

On the Importance of News Content Representation in Hybrid Neural Session-based Recommender Systems

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Research Questions

RQ1. What is the value of leveraging content information on hybrid neural session-based news recommendation?

RQ2. To what extent does the choice of the mechanism for encoding the article's text content affect recommendation performance?

News Recommender Systems Challenges

1. Preferences shift
2. Sparse user profiles
3. Fast growing number of items
4. Accelerated item's value decay

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Percentile of # clicks	Article Age
10%	< 4 hours
25%	< 5 hours
50%	< 8 hours
75%	< 14 hours
90%	< 26 hours

Articles age at click time distribution (G1 dataset)

News Recommender Systems Challenges

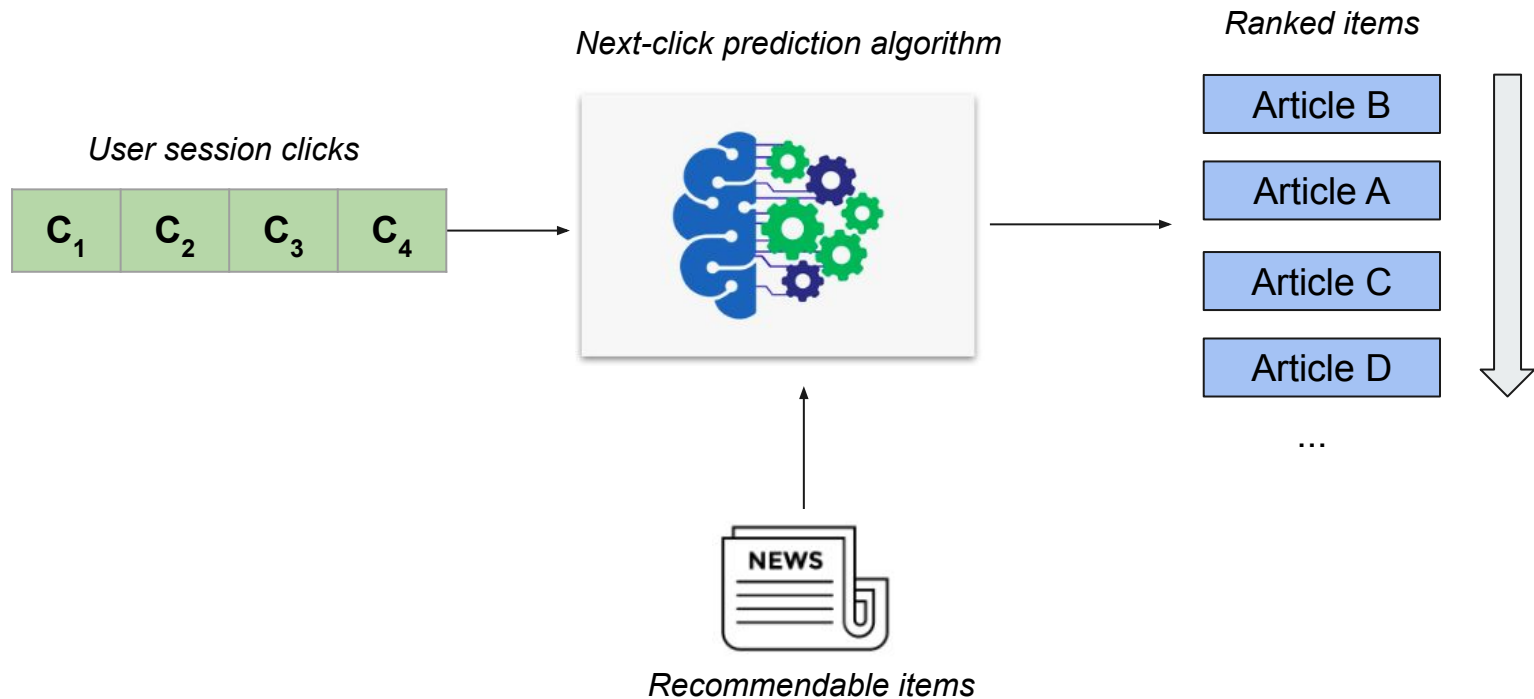
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Permanent User and Item Cold-Start Problem

Task: Next-click prediction for session-based recommendation





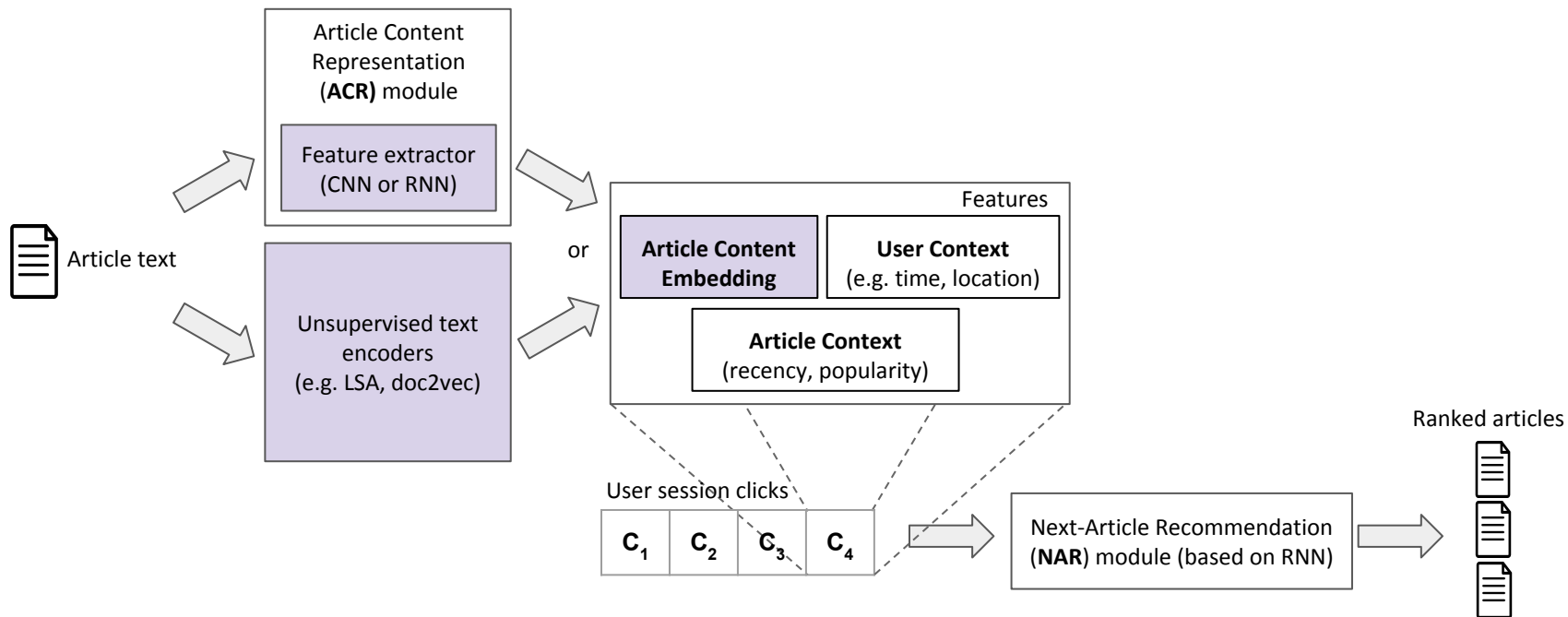
Experiments

CHAMELEON - A Deep Learning Meta-Architecture for News Recommendation ^[1]

- Designed to provide **session-based recommendation** in the **news domain**
- **Hybrid** recommendation approach, which tackles the item and user cold start problem leveraging **textual content**, the **article context** (e.g., recent popularity and recency) and the **user context** (e.g. time, location, device, session clicks).
- Models the sequence of session clicks using an **RNN**
- Trained on a listwise ranking approach, designed to allow the **recommendation of fresh articles** without retraining.

[1] Gabriel de Souza P. Moreira, Felipe Ferreira, and Adilson Marques da Cunha. 2018. **News Session-Based Recommendations using Deep Neural Networks**. In 3rd Workshop on Deep Learning for Recommender Systems (**DLRS 2018**), October 6, 2018, Vancouver, BC, Canada.

Experiments settings with CHAMELEON



Alternative content encoding techniques

<i>Technique</i>	<i>Input</i>	<i>Description</i>
No-ACE	None	In this setting, no content representation is used as input.
<i>Supervised (target = article category)</i>		
CNN	word2vec	A 1D CNN-based model.
GRU	word2vec	A GRU-based model.
<i>Unsupervised</i>		
LSA	Tokenized text	The Latent Semantic Analysis (<i>LSA</i>) (Deerwester, 1990).
W2V*TF-IDF	word2vec	<i>TF-IDF</i> weighted word embeddings.
doc2vec	Tokenized text	<i>Paragraph Vectors</i> (Le, 2014).

Recommendation evaluation

Task: For each item within a session, **predict the next-clicked item** from a set composed by the positive sample (read article) and **50 negative samples**.

Metrics:

Accuracy	HR@10	Hit Rate
	MRR@10	Mean Reciprocal Rank
Coverage	COV@10	$\frac{\# \text{ recommended articles @ top-n}}{\# \text{ recommendable articles}}$
Novelty	ESI-R@10	The negative log of the normalized popularity of the top-n ranked items

Baseline algorithms

Frequent patterns methods

- CO** A simple method of co-occurrence based on association rules of length two.
- SR** Sequential rules of size two.

kNN methods

- Item-kNN** Most similar articles to the last read one, in terms of the cosine similarity between the vector of their occurrence in sessions.

Non-personalized methods

- RP** Recently Popular - Most viewed articles during the last hour.
- CB** Content-Based - Most similar articles (content embedding) to the last user click.

Datasets

16 days of logged user interactions

	Language	users	sessions	clicks	articles
G1 (globo.com)	Portuguese	322 k	1,048 k	2,988 k	46 k
Adressa (adressa.no)	Norwegian	314 k	982 k	2,648 k	13 k

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The effect of content information on news recommendation

G1 dataset

Recommender	HR@10	MRR@10	COV@10	ESI-R@10
<i>CHAMELEON (LSA)</i>	0.6686*	0.3423*	0.6452	6.3833
<i>CHAMELEON (No-ACE)</i>	0.6281	0.3066	0.6429	6.3169
<i>SR</i>	0.5911	0.2889	0.2757	5.9743
<i>Item-kNN</i>	0.5707	0.2801	0.3892	6.5898
<i>CO</i>	0.5699	0.2625	0.2496	5.5716
<i>V-SkNN</i>	0.5469	0.2495	0.1348	5.1758
<i>RP</i>	0.4580	0.1994	0.0220	4.490
<i>CB</i>	0.3703	0.1746	0.6855*	8.1683*

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Comparison of different session-based recommenders

2 The effect of different content representations

G1 dataset

Recommender	HR@10	MRR@10
<i>No-ACE</i>	0.6281	0.3066
<i>Supervised</i>		
<i>CNN</i>	0.6585	0.3395
<i>GRU</i>	0.6585	0.3388
<i>Unsupervised</i>		
<i>W2V*TF-IDF</i>	0.6575	0.3291
<i>LSA</i>	0.6686*	0.3423
<i>doc2vec</i>	0.6368	0.3119

Comparison of different content encodings for CHAMELEON

2 The effect of different content representations

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Comparison of different content encodings for CHAMELEON

2 The effect of different content representations

Adressa dataset

Recommender	HR@10	MRR@10
<i>No-ACE</i>	0.6816	0.3252
<i>Supervised</i>		
<i>CNN</i>	0.6860	0.3333
<i>GRU</i>	0.6856	0.3327
<i>Unsupervised</i>		
<i>W2V*TF-IDF</i>	0.6913	0.3402
<i>LSA</i>	0.6935	0.3403
<i>doc2vec</i>	0.6898	0.3402

Comparison of different content encodings for CHAMELEON

Main Findings

In this context of session-based news recommendation using hybrid neural architectures based on RNN, considering data from two large news portals, it was possible to conclude that:

- RQ1** - Significant **accuracy improvements** are achieved when the article **content** is **leveraged**.

- RQ2** - The **technique** used to encode textual content **does affect accuracy**.
 - **Unsupervised techniques were in general better** - target quality and depth is important for supervised methods.
 - Surprisingly, the recommendation accuracy obtained with the **LSA-based encodings was quite competitive** compared to the embeddings produced by **neural networks (e.g., CNN, GRU)** using pre-trained word embeddings.

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