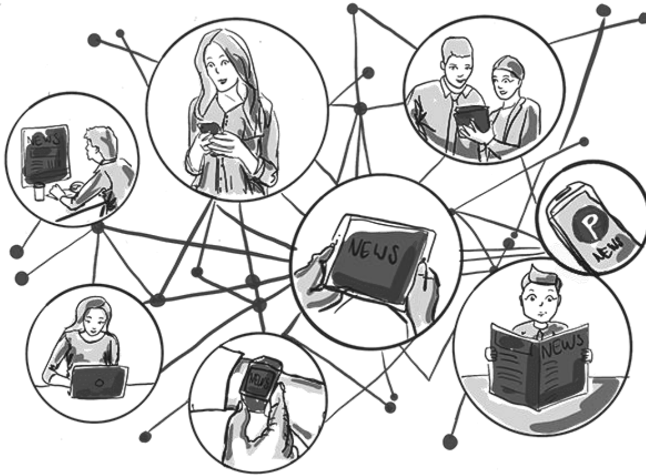

Being diverse is not enough:
Rethinking Diversity Evaluation to Meet Challenges of News Recommender Systems (NRS)

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1

Introduction

- Current challenges of NRS
- Diversity and NRS
- Evaluation of NRS

2

Experimental analysis

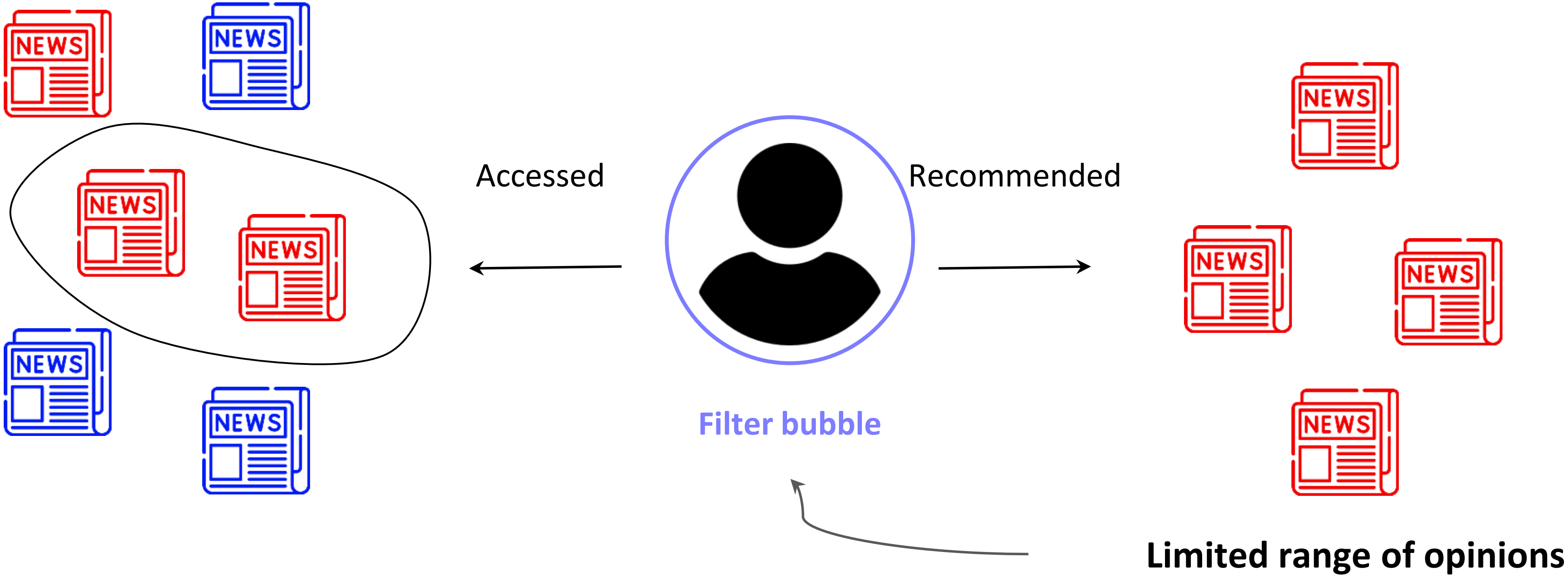
- Dataset selection
- Holistic analysis
- Temporal analysis

3

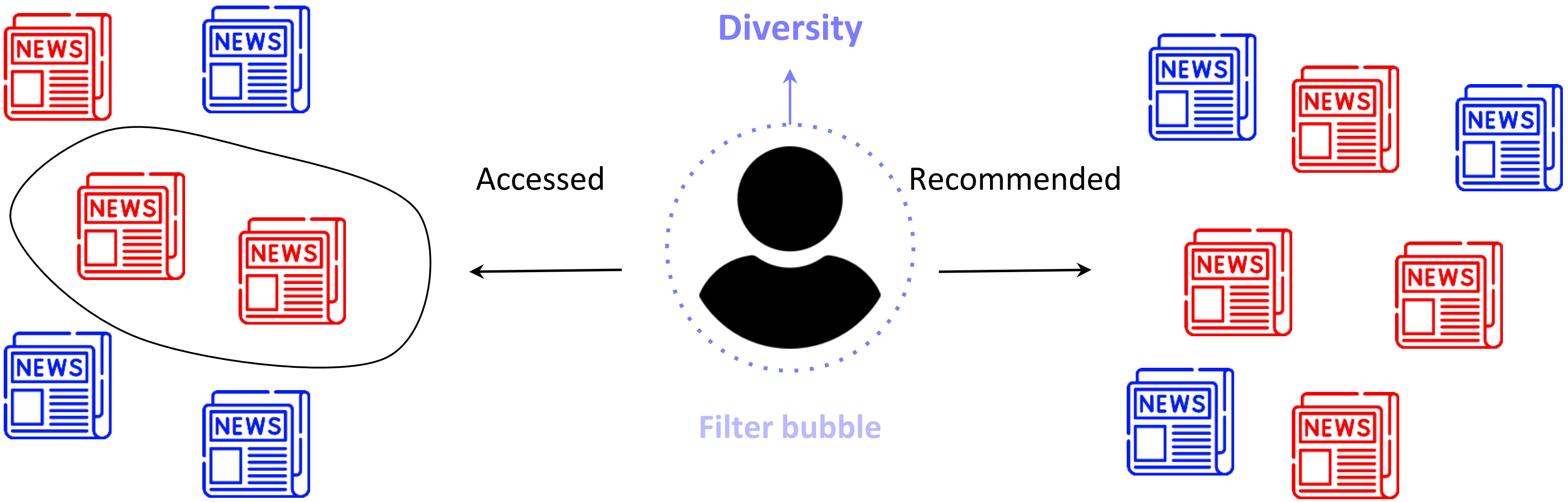
Take-home messages

Introduction

News Recommender Systems



News Recommender Systems



Diversity & NRS

- Provide a larger spectrum of opinions *(Heitz et al., 2022)*
- Ensure ethical and fair recommendations *(Lunardi et al., 2020)*
- Foster a healthy democratic debate *(Giunchiglia et al., 2021)*

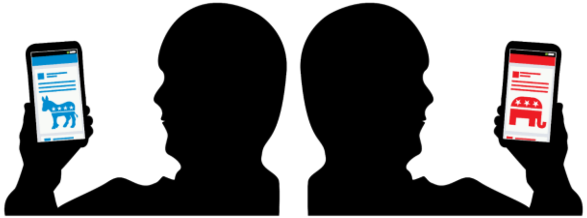
Role of diversity may be overestimated and must be finely controlled to help reduce polarization

⇒ **RQ1:** Does diversity of recommendations bring a systematic gain?

Evaluation of NRS

News characteristics: short lifespan, high turnover…

Democratic role of NRS *(Helberger, 2019)*



Adaptation of recommendation and evaluation

⇒ **RQ2:** Is it sufficient to measure the influence of an NRS afterward with single-number metrics, or does this influence occur with some variations over time?

Experimental analysis

NEWS MIND

Large-scale dataset for news recommendation research

Information about news

Users' interactions

5 weeks : October to November, 2019

Data selection ⇒1,475 users & 20,541 news

From URL
- News representation → ***LDA*** (Latent Dirichlet Allocation)
- Date of publication

User ID

History — *Week 1 to 4*

Recommended
Accessed — *Week 5*

MIND dataset

Average diversity *(Smyth & McClave, 2001) :*

$$Diversity(i_1, i_2, ..., i_n) = \frac{\sum_{k=1}^{n} \sum_{j=1}^{n} (1 - Similarity(i_k, i_j))}{\frac{n}{2} * (n-1)}$$

1. Holistic analysis

News of history

Recommended news

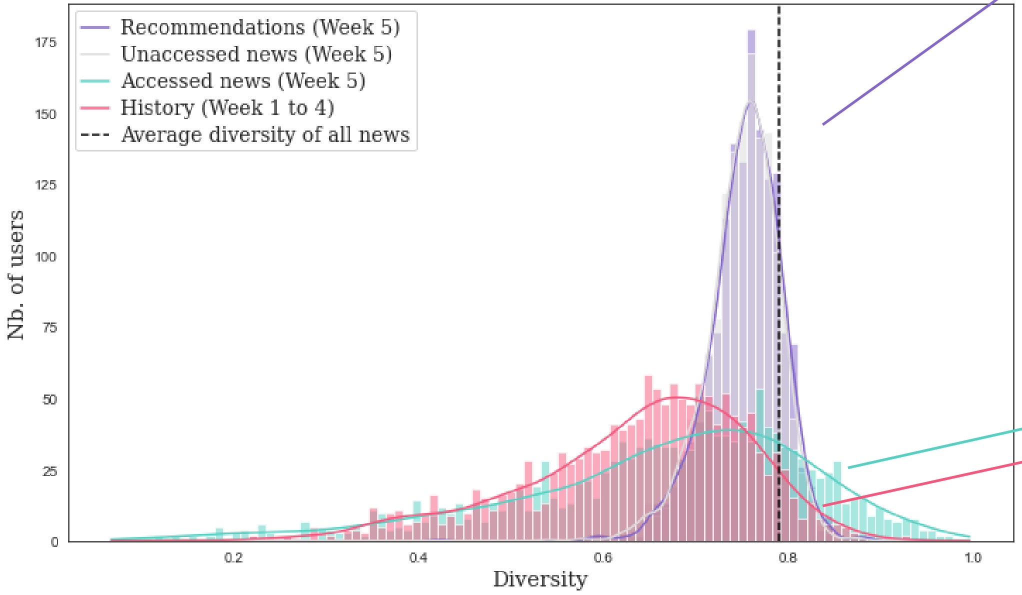
Accessed news

Unaccessed news

2. Temporal analysis

News accessed each week (1 to 5)

Analysis - *holistic*



Distribution of diversity among users

High average diversity *(0.75)* & small standard deviation *(0.04)*

Average diversity significantly lower

Great variability

Analysis - *holistic*

Conclusions:

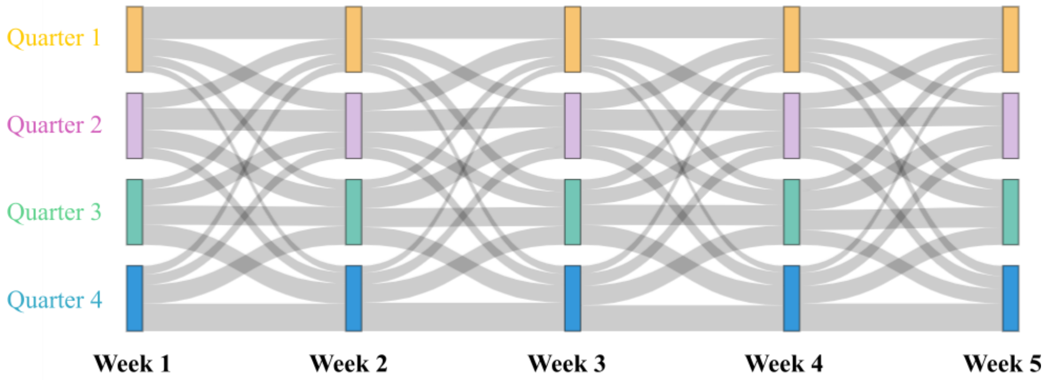
- Recommender system meets a predefined diversity level
- Impact of NRS on the news consumption
- Diversity input is not personalized

⇒ High diversity of recommendations does not systematically lead to a diverse news consumption **(RQ1)**

Analysis - *temporal*

Transition patterns remain stable over the weeks

⇒ Similar global impact of recommendations on users diversity of accessed news through weeks



Sankey diagram : variation flows over weeks

Analysis - *temporal*

Conclusions:

- Average diversity of accessed news differs over weeks
- Users observe diversity variations
- Impact is not the same for all users

3 types of users:

- Positively receptive users
- Negatively receptive users
- Resistant users

⇒ Single-number evaluations are insufficient

Need to take differences between users and temporal aspect into account **(RQ2)**

Overall conclusion

1. Diverse recommendations $\not\Rightarrow$ diverse consumption

   Need to adapt the evaluation

2. NRS does not impact all users equally

   Different classes of user behavior

Take-home messages

Take-home messages

1. Need of well-established methodologies to model users' diversity trajectories
2. Need of adapted diversity measures and personalized recommendation strategies
3. Lack of open datasets

Thank you - Thank you - Thank you - Thank you

Contact me!

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