Towards User-in-the-Loop Online Fashion Size Recommendation with Low Cognitive Load

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Size Recommendation

What are we trying to solve?

Given a customer c and an article a recommend size s^*

$$s^* = \operatorname{argmax}\left(P(R = kept, S = s | C = c, A = a)\right)$$

where R is the return status of the order.

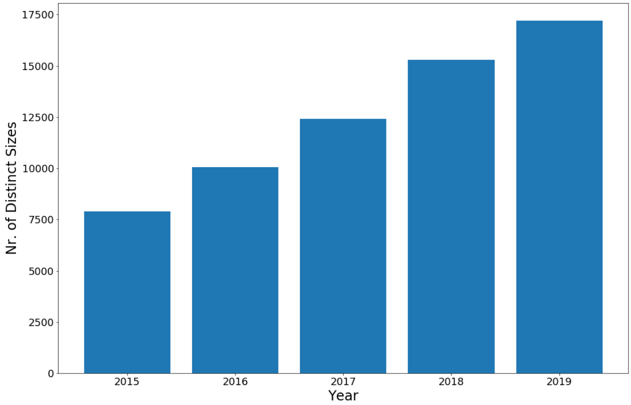
Why is it important?

- Customer Experience.
- Platform Profits.
- Environmental Impact.

Why is it difficult?

- Limitations and Coarseness of Sizing Systems.
- Grading from Target Sizes.
- Variety of Sizing Systems.
- Non-Standardization of Sizing Systems.
- Vanity Sizing.
- Subjective Aspect of Size and Fit.

Size Problem Complexity



Distinct Apparel Sizes

Assume customer c has bought article a in multiple sizes returning some.

- Customer offset

$$o_{ca} = \frac{1}{K_{ca}} \sum_{k=1}^{K_{ca}} s_{cak} - \frac{1}{R_{ca}} \sum_{r=1}^{R_{ca}} s_{car}$$

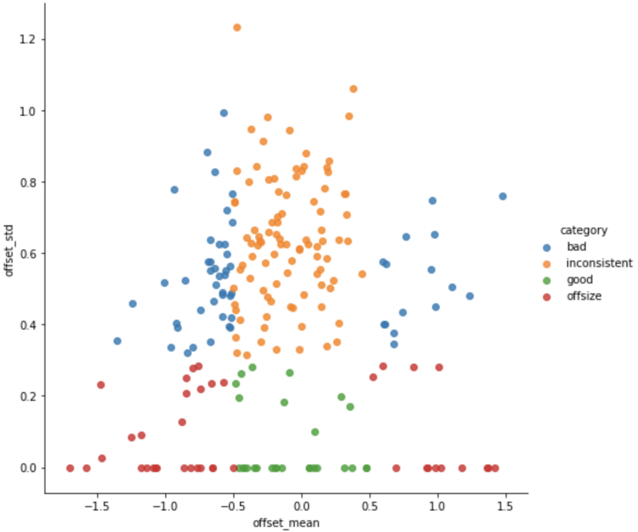
- Article offset distribution

$$\mathcal{N}_a \left(\frac{1}{N_C} \sum_{c=1}^{N_C} o_{ca}, \frac{1}{N_C - 1} \sum_{c=1}^{N_C} (o_{ca} - \mu_a)^2 \right)$$

If article a_i belonging to brand b has sales w_i.

- Brand offset distribution

$$\mathcal{N}_b\left(\frac{1}{\sum_{i=1}^{N_A} w_i}\sum_{i=1}^{N_A} w_i \mu_{a_i}, \frac{1}{\sum_{i=1}^{N_A} w_i}\sum_{i=1}^{N_A} w_i (\mu_{ai} - \mu_b)^2\right)$$



Brand Size Offsets σ,μ

- Size tables, article measurements.
- Article based size advice.
- Personalized order history based size reco.
- Customer in the loop personalized size reco.
- Computer vision and 3D approaches.

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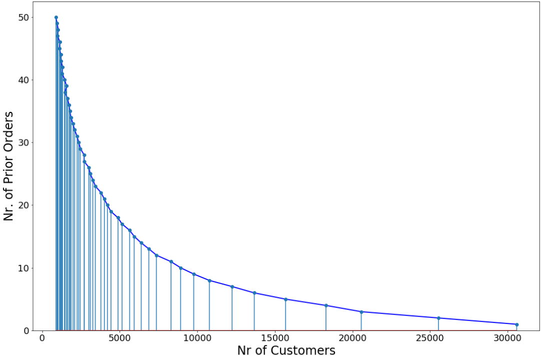
Cold Start



Number of customers vs. number of prior orders.

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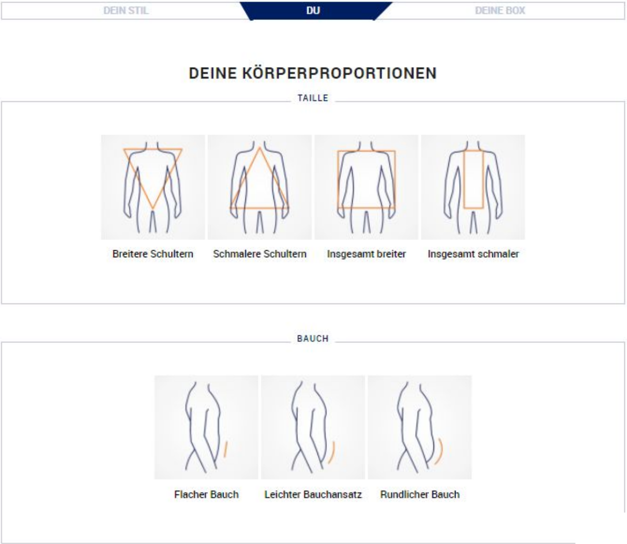
→ **Zalon** (styling service)

Type	Features
Overall	weight, height, age, gender
Upper body	top size, shirt collar size, shirt fit, proportion belly, top fit, proportion shoulder-waist, bust number, bust cup size, proportion shoulder-hip, blazer size
Lower body	pants size, jeans length, jeans width, proportion waist, pants waist-height , shoe size

Questionnaire Example



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Unfortunately that is not how it works :(

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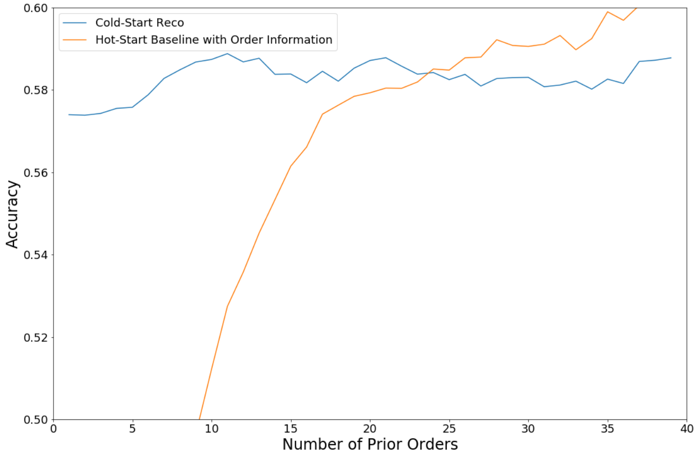
- Customers tend to under-report their size.
- Male Customers are more likely to under-report their size.

Then let's do ML!

Cross-validation experiments highlighted the benefits of **Gradient Boosted Trees.**

- An ensemble of Classification Trees built sequentially with boosting.
- Strong Performance + Interpretability + Robust to Overfitting.

Cold-Start Performance



The presented solution requires us to ask 20 size-related questions from the customer.

$\rightarrow$ This requires high engagement from the customer!

Cognitive Load

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→ This requires high engagement from the customer!

Can we retain performance while reducing cognitive load?

Performance vs Cognitive Load

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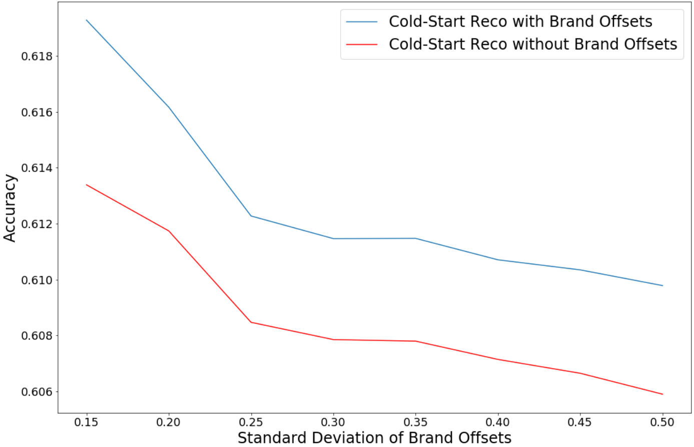
Top Size + Brand is the best alternative solution.

Dialogue Tile

Impact of Brand Offsets



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None of the presented solutions use order information.

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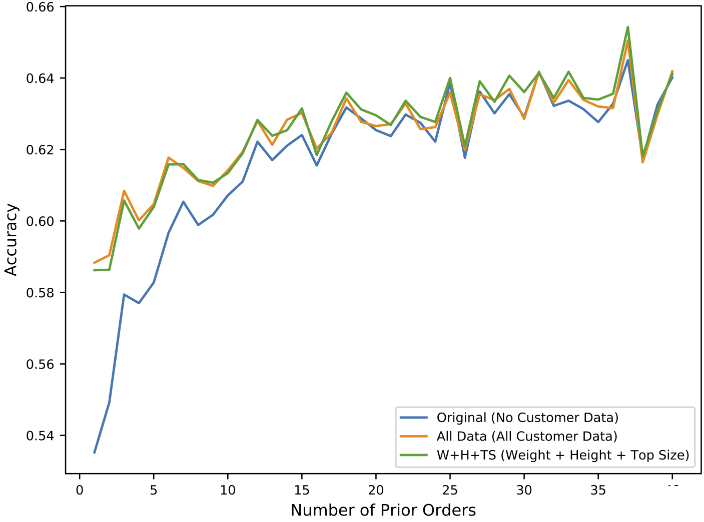
→ Can we build a personalized reco that leverages both forms of data?

→ Do our findings continue to hold in this case?

MetalSF (Lasserre et al. 2020)



Questions?