Cours 2022-2023:

Quel code neural pour les représentations mentales? Vector codes and the geometry of mental representations

Stanislas Dehaene Chaire de Psychologie Cognitive Expérimentale

Cours n°1

Cellules grand-mère ou vecteurs neuronaux : Les représentations mentales sont-elles localisées ou distribuées ?

> Grand-mother cells or neuronal vectors: Are mental representations localized or distributed ?



How do neurons encode our thoughts?

What is the code?

And if we understood it, could we decode it, or even manipulate it?



We need to identify bridging laws between psychology and neuroscience.

The bridge is unlikely to have a single arch, directly from individual concepts to individual neurons One concept ≠ one neuron

In this course, we will explore the hypothesis that: - Neural populations encode vector spaces - Mental representations are points in highdimensional space



Single neuron electrophysiology



http://newton.umsl.edu/tsytsarev_files/Lecture02.htm

Single-cell electrophysiology : the gold standard for decades of discoveries in neuroscience

Neurons are « feature detectors ».
Hubel and Wiesel in area V1 : simple, complex, hypercomplex cells.
Area V4: shape or color detectors.
Area V5/MT: motion detectors.
Infero-temporal cortex: face detectors.
Etc. etc.



Sensitivity to higher-level features in ventral visual cortex



Hegdé, J., & Van Essen, D. C. (2007). A comparative study of shape representation in macaque visual areas v2 and v4. Cerebral Cortex (New York, N.Y.: 1991), 17(5), 1100-1116. <u>https://doi.org/10.1093/cercor/bhl020</u>



Characterizing neurons along the ventral visual pathway: An emphasis on highly selective responses

Gross, Tanaka, Logothetis, Poggio, Perrett, Orban, Rolls, etc.

From Tamura, H., & Tanaka, K. (2001). Cerebral Cortex.

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A search for the defining features for a given cell





Tsunoda, ... & Tanifuji, Nature Neuroscience 2001

Concept cells in human anterior medial temporal lobe

Quiroga, R. Q. (2012). Concept cells : The building blocks of declarative memory functions. *Nature Reviews Neuroscience*, *13*(8), 587-597. Quiroga, R. Q., Reddy, L., Kreiman, G., Koch, C., & Fried, I. (2005). Invariant visual representation by single neurons in the human brain. *Nature*, *435*(7045), 1102-1107.



« Grand mother » cells and arguments against them

Quiroga, R. Q., Kreiman, G., Koch, C., & Fried, I. (2008). Sparse but not 'Grandmother-cell' coding in the medial temporal lobe. *Trends in Cognitive Sciences*, *12*(3), 87-91. <u>https://doi.org/10.1016/j.tics.2007.12.003</u>

Pushing things to the limit, some neuroscientist have entertained "the hypothesis that a single cell might respond to one and only one object or person, independently of, for example, its angle of gaze, location on the retina or facial expression."

→ 'grandmother cells', as named by Jerry Lettvin ; a.k.a. as 'pontificial cells' (Sherrington), 'gnostic cells' (Konorski) or 'cardinal cells' (Barlow)

But note that a "grandmother" code is **not** Rodrigo Quian-Quiroga's interpretation : he argues for a **sparse distributed code for concepts**.

Arguments against a grandmother code:

- If a concept was coded by a single neuron, the probability of finding it would be vanishingly small. The fact that, by random recording, we find such a cell implies that there must be tens of thousands of them
- In Quiroga's work, only ~200 pictures are explored \rightarrow we cannot exclude that each neuron responds to more than one picture...

and indeed this does occur.

A neuron that jointly responds to the Pisa tower and the Eiffel tower

Reddy, L., Kreiman, G., Koch, C., & Fried, I. (2005). Invariant visual representation by single neurons in the human brain. *Nature*, 435(7045), 1102-1107.



More arguments against « grand mother » cells

Quiroga, R. Q., Kreiman, G., Koch, C., & Fried, I. (2008). Sparse but not 'Grandmother-cell' coding in the medial temporal lobe. *Trends in Cognitive Sciences*, *12*(3), 87-91. <u>https://doi.org/10.1016/j.tics.2007.12.003</u>

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- Only ~200 pictures are explored \rightarrow we cannot exclude that each neuron responds to more than one picture, and indeed this does occur.
- The fact that ~200 pictures suffice to find one that makes a given neuron fire, implies that each neuron may respond to as many as 50-150 concepts.
- Only 40% of medial temporal lobe cells respond in this way others may have a different, possibly more distributed coding scheme.

Other arguments:

- Even if a neuron responds very selectively, it owes its selectivity to ~10,000 synaptic inputs that *collectively* suffice to characterize a given concept → a pre-synaptic distributed code.
- Single-cell coding makes learning extremely difficult. How could the brain keep a list of "unused" or "unaffected" cells and assign a new one to each new concept ?
- Problem of compositionality: There are simply not enough neurons to encode all the concepts or images that we can process.

Philip K Dick : "The electrical ant" (1968)

In this novel, the hero learns that he is not a human, but an organic robot. Furthermore, his subjective perception is entirely pre-programmed in a punched tape located inside his chest – each hole corresponds to a percept or concept! He discovers this by plugging some of the holes – and, for a short period, the corresponding parts of his subjective world vanish.

He reasons that, if all the holes were uncovered at the same time, he would experience all possible perceptions at once.



"He saw apples, and cobblestones, and zebras. He felt warmth, the silky texture of cloth; he felt the ocean lapping at him and a great wind, from the North, plucking at him as if to lead him somewhere.

(...) Butter relaxed into liquid on his tongue, and at the same time hideous odors and tastes assailed him: the bitter presence of poisons and lemons and blades of summer grass. He drowned; he fell; he lay in the arms of a woman in a vast white bed..."

Of course, the space of our perceptions is too large to be encoded by individual punches – unless the code is vastly combinatorial.

From single neurons to population recordings



The revolution of NeuroPixels

Jun, J. J., Steinmetz, N. A., Siegle, J. H., Denman, D. J., Bauza, M., Barbarits, B., ... Harris, T. D. (2017). Fully integrated silicon probes for high-density recording of neural activity. *Nature*, *551*(7679), 232–236.





NeuraLink : towards an industrialization of the brain-computer link



Sealed, implanted devices that receive, process and transmit neural signals.

LINK

NEURAL THREADS

Each small and flexible thread contains many electrodes for detecting neural signals.

The neuralink chip is able to record wirelessly from 1024 electrodes, implanted in the motor cortex, and sealed, with very low power.

Here, they implanted two chips, one in each motor cortex, and used them to decode motor intentions (more on this later!) and control various computer games.



The rise of brain-computer interfaces for paralyzed patients

Aflalo, T., Kellis, S., Klaes, C., Lee, B., Shi, Y., Pejsa, K., ... Andersen, R. A. (2015). Decoding motor imagery from the posterior parietal cortex of a tetraplegic human. Science (New York, N.Y.), 348(6237), 906–910. https://doi.org/10.1126/science.aaa5417

A 32-year-old tetraplegic patient was implanted with two arrays, each comprising 100 microelectrodes.

Those electrodes can be used to decode various parameters of the intended movement, but also to give the patient some tactile feedback.





Implant Location

Imagination allows the patient to take control over a single neuron

Aflalo, T., Kellis, S., Klaes, C., Lee, B., Shi, Y., Pejsa, K., ... Andersen, R. A. (2015). Decoding motor imagery from the posterior parietal cortex of a tetraplegic human. *Science (New York, N.Y.)*, *348*(6237), 906–910. <u>https://doi.org/10.1126/science.aaa5417</u>

The patient reports being able to control this particular neuron by imagining different activities:

- Activating = rotating his shoulder
- Inhibiting = touching his nose



Thousands of electrophysiology channels in the human brain

Tchoe, Y., Bourhis, A. M., Cleary, D. R., Stedelin, B., Lee, J., Tonsfeldt, K. J., Brown, E. C., Siler, D. A., Paulk, A. C., Yang, J. C., Oh, H., Ro, Y. G., Lee, K., Russman, S. M., Ganji, M., Galton, I., Ben-Haim, S., Raslan, A. M., & Dayeh, S. A. (2022). Human brain mapping with multithousand-channel PtNRGrids resolves spatiotemporal dynamics. Science Translational Medicine. https://doi.org/10.1126/scitranslmed.abj1441

Laptop #1 Intan 1024 Recording Controller #1 Amplifier board # Intan 1024 Recording Controller #2 sory Glove Control Nervou Systen 50 µm 10 µm

Figure S2. SEM images at different magnifications of the PtNRGrid and contacts.

The vector field and streamlines represent the propagating beta waves, and green scattered dots represent the high gamma activity.





Towards a restoration of fine vision through brain-computer interfaces



Optical imaging: recording from thousands of identified cells

Xie, Y., Hu, P., Li, J., Chen, J., Song, W., Wang, X.-J., Yang, T., Dehaene, S., Tang, S., Min, B., & Wang, L. (2022). Geometry of sequence working memory in macaque prefrontal cortex. Science, 375(6581), 632-639.

2- or even 3-photon imaging, combined with genetically encoded Calcium fluorescent indicators (usually GCaMP), allows to **visualize** (and not just record) hundreds or even thousands of neurons, in awake behaving monkeys, and to capture their spikes with a reasonable time resolution. Here: over several days, total of 5325 neurons in 2 monkeys !



Bin Min



Yang Xie Peiyao Hu

Shiming Tang (PKU)



DLPFC, GCaMP6s, Field of view of 0.5X0.5mm, 32f/s

Liping Wang

An example trial



Large-scale neurophysiology is compatible with awake, behaving animals.

Urai, A. E., Doiron, B., Leifer, A. M., & Churchland, A. K. (2022). Large-scale neural recordings call for new insights to link brain and behavior. *Nature Neuroscience*, 1-9. <u>https://doi.org/10.1038/s41593-021-00980-9</u>



Large-scale neural recordings in behaving animals. **a**, Confocal microscopy of all neurons in *C. elegans* as it freely moves on an adjustable platform. Adapted from ref. ¹²³ under a CC-BY license. **b**, Mesoscope two-photon imaging of the cortical surface while a mouse moves through a virtual reality by running on a ball. Adapted from ref. ¹²⁴ under a CC-BY license. **c**, High-density electrophysiological recordings using Neuropixels probes, while a monkey performs a psychophysical decision-making task.

An exponential growth in the scale of neurophysiological recordings

Urai, A. E., Doiron, B., Leifer, A. M., & Churchland, A. K. (2022). Large-scale neural recordings call for new insights to link brain and behavior. *Nature Neuroscience*, 1-9. <u>https://doi.org/10.1038/s41593-021-00980-9</u>

Such large-recordings "call for new insights":

- Analysis tools for dimension reduction
- Visualization: new graphics
- Theoretical tools to characterize how a population of neurons responds and how it can encode features and concepts.



Two « doctrines » for neuroscience : Single neurons versus population coding

- Ebitz, R. B., & Hayden, B. Y. (2021). The population doctrine in cognitive neuroscience. *Neuron*. <u>https://doi.org/10.1016/j.neuron.2021.07.011</u>
- Chung, S., & Abbott, L. F. (2021). Neural population geometry : An approach for understanding biological and artificial neural networks. *Current Opinion in Neurobiology*, 70, 137-144. <u>https://doi.org/10.1016/j.conb.2021.10.010</u> But also
- Hebb, D. O. (1949). The organization of behavior. Wiley.
- Braitenberg, V. (1978). Cell assemblies in the cerebral cortex. In G. Palm (Éd.), Theoretical approaches to complex systems. (p. 171-188). Springer.
- Hopfield, J. J. (1982). Neural networks and physical systems with emergent collective computational abilities. PNAS, 79(8), 2554-2558.
- Amit, D. (1989). Modeling brain function : The world of attractor neural networks. Cambridge University Press. and many others!

Five key concepts (from Ebitz & Hayden)

- (1) the <u>neural states</u> that provide a snapshot of a pattern of activity across the population
- (2) the manifold that encompasses the neural states that are possible (Manifold) or at least observed (manifold)
- (3) the coding dimensions
- (4) the subspaces that link neural states to behavior and cognition

(5) the <u>dynamics</u> that map activity from neural state to neural state, guiding how trajectories evolve through time and across the state space.

Consequence of this framework:

A "zoo" of individual cells with highly variable properties gets reinterpreted as

a vector with a dynamic trajectory

Main differences between the single-cell and the population view

Single-cell

Each cell is dedicated to a single feature or concept.

Composite states can only be encoded by coactivating several cells (e.g. for color, motion, and location).

Learning requires the dedication of specific, previous unused cells, or the splitting of an existing population.

Neural population

Each cell can participate in **multiple cell assemblies**. Each cell can have distinct **weights**, corresponding to its variable (up or down) activation in response to various concepts.

Composite states can be encoded by **superposition of orthogonal vectors**. A very large number of vectors can be superimposed, thus yielding a **factorial code**.

Learning requires either

- the allocation of a new, possibly random coding vector, orthogonal to previous ones (those are in very large supply).
- Or (at a slower time scale?) the reorganization of the entire manifold.

The first neuronal vector code: Research by Apostolos Georgopoulos (1980's)









Georgopoulos, A. P., Schwartz, A. B., & Kettner, R. E. (1986). Neuronal population coding of movement direction. *Science*, *233*(4771), 1416-1419. https://doi.org/10.1126/science.3749885





The population vector for movements in 3 dimensions

The idea can be generalized to movements in 3D: each neuron possesses a "weight" for its preference along the x, y and z directions of movement.

Firing (neuron i) = f_i

$$= a_i m_x + b_i m_y + c_i m_z$$

 $= k_i \cos(\theta_{movement, preferred})$

And the population vector can again be reconstituted by averaging the coefficients, each weighted by the neuron's firing:

$$V_x = \sum_i a_i f_i$$
, $V_y = \sum_i b_i f_i$, $V_z = \sum_i c_i f_i$

This simple idea works well because the preferred directions of the cells are roughly distributed equally across all directions.











Georgopoulos, A. P., Lurito, J. T., Petrides, M., Schwartz, A. B., & Massey, J. T. (1989). Mental Rotation of the Neuronal Population Vector. *Science*, *243*(4888), 234-236. <u>https://doi.org/10.1126/science.2911737</u>

The mental rotation hypothesis:

If the monkey changes its mind and decides to move in another direction, the neural population vector should reflect this internal change by **rotating** internally.



















Georgopoulos, A. P., Lurito, J. T., Petrides, M., Schwartz, A. B., & Massey, J. T. (1989). Mental Rotation of the Neuronal Population Vector. *Science*, *243*(4888), 234-236. <u>https://doi.org/10.1126/science.2911737</u>



The NeuraLink decoder uses some variant of the population vector

LINK

Sealed, implanted devices that receive, process and transmit neural signals.

NEURAL THREADS

Each small and flexible thread contains many electrodes for detecting neural signals.

N1

The neuralink blog suggests that they use a simple weighted-sum mechanism (with time delays and integration over multiple windows of 25 ms) to predict the intended speed on the x and y directions.

The video shows the weights assigned to each electrode where spikes are recorded.



Vector coding of goal direction in the bat

Sarel, A., Finkelstein, A., Las, L., & Ulanovsky, N. (2017). Vectorial representation of spatial goals in the hippocampus of bats. *Science*, *355*(6321), 176-180. <u>https://doi.org/10.1126/science.aak9589</u>

Vector coding by a "bump" of activity over a bank of neurons appears to be a very general strategy in many brains.

Here, bats were trained to land on a platform. in CA1 of the bat hippocampus, many neurons are tuned to the direction of the goal relative to the heading direction.



Distance is also encoded, often simply by increasing or decreasing the firing of the same neurons as a function of Euclidean distance.



Vector coding and vector arithmetic in the fly

Successive stages of the fly's brain represent stimuli (e.g. optic flow, target location) in egocentric coordinates, then world-centered, then back to egocentric motor commands.

The main principles of vector coding and arithmetic are well understood:

- 1. A **vector** is coded by a "**phasor**", a sinusoidal distribution of activity over a bank of neurons, whose amplitude represents vector size, and phase represents vector direction.
- 2. Vector **rotation** can be implemented by shifting the bump of activity left or right on this neural population
- Vector addition is as simple as adding the activity of the two neural "phasor" populations
- 4. Vector **projection** can be encoded by non-linearities in the neural response to a combination of two inputs.



Fig. 2 | The allocentric travelling direction can be computed by vector rotation and summation, which can be implemented by phasors. a, The

Lyu, C., Abbott, L. F., & Maimon, G. (2022). Building an allocentric travelling direction signal via vector computation. *Nature*, *601*(7891), 92-97. <u>https://doi.org/10.1038/s41586-021-04067-0</u>

Conclusions

The concept of **neuronal population vector** is extremely useful:

- To summarize hundreds of recordings
- To pool over the variability and peculiarities of individual neurons
- Above all, to track covert cognitive computations (mental rotation)

Multiple questions remain open, which will be addressed in the next courses:

- How can vectors encode non-geometrical objects, such as a face?
- Do neurons make use of the full power of **vector spaces**: subspaces, null spaces, vector addition, etc
- Can vectors be used to track the **dynamics** of brain activity for instance during **decision making**?
- Can vectors encode **concepts**?
- Can vectors encode sentences and syntax?

Vendredi 6 Janvier

COURS : Vecteurs neuronaux ou cellules grand-mère : les représentations mentales sont-elles localisées ou distribuées ? SÉMINAIRE : L'intelligence artificielle peut-elle modéliser le langage mathématique ? – François Charton (FAIR Paris)

Vendredi 13 Janvier

COURS : Géométrie des représentations visuelles : chaque visage est un vecteur SÉMINAIRE : Commonsense Physical Reasoning in man and machine – Ernest Davis (NYU, par zoom)

Vendredi 20 Janvier

COURS: Exploiter la factorisation et les sous-espaces vectoriels pour coder l'information et communiquer entre aires cérébrales SÉMINAIRE : Number symbols in the brain and mind — Daniel Ansari (University of Ontario)

Vendredi 27 Janvier

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SÉMINAIRE : Comment se développent les réseaux cérébraux associés aux concepts mathématiques ? — Marie Amalric (Université de Trento, Italie)

Vendredi 3 Février

COURS : La représentation vectorielle des mots et des concepts SÉMINAIRE : Les succès et les nouveaux défis de l'intelligence artificielle en mathématiques – Léon Bottou (FAIR, New York)

Vendredi 10 Février

COURS : La représentation vectorielle du langage : Comment représenter une phrase ?

SÉMINAIRE : Intuitions of mathematics and their refinement with age and education — Manuela Piazza (Université de Trento, Italie)