# Unsupervised Ensemble of Ranking Models for News Comments Using Pseudo Answers

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1. Tokyo Institute of Technology

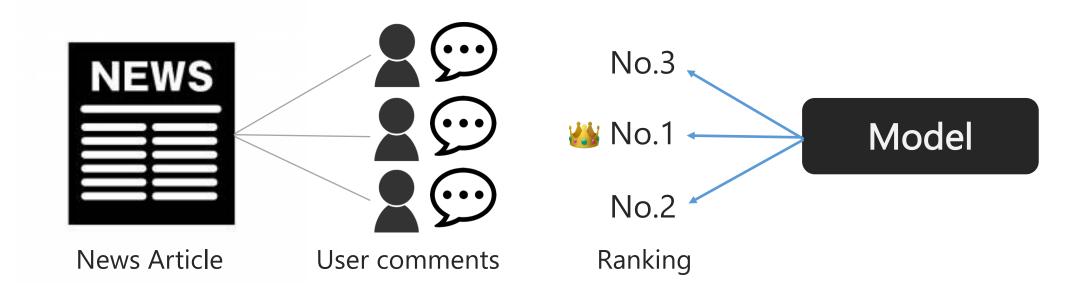
2. Yahoo Japan Corporation / RIKEN AIP

# Background

Task: Ranking comments on online news services

Goal: Display high quality comments

Problem: "high quality" has complex factors



# Ranking news comments is difficult

- We have <u>various situations</u> of judging whether a comment is good
  - Indicating rare user experiences
  - Providing new ideas
  - Causing discussions
- Ranking models often <u>fail to capture these information</u>

## How to deal with this problem? → Ensemble techniques

If we prepare many models, some models can capture these information

# Two Basic Ensemble Techniques

# Selecting

model outputs selected outputs





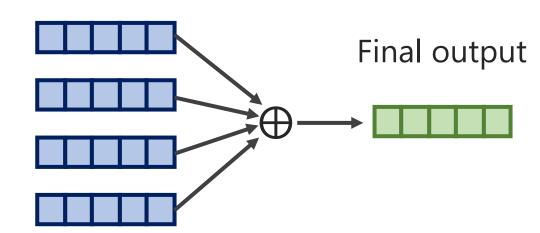




- Denoising lower accuracy model
- X Depend on a single model output

## **Averaging**

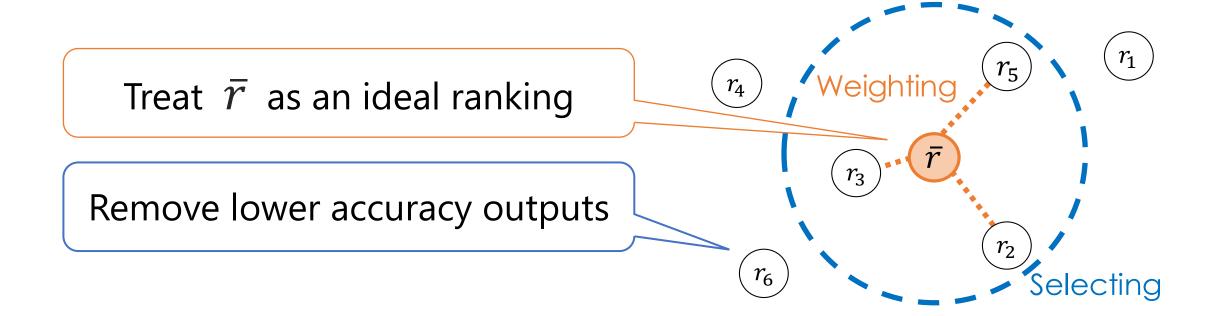
model outputs



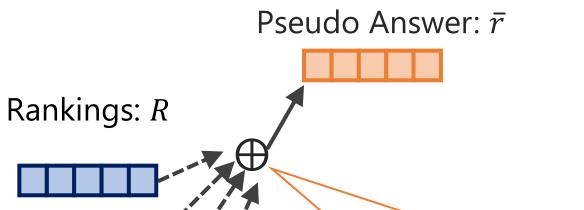
- ✓ Make up for other models' mistakes
- X Lower accuracy model could be noise

# Proposed method: HPA ensemble

- Hybrid method using the Pseudo Answer
  - Hybrid of an output selection and a typical averaging method
  - Dynamic denoising of outputs via a pseudo answer  $ar{r}$

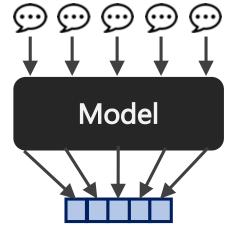


## Step1: Calculate a pseudo answer



Normalize & Average

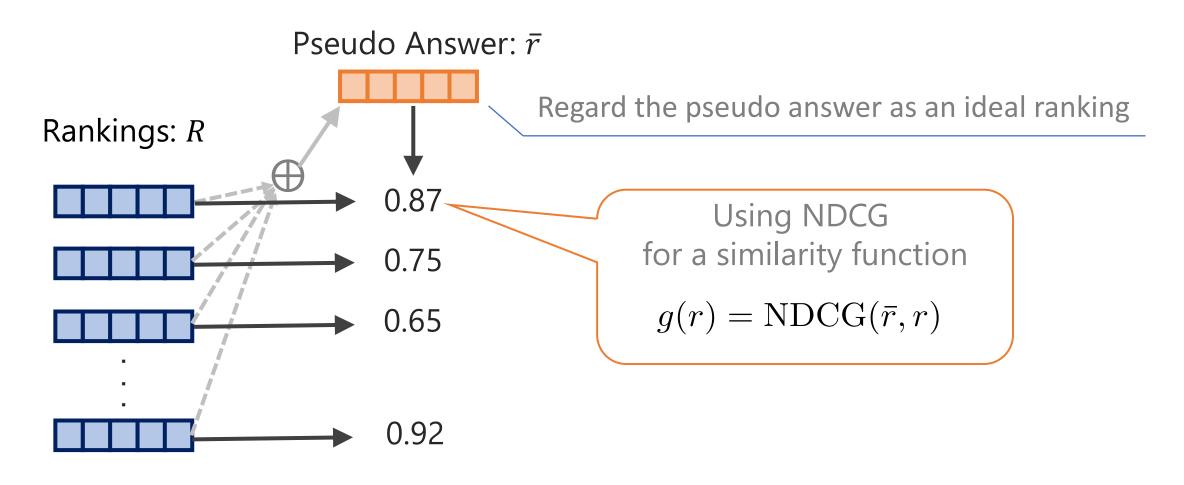
$$\bar{r} = \frac{1}{|R|} \sum_{r \in R} \frac{r}{||r||}$$



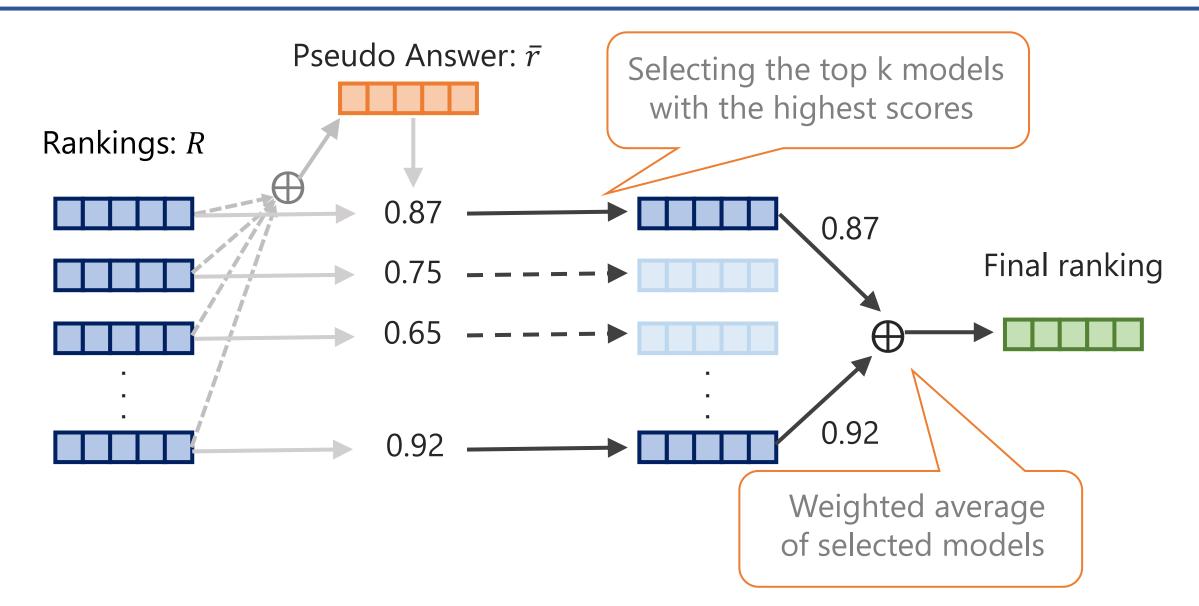
Each block represents a ranking score of a comment

Ranking scores: r

# Step2: Calculate similarity scores of each predicted ranking



# Step3: Calculate the final ranking from similarity scores



# **Experimental Settings**

## **Dataset**: YJ Constructive Comment Ranking Dataset

Train 1,300 articles, Validation 113 articles, Test 200 articles (each article associated with more than 100 comments)



Models: LSTM-based RankNet

Prepared 100 different models by random initialization

Metrics: NDCG@k and Precision@k ( $k \in \{1, 5, 10\}$ )

### **Evaluation Results**

Best single model
Unsupervised baseline
Supervised baseline
Ours Ours w/o weighting Ours w/o selecting

Methods	NDCG @1 @5 @10			Prec. @1 @5 @10		
RankNet	76.35	77.97	79.52	15.0	33.20	42.99
NormAvg	79.83	80.77	82.16	17.08	37.18	46.48
SupWeight	78.64	80.33	81.94	16.28	35.47	46.58
HPA	79.87	81.43	82.33	17.08	37.39	47.34
SPA WPA	79.68 <b>79.87</b>	80.96 81.39	82.19 82.17	17.08 17.08	35.87 <b>37.88</b>	46.68 46.63

This is a part of the results.

Please see Table 1 in our paper if you want to find other baselines.

#### **Evaluation Results**

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Unsupervised baseline

Supervised baseline

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Ours w/o selecting	WPA	79.87	81.39	82.17	17.08	37.88	46.63

Hybrid of weighting and selecting is effective

#### Conclusion

## **Proposed Method:**

- A hybrid unsupervised method using pseudo answers

#### Result:

- Our method achieved the best performance
- Denoising predicted rankings using the pseudo answer is effective

#### **Future work:**

- Combine various types of network structures
- Investigate effectiveness of our methods on other ranking datasets