Recommender Systems

Challenge 2022/23

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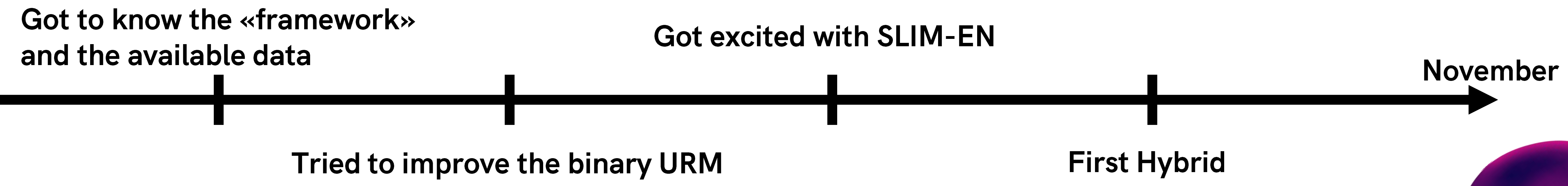
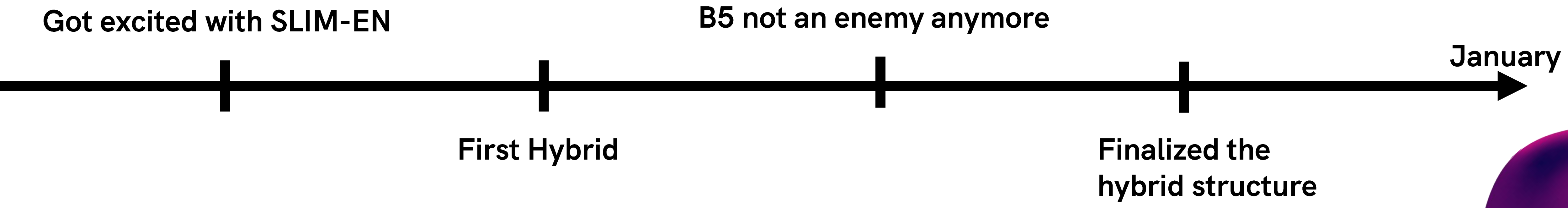
What we have done, briefly



What we have done, briefly



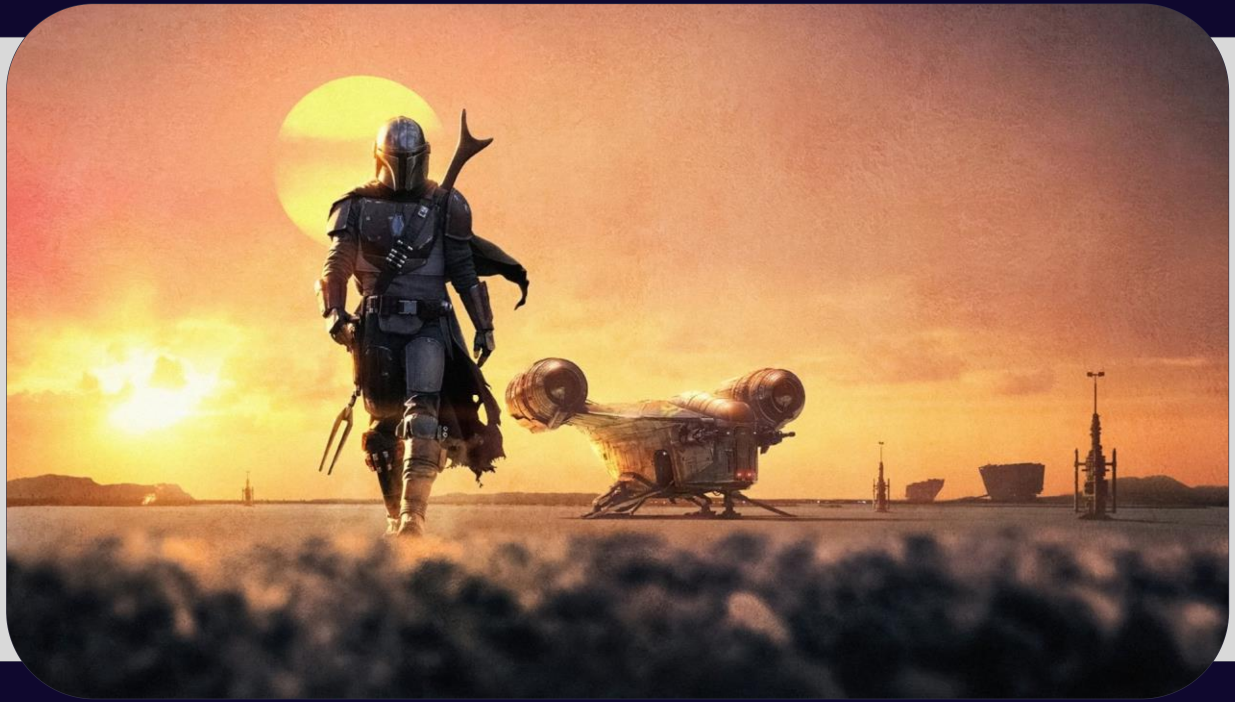
01

Dataset analysis: item length

There are movies or mono-episodes series

01

Dataset analysis: item length



There are series with more than one episode

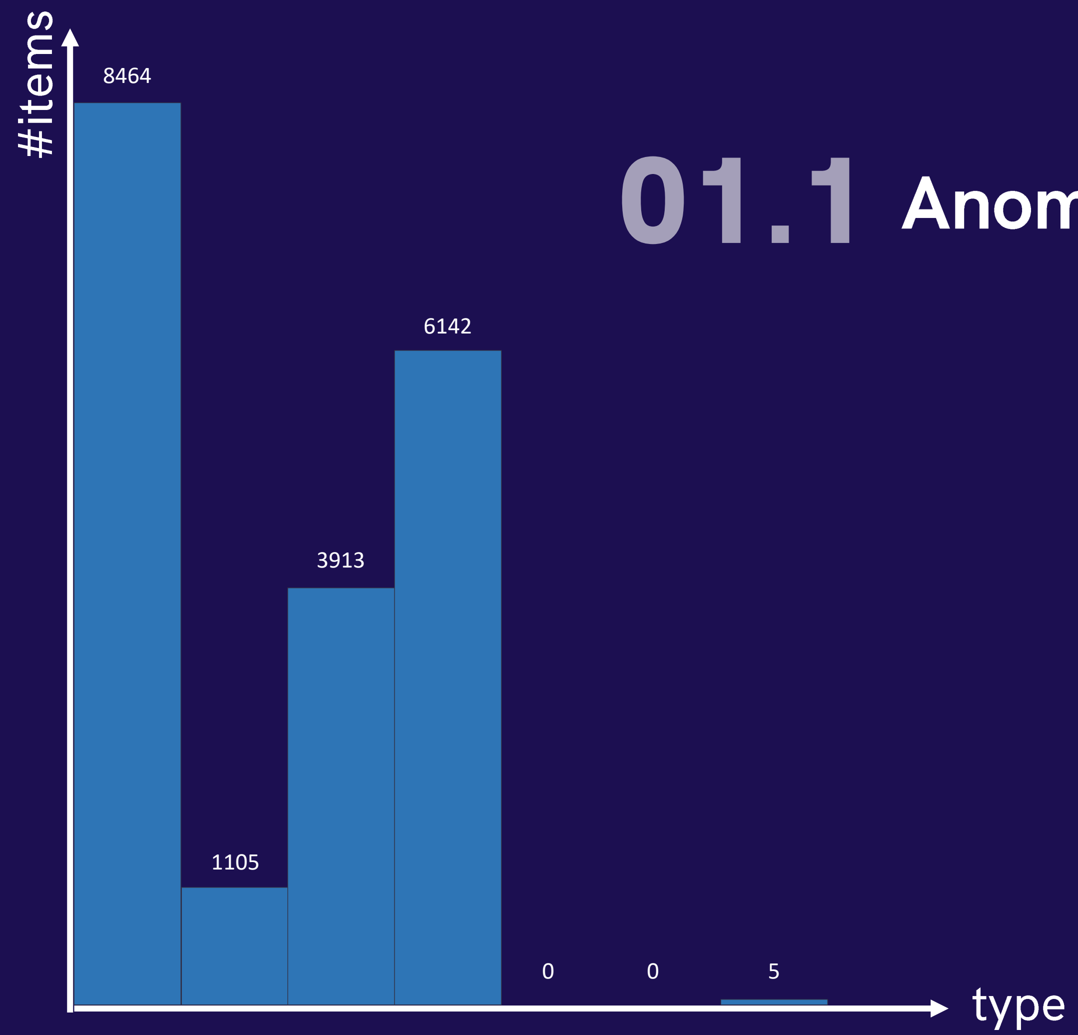
01

Dataset analysis: item length

There are series with probably “corrupted” values (10k)

01

Dataset analysis: item types, interactions



01.1 Anomalous item type distribution

01

Dataset analysis: item types, interactions

01.1 Anomalous item type distribution

01.2 No cold users

01

Dataset analysis: item types, interactions

01.1 Anomalous item type distribution

01.2 No cold users

01.3 3000 cold items

02

Our resources

02.1 Personal resources

Macbook Pro 2019

Lenovo Yoga Slim 7 Pro

02

Our resources

02.1 Personal resources

Macbook Pro 2019

Lenovo Yoga Slim 7 Pro

02.2 Cloud

Kaggle

Microsoft Azure Student

03 Approaches

What did work

Stacking URM + ICM
- Weighted stacking too

Binary URM and ICM

Non-binary URM
- Based on interaction count
- Normalized using tanh()

Hierarchical hybrids

What made us happy
at least once

List combination
- Round robin
- Condorcet-Schulze method

What did not work

Pipelined hybrids

Recommenders tailored on specific groups of users
- Using the profile length
- Using K-Means

Recommenders based on user-similarity

Feature weighting

03 Approaches

What did work

Stacking URM + ICM
Weighted stacking too

Binary URM and ICM

Non-binary URM
Based on interaction count
Normalized using tanh()

Hierarchical hybrids

But mostly

Trial and Error

04 Our solution The “binary-trained” hybrid

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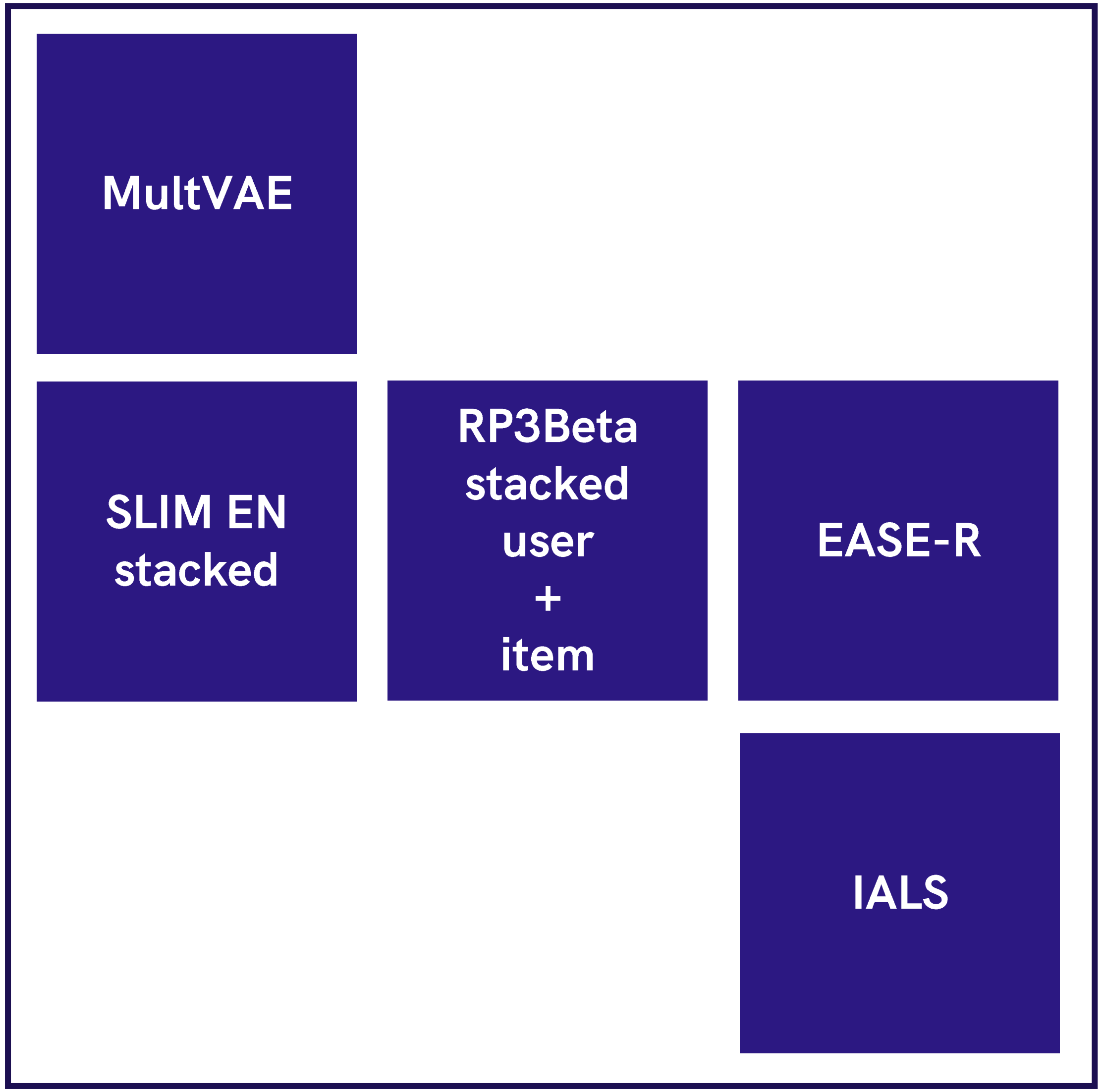
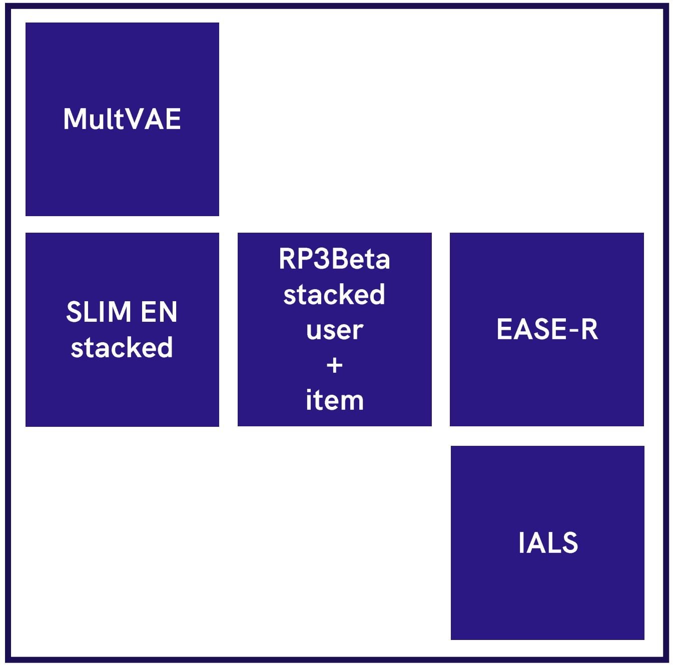
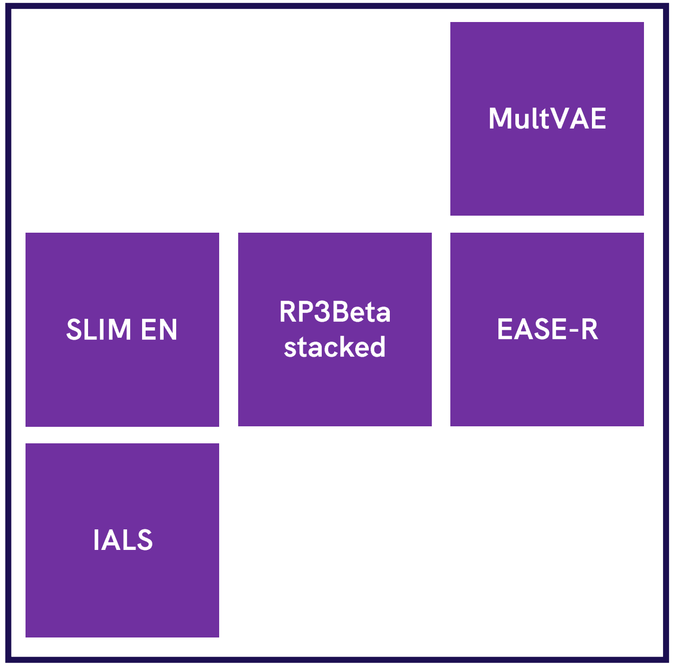


04 Our solution

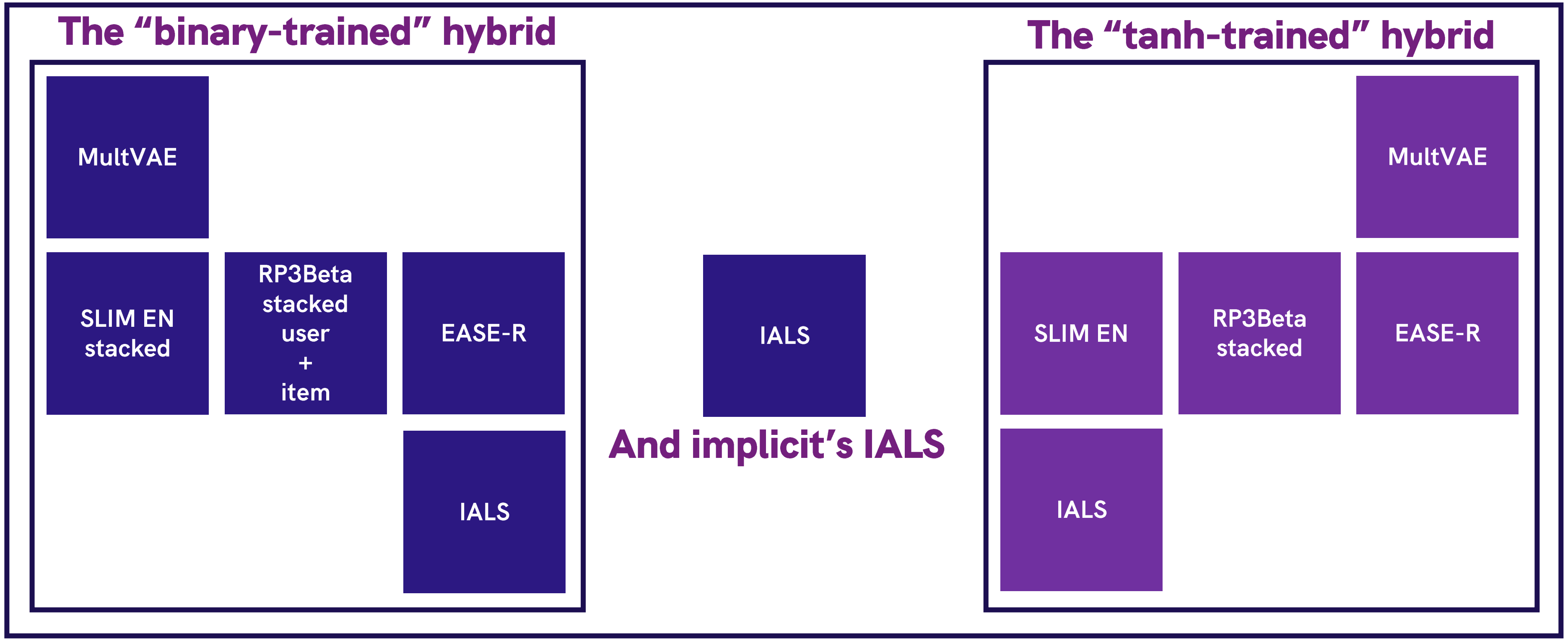
The “binary-trained” hybrid



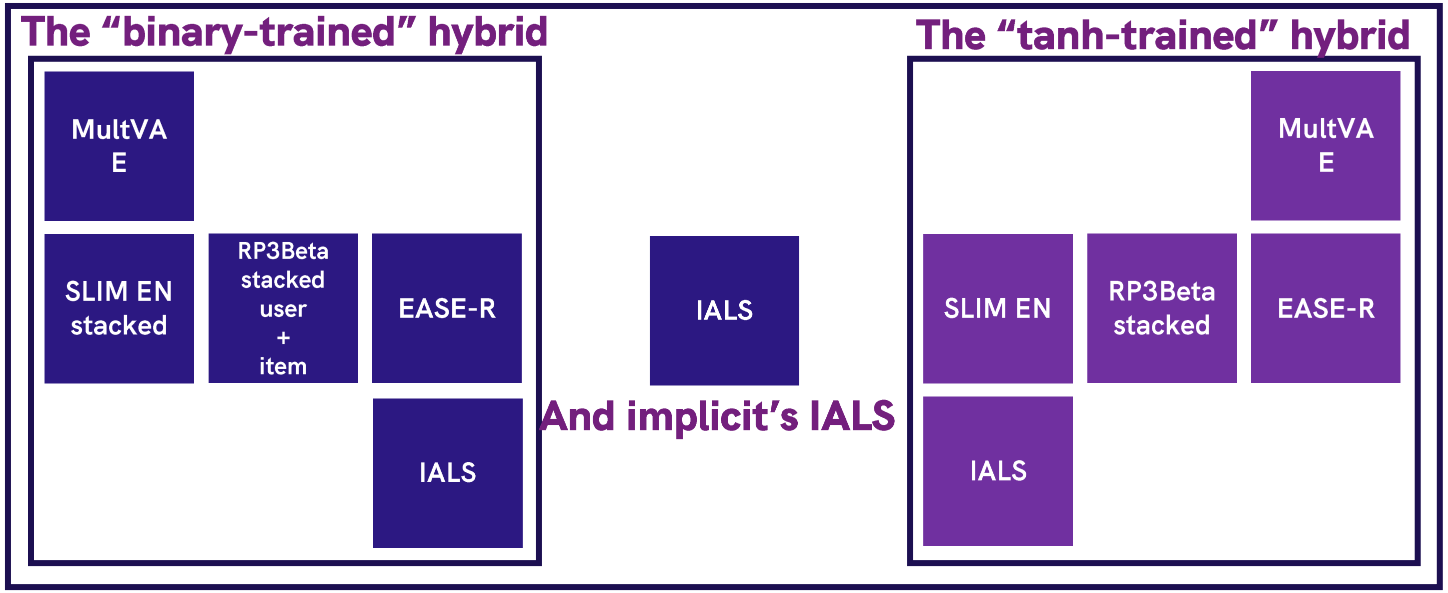
The “tanh-trained” hybrid



04 Our solution



04 Our solution



Final MAP@10:

0.06101 private
0.06200 public

Intuition:

Different URMs imply different results

Algorithms coefficients:

Binary:	6	
SLIM-EN:		400
IALS:		41
MultVAE:		4
RP3:		4
EASE:		27
TanH:	60	
SLIM-EN:		62
IALS:		22
MultVAE:		2
RP3:		200
EASE:		50
IALS:	169	

05 Further improvements

Reranking with XGBRanker

As seen in MaurizioFD's notebook

(even) More Tuning

Especially the «tanh» hybrid

Reranking with impressions

Such as impression discounting

Thanks

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MILANO 1863

eit Digital