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Scalable and Interpretable Contextual Bandits: A Literature Review and Retail Offer Prototype

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Introduction to Contextual Multi-Armed Bandits (CMABs)

- **What are CMABs?**
  - Framework for sequential decision-making under uncertainty
  - Agent learns to select actions (arms) based on observed contextual information
  - Goal: Maximize cumulative rewards over time
- **Exploration-Exploitation Dilemma:**
  - Balancing trying new actions to gather information and choosing actions known to yield high rewards
- **Use Case:** Personalized recommendations
- **Motivation for this Paper:**
  - Reviews key aspects of contextual bandits and outlines a prototype system
  - Prototype designed to explore approaches for addressing challenges such as interpretability, scalability, and practical deployment, particularly in a retail context

Key Challenges & Proposed Approach

- **Challenges in Retail Offer Selection:**
  - Addressing the challenge of fast-changing offers
  - Need for scalable and interpretable solutions
- **Proposed Approach Overview:**
  - Models context at the product category level, allowing offers to span multiple categories
  - Enables knowledge transfer across similar offers
  - Achieves scalability through efficient feature engineering and modular design
  - Utilizes advanced features such as MPG (Member Purchase Gap) and MF (Matrix Factorization)
- **Key Contribution: Interpretability at Scale:**
  - Logistic regression models yield transparent weight vectors
  - Accessible via a Large Language Model (LLM) interface for real-time, user-level tracking and explanation of evolving preferences

Literature Review: Algorithm Families

- **Upper Confidence Bound (UCB) Strategies:**
  - Estimate expected rewards, construct upper confidence bounds (UCBs), and select the arm with the highest UCB
  - **LinUCB:** Seminal algorithm, models expected rewards as a linear function
  - **Generalized Linear Models (GLMs):** LogisticUCB developed for binary outcomes
  - **Neural Network-based UCB:** NeuralUCB leverages deep learning to capture complex non-linear relationships
- **Epsilon-Greedy (ϵ-Greedy) Methods:**
  - Balances exploration (random action with probability ϵ) and exploitation (highest estimated reward with probability $1 - \epsilon$)
  - Ease of implementation and compatibility with various reward prediction models
- **Posterior Sampling (Thompson Sampling - TS):**
  - Bayesian approach, maintains a posterior distribution over reward model parameters
  - Noted for strong empirical performance, often outperforming UCB methods

Prototype Scope and Assumptions

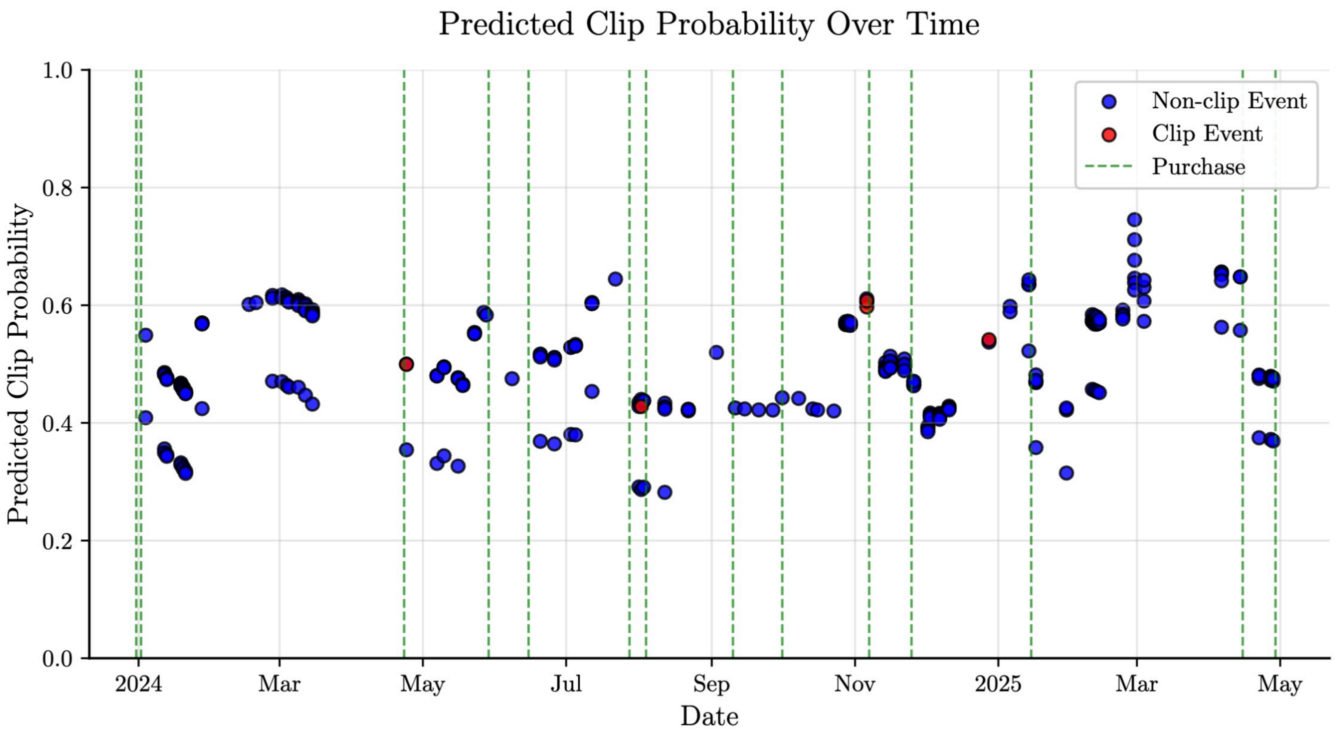
- **Model Used:** Online logistic regression with stochastic gradient descent (SGD) for binary outcomes
  - $P(y=1|x;w) = \sigma(w^I x)$, where $\sigma(z) = \frac{1}{1+e^{-z}}$
- **Context Features ($x_{t,a}$):**
  - Pre-defined user/item characteristics from upstream models
  - Examples: Member Purchase Gap (MPG), brand loyalty, seasonality, offer recency/duration, discount value, and matrix factorization (MF) scores as a bias
  - Does *not* use learned latent representations or dynamic feature adaptation
- **Online Weight Updates:**
  - SGD: $w \leftarrow w + \eta(y - \sigma(w^T x))x$,, optional boost $\alpha > 1$ for positive samples
  - Weights initialized using domain knowledge (or zeros) and backfitted on historical data
- **Key Feature: Interpretability via LLMs:**
  - Tracking member-specific weight trajectories over time
  - Accessible to Large Language Models (LLMs) for generating user-level explanations and behavioral personas
- **Exploration Strategy:** Randomized scoring via Beta distributions
  - $\tilde{p}_{o,m} \sim Beta(\kappa p_{o,m}, \kappa(1 - p_{o,m}))$, where κ can increase to reduce exploration over time

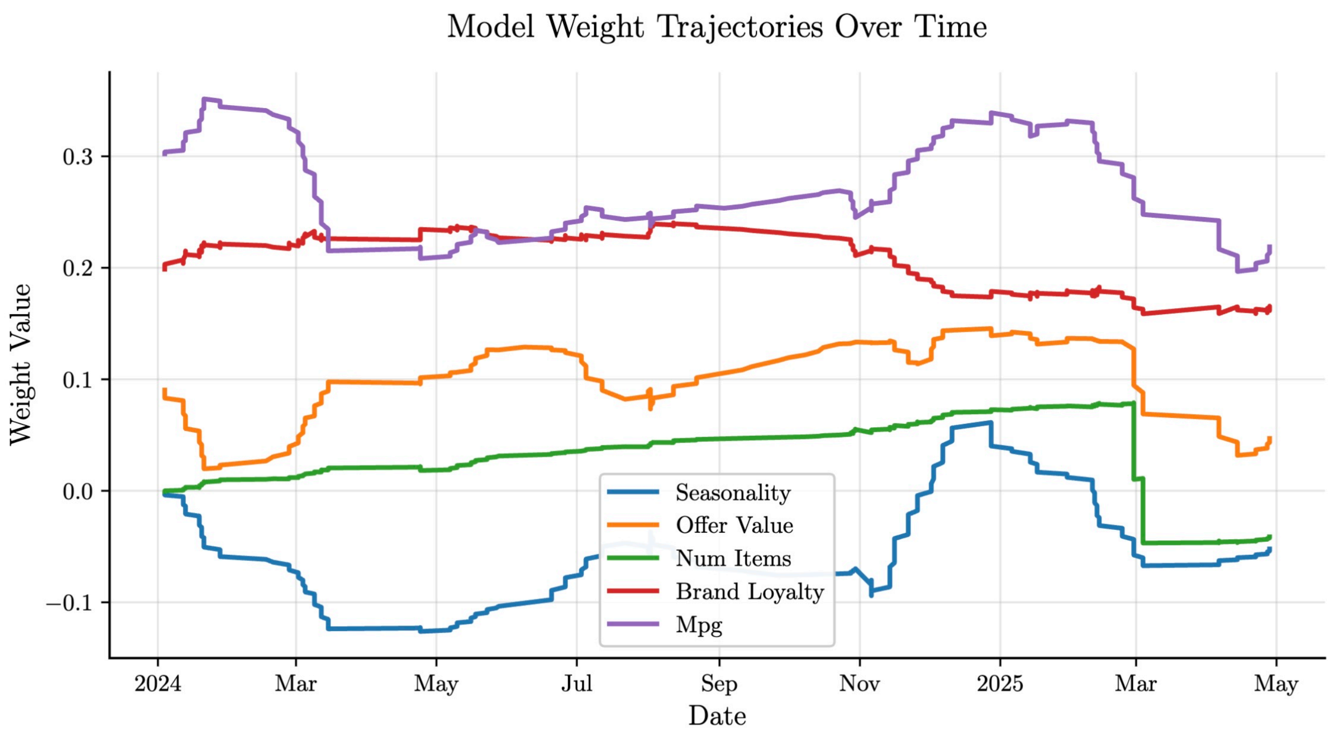
Experiment Design & Workflow

- **Experimental Setup:**
  - Contextual bandit model with logistic regression and stochastic gradient descent (SGD) for online learning
  - Processes real retail transaction logs to predict offer clip probabilities
  - Simulates a coupon gallery where users receive offers described by features like MPG, brand loyalty, seasonality, etc.
- **Two-Level Approach:**
  - Category-level logistic regression models predict clip probabilities
  - Probabilities are then aggregated to the offer level
- **Data Preprocessing:** All features are z-score normalized
- **Learning Process:**
  - CAMB algorithm first batch-trained on historical data (simulating PySpark)
  - Then learns online via SGD

Results: Interpretability through Weight Trajectories

- **Visualizations:**
  - Model weight trajectories over time
    - Shows how different features' influence evolves during the simulation
- ***AI-Generated Member Profiles (Example from LLM analysis):***
  - **Overall Profile:** "Overall, this is a brand-loyal, non-seasonal member whose clip behavior is timed around replenishment cycles and increasingly influenced by offer size rather than pure discount depth."
- **Benefit:** Such AI-generated interpretations enable personalized offer optimization.


Predicted Clip Probability Over Time
Predicted Clip Probability
1.0
0.8
0.6
0.4
0.2
0.0
2024
Mar
May
Jul
Sep
Nov
2025
Mar
May
Date
Non-clip Event
Clip Event
Purchase


Model Weight Trajectories Over Time
Weight Value
0.3
0.2
0.1
0.0
−0.1
2024
Mar
May
Jul
Sep
Nov
2025
Mar
May
Date
Seasonality
Offer Value
Num Items
Brand Loyalty
Mpg

Limitations

- **Operational Viability (Production Scale)**
- **Performance Benchmarking**
- **Feature Utility & Assumptions:**
  - Empirical utility of current features (e.g., MPG, MF scores) under real-world distribution shifts requires further validation
  - Assumption of stable conditions requires further validation, particularly for dynamic settings
- **Interpretability Evaluation:**
  - Practical benefits of interpretability from model outputs like weight trajectories need formal user evaluation

Future Work

- **Empirical Validation:**
  - Prioritize empirical validation via A/B tests and offline replay
- **Feature Representation:**
  - Developing richer, yet interpretable, feature representations (e.g., deep embeddings, hybrid models)
- **Temporal Adaptation:**
  - Incorporating temporal adaptation mechanisms (e.g., D-LinUCB variants) to handle non-stationarity
- **Exploration Strategies:**
  - Exploring theoretically grounded exploration strategies
- **Multi-objective Optimization:**
  - Supporting multi-objective reward functions like long-term customer value, revenue or customer engagement

Conclusion

- **Dynamic Field:** The field of contextual bandits is dynamic and rapidly advancing, expanding algorithmic sophistication, theoretical insight, and real-world applicability
- **Foundational Algorithms:** LinUCB, Epsilon-Greedy, and Thompson Sampling, with linear and logistic regression models, provide essential underpinnings
- **Emphasis on Scalability & Interpretability:** Recent work increasingly emphasizes scalability for millions of users and offers, and interpretability via LLMs for actionable insights
- **Our Prototype's Contribution:**
  - Demonstrates a scalable and interpretable contextual bandit framework
  - Leverages logistic regression with static features in a stationary environment
  - Crucially, exposes model weights in a form that can be directly interpreted by LLMs for transparent, user-level explanations
- **Significance:** Offers a controlled environment for investigating bandit behavior, while also highlighting the potential for interpretable, AI-powered personalization at production scale.
- **Next Steps:** Substantial empirical and technical refinement is necessary.