# Learning Joint Embedding with Modality Alignments for Cross-Modal Retrieval of Recipes and Food Images

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# ABSTRACT

This paper presents a three-tier modality alignment approach to learning text-image joint embedding, coined as JEMA, for crossmodal retrieval of cooking recipes and food images. The first tier improves recipe text embedding by optimizing the LSTM networks with term extraction and ranking enhanced sequence patterns, and optimizes the image embedding by combining the ResNeXt-101 image encoder with the category embedding using wideResNet-50 with word2vec. The second tier modality alignment optimizes the textual-visual joint embedding loss function using a double batchhard triplet loss with soft-margin optimization. The third modality alignment incorporates two types of cross-modality alignments as the auxiliary loss regularizations to further reduce the alignment errors in the joint learning of the two modality-specific embedding functions. The category-based cross-modal alignment aims to align the image category with the recipe category as a loss regularization to the joint embedding. The cross-modal discriminator-based alignment aims to add the visual-textual embedding distribution alignment to further regularize the joint embedding loss. Extensive experiments with the one-million recipes benchmark dataset Recipe1M demonstrate that the proposed JEMA approach outperforms the state-of-the-art cross-modal embedding methods for both image-to-recipe and recipe-to-image retrievals.

# CCS CONCEPTS

- Information systems  $\rightarrow$  Multimedia and multimodal retrieval.

### **KEYWORDS**

cross-modal retrieval, modality alignment, multi-modal learning

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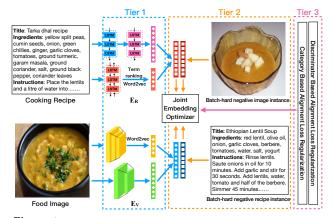


Figure 1: Cross-modal embedding with three-tier modality alignments.

# **1** INTRODUCTION

The prevalence of social media has enabled the rapid growth of usergenerated online recipes and food images [34], such as "Food.com" and "CookEatShare.com". Most recipes provide ingredients with their quantities and cooking instructions on how ingredients are prepared and cooked (e.g., steamed or deep-fried), providing a new source of references for food intake tracking and health monitoring and management. Learning cross-modal joint embeddings has been a growing area of interest for performing image to recipe and recipe to image retrieval tasks. Food images are diverse in terms of background, ingredient composition, visual appearance and ambiguity. Early works [16, 33] circumvented this problem by annotating images to perceive their latent semantics. These approaches, however, are supervised and require users to annotate at least a small portion of images. In comparison, the unsupervised solutions map images and recipe texts into a shared latent space in which their feature vectors can be compared in terms of vector similarity. Recent approaches have employed deep neural networks to cross-modal retrieval tasks, such as DeViSE[10], correspondence auto-encoder [9], adversarial cross-modal retrieval [35], or combing LSTM networks with CNN networks to generate the recipe embedding and image embedding respectively [2, 5, 11, 20, 29, 36, 41]. However, few existing approaches have provided modality alignment optimizations at all three tiers of a cross-modal joint embedding learning process: (1) modality-specific embeddings, such as recipe text embedding and food image embedding; (2) distance-based joint embedding loss optimization; and (3) loss regularization to further optimize cross-modal alignment.

In this paper, we present a three-tier modality alignment optimization framework for learning cross-modal joint embedding,

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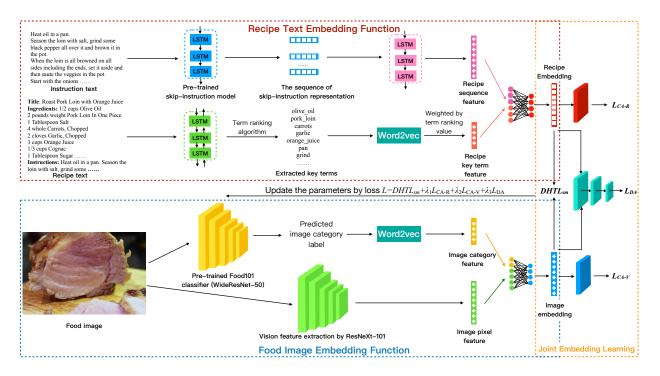


Figure 2: The system architecture of our JEMA cross-modal embedding learning approach.

coined as JEMA, aiming for supporting high-performance crossmodal information retrieval tasks. Figure 1 provides an illustrative overview of our JEMA three-tier modality alignment optimization process. This paper makes three main contributions. First, we introduce the term extraction and ranking enhanced recipe embedding approach to make the textual embedding more aligned with the visual features captured in the food image embedding, and we enhance image embedding learning with the category information to improve the alignment of the visual information with key ingredients in the recipe. Second, we develop an instance-class double sampling based batch-hard triplet loss with soft-margin optimization, coined as DHTL<sub>sm</sub>, which aims to effectively optimize the textual-visual distance alignment in the joint embedding space. Third, we further optimize the distance-based DHTL<sub>sm</sub> crossmodal alignment loss by two types of loss regularizations. The category-based loss regularization employs category-based modality alignment on both recipe and image embeddings to further reduce errors in DHTL<sub>sm</sub>. The cross-modal discriminator-based loss regularization adds the distribution-based alignment between the image and its corresponding recipe as another regularization to DHTL<sub>sm</sub>. Extensive experiments are conducted for image-to-recipe and recipe-to-image cross-modal retrieval tasks on the Recipe1M benchmark dataset [29], consisting of over 800K recipes (title, list of ingredients and cooking instructions) and 1 million associated food images. The evaluation results show that empowered by the threetier recipe-image alignment optimization techniques, our JEMA approach outperforms existing representative methods in terms of cross-modal retrieval performance for both image-to-recipe and recipe-to-image queries.

# 2 RELATED WORK

There are three popular learning tasks on food datasets: (1) Food recognition from images, which evolves from kernel-based model [17] to DNN approaches [18, 39]; (2) Food recommendation [7, 8], including ingredient identification [3], dietary recommendation for diabetics [27] and recipe popularity prediction [31]; (3) Crossmodal food retrieval for image to recipe and recipe to image queries [2, 4, 5, 11, 20, 29, 36, 41]. The most relevant work is the neural network approaches to learning cross-modal joint embeddings, represented by early efforts [1, 4, 9, 10, 26, 35] and most recent work, represented by JESR [29] and its extensions [2, 5, 11, 36, 41]. A recent effort [38] also provides a framework to compare some of the existing methods. SAN [4] applied a stacked attention network to locate ingredient regions in the image and learn joint embedding features. JESR [29] introduced the Recipe1M dataset and proposed a joint embedding learning approach by combining a pairwise cosine loss with a semantic regularization constraint. A few follow-up efforts have improved JESR by replacing the cosine loss optimizer. AMSR [5] improves JESR by using hierarchical attention on the recipes with a simple triplet loss. AdaMine [2] extends JESR by using the batch all triplet loss on both recipe and image embeddings in the joint latent space to leverage class-guided features. ACME [36] improves the cosine optimizer of JESR by using the batch-hard triplet loss [15] combined with adversarial cross-modal embedding [35]. Recipe Retrieval with GAN (R<sup>2</sup>GAN) [41], Recipe Retrieval with visual query of ingredients (Img2img+JESR) [20] and Modality-Consistent Embedding Network (MCEN) [11] are recent additions, although they cannot outperform ACME. In comparison, JEMA is the first to provide cross-modal alignment optimizations at all three tiers: learning modality-specific embedding functions, joint embedding loss optimization, and loss regularization optimization.

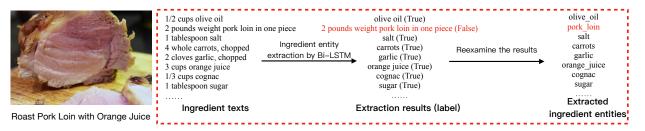


Figure 3: The workflow of extracting the ingredient entities is depicted in the red dashed box using an example recipe and the matched food image. JEMA refines the LSTM extracted key ingredient results in this example: identify the key term "pork\_loin" from the false results as the key ingredient, effectively correcting the errors made from LSTM sequence embedding.

# 3 JOINT EMBEDDING WITH MODALITY ALIGNMENTS

Let R and V denote the recipe domain and image domain respectively. For a set *T* of recipe-image pairs  $(\mathbf{r}_i, \mathbf{v}_i)$ , where a recipe  $\mathbf{r}_i \in \mathbf{R}$ and an image  $\mathbf{v}_i \in \mathbf{V}$  ( $1 \le i \le T$ ), we want to jointly learn two embedding functions,  $\mathbf{E}_V : \mathbf{V} \to \mathbb{R}^d$  and  $\mathbf{E}_R : \mathbf{R} \to \mathbb{R}^d$ , which encode each pair of raw recipe and food image into two d-dimensional vectors in the latent representation space  $\mathbb{R}^d$ : a recipe text embedding vector ( $\mathbf{E}_{R}(r_{i})$ ) and a visual image embedding vector ( $\mathbf{E}_{V}(v_{i})$ ) respectively, and the two embedding functions should satisfy the following condition: For  $1 \leq i, j \leq T$ , the distance between a recipe  $\mathbf{r}_i$  and an image  $\mathbf{v}_j$  in the latent d-dimensional embedding space should be closer when i = j and more distant when  $i \neq j$ . Furthermore, good embedding functions will answer cross-modal queries with high recall performance. To ensure efficient learning of the two embedding functions, we argue that modality alignment optimizations should be performed at all three tiers: the learning of modality-specific embedding functions:  $E_R$  and  $E_V$ , the joint embedding for modality alignment loss optimization, and the alignment loss regularization. First, we aim to optimize the recipe text embedding by using term extraction and ranking enhanced LSTM networks for learning word and sentence sequence based recipe embedding, and at the same time, optimize the image embedding by utilizing the ResNeXt-101 as the image encoder and combining it with the image category embedding obtained by wideResNet50 and word2vec [24], as shown in Figure 2. The first-tier modality alignment optimization achieves dual goals: the key term semantics and the category semantics help to make the recipe textual embedding more aligned with the visual features of the matching food images, and they also improve the image embedding to reflect the textual features of the matching recipes. The second-tier modality alignment optimizes the distance-based textual-visual alignment loss by utilizing the soft-margin based batch-hard triplet loss, empowered with a novel double negative sampling strategy, denoted as DHTL<sub>sm</sub>. Recall Figure 1, our DHTL<sub>sm</sub> optimizer will improve the recipe embedding by maximizing the embedding distance in  $\mathbb{R}^d$  to the *batch hard negative image example* chosen from those negative image embeddings in the same batch. Similarly, DHTL<sub>sm</sub> will optimize the image embedding by maximizing the embedding distance to the batch hard negative recipe example chosen from the negative recipe text embeddings in the same batch. The third-tier modality alignment optimization further improves the effectiveness of our DHTLsm optimizer for correcting modality

alignment by adding two types of loss regularizations. The categorybased alignment loss aims to regularize the joint embedding loss  $DHTL_{sm}$  with category-based alignment constraint on both image  $(L_{CA-V})$  and recipe  $(L_{CA-R})$ . The cross-modal discriminator based modality alignment aims to regularize the joint embedding loss  $DHTL_{sm}$  by leveraging discriminator based visual-textual distribution alignment loss  $(L_{DA})$  as an alternative distance-based alignment correctness measure. We below define the overall objective function for joint embedding loss optimization based on the second and third tier alignment optimizations:

$$L = DHTL_{sm} + \lambda_1 L_{CA-R} + \lambda_2 L_{CA-V} + \lambda_3 L_{DA}$$
(1)

where  $\lambda_1$ ,  $\lambda_2$  and  $\lambda_3$  are trade-off hyper-parameters. We have experimentally evaluated their impacts and observed that the best results can be obtained when  $\lambda_1$ ,  $\lambda_2$  and  $\lambda_3$  are all set as 0.005.

# 3.1 Modality Alignment in Embedding Functions

The first tier cross-modal optimization aims to perform early alignment of textual-visual information in learning and extracting latent features from raw training inputs of recipe and image pairs.

Recipe Text Embedding Function. We first enhance the LSTM based recipe embedding by leveraging key term features learned from recipes using term extraction and ranking algorithms. Our goal is to leverage those key terms that can uniquely distinguish a given recipe from other recipes in terms of ingredients (e.g., pork), cooking utensils (e.g., pan) and actions (e.g., stir), as illustrated in the top red dashed box in Figure 2. For the recipe sequence feature, a two-stage LSTM for representation learning of cooking instructions [29] is employed for representation learning of cooking instructions. As for the ingredients, we use the bi-directional LSTM networks to analyze the word sequence of each ingredient text, such as "two pounds weight pork loin", and learn to identify those word sequences that are ingredients with high probability, like "pork loin". Then we perform binary logistic regression on the extracted word sequence set to produce two clusters, labeled as true or false in the context of core ingredients. Those with true labels are regarded as the ingredient entities. To reduce errors, we re-examine those word sequences labeled as false by leveraging the set of true ingredient entities identified and collected from the whole training dataset. If a false-labeled word sequence contains any true ingredient entity, this ingredient entity will be extracted from the false word sequence, which ensures that our recipe text embedding learning does not miss any key ingredient. Figure 3

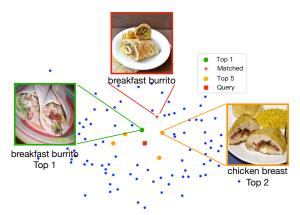


Figure 4: Illustration of instance-class double hard sampling strategy.

shows an illustrative example. For the cooking utensils and actions, we resort to the part-of-speech tagging approach [22] to extract the nouns and verbs in the recipe text where the ingredient entities are removed in advance. Given a training set of recipes, ingredients such as "olive oil", "salt" are common and more frequent than other less common ingredients, which may be unique to a small percentage of recipes. We utilize a term ranking algorithm (e.g., TFIDF [28], TextRank [23] or BERT [6] based approach) to capture the discrimination significance contributed by each key term to a given recipe and the visual information in its associated food image. To generate the key term feature, a word2vec model [24] is trained over the recipe texts on the entire training data to obtain the term embedding for each extracted key term. By combining the word2vec vectors of all key terms weighted by their term ranking values, we get the recipe key term feature, which is integrated with bi-directional LSTM as the training data preprocessing step. Finally, during the recipe text embedding learning phase, we combine the recipe sequence patterns and the key term features through concatenation and a fully connected layer to produce the recipe embedding in the *d*-dimensional latent space  $\mathbb{R}^d$ . Our JEMA recipe text embedding function can capture the key terms that are discriminative with respect to a specific recipe, and better reflect the visual components in the corresponding food image.

Food Image Embedding Function. In JEMA, we also optimize the image encoder used in existing methods, e.g., VGG-16 [32] and ResNet-50 [14]. We integrate the ResNeXt-101 model [37] with the category-based visual feature extracted by combining the Food-101 classifier using wideResNet-50 [40] and word2vec, followed by a fully-connected layer to get the final image embedding, as shown in the blue dotted box of Figure 2. This category-based enhancement is motivated by two observations. First, the neural features learned directly from the pixel grid of the image may not always be aligned well with the neural features learned from LSTM based recipe embedding. For example, some ingredients identified by LSTM networks, such as "olive oil", "salt", may not have visual correspondence in its associated image. Furthermore, the visual appearance of some ingredients, such as "pork\_loin" may be missed by LSTM based recipe embedding, recall Figure 3. Such text-visual alignment mismatch problems are common in food computing since a cooking recipe may have different visual appearances due to different ways of using ingredients and different decorations.

# 3.2 Joint Embedding Alignment Optimizations

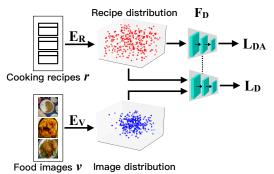
We perform the cross-modal joint embedding on the two embeddings using a distance-based loss optimizer, which performs the second tier modality alignment optimization between the recipe and image embeddings in the *d*-dimensional latent space  $\mathbb{R}^d$ . In JEMA, we improve the batch hard triplet loss by introducing a double hard sampling strategy and a soft-margin function to optimize modality alignment loss. Triplet loss [15] is calculated on the triplet of training samples  $(x_a, x_b, x_n)$ , where  $x_a$  represents a feature embedding as an anchor point in one modality and used as the ground truth to evaluate the corresponding modality embedding,  $x_p$  and  $x_n$ denote the positive and negative feature embeddings from the other modality. The triplet loss ensures that the positive instance in one modality should be close to the anchor point in the other modality, and the negative instance in one modality should be distant from the anchor point in the other modality. By selecting the hardest positive and negative samples for each anchor point within every batch when calculating the triplet loss, Hermans [15] shows that it often outperforms the batch-all triplet loss, which is based on the average distance from all negative examples to the anchor point.

Double Hard Sampling Method. In JEMA, we define two types of batch hard positive or negative examples. For instance level, given the anchor image (or recipe) embedding (i.e.,  $\in \mathbb{R}^d$ ) in each batch, there is only one positive recipe (or image) instance in the batch, which corresponds to this anchor image (or recipe), we call it the batch hardest positive example. For the rest of the recipe (or image) instances in the batch, they are considered negative examples of the anchor image (or recipe). We define the batch hardest negative recipe (or image) instance concerning this anchor as the one whose vector distance to the anchor image (or anchor recipe) is the smallest in the batch. In addition to instance level sampling, we also introduce class level sampling for computing the batch hard triplet loss. Those recipe (or image) instances that have the same category as the anchor image (or recipe) are considered as positive examples, and the rest with different categories are considered as negative examples for this anchor. We define the batch hardest positive or negative recipe (or image) example as the positive or negative example whose vector distance to the anchor image (or recipe) is the largest or smallest among all positive or negative examples in the batch respectively.

**Soft-margin based Batch Hard Triplet Loss** ( $DHTL_{sm}$ ). In addition, we use the softplus function  $ln(1 + \exp(\gamma(\cdot + m)))$  as a smooth approximation to replace the hinge function  $[m + \cdot]_+$  used in existing works [2, 5, 36], which assumes that the distance between the anchor point and negative instance is always larger than the distance between the anchor and positive instance by a fixed margin *m*. Our soft-margin based approach improves the hinge with an exponential decay instead of a threshold-based hard cut-off. The soft-margin based batch-hard triplet loss with a double sampling strategy, denoted by  $DHTL_{sm}$ , is given as:

$$DHTL_{sm} = \sum_{i=1}^{N} ln(1 + e^{\gamma(d(E_{r_i}^a, E_{r_i}^p) - \min d(E_{r_i}^a, E_{r_i}^n) + m)}) + \sum_{i=1}^{N} ln(1 + e^{\gamma(d(E_{v_i}^a, E_{r_i}^p) - \min d(E_{v_i}^a, E_{r_i}^n) + m)})$$
(2)

where  $d(\cdot)$  measures the Euclidean distance between two input vectors, *N* is the number of the different recipe-image pairs in a



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batch, subscripts *a*, *p* and *n* refer to anchor, positive and negative instances respectively,  $E_{r_i}$ ,  $E_{v_i}$  refer to the embeddings of the recipe and image in the *i*-th recipe-image pair respectively,  $\gamma$  is the scaling factor and *m* denotes the margin of error in the triplet loss.

Figure 5: Illustration of discriminator based alignment loss regularization.

Figure 4 illustrates the effectiveness of our instance-class double sampling strategy used in our  $DHTL_{sm}$  alignment loss optimizer. When only using the instance level batch-hard strategy, given a recipe query (denoted as the red square), the images in the red and green boxes would be the hardest positive and negative instances respectively. However, this negative instance shares the same category "breakfast burrito" as the anchor recipe query. In comparison, the class level batch hard negative example would be the chicken breast image in the orange box, which is the next closest negative instance to the anchor recipe. Therefore, given a recipe query about burrito, JEMA is more likely to return the results about burrito, rather than those about chicken breast.

# 3.3 Modality Alignment Loss Regularizations

Category-based Alignment Loss Regularization. The categorybased loss regularization aims to reduce the cross-entropy loss between each of the N modality-specific embeddings and the corresponding category from the total of  $N_c$  categories obtained from the recipe text and the associated food image (recall Figure 2). JEMA assigns every recipe-image pair to a category label without using the background class. The category assignment algorithm is based on the combination of the category labels of food101 [1], the bigram analysis on recipe titles in the Recipe1M dataset, and the TFIDF feature on the title and recipe text. As a result, JEMA obtains 1,005 category labels, avoiding assigning background labels to a large percentage of recipe-image pairs as done in existing approaches [2, 5, 29, 36]. We utilize the cross-modal category distribution alignment between the textual recipe and visual image as a regularization to our joint embedding loss optimization by DHTL<sub>sm</sub>. The category-based loss regularization is applied to both image and recipe as follows:

$$L_{CA-R} = -\sum_{i=1}^{N} \sum_{t=1}^{N_c} y_R^{i,t} \log(\hat{y}_R^{i,t}) \\ L_{CA-V} = -\sum_{i=1}^{N} \sum_{t=1}^{N_c} y_V^{i,t} \log(\hat{y}_V^{i,t})$$
(3)

where  $L_{CA-R}$  is the loss of regularization on the recipe embedding, while  $L_{CA-V}$  is on the image embedding.  $N_c$  is the number of category labels, N is the number of the different recipe-image pairs in a batch,  $y_R^{i,t}$  and  $\hat{y}_R^{i,t}$  are the true and estimated possibilities that the  $i^{th}$  recipe embedding belongs to the  $t^{th}$  category label, and similarly,  $y_V^{i,t}$  and  $\hat{y}_V^{i,t}$  are defined for image embedding. Cross-Modal Discriminator based Alignment Loss Regularization. This alignment loss regularization aims to utilize the competing strategy like those in GAN [12] with the gradient penalty [13] to further reduce possible errors inherent in our soft-margin based double batch hard triplet loss (DHTL<sub>sm</sub>). To further regularize the joint embedding loss optimization, during the learning of joint embedding, we also train a discriminator model such that for each pair of matched recipe and image, given an embedding from one modality, this discriminator can tell it is the image embedding or the embedding for the matching recipe text, which is against our goal of joint embedding learning. If the trained discriminator cannot accurately discriminate the embedding of one modality from the embedding of the other modality, it indicates that our joint embedding learning is very effective and the learned distributions of embeddings for matched recipe-image pairs are too close in the common latent space  $\mathbb{R}^d$  for the discriminator to tell them apart. Since the recipe and image embeddings play the same role during the discriminator learning, we select the image embedding as the target of the learned discriminator, which means receiving image embeddings, the learned discriminator would give a high confidence value while recipe embedding would result in low confidence value. The higher confidence values of recipe embeddings are obtained by our discriminator, the more aligned the distributions of recipe embeddings and image embeddings are in the joint space  $\mathbb{R}^d$ . The illustration of how discriminator works is showed in Figure 5. We below define the loss  $L_D$  for the discriminator networks, which is made up of three fully-connected layers and the cross-modal discriminator based alignment loss regularization L<sub>DA</sub> respectively:

$$L_{D} = \sum_{i=1}^{B} [\log(F_{D}(E_{R}(r_{i}))) + \log(1 - F_{D}(E_{V}(v_{i}))) + \lambda_{D}(\|\nabla_{x_{i}}\log(F_{D}(x_{i}))\|_{2} - 1)^{2}]$$
(4)

$$L_{DA} = \sum_{i=1}^{B} \log(1 - F_D(E_R(r_i)))$$
(5)

where  $F_D(\cdot)$  is the function of our trained discriminator, which outputs the confidence value in terms of how confident it is to distinguish the input embedding as the image embedding, *B* is the number of the different recipe-image pairs in a batch,  $\lambda_D$  is the trade-off parameter and set to 10 as suggested in [13],  $x_i$  is a random interpolation between the *i*<sup>th</sup> recipe embedding  $E_R(r_i)$  and image embedding  $E_V(v_i)$ .

### 4 **EXPERIMENTS**

**Dataset and Evaluation Metrics.** We evaluate the effectiveness of different approaches on Recipe1M dataset [29]. Experiment setup follows the literature: (i) Sample 10 unique subsets of 1,000 or 10,000 matching recipe-image pairs from the test set. (ii) Use each item in one modality as a query (e.g., an image), and rank instances in the other modality (e.g., recipes) by the Euclidean distance between the query embedding and each candidate embedding from the other modality in the test set. (iii) Calculate the median retrieval rank (MedR) and the recall percentage at top K (R@K), i.e., the percentage of queries for which the matching answer is included in the top K results (K=1,5,10). Note that even though many loss regularizations are added in our framework, these optimizations are only performed at the training stage and not used in the testing stage, only adding a little cost in the training phase and no cost in the testing.

Table 1: Performance comparison of our JEMA with eight existing representative methods on both 1K and 10K test set. The results of SAN, JESR,Img2img+JESR, AMSR, AdaMine, R<sup>2</sup>GAN, MCEN and ACME are quoted from [2, 5, 11, 20, 29, 36, 41] respectively. The symbol "-" indicates that the results are not available from the corresponding methods.

Size of	Annroachas	Ima	ge to rec	cipe retri	eval	Recipe to image retrieval			
test-set	Approaches	MedR↓	R@1↑	R@5↑	R@10↑	MedR↓	R@1↑	R@5↑	R@10↑
	SAN (MMM 2017) [4]	16.1	12.5	31.1	42.3	-	-	-	-
	JESR (CVPR 2017) [29]	5.2	24.0	51.0	65.0	5.1	25.0	52.0	65.0
	Img2img+JESR (SIGIR 2020) [20]	-	-	-	-	5.1	23.9	51.3	64.1
	AMSR (MM 2018) [5]	4.6	25.6	53.7	66.9	4.6	25.7	53.9	67.1
	AdaMine (SIGIR 2018) [2]	1.0	39.8	69.0	77.4	1.0	40.2	68.1	78.7
	R <sup>2</sup> GAN (CVPR 2019) [41]	2.0	39.1	71.0	81.7	2.0	40.6	72.6	83.3
1K	MCEN (CVPR 2020) [11]	2.0	48.2	75.8	83.6	1.9	48.4	76.1	83.7
IK	ACME (CVPR 2019) [36]	1.0	51.8	80.2	87.5	1.0	52.8	80.2	87.6
	JEMA(TextRank, ResNet-50)	1.0	51.9	81.5	88.9	1.0	53.0	82.1	89.1
	JEMA(DistilBERT, ResNet-50)	1.0	52.3	81.6	88.6	1.0	53.6	82.0	89.2
	JEMA(BERT, ResNet-50)	1.0	52.8	81.7	89.2	1.0	53.7	82.3	89.5
	JEMA(RoBERTa, ResNet-50)	1.0	54.6	83.3	90.4	1.0	55.2	83.7	90.7
	JEMA(TFIDF, ResNet-50)	1.0	57.2	85.2	91.2	1.0	57.4	85.7	91.7
	JEMA(TFIDF, ResNeXt-101)	1.0	58.1	85.8	92.2	1.0	58.5	86.2	92.3
10K -	JESR (CVPR 2017) [29]	41.9	-	-	-	39.2	-	-	-
	AMSR (MM 2018) [5]	39.8	7.2	19.2	27.6	38.1	7.0	19.4	27.8
	AdaMine (SIGIR 2018) [2]	13.2	14.9	35.3	45.2	12.2	14.8	34.6	46.1
	R <sup>2</sup> GAN (CVPR 2019) [41]	13.9	13.5	33.5	44.9	12.6	14.2	35.0	46.8
	MCEN (CVPR 2020) [11]	7.2	20.3	43.3	54.4	6.6	21.4	44.3	55.2
	ACME (CVPR 2019) [36]	6.7	22.9	46.8	57.9	6.0	24.4	47.9	59.0
	JEMA(TextRank, ResNet-50)	6.2	21.9	47.2	59.2	6.0	22.8	48.1	59.9
	JEMA(DistilBERT, ResNet-50)	6.0	22.7	48.3	60.1	6.0	23.7	48.8	60.5
	JEMA(BERT, ResNet-50)	6.0	23.2	48.8	60.6	6.0	24.0	49.6	61.2
	JEMA(RoBERTa, ResNet-50)	5.1	24.0	50.3	62.2	5.0	24.9	50.8	62.6
	<b>JEMA</b> (TFIDF, ResNet-50)	4.9	26.3	53.2	64.9	4.8	27.0	53.7	65.3
	JEMA(TFIDF, ResNeXt-101)	4.2	26.9	54.0	65.6	4.0	27.2	54.4	66.1

#### Recipe query

Provencal Artichoke Ragout

#### Ingredients:

baby artichokes, lemon, olive oil, sweet onion, celery stalks, red bell peppers, garlic cloves, salt, tomatoes, water, ground pepper, fresh thyme leaves, bay leaf, fresh basil

#### Instructions:

Fill a bowl with water, and add the juice of 1/2 lemon. Cut the stems off the artichokes, and with a sharp knife, cut away the tops about 1/2 inch from the top for baby artichokes, 1 inch for larger artichokes.

Rub the cut parts with the other half of the lemon.

Break off the tough outer leaves until you reach the lighter green leaves near the middle.

With a paring knife, trim the bottom of the bulb right above the stem by holding the knife at an angle and cutting around the artichoke, until you reach the light flesh beneath the tough

bottoms of the leaves. Cut small baby artichokes in half, or large artichokes into quarters, and cut away the chokes if the artichokes are mature. Top 5 retrieved images



Figure 6: Comparing our JEMA approach with two representative methods JESR [29] and ACME [36] on the recipe-to-image retrieval (1K test set). The matched images are marked in the red box. Words in red highlighted in recipe text indicate that they are selected with relatively high TFIDF value in our JEMA. We indicate the top-k position where the matched image is retrieved under each of the three methods.

**Implementation Details.** Word2vec model is trained using the Continuous Bag-of-Words (CBOW) architecture [25] on the

corpus of recipe texts in the Recipe1M dataset. The dimensions of joint embedding and word2vec embedding are set as 1024 and 300

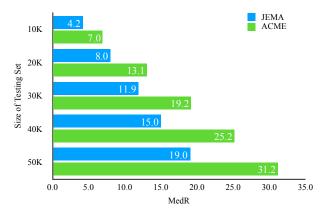


Figure 7: Scalability test between JEMA and ACME for image-torecipe retrieval (For MedR, lower is better).

Table 2: Evaluation of contributions of different components of theJEMA framework on the 1K test-set. MA consists of  $MA_R$  and  $MA_V$ .

Component	Image to recipe retrieval						
Component	MedR	R@1	R@5	R@10			
JEMA-b	4.1	25.9	56.4	70.1			
JEMA-b+MA <sub>V</sub>	3.4	28.1	59.5	73.1			
JEMA-b+MA <sub>R</sub>	3.0	29.4	60.0	73.4			
JEMA-b+MA	3.0	30.5	61.6	75.2			
JEMA-b+MA+CA	2.3	33.5	68.4	80.9			
JEMA-b+MA+DA	2.5	36.0	65.2	77.3			
JEMA-b+MA+DHTL <sub>sm</sub>	1.6	47.7	78.6	87.3			
JEMA-b+MA <sub>All</sub>	1.0	57.2	85.2	91.2			

respectively. Adam optimizer [19] is employed for model training with the initial learning rate set as  $10^{-4}$  in all experiments, with the mini bath size of 100. All deep neural networks are implemented on the Pytorch platform and trained on a single Nvidia Titan X Pascal server with 12GB of memory.

**Baselines for Comparison.** Eight baselines are considered: SAN [4], JESR [29], Img2img+JESR [20], AMSR [5], AdaMine [2], R<sup>2</sup>GAN [41], MCEN [11] and ACME [36].

### 4.1 Cross-Modal Retrieval Performance

We evaluate the performance of the JEMA approach for image-torecipe and recipe-to-image retrieval tasks against eight existing methods. Table 1 shows the results. We make two observations: (1) JEMA consistently outperforms all eight baselines with high Recall@K (K=1,5,10) for both image-to-recipe and recipe-to-image queries on 1K and 10K test data, showing the effectiveness of our three-tier textual-visual alignment optimizations for cross-modal joint embedding learning. (2) The attention mechanism introduced in SAN, AMSR and MCEN on top of the neural features aims to implicitly and approximately locate the key ingredients. However, the results are not effective, especially compared to JEMA, which utilizes the key terms from the key term extraction and ranking module and the image category for optimizing the text-visual modality alignments in three stages: (i) learning the two embedding functions, (ii) learning joint embedding with alignment loss optimization and (iii) alignment loss regularization.

Next, we discuss the impact of different term ranking algorithms: TFIDF, TextRank and three popular BERT models (BERT [6], DistilBERT [30] and RoBERTa [21]). TFIDF and TextRank can obtain the representative terms for the recipe considering the term occurrence frequency, while BERT methods mainly focus on the semantic correlation between each term and its recipe text. The experimental results are given in Table 1 under JEMA sections for 1K and 10K test data. We observe that the TFIDF approach offers the best performance in JEMA. We also vary the recent CNN models in the image embedding process by changing ResNet-50 to ResNet-152 [14], WideResNet-101 [40], ResNeXt-50 and ResNeXt-101 [37]. It turns out that using ResNeXt-101 as the image encoder can yield stable improvement for all five term ranking algorithms, and TFIDF remains to be the best in the context of JEMA.

To further illustrate the comparison results, we provide a visualization of recipe-to-image retrieval using an example recipe by comparing the performance of JEMA with JESR and ACME in Figure 6, since JESR and ACME have released their pre-trained models. We observe that JEMA successfully aligns the "tomato" ingredient in the recipe text with the red tomato component in the food image and the matched image is returned at Top 2 by JEMA. In comparison, both JESR and ACME fail to retrieve the matched image within the top 5 results, showing some problems in modality alignment between recipe text and food image. This example further illustrates the effectiveness of our three-tier alignment optimizations for improving the quality of cross-modal retrieval tasks.

**Scalability.** To investigate the robustness of JEMA against large datasets beyond 10K, we further compare its MedR performance against the state-of-the-art approach ACME. Figure 7 shows the results for image-to-recipe retrieval. The gap between our JEMA and ACME becomes larger as the testing set size increases. On the 50K testing set, which is almost equivalent to the original testing set [29], JEMA successfully ranks the ground-truth recipes by over 12 positions ahead of ACME on average. Similar results are also observed for the recipe-to-image retrieval, where JEMA outperforms ACME by over 11 positions on average for the 50K dataset.

### 4.2 Ablation Study

Ablation studies are conducted to evaluate the contributions of each core component in our JEMA approach. For a fair comparison with the baselines, ResNet-50 model is used in the image embedding and TFIDF approach is the default choice. We use JEMA-b to denote the joint embedding with batch-all triplet loss and without any recipe-image alignment techniques. We incrementally add one component at a time. First, we analyze the gains from employing the textual-visual alignment optimization to the two modality-specific embeddings,  $MA_V$  and  $MA_R$ . Also, we use MA to represent that the textual-visual alignment optimizations on both recipe and image embeddings are employed. Then we add the category-based alignment loss regularizations CA on both recipe and image embeddings, and add the cross-modal discriminator-based alignment loss regularization DA. Next, we replace the batch-all triplet loss in JEMA-b with our instance-class double sampling based batch-hard triplet loss DHTL<sub>sm</sub>. Finally, we use MA<sub>All</sub> to denote JEMA with all three-tier modality alignment optimizations. Table 2 reports the contributions of these components on the image-to-recipe retrieval.

Components	Image to recipe retrieval				Recipe to image retrieval			
Components	MedR↓	R@1↑	R@5↑	R@10↑	MedR↓	R@1↑	R@5↑	R@10↑
ingredient	5.0	25.0	51.4	63.1	5.0	26.1	52.0	63.4
ingredient+utensil	5.0	25.6	52.2	64.1	5.0	26.4	52.5	64.2
ingredient+utensil+action	5.0	26.3	53.2	64.9	4.9	27.0	53.7	65.3

Table 3: Evaluation of contributions of each component in the extracted key terms on the 10K test-set.

Table 4: Performance comparison of our JEMA using different key term filters on the 10K test set. ResNet-50 model is used here as the image encoder. The symbol "-" indicates that all the extracted key terms will be used to generate the key term feature.

Term Ranking	Threshold	Ima	ige to rec	ipe retri	eval	Recipe to image retrieval			
Algorithm	Threshold	MedR↓	R@1↑	R@5↑	R@10↑	MedR↓	R@1↑	R@5↑	R@10↑
	-	5.0	24.0	50.3	62.2	5.0	24.9	50.8	62.6
RoBERTa	0.05	5.0	25.1	51.7	63.5	5.0	25.8	52.3	64.0
RODERTa	0.10	5.0	24.2	50.4	62.5	5.0	25.3	51.2	62.7
	0.15	5.0	24.0	50.3	62.0	5.0	25.0	50.8	62.6
	-	5.0	26.3	53.2	64.9	4.9	27.0	53.7	65.3
TFIDF	0.05	5.0	26.1	53.1	64.8	5.0	26.7	53.7	65.2
ITIDT	0.10	5.0	25.3	51.7	63.4	5.0	26.1	52.5	64.1
	0.15	6.0	22.7	48.0	59.9	6.0	23.5	49.1	60.4



Figure 8: The results of recipe-to-image retrieval by our JEMA approach (10K test set). The matched images are boxed in red.

It shows that every proposed component positively contributes towards improving the cross-modal alignment between recipe text and food image and the overall performance.

# 4.3 Effect of Term Extraction and Ranking

The extracted key terms during the data preprocessing of the recipe text can be roughly divided into three types: ingredients, cooking utensils and actions. In this set of experiments, we want to evaluate the contributions of applying term extraction and ranking on each of three types of key terms on the overall performance of JEMA.

**Evaluation of Each Key Term Component.** For comparison, we use the TFIDF approach as the term ranking algorithm and

uses ResNet-50 to generate image embedding. First, we set our JEMA approach such that it only extracts the ingredients. Then we incrementally add the other two components: the cooking utensils and the cooking actions, one at a time. Table 3 reports the results. It shows that every proposed component positively contributes towards boosting the overall performance of cross-modal retrieval.

**Evaluation of the Key Term Filter.** In order to capture the level of discrimination significance contributed by each key term to its recipe text, in JEMA, we assign different weight to each key term extracted from the recipe text by several term ranking algorithms (i.e. TextRank, BERT based approach and TFIDF). The more discriminative the key term is for its recipe, the higher weight it

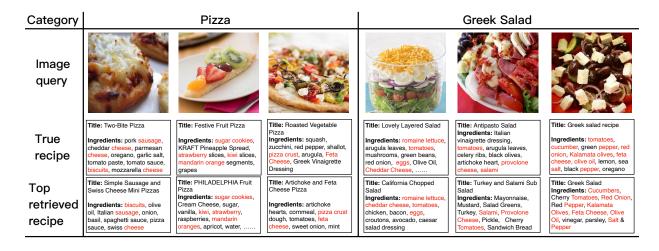


Figure 9: The results of image-to-recipe retrieval by our JEMA approach (10K test set). The common or similar ingredients in the true recipe and top retrieved recipe are highlighted in red.

will get. Since the terms with very low weights might be less useful or even harmful to the quality of the learned recipe embedding, in this set of experiments, we compare JEMA without rank-threshold based filer to denote that all key terms extracted and ranked will be utilized, which is the default, with the one using a thresholdbased filter. The terms with weights lower than a threshold t are removed when generating the recipe key term feature. Recall the experimental results of using different term ranking algorithms in Table 1, which shows that using the RoBERTa model and TFIDF approach can get better performance. Therefore, we compare the results of generating the recipe key term features by keeping all extracted key terms with the results of using the key term filter to remove those key terms with low weight, in terms of their impacts on improving the quality of the recipe embedding learning based on the RoBERTa model and the TFIDF approach. Table 4 reports the results. Although using the key term filter on the RoBERTa based term ranking algorithm can boost the performance when the weight threshold is set to 0.05, for TFIDF, no-filter offers consistently better cross-modal retrieval performance compared to different threshold settings, showing another benefit of the TFIDF based term ranking algorithm to the performance stability of JEMA.

# 4.4 Cross-Modal Visualization Results

We provide some visualization results of JEMA for both recipe-toimage and image-to-recipe retrieval tasks on the 10K dataset in Figure 8 and Figure 9 respectively. Figure 8 visualizes the results of retrieving the top 5 images using three different recipe queries. In all cases, most of the retrieved images share similar ingredients to the ground truth image. In the first example, all the retrieved images contain the visual component of pulled pork, as suggested by the category label. Also the top 1 and top 5 retrieved images both share the taco component with the ground truth image. In the second example, all top 5 results can be recognized as cheese cake and visually similar to the ground truth image. All retrieved images in the third example are visually similar and all are about fried rice with scallions. Figure 9 shows the ground truth recipes and the top retrieved recipes based on 6 different image queries under two recipe categories: *pizza* and *greek salad*. In each category, we list three image queries. We observe that almost all the significant ingredients of the true recipes and visual components in the image queries also appear in the top retrieved recipes. The results in Figure 8 and Figure 9 indicate that the joint embeddings learned by our JEMA approach are effective in aligning the textual and visual features and boosting the cross-modal retrieval performance.

# 5 CONCLUSIONS

We have presented JEMA, a three-tier modality alignment optimization approach to learning text-image cross-modal joint embedding for cross-modal retrieval of cooking recipes and food images. This paper makes three original contributions. First, we integrate the term extraction and ranking with recipe embedding to make the textual embedding more aligned with the visual features of images. We also incorporate the image category semantics into the image embedding to better reflect the textual features in recipes. Second, we effectively optimize the textual-visual distance alignment in the joint embedding loss optimization by introducing a double sampling based batch hard triplet loss with soft-margin optimization. Third, we further reduce the joint embedding alignment loss by integrating the category-based and cross-modal discriminator based alignment loss regularizations on both recipe and image embeddings. Extensive experiments on Recipe1M benchmark dataset show that by combining the three-tier modality alignment optimizations, JEMA can effectively boost the performance of cross-modal joint embedding learning and outperform the existing representative methods for image-to-recipe and recipe-to-image retrieval tasks.

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