

Session-based Complementary Fashion Recommendations

Jui-Chieh Wu, José Antonio Sánchez Rodríguez, Humberto Corona

WE OFFER A SUCCESSFUL AND CURATED ASSORTMENT

> 400,000

articles from

> 2,000

international brands



**HIGHLY
EXPERIENCED**
category management



11 private
labels



LOCALIZATION

of the assortment

**CURATED
SHOPPING**

with Zalon

About Zalando

Assortment



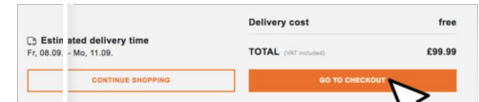
> 400,000



> 2,000

Brands

Active Customers



Wear it with



> 28 m

What is Complementary Item Recommendation?



Perfect pairings You might also like

[See more >](#)



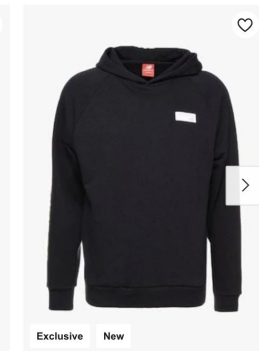
29,95 €
Print T-shirt - white/lime
New Balance



29,95 €
SPORT STYLE OPTIKS - Print T-shirt - black
New Balance



59,95 €
OLD SCHOOL - Sweatshirt - grey
Gianni Kavanagh



74,95 €
Hoodie - black lime
New Balance

Our Baseline

- Based on item-item collaborative filtering
- High score items in different category
- Items similar to high score items if not enough recommendations

Limitations of the Baseline

- Static recommendation for everyone
- Low CTR
- Low conversion rate

Problem Statement

For a given user with an interaction history x_h and the anchor item x_t ,
Select a list of complementary items y_1, y_2, \dots, y_k from a set of candidates y .

$$y_1, y_2, \dots, y_k \sim p(y \mid x_h, x_t)$$

How We Define Complementary Relationship

Two items x_i and x_j are complementary if they

1. Belong to different categories (shoe v.s. trousers)
2. Belong to two fashion-compatible categories

Problem Statement

$$\boxed{y_1, y_2, \dots, y_k} \sim p(\textcircled{y} \mid x_h, x_t)$$

Complementary of x_t Whole Catalog

The diagram illustrates a probabilistic model for recommendation. It shows the equation $y_1, y_2, \dots, y_k \sim p(y \mid x_h, x_t)$. The observed responses y_1, y_2, \dots, y_k are enclosed in a red box, with a red arrow pointing to the text 'Complementary of x_t '. The variable y in the probability function is circled in blue, with a blue arrow pointing to the text 'Whole Catalog'.

- Learn from the existing user response on the current baseline
- Learn from the re-sampled dataset

Creating a More Representative Dataset

Training a new model on top of the training data coming from the baseline constraints the capacity of the abstractions learned by the new model.

Solution

Instead of learning from the user behavior we observed on the current product, we sample behaviors from the *user interaction history* that satisfy our definition of complementary.

Creating a More Representative Dataset

User
Interaction
history

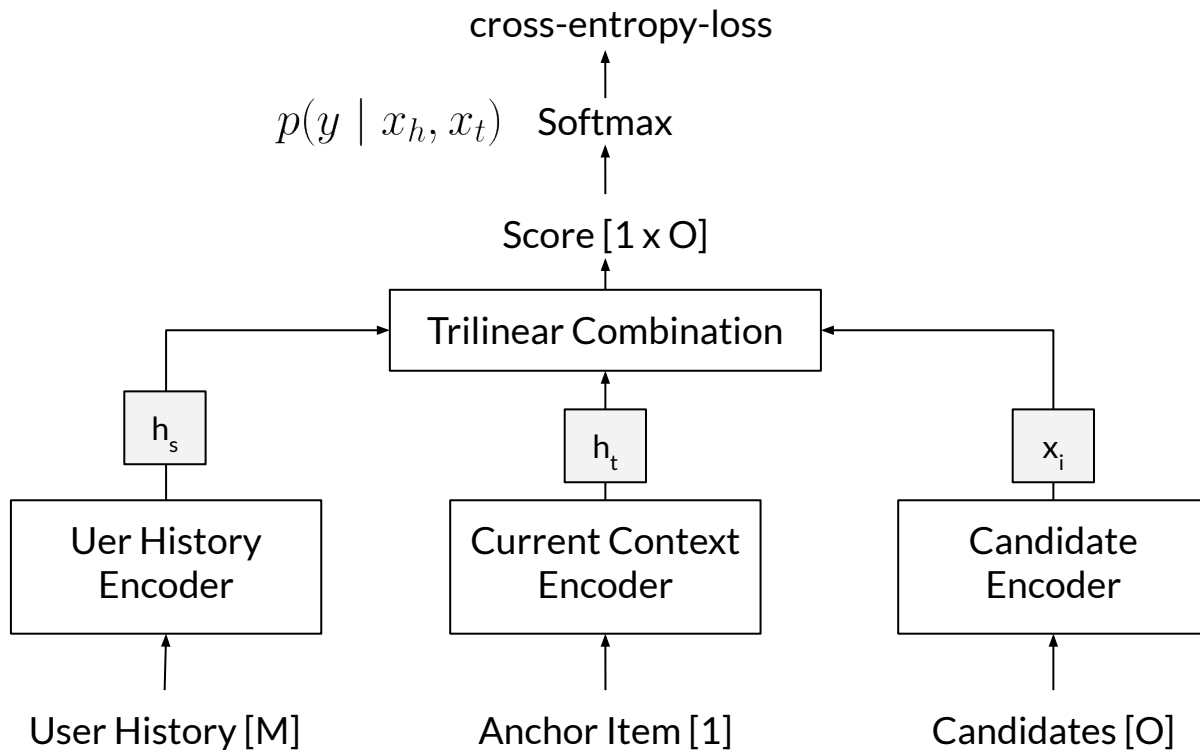


Timeline

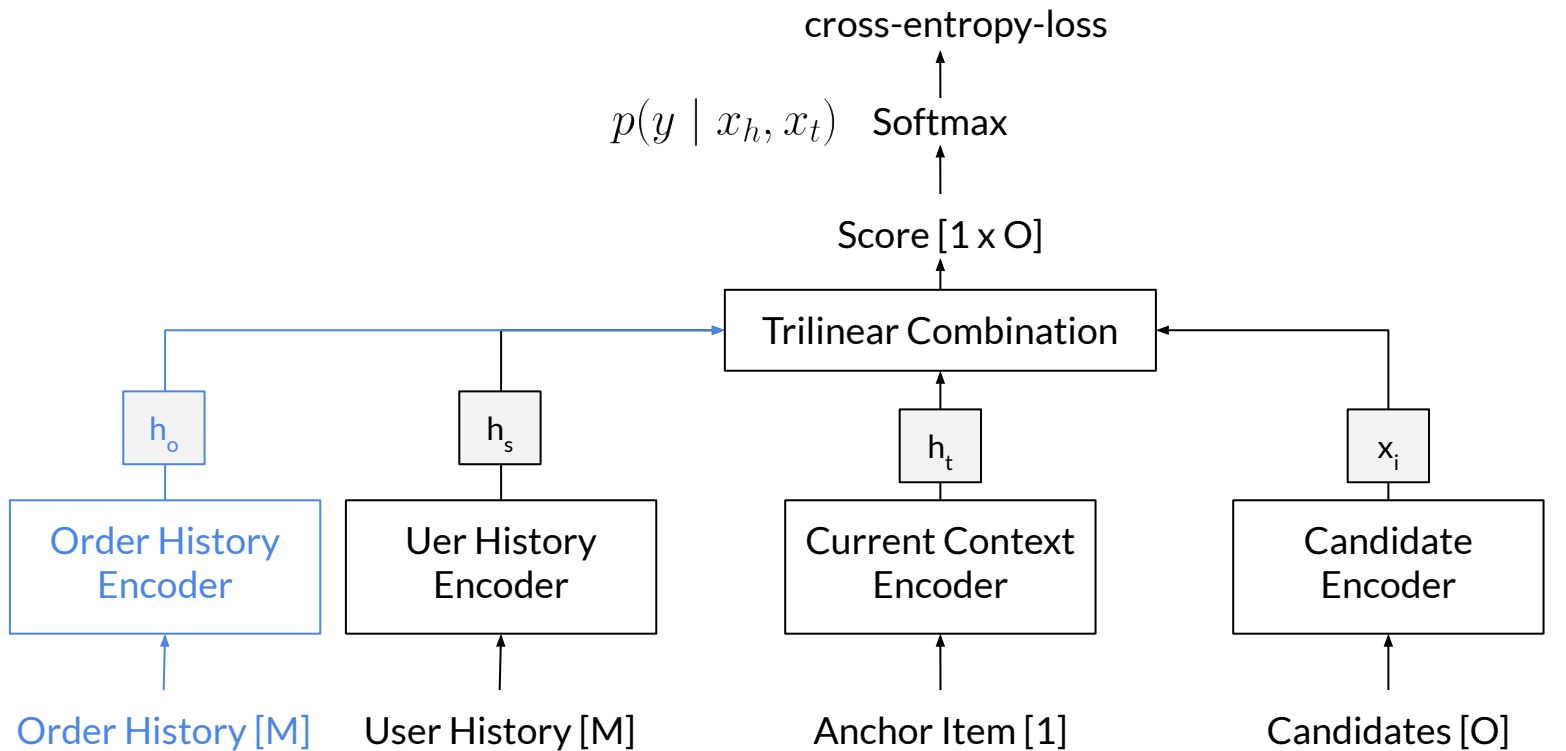
Creating a More Representative Dataset



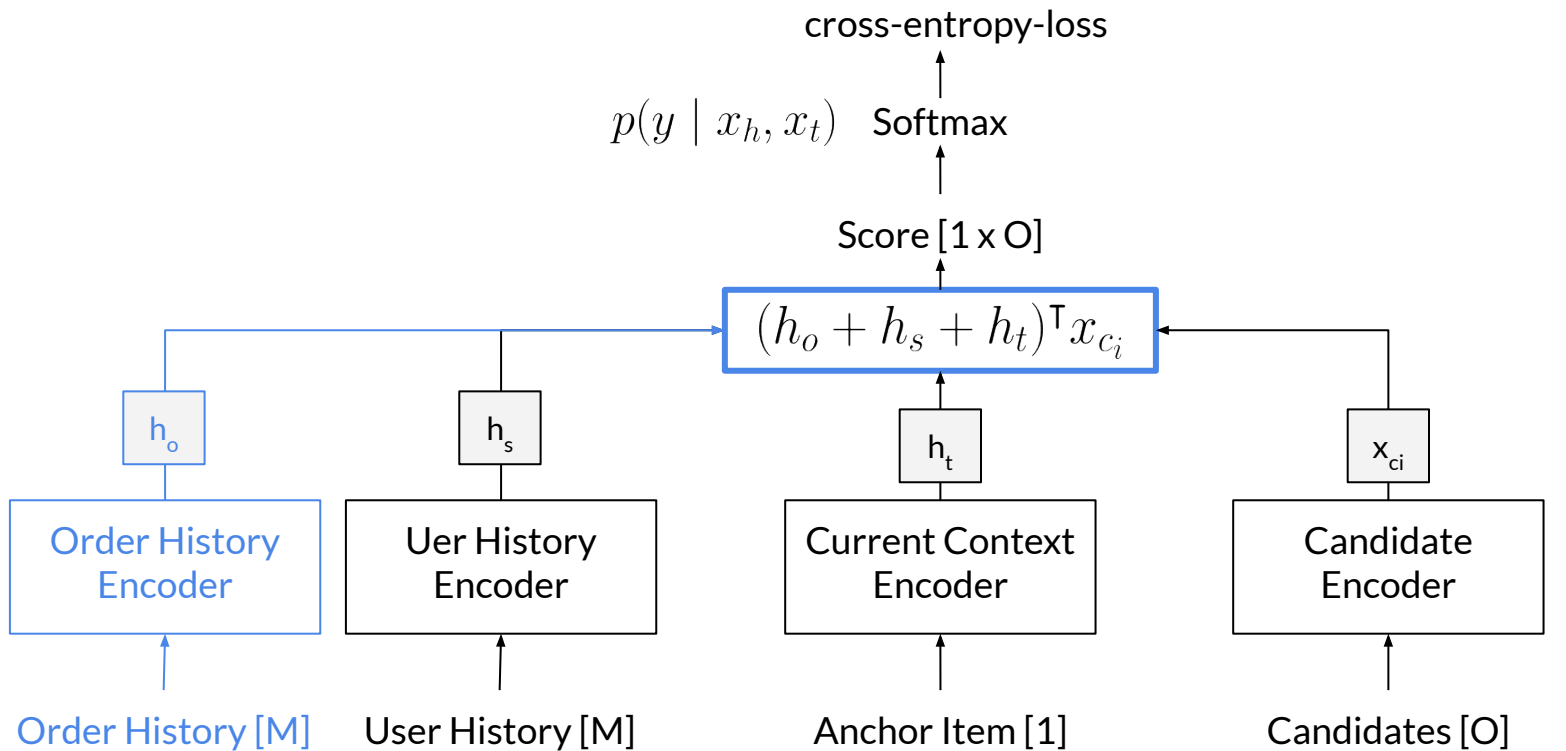
Model Architecture



Our Adjustments - Add Long Term Signals



Our Adjustments - Additive Combination Function



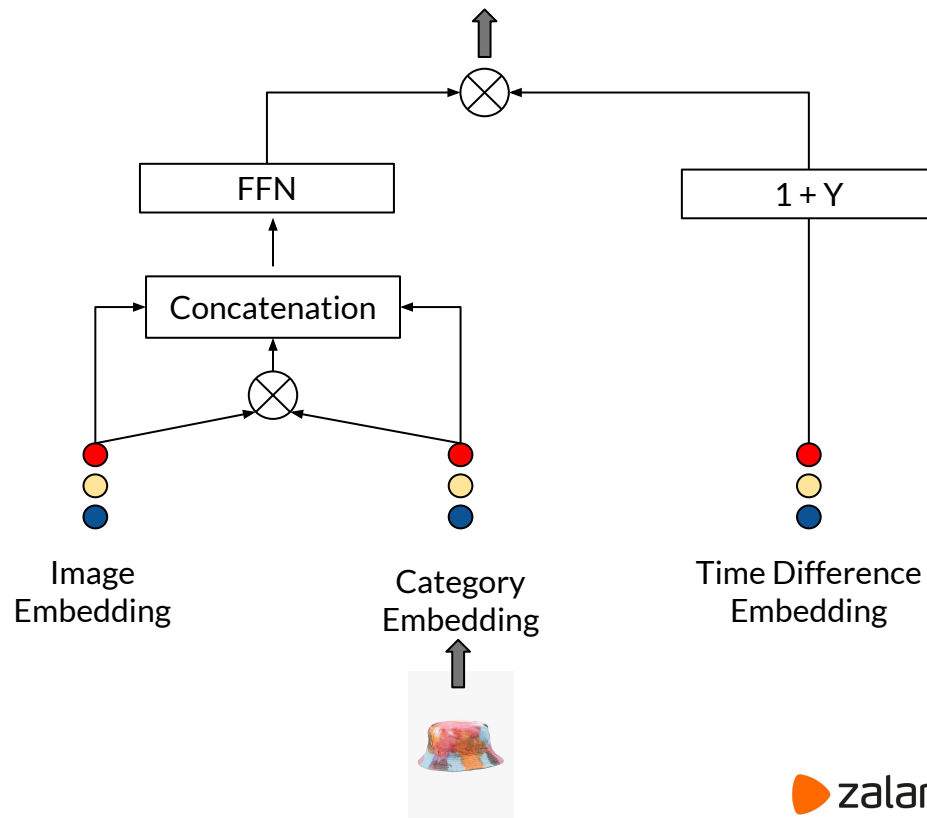
Our Adjustments - Context Information Added

STAMP



v.s.

Our Model



Evaluation Results - Offline

	Recall@5	Order Recall@5
Our Method	0.26	0.26
Collaborative Filtering	0.29	0.24

Evaluation Results - Online A/B Test

	CTR	# Items Ordered
Our Method	+6.23%	+3.24%

Evaluation Results - Offline Ablation Test

	Recall@5	Order Recall@5
STAMP	0.221	0.206
STAMP + Long Term Signal	0.241	0.223
STAMP + Context Information	0.258	0.255
STAMP + Image Feature	0.264	0.240
Our Method	0.264	0.267

Conclusion

- We devised a personalized complementary fashion recommender that outperformed the baseline in an A/B test.
- We tailored STAMP, one of the state-of-the-art session recommenders, and yields better performance on our dataset.
- Through the ablation test, we assures the efficacy of the model improvements



QUESTIONS?