Abstract

Image captioning systems have recently improved dramatically, but they still tend to produce captions that are insensitive to the communicative goals that captions should meet. To address this, we propose Issue-Sensitive Image Captioning (ISIC). In ISIC, a captioning system is given a target image and an issue, which is a set of images partitioned in a way that specifies what information is relevant. The goal of the captioner is to produce a caption that resolves this issue. To model this task, we use an extension of the Rational Speech Acts model of pragmatic language use. Our extension is built on top of state-of-the-art pre-trained neural image captioners and explicitly reasons about issues in our sense. We establish experimentally that these models generate captions that are both highly descriptive and issue-sensitive, and we show how ISIC can complement and enrich the related task of Visual Question Answering.

1 Introduction

Image captioning systems have improved dramatically over the last few years (Karpathy and Fei-Fei, 2015; Vinyals et al., 2015), creating new opportunities to design systems that are not just accurate, but also produce descriptions that include relevant, characterizing aspects of their inputs. Many of these efforts are guided by the insight that high-quality captions are implicitly shaped by the communicative goal of identifying the target image up to some level of granularity (Vedantam et al., 2017; Mao et al., 2016; Luo et al., 2018; Cohn-Gordon et al., 2018).

In this paper, we present a technique for more tightly controlling the information that a pretrained captioning system includes in its output texts. We call this Issue-Sensitive Image Captioning (ISIC). In ISIC, the captioning system’s inputs are image/issue pairs, where an issue is a partition on a subset of images, and the objective is to produce a caption that resolves that issue with respect to the target image, where resolution means identifying which cell of the partition contains the target. Figure 1 illustrates: in the top row, the images are partitioned into two sets based on body color, leading to a very different caption for the same target image.

Figure 1: Examples highlighting the power of an issuessensitive image capti oner. A single set of images is partition in two ways, each capturing different ways of grouping them into equivalence classes. The first row’s equivalence class is about the general body color of the bird. The second row’s equivalence classes are white eyebrows or not. The target image is the same in both cases, but the issue leads to different captions that key into the structure of the input issue.
In defining the task this way, we are inspired by recent work on Visual Question Answering (VQA; Antol et al. 2015), but ISIC differs from VQA in two crucial respects. First, we seek full image captions rather than direct answers. Second, our question inputs are not texts, but rather issues in the semantic sense: partitions on subsets of the available images. The ISIC module reasons about the cells in these partitions as alternatives to the target image, and our notion of answerhood is defined in these terms. Nonetheless, VQA and ISIC complement each other: issues (as partitions) can be automatically derived from available image captioning and VQA datasets (Section 6), opening up new avenues for VQA as well.

Our models are built directly on top of pretrained image captioning systems with no need for additional training or fine-tuning. This is achieved by extending those models according to the structure of the Rational Speech Acts model (Frank and Goodman, 2012; Goodman and Stuhlmüller, 2013), which has been applied successfully to many NLP tasks (Section 2.3). Our key modeling innovation lies in building issues into these models. In this, we are inspired by linguistic work on question-sensitive RSA (Goodman and Lassiter, 2015; Hawkins and Goodman, 2019).

Our central experiments are with the Caltech-UC San Diego-Bird dataset (CUB; Welinder et al. 2010). This dataset contains extensive attribute annotations that allow us to study the effects of our models in precise ways. Using CUB, we provide quantitative evidence that our RSA-based models generate captions that both richly describe the target image and achieve the desired kinds of issue-sensitivity. Following this, we show how to apply our methods to larger image captioning and VQA datasets that require more heuristic methods for defining issues. These experiments begin to suggest the potential value of issue-sensitivity in other domains that involve controllable text generation.

2 Related Work

2.1 Neural Image Captioning

The task of image captioning crosses the usual boundary between computer vision and NLP; a good captioner needs to recognize coherent parts of the image and describe them in fluent text. Karpathy and Fei-Fei (2015) and Vinyals et al. (2015) showed that large-capacity neural networks can get traction on this difficult problem. Much subsequent work has built on this insight, focusing on two aspects. The first is improving image feature quality: instead of fixed-dimensional image feature vectors, more advanced approaches use object-based features from computer vision models trained on object segmentation tasks (Anderson et al., 2018). The second is improving text generation quality by adopting techniques from reinforcement learning to directly optimize for the evaluation metric (Rennie et al., 2017). Our work rests on all of these innovations—our base image captioning systems are those of Hendricks et al. (2016) and Rennie et al. (2017), which motivate and employ these central advancements.

2.2 Visual Question Answering

In VQA, the model is given an image and a natural language question about that image, and the goal is to produce a natural language answer to the question that is true of the image (Antol et al., 2015; Goyal et al., 2017). This is a controllable form of (partial) image captioning. However, in its current form, VQA tends not to elicit linguistically complex texts; the majority of VQA answers are single words. Our goal, in contrast, is to produce linguistically complex, highly descriptive captions. Our task additionally differs from VQA in that it produces a caption in response to an issue, i.e., a partition of images, rather than a natural language question. In Section 4.2 and Section 6, we describe how VQA and ISIC can complement each other, by using VQA annotations to provide a map from natural language questions to issues.

2.3 The Rational Speech Acts Model

The Rational Speech Acts model (RSA) was developed by Frank and Goodman (2012) with important precedents from Lewis (1969), Jäger (2007), Franke (2009), and Golland et al. (2010). It has since been applied to a wide variety of diverse linguistic phenomena. Since RSA is a probabilistic model of communication, it is amenable for incorporation into many modern NLP architectures. A growing body of literature shows that adding RSA components to NLP architectures can help them to capture important aspects of context dependence in language, including referential description generation (Monroe and Potts, 2015; Andreas and Klein, 2016; Monroe et al., 2017), instruction following (Fried et al., 2018), collaborative problem solving (Tellex et al., 2014), and translation (Cohn-Gordon and Goodman, 2019).
Broadly speaking, there are two kinds of approaches to incorporating RSA into NLP systems. One class of approaches performs end-to-end learning of the RSA agents, as in Monroe and Potts 2015, Vedantam et al. 2017, and Mao et al. 2016. The other uses a pretrained system, and applies RSA at the decoding stage (Andreas and Klein, 2016; Monroe et al., 2017; Fried et al., 2018). We adopt this second approach, as it is highly scalable and highlights the ways in which our approach can imbue a wide range of existing systems with new capabilities.

### 2.4 Issue-Sensitivity in Language

Our extension of the above uses of RSA centers on what we call issues. In this, we build on a long tradition of linguistic research on the ways in which language use is shaped by the issues (often called Questions Under Discussion) that the discourse participants regard as relevant (Groenendijk and Stokhof, 1984; Ginzburg, 1996; Roberts, 1996). Issues in this sense can be reconstructed in many ways. Here, we follow Lewis (1988) and many others in casting an issue as a partition on a space of states into cells. Each cell represents a possible resolution of the issue. These ideas are brought into RSA by Goodman and Lassiter (2015) and Hawkins and Goodman (2019). We translate those ideas directly into the models for ISIC (Section 4), where an issue takes the form of a partition over a set of natural images.

### 3 Task Formulation

In standard image captioning, the input $i$ is an image drawn from a set of images $\mathcal{I}$, and the output $w$ is a sequence of tokens $[w_1, \ldots, w_n]$ such that each $w_i \in \mathcal{V}$, where $\mathcal{V}$ is the vocabulary.

In ISIC, we extend standard image captioning by redefining the inputs as pairs $(C, i)$, where $C$ is a partition$^1$ on a subset of elements of $\mathcal{I}$ and $i \in \bigcup_{u \in C}$. We refer to the partitions $C$ as issues, for the reasons discussed in Section 2.4. The goal of ISIC is as follows: given input $(C, i)$, produce a caption $w$ that provides a true resolution of $C$ for $i$, which reduces to $w$ identifying the cell of $C$ that contains $i$, as discussed in Section 2.4. Figure 2 presents an idealized example. (Figure 1 is a real example involving CUB and an ISIC captioner; see also Figure 4 and Figure 5 below.)

In principle, we could try to learn this kind of issue sensitivity directly from a dataset of examples $((C, i), w)$. We do think such dataset could be collected fairly straightforwardly, as discussed briefly in Section 7. However, our primary modeling goal is to show that such datasets need not be created. The issue-sensitive pragmatic model we introduce next can realize the goal of ISIC without training data of this kind.

### 4 Models

#### 4.1 Neural Pragmatic Agents

The pragmatic models we employ here define a hierarchy of increasingly sophisticated speaker and listener agents, in ways that mirror ideas from Gricean pragmatics (Grice, 1975) about how meaning can arise when agents reason about each other in both production and comprehension (see also Lewis 1969).

Our base agent is a speaker $S_0(w \mid i)$. In linguistic and psychological models, this is often a truth-conditional agent in that, for a given input state $i$, it defines a distribution over messages $w$.

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$^1$A set of sets $X$ is a partition of a set $X$ iff $u \cap v = \emptyset$ for all $u, v \in X$ and $\bigcup_{u \in X} = X$. 
that is proportional to their truth with respect to i, and possibly takes some notion of cost into account as well. In contrast, our $S_0$ is a trained neural image captioning system. Such systems have the same general format as their truth-conditional counterparts, but they are learned from data, with no need to hand-specify a semantic grammar or the like.

The pragmatic listener $L_1(i \mid w)$ defines a distribution over states i given a message w. The distribution is defined by applying Bayes’ rule to the $S_0$ agent:

$$L_1(i \mid w) = \frac{S_0(w \mid i)P(i)}{\sum_{i' \in I} S_0(w \mid i')P(i')}$$  \hspace{1cm} (1)

where $P(i)$ is a prior over states i (always flat in our work). This agent is pragmatic in the sense that it reasons about another agent, showing behaviors that align with the Gricean notion of conversational implicature (Goodman and Frank, 2016).

We can then define a pragmatic speaker using a utility function $U_1$, in turn defined in terms of $L_1$:

$$U_1(i, w) = \log L_1(i \mid w)$$ \hspace{1cm} (2)

$$S_1(w \mid i) = \frac{\exp(\alpha U_1(i, w) - cost(w))}{\sum_{w'} \exp(\alpha U_1(i, w') - cost(w'))}$$ \hspace{1cm} (3)

Here, $\alpha$ is a parameter defining how heavily $S_1$ is influenced by $L_1$. The term $cost(w)$ is a cost function which can penalize messages that are unusual or complex. In our models, we specify $cost(w)$ as $- \log(S_0(w \mid i))$.

### 4.2 Issue-Sensitive Speaker Agents

The agent in (3) has been widely explored and shown to deliver a powerful notion of context dependence (Andreas and Klein, 2016; Monroe et al., 2017). However, it is insensitive to the issues C that characterize ISIC. To make this connection, we extend (3) with a term for these issues:

$$U^C_1(i, w, C) = \log \left( \sum_{i' \in I} \delta_{[C(i) = C(i')]} L_1(i' \mid w) \right)$$ \hspace{1cm} (4)

$$S^C_1(w \mid i, C) \propto \exp(\alpha U^C_1(i, w, C) - cost(w))$$ \hspace{1cm} (5)

where $\delta_{[C(i) = C(i')]}$ is a partition function, returning 1 if i and i' are in the same cell in C, else 0. This is based on a similar model of Kao et al. (2014).

We use $C(i)$ to denote the cell to which image i belongs under C (a slight abuse of notation, since C is a set of sets).

The construction of the partitions C is deliberately left open at this point. In some settings, the set of images $I$ will have metadata that allows us to construct these directly. For example, in the CUB dataset, we can use the attributes to define intuitive partitions directly – e.g., the partition that groups images into equivalence classes based on the beak color of the birds they contain. The function can also be parameterized by a full VQA model $A$. For a given question text $q$ and image i, $A$ defines a map from (q, i) to answers a, and so we can partition a subset of $I$ based on equivalence classes defined by these answers a.

### 4.3 Penalizing Misleading Captions

The agent in (5) is issue-sensitive in the sense that it favors messages that resolve the issue C. However, it does not include a pressure against hyperspecificity. This poses two potential problems.

The first can be illustrated using the top row of Figure 2. All else being equal, our agent (5) would treat “A red square” and “A small red square” as equally good captions, even though the second includes information that is intuitively gratuitous given the issue. This might seem innocent here, but it can raise concerns in real environments. For instance, in a newspaper article about the party membership of various politicians, a caption that identifies the politician and gives their age or hair color could generate problematic inferences.

The second problem relates to the data-driven nature of the systems we are developing: in being hyper-specific, we observed that they often mentioned properties not true of the target but rather only true of members of their equivalence classes. For example, in Figure 2, the target could get incorrect properties from the image cell.

We propose to address both these issues with a second utility term $U_2$:

$$U_2(w, i, C) = H(L_1(i' \mid w) \cdot \delta_{[C(i) = C(i')]} )$$ \hspace{1cm} (6)

where H is the information-theoretic entropy. This encodes a pressure to choose utterances which result in the $L_0$ spreading probability mass as evenly as possible over the images in the target image cell. This discourages the production of very specific descriptions of any particular image in the target cell, thereby solving both of the problems we identified above.
We refer to this agent as \( S_1^{C+H} \). Its full specification is as follows:

\[
S_1^{C+H}(w | i, C) \propto \exp(\alpha ((1 - \beta)U_1 + \beta U_2) - \text{cost}(w)) \tag{7}
\]

where \( \beta \in [0, 1] \) is a hyperparameter that allows us to weight these two utilities differently.

### 4.4 Reasoning about Alternative Captions

A pressing issue which arises when computing probabilities using (3), (5), and (7) is that the normalization constant includes a sum over all possible captions \( w' \). In the present setting, the set of possible captions is infinite (or at least exponentially large in the maximum caption length), making this computation intractable.

There are two solutions to this intractability proposed in the literature: one is to use \( S_0 \) to first sample a small subset of captions from the full space, which then remains fixed throughout the computation (Andreas and Klein, 2016; Monroe et al., 2017). The drawback of this approach is that the diversity of captions that the \( S_1 \) can produce is restricted by the \( S_0 \). Since our goal is to generated captions which may heavily vary depending on the issue, this could prove to be a serious limitation.

The other approach is to alter the model so that the RSA reasoning takes place at the level of the generation of each successive word, word piece, or letter in the caption, so that the possible “utterances” at each step are drawn from a relatively small set of options (Cohn-Gordon et al., 2018). We opt for this incremental formulation and provide the full details on this model in Appendix A.

### 5 CUB Experiments

#### 5.1 Dataset

The Caltech UC San Diego-Bird (CUB) dataset contains 11,788 images for 200 species of North American birds (Welinder et al., 2010). Each image contains a single bird and is annotated with fine-grained information about the visual appearance of that bird, using a system of 312 binary attributes devised by ornithologists. The attributes have a \textit{property::value} structure, as in \textit{has\_wing\_color::brown}, and they are arranged hierarchically from high-level descriptors (e.g., \textit{bill}) down to very specific low-level attributes (e.g., \textit{belly pattern}). Figure 3 provides an illustration.

Reed et al. (2016) annotated each image in CUB with five captions. These captions were generated by crowdworkers who did not have access to the attribute annotations, and thus they vary widely in their specificity and alignment with the CUB annotations.

#### 5.2 Constructing CUB Partitions

CUB is ideal for testing our issue-sensitive captioning method because we can produce partitions directly from the attributes. For example, \textit{has\_wing\_color::brown} induces a binary partition into birds with brown wings and birds with non-brown wings, and \textit{has\_wing\_color} alone induces a partition that groups birds into equivalence classes based on their wing-color values. There are 26 such equivalence classes for different body parts.

#### 5.3 Base Captioning System

We trained a state-of-the-art model developed by Hendricks et al. (2016).\(^2\) We used a data split scheme similar to Hendricks et al. (2016), where we have 4,000 images for training, 1,994 images for validation, and 5,794 images for testing. The model is a two-layer long short-term memory model (Hochreiter and Schmidhuber, 1997) with 1000-dimensional hidden size and 1000-dimensional word embeddings. We trained for 50 epochs with a batch size of 128 and learning rate \(1e-3\). The final CIDEr score for our model is 0.52 on the test split. We use greedy decoding to generate our captions.

#### 5.4 Feature-in-Text Classifier

In order to examine the effectiveness of our issue-sensitive captioning models, we need to be able to identify whether the generated caption contains information regarding the issue. Even though each CUB image has a complete list of features for its bird, we must map these features to descriptions in

\(^2\)https://github.com/salaniz/pytorch-gve-lrcn

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**Figure 3:** A sample of features that describe a Carolina Wren. There can be multiple aspects for one body part. Some general descriptors, such as \textit{size} and \textit{shape}, do not have fine-grained aspects.
a small bird with a white breast and belly brown wings and tail and a pointed beak

this is a bird with a white belly brown back and a brown head

this is a reddish orange bird with black and white wings and a red crown

text. For example, in Figure 3, the bill shape has an attribute “All-purpose”, but the non-expert captions in CUB are likely to use an informal descriptive phrase like “pointy black beak”.

To link textual descriptions with attributes, we use a text classifier. It is not possible to build a learned attribute classifier on CUB because the caption and attributes are not aligned, given that the caption writers did not have access to the attribute values. To remedy this, we use a sliding window text classifier. First, we identify keywords that can describe body parts (e.g. “head”, “malar”, “cheek-patch”) and extract their positions in the text. Second, we look for keywords related to aspects (e.g., “striped”, “speckled”); if these occur before a body-part word, we infer that they modify the body part. Thus, for example, if “scarlet and pink head” is in the caption, then we infer that it resolves an issue about the color of the bird’s head.

5.5 Evaluating Attribute Coverage

We begin by assessing the extent to which our issue-sensitive pragmatic models produce captions that are more richly descriptive of the target image than a base neural captioner $S_0$ and its simple pragmatic variant $S_1$. For CUB, we can simply count how many attributes the caption specifies according to our feature-in-text classifier. More precisely, for each image and each model, we generate captions under all resolvable issues, concatenate those captions, and then use the feature-in-text classifier to obtain a list of attributes, which we can then compare to the ground truth for the image as given by the CUB dataset. For $S_0$ and $S_1$, the captions do not vary by issue, whereas our expectation is that they do vary for $S_1^C$ and $S_1^{C+H}$.

Table 1 reports on this evaluation. Precision for all models is very high; the underlying attributes in CUB are very comprehensive, so all high-quality captioners are likely to do well by this metric. In contrast, the recall scores vary substantially, and they clearly favor the issue-sensitive models, revealing them to be substantially more descriptive than $S_0$ and $S_1$. Figure 4 provides examples that highlight these contrasts: whereas the $S_0$ caption is descriptive, it simply doesn’t include a number of attributes that we can successfully coax out of an issue-sensitive model by varying the issue.

In Table 2, we provide a breakdown of these scores by body part. The issue-sensitive models are clear winners for all categories. It is noteworthy that the entropy term in $S_1^{C+H}$ seems to help for some categories but not others, suggesting underlying variation in the categories themselves.

5.6 Evaluating Issue Alignment

Our previous evaluation shows that varying the issue has a positive effect on the captions generated by our issue-sensitive models, but it does not assess whether these captions resolve individual issues in
Table 2: $F_1$ scores for each body part aspect. The issue-sensitive models are superior for all categories.

| Body part-aspect         | $S_0$ | $S_1$ | $S_C^1$ | $S_1^{C+H}$ |
|--------------------------|-------|-------|---------|-------------|
| back color               | 4.4   | 19.4  | 54.2    | 61.5        |
| back pattern             | 1.3   | 4.5   | 16.5    | 19.9        |
| belly color              | 54.9  | 60.3  | 89.2    | 91.3        |
| belly pattern            | 6.5   | 19.3  | 46.3    | 44.2        |
| bill color               | 33.2  | 48.1  | 69.3    | 69.8        |
| bill length              | 39.8  | 53.3  | 90.0    | 92.4        |
| bill shape               | 8.2   | 33.5  | 70.1    | 60.1        |
| breast color             | 42.4  | 57.4  | 89.8    | 91.2        |
| breast pattern           | 4.9   | 18.3  | 48.5    | 45.0        |
| crown color              | 34.3  | 44.2  | 58.2    | 60.8        |
| eye color                | 23.7  | 43.3  | 82.0    | 71.8        |
| forehead color           | 11.3  | 17.5  | 37.4    | 29.1        |
| head pattern             | 0.0   | 4.7   | 23.6    | 6.0         |
| leg color                | 9.3   | 28.4  | 65.1    | 29.3        |
| nape color               | 5.9   | 13.3  | 35.3    | 43.4        |
| primary color            | 0     | 3.8   | 20.4    | 5.6         |
| tail pattern             | 0     | 2.1   | 9.4     | 2.1         |
| tail shape               | 0     | 2.1   | 7.2     | 1.2         |
| throat color             | 17.8  | 39.9  | 79.2    | 79.5        |
| under tail color         | 0     | 0.7   | 4.9     | 0.5         |
| underparts color         | 59.2  | 70.9  | 95.1    | 94.3        |
| upper tail color         | 1.3   | 16.7  | 51.8    | 32.7        |
| upperparts color         | 87.6  | 89.5  | 98.7    | 98.9        |
| wing color               | 37.4  | 63.4  | 89.4    | 84.6        |
| wing pattern             | 2.8   | 12.9  | 36.8    | 28.3        |
| wing shape               | 1.3   | 4.0   | 18.0    | 7.8         |

Table 3: Issue alignment results. Precision is the rate at which an issue addressed by a model's caption is the target issue, and recall is the rate at which a model's caption addresses the target issue. $F_1$ is the harmonic mean of these two values.

|         | Precision | Recall | $F_1$ |
|---------|-----------|--------|-------|
| $S_0$   | 4.1       | 14.0   | 6.3   |
| $S_1$   | 4.0       | 12.8   | 6.1   |
| $S_C^1$ | 4.1       | 12.5   | 6.2   |
| $S_1^{C+H}$ | 4.5 | 16.7  | 7.1   |

The question posed by this method is as follows: for a given issue $C$, does the produced caption precisely resolve $C$? We can divide this into two sub-questions. First, does the caption resolve $C$, which is a notion of recall. Second, does the caption avoid addressing issues that are distinct from $C$, which is a notion of precision. The recall pressure is arguably more important, but the precision one can be seen as assessing how often the caption avoids irrelevant and potentially distracting information, as discussed in Section 4.3.

Table 3 reports on this issue-sensitive evaluation, with $F_1$ giving the usual harmonic mean between our versions of precision and recall. Overall, the scores reveal that this is a very challenging problem, which traces to the fine-grained issues that CUB supports. Our $S_1^{C+H}$ agent is nonetheless definitively the best, especially for recall.

6 MS COCO and VQA 2.0

The annotations in the CUB dataset allow us to generate nuanced issues that are tightly connected to the content of the images. It is rare to have this level of detail in an image dataset, so it is important to show that our method is applicable to less controlled, broader coverage datasets as well. As a first step in this direction, we now show how to apply our method using the VQA 2.0 dataset (Goyal et al., 2017), which extends MS COCO (Lin et al., 2014) with the question and answer annotations needed for VQA. While MS COCO does have instance-level annotations, they are mostly general category labels, so the attribute-dependent method we used for CUB isn’t effective here. However, VQA offers a benefit: one can now control captions by asking questions in natural language.

6.1 Dataset

MS COCO contains 328k images that are annotated with instance-level information. The images are mostly everyday objects and scenes from human life. A subset of them (204,721 examples) are annotated with whole image captions. Antol et al. (2015) built on this resource to create a VQA dataset, and Goyal et al. (2017) further extended that work to create VQA 2.0, which reduces certain linguistic biases that made aspects of the initial VQA task artificially easy. VQA 2.0 provides 1,105,904 question annotations for all the images.
| Target Image | Issues | Partitions | Issue-sensitive Caption | Base Caption |
|--------------|--------|------------|-------------------------|--------------|
| ![Image](image1.png) | What position is this man playing? | ![Partitions](partitions1.png) | a pitcher winding throwing ball on top of a field | a baseball player throwing a ball on a field |
| ![Image](image2.png) | What color is the wall? | ![Partitions](partitions2.png) | a glass vase with a red wall with a chandelier | a vase with flowers in it on a table |
| ![Image](image3.png) | What color is the sky? | ![Partitions](partitions3.png) | a black and white photo of an airplane in the sky | an airplane taking off from an airport runway |
| ![Image](image4.png) | How many toilets are there? | ![Partitions](partitions4.png) | a bathroom with two toilets and a tub | a bathroom with a tub and a toilet and a window |

Figure 5: Issue-sensitive pragmatic captions for MS COCO images with issues determined by the VQA 2.0 dataset. The left-hand cell in the ‘Partitions’ column is the cell that contains the target image, and right-hand cell is the union of the distractor cells. The ‘Base Caption’ texts are those produced by our $S_0$ model, and the ‘Issue-sensitive Caption’ texts were produced by $S_1^{C+H}$ with parameters $\alpha$ and $\beta$ tuned separately across examples.

from MS COCO.

### 6.2 Constructing Partitions

To generate issues, we rely on the ground-truth questions and answers in the VQA 2.0 dataset. Here, each image is already mapped to a list of questions and corresponding answers. Given an MS COCO image and a VQA question, we identify all images associated with that question and then partition these images into cells according to their ground-truth answers. Exactly the same procedure could be run using a trained VQA model rather than the ground-truth annotations in VQA 2.0.

### 6.3 Base Captioning System

We use a pretrained state-of-the-art Transformer model with self-critical sequence training (Rennie et al., 2017). This has 6 Transformer layers with a 2048-dimensional hidden states, 512-dimensional input embeddings, and 8 attention heads at each layer. We use image features extracted by Anderson et al. (2018). The model achieves a CIDEr score of 1.29 for the test split. We use beam search (with beam size 5) to generate our captions.

### 6.4 Example Captions

We show some examples for MS COCO in Figure 5. We chose these to highlight the potential of our model as well as remaining challenges. In datasets like this, the captioning model must reason about a large number of diverse issues, from objects and their attributes to more abstract concepts like types of food, sports positions, and relative distances (“How far can the man ride the bike?”; answer: “Far”). Our model does key into some abstract issues (e.g., “black and white photo” in row 3 of Figure 5), but more work needs to be done. Figure 5 also suggests shortcomings concerning over-informativity (e.g., the mention of a tub in response to an issue concerning numbers of toilets), paralleling the generally low scores for CUB that we saw in Section 5.6.

### 7 Conclusion

We defined the task of Issue-Sensitive Image Captioning (ISIC) and developed a Bayesian pragmatic model that allows us to address this task successfully using existing datasets and pretrained image captioning systems. We see two natural extensions of this approach that might be explored.

First, one might collect a dataset that exactly matched the structure of ISIC. This could allow for more free-form, naturalistic issues to arise, and would facilitate end-to-end training of models for ISIC. Such models could complement and extend the ones we can create using existing datasets and our issue-sensitive pragmatic captioning agents.

Second, one could extend our notion of issue-sensitivity to other domains. As we saw in Section 6, questions (as texts) naturally give rise to issues in our sense where the domain is sufficiently structured, so these ideas might find applicability in the context of question answering and other areas of controllable natural language generation.

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3https://github.com/ruotianluo/self-critical.pytorch
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A Incremental Pragmatic Reasoning

The normalization terms of $S_1$, $S_1^C$, and $S_1^{C+H}$ all require a sum over all messages, rendering them intractable to compute.

We now describe a variant of the $S_1$ which performs pragmatic reasoning incrementally. This method extends in an obvious fashion to $S_1^C$ and $S_1^{C+H}$.

We begin by noting that a neural captioning model, at decoding time, generates a caption $w$ one segment at a time (depending on the architecture, this segment may be a word, word piece, or character). We write $w = (w_1 \ldots w_n)$, where $w_i$ is the $i$th segment.

Concretely, a trained neural image captioneer can be specified as a distribution over the subsequent segment given the image and previous words, which we write as $S_0(w_{n+1} \mid w_1 \ldots w_n)$. This allows us to define incremental versions of $L_1$ and $S_1$, as follows:

\[
L_1(i \mid w_{n+1}, [w_1 \ldots w_n]) \propto S_0(w_{n+1} \mid i, [w_1 \ldots w_n])P(i)
\]

\[
U_1(i, w_{n+1}, [w_1, w_n]) = \log L_1(i \mid w_{n+1}, [w_1 \ldots w_n])
\]

\[
S_1(w_{n+1} \mid i, [w_1 \ldots w_n]) \propto \exp(\alpha U_1(i, w_{n+1}, [w_1, w_n]) - \text{cost}(w_{n+1}))
\]

Here, we define the cost as the negative log-likelihood of the $S_0$ producing $w_{n+1}$ given the image $i$ and previous segments $[w_1 \ldots w_n]$. We can then obtain a caption-level model, which we term $S_1^{INC}$ by contrast to the $S_1$ defined in (3):

\[
S_1^{INC}(w \mid i) = \prod_{i=1}^{n} S_1(w_i \mid [w_1 \ldots w_{i-1}], i)
\]
$S_{1}^{INC}(w \mid i)$ then serves as a tractable approximation of the caption-level $S_{1}(w \mid i)$, and the same approach is easily extended to $S_{1}^C$ and $S_{1}^{C+H}$. 