UNSW
THE UNIVERSITY OF NEW SOUTH WALES

9b. Vision and Language Reasoning

Never Stand Still | Faculty of Engineering | COMP9444 Week 9b

Sonit Singh

School of Computer Science and Engineering

Faculty of Engineering

The University of New South Wales, Sydney, Australia

sonit.singh@unsw.edu.au

Goal

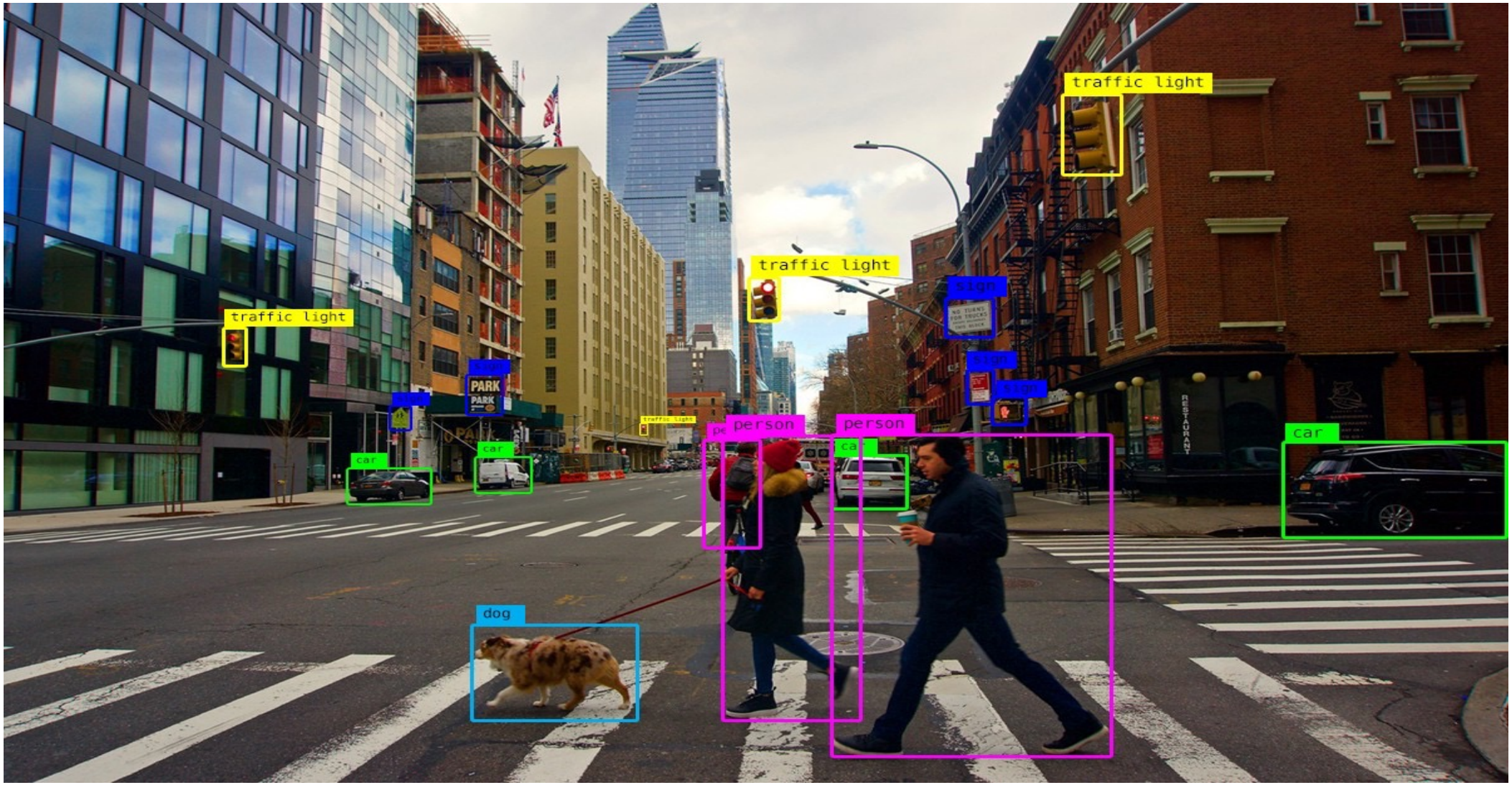
- To motivate the need for “Computer Vision + Natural Language Processing”
- After the session, everyone can confidently say: “yeah, I know various tasks at the intersection of computer vision and natural language processing”
- Focus on high-level overview, not technical details
- Focus on static images, not videos (although they are easy to translate to videos)
- Focus on selective set of papers for various tasks, not a comprehensive literature review

Agenda

- Computer Vision
- Natural Language Processing
- Computer Vision + Natural Language Processing
- Building Blocks
  - Convolutional Neural Networks (CNNs)
  - Recurrent Neural Networks (RNNs)
  - Attention Mechanism
- Encoder-Decoder Framework
- Image Captioning
- Visual Question Answering (VQA)
- Visual Dialog (VisDial)
- Vision-Language Navigation (VLN)
- Visual Grounding
- Summary

Computer Vision

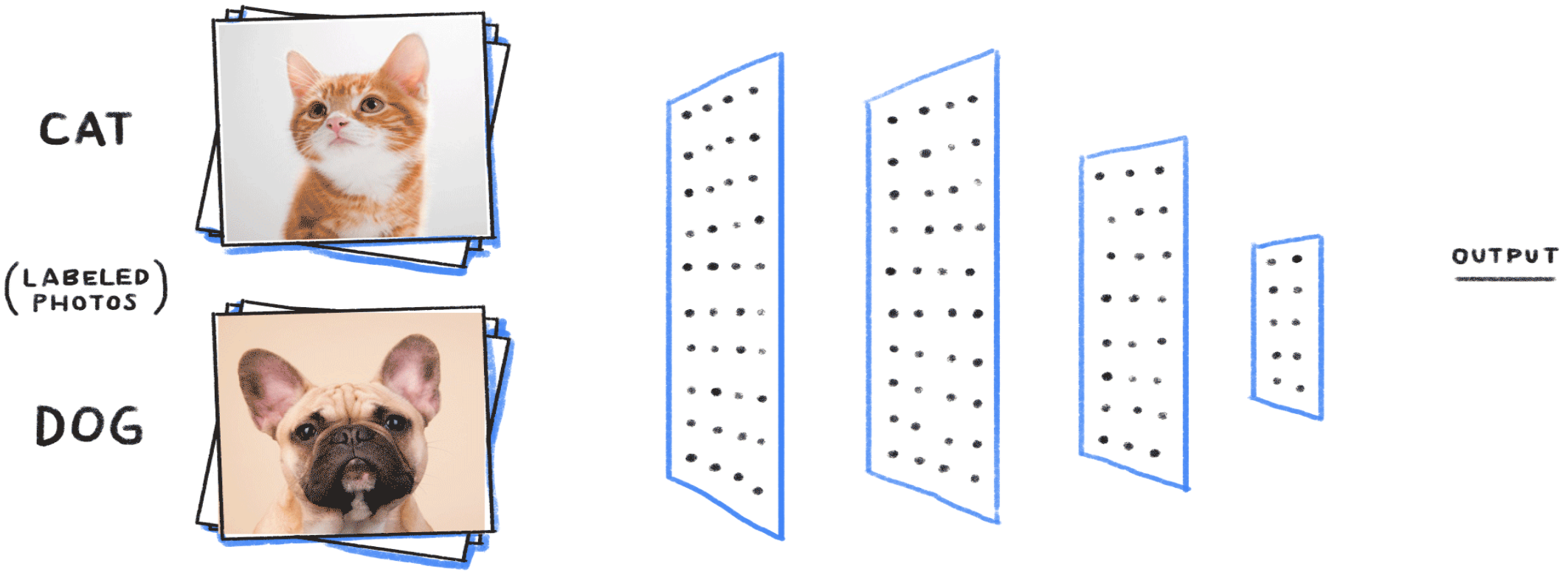
- Enabling machines to process, represent, understand, and generate visual data



Source: Computer Vision in Practice. https://levelup.gitconnected.com/deployment-computer-vision-in-practice-99b7bbb6aa7c

CV Applications

- Image Classification



Source: Medium: Introduction to CNN & Image Classification Using CNN in PyTorch. https://medium.com/swlh/introduction-to-cnn-image-classification-using-cnn-in-pytorch-11eefae6d83c

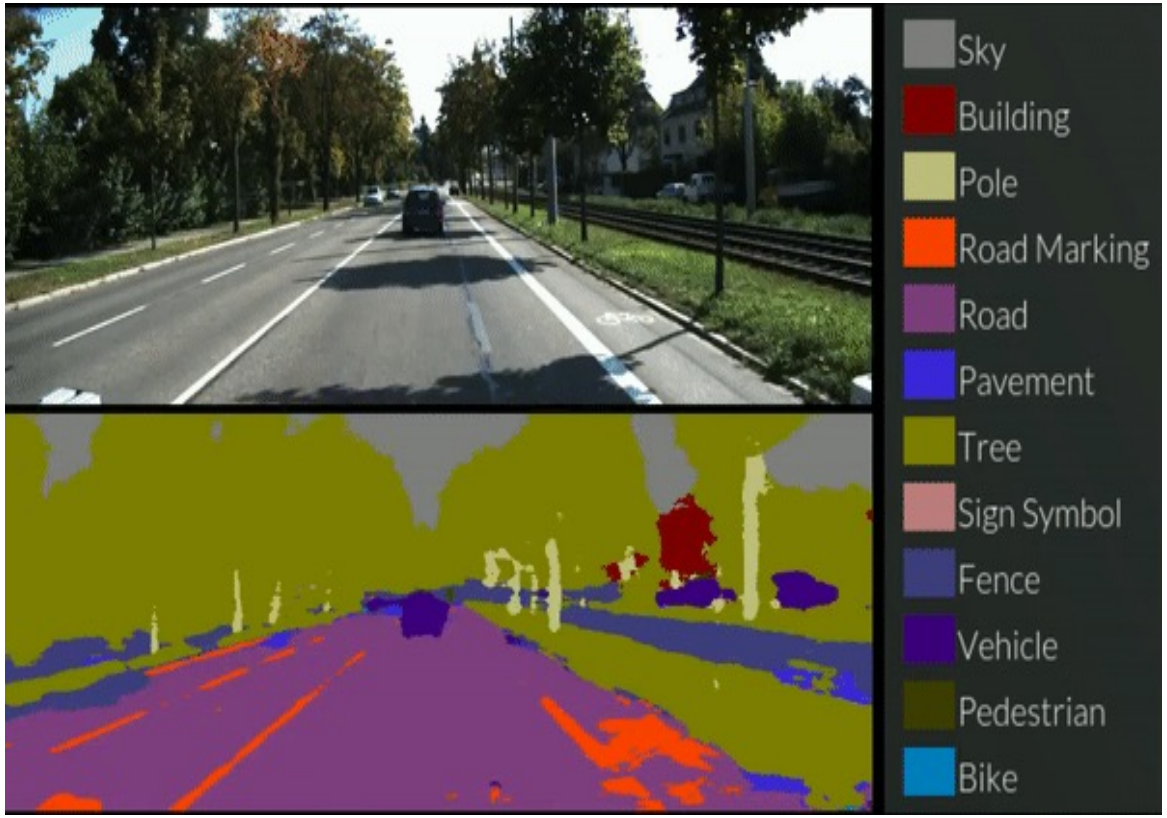
CV Applications

- Object Detection

Image Credit: Google Cloud Vision API. https://cloud.google.com/vision/docs/object-localizer

CV Applications

- Segmentation



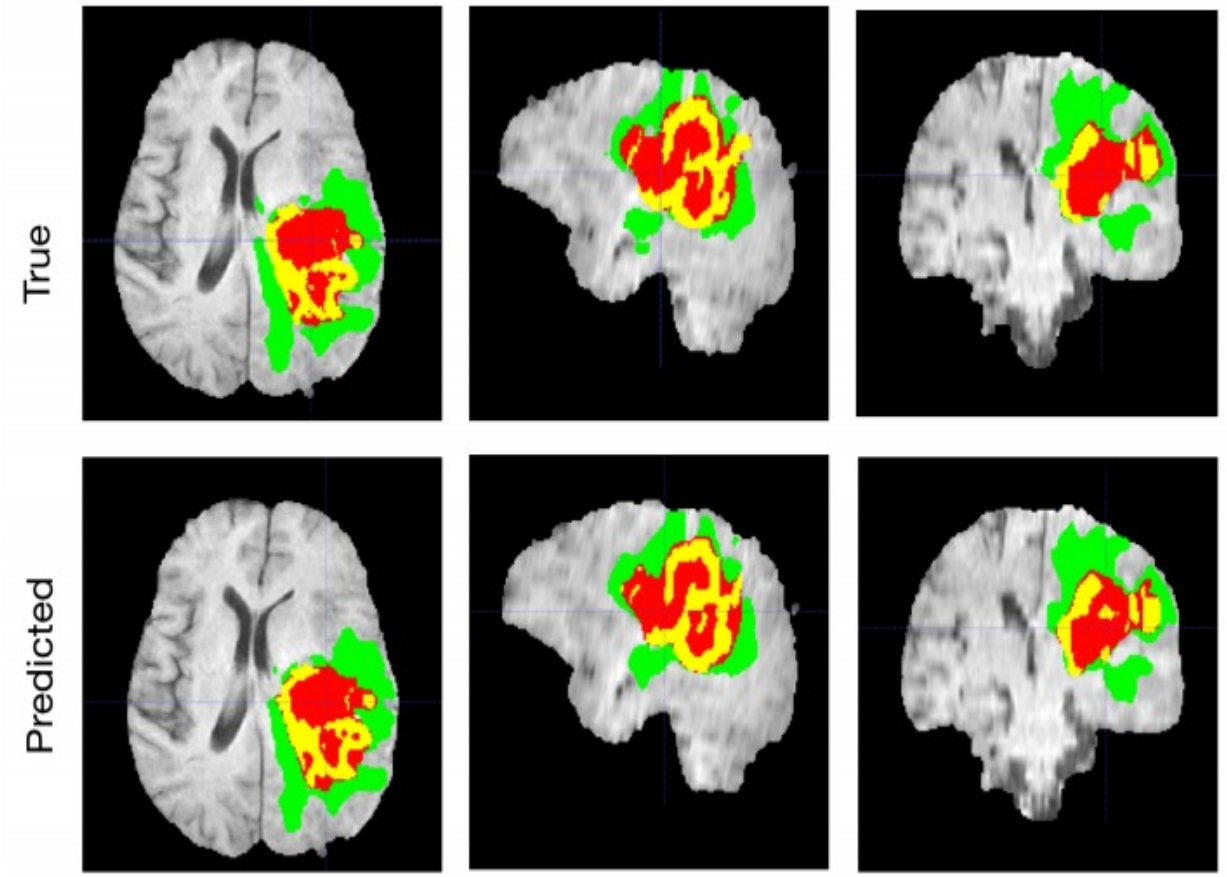


Image Credit: Analytics Vidhya: Introduction to Semantic Image Segmentation. https://medium.com/analytics-vidhya/introduction-to-semantic-image-segmentation-856cda5e5de8
Nvidia AI: Automatically segmenting brain tumours with AI. https://developer.nvidia.com/blog/automatically-segmenting-brain-tumors-with-ai/

Natural Language Processing

- Enabling machines to process, represent, understand, and generate languages

In fact, the Chinese NORP market has the three CARDINAL most influential names of the retail and tech space – Alibaba GPE , Baidu ORG , and Tencent PERSON (collectively touted as BAT ORG), and is betting big in the global AI GPE in retail industry space . The three CARDINAL giants which are claimed to have a cut-throat competition with the U.S. GPE (in terms of resources and capital) are positioning themselves to become the 'future AI PERSON platforms'. The trio is also expanding in other Asian NORP countries and investing heavily in the U.S. GPE based AI GPE startups to leverage the power of AI GPE . Backed by such powerful initiatives and presence of these conglomerates, the market in APAC AI is forecast to be the fastest-growing one CARDINAL , with an anticipated CAGR PERSON of 45% PERCENT over 2018 - 2024 DATE .

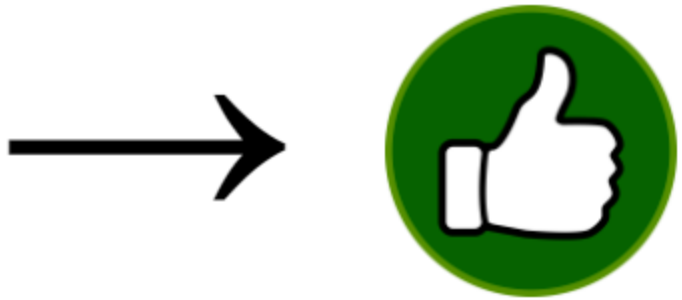
To further elaborate on the geographical trends, North America LOC has procured more than 50% PERCENT of the global share in 2017 DATE and has been leading the regional landscape of AI GPE in the retail market. The U.S. GPE has a significant credit in the regional trends with over 65% PERCENT of investments (including M&As, private equity, and venture capital) in artificial intelligence technology. Additionally, the region is a huge hub for startups in tandem with the presence of tech titans, such as Google ORG , IBM ORG , and Microsoft ORG .

Source: Hugging Face. https://twitter.com/huggingface/status/1230870653194121216

NLP Applications

- Text Understanding

"I love this movie.
I've seen it many times
and it's still awesome."

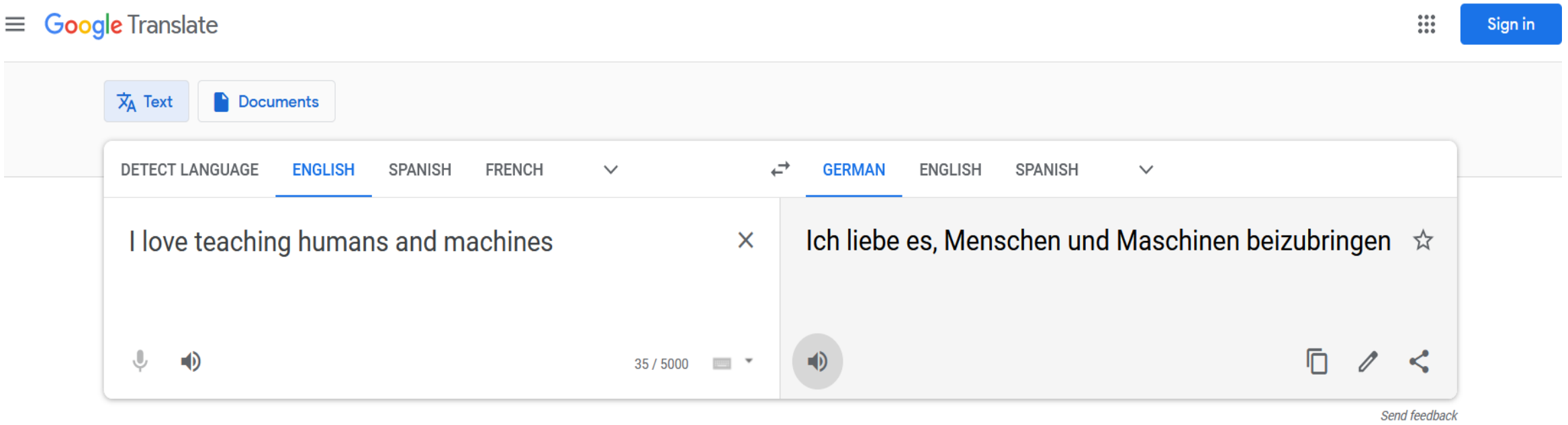


"This movie is bad.
I don't like it it all.
It's terrible."

Image Credit: Sentiment Analysis. https://colab.research.google.com/github/shangeth/Google-ML-Academy/blob/master/2-Deep-Neural-Networks/2_9_ANN_Natural_Language_Processing.ipynb

NLP Applications

- Machine Translation



NLP Applications

- Question Answering/Comprehension

Passage Sentence

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity.

Question

What causes precipitation to fall?

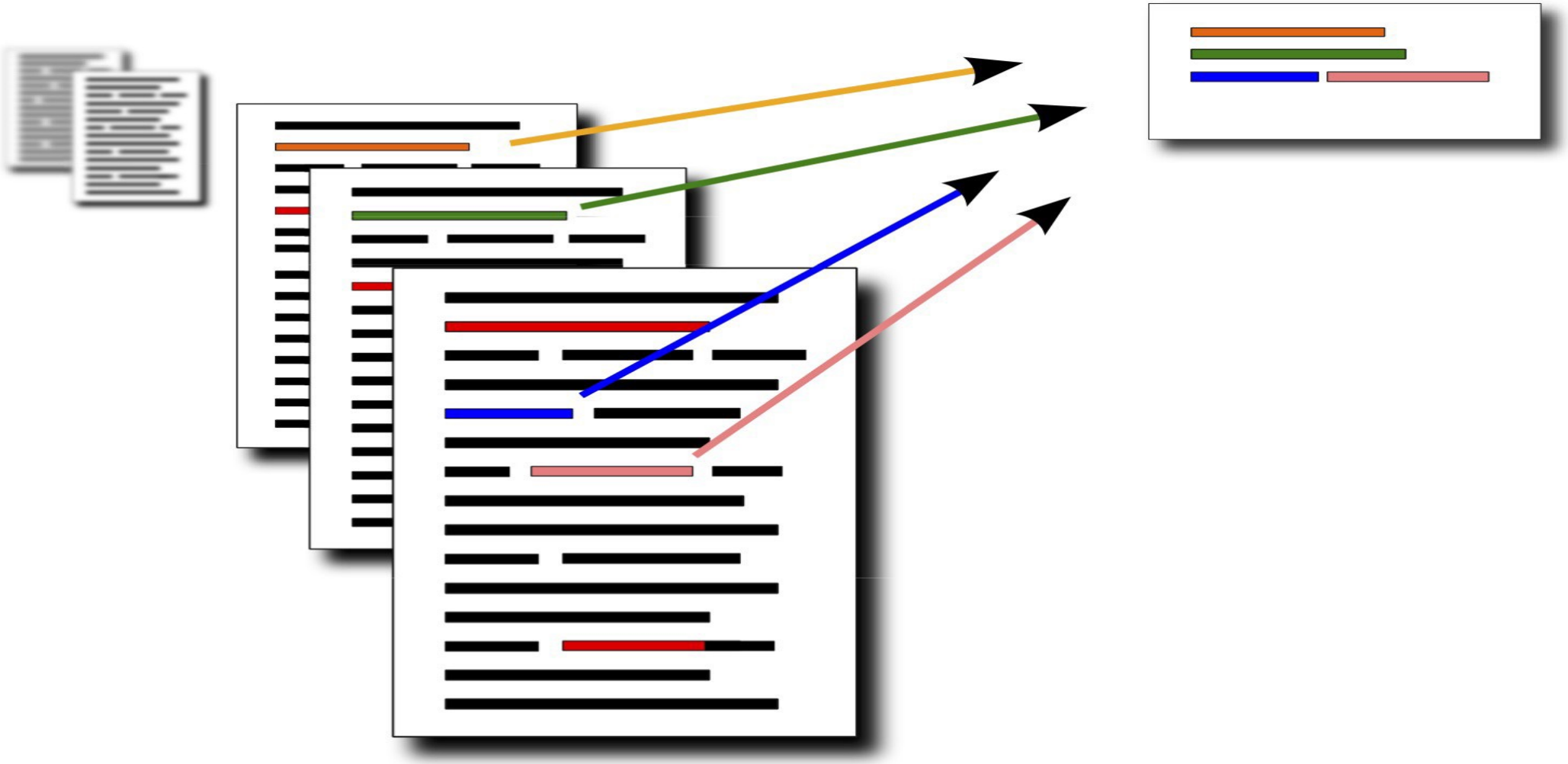
Answer Candidate

gravity

Source: The Stanford Question Answering Dataset (SQUAD). https://rajpurkar.github.io/mlx/qa-and-squad/

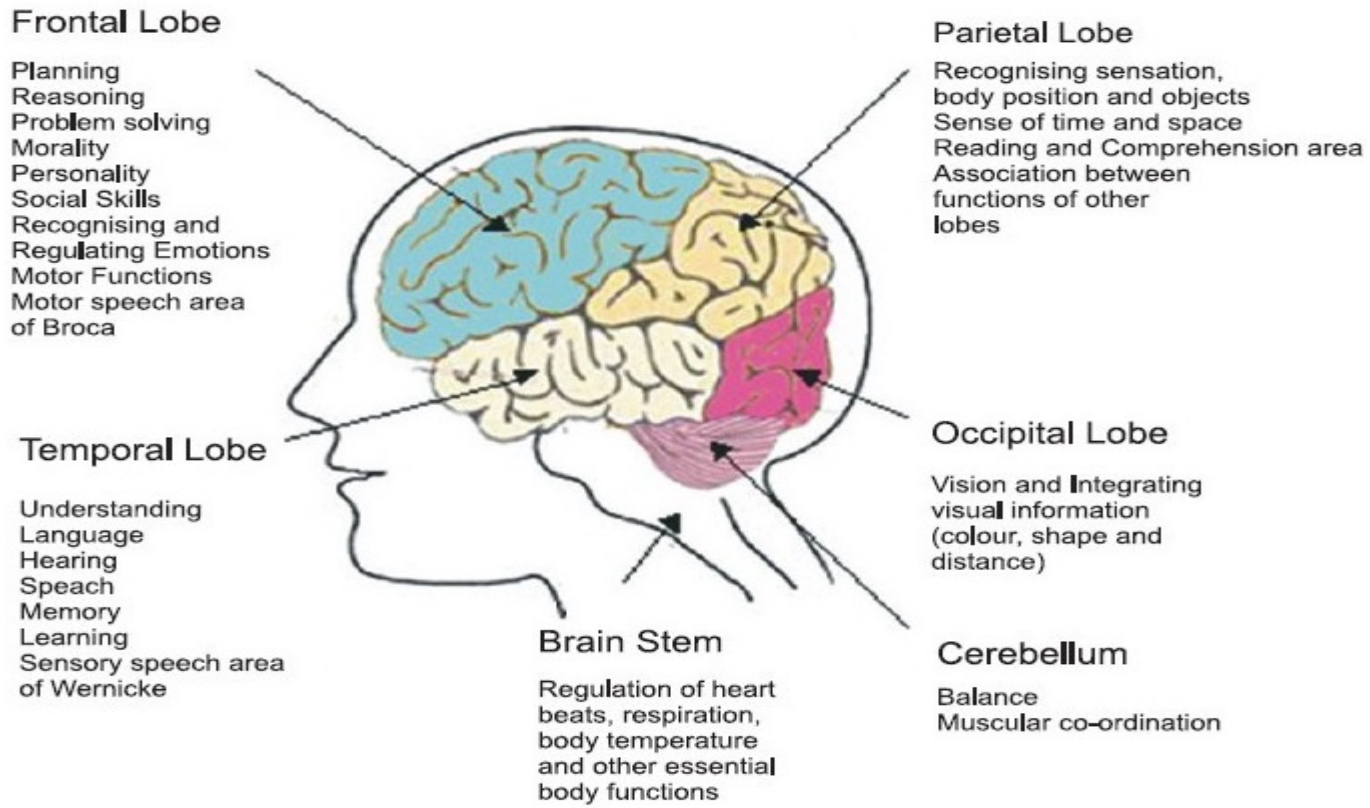
NLP Applications

- Text Summarization



Vision + Language

- Science Perspective
  - Vision is how we observe and understand the world
  - Language is how we communicate
- A move towards Artificial General Intelligence (AGI)



Source: Barrow Neurological Institute

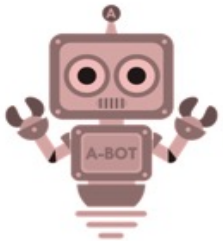
Applications at the intersection of Vision and Language

- To aid “visually impaired” people

Image Credit: https://www.bigrentz.com/blog/ultimate-guide-designing-navigating-spaces-people-vision-impairment

Applications at the intersection of Vision and Language

- To aid “situationally impaired” analysts



Did anyone enter this room last week?

Yes, 127 instances logged on camera

Show me images of anyone carrying a black bag.

...

Slide Credit: Peter Anderson. Connecting Language and Vision to Actions. https://lvatutorial.github.io/

Applications at the intersection of Vision and Language

- Personal Assistants

Add the chopped zucchini to the pan…

Hey, can you order more zucchini?

Done.

And what's next?

Applications at the intersection of Vision and Language

- Natural Language Instructions for Robots

Is there smoke in any room around you?

Yes, in one room

Go there and look for people

...

Applications at the intersection of Vision and Language

- Generating and summarizing radiology reports from medical images

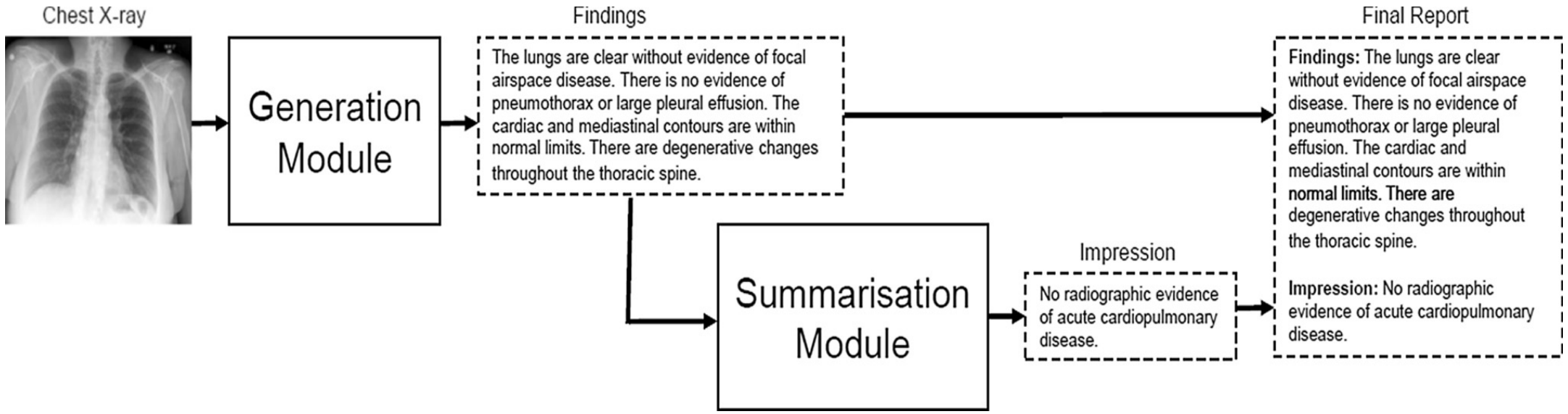
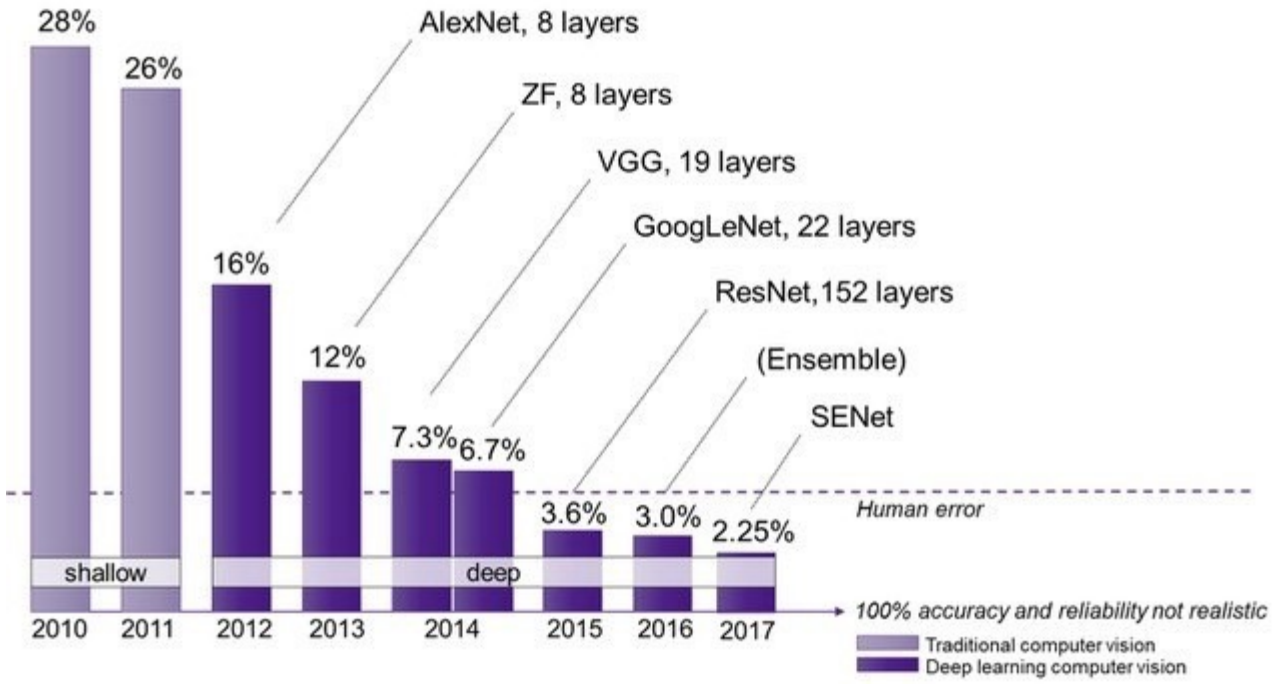


Image Credit: Singh et al., (2021). Show, tell and summarise: learning to generate and summarise radiology findings from medical images

Building Blocks: Convolutional Neural Networks (CNNs)

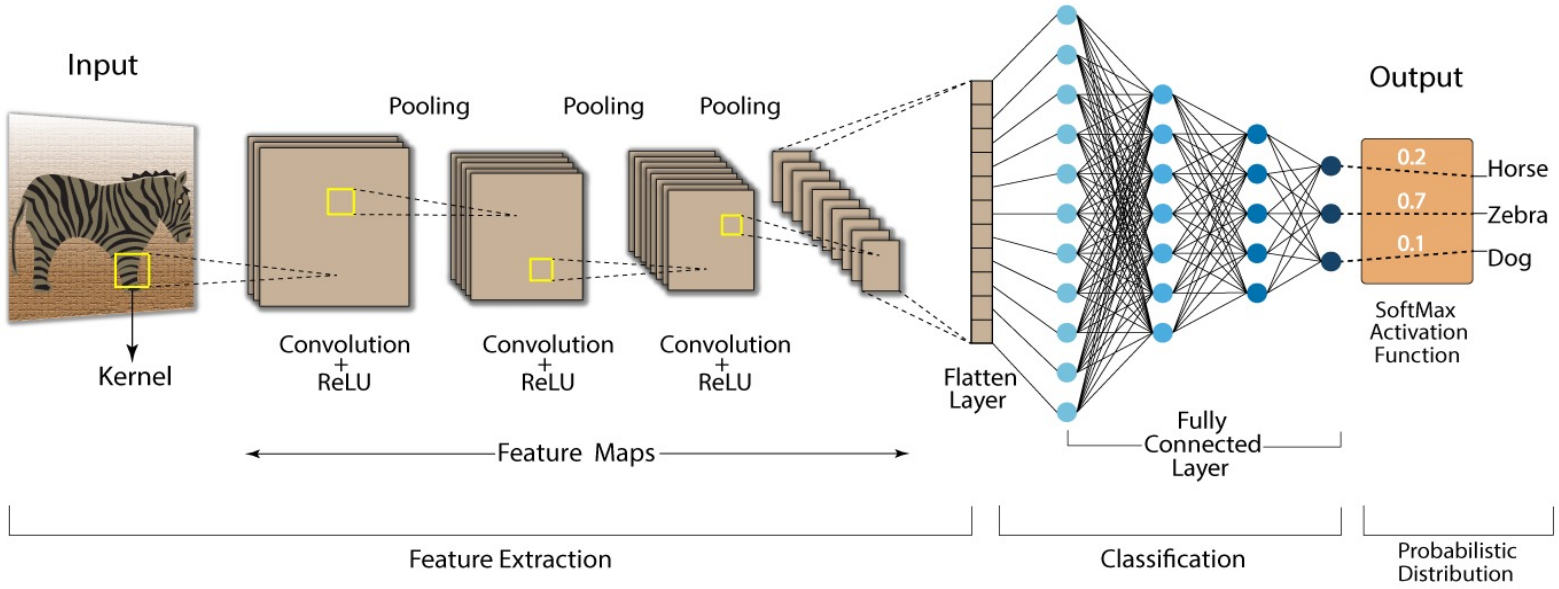
- A class of deep neural networks suitable for processing 2D/3D data. For e.g., Images and Videos
- CNNs can capture high-level representation of images/videos which can be used for end-tasks such as classification, object detection, segmentation, etc.
- A range of CNNs improving over the years



Source: Convolutional Neural Networks. https://medium.com/@rajat.k.91/convolutional-neural-networks-why-what-and-how-f8f6dbebb2f9

CNN Architecture

- A typical CNN architecture consists of the following layers:
  - Convolution layer
  - ReLU layer (non-linearity)
  - Pooling layer
  - Flattening
  - Fully-connected layer
  - Output layer

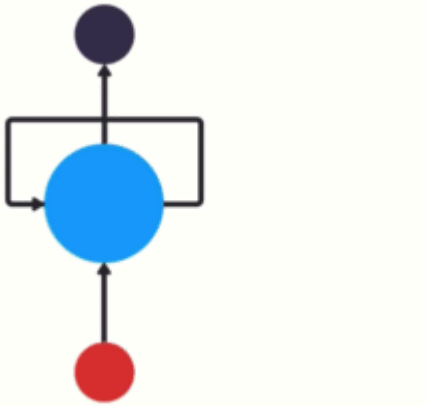


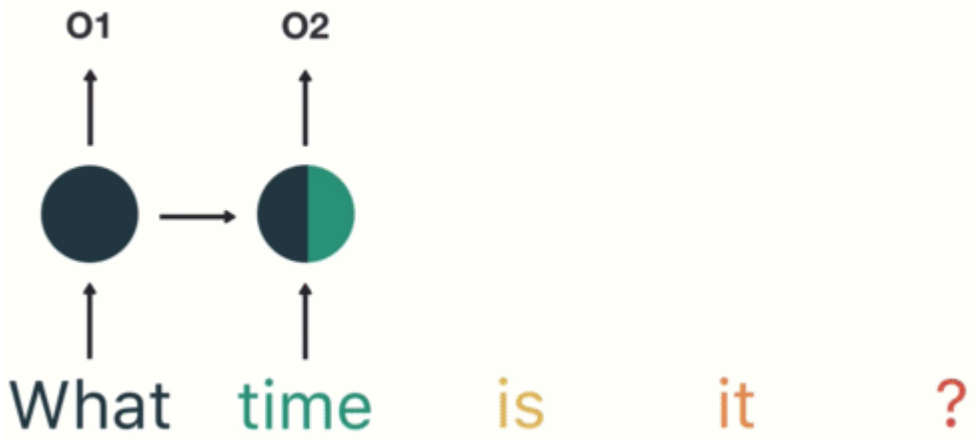
- There can be multiple steps of convolution followed by pooling, before reaching the fully connected layers.

Source: Convolutional Neural Networks. https://medium.com/@rajat.k.91/convolutional-neural-networks-why-what-and-how-f8f6dbebb2f9

Building Blocks: Recurrent Neural Networks (RNNs)

- A class of neural networks suitable for processing temporal or sequential data
- The basic unit of RNN is called “cell”, and each cell consists of layers and a series of cells that enables the sequential processing of recurrent neural network models
- RNNs have a looping mechanism that acts as a highway to allow information to flow from one step to the next. This information is the hidden state, which is a representation of previous inputs.





Credit: Michael Phi. Illustrated guide to RNNs. https://towardsdatascience.com/illustrated-guide-to-recurrent-neural-networks-79e5eb8049c9

Long-range Dependency problem

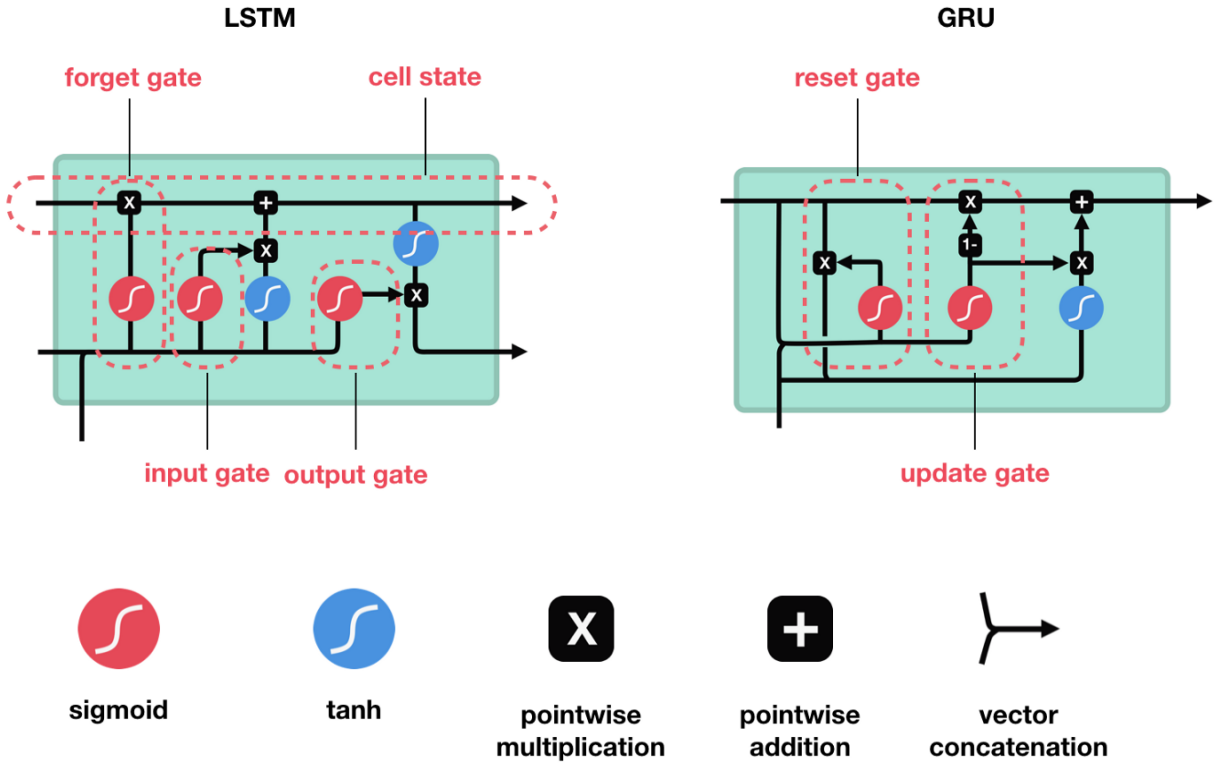
- Vanilla RNNs suffers from vanishing gradient problem
  - As the RNNs processes more steps, it has troubles retaining information from previous steps.
  - Due to back-propagation, the earlier layers fail to do any learning as the internal weights are barely being adjusted due to extremely small gradients.
  - Does not learn the long-range dependencies across time steps

"Once upon a time, there was a king who ruled a great and glorious nation. Favourite amongst his subjects was the court painter of whom he was very proud. Everybody agreed this wizzened old man painted the greatest pictures in the whole kingdom and the king would spend hours each day gazing at them in wonder. However, one day a dirty and disheveled stranger presented himself at the court claiming that in fact he was the greatest painter in the land. The indignant king decreed a competition would be held between the two artists, confident it would teach the vagabond an embarrassing lesson. Within a month they were both to produce a masterpiece that would out do the other. After thirty days of working feverishly day and night, both artists were ready. They placed their paintings, each hidden by a cloth, on easels in the great hall of the castle. As a large crowd gathered, the king ordered the cloth be pulled…"

Credit: https://www.goodreads.com/quotes/51722-once-upon-a-time-there-was-a-king-who-ruled

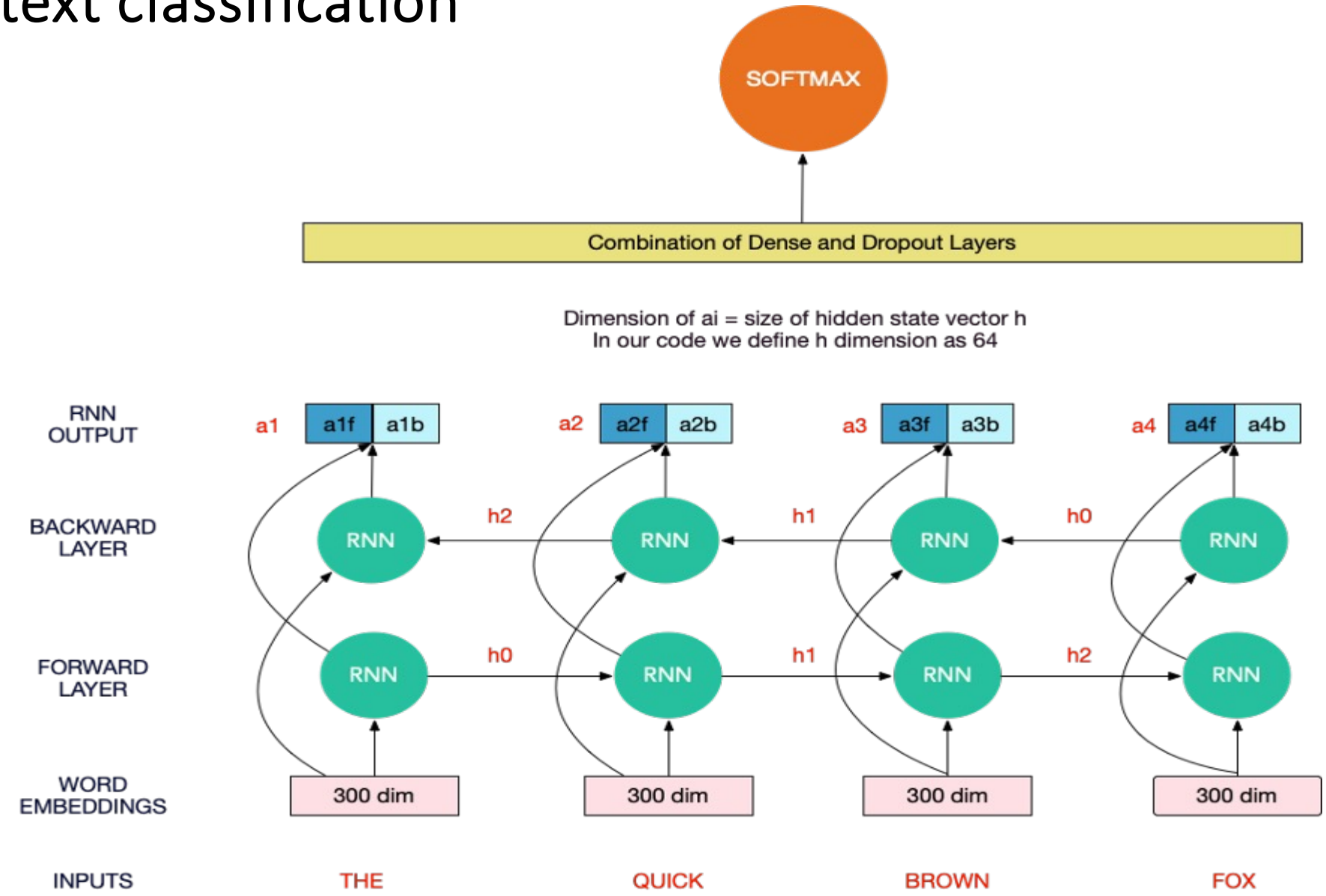
LSTMs/GRUs

- LSTMs and GRUs are two special RNNs, capable of learning long-term dependencies using mechanisms called **gates**.
- These gates are different tensor operations that can learn what information to add or remove to the hidden state.



Credit: Michael Phi. Towards Data Science. https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21

End-to-End text classification



Seq2Seq model

- Model has two parts: Encoder and Decoder (Encoder-Decoder Framework)

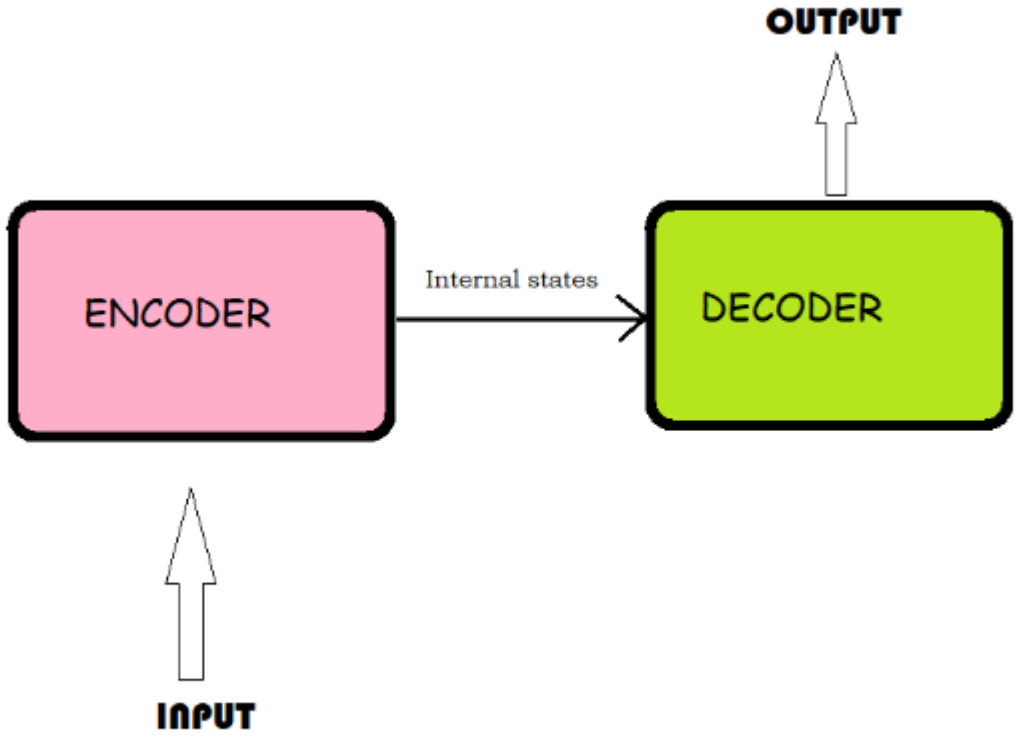
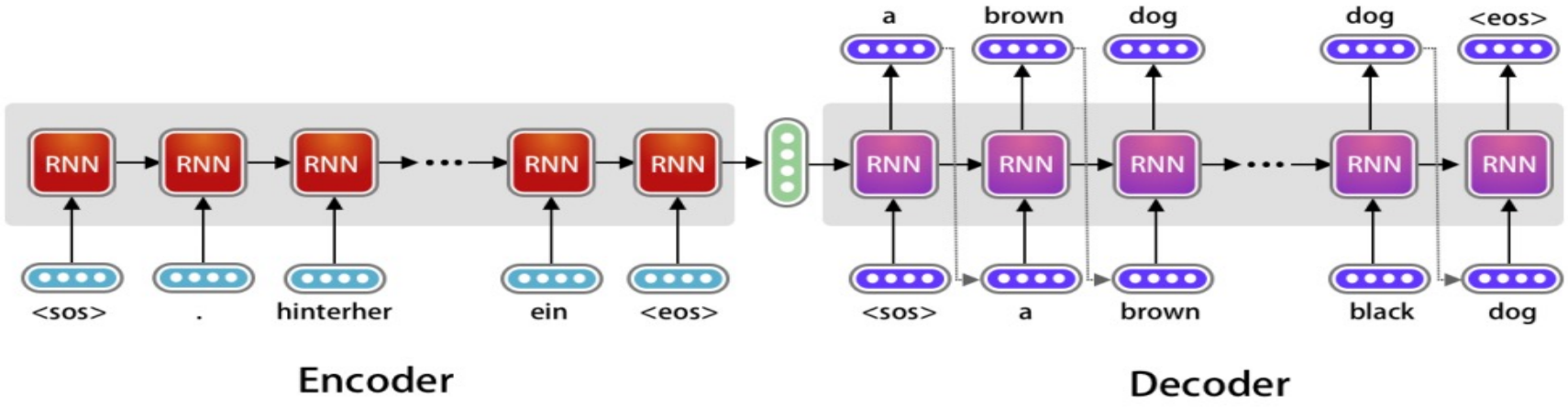


Image Credit: Machine Translation using Recurrent Neural Network and PyTorch. http://www.adeveloperdiary.com/data-science/deep-learning/nlp/machine-translation-recurrent-neural-network-pytorch/

Seq2Seq used for various NLP applications

- Machine Translation



- Automatic Email Reply

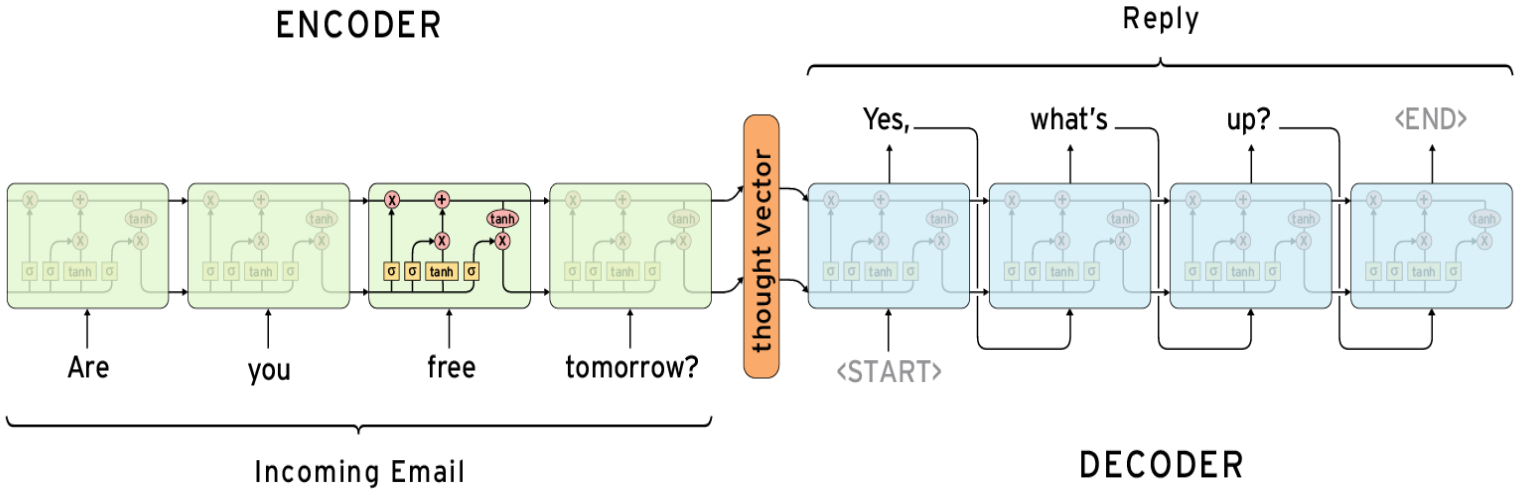
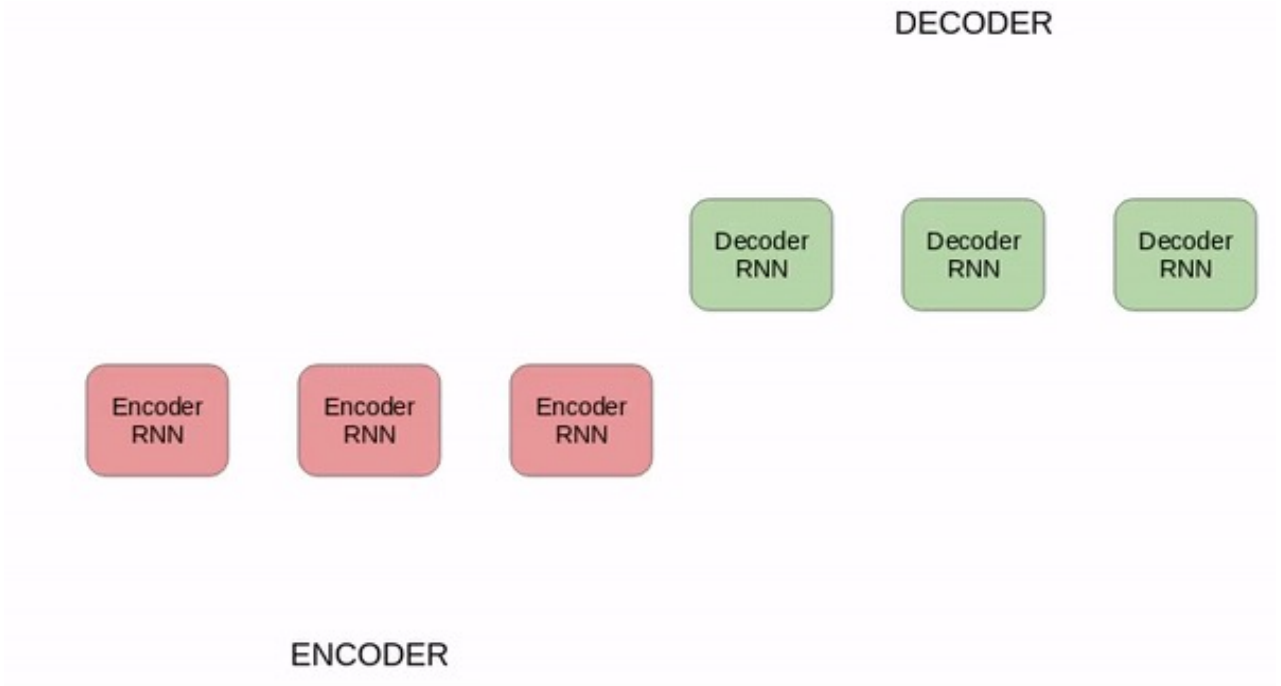


Image Credit: Machine Translation using Recurrent Neural Network and PyTorch. http://www.adeveloperdiary.com/data-science/deep-learning/nlp/machine-translation-recurrent-neural-network-pytorch/

Issues with RNNs for seq2seq tasks

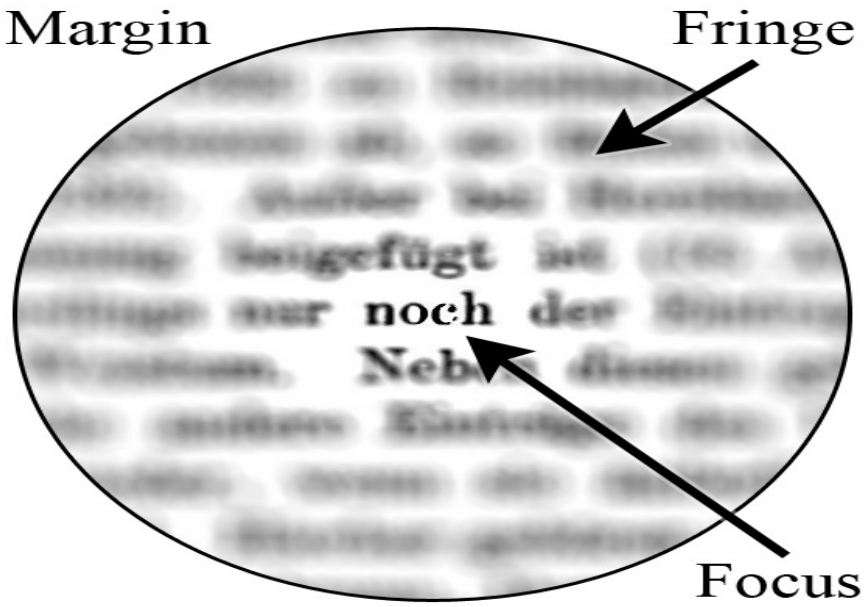
- Despite being very successful for various NLP tasks, there were challenges:
  - dealing with long-range dependencies
  - the sequential nature of the architecture prevents parallelization
- Attention mechanism helped to overcome first issue to certain extent



Credit: Encoder-Decoder Architecture for Machine Translation. https://www.analyticsvidhya.com/blog/2019/06/understanding-transformers-nlp-state-of-the-art-models/

Attention Mechanism

- A set of mechanisms that limit some processing to a subset of incoming stimuli (reducing computational demands)
- Attention in neural networks
  - A mechanism that learns to focus on a subset of the input that is relevant to the task.



task context representation

attended feature $\rightarrow \hat{v} = f(h, V)$

learned attention function (neural net)

set of attention candidates

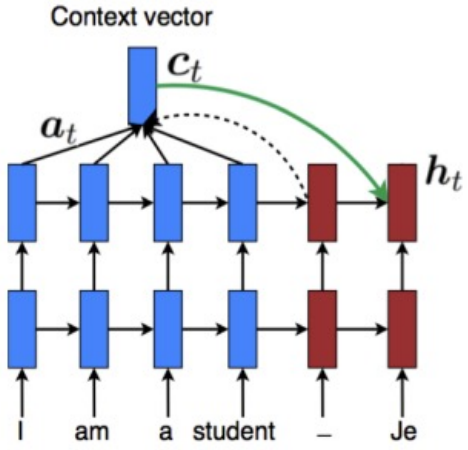
Neural Machine Translation by jointly Learning to Align and Translate

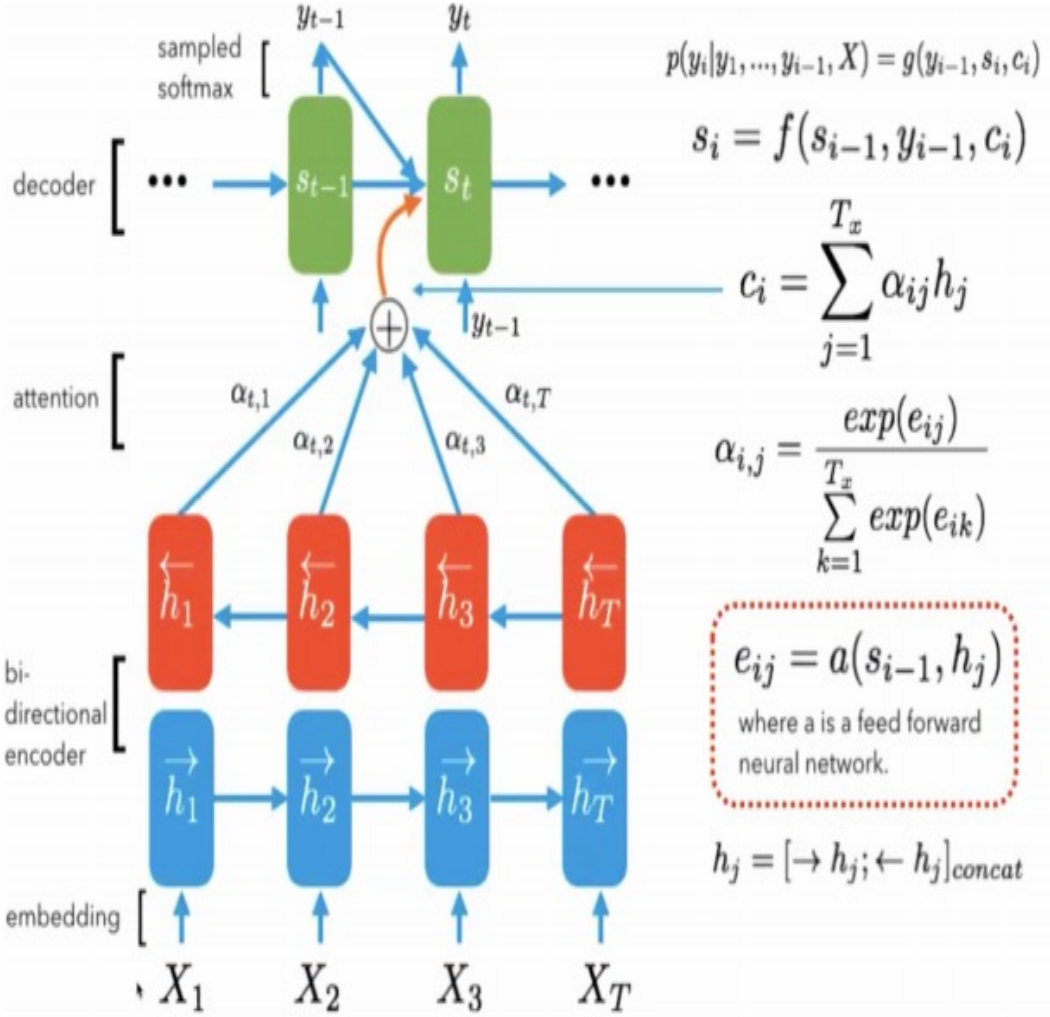
- Issue: The encoder-decoder framework compresses all the necessary information of a source sentence into a fixed-length vector.
- Solution: Enable the network to pay attention to specific areas of the input by adding new (weighted) connections

$$c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j$$

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})},$$

$$e_{ij} = a(s_{i-1}, h_j)$$

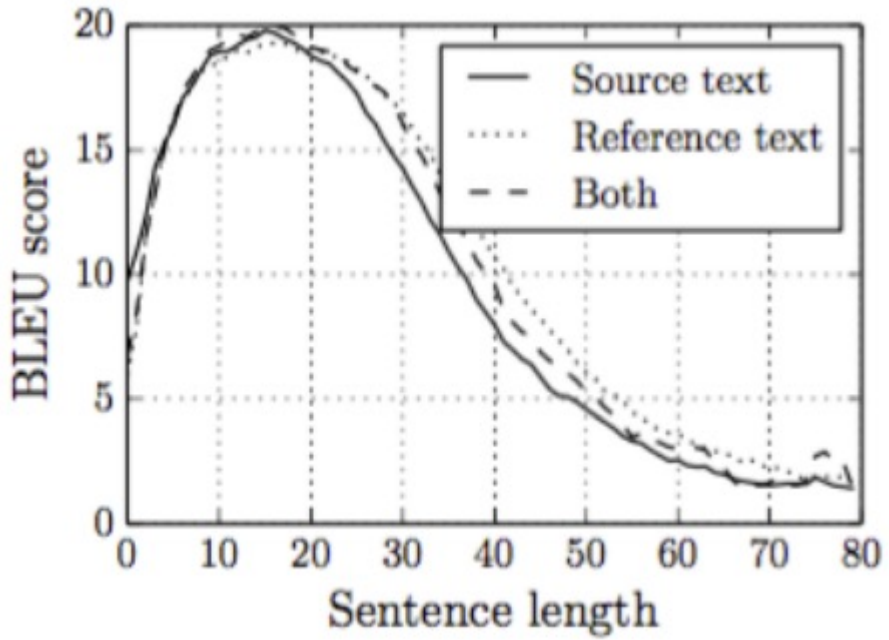




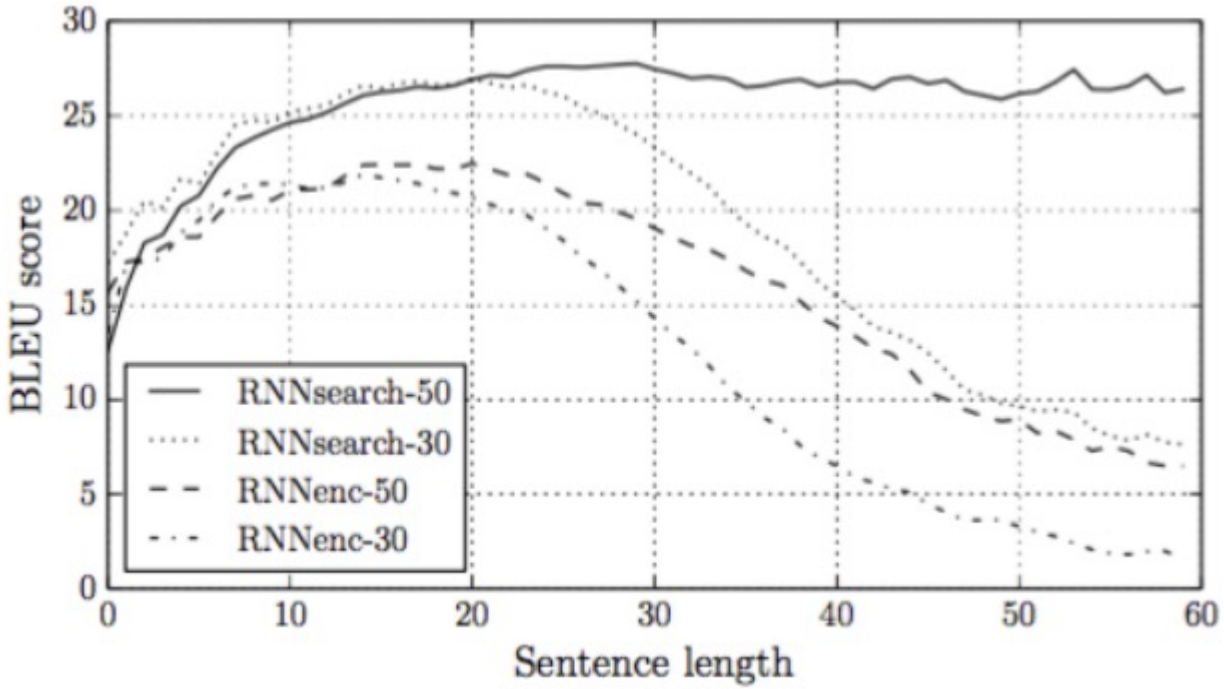
Credit: Bahdanau et al. (2015). Neural Machine Translation by jointly learning to Align and Translate. ICLR 2015.

NMT by jointly Learning to Align and Translate

Before Attention: Long sentences are very hard as they are compressed to a fixed length vector



After Attention: The attention mechanism helps to overcome the issue



Credit: Bahdanau et al. (2015). Neural Machine Translation by jointly learning to Align and Translate. ICLR 2015.

Image Captioning

- Developing models to generate textual description of an image

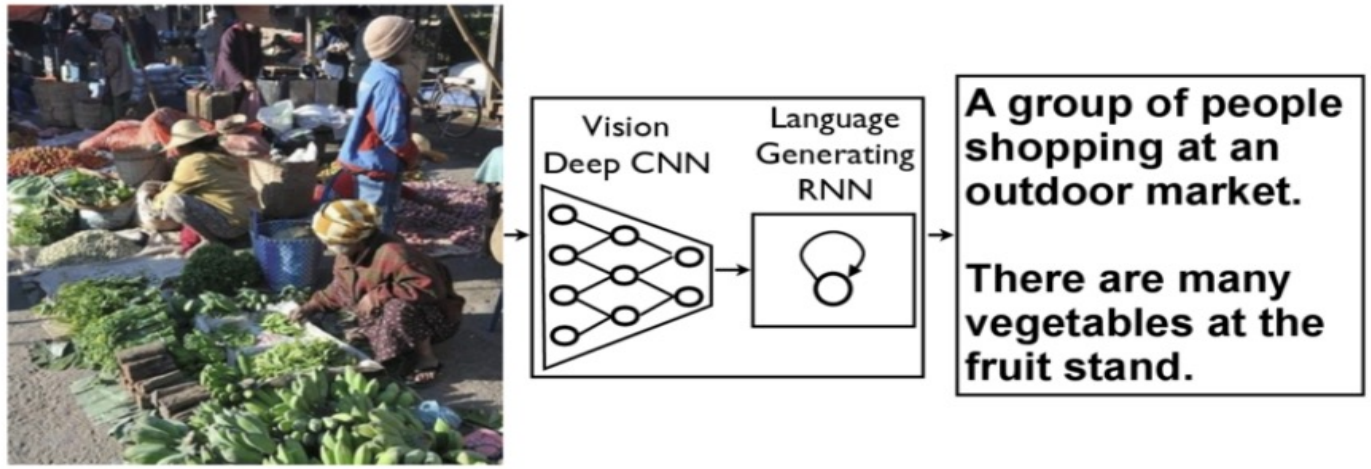
"man in black shirt is playing guitar."

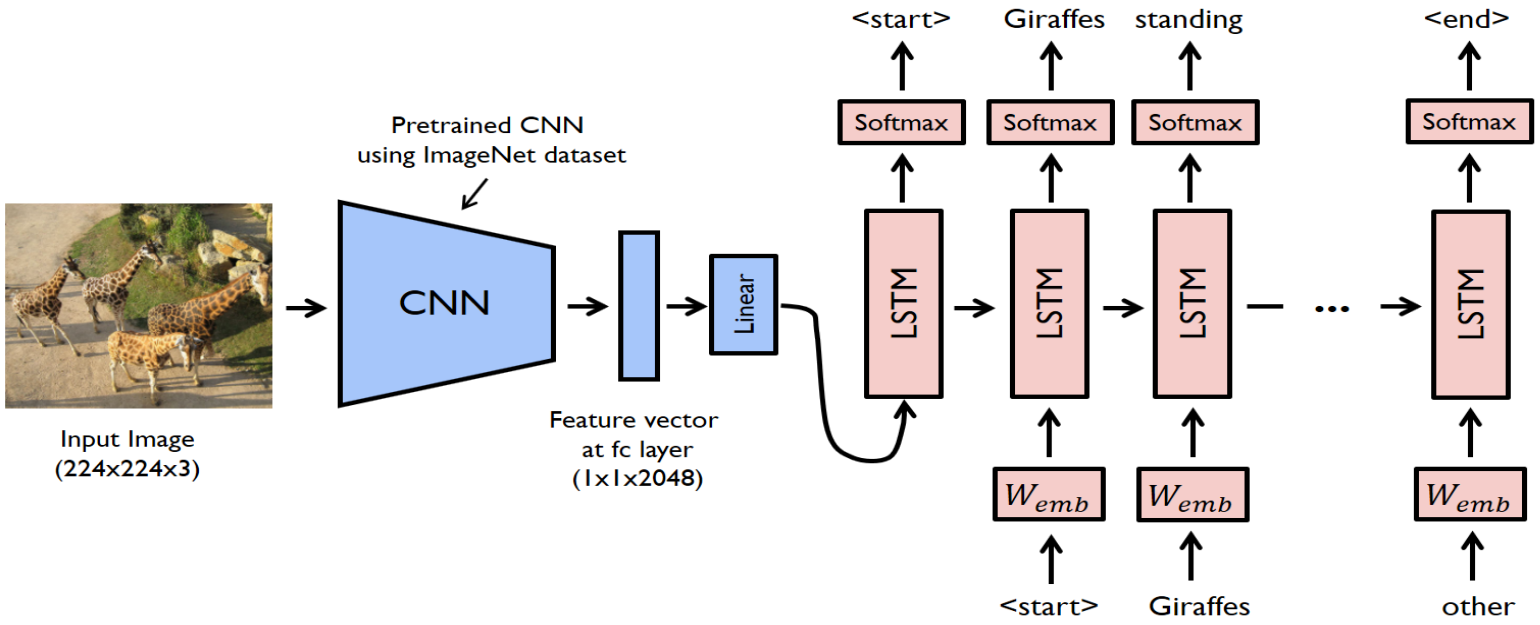
"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

Image Credit: Machine Translation using Recurrent Neural Network and PyTorch. http://www.adeveloperdiary.com/data-science/deep-learning/nlp/machine-translation-recurrent-neural-network-pytorch/

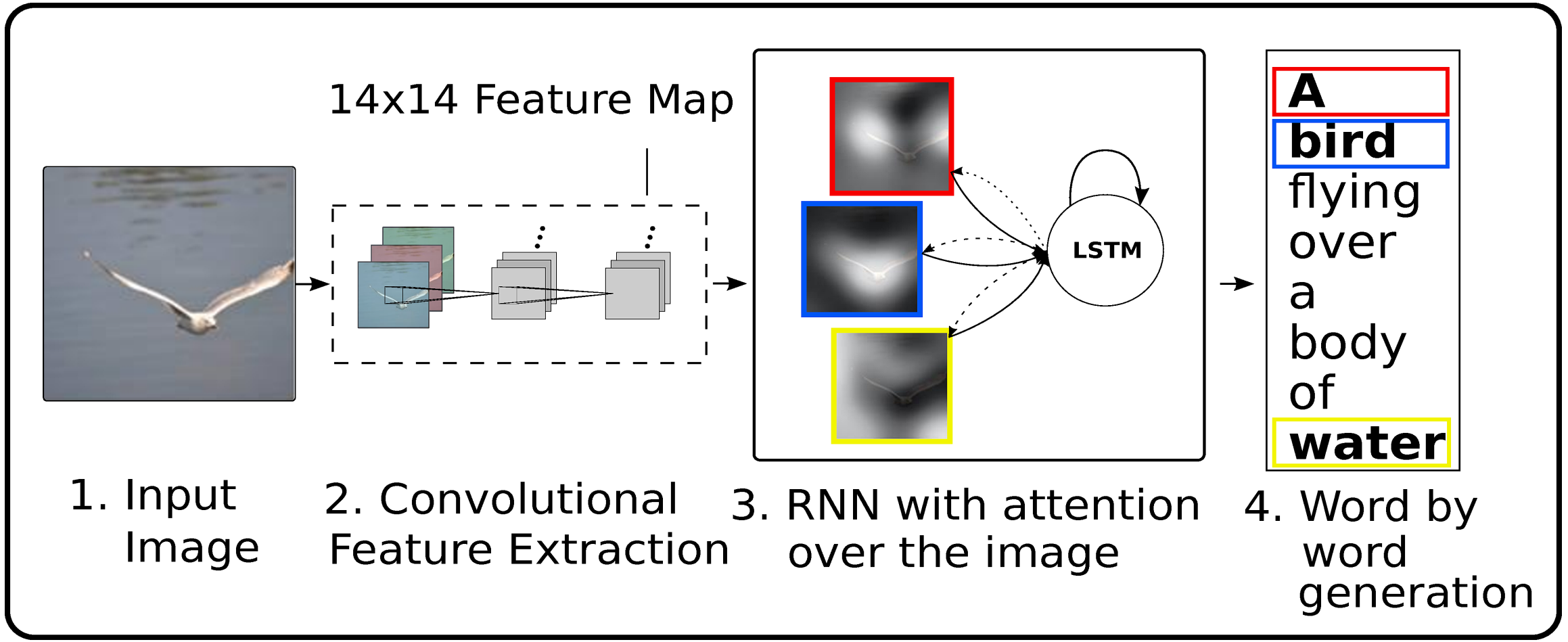
Show and Tell (Vinyals et al., 2015)





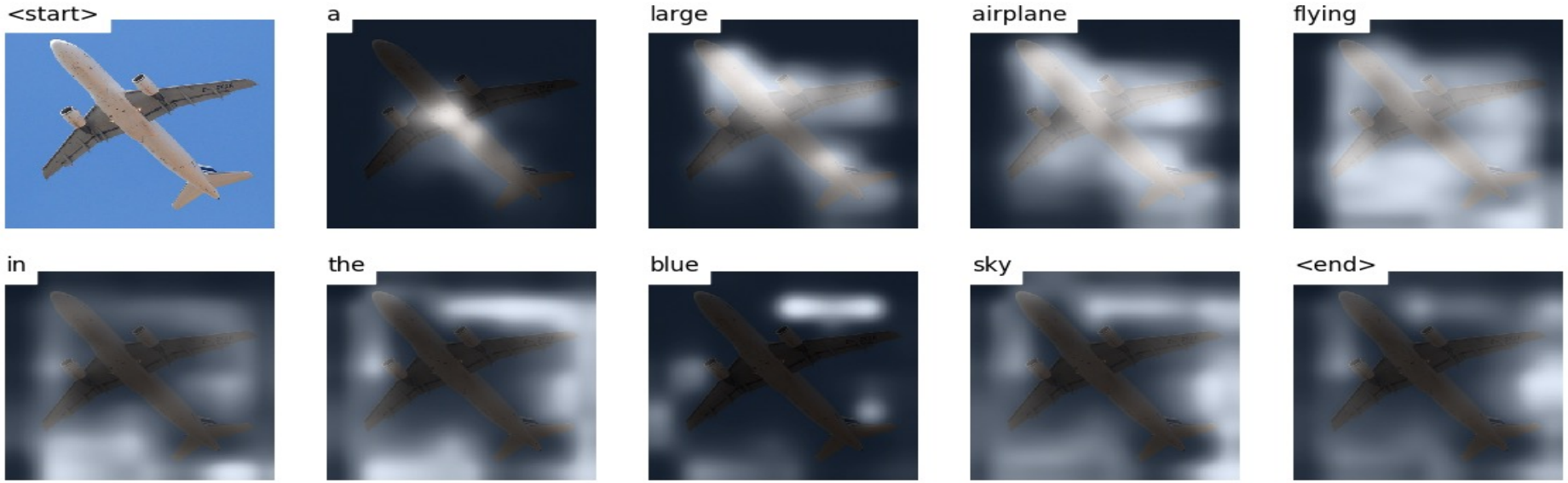
Show, Attend and Tell (Xu et al., 2015)

- "Rather than compressing an entire image into static representation, attention allows for **salient features** to dynamically come to forefront as needed"



Source: Xu et al., (2015). Show, Attend and Tell: Neural Image Caption Generation with Visual Attention

Show, Attend and Tell (Xu et al., 2015)



Source: Xu et al., (2015). Show, Attend and Tell: Neural Image Caption Generation with Visual Attention

Image Captioning with Semantic Attention (You et al., 2016)

- Learns to selectively attend to semantic concept proposals and fuse them into hidden states and outputs of RNNs.

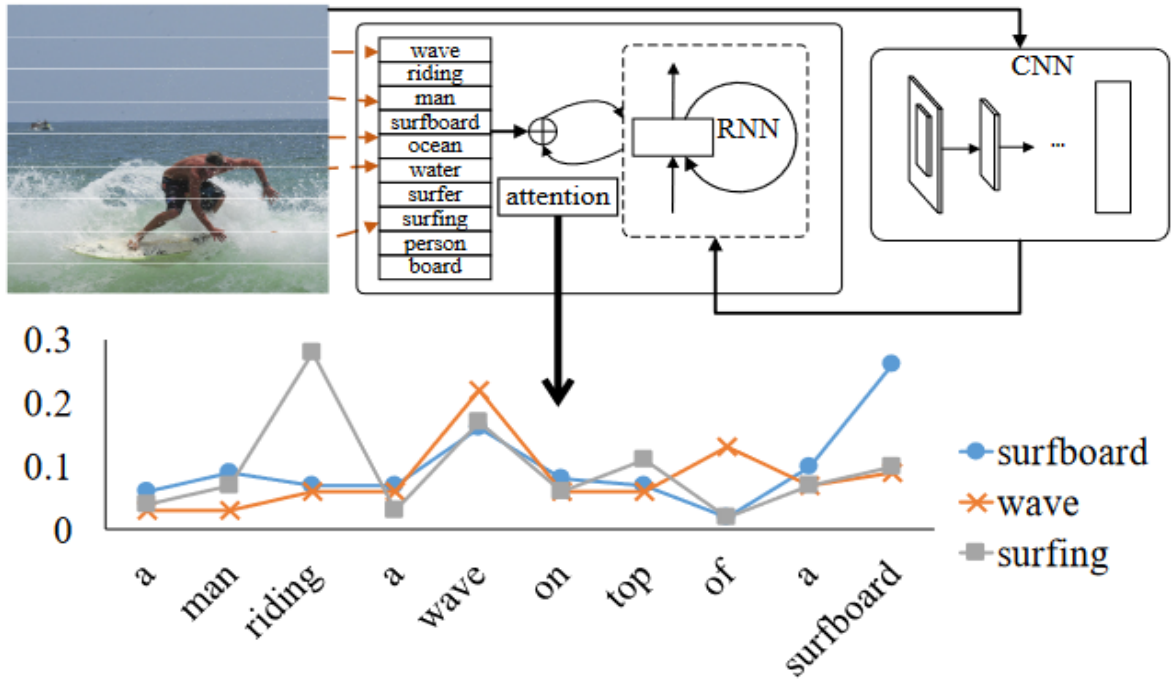


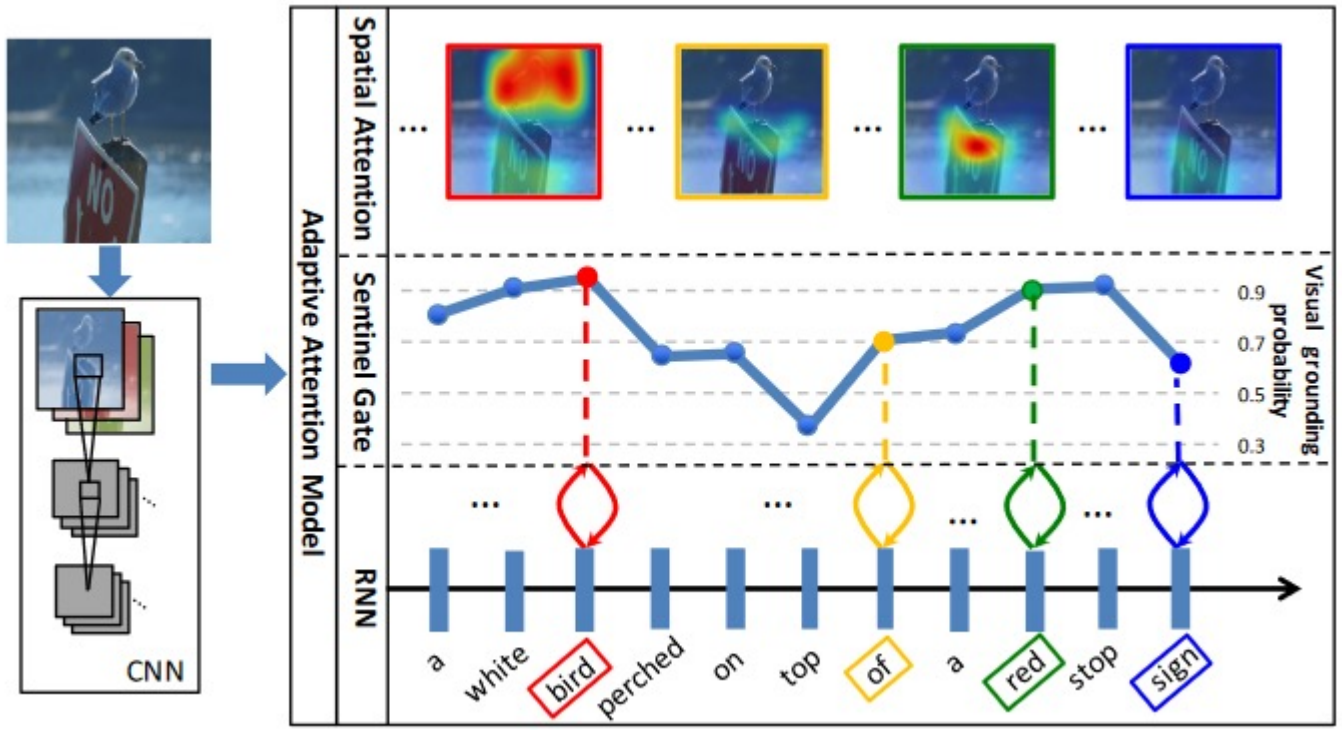
Image Captioning with Semantic Attention (You et al., 2016)

- Learns to selectively attend to semantic concept proposals and fuse them into hidden states and outputs of RNNs.

Source: You et al., (2016). Image Captioning with Semantic Attention

Knowing When to Look (Lu et al., 2017)

- Words such as “a”, “of”, “it” may be seen as not worth attending
- Words such as “woman”, “dog”, “traffic light” need attending to the image
- Automatically determines when to look (sentinel gate) and where to look (spatial attention) for word generation.



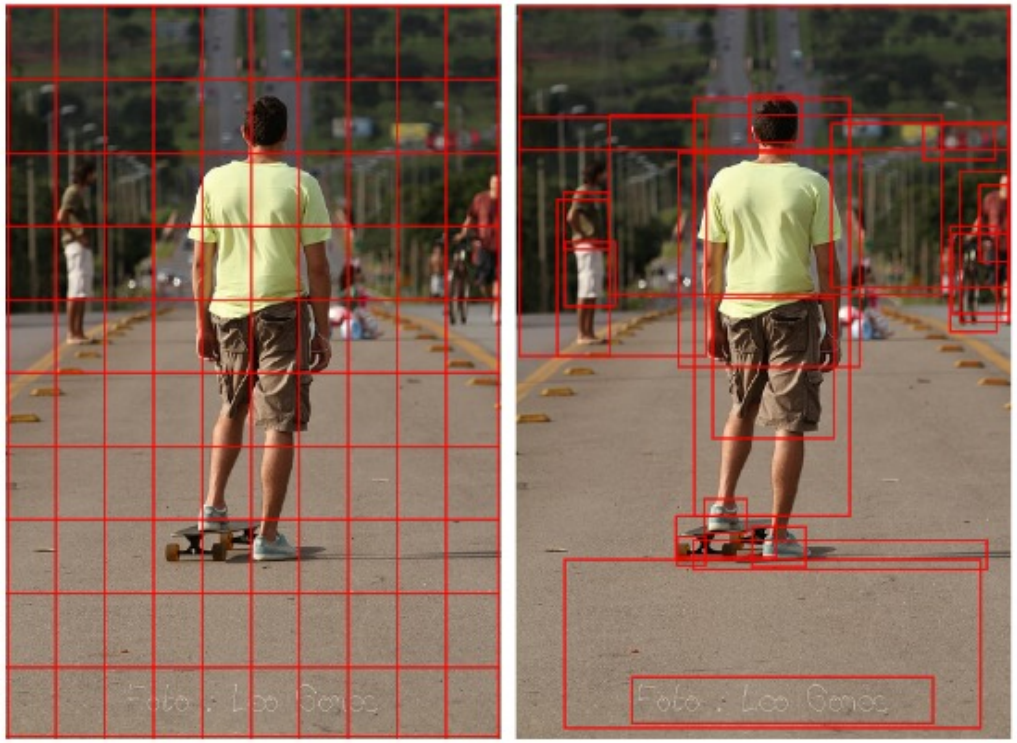
Knowing When to Look (Lu et al., 2017)

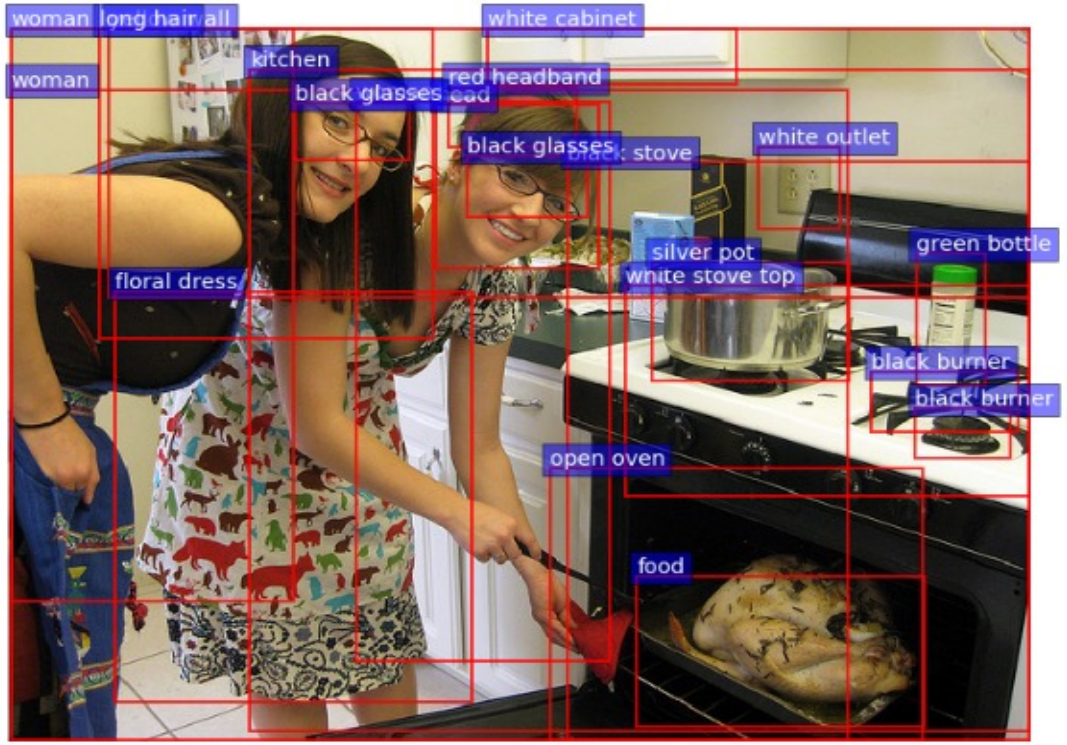
- Visualization of generated captions and image attention maps on COCO dataset

Source: Lu et al., (2017). Knowing When to Look: Adaptive Attention via A Visual Sentinel for Image Captioning

Bottom-up and Top-down attention (Anderson et al., 2018)

- Previous attention models operate on CNN features corresponding to a uniform grid of equally-sized image regions
- Bottom-up and Top-down enables attention to be calculated at the level of objects (or salient image regions)
- Features vectors extracted from Faster R-CNN are used





Source: Anderson et al., (2018). Bottom-Up and Top-Down Attention for Image Captioning and Visual Question Answering

Bottom-up and Top-down attention (Anderson et al., 2018)

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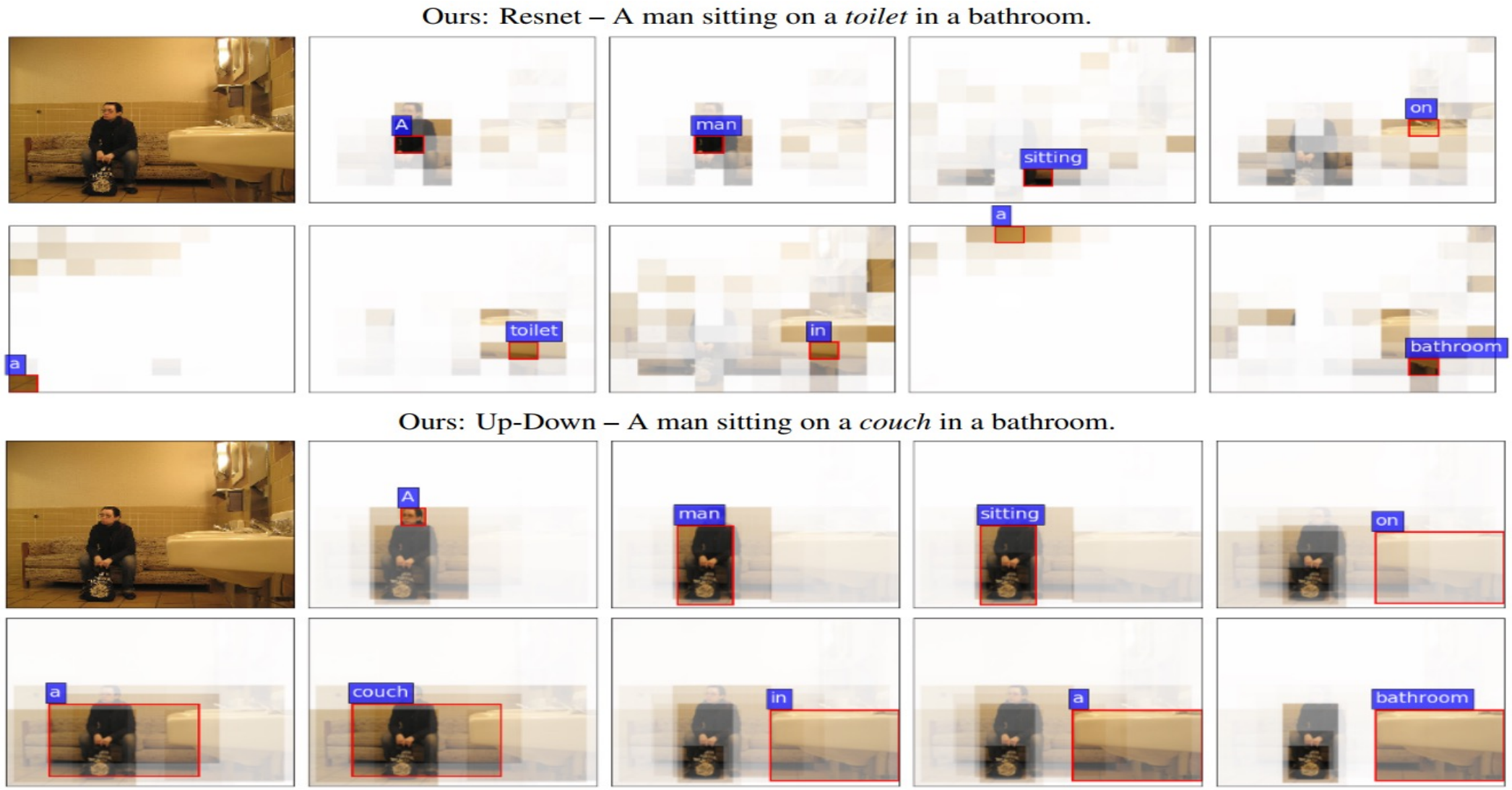


Source: Anderson et al., (2018). Bottom-Up and Top-Down Attention for Image Captioning and Visual Question Answering

And many more work …

- Show, Control and Tell: A Framework for Generating Controllable and Grounded Captions – Cornia M et al., CVPR 2019
- Pointing Novel Objects in Image Captioning, Li Y et al., CVPR 2019
- Describing like humans: on diversity in image captioning – Wang Q et al., CVPR 2019
- Length-Controllable Image Captioning – Deng C et al., ECCV 2020
- Transformer-based local-global guidance for image captioning – Parvin et al., 2023
- Show, tell and summarise: learning to generate and summarise radiology findings from medical images – Singh et al., Neural Computing & Applications, 2021.
- Medical image captioning via generative pretrained transformers – Selivanov et al. Scientific Reports, 2023

- Let's see Image captioning in action
  - https://milhidaka.github.io/chainer-image-caption/

Source: Awesome Image Captioning. https://githubmemory.com/repo/alibabadoufu/awesome-image-captioning

Visual Question Answering (VQA)

- Given an image, can our machine answer the corresponding questions in natural language?

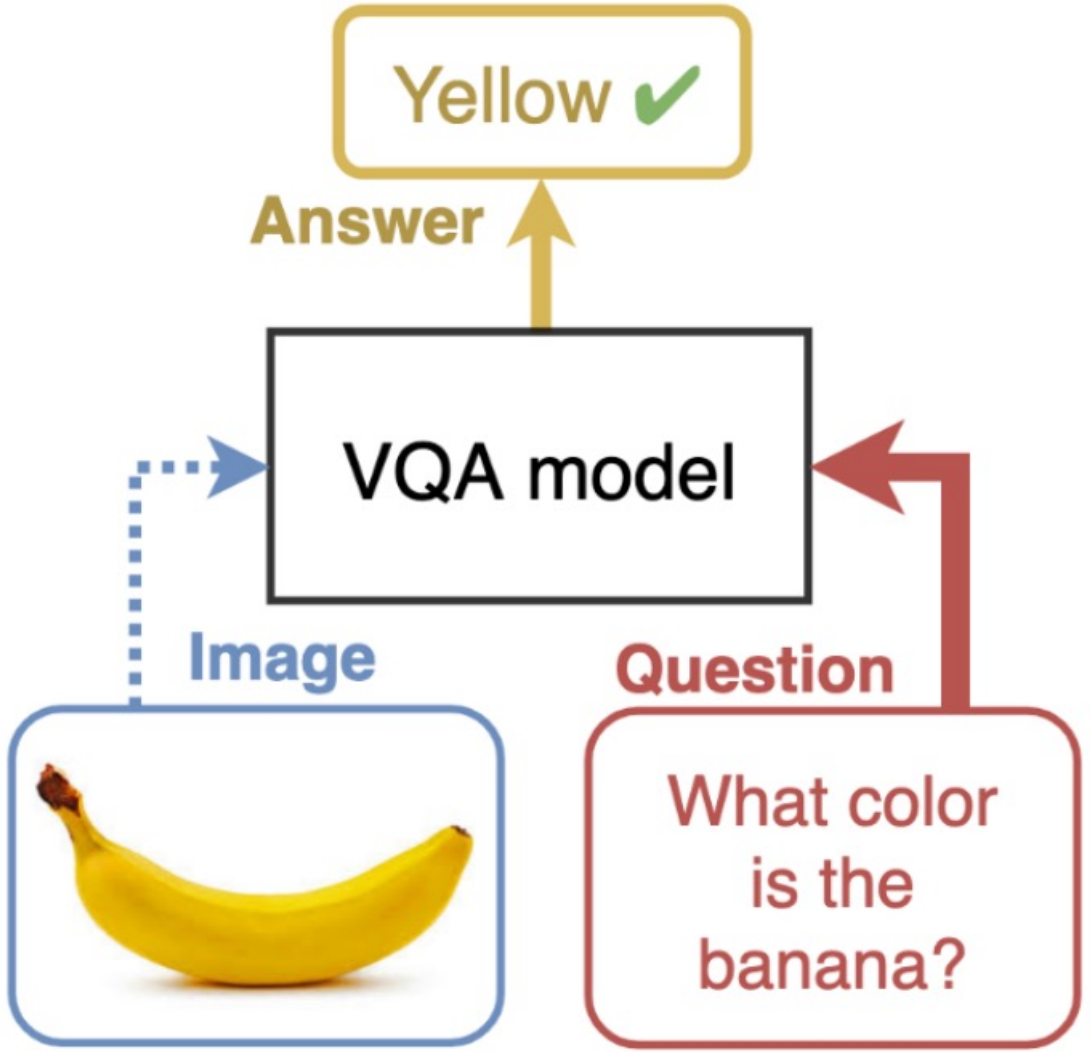


Image Credit: Corentin Dancette. https://cdancette.fr/2020/11/21/overview-bias-reductions-vqa/

VQA Dataset

➢

Who is wearing glasses?

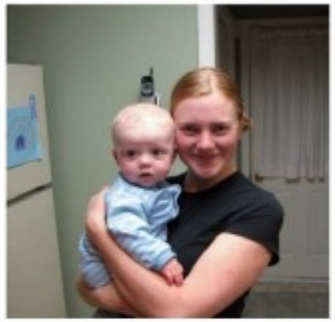
man

woman

Where is the child sitting?

fridge

arms



Is the umbrella upside down?

yes

no

How many children are in the bed?

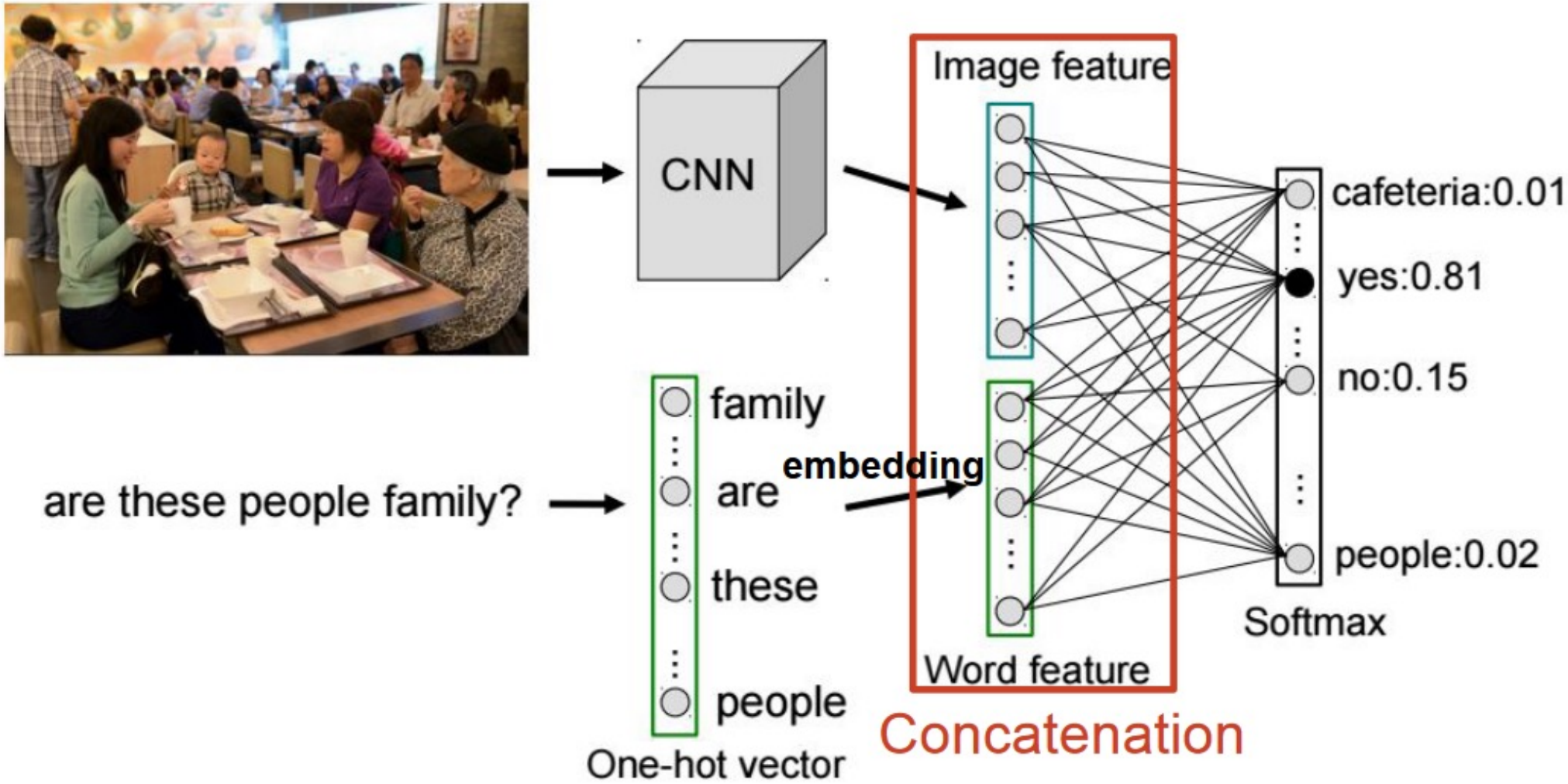
2

1

Source: Visual Question Answering. https://visualqa.org/

VQA Approach: Bag-of-words + Image feature (iBOWIMG)

- Combine image and word embeddings to predict answer



Zhou et al., (2015). Simple baseline for visual question answering

VQA Common Approach

- Combine CNN (for vision) and RNN (for language) to predict answer

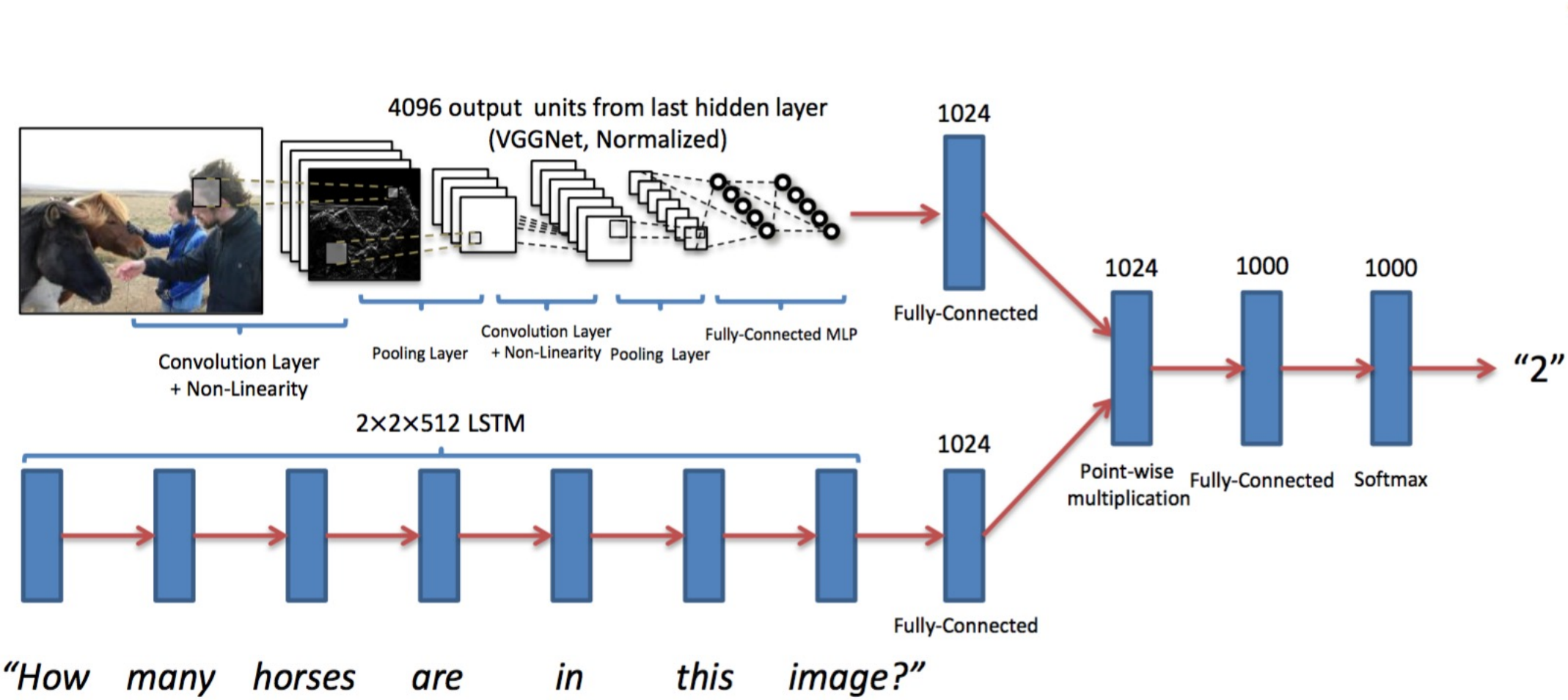


Image Credit: https://github.com/anantzoid/VQA-Keras-Visual-Question-Answering

VQA – set of problems

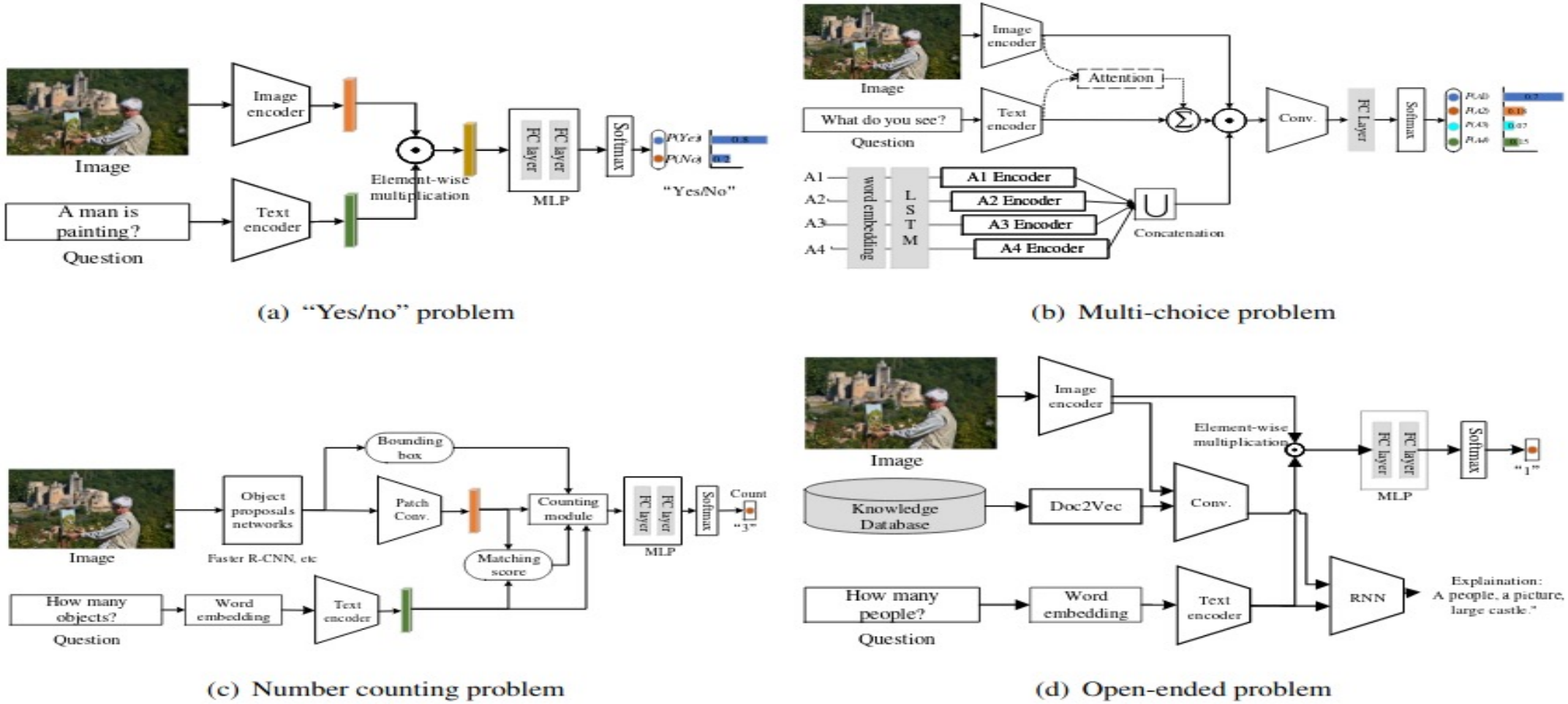
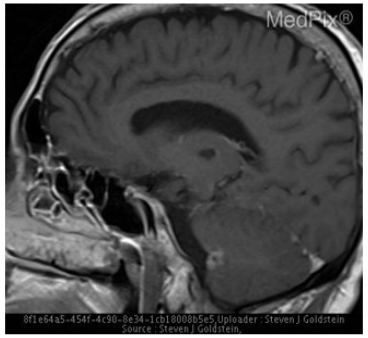


Figure 2 Common types of visual question answering. "Yes/No" problem and multi-choice problem can be regarded as a classification problem, while number counting problem and open-ended problem can be viewed as a caption generation problem.

Source: Chen et al., (2020). New Ideas and Trends in Deep Multimodal Content Understanding: A Review

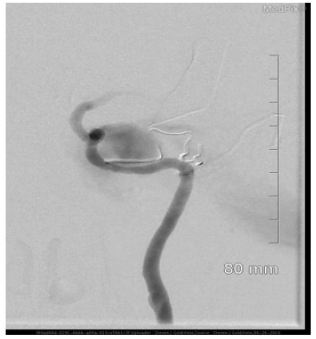
VQA in the Medical Domain

- Aims to create a system that can answer natural language questions based on a given medical image.
- VQA-Med 2019 Challenge dataset

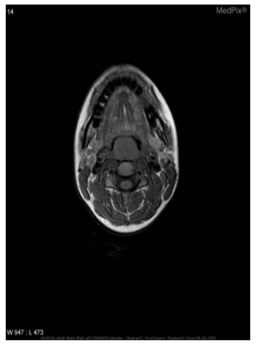


Q: What is the plane of this MRI?
A: Sagittal

Q: The CT scan shows what organ system?
A: Spine and contents



Q: With what modality is this image taken?
A: AN - angiogram



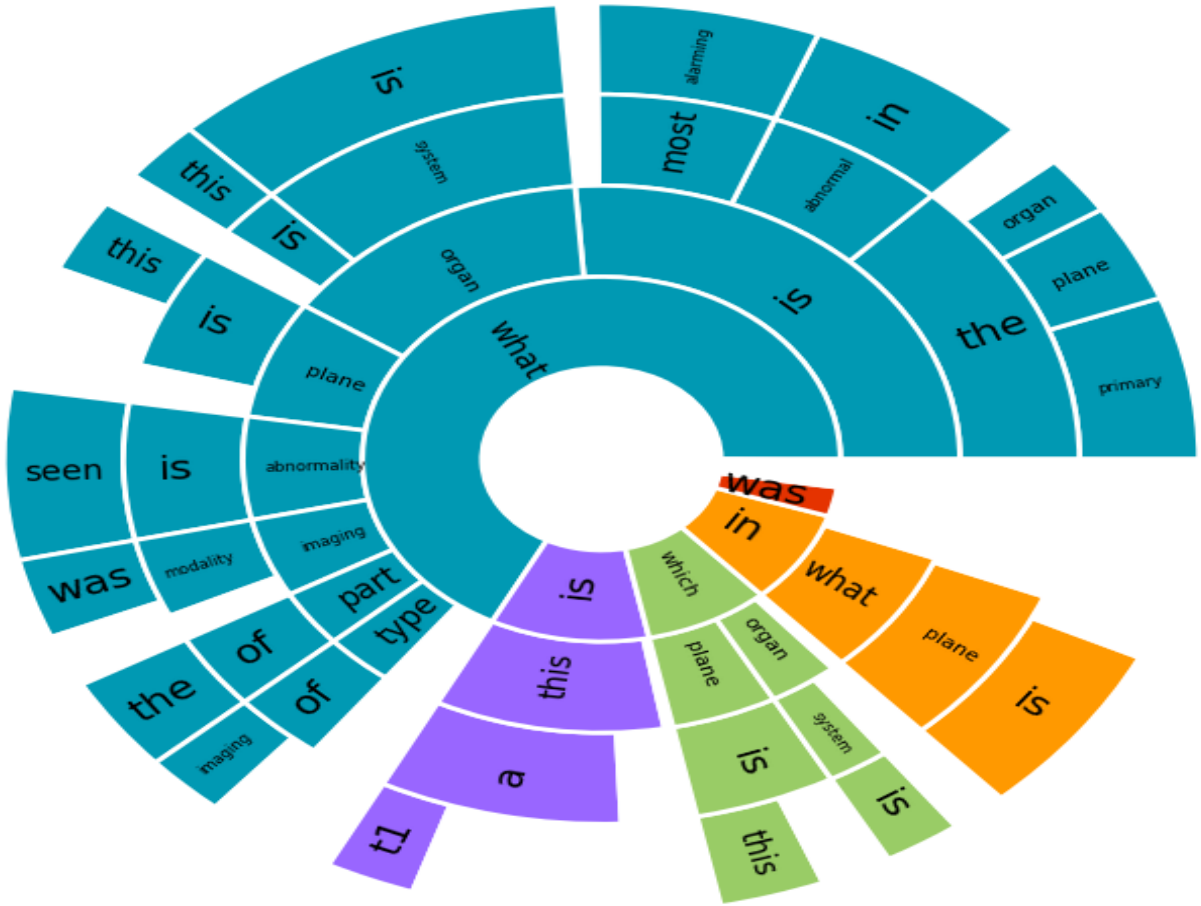
Q: What is most alarming about this MRI?
A: Schwannoma

Source: Canepa et al. (2023). Visual Question Answering in the Medical Domain. DICTA. 2023.

VQA-Med

- Most questions in VQA-Med 2019 dataset are “close-ended”
- More than 50% of answers consists of only one word, and more than 82% of answers have between one and three words.
- Best strategy is to do classification

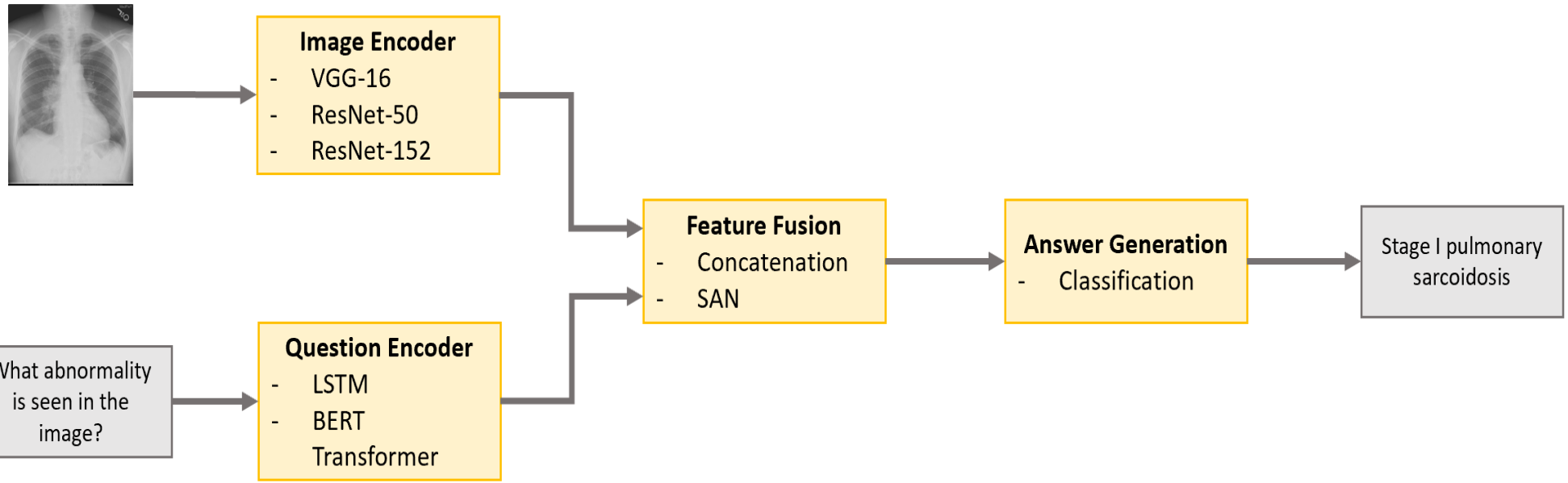
  rather than generation



Source: Canepa et al. (2023). Visual Question Answering in the Medical Domain. DICTA. 2023.

VQA-Med Methodology

- Contributions
  - Incorporating medical domain knowledge
    - Image encoder – applied self-supervised pretraining using Radiology Objects in COntext (ROCO) dataset
    - Question encoder – used BioBERT, pretrained on same tasks as BERT, but using the PubMed corpus
  - Evidence verification
    - Gradient Weighted Class Activation Map (Grad-CAM) for evidence verification



Source: Canepa et al. (2023). Visual Question Answering in the Medical Domain. DICTA. 2023.

Results

- Test accuracy achieved by each model variation

Model Variation	Test Accuracy
VGG-16 + LSTM + Concatenation	0.56
ResNet-50 + LSTM + Concatenation	0.54
ResNet-152 + LSTM + Concatenation	0.53
VGG-16 + BERT + Concatenation	**0.60**
VGG-16 + BERT + SAN	0.58
VGG-16 + BioBERT + Concatenation	**0.60**
Pretrained VGG-16 + BERT + Concatenation	**0.60**

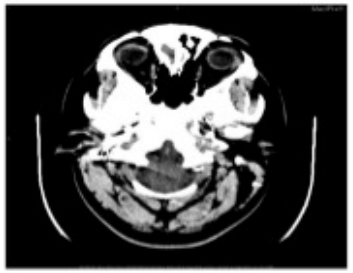
- Accuracy of the baseline vs. BERT model per category type

Model Variation	Baseline	+BERT
Modality	0.64	0.76
Plane	0.78	0.77
Organ	0.74	0.74
Abnormality	0.06	0.08
Overall	0.56	**0.60**

Source: Canepa et al. (2023). Visual Question Answering in the Medical Domain. DICTA. 2023.

Results

- Effect of using BERT vs. LSTM



Q: What imaging modality was used to take this image?
GT: CT with IV contrast
Baseline: Skull fracture from cell phone
+BERT: CT with IV contrast

(a) Category misclassification

Q: What was this image taken with?
GT: MR – PDW proton density
Baseline: Yes
+BERT: MR – PDW proton density

(b) Wrong answer type

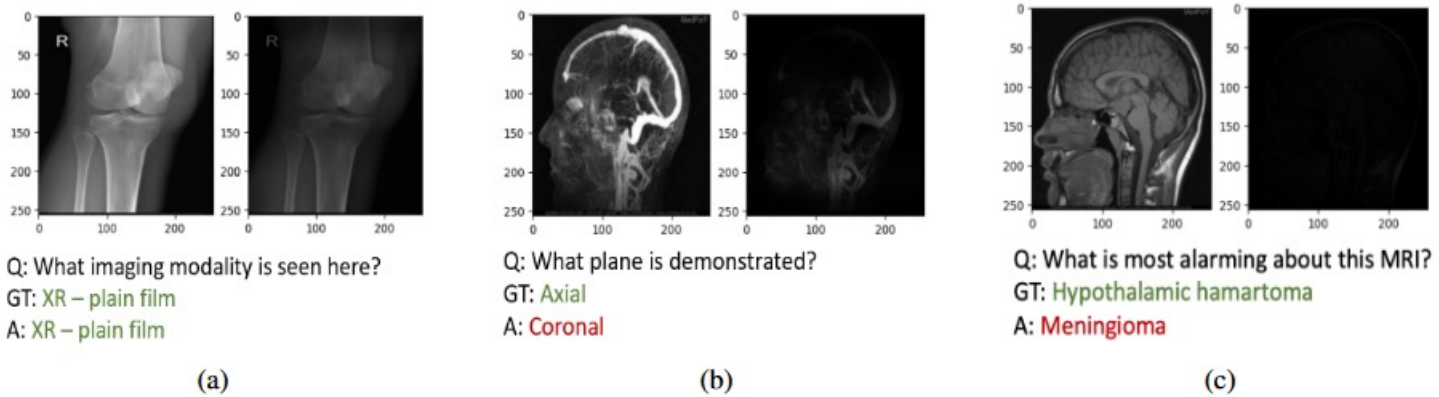
Q: Is this a contrast or noncontrast MRI?
GT: Noncontrast
Baseline: MR – flair
+BERT: Noncontrast

(c) Not choosing from options

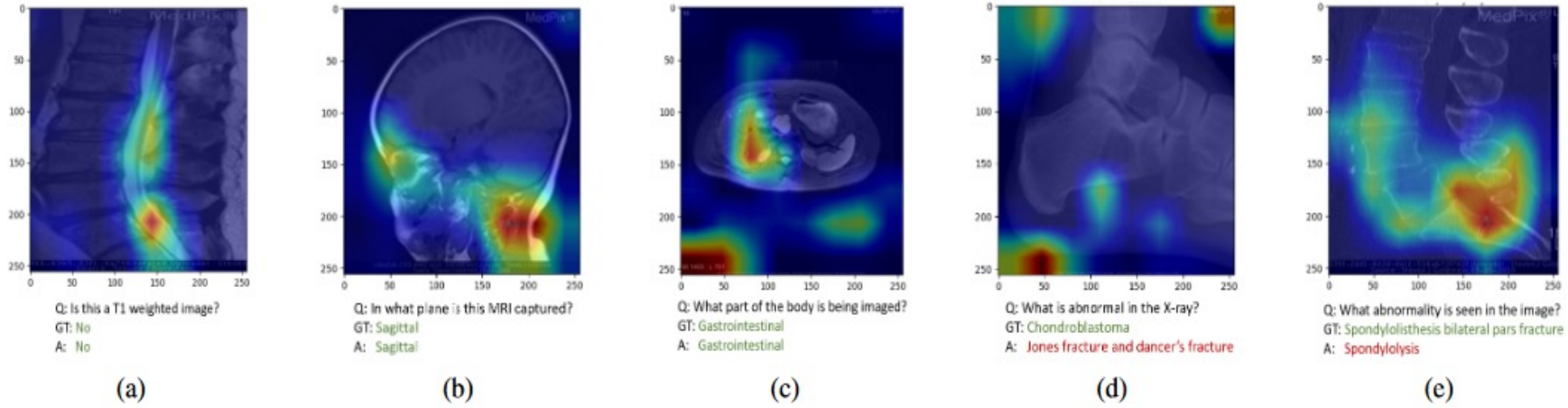
Source: Canepa et al. (2023). Visual Question Answering in the Medical Domain. DICTA. 2023.

Evidence verification

- Attention distribution output by Stacked Attention Network (SAN) fusion method



- Grad-CAM output



Source: Canepa et al. (2023). Visual Question Answering in the Medical Domain. DICTA. 2023.

Let’s see in action

- https://visualqa.org/visualize/
- https://demo.allennlp.org/visual-question-answering

Image Credit: https://github.com/anantzoid/VQA-Keras-Visual-Question-Answering

Visual Dialog

- Ability to hold a meaningful dialog with humans in natural language about visual content
- **Given an image** I, a **history of dialog consisting** of sequence of **question-answer pairs**, and a natural language **follow-up question**, the task for the machine is to **answer the question** in free-from natural language.

Image Credit: Visual Dialog. https://visualdialog.org/

Image Captioning vs. VQA vs. Visual Dialog

VQA

Q: How many people on wheelchairs ?

A: Two

Q: How many wheelchairs ?

A: One

Captioning

Two people are in a wheelchair and one is holding a racket.

Visual Dialog

Q: How many people are on wheelchairs ?

A: Two

Q: What are their genders ?

A: One male and one female

Q: Which one is holding a racket ?

A: The woman

Visual Dialog

Q: What is the gender of the one in the white shirt ?

A: She is a woman

Q: What is she doing ?

A: Playing a Wii game

Q: Is that a man to her right

A: No, it's a woman

Session Variables

Image Credit: Das et al., (2017) Visual Dialog. https://visualdialog.org/

Visual Dialog – Late Fusion Encoder

- Entire history H is concatenated and encoded by LSTM

Image I

Do you think the woman is with him?

Question Q_t

The man is riding his bicycle on the sidewalk. Is the man wearing a helmet? No he does not have a helmet on. ... Are there any people nearby? Yes there's a woman walking behind him.

t rounds of history (concatenated)

CNN

LSTM

LSTM

4096

512

512

512

Decoder

No I don't think they are together

Answer A_t

A fully-connected layer and tanh nonlinearity

Visual Dialog – Hierarchical Recurrent Encoder

- Each QA-pairs in history H separately encoded by the LSTM

Image I

Do you think the woman is with him?

Question Q_t

The man is riding his bicycle on the sidewalk.
Is the man wearing a helmet? No he does not have a helmet on.
How old is the man? He looks around 40 years old.
What color is his bike? It has black wheels and handlebars. I can't see the body of the bike that well.
Is anyone else riding a bike? No he's the only one.
Are there any people nearby? Yes there's a woman walking behind him.

t rounds of history

{(Caption), (Q_1,A_1), ..., (Q_{t-1}, A_{t-1})}

CNN

LSTM

$I+Q_t$

LSTM

H_{t-5} H_{t-4} H_{t-3} H_{t-2} H_{t-1} H_t

$I+Q_{t-1}$ $I+Q_{t-2}$ $I+Q_{t-3}$

512 512

t t-1 t-2 t-3 t-4 t-5

GRU

Decoder

No I don't think they are together

Answer A_t

Each QA-pair in dialog history is independently encoded by another LSTM with shared weights

The image-question representation, computed for every round from 1 through t , is concatenated with history representation from the previous round and constitutes a sequence of question-history vectors

Image Credit: Das et al., (2017) Visual Dialog. https://visualdialog.org/

Visual Dialog – Hierarchical Recurrent Encoder

- Compute inner product of question vector with each history vector to get scores over previous rounds, which are fed to a SoftMax to get attention-over-history probabilities.

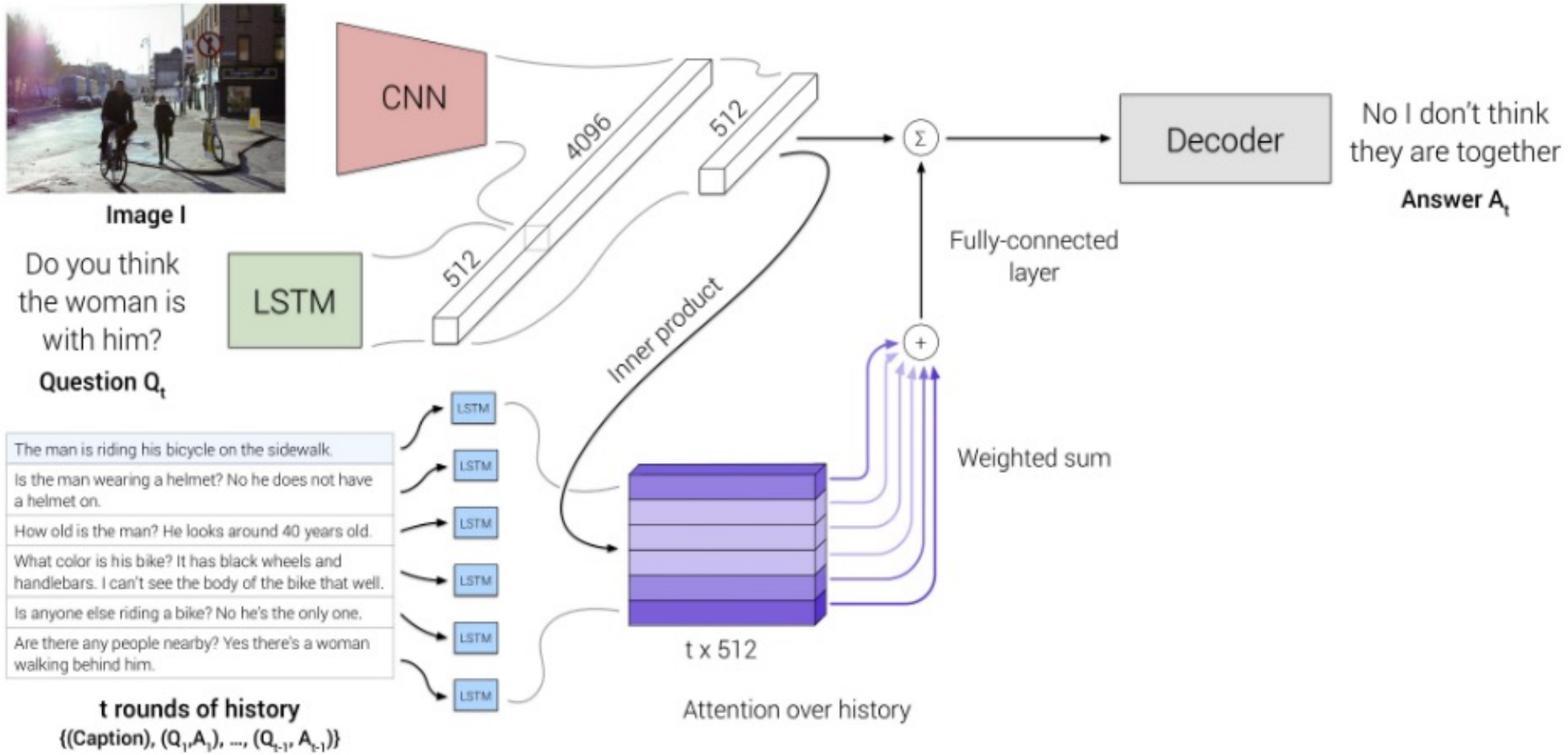


Image Credit: Das et al., (2017) Visual Dialog. https://visualdialog.org/

Improving Visual Dialog (and few examples)

- Generates more diverse, image relevant and fluent dialog.

Image + Caption	GT dialog (Das et al., 2017a)	Q-BOT-A-BOT dialog	Diverse-Q-BOT-A-BOT dialog
	what color is the cutting board? blue how big is it about the size of a regular laptop screen how many carrots are there ? 4 are they the orange kind ? 2 are orange , 2 are white what kind of cell phone is it ? a samsung can you see any text on the screen ? a recipe for UNK UNK soup do you see the room ? just the counter are there people ? not visible what color is the counter ? white	is the photo in color ? no how many people do you see ? no people is this a close up ? no is this a close up ? zebra is is this a close up ? no is this a close up ? no is this a close up ? no is this a close up ? no is this a close up ? no is this a close up ? no	is the photo in color ? 1 picture is in color is the photo close up ? black and white is the photo in color ? no it 's black and white is it a close up ? no it 's a close up of the cake can you tell what brand it is ? no i ca n't see the brand can you tell if it 's a male or female ? no i ca n't tell can you tell if it 's a male or female ? no i ca n't tell is this in a kitchen ? nope it 's in a home are there any utensils ? no are there any utensils ? nope
a cutting board with carrots next to a cell phone.			
	is the field large ? yes is the grass green or brown ? green can you see a barn ? no can you see a fence ? no can you see a water supply ? yes can you see any people ? no can you see trees ? yes can you see mountains in the background ? no is the grass tall or short ? short	what color are the cows ? they are brown and white how many cows are there ? 4 what color are the cows ? they are brown and white can you see the sky ? it is not visible do you see any trees ? i do not see any trees can you see the sky ? green sky are there any clouds ? the sky is not visible how many cows are there ? 2 what color are the cows ? the cows are brown and white what color are the cows ? they are brown	do you see any people ? 1 do you see a fence ? a small 1 how many cows are there ? 5 what color are the cows ? black and white can you see the sky ? some can you see the sky ? nope are there any other animals ? not that i can see can you see the sky ? not at all are there any trees ? in the background can you see the sky ? not at all
many brown and black cows standing in the grass			
	what type of building ? may be part of a zoo how many elephants ? about 4 is it sunny ? clear day , yes any trees ? yes what color is the building ? dark grey are there other animals ? no are there any people ? yes what are they wearing ? shorts and shirts how many ? 3	how many elephants are there ? ca n't tell what color are the elephants ? ca n't tell how many elephants are there ? ca n't tell what color is the fence ? i ca n't tell can you see the sky ? i ca n't see the sky are there any trees ? just a few does this look like a zoo ? 1 of them is are there any people ? nothing in the picture how many elephants are there ? just 1 can you see the sky ? just a little	how many elephants are there ? 1 any people ? ca n't see any male or female ? not sure what is the elephant doing ? just standing there male or female ? there are 2 males and 1 female can you see the sky ? 1 of it what color is the building ? just a black and white picture do you see any trees ? there are trees in the background are there any other animals ? red and white do you see any trees ? i see some in the background
many elephants standing in an enclosure near a building			
	is the photo in color ? yes is there humans in the photo ? no is there any animals in the photo ? no what color are the walls ? tan what color is the sink ? white is there any towels ? no is there any pictures on the wall ? no what color is the tub ? white can you see the floor ? no	is the photo in color ? 5 of them are are there any people ? it 's a close up so i ca n't see any people what color is the sink ? about the same color as the toilet do you see a mirror ? no what color is the sink ? yes it is white what color is the sink ? yes it is white what shape is the mirror ? yes , it 's a rectangle are there any towels ? he 's on a towel rack are there any towels ? i do n't see any towels are there any towels ? i do n't see any towels	is the photo in color ? no is there any people ? 5 what color walls ? i ca n't see the walls is there a mirror ? yes is there a mirror ? yes is there a mirror ? yes are the walls seen ? no what color are the walls ? no walls what is the floor made of ? yes what color is the floor ? i ca n't see the floor
a reflection of the tub is in the bathroom mirror along with the sink , you can see all the room			

Source: Murahari et al., (2019) Improving Generative Visual Dialog by Answering Diverse Questions.

Many more tasks at CV+NLP

- Vision-Language Navigation (VLN)

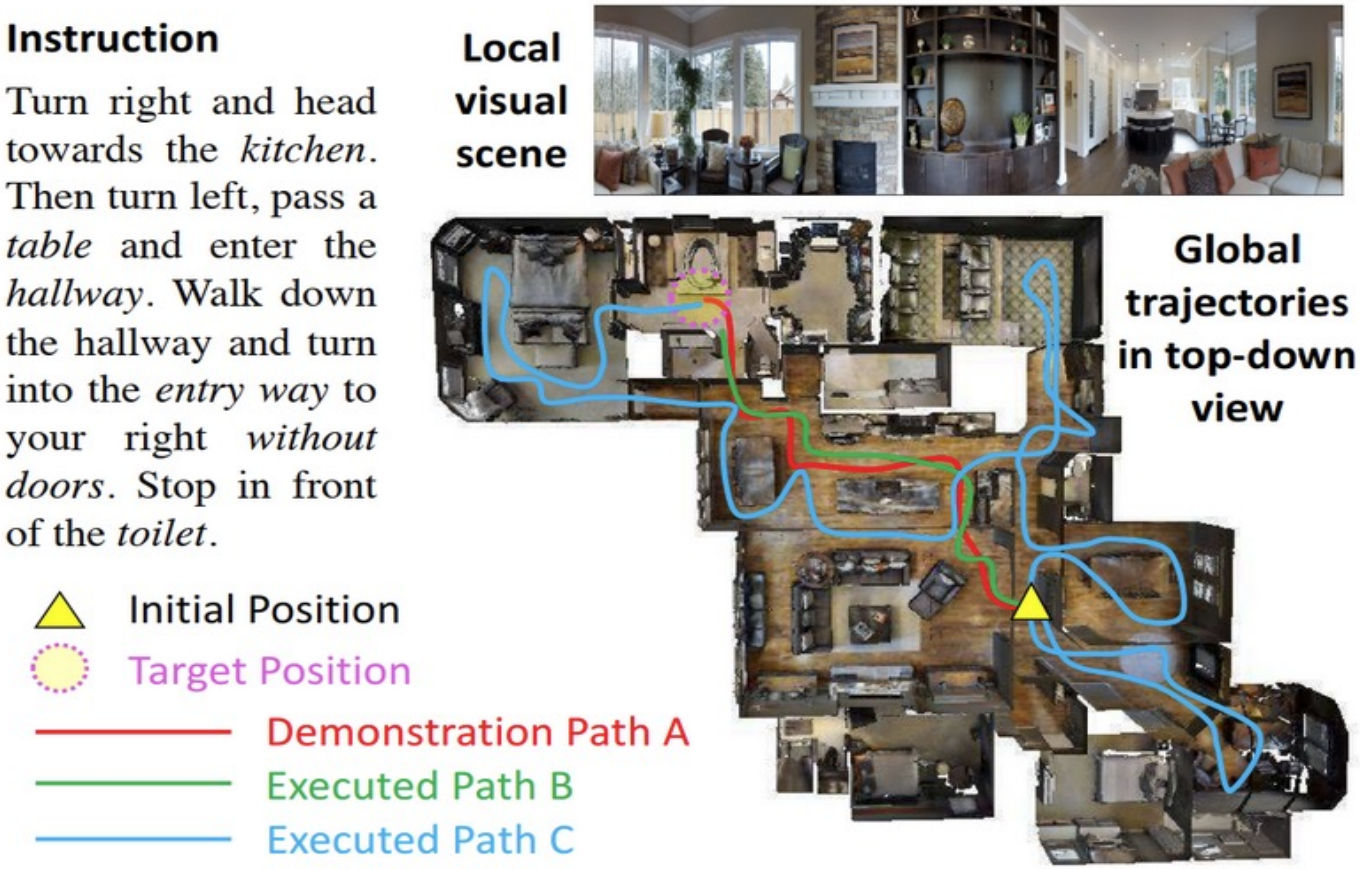


Figure 1: Demonstration of the VLN task. The instruction, the local visual scene, and the global trajectories in a top-down view. The agent does not have access to the top-down view. Path A is the demonstration path following the instruction. Path B and C represent two different paths executed by the agent. Figure credit: Wang et al. (2019).

Source: Wang et al. (2019) Reinforced Cross-Modal Matching and Self-Supervised Imitation Learning for Vision-Language Navigation

Many more tasks at CV+NLP

- Visual grounding for referring expressions
  - Grounding an utterance to refer to something or someone in image

Fig. 1: Interactive visual grounding of referring expressions. (*a*) Ground self-referential expressions. (*b*) Ground relational expressions. (*c*) Ask questions to resolve ambiguity. Red boxes indicate referred objects. Blue dashed boxes indicate candidate objects. See also the accompanying video at http://bit.ly/INGRESSvid.

- Let's see video in action: http://bit.ly/INGRESSvid

Source: Sridhar et al. (2018). Interactive Visual Grounding of Referring Expressions for Human-Robot Interaction

Many more tasks at CV+NLP

- Fun stuff: Comic books

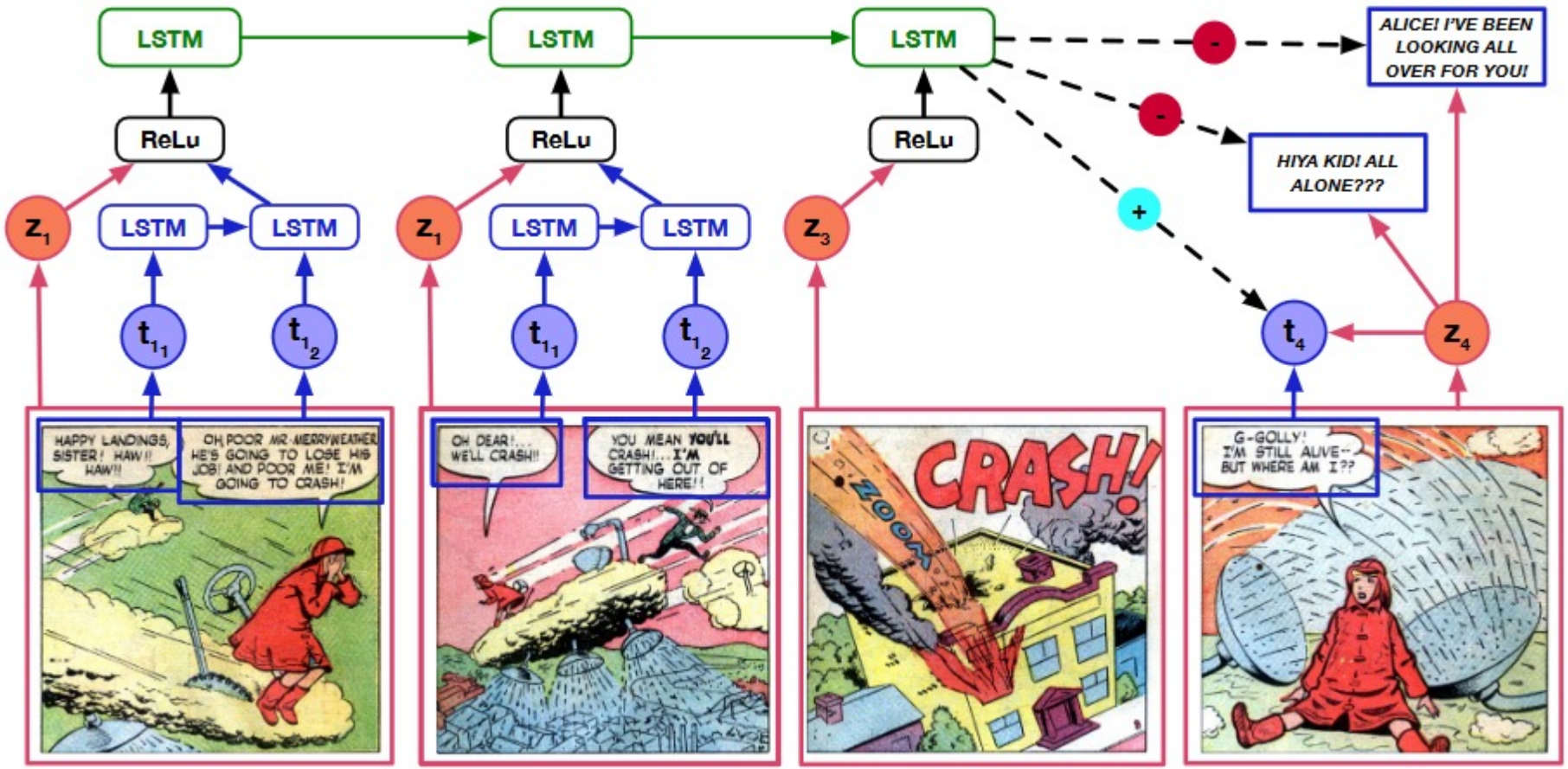
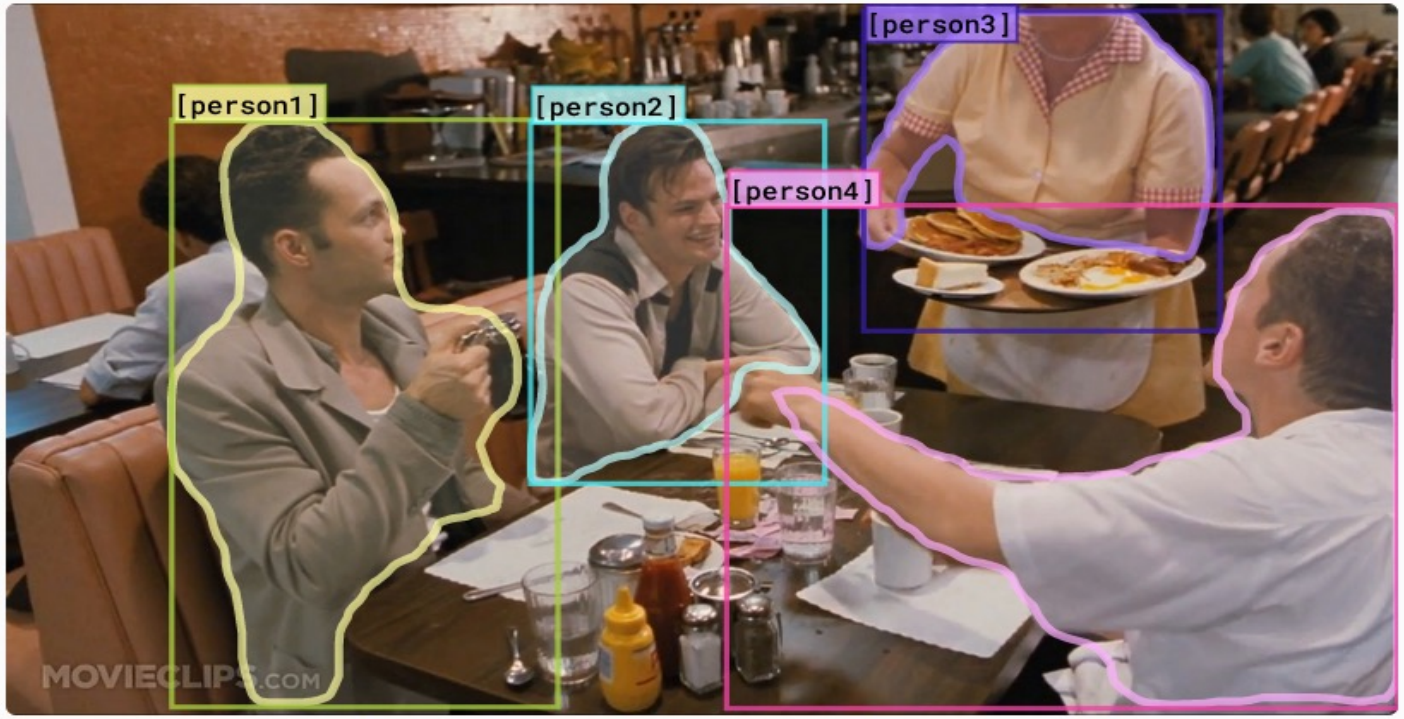


Figure 5. The **image-text** architecture applied to an instance of the *text cloze* task. Pretrained image features are combined with learned text features in a hierarchical LSTM architecture to form a context representation, which is then used to score text candidates.

Source: Iyyer et al. (2017) The Amazing Mysteries of the Gutter: Drawing Inferences Between Panels in Comic Book Narratives

Many more tasks at CV+NLP

- From Recognition to Cognition: Visual Commonsense Reasoning



hide all | show all | [person1] | [person2] | [person3] | [person4]

more objects »

Why is [person4] pointing at [person1]?

a) He is telling [person3] that [person1] ordered the pancakes.

b) He just told a joke.

c) He is feeling accusatory towards [person1].

d) He is giving [person1] directions.

Rationale: I think so because...

a) [person1] has the pancakes in front of him.

b) [person4] is taking everyone's order and asked for clarification.

c) [person3] is looking at the pancakes both she and [person2] are smiling slightly.

d) [person3] is delivering food to the table, and she might not know whose order is whose.

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

Summary

- Vision + Language: Help us to understand human brain functioning better
- Visual Turing Test for modern AI systems
- A step towards Artificial General Intelligence (AGI)
- Variety of applications:
  - Helping visually-impaired people
  - Early child education
  - Personal assistants
  - Robot navigation
  - Video surveillance systems
  - Search engines

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Questions?

If you feel fascinated and want to get involved in research, feel fee to reach out at https://research.unsw.edu.au/people/dr-sonit-singh