Multilingual and multimodal language models

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Slides: https://elliottd.github.io/vlprimer/

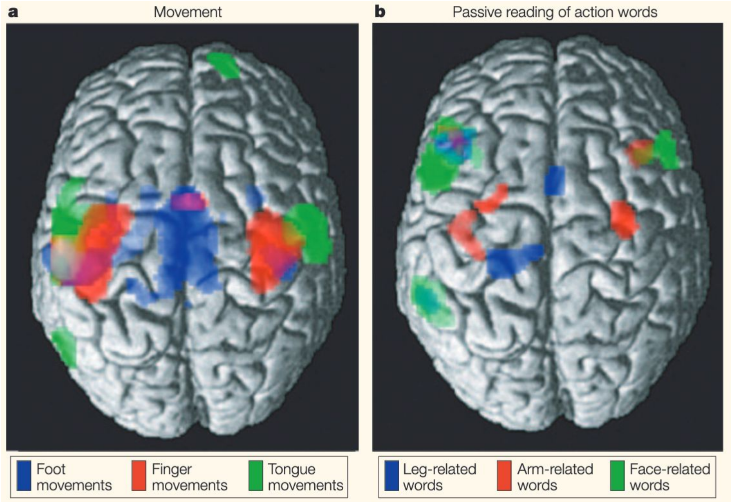
Working Definition

Multimodal models jointly processes information from two or more input modalities, e.g. images and text, speech and video, etc.

Image adapted from https://xkcd.com/1838/ (CC BY-NC 2.5)

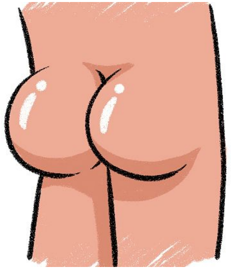
Why Multimodality?

- Humans ground conceptual knowledge in modality processing systems in the brain
- Evidence that grounding activates similar brain regions for different input modalities



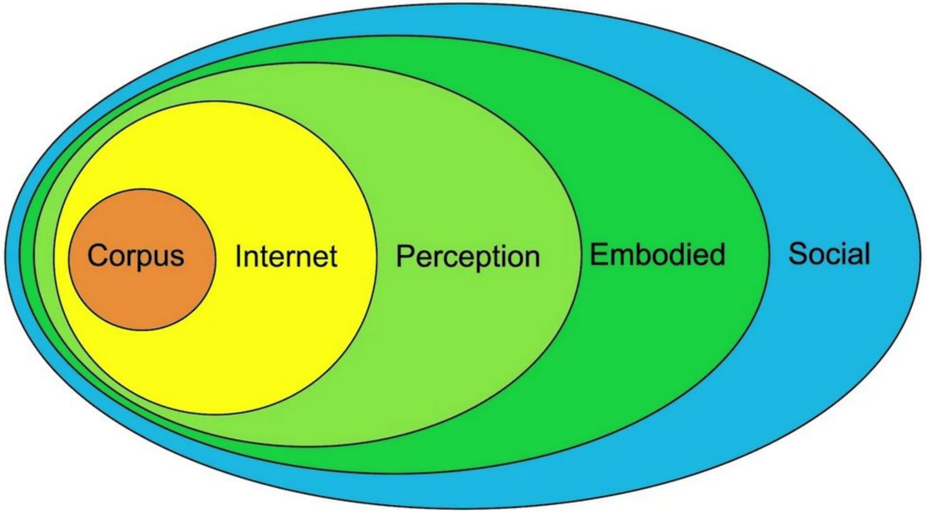
Barsalou et al. (2003). Grounding conceptual knowledge in modality-specific systems. Trends in cognitive sciences, 7(2):84–91.
Pulvermüller. (2005). Brain mechanisms linking language and action. Nature reviews neuroscience, 6(7), 576-582.

Multimodality reduces ambiguity



You Cannot Learn Language From

- The radio without grounding *(lack perception)*
- The television without actions *(lack embodiment)*
- *W*ithout interacting with others *(lack social)*



Bisk et al. (2020). Experience Grounds Language. EMNLP.

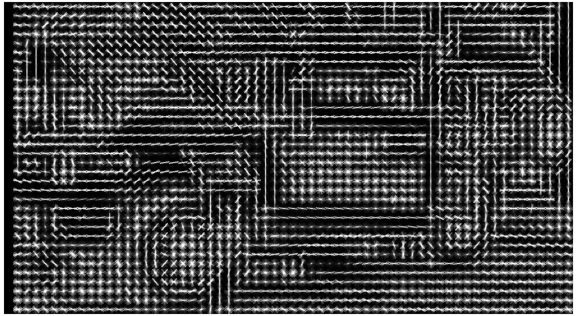
(At Least) Five Major Areas

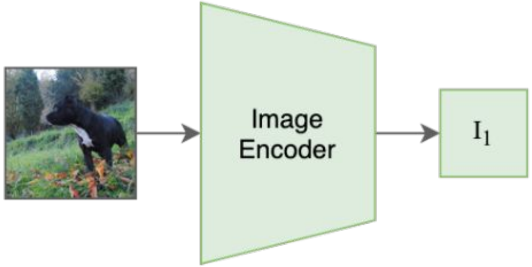
- **Representation**: how to convert raw inputs into a usable format
- **Translation**: transform from one modality to another
- **Alignment**: predict relationships between elements across modalities
- **Fusion**: join features from modalities to support prediction
- **Co-learning**: transferring knowledge from one modality to another

Baltrušaitis, Ahuja, and Morency, (2018). Multimodal machine learning: A survey and taxonomy. IEEE PAMI, 41(2), 423-443.

Representation

- Great deal of work over the last decade, from HOG features in the early 2000s to CLIP features in the 2020s.

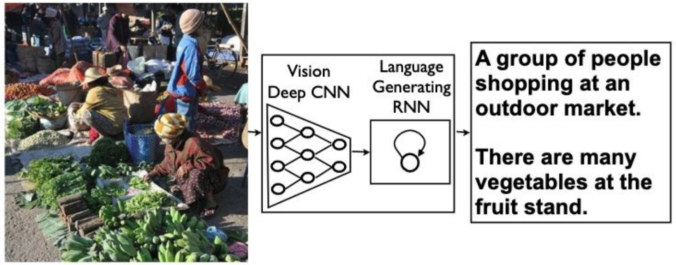


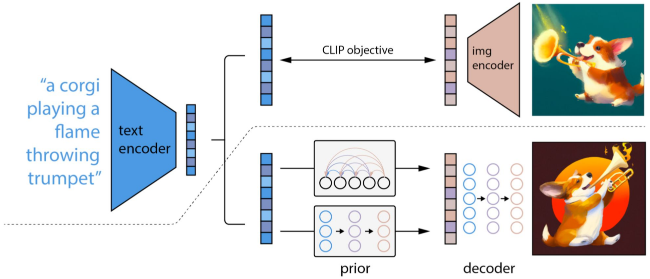


Dalal & Triggs. (2005). Histograms of oriented gradients for human detection. CVPR
Radford et al. (2021) Learning transferable visual models from natural language supervision. ICML.

Translation

- Explosion of end-to-end neural network models since the mid 2010s

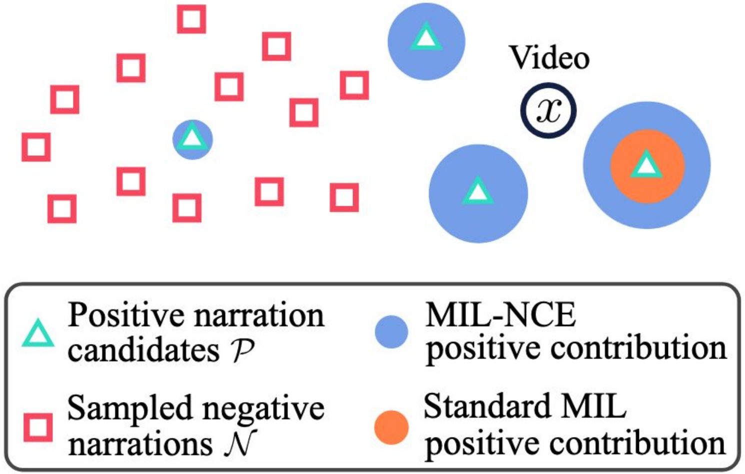




Vinyals et al. (2015). Show and tell: A neural image caption generator. CVPR.
Ramesh et al. (2022). Hierarchical Text-Conditional Image Generation with CLIP Latents. arXiv.

Alignment

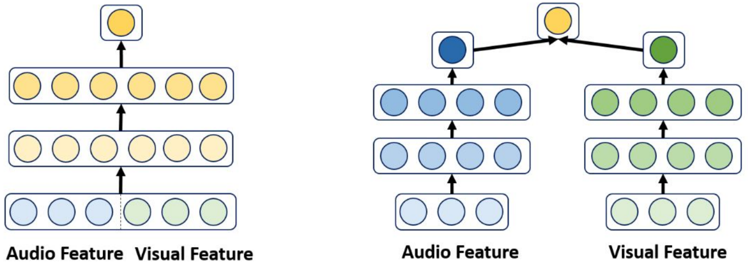
- Important for self-supervised learning and also for phrase grounding

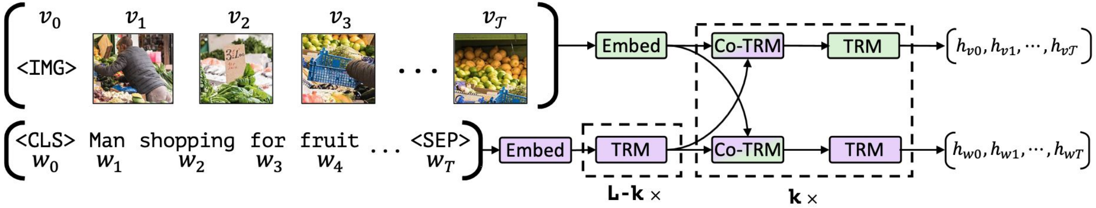


Miech et al. (2020). End-to-end learning of visual representations from uncurated instructional videos. CVPR.
Kamath et al. (2021). MDETR-modulated detection for end-to-end multi-modal understanding. ICCV.

Fusion

- Early work studied the differences between early and late fusion.
- Multi-head self-attention now provides model-based fusion.

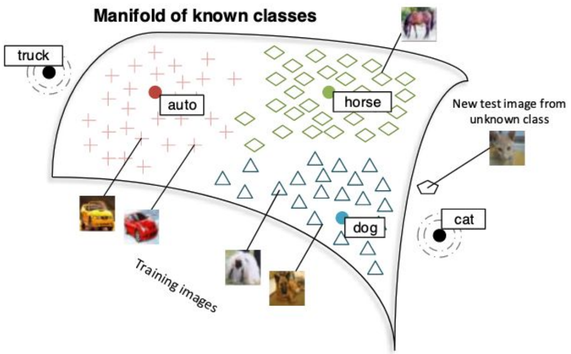


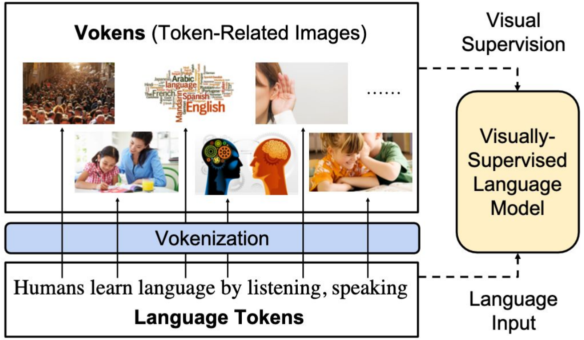


Chen and Jin (2016). Multi-modal conditional attention fusion for dimensional emotion prediction. MM.
Lu et al. (2019). ViLBERT: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks. *NeurIPS.*

Co-learning

- Zero-shot transfer across modalities, or using visual grounding to improve language models on text-only tasks.





Socher et al. (2013). Zero-shot learning through cross-modal transfer. NeurIPS.
Tan & Bansal. (2020). Vokenization: Improving Language Understanding with Contextualized, Visual-Grounded Supervision. EMNLP

Roadmap

Part 1

1. Datasets for Multimodal Learning

   📚 Visually Grounded Reasoning across Languages and Cultures

2. Data Representation
3. Modelling Techniques

   📚 Retrieval-Augmentation in Image Captioning

Part 2

4. Understanding Multimodal Models

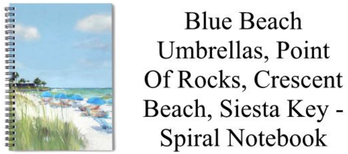
5. Future Directions

   📚 Language Modelling with Pixels

1. Datasets for Multimodal Learning

Two Types of Dataset

- **General-purpose**: visual data with descriptive annotations
    - Conceptual Captions
    - LAION-2/5B
    - Speech-COCO



- **Task-specific**: visual data with e.g. classification labels
    - Image / Video Captioning
    - Visual Question Answering
    - Visually Grounded Reasoning

Degree of Multimodality

Social media platforms often form 'echo chambers' that encourage users to only read content that confirms beliefs they already hold (Getty)

A woman in a dark grey suit is giving a speech

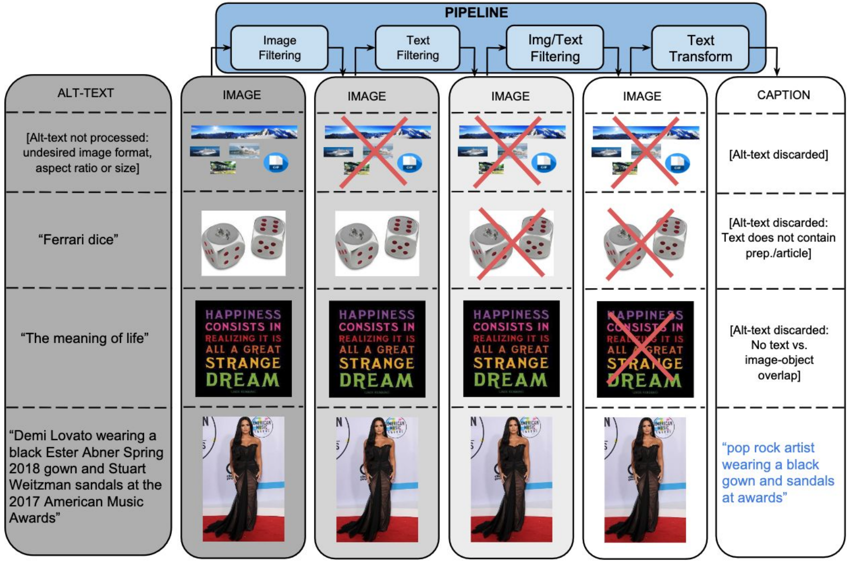
Weak

Strong

Panofsky. (1939). Studies in Iconology.
https://www.independent.co.uk/news/angela-merkel-says-internet-search-engines-endangering-debate-algorithms-should-be-revealed-a7383811.html

Conceptual Captions

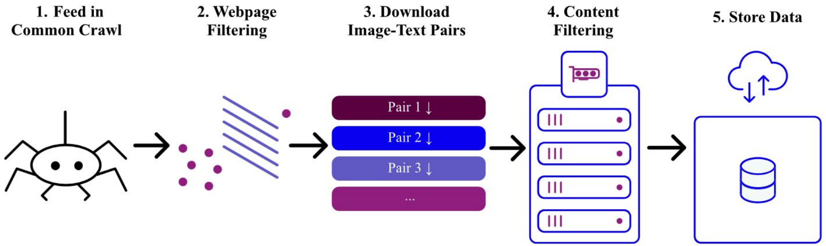
- Used for pretraining
- 3M Images and *normalized* English captions.
- Normalization is not public.
- Due to *linkrot*, much less data is currently available.

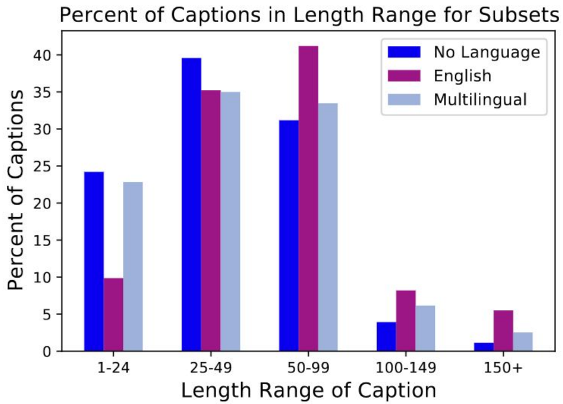


Sharma et al. (2018). Conceptual captions: A cleaned, hypernymed, image alt-text dataset for automatic image captioning. ACL.
Changpinyo et al. (2021). Conceptual 12M: Pushing web-scale image-text pre-training to recognize long-tail visual concepts. CVPR.
Download your own: https://github.com/igorbrigadir/DownloadConceptualCaptions

LAION

- Used for pretraining
- Image and multilingual *raw* captions harvested from within Common Crawl
- Data behind Stable Diffusion and OpenCLIP
- 5B variant removed due to illegal material





Schuhmann et al. (2022). LAION-5B: An open large-scale dataset for training next generation image-text models. NeurIPS.
Thiel. (2023). Identifying and Eliminating CSAM in Generative ML Training Data and Models

COCO

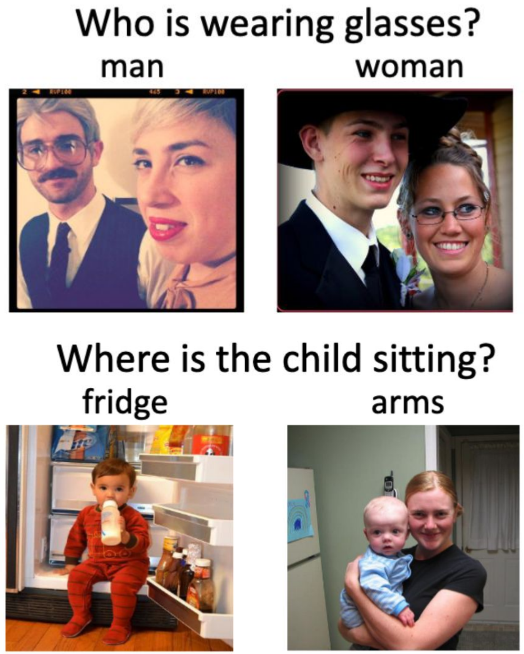
- Used both a **general-purpose** and **task-specific** dataset
- Images covering 80 *co*mmon objects in *co*ntext with multiple human-authored captions.
- Object segmentation data too!

some sheep walking in the middle of a road
a herd of sheep with green markings walking down the road
a herd of sheep walking down a street next to a lush green grass covered hillside.
sheared sheep on roadway taken from vehicle, with green hillside in background.
a flock of freshly sheered sheep in the road.

Chen et al. (2015). Microsoft COCO captions: Data collection and evaluation server. *arXiv.*

VQAv2

- Answer questions about images
- Task with multimodal inputs:
  - Image
  - Question
- Commonly tackled as classification but increasing efforts as NLG
- 1.1M image–question pairs with balanced distribution of answers



Goyal et al. (2017). Making the V in VQA matter: Elevating the role of image understanding in visual question answering. CVPR.

NLVR2

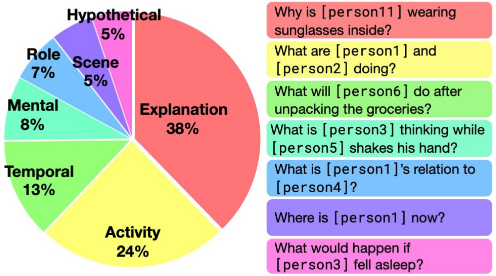
- Binary classification task that requires jointly reasoning over a pair of images and a sentence.
- Human-created hard negatives.
- 107K examples in total.

The left image contains twice the number of dogs as the right image, and at least two dogs in total are standing.

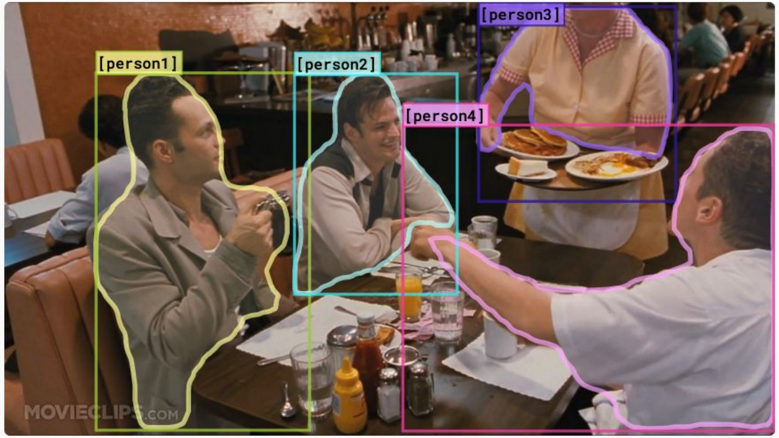
Suhr et al. (2019). A Corpus for Reasoning about Natural Language Grounded in Photographs. ACL.

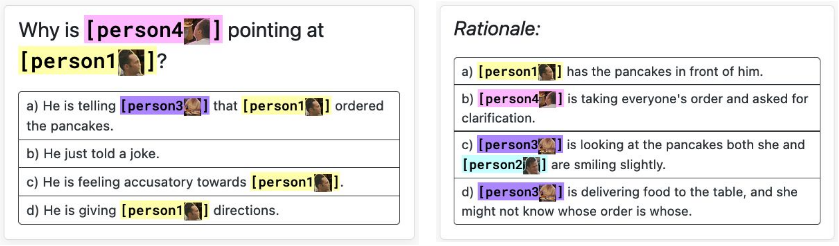
Visual Commonsense Reasoning

- 290,000 multiple-choice VQA examples derived from movies.



- In addition to Question Answering, the dataset includes rationale selection too!





Zellers et al. (2019). From Recognition to Cognition: Visual Commonsense Reasoning. CVPR.

Multi30K

- Multilingual aligned image–sentence dataset in many languages
    - English, German, French, Czech, Arabic, Japanese, Turkish, Ukranian

A group of people are eating noodles.

Eine Gruppe von Leuten isst Nudeln.

Un groupe de gens mangent des nouilles.

Skupina lidí jedí nudle.

Elliott et al. (2016). Multi30K: Multilingual English-German Image Descriptions. ACL Workshop.

BOBSL

- BBC-Oxford British Sign Language Dataset
- Sign spotting and sentence localization tasks
- 1,400 hours of signed shows
  - Factual, entertainment, drama, comedy, children’s shows

Albanie et al. (2021). BBC-Oxford British Sign Language Dataset. arXiv.

Many Many More

- Visual Storytelling, e.g. VIST
- Grounded Referring Expression, e.g. Flickr30K Entities, Visual Genome
- Visual Entailment, e.g. SNLI-VE
- Vision & Language Navigation, e.g. RxR
- Visual Common Sense Reasoning: VCR
- Text-to-Image Generation, e.g. DALLEval
- Abstract reasoning, e.g. KiloGram, CRAFT
- Sign Language Processing, e.g. How2Sign
- *and more and more and more and more*

Ethical Issues

- Multimodal datasets are usually data scraped from the web with *unknown degrees of conformance*, or information about, licensing.

CC BY: This license allows reusers to distribute, remix, adapt, and build upon the material in any medium or format, so long as attribution is given to the creator. The license allows for commercial use.

- As of 2022, there are an estimated 2.5B CC-licensed objects online.

State of the Commons 2022. Creative Commons Foundation.

A Problem with Scale

- Build multimodal systems that perpetuate harmful stereotypes

(Eileen Collins, American astronaut)

`cos(·,·)`

0.276 ← This is a portrait of an astronaut with the American flag

0.308 ← This is a photograph of a smiling housewife in an orange jumpsuit with the American flag

Birhane et al. (2021) Multimodal datasets: misogyny, pornography, and malignant stereotypes. arXiv.

Q: How can we collect multimodal data that better reflects the diversity of the world?

Visually Grounded Reasoning across Languages and Cultures

EMNLP 2021


F. Liu*


E. Bugliarello*


E.M. Ponti


S. Reddy

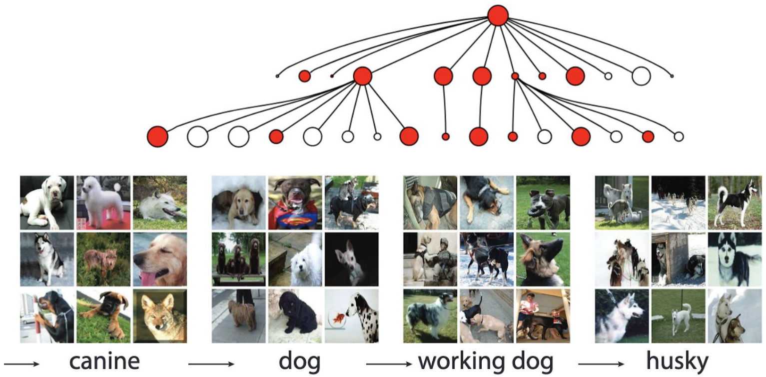

N. Collier


D. Elliott

Typical Vision and Language DATA

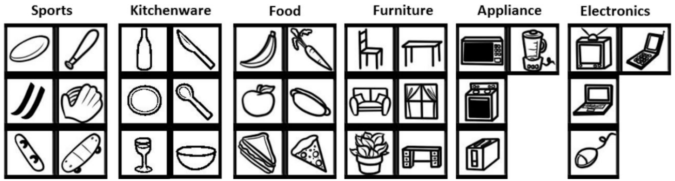
ImageNet (Deng et al. 2009)

- Train visual encoders
- Millions of labelled images
- Derived from the WordNet hierarchy



Common Objects in Context (Lin et al. 2014)

- Train and evaluate multimodal models
- 330K labelled images
    - 80 types of commonly occurring objects



Rethinking Vision and Language DATA

Languages

- Mostly in English
- Or some Indo-European Languages

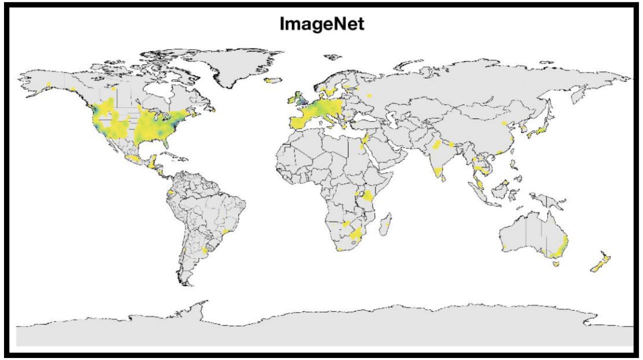
ENG: An unusual looking vehicle …

NLD: Een mobiel draaiorgel …

Example from van Miltenburg+ 2017

Image sources

- Mostly from ImageNet or COCO
- Reflecting North American and European cultures



Density map of geographical distribution of images in ImageNet (DeVries+, 2019)

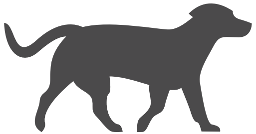
Implications for V&L models

- Narrow linguistic/cultural domain
- No way to assess their real-world comprehension

Concepts and Hierarchies

Category: objects with similar properties (Aristotle 40 BCE, …)

Concept: mental representation of a category (Rosch 1973)



"Dog" concept

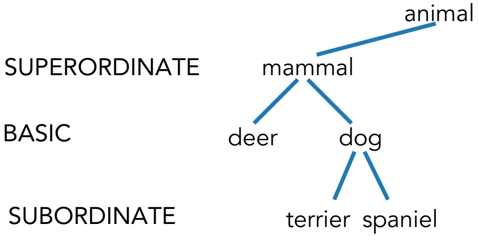
"Dog" category

Categories form a *hierarchy*

- Basic-level categories (Rosch 1976)

Somewhat universal

- Different cultures (Berlin 2014)
- Familiarity of individuals (Wisniewski and Murphy, 1989)



Concrete Concepts in Cultural Context

- Some concepts are most immediately understood within a cultural background

Culture: The way of life of a collective of people that distinguishes them from other people (Mora, 2013; Shweder et al. 2007).

Pilota / Jai-alai

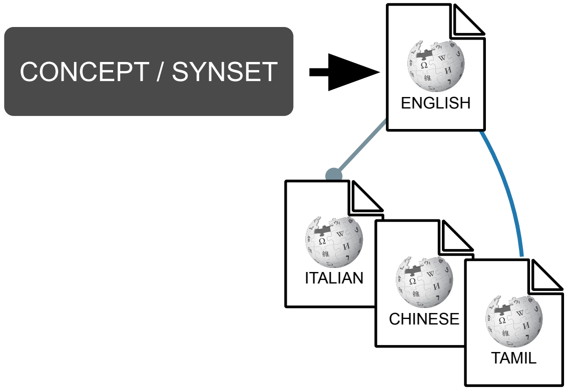
Sanxian / Shamisen

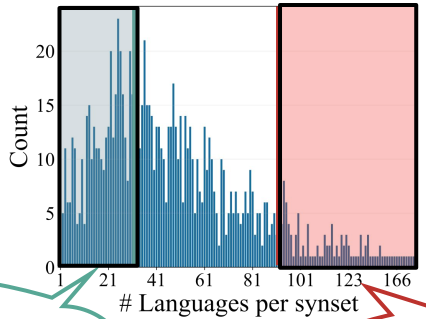
Clavie

See Hershcovich et al. ACL 2022 for an overview of Cross-cultural strategies in NLP

Are ImageNet Concepts Cross-Lingual?

- The ImageNet, COCO and Visual Genome datasets use English WordNet concepts
- Idea: estimate cross-linguality using Wikipedia as a proxy





Most concepts in <30 languages

Only a few "universal" concepts

MaRVL Multicultural Reasoning over Vision and Language

Representative of annotators' cultures

5 typologically diverse languages

Independent, culture-specific annotations

MaRVL-id Bola basket

MaRVL-sw Mpira wa kikapu

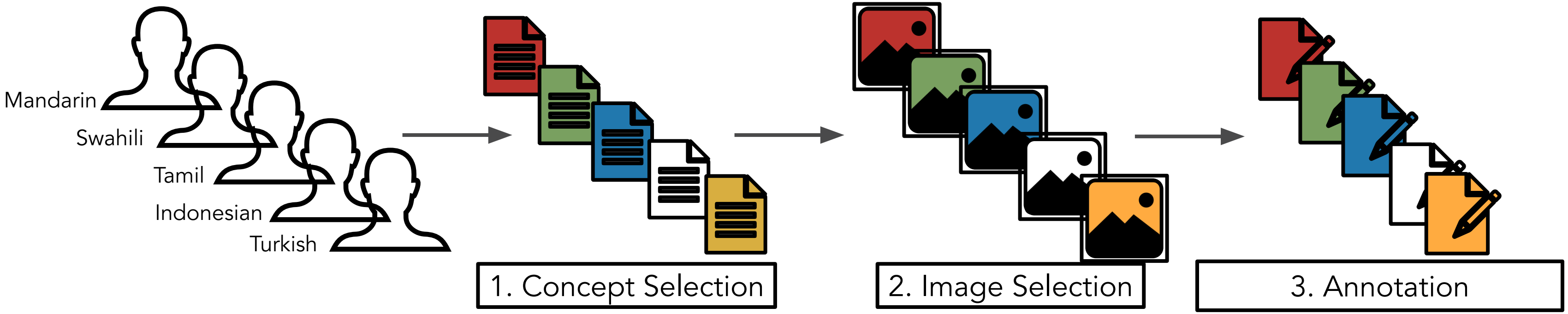
MaRVL-tr Basketbol

MaRVL-zh 篮球

MaRVL-ta கூடைப்பந்தாட்டம்

Collecting MaRVL data

Native speaker-driven protocol



Visual Reasoning Task (Suhr et al. ACL 2019)

- **Datapoint**: two images (v_1, v_2) paired with a sentence x
- **Task**: Predict whether x is a true description of the pair of images v_1 v_2


இரு படங்களில் ஒன்றில்
இரண்டிற்கும் மேற்பட்ட
மஞ்சள் சட்டை அணிந்த
வீரர்கள் காளையை அடக்கும்
பணியில் ஈடுப்பட்டிருப்பதை
காணமுடி.

x

True

y

MaRVL is created from Universal Concepts

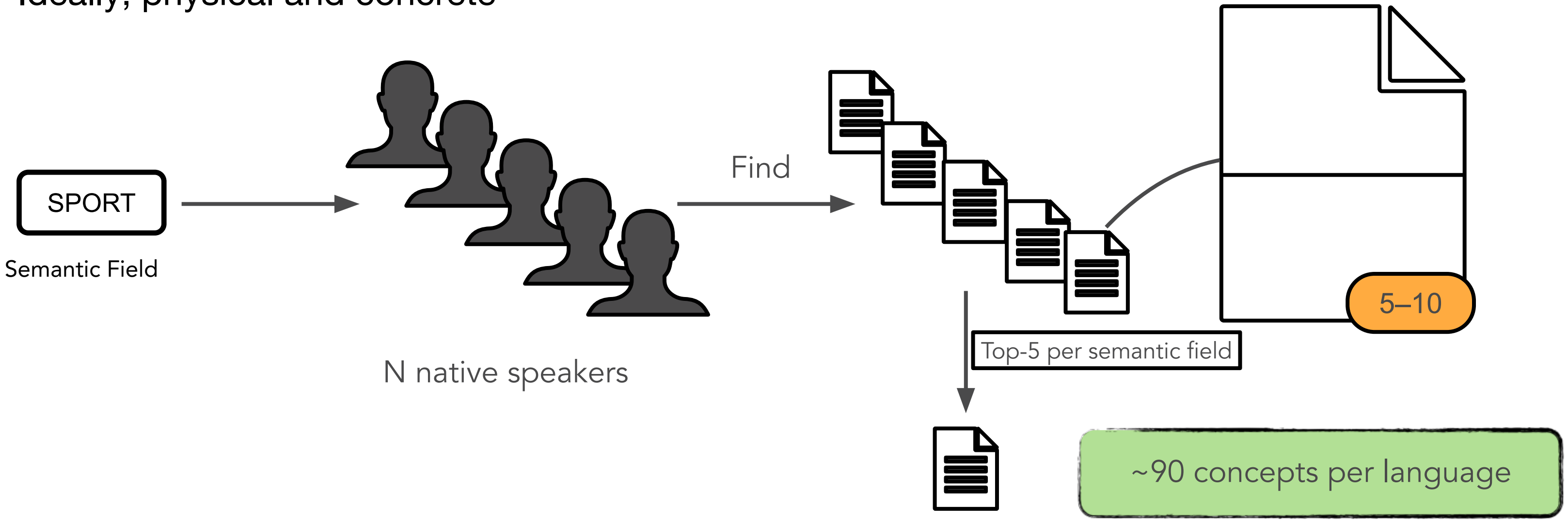
- Taken from the *Intercontinental Dictionary Series* (Key & Comrie, 2015)
  - 18/22 chapters with concrete objects & events

Chapter	Semantic Field
Animal	Bird, mammal
Food and Beverages	Food, Beverages
Clothing and grooming	Clothing
The house	Interior, exterior
Agriculture and vegetation	Flower, fruit, vegetable, agriculture
Basic actions and technology	Utensil/tool
Motion	Sport
Time	Celebrations
Cognition	Education
Speech and language	Music (instruments), visual arts
Religion and belief	Religion

Step 1. Language-Specific Concept Selection

Defined by native speakers

- Commonly seen or representative in their culture
- Ideally, physical and concrete



Overview of Resulting Concepts

Step 2. Image Collection

Collected by native speakers

- Representative of the language population
- NLVR2 (Suhr et al. ACL 2019) requirements

1. Contains more than one instance of a concept
2. Shows an instance of the concept interacting with other objects
3. Shows an instance of the concept performing an activity
4. Displays a set of diverse objects or features

MaRVL-zh 花椰菜 (Cauliflower)

MaRVL-ta மோர் (Buttermilk)

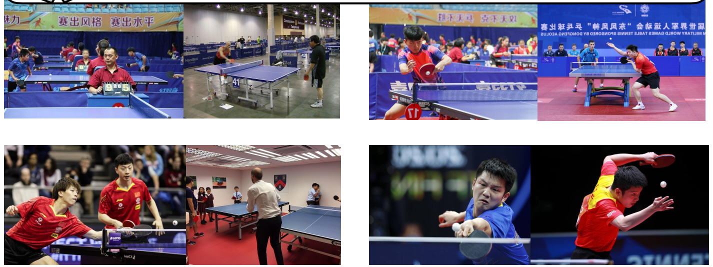
MaRVL-sw Jembe (Shovel)

MaRVL-tr Rakı (Raki)

Step 3. Language Annotation

Written by native speakers

MATCH 4 PAIRS AT RANDOM



WRITE CAPTION TRUE ONLY FOR 2 PAIRS

右图中的人在发球，左图中的人在接球。

VALIDATE ANNOTATIONS

右图中的人在发球，左图中的人在接球。

FINAL VALIDATION

右图中的人在发球，左图中的人在接球。

(The man in the right image is serving a ball while the man in the left image is returning a ball.)

Fleiss' kappa: 93%

Dataset Examples

MaRVL-tr Kanun (çalgı)

Görsellerden birinde dizlerinde kanun bulunan birden çok insan var

(In one of the images, there are multiple people with qanuns on their knees)

Label: True

MaRVL-ta ைம (Vada)

இரண்டு படங்களிலும் நிறைய மசால் வடைகள் உள்

(Both images contain a lot of masala vadas)

Label: False

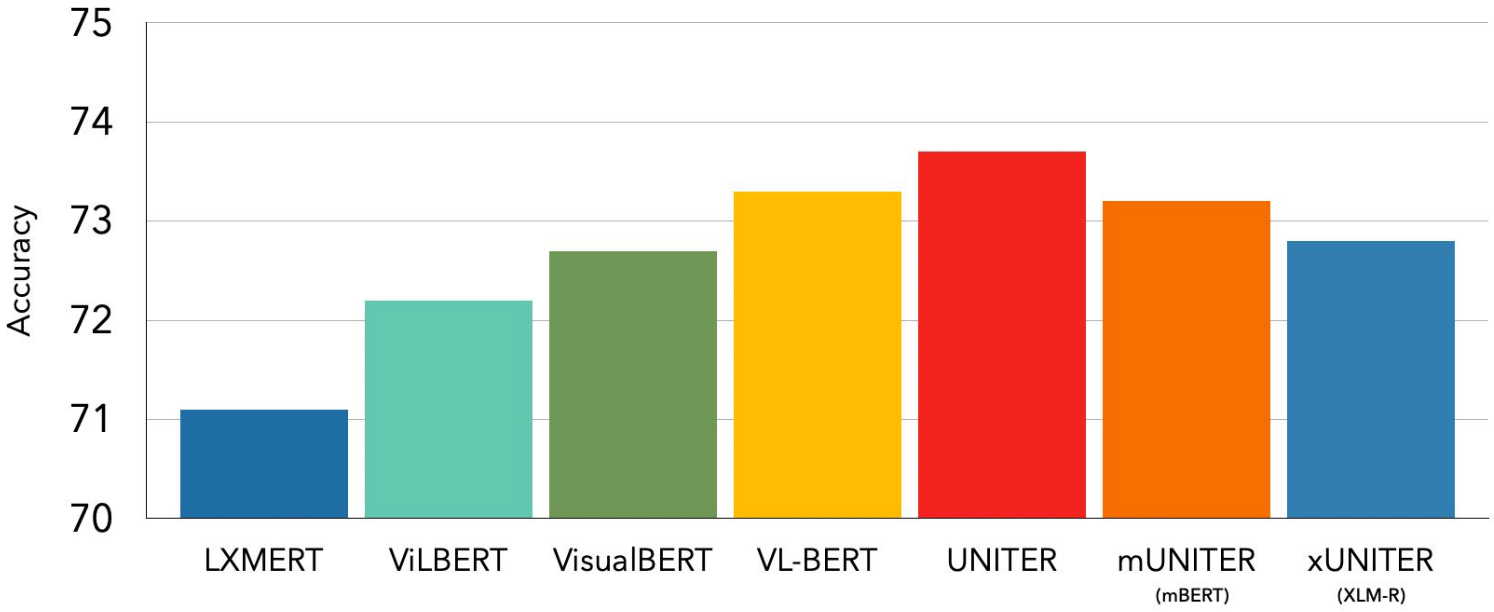
Pretraining and Finetuning

- Two new multilingual UNITER-based models
  - Pretrained on English Conceptual Captions + 104 languages Wikipedia
    - mUNITER: Initialised from mBERT
    - xUNITER: Initialised from XLM-R

- Finetune on 86,373 data points in **English** NLVR2 (Suhr+, 2019)

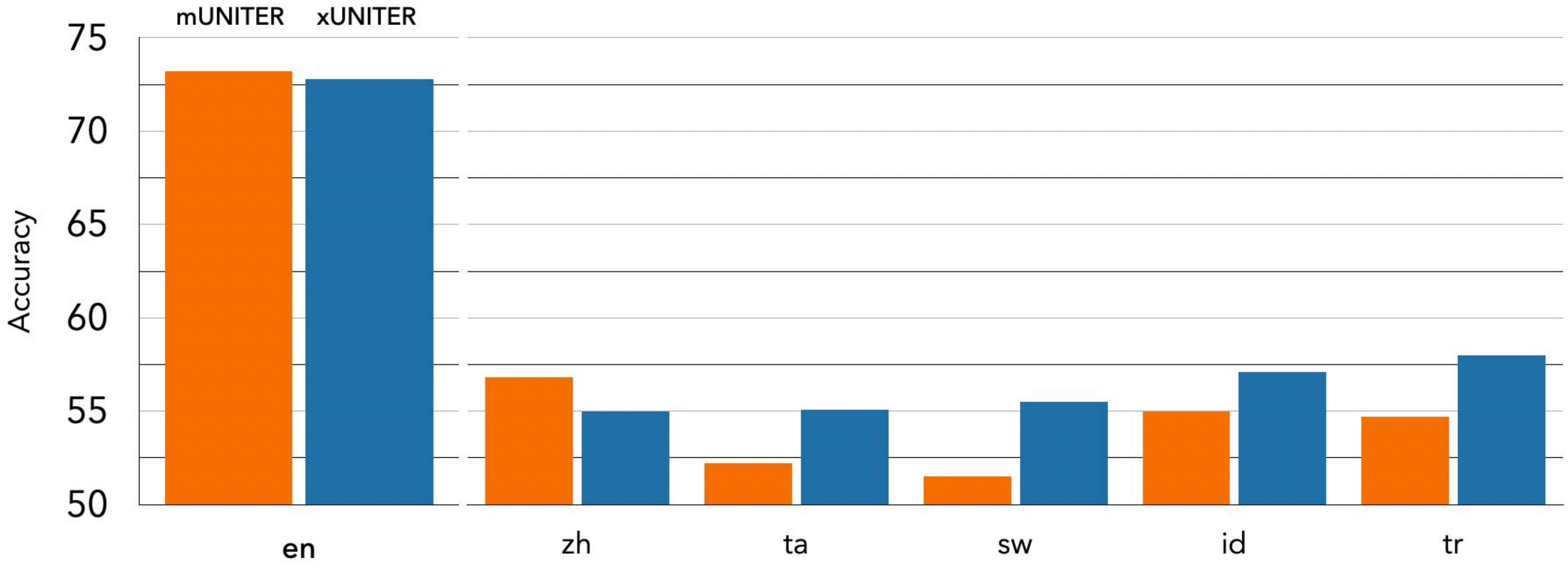
- Test on 5,560 datapoints in MaRVL (5,560 datapoints)
  - **Zero-shot**: Multilingual inputs directly in a cross-lingual approach
  - **Translate-test**: English models by machine translating language data

English NLVR2 Results (Sanity check)



m/xUNITER perform similarly to English-only models

MaRVL Zero-shot Results



Zero-shot transfer: substantial drop in performance

Conclusions

- Concepts and images in existing V&L datasets have an NA/EU bias
- Devise a new protocol for data creation driven by native speakers
- MaRVL: V&L reasoning dataset in 5 typologically diverse languages

- Implications beyond vision and language research
  - Multilingual datasets should not just be translations of English data

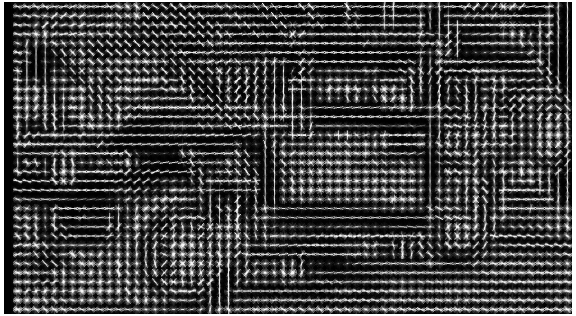
Everything: https://marvl-challenge.github.io/

2. Data Representation

Three Levels of Representation

- Perceptual
- Pre-processed features
- Raw input

- ❏ Yellow
- ❏ Has wheels
- ❏ Metal
- ❏ Five-door
- ❏ Can transport
- ❏ …



Images: http://www.cs.columbia.edu/~vondrick/ihog/

Perceptual Norms

- Ask people to write down the words that are triggered by textual stimuli.
- Stimuli: 541 noun concepts
- Norms are categorized into the likely knowledge source

Moose

is large	27	visual–form and surface
has antlers	23	visual–form and surface
has legs	14	visual–form and surface
has four legs	12	visual–form and surface
has fur	7	visual–form and surface
has hair	5	visual–form and surface
has hooves	5	visual–form and surface
is brown	10	visual–color
hunted by people	17	function
eaten as meat	5	function
lives in woods	14	encyclopedic
lives in wilderness	8	encyclopedic
an animal	17	taxonomic
a mammal	9	taxonomic
an herbivore	8	taxonomic

McRae et al. (2005). Semantic feature production norms for a large set of living and nonliving things. *Behavior research methods*, *37*(4), 547.

Perceptual Norms: Pros / Cons

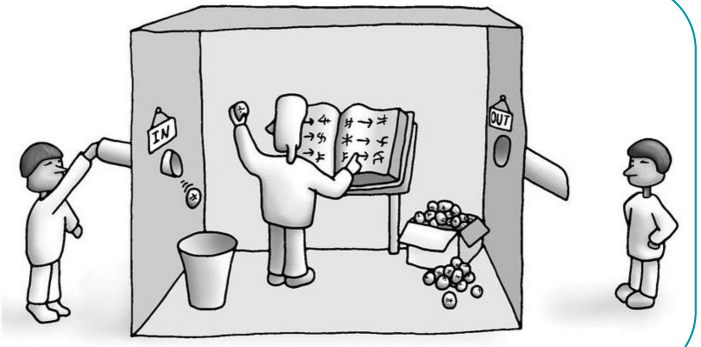
Pros

- Seemingly simple task
- Rich features

Cons

- Can it scale?
- Handling ambiguity

What does it mean to only understand symbols as defined by other symbols?

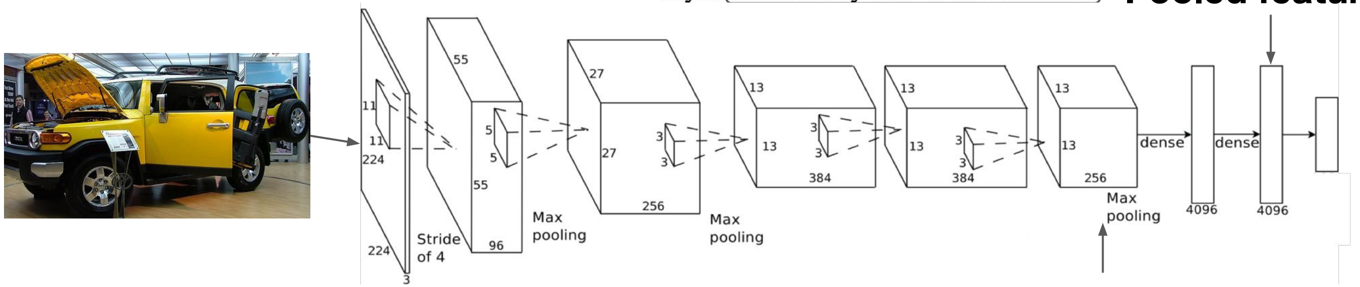


Searle. (1980). Minds, Brains and Programs. *Behavioral and Brain Sciences*, 3: 417–57

Spatial and Pooled Visual Features

- Earliest work in neural-network era used pooled or spatial preserving features from a pretrained Convolutional Neural Network.

"where $CNN(I_b)$ transforms the pixels inside bounding box I_b into $\boxed{\text{4096-dimensional activations}}$ of the fully connected layer $\boxed{\text{immediately before the classifier.}}$" **Pooled features**

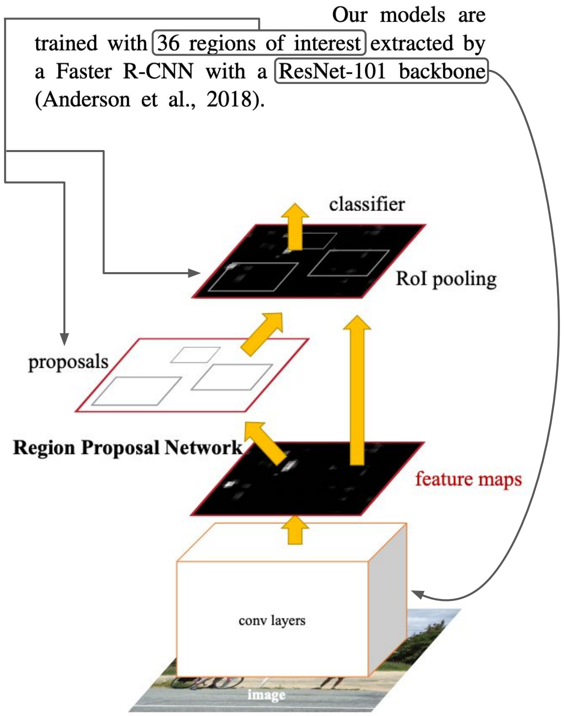


Spatial features "In our experiments we use the $\boxed{14\times14\times512 \text{ feature map}}$ of the fourth convolutional layer before max pooling."

Karpathy & Fei-Fei (2015). Deep visual-semantic alignments for generating image descriptions. CVPR.
Xu et al. (2015). Show, attend and tell: Neural image caption generation with visual attention. ICML.

Pre-processed Visual Features

- Faster R-CNN region-based feature vectors
  - Trained on the Visual Genome Dataset
  - The Region Proposal Network suggests the location of *regions of interest*.
  - RoI pooling performs spatial pooling in the final CNN layer to give a 2048D vector.



Ren et al. (2015). Faster r-cnn: Towards real-time object detection with region proposal networks. *NeurIPS.*
Bugliarello et al. (2021). Multimodal Pretraining Unmasked: A Meta-Analysis and a Unified Framework of Vision-and-Language BERTs. TACL.

Pre-processed: Pros / Cons

Pros

- Long-established practice
- Usually an offline process: do it once and forget

Cons

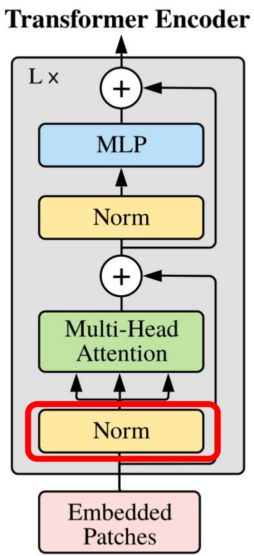
- Large datasets require specialized storage
- Not obvious how to randomly augment data
- Specialist knowledge can be opaque to newcomers

Raw Input

- Directly process data from the raw images or speech signal.
- Images:
  - Vision Transformer (ViT)
  - Swin Transformer
- Speech
  - Spectrogram Transformer
  - AudioMAE

Vision Transformer

- Good news! You are already almost an expert in how the Vision Transformer works
  - Split image into K patches
  - Embed each patch
  - Add position information
  - Encode using Transformer blocks that include an extra pre-norm layer for stability.



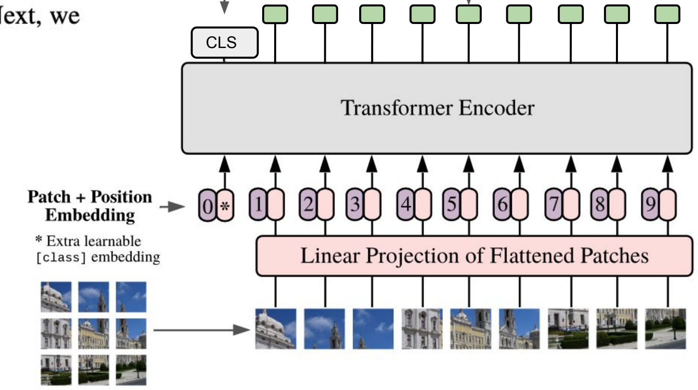
Dosovitskiy et al. (2021). An image is worth 16x16 words: Transformers for image recognition at scale. ICLR.
Baevski & Auli (2018). Adaptive input representations for neural language modeling. *ICLR.*

Extracting ViT Features

- Extract pooled features or patch-level features

To extract visual information from an image x^i, we use the visual encoder of a pre-trained CLIP [29] model. Next, we

For the CLIP encoders, we extract the feature grid before the pooling layers, resulting in an $N \times N$ grid, where $N = 7, 7, 12$ for the ViT-B/32, RN50x4 and RN50x16 variants of CLIP respectively.



Raw input: Pros / Cons

Pros

- Data augmentation is straightforward because you always have the raw input
- Fewer preprocessing steps means fewer creeping errors

Cons

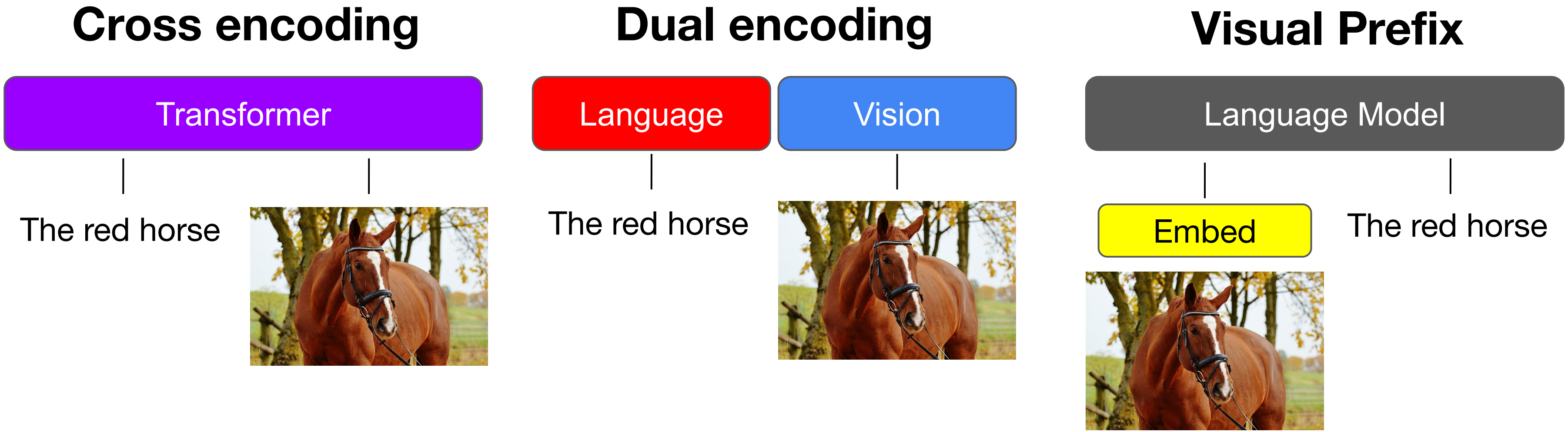
- Smaller batches with an extra model on the GPU
- Potentially many inputs

Summary

- Many options for how to represent your multimodal inputs
  - Language-oriented
  - Object / stuff oriented
  - Raw inputs
- **No universally best option** but raw inputs are promising because the visual representation model can be fully differentiable.

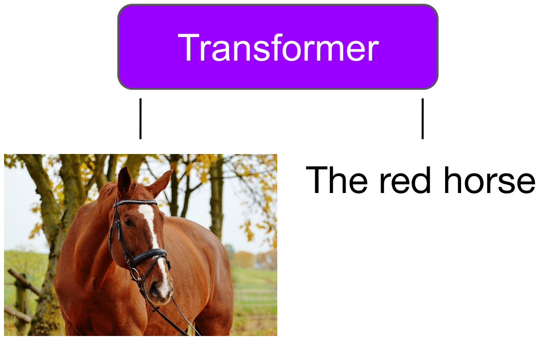
3. Modelling

Main Approaches



Cross-encoding Models

- Emerged as a key modelling approach in 2019 with a flurry of approaches to creating visually-grounded BERT models.
- This is a form of *model-based fusion*
- The backbone consists of two components:
  - language model
  - visual encoder



Tan & Bansal (2019). LXMERT: Learning Cross-Modality Encoder Representations from Transformers. EMNLP-IJCNLP.
Lu et al. (2019). ViLBERT: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks. NeurIPS.

High-level Overview

Image:
Faster R-CNN, or
raw pixels + ViT

Language:
BERT tokens

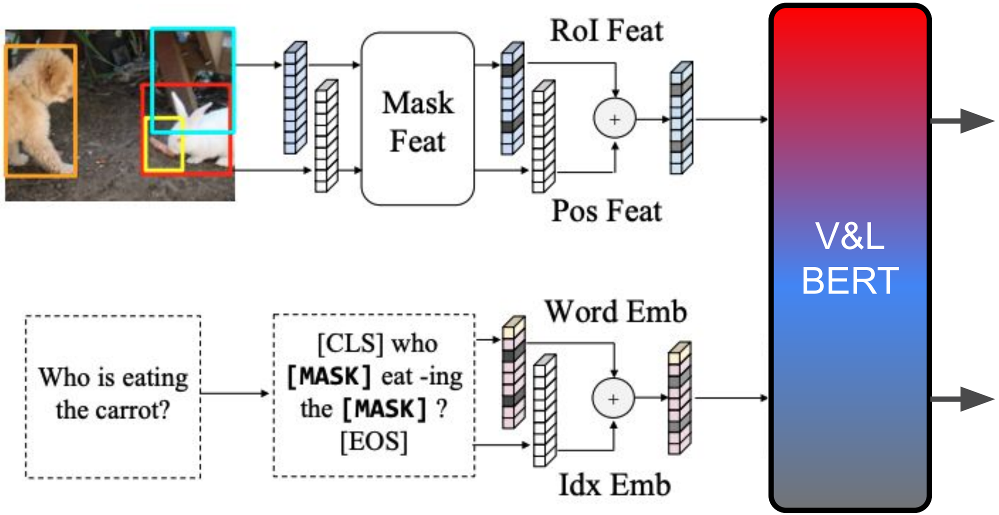
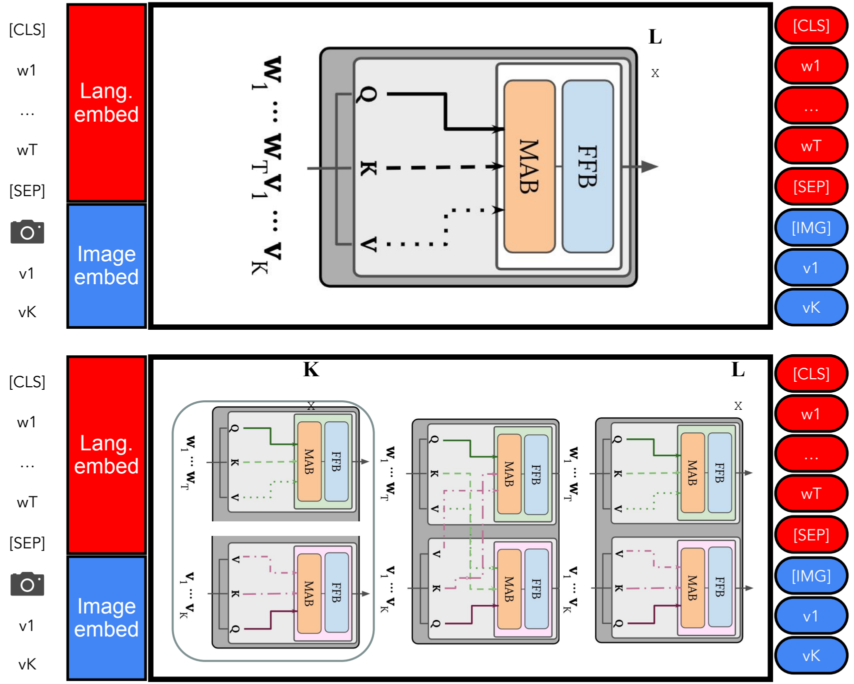


Figure: Tan & Bansal (2019). LXMERT: Learning Cross-Modality Encoder Representations from Transformers. EMNLP-IJCNLP

Single- & Dual-Stream Architectures

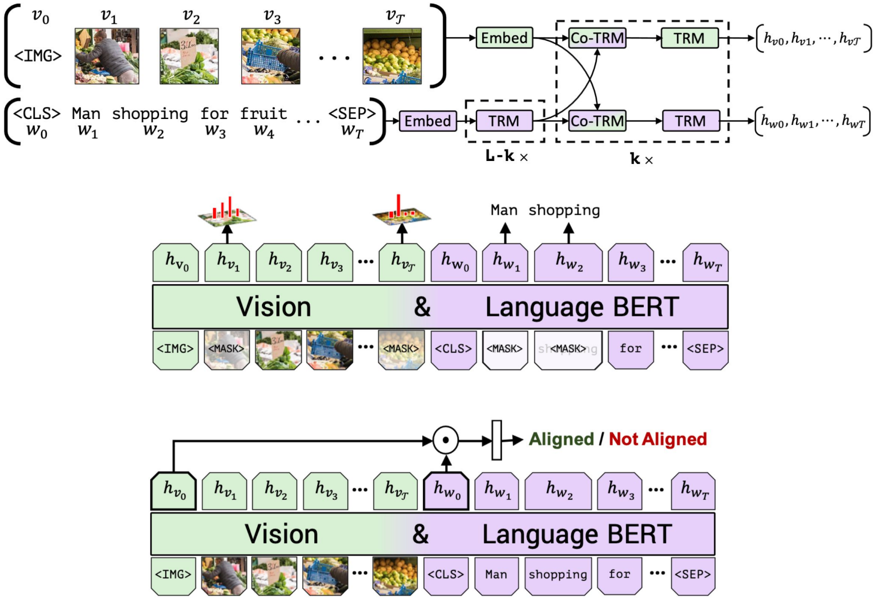
- Single-stream
  - Concatenate inputs into one sequence
- Dual-stream
  - Process modalities independently
    - Intra-modal
    - Inter-modal



Bugliarello et al. 2021. Multimodal Pretraining Unmasked: A Meta-Analysis and a Unified Framework of Vision-and-Language BERTs. TACL.

2019: ViLBERT

- Dual-stream model
- Initialized from BERT
- Visual features extracted from 10-36 regions using Faster-RCNN
- Pretrained on Conceptual Captions
  - Masked Language Modelling
  - Masked Region Classification
  - Image-Text Matching



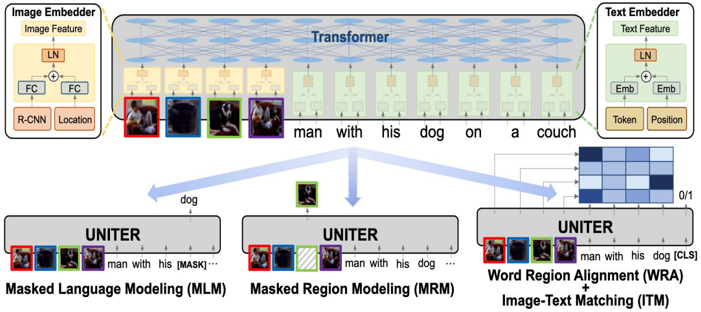
Lu et al. (2019). ViLBERT: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks. NeurIPS.

MLM, MRC, ITM

- Masked Language Modelling $\mathcal{L}_{\mathrm{MLM}}(\theta) = -\mathbb{E}_{(\mathbf{w},\mathbf{v})\sim D} \log P_\theta(\mathbf{w_m}|\mathbf{w}_{\backslash\mathbf{m}}, \mathbf{v})$
  - Same as BERT et al.
- Masked Region Classification $\mathcal{L}_{\mathrm{MRM}}(\theta) = \mathbb{E}_{(\mathbf{w},\mathbf{v})\sim D} f_\theta(\mathbf{v_m}|\mathbf{v}_{\backslash\mathbf{m}}, \mathbf{w})$
  - Mean Squared Error Regression over the 2048D feature vector; or
  - Predict the probability distribution over the 1600 Faster R-CNN classes
- Image-Text Matching $\mathcal{L}_{\mathrm{ITM}}(\theta) = -\mathbb{E}_{(\mathbf{w},\mathbf{v})\sim D}[y \log s_\theta(\mathbf{w},\mathbf{v}) + (1-y)\log(1-s_\theta(\mathbf{w},\mathbf{v}))])$
  - 50% chance of randomly sampling a mis-matched sentence
  - Predict with a binary classifier (aka Next Sentence Prediction)
- Note: 15% masking usually spans both modalities

2020: UNITER

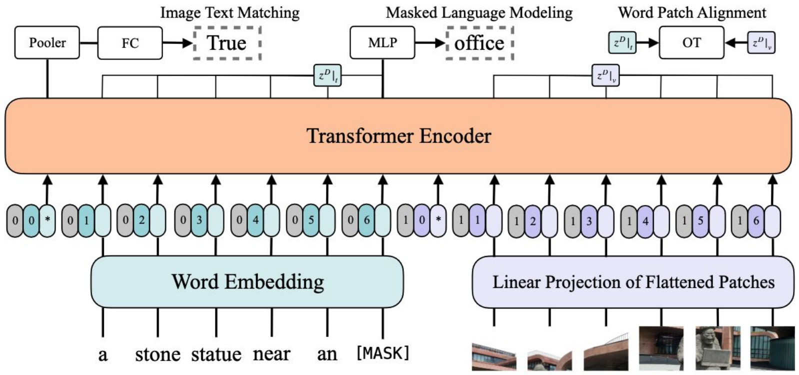
- Single-stream model
- Initialized from BERT
- Visual features from Faster-RCNN
- Pretrained on Conceptual Captions, Visual Genome, COCO, SBU Captions
    - Masked Language Modelling
    - Masked Region Classification
    - Image-Text Matching
    - Word-Region Alignment



Chen et al. (2020). UNITER: Universal image-text representation learning. ECCV.

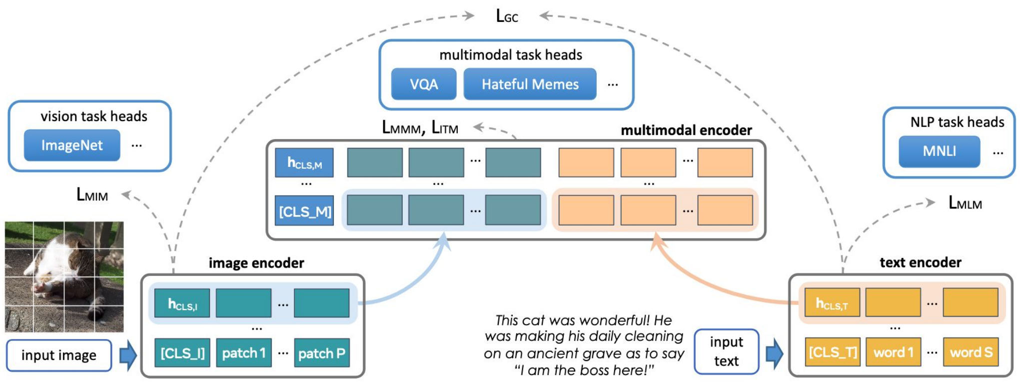
2021: ViLT

- Single-stream model
- Initialized from BERT
- Visual features extracted from ViT-B/32
- Pretrained on Conceptual Captions, Visual Genome, COCO, SBU Captions
    - Masked Language Modelling
    - Image-Text Matching
    - Word-Patch Alignment



Kim et al. (2021). ViLT: Vision-and-language transformer without convolution or region supervision. ICML.

2022: FLAVA



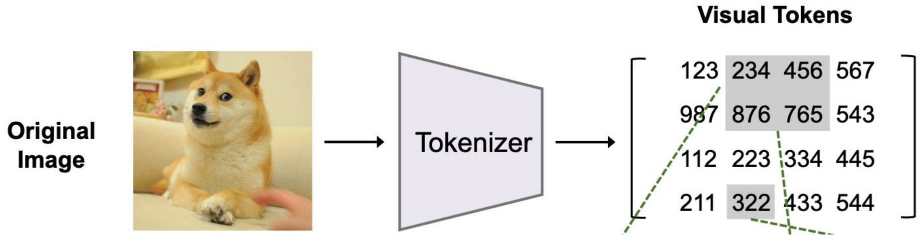
- Dual-stream Visual features extracted from ViT-B/16
- Pretrained on PMD70M
  - Masked Language Modelling, Masking Image Modelling
  - Image-Text Matching, Masked Multimodal Modelling
  - Global Contrastive Matching

Singh et al. (2022). FLAVA: A foundational language and vision alignment model. CVPR.

MIM and CL

- Masked Image Modelling
  - Immediately after the image encoder and before multimodal encoding
  - Tokens from a discrete VAE (BEIT)

$$\sum_{i\in\mathcal{M}} \log p_{\mathrm{MIM}}(z_i|x^{\mathcal{M}})$$

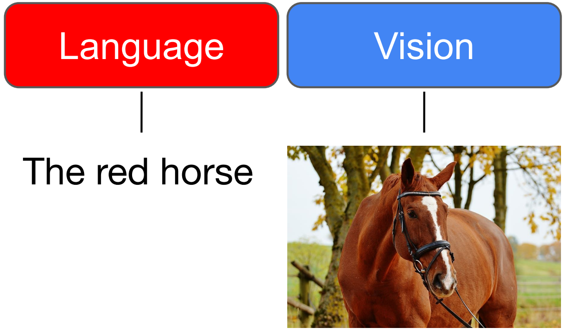


- Contrastive Loss
  - On the CLS embedding of each unimodal encoder $\mathcal{L}_{\mathrm{InfoNCE}} = -\mathbb{E}\left[\log \frac{f(\mathbf{t},\mathbf{i})}{\sum_{\mathbf{t}'\in T} f(\mathbf{t}',\mathbf{i})}\right]$

Bao et al. (2021). BEiT: BERT Pre-Training of Image Transformers. ICLR.
Radford et al. (2021). Learning transferable visual models from natural language supervision. ICML.

Dual-encoding Models

- Emerged as a sample-efficient alternative to cross-encoding.
- The backbone consists of two separate components:
  - language encoder
  - visual encoder



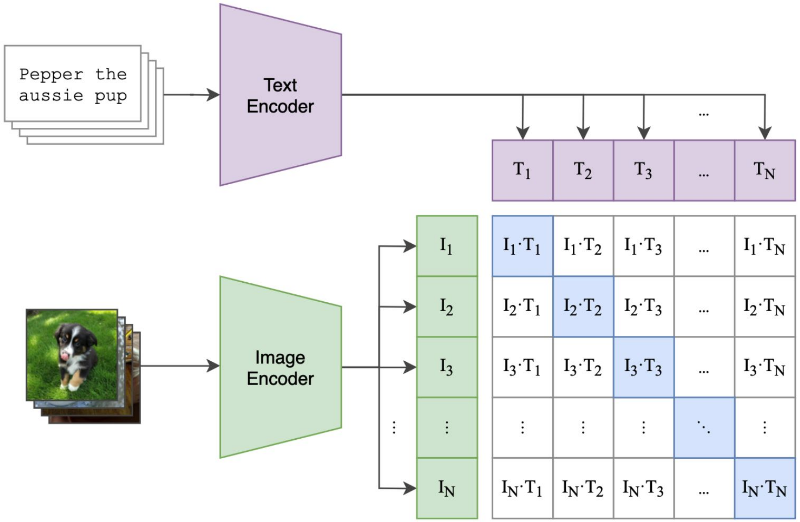
Radford et al. (2021). Learning transferable visual models from natural language supervision. ICML.

CLIP

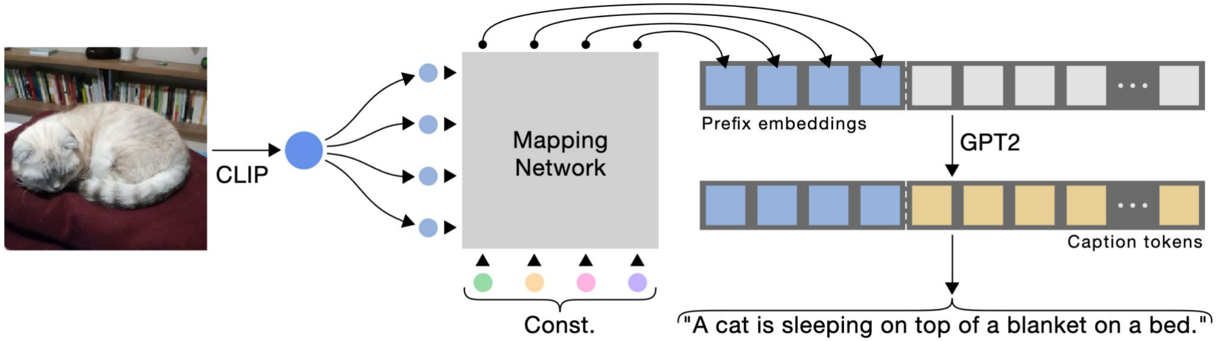
- 12 Layer Transformer Encoder
- ViT or ResNet Visual Encoder

- Maximize the similarity of the embeddings of paired examples (I, T):

$$\mathcal{L}_{\text{InfoNCE}} = -\mathbb{E}\left[\log \frac{f(\mathbf{t}, \mathbf{i})}{\sum_{\mathbf{t}' \in T} f(\mathbf{t}', \mathbf{i})}\right]$$



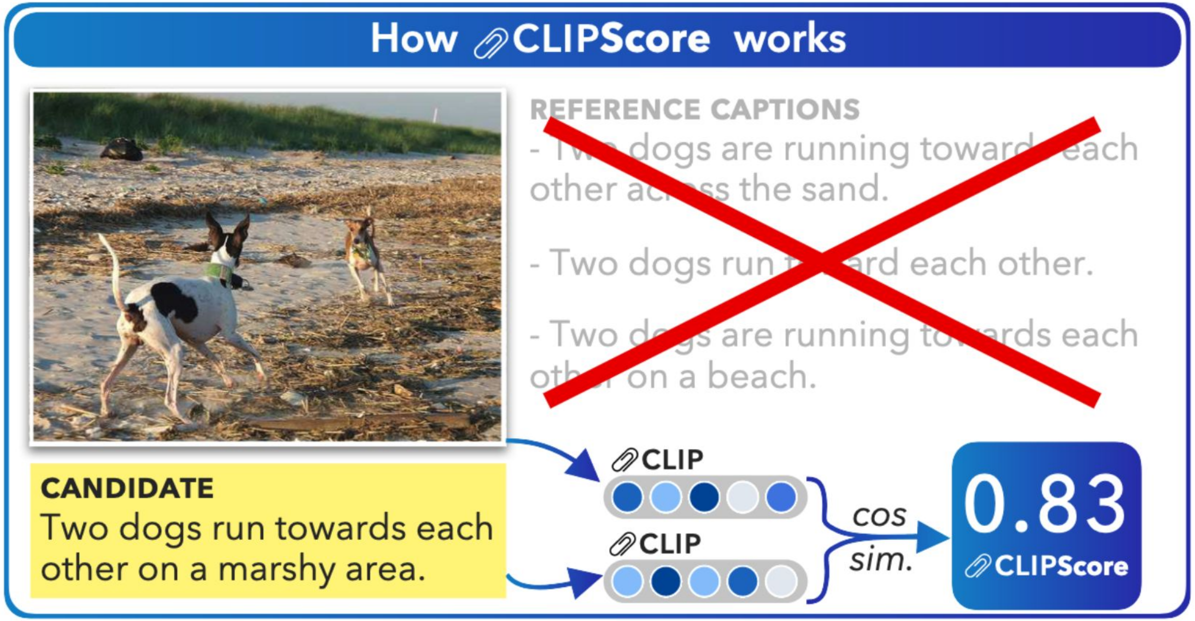
CLIP for Captioning



- Use CLIP as a feature extractor and GPT-2 as a language model.
  - Only train the mapping network to generate prefix embeddings
  - Lightweight system that exploits pretrained models

Mokady et al. (2021). ClipCap: CLIP Prefix for Image Captioning. arXiv.

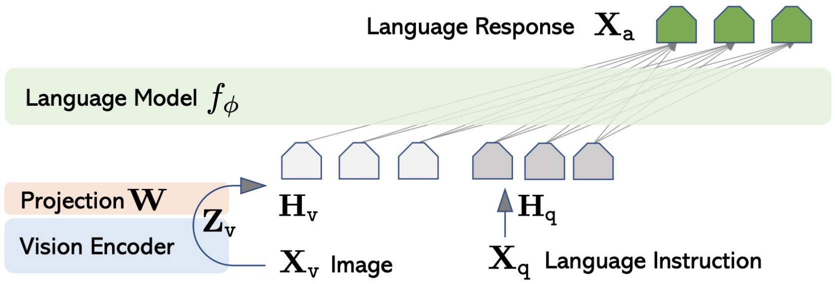
CLIP for Evaluation

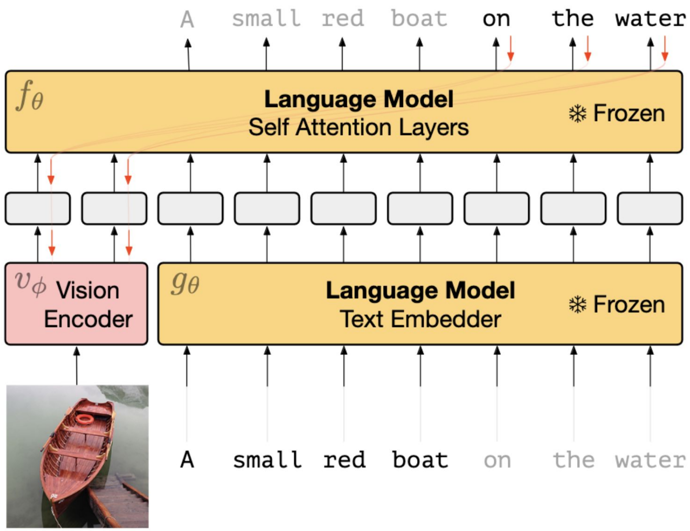


Hessel et al. (2021). CLIPScore: A Reference-free Evaluation Metric for Image Captioning. EMNLP.

Visual Prefix Learning

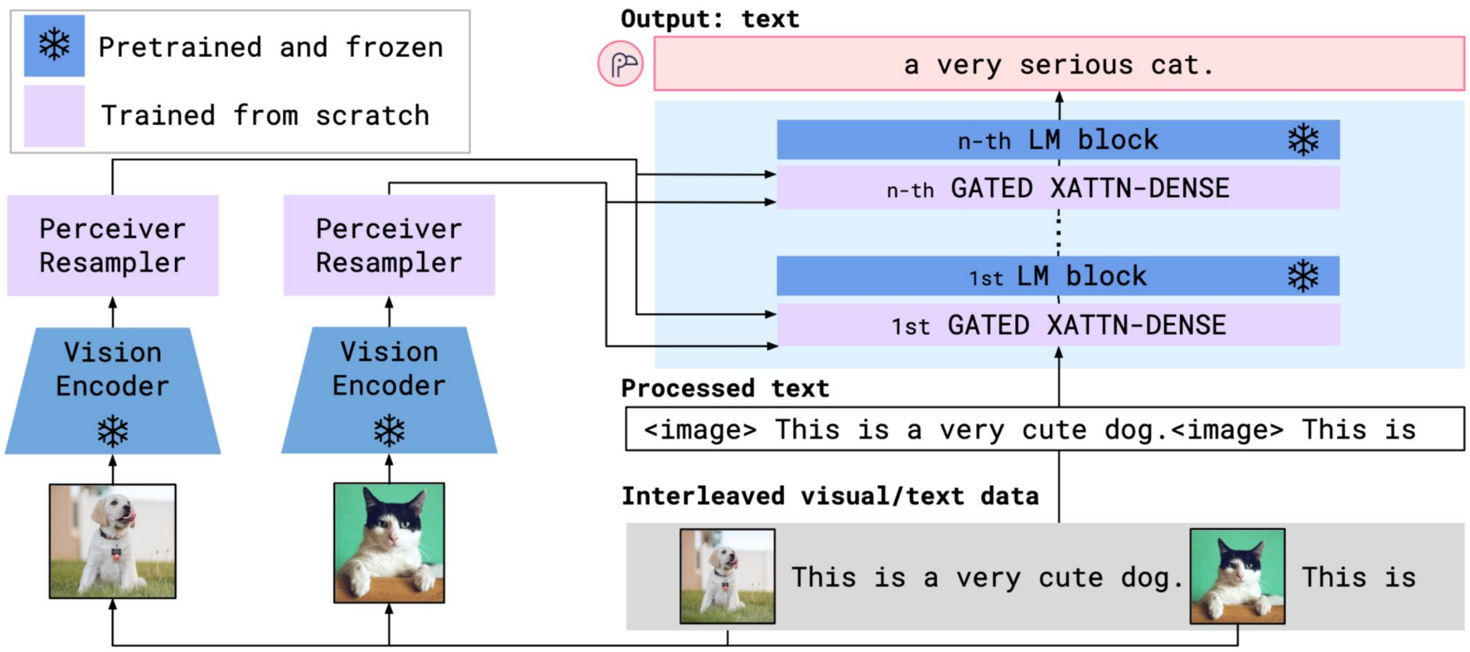
- Exploit the representations learned during large-scale modality specific pretraining





Tsimpoukelli et al. NeurIPS 2021. Multimodal Few-Shot Learning with Frozen Language Models.
Liu et al. NeurIPS 2023. Visual Instruction Tuning.

Learning Dense Cross-Attention



Alayrac et al. NeurIPS 2022. Flamingo: a Visual Language Model for Few-Shot Learning

Summary

- Cross-encoding:
  - Many advances in which parts of the input contribute to loss
  - Shift from regions-of-interest to Vision Transformers
- Dual-encoding:
  - Excellent cross-domain transfer to a wide range of problems
- Visual Prefix Learning:
  - Exploit the benefits of single-modality pretraining

Q: Do we need to learn everything for image captioning in-weights?

SmallCap: Lightweight Image Captioning Prompted with Retrieval Augmentation

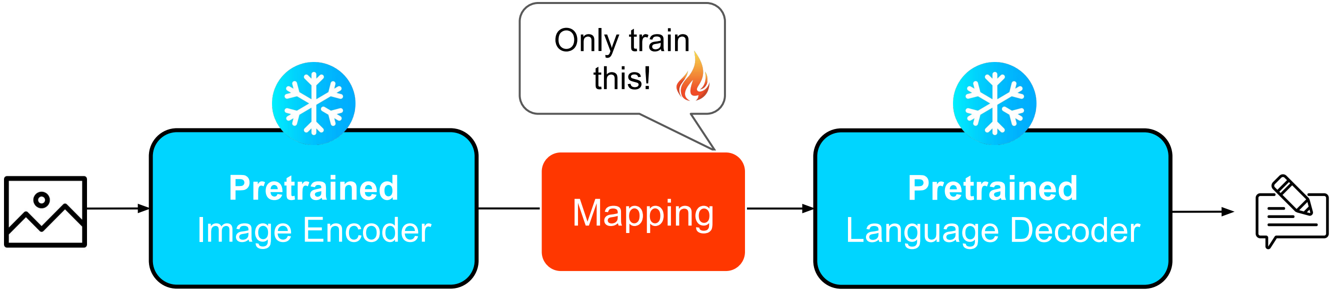
CVPR 2023




R. Ramos B. Martins D. Elliott Y. Kementchedjhieva

Motivation

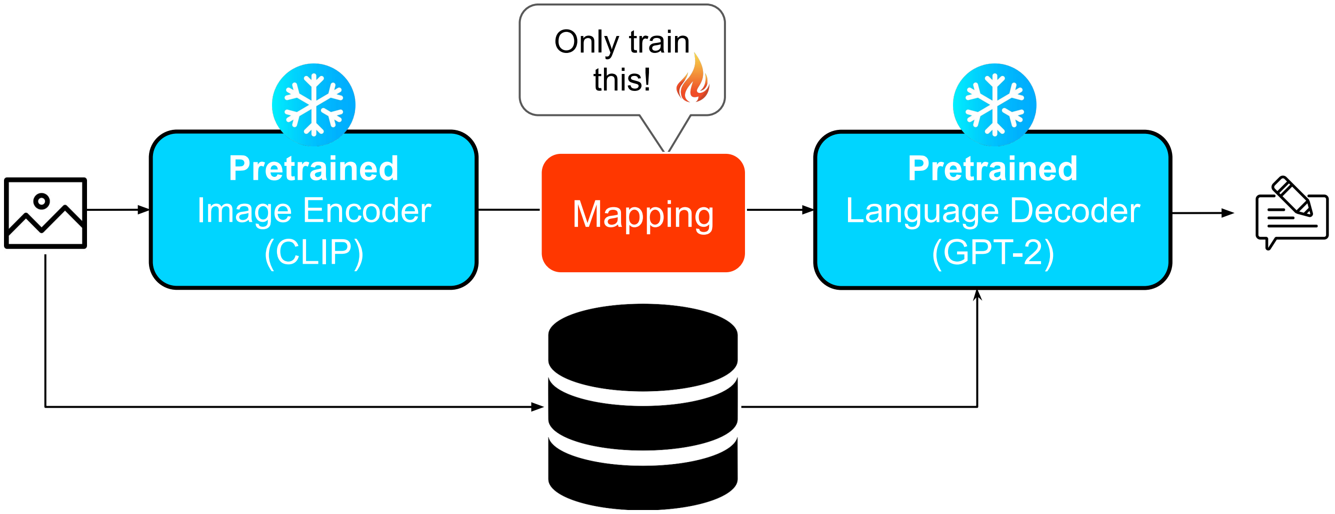
- Main trend in V&L is training bigger models on more data
- Alternative is emerging that re-uses independent backbone models
  - CLIPCap, I-Tuning



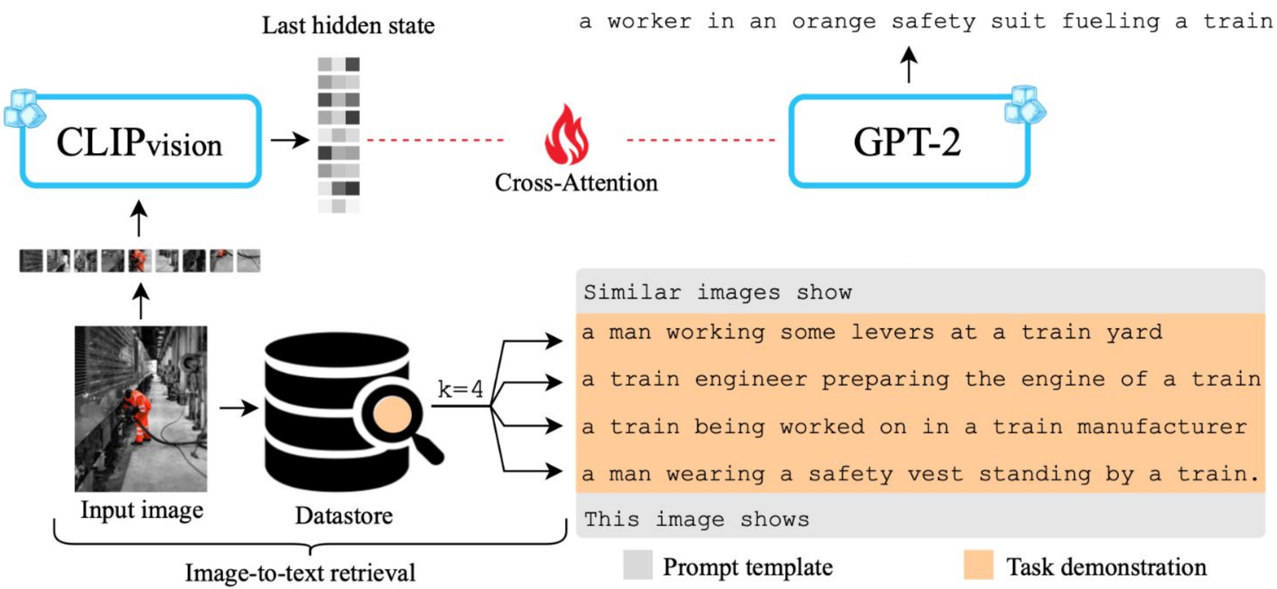
Mokady et al. (2021). ClipCap: CLIP Prefix for Image Captioning. arXiv.
Luo et al. (2023). I-Tuning: Tuning Frozen Language Models with Image for Lightweight Image Captioning. ICASSP.

Lightweight Training trough Retrieval

- Given the success of multimodal retrieval augmentation, can we extend this to the lightweight training paradigm?

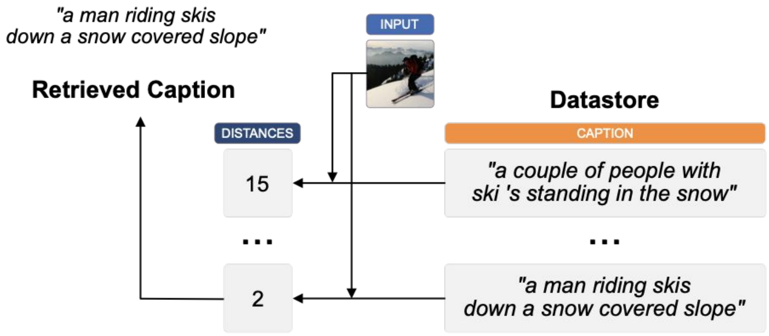


SmallCap Model



Retrieval System

- Build a FAISS datastore: store high-dimensional vectors
  - Captions of images represented with CLIP embeddings
- Retrieve k nearest-neighbours captions from datastore
  - Image embedding compared against datastore caption vectors



Johnson et al. (2019). Billion-scale similarity search with GPUs. IEEE Big Data

Experimental Setup

- Pretrained CLIP-ViT-B/32 and GPT/OPT backbone models
- Randomly initialize the cross-attention layer
- Train only on COCO in only 8 hours on 1 x 40GB NVIDIA A100 GPU

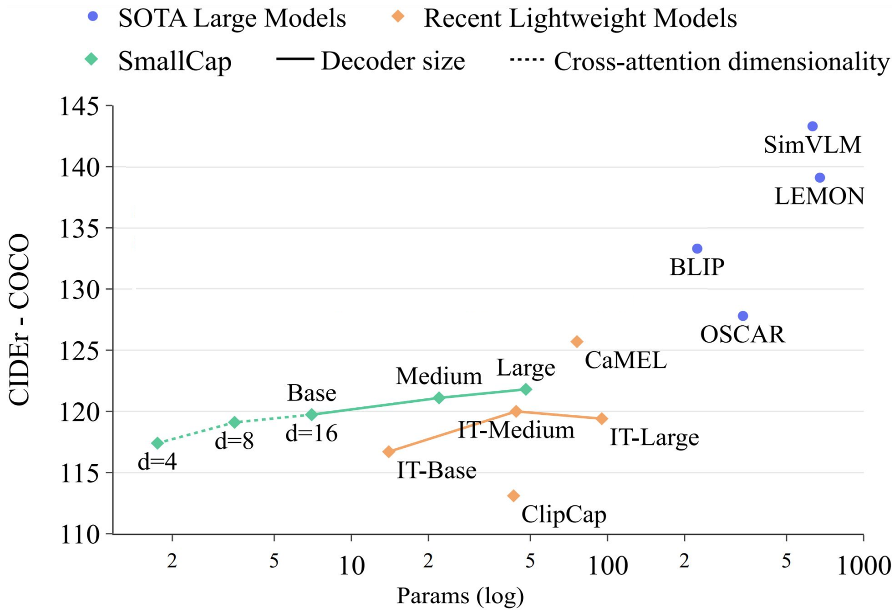
Low-rank cross-attention

$$\mathrm{Att}(\mathbf{QW}_i^Q, \mathbf{KW}_i^K, \mathbf{VW}_i^V)$$

$W_i^K, W_i^Q, W_i^V \in R^{d\_encoder \times \mathbf{d}}$

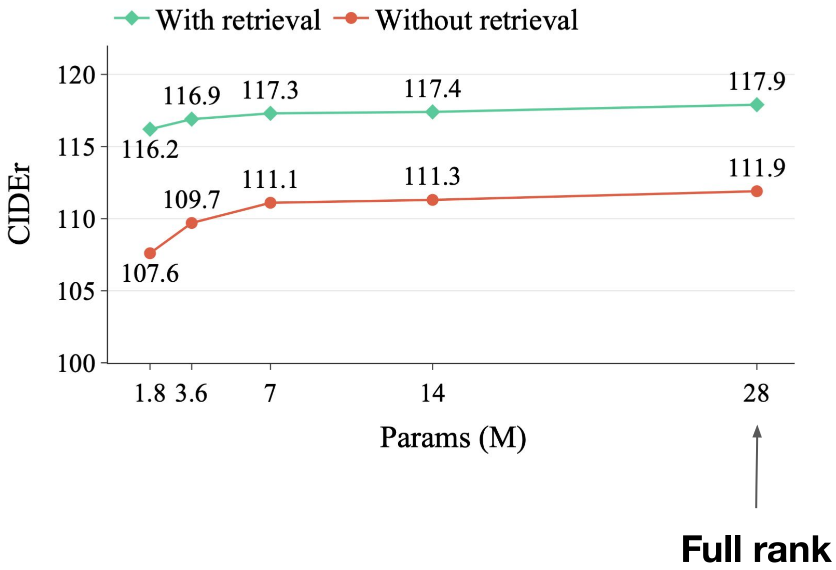
Attention rank	Params
d=64 (Full)	22M
d=16	7M
d=8	3.6M
d=4	1.8M

Results



- Outperform other lightweight approaches
- Effective with low-rank matrices: 4,8,16 << 64
- Larger pretrained decoders further improve performance

Importance of Retrieval Augmentation



- With retrieval:
  - Performance is stable across the range of cross-attention sizes
- Without retrieval:
  - SMALLCAP model performance degrades at a higher rate

Training-Free Domain Transfer

- SmallCap was trained on COCO but we can easily swap the datastore.
- Much stronger performance than other lightweight approaches

	Flickr30k	VizWiz	MSR-VTT
ClipCap	41.2	28.3	12.5
CaMEL	55.2	37.6	20.7
SMALLCAP	**60.6**	**55.0**	**28.4**

Qualitative Example on VizWiz

COCO

- some carrots potatoes garlic an onion and some chicken broth
- a selection of ingredients for soup includes carrots, meat, and prepackaged broth
- this is the makings of a meal with chicken and vegetables
- the meal has chicken, bread, and cole slaw

Generated caption:

a close up of a plate of food on a table

VizWiz

- a can of swanson fat free chicken broth
- a can of swanson brand chicken broth with less sodium
- a 14,5 ounce can of swanson branded chicken broth
- a can of swanson chicken broth on a table

Generated caption:

a can of swanson brand chicken broth on a table

Try it yourself

Demo: https://huggingface.co/spaces/RitaParadaRamos/SmallCapDemo

Conclusions

- SmallCap:
  - light to train
  - easily transferred across domains without retraining
- Prompt-based conditioning method, wherein retrieved captions are used as a prompt to a generative language model
- Strong performance in out-of-domain settings

Q: Do you even need to train?

LMCap: Few-shot Multilingual Image Captioning by Retrieval Augmented Language Model Prompting

Findings of ACL 2023


R. Ramos


B. Martins


D. Elliott

Socratic Models

- Enable models to "communicate" with each other through their output labels, prompting, and ranking

$$f^3_{\text{VLM}}(f^2_{\text{LM}}(f^1_{\text{VLM}}(\text{image})))$$

detect things

generate captions

re-rank

I am an intelligent image captioning bot. This image is a {img_type}. There {num_people}. I think this photo was taken at a {place1}, {place2}, or {place3}. I think there might be a {object1}, {object2}, {object3},... in this {img_type}. A creative short caption I can generate to describe this image is:

SM (ours): This image shows an inviting dining space with plenty of natural light.

ClipCap: A wooden table sitting in front of a window.

Zeng et al. (2023). Socratic Models: Composing Zero-Shot Multimodal Reasoning with Language. ICLR.

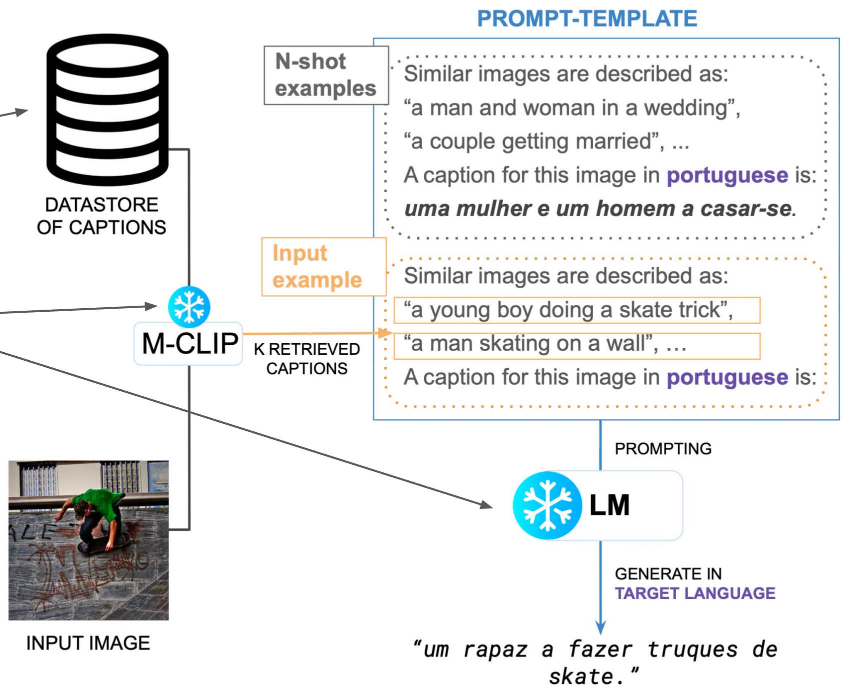
Multilingual Captioning with Retrieval Augmentation

$$f^3_{\mathrm{VLM}}(f^2_{\mathrm{LM}}(f^1_{\mathrm{VLM}}(\text{image})))$$

detect things

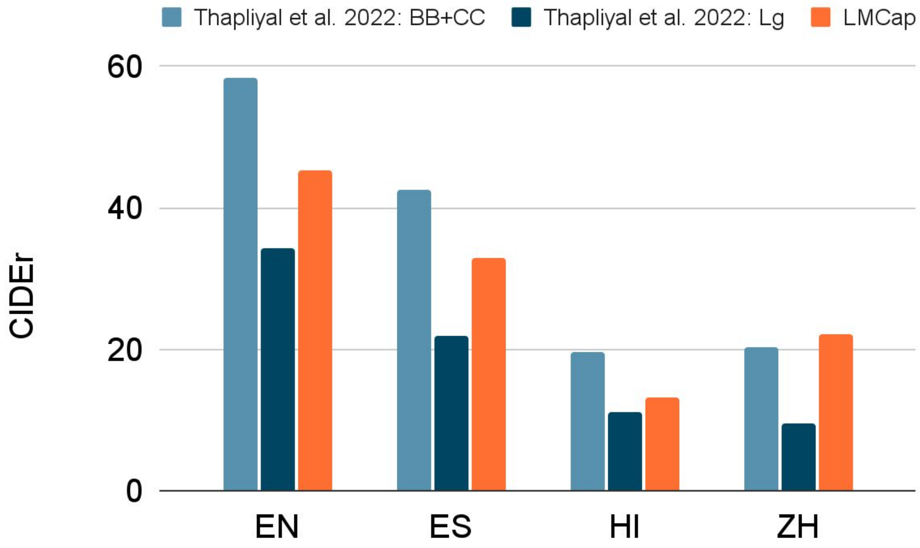
generate captions

re-rank



- Prompt with N-shot examples of transforming captions into the target language

Results



Params	RAM	en	es	hi	zh
564M	6G	0.411	0.094	0.030	0.146
1.7B	12G	0.637	0.143	0.066	0.272
2.9B	16G	0.767	0.454	0.334	0.584
7.5B	22G	**0.787**	**0.489**	**0.365**	**0.644**

Competitive against **fully supervised** models

Need **at least 2.9B** parameter decoder for multilingual generation

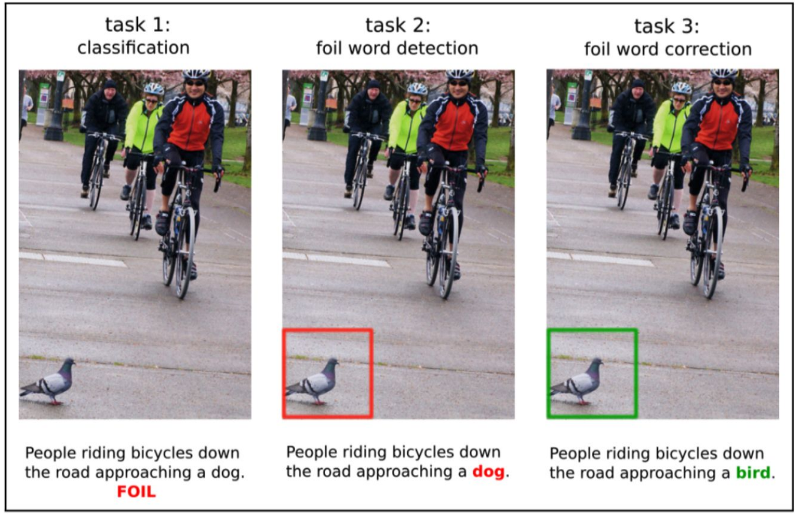
4. Understanding Multimodal Models

Beyond Benchmarking

- Many questions about what drives the success of these models?
  - Better contextualization: make better use of the multimodal inputs
  - Acquire certain “skills”, e.g. counting or localization
  - Understand linguistic structures
  - Something else?
- Model-internal behaviour
  - Attention mechanism patterns
- Probing
  - Tasks related to different skills

FOIL Captions

- Do V&L models really understand the relationship between words and images?
- Crowdsource datasets that contain contextually plausible but incorrect image–text pairs



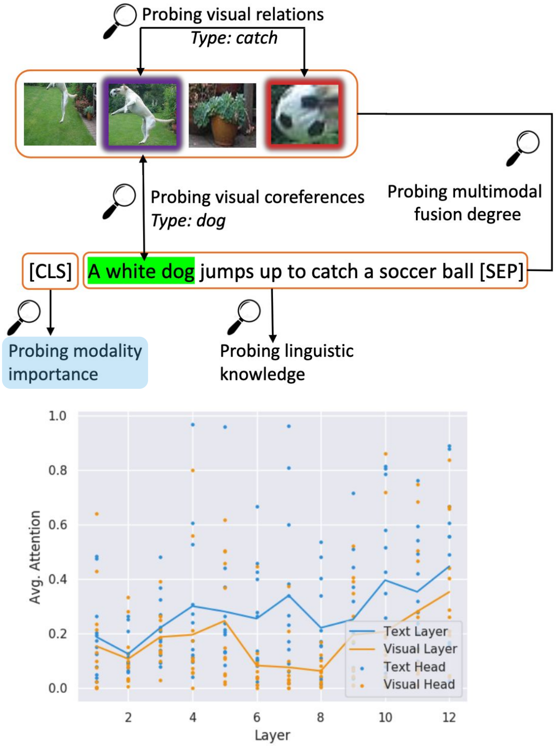
Shekhar et al. (2017). FOIL it! Find One mismatch between Image and Language caption. ACL.

Vision and Language Understanding Evaluation

- Suite of five model probing tasks
- **Modality Influence**: Estimate the layer-wise contribution of each modality to the `[CLS]` embedding:

$$I_{M,j} = \sum_{i \in S} \mathbb{1}(i \in M) \cdot \alpha_{ij}$$

  - The UNITER model relies more on textual features when fusing modalities throughout the model



Cao et al. (2020). Behind the scene: Revealing the secrets of pre-trained vision-and-language models. ECCV.

VALSE Benchmark

- Test visio-linguistic capabilities with image-sentence foil pairs
- Image-sentence matching task
  - Existential quantifiers
  - Semantic number
  - Counting
  - Prepositional relations
  - Action replacement / swap
  - Co-reference

A small copper vase with some flowers / exactly one flower in it.

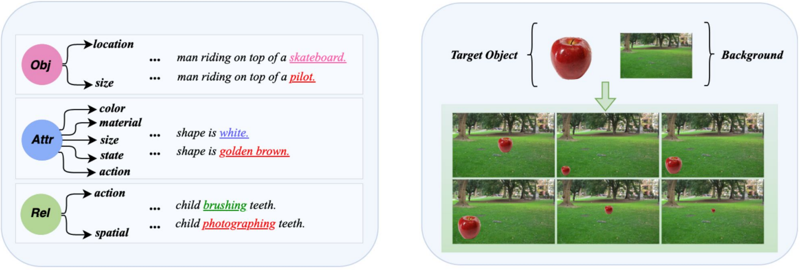
Metric	Model	Avg.
	Random	50.0
acc_r	GPT1*	60.7
	GPT2*	60.1
	CLIP	64.0
	LXMERT	59.6
	ViLBERT	63.7
	12-in-1	**75.1**
	VisualBERT	46.4

$$p(caption, img) > p(foil, img)$$

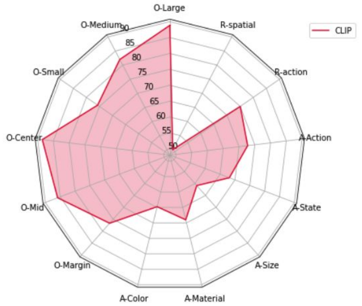
Parcalabescu et al. (2022). VALSE: A Task-Independent Benchmark for Vision and Language Models Centered on Linguistic Phenomena. ACL.

VL-CheckList

- Evaluate V&L models based on automatic manipulations to vision and language data.
- Image-Sentence matching task
- Radar chart overviews based on object / attribute / relationship variations



(a) Language Variation
(b) Vision Variation



Zhao et al. (2022). An Explainable Toolbox for Evaluating Pre-trained Vision-Language Models. EMNLP.

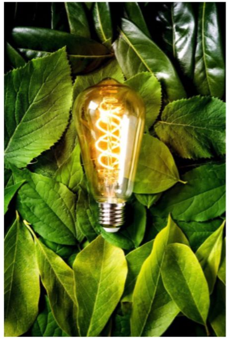
Subject-Verb-Object Probes

- Large-scale dataset with SVO triplets mined from Conceptual Captions and 14K images and with crowdsourced captions
- Foil detection formulation

Hendricks and Nematzadeh. (2021). Probing Image–Language Transformers for Verb Understanding. ACL.

WinoGround

- 1,600 text-image pairs to evaluate compositional understanding



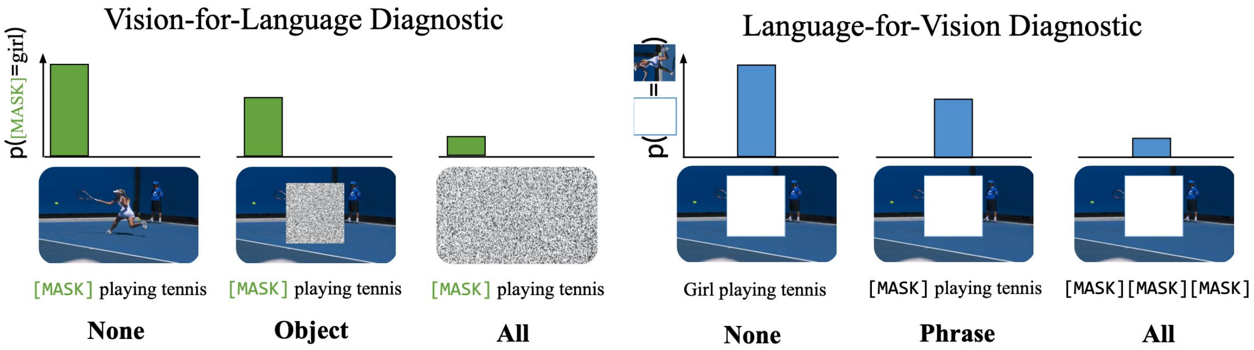
some plants surrounding a lightbulb

a lightbulb surrounding some plants

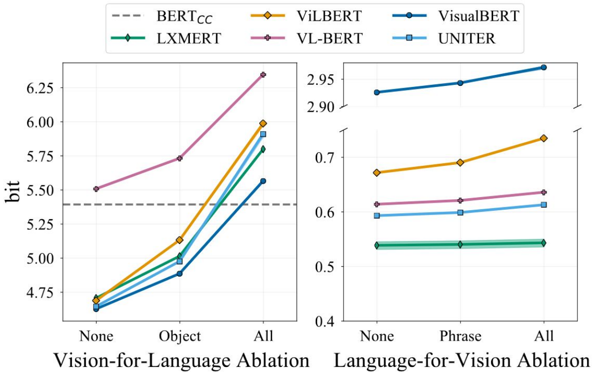
- Images sourced **with permission** from Getty.
- Differences are categorised into: swap dependent, swap-independent, and visual differences

Thrush et al. (2022). Winoground: Probing vision and language models for visio-linguistic compositionality. CVPR.

Vision-for-Language?



- Pair of diagnostic evaluations that can be applied to any model that makes MLM and MRC predictions.



Frank et al. (2021). Vision-and-Language or Vision-for-Language? On Cross-Modal Influence in Multimodal Transformers. EMNLP.

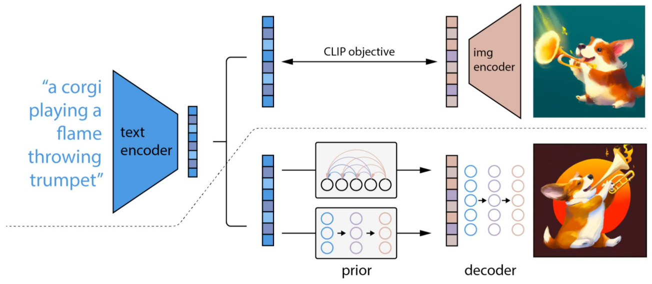
Summary

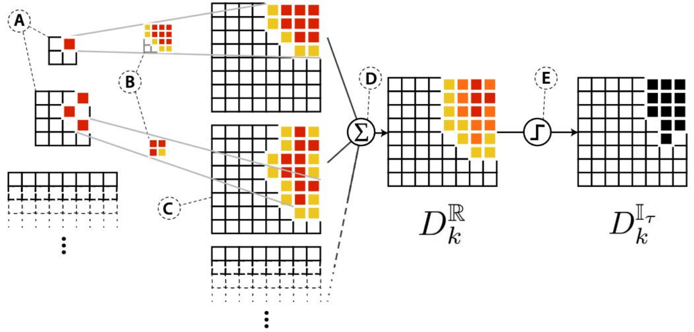
- Understanding and analysis is a vibrant area of research
- Foil detection is the most popular methodology
- Witnessing a methodological shift
  - attention analyses to linguistically-informed analyses
  - hand-crafted datasets
  - simpler accuracy-based metrics

5. Future Directions

Text-to-Image Generation

- Two main approaches: VQVAE and Conditional diffusion
- Big questions:
  - Do these models produce verifiably correct outputs?
  - How can they deal with cross-cultural generation?

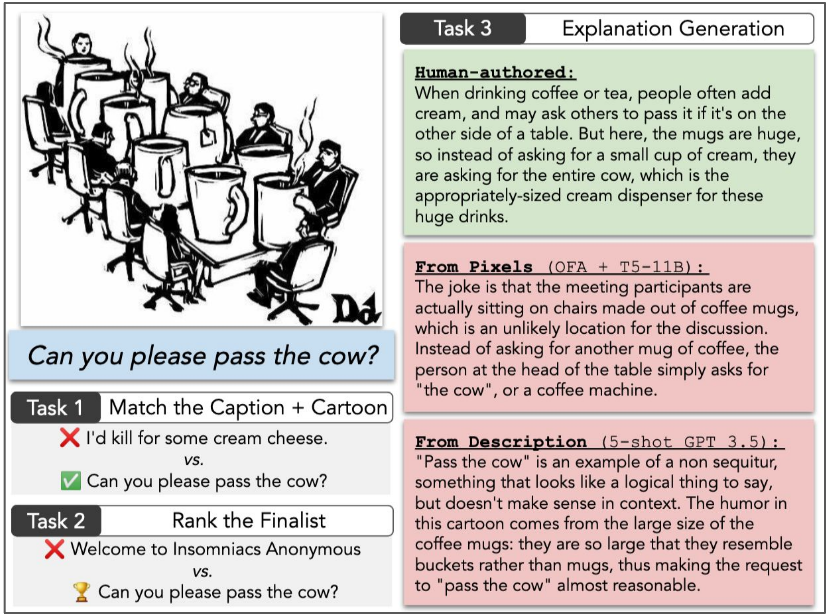




Tang et al. (2023). What the DAAM: Interpreting Stable Diffusion Using Cross Attention. ACL.

Humour

- Could humour a new frontier in multimodal understanding?
    - Non-literal understanding
    - Deeper multimodal interaction
    - Social / world-level knowledge



Hessel et al. (2023). Do Androids Laugh at Electric Sheep? Humor “Understanding” Benchmarks from The New Yorker Caption Contest. ACL.

Physical Understanding

- Predicting and explaining physical actions in the world will become of increasing importance as we create embodied agents

Q: How many objects are prevented by the tiny green triangle from falling into the basket?

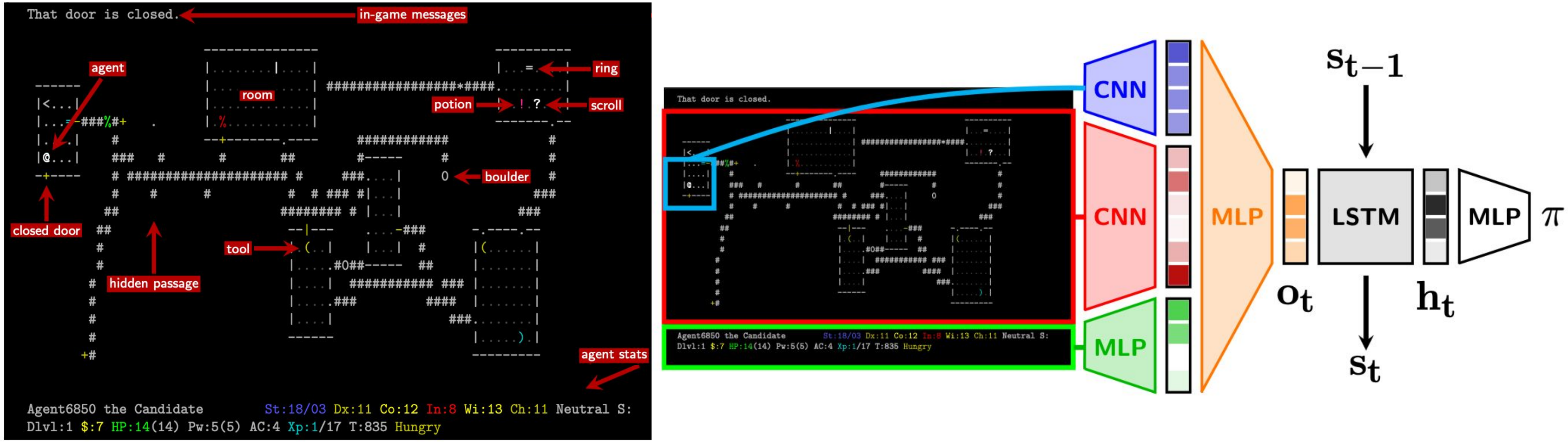
Q: What is the color of the last object that collided with the tiny red circle?

Q: If any of the other objects are removed, will the tiny green circle end up in the basket?

Ates et al. (2022). CRAFT: A Benchmark for Causal Reasoning About Forces and inTeractions. ACL.

Multimodality and Interaction

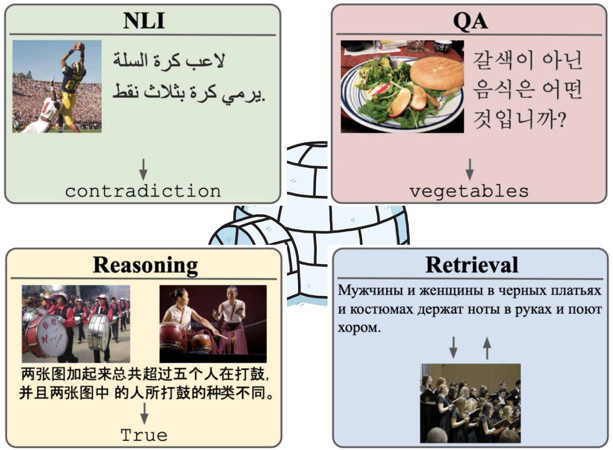
- Learning to act in procedurally-generated video game environments with rich contexts, action spaces, and long-term rewards



Küttler et al. (2020). The NetHack Learning Environment. NeurIPS.

Multilinguality

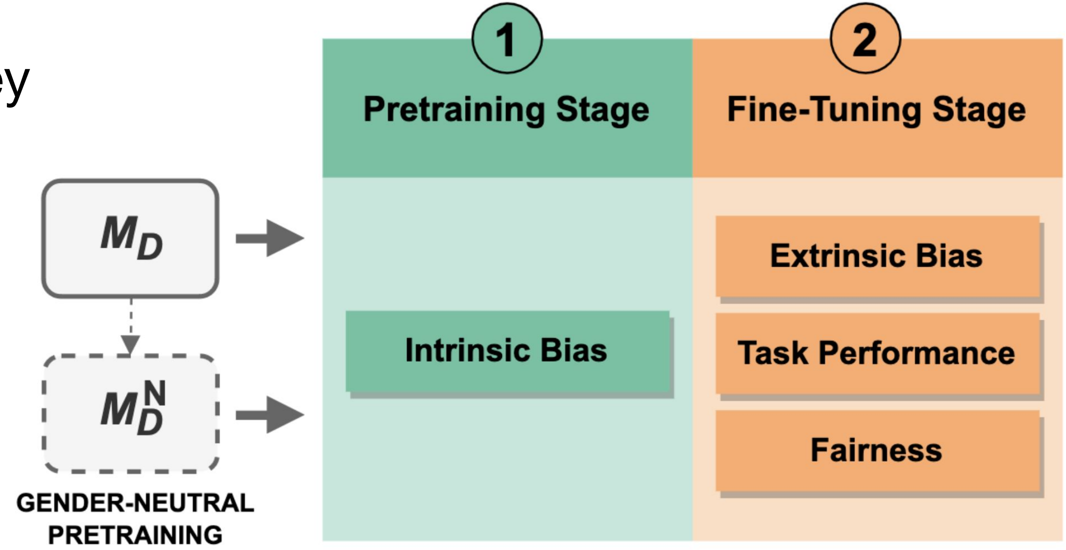
- The majority of Vision and Language research is in English
- We need resources, models, and evaluations to create useful multilingual multimodal models
- High-quality data requires:
  - time
  - money
  - community engagement



Bugliarello et al. (2022). IGLUE: Image-Grounded Language Understanding Evaluation. ICML.

Bias and Fairness

- What are the intrinsic biases learned during multimodal pretraining and how do they affect downstream task performance?



Cabello et al. EMNLP 2023. Evaluating Bias and Fairness in Gender-Neutral Pretrained Vision-and-Language Models

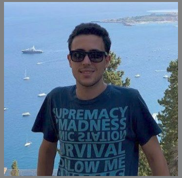
Q: What if we treated language as vision?

Language Modelling with Pixels

ICLR 2023


P. Rust


J. F. Lotz


E. Bugliarello

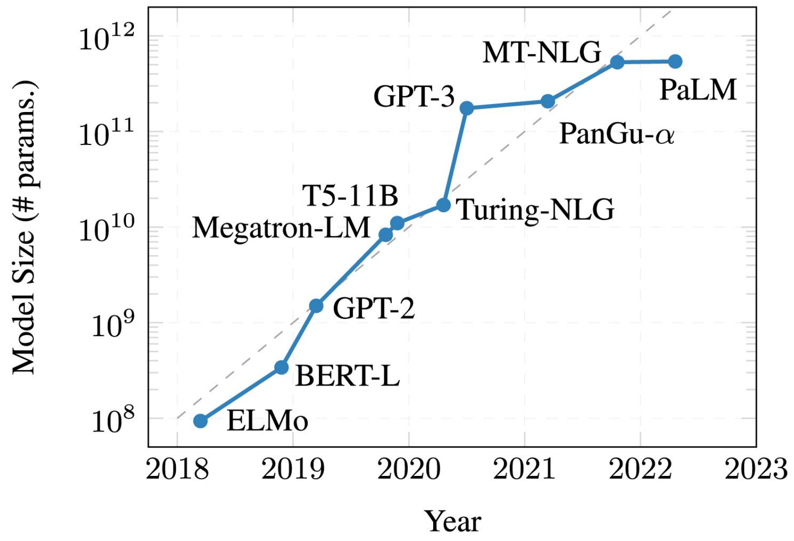

E. Salesky

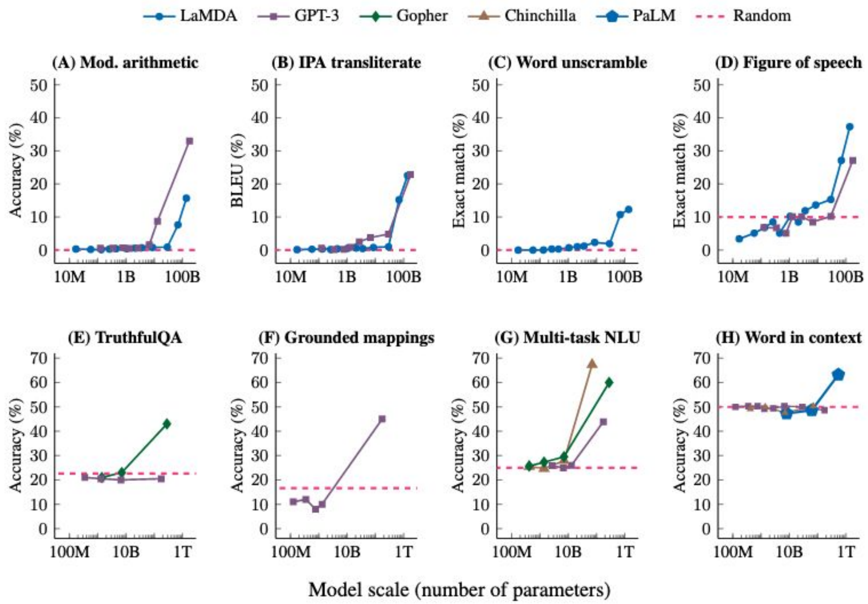

M. de Lhoneux


D. Elliott

Warning: The final part of this section contains dataset samples that are racist in nature.

NLP in the Era of Scale

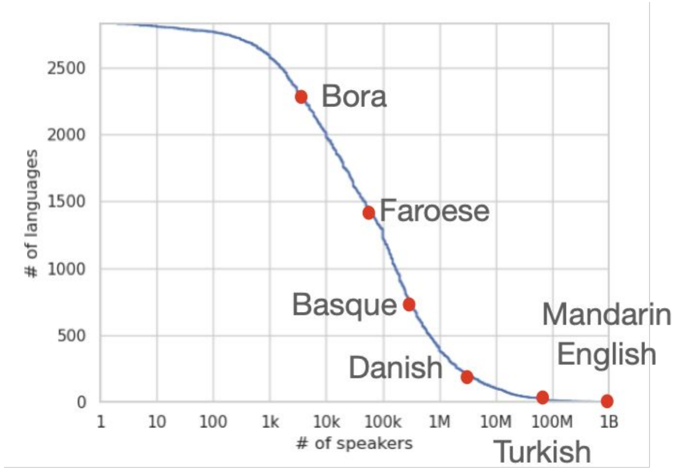




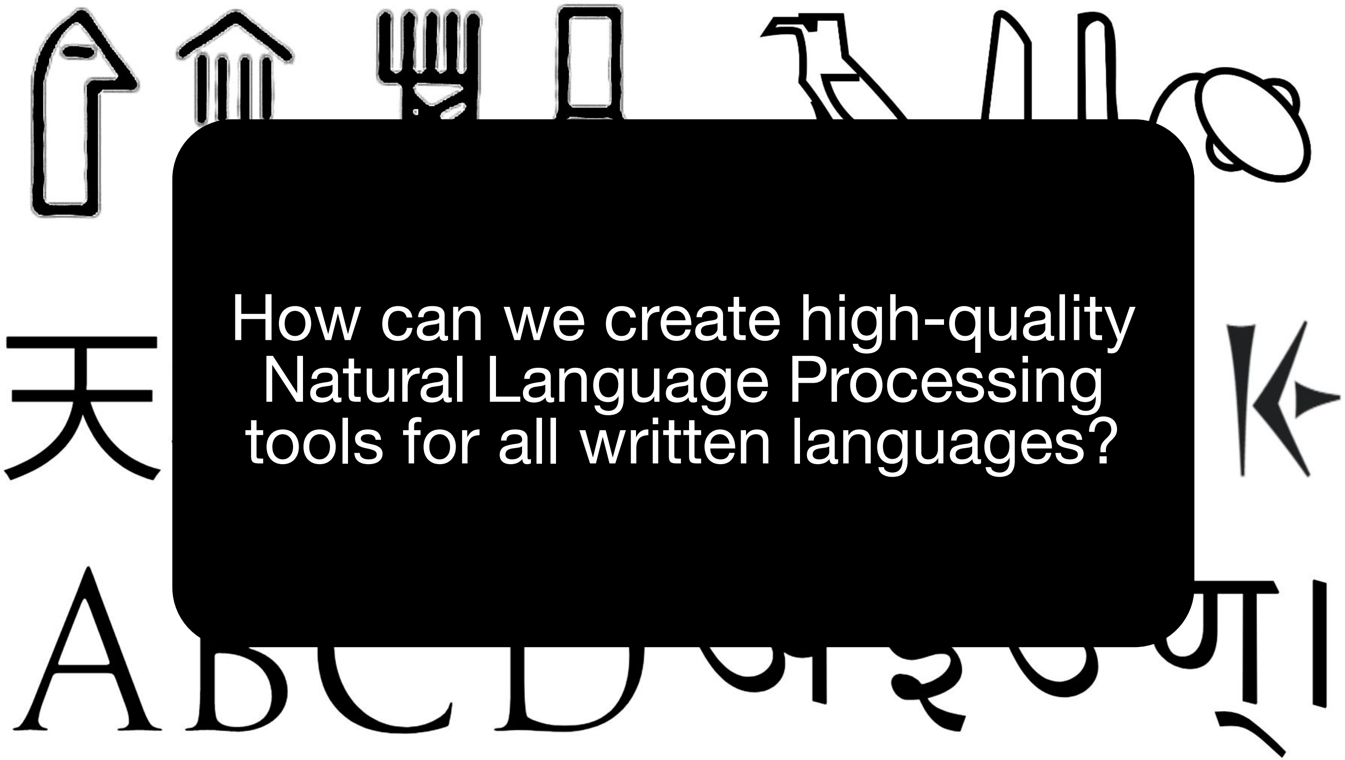
Treviso et al. 2023. Efficient Methods for Natural Language Processing: A Survey. TACL
Wei et al. 2022. Emergent Abilities of Large Language Models. TMLR

NLP for **All** Written Languages

- There are 3,000 written languages
  - 400 with >1M speakers
- NLP usually covers 100 languages
  - Technological exclusion for billions

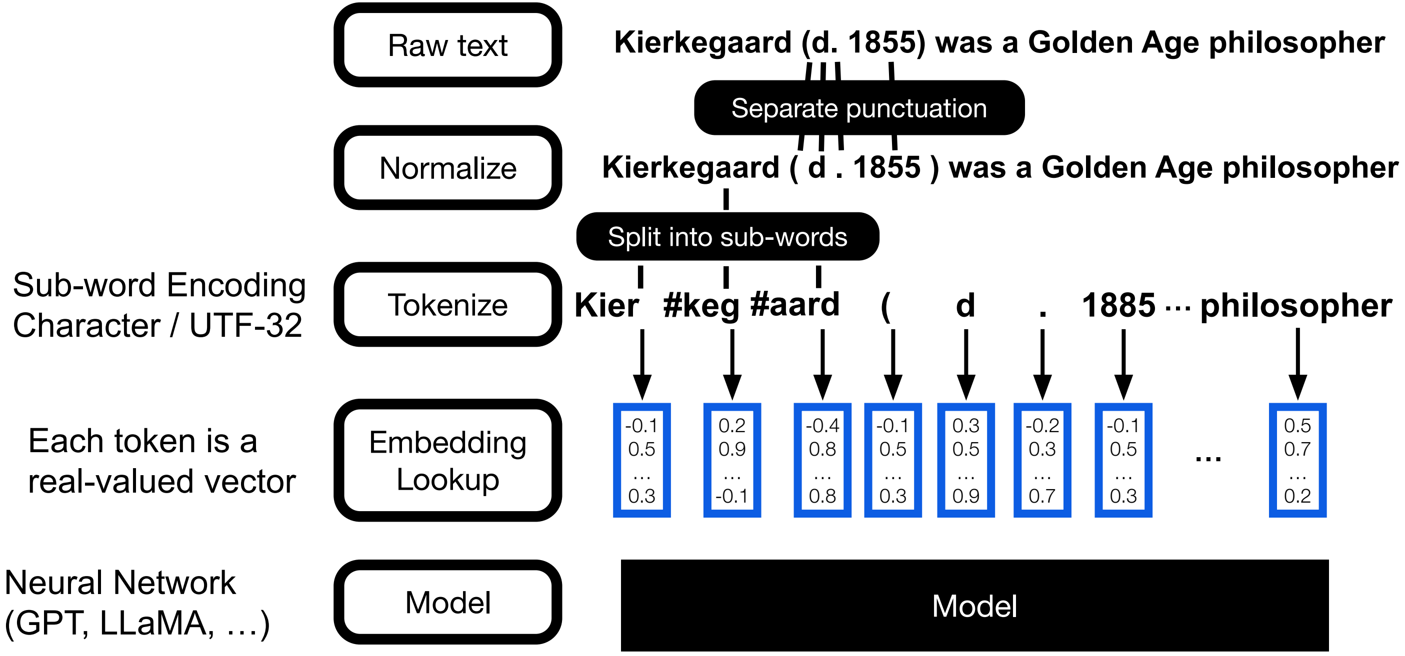


van Esch et al. Writing System and Speaker Metadata for 2,800+ Language Varieties. LREC 2022.
Joshi et al. The State and Fate of Linguistic Diversity and Inclusion in the NLP World. ACL 2020.



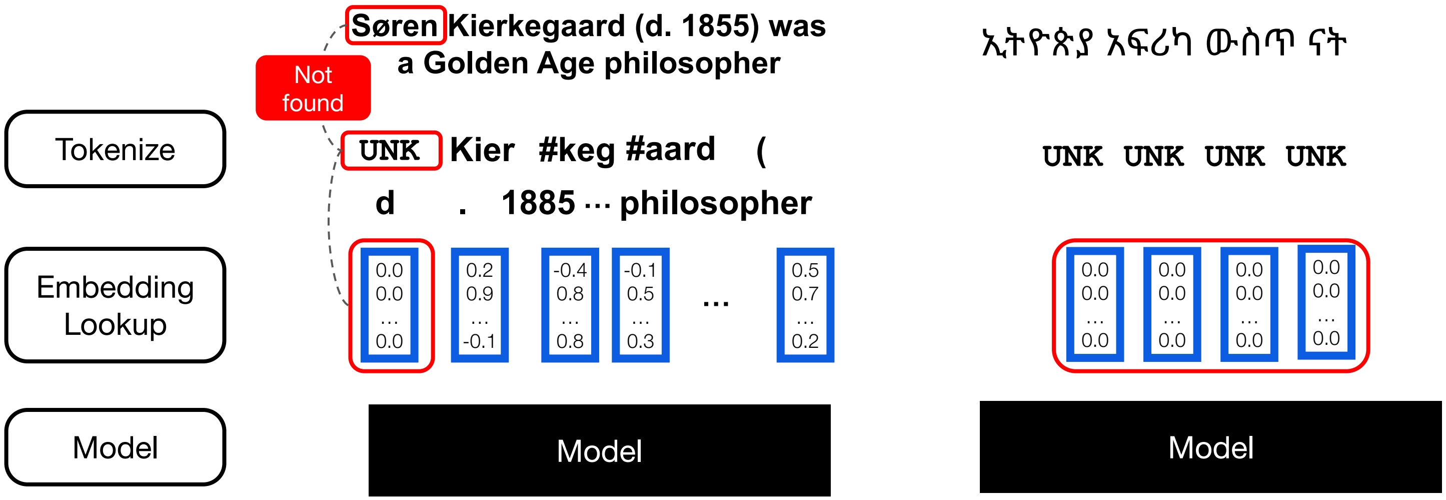
How can we create high-quality Natural Language Processing tools for all written languages?

NLP is a pipeline …



Syntactic / Semantic analysis

… that is easily broken

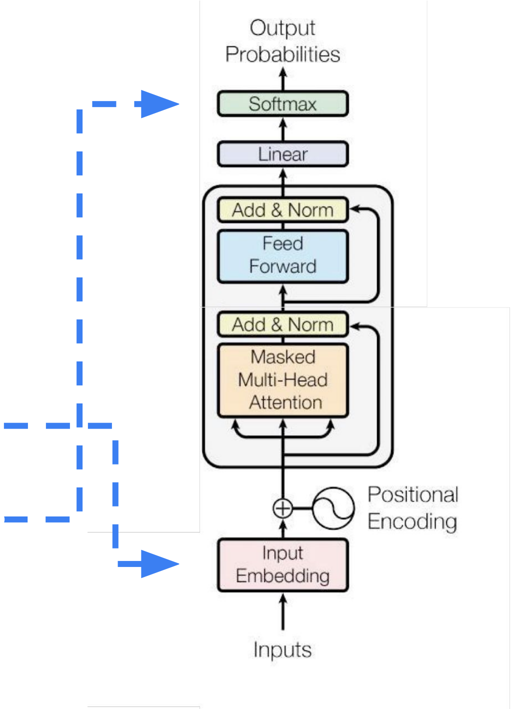


This issue disproportionately affects low-resource languages

The Vocabulary Bottleneck

- NLP is an **open vocabulary problem** and the ability of a model is determined by its vocabulary:
  1. tokens, characters, sub-words, etc.

- This creates a bottleneck in two places:
  1. *Representational bottleneck* in the Embedding layer
  2. *Computational bottleneck* in the Output layer



Where’s the sweet spot?

Long sequence lengths

Bytes (ByT5)

(CANINE, CharFormer) *Characters*

Small subword vocab (BERT: 30K)

(RoBERTa: 50K) *Medium subword vocab*

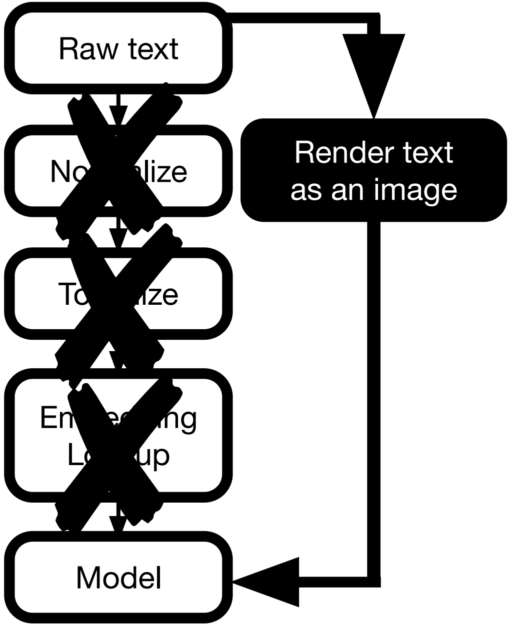
Full unicode coverage (ByT5, CANINE)

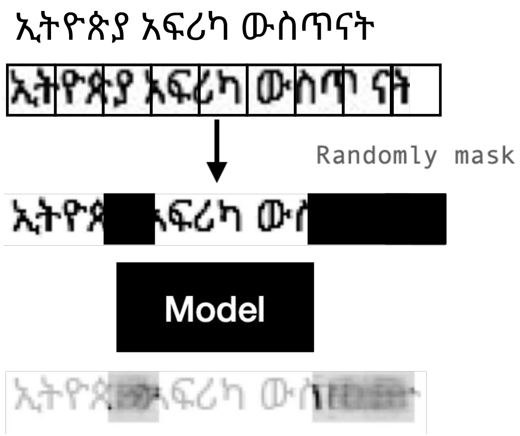
(XML-R: 250K) *Large subword vocab*

Words (word2vec: 3M)

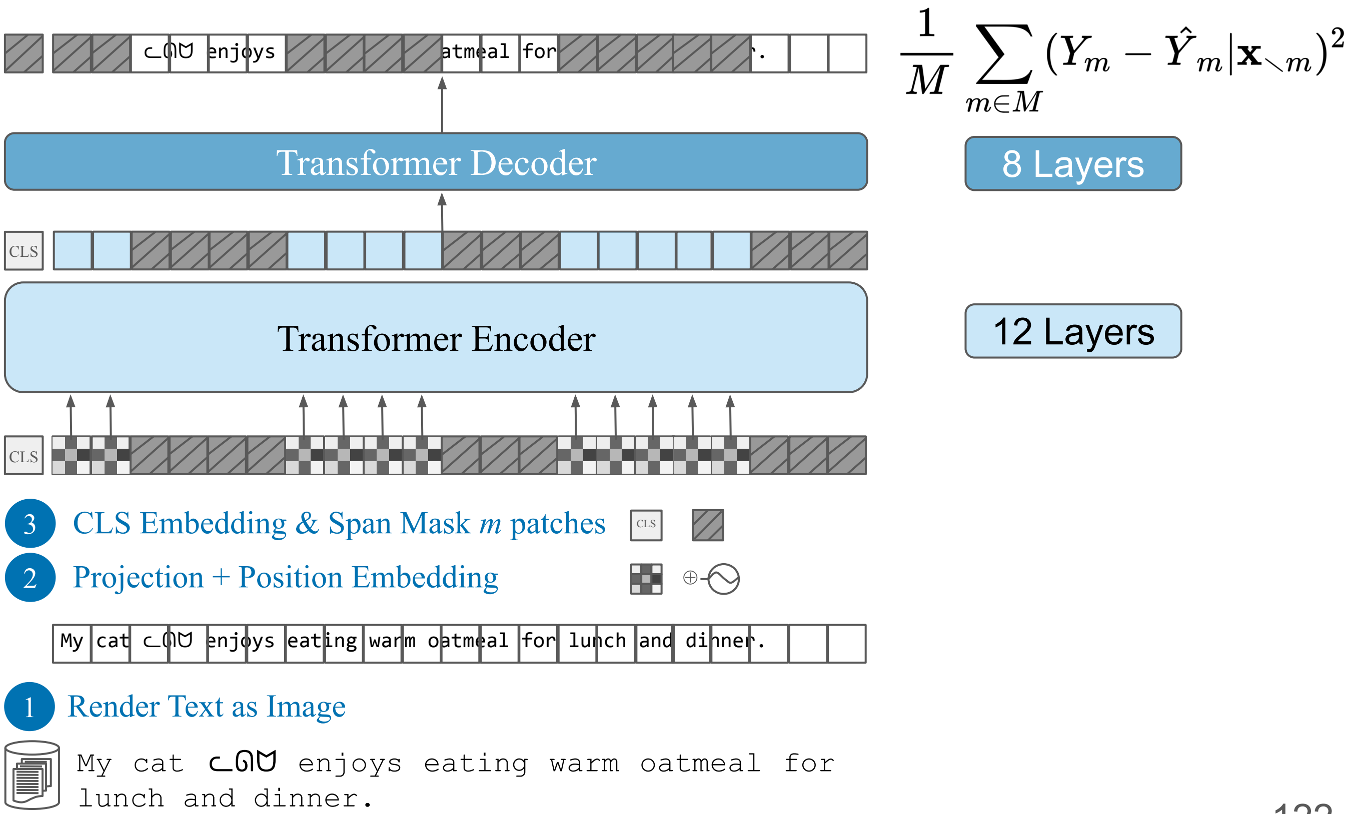
Large vocabulary

Treat language as vision





The Model



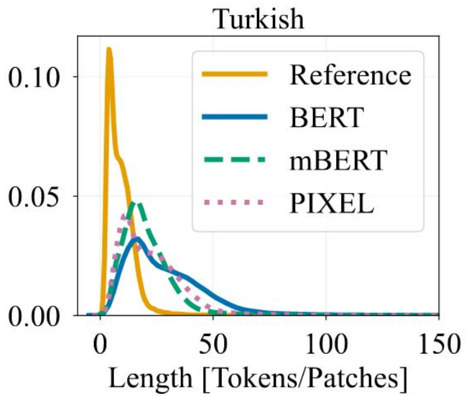
16pixel x 16pixel patch

Google Noto Fonts

PyGame / PangoCairo

Rendered Text is Compact

- PIXEL encoding produces sequence lengths that are at least as long as as BERT.
  - Universal Dependencies datasets with human reference segmentations
  - No length penalty for any language, unlike some LLMs (Ahia et al. 2023)



Proportion of text that is encoded as k subwords / patches.

Pretraining

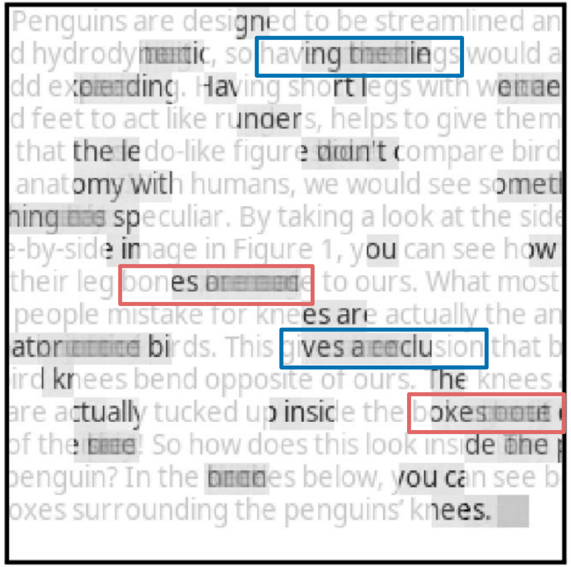
- **English Dataset**: English Wikipedia and Books Corpus
- **Masking:** 25% Span Masking
- **Maximum sequence length**: 529 patches (`16x8464` pixels)
- **Compute**: 8 x 40GB A100 GPUs for 8 days
- **Parameters**: 86M encoder + 26M decoder

There is only 0.05% non-English text in our pretraining data (estimated by Blevins and Zettlemoyer 2022)

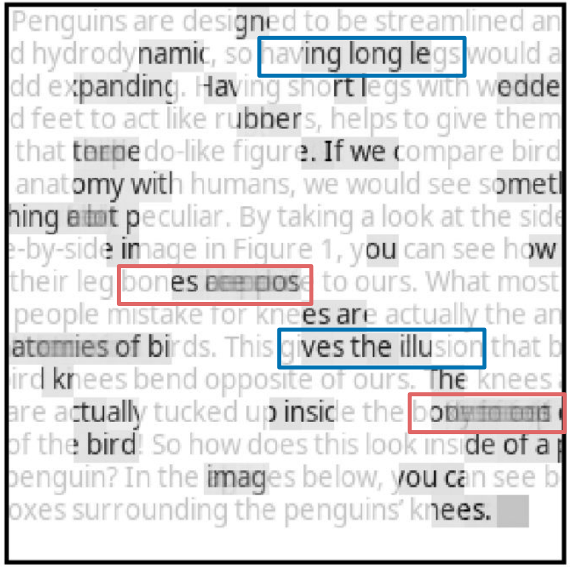
The **Great Wall of China** (traditional Chinese: 萬里長城; simplified Chinese: 万里长城; pinyin: *Wànlǐ Chángchéng*)

`Pretrained model: https://huggingface.co/Team-PIXEL/pixel-base`

A new type of generative model



Try for yourself



100K steps → **500K steps** → **1M steps**

Downstream Tasks

- **Datasets**: Universal Dependencies, MasakhaNER, GLUE, Zeroé
- **Models:**

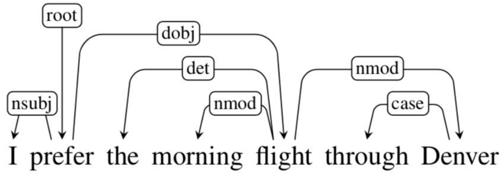
	Parameters	Pretraining Data
$\text{PIXEL}_{\text{BASE}}$	86M	English Wikipedia + Bookcorpus
$\text{BERT}_{\text{BASE}}$	110M	—
CANINE-C	127M	104-languages from Wikipedia

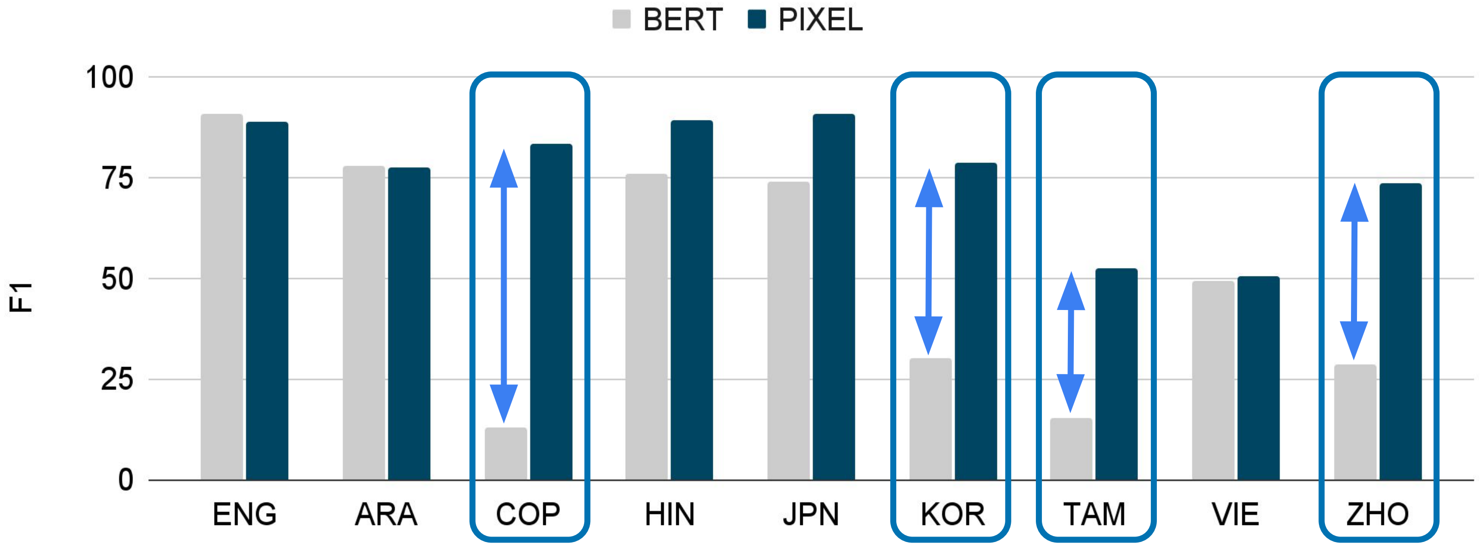
Similar pretraining setup

Tries to solve the same problem using UTF-32

Code: `https://github.com/xplip/pixel`

Dependency Parsing Results



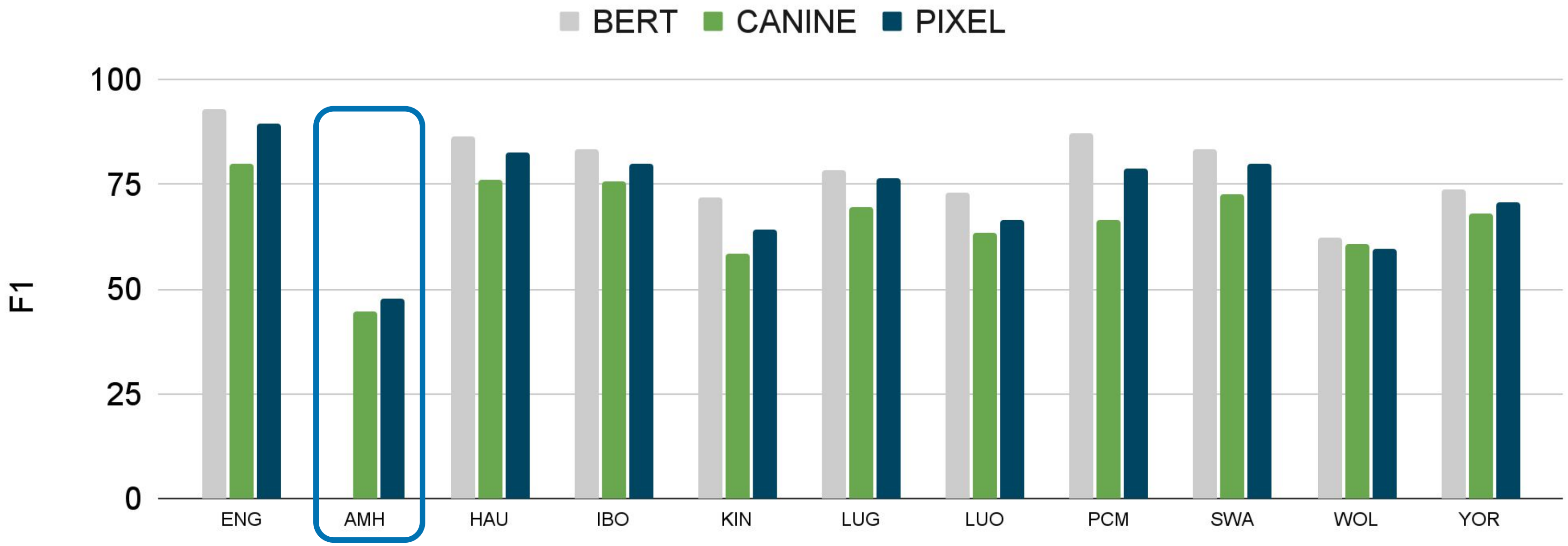


BERT UNK	0%	1%	94%	33%	46%	85%	82%	5%	73%

PIXEL vastly outperforms BERT on unseen scripts

Named Entity Recognition in African Languages

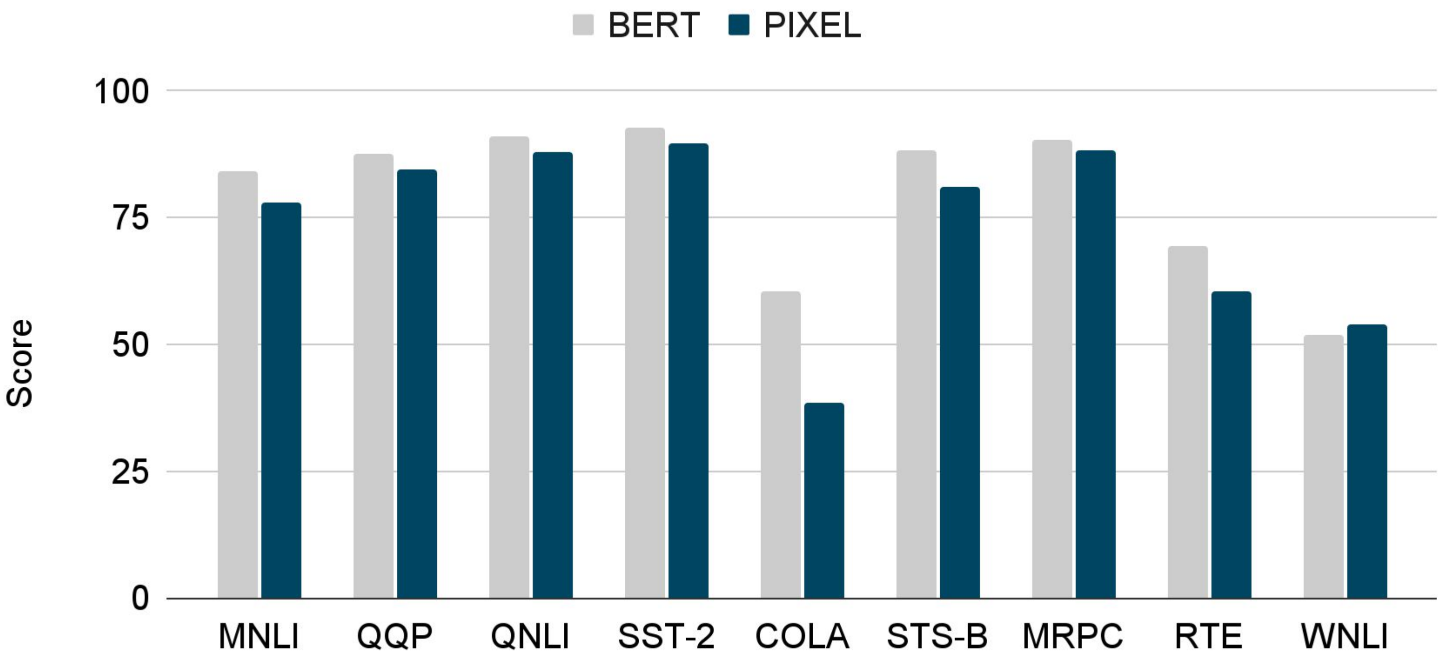
Emir of Kano turban Zhang wey don spend 18 years for Nigeria



PIXEL outperforms BERT on the non-Latin script

PIXEL outperforms the multilingually pretrained CANINE-C

GLUE: Sentence-level Understanding



BERT outperforms PIXEL on English sentence-level tasks

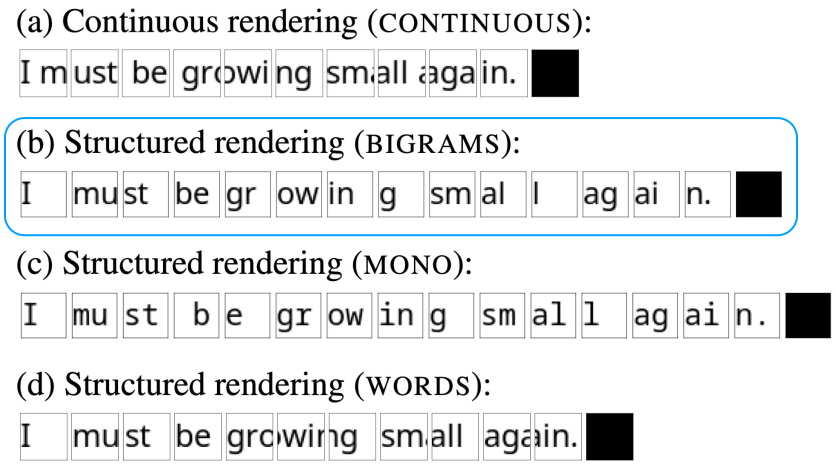
Text Rendering Matters

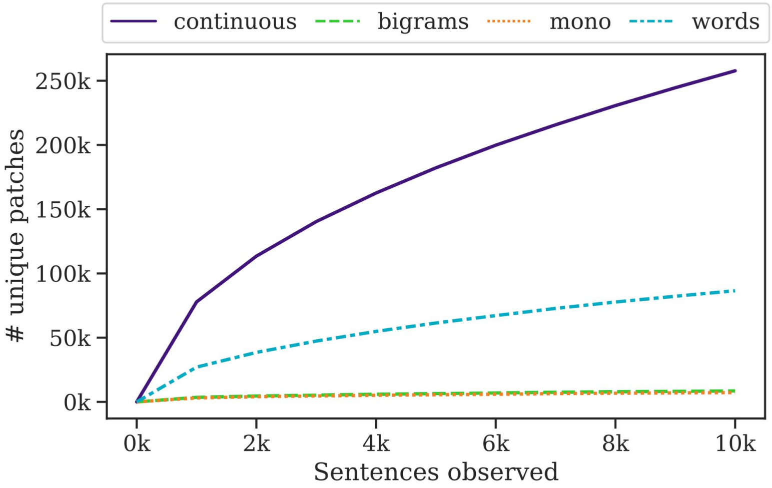
- Our original text renderer produces many nearly-identical patches
    - This is representation- and compute-wasteful

Can we do better?

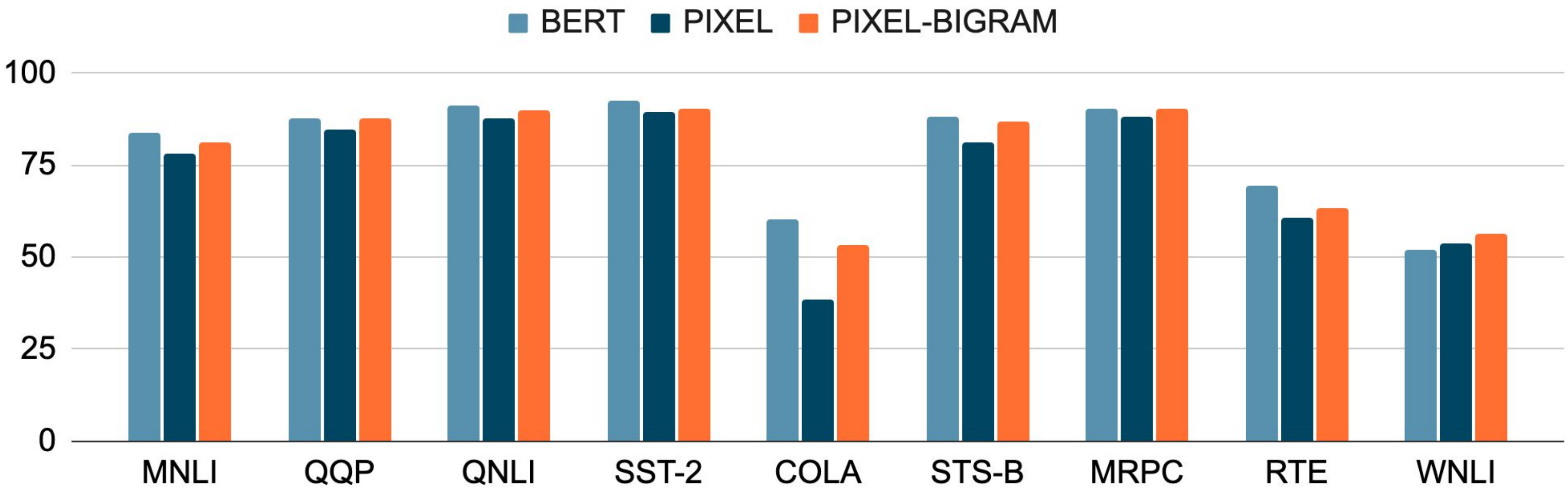
Lotz et al. Text Rendering Strategies for Pixel Language Models. EMNLP 2023.

Alternative Text Renderers





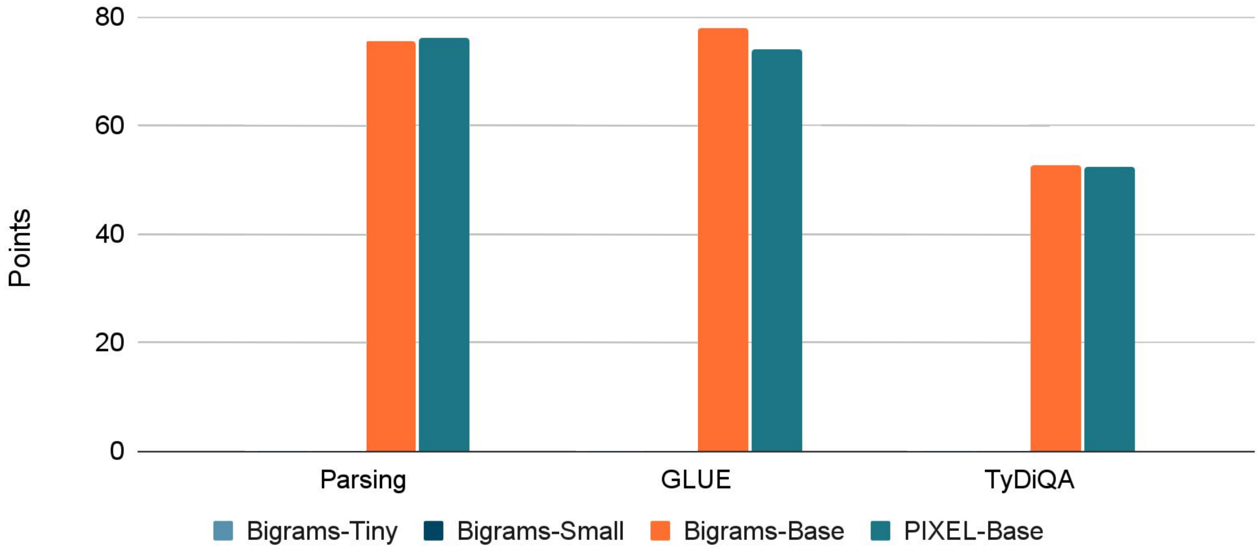
GLUE (revisited)



Bigram text rendering produces better models

Scaling Down ↓

- Better text rendering can create effective models at smaller scales



5M 22M 86M 86M

Open Questions

- Does this work based on orthographic similarity or something else?
- How should we train a multilingual PIXEL encoder?
  - Language-based or script-based data selection
- How can we apply this type of model to language generation tasks?

Conclusions

- PIXEL is a new type of language model that tackles the open vocabulary problem using visually rendered text.
    1. This enables high-quality transfer to unseen scripts.
    2. Robustness to orthographic attacks
    3. Can also process historical documents

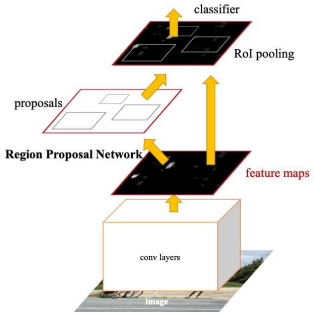
- *My* opinion: Language is special but its computer format should be as flexible and expressive as possible.

Wrap-up

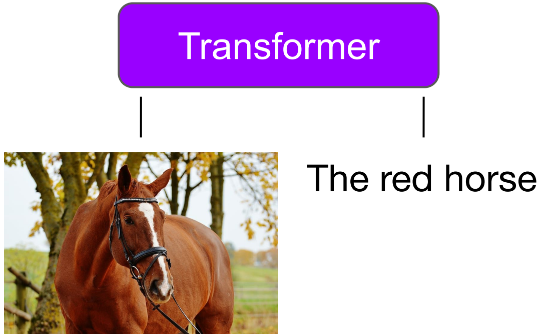
1. Datasets

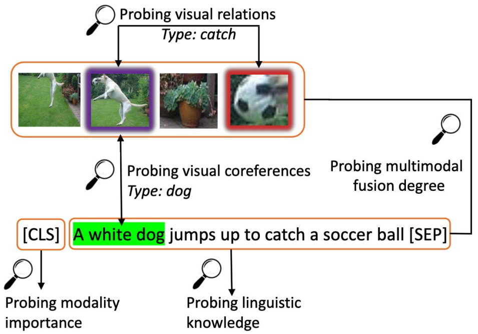
some sheep walking in the middle of a road
a herd of sheep with green markings walking down the road
a herd of sheep walking down a street next to a lush green grass covered hillside.
sheared sheep on roadway taken from vehicle, with green hillside in background.
a flock of freshly sheered sheep in the road.

2. Representation

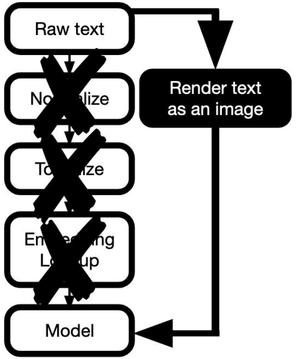


3. Modelling





4. Understanding



5. New Ideas

Where to find more research?

- CVPR
- NeurIPS
- ACL
- NAACL
- LREC
- ICML
- EACL
- ECCV
- ICCV
- IJCAI
- ICLR
- COLING
- arXiv
- …

DALL-E 2: “digital art of someone drinking from arxiv firehose every morning”

Predictions & Speculations

- Increasing societal impact of V&L models
  - Both for entertainment and for misinformation
- Shift in focus to zero-shot instruction-based models
  - Fine-tuning is too expensive for each task
- Concentrated focus on understanding how models work
  - Bigger and better datasets will continue to be major contributions
- Big challenge to evaluate bidirectional generative models

Acknowledgements


W. Li


R. Ramos


B. Martins

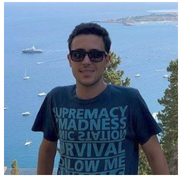

L. Cabello


S. Brandl


N. Borenstein


P. Rust


I. Augenstein


E. Bugliarello


E. Salesky


M. de Lhoneux


F. Liu


E.M. Ponti


S. Reddy


N. Collier


Y. Kementchedjhieva

VILLUM FONDEN