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From Applied Deep Learning to Artificial General Intelligence


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Predictions

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”10 years from now, AI will overcome NI (natural intelligence)”

Estimates of when AGI will arrive

Year prediction made	Predicted year	Number of years	Predictor	Contemporaneous source
1965	1985 or sooner	20 or less	Herbert A. Simon	*The shape of automation for men and management*[69][72]
1993	2023 or sooner	30 or less	Vernor Vinge, science fiction writer	"The Coming Technological Singularity"[73]
1995	2040 or sooner	45 or less	Hans Moravec, robotics researcher	Wired[74]
2008	Never		Gordon E. Moore, inventor of Moore's Law	IEEE Spectrum[75]
2017	2029	12	Ray Kurzweil	Interview[76]

from Wikpedia

AI pioneer and economist **Herbert A. Simon** inaccurately predicted in 1965:

→ "Machines will be capable, within twenty years, of doing any work a man can do".

In 1970 **Marvin Minsky** wrote that

→ "Within a generation... the problem of creating artificial intelligence will substantially be solved."[69]

Bill Gates in 1998

→ Dialogue systems will be working in 10 years

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Content

From Applied Deep Learning to Artificial General Intelligence

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- **Crowdsourced** *or* **Natural** INTELLIGENCE QUOTIENT is larger?
    - Putative EXAMPLE on crowdsourced, **MANY COMPONENT DEEP-NETWORKS** with ***CONSISTENCY SEEKING*** followed by actions and self-training
- APPLICATIONS ARE *”EASY” WITH* DEEP NETWORKS → examples from my group
- The MYSTERY of **Natural Intelligence (NI)** → What is NI made of?
    - What could be the main **problem for NI**?
    - How did Nature solve it? What is the ”invention” of the mammalian brain?
- A recent application (on face and facial expression)
    - avoids crowdsourcing
    - hits at the core of the ”invention”…

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Crowdsourced Intelligence

Putative example on

- crowdsourced, many component deep-networks with
- consistency seeking followed by
- actions and self-training

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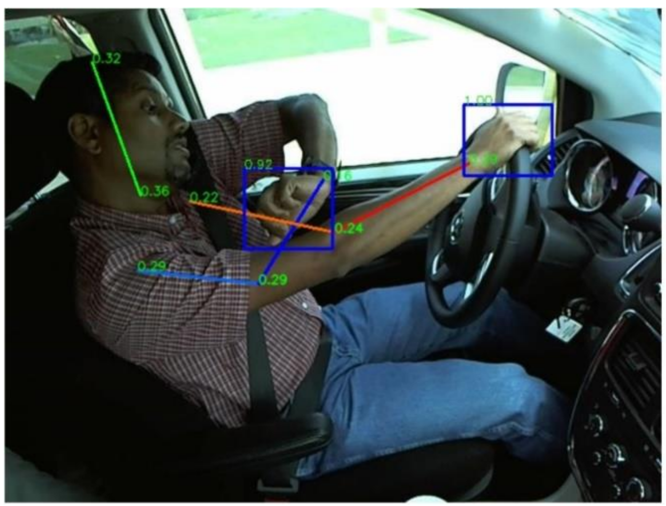
Self-training 1: **Inference** on NN outputs

Blue: right
Red: left

- Contradiction! He has two **right** hands!
- Score on the steering wheel is high: this is the **right hand…**
- The other one is the **left hand…**
- Evaluation should be constrained accordingly…



- AI has two new **SAMPLES** for self-training…

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Self-training 1: **Inference** on NN outputs

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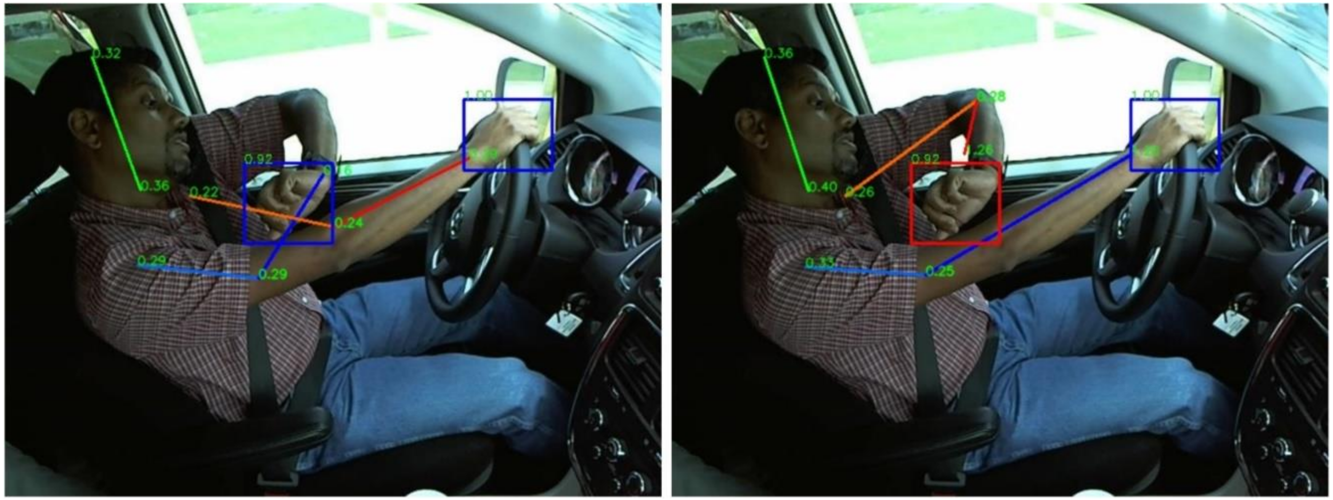

OK!!

- AI has two new **SAMPLES** for self-training…

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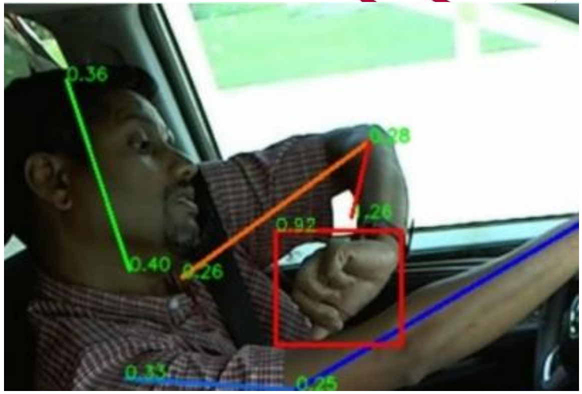
Self-training 2: Inference on BIG DATA

- What is the driver looking at?
- Send to Google Images and read captions: **it is an animal**
  - Hmmm… in a car, in the driver's seat?
- The target of the gaze is close to the wrist
- Restrict search by the word wrist. Captions say: **wristwatch**



(a) (b) (c) (d)

Lőrincz, A., Máté Csákvári, Áron Fóthi, Z. Ádám Milacski, András Sárkány, and Z. Tősér. "Towards reasoning based representations: Deep Consistence Seeking Machine." *Cognitive Systems Research* 47 (2018): 92-108.

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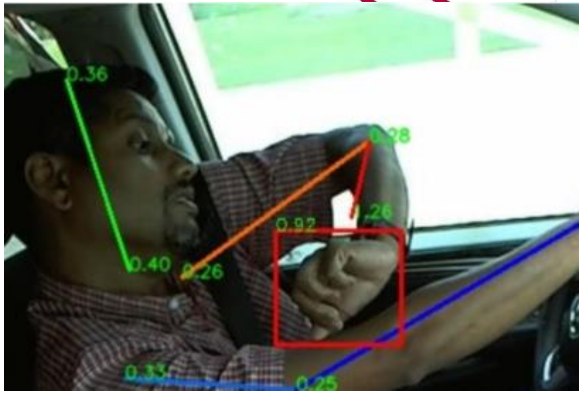
Self-training 3: **Inference** on knowledge base



Thus, he is looking at his wristwatch

What is the wristwatch used for? Ask ConceptNet:

$$\text{“wristwatch} \xrightarrow{\text{UsedFor}} \text{time something or somebody"}$$

$$\text{“wristwatch} \xrightarrow{\text{IsA}} \text{way to tell time"}$$

(a) (b) (c) (d)

⇒ Puzzle solved, action has become possible…

⇒ **MACHINE WILL LEARN FROM BEHAVIORAL FEEDBACK**

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Applications have become easy

→ examples from my group

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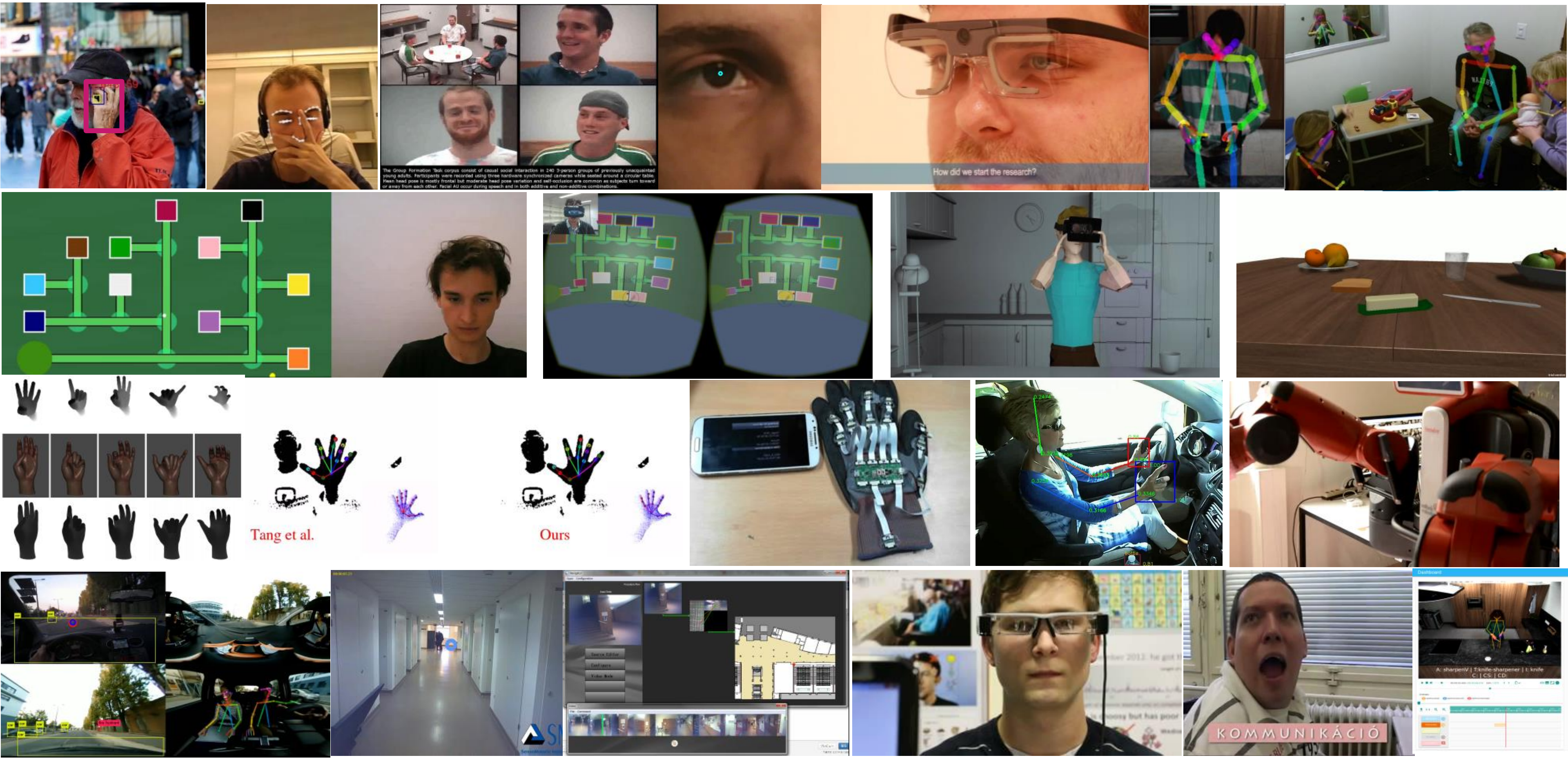
Some of our applications



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The MYSTERY of **Natural Intelligence (NI)**
→ What is NI made of?

- What could be the main **problem for NI**?
- How did Nature solve it? What is the ”INVENTION” of the mammalian brain?

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The mystery of intelligence…

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Scientific discoveries of 20 000 thousand years – **many—many years and many-many milliard people**
➔ can be transferred to a child in about 20 years (for the end of the university)

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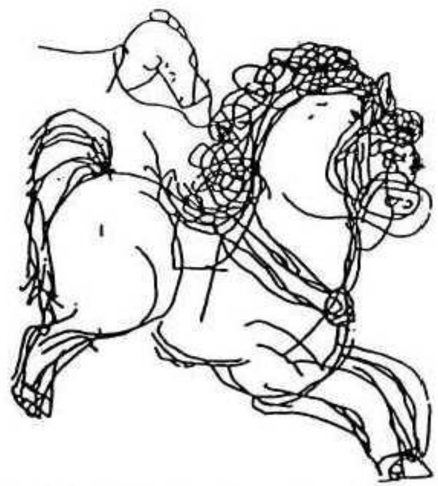
How does our intelligence look like?

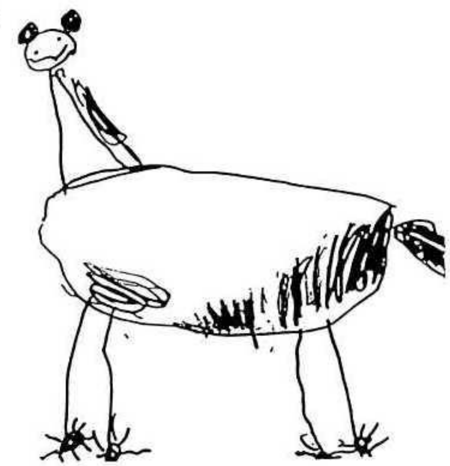
- First type of recognition
  - What is this?



- Horse
  - How do you know?

- Second type of recognition
  - What is this?

(b)



- Horse?
  - Why do you think so?

https://www.theguardian.com/artanddesign/2015/dec/09/nadia-chomyn and the references from Lorna Selfe of the author of the link

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How does our intelligence look like?

Same autistic person at the age of 20 years
She could draw the components of the horse…

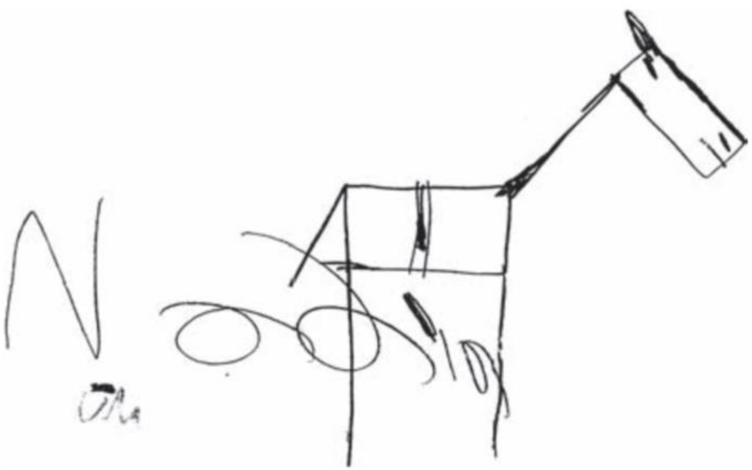
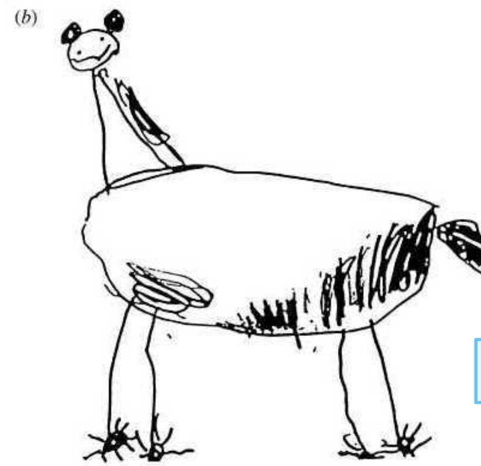


Figure 2.46 A horse; drawn by Nadia in her early 20s.

Autistic child, age: 3.5 years
has problems with recognizing parents
“My mother looks so different
from time to time”

- Second type of recognition
  - What is this?



because of the components!

- Nothing to learn if we know the components
- Easy to communicate
- Easy to extend, e.g., for zebra
  - cf. zero shot learning

4 yr old normal child

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The mystery of intelligence

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Scientific discoveries of 20 000 thousand years – **many—many years and many-many milliard people**

- → can be transferred to a child in about 20 years (for the end of the university)

- → it is very fast, due to
  - → component learning
  - → **linear proofs** of combinatorial problems, e.g.,
    - → traveling salesman problem
    - → mathematical theorems
    - → scientific papers

Issues

- → Learning of components *in order to* overcome the curse of dimensions
- → Manipulation of components *in order to* make statements with linear proofs
- → Context based modulation of the interpretation of the components
- → Rule based correction of decisions and classifications
- → Self-training via rule based corrections

Missing

Crowdsourced databases may make it surprisingly efficient

→ **IS IT HARD TO FIND THE COMPONENTS?**

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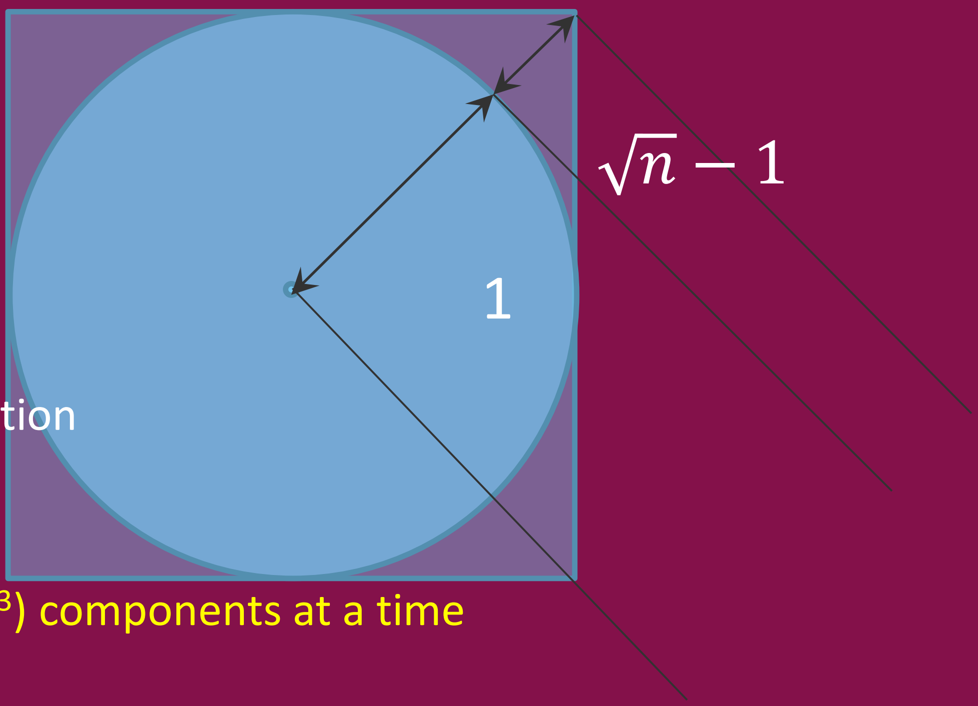
The main problem: **Curse of dimensionality**

Consider a finite world of dimension n (number of variables)
→ normalize all dimensions to scale between -1 and +1
→ draw the maximal 'sphere'



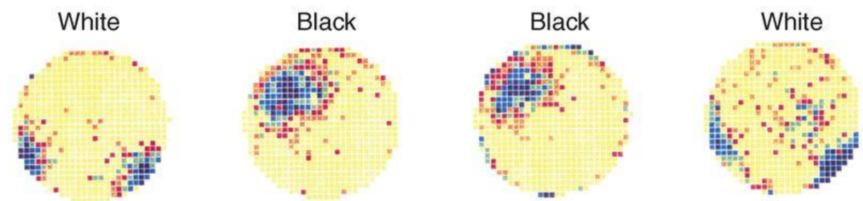
The curse
→ dimension of HD image ~ 10^6
→ $2^{1,000,000}$ 'hedgehog thorns' (!!!)
→ of length of 999 (!)
makes hard to search for the optimal solution

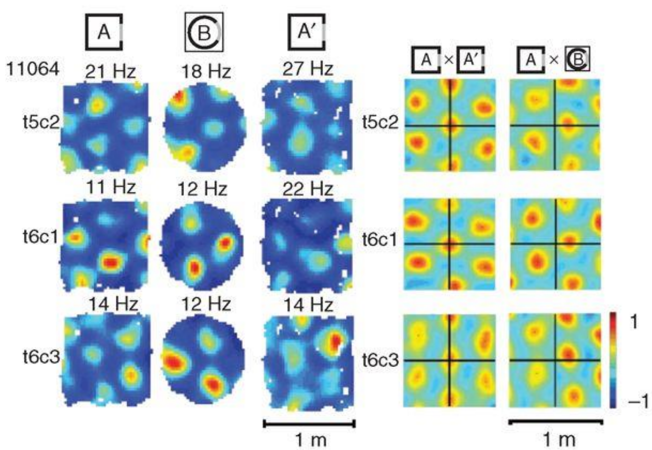
Furthermore, the human brain
→ can handle not more than cca. 7 ± 2 ($\sim 2^3$) components at a time

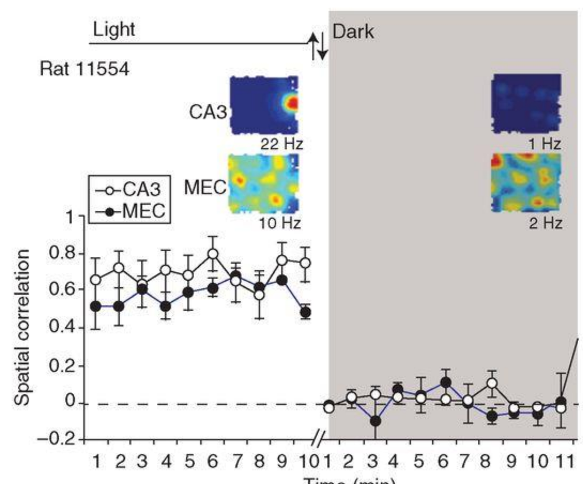
Mammalian (e.g., rat & monkey) brain ’knows’ the trick

May-Britt Moser et al. Cold Spring Harb Perspect Biol 2015;7:a021808
Nobel Laurates (2014) O’Keefe + Edvard Moser + May-Britt Moser

Place







Metric

Adaptation

How about bats?

How about other tasks to be learned?

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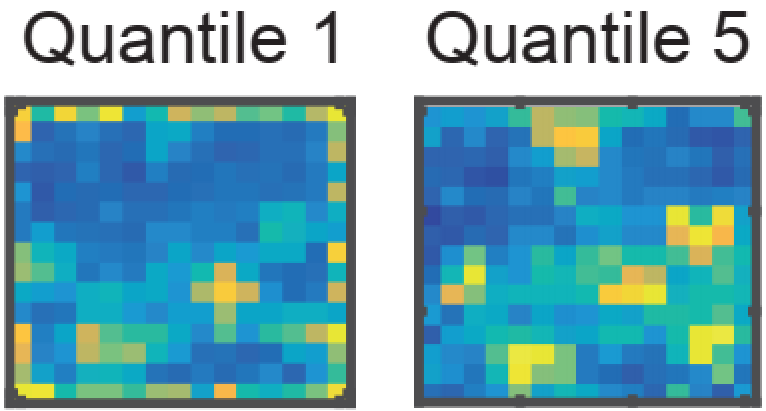
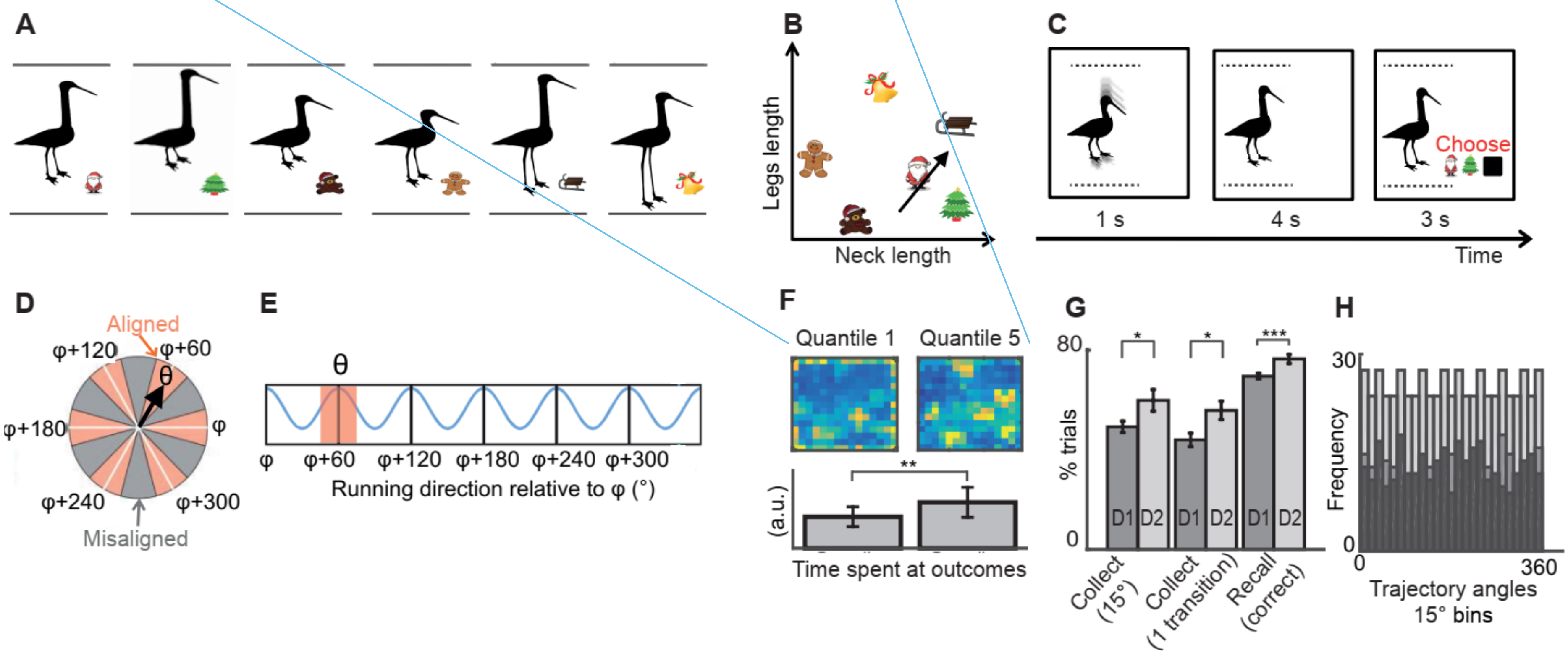
Constantinescu, A.O., O'Reilly, J.X. and Behrens, T.E.
Organizing conceptual knowledge in humans with a gridlike code.
Science, *352* (6292), pp.1464-1468 (2016)



Beginning of training   End of training



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Component and metric learning

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It comes easy for us, for some components, such as

  - place, direction, distance, weight, size, pitch of sound,

- but it is harder for other components, such as

  - number, angle, mass, energy, conductivity, quasi-particles, pH, etc.

Nonlinear transformation *and* projection to an **APPROX LINEAR LOW DIMENSIONAL SPACE**

Many solutions exist for modelling the mammalian innovation. They are imperfect

i. due to assumptions about pre-processing algorithms

ii. due to assumptions about neurally feasible algorithm

  ➢ but they are close… (*)

(*) Two recent ones from the list use semi-supervision:

[1] Lőrincz A and Sárkány A. "Semi-Supervised Learning of Cartesian Factors: A Top-Down Model of the Entorhinal Hippocampal Complex." *Frontiers in Psychology* 8 (2017): 215.

[2] Banino A, Barry C, Uria 5, Blundell C, Lillicrap T, Mirowski P, Pritzel A, Chadwick MJ, Degris T, Modayil J, Wayne G, Soyer H, Viola F, Zhang B, Goroshin R, Rabinowitz N, Pascanu R, Beattie C, Petersen S, Sadik A, Gaffney S, King H, Kavukcuoglu K, Hassabis D, Hadsell R, and Kumaran D. "Vector-based navigation using grid-like representations in artificial agents." *Nature* 557, no. 7705 (2018): 429.

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Uncovering the mystery of the mammalian brain

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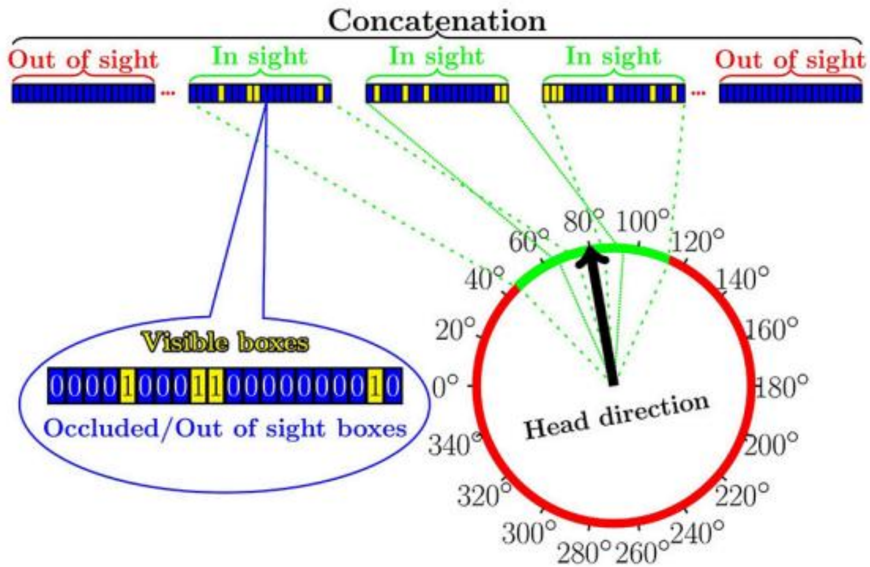
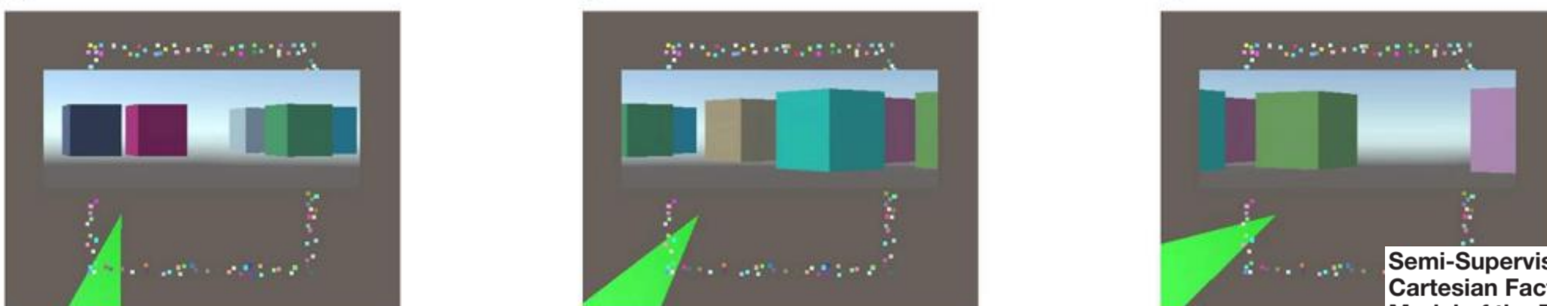
A



B

C

D



Semi-Supervised Learning of Cartesian Factors: A Top-Down Model of the Entorhinal Hippocampal Complex

András Lőrincz and András Sárkány*

frontiers in Psychology

ORIGINAL RESEARCH
published: 21 February 2017
doi: 10.3389/fpsyg.2017.00215

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Place cells

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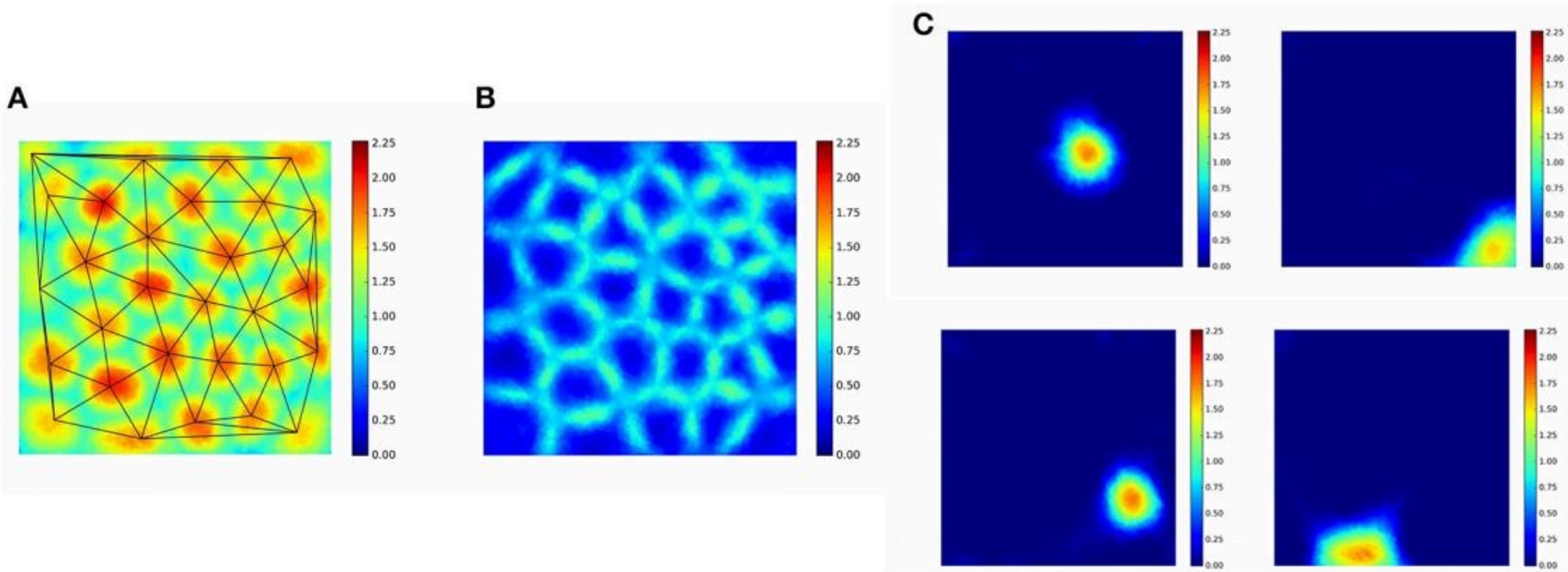

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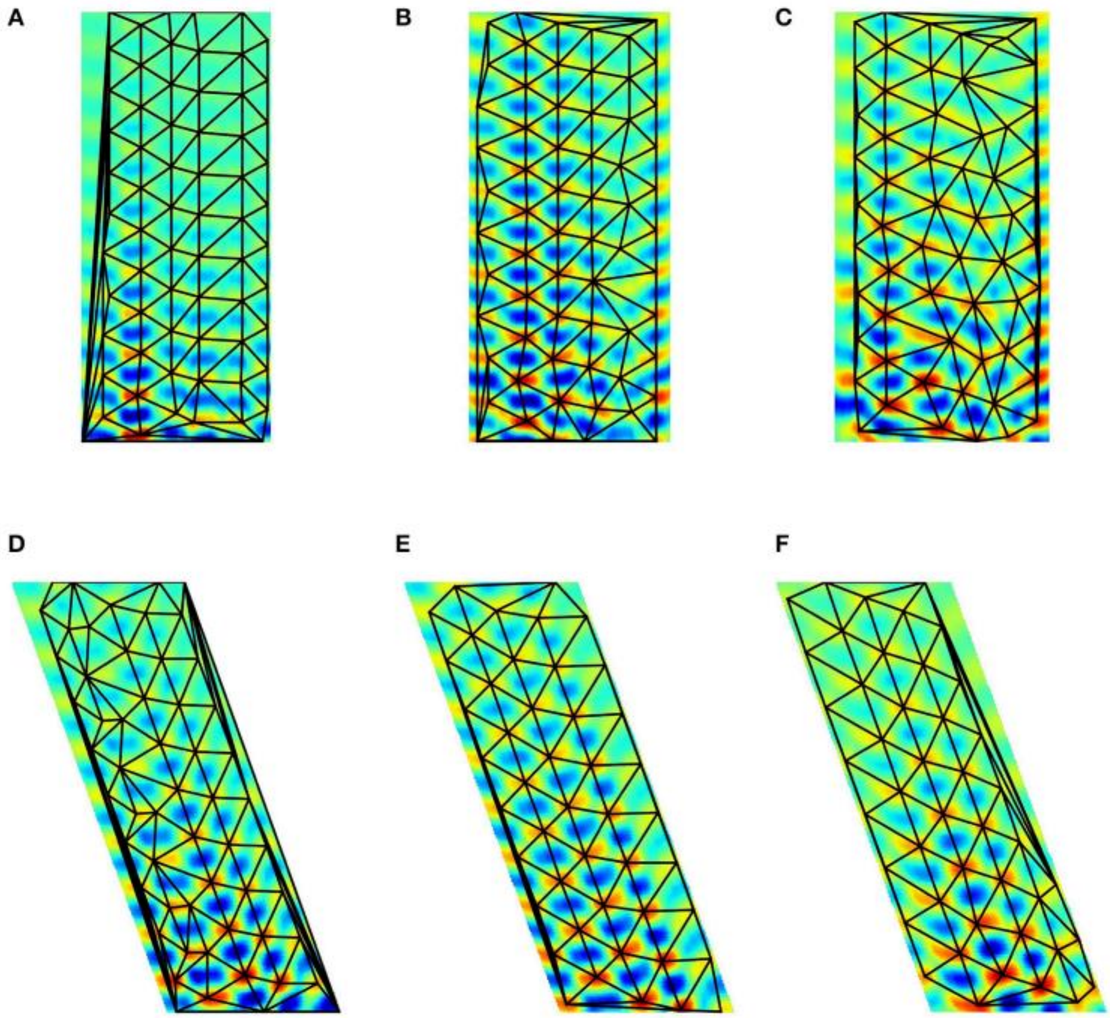
Directed grid cells



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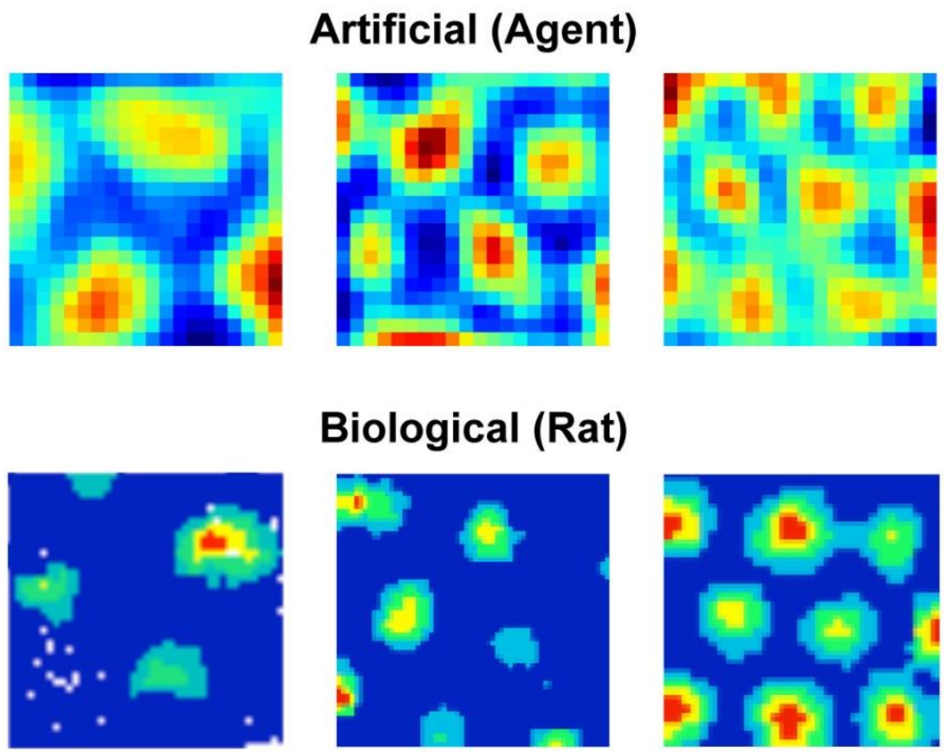
Direction free grid cells – DeepMind



Our experiments with artificial agents yielded grid-like representations ("grid units") that were strikingly similar to biological

17 MAY 2018 | VOL 557 | NATURE | 429

LETTER

https://doi.org/10.1038/s41586-018-0102-6

Vector-based navigation using grid-like representations in artificial agents

Andrea Banino[1,2,3,5]*, Caswell Barry[2,5]*, Benigno Uria[1], Charles Blundell[1], Timothy Lillicrap[1], Piotr Mirowski[1], Alexander Pritzel[1], Martin J. Chadwick[1], Thomas Degris[1], Joseph Modayil[1], Greg Wayne[1], Hubert Soyer[1], Fabio Viola[1], Brian Zhang[1], Ross Goroshin[1], Neil Rabinowitz[1], Razvan Pascanu[1], Charlie Beattie[1], Stig Petersen[1], Amir Sadik[1], Stephen Gaffney[1], Helen King[1], Koray Kavukcuoglu[1], Demis Hassabis[1,4], Raia Hadsell[1] & Dharshan Kumaran[1,3]*

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Component and metric learning

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- place, direction, distance, weight, size, pitch of sound,

- but it is harder for other components, such as
    - number, angle, mass, energy, conductivity, quasi-particles, pH, etc.

Nonlinear transformation *and* projection to an approx linear low dimensional space

Many solutions exist for modelling the mammalian innovation. They are imperfect

i. due to assumptions about pre-processing algorithms
ii. due to assumptions about neurally feasible algorithm
    - ➢ but the are close… (*)

Plus, algorithmic solutions are not having biological constraints…

(*) Two recent ones from the list use semi-supervision:

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A recent application (on face and facial expression)

- avoids crowdsourcing
- hits the core of the ”invention”…

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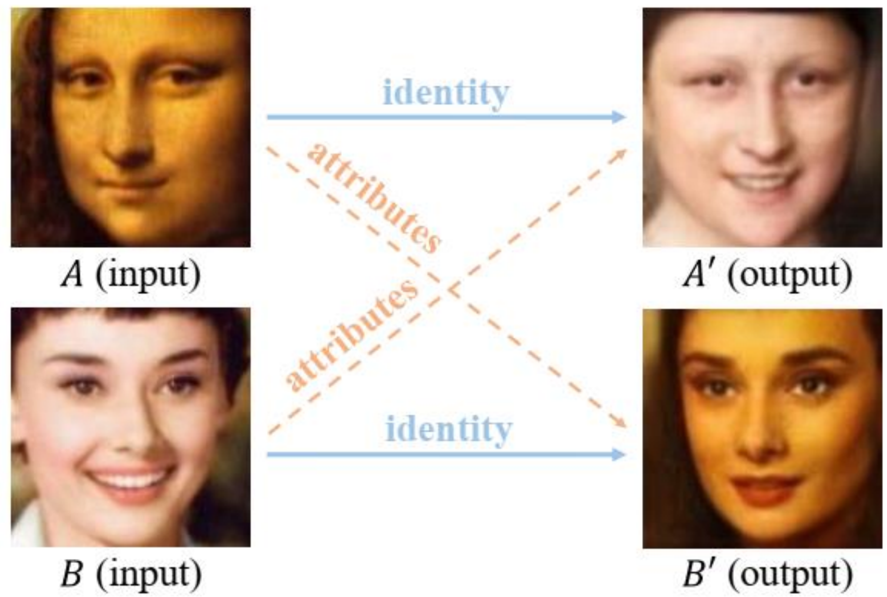
Novel solution (at least a trial) for component learning

Need: Annotation (crowdsourcing) takes time, is expensive, and is never sufficient
Option: Identities on photos are annotated (semi-supervision)
1st Question: Do we have to annotate facial expressions?
2nd Question: Can we control facial expressions on a face? → Here, it is ”imitation”

Identity of a face
→ some kind of constancy within a face
→ that changes from face to face

Attributes of the facial expressions
→ changes for one face
→ similar for all faces



Bao, Jianmin, Dong Chen, Fang Wen, Houqiang Li, and Gang Hua.
"Towards Open-Set Identity Preserving Face Synthesis."
In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 6713-6722. Jun 18—Jun 22, 2018.

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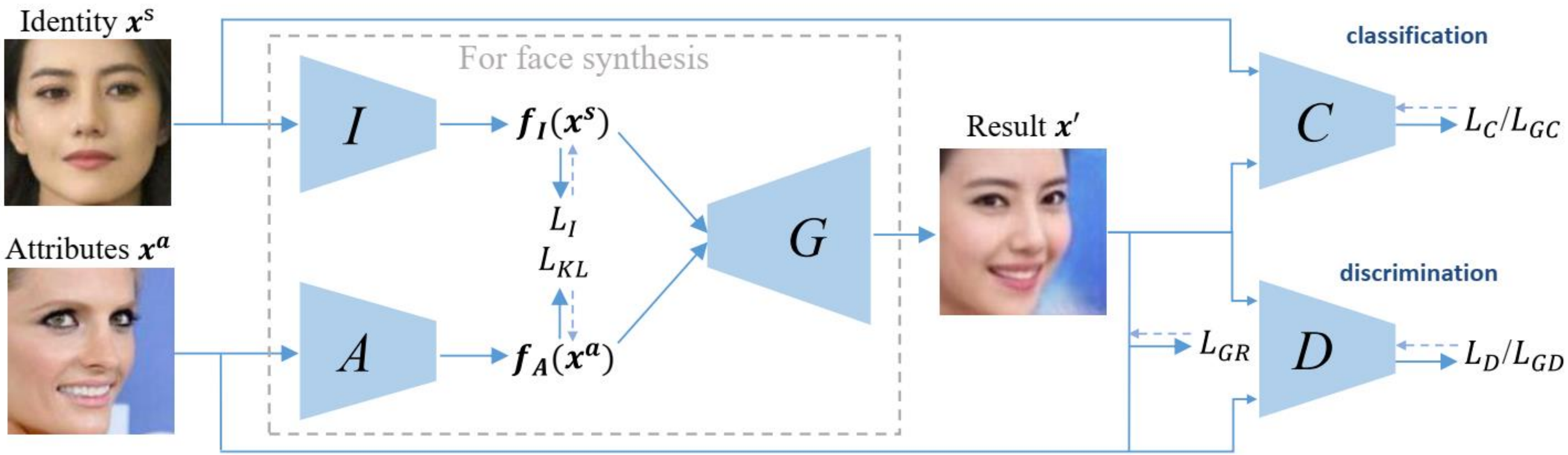
Combination of networks



We don't have input-output samples. We have freedom in

i. architectural design
ii. cost functions for learning

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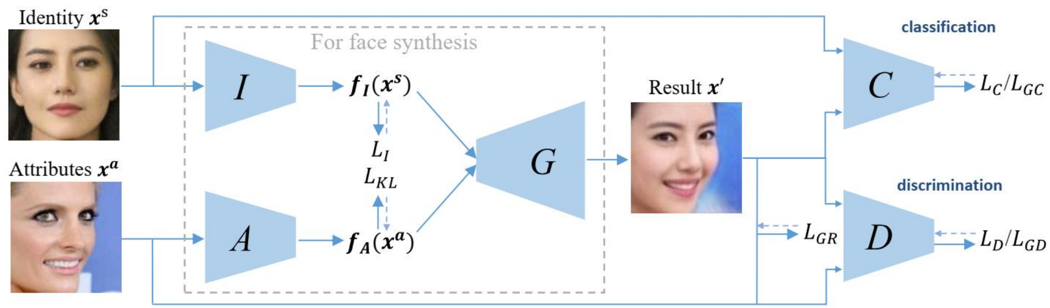
Losses



1. Loss on identity. In the training data, they only have the annotation of the identity of each face, without any annotation of the attribute information. This is because face images with category annotations are relatively easy to obtain. ➔ semi-supervised factor learning.

$$\mathcal{L}_{\mathcal{I}} = -\mathbb{E}_{\boldsymbol{x}\sim P_r}[\log P(c|\boldsymbol{x}^s)],$$

- softmax loss for training network to perform face classification task
- inputs from the same individual have approximately the same features to be used as the identity vector.

2. Reconstruction loss. There are two situations: whether subject image x^s is the same as attribute image x^a or not. In both cases, we require the result image x' to reconstruct attribute image x^a, but with different loss weight.

$$\mathcal{L}_{GR} = \begin{cases} \frac{1}{2}||\boldsymbol{x}^a - \boldsymbol{x}'||_2^2 & \text{if } \boldsymbol{x}^s = \boldsymbol{x}^a \\ \frac{\lambda}{2}||\boldsymbol{x}^a - \boldsymbol{x}'||_2^2 & \text{otherwise} \end{cases}$$

raw pixel reconstruction loss
background, overall illumination, and pose

Supposing there are various face images of an identity, the identity vector $f_I(x)$ is almost the same for all samples. But the reconstruction using the $f_I(x)$ and $f_A(x)$ of different samples are all different. ➔ The reconstruction loss will force the attribute encoder network A to learn different attributes representation $f_A(x)$.

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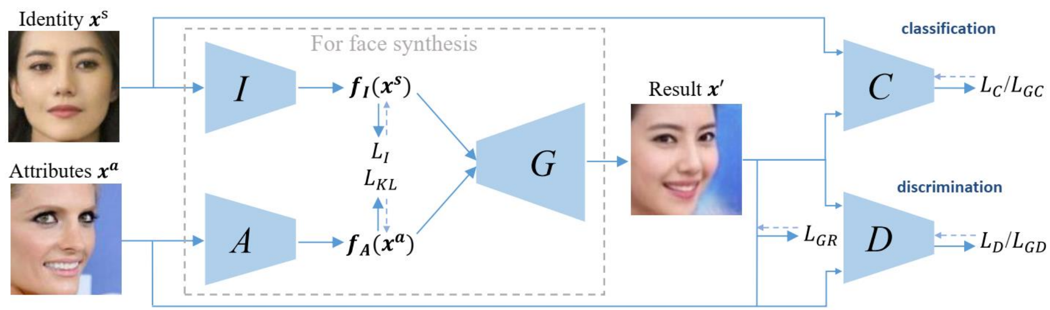
Further losses



3. *Kullback-Leibler divergence* loss. Helps the attributes encoder network learn. It regularizes the attribute vector with an appropriate prior $P_a(\xi) \sim N(0;1)$. The *KL* divergence loss limits the distribution range of the attribute vector. → It does not contain much identity information. The network *A* outputs the mean $\boldsymbol{\mu}$ and covariance of the latent vector: reduces the gap between the prior $P_a(\xi)$ and the learned distributions.

$$\mathcal{L}_{KL} = \frac{1}{2}\left(\boldsymbol{\mu}^T\boldsymbol{\mu} + \sum_{j=1}^{J}(\exp(\boldsymbol{\epsilon}) - \boldsymbol{\epsilon} - 1)\right)$$

4. Loss for General Adversarial Network (GAN)

$$\boldsymbol{z} = [\boldsymbol{f_I}(\boldsymbol{x^s})^T, \boldsymbol{f_A}(\boldsymbol{x^a})^T]^T$$

$$\mathcal{L}_D = -\mathbb{E}_{\boldsymbol{x}\sim P_r}[\log D(\boldsymbol{x^a})] - \mathbb{E}_{\boldsymbol{z}\sim P_{\boldsymbol{z}}}[\log(1 - D(G(\boldsymbol{z})))],$$

5. Conditional Variational Encoder-GAN-like loss

$$\mathcal{L}_{GD} = \frac{1}{2}||\boldsymbol{f_D}(\boldsymbol{x}') - \boldsymbol{f_D}(\boldsymbol{x^a})||_2^2.$$

This task is too easy task,
Avoid trivial solutions!

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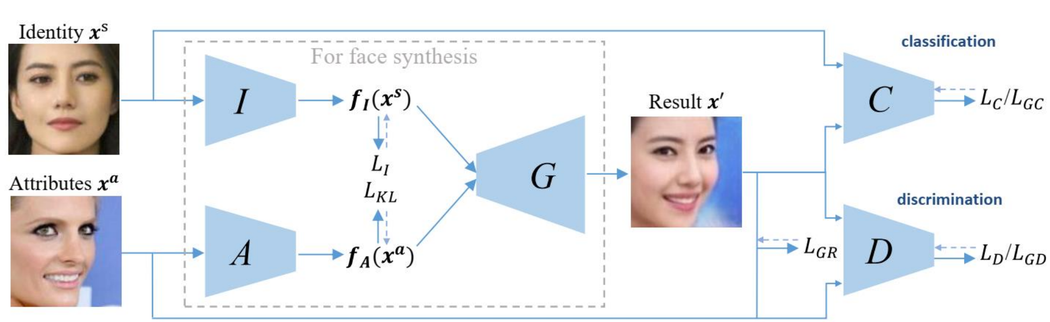
Further losses



***Loss for* identity-preserving faces**

$$\mathcal{L}_C = -\mathbb{E}_{\boldsymbol{x}\sim P_r}[\log P(c|\boldsymbol{x^s})].$$

is extended with a similar term as in **5.** but on x^s

6. Feature representation loss at (an) internal layer/s

$$\mathcal{L}_{GC} = \frac{1}{2}||\boldsymbol{f_C}(\boldsymbol{x}') - \boldsymbol{f_C}(\boldsymbol{x^s})||_2^2.$$

Summary

$$\begin{aligned}
&\mathcal{L}_I \leftarrow -\log(P(c|\boldsymbol{x^s}))\\
&\mathcal{L}_C \leftarrow -\log(P(c|\boldsymbol{x^s}))\\
&\boldsymbol{f_I}(\boldsymbol{x^s}) \leftarrow I(\boldsymbol{x^s});\ \boldsymbol{f_A}(\boldsymbol{x^a}) \leftarrow A(\boldsymbol{x^a})\\
&\mathcal{L}_{KL} \leftarrow KL(\boldsymbol{f_A}(\boldsymbol{x^a})||P(\boldsymbol{z}))\\
&\boldsymbol{x}' \leftarrow G([\boldsymbol{f_I}(\boldsymbol{x^s})^T, \boldsymbol{f_A}(\boldsymbol{x^a})^T]^T)\\
&\mathcal{L}_D \leftarrow -(\log(D(\boldsymbol{x^a})) + \log(1\text{- } D(\boldsymbol{x}')))\\
&\mathcal{L}_{GR} \leftarrow \tfrac{1}{2}||\boldsymbol{x^a} - \boldsymbol{x}'||_2^2\\
&\mathcal{L}_{GD} \leftarrow \tfrac{1}{2}||\boldsymbol{f_D}(\boldsymbol{x^a}) - \boldsymbol{f_D}(\boldsymbol{x}')||_2^2\\
&\mathcal{L}_{GC} \leftarrow \tfrac{1}{2}||\boldsymbol{f_C}(\boldsymbol{x^s}) - \boldsymbol{f_C}(\boldsymbol{x}')||_2^2
\end{aligned}$$

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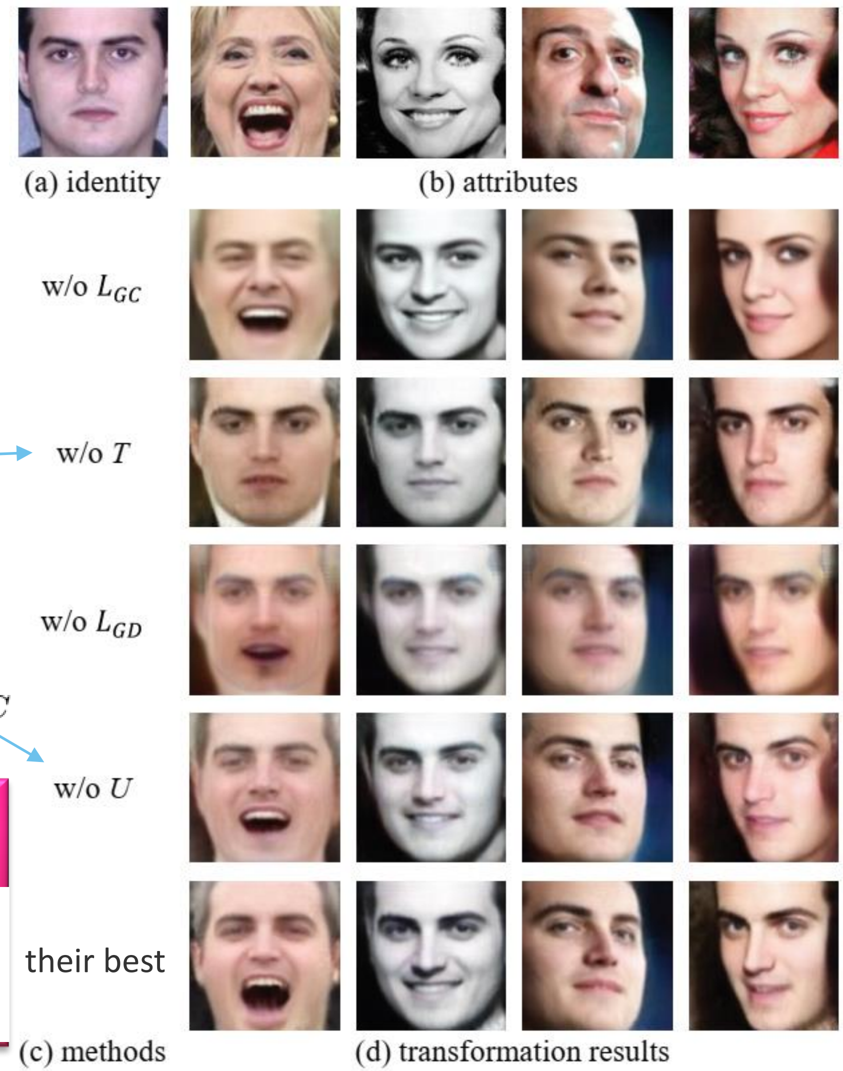
Results

$$
\begin{aligned}
&\mathcal{L}_I \leftarrow -\log(P(c|\boldsymbol{x}^s))\\
&\mathcal{L}_C \leftarrow -\log(P(c|\boldsymbol{x}^s))\\
&\boldsymbol{f_I}(\boldsymbol{x}^s) \leftarrow I(\boldsymbol{x}^s);\ \boldsymbol{f_A}(\boldsymbol{x}^a) \leftarrow A(\boldsymbol{x}^a)\\
&\mathcal{L}_{KL} \leftarrow KL(\boldsymbol{f_A}(\boldsymbol{x}^a)||P(\boldsymbol{z}))\\
&\boldsymbol{x}' \leftarrow G([\boldsymbol{f_I}(\boldsymbol{x}^s)^T, \boldsymbol{f_A}(\boldsymbol{x}^a)^T]^T)\\
&\mathcal{L}_D \leftarrow -(\log(D(\boldsymbol{x}^a)) + \log(1\text{-}\ D(\boldsymbol{x}')))\\
&\mathcal{L}_{GR} \leftarrow \tfrac{1}{2}||\boldsymbol{x}^a - \boldsymbol{x}'||_2^2\\
&\mathcal{L}_{GD} \leftarrow \tfrac{1}{2}||\boldsymbol{f_D}(\boldsymbol{x}^a) - \boldsymbol{f_D}(\boldsymbol{x}')||_2^2\\
&\mathcal{L}_{GC} \leftarrow \tfrac{1}{2}||\boldsymbol{f_C}(\boldsymbol{x}^s) - \boldsymbol{f_C}(\boldsymbol{x}')||_2^2
\end{aligned}
$$

w/o $\boldsymbol{x}^a \neq \boldsymbol{x}^s$

w/o $\mathcal{L}_I$ and $\mathcal{L}_C$



Combinations of costs look efficient for component learning.

➢ It is "hard" → Consider, e.g., **AUTISTIC SPECTRUM CONDITION**

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Conclusions

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1. Intelligence is limited by the CURSE OF DIMENSIONALITY
   - ➢ component discovery and dimension reduction are necessary
2. Intelligence demonstrates itself via LINEAR / TEMPORAL – TESTABLE – PROOFS
   - ➢ such as arguments, solutions, explanations

   for combinatorial component manipulation tasks – like in the Traveling Salesmen Problem
3. Nature has found a solution for COMPONENT DISCOVERY (which is not yet fully resolved)
   - ➢ works smoothly for space, distances, faces, facial expressions and alike if properly prewired
   - ➢ but it is hard if the evolutionary system is spoiled – like in autistic spectrum condition

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Conclusions

1. Intelligence is limited by the CURSE OF DIMENSIONALITY
   - component discovery and dimension reduction are necessary
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   for combinatorial component manipulation tasks – like in the Traveling Salesmen Problem

TAKE HOME MESSAGE

3. Nature has found a solution for COMPONENT DISCOVERY (which is not yet fully resolved)
   - works smoothly for space, distances, faces, facial expressions and alike if properly prewired
   - but it is hard if the evolutionary system is spoiled – like in autistic spectrum condition
4. AGI HAS NO STRUCTURAL OR TEMPORAL CONSTRAINTS.
   - DNN evolution is over. **EVOLUTION OF DNN & COST FUNCTION ASSEMBLIES** is happening
   - driving force: R+D+I on *"CROWDSOURCING FREE APPLICATIONS"*
     - it advances **BUSINESS and HIGH QUALITY AGI** solutions

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Thank you

for your

attention!

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Components and the context – *both* – are relevant

NI abilities

What is this?

Are you sure?

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Deep network abilities

Deep networks can behave similarly

(a): training example
(b): on road
(c): accross the road…
(d): at the office desk…

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