

# Multi-dialect Neural Machine Translation and Dialectometry

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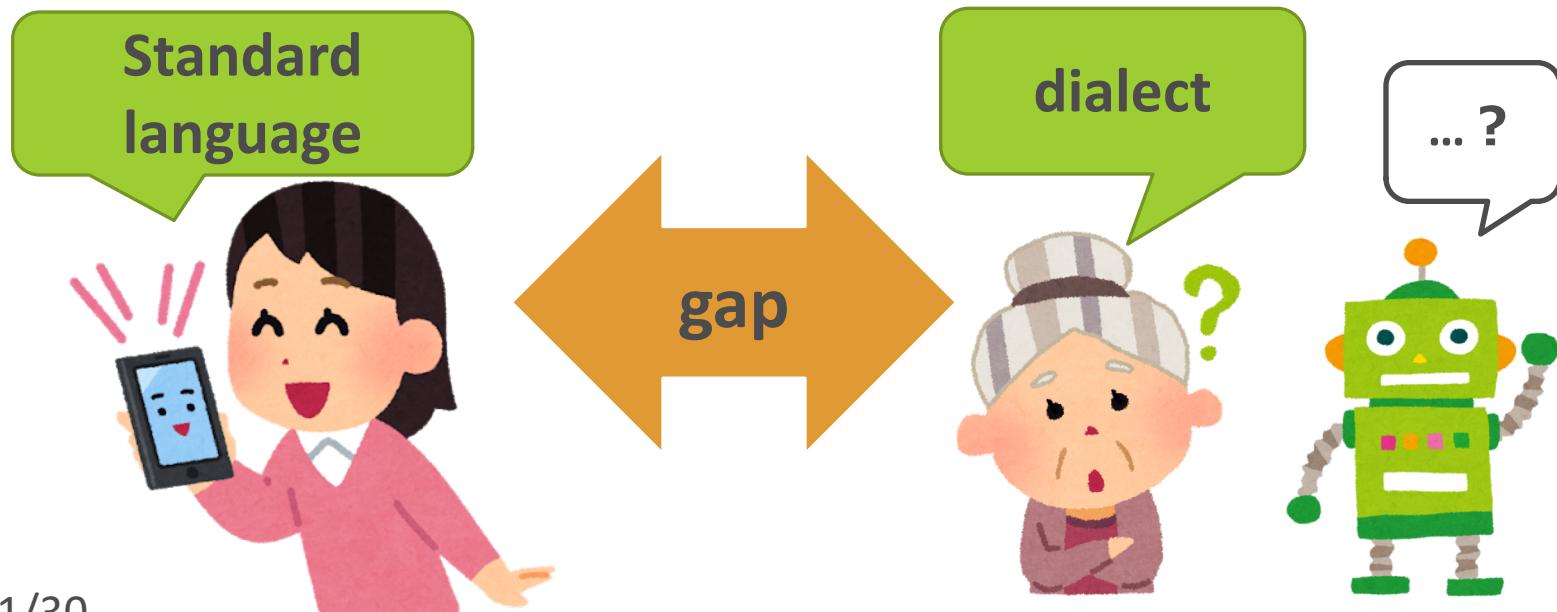
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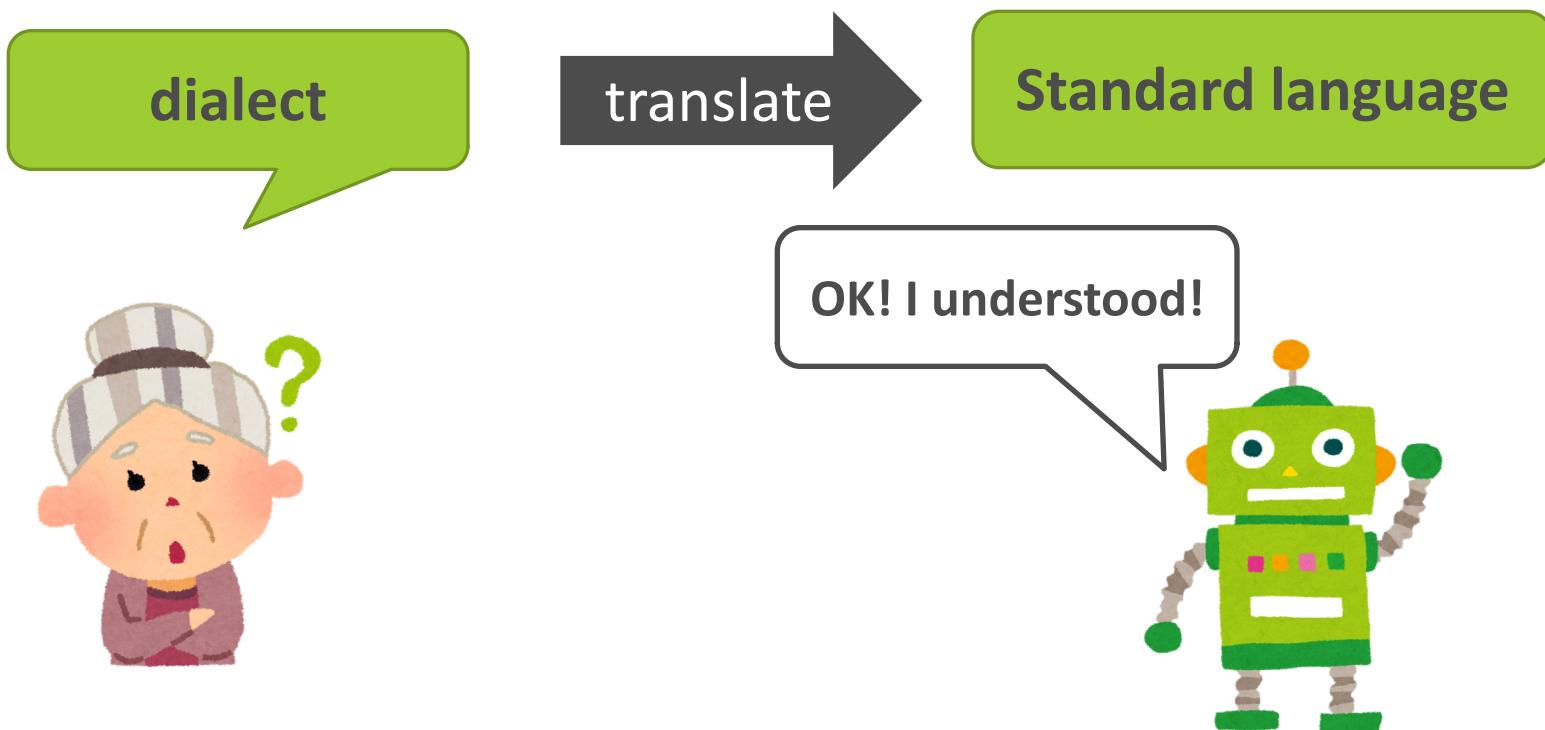
# Background

- Recently, smart speakers(e.g. Siri) can understand standard languages in the world
- However, (especially in Japan,) humans sometimes use ***regional dialects*** to talk



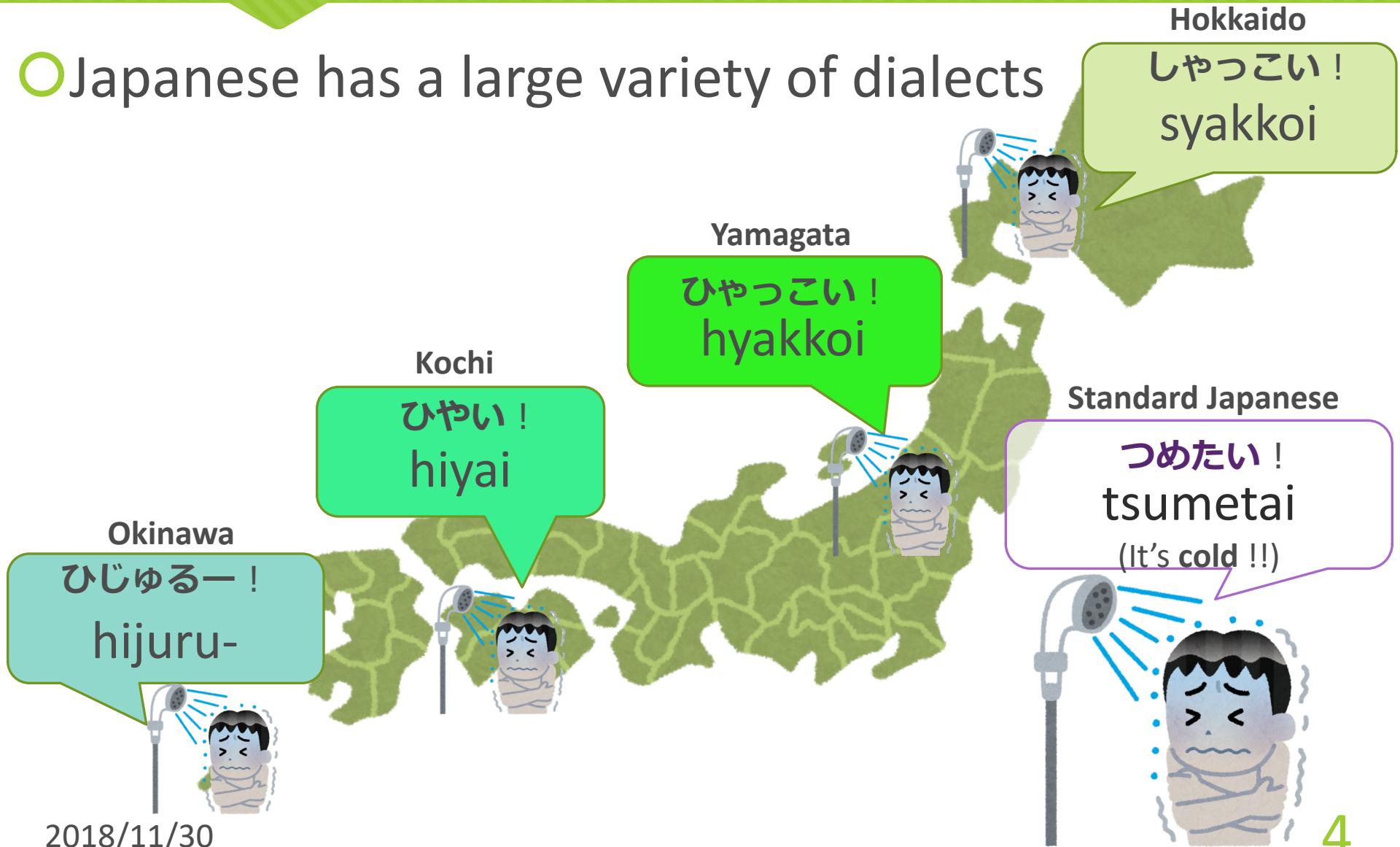
# Motivation

- *Dialect translation* enables smart speakers to understand a request in a dialect



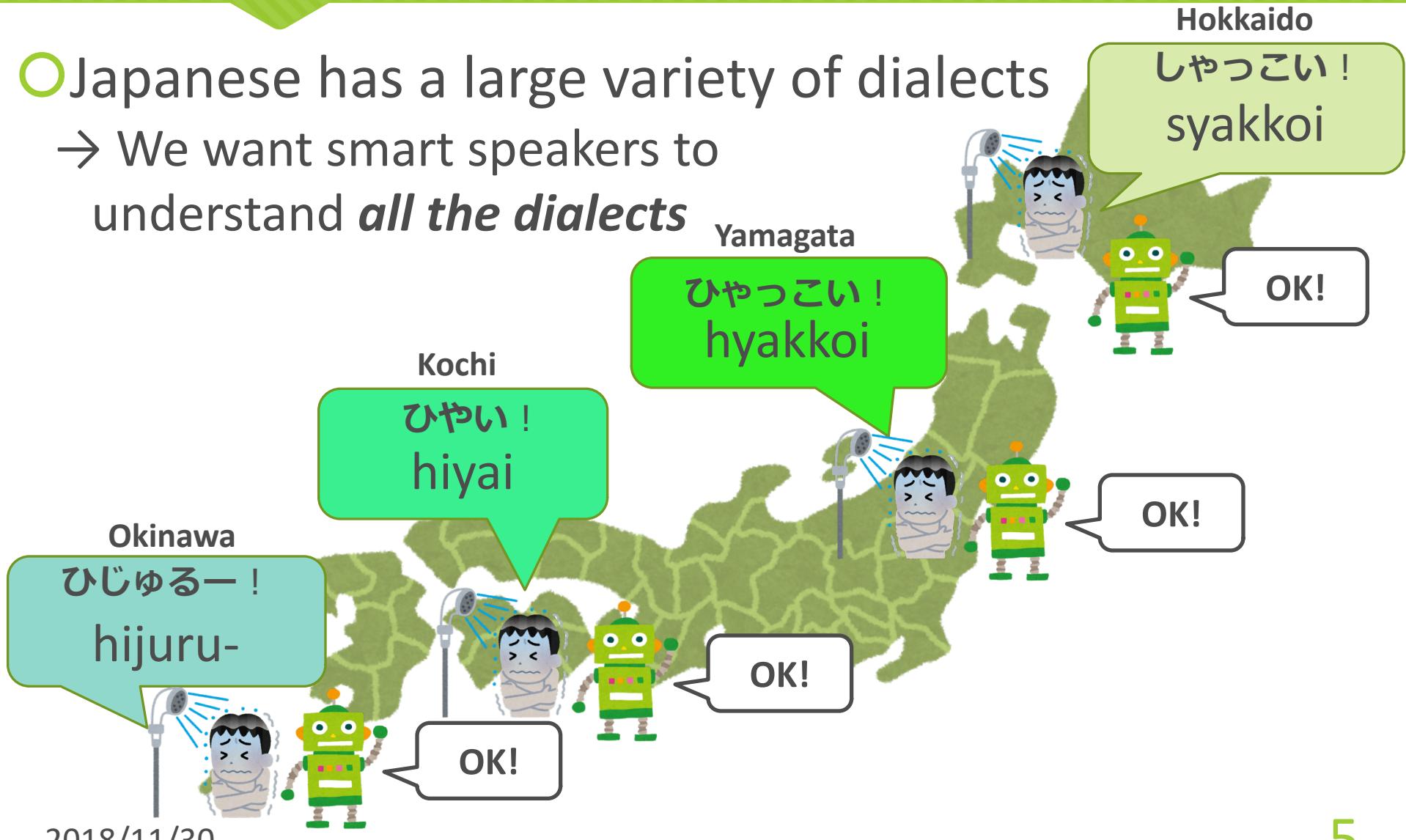
# Problem: A variety of Japanese Dialects

- Japanese has a large variety of dialects



# Problem: A variety of Japanese Dialects

- Japanese has a large variety of dialects  
→ We want smart speakers to understand *all the dialects*



# Problem: Lack of Dialect Corpus

- Japanese Dialect Corpus:

- 48 dialects × 30 minutes dialog

→ 34,117 sentence pairs of Transcript  
(718 sentence pairs per dialect)

Dialects are **spoken**  
rather than written

**It's too small !!!**

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**It's too small !!!**

- We should consider how to make the best use of this small language resource

# Relation between a Japanese Dialect and Standard Japanese

- From a Japanese dialect to standard Japanese,
- Change : **vocabulary** and **particular syllables**
- Unchange : **word order**

Example : My mother said “It's cold !”

Aomori Dialect おが が “しゃっこい！” と ゆった  
oga ga “syakkoi !” to yutta

Standard Japanese はは が “つめたい！” と いった  
haha ga “tsumetai !” to itta  
My mother “It's cold” said

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Aomori Dialect

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Standard Japanese

はは  
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“tsumetai !”

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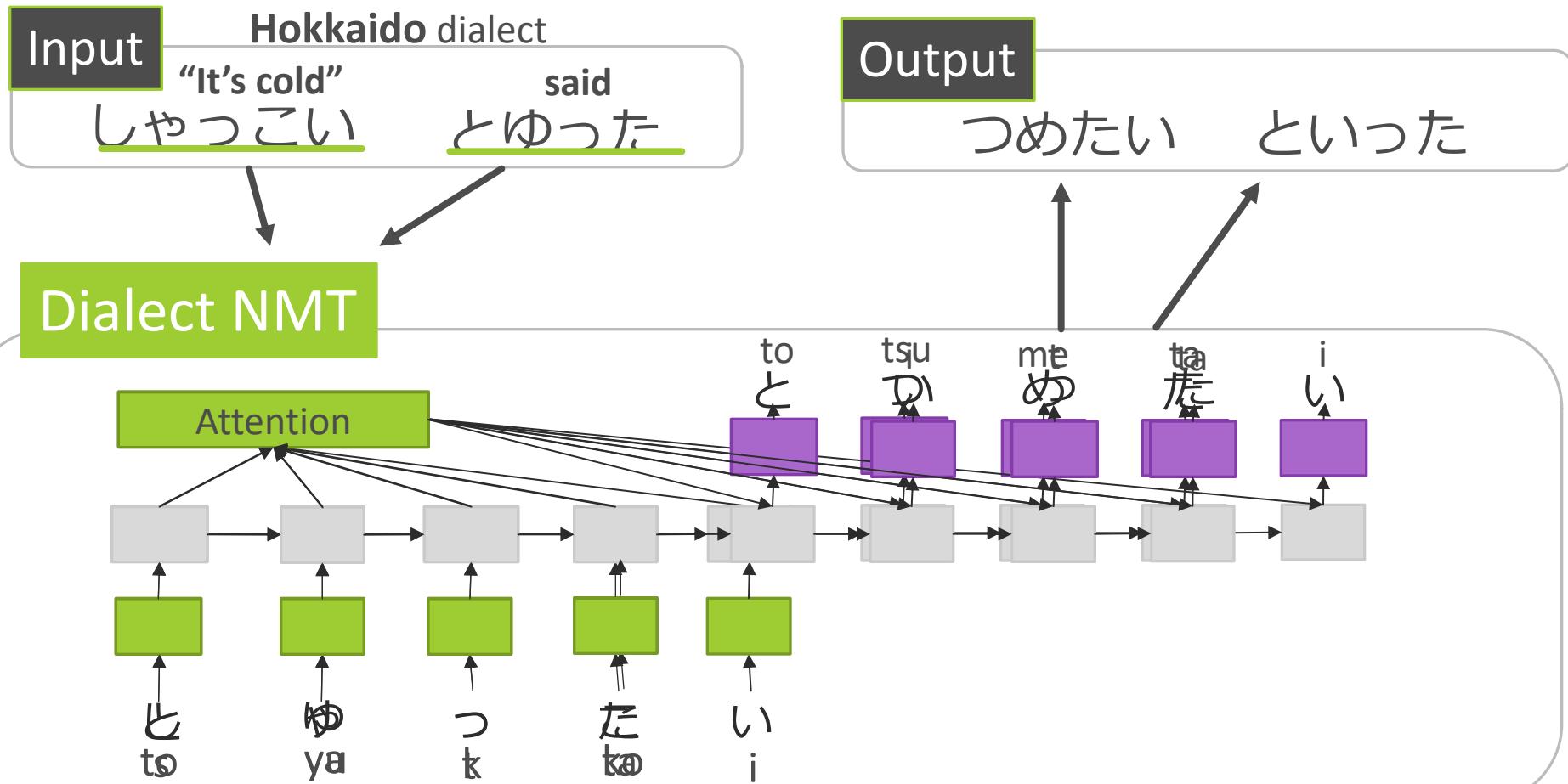
My mother

“It's cold”

said

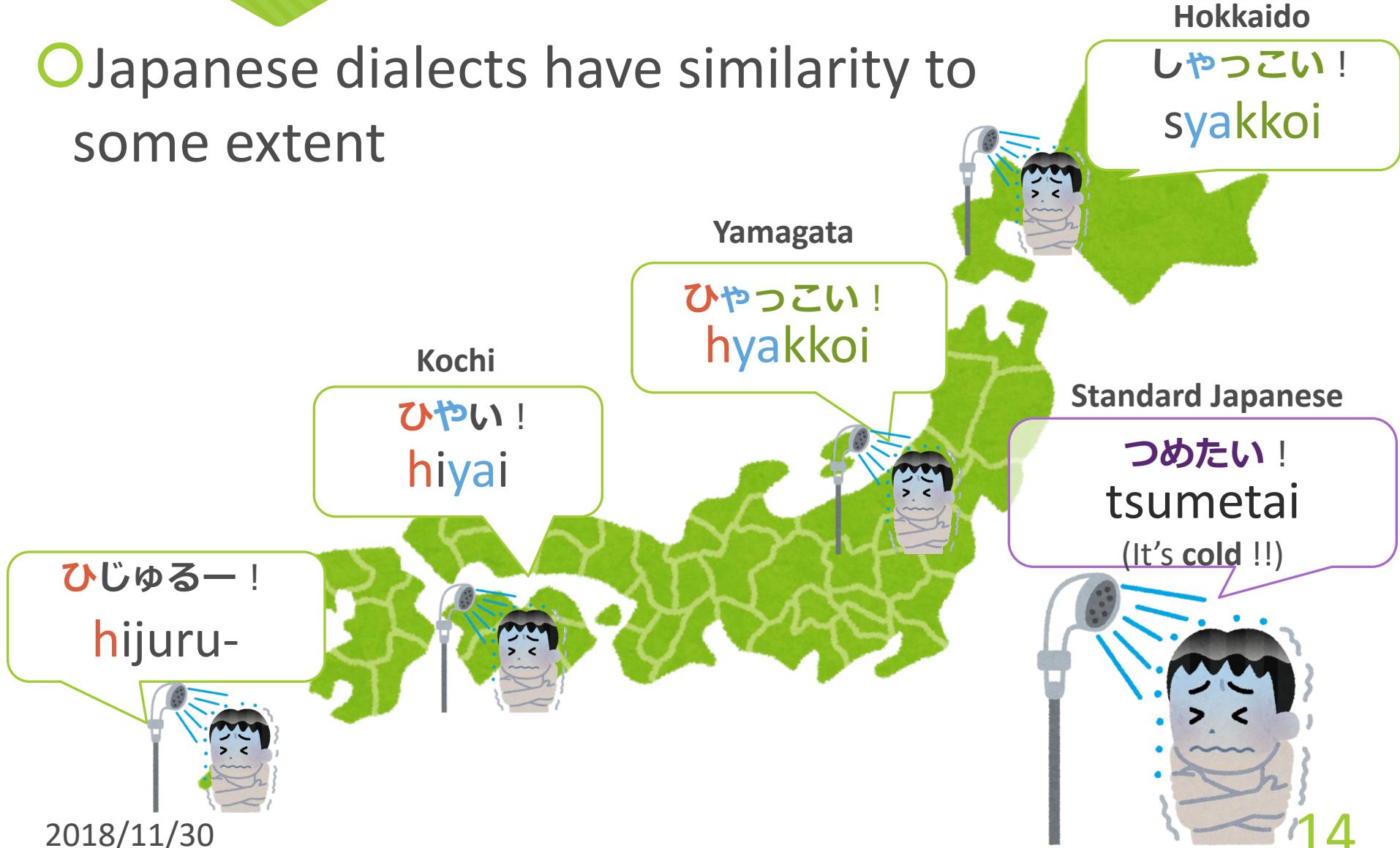
# Model (Fixed-order + Character)

## ○ Fixed-order + Character NMT



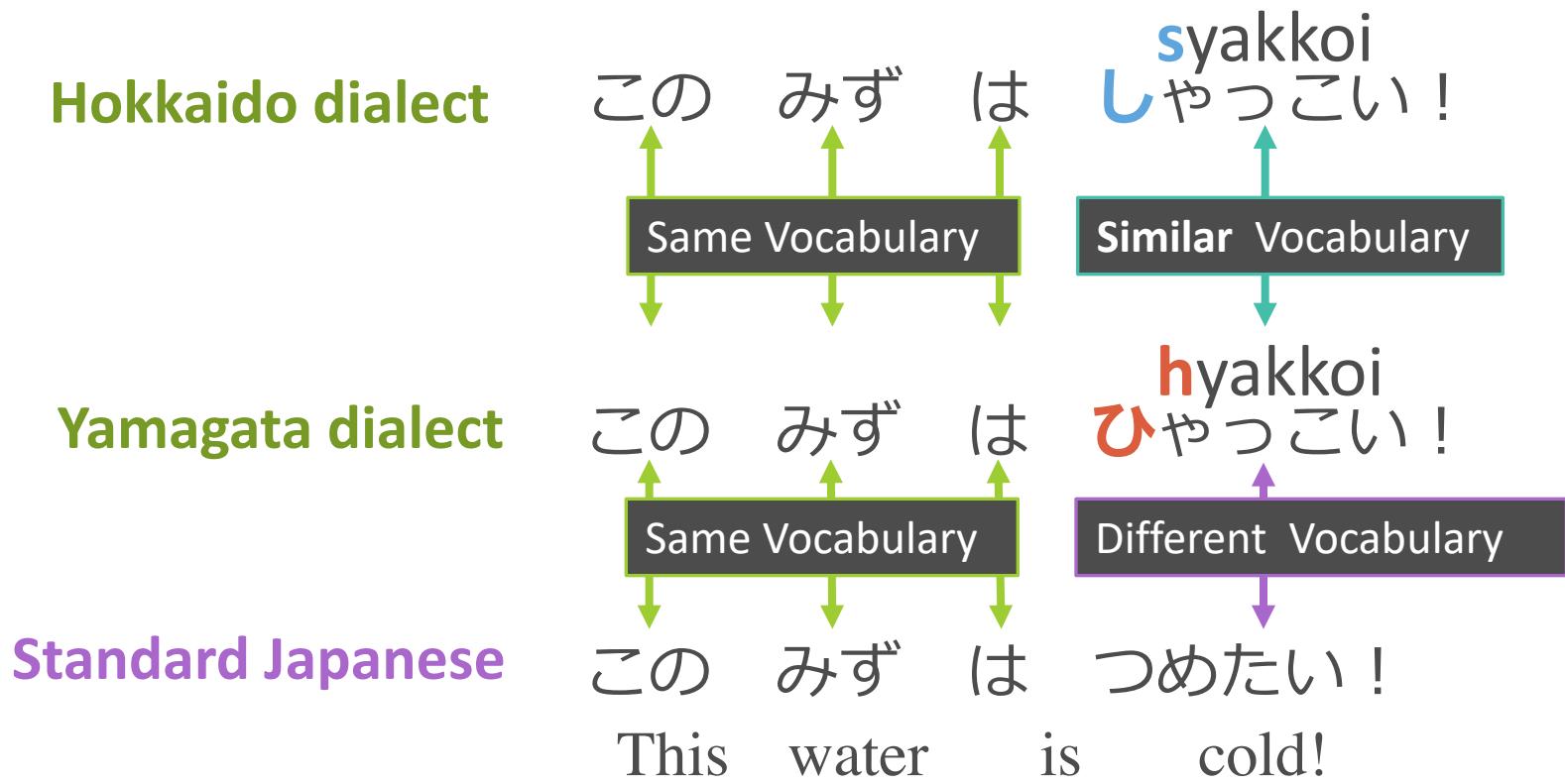
# Japanese Dialects

- Japanese dialects have similarity to some extent



# Similarity between Japanese Dialects

- Most of the dialects share fundamental properties
  - Same or Similar Vocabulary



# Similarity between Japanese Dialects

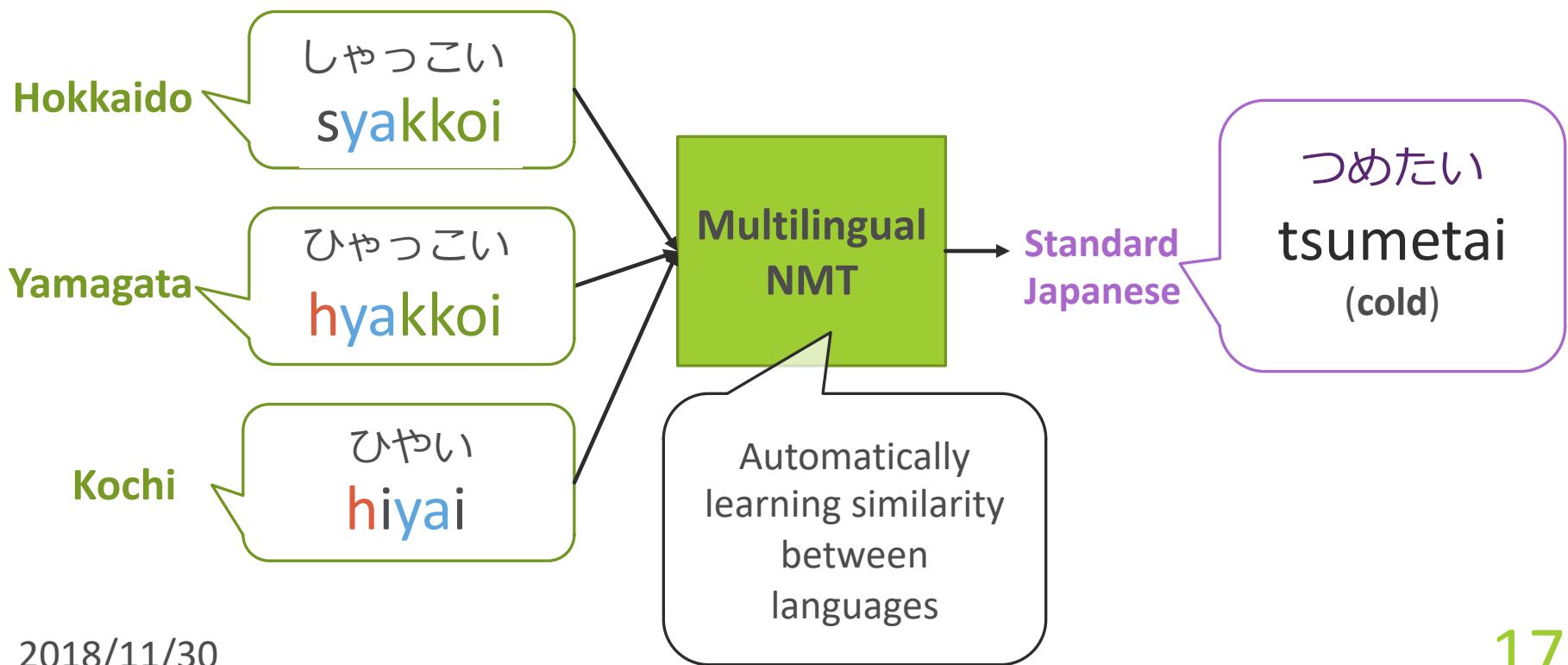
- Most of the dialects share fundamental properties
  - Phonetic correspondence rules

Hokkaido dialect	imawa いまは	soudewa そうでは	naigedona ないげどな
Standard Japanese	imawa いまは Now	soudewa そうでは it is	naikedona ないけどな
Yamagata dialect	sakana さかな	ga が	yageda やげだ
Standard Japanese	sakana さかな Fish	ga が	yaketa やけた grilled

**Same rule**

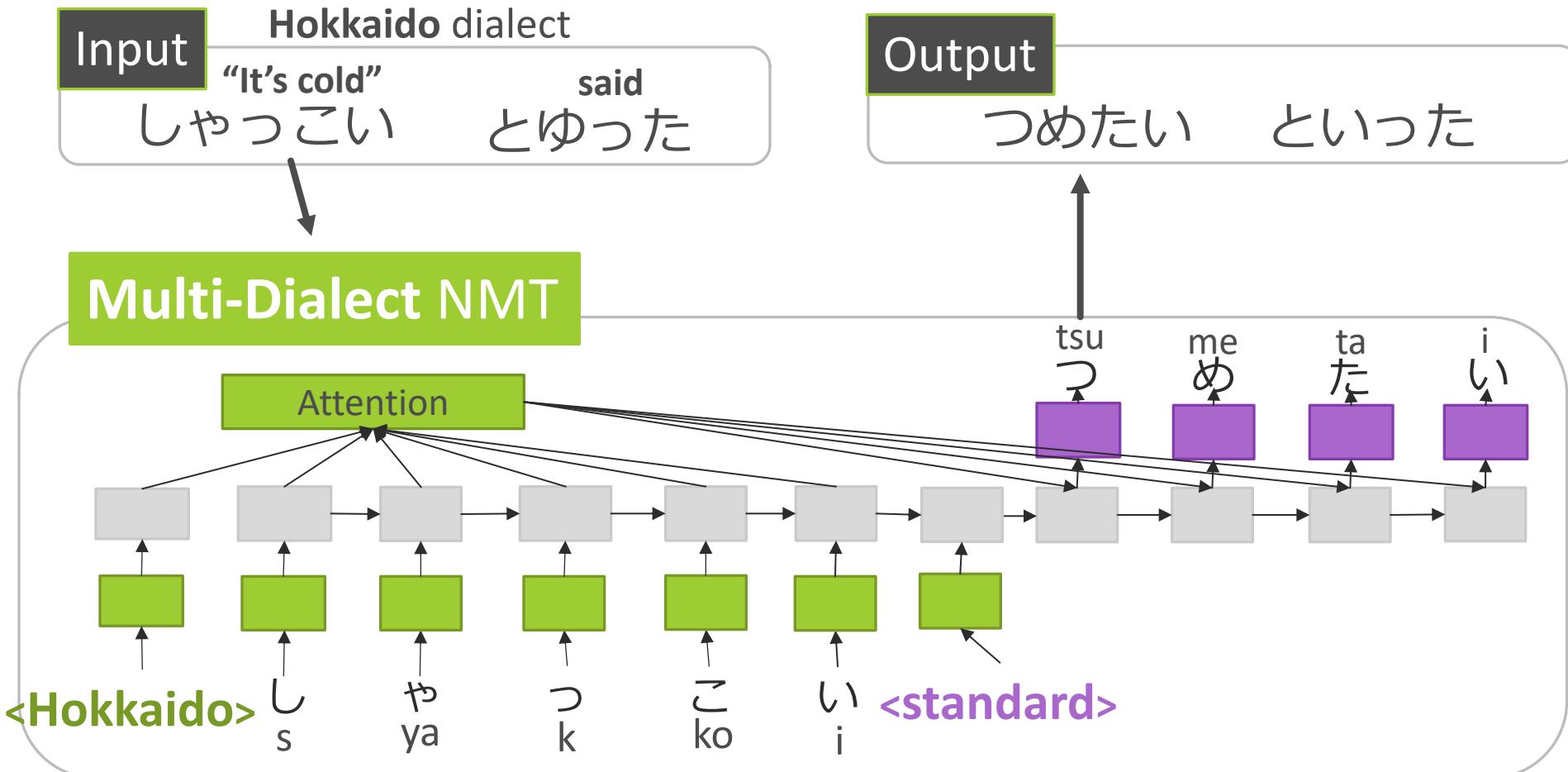
# Approach (Multilingual NMT)

- A multilingual NMT [Johnson+, 2017] utilizes shared properties between dialects by way of a unified model that learns multiple languages jointly



# Model (Character + Fixed-order + Multilingual)

## ○Character-level + Fixed-order + Multilingual NMT



# Experiments

2018/11/30

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# Setting

- Corpus :

- 48 dialects × 30 minutes dialog  
→ **34,117 sentence pairs** (116,928 “bunsetsu” pairs)  
(718 sentence, 2436 “bunsetsu” pairs per dialect)

- Train : Validation : Test = 8 : 1 : 1

- Evaluation : BLEU (**character-level**)

- System

- NMT : OpenNMT-py
  - SMT (baseline system) : Moses

# Evaluation

○ Our model archived the best performance

System	Charact er-level	Fixed- order	Dialect labels	jointly learning	BLEU
Original					35.10
Multi NMT	○	○	○	○	75.66
Mono NMT	○	○	✗	✗	22.45
Sentence-Multi NMT	○	✗	○	○	71.29
Multi NMT (w/o labels)	○	○	✗	○	69.74
Mono SMT	○	○	✗	✗	52.98
Multi SMT (w/o labels)	○	○	✗	○	73.54

# Mono NMT vs. Multi NMT

System	Charact er-level	Fixed- order	Dialect labels	jointly learning	BLEU
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Multi	● Multilingual NMT performs significantly better than monolingual NMT				73.54

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- Mono NMT could not learn translation rules because each monolingual dialect-to-standard corpus is too small

# Sentence vs. Fixed-order

System	Charact er-level	Fixed- order	Dialect labels	jointly learning	BLEU
Original					35.10
Multi NMT	○	○	○	○	75.66
Mono NMT	○	○	✗	✗	22.45
Sentence-Multi NMT	○	✗	○	○	71.29
Multi NMT (w/o labels)	○	○	✗	○	69.74
M	● Although it has a weak point that it cannot consider context, the strategy of fixed-order translation is effective				
Multi SMT (w/o labels)	○	○	✗	○	73.54

# With labels vs. Without labels

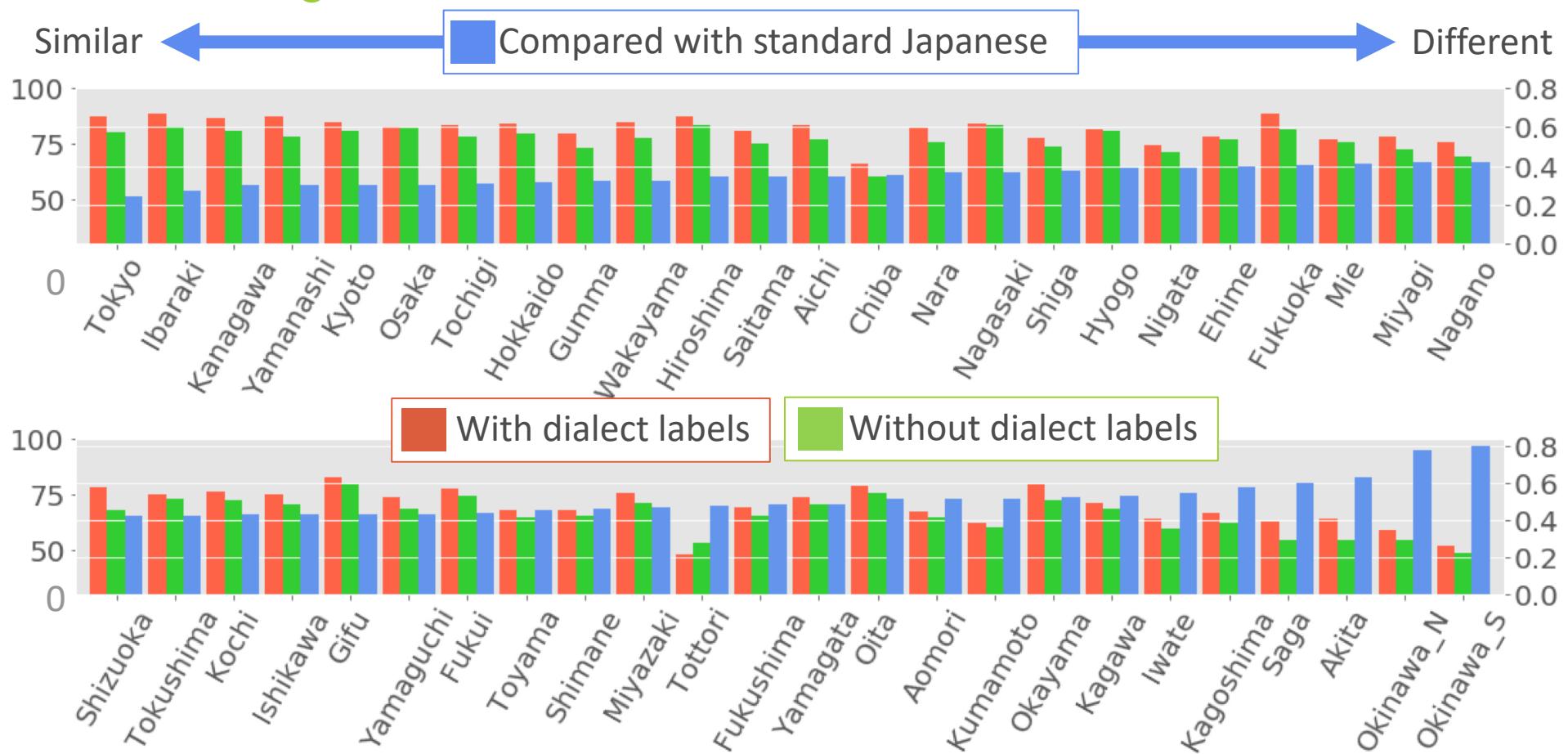
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Multi SMT (w/o labels)	○	○	...	...	72.54

- Dialect labels contribute to increasing the BLEU score because it clearly teach the NMT what the input dialect is

# SMT vs. NMT

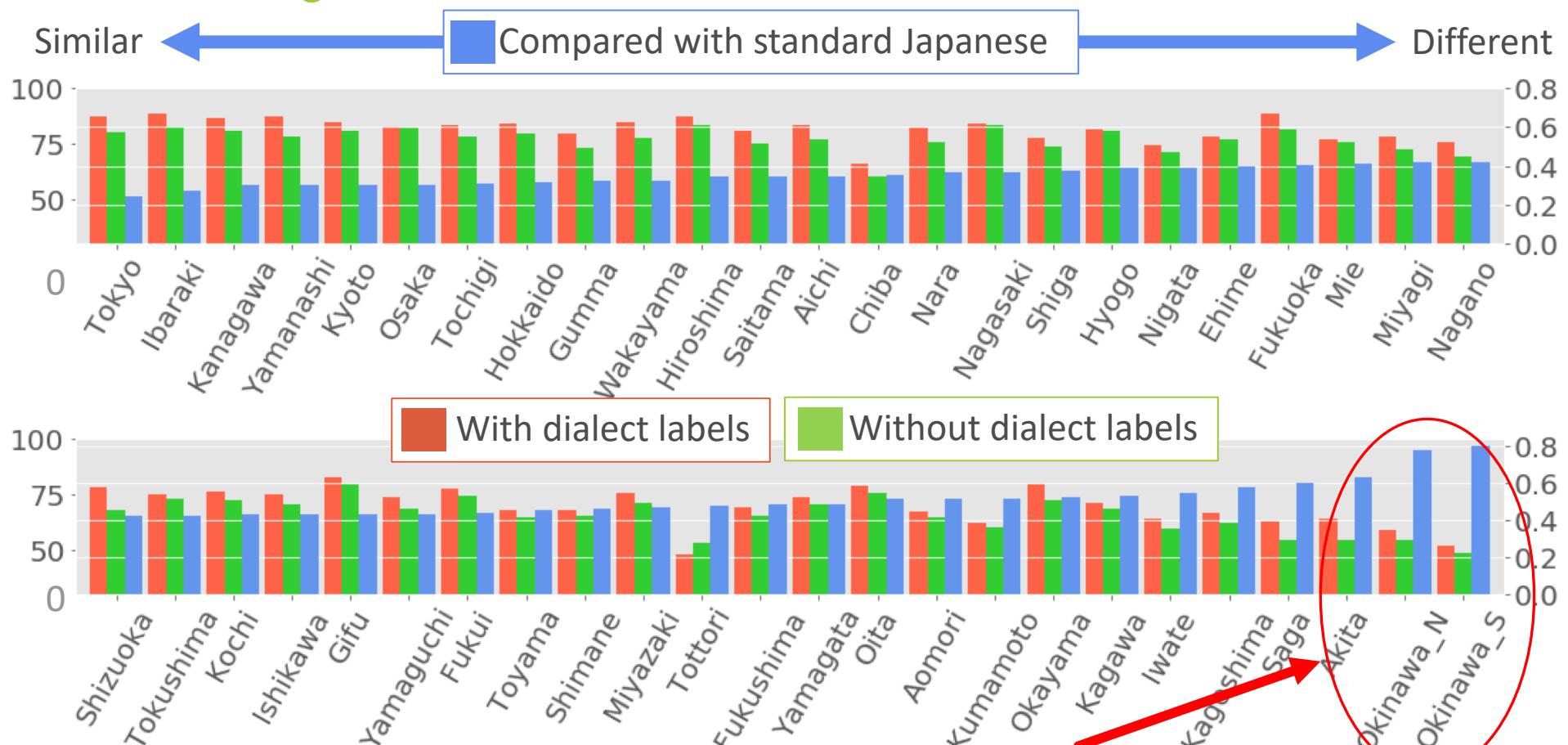
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Mono NMT	○	○	✗	✗	22.45
Sent:	● Our model outperformed standard SMT models!				
Multi NMT (w/o labels)	○	○	✗	○	69.74
<b>Mono SMT</b>	○	○	✗	✗	<b>52.98</b>
<b>Multi SMT (w/o labels)</b>	○	○	✗	○	<b>73.54</b>

# Effectiveness of Dialect labels



**Dialect labels** which teach what the dialect is contribute to increasing BLEU scores in most of the dialects

# Effectiveness of Dialect labels



Our model could not much perform in Okinawa dialect because it is quite different from standard Japanese

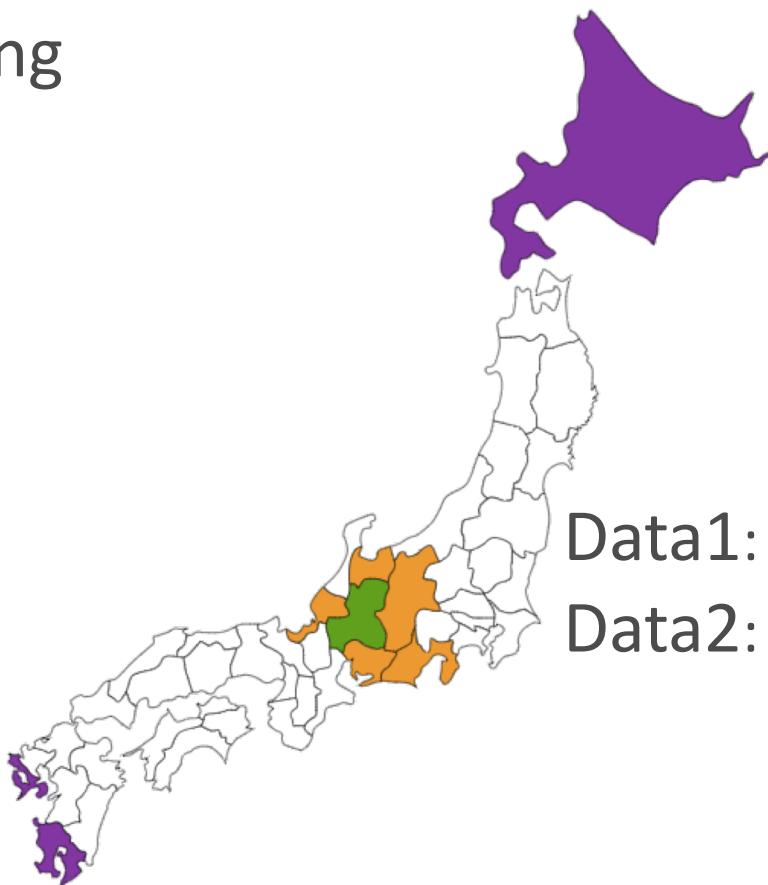
# Analysis

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# Effect of Nearby Dialects

- Assumption: the data of **nearby dialects** might contribute to the high performance under the multilingual architecture
- Setting



For "**Gifu**" dialect ...

- Data1: Removed the **nearest 5** dialects
- Data2: Removed the **farthest 5** dialects

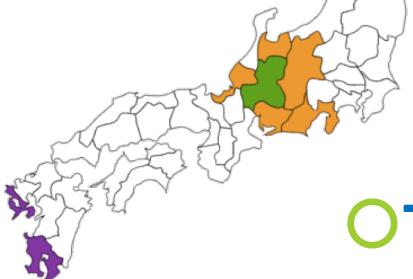
# Analysis (Effect of Nearby Dialects)

- Evaluating whether neighbor dialect data improves a BLEU score



Dataset	Avg. $\Delta$	#Regions BLEU decreased
All -nearest 5	-0.94	34/48(71%)
All -farthest 5	-0.22	31/48(65%)

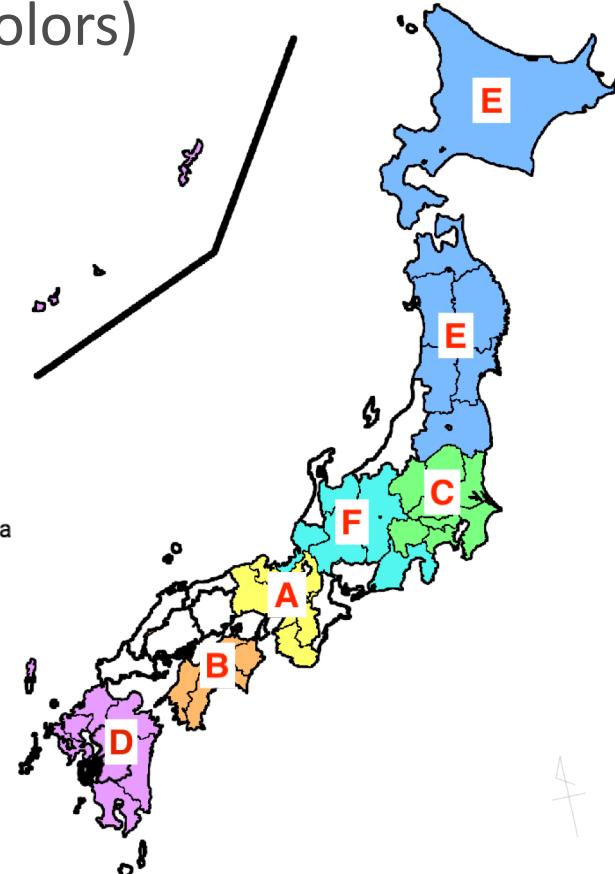
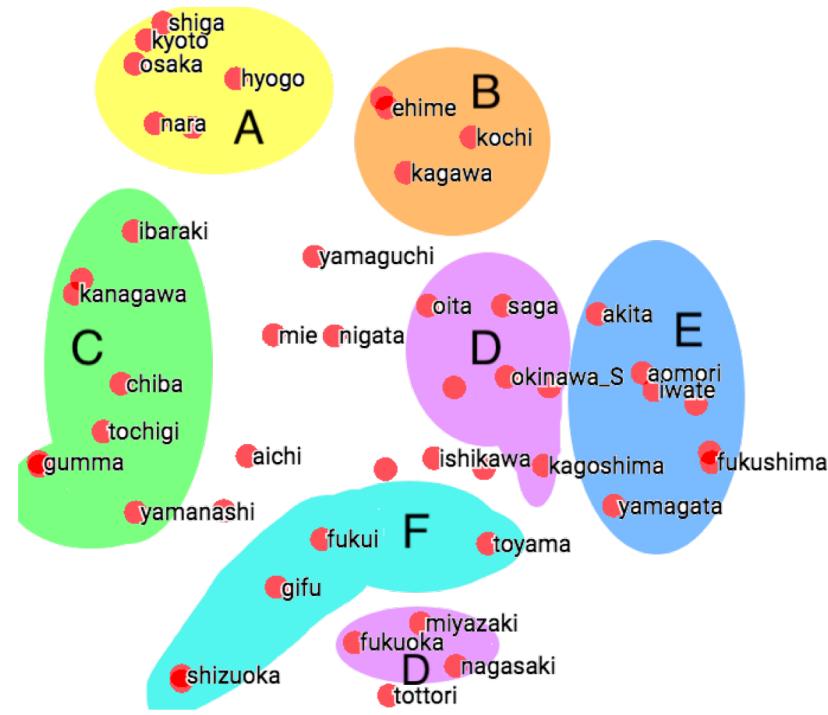
- The data of near areas are more effective for multilingual NMT



- The lack of 5 dialects in supervision data affect translation accuracy in a low-resource setting

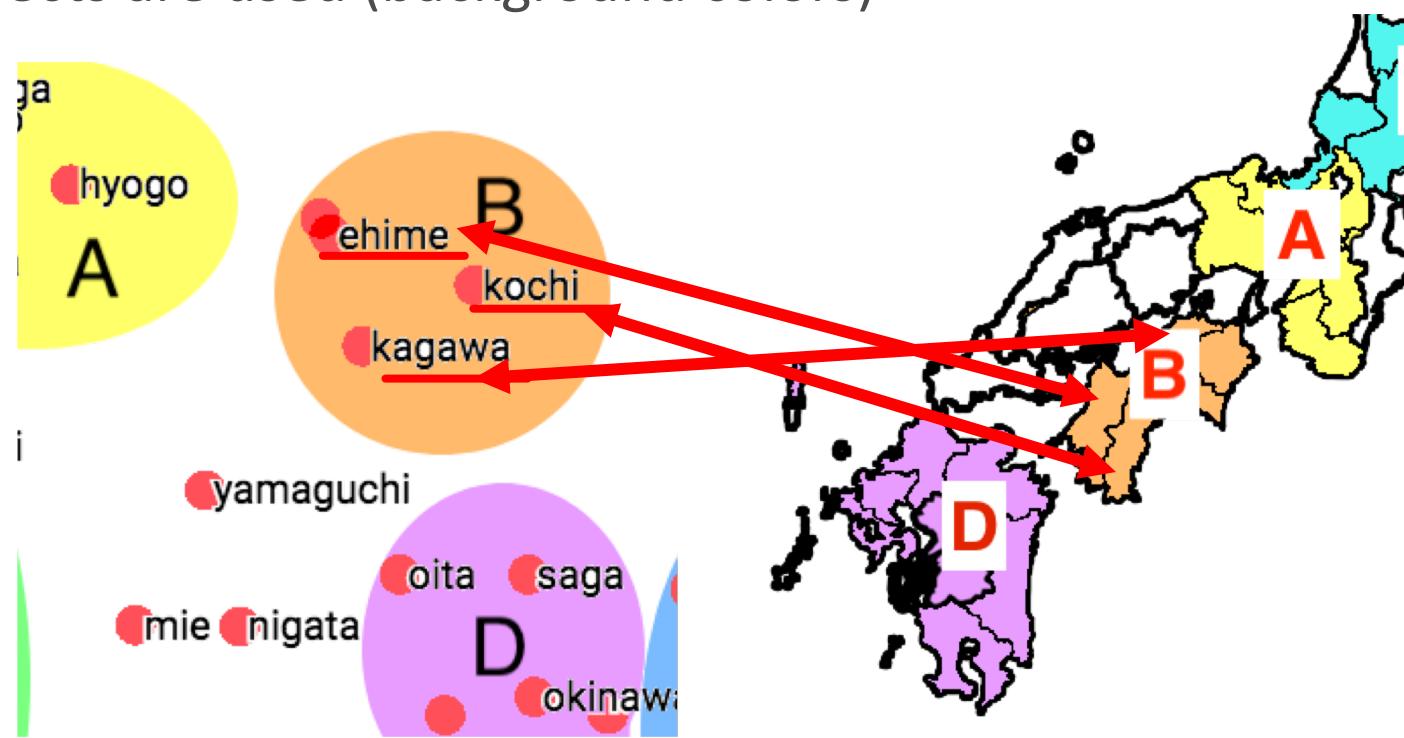
# Analysis (Visualize dialect embeddings)

- A t-SNE projection of dialect embeddings follows dialectological typology
- The nearer the distance between two areas is, the more similar dialects are used (background colors)



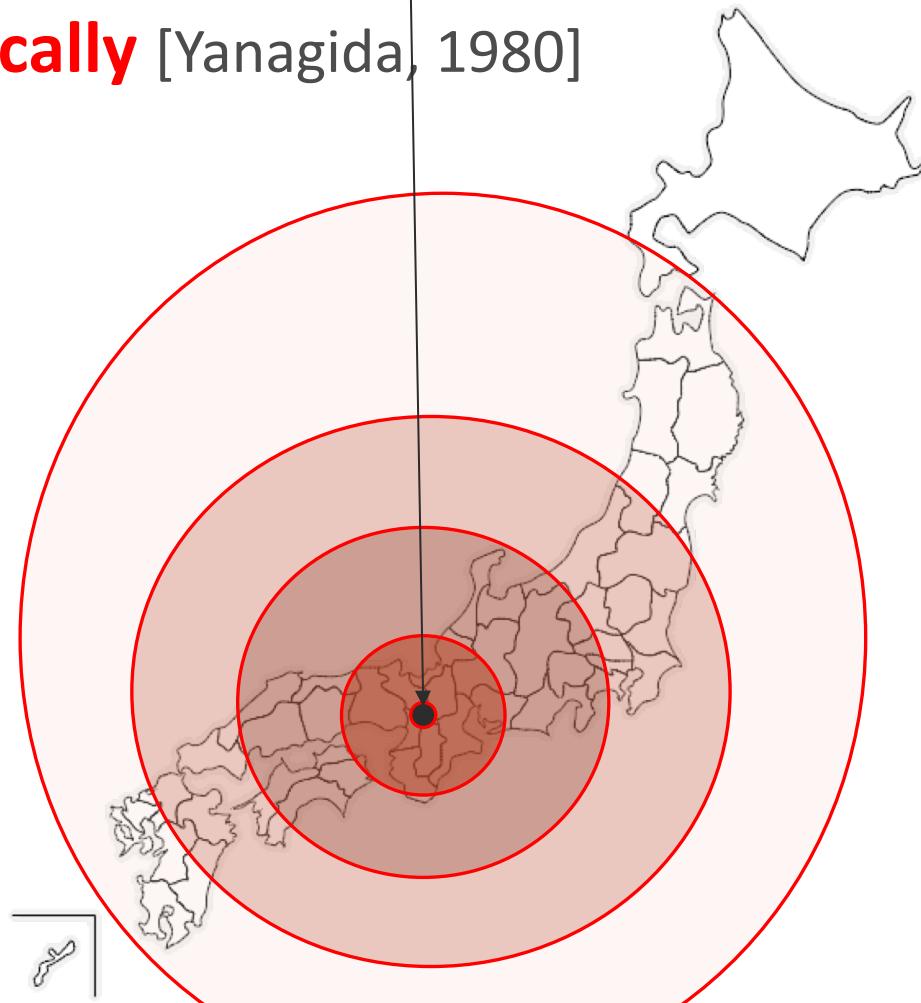
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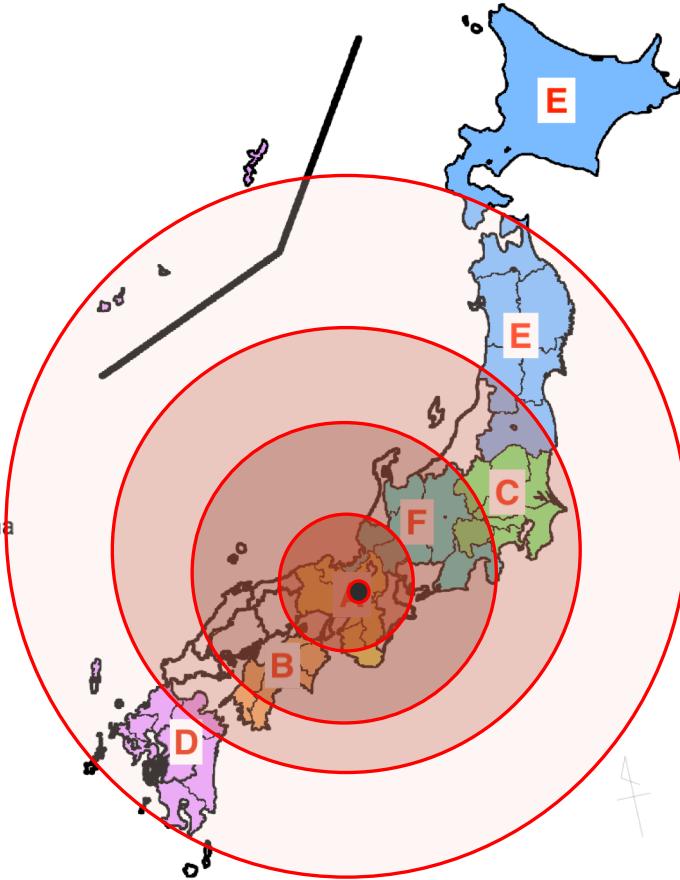
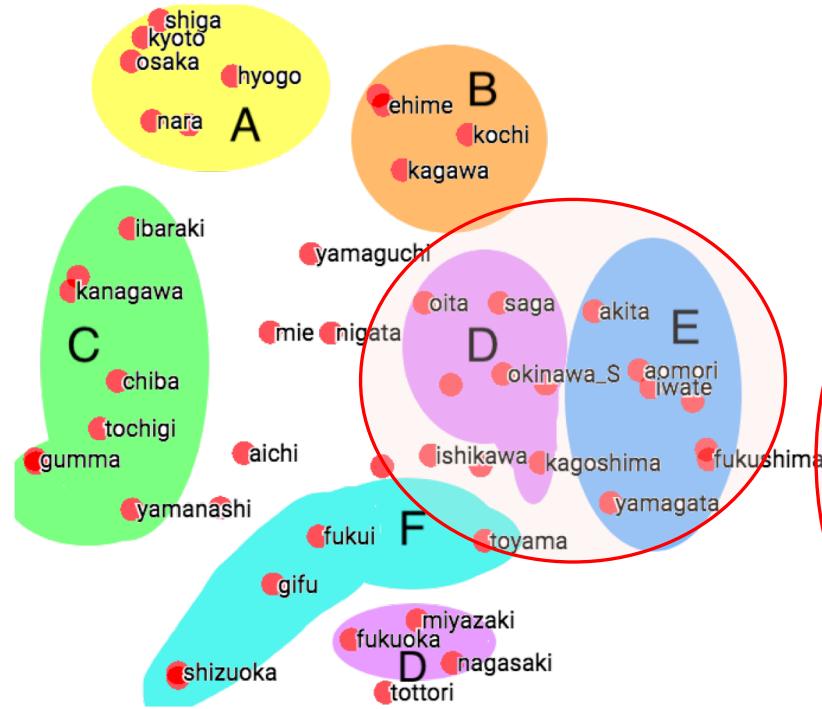
# Japanese dialectal typology

- Dialectological researcher said that dialects spread from an ancient capital city to remote areas **concentrically** [Yanagida, 1980]



# Analysis (Visualize dialect embeddings)

- A t-SNE projection of dialect embeddings follows dialectological typology
- Though the distance between **D** and **E** is far away, similar dialects are used



# Conclusions

- We presented Multi-dialect NMT system
  - character-level + fixed-order + multilingual
- The unified model that learns **similar** multiple dialects jointly is effective for multi-dialect translation
- We can observe similar relationships to the existing dialect typology in some dialects by analyzing similarity of the dialect embeddings

# References

- [Johnson+, 2017] Google’s Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation, ACL2017
- [Yanagida, 1980] Kunio Yanagida. 1980. “*Kagyuko*”. Iwanami Shoten, Publishers.

# Appendix

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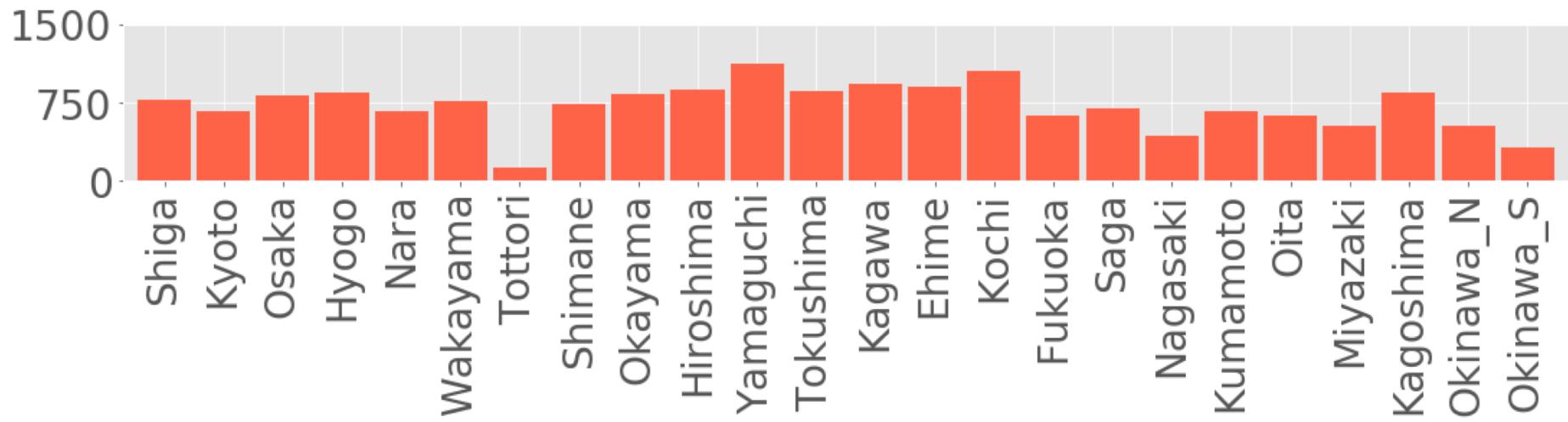
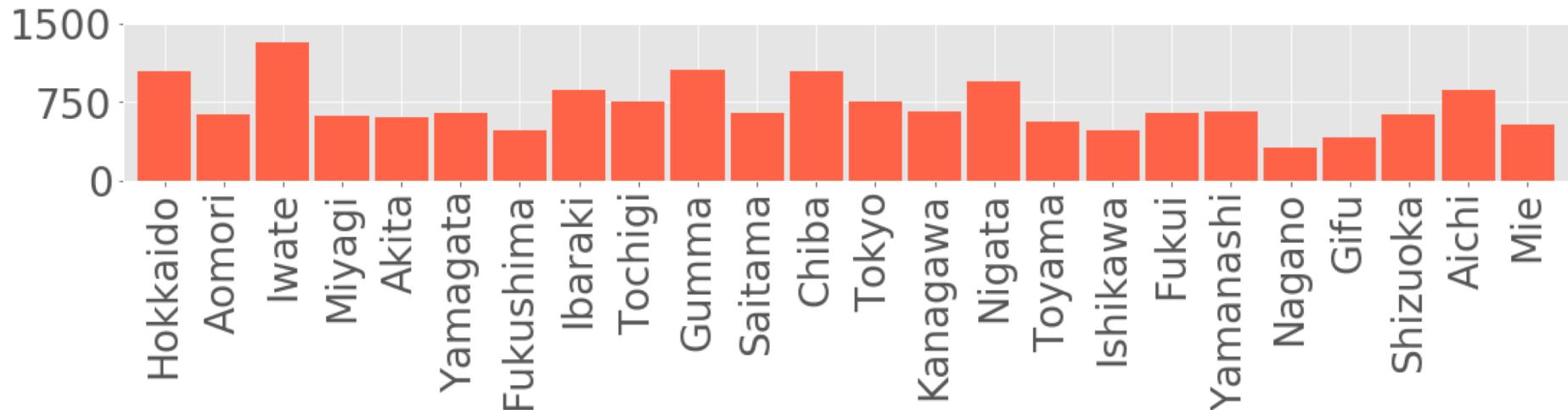
# FAQ

- Can you construct standard-to-dialect Multi NMT with the same model?
  - Yes (But the translation accuracy dropped)
  - Due to a weak language model in each target dialect
- Why is there not a “Multi SMT (w/ label)” setting ?
  - We could not devise an alternative to dialect labels in SMT

# Is Word Order really unchanged?

- We checked 100 dialect-standard sentence pairs in all 48 dialects
- All the pairs are unchanged

# The Sentence Pairs of each dialect



# Analysis (Translation Examples: Good)

- The output of Multi NMT completely agree with the reference

Example : "(We) had skated, aren't we?"

Source (Aomori dialect)	shi ke - to / no ri su ta de ba - しけーと / のりすたではー
Reference	su ke - to / no tsu ta de ha na i de su ka すけーと / のつたではないですか
Multi NMT	su ke - to / no tsu ta de ha na i de su ka すけーと / のつたではないですか
Sentence-Multi NMT	u ke i to / no ri shi ta de ha na i de su ka うけいと / のりしたではないですか
Multi NMT (w/o labels)	shi ke - to / no tsu ta de ha na i de su ka しけーと / のつたではないですか
Multi SMT (w/o labels)	su ke - to / no tsu ta de ha na i de su すけーと / のつたないです

# Analysis (Translation Examples: Bad)

- Multi NMT could not translate **too rare word**

Example : "(I) ran a horse"	
Source (Okinawa dialect)	ma - / pa ra - chi ya - まー / ぱらーちやー
Reference	u ma / ha shi ra se te ne うま / はしらせてね
Multi NMT	u ma / ha ra de ha うま / はらでは
Sentence-Multi NMT	a a / ha ra u shi ya ああ / はらうしや
Multi NMT (w/o labels)	ma a / ha na shi te ha まあ / はなしては
Multi SMT (w/o labels)	ma a / pa ra - to ne まあ / ぱらーとね