

# Move fast and test things

Well-rounded evaluation for  
recommendation engines



# Ciao!



## Serial Entrepreneur

- Founder of Tooso, acquired by [TSX:CVO](#)
- Led AI at Coveo from growth to IPO
- Now building [Bauplan!](#)!

## R&D at Reasonable Scale

- 25+ papers in 3 years on ML/NLP/IR ([best paper](#) at NAACL 21)
  - Collaborations with Stanford, NVIDIA, Mozilla, Farfetch, Microsoft, etc.
- Organizer of SIGIR eCommerce and [EvalRS](#)
- Adj. Prof. of [MLSys at NYU](#)

## Open source

- ~2k ★ in open source projects
- Released 3 massive e-commerce [IR datasets](#)
- Trained the 1st [industry-aware CLIP](#),  
FashionCLIP (~500k downloads in 3 months!)



# It takes a (distributed) village

- While I am the only speaker today, Patrick-John, Federico, Chloe and Ciro (and others, unfortunately without a chibi) share with me the credit for whatever value these ideas may have.
- Obviously, all the remaining mistakes are theirs 😊



*Jacopo*



*Patrick John*



*Federico*



*Chloe*



*Ciro*



# Testing ML systems is hard

(2d20 malus for IR)



Brenan Keller  
@brenankeller

A QA engineer walks into a bar. Orders a beer. Orders 0 beers. Orders 99999999999 beers. Orders a lizard. Orders -1 beers. Orders a ueicbksjdhd.

First real customer walks in and asks where the bathroom is. The bar bursts into flames, killing everyone.

4:21 PM · Nov 30, 2018 · Twitter for iPhone



# IR is everywhere



*watch next*



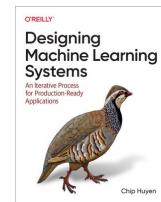
*RecSys*



*read next*



*Sponsored Search*



*buy next*



*Digital Ads*





38% of users stop shopping  
if shown non-relevant  
recommendations.\*

\*According to people selling RecSys APIs.

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Dr. Martens  
Kids' Zavala Combat Lace Up  
Boot Little/Big Kid  
\$64.99  
★ ★ ★ ★ ☆



Dr. Martens  
Women's Dorian Chelsea  
Leather Boot  
\$119.99  
★ ★ ★ ★ ☆



70% of people receive  
irrelevant ads once a  
month.\*

\*According to [what I googled](#) on my plane.

The New York Times

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*Why Are You Seeing So Many Bad Digital Ads Now?*

Scrolling past ads has rarely been enjoyable. But in recent months, people say the experience seems so much worse.



# Testing Matters\*

\*According to an editorial citing  
Tagliabue *et al* (2022).

nature machine intelligence

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Editorial | [Published: 23 February 2023](#)

**Algorithmic recommendations, anyone?**



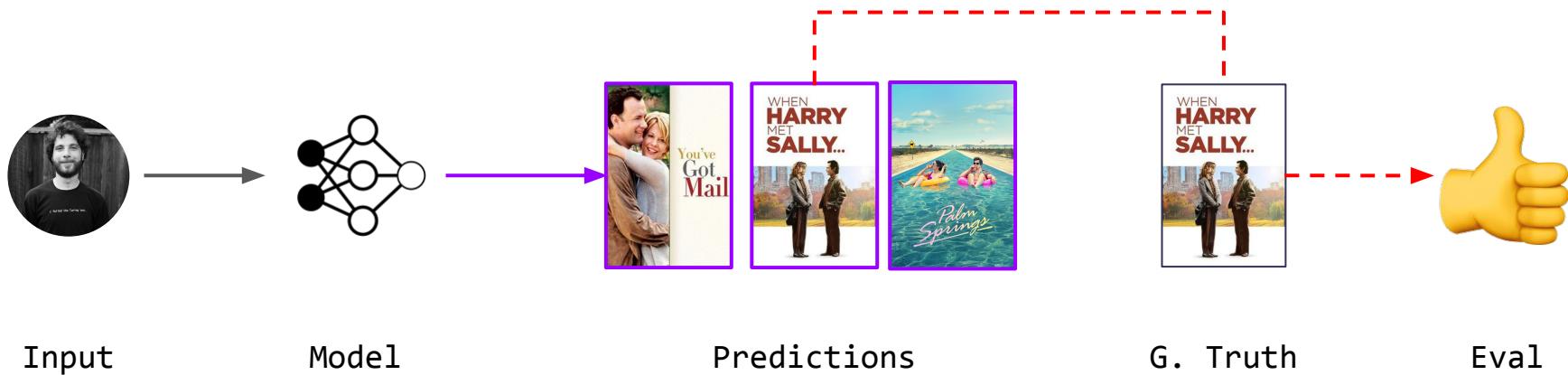
# Why do we even test?

1. Generalization
2. Model comparison



# Testing checklist

1. Create a train / test split and train a model
2. Loop over test cases with ground truths and count “successes”
3. Make a decision based on the final number: Model A KPI is 0.424, B is 0.41, *therefore A > B*





# Lies, big lies, IR metrics

1. Create a train / test split and train a model
2. Loop over test cases with ground truths and **count** “successes”
3. Make a decision based on the final number: Model A KPI is 0.424, B is 0.41, *therefore A > B*



Input

G. Truth



Predictions Model A



Predictions Model B





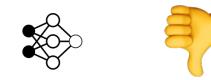
# The importance of being “less wrong”

1. Create a train / test split and train a model
2. Loop over test cases with ground truths and count “**successes**”
3. Make a decision based on the final number: Model A KPI is 0.424, B is 0.41, *therefore A > B*



Input

G. Truth



Model A



Model B



Model C



# Hit Rate is deceitful above all things

1. Create a train / test split and train a model
2. Loop over test cases with ground truths and count “successes”
3. Make a decision based on the **final number**: Model A KPI is 0.424, B is 0.41, *therefore A > B*

50 / 100  
Hits



7 / 10 Hits



VS

56 / 100  
Hits



1 / 10 Hits



HR 57/100: 0.52

HR 57/100: 0.52



# Why do we even test?

1. Generalization
2. Model comparison



# Testing Re-Imagined\*

\* In theory, there is no difference between theory and practice. In practice, there is.

## Beyond NDCG: behavioral testing of recommender systems with RecList

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### ABSTRACT

As with most Machine Learning systems, recommender systems are typically evaluated through performance metrics computed over held-out data points. However, real-world behavior is undoubtedly nuanced: *ad hoc* error analysis and tests must be employed to ensure the desired quality in actual deployments. We introduce RecList, a testing methodology providing a general plug-and-play framework

bar bursts into flames, killing everyone\* – B. Keller  
(random tweet).

In recent years, recommender systems (hence RSs) have played an indispensable role in providing personalized digital experiences to users, by fighting information overload and helping with navigating inventories often made of millions of items [5, 9, 26, 36, 39]. RSs' ability to generalize, both in industry and academia, is ofte



# From point-wise to bin-wise metrics

- Instead of reporting just HR over the full distribution, report HR per frequency!

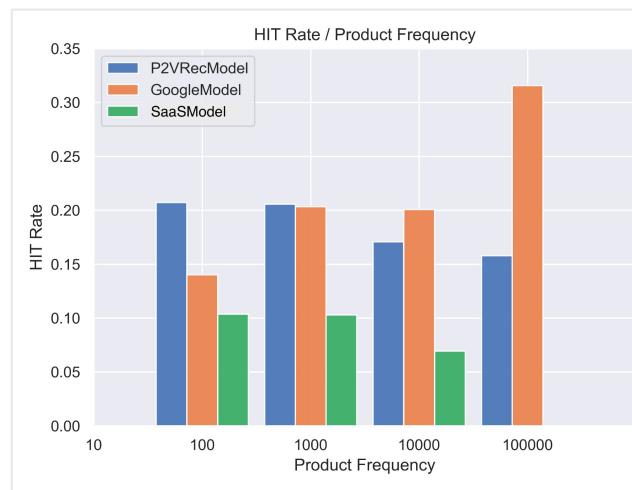


Table 1: Results for a complementary *RecList*.

| Test               | P2V            | GOO            | S1      |
|--------------------|----------------|----------------|---------|
| HR@10              | 0.197          | <b>0.199</b>   | 0.094   |
| MRR@10             | 0.091          | <b>0.102</b>   | 0.069   |
| Coverage@10        | 1.01e-2        | <b>1.99-e2</b> | 3.00e-3 |
| Popularity Bias@10 | <b>9.91e-5</b> | 1.41e-4        | 1.20e-4 |



# From point-wise to category-wise metrics

- Instead of reporting just HR over the full distribution, report HR per item type!

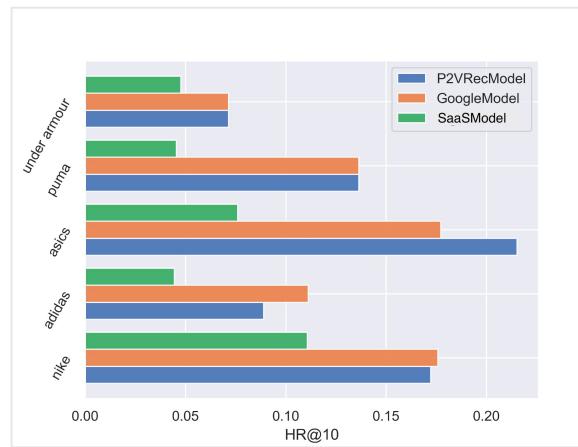


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# How do we know when something is “less wrong”?

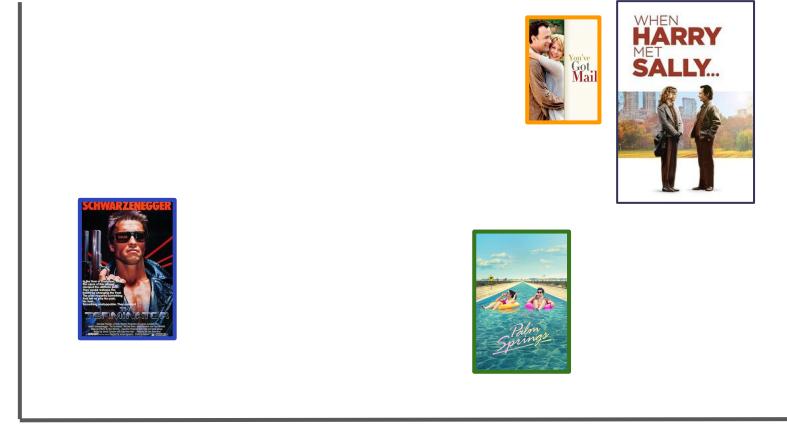
- Ideally, we would just ask people to provide similarity judgements for the mistakes! But that does not scale:
  - Use representational learning and approximate relevance as distance in the underlying space (2022);
  - Ask a Large Language Model (2023).



Input



G. Truth





# Meet RecList\*

\* Talk is cheap, show me the code

```
from reclist.datasets import CoveoDataset
from reclist.recommenders.prod2vec import CoveoP2VRecModel
from reclist.reclist import CoveoCartRecList

coveo_dataset = CoveoDataset()

model = CoveoP2VRecModel()
model.train(coveo_dataset.x_train)

# instantiate rec_list object
rec_list = CoveoCartRecList(
    model=model,
    dataset=coveo_dataset
)
# invoke rec_list to run tests
rec_list(verbose=True)
```



# The RecList project

- RecList spawned a popular open source package, the CIKM 2022 data challenge, the EVALRS23@KDD workshop, and three papers.

README.rst

## RecList

pypi v0.3.1 docs passing Python package contributors 5 License MIT downloads 5k youtube video

RecList

- Free software: MIT license
- Documentation: <https://reclist.readthedocs.io>.

### Overview

RecList is an open source library providing behavioral, "black-box" testing for recommender systems. Inspired by the pioneering work of Ribeiro et al. 2020 in NLP, we introduce a general plug-and-play procedure to scale up behavioral testing, with an easy-to-extend interface for custom use cases.

nature machine intelligence

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Challenge Accepted | Published: 26 January 2023

## A challenge for rounded evaluation of recommender systems

Jacopo Tagliabue, Federico Bianchi, Tobias Schnabel, Giuseppe Attanasio, Ciro Greco, Gabriel de Souza Moreira & Patrick John Chia

README.md

## EvalRS-KDD-2023

Official Repository for EvalRS @ KDD 2023, the Second Edition of the workshop on well-rounded evaluation of recommender systems.

Open in Colab

*EvalRS23*

### A ROUNDED EVALUATION OF RECOMMENDER SYSTEMS



# EvalRS @ KDD: papers, hackathon, party

- 2 keynotes
- 5 talks
- 1 new open dataset
- \$2500 in hackathon prizes
- Unlimited\* drinks

\* Conditions apply!



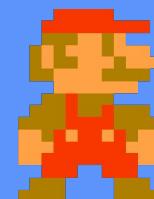
<https://reclist.io/kdd2023-cup/>



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