Compositional Captioning: Describing Novel Object Categories without Paired Training Data

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Visual Description



Berkeley LRCN: A brown bear standing on top of a lush green field.

MS CaptionBot: A large brown bear walking through a forest.

LRCN: Donahue, Jeff et al. CVPR 2015. Microsoft CaptionBot: http://captionbot.ai/





A brown bear walking across a lush green field.

A large brown bear walking through a forest.



A brown bear walks in the grass in front of trees.







A large brown bear walking across a lush green field.

A brown bear sitting on top of a green field.

op of A brown bear walking on a grassy field next to trees.

Problems with Visual Description



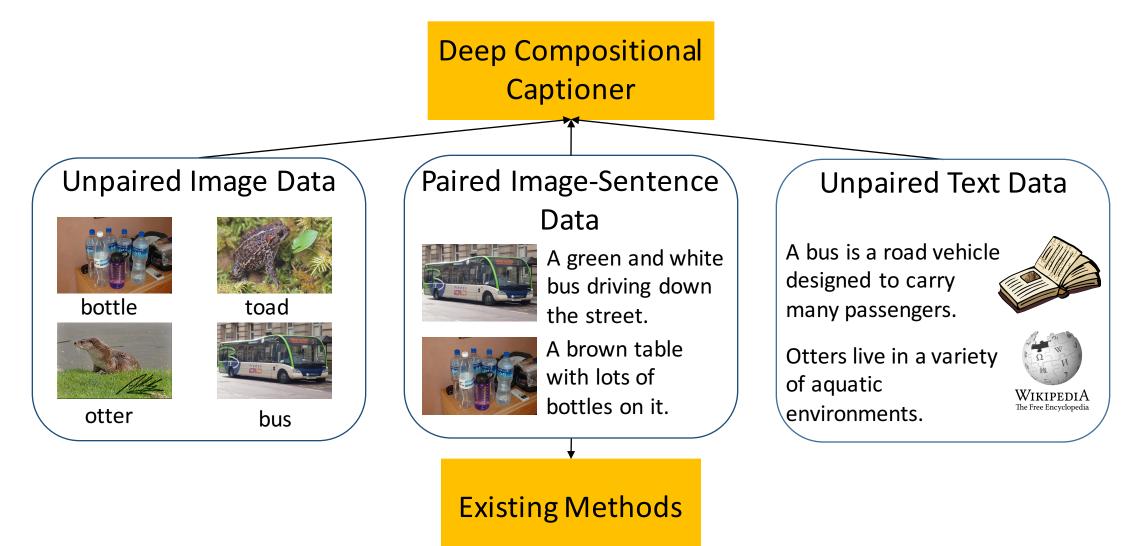
LRCN: Donahue, Jeff et al. CVPR 2015. CaptionBot: http://captionbot.ai/ Berkeley LRCN: "A black bear is standing in the grass."

MS CaptionBot: "A bear that is eating some grass."

Ours:

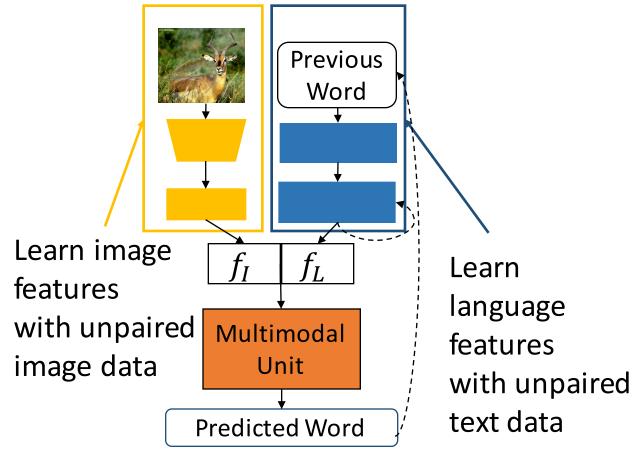
"A anteater is standing in the grass."

We present the **D**eep **C**ompositional **C**aptioner (DCC) which can compose descriptions about novel objects in context.

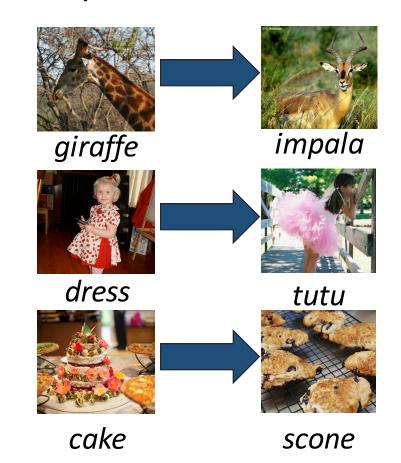


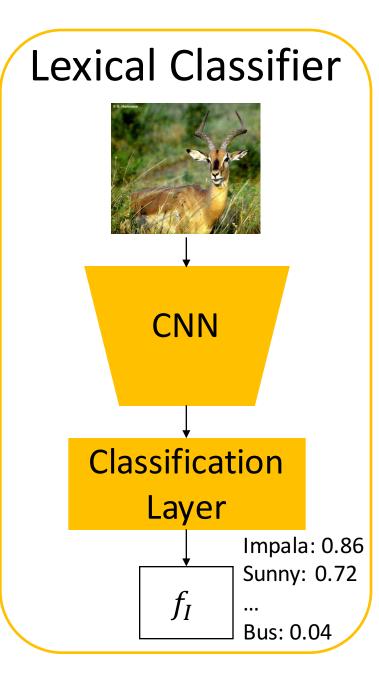
DCC Key Insights

1. Effectively train with outside data



2. Transfer knowledge between related concepts





Training Data: Unpaired Image Data

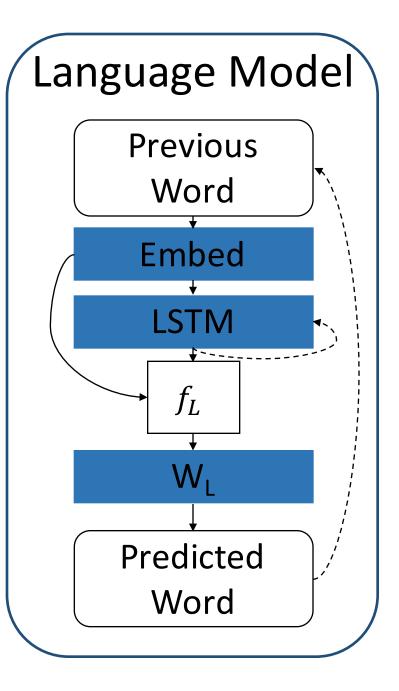
Network: VGG + multilabel loss (sigmoid cross entropy)

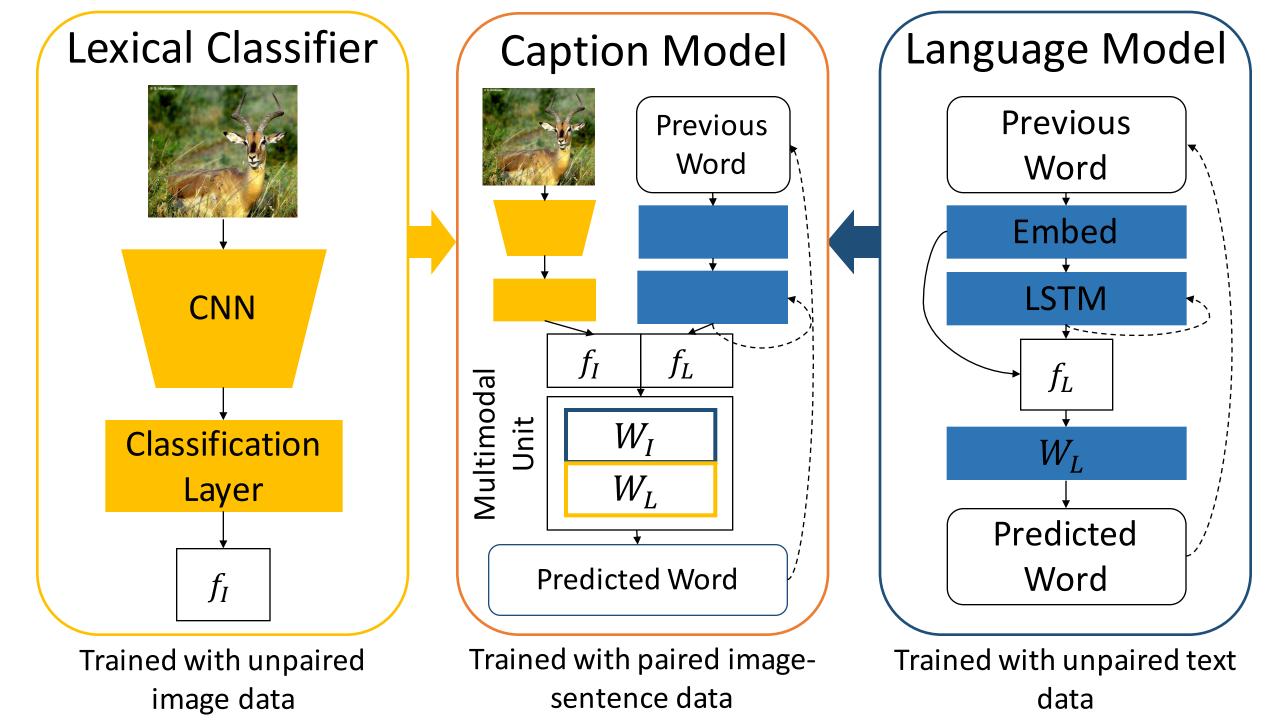
Feature: Vector with activations corresponding to scores for visual concepts in an image.

Training Data: Unpaired Text Data

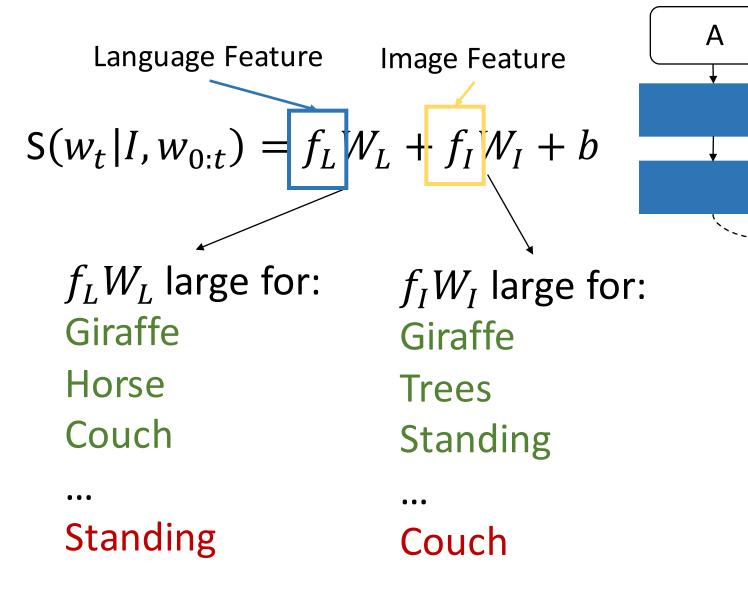
Network: Embed layer + LSTM unit. Model trained to predict a word, w_t , given the previous words in a sentence, $w_{0:t-1}$.

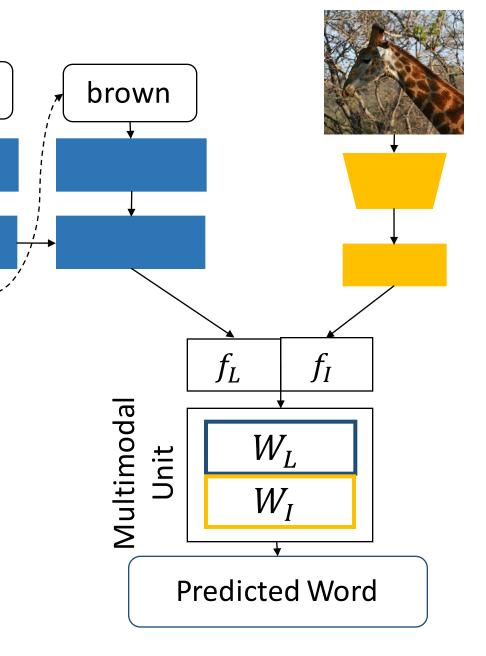
Feature: Vector which encodes previous words in the sentence.



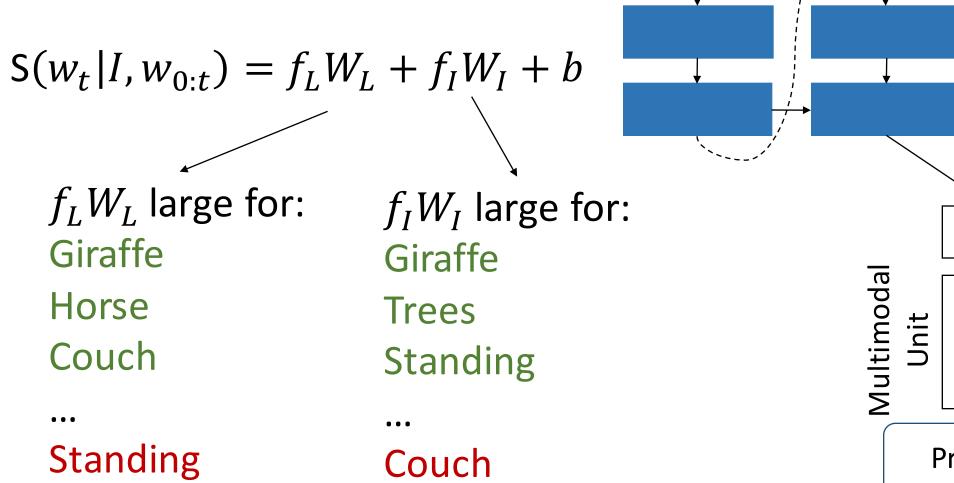


Multimodal Unit

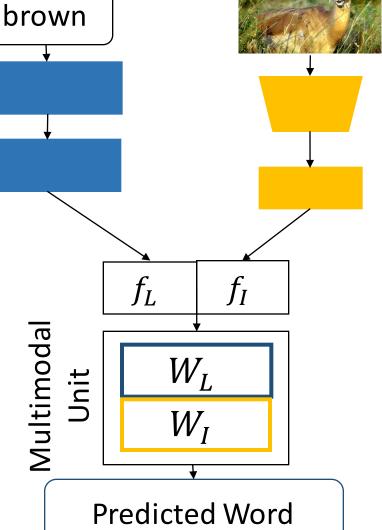




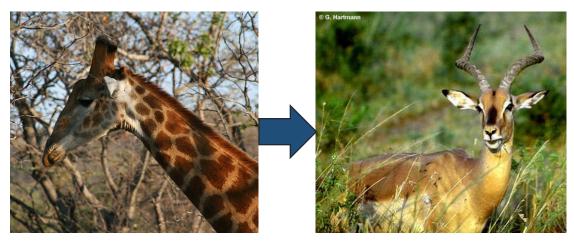
Multimodal Unit



Α



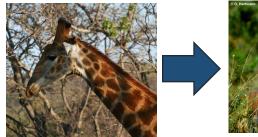
Weight Transfer



Transfer pair chosen using word2vec

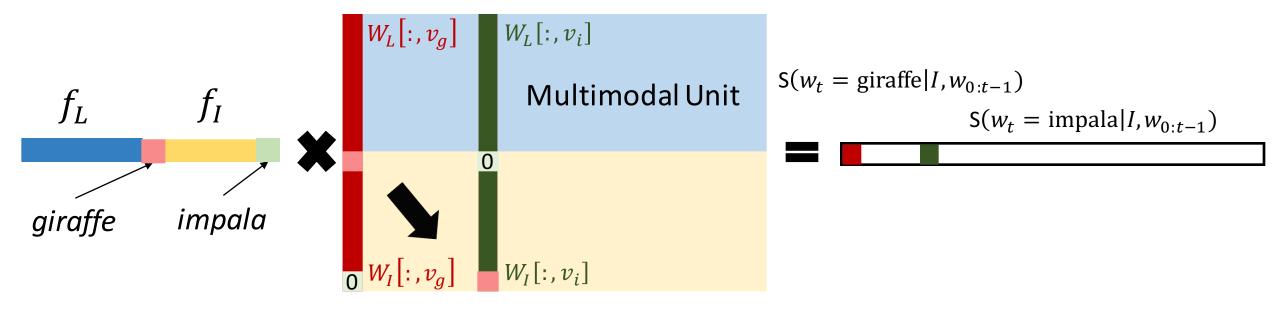
Weight Transfer

 $S(w_{t} = \text{giraffe}|I, w_{0:t-1}) = f_{L}W_{L}[:, v_{g}] + f_{I}W_{I}[:, v_{g}] + b_{g}$ $S(w_{t} = \text{impala}|I, w_{0:t-1}) = f_{L}W_{L}[:, v_{i}] + f_{I}W_{I}[:, v_{i}] + b_{i}$





Transfer pair chosen using word2vec



Evaluation

MSCOCO Unpaired Image Data



Elephant, Galloping, Green, Grass



People, Playing, Ball, Field



Black, Train, Tracks





Eat, Pizza



MSCOCO Paired











"An elephant galloping in the green grass"

- "Two people playing ball in a field"
- "A black train stopped on the tracks"
- "Someone is about to eat some pizza"

"A kitchen counter with a microwave on it"

MSCOCO Unpaired Text Data

"An elephant galloping in the green grass"

"Two people playing ball in a field"

"A black train stopped on the tracks"

"Someone is about to eat some pizza"

"A microwave is sitting on top of a kitchen counter "

Evaluation

MSCOCO Unpaired Image Data



Elephant, Galloping, Green, Grass



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Microwave

MSCOCO Paired **Image-Sentence Data**





"An elephant galloping in the green grass"

> "Two people playing ball in a field"

"A black train stopped on the tracks"

"Someone in bout to nizza"

"A kitchen comter with e on it"

MSCOCO Unpaired Text Data

"An elephant galloping in the green grass"

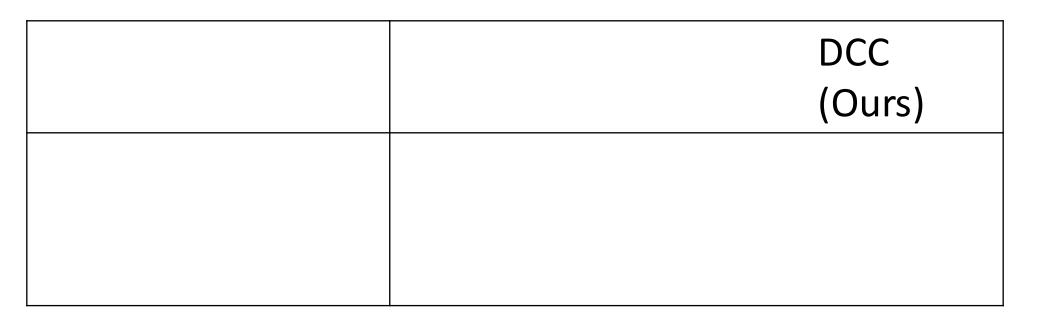
"Two people playing ball in a field"

"A black train stopped on the tracks"

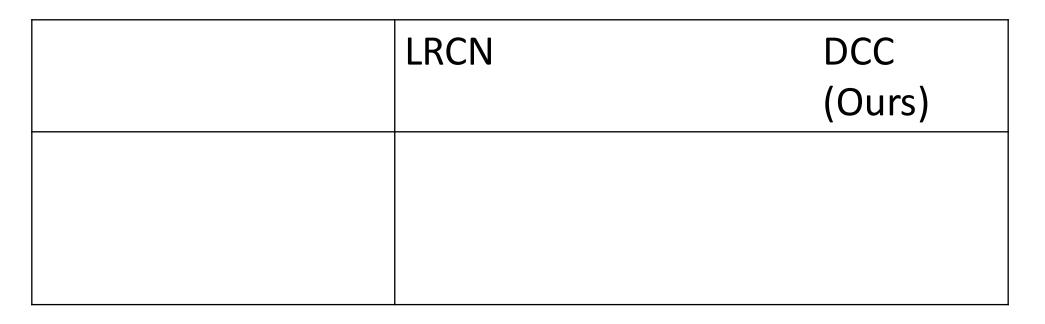
"Someone is about to eat some pizza"

"A microwave is sitting on top of a kitchen counter "

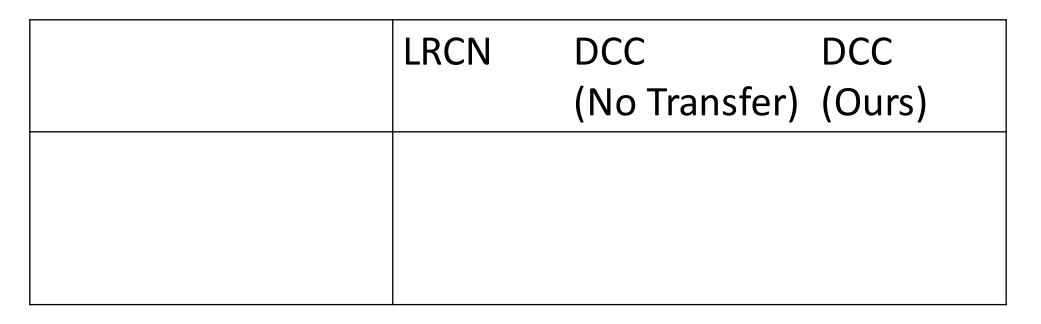
Held-out dataset



- High F1 score indicates DCC can describe words outside of paired image sentence data
- Increased METEOR indicates DCC produces better sentences



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	LRCN	DCC (No Transfer)	DCC (Ours)
Efficacy (F1)			

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	LRCN	DCC (No Transfer)	DCC (Ours)
Efficacy (F1)			
Sentence Quality (METEOR)			

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	LRCN	DCC	DCC
		(No Transfer)	(Ours)
Efficacy (F1)	0.00	0.00	39.78
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Sentence Quality (METEOR)	19.33	19.90	21.00

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Empirical Evaluation

MSCOCO Unpaired Image Data

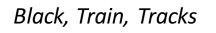


Elephant, Galloping, Green, Grass



People, Playing, Ball, Field







Pizza

Microwave

MSCOCO Paired

Image-Sentence Data





"An elephant galloping in the green grass"

> "Two people playing ball in a field"

"A black train stopped on the tracks"

"Someone is bout to

"A kitchen comter with

MSCOCO Unpaired Text Data

"An elephant galloping in the green grass"

"Two people playing ball in a field"

"A black train stopped on the tracks"

"Pepperoni is a popular pizza topping."



"All microwaves use a timer for the cooking time"

Out-of-Domain Held Out Dataset

Results: MSCOCO Out-Of-Domain

	Unpaired Image Data	Unpaired Text Data	METEOR	F1
LRCN	N/A	N/A	19.33	0.00
DCC (No Transfer)	MSCOCO	MSCOCO	19.90	0.00
DCC (Ours)	MSCOCO	MSCOCO	21.00	39.78

DCC performs well when using out of domain data to train the lexical classifier and language model.

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DCC (Ours)	ImageNet	MSCOCO	20.71	33.60

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Results: MSCOCO Out-of-Domain

	Unpaired Image Data	Unpaired Text Data	METEOR	F1
LRCN	N/A	N/A	19.33	0.00
DCC (No Transfer)	MSCOCO	MSCOCO	19.90	0.00
DCC (Ours)	MSCOCO	MSCOCO	21.00	39.78
DCC (Ours)	ImageNet	MSCOCO	20.71	33.60
DCC (Ours)	ImageNet	CaptionTxt	20.66	35.53
DCC (Ours)	ImageNet	WebCorpus	20.66	34.94

DCC performs well when using out of domain data to train the lexical classifier and language model.



No transfer: A green and white street sign on a city street. DCC: A green and white **bus** parked on the side of the street.



No transfer: A dog lying on a bed with a large brown dog. DCC: A dog lying on a **couch** with a large window in the background.



No transfer: *Two giraffes are eating grass in the field*. DCC: *Two zebra* grazing in a green grass field.



No transfer: A white and black cat is sitting on a toilet. DCC: A white **microwave** sitting on a brick wall.

DCC can describe over 300 ImageNet visual concepts in diverse contexts.



DCC:

A person is holding a **gecko** in their hand.

Berkeley LRCN: A person holding a piece of food in their hand.

MS CaptionBot: A close up of a person holding a baby.



DCC: A **gecko** is standing on a branch of a tree.

Berkeley LRCN: A bird is standing on the edge of a rock.

MS CaptionBot: A bird that is standing in the water.

DCC can describe over 300 ImageNet visual concepts in diverse contexts.



A woman in a **chiffon tutu**.



A bunch of a **lychee** are in a market.



A black and white photo of a **candelabra** in a room.



A close up of a **scone** on a plate.



A group of people standing around a **baobab** in a field.



A white **centrifuge** is sitting on the table.



A close up of a wooden table with a bottle of **whisky**.



A brown **bobcat** in a green field.

Failure Cases



A woman is riding a **unicycle** on a **unicycle**.



A group of people standing around a **foxhunting** on a field.

Results: Video Description

	METEOR	F1
Baseline (No Transfer)	28.80	0.0
+DCC (ours)	28.9	6.0
+ ILSVRC Videos (No Transfer)	29.0	0.0
+ DCC (ours) + ILSVRC Videos	29.10	22.2



No Transfer: A horse is riding on a horse. DCC: A zebra is walking around in the wild.

Novel Object Captioner



NOC: Jointly train on multiple sources with auxiliary objectives. IMAGENET+ MSCOCO +

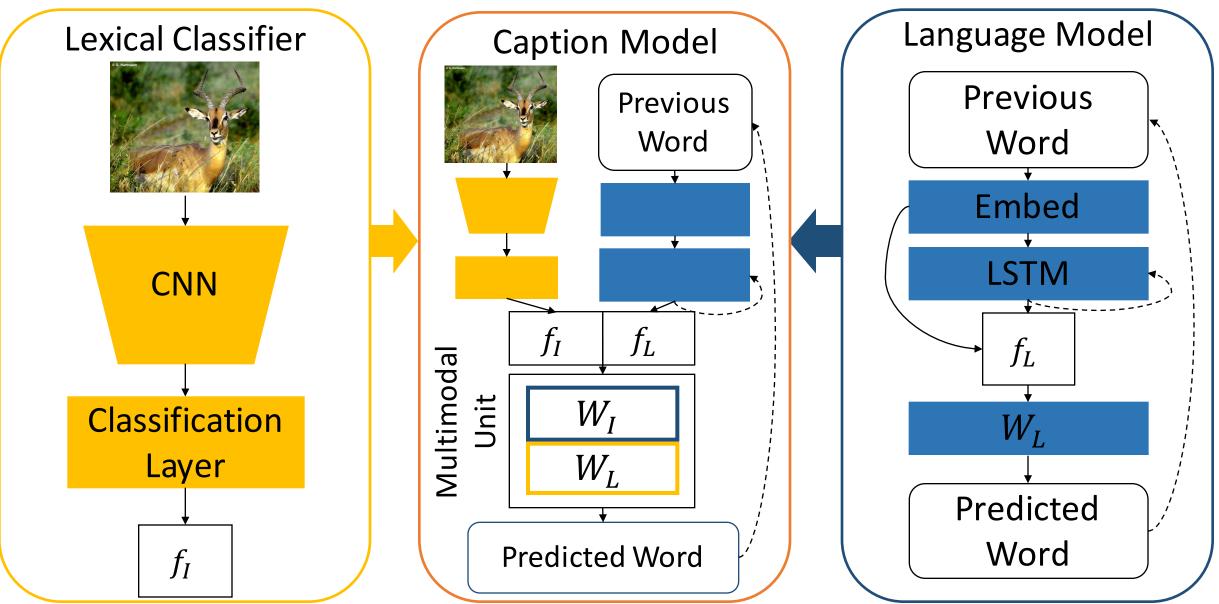
A woman is holding a large **megaphone** in her hand.

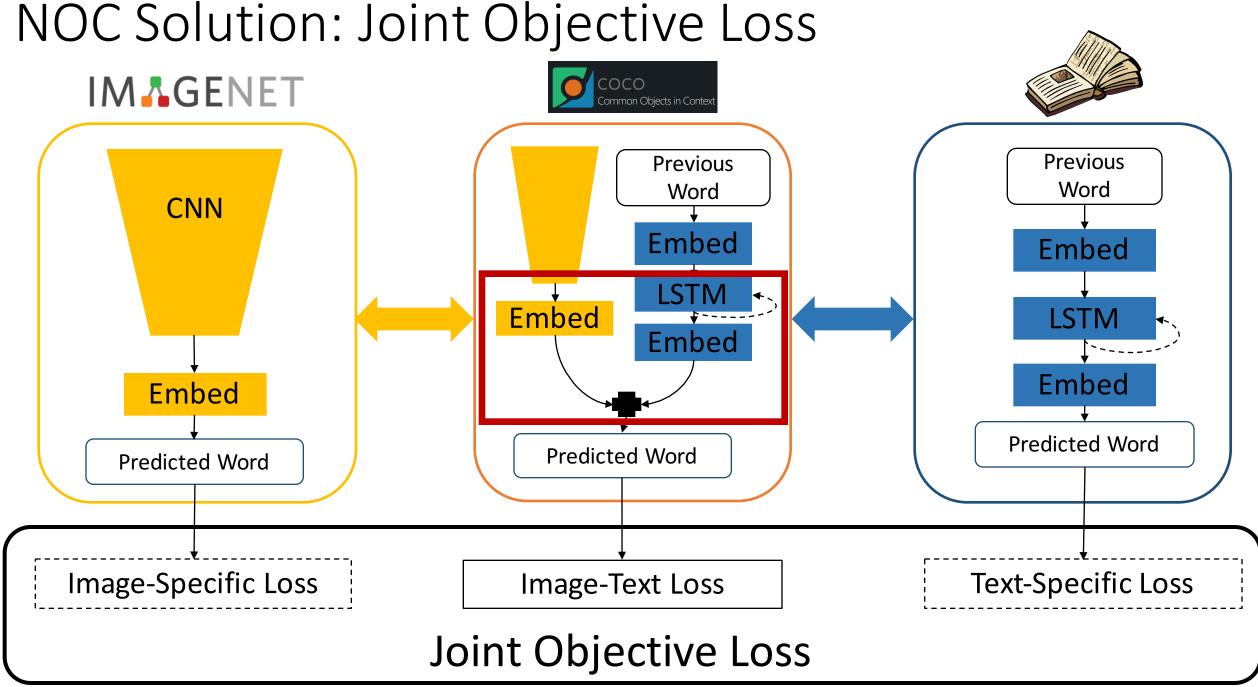
Training only on image-caption data.

A woman is sitting on a bench in front of a building.

"Captioning Images with Diverse Objects" Venugopalan 2016 http://arxiv.org/abs/1606.07770

DCC Issue: Not End-to-End Trainable





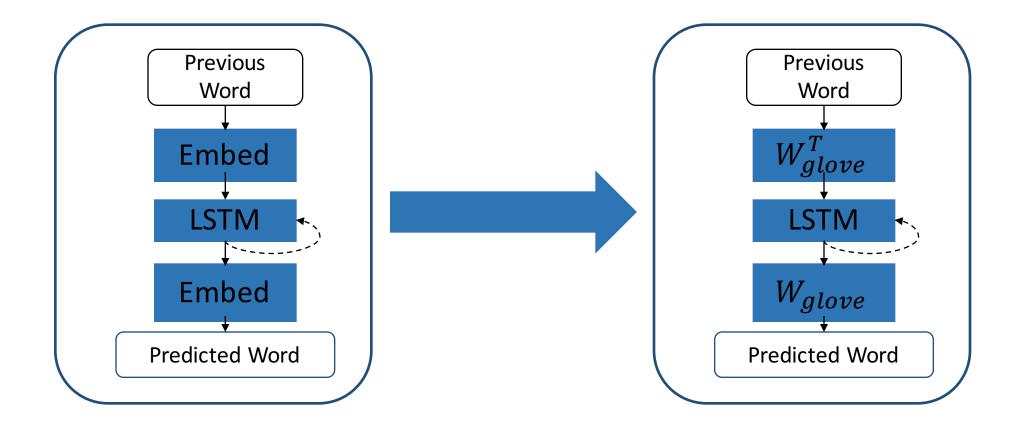
NOC Solution: Joint Objective Loss

DCC Issue: Transfer Mechanism

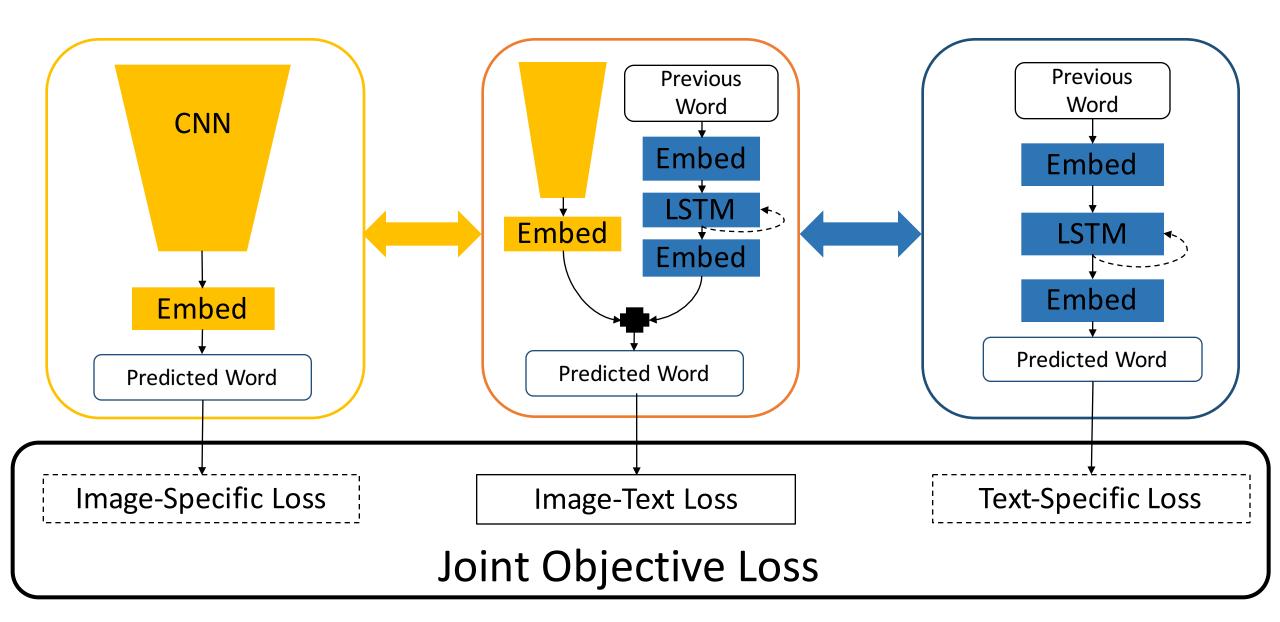


A man is playing **racket** on a **racket**.

NOC Solution: Semantic Embedding



Training



F1 Scores for NOC and DCC

	Bottle	Bus	Couch	Microwave	Pizza	Racket	Suitcase	Zebra	Average
DCC	4.63	29.79	45.87	28.09	64.59	52.24	13.16	79.88	39.78
NOC	19.02	69.34	33.25	26.46	69.16	62.45	34.65	89.78	50.51

Ablation: Auxiliary Objective

Contributing Factor	Glove	LM Pretrain	lmage Pretrain	Auxiliary Objective	Meteor	F1
Pretraining & Glove	X	Х	Х		19.80	25.38
Fix Image Model	X	X	Fixed		18.91	39.70
All	X	X	X	X	20.69	50.51

Ablation: Glove Embedding

Contributing Factor	Glove	LM Pretrain	lmage Pretrain	Auxiliary Objective	Meteor	F1
Auxiliary Objective			X	Х	15.78	14.41
Glove	X		X	Х	19.69	47.02
All	x	X	X	X	20.69	50.51

Training with Outside Data

Image Data	Text Data	Meteor	F1
MSCOCO	MSCOCO	20.69	50.51
MSCOCO	WebCorpus	19.15	41.74
ImageNet	WebCorpus	17.55	36.50

Describing ImageNet



A **otter** is sitting on a rock in the sun.



A large **glacier** with a mountain in the background.



A large **flounder** is resting on a rock.



A man is standing on a beach holding a snapper.



A table with a plate of **sashimi** and vegetables.



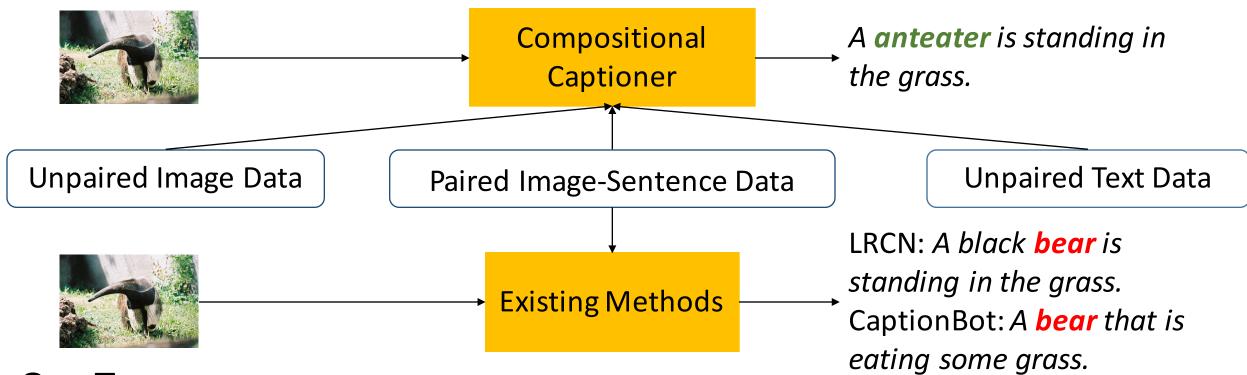
A group of people standing around a large white **warship**. Errors



A chainsaw is sitting on a chainsaw near a chainsaw.



A **volcano** view of a **volcano** in the sun.



Our Team:



Lisa Anne Subhashini Hendricks Venugopalan



Marcus Rohrbach



Raymond Mooney



Kate Saenko



Trevor Darrell