Recipe1M

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Recipe1M: A Dataset for Learning Cross-Modal Embeddings for Cooking Recipes and Food Images

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Abstract—In this paper, we introduce Recipe1M, a new large-scale, structured corpus of over one million cooking recipes and 13 million food images. As the largest publicly available collection of recipe data, Recipe1M affords the ability to train high-capacity models on aligned, multi-modal data. Using these data, we train a neural network to learn a joint embedding of recipes and images that yields impressive results on an image-recipe retrieval task. Moreover, we demonstrate that regularization via the addition of a high-level classification objective both improves retrieval performance to rival that of humans and enables semantic vector arithmetic. We postulate that these embeddings will provide a basis for further exploration of the Recipe1M dataset and food and cooking in general. Code, data and models are publicly available.

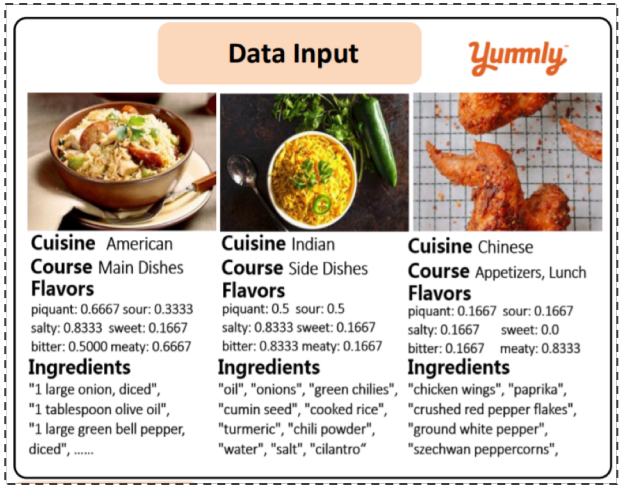
Index Terms—Cross-modal, deep learning, cooking recipes, food images

Contributions

- Address data limitation for food
- Multimodal neural model

Related Work

- Herranz et al
- Min et al
- Carvalho et al
- Chen et al



Data Collection

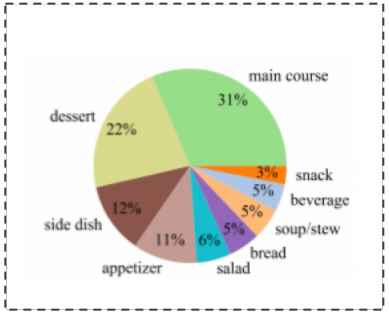
- Recipe1M
- Recipe1M+

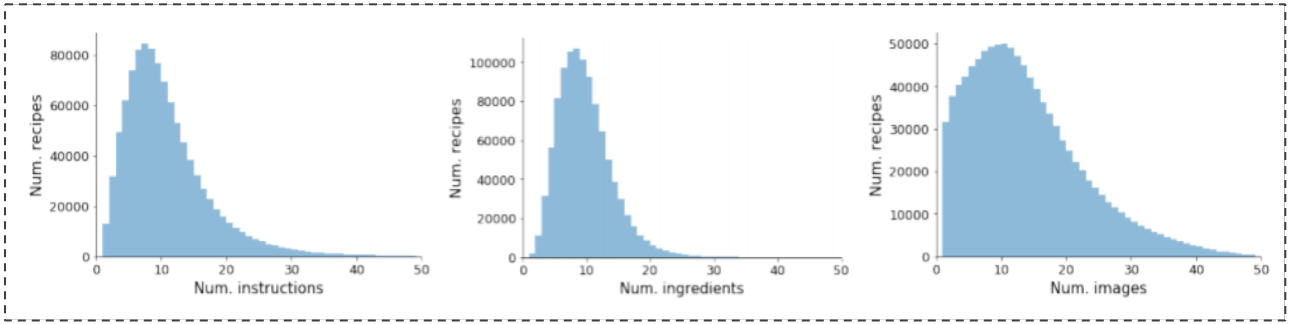
TABLE 1
Recipe1M dataset. Number of recipes and images in training, validation and test sets.

		Recipe1M	intersection	Recipe1M+
Partition	# Recipes	# Images	# Images	# Images
Training	720,639	619,508	493,339	9,727,961
Validation	155,036	133,860	107,708	1,918,890
Test	154,045	134,338	115,373	2,088,828
Total	1,029,720	887,706	716,480	13,735,679

Data Structure

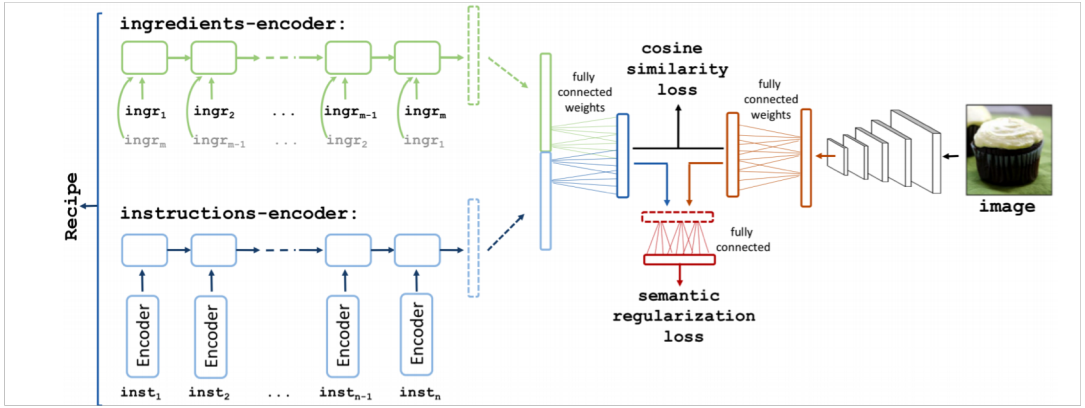
- Recipe1M
- Recipe1M+





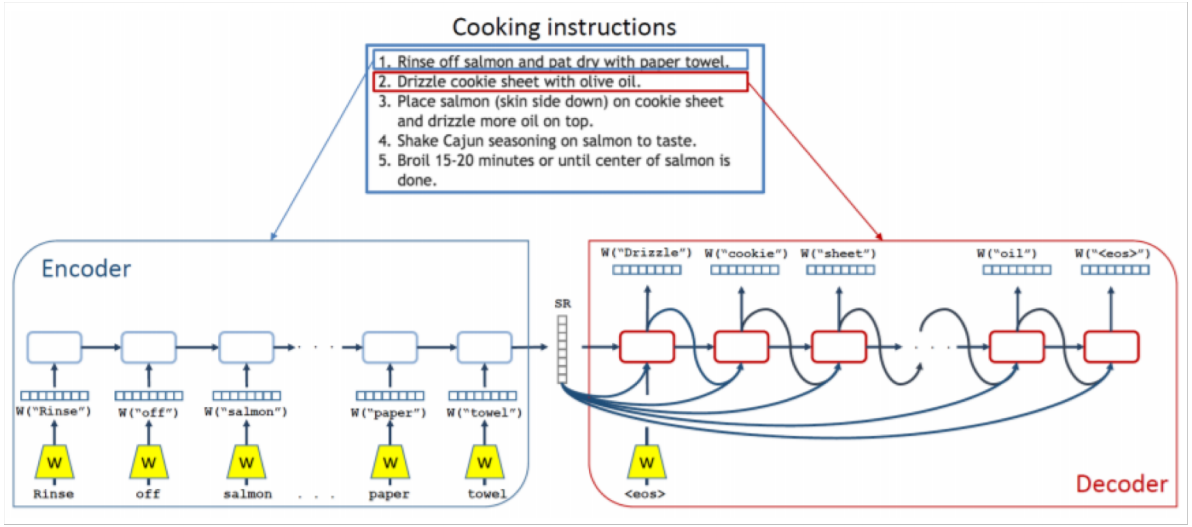
Learning Embeddings

- Ingredients
- Cooking Instructions
- Images



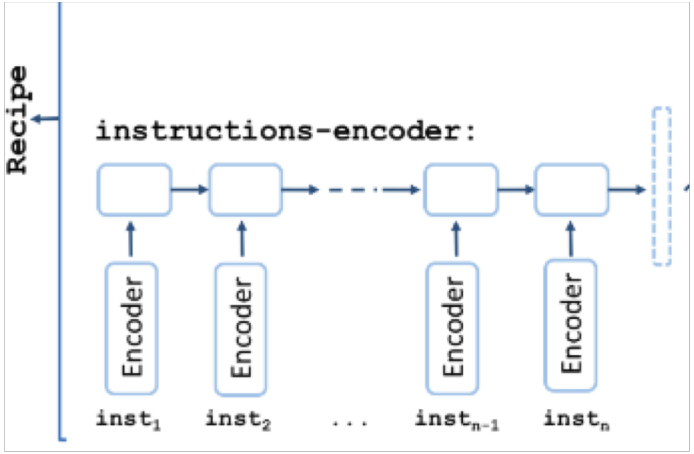
Cooking Instructions Model

First Stage



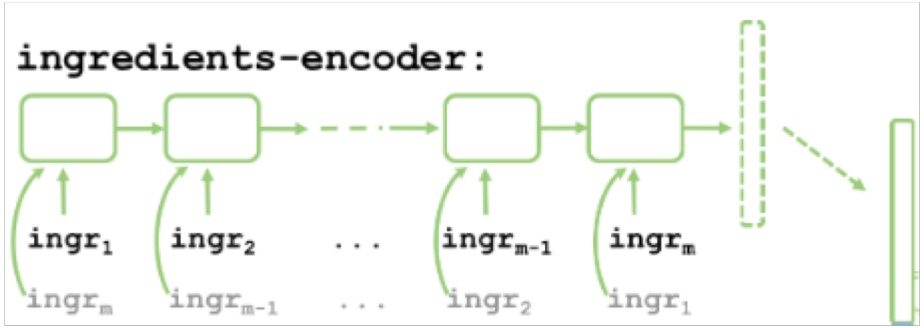
Cooking Instructions Model

Second stage



Ingredients Model

Bi-Directional LSTM



Joint Neural Embedding

Loss Function

$$\phi^r = W^r h_k^r + b^r \text{ and } \phi^v = W^v h_k^v + b^v$$

$$L_{cos}(\phi^r, \phi^v, y) = \begin{cases} 1 - \cos(\phi^r, \phi^v), & \text{if } y = 1 \\ \max(0, \cos(\phi^r, \phi^v) - \alpha), & \text{if } y = -1 \end{cases}$$

Semantic Regularization

$$L(\phi^r, \phi^v, c_r, c_v, y) = L_{cos}(\phi^r, \phi^v, y) + \lambda L_{reg}(\phi^r, \phi^v, c_r, c_v)$$

Implementation and Optimization

- LMDB data format
- 3-stage training
- MedR as performance measure

Experiments

Retrieval

	im2recipe				recipe2im			
	medR	R@1	R@5	R@10	medR	R@1	R@5	R@10
random ranking	500	0.001	0.005	0.01	500	0.001	0.005	0.01
CCA w/ skip-thoughts + word2vec (GoogleNews) + image features	25.2	0.11	0.26	0.35	37.0	0.07	0.20	0.29
CCA w/ skip-instructions + ingredient word2vec + image features	15.7	0.14	0.32	0.43	24.8	0.09	0.24	0.35
joint emb. only	7.2	0.20	0.45	0.58	6.9	0.20	0.46	0.58
joint emb. + semantic	5.2	0.24	0.51	0.65	5.1	0.25	0.52	0.65

Experiments

Retrieval

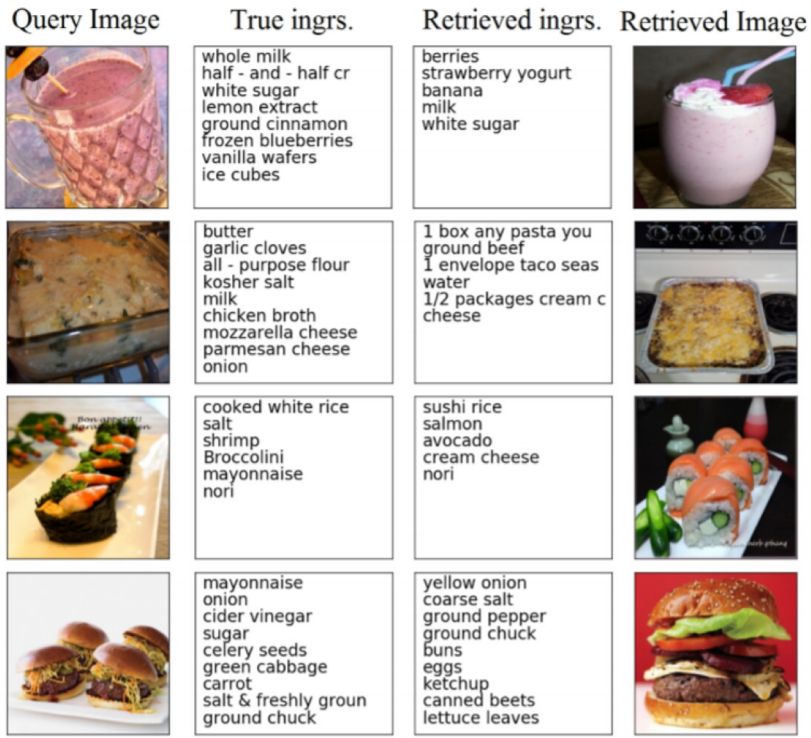


Fig. 8. **Im2recipe retrieval examples.** From left to right: (1) the query image, (2) its associated ingredient list, (3) the retrieved ingredients and (4) the image associated to the retrieved recipe.

Experiments

Ablation Studies

- Changing test sizes

TABLE 4

Ablation studies. Effect of the different model components to the median rank, medR (the lower is better).

	Joint emb. methods	im2recipe			recipe2im		
		medR-1K	medR-5K	medR-10K	medR-1K	medR-5K	medR-10K
VGG-16	fixed vision	15.3	71.8	143.6	16.4	76.8	152.8
	finetuning (ft)	12.1	56.1	111.4	10.5	51.0	101.4
	ft + semantic reg.	8.2	36.4	72.4	7.3	33.4	64.9
ResNet-50	fixed vision	7.9	35.7	71.2	9.3	41.9	83.1
	finetuning (ft)	7.2	31.5	62.8	6.9	29.8	58.8
	ft + semantic reg.	5.2	21.2	41.9	5.1	20.2	39.2

Experiments

Human performance comparison

AMT worker

TABLE 5

Comparison with human performance on im2recipe task. The mean results are highlighted as bold for better visualization. Note that on average our method with semantic regularization performs better than average AMT worker.

	all recipes	course-specific recipes						dish-specific recipes								
		dessert	salad	bread	beverage	soup-stew	course-mean	pasta	pizza	steak	salmon	smoothie	hamburger	ravioli	sushi	dish-mean
human	**81.6 ± 8.9**	52.0	70.0	34.0	58.0	56.0	**54.0 ± 13.0**	54.0	48.0	58.0	52.0	48.0	46.0	54.0	58.0	**52.2 ± 04.6**
joint-emb. only	**83.6 ± 3.0**	76.0	68.0	38.0	24.0	62.0	**53.6 ± 21.8**	58.0	58.0	58.0	64.0	38.0	58.0	62.0	42.0	**54.8 ± 09.4**
joint-emb.+semantic	**84.8 ± 2.7**	74.0	82.0	56.0	30.0	62.0	**60.8 ± 20.0**	52.0	60.0	62.0	68.0	42.0	68.0	62.0	44.0	**57.2 ± 10.1**

Experiments

Recipe1M vs Recipe1M+ Comparison

TABLE 6

Comparison between Recipe1M and Recipe1M+ trained models. Median ranks and recall rate at top K are reported for both models. They have similar performance on the Recipe1M test set in terms of medR and R@K. However, when testing on the Recipe1M+ test set, the model trained on Recipe1M+ yields significantly better medR and better R@5 and R@10 scores.

	Recipe1M test set				Recipe1M+ test set			
	im2recipe							
	medR	R@1	R@5	R@10	medR	R@1	R@5	R@10
Recipe1M training set	5.1	0.24	0.52	0.64	13.6	0.15	0.35	0.46
Recipe1M+ training set	5.7	0.21	0.49	0.62	8.6	0.17	0.42	0.54
	recipe2im							
	medR	R@1	R@5	R@10	medR	R@1	R@5	R@10
Recipe1M training set	4.8	0.27	0.54	0.65	11.9	0.17	0.38	0.48
Recipe1M+ training set	4.6	0.26	0.54	0.66	6.8	0.21	0.46	0.58

Experiments

Model Generalization Ability Comparison

TABLE 7
Im2recipe retrieval comparisons on Food-101 dataset. Median ranks and recall rate at top K are reported for both models. Note that the model trained on Recipe1M+ performs better than the model trained on Recipe1M.

	im2recipe			
	medR	R@1	R@5	R@10
Recipe1M training set	17.35	16.13	33.68	42.53
Recipe1M+ training set	10.15	21.89	42.31	51.14
	recipe2im			
Recipe1M training set	4.75	26.19	54.52	67.50
Recipe1M+ training set	2.60	37.38	65.00	76.31

Experiments: (Analysis of the Learned Embedding)

Neuron visualization

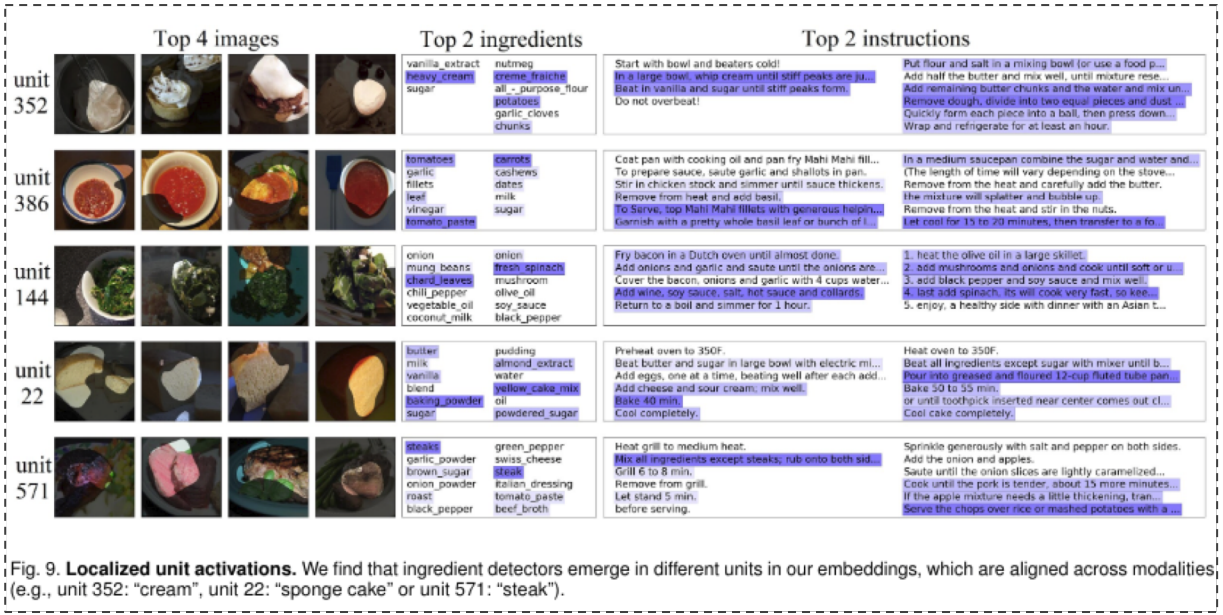


Fig. 9. **Localized unit activations.** We find that ingredient detectors emerge in different units in our embeddings, which are aligned across modalities (e.g., unit 352: “cream”, unit 22: “sponge cake” or unit 571: “steak”).

Experiments

Semantic Vector Arithmetic

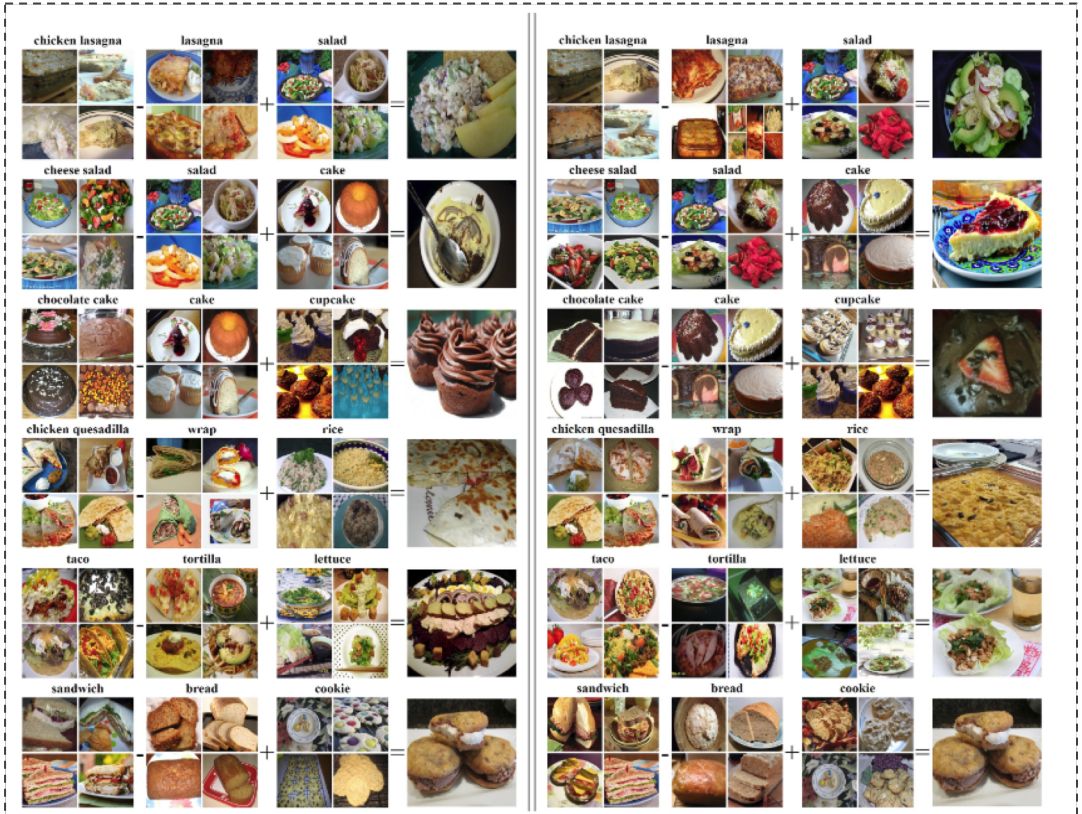


Fig. 10. **Analogy arithmetic results using recipe embeddings** on the Recipe1M test set. On the left hand side are arithmetic results using the model trained on Recipe1M. On the right hand side are the arithmetic results for the model trained on Recipe1M+. We represent the average vector of a query with the images from its 4 nearest neighbors. In the case of the arithmetic result, we show the nearest neighbor only.

Experiments

Fractional Arithmetic

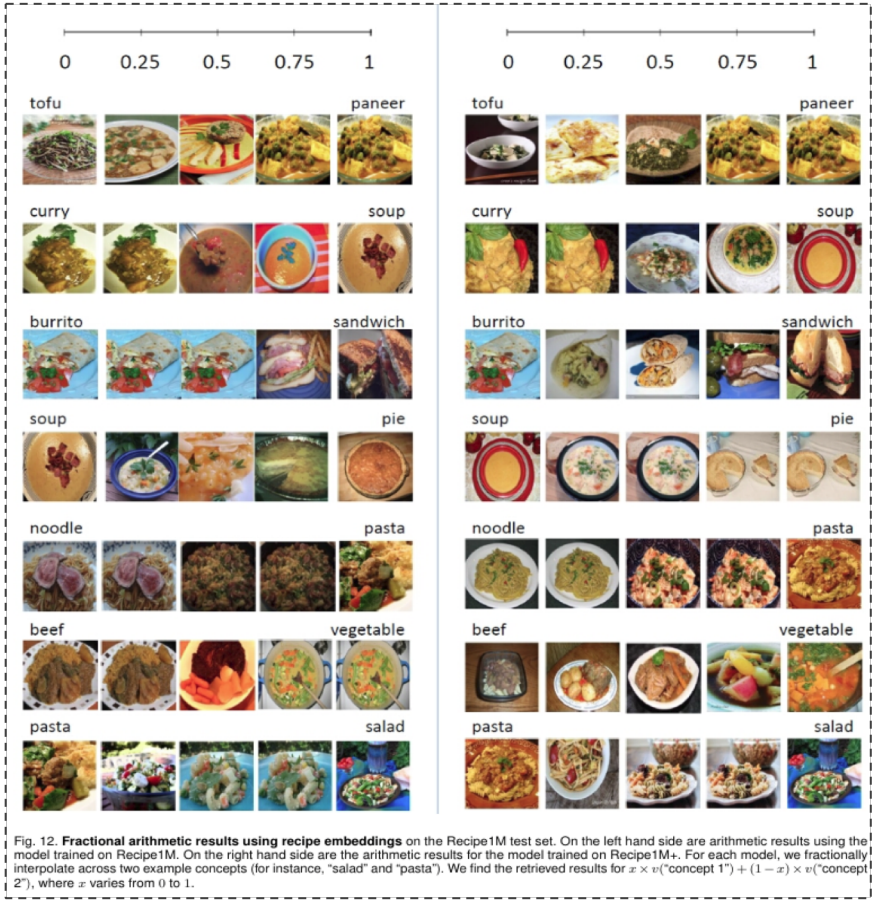
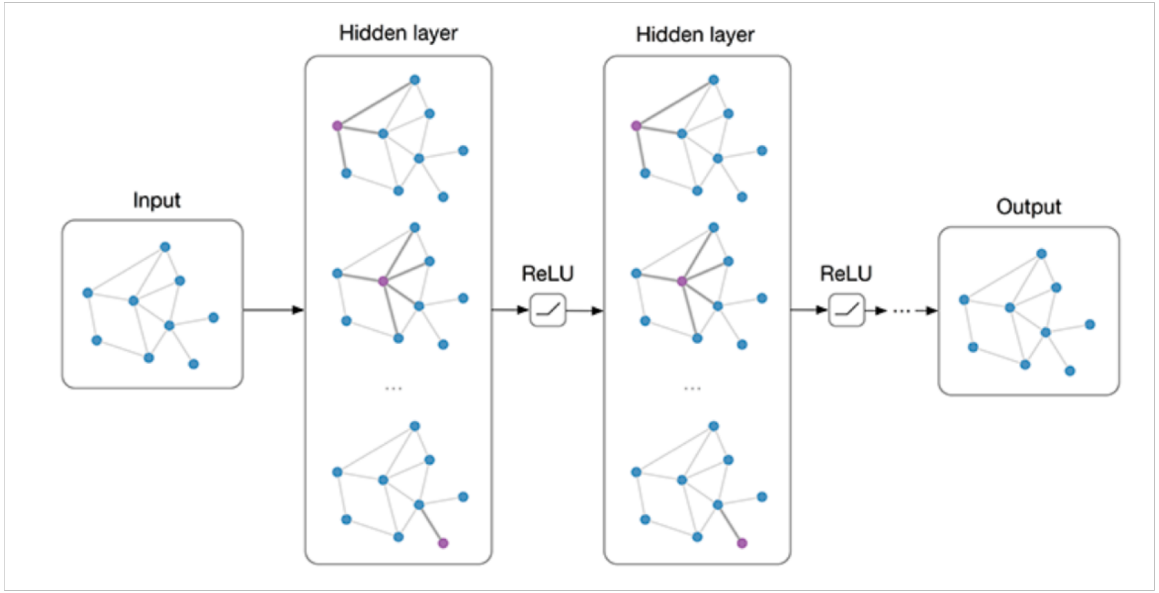


Fig. 12. **Fractional arithmetic results using recipe embeddings** on the Recipe1M test set. On the left hand side are arithmetic results using the model trained on Recipe1M. On the right hand side are the arithmetic results for the model trained on Recipe1M+. For each model, we fractionally interpolate across two example concepts (for instance, "salad" and "pasta"). We find the retrieved results for $x \times v(\text{"concept 1"}) + (1-x) \times v(\text{"concept 2"})$, where x varies from 0 to 1.

Additional thoughts

Graph Model



Ingredients Model

Node Initialization

Adjacency Matrix

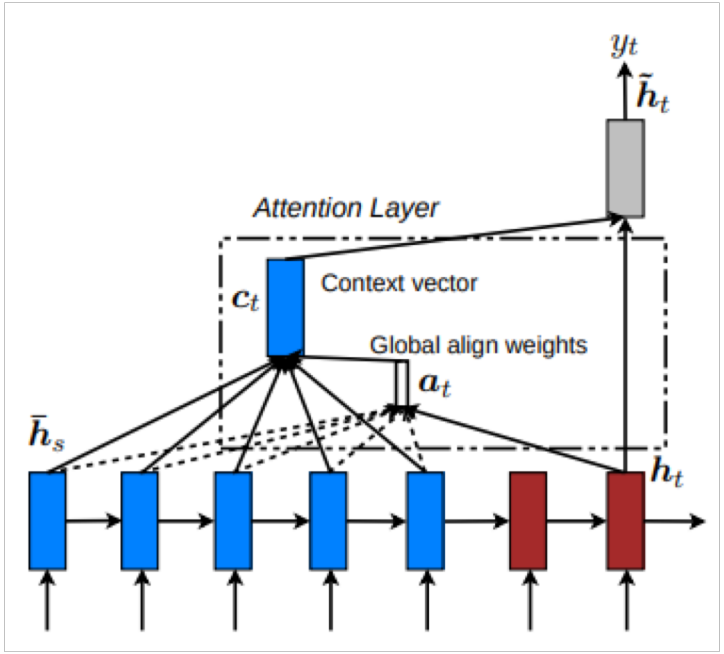
Edge Weights

$$a_v^{(k)} = \text{MEAN}\left(\left\{\text{ReLU}\left(W \cdot h_u^{(k-1)}\right), \forall u \in \mathcal{N}(v)\right\}\right)$$

$$h_G = \text{READOUT}\left(\left\{h_v^{(K)} \mid v \in G\right\}\right)$$

Additional Thoughts

Attention



Questions?