

Construction of Japanese Prefectural Assembly Minutes Datasets Across Three Electoral Terms: Comparative Analysis of 2011, 2015, and 2019 Four-Year Periods

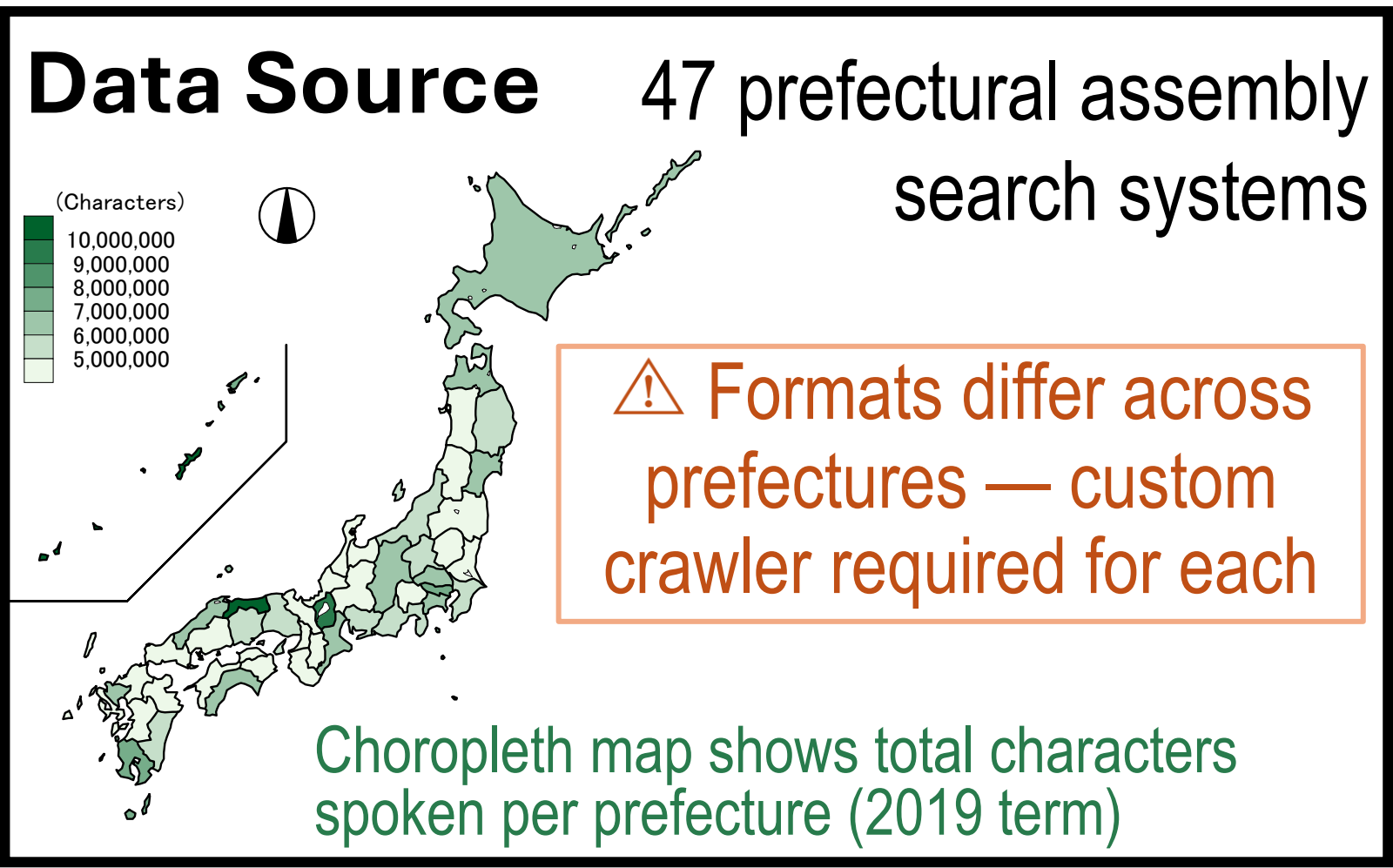
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Background and Motivation

- Local government assembly minutes capture **authentic political discourse** at the subnational level.
- They offer valuable data for **corpus linguistics, dialectology, and political science**.
- However, **longitudinal cross-regional analysis** of such records has remained **limited**.
- We construct a **12-year, 47-prefecture longitudinal corpus** spanning three electoral terms.

Dataset Construction



Overall Size of our Datasets
Assembly minutes data from all **47** prefectures
3 electoral terms, **12 yrs** longitudinal data
743M chars, **471M** tokens, **12.2M** remarks

Crawl & Segment Split into individual remarks by sentence-final periods

Normalize & Annotate Speaker name / Meeting name / Date

△ Name notation inconsistencies
Manual verification and disambiguation required
Hiragana / Kanji notation variants — Stage / ring name vs. legal name

Assign Speaker IDs Unique ID per member consistent across all three terms

Assembly Members DB
provided by SeijiYama, Election candidates DB

Birth Year / Gender / Name
Electoral district / Election results

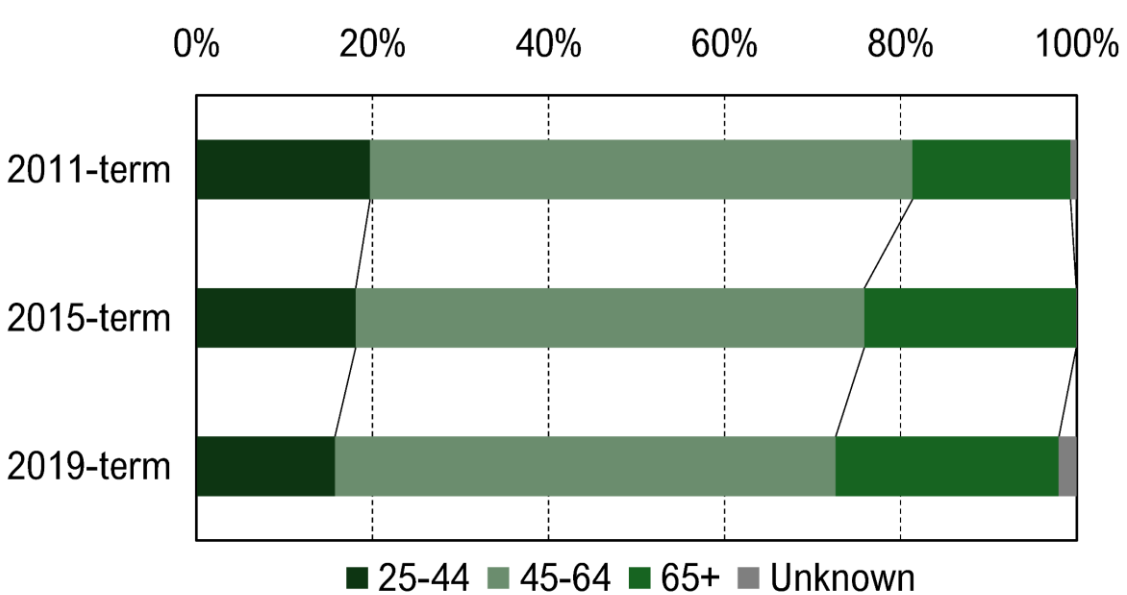
Linking

2011-2014
2015-2018
2019-2022

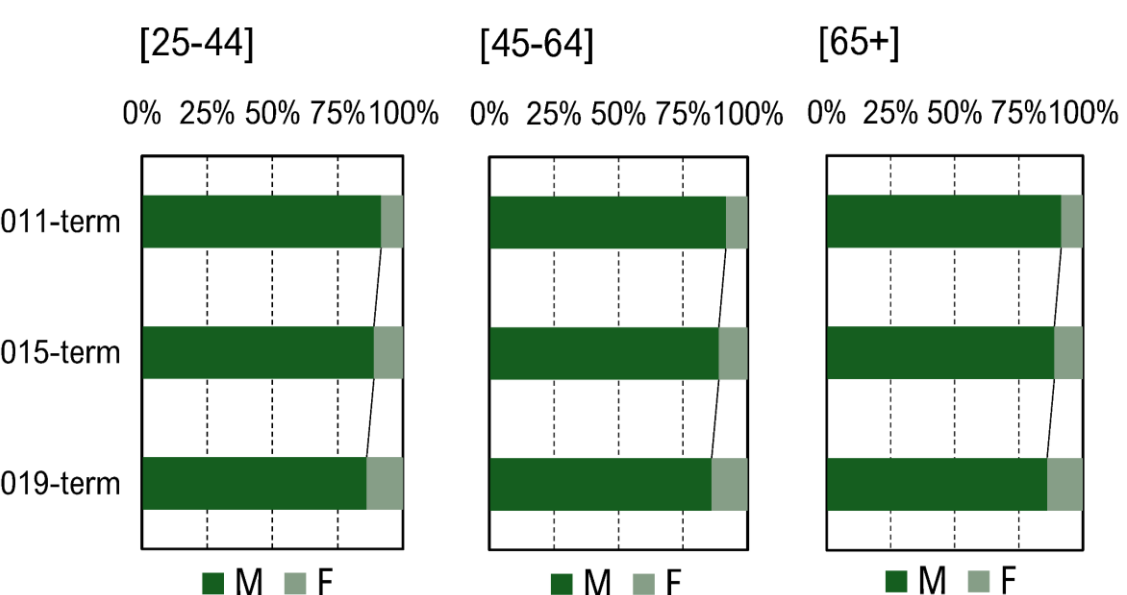
Comparative Analysis

Member composition

The proportion of members **aged 25–44** has declined across terms, while those aged **65+** have increased.



Female representation has increased in all age groups across terms, yet remained at **only 12%** even in the 2019 term.



Volume of speech

Term	Gender	24-44	45-65	65+
2011	M	43,583	44,626	31,299
	F	44,455	59,969	59,366
2015	M	45,814	45,378	30,469
	F	42,886	55,950	66,057
2019	M	46,921	45,448	32,262
	F	46,824	52,745	59,147

Female members speak more characters than male counterparts in almost all age groups and terms, with opposite age trends: **female speech volume increases with age**, while **male speech volume decreases**.

Non-speaking Rate

The proportion of members who never speak varies from under 2% for **younger females** to over 10% for **males aged 65+**.

Term	Gender	24-44	45-65	65+
2011	M	9(1.7%)	76(4.6%)	62(12.5%)
	F	1(2.0%)	2(1.2%)	2(6.3%)
2015	M	9(2.0%)	38(2.7%)	71(11.3%)
	F	0(0.0%)	2(1.1%)	1(2.5%)
2019	M	7(1.9%)	36(2.6%)	76(11.7%)
	F	0(0.0%)	3(1.5%)	3(5.3%)

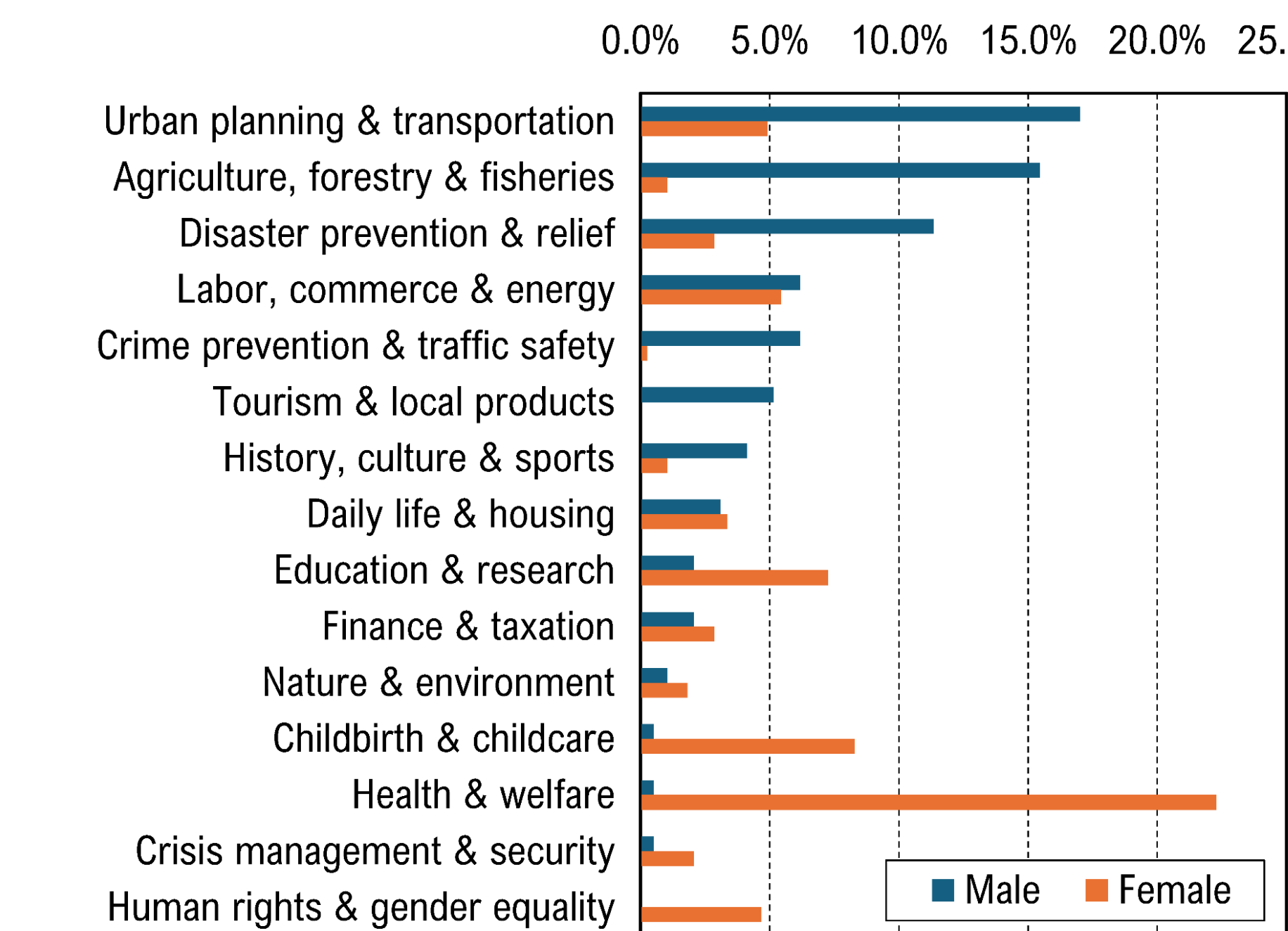
Retiring or defeated members show **significantly higher non-speaking rates** (up to 10.8%), whereas **newcomers and returning members** show **markedly lower rates** (as low as 0.3%) — a finding only possible through longitudinal multi-term analysis.

Use Cases and Downstream Applications

Gender and Age Analysis in Political Discourse

Using log-likelihood ratios, we extracted gender-specific political vocabulary from the corpus.

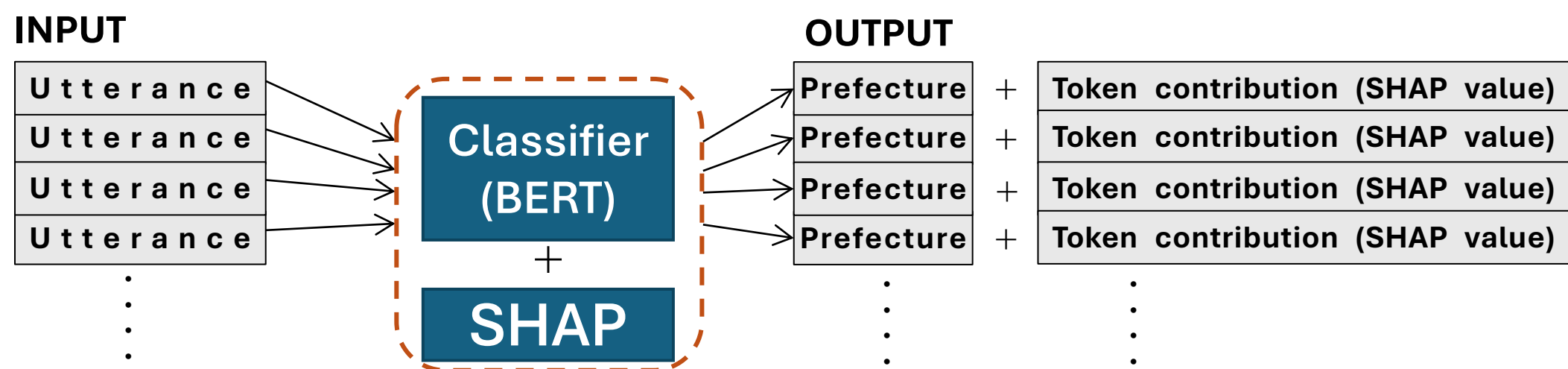
Female members used significantly more terms related to **health & welfare, childcare, and education**, while **male** members favored **urban planning, agriculture, and disaster prevention**.



Distribution of political characteristic terms by gender

Yuzu Uchida, Keiichi Takamaru, Hokuto Ototake, and Yasutomo Kimura. 2019. Visualization of activity of local assembly members based on log-likelihood ratio and political vocabulary ratio (in Japanese). *Journal of Japan Society for Fuzzy Theory and Intelligent Informatics*, 31(2):662–671.

Computational Dialectology with eXplainable AI



A BERT-based classifier was trained to predict the prefecture of origin from assembly utterances. XAI (SHAP) then identified which tokens contributed most to each prediction — revealing dialect words and region-specific expressions as key features.

はぐっていただきまして、62 ページ、5 目
農地 費 733 万 2,000 円 でございます。

Hagutte itadakimashite, 62 peeji, 5-moku noochi-hi 733 man 2000 en de gozaimasu.
Please turn to page 62, and the land expenses for item 5 are 7,332,000 yen.

Example of output

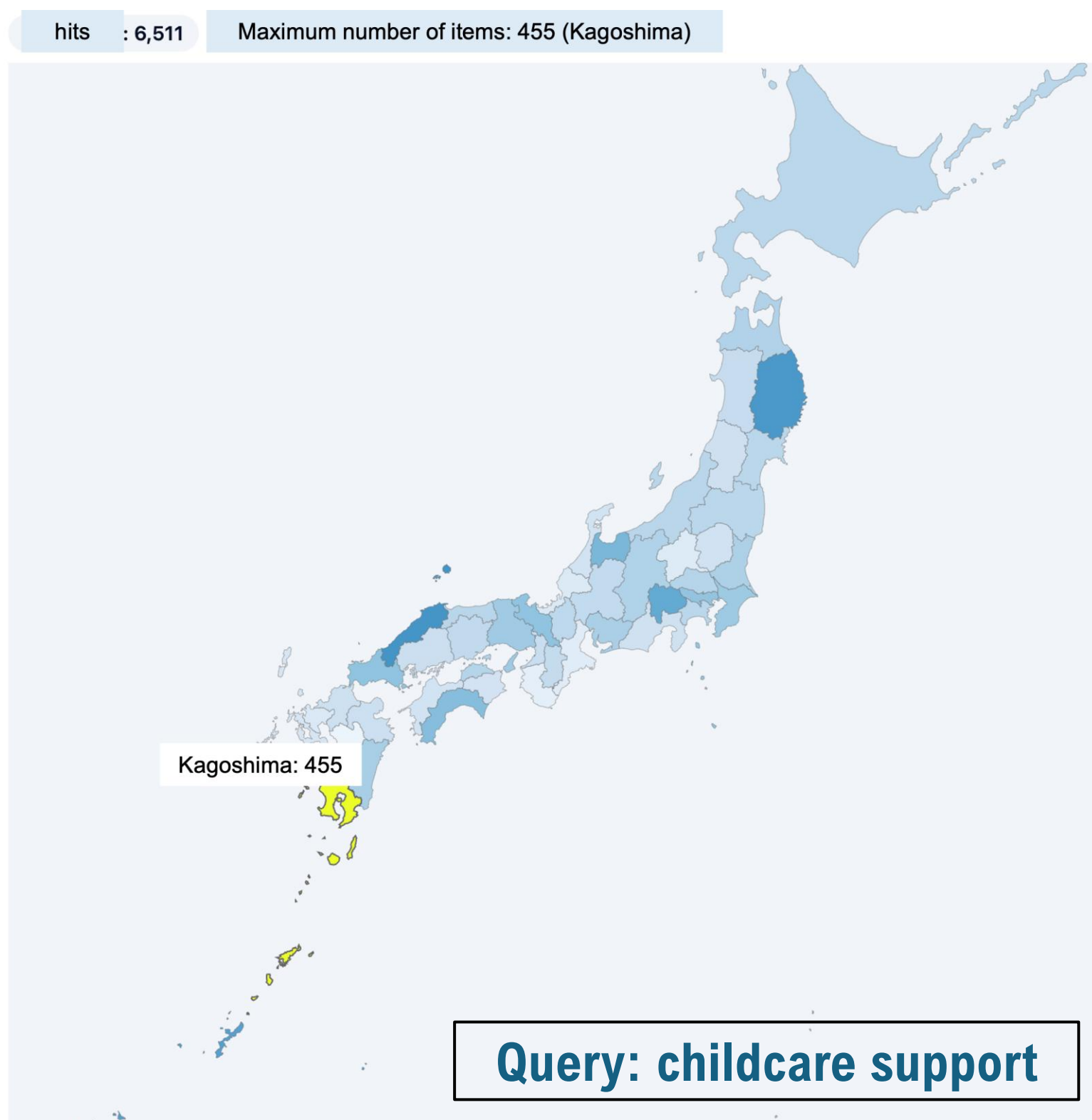
A word **hagutte** (‘to turn a page’) — embedded in a formulaic parliamentary expression — was automatically identified as a regional marker in **Tottori Prefecture**. It is thought to be a **dialect feature** used without awareness in formal settings.

Prefecture	Freq.
Tochigi	1
Chiba	1
Niigata	5
Tottori	224
Okayama	9
Total	236

Keiichi Takamaru and Hokuto Ototake. 2023. An exploratory survey of dialects in minutes of local assemblies: A dialectological study using machine learning and XAI (in Japanese). *Studies in Dialects*, 9:27–51.

Giimiru: a Web-based Search and Visualization System

Giimiru provides public access via five functionalities: **keyword search, semantic similarity search, geographic visualization, time-series analysis, and cross-tabulation** — supporting research in sociolinguistics, political science, and econometrics.



Example of geographic visualization

Hokuto Ototake, Hiroki Sakaji, Keiichi Takamaru, Akio Kobayashi, Yuzu Uchida, and Yasutomo Kimura. 2018. Web-based system for Japanese local political documents. *International Journal of Web Information Systems*, 14(3):357–371.

Data Availability

The datasets are accessible for research purposes upon request. Public query access is also available through the web-based interface **Giimiru**.



<http://local-politics.jp/>

This work was supported in part by JSPS KAKENHI Grant Numbers 25K04045 and 24K15196, and by JST RISTEX Grant Number JPMJRS25L2.