#### **Contrast and Classify: Alternate Training for Robust VQA**



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#### **Inconsistency in VQA Models**



	Prediction
What is in the basket?	banana
What is contained in the basket?	pizza
What can be seen inside the basket?	remote
What does the basket mainly contain?	paper

## **Data Augmentation with Back Translation**



- Related works have proposed to augment the training data with paraphrases.
- One way to generate paraphrases is to use Back Translation using a pair pre-trained MT models<sup>1</sup>.
- Back Translation involves converting converting the original question to a second language and translating it back to english using two pretrained MT models.

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- One way to generate paraphrases is to use Back Translation using a pair pre-trained MT models<sup>1</sup>.
- Back Translation involves converting converting the original question to a second language and translating it back to english using two pretrained MT models.
- We augment the VQA dataset with rephrased samples.

# Data Augmentation with VQG



- Another way to generate paraphrases is by using a visual question generation (VQG) module.
- Given an image-answer pair from the VQA dataset it attempts to generate a rephrasing of the original question.
- To ensure that the generated question is a paraphrase of the original it is trained using a Question Consistency loss.

#### VQG Module

#### **Data Augmentation with VQG**



- Another way to generate paraphrases is by using a VQG module.
- Given an image-answer pair it generates a question.

#### Can we utilize the *structure* in our augmented data to learn better?



**VQG Module** 

## **Supervised Contrastive Loss**



- SCL helps us to pull closer the joint V+L representations of reference and paraphrased sample closer.
- **Positives:** In addition to paraphrased samples, we also pull closer samples with same ground truth.

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- SCL helps us to pull closer the joint V+L representations of reference and paraphrased sample closer.
- **Positives:** In addition to paraphrased samples, we also pull closer samples with same ground truth.
- While pulling positives closer we also push negatives apart.
  - **Negatives:** We categorize the negatives in three types Image, Question and Random

#### **Scaled Supervised Contrastive Loss**



- VQA is a skewed dataset, and while creating batches for SCL the number of intra-class positives outnumber the paraphrased positives by a big margin for common answer categories ('yes', 'no', etc.).
- **Scaling:** To mitigate the above problem we scale the loss between the reference and the corresponding paraphrased positive sample.
  - SCL batches are curated by sampling from sets of positive and negative types (not random).

V+L Representation

# **Training Scheme**

#### **SSCL** Iteration:

- 1. Curate batch with positives and negatives
- 2. Minimize the Scaled Supervised Contrastive Loss

#### **CE** Iteration:

- 1. Randomly sample batch
- 2. Minimize the Cross Entropy Loss

- Joint: We use a linear combination of the SCL and Cross Entropy losses as our objective. *Drawback of this* approach is that either Cross Entropy is forced to operate on batches curated for SCL or vice-versa.
- Alternate: We alternately optimize for SCL and Cross Entropy across different iterations. This allows using curated batches for SCL and random batches for Cross Entropy.

#### Contrast and Classify: Alternate Training for Robust VQA (ConCAT)



		Model	DA	Seeling	~ N T	Со	nsensu	s Score	VQA Score			
<b>D</b>		Model	DA	Scaling	IN-Type	k=1	k=2	k=3	k=4	val	test-dev	test-std
Work	1	Pythia (2018)	-	-	-	63.43	52.03	45.94	39.49	65.78	68.43	-
WORK	2	BAN (2018)	-	-	-	64.88	53.08	47.45	39.87	66.04	69.64	-
	3	Pythia + CC (2019)	-	-	-	64.36	55.45	50.92	44.30	66.03	68.88	-
	4	BAN + CC (2019)	-	-	-	65.77	56.94	51.76	48.18	66.77	69.87	-
	5	MMT + CE	-	_	_	67.74	59.82	55.10	51.82	66.46	_	-
		MMT + CE	VQG			66.53	59.26	54.92	51.85	64.50		
		MMT + ConCAT	VQG	$\checkmark$		66.49	59.55	55.33	52.31	64.74		
		MMT + CE	BT	-		67.58	60.04	55.53	52.36	66.31	69.51	69.22
		$MMT + (SCL \rightarrow CE)$	BT	X		65.34	57.39	52.63	49.20	64.21		
		MMT + (CE + SCL)	BT	X		66.95	59.70	55.32	52.20	65.10	-	
		MMT + ConCAT	BT	X		68.35	60.97	56.49	53.30	66.73		
		MMT + ConCAT	BT	$\checkmark$		68.19	60.92	56.53	53.42	66.62		
		MMT + ConCAT	BT	$\checkmark$		68.41	61.24	56.88	53.77	66.97		
		MMT + ConCAT	BT	$\checkmark$		68.47	61.28	56.91	53.79	66.93	_	-
		MMT + ConCAT	BT	X		68.20	60.90	56.49	53.36	66.60		
		MMT + ConCAT	BT	1		68.62	61.42	57.08	53.99	66.98	69.80	70.00

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Arch. Change	5	MMT + CE	-	-	-	67.74	59.82	55.10	51.82	66.46	-	-
-	6	MMT + CE	VQG	-	-	66.53	59.26	54.92	51.85	64.50	_	-
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Work	1	Pythia (2018)	-	-	-	63.43	52.03	45.94	39.49	65.78	68.43	-
mon	2	BAN (2018)	-	-	-	64.88	53.08	47.45	39.87	66.04	69.64	-
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Baseline	8	MMT + CE	BT	-	-	67.58	60.04	55.53	52.36	66.31	69.51	69.22
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Arcn. Change	5	MMT + CE	-	-	-	67.74	59.82	55.10	51.82	66.46	-	-
	6	MMT + CE	VQG	-		66.53	59.26	54.92	51.85	64.50	-	
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	11	MMT + ConCAT	BT	X	R	68.35	60.97	56.49	53.30	66.73	-	-
Ablationa	12	MMT + ConCAT	BT	$\checkmark$	R	68.19	60.92	56.53	53.42	66.62	-	-
ADIALIONS	13	MMT + ConCAT	BT	$\checkmark$	RQ	68.41	61.24	56.88	53.77	66.97	-	-
	14	MMT + ConCAT	BT	$\checkmark$	RI	68.47	61.28	56.91	53.79	66.93	-	-
	15	MMT + ConCAT	BT	×	RQI	68.20	60.90	56.49	53.36	66.60	-	-
	16	MMT + ConCAT	BT	$\checkmark$	RQI	68.62	61.42	57.08	53.99	66.98	69.80	70.00

# Thank You