A. Implementation Details

For a fair comparison, we follow a similar hyperparameter setup as our baseline, T-Food [24]. While all Transformer models are trained from scratch, we initialize the CLIP-ViT encoder using CLIP weights. The image encoder remains frozen for the first 20 epochs and then all modules are trained using Adam optimizer [9] with a constant learning rate of 1e-5 (except CLIP-ViT that has 1e-6 learning rate). The triplet loss dynamic margin is initially set to $\alpha = 0.05$ and is incremented by 0.005 per epoch until it reaches 0.3. Furthermore, for the triplet loss, the associated sample from other modalities is considered positive, and all other samples are considered negatives. For \mathcal{L}_{sem} , the samples from the same class are considered positive, and all the other classes are considered negatives. Similarly, class information is used to define the similarity between samples for the hyperbolic loss function. For the fine-grained alignment loss functions \mathcal{L}_{itc} and \mathcal{L}_{he} , we set the weight equal to $\alpha = 1/m$, where m = 4 is the number of different pairs considered in the loss function. We use $\lambda_{itc} = \frac{1}{n_{itc}}$, where n_{itc} is the number of components in \mathcal{L}_{itc} . Similarly, we use $\lambda_{he} = \frac{1}{n_{he}}$, where n_{he} is the number of components in \mathcal{L}_{he} . For all other hyperparameters, we follow a similar setup as T-Food [24]. Unless otherwise specified, we train all models for 120 epochs, with a batch size of 100 using two NVIDIA A100 GPUs.

B. Ablation Studies

Intra-Modality Alignment Following H-T [22], we experiment with the intra-modality loss alignment in Table 4. In this experiment, we modify Eq. (6) to also include intra-modality alignment as shown in Eq. (16).

$$\mathcal{L}_{itc}^{\dagger} = \mathcal{L}_{c}(\mathcal{G}_{ttl}, \mathcal{G}_{img}) + \mathcal{L}_{c}(\mathcal{G}_{ing}, \mathcal{G}_{img}) + \mathcal{L}_{c}(\mathcal{G}_{ins}, \mathcal{G}_{img}) + \mathcal{L}_{c}(\mathcal{G}_{rec}, \mathcal{G}_{img}) + \mathcal{L}_{c}(\mathcal{G}_{ttl}, \mathcal{G}_{ing}) + \mathcal{L}_{c}(\mathcal{G}_{ttl}, \mathcal{G}_{ins}) + \mathcal{L}_{c}(\mathcal{G}_{ing}, \mathcal{G}_{ins}).$$

$$(16)$$
intra-modality

We observe that intra-modality alignment loss hurts performance, with a 0.8 and 1.5 percentage point drop in R@1 for the image-to-recipe and recipe-to-image tasks, respectively.

Fine-Grained Alignment with Recipe Embedding We further conduct experiments where we align the recipe component embeddings with the recipe embedding, instead of the image embedding. Specifically, we modify Eq. (6) as follows:

$$\mathcal{L}_{itc}^{\ddagger} = \mathcal{L}_{c}(\mathcal{G}_{ttl}, \mathcal{G}_{rec}) + \mathcal{L}_{c}(\mathcal{G}_{ing}, \mathcal{G}_{rec}) + \mathcal{L}_{c}(\mathcal{G}_{ins}, \mathcal{G}_{rec}) + \mathcal{L}_{c}(\mathcal{G}_{rec}, \mathcal{G}_{img}).$$

$$(17)$$

We observe that alignment with image embedding performs significantly better than alignment with recipe embedding, achieving 0.6 and 2.8 percentage points performance improvements on the image-to-recipe and recipe-to-image 1k tasks, respectively. Results further indicate that the fine-grained alignment with the image embedding is particularly important for the recipe-to-image retrieval task, possibly due to the component embeddings having additional alignment signals about the corresponding images.

Hyperbolic Loss without Fine-Grained Alignment We also experiment with aligning the recipe embeddings with the image embedding without the use of any fine-grained alignments in the hyperbolic space. More specifically, we modify Eq. (13) as follows:

$$\mathcal{L}_{he}^{\pm} = \underline{\mathcal{L}_{h}}(\mathcal{G}_{ttt}, \mathcal{G}_{img}) + \underline{\mathcal{L}_{h}}(\mathcal{G}_{ing}, \mathcal{G}_{img}) + \underline{\mathcal{L}_{h}}(\mathcal{G}_{rec}, \mathcal{G}_{img}) + \mathcal{L}_{h}(\mathcal{G}_{rec}, \mathcal{G}_{img}).$$
(18)

In Table 6, we observe that hyperbolic loss is much more effective when using fine-grained alignment, achieving 1.7 and 2.3 percentage points on the image-to-recipe and recipe-to-image 1k tasks, compared to FARM (+ \mathcal{L}_{he}^{\pm}) where only the recipe embedding and image embedding are aligned in the hyperbolic space. This further shows the effectiveness of the proposed fine-grained alignment.

C. Qualitative Analysis

We provide qualitative analysis examples of retrieved results on recipe-to-image (Figure 6) and image-to-recipe (Figure 7) retrieval for both FARM and T-Food. In Figure 6 we observe that, while both methods retrieve the correct recipe image, all top-5 retrieved images by FARM are semantically related, consistently featuring noodles or baking. In contrast, T-Food often retrieves irrelevant images, suggesting a tendency to emphasize on peripheral recipe components such as incidental ingredients within the dish or subtext ('whole wheat', 'pasta', 'lemon', etc). These results demonstrate FARM's ability in associating textual recipe descriptions with visually aligned images. Similarly, in Figure 7, both FARM and T-Food retrieve the correct recipe based on the image, however T-Food results contain irrelevant recipes such as 'sweet potato fries' ranked top, 'bean sprout omelet', etc. In contrast, all retrieved items by FARM are sematically relevant and pertain to salmon recipes for the first example, or contain chicken and past for the second example, or shrimp for the third example. This observation highlights that FARM effectively leverages class information to improve the relevance and consistency of retrieval results.

Table 4. Ablation study on intra-modality loss alignment, on image-to-recipe and recipe-to-image retrieval tasks with 1k and 10k pairs. FARM with the proposed \mathcal{L}_{itc} (top row) outperforms a variation with intra-modality alignment (bottom row).

	$\mathcal{L}_{itc}^{\dagger}$	1k							10k								
Method		image-to-recipe				recipe-to-image			image-to-recipe				recipe-to-image				
		medR ↓	R@1↑	R@5↑	R@10↑	medR ↓	R@1 ↑	R@5↑	R@10↑	medR ↓	R@1↑	R@5↑	R@10↑	medR ↓	R@1↑	R@5↑	R@10↑
FARM (w/o \mathcal{L}_{he})	√	1.0	71.7	89.7	93.0	1.0	71.3	89.7	92.9	2.0	44.5	71.1	79.4	2.0	43.2	70.6	79.2
FARM (w/o \mathcal{L}_{he})	X	1.0	72.5	90.2	93.0	1.0	72.8	90.7	93.2	2.0	44.2	71.0	79.4	2.0	43.9	71.0	79.5

Table 5. Ablation study on fine-grained alignment, on image-to-recipe and recipe-to-image retrieval tasks with 1k and 10k pairs. FARM with the proposed \mathcal{L}_{itc} (top row) outperforms a variant with fine-grained alignment with recipe instead of image embeddings (bottom row).

Method	$\mathcal{L}_{itc}^{\ddagger}$	1k							10k								
		image-to-recipe				recipe-to-image			image-to-recipe				recipe-to-image				
		medR ↓	R@1↑	R@5↑	R@10↑	medR ↓	R@1↑	R@5↑	R@10↑	medR ↓	R@1↑	R@5↑	R@10↑	medR↓	R@1↑	R@5↑	R@10↑
FARM (w/o \mathcal{L}_{he})	√	1.0	72.5	90.2	93.0	1.0	72.8	90.7	93.2	2.0	44.2	71.0	79.4	2.0	43.9	71.0	79.5
FARM (w/o \mathcal{L}_{he})	X	1.0	71.9	89.9	92.9	1.0	70.0	89.8	92.5	2.0	44.0	70.8	79.1	2.0	41.9	69.6	78.4

Table 6. Ablation study on hyperbolic loss aligning only the image embedding with the recipe embedding, on image-to-recipe and recipe-to-image retrieval tasks with 1k and 10k pairs. FARM with the proposed \mathcal{L}_{he} (top row) outperforms its simplified counterpart without fine-grained alignment in the hyperbolic space (bottom row).

image-to-recipe

recipe-to-image

R@10↑ medR↓

 \mathcal{L}_{he}

Method

	3.7 90.7 93.4 1.0 2.0 89.7 92.9 1.0	73.6 90.8 71.3 89.4	93.5 2.0 92.9 2.0	44.9 71.8 44.5 71.6	80.0 2.0 79.9 2.0		80.0 79.9
Recipe	Ground Truth	Retrieved #1	Retrieved #2	Retrieved #3	Retrieved #4	Retrieved #5	
Title: peanut butter and ginger noodles Ingredients:	L						Tfood
ounces organic whole wheat noodles 1,2 cup peanut butter Instructions: cook the whole wheat pasta according to manufacturer 's directions							Farm
Title: lemon brownies Ingredients:							Tfood
1, 2 cup flour 1 tsp salt Instructions: preheat oven to 350 spray pan with nonstick cooking spray							Farm
Title: coffee cake							Tfood
2 eggs 3,4 cup sugar Instructions: mix coffee cake ingredients							Farm

Figure 6. Qualitative examples of FARM on the recipe-to-image task. On each row, the top-5 retrieved images are shown for each recipe.

Recipe	Ground Truth	Retrieved #1	Retrieved #2	Retrieved #3	Retrieved #4	Retrieved #5		
		Title: sweet potato fries	Title: tandoori salmon	Title: seared salmon	Title: bean sprout omelet	Title: steamed swai fish fillets		
	Title: tandoori salmon	Ingredients: 3 bananas mashed	Ingredients: 2 pieces salmon filets	Ingredients: 4 salmon fillets	Ingredients: 2 slice thinly sliced pork belly	Ingredients: 2 swai fillets	Lfood	
	Ingredients: 2 pieces salmon filets 1 tsp cooking sake	Instructions: cook the beans with the water till tender	Instructions: heat oil in skillet	Instructions: peel off the skin from the cucumber	Instructions: in a large skillet saute the veggies	Instructions: combine all ingredients except the cheese		
	i isp cooking sake	Title: tandoori salmon	Title: blackened salmon	Title: baked salmon	Title: baked salmon			
	Instructions: in a skillet saute the veggies in 2 3 tbs of cooking oil	Ingredients: 2 pieces salmon filets	Ingredients: 4 whole fillets	Ingredients: 1 piece salmon	Ingredients: 4 tablespoons butter	Ingredients: 4 salmon filets	Farm	
		Instructions: in a skillet saute the veggies	Instructions: preheat oven to 325	Instructions: preheat oven to 325	Instructions: using a mortar and pestle mash the garlic	Instructions: rub sugar on both sides of the chicken breast		
		Title: smoky spicy tomatillo salsa	Title: pressure cooker double dhal	Title: curried beef	Title: grilled zucchini hummus	Title: simple genovese sauce		
	Title: smoky spicy tomatillo salsa	Ingredients: 2 pieces salmon filets	Ingredients: 1,2 cups channa dal	Ingredients: 2 tablespoons vegetable oil	Ingredients: 1 lb zucchini	Ingredients: 30 grams fresh basil	Tfood	
	Ingredients: 2 pieces salmon	Instructions: combine onion vinegar	Instructions: measure 1 cup beet juice	Instructions: cut avocados in half	Instructions: fry one finely chopped onion	Instructions: measure 1 cup beet juice	ľ	
	filets	Title: simple spinach dip	Title: smoky spicy tomatillo salsa	Title: anchovy salad dressing	Title: cherry avocado smoothie	Title: black bean & poblano dip		
	Instructions: combine onion vinegar	Ingredients: 4 cups baby spinach	Ingredients:1 lb tomatillo cut into quarters	Ingredients: 6 tablespoons olive oil	Ingredients: 1 avocado without skin	Ingredients: 2 cups poblano chiles	Farm	
		Instructions: cut pork into 8 pieces	Instructions: heat the oil over moderate heat	Instructions: pour milk into blender	Instructions: trim and discard the ends of the eggplant	Instructions: heat the oil over moderate heat		
		Title: shrimp in garlic sauce	Title: simple rice pilaf	Title: mild teriyaki hamburger steak	Title: chewy oatmeal cookies	Title: corn salad		
	Title: shrimp in garlic sauce	Ingredients: 1, 3 cup olive oil	Ingredients: 1 2 sticks unsalted butter	Ingredients: 1, 2 cups butter softened	Ingredients: 4 tpns water	Ingredients: 3 cups cooked corn kernels	Tfood	
	Ingredients: 1, 3 cup olive oil	Instructions: season with salt and pepper	Instructions: preheat oven to 325 degrees	Instructions: mix together honey mustard and cayenne spread	Instructions: mix together all of the ingredients	Instructions: combine all ingredients in large non stick skillet		
		Title: shrimp in garlic sauce	Title: poached shrimp with thai basil	Title: spicy baked shrimp	Title: shrimp & bacon pasta	Title: shrimp scampi		
	Instructions: season with salt and pepper	Ingredients: 1, 3 cup olive oil	Ingredients: kosher salt as needed	Ingredients: vegetable cooking spray Instructions: combine pie	Ingredients: salt and pepper	Ingredients: 1 env . good seasons garlic	Farm	
		Instructions: season with salt and pepper	Instructions: combine pie filling pecans and cinnamon	filling pecans and cinnamon	Instructions: rub sugar on both sides of the chicken breast	Instructions: stir white chocolate and pineapple juice		

Figure 7. Qualitative analysis of FARM on the image-to-recipe task. On each row, the top-5 retrieved recipes are shown for each image.