

Subjective Behaviors and Preferences in LLM: Language of Browsing

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Abstract

A Large Language Model (LLM) offers versatility across domains and tasks, purportedly benefiting users with a wide variety of behaviors and preferences. We question this perception about an LLM when users have inherently subjective behaviors and preferences, as seen in their ubiquitous and idiosyncratic browsing of websites or apps. The sequential behavior logs of pages, thus generated, form something akin to each user's self-constructed "language", albeit without the structure and grammar imbued in natural languages. We ask: (i) Can a small LM represent the "language of browsing" better than a large LM? (ii) Can an LM with a single set of parameters (or, single LM) adequately capture myriad users' heterogeneous, subjective behaviors and preferences? (iii) Can a single LM with high average performance, yield low variance in performance to make alignment good at user level? We introduce clusterwise LM training, HeTLM (Heterogeneity aware Training of Language Model), appropriate for subjective behaviors. We find that (i) a small LM trained using a page-level tokenizer outperforms large pretrained or finetuned LMs; (ii) HeTLM with heterogeneous cluster specific set of parameters outperforms a single LM of the same family, controlling for the number of parameters; and (iii) a higher mean and a lower variance in generation ensues, implying improved alignment.

1 Introduction

Large Language Models (LLMs) fuel expectations that a *single* trained model can effectively align with preferences of myriad users for a given task within a domain. We term a *single* LM as a specific LM with a *single set* of parameters, regardless of its size. Examples of tasks in the domain of natural language are question-answer, summarization, etc.; and in the business domain - prediction of business

[†]Work done while authors were at Adobe Research

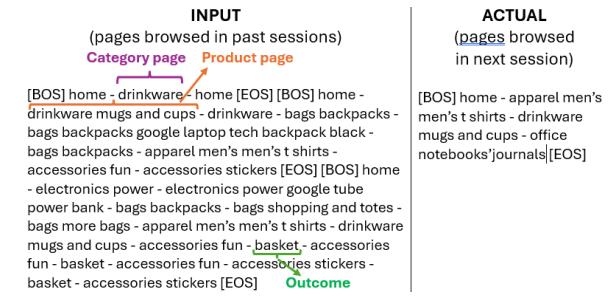


Figure 1: *Language of Browsing*: A user's 4 successive sessions are shown; 3 form the Input, 4th is Actual, used to compare generation. ([BOS], [EOS]) demarcate sessions. Sequential page browsing is seen; sequence-length varies by sessions, and by users. Session's structure is a combination of *Category Page*, *Product Page*, and *Outcome* if it occurs. Outcome: Cart (Basket) or Purchase, is a firm desired target label, and occurs only in a few sessions.

metrics such as conversion, etc. Domain-mapping, task-calibration and preference alignment, can be presumably conquered through provisioning of specific context, instructions, examples, in-context learning, prompting, learning from human preference, finetuning or pretraining on domain-specific data, retrieval augmented generation, applied to a single LM. We question the paradigm of a single LM satisfying alignment for subjective behaviors of myriad users for a given task and domain.

Users' everyday interactions with websites and apps occur in an *idiosyncratic* manner, generating a language of sequence of webpages (or, pages), termed *language of browsing*. Fig 1 shows an example of this. This language *exemplifies* subjective behaviors and preferences, which are *heterogeneous* and *crucially* do not conform to oracle like behavior nor oracle-preference. Even if a single LM produces good average performance in generation across users, the variance in performance across users may be weak, making user level alignment weak. Thus, alignment with some *ideal* oracle or

with the average across users, is less meaningful. The language of browsing is ubiquitous in the form of pageurl-logs that online firms collect. We study users' heterogeneity of behaviors to examine the effectiveness of a single LM. Domain adaptation of LM addresses aspects of heterogeneity in domains and tasks, but none of these works tackle the important problem of heterogeneity in users' subjective behaviors and preferences, embodied in the sequential pages browsed. We learn the language intrinsic to such sequences, using decoder LM. For online firms, prediction of outcomes such as user conversion is of utmost importance. We thus consider three goals: (a) average performance in generation of pages, (b) variance of performance in generation of pages across users, and (c) performance on outcome prediction, where (b) and (c) are unattended in LM prior art.

We find that small LMs, pretrained using a page-level tokenizer, outperform GPT4o with prompting, and fine-tuned versions of LLaMa-3-8B, Mistral-7B, Gemma-7B. The small LMs, are then finetuned clusterwise through our proposed **HeTLM (Heterogeneity aware Training of Language Model)**, where both the number of clusters K and assignment of users to clusters are *endogenously* determined as finetuning progresses. The average performance in generation across users for HeTLM is better than the single LM of larger size in the same family, and the variance in performance is lower. Also, HeTLM performs well on prediction of outcomes available in the data—*add to cart* and *purchase*. These show that HeTLM improves performance for both page generation and outcome prediction.

Our **contributions** are: **(i)** Drawing attention to Language of Browsing for LLMs; **(ii)** Showing that a small model can outperform a large model for outcome prediction with effective pretraining; **(iii)** Introducing heterogeneity of users' subjective behaviors and preferences in LLMs; **(iv)** Offering a network architecture to train LLM clusterwise.

2 Related Work

Heterogeneity: Heterogeneity of subjective preferences inspires our inquiry (Lu et al., 2022b). Heterogeneity drives research in clustering. Clustering algorithms have evolved with online data (Aljalbout et al., 2018; Chen et al., 2017; Ezenkuw et al., 2015; Alkhayrat et al., 2020) - unsupervised and supervised (Shin et al., 2019; Ghasemi et al., 2021).

However, our goal is not to cluster purely based on the user browsing sequence. (Lee and van der Schaar, 2020) learn discrete representations of time-series data by minimizing the KL divergence between individual and cluster-level outcome distributions. We extend this method to an LLM-based setting, where we train multiple cluster-specific LLMs so that at inference time, any arbitrary user's input can be given more accurate generation by invoking the LLM of the nearest cluster. To our best knowledge, such endogenous clusterwise LLM training and its use is not present in prior art.

Recommendation: A growing body of work apply LLMs to recommendation tasks (Wu et al., 2024; Yang et al., 2023). Their focus is on improving recommendations, but not on training LLMs for heterogeneous users with subjective preferences.

Domain Adaptation: Extensive research has addressed domain adaptation by pretraining LLMs on large, domain-specific datasets (i.a., Alsentzer et al., 2019; Lu et al., 2022a; Lee et al., 2019), BioBERT (Lee et al., 2020), BlueBERT (Peng et al., 2019), BioClinicalBERT (Alsentzer et al., 2019), diseaseBERT (He et al., 2020), SciFive (Phan et al., 2021) and BioBART (Yuan et al., 2022). Subsequent work has explored fine-tuning these pre-trained models on downstream tasks (Wang et al., 2023; Mishra et al.). Chen et al., (Chen et al., 2020) pointed out the complexity of adopting general language models blindly to downstream tasks by finetuning. Another line of research employs prompt learning for domain adaptation (Goswami et al., 2023). More recently, methods that infuse task-relevant information from related sources, rather than adapting to an entire domain, have shown promise (Borgeaud et al., 2022; Dai et al., 2023; He et al., 2023; Izacard et al., 2022; Lewis et al., 2020). He et al. (He et al., 2023) proposed LLM based reasoning by decomposing tasks into multiple reasoning steps.

3 Datasets

We show implementation on two public datasets*, each containing pageurls of consumer interactions. The pageurls are sequence of page-names browsed by each consumer, in each session, and sequenced by timestamp. To conserve space, all results for and the description of Dataset II are available in Appendix A.3. Now, we confine to Dataset I.

Dataset I (Google, 2018). Train : Test split =

*The processed datasets are provided here ([link](#))

47,274 : 5,253 samples. Number of unique pages = 1,123. We filter out very short sessions, incomplete data and extremely long sessions based on a percentile cutoff to create the dataset for experiments.

Fig. 1 shows an example of Input data from Dataset I, as a sequence of pages. **Category Level**, **Product Level**, and **Outcome** pages form the tokens we use. **Outcomes** available in pageurls are: *Cart* (Basket, in Dataset I) and *Purchase*; these Outcome pages are generated by the LM and also used as *target labels* to evaluate Outcome prediction against ground truth of the Actual (next) session.

4 Model

4.1 Small LM and Tokenization

To study our thesis, we want an open, small LM which has larger sized variants available, as an open LM allows pretraining. To create a just comparison of the small variant, which when trained in a clusterwise manner has its total number of parameters increase by the multiple of the number of clusters, we need a large variant having at least the same number of total parameters. Since architectures differ by families of LM, it makes sense to select small and larger sized LMs of the same decoder family for a careful comparison. Also, the growing importance of the inference phase (Snell et al., 2024) calls for a small LM with relatively few number of finalized clusters, so that the total number of parameters needed for inference does not blow up in HeTLM. Finally, a small, open LM allows for use of a custom tokenizer with a reduced vocabulary size, which can improve adherence to the desired output format. For this, we employ a custom tokenizer that performs page-level tokenization, including only the unique pages in the vocabulary. For HeTLM clusterwise training we use three small LMs: OPT-350M, QWEN-2.5-500M, and SmollM2-360M.

4.2 Exogenous Clusterwise Training: Kmeans

User sessions are clustered using their SBERT embeddings, with fixed K , using the Kmeans algorithm. Then, cluster-wise, K different small LMs of the same family are finetuned. This approach, which also recognizes the heterogeneity of users, is straightforward and a useful baseline. The limitations are that K is fixed and user sessions are assigned to clusters based purely on embeddings, and are not re-assigned endogenously as proposed in HeTLM, which is described next.

4.3 Endogenous Clusterwise Training: HeTLM

We propose **HeTLM** (**H**eterogeneity aware **T**raining of **L**anguage **M**odels). Fig. 2 shows the architecture of **HeTLM** which integrates embedding-based clustering and fine-tuning endogenously, where clustering is informed by fine-tuning and fine-tuning is guided by clustering. By clustering user session embeddings and fine-tuning a dedicated LM for each cluster, it captures user-specific patterns more effectively than a single-model or exogenous methods like K-means. We use an Actor–Critic framework to iteratively refine both the clustering and the number of clusters, K , based on prediction quality. The theoretical basis for our method is given in A.1. The model has three components: the *Encoder* (SBERT (Reimers and Gurevych, 2019)), the *Selector* (MLP), and the *Predictor* (Zhang et al., 2022)). A small-LM serves as the *Predictor*.

- (1) The *Encoder* processes a batch of user sessions (x_b) and generates embedding representations (z_b) for each sample. These embeddings serve as input to the *Selector*. We choose SBERT for the encoder due to its efficiency in generating high-quality embeddings for sentence-level data.
- (2) The *Selector* takes these embeddings and generates a probability distribution over K clusters for each user session. It is pretrained to mimic Kmeans cluster assignments. Based on these probabilities, the user sessions are grouped and passed to the corresponding *Predictor* models. The Selector, an MLP, efficiently maps session embeddings to clusters, where the number of clusters is *endogenous*.
- (3) The *Predictor* consists of K instances of the small LM model, each pretrained on the entire dataset. We use a custom tokenizer with a vocabulary constrained to the set of pages in the dataset, resulting in better adherence to the output format. Each Predictor is then fine-tuned only on the user sessions assigned to its corresponding cluster by the Selector. By allowing a different set of parameter weights for each cluster, we allow each cluster-wise LM to specialize in behavior patterns of its assigned users, improving predictive accuracy.
- (4) The *Selector* is the *Actor*, and the *Predictor* is the critic. The Selector’s cluster assignments are refined through three loss functions, defined in Sec 4.4 and 4.5. Loss \mathcal{L}_1 , is the negative log-likelihood (NLL) of each Predictor on its assigned sessions, which encourages assignments that yield strong specialization. Loss \mathcal{L}_2 , is the NLL of the cluster assignment probabilities which encourages

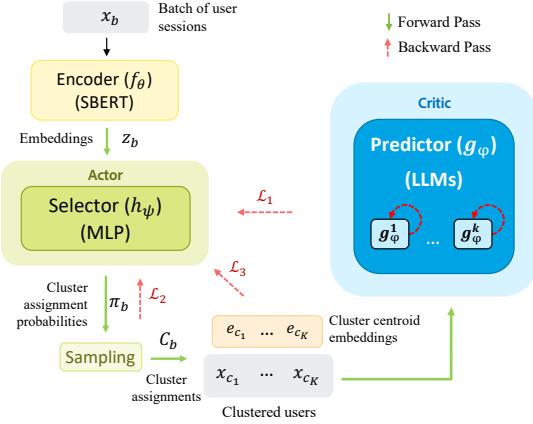


Figure 2: HeTLM Architecture

a sharper probability distribution. Loss, \mathcal{L}_3 , is obtained from the Manhattan distance between centroid embeddings of pairwise clusters, promoting separation between the clusters. Description of the losses and training procedure follow next.

4.4 LLM Loss

Each sequence of user sessions consists of pages separated by delimiters. Given a target sequence of pages $x = a_1 - a_2 - \dots - a_m$, we define its token representation as $T = t_1, t_2, \dots, t_n$, where n is the number of tokens. The corresponding one-hot encoded matrix is given by $\mathcal{O} = [O_1, O_2, \dots, O_n]$, where O_i is one-hot vector of length equal to the vocabulary size, representing the token t_i , and n is the token sequence length.

A language model generates probability distributions corresponding to each token, represented as $\mathfrak{P} = [P_1, P_2, \dots, P_n]$, where each P_i is a probability distribution for the next token over the vocabulary. The loss function is computed as the sum of negative log-likelihoods (NLL) between the one-hot encoded O_i and the generated probability distribution G_i : $\mathcal{L}_{LLM} = -\sum_{i=1}^n O_i \log P_i$

4.5 HeTLM: Actor-Critic

Our proposed HeTLM method follows an Actor-Critic paradigm, where an Encoder first extracts user representations, and then an Actor (Selector) and Critic (LLM) operate on these embeddings. Let \mathcal{X} represent the user sessions in the dataset and \mathcal{Z} represent the embedding space of the Encoder. Let V be the vocabulary size of the model.

Encoder $f_\theta : \mathcal{X} \rightarrow \mathcal{Z}$ maps a user's session sequence $x \in \mathcal{X}$ to a session embedding $z \in \mathcal{Z}$. We utilize the SBERT model to produce these embeddings. The hidden vector z represents the latent

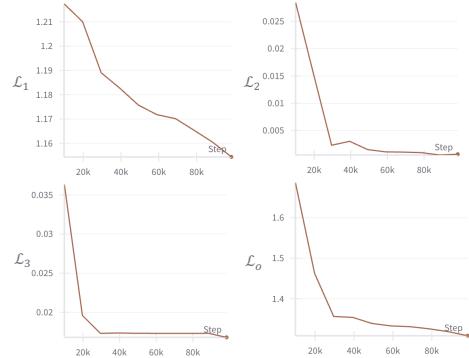


Figure 3: Dataset I. Validation losses for $\alpha = 5, \beta = 9$

tendency of a user, and is used for clustering. The Encoder weights are kept frozen.

Selector $h_\psi : \mathcal{Z} \rightarrow \Delta^{K-1}$ is a MLP that assigns z to one of K clusters, computing a probability distribution π where $\pi(k)$ is the probability of assigning z to cluster k .

Predictor $g_\phi^k : \mathcal{X} \rightarrow \mathbb{R}^{n \times V}$ is an LLM which maps a user session corresponding to cluster k to a matrix, where each row represents a probability distribution $P_i \in \Delta^{V-1}$ for each token.

Embedding Dictionary \mathcal{E} : stores the centroids of the session embeddings of K clusters. Given a cluster assignment c_k , it stores the corresponding centroid embedding $e_{c_k} \in \mathcal{H}$.

4.6 Losses and Training

The following steps are used:

1. Generate Encoder embeddings z for all $x \in \mathcal{X}$
2. Initialize the cluster embeddings using K-means on the embeddings z and pre-train the Selector to mimic K-means
3. Pretrain each of the Predictors on all $x \in \mathcal{X}$
4. Perform Actor-Critic Finetuning to iteratively improve the Selector and the Predictors

The overall selector loss $\mathcal{L}_O(\theta, \phi, \psi) = \mathcal{L}_1 + \alpha \mathcal{L}_2 + \beta \mathcal{L}_3$ combines the 3 losses as described below, with α and β as hyperparameters.

The loss term \mathcal{L}_1 ensures effective specialization within the predictors. We take the weighted average over the cluster probabilities of the LLM loss for all $x \in \mathcal{X}$ to allow for backpropagation.

$$\mathcal{L}_1(\theta, \phi, \psi) = \sum_{k \in K} \pi_k [l_1^k] \quad (1)$$

where, $l_1^k = \mathcal{L}_{LLM}$, is the negative log likelihood of the LLM g_ϕ^k . The critic's loss, which is the loss for each of the Predictors, is:

$$\mathcal{L}_c^k(\phi) = \mathbf{1}_{\{argmax(\pi)=k\}} [l_1^k] \quad (2)$$

The loss term \mathcal{L}_2 promotes sparse cluster assignment such that each user belongs to one cluster with high probability. It is given by:

$$\mathcal{L}_2(\theta, \psi) = - \sum_{k \in K} \pi_k \log \pi_k \quad (3)$$

Further, to promote well-separated cluster centroids in embedding representation, the loss \mathcal{L}_3 is used, which is the negated sum of Manhattan distance between pairwise cluster centroid embeddings passed through a sigmoid function,

$$\mathcal{L}_3(\theta, \phi, \psi) = \sigma \left(- \sum_{k \neq k'} \|\mathbf{e}_{c_k} - \mathbf{e}_{c_{k'}}\|_1 \right) \quad (4)$$

For efficiency, training is performed in batches. The validation losses over steps are shown in Fig. 3 and the training steps are shown in Algorithm 1. Training hyperparameters are included in A.4.

Algorithm 1 Actor-Critic Fine-Tuning

```

1: Generate: embeddings  $\mathbf{z} = f_\theta(x)$  for all  $x \in \mathcal{X}$ 
2: Initialize: Selector  $h_\psi$  with K-means clusters
3: Pretrain: Predictors  $g_\phi^k$  on all  $x \in \mathcal{X}$ 
4: Train  $h_\psi, g_\phi^k$  using Actor-Critic Finetuning
5: while not converged do
6:   sample batch  $x_b \in \mathcal{X}$ 
7:   Compute embeddings  $\mathbf{z}_b = f_\theta(\mathbf{x}_b)$ 
8:   Compute cluster probs  $\pi_b = h_\psi(\mathbf{z}_b)$ 
9:   Assign clusters  $C_b = argmax(\pi_b)$ 
10:  Critic loss:  $\mathcal{L}_C = \mathcal{L}_1$ 
11:  Update  $\phi$  via gradient descent on  $\mathcal{L}_C$ 
12:  Selector loss:  $\mathcal{L}_O = \mathcal{L}_1 + \alpha \mathcal{L}_2 + \beta \mathcal{L}_3$ 
13:  Update  $\psi$  via gradient descent on  $\mathcal{L}_O$ 
14: end while

```

5 Empirical Strategy for Experiments

We adopt a 2-step empirical strategy.

Step 1: Compare single LMs - small vs. large.

On Dataset I, as appropriate, each LM is—pretrained, or finetuned, or prompt-tuned—as the case may be, and compared on Mean performance metrics conforming to both Page Generation and Outcome Prediction for the Next session, across all users in test data. The performance of the small LMs is checked.

Step 2: Compare HeTLM clusterwise, small LM vs. larger, single LM. Using Dataset I, each small LM is pretrained with the HeTLM architecture (Fig. 2) to produce K clusterwise versions of this LM, where both K and assignment of users to clusters are

endogenously determined. We get K different sets of parameters for K LMs, meant to better align overall with users in K clusters. Fetch an LM of the same family as the small LM, but one with a larger size, so that its number of parameters is larger than the total number of parameters of K small LMs. Pre-train the large LM with a page-level custom tokenizer on Dataset I. Compare performance of HeTLM clusterwise, small LMs with the larger single LM in average performance metrics, as well as, in Variance of performance in Page Generation across all users in test data. For indepth comparison, we use an expanded set of metrics.

5.1 Evaluation Metrics for Step 1

All evaluations are performed by comparing page generation in next session against the pages in the Actual next session (e.g., Fig. 1). We use a broad set of metrics to support three key aspects of our approach. (1) Variance metrics in page generation are introduced to capture variability across users—an aspect overlooked in prior work but central to our premise of subjectivity in user heterogeneity. This aligns with our thesis of clusterwise LMs and is described in 5.2.2. (2) Page generation metrics are aligned with prior work on language models and allow standard benchmarking. (3) Outcome prediction metrics (Accuracy, Precision, Recall, F1) are widely used in prior art and are essential for evaluating business impact. We further disaggregate these by outcome type (e.g., cart vs. purchase) to give the reader a more complete view of model behavior. Rather than reducing to a minimal set, we provide comprehensive metrics so readers can interpret results according to their own priorities. To aid in comparison across models, we also include composite metrics in Sec. 5.3. In Step 1, our first level comparison, we use 6 evaluation metrics. In Step 2, we use 14 additional metrics to deep dive for detailed comparisons.

5.1.1 Page Generation - Mean across Users

A common objective for LLMs, we use the following 2 metrics in Step 1, which are defined per user. We report the Mean across all users, *higher is better*.

[IoA] *Intersection over Actual:* Ratio of number of correctly generated pages to that of *actual* pages; same as, *1 minus False Negative*.

[IoP] *Intersection over Predicted (Generated):* Ratio of number of correctly generated pages to that of *generated* pages; same as, *1 minus False Positive*.

5.1.2 Outcome Prediction - Mean across Users

Important business Outcomes of interest are: Add-to-cart and Purchase. For each consumer we check whether generated pages in the Next session contain either Cart or Purchase page, and evaluate against the Actual session pages containing them. We use 4 outcome metrics, defined as Mean across all users. While F1 is a composite, recall and precision provide useful, incremental information and thus we use them. *Higher is better.*

[Acc] Accuracy for Cart / Purchase.

[Rec] Recall for Cart / Purchase.

[Prec] Precision for Cart / Purchase.

[F1] F1-score for Cart / Purchase.

5.2 Additional Evaluation Metrics for Step 2

5.2.1 Page Generation - Mean across Users

We use the following 4 *additional* metrics in Step 2. Each metric is computed per user and then reported as Mean across all users. *Higher is better.*

[HR] Hit Rate: Per user, at least one common page in generation and actual is scored 1; 0, otherwise.

[IoU] Intersection over Union: Per user, ratio of the number of correctly generated pages to the union of the number of *generated* and *actual* pages.

[Val-P] Valid Page Score: Per user, ratio of the number of valid pages to the number of all pages in generation, per user. This cautions about *hallucination*, by having a score closer to 1.

[New-P] New Page Score: Per user, ratio of the number of pages not in input to the number of valid pages in generation. Indicating a degree to which pages generated are outside of the pages in input, it captures new generation instead of merely retrieval.

5.2.2 Introducing Variance in Page Generation metrics for User alignment

Per user, we can measure alignment since the Ground truth of Next session is available in the Language of Browsing. For the following metrics we compute Variance across users as a degree of alignment in Page Generation. *Lower variance is better*, since it suggests better alignment.

[IoA-var] Intersection over Actual Variance.

[IoG-var] Intersection over Generated Variance.

[IoU-var] Intersection over Union Variance.

[HR-var] Hit Rate Variance.

5.2.3 Outcome Prediction separately for Cart and for Purchase

For a more complete picture to emerge, we also consider Accuracy, Recall, Precision separately for

Cart and for Purchase predictions.

5.3 Composite Metrics

To make comparison easier over the 20 metrics, we introduce composite metrics, where each is a scalar value. Defined with competing Single LM as benchmark, it is = *Number of metrics where HeTLM scores greater than single LM* / 20. This metric is intuitive, bounded between 0 and 1, where score greater (less) than 0.5 favors (*disfavors*) HeTLM, versus single LLM. For each of Page Generation-Mean, Outcome Prediction-Mean, Page Generation-Variance, and for Overall (across all these three metrics) we present a composite metric.

6 Experiment Results: Dataset I

Model	IoA	IoP	Acc Cart or Purchase	Rec Cart or Purchase	Prec Cart or Purchase	F1 Cart or Purchase
GPT-4o Zero-shot	0.275	0.175	0.928	0.400	0.488	0.440
GPT-4o Few-shot	0.400	0.276	0.869	0.628	0.367	0.464
Llama2-7B Chat-Few-shot	0.329	0.251	0.932	0.305	0.424	0.355
Llama3-8B LORA-32R	0.327	0.339	0.914	0.390	0.409	0.399
Llama3-8B FullFineTune	0.295	0.307	0.871	0.399	0.437	0.417
Mistral-7B LORA-32R	0.124	0.129	0.904	0.360	0.376	0.368
Gemma-7B LORA-32R	0.269	0.266	0.905	0.442	0.424	0.433
OPT-350M Pre-train	0.334	0.314	0.872	0.447	0.514	0.478
QWEN-2.5-500M Pre-train	0.408	0.426	0.918	0.515	0.571	0.542
SmollM2-360M Pre-train	0.431	0.424	0.92	0.502	0.542	0.521

Table 1: **Dataset I.** Small LMs, QWEN-2.5-500M, SmollM2-360M, OPT-350M dominate the collection of large LMs in 5 metrics, except in Rec - Cart or Purchase.

6.1 Results: Step 1

Small LMs, OPT-350M, QWEN-2.5-500M and SmollM2-360M, are pretrained on Dataset I, while large LMs, Llama3-8B, Mistral-7B and Gemma-7B, are finetuned on the same data. Two variations of Llama3-8B are used - LORA finetuned and full finetuned. Per Table 1, small LMs outperform large LMs, namely, GPT-4o-200B+, LLaMa2-7B, Llama3-8B, Mistral-7B, Gemma-7B. Step 2 HeTLM clusterwise experiments are done with small LMs.

6.2 Results: Step 2

Here we present results for OPT and QWEN2.5; SmollM2 results are in Appendix A.2. In each table, the row **Combined** shows an average of all 5,253 users across clusters. First, see Table 2. Comparative results are shown for OPT-350M and QWEN-2.5-500M because each has a large-sized LM, which is necessary for a just comparison, per Sec. 4.1. Since the clusterwise HeTLM for

Model	<i>N</i>	HR	IoA	IoP	IoU	New-P	Val-P
OPT 2.7B	5253	0.813	0.424	0.417	0.31	0.183	0.035
OPT-350M Kmeans, K=6							
Cluster 1	438	0.838	0.419	0.31	0.228	0.196	0.028
Cluster 2	1359	0.703	0.221	0.165	0.104	0.018	0.003
Cluster 3	638	0.803	0.327	0.26	0.169	0.205	0.035
Cluster 4	330	0.745	0.472	0.451	0.362	0.364	0.078
Cluster 5	573	0.696	0.277	0.341	0.209	0.265	0.071
Cluster 6	1915	0.794	0.309	0.301	0.188	0.241	0.049
Combined	5253	0.761	0.304	0.275	0.18	0.186	0.038
OPT-350M Kmeans, K=2							
Combined	5253	0.776	0.347	0.324	0.225	0.134	0.027
OPT-350M HeTLM ($\alpha=2, \beta=1$)							
Cluster 1	948	0.795	0.355	0.354	0.24	0.172	0.033
Cluster 2	319	0.881	0.63	0.657	0.538	0.0	0.0
Cluster 3	2875	0.8	0.367	0.396	0.264	0.181	0.042
Cluster 4	277	0.686	0.298	0.406	0.245	0.051	0.016
Cluster 5	759	0.783	0.288	0.334	0.188	0.159	0.043
Combined	5253	0.796	0.367	0.397	0.265	0.156	0.036
OPT-350M HeTLM ($\alpha=5, \beta=9$)							
Cluster 1	305	0.879	0.616	0.713	0.572	0.0	0.0
Cluster 2	4797	0.819	0.373	0.387	0.265	0.216	0.048
Cluster 3	151	0.57	0.31	0.439	0.286	0.0	0.0
Combined	5253	0.816	0.385	0.407	0.284	0.197	0.044
QWEN-2.5-7B							
Combined	5253	0.699	0.253	0.265	0.156	0.136	0.044
QWEN-2.5-500M HeTLM ($\alpha=5, \beta=9$)							
Cluster 1	3101	0.809	0.437	0.39	0.30	0.223	0.041
Cluster 2	316	0.87	0.64	0.71	0.587	0.022	0.005
Cluster 3	1673	0.80	0.401	0.414	0.30	0.175	0.037
Cluster 4	163	0.595	0.322	0.391	0.27	0.006	0.001
Combined	5253	0.803	0.434	0.417	0.314	0.189	0.036

Table 2: Dataset I. Page Generation Results. *Higher is Better*. **Combined** shows the average across clusters for each HeTLM.

OPT-350M has $K = 6$ times as many parameters ($6*350M=2.1B$), we compare against a larger, single LM, namely, OPT-2.7B. Similarly, we compare HeTLM for QWEN-2.5-500M with ($6*500M=3.0B$) parameters against larger, single LM, QWEN-2.5-7B. Results for Kmeans and HeTLM are shown. Varying α, β for HeTLM adjusts weights on losses in $\mathcal{L}_{\mathcal{O}}$, leading to major changes in number of clusters and size. OPT-350M-HeTLM Combined ($\alpha=5, \beta=9$) outperforms all others and the baseline of single LM OPT-2.7B on all 6 metrics. For each combination of α, β (i) there is a large variation in evaluation metrics across clusters, implying that alignment with users varies across clusters, and (ii) cluster-specific metrics vary from the single LM, OPT-2.7B.

Echoing results from Page Generation, in Outcome Prediction (Table 4), HeTLM outperforms single LM, within each family OPT and QWEN-2.5. For Variance in Page Generation, Table 3 comparison of HeTLM $\alpha=5, \beta=9$ with respective LM shows for each combination of α, β (i) there is difference in variances across clusters for each metric, and (ii) cluster specific variances vary from the single LL

Model	<i>N</i>	HR-var	IoA-var	IoP-var	IoU-var
OPT 2.7B	5253	0.152	0.121	0.119	0.109
OPT-350M: Kmeans, K=6					
Cluster 1	438	0.136	0.088	0.076	0.053
Cluster 2	1359	0.209	0.047	0.031	0.015
Cluster 3	638	0.158	0.068	0.06	0.031
Cluster 4	330	0.19	0.155	0.148	0.129
Cluster 5	573	0.211	0.087	0.108	0.075
Cluster 6	1915	0.163	0.069	0.07	0.044
Combined	5253	0.182	0.077	0.074	0.048
OPT-350M: Kmeans, K=2					
Combined	5253	0.174	0.096	0.092	0.071
OPT-350M: HeTLM ($\alpha=2, \beta=1$)					
Cluster 1	948	0.163	0.094	0.09	0.071
Cluster 2	319	0.105	0.138	0.122	0.129
Cluster 3	2875	0.16	0.1	0.102	0.083
Cluster 4	277	0.215	0.102	0.133	0.091
Cluster 5	759	0.17	0.061	0.072	0.037
Combined	5253	0.162	0.101	0.103	0.082
OPT-350M: HeTLM ($\alpha=5, \beta=9$)					
Cluster 1	305	0.107	0.137	0.129	0.144
Cluster 2	4797	0.148	0.096	0.097	0.082
Cluster 3	151	0.245	0.143	0.185	0.137
Combined	5253	0.15	0.103	0.107	0.092
QWEN-2.5-7B					
Combined	5253	0.211	0.064	0.067	0.036
QWEN-2.5-500M: HeTLM ($\alpha=5, \beta=9$)					
Cluster 1	3101	0.154	0.125	0.103	0.098
Cluster 2	316	0.113	0.143	0.135	0.151
Cluster 3	1673	0.161	0.123	0.115	0.109
Cluster 4	163	0.241	0.14	0.170	0.128
Combined	5253	0.158	0.129	0.117	0.111

Table 3: Dataset I. Variance in Page Generation across users. *Lower is Better*. Results for same models as in Table 4.

OPT-2.7B. The reduction in variance seen in Table 3 from HeTLM’s Combined evaluation supports the clustering approach.

Table 5 has a composite evaluation across all 20 metrics (see Sec. 5.3). The overall Composite shows that respectively, 60% and 80% of times HeTLM for OPT-350M and QWEN-2.5-500M with $\alpha=5, \beta=9$ outperform the single, LM baselines, OPT-2.7B and QWEN-2.5-7B. For OPT, this is much higher than what exogenous clustering Kmeans achieves. In sum, page generation alignment vary across clusters and shows the downside of using a single LM to meet users’ heterogeneous and subjective behaviors and preferences. HeTLM offers better alignment with users.

In addition to results shown for Kmeans, K=6, we also show results for K=2 (decided based on Silhouette Coefficient). See Tables 2 - 5. We find that K=2 produces worse performance than K=6 for Kmeans, where choice of number of clusters is

Model	N	Acc-Cart	Acc-Purchase	Acc-Cart/Purchase	Rec-Cart	Rec-Purchase	Rec-Cart/Purchase	Prec-Cart	Prec-Purchase	Prec-Cart/Purchase	F1-Cart/Purchase
OPT-2.7B	5253	0.74	0.869	0.917	0.55	0.402	0.551	0.532	0.255	0.533	0.542
OPT-350M Kmeans, K=6											
Cluster 1	438	0.589	0.653	0.797	0.680	0.52	0.676	0.483	0.169	0.483	0.564
Cluster 2	1359	0.617	0.76	0.816	0.381	0.339	0.381	0.354	0.131	0.353	0.366
Cluster 3	638	0.633	0.82	0.884	0.545	0.2	0.545	0.339	0.05	0.339	0.418
Cluster 4	330	0.746	0.939	0.949	0.156	0.0	0.156	0.132	0.0	0.13	0.141
Cluster 5	573	0.745	0.944	0.951	0.248	0.238	0.248	0.333	0.238	0.333	0.284
Cluster 6	1915	0.688	0.786	0.858	0.509	0.479	0.509	0.486	0.201	0.488	0.498
Combined	5253	0.665	0.799	0.861	0.467	0.4	0.466	0.41	0.159	0.411	0.437
OPT-350M Kmeans, K=2											
Combined	5253	0.698	0.831	0.884	0.467	0.376	0.466	0.458	0.184	0.458	0.462
OPT-350M HeTLM ($\alpha=2, \beta=1$)											
Cluster 1	948	0.688	0.756	0.857	0.576	0.475	0.575	0.539	0.212	0.542	0.558
Cluster 2	319	0.865	0.966	0.969	0.136	0.1	0.136	0.545	0.333	0.545	0.218
Cluster 3	2875	0.745	0.865	0.917	0.530	0.391	0.529	0.577	0.267	0.577	0.552
Cluster 4	277	0.830	0.957	0.964	0.204	0.0	0.204	0.733	0.0	0.733	0.319
Cluster 5	759	0.696	0.80	0.862	0.459	0.417	0.459	0.364	0.103	0.364	0.407
Combined	5253	0.74	0.849	0.906	0.501	0.397	0.50	0.535	0.216	0.536	0.518
OPT-350M HeTLM ($\alpha=5, \beta=9$)											
Cluster 1	305	0.872	0.974	0.974	0.073	0.0	0.073	0.75	0.0	0.75	0.133
Cluster 2	4797	0.728	0.859	0.912	0.529	0.383	0.528	0.536	0.245	0.536	0.532
Cluster 3	151	0.874	0.974	0.98	0.05	0.0	0.05	1.0	0.0	1.0	0.095
Combined	5253	0.741	0.869	0.918	0.51	0.371	0.508	0.537	0.245	0.537	0.522
QWEN-2.5-7B											
QWEN-2.5-500M HeTLM ($\alpha=5, \beta=9$)											
Cluster 1	3101	0.728	0.864	0.918	0.626	0.453	0.625	0.529	0.292	0.529	0.573
Cluster 2	316	0.88	0.975	0.978	0.273	0.111	0.273	0.667	1.0	0.667	0.387
Cluster 3	1673	0.725	0.885	0.917	0.549	0.475	0.548	0.530	0.301	0.530	0.539
Cluster 4	163	0.859	0.969	0.969	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Combined	5253	0.74	0.881	0.923	0.58	0.446	0.579	0.531	0.296	0.531	0.554

Table 4: Dataset I. Outcome Prediction Results. *Higher is Better*. Bold indicates highest value in column. For OPT, HeTLM Combined results for $\alpha=5, \beta=9$, outperform OPT-350M-2.7B on 6 metrics, equals on 1, and is outperformed by 3. We find even stronger results favoring HeTLM for QWEN2.5.

fixed exogenously. However, notably for HeTLM, choice of number of clusters is endogenous and HeTLM outperforms Kmeans.

phasize the importance of recognizing heterogeneity in users' subjective behaviors when training LMs so that better alignment ensues across users.

Model	Outcome Prediction	Page Gen Mean	Page Gen Var	Overall Composite
Compared with OPT-2.7B				
OPT-350M - Combined				
Kmeans, K=6	0.0	0.333	0.75	0.25
Kmeans, K=2	0.1	0.0	0.5	0.15
HeTLM ($\alpha=2, \beta=1$)	0.3	0.167	0.75	0.35
HeTLM ($\alpha=5, \beta=9$)	0.5	0.5	1.0	0.6
Compared with QWEN-2.5-7B				
QWEN-2.5-500M - Combined				
HeTLM ($\alpha=5, \beta=9$)	1.0	0.833	0.25	0.8

Table 5: Dataset I. Composite metrics of Sec. 5.3. Overall Composite clearly favors HeTLM $\alpha=5, \beta=9$ over other variation and exogenous clusterwise Kmeans.

6.3 BLEU and BERT metrics

See Table 6. Remarkably, each small, single LM outperforms each large, single LM in BLEU and in all 3 BERT metrics. Within QWEN-2.5, QWEN2.5-HeTLM Combined performs better than the single LM, QWEN-2.5 7B, in all metrics, and also performs better than all LMs shown. The improvements at cluster level (Cluster 2 for QWEN-2.5-HeTLM, Cluster 1 for OPT-350M-HeTLM) and differences across clusters in the metrics are notable. The results em-

6.4 Ablation: OPT-350M

We ran two ablations to examine the effect of the sharpness of the selector probability distribution (α) and the presence of cluster separation (β). The hyperparameters α, β are selected empirically and these are dataset and LM specific. We provide a snapshot of composite metrics in Table 7. By comparing with results of HeTLM for OPT-350M in Table 5, we find that the proposed architecture with non-zero $\alpha=5, \beta=9$ performs appreciably better than suppressing either α , or β . General trends may be identified with a more indepth analysis which is beyond the scope of this paper.

7 Conclusion and Discussion

We address a specific research gap in the otherwise vast and growing literature in LLMs. This gap emanates from lack of attention to the language of browsing, which is idiosyncratically generated as sequences of pages, by each user as s/he subjectively browses websites or apps. This language does not have the grammar and structure of natural language. Working with the language of browsing, users' heterogeneity of behaviors and subjective

Model	BLEU	BERT-P	BERT-R	BERT-F1
LLaMa-3-8B	0.253	0.891	0.889	0.889
Mistral-7B	0.196	0.888	0.88	0.883
Gemma-7B	0.255	0.889	0.88	0.889
Small-LMs				
OPT-350M	0.320	0.903	0.896	0.899
SmolLM2-360M	0.360	0.906	0.903	0.904
QWEN-2.5-500M	0.355	0.903	0.902	0.902
OPT 2.7B	0.376	0.906	0.908	0.907
OPT-350M Kmeans, K=6				
Cluster 1	0.241	0.861	0.889	0.874
Cluster 2	0.137	0.814	0.844	0.828
Cluster 3	0.20	0.855	0.878	0.866
Cluster 4	0.39	0.903	0.906	0.904
Cluster 5	0.305	0.917	0.890	0.903
Cluster 6	0.268	0.891	0.888	0.888
Combined	0.235	0.868	0.878	0.871
OPT-350M HeTLM ($\alpha=5, \beta=9$)				
Cluster 1	0.637	0.954	0.944	0.949
Cluster 2	0.339	0.902	0.901	0.901
Cluster 3	0.403	0.951	0.895	0.922
Combined	0.358	0.907	0.904	0.905
QWEN-2.5-7B	0.254	0.892	0.888	0.889
QWEN-2.5-500M HeTLM ($\alpha=5, \beta=9$)				
Cluster 1	0.359	0.907	0.907	0.907
Cluster 2	0.63	0.954	0.945	0.948
Cluster 3	0.365	0.911	0.903	0.906
Cluster 4	0.396	0.940	0.898	0.918
Combined	0.378	0.912	0.908	0.909

Table 6: Dataset I. BLEU and BERT scores. Bold indicates the highest value in the column. Underline shows comparison of the larger LM with HeTLM for small LM of the same family.

preferences call for a model with endogenous clusterwise training to balance between performances on page generation, outcome prediction and reducing variance in alignment. While training an LM satisfying these objectives is the primary goal, as way of applications, we propose using the LM thus trained to derive solutions to make a variety of everyday business tasks *predictive*. These tasks range from predictive targeting (based on product page in next session), predictive journey (based on sequence of pages in next session), segmentation (based on predictive journey) and recommendation. Future work can overcome some limitations of this paper by delving into larger browsing datasets and these predictive tasks, and compare with conventional models. Also, HeTLM shows lower inference time than a relevant single LM (Appendix Table 18).

Model	Outcome Prediction	Page Gen Mean	Page Gen Var	Overall Composite
Compared with OPT-2.7B				
OPT-350M - Combined				
HeTLM ($\alpha=1, \beta=0$)	0.1	0.0	0.75	0.2
HeTLM ($\alpha=1, \beta=3$)	0.4	0.167	0.75	0.4
HeTLM ($\alpha=9, \beta=0$)	0.1	0.167	0.75	0.25
HeTLM ($\alpha=9, \beta=3$)	0.1	0.0	0.75	0.2

Table 7: Dataset I. Ablation. Composite metrics of Sec. 5.3. Ablation with OPT-350M, Pre-training, by varying α, β .

Limitations

There are a few limitations to which we draw attention. For context, the language of browsing is commonplace since every online firm collects behavior logs of sequences of pages every user clicks on its website or app. Yet, unlike natural language data that are readily available on the internet, this type of data is private to the firm and reside in a protected data lake. We obtained two datasets put out in the public domain and show experiments with those. We tried to make the most of these datasets by performing experiments on 3 small LMs and 6 large LMs to provide a fair comparison.

As limitations: One, to generalize our findings, it will be valuable to run our proposed HeTLM on other language of browsing datasets. Two, due to the fundamental differences between browsing sequences and natural language, standard NLP datasets could not be used for evaluation. Three, a scalability analysis, out of scope for the paper and given our access to limited compute, will be useful going forward. Four, staying with single LMs, we compare small versus large LMs to show better performance of small LMs, where the large LMs up to 8B in size are finetuned on our data. Extending this to much larger sized LMs, such as Llama-70B or others which are finetunable, will provide additional test of our proposition of using small LMs for language of browsing.

References

Amazon ec2 p4d instances – aws. <https://aws.amazon.com/ec2/instance-types/p4/>. (Accessed on 10/18/2024).

Elie Aljalbout, Vladimir Golkov, Yawar Siddiqui, Maximilian Strobel, and Daniel Cremers. 2018. Clustering with deep learning: Taxonomy and new methods. *arXiv preprint arXiv:1801.07648*.

Maha Alkhayrat, Mohamad Aljnidi, and Kadan

Aljoumaa. 2020. A comparative dimensionality reduction study in telecom customer segmentation using deep learning and pca. *Journal of Big Data*, 7(1):1–23.

Emily Alsentzer, John R. Murphy, Willie Boag, Wei-Hung Weng, Di Jin, Tristan Naumann, and Matthew B. A. McDermott. 2019. [Publicly available clinical BERT embeddings](#). *CoRR*, abs/1904.03323.

axolotl-ai cloud. 2023. Axolotl. <https://github.com/axolotl-ai-cloud/axolotl>.

Sebastian Borgeaud, Arthur Mensch, Jordan Hoffmann, Trevor Cai, Eliza Rutherford, Katie Millican, George van den Driessche, Jean-Baptiste Lespiau, Bogdan Damoc, Aidan Clark, Diego de Las Casas, Aurelia Guy, Jacob Menick, Roman Ring, Tom Hennigan, Saffron Huang, Loren Maggiore, Chris Jones, Albin Cassirer, and 9 others. 2022. [Improving language models by retrieving from trillions of tokens](#). In *International Conference on Machine Learning, ICML 2022, 17-23 July 2022, Baltimore, Maryland, USA*, volume 162 of *Proceedings of Machine Learning Research*, pages 2206–2240. PMLR.

Sanyuan Chen, Yutai Hou, Yiming Cui, Wanxiang Che, Ting Liu, and Xiangzhan Yu. 2020. [Recall and learn: Fine-tuning deep pretrained language models with less forgetting](#). In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020*, pages 7870–7881. Association for Computational Linguistics.

Xiaojun Chen, Yixiang Fang, Min Yang, Feiping Nie, Zhou Zhao, and Joshua Zhuxue Huang. 2017. Purtreeclust: A clustering algorithm for customer segmentation from massive customer transaction data. *IEEE Transactions on Knowledge and Data Engineering*, 30(3):559–572.

Jack Choquette, Wishwesh Gandhi, Olivier Giroux, Nick Stam, and Ronny Krashinsky. 2021. [Nvidia a100 tensor core gpu: Performance and innovation](#). *IEEE Micro*, 41(2):29–35.

Zhuyun Dai, Vincent Y. Zhao, Ji Ma, Yi Luan, Jianmo Ni, Jing Lu, Anton Bakalov, Kelvin Guu, Keith B. Hall, and Ming-Wei Chang. 2023. [Promptagator: Few-shot dense retrieval from 8 examples](#). In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net.

Chinedu Pascal Ezenku, Simeon Ozuomba, and Constance Kalu. 2015. Application of k-means algorithm for efficient customer segmentation: a strategy for targeted customer services.

Zahra Ghasemi, Hadi Akbarzadeh Khorshidi, and Uwe Aickelin. 2021. A survey on optimisation-based semi-supervised clustering methods. In *2021 IEEE International Conference on Big Knowledge (ICBK)*, pages 477–482. IEEE.

Google. 2018. [Google analytics sample dataset](#).

Koustava Goswami, Lukas Lange, Jun Araki, and Heike Adel. 2023. [Switchprompt: Learning domain-specific gated soft prompts for classification in low-resource domains](#). In *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics, EACL 2023, Dubrovnik, Croatia, May 2-6, 2023*, pages 2681–2687. Association for Computational Linguistics.

Hangfeng He, Hongming Zhang, and Dan Roth. 2023. [Rethinking with retrieval: Faithful large language model inference](#). *CoRR*, abs/2301.00303.

Yun He, Ziwei Zhu, Yin Zhang, Qin Chen, and James Caverlee. 2020. [Infusing disease knowledge into BERT for health question answering, medical inference and disease name recognition](#). In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020*, pages 4604–4614. Association for Computational Linguistics.

Gautier Izacard, Patrick S. H. Lewis, Maria Lomeli, Lucas Hosseini, Fabio Petroni, Timo Schick, Jane Dwivedi-Yu, Armand Joulin, Sebastian Riedel, and Edouard Grave. 2022. [Few-shot learning with retrieval augmented language models](#). *CoRR*, abs/2208.03299.

Mikhail Kechinov. 2019. [ecommerce behavior data from multi-category store](#).

Changhee Lee and Mihaela van der Schaar. 2020. [Temporal phenotyping using deep predictive clustering of disease progression](#). *Preprint*, arXiv:2006.08600.

Jinhyuk Lee, Wonjin Yoon, Sungdong Kim, Donghyeon Kim, Sunkyu Kim, Chan Ho So, and Jaewoo Kang. 2019. [BioBERT: a pre-trained biomedical language representation model for biomedical text mining](#). *Bioinformatics*, 36(4):1234–1240.

Jinhyuk Lee, Wonjin Yoon, Sungdong Kim, Donghyeon Kim, Sunkyu Kim, Chan Ho So, and Jaewoo Kang. 2020. [Biobert: a pre-trained biomedical language representation model for biomedical text mining](#). *Bioinform.*, 36(4):1234–1240.

Patrick S. H. Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. 2020. [Retrieval-augmented generation for knowledge-intensive NLP tasks](#). In *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*.

Qiuhan Lu, Dejing Dou, and Thien Huu Nguyen. 2022a. [Clinical5: A generative language model for clinical text](#). In *Findings of the Association for Computational Linguistics: EMNLP 2022, Abu Dhabi, United Arab Emirates, December 7-11, 2022*, pages 5436–5443. Association for Computational Linguistics.

Yunfei Lu, Peng Cui, Linyun Yu, Lei Li, and Wenwu Zhu. 2022b. Uncovering the heterogeneous effects of preference diversity on user activeness: A dynamic mixture model. In *Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pages 3458–3467.

Vaibhav Mishra, Somaditya Singh, Mohd Zaki, Har-gun Singh Grover, Santiago Miret, NM Anoop Krishnan, and 1 others. Lllamat: Large language models for materials science. In *AI for Accelerated Materials Design-Vienna 2024*.

Yifan Peng, Shankai Yan, and Zhiyong Lu. 2019. Transfer learning in biomedical natural language processing: An evaluation of BERT and elmo on ten benchmarking datasets. In *Proceedings of the 18th BioNLP Workshop and Shared Task, BioNLP@ACL 2019, Florence, Italy, August 1, 2019*, pages 58–65. Association for Computational Linguistics.

Long N. Phan, James T. Anibal, Hieu Tran, Shaurya Chanana, Erol Bahadroglu, Alec Peltekian, and Grégoire Altan-Bonnet. 2021. *Scifive: a text-to-text transformer model for biomedical literature*. *CoRR*, abs/2106.03598.

Nils Reimers and Iryna Gurevych. 2019. *Sentence-bert: Sentence embeddings using siamese bert-networks*. *Preprint*, arXiv:1908.10084.

Jaehyeok Shin, Alessandro Rinaldo, and Larry Wasserman. 2019. Predictive clustering. *arXiv preprint arXiv:1903.08125*.

Charlie Snell, Jaehoon Lee, Kelvin Xu, and Aviral Kumar. 2024. Scaling LLM test-time compute optimally can be more effective than scaling model parameters. *CoRR*, abs/2408.03314.

Guangyu Wang, Guoxing Yang, Zongxin Du, Longjun Fan, and Xiaohu Li. 2023. Clinicalgpt: Large language models finetuned with diverse medical data and comprehensive evaluation. *CoRR*, abs/2306.09968.

Likang Wu, Zhi Zheng, Zhaopeng Qiu, Hao Wang, Hongchao Gu, Tingjia Shen, Chuan Qin, Chen Zhu, Hengshu Zhu, Qi Liu, and 1 others. 2024. A survey on large language models for recommendation. *World Wide Web*, 27(5):60.

Fan Yang, Zheng Chen, Ziyan Jiang, Eunah Cho, Xiaojiang Huang, and Yanbin Lu. 2023. Palr: Personalization aware llms for recommendation. *arXiv preprint arXiv:2305.07622*.

Hongyi Yuan, Zheng Yuan, Ruyi Gan, Jiaxing Zhang, Yutao Xie, and Sheng Yu. 2022. Biobart: Pretraining and evaluation of A biomedical generative language model. In *Proceedings of the 21st Workshop on Biomedical Language Processing, BioNLP@ACL 2022, Dublin, Ireland, May 26, 2022*, pages 97–109. Association for Computational Linguistics.

Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher De-wan, Mona Diab, Xian Li, Xi Victoria Lin, Todor Mi-haylov, Myle Ott, Sam Shleifer, Kurt Shuster, Daniel Simig, Punit Singh Koura, Anjali Sridhar, Tianlu Wang, and Luke Zettlemoyer. 2022. *Opt: Open pre-trained transformer language models*. *Preprint*, arXiv:2205.01068.

A Appendix

A.1 Theoretical Basis of HeTLM

Following (Lee and van der Schaar, 2020), we formulate the problem of identifying user clusters with similar browsing behaviors and preferences as a predictive clustering problem. Let $X \in \mathcal{X}$ and $Y \in \mathcal{Y}$ be random variables for input browsing sessions and output next session pages with a joint distribution p_{XY} , where \mathcal{X} is the input session space and \mathcal{Y} is the next session page space.

For each user n , we are given sequences of browsing sessions x^n . Our aim is to identify a set of K predictive clusters, $\mathcal{C} = \{\mathcal{C}(1), \dots, \mathcal{C}(K)\}$, where each cluster consists of users with similar browsing behaviors and preferences.

We define a cluster as $\mathcal{C}(k) = \{x^n | t, s^n = k\}$ for $k \in \{1, \dots, K\}$ where $s^n \in \{1, \dots, K\}$ is the cluster assignment for user n . This allows us to flexibly update the cluster assignment to which a user belongs as the cluster representations are updated over time.

Let S be a random variable for the cluster assignment. We want to find an optimal partitioning of users into K clusters such that the difference in the next session distribution conditioned on the input sessions X and the cluster assignment S is minimized, while optimizing the number of clusters K . This can be achieved by minimizing the following Kullback-Leibler (KL) divergence:

$$\underset{K}{\text{minimize}} \sum_{k=1}^K \sum_{x \in \mathcal{C}(k)} KL(Y|X = x \| Y|S = k) \quad (5)$$

The optimization problem is non-trivial, and we estimate this objective function through the LLM loss (\mathcal{L}_1) described in Sec. 4.5. Minimizing \mathcal{L}_1 is equivalent to minimizing the KL divergence in Eq. 5 since the former term is independent of our optimization procedure. To avoid trivial solutions in this unsupervised setting, such as all embeddings collapsing to a single point or the selector assigning equal probability to all clusters regardless of the input sequence, we introduce two auxiliary loss functions, \mathcal{L}_2 and \mathcal{L}_3 , as detailed in Sec. 4.5.

A.2 Experimental Results: HeTLM for SmoLLM2-360M

For small LM, SmoLLM2-360M, we present results for clusterwise training. The clusterwise HeTLM results here show considerable variations across clusters in all metrics of Tables 8, 9, and 10. This calls

Model	N	HR	IoA	IoP	IoU	New-P	Val-P
SmoLLM2-360M: HeTLM ($\alpha=5, \beta=9$)							
Cluster 1	296	0.889	0.661	0.585	0.493	0.014	0.002
Cluster 2	4806	0.809	0.419	0.348	0.253	0.262	0.05
Cluster 3	151	0.570	0.310	0.439	0.29	0.0	0.0
Combined	5253	0.806	0.429	0.364	0.268	0.24	0.046

Table 8: Dataset I. Page Generation Results. *Higher is better*. One HeTLM for SmoLLM2-360M version is shown.

attention to the importance of clusterwise training to achieve better alignment of users' behaviors.

Model	N	HR-var	IoA-var	IoP-var	IoU-var
SmoLLM2-360M: HeTLM ($\alpha=5, \beta=9$)					
Cluster 1	296	0.099	0.125	0.091	0.09
Cluster 2	4806	0.155	0.113	0.082	0.068
Cluster 3	151	0.245	0.145	0.187	0.142
Combined	5253	0.156	0.118	0.088	0.075

Table 9: Dataset I. Variance in Page Generation across users. *Lower is better*. One HeTLM for SmoLLM2-360M version is shown.

A.3 Dataset II: Experiments

This dataset is public as well (Kechinov, 2019). Train : Test split = 1M : 10,000 samples. Number of unique pages = 17,310. The dataset has millions of consumers; after applying filters for excluding very short sessions and incomplete data, we randomly select 1.01M samples. **Outcomes** available in the pageurls are: *Cart* (Add to Cart, in Dataset II) and *Purchase*, these Outcome pages are generated by the LM and also used as *target labels* to evaluate Outcome prediction.

A.3.1 Experimental Results: Dataset II

We present comparison of HeTLM with OPT-2.7B. In Page Generation, comparing the respective Combined row in Table 12 with OPT-2.7B shows that except Val-P, in all other metrics Kmeans and HeTLM perform slightly better. For HeTLM, the variations in number of clusters and size of clusters and their differences in metrics justify endogenous clustering based training. In Outcome Prediction (Table 11) across its 10 metrics HeTLM has an edge over OPT-2.7B. For Variance in Page Generation (Table 13) both models perform similarly. Reviewing Overall Composite metric in Table 14 finds HeTLM outperforming OPT-2.7B, as the values [0.7, 0.6] are > 0.5 . APPENDIX contains additional results from Dataset II for more variations of HeTLM and Kmeans.

Model	<i>N</i>	Cart Acc	Acc-Purchase	Acc-Cart/Purchase	Rec-Cart	Rec-Purchase	Rec-Cart/Purchase	Prec-Cart	Prec-Purchase	Prec-Cart/Purchase	F1-Cart/Purchase
SmolLM2-360M: HeTLM ($\alpha=5, \beta=9$)											
Cluster 1	296	0.868	0.97	0.976	0.225	0.0	0.225	0.529	0.0	0.529	0.316
Cluster 2	4806	0.710	0.845	0.902	0.609	0.489	0.608	0.503	0.249	0.504	0.511
Cluster 3	151	0.868	0.974	0.974	0.05	0.0	0.05	0.5	0.0	0.5	0.091
Combined	5253	0.724	0.856	0.908	0.591	0.474	0.590	0.504	0.249	0.504	0.544

Table 10: Dataset I. Outcome Prediction Results *Higher is better*. HeTLM for SmolLM2-360M

Model	<i>N</i>	Cart Acc	Acc-Purchase	Acc-Cart/Purchase	Rec-Cart	Rec-Purchase	Rec-Cart/Purchase	Prec-Cart	Prec-Purchase	Prec-Cart/Purchase	F1-Cart/Purchase
Single LLM											
OPT 2.7B	10000	0.689	0.874	0.935	0.629	0.504	0.627	0.475	0.341	0.482	0.545
Kmeans, K=2											
Cluster 1	5421	0.716	0.904	0.94	0.452	0.401	0.451	0.448	0.313	0.454	0.453
Cluster 2	4579	0.666	0.857	0.942	0.76	0.49	0.757	0.499	0.384	0.508	0.608
Combined	10000	0.693	0.883	0.941	0.612	0.453	0.612	0.48	0.355	0.488	0.543
HeTLM ($\alpha=5, \beta=9$)											
Cluster 1	121	0.587	0.835	0.917	0.617	0.143	0.604	0.475	0.2	0.475	0.532
Cluster 2	9879	0.706	0.875	0.933	0.578	0.514	0.578	0.496	0.344	0.504	0.538
Combined	10000	0.705	0.875	0.933	0.578	0.508	0.578	0.496	0.343	0.504	0.538

Table 11: Dataset II. Outcome Prediction Results *Higher is better*. Top performing versions of Kmeans and HeTLM are shown. Results of other versions for Dataset II are in Appendix.

Model	<i>N</i>	HR	IoA	IoP	IoU	New-P	Val-P
OPT 2.7B	10000	0.542	0.232	0.311	0.186	1.0	0.917
Kmeans, K=2							
Cluster 1	5421	0.462	0.171	0.25	0.136	1.0	0.932
Cluster 2	4579	0.642	0.304	0.392	0.248	1.0	0.897
Combined	10000	0.544	0.232	0.315	0.187	1.0	0.916
HeTLM ($\alpha=5, \beta=9$)							
Cluster 1	121	0.512	0.215	0.2	0.136	0.983	0.672
Cluster 2	9879	0.545	0.236	0.312	0.188	1.0	0.904
Combined	10000	0.544	0.236	0.311	0.188	1.0	0.901

Table 12: Dataset II. Page Generation Results. *Higher is better*. Top version of Kmeans model, top HeTLM versions are shown.

Model	<i>N</i>	HR-var	IoA-var	IoP-var	IoU-var
OPT 2.7B	10000	0.248	0.077	0.118	0.058
Kmeans, K=2					
Cluster 1	5421	0.249	0.057	0.103	0.042
Cluster 2	4579	0.23	0.089	0.129	0.071
Combined	10000	0.248	0.076	0.12	0.059
HeTLM ($\alpha=5, \beta=9$)					
Cluster 1	121	0.25	0.072	0.057	0.031
Cluster 2	9879	0.248	0.079	0.117	0.059
Combined	10000	0.248	0.079	0.116	0.058

Table 13: Dataset II. Variance in Page Generation across users *lower is better*.

Model	Outcome	Page Gen	Page Gen	Overall
	Pred	Mean	Var	Composite
Kmeans, K=2	0.6	0.5	0.5	0.55
HeTLM ($\alpha=5, \beta=9$)	0.6	0.667	0.5	0.6

Table 14: Dataset II. Composite metrics. HeTLM outperforms OPT-2.7B and Kmeans in 3 metrics, and equals in Page Generation - Variance.

ity of SBERT embeddings with the user’s input sessions: “Learn from similar users browsing sequences given below: INPUT-OUTPUT PAIRS”.

A.4 Experimental Setup Details

All our experiments are performed on EC2 p4de.24xlarge ([Ama](#)) instances with 8 A100 GPUs ([Choquette et al., 2021](#)) with each having 80 GB GPU (HBM) memory. For fine-tuning we used the open-source Axolotl library ([axolotl-ai cloud](#), 2023). We provide the hyperparameters used in our experiments for small model pretraining, heterogeneity-aware model training, and large model fine-tuning below.

A.4.1 Prompt Templates

The zero-shot setup used a basic instruction prompt: “A user’s website browsing sequence of pages over multiple sessions is given as Input. INPUT SESSIONS [BOS] denotes beginning of session, [EOS] denotes end of session. Based on activity in the given input sessions, predict the next session as a sequence of pages highly likely to be visited by the user”. For the few-shot setup we add 3 examples of input-output pairs based on cosine similar-

A.4.2 Small Model Pretraining

Table 16 presents the hyperparameters for pretraining the small LM. This model was pretrained on browsing session data before being used in other experiments.

A.4.3 HeTLM Training

Table 15 details the hyperparameters used for training our proposed Heterogeneity-aware Training of Language Models (HeTLM). These parameters

Hyperparameter	Value
<i>General Configuration</i>	
Base Model	OPT-350M (Pretrained)
Tokenizer Type	Custom (page level)
Batch Size	16
Maximum Sequence Length	512
Validation Set Size	0.05
Number of Epochs	10
Number of Clusters (Initial)	6
<i>Optimizer Settings</i>	
Selector Learning Rate	5e-5
Predictor Learning Rate	1e-5
Selector Weight Decay	1e-4
Predictor Weight Decay	0.01
<i>Loss Weights</i>	
α (Loss \mathcal{L}_2 weight)	0.5–5.0
β (Loss \mathcal{L}_3 weight)	1.0–9.0
<i>Encoder Configuration</i>	
Encoder Type	Sentence Transformers
Encoder Path	all-MiniLM-L6-v2

Table 15: HeTLM Training Hyperparameters

Hyperparameter	Value
Base Model	OPT-350M
Tokenizer Type	Custom (page level)
Learning Rate	1e-5
Weight Decay	0.01
Batch Size	32
Maximum Sequence Length	512
Validation Set Size	0.05
Number of Epochs	100
Gradient Accumulation Steps	4
Warmup Ratio	0.05

Table 16: Small LM Pretraining Hyperparameters

control the Actor-Critic architecture and the weight of various loss components.

A.4.4 Large Model LoRA Finetuning

Table 17 lists the hyperparameters used for finetuning large LMs using Low-Rank Adaptation (LoRA). These settings were applied across different model architectures for comparison purposes.

A.4.5 Inference Time Comparison

Table 18 compares total inference time for different model configurations on Dataset I (10k samples). All measurements were conducted under identical hardware settings with maximum GPU utilization.

Hyperparameter	Value
<i>Model Configuration</i>	
Base Models	Meta-Llama-3-8B
Load in 8-bit	Mistral-7B-v0.3
	Gemma-7B
	QWEN-2.5-7B
	True
<i>Training Configuration</i>	
Sequence Length	512
Sample Packing	True
Pad to Sequence Length	True
Validation Set Size	0.05
Number of Epochs	10
Gradient Accumulation Steps	4
Micro Batch Size	2
Optimizer	adamw_bnb_8bit
Learning Rate Scheduler	cosine
Learning Rate	2e-4
Weight Decay	0.0
Warmup Steps	10
<i>LoRA Configuration</i>	
LoRA Rank	32
LoRA Alpha	16
LoRA Dropout	0.05
Target Linear Layers	True

Table 17: Large LM LoRA Finetuning Hyperparameters

Model	Inference Time (s)
<i>Single Model</i>	
OPT-350M	110.95
OPT-2.7B	363.71
<i>HeTLM</i>	
OPT-350M ($\alpha = 5, \beta = 9, 3$ clusters)	140.55
OPT-350M ($\alpha = 3, \beta = 1, 5$ clusters)	163.99
OPT-350M ($\alpha = 1, \beta = 0, 6$ clusters)	194.86

Table 18: Inference Time Comparison on Dataset I

Notably, our HeTLM approach achieves faster inference times than larger single models while having better performance (Sec. 6).