FedMGP: Personalized Federated Learning with Multi-Group Text-Visual Prompts

Weihao Bo[1], **Yanpeng Sun**[2,*], **Yu Wang**[3], **Xinyu Zhang**[4], **Zechao Li**[1]
[1]Nanjing University of Science and Technology
[2]National University of Singapore
[3]Baidu VIS
[4]University of Auckland

Abstract

In this paper, we introduce **FedMGP**, a new paradigm for personalized federated prompt learning in vision-language models (VLMs). Existing federated prompt learning (FPL) methods often rely on a single, text-only prompt representation, which leads to client-specific overfitting and unstable aggregation under heterogeneous data distributions. Toward this end, FedMGP equips each client with *multiple groups* of paired textual and visual prompts, enabling the model to capture diverse, fine-grained semantic and instance-level cues. A diversity loss is introduced to drive each prompt group to specialize in distinct and complementary semantic aspects, ensuring that the groups collectively cover a broader range of local characteristics. During communication, FedMGP employs a dynamic prompt aggregation strategy based on similarity-guided probabilistic sampling: each client computes the cosine similarity between its prompt groups and the global prompts from the previous round, then samples s groups via a softmax-weighted distribution. This soft selection mechanism preferentially aggregates semantically aligned knowledge while still enabling exploration of underrepresented patternseffectively balancing the preservation of common knowledge with client-specific features. Notably, FedMGP maintains parameter efficiency by redistributing a fixed prompt capacity across multiple groups, achieving state-of-the-art performance with the lowest communication parameters (5.1k) among all federated prompt learning methods. Theoretical analysis shows that our dynamic aggregation strategy promotes robust global representation learning by reinforcing shared semantics while suppressing client-specific noise. Extensive experiments demonstrate that FedMGP consistently outperforms prior approaches in both personalization and domain generalization across diverse federated vision-language benchmarks. The code will be released on `https://github.com/weihao-bo/FedMGP.git`.

1 Introduction

Large-scale vision-language models (VLMs) have demonstrated impressive performance across a wide range of multimodal tasks [1, 31, 15, 43, 19–21, 42]. As these models are increasingly deployed in privacy-sensitive and decentralized environmentsincluding healthcare, mobile devices, and industrial systemsthere is a growing need to adapt them privately without direct access to raw data [5]. In such settings, data remains local, and client distributions are often highly heterogeneous [16, 8]. To fully utilize local data, personalized federated learning (PFL) [12, 50] has emerged as an effective framework for adapting shared models across clients with non-identical data, while preserving privacy. In parallel, prompt-based tuning has shown great promise for parameter-efficient adaptation of frozen VLMs. The integration of these two ideas has led to the rise of federated prompt learning (FPL)a lightweight and scalable approach to adapting VLMs in federated settings[17, 23].

*Corresponding author.

39th Conference on Neural Information Processing Systems (NeurIPS 2025).

Despite its potential, existing FPL methods face key limitations. Most approaches rely solely on textual prompts, which encode static class-level semantics. While efficient, these prompts lack the expressiveness to capture personalized visual cues specific to each client, limiting their ability to handle diverse or complex inputs. Furthermore, many methods adopt a local-global prompt framework [27, 9, 37], in which each client maintains a local prompt and contributes a single global prompt for aggregation. This framework introduces two critical problems: **(1)** A single prompt per client is often insufficient to capture the diversity of local dataespecially when multiple semantic concepts or visual styles coexist within a client. **(2)** Aggregating one prompt per client leads to biased global representations, as the shared prompt tends to overfit to dominant local patterns while overlooking less frequent but informative ones from other clients. Together, these issues undermine both local personalization and cross-client generalization, particularly under severe data heterogeneity.

To overcome these limitations, we propose Personalized **Fed**erated Learning via **M**ulti-Group Text-Visual **P**rompt **(FedMGP)**, a new paradigm for personalized federated adaptation of vision-language models. Each client in FedMGP maintains multiple paired groups of textual and visual prompts, where each group captures distinct semantic and instance-level characteristics of the local data. To ensure prompt groups specialize in different aspects, we introduce a diversity loss that encourages representational separation within each client. For server aggregation, we develop a dynamic prompt selection strategy based on the similarity between local prompt groups and the global prompt from the previous round, ensuring that semantically aligned groups are more likely to be selected, while still allowing exploration of less dominant patterns. This balanced approach reinforces common cross-client patterns while suppressing client-specific noise.

FedMGP is both parameter-efficient and communication-aware: with the lowest communication parameters (5.1k) among all federated prompt learning methods, it achieves state-of-the-art performance while distributing a fixed prompt capacity across multiple groups. Empirical results across various heterogeneous data settings, including pathological non-IID, Dirichlet distribution, and domain generalization, demonstrate that FedMGP successfully balances personalization accuracy on local client data with generalization capability to unseen domains.

2 Related Work

2.1 Prompt Learning for Vision-Language Models

Vision-language models (VLMs) like CLIP [43] have demonstrated strong zero-shot capabilities through contrastive learning on massive image-text pairs [56, 55, 49, 11, 48]. To efficiently adapt these models to downstream tasks, prompt learning introduces a small set of learnable parameters while keeping the original model weights frozen [60, 30, 58]. Various prompt learning approaches have been proposed, including enriching text representations through class-related descriptions [53, 35], additional descriptive sentences [40, 57, 44], external knowledge [22], and visual annotations [46, 45]. As highlighted in our introduction, recent methods have begun addressing the critical balance between fitting to seen classes and maintaining generalization capabilities to unseen classes. For instance, CoCoOp [59] introduces instance-conditioned prompts to capture fine-grained visual cues while preserving general knowledge, and ProGrad [61] proposes prompt alignment gradients to maintain the model's inherent knowledge. However, these methods predominantly operate in centralized settings with direct access to all training data, overlooking privacy concerns and the challenges of heterogeneous data distributions across multiple clientscritical limitations that necessitate new frameworks for privacy-preserving, distributed adaptation of VLMs [29].

2.2 Federated Prompt Learning

Federated Prompt Learning (FPL) [17, 16, 51, 32] combines prompt learning with federated learning [34, 3, 8, 52, 28] to enable privacy-preserving adaptation of vision-language models across distributed environments. PromptFL [17] pioneered this approach by integrating prompt learning into federated frameworks with theoretical convergence guarantees. To address client heterogeneity, several researchers [27, 37, 16] developed local-global paradigms where clients maintain personalized prompts while contributing to shared global prompts. This approach improves local performance but often compromises generalization under non-IID data distributions. Recent work [9] attempted to balance personalization and generalization through additional constraints. Despite progress, ex-

isting FPL methods have two key limitations. First, they rely solely on textual prompts, missing crucial visual cues needed for robust multimodal adaptation. Second, they lack effective prompt learning strategies and aggregation mechanisms tailored specifically for federated settings that can simultaneously maintain personalization while enhancing cross-client generalization.

3 Method

In this paper, we introduces FedMGP, a novel approach designed to address data heterogeneity and model stability challenges in federated learning. We first present the fundamentals of federated prompt learning (Section 3.1), including the core concepts of prompt learning and its application in federated settings. Then, we elaborate on two key mechanisms of FedMGP: the multimodal prompt co-learning mechanism (Section 3.2.1), which enhances representation capabilities through the synergistic interaction between text and visual prompts, and the dynamic prompt aggregation strategy (Section 3.2.2), which effectively balances global knowledge sharing with local feature preservation.

3.1 Preliminary: Federated Prompt Learning

Prompt learning is a parameter-efficient strategy for adapting large pre-trained Vision-Language Models (VLMs), such as CLIP [43], to diverse downstream tasks. It introduces a small set of learnable parameters called "prompts" while keeping the VLM's encoder weights frozen. These learnable prompt vectors are combined with class name embeddings to create class-specific textual prompts that effectively adapt the model to downstream tasks.

A VLM typically consists of an image encoder $f(\cdot)$ and a text encoder $g(\cdot)$. The core workflow involves: (1) processing an input image through the image encoder to obtain visual features, (2) processing text prompts through the text encoder to obtain textual features, and (3) computing similarity scores between these features to determine class probabilities. The key prediction formula is:

$$p(\hat{y} = k|x; p_t) = \frac{\exp(\text{sim}(f(x), g(t_k))/\tau)}{\sum_{j=1}^{K} \exp(\text{sim}(f(x), g(t_j))/\tau)}. \tag{1}$$

where $t_k = \{p_t, c_k\}$ represents the text input formed by concatenating the learnable text prompt p^t with the embedding of class name c_k. Here, $\text{sim}(\cdot, \cdot)$ represents cosine similarity, K is the number of classes, and τ is a temperature scaling factor.

Federated Prompt Learning (FPL) extends this approach to distributed settings where multiple clients collaborate without sharing their raw data. The federated training process follows a cyclic pattern: (1) The server distributes the current global prompt to selected clients; (2) Clients perform local updates using their private data; (3) Updated local prompts are sent back to the server; (4) The server aggregates these local prompts to form an improved global prompt. This process repeats for multiple communication rounds, gradually refining the global prompt to work well across all clients.

Despite its privacy-preserving benefits, standard FPL faces significant challenges with heterogeneous client data distributions. Client-specific optimization may lead to overfitting to local patterns, while naive aggregation methods like FedAvg [34] often struggle to preserve client-specific knowledge while extracting common patterns. Our proposed FedMGP framework specifically addresses these limitations through a multi-group prompt architecture and dynamic prompt aggregation strategy.

3.2 FedMGP:Federated Learning via Multi-Group Text-Visual Prompt

To address the fundamental limitations of existing federated prompt learning methods, particularly their reliance on single text-only prompts and vulnerability to client-specific overfitting, we propose FedMGP. (The complete pseudocode can be found in appendix A.) As illustrated in figure 1, our framework introduces a novel multi-group mechanism that enhances both prompt diversity and robustness through complementary prompt groups. For each client in the federation of N clients, we define a set of prompts $P = \{p_{t,1}, \ldots, p_{t,G}, p_{v,1}, \ldots, p_{v,G}\}$, where $p_{t,j}$ represents the j-th text

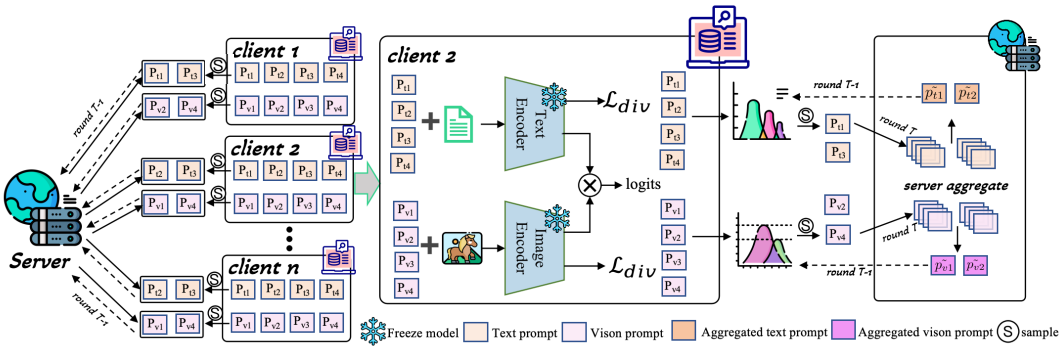


Figure 1: Overview of FedMGP: The left portion shows the server distributing global prompts to clients; the middle portion illustrates the multi-group text-visual prompt co-learning mechanism within each client; and the right portion demonstrates the dynamic prompt aggregation strategy across communication rounds.

prompt and $p_{v,j}$ represents the j-th visual prompt, with G being the number of prompt groups. We use $\tilde{P}$ to denote the global aggregated prompts at the server and T denote the communication round.

This design offers two significant advantages. First, integrating visual and textual modalities enriches contextual representation, capturing instance-specific information more comprehensively than static class names. Second, distributing knowledge across multiple specialized prompt units enhances aggregation robustnesseven if certain prompt groups overfit to local distributions, others may capture generalizable patterns, significantly improving model adaptability under heterogeneous data distributions without increasing the total parameter count.

3.2.1 Multimodal Prompt Co-learning Mechanism

For any local client, the multi-group prompt learning process operates as follows. During training, for each group j, the text prompt $p_{t,j}$ is concatenated with the class embedding c_k to form $t_{k,j} = \{p_{t,j}, c_k\}$, which is fed into a text encoder $g(\cdot)$. Simultaneously, the image x is combined with the visual prompt $p_{v,j}$ to form $v_j = \{x, p_{v,j}\}$, which is passed through the image encoder $f(\cdot)$. The predictive probability for class k is computed based on the similarity between the corresponding text and visual features:

$$p(\hat{y} = k \mid x; p_{t,j}, p_{v,j}) = \frac{\exp(\text{sim}(f(v_j), g(t_{k,j}))/\tau)}{\sum_{l=1}^{K} \exp(\text{sim}(f(v_j), g(t_{l,j}))/\tau)}. \tag{2}$$

The classification loss is defined as the average cross-entropy across all G prompt groups:

$$\mathcal{L}_{\text{CE}} = \frac{1}{G} \sum_{j=1}^{G} -\log p(\hat{y} = y \mid x; p_{t,j}, p_{v,j}) \tag{3}$$

To ensure that different prompt groups capture diverse semantic perspectives, we introduce a diversity loss that minimizes the cosine similarity between group-wise features within the same modality:

$$\mathcal{L}_{\text{div}} = \sum_{k=1}^{K} \sum_{j \neq j'} (1 - \cos(g(t_{k,j}), g(t_{k,j'}))) + \sum_{j \neq j'} (1 - \cos(f(v_j), f(v_{j'}))) \tag{4}$$

This encourages each group to specialize in different aspects of the input, thereby reducing redundancy and enhancing representational richness. The overall training objective combines both losses:

$$\mathcal{L} = \mathcal{L}_{\text{CE}} + \lambda \cdot \mathcal{L}_{\text{div}} \tag{5}$$

At inference time, we leverage all prompt groups by computing predictions independently for each group and averaging the resulting logits:

$$p(\hat{y} = k \mid x) = \frac{1}{G} \sum_{j=1}^{G} p(\hat{y} = k \mid x; p_{t,j}, p_{v,j}) \tag{6}$$

This group-wise ensemble enhances robustness by aggregating complementary semantic views, improving prediction stability across heterogeneous inputs while incurring minimal overhead.

3.2.2 Dynamic Prompt Aggregation Strategy

To address the aggregation instability issues prevalent in traditional federated learning, FedMGP employs a novel dynamic prompt aggregation strategy, as illustrated in the right portion of Figure 1. This approach is based on a fundamental insight: each prompt can be conceptually decomposed into information that is common across clients (global knowledge) and information that is unique to a specific client (local knowledge). Therefore, we propose this dynamic aggregation mechanism that adaptively balances the preservation of global knowledge with the exploration of client-specific features. In Appendix F, we provide theoretical analysis demonstrating the superiority of our dynamic aggregation strategy over both full prompt aggregation methods[17, 34] and explicit global-local paradigms [27, 9, 37], offering formal justification for our approach.

In this section, we use P without subscripts to refer to the entire set of prompts, while $P_j = \{p_{t,j}, p_{v,j}\}$ refers to the j-th group within that set. The global aggregated prompts are denoted by $\tilde{P}$, where $\tilde{P}$ consists of top-s selected prompt groups.

In each communication round, our strategy dynamically selects a subset of top-s prompts from each client for aggregation, where $s \leq G$ and G is the total number of prompt groups. When $s = G$, our method reduces to standard FedAvg. By selecting only the most relevant prompts, we focus the aggregation on shared knowledge while preserving client specificity. The key steps of our dynamic aggregation strategy are as follows:

For communication round T, we first compute the cosine similarity between each client's local prompts and the global prompts from the previous round. This process is performed separately for text and visual prompts, but follows the same procedure. For each local prompt group P_j^T and its corresponding global prompt $\tilde{P}_i^{T-1}$ (where $i \in \{1, 2, \ldots, s\}$ indexes the top-s selected groups):

$$\text{sim}(P_j, \tilde{P}^{T-1}) = \sum_{i=1}^{s} \frac{P_j^T \cdot \tilde{P}_i^{T-1}}{||P_j^T|| \cdot ||\tilde{P}_i^{T-1}||} \tag{7}$$

To avoid overly deterministic selection that might lead to prompt homogenization, we convert these similarity scores into selection probabilities using a softmax function with temperature parameter τ:

$$\text{prob}(P_j^T) = \frac{\exp(\text{sim}(P_j^T, \tilde{P}^{T-1})/\tau)}{\sum_{j=1}^{G} \exp(\text{sim}(P_j^T, \tilde{P}^{T-1})/\tau)} \tag{8}$$

Based on these probabilities, we sample s prompt groups from each client. For the first communication round ($T = 1$), when no previous global prompts exist, we employ random selection to establish initial diversity, as described in Appendix A.

After selecting the top-s most relevant prompt groups from each client, the server aggregates these prompts across all participating clients to form the updated global prompts for round T. For the i-th selected prompt group:

$$\tilde{P}_i^T = \sum_{c \in C_T} \frac{n_c}{\sum_{c' \in C_T} n_{c'}} P_{i,c}^T, \tag{9}$$

where C_T represents the set of clients participating in round T, n_c denotes the number of samples at client c and P_i^c represents the i-th selected prompt group from client c.

This dynamic prompt aggregation strategy offers several key advantages. First, by favoring prompts with higher similarity to previous global prompts, we effectively filter out client-specific idiosyncrasies that might arise from local data distribution peculiarities. Second, the dynamic nature of our selection process prevents premature convergence to a static set of prompts, allowing the model to continually explore the prompt space and adapt to evolving patterns in the data. Third, this approach naturally balances the preservation of common knowledge with the exploration of diverse prompt configurations, leading to more robust federated learning.

After aggregation, the server distributes the updated global prompts back to the clients for the next round, continuing this process for multiple communication rounds to gradually refine the global prompts to work well across all clients.

4 Experiment

In this section, we conduct comprehensive experiments to validate the dual capabilities of FedMGP: (1) maintaining strong personalization for individual clients while achieving robust cross-client generalization, and (2) demonstrating superior performance across various heterogeneous data distributions. Our evaluation spans multiple scenarios including non-IID data partitions and Dirichlet distributions with varying concentration parameters, demonstrating FedMGP's effectiveness in addressing the fundamental challenges of federated learning with prompt-based multimodal adaptation.

4.1 Experimental Setup

Datasets and Data Heterogeneity. To thoroughly evaluate FedMGP's dual capabilities of personalization and generalization across heterogeneous data distributions, we design experiments with three distinct scenarios. First, following [9, 16], we select nine diverse datasets to assess base-to-novel class generalization: Caltech101 [13] for general object classification; OxfordPets [38], Flowers102 [36], Food101 [4], Stanford Cars [25], and FGVC Aircraft [33] for fine-grained classification; DTD [7] for texture classification; UCF101 [47] for action recognition; and SUN397 [54] for scene recognition. We create a pathological non-IID setting by equally splitting each dataset into base and novel classes, then assigning non-overlapping base classes to different clients. Each client's model is trained on local classes and evaluated on three test sets: local classes (personalization), base classes seen by other clients (cross-client knowledge transfer), and novel classes unseen during training (generalization to new concepts).Second, to evaluate personalization under label distribution shift, we employ CIFAR-10 and CIFAR-100 [26], partitioning data among clients using Dirichlet distribution Dir(α) with varying concentration parameters. This creates realistic heterogeneity where clients possess varying class proportions, allowing us to examine how effectively FedMGP's multi-group prompt mechanism adapts to imbalanced class distributions.Third, to assess performance under both feature and label distribution shifts, we test FedMGP on multi-domain datasets: DomainNet [39] with six distinct visual domains and Office-Caltech10 [14] with four domains. This evaluates how effectively our text-visual prompt co-learning bridges domain gaps while maintaining local specialization. Comprehensive dataset details are provided in Appendix C.1.

Implementation Details. To ensure fair comparison with existing methods, we establish a unified experimental framework by re-implementing all baseline approaches using their official code repositories under identical settings. Specifically, we adopt ViT-B/16 [10] as the backbone for all methods. For base-to-novel generalization experiments, we set communication rounds $T = 10$ with 100% client participation rate, local epochs $E = 2$, and use 16-shot samples per class. For CIFAR-10 and CIFAR-100 experiments, we simulate a realistic federated environment with Dir($\alpha = 0.5$) distribution across 100 clients, with 10% client participation rate per round, utilizing the full training dataset. All models are trained using stochastic gradient descent (SGD) with an initial learning rate of 0.001

Table 2: Results on CIFAR10 and CIFAR100 with label shift with Dir partition($\alpha = 0.5$) into 100 clients.

Methods	CIFAR10	CIFAR100
PromptFL [17]	91.36	72.04
FedOTP [27]	94.73	75.15
FedTPG [41]	92.44	74.39
FedPGP [9]	92.41	74.11
PromptFolio [37]	93.33	74.14
FedMGP	**95.48**	**75.39**

Table 1: Accuracy comparison (%) on clients' local accuracy and generalization.

(a) Average over 9 datasets.

Methods	Local	Base	Novel	CM
PromptFL [17]	71.19	71.70	71.46	71.31
FedOTP [27]	92.53	16.84	31.66	57.10
FedTPG [41]	71.62	71.91	68.32	70.66
FedPGP [9]	84.32	72.45	68.97	77.42
PromptFolio [37]	96.02	39.75	51.02	70.29
FedMGP	93.17	68.49	72.99	**81.85**

(b) OxfordPets.

Methods	Local	Base	Novel	CM
PromptFL [17]	89.77	90.01	97.20	91.62
FedOTP [27]	100.00	26.68	57.16	68.19
FedTPG [41]	94.24	94.31	96.64	94.85
FedPGP [9]	96.20	95.01	96.89	96.07
PromptFolio [37]	99.90	66.23	83.38	86.86
FedMGP	97.15	93.83	97.04	**96.28**

(c) Flowers102.

Methods	Local	Base	Novel	CM
PromptFL [17]	70.33	71.79	75.39	71.94
FedOTP [27]	99.73	13.06	21.51	57.99
FedTPG [41]	79.43	78.92	73.26	77.71
FedPGP [9]	91.83	80.22	68.46	82.85
PromptFolio [37]	99.82	27.36	39.34	66.05
FedMGP	98.41	70.06	74.71	**85.36**

(d) DTD.

Methods	Local	Base	Novel	CM
PromptFL [17]	55.32	57.06	44.32	52.60
FedOTP [27]	96.44	20.06	41.23	61.71
FedTPG [41]	56.90	59.26	40.46	52.49
FedPGP [9]	78.47	67.22	50.93	68.21
PromptFolio [37]	97.18	26.53	37.39	64.11
FedMGP	92.87	53.60	55.62	**73.73**

(e) Caltech101.

Methods	Local	Base	Novel	CM
PromptFL [17]	94.16	95.35	94.98	94.66
FedOTP [27]	99.96	28.28	62.26	69.43
FedTPG [41]	96.17	97.16	91.92	95.32
FedPGP [9]	96.91	97.35	94.37	96.37
PromptFolio [37]	99.79	73.69	81.10	88.50
FedMGP	99.47	96.02	93.61	**97.13**

(f) Food101.

Methods	Local	Base	Novel	CM
PromptFL [17]	89.75	89.79	90.86	90.04
FedOTP [27]	95.44	19.16	45.89	61.24
FedTPG [41]	90.36	90.42	91.78	90.73
FedPGP [9]	90.51	90.48	91.12	90.65
PromptFolio [37]	97.24	57.40	67.64	79.67
FedMGP	95.08	88.47	89.53	**92.04**

(g) UCF101.

Methods	Local	Base	Novel	CM
PromptFL [17]	77.08	76.94	70.36	75.29
FedOTP [27]	92.39	16.33	19.07	54.99
FedTPG [41]	76.22	75.96	72.09	75.10
FedPGP [9]	82.61	71.78	68.45	76.34
PromptFolio [37]	96.15	31.94	42.00	66.22
FedMGP	92.69	68.38	72.86	**81.62**

(h) SUN397.

Methods	Local	Base	Novel	CM
PromptFL [17]	76.25	76.20	75.68	76.09
FedOTP [27]	93.40	11.38	19.11	53.83
FedTPG [41]	73.72	73.71	75.17	74.08
FedPGP [9]	89.43	66.51	67.43	78.20
PromptFolio [37]	95.18	32.89	44.47	66.50
FedMGP	91.83	68.51	72.20	**81.07**

(i) Stanford Cars.

Methods	Local	Base	Novel	CM
PromptFL [17]	62.98	63.14	69.87	64.66
FedOTP [27]	91.06	9.32	10.62	50.49
FedTPG [41]	65.50	65.47	69.10	66.37
FedPGP [9]	85.37	57.63	60.19	72.13
PromptFolio [37]	96.44	29.43	46.77	66.28
FedMGP	92.61	56.48	71.19	**77.80**

(j) FGVC Aircraft.

Methods	Local	Base	Novel	CM
PromptFL [17]	25.03	25.03	24.48	24.89
FedOTP [27]	64.34	7.27	8.12	36.01
FedTPG [41]	12.00	12.00	4.50	9.27
FedPGP [9]	47.59	25.89	22.89	35.94
PromptFolio [37]	82.50	12.29	17.09	48.40
FedMGP	78.46	21.03	30.15	**51.62**

and a single-step learning rate scheduler. All other implementation specifics, including additional hyperparameter settings, optimization strategies, and evaluation protocols, are detailed in the appendix to ensure reproducibility. For more details, please refer to Appendix C.2.

Baselines. We compare FedMGP against state-of-the-art Federated Prompt Learning (FPL) methods, including PromptFL [17], FedOTP [27], FedTPG [41], FedPGP [9], and PromptFolio [37]. These baselines represent the full spectrum of existing FPL paradigms: from standard aggregation approaches to local-global frameworks and constrained local-global architectures. This comprehensive comparison allows us to evaluate how effectively FedMGP addresses the critical balance between personalization and generalization that many existing methods struggle to achieve, particularly under severe data heterogeneity.

4.2 Performance Evaluation

Analysis of Base-to-Novel Generalization Results. To comprehensively assess both personalization and generalization capabilities, we introduce a Combined Metric (CM) that balances local adaptation and cross-domain transfer. Following the approach in [17] for local accuracy evaluation and [60] for harmonized accuracy calculations, CM is computed as $\text{CM} = (\text{Local} + \text{HM})/2$, where HM is the Harmonic Mean defined as $\text{HM} = 2 \times \text{Base} \times \text{Novel}/(\text{Base} + \text{Novel})$. This metric

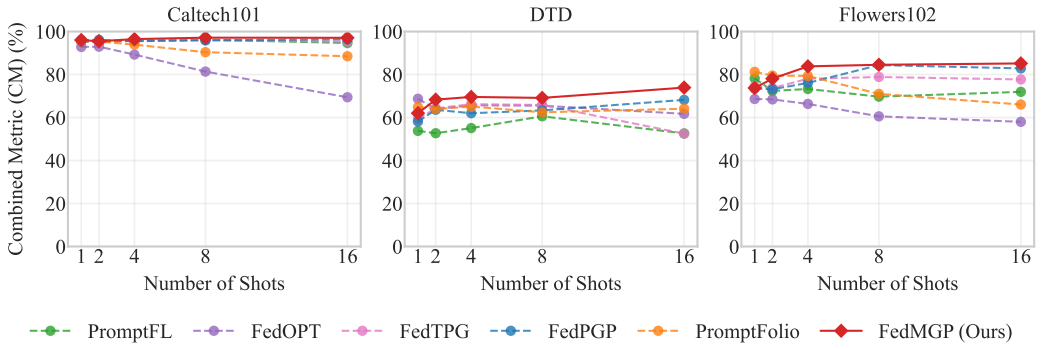


Figure 2: Few shot experiment from 1 to 16 shots

effectively quantifies a model's ability to simultaneously achieve personalization (measured by local accuracy) and generalization (measured by harmonized performance on base and novel classes). As shown in Table 1, FedMGP achieves the highest CM score (81.85%) averaged over all nine datasets, demonstrating superior overall performance while maintaining excellent balance between personalization (93.17% on local classes) and generalization (68.49% on base classes and 72.99% on novel classes). In contrast, methods like FedOTP and PromptFolio achieve exceptional local accuracy (92.53% and 96.02% respectively) but struggle with generalization to base classes (16.84% and 39.75%), indicating severe overfitting to local distributions. FedPGP, though more balanced, still falls short of FedMGP in comprehensive performance. These results confirm our analysis that existing approaches either excel at personalization at the expense of generalization or achieve moderate performance on both fronts without fully resolving the tension between these competing objectives.

Table 3: Parameter analysis of FedMGP and other state-of-the-art methods.

Method	Trained	Communication	CM
PromptFL [17]	8.2k	8.2k	80.27
FedOTP [27]	16.4k	8.2k	63.74
FedTPG [41]	4208.1k	4208.1k	82.37
FedPGP [9]	24.8k	16.4k	86.94
PromptFolio [37]	16.4k	8.2k	77.10
FedMGP	12.8k	5.1k	**88.34**

Table 4: Ablation study on prompt leangth(l)

Setting	Local	Base	Novel	CM
FedMGP (l=4)	97.18	72.49	72.17	84.75
FedMGP (l=8)	98.05	64.00	64.91	81.25
FedMGP (l=16)	97.62	57.47	61.56	78.53
FedMGP (l=2)	96.92	73.23	74.65	**85.43**

Performance on Label Distribution Shift. We evaluate FedMGP's effectiveness in handling realistic federated learning scenarios with 100 clients following a Dirichlet distribution ($\alpha = 0.5$), which creates substantial heterogeneity in class distributions. As shown in Table 2, FedMGP consistently outperforms all baseline methods on both CIFAR-10 and CIFAR-100 datasets. The multi-group prompt mechanism effectively captures diverse client data patterns through text-visual prompt co-learning and similarity-based selection, enabling robust performance even under severe label imbalance. Notably, while other methods struggle with the increased complexity of CIFAR-100, FedMGP maintains its relative advantage, demonstrating strong scalability in federated learning with numerous clients and classes.

Few-Shot Analysis. Figure 2 demonstrates FedMGP's effectiveness across few-shot settings (1-16 shots per class). While FedMGP exhibits limitations in extreme 1-shot scenarios, it quickly surpasses competing methods with 2+ shots. This performance pattern aligns with our theoretical framework: in extremely limited data regimes, the multi-group mechanism struggles to effectively decompose knowledge into common and client-specific componentsa decomposition that is fundamental to our approach as described in Section 3.2.2. Specifically, with insufficient samples, prompt groups cannot effectively disentangle specialized representations nor establish robust text-visual correlations across client distributions. As sample size increases, FedMGP's dynamic prompt selection strategy activates its full potential, enabling superior cross-client knowledge transfer while preserving client-specific information. Detailed discussions on FedMGP's limitations and future research directions can be found in Appendix B.

Table 5: Ablation study on Prompt Groups(m)

Setting	Local	Base	Novel	CM
FedMGP (m=4)	96.60	73.28	73.99	85.12
FedMGP (m=3)	89.95	77.68	74.48	83.00
FedMGP (m=2)	82.88	82.15	74.05	80.38
FedMGP (m=1)	78.85	79.68	70.67	76.88
FedMGP (m=5)	96.92	73.23	74.65	**85.43**

Table 6: Ablation study on Top-s.

Setting	Local	Base	Novel	CM
FedMGP (Top-s=1)	97.88	69.17	74.10	84.72
FedMGP (Topk-s=3)	92.93	76.88	74.85	84.39
FedMGP (Topk-s=4)	86.77	79.44	74.89	81.93
FedMGP (Topk-s=2)	96.92	73.23	74.65	**85.43**

Parameter Efficiency. Table 3 highlights FedMGP's remarkable communication efficiency (5.1k parameters)significantly lower than all competitors while achieving superior performance. This validates our core design: rather than increasing parameter count, FedMGP strategically distributes a fixed capacity across multiple specialized prompt groups, more effectively capturing diverse client data characteristics with minimal communication overhead. Additional evaluation like domain evaluation results are presented in Appendix D.

4.3 Ablation Study

To thoroughly understand FedMGP's design choices, we conduct extensive ablation studies examining key components including prompt length, number of prompt groups, top-s selection size, vision-text modality contributions, and diversity loss. For comprehensive evaluation and efficiency, all results are reported as the average performance across Caltech101, Flowers102, and DTD datasets, providing insights into FedMGP's optimal configuration.

Impact of prompt length. Table 4 reveals that increasing prompt length beyond l=2 causes consistent performance degradation. In heterogeneous federated environments, compact prompts excel by capturing essential semantic patterns without overfitting to client-specific details, enabling more effective knowledge sharing across diverse client distributions.

Table 7: Ablation study on the impact of vision and text prompt.

Setting	Local	Base	Novel	CM
FedMGP (Vision Only)	75.94	76.48	72.92	75.30
FedMGP (Text Only)	95.23	73.60	73.80	84.46
FedMGP (Vision + Text)	96.92	73.23	74.65	**85.43**

Table 8: Ablation study on $\mathcal{L}_{\text{div}}$.

Setting	Local	Base	Novel	CM
FedMGP (w/o $\mathcal{L}_{\text{div}}$)	94.53	72.97	72.48	83.63
FedMGP ($\mathcal{L}_{\text{div}}$=2)	95.78	74.88	74.98	85.35
FedMGP ($\mathcal{L}_{\text{div}}$=5)	96.35	73.50	74.31	85.13
FedMGP ($\mathcal{L}_{\text{div}}$=10)	95.78	73.09	74.35	84.75
FedMGP ($\mathcal{L}_{\text{div}}$=1)	96.92	73.23	74.65	**85.43**

Effect of Group Number. Table 5 shows that multiple prompt groups are crucial for FedMGP's effectiveness, with performance declining as group count decreases. Our results indicate that 5 groups achieves optimal performance, with additional groups likely offering diminishing returns relative to the increased parameter count. This validates our multi-group design which effectively balances personalization and generalization without rigid global-local separation.

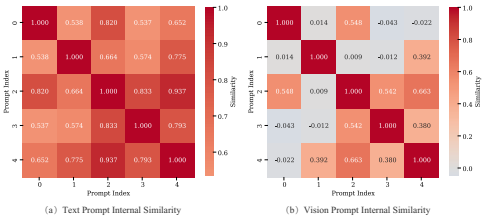
Selection Strategy Analysis. Table 6 demonstrates how our dynamic prompt aggregation strategy navigates the critical personalization-generalization trade-off. With smaller selection size (Top-s=1), the model preserves client specificity but limits knowledge sharing, while larger selection size (Top-s=4) improves generalization but significantly compromises personalization. Top-s=2 emerges as the optimal balance point, effectively addressing the aggregation instability issues.

Effect of Vision and Text Components. Table 7 confirms the necessity of incorporating both vision and text components in FedMGP. Removing either modality leads to noticeable performance degradation, highlighting the complementary roles they play. While textual prompts capture high-level semantic categories, visual prompts provide fine-grained, instance-specific cues. Their joint contribution enables FedMGP to better represent diverse client data and facilitates more effective cross-client knowledge transfer. This finding supports the design choice of our multi-group text-visual prompt co-learning framework.

Impact of diversity Loss. Table 8 demonstrates the critical importance of diversity loss in FedMGP, with its removal causing a significant performance drop (CM decreases by 1.8%). This component

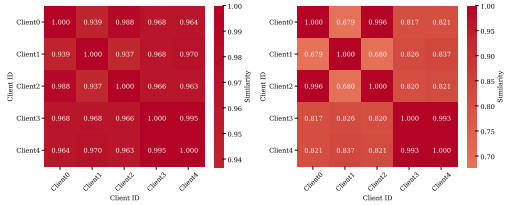
ensures effective separation between prompt groupsa fundamental mechanism we analyze in detail in Appendix E. Remarkably, performance remains stable across different weight values (1-10), confirming its insensitivity to hyperparameter settingsa significant advantage in federated environments with heterogeneous data distributions. Appendix E contains additional ablation studies on temperature parameters, diversity loss formulations, and other design choices.

4.4 Visual Analysis



(a) Text Prompt Internal Similarity (b) Vision Prompt Internal Similarity

Figure 3: Intra-client prompt similarity visualization. (a) Text prompt similarity matrix showing moderate inter-group diversity. (b) Visual prompt similarity matrix showing higher inter-group diversity.



(a) Inter-Client Text Prompt Internal Similarity (b) Inter-Client Vision Prompt Internal Similarity

Figure 4: Inter-client prompt similarity visualization. (a) Text prompt similarity matrix showing high correlations (0.9-1.0). (b) Visual prompt similarity matrix showing moderate diversity (0.7-0.9).

To validate our diversity loss mechanism, we analyze internal prompt similarity patterns within a representative client after FedMGP training on Caltech101. Figure 3 presents similarity matrices for text and visual prompt groups, revealing distinct specialization. Text prompts show moderate inter-group correlations (0.5-0.8), maintaining shared linguistic patterns, while visual prompts exhibit significantly lower correlations (often near zero or negative), achieving superior diversification. This confirms that visual prompts capture more fine-grained, instance-specific features than text prompts. The diversity loss successfully encourages each prompt group to specialize in distinct patterns, enabling comprehensive local data coverage while supporting both personalization and cross-client generalization.

To further validate our dynamic aggregation mechanism, we examine inter-client prompt similarity patterns. Figure 4 shows that text prompts maintain consistently high correlations (0.9-1.0) across clients, preserving common semantic knowledge while avoiding the complete homogenization in PromptFL [17]. Visual prompts show moderate correlations (0.7-0.9), striking an optimal balance between knowledge transfer and client-specific adaptation. Unlike FedOPT's [27] global-local paradigm that often results in excessive divergence, our approach maintains sufficient similarity for knowledge sharing while preserving diversity for personalized learning. This confirms that FedMGP's dynamic aggregation effectively prevents over-homogenization and excessive divergence, achieving superior performance across heterogeneous client distributions.

5 Conclusion

This paper presents FedMGP, a novel federated learning paradigm that addresses the fundamental trade-off between personalization and generalization in existing federated prompt learning methods through multi-group text-visual prompt co-learning. The key innovations of FedMGP include: (1) leveraging multiple text-visual prompt pairs to overcome the limited expressiveness of single prompts, with each prompt group focusing on different semantic features; (2) introducing diversity loss to ensure representation separation between prompt groups, enhancing the model's expressive power; (3) designing a similarity-based dynamic prompt selection strategy that effectively balances shared knowledge and client-specific features. Extensive experiments demonstrate that FedMGP achieves superior balance between personalization and generalization capabilities across various heterogeneous data environments while maintaining minimal communication parameters. In future work, we will explore alternative regularization constraints and integrate category-specific linguistic information to further enhance diverse representations across prompt groups, while investigating more sophisticated text-visual prompt collaboration mechanisms to improve cross-modal alignment in federated settings.

Acknowledge This work was supported by National Natural Science Foundation of China (Grant No. 62425603) and Basic Research Program of Jiangsu Province (Grant No. BK20240011).

References

[1] Jameel Abdul Samadh, Mohammad Hanan Gani, Noor Hussein, Muhammad Uzair Khattak, Muhammad Muzammal Naseer, Fahad Shahbaz Khan, and Salman H Khan. Align your prompts: Test-time prompting with distribution alignment for zero-shot generalization. In *Advances in Neural Information Processing Systems*, pages 80396–80413, 2024.

[2] Zeyuan Allen-Zhu and Yuanzhi Li. Towards understanding ensemble, knowledge distillation and self-distillation in deep learning. In *The Eleventh International Conference on Learning Representations*.

[3] Keith Bonawitz, Hubert Eichner, Wolfgang Grieskamp, Dzmitry Huba, Alex Ingerman, Vladimir Ivanov, Chloe Kiddon, Jakub Konečnỳ, Stefano Mazzocchi, Brendan McMahan, et al. Towards federated learning at scale: System design. *Proceedings of machine learning and systems*, 1:374–388, 2019.

[4] Lukas Bossard, Matthieu Guillaumin, and Luc Van Gool. Food-101–mining discriminative components with random forests. In *Proceedings of the European Conference on Computer Vision*, pages 446–461, 2014.

[5] Zhongyi Cai, Ye Shi, Wei Huang, and Jingya Wang. Fed-co _{2}: Cooperation of online and offline models for severe data heterogeneity in federated learning. In *Advances in Neural Information Processing Systems*, pages 21343–21367, 2023.

[6] Yuan Cao, Zixiang Chen, Misha Belkin, and Quanquan Gu. Benign overfitting in two-layer convolutional neural networks. In *Advances in Neural Information Processing Systems*, pages 25237–25250, 2022.

[7] Mircea Cimpoi, Subhransu Maji, Iasonas Kokkinos, Sammy Mohamed, and Andrea Vedaldi. Describing textures in the wild. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3606–3613, 2014.

[8] Liam Collins, Hamed Hassani, Aryan Mokhtari, and Sanjay Shakkottai. Fedavg with fine tuning: Local updates lead to representation learning. In *Advances in Neural Information Processing Systems*, pages 10572–10586, 2022.

[9] Tianyu Cui, Hongxia Li, Jingya Wang, and Ye Shi. Harmonizing generalization and personalization in federated prompt learning. In *Proceedings of the International Conference on Machine Learning*, pages 9646–9661, 2024.

[10] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. In *Proceedings of the International Conference on Learning Representations*, pages 11960–11973, 2020.

[11] Penghui Du, Yu Wang, Yifan Sun, Luting Wang, Yue Liao, Gang Zhang, Errui Ding, Yan Wang, Jingdong Wang, and Si Liu. Lami-detr: Open-vocabulary detection with language model instruction. In *European Conference on Computer Vision*, pages 312–328. Springer, 2024.

[12] Alireza Fallah, Aryan Mokhtari, and Asuman Ozdaglar. Personalized federated learning: A meta-learning approach. *arXiv preprint arXiv:2002.07948*, 2020.

[13] Li Fei-Fei, Rob Fergus, and Pietro Perona. Learning generative visual models from few training examples: An incremental bayesian approach tested on 101 object categories. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshop*, pages 178–178, 2004.

[14] Boqing Gong, Yuan Shi, Fei Sha, and Kristen Grauman. Geodesic flow kernel for unsupervised domain adaptation. In *2012 IEEE conference on Computer Vision and Pattern Recognition*, pages 2066–2073. IEEE, 2012.

[15] Mingzhe Guo, Zhipeng Zhang, Liping Jing, Haibin Ling, and Heng Fan. Divert more attention to vision-language object tracking. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 46(12):8600–8618, 2024.

[16] Tao Guo, Song Guo, and Junxiao Wang. Pfedprompt: Learning personalized prompt for vision-language models in federated learning. In *Proceedings of the ACM Web Conference 2023*, pages 1364–1374, 2023.

[17] Tao Guo, Song Guo, Junxiao Wang, Xueyang Tang, and Wenchao Xu. Promptfl: Let federated participants cooperatively learn prompts instead of models–federated learning in age of foundation model. *IEEE Transactions on Mobile Computing*, 23(5):5179–5194, 2023.

[18] Wei Huang, Ye Shi, Zhongyi Cai, and Taiji Suzuki. Understanding convergence and generalization in federated learning through feature learning theory. In *The Twelfth International Conference on Learning Representations*, 2023.

[19] Xin Jiang, Hao Tang, Junyao Gao, Xiaoyu Du, Shengfeng He, and Zechao Li. Delving into multimodal prompting for fine-grained visual classification. In *Proceedings of the AAAI conference on artificial intelligence*, pages 2570–2578, 2024.

[20] Xin Jiang, Hao Tang, and Zechao Li. Global meets local: Dual activation hashing network for large-scale fine-grained image retrieval. *IEEE Transactions on Knowledge and Data Engineering*, 36(11):6266–6279, 2024.

[21] Xin Jiang, Hao Tang, Rui Yan, Jinhui Tang, and Zechao Li. Dvf: Advancing robust and accurate fine-grained image retrieval with retrieval guidelines. In *Proceedings of the 32nd ACM International Conference on Multimedia*, pages 2379–2388, 2024.

[22] Baoshuo Kan, Teng Wang, Wenpeng Lu, Xiantong Zhen, Weili Guan, and Feng Zheng. Knowledge-aware prompt tuning for generalizable vision-language models. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 15670–15680, 2023.

[23] Muhammad Uzair Khattak, Muhammad Ferjad Naeem, Muzammal Naseer, Luc Van Gool, and Federico Tombari. Learning to prompt with text only supervision for vision-language models. *arXiv preprint arXiv:2401.02418*, 2024.

[24] Yiwen Kou, Zixiang Chen, Yuanzhou Chen, and Quanquan Gu. Benign overfitting in two-layer relu convolutional neural networks. In *International Conference on Machine Learning*, pages 17615–17659. PMLR, 2023.

[25] Jonathan Krause, Michael Stark, Jia Deng, and Li Fei-Fei. 3d object representations for fine-grained categorization. In *Proceedings of the IEEE International Conference on Computer Vision Workshops*, pages 554–561, 2013.

[26] Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009.

[27] Hongxia Li, Wei Huang, Jingya Wang, and Ye Shi. Global and local prompts cooperation via optimal transport for federated learning. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 12151–12161, 2024.

[28] Qinbin Li, Bingsheng He, and Dawn Song. Model-contrastive federated learning. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pages 10713–10722, 2021.

[29] Zengxiang Li, Zhaoxiang Hou, Hui Liu, Tongzhi Li, Chengyi Yang, Ying Wang, Chao Shi, Longfei Xie, Weishan Zhang, Liang Xu, et al. Federated learning in large model era: Vision-language model for smart city safety operation management. In *Companion Proceedings of the ACM Web Conference 2024*, pages 1578–1585, 2024.

[30] Haodong Lu, Xinyu Zhang, Kristen Moore, Jason Xue, Lina Yao, Anton van den Hengel, and Dong Gong. Continual learning on clip via incremental prompt tuning with intrinsic textual anchors, 2025.

[31] Timo Lüddecke and Alexander Ecker. Image segmentation using text and image prompts. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 7086–7096, 2022.

[32] Jun Luo, Chen Chen, and Shandong Wu. Mixture of experts made personalized: Federated prompt learning for vision-language models. *arXiv preprint arXiv:2410.10114*, 2024.

[33] Subhransu Maji, Esa Rahtu, Juho Kannala, Matthew Blaschko, and Andrea Vedaldi. Fine-grained visual classification of aircraft. *arXiv preprint arXiv:1306.5151*, 2013.

[34] Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguera y Arcas. Communication-efficient learning of deep networks from decentralized data. In *Artificial intelligence and statistics*, pages 1273–1282. PMLR, 2017.

[35] Sachit Menon and Carl Vondrick. Visual classification via description from large language models. In *Proceedings of the International Conference on Learning Representations*, 2023.

[36] Maria-Elena Nilsback and Andrew Zisserman. Automated flower classification over a large number of classes. In *Proceedings of the Indian Conference on Computer Vision, Graphics & Image Processing*, pages 722–729, 2008.

[37] Bikang Pan, Wei Huang, and Ye Shi. Federated learning from vision-language foundation models: Theoretical analysis and method. In *Advances in Neural Information Processing Systems*, pages 30590–30623, 2024.

[38] Omkar M. Parkhi, Andrea Vedaldi, Andrew Zisserman, and C. V. Jawahar. Cats and dogs. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3498–3505, 2012.

[39] Xingchao Peng, Qinxun Bai, Xide Xia, Zijun Huang, Kate Saenko, and Bo Wang. Moment matching for multi-source domain adaptation. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 1406–1415, 2019.

[40] Sarah Pratt, Ian Covert, Rosanne Liu, and Ali Farhadi. What does a platypus look like? generating customized prompts for zero-shot image classification. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 15691–15701, 2023.

[41] Chen Qiu, Xingyu Li, Chaithanya Kumar Mummadi, Madan Ravi Ganesh, Zhenzhen Li, Lu Peng, and Wan-Yi Lin. Federated text-driven prompt generation for vision-language models. In *The Twelfth International Conference on Learning Representations*, 2024.

[42] Hongyu Qu, Rui Yan, Xiangbo Shu, Hailiang Gao, Peng Huang, and Guo-Sen Xie. Mvp-shot: Multi-velocity progressive-alignment framework for few-shot action recognition. *IEEE Transactions on Multimedia*, 2025.

[43] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *International conference on machine learning*, pages 8748–8763. PmLR, 2021.

[44] Karsten Roth, Jae Myung Kim, A Koepke, Oriol Vinyals, Cordelia Schmid, and Zeynep Akata. Waffling around for performance: Visual classification with random words and broad concepts. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 15746–15757, 2023.

[45] Cheng Shi and Sibei Yang. Logoprompt: Synthetic text images can be good visual prompts for vision-language models. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 2932–2941, 2023.

[46] Aleksandar Shtedritski, Christian Rupprecht, and Andrea Vedaldi. What does clip know about a red circle? visual prompt engineering for vlms. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 11987–11997, 2023.

[47] K Soomro. Ucf101: A dataset of 101 human actions classes from videos in the wild. *arXiv preprint arXiv:1212.0402*, 2012.

[48] Yanpeng Sun, Qiang Chen, Xiangyu He, Jian Wang, Haocheng Feng, Junyu Han, Errui Ding, Jian Cheng, Zechao Li, and Jingdong Wang. Singular value fine-tuning: Few-shot segmentation requires few-parameters fine-tuning. In *Advances in Neural Information Processing Systems*, pages 37484–37496. Curran Associates, Inc., 2022.

[49] Yanpeng Sun, Jiahui Chen, Shan Zhang, Xinyu Zhang, Qiang Chen, Gang Zhang, Errui Ding, Jingdong Wang, and Zechao Li. Vrp-sam: Sam with visual reference prompt. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 23565–23574, 2024.

[50] Canh T Dinh, Nguyen Tran, and Josh Nguyen. Personalized federated learning with moreau envelopes. In *Advances in Neural Information Processing Systems*, pages 21394–21405, 2020.

[51] Linh Tran, Wei Sun, Stacy Patterson, and Ana Milanova. Privacy-preserving personalized federated prompt learning for multimodal large language models. In *The Thirteenth International Conference on Learning Representations*.

[52] Hao Wang, Zakhary Kaplan, Di Niu, and Baochun Li. Optimizing federated learning on non-iid data with reinforcement learning. In *IEEE INFOCOM 2020-IEEE Conference on computer communications*, pages 1698–1707. IEEE, 2020.

[53] Yubin Wang, Xinyang Jiang, De Cheng, Dongsheng Li, and Cairong Zhao. Learning hierarchical prompt with structured linguistic knowledge for vision-language models. In *Proceedings of the AAAI Conference on Artificial Intelligence*, pages 5749–5757, 2024.

[54] Jianxiong Xiao, James Hays, Krista A Ehinger, Aude Oliva, and Antonio Torralba. Sun database: Large-scale scene recognition from abbey to zoo. In *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pages 3485–3492, 2010.

[55] Peng Xu, Wenqi Shao, Kaipeng Zhang, Peng Gao, Shuo Liu, Meng Lei, Fanqing Meng, Siyuan Huang, Yu Qiao, and Ping Luo. Lvlm-ehub: A comprehensive evaluation benchmark for large vision-language models. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2024.

[56] Xiaohua Zhai, Xiao Wang, Basil Mustafa, Andreas Steiner, Daniel Keysers, Alexander Kolesnikov, and Lucas Beyer. Lit: Zero-shot transfer with locked-image text tuning. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pages 18123–18133, 2022.

[57] Renrui Zhang, Xiangfei Hu, Bohao Li, Siyuan Huang, Hanqiu Deng, Yu Qiao, Peng Gao, and Hongsheng Li. Prompt, generate, then cache: Cascade of foundation models makes strong few-shot learners. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 15211–15222, 2023.

[58] Xinyu Zhang, Jiahui Chen, Junkun Yuan, Qiang Chen, Jian Wang, Xiaodi Wang, Shumin Han, Xiaokang Chen, Jimin Pi, Kun Yao, Junyu Han, Errui Ding, and Jingdong Wang. CAE v2: Context autoencoder with CLIP latent alignment. *Transactions on Machine Learning Research*, 2023.

[59] Kaiyang Zhou, Jingkang Yang, Chen Change Loy, and Ziwei Liu. Conditional prompt learning for vision-language models. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 16816–16825, 2022.

[60] Kaiyang Zhou, Jingkang Yang, Chen Change Loy, and Ziwei Liu. Learning to prompt for vision-language models. *International Journal of Computer Vision*, 130(9):2337–2348, 2022.

[61] Beier Zhu, Yulei Niu, Yucheng Han, Yue Wu, and Hanwang Zhang. Prompt-aligned gradient for prompt tuning. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 15659–15669, 2023.

NeurIPS Paper Checklist

1. **Claims**

   Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

   Answer: [Yes]

   Justification: We empirically verify the claims and contributions made in the abstract and introduction through extensive experiments across diverse federated vision-language benchmarks. Our theoretical analysis further supports the design motivations, including prompt diversity, probabilistic sampling, and cross-modal pairing.

   Guidelines:

   - The answer NA means that the abstract and introduction do not include the claims made in the paper.
   - The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
   - The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
   - It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. **Limitations**

   Question: Does the paper discuss the limitations of the work performed by the authors?

   Answer: [Yes]

   Justification: We include a discussion of the limitations of our work in the appendix, highlighting potential areas for improvement and directions for future research.

   Guidelines:

   - The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
   - The authors are encouraged to create a separate "Limitations" section in their paper.
   - The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
   - The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
   - The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
   - The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
   - If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
   - While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. **Theory assumptions and proofs**

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [Yes]

Justification: We provide the full set of assumptions and complete proofs for our theoretical results in the appendix, ensuring correctness and clarity of the analysis.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. **Experimental result reproducibility**

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: We provide detailed descriptions of all experimental settings, including dataset splits, model architecture, training hyperparameters, and evaluation metrics. These details are sufficient to reproduce the main results and support the core claims of the paper.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general. releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
  (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
  (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
  (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).

(d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. **Open access to data and code**

   Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

   Answer: [No]

   Justification: We will release our code upon acceptance.

   Guidelines:

   - The answer NA means that paper does not include experiments requiring code.
   - Please see the NeurIPS code and data submission guidelines (`https://nips.cc/public/guides/CodeSubmissionPolicy`) for more details.
   - While we encourage the release of code and data, we understand that this might not be possible, so No is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
   - The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (`https://nips.cc/public/guides/CodeSubmissionPolicy`) for more details.
   - The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
   - The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
   - At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
   - Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. **Experimental setting/details**

   Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

   Answer: [Yes]

   Justification: The training and test details are presented in section 4.1

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
   - The full details can be provided either with the code, in appendix, or as supplemental material.

7. **Experiment statistical significance**

   Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

   Answer: [No]

   Justification: This paper does not report error bars or statistical significance measures. The results are presented as aggregate performance metrics without confidence intervals or variance analysis.

   Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. **Experiments compute resources**

   Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

   Answer: [Yes]

   Justification: All experiments were conducted on either 1 NVIDIA 4090-D GPU (24 GB) or 1 NVIDIA A100 GPU (40 GB), with each training run completing within 24 hours for all datasets.

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
   - The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
   - The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. **Code of ethics**

   Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics `https://neurips.cc/public/EthicsGuidelines`?

   Answer: [Yes]

   Justification: We have carefully reviewed and adhered to the code of ethics throughout our research and writing process.

   Guidelines:

   - The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
   - If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
   - The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. **Broader impacts**

    Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [Yes]

Justification: We discuss the broader impacts in Appendix.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. **Safeguards**

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [NA]

Justification: Our work poses no such risks.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. **Licenses for existing assets**

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: All publicly available assets (models, code, and data) used in this work have been properly credited, and their respective licenses and terms of use have been explicitly mentioned and adhered to.

Guidelines:

- The answer NA means that the paper does not use existing assets.

- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, `paperswithcode.com/datasets` has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New assets**

    Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

    Answer: [NA]

    Justification: We do not release new assets in the submission.

    Guidelines:

    - The answer NA means that the paper does not release new assets.
    - Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
    - The paper should discuss whether and how consent was obtained from people whose asset is used.
    - At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and research with human subjects**

    Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

    Answer: [NA]

    Justification: The paper does not involve crowdsourcing nor research with human subjects.

    Guidelines:

    - The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
    - Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
    - According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional review board (IRB) approvals or equivalent for research with human subjects**

    Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

    Answer: [NA]

    Justification: The paper does not involve crowdsourcing nor research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. **Declaration of LLM usage**

    Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

    Answer: [NA]

    Justification: The paper does not use Large Language Models (LLMs) as an important, original, or non-standard component of the core methods.

    Guidelines:

    - The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
    - Please refer to our LLM policy (`https://neurips.cc/Conferences/2025/LLM`) for what should or should not be described.

Supplementary organization:

A FedMGP ALGORITHM

Algorithm 1 FEDMGP: Federated Learning via Multi-Group Text-Visual Prompt Co-Learning

Inputs: Communication rounds T, local epochs R, number of clients N, local datasets $\{D_c\}_{c=1}^{N}$, image encoder $f(\cdot)$, text encoder $g(\cdot)$, number of prompt groups G, top-s size for aggregation, temperature τ, diversity loss weight λ, learning rate η.
Outputs: Personalized multi-group prompts $\{P_c\}_{c=1}^{N}$, where $P_c = \{p_{t,1}, \ldots, p_{t,G}, p_{v,1}, \ldots, p_{v,G}\}$.

Server Executes:
Initialize global prompts $\tilde{P}^0 = \{\tilde{p}_{t,1}, \ldots, \tilde{p}_{t,G}, \tilde{p}_{v,1}, \ldots, \tilde{p}_{v,G}\}$.
for each client $c = 1, \ldots, N$ **do**
    Distribute copies: $P_c \leftarrow \tilde{P}^0$.
end for
for each communication round $T = 1, \ldots, T_{max}$ **do**
    Server selects a subset of clients C_T.
    for each client $c \in C_T$ **in parallel do**
        $P_c^T \leftarrow \text{CLIENTUPDATE}(c, P_c, D_c, R, f, g, G, \tau, \lambda, \eta)$
    end for
    ▷ Dynamic prompt aggregation stage
    for each client $c \in C_T$ **do**
        if $T = 1$ **then**
            Select s prompt groups randomly from P_c^T, denoted as $P_{c,selected}^T$
        else
            Compute similarity scores between client prompts P_c^T and global prompts $\tilde{P}^{T-1}$ using Eq. (7)
            Convert similarities to probabilities using Eq. (8)
            Probabilistically select s prompt groups from P_c^T based on these probabilities, denoted as $P_{c,selected}^T$
        end if
        Send $P_{c,selected}^T$ to server.
    end for
    Server aggregates collected prompts to form $\tilde{P}^T$ using Eq. (9)
    for each client $c \in C_T$ **do**
        Update the selected prompt groups in P_c with corresponding prompts from $\tilde{P}^T$
    end for
end for
return Final personalized prompts $\{P_c\}_{c=1}^{N}$

procedure CLIENTUPDATE($c, P_c, D_c, R, f, g, G, \tau, \lambda, \eta$)
    Let local prompts $P_c = \{p_{t,1}, \ldots, p_{t,G}, p_{v,1}, \ldots, p_{v,G}\}$
    for each epoch $e = 1, \ldots, R$ **do**
        Sample mini-batch $(x, y) \sim D_c$
        for each prompt group $j = 1, \ldots, G$ **do**
            Form visual input $v_j = \{x, p_{v,j}\}$ and compute $f(v_j)$
            for each class k **do**
                Form text input $t_{k,j} = \{p_{t,j}, c_k\}$ and compute $g(t_{k,j})$
                Compute logits using Eq. (2)
            end for
        end for
        Compute classification loss $\mathcal{L}_{\text{CE}}$ using Eq. (3)
        Compute diversity loss $\mathcal{L}_{\text{div}}$ using Eq. (4)
        Total loss $\mathcal{L} \leftarrow \mathcal{L}_{\text{CE}} + \lambda \cdot \mathcal{L}_{\text{div}}$
        Update prompt parameters P_c using gradient descent with learning rate η
    end for
    return Updated prompts P_c
end procedure

B Limitations and Broader Impacts

As shown in Table 9, while FedMGP consistently outperforms existing methods across most settings, it shows limitations in extremely data-scarce scenarios (1-2 shots). This stems from our multi-group prompt mechanism, which requires sufficient data to effectively disentangle different semantic aspects. With minimal samples, prompt groups cannot specialize properly, leading to unstable training. The text-visual co-learning mechanism further compounds this challenge, as establishing robust cross-modal correlations requires visual diversity absent in 1-shot settings. Additionally, our dynamic aggregation strategy becomes less reliable when prompt representations are unstable due to data scarcity. Simpler methods like PromptFolio occasionally perform better in these extreme low-shot scenarios precisely because they avoid the complexity that makes FedMGP powerful in data-rich environments.

To address these limitations, several future directions emerge: (1) developing adaptive mechanisms to dynamically adjust the number of prompt groups based on available data, reducing groups when data is scarce; (2) initializing prompt groups with knowledge from related tasks to provide stronger starting points for specialization; and (3) incorporating meta-learning techniques to improve learning efficiency from limited examples. While FedMGP contributes positively to privacy-preserving adaptation of vision-language models in decentralized environments, we acknowledge that, like all federated learning systems, it may remain vulnerable to various attacks. As these technologies advance toward deployment in sensitive domains, continued research must address both technical limitations and broader societal implications.

Table 9: Performance Comparison of Different Methods on 1-16 shots

Dataset	Method	1-shot	2-shots	4-shots	8-shots	16-shots
Caltech101	PromptFL	95.23	95.30	95.62	96.20	94.66
	FedOPT	92.81	92.95	89.27	81.37	69.43
	FedTPG	95.74	94.88	96.00	96.02	95.32
	FedPGP	96.02	**96.13**	95.54	95.87	96.37
	PromptFolio	95.84	95.39	93.90	90.39	88.50
	FedMGP (Ours)	**96.03**	95.48	**96.48**	**97.14**	**97.07**
DTD	PromptFL	53.78	52.69	55.08	60.58	52.60
	FedOPT	**68.73**	63.93	65.68	65.51	61.71
	FedTPG	59.30	64.28	66.22	65.85	52.49
	FedPGP	58.15	63.60	62.00	63.31	68.21
	PromptFolio	64.86	63.92	65.11	62.42	64.11
	FedMGP (Ours)	62.00	**68.32**	**69.58**	**69.12**	**73.92**
Flowers102	PromptFL	78.20	72.37	73.27	69.71	71.94
	FedOPT	68.62	68.42	66.32	60.54	57.99
	FedTPG	74.59	73.71	78.05	78.85	77.71
	FedPGP	73.49	73.16	76.09	84.39	82.85
	PromptFolio	**81.24**	**79.51**	79.35	70.99	66.05
	FedMGP (Ours)	73.75	78.07	**83.80**	**84.53**	**85.16**

C Experimental Details

C.1 Dataset Setup

Our evaluation leverages nine diverse visual classification datasets, spanning fine-grained recognition, texture analysis, general object classification, and domain adaptation tasks. Table 10 provides comprehensive details about these datasets, including classes, sample sizes, domains, and training protocols.

For our base-to-novel generalization experiments (Oxford-Pets to Food101), we employ a few-shot training paradigm, where each client is provided with only 16 samples per class (16-shot) for the main experiments. These datasets are partitioned by splitting classes equally into base and novel

categories, with non-overlapping base classes distributed across clients to establish the pathological non-IID setting described in Section 4.

For label distribution shift experiments, we utilize CIFAR10 and CIFAR100 with Dirichlet distribution partitioning ($\alpha = 0.5$) across 100 clients, using the full training set. This creates realistic client heterogeneity with varying class proportions.

For domain adaptation scenarios, we leverage Office-Caltech10 with its four domains (Amazon, Caltech, DSLR, and WebCam) and DomainNet with six domains (Clipart, Infograph, Painting, Quickdraw, Real, and Sketch). Each domain is split into 5 clients under Dirichlet distribution ($\alpha = 0.3$), resulting in a total of 20 and 30 clients respectively. This setup introduces natural feature shifts across domains and moderate label skew within each domain.

Table 10: Statistical details of datasets used in experiments.

Dataset	Classes	Train	Test	Domains	Training Protocol	Task
OxfordPets [38]	37	2,944	3,669	1	Few-shot (16-shot)	Pets recognition
Flowers102 [36]	102	4,093	2,463	1	Few-shot (16-shot)	Flowers recognition
DTD [7]	47	2,820	1,692	1	Few-shot (16-shot)	Texture recognition
Caltech101 [13]	100	4,128	2,465	1	Few-shot (16-shot)	Object recognition
Food101 [4]	101	50,500	30,300	1	Few-shot (16-shot)	Food recognition
Stanford Cars [25]	196	6,509	8,041	1	Few-shot (16-shot)	Cars recognition
FGVC Aircraft [33]	100	3,334	3,333	1	Few-shot (16-shot)	Aircraft recognition
UCF101 [47]	101	7,639	3,783	1	Few-shot (16-shot)	Action recognition
SUN397 [54]	397	15,880	19,850	1	Few-shot (16-shot)	Scene recognition
CIFAR10 [26]	10	50,000	10,000	1	Full dataset	Image classification
CIFAR100 [26]	100	50,000	10,000	1	Full dataset	Image classification
DomainNet [39]	10	18,278	4,573	6	Full dataset	Domain adaptation
Office-Caltech10 [14]	10	2,025	508	4	Full dataset	Domain adaptation

C.2 Experimental Setup

We employ SGD optimizer with learning rate $\eta = 0.001$ and single-step learning rate scheduler across all experiments. All implementations are based on PyTorch and experiments were conducted on NVIDIA RTX 4090 (24GB) or A100 (40GB) GPUs. Across all experiments, we use ViT-B/16 pretrained on ImageNet as the backbone. Images are resized to 224×224 using bicubic interpolation with standard data augmentation (random resized crop, random flip, and normalization). For FedMGP, we set both text and visual prompt lengths to 2, use 5 prompt groups for each modality, and initialize with the text "a photo of a". All models are trained with mixed precision (fp16) for computational efficiency.

The following sections detail the specific configurations for different experimental scenarios.

Base-to-Novel Class Generalization. For the five fine-grained classification datasets, we partition each dataset equally into base and novel classes, then distribute non-overlapping base classes to each of the 10 clients. We employ a few-shot (16-shot by default) training paradigm with batch size 8. The federated learning process proceeds for 10 communication rounds with 100% client participation and 2 local epochs per round. Each client trains on their local classes, and we evaluate performance on: (1) local classes (personalization), (2) base classes (classes seen by other clients), and (3) novel classes (unseen during training). The Combined Metric (CM) is computed as CM = (Local + HM)/2, where HM is the harmonic mean of Base and Novel accuracies.

Label Distribution Shift. For CIFAR-10 and CIFAR-100, we partition the full training set among 100 clients following a Dirichlet distribution with concentration parameter $\alpha = 0.5$. Communication proceeds for 100 rounds with 10% client participation per round and 2 local epochs per round. We use batch size 32 for training and 300 for testing. This creates a realistic heterogeneous environment with varying class proportions across clients.

Domain Adaptation. For Office-Caltech10 and DomainNet, we leverage their inherent domain structure (4 domains for Office-Caltech10 and 6 domains for DomainNet). Each domain is assigned 5 clients, resulting in a total of 20 clients for Office-Caltech10 and 30 clients for DomainNet. This setup introduces both feature shift and label skew. The federated learning process runs for 25 rounds with 25% client participation per round and 1 local epoch per round. We evaluate each client's performance on all domains to assess cross-domain generalization.

D Additional Experimental Results

D.1 Domain Generalization for DomainNet

Table 11: Results on DomainNet with feature shift and label shift with Dir($\alpha = 0.3$) partition into 5 clients/domain

	Clipart	Infograph	Painting	Quickdraw	Real	Sketch	Average
PromptFL [17]	$25.80_{\pm 20.82}$	$10.48_{\pm 11.13}$	$16.05_{\pm 7.40}$	$15.39_{\pm 16.48}$	$14.72_{\pm 8.17}$	$6.29_{\pm 6.45}$	$14.79_{\pm 14.18}$
FedOPT [27]	$43.25_{\pm 10.90}$	$43.55_{\pm 16.89}$	$28.07_{\pm 7.05}$	$35.56_{\pm 3.37}$	$28.45_{\pm 11.28}$	$33.64_{\pm 20.15}$	$35.42_{\pm 14.33}$
FedTPG [41]	$17.16_{\pm 18.26}$	$23.56_{\pm 17.77}$	$13.58_{\pm 9.41}$	$16.25_{\pm 14.75}$	$17.13_{\pm 4.95}$	$9.16_{\pm 5.19}$	$16.14_{\pm 13.66}$
FedPGP [9]	$12.01_{\pm 10.21}$	$10.49_{\pm 3.40}$	$11.39_{\pm 7.62}$	$21.77_{\pm 15.76}$	$14.29_{\pm 5.59}$	$10.13_{\pm 12.44}$	$13.35_{\pm 10.83}$
PromptFolio [37]	$41.80_{\pm 11.21}$	$42.38_{\pm 15.51}$	$29.69_{\pm 8.33}$	$34.70_{\pm 2.30}$	$28.99_{\pm 10.23}$	$35.72_{\pm 13.73}$	$35.55_{\pm 12.23}$
FedMGP	$48.48_{\pm 8.07}$	$47.76_{\pm 13.61}$	$30.36_{\pm 6.98}$	$35.19_{\pm 4.73}$	$33.02_{\pm 6.40}$	$36.74_{\pm 18.47}$	$38.59_{\pm 12.90}$

The values in Table 11 represent the maximum and minimum accuracies among the five clients within each domain under the Dirichlet distribution, illustrating the performance variation of multiple clients sharing the same domain characteristics. The domain adaptation experiments on DomainNet demonstrate FedMGP's superior performance in handling domain shifts and label distribution heterogeneity. As shown in Table 11, FedMGP achieves an average accuracy of 38.59%, significantly outperforming the closest competitors PromptFolio (35.55%) and FedOPT (35.42%). FedMGP exhibits particularly strong performance on domains with high visual abstraction, such as Clipart (48.48%) and Infograph (47.76%), substantially outperforming other methods. This demonstrates that our multi-group text-visual prompt co-learning mechanism can effectively capture and adapt to different visual representations across DomainNet's diverse artistic styles. The performance stability across diverse domains, evidenced by comparatively lower standard deviations, confirms our theoretical analysis that the multi-group architecture effectively decomposes knowledge into common and client-specific components. The visual prompts capture domain-specific artistic features while text prompts provide cross-domain semantic connections, enabling FedMGP to maintain both domain adaptability and semantic consistency. This approach effectively addresses the core challenge of domain generalization in federated learning by simultaneously preserving domain-specific knowledge while enabling cross-domain knowledge transfer across DomainNet's six distinct visual domains.

D.2 Domain Generalization for Office-Caltech10

Table 12: Results on `Office-Caltech10` with feature shift and label shift with Dir($\alpha = 0.3$) partition into 5 clients/domain

	Amazon	Caltech	DSLR	Webcam	Average
PromptFL [17]	$9.23_{\pm 8.55}$	$16.88_{\pm 14.97}$	$8.33_{\pm 10.54}$	$25.59_{\pm 26.65}$	$15.01_{\pm 18.11}$
FedOPT [27]	$28.20_{\pm 5.12}$	$35.22_{\pm 13.17}$	$23.67_{\pm 8.72}$	$30.71_{\pm 11.48}$	$29.45_{\pm 10.92}$
FedTPG [41]	$6.94_{\pm 7.26}$	$9.10_{\pm 11.60}$	$16.33_{\pm 15.29}$	$28.11_{\pm 25.73}$	$15.12_{\pm 18.41}$
FedPGP [9]	$8.50_{\pm 7.75}$	$19.33_{\pm 12.60}$	$11.33_{\pm 15.72}$	$24.89_{\pm 14.34}$	$16.01_{\pm 14.49}$
PromptFolio [37]	$32.48_{\pm 13.34}$	$36.21_{\pm 9.40}$	$20.33_{\pm 12.93}$	$11.59_{\pm 2.88}$	$25.15_{\pm 14.36}$
FedMGP	$31.32_{\pm 5.94}$	$38.28_{\pm 7.21}$	$41.33_{\pm 15.55}$	$44.73_{\pm 19.01}$	$38.92_{\pm 17.31}$

For the Office-Caltech10 dataset, as shown in Table 12, FedMGP demonstrates even more substantial improvements, with an average accuracy of 38.92% compared to the second-best performer

FedOPT (29.45%). Unlike DomainNet's artistic style variations, Office-Caltech10 presents challenges related to imaging conditions and equipment specifications. The advantage is particularly pronounced on specialized equipment captures like DSLR (41.33%) and Webcam (44.73%), where FedMGP outperforms other methods by large margins. These results validate the effectiveness of our approach in handling technical domain shifts beyond artistic variations. Most baseline methods exhibit substantial performance variations across domains, indicating their vulnerability to domain-specific overfitting in equipment-based scenarios. In contrast, FedMGP maintains more consistent performance, demonstrating its robustness to both artistic and technical domain shifts. This confirms that integrating visual and textual modalities enriches contextual representation, capturing instance-specific information more comprehensively than text-only approaches across different types of domain variations. The performance on Office-Caltech10 confirms that FedMGP's multi-group architecture effectively distributes knowledge across specialized prompt units rather than concentrating it in a single structure, enabling robust cross-domain generalization while preserving domain-specific adaptation capabilities for both artistic and technical domain characteristics.

D.3 Stability of Prompt Group Selection

Table 13: Selection frequency of each prompt group across training rounds on OxfordPets dataset. Values show the number of clients (out of 20 total) selecting each group, with percentages in parentheses.

Round	t_g1	t_g2	t_g3	t_g4	t_g5	v_g1	v_g2	v_g3	v_g4	v_g5
1	3(15%)	2(10%)	6(30%)	5(25%)	4(20%)	3(15%)	2(10%)	6(30%)	5(25%)	4(20%)
2	6(30%)	2(10%)	6(30%)	3(15%)	3(15%)	6(30%)	2(10%)	6(30%)	3(15%)	3(15%)
3	7(35%)	2(10%)	5(25%)	3(15%)	3(15%)	7(35%)	2(10%)	5(25%)	3(15%)	3(15%)
4	6(30%)	3(15%)	5(25%)	3(15%)	3(15%)	7(35%)	3(15%)	4(20%)	2(10%)	4(20%)
5	6(30%)	3(15%)	3(15%)	3(15%)	5(25%)	7(35%)	3(15%)	3(15%)	2(10%)	5(25%)
6	6(30%)	4(20%)	3(15%)	2(10%)	5(25%)	7(35%)	4(20%)	3(15%)	1(5%)	5(25%)
7	7(35%)	4(20%)	4(20%)	1(5%)	4(20%)	7(35%)	4(20%)	4(20%)	1(5%)	4(20%)
8	6(30%)	4(20%)	4(20%)	2(10%)	4(20%)	7(35%)	4(20%)	5(25%)	1(5%)	3(15%)
9	4(20%)	5(25%)	6(30%)	1(5%)	4(20%)	5(25%)	5(25%)	7(35%)	0(0%)	3(15%)
10	5(25%)	5(25%)	5(25%)	2(10%)	3(15%)	4(20%)	7(35%)	6(30%)	1(5%)	2(10%)

Table 13 presents the selection frequency of each prompt group across ten training rounds on the OxfordPets dataset, demonstrating the stability of prompt group assignments in FedMGP. The results reveal that while prompt groups exhibit dynamic selection patterns, their roles remain relatively stable throughout training. Notably, certain groups consistently receive higher selection frequencies (e.g., text group 1 and visual group 1 maintain 30-35% selection after round 3), indicating their specialization in capturing shared global knowledge that benefits multiple clients. Conversely, other groups show lower but persistent selection rates (e.g., text group 4 ranges from 5-15%), suggesting their focus on client-specific local features. This pattern validates our dynamic aggregation mechanism's design principle: rather than forcing uniform participation, the similarity-guided probabilistic sampling naturally guides prompt groups to specialize in complementary aspectssome evolving to capture common patterns through frequent selection, while others preserve personalized knowledge through selective aggregation. The temperature parameter τ in our selection process plays a crucial role in maintaining this dynamic balance, preventing any prompt group from being permanently excluded (as evidenced by the absence of consistently zero selections) while still allowing meaningful specialization. This ensures that FedMGP retains both strong generalization capabilities through shared knowledge and effective personalization through client-specific features, achieving the optimal trade-off demonstrated in our main experimental results.

E Additional ablation study

In this section, we present additional ablation studies to further analyze the effectiveness of different components and design choices in FedMGP. These experiments provide deeper insights into the model behavior and validate the design decisions discussed in the main paper.

E.1 Effect of Temperature Parameter in Prompt Selection

Table 14: Effect of Temperature (τ) on FedMGP Performance

Setting	Local	Base	Novel	CM
FedMGP (τ=0.1)	84.84	95.92	72.54	83.72
FedMGP (τ=0.5)	85.45	96.46	73.47	84.43
FedMGP (τ=0.8)	84.40	95.31	72.94	83.52
FedMGP (τ=2.0)	85.17	96.63	72.61	84.04
FedMGP (τ=1.0)	96.92	73.23	74.65	**85.43**

The temperature parameter τ in our dynamic prompt selection strategy plays a critical role in balancing exploration and exploitation during federated learning. As shown in Table 14, the optimal performance is achieved at $\tau = 1.0$ with a Combined Metric (CM) of 85.43%, significantly outperforming both lower temperatures ($\tau = 0.1, 0.5$) and higher temperatures ($\tau = 2.0$). Lower temperatures lead to more deterministic selection based on prompt similarity, resulting in stronger base class performance (96.46% at $\tau = 0.5$) but weaker local personalization. Conversely, higher temperatures introduce more randomness, allowing for greater exploration but potentially disrupting the convergence of shared knowledge. This confirms our theoretical framework in Section 3.2.2

E.2 Inference-Time Prompt Group Weighting Strategies

Table 15: Effect of Different Inference Strategies on FedMGP Performance

Setting	Local	Base	Novel	CM
FedMGP (Max logits)	81.96	89.48	74.79	81.72
FedMGP (Feature avg)	85.09	95.56	74.32	84.35
FedMGP (Group 0)	79.65	85.80	73.08	79.29
FedMGP (Group 1)	78.19	83.65	72.68	77.99
FedMGP (Group 2)	77.92	83.69	72.66	77.85
FedMGP (Group 3)	80.70	96.94	61.52	77.99
FedMGP (Group 4)	80.52	90.76	69.37	79.58
FedMGP (Average)	96.92	73.23	74.65	**85.43**

The effectiveness of different inference-time strategies for combining predictions from multiple prompt groups is examined in Table 15. Simple logit averaging across all groups yields the best overall performance (CM=85.43%), significantly outperforming alternative strategies such as maximum logit selection (CM=81.72%) and feature-level averaging (CM=84.35%). Notably, relying on any single prompt group (groups 0-4) substantially degrades performance, with the best individual group achieving only CM=79.58%. This confirms our hypothesis presented in Section 3.2.1 that the multi-group architecture enables different prompt groups to specialize in complementary aspects of the input data. The superior performance of ensemble averaging demonstrates that each prompt group contributes unique and valuable semantic perspectives, collectively enhancing model robustness. Group 3 exhibits the highest base class accuracy (96.94%) but poor novel class performance (61.52%), indicating its specialization in capturing shared patterns across clients rather than generalizable featuresprecisely the type of specialization our diversity loss was designed to encourage. These results validate our core design principle of distributing knowledge across multiple specialized prompt units rather than concentrating it in a single monolithic structure.

E.3 Diversity Loss Formulation Variants

The choice of diversity loss function significantly impacts FedMGP's ability to learn specialized prompt representations. As shown in Table 16, the L1-based diversity formulation achieves the best overall performance (CM=85.43%), outperforming both cosine similarity (CM=83.96%) and L2-based approaches (CM=83.83%). The L1 formulation leads to substantially better local accuracy

Table 16: Effect of Diversity Loss Type on FedMGP Performance

Setting	Local	Base	Novel	CM
FedMGP (COS)	84.72	95.68	73.61	83.96
FedMGP (L2)	84.57	94.76	73.98	83.83
FedMGP (L1)	96.92	73.23	74.65	**85.43**

(96.92%) compared to cosine (84.72%) and L2 (84.57%), while maintaining comparable performance on novel classes. This performance pattern aligns with our analysis in Section 3.2.1, where we emphasized the importance of encouraging prompt groups to capture diverse semantic perspectives. The L1 norm's sparsity-inducing property appears to create cleaner separation between prompt groups, allowing each to specialize more effectively in different aspects of the data distribution. Cosine similarity, while effective at enforcing orthogonality, appears less suited to the federated setting where capturing complementary rather than strictly orthogonal features is beneficial. These results validate our diversity loss design as a key component of FedMGP's architecture, enabling effective knowledge distribution across prompt groups and contributing to the model's strong performance balance between personalization and generalization.

E.4 Dynamic Aggregation Strategy

Table 17: Comparison of Different Aggregation Strategies (averaged over 5 datasets)

Setting	Local	Base	Novel	CM
CAM	86.13	85.94	83.57	85.43
FAM	97.37	77.47	78.71	87.73
DAM	96.65	79.20	80.86	**88.34**

To validate the effectiveness of our dynamic aggregation mechanism, we compare three aggregation strategies as shown in Table 17. Complete Aggregation Mechanism (CAM) aggregates all prompt groups across clients at each communication round, resulting in identical parameters across clients (similarity=1.0). While this ensures strong base class performance (85.94%), it sacrifices local personalization (86.13%) by forcing uniform representations. Fixed Aggregation Mechanism (FAM) maintains certain prompt groups without aggregation, achieving the highest local accuracy (97.37%) but severely compromising generalization on base (77.47%) and novel classes (78.71%) due to insufficient cross-client knowledge transfer.

Our Dynamic Aggregation Mechanism (DAM) strikes an optimal balance, achieving the best Combined Metric (88.34%) by selectively aggregating the most similar prompt groups between clients at each round. This similarity-guided probabilistic sampling reduces the weight of client-specific biased features while preserving personalization. The temperature parameter ensures every prompt group has opportunities for aggregation, enabling FedMGP to learn parameters with high inter-client similarity (promoting generalization) while maintaining diversity within each client's prompt groups (enabling personalization). This explains why FedMGP achieves strong local accuracy (96.65%) comparable to FAM while maintaining substantially better performance on base (79.20%) and novel classes (80.86%) than FAM, demonstrating superior generalization capability through dynamic cross-client knowledge transfer.

F Theoretical Analysis

In this section, we present a comprehensive theoretical analysis that establishes the formal guarantees for FedMGP's effectiveness in heterogeneous federated learning environments. We demonstrate that our dynamic aggregation strategy consistently outperforms both full aggregation (represented by PromptFL [17]) and fixed aggregation (represented by FedOTP [9]) approaches, particularly under non-IID data distributions. We begin by establishing the foundational assumptions and notations

that frame our analysis (Section F.1), including how prompts can be decomposed into global, local, and noise components. We then formalize the three competing aggregation strategies (Section F.2), highlighting their distinct characteristics in balancing global knowledge with client-specific features. Next, we introduce a signal-noise decomposition framework (Section F.3) that enables quantitative comparison between different strategies through their signal-to-noise ratios. Finally, we present and prove our main theoretical result (Section F.4): the dynamic aggregation superiority theorem, which establishes that FedMGP's approach achieves strictly better signal-to-noise ratios than alternative strategies, directly translating to improved classification performance in practice.

F.1 Assumptions and Notation Definitions

To establish a rigorous theoretical framework, we first define the notation and key assumptions that underpin our analysis. The notation used in this section and their meanings are as follows:

- N: Total number of clients;
- G: Number of prompt groups per client;
- s: Number of prompt groups selected for aggregation in each round, where $1 \leq s \leq G$;
- $C_T \subseteq \{1, \ldots, N\}$: Set of clients participating in aggregation at round T, with $n = |C_T|$;
- $c \in C_T$: Client index;
- $j \in \{1, \ldots, G\}$: Prompt group index;
- $P_{j,c}^T \in \mathbb{R}^d$: The j-th prompt group of client c at round T;
- $\tilde{P}_j^T \in \mathbb{R}^d$: The j-th global prompt group at the server after round T aggregation;
- $S_c^T \subseteq \{1, \ldots, G\}$: Set of prompt group indices selected from client c in round T for aggregation, with $|S_c^T| = s$;
- $\alpha_{j,c}^T$: Selection score for the j-th group from client c in round T, computed based on similarity to global prompts;
- $\tau > 0$: Temperature parameter controlling selection score smoothness;
- $\mathrm{sim}(x, y)$: Similarity measure (e.g., cosine similarity);
- $\mu^G \in \mathbb{R}^d$: Unit vector representing global task-related features shared across all clients;
- $\mu_c \in \mathbb{R}^d$: Unit vector representing local task-related features specific to client c;
- L: Total number of noise feature dimensions in the latent space;
- $\xi_l \in \mathbb{R}^d$: The l-th unit vector representing task-irrelevant noise features;
- $\beta_{j,c}^T \in \mathbb{R}$: Coefficient quantifying the contribution of global features to prompt $P_{j,c}^T$;
- $\gamma_{j,c}^T \in \mathbb{R}$: Coefficient quantifying the contribution of client-specific features to prompt $P_{j,c}^T$;
- $\phi_{j,c,l}^T \in \mathbb{R}$: Coefficient quantifying the contribution of the l-th noise feature to prompt $P_{j,c}^T$;
- $\chi_c \in \mathbb{R}$: Metric quantifying the degree of data heterogeneity for client c.

Our analysis is based on the following assumptions, which are grounded in feature learning theory and previous work on federated learning:

Assumption 1 (Feature Space Decomposition)**.** *According to feature learning theory [37, 2, 6], the latent feature space can be decomposed into three orthogonal subspaces:*

1. *Global task-related features represented by a unit vector μ^G (shared across all clients)*
2. *Local task-related features represented by unit vectors $\{\mu_c\}_{c=1}^N$ (client-specific)*
3. *Task-irrelevant noise features represented by unit vectors $\{\xi_l\}_{l=1}^L$ (noise)*

These three subspaces are mutually orthogonal, i.e., $\langle \mu^G, \mu_c \rangle = 0$, $\langle \mu^G, \xi_l \rangle = 0$, and $\langle \mu_c, \xi_l \rangle = 0$ for all $c \in \{1, \ldots, N\}$ and $l \in \{1, \ldots, L\}$. Here, L represents the dimensionality of the noise subspace, which can be significantly larger than the dimensionality of task-relevant subspaces. This decomposition allows us to separately analyze the impact of each component on the aggregation process and quantify the information content in prompts.

Assumption 2 (Prompt Representation)**.** *Each prompt group j of client c at round T can be represented as a linear combination of features from the three orthogonal subspaces:*

$$P_{j,c}^T = \beta_{j,c}^T \mu^G + \gamma_{j,c}^T \mu_c + \sum_{l=1}^{L} \phi_{j,c,l}^T \xi_l \tag{10}$$

where:

- $\beta_{j,c}^T$ *represents the coefficient for global features, indicating how much the prompt captures knowledge shared across all clients*
- $\gamma_{j,c}^T$ *represents the coefficient for local features, indicating how much the prompt captures client-specific knowledge*
- $\phi_{j,c,l}^T$ *represents the coefficient for the l-th noise feature dimension*

Since μ^G, μ_c, and ξ_l are unit vectors as defined in Assumption 1, this representation directly quantifies the strength of each component in the prompt. This allows us to analyze how each prompt captures common knowledge versus client-specific knowledge versus irrelevant noise [18, 24].

Assumption 3 (Data Heterogeneity)**.** *The degree of data heterogeneity between clients is defined by the metric:*

$$\chi_c = \sum_{c'=1}^{N} \langle \mu_c, \mu_{c'} \rangle \tag{11}$$

This simplification is valid because μ_c is a unit vector, so $||\mu_c||_2^2 = 1$. This metric measures how similar client c's local features are to those of other clients. When χ_c approaches N, it indicates that client c's features are highly aligned with other clients, suggesting an IID (Independent and Identically Distributed) data scenario. Conversely, when χ_c is close to 1 (its minimum value, representing alignment only with itself), it indicates that client c's features have limited overlap with other clients, suggesting a highly non-IID data distribution [37, 27]. This metric allows us to relate the performance of different aggregation strategies to the level of data heterogeneity and provides a quantitative basis for analyzing the effectiveness of our approach in various federation settings.

F.2 Formalization of Three Aggregation Strategies

We now formally define three different prompt aggregation strategies that represent the spectrum of approaches in federated prompt learning. Each strategy has distinct characteristics in how it handles the balance between preserving global knowledge and managing client-specific variations.

Full Aggregation (PromptFL) The full aggregation strategy, as employed in PromptFL [17], aggregates all prompt groups from all participating clients. This represents the most straightforward application of federated averaging [34] to prompt learning:

$$\tilde{P}_j^T = \frac{1}{n} \sum_{c \in C_T} P_{j,c}^T. \tag{12}$$

While this approach maximizes knowledge sharing, it may suffer from interference between client-specific features when data distributions are heterogeneous.

Fixed Aggregation (FedOTP) The fixed aggregation strategy, inspired by approaches like FedOTP [9], only aggregates a predetermined subset of prompt groups (typically the first s groups), setting all others to zero:

$$\tilde{P}_j^T = \begin{cases} \frac{1}{n} \sum_{c \in C_T} P_{j,c}^T, & j = 1, \ldots, s, \\ \mathbf{0}, & j = s+1, \ldots, G. \end{cases} \tag{13}$$

This static partition-based approach attempts to balance shared knowledge with client specificity, but lacks adaptivity to evolving knowledge patterns across communication rounds.

Dynamic Aggregation (FedMGP) Our proposed dynamic aggregation strategy selects prompt groups based on their similarity to the global prompts from the previous round. First, it computes selection scores:

$$\alpha_{j,c}^T = \frac{\exp\big(\text{sim}(P_{j,c}^T, \tilde{P}_j^{T-1})/\tau\big)}{\sum_{j'=1}^{G} \exp\big(\text{sim}(P_{j',c}^T, \tilde{P}_{j'}^{T-1})/\tau\big)}, \tag{14}$$

where $\tilde{P}_j^{T-1}$ is the j-th global prompt from the previous round. Then, for each client c, we select the top-s groups with the highest selection scores to form S_c^T, and aggregate only the selected groups:

$$\tilde{P}_j^T = \frac{1}{n} \sum_{c \in C_T} \mathbb{I}(j \in S_c^T)\, P_{j,c}^T. \tag{15}$$

where $\mathbb{I}(j \in S_c^T)$ is the indicator function denoting whether group j is selected from client c in round T. This adaptive approach balances knowledge sharing and client specificity in a data-driven manner, potentially offering advantages over fixed strategies.

F.3 Signal-Noise Decomposition and Performance Metrics

To analyze the effectiveness of different aggregation strategies, we introduce a signal-noise decomposition framework that allows us to quantitatively compare their performance. This approach enables us to examine how effectively each strategy preserves important information while suppressing noise.

From Assumption 2, we have the representation of each prompt as:

$$P_{j,c}^T = \beta_{j,c}^T\, \mu^G + \gamma_{j,c}^T\, \mu_c + \sum_{l=1}^{L} \phi_{j,c,l}^T\, \xi_l, \tag{16}$$

For individual prompts, we can define their total signal and noise components. The signal components include both global and local task-related information:

$$\text{Signal}_{j,c}^{\text{total}} = (\beta_{j,c}^T)^2 + (\gamma_{j,c}^T)^2 \tag{17}$$

while the noise component represents the irrelevant information:

$$\text{Noise}_{j,c} = \sum_{l=1}^{L} (\phi_{j,c,l}^T)^2 \tag{18}$$

However, when evaluating aggregated global prompts in federated learning, we are primarily interested in how well they preserve global knowledge. From this perspective, even client-specific features $\gamma_{j,c}^T \mu_c$ can be considered as interference when aggregated across heterogeneous clients. Therefore, for evaluating global prompts, we define:

$$\text{Global Signal}_j^T = (\beta_j^T)^2 \tag{19}$$

$$\text{Global Noise}_j^T = \text{(Client-specific noise)} + \text{(Task-irrelevant noise)} \tag{20}$$

The key performance metric we use to evaluate the quality of aggregated prompts is the signal-to-noise ratio (SNR):

$$\text{SNR}_j = \frac{\text{Global Signal}_j^T}{\text{Global Noise}_j^T} = \frac{(\beta_j^T)^2}{\phi_j^T}, \tag{21}$$

where β_j^T is the coefficient of the global feature μ^G in the aggregated prompt $\tilde{P}_j^T$, and ϕ_j^T quantifies the total noise power including both client-specific variations and task-irrelevant noise.

This metric is directly related to the generalization performance of the model: a higher SNR indicates better preservation of global features and more effective suppression of noise, which translates to improved classification performance and lower test error [6, 18].

F.4 Dynamic Aggregation Superiority Theorem and Detailed Proof

We now present our main theoretical result, which establishes the superiority of FedMGP's dynamic aggregation strategy over both full aggregation and fixed aggregation strategies. Based on equation (21), a higher signal-to-noise ratio leads to lower classification error. The following theorem and proof demonstrate that:

$$\mathrm{SNR}_{\mathrm{full}} \ \leq \ \mathrm{SNR}_{\mathrm{fixed}} \ < \ \mathrm{SNR}_{\mathrm{dyn}}.$$

Theorem F.1 (Dynamic Aggregation Superiority)**.** *Under Assumptions 1, 2, and 3, for any number of selected prompt groups $s \in [1, G]$, we have:*

$$\mathrm{SNR}_{\mathrm{full}} \ \leq \ \mathrm{SNR}_{\mathrm{fixed}} \ < \ \mathrm{SNR}_{\mathrm{dyn}}.$$

Proof. The proof consists of three parts: first analyzing the SNR of full aggregation, then comparing it with fixed aggregation, and finally establishing the superiority of dynamic aggregation.

(1) Analysis of Full Aggregation $\mathrm{SNR}_{\mathrm{full}}$**.** From equation (12) and decomposition (16), we can express the global and noise coefficients for the full aggregation strategy:

$$\beta_j^{\mathrm{full}} = \frac{1}{n} \sum_{c \in C_T} \beta_{j,c}^T$$

For the noise term, we must consider both the pure noise components $\phi_{j,c,l}^T \xi_l$ and the client-specific features $\gamma_{j,c}^T \mu_c$ which act as interference when aggregated across heterogeneous clients. The total noise power after aggregation is:

$$\phi_j^{\mathrm{full}} = \frac{1}{n^2} \sum_{c \in C_T} \sum_{l=1}^{L} (\phi_{j,c,l}^T)^2 + \frac{1}{n^2} \sum_{c \in C_T} (\gamma_{j,c}^T)^2$$

The first term represents the traditional noise components, while the second term accounts for client-specific features that do not align globally. This is a more complete characterization of noise in federated settings.

For the signal-to-noise ratio of group j, we have:

$$\mathrm{SNR}_{\mathrm{full}}(j) = \frac{(\beta_j^{\mathrm{full}})^2}{\phi_j^{\mathrm{full}}} = \frac{\left(\frac{1}{n} \sum_{c \in C_T} \beta_{j,c}^T\right)^2}{\frac{1}{n^2} \sum_{c \in C_T} \sum_{l=1}^{L} (\phi_{j,c,l}^T)^2 + \frac{1}{n^2} \sum_{c \in C_T} (\gamma_{j,c}^T)^2}$$

A key observation is that full aggregation can actually enhance SNR through constructive signal accumulation. When client signals are positively correlated (as is typically the case for global knowledge), the numerator grows quadratically with n, while the noise terms in the denominator grow linearly if they are uncorrelated across clients. This is the fundamental principle behind why federated learning works.

The overall SNR of full aggregation is determined by the worst-performing group:

$$\mathrm{SNR}_{\mathrm{full}} = \min_{j \leq G} \mathrm{SNR}_{\mathrm{full}}(j)$$

(2) Analysis of Fixed Aggregation $\mathrm{SNR}_{\mathrm{fixed}}$**.** From equation (13), for $j \leq s$ (groups that are aggregated), we have:

$$\beta_j^{\mathrm{fixed}} = \beta_j^{\mathrm{full}}, \quad \phi_j^{\mathrm{fixed}} = \phi_j^{\mathrm{full}},$$

therefore $\mathrm{SNR}_{\mathrm{fixed}}(j) = \mathrm{SNR}_{\mathrm{full}}(j)$ for these groups.

For $j > s$ (groups that are not aggregated), we have $\tilde{P}_j^T = \mathbf{0}$ according to equation (13), which means these groups do not contribute to the model's predictions. We exclude these groups from the SNR calculation since they do not affect model performance.

The overall SNR of fixed aggregation is determined by the worst-performing group among the aggregated ones:

$$\mathrm{SNR}_{\mathrm{fixed}} = \min_{j \leq s} \mathrm{SNR}_{\mathrm{full}}(j) \geq \min_{j \leq G} \mathrm{SNR}_{\mathrm{full}}(j) = \mathrm{SNR}_{\mathrm{full}}.$$

This shows that fixed aggregation guarantees an SNR at least as good as full aggregation, since it excludes potentially noisy groups that might degrade the overall performance. The inequality is strict when at least one group $j > s$ has a lower SNR than all groups $j \leq s$.

(3) Proving $\mathrm{SNR}_{\mathrm{dyn}} > \mathrm{SNR}_{\mathrm{fixed}}$. For dynamic aggregation, we select prompt groups based on their similarity to the global prompts from the previous round, as defined in equation (14). To be precise about our selection mechanism: for each client c, we compute similarity scores between each of its prompt groups and the corresponding global prompts, then select the top-s groups with highest similarity. This deterministic selection can be expressed as:

$$S_c^T = \{j \in \{1, \ldots, G\} : \alpha_{j,c}^T \text{ is among the top-}s \text{ highest for client } c\}$$

The selection score $\alpha_{j,c}^T$ in equation (14) serves as a normalized measure of similarity between local and global prompts, with lower temperature τ making the scores more concentrated on the highest similarities.

Let us define the global and noise coefficients for dynamic aggregation:

$$\beta_j^{\mathrm{dyn}} = \frac{1}{n} \sum_{c \in C_T} \mathbb{I}(j \in S_c^T) \beta_{j,c}^T$$

$$\phi_j^{\mathrm{dyn}} = \frac{1}{n^2} \sum_{c \in C_T} \mathbb{I}(j \in S_c^T) \left(\sum_{l=1}^{L} (\phi_{j,c,l}^T)^2 + (\gamma_{j,c}^T)^2 \right)$$

The key insight is that our selection mechanism preferentially selects groups with higher global signal $\beta_{j,c}^T$ and lower noise (both $\phi_{j,c,l}^T$ and $\gamma_{j,c}^T$). This is because groups with higher similarity to global prompts tend to have higher global signal components and lower noise components.

Let us define $N_j = \sum_{c \in C_T} \mathbb{I}(j \in S_c^T)$ as the number of clients that select group j for aggregation. This value depends on the "popularity" of group j across clients. For a particular group j:

1. If j represents important global knowledge (high $\beta_{j,c}^T$ across clients), then many clients will select it, resulting in a large N_j. 2. If j captures primarily client-specific knowledge or noise, fewer clients will select it, resulting in a small N_j.

For groups that are selected by at least one client (i.e., $N_j > 0$), we can rewrite:

$$\beta_j^{\mathrm{dyn}} = \frac{N_j}{n} \cdot \frac{1}{N_j} \sum_{c \in C_T : j \in S_c^T} \beta_{j,c}^T = \frac{N_j}{n} \cdot \overline{\beta}_j^{\mathrm{sel}}$$

$$\phi_j^{\mathrm{dyn}} = \frac{N_j}{n^2} \cdot \frac{1}{N_j} \sum_{c \in C_T : j \in S_c^T} \left(\sum_{l=1}^{L} (\phi_{j,c,l}^T)^2 + (\gamma_{j,c}^T)^2 \right) = \frac{N_j}{n^2} \cdot \overline{\phi}_j^{\mathrm{sel}}$$

where $\overline{\beta}_j^{\mathrm{sel}}$ is the average $\beta_{j,c}^T$ among clients that selected group j, and $\overline{\phi}_j^{\mathrm{sel}}$ is the average noise power among clients that selected group j.

The key to our dynamic selection advantage is that $\overline{\beta}_j^{\mathrm{sel}} > \overline{\beta}_j$ and $\overline{\phi}_j^{\mathrm{sel}} < \overline{\phi}_j$, where $\overline{\beta}_j$ and $\overline{\phi}_j$ are the averages across all clients. This is because our selection mechanism favors high-signal, low-noise prompt groups.

For quantitative analysis, we can use a parameter $\delta_j > 1$ to capture this selection advantage:

$$\overline{\beta}_j^{\mathrm{sel}} \geq \delta_j \cdot \overline{\beta}_j \quad \text{and} \quad \overline{\phi}_j^{\mathrm{sel}} \leq \frac{1}{\delta_j} \cdot \overline{\phi}_j$$

where $\overline{\beta}_j = \frac{1}{n} \sum_{c \in C_T} \beta_{j,c}^T = \beta_j^{\mathrm{full}}$ and $\overline{\phi}_j = \frac{1}{n} \sum_{c \in C_T} \left(\sum_{l=1}^{L} (\phi_{j,c,l}^T)^2 + (\gamma_{j,c}^T)^2 \right) = n \cdot \phi_j^{\mathrm{full}}$.

This leads to:

$$\beta_j^{\text{dyn}} \geq \frac{N_j}{n} \cdot \delta_j \cdot \overline{\beta}_j = \frac{N_j \cdot \delta_j}{n} \cdot \beta_j^{\text{full}}$$

$$\phi_j^{\text{dyn}} \leq \frac{N_j}{n^2} \cdot \frac{1}{\delta_j} \cdot \overline{\phi}_j = \frac{N_j}{n \cdot \delta_j} \cdot \phi_j^{\text{full}}$$

The SNR for dynamically aggregated group j is therefore:

$$\text{SNR}_{\text{dyn}}(j) = \frac{(\beta_j^{\text{dyn}})^2}{\phi_j^{\text{dyn}}} \geq \frac{\left(\frac{N_j \cdot \delta_j}{n} \cdot \beta_j^{\text{full}}\right)^2}{\frac{N_j}{n \cdot \delta_j} \cdot \phi_j^{\text{full}}} = \frac{N_j \cdot \delta_j^3}{n} \cdot \frac{(\beta_j^{\text{full}})^2}{\phi_j^{\text{full}}} = \frac{N_j \cdot \delta_j^3}{n} \cdot \text{SNR}_{\text{full}}(j)$$

For groups $j \leq s$ that would be selected by the fixed strategy, we have $\text{SNR}_{\text{full}}(j) \geq \text{SNR}_{\text{fixed}}$ (since $\text{SNR}_{\text{fixed}} = \min_{k \leq s} \text{SNR}_{\text{full}}(k)$). Therefore:

$$\text{SNR}_{\text{dyn}}(j) \geq \frac{N_j \cdot \delta_j^3}{n} \cdot \text{SNR}_{\text{full}}(j) \geq \frac{N_j \cdot \delta_j^3}{n} \cdot \text{SNR}_{\text{fixed}}$$

Under reasonable assumptions about our selection mechanism, we can establish that for important groups (those containing significant global knowledge):

1. N_j will be high, as many clients will select these groups 2. δ_j will be significantly greater than 1, as the selection process effectively identifies high-signal, low-noise components

For these important groups, the factor $\frac{N_j \cdot \delta_j^3}{n} > 1$ even when $N_j < n$, because the cubic term δ_j^3 provides powerful amplification of the selection advantage. This is particularly true for groups that represent core global knowledge, which will have the highest δ_j values.

Taking the minimum over all selected groups, we have:

$$\text{SNR}_{\text{dyn}} = \min_{j:N_j>0} \text{SNR}_{\text{dyn}}(j) > \text{SNR}_{\text{fixed}}$$

This inequality is strict for the following reason: Our dynamic selection mechanism ensures that each client selects its best s groups in terms of similarity to global knowledge. This means that the dynamic strategy will: 1. Select any globally important groups that the fixed strategy would select 2. Replace any poor-quality groups that the fixed strategy would select with better alternatives 3. Achieve higher δ_j values for the selected groups through its adaptive selection process

In the extreme case where fixed selection is optimal, dynamic selection would converge to the same selection pattern, matching its performance. However, in practice, especially with heterogeneous data, dynamic selection will identify better groups than a predetermined fixed selection, leading to strictly better performance.

In conclusion, $\text{SNR}_{\text{full}} \leq \text{SNR}_{\text{fixed}} < \text{SNR}_{\text{dyn}}$, establishing that FedMGP's dynamic aggregation strategy is strictly superior to both full aggregation and fixed aggregation strategies in terms of signal-to-noise ratio. This theoretical advantage directly translates to improved classification performance and lower test error in practical applications, particularly under heterogeneous data distributions. □