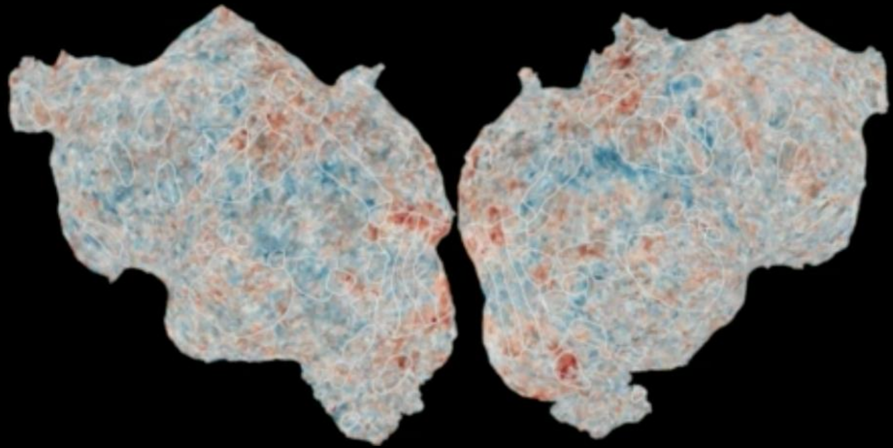
Deep multi-view representation learning of brain responses to natural stimuli



Leila Wehbe*, Anwar Nunez-Elizalde*,
Alex Huth, Fatma Imamoglu, Natalia Bilenko,
Jack Gallant

UC Berkeley

How does the human brain represent information?

- Machine Learning

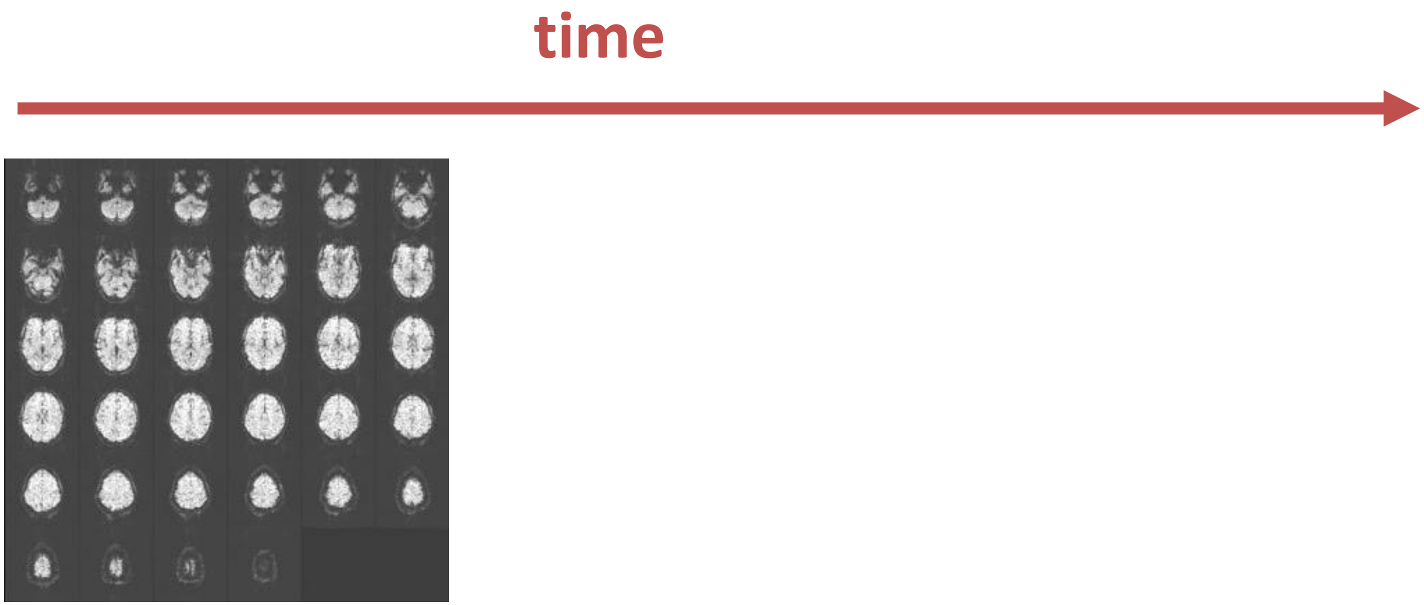
- Non-invasive imaging, e.g. fMRI

An fMRI experiment

- generate time series of functional volumes

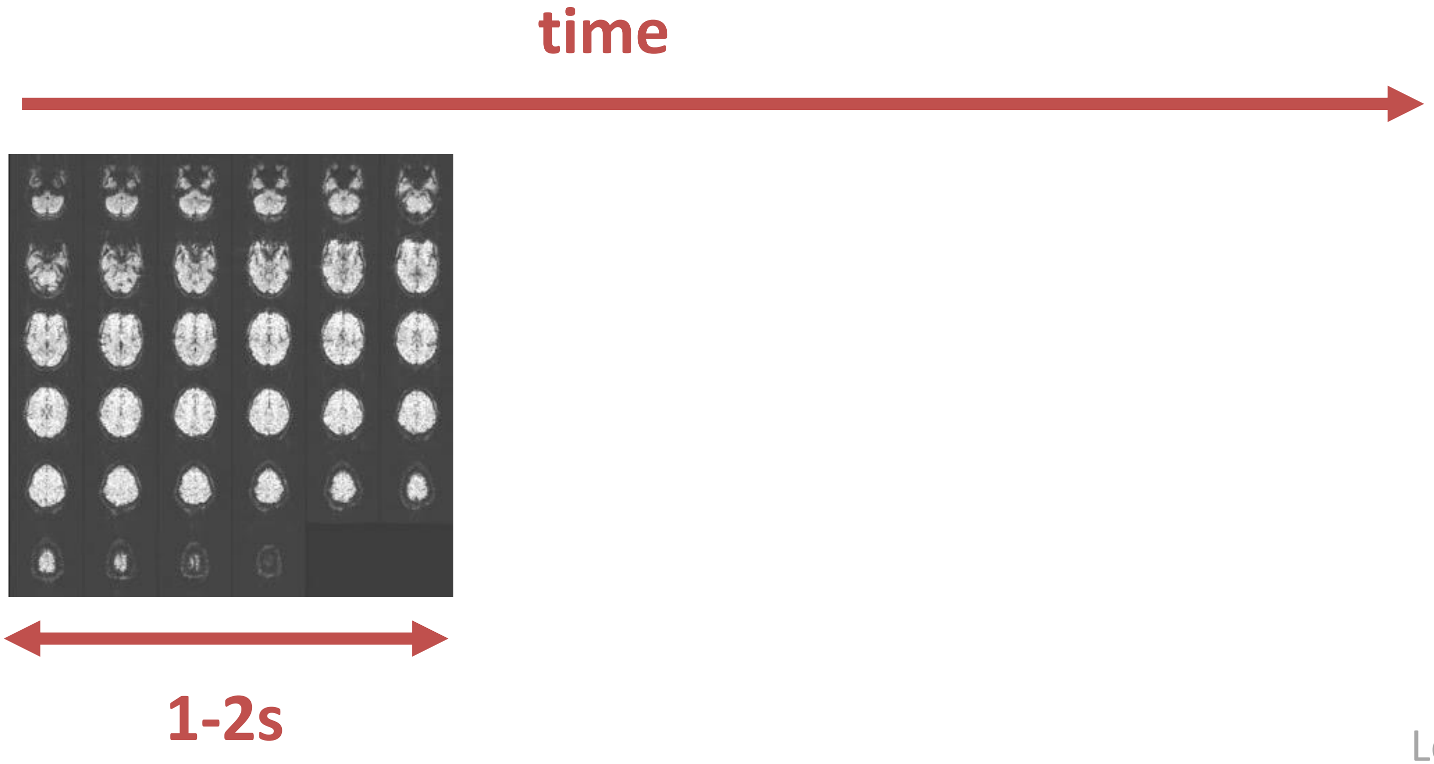
An fMRI experiment

- generate time series of functional volumes



An fMRI experiment

- generate time series of functional volumes



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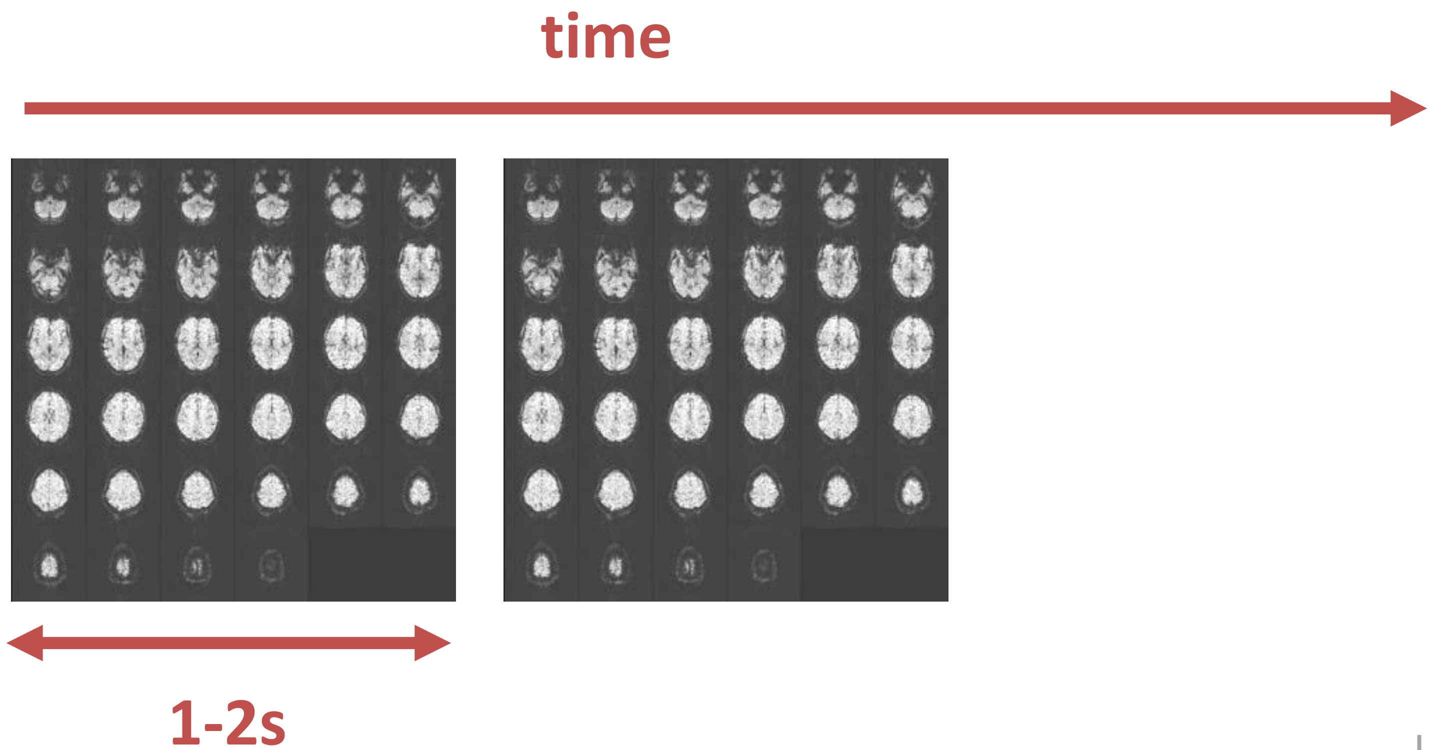

An fMRI experiment

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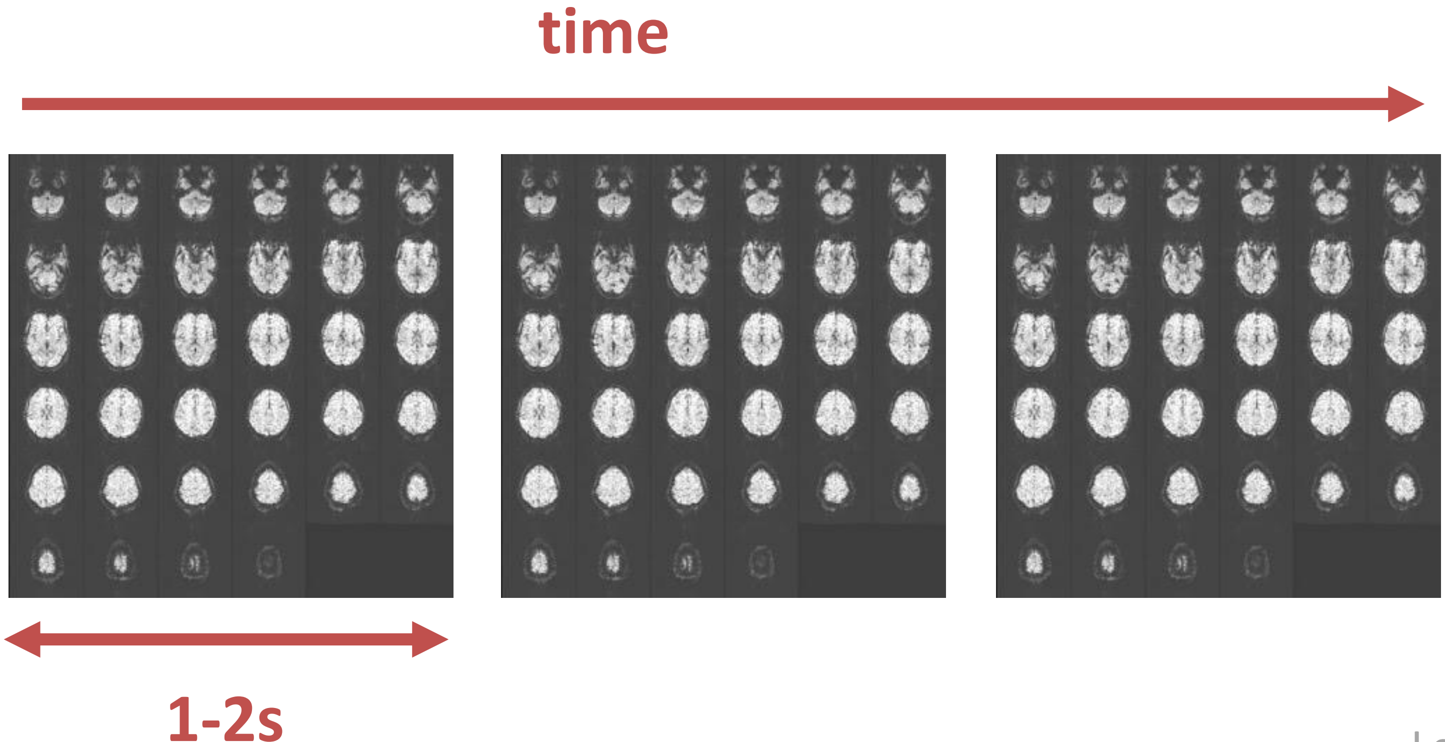

An fMRI experiment

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- Typically:
  - Isolate a specific
  - Two or a few conditions
  - Find regions that differ in activity

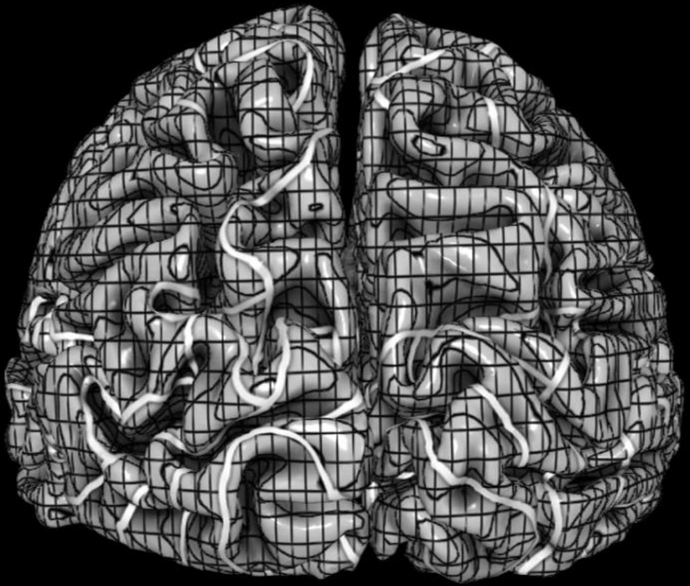
An fMRI experiment

- Typically:
  - Isolate a specific
  - Two or a few conditions
  - Find regions that differ in activity

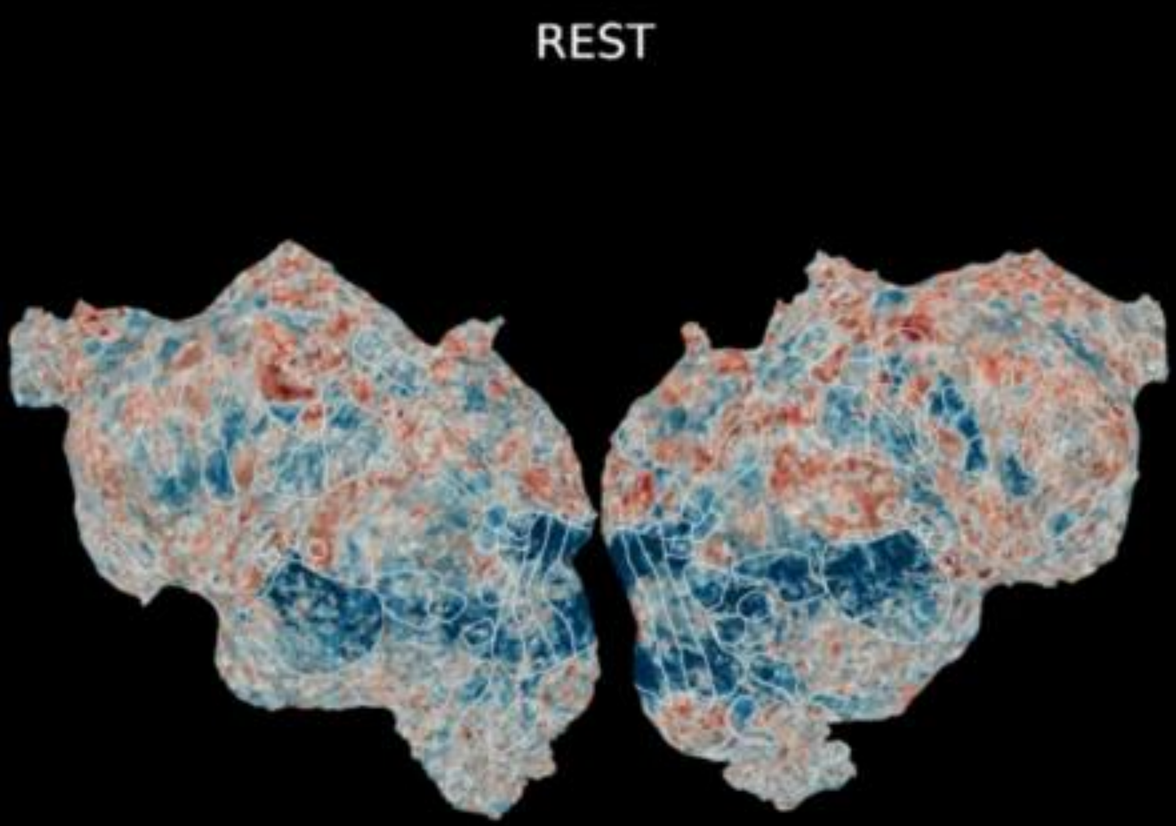
- Problems:
  - Hard to generalize
  - Infinite number of binary comparisons

Naturalistic experiments

- Make subjects do a real life complex task:
  - Watch movies
  - Listen / read stories



Video by James Gao and Anwar Nunez-Elizalde



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Naturalistic Experiments

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  - Classification techniques are not useful/interesting here

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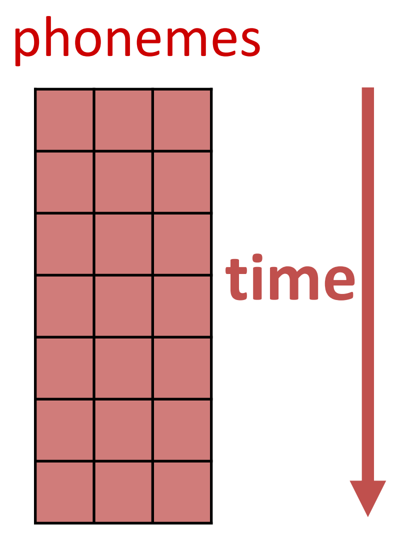
Naturalistic Experiments

- No clear classes
  - Classification techniques are not useful/interesting here
- Highly complex input varying along multiple levels
  - Model it!

Build feature spaces!

- **Stories** have acoustic and semantic properties:
  - phonemes: Count of the occurrence of 39 phonemes



Leila Wehbe

Build feature spaces!

- **Stories** have acoustic and semantic properties:
  - word2vec: Bag of words model of the words occurring at each 2s

Build feature spaces!

- **Movies** have visual and semantic properties:
  - word2vec: Bag of words model of the objects occurring at each 2s

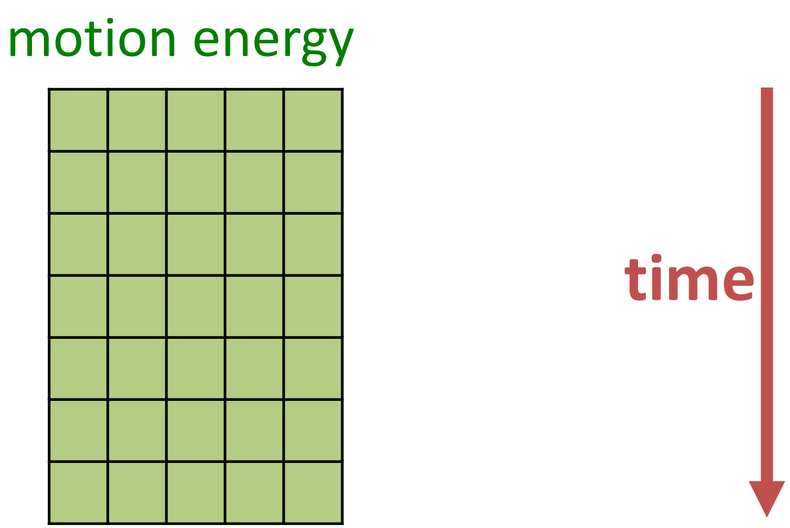
Build feature spaces!

- Movies have visual and semantic properties:
  - motion energy filters: spatio-temporal Gabor pyramids

Video by Mark Lescroart

Build feature spaces!

- Movies have visual and semantic properties:
  - motion energy: spatio-temporal Gabor pyramids



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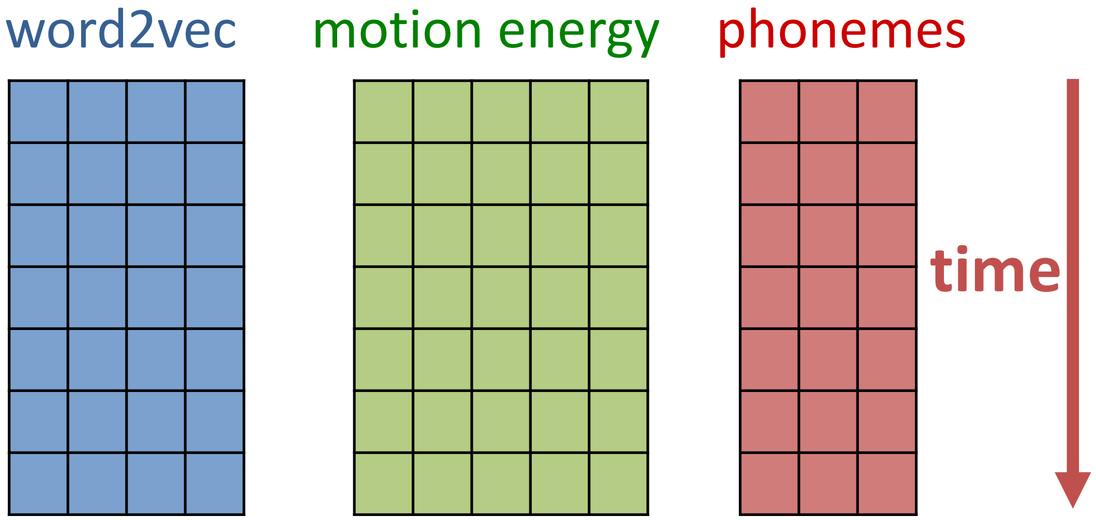
Build feature spaces!



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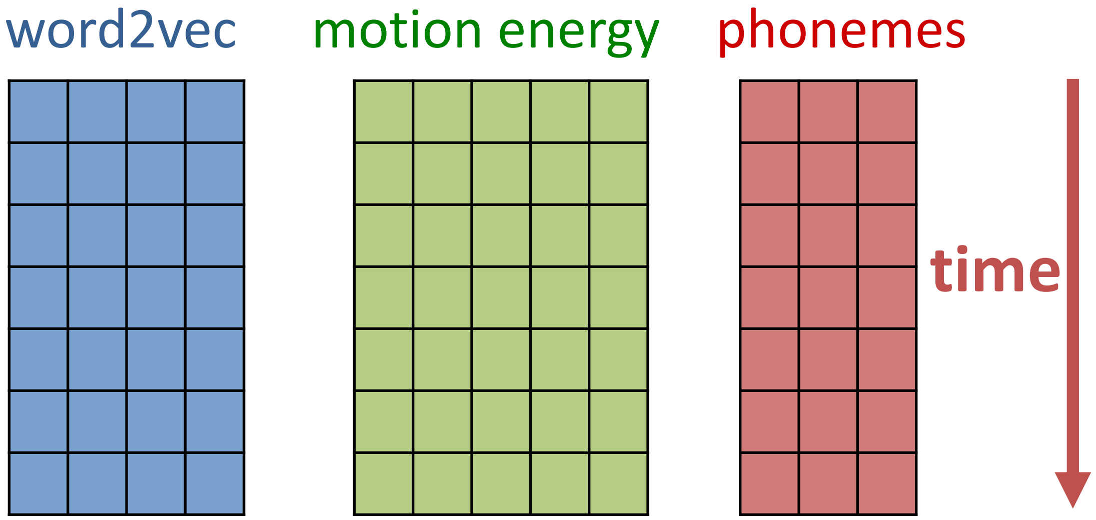
Build feature spaces!

- Data from 4 subjects for both experiments
  - Story Listening (Huth et al. 2016)
  - Natural Movies (Nishimoto et al. 2011)
- Each subject has 30-50 thousand voxels
  - And ~ 3600 time points per experiment



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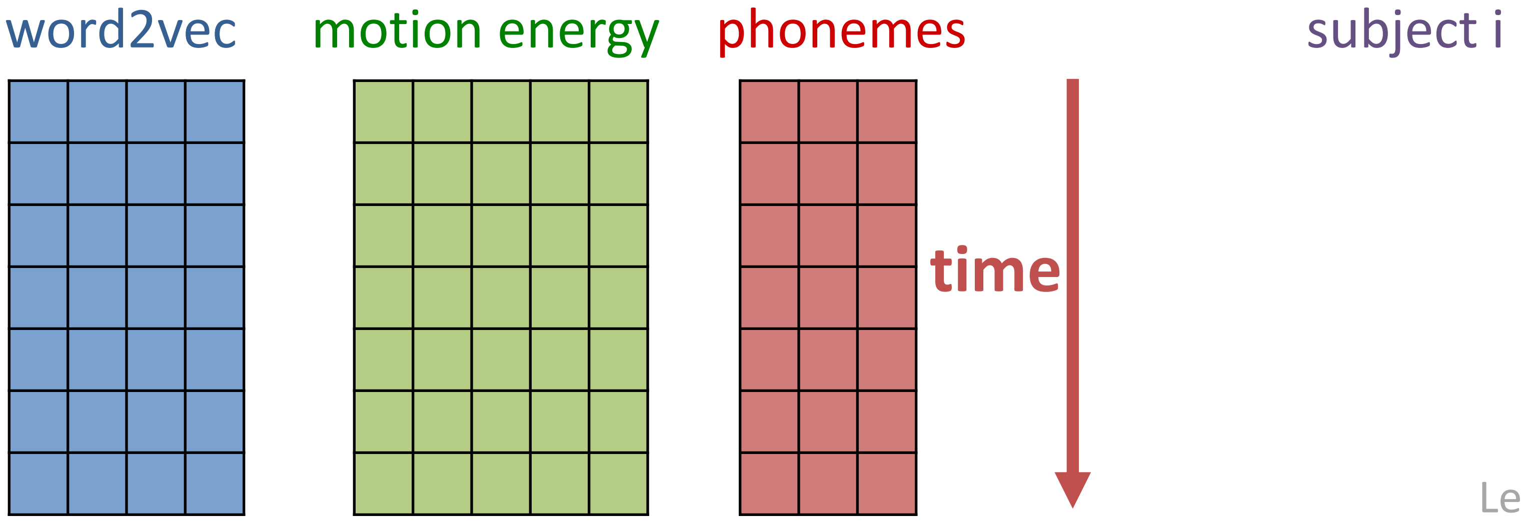

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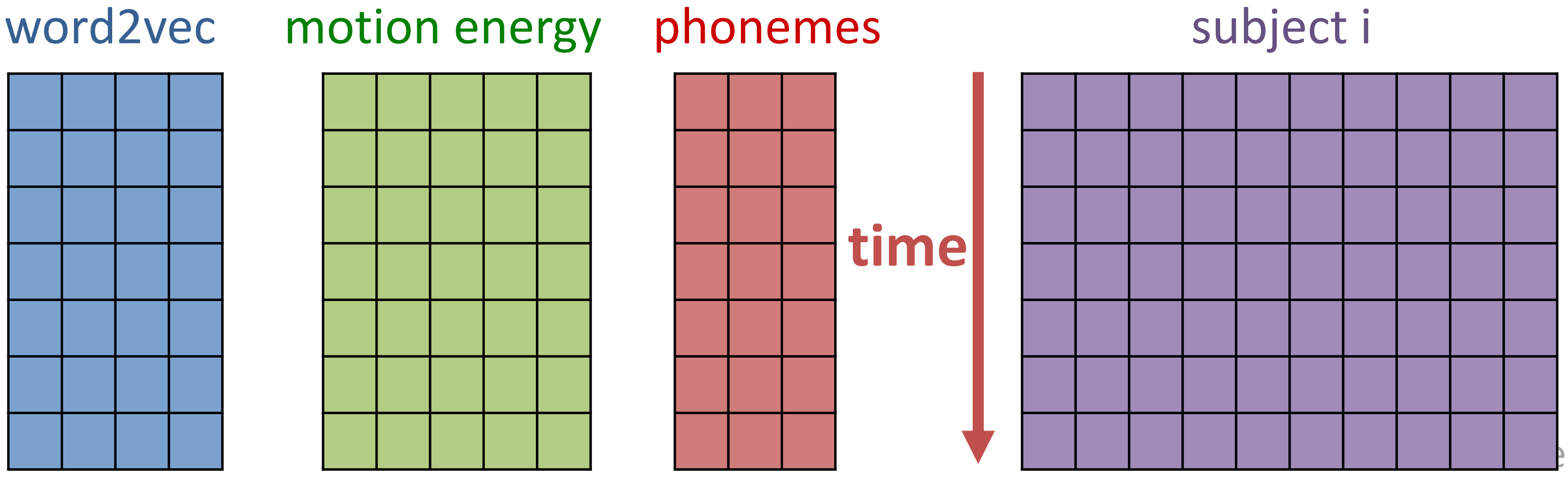

Small data / complex brains

Small data / complex brains

- Small data scenario!
  - … and low SNR

Small data / complex brains

- Small data scenario!
  - … and low SNR
- We want to generalize:
  - Across subjects
  - Across feature spaces
  - And across experiments and cognitive domains

Useful Neuroimaging Tasks

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- Predict data from features

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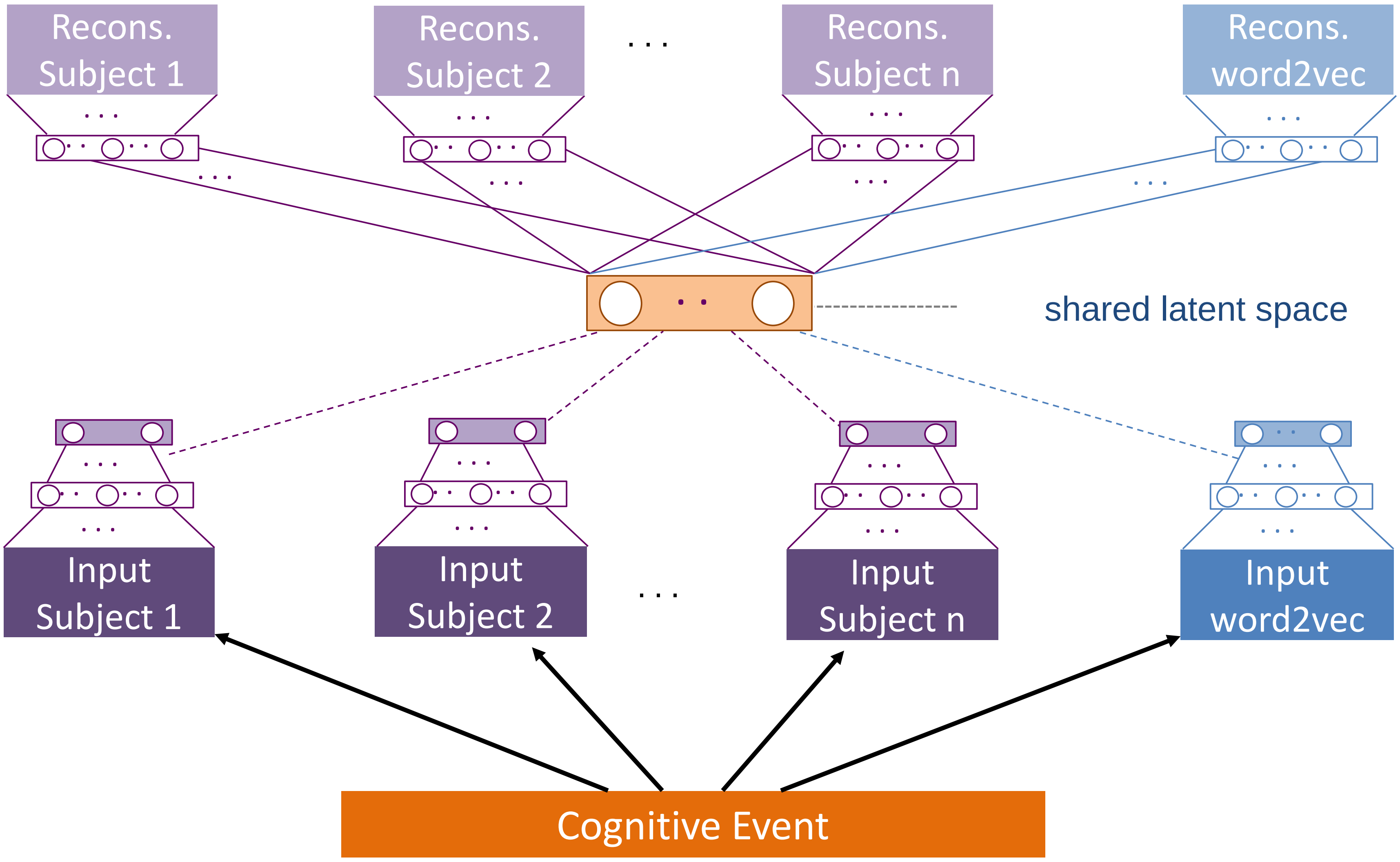
Useful Neuroimaging Tasks

- Predict data from features
- Predict features from data (decoding)
- Combine data across subjects
- Predict one subject from another

Cognitive Space Multi-view Autoencoder



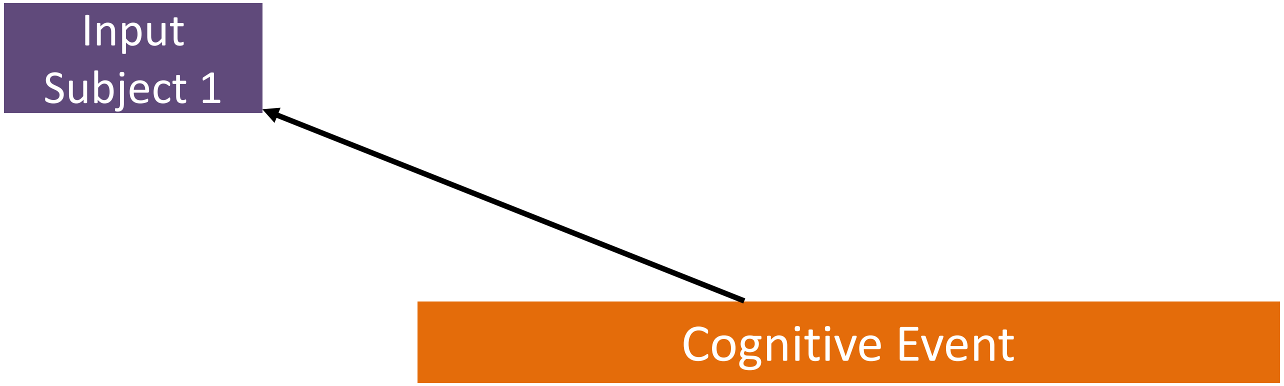
Cognitive Space Multi-view Autoencoder

Cognitive Event

E.g., perception of:

"… was running away as fast as he could …"

Cognitive Space Multi-view Autoencoder



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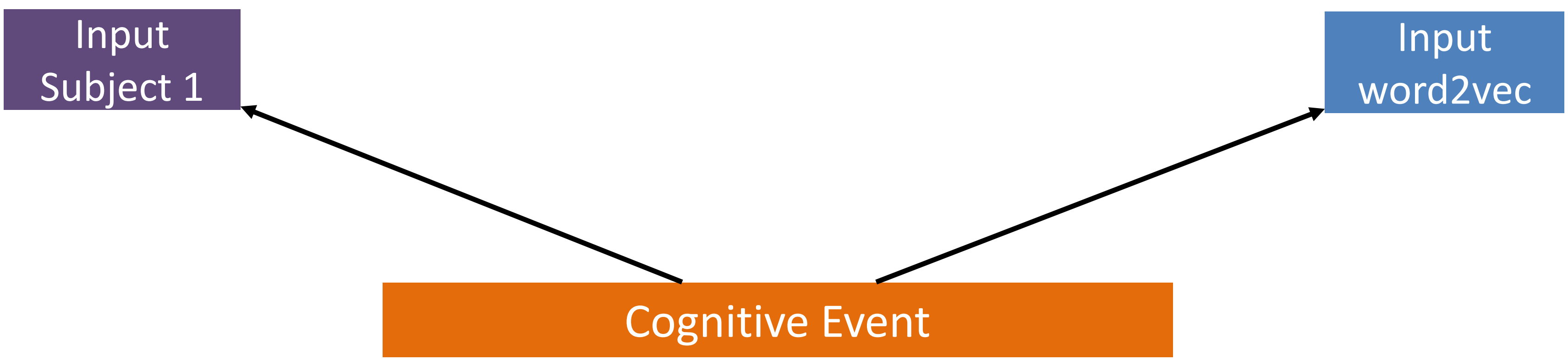

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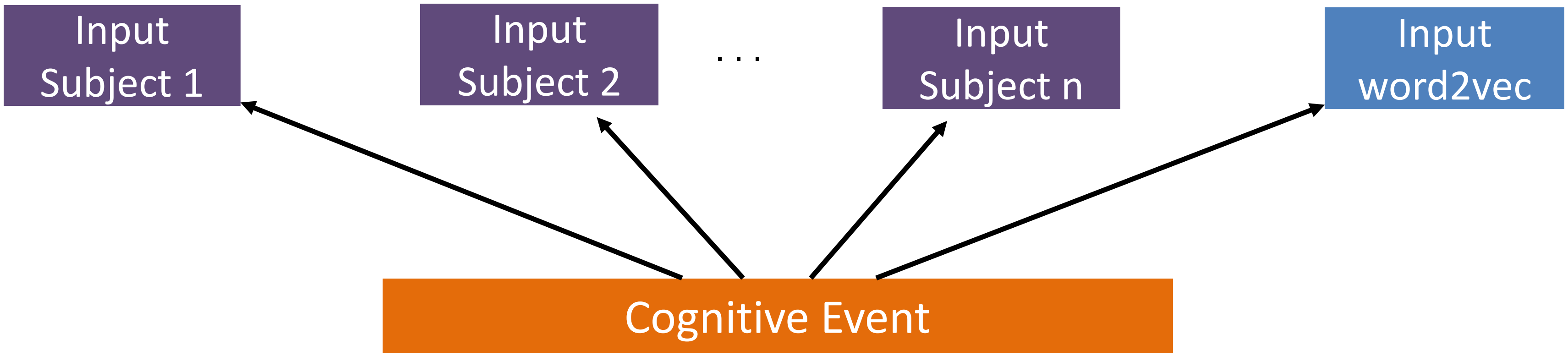

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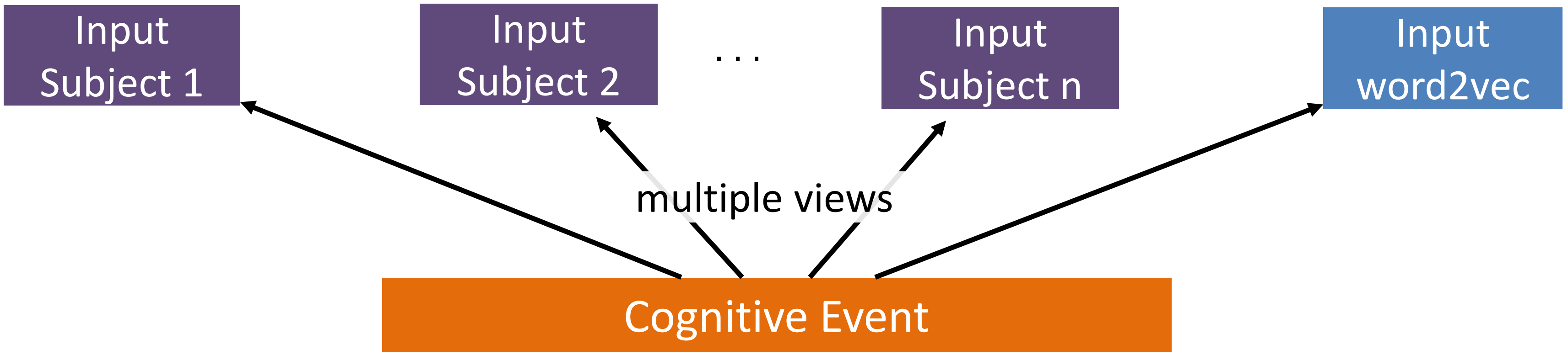

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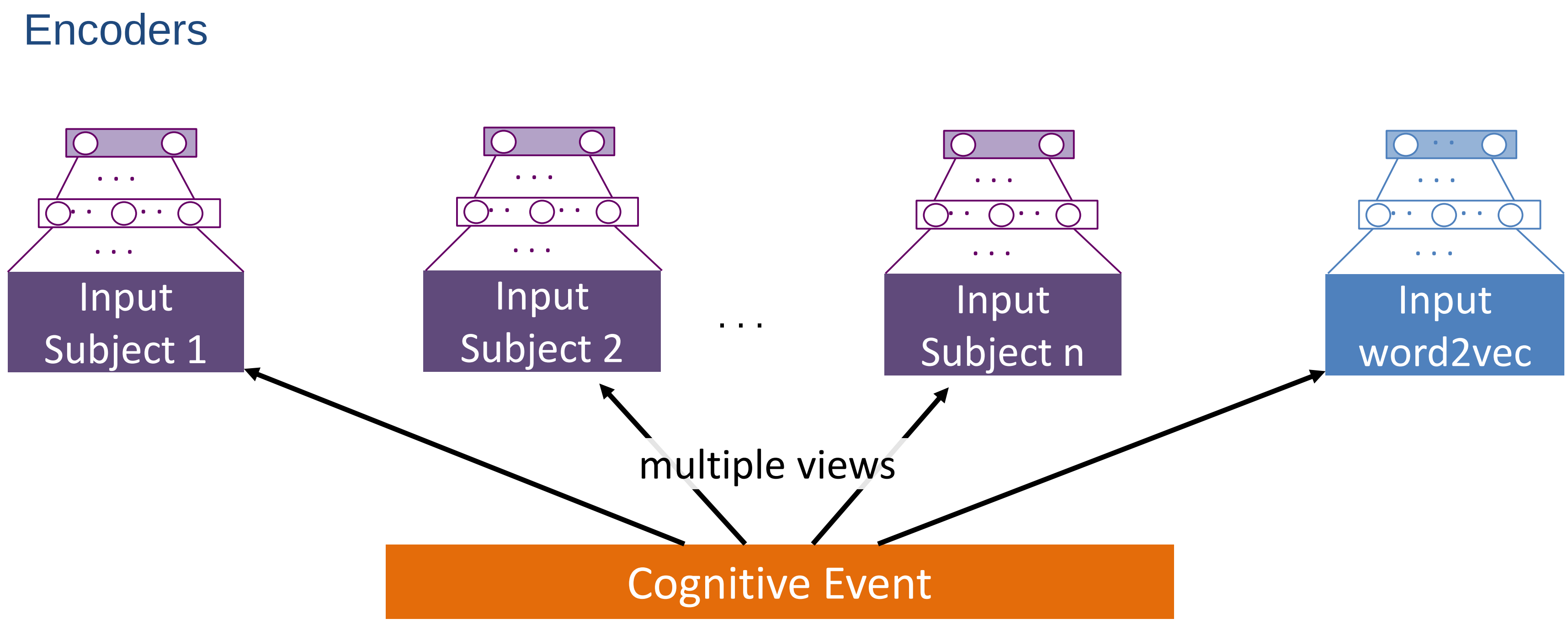

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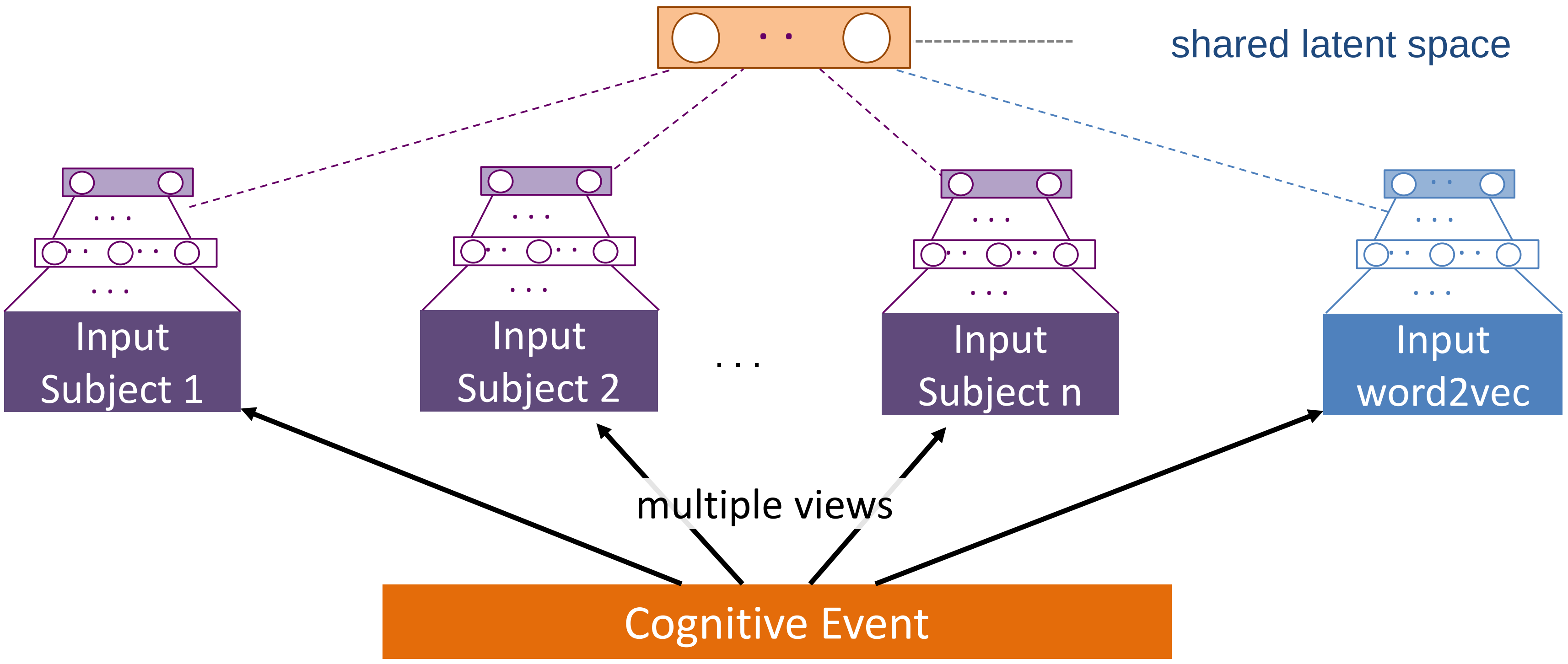

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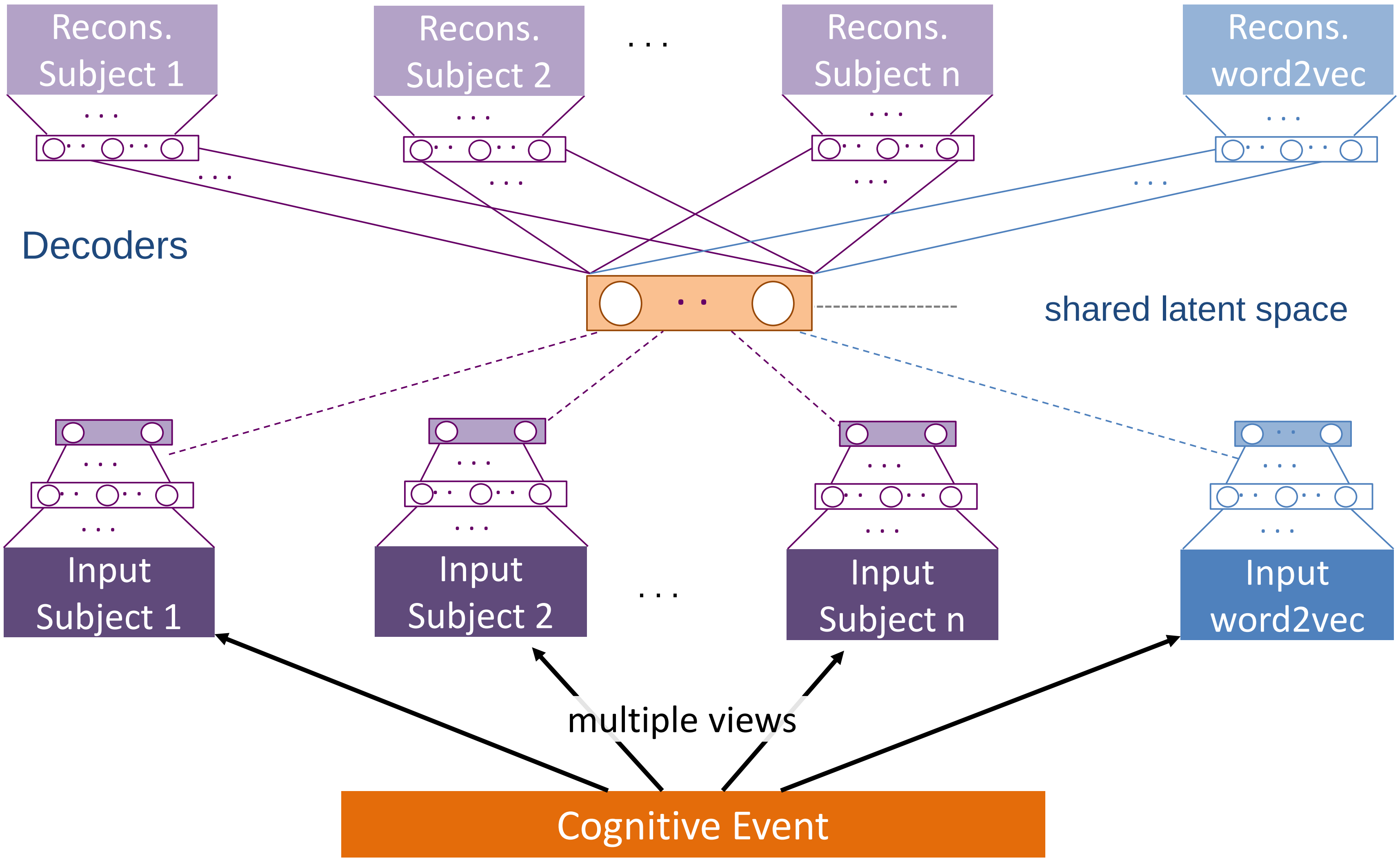

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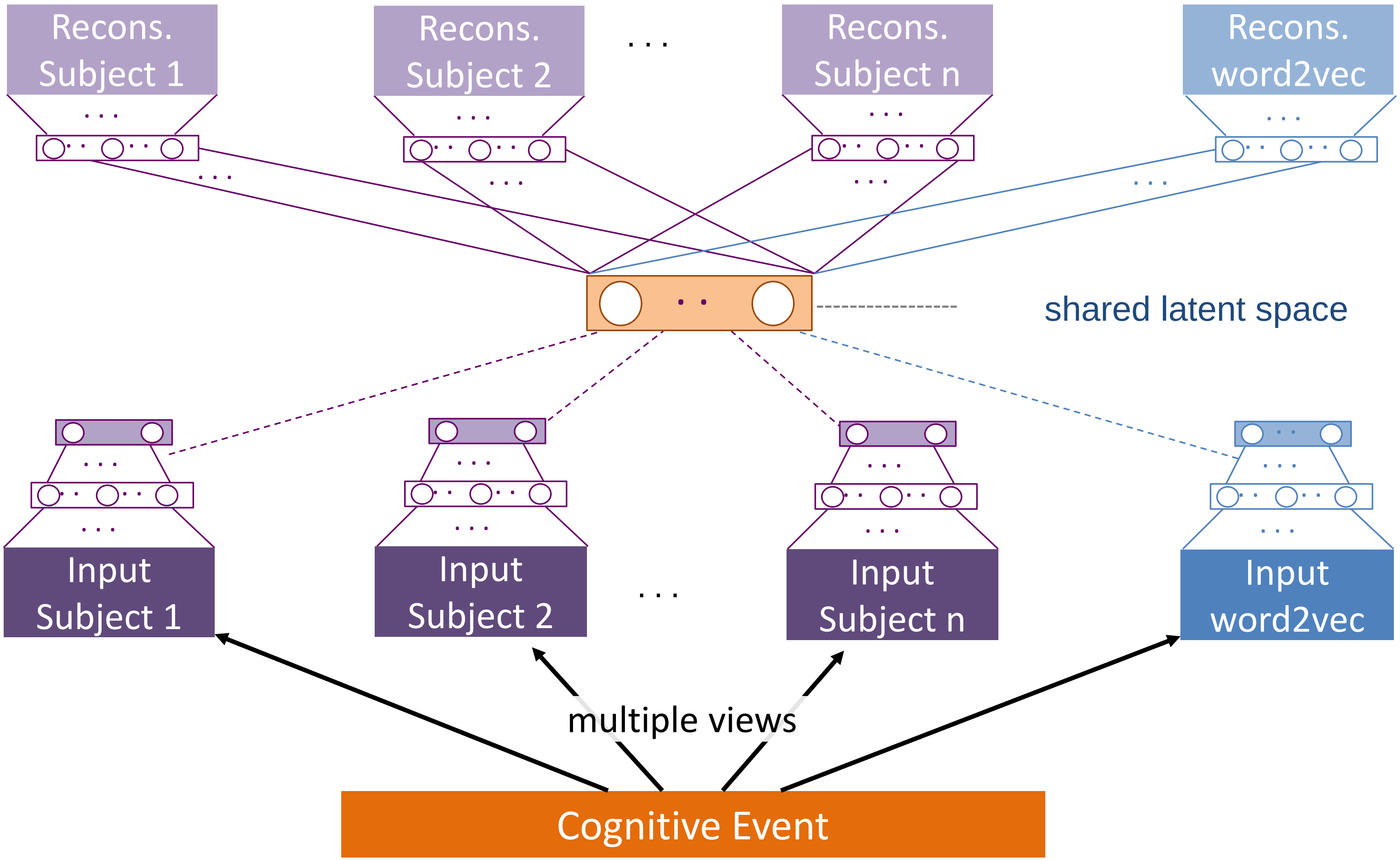

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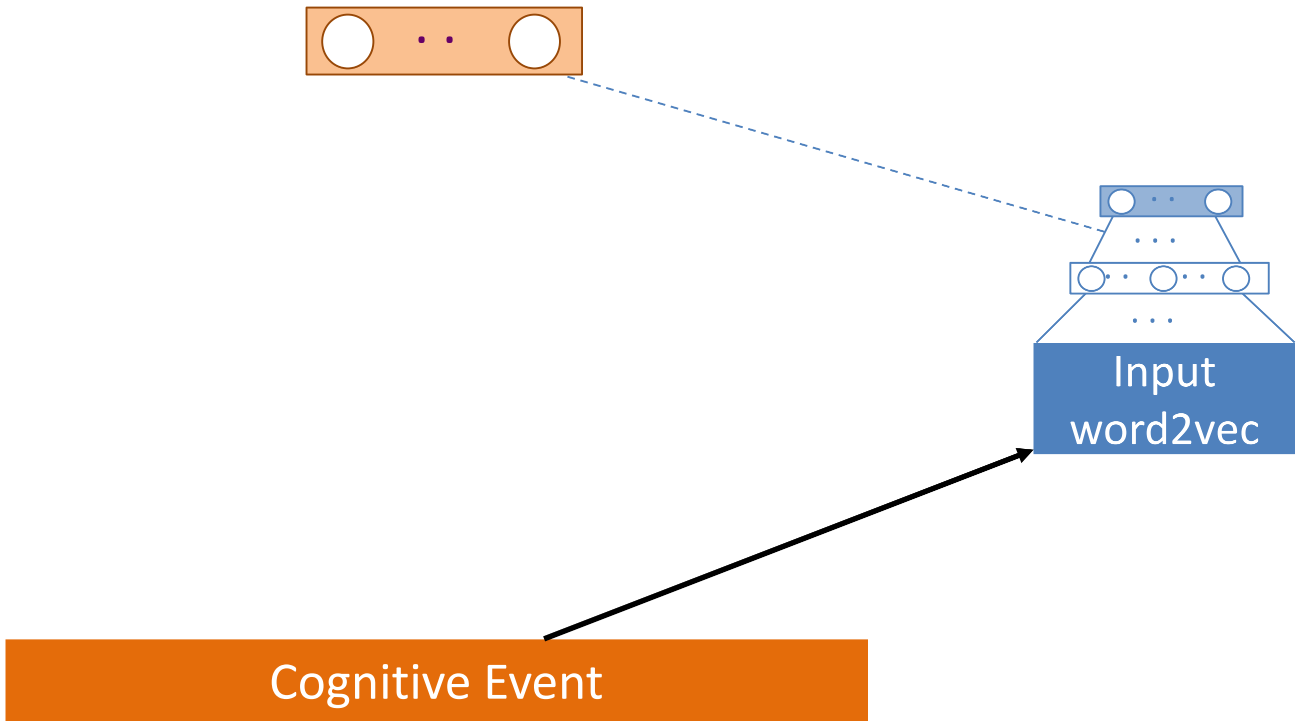
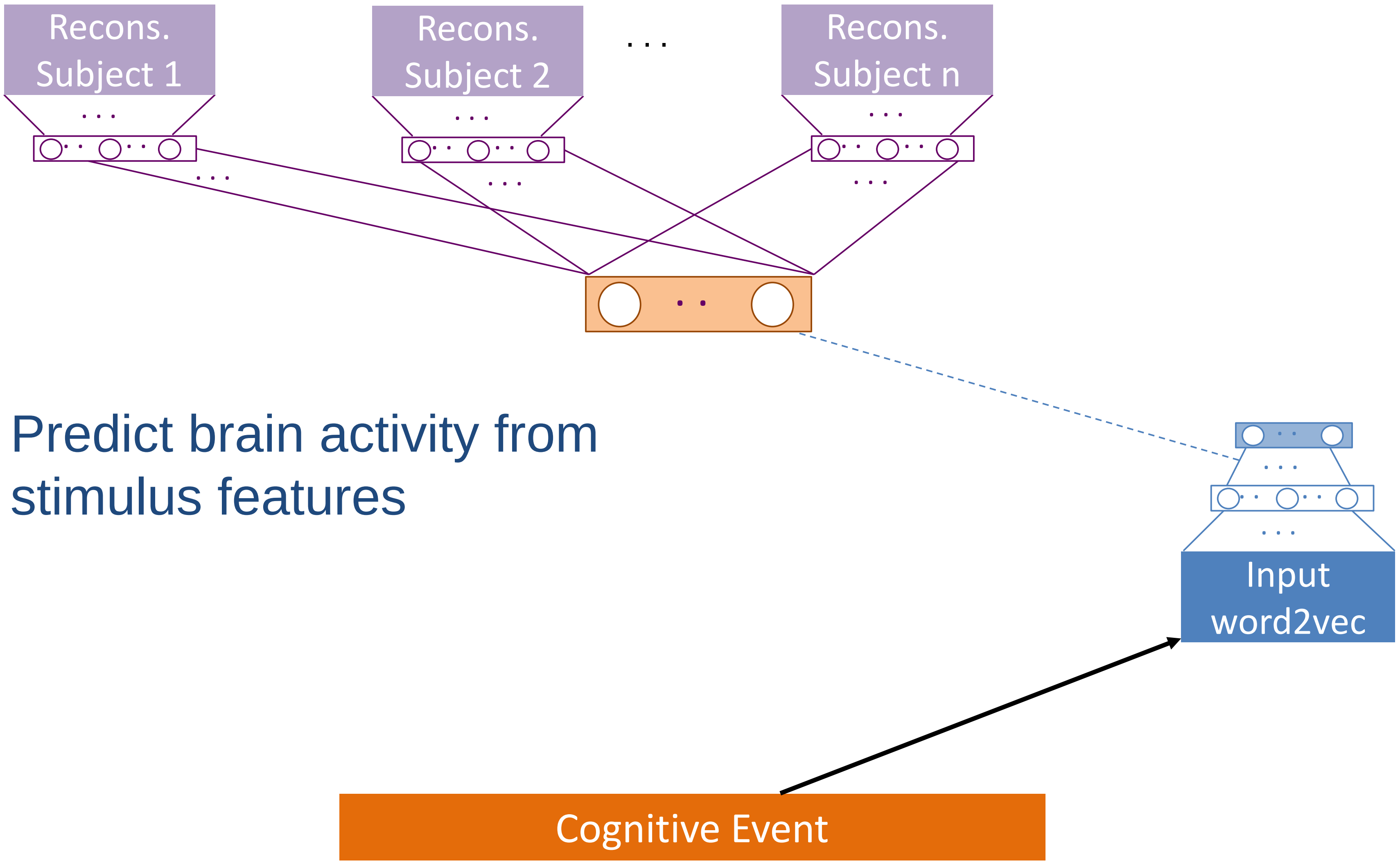
Estimation

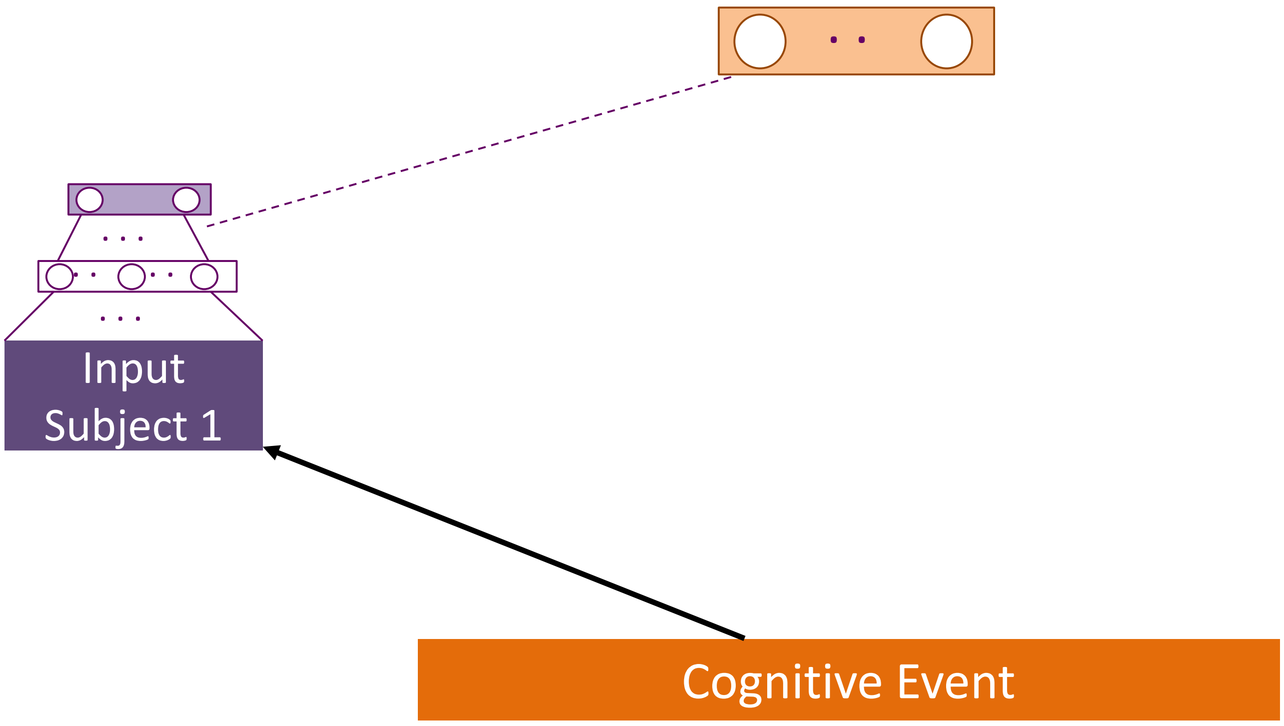


Estimation



Predict brain activity from stimulus features

Estimation



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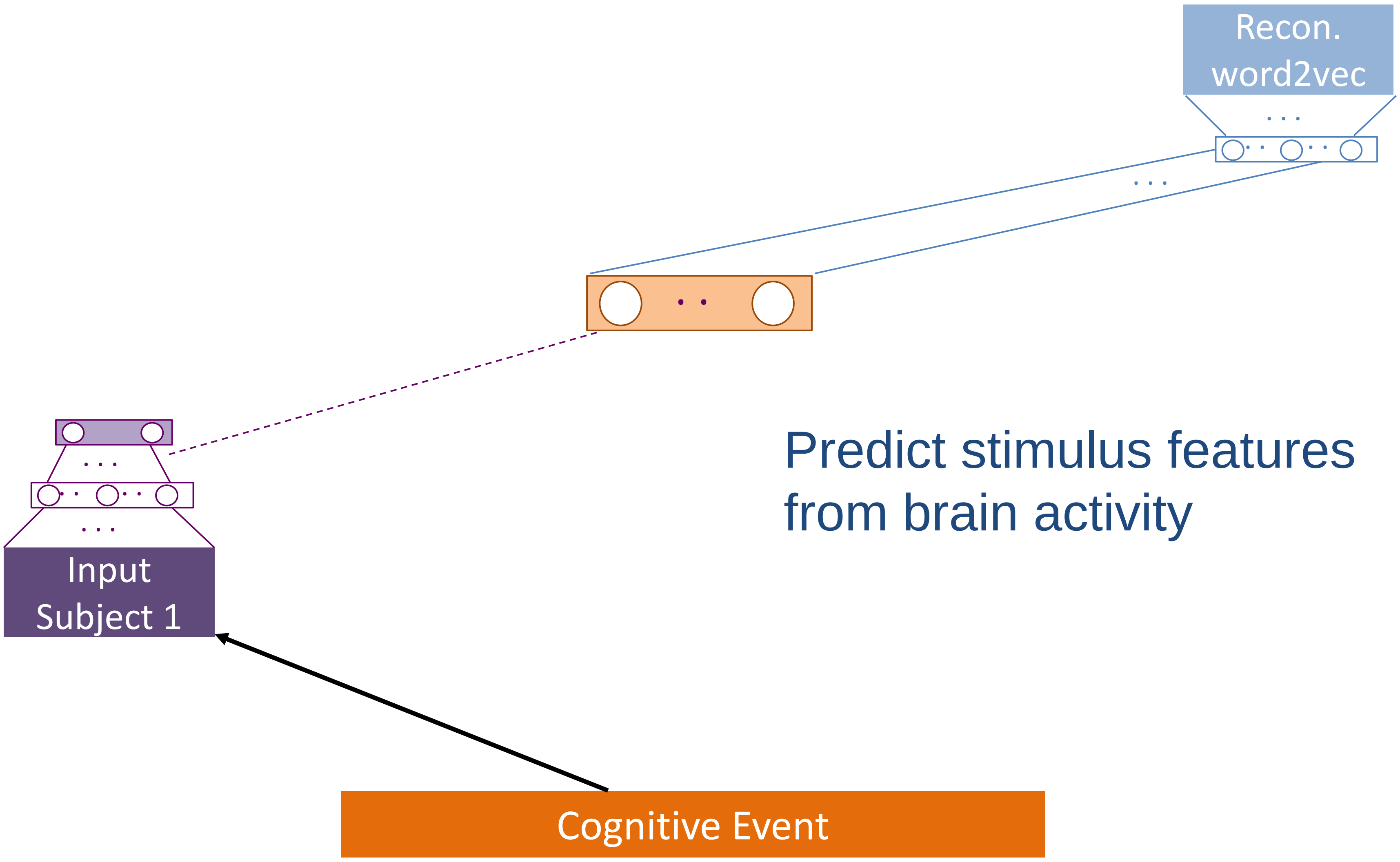

Predict stimulus features from brain activity

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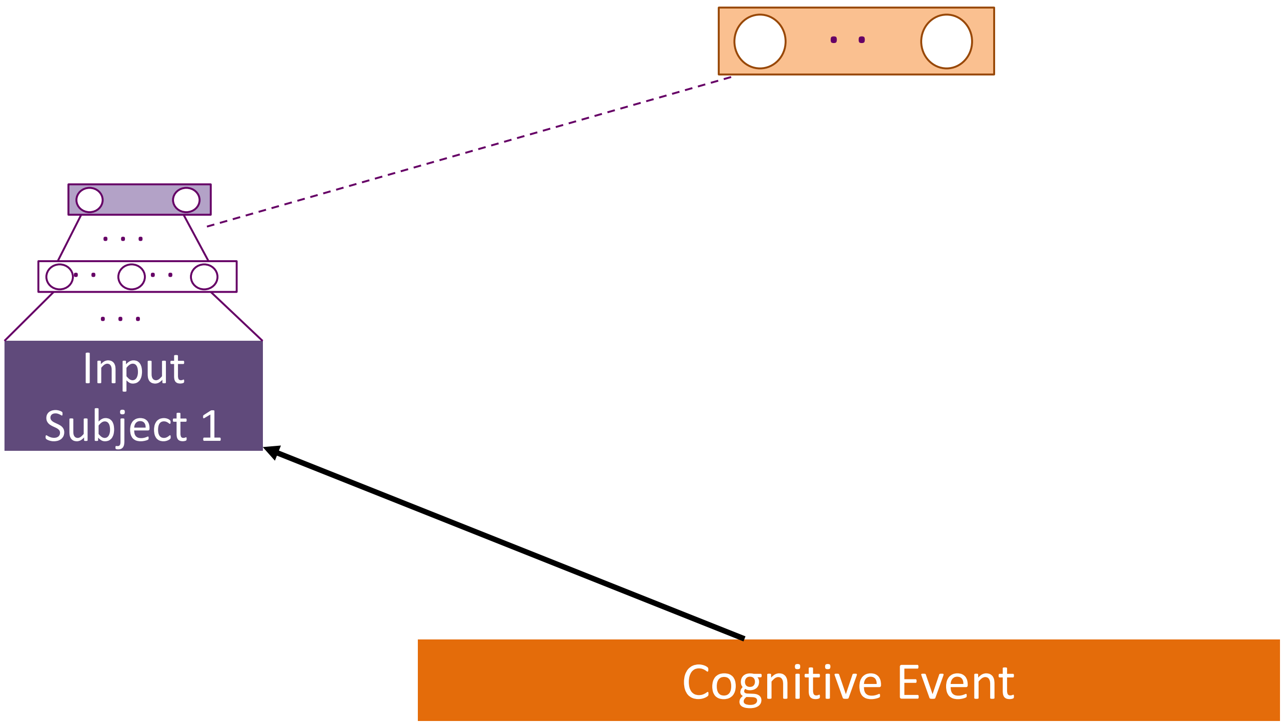

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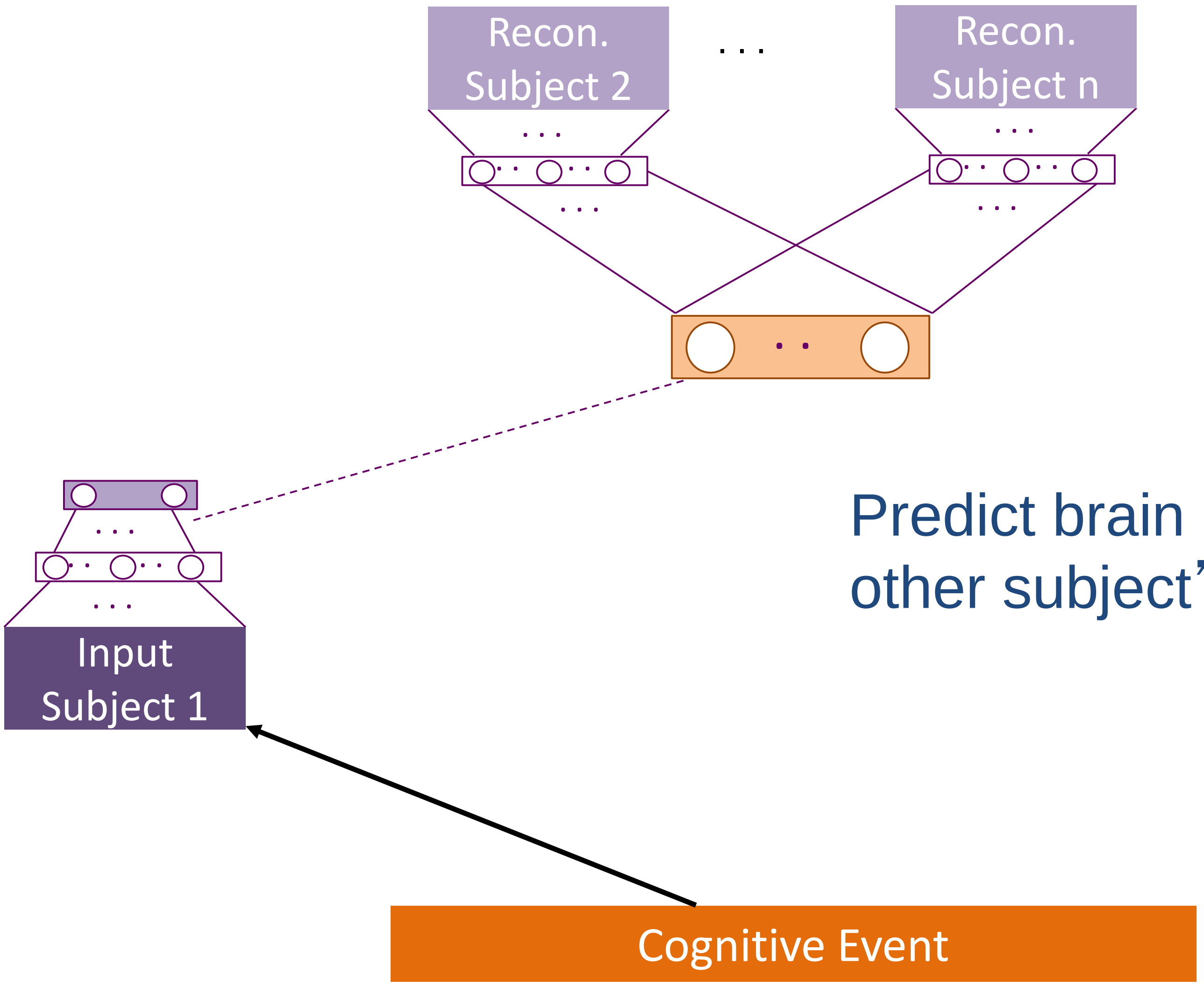
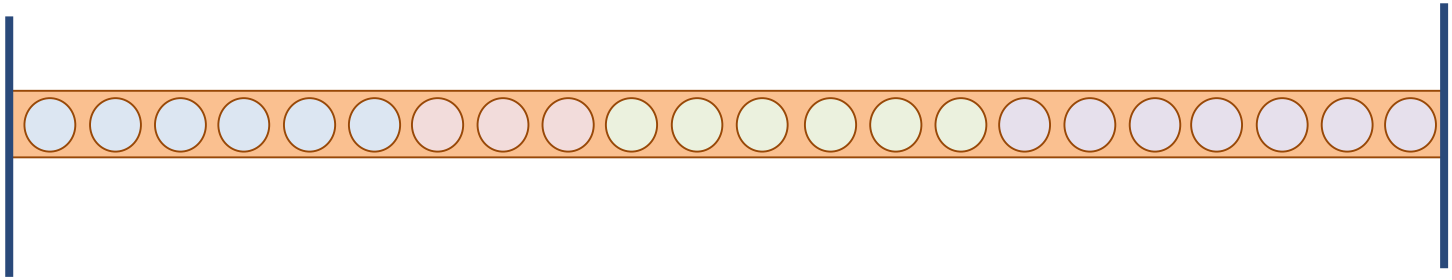


Predict brain activity from other subject's activity

Bottleneck Layer



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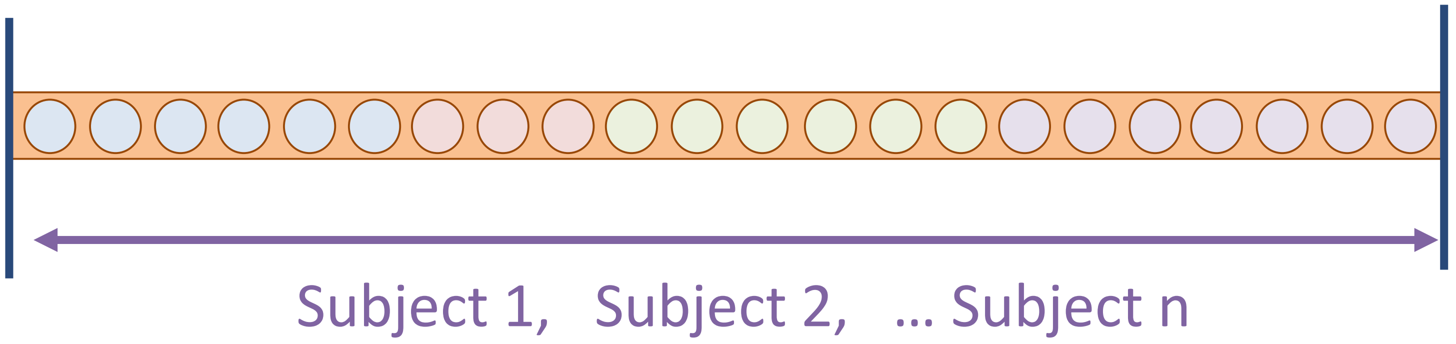

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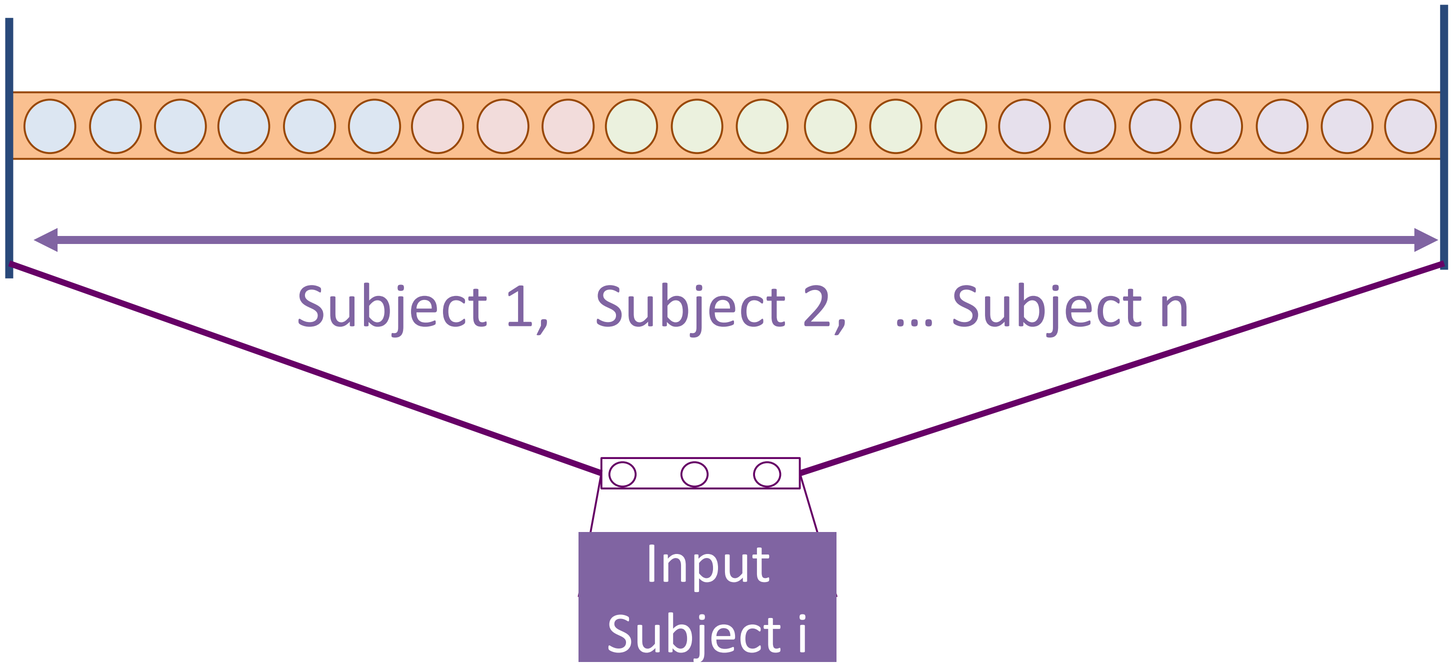

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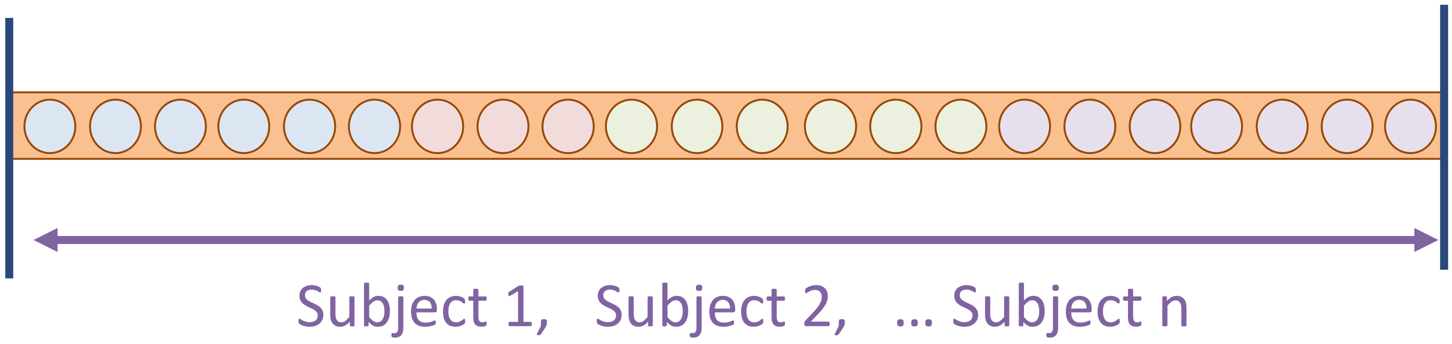

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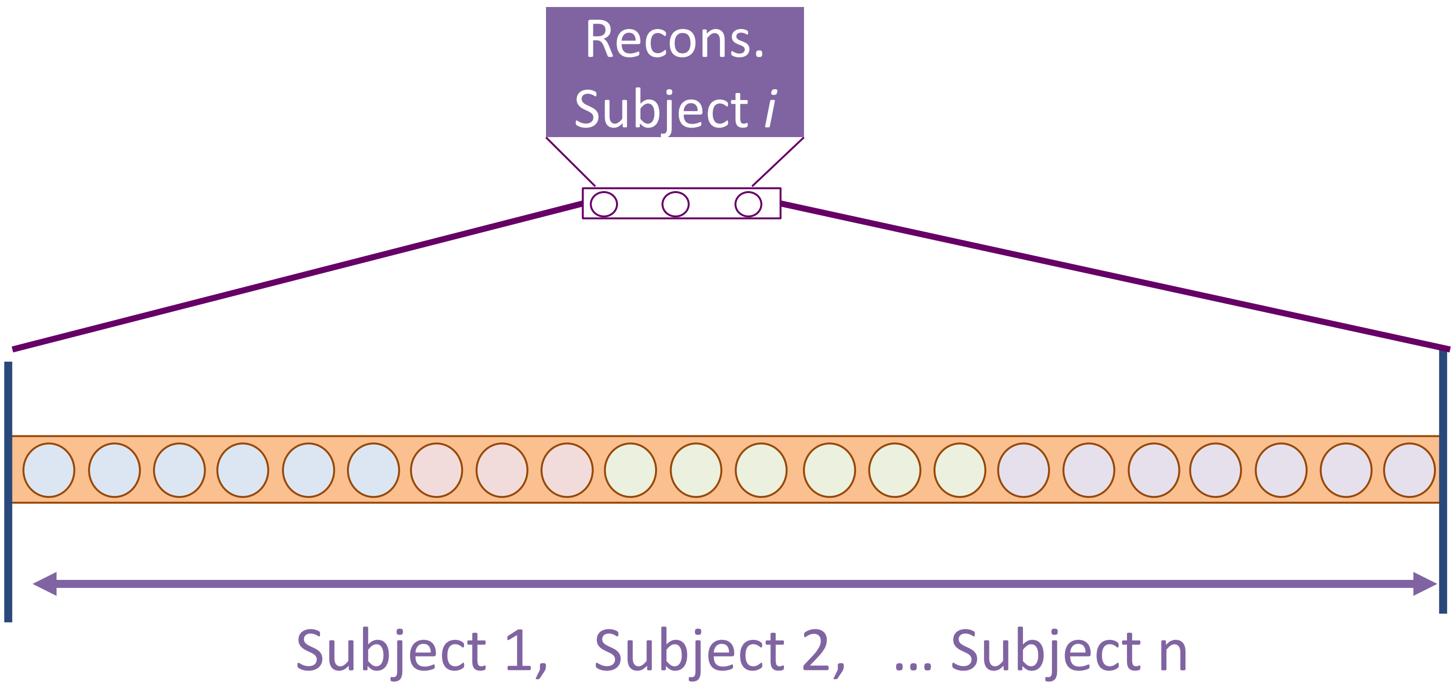

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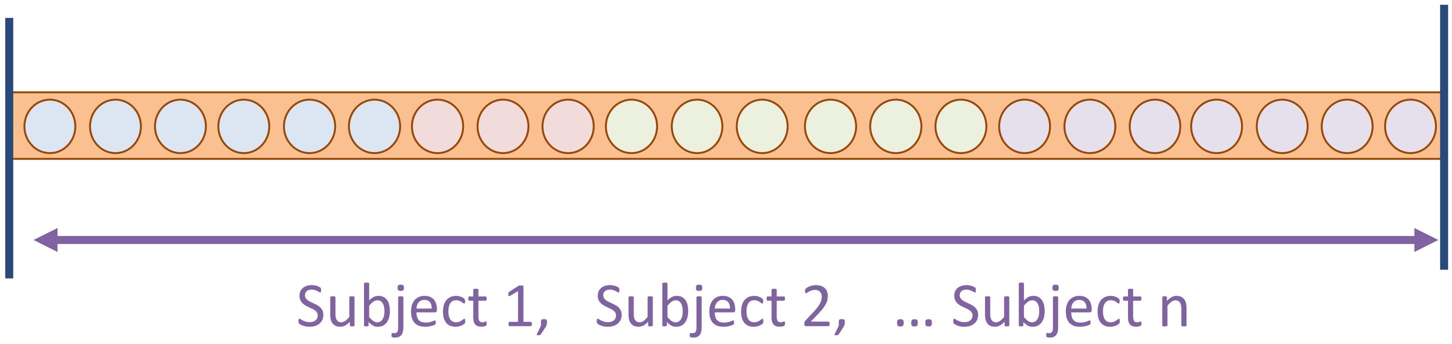

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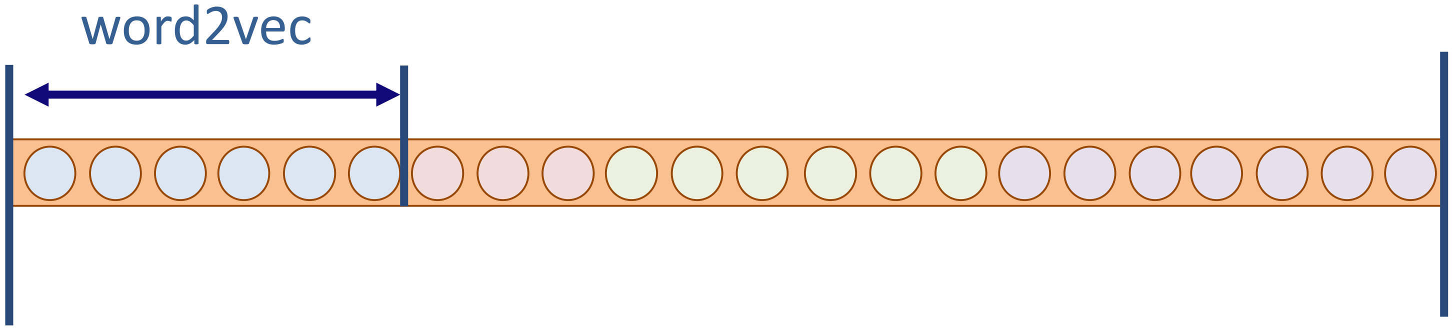

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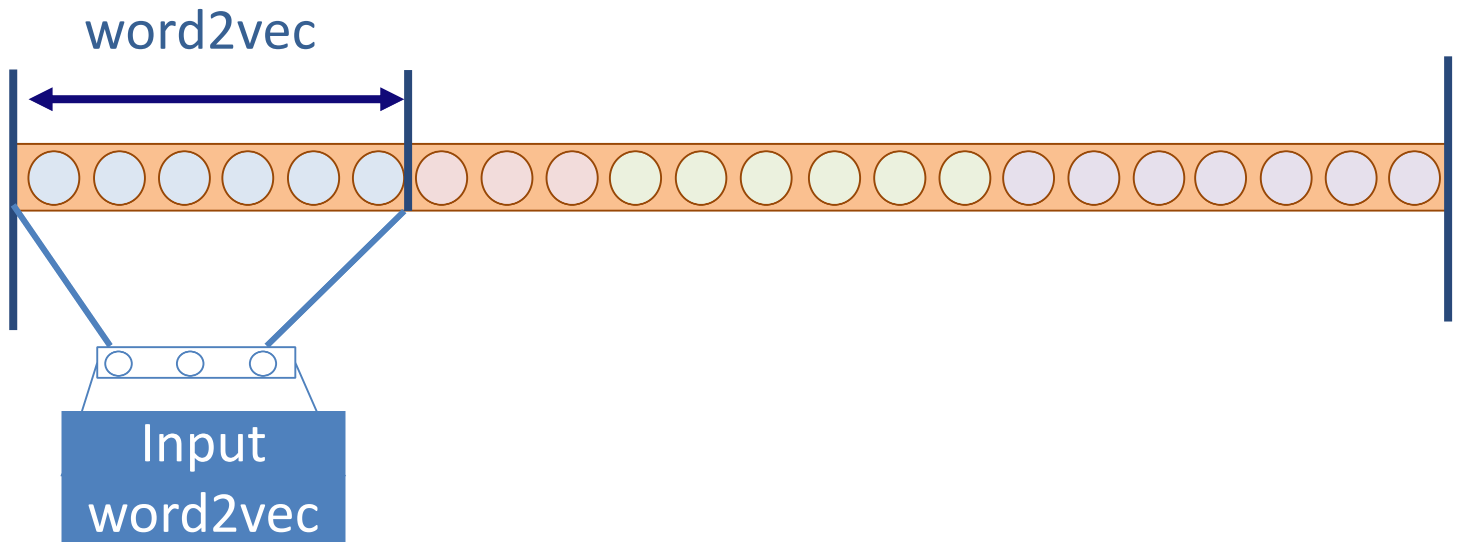

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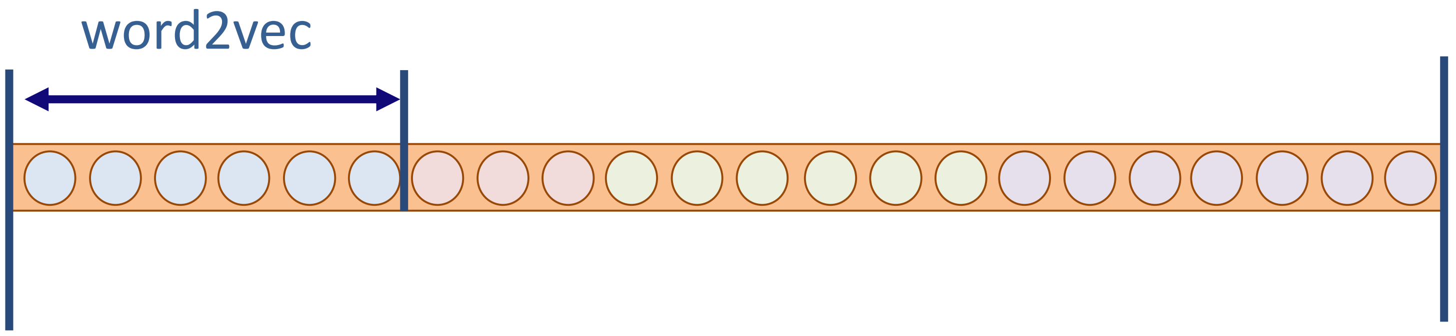

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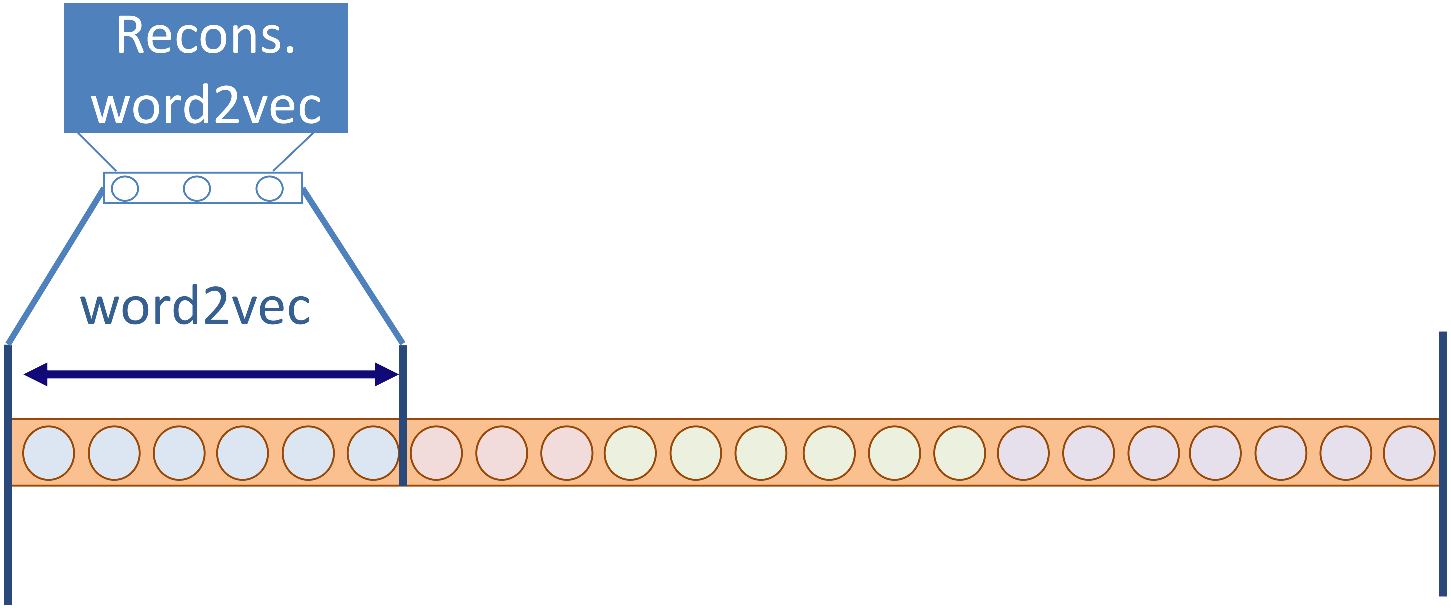

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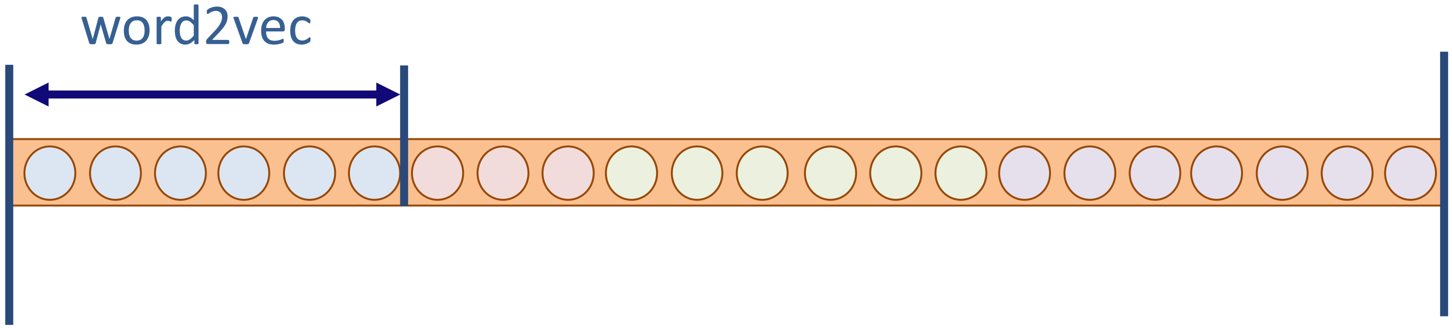

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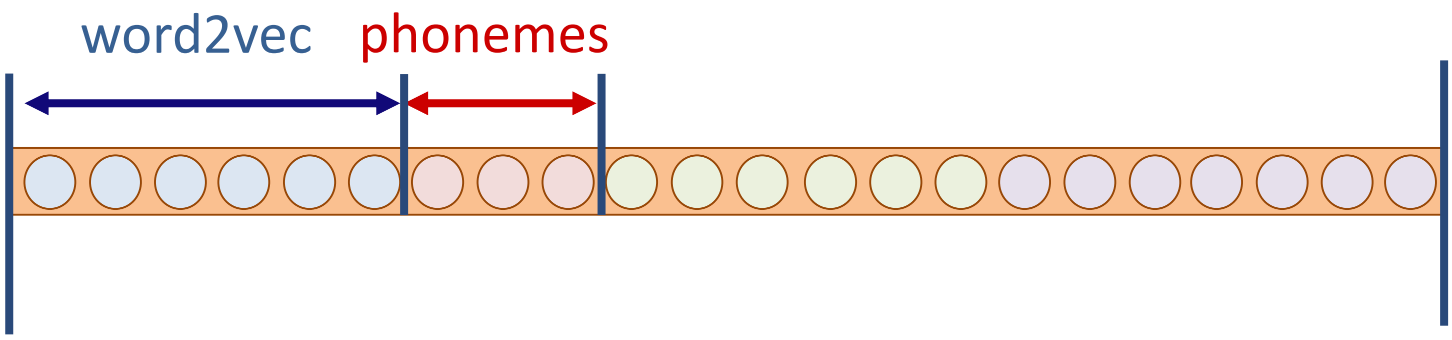

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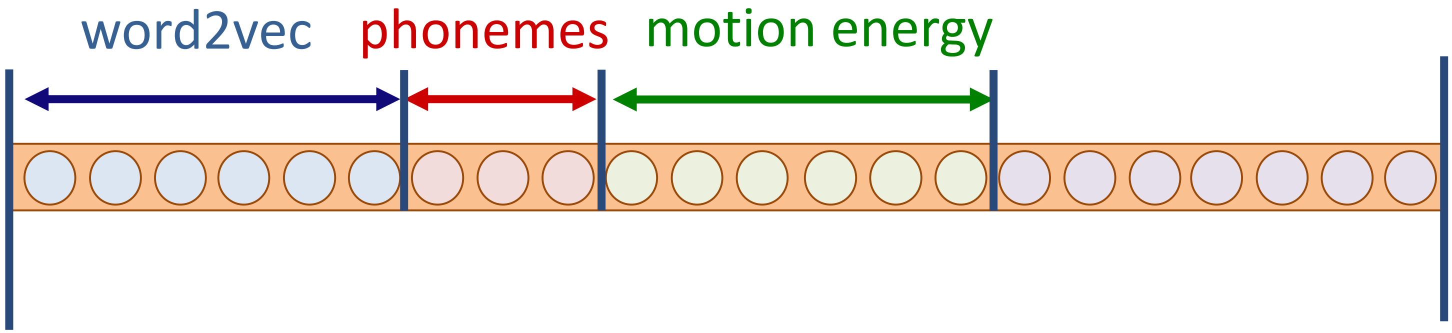

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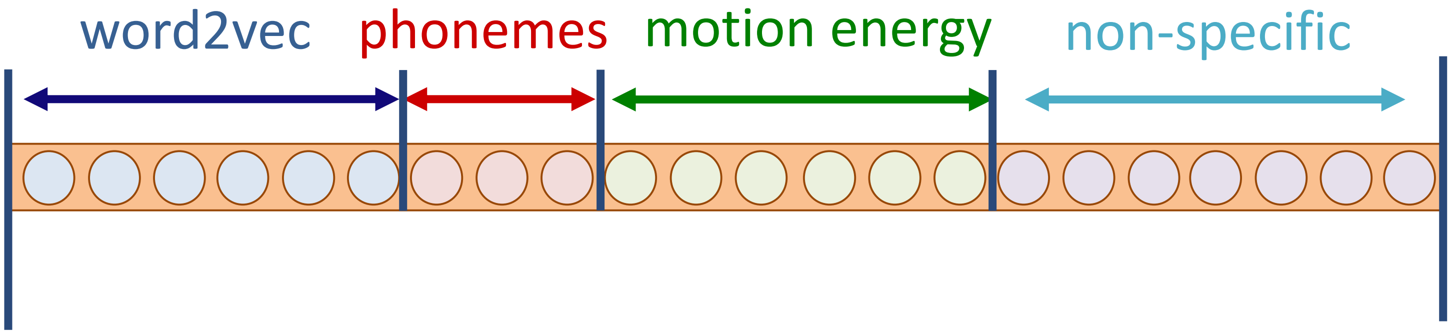

Multimodal representations

- We saw this in the school already
- Bimodal / split auto encoder (Ngiam et al. 2011)
- DCCA, DCCAE (Wang et al. 2015)

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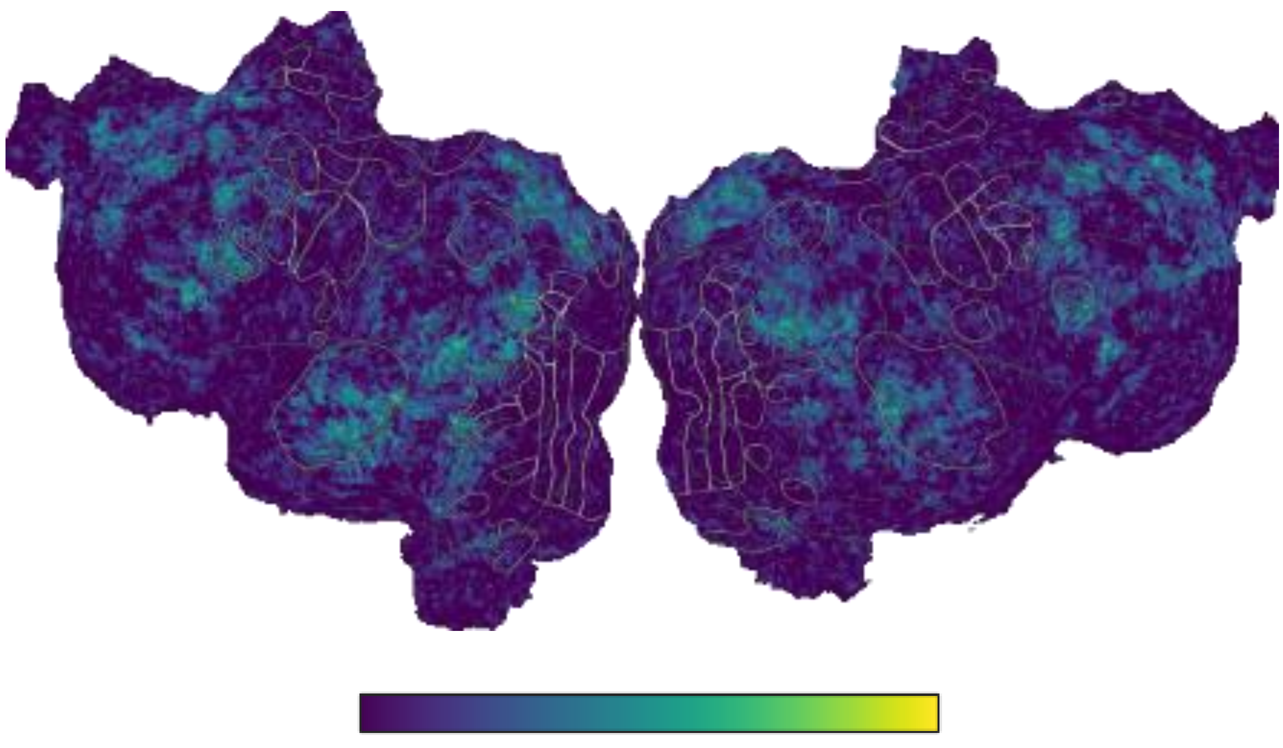
Multimodal fusion of brain structural and functional imaging with a deep neural machine translation approach

Md Faijul Amin[*], Sergey M. Plis[*], Eswar Damaraju[*], Devon Hjelm[*], KyungHyun Cho[†], Vince D. Calhoun[*‡]
[*]The Mind Research Network, 1101 Yale Blvd, Albuquerque, NM 87106, USA
[†]Courant Institute & Center for Data Science, New York University, New York, NY 10012, USA
[‡]Department of ECE, University of New Mexico, Albuquerque, NM 87106, USA

Results: predicting brain activity

Input = word2vec

Output = story data



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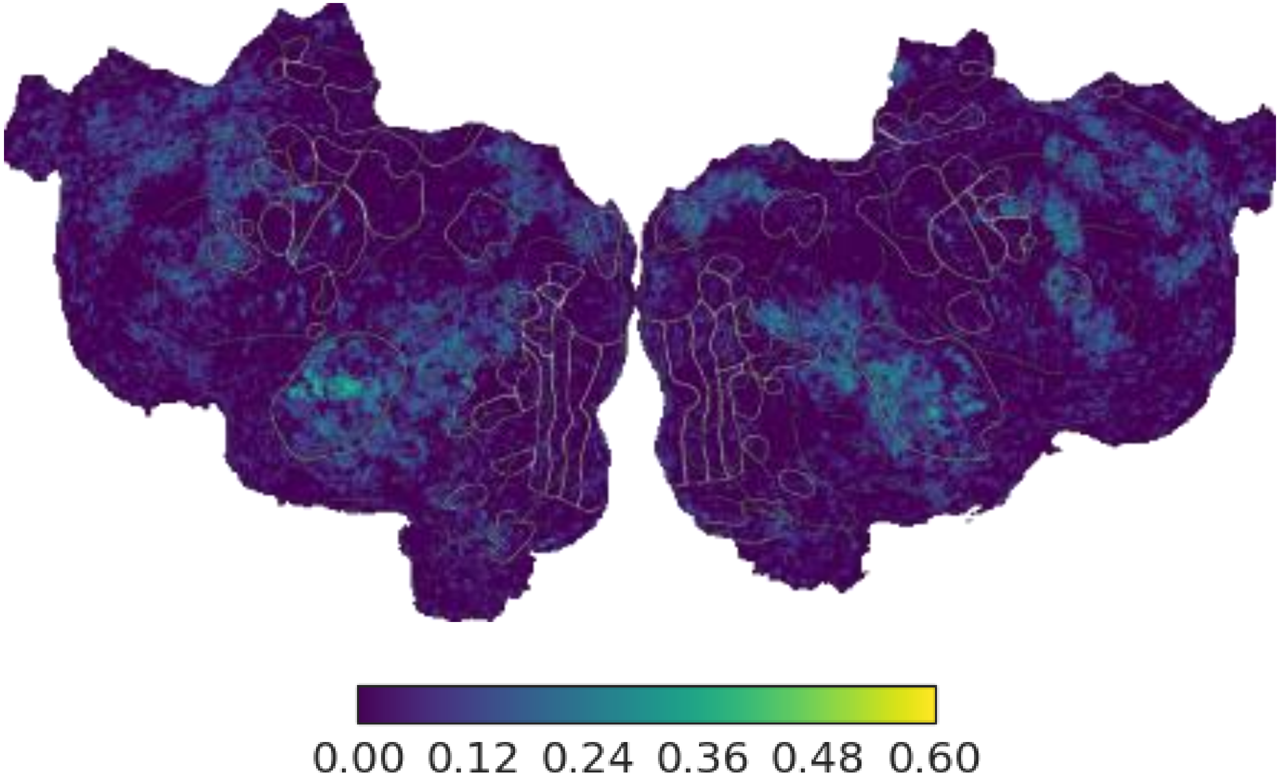
Results: predicting brain activity

Input = phonemes
Output = story data



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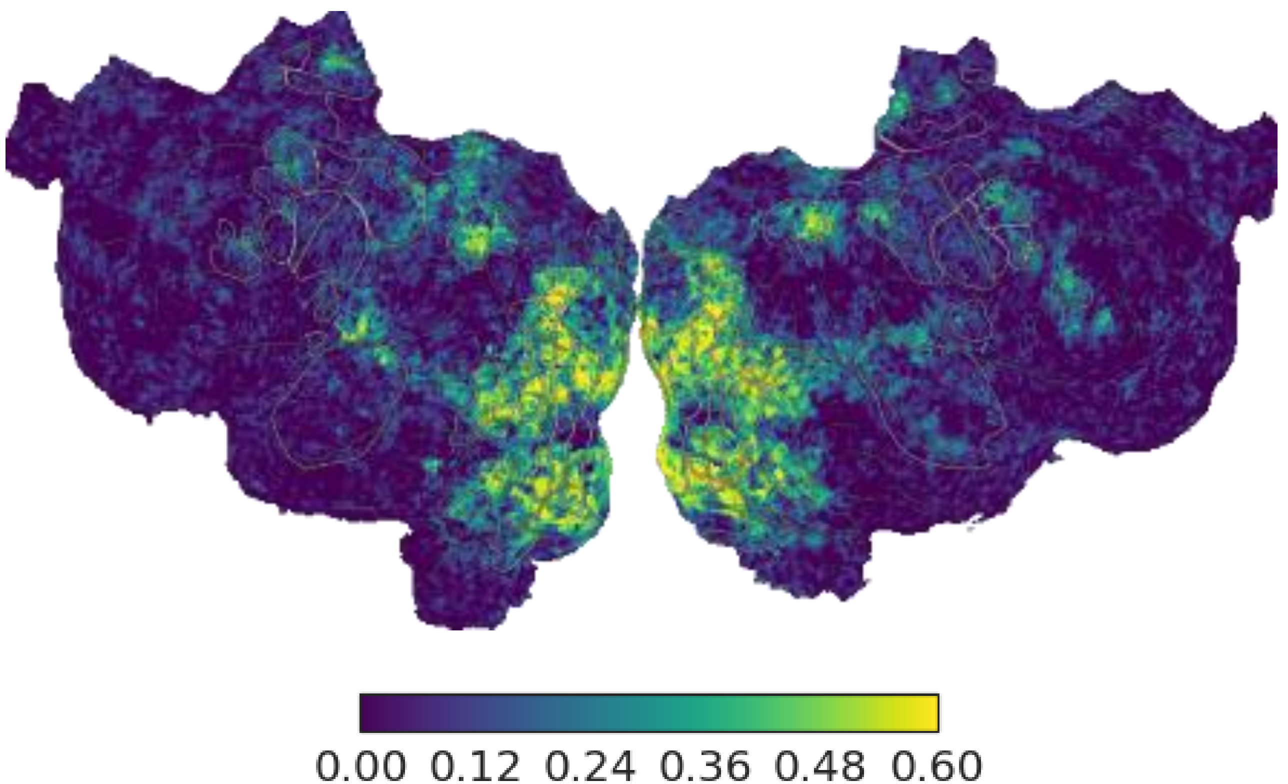
Results: predicting brain activity

Input = motion energy
Output = movie data



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Results: predicting brain activity

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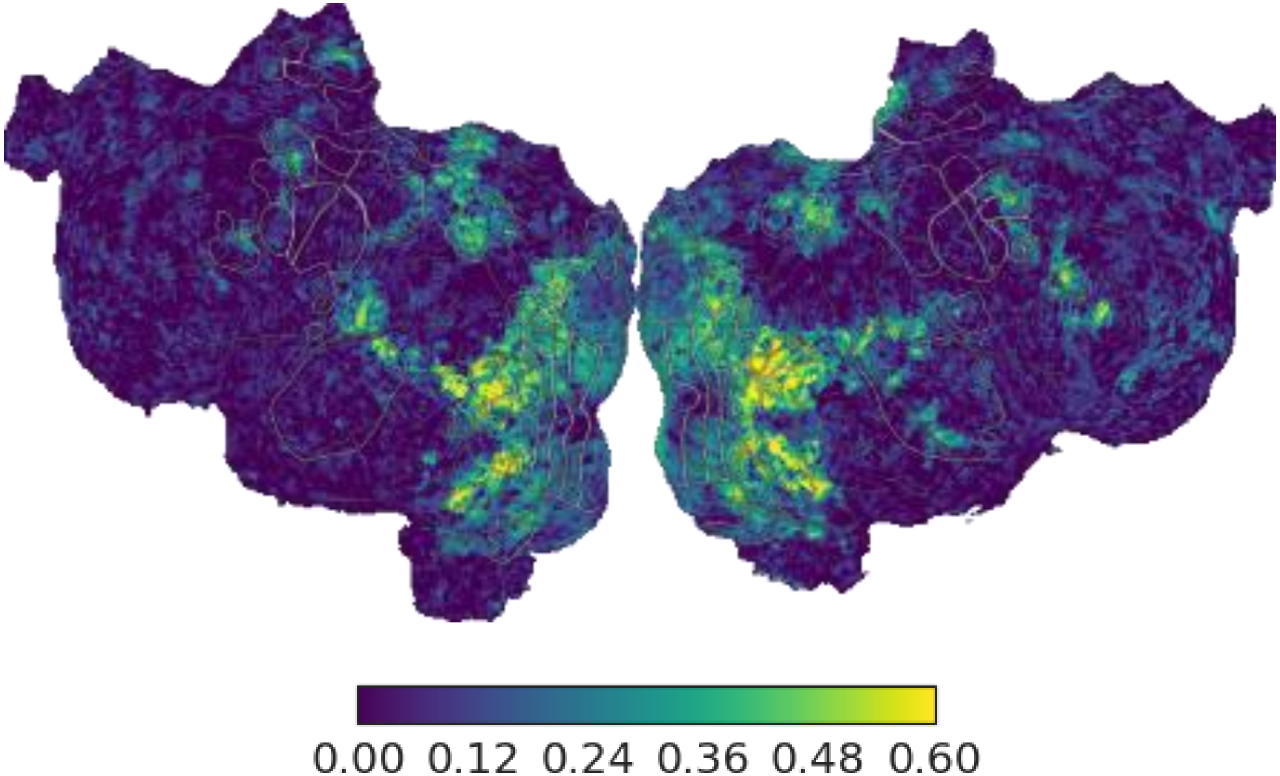
Output = movie data



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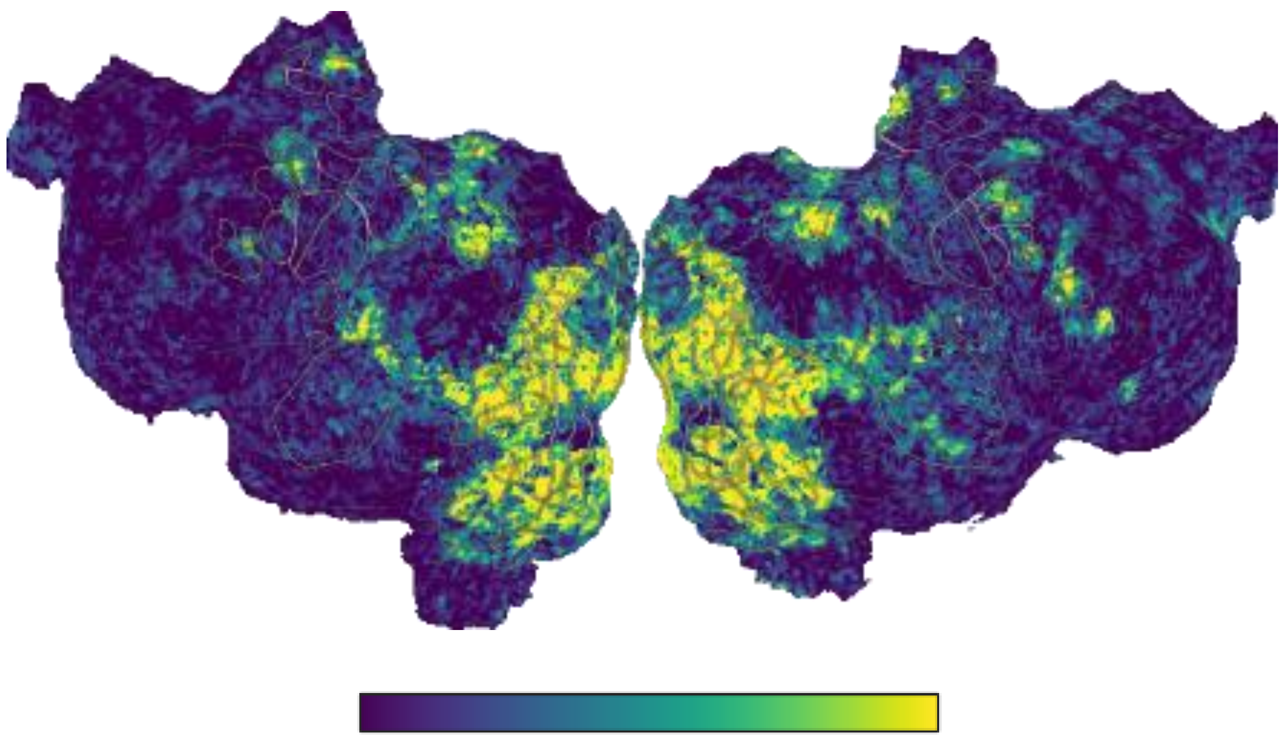
Results: predicting brain activity

Input = S2

Output = movie data (S1)



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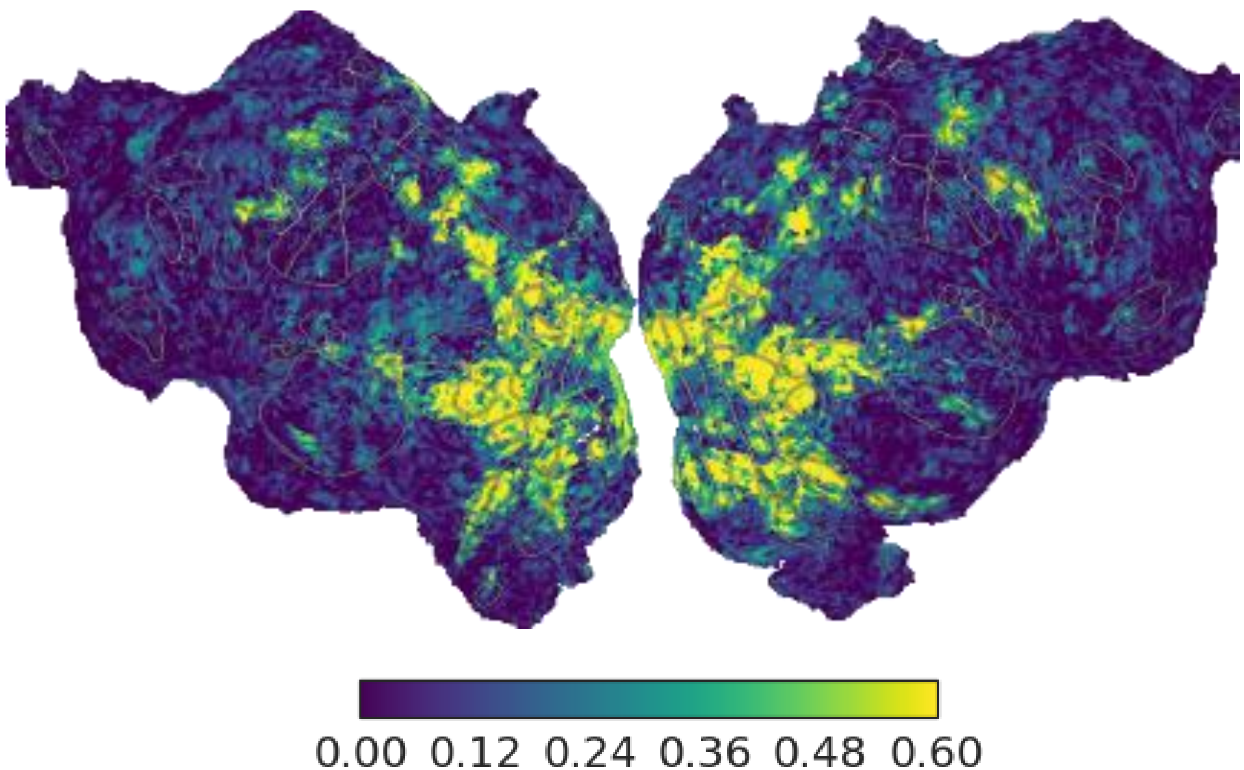
Results: predicting brain activity

Input = S1

Output = movie data (S2)



Leila Wehbe

A unified model

A unified model

- For experiments, subjects and feature spaces

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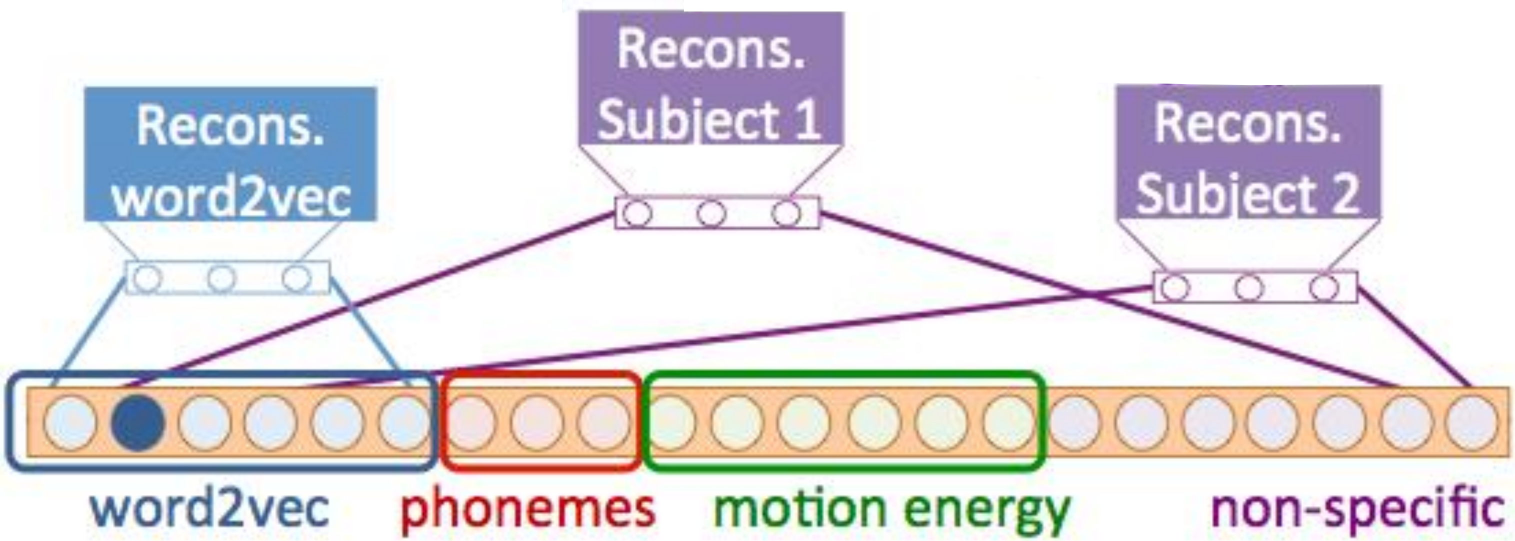
- For experiments, subjects and feature spaces
- Enables standard neuroimaging tasks
  - Good performance

A unified model

- For experiments, subjects and feature spaces
- Enables standard neuroimaging tasks
  - Good performance

- Also learns an embedding space for brain responses / stimulus features

Exploring the learned space



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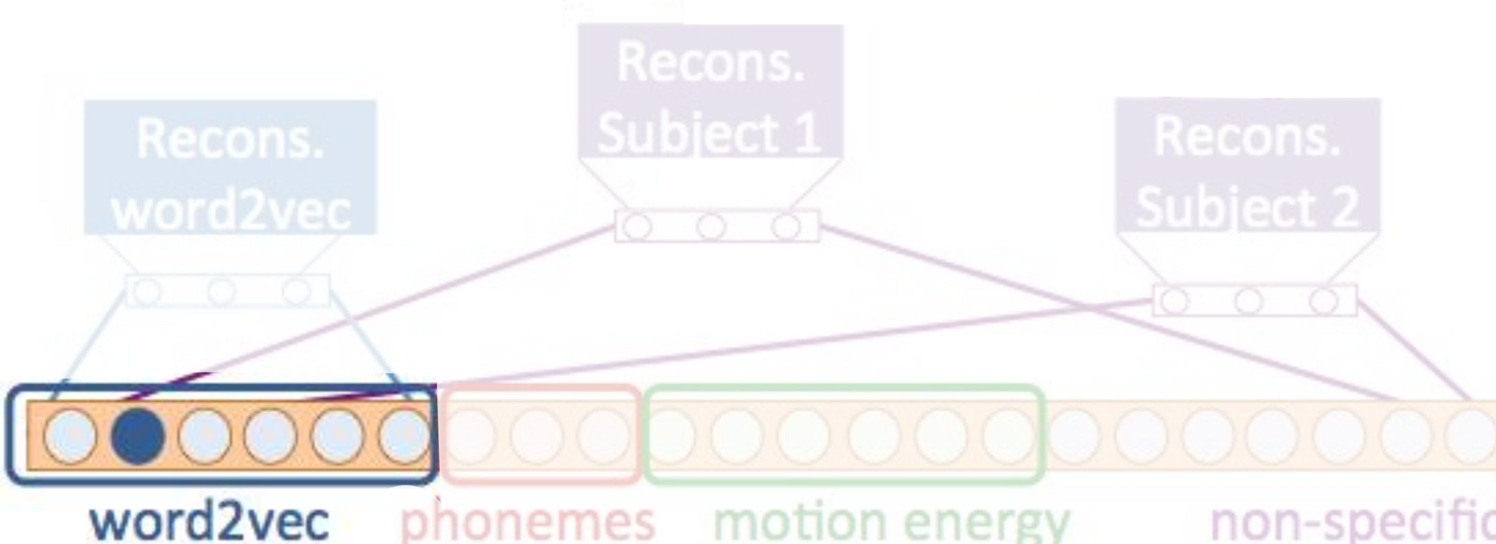

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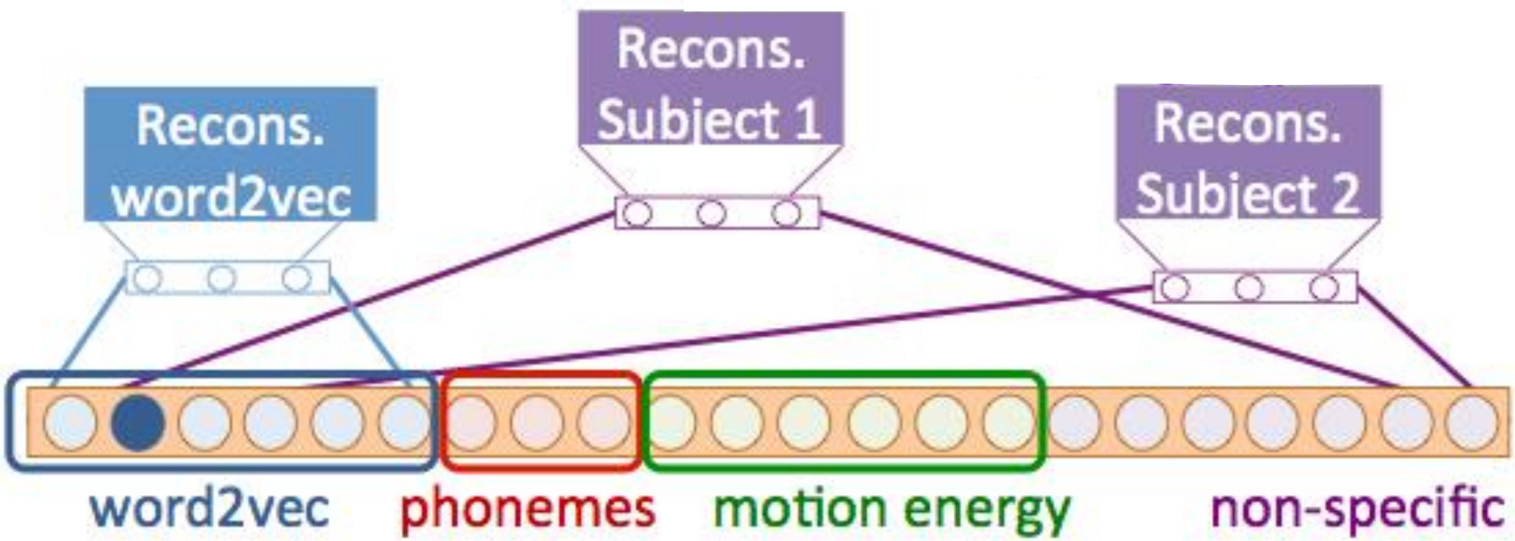
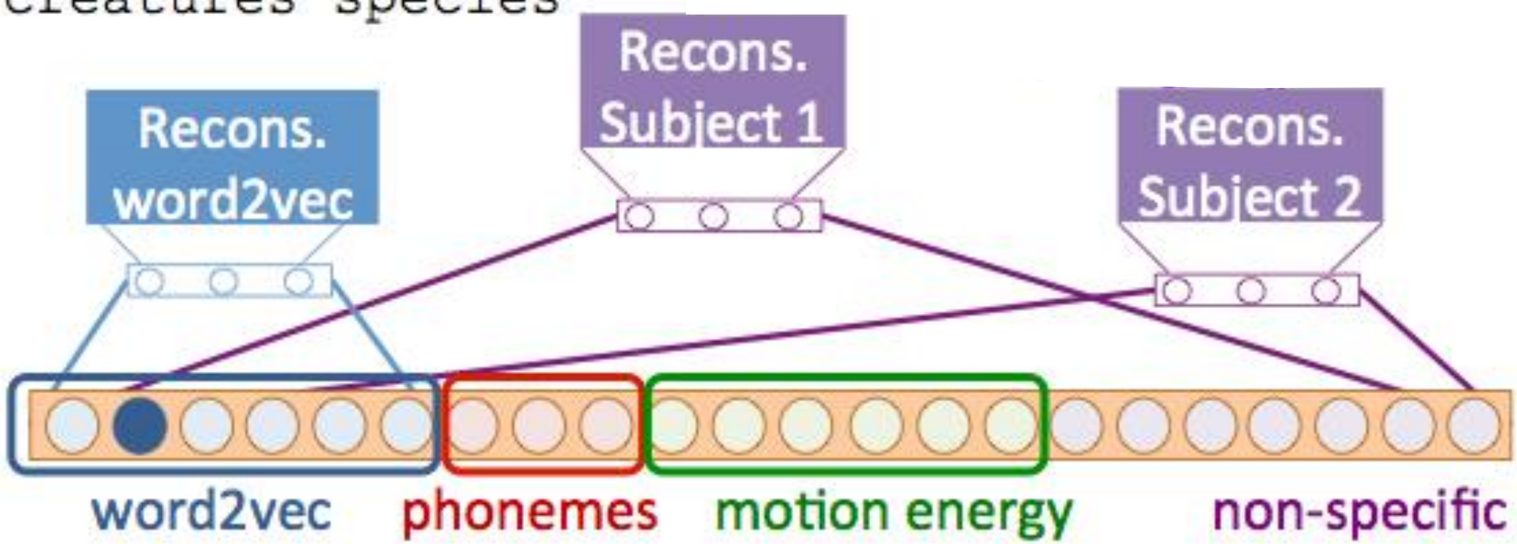


Exploring the learned space

Top-n similar: mammals

mammal marine_mammals
primates organisms
microorganisms humans
microbial animal
microbes reptiles
creatures species



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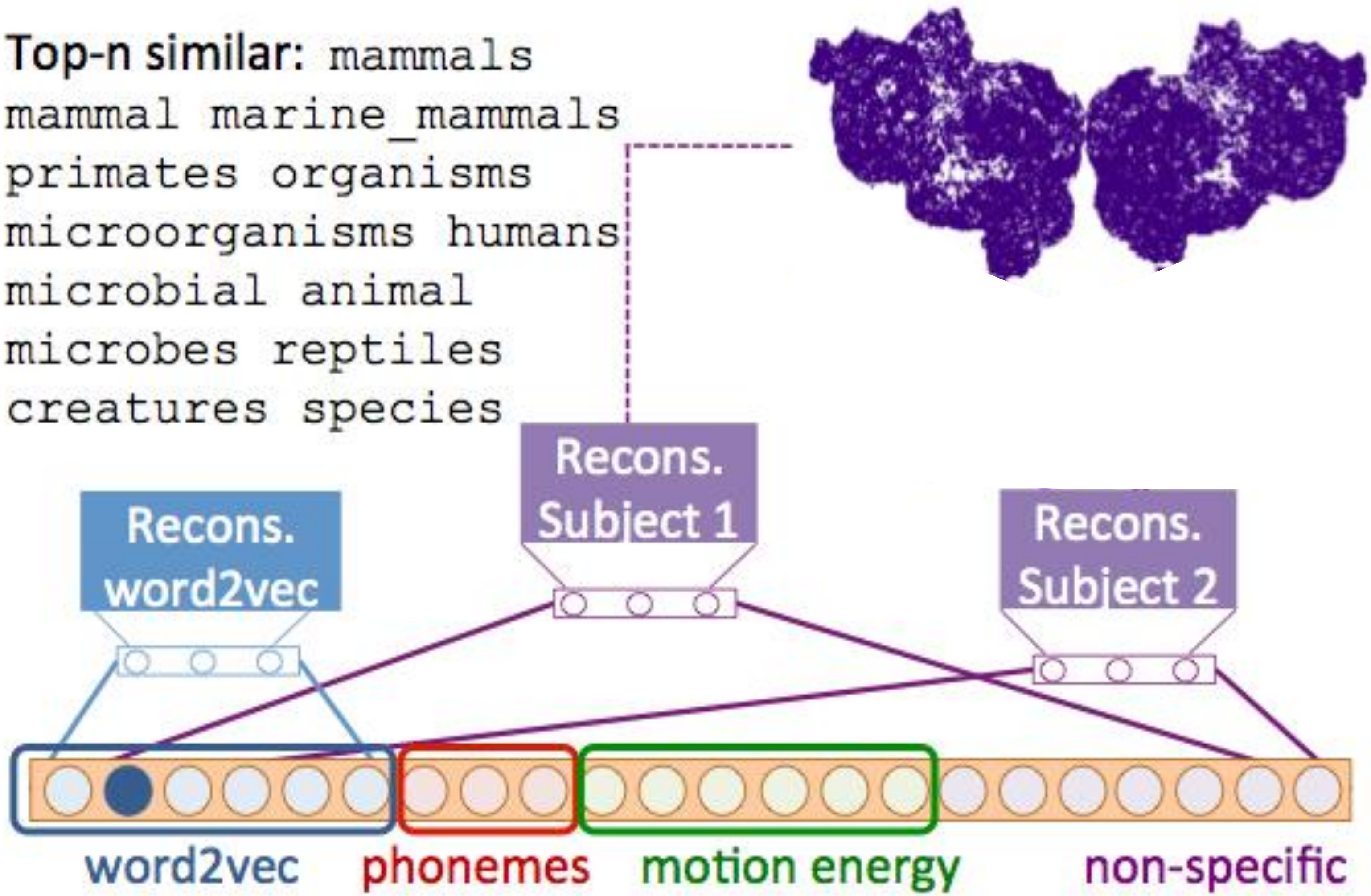

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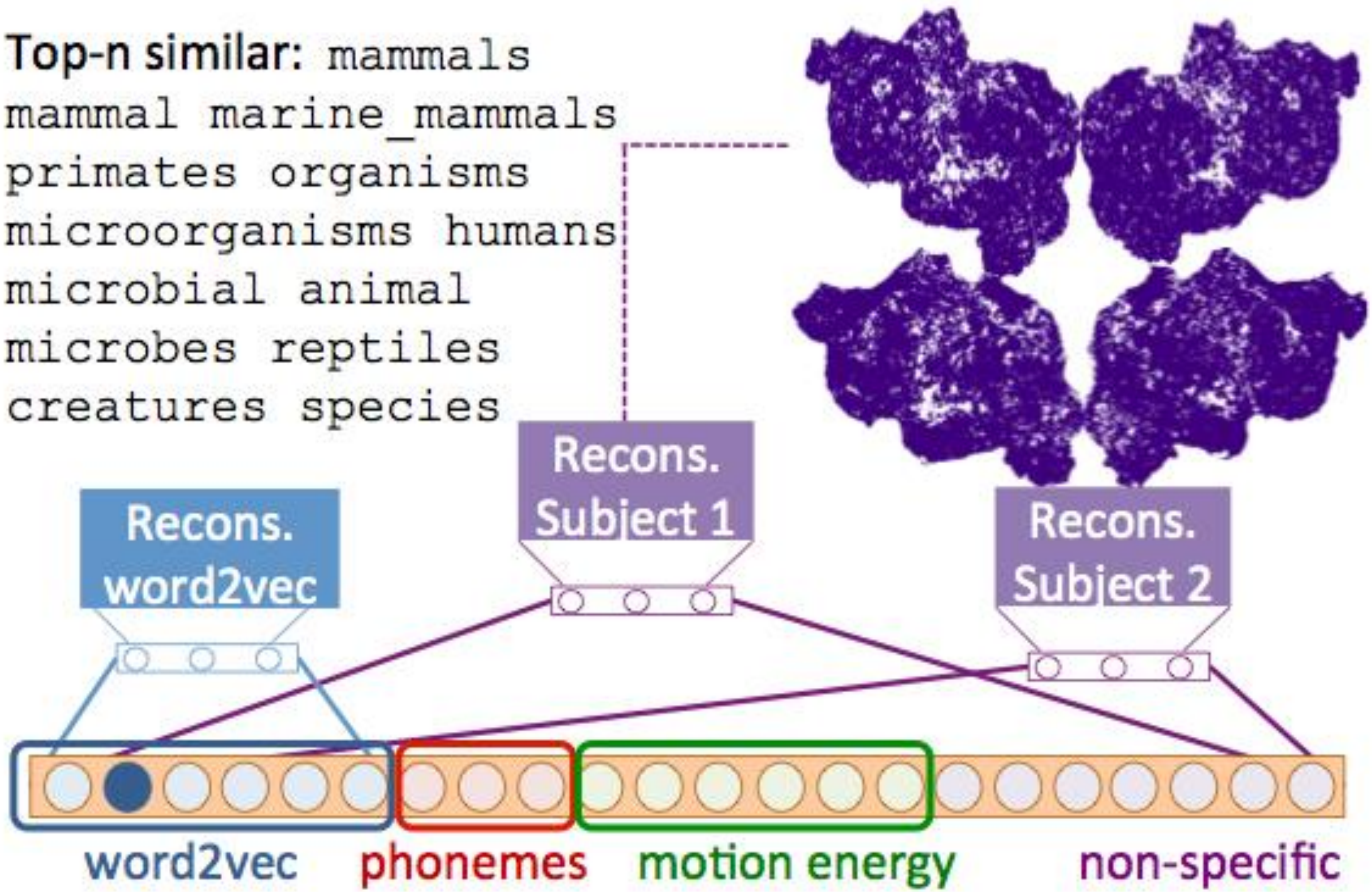


Future work

Future work

- Use spatial information

Future work

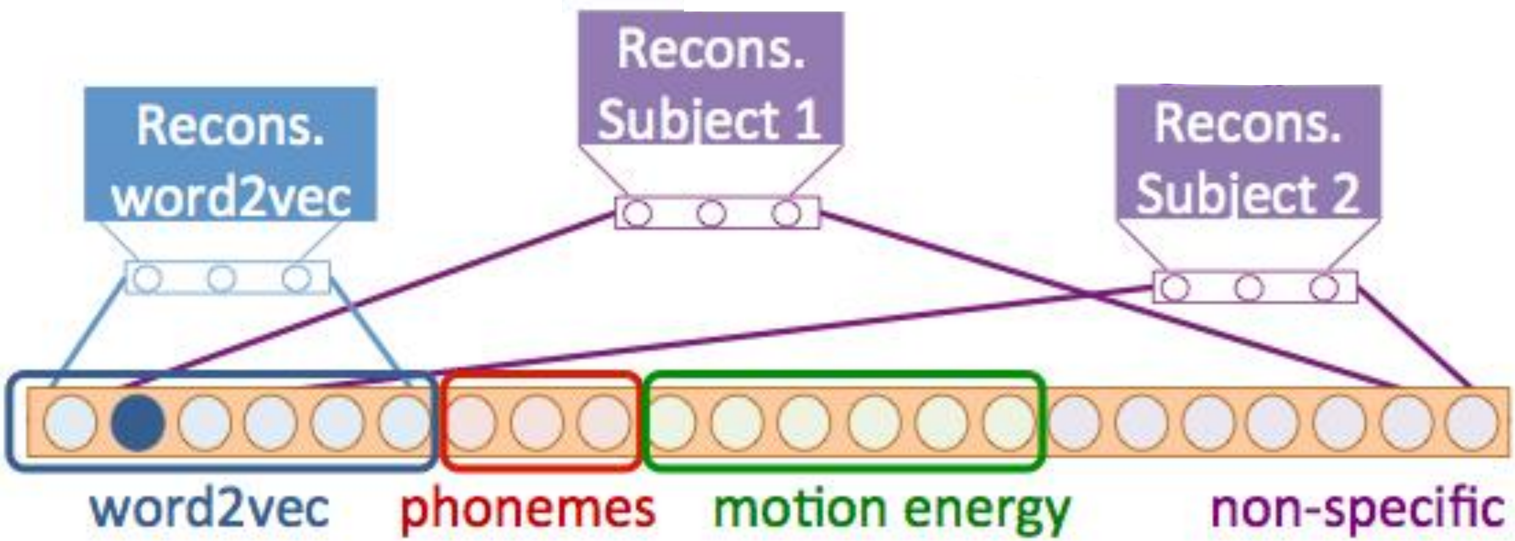
- Use spatial information

- Use temporal information

Future work

- Use spatial information
- Use temporal information
- Learn allocation of feature spaces automatically, not as hyper parameter

Thank you


Recons.
word2vec
Recons.
Subject 1
Recons.
Subject 2
word2vec
phonemes
motion energy
non-specific