An Introduction to E-Commerce

with a Focus on Machine Learning, Deep Learning, and Artificial Intelligence

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Session plan (90 minutes)

1. Foundations: e-commerce as a socio-technical system (10 min)
2. AI/ML/DL essentials for e-commerce (10 min)
3. ML across the e-commerce lifecycle (30 min)
4. Deep learning in modern commerce stacks (20 min)
5. Data/architecture/MLOps + evaluation (15 min)
6. Risks, ethics, and future directions (5 min)

Learning objectives

By the end of this lecture, you should be able to:

- Explain core e-commerce models (B2C, B2B, C2C, C2B) and the value chain.
- Map AI/ML/DL techniques to e-commerce use-cases (recsys, search, pricing, fraud, forecasting).
- Reason about offline training vs. online serving, experimentation, and monitoring.
- Identify key risks (bias, privacy, explainability, cost) and mitigation strategies.

What is e-commerce?

Definition

Buying and selling goods/services over electronic networks (primarily the internet).

Common transaction models

- B2C (online retail)
- B2B (procurement platforms)
- C2C (marketplaces)
- C2B (influencers, freelancing)

Why it matters for AI

- High-velocity decisions
- Strong feedback loops
- Massive behavioral data

E-commerce as a socio-technical system

Product-facing

- Web / mobile / conversational UI
- Catalog, cart, checkout
- Reviews, Q&A, support

Back-end & operations

- Payments + risk engine
- Fulfillment + logistics
- Data pipelines + analytics
- AI/ML services (ranking, prediction, automation)

Key idea

The **platform** is the product; ML models are **components** inside a larger system.

The e-commerce value chain (where AI shows up)

1. **Acquire** traffic (ads, SEO, targeting)
2. **Discover** products (search, recommendations, reviews)
3. **Convert** (checkout, payments, risk checks)
4. **Fulfill** (inventory, warehouse, routing)
5. **Engage** post-purchase (support, loyalty, reactivation)

Data richness

Page views, searches, clicks, add-to-cart, purchases, returns, time-to-decision $\rightarrow$ behavioral logs + metadata.

AI vs. ML vs. DL (relationship)

Definitions

- **AI**: systems that exhibit intelligent behavior (reasoning, learning, decision-making).
- **ML**: algorithms that learn patterns from data rather than explicit rules.
- **DL**: ML using deep neural networks that learn representations from large-scale data.

$$\mathbf{DL} \subset \mathbf{ML} \subset \mathbf{AI}$$

Learning paradigms with e-commerce examples

Supervised

- Conversion prediction
- Fraud classification
- Demand forecasting (as regression)

Unsupervised

- Customer segmentation
- Anomaly detection
- Product/user embeddings

Reinforcement learning

- Explore/exploit in recommendations
- Dynamic pricing policies

Representation learning (often DL)

- Session embeddings (Transformers)
- Image/text embeddings for products

(1) Recommendations: problem framing

Goal

Suggest items a user is likely to engage with or buy.

- Inputs: user history, context, item metadata, interactions (views, clicks, purchases).
- Outputs: ranked list (top-k) under latency constraints.

System view

Recommendations are typically a **multi-stage pipeline**: candidate generation $\rightarrow$ ranking $\rightarrow$ re-ranking/business rules.

Collaborative filtering (classical baseline)

Interaction matrix $R = [r_{ui}]$ where r_{ui} is an implicit/explicit signal.

Matrix factorization

$$\hat{r}_{ui} = \mathbf{p}_u^\top \mathbf{q}_i$$

where $\mathbf{p}_u$ and $\mathbf{q}_i$ are latent embeddings.

- Pros: simple, scalable, strong baseline.
- Cons: cold start; limited context modeling.

(2) Search and ranking

- **Query understanding**: spelling correction, synonyms, intent classification.
- **Retrieval**: candidate set (BM25 / dense retrieval / hybrid).
- **Learning to rank**: optimize relevance + engagement + business KPIs.
- **Personalized re-ranking**: adapt results to user context/history.

Key distinction

Search is **query-driven**; recommendations are **user-driven**. Many systems unify both via embeddings + ranking models.

(3) Segmentation and customer lifetime value (CLV)

Segmentation (unsupervised)

- Features: recency, frequency, monetary value (RFM), categories, engagement.
- Methods: k-means, GMMs, density-based clustering.

Predictive (supervised)

- Churn probability
- CLV forecasting

Why it is hard

Feedback loops + non-stationarity: your marketing changes the data you learn from.

(4) Dynamic pricing and promotions

- Learn demand as a function of price, seasonality, competition, segments.
- Optimize expected profit subject to constraints (inventory, regulations, fairness).
- Online experimentation: A/B testing; bandits for faster learning.

Common modeling choices

Gradient boosted trees for demand, bandits/RL for policy selection, plus rule constraints for safety.

(5) Forecasting and inventory management

- Objective: avoid stockouts and overstock (service level vs. holding cost).
- Inputs: historical sales, promotions, product lifecycle, holidays, weather signals.
- Methods: ARIMA/ETS; tree ensembles; sequence models.

Operational constraint

Forecast accuracy is not enough; you need **actionable** forecasts aligned with replenishment cycles.

(6) Fraud detection and transaction security

- Threats: payment fraud, account takeover, promo abuse, bot activity.
- Features: device fingerprint, IP/geo, velocity, historical behavior, item/merchant signals.
- Models: logistic regression/GBDT/RF/NN; anomaly detection; graph-based methods.

Two-sided cost

False negatives $\rightarrow$ fraud loss; false positives $\rightarrow$ blocked good customers $+$ churn.

(7) Customer service: chatbots and assistants

- Intent classification + NER
- Dialogue management (rules, ML, RL)
- Response: templates, retrieval, or generative models

Good practice

Use safe escalation: route complex or sensitive cases to humans; log outcomes for improvement.

Why deep learning?

DL shines when data are:

- Large-scale (millions of users/items, billions of events)
- High-dimensional (sparse IDs + rich metadata)
- Unstructured (text, images) or sequential (sessions)
- Relational (graphs of interactions)

Neural recommendation systems

- Replace dot-product scoring with a neural scorer $f_\theta(\mathbf{p}_u, \mathbf{q}_i, \mathbf{c})$.
- Sequence models (RNN/Transformer) capture short-term intent.
- Context-aware models incorporate device/time/location/campaign.

Takeaway

Better accuracy often comes with higher compute cost and more complex monitoring.

NLP for commerce text

What text exists?

- Titles/descriptions
- Reviews + Q&A
- Support conversations

Tasks

- Sentiment/aspect mining
- Semantic search + query rewriting
- Conversational agents

- Image embeddings for similarity search (“shop the look”).
- Classification/detection for quality control and moderation.
- Multimodal matching: image $\leftrightarrow$ text $\leftrightarrow$ attributes.

Typical architecture

CNN/ViT backbone $\rightarrow$ embedding index (ANN) $\rightarrow$ ranking model.

Sequences and graphs

- **Sequential models**: model user sessions, funnels, repeat cycles.
- **GNNs**: user–item graphs, co-purchase, fraud rings.

When to use graphs

When relationships (who interacts with whom/what) carry signal beyond individual features.

Data sources and feature engineering

Core sources

- Behavioral logs (clickstream)
- Transactions (orders, refunds, chargebacks)
- Catalog (attributes, text, images)
- Context (time, location, campaigns)

Common features

- Recency/frequency aggregates
- Ratios and velocities
- Embeddings (user/item/text/image)
- Time-series features

Offline training vs. online serving

Offline (batch)

- Clean + join data
- Train/tune model
- Offline metrics (AUC, NDCG, RMSE)

Online (real-time)

- Feature store / streaming features
- Low-latency inference APIs
- Logging + monitoring + drift detection

Key engineering constraint

Training can take hours; serving often has a budget of **tens of milliseconds**.

Evaluation: offline metrics vs. business KPIs

- Offline: AUC, logloss, precision@k, recall@k, NDCG.
- Online: conversion rate (CVR), CTR, revenue/session, AOV, retention, fraud loss.

Gold standard

Randomized online experiments (A/B tests) to estimate **incremental** impact.

Monitoring and model governance

Monitor:

- Data drift (feature distributions)
- Performance drift (metrics over time)
- Bias/fairness indicators
- Latency, throughput, and cost

Operational reality

A "good" model can be harmful if it degrades silently or changes user behavior in unintended ways.

Challenges and risks

- Data quality + bias (feedback loops, exposure bias).
- Privacy/security (regulatory obligations; breaches).
- Explainability (fraud blocks, credit-like decisions).
- Scalability + cost (training/serving at scale).
- Org readiness (MLOps, product alignment, legal).

Future directions

- Generative AI for product content and conversational shopping.
- Causal inference/uplift modeling for promotions and recommendations.
- RL at scale for long-term value optimization.
- Multimodal unified models (text+image+behavior).
- Sustainability-aware optimization (logistics, returns).

Recap

- E-commerce is a data-rich system spanning discovery, transactions, and operations.
- AI/ML/DL appear across the value chain: recsys, search, pricing, fraud, forecasting, support.
- Success requires systems thinking: deployment, experimentation, monitoring, and governance.

Prompt for discussion

Where do you expect the **largest** gains from AI in e-commerce: discovery, pricing, or operations—and why?