

CM3: A CAUSAL MASKED MULTIMODAL MODEL OF THE INTERNET

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ABSTRACT

We introduce CM3, a family of causally masked generative models trained over a large corpus of **structured multi-modal documents** that can contain both text and image tokens. Our new causally masked approach generates tokens left to right while also masking out a small number of long token spans that are generated at the end of the string, instead of their original positions. The causal masking object provides a type of hybrid of the more common causal and masked language models, by enabling full generative modeling while also providing bidirectional context when generating the masked spans. We train causally masked language-image models on large-scale web and Wikipedia articles, where each document contains all of the text, hypertext markup, hyperlinks, and image tokens (from a VQVAE-GAN), provided in the order they appear in the original HTML source (before masking). The resulting CM3 models can **generate rich structured, multi-modal outputs** while conditioning on arbitrary masked document contexts, and thereby implicitly learn a wide range of text, image, and cross modal tasks. They can be prompted to recover, in a zero-shot fashion, the functionality of models such as DALL-E, GENRE, and HTLM (Ramesh et al., 2021; De Cao et al., 2020; Aghajanyan et al., 2021). We set the new state-of-the-art in zero-shot summarization, entity linking, and entity disambiguation while maintaining competitive performance in the fine-tuning setting. We can generate images unconditionally, conditioned on text (like DALL-E) and do captioning all in a zero-shot setting with a single model.

1 INTRODUCTION

Recent advancements in large-scale generative sequence modeling have significantly improved zero-shot performance on multiple modalities, including text Brown et al. (2020); Fabbri et al. (2020); Aghajanyan et al. (2021) and images Ramesh et al. (2021). Recent work has also shown how to use document structure, e.g., as provided by HTML web markup, to enable more effective zero-shot prompting for text-only tasks (Aghajanyan et al., 2021). In this paper, we show it is possible to learn multi-modal document-structured generative models, to jointly represent formatted hypertext and images as they naturally co-occur within full document contexts.

We introduce CM3, a family of causally masked generative models trained over a large corpus of structured multi-modal documents. Causally masked models generate tokens left to right, just like a causal language model, but also mask out a small number of long token spans, which are then generated at the end of the string instead of their original positions. This provides a new hybrid of causal and masked language models, enabling full generative modeling with bidirectional context. For example, it can also be used in our setting to infill complete images or larger structured text sections, conditioned on the rest of the document.

We train CM3 models on close to a terabyte of web-based data following Aghajanyan et al. (2021), extended to include images through VQVAE-GAN tokens (Esser et al., 2021) and additional hypertext link structure. This data is in strong contrast to previous methods that were either uni-modal or

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carefully curated the image-text alignment (e.g., for image captioning Radford et al. (2021); Ramesh et al. (2021)). We train a 2.7 billion and 13 billion causally masked model on this data which we call CM3-Medium and CM3-Large respectively.

Extensive experiments demonstrate that these models are able to perform a wide range of zero-shot uni- and cross-modal tasks. We show both qualitatively and quantitatively that CM3 can be prompted for non-trivial image generation, similar to that of DALL-E. We also show that CM3 models are capable of improving over state-of-the-art zero-shot summarization, entity linking, entity disambiguation, highlighting the structure that comes from the hypertext during training. Finally, we show that by fine-tuning CM3 we set the new state-of-the-art for entity linking and entity disambiguation in general.

To summarize, our contributions include:

- We present the first hyper-text language-image model, trained on close to a Terabyte of multi-modal simplified HTML data from the common crawl.
- We present the causally masked objective, a hybrid of causal and masked language models that allows for bidirectional context control during generative mask infilling.
- We demonstrate consistently strong transfer from CM3 to a range of uni-modal and multi-modal tasks at differing supervision levels, including stating state-of-the-art on entity disambiguation and zero-shot summarization.
- We release all code and models to support future CM3 research.

2 CAUSALLY MASKED OBJECTIVE

Traditional approaches to pre-training have focused on mixing the architectural choices (i.e., encoder-only, decoder-only, encoder-decoder) with objective choices (i.e., masking, causal language modeling). For example, masked encoder-only models such as BERT (Devlin et al., 2018) and RoBERTa (Liu et al., 2019) excel in non-generative fine-tuning tasks. Masked encoder-decoder models such as BART (Lewis et al., 2019) and T5 (Raffel et al., 2019) excel in both discriminative and generative fine-tuning. Brown et al. (2020) on the other hand, showed that causal language models (de-facto, decoder only) are capable of non-trivial performance without the need of fine-tuning by simply prompting with appropriate string to control the generated outputs Radford et al. (2019); Brown et al. (2020); Artetxe et al. (2021).

There are pros and cons to both masked and causal language modeling in the context of prompting. Masking offers the critical ability to encode bi-directionality within the prompts at the cost of only decoding roughly 15% of the tokens of the input sequence during training (Devlin et al., 2018; Liu et al., 2019; Lewis et al., 2019). Conversely, decoder-only causal language models decode every token in the input sequence in the training but are typically limited to left-only contexts. Empirically, more work has also been done on scaling causal decoder-only rather than their counterparts.

In an effort to get most of the best of both worlds, we introduce a novel objective that combines the benefit of per-token generation with optional bi-directionality specifically tailored to prompting. For a document of size s we select $n \sim \text{Clamp}(\text{Poisson}(1), 1, 16)$ masks and for each of those masks we select span $m \sim (\text{Uniform}(0, s), \text{Uniform}(0, s))$ which does not intersect with any other m . These values are chosen to, on average, select relatively few relatively long spans, which we expect will allow the model to learn to infill long spans. We then order these masks by the order that they appear in the source document, replace the span of the mask in the source document with an enumerated mask token (i.e., $\langle \text{mask}:0 \rangle$, $\langle \text{mask}:1 \rangle$), and move the masked spans to the end of the document followed by a unique end of document token.

Figure 1 shows the complete process.

We also augment the standard cross-entropy loss to weigh the loss of predicting mask tokens as 0, as they are placed at random locations which carry no information to the underlying sequence modeling objective.

The complete array of benefits will become more apparent when designing prompts for uni/cross-modal tasks in § 4. However, at the core, the causally masked objective can do causal language modeling while optionally allowing for bidirectionality when needed.

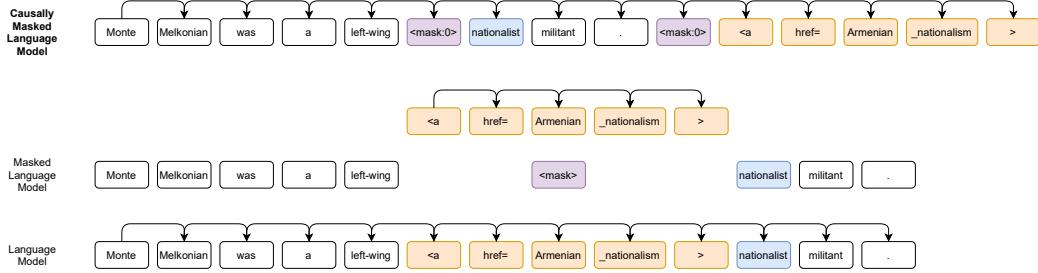


Figure 1: A visual representation of various language modeling objectives as well as our proposed causal language modeling objective with a single mask ($n = 1$). Given the left-to-right nature of causal language models (bottom row) we would not be able to generate the Wikipedia entity link highlighted in orange.

3 CM3

Aghajanyan et al. (2021) used structured documents for text-only pre-training with strong zero-shot performance. **Causally-Masked Multimodal Modeling (CM3)** extends this work by modeling **full document structure including images and hypertext links**. Furthermore, we move away from the BART-like objective of Aghajanyan et al. (2021) to use our new causally masked objective with decoder-only models.

3.1 DATA

Following Aghajanyan et al. (2021) we aim to implement a transform over HTML documents to extract out to minimal-HTML, i.e., the minimal set of text that is semantically relevant for end tasks.

Birhane et al. (2021) gave in-depth criticisms of Common Crawl based multi-modal datasets and showed the existence of highly problematic examples (i.e., explicit images and text pairs of rape, pornography, and ethnic slurs). Given these severe ethical concerns, we opt-out of processing all of Common Crawl and instead opt into using a subset of the Common Crawl News (CC-NEWS) dataset and all of English Wikipedia.

Given a valid HTML DOM¹ per document, we run several passes to strip down the DOM to the elements of maximal semantic value. We first remove all elements which do not contain textual elements. We also filter out all *headers*, *footers*, *copyrights*, *forms*, *dialog boxes* and *iFrames*. We fold consecutive `<div>` elements into a singular `<div>` element with merged attributes. Furthermore we strip all the attributes from every element which are not derived from structured graphs such as OpenGraph, Schema and Twitter.

For every `` tag in the document with a valid `src` attribute URL, we download the image, resize to 256x256 pixels with random cropping and then tokenize it with VQVAE-GAN from Esser et al. (2021). This amounts to 256 tokens for every image. We then insert the string value of the tokens joined with a space back into the `src` attribute.

We do not place any restrictions on the number of images or their locations. We present a set of high-level statistics in Table 1.

	Documents (Million)	Size (GB)	Unique Images (Million)	Tokens (Billion)
CC-NEWS	45	460	18	121
En-Wikipedia	16	383	7	102
Total	61	843	25	223

Table 1: High level statistics of the data used to train CM3.

¹The DOM or Document Object Model is an interface that treats an HTML document as a tree structure wherein each node is an object representing a part of the document.

For experimentation, we create two test sets from each data source with 10,000 unique documents for each. We de-duplicated our test sets to ensure no overlap between test and train sets to the best of our abilities.

3.2 SIZE HINTS

Aghajanyan et al. (2021) introduced the concept of size hints which allows the user to guide the model during sample generation through token conditioning. Specifically, HTLM inserts a probabilistic estimate of the size of the mask as a token post the mask token (e.g., <mask>12 for a probabilistic size of 12). For CM3, we noticed that size-hints degraded not only end-perplexity but also the zero-shot performance on a significant set of evaluation tests.

We also note that we can implicitly give a size hint during mask generation for a single mask by asking the model to generate causally `max_sequence_length - size_hint` tokens before placing the secondary `<mask : 0>` token.

3.3 TRAINING

We train 4 models; 125M, 800M, 2.7B, and 13B parameters. The purpose of the two smaller models was to establish basic hyper-parameters that are viable for the causally masked language modeling objective and therefore were under-trained. However, all downstream tasks will be evaluated with our 2.7B model (CM3-Medium) and our 13B model (CM3-Large). HTLM-Medium was trained on 240 V100 GPU for 28 days, while HTLM-Large was trained on 384 A100 GPU for 24 days. Our implementation was in PyTorch (Paszke et al., 2019) using fairseq (Ott et al., 2019) and fairscale (Baines et al., 2021). For every model, our per GPU batch size was 8, with a maximum token sequence length of 2048. We use the polynomial decay learning rate scheduler available in Paszke et al. (2019) with 1500 warmup updates. We clipped the gradient norms to 1.0 and used the Adam optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.98$ (Kingma & Ba, 2014). We defer our model architecture description to § A.1.

3.4 SCALING LAWS

Our training setting has a couple of new parameters that can impact the traditional scaling laws of causal language models. The multi-modal nature of our proposed model breaks the standard assumptions of token distributionality. Traditionally language tokens are said to follow a Zipfian distribution (Piantadosi, 2014), while image tokens are strictly uniform (see § A.2). Furthermore, the unrestricted locations of the images and text introduce unpredictable complexity. Lastly, although we are still computing the joint probability of the document, we do so in a roundabout way through shuffling of the document via the causally masked objective. These fundamental differences warrant a quick look into the scaling laws of CM3.

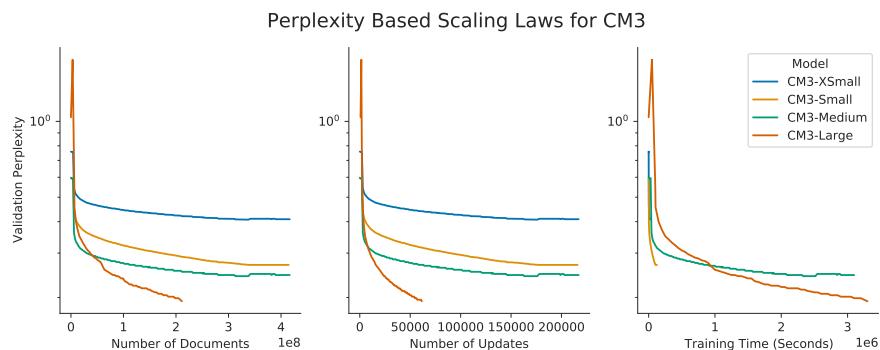


Figure 2: Basic perplexity based scaling laws for the proposed CM3 objective and training set-up.

We present the various perplexity curves for the four models of varying sizes we trained. Given that our models were trained on various hardware set-ups, we normalize the training time by linearly scaling each experiment timing to 256 GPU. Most importantly, we see healthy scaling, similar to

Kaplan et al. (2020) without any pathological cases, implying there is still a good amount of gains to be achieved with further scaling. An in-depth analysis of the scaling laws of the causally masked objective is outside this current work’s scope and will be considered for future work.

4 ZERO/FEW-SHOT PROMPTING

4.1 IMAGE MODALITY

Although we do not train on pure image documents, CM3 can still operate over image tasks. To do so, we must cleverly describe the task through a textual prompt, using the `` tag.

4.1.1 UNCONDITIONAL IMAGE GENERATION

To sample from the distribution of images available to CM3, we can simply ask the model to produce the next set of tokens after the following prompt: ``.

Interestingly enough, CM3 prefers to first generate a short description of the image through the `alt` attribute and then generate the image tokens via the `src` attribute. We can force the model to directly generate image tokens without first giving a description with the following prompt: `<mask:0>`

Using the same decoding strategies described in § 4.1.1 we generate unconditional infilled images with only CM3-Large and present qualitative results in Figure 4. Overall we see that CM3-Large is capable of generating semantically coherent infills even without grounding in text.

4.2 TEXT-IMAGE MODALITY

4.2.1 CONDITIONAL IMAGE IN-FILLING

Additionally, CM3 can further perform image in-filling condition on the additional text context. This can be achieved by slightly augmenting the prompt as follows:

Conditional Infilling Prompt:

`<mask:0>`

We show qualitative results in Figure 4. Immediately we notice the substantial improvement in the generated image when grounded in ground truth text vs. unconditional image-infilling.

4.2.2 CONDITIONAL IMAGE GENERATION

We can do conditional text generation using CM3 similar to DALL-E by using a proper prompt. Specifically by conditioning using the `alt` attribute of the `img` tag.

Conditional Generation Prompt: ``

We present qualitative conditional image generation results in Figure 5. Specifically, we sample 32 images for every prompt given and re-rank using CLIP to get the top-4 images (Radford et al., 2021). Overall we see that CM3 can generate recognizable images of the input text. There are still failure cases, such as the second image in the second prompt, where the model easily generates a landscape but forgets to generate the red car. The third prompt, CM3, is incapable of drawing the face of a sheep while getting the general body and texture correct.

We note that CM3 trains with an order of magnitude less unique images than DALL-E, and the subset of images available to CM3 are the images available in news and Wikipedia articles; therefore, CM3 does not generate fictional images well. That being said, casting a larger pool for CLIP selection by randomly sampling a larger set qualitatively fixes some of these issues.

For quantitative analysis, we compute FID on MS-COCO following the methodology provided by Nichol et al. (2021). Specifically, we sample 30k samples conditioned on MS-COCO captions. For all models, we use a temperature of 0.85 and do straightforward sampling.

We present our FID results on MS-COCO 256x256 in Table 2. In general CM3 is capable of generating semantically coherent images on-par with modern GANs. Furthermore, our conditional CM3-Large model approaches the performance of the DALL-E model while using an order of magnitude fewer data.

4.2.3 CAPTIONING

We next look at the dual-task to conditional image generation and image captioning. We can prompt CM3 to do zero-shot image captioning by asking the model to generate either the `alt` or `title`

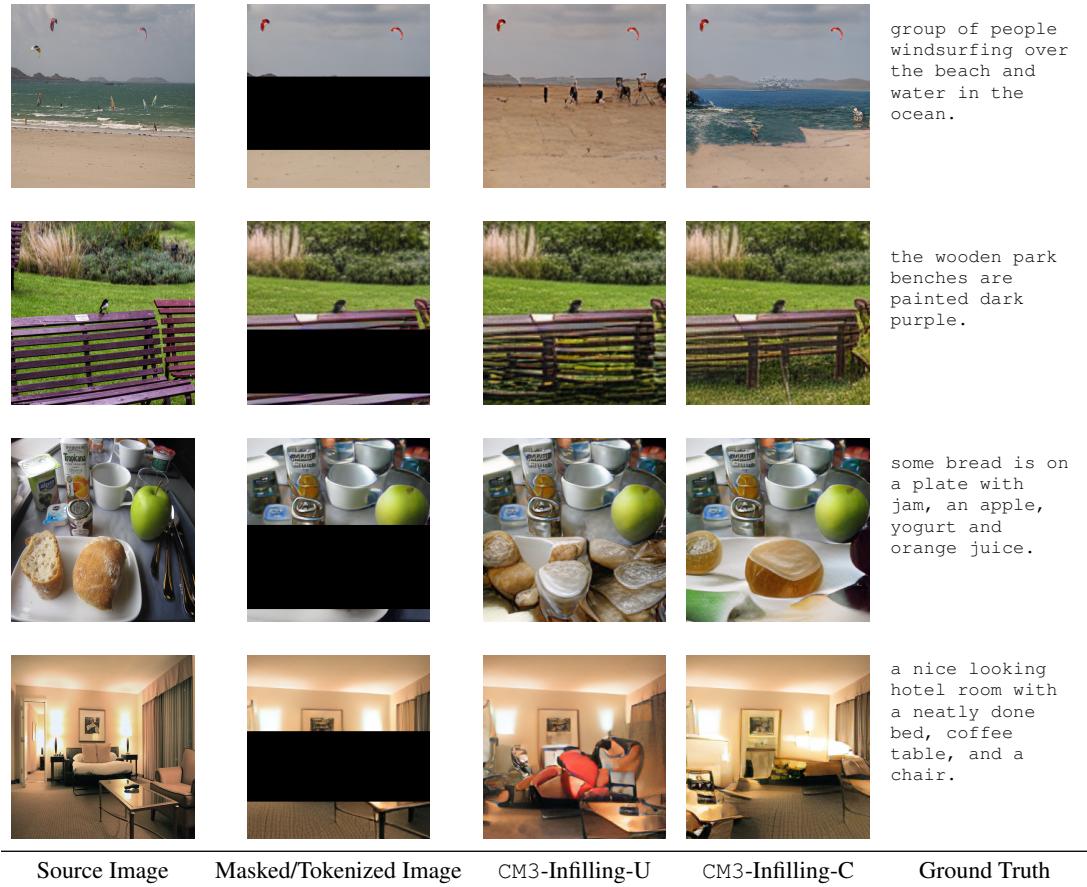


Figure 4: We provide qualitative samples for zero-shot **image-infilling** using the CM3-Large model using the aforementioned prompts. CM3-Infilling-U refers to infilling without conditioning on **text** while CM3-Infilling-C refers to conditioning on the ground truth text.

attributes of a properly set `` tag. Due to attributes always appearing in alphabetical order in order to generate `alt` attribute (which appears before `src`), we need to use the masking capabilities of CM3.

Captioning Masked Prompt #1: `<img alt="Photo: A photo taken of<mask:0>" src="{image}">`

Captioning Causal Prompt #1: `8.12 | |
DALL-E (Ramesh et al., 2021)		~ 28
LAFITE (Zhou et al., 2021)		26.94
GLIDE (Nichol et al., 2021)		12.24
Unconditional CM3-Medium	40.65	
Unconditional CM3-Medium	36.51	
Conditional CM3-Medium	36.78	
Conditional CM3-Large	29.56	

Table 2: We compare FID on MS-COCO 256×256 . Following Nichol et al. (2021) we sample roughly 30k conditioned samples for our models, and compare against the entire validation set. We use a temperature of 0.85 for both CM3 models. We use the implementation available from Seitzer (2020).

to the loss of texture from representing images through discrete tokens (e.g., the text of the train station is blurred, as is the text on the bus).

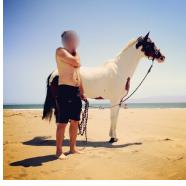
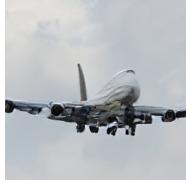
Source Image	Tokenized Image	CM3-Caption-Beam	CM3-Caption-CLIP	Ground Truth
		the main entrance of the U.S. Department of State in Washington, D.C.	the white marble exterior standing atop of its façade.	outside of a train station building from across the street.
		a pickup truck parked in a layby on a highway.	a large bus parked in a layby	a tall red bus is coming down some tracks
		a man posing for a photo.	a man next to a large horse.	a man standing next to a horse on a beach
		a U.S. Air Force B-52H Stratofortress on the flight line at Barksdale Air Force Base, Louisiana	the Austrian Airbus A321 aircraft with its Austrian registration	a jet airliner flying with a cloudy sky in the background.

Figure 6: We provide qualitative samples for zero-shot image-captioning using the CM3-Large model. Caption-Beam refers to generating caption using beam over prompts, while Caption-CLIP uses CLIP to get the top-ranked caption from a 128 candidate set (64 from masked prompt, 64 from causal prompt).

Quantitatively we measure the quality of CM3 zero-shot captioning by evaluating using BERT-Score² (Zhang et al., 2019) with the RoBERTa-Large models (Liu et al., 2019) on the validation set from MS-COCO. We opt for the use of semantic evaluation versus classical metrics such as BLEU/METEOR because we notice that the vocabulary and sentence structure of zero-shot captioning with CM3 is not compatible with MS-COCO ground truth labels, although the generated content is semantically similar. We present our quantitative result in Table 3. CM3-Large is capable of achieving reasonable zero-shot captioning performance on the MS-COCO dataset.

	Precision	Recall	F1
CM3-Caption-Beam	0.781	0.789	0.785
CM3-Caption-CLIP	0.863	0.866	0.864

Table 3: BERTScore numbers for zero-shot captioning with CM3.

²We use the open-source BERTScore at: https://github.com/Tiiiger/bert_score. The evaluation method is: roberta-large_L17_no-idf_version=0.3.11(hug_trans=4.11.3)_fast-tokenizer

4.3 TEXT MODALITY

CM3 is not only a cross-modal model but is fully capable of acting as a stand-alone language model. This is even reflected in our data, where we do not enforce every document to have images; therefore, pure language modeling will also occur during training. We evaluate our CM3 models on a wide set of varying language tasks.

4.3.1 ENTITY DISAMBIGUATION

We reproduce the evaluation setting described by De Cao et al. (2020) and Le & Titov (2018) using the same candidate sets, datasets and evaluating using the InKB micro-F1 metric.

We aim to find a prompt capable of representing the more general end-to-end entity linking task in the CM3 model. From there, a proper sequence scoring of the candidate set will provide us with an approach to zero-shot entity disambiguation. Luckily HTML based Wikipedia contains very rich annotations. Specifically below, we show an example of naturally occurring entity linking that would occur in our Wikipedia subset of CM3 training data.

Original: *Manetho writes that these kings ruled from Memphis*

Prompt: *Manetho writes that these kings ruled from <a title="*

Target: *Manetho writes that these kings ruled from <a title="*

Using our scoring approach we can simply score the **Target** while swapping out the postfix after `<mask:0>`.

Model Type	Method	In-domain			Out-of-domain			Avg.
		AIDA	MSNBC	AQUAINT	ACE2004	CWEB	WIKI*	
<i>Direct Supervision</i>	Ganea & Hofmann (2017)	92.2	93.7	88.5	88.5	77.9	77.5	86.4
	Guo & Barbosa (2018)	89	92	87	88	77	84.5	86.2
	Yang et al. (2018)	95.9	92.6	89.9	88.5	81.8	79.2	88.0
	Shahbazi et al. (2019)	93.5	92.3	90.1	88.7	78.4	79.8	87.1
	Yang et al. (2019)	93.7	93.8	88.2	90.1	75.6	78.8	86.7
	Le & Titov (2019)	89.6	92.2	90.7	88.1	78.2	81.7	86.8
	Fang et al. (2019)	94.3	92.8	87.5	91.2	78.5	82.8	87.9
<i>Direct Supervision</i>	De Cao et al. (2020)	93.3	94.3	89.9	90.1	77.3	87.4	88.8
	{ CM3-Medium	93.5	94.2	90.1	90.4	76.5	86.9	88.6
<i>Self Supervision (0-Shot)</i>	{ CM3-Large	94.8	94.8	91.1	91.4	78.4	88.7	89.8
	{ CM3-Medium	78.0	80.1	75.4	81.4	68.5	76.2	76.6
	{ CM3-Large	80.1	80.8	77.7	82.8	72.4	80.2	79.0

Table 4: Aligned with GENRE’s evaluation, we use Micro F_1 (InKB) for the named entity disambiguation task. **Bold** indicates best model. We note that although *WIKI can be thought of as being out-of-domain, given that English Wikipedia was used to pre-train CM3, it can be considered in-domain as well.

As an additional datapoint for the representations learned from CM3 we completely replicate the training and evaluation for the GENRE model (De Cao et al., 2020).³. Specifically we first fine-tune CM3 on the BLINK data (Wu et al., 2019). For the in-domain scenario, we fine-tune CM3 on the AIDA-CoNLL dataset (Hoffart et al., 2011). We evaluate on the AIDA-CoNLL dataset for the in-domain scenario and the MSNBC, AQUAINT, ACE2004, WNED-CWEB (CWEB) and WNED-WIKI (WIKI) for the out-of-domain scenario (De Cao et al., 2020; Guo & Barbosa, 2018). We present our results in Figure 4.

Given the strong supervision naturally available in Wikipedia HTML, it is unsurprising that CM3 shows strong, non-trivial zero-shot performance on the named entity disambiguation across a wide array of named entity disambiguation tasks.

³<https://github.com/facebookresearch/GENRE>

Furthermore, the fine-tuned HTLM-Large model outperforms previous entity linking specific models to achieve a new SOTA over the benchmarked datasets.

4.3.2 ENTITY LINKING

We next consider the more general entity linking task. We experiment with two settings zero-shot assuming we know the location of the entities and the full fine-tuning setting following the exact methodology proposed in De Cao et al. (2020). Specifically for the end-to-end Entity Linking, we aim to reproduce the setting of Kolitsas et al. (2018). We evaluate using the aforementioned *InKB* micro- F_1 with the same defined in-domain and out-of-domain datasets as described by De Cao et al. (2020). We use the exact same *in-domain* and *out-of-domain* datasets as well as evaluating the *InKB* micro- F_1 on the GERBIL benchmark platform (Röder et al., 2018). Furthermore, we use the same decoding strategy for the zero-shot case by limiting the generative tokens to only available candidate entities. Please refer to De Cao et al. (2020) for the full fine-tuning setup.

For both setting we evaluate on seven test sets: MSNBC, Derczynski (Der) (Derczynski et al., 2015), KORE 50 (K50) (Hoffart et al., 2012), N3-Reuters-128 (R128), N3-RSS-500 (R500) (Röder et al., 2014), and OKE challenge 2015 and 2016 (OKE15 and OKE16) (Nuzolese et al., 2015).

Method	In-domain	Out-of-domain						Avg.		
		AIDA	MSNBC	Der	K50	R128	R500			
Direct Supervision	Hoffart et al. (2011)	72.8	65.1	32.6	55.4	46.4	42.4	63.1	0.0	47.2
	Steinmetz & Sack (2013)	42.3	30.9	26.5	46.8	18.1	20.5	46.2	46.4	34.7
	Moro et al. (2014)	48.5	39.7	29.8	55.9	23.0	29.1	41.9	37.7	38.2
	Kolitsas et al. (2018)	82.4	72.4	34.1	35.2	50.3	38.2	61.9	52.7	53.4
	Broscheit (2020)	79.3	-	-	-	-	-	-	-	-
	Martins et al. (2019)	81.9	-	-	-	-	-	-	-	-
	van Hulst et al. (2020) [†]	80.5	72.4	41.1	50.7	49.9	35.0	63.1	58.3	56.4
Direct Supervision	De Cao et al. (2020)	83.7	73.7	54.1	60.7	46.7	40.3	56.1	50.0	58.2
	CM3-Medium	71.4	68.5	48.6	58.3	44.9	41.1	61.9	37.7	54.1
Self Supervision (0-Shot)	CM3-Large	79.9	74.8	53.2	62.4	47.1	42.8	61.9	52.7	59.3
	CM3-Medium	20.4	18.6	20.1	35.1	30.6	32.1	36.6	0.0	24.2
	CM3-Large	24.8	21.4	25.6	39.0	31.1	34.9	37.1	0.0	26.7

Table 5: We report Micro F_1 on our test sets for our entity linking task. **Bold** indicates best model. Following De Cao et al. (2020) we use a [†] to indicate results from the Wikipedia 2019 setting as opposed to the 2014 setting (which has older dump and fewer entities).

We present our results in Table 5. We see that our CM3 are extremely competitive with entity-linking specific models and that our CM3-Large model sets a new state-of-the-art. Furthermore, although our zero-shot numbers are substantially worse, they are still non-trivial, implying that CM3 learns a significant amount of implicit entity linking through our training setting.

4.3.3 SUMMARIZATION

We next look at CM3 performance on the zero-shot summarization task, specifically we replicate the zero-shot evaluation methodology of Aghajanyan et al. (2021). For all summarization benchmarks, we use ROUGE-1/2/L as our primary metrics to stay consistent with other literature (Lin, 2004). We look at the same datasets as HTLM.

Gigaword consists of headlines from news articles (Napoles et al., 2012). The target summaries are relatively short, consisting roughly on average of 10 BPE tokens.

CNN/Dailymail (Hermann et al., 2015) provides multi-sentence target summaries close to 3 sentences, or roughly 50 tokens.

Reddit TIFU (Kim et al., 2018) contains summaries of Reddit posts. Specifically, we use the *short* subset of data . Compared to our other summarization datasets, this dataset is highly abstractive and not based on news articles.

XSum (Narayan et al., 2018) provides abstractive single sentence summaries of news articles.

We utilize the same prompts as available in Aghajanyan et al. (2021). We use the same available size hints but using the implicit size-hint methodology described in § 3.2. Most prompts follow the

same theme of infilling either a `title` element or an element describing a headline (either through attributes or using the `meta` tag). For completeness, below is an example of a prompt that can do basic summarization.

Model	Gigaword	CNN/DM	Reddit TIFU	XSum
PEGASUS-0S	23.39/07.59/20.20	32.90/13.28/29.38	14.66/3.06/10.17	19.27/3.00/12.72
HTLM-Auto-NS	27.56/10.17/24.57	33.40/13.45/30.10	06.71/1.98/07.86	15.15/2.54/10.91
HTLM-Auto-S	28.73/11.31/26.49	34.65/14.54/32.15	08.15/2.92/09.75	17.14/3.41/13.43
HTLM-Manual-S	31.61/10.80/28.60	38.51/16.10/33.89	15.81/2.98/10.54	22.34/4.12/14.56
CM3-M-Manual	29.15/09.70/27.87	37.16/14.75/31.42	09.56/2.65/07.48	20.14/3.15/13.89
CM3-L-Manual	32.12/10.95/28.78	38.88/16.27/34.16	12.14/2.12/07.98	24.86/6.08/16.32

Table 6: CM3 results on zero-shot summarization. HTLM-Manual denotes manually engineered prompts with size hints, while HTLM-Auto-S and HTLM-Auto-NS indicate auto-prompting with and without size hints, respectively. The metrics shown are ROUGE-1/ROUGE-2/ROUGE-L, respectively. CM3-Large sets a new state-of-the-art on three news-based summarization datasets.

We present our results in Table 6. Both CM3 models saw significantly less text than the HTLM model, with 2.7TB of text. Furthermore, the prompts being used were tuned specifically for the HTLM model and are being used with no changes for CM3. With these challenges, we still see that CM3-Large sets new state-of-the-art zero-shot summarization for three datasets. We attribute the performance degradation in Reddit-TIFU data to CM3 pre-training data only containing CC-NEWS and Wikipedia, which will not contain the type of summarizations needed for Reddit-TIFU.

5 FINE-TUNING

We next want to measure the quality of internal representations for the end goal of fine-tuning. We compare CM3 with a wide array of masked language model derived models such as T5 (Raffel et al., 2019), RoBERTa (Liu et al., 2019), HTLM (Aghajanyan et al., 2021) tested on the standard GLUE benchmark (Wang et al., 2018). For CM3 we look at three settings for fine-tuning; standard fine-tuning, better fine-tuning using adversarial methods (Aghajanyan et al., 2020), and better fine-tuning over prompts derived from Aghajanyan et al. (2021). We delegate the specifics hyper-parameters of the fine-tuning experiments to § A.3

	MNLI Acc-m/mm	QQP Acc	RTE Acc	QNLI Acc	MRPC Acc	CoLA Mcc	SST-2 Acc	# Params
T5-Base	87.1/86.2	89.4	80.1	93.7	87.5	51.1	95.2	220M
RoBERTA	90.2/-	92.2	86.6	94.7	89.1	68.0	96.4	330M
RoBERTa-R3F	91.1/91.3	92.4	88.5	95.3	91.6	71.2	97.0	330M
BART-Large	89.9/90.1	92.5	87.0	94.9	90.4	62.8	96.6	400M
HTLM	90.3/91.4	92.6	87.1	95.1	90.8	64.3	96.9	400M
HTLM-R3F	91.4/92.1	92.8	89.1	95.4	91.5	69.4	97.1	400M
HTLM-R3F-Prompt	91.6/91.2	92.9	89.4	95.7	91.7	69.8	97.3	400M
T5-Large	89.9/89.6	89.9	87.2	94.8	89.9	61.2	96.3	770M
T5-3B	91.4/91.2	89.7	91.1	96.3	90.0	67.1	97.4	3B
T5-11B	92.2/91.9	90.6	92.8	96.9	90.4	71.6	97.5	11B
CM3-Medium	89.9/89.7	89.6	89.1	93.1	86.5	63.1	94.9	2.7B
CM3-Medium-Prompt	90.8/91.0	89.9	90.5	95.1	89.9	66.2	96.3	2.7B
CM3-Medium-RXF-Prompt	90.9/91.1	90.0	90.7	95.3	90.0	67.1	96.9	2.7B
CM3-Large	91.1/91.0	89.9	91.9	95.6	89.6	64.6	94.2	13B
CM3-Large-Prompt	91.5/91.4	90.1	92.4	96.2	90.1	70.9	97.1	13B
CM3-Large-RXF-Prompt	91.9/91.5	91.1	92.5	96.4	90.3	70.8	97.3	13B

Table 7: Results on the GLUE development set for various fine-tuning methods applied to CM3.

We present our results in Table 7. Overall we see that both CM3 models are competitive against T5 given the same parameter setting. Furthermore, aligning with the results from Aghajanyan et al.

(2021) we see that placing the natural language utterances of the various GLUE tasks into an HTML prompt while fine-tuning non-trivially improves end-finetuning performance. The following experiments show that the causally masked language modeling approach is not detrimental to learning fine-tunable representations, and neither is jointly modeling image tokens.

6 ETHICAL CONSIDERATIONS

Prior work has explored the extent to which language models encode harmful gender and racial biases that parallel humans through the Word Embedding Association Test (WEAT) (Caliskan et al., 2017), the Sentence Encoder Association Test (SEAT) (May et al., 2019) and the Grounded-WEAT/Grounded-SEAT (Ross et al., 2021) metrics for multimodal language models (Tan & Celis, 2019). Given the generative nature of CM3 in both the language and visual modalities, we used GWEAT/GSEAT to probe our model. Overall, we evaluated six bias tests for gender and seven bias tests for race and found that our family of CM3 models show significantly less bias than other models, specifically VisualBERT (Li et al., 2019) and ViLBert (Lu et al., 2019).

	Level	VisualBert	ViLBert	CM3-Medium	CM3-Large
C6: M/W, Career/Family	S	<u>1.05</u>	<u>1.14</u>	0.00	<u>0.98</u>
	W	<u>0.54</u>	<u>0.51</u>	0.10	0.12
C8: Science/Arts, M/W	S	<u>0.86</u>	<u>1.05</u>	-0.09	0.42
	W	<u>0.62</u>	<u>0.14</u>	0.08	0.07
C11: M/W, Pleasant/Unpleasant	S	-0.74	-0.84	0.00	-0.64
	W	-0.66	-0.31	-0.20	-0.48
Double Bind: M/W, Competent	S	-0.10	-0.04	0.01	-0.01
	W	-0.23	<u>0.30</u>	-0.07	-0.27
Double Bind: M/W, Likeable	S	-0.11	-1.12	-0.24	-0.59
	W	-0.60	0.09	0.00	0.10
Occupations: M/W, Occupation	S	<u>0.98</u>	<u>1.82</u>	0.03	<u>0.62</u>
	W	<u>0.91</u>	<u>1.80</u>	0.00	0.58
Total Significant Bias Count	-	5	6	0	2

Table 8: Following Ross et al. (2021) we present the results for all gender bias classes on answering the question: “Do joint embeddings contain biases”? The numbers in our table represent effect sizes, and are underlined if their respective p-values are below 0.05. Each bias type and model are tested three times against Word embeddings (W) and Sentence embeddings (S).

We present our empirical results for gender and race bias in Table 8 and Table 9 respectively. Overall, both CM3 have significantly less bias than other competing models, most likely due to our choice to use only Wikipedia and CC-NEWS articles as training sources (and recent CC-NEWS articles at that). Furthermore, we believe the fact that CM3-Medium shows no to very little signs of bias can be an indicator of under-fitting as the large model is, unfortunately, able to show some bias from our training data.

We also qualitatively experiment with whether CM3 can be prompted to produce harmful or objectionable images. In general, we noticed it was incredibly hard to produce such content, additionally the lack of the ability to generate distinctive features of VQVAE-GAN acts to our benefit in terms of preserving privacy.

7 RELATED WORK

Fundamentally our work is an extension of the HTLM work proposed by Aghajanyan et al. (2021) to using the newly proposed causally masked objective, integrating images through VQVAE-GAN tokens, and scaling up over an order of magnitude. From there, the individual capabilities of our models are comparable to individual approaches.

	Level	VisualBert	ViLBert	CM3-Medium	CM3-Large
C3: EA/AA, Pleasant/Unpleasant	W	<u>0.23</u>	<u>0.14</u>	-0.44	0.10
	S	<u>0.31</u>	-0.14	-0.057	0.05
C12: EA/AA, Career/Family	W	-0.29	<u>0.43</u>	0.117	<u>0.23</u>
	S	-0.54	<u>0.34</u>	-0.049	<u>0.28</u>
C13: EA/AA, Science/Arts	W	0.04	<u>0.21</u>	0.325	0.12
	S	<u>0.12</u>	<u>0.68</u>	<u>0.169</u>	<u>0.465</u>
Double Bind: EA/AA, Competent	W	<u>0.61</u>	<u>0.87</u>	-0.535	<u>0.42</u>
	S	0.24	0.25	0.0	0.18
Double Bind: EA/AA, Likeable	W	0.21	-0.23	-0.535	0.19
	S	<u>0.27</u>	-0.74	-0.535	0.21
Occupations: EA/AA, Occupation	W	-0.40	0.02	-0.51	0.01
	S	-0.41	<u>0.46</u>	-0.17	0.38
Angry Black Woman Stereotype	W	-0.07	0.26	-1.89	0.21
	S	-0.50	<u>0.47</u>	0.0	-0.10
Total Significant Bias Count	-	4	5	1	3

Table 9: Following Ross et al. (2021) we present the results for all racial bias classes on answering the question: “Do joint embeddings contain biases”? Our table uses the same annotations as Table 8.

For example, the conditional and unconditional image generation capabilities of our model are most similar in approach to DALL-E, which trains a left-to-right causal model over the concatenation of textual tokens and VQ-VAE visual tokens (Ramesh et al., 2021). At the same time, the use of auto-regressive modeling in entity linking and disambiguation was proposed by the GENRE in De Cao et al. (2020).

The method of tokenizing non-discrete modalities to use standard sequence modeling approaches have been extensively explored with DALL-E for images, Jukebox for Music (Dhariwal et al., 2020) and vq-wav2vec for Speech (Baevski et al., 2019).

8 CONCLUSION

In this paper, we present the CM3 model, a causally masked trained language model that is capable of non-trivial zero-shot performance on a wide range of zero-shot uni- and cross-modal tasks. We first describe a new sequence modeling objective we call causally masked, enabling both full generative modeling with bidirectional context.

Through extensive experimentation, we show that as a single model CM3 can be prompted to recover the functionality of many other models being able to do image generation, image captioning, unconditional image generation, and more. Empirically we improve over state-of-the-art zero-shot summarization, entity linking, entity disambiguation, highlighting the structure from the hypertext during training. We show that representations learned by CM3 are not only useful for zero-shot prompting but for fine-tuning by fine-tuning CM3 and state-of-the-art for entity linking and entity disambiguation in general, all while staying highly competitive with T5 models on the GLUE benchmark.

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A APPENDIX

A.1 MODEL ARCHITECTURE

For model architecture we use the same exact architecture for CM3-Medium and CM3-Large as the dense 2.7B and 13B models described in Artetxe et al. (2021).

	CM3-Large	CM3-Medium
-decoder-embed-dim	5120	2560
-decoder-output-dim	5120	2560
-decoder-input-dim	5120	2560
-decoder-ffn-embed-dim	20480	10240
-decoder-layers	40	32
-decoder-normalize-before	True	True
-decoder-attention-heads	40	32
-share-decoder-input-output-embed	True	True
-decoder-learned-pos	False	False

Table 10: FairSeq architecture designation for CM3 models

A.2 UNIFORMITY OF VQVAE-GAN TOKENS

We plot a histogram of all image tokens in a subset of our data spanning 100k tokens. We see a somewhat clear uniformity in tokens used.

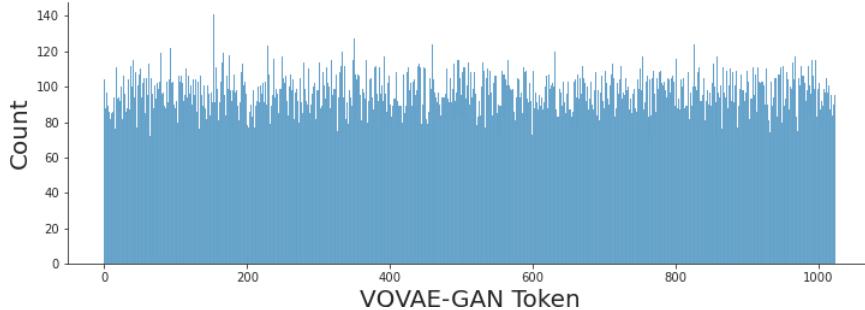


Figure 7: Histogram of VQ-VAE-GAN Tokens in the CM3 Training Dataset.

A.3 FINETUNING GLUE HYPER-PARAMETERS

For our fine-tuning GLUE related experiments with the RXF method we use the following hyper-parameters.

Hyper Parameter	MNLI	QNLI	QQP	SST-2	RTE	MRPC	CoLA
Learning Rate	5e-6	5e-6	5e-6	5e-6	1e-5	1e-5	1e-5
Max Updates	123873	33112	113272	20935	3120	2296	5336
Max Sentences	8	8	32	32	8	16	16

Table 11: Task specific hyper parameters for GLUE experiments

Hyper parameter	Value	Hyper parameter	Value
Optimizer	Adam		
Adam-betas	(0.9, 0.98)		
Adam-eps	1e-6		
LR Scheduler	polynomial decay		
Dropout	0.1		
Weight Decay	0.01		
Warmup Updates	0.06 * max updates		
		λ	[0.1, 0.5, 1.0, 5.0]
		Noise Types	[\mathcal{U} , \mathcal{N}]
		σ	$1e - 5$

Table 12: Hyper parameters for fine-tuning experiments on GLUE