Japanese Short Songs with Brain

Daichi Mochihashi
The Institute of Statistical Mathematics
daichi@ism.ac.jp

Symposium on Emotional Intelligence
2024-7-21 (Sun)
The University of Tokyo

Overview

- Language team targeted emotional analysis of literary arts, esp. Japanese short songs
- We conducted two main research:
  - fMRI analysis when the subject is reading Japanese short song (aka. Tanka)
  - Statistical analysis of contemporary Tanka evaluations by college Tanka club students

What is *Tanka* (Japanese Short Song)?

- Japanese short poem, lasting over 1,000 years

  白犀は心の水の深きまで沈みつ水の春は熟れゆく
  レシートに冬の日付は記されて左から陽の射していた道
  青春はみづきの下をかよふ風あるいは遠い線路のかがやき
  切り終へて包丁の刃の水平を見る眼の薄き水なみだちぬ
  ほんとうにおれのもんかよ冷蔵庫の卵置き場に落ちる涙は

  - 5-7-5-7-7=31 syllables
  - “Contemporary tanka” lately becomes popular among young generations
- First half of the song became *Haiku* in history

Why not using *Haiku*?

- *Haiku* is derived from the fist part of *Tanka*
  - Very short, only 5-7-5=17 syllables

赤い椿白い椿と落ちにけり
蛭泳ぐ自在に蛭を司り
生家てふ市営アパート星月夜

- *Haiku* heavily depends on symbolic knowledge, including *Kigo* (seasonal word): not ideal for emotional analysis
  - eg: 椿→death, 星月夜→dream, ...

fMRI analysis during reading Tanka

Anna Sato and Ichiro Kobayashi
(Ochanomizu University), ICANN 2023

Investigation of Information Processing Mechanisms in the Human Brain during Reading Tanka Poetry

〇Anna Sato[1], Junichi Chikazoe[2], Shotaro Funai[2], Daichi Mochihashi[3], Yutaka Shikano[4], Masayuki Asahara[5], Satoshi Iso[6], and Ichiro Kobayashi[1]

[1] Ochanomizu University, [2] Araya Inc., [3] Institute of Statical Mathematics, [4] Gunma University, [5] National Institute for Japanese Language and Linguistics, and [6] High Energy Accelerator Research Organization

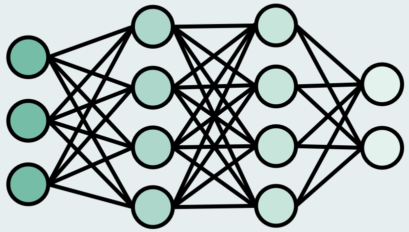
Recent integration of neuroscience and deep learning

Advances in non-invasive brain imaging

fMRI, MEG, EEG…

Development of machine learning techniques

Transformer, CNN, RNN…



- Elucidating the information processing mechanisms in the human brain
- Quantitative understanding of values

Research Objectives

- How are emotions induced by literary art represented in the human brain?
  ⇒ Use LLM to analyze brain activity during reading **Tanka** poetry
  Large Language Model

What is a Tanka?

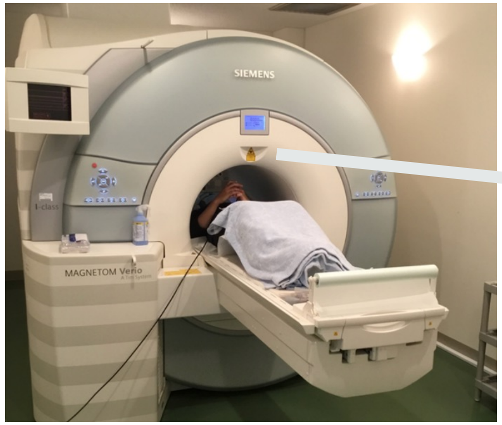
- An ancient form of Japanese poetry (older than Haiku)
- Consists of five syllables units 5-7-5-7-7
- Generally expresses the poet's feeling

An example of a tanka

Japanese		English
東海の	*Tōkai no*	In the Eastern Sea,
小島の磯の	*kojima no iso no*	Of the beach of a small island,
白砂に	*shirasuna ni*	On the white sand.
われ泣きぬれて	*ware naki nurete*	I, my face streaked with tears,
蟹とたわむる	*kani to tawamuru*	Am playing with a crab
(Ishikawa Takuboku)		

fMRI Experiment

- **Subjects**: 32 healthy young adults (age range: 18-34)
- **Stimuli**: 300 sentences from BCCJW[1] Japanese corpus
  - 150 tanka poetries
  - 150 plain texts (that sentences of roughly the same length as a tanka)
- Read and evaluated each sentence whether or not they felt it poetic



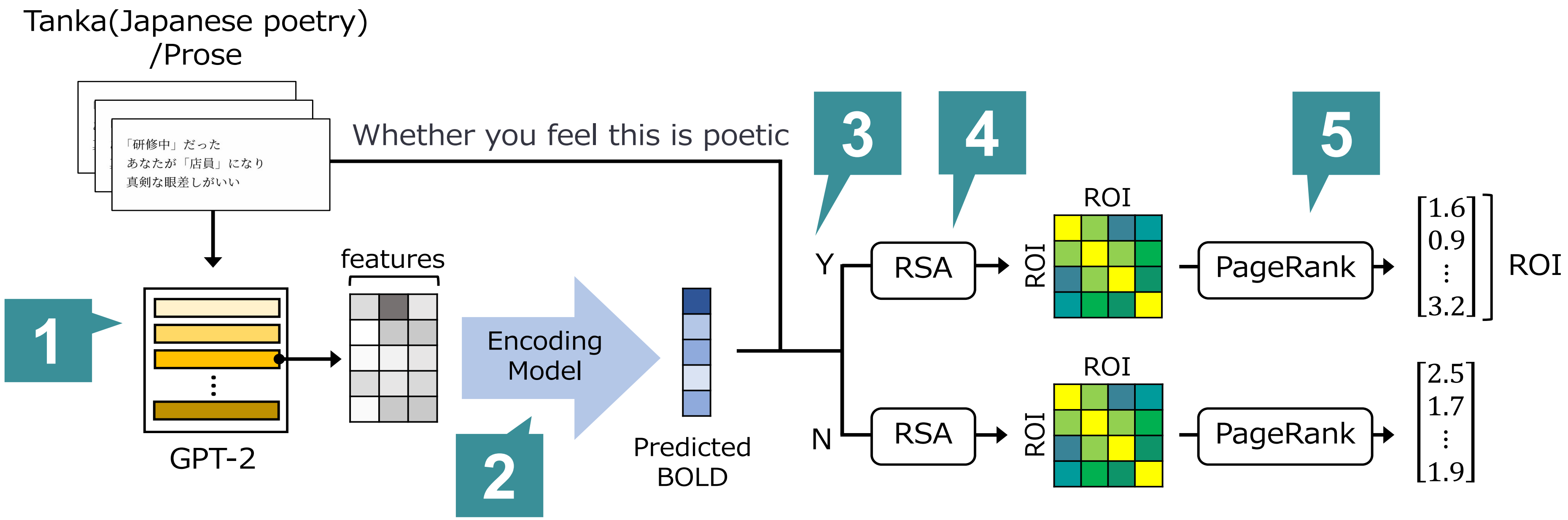
e.g.

Tanka	人間に生きつつ或る夜 さびしくて鏡のなかに 我を呼び出す	While living as a human, one night, feeling lonely, I call upon myself in the mirror.
Plain text	家や友人の家などに 警察がくる可能性は ありますか？	Is there a possibility that the police may come to my house or my friend's house?

[1] The Balanced Corpus of Contemporary Written Japanese,https://clrd.ninjal.ac.jp/bccwj/en/.

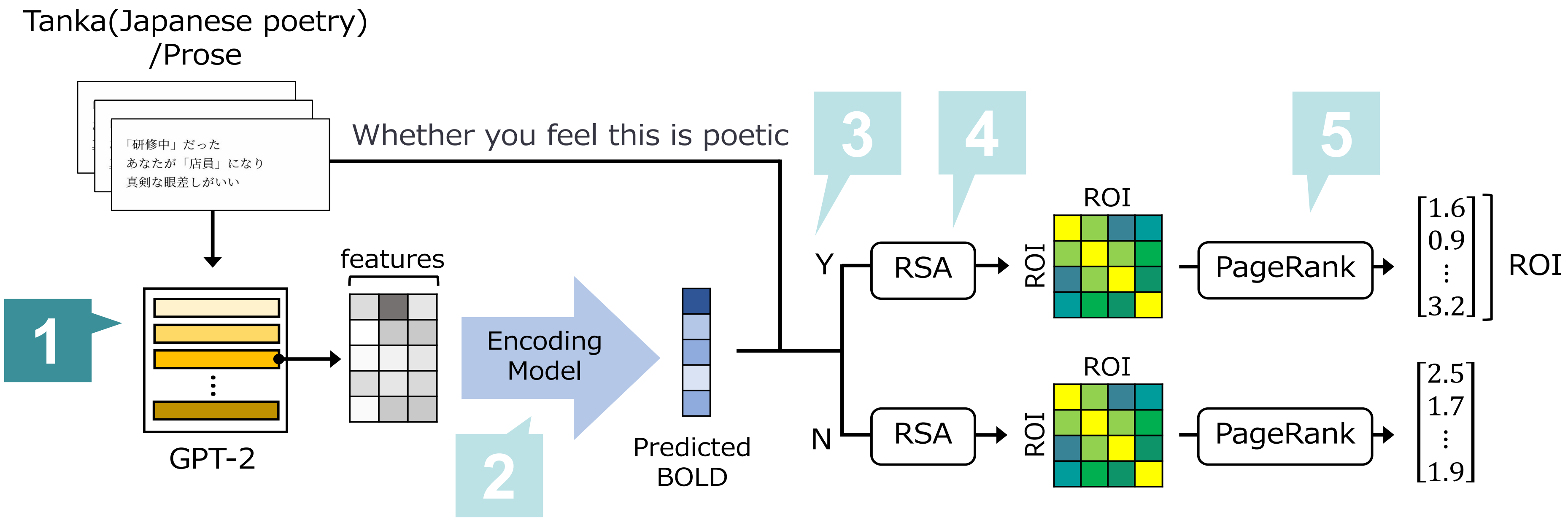
Analysis of Brain Activity under Language Stimuli

1. Input sentences to a language model and extract their activations
2. Construct an encoding model (ridge regression) to predict neural responses
3. Extract predicted brain activities based on stimuli answered “poetic” or “non-poetic”
4. Apply RSA to create a RDM that represents connectivity between each brain region
5. Apply PageRank algorithm to find hub regions in the brain network



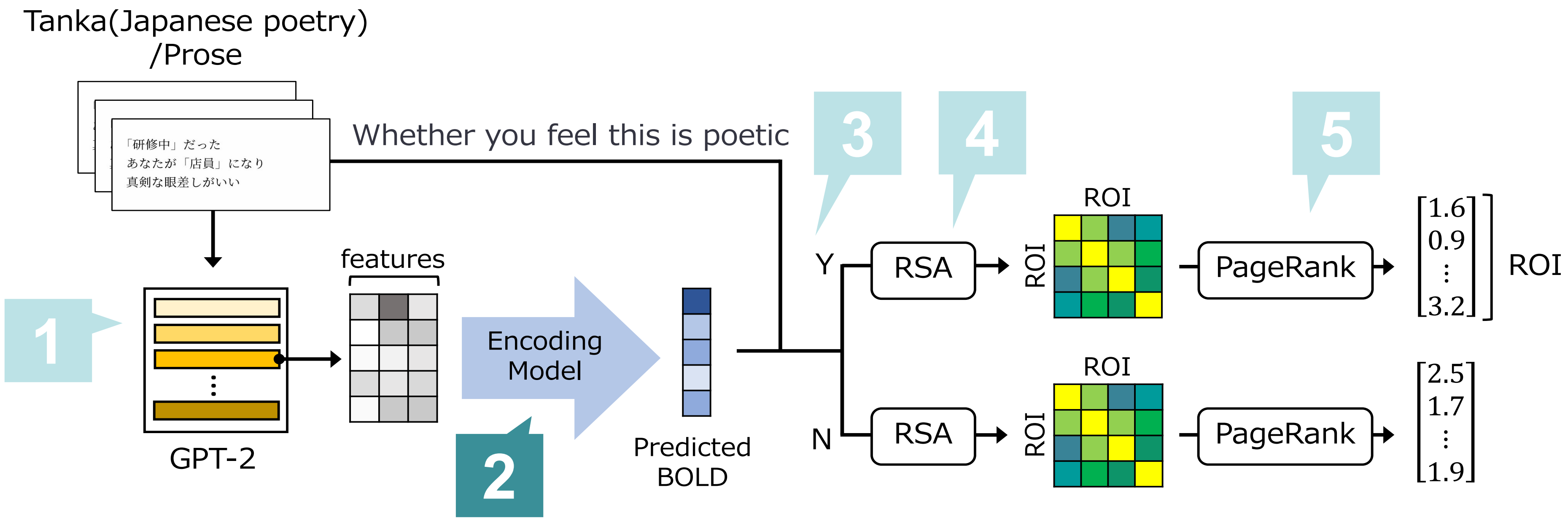
Analysis of Brain Activity under Language Stimuli

1. Input sentences to a language model and extract their activations
2. Construct an encoding model (ridge regression) to predict neural responses
3. Extract predicted brain activities based on stimuli answered “poetic” or “non-poetic”
4. Apply RSA to create a RDM that represents connectivity between each brain region
5. Apply PageRank algorithm to find hub regions in the brain network



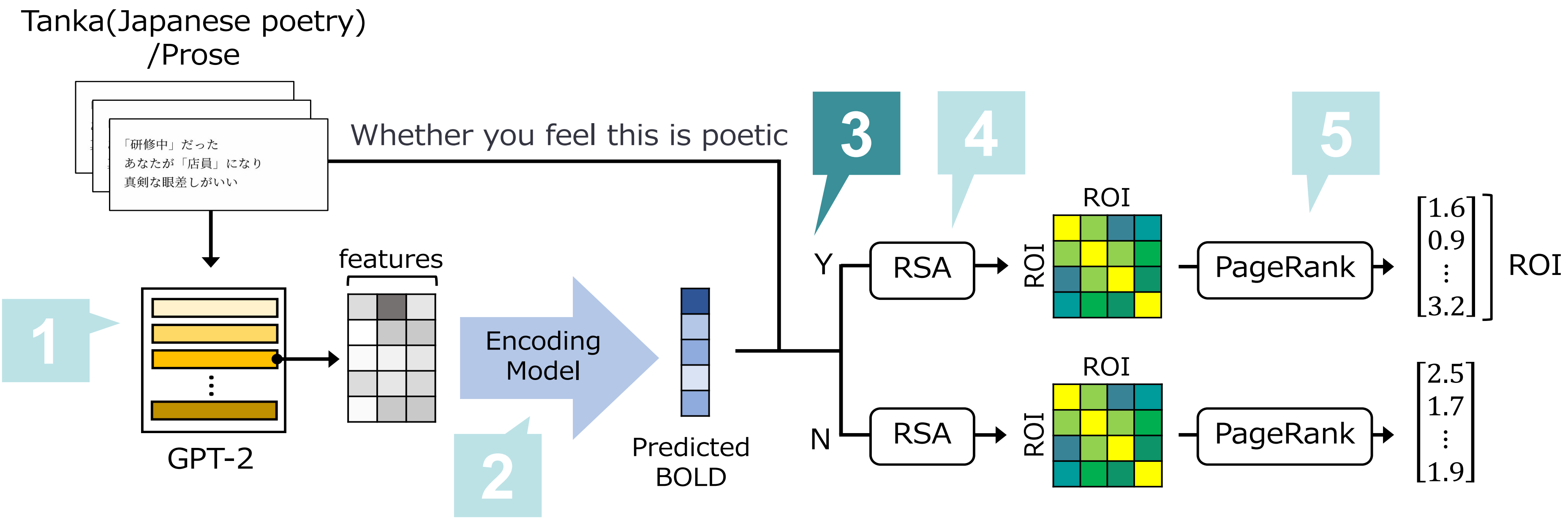
Analysis of Brain Activity under Language Stimuli

1. Input sentences to a language model and extract their activations
2. Construct an encoding model (ridge regression) to predict neural responses
3. Extract predicted brain activities based on stimuli answered “poetic” or “non-poetic”
4. Apply RSA to create a RDM that represents connectivity between each brain region
5. Apply PageRank algorithm to find hub regions in the brain network



Analysis of Brain Activity under Language Stimuli

1. Input sentences to a language model and extract their activations
2. Construct an encoding model (ridge regression) to predict neural responses
3. Extract predicted brain activities based on stimuli answered “poetic” or “non-poetic”
4. Apply RSA to create a RDM that represents connectivity between each brain region
5. Apply PageRank algorithm to find hub regions in the brain network

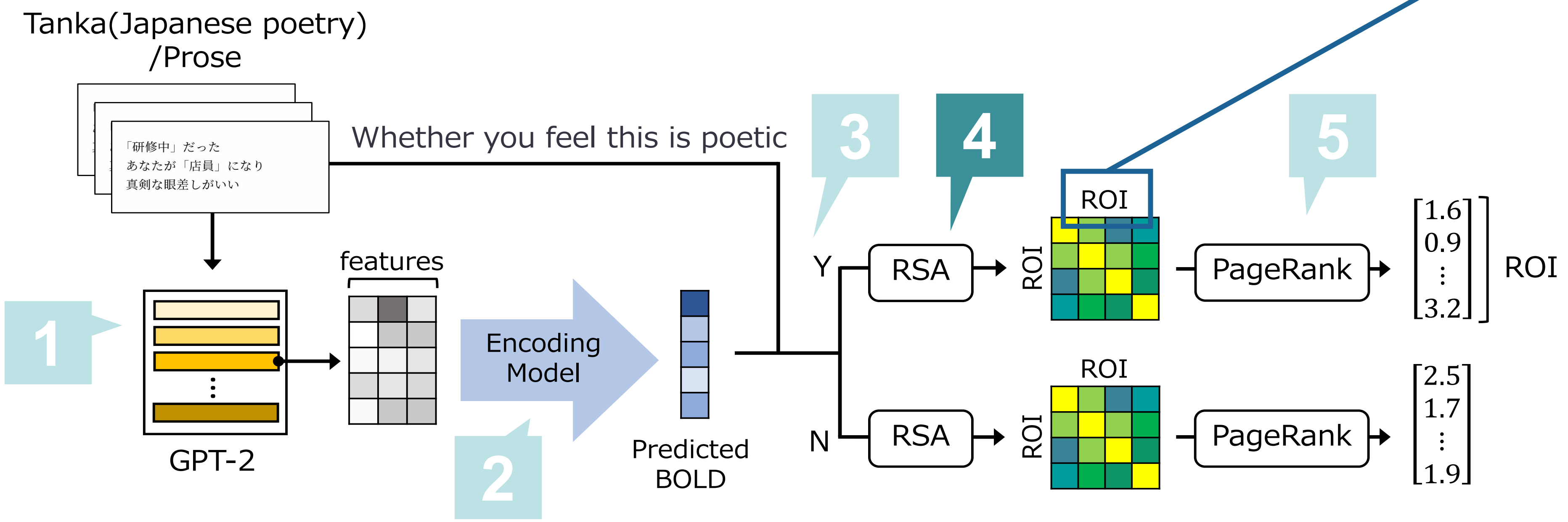


Analysis of Brain Activity under Language Stimuli

Representational Similarity Analysis

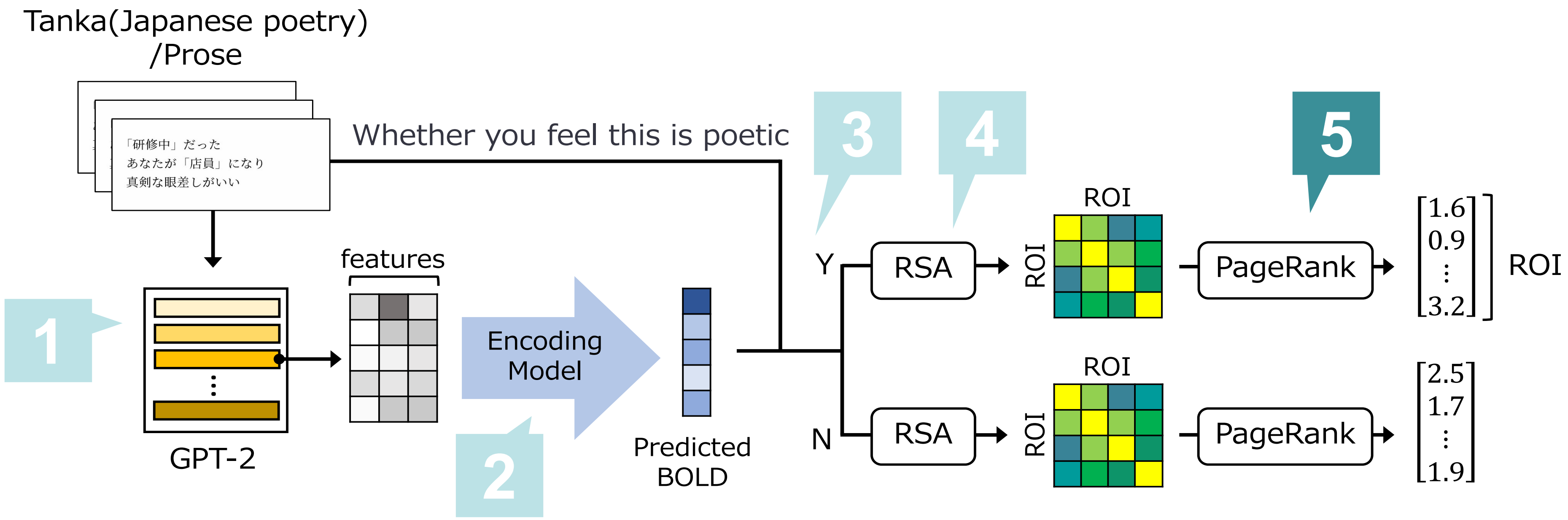
Representational Dissimilarity Matrix

1. Input sentences to a language model and extract their activations
2. ... din ...) to predict neural responses
3. Extra ... edicted brain acti ... s based on stimuli answered “poetic” or “non-poetic”
4. Apply RSA to create a RDM that represents connectivity between each brain region
5. Apply PageRank algorithm to find hub regions in the brain network



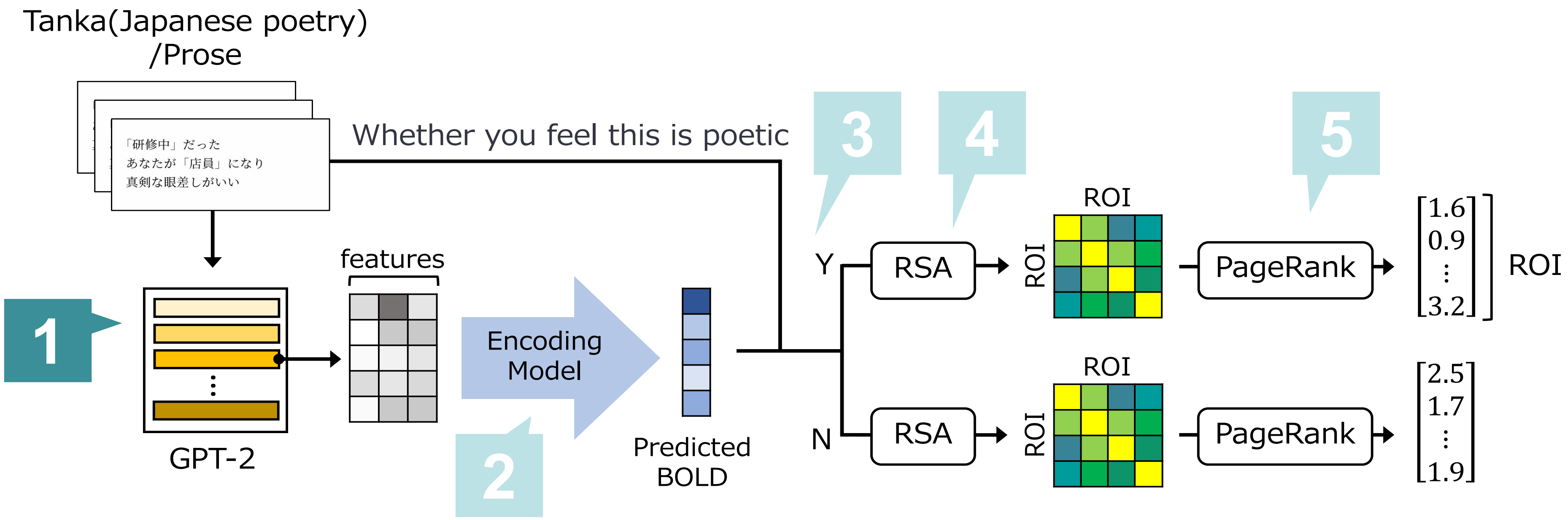
Analysis of Brain Activity under Language Stimuli

1. Input sentences to a language model and extract their activations
2. Construct an encoding model (ridge regression) to predict neural responses
3. Extract predicted brain activities based on stimuli answered “poetic” or “non-poetic”
4. Apply RSA to create a RDM that represents connectivity between each brain region
5. Apply PageRank algorithm to find hub regions in the brain network



Analysis of Brain Activity under Language Stimuli

1. Input sentences to a language model and extract their activations
2. Construct an encoding model (ridge regression) to predict neural responses
3. Extract predicted brain activities based on stimuli answered poetic or non-poetic
4. Apply RSA to create a RDM that represents connectivity between each brain region
5. Apply PageRank algorithm to find hub regions in the brain network



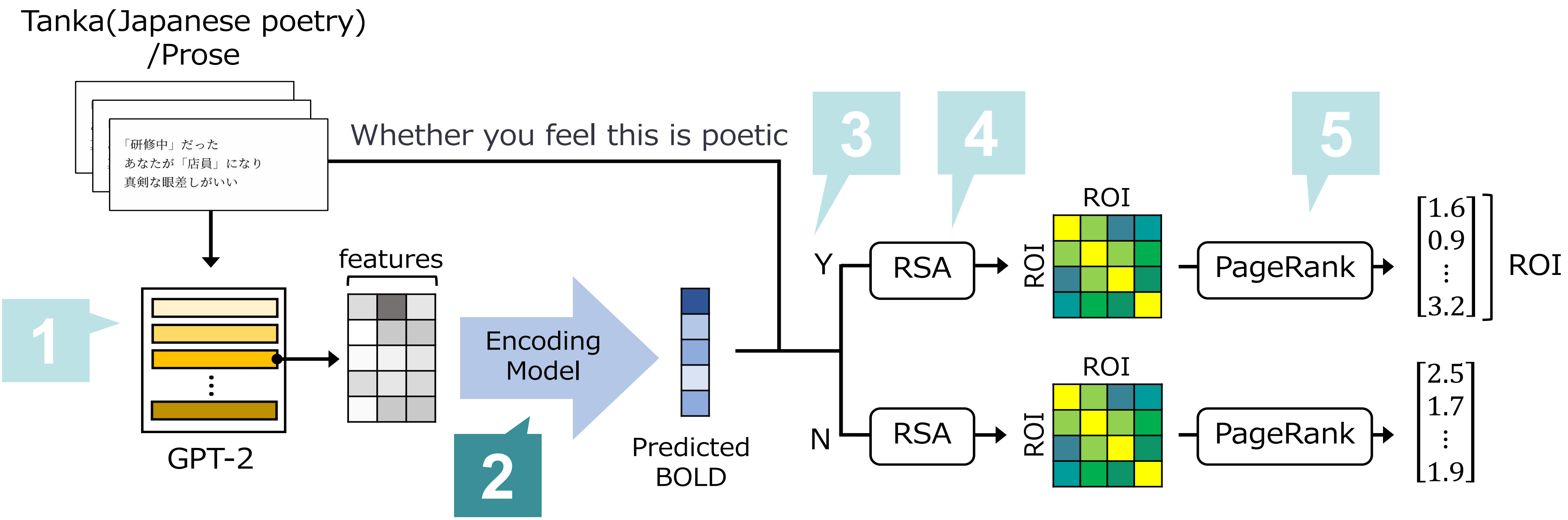
Extract sentence features from language models

- **GPT-2**[Radford+, 2019]
  - Pretrained model: rinna/japanese-gpt2-medium[2] （24 Transformer layers)
  - Multi-step Fine-tuning:
    1. Fine-tune on Tanka poetries (task: Causal language modeling)
       Data: 3571 tanka, not used in the fMRI experiment, from BCCWJ corpus
    2. Classification of whether a text is poetic or not
       Data: 250 sentences used in the experiment and not included in the test data
- Input sentences and extract activtations from each layer of Transformer

[2] https://huggingface.co/rinna/japanese-gpt2-medium.

Analysis of Brain Activity under Language Stimuli

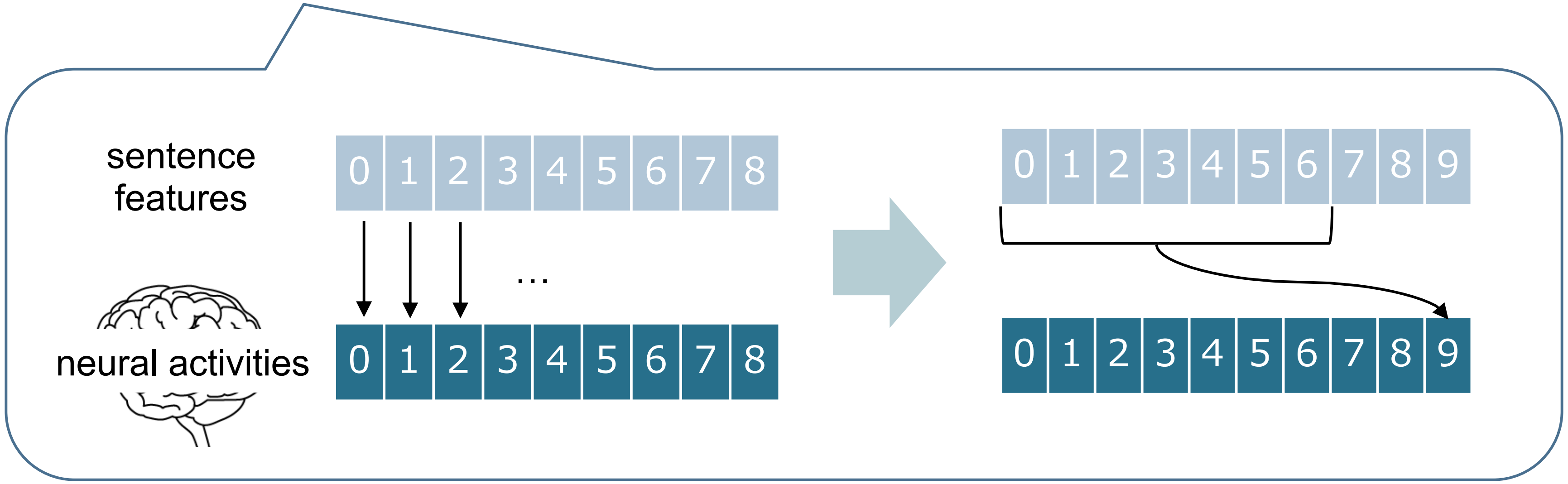
1. Input sentences to a language model and extract their activations
2. Construct an encoding model (ridge regression) to predict neural responses
3. Extract predicted brain activities based on stimuli answered “poetic” or “non-poetic”
4. Apply RSA to create a RDM that represents connectivity between each brain region
5. Apply PageRank algorithm to find hub regions in the brain network



Encoding Model[Naselaris+, 2011]

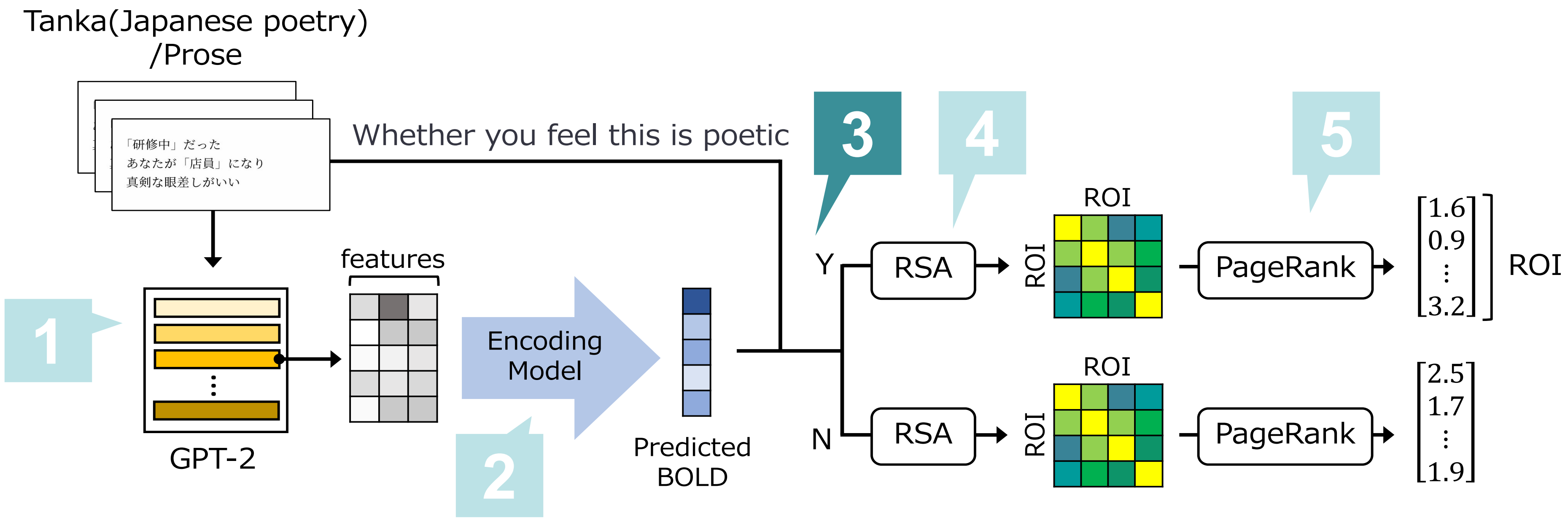
- Regression of brain activity from the activations extracted from the intermediate layers of the language model
- The Blood Oxygen Level-Dependent(BOLD) signal measured by fMRI is known to activate with a delay in response to stimuli (Hemodynamic response)

  ⇒ Combine sentences features from 3 to 9 TRs prior (1TR=0.75sec) and perform regression



Analysis of Brain Activity under Language Stimuli

1. Input sentences to a language model and extract their activations
2. Construct an encoding model (ridge regression) to predict neural responses
3. Extract predicted brain activities based on stimuli answered “poetic” or “non-poetic”
4. Apply RSA to create a RDM that represents connectivity between each brain region
5. Apply PageRank algorithm to find hub regions in the brain network



Predicted brain activities

Participant selection:

- Using only the predicted brain activity of subjects that have a significant positive correlation with the actual brain activity ($p < 0.01$)

The p-value: The proportion of random sequences, out of the 200, that have a higher correlation with the measured brain activity than the correlation between the measured and predicted brain activities.

⇒ 19 out of 32 subjects

Voxel selection:

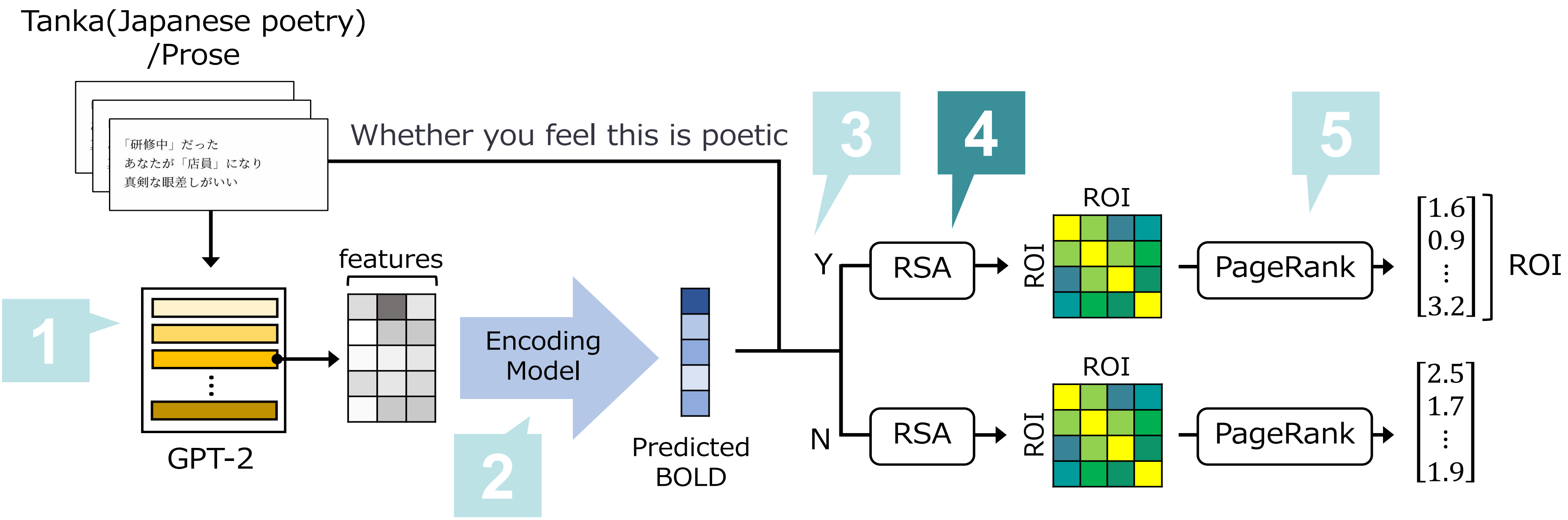
- Applied False Discovery Rate(FDR) correction ($q < 0.05$)

Labeling:

- Labeled the brain activity based on whether the sentences used for prediction were responded to as poetic or not

Analysis of Brain Activity under Language Stimuli

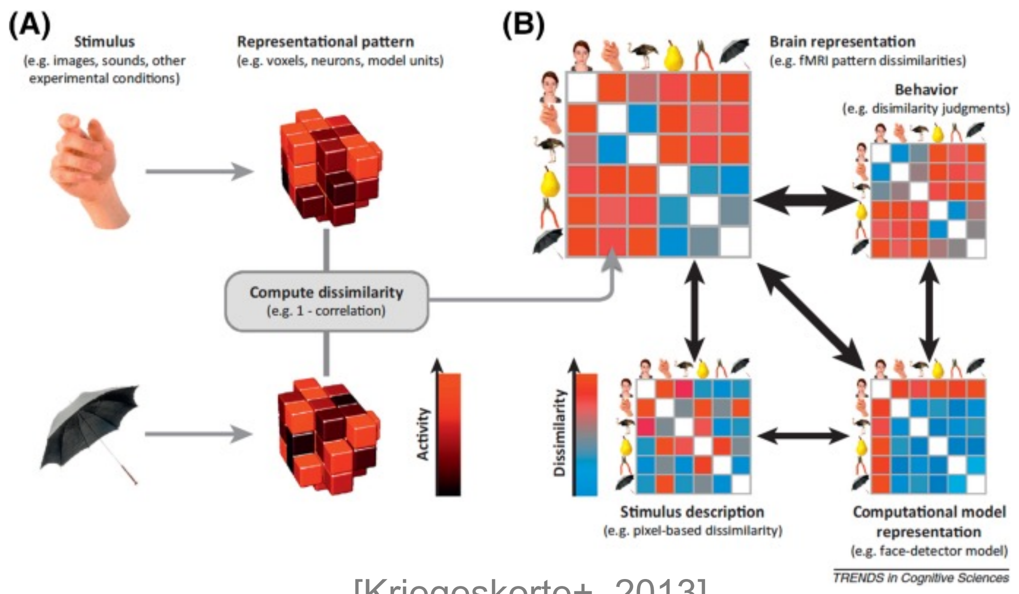
1. Input sentences to a language model and extract their activations
2. Construct an encoding model (ridge regression) to predict neural responses
3. Extract predicted brain activities based on stimuli answered “poetic” or “non-poetic”
4. Apply RSA to create a RDM that represents connectivity between each brain region
5. Apply PageRank algorithm to find hub regions in the brain network



Contruct Representational Dissimilarity Matrix(RDM)

Representational Similarity Analysis(RSA)[Kreigstrok+,2008]

- A comparison method that used to extract information about patterns of representations
- The RDM assembles the dissimilarities for all pairs of stimuli
- RDMs can be used like a table to look up the dissimilarity between any two stimuli



[Kriegeskorte+, 2013]

- Create layer-wise RDMs representing the dissimilarity of behaviors between brain regions, and further compare these matrices
  ⇒ Observe the transitions in brain pattern predicted by each layer of the LLM

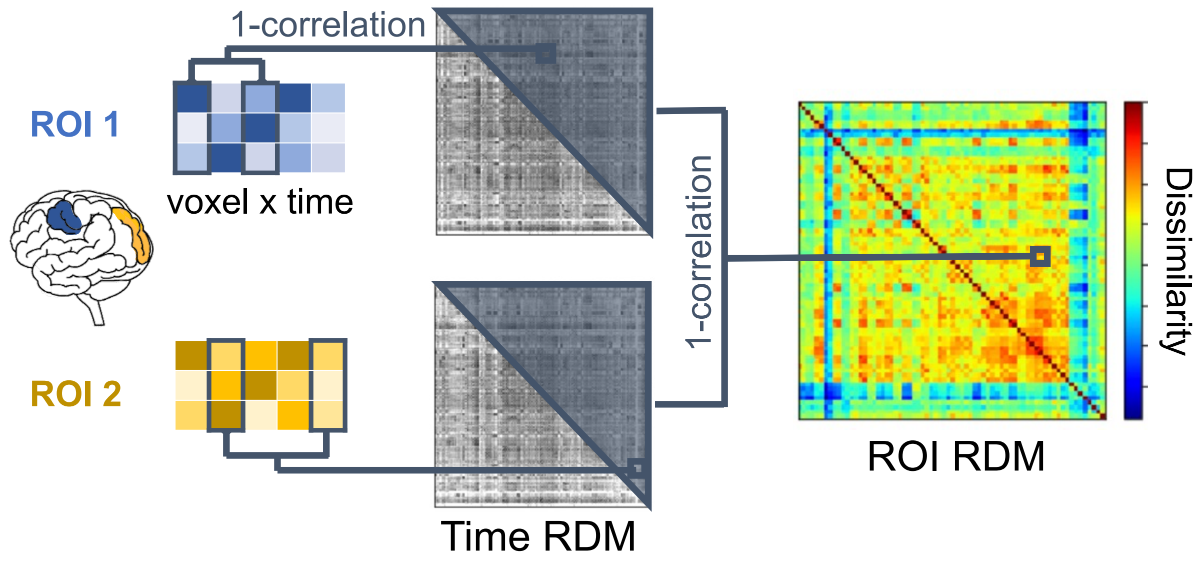
Similarity of brain activity by layer

STEP 1.

Construct a layer-wise ROI RDM by using brain activity that

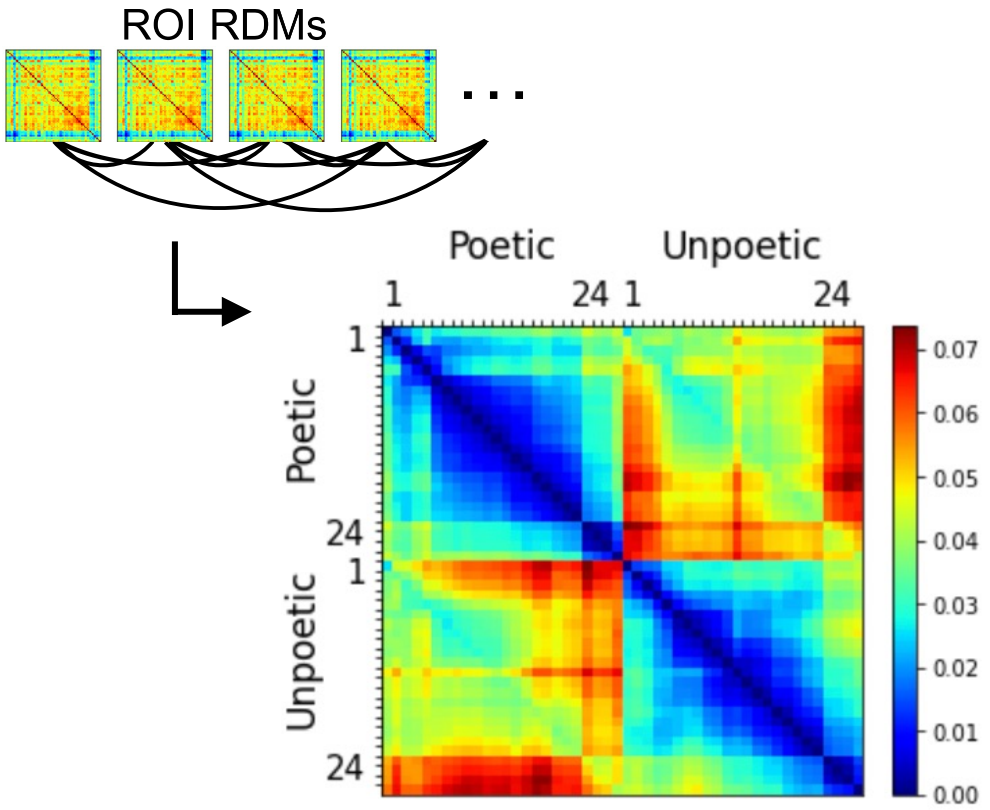
- predicted from **L** layer of language model
- labeled **S**

L={1,2,…,24}, **S** = {“poetic”, “non-poetic”}

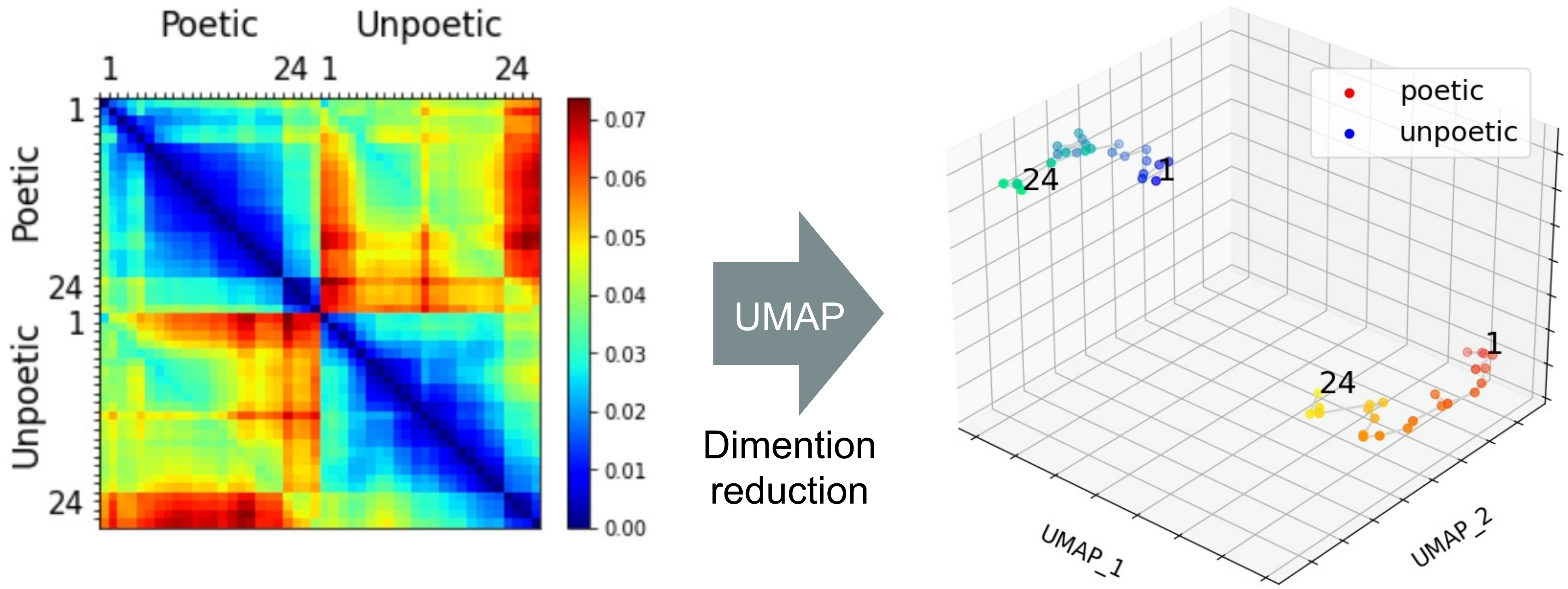


STEP 2.

Construct a layer RDM by computing the pairwise dissimilarity of ROI RDMs



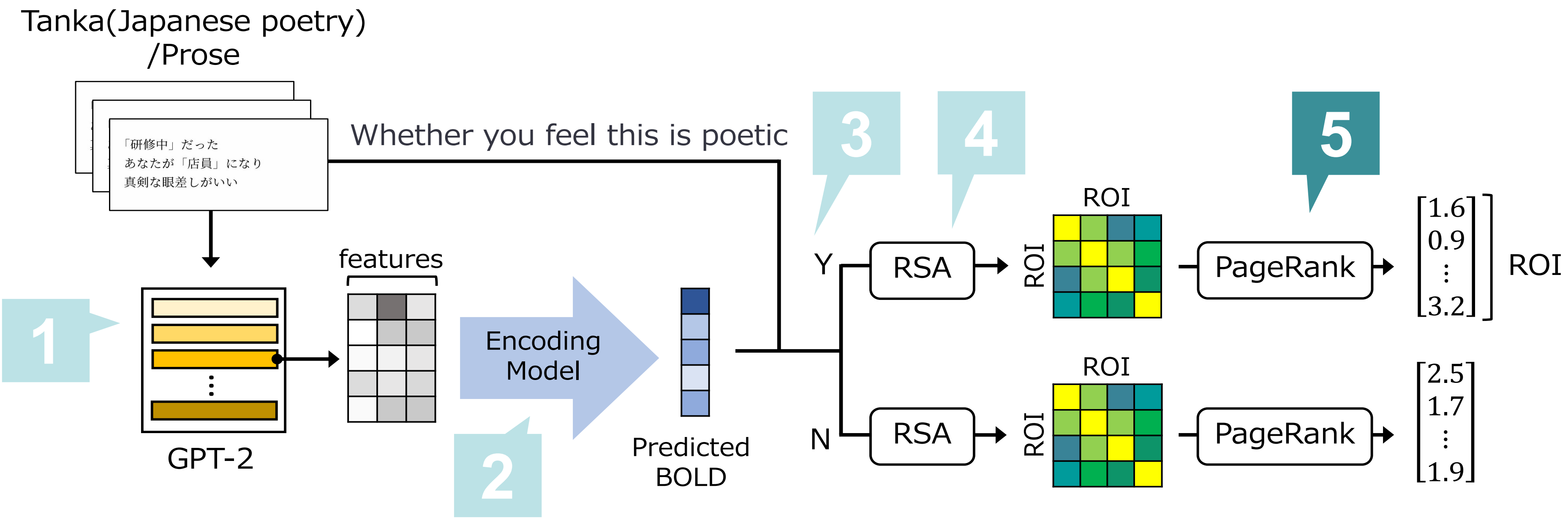
Similarity of brain activity by layers



- Brain patterns predicted from neighboring intermediate layers are similar
- The patterns are gradually changing as they moves toward the output layer

Analysis of Brain Activity under Language Stimuli

1. Input sentences to a language model and extract their activations
2. Construct an encoding model (ridge regression) to predict neural responses
3. Extract predicted brain activities based on stimuli answered “poetic” or “non-poetic”
4. Apply RSA to create a RDM that represents connectivity between each brain region
5. Apply PageRank algorithm to find hub regions in the brain network



Detection of hub regions in brain network

- So far, we found the brain patterns are gradually changing
  ⇒ How is it changing in the human brain?

PageRank [Page+, 1998]

An algorigh to measure web pages' importance

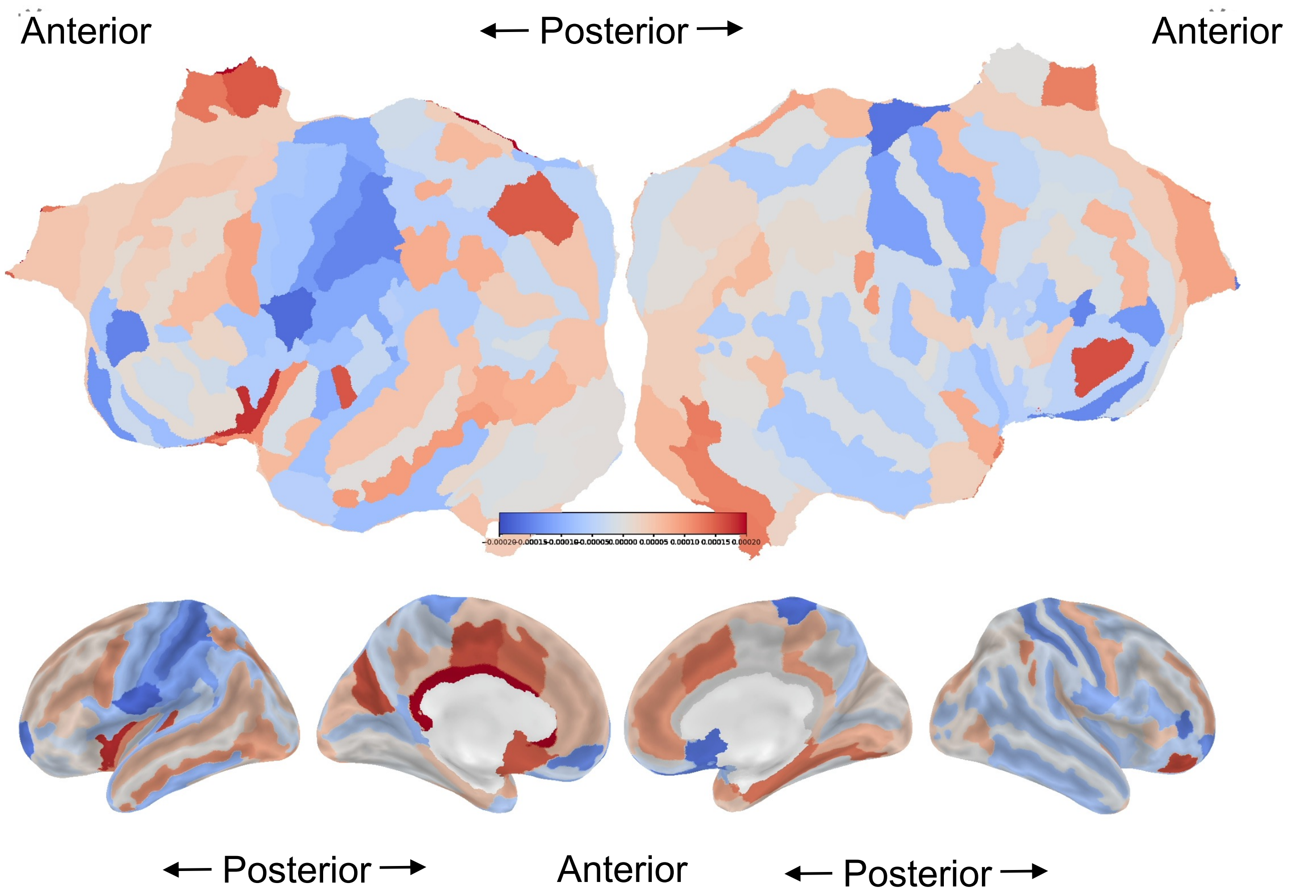
$$r_{k+1}(P_i) = \sum_{P_j \in B_{P_i}} \frac{r_k(P_j)}{|P_j|}$$

- $r(P_j)$: the PageRank of page P_j
- B_P : all pages that link to page P_j
- $|P_j|$: the number of outbound links from page P_j

- Apply this algorithm to the similarity matrix representing the connectivity of ROIs
  ⇒ consider the entire brain as a web network and each ROI as a webpage
- Aim to identify regions that play a crucial role when feeling poetic

Visualization of the difference in PageRank values

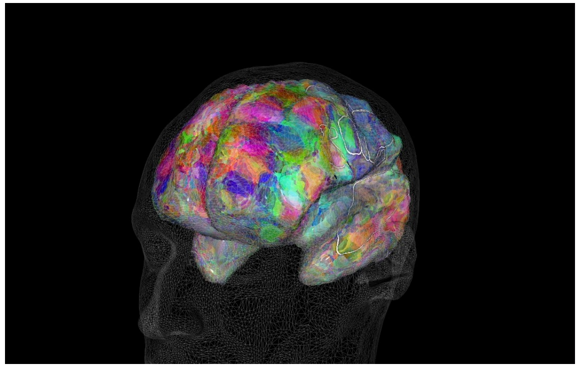
PageRank score when feeling **poetic** — PageRank score when feeling **not poetic**



ROIs colored red
⇒ more important
when feeling **poetic**

Layer
1

Brain map explanation



https://gallantlab.org/viewer-huth-2016/

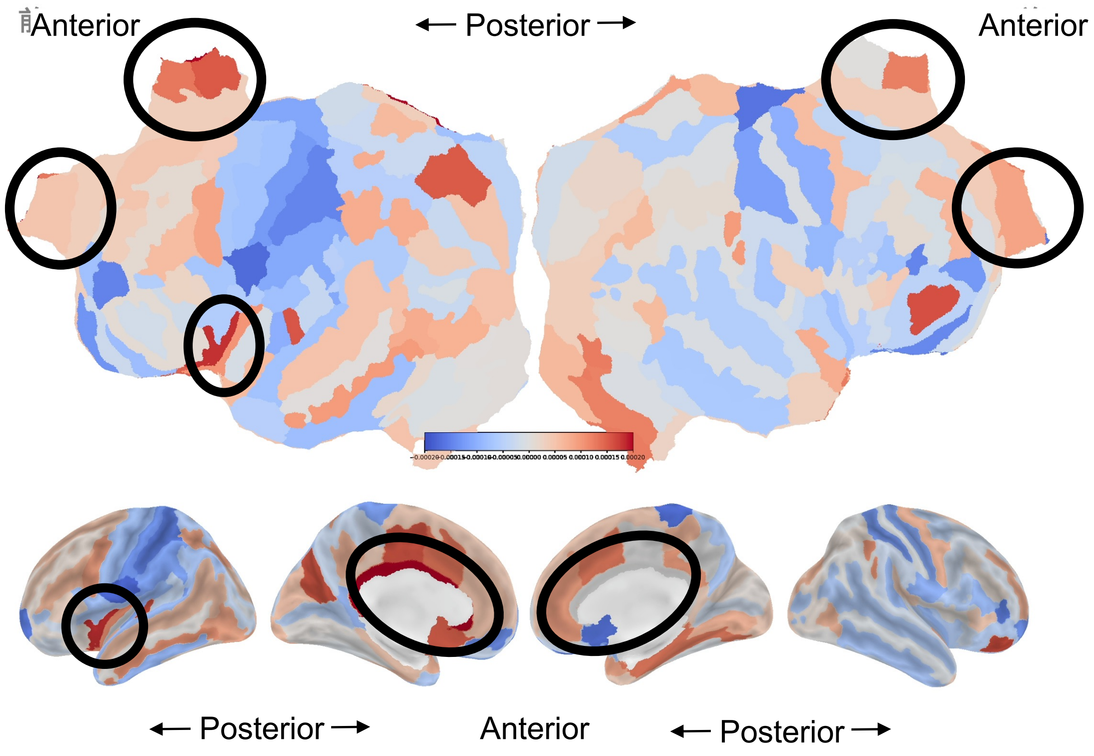
Regions with higher hubness when feeling poetic

Cingulate cortex

- Areas associated with emotional formation and processing
- Align with a previous research
  - Investigated brain activity when reading poetry and prose[Zeman+,2013]
  - As the literariness of the text increased, this region was activated

Insula cortex

- Areas also Important for regulating emotions
- A part of the cerebral limbic system

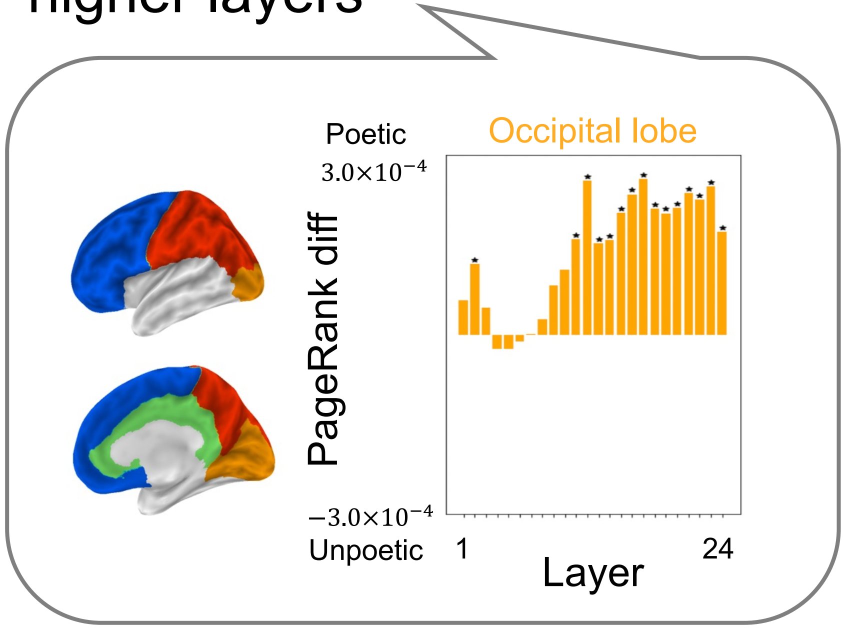


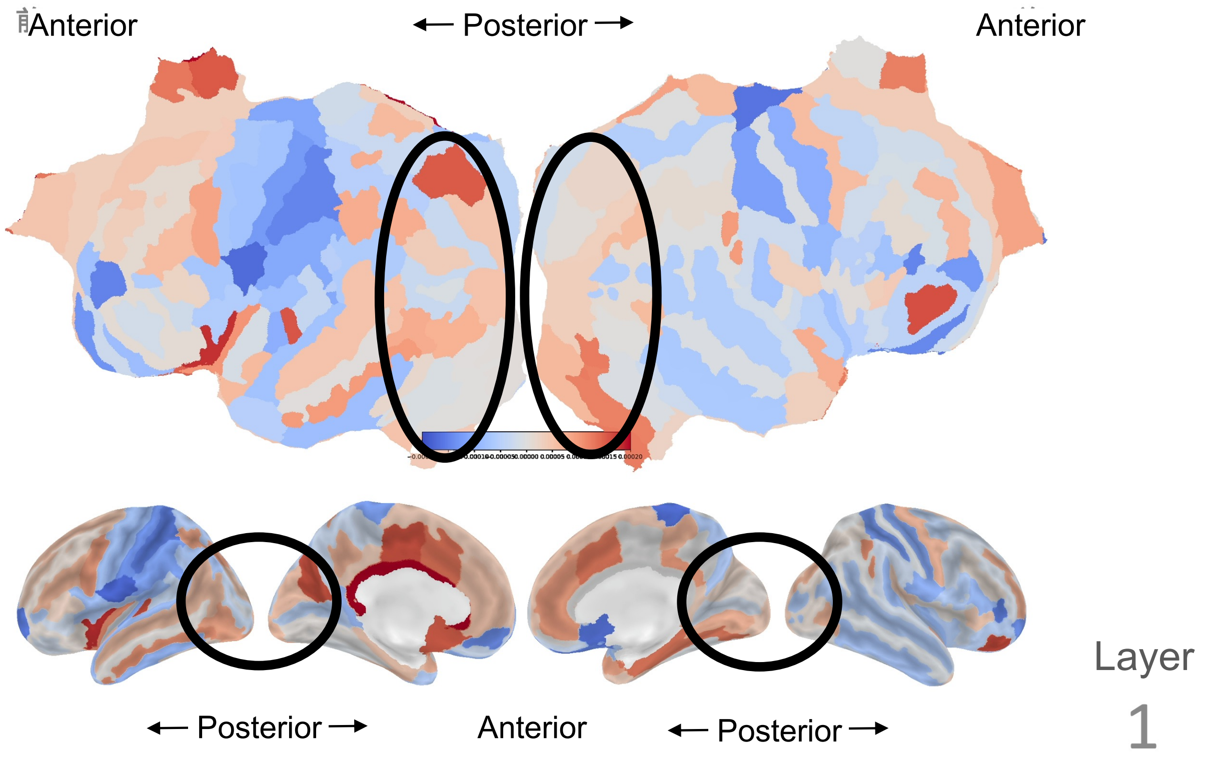
Layer
1

Regions with higher hubness when feeling poetic

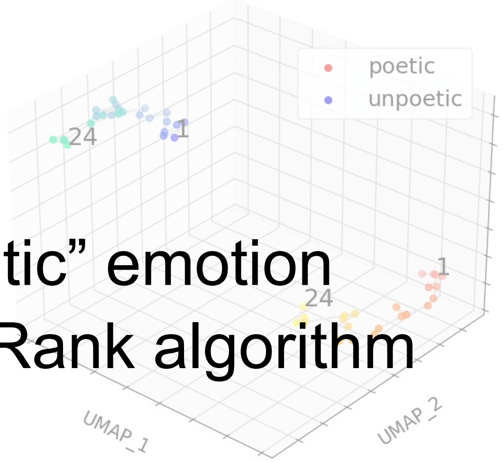
Occipital lobe

- A region containing the primary visual cortex and considered the central area for visual perception
- The value increases as shifting to higher layers

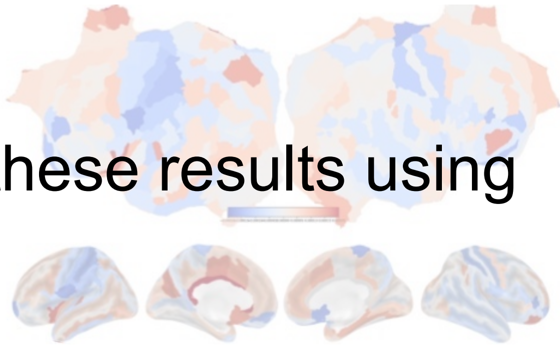




Conclusions



- We aimed to elucidate brain information processing about "poetic" emotion evoked by traditional Japanese poetry by LLM, RSA and PageRank algorithm
- We found that:
  - Brain activities predicted from neighboring layers are similar, and their patterns are gradually changing as they moves toward the output layer
  - The cingulate cortex, left insula and occipital lobe play a crucial role when feeling poetic



- Further investigation is necesseary to fully understand these results using other methods, e.g., searchlight analysis

Multi-dimensional Item Response Theory for evaluating Tanka

Hirono Kawashima (Keio University) and
Daichi Mochihashi (ISM), SIGNL 256

What is “Good Tanka”?

- As a poetry, there are clearly good Tanka and Bad tanka:

  白犀は心の水の深きまで沈みつ水の春は熟れゆく
  切り終へて包丁の刃の水平を見る眼の薄き水なみだちぬ

  宮跡に祖父と孫とが凧競ふ若草山の空を目指すか
  何年も同じコメント年賀状「今年は飲もう」今年も書き足す

- Where does this distinction come from?

Evaluating Tanka

Tanka＼Evaluator	u_1	u_2	u_3	$\cdots$	u_j
s_1	3	4	5	$\cdots$	x_{1j}
s_2	1	3	4	$\cdots$	x_{2j}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
s_i	x_{i1}	x_{i2}	x_{i3}	$\cdots$	x_{ij}

- 40 members from university Tanka club (京大短歌, 早稲田短歌会) evaluated the same 100 Tankas
  - 1-7 scale, 1=worst, 7=best
  - Two criteria: “Good-Bad” scale and “Like-Dislike” scale (each evaluator gives 2x100 scores)
- How to analyze this data?

Actual data with respect to “good-bad”

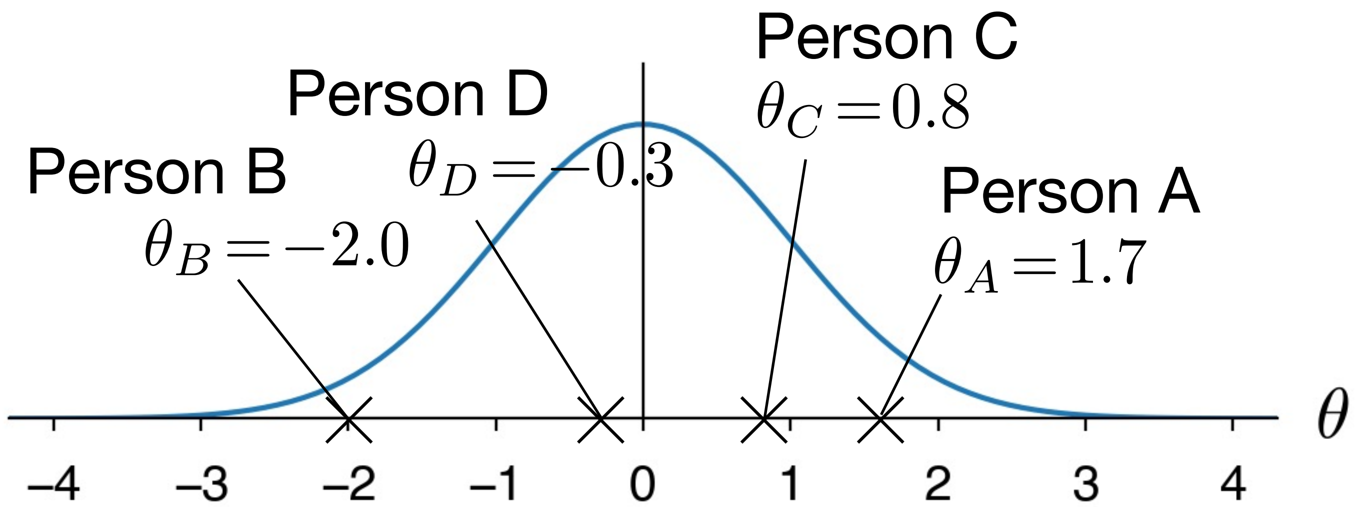
	A	B	C	D	E	F	G	H	I
1	抜かれても雲は車を追いかけない雲には雲のやり方がある	2	5	4	5	6	6	5	4
2	人間のための明かりを消ししのち闇にはうごく機械七台	4	5	3	5	6	6	5	5
3	少女群 紺の水着の胸うすくみづにあるときひとたばの葦	4	4	3	5	7	7	4	6
4	がらんどうの海は冷えゐて此処に立つ吾らのほかに彩をもたない	5	5	3	5	6	5	7	6
5	カップ焼きそばにてお湯を切るときにへこむ流しのかなしきしらべ	5	5	3	6	6	5	3	5
6	郊外のショッピングモールへ近づけば満州国に来た心地する	6	4	2	3	6	4	1	3
7	瞬間のやはらかき笑み受くるたび水切りさるるわれと思へり	5	5	5	6	7	5	3	5
8	ブラインド下りたる昼の図書館を浸す水中のやうなる時間	3	4	4	5	5	3	5	5
9	もしぼくが男だったらためらわず凭れた君の肩であろうか	4	5	2	3	7	7	7	6
10	生殖とかかわりのない愛なども容れてどこへもゆかぬ方舟	6	5	3	3	6	5	6	7
11	逢えばくるうこころ逢わなければくるうこころ愛に友だちはいない	4	5	5	4	5	6	7	4
12	すきなひとに干してもらえた下着たち来世はきっと梨になれるよ	3	5	2	4	5	5	3	5
13	中央線に揺られる少女の精神的外傷(トラウマ)をバターのように溶かせ夕焼け	2	5	2	6	5	6	7	4
14	天井まで「少年ジャンプ」積んでいた小坂の部屋から見た夕焼け	3	4	2	6	6	5	1	2
15	どの犬も目を合わせないこれまでもすきなだけではだめだったから	4	5	2	5	6	5	2	5
16	花火ってひらくばっかり剥き出しのただたくさんの副詞となって	4	5	5	6	6	6	2	6

We used this data

- 100 Tankas are the same as fMRI experiments

Item Response Theory (IRT)

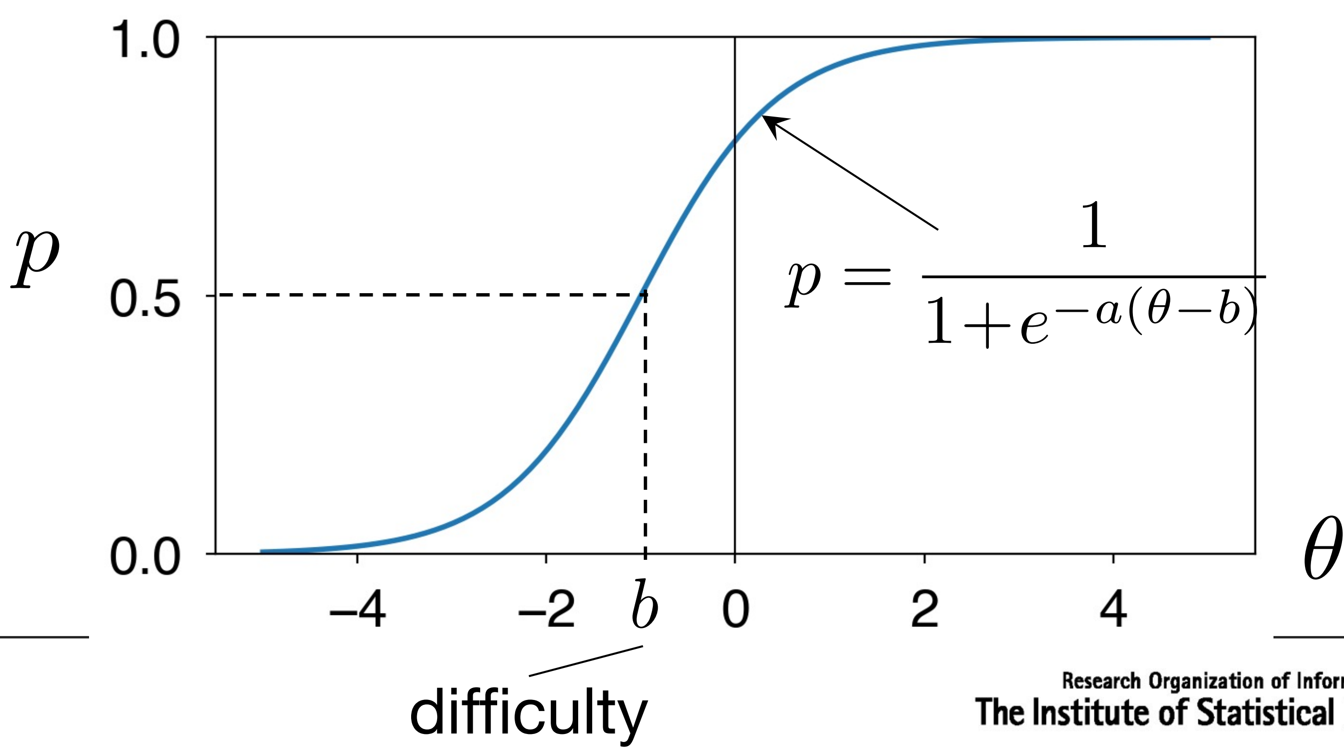
- IRT in psychometrics assumes latent ability $\theta \sim \mathcal{N}(0, 1)$ for each person



Item Response Theory (2)

- If θ is large, probability p of answering correctly for a problem is high:

$$p = \frac{1}{1+e^{-a(\theta-b)}}$$



Binary response data

	Mr. A	Mr. B	Mr. C	Mr. D
Problem 1	1	0	1	0
Problem 2	1	1	1	1
Problem 3	1	0	—	1
Problem 4	0	0	0	0
:				
Problem20	1	0	1	—

$\rightarrow$ Difficulty b_1

$\rightarrow$ Difficulty b_2 easier?

$\downarrow$ Ability θ_A higher?

$\downarrow$ Ability θ_B lower?

Probability of answering correctly:

$$p = \frac{1}{1+e^{-a(\theta_B - b_1)}}$$

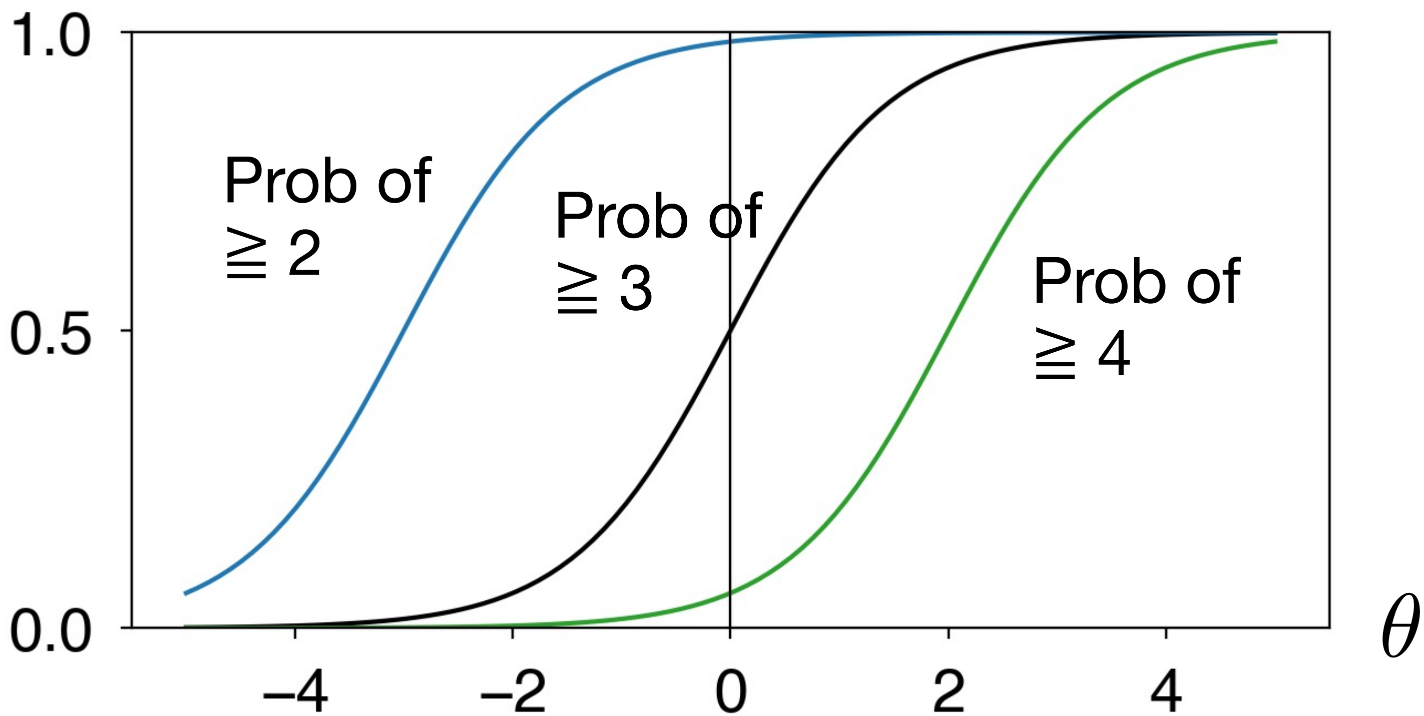
How about 1-7 responses?

	A	B	C	D	E	F	G	H	I
1	抜かれても雲は車を追いかけない雲には雲のやり方がある	2	5	4	5	6	6	5	4
2	人間のための明かりを消ししのち闇にはうごく機械七台	4	5	3	5	6	6	5	5
3	少女群 紺の水着の胸うすくみづにあるときひとたばの葦	4	4	3	5	7	7	4	6
4	がらんどうの海は冷えゐて此処に立つ吾らのほかに彩をもたない	5	5	3	5	6	5	7	6
5	カップ焼きそばにてお湯を切るときにへこむ流しのかなしきしらべ	5	5	3	6	6	5	3	5
6	郊外のショッピングモールへ近づけば満州国に来た心地する	6	4	2	3	6	4	1	3
7	瞬間のやはらかき笑み受くるたび水切りさるるわれと思へり	5	5	5	6	7	5	3	5
8	ブラインド下りたる昼の図書館を浸す水中のやうなる時間	3	4	4	5	5	3	5	5
9	もしぼくが男だったらためらわず凭れた君の肩であろうか	4	5	2	3	7	7	7	6
10	生殖とかかわりのない愛なども容れてどこへもゆかぬ方舟	6	5	3	3	6	5	6	7
11	逢えばくるうこころ逢わなければくるうこころ愛に友だちはいない	4	5	5	4	5	6	7	4
12	すきなひとに干してもらえた下着たち来世はきっと梨になれるよ	3	5	2	4	5	5	3	5
13	中央線に揺られる少女の精神的外傷(トラウマ)をバターのように溶かせ夕焼け	2	5	2	6	5	6	7	4
14	天井まで「少年ジャンプ」積んでいた小坂の部屋から見た夕焼け	3	4	2	6	6	5	1	2
15	どの犬も目を合わせないこれまでもすきなだけではだめだったから	4	5	2	5	6	5	2	5
16	花火ってひらくばっかり剥き出しのただただくさんの副詞となって	4	5	5	6	6	6	2	6

- Graded response model (Samejima 1973)
  - There is also Generalized partial credit model (Muraki 1992)

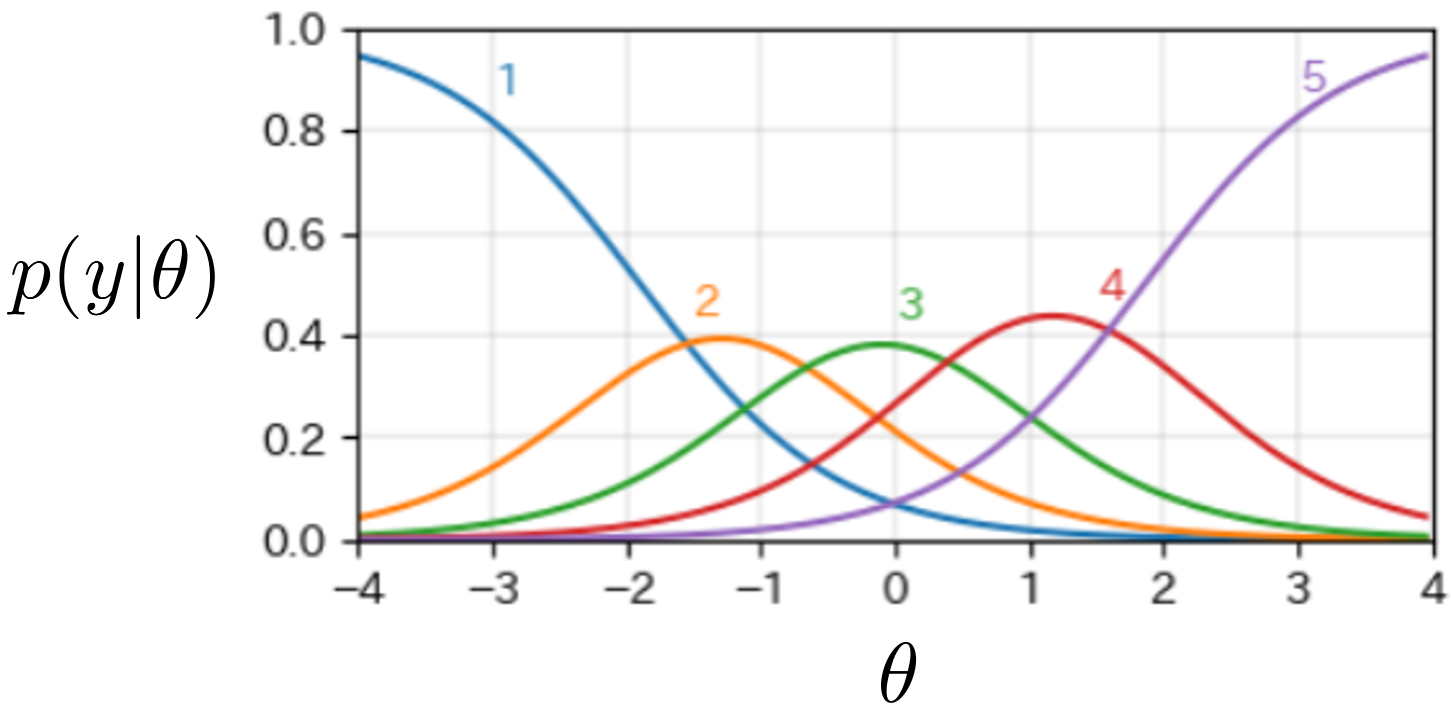
Graded response model

- Probability of answering “3” from 1-4 scale
  = [Prob of >= 4] – [Prob of >=3]



Graded response model (2)

- Subtracting neighboring curves,
  we get item response curves for the grades on θ :



  – This curve is different for each person and problem

Multi-dimensional extension

$$p(y = c|\theta) = p(y \geq c+1|\theta) - p(y \geq c)$$
$$= \frac{1}{1+e^{-\boxed{a(\theta}-b_{c+1})}} - \frac{1}{1+e^{-a(\theta-b_c)}}$$

- This is a linear model in θ and a !
  → Multi-dimensional extension is possible

$$p(y \geq c) = \frac{1}{1+e^{-(\boldsymbol{a}^T\boldsymbol{\theta}-b_c)}}$$

  – where

$$\boldsymbol{\theta} = (\theta_1, \cdots, \theta_K),$$
$$\boldsymbol{a} = (a_1, \cdots, a_K)$$

Our case of Tanka evaluation

$\boldsymbol{a}_F$

$\boldsymbol{\theta}_4$

	A	B	C	D	E	F	G	H	I
1	抜かれても雲は車を追いかけない雲には雲のやり方がある	2	5	4	5	6	6	5	4
2	人間のための明かりを消ししのち闇にはうごく機械七台	4	5	3	5	6	6	5	5
3	少女群 紺の水着の胸うすくみづにあるときひとたばの葦	4	4	3	5	7	7	4	6
4	がらんどうの海は冷えゐて此処に立つ吾らのほかに彩をもたない	5	5	3	5	$\boxed{6}$	5	7	6
5	カップ焼きそばにてお湯を切るときにへこむ流しのかなしきしらべ	5	5	3	6	6	5	3	5
6	郊外のショッピングモールへ近づけば満州国に来た心地する	6	4	2	3	6	4	1	3
7	瞬間のやはらかき笑み受くるたび水切りさるるわれと思へり	5	5	5	6	7	5	3	5
8	ブラインド下りたる昼の図書館を浸す水中のやうなる時間	3	4	4	5	5	3	5	5
9	もしぼくが男だったらためらわず凭れた君の肩であろうか	4	5	2	3	7	7	7	6
10	生殖とかかわりのない愛なども容れてどこへもゆかぬ方舟	6	5	3	3	6	5	6	7
11	逢えばくるうこころ逢わなければくるうこころ愛に友だちはいない	4	5	5	4	5	6	7	4
12	すきなひとに干してもらえた下着たち来世はきっと梨になれるよ	3	5	2	4	5	5	3	5
13	中央線に揺られる少女の精神的外傷(トラウマ)をバターのように溶かせ夕焼け	2	5	2	6	5	6	7	4
14	天井まで「少年ジャンプ」積んでいた小坂の部屋から見た夕焼け	3	4	2	6	6	5	1	2
15	どの犬も目を合わせないこれまでもすきなだけではだめだったから	4	5	2	5	6	5	2	5
16	花火ってひらくばっかり剥き出しのただたくさんの副詞となって	4	5	5	6	6	6	2	6

- Each tanka i has latent goodness: $\boldsymbol{\theta}_i$
- Each evaluator j has latent axis of evaluation: $\boldsymbol{a}_j$
- Each evaluator j has latent threshold for grade c: b_{jc}

Likelihood of data

- We want to maximize the log probability of data given latent parameters $\boldsymbol{a}, b$: (if $\boldsymbol{\theta}$ is 1D)

$$\log p(\mathbf{X},\Theta) = \sum_{i=1}^{N}\left[\log p(\theta_i) + \sum_{j=1}^{J}\sum_{c=1}^{C}\mathbb{I}(x_{ij}=c)\log p(y=c\,|\,\theta)\right]$$

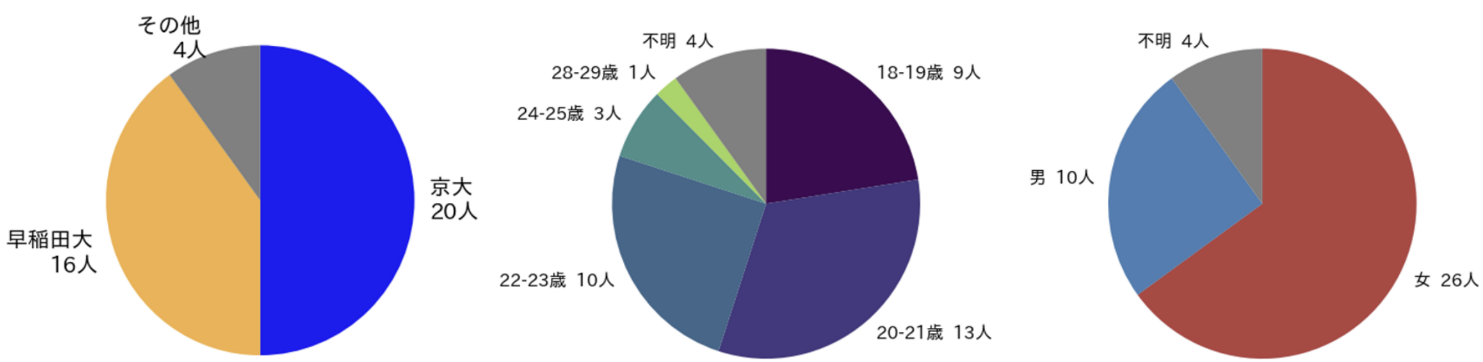
$$= \sum_{i=1}^{N}\left[-\frac{1}{2}\theta_i^2 + \sum_{j=1}^{J}\sum_{c=1}^{C}\mathbb{I}(x_{ij}=c)\log\left\{\sigma(a_j(\theta_i-b_{jc})) - \sigma(a_j(\theta_i-b_{jc+1}))\right\}\right]$$

  – where $\sigma(x)=\dfrac{1}{1+e^{-x}}$

- Number of parameters (if $\boldsymbol{\theta}$ is 2D): 2x100(problems)+2x40(evaluators)+6x40(evaluators) = 520
  – We solve this optimization via MCMC

Experiments

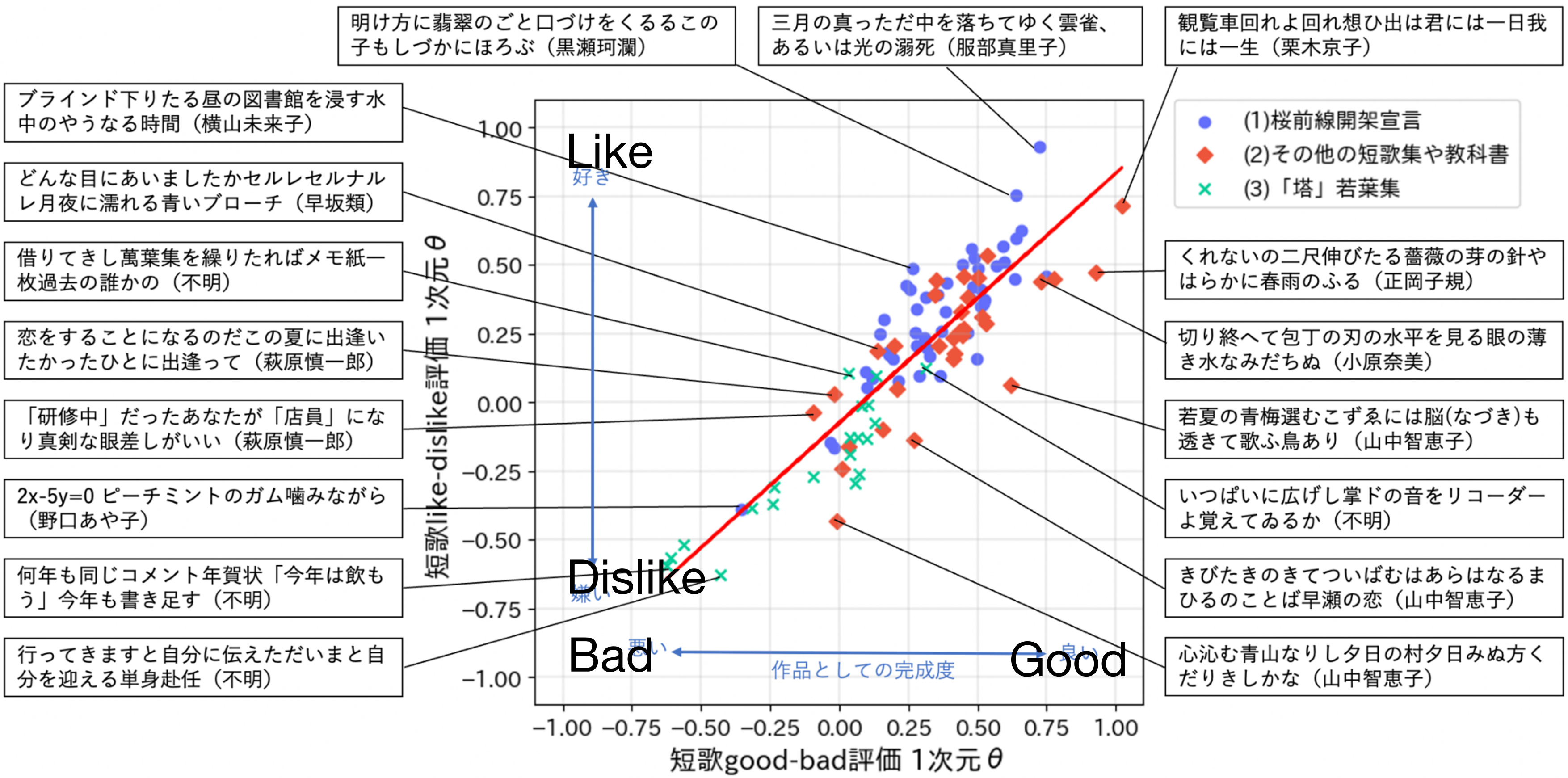
- Tanka evaluations: 4,000x2 (40 evaluators, 100 tankas)
  - "Good-bad" axis & "Like-dislike" axis
- Evaluator statistics:
  - Kyoto-U tanka club: 20, Waseda-U tanka club: 16
  - Age range: 18-29
  - Female: 26, Male: 10



(a) 所属短歌会 (b) 年齢 (c) 性別

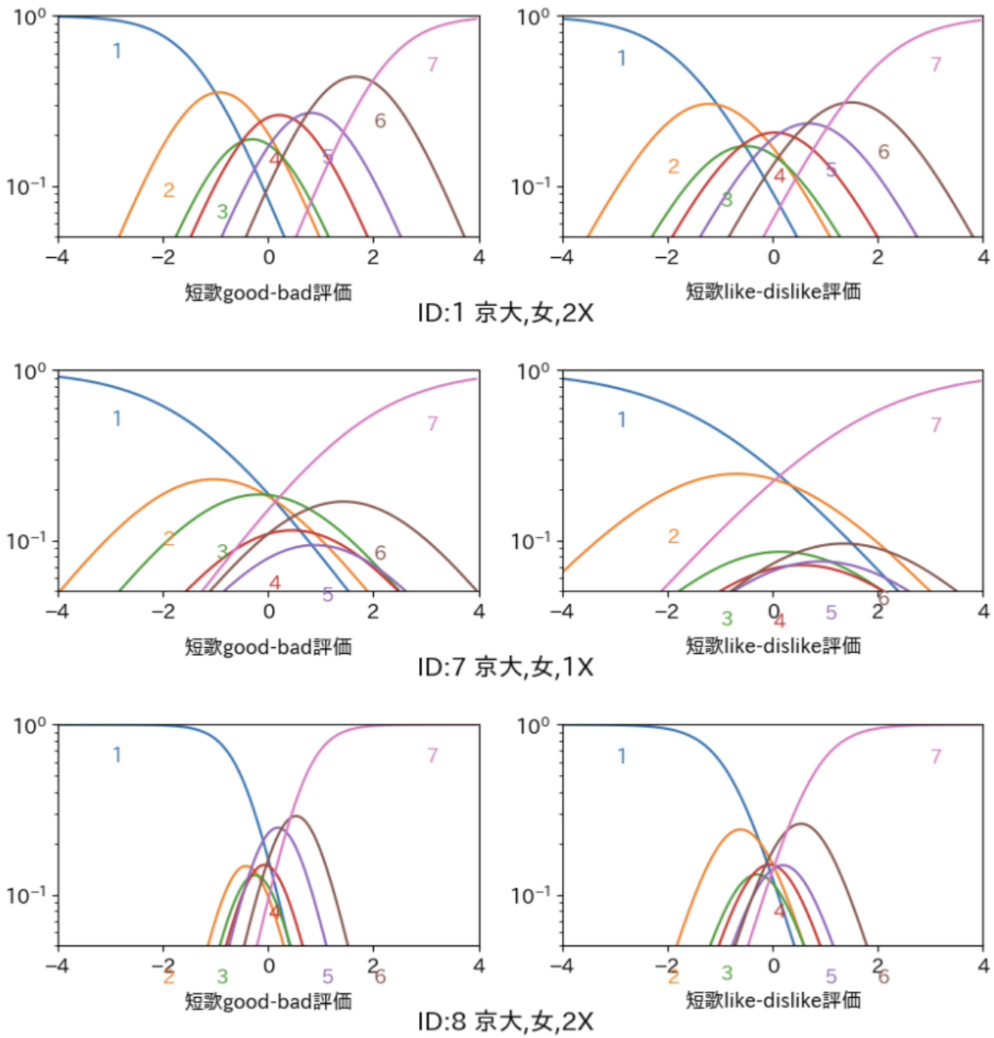
One-dimensional θ

- Correlation between good-bad and like-dislike



Mainly aligned, but has some exceptions

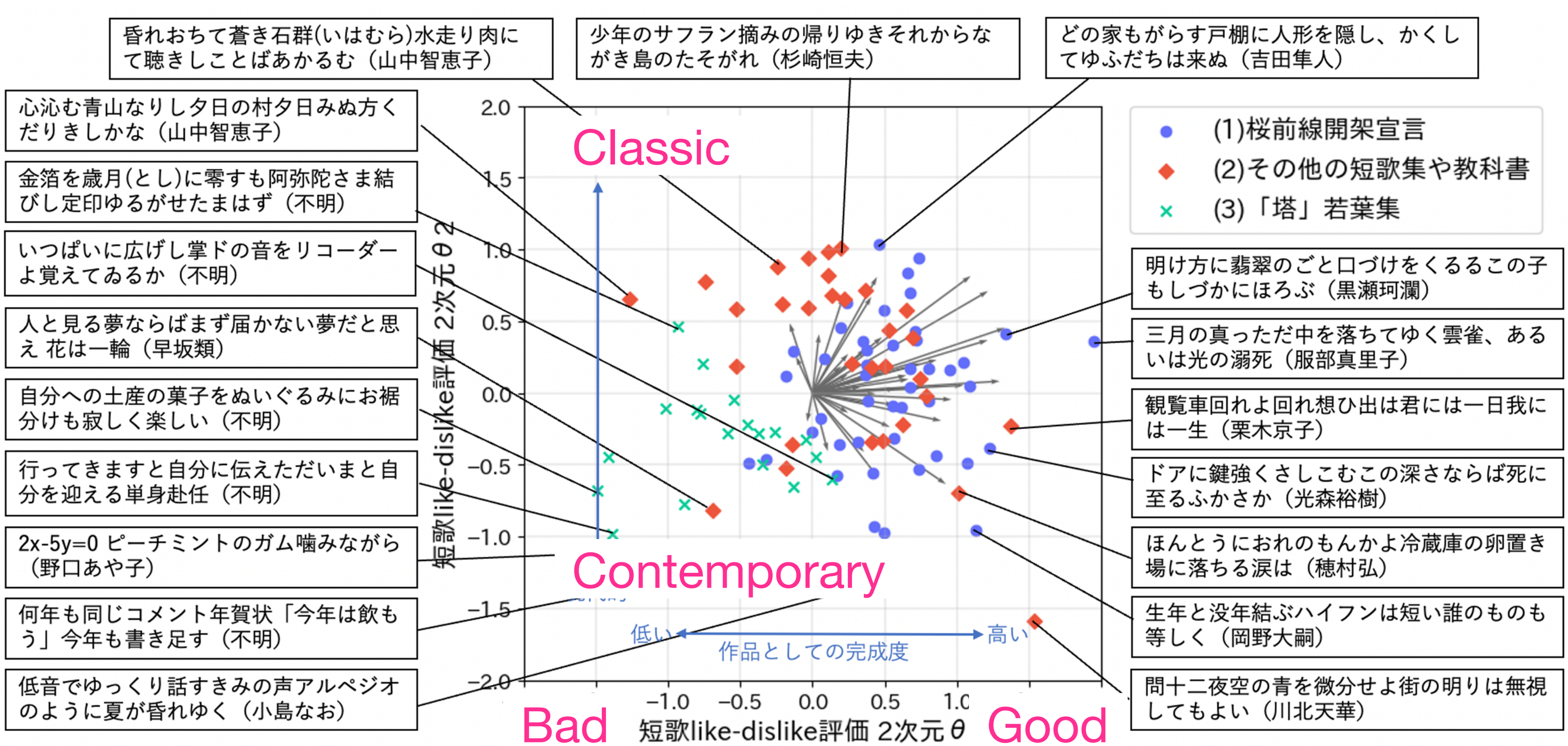
Response curves of each evaluator



- Showing the curves in log-scale
- Different thresholds and sensitivity for each evaluator

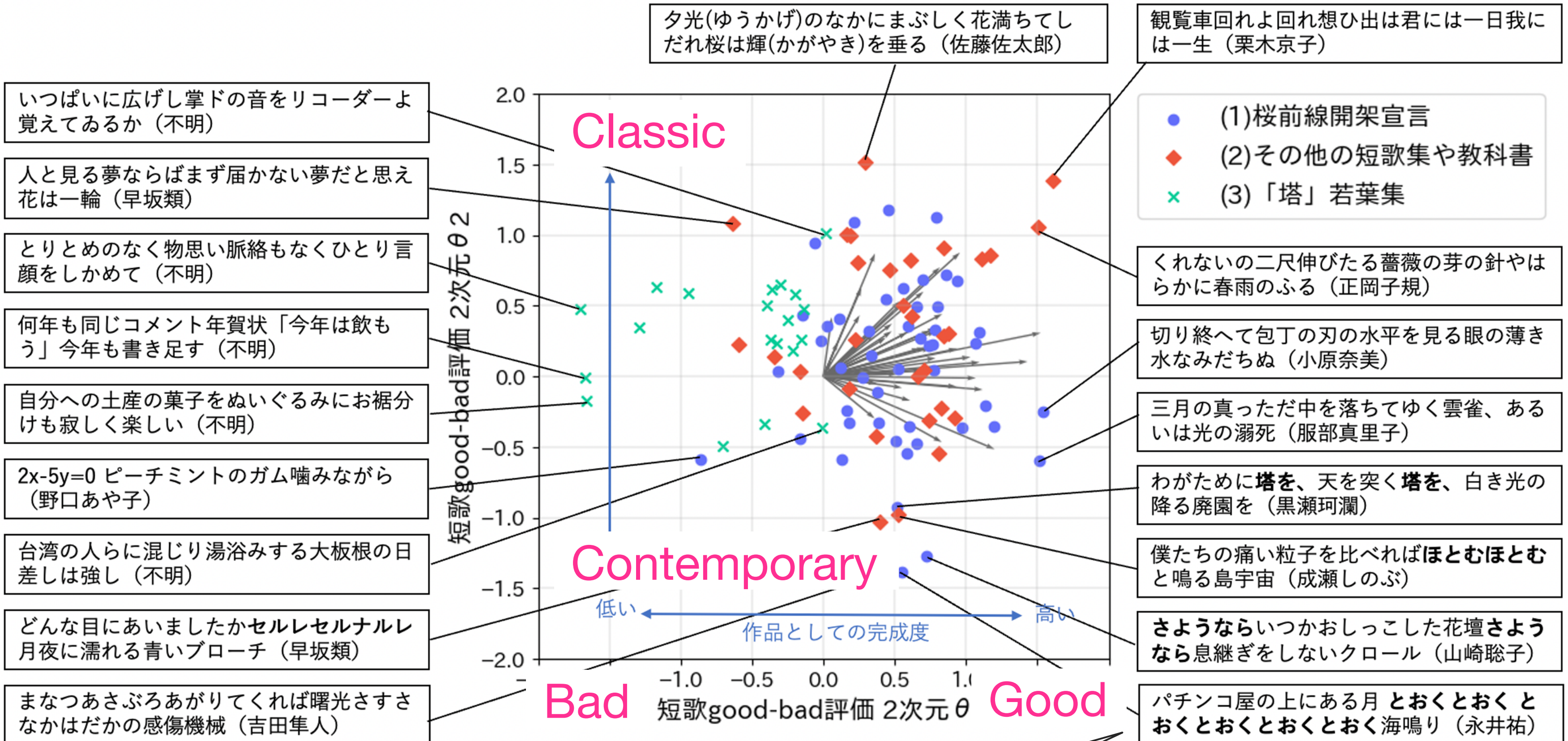
Two-dimensional θ

- Case of “like-dislike”:



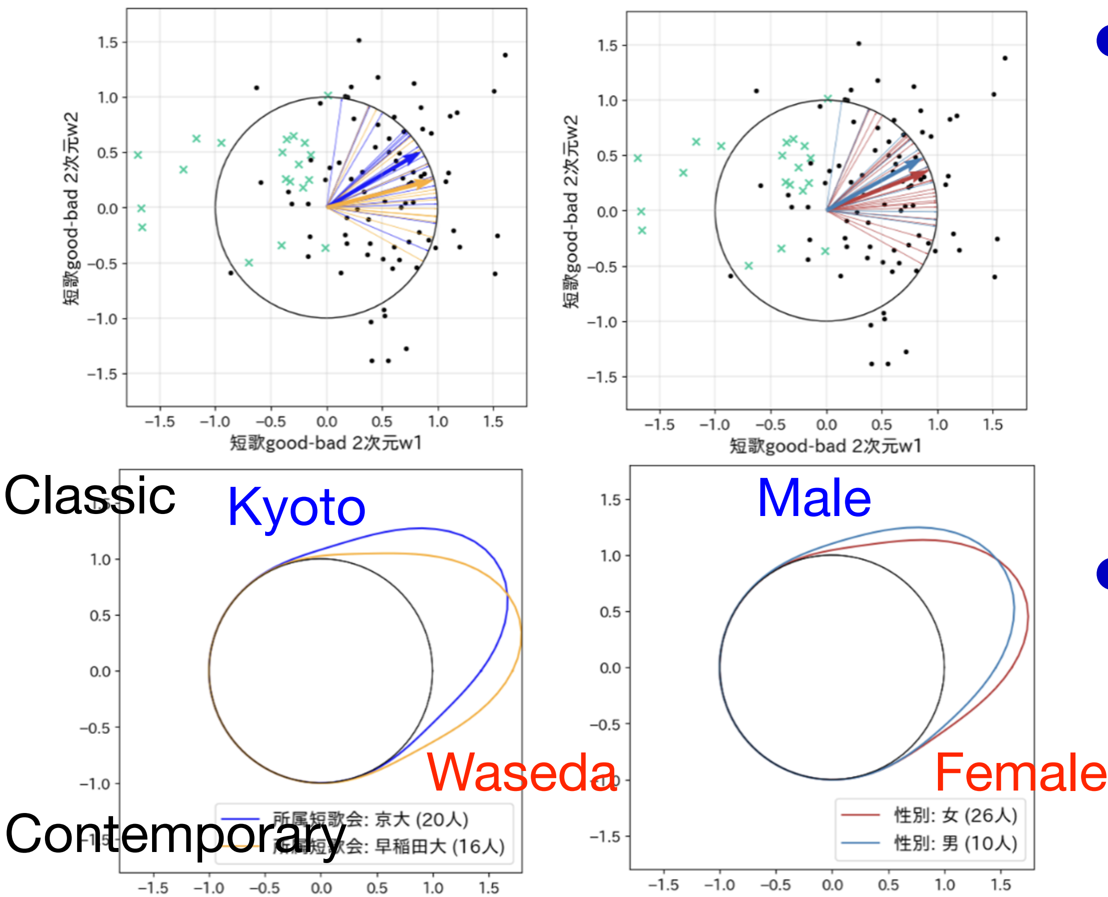
Two-dimensional θ

- Case of “good-bad”:



Sensory expressions only from evaluations (not using text)

Difference between evaluators



(a) 所属短歌会 (c) 性別

- Kyoto and Waseda members have different evaluation axes
  - Fit by von Mises-Fisher distribution
- Male-Female differences are not evident

Future Work

- We do not use the texts of Tanka: only evaluations
  - Seeking collaborators in NLP!
- Ongoing: collaborating with Asahi newspaper company, media laboratory
  - analyzing Asahi Kadan (weekly Tanka selections), which has a long history