LUMOS: Large User MOdel Series

Building Foundation Models for User Behavior at Scale

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March 4, 2026

Talk at Swiggy

Thank You, Swiggy

World class product. Great engineering culture.

What We'll Cover Today

1. **Systems & Scale** – brief overview (numbers, infra, pipeline)
2. **Scaling Laws** – power law relationships for user behavior models
3. **LLM Concepts Refresher** – tokenization, embeddings, attention
4. **LUMOS Architecture Deep Dive** – where we'll spend most time

Full details in our paper: **arXiv:2512.08957**

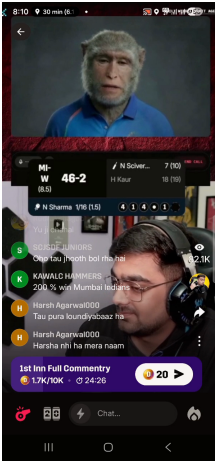
Is Dream11 Still Running?

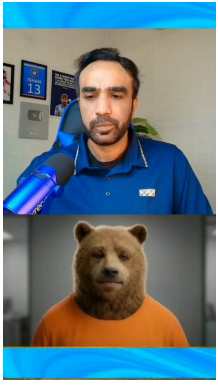
Yes! And we're now a **live streaming sports platform**!

Last India WC match: **15M users**, **360K concurrency**

If India reaches finals: Expecting **double concurrency**

AI Companion Demos





About Me

Currently @ Dream11:

- **AI Companion**: real-time sports AI, ~2s latency, 10M+ viewers
- **LUMOS**: 250M user foundation model (today's talk)
- **ForeCal**: probability calibration, published **KDD 2024**
- RL agent for discounts: **+2% WAU** uplift

Previously: Protium (12th employee, founding ML eng; DL models beat CIBIL by 12% AUC, $500M loans underwritten) and **CLSA** (quant trading, $1bn+/day sub-10ms; profitable stat-arb, Sharpe 1.3)

Education:

- **IIT Bombay** – B.Tech + M.Tech, Electrical Engineering (Signal Processing)

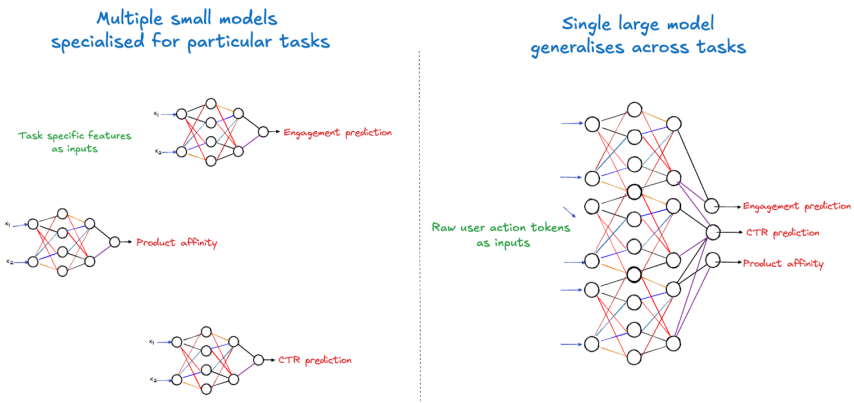
Open Source:

- **LiveKit Agents** (voice AI SDK)
- **veRL** (post-training RL, ByteDance)

Writing:

- **ML Trenches** – blog on deploying ML while staying sane

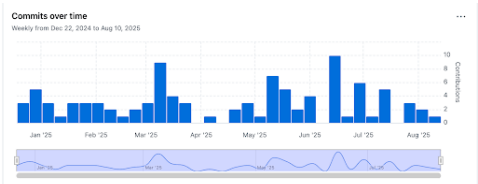
The Paradigm Shift



Many task-specific models → **One foundation model**

LUMOS: The Scale

Users:	**250M**
Data:	~**48 TB** processed
Tokens:	**1.7 trillion** activity tokens
Codebase:	**17,000+ LOC**
Models:	~**200 LOC (1%)**
New model:	<**10 LOC** to train
Inference:	~**50M users/day** scored



ML in production is 99% systems engineering

Training Infrastructure

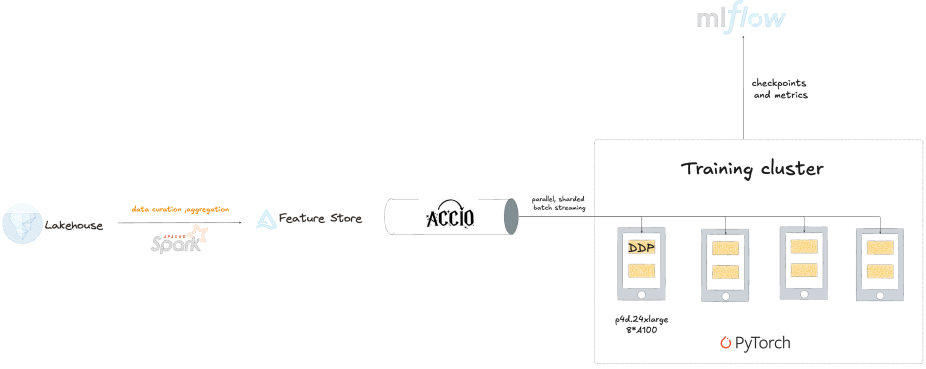
Hardware:

- **8× A100 40GB** (p4d.24xlarge)
- **576 A100 GPU-hours** (72h wall time)
- **BF16** mixed precision
- Batch size **4096** (512/GPU × 8)

Tech Stack:

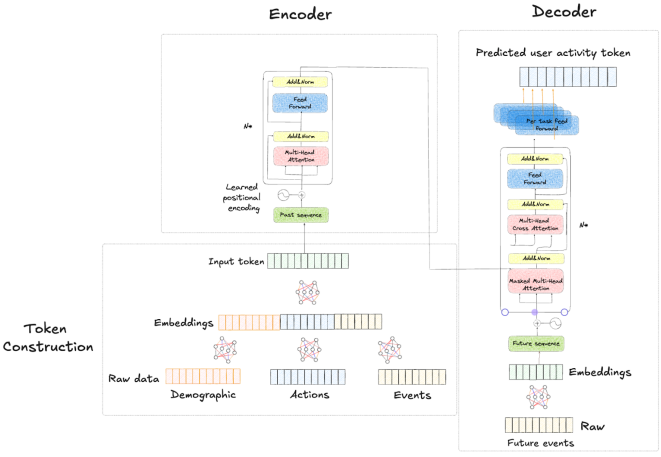
- **PySpark** – data processing
- **Delta Lake** – versioned storage
- **Accio** – custom streaming dataloader
- **PyTorch DDP** – distributed training
- **MLflow** + **Databricks**
- Migrating to **Ray Data** + **Ray Train**

Training Pipeline



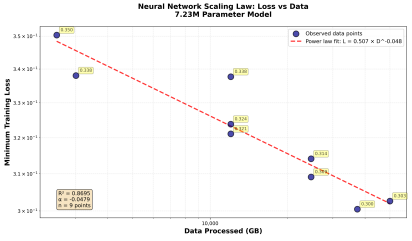
Raw Data → **PySpark** → **Delta Lake** → **Accio** → **DDP Training**

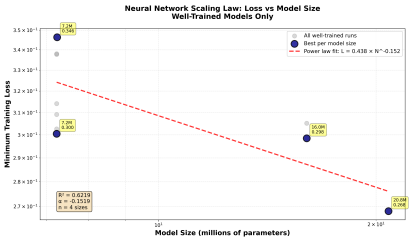
LUMOS Architecture



7.23M params · 6+6 layers · 8 heads · d_{model}=512 · SwiGLU · Pre-LayerNorm

Scaling Laws





Data scaling:

$L(D) = 0.507 \times D^{-0.048}$

Model scaling:

$L(N) = 0.438 \times N^{-0.152}$

(3× stronger than data)

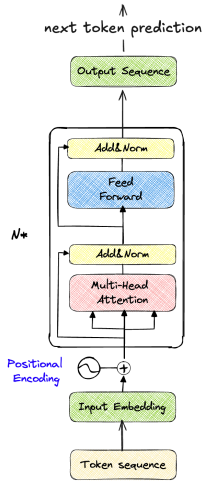
Config	Params	Loss
Small	7.23M	0.3347
Medium	12.18M	0.3298
Large	16.42M	0.3271
X-Large	**20.81M**	**0.3254**

LLM Architecture Foundation

Standard LLM Architecture: Decoder-Only

4 Core Components:

1. Tokenization
2. Token Embeddings
3. Positional Embeddings
4. Self-Attention



Tokenization & Embeddings

Tokenization: Text $\rightarrow$ discrete tokens via BPE/WordPiece

$$\text{Text} \rightarrow T = \{t_1, t_2, \ldots, t_n\}$$

Token Embeddings: One-hot $\rightarrow$ dense vectors via learnable matrix

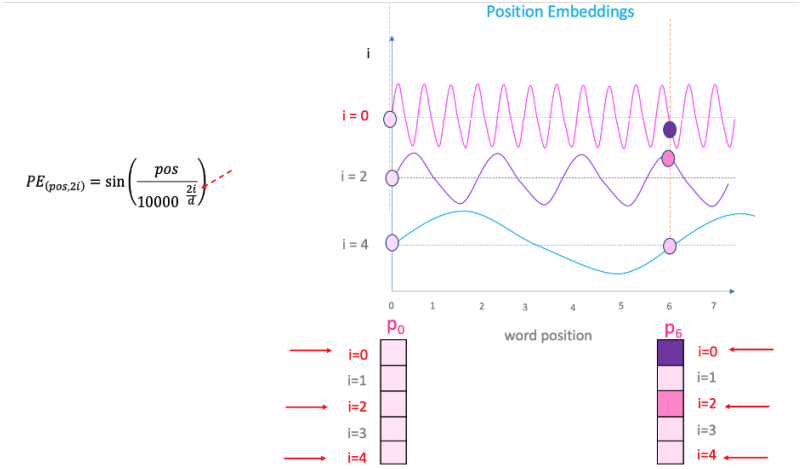
$$E = W_e \cdot t_i$$

Positional Embeddings: Inject sequence order (self-attention is permutation-invariant)

$$PE_{(pos,2i)} = \sin(pos/10000^{2i/d_{\text{model}}})$$

Positional Embeddings: Illustration

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{\frac{2i}{d}}}\right)$$



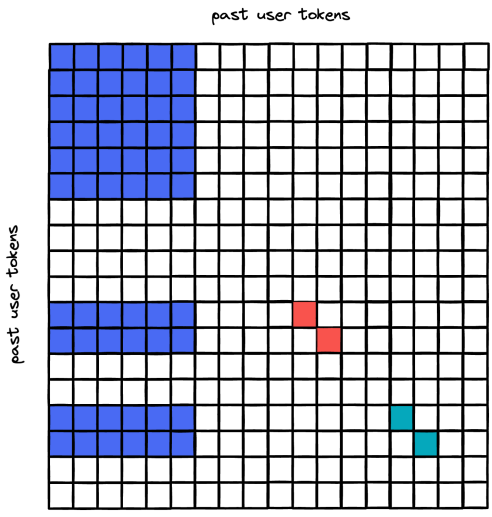
Self-Attention

Each token attends to all others.

Weights = similarity between query and keys.

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

$$z_i = \sum_{j=1}^{N} \alpha_{ij} v_j$$



LUMOS Architecture Deep Dive

LUMOS Tokenization: Multi-Modal Daily Tokens

User Behavior

13 Features

- Joins, deposits
- Withdrawals, wins
- Activity counts

Supply Data

32 Features

- Sports calendar
- Event counts
- Event timing

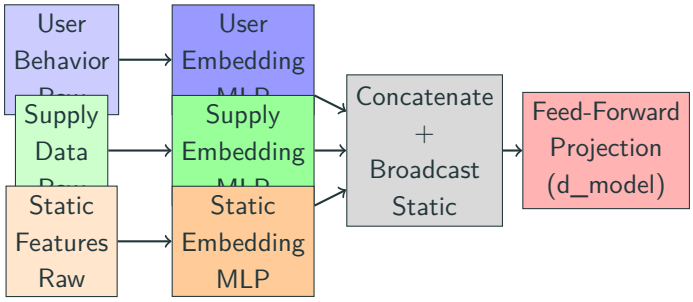
Static Features

9 Attributes

- Demographics
- Device info
- Registration data

Embed $\rightarrow$ Concatenate $\rightarrow$ Feed-Forward $\rightarrow$ **Rich Daily Token**

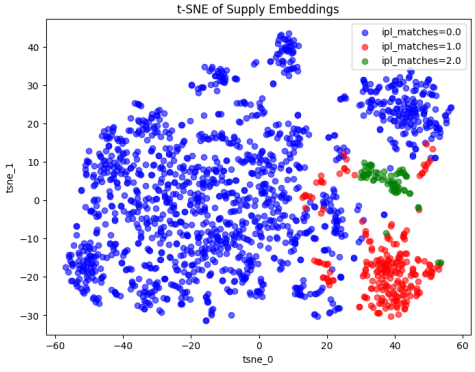
Token Construction Process



vs. LLMs

LLMs: Discrete text tokens from fixed vocabulary **LUMOS:** Continuous multi-modal daily vectors

Specialized Embeddings



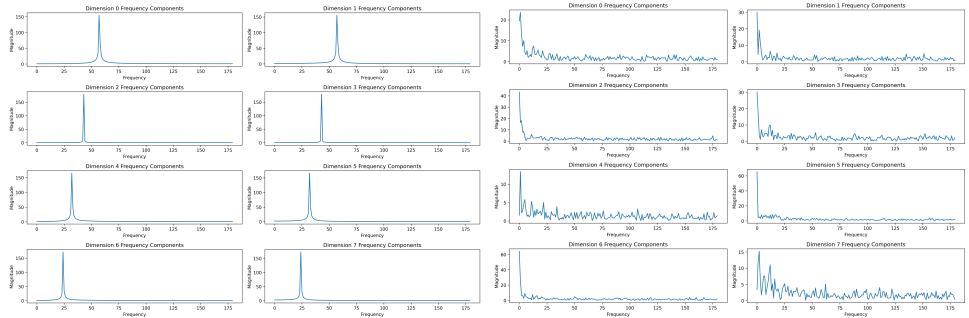
1. **Static User Embeddings**
   - New user personalization
   - Cold-start scenarios
2. **Supply Embeddings**
   - Supply similarity analysis
   - “What-if” scenarios

Positional Embeddings: Ablation Study

Method	Validation Loss	ROC-AUC
Learned	**0.3347**	**0.9296**
Sinusoidal	0.3372	0.9284
TAPE	0.3394	0.9275
Absolute	0.3556	0.9207

Learned embeddings win – adaptable to dataset-specific temporal patterns.

Sinusoidal vs. Learned Embeddings



Learned embeddings capture **lower frequencies** – precise positional encoding less critical for user behavior sequences.

Cross-Attention: The Key Innovation

Conditioning predictions on future known events

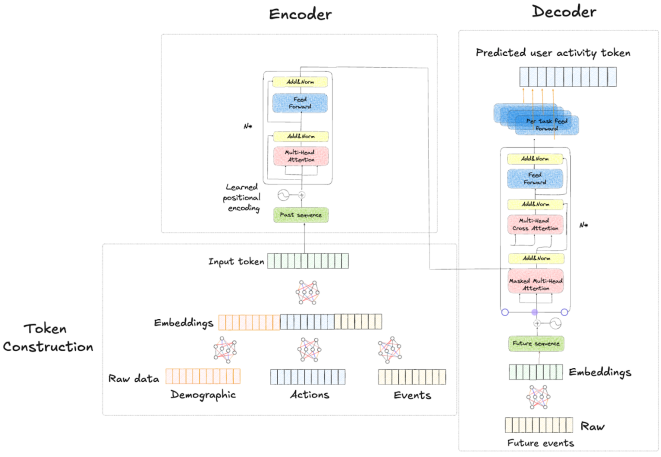
Self-Attention (Encoder):

- Historical context processing
- Information diffusion within sequence

Cross-Attention (Decoder):

- **Queries**: Future supply data
- **Keys/Values**: Historical user context
- **Innovation**: Condition on known future events

LUMOS Architecture (Recap)

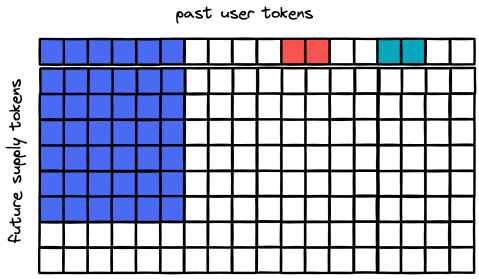


Encoder processes history via self-attention → Decoder uses cross-attention to condition on future supply → Masked prediction

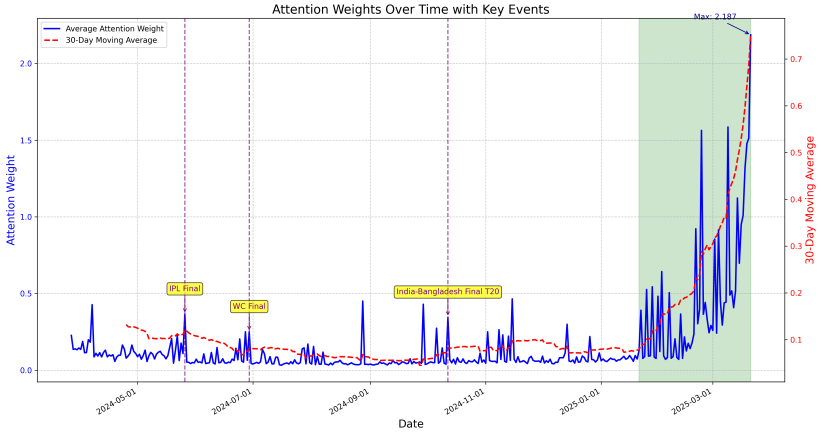
Visualizing Cross-Attention

Non-square matrix: Future Supply $\times$ History

- Dimensions: 28×360
- Rows = future supply queries
- Columns = historical user behavior
- Cell (i, j) = attention from future day i to past day j



Attention Pattern Analysis



Ablation Study: Role of Supply Data

Configuration	Validation Loss	ROC-AUC
Full Model	**0.3331**	**0.9300**
No Past Supply	0.3349	0.9297
No Future Supply	0.3350	0.9294
No Supply Data	0.3345	0.9298

Both past and future supply data improve predictions.

Beyond Next Token Prediction

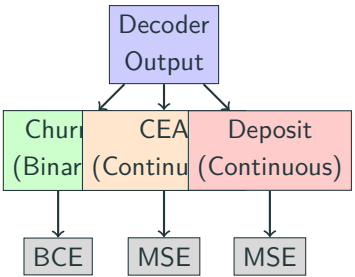
Masked Prediction:

- Predict **full cardinality** of user raw tokens daily
- Mirrors input transaction data

Multi-Task Learning:

- **Churn** (binary)
- **CEA** (continuous)
- **Deposit amount** (continuous)

Loss: MultiTaskLoss with uncertainty weighting



Uncertainty-Based Loss Function

$$\mathcal{L} = \sum_{i=1}^{d_u} \underbrace{\frac{1}{2\sigma_i^2}}_{\text{dynamic weight}} \mathcal{L}_i(\mathbf{U}_i^{fut}, \hat{\mathbf{U}}_i^{fut}) + \underbrace{\log \sigma_i^2}_{\text{regularizer}}$$

$\mathcal{L}_i$	Task-specific loss (BCE for binary, MSE for continuous)
σ_i^2	**Learnable** uncertainty per behavior dimension
$\frac{1}{2\sigma_i^2}$	High uncertainty $\rightarrow$ lower weight (auto-balancing)
$\log \sigma_i^2$	Prevents $\sigma_i^2 \rightarrow \infty$ (can't ignore any task)

Model jointly learns **predictions + task uncertainties**.
Hard tasks get lower weight automatically.

User Embeddings

Extracting User Embeddings: Key Considerations

1. **Extraction Point:**
   - Pre-Encoder vs. **Post-Encoder**
2. **Aggregation:**
   - Mean, Max, or Exp. Weighted Avg
3. **Recency (λ):**
   - Low λ = long-term patterns
   - High λ = recent behavior
4. **Training Objective:**
   - **Multi-Task** vs. Single-Task

User Embedding Performance

Model	Method (Extraction, λ)	Churn AUC	CEA Spear.	Pub. CEA Spear.	Net Win AUC	Withdraw AUC
Multi-Task	('post_encoder', 0)	0.9086	**0.3198**	0.4414	0.7121	0.9054
Multi-Task	('post_encoder', 0.1)	0.9087	0.3172	**0.4429**	0.7128	0.9059
Multi-Task	('post_encoder', 1)	0.9090	0.3047	0.4422	0.7141	0.9768
Multi-Task	**('post_encoder', 10)**	**0.9802**	0.1518	0.4403	**0.7219**	**0.9077**
Single-Task	('post_encoder', 0)	0.9063	0.3820	0.4107	0.6544	0.9735
Single-Task	('post_encoder', 0.1)	0.9063	0.3737	0.4125	0.6543	0.9736
Single-Task	('post_encoder', 1)	0.9067	0.3764	0.4087	0.6574	0.9740
Single-Task	('post_encoder', 10)	0.9077	0.3333	0.3931	0.6708	0.9048

Do You Need a Transformer?

Architecture	Parameters	Validation Loss
Transformer (LUMOS)	**2.49M**	**0.3347**
Large Deep NN	11.57M	0.3566
Small Deep NN	2.30M	0.3575

2.49M params beats 11.57M params. Transformers win.

Closing

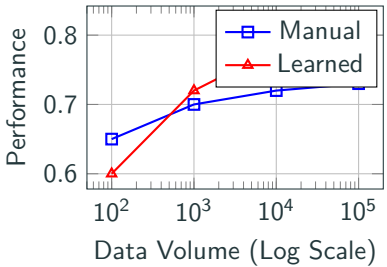
End Feature Engineering

Traditional:

- Manual feature engineering
- Domain expert required
- Brittle, hard to maintain

LUMOS:

- **Learned representations**
- End-to-end optimization
- Scales with data volume



Learned representations scale.
Manual features plateau.

Key Takeaways

1. **ML in production = 99% systems engineering**
   17K LOC platform, models are 1%
2. **Foundation models enable rapid iteration**
   $<$10 LOC to train a new model variant
3. **Scaling laws hold for user behavior**
   Power law relationships, model capacity $>$ data quantity
4. **One model to rule them all**
   250M users, 48TB, 576 GPU-hours $\rightarrow$ churn + CEA + deposits + embeddings

Thank You

Questions?

Online A/B Test Results

Experiment Design:

- Deployed via **Pacman** (intelligent offers engine)
- **700K users/cohort**, 18-day controlled test
- LUMOS predictions vs. legacy specialized models

Metric	Result
DAU Increase	**+3.15%**
Offer Cost Reduction	**-2.47%**
Avg AUC Improvement (offline)	**+0.025**
MAPE Reduction (offline)	**-4.6%**

More users, less cost. Offline gains translate to online impact.

Accio: Custom Streaming DataLoader

Problem: Dataset too large for memory + DDP needs balanced sharding.

Solution: Stream partition-by-partition from Delta Lake tables.

- PyTorch-compatible, designed for large sequence models on Delta tables
- Worker-aware sharding: each DDP process gets disjoint partitions
- No redundant data loading across workers
- Deterministic and balanced across all GPUs

Delta Tables $\rightarrow$ **Accio** $\rightarrow$ DDP Workers (8$\times$ A100)

Forward Pass: CrossAttentionForecaster

```
def forward(self, user_history,
            supply_history,
            static_features,
            future_supply):
  B, T_hist, _ = user_history.shape
  _, T_future, _ = future_supply.shape

  # 1) Encoder Input
  uh = self.user_embed(user_history)
  sh = self.supply_embed(supply_history)
  st = self.static_embed(
      static_features.unsqueeze(1))
  st = st.repeat(1, T_hist, 1)

  hist_concat = torch.cat(
      [uh, st, sh], dim=-1)
  hist_enc_in = self.hist_proj(hist_concat)
```

```
# Add positional embeddings
hist_pos = self.pos_embed.get_embedding(
    0, T_hist)
hist_enc_in = hist_enc_in + hist_pos

# Run encoder
enc_out = self.encoder(hist_enc_in)

# 2) Decoder Input (future supply)
fs = self.supply_embed(future_supply)
dec_in = self.future_proj(fs)
future_pos = self.pos_embed.get_embedding(
    T_hist, T_future)
dec_in = dec_in + future_pos

# 3) Cross-attention decoder
dec_out = self.decoder(
    x=dec_in, enc_out=enc_out)

# 4) Final projection
return self.out(dec_out)
```

User Embedding Extraction

```
def historical_user_embedding(self, user_hist_raw, supply_hist_raw, static_raw,
                              reduction="mean", exp_alpha=1.0,
                              embedding_stage="post_encoder"):
    B, T, D = user_hist_raw.shape
    uh = self.user_embed(user_hist_raw)
    sh = self.supply_embed(supply_hist_raw)
    st = self.static_embed(static_raw.unsqueeze(1)).repeat(1, T, 1)
    hist_concat = torch.cat([uh, st, sh], dim=-1)
    hist_enc_in = self.hist_proj(hist_concat)

    to_reduce = hist_enc_in
    if embedding_stage == "post_encoder":
        hist_pos = self.pos_embed.get_embedding(0, T)
        to_reduce = self.encoder(hist_enc_in + hist_pos)

    if reduction == "mean":     return to_reduce.mean(dim=1)
    elif reduction == "max":    return to_reduce.max(dim=1).values
    elif reduction == "expavg":
        t = torch.linspace(0, 1, T, device=to_reduce.device)
        weights = torch.softmax(exp_alpha * t, dim=0).unsqueeze(0).unsqueeze(-1)
        return (to_reduce * weights).sum(dim=1)
```