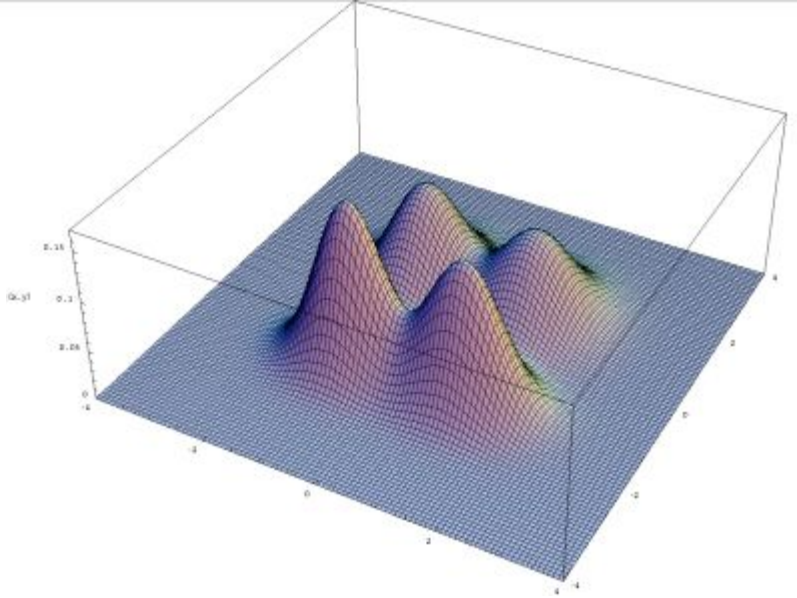
Multimodal Deep Learning

with an NLP focus

CS224n

What is multimodality?



multimodal adjective

mul·ti·mod·al ˌməl-tē-ˈmō-dᵊl -ˌtī-

: having or involving several modes, modalities, or maxima

> *multimodal* distributions

> *multimodal* therapy

In our case, focusing on NLP: text + one or more other *modality* (images, speech, audio, olfaction, others). We'll mostly focus on images as the other modality.

Why does multimodality matter?

A range of very good reasons:

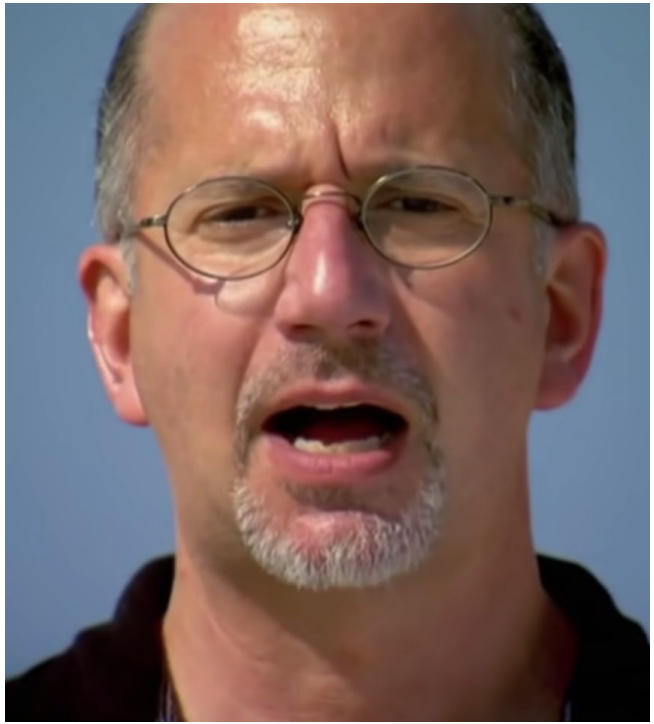
- Faithfulness: Human experience is multimodal
- Practical: The internet & many applications are multimodal
- Data efficiency and availability:
  - Efficiency: Multimodal data is rich and “high bandwidth” (compared to language; quoting LeCun, “an imperfect, incomplete, and low-bandwidth serialization protocol for the internal data structures we call thoughts”), so better for learning?
  - Scaling: More data is better, and we’re running out of high quality text data.

Multimodality is one of the main frontiers of the new foundation model revolution.

Multimodal brains

McGurk effect (McGurk & MacDonald, 1976)

https://www.youtube.com/watch?v=2k8fHR9jKVM



Multimodal applications

Let’s say we’re dealing with two modalities – text, and images:

- Retrieval (image <> text)
- Captioning (image -> text)
- Generation (text -> image)
- Visual question answering (image+text -> text)
- Multimodal classification (image+text -> label)
- Better understanding/generation (image+text -> label/text)

Multimodal is hot right now

.. and/but has been “the next big thing” for almost a decade!

Language Is Not All You Need: Aligning Perception with Language Models

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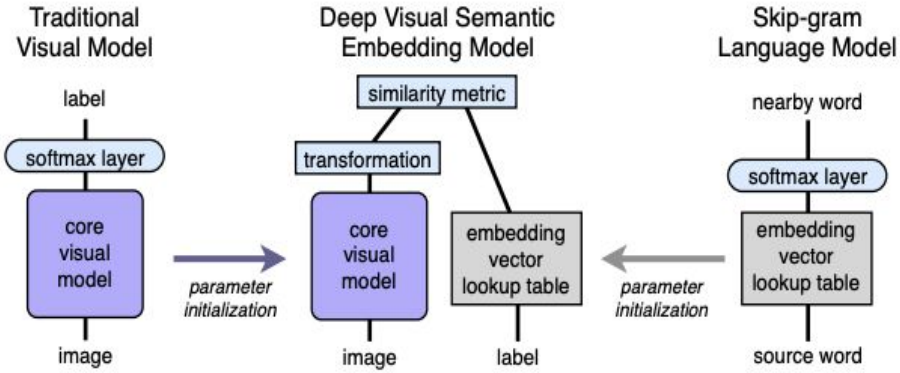
Outline

1. **Early models**
2. Features and fusion
3. Contrastive models
4. Multimodal foundation models
5. Evaluation
6. Beyond images: Other modalities
7. Where to next?

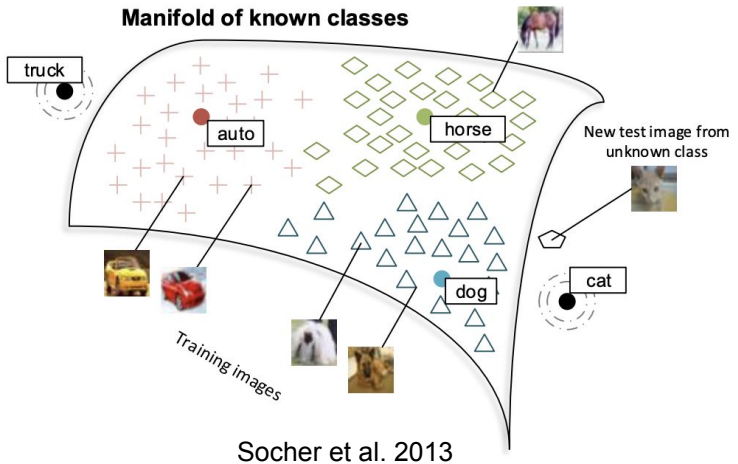
Cross-modal “Visual-Semantic Embeddings”

WSABI (Weston et al 2010), DeVise (Frome et al 2013),
Cross-Modal Transfer (Socher et al 2013)



Frome et al. 2013

$$loss(image, label) = \sum_{j \neq label} \max[0, margin - \vec{t}_{label} M\vec{v}(image) + \vec{t}_j M\vec{v}(image)]$$



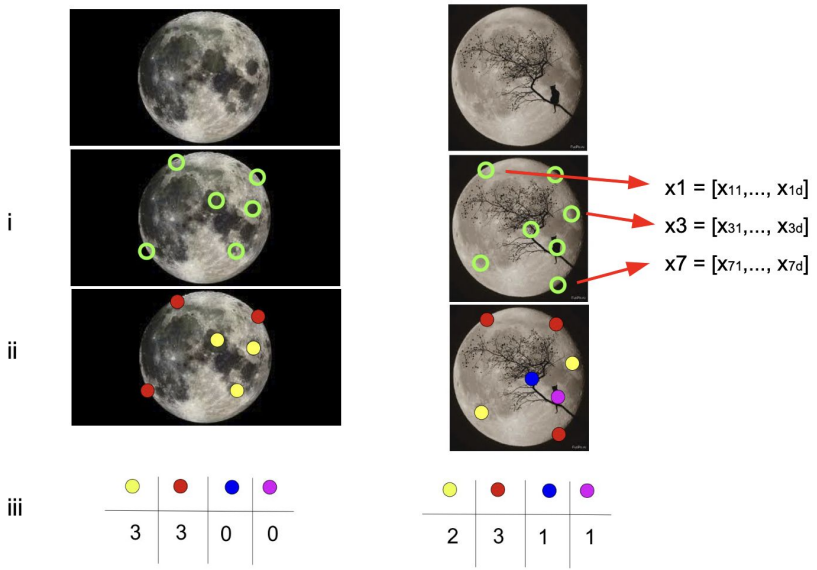
Socher et al. 2013

Multimodal distributional semantics (Bruni et al., 2014)

Algorithm:

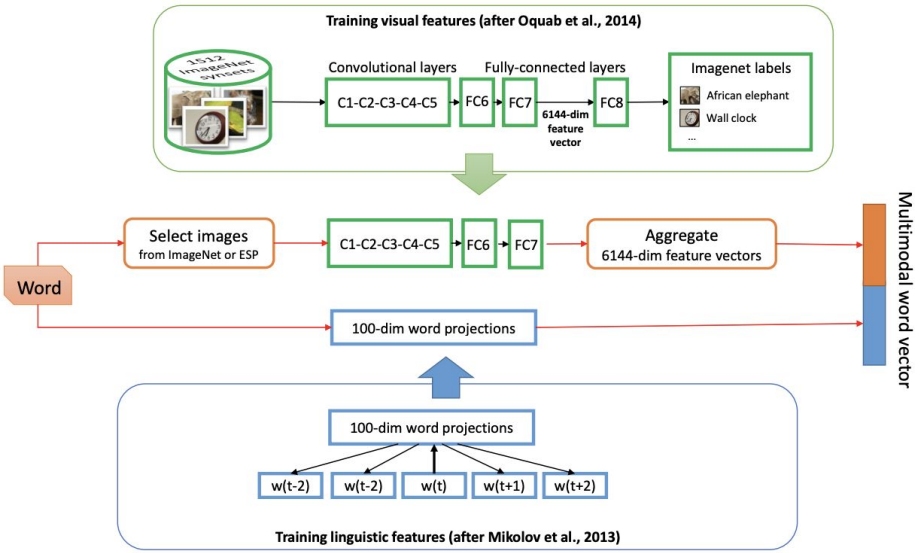
- Obtain visual “word vector” via BOVW:
  - Identify keypoints and get their descriptors
  - Cluster these and map to counts
- Concatenate with textual word vector
- Apply SVD to “fuse” information

This approach was shown to lead to better word representations on human similarity judgment datasets.

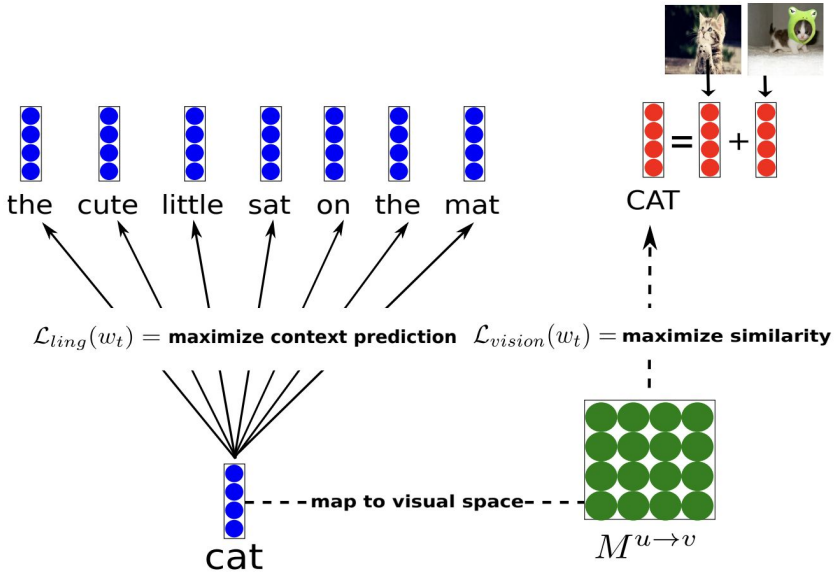


Bag of visual words (BOVW) illustration. Bruni et al., 2014.

Neural version (KB, 2014; Lazaridou et al., 2015)



Kiela & Bottou, 2014

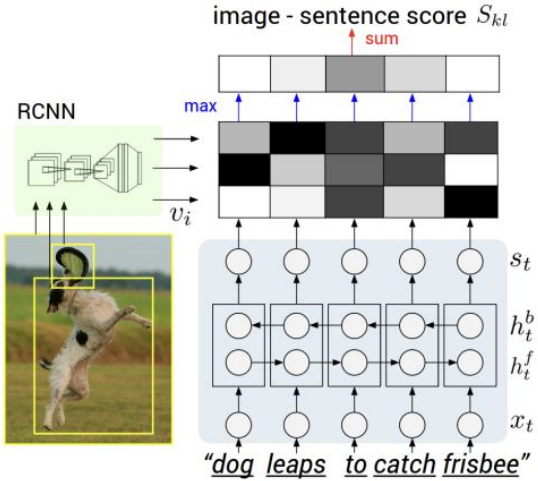


Lazaridou et al., 2015

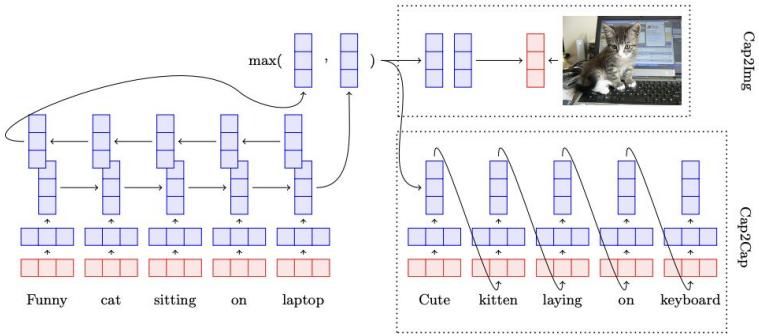
Beyond words: Sentence level alignment

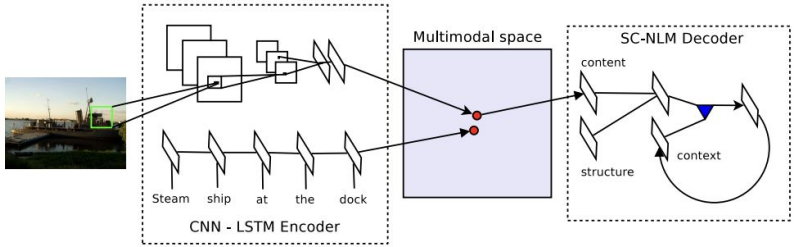
Grounded Compositional Semantics (Socher et al., 2013)
Visual-Semantic Embeddings (Kiros et al., 2014; Faghri et al., 2015)
Visual-Semantic Alignments (Karpathy & Li, 2015)
Grounded Sentence Representations (Kiela et al., 2016)

Hinge/margin-like loss as in WSABI/DeViSE.



Karpathy & Li, 2015



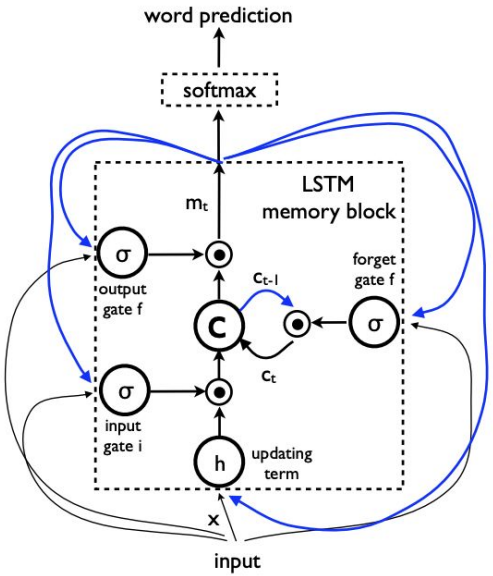


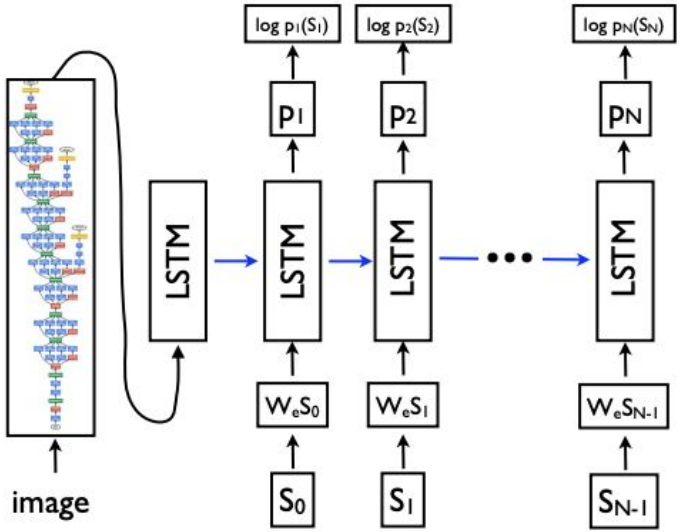
Kiros et al., 2014

Image to text: Captioning

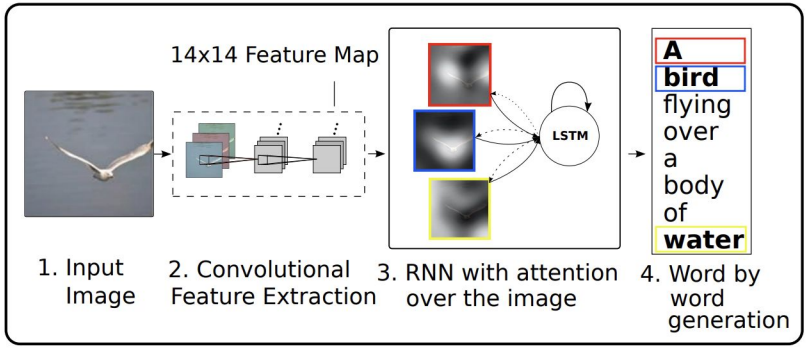
Show and tell (Vinyals et al., 2015)

Show, attend and tell (Xu et al., 2016)





Vinyals et al., 2015



Xu et al., 2016

Attention as visual-semantic alignment

A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.

A stop sign is on a road with a mountain in the background.

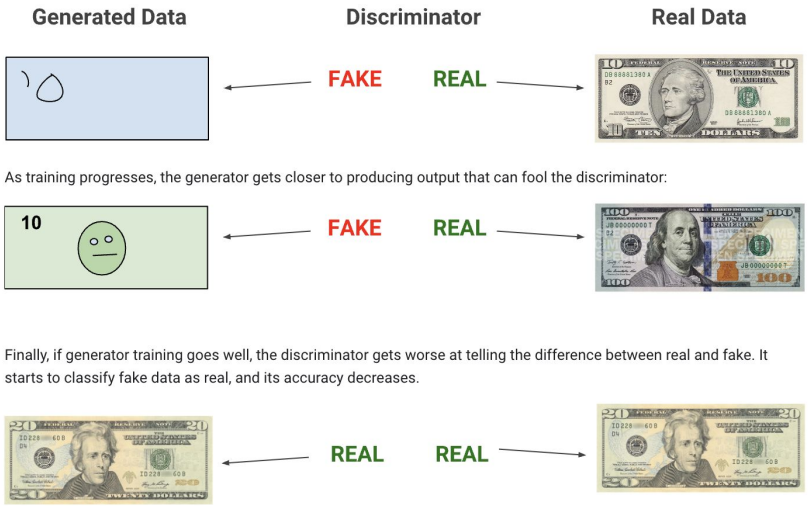
A little girl sitting on a bed with a teddy bear.

A group of people sitting on a boat in the water.

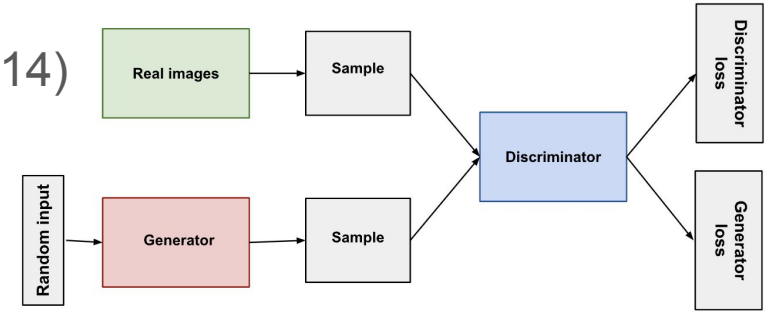
A giraffe standing in a forest with trees in the background.

Text to image: Conditional image synthesis

Generative adversarial nets (Goodfellow et al. 2014)



Source: Google



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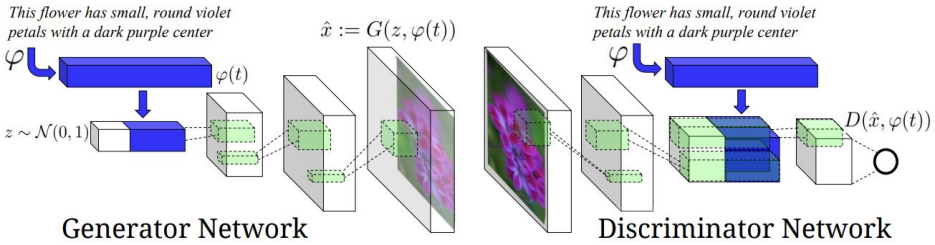

Reed et al., 2016

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Problems with multimodality

If it’s so important, why isn’t every system multimodal from first principles?

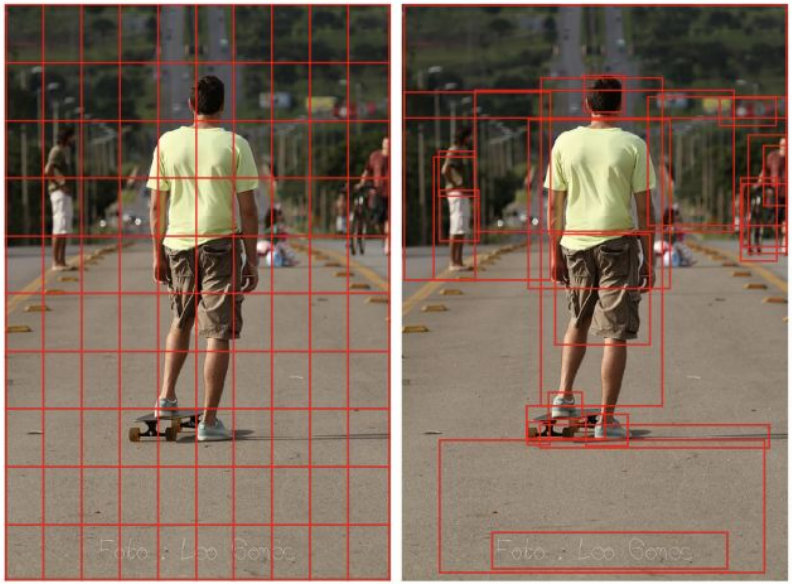
- One modality can dominate other modalities.
- Additional modalities can add noise.
- Full coverage over modalities is not guaranteed.
- We are (were) not ready.
- It’s complicated.

Features

Featurizing text: Batch_size x Sequence_length x Hidden_size.

Featurizing images:

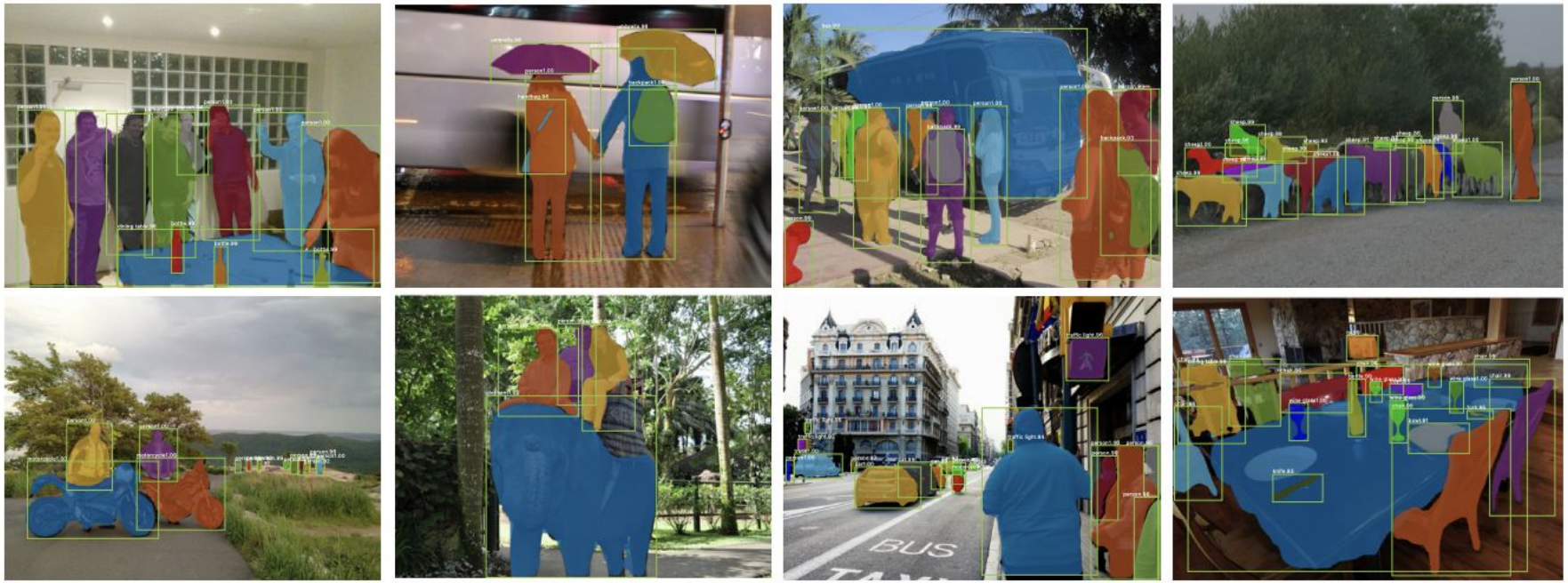
- Sparse “region” features:
  - Object detectors
- Dense features:
  - ConvNet layer(s) or feature maps
  - Vision Transformer layers



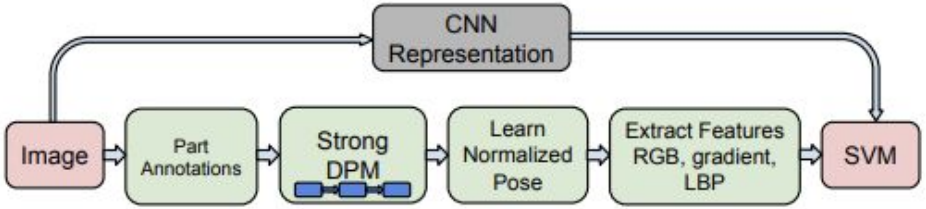
Anderson et al., 2018

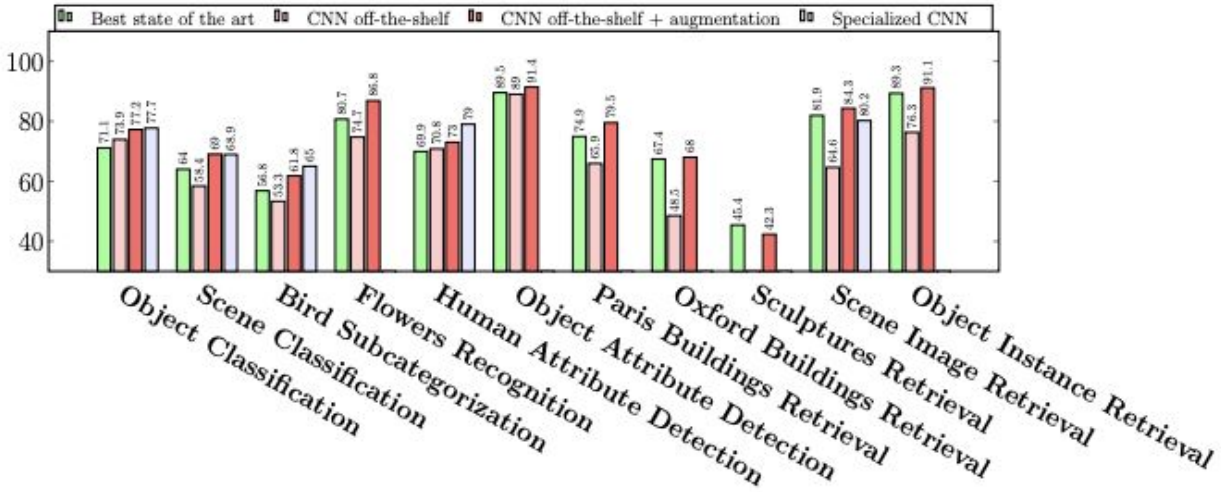
Region features

- R-CNN (Girshick et al., 2014); Fast R-CNN (Girshick, 2015); Faster R-CNN (Ren et al., 2015); YOLO (you only look once) vX..

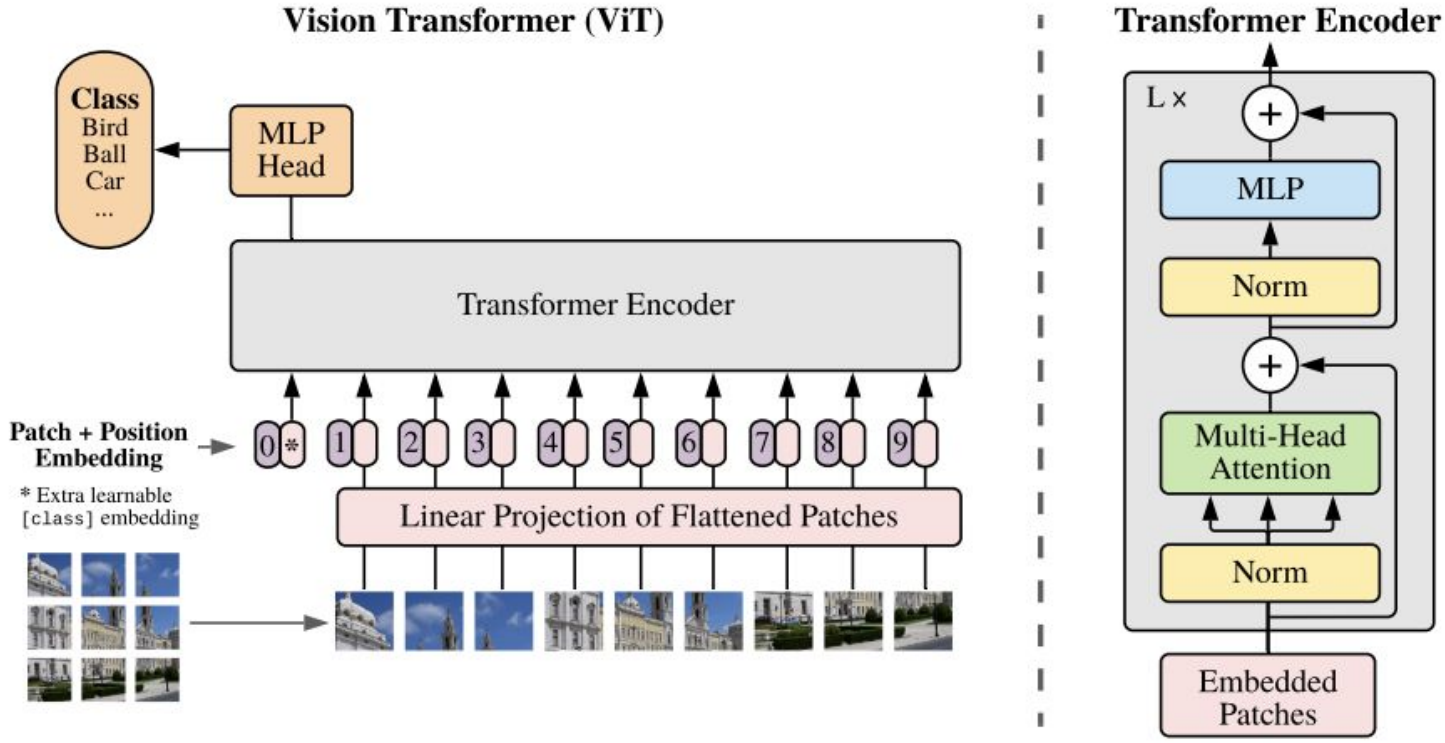


“Off the shelf” ConvNet features (Razavian et al., 2014)





Vision Transformers (Dosovitskiy et al., 2020)



Multimodal fusion

Similarity

- Inner product: $\mathbf{u}\mathbf{v}$

Linear / sum

- Concat: $W[\mathbf{u},\mathbf{v}]$
- Sum: $W\mathbf{u}+V\mathbf{v}$
- Max: $\max(W\mathbf{u}, V\mathbf{v})$

Multiplicative

- Multiplicative: $W\mathbf{u}\odot V\mathbf{v}$
- Gating: $\sigma(W\mathbf{u})\odot V\mathbf{v}$
- LSTM-style: $\tanh(W\mathbf{u})\odot V\mathbf{v}$

Attention

- Attention: $\alpha W\mathbf{u}+\beta V\mathbf{v}$
- Modulation: $[\alpha\mathbf{u},(1-\alpha)\mathbf{v}]$

Bilinear

- Bilinear: $\mathbf{u}W\mathbf{v}$
- Bilinear gated: $\mathbf{u}W\boldsymbol{\sigma}(\mathbf{v})$
- Low-rank bilinear: $\mathbf{u}U^{T}V\mathbf{v}=P(U\mathbf{u}\odot V\mathbf{v})$
- Compact bilinear: $FFT^{-1}(FFT(\Psi(\mathbf{x},\mathbf{h}_1,\mathbf{s}_1))\odot FFT(\Psi(\mathbf{x},\mathbf{h}_2,\mathbf{s}_2)))$

Early middle and late

Suppose we have a binary classifier MLP and two input vectors.

Early - mix inputs:

- $\sigma(W_2\sigma(W_1[\mathbf{u},\mathbf{v}]+b_1)+b_2)$

Middle - concatenate features:

- $\sigma(W_2[\sigma(W_1[\mathbf{v}]+b_1), \sigma(W'_1[\mathbf{v}]+b'_1)] +b_2)$

Late - combine final scores:

- $1/2\ (\sigma(W_2\sigma(W_1[\mathbf{u}]+b_1)+b_2) + \sigma(V_2\sigma(V_1[\mathbf{u}]+b'_1)+b'_2))$

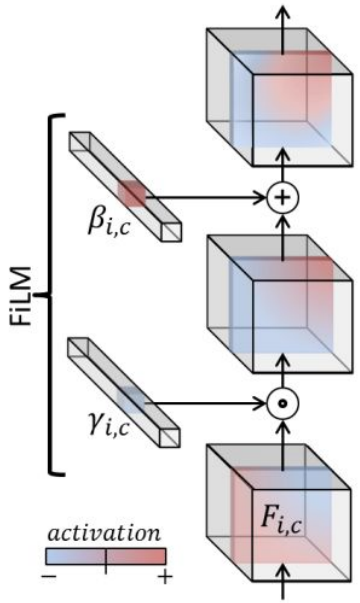
FiLM (Perez et al., 2017)

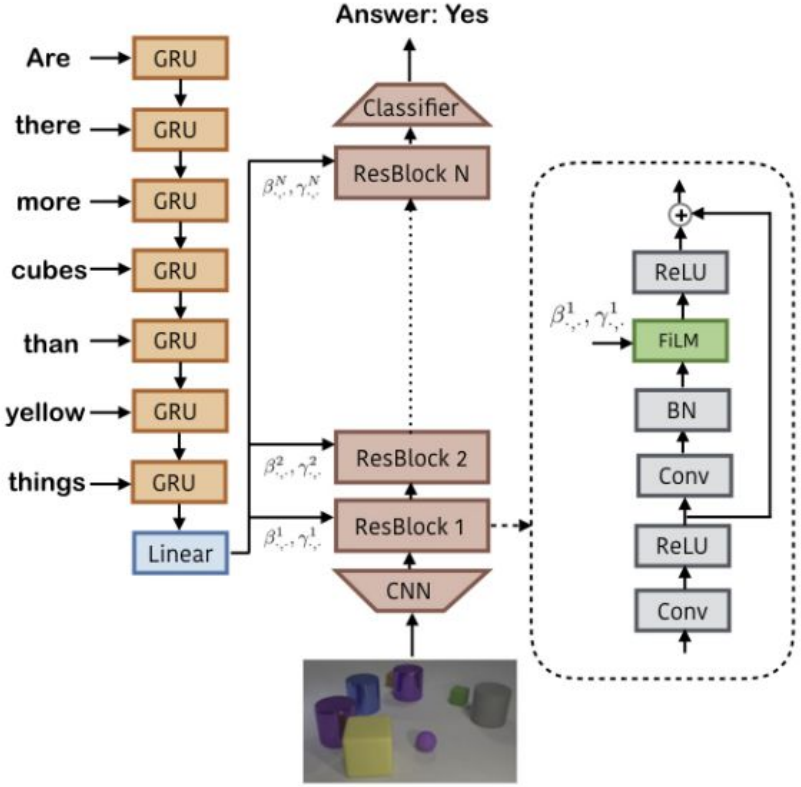
Modulate one modality, layerwise, by the other.

$\gamma_{i,c} = f_c(x_i)$

$\beta_{i,c} = h_c(x_i)$

$\mathrm{FiLM}(F_{i,c} \mid \beta_{i,c}, \gamma_{i,c}) = \gamma_{i,c} F_{i,c} + \beta_{i,c}$





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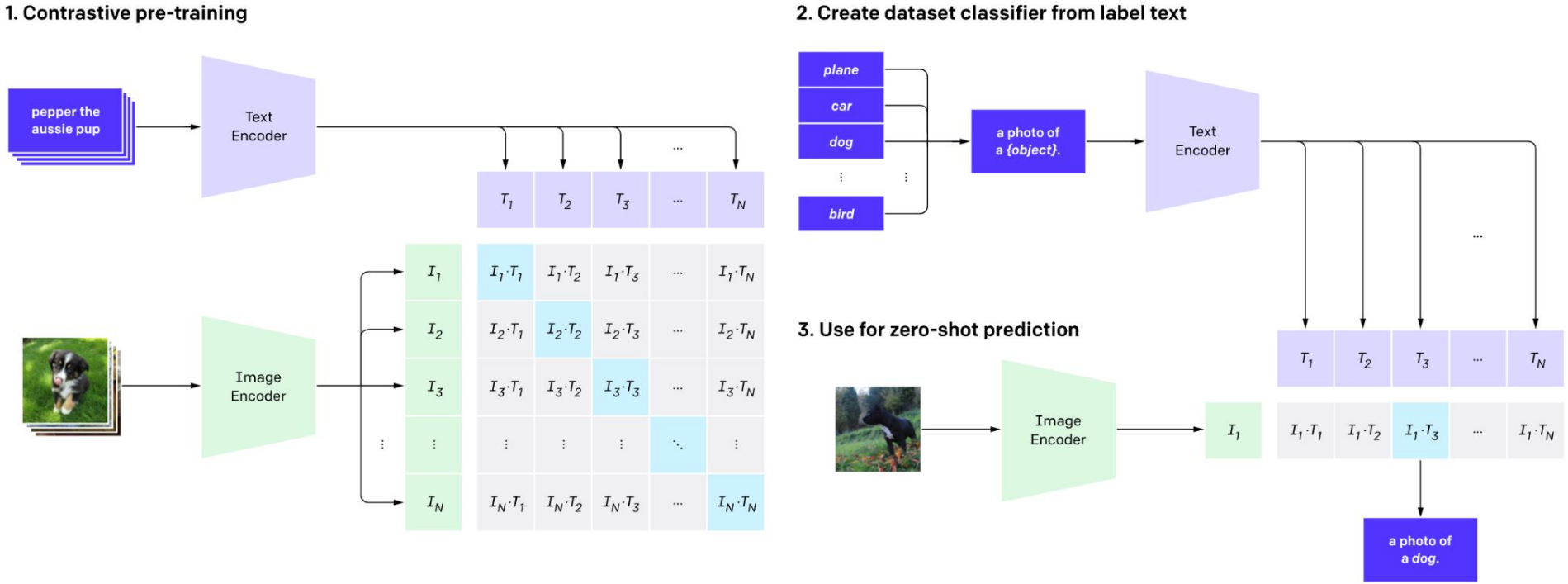
CLIP (Radford et al. 2021)

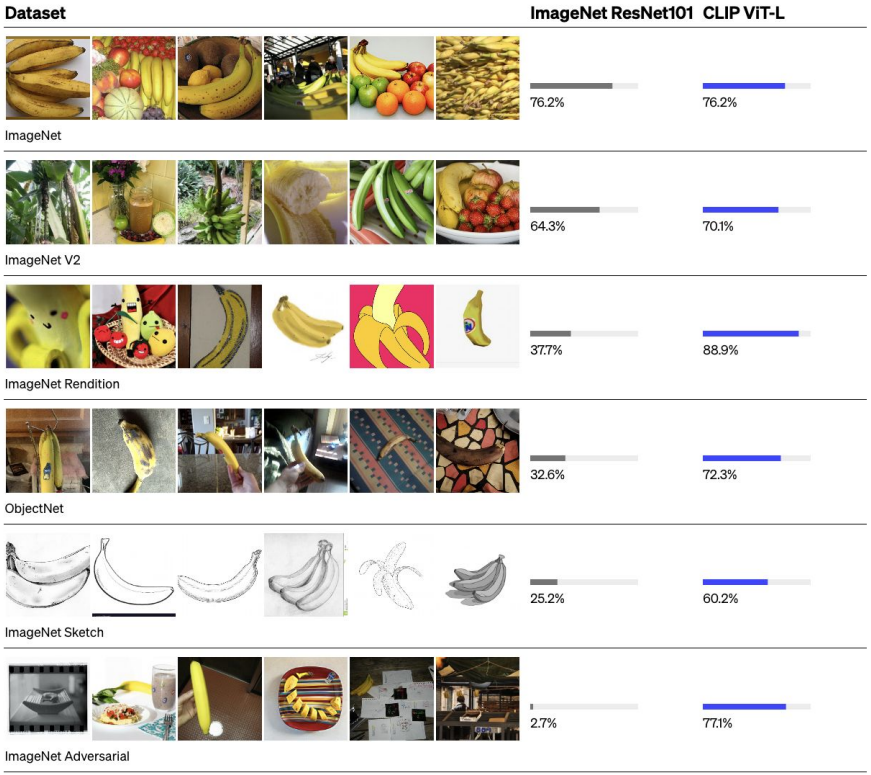
Exact same contrastive loss as earlier, but.. Transformers and *web data*!



CLIP Robustness

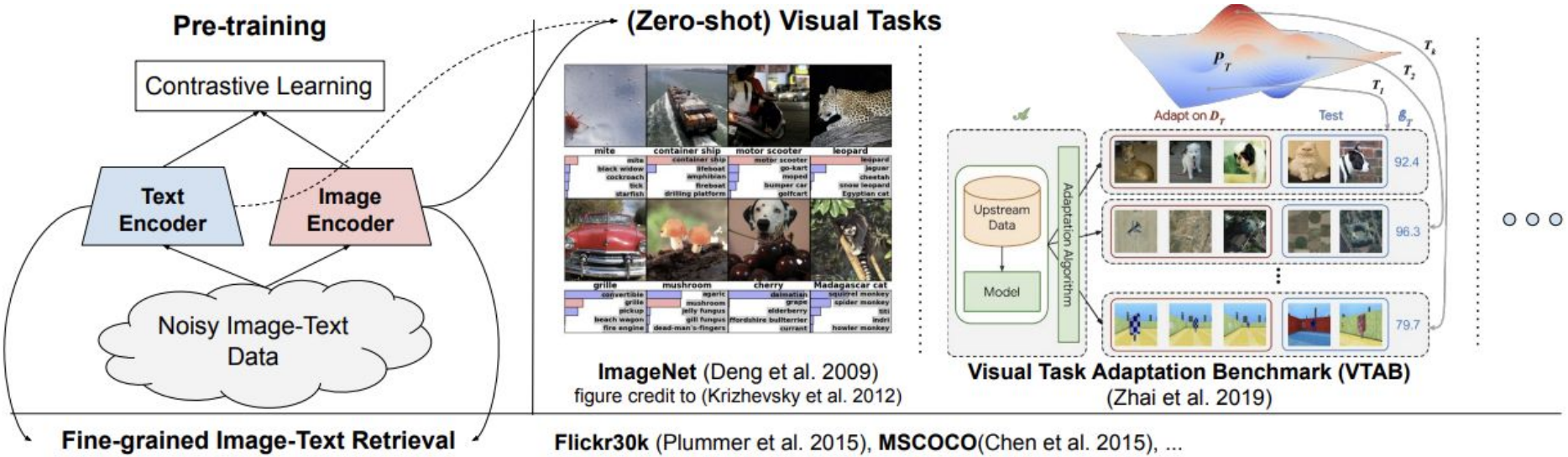
IMHO one of the best papers ever written in our field: extremely thorough, worth a close read.

Generalizes MUCH better →



ALIGN (Jia et al., 2021)

Same idea, but EVEN MORE data (JFT at 1.8B image-text pairs vs CLIP's 300m).



Aligned datasets

HUGE open source datasets of image-text pairs now exist.

Used to train eg StableDiffusion (Rombach et al., 2022).

https://laion.ai/blog/laion-5b/

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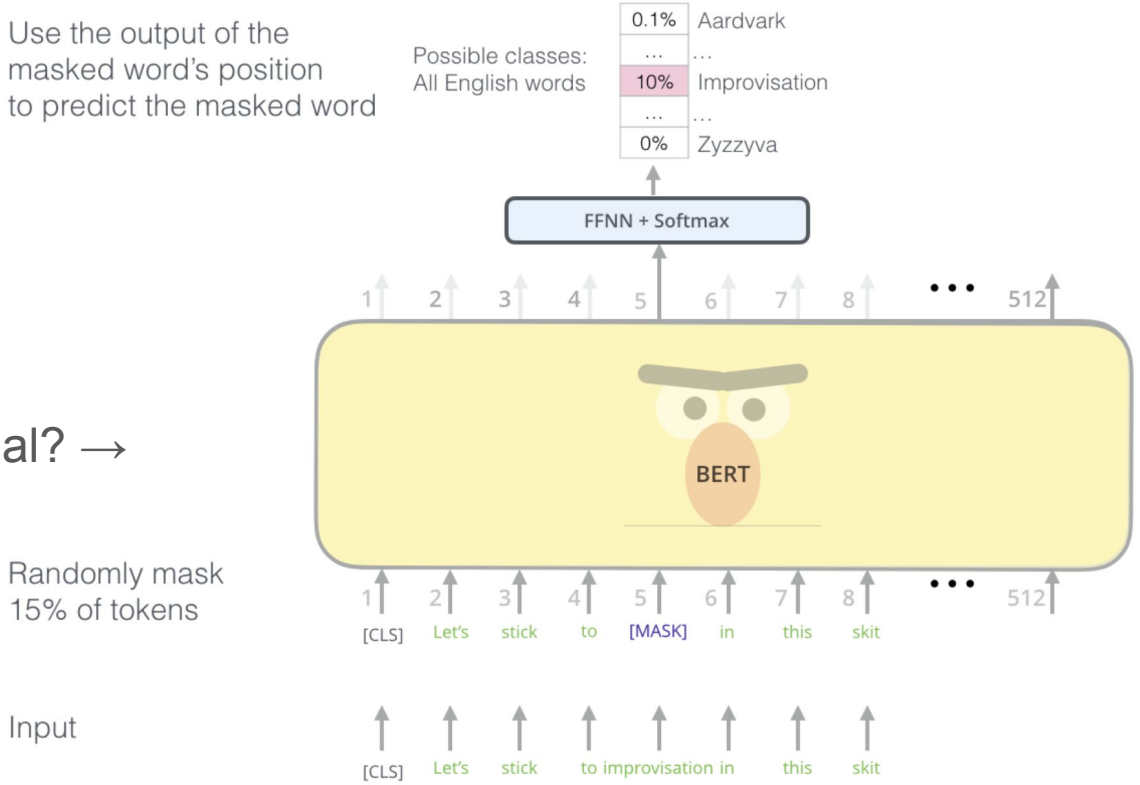
BERT Refresher

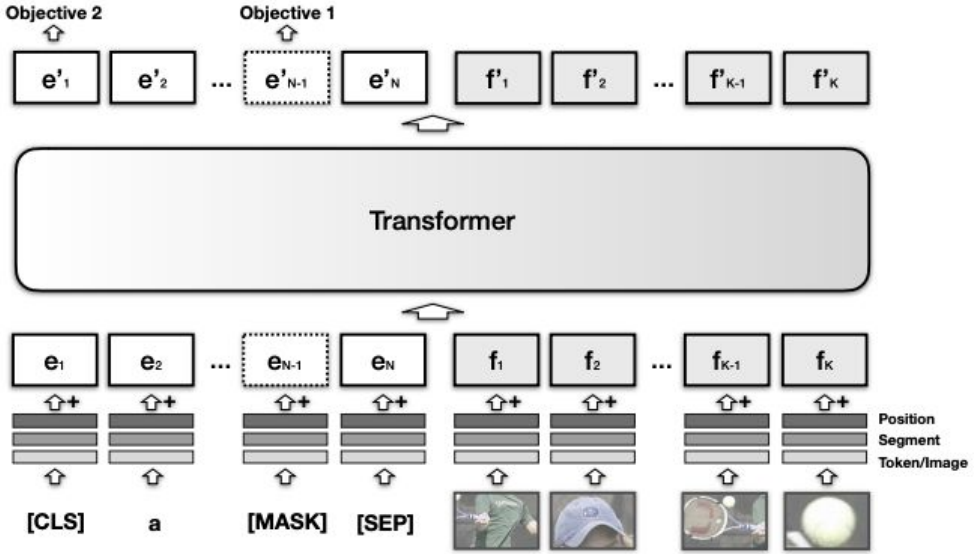
How do we make this multimodal? →



Alammar (2018), Illustrated Bert

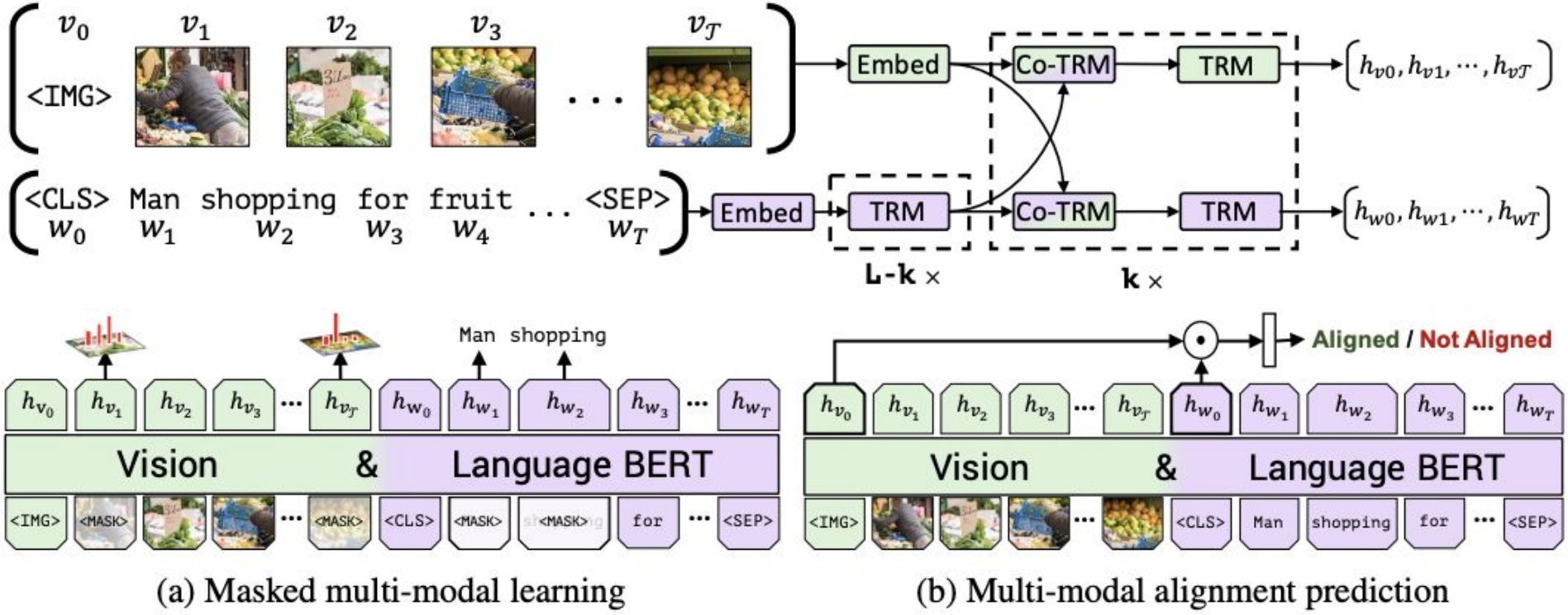
Visual BERTs: VisualBERT

A person hits a ball with a tennis racket



VisualBERT Li et al. 2019

Visual BERTs: ViLBERT



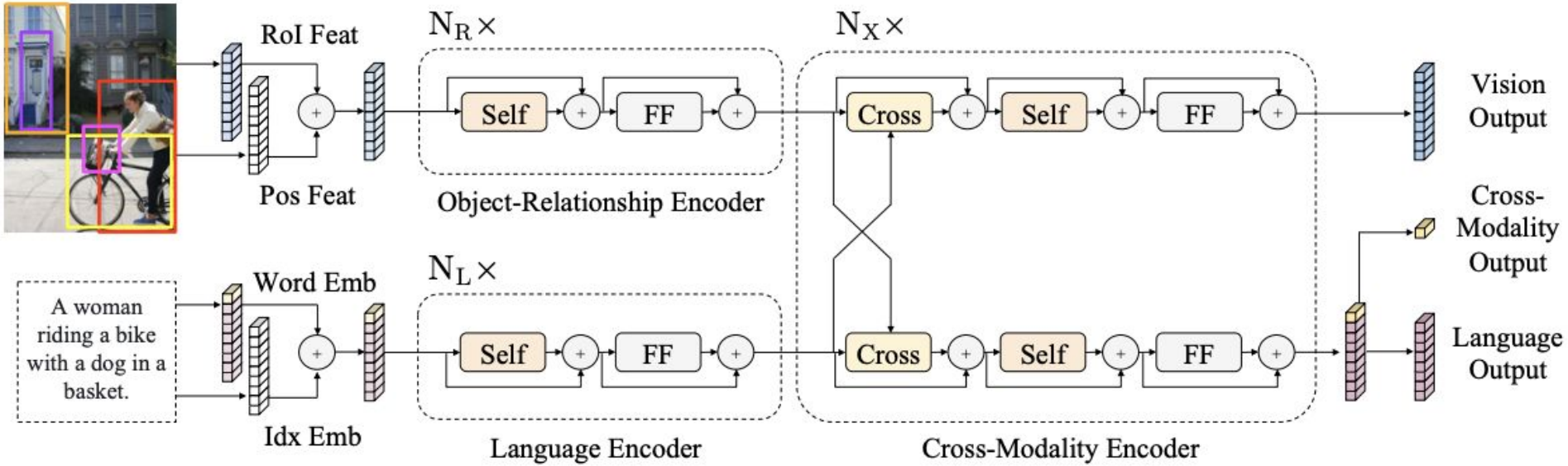
(a) Masked multi-modal learning

(b) Multi-modal alignment prediction

ViLBERT Lu et al. 2019

Visual BERTs: LXMERT

Learning Cross-Modality Encoder Representations from Transformers



LXMERT Tan & Bansal 2019

Visual BERTs: Supervised Multimodal Bitransformers

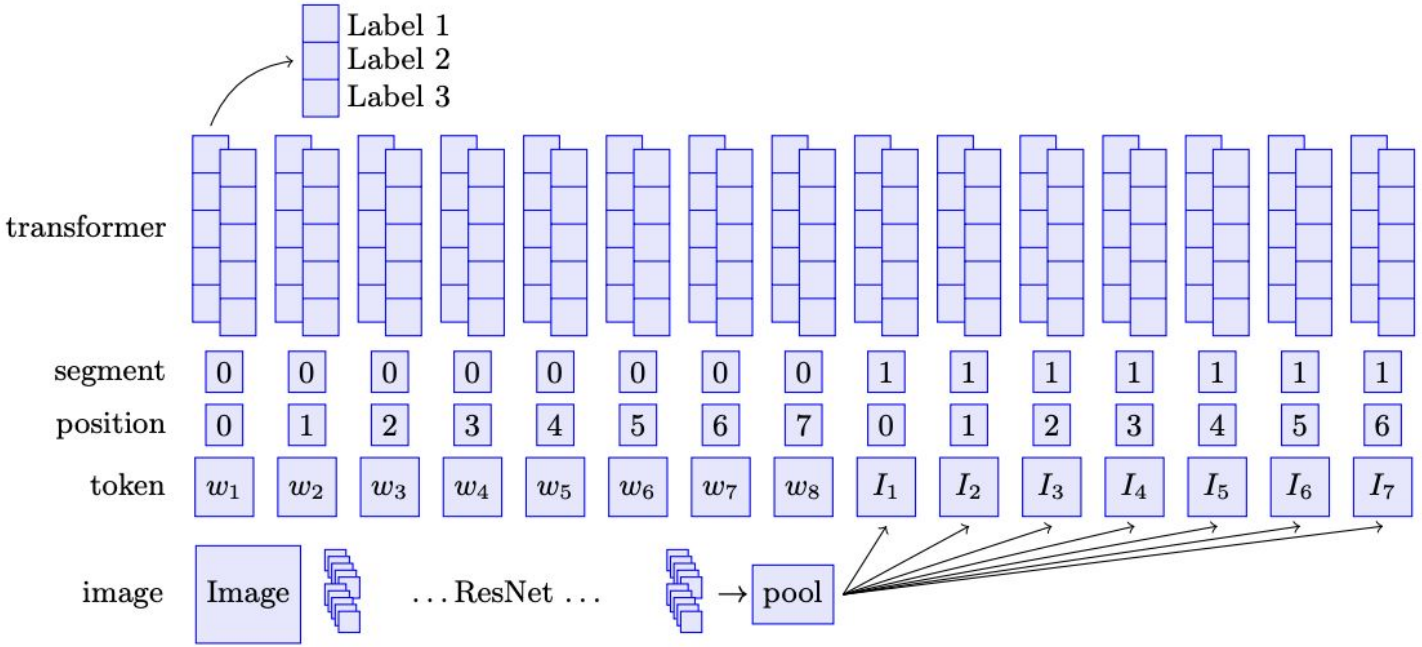
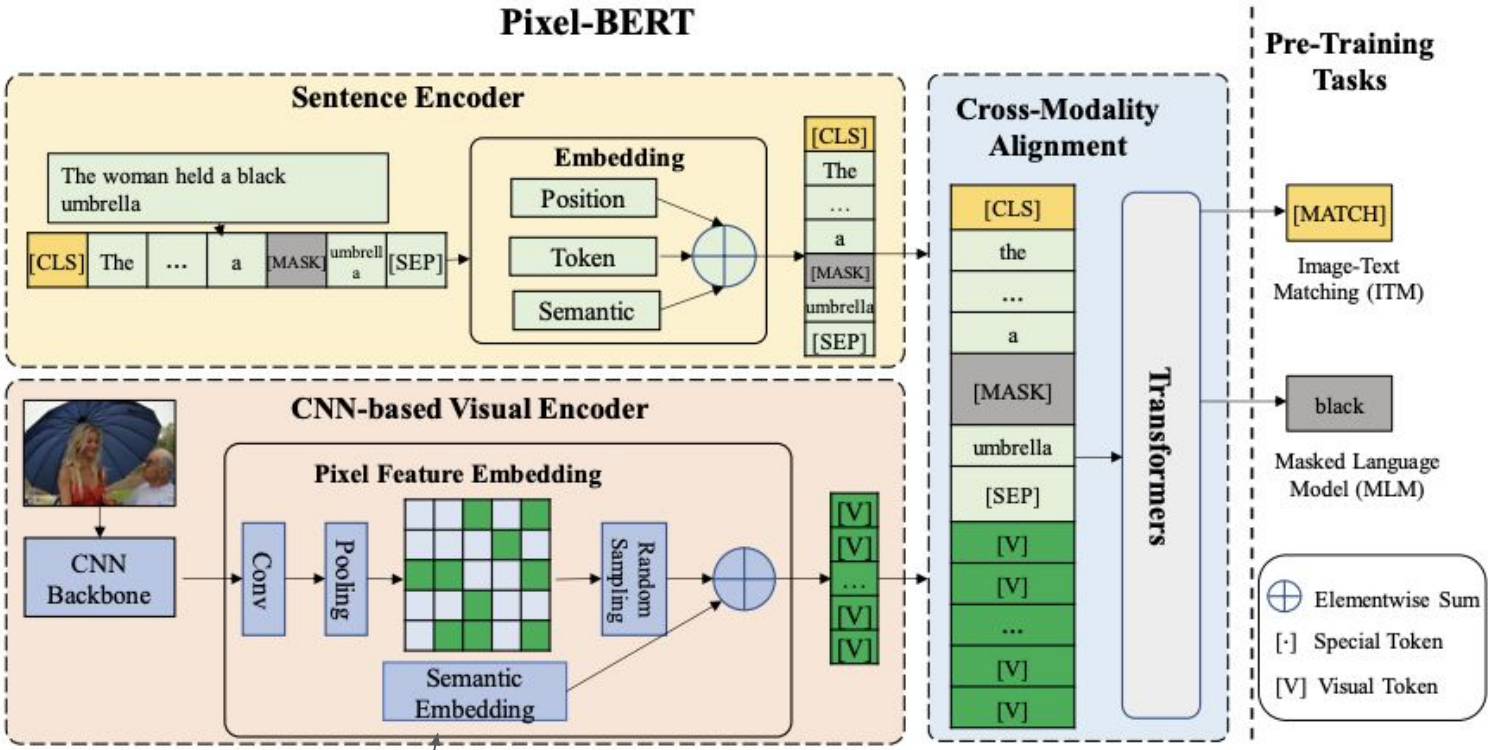


Figure 1: Illustration of the multimodal bitransformer architecture.

MMBT Kiela et al. 2019

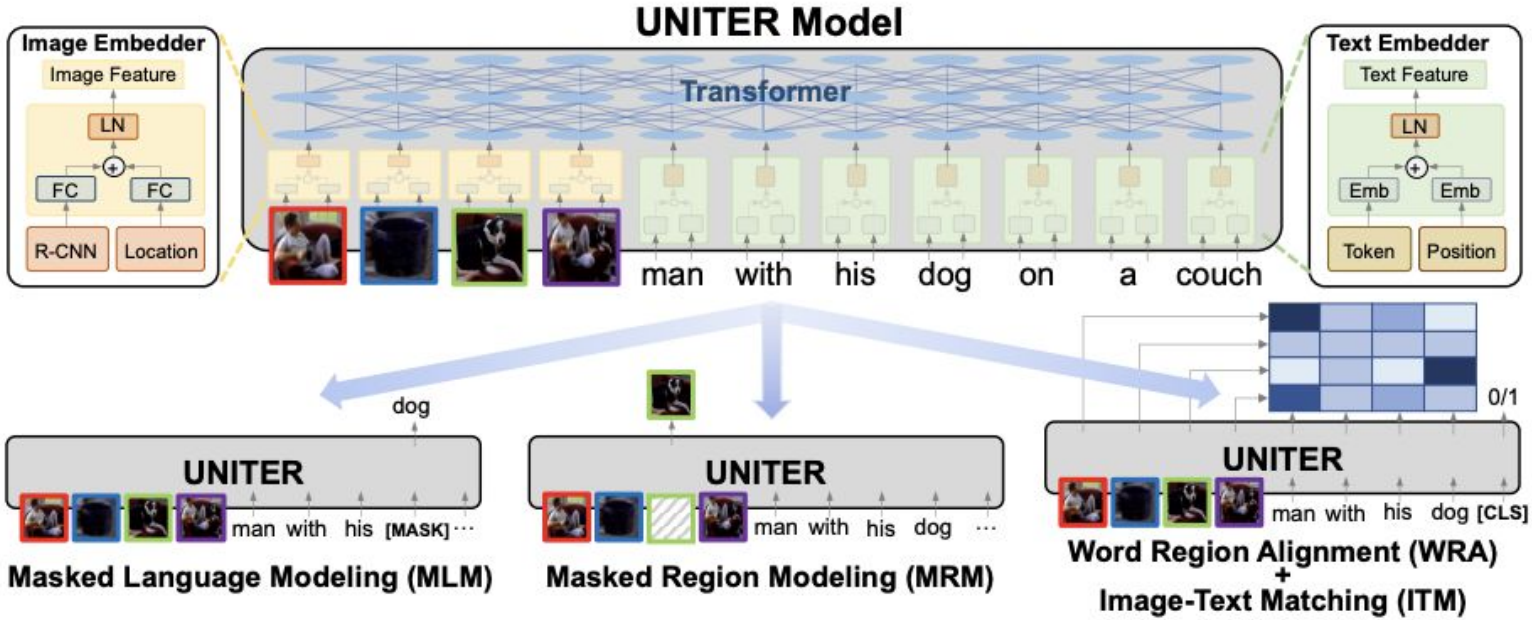
Visual BERTs: PixelBert



PixelBert Huang et al. 2020

Misnomer: they mean segment embedding

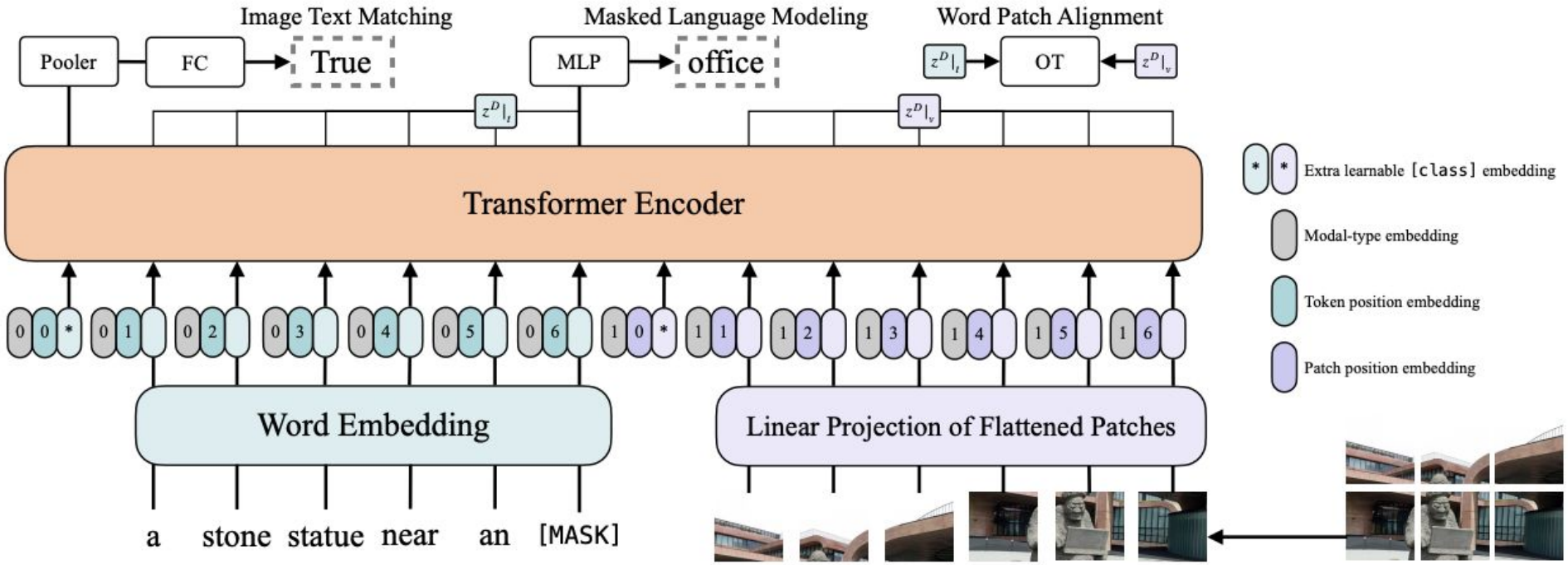
UNITER



Chen, Yi, Lu, et al. 2020

ViLT (Kim et al. 2021)

Feeding data directly to the transformer.



So many models

VL-PTM	Text encoder	Vision encoder	Fusion scheme	Pre-training tasks	Multimodal datasets for pre-training
Fusion Encoder					
VisualBERT [2019]	BERT	Faster R-CNN	Single stream	MLM+ITM	COCO
Uniter [2020]	BERT	Faster R-CNN	Single stream	MLM+ITM+WRA+MRFR+MRC	CC+COCO+VG+SBU
OSCAR [2020c]	BERT	Faster R-CNN	Single stream	MLM+ITM	CC+COCO+SBU+Flickr30k+VQA
InterBert [2020]	BERT	Faster R-CNN	Single stream	MLM+MRC+ITM	CC+COCO+SBU
ViLBERT [2019]	BERT	Faster R-CNN	Dual stream	MLM+MRC+ITM	CC
LXMERT [2019]	BERT	Faster R-CNN	Dual stream	MLM+ITM+MRC+MRFR+VQA	COCO+VG+VQA
VL-BERT [2019]	BERT	Faster R-CNN+ ResNet	Single stream	MLM+MRC	CC
Pixel-BERT [2020]	BERT	ResNet	Single stream	MLM+ITM	COCO+VG
Unified VLP [2020]	UniLM	Faster R-CNN	Single stream	MLM+seq2seq LM	CC
UNIMO [2020b]	BERT, RoBERTa	Faster R-CNN	Single stream	MLM+seq2seq LM+MRC+MRFR+CMCL	COCO+CC+VG+SBU
SOHO [2021]	BERT	ResNet + Visual Dictionary	Single stream	MLM+MVM+ITM	COCO+VG
VL-T5 [2021]	T5, BART	Faster R-CNN	Single stream	MLM+VQA+ITM+VG+GC	COCO+VG
XGPT [2021]	transformer	Faster R-CNN	Single stream	IC+MLM+DAE+MRFR	CC
Visual Parsing [2021]	BERT	Faster R-CNN + Swin transformer	Dual stream	MLM+ITM+MFR	COCO+VG
ALBEF [2021a]	BERT	ViT	Dual stream	MLM+ITM+CMCL	CC+COCO+VG+SBU
SimVLM [2021b]	ViT	ViT	Single stream	PrefixLM	C4+ALIGN
WenLan [2021]	RoBERTa	Faster R-CNN + EffcientNet	Dual stream	CMCL	RUC-CAS-WenLan
ViLT [2021]	ViT	Linear Projection	Single stream	MLM+ITM	CC+COCO+VG+SBU
Dual Encoder					
CLIP [2021]	GPT2	ViT, ResNet		CMCL	self-collected
ALIGN [2021]	BERT	EffcientNet		CMCL	self-collected
DeCLIP [2021b]	GPT2, BERT	ViT, ResNet, RegNetY-64GF		CMCL+MLM+CL	CC+self-collected
Fusion Encoder+ Dual Encoder					
VLMo [2021a]	BERT	ViT	Single stream	MLM+ITM+CMCL	CC+COCO+VG+SBU
FLAVA [2021]	ViT	ViT	Single stream	MMM+ITM+CMCL	CC+COCO+VG+SBU+RedCaps

Du et al. 2022 VLP Survey

Recommended paper

Bugliarello et al. (2021). *Multimodal Pretraining Unmasked: A Meta-Analysis and a Unified Framework of Vision-and-Language BERTs*. Finding: in the same conditions, models perform *very* similarly.

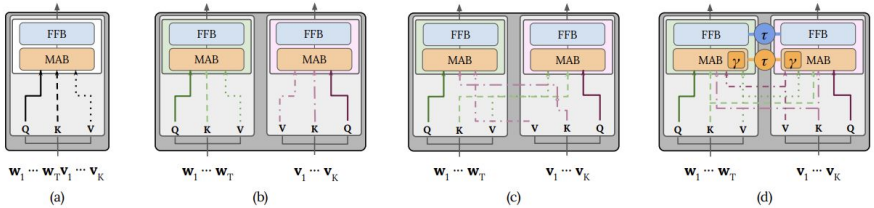


Figure 3: Visualisation of the (a) single-stream, (b) dual-stream intra-modal and (c) dual-stream inter-modal Transformer layers. (d) shows our gated bimodal layer. The inter-modal layer attends across modalities, while the intra-model layer attends within each modality. Ours can attend to either or both.

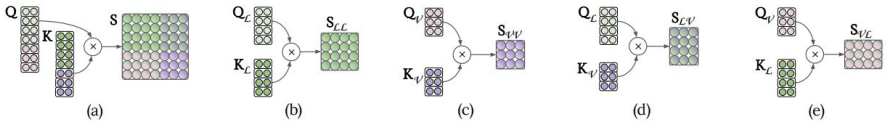
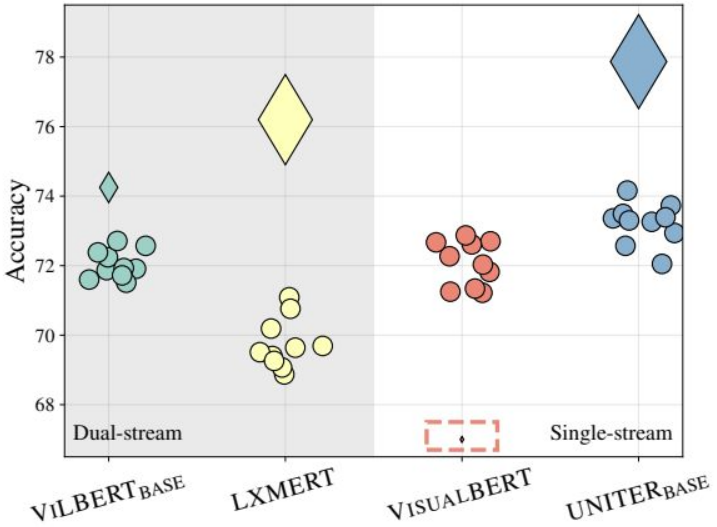


Figure 4: Visualisation of the score matrix for (a) single-stream, (b) text–text, (c) vision–vision, (d) text–vision, and (e) vision–text interactions. Shades of green denote the text modality, while purple ones denote the vision modality. Dual-stream scores are sub-matrices of the single-stream scores matrix.



FLAVA (Singh et al., 2021)

Holistic approach to multimodality.

One foundation model spanning V&L, CV and NLP.

Jointly pretrained on:

- unimodal text data (CCNews + BookCorpus)
- unimodal image data (ImageNet)
- public paired image-text data (70M)

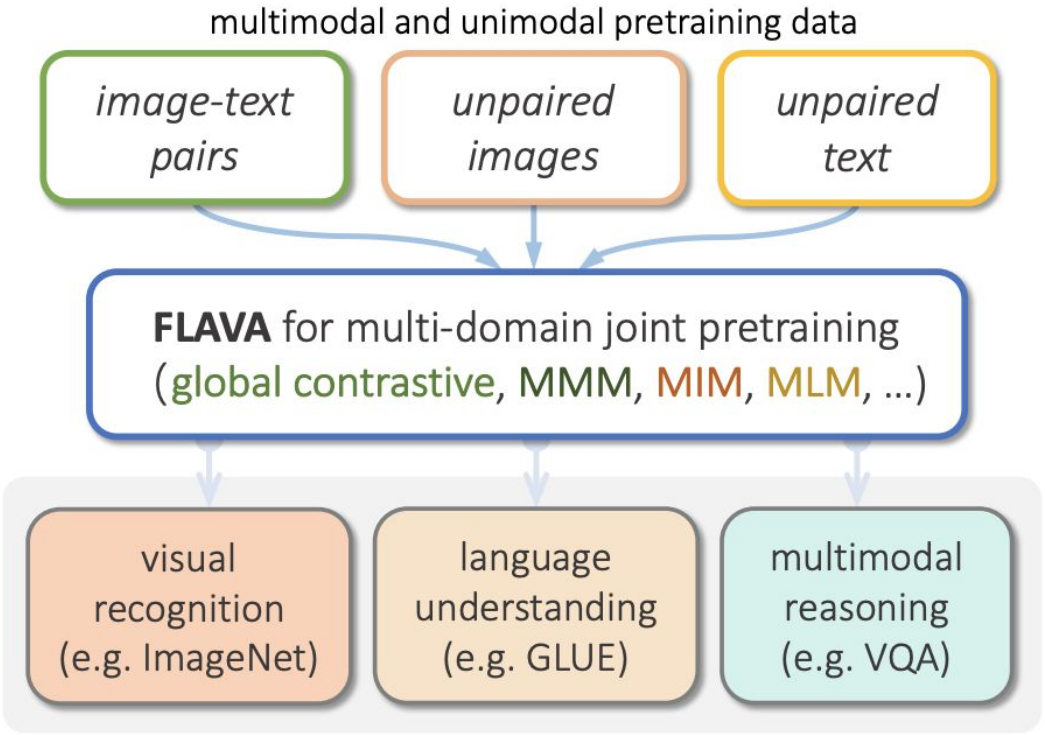
All data/models are publicly released.

The PMD dataset

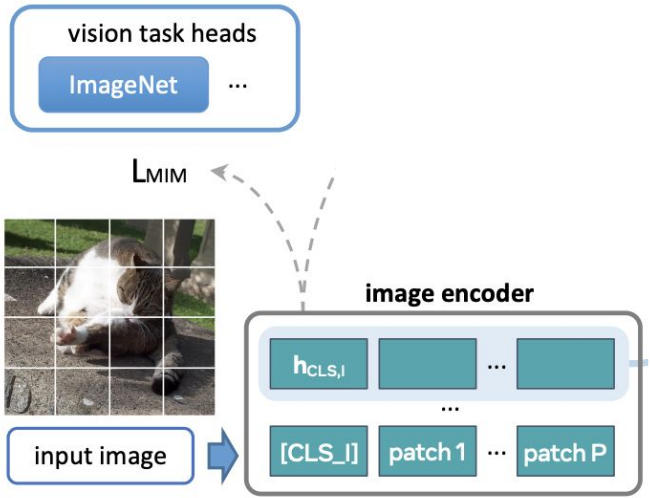
- 70M image-text pairs from public sources

COCO	Visual Genome	SBU captions	Localized narratives	WIT	RedCaps	CC12M	YFCC filtered
							
A close up view of a pizza sitting on a table with a soda in the back.	a lenovo laptop rebooting	Front view of basket 13, from the sidewalk in front of the basket.	The woman is touching a utensil in front of her on the grill stand.	Typocerus balteatus, Subfamily: Flower Longhorns	Deigdoh falls in india	Jumping girl in a green summer dress stock illustration	In the kitchen at the Muse Nissim de Camondo

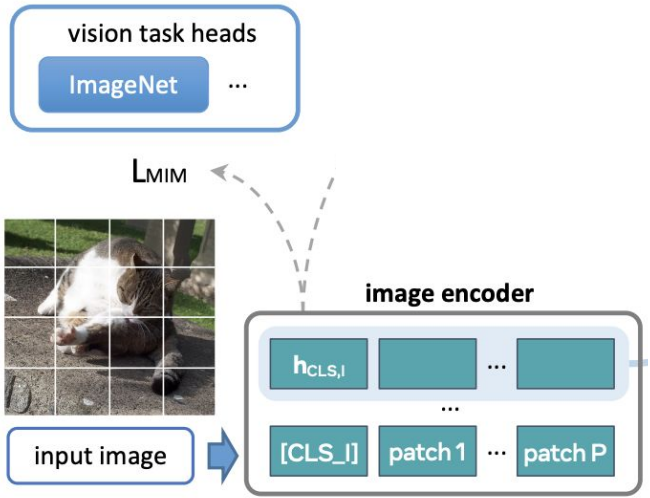
Problem to solve

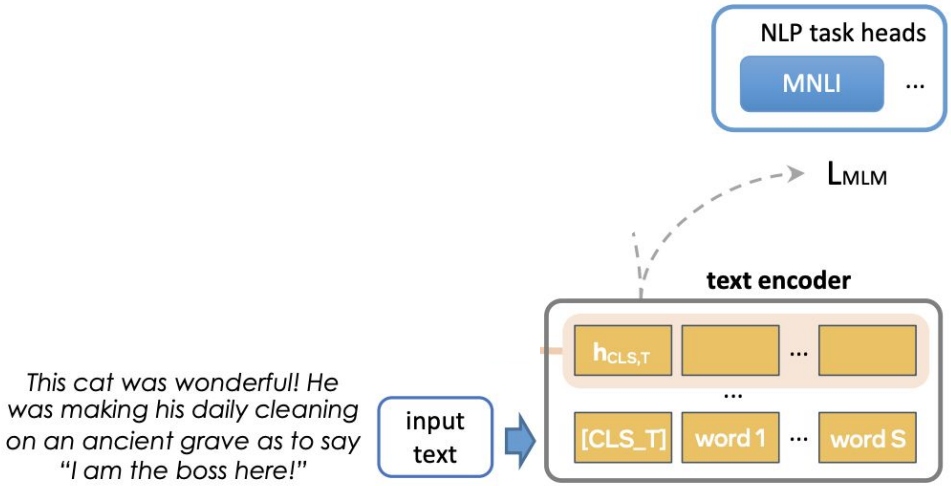


How does FLAVA work?

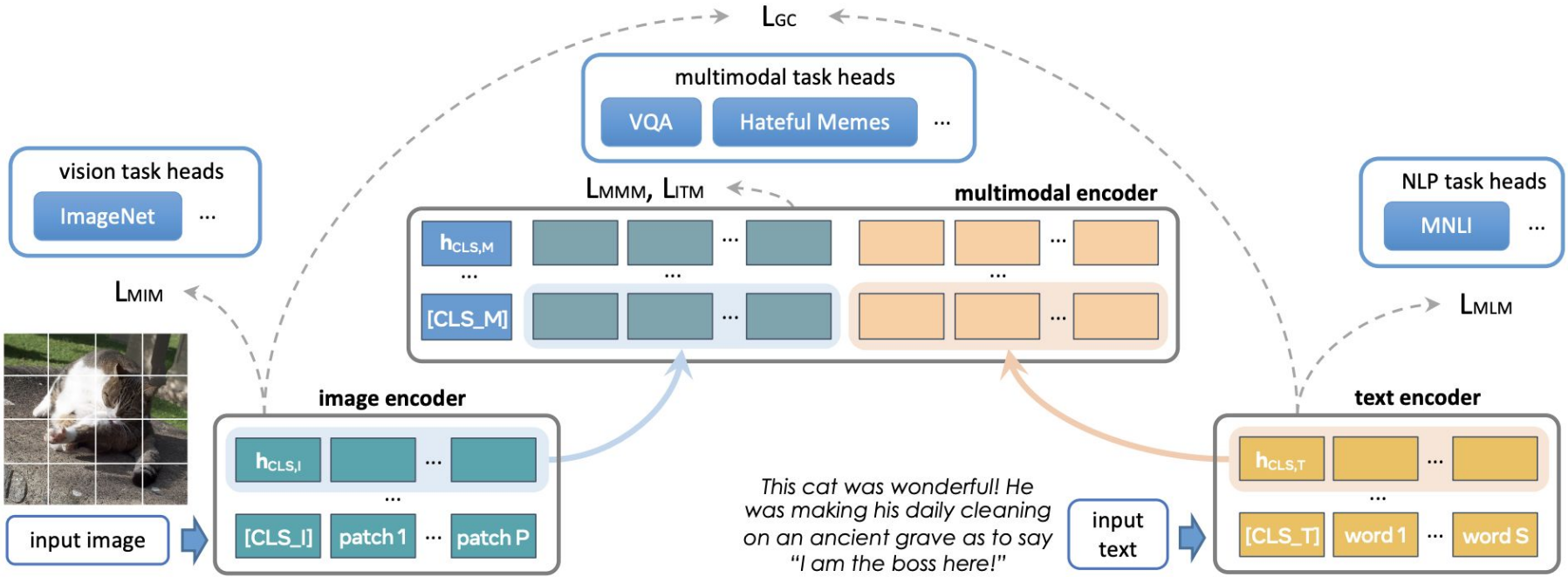


How does FLAVA work?



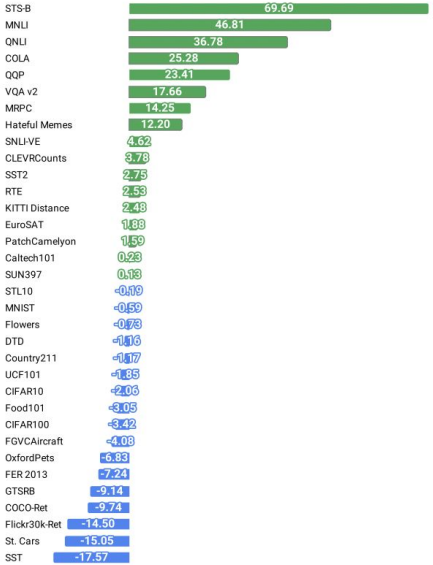


How does FLAVA work?



How well does it work?

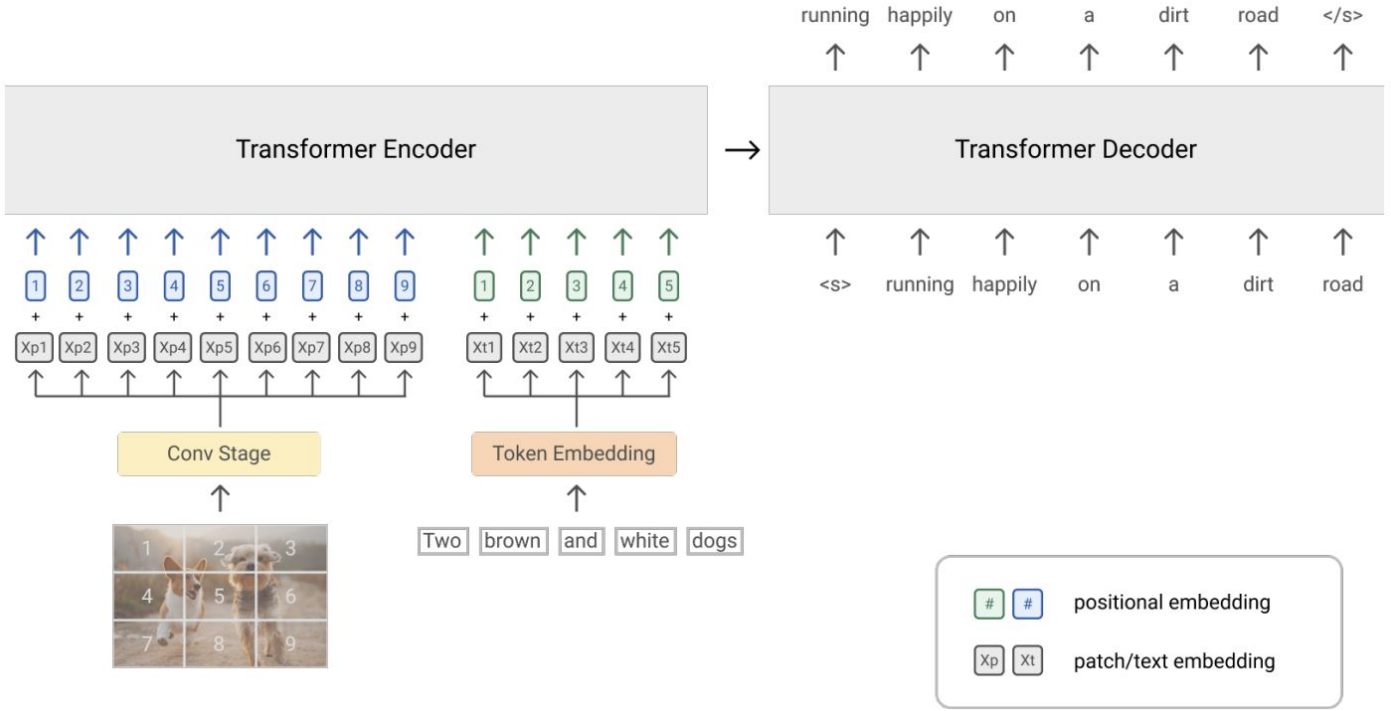
- On average, over 35 tasks, FLAVA obtains impressive performance



		MIM 1	MLM 2	FLAVA$_C$ 3	FLAVA$_{MM}$ 4	FLAVA w/o init 5	FLAVA 6	CLIP 7	CLIP 8
Datasets	Eval method	PMD	PMD	PMD	PMD	(PMD+IN-1k+CCNews+BC)		PMD	400M [83]
MNLI [111]	fine-tuning	–	73.23	70.99	76.82	78.06	**80.33**	32.85	33.52
CoLA [110]	fine-tuning	–	39.55	17.58	38.97	44.22	**50.65**	11.02	25.37
MRPC [29]	fine-tuning	–	73.24	76.31	79.14	78.91	**84.16**	68.74	69.91
QQP [49]	fine-tuning	–	86.68	85.94	88.49	98.61	**88.74**	59.17	65.33
SST-2 [97]	fine-tuning	–	87.96	86.47	89.33	90.14	**90.94**	83.49	88.19
QNLI [88]	fine-tuning	–	82.32	71.85	84.77	86.40	**87.31**	49.46	50.54
RTE [7, 25, 36, 40]	fine-tuning	–	50.54	51.99	51.99	54.87	**57.76**	53.07	55.23
STS-B [1]	fine-tuning	–	78.89	57.28	84.29	83.21	**85.67**	13.70	15.98
NLP Avg.		–	71.55	64.80	74.22	75.55	**78.19**	46.44	50.50
ImageNet [90]	linear eval	41.79	–	74.09	74.34	73.49	**75.54**	72.95	80.20
Food101 [11]	linear eval	53.30	–	87.77	87.53	87.39	**88.51**	85.49	91.56
CIFAR10 [58]	linear eval	76.20	–	**93.44**	92.37	92.63	92.87	91.25	94.93
CIFAR100 [58]	linear eval	55.57	–	**78.37**	78.01	76.49	77.68	74.40	81.10
Cars [56]	linear eval	14.71	–	**72.12**	72.07	66.81	70.87	62.84	85.92
Aircraft [74]	linear eval	13.83	–	**49.74**	48.90	44.73	47.31	40.02	51.40
DTD [20]	linear eval	55.53	–	76.86	76.91	75.80	**77.29**	73.40	78.46
Pets [79]	linear eval	34.48	–	**84.98**	84.93	82.77	84.82	79.61	91.66
Caltech101 [32]	linear eval	67.36	–	94.91	95.32	94.95	**95.74**	93.76	95.51
Flowers102 [76]	linear eval	67.23	–	96.36	**96.39**	95.58	96.37	94.94	97.12
MNIST [60]	linear eval	96.40	–	98.39	98.58	**98.70**	98.42	97.38	99.01
STL10 [21]	linear eval	80.12	–	98.06	98.31	98.32	**98.89**	97.29	99.09
EuroSAT [41]	linear eval	95.48	–	97.00	96.98	97.04	**97.26**	95.70	95.38
GTSRB [100]	linear eval	63.14	–	78.92	77.93	77.71	**79.46**	76.34	88.61
KITTI [35]	linear eval	86.03	–	87.83	88.84	88.70	**89.04**	84.89	86.56
PCAM [106]	linear eval	85.10	–	85.02	85.51	**85.72**	85.31	83.99	83.72
UCF101 [98]	linear eval	46.34	–	82.69	82.90	81.42	**83.32**	77.85	85.17
CLEVR [52]	linear eval	61.51	–	79.35	**81.66**	80.62	79.66	73.64	75.89
FER 2013 [38]	linear eval	50.98	–	59.96	60.87	58.99	**61.12**	57.04	68.36
SUN397 [113]	linear eval	52.45	–	81.27	81.41	81.05	**82.17**	79.96	82.05
SST [83]	linear eval	57.77	–	56.67	**59.25**	56.40	57.11	56.84	74.68
Country211 [83]	linear eval	8.87	–	27.27	26.75	27.01	**28.92**	25.12	30.10
Vision Avg.		57.46	–	79.14	79.35	78.29	**79.44**	76.12	82.57
VQAv2 [39]	fine-tuning	–	–	67.13	71.69	71.29	**72.49**	59.81	54.83
SNLI-VE [114]	fine-tuning	–	–	73.27	78.36	78.14	**78.89**	73.53	74.27
Hateful Memes [53]	fine-tuning	–	–	55.58	70.72	**77.45**	76.09	56.59	63.93
Flickr30K [81] TR R@1	zero-shot	–	–	68.30	**69.30**	64.50	67.70	60.90	82.20
Flickr30K [81] TR R@5	zero-shot	–	–	93.50	92.90	90.30	**94.00**	88.90	96.60
Flickr30K [81] IR R@1	zero-shot	–	–	60.56	63.16	60.04	**65.22**	56.48	62.08
Flickr30K [81] IR R@5	zero-shot	–	–	86.68	87.70	86.46	**89.38**	83.60	85.68
COCO [66] TR R@1	zero-shot	–	–	43.08	**43.48**	39.88	42.74	37.12	52.48
COCO [66] TR R@5	zero-shot	–	–	75.82	**76.76**	72.84	**76.76**	69.48	76.68
COCO [66] IR R@1	zero-shot	–	–	37.59	**38.46**	34.95	38.38	33.29	33.07
COCO [66] IR R@5	zero-shot	–	–	67.28	**67.68**	64.63	67.47	62.47	58.37
Multimodal Avg.		–	–	66.25	69.11	67.32	**69.92**	62.02	67.29
Macro Avg.		19.15	23.85	70.06	74.23	73.72	**75.85**	61.52	66.78

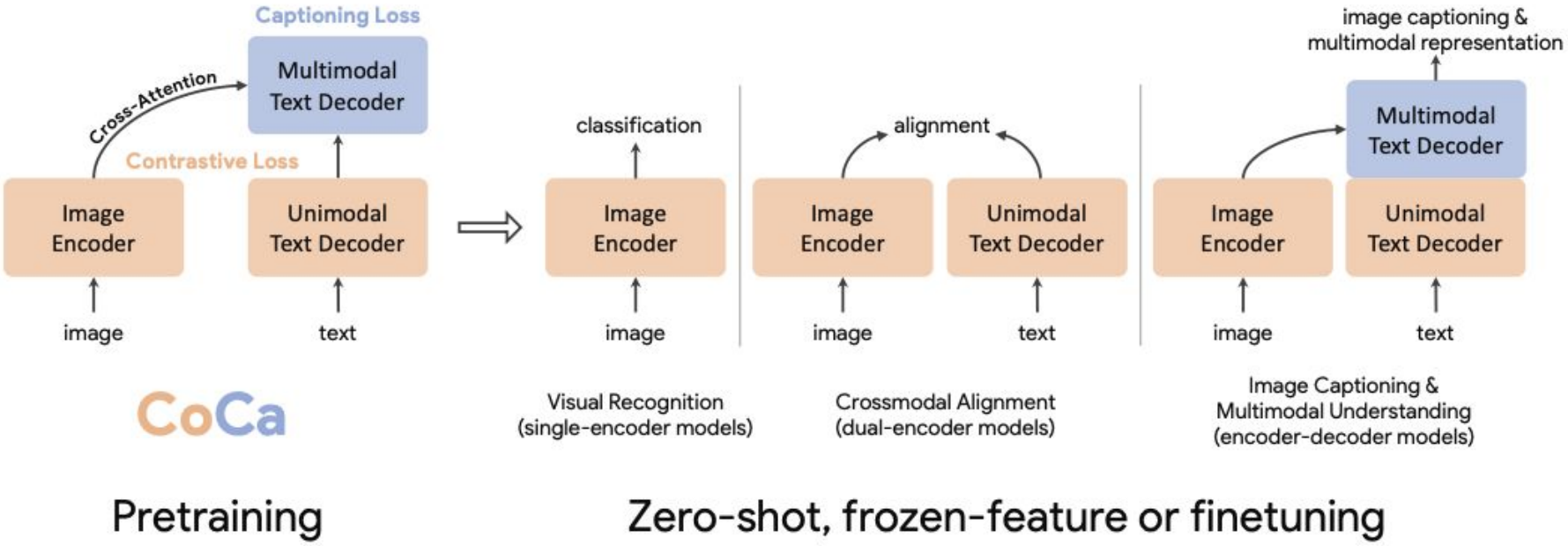
SimVLM (Wang et al., 2022)

Slowly moving from contrastive/discriminative to generative.



CoCa Contrastive Captioner (Yu et al., 2022)

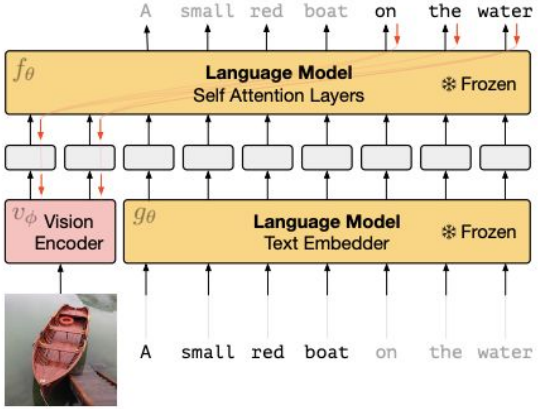
Best of both (contrastive and generative) worlds.

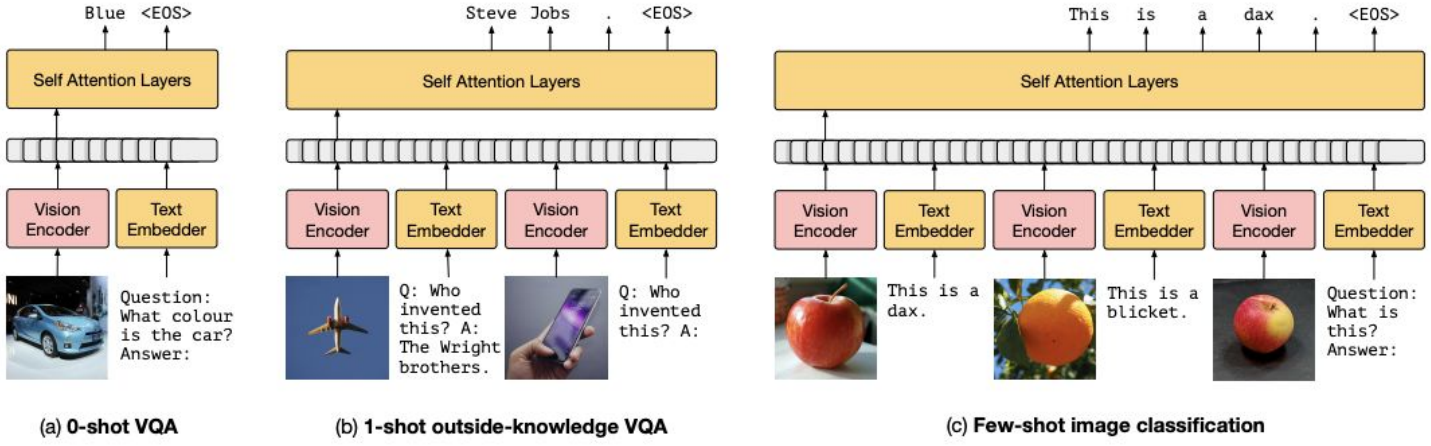


Frozen (Tsimpoukelli, Menick, Cabi, et al., 2021)

Kind of like MMBT but with a better LLM (T5) and a better vision encoder (NF-ResNet).

Multi-Modal Few-Shot Learners!

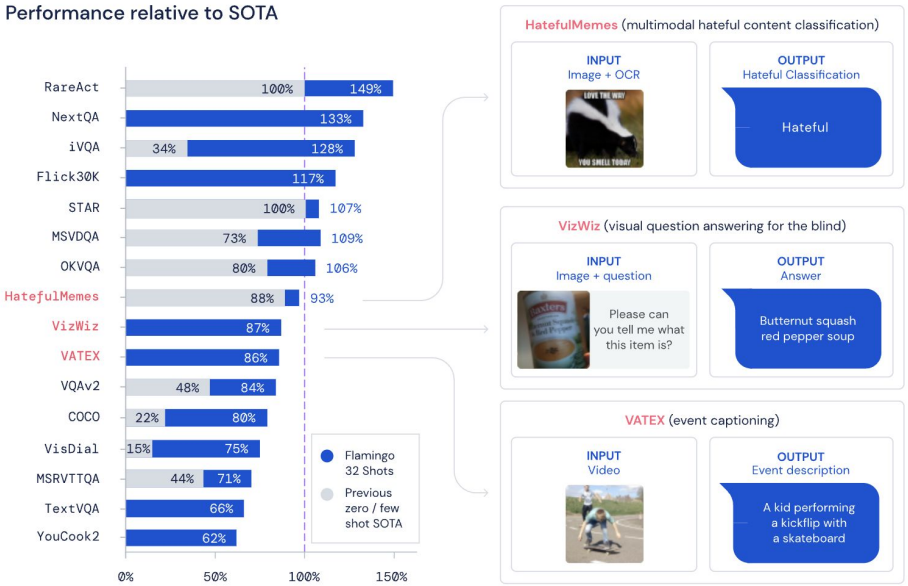


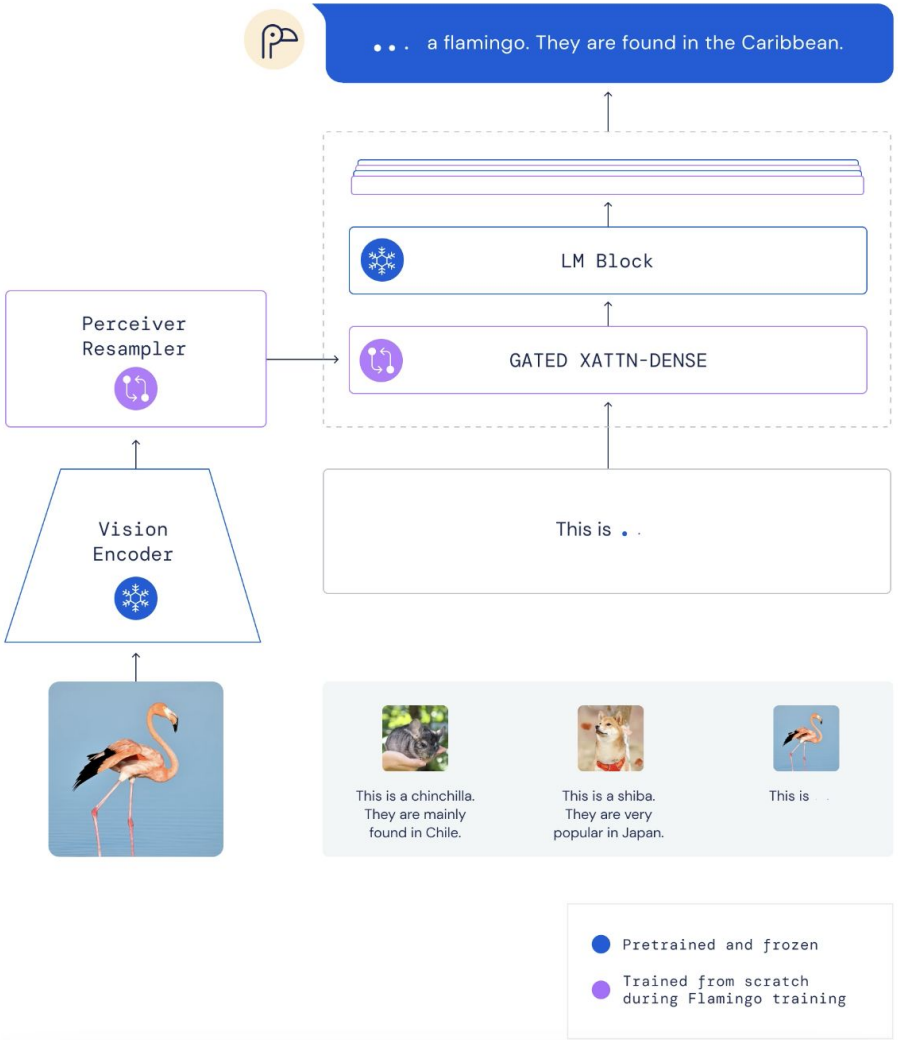


(a) **0-shot VQA** (b) **1-shot outside-knowledge VQA** (c) **Few-shot image classification**

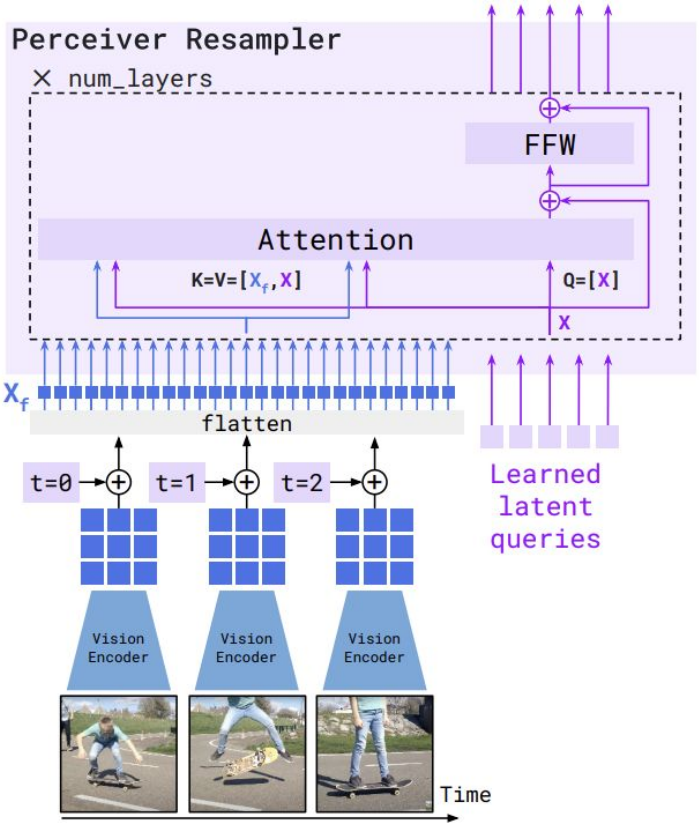
Flamingo (Alayrac et al., 2022)

80b param model based on Chinchilla.
Multi-image.





Perceiver Resampler

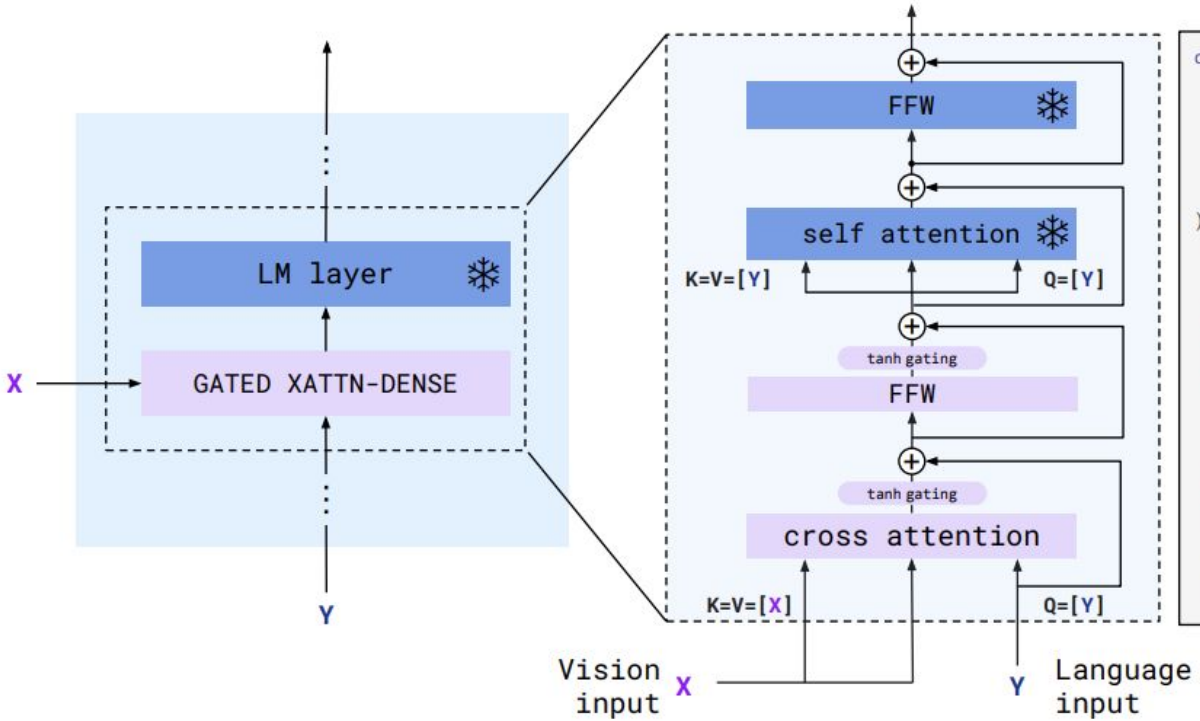



```
def perceiver_resampler(
    x_f,  # The [T, S, d] visual features (T=time, S=space)
    time_embeddings,  # The [T, 1, d] time pos embeddings.
    x,  # R learned latents of shape [R, d]
    num_layers,  # Number of layers
):
  """The Perceiver Resampler model."""

  # Add the time position embeddings and flatten.
  x_f = x_f + time_embeddings
  x_f = flatten(x_f)  # [T, S, d] -> [T * S, d]
  # Apply the Perceiver Resampler layers.
  for i in range(num_layers):
    # Attention.
    x = x + attention_i(q=x, kv=concat([x_f, x]))
    # Feed forward.
    x = x + ffw_i(x)
  return x
```

Gated XATTN

Inject visual info directly into a frozen LM via cross-attention (remember FiLM?).



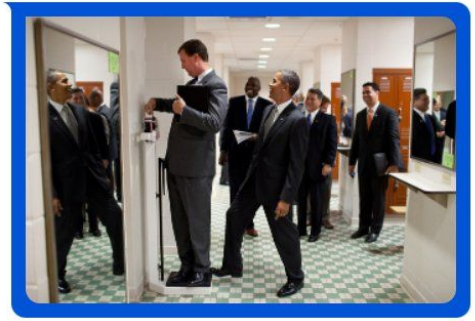

```
def gated_xattn_dense(
    y,  # input language features
    x,  # input visual features
    alpha_xattn, # xattn gating parameter – init at 0.
    alpha_dense, # ffw gating parameter – init at 0.
):
  """Applies a GATED XATTN-DENSE layer."""

  # 1. Gated Cross Attention
  y = y + tanh(alpha_xattn) * attention(q=y, kv=x)
  # 2. Gated Feed Forward (dense) Layer
  y = y + tanh(alpha_dense) * ffw(y)

  # Regular self-attention + FFW on language
  y = y + frozen_attention(q=y, kv=y)
  y = y + frozen_ffw(y)
  return y  # output visually informed language features
```

Why is this funny?

Original image from Karpathy as a “visual Turing test” →



This is a picture of Barack Obama. He is a former president of the United States.

How many people are there in this picture?

There are at least 5 people in this picture.

Where was this picture taken?

It was taken in a school.

How many mirrors are there?

There are at least 2 mirrors in this picture.

What is the person standing on?

The person is standing on a rug.

He is standing on a scale.

I think you are right.

What is he doing?

He is looking at the scale.

Where is Obama's foot positioned?

Obama's foot is positioned on the right side of the scale.

What happens as a result?

The scale shows a higher weight.

Is the person on the scale aware of it?

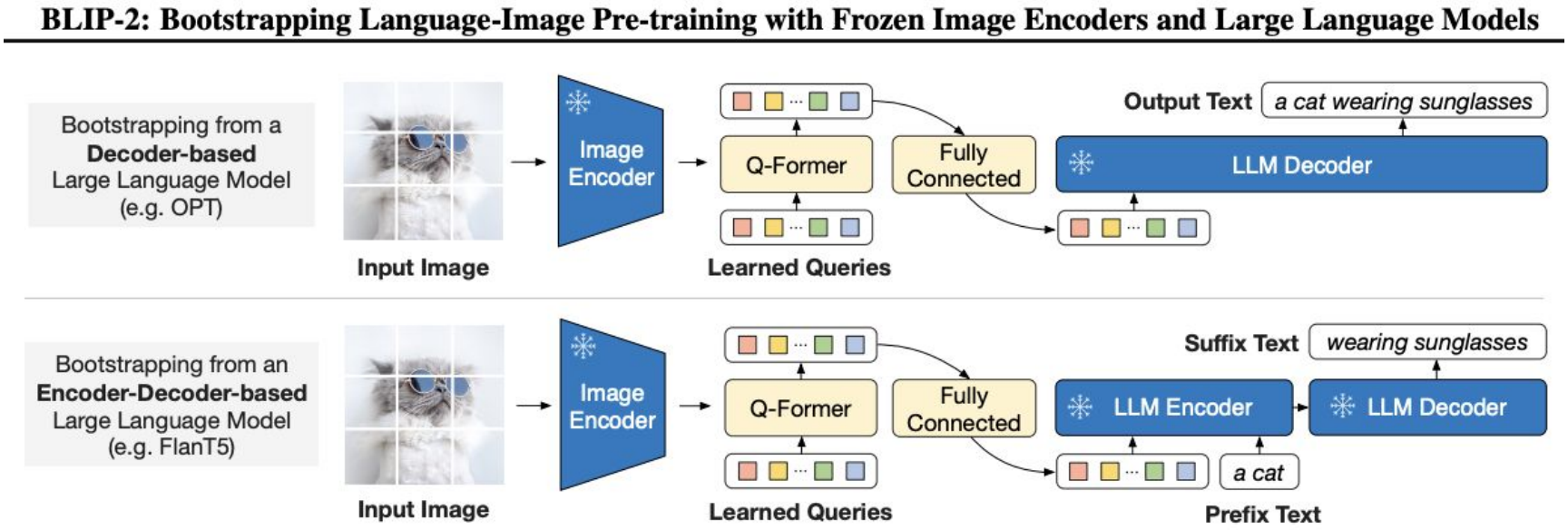
I think he is not aware of it.

Do you think that's why people are laughing?

I think so.

BLIP/BLIP2 (Li et al., 2023)

Freeze it all (CLIP-ViT / OPT decoder / FlanT5 encoder-decoder)



Explain the advantages of this product.

The audi e-tron quattro concept is a plug-in hybrid electric sports car that has a range of 310 miles and can accelerate from 0 to 60 mph in just 4 seconds.

Tell me something about the history of this place.

The great wall of china was built in 221 bc by emperor qin shihuang to protect the emperor's capital from invaders from the north.

Write down the facts that you know about this flower.

It is a genus of flowering plants in the orchid family, orchidaceae. It is native to eastern asia and south east asia. It is a perennial flowering plant that grows up to a height of 1 m.

Is this photo unusual?

Yes, it's a house that looks like it's upside down.

How could someone get out of the house?

It has a slide on the side of the house.

What are shown in the photo?

A man and a chicken.

What does the man feel and why?

He is scared of the chicken because it is flying at him.

What are the ingredients I need to make this?

Pepperoni, mozzarella cheese, pizza sauce, olive oil, salt, pepper, basil.

What is the first step?

Place the pizza dough on a baking sheet, brush with olive oil, sprinkle with salt, pepper, and basil.

Which city is this?

Singapore.

Why do you think so?

The city has a statue of a merlion.

What happened at the end of this movie?

The titanic sank.

Did Leonardo Dicaprio's character survive?

No, he drowned.

What is in the photo?

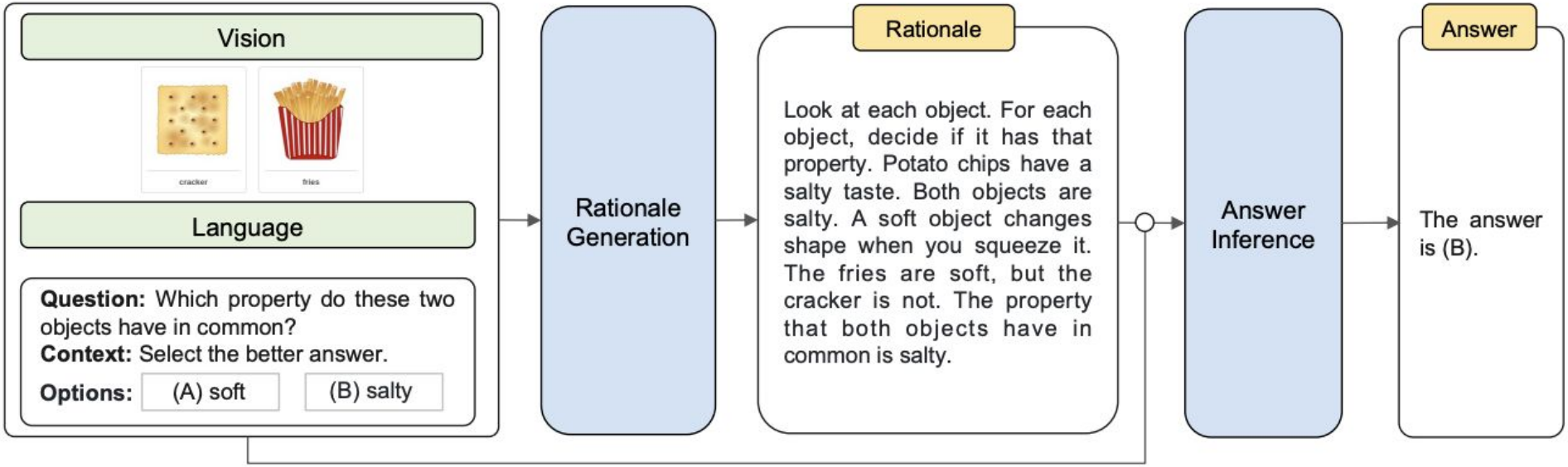
A pizza that looks like a cat.

What is the nose made of?

A slice of pepperoni.

Multimodal “Chain of Thought” (Zhang et al., 2023)

Providing a rationale helps give the right answer.



KOSMOS-1 (Huang et al., 2023)

LLMs => MLLMs == FMs

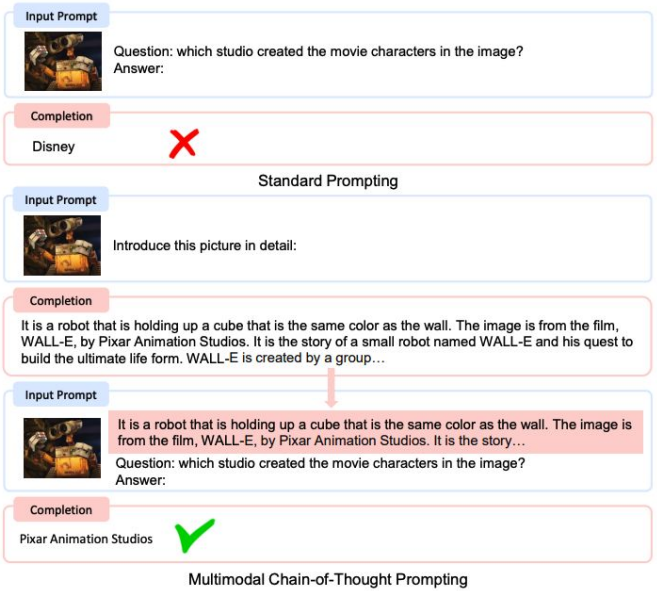
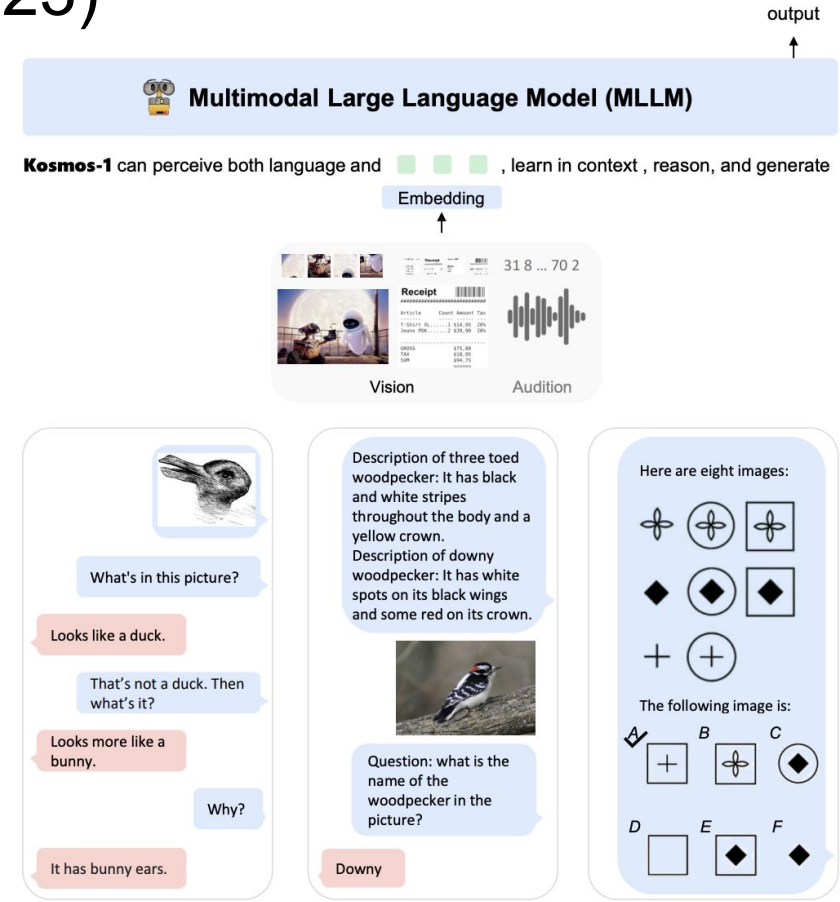


Figure 5: Multimodal Chain-of-Thought prompting enables KOSMOS-1 to generate a rationale first, then to tackle complex question-answering and reasoning tasks.



Outline

1. Early models
2. Features and fusion
3. Contrastive models
4. Multimodal foundation models
5. **Evaluation**
6. Beyond images: Other modalities
7. Where to next?

COCO - Common Objects in Context

Super impactful datasets (Lin et al. 2014; Chen et al. 2015)

Main multimodal tasks:

- Image captioning
- Image-caption retrieval

The man at bat readies to swing at the pitch while the umpire looks on.

Similar datasets:

- Flickr30k, ConceptualCaptions, VisualGenome, SBU, RedCaps, LAION

What is COCO?

COCO is a large-scale object detection, segmentation, and captioning dataset. COCO has several features:

- **Object segmentation**
- **Recognition in context**
- **Superpixel stuff segmentation**
- **330K images (>200K labeled)**
- **1.5 million object instances**
- **80 object categories**
- **91 stuff categories**
- **5 captions per image**
- **250,000 people with keypoints**

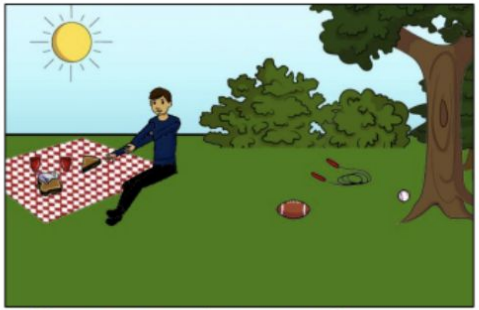
cocodataset.org

VQA - Visual Question Answering (Antol et al., 2015)

- The dominant task in vision and language.
  - VQA/VQAv2 citations: 4305+1684
  - COCO Captions: 1647
  - Flickr30k: 1228
- At first the “V” in VQA was found to not matter all that much, so a follow-up VQAv2 dataset was created (Goyal et al., 2017).
- There’s also GQA (Hudson & Manning, 2019).

What color are her eyes?
What is the mustache made of?

How many slices of pizza are there?
Is this a vegetarian pizza?



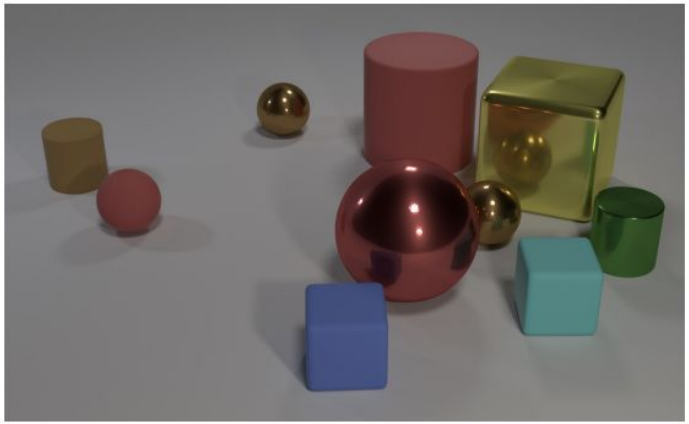
Is this person expecting company?
What is just under the tree?

Does it appear to be rainy?
Does this person have 20/20 vision?

CLEVR (Johnson et al., 2016)

Compositional language and elementary visual reasoning diagnostics in a controlled setting.

Hand crafted for measuring compositionality.

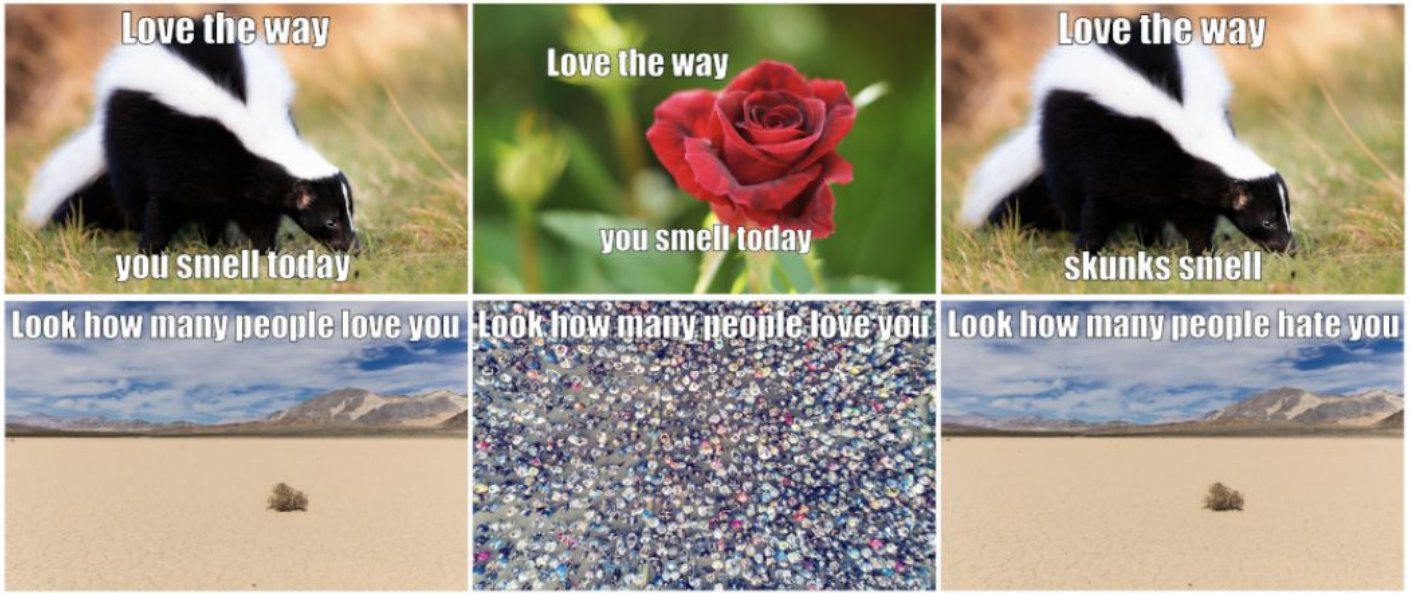


Q: Are there an equal number of large things and metal spheres?
Q: What size is the cylinder that is left of the brown metal thing that is left of the big sphere? **Q:** There is a sphere with the same size as the metal cube; is it made of the same material as the small red sphere?
Q: How many objects are either small cylinders or metal things?

Figure 1. A sample image and questions from CLEVR. Questions test aspects of visual reasoning such as attribute identification, counting, comparison, multiple attention, and logical operations.

Hateful Memes (Kiela et al., 2020)

Motivated by the shortcomings of other V&L datasets: we need something that is harder, more realistic, and requires true multimodal reasoning and understanding.



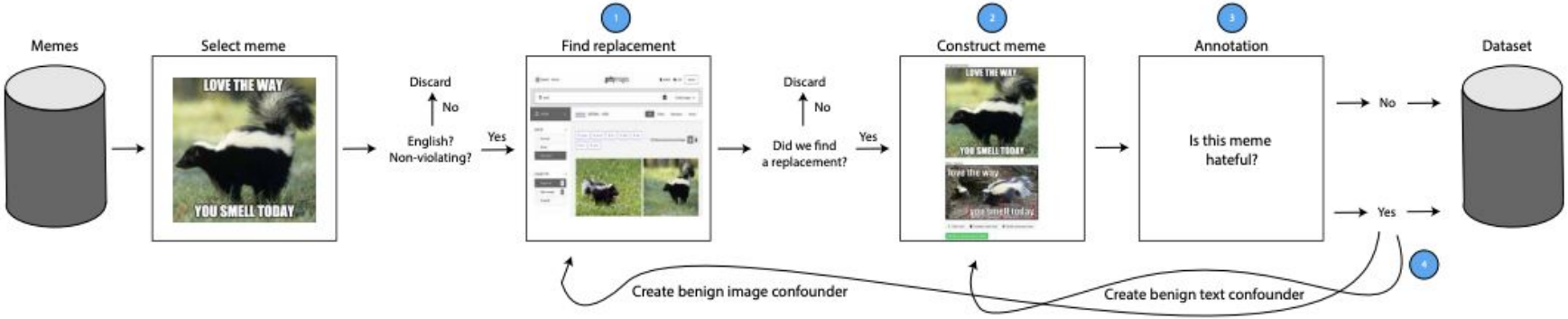
“Mean meme” examples for illustrative purposes – not actually in the dataset

Hateful Memes

Highly trained annotators, so: decent quality but small and expensive

Key concept: benign confounders

A “challenge set” for the community to do zero-shot/finetuning from pretrained



Hateful Memes

Findings in the paper:

- Big gap with human performance.
- Region features (as opposed to grid) seem to help.
- Earlier fusion is better than middle, is better than late.
- Multimodal pretraining doesn't really work.

Type	Model	Validation Acc.	Validation AUROC	Test Acc.	Test AUROC
	Human	-	-	84.70	-
Unimodal	Image-Grid	50.67	52.33	52.73±0.72	53.71±2.04
	Image-Region	52.53	57.24	52.36±0.23	57.74±0.73
	Text BERT	58.27	65.05	62.80±1.42	69.00±0.11
Multimodal (Unimodal Pretraining)	Late Fusion	59.39	65.07	63.20±1.09	69.30±0.33
	Concat BERT	59.32	65.88	61.53±0.96	67.77±0.87
	MMBT-Grid	59.59	66.73	62.83±2.04	69.49±0.59
	MMBT-Region	64.75	72.62	67.66±1.39	73.82±0.20
	ViLBERT	63.16	72.17	65.27±2.40	73.32±1.09
	Visual BERT	65.01	74.14	66.67±1.68	74.42±1.34
Multimodal (Multimodal Pretraining)	ViLBERT CC	66.10	73.02	65.90±1.20	74.52±0.06
	Visual BERT COCO	65.93	74.14	69.47±2.06	75.44±1.86

Hateful Memes Competition

After the paper came a $100k competition on an unseen test set:

Type	Model	Unseen Dev Acc.	Unseen Dev AUROC	Unseen Test Acc.	Unseen Test AUROC
Unimodal	Image-Region	61.48	53.54	60.28±0.18	54.64±0.80
	Text BERT	60.37	60.88	63.60±0.54	62.65±0.40
Multimodal (Unimodal Pretraining)	Late Fusion	61.11	61.00	64.06±0.02	64.44±1.60
	Concat BERT	64.81	65.42	65.90±0.82	66.28±0.66
	MMBT-Grid	67.78	65.47	66.85±1.61	67.24±2.53
	MMBT-Region	70.04	71.54	70.10±1.39	72.21±0.20
	ViLBERT	69.26	72.73	70.86±0.70	73.39±1.32
	Visual BERT	69.67	71.10	71.30±0.68	73.23±1.04
Multimodal (Multimodal Pretraining)	ViLBERT CC	70.37	70.78	70.03±1.07	72.78±0.50
	Visual BERT COCO	70.77	73.70	69.95±1.06	74.59±1.56

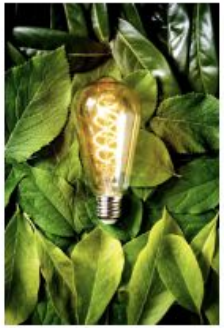
#	Team	AUROC	Acc.
1	Ron Zhu	0.844977	0.7320
2	Niklas Muennighoff	0.831037	0.6950
3	Team HateDetectron	0.810845	0.7650
4	Team Kingsterdam	0.805254	0.7385
5	Vlad Sandulescu	0.794321	0.7430

Winner characteristics: frameworks matter, SOTA pretrained models, ensembles, entities, faces and external knowledge. STILL FAR FROM SOLVED.

Winoground

How good is CLIP really?

Some relevant ideas/findings from NLP:



(a) some plants surrounding a lightbulb

(b) a lightbulb surrounding some plants

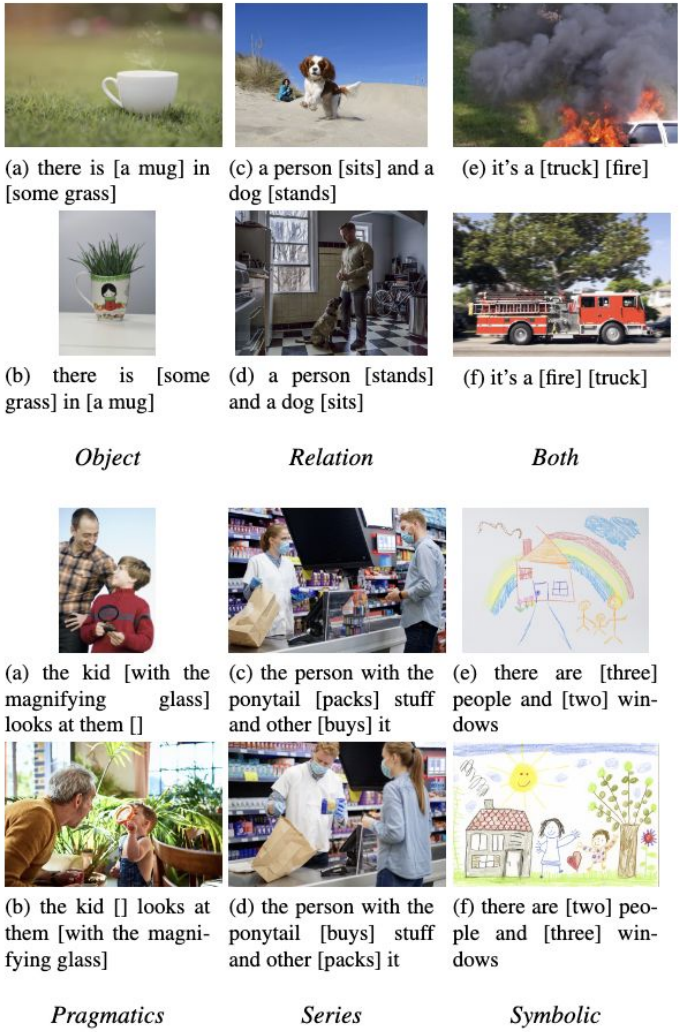
- Winograd schemas
  “The [trophy] doesn't fit in the [suitcase] because *it* is too [large/small]”
- Word order may not matter all that much

Masked Language Modeling and the Distributional Hypothesis: Order Word Matters Pre-training for Little

Koustuv Sinha[†‡] **Robin Jia**[†] **Dieuwke Hupkes**[†] **Joelle Pineau**[†‡]
Adina Williams[†] **Douwe Kiela**[†]

Winoground

- Examples written by linguist experts
- Using Getty Images API
- Simple way to measure by comparing scores
- In some cases, very difficult and requiring world knowledge



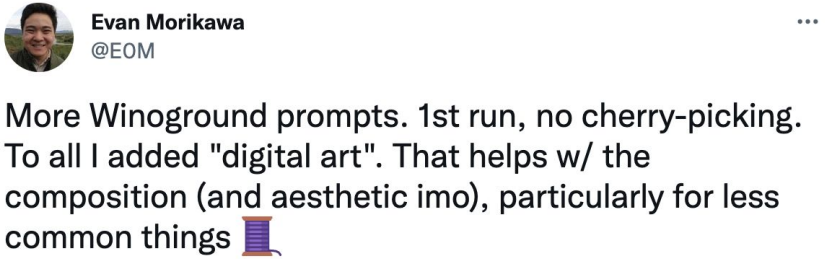
Winoground Findings

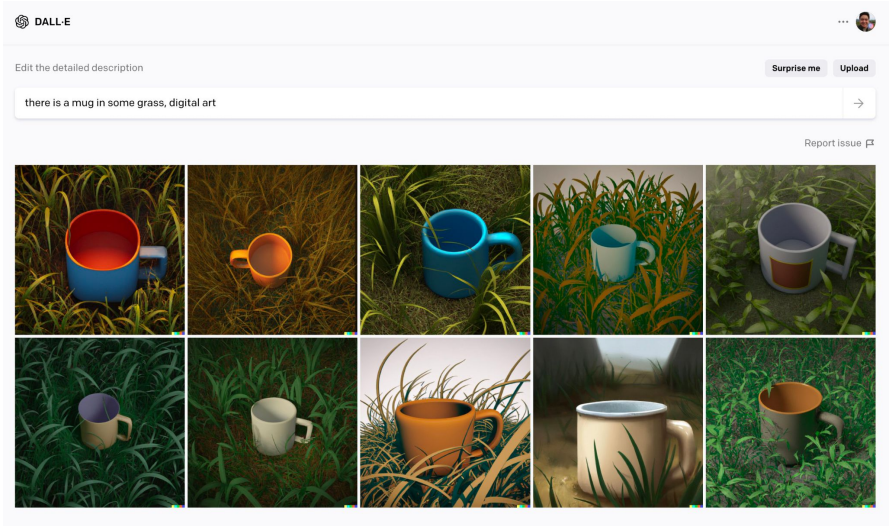
SOTA models often perform *below chance*.

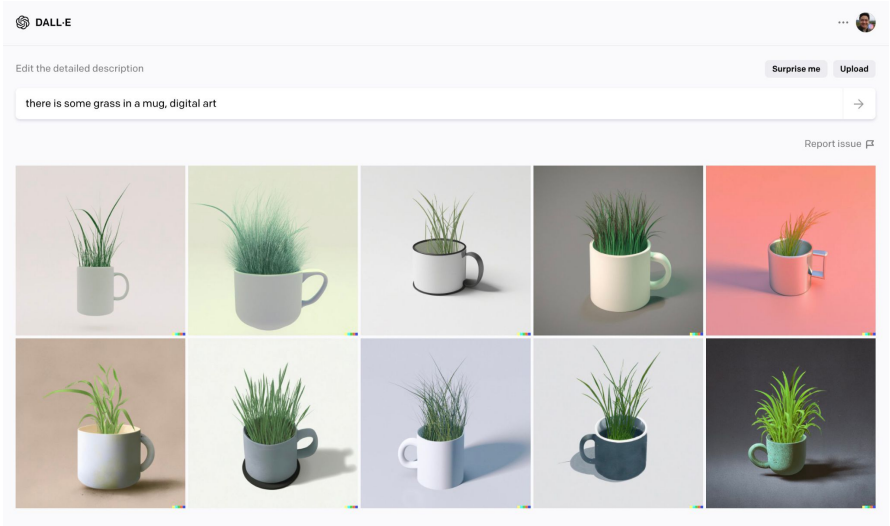
Model	Text	Image	Group
MTurk Human	**89.50**	**88.50**	**85.50**
Random Chance	25.00	25.00	16.67
VinVL	**37.75**	17.75	14.50
UNITER$_{large}$	**38.00**	14.00	10.50
UNITER$_{base}$	**32.25**	13.25	10.00
ViLLA$_{large}$	**37.00**	13.25	11.00
ViLLA$_{base}$	**30.00**	12.00	8.00
VisualBERT$_{base}$	15.50	2.50	1.50
ViLT (ViT-B/32)	**34.75**	14.00	9.25
LXMERT	19.25	7.00	4.00
ViLBERT$_{base}$	23.75	7.25	4.75
UniT$_{ITMfinetuned}$	19.50	6.25	4.00
CLIP (ViT-B/32)	**30.75**	10.50	8.00
VSE++$_{COCO}$ (ResNet)	22.75	8.00	4.00
VSE++$_{COCO}$ (VGG)	18.75	5.50	3.50
VSE++$_{Flickr30k}$ (ResNet)	20.00	5.00	2.75
VSE++$_{Flickr30k}$ (VGG)	19.75	6.25	4.50
VSRN$_{COCO}$	17.50	7.00	3.75
VSRN$_{Flickr30k}$	20.00	5.00	3.50

STILL FAR FROM SOLVED.

DALL-E2 on Winoground I



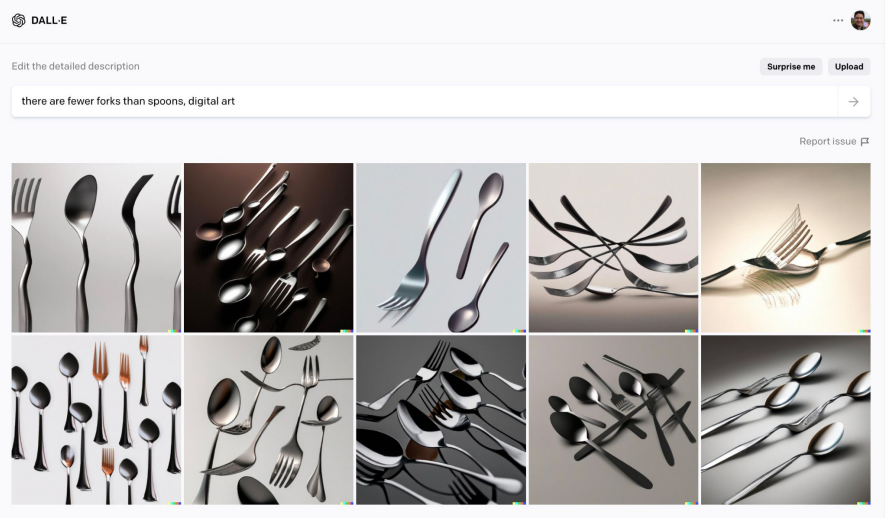


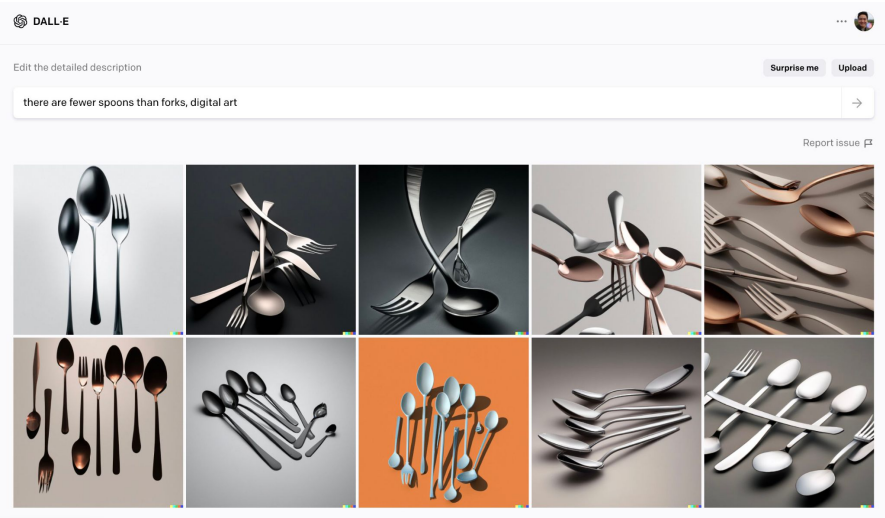


DALL-E2 on Winoground II

Evan Morikawa
@E0M

More Winoground prompts. 1st run, no cherry-picking. To all I added "digital art". That helps w/ the composition (and aesthetic imo), particularly for less common things 🧵





STILL NOT SOLVED

Outline

1. Early models
2. Features and fusion
3. Contrastive models
4. Multimodal foundation models
5. Evaluation
6. **Beyond images: Other modalities**
7. Where to next?

Speech / audio

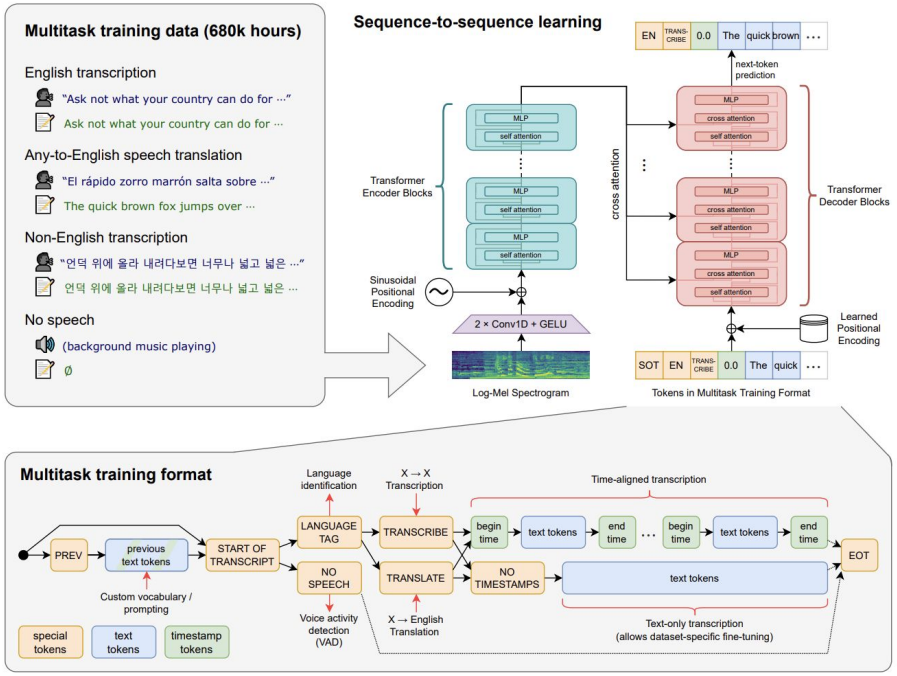
Can EASILY do another full lecture just on this topic.

Recent cool example: Whisper, trained on 680,000 hours of multilingual multitask data.

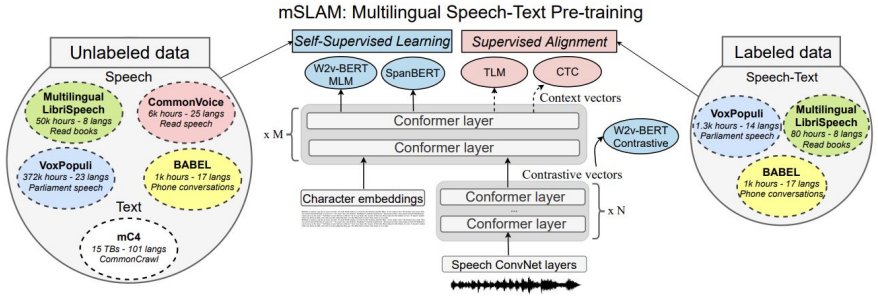
We can also just treat audio as vision ;)

Figure 3: Illustration of the Neural Auditory Embedding method, using a convolutional neural network. The auditory signal is converted to a spectrogram which is fed to the neural network for classification. The pre-softmax layer, FC7, is transferred and taken as the neural audio embedding (NAE) for the given sound file.

Kiela et al., 2017



Radford et al., 2022

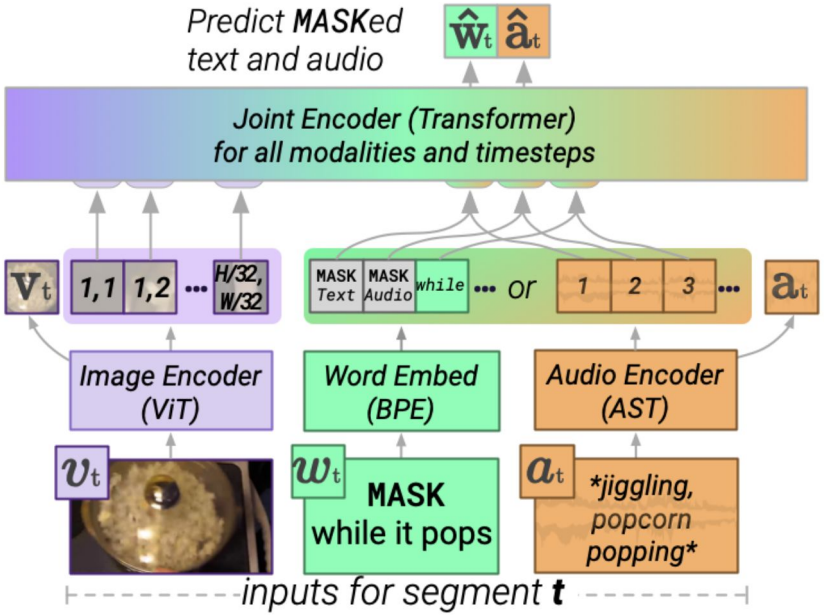


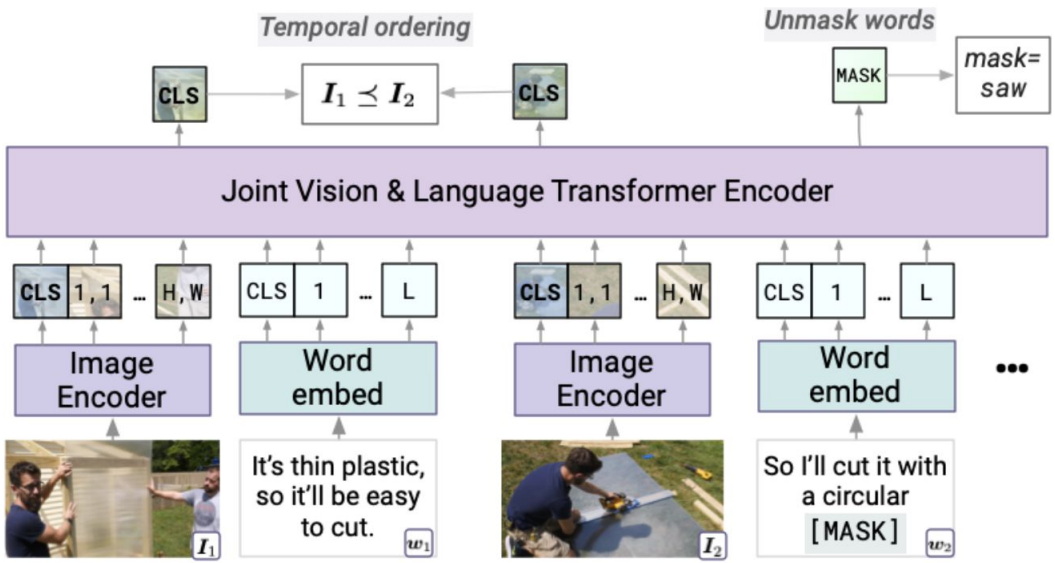
Bapna et al., 2022

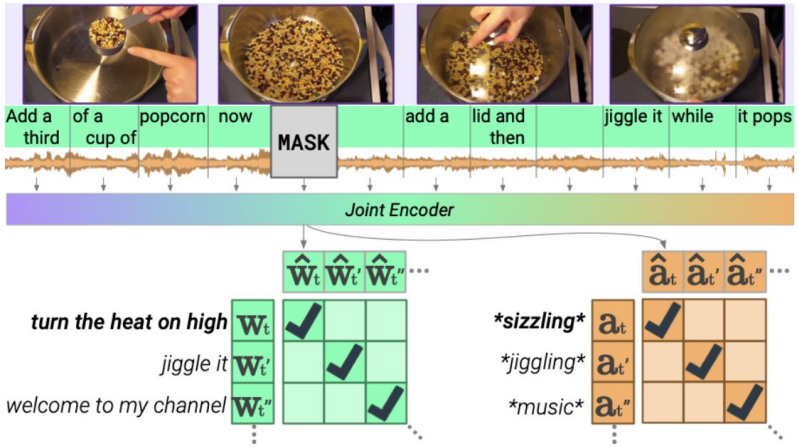
Video and text and audio

MERLOT (Zellers et al., 2021)

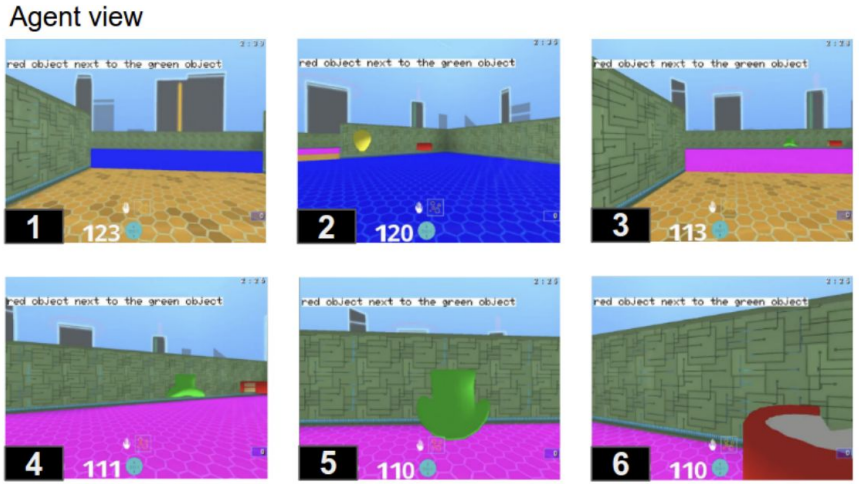
MERLOT Reserve (idem, 2022)



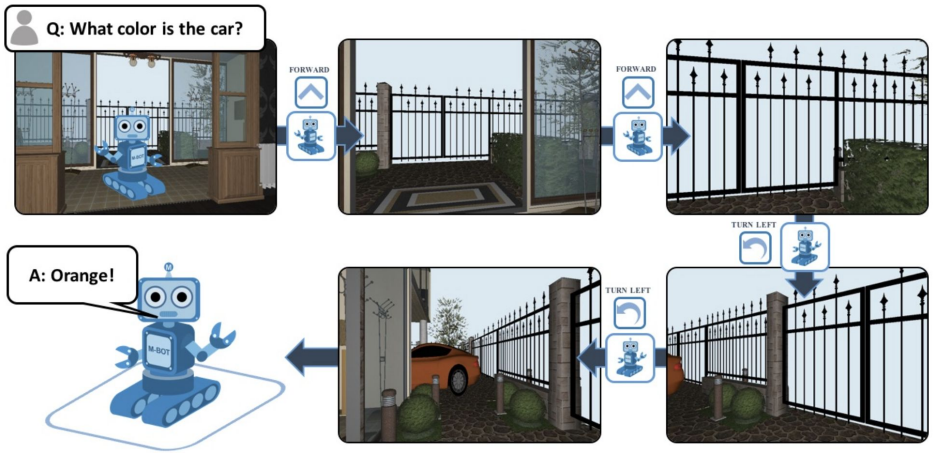




Grounded language learning in simulated environments



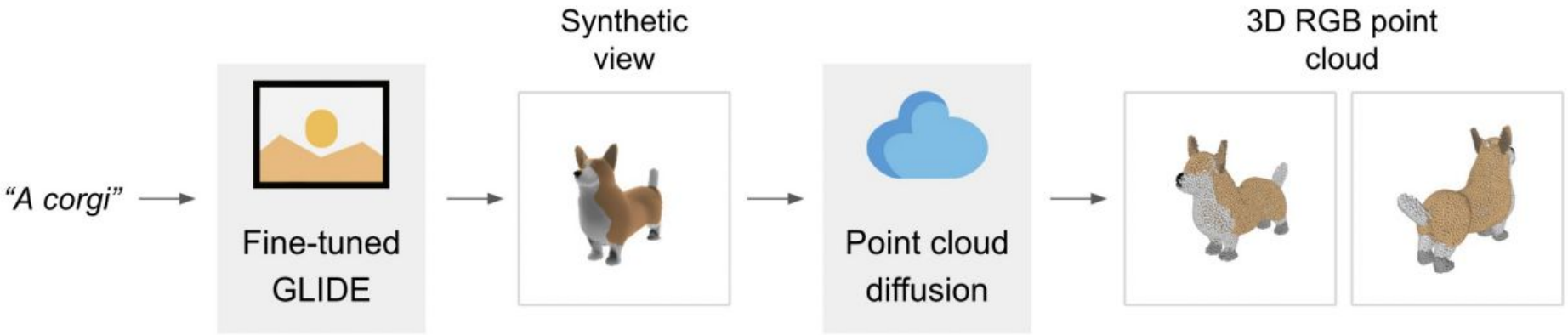
Hermann, Hill, et al. 2017



Das et al., 2018

Text to 3D

POINT-E (Nichol, Jun, et al., 2022)



Olfactory embeddings (Kiela et al., 2015)

Bag of chemical compounds model.

apple	bacon	brandy	cashew
pear	smoky	rum	hazelnut
banana	roasted	whiskey	peanut
melon	coffee	wine-like	almond
apricot	mesquite	grape	hawthorne
pineapple	mossy	fleshy	jam
chocolate	lemon	cheese	caramel
cocoa	citrus	grassy	nutty
sweet	geranium	butter	roasted
coffee	grapefruit	oily	maple
licorice	tart	creamy	butterscotch
roasted	floral	coconut	coffee

	MEN	OMEN	SLex	OSLex
Linguistic	0.78	0.38	0.44	0.30
→BoCC-Raw	0.38	0.36	0.19	0.23
→BoCC-SVD	0.46	0.51	0.23	0.48
Multi-modal	0.69	0.53	0.40	0.49

	Chemical Compound				
Smell label	Phenethyl acetate	Isoamyl butyrate	Anisyl butyrate	Myrcene	Syringaldehyde
Melon	✓	✓			
Pineapple	✓				✓
Licorice			✓		
Anise			✓	✓	
Beer				✓	✓

Table 2: A BoCC model.

Outline

1. Early models
2. Multimodal fusion
3. Contrastive models
4. Multimodal foundation models
5. Other modalities
6. Evaluation
7. **Where to next?**

One foundation model to rule them all

There will modality-agnostic foundation models that can read and generate many modalities.

These models can be bigger and be trained on vastly more data. Parameters will be shared in interesting ways.

Automatic alignment from unpaired unimodal data will become a big topic.

Multimodal scaling laws

We are just beginning to understand multimodal scaling laws, lots of interesting work to do here in understanding trade-offs.

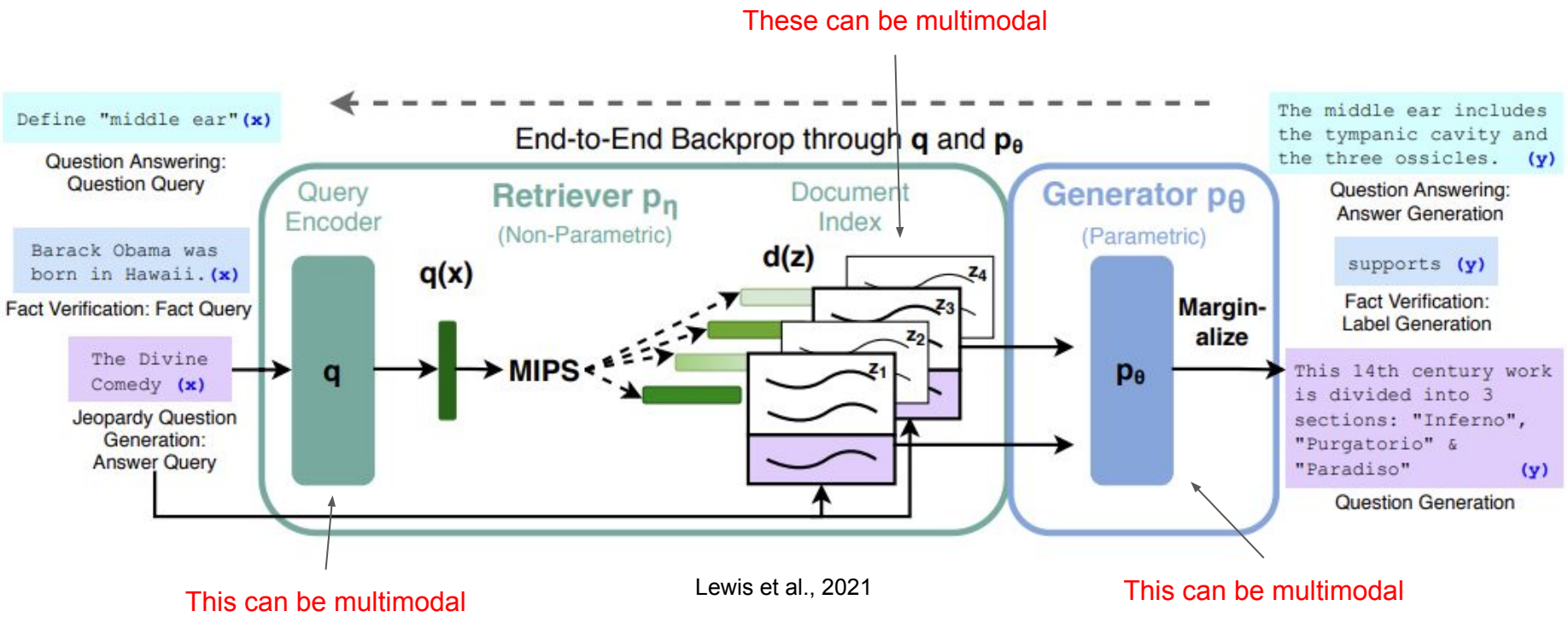
SCALING LAWS FOR GENERATIVE MIXED-MODAL LANGUAGE MODELS

Armen Aghajanyan[*†], **Lili Yu**[*†], **Alexis Conneau**[†], **Wei-Ning Hsu**[†]

Karen Hambardzumyan[◇], **Susan Zhang**[†], **Stephen Roller**[†], **Naman Goyal**[†]

Omer Levy[†] **& Luke Zettlemoyer**[†,♡]

Retrieval augmented generative multimodal models

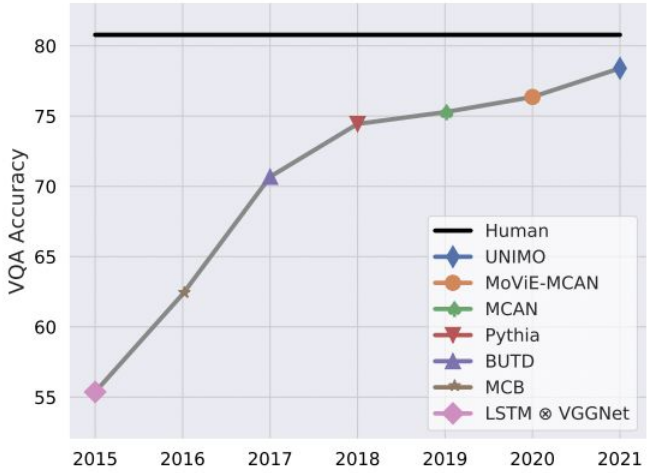


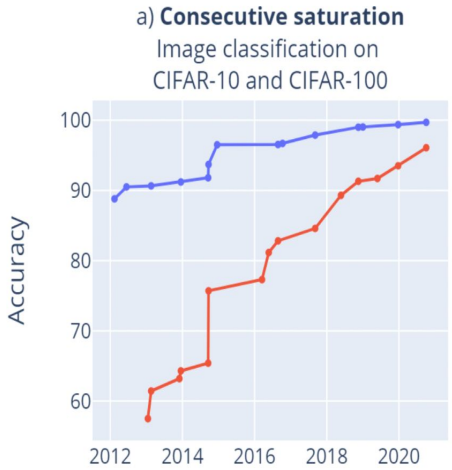
Lewis et al., 2021

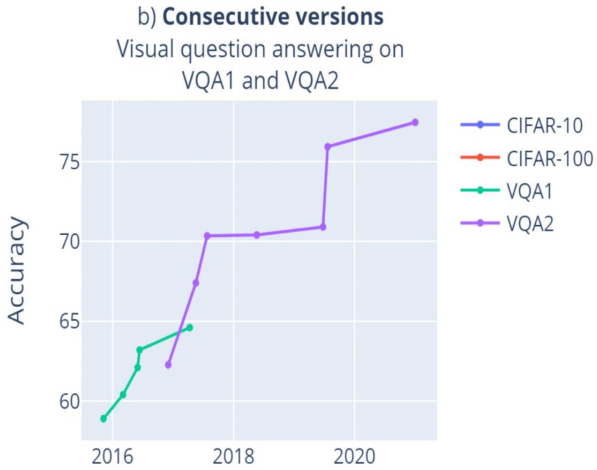
Better evaluation and benchmarking

We need better measurement.

Kiela et al. 2020







Barbosa-Silva et al. 2022

Thanks for listening!

Thank you!

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Twitter: @douwekiela