

Experiments with Recommending Financial News

RecSysNL meetup

19 November 2019

Anca Dumitrache

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Team:



Feng



Anca



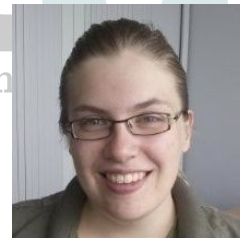
David



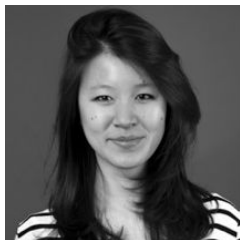
Bahadir



Dung



Maya



Li'ao



Philippe



Kimberly



Klaus



Oberon



Manon



Azamat

Domain: Het Financieele Dagblad (FD) is a daily Dutch newspaper focused on business & financial news

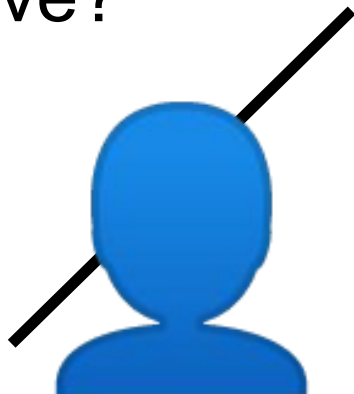


Goal: Personalized article recommendations for FD readers

Requirements: Recommended articles have to be recently published (cold start problem)

Context: Google DNI project on news personalization

What data do we have?



+



fd.
het financieele dagblad

Working with implicit feedback

fd. Mijn nieuws Laatste nieuws Krant Dossiers Beurs Meer ▾ DOWJ 26.717,43 ... Abonneren

Job Woudt za 29 jun Tekst Krant

TELECOM

112-crisis in Nederland: Pas op voor digitale hypochondrie

Een softwarefout en het ganze land ligt plat. Toch is er alle reden om na de 112-crisis van afgelopen maandag niet meteen in paniek te raken

Wie een nieuwtje wil doorbellen naar de Telegraaf-tiplijn strandt vrijdag op de mededeling dat het nummer niet bereikbaar is. De lijn ligt eruit, nadat de telefoon eerder deze week roodgloeiend stond. Zeker vierhonderd meldingen kwamen maandagmiddag binnen. Over onwelwordingen, branden, een inbraakpoging en verkeersongelukken. Ze waren alleen niet bedoeld voor de krant.

Paniek in de tent? De overheid had een bericht het land in gestuurd. Daarin adviseerde ze de burgers 0613650952 te bellen als één van de alternatieven voor het dan onbereikbare 112. Het 06-nummer was dus van de krant.



Omdat 112 niet bereikbaar was stuurde de overheid een alert uit met een alternatief telefoonnummer. Foto: Rob

Routeringsplatform ontregeld

Volgen via mijn nieuws

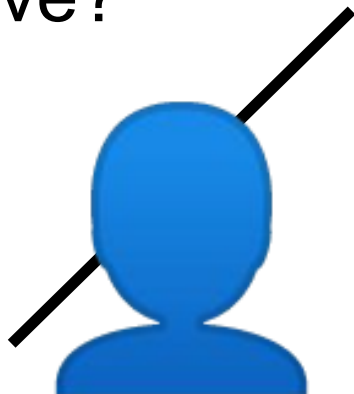
- Ramp + Volg
- Software + Volg
- Telecom + Volg

Laatste nieuws

- 14:00 Waterstof moet Rotterdamse industrie vergroenen
- 13:48 Mollie mikt met vers groeigeld op Europese klanten
- 13:47 ASML nieuwe partner Van Gogh Museum

Articles seen
but not clicked

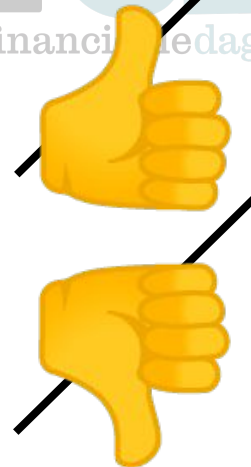
What data do we have?



+

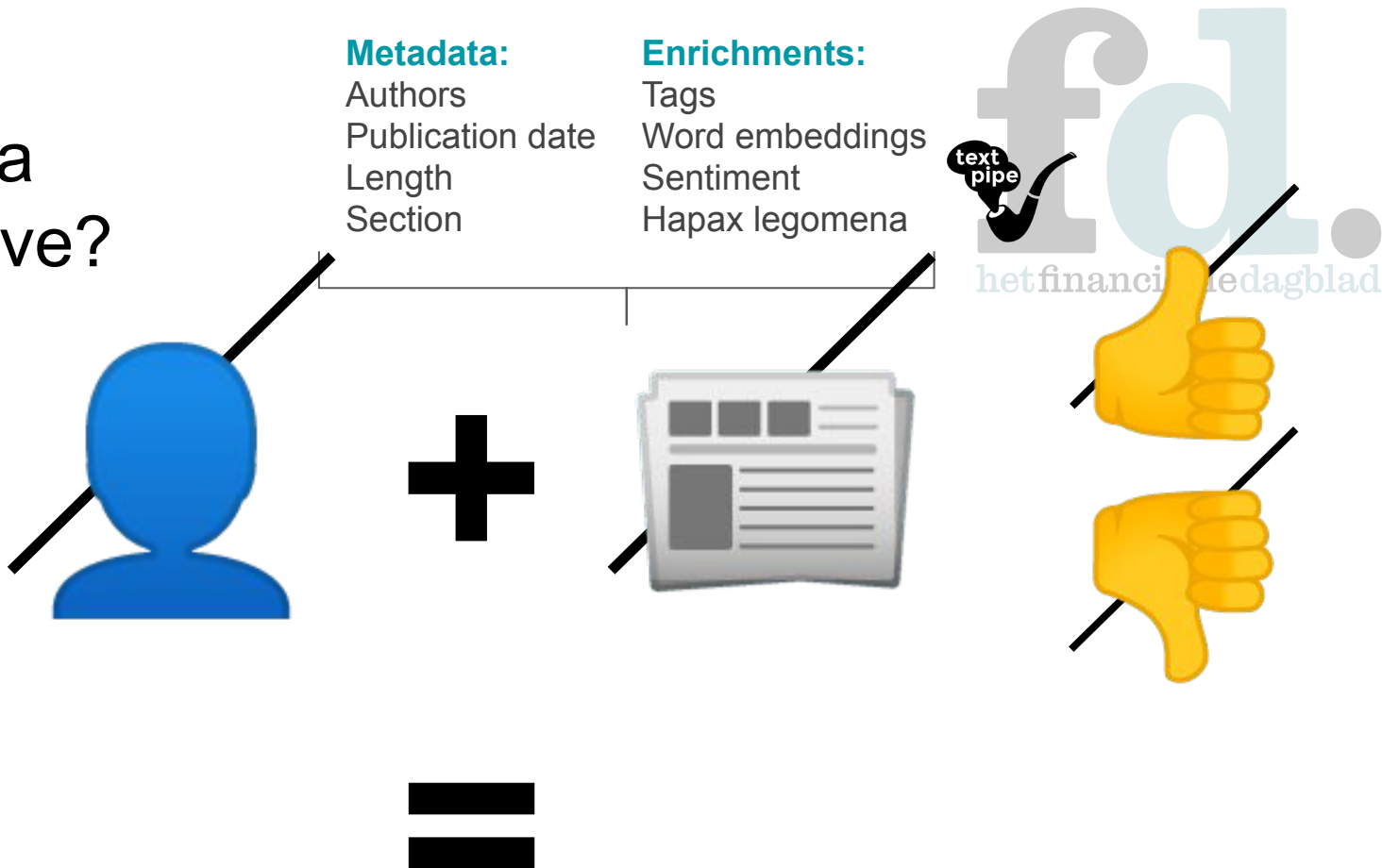


fdl.
het financieel dagblad



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What data do we have?



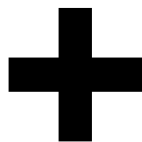
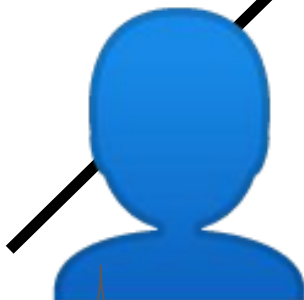
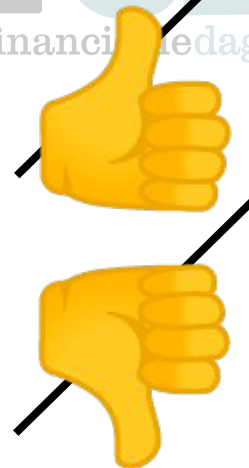
What data do we have?

Metadata:

Authors
Publication date
Length
Section

Enrichments:

Tags
Word embeddings
Sentiment
Hapax legomena



Aggregated reading behavior:

Most read tags
Most read authors
Average read article length
Average read article word embeddings

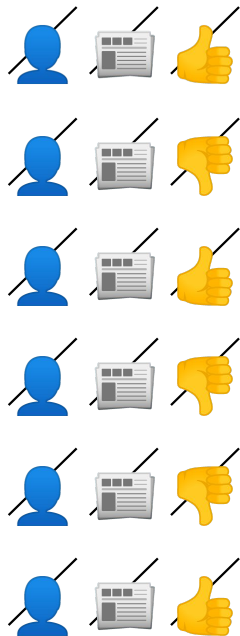
Metadata:

Tags followed



Train data:

clicks from the past



...

Predict data:

clicks from tomorrow



Training process

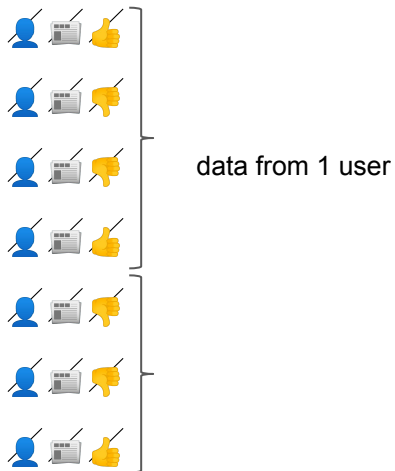
Train data



...

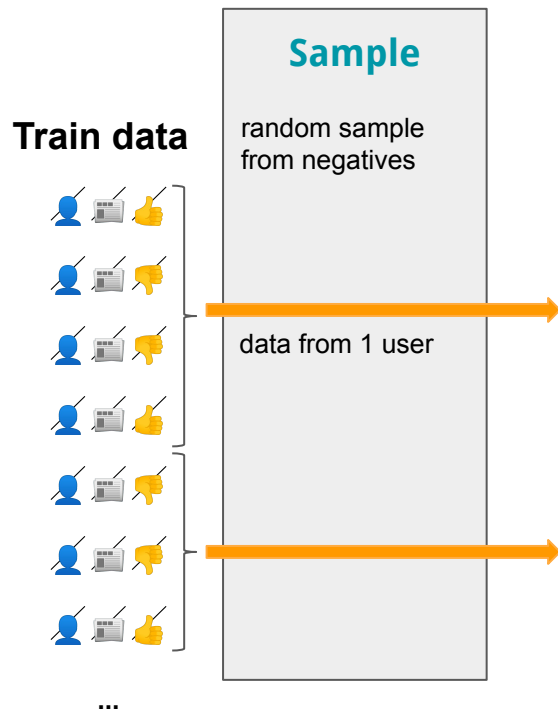
Training process

Train data

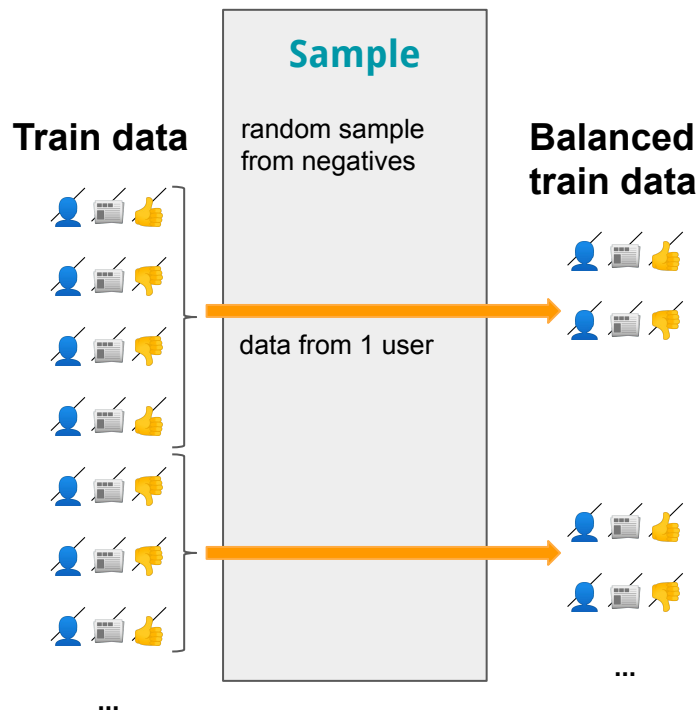


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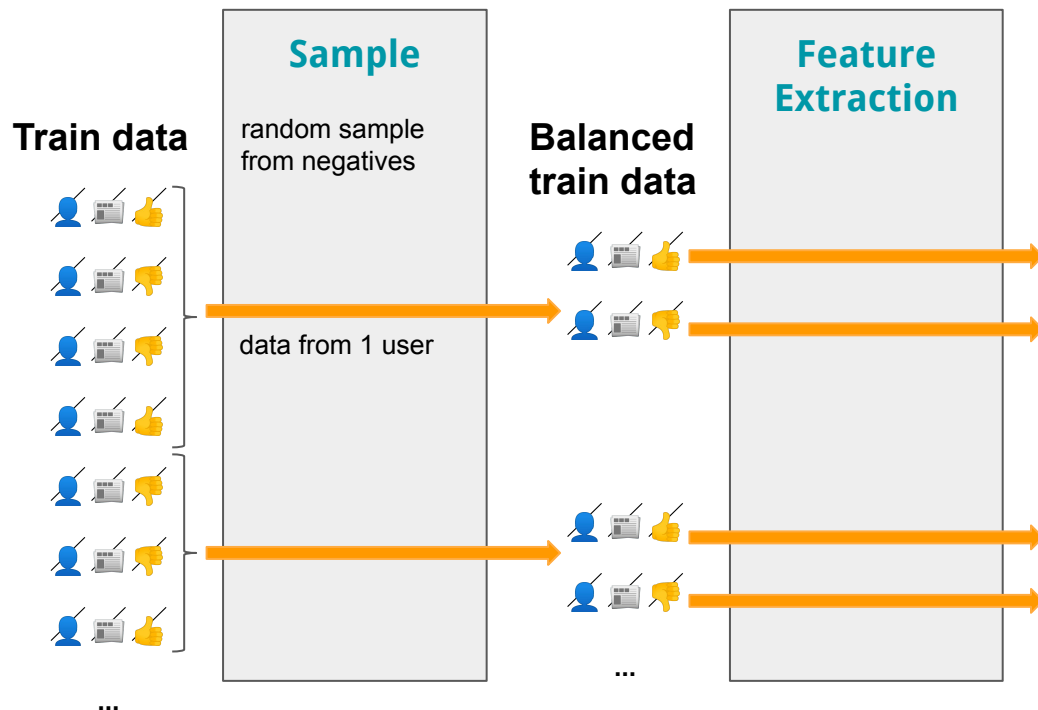
Training process



Training process



Training process



Features



Article features

encoded: authors, tags

embedded: average & var of word embeddings (FastText)

length-based: number of words, paragraphs, average word length

stylometry: sentiment, hapax legomena

time: publication timestamp

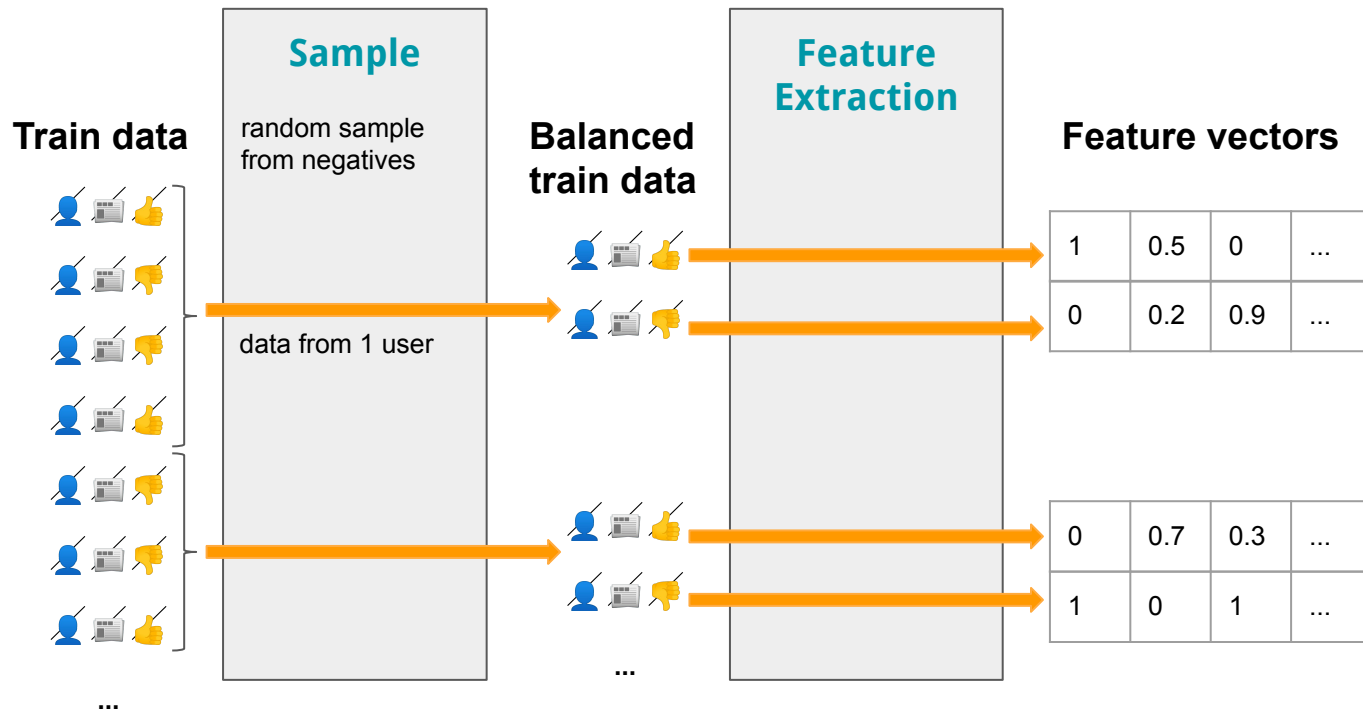
Features

Article features	User features
encoded: authors, tags	encoded: tags followed
embedded: average word embeddings (FastText)	aggregated reading behavior: avg. article word embeddings avg. article length features
length-based: number of words, paragraphs, average word length	
stylometry: sentiment, hapax legomena	
time: publication timestamp	

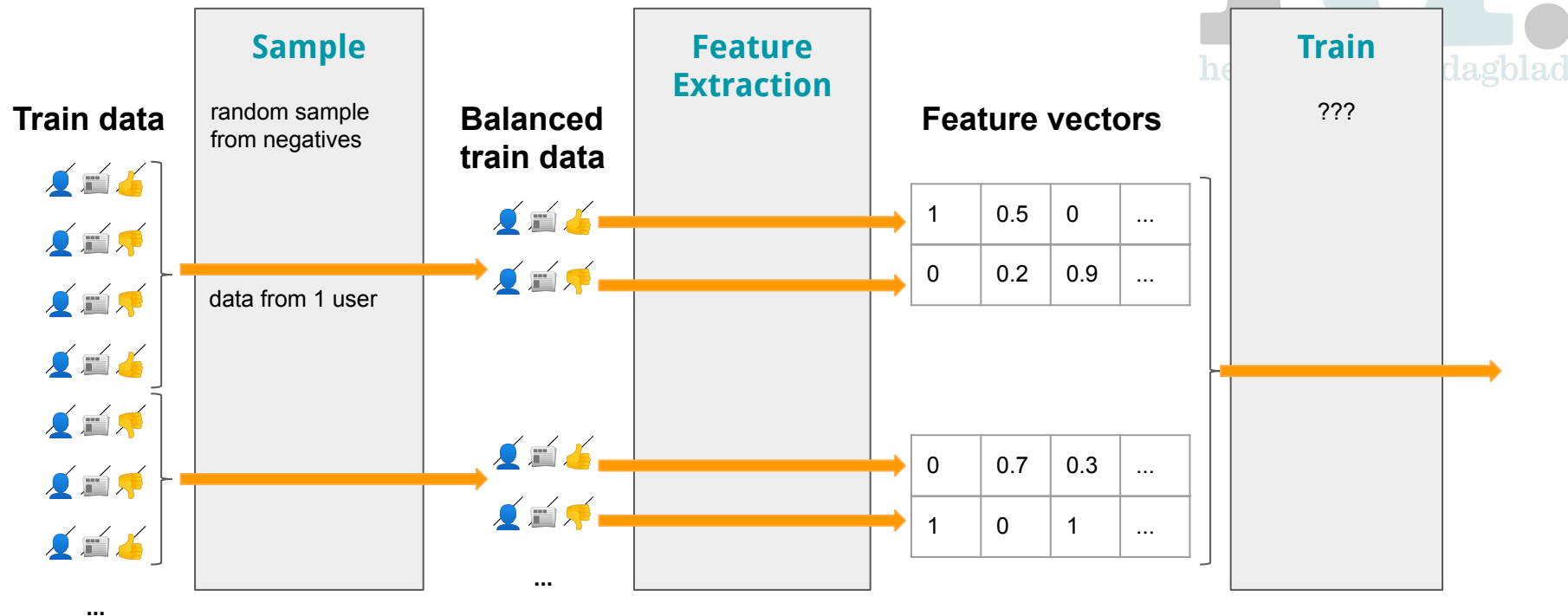
Features

Article features	User features	User-article features
encoded: authors, tags	encoded: tags followed	set overlap: article & top user tags, article & top user authors
embedded: average word embeddings (FastText)	aggregated reading behavior: avg. article word embeddings avg. article length features	
length-based: number of words, paragraphs, average word length		cosine similarity: article & user avg. word embeddings
stylometry: sentiment, hapax legomena		numeric comparison: difference between article & user avg. length, article & user avg. hapax legomena
time: publication timestamp		

Training process



Training process



Research Questions

1. What **model**?
2. What **data**?
3. What **features**?

Experimental Setup

Data: offline interactions from January 2019 (1-27 Jan train; 28-29 Jan val)

Evaluation metrics: user nDCG (ranking) & MAP (ranking + classification)

1. What model?

Models:

- Gradient Boosted Decision Trees (GBDT)
- GBDT + Logistic Regression

Practical Lessons from Predicting Clicks on Ads at Facebook. He et al. 2014.

Training methods:

- **fit**: train new model every day
- **partial fit**: re-train previous day's model with today's data, without adding new trees
- **partial fit grow**: re-train previous day's model with today's data, with new trees

What is GBDT?

- Machine learning model that iteratively constructs an **ensemble** of weak decision tree learners through **gradient boosting**.
- At each iteration, a **subsample of the training data** is drawn at random (without replacement), to fit the model on.
- The model captures **interactions amongst predictors**.

Why GBDT?



- Deals with a heterogeneous mix of continuous, discrete, categorical features
- Feature normalization is not required
- Feature selection is inherently performed during the learning process
- Can easily capture non-linear, non-additive relations

2. What data?

Data recency: How many days in the past should we look?

Data volume: Do we need to train on all the interactions?

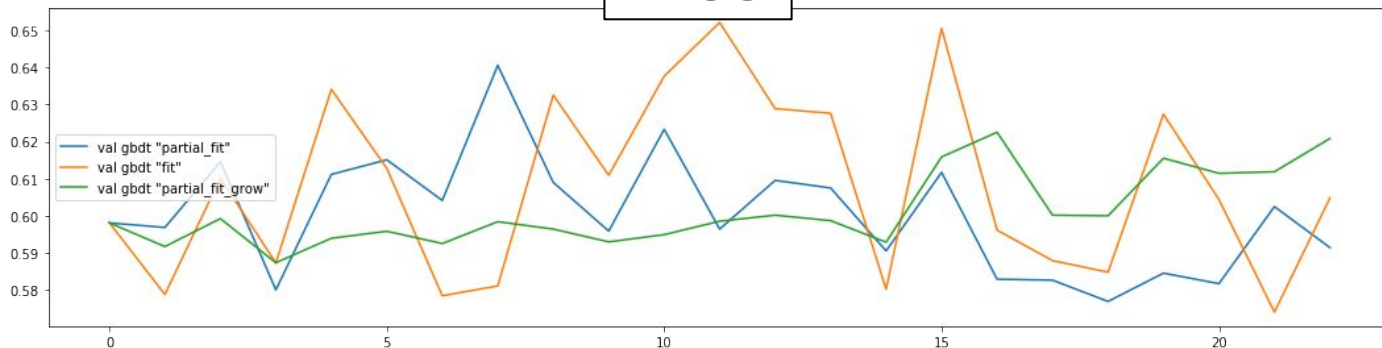


3. What features?

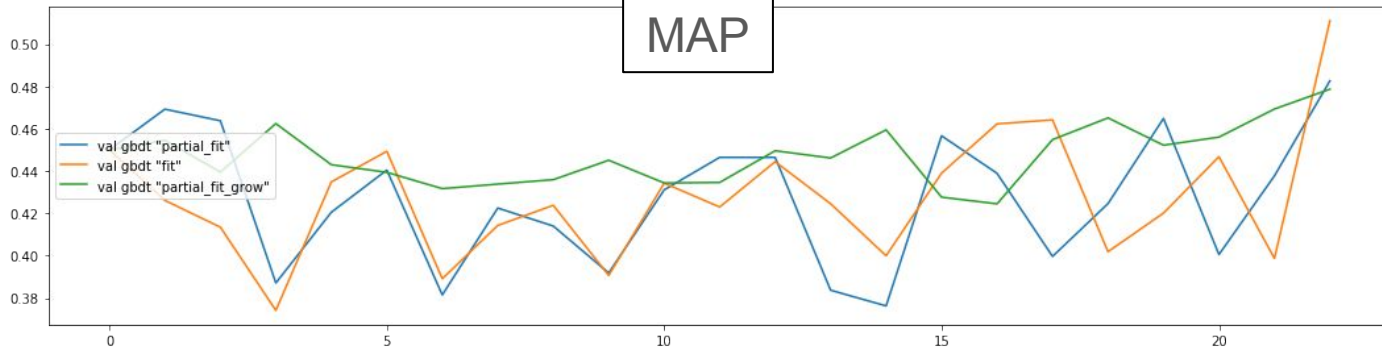
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time: publication date		

1. What model?

nDCG



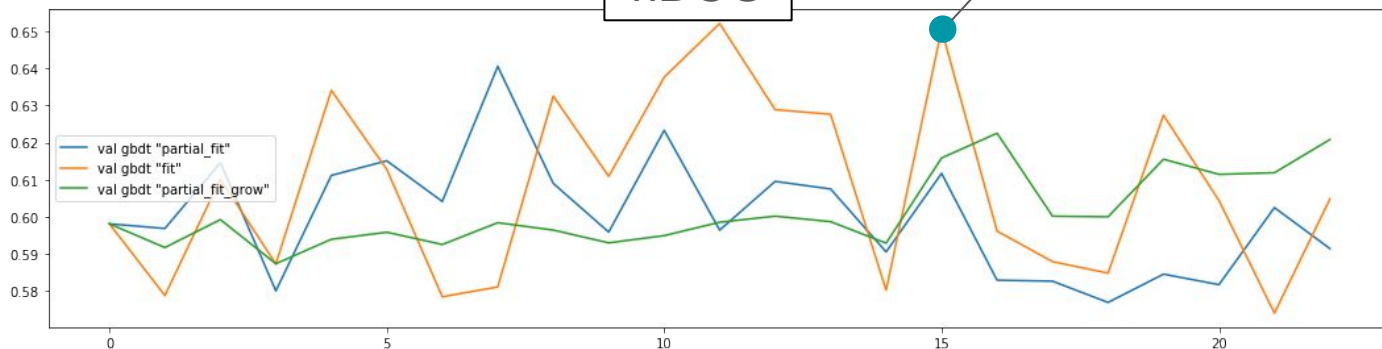
MAP



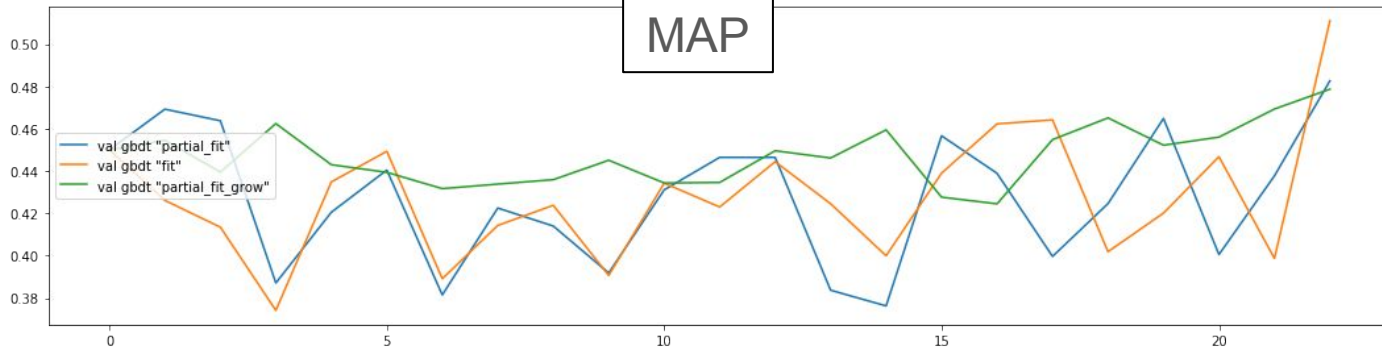
1. What model?

nDCG

GBDT fit model trained on data from that day



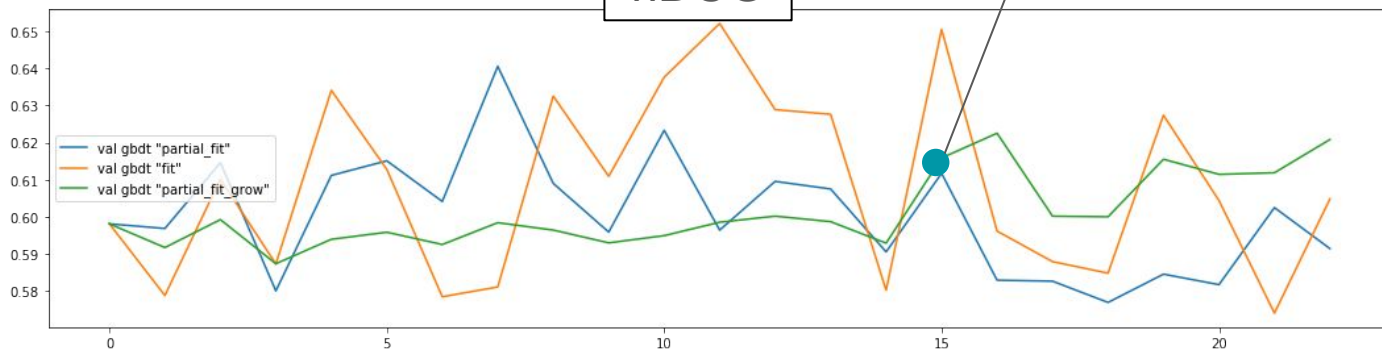
MAP



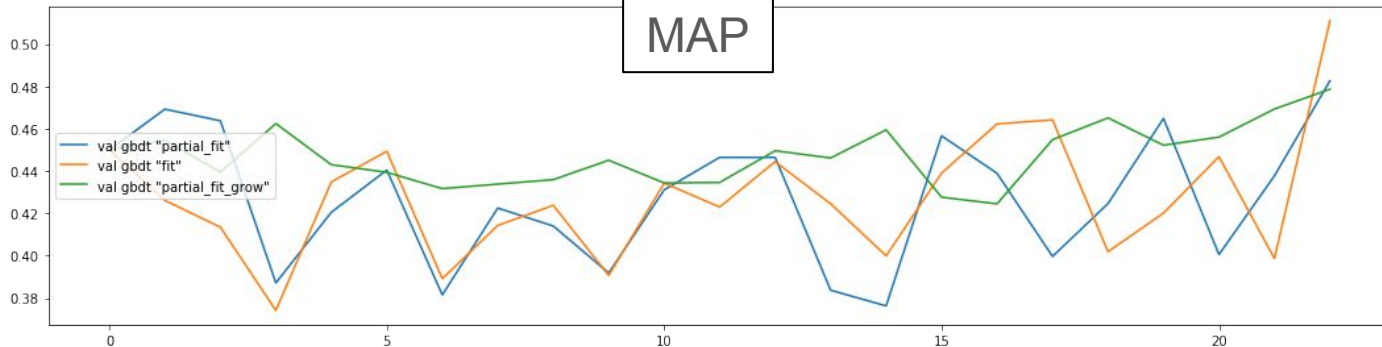
1. What model?

nDCG

GBDT partial fit grow model trained on data from previous 7 days, including today



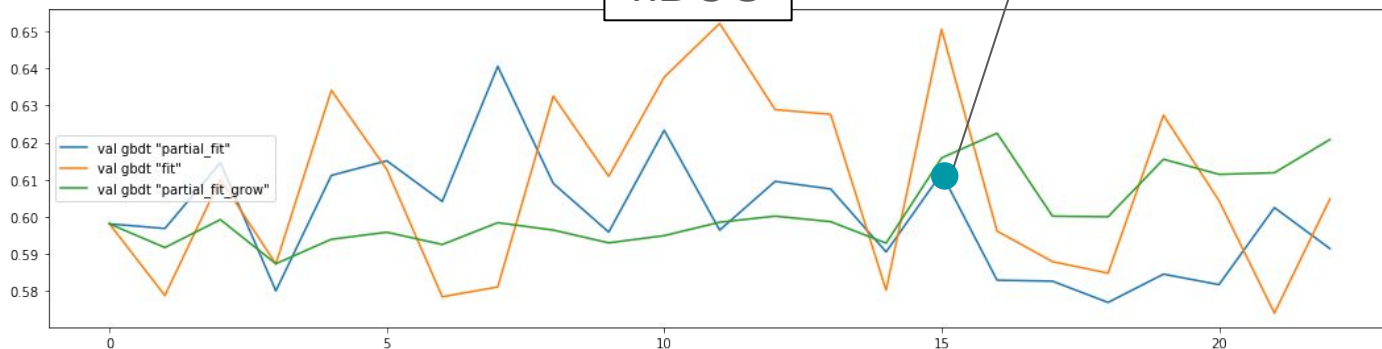
MAP



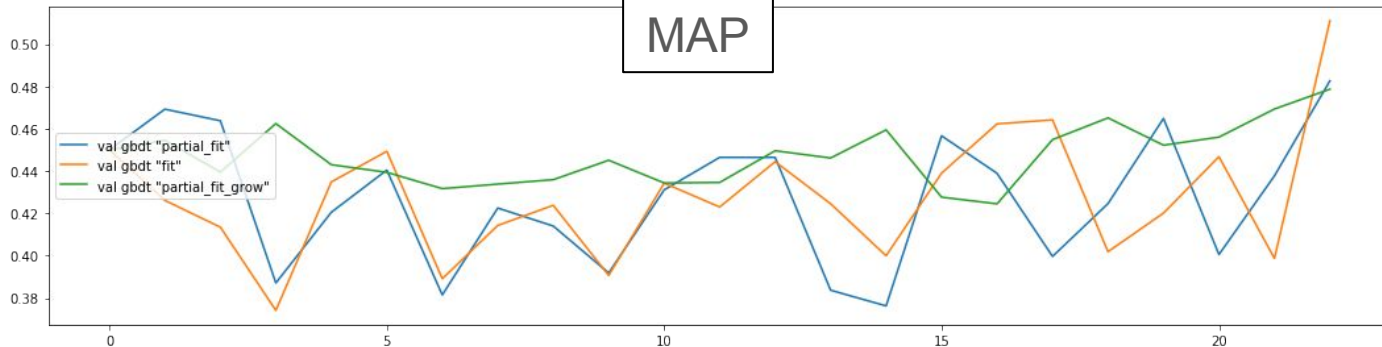
1. What model?

nDCG

GBDT partial fit model trained on data from previous 7 days, including today

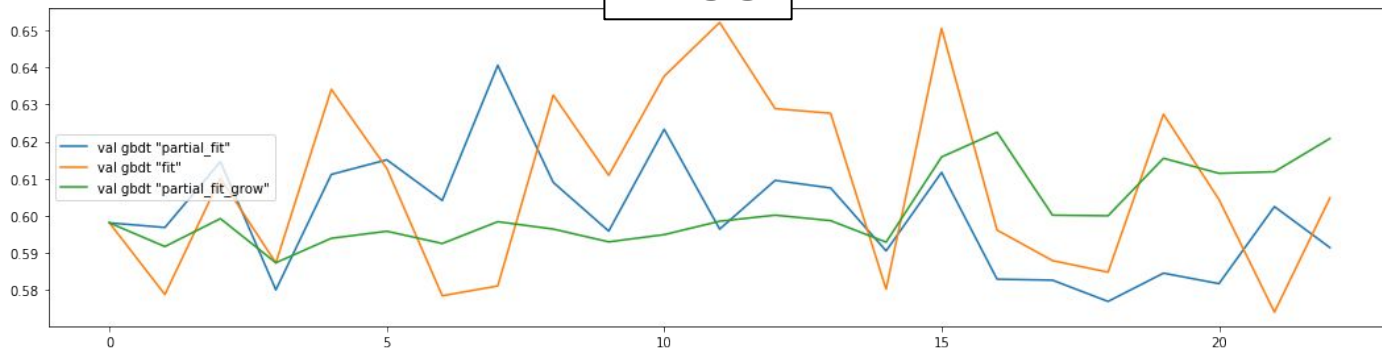


MAP

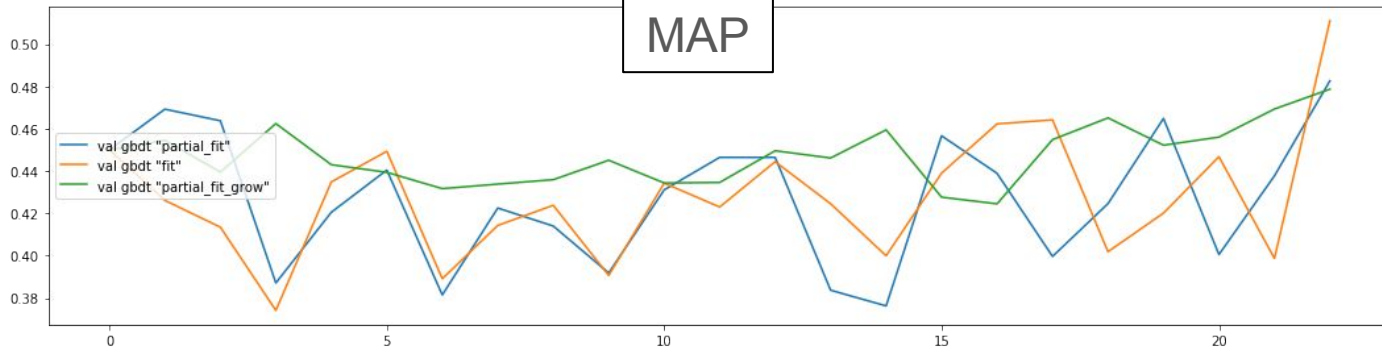


1. What model?

nDCG



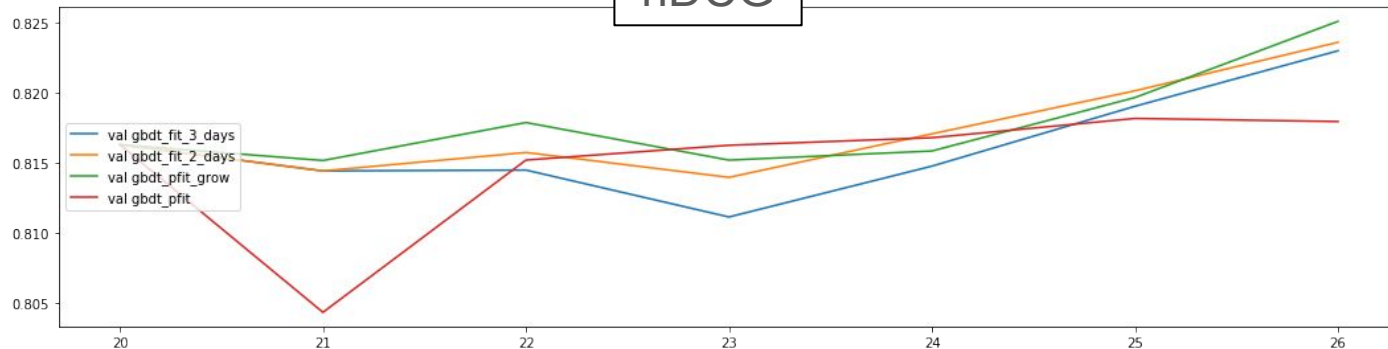
MAP



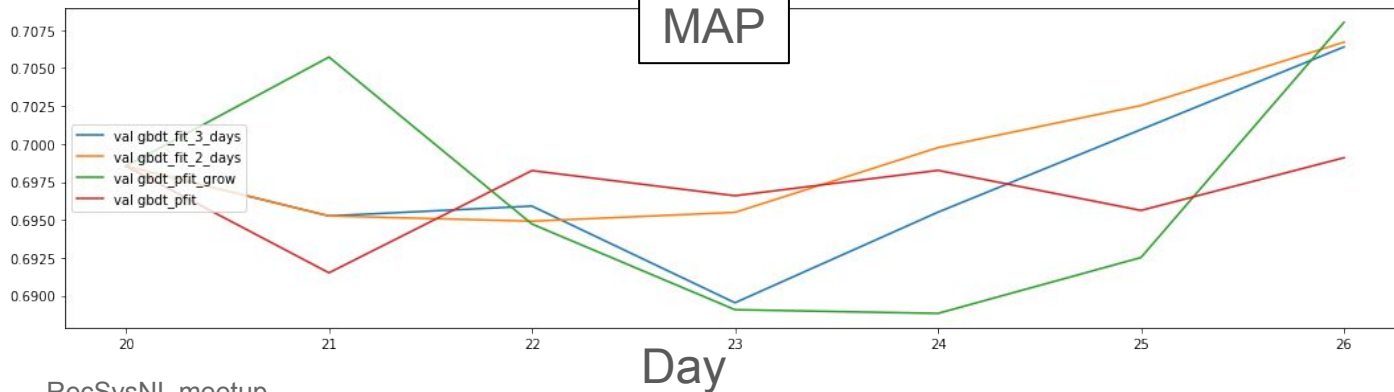
GBDT partial fit grow
has the most stable
performance, overall
better evaluation
results.

1. What model?

nDCG

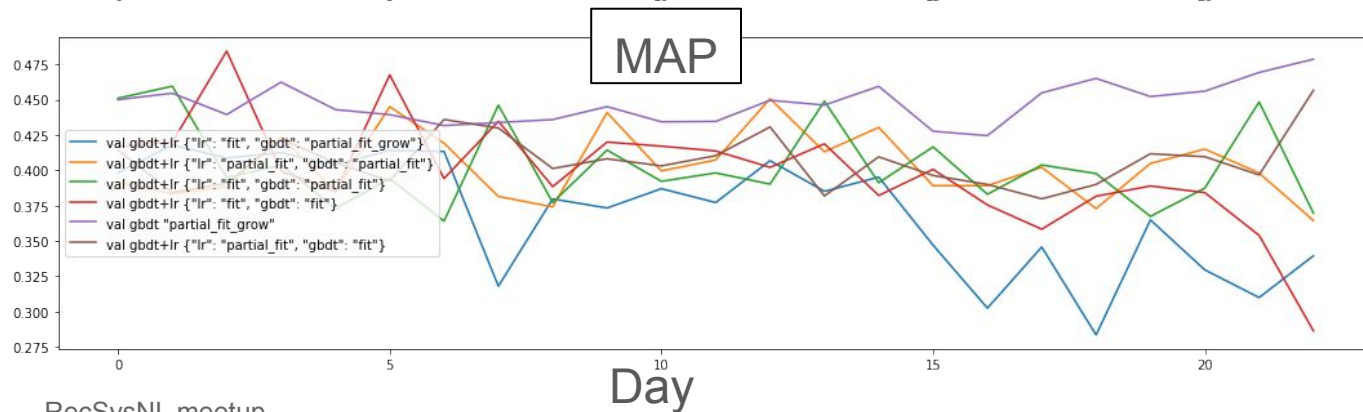
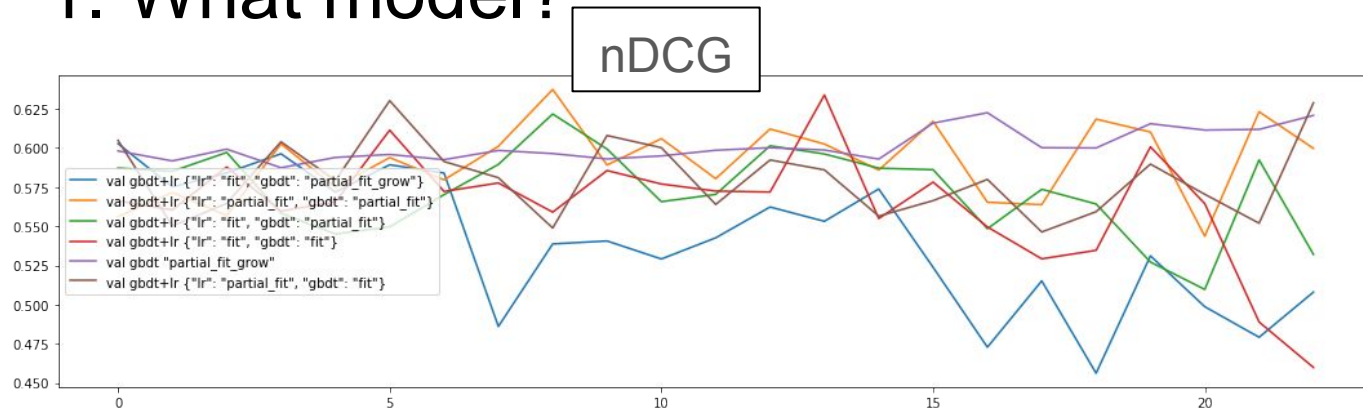


MAP



GBDT fit does do better when training on previous 2 & 3 days, but these models are **very expensive** (all in memory)!

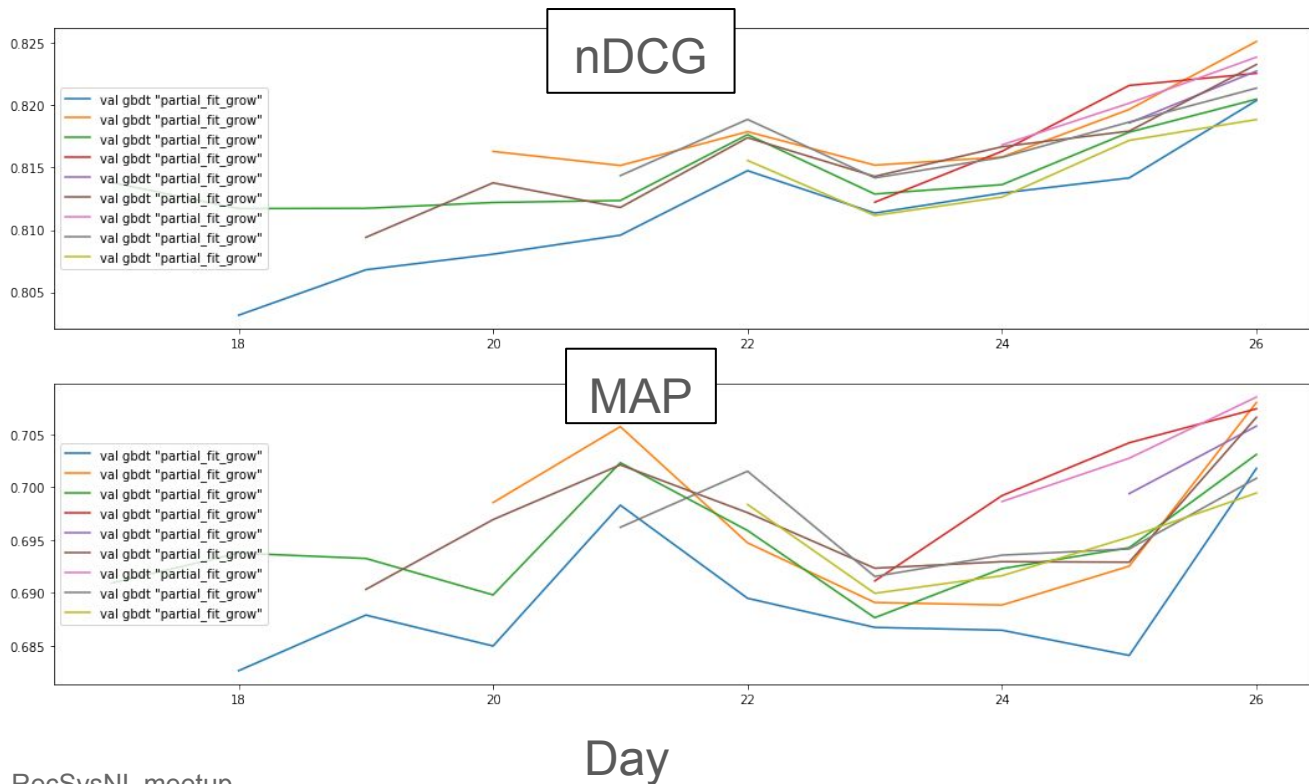
1. What model?



GBDT+LR models perform similarly, and not as well as GBDT partial fit grow.

The LR layer is difficult to tune, because the GBDT output is not interpretable.

2. How many days in the past should we train on?

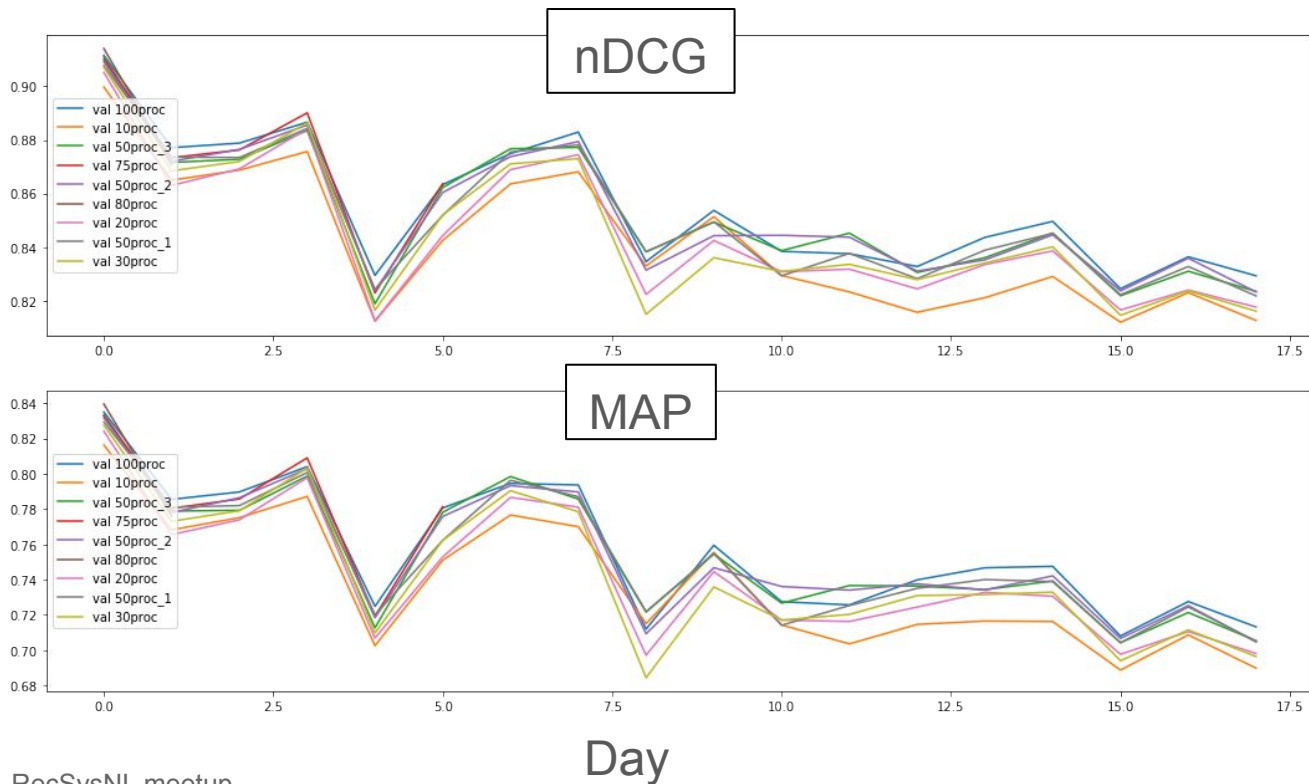


More data is not always better, because **data recency is important**.

Relation between number of days & performance is **not linear**.

3 & 7 days in train is best.

2. Do we need all interactions?



Training on **50% of the user interactions** results in average 0.01 decrease in performance.

3. What features?

Extensive feature ablation experiments show we **need all the features** 😲
→ batch removing of low performing features takes out full chunks from the decision tree

User-article features are the most important, particularly:
user-article author overlap
user-article tag overlap

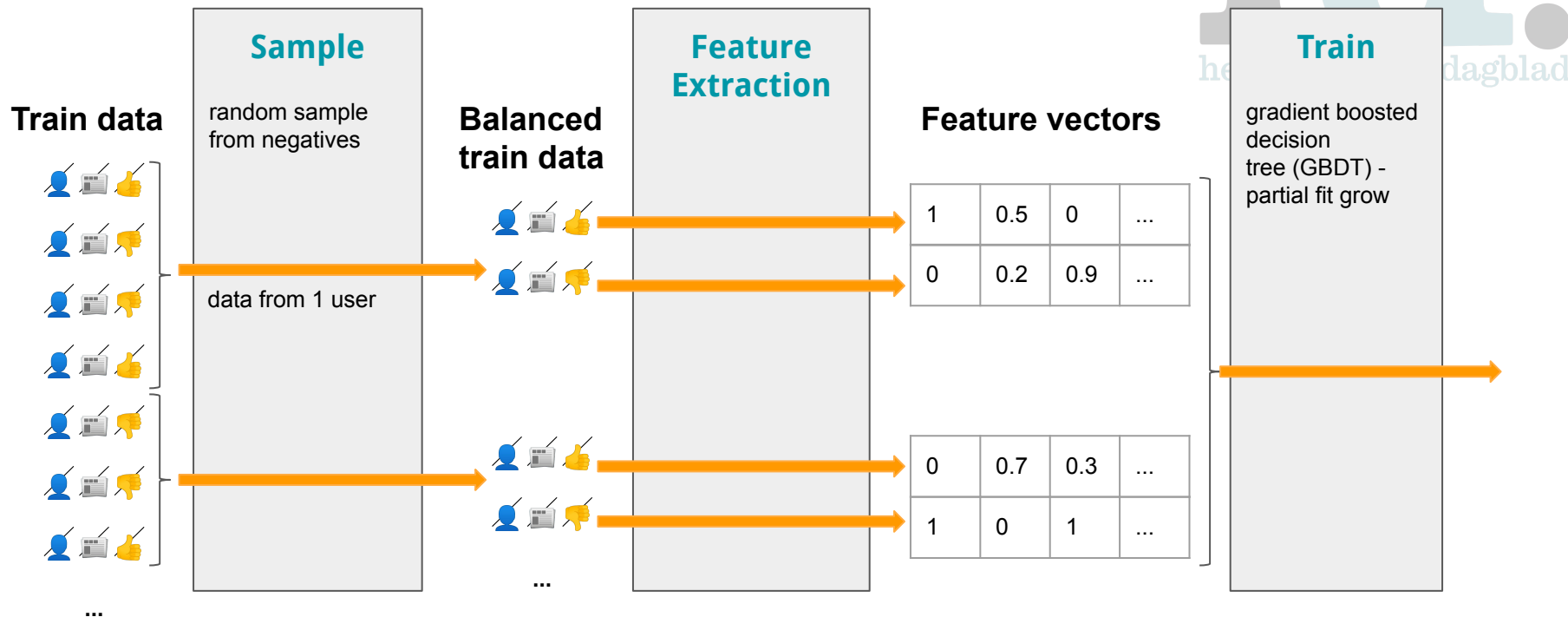
Experiment Conclusions

Simpler model (GBDT) is sometimes better + easier to understand.

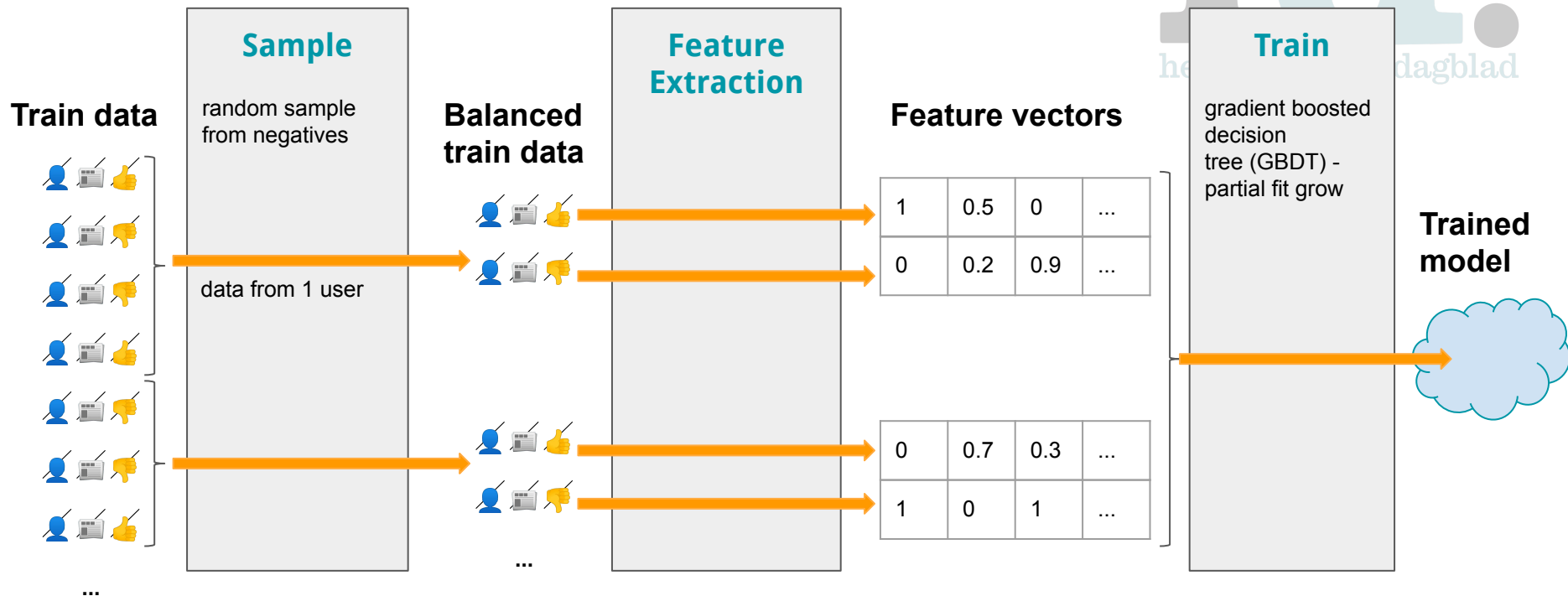
Less data (days, user interactions) does not mean worse performance.

Combined user-article features are the most meaningful, but all features contribute a little.

Training process



Training process



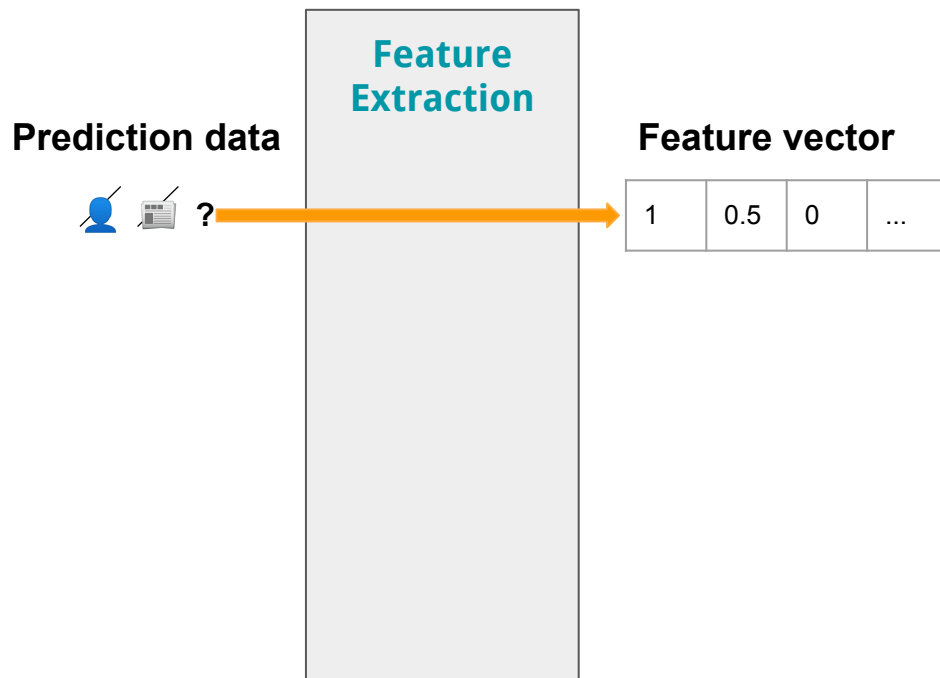
Prediction process



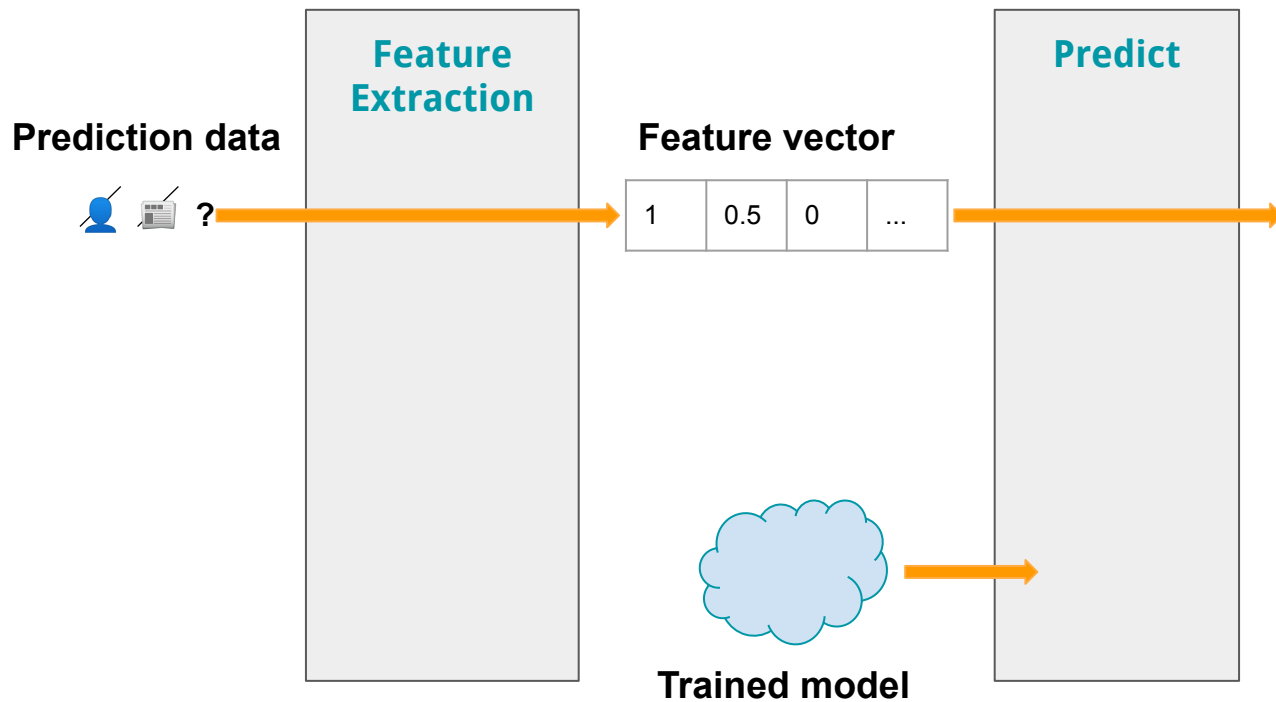
Prediction data



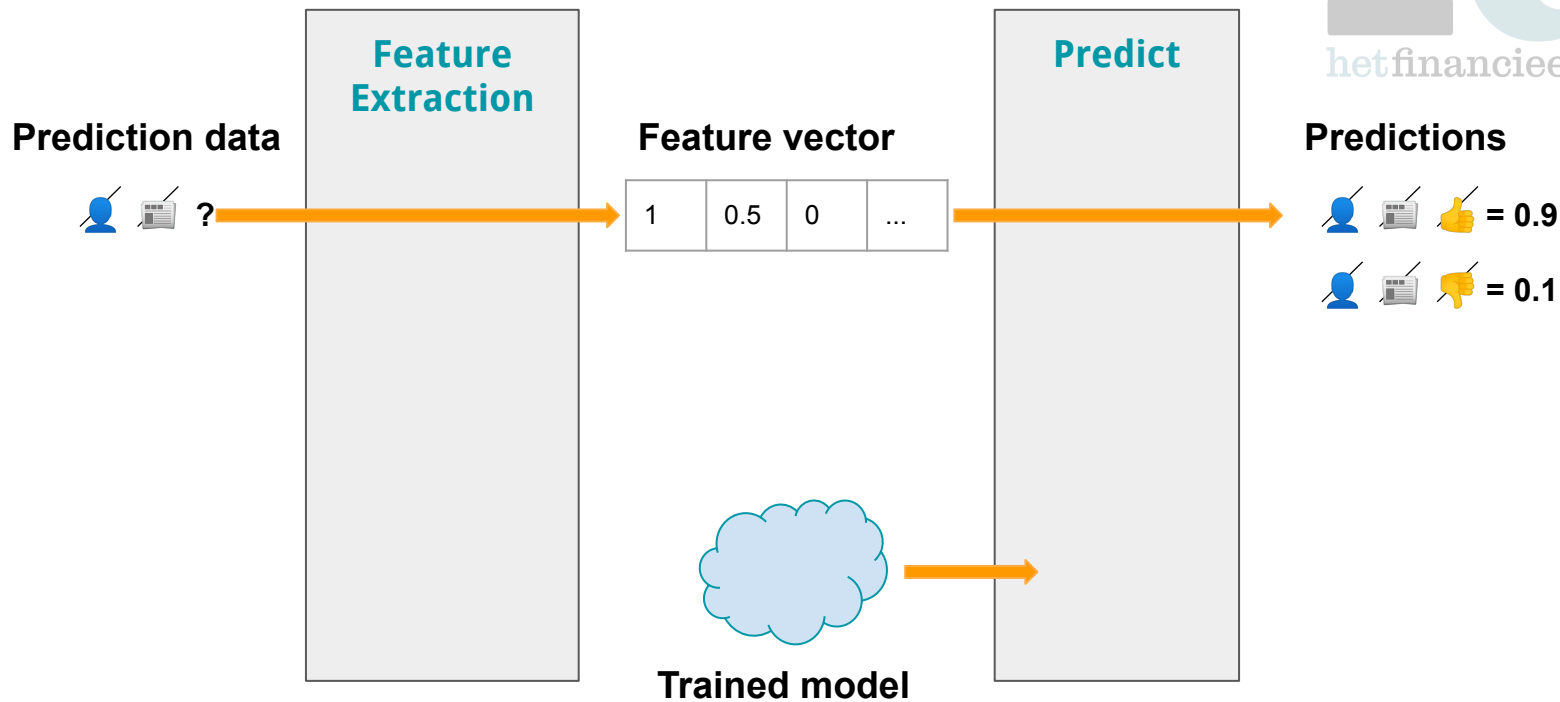
Prediction process



Prediction process



Prediction process



How it looks on FD.nl

articles from the past 7 days

Gemist de afgelopen 7 dagen?

→ MIJN NIEUWS

AANBEVOLEN VOOR U

Dit kan er beter in de zorgverzekering

Deze week maakten de zorgverzekeraars de nieuwe premies voor de basisverzekering bekend. Waarom verschilt de prijs voor dezelfde zorg? En werkt het systeem eigenlijk wel goed genoeg?

🔖 Bewaren

AANBEVOLEN VOOR U

VEB kritisch over transactie tussen Mountainshield en DGB

Vereniging voor Effectenbezitters zet vraagtekens bij aandelentransactie van Mountainshieldfonds, dat in een half jaar tijd €3,7 mln fondsvermogen verloor.

🔖 Bewaren

AANBEVOLEN VOOR U

Kapitalisme reddt, met wat hulp, de aarde

MIT's Andrew McAfee schrijft deze keer een optimistisch boek: Meer uit minder

🔖 Bewaren

AANBEVOLEN VOOR U

Bouwers nieuwe windmolen gooien modder bij Ondernemingskamer

De mogelijkheden leken ongekend. Een windmolen die met minder overlast net zoveel vermogen levert als de standaardmodellen. De initiatiefnemers van windmolenbouwer Mega Windforce zagen gouden bergen. Nog geen drie jaar later dreigt de ondergang. Deze week diende de zaak in de Ondernemingskamer.

🔖 Bewaren

articles from the past 24h

AANBEVOLEN VOOR U

NET BINNEN

PRIVACY EN CYBERSECURITY

Justitie dwingt Microsoft tot aanpassing wereldwijde cloudcontracten

TECH EN MEDIA

SoftBank probeert met Japanse internetkampioen op te boksen tegen Google

FINANCIËLE SECTOR

VEB kritisch over transactie tussen Mountainshield en DGB

MARKTEN

Franse toezichthouder eist €5mln van persbureau Bloomberg

OPINIE

Mkb'ers kunnen wél meer investeren, ook in mensen

→ MIJN NIEUWS

Future work

Online **testing** - currently ongoing

Measuring **usefulness** (dynamicness, serendipity, diversity) aspects of recommendations & seeing how readers respond to them

Closing the loop: tweaking the model based on how the recommendations are presented to readers

Conclusions

Simpler model (GBDT) is sometimes better + easier to understand.

Less data (days, user interactions) does not mean worse performance.

Combined user-article features are the most meaningful, but all features contribute a little.