Click A, Buy B: Rethinking Conversion Attribution in E-Commerce Recommendations

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Executive Summary

- Users often click Product A but purchase Product B — the CABB problem.
- 44% of conversions show CABB behavior.
- Traditional attribution over-rewards clicks that correlate, not cause.
- Our approach: multitask learning with similarity-weighted CABB signals.

Agenda & Roadmap

- The CABB Problem (5 min)
- Our Multitask Solution (8 min)
- Experimental Results (7 min)
- Future Work & Discussion (5 min)

THE CABB PROBLEM

Understanding user behavior and model bias

The CABB Phenomenon

- • Click A → Buy B violates standard attribution.
- • 3 scenarios:
-   1. CABA – Buy what you click.
-   2. Meaningful CABB – Buy a related item.
-   3. Noisy CABB – Buy an unrelated item.

Scale of the Problem

- • 44% of conversions = CABB.
- • 81% of buys are within same product set.
- • Biased attribution reduces recommendation diversity.

Why Traditional Models Fail

- • Last-click attribution = correlation ≠ causation.
- • Example: Click iPhone, buy iPad, iPhone gets credit.
- • Leads to overvaluing popular click-inducing products.

Business Impact

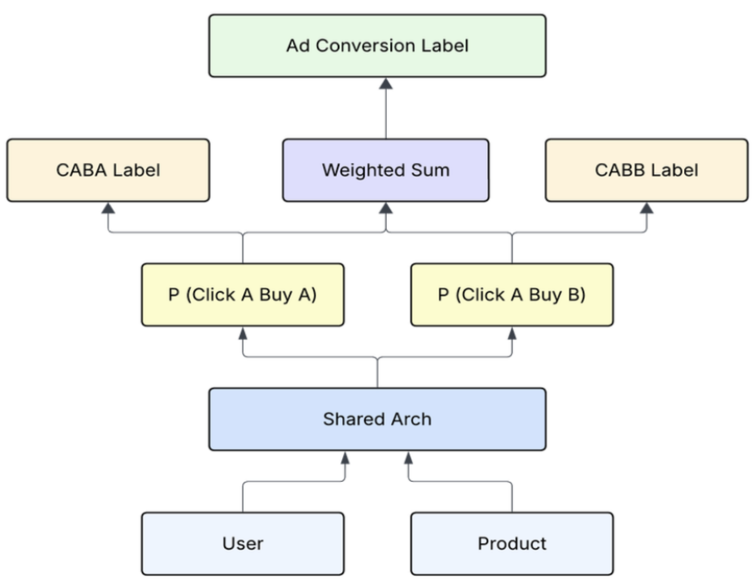
- • Suboptimal recommendations.
- • Advertisers undervalued or over-credited.
- • Misaligned incentives for diversity and user satisfaction.

TECHNICAL SOLUTION

Multitask architecture and similarity-aware weighting

Our Approach Overview

- • Multitask Learning + Similarity Weighting.
- • Two heads:
- - CABA: Click A → Buy A.
- - CABB: Click A → Buy B.
- • Similarity-aware reweighting based on taxonomy.



Multitask Architecture

- • Shared embedding layers for features.
- • Separate output layers for CABA and CABB.
- • Loss functions combined with weight λ.

Taxonomy-Aware Similarity

- • Products mapped to leaf taxonomy categories.
- • Co-engagement patterns aggregated at category level.
- • Similarity matrix via collaborative filtering.

Similarity Weighting Formula

- • Category vector $v_c \in \mathbb{R}^{|U|}$ from user interactions.
- • Cosine similarity: $S(c_i, c_j)$.
- • Final weight: $\alpha^{(AB)} = S(cat(A), cat(B))$.

Training Objective

- • CABA Loss: Binary cross-entropy.
- • CABB Loss: Weighted cross-entropy.
- • Final loss: $\mathcal{L} = \mathcal{L}$_CABA + λ $\mathcal{L}$_CABB.

EXPERIMENTAL RESULTS

Offline and online validation of model performance

Experimental Setup

- • Real-world e-commerce session logs.
- • CABA and CABB events identified.
- • Normalized Entropy (NE) as evaluation metric.

Overall Performance

- • 13.9% reduction in NE vs. last-click baseline.
- • NE dropped from 0.575 → 0.495.
- • Validates benefit of CABB-aware multitask model.

Task-Level Analysis

- • CABB performance improves as λ increases.
- • Optimal λ = 0.75 (balanced NE across tasks).
- • Joint training enhances both CABA and CABB.

Online A/B Test Results

- • +0.25% lift in business metric.
- • +1.27% increase in CABA rate.
- • More relevant, personalized recommendations.

ANALYSIS & DISCUSSION

Deep dive into weighting, features, and limitations

Ablation Studies

- • Static weighting introduces noise.
- • i2i similarity underperforms.
- • Taxonomy + CF yields best CABA NE (0.441).

Feature Importance Analysis

- • CABA: Personalization-heavy (e.g., past views).
- • CABB: Semi-personalized + popularity-based signals.
- • Confirms differences in task dependencies.

Limitations & Challenges

- • Taxonomy quality sensitivity.
- • Noisy co-engagement signals.
- • λ tuning requires careful experimentation.

FUTURE WORK & CONCLUSION

Expanding the CABB framework

Future Directions

- • LLM-based similarity labeling.
- • Dynamic λ via attention-based learning.
- • Extend attribution beyond session boundaries.

Key Takeaways

- • CABB: 44% of conversions, major attribution challenge.
- • Solution: Multitask + taxonomy similarity weighting.
- • Results: 13.9% NE drop, +0.25% online lift.
- • Deployment: Running successfully in production.

Questions & Discussion

- • Thank you!
- • Questions?
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- • Paper: AdKDD 2025 - Click A, Buy B