



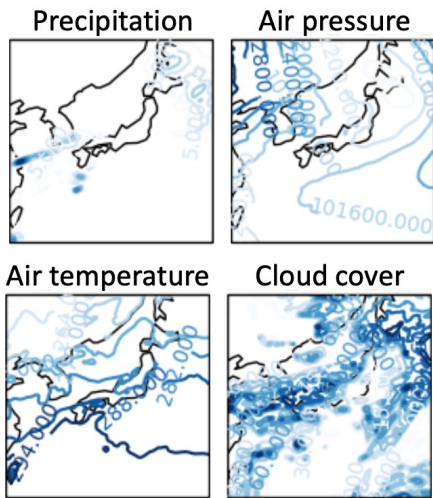
Tokyo Tech

Generating Weather Comments from Meteorological Simulations

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Automatic generation of weather comments

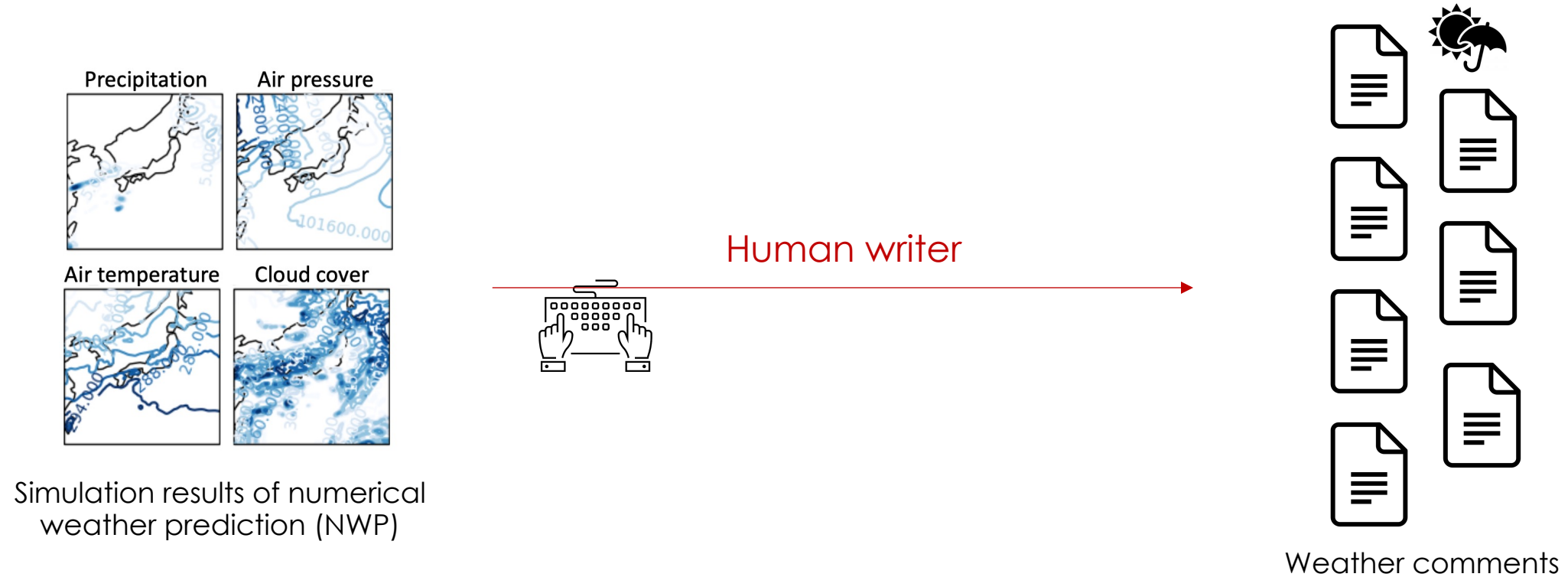


Simulation results of numerical
weather prediction (NWP)

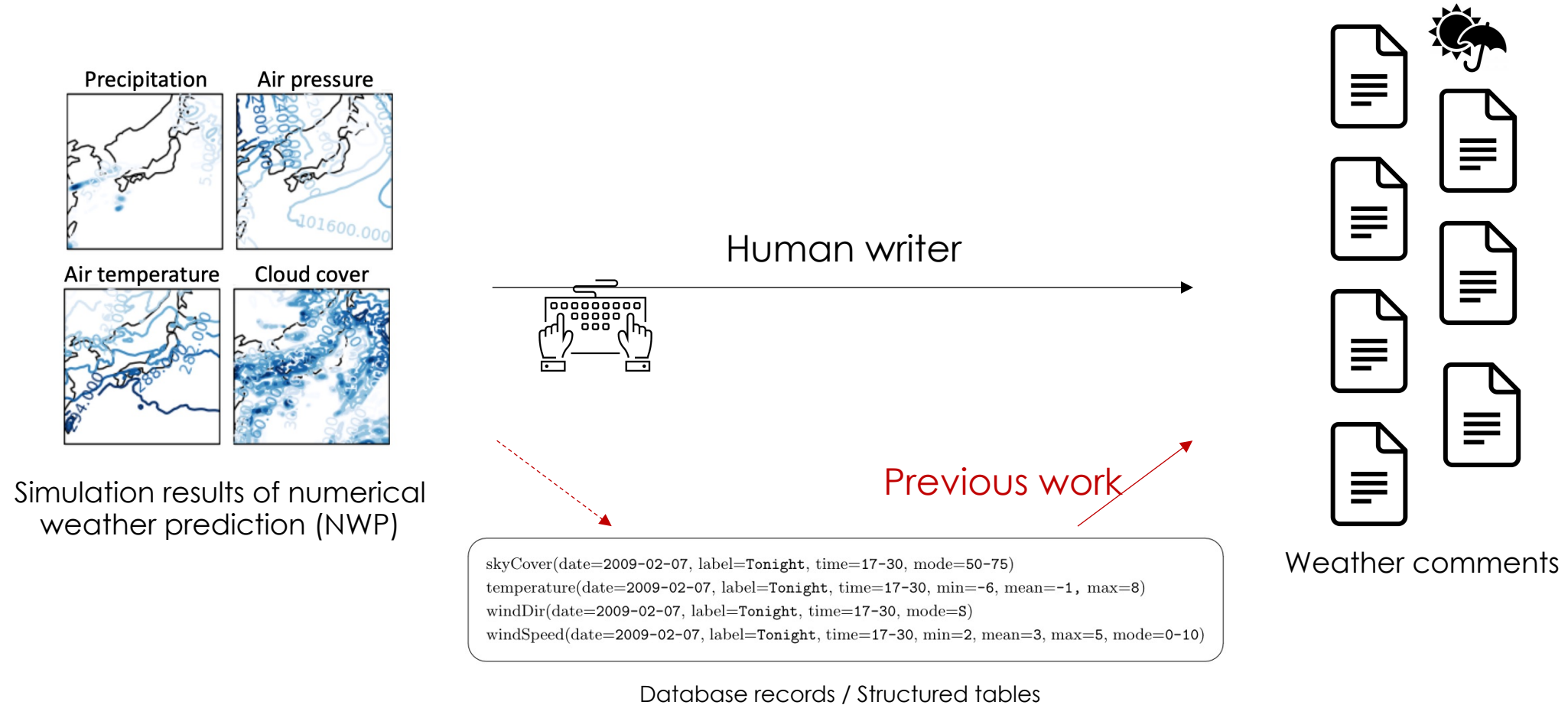


Weather comments

Automatic generation of weather comments



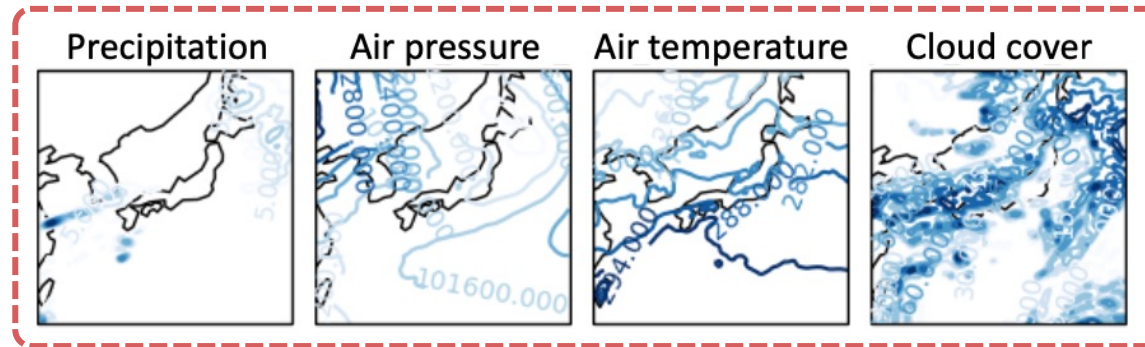
Automatic generation of weather comments



Automatic generation of weather comments



Three characteristic problems of the task



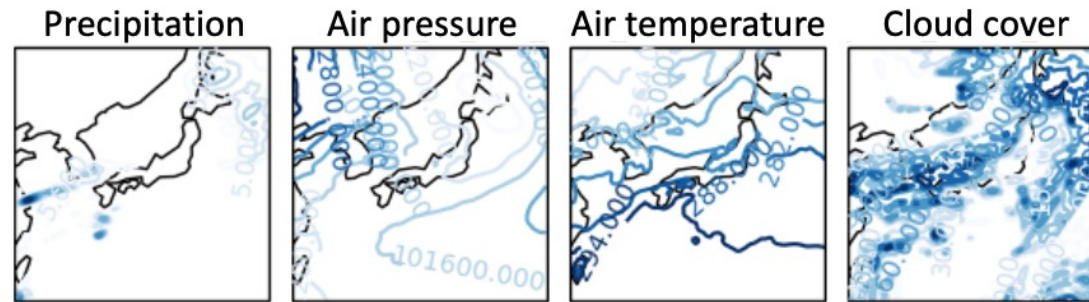
First problem

How can we consider the changes in numerical values for various physical quantities ?

Delivery time: 05:51 a.m. on 06 April, Tokyo

Today patches of blue sky will appear, but the sky will become cloudy and it will gradually start to rain in the evening. Please bring an umbrella when you go out, even if it's not raining.

Three characteristic problems of the task



First problem

How can we consider the changes in numerical values for various physical quantities ?

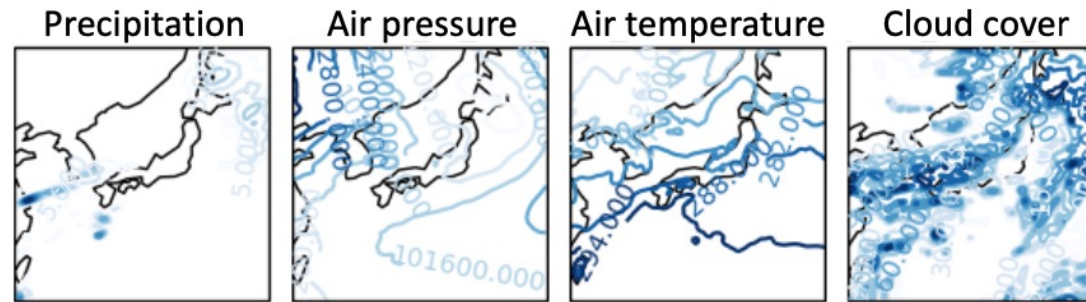
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Today patches of blue sky will appear, but the sky will become cloudy and it will gradually start to rain in the evening. Please bring an umbrella when you go out, even if it's not raining.

Second problem

Weather comments should be dependent on delivery time and area information.

Three characteristic problems of the task



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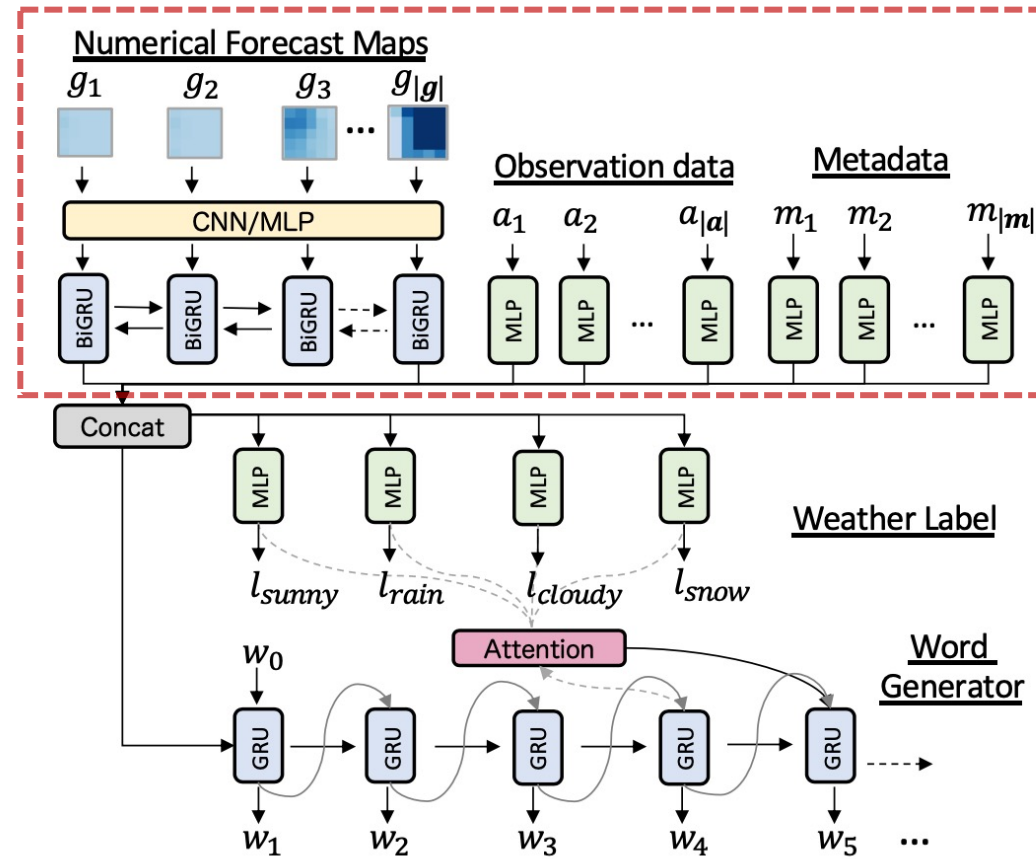
How can we consider the changes in numerical values for various physical quantities ?



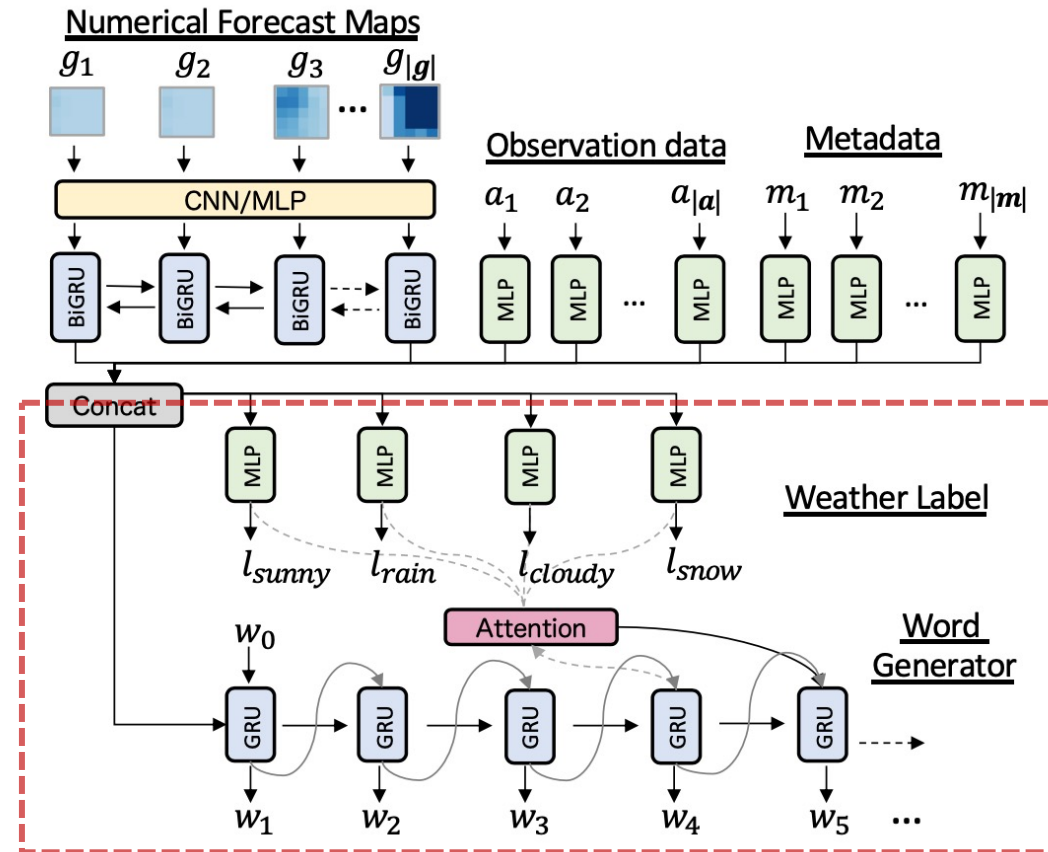
Third problem

Weather comments should provide useful information for users.

Overview of our model

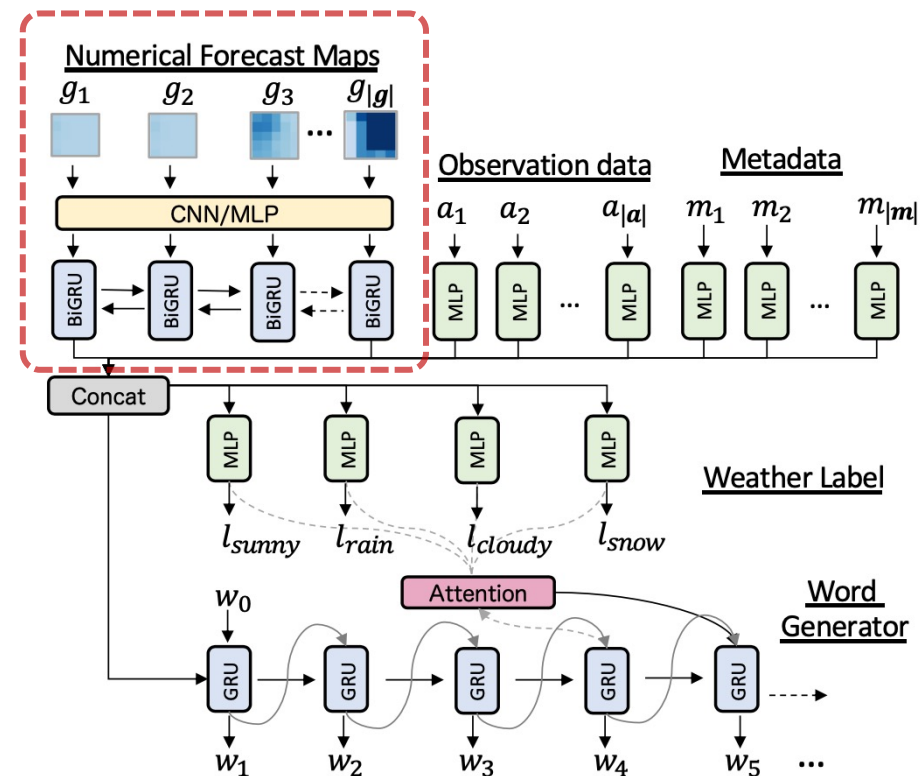


Overview of our model



Encoding numerical forecast maps

- The task can be seen as video captioning
- Two encoding methods
 - CNN-based Encoding
 - MLP-based Encoding
- Bi-RNN for capturing value changes in the sequence.

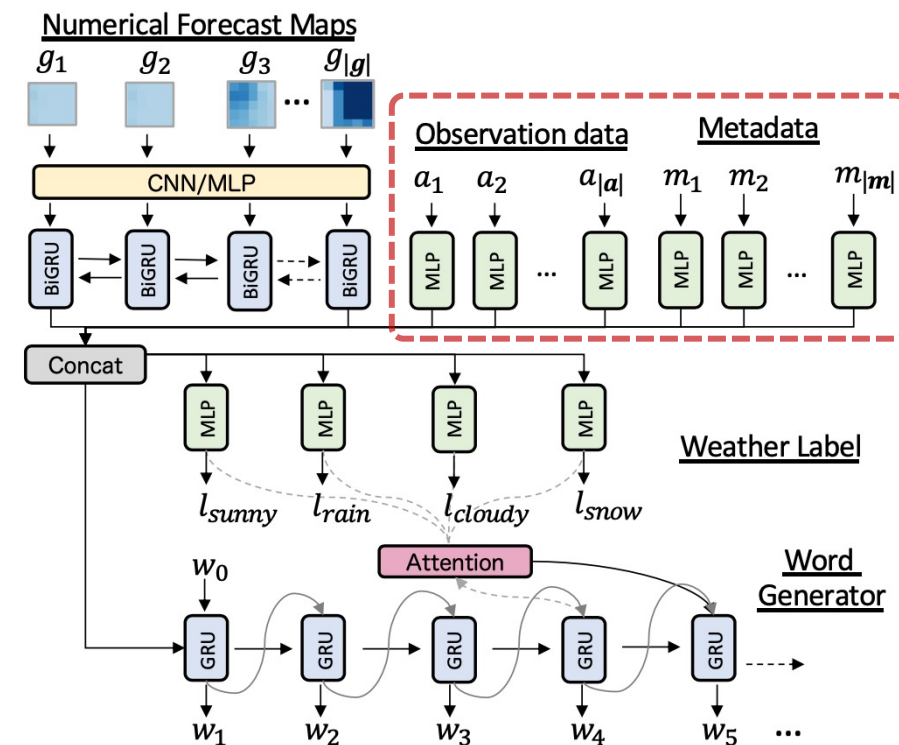


Introducing observation data and meta-data

- Observation data
 - precipitation, wind speed, temperature, sunshine duration for last 24 hours.
- Meta-data
 - delivery date, time, and area name (e.g., April, Monday, 5 a.m., Tokyo)

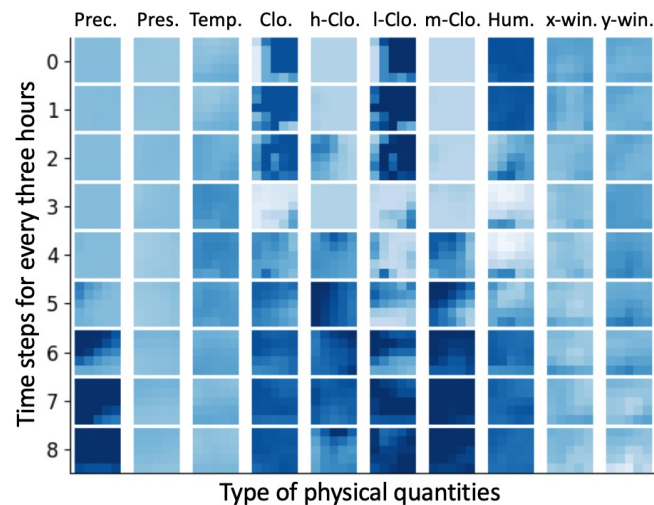
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Necessity of content selection

- Consumers are primarily interested in weather information such as sunny and rain.
- We need to explicitly perform “content selection” to help the model describe useful information.

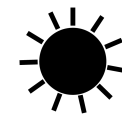


Content selection



Weather labels

Sunny



Rain



Cloudy



Snow



Predicting weather labels from input data (1/2)

- How can we define content plans ?
 - We extract content plans from “only text” instead of aligning input data with text.
- Weather label extraction
 - Weather labels are extracted by matching the clue words and words in weather comments

Examples of clue words

Label	Clue words
SUNNY	晴れ (<i>sunny</i>), 日差し (<i>sunlight</i>), 青空 (<i>blue sky</i>)
RAIN	雨 (<i>rain</i>), 大雨 (<i>heavy rain</i>), にわか雨 (<i>shower</i>)
CLOUDY	曇り (<i>cloudy</i>), 曇 (<i>cloudy</i>), 雲 (<i>cloud</i>)
SNOW	雪 (<i>snow</i>), 吹雪 (<i>blizzard</i>), 小雪 (<i>light snowfall</i>)

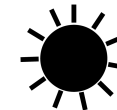
Delivery time: 05:51 a.m. on 06 April, Tokyo

Today patches of **blue sky** will appear, but the sky will become **cloudy** and it will gradually start to **rain** in the evening. Please bring an **umbrella** when you go out, even if it's not raining.



Extracted weather labels

Sunny



Cloudy

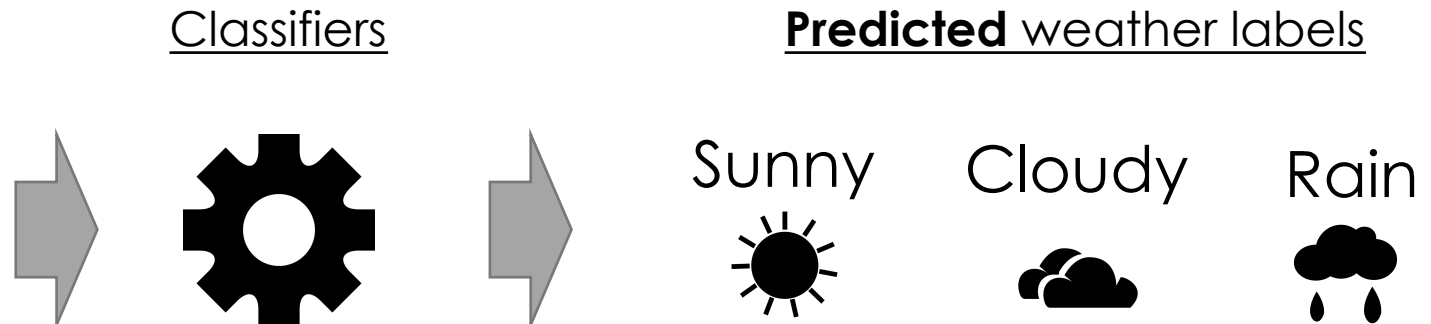
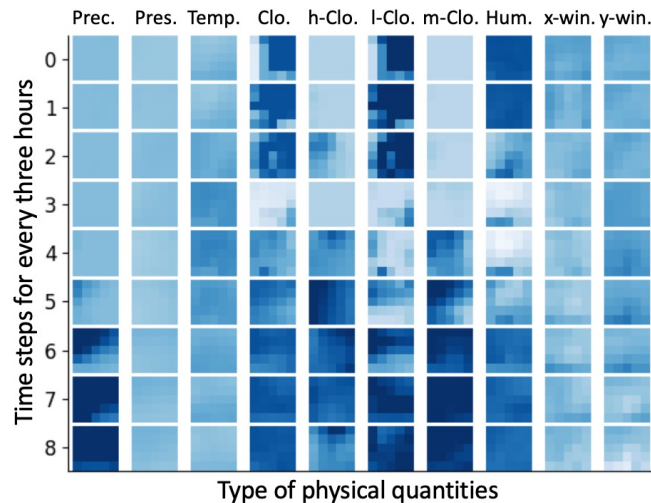


Rain



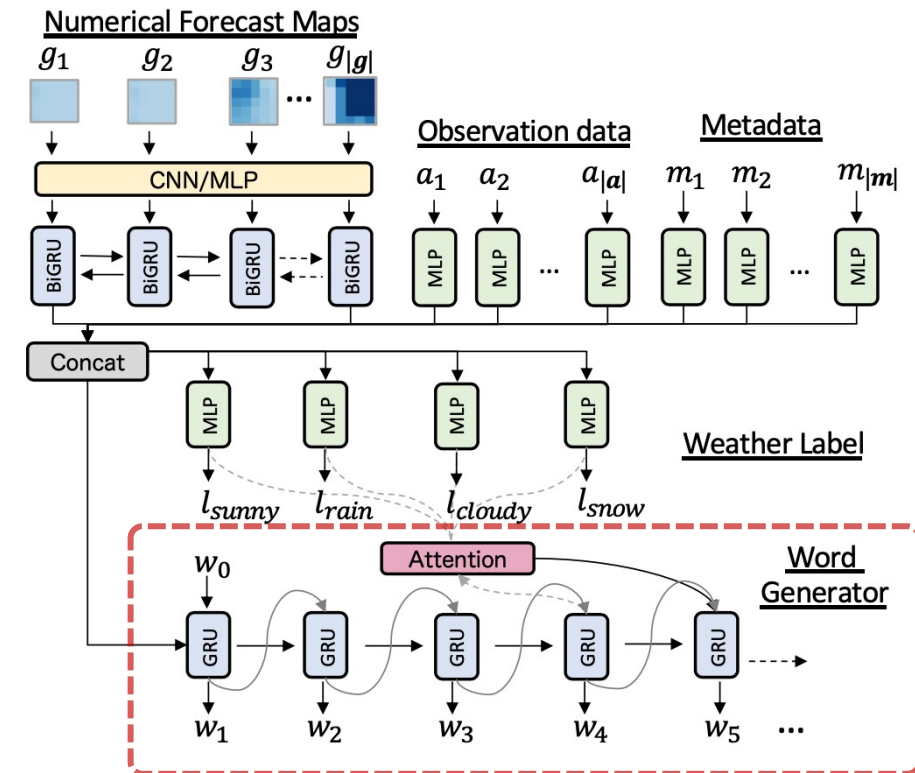
Predicting weather labels from input data (2/2)

- At the inference phase, the classifier predicts weather labels from the input data.
- The predicted labels are considered as “content plans” to generate weather comments.



Word generator

- The word generator takes the outputs of the encoders and then generates weather comments.
- The predicted weather labels are also considered through the attention mechanism.



Experimental settings

- Dataset

- Weather comments, provided by Weathernews Inc.
- Numerical forecast maps
- Weather observation data

Statistics of weather comments

Train	28,555
Valid	14,464
Test	14,393

- Evaluation metrics

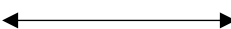
- Word-based metrics
 - BLEU, ROUGE
- Content-based metrics
 - Precision/Recall/F1 of weather labels, extracted from generated texts
- Human evaluation (w/ five evaluators)
 - Informativeness, consistency, grammaticality (1/2/3)

Automatic evaluation results

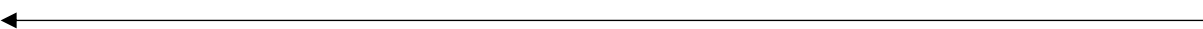
- Model (4) outperformed all other models except (5), which can use oracle labels.

Table: Results of automatic evaluation

	Model	Components			Word Overlap		SUNNY			RAIN			CLOUDY			SNOW		
		Enc.	Weather	CL	BLEU	ROUGE	P%	R%	F ₁ %	P%	R%	F ₁ %	P%	R%	F ₁ %	P%	R%	F ₁ %
Baseline	(1)	CNN	—	—	12.7	42.8	83.5	67.6	74.7	72.8	83.6	77.8	58.5	59.8	59.0	75.2	50.1	60.2
	(2)	MLP	—	—	13.0	43.5	83.2	68.4	74.9	74.6	83.5	78.8	59.8	60.3	59.9	75.7	53.3	62.3
Proposed model	(3)	MLP	Pred.	—	12.9	43.8	81.0	78.5	79.7	78.6	80.0	79.3	62.5	55.9	58.9	75.9	60.4	67.2
	(4)	MLP	Pred.	✓	13.2	43.9	81.0	78.4	79.7	76.6	84.1	80.2	60.6	59.3	59.8	77.7	58.5	66.6
	(5)	MLP	Orac.	✓	14.6	45.5	94.9	84.5	89.4	84.4	92.9	88.4	84.7	85.6	85.1	91.3	63.8	75.1



Word-based metrics



Content-based metrics

Automatic evaluation results

- Models (3) and (4) significantly improved F1 scores for the sunny and snow labels by around 5% in comparison to the baselines.

Table: Results of automatic evaluation

	Model	Components			Word Overlap		SUNNY			RAIN			CLOUDY			SNOW		
		Enc.	Weather	CL	BLEU	ROUGE	P%	R%	F ₁ %	P%	R%	F ₁ %	P%	R%	F ₁ %	P%	R%	F ₁ %
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Word-based metrics

Content-based metrics

Automatic evaluation results

- Model (5) significantly improved the correctness of each weather label since it can use the oracle labels, but the improvement in BLEU and ROUGE scores was limited.

Table: Results of automatic evaluation

	Model	Components			Word Overlap		SUNNY			RAIN			CLOUDY			SNOW		
		Enc.	Weather	CL	BLEU	ROUGE	P%	R%	F ₁ %	P%	R%	F ₁ %	P%	R%	F ₁ %	P%	R%	F ₁ %
Baseline	(1)	CNN	—	—	12.7	42.8	83.5	67.6	74.7	72.8	83.6	77.8	58.5	59.8	59.0	75.2	50.1	60.2
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	(5)	MLP	Orac.	✓	14.6	45.5	94.9	84.5	89.4	84.4	92.9	88.4	84.7	85.6	85.1	91.3	63.8	75.1

Word-based metrics

Content-based metrics

Effect of meta-data

- We conducted an ablation study between Model (4) and w/o Meta.
- Model (4), which takes into account the meta-data, can more accurately provide time-dependent expressions than w/o Meta.

Table: F1 scores or time-dependent expressions

Expression	Model (4)	w/o Meta	Δ
今日 (<i>Today</i>)	99.3	97.3	+2.0
明日 (<i>Tomorrow</i>)	95.1	91.1	+4.0
月 (<i>Monday</i>)	29.3	0.0	+29.3
火 (<i>Tuesday</i>)	29.2	0.0	+29.2
春 (<i>Spring</i>)	14.0	2.4	+11.6
夏 (<i>Summer</i>)	19.1	12.4	+6.7
BLEU	13.2	12.7	+0.5

Human evaluation results

- Model (4), which explicitly performs content selection by using weather labels, outperformed model (2), which does not, in terms of informativeness.

Table: Results of human evaluation

Label	Model(2)			Model(4)			# of cases
	Info.	Con.	Gra.	Info.	Con.	Gra.	
SUNNY	1.92	2.91	2.91	2.10	2.82	2.88	26
RAIN	2.02	2.93	2.92	2.13	2.88	2.90	26
CLOUDY	1.99	2.93	2.94	2.12	2.83	2.89	19
SNOW	1.88	2.95	2.92	1.95	2.91	2.94	13
Overall	1.98	2.92	2.92	2.10	2.86	2.90	40

Human evaluation results

- However, model (4) was inferior to model (2) in terms of consistency, although the score is still significantly high.

Table: Results of human evaluation

Label	Info.	Model(2)		Info.	Model(4)		# of cases
		Con.	Gra.		Con.	Gra.	
SUNNY	1.92	2.91	2.91	2.10	2.82	2.88	26
RAIN	2.02	2.93	2.92	2.13	2.88	2.90	26
CLOUDY	1.99	2.93	2.94	2.12	2.83	2.89	19
SNOW	1.88	2.95	2.92	1.95	2.91	2.94	13
Overall	1.98	2.92	2.92	2.10	2.86	2.90	40

Conclusion

- We proposed a data-to-text model and incorporated three types of encoders for forecast maps, observation data, and meta-data into the model.
- We introduced weather labels representing the content of weather information to improve the correctness of information in generated comments.

