Conditional Self-Attention for Query-based Summarization

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Abstract

Self-attention mechanisms have achieved great success on a variety of NLP tasks due to its flexibility of capturing dependency between arbitrary positions in a sequence. For problems such as query-based summarization (Qsumm) and knowledge graph reasoning where each input sequence is associated with an extra query, explicitly modeling such conditional contextual dependencies can lead to a more accurate solution, which however cannot be captured by existing self-attention mechanisms. In this paper, we propose conditional self-attention (CSA), a neural network module designed for conditional dependency modeling. CSA works by adjusting the pairwise attention between input tokens in a self-attention module with the matching score of the inputs to the given query. Thereby, the contextual dependencies modeled by CSA will be highly relevant to the query. We further studied variants of CSA defined by different types of attention. Experiments on Debatepedia and HotpotQA benchmark datasets show CSA consistently outperforms vanilla Transformer and previous models for the Qsumm problem.

1 Introduction

Contextual dependency is believed to provide critical information in a variety of NLP tasks. Among the popular neural network structures, convolution is powerful in capturing local dependencies, while LSTM is good at modeling distant relations. Self-attention has recently achieved great success in NLP tasks due to its flexibility of relating two elements in a distance-agnostic manner. For each element, it computes a categorical distribution that reflects the dependency of that element to each of the other elements from the same sequence. The element’s context-aware embedding is then computed by weighted averaging of other elements with the probabilities. Hence, self-attention is powerful for encoding pairwise relationship into contextual representations.

However, higher-level language understanding often relies on more complicated dependencies than the pairwise one. One example is the conditional dependency that measures how two elements are related given a premise. In NLP tasks such as query-based summarization and knowledge graph reasoning where inputs are equipped with extra queries or entities, knowing the dependencies conditioned on the given query or entity is extremely helpful for extracting meaningful representations. Moreover, conditional dependencies can be used to build a large relational graph covering all elements, and to represent higher-order relations for multiple (>2) elements. Hence, it is more expressive than the pairwise dependency modeled by self-attention mechanisms.

In this paper, we develop conditional self-attention as a versatile module to capture the conditional dependencies within an input sequence. CSA is a composite function that applies a cross-attention mechanism inside an ordinary self-attention module. Given two tokens from the input sequence, it first computes a dependency score for each token with respect to the condition by cross-attention, then scales tokens by the computed condition-dependency scores, and applies self-attention to the scaled tokens. In this way CSA is capable of selecting tokens that are highly correlated to the condition, and guiding contextual embedding generation towards those tokens. In addition, when applied to a highly-related token and a loosely-related token, CSA reduces to measuring the global dependency (i.e., single-token importance) of the former. Hence, CSA can capture both local (e.g., pairwise) and global de-
pendency in the same module, and automatically switch between them according to the condition. In contrast, previous works usually need two modules to capture these two types of information.

We then apply CSA to Query-based summarization (Qsumm) task. Qsumm is a challenging task in which accurate retrieval of relevant contexts and thorough comprehension are both critical for producing high-quality summaries. Given a query, it tries to generate from passage a summary pertaining to the query, in either an extractive query, it tries to generate from passage a summary for producing high-quality summaries. Given a passage in which accurate retrieval of relevant contexts and thorough comprehension are both critical for producing high-quality summaries. Given a passage in which accurate retrieval of relevant contexts is achieved by computing the expectation of a categorical distribution $p(z|x, c)$ defined as

$$a = [f(x_i, c)]_{i=1}^n,$$

$$p(z = i|x, c) = \text{softmax}(a[i]), \quad \forall i \in [n],$$

where larger $p(z = i|x, c)$ implies that $x_i$ is more relevant to $c$. A context-aware representation $u$ of $x$ is achieved by computing the expectation of sampling a token according to $p(z|x, c)$, i.e.,

$$u = \sum_{i=1}^n p(z = i|x, c)x_i = \mathbb{E}_{i \sim p(z|x, c)}(x_i).$$

Multiplicative attention (Vaswani et al., 2017; Sukhbaatar et al., 2015; Rush et al., 2015) and additive attention (multi-layer perceptron attention) (Bahdanau et al., 2015; Shang et al., 2015) are two commonly used attention mechanisms with different compatibility functions $f(\cdot, \cdot)$ defined below respectively,

$$f(x_i, c) = \langle W^{(1)}_a x_i, W^{(2)}_c c \rangle,$$

$$f(x_i, c) = w^T \sigma(W^{(1)}_a x_i + W^{(2)}_c c + b) + b,$$

where $W^{(1)}_a \in \mathbb{R}^{d_w \times d_e}$, $W^{(2)}_c \in \mathbb{R}^{d_w \times d_c}$, $w \in \mathbb{R}^{d_w}$, $b$ and $b$ are learnable parameters, and $\sigma(\cdot)$ is an activation function.

**Self-attention (SA)** is a variant of attention modeling the pairwise relationship between tokens from the same sequence. One line of work a.k.a **Token2Token self-attention (T2T)** (Hu et al., 2017; Shen et al., 2017) produces context-aware representation for each token $x_j$ based on its dependency to other tokens $x_i$ within $x$ by replacing $c$ in Eq. (1)-(3) with $x_j$. Notably in Transformer (Vaswani et al., 2017), a multi-head attention computes $u$ in multiple subspaces of $x$ and $c$, and concatenates the results as the final representation. **Source2Token self-attention (S2T)** (Lin et al., 2017; Shen et al., 2017; Liu et al., 2016), on the other hand, explores the per-token importance with respect to a specific task by removing $c$ from Eq. (1)-(3). Its output $u$ is an average of all tokens weighted by their corresponding importance.

**3 Conditional Self-Attention**

Conditional self-attention computes the self-attention score between any two tokens $x_i$ and $x_j$ based on the representation $c$ of a given condition. Specifically, to incorporate the conditional information, CSA first applies a cross-attention module (multiplicative or additive attention) to
compute the dependency scores of $x_i$ and $x_j$ to $c$ by Eq. (1)–(2), i.e., $p_i \triangleq p(z = i|x, c)$ and $p_j \triangleq p(z = j|x, c)$. Inputs $x_i$ and $x_j$ are then scaled by $p_i$ and $p_j$ to obtain $h_i \triangleq p_i x_i$ and $h_j \triangleq p_j x_j$. Finally, an additive self-attention is applied to $h_i$ and $h_j$ with compatibility function

$$f_{\text{csa}}(x_i, x_j | c) \triangleq w^T \sigma(W^{(1)}_\text{sa} h_i + W^{(2)}_\text{sa} h_j + b_\text{sa}) + b_\text{csa},$$

resulting in context-aware embedding $u_j$ for $x_j$:

$$u_j = \sum_{i=1}^n \text{softmax}([f_{\text{csa}}(h_i, h_j)]_{i=1}^n)[i] \times h_i.$$  (7)

We extend the above model by using multi-head mechanism and position-wise feed-forward networks (PFN) proposed in Vaswani et al. (2017): Eq. (6)–(7) are applied to $K$ subspaces of $h$ from $[h^{(k)}_i]_{k=1}^K$, whose outputs $[u^{(k)}_j]_{k=1}^K$ are then concatenated and processed by a linear projection (with $w_{\text{head}} \in \mathbb{R}^K$) and a PFN layer

$$u_j = \text{PFN} \left( \left[u^{(1)}_j; u^{(2)}_j; \ldots; u^{(K)}_j\right] w_{\text{head}} \right).$$  (8)

4 Query-based Summarization Model

In QSumm, each data instance is a triplet $(x, q, s)$, representing passage, query, and a summary of passage conditioned on query. Summary $s$ should not only focus on the content in $x$ that is most relevant to $q$, but it also needs to be a complete summary rather than a short answer to $q$ as opposed to QA. In other words, it should cover any background information and related key points about $q$ if they are also covered by $x$.

Figure 2 illustrates our Transformer-style neural network for QSumm. It is built with CSA modules containing two encoders, a CSA layer and a decoder, which are elaborated below.

**Encoder of passage $x$** We adopt hierarchical block self-attention (Shen et al., 2018; Liu et al., 2018) for the sake of memory efficiency when processing long passages by splitting $x$ into $n$ blocks (subsequences). For each block, we apply a few Transformer encoding layers with shared parameters across the blocks, followed by a 2T self-attention layer that compresses the subsequence into a compact vector. Thereby, we get a shorter sequence of $n$ vectors, on which we apply a few more Transformer encoding layers to obtain the final sequence $v$.

**Encoder of query $q$** Given a query $q$ as a sequence of tokens, we apply a few Transformer encoding layers, followed by an 2T self-attention layer, to produce a vector $c$ as representation of the condition in CSA.

**Conditional self-attention layer** Given the encoded query $c$ and the encoded passage $v$, a conditional self-attention module as in Figure 1 (with input $x = v$) produces a sequence of context-and-condition-aware representations $u$.

**Decoder** Depending on whether the output summary is abstractive or extractive, we apply different decoders to $u$. We will elaborate which decoder is used for each dataset in the experiments.

5 Experiments

We evaluate CSA-Transformer for abstractive summarization task on Debatepedia (Nema et al., 2017) and extractive summarization task on HotpotQA (Yang et al., 2018), with different decoders applied. We consider two variants that use CSA module with additive or multiplicative cross-attention. We first compare them with baselines that does not consider queries, namely Transformer (Vaswani et al., 2017) and Universal Transformer (UT) (Dehghani et al., 2019). We further compare them with the following baselines:

**SD2:** See Nema et al. (2017);

**CONCAT:** Concatenate the query and the passage, and feed it into Transformer;

**ADD:** Add the query encoded vector to every words word embedding from the passage encoder, and feed it to the decoder, i.e., $u_i = v_i + c$;

Note that Debatepedia dataset is also tested in Baumel et al. (2018). However, as claimed in Section 5.4 of Baumel et al. (2018), their model targets a different setting and yields summaries ten times longer than required on this dataset. Therefore, their result is not directly comparable with ours.
Table 1: Query-based summarization on Debatepedia (abstractive) and HotpotQA (extractive). Two CSA models are evaluated: (Mul) and (Add) refer to multiplicative and additive cross-attention used in CSA.

| Model                      | Debatepedia (Nema et al., 2017) | HotpotQA (Yang et al., 2018) |
|----------------------------|----------------------------------|------------------------------|
|                            | ROUGE-1 | ROUGE-2 | ROUGE-L | ROUGE-1 | ROUGE-2 | ROUGE-L |
| Transformer (Vaswani et al., 2017) | 28.16   | 17.48   | 27.28   | 35.45   | 28.17   | 30.31   |
| UT (Dehghani et al., 2019)     | 36.21   | 26.75   | 35.53   | 41.58   | 32.28   | 34.88   |
| SD2 (Nema et al., 2017)        | 41.26   | 18.75   | 40.43   | –       | –       | –       |
| CONCAT                      | 41.72   | 33.62   | 41.25   | 28.23   | 24.50   | 24.76   |
| ADD                        | 41.10   | 33.35   | 40.72   | 32.84   | 28.01   | 28.53   |
| CSA Transformer (Mul)       | 41.70   | 32.92   | 41.29   | 59.57   | 49.89   | 48.34   |
| CSA Transformer (Add)       | **46.44** | **37.38** | **45.85** | **47.00** | **37.78** | **39.52** |

Figure 3: An example of query-based summarization on Debatepedia: the passage is highlighted according to the cross-attention scores $p_i$, and the abstractive summary is produced by CSA Transformer (Add).

5.1 Abstractive Query-based Summarization

Debatepedia (Nema et al., 2017) is crawled from 663 debates of 53 categories such as Politics, Law, Crime, etc. It has 12000 training data, 719 validation data, and 1000 test data. Examples of the data instances can be found in Appendix.

Setup Since the passages in Debatepedia are relatively short (66.4 tokens per instance on average), we use a Transformer encoding layer as the passage encoder without splitting the passage into blocks. Transformer decoding layer is used for decoding. Please refer to Appendix for more details.

Result Table 1 shows both two CSA models consistently achieve better ROUGE scores (Lin and Och, 2004) than the baselines. Note our models have much higher ROUGE-2 scores than baselines, which suggests the summarization generated by CSA is more coherent. Figure 3 is an example of CSA summary, with the passage highlighted by cross-attention score $p_i$. The learned attention scores emphasize not only lexical units such as "coal-electricity" but also conjunctive adverb such as "therefore." More example summaries can be found in Appendix.

5.2 Extractive Query-based Summarization

HotpotQA (Yang et al., 2018) is a multi-hop QA dataset including 113k Wikipedia-based instances, each of which consist of four parts: a question (query), a context, a short answer, and support facts that the answer is extracted from. The support facts are sentences selected from the context and contain reasonably more information of the context than the answer.

We adapt HotpotQA as a benchmark for extractive query-based summarization by removing the answer of each instance and treating the context as passage $x$, the question as query $q$, and the support facts as summary $s$ in $Qsumm$. Since the test set has not been released, in order to compute ROUGE score in evaluation, we randomly split the original training set to a training set of 85564 instances and a validation set of 5000 instances, and use the original validation set as our test set.

Setup We split the passage into blocks, each to be one of its sentences. The decoder is 2 Transformer decoder layers, whose output is a sequence of vectors, followed by a projection to a sequence of scalars, each representing a sentence. Each scalar is processed by a sigmoid function for binary classification deciding whether the sentence should be selected. We use cross-entropy as our loss function. Please refer to Appendix for more details.

Result Both CSA models achieve significantly better ROUGE scores than the baselines in Table 1. Different from Debatepedia results, CSA module with multiplicative cross-attention performs better than the additive one. This is because in each dataset we adopt the same hyper-parameters for both variants – in Debatepedia the hyper-parameters favor multiplicative cross-attention, while in HotpotQA they prefer the additive one. The experimental results show that both variants can have significantly better performance than the baselines. It also suggests that we cannot simply adopt the hyper-parameters from another tasks without fine-tuning – although the model can be more compelling than the baselines if we do so.

6 Conclusion

This paper introduces conditional self-attention (CSA) and its variants as versatile and plugin mod-
ules for conditional contextual dependency modeling. We develop an attention-only neural network built from CSA and Transformer for query-based summarization. It consistently outperforms vanilla Transformer and other baselines for abstractive and extractive Qsumm tasks on Debatepedia and HotpotQA datasets.

Due to its capability of modeling conditional dependencies, CSA can be naturally applied to tasks defined on graph structure, e.g., classification and clustering on graph(s), logical reasoning, knowledge graph reasoning, to name a few. To handle multiple queries, we can apply a CSA module per query and combining their outputs by an S2T self-attention module.

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Appendix

A Related Works

Attention Attention mechanisms (Bahdanau et al., 2015; Sutskever et al., 2014; Chen et al., 2018b), especially self-attention mechanisms have achieved great success on variety of NLP tasks (Vaswani et al., 2017; Devlin et al., 2019; Chen et al., 2018a; Radford et al., 2019). Our work can be viewed as an extension of Transformer (Vaswani et al., 2017). Also, our work adapts the source to token layers (S2T) from Lin et al. (2017) and Shen et al. (2017).

We notice that the BERT (Devlin et al., 2019) model (released after we achieved our main results) can implicitly capture conditional dependency by taking the concatenation of the passage and query with a separation symbol as input. However, CSA is specifically designed for modeling conditional dependency explicitly, and can potentially improve Transformer, BERT, GPT-2 (Radford et al., 2019) or other models trained for tasks such as Qsumm.

Query-based Summarization Many works are devoted to do summarization with attention mechanism (Sutskever et al., 2014; Tan et al., 2017), but few considers the conditional dependency on query. Many works are devoted to do query-based summarization (Wan and Yang, 2008; Zhao et al., 2009; Park et al., 2006; Schilder and Kondadadi, 2008), but few adopts deep learning based methods. Hasselqvist et al. (2017) and Cao et al. (2016) propose to do query-based summarization using deep networks with different setting – in their setting, the query is a key word, instead of a question. A very related work is Nema et al. (2017). Their setting is the same as us, and crawled Debatepedia dataset.

B Implementation Detail

In this section, we elaborate more detail on the experiments.

B.1 Final Settings of the Experiments

| Dataset     | Debatepedia | HotpotQA              |
|-------------|-------------|-----------------------|
| Pre-trained embedding | None        | glove.840B.300d.txt  |
| Batch size  | 64          | 32                    |
| Embedding dimension | 128         | 300                   |
| Hidden dimension  | 128         | 300                   |
| CSA inner dimension | 16          | 16                    |
| #heads in CSA layer | 4           | 4                     |
| #SA layers before block | 1          | 2                     |
| #SA layers after block | 0          | 2                     |
| #SA layers in query | 1           | 2                     |
| #SA layers after CSA | 1           | 2                     |
| #heads in SA layer | 4           | 4                     |
| Loss        | Cross-entropy | Cross-entropy (binary) |
| Dropout     | 0.2         | 0.1                   |
| Learning rate | 0.5         | $10^{-4}$             |
| Learning rate decay | Expo. with factor 0.8 per 3000 iterations | Expo. with factor 0.9 per epoch |

In every experiment, we pad the sequence $x$ and query $q$ in each batch to have the same length, for the convenience of parallelization. Correspondingly, a mask for the padded entries is used in every layers of the model.

Also, for HotpotQA, we use binary classification to decide whether this sentence is picked. In order to do that, we need to pick a threshold – if the classification score of this sentence is larger than the
threshold, we pick this sentence; if not, we do not pick it. This threshold is set to be 0.25.

We also use pointing mechanism and coverage mechanism (See et al., 2017) for abstractive summarization.

B.2 Tuning Process

For both dataset, the following parameters are tuned: hidden dimension from 64 to 300, CSA inner dimension from 16 to 64, number of layers in each part from 0 to 3, learning rate. We remark the following two aspects largely affect the performance:

1. The model size. The two datasets are different in size. Debatepedia is smaller. To achieve a good performance, the embedding dimension, hidden dimension and number of layers are smaller. HotpotQA is larger, so that we set the embedding dimension, hidden dimension and number of layers to be also larger.

2. The learning rate. We notice that usually smaller learning rate can converge to better result than larger ones, although may be slower.

For Debatepedia, the performance of CSA Transformer (Add) is better than other three. For HotpotQA, the performance of CSA Transformer (Mul) is better than other three by a large margin. This is because in the tuning process, we fix the kind of CSA layer, and tune the other parameters. After we get a good set of other parameters, we use the setting for three other kinds of CSA layers. That is why one setting of CSA layer is much better than the other three. The other three settings are not extensively tuned than the one with better performance.

B.3 Implementation of the baselines

The results of two baselines, Transformer (Vaswani et al., 2017) and Universal Transformer (Dehghani et al., 2019) is run by us. The implementation of Transformer model and some of the parameter setting is largely borrowed from https://github.com/jadore801120/attention-is-all-you-need-pytorch. For both datasets, we use the same number of layers in each part. The implementation of Universal Transformer model and some of the parameter setting is largely borrowed from https://github.com/andreamad8/Universal-Transformer-Pytorch. For both datasets, since Adaptive Computation Time (ACT) is used, we only use one layer for each “SA layers” block in the encoder part. For decoder, we use exactly the same decoder for both Transformer and Universal Transformer as CSA based methods. We also remark that the structure of our implementation is adapted from https://github.com/OpenNMT/OpenNMT-py.

C Summary Examples

In this section, we show a few summarization examples.

C.1 HotpotQA

| Example 1 |
|-----------|
| **Passage:** |
| Ed Wood is a 1994 American biographical period comedy-drama film directed and produced by Tim Burton, and starring Johnny Depp as cult filmmaker Ed Wood. The film concerns the period in Wood’s life when he made his best-known films as well as his relationship with actor Bela Lugosi, played by Martin Landau. Sarah Jessica Parker, Patricia Arquette, Jeffrey Jones, Lisa Marie, and Bill Murray are among the supporting cast. Scott Derrickson (born July 16, 1966) is an American director, screenwriter and producer. He lives in Los Angeles, California. He is best known for directing horror films such as “Sinister”, “The Exorcism of Emily Rose”, and “Deliver Us From Evil”, as well as the 2016 Marvel Cinematic Universe installment, “Doctor Strange.” |
Woodson is a census-designated place (CDP) in Pulaski County, Arkansas, in the United States. Its population was 403 at the 2010 census. It is part of the Little RockNorth Little RockConway Metropolitan Statistical Area. Woodson and its accompanying Woodson Lake and Wood Hollow are the namesake for Ed Wood Sr., a prominent plantation owner, trader, and businessman at the turn of the 20th century. Woodson is adjacent to the Wood Plantation, the largest of the plantations owned by Ed Wood Sr.

Tyler Bates (born June 5, 1965) is an American musician, music producer, and composer for films, television, and video games. Much of his work is in the action and horror film genres, with films like “Dawn of the Dead, 300, Sucker Punch,” and “John Wick.” He has collaborated with directors like Zack Snyder, Rob Zombie, Neil Marshall, William Friedkin, Scott Derrickson, and James Gunn. With Gunn, he has scored every one of the director’s films; including “Guardians of the Galaxy”, which became one of the highest grossing domestic movies of 2014, and its 2017 sequel. In addition, he is also the lead guitarist of the American rock band Marilyn Manson, and produced its albums “The Pale Emperor” and “Heaven Upside Down”.

Edward Davis Wood Jr. (October 10, 1924 December 10, 1978) was an American filmmaker, actor, writer, producer, and director.

Deliver Us from Evil is a 2014 American supernatural horror film directed by Scott Derrickson and produced by Jerry Bruckheimer. The film is officially based on a 2001 non-fiction book entitled “Beware the Night” by Ralph Sarchie and Lisa Collier Cool, and its marketing campaign highlighted that it was “inspired by actual accounts”. The film stars Eric Bana, dgar Ramrez, Sean Harris, Olivia Munn, and Joel McHale in the main roles and was released on July 2, 2014.

Adam Collis is an American filmmaker and actor. He attended the Duke University from 1986 to 1990 and the University of California, Los Angeles from 2007 to 2010. He also studied cinema at the University of Southern California from 1991 to 1997. Collis first work was the assistant director for the Scott Derrickson’s short “Love in the Ruins” (1995). In 1998, he played “Crankshaft” in Eric Koyanagi’s “Hundred Percent”.

Sinister is a 2012 supernatural horror film directed by Scott Derrickson and written by Derrickson and C. Robert Cargill. It stars Ethan Hawke as fictional true-crime writer Ellison Oswalt who discovers a box of home movies in his attic that puts his family in danger.

Conrad Brooks (born Conrad Biedrzycki on January 3, 1931 in Baltimore, Maryland) is an American actor. He moved to Hollywood, California in 1948 to pursue a career in acting. He got his start in movies appearing in Ed Wood films such as “Plan 9 from Outer Space”, “Glen or Glenda”, and “Jail Bait.” He took a break from acting during the 1960s and 1970s but due to the ongoing interest in the films of Ed Wood, he reemerged in the 1980s and has become a prolific actor. He also has since gone on to write, produce and direct several films.

Doctor Strange is a 2016 American superhero film based on the Marvel Comics character of the same name, produced by Marvel Studios and distributed by Walt Disney Studios Motion Pictures. It is the fourteenth film of the Marvel Cinematic Universe (MCU). The film was directed by Scott Derrickson, who wrote it with Jon Spaihts and C. Robert Cargill, and stars Benedict Cumberbatch as Stephen Strange, along with Chiwetel Ejiofor, Rachel McAdams, Benedict Wong, Michael Stuhlbarg, Benjamin Bratt, Scott Adkins, Mads Mikkelsen, and Tilda Swinton. In “Doctor Strange”, surgeon Strange learns the mystic arts after a career-ending car accident.

Query: Were Scott Derrickson and Ed Wood of the same nationality?

Ground Truth: Scott Derrickson (born July 16, 1966) is an American director, screenwriter and producer. Edward Davis Wood Jr. (October 10, 1924 December 10, 1978) was an American filmmaker, actor, writer, producer, and director.

CSA Summary: Scott Derrickson (born July 16, 1966) is an American director, screenwriter and producer. Edward Davis Wood Jr. (October 10, 1924 December 10, 1978) was an American filmmaker, actor, writer, producer, and director.
Meet Corliss Archer, a program from radio’s Golden Age, ran from January 7, 1943 to September 30, 1956. Although it was CBS’s answer to NBC’s popular “A Date with Judy”, it was also broadcast by NBC in 1948 as a summer replacement for “The Bob Hope Show”. From October 3, 1952 to June 26, 1953, it aired on ABC, finally returning to CBS. Despite the program’s long run, fewer than 24 episodes are known to exist.

Shirley Temple Black (April 23, 1928 – February 10, 2014) was an American actress, singer, dancer, businesswoman, and diplomat who was Hollywood’s number one box-office draw as a child actress from 1935 to 1938. As an adult, she was named United States ambassador to Ghana and to Czechoslovakia and also served as Chief of Protocol of the United States.

Janet Marie Waldo (February 4, 1920 – June 12, 2016) was an American radio and voice actress. She is best known in animation for voicing Judy Jetson, Nancy in “Shazzan”, Penelope Pitstop, and Josie in “Josie and the Pussycats”, and on radio as the title character in “Meet Corliss Archer”.

Meet Corliss Archer is an American television sitcom that aired on CBS (July 13, 1951 - August 10, 1951) and in syndication via the Ziv Company from April to December 1954. The program was an adaptation of the radio series of the same name, which was based on a series of short stories by F. Hugh Herbert.

The post of Lord High Treasurer or Lord Treasurer was an English government position and has been a British government position since the Acts of Union of 1707. A holder of the post would be the third-highest-ranked Great Officer of State, below the Lord High Steward and the Lord High Chancellor.

A Kiss for Corliss is a 1949 American comedy film directed by Richard Wallace and written by Howard Dimsdale. It stars Shirley Temple in her final starring role as well as her final film appearance. It is a sequel to the 1945 film “Kiss and Tell”. “A Kiss for Corliss” was retitled “Almost a Bride” before release and this title appears in the title sequence. The film was released on November 25, 1949, by United Artists.

Kiss and Tell is a 1945 American comedy film starring then 17-year-old Shirley Temple as Corliss Archer. In the film, two teenage girls cause their respective parents much concern when they start to become interested in boys. The parents’ bickering about which girl is the worse influence causes more problems than it solves.

The office of Secretary of State for Constitutional Affairs was a British Government position, created in 2003. Certain functions of the Lord Chancellor which related to the Lord Chancellor’s Department were transferred to the Secretary of State. At a later date further functions were also transferred to the Secretary of State for Constitutional Affairs from the First Secretary of State, a position within the government held by the Deputy Prime Minister.

The Village Accountant (variously known as “Patwari”, “Talati”, “Patel”, “Karnam”, “Adhikari”, “Shanbogaru”, “Patnaik” etc.) is an administrative government position found in rural parts of the Indian sub-continent. The office and the officeholder are called the “patwari” in Telangana, Bengal, North India and in Pakistan while in Sindh it is called “tapedar”. The position is known as the “karnam” in Andhra Pradesh, “patnaik” in Orissa or “adhikari” in Tamil Nadu, while it is commonly known as the “talati” in Karnataka, Gujarat and Maharashtra. The position was known as the “kulkarni” in Northern Karnataka and Maharashtra. The position was known as the “shanbogaru” in South Karnataka.
Charles Craft (May 9, 1902 – September 19, 1968) was an English-born American film and television editor. Born in the county of Hampshire in England on May 9, 1902, Craft would enter the film industry in Hollywood in 1927. The first film he edited was the Universal Pictures silent film, “Painting the Town”. Over the next 25 years, Craft would edit 90 feature-length films. In the early 1950s he would switch his focus to the small screen, his first show being “Racket Squad”, from 1951-53, for which he was the main editor, editing 93 of the 98 episodes. He would work on several other series during the 1950s, including “Meet Corliss Archer” (1954), “Science Fiction Theatre” (1955-56), and “Highway Patrol” (1955-57). In the late 1950s and early 1960s he was one of the main editors on “Sea Hunt”, starring Lloyd Bridges, editing over half of the episodes. His final film work would be editing “Flipper’s New Adventure” (1964, the sequel to 1963’s “Flipper”. When the film was made into a television series, Craft would begin the editing duties on that show, editing the first 28 episodes before he retired in 1966. Craft died on September 19, 1968 in Los Angeles, California.

**Query:** What government position was held by the woman who portrayed Corliss Archer in the film Kiss and Tell?

**Ground Truth:** Shirley Temple Black (April 23, 1928 – February 10, 2014) was an American actress, singer, dancer, businesswoman, and diplomat who was Hollywood’s number one box-office draw as a child actress from 1935 to 1938. As an adult, she was named United States ambassador to Ghana and to Czechoslovakia and also served as Chief of Protocol of the United States. Kiss and Tell is a 1945 American comedy film starring then 17-year-old Shirley Temple as Corliss Archer.

**CSA Summary:** Shirley Temple Black (April 23, 1928 – February 10, 2014) was an American actress, singer, dancer, businesswoman, and diplomat who was Hollywood’s number one box-office draw as a child actress from 1935 to 1938. A Kiss for Corliss is a 1949 American comedy film directed by Richard Wallace and written by Howard Dimsdale.
C.2 Debatepedia

In the visualization of the cross-attention score $p_i$, we use the following stop words to avoid messiness: “to”, “is”, “and”, “in”, “the”, “of”. For all visualizations, the darker color represents the larger value.

Sample Passage:
Query: vs. “clean coal”: how does solar energy compare to “clean coal”?  
Groundtruth Summary: solar energy can not produce enough energy to replace coal.  
Output Summary: solar energy can not produce much energy to replacing coal.

Figure 4: Sample passages with attention. Highlighted with $p_i$.

Figure 5: Sample attention score of $f_{vd}(h_i,h_j)$ corresponding to the passage in Figure 4.
Russian photographer Nick Larionstev captured a video of mould growing. It shows five different species of fungi forming stomach-churning mounds. As the fungi filaments spread they form stalks with dust-like spores on top. Each sequence took between two and eight days to film using a special rig.

Generated summary (highlighted = high generation probability) says Spencer Ackerman.

"What we've learned at painful cost over years and years and years is that the issue is not the leader of an extremist movement, it is the network that supports it, and the conditions that allow it to take root among a population.

"The pros and cons of killer drones-the Atlantic Wire by B.F. Carlson August 2009

Figure 6: Sample passages with attention. Highlighted with $p_i$.

Figure 7: Sample attention score of $f_{cda}(h_i, h_j)$ corresponding to the passage in Figure 6.
Failed to load attn_vis_data.json

Sample Passage:

"obama for president " , boston globe , 13 oct . 2008 --- vague unease about the economy has turned into outright fear as the financial system sank into quicksand and 500-point-plus plunges on the stock market have become a near-daily occurrence . obama ’ s opponent senator john mccain would try to solve all these problems by going back to the same republican set of tools — tough talk abroad tax cuts for the richest at home . "

Query: economics: who has the better economic and tax plan ?

Output Summary: mccain adopted same failed economic policies as bush

Figure 8: Sample passages with attention. Highlighted with $p_v$.

Figure 9: Sample attention score of $f_{cov}(h_i, h_j)$ corresponding to the passage in Figure 8.