



EMNLP conference
Highlights

Review by **Dominika Basaj**

EMNLP in numbers



- 2100 submitted papers
- 549 accepted papers (24% acceptance rate)
- 72 demo submissions (40% acceptance rate)
- 2500 attendees

Trends

- Critical analysis of ML models
- More difficult tasks and thus datasets
- Language modelling
- Unsupervised machine translation

Critical analysis of ML models

Pathologies of Neural Models make Interpretations Difficult

<https://arxiv.org/abs/1804.07781>

$$\sum_{(\mathbf{x}, y) \in (\mathcal{X}, \mathcal{Y})} \log(f(y | \mathbf{x})) + \lambda \sum_{\tilde{\mathbf{x}} \in \tilde{\mathcal{X}}} \mathbb{H}(f(y | \tilde{\mathbf{x}})), \quad (2)$$

SQUAD

Context

In 1899, John Jacob Astor IV invested \$100,000 for Tesla to further develop and produce a new lighting system. Instead, Tesla used the money to fund his Colorado Springs experiments.

Original

What did Tesla spend Astor's money on ?

Answer

Colorado Springs experiments

Before

did

After

spend Astor money on ?

Confidence

0.78 → 0.91 → 0.52

SNLI

Premise

Well dressed man and woman dancing in the street

Original

Two man is dancing on the street

Answer

Contradiction

Before

dancing

After

two man dancing

Confidence

0.977 → 0.706 → 0.717

VQA

Original

What color is the flower ?

Answer

yellow

Before

flower ?

After

What color is flower ?

Confidence

0.847 → 0.918 → 0.745

Critical analysis of ML models

How much reading does reading comprehension require? A critical investigation of popular benchmarks.

<https://arxiv.org/pdf/1808.04926.pdf>

Best Short Paper

| Task | Full | Q-only | P-only | $\Delta(min)$ |
|---------------------------|--------------|--------------|--------|---------------|
| Key-Value Memory Networks | | | | |
| CBT-NE | 35.0% | 29.1% | 24.1% | -5.9 |
| CBT-CN | 37.6% | 32.4% | 24.4% | -5.2 |
| CBT-V | 52.5% | 55.7% | 36.0% | +3.2 |
| CBT-P | 55.2% | 56.9% | 30.1% | +1.7 |
| Gated Attention Reader | | | | |
| CBT-NE | 74.9% | 50.6% | 40.8% | -17.5 |
| CBT-CN | 70.7% | 54.0% | 36.7% | -16.7 |
| CNN | 77.8% | 25.6% | 38.3% | -39.5 |
| WdW | 67.0% | 41.8% | 52.2% | -14.8 |
| WdW-R | 69.1% | 50.0% | 50.6% | -15.6 |

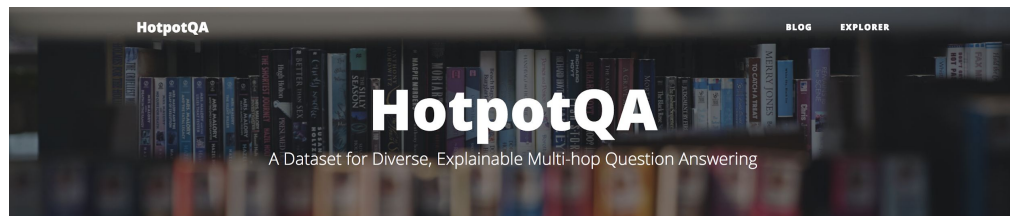
| Metric | Full | Q-only | P-only | $\Delta(min)$ |
|--------|--------------|--------|--------|---------------|
| EM | 70.7% | 0.6% | 10.9% | -59.8 |
| F1 | 79.1% | 4.0% | 14.8% | -64.3 |

Table 4: Performance of QANet on SQuAD

More difficult tasks

HotPotQA: A dataset for diverse, explainable multi-hop question answering

<https://arxiv.org/pdf/1809.09600.pdf>



What is HotpotQA?

HotpotQA is a question answering dataset featuring natural, multi-hop questions, with strong supervision for supporting facts to enable more explainable question answering systems. It is collected by a team of NLP researchers at [Carnegie Mellon University](#), [Stanford University](#), and [Université de Montréal](#).

For more details about HotpotQA, please refer to our EMNLP 2018 paper:

(Yang, Qi, Zhang, et al. 2018)

Leaderboard (Distractor Setting)

In the distractor setting, a question-answering system reads 10 paragraphs to provide an answer (Ans) to a question. They must also justify these answers with supporting facts (Sup).

| Model | Code | Ans | | Sup | | Joint | |
|-------------------------------|-----------------------------------------------------------------------------------------------|-------|----------------|-------|----------------|-------|----------------|
| | | EM | F ₁ | EM | F ₁ | EM | F ₁ |
| Baseline Model (single model) | | | | | | | |
| 1 | Carnegie Mellon University, Stanford University, & Université de Montréal | 45.60 | 59.02 | 20.32 | 64.49 | 10.83 | 40.16 |
| Oct 10, 2018 | (Yang, Qi, Zhang, et al. 2018) | | | | | | |

Paragraph A, Return to Olympus:

[1] *Return to Olympus* is the only album by the alternative rock band Malfunkshun. [2] It was released after the band had broken up and after lead singer Andrew Wood (later of Mother Love Bone) had died of a drug overdose in 1990. [3] Stone Gossard, of Pearl Jam, had compiled the songs and released the album on his label, Loosegroove Records.

Paragraph B, Mother Love Bone:

[4] *Mother Love Bone* was an American rock band that formed in Seattle, Washington in 1987. [5] The band was active from 1987 to 1990. [6] Frontman Andrew Wood's personality and compositions helped to catapult the group to the top of the burgeoning late 1980s/early 1990s Seattle music scene. [7] Wood died only days before the scheduled release of the band's debut album, "Apple", thus ending the group's hopes of success. [8] The album was finally released a few months later.

Q: What was the former band of the member of Mother Love Bone who died just before the release of "Apple"?

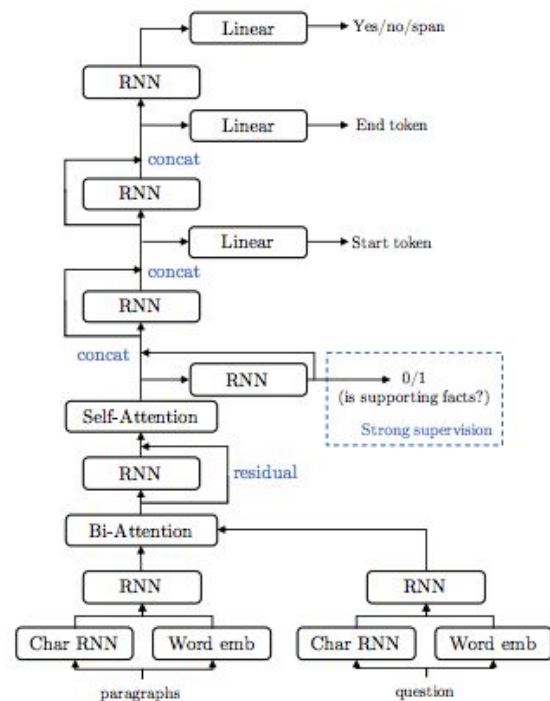
A: Malfunkshun

Supporting facts: 1, 2, 4, 6, 7

More difficult tasks


| Reasoning Type | % | Example(s) |
|-------------------------------------------------------------------------------------------------|----|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Inferring the bridge entity to complete the 2nd-hop question (Type I) | 42 | <p>Paragraph A: The 2015 Diamond Head Classic was a college basketball tournament ... Buddy Hield was named the tournament's MVP.</p> <p>Paragraph B: Chavano Rainier "Buddy" Hield is a Bahamian professional basketball player for the Sacramento Kings of the NBA...</p> <p>Q: Which team does the player named 2015 Diamond Head Classic's MVP play for?</p> |
| Comparing two entities (Comparison) | 27 | <p>Paragraph A: LostAlone were a British rock band ... consisted of Steven Battelle, Alan Williamson, and Mark Gibson...</p> <p>Paragraph B: Guster is an American alternative rock band ... Founding members Adam Gardner, Ryan Miller, and Brian Rosenworcel began...</p> <p>Q: Did LostAlone and Guster have the same number of members? (yes)</p> |
| Locating the answer entity by checking multiple properties (Type II) | 15 | <p>Paragraph A: Several current and former members of the Pittsburgh Pirates ... John Milner, Dave Parker, and Rod Scurry...</p> <p>Paragraph B: David Gene Parker, nicknamed "The Cobra", is an American former player in Major League Baseball...</p> <p>Q: Which former member of the Pittsburgh Pirates was nicknamed "The Cobra"?</p> |
| Inferring about the property of an entity in question through a bridge entity (Type III) | 6 | <p>Paragraph A: Marine Tactical Air Command Squadron 28 is a United States Marine Corps aviation command and control unit based at Marine Corps Air Station Cherry Point...</p> <p>Paragraph B: Marine Corps Air Station Cherry Point ... is a United States Marine Corps airfield located in Havelock, North Carolina, USA ...</p> <p>Q: What city is the Marine Air Control Group 28 located in?</p> |
| Other types of reasoning that require more than two supporting facts (Other) | 2 | <p>Paragraph A: ... the towns of Yodobashi, Okubo, Totsuka, and Ochiai town were merged into Yodobashi ward. ... Yodobashi Camera is a store with its name taken from the town and ward.</p> <p>Paragraph B: Yodobashi Camera Co., Ltd. is a major Japanese retail chain specializing in electronics, PCs, cameras and photographic equipment.</p> <p>Q: Aside from Yodobashi, what other towns were merged into the ward which gave the major Japanese retail chain specializing in electronics, PCs, cameras, and photographic equipment its name?</p> |

Baseline model



More difficult tasks

In the *distractor* setting, a question-answering system reads 10 paragraphs to provide an answer (Ans) to a question. They must also justify these answers with supporting facts (Sup).

| | Model | Code | Ans | | Sup | | Joint | |
|---|-------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|-------|----------------|-------|----------------|-------|----------------|
| | | | EM | F ₁ | EM | F ₁ | EM | F ₁ |
| 1 | Baseline Model (single model) Carnegie Mellon University, Stanford University, & Universite de Montreal (Yang, Qi, Zhang, et al. 2018) |  | 45.60 | 59.02 | 20.32 | 64.49 | 10.83 | 40.16 |

Leaderboard (Fullwiki Setting)

In the *fullwiki* setting, a question-answering system must find the answer to a question in the scope of the entire Wikipedia. Similar to in the distractor setting, systems are evaluated on the accuracy of their answers (Ans) and the quality of the supporting facts they use to justify them (Sup).

| | Model | Code | Ans | | Sup | | Joint | |
|---|-------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|-------|----------------|------|----------------|-------|----------------|
| | | | EM | F ₁ | EM | F ₁ | EM | F ₁ |
| 1 | Baseline Model (single model) Carnegie Mellon University, Stanford University, & Universite de Montreal (Yang, Qi, Zhang, et al. 2018) |  | 23.95 | 32.89 | 3.86 | 37.71 | 1.85 | 16.15 |

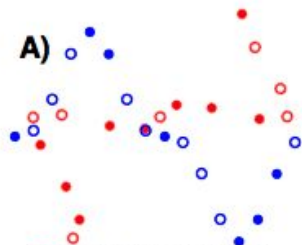
Unsupervised MT

Phrased-Based & Neural Unsupervised Machine Translation

<https://arxiv.org/abs/1804.07755>

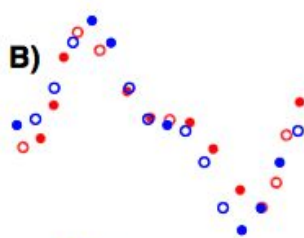
- This work investigates how to learn to translate when having access to only large monolingual corpora in each language.
- We apply these methods to distant and low-resource languages, like English-Russian, English-Romanian and English-Urdu, and report competitive performance against both semi-supervised and supervised baselines.

Two monolingual datasets



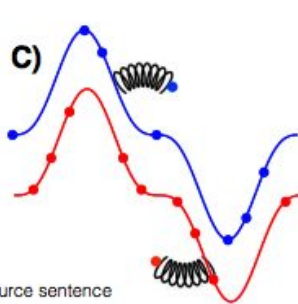
● observed source sentence
○ unobserved translation of a target sentence
× system translation of a target sentence

Initialization

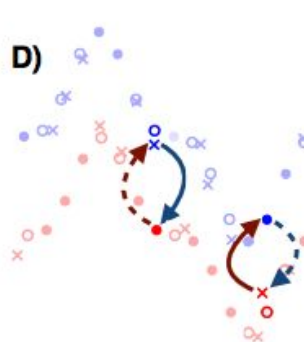


● observed target sentence
○ unobserved translation of a source sentence
× system translation of a source sentence

Language model



Back-translation



Unsupervised MT

Phrased-Based & Neural Unsupervised Machine Translation

<https://arxiv.org/abs/1804.07755>

Algorithm 1: Unsupervised MT

- 1 **Language models:** Learn language models P_s and P_t over source and target languages;
 - 2 **Initial translation models:** Leveraging P_s and P_t , learn two initial translation models, one in each direction: $P_{s \rightarrow t}^{(0)}$ and $P_{t \rightarrow s}^{(0)}$;
 - 3 **for** $k=1$ **to** N **do**
 - 4 **Back-translation:** Generate source and target sentences using the current translation models, $P_{t \rightarrow s}^{(k-1)}$ and $P_{s \rightarrow t}^{(k-1)}$, factoring in language models, P_s and P_t ;
 - 5 Train new translation models $P_{s \rightarrow t}^{(k)}$ and $P_{t \rightarrow s}^{(k)}$ using the generated sentences and leveraging P_s and P_t ;
 - 6 **end**
-

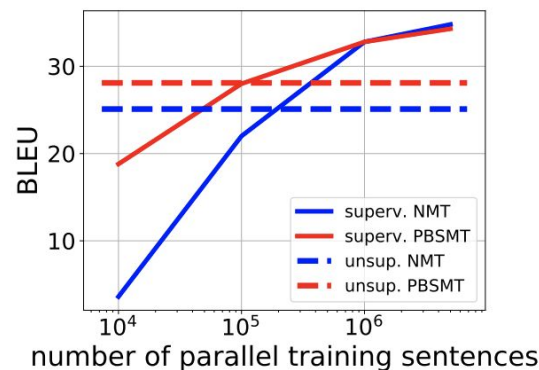


Figure 2: Comparison between supervised and unsupervised approaches on WMT'14 En-Fr, as we vary the number of parallel sentences for the supervised methods.

4D: Visual QA


16:30 – 18:00


Hall 100 / Hall 400


Choose All Remove All


Chair: [Carina Silberer](#)


Tell-and-Answer: Towards Explainable

16:30–
16:48 **Visual Question Answering using
Attributes and Captions.** *Qing Li, Jianlong
Fu, Dongfei Yu, Tao Mei and Jiebo Luo* 

16:48–
17:06 **Learning a Policy for Opportunistic Active
Learning.** *Aishwarya Padmakumar, Peter
Stone and Raymond Mooney* 

17:06–
17:24 **RecipeQA: A Challenge Dataset for
Multimodal Comprehension of Cooking
Recipes.** *Semih Yagcioglu, Aykut Erdem,
Erkut Erdem and Nazli Ikizler-Cinbis* 

17:24–
17:42 **TVQA: Localized, Compositional Video
Question Answering.** *Jie Lei, Licheng Yu,
Mohit Bansal and Tamara Berg* 

17:42–
18:00 **Localizing Moments in Video with
Temporal Language.** *Lisa Anne Hendricks,
Oliver Wang, Eli Shechtman, Josef Sivic,
Trevor Darrell and Bryan Russell* 

Visual QA

TVQA: Localized, Compositional Video Question Answering

<http://aclweb.org/anthology/D18-1167>

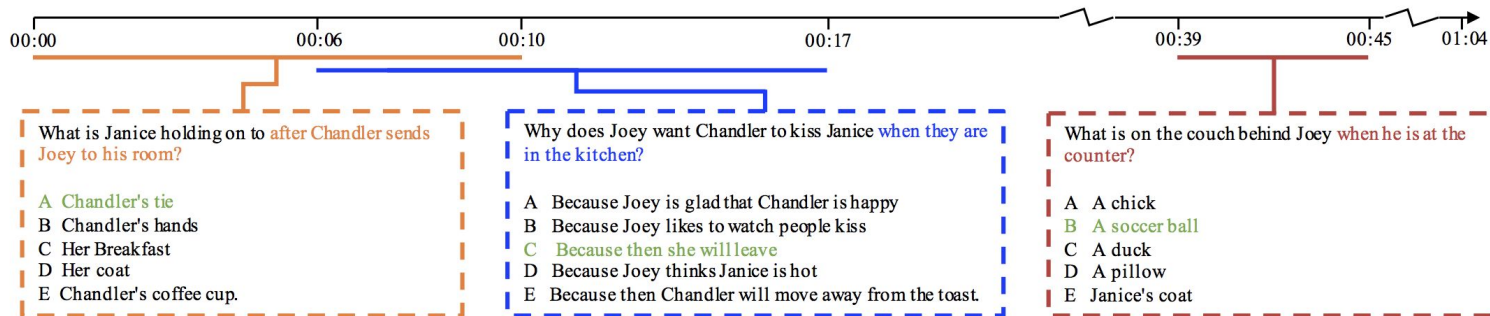


00:00.755 --> 00:02.655
(Chandler:) Go to your room!
00:06.961 --> 00:08.622
(Janice:) I gotta go, I gotta go.

00:08.829 --> 00:10.057
(Janice:) Not without a kiss.
00:10.264 --> 00:12.391
(Chandler:) Maybe I won't kiss you so you'll stay.

00:12.600 --> 00:14.761
(Joey:) Kiss her. Kiss her!
00:16.771 --> 00:19.137
(Janice:) I'll see you later, sweetie. Bye, Joey.

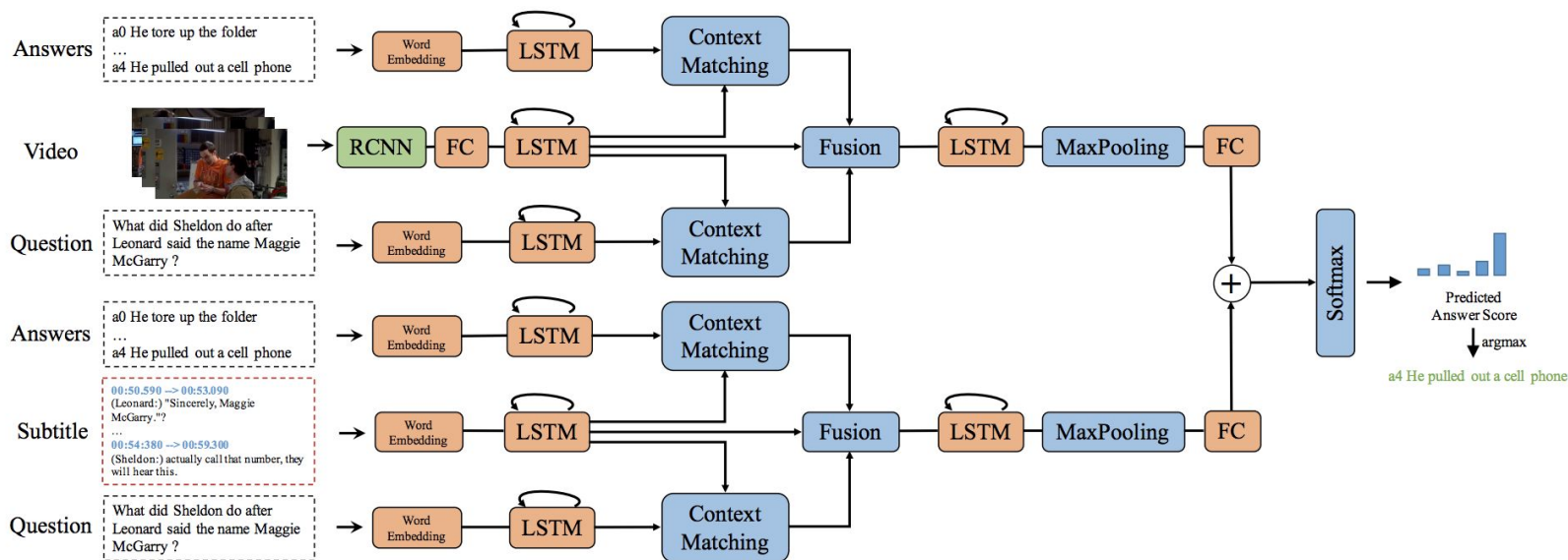
...
00:39.327 --> 00:40.760
(Chandler:) She makes me happy.
00:41.596 --> 00:44.087
(Joey:) Okay. All right.



- All questions and answers are attached to 60–90 seconds long clips.
- Some questions can be answered using subtitles or videos alone, while some require information from both modalities

Visual QA

TVQA: Localized, Compositional Video Question Answering <http://aclweb.org/anthology/D18-1167>



Visual QA

Tell-and-Answer: Towards Explainable Visual Question Answering using Attributes and Captions

<http://aclweb.org/anthology/D18-1164>

In this work, we propose to break up the end-to-end VQA into two steps: **explaining and reasoning**, in an attempt towards a more explainable VQA by shedding light on the intermediate results between these two steps.



Attributes:

sit, phone, bench, cell, talk, woman, chair, park

Caption:

a woman sitting on a bench talking on a cell phone.

What is the woman doing
sitting on the bench?



**Answer
Reasoning**



talking on phone

We first extract attributes in the image such as “sit”, “phone” and “woman.” A caption is also generated to encode the relationship between these attributes, e.g. “woman sitting on a bench.”

Visual QA

Tell-and-Answer: Towards Explainable Visual Question Answering using Attributes and Captions

<http://aclweb.org/anthology/D18-1164>

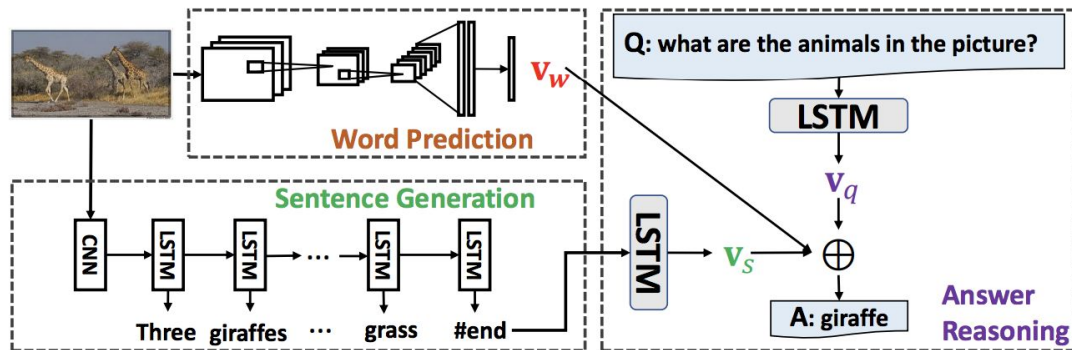









Figure 3: An overview of the proposed framework for VQA with three modules: word prediction (upper left), sentence generation (lower left), answer reasoning (right). **Explaining:** in word prediction, the image is fed into pre-trained visual detectors to extract word-level explanation, which is represented by probability vector \mathbf{v}_w ; in sentence generation, we input the image to pre-trained captioning model to generate a sentence-level explanation. **Reasoning:** the caption and question are encoded by two different LSTMs into \mathbf{v}_s and \mathbf{v}_q , respectively. Then \mathbf{v}_q , \mathbf{v}_w and \mathbf{v}_s are concatenated and fed to a fully connected layer with softmax to predict an answer.

Visual QA

RecipeQA: A Challenge Dataset for Multimodal Comprehension of Cooking Recipes

<http://aclweb.org/anthology/D18-1166>

| Text Cloze Style Question | | Context Modalities: Images and Descriptions of Steps | | | |
|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| Recipe: Last-Minute Lasagna | | | | | |
| <ol style="list-style-type: none">1. Heat oven to 375 degrees F. Spoon a thin layer of sauce over the bottom of a 9-by-13-inch baking dish.2. Cover with a single layer of ravioli.3. Top with half the spinach half the mozzarella and a third of the remaining sauce.4. Repeat with another layer of ravioli and the remaining spinach mozzarella and half the remaining sauce.5. Top with another layer of ravioli and the remaining sauce not all the ravioli may be needed. Sprinkle with the Parmesan.6. Cover with foil and bake for 30 minutes. Uncover and bake until bubbly, 5 to 10 minutes.7. Let cool 5 minutes before spooning onto individual plates. | |  |  |  |  |
| | | Step 1 | Step 2 | Step 3 | Step 4 |
| | |  |  |  | |
| | | Step 5 | Step 6 | Step 7 | |
| Question | Choose the best text for the missing blank to correctly complete the recipe Cover. _____. Bake. Cool, serve. | | | | |
| Answer | A. Top, sprinkle B. Finishing touches C. Layer it up D. Ravioli bonus round | | | | |

Visual QA

RecipeQA: A Challenge Dataset for Multimodal Comprehension of Cooking Recipes

<http://aclweb.org/anthology/D18-1166>

















| | train | valid | test |
|-------------------------------|--------|--------|--------|
| # of recipes | 15847 | 1963 | 1969 |
| ... avg. # of steps | 5.99 | 6.01 | 6.00 |
| ... avg. # of tokens (titles) | 17.79 | 17.40 | 17.67 |
| ... avg. # of tokens (descr.) | 443.01 | 440.51 | 435.33 |
| ... avg. # of images | 12.67 | 12.74 | 12.65 |
| # of question-answers | 29657 | 3562 | 3567 |
| ... textual cloze | 7837 | 961 | 963 |
| ... visual cloze | 7144 | 842 | 848 |
| ... visual coherence | 7118 | 830 | 851 |
| ... visual ordering | 7558 | 929 | 905 |

| Context Modalities: Titles and Descriptions of Steps | |
|------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Recipe: Bacon Sushi | |
| Step 1: What You'll Need | This recipe makes enough bacon sushi to feed 2 - 4 people. 2 x 500g(1 lb.) packages of bacon (I chose an applewood smoked bacon, but any type would work). 3 tbsp. oil. 1 medium onion, finely diced. 1 l... |
| Step 2: Cooking the Bacon | The bacon "nori" will have to be partially cooked before it can be rolled with the risotto filling. Preheat the oven to 350 degrees F. Lay half a package of bacon on the rack of the roasting pan, then bak... |
| Step 3: Making the Risotto Filling | I once made risotto with sushi rice, since I had no Arborio rice on hand, and I decided that the starchiness was similar in the two. My experiment was a success, and the resulting dish was just as deli... |
| Step 4: Jazzing Up the Risotto | Risotto is a wonderfully customizable dish, and a quick search on the internet will result in a multitude of variations. Here are two of my favorites: Asian mushroom risotto. 1 tbsp. oil. 1 package... |
| Step 5: Rolling the Sushi | Cover the sushi rolling mat with a large piece of aluminum foil as protection from the risotto and bacon grease. (You don't want your next sushi dinner tasting like bacon. Or maybe you do...) Lay the stri... |
| Step 6: Baking and Slicing | Preheat the oven to 350 degrees F. Place the aluminum foil-covered sushi rolls in the oven and bake for 20 minutes. This will warm all the ingredients and crisp the bacon a little more. It will also melt a... |
| Step 7: And You're Done! | Serve the sushi with a light crispy vegetable side dish, such as refreshing cucumber sticks, or a green salad. White wine makes an excellent compliment to the meal, especially if it is the same wine used in ... |

Visual QA

RecipeQA: A Challenge Dataset for Multimodal Comprehension of Cooking Recipes

<http://aclweb.org/anthology/D18-1166>

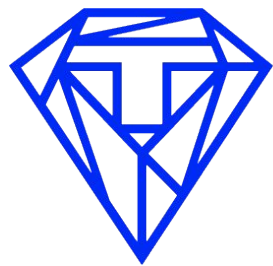
| | | | | | |
|------------------------------------|----------|---------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| Visual Cloze Style Question | Question | Choose the best image for the missing blank to correctly complete the recipe | | | |
| | |  |  |  |  |
| | |  |  |  |  |
| | Answer | A. | B. | C. | D. |
| Visual Coherence Style Question | Question | Select the incoherent image in the following sequence of images | | | |
| | |  |  |  |  |
| | Answer | A. | B. | C. | D. |
| Visual Ordering Style Question | Question | Choose the correct order of the images to make a complete recipe | | | |
| | |  |  |  |  |
| | | (i) | (ii) | (iii) | (iv) |
| | Answer | A. (iv)-(iii)-(ii)-(i) B. (iv)-(iii)-(i)-(ii) C. (i)-(ii)-(iii)-(iv) D. (ii)-(iv)-(i)-(iii) | | | |



Thank you!

Questions?





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