

OpenRec: A Modular Framework for Extensible and Adaptable Recommendation Algorithms



Longqi Yang



Eugene Bagdasaryan



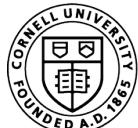
Joshua Gruenstein



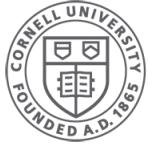
Cheng-Kang(Andy)
Hsieh



Deborah Estrin



**CORNELL
TECH**



Cornell CIS
Computer Science

Funders:



Oath:
A Verizon company

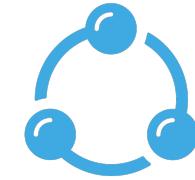
Promising future of personalization and recommender systems



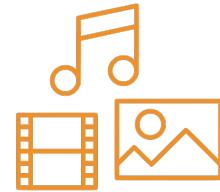
Education



Healthcare



Social network



Media



Food and Diet

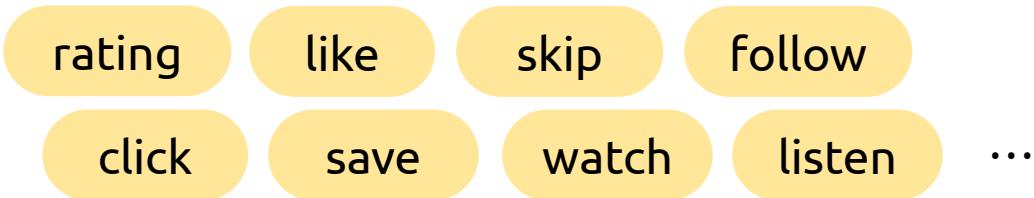


e-Commerce

Recommendation algorithms are increasingly complex

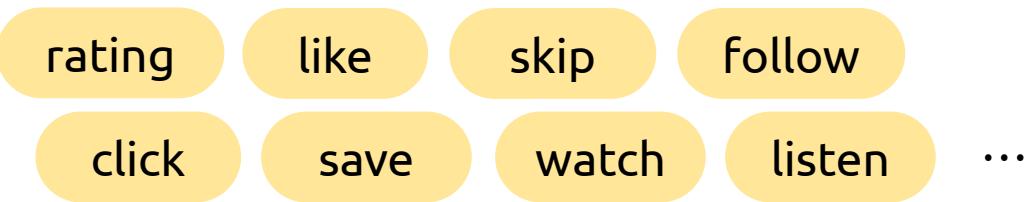
Recommendation algorithms are increasingly complex

Diverse user feedback signals

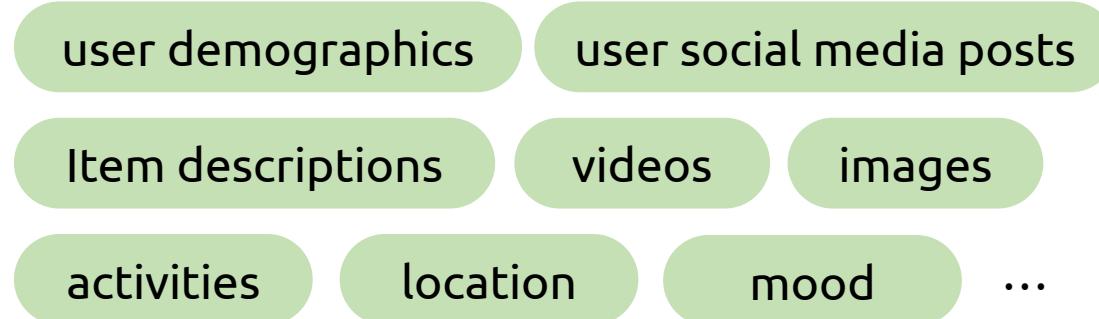


Recommendation algorithms are increasingly complex

Diverse user feedback signals



Heterogeneous data streams and context



Recommendation algorithms are increasingly complex

Diverse user feedback signals

rating like skip follow
click save watch listen ...

Heterogeneous data streams and context

user demographics user social media posts
Item descriptions videos images
activities location mood ...

Complex goals

accuracy
diversity
novelty
fairness
quality
interpretability ...

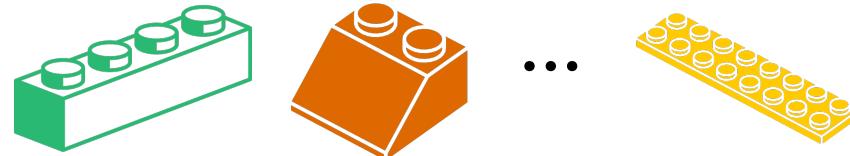
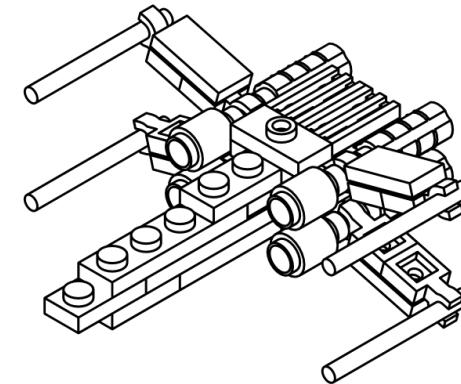
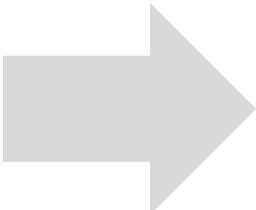


Bag of algorithms

However, current recommendation algorithms lack
simplicity and modularity.

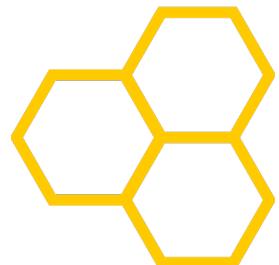


Bag of algorithms



OpenRec

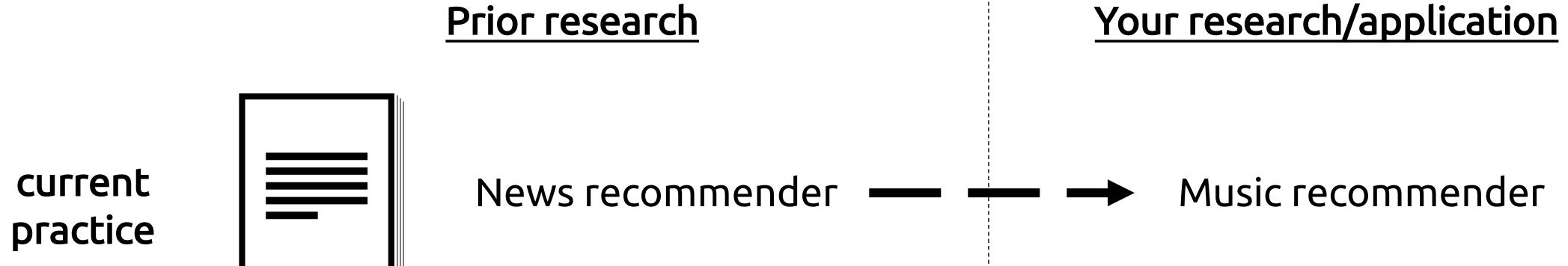
Apache License 2.0



Modularity

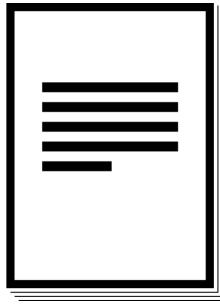
- Easy to **extend** and **adapt** to various scenarios.
- Quick experimentation (e.g., model selection) and idea exploration.
- Comparable (sometimes even better) performance.

Current practice vs. OpenRec



Current practice vs. OpenRec

current
practice



Prior research

News recommender

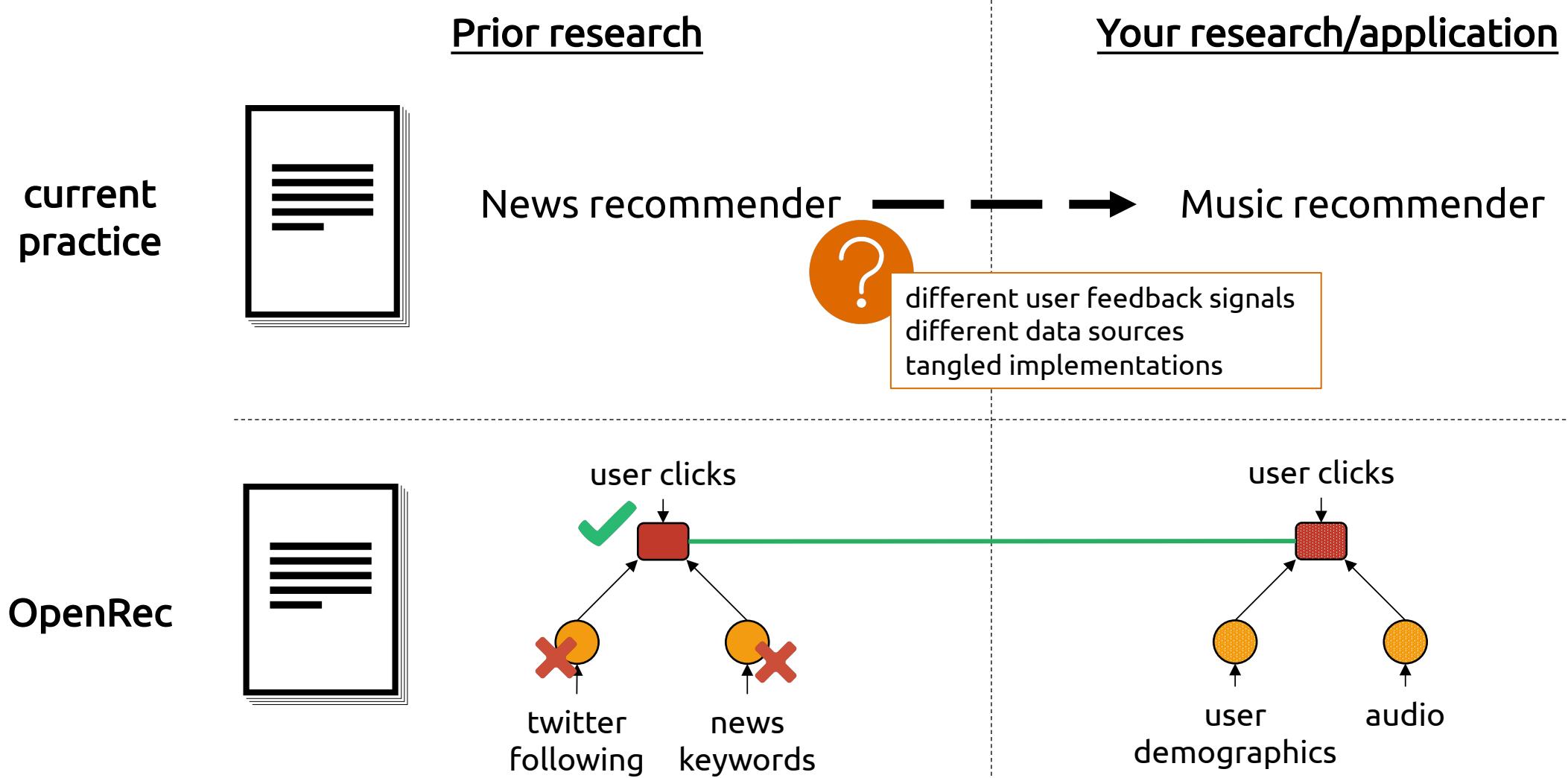


Your research/application

Music recommender

different user feedback signals
different data sources
tangled implementations

Current practice vs. OpenRec



1

Abstraction and interface

2

Implementations

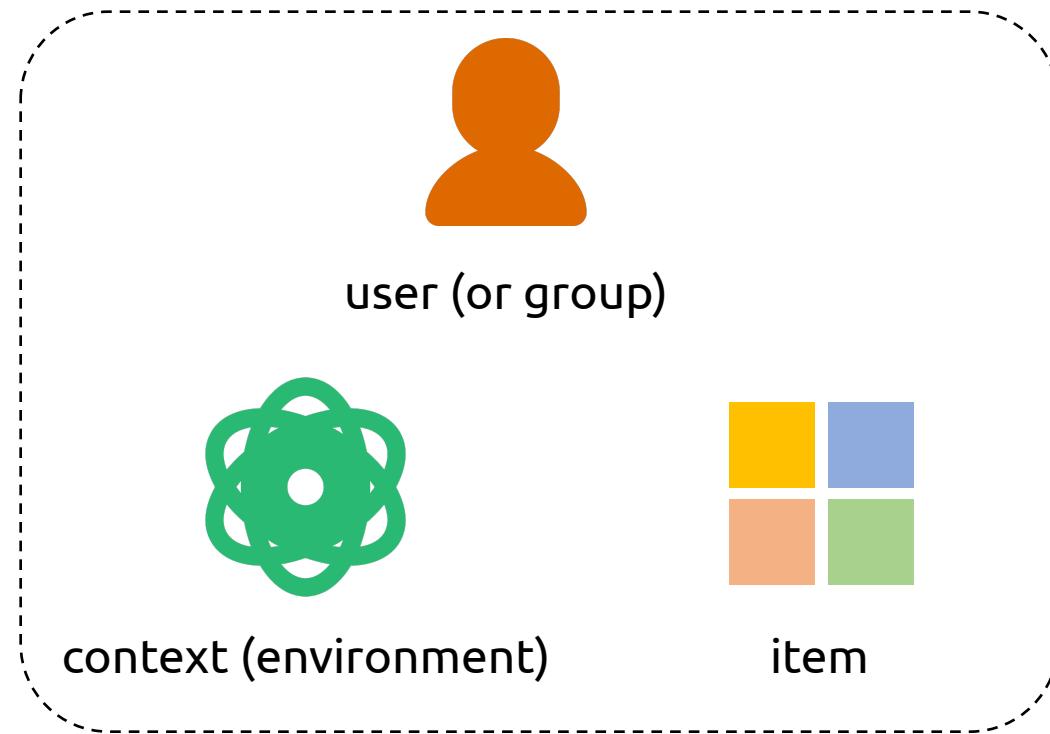
3

Simple use cases

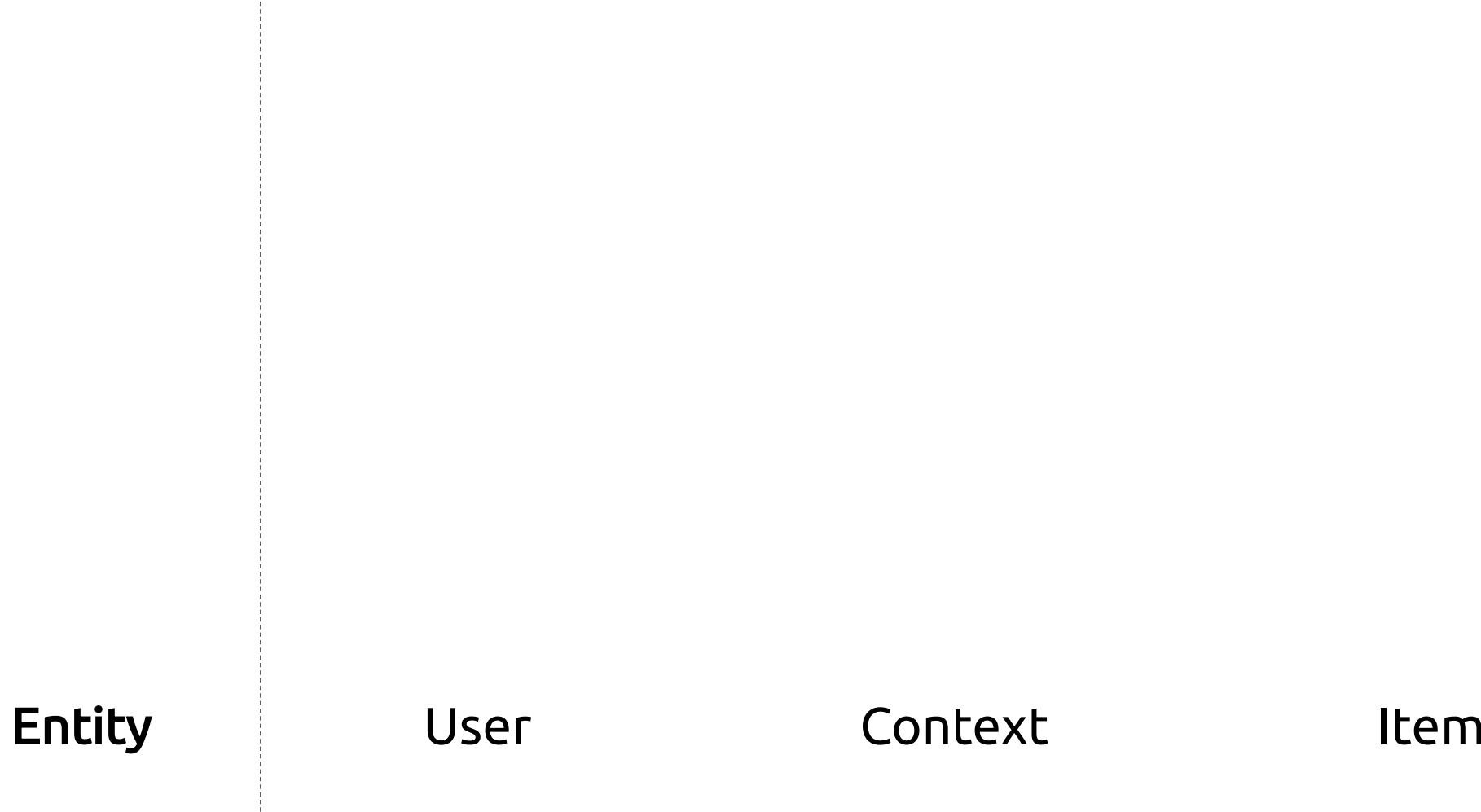
4

Takeaways and Future work

Abstract entities in recommendation algorithms



Building a recommendation algorithm



Building a recommendation algorithm

Profile

Entity

User

Context

Item

Building a recommendation algorithm

Profile



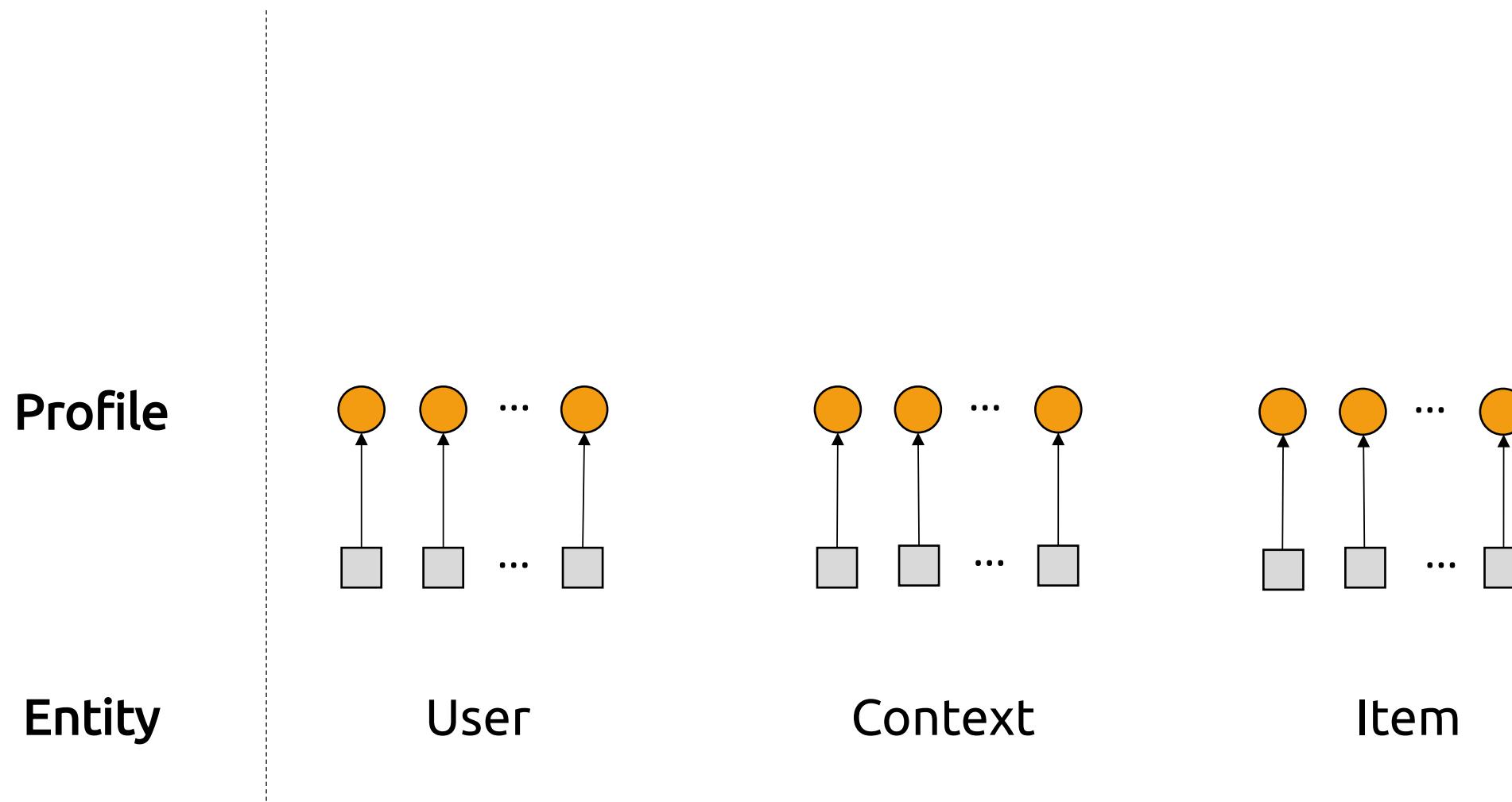
Entity

User

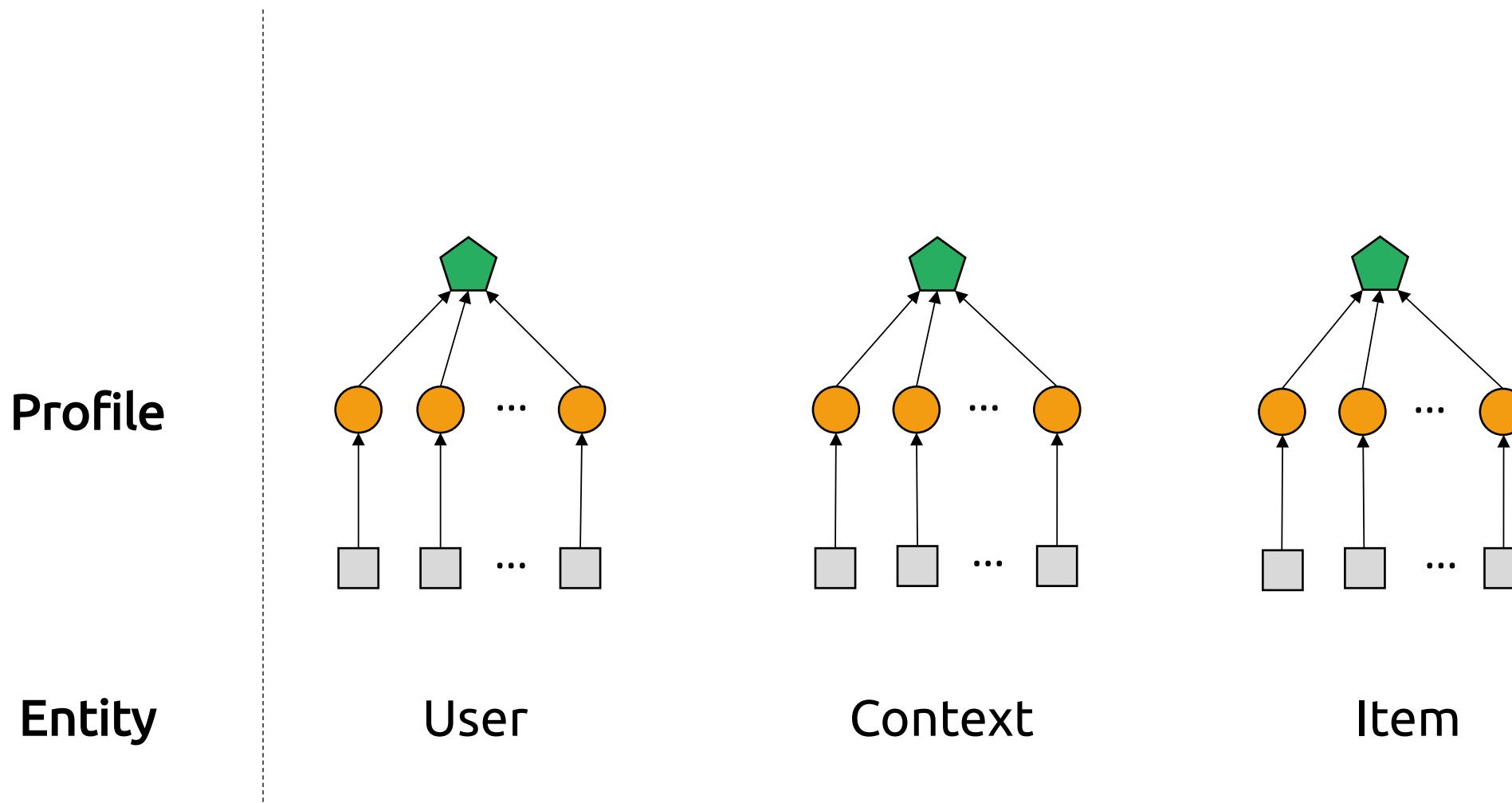
Context

Item

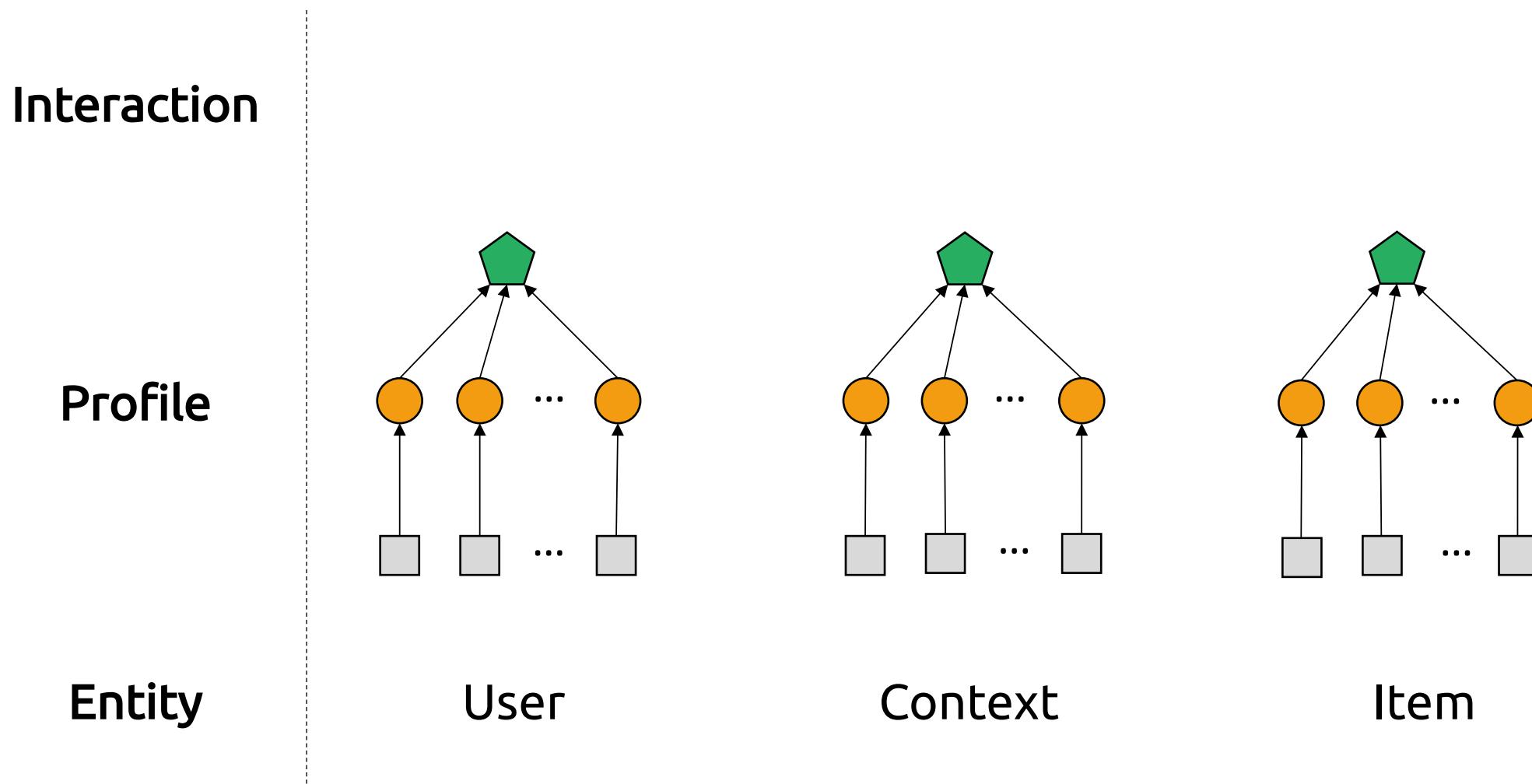
Building a recommendation algorithm



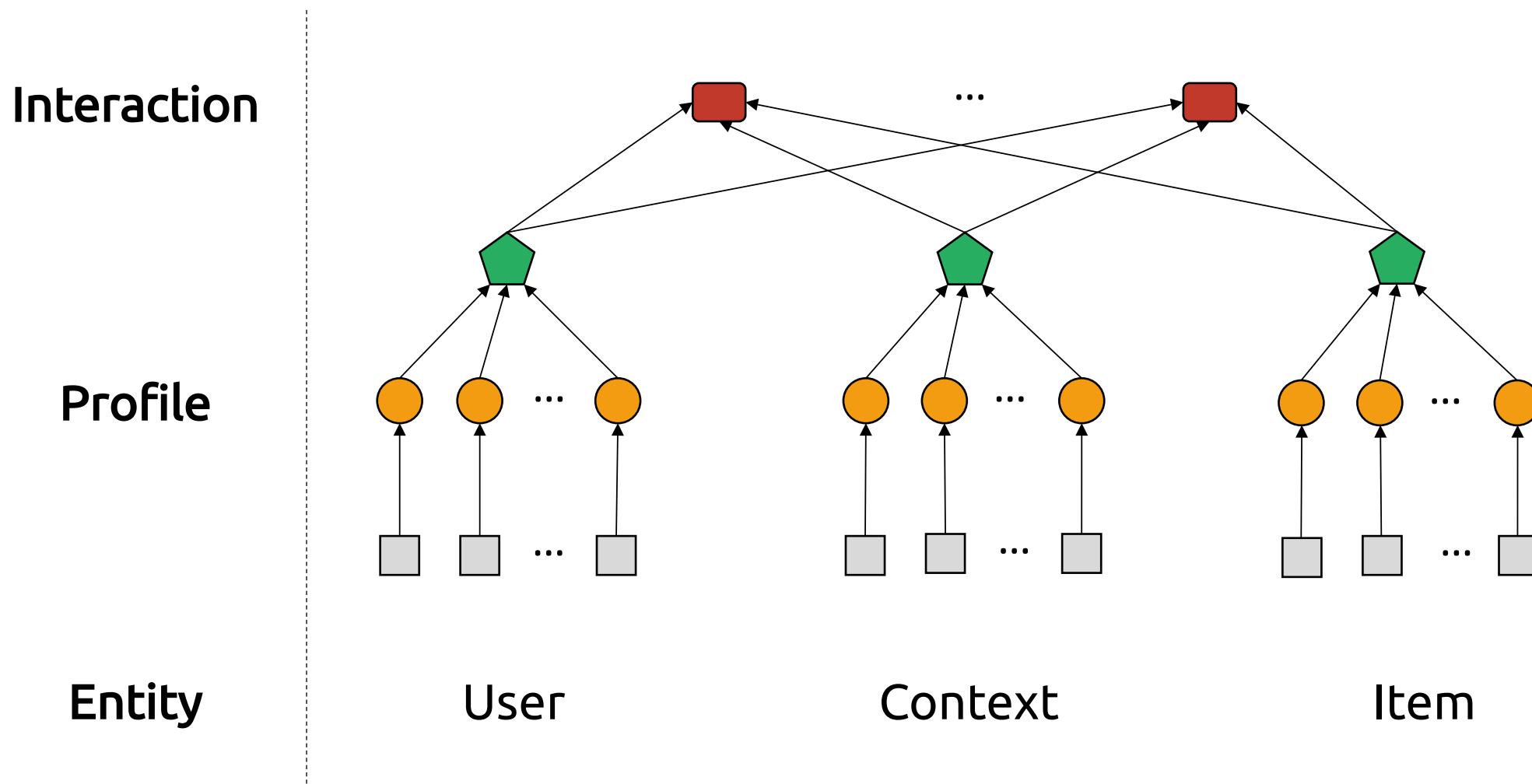
Building a recommendation algorithm



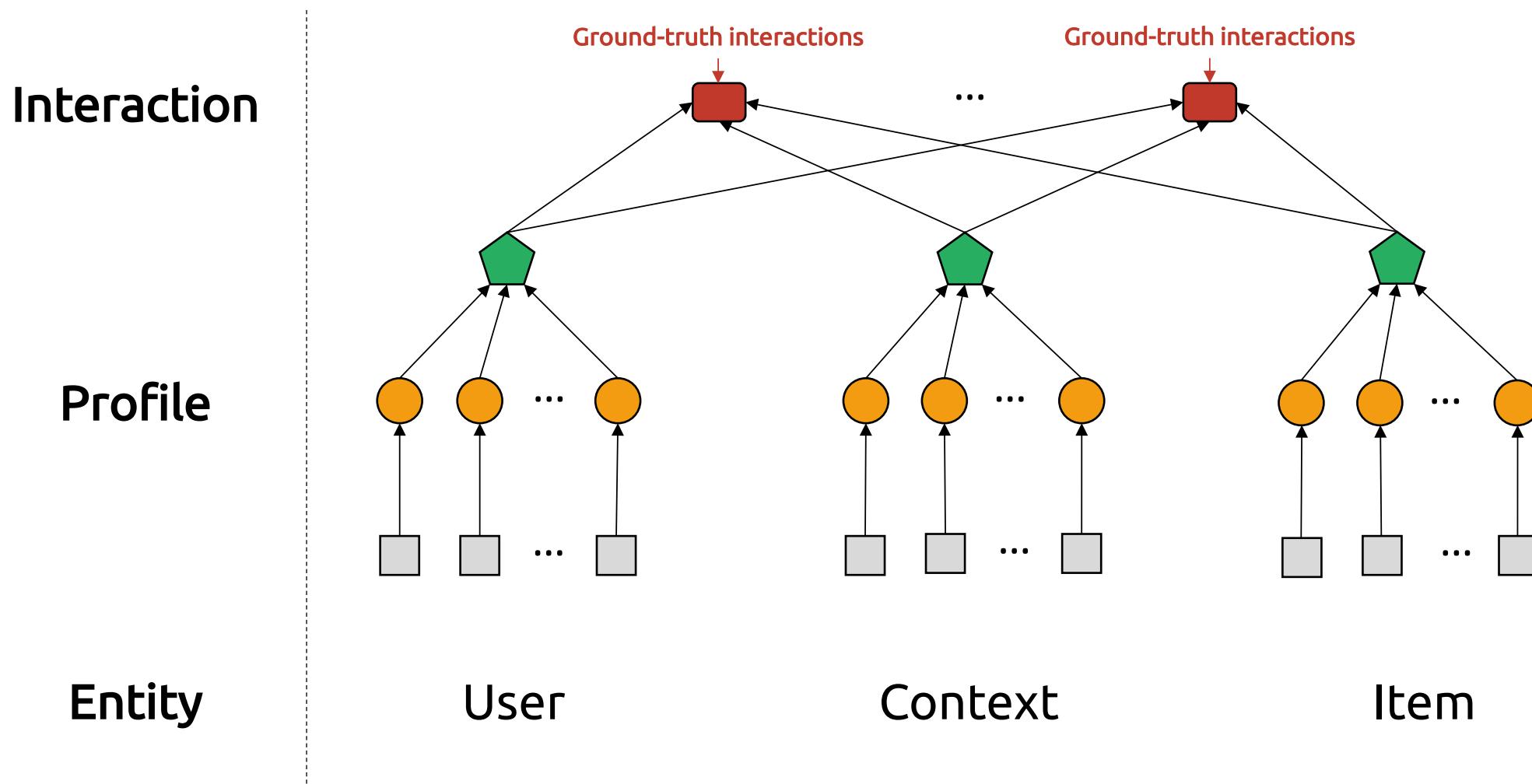
Building a recommendation algorithm



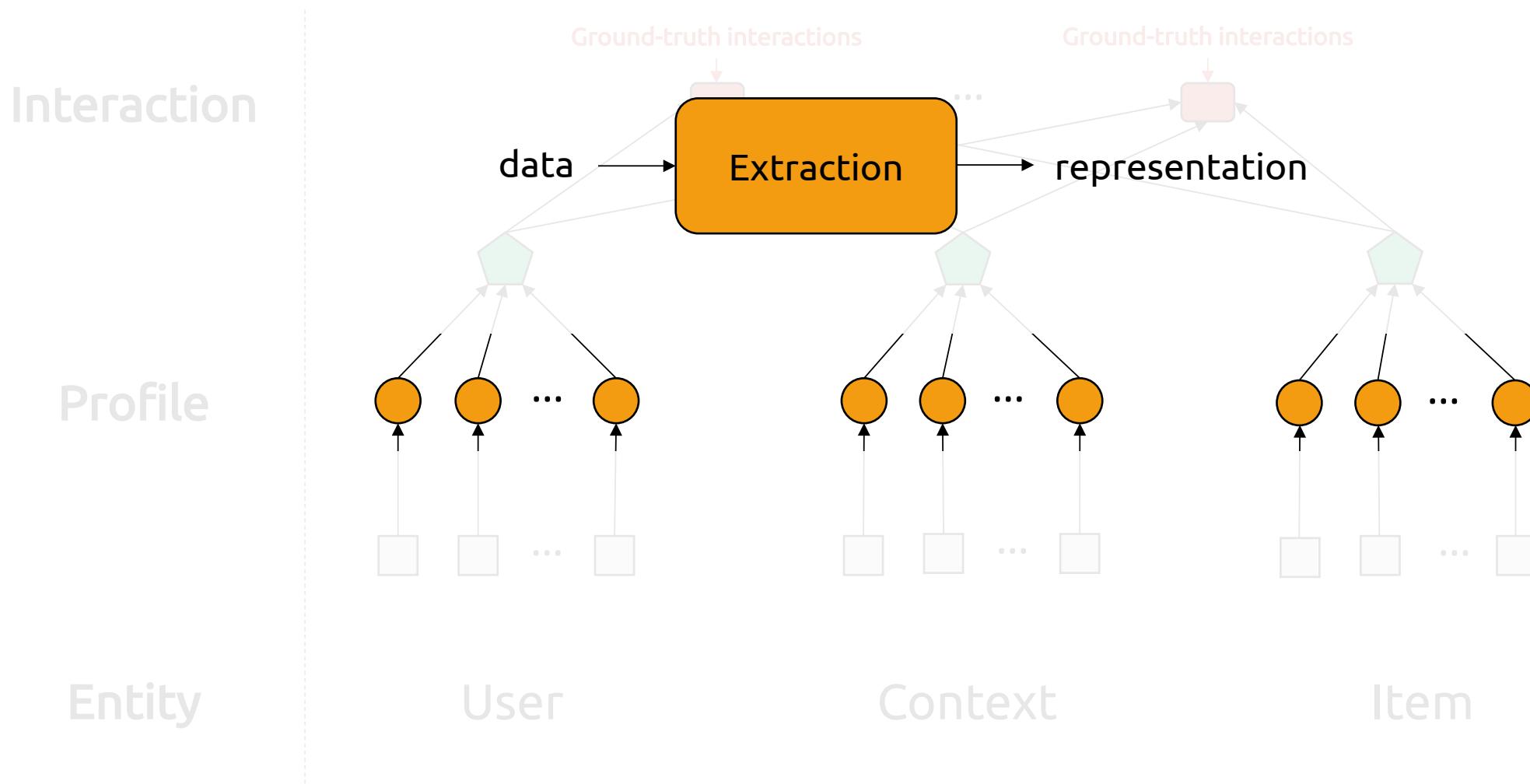
Building a recommendation algorithm



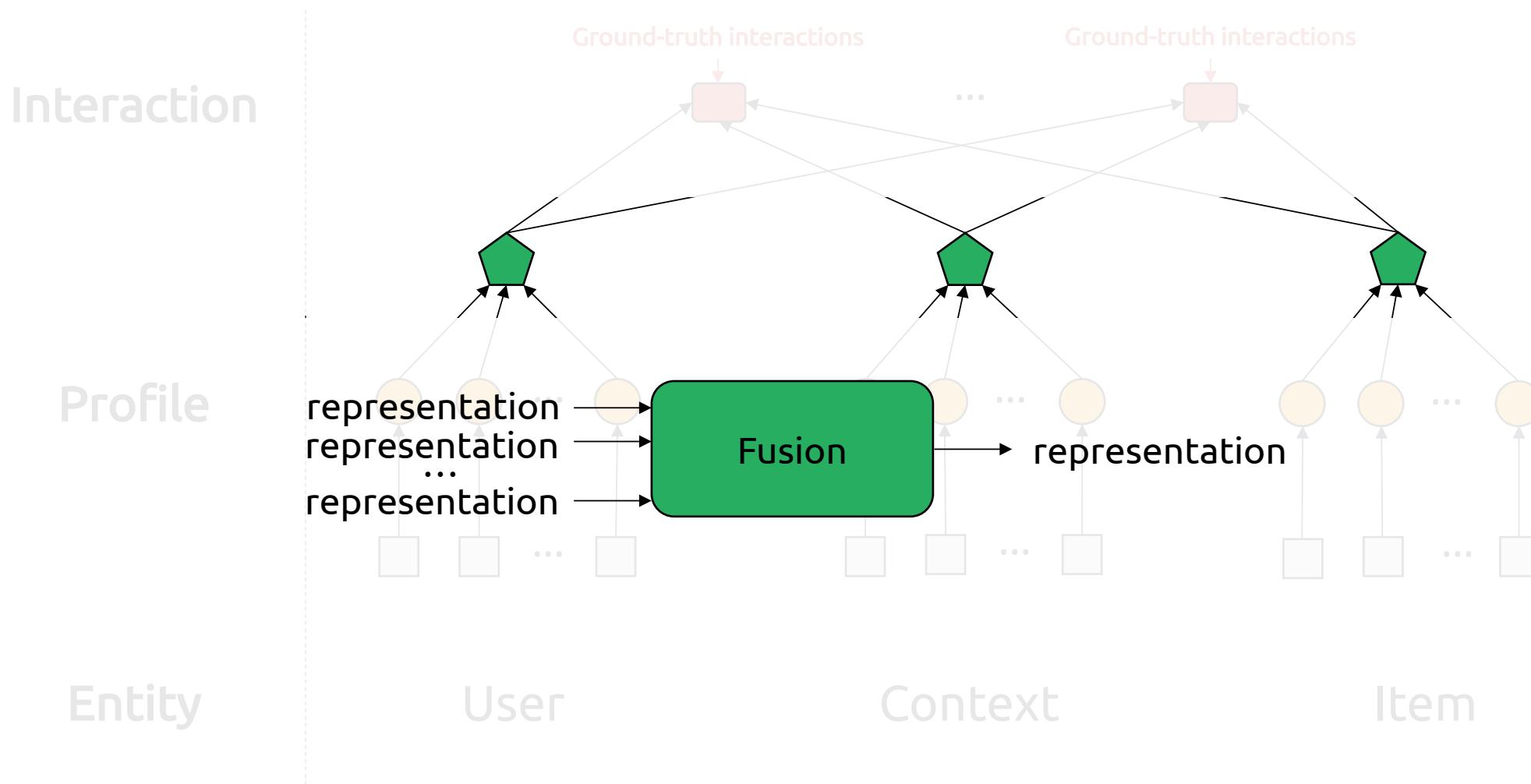
Building a recommendation algorithm



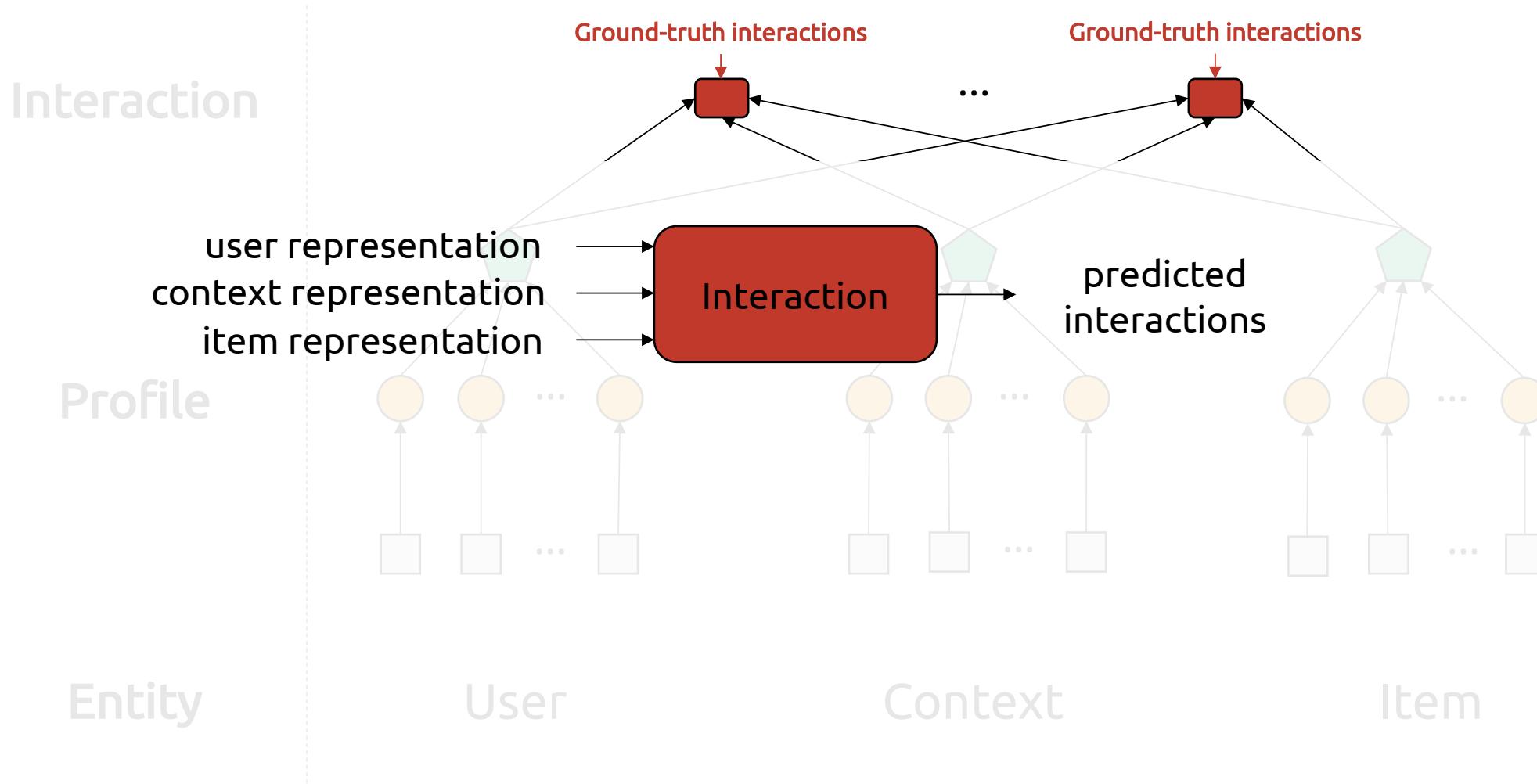
Extraction: extract representations



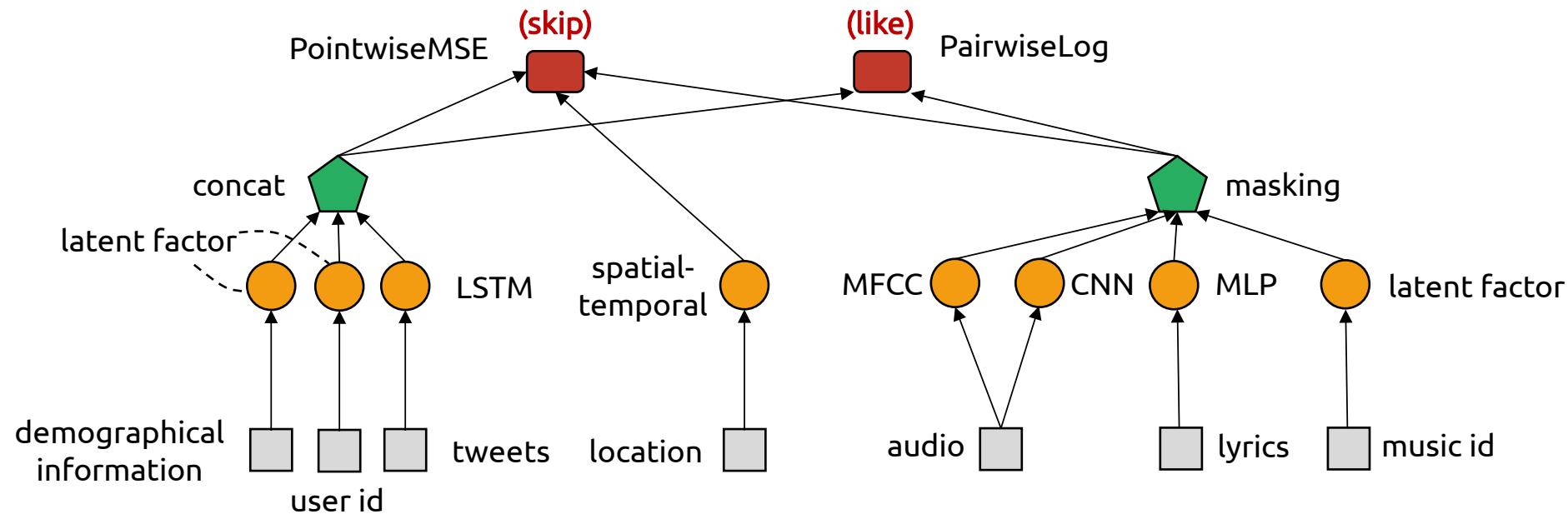
Fusion: fuse representations



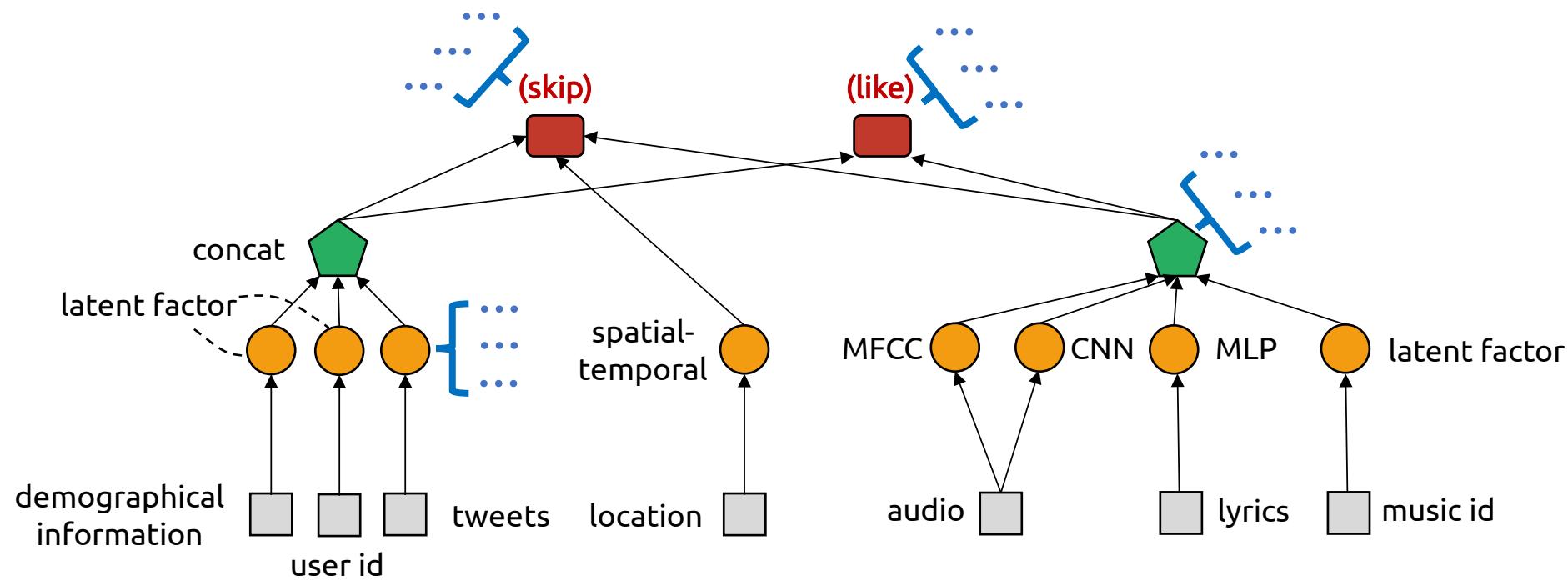
Interaction: predict clicks/likes/ratings...



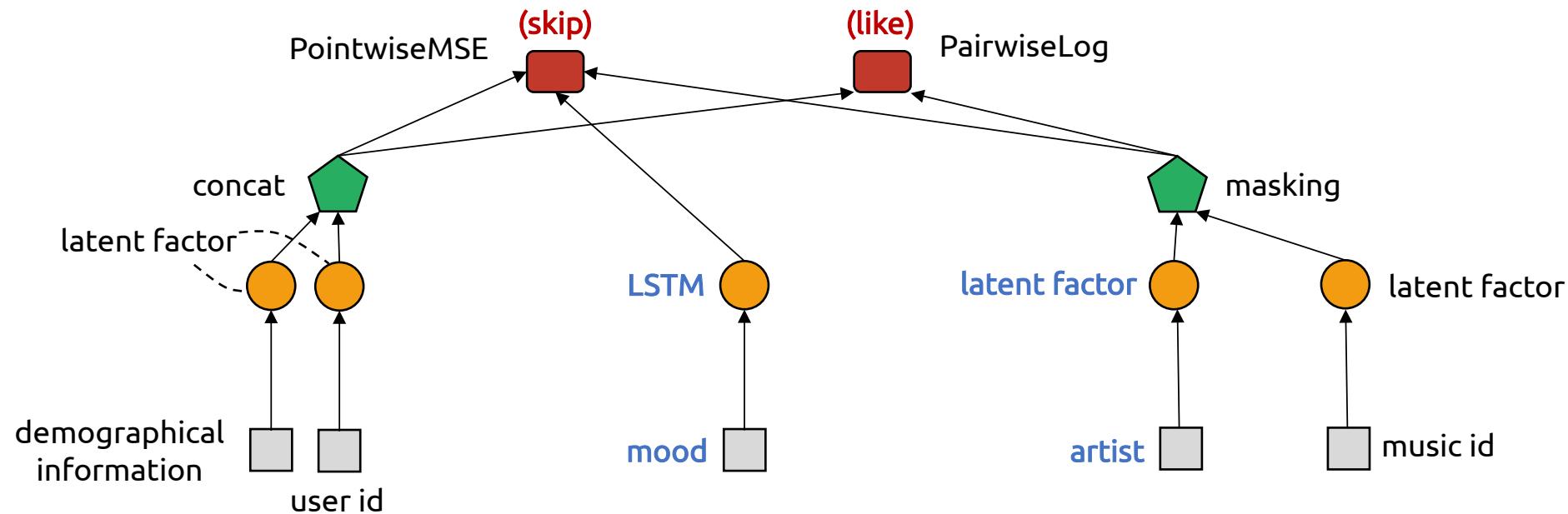
A hypothetical music recommendation algorithm



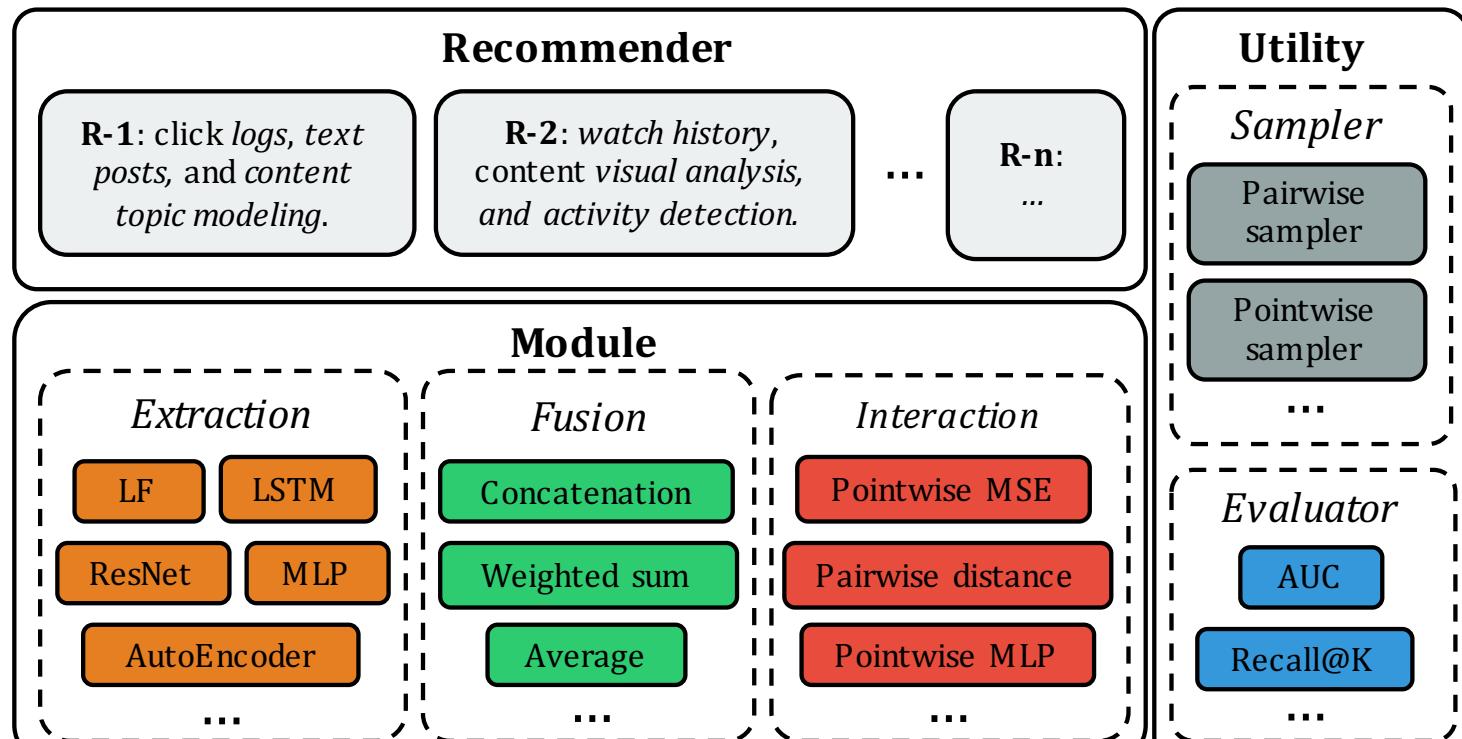
A hypothetical music recommendation algorithm



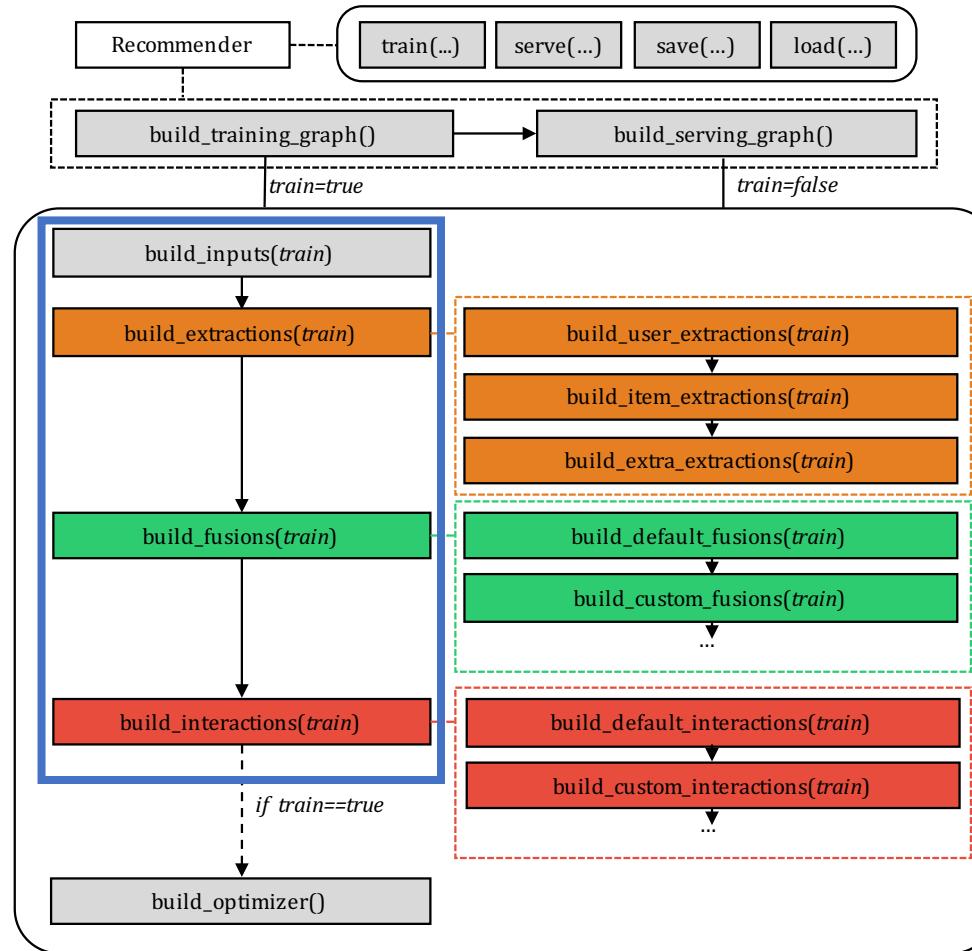
A hypothetical music recommendation algorithm



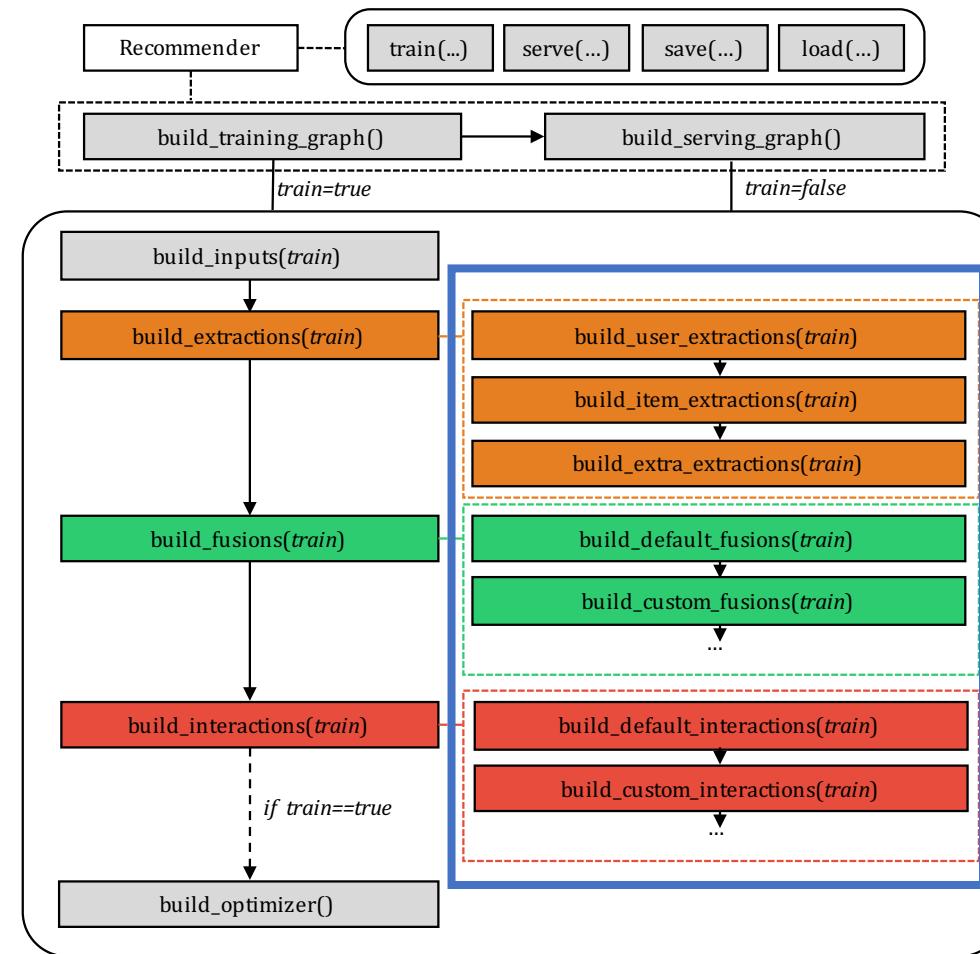
OpenRec framework structure



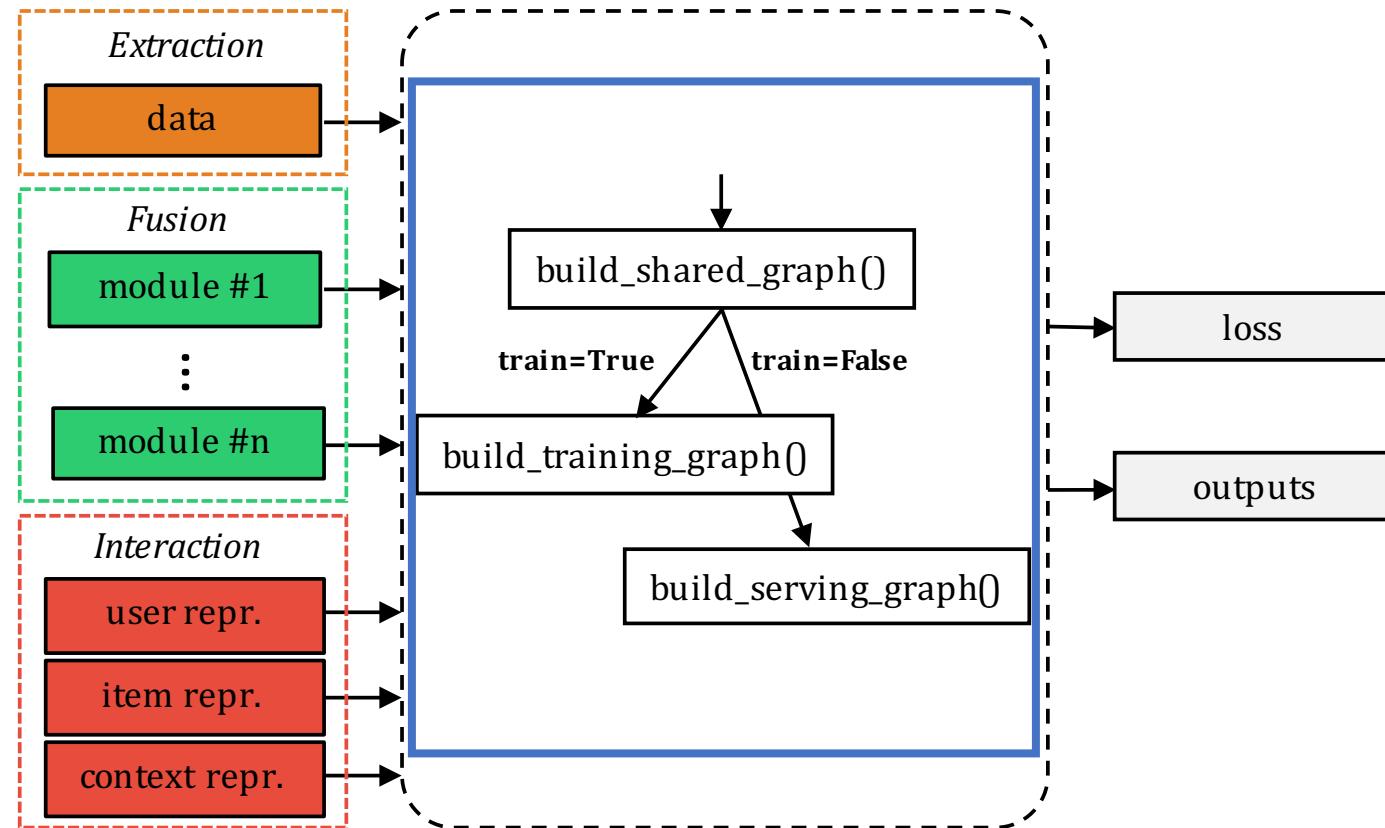
Inside a Recommender



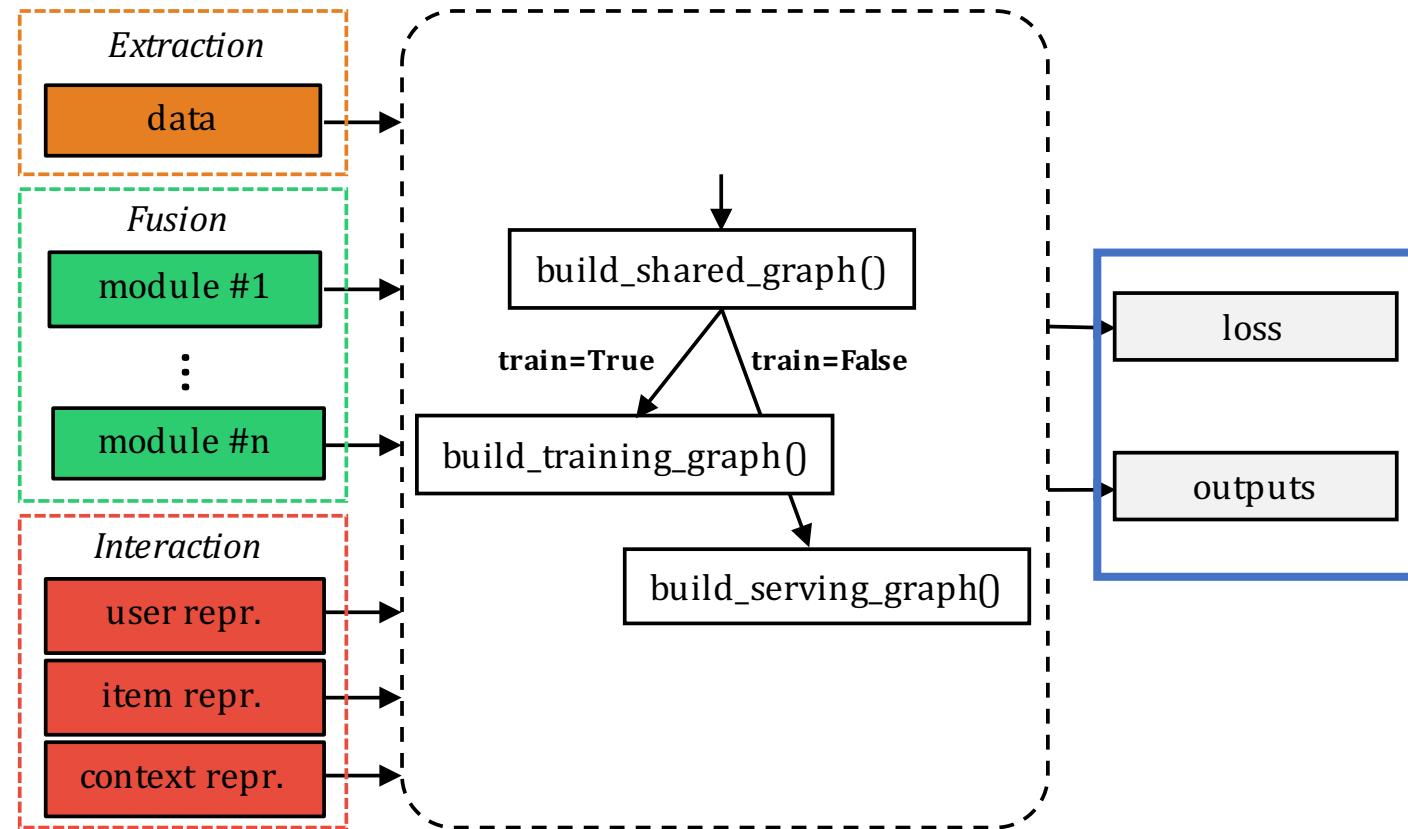
Inside a Recommender



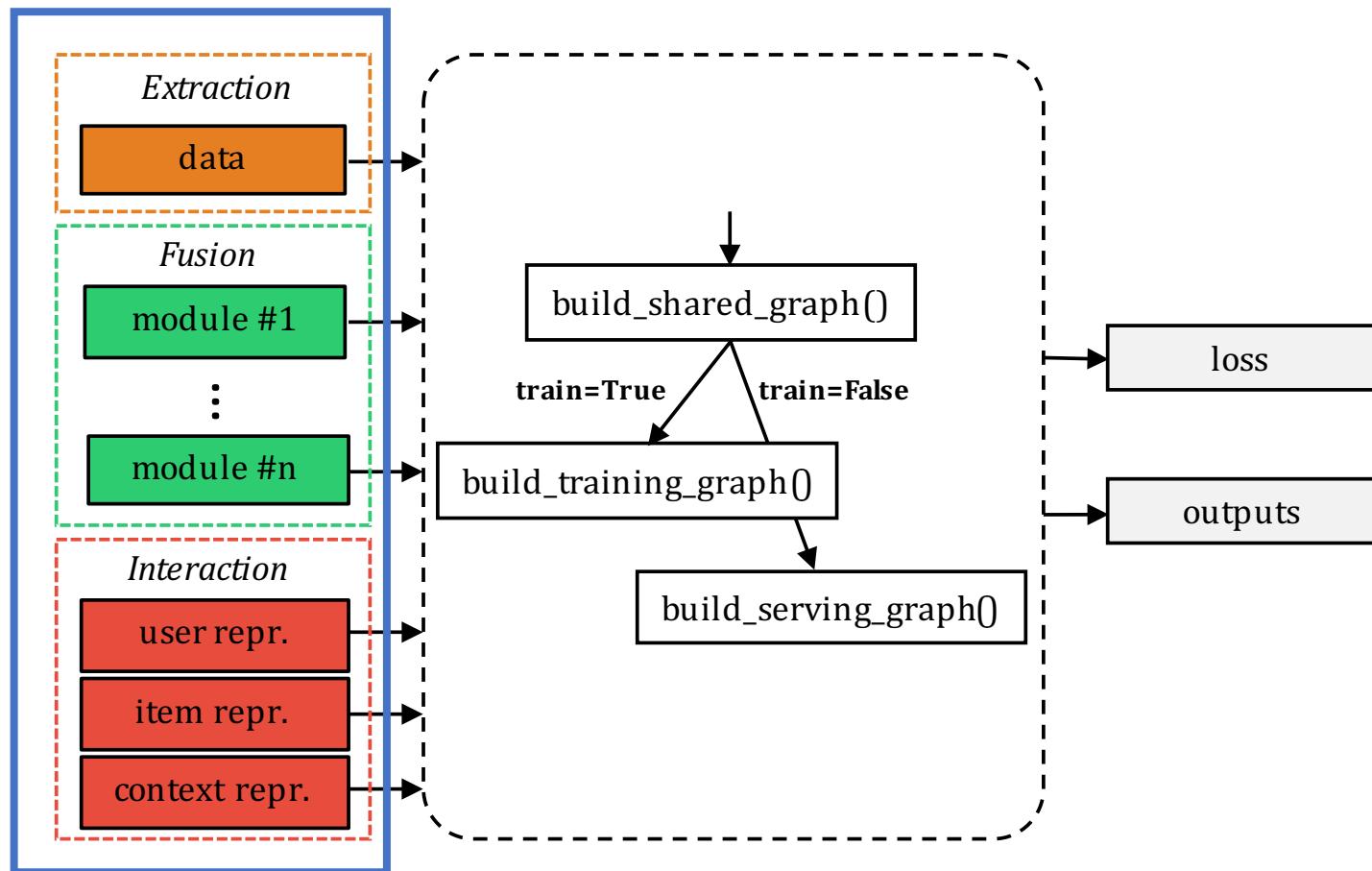
Inside a *Module*



Inside a *Module*



Inside a *Module*



3

Simple use cases

- Conduct model selection (E-commerce book recommendation).
- Develop new algorithms – *brief*
- Compare modular and monolithic implementations.

Two kinds of model selection

structure selection: what data traces to incorporate and how

module selection: select best modules given a structure

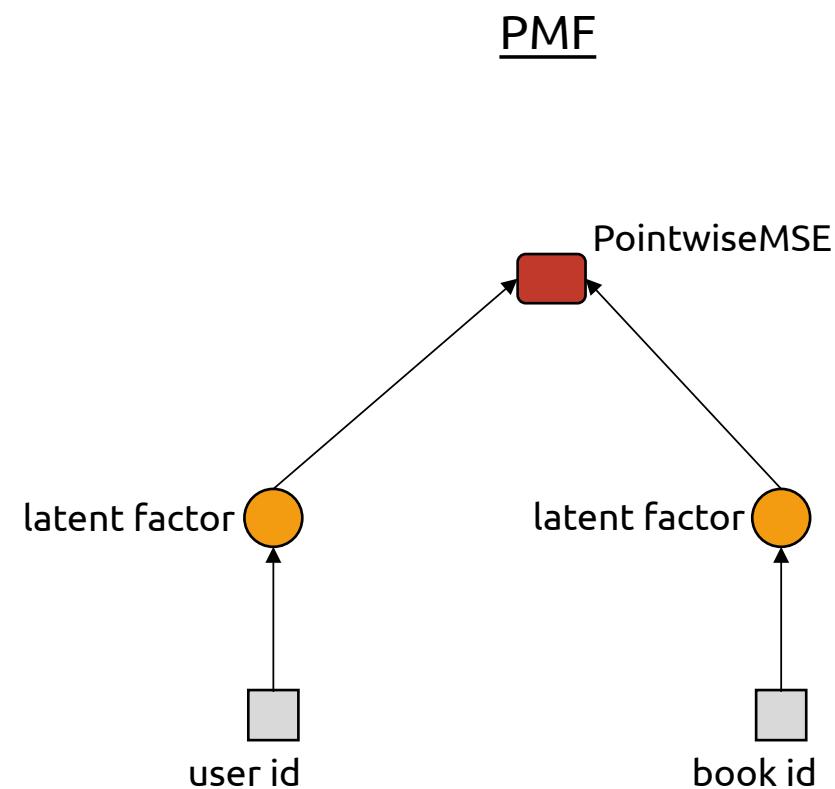
Amazon dataset [McAuley et. al. 15]

User data: user id & purchases in other categories

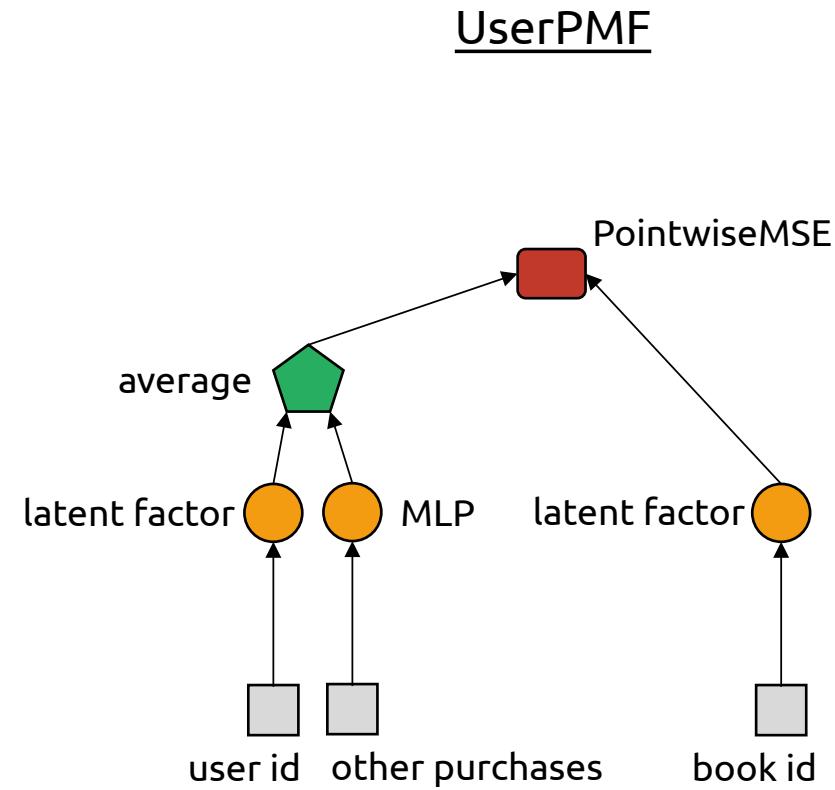
Book data: book id & book cover image

Interaction data: user reviews

Exp 1. structure selection

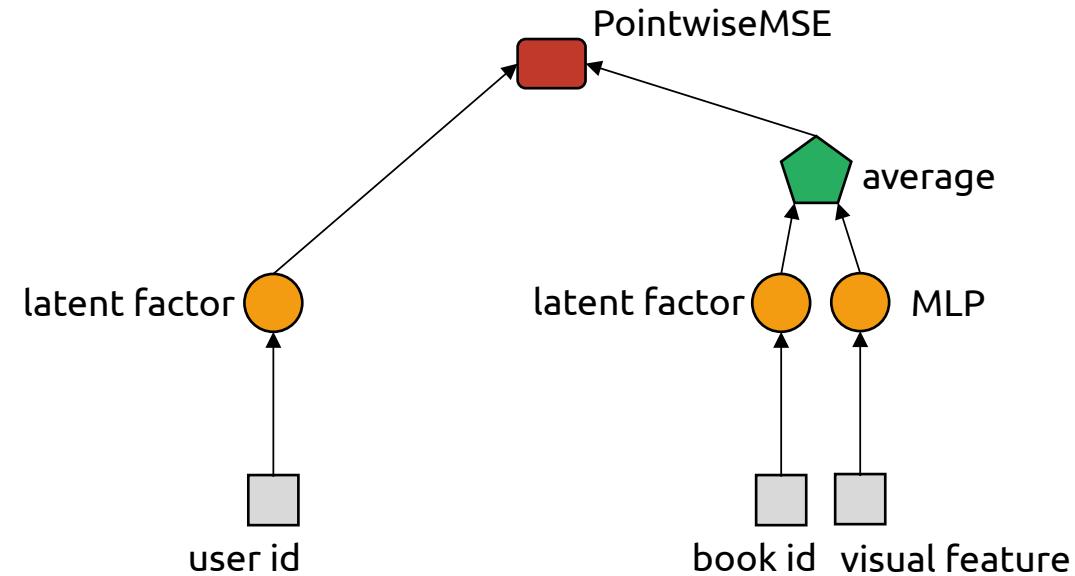


Exp 1. structure selection



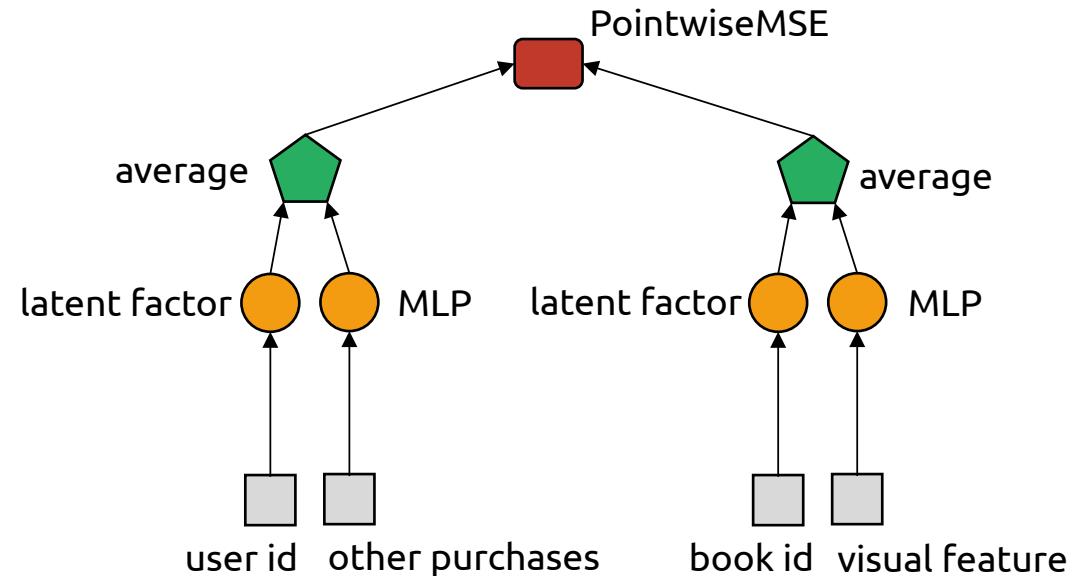
Exp 1. structure selection

VisualPMF



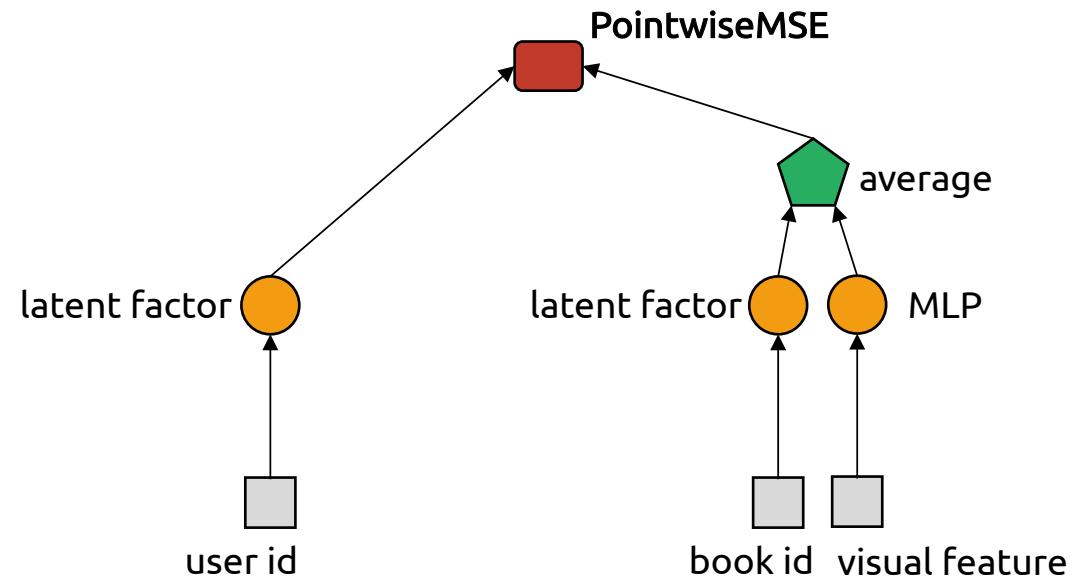
Exp 1. structure selection

UserVisualPMF



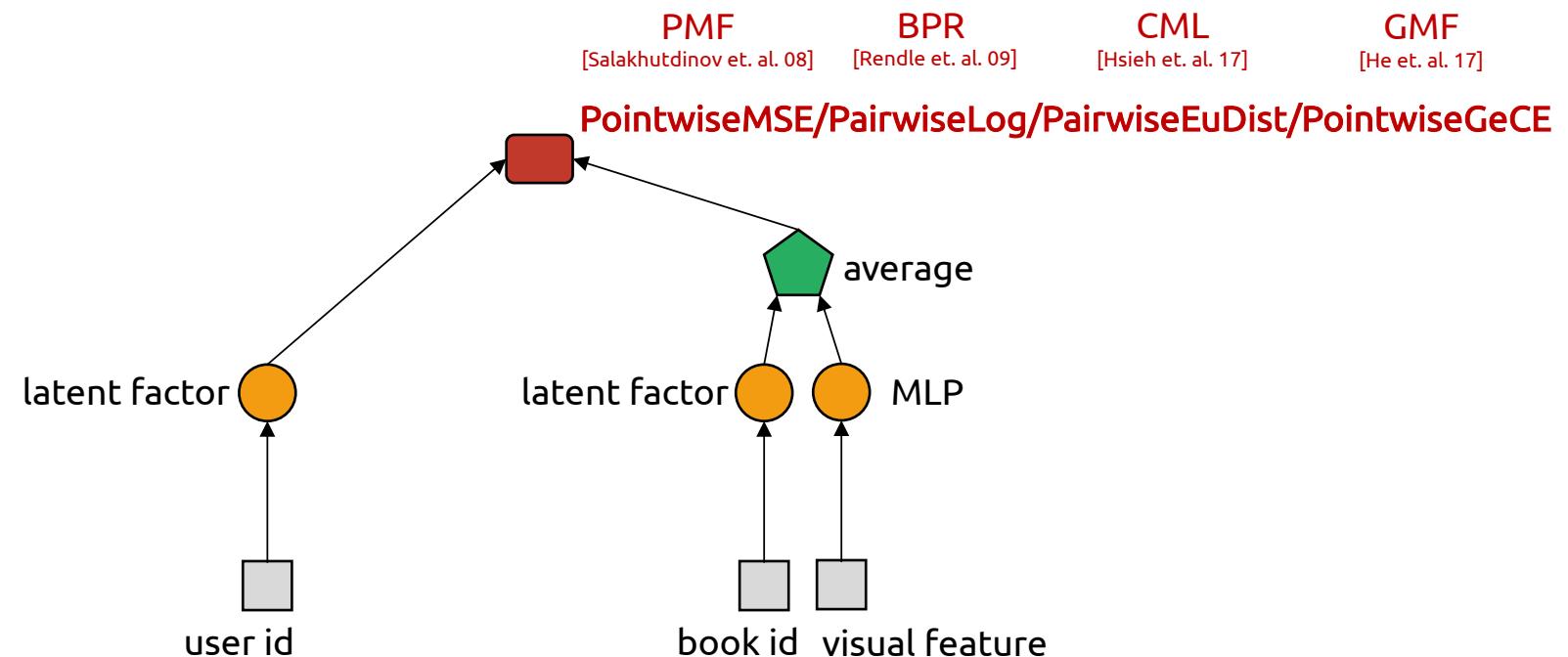
Exp 2. module selection

VisualPMF



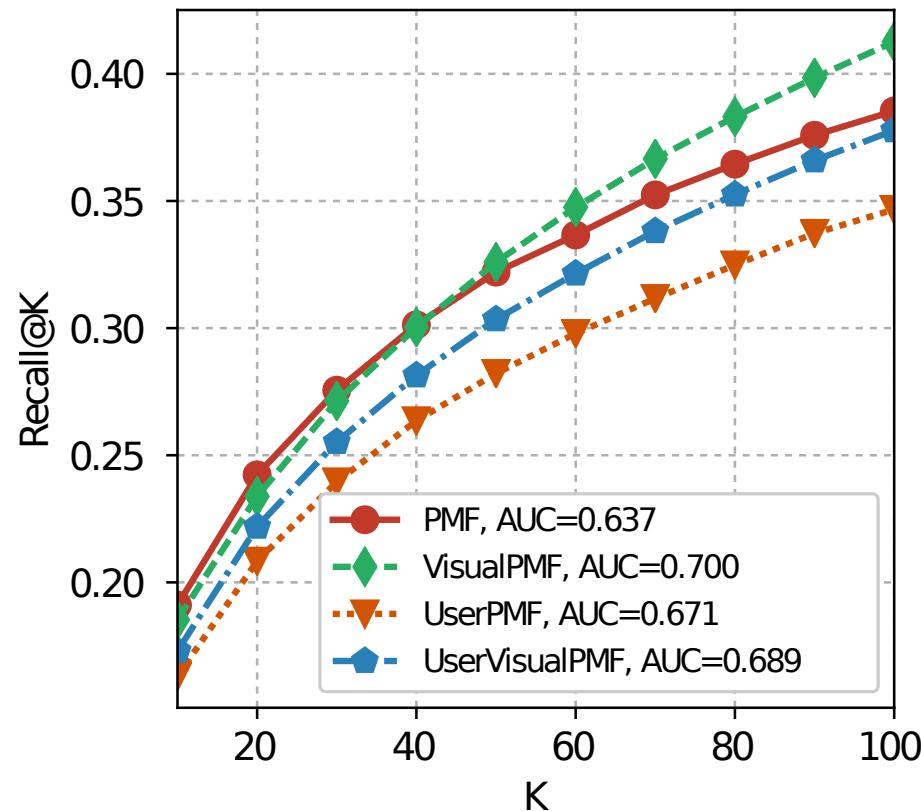
Exp 2. module selection

VisualPMF/VisualBPR/VisualCML/VisualGMF

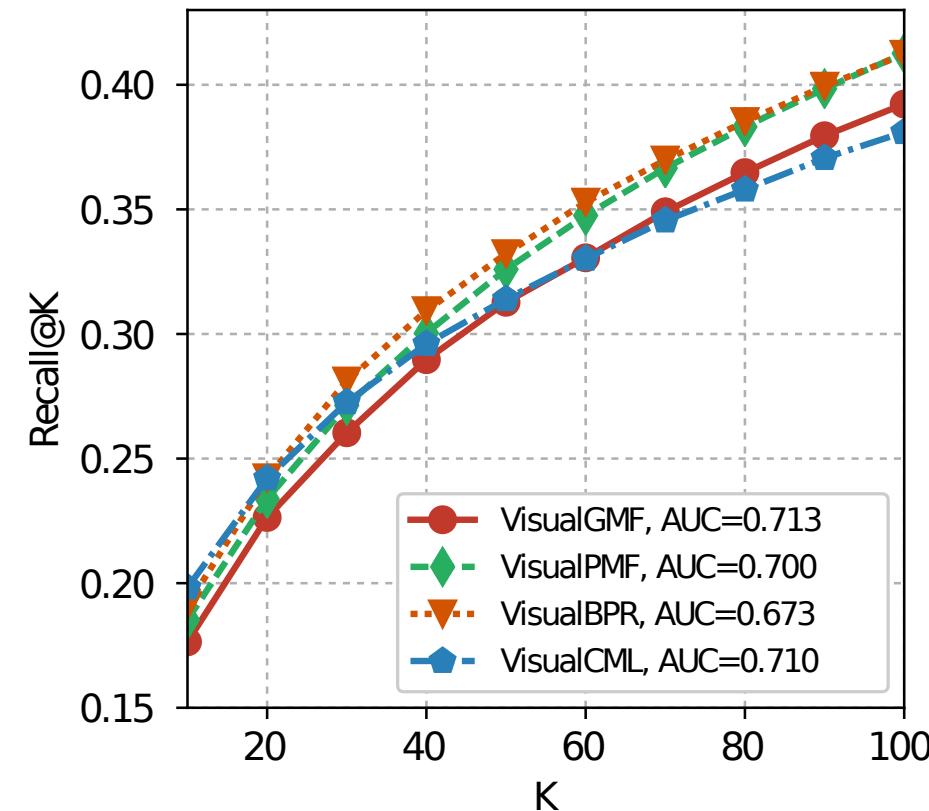


Experimental Results

Structure selection



Module selection



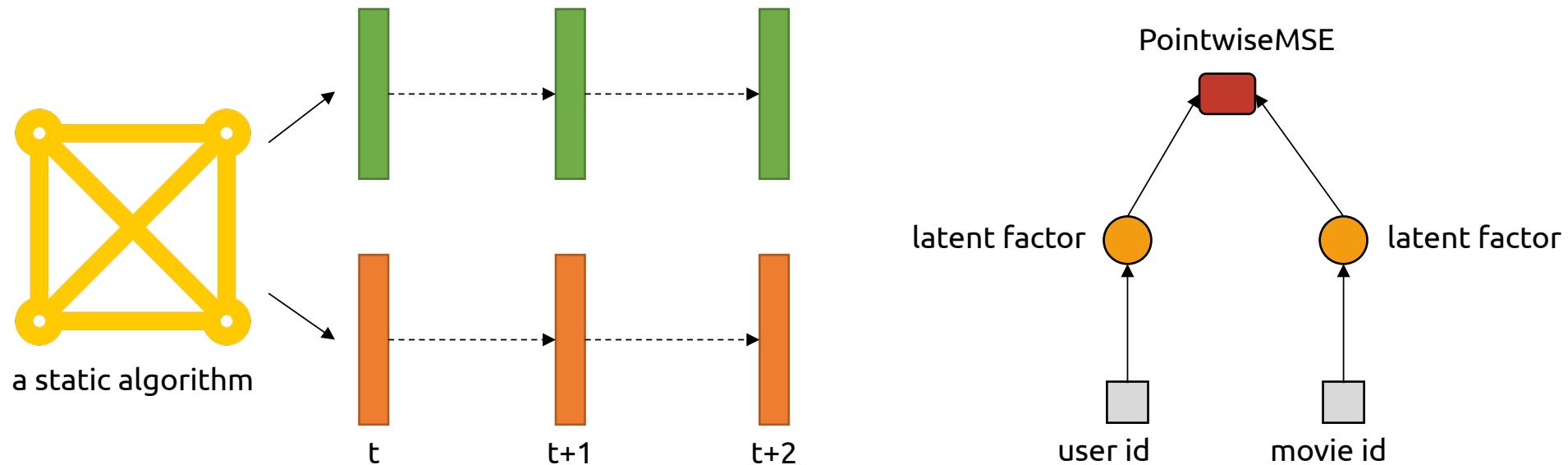
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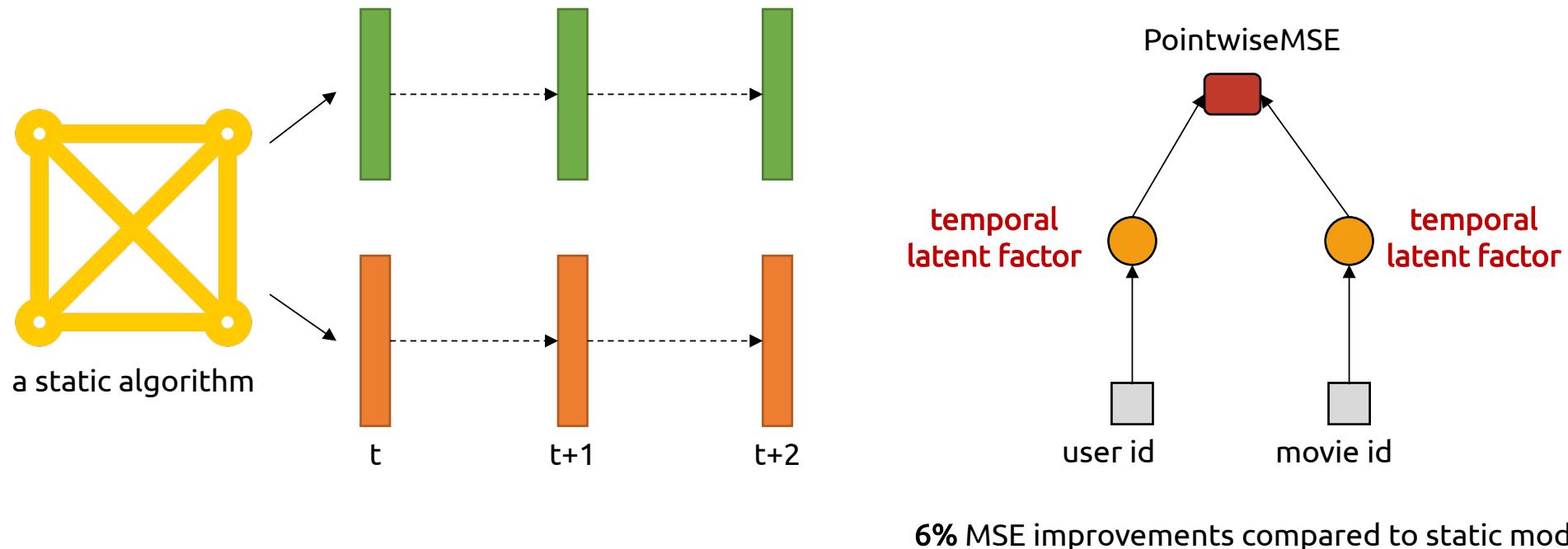
Iterative recommendation

Netflix dataset



Iterative recommendation

Netflix dataset



Takeaways

OpenRec for researchers:

- Demonstrate model generalizability.
- Facilitate comparisons.
- Encourage usage.

OpenRec for practitioners:

- Select models/parameters.
- Adapt state-of-the-art solutions.

Share the same programming model and low-level APIs with Tensorflow/Keras.

Future work

Enriching modules, recommenders and utility functions.

- Your recommendation paper/code.
- Your favorite recommendation algorithms.
- Become a contributor.

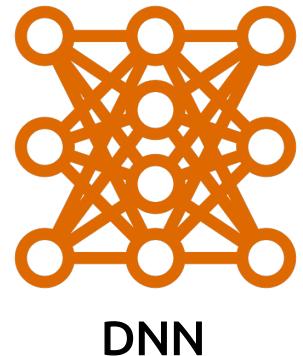
Non-neural network models.

- Tree and graph based models.

Modularity in other domains



Programming
language



DNN

Machine
language

Specify where to
store each bit

High-level
languages

OS, file system,
virtual memory

Modern
languages

More abstractions,
e.g., save, load.

Pre-cafe era

Write CUDA code
for any matrix
operation

caffe era

Some layer
implementations
in C++

Post-cafe era
(Tensorflow, Pytorch,
mxnet, etc.)

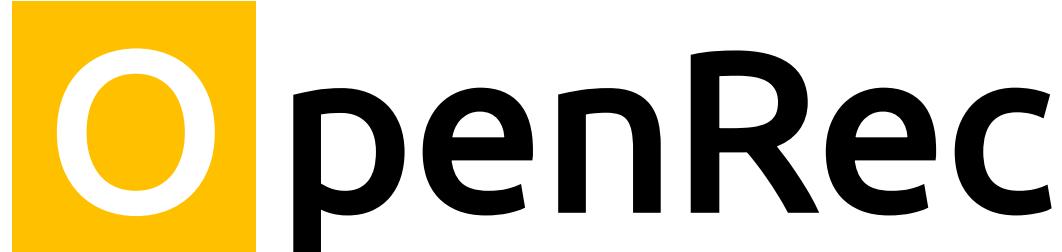
High-level python API

“You will never succeed in extracting simplicity If don’t recognize it is different from mastering complexity.”

- *Scott Shenker*

“Modularity based on abstractions is the way things get done”

- *Barbara Liskov*



<http://www.openrec.ai>

Github link, documents, and tutorials

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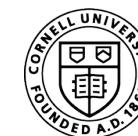
Twitter: [@ylongqi](https://twitter.com/ylongqi)

Connected Experiences Lab

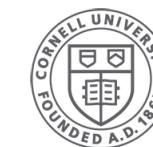
<http://cx.jacobs.cornell.edu/>

Small Data Lab

<http://smalldata.io/>



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