

GILT: Generating Images from Long Text

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Abstract

Creating an image reflecting the content of a long text is a complex process that requires a sense of creativity. For example, creating a book cover or a movie poster based on their summary or a food image based on its recipe. In this paper we present the new task of generating images from long text that does not describe the visual content of the image directly. For this, we build a system for generating high-resolution 256×256 images of food conditioned on their recipes. The relation between the recipe text (without its title) to the visual content of the image is vague, and the textual structure of recipes is complex, consisting of two sections (ingredients and instructions) both containing multiple sentences. We used the recipe1M [11] dataset to train and evaluate our model that is based on a the StackGAN-v2 architecture [15].

1. Introduction

Generating images from text is a challenging task and has many applications in computer vision. Recent works have shown that Generative Adversarial Networks (GAN) are effective in synthesizing high-quality, realistic images from datasets with low variability and low-resolution [8, 3]. Further work also showed that given a text description, conditional GANs (cGAN) [5] generate convincing images related directly to the text content [9].

All recent text to image synthesis cGANs used a short visual description of the image, with low complexity and a consistent pattern of descriptions, and the images themselves had low variability. E.g. Zhan et al. [15, 16] used the CUB dataset [14] containing 200 bird species with 11,788 images and corresponding description and Oxford-102 dataset [6] containing 8,189 images of flowers from 102 different categories (see Figure 1). Recently the dataset recipe1M, containing 800K pairs of recipes and their corresponding images, was published as part of [11]. In comparison to the CUB and Oxford-102 datasets, this dataset

has a high variability due to the variety of food categories and subcategories. Moreover, the text related to the image is complex. It consists of 2 sections (ingredients and instructions), that together might contain tens of lines (e.g. Figure 2).



Figure 1. Image samples from CUB and Oxford-102 datasets, and their corresponding text descriptions

We propose a novel task of synthesizing images from long text, that is related to the image but does not contain visual description of it. Specifically, We propose a baseline to this task by combining the state-of-the-art Stacked Generative Adversarial Network [15] and the two proposals of recipe embeddings computed in im2recipe [11] to generate food images conditioned on their recipes. We also present extensive qualitative and quantitative experiments using hu-

man ranking, MS-SSIM [13] and inception scores [10], to compare the effectiveness of the two embedding methods.

Our code is available at

<https://github.com/netanelyo/Recipe2ImageGAN>.

2. Related Work

Generating high-resolution images conditioned on text descriptions is a fundamental problem in computer vision. This problem is being studied extensively and various approaches were suggested to tackle it. Deep generative models, such as [16, 15, 12, 17], achieved tremendous progress in this domain. In order to get high-resolution images they used multi-stage GANs, where each stage corrects defects and adds details w.r.t. the previous stage. In [12], Xu et al. use Deep Attentional Multimodal Similarity Model (DAMSM) for text embedding. DAMSM learns two neural networks that map sub regions of the image and words of the sentence to a common semantic space. Thus, measures the image-text similarity at the word level to compute a fine-grained loss for image generation.

3. Learning Embeddings

Our cGAN uses the embedding of the entire recipe (except for its title) as a condition. To generate that embedding we leverage the methods used in [11]. They [11] proposed two types of embedding methods, where the second adds a semantic regularization loss component. Throughout this paper we will refer to the first method without semantic regularization as NORREG, and the second with semantic regularization as REG. The embedding methods are composed of the following steps (for the concrete architecture see the original paper).

1. Preliminary embedding of the ingredients.
2. Preliminary embedding of the cooking instructions.

Potato & Smoked Sausage Hash

Instructions:

- 1) Heat 1 tablespoon oil in a cast-iron skillet over medium-high heat.
- 2) Add the potatoes, season with seasoning salt and pepper, and allow them to get a brown crust on one side before stirring.
- 3) Continue to brown the potatoes until they have a brown crust on at least two sides.
- 4) When the potatoes are browned and crisp, push them to one side of the pan and add the smoked sausage, getting a nice browning on the sausage as well.
- 5) Meanwhile, heat remaining oil in another skillet over medium-high heat.
- 6) Add the peppers and red onion, stirring often.
- 7) Cook until the vegetables are tender and begin to brown.
- 8) Add the cooked peppers and onions to the cast iron skillet with the potatoes and sausage and toss to combine.
- 9) Taste for seasoning and add more salt and pepper if needed.
- 10) Serve promptly, preferably with ketchup and/or hot sauce on the side.
- 11) Note: I par-bake my potatoes in the microwave for 5-7 minutes, then peel and chop.
- 12) You want them to be soft on the outside, but still slightly underdone in the middle.
- 13) If they are fully baked, they will turn to mush in the pan.
- 14) You want them to keep their shape but be soft on the exterior so that you can get that nice brown crust on them in the skillet.



Ingredients:

- 1) 2 Tablespoons Canola Oil, Divided
- 2) 4 whole Medium Potatoes, Par-baked*, Peeled, And Cubed
- 3) 1/2 teaspoons Seasoning Salt
- 4) 1/2 teaspoons Pepper
- 5) 13 ounces, weight Smoked Sausage, Sliced Into 1-inch Pieces
- 6) 1 whole Green Bell Pepper, Seeded and Chopped Into 1 Inch Pieces
- 7) 1 whole Red Bell Pepper, Seeded and Chopped Into 1-inch Pieces
- 8) 1 whole Small Red Onion, Chopped Into 1-inch Pieces

Figure 2. Food image and its corresponding text descriptions (recipe) sampled from [11]

3. Joint neural embedding of the entire recipe (using the concatenation of the former preliminary embeddings) and the image into a common space, using cosine similarity loss between the embeddings of recipe-image pairs.

4. Adding a semantic regularization loss using a high-level classification objective (used in REG only)

We employ these methods as explained in the original paper.

4. Stacked Generative Adversarial Networks

Originally, GANs [4] are a combination of two models that are trained to compete with each other. In the training process both the generator G and the discriminator D are trained. G is optimized to reproduce images similar to the original data distribution, by generating images that are difficult for the discriminator D to differ from the true images. D is trained to distinguish between real images and fake synthetic ones, generated by G . This training is similar to solving a minimax of 2 players game, with the objective function, [4]

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{data}} [\log D(x)] + \mathbb{E}_{z \sim p_z} [\log(1 - D(G(z)))] \quad (1)$$

where x is an image sampled from the real distribution p_{data} and z is the noise vector, which is sampled from a prior distribution p_z (e.g Uniform or Gaussian), used by G to generate the synthetic image.

In the case of Conditional GANs [12, 15, 16, 9] both the generator and the discriminator are compelled to consider another variable c . We denote $D(x, c)$ and $G(z, c)$ to be the generator G and the discriminator D conditioned by c , respectively. Meaning that G is able to generate images, and D discriminate them, conditioned on c .

The StackGAN-v2 model, introduced in StackGAN++, by Zhang et al. [15], is an end-to-end network for modeling a series of multi-scale image distributions. The architecture of this model is consisted of several generators and discriminators in a tree-like structure framework (for the concrete architecture see the original paper). Given a noise vector $z \sim p_z$ and condition c StackGAN-v2 generates images from low-resolution to high-resolution from different branches of the tree. In our case c is one of the recipe embeddings from section 4. Overall, we have one model for each of the two embeddings.

5. Implementation details

We compare two types of embedding methods from [11]. The first method is based on cosine-similarity loss only and is of size 1024. The second method uses additionally a high-level classification objective to compute embedding of size



Figure 3. Comparison of the real image, the generated image using the semantic-regularization (REG), and without the regularization (NOREG), **where most humans preferred the regularized images**.

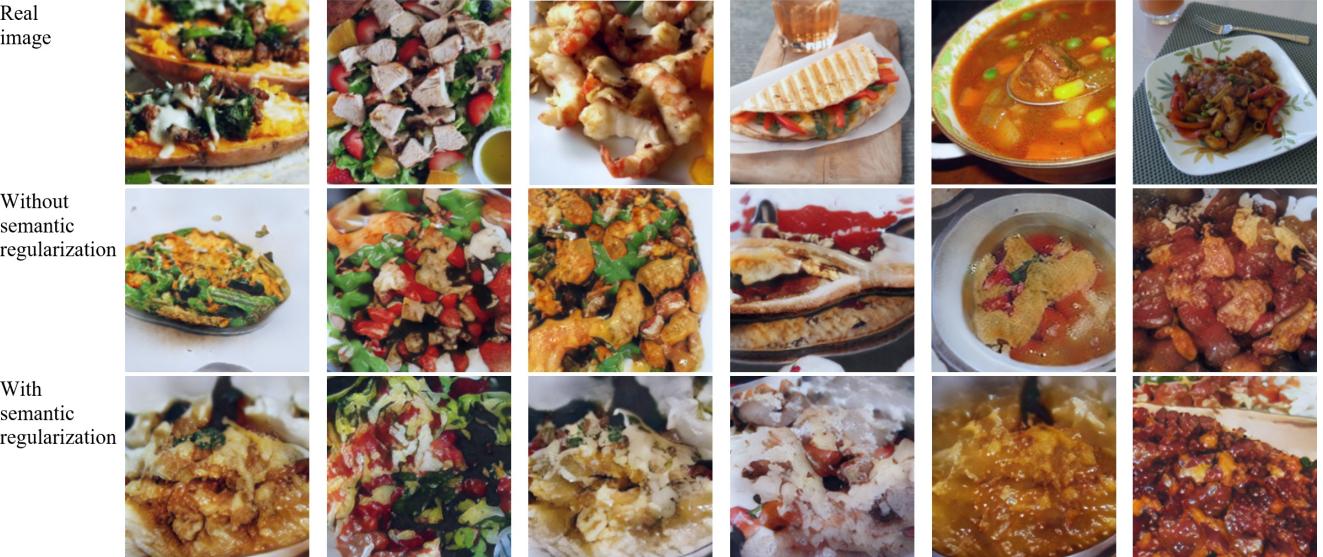


Figure 4. Comparison of the real image, the generated image without using the semantic-regularization (NOREG), and with semantic-regularization (REG), **where most humans preferred the non-regularized images**.

1048. For training the StackGAN-v2 [15] model we used a batch size of 24. Trying to use a larger batch size resulted in a mode-collapse. The text-embedding dimension parameter presented in StackGAN-v2 was of size 128. At first we used this parameter with our training and got poor results. We realized that by projecting the rich text on this small dimension, we might omit discriminative subtleties between different recipes. As a result we used 1024 as the text-embedding dimension parameter for both of the embeddings methods. In order to accelerate the training process we used hdf5 (hierarchical data format) to map files to memory. All neural models were implemented using PyTorch framework. All other parameters are identical to [11]

and [15]. The models were trained on 3 Nvidia Titan-X GPUs, each has 12GB of memory, for 100 epochs on each of the embedding methods.

6. Experiments

To evaluate our models, we conduct quantitative, in the form of Inception Score (IS) [10], and qualitative, in the form of Human Rankings (HR), evaluations. We compare the aforementioned evaluation methods on images generated by two different text embedding methods, which both are computed using [11]. In addition, we show outputs from several state-of-the-art and previous state-of-the-art text-to-image synthesis models, which indicate that generating re-

Real image		Salad with Grilled Chicken and Citrus Poppy Seed Dressing ingredients 1/2 cups Orange Juice, Freshly Squeezed 1/4 cup Water 2 teaspoons Distilled Vinegar 1/2 teaspoons Stevia Or Granulated Sugar 2 teaspoons Poppy Seeds 1 dash Salt 8 ounces, weight Boneless, Skinless Chicken Breasts 4 cups Romaine Lettuce, Chopped 1/2 cups Strawberries, Diced 1/2 cups Blueberries 1 whole Orange Or Mandarin Orange, Peeled, Cut Into Pieces 1/4 cups Pineapple, Sliced Into Thin Pieces 2 Tablespoons Walnuts, Roughly Chopped 1/2 cups Poppy Seed Dressing instructions For the dressing: In a bowl, add orange juice, water, vinegar, Stevia, poppy seeds and salt and whisk together until combined. Recipe makes 3/4 cups. For chicken: Marinate chicken breasts in 1/4 cup of poppy seed dressing for 1-4 hours. When ready to cook: Heat grill to medium. Cook chicken for about 7 minutes per side until no longer pink. When done, remove it from the grill. Once cool enough to handle, cut it into chunks. To assemble salad: Meanwhile on two plates, evenly divide the lettuce, strawberries, blueberries, orange, pineapple and walnuts. Add chicken to each plate. Top with 2 tablespoons of poppy seed dressing for each salad.
With semantic regularization		Cashew Rice Pilaf ingredients 13 cup onion, finely chopped 1 garlic clove, minced 14 cup butter, melted 2 cups chicken broth 1 cup long-grain rice, uncooked 12 teaspoon salt 12 cup cashews, chopped 14 cup fresh parsley, chopped instructions Saute the onion in the melted butter in a large skillet over medium-high heat, stirring constantly (about 4 minutes). When the onions are almost tender, reduce the heat and add the minced garlic. Cook for 2 minutes more. Add the chicken broth, rice and salt; bring to a boil. Cover and reduce heat. Simmer for 25 minutes or until the rice is tender and the liquid is absorbed. Remove from heat, and stir in the cashews and parsley.
Without semantic regularization		Rice Pilaf instructions Saute the onion in the melted butter in a large skillet over medium-high heat, stirring constantly (about 4 minutes). When the onions are almost tender, reduce the heat and add the minced garlic. Cook for 2 minutes more. Add the chicken broth, rice and salt; bring to a boil. Cover and reduce heat. Simmer for 25 minutes or until the rice is tender and the liquid is absorbed. Remove from heat, and stir in the cashews and parsley.

Figure 5. Comparison of the real image, the generated image with using the semantic-regularization (REG) and without semantic-regularization (NOREG), top-to-bottom, and the corresponding recipe. One can notice that in the generated image using semantic-regularization (on the right side), it has a dominant green color, which is, probably, due to the parsley that in the ingredients, and is different than the real image.

alistic food-images based on their description is a challenging task, and all the more so based on their recipe. Moreover, we examine the diversity of the generated images using MS-SSIM [13].

6.1. Datasets and evaluation metrics

Recipe1M [11] contains over 1 million recipes and 800k food images. Due to hardware limitations, we used a training set of 52k and an evaluation set of 24k recipe-image pairs. In the pre-processing stage, the images were down-scaled from 256×256 to 128×128 and 64×64 , in-order to train on different image scales. Further more, the images were cropped and horizontally flipped randomly. This was a best-effort to focus on the food object in the image, but from time to time, the cropping eliminated important details from the original image.

Evaluation metrics. Even though evaluating generative models is often a difficult task (as mentioned in [1]), to compare between the generated images in both embedding methods quantitatively (numerically) we use Inspection-Score,

$$IS = \exp(\mathbb{E}_{\mathbf{x}} D_{KL}(p(y|\mathbf{x}) || p(y))), \quad (2)$$

Where \mathbf{x} denotes a single generated sample, y is the predicted label, $p(y|\mathbf{x})$ and $p(y)$ are the conditional and marginal class distributions, respectively, and D_{KL} is the Kullback-Leibler (KL) divergence. Intuitively, the IS measures the diversity, with respect to ImageNet [2] classes, and clarity of the generated images. Therefore, the KL-divergence (hence the IS), of a successful generator should be large. We evaluate the IS on the evaluation set, which contains 24k randomly chosen samples. In spite of the sub-optimality of IS, stated in [1], it is the most popular method to evaluate generative models.

Metric \ Embedding Type		REG	NOREG
Inception Score		4.42 ± 0.17	4.55 ± 0.20
Human Ranking	Q 1 Q 2 Q 3	2.62 2.24 3.05	2.88 2.70 3.72

Table 1. Inception scores and average human rankings of our results.



Figure 6. Example results of food images generated by HDGAN [17], AttnGAN [12] and StackGAN++ [15] conditioned on text descriptions.

Due to the aforementioned suboptimality of IS and the fact that it does not reflect the correlation between the generated image and the recipe it is conditioned on, a qualitative evaluation metric was used. Therefore, 30 people were asked to rank, a total of 10 samples, in several aspects:

1. The strength of the relation between a generated image and its corresponding recipe.
2. The strength of the relation between a generated image and its corresponding real image.
3. In which degree the image appears to be a real food image.

The final human rankings are the average of the above.

Embedding Type	MS-SSIM score
REG	0.17
NOREG	0.07

Table 2. MS-SSIM[13] score of randomly chosen images from our results.

6.2. Quantitative and qualitative results

As one can see by the examples shown in Figure 6, the state-of-the-art and previous state-of-the-art text-to-image synthesis models yields unsatisfying results, in spite of the concise and visually descriptive text on which it is conditioned.

We compare our model between the two mentioned text embedding methods, *i.e.*, embedding with semantic regularization and without it. The inception scores and average human ranks for our models are reported in Table 1. As can be seen in the table, the embedding without semantic regularization achieves the better IS and HR (in all aspects) scores. Representative examples are compared in Figures 3, 4 and 5.

Human rankings. 10 corresponding pairs of generated images were chosen, from each embedding method evaluation results (*i.e.*, images that were generated conditioned on the same recipe). Our subjects were asked to rank the images in the aforementioned aspects, on a scale of 1 to 5. As mentioned earlier, the model trained conditioned on the cosine-similarity based embedding method yielded results that are close to real-like images. It is worth mentioning that there were real food images that were given less-than-or-equal rank in comparison to generated images (in the cosine-similarity embedding evaluation).

6.3. Diversity

The most successful method to evaluate image similarity, as mentioned in [7], is multi-scale structural similarity (MS-SSIM [13]). The method attempts to discount the image aspects that are not important to the human eye. To evaluate the diversity of the images generated by our model, 200 random images from the evaluation set were chosen, and we calculated the MS-SSIM score for each pair. The results can be seen in Table 2. One can see that the embedding method without semantic regularization, achieved better score (lower is better), *i.e.*, generated more diverse images. These results might be explained by the fact that - when using semantic regularization, the classification based regularization aims to map the recipe embedding to one of the 1048 classes in a discrete manner, instead of utilizing the entire space.

7. Conclusions

In this paper, we propose an end-to-end system for high-resolution long text to image synthesis using Stacked Generative Adversarial Network (StackGAN-v2). We compare two embedding types, one based on cosine-similarity (NOREG) and the second combines a high-level classification objective (REG). The proposed methods prove their

ability to generate photo-realistic images of food from their text recipe (ingredients and instructions only). Herein, we provide a baseline for this novel task. It is worth mentioning that the quality of the images in the recipe1M dataset [11] is low in comparison to the images in CUB [14] and Oxford-102 datasets [6]. This is reflected by lots of blurred images with bad lighting conditions, "porridge-like images" and the fact that the images are not square shaped (which makes it difficult to train the models). This fact might give an explanation to the fact that both models succeeded in generating "porridge-like" food images (e.g. pasta, rice, soups, salad) but struggles to generate food images that have a distinctive shape (e.g. hamburger, chicken, drinks). From the results, it is evident that the method NOREG outperforms the method REG, by generating more vivid images with more photo-realistic details. Moreover, the inception score and diversity measures of the former is better than the latter. Overall, we show that although REG outperforms NOREG in a classification task (see [11]) it is inferior for generating new images.

References

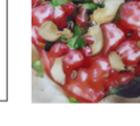
- [1] S. Barratt and R. Sharma. A Note on the Inception Score. *ArXiv e-prints*, Jan. 2018. [4](#)
- [2] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. Imagenet: A large-scale hierarchical image database. In *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on*, pages 248–255. Ieee, 2009. [4](#)
- [3] E. Denton, S. Chintala, A. Szlam, and R. Fergus. Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks. *ArXiv e-prints*, June 2015. [1](#)
- [4] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. Generative Adversarial Networks. *ArXiv e-prints*, June 2014. [2](#)
- [5] M. Mirza and S. Osindero. Conditional Generative Adversarial Nets. *ArXiv e-prints*, Nov. 2014. [1](#)
- [6] M.-E. Nilsback and A. Zisserman. Automated flower classification over a large number of classes. In *Proceedings of the Indian Conference on Computer Vision, Graphics and Image Processing*, Dec 2008. [1, 5](#)
- [7] A. Odena, C. Olah, and J. Shlens. Conditional Image Synthesis With Auxiliary Classifier GANs. *ArXiv e-prints*, Oct. 2016. [5](#)
- [8] A. Radford, L. Metz, and S. Chintala. Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks. *ArXiv e-prints*, Nov. 2015. [1](#)
- [9] S. Reed, Z. Akata, X. Yan, L. Logeswaran, B. Schiele, and H. Lee. Generative Adversarial Text to Image Synthesis. *ArXiv e-prints*, May 2016. [1, 2](#)
- [10] T. Salimans, I. J. Goodfellow, W. Zaremba, V. Cheung, A. Radford, and X. Chen. Improved techniques for training gans. *CoRR*, abs/1606.03498, 2016. [2, 3](#)
- [11] A. Salvador, N. Hynes, Y. Aytar, J. Marin, F. Ofli, I. Weber, and A. Torralba. Learning cross-modal embeddings for

- cooking recipes and food images. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2017. [1](#), [2](#), [3](#), [4](#), [5](#)
- [12] Q. H. H. Z. Z. G. X. H. X. H. Tao Xu, Pengchuan Zhang. AttnGAN: Fine-grained text to image generation with attentional generative adversarial networks. 2018. [2](#), [4](#)
 - [13] Z. Wang, E. P. Simoncelli, and A. C. Bovik. Multiscale structural similarity for image quality assessment. In *The Thirty-Seventh Asilomar Conference on Signals, Systems Computers*, 2003, volume 2, pages 1398–1402 Vol.2, Nov 2003. [2](#), [4](#), [5](#)
 - [14] P. Welinder, S. Branson, T. Mita, C. Wah, F. Schroff, S. Belongie, and P. Perona. Caltech-UCSD Birds 200. Technical Report CNS-TR-2010-001, California Institute of Technology, 2010. [1](#), [5](#)
 - [15] H. Zhang, T. Xu, H. Li, S. Zhang, X. Wang, X. Huang, and D. Metaxas. Stackgan++: Realistic image synthesis with stacked generative adversarial networks. *arXiv: 1710.10916*, 2017. [1](#), [2](#), [3](#), [4](#)
 - [16] H. Zhang, T. Xu, H. Li, S. Zhang, X. Wang, X. Huang, and D. Metaxas. Stackgan: Text to photo-realistic image synthesis with stacked generative adversarial networks. In *ICCV*, 2017. [1](#), [2](#)
 - [17] Z. Zhang, Y. Xie, and L. Yang. Photographic text-to-image synthesis with a hierarchically-nested adversarial network. *CoRR*, abs/1802.09178, 2018. [2](#), [4](#)

Supplementary Materials

More Results of Generated Images by Both Embedding Methods and their Corresponding Recipes.

Real image		Sautéed kale with pancetta ingredients 1 kale 1 pancetta 2 leeks 1 lemon 1 garlic 1 chili pepper 1 salt 1 pepper 1 apple 1 parmesan cheese instructions Add leeks, apple, chili pepper, garlic, zest and juice of 1 lemon		Hot Pepper and Garlic Shrimp ingredients 2 lbs large shrimp, peeled and deveined 10 large garlic cloves, peeled and thinly sliced 14 teaspoon crushed red pepper flakes 12 teaspoon fine sea salt 13 cup extra virgin olive oil 1 tablespoon fresh lemon juice instructions Pat shrimp dry. Heat oil in a large heavy skillet over moderately low heat and add garlic, red pepper flakes and sea salt. Cook until garlic is pale golden, about 4 to 5 minutes. Increase heat to moderately high and add shrimp. Sauté shrimp turning occasionally, about 3 to 4 minutes. Remove from heat and stir in lemon juice and transfer to a serving bowl.
With semantic regularization				
Without semantic regularization				
Real image		Southwest Chicken Panini ingredients 1 (6 inch) flour tortillas 1 tablespoon chipotle mayonnaise (suggested, Kraft reduced-fat) 4 slices lunch meat (suggested, Oscar Mayer Deli Fresh Rotisserie Seasoned Chicken Breast) 1 slice colby-monterey jack cheese (suggested, Kraft Big Slice) 14 cup red pepper, cut into strips 2 tablespoons chopped fresh cilantro instructions Heat panini grill sprayed with cooking spray. Spread tortilla with mayonnaise. Layer remaining ingredients on half of tortilla; fold tortilla in half. Grill 2 to 3 minutes or until golden brown. Variations: No Panini Grill? Use a skillet. Heat skillet on medium heat. Cook sandwich 3 minutes on each side or until cheese is melted and sandwich is golden brown on both sides, gently pressing down top of sandwich with spatula to flatten slightly as it cooks.		Bang Bang Pasta ingredients 8 oz Linguine Noodles 1/4 cup Thai Sweet Chili Sauce 1/2 cup Mayonnaise 1 tbsp Lime Juice 2 tbsp Sriracha Sauce 1 Green Onions for Garnish 1/2 lb Boneless Chicken Breast (Mine was Pre-Made and Cut) 1/2 tsp Honey instructions Cook pasta noodles as directed. While pasta is cooking mix together Sriracha, mayonnaise, lime juice, chili sauce and honey. Mix chicken into the sauce. Mix together chicken into the noodles until everything is combined. Serve and enjoy!
With semantic regularization				
Without semantic regularization				
Real image		Steak Soup ingredients 2 tablespoons butter 2 tablespoons vegetable oil 1 1/2 pounds lean boneless beef round steak, cut into cubes 1/2 cup chopped onion 3 tablespoons all-purpose flour 1 tablespoon paprika 1 teaspoon salt 1/4 teaspoon ground black pepper 4 cups beef broth 2 cups water 4 sprigs fresh parsley, chopped 2 tablespoons chopped celery leaves 1 bay leaf 1/2 teaspoon dried marjoram 1 1/2 cups peeled, diced Yukon Gold potatoes 1 1/2 cups sliced carrots 1 1/2 cups chopped celery 1 (15.25 ounce) can whole kernel corn, drained instructions Melt butter and oil in a large skillet over medium heat until the foam disappears from the butter, and stir in the meat cubes and onion. Cook and stir until the meat and onion are browned, about 10 minutes. While it's browning, mix together flour, paprika, salt, and pepper in a bowl. Sprinkle the flour mixture over the browned meat, and stir to coat. In a large soup pot, pour in the beef broth and water, and stir in the parsley, celery leaves, bay leaf, and marjoram. Stir in beef mixture, and bring to a boil. Reduce heat to medium-low, cover the pot, and simmer, stirring occasionally, until meat is tender, about 45 minutes. Mix in the potatoes, carrots, celery, tomato paste, and corn; bring the soup back to a simmer, and cook uncovered, stirring occasionally, until the vegetables are tender and the soup is thick, 15 to 20 minutes. Remove bay leaf and serve hot.		Sugar Free Granola ingredients 1 cup chopped dates 1 cup water 8 cups rolled oats 1/2 cup chopped walnuts 1 cup wheat germ 1/2 cup sunflower seeds 1/2 cup slivered almonds 2 cups shredded coconut 1/4 cup vegetable oil 1/4 cup frozen apple juice concentrate, thawed instructions Preheat the oven to 350 degrees F (175 degrees C). In a small saucepan over medium heat, combine the dates and water. Cook stirring occasionally until the mixture forms a thick paste. Remove from heat and set aside. In a large bowl, mix together the oats, walnuts, raisins, wheat germ, sunflower seeds, and coconut. Spread out in a thin layer onto a baking sheet. If baking sheet is small, this can be done in batches. Bake for 7 minutes in the preheated oven, or until lightly toasted. Transfer the mixture back into the bowl, and mix in the date paste, apple juice concentrate, and oil. Return to the baking sheet and bake for an additional 7 to 10 minutes, stirring occasionally until lightly browned. Granola will become more crispy as it cools. Store in an airtight container.
With semantic regularization				
Without semantic regularization				

Real image		<p>Country Captain for the Slow-Cooker</p> <p>ingredients</p> <ul style="list-style-type: none">8 oz chicken, excess fat trimmed, with bone and skinsalt & pepper (I use Johnny's) or your favorite seasoning (I use Johnny's)1 tablespoon olive oil2 onions, chopped coarse1 green bell pepper, seeded and chopped coarse1 (14 1/2 ounce) can chicken broth1 (14 1/2 ounce) can diced tomatoes1 (6 ounce) can smoky paprika12 ounces mango chutney, Laurel's Mango Chutney OR 2 (9 ounce) jars bottled chutney, such as Major Grey's Cutney, large pieces of mango snipped6 garlic cloves, minced2 tablespoons Madras curry powder1 1/2 teaspoons paprika1 teaspoon dried thyme12 teaspoon cayenne (to taste)shredded coconut (for garnish)toasted sliced almonds (for garnish) <p>instructions</p> <ul style="list-style-type: none">Heat oil in a skillet, season chicken and brown on both sides, about 10 minutes. Remove chicken to platter. Let cool a bit, remove and discard skin.Put chicken in crockpot.Pour off all but 1 Tablespoon fat and cook onions and bell pepper with about 1/2 teaspoon salt until somewhat tender, about 5 minutes.Add broth, tomatoes and tomato paste and scrape up browned bits and cook and stir until slightly thickened and smooth, only about 3 minutes.Remove from heat and add cayenne, garlic, curry powder, thyme, paprika and cayenne. Pour this mixture over chicken in crockpot.Cover and cook on low for 5 hours.Stir before serving over white rice.Add coconut and sliced almonds on top. <p>This is necessary for the most authentic taste of Country Captain!</p>	  	<p>Yummy Mexican Lasagna W/ a Healthier Kick!</p> <p>ingredients</p> <ul style="list-style-type: none">2 lbs ground turkey1 yellow onion (chopped)2 teaspoons garlic, minced1 (16 ounce) can taco sauce1 (10 ounce) can rotel1 (2 ounce) can black olives, slice1 (10 ounce) can refried beans1 (10 ounce) can fat-free refried beans1 (28 ounce) Mexican cheese blend <p>instructions</p> <p>Preheat Oven to 350.</p> <p>brown Turkey in skillet over medium heat for 5 mins, add onion and garlic and sautee another 5 mins, add taco sauce, rotel, black olives, refried beans and simmer on low for 15 minutes</p> <p>In a 3 quart casserole dish put a thin layer of meat mixture at the bottom, place 2 overlapping tortillas on top.</p> <p>Then add a layer of meat mixture and cheese, repeat w/ tortillas, meat, cheese until tortillas are gone -- leaving a layer of the meat mixture w/ loads of cheese on top.</p> <p>Bake at 350 for 20 mins or until cheese is melted and bubbly.</p> <p>Enjoy!</p>
With semantic regularization		<p>Without semantic regularization</p> <p>Without semantic regularization</p>		
Real image		<p>Bavarian Apple Torte</p> <p>ingredients</p> <ul style="list-style-type: none">12 cup butter13 cup sugar14 teaspoon vanilla1 cup flour14 cup raspberry jam8 ounces cream cheese14 cup sugar1 egg12 teaspoon vanilla13 cup sugar12 teaspoon cinnamon4 cups apples, peeled,cored & sliced12 cup sliced almonds <p>instructions</p> <p>Preheat oven to 450.</p> <p>cream cheese and vanilla.</p> <p>Mix in flour.</p> <p>Press into 9" springform pan and spread with jam.</p> <p>Combine cream cheese and sugar.</p> <p>Add egg and vanilla.</p> <p>Mix well.</p> <p>Pour over jam.</p> <p>Topping: Toss apples with sugar and cinnamon and spoon over cheese.</p> <p>Sprinkle almonds on top.</p> <p>Bake at 450 for 10 minutes; then 400 for 25 minutes.</p> <p>Cool.</p>	  	<p>Fusion Aloo Rasadar</p> <p>ingredients</p> <ul style="list-style-type: none">3 large potatoes, diced3 tomatoes, diced4 tablespoons oil1 teaspoon cumin seed1 pinch asafoetida powder34 teaspoon turmeric powder34 teaspoon chili powder1 teaspoon coriander powder1 teaspoon salt1 cup water12 teaspoons garam masala1 cup dried Chinese mushrooms, shredded <p>instructions</p> <p>Heat oil and add cumin seeds and asafoetida powder.</p> <p>Let it sizzle for about 30 seconds.</p> <p>Add the tomatoes, turmeric, chilli, salt, and coriander powder and fry for 30 seconds.</p> <p>Add your potatoes in and fry for 2 minutes.</p> <p>Add in water, bring to a boil, lower to a simmer and cook, covered, for about 10 minutes.</p> <p>Stir in mushrooms and garam masala.</p> <p>Stir well for 1 min and cover for around another 5 minutes.</p> <p>Serve.</p>
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Real image		<p>Baked Sweet Potatoes with Spicy Turkey Sausage and Broccoli Rabe</p> <p>ingredients</p> <ul style="list-style-type: none">4 whole Medium Sweet Potatoes, Halved Lengthwise4 Tablespoons Olive Oil + Plus More To Brush On Sweet Potatoes22 ounces Spicy Italian Turkey Sausage, Casings Removed2 pieces Shallots, Thinly Sliced1 bunch Broccoli Rabe, Tough Stems Trimmed2 cloves Garlic, Thinly Sliced1/2 teaspoons Paprika1/2 teaspoons Salt1/2 cups Shredded Cheddar Cheese <p>instructions</p> <p>Bake at 400 degrees F.</p> <p>Cut the sweet potatoes in half lengthwise.</p> <p>Brush with olive oil and place face-side down on a parchment-lined baking sheet.</p> <p>Bake until fork-tender, about 25 to 30 minutes.</p> <p>Set aside until cool enough to touch.</p> <p>Meanwhile, heat 1 tablespoon olive oil in a large cast iron skillet.</p> <p>Brown the sausage over medium-high heat, breaking it into pieces with your spatula, until cooked through, 5 minutes.</p> <p>Add the shallots and broccoli rabe and cook, stirring occasionally, until soft and lightly charred, 5 minutes.</p> <p>Add the garlic, paprika, and salt.</p> <p>Cook one minute more.</p> <p>Remove from heat.</p> <p>Using a fork, carefully fluff the center of the sweet potato, creating a well for the filling.</p> <p>Sprinkle each sweet potato with 1 tablespoon of the cheese.</p> <p>Divide the sausage mixture between the potatoes, gently patting the filling into the center of the potatoes.</p> <p>Top with the remaining cheese.</p> <p>Return the potatoes to the oven until the cheese is melted and beginning to brown, 5 to 10 minutes.</p> <p>Serve immediately.</p>	  	<p>Cantaloupe and Capicola Bites with Basil and Balsamic Reduction</p> <p>ingredients</p> <ul style="list-style-type: none">24 slices Capicola, Thinly Sliced3/4 cups Balsamic Vinegar1/2 whole Cantaloupe12 leaves Basil <p>instructions</p> <p>Pre-heat oven to 400 degrees F. Place capicola slices into the holes in a 24-count mini muffin tin.</p> <p>Press the capicola in firmly to form a cup.</p> <p>Place in the oven and bake for 8 to 10 minutes until slightly crispy.</p> <p>While the capicola is baking, bring the balsamic vinegar to a boil in a saucepan.</p> <p>Once it boils, lower the heat to medium-low and simmer for about 8 to 10 minutes until the vinegar has reduced by half creating a sweet and tangy syrup.</p> <p>Next, halve a cantaloupe and deseed it.</p> <p>Cut the half into quarters, cut the rind away and dice the cantaloupe into small cubes.</p> <p>Chiffonade the basil by stacking the leaves on top of each other and rolling it into a cigar shape.</p> <p>Thinly slice the basil into thin slices.</p> <p>Once the capicola is cooked and the balsamic has reduced, assemble the cantaloupe and capicola bites.</p> <p>Place the capicola on a serving plate and fill the capicola bowls with 3 to 5 cubes of cantaloupe.</p> <p>Next drizzle the balsamic reduction over the capicola cantaloupe bowls with a spoon.</p> <p>Finish by garnishing each piece with basil. Enjoy.</p>
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