

# News à la carte?

developing recommender systems  
for news articles

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# Motivation

- in the **Age of Information**, recommendations are generally extremely important
- in the context of news articles, **regular challenges for recommender systems are aggravated**: because more classical algorithms rely on previous interactions between users and items (articles), it is **difficult to give recommendations for new items and/or users**
- also, the **societal implications of personalized news consumption** have to be taken into account



# Goals

- the **implementation and discussion of classical and deep learning recommendation methods**
- **technical improvements** for *news* recommendation
- conceptualization of **revisions concerning socio-psychological consequences**

# The Data

the **MI**crosoft **N**ews **D**ataset  
we worked with:

click log of ~ **575,000** anonymous Microsoft News **readers**



~ **100,000** individual **news** **articles**

# The Data

the information we worked with:



title

abstract

category

click  
behavior

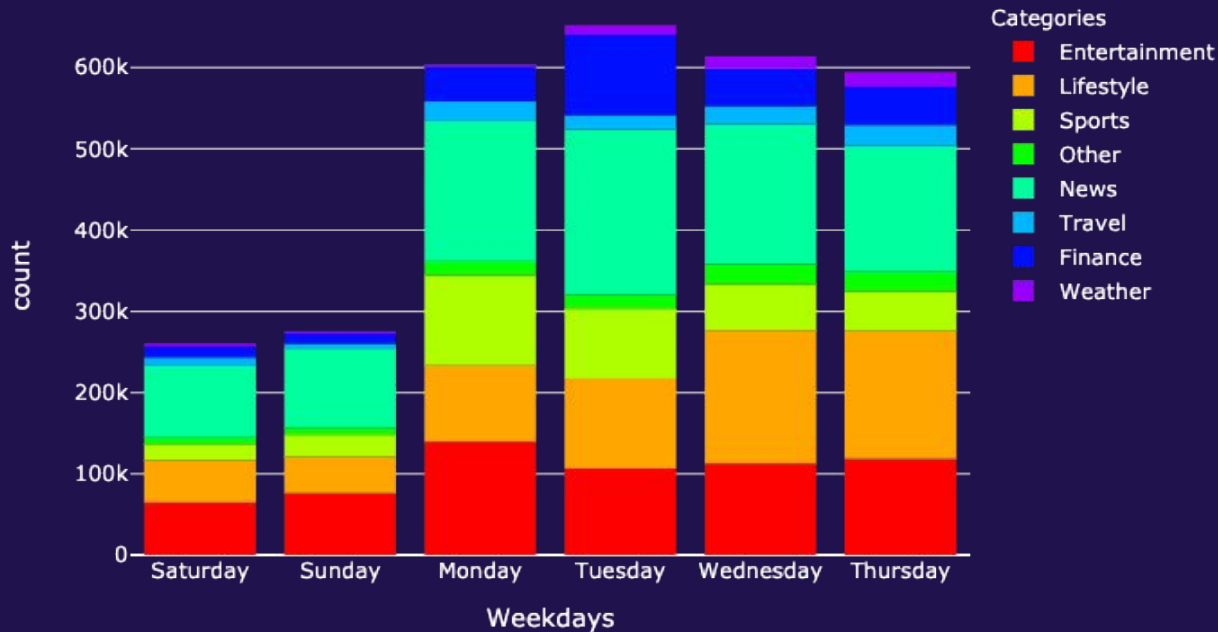
reading history

date and  
daytime



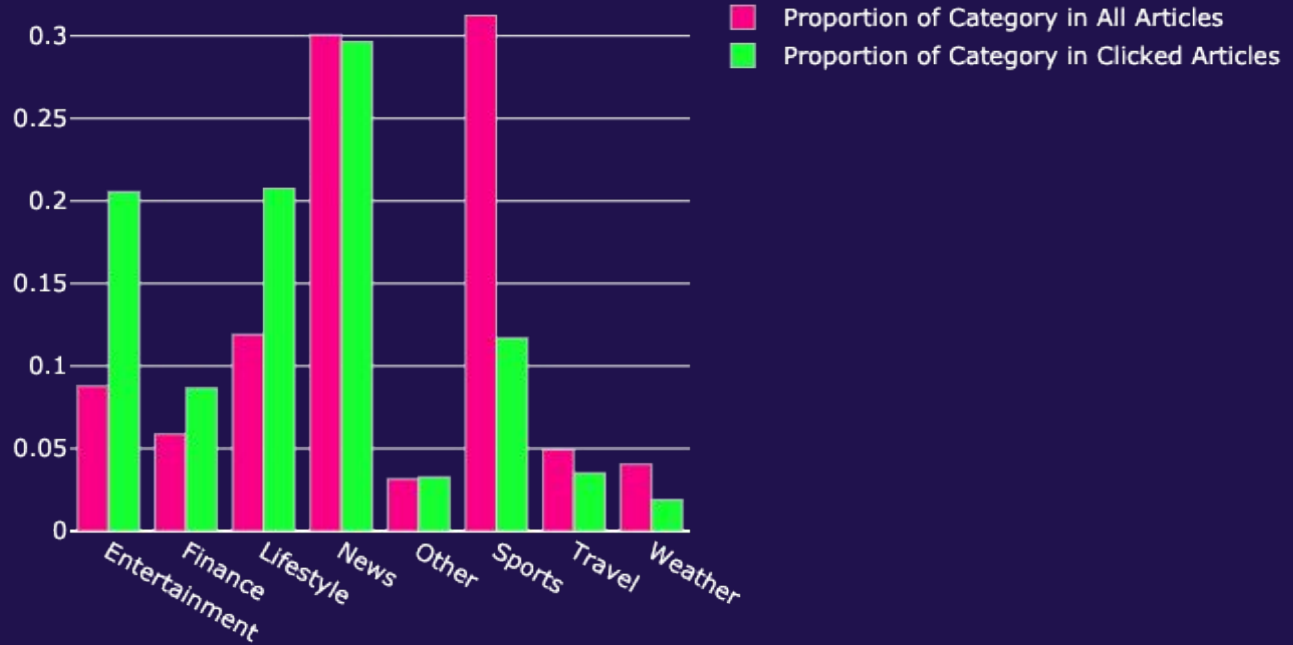
# Clicks on Weekdays

there are twice  
as many clicks  
on working days  
and there seems  
to be a higher  
interest in  
sports news  
during the week  
as well



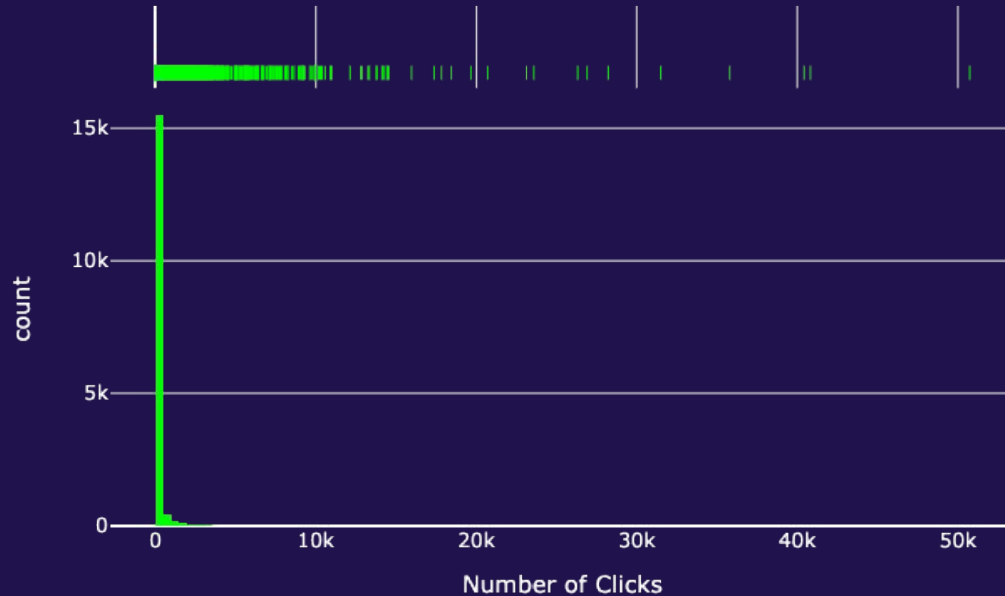
# Available News vs. Clicked News

sports articles are clearly over-represented in news supply, whereas lifestyle, entertainment and finance news are proportionally more clicked



# Clicked Articles at Session

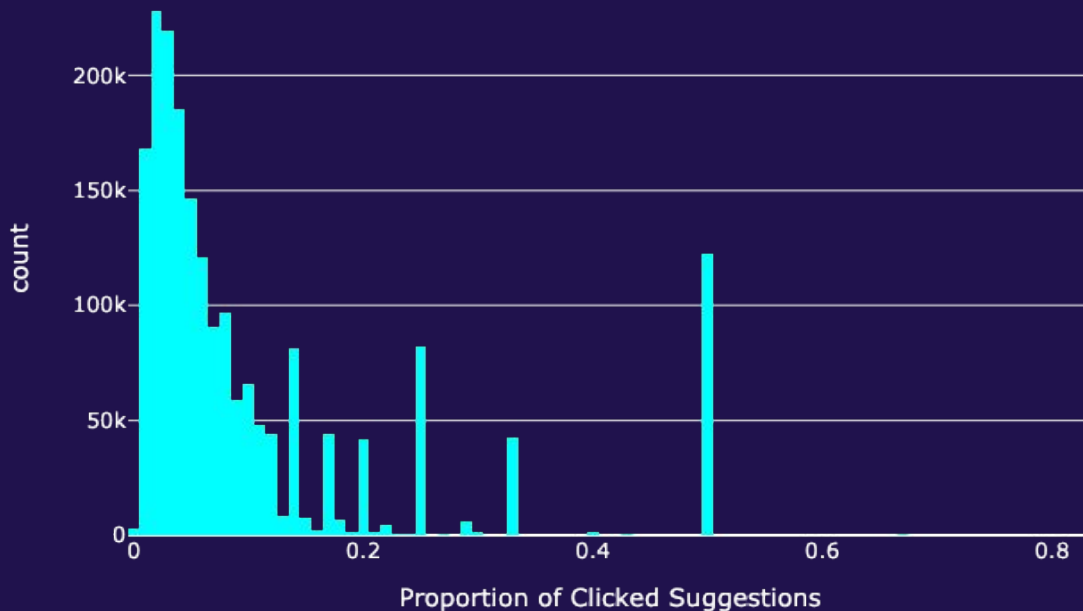
there are many articles  
with fewer than 500  
clicks and only very few  
with tens of thousands  
of clicks





# Click Ratios at Sessions

there are many session  
where less than 20% of  
suggestions have been  
clicked



# The Way We Tested

in order to assess our models' performances, we had to  
devise a testing procedure



the targeted metric was **Mean Reciprocal Rank**, which indicates how high a known relevant document ranks under assumably irrelevant ones on average

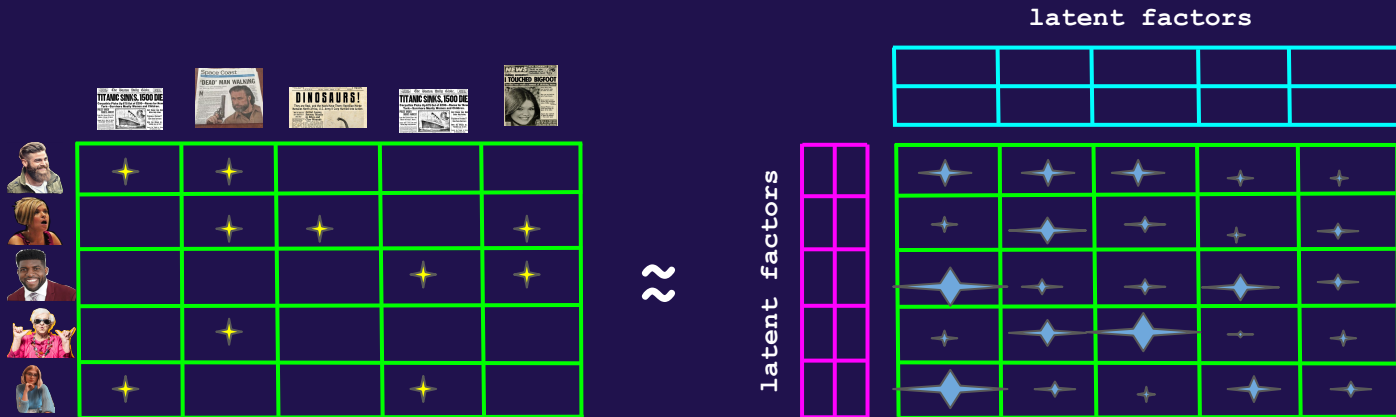
we thus **excluded one reader-article interaction for every user from training** and **ranked** our models prediction for this interaction **under the prediction for 99 known non-interactions** and  
we tested on a subset of MIND, containing ~50.000 Articles and ~150.000 Users



# Collaborative Filtering

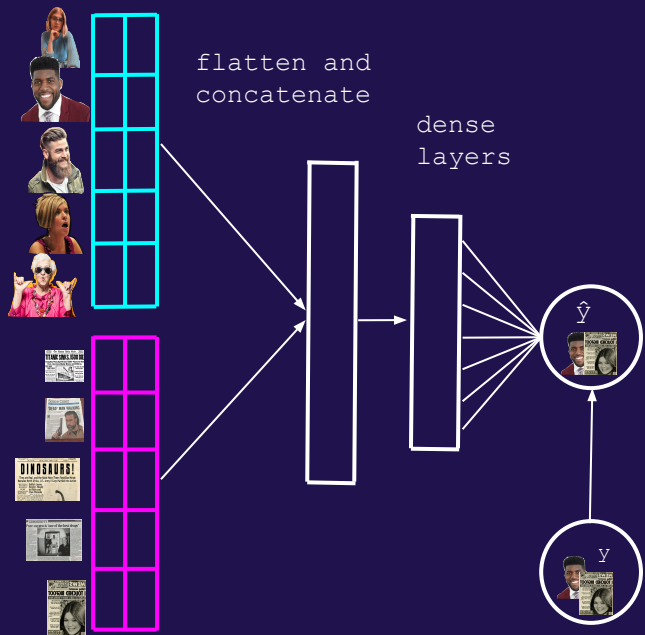
with a **matrix factorization** approach, we generate a densely populated matrix from a sparse user-article-interaction matrix, by **learning two smaller embedding matrices, representing k latent factors**

using **LightFM\***, the **best mrr (0,06)** was attained using weighted approximate rank pairwise loss, employing 20 latent factors for 20 epochs



\* Kula 2017: Metadata Embeddings for User and Item Cold-start Recommendations

# Neural Collaborative Filtering



with **neural collaborative filtering**\*, we still have have 'rigid' embeddings for users and articles, but now, they can have **different numbers of dimensions**, **non linear relationships** can be learned and **latent factors will be weighted**

with an architecture of **64, 32, 16, 8**, a learning rate of **0.001**, **binary crossentropy** as the objective function and **adam** as optimizer, we reached a **mrr of 0.39**

first results on the large dataset showed an improvement of  $\sim 0.1$

\* Xiangnan He et al. 2017: *Neural Collaborative Filtering*

# Learning Article Trajectories via RNNs

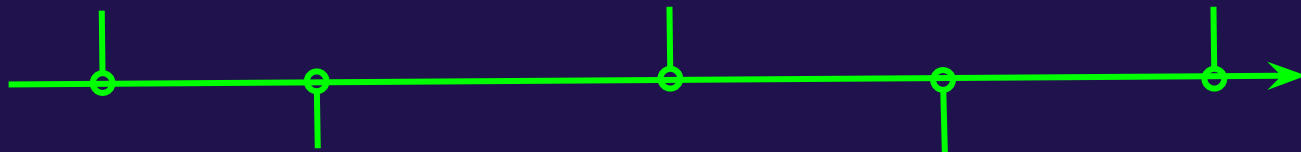
## Jeff's Timeline



"Renovations To Make  
and Skip Before  
Selling Your Home"

"Dad thought he dressed toddler  
daughter in a hat, but he was  
hilariously wrong!"

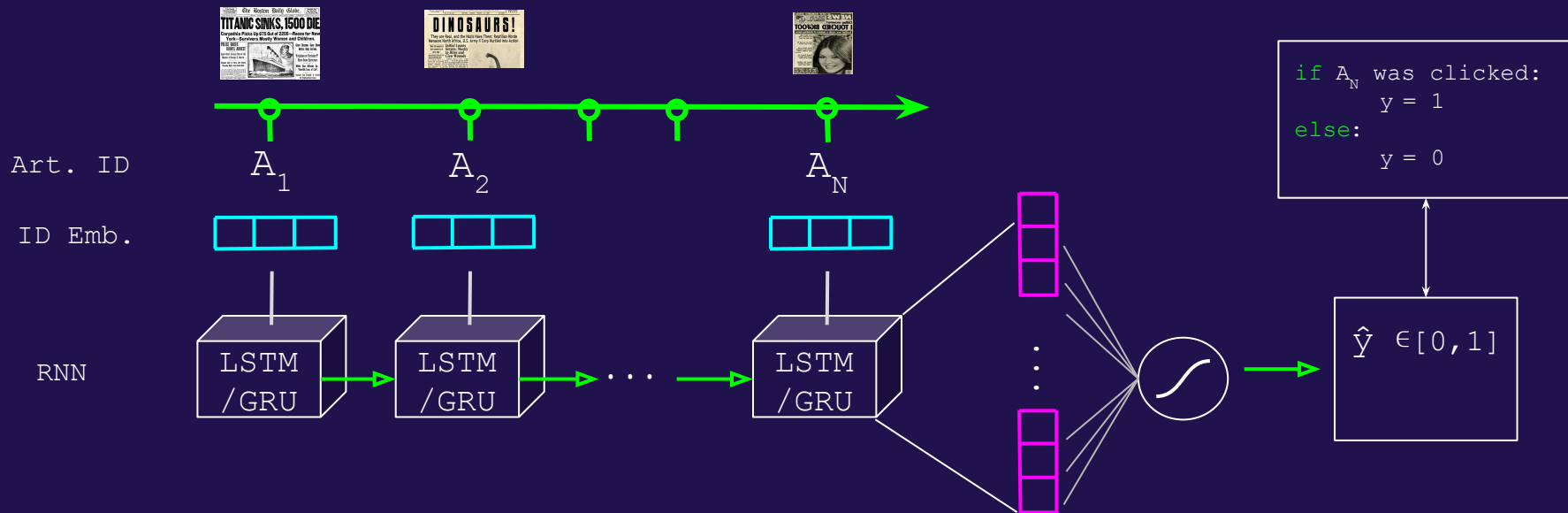
?



"What Came First,  
the Chicken or  
the Dumpling?"

"Dog Learning to Talk By Using a  
Custom Soundboard to Speak:  
'I'm in Constant Amazement'"

# Learning Article Trajectories via RNNs

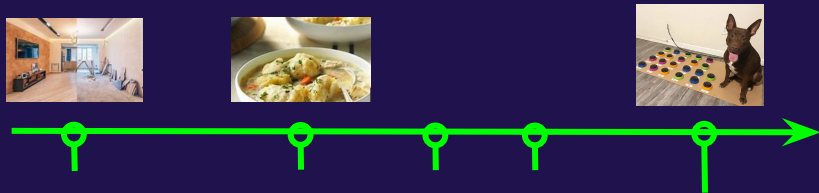


with learning article trajectories, the goal is to free our models from rigid user embeddings and **represent the users via their reading histories**

here, we took into account the clicked articles at a session and learned them against the not-clicked suggestions

with article emb. dim. of **64**, **LSTM dim. of 128** and **one hidden layer with 10 neurons**:  
**mrr ~ 0.2**

# Reading Trajectories with a Title Encoder



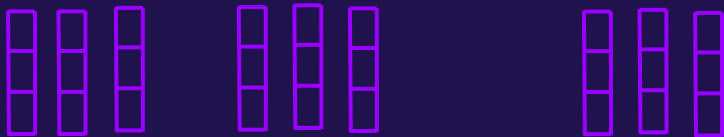
Title

"Renovations To  
Make and Skip  
Before Selling  
Your Home"

"What Came  
First,  
the Chicken or  
the Dumpling?"

"Dog Learning to Talk By  
Using a Custom Soundboard to  
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'I'm in Constant Amazement' "

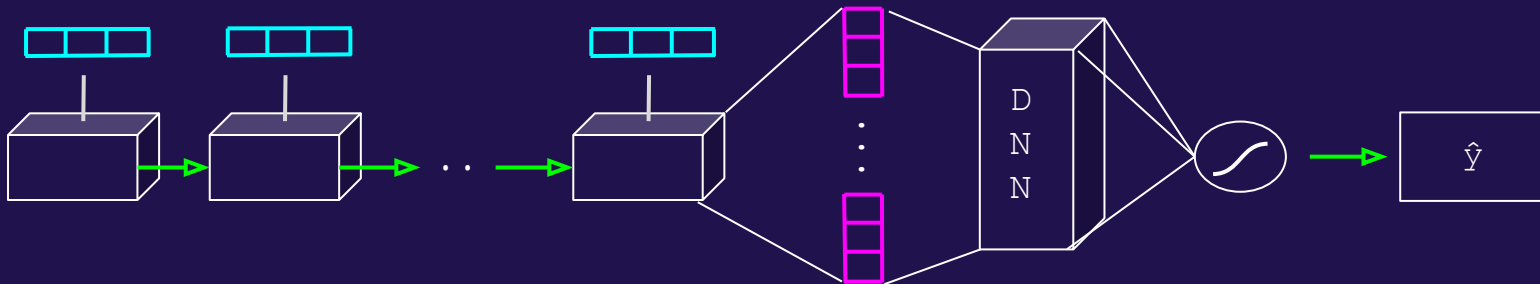
Word  
Emb.



Title  
Emb.



RNN



the utilization of a text encoder even **frees us from fixed article representations**: with this architecture, we can easily now **process new articles and users, needing only a small number of clicked** (and potentially new) **articles**

# Outlook

- the RNN approach can be taken much further: full text, entity embeddings, picture and video data (where available) can be utilized to distill **more fine grained and holistic consumption trajectories** (CNNs could be applied here as well)
- when really needed, **post filtering with sentiment analysis and even partial recommendation of relatively distant content** can be undertaken to counter the emergence of extreme filter bubbles
- especially in context of **news** recommendation, **information on time of publication should be included!**



Thank You!

