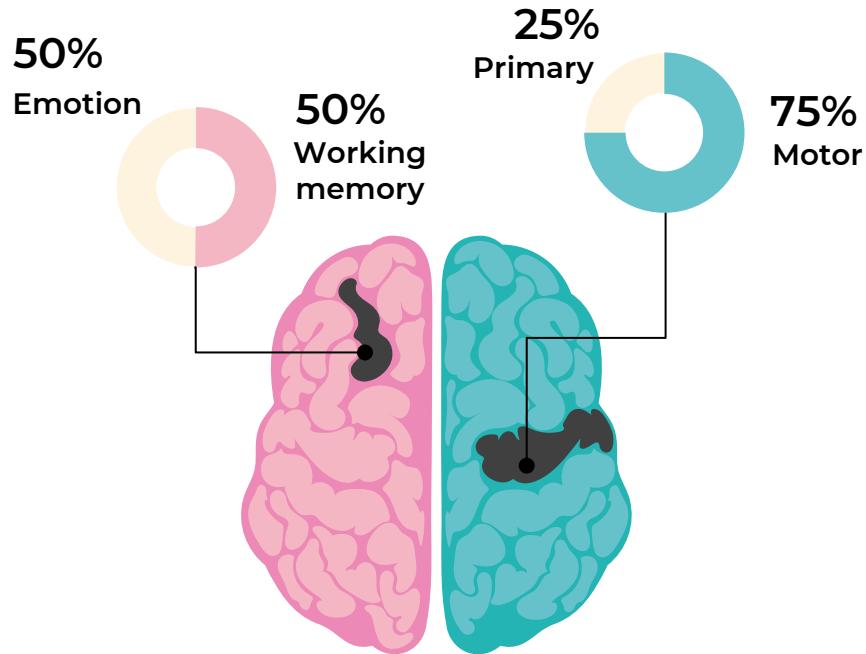


Meta-analytic  
**Functional  
Decoding**

Youngjo Song

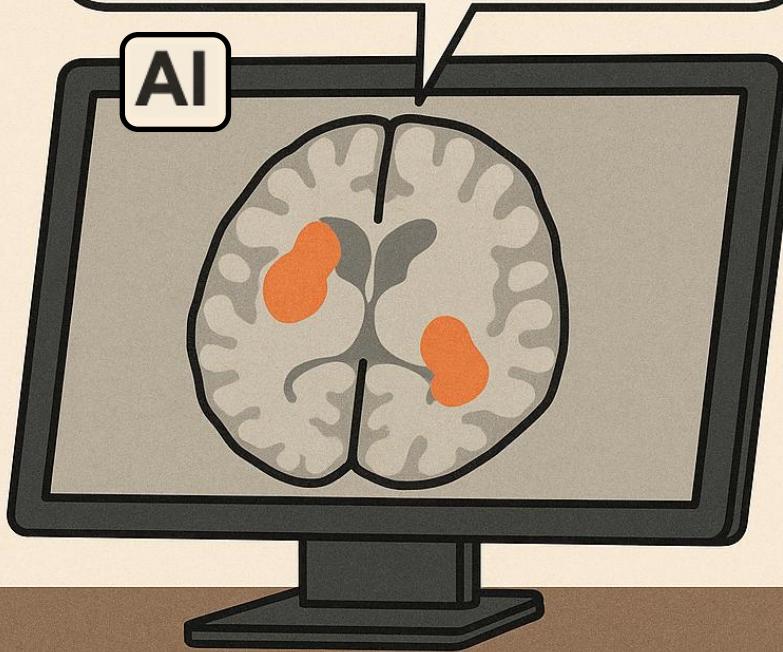


In Old Days,...

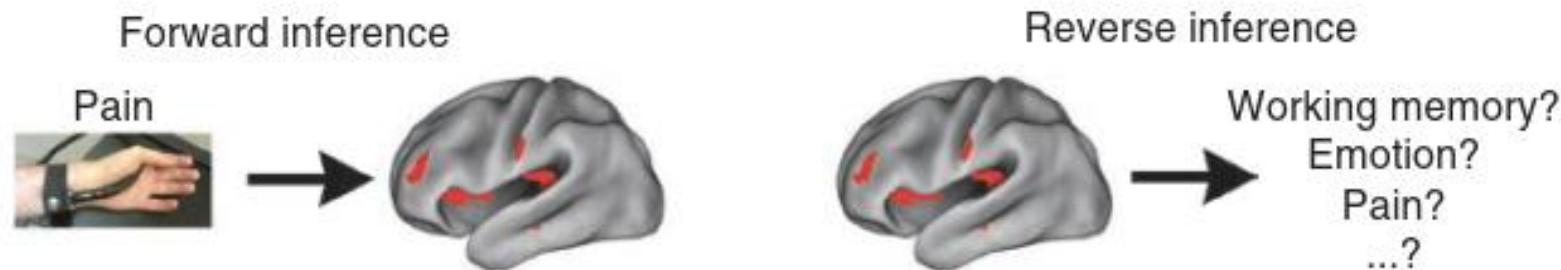


But  
Now,

**working memory 54%**  
**emotion 32 %**  
**language 14 %**

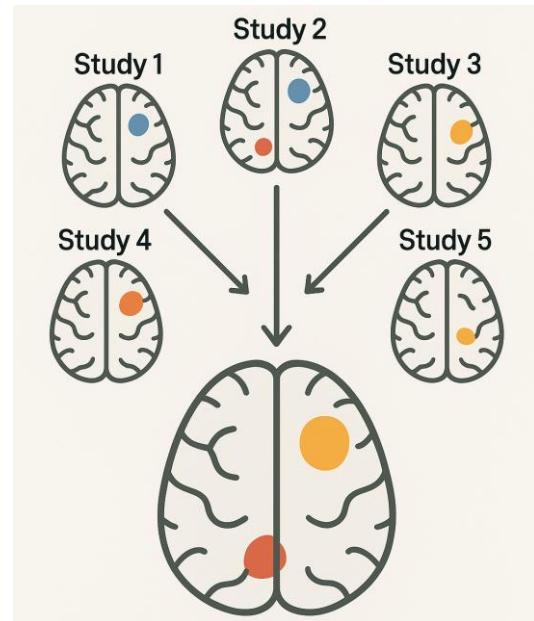


# Forward/Reverse Inference



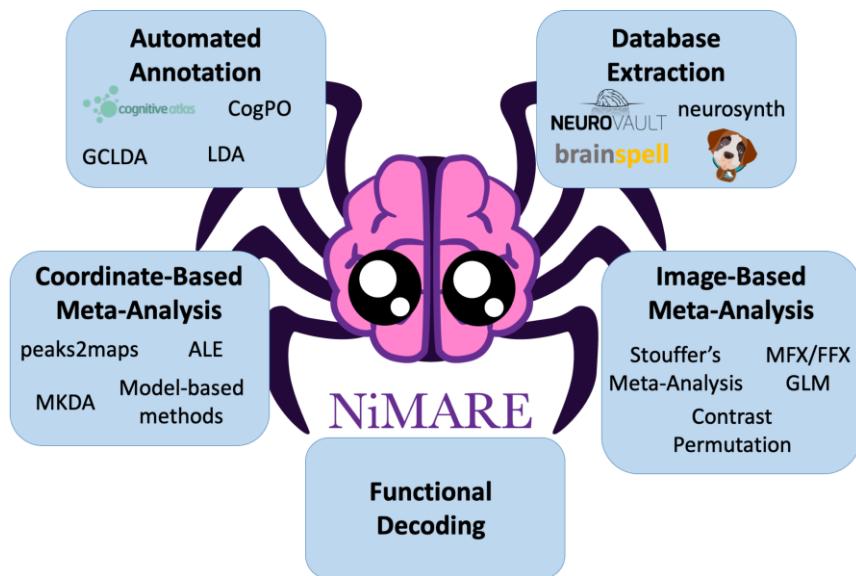
# Why We Need Meta-Analysis in fMRI Research

- Rapid growth of fMRI studies has produced massive amounts of data.
- Individual studies are often underpowered and prone to false positives.
- Reliable conclusions require evidence across multiple studies.
- Meta-analysis enables large-scale data aggregation and synthesis.



# NiMARE: Neuroimaging Meta-Analysis Research Environment

- NiMARE is a **Python package** for conducting meta-analyses of neuroimaging studies.
- It provides a **standardized, flexible** interface for multiple algorithms and databases



 Changelog.md	version bump	7 years ago
 Dockerfile	Fix issues with PR.	8 years ago
 LICENSE	initial commit	13 years ago
 MANIFEST	docstring edits for PEP8 compliance	11 years ago
 MANIFEST.in	RF: Move resources/ under neurosynth + do not rely on os-s...	12 years ago
 README.md	Update README.md	last year
 requirements.txt	Update requirements.txt	4 years ago
 setup.cfg	setup/testing tweaks	10 years ago
 setup.py	Add biopython to dependencies	8 years ago

 README  MIT license

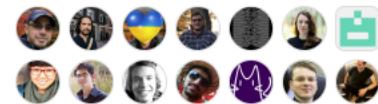


 Note: this package is no longer actively maintained; most of its functionality has been integrated into the much more expansive [NiMARE](#) package, which we recommend using instead.

## What is Neurosynth?

Neurosynth is a Python package for large-scale synthesis of functional neuroimaging data.

### Contributors 16



[+ 2 contributors](#)

### Languages

Python 99.1% Dockerfile 0.9%

# Contents



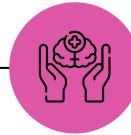
## fMRI Meta-analysis via NiMARE

01



Overview of fMRI  
Meta-Analysis  
Workflow

02



Using NiMARE:  
Practical Guide  
and Example

03

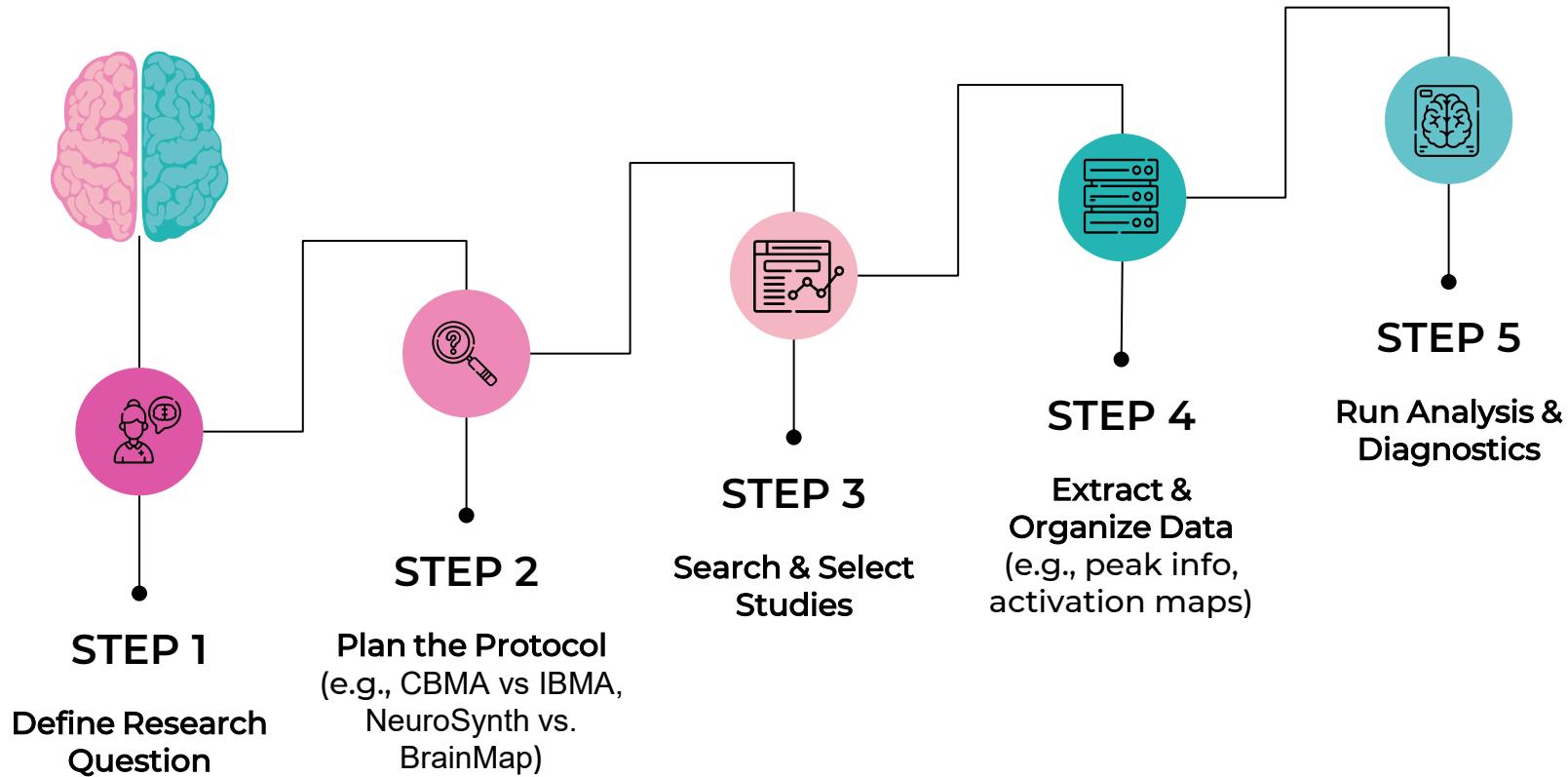


Alternative  
Options and Key  
Details

01

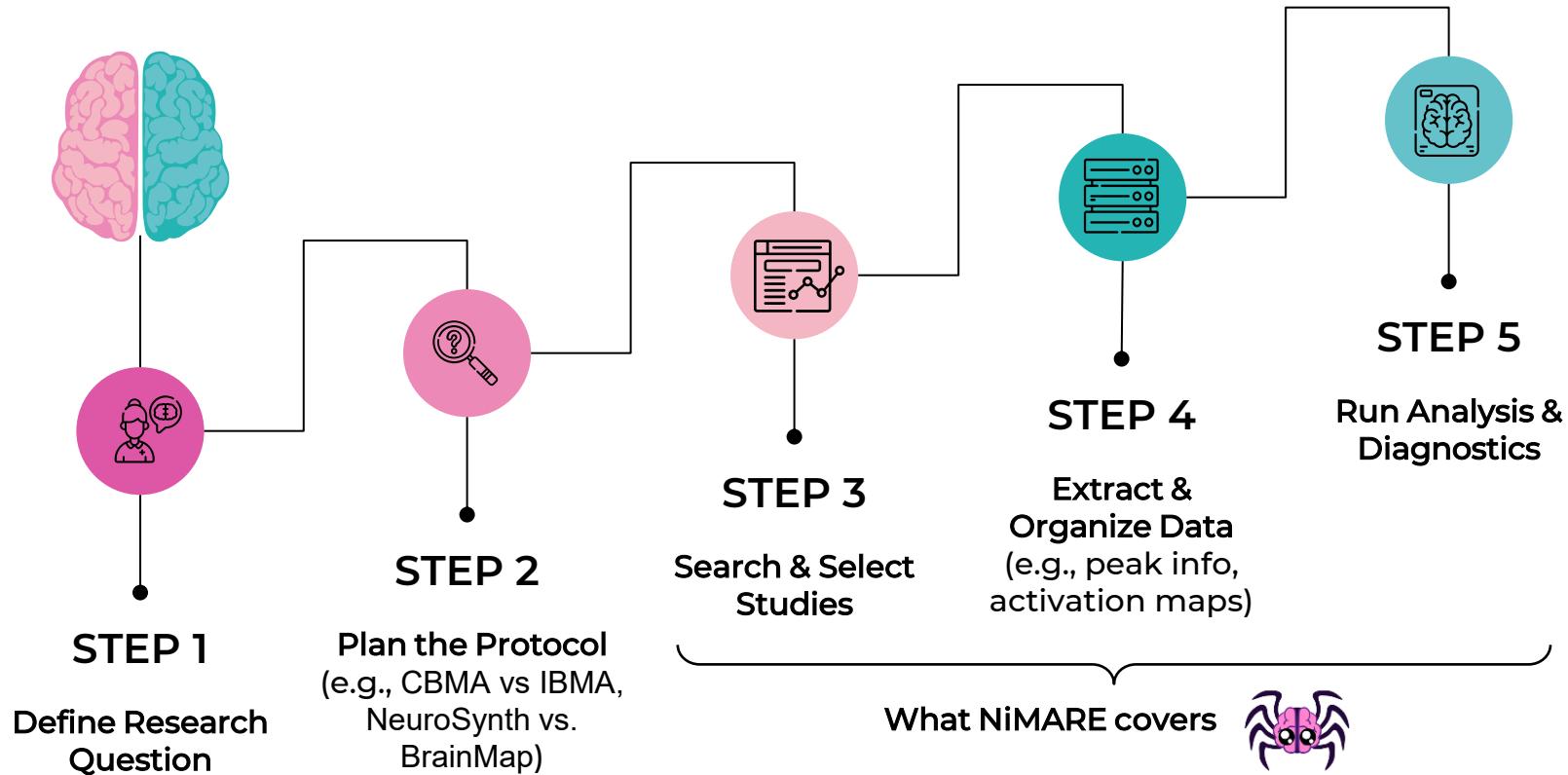
# **Overview of fMRI Meta- Analysis Workflow**

# An Overview of Meta-analysis

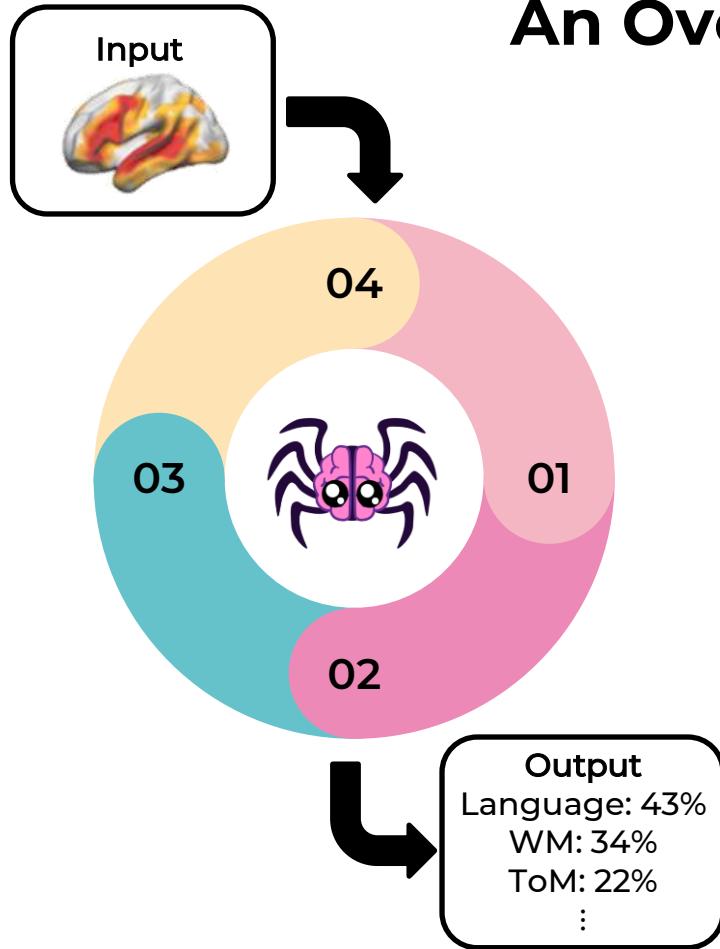


Müller, V. I., Cieslik, E. C., Laird, A. R., Fox, P. T., Radua, J., Mataix-Cols, D., ... & Eickhoff, S. B. (2018). Ten simple rules for neuroimaging meta-analysis. *Neuroscience & Biobehavioral Reviews*, 84, 151-161.

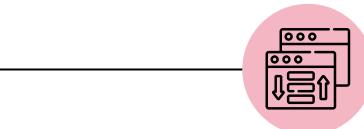
# An Overview of Meta-analysis



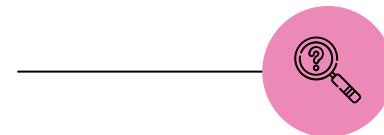
# An Overview of NiMARE



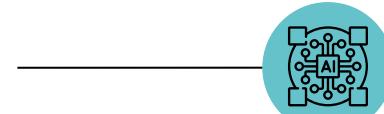
01 Download Dataset



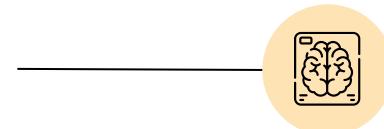
02 Specify Terms of Interest



03 Choose and Train Decoder



04 Decode



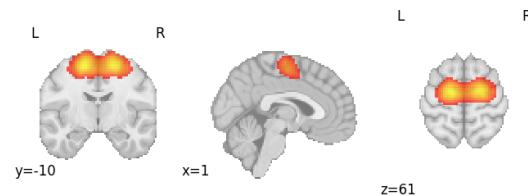
02

# Using NiMARE: Practical Guide and Example

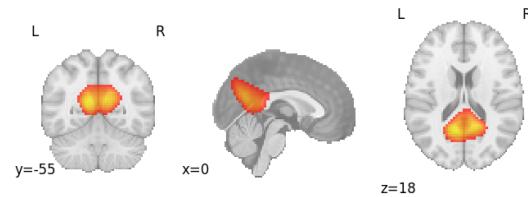
# Goal: Characterizing a Given Spatial Map

- We aim to interpret three spatial maps.
  - These maps are three different components from NeuroMark 2.2 template.

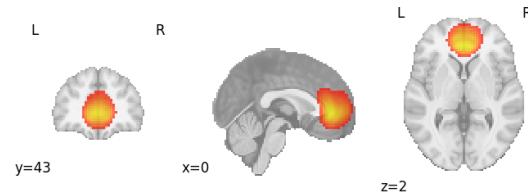
**Sensorimotor**



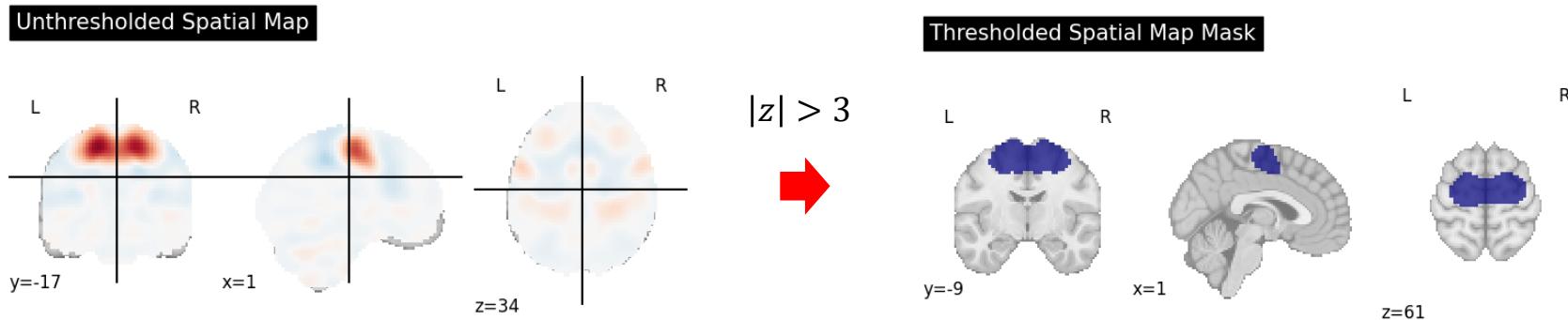
**DMN (Precu)**



**DMN (MPFC)**



# You need to threshold the spatial maps to retain only the most significant regions.

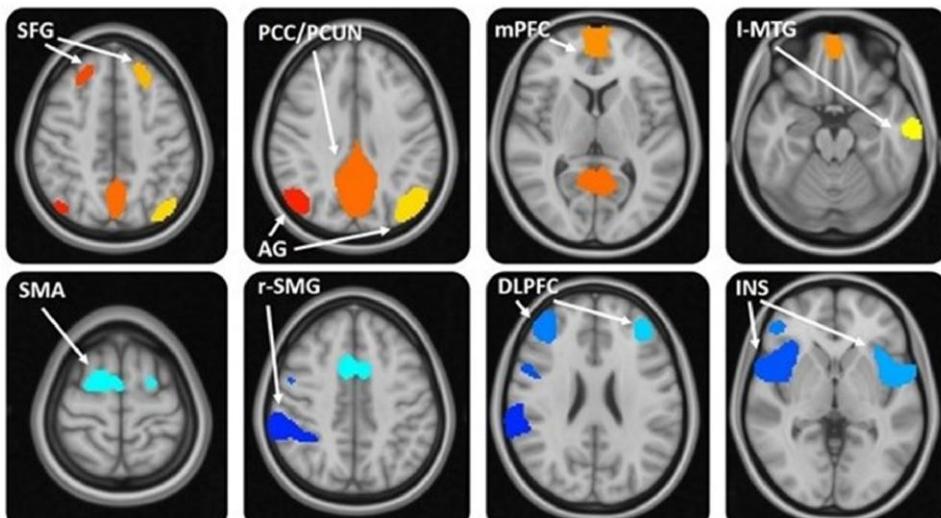


This step is required in order to use the NeuroSynth Decoder.

**How can we gather the data from the studies?**

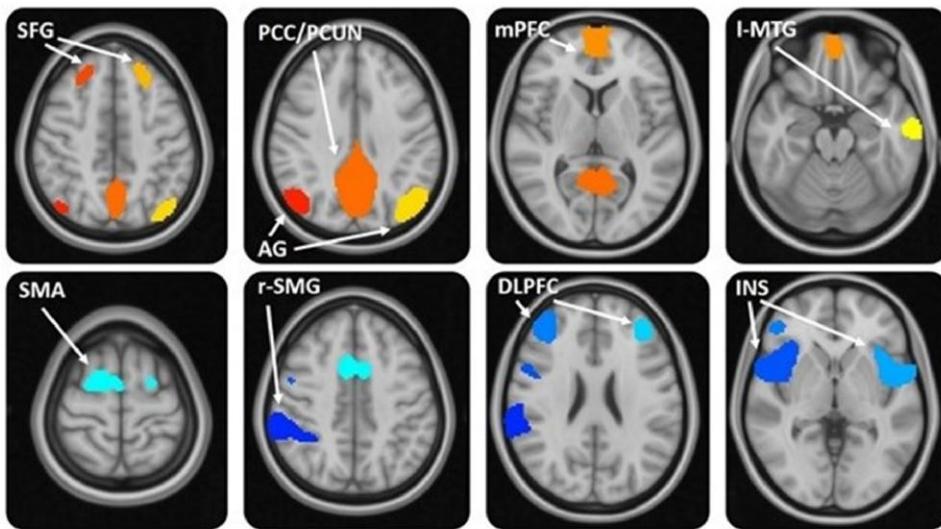
# Activation patterns are reported based on the local maxima (i.e., peaks).

Region of interest	Peak coordinates			
	MNI <sub>x</sub>	MNI <sub>y</sub>	MNI <sub>z</sub>	N <sub>vox</sub>
<b>Default Mode Network</b>				
PCC/PCUN	-1	-57	26	5561
mPFC	-1	59	2	2537
right-AG	48	-66	31	1024
left-AG	-45	-69	31	1712
right-SFG	24	33	45	170
left-SFG	-22	34	45	267
left-MTG	-61	-12	-21	287
<b>Anti-Correlated Network</b>				
SMA	7	4	53	1630
right-SMG	56	-38	38	2142
right-INS	48	10	3	2093
left-INS	-47	6	-0	1406
right-DLPFC	40	42	19	1074
left-DLPFC	-37	41	22	347



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We need to extract this.

**Good news is ...**

# NeuroSynth provides a database that stores the extracted peaks

 [neurosynth-data](#) Public

Watch 10

---

master 2 Branches 4 Tags Go to file Add file Code

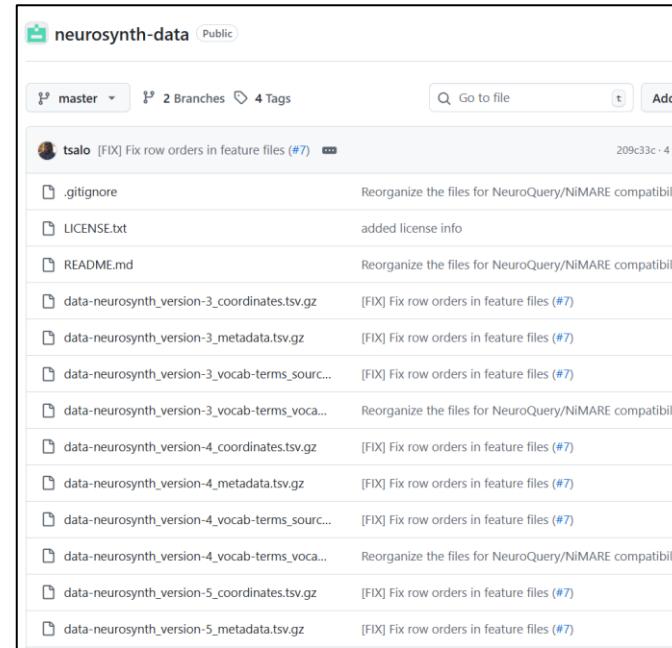
---

tsalo	[FIX] Fix row orders in feature files (#7)	209c33c · 4 years ago	22 Commits
<a href="#">.gitignore</a>	Reorganize the files for NeuroQuery/NiMARE compatibility (...)	4 years ago	
<a href="#">LICENSE.txt</a>	added license info	8 years ago	
<a href="#">README.md</a>	Reorganize the files for NeuroQuery/NiMARE compatibility (...)	4 years ago	
<a href="#">data-neurosynth_version-3_coordinates.tsv.gz</a>	[FIX] Fix row orders in feature files (#7)	4 years ago	
<a href="#">data-neurosynth_version-3_metadata.tsv.gz</a>	[FIX] Fix row orders in feature files (#7)	4 years ago	
<a href="#">data-neurosynth_version-3_vocab-terms_sourc...</a>	[FIX] Fix row orders in feature files (#7)	4 years ago	
<a href="#">data-neurosynth_version-3_vocab-terms_voca...</a>	Reorganize the files for NeuroQuery/NiMARE compatibility (...)	4 years ago	

**All we need is just downloading the data.**

# STEP 1. Download datasets

- First, we need to download the dataset that will be used to train the NeuroSynth decoder.
  - The activation peak coordinates extracted and study-annotated data are provided by NeuroSynth via GitHub.



<https://github.com/neurosynth/neurosynth-data>

Check “Code01\_Download\_Datasets.ipynb”

```
#####
# Download Neurosynth
# -----
# Neurosynth's data files are stored at https://github.com/neurosynth/neurosynth-data.

from nimare import extract
import os
from nimare import io

# The overall procedure may take a while (~10 minutes)
# Download the desired version of Neurosynth from GitHub.
files = extract.fetch_neurosynth(
    data_dir='./neurosynth_data',
    version="7",
    source="abstract",
    vocab="terms",
    overwrite=True,
)
print(files)
neurosynth_db = files[0]

# Convert the files to a Dataset.
neurosynth_dset = io.convert_neurosynth_to_dataset(
    coordinates_file=neurosynth_db["coordinates"],
    metadata_file=neurosynth_db["metadata"],
    annotations_files=neurosynth_db["features"],
)

# Save the Dataset for later use.
neurosynth_dset.save(os.path.join('./neurosynth_data', "neurosynth_dataset.pkl.gz"))
```

```
INFO:nimare.extract.utils:Dataset created in ./neurosynth_data/neurosynth
INFO:nimare.extract.extract:Searching for any feature files matching the following criteria: [('source-abstract', 'vocab-terms', 'data-neurosynth', 'version-7')]
Downloading data-neurosynth_version-7_coordinates.tsv.gz
Downloading data-neurosynth_version-7_metadata.tsv.gz
Downloading data-neurosynth_version-7_vocab-terms_source-abstract_type-tfidf_features.npz
Downloading data-neurosynth_version-7_vocab-terms_vocabulary.txt
[{'coordinates': '/home/users/ysong30/Documents/Projects/Functional_Decoding_Tutorial/neurosynth_data/neurosynth/data-neurosynth_version-7_coordinates.tsv.gz', 'metadata': '/home/users/ysong30/Documents/Projects/Functional_Decoding_Tutorial/neurosynth_data/neurosynth/data-neurosynth_version-7_metadata.tsv.gz', 'features': [{'features': '/home/users/ysong30/Documents/Projects/Functional_Decoding_Tutorial/neurosynth_data/neurosynth/data-neurosynth_version-7_vocab-terms_source-abstract_type-tfidf_features.npz', 'vocabulary': '/home/users/ysong30/Documents/Projects/Functional_Decoding_Tutorial/neurosynth_data/neurosynth/data-neurosynth_version-7_vocab-terms_vocabulary.txt'}]}]
WARNING:nimare.utils:Not applying transforms to coordinates in unrecognized space 'UNKNOWN'
```

```
# Checks how many studies are included in this dataset.  
# ALL coordinates are represented in MNI152 space.  
print(neurosynth_dset)
```

```
Dataset(14371 experiments, space='mni152_2mm')
```

```
# Check which studies are included.  
neurosynth_dset.metadata.head()
```

	<b>id</b>	<b>study_id</b>	<b>contrast_id</b>	<b>authors</b>	<b>journal</b>	<b>year</b>	<b>title</b>
0	10022492-1	10022492	1	Callicott JH, Mattay VS, Bertolino A, Finn K, ...	Cerebral cortex (New York, N.Y. : 1991)	1999	Physiological characteristics of capacity cons...
1	10022494-1	10022494	1	Toni I, Schluter ND, Josephs O, Friston K, Pas...	Cerebral cortex (New York, N.Y. : 1991)	1999	Signal-, set- and movement-related activity in...
2	10022496-1	10022496	1	Lockwood AH, Salvi RJ, Coad ML, Arnold SA, Wac...	Cerebral cortex (New York, N.Y. : 1991)	1999	The functional anatomy of the normal human aud...
3	10051677-1	10051677	1	Denton D, Shade R, Zamarippa F, Egan G, Blair...	Proceedings of the National Academy of Science...	1999	Correlation of regional cerebral blood flow an...
4	10191322-1	10191322	1	Chee MW, Tan EW, Thiel T	The Journal of neuroscience : the official jou...	1999	Mandarin and English single word processing st...
				⋮			

```
# The coordinates of activation peaks are extracted for each study.  
neurosynth_dset.coordinates.head()
```

	<b>id</b>	<b>study_id</b>	<b>contrast_id</b>		<b>x</b>	<b>y</b>	<b>z</b>	<b>space</b>
1483	10022492-1	10022492		1	36.0	-58.0	52.0	mni152_2mm
1499	10022492-1	10022492		1	48.0	24.0	20.0	mni152_2mm
1498	10022492-1	10022492		1	-42.0	26.0	20.0	mni152_2mm
1497	10022492-1	10022492		1	-36.0	30.0	16.0	mni152_2mm
1496	10022492-1	10022492		1	-30.0	32.0	0.0	mni152_2mm
	⋮							

**How can we know each study or each peak is related to which cognitive aspect?**

# Article annotation

- The content of each article is represented as a TF-IDF vector, where each element corresponds to a cognitive term (or label).
- The raw text used to annotate the NeuroSynth database is the article abstract.

## Physiological Characteristics of Capacity Constraints in Working Memory as Revealed by Functional MRI

A fundamental characteristic of working memory is that its capacity to handle information is limited. While there have been many brain mapping studies of working memory, the physiological basis of its capacity limitation has not been explained. We identified characteristics of working memory capacity using functional magnetic resonance imaging (fMRI) in healthy subjects. Working memory capacity was studied using a parametric 'n-back' working memory task involving increasing cognitive load and ultimately decreasing task performance. Loci within dorsolateral prefrontal cortex (DLPFC) evinced exclusively an 'inverted-U' shaped neurophysiological response from lowest to highest load, consistent with a capacity-constrained response. Regions outside of DLPFC, in contrast, were more heterogeneous in response and often showed early plateau or continuously increasing responses, which did not reflect capacity constraints. However, sporadic loci, including in the premotor cortex, thalamus and superior parietal lobe, also demonstrated putative capacity-constrained responses, perhaps arising as an upstream effect of DLPFC limitations or as part of a broader network-wide capacity limitation. These results demonstrate that regionally specific nodes within the working memory network are capacity-constrained in the physiological domain, providing a missing link in current explorations of the capacity characteristics of working memory.

TF-IDF vector



:	
0	pain
0	visual
0.32	working memory
0	motor
0.1	response
0	social
0	ToM
0	reward
:	

TF-IDF: term frequency-inverse document frequency

- ✓ A measure of importance of a word to a document in a collection or corpus, adjusted for the fact that some words appear more frequently in general.

# Cognitive Terms

- You can check the all the terms are used to annotate the studies.
- A frequency vector of each term represents a single study.

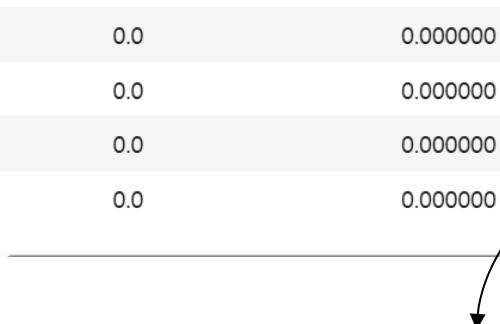
```
# Cognitive Labels to describe studies
neurosynth_dset.annotations.columns.tolist()[100:110]

['terms_abstract_tfidf_actively',
 'terms_abstract_tfidf_activities',
 'terms_abstract_tfidf_acts',
 'terms_abstract_tfidf_actual',
 'terms_abstract_tfidf_actually',
 'terms_abstract_tfidf_acute',
 'terms_abstract_tfidf_ad',
 'terms_abstract_tfidf_adaptation',
 'terms_abstract_tfidf_adapted',
 'terms_abstract_tfidf_adaptive']
```

# TF-IDF

terms_abstract_tfidf_words	terms_abstract_tfidf_work	terms_abstract_tfidf_working	terms_abstract_tfidf_working_memory
0.0	0.0	0.317592	0.320417
0.0	0.0	0.000000	0.000000
0.0	0.0	0.000000	0.000000
0.0	0.0	0.000000	0.000000
0.0	0.0	0.000000	0.000000

TF-IDF value for working memory



```
# This dataset includes annotations for each study using TF-IDF (Term Frequency-Inverse Document Frequency).  
neurosynth_dset.annotations.head()
```

	<code>id</code>	<code>study_id</code>	<code>contrast_id</code>	<code>terms_abstract_tfidf_001</code>	<code>terms_abstract_tfidf_01</code>	<code>terms_abstract_tfidf_05</code>	<code>terms_abstract_tfidf_10</code>	<code>terms_abstract_tfidf_100</code>	<code>terms_abstract_tfidf_11</code>	<code>terr</code>
0	10022492-1	10022492	1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	10022494-1	10022494	1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	10022496-1	10022496	1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	10051677-1	10051677	1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	10191322-1	10191322	1	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows x 3231 columns

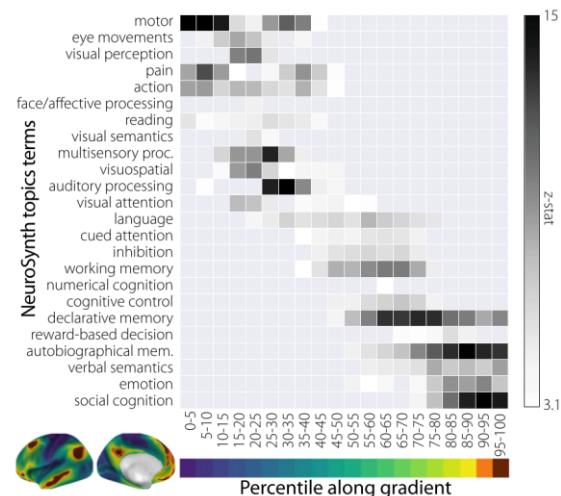
→ 3228 terms are used to annotate each study.

Check “Code02\_Decoding\_with\_neurosynth\_data.ipynb”

# STEP 2. Specify Terms of Interest

- More than 3,000 terms are used for annotation in the NeuroSynth dataset.
  - However, these include non-cognitive terms (e.g., brain regions or demographic information) and semantically duplicated terms (e.g., *short-term memory* vs. *working memory*).
- Refining these terms can improve both decoding efficiency and interpretability

Only 24 topic terms were used in Margulies et al. (2016)'s work.



```
#### Specify the scope of cognitive terms ####
neuroquery_dset_copy = neuroquery_dset.copy()
neuroquery_dset_copy.annotations=neuroquery_dset_copy.annotations.iloc[:, [0,1,2,
71-1, 452-1, 478-1, 511-1, 1084-1, 1806-1, 1956-1, 1967-1, 2721-1, 2932-1, 3347-1,
3509-1, 3557-1, 3777-1, 3964-1, 4674-1, 4850-1, 5259-1, 6143-1,
6150-1, 6168-1, 6184-1, 6280-1]]
```

```
# display the selected cognitive terms
column_names = neuroquery_dset_copy.annotations.columns.tolist()
new_column_names = column_names[:3]
for i in range(3,len(column_names)):
    cleaned_term = column_names[i].split("__")[1]
    print(cleaned_term)
    new_column_names.append(cleaned_term)

# Replace column names
neuroquery_dset_copy.annotations.columns = new_column_names
```

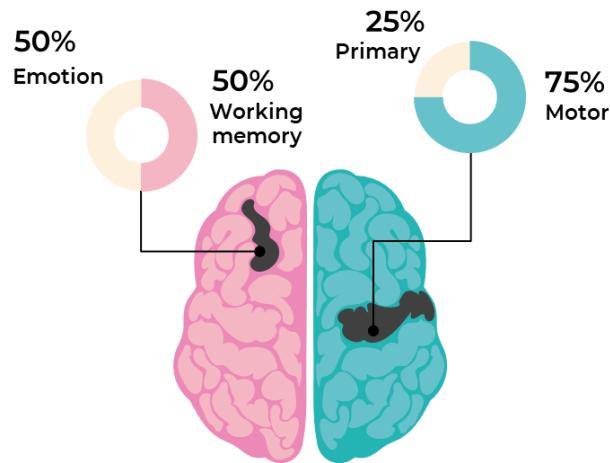
```
action
attention
auditory
autobiographical
cognitive control
emotional
eye movement
face
inhibition
language
memory
motor
multisensory
numerical
pain
reading
reward
social cognition
visual
visual attention
visual perception
visuospatial
working memory
```

You should select cognitive terms for decoding.

Here, for demonstration purposes, I used terms similar to those in Margulias et al. (2016).

# STEP 3. Choose and Train a Decoder

- Several decoding algorithms are available in NiMARE:
  - NeuroSynth decoder
  - BrainMap decoder
  - ROI Association Decoder
  - Correlation Decoder
- These algorithms are based on different assumptions and inference approaches.



Since ROI decoders essentially perform Bayesian inference for functional decoding, there isn't much to fit (i.e., train) although NiMARE uses the basic fit-transform.

```
#### Training NeuroSynth Decoder ####

from nimare.decode import discrete

# Get studies with voxels in the mask
ids = neurosynth_dset.get_studies_by_mask(ICN_SM_thres_mni152)

# Train the decoder
decoder = discrete.NeuroSynthDecoder(correction=None)
decoder.fit(neurosynth_dset_copy)
```

# STEP 4. Decode

- Perform Bayesian inference to quantify the degree of association between term use and voxel activation.
  - If probReverse is high, a given region activates more consistently in studies that mention the current term than in those that do not.

Major outputs for reports



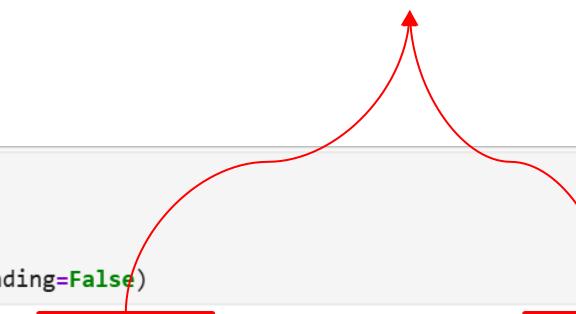
Term	pForward	zForward	probForward	pReverse	zReverse	probReverse
motor	0.000000e+00	inf	0.416853	5.714893e-180	28.605651	0.674786
eye movements		NaN	0.436507	1.255302e-07	5.285254	0.631976
action	5.912026e-14	7.510016	0.400493	1.467755e-27	10.877983	0.610139
visual attention		NaN	0.382826	3.987689e-03	2.879134	0.579309
visuospatial		NaN	0.372239	4.167178e-04	3.529264	0.568481
attention	3.370160e-116	22.913990	0.348409	6.875312e-09	5.793942	0.548643
pain	9.181554e-30	-11.331315	0.355107	1.024070e-03	3.283829	0.548476
working memory	4.255896e-09	5.873927	0.348996	3.509021e-05	4.137636	0.543657
inhibition	1.708363e-15	-7.960868	0.350032	2.608555e-03	3.010456	0.541904
visual perception		NaN	0.348176	3.253452e-01	0.983533	0.536358
cognitive control	2.971511e-19	-8.969764	0.341351	4.210679e-02	2.032463	0.529080
visual	0.000000e+00	inf	0.330133	9.353038e-03	2.598873	0.518645
numerical		NaN	0.323850	9.742068e-01	0.032333	0.501098
memory	3.035747e-231	32.467821	0.321518	5.946423e-01	-0.532121	0.495893
multisensory		NaN	0.319151	8.337580e-01	-0.209884	0.493604
social cognition		NaN	0.313993	5.520877e-01	-0.594635	0.484956
auditory	3.268939e-04	3.592999	0.314631	1.357842e-01	-1.491676	0.483603
verbal	2.444843e-15	-7.916401	0.312389	1.778519e-01	-1.347399	0.480830
emotion	1.525824e-02	-2.426191	0.302649	1.481385e-03	-3.178306	0.460416
reading	2.043242e-60	-16.395978	0.300651	2.009105e-02	-2.324643	0.459656

Ref: <https://neurosynth.org/faq/#q18>

What's the difference?

```
#### Decode ####
```

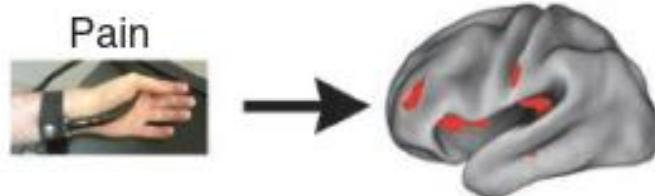
```
decoded_df = decoder.transform(ids=ids)
decoded_df.sort_values(by="probReverse", ascending=False)
```



	Term	pForward	zForward	probForward	pReverse	zReverse	probReverse
	<b>motor</b>	0.000000e+00	inf	0.416853	5.714893e-180	28.605651	0.674786
	<b>eye movements</b>		NaN	NaN	0.436507	1.255302e-07	5.285254
	<b>action</b>	5.912026e-14	7.510016	0.400493	1.467755e-27	10.877983	0.610139
	<b>visual attention</b>		NaN	NaN	0.382826	3.987689e-03	2.879134

# Forward/Reverse Inference

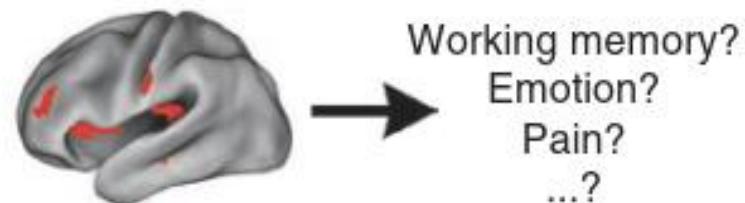
Forward inference



a.k.a. Uniformity test

The degree to which each voxel is consistently activated in studies that use a given term.

Reverse inference



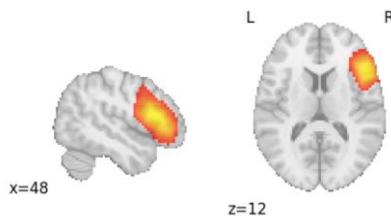
a.k.a. Association test

The degree to which a given region activates more consistently in studies that mention the current term than in those that do not

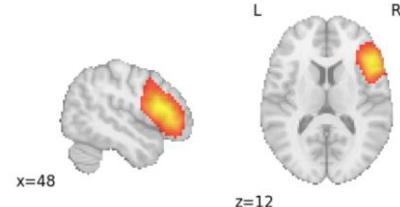
# Forward/Reverse Inference for Emotion

If a given brain area is **all activated** during working memory-, emotion-, and language-mentioned studies, ...

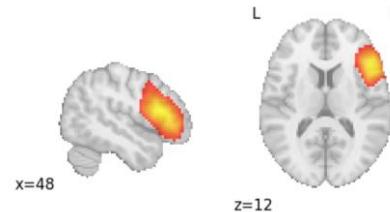
Working Memory



Emotion



Language

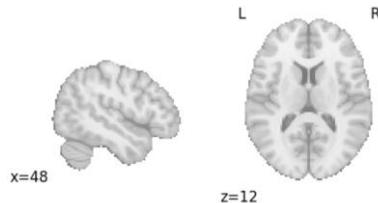


Forward probability ( $p(\text{activation}|\text{term})$ ) of this area is **high**.  
Reverse probability ( $p(\text{term}|\text{activation})$ ) of this area is **low**.

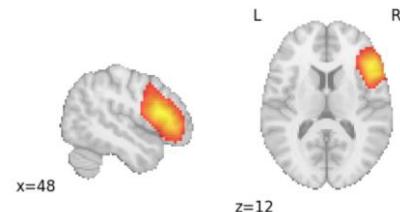
# Forward/Reverse Inference for Emotion

If a given brain area is **specifically activated** during emotion-mentioned task, ...vv

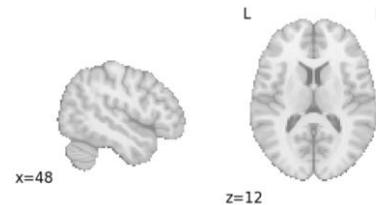
Working Memory



Emotion



Language



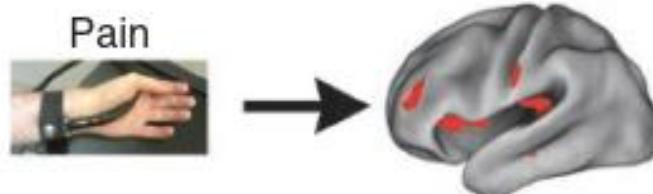
Forward probability ( $p(\text{activation}|\text{term})$ ) of this area is **high**.  
Reverse probability ( $p(\text{term}|\text{activation})$ ) of this area is **high**.

**Caution:** The default **prior** for this inference is set primarily for **practical purposes**. Therefore, it should not be interpreted as a true probability but rather as a degree of association.

# Forward/Reverse Inference

I highly recommend you to understand the formula to get the nuances in these two probability.

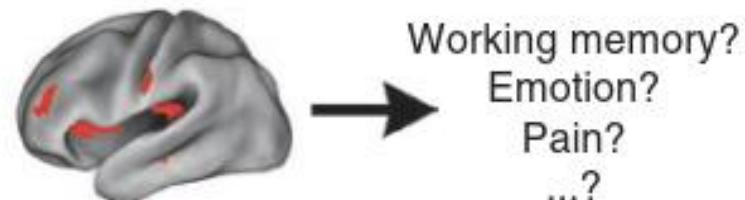
Forward inference



a.k.a. Uniformity test

$$p(A_j = 1|T_k = 1) = \left[ \sum_i A_{ij} T_{ik} + 1 \right] / \left[ \sum_i T_{ik} + 2 \right]$$

Reverse inference



a.k.a. Association test

$$p(T_k = 1|A_j = 1) = p(A_j = 1|T_k = 1)p(T_k = 1)/p(A_j = 1)$$
$$p(T_k = 1) = p(T_k = 0) = 0.5$$

$T_{ik}$ : Whether term  $k$  is present in study  $i$  (0 or 1).

$A_{ij}$ : Whether voxel  $j$  is activated in study  $i$  (0 or 1).

$A_j$ : Whether voxel  $j$  is activated (0 or 1).

$T_k$ : Whether term  $k$  is present (0 or 1).

Yarkoni, T., Poldrack, R. A., Nichols, T. E., Van Essen, D. C., & Wager, T. D. (2011). Large-scale automated synthesis of human functional neuroimaging data. *Nature methods*, 8(8), 665-670.

# STEP 4. Decode

- NeuroSynth decoder accesses statistical significance by performing a **chi-square test** to determine if presence of the label and selection are independent.

Ref:

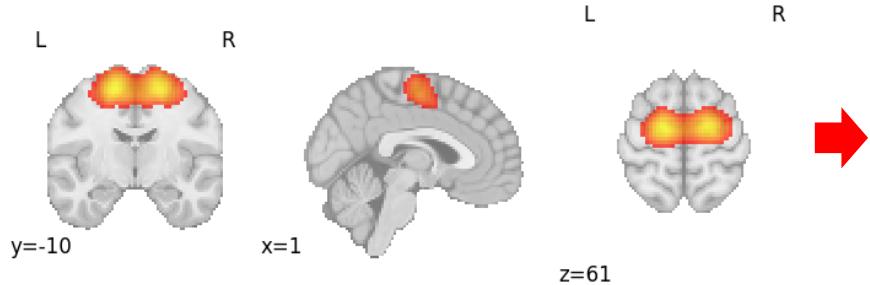
<https://nimare.readthedocs.io/en/0.0.11/decoding.html#the-neurosynth-roi-association-approach>

Statistical significance



Term	pForward	zForward	probForward	pReverse	zReverse	probReverse
motor	0.000000e+00	inf	0.416853	5.714893e-180	28.605651	0.674786
eye movements		NaN	0.436507	1.255302e-07	5.285254	0.631976
action	5.912026e-14	7.510016	0.400493	1.467755e-27	10.877983	0.610139
visual attention		NaN	0.382826	3.987689e-03	2.879134	0.579309
visuospatial		NaN	0.372239	4.167178e-04	3.529264	0.568481
attention	3.370160e-116	22.913990	0.348409	6.875312e-09	5.793942	0.548643
pain	9.181554e-30	-11.331315	0.355107	1.024070e-03	3.283829	0.548476
working memory	4.255896e-09	5.873927	0.348996	3.509021e-05	4.137636	0.543657
inhibition	1.708363e-15	-7.960868	0.350032	2.608555e-03	3.010456	0.541904
visual perception		NaN	0.348176	3.253452e-01	0.983533	0.536358
cognitive control	2.971511e-19	-8.969764	0.341351	4.210679e-02	2.032463	0.529080
visual	0.000000e+00	inf	0.330133	9.353038e-03	2.598873	0.518645
numerical		NaN	0.323850	9.742068e-01	0.032333	0.501098
memory	3.035747e-231	32.467821	0.321518	5.946423e-01	-0.532121	0.495893
multisensory		NaN	0.319151	8.337580e-01	-0.209884	0.493604
social cognition		NaN	0.313993	5.520877e-01	-0.594635	0.484956
auditory	3.268939e-04	3.592999	0.314631	1.357842e-01	-1.491676	0.483603
verbal	2.444843e-15	-7.916401	0.312389	1.778519e-01	-1.347399	0.480830
emotion	1.525824e-02	-2.426191	0.302649	1.481385e-03	-3.178306	0.460416
reading	2.043242e-60	-16.395978	0.300651	2.009105e-02	-2.324643	0.459656

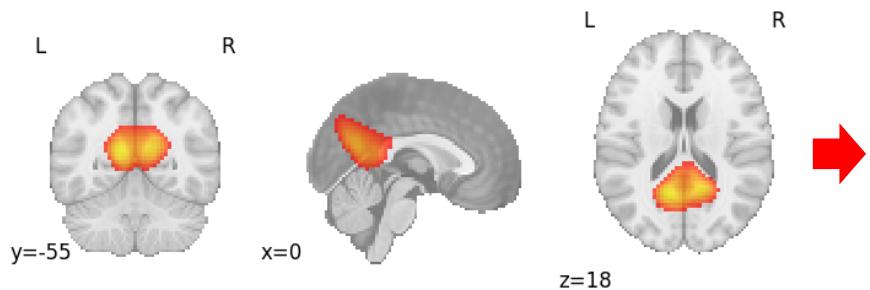
# Decoding Results – sensorimotor



Term	pForward	zForward	probForward	pReverse	zReverse	probReverse
<b>motor</b>	0.000000e+00	inf	0.416853	5.714893e-180	28.605651	0.674786
<b>eye movements</b>		NaN	NaN	0.436507	1.255302e-07	5.285254
<b>action</b>	5.912026e-14	7.510016	0.400493	1.467755e-27	10.877983	0.610139
<b>visual attention</b>		NaN	NaN	0.382826	3.987689e-03	2.879134
<b>visuospatial</b>		NaN	NaN	0.372239	4.167178e-04	3.529264
<b>attention</b>	3.370160e-116	22.913990	0.348409	6.875312e-09	5.793942	0.548643
<b>pain</b>	9.181554e-30	-11.331315	0.355107	1.024070e-03	3.283829	0.548476
<b>working memory</b>	4.255896e-09	5.873927	0.348996	3.509021e-05	4.137636	0.543657
<b>inhibition</b>	1.708363e-15	-7.960868	0.350032	2.608555e-03	3.010456	0.541904
<b>visual perception</b>		NaN	NaN	0.348176	3.253452e-01	0.983533
<b>cognitive control</b>	2.971511e-19	-8.969764	0.341351	4.210679e-02	2.032463	0.529080
<b>visual</b>	0.000000e+00	inf	0.330133	9.353038e-03	2.598873	0.518645
<b>numerical</b>		NaN	NaN	0.323850	9.742068e-01	0.032333
						0.501098

Only displaying terms with  
probReverse > 0.5

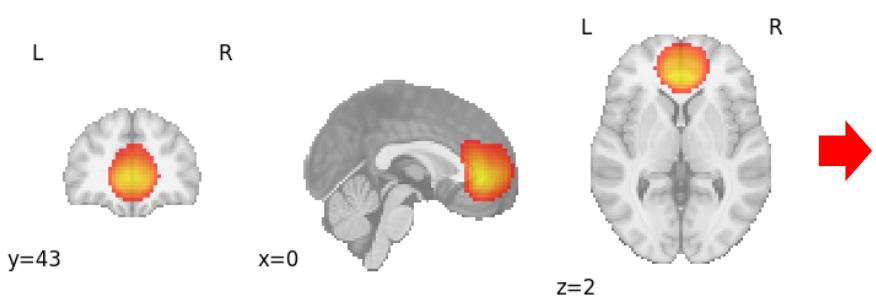
# Decoding Results – DMN (Precuneus)



Term	pForward	zForward	probForward	pReverse	zReverse	probReverse
autobiographical memory	NaN	NaN	0.542011	6.442063e-20	9.136644	0.713832
social cognition	NaN	NaN	0.378158	1.934541e-05	4.272315	0.588979
memory	0.000000e+00	inf	0.346241	6.281016e-28	10.955098	0.577842
cognitive control	1.091679e-11	-6.793866	0.321618	3.273422e-01	0.979481	0.514747
emotion	2.689682e-05	4.198265	0.320259	2.513005e-01	1.147196	0.513387
attention	8.750443e-93	20.431645	0.318295	2.138231e-01	1.243121	0.511326
working memory	8.573893e-07	4.921829	0.317382	4.714466e-01	0.720127	0.508284
reward	4.277601e-01	0.793030	0.314683	7.979939e-01	0.255944	0.503210

Only displaying terms with  
probReverse > 0.5

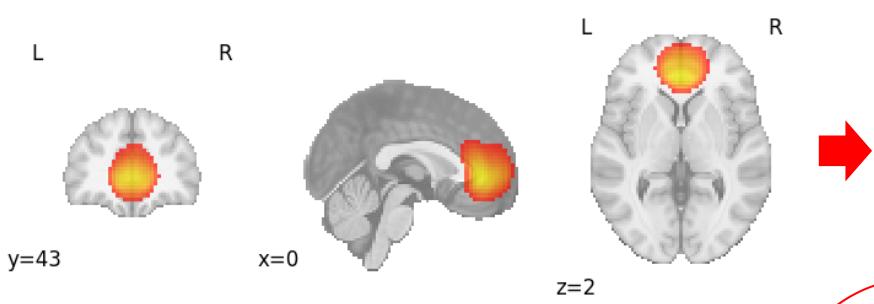
# Decoding Results – DMN (MPFC)



Term	pForward	zForward	probForward	pReverse	zReverse	probReverse
autobiographical memory	NaN	NaN	0.535312	9.027011e-12	6.821221	0.667168
social cognition	NaN	NaN	0.472863	4.280846e-13	7.246372	0.624821
reward	8.437706e-42	13.545379	0.443557	5.480242e-33	11.964079	0.610085
emotion	2.670773e-41	13.460507	0.416818	1.069867e-18	8.827557	0.581853
pain	5.044729e-10	-6.217707	0.406055	1.815443e-06	4.772953	0.563180
inhibition	9.747957e-04	-3.297702	0.397881	1.641752e-05	4.308756	0.554101
cognitive control	1.803367e-05	-4.287941	0.389350	7.586440e-04	3.367459	0.543312
memory	0.000000e+00	inf	0.364064	7.328978e-02	1.791022	0.512517
attention	1.196019e-107	22.039824	0.358597	9.702710e-01	0.037268	0.500312

Only displaying terms with  
probReverse > 0.5

# Decoding Results – DMN (MPFC)



Term	pForward	zForward	probForward	pReverse	zReverse	probReverse
autobiographical memory	NaN	NaN	0.535312	9.027011e-12	6.821221	0.667168
social cognition	NaN	NaN	0.472863	4.280846e-13	7.246372	0.624821
reward	8.437706e-42	13.545379	0.443557	5.480242e-33	11.964079	0.610085
emotion	2.670773e-41	13.460507	0.416818	1.069867e-18	8.827557	0.581853
pain	5.044729e-10	-6.217707	0.406055	1.815443e-06	4.772953	0.563180
inhibition	9.747957e-04	-3.297702	0.397891	1.641752e-05	4.308756	0.554101
cognitive control	1.803367e-05	-4.287941	0.389350	7.586440e-04	3.367459	0.543312
memory	0.000000e+00	inf	0.364064	7.328978e-02	1.791022	0.512517
attention	1.196019e-107	22.039824	0.358597	9.702710e-01	0.037268	0.500312

Compared to the Precuneus, Reward/Emotion shows a higher rank and statistical significance in the MPFC.

Only displaying terms with probReverse > 0.5

03

## **Alternative Options and Key Details**

# Alternative Option – NeuroQuery Dataset

- NeuroQuery is a tool for meta-analysis of neuroimaging studies.
- Unlike NeuroSynth, NeuroQuery is focused on producing a brain map that *predicts* where in the brain a study on the topic of interest is likely report observations.

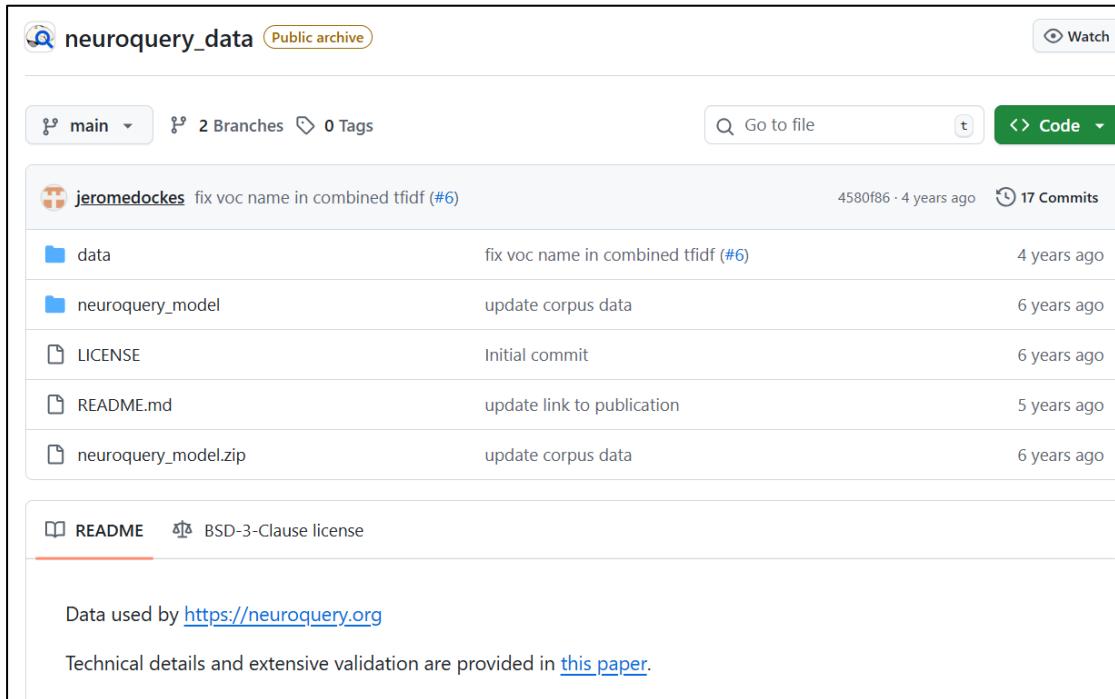


# Alternative Option – NeuroQuery Dataset

- The dataset used in NeuroQuery includes more diverse cognitive terms for annotation and covers a wider range of journals.

	NeuroSynth	NeuroQuery
Dataset size		
articles	14 371	13 459
terms	3 228 (1 335 online)	7 547
journals	60	458
raw text length (words)	≈4 M	≈75 M
unique term occurrences	1 063 670	5 855 483
unique term occurrences in voc intersection	677 345	3 089 040
coordinates	448 255	418 772
Coordinate extraction errors on conflicting articles		
articles with false positives / 40	20	3
articles with false negatives / 40	28	8

# They provide the dataset through GitHub.



The screenshot shows a GitHub repository page for 'neuroquery\_data'. The repository is public and has 2 branches and 0 tags. The commit history is as follows:

Commit	Message	Time
jeromedockes	fix voc name in combined tfidf (#6)	4580f86 · 4 years ago
data	fix voc name in combined tfidf (#6)	4 years ago
neuroquery_model	update corpus data	6 years ago
LICENSE	Initial commit	6 years ago
README.md	update link to publication	5 years ago
neuroquery_model.zip	update corpus data	6 years ago

The README file contains the following text:

Data used by <https://neuroquery.org>  
Technical details and extensive validation are provided in [this paper](#).

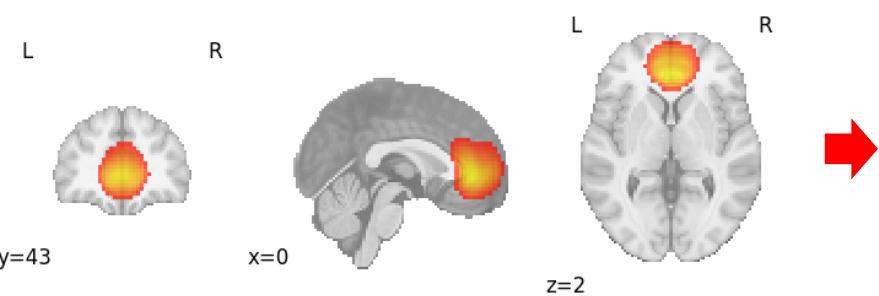
We can use this for decoding!

[https://github.com/neuroquery/neuroquery\\_data/](https://github.com/neuroquery/neuroquery_data/)

Check “Code03\_Decoding\_with\_neuroquery\_data.ipynb”

# Decoding Results – DMN (MPFC)

# NeuroSynth Decoder trained with the NeuroQuery Dataset



	pForward	zForward	probForward	pReverse	zReverse	probReverse
Term						
<b>autobiographical</b>	NaN	NaN	0.499960	4.829034e-47	14.404773	0.625802
<b>emotional</b>	0.000000e+00	inf	0.400049	1.192973e-92	20.416506	0.608044
<b>reward</b>	9.894976e-01	-0.013163	0.435347	2.677134e-51	15.066814	0.589664
<b>social cognition</b>	NaN	NaN	0.447569	3.299004e-21	9.452795	0.578420
<b>pain</b>	0.000000e+00	-inf	0.421356	6.375812e-11	6.534651	0.549733
<b>cognitive control</b>	7.322371e-12	-6.851218	0.412854	3.366900e-14	7.583371	0.547715
<b>inhibition</b>	2.706134e-11	6.661735	0.398485	6.474637e-06	4.510266	0.526218
<b>attention</b>	0.000000e+00	inf	0.384278	5.011440e-05	4.055093	0.523276
<b>memory</b>	0.000000e+00	inf	0.387311	5.985336e-03	2.748584	0.515232
<b>face</b>	2.016254e-16	8.221112	0.391470	2.858343e-01	1.067305	0.506159
<b>action</b>	2.413422e-14	7.626431	0.389724	9.894885e-01	0.013175	0.500076

## Results should be similar.

Only displaying terms with  
probReverse > 0.5

# Alternative Option - BrainMap Decoder



**brainmap.org**

- BrainMap decoder accounts for the number of activation foci per study.



<https://www.brainmap.org/>

<https://nimare.readthedocs.io/en/0.0.11/decoding.html#the-brainmap-approach>

```
#### BrainMap Decoder ####

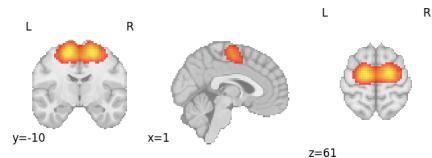
from nimare.decode import discrete

# Get studies with voxels in the mask
ids = neurosynth_dset.get_studies_by_mask(ICN_SM_thres_mni152)

# Decode
decoder = discrete.BrainMapDecoder(correction="fdr_bh")
decoder.fit(neurosynth_dset_copy)
decoded_df = decoder.transform(ids=ids)
decoded_df.sort_values(by="probReverse", ascending=False)

/home/users/ysong30/anaconda3/envs/fmri/lib/python3.11/site-packages/numpy/_core/fromnumeric.py:84: FutureWarning: in a future version this will reduce over both axes and return a scalar. To retain the old behavior, pass return reduction(axis=axis, out=out, **passkwargs)
```

Term	pForward	zForward	likelihoodForward	pReverse	zReverse	probReverse
<b>motor</b>	0.000000e+00	inf	1.441339	5.714893e-180	28.605651	0.163733
<b>visual</b>	4.085129e-01	8.265135e-01	1.006461	9.353038e-03	2.598873	0.138624
<b>memory</b>	9.691869e-01	3.862815e-02	0.938963	5.946423e-01	-0.532121	0.114108
<b>attention</b>	1.838037e-05	4.283708e+00	1.171541	6.875312e-09	5.793942	0.095001
<b>working memory</b>	5.194925e-03	2.794692e+00	1.134622	3.509021e-05	4.137636	0.054822
<b>action</b>	2.170422e-10	6.348771e+00	1.366431	1.467755e-27	10.877983	0.053617
<b>auditory</b>	9.854723e-01	1.820873e-02	0.894990	1.357842e-01	-1.491676	0.049625
<b>emotion</b>	9.798428e-01	-2.526605e-02	0.887025	1.481385e-03	-3.178306	0.040738
<b>language</b>	9.999966e-01	-4.204964e-06	0.780283	6.593925e-04	-3.405929	0.038047
<b>reward</b>	9.327199e-01	-8.442331e-02	0.909637	1.069239e-03	-3.271645	0.037143
<b>inhibition</b>	3.175586e-04	-3.600539e+00	1.259354	2.608555e-03	3.010456	0.033520
<b>cognitive control</b>	3.352167e-03	-2.933451e+00	1.204387	4.210679e-02	2.032463	0.031897



Check “Code02\_Decoding\_with\_neurosynth\_data.ipynb”

# Alternative Option – ROI Association Decoder

- The ROI association decoding method computes the correlation between averaged modeled activation within a target ROI and term weights for all labels, yielding one correlation coefficient per label

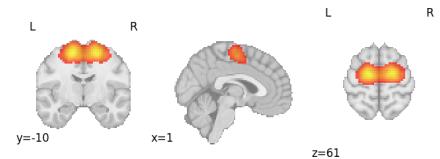
```
#### ROI Association Decoder (used in Margulies et al. 2016) ####

from nimare.decode import discrete

decoder = discrete.ROIAssociationDecoder(ICN_SM_thres_mni152)
decoder.fit(neurosynth_dset_copy)

# The `transform` method doesn't take any parameters.
decoded_df = decoder.transform()
decoded_df.sort_values(by="r", ascending=False)
```

feature	r
<b>motor</b>	0.300255
<b>action</b>	0.089180
<b>eye movements</b>	0.072698
<b>attention</b>	0.034519
<b>working memory</b>	0.029189
<b>visuospatial</b>	0.026658
<b>inhibition</b>	0.022357
<b>pain</b>	0.011743
<b>visual attention</b>	0.006437
<b>visual</b>	0.003127
<b>cognitive control</b>	-0.001027
<b>visual perception</b>	-0.002997
<b>numerical</b>	-0.003374
<b>reading</b>	-0.007402
<b>social cognition</b>	-0.009577
<b>multisensory</b>	-0.010492
<b>verbal</b>	-0.013694



Check “Code02\_Decoding\_with\_neurosynth\_data.ipynb”

# Useful references...

- NeuroSynth paper: Yarkoni, T., Poldrack, R. A., Nichols, T. E., Van Essen, D. C., & Wager, T. D. (2011). Large-scale automated synthesis of human functional neuroimaging data. *Nature methods*, 8(8), 665-670.
- NiMARE paper:  
[https://preprint.neurolibre.org/10.55458/neurolibre.00007/00\\_abstract.html](https://preprint.neurolibre.org/10.55458/neurolibre.00007/00_abstract.html)
- NiMARE docs: <https://nimare.readthedocs.io/en/stable/index.html>

**Enjoy exploring it!**