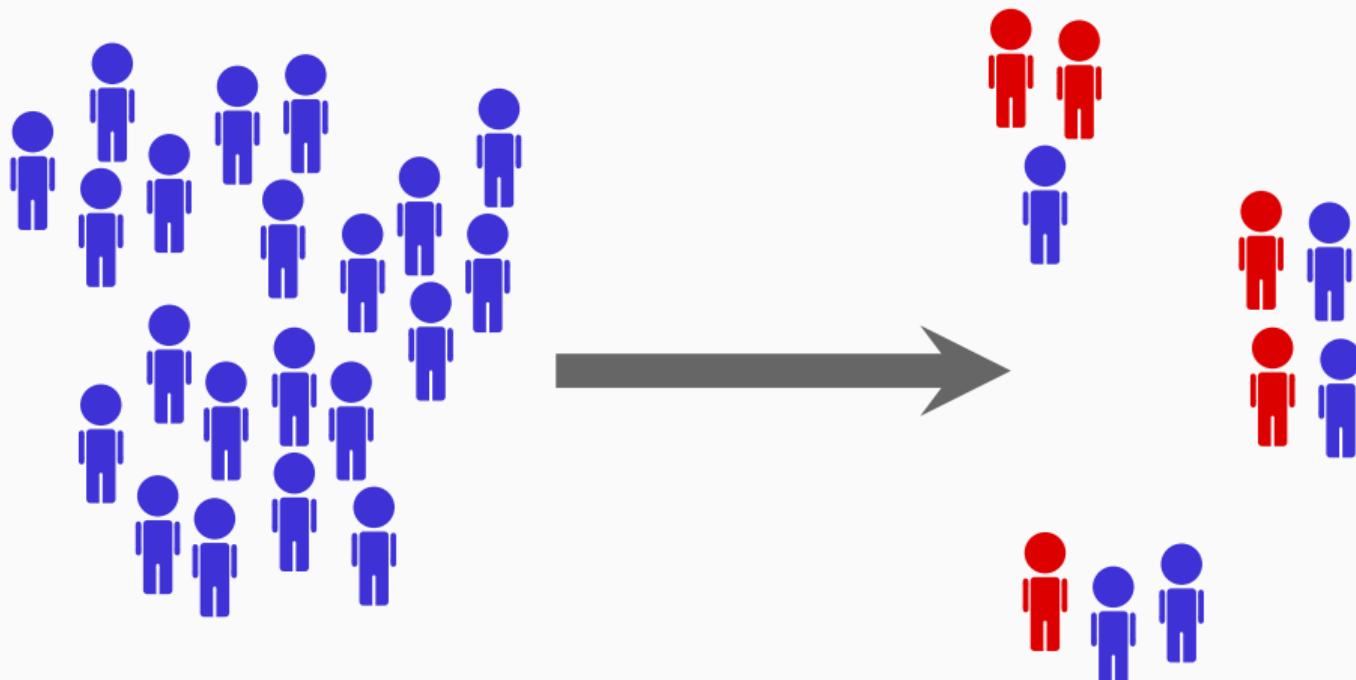
# Deep learning on MRI data



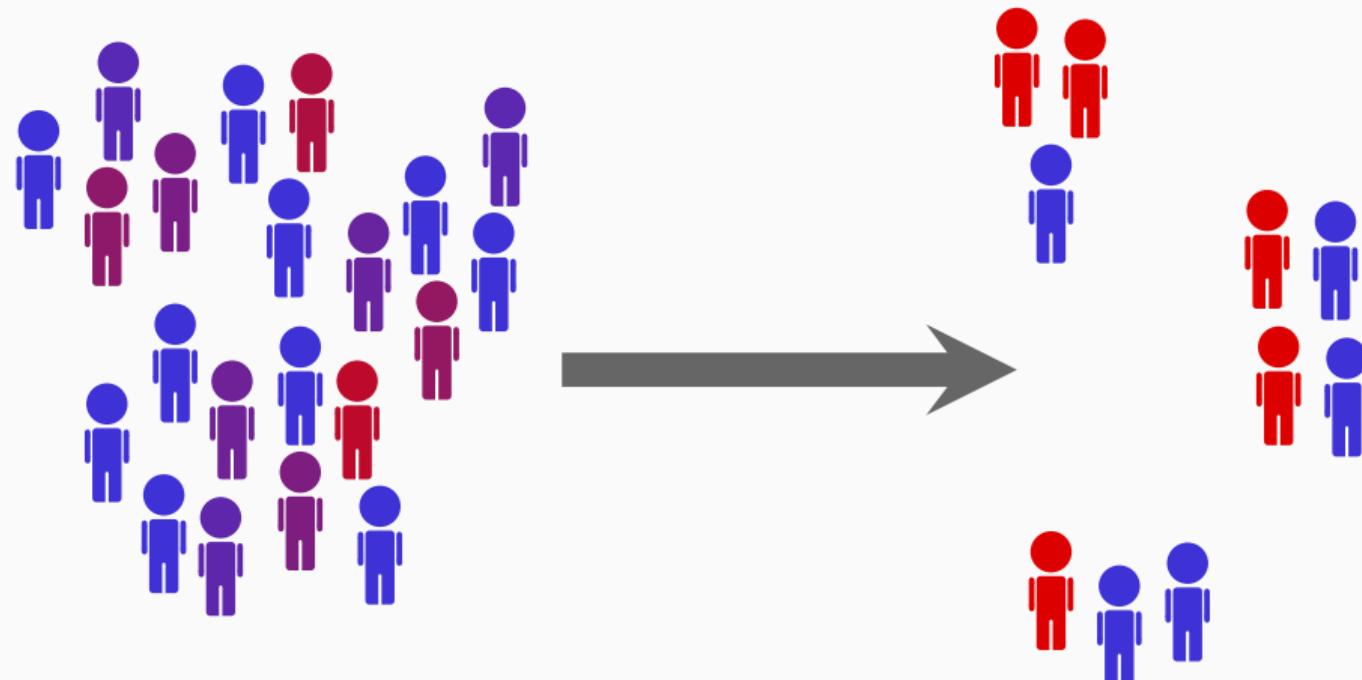
# Deep learning on MRI data



# Deep learning on MRI data



# Deep learning on MRI data



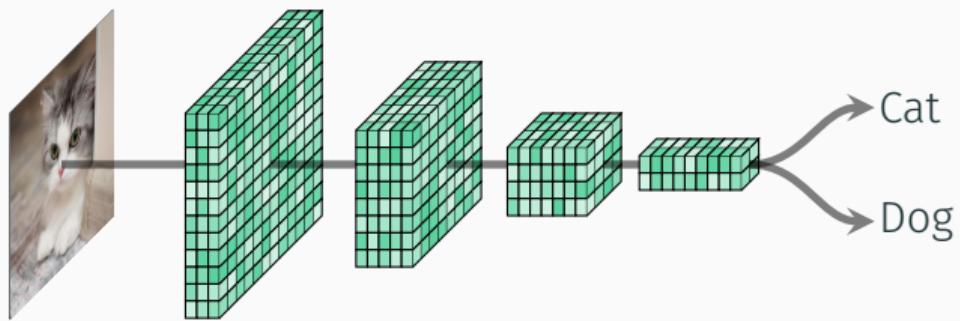
# Transfer learning

---

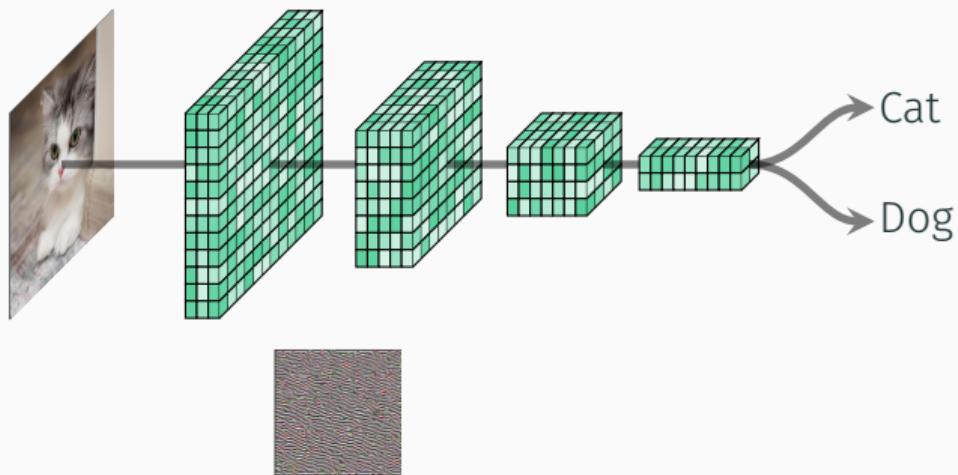


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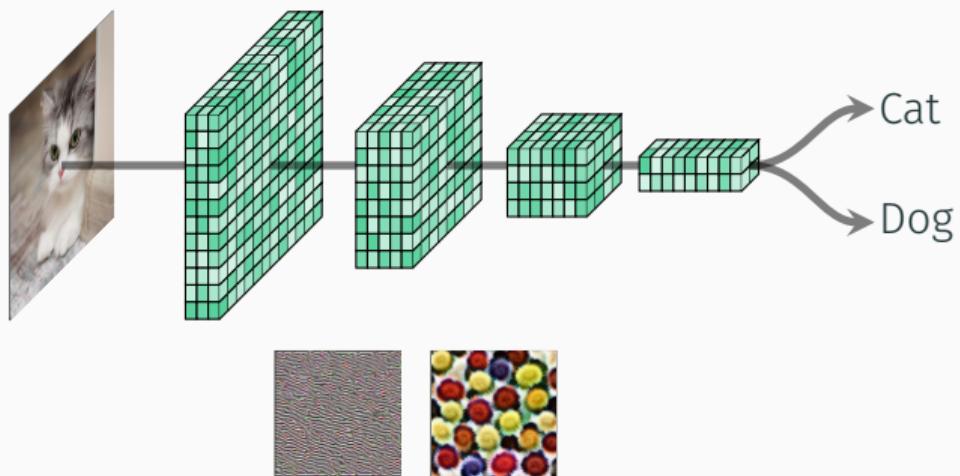
# How does CNNs work



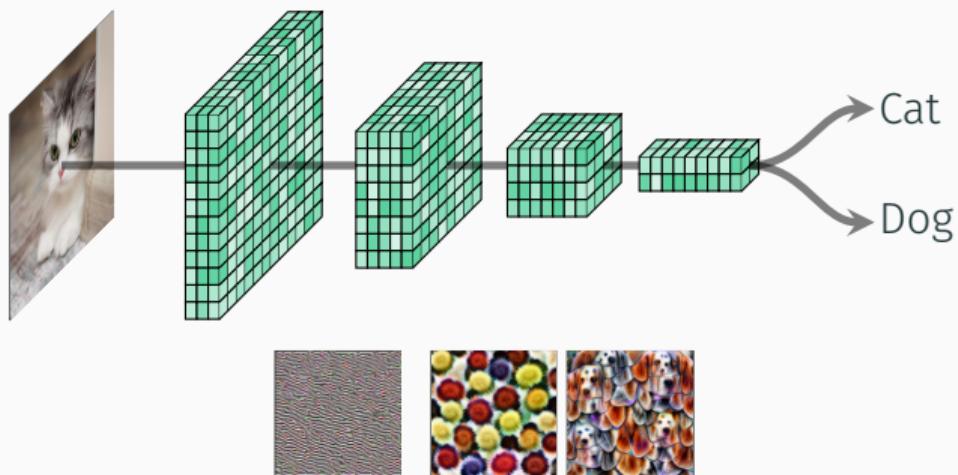
# How does CNNs work



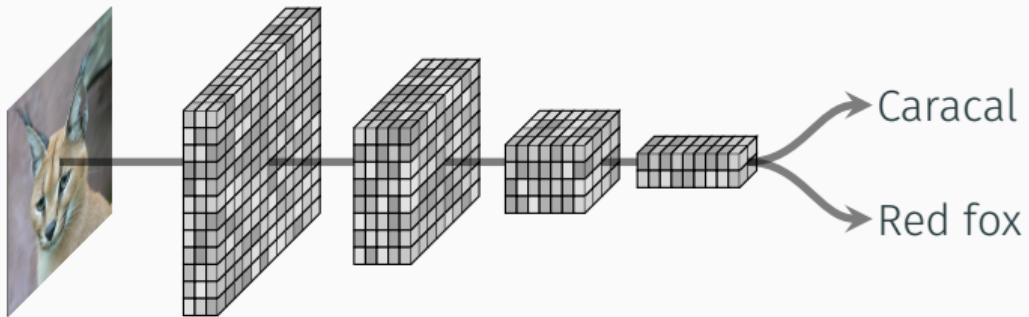
# How does CNNs work



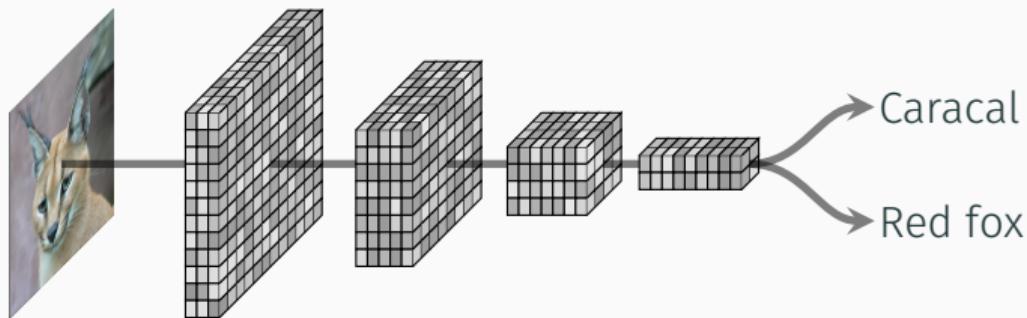
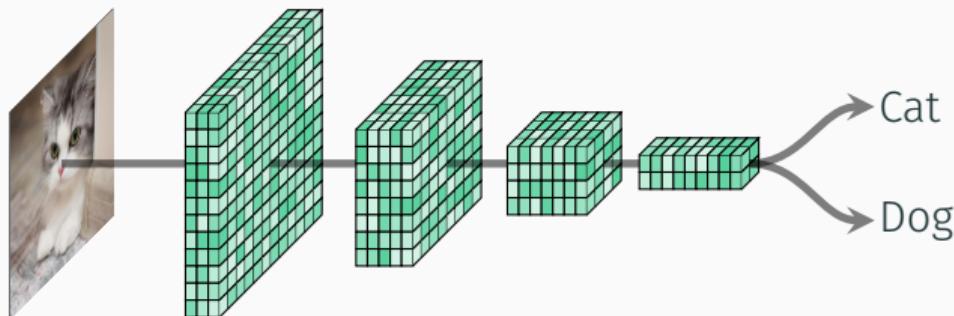
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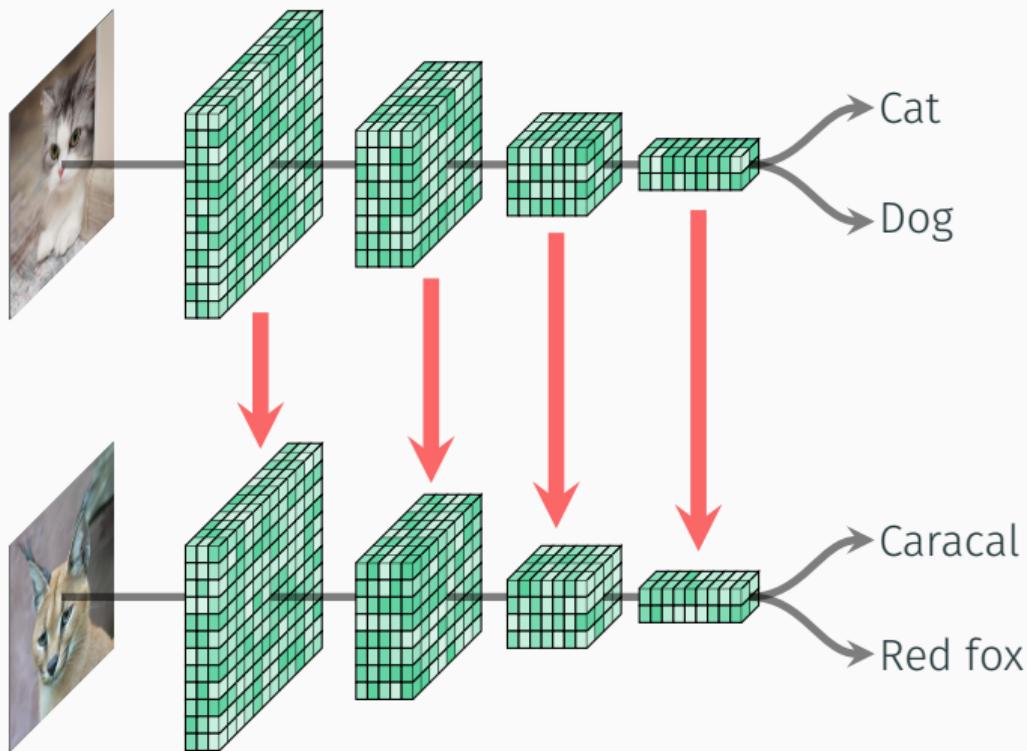
# Transfer learning



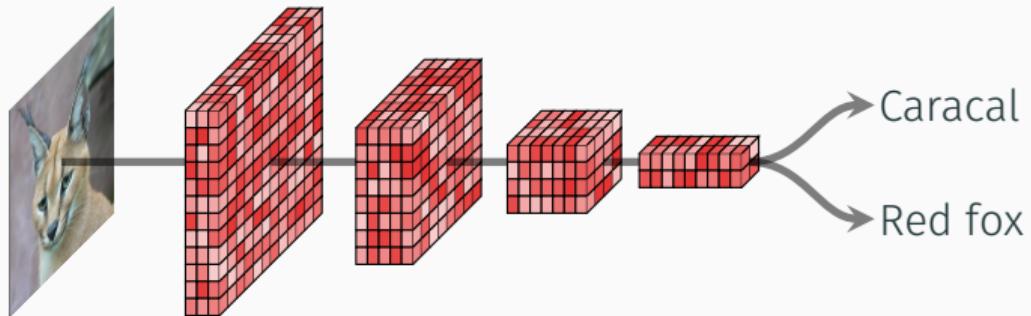
# Transfer learning



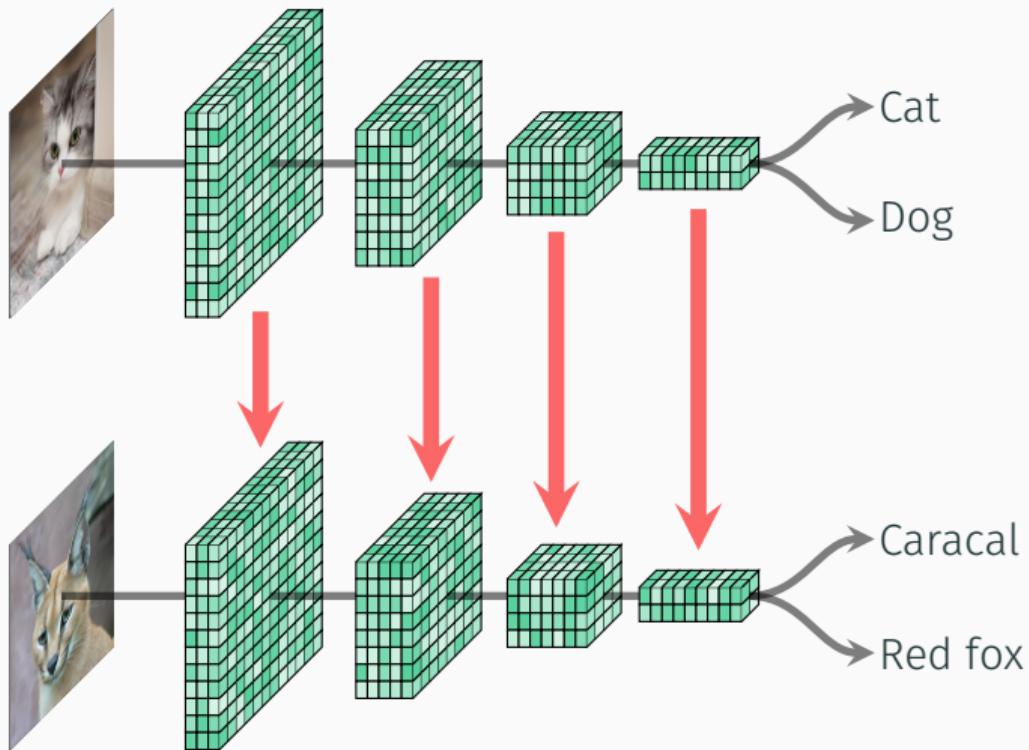
# Transfer learning



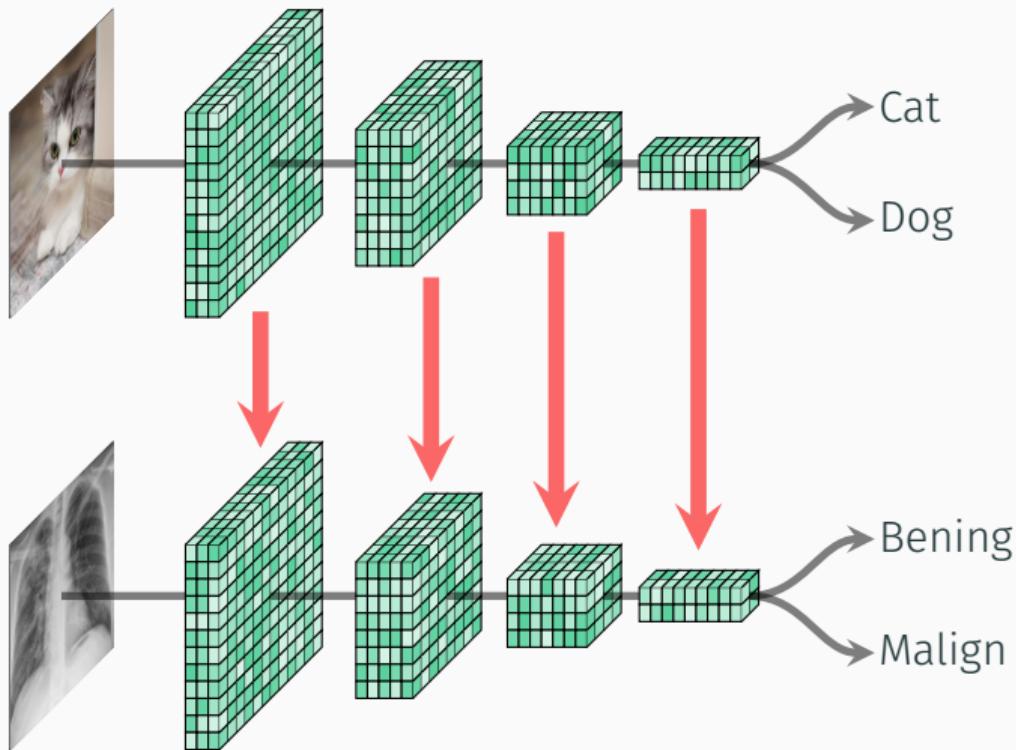
# Transfer learning



# Transfer learning



# Transfer learning



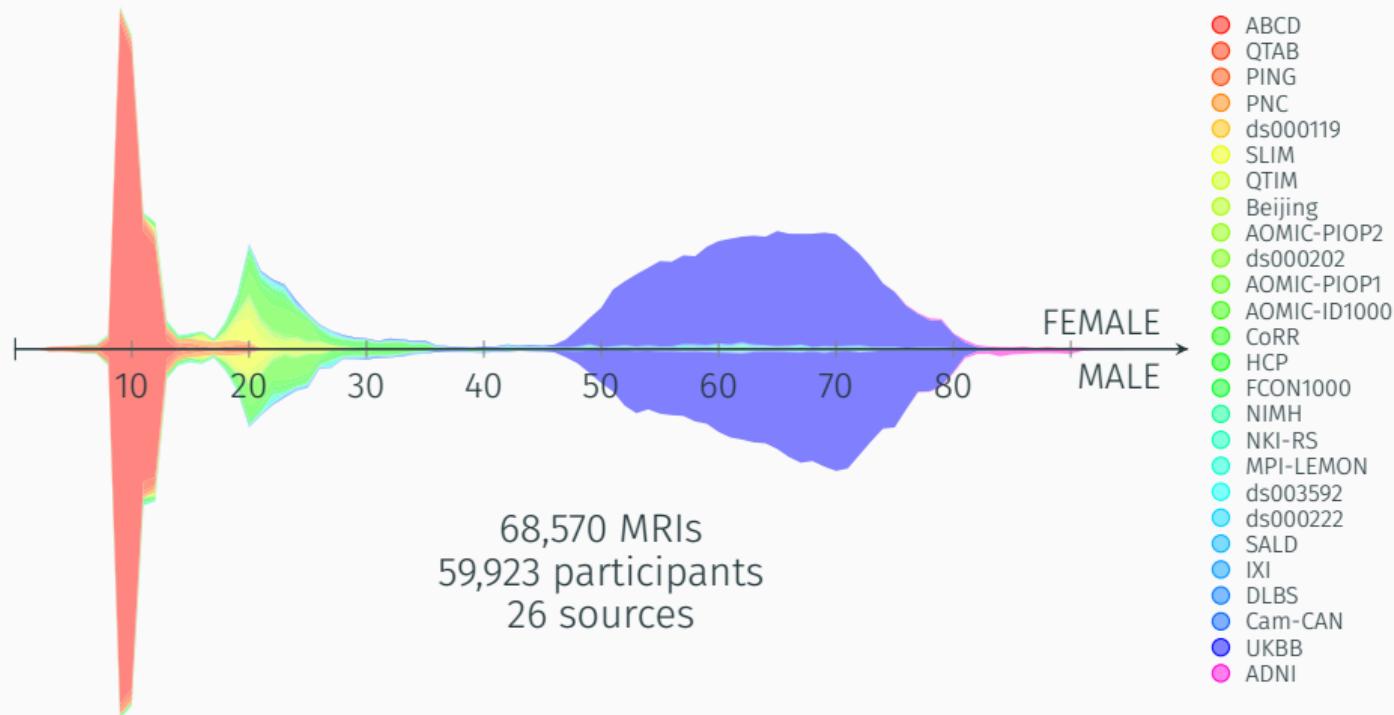
# Our work

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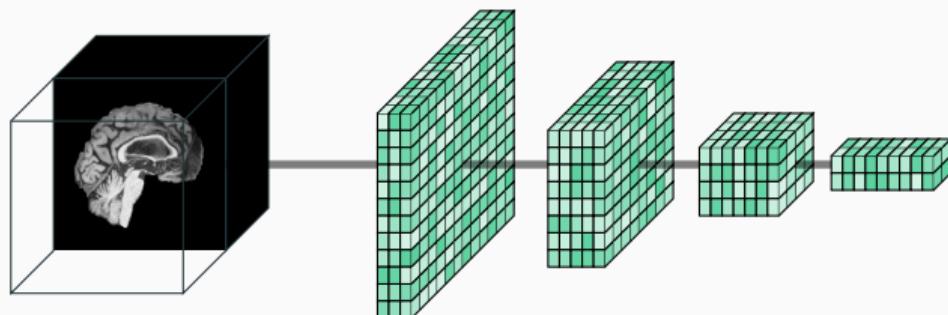


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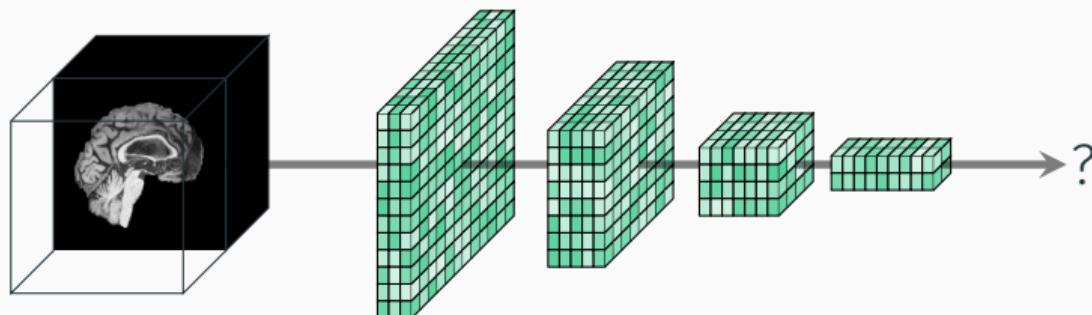
## Methods: Training dataset



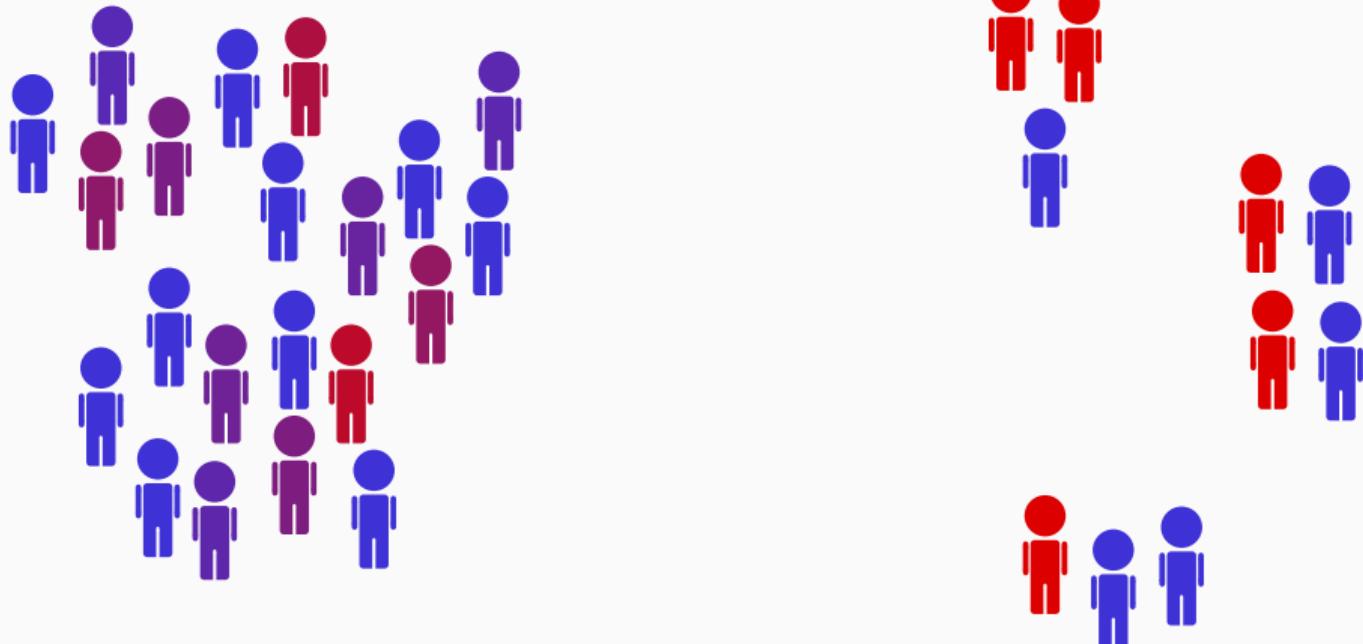
## Methods: Modelling



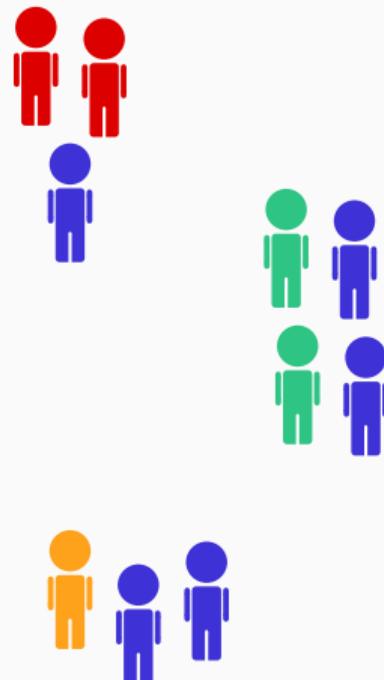
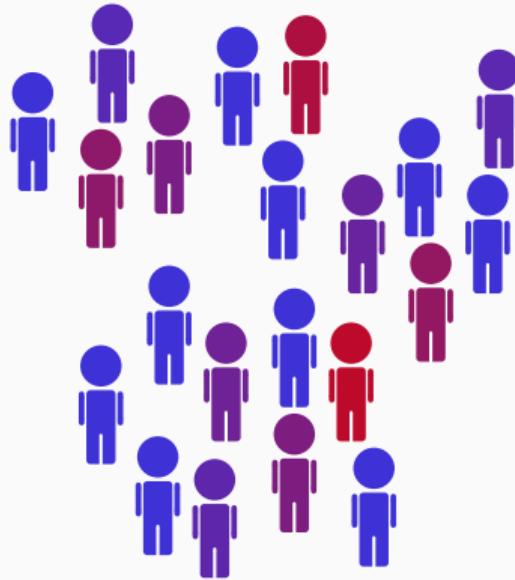
## Methods: Modelling



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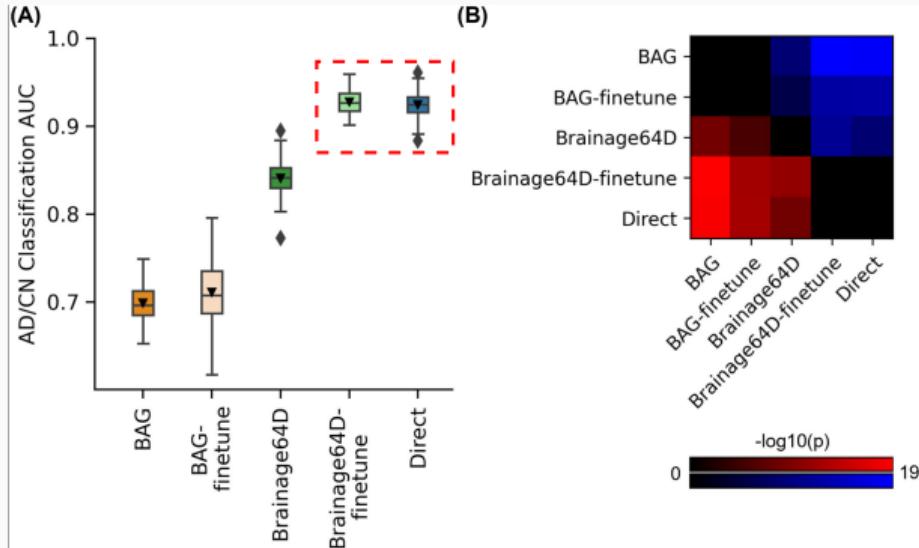
## Methods: Modelling

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



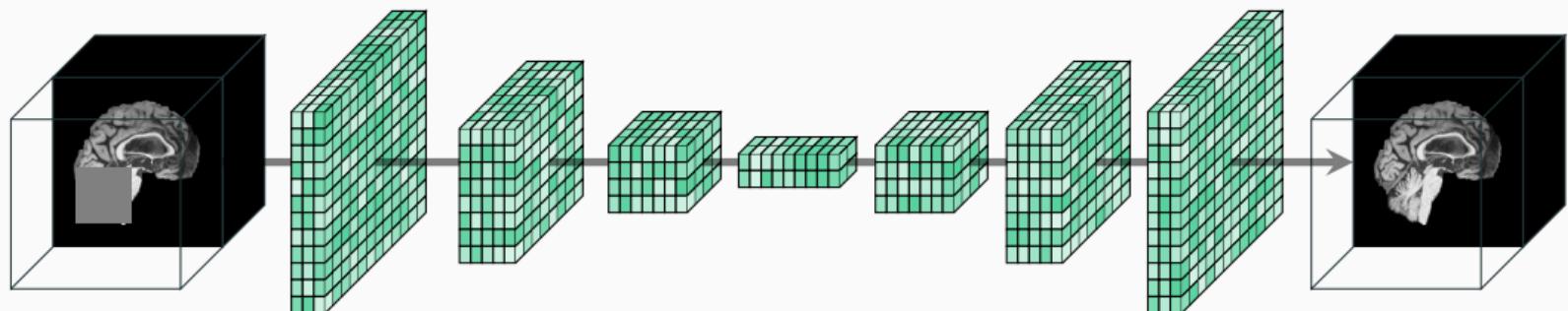
# Methods: Modelling

Brain age

Self-supervised  
approaches



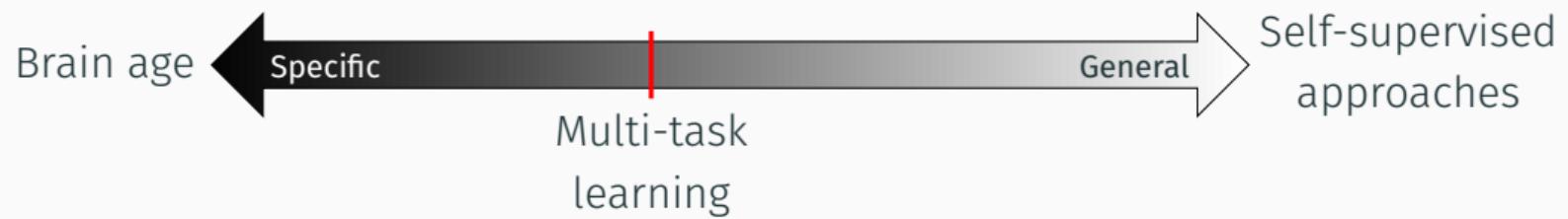
## Methods: Modelling



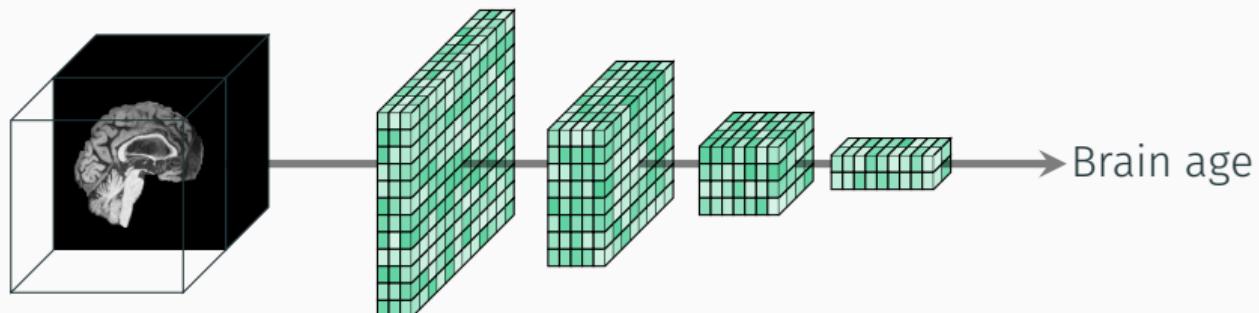
## Methods: Modelling



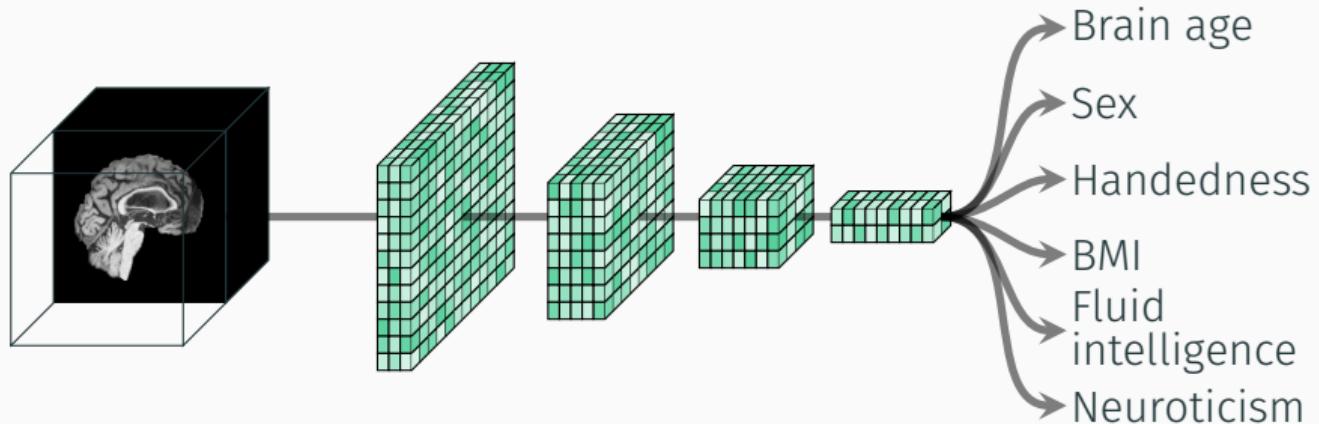
## Methods: Modelling



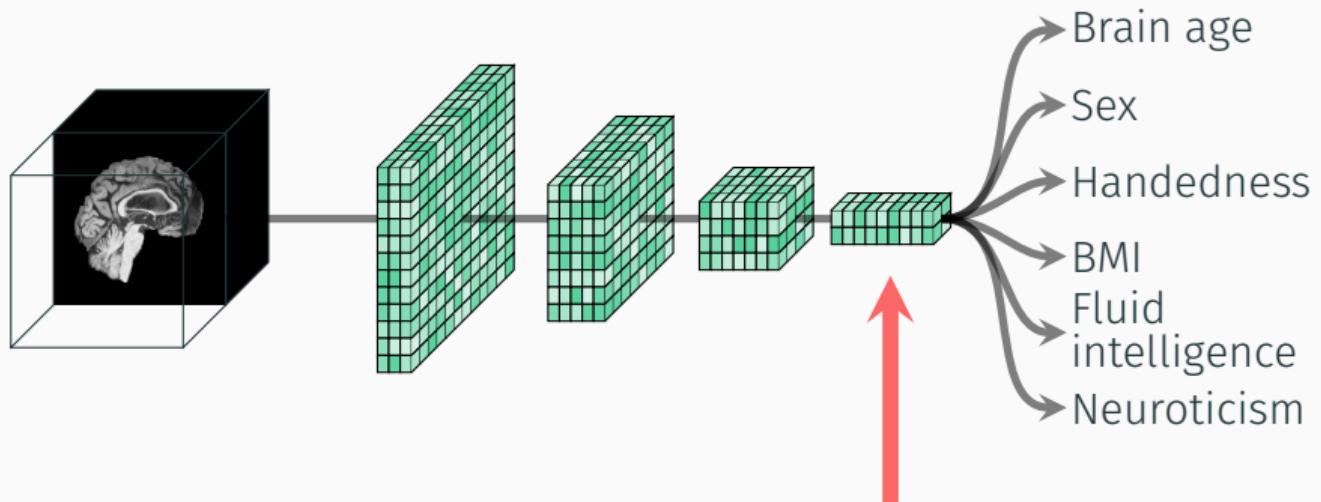
## Methods: Multi-task learning



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## Methods: Multi-task learning

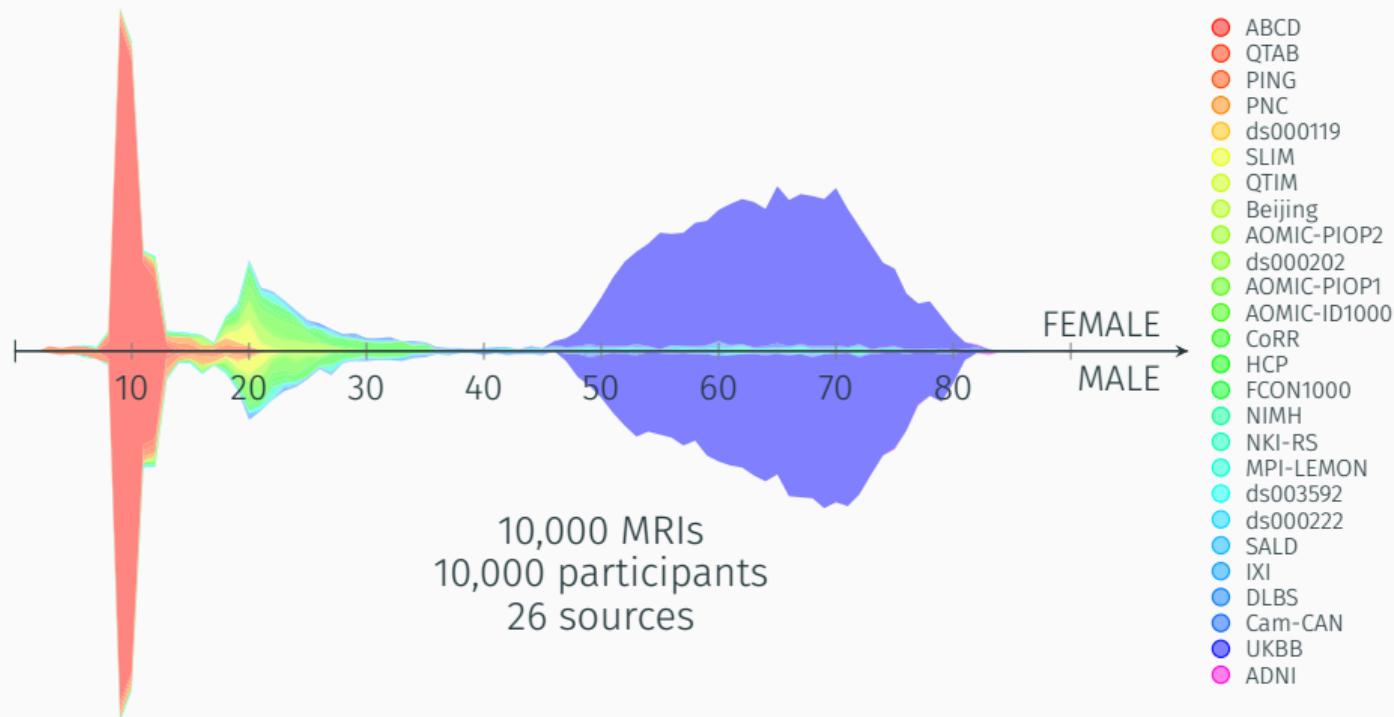


## Methods: Multi-task learning

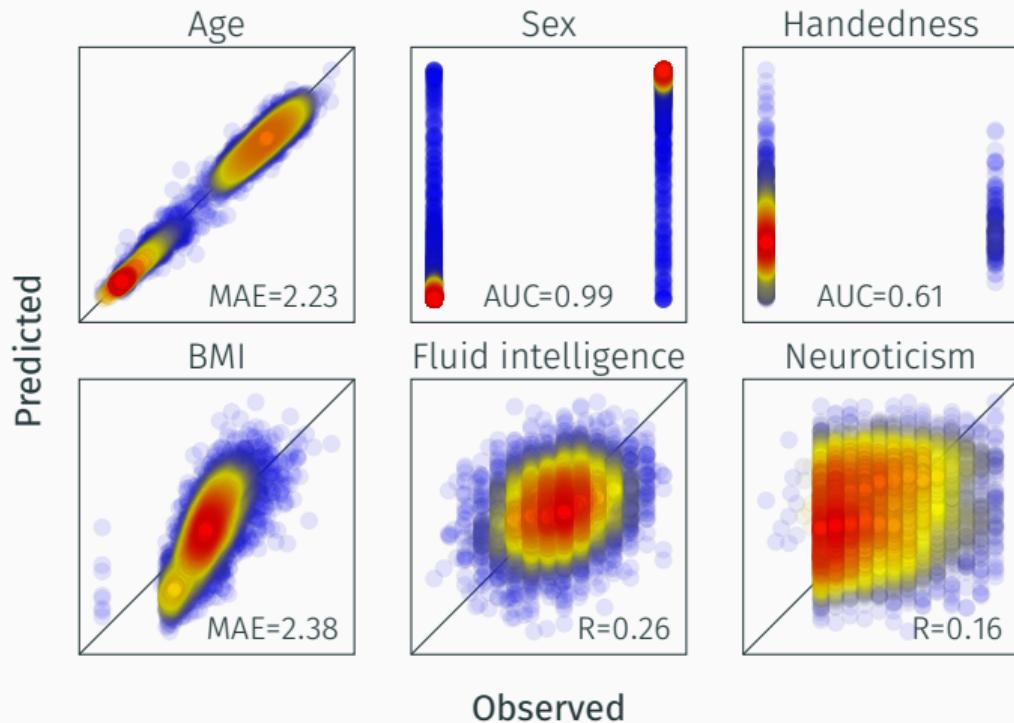
Age	1	0	0.02	0.52	-0.1	-0.04
Sex	0	1	0.03	0.04	-0.15	0.04
Handedness	-0.02	0.03	1	0	0.03	-0.03
BMI	0.52	0.04	0	1	-0.03	-0.05
Fluid intelligence	-0.1	-0.15	0.03	-0.03	1	-0.04
Neuroticism	-0.04	0.04	-0.03	-0.05	-0.04	1



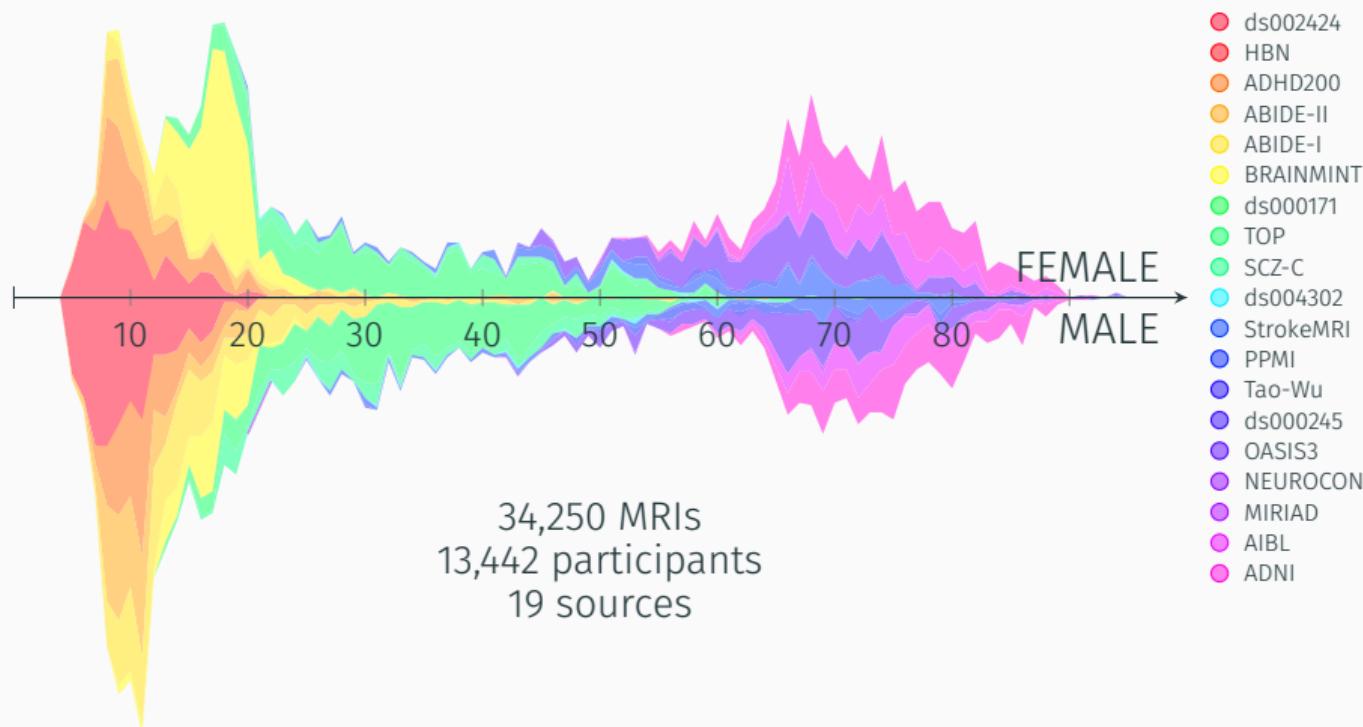
## Results: Validation



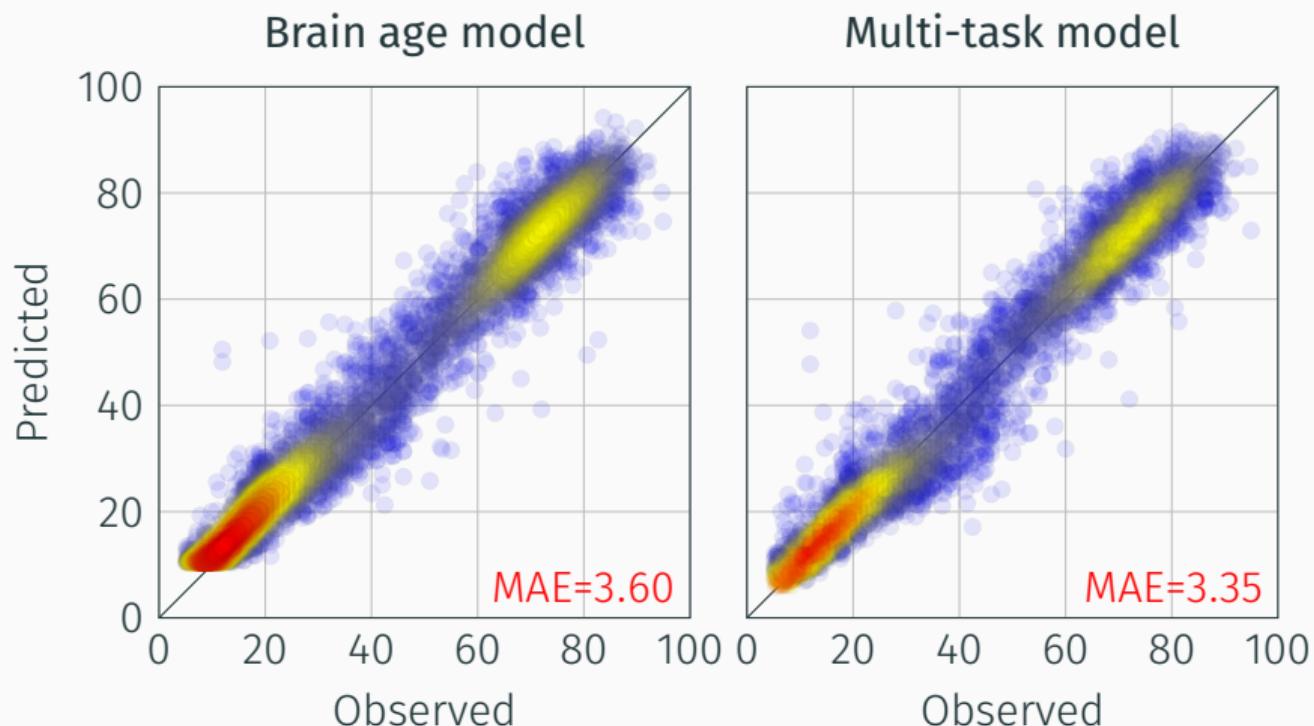
## Results: Validation



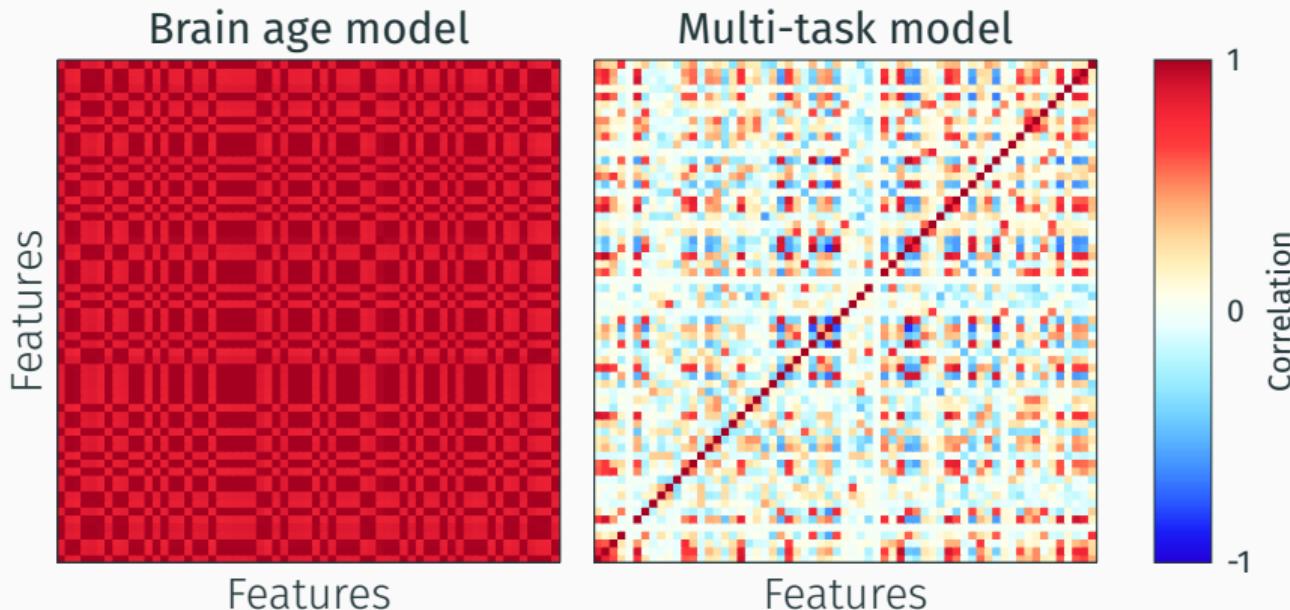
## Results: Brain age



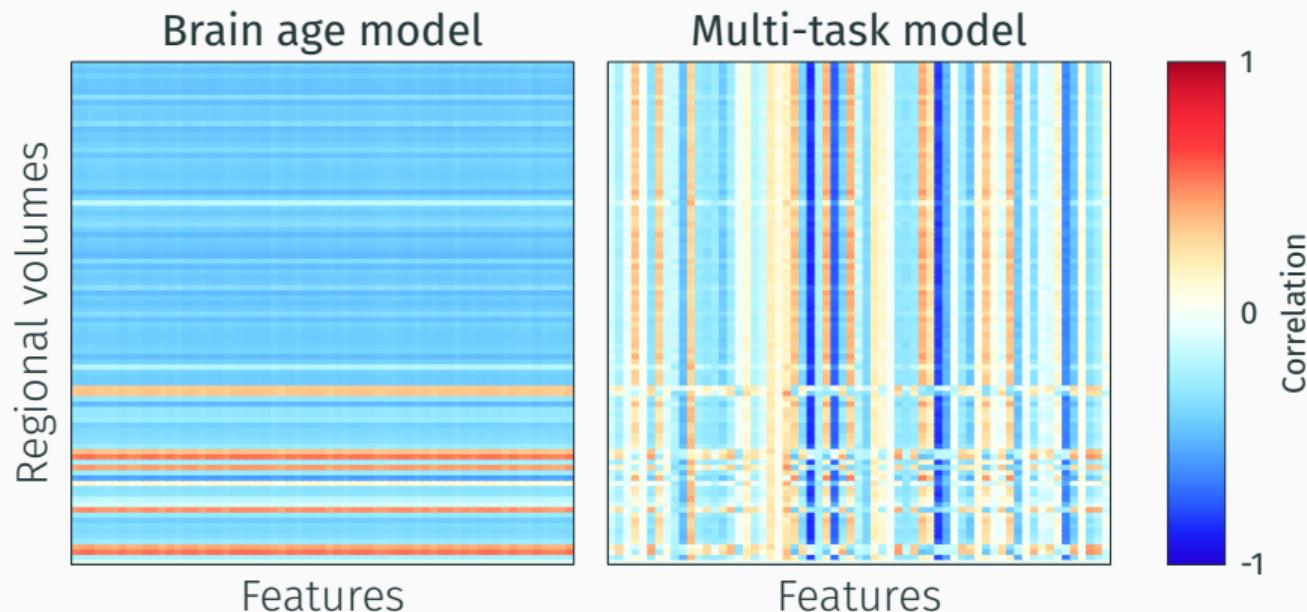
## Results: Brain age



## Results: Feature spaces



## Results: Feature spaces



## 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

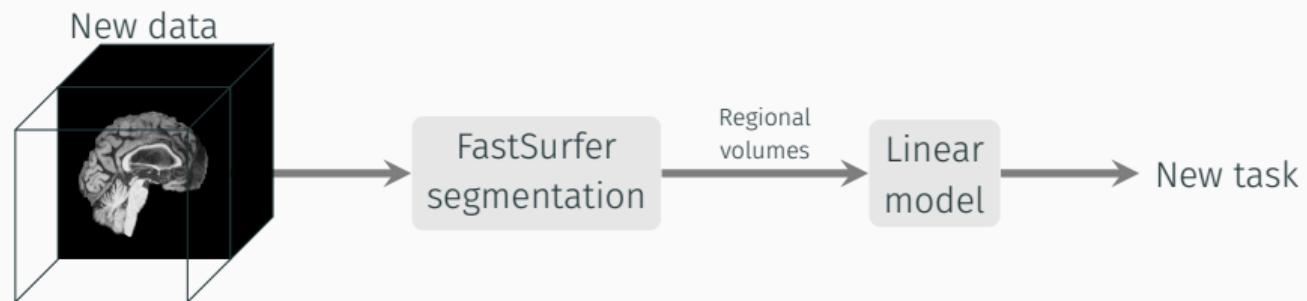
Four prediction tasks:

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

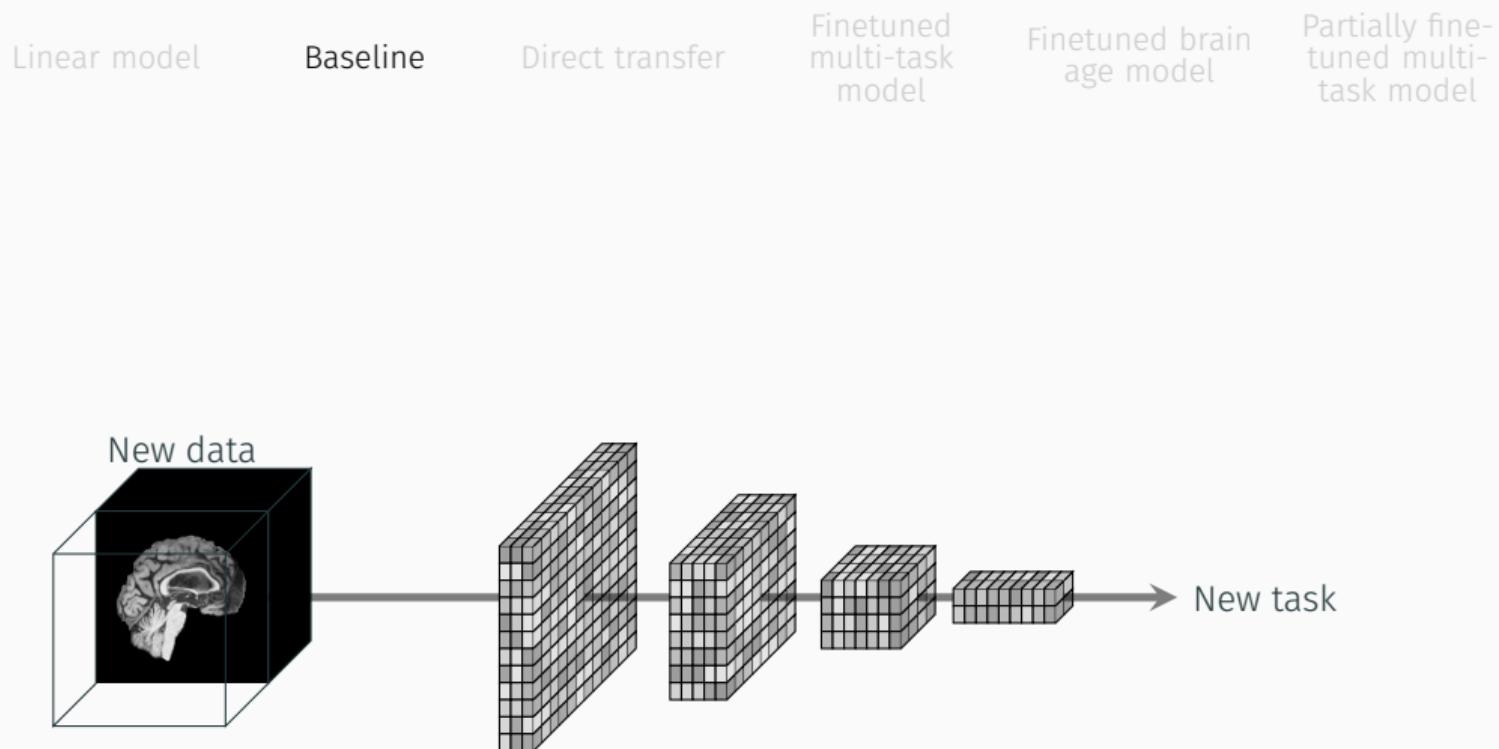


# Transfer learning: Modelling approaches

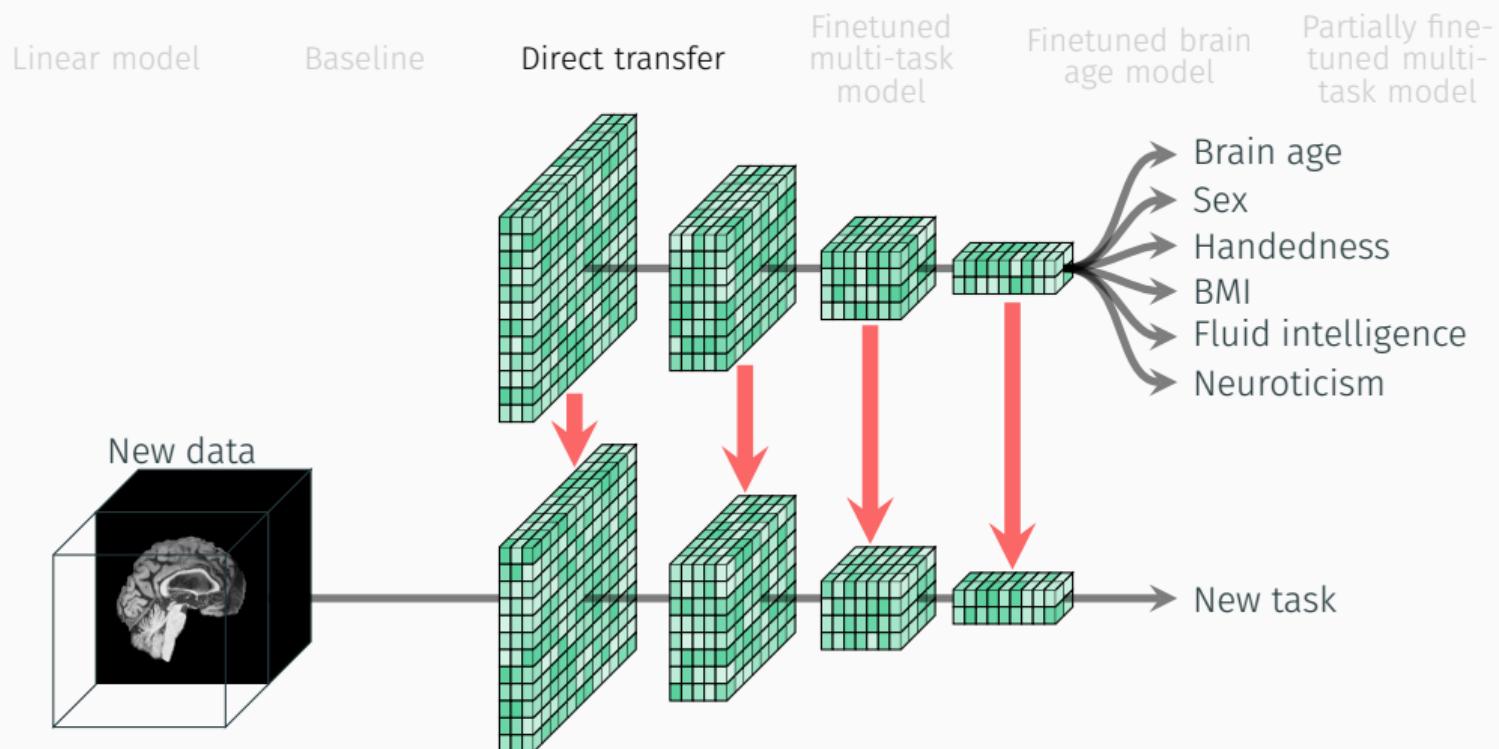
Linear model      Baseline      Direct transfer      Finetuned multi-task model      Finetuned brain age model      Partially fine-tuned multi-task model



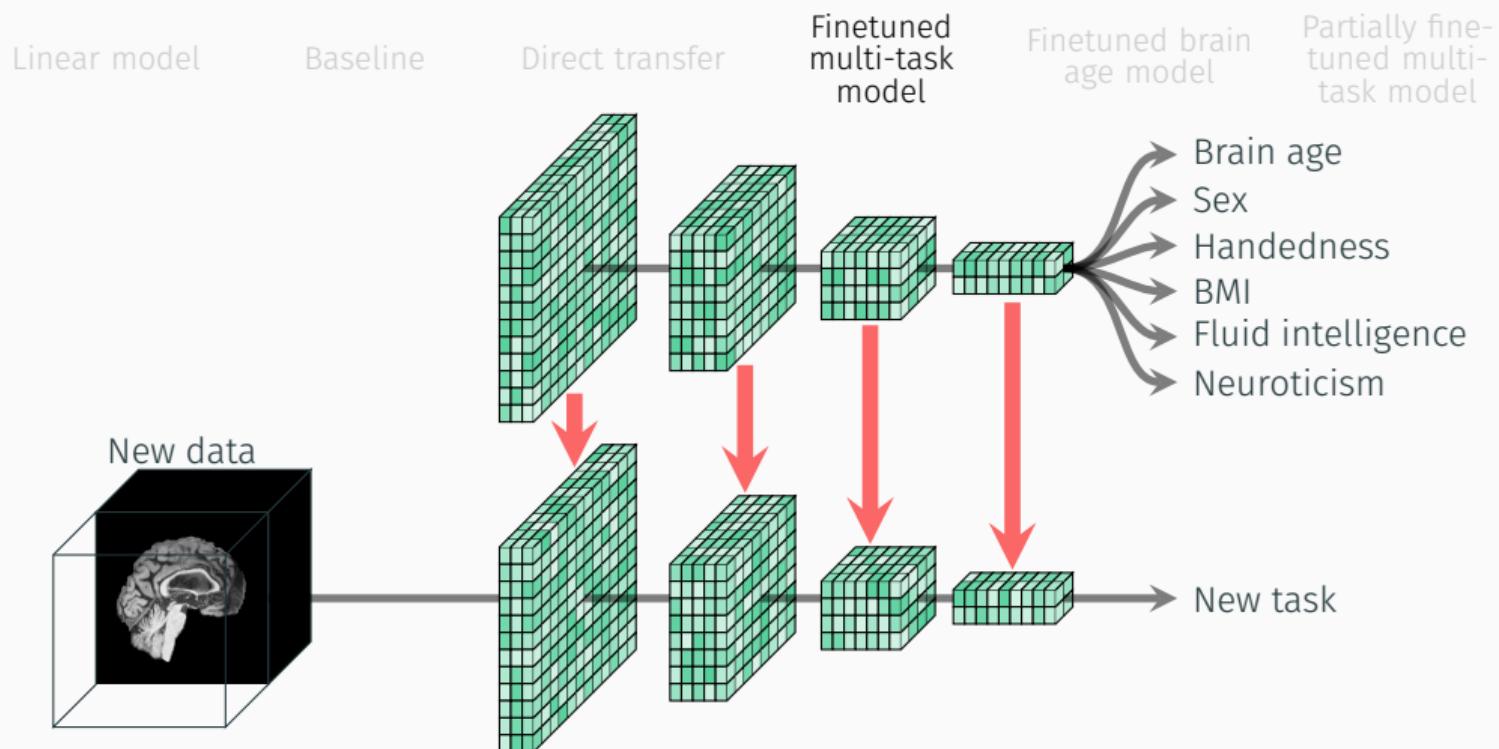
# Transfer learning: Modelling approaches



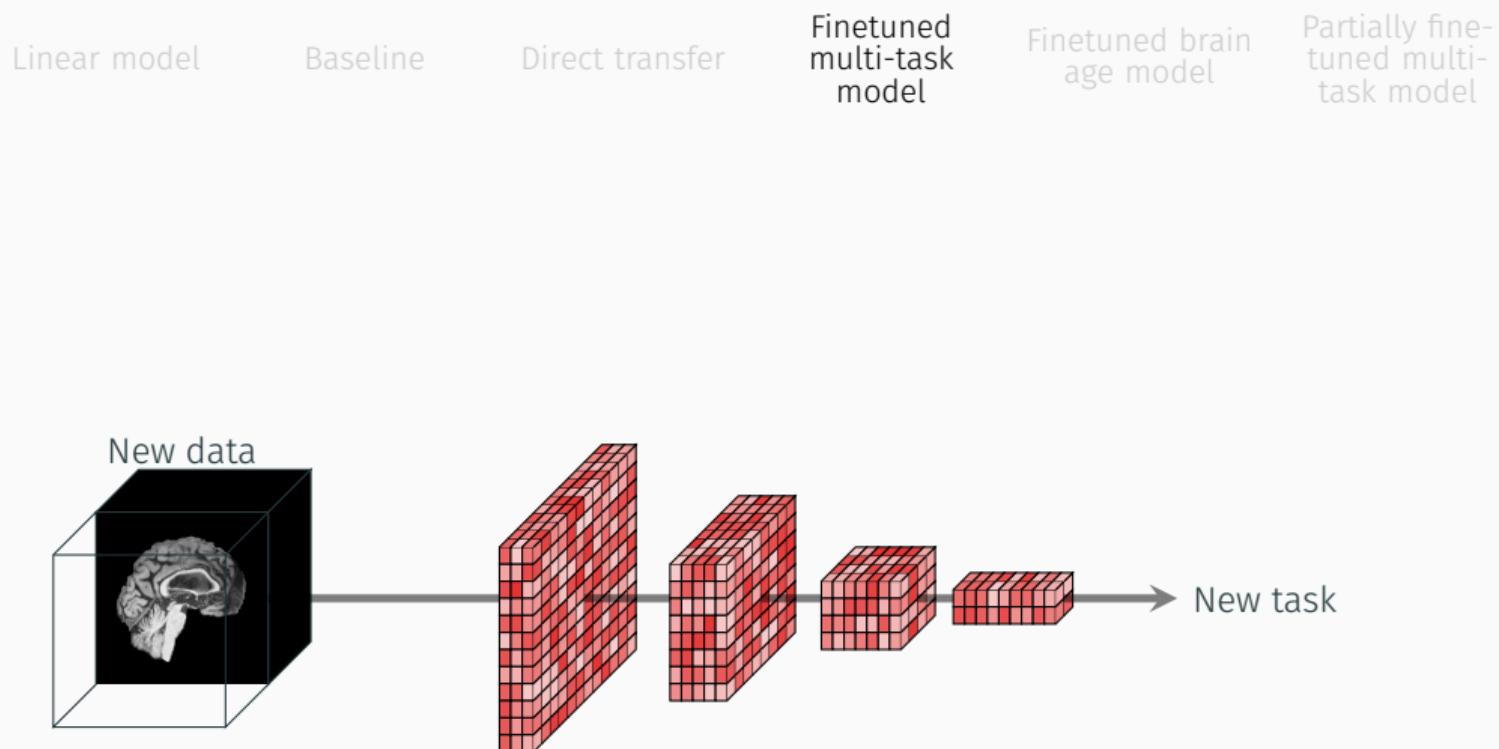
# Transfer learning: Modelling approaches



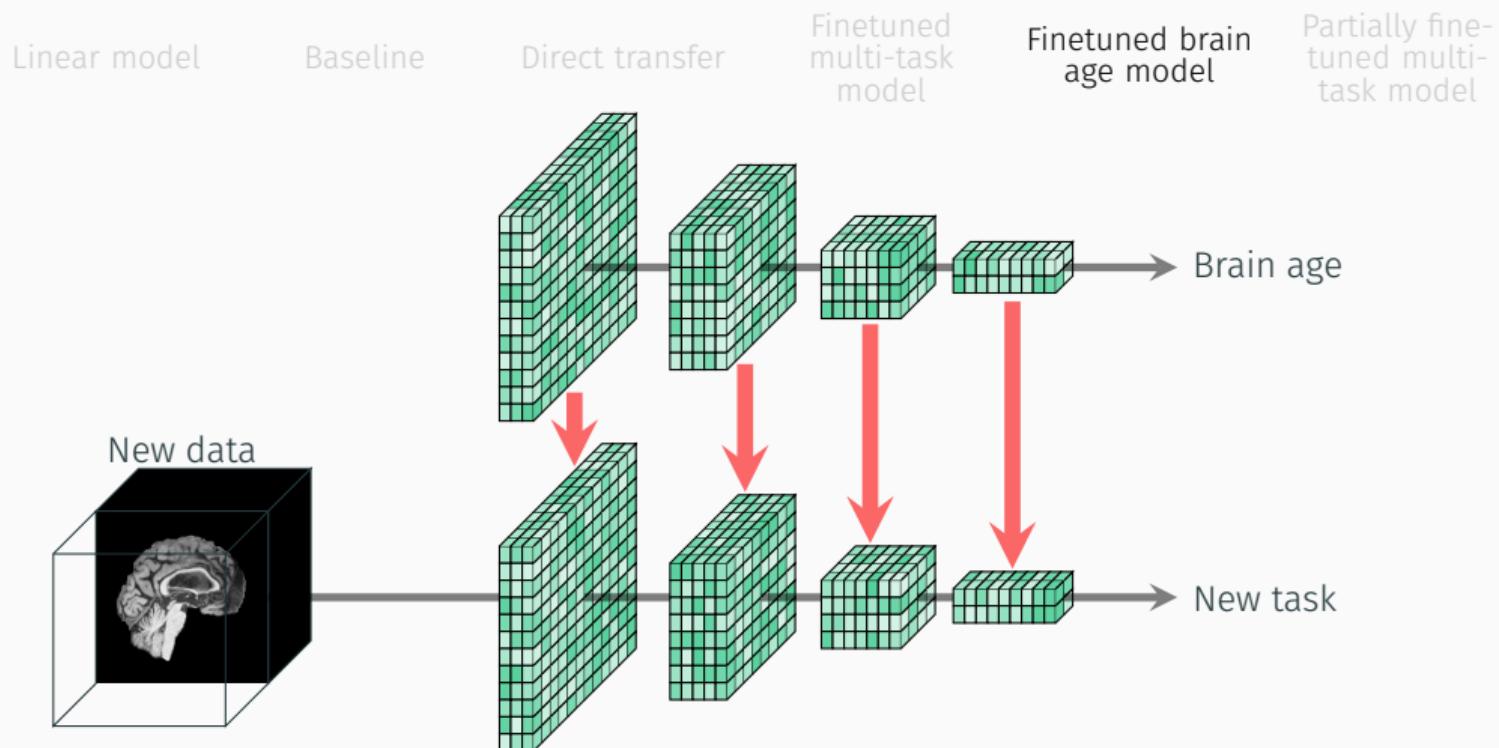
# Transfer learning: Modelling approaches



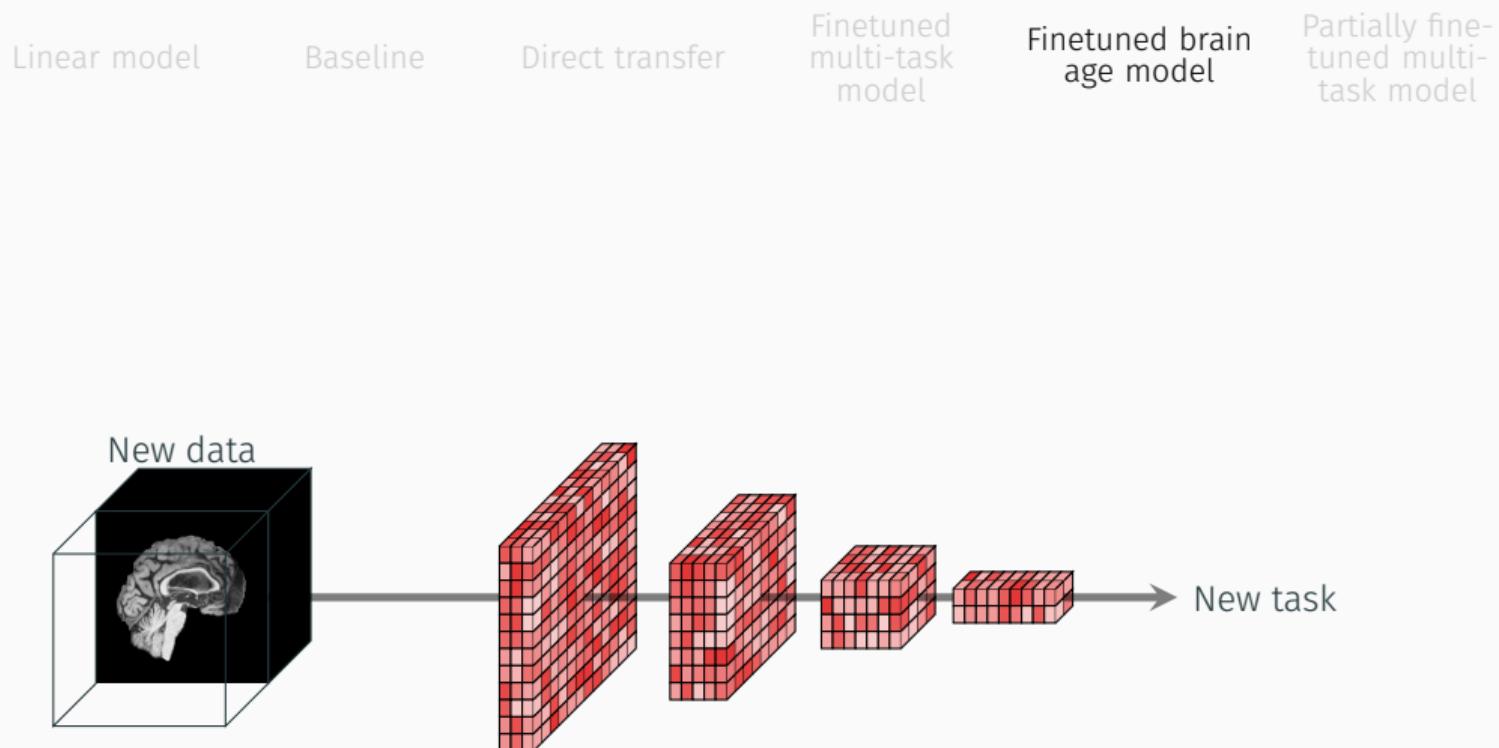
# Transfer learning: Modelling approaches



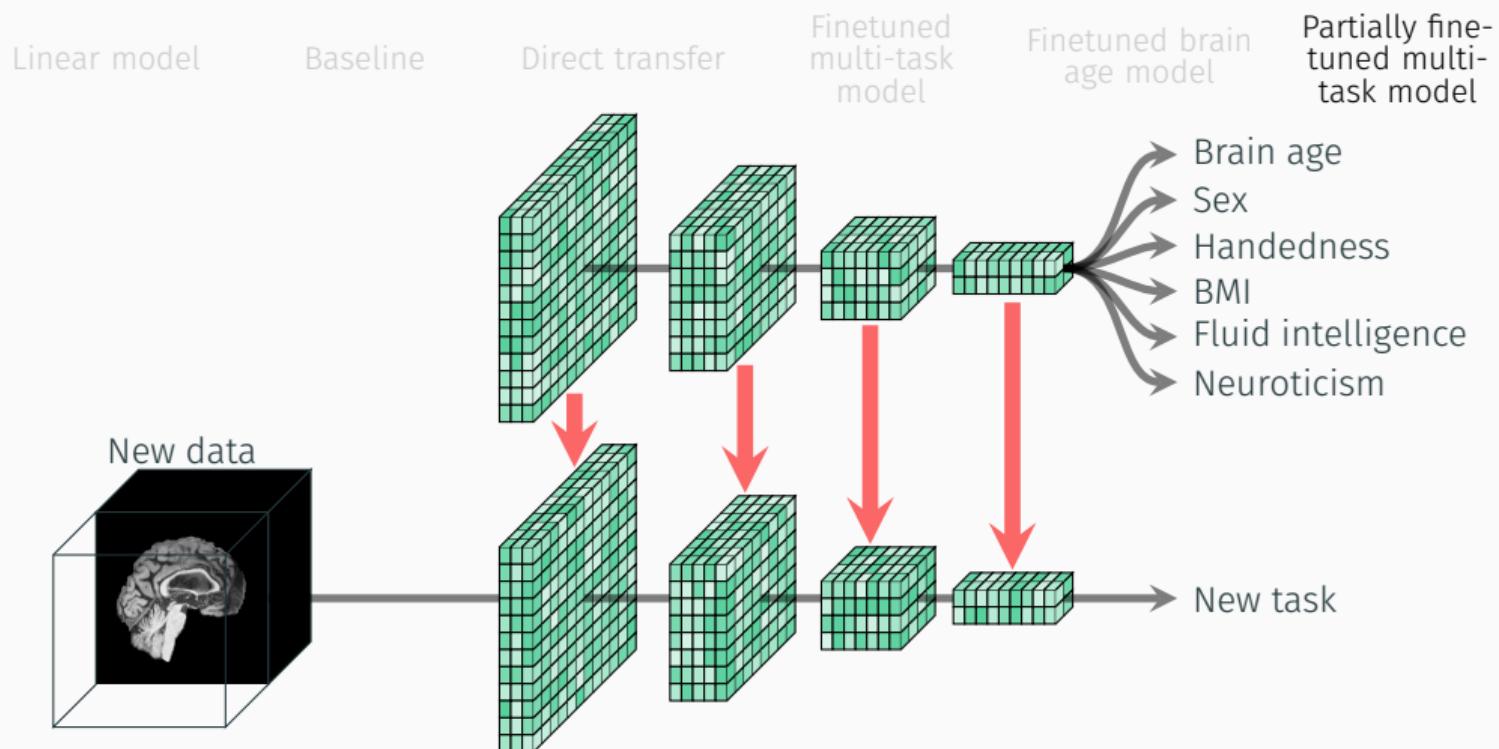
# Transfer learning: Modelling approaches



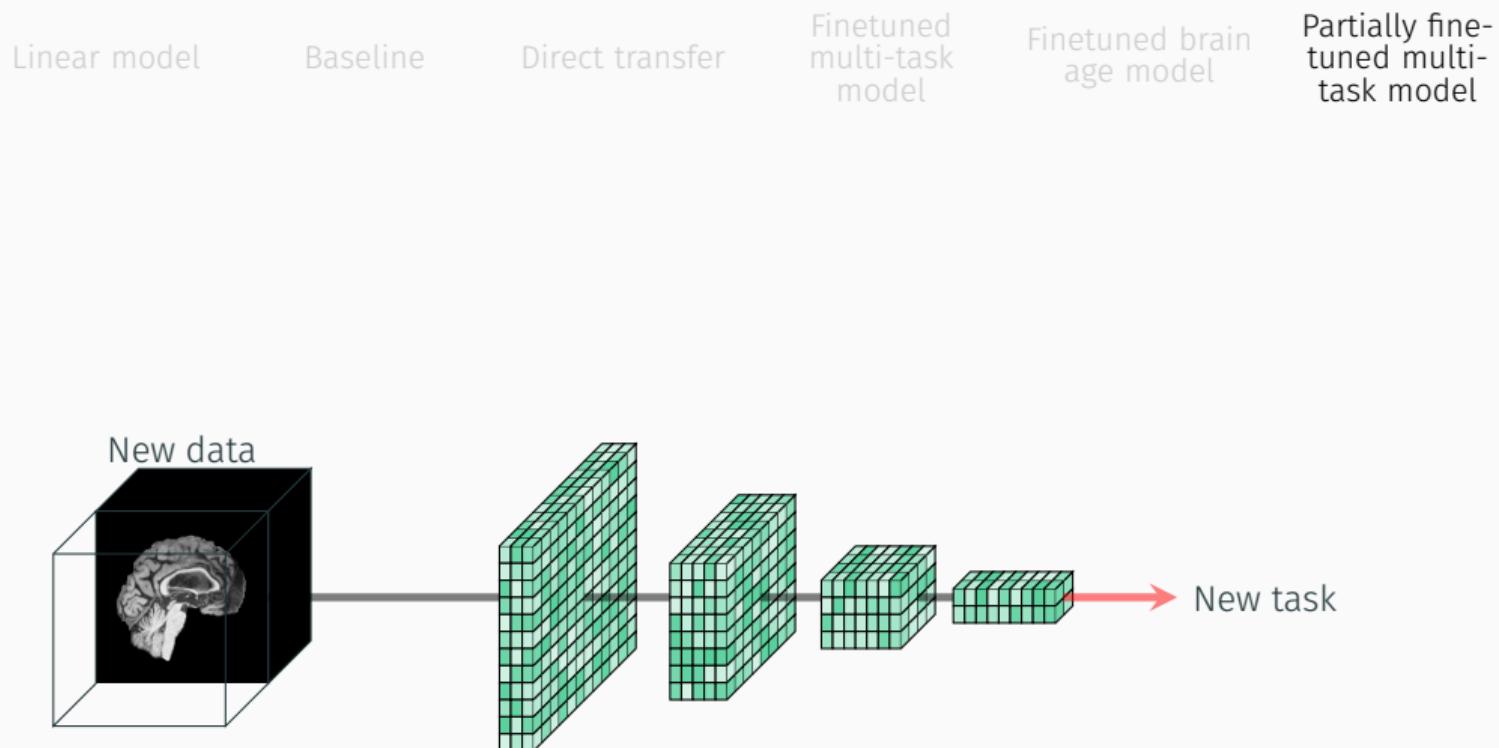
# Transfer learning: Modelling approaches



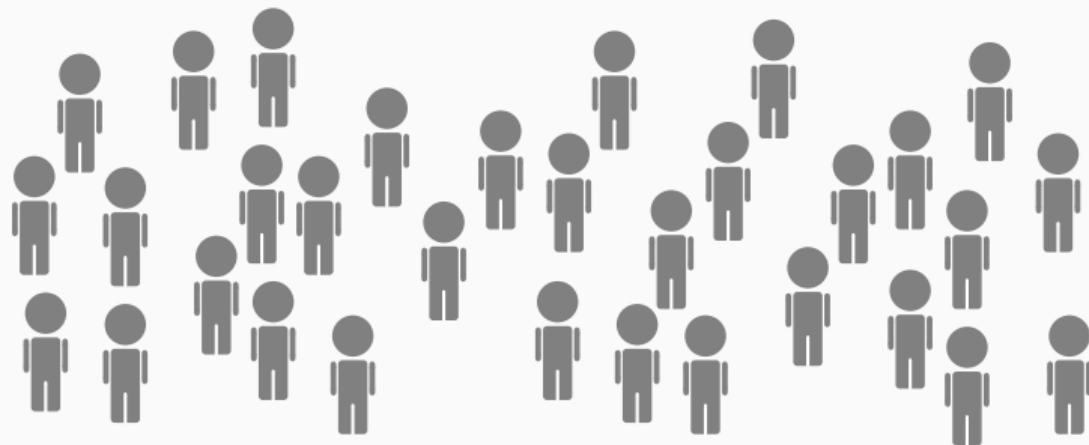
# Transfer learning: Modelling approaches



# Transfer learning: Modelling approaches

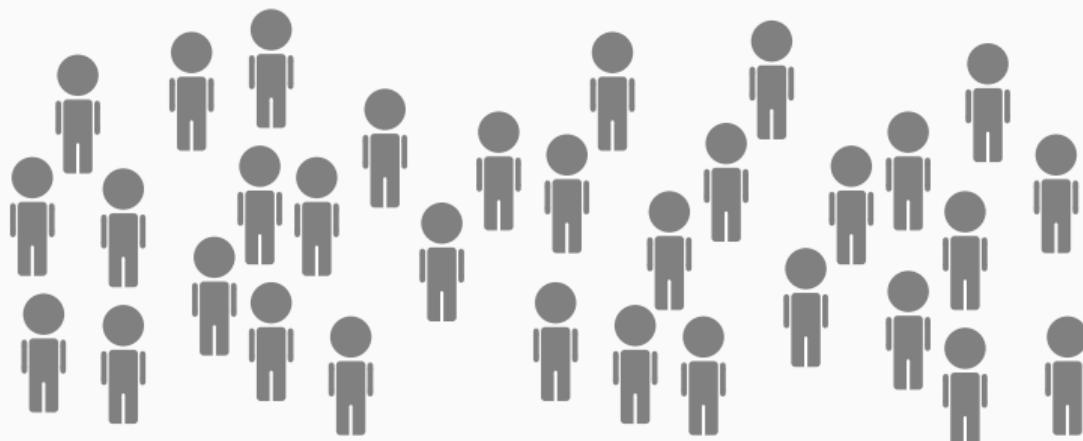


# Transfer learning: Sampling



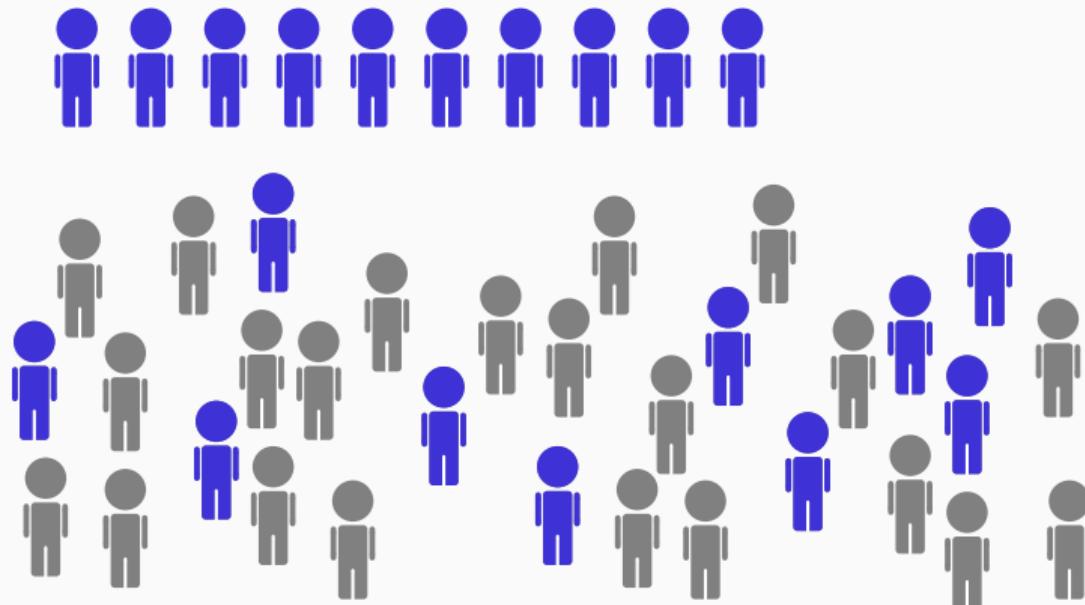
# Transfer learning: Sampling

n=100



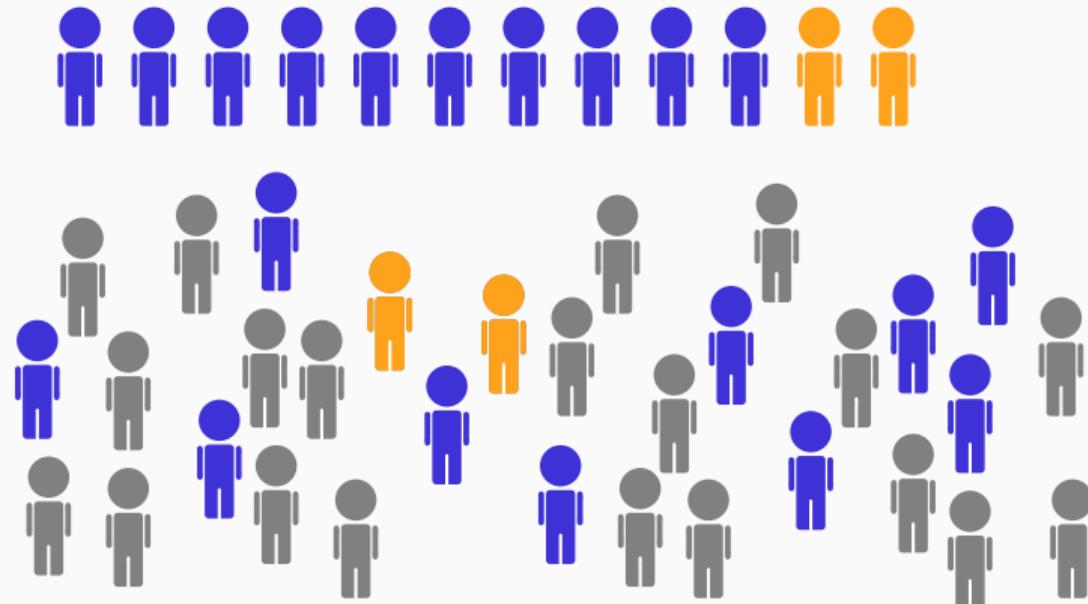
## Transfer learning: Sampling

n=100



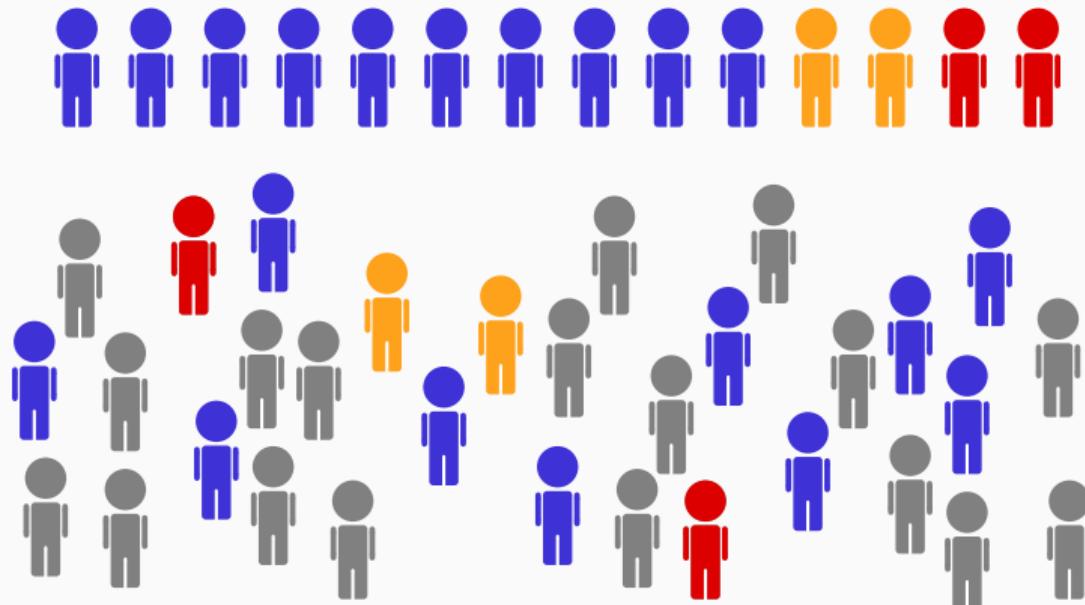
## Transfer learning: Sampling

n=100

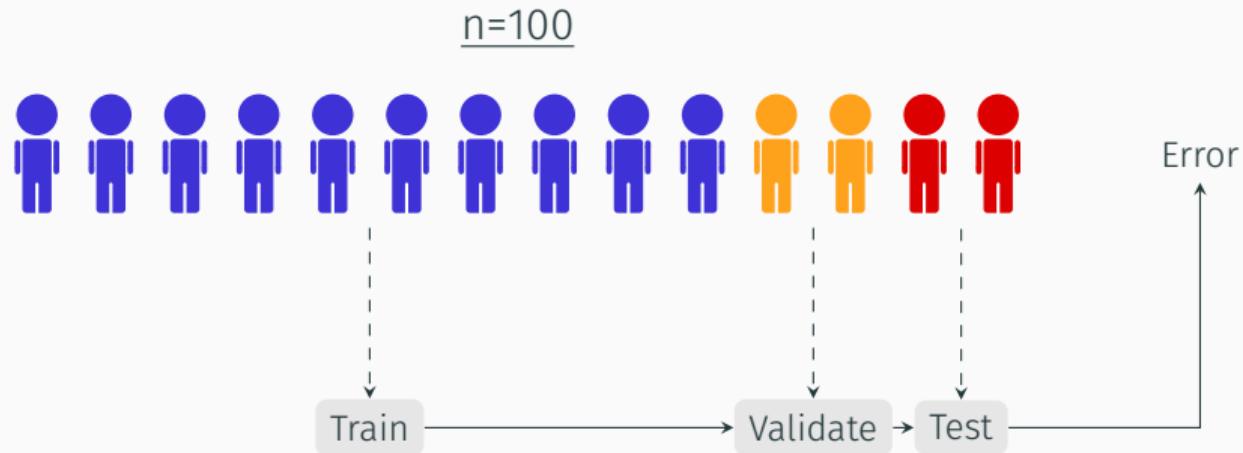


## Transfer learning: Sampling

n=100

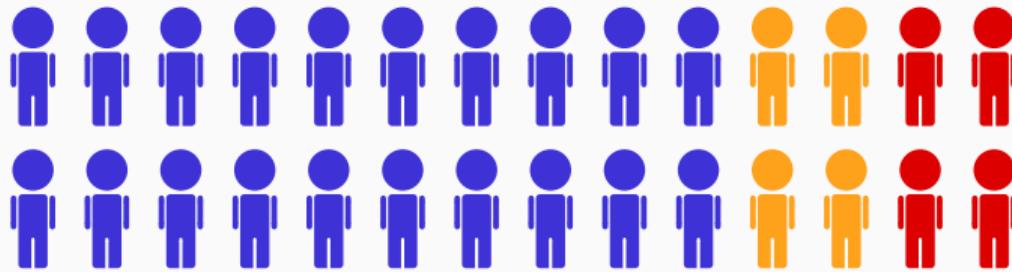


# Transfer learning: Sampling



## Transfer learning: Sampling

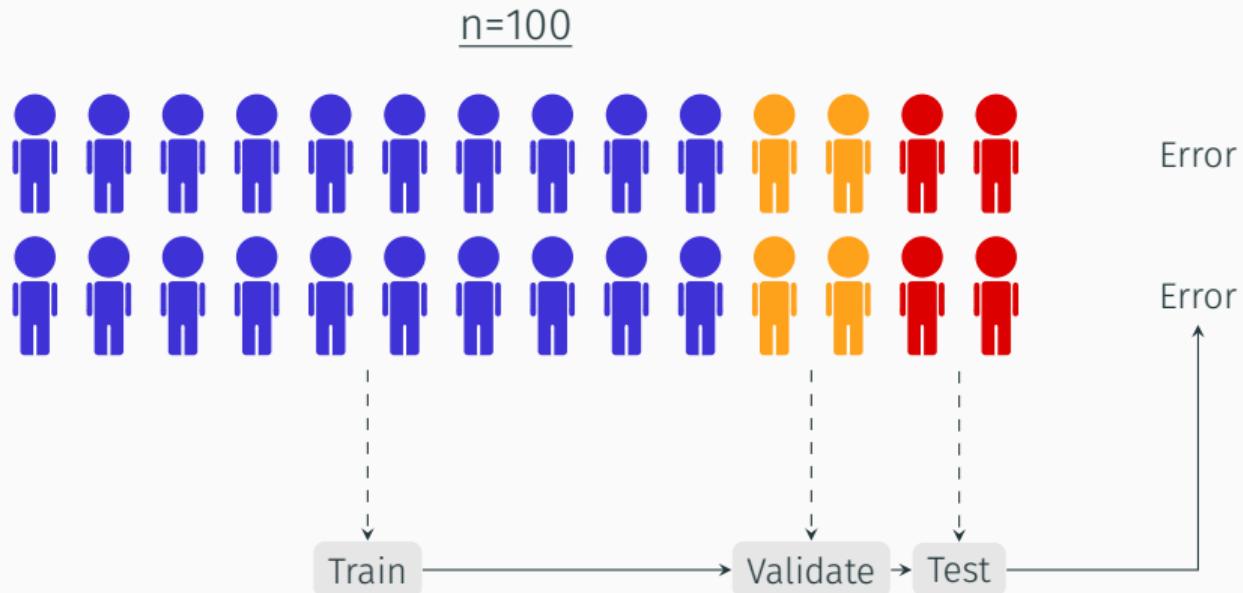
n=100



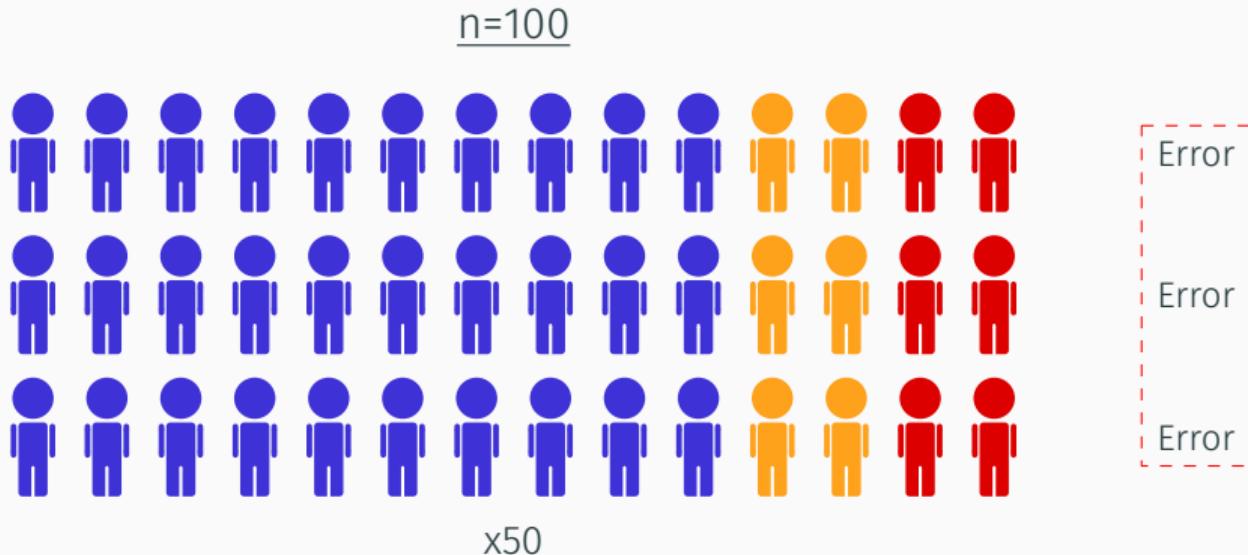
Error



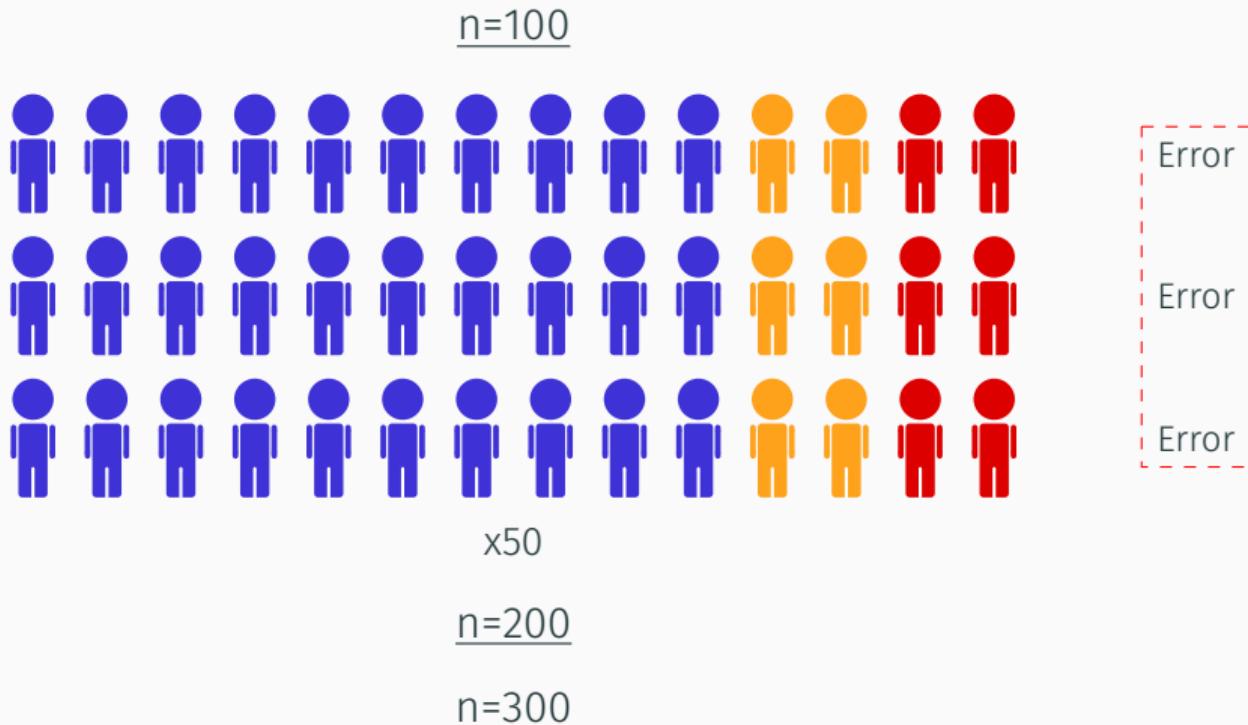
# Transfer learning: Sampling



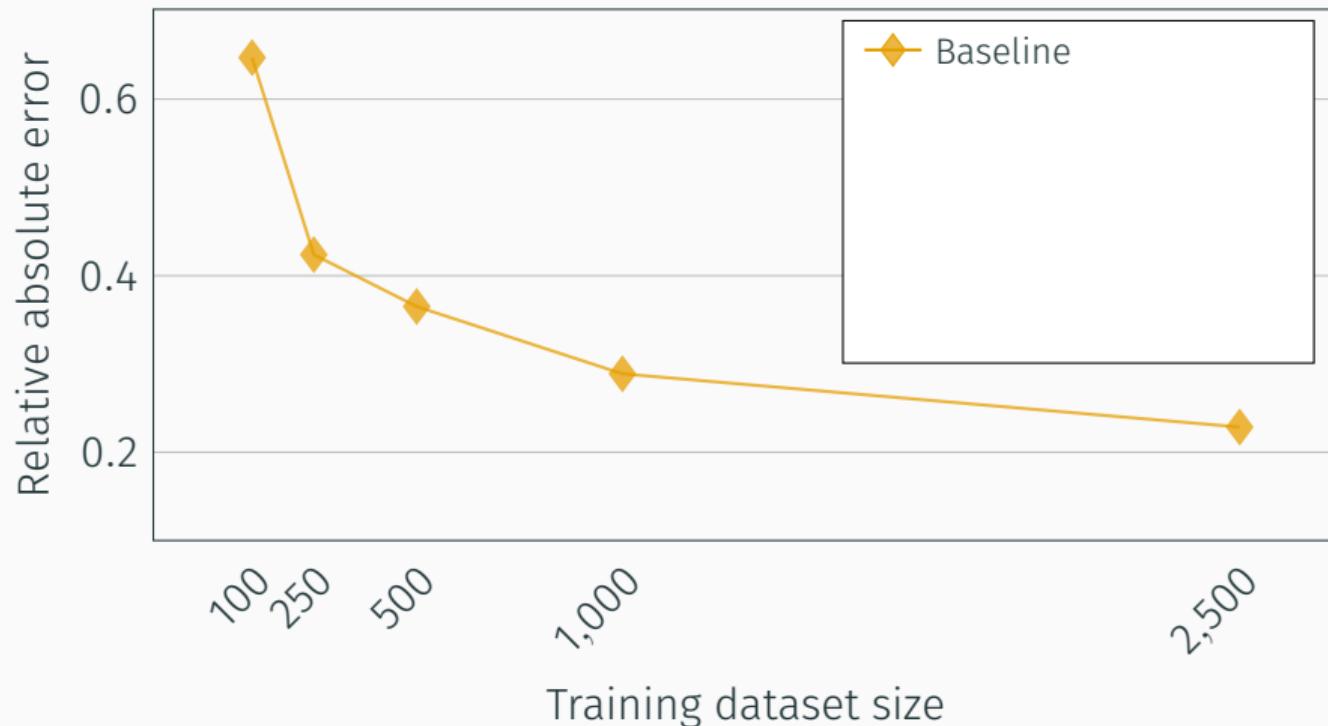
## Transfer learning: Sampling



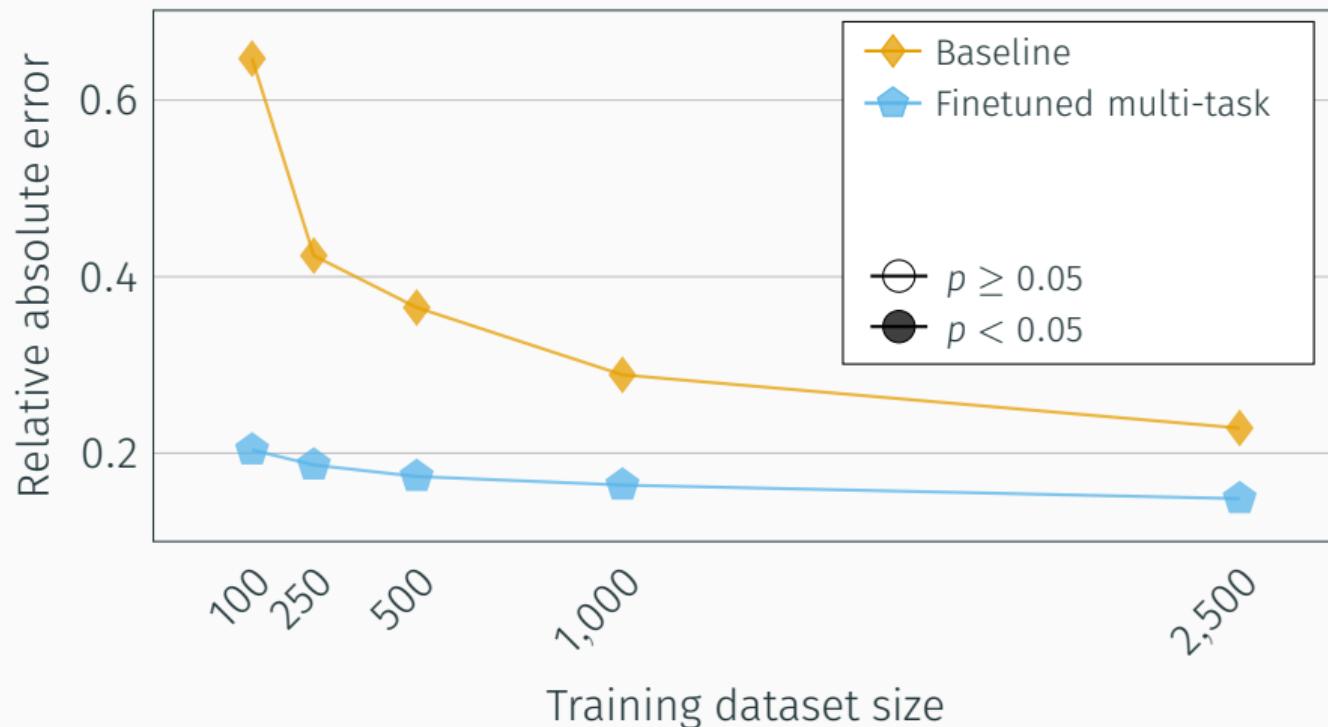
## Transfer learning: Sampling



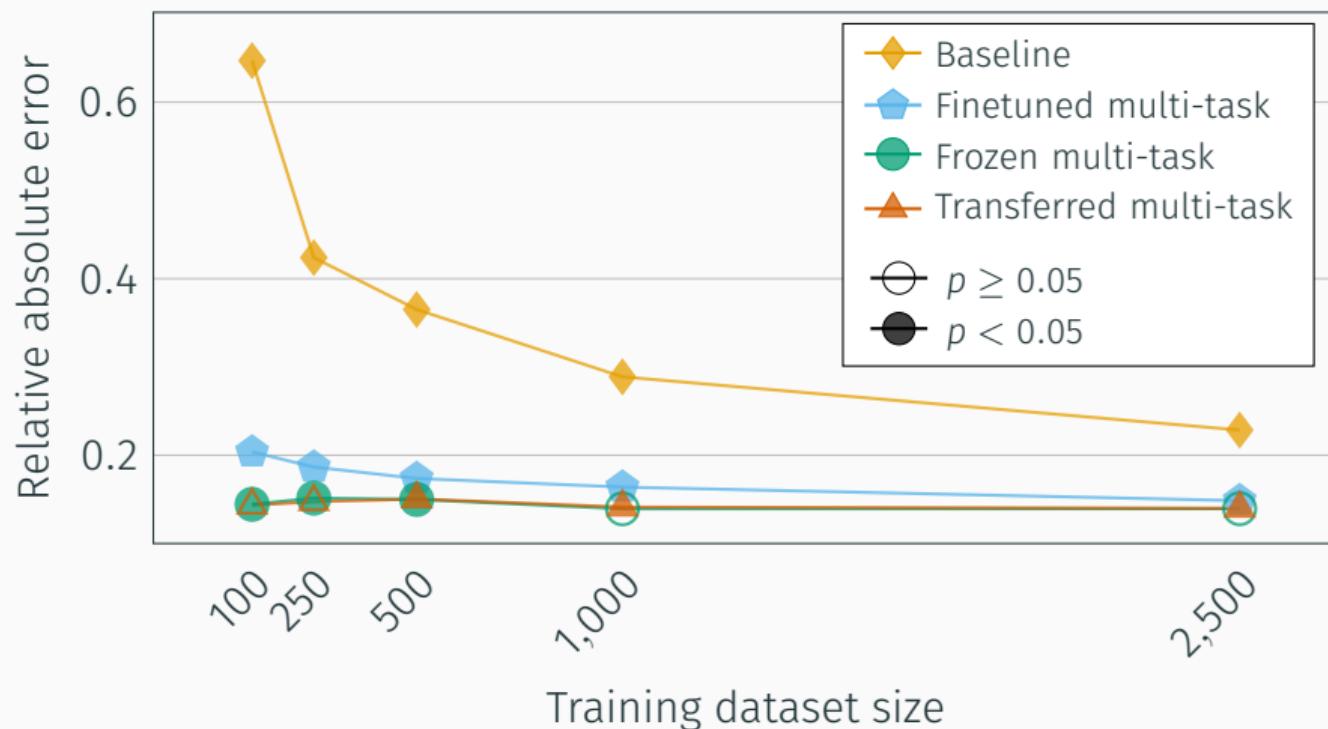
## Results: Heterogeneous brain age predictions



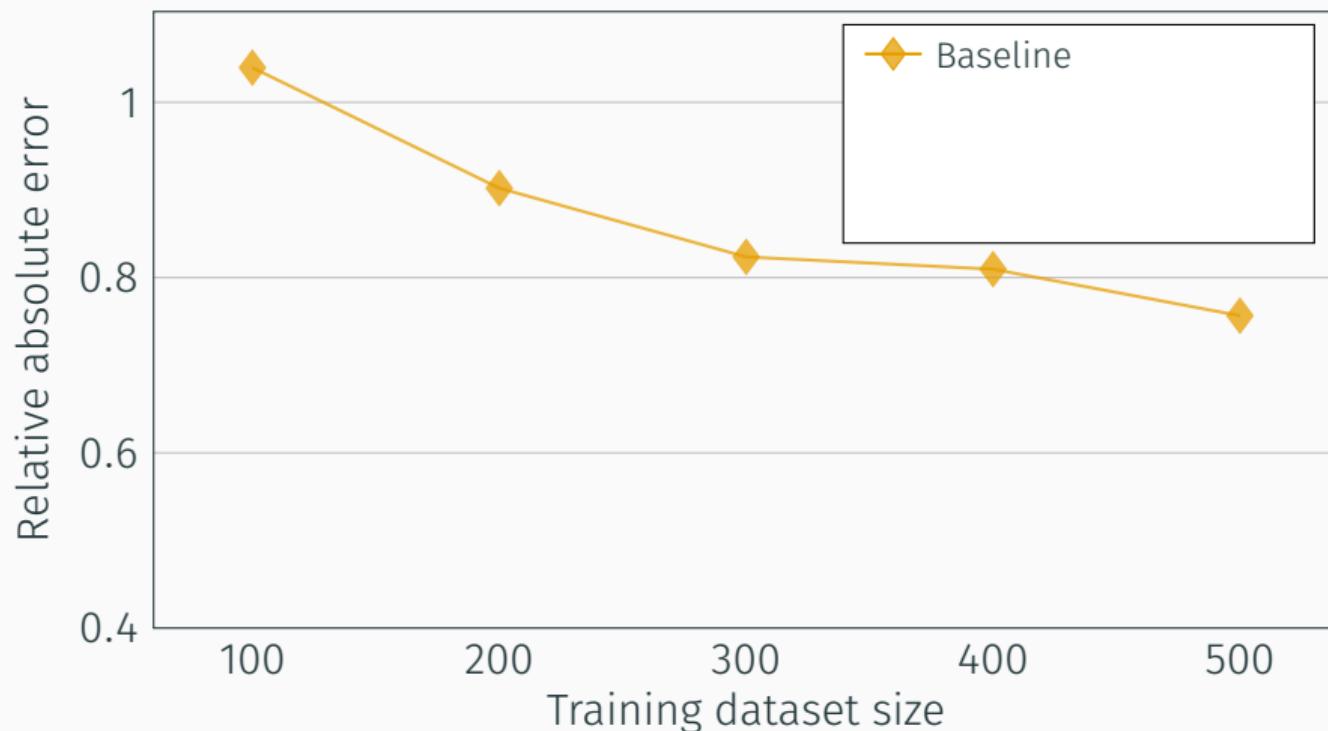
## Results: Heterogeneous brain age predictions



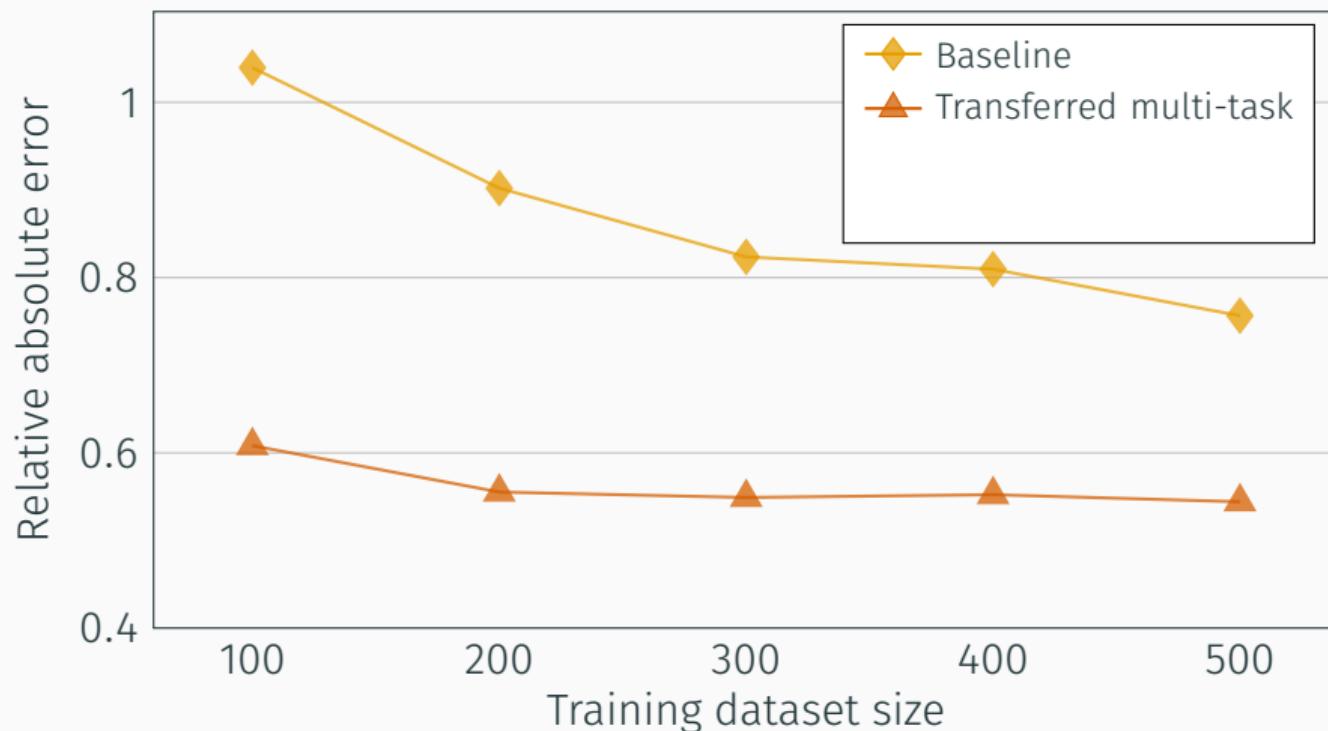
## Results: Heterogeneous brain age predictions



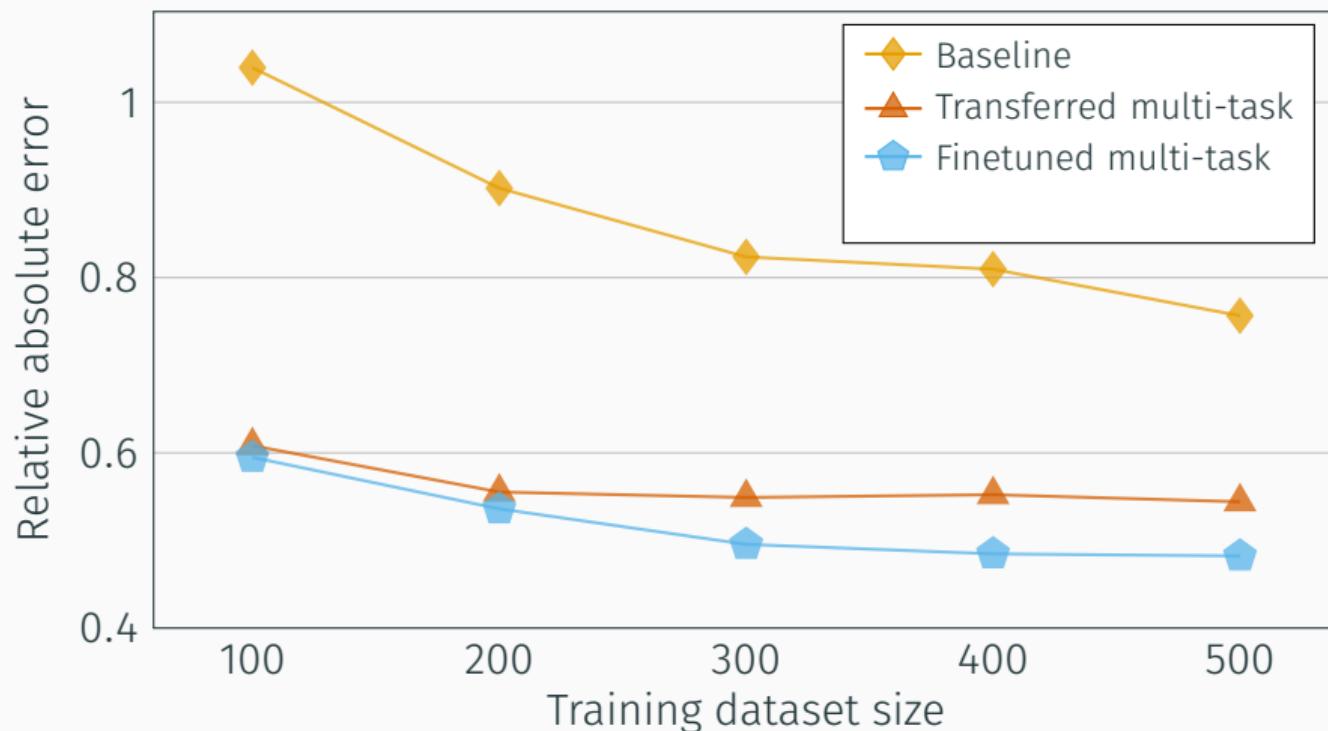
## Results: Homogeneous brain age predictions



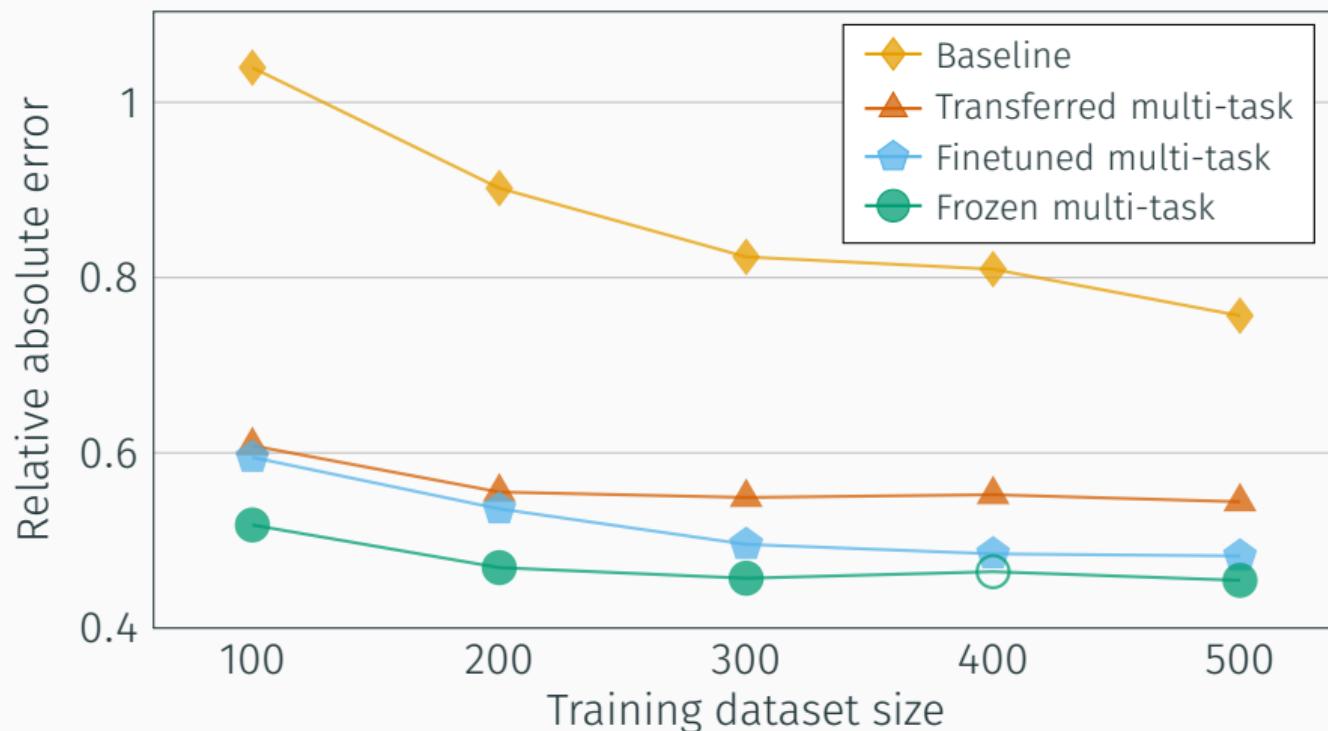
## Results: Homogeneous brain age predictions



## Results: Homogeneous brain age predictions



## Results: Homogeneous brain age predictions



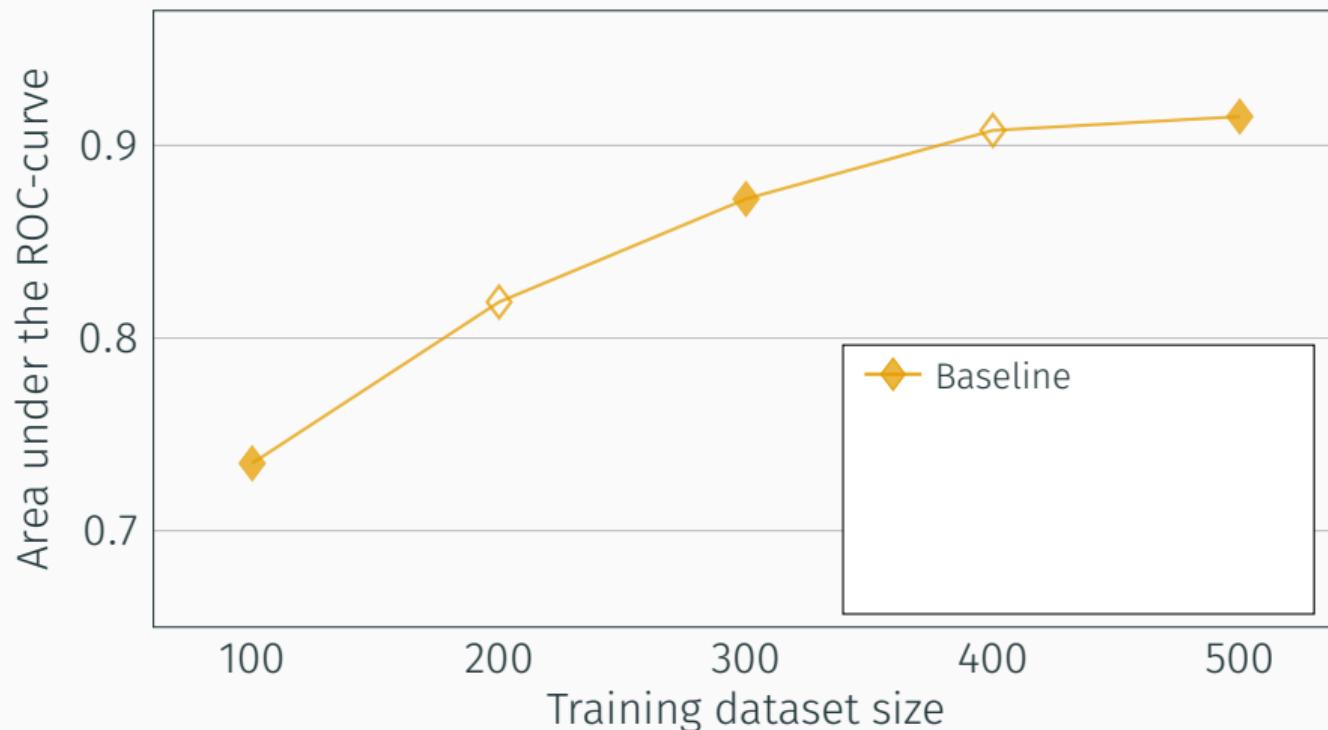
## Results: Brain age

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

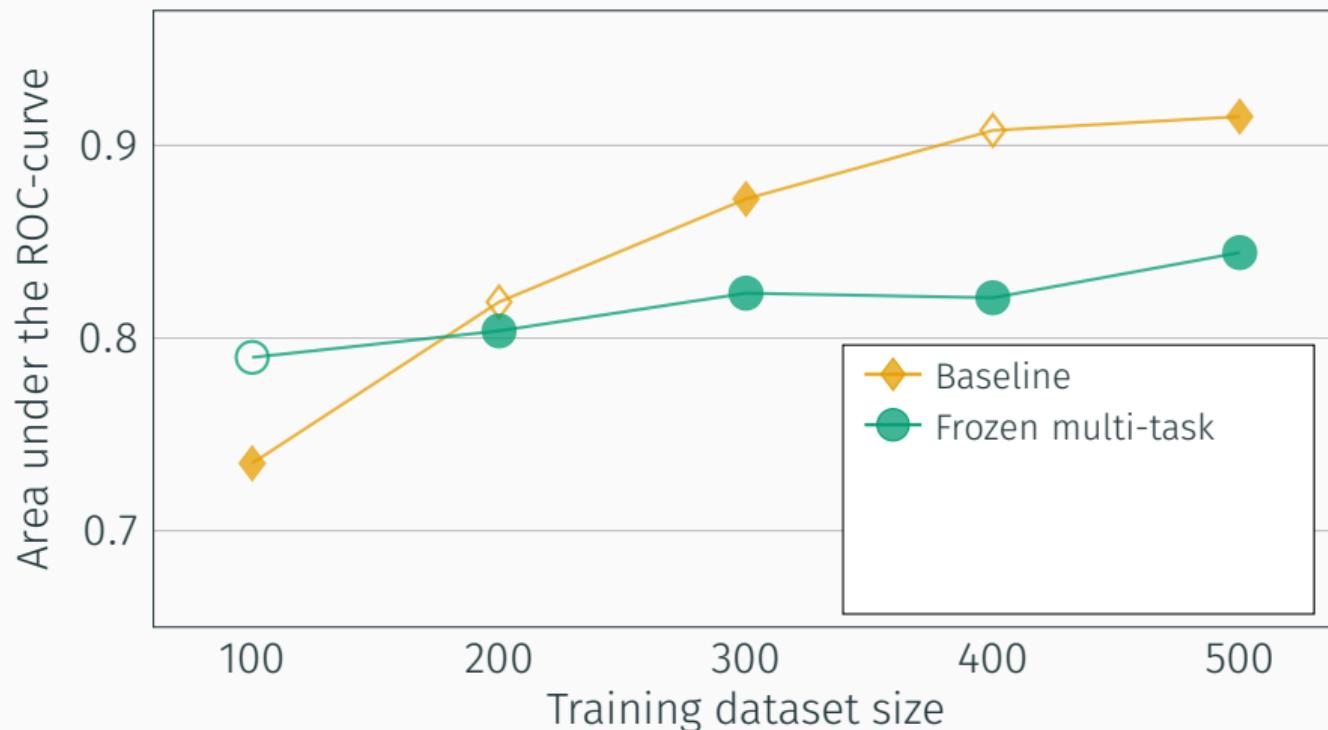
- You should *always* use a pretrained model
- In smaller, homogeneous, samples the model should ideally be finetuned, but using a pretrained model off-the-shelf works reasonably well



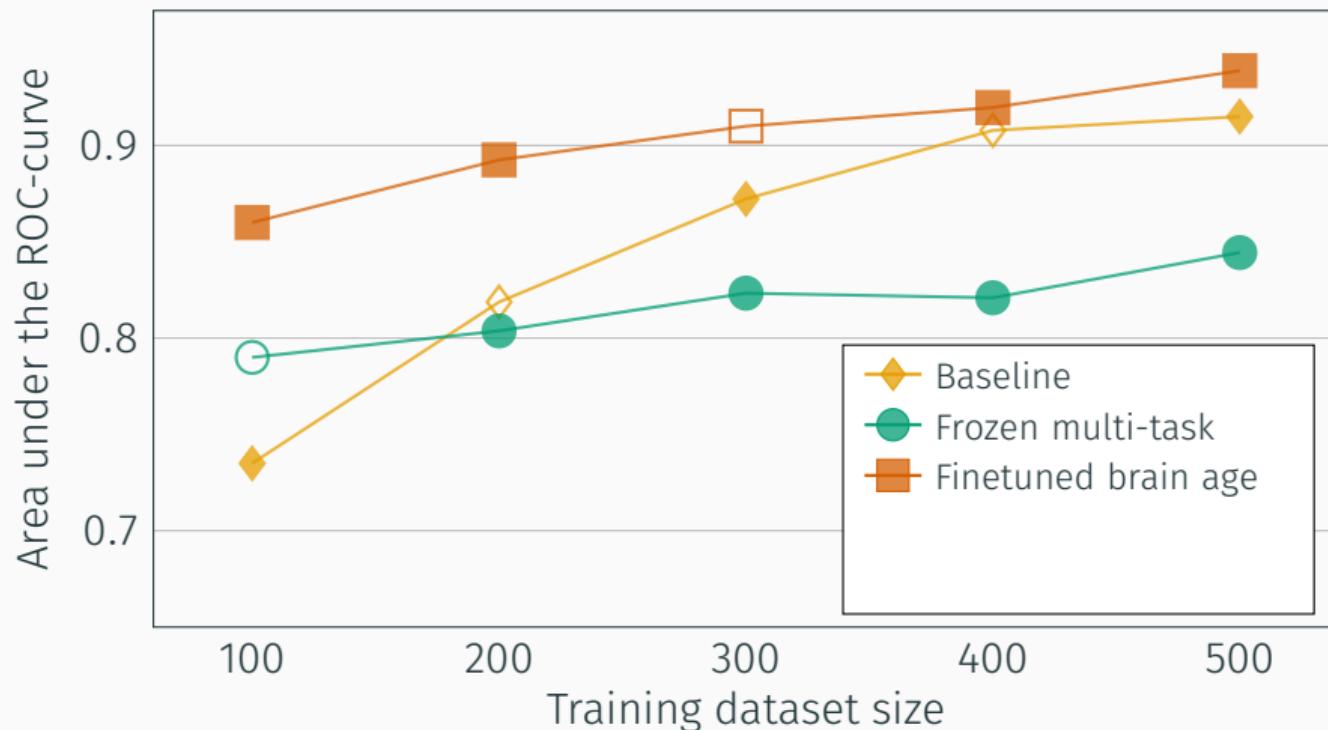
## Results: AD vs HC classification



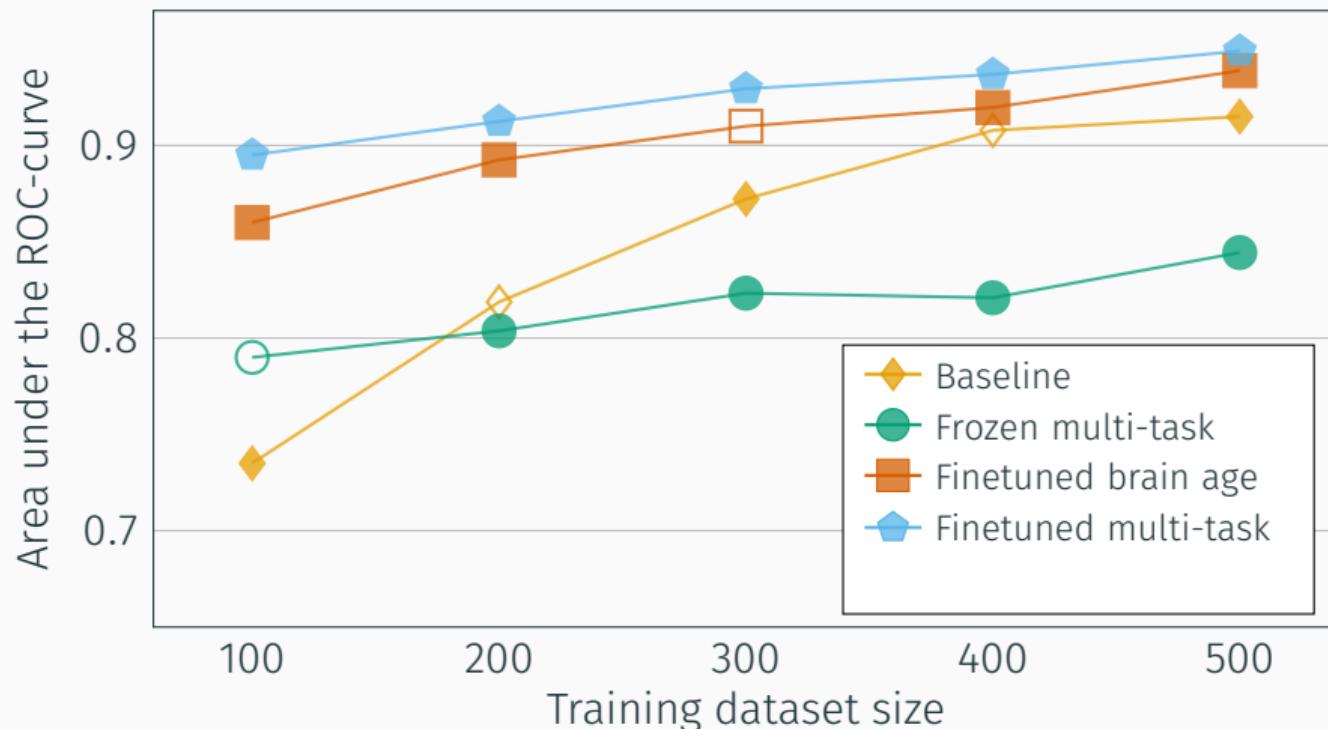
## Results: AD vs HC classification



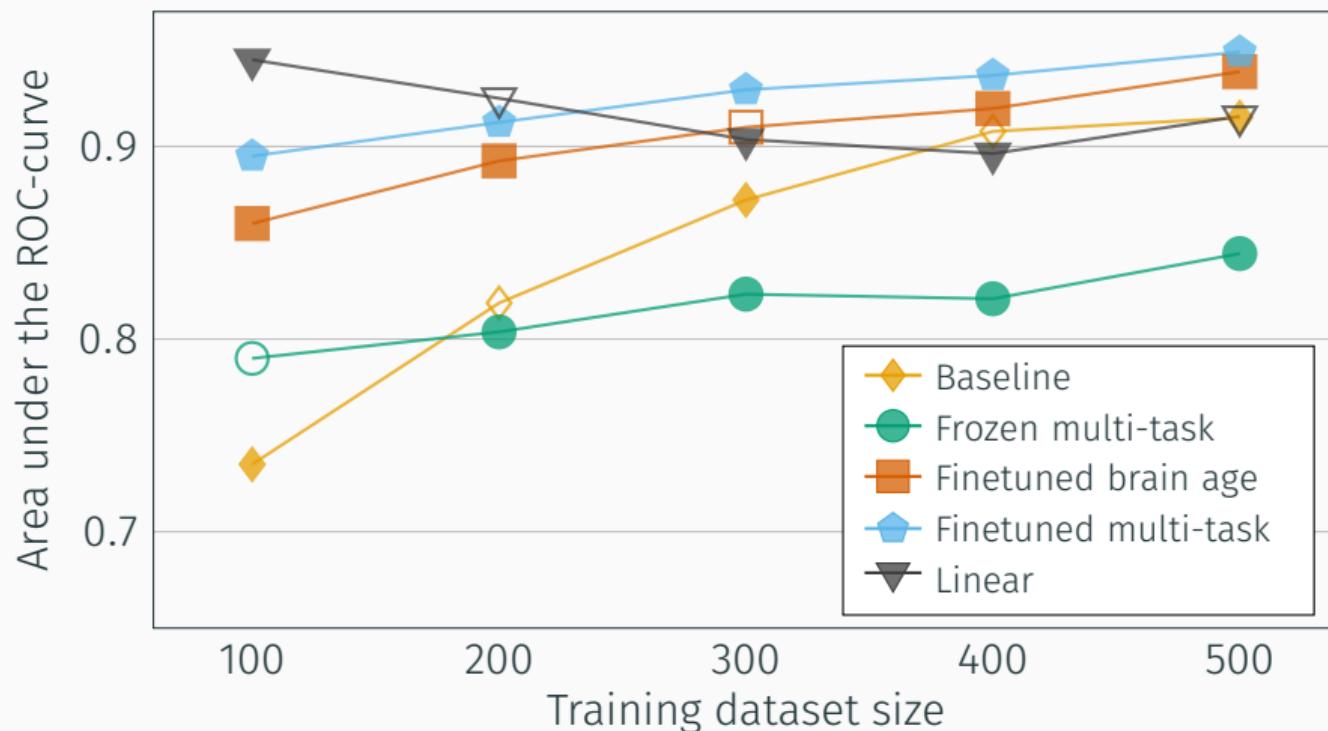
## Results: AD vs HC classification



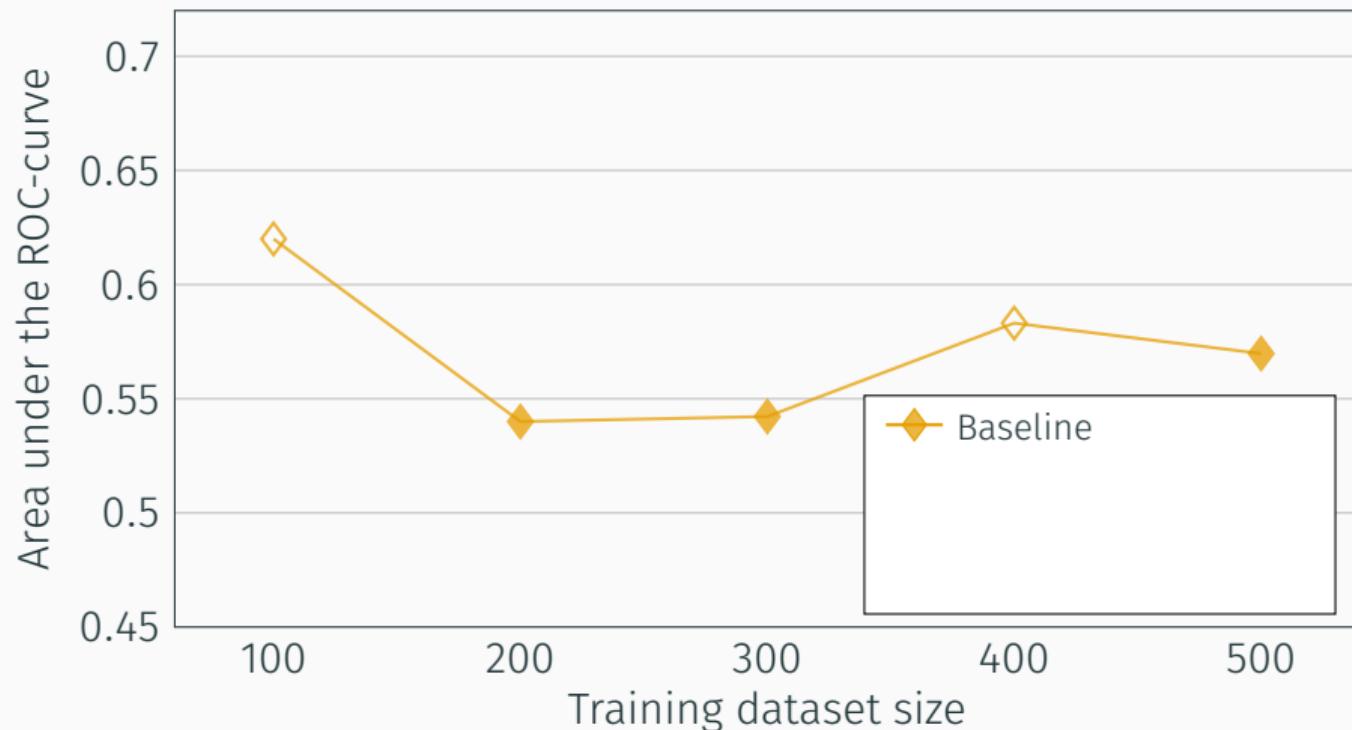
## Results: AD vs HC classification



## Results: AD vs HC classification



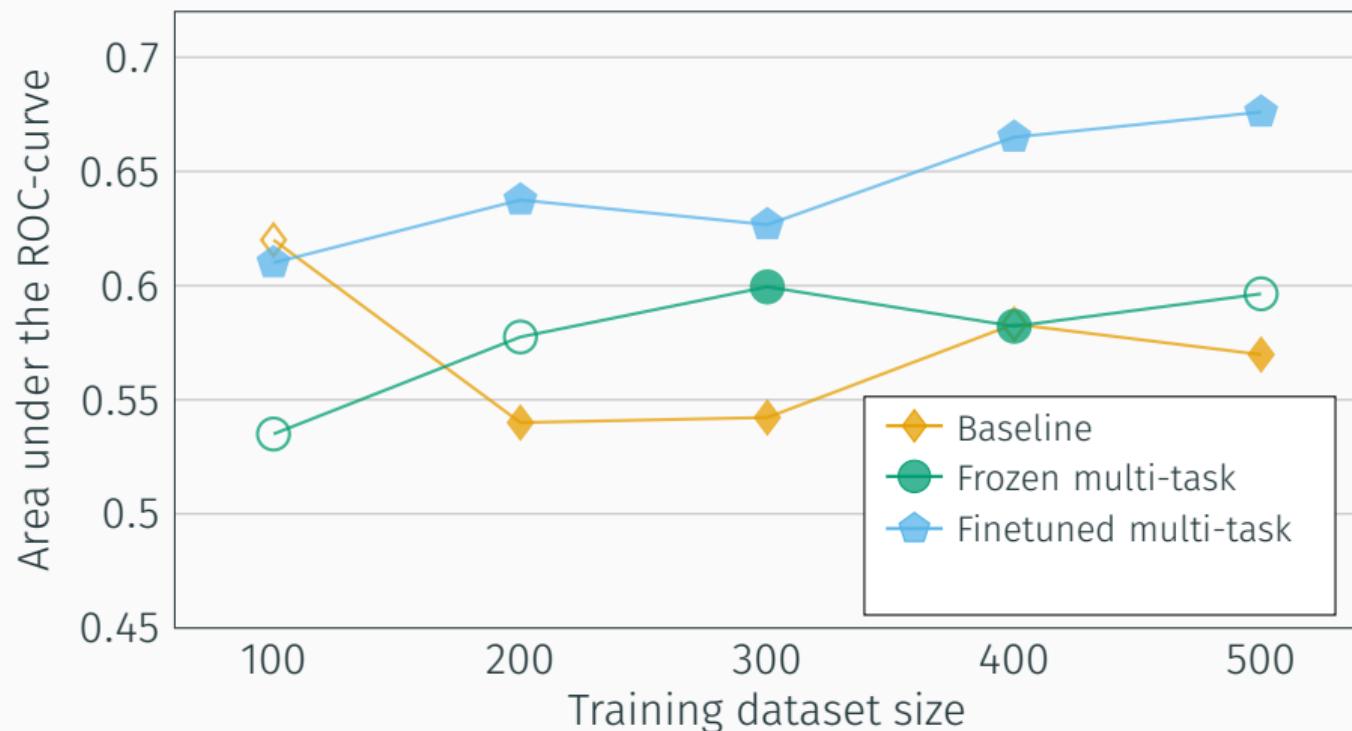
## Results: SCZ vs BD classification



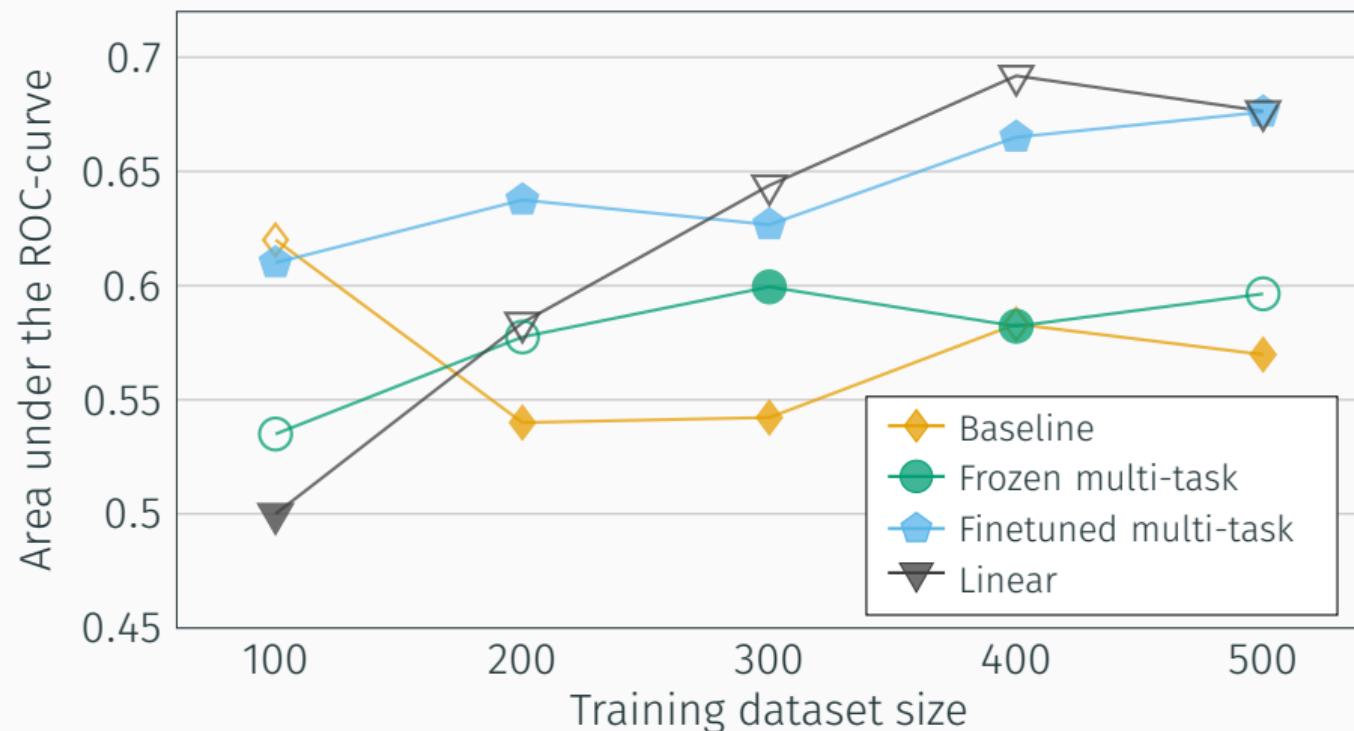
## Results: SCZ vs BD classification



## Results: SCZ vs BD classification



## Results: SCZ vs BD classification



## Results: Brain age

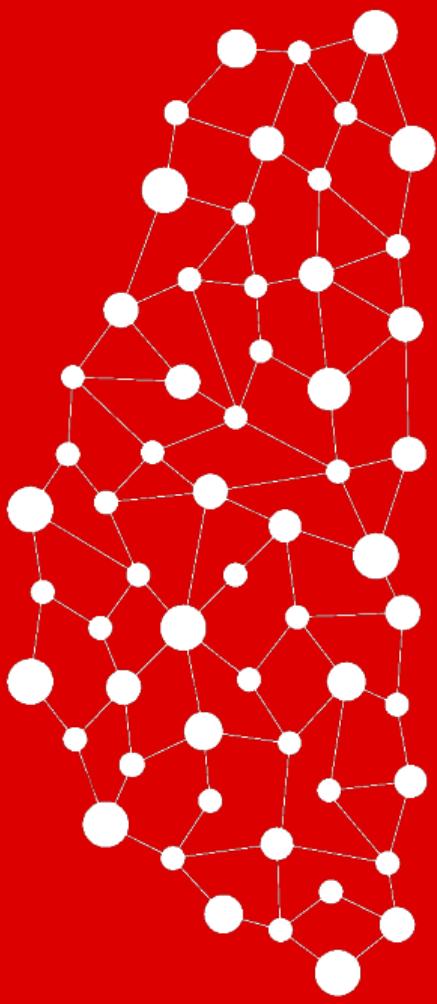
If you want to accurately predict anything<sup>1</sup> in new samples:

- If you are using a CNN, you should *always*<sup>2</sup> use a pretrained model.
  - The multi-task model outperforms a single-task model even when the pretraining task is closely related to the downstream task
- However, apparently<sup>3</sup>, 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!  
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