University of Amsterdam

Symposium Computational cognitive neuroscience: What, why and how

Flavors of modelling in cognitive neuroscience

Lukas Snoek

Contents

- Aims of cognitive neuroscience
- Explanations in cognitive neuroscience
- Types of computational models
  - Stimulus-based vs. behavior-based
- Techniques to relate models to the brain
  - Encoding models
  - Representational similarity analysis (RSA)

Let’s take a step back …

What do we want to know at our department (brain & cognition)?

Adapted from Gazzaniga et al., 2014

Aim of brain & cognition (cogn. neuro.)

- First and foremost: understand **behavior and cognition**
  - We're psychologists, not biologists
- … but also use the **brain** in our explanations
  - We're the department of **brain** & cognition
  - Also: because this is what gives rise to cognition and behavior, after all

In other words...

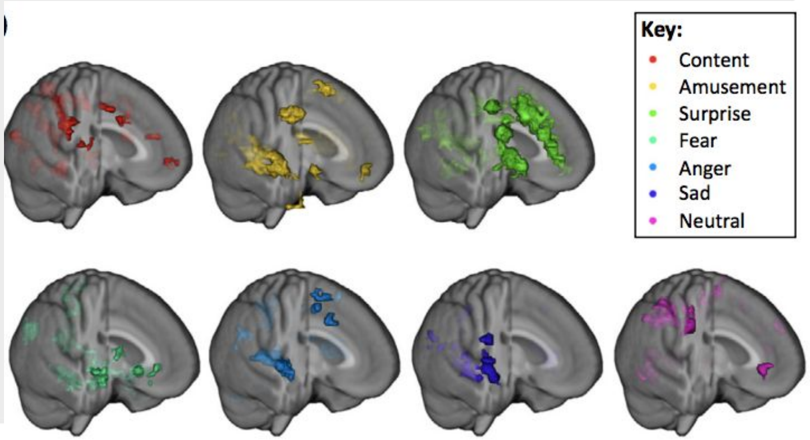
- Closing **Leibniz' gap**: how does the brain give rise to psychological phenomena?
- Explaining psychological effects (explananda) by functional analysis (decompose effect into underlying properties and mechanism)
  - Constrained/influenced by brain measurements

So, how have we gone about using the brain in our explanations?

Kragel & LaBar, 2016

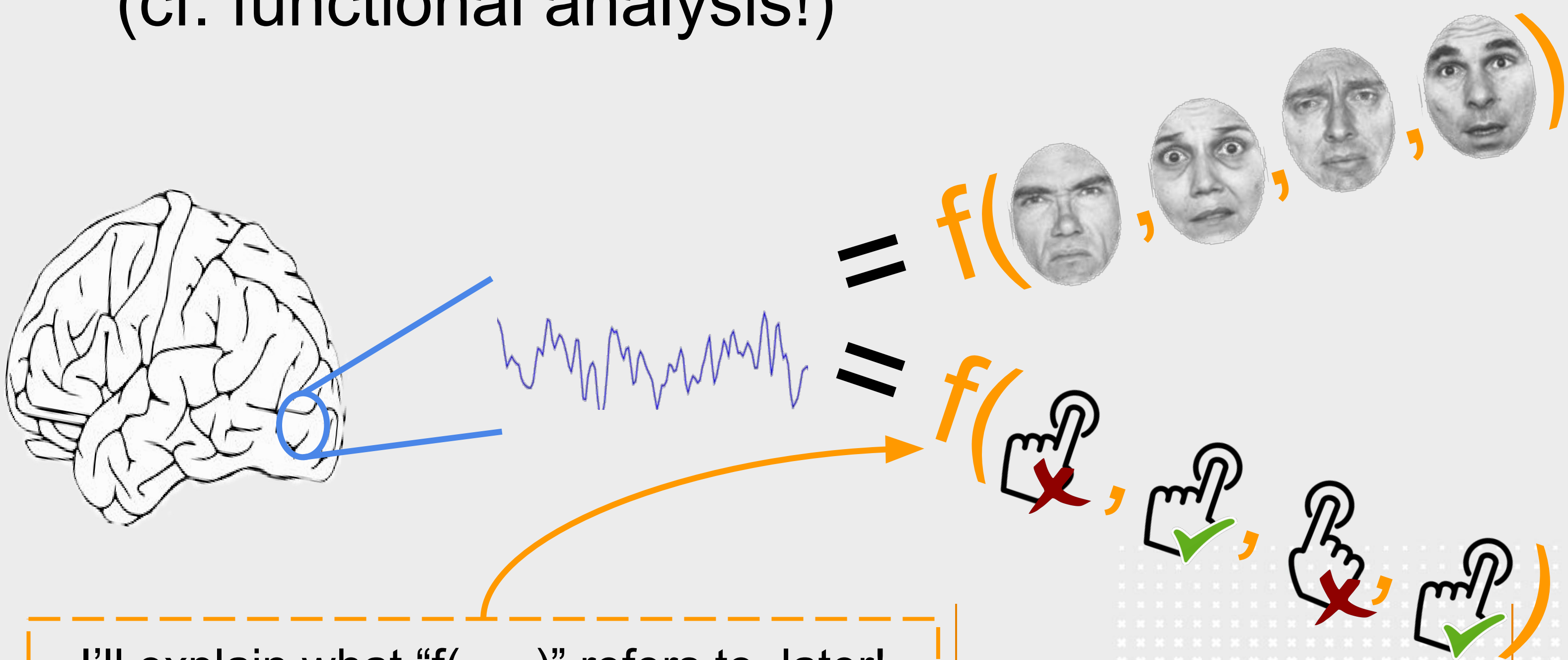
Explanations in cognitive neuroscience

- One way we use the brain is to **validate** our theories and hypotheses about behavior and cognition
- For example, the theory that there are 6 categorical emotion categories has been "verified" with fMRI



Explanations in cognitive neuroscience

- In other words, we model brain measurements as a **function of stimulus or behavior properties** (cf. functional analysis!)

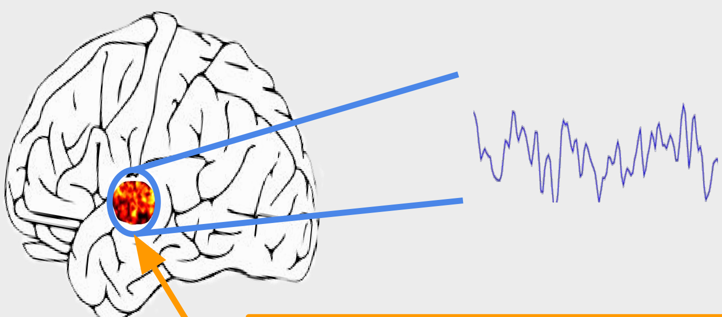


I'll explain what "f(…)" refers to, later!

Explanations in cognitive neuroscience

- Implicit assumption:

  "If we can accurately predict the responses of all neurons in an area, we have captured the computations up to that area." (Kriegeskorte & Kievit, 2013)



= f(anger)

Given that there is a (specific) region for anger, anger must be a basic, real concept represented/computed by the brain

So, what is this “computational” or “model-based” cognitive neuroscience, then?

Based on Kay, 2017

Every analysis is a model!

- *All analyses that relate stimuli/cognition/behavior to the brain are (computational) models!*
  - Including standard EEG/MEG/fMRI analyses
  - Difference faces / houses, unattended / attended — all models!

Based on Kay, 2017

Every analysis is a model!

- All analyses that relate stimuli/cognition/behavior to the brain are (computational) models!
- But models differ in their **computational details** and **sophistication**

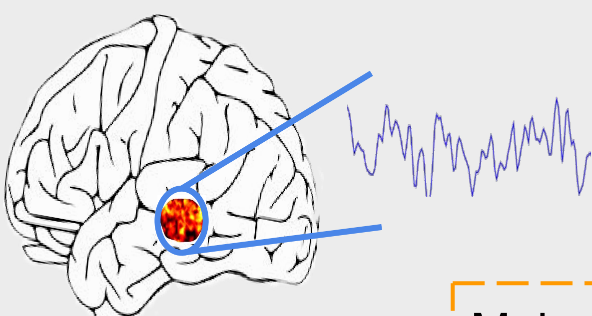
Based on Kay, 2017

Every analysis is a model!

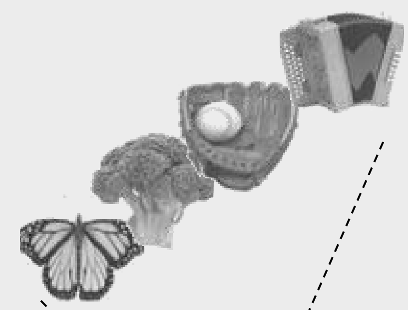
- All analyses that relate stimuli/cognition/behavior to the brain are (computational) models!
- But models differ in their **computational details** and **sophistication**
- We can specify models based on “folk psychology”, computationalism, or connectionism, which all differ in how “computationally sophisticated” they are

Folk psychological models

- Very common in cognitive neuroscience
  - e.g., research on “object representation”



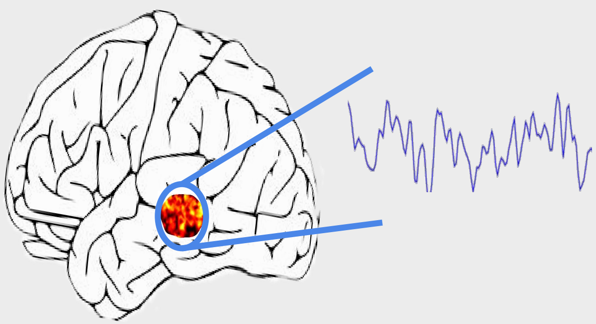
= **f(**object category**)**



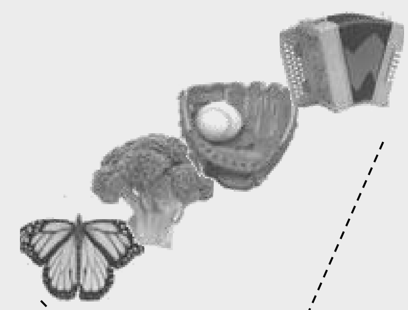
Majority of the traditional “brain mapping” studies: face vs. house, attended vs. unattended, etc.

Computationalism-inspired models

- Gaining popularity in cognitive neuroscience
  - e.g., research on “object representation”

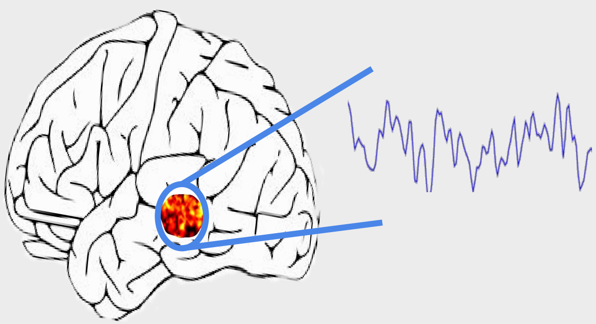


= f(δ(object, exemplar))

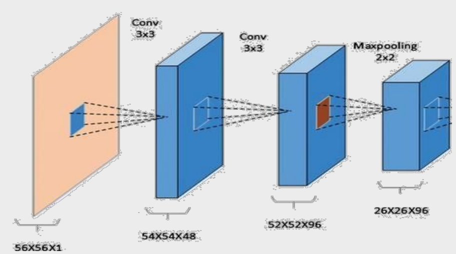


Connectionism-inspired models

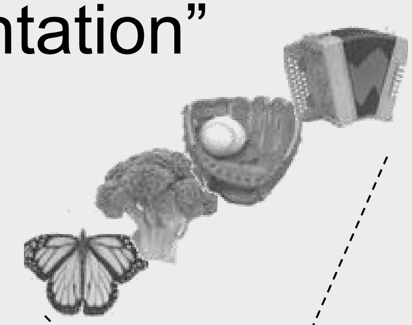
- Revival in cognitive neuroscience due to regained interest in artificial neural networks
  - e.g., research on “object representation”



= f(

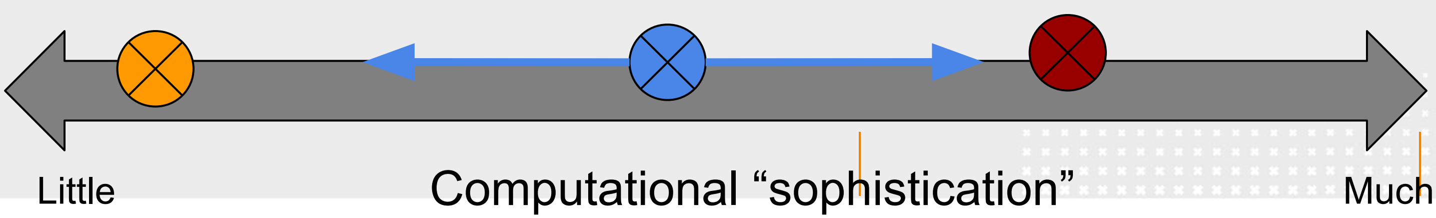


)



Every analysis is a model

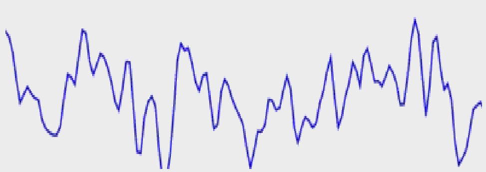
- All analyses that relate stimulus or behavioral properties to the brain are "computational" or "model-based"
- Models can be inspired by **folk psychology** concepts, **computational** principles, or **connectionist** (ANN) properties



How to decide on your model?

It’s all in the “features”

- A model should reflect **your hypothesis** of how the brain represents/processes the stimulus/task
- Your hypothesis can be summarized in one or multiple “**features**”, i.e., whatever goes inside the function:

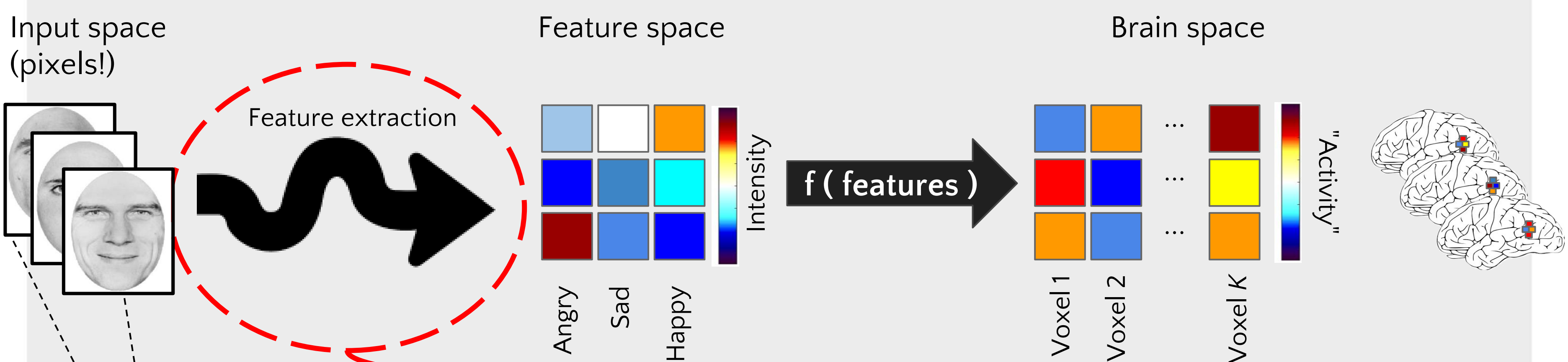


$= f(\ldots)$

Based on Naselaris & Kay (2011)

Input space, feature space, brain space

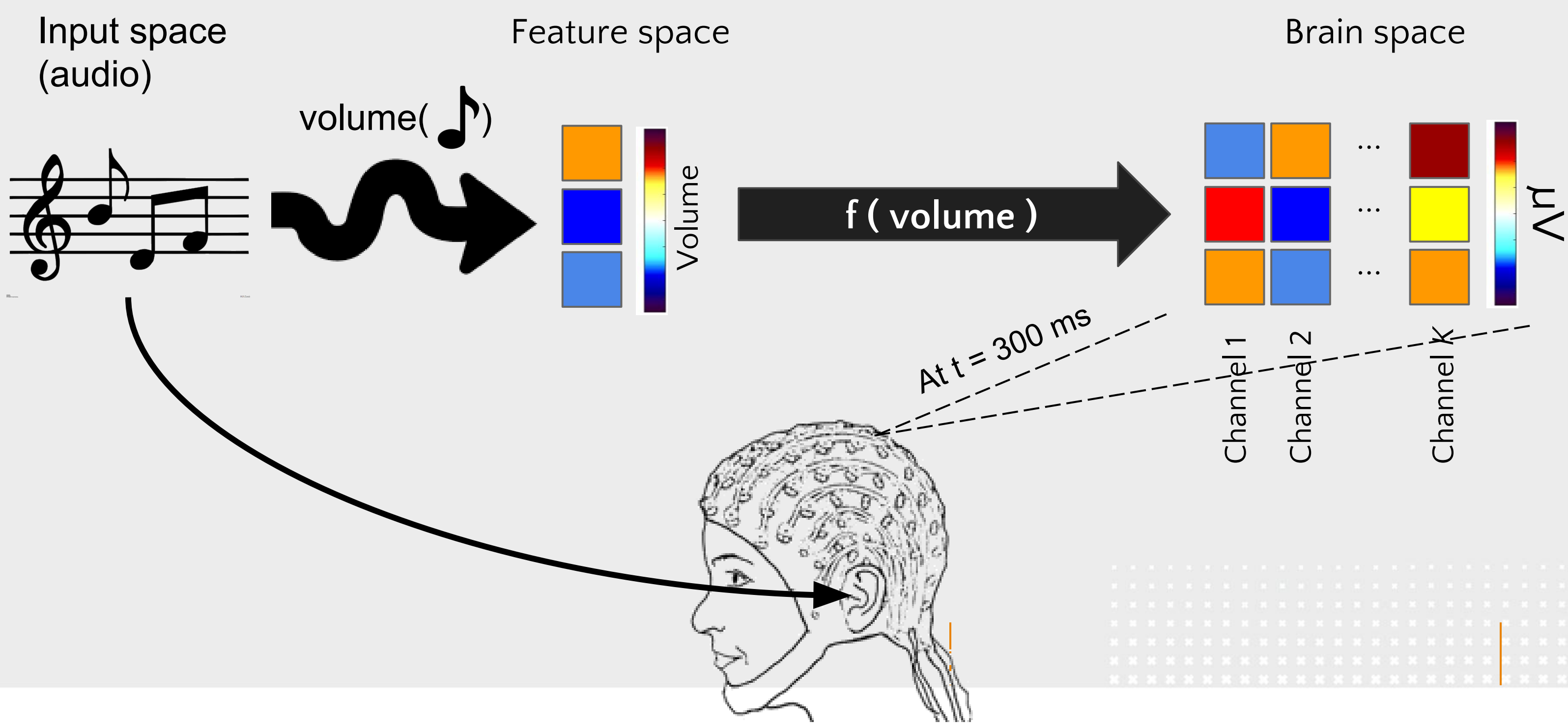
(Note: this is an example of a “folk psychology” model!)



How we infer/compute/define our features represents our hypothesis (model) of how the brain does this!

Another example:

How does the brain process auditory information over time?



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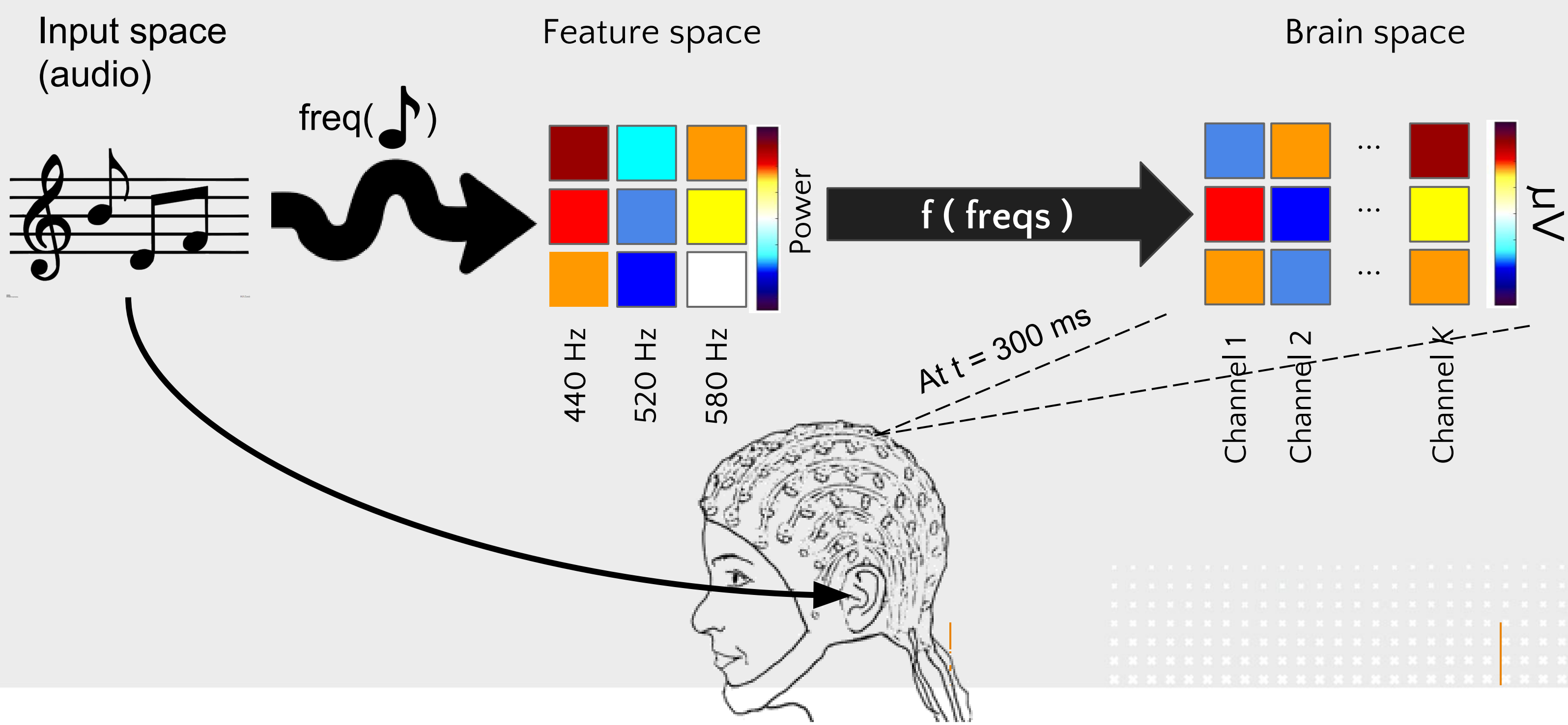
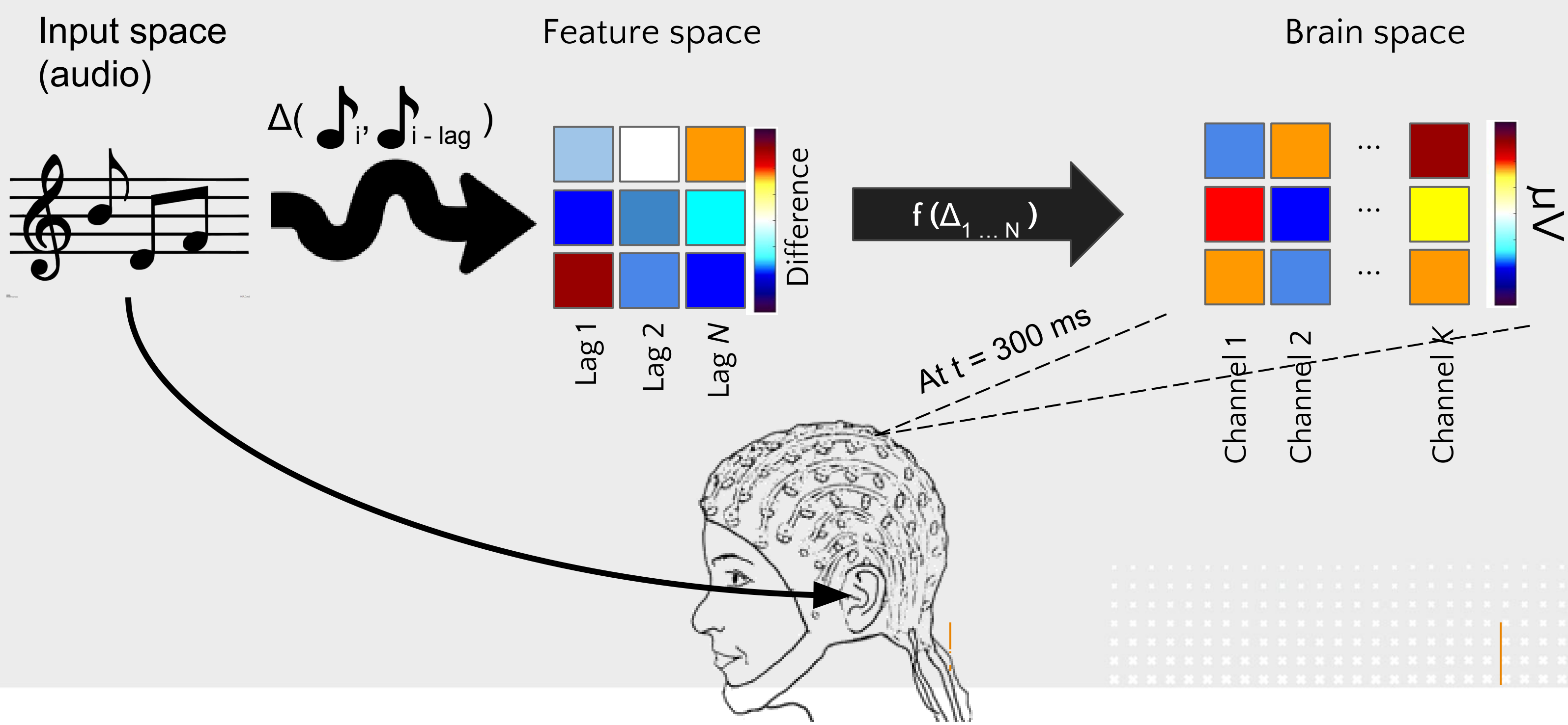


Another example:

How does the brain process auditory information over time?

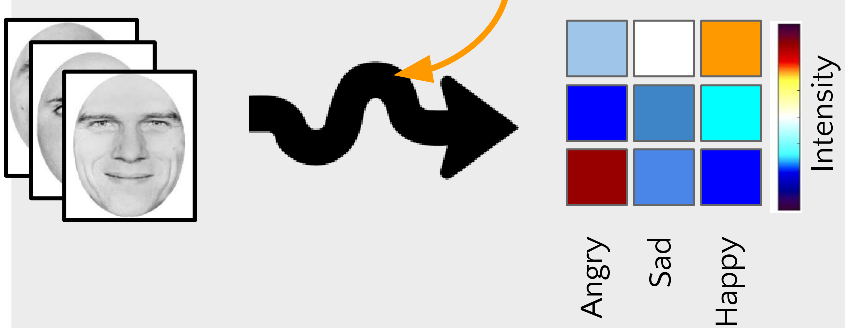


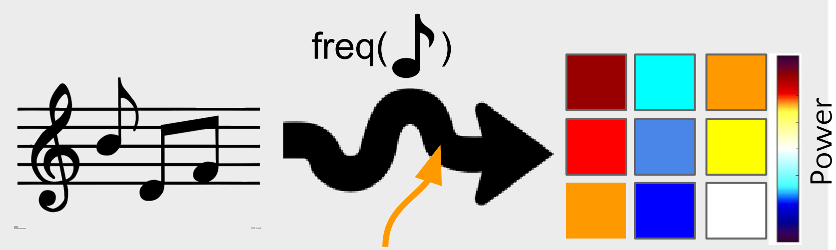
Conceptual vs. computational

Relative!

- Conceptual models do not *compute* (but "hard code") features
- Computational models *do* compute features (and thus specify a mechanism)

"Oracle", "epiphenomenal", "folk psychology models





$$\mathbf{F}(n) = \sum_{k=0}^{N-1} f(k)\, e^{-j2\pi nk/N}$$

Interim summary

- All analyses are computational, but the relative complexity depends on how you define/compute/extract your **features**
- Your model on which you base your features should reflect your **hypothesis** about the corresponding brain mechanism

From parameter testing → prediction

- Traditional analyses often focus on **parameter inference** (is my factor significantly different?)
  - ERPs and contrast-analyses in fMRI
  - $y_{\mu V,\, t\, =\, 300} = X_{freq\, =\, 400}\boldsymbol{\beta_1} + X_{freq\, =\, 500}\boldsymbol{\beta_2} + \varepsilon$
- Computational models (often) focus on **model fit** primarily ("How accurate is my model?")
  - Prediction, $\hat{y} = X_{freq\, =\, 400}\mathbf{b_1} + X_{freq\, =\, 500}\mathbf{b_2}$
  - Model fit = correlation(y, $\hat{y}$)

Model comparison

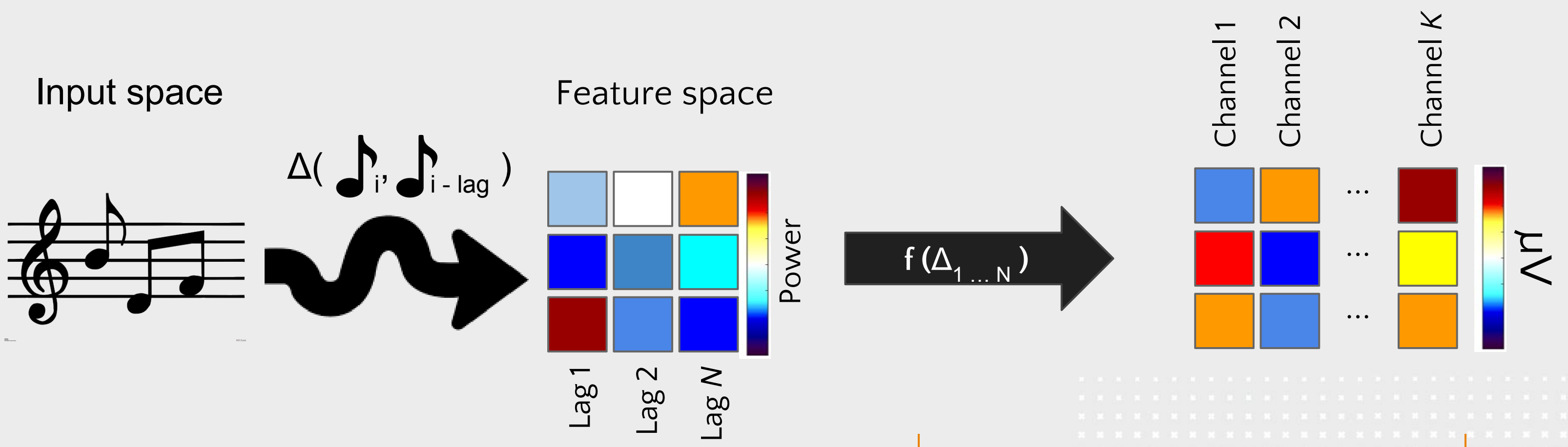
- Focusing on model fit allows for easy model comparison
- Is my **volume**-model better than my **frequency**-model in explaining activity during auditory processing?
  - correlation($\hat{y}$, f(X_{volume})) > correlation($\hat{y}$, f($X_{frequency}$)) ???
- Compare across **time** (EEG/MEG) or **space** (fMRI):
  - e.g., frequency model best at 70-150 ms, but frequency better at 150-300

What are the major ‘flavors’ of computational models in cognitive neuroscience?

University of Amsterdam

Flavors of computational models

- **Stimulus**-based models
  - Bread-and-butter of sensory neuroscience



Flavors of computational models

- **Stimulus**-based models
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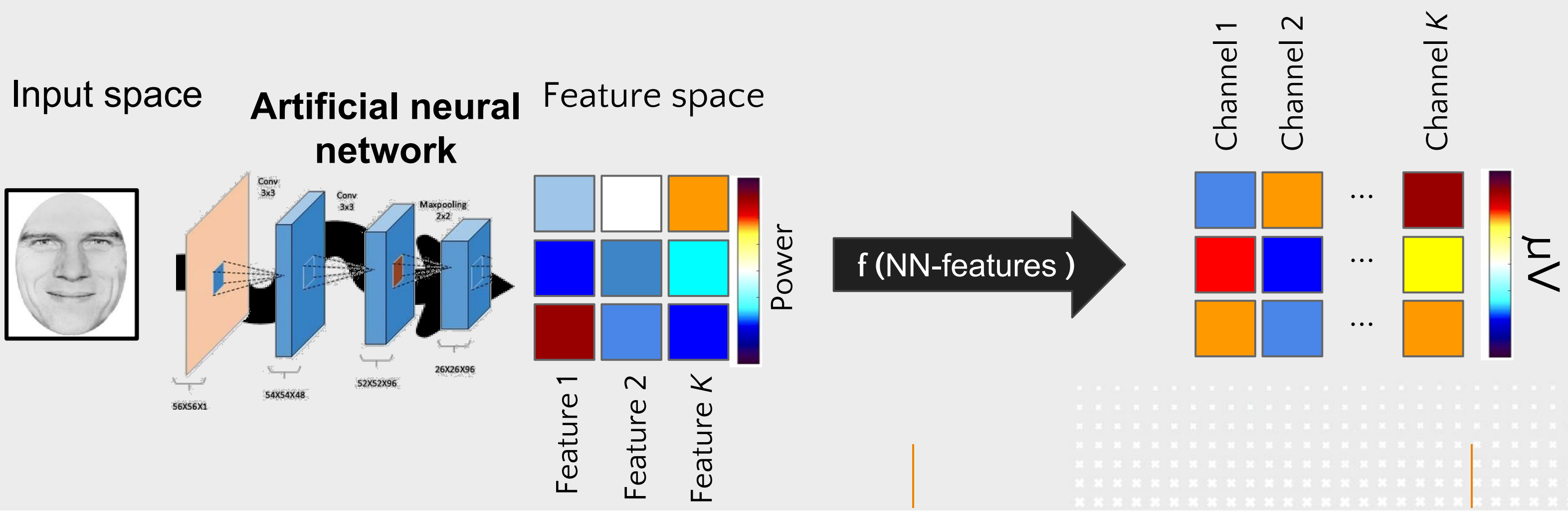
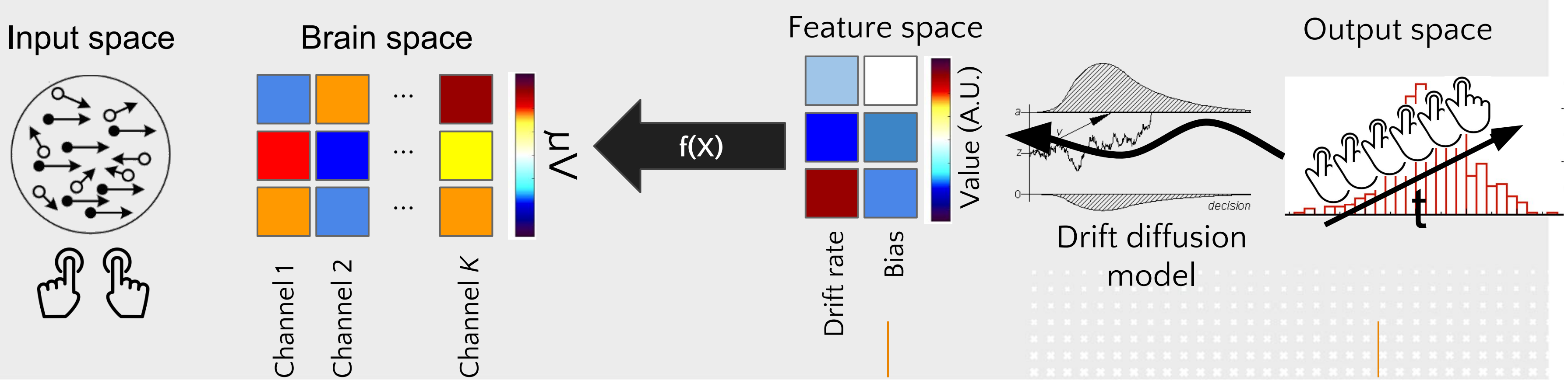


Flavors of computational models

- Stimulus-based models
- **Behavior**-based models
  - Often inspired by existing cognitive models



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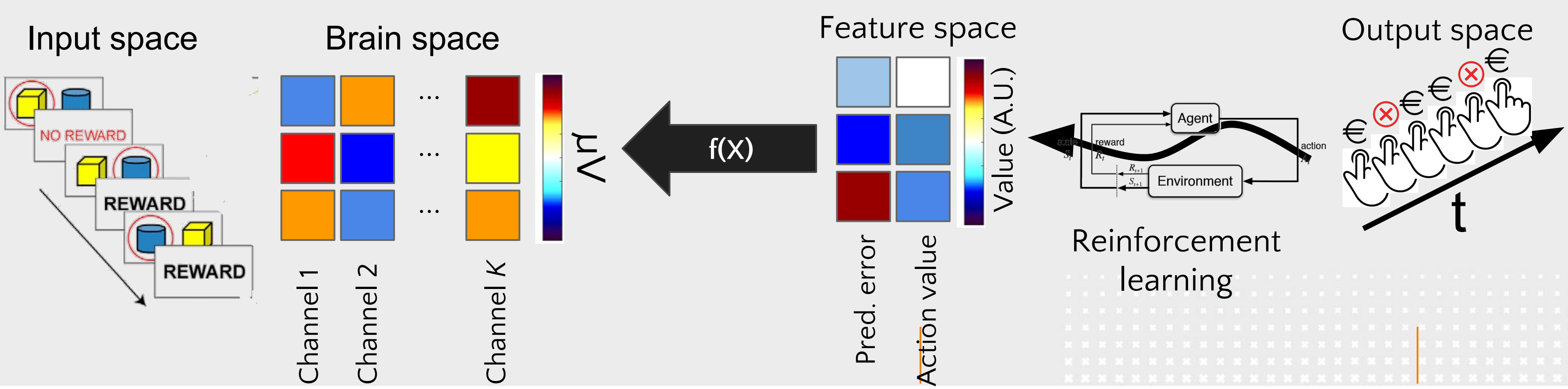


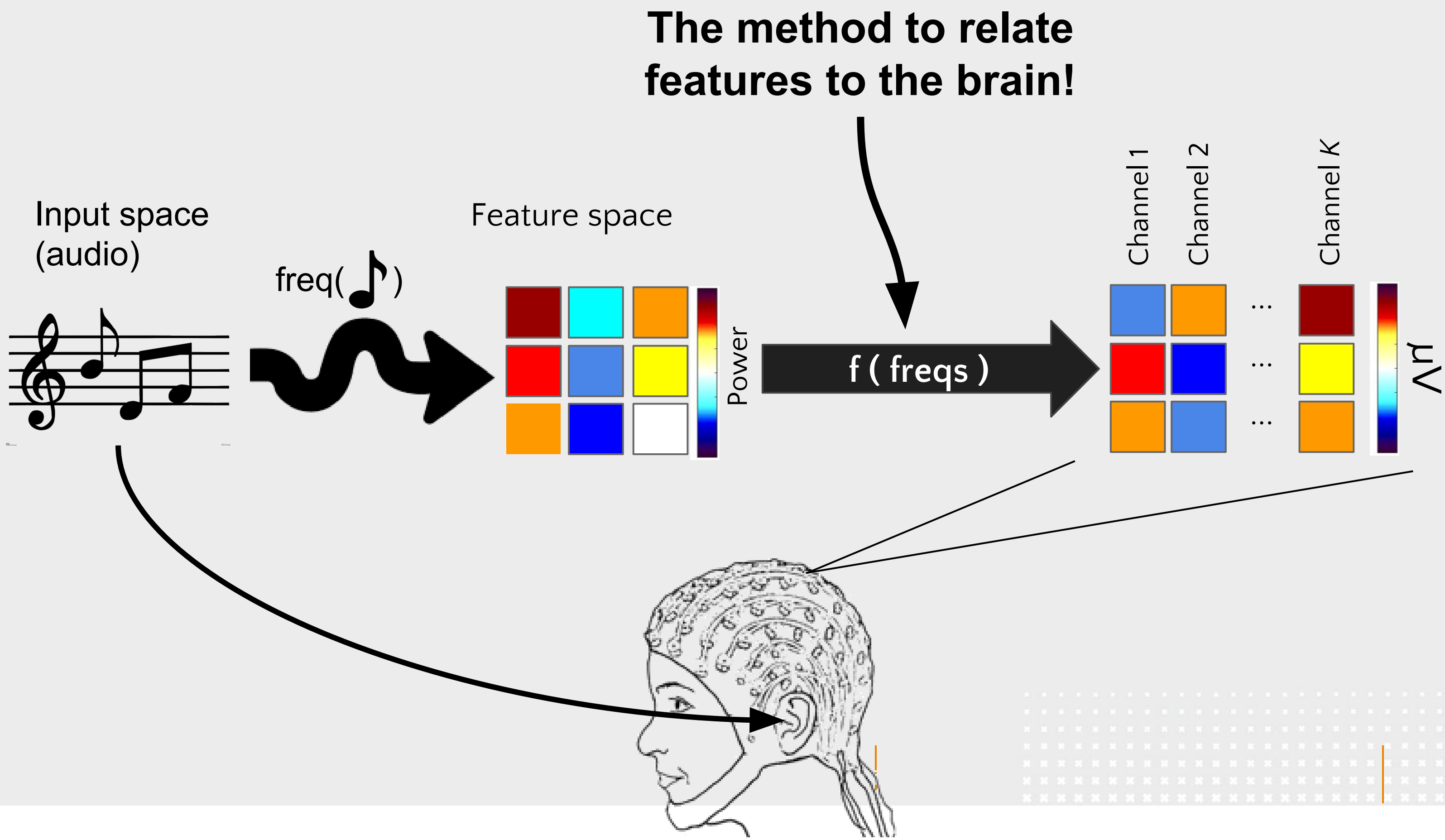
Interim summary

- The strength of computational research is often not due to state-of-the-art **methods**, but due to smart **operationalizations of features**
  - Derived from existing cognitive/behavioral models or artificial neural networks

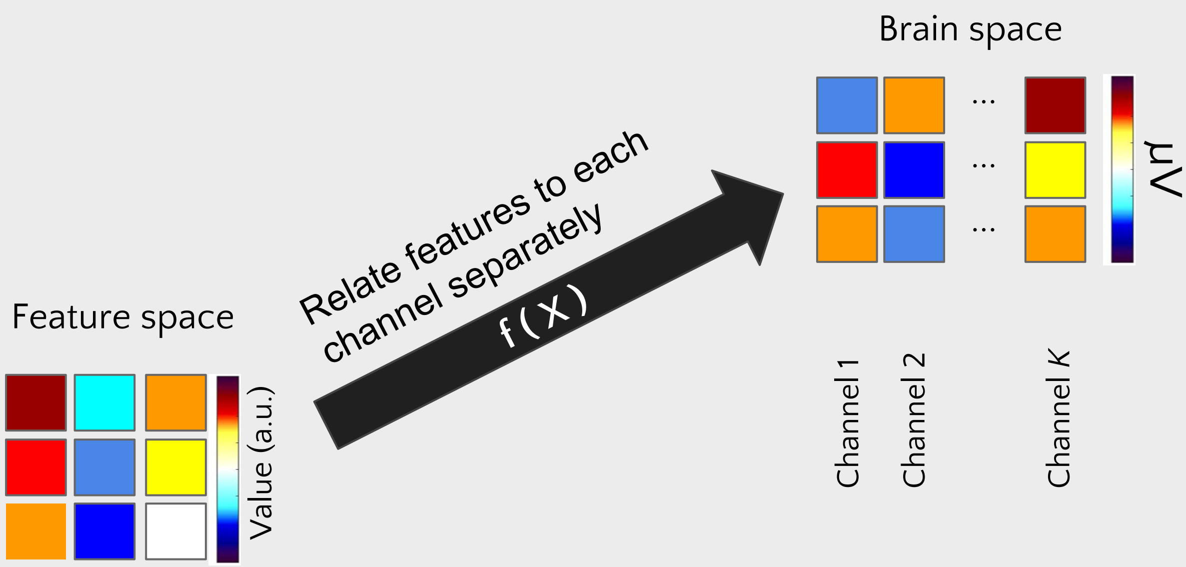
Methods for relating features to brain measurements

or: what on earth do you mean with **f(** … **)**?

What on earth is "f()"?

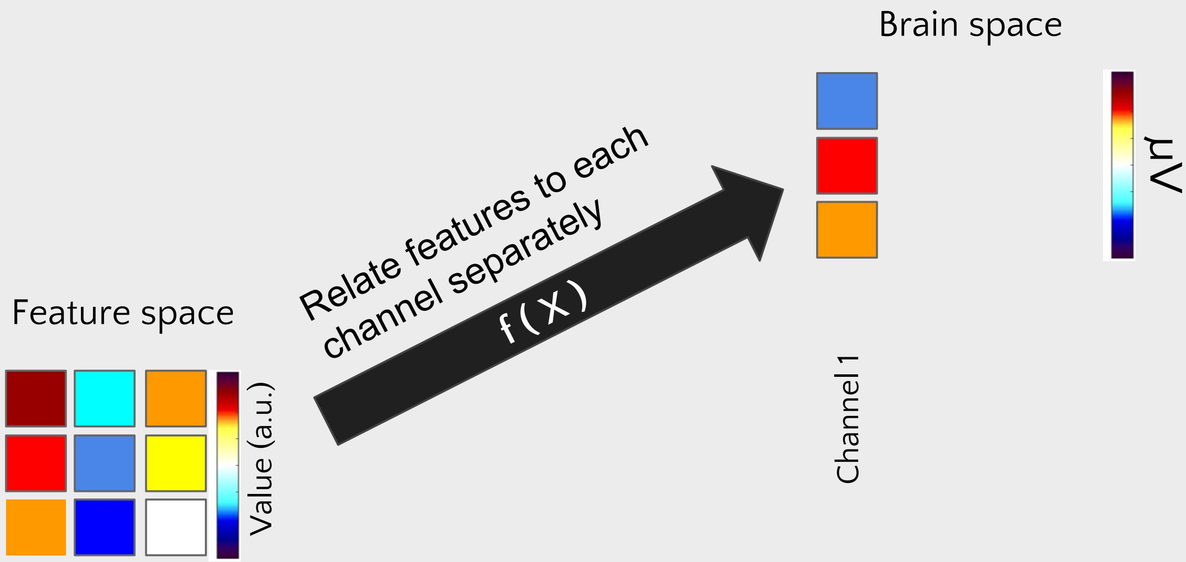


Two types of methods



ENCODING MODEL

Two types of methods



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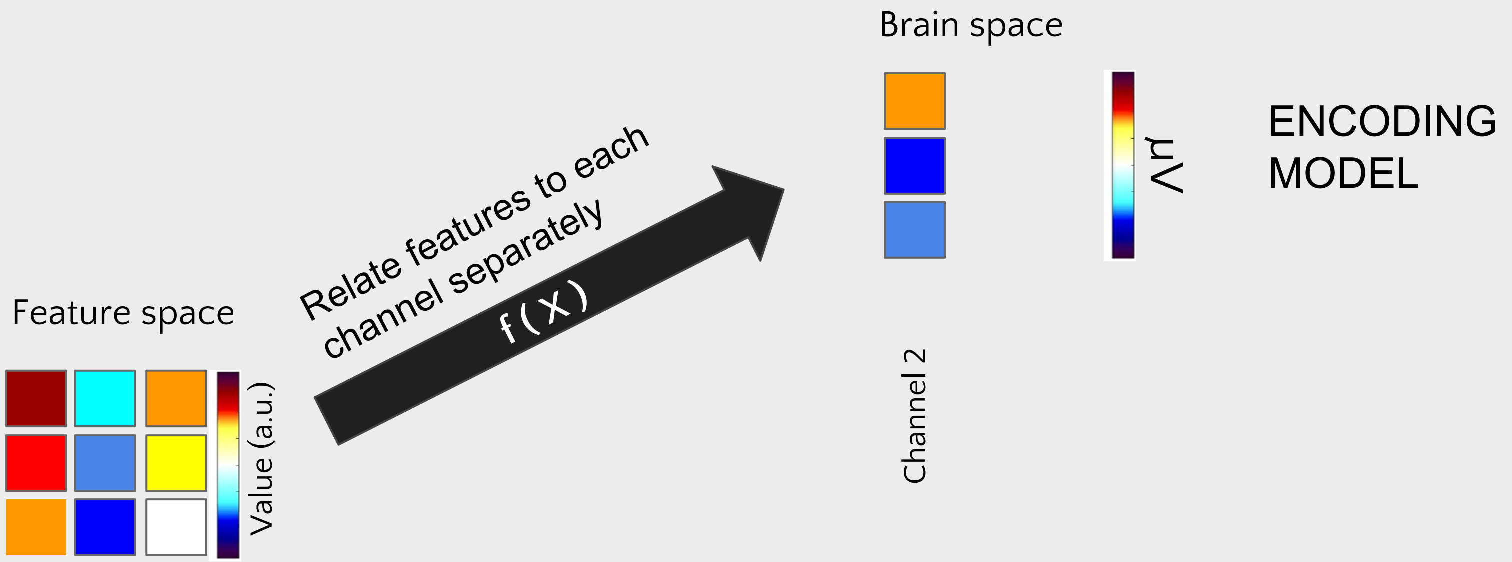
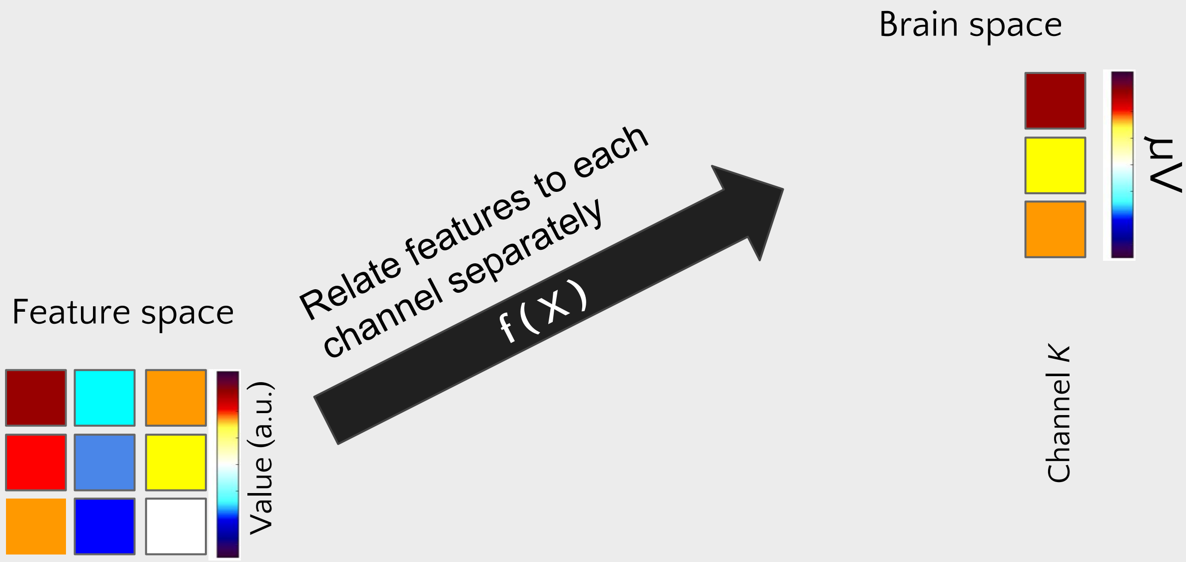


Two types of methods



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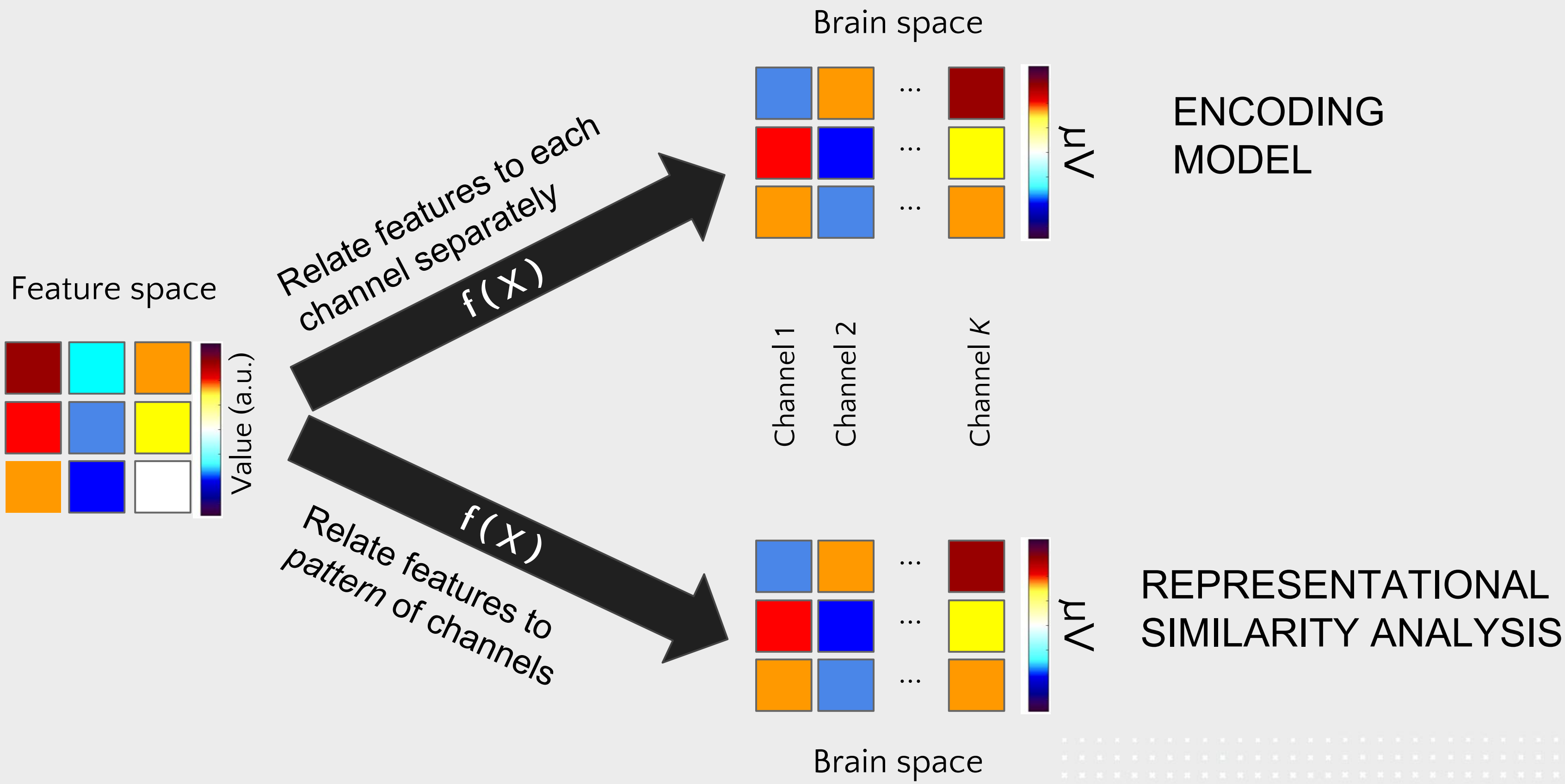
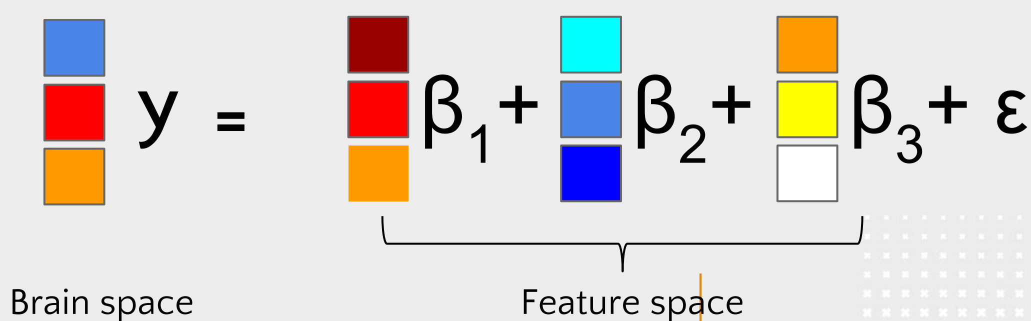


Encoding models

- Encoding models relate features (X) to brain measurements (y), often using linear regression models
  - The good ol' GLM: $y = X\beta + \varepsilon$



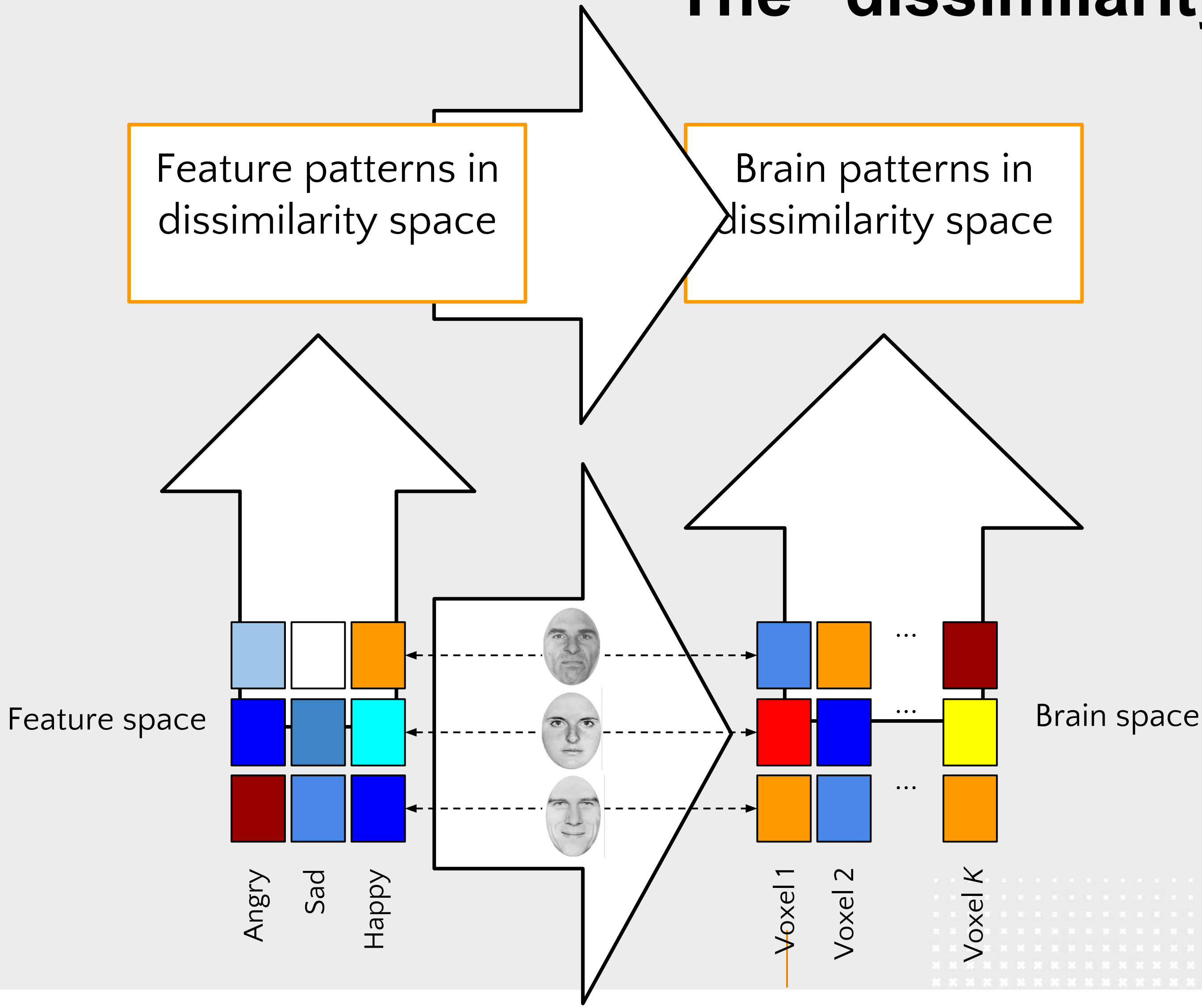
Regularization

- Sometimes, machine learning tricks ("**regularization**") are used to deal with many features (e.g., artificial NNs: K > 100,000!)
  - "Ridge regression", "LASSO"
  - Think of it as slightly extended GLMs

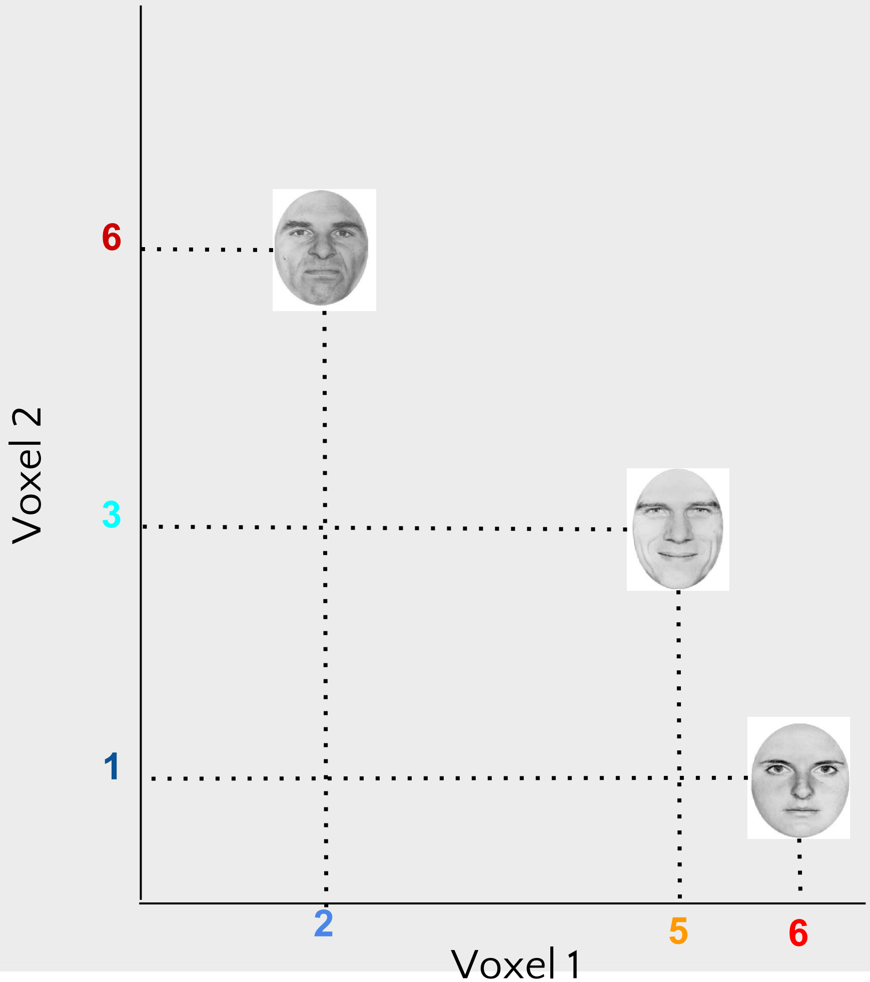
RSA

- Encoding models relate features to **single** voxels/channels
- RSA relates features to **patterns** of voxels/channels, using the “dissimilarity trick”

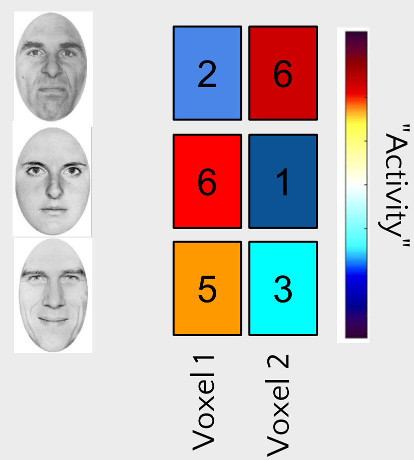
The "dissimilarity trick"



Dissimilarity space



"Dissimilarity" is the distance of points in N-dimensional space



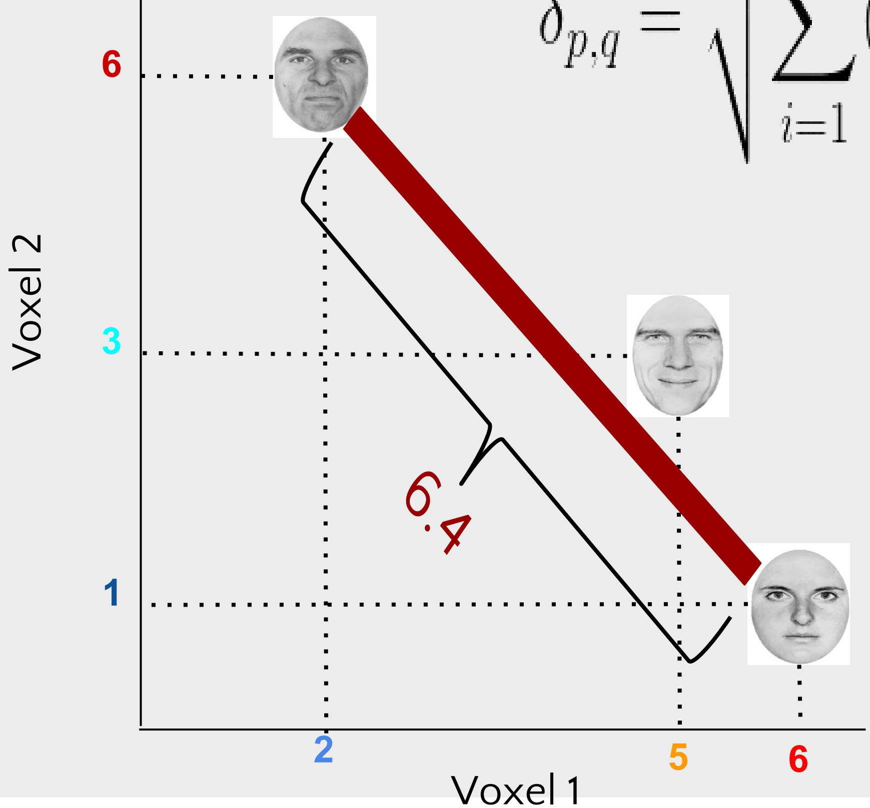
Note: the visualization is in 2-dimensional space, but usually K > 2!

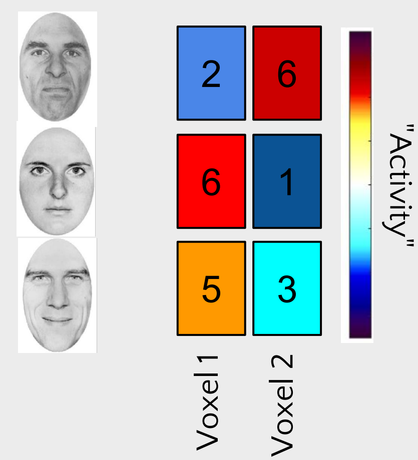
Dissimilarity space

$$\delta_{(\text{face}_1,\text{face}_2)} = \sqrt{(2-6)^2 + (6-1)^2} = 6.4$$

$$\delta_{p,q} = \sqrt{\sum_{i=1}^{K} (p_i - q_i)^2}$$

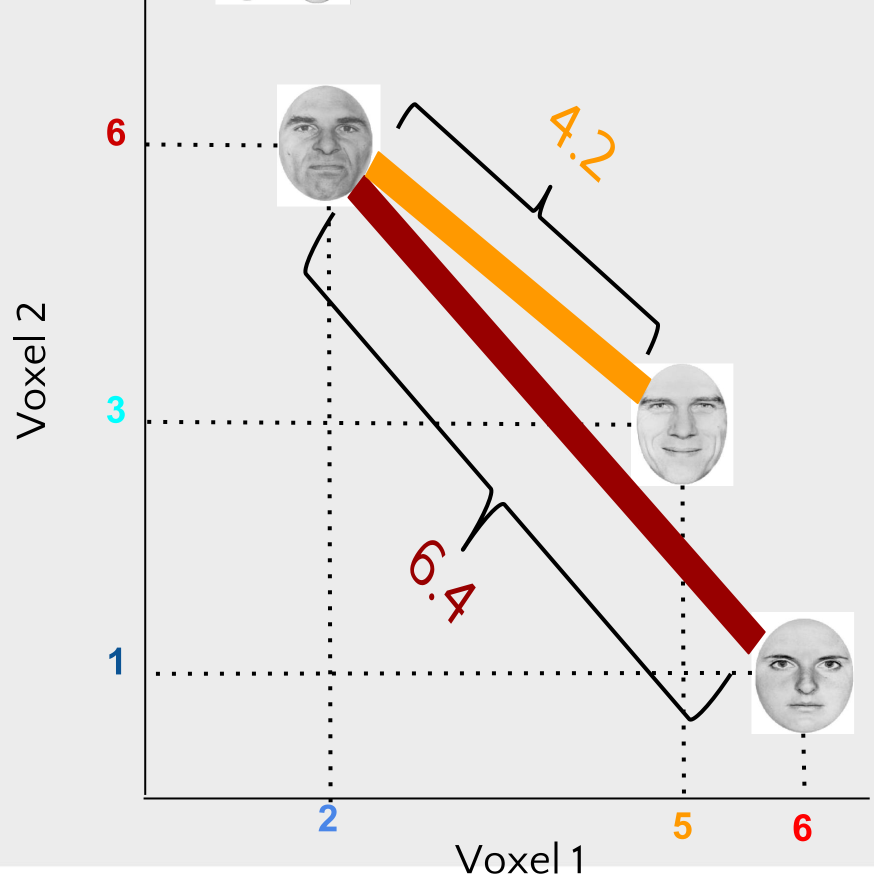
Euclidean distance

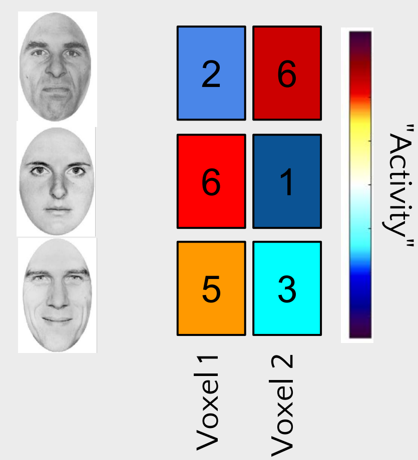




Dissimilarity space

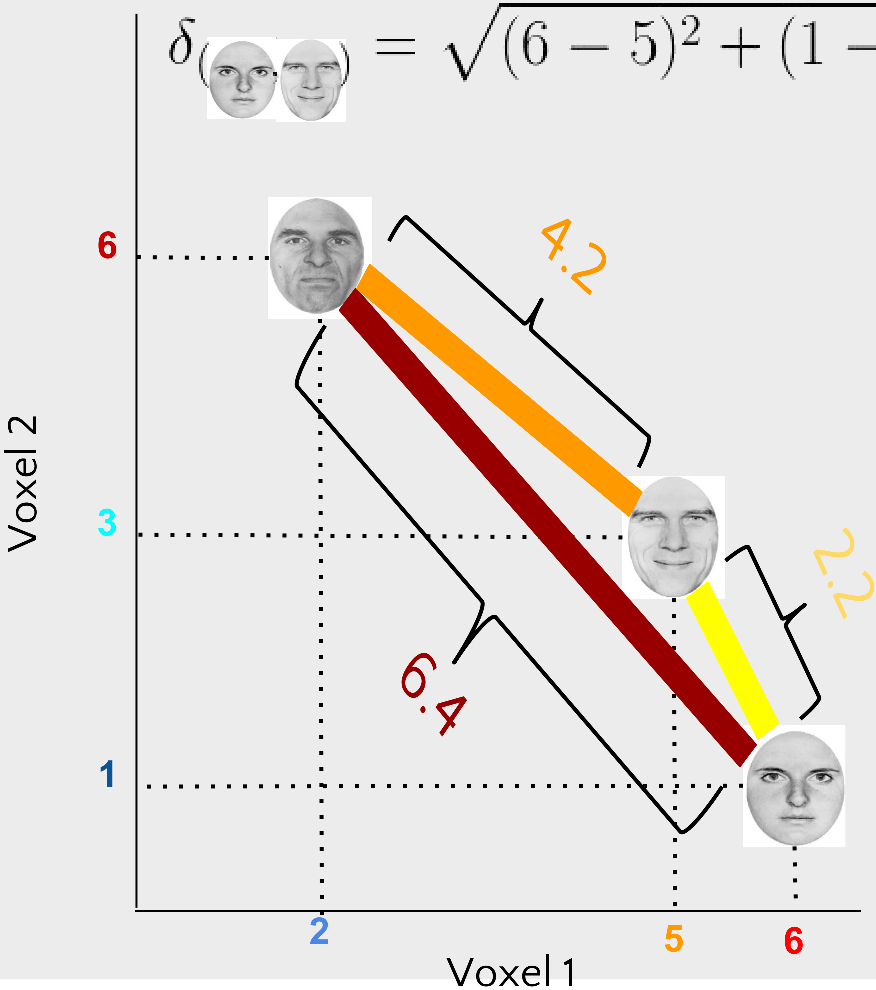
$$\delta = \sqrt{(2-5)^2 + (6-3)^2} = 4.2$$

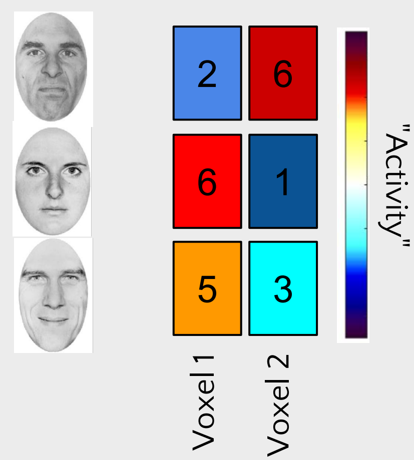




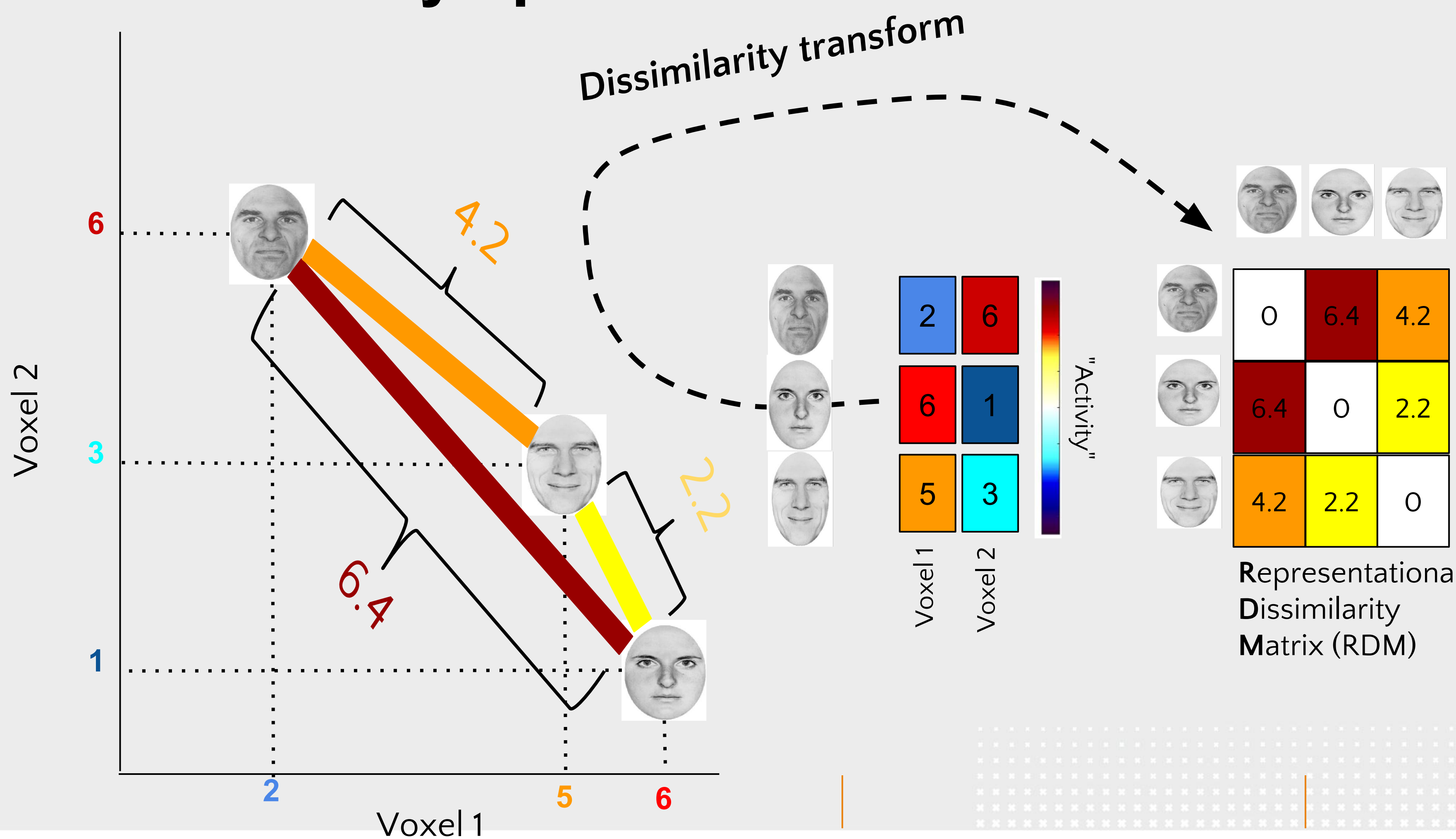
Dissimilarity space

$$\delta_{(\cdot,\cdot)} = \sqrt{(6-5)^2 + (1-3)^2} = 2.2$$





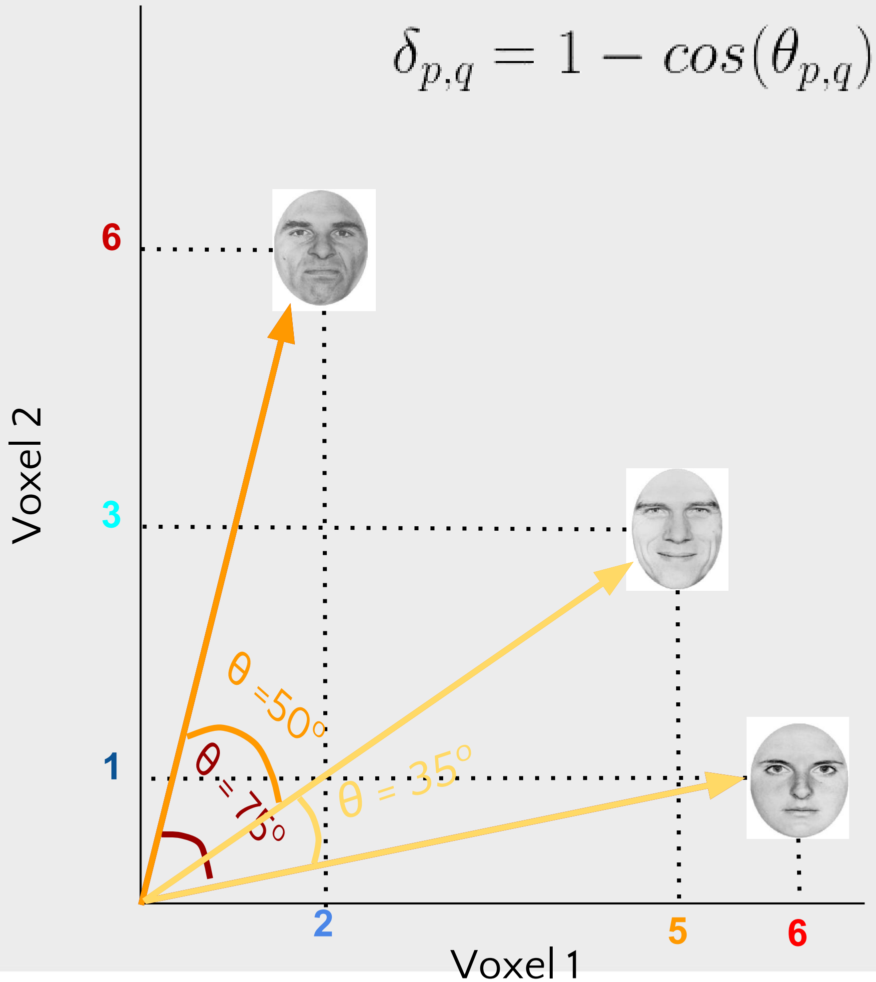
Dissimilarity space

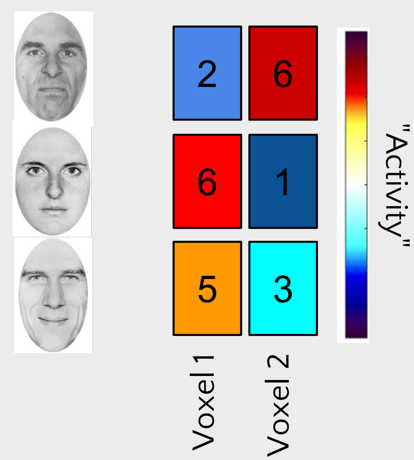


Dissimilarity space

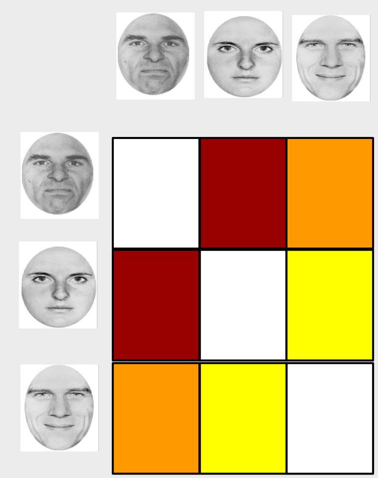
$$\delta_{p,q} = 1 - cos(\theta_{p,q})$$

Cosine distance



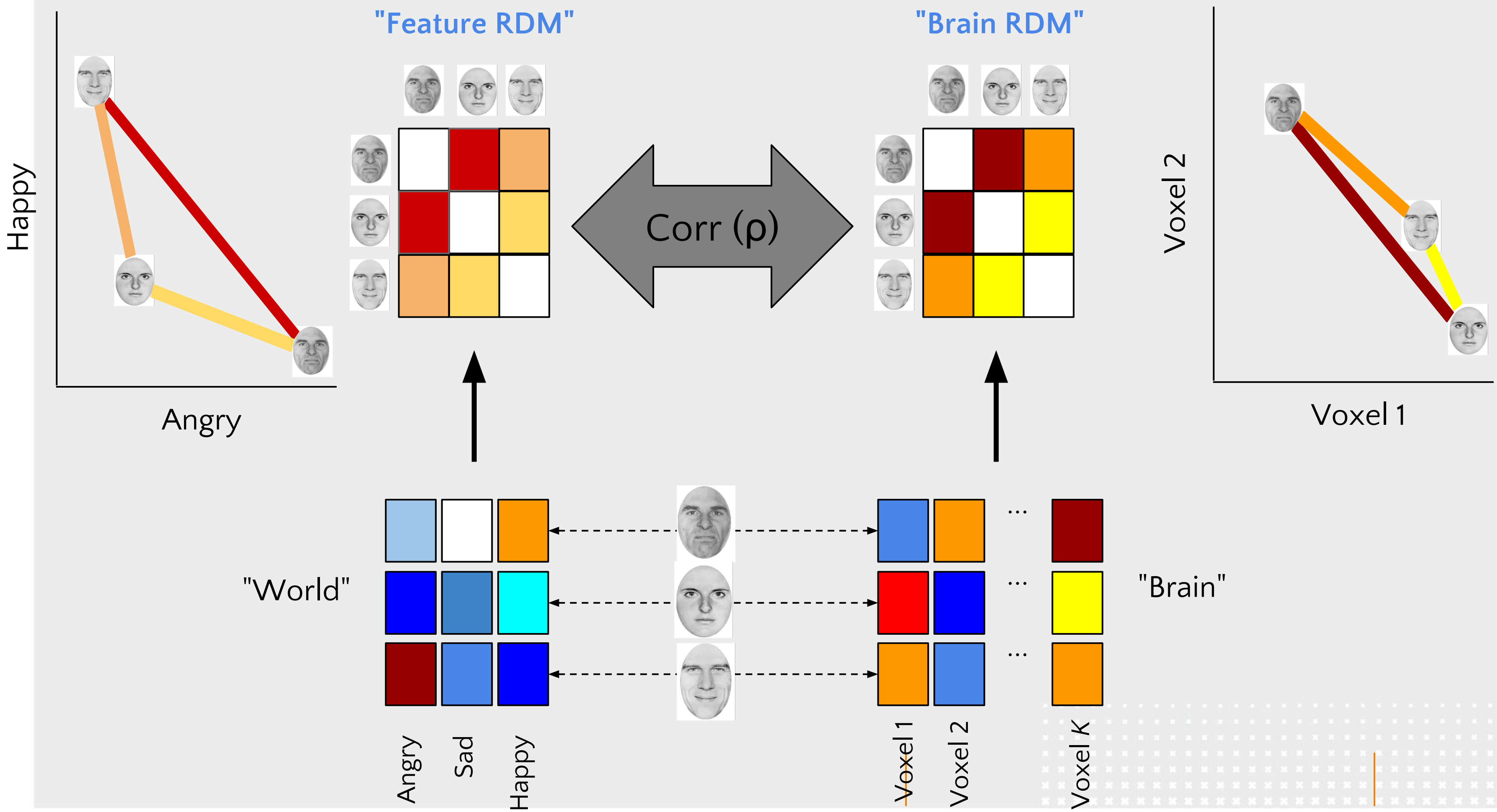


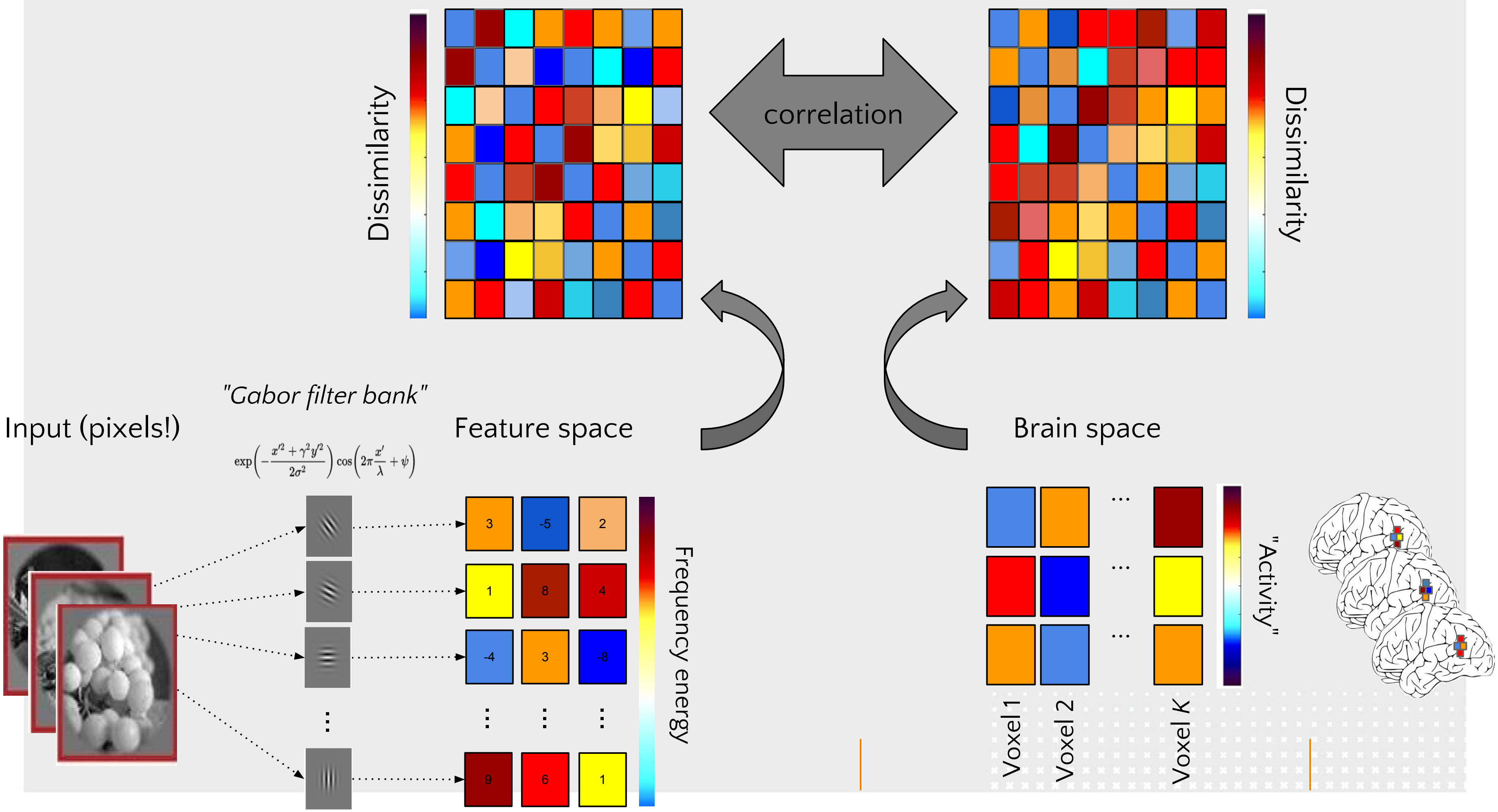
1 – cos(x)



Representational **D**issimilarity **M**atrix (RDM)

RSA


"Feature RDM"
"Brain RDM"
Corr (ρ)
Happy
Angry
Voxel 2
Voxel 1
"World"
"Brain"
Angry
Sad
Happy
Voxel 1
Voxel 2
...
Voxel K


Dissimilarity
correlation
Dissimilarity
"Gabor filter bank"
Input (pixels!)
$\exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda}+\psi\right)$
Feature space
3
-5
2
1
8
4
-4
3
-8
9
6
1
Frequency energy
Brain space
"Activity"
Voxel 1
Voxel 2
Voxel K

Summary

- Encoding models and RSA both relate features to brain measurements
  - Encoding models: features → single units
  - RSA: features → patterns
- Choice depends on how your feature is encoded in the brain
  - Spatial frequency → single channels
  - Object category → patterns (?)

Questions?