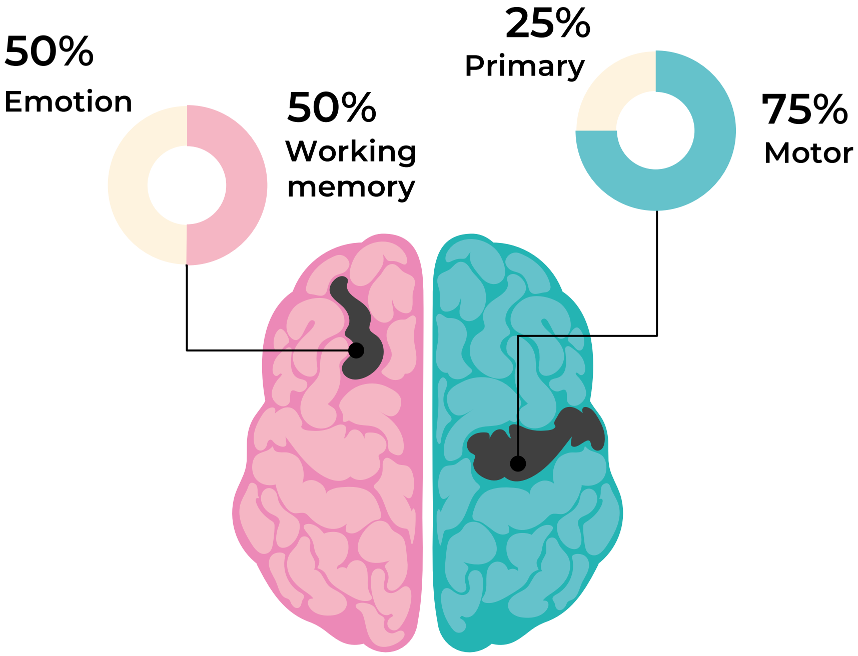
Meta-analytic

Functional Decoding

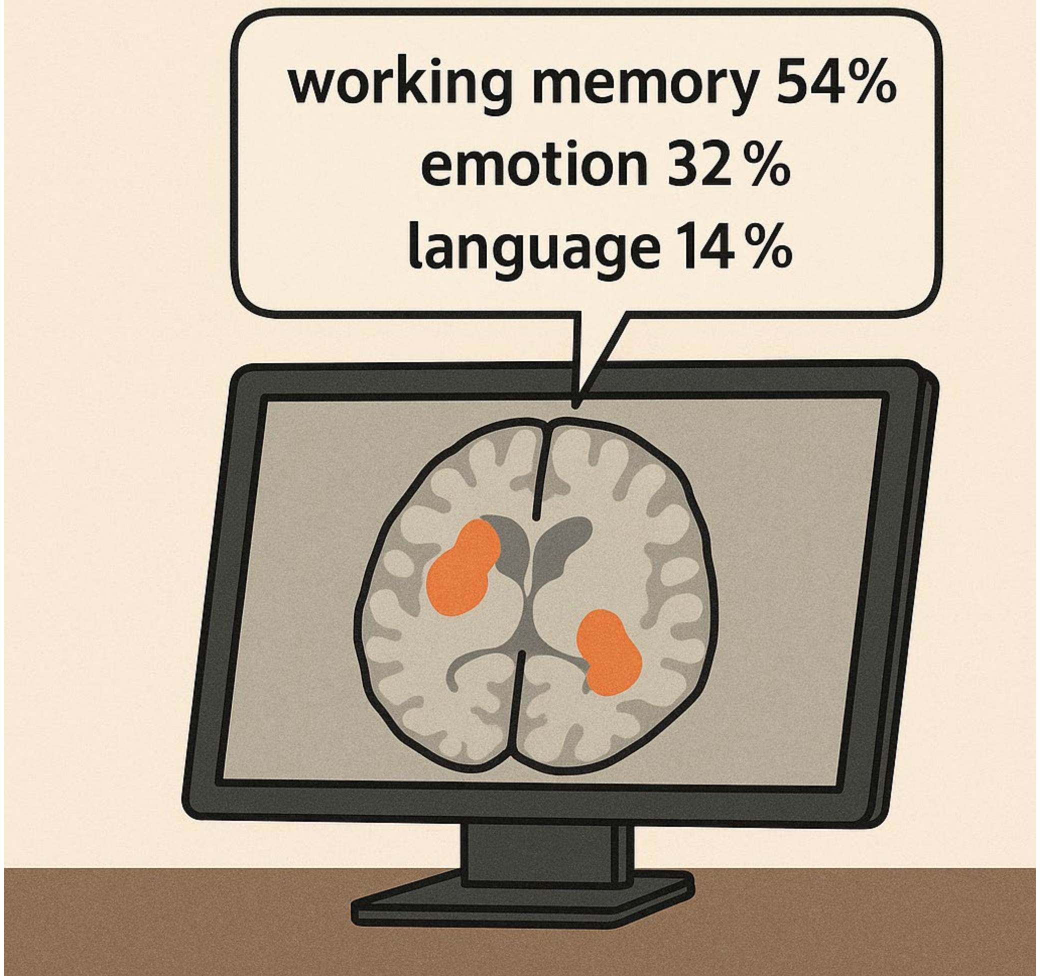
Youngjo Song



Example codes: https://github.com/YJ-0000/NiMARE_Functional_Decoding_Examples

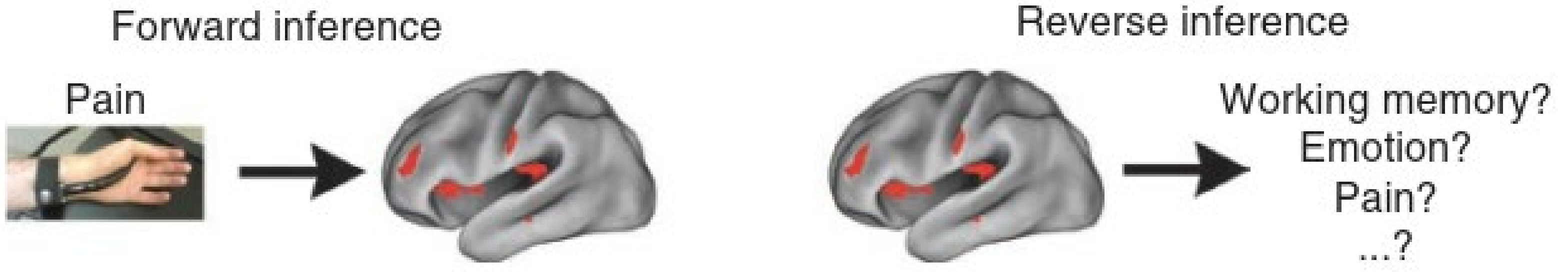
In Old Days,...

But we can ...



Massive prior fMRI studies

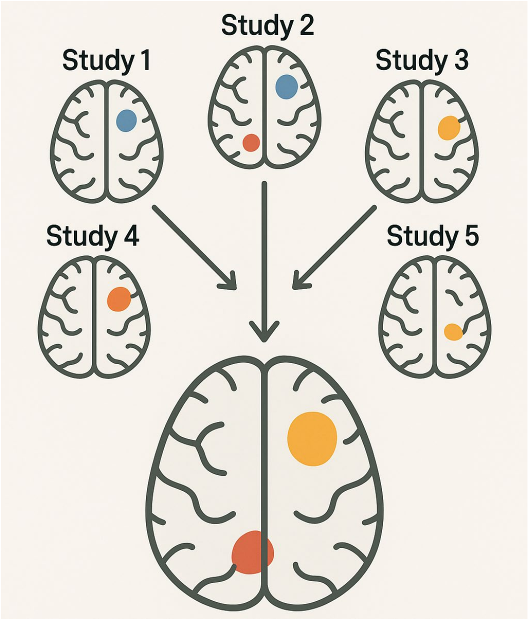
Forward/Reverse Inference



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.

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.

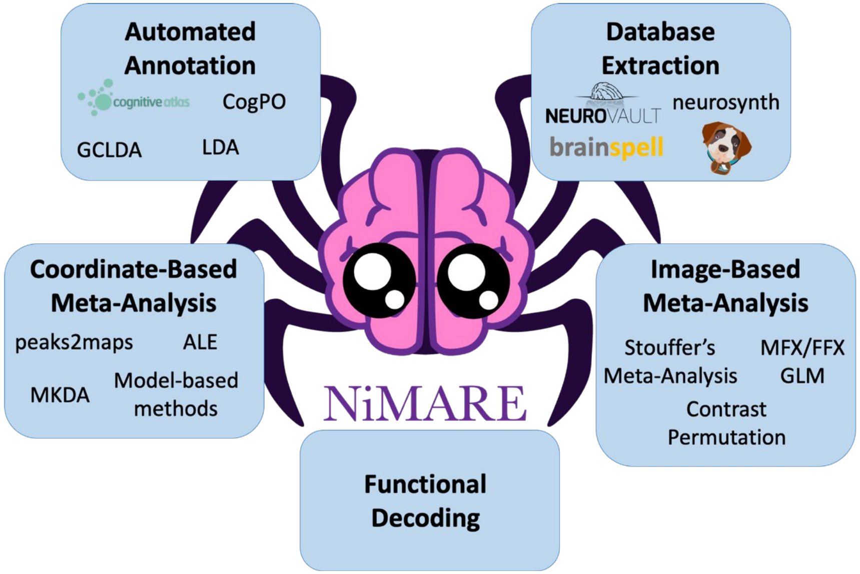


Yarkoni, T., Poldrack, R. A., Nichols, T. E., Van Essen, D. C., & Wager, T. D. (2011). Large-scale automated synthesis of human functional neuroimaging data. Nature methods, 8(8), 665-670.

NiMARE: 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



https://nimare.readthedocs.io/

github.com/neurosynth/neurosynth

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

Contributors 16

+ 2 contributors

Languages

Python 99.1% Dockerfile 0.9%

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.

https://github.com/neurosynth/neurosynth

Contents

fMRI Meta-analysis via NiMARE

01 Overview of fMRI Meta-Analysis Workflow

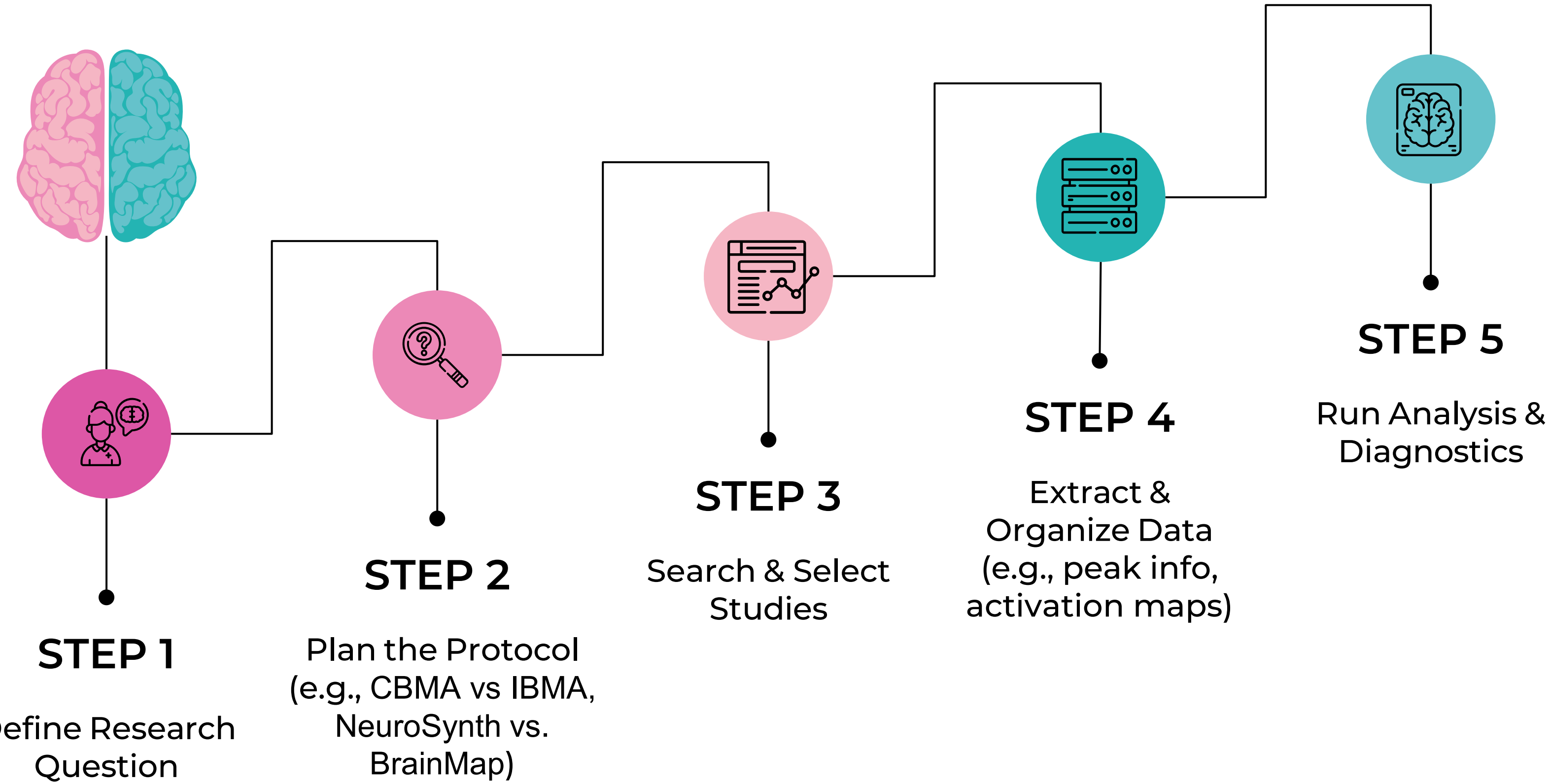
02 Using NiMARE: Practical Guide and Example

03 Alternative Options and Key Details

01

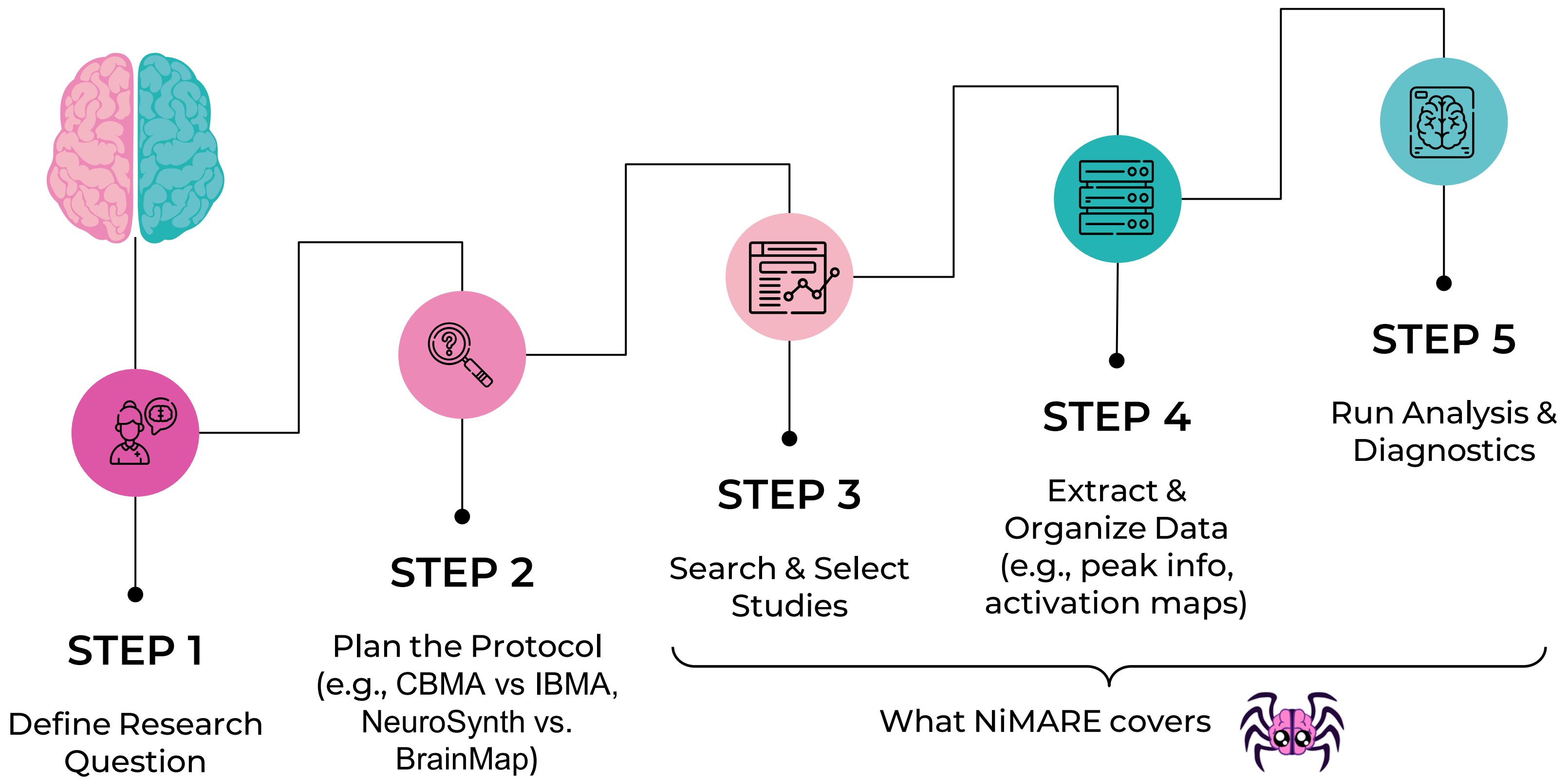
Overview of fMRI Meta-Analysis Workflow

An Overview of Meta-analysis

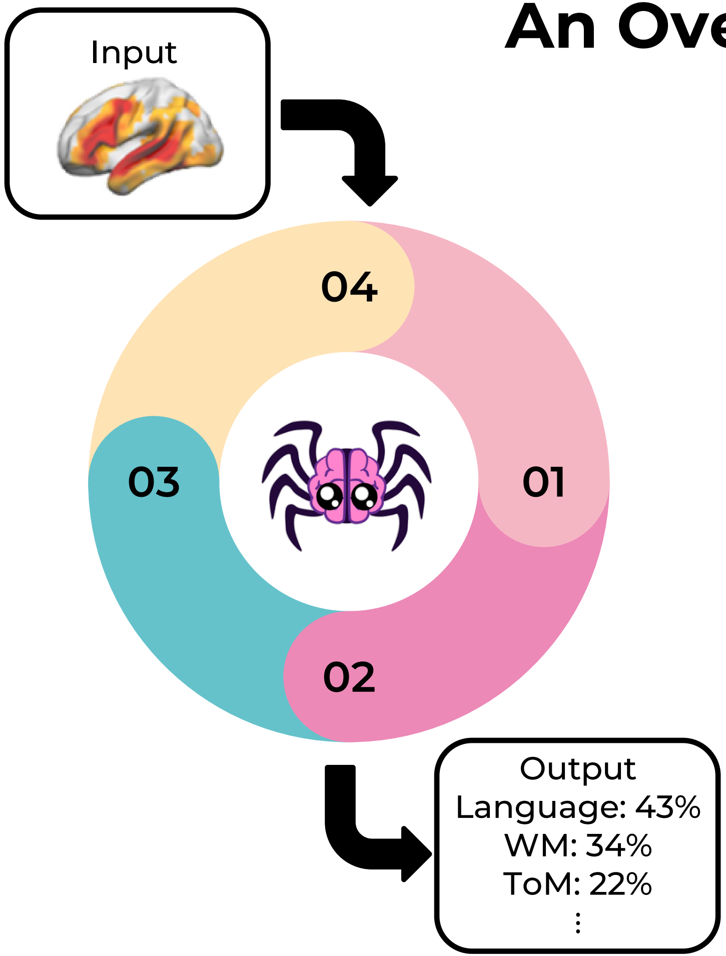


Müller, V. I., Cieslik, E. C., Laird, A. R., Fox, P. T., Radua, J., Mataix-Cols, D., ... & Eickhoff, S. B. (2018). Ten simple rules for neuroimaging meta-analysis. *Neuroscience & Biobehavioral Reviews*, *84*, 151-161.

An Overview of Meta-analysis



An Overview of NiMARE



01 Download Dataset

02 Specify Terms of Interest

03 Choose and Train Decoder

04 Decode

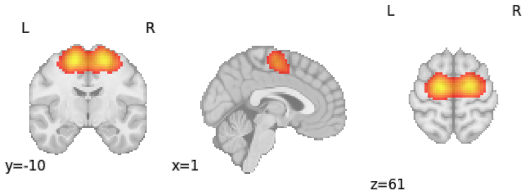
02

Using NiMARE: Practical Guide and Example

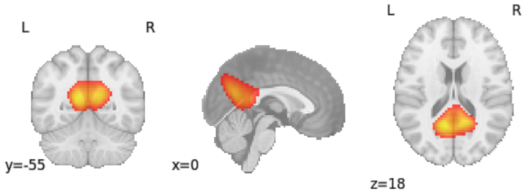
Goal: Functionally Characterizing a Given Spatial Map

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

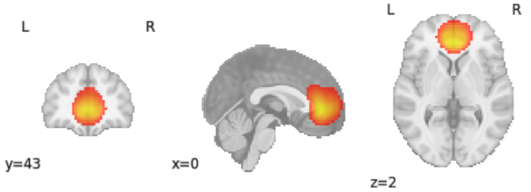
Sensorimotor



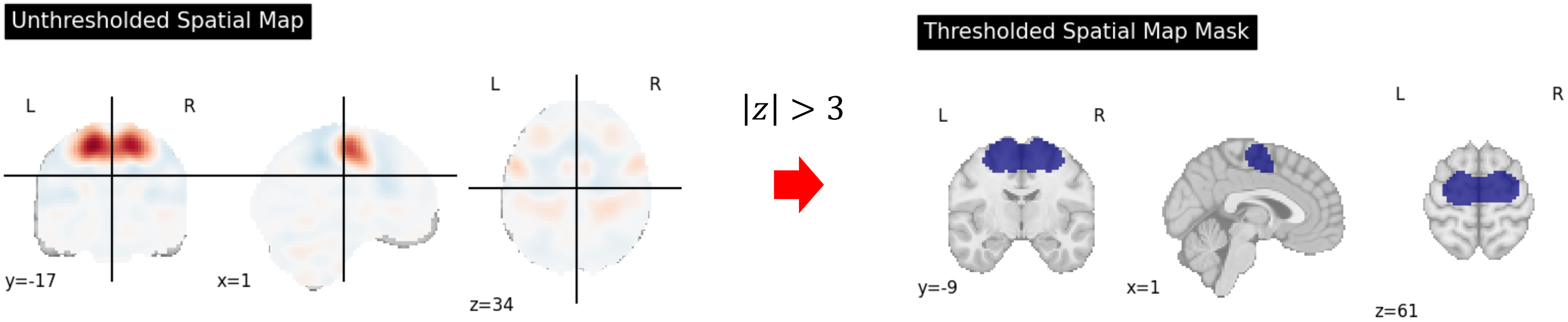
DMN (Precu)



DMN (MPFC)



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

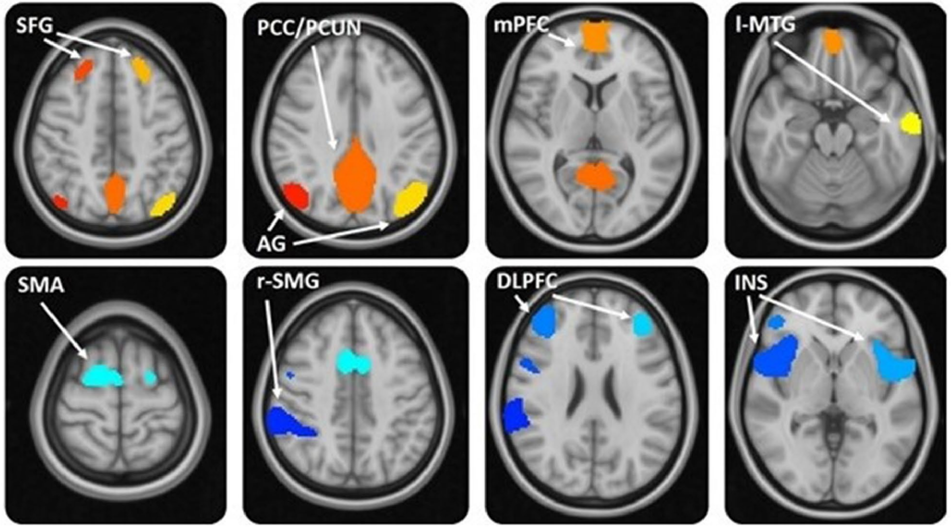


This step is required in order to use the NeuroSynth Decoder.

How can we collect data from the studies for meta-analysis?

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

Region of interest	Peak coordinates MNI_x	MNI_y	MNI_z	N_{vox}
Default Mode Network				
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
Anti-Correlated Network				
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



Groot, J. M., Boayue, N. M., Csifcsák, G., Boekel, W., Huster, R., Forstmann, B. U., & Mittner, M. (2021). Probing the neural signature of mind wandering with simultaneous fMRI-EEG and pupillometry. *NeuroImage*, *224*, 117412.

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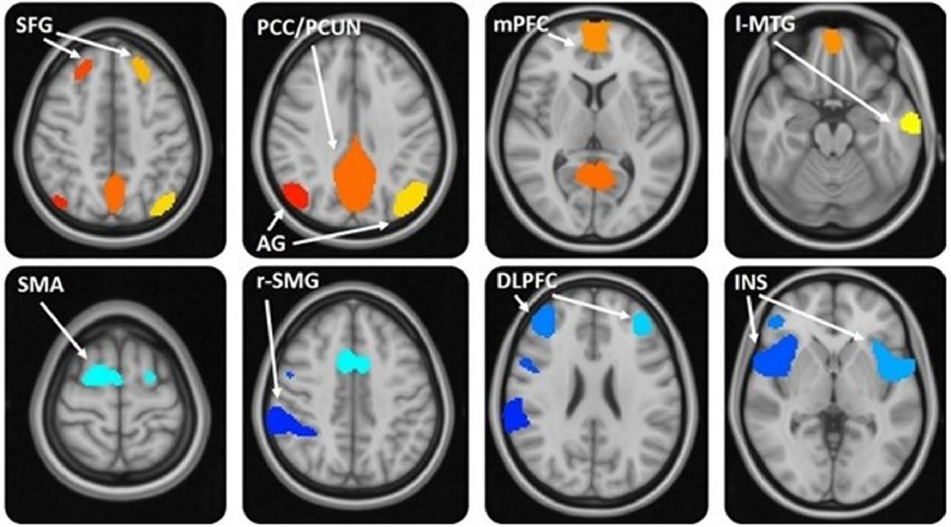
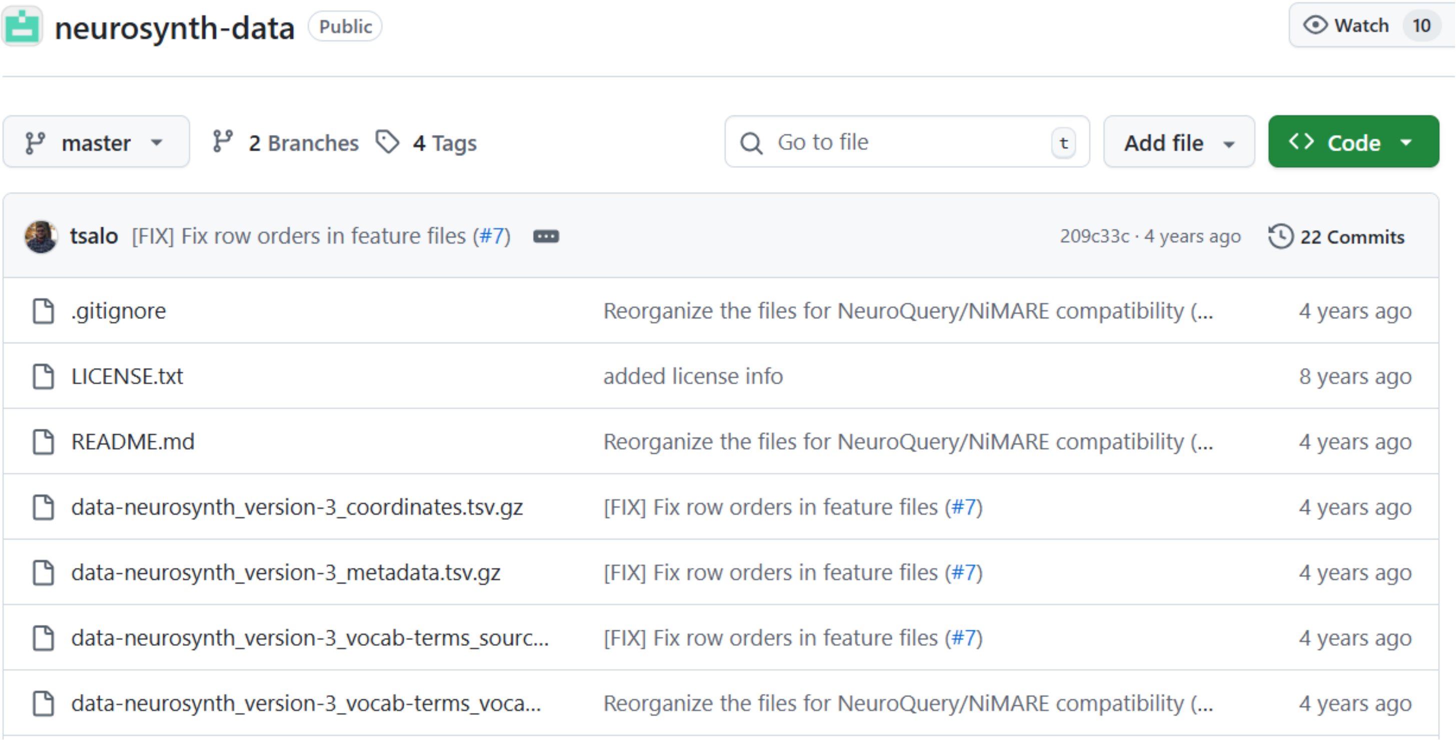


We need to extract these.

Groot, J. M., Boayue, N. M., Csifcsák, G., Boekel, W., Huster, R., Forstmann, B. U., & Mittner, M. (2021). Probing the neural signature of mind wandering with simultaneous fMRI-EEG and pupillometry. *NeuroImage*, *224*, 117412.

Good news is …

NeuroSynth provides a database that stores the extracted peaks

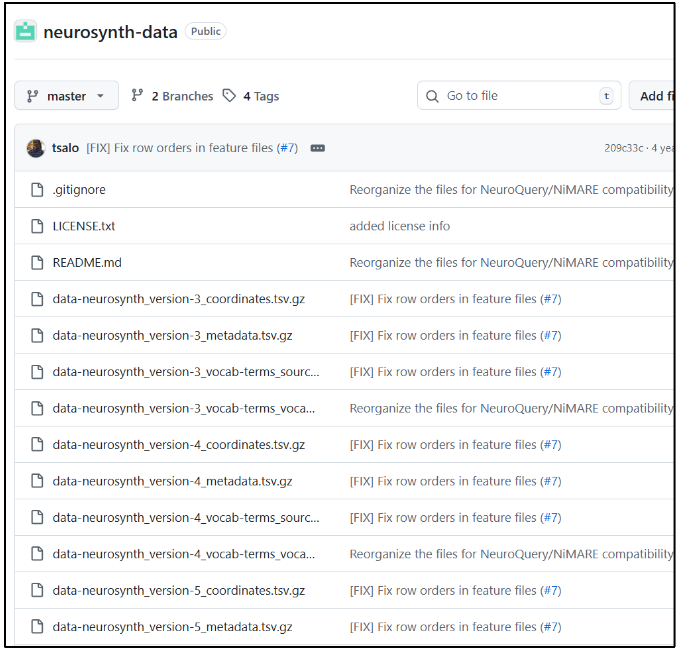


https://github.com/neurosynth/neurosynth-data

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”

```python
###############################################################################
# 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'
```

```python
# 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')
```

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

	id	study_id	contrast_id	authors	journal	year	title
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...

⋮

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

	id	study_id	contrast_id	x	y	z	space
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 neuro-physiological 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 lobule, 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

$$
\begin{array}{cl}
\left[\begin{array}{c} \vdots \\ 0 \\ 0 \\ 0.32 \\ 0 \\ 0.1 \\ 0 \\ 0 \\ 0 \\ \vdots \end{array}\right] &
\begin{array}{l} \\ \text{pain} \\ \text{visual} \\ \text{working memory} \\ \text{motor} \\ \text{response} \\ \text{social} \\ \text{ToM} \\ \text{reward} \\ \\ \end{array}
\end{array}
$$

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']
```

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

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

	id	study_id	contrast_id	terms_abstract_tfidf__001	terms_abstract_tfidf__01	terms_abstract_tfidf__05	terms_abstract_tfidf__10	terms_abstract_tfidf__100	terms_abstract_tfidf__11	terr
0	10022492-1	10022492	1	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	
2	10022496-1	10022496	1	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	
4	10191322-1	10191322	1	0.0	0.0	0.0	0.0	0.0	0.0	

5 rows × 3231 columns

3228 terms are used to annotate each study.

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

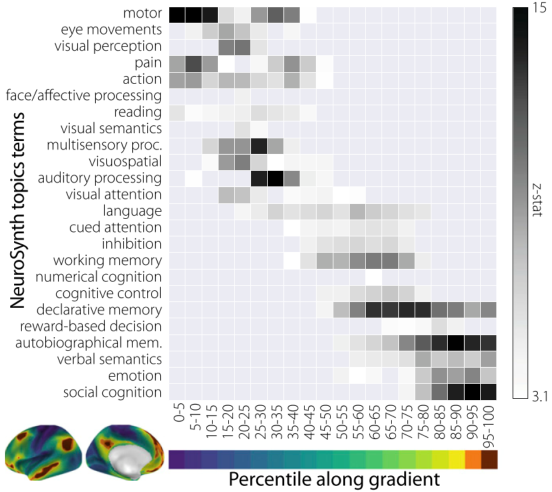
TF-IDF value for working memory

Check “Code02_Decoding_with_neurosynth_data.ipynb”

STEP 2. Specify Terms of Interest

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

- 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



Margulies, D. S., Ghosh, S. S., Goulas, A., Falkiewicz, M., Huntenburg, J. M., Langs, G., ... & Smallwood, J. (2016). Situating the default-mode network along a principal gradient of macroscale cortical organization. *Proceedings of the National Academy of Sciences*, *113*(44), 12574-12579.

```
#### 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
```

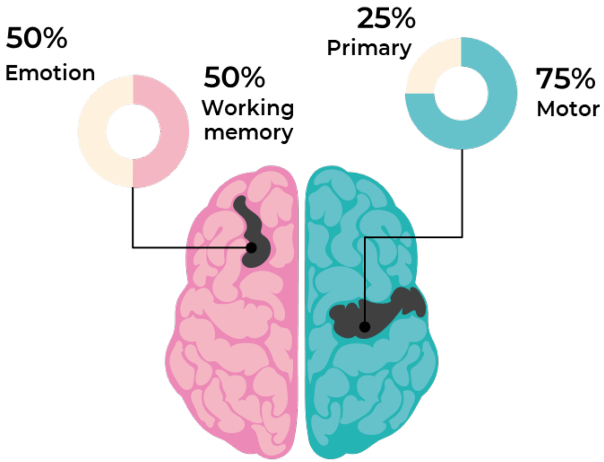
You should select cognitive terms for decoding.

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.

```python
#### 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.

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

Major outputs for reports

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

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

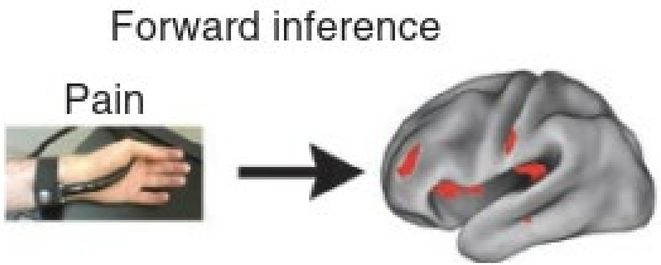
Term	pForward	zForward	probForward	pReverse	zReverse	probReverse
motor	0.000000e+00	inf	0.416853	5.714893e-180	28.605651	0.674786
eye movements	NaN	NaN	0.436507	1.255302e-07	5.285254	0.631976
action	5.912026e-14	7.510016	0.400493	1.467755e-27	10.877983	0.610139
visual attention	NaN	NaN	0.382826	3.987689e-03	2.879134	0.579309
visuospatial	NaN	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	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	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	NaN	0.319151	8.337580e-01	-0.209884	0.493604
social cognition	NaN	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

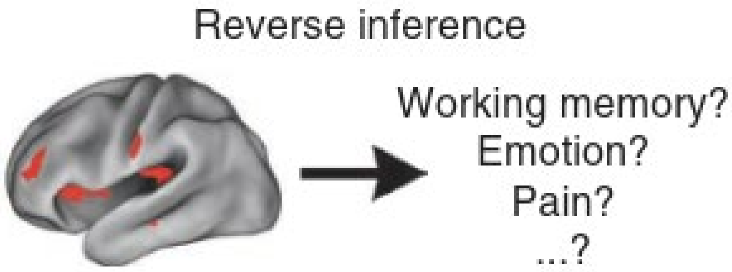
What's the difference?

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

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

	pForward	zForward	probForward	pReverse	zReverse	probReverse
Term						
motor	0.000000e+00	inf	0.416853	5.714893e-180	28.605651	0.674786
eye movements	NaN	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	NaN	0.382826	3.987689e-03	2.879134	0.579309

Forward/Reverse Inference





a.k.a. Uniformity test

a.k.a. Association test

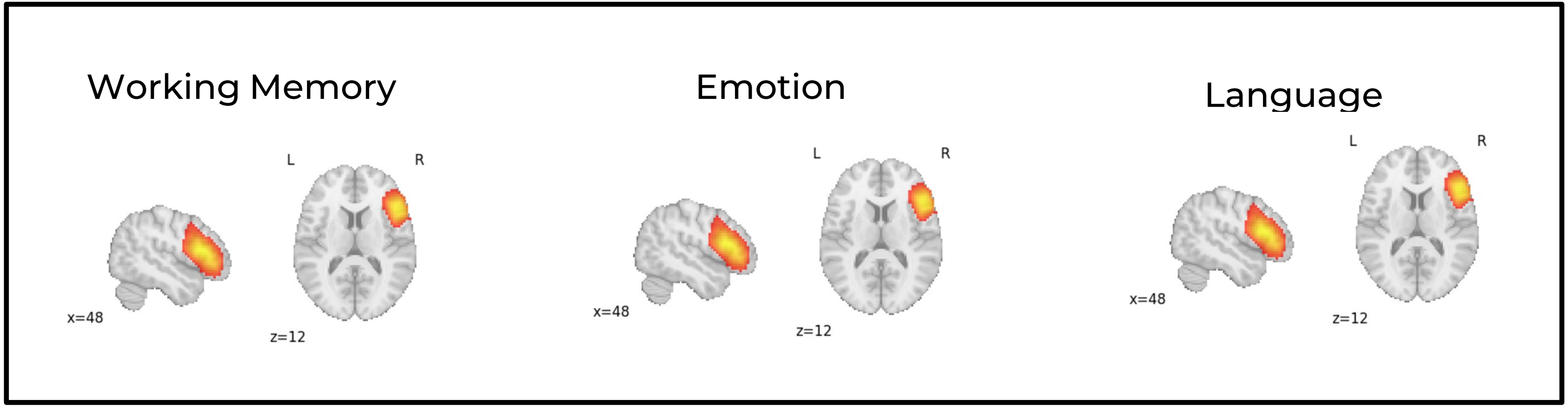
The degree to which each voxel is consistently activated in studies that use a given term.

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

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.

Forward/Reverse Inference for Emotion

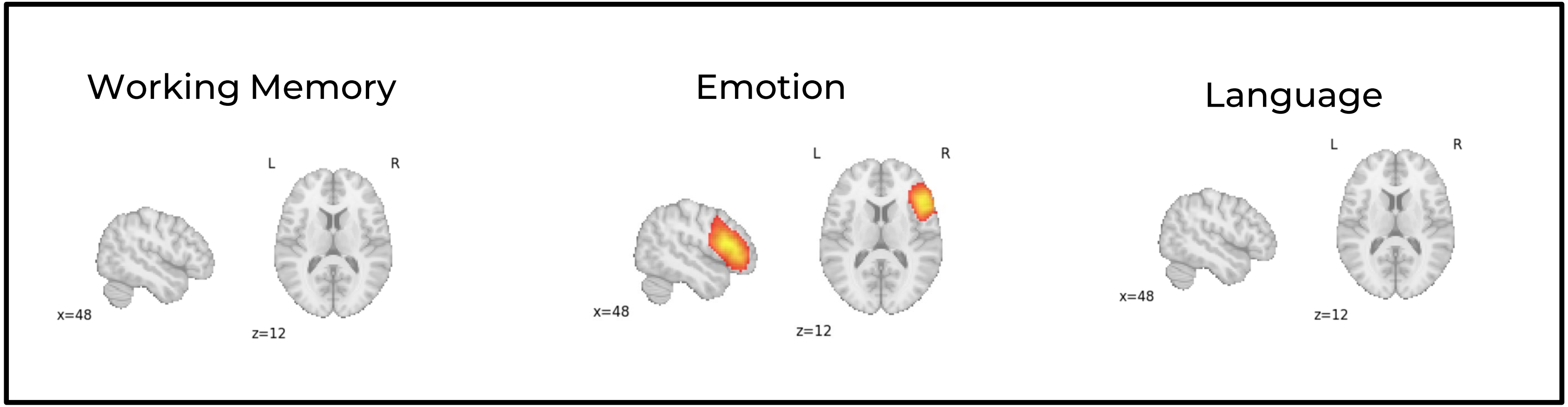
If a given brain area is all activated during working memory-, emotion-,
and language-mentioned studies, ...



Forward probability ($p(\text{activaiton}|\text{term})$) 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

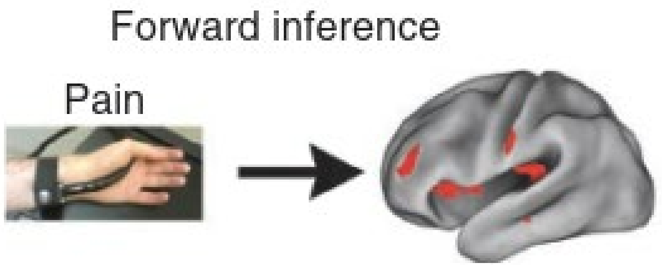


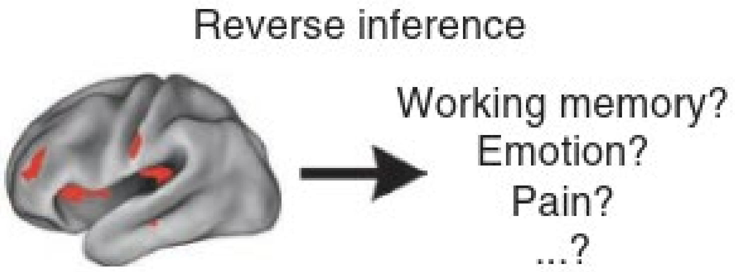
Forward probability ($p(\text{activaiton}|\text{term})$) of this area is high.
Reverse probability ($p(\text{term}|\text{activation})$) of this area is high.

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 nuiances in these two probability.





a.k.a. Uniformity test

a.k.a. Association test

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

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

$$p(T_k = 1) = p(T_k = 0) = 0.5$$

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

Statistical significance

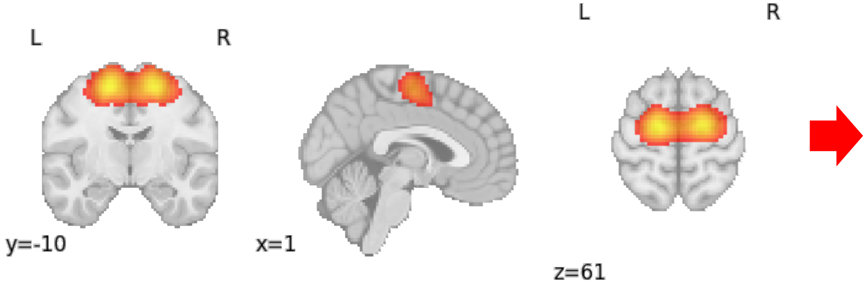
```
#### Decode ####

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

Term	pForward	zForward	probForward	pReverse	zReverse	probReverse
motor	0.000000e+00	inf	0.416853	5.714893e-180	28.605651	0.674786
eye movements	NaN	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	NaN	0.382826	3.987689e-03	2.879134	0.579309
visuospatial	NaN	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	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	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	NaN	0.319151	8.337580e-01	-0.209884	0.493604
social cognition	NaN	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

- 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

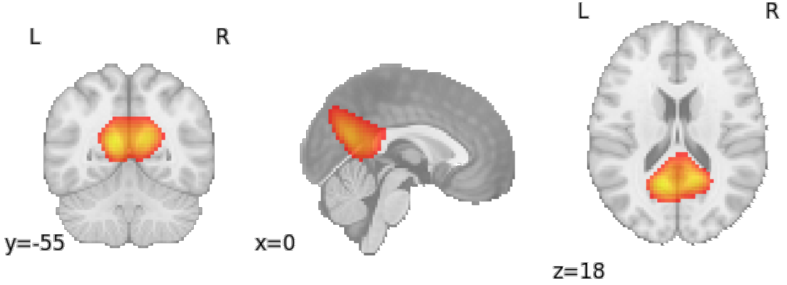
Decoding Results – sensorimotor



Term	pForward	zForward	probForward	pReverse	zReverse	probReverse
motor	0.000000e+00	inf	0.416853	5.714893e-180	28.605651	0.674786
eye movements	NaN	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	NaN	0.382826	3.987689e-03	2.879134	0.579309
visuospatial	NaN	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	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	NaN	0.323850	9.742068e-01	0.032333	0.501098

Only displaying terms with probReverse > 0.5

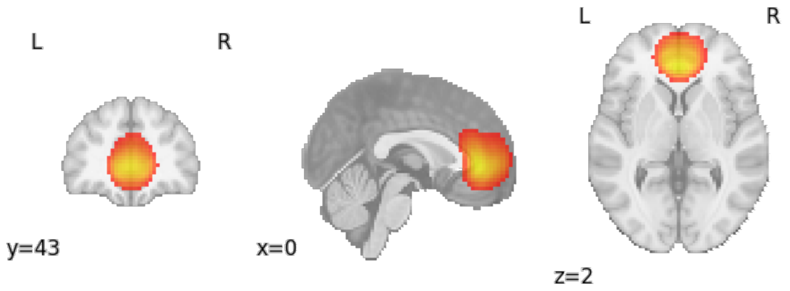
Decoding Results – DMN (Precuneus)



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

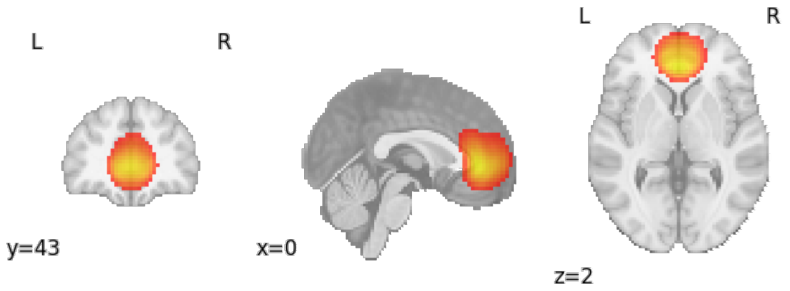
Decoding Results – DMN (MPFC)



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	0.397881	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

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.

https://neuroquery.org/

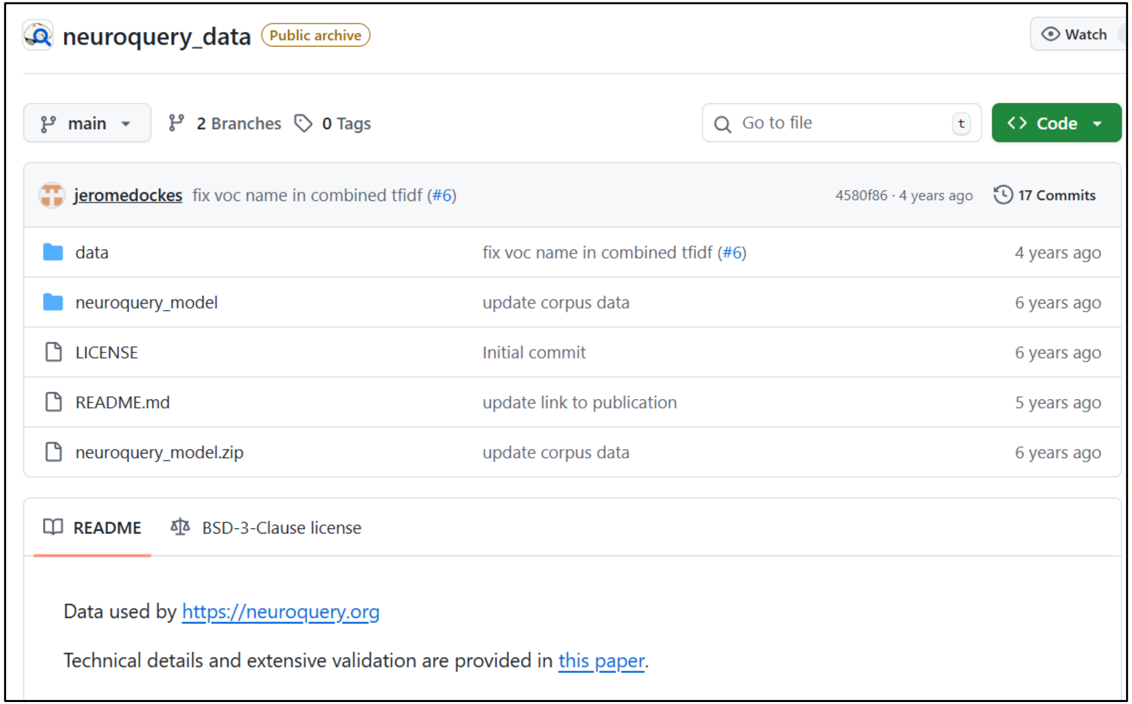
Alternative Option – NeuroQuery Dataset

- 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

Dockès, J., Poldrack, R. A., Primet, R., Gözükan, H., Yarkoni, T., Suchanek, F., ... & Varoquaux, G. (2020). NeuroQuery, comprehensive meta-analysis of human brain mapping. elife, 9, e53385.

They provide the dataset through GitHub.



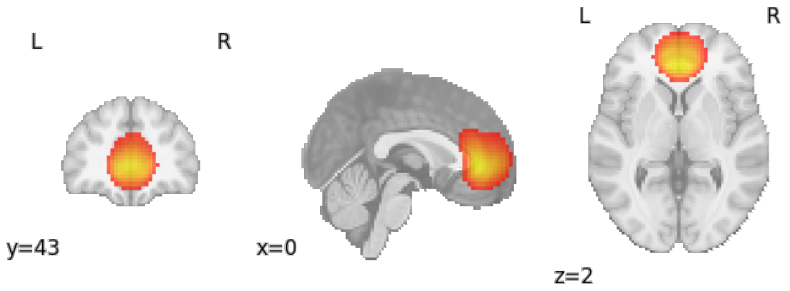
We can use this for decoding!

https://github.com/neuroquery/neuroquery_data/

Check “Code03_Decoding_with_neuroquery_data.ipynb”

Decoding Results – DMN (MPFC)

NeuroSynth Decoder trained with the NeuroQuery Dataset



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

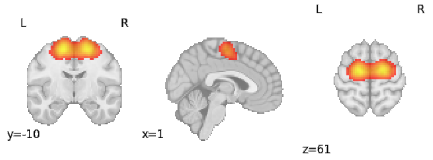
- BrainMap decoder accounts for the number of activation foci per study.

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

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



Check “Code02_Decoding_with_neurosynth_data.ipynb”

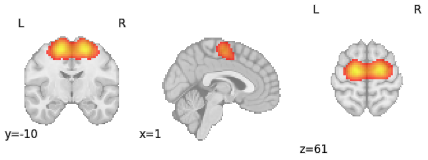
Alternative Option – ROI Association Decoder

- 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

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

```python
#### ROI Assoicaiton Decoder (used in Margulias 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
motor	0.300255
action	0.089180
eye movements	0.072698
attention	0.034519
working memory	0.029189
visuospatial	0.026658
inhibition	0.022357
pain	0.011743
visual attention	0.006437
visual	0.003127
cognitive control	-0.001027
visual perception	-0.002997
numerical	-0.003374
reading	-0.007402
social cognition	-0.009577
multisensory	-0.010492
verbal	-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

- NiMARE docs: https://nimare.readthedocs.io/en/stable/index.html

Enjoy exploring it!