

2022 CSDI Workshop
Paris, 4 April 2022

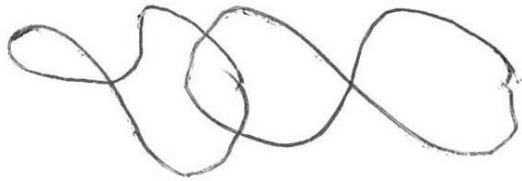


AUTOMATIC SCORING OF COGNITION DRAWINGS

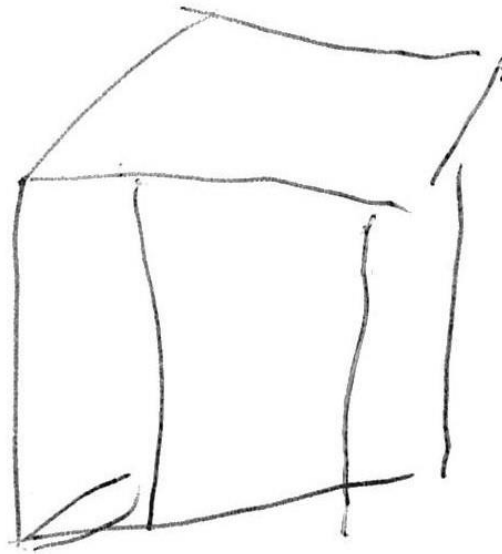
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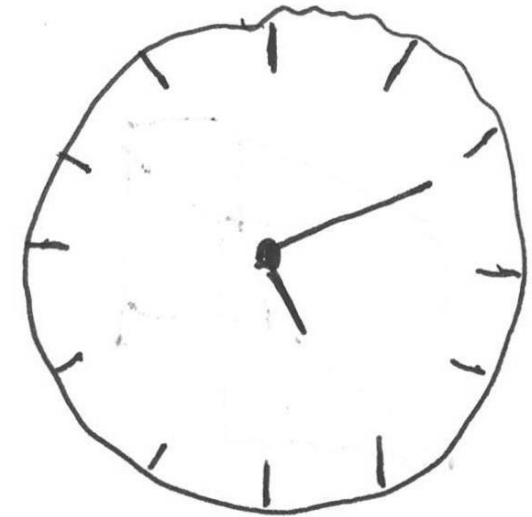
- Since wave 8 SHARE contains three „constructional praxis tests“ (Wagner & Douhou, 2021)



Infinity loops



Cube

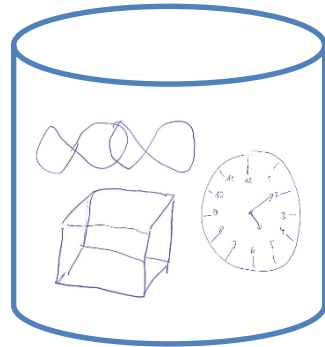


Clock

- Part of several screening tests (e.g. MoCA) for early signs of cognitive decline



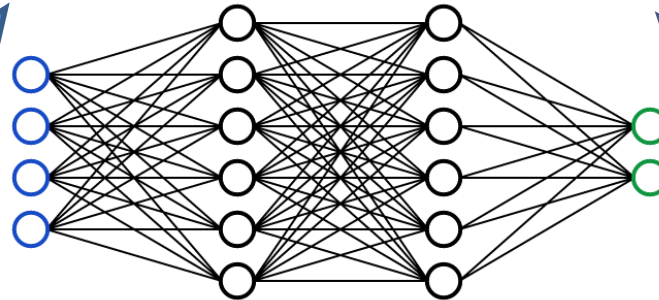
Respondents draw pictures



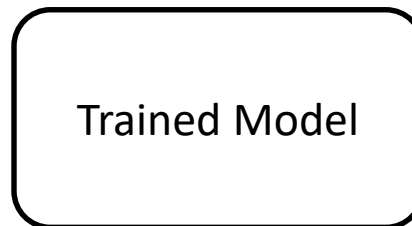
Interviewers score drawings



Use drawings as examples



Use scores as labels



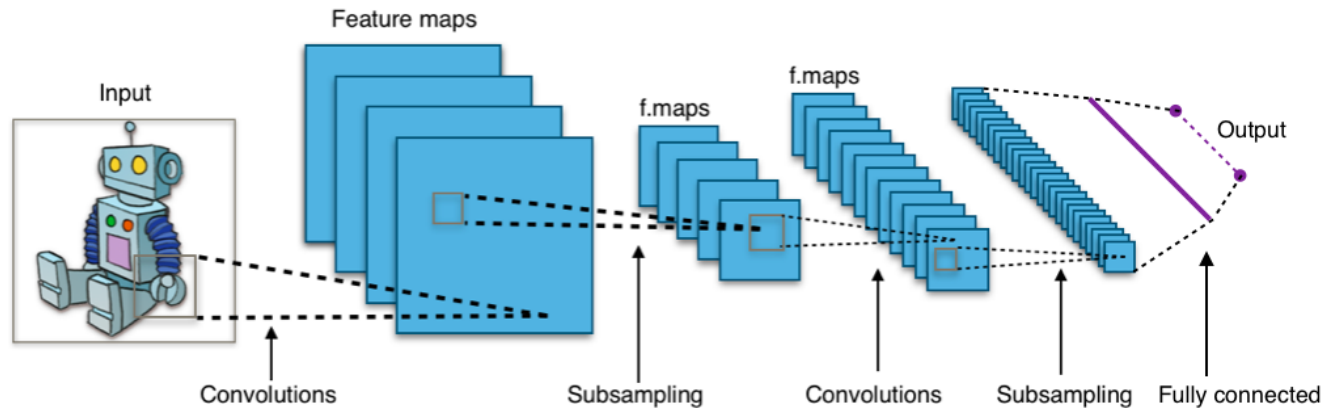
Can be used to score unlabeled data automatically

- Scanned 2,109 SHARE DE recording booklets
- Linked to survey data
- Processed and enhanced images

**Thank you, Amany, Julia, Pandora,
Claudia and Charlotte!**

- Collected ~10,000 recording booklets from 9 additional countries

- Convolutional Neural Networks
 - Work horse for image recognition tasks
 - Initially used to digitize handwritten numbers (LeCun et al. 1989)
 - Made dramatical improvements in recent years and is the basis of the Deep Learning „hype“



“Fully connected convolutional neural network” by Aphex34 is licensed under CC BY-SA 4.0

Preliminary results

Model architecture	Layers	Trainable parameters (millions)	% classified correctly		
			Clock / Cube / Loops 3 classes	Cube: (partially) correct / wrong 2 classes	Cube: correct / partially / wrong 3 classes
AlexNet ^[1]	8	62	99.8	84.9	68.4
VGG (BN) ^[2]	19	144	99.8	86.6	71.2
ResNet ^[3]	18	11	99.8	86.7	70.3
	50	26	99.8	86.2	68.4
			$N_{\text{Clock}} = 1,907$ $N_{\text{Cube}} = 1,882$ $N_{\text{Loops}} = 1,891$	$N_{\text{(Partially) Correct}} = 1,417$ (80.5%) $N_{\text{Wrong}} = 343$	$N_{\text{Correct}} = 1,088$ (61.8%) $N_{\text{Partially}} = 329$ $N_{\text{Wrong}} = 343$

Best out of 20 epochs; Validation set = 30%; All models pretrained on ImageNet (<https://www.image-net.org/>)

^[1] Krizhevsky, Sutskever & Hinton (2012); ^[2] Simonyan & Zisserman (2015); ^[3] He et al. (2015)

Software: PyTorch 1.10.0, fastai 2.5.3; Hardware: NVIDIA GeForce RTX 3070 Ti

- **Fiddle with models**

longer training, hyperparameter tuning, newer architectures, class imbalances, data augmentation, better pre-training datasets ...

- **Get more data**

scan available recording booklets, collect wave 9 drawings

- **Improve scoring**

Prediction performance could be impaired by bad scoring due to:

- Interviewers not sticking to the rules
- Rules being sub-optimal
- Scoring not lending itself well to exact rules

→ Investigate error sources and get closer to bayes error rate

- **Make „gold standard“ scoring**
 - Check performance of interviewers compared to gold standard
 - Use as improved labels for the training data
- **Visualize predictive features in drawings**

(cf. e.g. Zeiler & Fergus 2013)

 - Check whether interviewers stick to rules: features indicated by rules should be predictive of interviewers' scores
 - Check if rules work as intended: try to predict other criteria of cognitive decline with drawings and see if features indicated by rules are predictive

- **Phase 1 (2020-2022):**
 - Scan initial batch of SHARE DE drawings (~2,000)
 - Make proof-of-concept models
 - Assess feasibility and sketch further plans
- **Phase 2 (2022-2023):**
 - Find funding
 - Scan all available wave 8 drawings (~10,000)
 - First substantial publications
- **Phase 3 (2023-2024):**
 - Scan wave 9 drawings (~60,000)
 - More data intensive analyses (e.g. clock draws)
 - Release as well curated, strictly anonymous open dataset
 - Release access restricted linked dataset



SHARE

SURVEY OF HEALTH, AGEING
AND RETIREMENT IN EUROPE

THANK YOU!

With any questions/issues please don't hesitate to contact me:

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