

# META LATTICE: Model Space Redesign for Cost-Effective Industry-Scale Ads Recommendations

Liang Luo, Yuxin Chen, Zhengyu Zhang, Mengyue Hang, Andrew Gu, Buyun Zhang, Boyang Liu, Chen Chen, Chengze Fan, Dong Liang, Fan Yang, Feifan Gu, Huayu Li, Jade Nie, Jiayi Xu, Jiyan Yang, Jongsoo Park, Laming Chen, Longhao Jin, Qianru Li, Qin Huang, Shali Jiang, Shiwen Shen, Shuaiwen Wang, Sihan Zeng, Siyang Yuan, Tongyi Tang, Weilin Zhang, Wenjun Wang, Xi Liu, Xiaohan Wei, Xiaozhen Xia, Yuchen Hao, Yunlong He, Yasmine Badr, Zeliang Chen, Maxim Naumov, Yantao Yao, Wenlin Chen, Santanu Kolay, GP Musumeci, Ellie Dingqiao Wen

Meta AI

Menlo Park, California, USA

## Abstract

The rapidly evolving landscape of products, surfaces, policies, and regulations poses significant challenges for deploying state-of-the-art recommendation models at industry scale, primarily due to data fragmentation across domains and escalating infrastructure costs that hinder sustained quality improvements.

To address this challenge, we propose Lattice, a recommendation framework centered around *model space redesign* that extends Multi-Domain, Multi-Objective (MDMO) learning beyond models and learning objectives. Lattice addresses these challenges through a comprehensive model space redesign that combines cross-domain knowledge sharing, data consolidation, model unification, distillation, and system optimizations to achieve significant improvements in both quality and cost-efficiency.

Our deployment of Lattice at Meta has resulted in 10% revenue-driving top-line metrics gain, 11.5% user satisfaction improvement, 6% boost in conversion rate, with 20% capacity saving.

## 1 Introduction

The discovery of scaling laws in recommendation models [6, 23, 25, 113] has unveiled new avenues for enhancing recommendation performance. However, translating these theoretical insights into practical deployment at industry scale faces challenges.

The first challenge is economic scalability. Modern recommenders operate across thousands of domain-objective pairs (called *portfolios*), each traditionally requiring a dedicated model [15, 63, 73, 94, 113]. While scaling laws demonstrate clear performance benefits from larger models [35, 113], the prohibitive infrastructure costs make it impractical to upscale every model independently. This forces practitioners to focus optimization on only a small subset of key portfolios, leaving significant performance gains unrealized.

The second challenge is data fragmentation. Large-scale models are inherently data-hungry, yet maintaining separate datasets for each portfolio creates artificial barriers to knowledge sharing. This fragmentation restricts cross-product understanding of user preferences and limits the data available to individual models, creating a scalability bottleneck due to data scarcity in specialized domains.

The third challenge is deployment constraints. Industrial production environments impose stringent inference latency requirements that severely limit the complexity of models that can be practically deployed, creating a fundamental tension between model capability and operational feasibility.

To address these interconnected challenges and unlock the full potential of large recommendation models, we propose moving beyond traditional per-portfolio scaling toward model space redesign via Lattice (Figure 1)—a transformative framework that tackles the three fundamental challenges.

For economic scalability, Lattice reduces the overall number of models required by consolidating portfolios to harness scaling laws while minimizing costs—a single invocation on Lattice models can simultaneously generate predictions for multiple portfolios. For data fragmentation, Lattice enriches training data per model by facilitating cross-portfolio sharing, allowing models to learn from broader and more diverse datasets. For deployment constraints, Lattice overcomes latency barriers through a hierarchical model space design where large-scale foundational models [48] are decoupled from real-time serving and act as teachers, transferring knowledge to smaller, highly-optimized user-facing models.

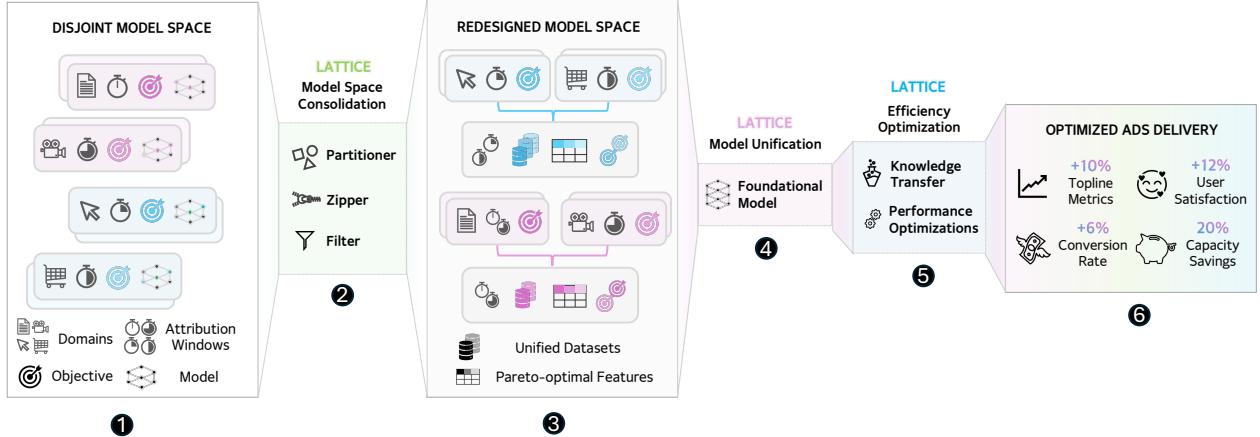
However, effective portfolio consolidation introduces technical challenges that extend far beyond traditional MDMO approaches, which primarily focus on tweaking model architectures and learning objectives while assuming clean, readily available datasets.

First, the delayed feedback problem: Ad recommenders face different attribution windows (time windows for collecting positive signals [14, 38, 97]), creating a critical trade-off between data freshness and correctness. Lattice addresses this through *Lattice Zipper*, which integrates datasets by associating each ad impression with a randomly selected attribution window, infusing both freshness and correctness into unified datasets.

Second, the feature selection problem: Ensuring model performance across consolidated portfolios while adhering to resource constraints requires optimal feature selection from vastly expanded feature spaces. Lattice employs *Lattice Filter*, a Pareto-optimal algorithm that selects features from merged datasets to guarantee pareto-optimal quality across all portfolios.

Third, the architecture design problem: With data and features consolidated, Lattice constructs *Lattice Networks*, a family of MDMO models featuring novel architectures tailored to handle diverse input formats through interleaved learning while mitigating domain conflicts via parameter untying.

Fourth, the knowledge transfer problem: To fully harness scaling laws without sacrificing inference performance, Lattice implements *Lattice KTAP*, a highly-scalable mechanism leveraging asynchronous precompute for hierarchical knowledge transfer at inference



**Figure 1: Lattice overview:** ① Even with MDMO frameworks, current model space remains scattered, with heterogeneous datasets, assorted attribution windows and siloed models and objectives. ②-③ Lattice redesigns the model space by consolidating datasets of heterogeneous formats, attribution windows and selects features on the pareto-front to form a small set of consolidated portfolios, improving knowledge sharing across domains and cutting down serving cost. ④ Foundational Lattice Network employs a MDMO-based, unified model architecture to consume multiple data formats and produces predictions for all consolidated objectives. ⑤ These models are further distilled to lean user-facing models via novel knowledge transfer and efficiency optimizations. ⑥ Deployed Lattice at Meta results in significant improvements in all key metrics and cost reduction.

time, augmenting knowledge distillation efficacy while maintaining real-time serving requirements.

The unified model architecture enables focused efficiency optimizations. We develop *Lattice Sketch*, an automated search tool for model hyperparameters and parallelization strategies, guided by scaling laws to balance quality and performance. Additionally, the consolidated model space requires only a small number of models, enabling careful optimization through customized GPU kernels and low-precision training and inference.

Finally, Lattice incorporates *Lattice Partitioner*, a policy tool that guides portfolio consolidation, improving knowledge sharing, reducing data conflicts, and maximizing global model performance within resource budgets while ensuring privacy compliance.

We evaluate Lattice through extensive experiments across both public benchmarks and industry-scale datasets with real-world recommendation scenarios. Our results demonstrate that Lattice consistently outperforms 10 state-of-the-art baselines, achieving up to 1% improvement in prediction loss while delivering up to 1.3× hardware efficiency gains on 1024 GPUs. Our production deployment of Lattice across a representative set of Meta’s ads model types has delivered substantial real-world impact: 10% improvement in revenue-driving top-line metrics, 11.5% uplift in user satisfaction, 6% boost in conversion rate, accompanied by 20% capacity savings, demonstrating that Lattice successfully bridges the gap between theoretical advances and practical industry deployment at scale.

## 2 Related Work and Opportunities

This section provides a review on the recent advancements and further opportunities to improve with Lattice.

### 2.1 Portfolio Consolidation

**Status Quo** Current recommendation systems optimize narrow objective sets within specific domains [15, 63, 73, 94, 113], becoming inefficient as domains and objectives proliferate.

Multi-Domain, Multi-Objective (MDMO) approaches [42, 43, 54, 60, 62, 82, 88, 95, 96, 98, 106–108] use models consuming all-domain data for all tasks, but monolithic designs limit model complexity due to latency constraints and task interference issues [28, 89]. Traditional ensemble approaches that combine separate models increase rather than reduce computational costs.

**Opportunities** Portfolio consolidation extends MDMO to broader settings, capturing massive domains without compromising deployability through multiple foundational models within latency envelopes while separating competing domains and objectives to mitigate interference [28, 89].

### 2.2 Data Integration

**Status Quo** Most MDMO research assumes clean, readily available datasets [12, 116], simulating MDMO setups by partitioning coherent datasets [40, 117]. Real-world datasets are heterogeneous (diverse data types and formats [112]), fragmented across product surfaces, sparse due to rare positive signals, and dynamic with shifting user behaviors. For example, delayed feedback creates additional challenges where different attribution windows introduce trade-offs between label completeness and freshness [14, 38, 97].

**Opportunities** Data integration enables sustainable model scaling by addressing data scarcity while enhancing model quality through cross-domain knowledge sharing, optimal feature selection, and effective attribution window blending.

### 2.3 Model Unification

**Status Quo** Representative MDMO models use a common-then-specialize paradigm, including MMoE [60] with multi-gate mixture-of-experts, M2M [116] using meta units and tower modules, M<sup>3</sup>oE [117] with two-level feature extraction mechanisms, PEPNet [12] employing personalized embedding networks, and

M3REC [40] using meta-learning for unified embedding representation. However, these approaches assume homogeneous input formats and struggle with cross-domain interference [89].

**Opportunities** Portfolio consolidation requires architectures that efficiently process heterogeneous input formats—dense, sparse, and sequential data [55, 112]—while mitigating learning interference across consolidated domains through novel architectural designs and parameter isolation techniques.

## 2.4 Efficiency Improvement

**Status Quo** Recommendation models face efficiency challenges from large embedding tables [47] and poor hardware utilization [59]. Existing approaches target architecture [53, 85, 113], topology-aware designs [59, 111, 114], specialized hardware [3], and knowledge distillation [29]. Training stability from distribution shifts and MDMO learning are addressed through gradient clipping [76, 89], better feature interactions [5], and normalization [7, 81].

**Opportunities** Portfolio consolidation enables focused efficiency optimizations across fewer, unified models while requiring joint optimization strategies that traditional approaches cannot provide, for example, low-precision training and inference, successful in LLMs [17], remain largely unexplored in recommendation due to scattered model landscape as they need to be tuned per-model.

## 3 Meta Lattice

We present Lattice, a comprehensive framework that advances state-of-the-art recommendation at industry scale through co-design of data, model, and efficiency strategies.

### 3.1 Portfolio Consolidation: Lattice Partitioner

Grounded in established theories that sample complexity and estimation error decrease when tasks are related [8, 64], we partition domain-objective pairs into manageable recommendation groups, reducing the total number of required models while leveraging foundational model [10], auxiliary learning [28], multi-task learning [43], and transfer learning [74] theories to address data fragmentation and improve cross-domain knowledge sharing [61, 68].

When grouped, domain-objective pairs merge their associated datasets, features, and objectives, requiring only a single model per group. However, naive consolidation causes training instability and quality degradation due to domain conflicts [28, 90].

Lattice Partitioner addresses this through a policy-driven approach that:

- **Prioritizes overlapping ID spaces:** Merges domains with substantial user/item overlap (e.g., combining "News Ads" and "Video Ads" which share users, versus keeping "Marketplace" separate due to distinct item) to facilitate knowledge sharing.
- **Groups objectives by feedback characteristics:** Separates (1) fresh, dense feedback tasks (click, like, follow) from (2) delayed, sparse feedback tasks (purchase, conversion). Task similarity within groups is assessed via empirical loss weighting [70, 77] or gradient-based metrics [4, 22], and subgroups can be further created if similarity is low. Conflicts within a group are mitigated through parameter untying (§3.3.4), supervision changes (§3.3.5), and MetaBalance [28].
- **Ensures compliance:** Respects privacy policies and data sharing restrictions.

- **Allocates resources:** Distributes compute and storage budgets based on estimated revenue impact.

### 3.2 Data Integration: Lattice Zipper & Filter

Lattice creates unified datasets and selects relevant features to facilitate cross-domain knowledge sharing and mitigate data scarcity for consolidated recommendation portfolios.

**Unified Dataset Construction:** We concatenate multiple datasets, where the feature set becomes the union of all features. Each record contains an original entry from one domain with non-existent features zero-padded, enabling models to learn cross-domain patterns while handling heterogeneous feature spaces.

**3.2.1 Mixing Attribution Windows via Lattice Zipper** Unlike typical recommenders that focus on real-time user feedback, ad recommenders face delayed feedback challenges. User conversions (e.g., purchases) can occur anywhere from minutes to days after an ad impression. To capture these delayed conversions, advertisers define *attribution windows*—time periods during which post-impression actions are credited to the ad. However, this creates a fundamental trade-off: shorter windows provide fresher training data but miss delayed conversions, while longer windows capture more conversions but introduce staleness.

Traditionally, this is addressed by ensembling  $K$  models trained on datasets with different attribution windows, or through multi-pass training that updates models as attribution windows close. Both increase training costs by  $K \times$  and can cause overfitting or instability due to conflicting labels for the same impression [56].

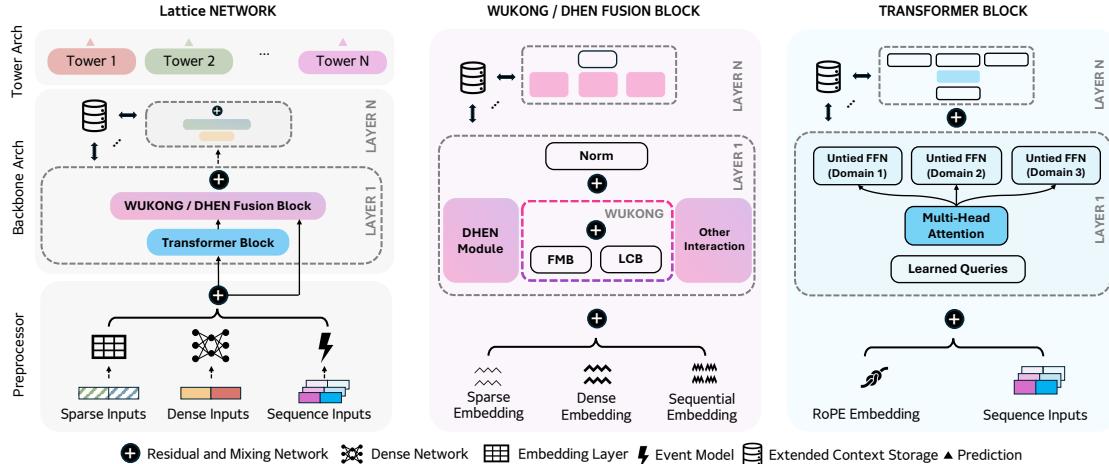
Instead of maintaining  $K$  separate datasets, Lattice Zipper creates a single unified dataset by randomly assigning each impression to one attribution window based on a tunable probability distribution (usually uniform random). The assignment uses deterministic hashing of the impression signature (user ID, ad ID, timestamp).

We then modify the model architecture to include separate prediction heads for each attribution window incorporated in the dataset. During training, impressions are routed to their assigned prediction head, allowing the model to learn from data at different freshness-correctness trade-off points simultaneously. The longest attribution window serves as the "oracle" head, learning from the most complete data, while shorter windows provide fresher signals that improve the shared backbone representation.

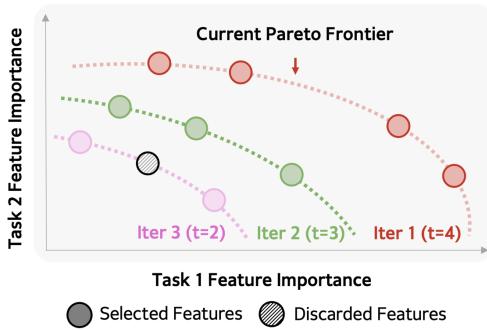
At serving time, we use only the oracle prediction head, which benefits from both the complete long-window data and the fresher shorter windows during training.

**3.2.2 Pareto-Optimal Feature Selection via Lattice Filter** Although tens of thousands of features characterizing users and items are available, resource constraints limit models to using only selective features (typically thousands). Portfolio consolidation introduces a new challenge: selecting features that achieve optimal performance across *multiple* consolidated portfolios simultaneously, where each portfolio may value different feature subsets.

Standard feature selection approaches optimize for single tasks or use weighted combinations across tasks, which can result in degradation of specific portfolios when one dominates the optimization objective. This is problematic when consolidated portfolios have different business importance or data characteristics.



**Figure 2: Lattice Networks interleave sequence and non-sequence learning to handle diverse input types in merged domains.**



**Figure 3: Illustration: Lattice Filter with  $T = 9$  and  $|\mathcal{F}| = 10$  via 3 iterations.**

Lattice Filter addresses this through Pareto-optimal selection, ensuring no portfolio is unfairly penalized while maximizing overall quality across all consolidated portfolios.

Lattice Filter begins by computing a feature importance score vector for each feature in the set  $\mathcal{F}$ . For the  $i$ -th feature across  $N$  tasks (representing all objectives from consolidated portfolios), we denote its importance scores as  $\mathbf{F}_i = (f_{i,1}, \dots, f_{i,N})$ , where  $f_{i,j}$  represents the importance of feature  $i$  in task  $j$ , computed using permutation-based importance [11].

We establish a partial order relationship "dominated by" ( $\preccurlyeq$ ):  $\mathbf{F}_i \preccurlyeq \mathbf{F}_k$  if and only if  $f_{i,j} \leq f_{k,j}$  for all  $j \in [1, N]$ . When feature  $k$ 's importance vector dominates feature  $i$ , feature  $i$  is not on the current pareto front and hence excluded from immediate selection.

Given target feature count  $T$ , Lattice Filter iteratively identifies features on the current Pareto frontier. In each iteration, features from the current frontier are selected. If there are more features on the pareto frontier than the budget, remaining quota is filled by randomly picking features on the current frontier. This random process ensures quality because features are pre-sorted by importance, critical ones are chosen in earlier iterations, they should have already appeared on previous frontiers. It also does not introduce bias because selection freezes the current frontier. This process continues until  $T$  features are selected. Figure 3 provides an illustration of Lattice Filter.

Lattice Filter ensures balanced performance across all portfolios. The approach can be extended to incorporate additional criteria such as feature computation cost, storage requirements, portfolio importance, and data freshness, enabling rich multi-objective optimization for feature selection.

### 3.3 Model Unification: Lattice Networks

Each Lattice Network covers one recommendation group. When domains with different input formats are merged, a unified model architecture must handle diverse input types while maintaining the ability to learn domain-specific patterns.

Lattice Networks process mix-format, multi-modal inputs: categorical features ( $\mathcal{F}_c$ ) such as user/item IDs, dense features ( $\mathcal{F}_d$ ) like user age or item price, and sequence features ( $\mathcal{F}_s$ ) such as user interaction histories or raw contents. Each sample in a batch  $B$  produces one prediction per consolidated task.

Lattice Networks adopt a novel three-stage preprocessor-backbone-task architecture with interleaving of sequence and non-sequence processing plus parameter untying (Figure 2). This design first unifies disparate input representations, then performs cross-domain interaction through specialized modules, and finally generates task-specific predictions.

**3.3.1 Feature Processors** unify input representations and project them into a common embedding space with uniform dimension  $d$ , enabling subsequent modules to operate on standardized inputs for all original data types:

- **Categorical Features ( $\mathcal{F}_c$ ):** Processed through embedding tables, producing output  $O_c$  with shape  $(B, |\mathcal{F}_c|, d)$ .
- **Dense Features ( $\mathcal{F}_d$ ):** Processed by MLPs to handle numerical inputs, producing output  $O_d$  with shape  $(B, |\mathcal{F}_d|, d)$ .
- **Sequence Features ( $\mathcal{F}_s$ ):** Processed by attention-based event models. This produces sequence embeddings  $O_s$  with shape  $(B, |\mathcal{F}_s| \times K, d)$ , where  $K$  represents the output feature count per event source.

A mixing network then concatenates  $O_c$  and  $O_d$  and normalizes them to form unified non-sequence representation  $O_{cd}$ , while preserving  $O_s$  separately. This separation enables the backbone to apply interleaved learning.

**3.3.2 Backbone** The Lattice Network backbone is designed for efficient dense scaling [83, 113, 115], leveraging modern hardware’s superior compute capabilities over memory and network resources [57, 58]. The architecture addresses the core challenge of processing both sequence and non-sequence data effectively through interleaved learning.

**Extended Context Storage (ECS)** provides a global key-value store supporting DenseNet [32]-style residual connections and intermediate activation access, enabling high-bandwidth information flow across layers and components which significantly helps with deeper networks [103].

**Transformer Blocks (TB)** process RoPE-encoded [87] input sequences  $O_s$ , producing contextualized sequences  $O'_s$  using standard transformer layers [93]:  $O'_s = TB(ROPE(O_s))$ . To enable better user-ad feature interactions, cross-attention layers and adaptive parameter generation networks [105] are adopted in FFN layers.

**DHEN/Wukong Fusion Blocks (DWFB)** address transformer limitations in processing non-sequence data by capturing bit-wise interactions [94]. DWFBs flatten  $O'_s$ , concatenate with  $O_{cd}$ , and produce updated non-sequence representations  $O'_{cd}$  using Factorization Machine Blocks (FMB) and Linear Compression Blocks (LCB) [113, 114]:  $O'_{cd} = DWFB([O'_s; O_{cd}])$ .

Evidently, each backbone block applies specialized processing to sequence versus non-sequence data by different modules that are optimized for different data modalities, facilitating the higher-level interactions between sequences and non-sequences [110].

**3.3.3 Task Modules** Task-specific adaptation uses lightweight MLP layers (one per objective) that project shared backbone embeddings to task-specific output spaces, enabling specialization while maintaining shared representations.

**3.3.4 Architecture Changes** To address instability issues inherent in MDMO training across diverse domains and objectives, we employ several architectural techniques:

**Modality Contention Mitigation:** On mixed-modal datasets, we mitigate contention among different modalities [92] via QK-norm [18] in attention mechanisms.

**Parameter Untying for Domain Conflicts:** Lattice Networks adopt parameter untying [19, 50–52, 100, 104] to mitigate learning conflicts not resolved by Lattice Partitioner. By dedicating weights for conflicting domains in backbone layers, Lattice Networks capture different distributions without causing interference.

**Low-precision Friendly Architecture** To enable stable low-precision training (e.g., FP8) while maintaining quality, we implement several architectural modifications:

- **Bias-less Backbone Layers** Remove bias terms from linear and normalization layers to prevent unbounded growth and numerical overflow in deep MLPs [24].
- **Stabilized Interactions** Apply proper normalization to input/output tensors in modules like Deep Cross Nets [94] that cause training instability in DHEN ensembles.
- **Swish RMSNorm (SwishRN)** Combine Swish activation [78] with RMSNorm for FFN layers for expressivity and stability:  $X_{out} = RMSNorm(X_{in}) \odot Sigmoid(RMSNorm(X_{in}))$ . RMSNorm avoids catastrophic cancellation issues of LayerNorm when elements are near the mean, while the additional RMSNorm on self-gating improves numerical stability.

**3.3.5 Supervision Changes** When portfolios are consolidated, models must learn representations that work well across multiple domains simultaneously. Without proper supervision, models tend to optimize each domain’s loss independently, leading to conflicting gradients and suboptimal cross-domain knowledge transfer.

Lattice Partitioner introduces a cross-domain correlation loss to align representation spaces across consolidated domains:  $\mathcal{L}_{corr}(X, Y) = 1 - \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y}$ , where  $X$  represents the ground truth label distribution across domains in a batch and  $Y$  represents the predicted label distribution from the model. Cov denotes covariance and  $\sigma$  denotes standard deviation. This auxiliary loss is computed per batch and added to the primary objective during training.

The correlation loss encourages the model to maintain consistent prediction patterns across domains by: (1) Preventing domain isolation. Without this loss, models can optimize per-domain objectives independently, leading to conflicting representations rather than beneficial knowledge sharing across consolidated portfolios; (2) Balancing domain confidence. The loss prevents models from becoming overconfident in domains with abundant data while remaining underconfident in data-sparse domains, promoting more balanced learning across the consolidated portfolio. By aligning prediction distributions, the shared backbone learns representations that generalize better across all consolidated domains.

When optimizing multiple objectives simultaneously, gradient magnitudes can vary significantly across tasks, causing training instability. We address this using MetaBalance [28], which adaptively weighs gradients to ensure stable multi-objective optimization. We use a second-order optimizer [26] to optimize Lattice Networks.

### 3.4 Enabling Inference-Time Knowledge Transfer via Lattice KTAP

Knowledge distillation is commonly used to improve low-latency, user-facing models via powerful teachers. However, traditional soft-label distillation transfers knowledge only during training.

We design Lattice KTAP to address this fundamental limitation through asynchronous precompute and feature-based knowledge transfer, enabling continuous knowledge transfer from teacher models to smaller student models during both training and inference:

- **Background Teacher Computation** Teacher Lattice Networks maintain background jobs that continuously evaluate the most relevant items (identified by earlier-stage ranking services) for each user, storing the final backbone layer embeddings for each user-item pair with time-to-live (TTL) metadata.
- **Student Query Mechanism** During both training and inference, student Lattice Networks query each user-item pair to retrieve precomputed teacher embeddings, checking TTL validity (typically a few hours) to ensure freshness.
- **Embedding Integration** Valid teacher embeddings are directly incorporated as additional input features to the student model. For expired or missing embeddings, the user-item pair is queued for the teacher’s next refresh cycle, while zero tensors serve as placeholders in the student.
- **Dual Knowledge Transfer** In addition to feature-based transfer, teacher prediction logits are provided to students for traditional label-based distillation, creating a comprehensive knowledge transfer mechanism.

Unlike traditional knowledge distillation that relies solely on teacher labels for loss computation, Lattice KTAP incorporates both precomputed embeddings as model inputs and teacher labels in the loss function. This dual approach significantly enhances the knowledge transfer ratio during both training and inference, providing richer supervision signals than conventional methods.

Lattice KTAP achieves an optimal balance between staleness and computational efficiency by leveraging the natural stability of user interests over short periods. Since user preferences typically remain consistent within a few hours, teacher embeddings retain their relevance, enabling effective student model enhancement during inference without requiring real-time teacher computation.

To ensure cost-effective deployment, Lattice KTAP employs caching and clustering techniques that minimize computational overhead. The system provides flexible resource allocation by allowing dynamic adjustment of precomputed embedding volumes based on real-time traffic patterns and business priorities, making it highly scalable across varying workloads.

Lattice KTAP incorporates feature clipping [91] on teacher embeddings and label smoothing [71] on teacher labels to further improve training stability and convergence properties.

### 3.5 Efficiency Optimizations

This section details efficiency improvements for Lattice.

**3.5.1 Distributed Training Optimizations** We utilize hybrid parallelism [69] with TorchRec [33] for embedding table sharding and FSDP [49, 118] for dense parameter synchronization. Small parameters use DDP [44] with pre-allocated static GPU storage to eliminate padding overhead and enable efficient gradient bucketing.

**3.5.2 Low-precision Training and Inference** Leveraging architectural changes from §3.3.4, we employ mixed-precision FP8/BF16/FP32 training and FP8 inference. Linear layer GEMMs use FP8 or BF16 based on performance trade-offs, while normalization layers upcast to FP32 for stability. Inference converts weights to FP8 for reduced storage and quantization costs.

Unlike block-wise scaling approaches [17], we use tensor-wise or row-wise scalers with FBGEMM kernels [36]. Fast accumulation [79] is disabled during training but enabled for inference.

**3.5.3 Optimized GPU Kernels** We combine automatic optimization via Torch Compile with manual kernel fusion for SwishRN operators. Our BlockNorm strategy operates on local GEMM tiles to avoid cross-SM synchronization, fusing with preceding GEMM kernels to leverage L1/L2 cache locality. We replace Sigmoid with HardSigmoid [31] to eliminate expensive exponential operations.

**3.5.4 Iterative Execution Refinements with Lattice Sketch** To optimize model execution efficiency without compromising quality, we propose Lattice Sketch, a unified search framework maximizing the (model quality, throughput) tuple given latency budget  $T$  and quality threshold  $Q$ .

**Alternating Optimization Phase:** Lattice Sketch’s search space consists of FSDP sharding strategies and model hyperparameters. It alternates solving phases via beam search of width  $K$ , with each phase optimizing either hyperparameters or sharding strategies. Each phase contains  $S$  steps guided by parallel Bayesian optimizers [84], with configurations violating  $T$  or  $Q$  constraints receiving zero scores. The algorithm initializes  $K$  seeding configurations, then

enters sharding strategy optimization where hyperparameters are fixed and  $S$  mutated sharding strategies are evaluated on cluster. Initial seeds are replaced by higher throughput configurations before transitioning to hyperparameter search phase. This alternative optimization strategy allows us to make better use of clusters, such that hyperparameters-related tunings only need to happen locally.

**Scaling Law-Guided Search Space Reduction:** To accelerate search, Lattice Sketch leverages established scaling laws [30, 35, 83] to shrink hyperparameter spaces. For Wukong, we simultaneously scale output embedding counts in LCB and FMB; for transformers, hyperparameter modifications show minimal quality impact [72] with a fixed FLOPs budget.

**Dynamic Programming Bootstrapping:** We bootstrap FSDP sharding strategy search by profiling execution latency  $T_b(s_l)$  and memory usage  $R_b(s_l)$  for each layer  $l$  with batch size  $b$  and sharding strategy  $s_l$ , plus communication latency  $C(s_l)$ . Using dynamic programming with GPU memory capacity  $R$ , we find optimal configurations  $ANS_b^*$  by enumerating batch sizes (powers of 2).

*Border condition:*

$$OPT_b[l, r] = \infty, ANS_b[l, r] = 0, \forall_x x \leq 0 \vee r > R \vee x > L$$

*Recurrence:*

$$s_{l+1,r}^* = \operatorname{argmin}_{s \in S} OPT_b[l, r - R_b(s)] + T_b(s) + C(s)$$

$$OPT_b[l+1, r] = \min_{s \in S} OPT_b[l, r - R_b(s)] + T_b(s) + C(s)$$

$$ANS_b[l+1, r] = ANS_b[l, r - R_b(s_{l+1,r}^*)] \leftarrow s_{l+1,r}^*$$

*Output (algorithm complexity  $O(|K| \times |S| \times LR)$  given  $b$ :*

$$ANS_b^* = ANS_b[L-1, \operatorname{argmin}_r OPT_b[L-1, r]]$$

## 4 Evaluation

We evaluate each Lattice component’s contribution to cost-efficient recommendation at industry scale.

### 4.1 Evaluation Setup

**Datasets and Baselines** We evaluate Lattice on one public dataset (Kuaishou [39]) and multiple internal datasets (1-3K features each), comparing against 10 state-of-the-art baselines: AFN+ [15], AutoInt+ [85], DLRM [73], DCnv2 [94], FinalMLP [63], MaskNet [99], xDeepFM [46], BST [13], APG [105], and Wukong [113].

**Metrics** We report AUC and binary cross-entropy (BCE) loss for public datasets, and relative BCE improvement over baselines for internal datasets (0.01% improvement is significant at our scale). Throughput is measured in queries per second (QPS). Teacher models are applied equally across all internal evaluations, and they have negligible cost (teacher:student GPU ratio  $\approx 1:100$ ) hence is omitted.

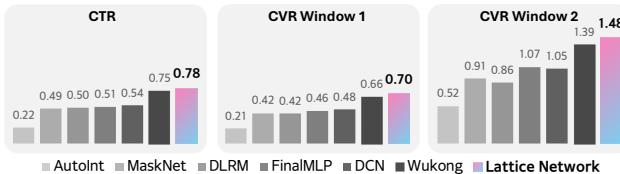
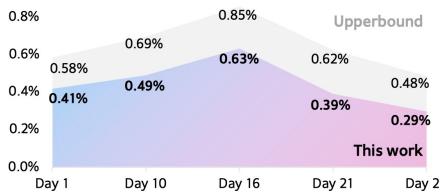
We provide an ablation of overall gain in §5.2.

### 4.2 Effectiveness of Data Consolidation

We evaluate Lattice Zipper and Lattice Filter on their abilities to consolidate multi-attribution window datasets and select pareto-optimal features using industry-scale datasets.

**Lattice Zipper** We apply Lattice Zipper to consolidate two datasets with 90-minute and 1-day attribution windows, assessing its ability to balance freshness and correctness. To establish performance bounds, we simulate an ideal case where all ground-truth labels are immediately available as “Upperbound”. We evaluate models under daily incremental training over one month. Our baseline uses only the 1-day attribution window model (we omit the 90-minute-only model for visual clarity as it consistently shows 1%

Task Type	Loss Improvements (%)
CTR of multiple domains	0.2 ~ 0.5
CVR of multiple domains	0.12 ~ 0.17
CTR+CVR of a single domain	0.1 ~ 0.5
CTR+Quality of a single domain	0.06

**Table 1: Evaluation of Lattice Filter.****Figure 4: Relative Loss Improvement (%) over AFN on an industry-scale dataset.****Figure 5: Relative Loss Improvement (%) of Lattice Zipper across various dates in a month, compared to an upperbound.**

regression). We compare Lattice Zipper against existing solutions: delayed feedback modeling [14, 97], continuous training with negative samples [38, 97], and label correction with reweighing [14]. All baseline approaches requiring multi-pass training exhibited severe divergence or loss regression on our datasets while being less efficient. Figure 5 shows Lattice Zipper achieves consistent improvements across all evaluation dates. It's worth noting that the effectiveness of Lattice Zipper extends beyond the two-window consolidation. Specifically, we see additional gain on the 7d head when consolidating 90min/1d/7d combination. Adding more consolidation windows to the mix yield additional yet diminishing returns.

**Lattice Filter** We apply Lattice Filter to select approximately 2K features from a pool of 12K features in a consolidated dataset.

We compare against a standard weighted loss-based feature selection baseline [16, 34]. Table 1 shows relative loss improvements across 10 models spanning 4 optimization goals: Lattice Filter generalizes well across diverse tasks and combinations compared to traditional approaches.

### 4.3 Effectiveness of Lattice Networks

We focus our evaluation on the quality gains from adopting Lattice Networks on a public dataset and industry-scale datasets.

**Open Source MDMO Dataset: KuaiVideo** We simultaneously predict the labels for *like*, *follow*, and *click* to test the models' MDMO performance, following established approaches [120, 122]. We report final test performance in Table 2 after learning rate tuning for all models. Best and second-best performing models are bolded and underlined. Lattice Networks match or outperform state-of-the-art performance in 7 out of 8 metrics with comparable or lower complexity.

**Industry-Scale Dataset: Non-sequence Data** We upscale selected models to 30-40 GFLOPs/sample and evaluate on our industry-scale dataset with 100B samples for scalability testing. We use three tasks: one CTR and two CVR tasks. We present results in Figure 4, using AFN as a baseline. Lattice Networks continue to significantly outperform other state-of-the-art models, improving loss by up to 1.14%, demonstrating the scalability of Lattice Networks and the quality improvements from the architectural changes described in §3.3.4.

**Industry-Scale Dataset: Mixed Sequence and Non-sequence Data** We compare Lattice Network's performance with scaled-up Wukong on a mixed-format dataset with 50B samples merged from domains with mixed sequence data. We predict O(10) objectives among click (CTR), conversion (CONV), and ads quality (QLT) types. Table 3 summarizes results for overall CTR, CVR, QLT, and selectively reports two conversion types: lead generation (LG) and post engagements (PE) to demonstrate effectiveness on finer-grain breakdowns. Lattice Networks significantly outperform Wukong in every task with comparable complexity, demonstrating the effectiveness of interleaved learning (§3.3.2) and our architectural changes (§3.3.4).

### 4.4 Effectiveness of Portfolio Consolidation

We evaluate the effectiveness of portfolio consolidation, guided by Lattice Partitioner, in a challenging scenario involving CTR prediction on two product surfaces (A and B). These were originally handled by two separate models with 1.33T and 0.71T parameters and training complexity of 20 GFLOPs and 12 GFLOPs/sample, respectively. We merge the task modules, data, and features as necessary for consolidation, building on the 20 GFLOPs baseline. Table 4 shows an immediate benefit for Domain B at the cost of quality loss for Domain A – a typical manifestation of cross-domain interference in multi-objective setups. However, applying supervision changes (§3.3.5) produces a significant performance boost that surpasses the unconsolidated baseline. Overall, portfolio consolidation guided by Lattice Partitioner achieves 1.5× FLOPs and 1.04× parameter savings<sup>1</sup> with significant performance improvements in both domains. The minimal complexity increase indicates that Lattice portfolio consolidation facilitates knowledge transfer between domains, underscoring its key advantage: *the cost of serving a consolidated portfolio is significantly lower than serving portfolios separately*.

### 4.5 Inference-time Knowledge Transfer Gains

We measure improvements using Lattice KTAP, by comparing the loss improvements of a distilled Lattice Network over a non-distilled version via: (1) traditional soft-label distillation; (2) Lattice KTAP with a typical observed cache hit rate of 0.6 and (3) Lattice KTAP with an ideal case of 1.0 cache hit rate, on a CTR task. We set TTL to 6 hours. The teacher, student and baseline models are Lattice Networks with complexity of 2.7 GFLOPs and 0.42 GFLOPs.

Shown in Table 5, we observe over a 1.3× boost in knowledge transfer efficiency in typical settings, harnessing most of the benefit in the ideal case of 100% hit rate.

<sup>1</sup>Parameter count is dominated by embedding table size, determined by the total number of features consolidated, hence smaller savings compared to FLOPs.

Model	AUC				Loss			Complexity		
	Click	Follow	Like	Avg	Click	Follow	Like	Avg	MFLOPs	MParams
AFN+	0.7172	0.7703	0.8466	0.7780	0.4572	0.0074	0.8466	0.1604	10.96	79.60
AutoInt+	0.7181	0.7882	0.8725	0.7929	0.4607	0.0075	0.0156	0.1617	79.27	41.75
DLRM	0.7088	0.6743	0.7734	0.7188	0.4874	0.0081	0.0175	0.1710	1.996	39.24
DCNv2	0.7225	0.7954	0.8804	0.7995	0.4534	<b>0.0073</b>	<b>0.0152</b>	0.1586	9.159	40.44
FinalMLP	0.7176	0.7627	0.8624	0.7809	0.4690	0.0080	0.0163	0.1645	12.22	571.4
MaskNet	0.7133	0.7143	0.8599	0.7625	0.4650	0.0077	0.0156	0.1627	4.299	39.63
xDeepFM	0.7189	0.7704	0.8706	0.7866	0.4642	0.0079	0.0156	0.1626	6.810	51.60
APG (DeepFM)	0.7066	0.7464	0.8515	0.7682	0.4915	0.0080	0.0166	0.1720	11.74	52.40
BST	0.7217	0.7664	0.8707	0.7863	<b>0.4512</b>	0.0076	0.0153	<b>0.1581</b>	326.1	40.63
Wukong	0.7251	0.7947	0.8842	0.8014	0.4580	0.0075	0.0155	0.1603	22.62	42.59
Lattice Network (Expert Tuned)	<b>0.7281</b>	<b>0.7997</b>	0.8793	0.8024	<b>0.4513</b>	<b>0.0073</b>	0.0154	<b>0.1580</b>	25.54	43.08
Lattice Network (Lattice Sketch)	0.7249	0.7984	<b>0.8861</b>	<b>0.8031</b>	0.4529	<b>0.0073</b>	<b>0.0151</b>	0.1584	<b>1.575</b>	<b>39.17</b>

Table 2: Test performance on KuaiVideo across 3 tasks. Lattice Networks achieve best performance with least resources.

CTR	Conv	QLT		LG		PE		
		T1	T2	T1	T2	T1	T2	T3
0.27	0.36	0.38	0.39	0.48	0.63	0.59	0.68	1
								1.14

Table 3: Relative Loss Improvement (%) of Lattice Network over Wukong on an industry-scale, mixed-sequence dataset.

Consolidation Type	Loss Improvements		FLOPs Saving	Params Saving
	CTR on A	CTR on B		
Data	-0.15%	0.36 %	1.59×	1.04×
Data + Aux Loss	0.13%	0.46 %	1.50×	1.04×

Table 4: Effectiveness of Portfolio Consolidation.

Knowledge Transfer Type	Loss Improvements (%)
Soft-label Distillation	0.12
Lattice KTAP (Hit Rate 0.6)	0.24
Lattice KTAP (Hit Rate 1.0, Upperbound)	0.43

Table 5: Effectiveness of Lattice KTAP.

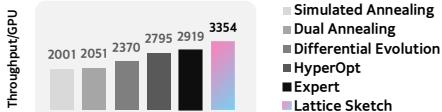


Figure 6: Lattice Sketch improves throughput by 20% on 128 A100 GPUs through iterative refinements.

## 4.6 Cost-efficiency Improvements

We evaluate Lattice Sketch’s efficacy on hyperparameter tuning and throughput improvements.

**Lattice Sketch on Quality** We set up a search space for Lattice Sketch with 4 trillion choices and apply it to Lattice Network on the KuaiVideo dataset. We set the objective to  $\max O_{VM} = \max \frac{AUC}{f^{0.003}}$  on the validation set, reflecting our expectation that Lattice’s AUC scales linearly with  $f^{0.003}$ . This modification biases the search slightly toward lower-latency configurations that outperform the scaling baseline in efficiency (as prescribed by the  $f^0.003$  scaling law slope). We use Lattice Sketch with a budget of 1200 steps. We present results in Table 2. The tuned model achieves state-of-the-art results in 4 out of 8 metrics, outperforming the expert-tuned model with 17× fewer FLOPs.

**Lattice Sketch on Training Throughput** We evaluate Lattice Sketch’s throughput improvement by simultaneously adjusting batch size and FSDP parallelization strategy for each DWFB on 128 Nvidia A100 GPUs for an 8-layer Lattice Network. Figure 6

summarizes the results. Compared to an expert-tuned baseline and 4 state-of-the-art optimizers—including HyperOpt [9], annealing [37], dual annealing [2], and differential evolution [86]—given the same search budget of 500 attempts, Lattice Sketch delivers up to 1.6× better throughput.

**Other Efficiency Improvements** When coupled with the optimizations in §3.5.1, Lattice Network achieves an additional 26% faster inference speed with FP8 inference, where 10% is contributed by kernel optimizations.

## 5 Industrial Deployment and Impacts

The surging demand for recommendation systems in recent years [69, 75, 101, 112] has made Lattice essential for sustained growth of recommendation at Meta.

### 5.1 Deployment Baseline and Methodology

We deployed Lattice across a critical set of ads model types serving global Meta users across platforms. Our baseline is the prior production system without Lattice, where each portfolio was served by a separate model trained on isolated datasets. During testing, both Lattice and the baseline predict CTR/CVR metrics for live traffic in the form of (user, ad) pairs, with the highest-ranked pairs presented to users based on predictions and other factors.

We measure Lattice’s impact using: (1) revenue-driving top-line metrics, (2) relevance metrics such as (CTR, CVR, ads quality (user satisfaction [1]), and (3) cost metrics (capacity savings in power usage). Our blog posts [65, 66] have more details.

### 5.2 Results and Ablation

Lattice has delivered substantial real-world impact: 10% top-line metric gains, 11.5% improvement in ads quality, and up to 6% increase in ad conversions while achieving 20% capacity savings.

We ablated the top-line metric contributions as follows: Lattice Partitioner (36%), Lattice Zipper (11%), Lattice Filter (13%), Lattice Networks (23%), and Lattice KTAP (17%). The capacity savings result entirely from reducing model count and sharing compute through improved efficiency across portfolios, and has factored in the cost associated with tuning Lattice.

### 5.3 Deployment Trade-offs

Our deployment experience demonstrates that Lattice achieves cost reduction without quality trade-offs. Small models benefit from upscaling, while potential conflicts between objectives and domains are prevented by Lattice Partitioner (§3.1) and mitigated

through auxiliary loss (§3.3.5), parameter untying (§3.3.4), and domain-specific towers (§3.3.3). To balance model complexity and latency, Lattice employs efficient architectures (§3.3.4), low-precision (BF16/FP8) execution, optimized GPU kernels (§3.5.2–3.5.3), and optimal execution strategies via Lattice Sketch (§3.5.4).

## 6 Discussion and Limitations

**Comparison with State-of-the-Art** The holistic approach to portfolio, data, and model consolidation distinguishes Lattice from existing methods that focus solely on model design [20, 41, 60, 67, 117] or efficiency [33, 59, 69, 111] in isolation, addressing a critical gap in the literature regarding data curation for MDMO learning in industrial settings and improving upon feature selection schemes that directly compute importance scores (e.g., using Shapley values [80]) and selecting top-K features with lowest loss [61, 102, 109] to avoid loss-gaming. Compared to neural architecture search (NAS) [21], Lattice Sketch leverages established scaling laws and does not require waiting for slow quality signals, enabling faster iteration.

**Limitations** While we strive to share generalizable deployment insights with the broader community, some findings contain Meta-specific elements. For example, Meta’s business requirements and partner relationships define the problem spaces of by Lattice.

## 7 Conclusion

Through comprehensive model space redesign that integrates portfolio consolidation, data unification, architectural innovations, and efficiency optimizations, Meta Lattice demonstrates substantial real-world impact: 10% improvement in revenue-driving top-line metrics, 11.5% enhancement in ads quality, 6% increase in conversion rates, and 20% capacity savings. These results validate Lattice’s effectiveness in bridging the gap between theoretical advances in recommendation systems and practical industry deployment.

## References

- [1] [n. d.]. Ads Quality. <https://www.facebook.com/business/help/423781975167984>. [Accessed 11-07-2025].
- [2] [n. d.]. dual annealing scipy manual – docs.scipy.org. [https://docs.scipy.org/doc/scipy/reference/generated/scipy.optimize.dual\\_annealing.html](https://docs.scipy.org/doc/scipy/reference/generated/scipy.optimize.dual_annealing.html). [Accessed 05-07-2025].
- [3] [n. d.]. Our next generation Meta Training and Inference Accelerator. <https://ai.meta.com/blog/next-generation-meta-training-inference-accelerator-AI-MTIA/>. (Accessed on 05/29/2024).
- [4] Alessandro Achille, Michael Lam, Rahul Tewari, Avinash Ravichandran, Subhransu Maji, Charles Fowlkes, Stefano Soatto, and Pietro Perona. 2019. Task2vec: Task embedding for meta-learning. In *Proceedings of the IEEE/CVF international conference on computer vision*. 6430–6439.
- [5] Muhammad Adnan, Yassaman Ebrahizadeh Maboud, Divya Mahajan, and Prashant J. Nair. 2023. Ad-Rec: Advanced Feature Interactions to Address Covariate-Shifts in Recommendation Networks. [arXiv:2308.14902](https://arxiv.org/abs/2308.14902) [cs.IR]
- [6] Newsha Ardalani, Carole-Jean Wu, Zeliang Chen, Bhargav Bhushanam, and Adnan Aziz. 2022. Understanding scaling laws for recommendation models. [arXiv preprint arXiv:2208.08489](https://arxiv.org/abs/2208.08489) (2022).
- [7] Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E. Hinton. 2016. Layer Normalization. [arXiv:1607.06450](https://arxiv.org/abs/1607.06450) [stat.ML] <https://arxiv.org/abs/1607.06450>
- [8] J. Baxter. 2000. A Model of Inductive Bias Learning. *Journal of Artificial Intelligence Research* 12 (March 2000), 149–198. <https://doi.org/10.1613/jair.731>
- [9] James Bergstra, Dan Yamins, David D Cox, et al. 2013. Hyperopt: A Python Library for Optimizing the Hyperparameters of Machine Learning Algorithms. *SciPy* 13 (2013), 20.
- [10] Rishi Bommasani, Drew A Hudson, Ehsan Adeli, Russ Altman, Simran Arora, Sydney von Arx, Michael S Bernstein, Jeannette Bohg, Antoine Bosselut, Emma Brunskill, et al. 2021. On the opportunities and risks of foundation models. [arXiv preprint arXiv:2108.07258](https://arxiv.org/abs/2108.07258) (2021).
- [11] Leo Breiman. 2001. Random forests. *Machine learning* 45 (2001), 5–32.
- [12] Jianxin Chang, Chenbin Zhang, Yiqun Hui, Dewei Leng, Yanan Niu, Yang Song, and Kun Gai. 2023. PEPNet: Parameter and Embedding Personalized Network for Infusing with Personalized Prior Information. In *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining* (, Long Beach, CA, USA,) (KDD ’23). Association for Computing Machinery, New York, NY, USA, 3795–3804. <https://doi.org/10.1145/3580305.3599884>
- [13] Qiwei Chen, Huan Zhao, Wei Li, Pipei Huang, and Wenwu Ou. 2019. Behavior Sequence Transformer for E-commerce Recommendation in Alibaba. [arXiv:1905.06874](https://arxiv.org/abs/1905.06874) [cs.IR] <https://arxiv.org/abs/1905.06874>
- [14] Yu Chen, Jiaqi Jin, Hui Zhao, Pengjie Wang, Guojun Liu, Jian Xu, and Bo Zheng. 2022. Asymptotically unbiased estimation for delayed feedback modeling via label correction. In *Proceedings of the ACM Web Conference 2022*. 369–379.
- [15] Weiyu Cheng, Yanyan Shen, and Lipeng Huang. 2020. Adaptive factorization network: Learning adaptive-order feature interactions. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 34. 3609–3616.
- [16] Souvik Debnath, Niloy Ganguly, and Pabitra Mitra. 2008. Feature weighting in content based recommendation system using social network analysis. In *Proceedings of the 17th international conference on World Wide Web*. 1041–1042.
- [17] DeepSeek-AI, Aixin Liu, Bei Feng, Bing Xue, Bingxuan Wang, Bochao Wu, Chenglu Lu, Chenggang Zhao, Chengqi Deng, Chenyu Zhang, Chong Ruan, Damai Dai, Daya Guo, Dejian Yang, Deli Chen, Dongjie Ji, Erhang Li, Fangyun Lin, Fucong Dai, Fulu Luo, Guangbo Hao, Guanting Chen, Guowei Li, H. Zhang, Han Bao, Hanwei Xu, Haocheng Wang, Hanwei Zhang, Honghui Ding, Huajian Xin, Huazuo Gao, Hui Li, Hui Qu, J. L. Cai, Jian Liang, Jianzhong Guo, Jiaqi Ni, Jiashi Li, Jiawei Wang, Jin Chen, Jingchang Chen, Jingyang Yuan, Junjie Qiu, Junlong Li, Junxiao Song, Kai Dong, Kai Hu, Kaige Gao, Kang Guan, Kexin Huang, Kuai Yu, Lean Wang, Lecong Zhang, Lei Xu, Leyi Xia, Liang Zhao, Litong Wang, Liyue Zhang, Meng Li, Miaojuan Wang, Mingchuan Zhang, Minghua Zhang, Minghui Tang, Mingming Li, Ning Tian, Panpan Huang, Peiyi Wang, Peng Zhang, Qiancheng Wang, Qihao Zhu, Qinyu Chen, Qiushi Du, R. J. Chen, R. L. Jin, Ruiqi Ge, Ruisong Zhang, Ruizhe Pan, Runji Wang, Runxin Xu, Ruoyu Zhang, Ruyi Chen, S. S. Li, Shanghai Lu, Shangyan Zhou, Shanhuan Chen, Shaoging Wu, Shengfeng Ye, Shengfeng Ye, Shirong Ma, Shiyu Wang, Shuang Zhou, Shuiping Yu, Shunfeng Zhou, Shuteng Pan, T. Wang, Tao Yun, Tian Pei, Tianyu Sun, W. L. Xiao, Wangding Zeng, Wanjia Zhao, Wei An, Wen Liu, Wenfeng Liang, Wenjia Gao, Wenqin Yu, Wentao Zhang, X. Q. Li, Xiangyue Jin, Xianzu Wang, Xiao Bi, Xiaodong Liu, Xiaohan Wang, Xiaojin Shen, Xiaokang Chen, Xiaokang Zhang, Xiaosha Chen, Xiaotao Nie, Xiaowen Sun, Xiaoxiang Wang, Xin Cheng, Xin Liu, Xin Xie, Xingchao Liu, Xingkai Yu, Xinnan Song, Xinxia Shan, Xinyi Zhou, Xinya Yang, Xinyuan Li, Xuecheng Su, Xuheng Lin, Y. K. Li, Y. Q. Wang, Y. X. Wei, Y. X. Zhu, Yang Zhang, Yanhong Xu, Yanhong Xu, Yanping Huang, Yao Li, Yao Zhao, Yaofeng Sun, Yaohui Li, Yaohui Wang, Yi Yu, Yi Zheng, Yichao Zhang, Yifan Shi, Yiliang Xiong, Ying He, Ying Tang, Yishi Piao, Yisong Wang, Yixuan Tan, Yiyang Ma, Yiyuan Liu, Yongqiang Guo, Yu Wu, Yuan Ou, Yuchen Zhu, Yuduan Wang, Yue Gong, Yuheng Zou, Yujia He, Yukun Zha, Yunfan Xiong, Yunxian Ma, Yuting Yan, Yuxiang Luo, Yuxiang You, Yuxuan Liu, Yuyang Zhou, Z. F. Wu, Z. Z. Ren, Zehui Ren, Zhangli Sha, Zhe Fu, Zhean Xu, Zhen Huang, Zhen Zhang, Zhenda Xie, Zhengyan Zhang, Zhenwen Hao, Zhibin Gou, Zhicheng Ma, Zhigang Yan, Zhihong Shao, Zipeng Xu, Zhiyu Wu, Zhongyu Zhang, Zhuoshu Li, Zhihui Gu, Zijia Zhu, Zijun Liu, Zilin Li, Ziwei Xie, Ziyang Song, Ziyi Gao, and Zizheng Pan. 2025. DeepSeek-V3 Technical Report. [arXiv:2412.19437](https://arxiv.org/abs/2412.19437) [cs.CL] <https://arxiv.org/abs/2412.19437>
- [18] Mostafa Dehghani, Josip Djolonga, Basil Mustafa, Piotr Padlewski, Jonathan Heek, Justin Gilmer, Andreas Peter Steiner, Mathilde Caron, Robert Geirhos, Ibrahim Alabdulmohsin, et al. 2023. Scaling vision transformers to 22 billion parameters. In *International Conference on Machine Learning*. PMLR, 7480–7512.
- [19] Chaorui Deng, Deyao Zhu, Kunchang Li, Chenhui Gou, Feng Li, Zeyu Wang, Shu Zhong, Weihao Yu, Xiaonan Nie, Ziang Song, Guang Shi, and Haoqi Fan. 2025. Emerging Properties in Unified Multimodal Pretraining. [arXiv preprint arXiv:2505.14683](https://arxiv.org/abs/2505.14683) (2025).
- [20] Mark Dredze, Alex Kulesza, and Koby Crammer. 2010. Multi-domain learning by confidence-weighted parameter combination. *Machine Learning* 79 (2010), 123–149.
- [21] Thomas Elsken, Jan Hendrik Metzen, and Frank Hutter. 2019. Neural architecture search: A survey. *Journal of Machine Learning Research* 20, 55 (2019), 1–21.
- [22] Chris Fifty, Ehsan Amid, Zhe Zhao, Tianhe Yu, Rohan Anil, and Chelsea Finn. 2021. Efficiently identifying task groupings for multi-task learning. *Advances in Neural Information Processing Systems* 34 (2021), 27503–27516.
- [23] Shijie Geng, Juntao Tan, Shuchang Liu, Zuohei Fu, and Yongfeng Zhang. 2023. Vip5: Towards multimodal foundation models for recommendation. [arXiv preprint arXiv:2305.14302](https://arxiv.org/abs/2305.14302) (2023).
- [24] Dirk Groeneveld, Iz Beltagy, Pete Walsh, Akshita Bhagia, Rodney Kinney, Oyvind Tafjord, Ananya Harsh Jha, Hamish Ivison, Ian Magnusson, Yizhong Wang, Shane Arora, David Atkinson, Russell Author, Khyathi Raghavi Chandu, Arman Cohan, Jennifer Dumas, Yanai Elazar, Yuling Gu, Jack Hessel, Tushar Khot, William Merrill, Jacob Morrison, Niklas Muennighoff, Aakanksha Naik, Crystal Nam, Matthew E. Peters, Valentina Pyatkin, Abhilasha Ravichander, Dustin Schwenk, Saurabh Shah, Will Smith, Emma Strubell, Nishant Subramani, Mitchell Wortsman, Pradeep Dasigi, Nathan Lambert, Kyle Richardson, Luke Zettlemoyer, Jesse Dodge, Kyle Lo, Luca Soldaini, Noah A. Smith, and Hananeh Hajishirzi. 2024. OLMo: Accelerating the Science of Language Models.

- arXiv:2402.00838 [cs.CL] <https://arxiv.org/abs/2402.00838>
- [25] Xingzhuo Guo, Junwei Pan, Ximei Wang, Baixu Chen, Jie Jiang, and Mingsheng Long. 2023. On the Embedding Collapse when Scaling up Recommendation Models. *arXiv preprint arXiv:2310.04400* (2023).
- [26] Vineet Gupta, Tomer Koren, and Yoram Singer. 2018. Shampoo: Preconditioned Stochastic Tensor Optimization. *arXiv:1802.09568* [cs.LG] <https://arxiv.org/abs/1802.09568>
- [27] Xinran He, Junfeng Pan, Ou Jin, Tianbing Xu, Bo Liu, Tao Xu, Yanxin Shi, Antoine Atallah, Ralf Herbrich, Stuart Bowers, and Joaquin Quiñonero Candela. 2014. Practical Lessons from Predicting Clicks on Ads at Facebook. In *Proceedings of the Eighth International Workshop on Data Mining for Online Advertising* (New York, NY, USA) (ADKDD'14). Association for Computing Machinery, New York, NY, USA, 1–9. <https://doi.org/10.1145/2648584.2648589>
- [28] Yun He, Xue Feng, Cheng Cheng, Geng Ji, Yunsong Guo, and James Caverlee. 2022. Metabalance: improving multi-task recommendations via adapting gradient magnitudes of auxiliary tasks. In *Proceedings of the ACM Web Conference 2022*. 2205–2215.
- [29] Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. 2015. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531* (2015).
- [30] Jordan Hoffmann, Sebastian Borgeaud, Arthur Mensch, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, Tom Hennigan, Eric Noland, Katie Millican, George van den Driessche, Bogdan Damoc, Aurelia Guy, Simon Osindero, Karen Simonyan, Erich Elsen, Jack W. Rae, Oriol Vinyals, and Laurent Sifre. 2022. Training Compute-Optimal Large Language Models. *arXiv:2203.15556* [cs.CL] <https://arxiv.org/abs/2203.15556>
- [31] Andrew Howard, Mark Sandler, Grace Chu, Liang-Chieh Chen, Bo Chen, Mingxing Tan, Weijun Wang, Yukun Zhu, Ruoming Pang, Vijay Vasudevan, Quoc V. Le, and Hartwig Adam. 2019. Searching for MobileNetV3. *arXiv:1905.02244* [cs.CV] <https://arxiv.org/abs/1905.02244>
- [32] Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q. Weinberger. 2017. Densely Connected Convolutional Networks. In *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 2261–2269. <https://doi.org/10.1109/CVPR.2017.243>
- [33] Dmytro Ivcchenko, Dennis Van Der Staey, Colin Taylor, Xing Liu, Will Feng, Rahul Kindi, Anirudh Sudarshan, and Shahin Sefati. 2022. Torchrec: a pytorch domain library for recommendation systems. In *Proceedings of the 16th ACM Conference on Recommender Systems*. 482–483.
- [34] Himanshu Jain, Yashoteja Prabhu, and Manik Varma. 2016. Extreme multi-label loss functions for recommendation, tagging, ranking & other missing label applications. In *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*. 935–944.
- [35] Jared Kaplan, Sam McCandlish, Tom Henighan, Tom B Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. 2020. Scaling laws for neural language models. *arXiv preprint arXiv:2001.08361* (2020).
- [36] Daya Khudia, Jianyu Huang, Protom Basu, Summer Deng, Haixin Liu, Jongsoo Park, and Mikhail Smelyanskiy. 2021. FBGEMM: Enabling High-Performance Low-Precision Deep Learning Inference. *arXiv:2101.05615* [cs.LG] <https://arxiv.org/abs/2101.05615>
- [37] Scott Kirkpatrick, C Daniel Gelatt Jr, and Mario P Vecchi. 1983. Optimization by simulated annealing. *science* 220, 4598 (1983), 671–680.
- [38] Sofia Ira Ktena, Alykhan Tejani, Lucas Theis, Pranay Kumar Myana, Deepak Dilipkumar, Ferenc Huszár, Steven Yoo, and Wenzhi Shi. 2019. Addressing delayed feedback for continuous training with neural networks in CTR prediction. In *Proceedings of the 13th ACM conference on recommender systems*. 187–195.
- [39] KuaiShou. [n. d.]. <https://www.kuaiShou.com/activity/uimc>
- [40] Zerong Lan, Yingyi Zhang, and Xianpeng Li. 2023. M3REC: A Meta-based Multi-scenario Multi-task Recommendation Framework. In *Proceedings of the 17th ACM Conference on Recommender Systems* (Singapore, Singapore) (RecSys '23). Association for Computing Machinery, New York, NY, USA, 771–776. <https://doi.org/10.1145/3604915.3608828>
- [41] Chao Li, Zhiyuan Liu, Mengmeng Wu, Yuchi Xu, Huan Zhao, Pipei Huang, Guoliang Kang, Qiwei Chen, Wei Li, and Dik Lun Lee. 2019. Multi-interest network with dynamic routing for recommendation at Tmall. In *Proceedings of the 28th ACM international conference on information and knowledge management*. 2615–2623.
- [42] Danwei Li, Zhengyu Zhang, Siyang Yuan, Mingze Gao, Weilin Zhang, Chaofei Yang, Xi Liu, and Jiyang Yang. 2023. AdaTT: Adaptive Task-to-Task Fusion Network for Multitask Learning in Recommendations. In *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. 4370–4379.
- [43] Pan Li and Alexander Tuzhilin. 2020. Ddtcdr: Deep dual transfer cross domain recommendation. In *Proceedings of the 13th International Conference on Web Search and Data Mining*. 331–339.
- [44] Shen Li, Yanli Zhao, Rohan Varma, Omkar Salpekar, Pieter Noordhuis, Teng Li, Adam Paszke, Jeff Smith, Brian Vaughan, Pritam Damania, and Soumith Chintala. 2020. PyTorch Distributed: Experiences on Accelerating Data Parallel Training. *arXiv:2006.15704* [cs.DC] <https://arxiv.org/abs/2006.15704>
- [45] Yonggi Li, Meng Liu, Jianhua Yin, Chaoran Cui, Xin-Shun Xu, and Liqiang Nie. 2019. Routing Micro-videos via A Temporal Graph-guided Recommendation System. In *Proceedings of the 27th ACM International Conference on Multimedia* (Nice, France) (MM '19). Association for Computing Machinery, New York, NY, USA, 1464–1472. <https://doi.org/10.1145/3343031.3350950>
- [46] Jianxun Lian, Xiaohuan Zhou, Fuzheng Zhang, Zhongxia Chen, Xing Xie, and Guangzhong Sun. 2018. xdeepfm: Combining explicit and implicit feature interactions for recommender systems. In *Proceedings of the 24th ACM SIGKDD international conference on knowledge discovery & data mining*. 1754–1763.
- [47] Xiangru Lian, Binhang Yuan, Xuefeng Zhu, Yulong Wang, Yongjun He, Honghuan Wu, Lei Sun, Haodong Lyu, Chengjun Liu, Xing Dong, Yiqiao Liao, Mingnan Luo, Congfei Zhang, Jingru Xie, Haonan Li, Lei Chen, Renjie Huang, Jianying Lin, Chengchun Shu, Xuezhong Qiu, Zhishan Liu, Dongying Kong, Lei Yuan, Hai Yu, Sen Yang, Ce Zhang, and Ji Liu. 2021. Persia: An open, hybrid system scaling deep learning-based recommenders up to 100 trillion parameters. (Nov. 2021). *arXiv:2111.05897* [cs.LG]
- [48] Mingfu Liang, Xi Liu, Rong Jin, Boyang Liu, Qiuling Suo, Qinghai Zhou, Song Zhou, Laming Chen, Huai Zheng, Zhiyuan Li, Shali Jiang, Jiyang Yang, Xiaozhen Xia, Fan Yang, Yasmina Badr, Ellie Wen, Shuyu Xu, Hansey Chen, Zhengyu Zhang, and Huayu Li. 2025. External Large Foundation Model: How to Efficiently Serve Trillions of Parameters for Online Ads Recommendation. <https://doi.org/10.48550/arXiv.2502.17494>
- [49] Wanchao Liang, Tianyu Liu, Less Wright, Will Constable, Andrew Gu, Chien-Chin Huang, Iris Zhang, Wei Feng, Howard Huang, Junjie Wang, Sanket Purandare, Gokul Nadathur, and Stratos Idreos. 2024. TorchTitan: One-stop PyTorch native solution for production ready LLM pre-training. *arXiv:2410.06511* [cs.CL] <https://arxiv.org/abs/2410.06511>
- [50] Weixin Liang, Lili Yu, Liang Luo, Srinivasan Iyer, Ning Dong, Chunting Zhou, Gargi Ghosh, Mike Lewis, Wen-tau Yih, Luke Zettlemoyer, and Xi Victoria Lin. 2024. Mixture-of-Transformers: A Sparse and Scalable Architecture for Multi-Modality Foundation Models. *arXiv:2411.04996* [cs.CL] <https://arxiv.org/abs/2411.04996>
- [51] Chai Liao, Liyang Liu, Xun Wang, Zhengxiong Luo, Xinyu Zhang, Wenliang Zhao, Jie Wu, Liang Li, Zhi Tian, and Weilin Huang. 2025. Mogao: An Omni Foundation Model for Interleaved Multi-Modal Generation. *arXiv:2505.05472* [cs.CV] <https://arxiv.org/abs/2505.05472>
- [52] Xi Victoria Lin, Akshat Shrivastava, Liang Luo, Srinivasan Iyer, Mike Lewis, Gargi Gosh, Luke Zettlemoyer, and Armen Aghajanyan. 2024. MoMa: Efficient Early-Fusion Pre-training with Mixture of Modality-Aware Experts. *arXiv:2407.21770* [cs.AI] <https://arxiv.org/abs/2407.21770>
- [53] Chengkai Liu, Jianghao Lin, Jianling Wang, Hanzhou Liu, and James Caverlee. 2024. Mamba4rec: Towards efficient sequential recommendation with selective state space models. *arXiv preprint arXiv:2403.03900* (2024)
- [54] Junning Liu, Xinjian Li, Bi An, Zijie Xia, and Xu Wang. 2022. Multi-faceted hierarchical multi-task learning for recommender systems. In *Proceedings of the 31st ACM International Conference on Information & Knowledge Management*. 3332–3341.
- [55] Qidong Liu, Jiaxi Hu, Yutian Xiao, Xiangyu Zhao, Jingtong Gao, Wanyu Wang, Qing Li, and Jiliang Tang. 2024. Multimodal Recommender Systems: A Survey. *arXiv:2302.03883* [cs.IR] <https://arxiv.org/abs/2302.03883>
- [56] Zhaocheng Liu, Zhongxiang Fan, Jian Liang, Dongying Kong, and Han Li. 2023. Multi-epoch learning for deep Click-Through Rate prediction models. *arXiv [cs.IR]* (May 2023).
- [57] Liang Luo, Jacob Nelson, Luis Ceze, Amar Phanishayee, and Arvind Krishnamurthy. 2018. Parameter hub: a rack-scale parameter server for distributed deep neural network training. In *Proceedings of the ACM Symposium on Cloud Computing*. 41–54.
- [58] Liang Luo, Peter West, Jacob Nelson, Arvind Krishnamurthy, and Luis Ceze. 2020. Plink: Discovering and exploiting locality for accelerated distributed training on the public cloud. *Proceedings of Machine Learning and Systems 2* (2020), 82–97.
- [59] Liang Luo, Buyun Zhang, Michael Tsang, Yinbin Ma, Ching-Hsiang Chu, Yuxin Chen, Shen Li, Yuchen Hao, Yanli Zhao, Guna Lakshminarayanan, et al. 2024. Disaggregated Multi-Tower: Topology-aware Modeling Technique for Efficient Large-Scale Recommendation. *arXiv preprint arXiv:2403.00877* (2024).
- [60] Jiaqi Ma, Zhe Zhao, Xinyang Yi, Jili Chen, Lichan Hong, and Ed H Chi. 2018. Modeling task relationships in multi-task learning with multi-gate mixture-of-experts. In *Proceedings of the 24th ACM SIGKDD international conference on knowledge discovery & data mining*. 1930–1939.
- [61] Xiao Ma, Lipin Zhao, Guan Huang, Zhi Wang, Zelin Hu, Xiaoqiang Zhu, and Kun Gai. 2018. Entire space multi-task model: An effective approach for estimating post-click conversion rate. In *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval*. 1137–1140.
- [62] Aakarsh Malhotra, Mayank Vatsa, and Richa Singh. 2022. Dropped scheduled task: Mitigating negative transfer in multi-task learning using dynamic task dropping. *Transactions on Machine Learning Research* (2022).
- [63] Kelong Mao, Jieming Zhu, Liangcai Su, Guohao Cai, Yuru Li, and Zhenhua Dong. 2023. FinalMLP: An Enhanced Two-Stream MLP Model for CTR Prediction. *arXiv preprint arXiv:2304.00902* (2023).

- [64] Andreas Maurer. 2006. Bounds for Linear Multi-Task Learning. *J. Mach. Learn. Res.* 7 (Dec. 2006), 117–139.
- [65] Meta AI. 2023. *AI Ads: Performance and Efficiency with Meta Lattice*. <https://ai.meta.com/blog/ai-ads-performance-efficiency-meta-lattice/>
- [66] Meta Production Engineering. 2024. *The Andromeda Advantage: How Meta's Next-Gen Retrieval Engine Automates Personalized Ads*. <https://engineering.fb.com/2024/12/02/production-engineering/meta-andromeda-advantage-automation-next-gen-personalized-ads-retrieval-engine/>
- [67] Ishan Misra, Abhinav Shrivastava, Abhinav Gupta, and Martial Hebert. 2016. Cross-stitch networks for multi-task learning. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 3994–4003.
- [68] Taylor Mordan, Nicolas Thome, Gilles Hennaff, and Matthieu Cord. 2018. Revisiting multi-task learning with rock: a deep residual auxiliary block for visual detection. *Advances in neural information processing systems* 31 (2018).
- [69] Dheevatsa Mudigere, Yuchen Hao, Jianyu Huang, Andrew Tulloch, Srinivas Sridharan, Xing Liu, Mustafa Ozdal, Jade Nie, Jongsoo Park, Liang Luo, et al. 2021. High-performance, distributed training of large-scale deep learning recommendation models. *arXiv preprint arXiv:2104.05158* (2021).
- [70] Keerthiran Murugesan, Hanxiao Liu, Jaime Carbonell, and Yiming Yang. 2016. Adaptive smoothed online multi-task learning. *Advances in Neural Information Processing Systems* 29 (2016).
- [71] Rafael Müller, Simon Kornblith, and Geoffrey Hinton. 2020. When Does Label Smoothing Help? *arXiv:1906.02629* [cs.LG] <https://arxiv.org/abs/1906.02629>
- [72] Sharan Narang, Hyung Won Chung, Yi Tay, William Fedus, Thibault Fevry, Michael Matena, Karishma Malkan, Noah Fiedel, Noam Shazeer, Zhenzhong Lan, et al. 2021. Do transformer modifications transfer across implementations and applications? *arXiv preprint arXiv:2102.11972* (2021).
- [73] Maxim Naumov, Dheevatsa Mudigere, Hao-Jun Michael Shi, Jianyu Huang, Narayanan Sundaram, Jongsoo Park, Xiaodong Wang, Udit Gupta, Carole-Jean Wu, Alisson G Azzolini, et al. 2019. Deep learning recommendation model for personalization and recommendation systems. *arXiv preprint arXiv:1906.00091* (2019).
- [74] Sinno Jialin Pan and Qiang Yang. 2010. A Survey on Transfer Learning. *IEEE Transactions on Knowledge and Data Engineering* 22, 10 (2010), 1345–1359. <https://doi.org/10.1109/TKDE.2009.191>
- [75] Jongsoo Park, Maxim Naumov, Protonu Basu, Summer Deng, Aravind Kalaiah, Daya Shanker Khudia, James Law, Parth Malani, Andrey Malevich, Nadathur Satish, Juan Miguel Pino, Martin Schatz, Alexander Sidorov, Viswanath Sivakumar, Andrew Tulloch, Xiaodong Wang, Yiming Wu, Hector Yuen, Utku Diril, Dmytro Dzhulgakov, Kim M. Hazelwood, Bill Jia, Yangqing Jia, Lin Qiao, Vijay Rao, Nadav Rotem, Sungjoo Yoo, and Mikhail Smelyanskiy. 2018. Deep Learning Inference in Facebook Data Centers: Characterization, Performance Optimizations and Hardware Implications. *CoRR* abs/1811.09886 (2018). arXiv:1811.09886 <http://arxiv.org/abs/1811.09886>
- [76] Razvan Pascanu, Tomas Mikolov, and Yoshua Bengio. 2013. On the difficulty of training recurrent neural networks. In *International conference on machine learning*. PMLR, 1310–1318.
- [77] Anastasia Pentina and Christoph H Lampert. 2017. Multi-task learning with labeled and unlabeled tasks. In *International conference on machine learning*. PMLR, 2807–2816.
- [78] Prajit Ramachandran, Barret Zoph, and Quoc V. Le. 2017. Swish: a Self-Gated Activation Function. *arXiv: Neural and Evolutionary Computing* (2017). <https://api.semanticscholar.org/CorpusID:196158220>
- [79] Colfax Research. 2025. DeepSeek-R1 and FP8 Mixed-Precision Training. <https://research.colfax-intl.com/deepseek-r1-and-fp8-mixed-precision-training/> Discussion of FP8 accumulation strategies including tensor core vs CUDA core accumulation.
- [80] Alvin E Roth. 1988. *The Shapley value: essays in honor of Lloyd S. Shapley*. Cambridge University Press.
- [81] Shibani Santurkar, Dimitris Tsipras, Andrew Ilyas, and Aleksander Madry. 2018. How does batch normalization help optimization? *Advances in neural information processing systems* 31 (2018).
- [82] Xiang-Rong Sheng, Liqin Zhao, Guorui Zhou, Xinyao Ding, Binding Dai, Qiang Luo, Siran Yang, Jingshan Lv, Chi Zhang, Hongbo Deng, et al. 2021. One model to serve all: Star topology adaptive recommender for multi-domain ctr prediction. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*. 4104–4113.
- [83] Kyuyong Shin, Hanock Kwak, Su Young Kim, Max Nihlén Ramström, Jisu Jeong, Jung Woo Ha, and Kyung-Min Kim. 2023. Scaling law for recommendation models: Towards general-purpose user representations. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 37. 4596–4604.
- [84] Jasper Snoek, Hugo Larochelle, and Ryan P Adams. 2012. Practical bayesian optimization of machine learning algorithms. *Advances in neural information processing systems* 25 (2012).
- [85] Weiping Song, Chence Shi, Zhiping Xiao, Zhijian Duan, Yewen Xu, Ming Zhang, and Jian Tang. 2019. Autoint: Automatic feature interaction learning via self-attentive neural networks. In *Proceedings of the 28th ACM international conference on information and knowledge management*. 1161–1170.
- [86] Rainer Storn and Kenneth Price. 1997. Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces. *Journal of global optimization* 11 (1997), 341–359.
- [87] Jianlin Su, Yu Lu, Shengfeng Pan, Ahmed Murtadha, Bo Wen, and Yunfeng Liu. 2023. RoFormer: Enhanced Transformer with Rotary Position Embedding. *arXiv:2104.09864* [cs.CL] <https://arxiv.org/abs/2104.09864>
- [88] Hongyan Tang, Junning Liu, Ming Zhao, and Xudong Gong. 2020. Progressive layered extraction (ple): A novel multi-task learning (mtl) model for personalized recommendations. In *Proceedings of the 14th ACM Conference on Recommender Systems*. 269–278.
- [89] Jiaxi Tang, Yoel Drori, Daryl Chang, Maheswaran Sathiamoorthy, Justin Gilmer, Li Wei, Xinyang Yi, Lichan Hong, and Ed H Chi. 2023. Improving training stability for multitask ranking models in recommender systems. In *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. 4882–4893.
- [90] Jiaxi Tang, Yoel Drori, Daryl Chang, Maheswaran Sathiamoorthy, Justin Gilmer, Li Wei, Xinyang Yi, Lichan Hong, and Ed H Chi. 2023. Improving Training Stability for Multitask Ranking Models in Recommender Systems. *arXiv preprint arXiv:2302.09178* (2023).
- [91] Linwei Tao, Minjing Dong, and Chang Xu. 2024. Feature Clipping for Uncertainty Calibration. *arXiv:2410.19796* [cs.CV] <https://arxiv.org/abs/2410.19796>
- [92] Chameleon Team. 2024. Chameleon: Mixed-Modal Early-Fusion Foundation Models. *arXiv:2405.09818* [cs.CL]
- [93] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *Advances in neural information processing systems* 30 (2017).
- [94] Ruoxi Wang, Rakesh Shivanna, Derek Cheng, Sagar Jain, Dong Lin, Lichan Hong, and Ed Chi. 2021. Dcn v2: Improved deep & cross network and practical lessons for web-scale learning to rank systems. In *Proceedings of the web conference 2021*. 1785–1797.
- [95] Yichao Wang, Huifeng Guo, Bo Chen, Weiwen Liu, Zhirong Liu, Qi Zhang, Zhicheng He, Hongkun Zheng, Weiwei Yao, Muyu Zhang, et al. 2022. Causalint: Causal inspired intervention for multi-scenario recommendation. In *Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. 4090–4099.
- [96] Yuyan Wang, Xuezhi Wang, Alex Beutel, Flavien Prost, Jilin Chen, and Ed H Chi. 2021. Understanding and improving fairness-accuracy trade-offs in multi-task learning. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*. 1748–1757.
- [97] Yanshi Wang, Jie Zhang, Qing Da, and Anxiang Zeng. 2020. Delayed feedback modeling for the entire space conversion rate prediction. *arXiv preprint arXiv:2011.11826* (2020).
- [98] Yuyan Wang, Zhe Zhao, Bo Dai, Christopher Fifty, Dong Lin, Lichan Hong, Li Wei, and Ed H Chi. 2022. Can small heads help? understanding and improving multi-task generalization. In *Proceedings of the ACM Web Conference 2022*. 3009–3019.
- [99] Zhiqiang Wang, Qingyun She, and Junlin Zhang. 2021. MaskNet: Introducing feature-wise multiplication to CTR ranking models by instance-guided mask. *arXiv preprint arXiv:2102.07619* (2021).
- [100] Chengyue Wu, Xiaokang Chen, Zhiyu Wu, Yiyang Ma, Xingchao Liu, Zizheng Pan, Wen Liu, Zhenda Xie, Xingkai Yu, Chong Ruan, and Ping Luo. 2024. Janus: Decoupling Visual Encoding for Unified Multimodal Understanding and Generation. *arXiv:2410.13848* [cs.CV] <https://arxiv.org/abs/2410.13848>
- [101] Carole-Jean Wu, Ramya Raghavendra, Udit Gupta, Bilge Acun, Newsha Ardalani, Kiwan Maeng, Gloria Chang, Fiona Aga, Jinshi Huang, Charles Bai, et al. 2022. Sustainable ai: Environmental implications, challenges and opportunities. *Proceedings of Machine Learning and Systems* 4 (2022), 795–813.
- [102] Dongbo Xi, Zhen Chen, Peng Yan, Yinger Zhang, Yongchun Zhu, Fuzhen Zhuang, and Yu Chen. 2021. Modeling the sequential dependence among audience multi-step conversions with multi-task learning in targeted display advertising. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*. 3745–3755.
- [103] Da Xiao, Qingye Meng, Shengping Li, and Xingyuan Yuan. 2025. MUDDFormer: Breaking Residual Bottlenecks in Transformers via Multiway Dynamic Dense Connections. *arXiv:2502.12170* [cs.LG] <https://arxiv.org/abs/2502.12170>
- [104] Jiayi Xin, Sukwon Yun, Jie Peng, Inyoung Choi, Jenna L. Ballard, Tianlong Chen, and Qi Long. 2025. I2MoE: Interpretable Multimodal Interaction-aware Mixture-of-Experts. *arXiv:2505.19190* [cs.LG] <https://arxiv.org/abs/2505.19190>
- [105] Bencheng Yan, Pengjie Wang, Kai Zhang, Feng Li, Hongbo Deng, Jian Xu, and Bo Zheng. 2022. APG: Adaptive Parameter Generation Network for Click-Through Rate Prediction. In *Advances in Neural Information Processing Systems*, S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh (Eds.), Vol. 35. Curran Associates, Inc., 24740–24752. [https://proceedings.neurips.cc/paper\\_files/paper/2022/file/9cd0c57170f48520749d5ae62838241f-Paper-Conference.pdf](https://proceedings.neurips.cc/paper_files/paper/2022/file/9cd0c57170f48520749d5ae62838241f-Paper-Conference.pdf)
- [106] Huan Yan, Xiangning Chen, Chen Gao, Yong Li, and Depeng Jin. 2019. Deepapf: Deep attentive probabilistic factorization for multi-site video recommendation. *TC* 2, 130 (2019), 17–883.

- [107] Enneng Yang, Junwei Pan, Ximei Wang, Haibin Yu, Li Shen, Xihua Chen, Lei Xiao, Jie Jiang, and Guibing Guo. 2023. Adatask: A task-aware adaptive learning rate approach to multi-task learning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 37. 10745–10753.
- [108] Xuanhua Yang, Xiaoyu Peng, Penghui Wei, Shaoguo Liu, Liang Wang, and Bo Zheng. 2022. Adasparse: Learning adaptively sparse structures for multi-domain click-through rate prediction. In *Proceedings of the 31st ACM International Conference on Information & Knowledge Management*. 4635–4639.
- [109] Taisuke Yasuda, Mohammadhossein Bateni, Lin Chen, Matthew Fahrbach, Gang Fu, and Vahab Mirrokni. 2022. Sequential Attention for Feature Selection. In *The Eleventh International Conference on Learning Representations*.
- [110] Zhichen Zeng, Xiaoliu Liu, Mengyu Hang, Xiaoyi Liu, Qinghai Zhou, Chaofei Yang, Yiqun Liu, Yichen Ruan, Laming Chen, Yuxin Chen, Yujia Hao, Jiaqi Xu, Jade Nie, Xi Liu, Buyun Zhang, Wei Wen, Siyang Yuan, Kai Wang, Wen-Yen Chen, Yiping Han, Huayu Li, Chunzhi Yang, Bo Long, Philip S. Yu, Hanghang Tong, and Jiyan Yang. 2024. InterFormer: Towards Effective Heterogeneous Interaction Learning for Click-Through Rate Prediction. arXiv:2411.09852 [cs.IR]. <https://arxiv.org/abs/2411.09852>
- [111] Daochen Zha, Louis Feng, Liang Luo, Bhargav Bhushanam, Zirui Liu, Yusuo Hu, Jade Nie, Yuzhen Huang, Yuandong Tian, Arun Kejariwal, et al. 2023. Pre-train and Search: Efficient Embedding Table Sharding with Pre-trained Neural Cost Models. *Proceedings of Machine Learning and Systems* 5 (2023).
- [112] Jiaqi Zhai, Lucy Liao, Xing Liu, Yueming Wang, Rui Li, Xuan Cao, Leon Gao, Zhaojie Gong, Fangda Gu, Michael He, et al. 2024. Actions Speak Louder than Words: Trillion-Parameter Sequential Transducers for Generative Recommendations. *arXiv preprint arXiv:2402.17152* (2024).
- [113] Buyun Zhang, Liang Luo, Yuxin Chen, Jade Nie, Xi Liu, Daifeng Guo, Yanli Zhao, Shen Li, Yuchen Hao, Yantao Yao, et al. 2024. Wukong: Towards a Scaling Law for Large-Scale Recommendation. *arXiv preprint arXiv:2403.02545* (2024).
- [114] Buyun Zhang, Liang Luo, Xi Liu, Jay Li, Zeliang Chen, Weilin Zhang, Xiaohan Wei, Yuchen Hao, Michael Tsang, Wenjun Wang, et al. 2022. DHEN: A deep and hierarchical ensemble network for large-scale click-through rate prediction. *arXiv preprint arXiv:2203.11014* (2022).
- [115] Gaowei Zhang, Yupeng Hou, Hongyu Lu, Yu Chen, Wayne Xin Zhao, and Ji-Rong Wen. 2023. Scaling Law of Large Sequential Recommendation Models. *arXiv preprint arXiv:2311.11351* (2023).
- [116] Qianqian Zhang, Xinru Liao, Quan Liu, Jian Xu, and Bo Zheng. 2022. Leaving No One Behind: A Multi-Scenario Multi-Task Meta Learning Approach for Advertiser Modeling. In *Proceedings of the Fifteenth ACM International Conference on Web Search and Data Mining* (Virtual Event, AZ, USA) (WSDM '22). Association for Computing Machinery, New York, NY, USA, 1368–1376. <https://doi.org/10.1145/3488560.3498479>
- [117] Zijian Zhang, Shuchang Liu, Jiaoyu Yu, Qingpeng Cai, Xiangyu Zhao, Chunxu Zhang, Ziru Liu, Qidong Liu, Hongwei Zhao, Lantao Hu, et al. 2024. M3oE: Multi-Domain Multi-Task Mixture-of-Experts Recommendation Framework. *arXiv preprint arXiv:2404.18465* (2024).
- [118] Yanli Zhao, Andrew Gu, Rohan Varma, Liang Luo, Chien-Chin Huang, Min Xu, Less Wright, Hamid Shojanazeri, Myle Ott, Sam Shleifer, et al. 2023. Pytorch FSDP: experiences on scaling fully sharded data parallel. *arXiv preprint arXiv:2304.11277* (2023).
- [119] Jieming Zhu, Guohao Cai, Junjie Huang, Zhenhua Dong, Ruiming Tang, and Weinan Zhang. 2023. ReLoop2: Building Self-Adaptive Recommendation Models via Responsive Error Compensation Loop. In *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining* (Long Beach, CA, USA) (KDD '23). Association for Computing Machinery, New York, NY, USA, 5728–5738. <https://doi.org/10.1145/3580305.3599785>
- [120] Jieming Zhu, Quanyu Dai, Liangcai Su, Rong Ma, Jinyang Liu, Guohao Cai, Xi Xiao, and Rui Zhang. 2022. BARS: Towards Open Benchmarking for Recommender Systems. In *SIGIR '22: The 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*, Madrid, Spain, July 11 - 15, 2022, Enrique Amigó, Pablo Castells, Julio Gonzalo, Ben Carterette, J. Shane Culpepper, and Gabriella Kazai (Eds.). ACM, 2912–2923. <https://doi.org/10.1145/3477495.3531723>
- [121] Jieming Zhu, Quanyu Dai, Liangcai Su, Rong Ma, Jinyang Liu, Guohao Cai, Xi Xiao, and Rui Zhang. 2022. BARS: Towards Open Benchmarking for Recommender Systems. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval* (Madrid, Spain) (SIGIR '22). Association for Computing Machinery, New York, NY, USA, 2912–2923.
- <https://doi.org/10.1145/3477495.3531723>
- [122] Jieming Zhu, Jinyang Liu, Shuai Yang, Qi Zhang, and Xiuqiang He. 2021. Open Benchmarking for Click-Through Rate Prediction. In *CIKM '21: The 30th ACM International Conference on Information and Knowledge Management, Virtual Event, Queensland, Australia, November 1 - 5, 2021*, Gianluca Demartini, Guido Zuccon, J. Shane Culpepper, Zi Huang, and Hanghang Tong (Eds.). ACM, 2759–2769. <https://doi.org/10.1145/3459637.3482486>
- [123] Jieming Zhu, Jinyang Liu, Shuai Yang, Qi Zhang, and Xiuqiang He. 2021. Open Benchmarking for Click-Through Rate Prediction. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management (Virtual Event, Queensland, Australia) (CIKM '21)*. Association for Computing Machinery, New York, NY, USA, 2759–2769. <https://doi.org/10.1145/3459637.3482486>

## A Appendix

### A.1 Detailed Experimental Setup

**A.1.1 Datasets** We evaluate Lattice on both public and internal datasets. The public dataset KuaiVideo is an representative competition dataset released by Kuaishou [39] as used in [45, 113, 119]. This dataset has 13M entries with 8 features. We use this dataset as a standard benchmark for recent state-of-the-art models in multi-objective recommendation. We use the train/test split provided by the BARS [121] benchmark suite, and we further perform 9 to 1 train and validation split. We use and extend the FuxiCTR framework [123] for experimentation on public dataset. We use two internal datasets, with and without sequence features to evaluate model performance. The dataset without event feature has about 1K features. The dataset with event features contains roughly 2K features and 9 event sources. For evaluating data strategy, we use an internal dataset with about 2K nonsequence features, selected from a pool of 12K features.

**A.1.2 Metrics and Objectives** For KuaiVideo, we report AUC and loss; for internal datasets, we report improved normalized entropy (NE) [27] over a baseline, following prior arts.

Due to lack of a common fundamental task across all recommendation tasks, we use a collection of representative tasks to *approximate* a foundational task from which all downstream tasks can benefit. For the Kuaishou dataset, we predict three tasks: *is\_like*, *is\_follow* and *is\_click* and use the average loss as the final loss. For internal dataset, we create 3 tasks derived from a combination of click and conversion rate prediction across various attribution windows, and we train each model sufficiently long enough to draw conclusions and report metrics.

**A.1.3 Baselines** We focus on comparing with recent state-of-the-art recommendation models including AFN+ [15], AutoInt+ [85], DLRM [73], DCNv2 [94], FinalMLP [63], MaskNet [99], xDeepFM [46], BST [13], APG [105] and Wukong [113]. For public dataset, we use the best-tuned config from BARS if available, otherwise we use the configuration used by [113]. For internal dataset, we use the model tunings adopted by [113]. We report model complexity and parameter count for fair comparison. Note that we may use different model configurations to highlight the effectiveness of different components, which we detail in their respective sections.