Can *language* representations emerge from a purely *image*-pretrained model?

-- An initial exploration in multimodal learning:
Look Twice as Much as You Say: Scene Graph Contrastive Learning for Self-Supervised Image Caption Generation, CIKM'22, Chunhui Zhang, et al.

Look Twice as Much as You Say

- ❑ Introduction - *vision language learning*
- ❑ Method
- ❑ Experiment
- ❑ Discussion

About me:
Hello, my name is Chunhui Zhang, and I am currently a Ph.D. student in Computer Science at Dartmouth College. My research interests and experience span a range of areas, including learning representations from diverse modalities, trustworthy machine learning, and efficient machine learning.
My prior works have been accepted to top-tier conferences, such as ICLR'23, NeurIPS'22, WWW'23, CIKM'22, etc.

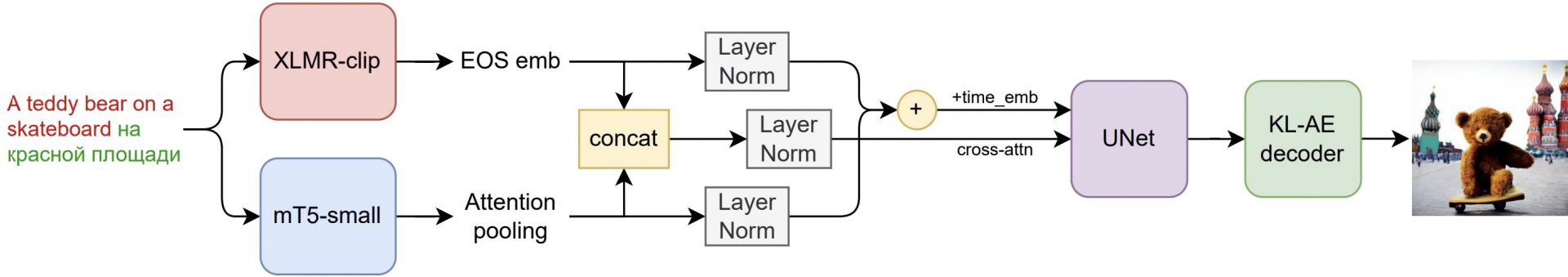
Introduction - Vision Language Learning (modality gap between vision and language is large)

❑ 1. Image2Text (e.g., M^2 Transformer)

GT: A cat looking at his reflection in the mirror.
Transformer: A cat sitting in a window sill looking out.
$\mathcal{M}^2$ **Transformer:** A cat looking at its reflection in a mirror.

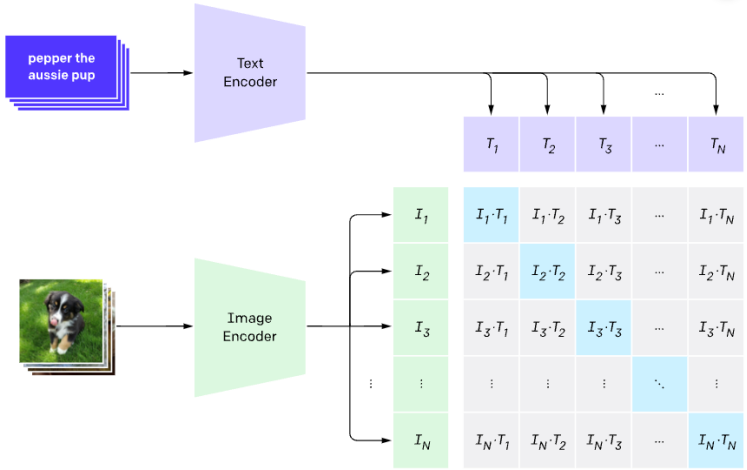
GT: A plate of food including eggs and toast on a table next to a stone railing.
Transformer: A group of food on a plate.
$\mathcal{M}^2$ **Transformer:** A plate of breakfast food with eggs and toast.

❑ 2. Text2Image (e.g., Diffusion Model)

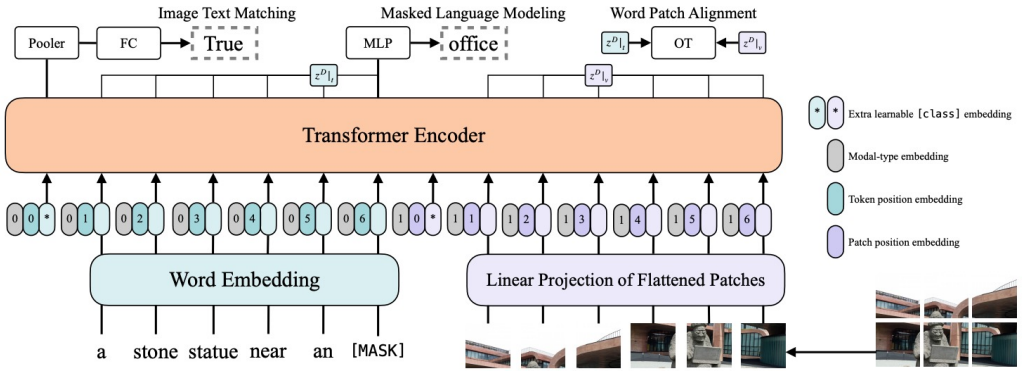


Introduction - Vision Language Learning (modality gap between vision and language is large)

- 3. Models for both modalities (e.g., CLIP, ViLT)



(a) CLIP



(b) ViLT

Introduction - Vision Language Learning (modality gap between vision and language is large)

Summary:

- ❑ Method 1 requires ***ground-truth text*** for supervised loss (e.g., CE loss)
- ❑ Method 2 requires ***ground-truth image*** for supervised loss (e.g., MSE loss)
- ❑ Method 3 requires ***well-paired image-text input*** for (un)supervised loss

All three of the above popular cross-modal learning paradigms have **limitations** on the training data, to mitigate the large modality **gap** between vision and language.

To tackle these limitations, we start with a question in image caption generation:

Can language representations emerge from a purely image-pretrained model?

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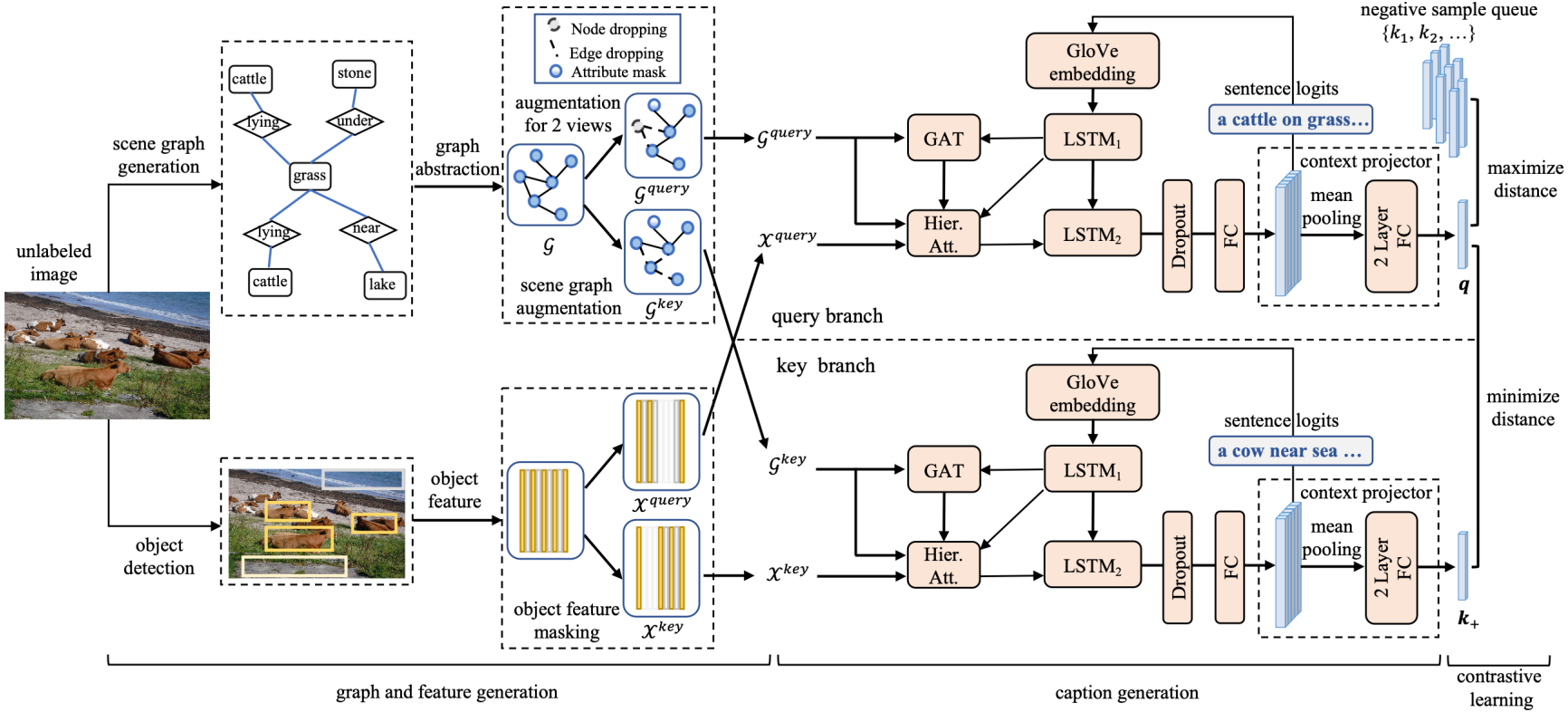
Method – Scene Graph Contrastive Learning

- Contrastive training with purely visual Inputs, to learn (pseudo) caption sentence generation



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- ❑ Introduction - *vision language learning*
- ❑ Method - Scene Graph Contrastive Learning
- ❑ Experiment - effectiveness of emerged language representations in image-pretrained model on captioning
- ❑ Discussion

Experiment – Effectiveness of emerged language representations

- Performance: finetuning with very few ground-truth captions

image:

1% labels **are used:**

M^2-T:	A sheep standing in a a a.	A man girl a a a a a.	A girl tennis a a tennis tennis	A elephant of in a a a.	A cow standing standing a a a.
SGAE:	A sheep of standing a a a.	A man is a a a a a.	A man girl a a a a a.	A man is a a a a a.	A sheep of in a a a a a.
VSUA:	A sheep of in a a a.	A man standing a a a a.	A girl girl a a a a a.	A people of a a a a a a.	A cow cow cow a a a a a.
C-GAT:	A group of a a a a.	A man is a a a a a.	A man girl a a a a a.	A street of a a a a.	A sheep of a a a.
SGCL:	**A couple of sheep standing in the grass in a field.**	**A group of people playing a frisbee standing by the sea.**	**A woman is holding a tennis racket on a tennis ball.**	**A group of people standing in a street with a building.**	**A herd of cows walking down a road in the grass.**

30% labels **are used:**

M^2-T:	A group of sheep standing in a fenced area.	Two men playing frisbee on a dirt field.	A woman is holding a tennis racket in her hand.	A man riding an elephant in front of a building.	A group of cows standing next to each other on a field.
SGAE:	A white sheep is standing in the grass.	A group of men playing a game of frisbee.	A man hitting a tennis ball on a tennis court.	A group of people standing next to an elephant.	A cow standing on top of a lush green field.
VSUA:	A couple of sheep standing next to each other.	A man holding a frisbee in his hand.	Two men playing frisbee on a dirt field.	An elephant standing in front of a building.	A group of cows are standing in the grass.
C-GAT:	A group of sheep grazing in a grassy field.	A man holding a frisbee in his hand.	A woman is playing tennis on the court.	A man riding on the back of an elephant.	A brown cow standing next to a brown cow.
SGCL:	**A couple of sheep standing on a lush green field near a fence.**	**A man is jumping in the air to catch a frisbee on a sea beach.**	**A woman is trying to hitting a tennis ball on a tennis court.**	**An elephant walking down a street with people in the background.**	**A herd of black cows standing next to each other on a lush green field.**

Experiment – Effectiveness of emerged language representations

- Comparisons with popular baselines in caption metrics

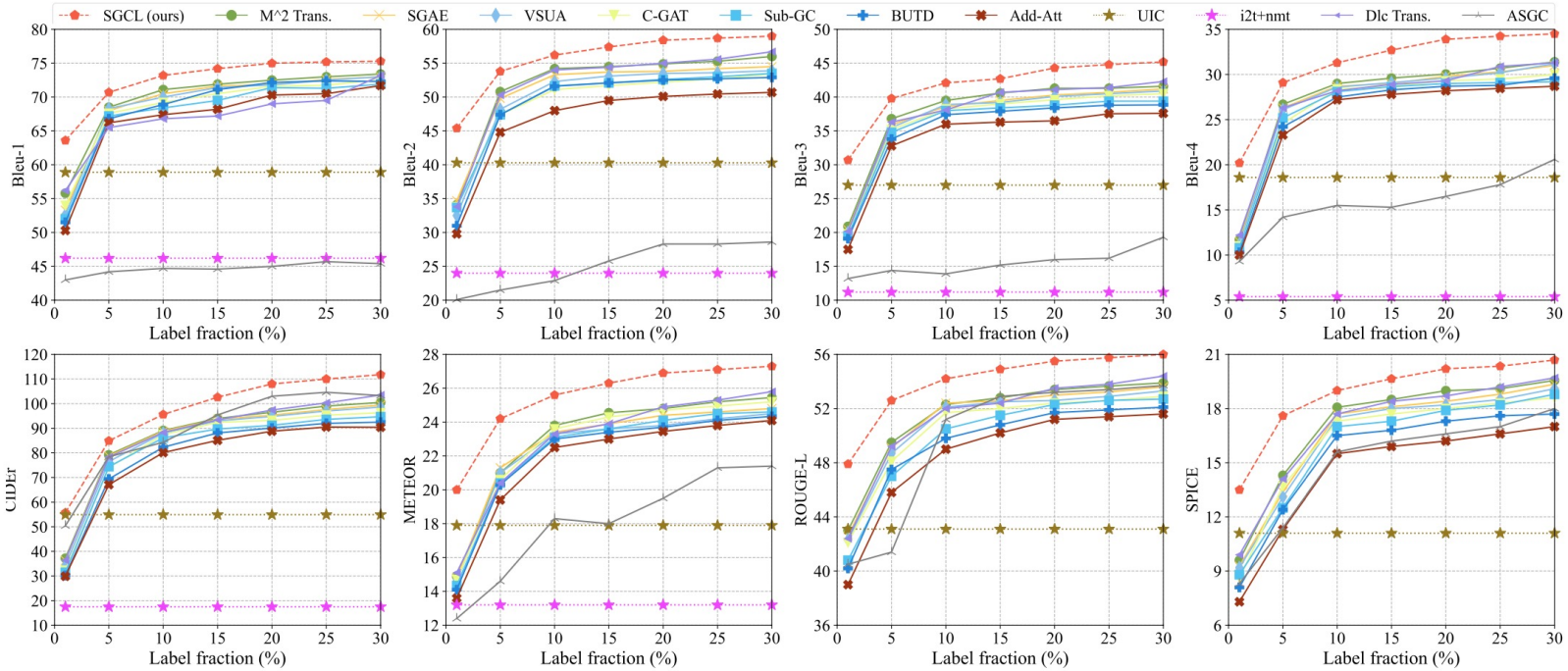

Figure 3: Performances of all models with limited labels (Note that ROUGE-L and SPICE of i2t+nmt are not shown due to missing values in the original work).

Experiment – Effectiveness of emerged language representations

- Ablation study: effectiveness of scene graph augmentation in contrastive learning

Table 1: Performances of different model variants with various graph augmentation strategies (Note: N - node dropping, E - edge dropping, A - node attribute masking, O - object feature masking).

Label	N	E	A	O	B-1	B-2	B-3	B-4	C.	M.	R.-L	S.
1%					61.8	43.8	28.9	18.2	47.7	18.5	46.3	11.9
				✓	62.5	44.6	30.0	19.1	49.2	19.9	47.0	13.1
	✓			✓	62.5	44.5	29.0	18.5	52.9	19.1	47.3	13.2
		✓		✓	63.1	44.3	28.8	18.6	52.2	19.3	47.2	13.0
			✓	✓	63.0	45.1	29.9	19.3	53.3	19.6	47.5	13.3
	✓	✓	✓	✓	**63.6**	**45.4**	**30.7**	**20.2**	**55.0**	**20.0**	**47.9**	**13.5**
5%					69.4	51.7	36.6	26.2	75.9	22.2	49.4	16.3
				✓	70.3	53.0	38.6	27.9	79.4	23.9	51.9	17.3
	✓			✓	62.5	52.8	38.9	28.5	81.4	19.1	51.9	17.2
		✓		✓	63.1	53.5	38.7	28.6	82.2	19.3	52.0	17.1
			✓	✓	70.3	53.3	39.2	28.1	82.3	24.1	52.2	17.4
	✓	✓	✓	✓	**70.7**	**53.8**	**39.8**	**29.1**	**84.9**	**24.2**	**52.6**	**17.6**

Experiment – Effectiveness of emerged language representations

- Ablation study: effectiveness of big dropout rate in contrastive learning

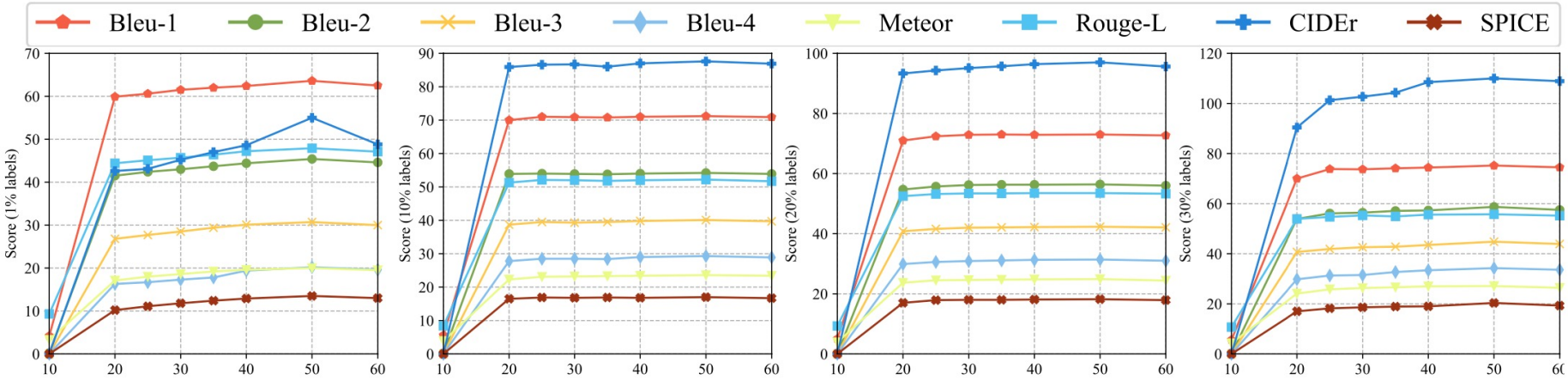

Figure 4: Impact of dropout rate at the output layer on model performance.

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- ❑ Discussion - conclusion and hypothesis

Discussion

Conclusion

- Language representations ***can*** emerge from a purely image-pretrained model, even on small model in this work (i.e., LSTM_1 -> Attention -> GAT -> Attention -> LSTM_2).
- Although the image captioning model only uses **pseudo** sentence logits in the calculation of contrastive loss, the pre-trained model weights provide an effective initialization (i.e., 1% label finetuning brings impressive caption performance).

Hypothesis - *for potential future exploration*

- LSTM brings architecture prior related to NLP: it projects the image representation to the language dimension in a sequential manner like sentence.
- GAT introduces semantic representations: it extracts scene graph representation as one of the inputs to LSTM, which encodes object attributes and relations in images and enhance the semantic/language representations learned by LSTM.

Thank you!

Q & A