

The Hebrew

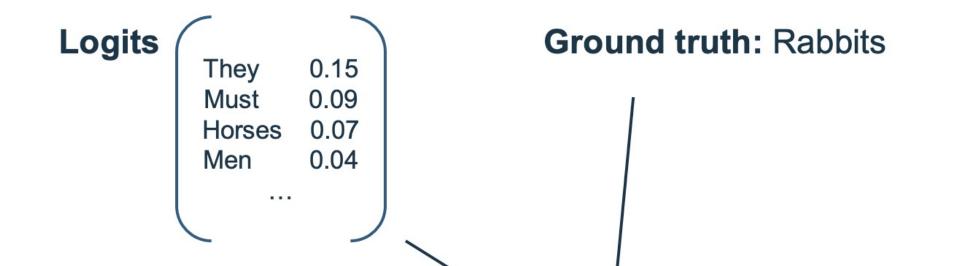
# Data Efficient Masked Language Modeling for Vision and Language

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### Overview

Masked language modeling (MLM) is a key pre-training objective in text transformers.

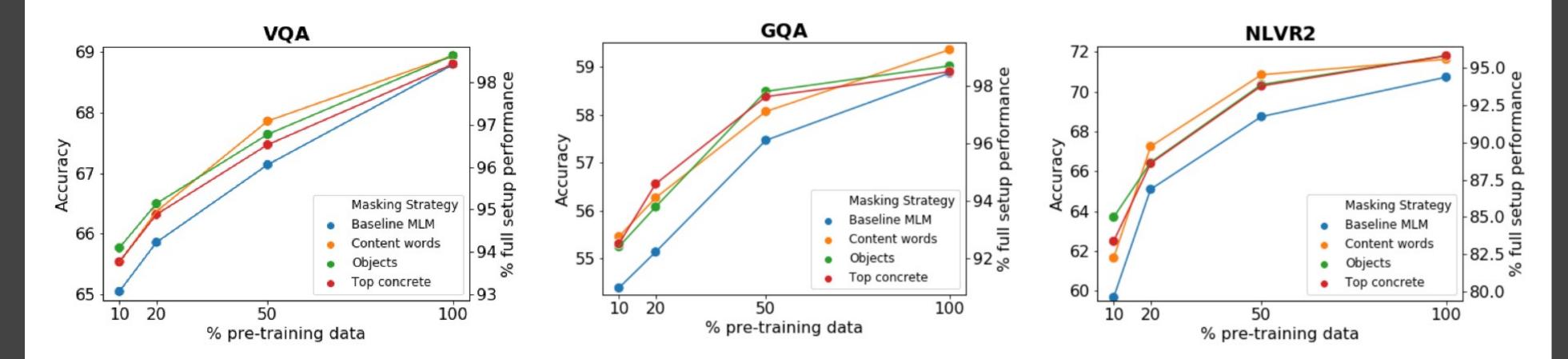
[MASK] have muscled hind legs that allow for maximum force, maneuverability, and acceleration



### Experiments

#### **Downstream tasks**

Our alternative masking strategies consistently outperform the baseline MLM strategy, especially in low resource settings



Cross Entropy (P, GT)

The difference in the cross-modal setting, is that the model takes into account both the textual context and the image <sup>SO</sup>.

#### A [MASK] is eating the carrot

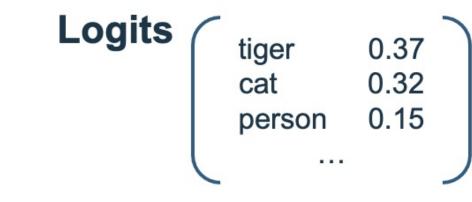


Ground truth: rabbit

Logits	rabbit chipmunk squirrel	0.49 0.32 0.21
		J



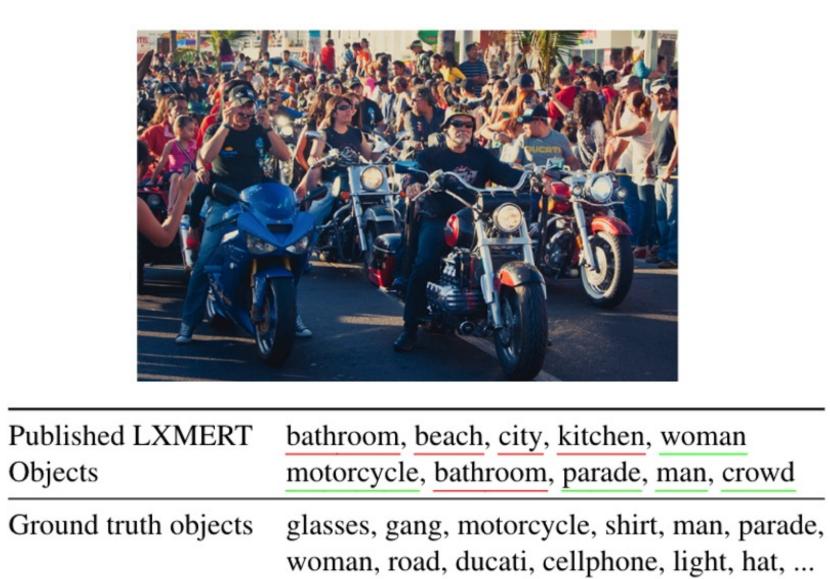
Ground truth: tiger

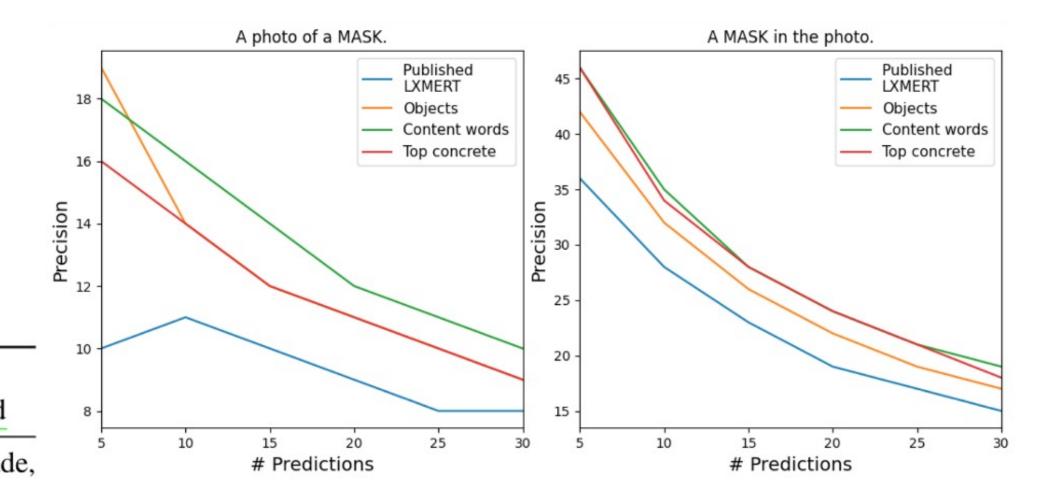


We find the current MLM objective sub-optimal for vision and language, as it does not make efficient use of training data **\$**.

#### **Prompt based object detection**

Our alternative models are more responsive to the image contents







Input sequence length is short (20 tokens)

Input sequence length is long (512 tokens)

In many cases, no token is masked

~50% of tokens in pre-train data are stop-words or punctuation marks

Focusing on stop-words is leading to under-utilization of the image **[2]**.

Sentence	A person performs a stunt jump on a [MASK].	
Masked token	motorcycle	
Top 5 predictions	motorcycle, bike, ramp, bicycle, cycle	
Top 5 predictions w/o image	building, wall, beach, field, street	
Loss	0.25	6
Loss w/o image	3.96	C
$\Delta$ image loss	3.71	

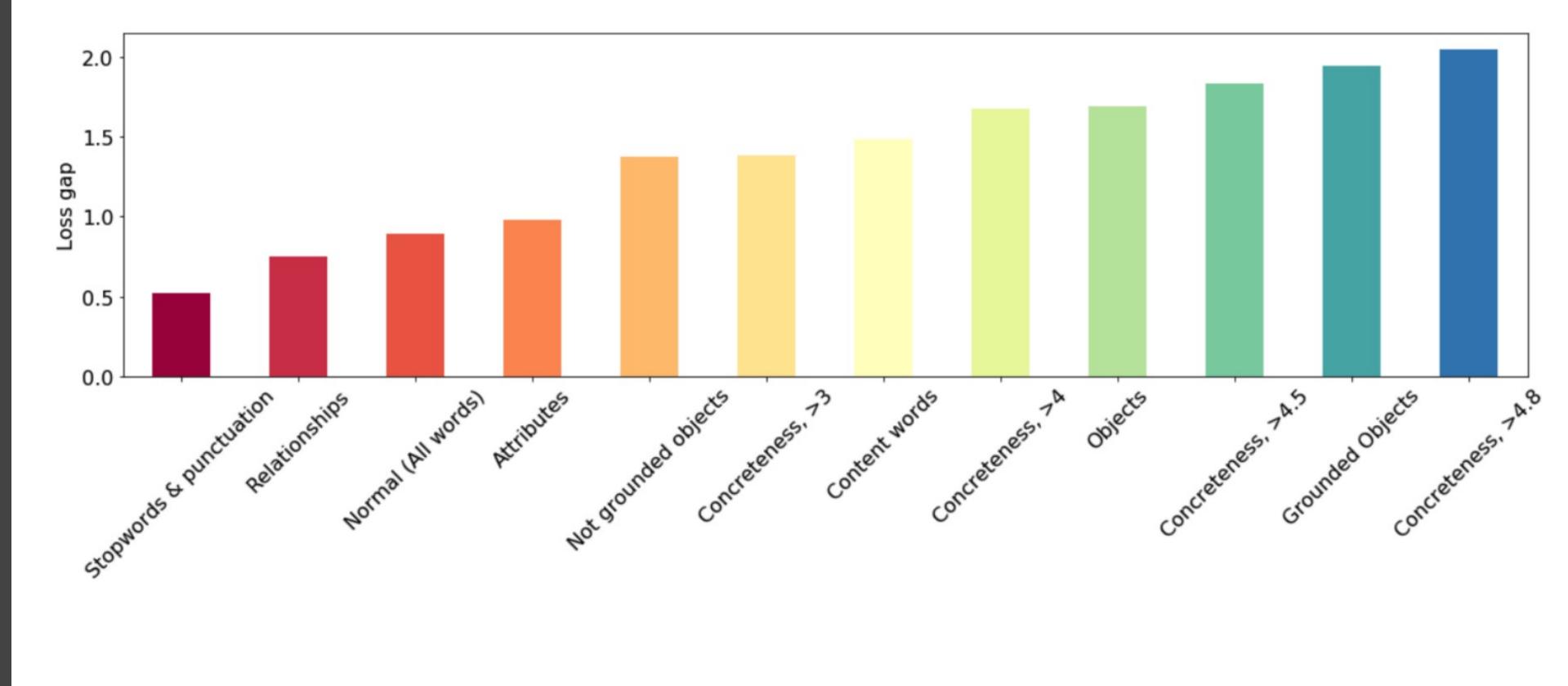
Masking strategy	With Image		Without Image		Image Necessity	
Metric	image loss (exp)	Accuracy @ 5	image loss (exp)	Accuracy @ 5	$\Delta$ image loss (exp)	Accuracy @ 5
<b>Baseline MLM</b>	3.2	89%	8.9	78%	5.7	10%
Stop-words & punctuation, 15%	1.5	98%	2.9	96%	1.4	2%
Content words, 15%	9.4	76%	38.7	56%	29.3	20%

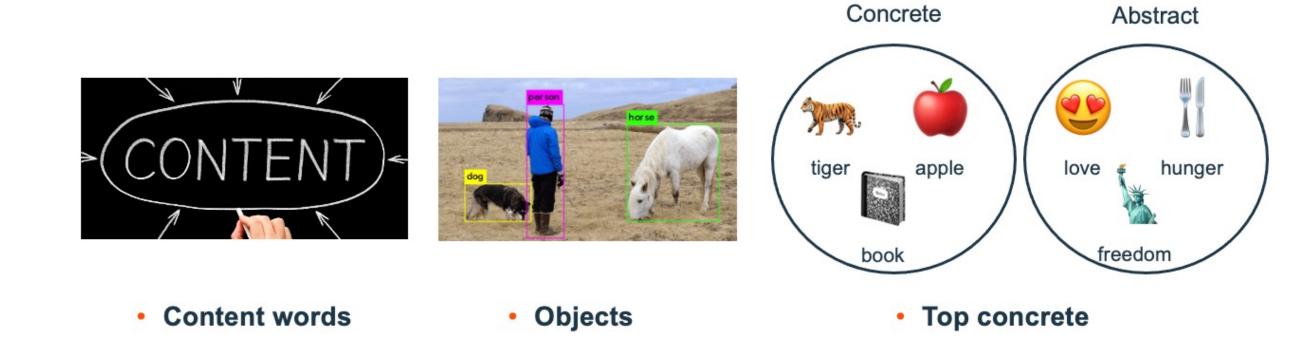
We suggest alternative masking strategies, specific to the cross-modal settings, addressing these shortcomings  $\swarrow$ .

## Analysis

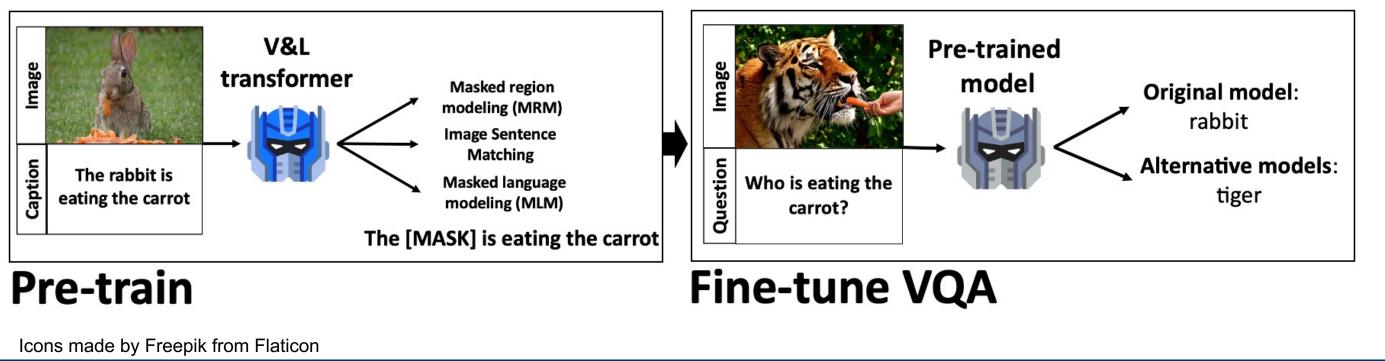
#### **Hierarchy of Masked Semantic Classes**







Our method masks words that require the image in order to be predicted. Our pre-train masking strategy consistently improves over the baseline strategy in two evaluation setups.



Does a model trained with Objects strategy | learn to complete words from other classes? | MLM Performance across Word Classes Model **Objects Baseline MLM Content words Top concrete** Masking Strategy **Baseline MLM** 87% 27% 70% 36% 80% 13% Stop-words & punctuation, 15% 98% 4% 74% 62% Content words, 15% 57% 62% Objects 76% 83% 85% 82% Attributes 70% 22% 59% 50% Relationships 89% 75% 25% 15%