Skews in the Phenomenon Space Hinder Generalization in Text-to-Image Generation

Yingshan Chang, Yasi Zhang, Zhiyuan Fang, Yingnian Wu, Yonatan Bisk, and Feng Gao

SoTA Text-to-Image Models Struggle at Spatial Relations

A horse riding an astronaut

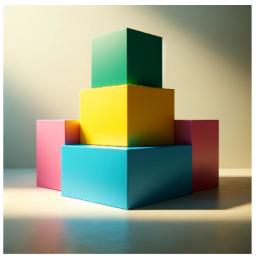


A mouse chasing a cat

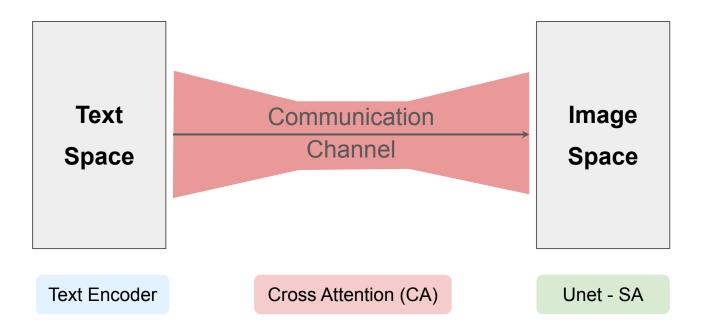


(b)

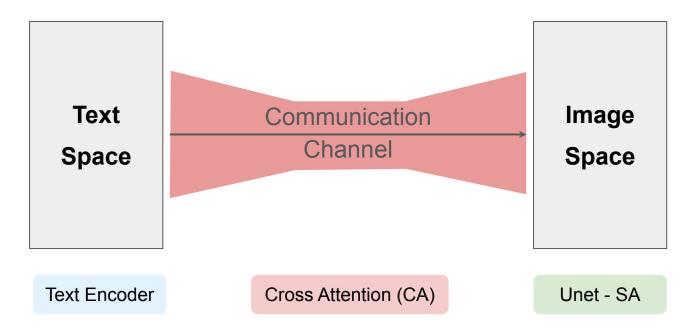
A pink box is on top of blue box, which is on top of a yellow box, which is on top of a green box.



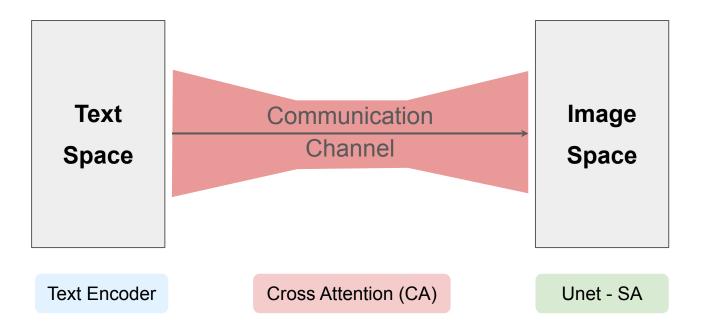
(c)



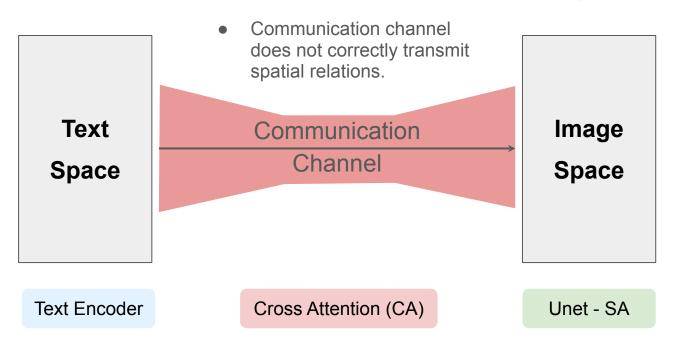
• Text encoder does not correctly encode positions

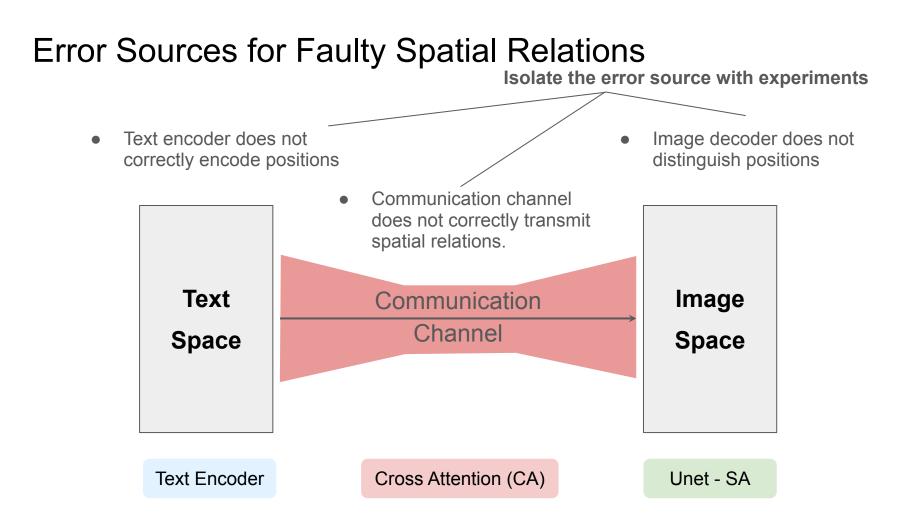


 Text encoder does not correctly encode positions Image decoder does not distinguish positions



 Text encoder does not correctly encode positions Image decoder does not distinguish positions





Error Source 1: Are positions correctly encoded from text?

• Text encoder does not correctly encode positions

Text Space



Error Source 1: Are positions correctly encoded from text?

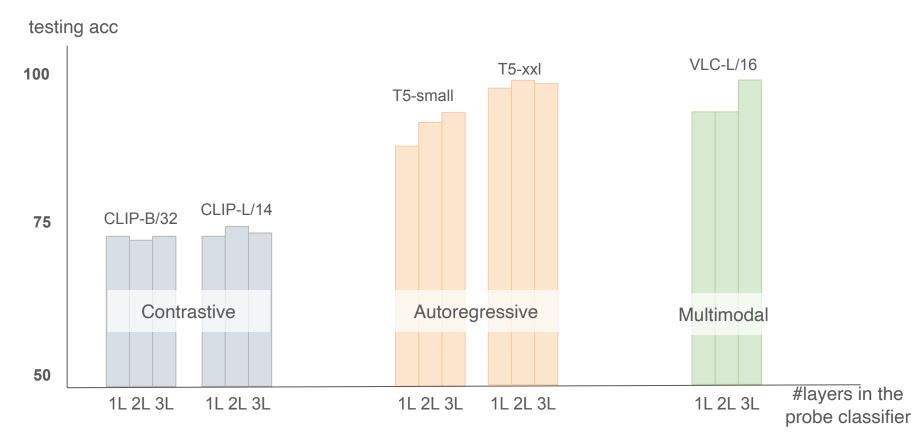
Experiment: probe position information from token encodings

• Text encoder does not correctly encode positions

	<noun1> is or</noun1>	n top of <noun2></noun2>	<noun1> is at t</noun1>	he bottom of <noun2></noun2>		
	Text E	Text Encoder		Text Encoder		
Text	↓ T	↓ B	↓ T	↓ B		
Space	Training: nour	Training: noun1, noun2 randomly sampled from $S_{train} = \{English nouns\}$.				
Testing: noun1, noun2 randomly sampled from Stest; Stest and Strain don't overlap.						
Text Encoder	Stest	anu Strain uon LOVE	nap.			

Error Source 1: Are positions correctly encoded from text?

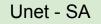
Results



Error Source 2: Is position info available in image decoders?

 Image decoder does not distinguish positions (e.g. being invariant to positions)





Error Source 2: Is position info available in image decoders?

Experiment: ablate position-embeddings from image decoders

denoising step crossattention

Image decoder does not Class Bird MLP distinguish positions (e.g. Ball Head Car being invariant to positions) Transformer Encoder Patch + Position Embedding **0*** $\begin{bmatrix} 1 \end{bmatrix}$ * Extra learnable Linear Projection of Flattened Patches [class] embedding Image Space Latent Space Diffusion Process Denoising U-Net ϵ_{θ} K_{i} Pixel Space •__ Unet - SA

Vision Transformer (ViT)

Stable Diffusion: No image positional embeddings by default!

skip connection

switch

1

[8]

Conditioning Semantic

Map

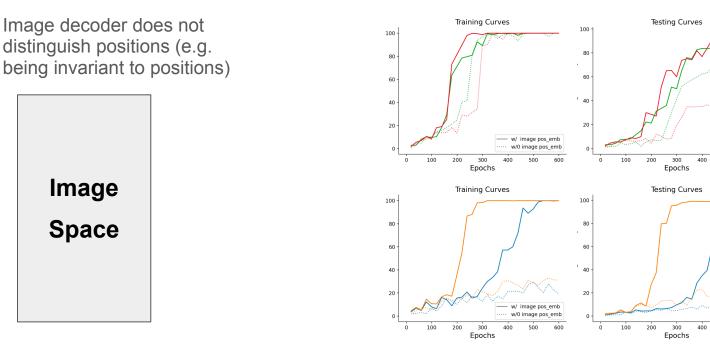
 τ_{θ}

<u>≺</u>

concat

Text Repres entations Images

Error Source 2: Is position info available in image decoders?



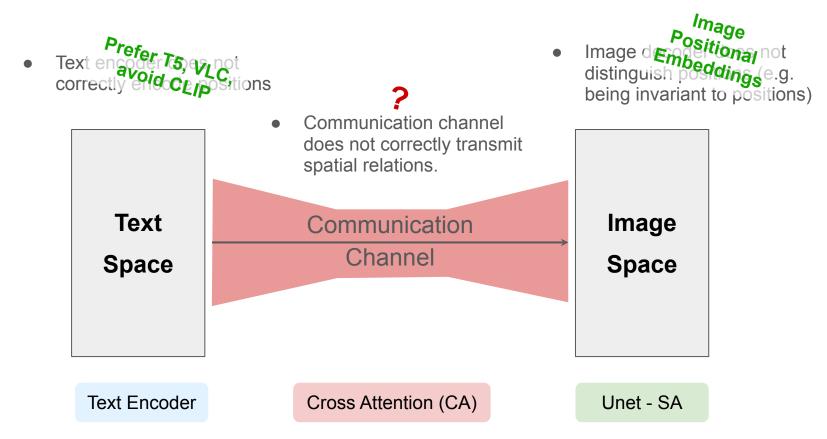
Results

Unet - SA

Models w/o image positional embeddings exhibit both **slower** convergence in training and worse performance in testing.

500 600

500 600

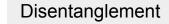


Why is the communication of spatial relations hard?

A relation does not take any perceptible form.

A relation can only be observed with concrete objects, but it should not be permanently associated with those objects.

A relation can be associated with "unseen" objects after learning.



Abstractness

Composition

Formalization

When a message specifies spatial relation between objects, what a formal structure does it entail?

Role-filler bindings

Fillers: concrete values, e.g. objects



cap book

obj

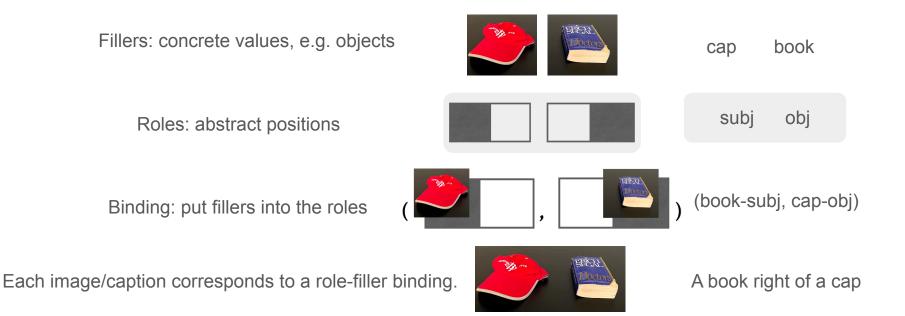
subj

Roles: abstract positions

Formalization

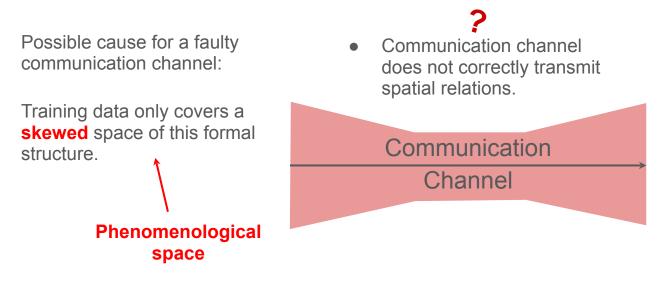
When a message specifies spatial relation between objects, what a formal structure does it entail?

Role-filler bindings

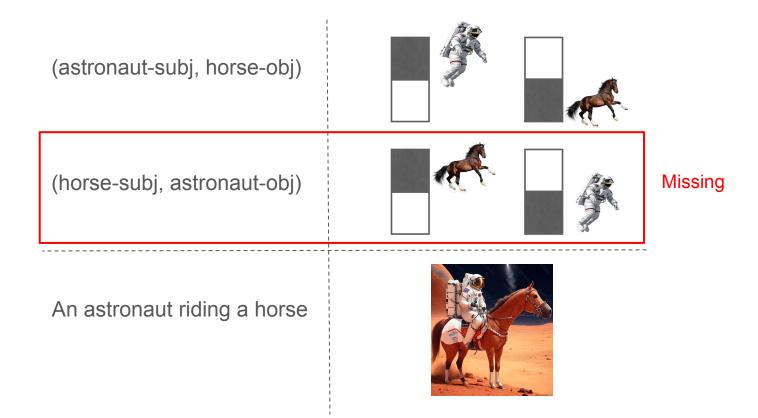


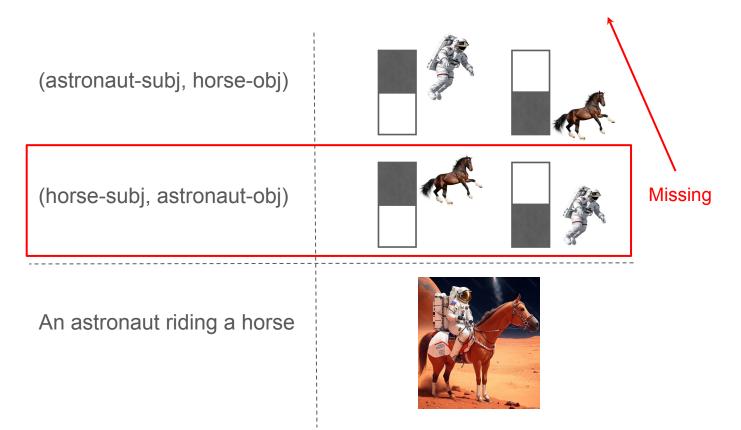
When a message specifies spatial relation between objects, what a formal structure does it entail?

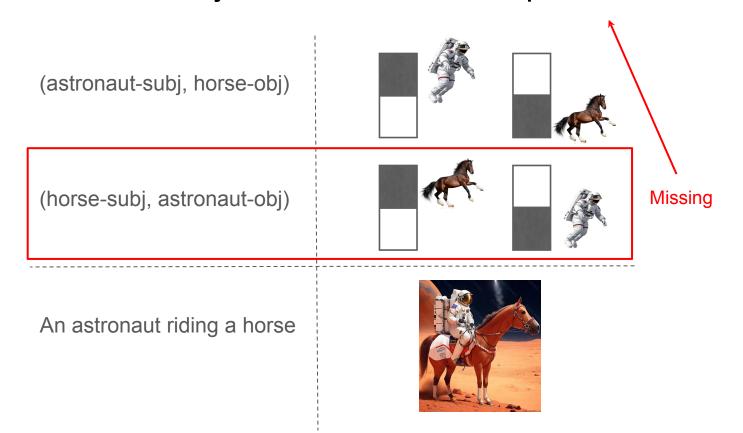
Role-filler bindings



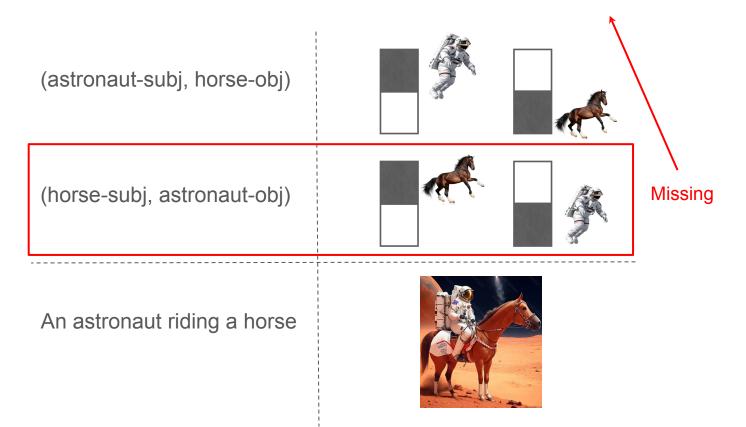
Cross Attention (CA)



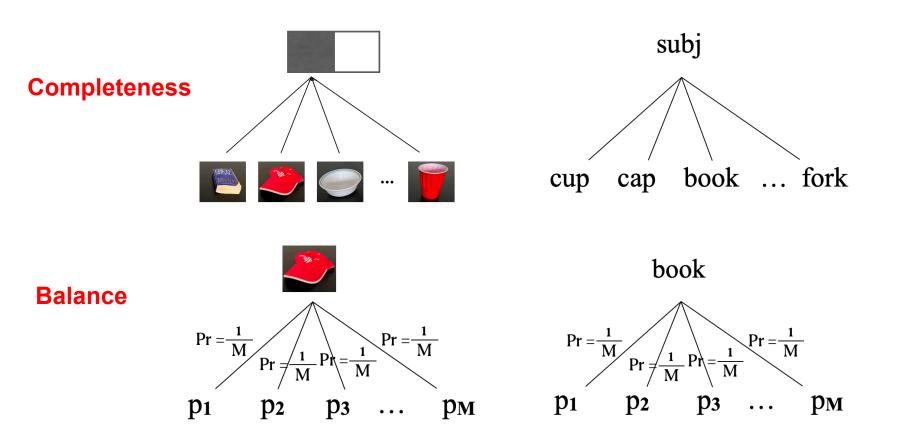




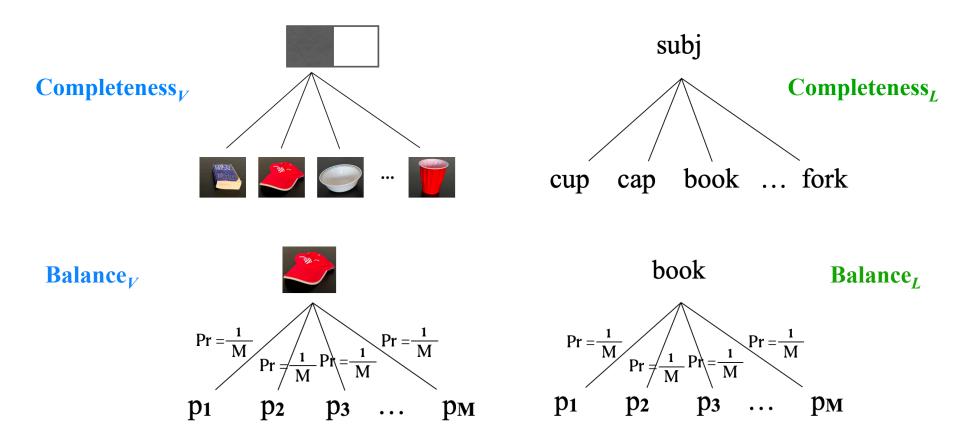
Error Source 3: Skew in the phenomenological space!



Two Metrics to Quantify Skew



Two Metrics to Quantify Skew



Experimental Design

Hypothesis: Completeness_L, Balance_L, Completeness_V, Balance_V Generalization Generalization

Visual fillers: Synthetic icons Linguistic fillers: English nouns

∦	⊄	⊅	≁
soda	backpack	vase	piano
人	≬	∀	ි
dumpling	screen	sweater	cupcake
iacket	Larrot	الله keyboard	

Experimental Design

Hypothesis: Completeness_L, Balance_L, Completeness_V, Balance_V | Generalization |

Visual fillers: Synthetic icons Linguistic fillers: English nouns

∦	⊄	⊅	⊬
soda	backpack	_{vase}	piano
人	Ø	∀	ជ្
dumpling	screen	sweater	cupcake
iacket	▲	🖄	↔
	carrot	keyboard	soap

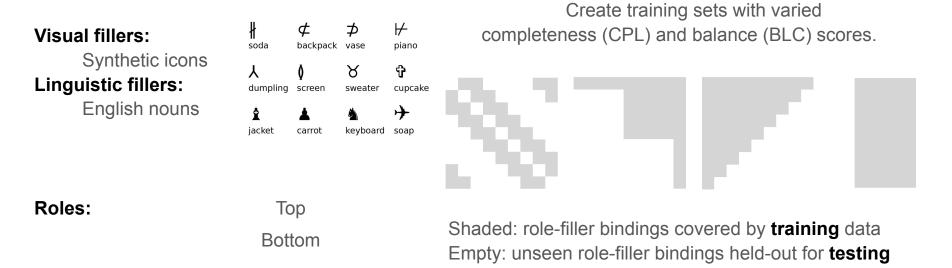
Roles:

Тор Bottom

Experimental Design

Hypothesis: Completeness_L, Balance_L, Completeness_V, Balance_V

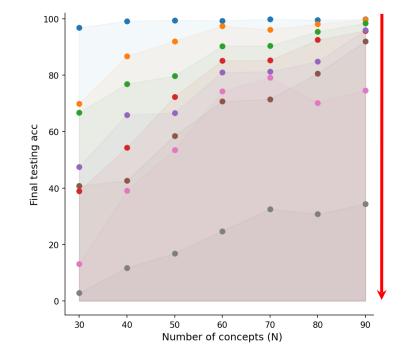
Generalization



Metric: accuracy (1 if both objects and the relation is correct, otherwise 0)

Results



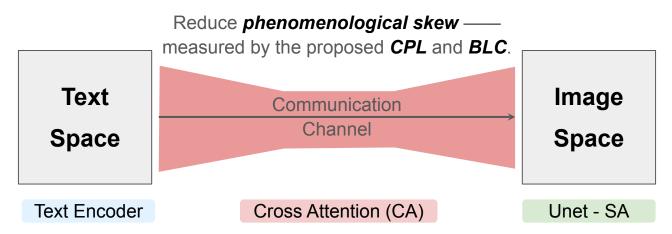


Incomplete or unbalanced data greatly harms generalization.

That's Everything!

Thank you!

Why current text-to-image models are prone to faulty spatial relations?



Autoregressive & *multimodal* models should be preferred over *contrastively* pre-trained ones.

Make sure the image SA layers take *image positional embeddings* as input.

New *dataset/augmentation* with better CPL and BLC New *architecture* that generalizes even when trained under skewed data source.