

Belief Revision based Caption Re-ranker with Visual Semantic Information

Ahmed Sabir¹, Francesc Moreno-Noguer²,
Pranava Madhyastha³, Lluís Padró¹

¹ TALP Research Center, Universitat Politècnica de Catalunya, Barcelona, Spain

² Institut de Robòtica i Informàtica Industrial (CSIC-UPC), Barcelona, Spain

³ City, University of London, UK

COLING 2022



Overview

Background

Proposed Architecture

Experiments & Results

Conclusion

Overview

Background

Proposed Architecture

Experiments & Results

Conclusion

Background

- While SoTA models generate captions that are comparable to human. They are known to **lack lexical diversity**. One of the limitations is that the **narrow beam search** may not result in the most description caption of the image.
- Also they are lack of **semantic understanding** of the relation between objects in the image.



Caption Beam search

a baby is eating in front of a birthday cake

a baby sitting in front of a giant cake

a baby sitting in front of a cake

a baby sitting in front of a white cake

....

a baby **sitting** in front of a **birthday cake**

Image credit: COCO-Captions (Lin et al., 2014)

Background

- Recent works use a beam search directly to produce diverse captions by forcing richer lexical **word choices** (Ippolito et al., 2019; Vijayakumar et al., 2018; Wang and Chan, 2019; Wang et al., 2020).
- However, this does not guarantee to include all objects in the image that are **semantically related**, which results in an incorrect diverse caption.



Caption Beam search

a baby is eating in front of a birthday cake



a baby sitting in front of a giant cake

a baby sitting in front of a cake

a baby sitting in front of a white cake

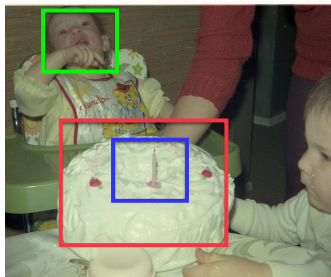
....

a baby **sitting** in front of a **birthday cake**

Image credit: COCO-Captions (Lin et al., 2014)

Background

- Recent works use a beam search directly to produce diverse captions by forcing richer lexical word choices (Ippolito et al., 2019; Vijayakumar et al., 2018; Wang et al., 2019; Wang et al., 2020).
- We propose a post-process based **Visual Beam** re-ranker that intends to visually ground the most closely related candidate beam to its related visual context.



- baby
- cake
- candel

Caption Beam search

a baby is eating in front of a birthday cake ■ ■ ■

a baby sitting in front of a giant cake ■ ■

a baby sitting in front of a cake ■ ■

a baby sitting in front of a white cake ■ ■

....

a baby **sitting** in front of a **birthday cake** ■ ■ ■

Image credit: COCO-Captions (Lin et al., 2014)

Background

Modern sophisticated image captioning systems focus heavily on **visual grounding** (object) to capture the detail of a static story in the image.

Visual Re-ranking

Fang et al. (2015)

visual detector to guide the image captioning

Object Freq Count

Wang et al. (2018)

investigates **informativeness** of object info

Controlled Caption

Cornia et al. (2019)

language grounding via object information

Semantic Coherency

Zhang et al. (2021)

explore reasoning in object grounding

Background

Modern sophisticated image captioning systems focus heavily on **visual grounding** (object) to capture the detail of a static story in the image.

Visual Re-ranking

Fang et al. (2015)

visual detector to guide the image captioning

Object Freq Count

Wang et al. (2018)

investigates **informativeness** of object info

Controlled Caption

Cornia et al. (2019)

language grounding via object information

Semantic Coherency

Zhang et al. (2021)

explore reasoning in object grounding

Background

Modern sophisticated image captioning systems focus heavily on **visual grounding** (object) to capture the detail of a static story in the image.

Visual Re-ranking

Fang et al. (2015)

visual detector to guide the image captioning

Object Freq Count

Wang et al. (2018)

investigates **informativeness** of object info

Controlled Caption

Cornia et al. (2019)

language grounding via object information

Semantic Coherency

Zheng et al. (2021)

explores reasoning in object grounding

Background

Modern sophisticated image captioning systems focus heavily on **visual grounding** (object) to capture the detail of a static story in the image.

Visual Re-ranking

Fang et al. (2015)

visual detector to guide the image captioning

Object Freq Count

Wang et al. (2018)

investigates **informativeness** of object info

Controlled Caption

Cornia et al. (2019)

language grounding via object information

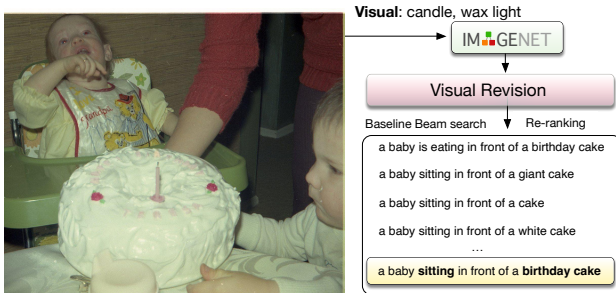
Semantic Coherency

Zhang et al. (2021)

explores reasoning in object grounding

Contributions

- Enhance the performance of any typical image captioning system without the necessity for additional training.
- Propose a human-inspired general approach that aims to **calibrate the original likelihood of top- n captions by beam search** to re-rank the most closely related caption to the visual information in the image.



Overview

Background

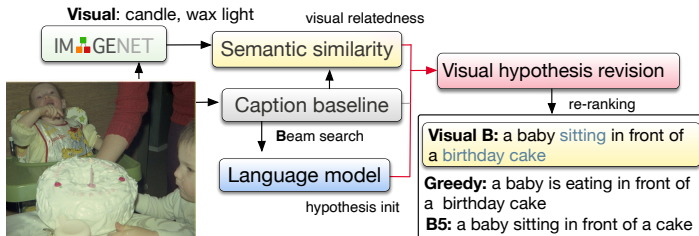
Proposed Architecture

Experiments & Results

Conclusion

Proposed Architecture: Visual Hypothesis Revision

- Language Model (Autoregressive Language Model e.g. GPT)
- Visual Concept (Visual Classifier e.g. ResNet (He et al., 2019))
- Similarity (Mask Language Model e.g. BERT (Devlin et al., 2019))



Probability from Similarity (Blok et al., 2003)

SimProb is a concept based on **belief revision** concept. Belief revision is a process of formatting a belief by **bring into account a new piece of information**.

obs 1 Tigers **can bit through wire**, therefore Jaguars **can bit through wire**.

obs 2 Kitten **can bit through wire**, therefore **Jaguars can bit through wire**.

obs 1 seem logical because it match the expectation. This **obs 1** is consistent with our previous believe (Tigers are similar to Jaguars in terms of strength), and **no need to revise it**.

Probability from Similarity (Blok et al., 2003)

SimProb is a concept based on **belief revision** concept. Belief revision is a process of formatting a belief by **bring into account a new piece of information**.

obs 1 Tigers **can bit through wire**, therefore Jaguars **can bit through wire**.

obs 2 **Kitten** can bit through wire, therefore **Jaguars can bit through wire**.

obs 2 is surprising because our prior belief is that kittens are not so strong, then we need to **revise and update our prior belief about kitten strength**.

Blok, Sergey, Douglas Medin, and Daniel Osherson. "Probability from similarity." AAAI. 2003.

Probability from Similarity SimProb

SimProb is a concept based on **belief revision** concept. Belief revision is a process of formatting a belief by **bring into account a new piece of information**.

$$P(Q_c|Q_a) = P(Q_c)^\alpha$$

Hypothesis: $P(Q_c)$

Informativeness: $1 - P(Q_a)$

Similarities: $\alpha = \left[\frac{1 - \text{sim}(a, c)}{1 + \text{sim}(a, c)} \right]^{1 - P(Q_a)}$

Probability from Similarity SimProb

SimProb is a concept based on **belief revision** concept. Belief revision is a process of formatting a belief by **bring into account a new piece of information**.

$$P(Q_c|Q_a) = P(Q_c)^\alpha$$

Hypothesis: $P(Q_c)$ Original belief

Informativeness: $1 - P(Q_a)$ New information

Similarities: $\alpha = \left[\frac{1 - \text{sim}(a, c)}{1 + \text{sim}(a, c)} \right]^{1 - P(Q_a)}$ Degree of similarity

Probability from Similarity SimProb

SimProb is a concept based on **belief revision** concept. Belief revision is a process of formatting a belief by **bring into account a new piece of information**.

$$P(Q_c|Q_a) = P(Q_c)^\alpha$$

Hypothesis: $P(Q_c)$ Language Model

Informativeness: $1 - P(Q_a)$ Visual Context Information

Similarities: $\alpha = \left[\frac{1 - \text{sim}(a, c)}{1 + \text{sim}(a, c)} \right]^{1 - P(Q_a)}$ Semantic Similarity

Sent Embedding is trained on hypothesis (w) to visual context (c)

$$C = \underset{P(c_i) \geq \beta}{c_i \in \text{Image}} \text{sim}(w, c_i)$$

$$\text{sim}(w, c) = \frac{\vec{w} \cdot \vec{c}}{|\vec{w}| \cdot |\vec{c}|}$$

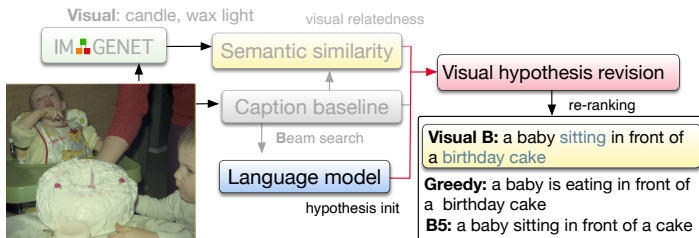
We convert the semantic score to probability according to assumption $p(w|c) \geq p(w)$. Thus the visual context assist the language model:

$$P(w|c) = P(LM)^\alpha \quad \text{where } \alpha = \left(\frac{1 - \text{sim}(w, c)}{1 + \text{sim}(w, c)} \right)^{1 - P(c)}$$

If there is no visual context information, α goes to $= 1$ the bare unigram probability is used.

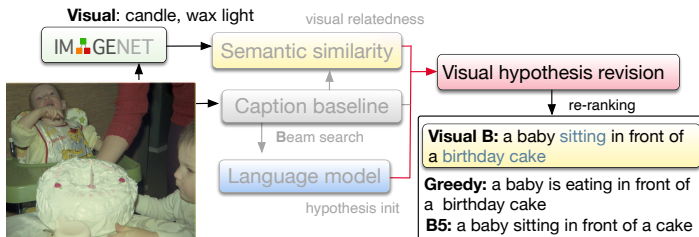
Hypothesis

- As this approach is inspired by humans, the hypothesis $P(w)$ needs to be initialized by a common observation from general text.
- We employ GPT-2 (Radford et al., 2019) to initialize the hypothesis. We set $P(w)$ as the mean token probability.



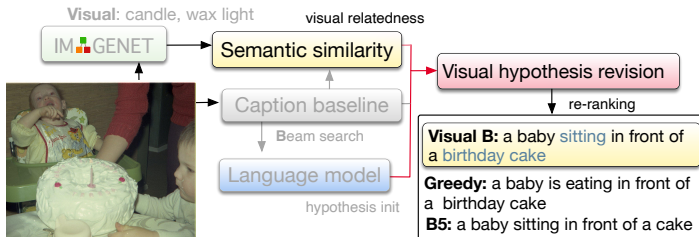
Informativeness

- The informativeness is the new information set $P(c)$ that causes the hypothesis revision.
- We leverage ResNet and Inception-ResNet v2 based faster R-CNN (Huang et al., 2017) to extract the visual information from the image.



Similarities

- Hypothesis revision is more likely if there is a close relation between the hypothesis and new information.
- We employ BERT (fine-tuned) to compute the semantic similarity between the hypothesis (caption) and its related visual context.



Text hypothesis

For Training: the five human annotated from caption COCO-Caption.

For Testing: Top-20 Beam search from the baseline (Karpathy split).

Visual context

Object classifier Resnet152 ([He et al., 2016](#)) 1000 classes.

Inception-ResNet Faster R-CNN ([Huang et al., 2017](#)) 80 classes.

VC ₁	VC ₂	VC ₃	Text hypothesis (Caption)
cheeseburger	plate	hotdog	a plate with a hamburger fries and tomatoes
bakery	dining table	web site	a table having tea and a cake on it
gown	groom	apron	its time to cut the cake at this couples wedding
racket	scoreboard	tennis ball	a crowd is watching a tennis game being played
laptop	screen	desktop computer	a grey kitten laying on a windows laptop
washbasin	toilet	seat tub	a bathroom toilet sitting on a stand next to a tub and sink

Overview

Background

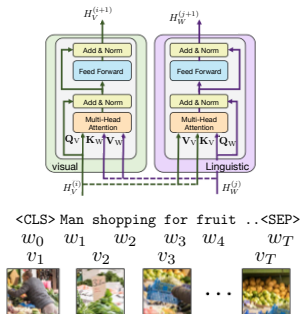
Proposed Architecture

Experiments & Results

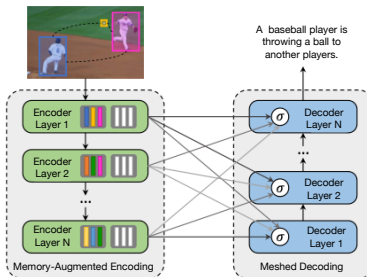
Conclusion

Baselines

- Transformer Caption Generator (12-layer Mech Transformer)
- ViBERT Pre-trained Model (12-in-1 datasets)



ViBERT Pre-trained Model (Lu et., 2020)

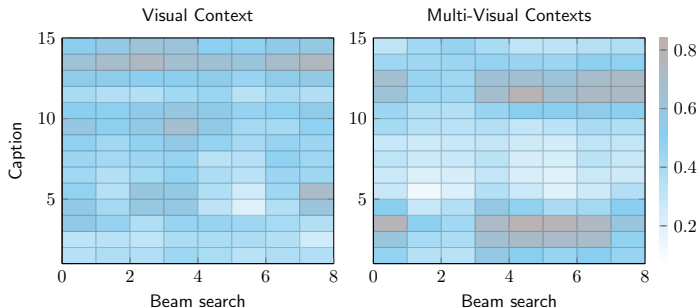


Mesh-Caption Transformer (Cornia et al., 2020)

Model	B-1	B-4	M	R	C	S	BERTscore
ViBERT (Lu et al., 2020)							
Vil _{Greedy}	0.751	0.330	0.272	0.554	1.104	0.207	0.9352
Vil _{BeamS}	0.752	0.351	0.274	0.557	1.115	0.205	0.9363
Vil+VR _{W-Object} (Fang et al., 2015)	0.756	0.348	0.274	0.559	1.123	0.206	0.9365
Vil+VR _{Object} (Wang et al., 2018)	0.756	0.348	0.274	0.559	1.120	0.206	0.9364
Vil+VR _{Control} (Cornia et al., 2019)	0.753	0.345	0.274	0.557	1.116	0.206	0.9361
Vil+VR _{BERT} (only sim)	0.753	0.343	0.273	0.556	1.112	0.206	0.9361
Vil+VR _{BERT}	0.752	0.351	0.274	0.557	1.115	0.205	0.9365
Vil+VR _{BERT-Object}	0.752	0.352	0.277	0.560	1.129	0.208	0.9365
Vil+VR _{RoBERTa}	0.753	0.353	0.276	0.559	1.128	0.207	0.9366
Vil+VR _{RoBERTa-Object}	0.758	0.344	0.262	0.555	1.234	0.206	0.9365
Vil+VR _{BERT-Multi-class}	0.753	0.353	0.276	0.559	1.131	0.208	0.9365
Vil+VR _{BERT-Multi-object}	0.752	0.351	0.276	0.558	1.123	0.208	0.9364
Vil+VR _{RoBERTa-Multi-class}	0.751	0.351	0.277	0.561	1.137	0.208	0.9366
Vil+VR _{RoBERTa-Multi-object}	0.752	0.353	0.277	0.559	1.131	0.208	0.9366
Transformer based caption generator (Cornia et al., 2020)							
Trans _{Greedy}	0.787	0.368	0.276	0.574	1.211	0.215	0.9376
Trans _{BeamS}	0.793	0.387	0.281	0.582	1.247	0.220	0.9399
Trans+VR _{W-Object} (Fang et al., 2015)	0.786	0.378	0.277	0.579	1.228	0.216	0.9388
Trans+VR _{Object} (Wang et al., 2018)	0.790	0.383	0.280	0.580	1.237	0.219	0.9391
Trans+VR _{Control} (Cornia et al., 2019)	0.791	0.388	0.281	0.583	1.248	0.220	0.9398
Trans+VR _{BERT} (only sim)	0.789	0.380	0.279	0.579	1.234	0.219	0.9389
Trans+VR _{BERT}	0.793	0.388	0.282	0.583	1.250	0.220	0.9399
Trans+VR _{BERT-Object}	0.793	0.385	0.281	0.581	1.242	0.219	0.9396
Trans+VR _{RoBERTa}	0.792	0.386	0.280	0.582	1.244	0.219	0.9395
Trans+VR _{RoBERTa-Object}	0.792	0.386	0.281	0.582	1.242	0.219	0.9396
Trans+VR _{BERT-Multi-class}	0.794	0.385	0.281	0.582	1.248	0.220	0.9395
Trans+VR _{BERT-Multi-object}	0.792	0.385	0.281	0.582	1.244	0.220	0.9395
Trans+VR _{RoBERTa-Multi-class}	0.791	0.385	0.280	0.581	1.244	0.219	0.9395
Trans+VR _{RoBERTa-Multi-object}	0.791	0.385	0.281	0.582	1.243	0.219	0.9395

Multiple Visual Contexts

We observe that longer captions benefit from more context via multiple visuals.



Diversity Evaluation

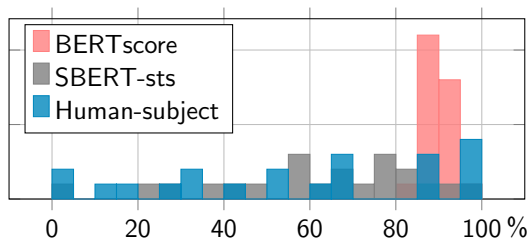
- **Lexical Diversity:** Textual Lexical Diversity (MTLD), Type Token Ratio (TTR) and Word per Caption (WPC)
- **N-gram Diversity:** Div-1 (n-gram), Div-2 (bi-gram) and mBLEU
- **Semantic Diversity:** Self-CIDEr and sentence BERT-sts

	Lexical Diversity				Voc Dist	mBLEU↓		n-gram Diversity		Semantic Diversity	
	MTLD	TTR	Uniq	WPC		best-5	best Beam*	Div-1	Div-2	Self-CIDEr	SBERT-sts
Human	19.56	0.90	9.14	14.5	3425						
VilBERT											
VilBeamS	17.28	0.87	8.05	10.5	894	0.899	0.454	0.38	0.44	0.661	0.7550
Vil+VR _{w-Object}	15.90	0.87	8.02	9.20	921	0.899	0.455	0.38	0.44	0.662	0.7605
Vil+VR _{Object}	15.77	0.87	8.03	9.19	911	0.899	0.455	0.38	0.44	0.661	0.7570
Vil+VR _{Control}	15.69	0.87	8.07	9.21	935	0.899	0.452	0.38	0.44	0.661	0.7567
Vil+VR _{RoBERTa} (ours)	17.70	0.87	8.14	10.8	892	0.896	0.451	0.38	0.44	0.661	0.7562
Transformer based caption generator											
Trans _{BeamS}	14.77	0.86	7.44	9.62	935	0.954	0.499	0.26	0.29	0.660	0.7707
Trans+VR _{w-Object}	13.14	0.85	7.37	8.62	965	0.958	0.498	0.25	0.29	0.660	0.7709
Trans+VR _{Object}	13.38	0.86	7.45	8.69	982	0.958	0.495	0.25	0.28	0.660	0.7700
Trans+VR _{Control}	13.25	0.86	7.44	8.64	961	0.958	0.498	0.25	0.29	0.660	0.7716
Trans+VR _{BERT} (ours)	14.78	0.86	7.45	9.76	980	0.963	0.338	0.26	0.30	0.660	0.7711






















please refer to the paper for all the metrics references.

Human Evaluation

- We conducted a human study to investigate human preferences over the visual re-ranked caption.
- We can observe that 46% of **native speakers** agreed with our visual re-ranker. Meanwhile, the result for **non-native** speakers is 61%



Result - Examples

Model	Caption	BERTscore	SBERT-sts	Human%	Visual
BeamS	a close up of a plate of food	0.89 	0.27 	40 	trifle 
VR	piece of food sitting on top of a white plate	0.91 	0.53 	60 	
Human refe	a white plate and a piece of white cake				
BeamS	a group of men on a field playing baseball	0.88 	0.58 	33.3 	baseball 
VR	a batter catcher and umpire during a baseball game	0.91 	0.84 	66.7 	
Human refe	batter catcher and umpire anticipating the next pitch				
BeamS	a laptop computer sitting on top of a desk	0.91 	0.69 	25 	desk 
VR	a desk with a laptop and computer monitor	0.95 	0.77 	75 	
Human refe	an office desk with a laptop and computer monitor				

Ablation study

- Belief Revision relies on a different block (*i.e.* LM, similarity and visual context)
- We perform an ablation study over a random 100 samples from the test set to investigate the effectiveness

Model	B-4	M	R	C	S
ViLBERT-VR-GPT-2 + ResNet					
+ RoBERTa (proposed)	0.346	0.266	0.541	1.171	0.205
+ DistilSBERT (Reimers et al., 2019)	0.335	0.266	0.537	1.128	0.205
+ SimCSE (Gao et al., 2021)	0.324	0.263	0.529	1.122	0.207
+ SimCSE (unervised)	0.349	0.267	0.539	1.164	0.205
+ CLIP (Radford et al., 2021)	0.335	0.261	0.527	1.142	0.202
Trans - VR-GPT-2 + ResNet					
+ BERT (proposed)	0.363	0.268	0.565	1.281	0.207
+ DistilSBERT (Reimers et al., 2019)	0.355	0.260	0.557	1.249	0.205
+ SimCSE (Gao et al., 2021)	0.356	0.265	0.564	1.272	0.207
+ SimCSE (unsupervised)	0.356	0.263	0.560	1.253	0.208
+ CLIP (Radford et al., 2021)	0.349	0.260	0.555	1.243	0.203

Belief Revision with Negative Evidence

SimProb with Negative Evidence (Blok et al., 2007)

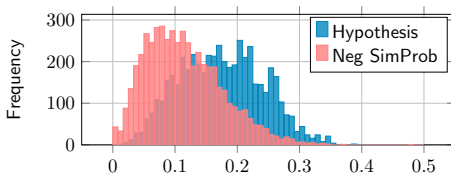
The Negative Evidence refers to the cases where the absence of visual evidence ($\neg c$) leads to a decrease in the probability of the hypothesis.

$$P(w \mid \neg c) = 1 - (1 - P(w))^\alpha$$

Belief Revision with Negative Evidence

SimProb with Negative Evidence (Blok et al., 2007)

The Negative Evidence refers to the cases where the absence of visual evidence ($\neg c$) leads to a decrease in the probability of the hypothesis.



Sergey V Blok, Douglas L, and Daniel Osherson. "Induction as conditional probability judgment." *Memory & Cognition* 2007.

- A **False Positive Visual Context (VR^{-low})**: We employ the false-positive produced by the visual classifier as negative information to decrease the hypotheses.

- A **False Positive Visual Context (VR^{-low})**: We employ the false-positive produced by the visual classifier as negative information to decrease the hypotheses.
- B **Absent Visual Context (VR^{-high})**: The negative information here is a set of visual information extracted from the original visual context that does not exist in the image but has some relation.















Belief Revision with Negative evidence

- A **False Positive Visual Context (VR^{-low})**: We employ the false-positive produced by the visual classifier as negative information to decrease the hypotheses.
- B **Absent Visual Context (VR^{-high})**: The negative information here is a set of visual information extracted from the original visual context that does not exist in the image but has some relation.
- C **Positive Visual Context (VR^{-pos})**: We approach this from a positive belief revision perspective but as negative evidence. (1) the similarity is computed without the context of the sentence and (2) the static embedding is computed without knowing the sense of the word.

Model	B-1	B-4	M	R	C	S	BERTscore
ViLBERT							
Vil _{Greedy}	0.751	0.330	0.272	0.554	1.104	0.207	0.9352
Vil _{BeamS}	0.752	0.351	0.274	0.557	1.115	0.205	0.9363
Vil+VR _{W-Object}	0.756	0.348	0.274	0.559	1.123	0.206	0.9365
Vil+VR _{Object}	0.756	0.348	0.274	0.559	1.120	0.206	0.9364
Vil+VR _{Control}	0.753	0.345	0.274	0.557	1.116	0.206	0.9361
Vil+VR _{RoBERTa} (positive)	0.753	0.353	0.276	0.559	1.128	0.207	0.9366
Vil+VR _{RoBERTa} ^{-low}	0.748	0.349	0.275	0.557	1.116	0.206	0.9362
Vil+VR _{RoBERTa} ^{-high}	0.748	0.349	0.275	0.557	1.116	0.206	0.9364
Vil+VR _{GloVe} ^{-pos}	0.751	0.351	0.276	0.558	1.123	0.207	0.9364
Vil+VR _{RoBERTa+GloVe} ^{-joint}	0.750	0.351	0.276	0.559	1.126	0.208	0.9365
Transformer based caption generator							
Trans _{Greedy}	0.787	0.368	0.276	0.574	1.211	0.215	0.9376
Trans _{BeamS}	0.793	0.387	0.281	0.582	1.247	0.220	0.9399
Vil+VR _{W-Object}	0.786	0.348	0.274	0.559	1.123	0.206	0.9365
Trans+VR _{Object}	0.790	0.383	0.280	0.580	1.237	0.219	0.9391
Trans+VR _{Control}	0.791	0.388	0.281	0.583	1.248	0.220	0.9398
Trans+VR _{BERT} (positive)	0.793	0.388	0.282	0.583	1.250	0.220	0.9399
Trans+VR _{BERT} ^{-low}	0.791	0.387	0.280	0.582	1.242	0.218	0.9396
Trans+VR _{BERT} ^{-high}	0.793	0.385	0.282	0.582	1.243	0.219	0.9397
Trans+VR _{GloVe} ^{-pos}	0.794	0.388	0.282	0.583	1.249	0.220	0.9399
Trans+VR _{BERT+GloVe} ^{-joint}	0.793	0.387	0.281	0.582	1.247	0.220	0.9398

Dataset: Object-to-caption low/high score annotation

Visual information: Object classifier failure cases

Model	Caption	BERTscore	SBERT-sts	Human%	Visual
BeamS	a pile of trash sitting inside of a building	0.88 	0.38 	100 	<div>X vacuum</div> 
VR	a pile of trash sitting in front of a building	0.88 	0.27 	0 	
Human refe	an older floor light sits deserted in an abandoned hospital				
BeamS	a kitchen with black counter tops and wooden cabinets	0.88 	0.44 	100 	<div>X barbershop</div> 
VR	a kitchen counter with a black counter top	0.88 	0.40 	0 	
Human refe	a kitchen with a sink bottles jars and a dishwasher				

Overview

Background

Proposed Architecture

Experiments & Results

Conclusion

Contributions

- We demonstrate that the Belief Revision (BR) approach that works well with human judgment can be applied to Image Captioning by employing human-inspired reasoning via a pre-trained model.
- We propose two models to improve image caption systems (1) BR with positive visual evidence (increase the hypothesis) and (2) negative evidence (decrease the hypothesis), with wrong visual.

Future Work

We plan to apply the Belief Revision Score to many re-ranking tasks in NLP such as text generation, multimodal MT, and lexical selection.



Thank You