Lecture 8: LSTM for Computer Vision

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CIS 6217 – Computer Vision for Data Representation

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Outline

1. Recurrent Neural Networks (RNNs)
2. Long Short Term Memory
3. Applications in Computer Vision
4. Language Modeling & Image Captioning
5. Vision and Language Integration
6. Attention Mechanism

Learning Outcomes

- **Explain** the principles of **recurrent neural networks (RNNs)** and their role in modeling sequential data in computer vision.
- **Describe** the internal architecture and gating mechanisms of **Long Short-Term Memory (LSTM)** networks.
- **Analyze** how LSTMs overcome the vanishing gradient problem in sequence learning.
- **Apply** CNN–LSTM architectures to model **temporal and contextual features** in videos and sequential visual data.
- **Construct** encoder–decoder models for **image captioning** and **video description** tasks.
- **Discuss** the role of **attention mechanisms** in enhancing visual–linguistic models.
- **Evaluate** recent advances from LSTM-based models to **transformer-based** vision–language architectures.

What is the motivation behind RNN?

RNN

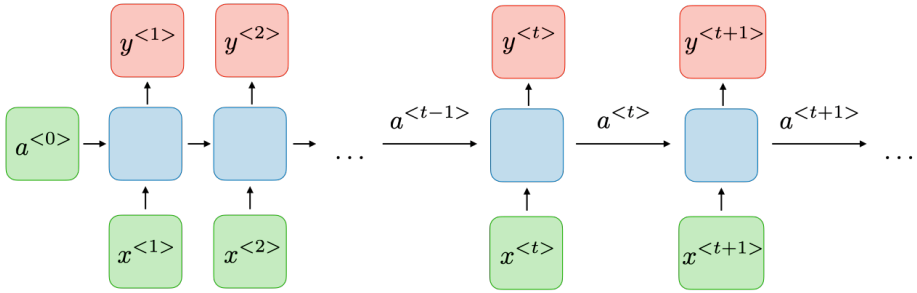
Recurrent Neural Network

RNN Overview

- Handles Sequential data
- Neural networks with feedback connections that retain information from previous inputs

$$a^{<t>} = g_1(W_{aa}a^{<t-1>} + W_{ax}x^{<t>} + b_a$$

$$y^t = g_2(W_{ya}a^{<t>} + b_y)$$

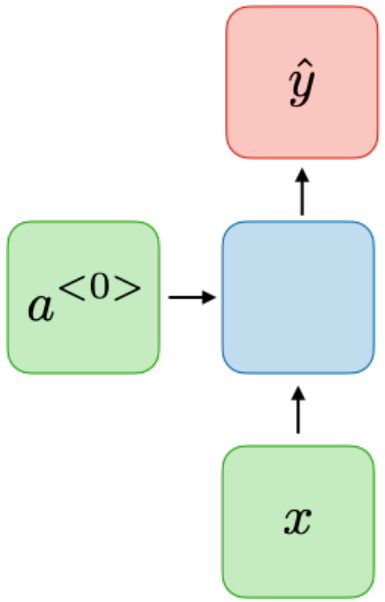


Recurrent neural networks cheatsheet star. CS 230 - Recurrent Neural Networks Cheatsheet. (n.d.).

RNN Architectures

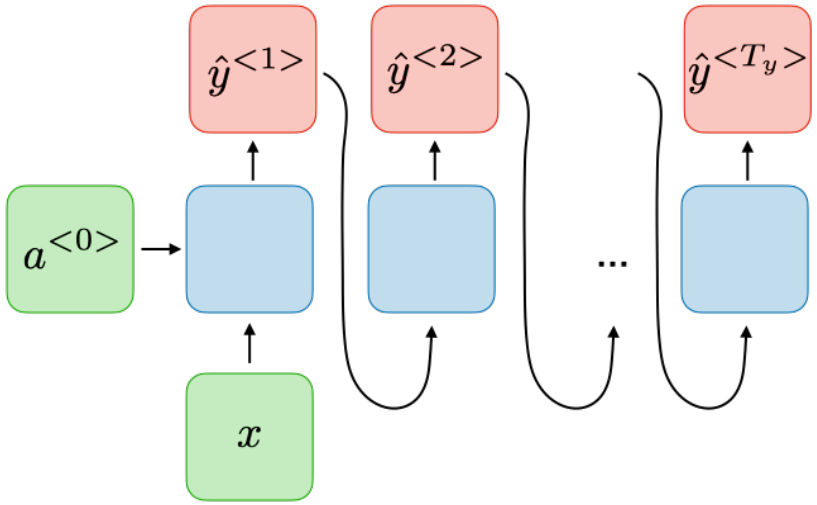
- One-to-One:

$$T_x = T_y = 1$$



- One-to-Many:

$$T_x = 1, T_y > 1$$



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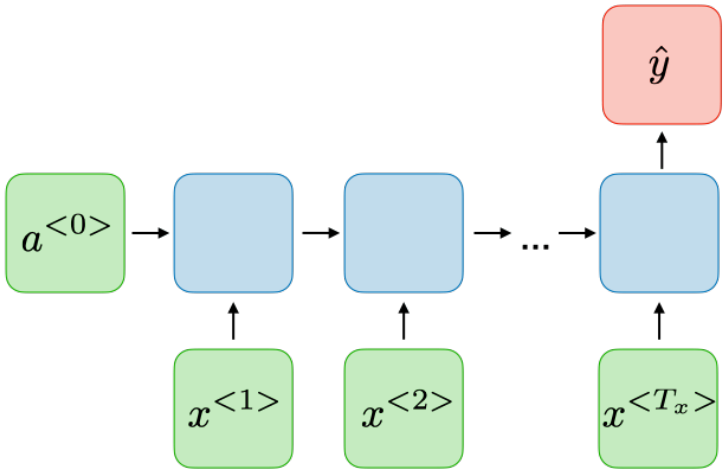
RNN Architectures

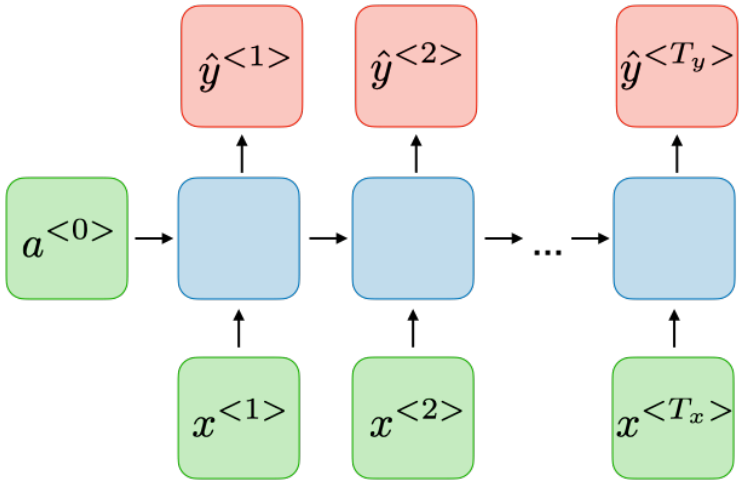
- Many-to-one

$$T_x > 1, T_y = 1$$



- Many-to-Many

$$T_x = T_y$$

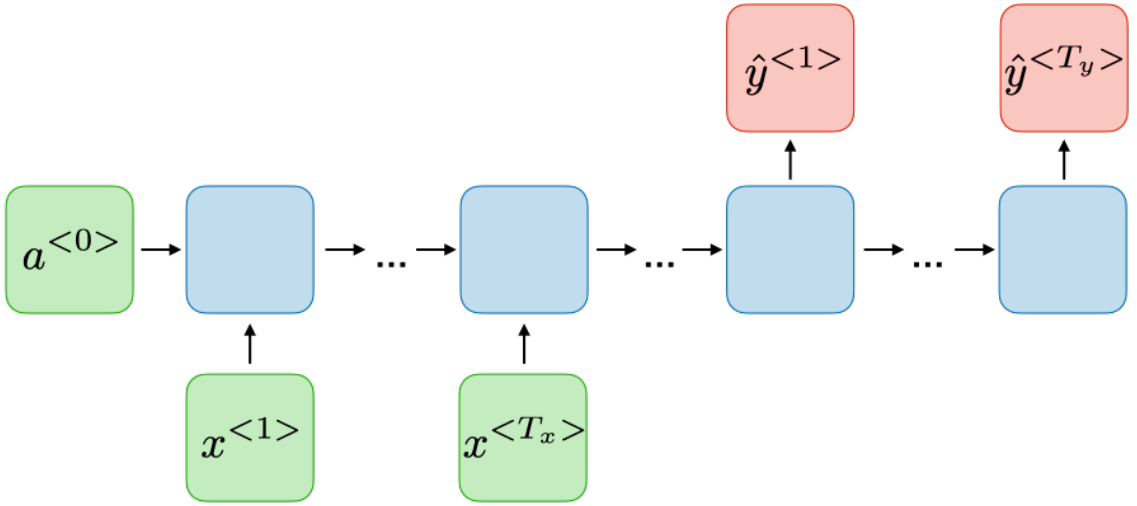


Recurrent neural networks cheatsheet star. CS 230 - Recurrent Neural Networks Cheatsheet. (n.d.).

RNN Architecture

- Many-to-Many

$$T_x \neq T_y$$



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Pros and Cons

- Possibility of processing input of any length
- Model size not increasing with size of input
- Computation takes into account historical information
- Weights are shared across time

- Computation being slow
- Difficulty of accessing information from a long time ago
- Cannot consider any future input for the current state

Challenges of RNN

- Vanishing Gradient
- Exploding Gradient

LSTM

Long Short Term Memory

LSTM Overview

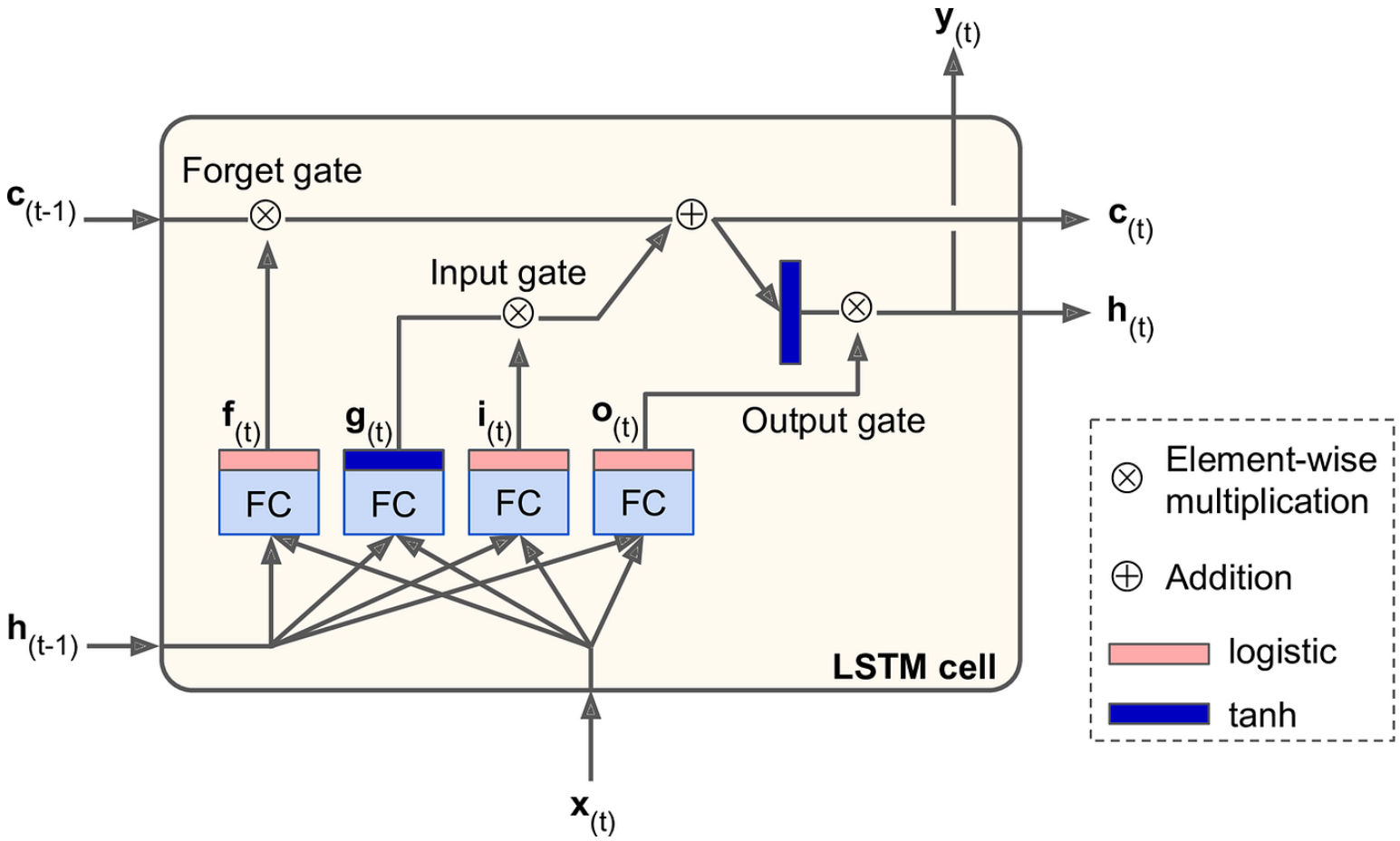
LSTMs are designed to handle the vanishing gradient problem by introducing a memory cell that can maintain information over long periods.

Components:

- **Cell State**: Stores long-term dependencies.
- **Gates**:
  - **Input Gate**: Controls how much new information flows into the cell.
  - **Forget Gate**: Decides what information to discard from the cell.
  - **Output Gate**: Determines what information to output.

Use-Case: Ideal for tasks requiring long-term memory, like essay writing or speech recognition.

LSTM Architecture



Source: Neural Networks and deep learning, **by Aurélien Géron** Oriely

Applications

Sequence Learning in Vision

- Video classification: sequence of frames → label (e.g., “playing guitar”).
- CNN extracts features per frame.
- LSTM models temporal evolution
  - $ht=LSTM(CNN(framet),ht-1)$
- Applications:
  - Human action recognition
  - Emotion detection
  - Object tracking over time

Image Captioning

- Goal: Generate a natural language description of an image.
- Pipeline:
  - CNN: extracts image features.
  - LSTM: generates sentence word-by-word.
  - Combined via feature vector → language decoder.

Vision + Language

- Combines visual and linguistic embeddings.
- Two networks:
  - Vision encoder (CNN, ViT)
  - Language encoder (RNN, LSTM, Transformer)
- Applications:
  - Visual Question Answering (VQA)
  - Image Retrieval by Text
  - Multimodal Translation

Attention Mechanism

Attention Mechanism

- LSTMs struggle with long sequences
- Core idea: focus on relevant parts of the input at each time step.
- Enables model to “look” at specific image regions when generating each word.

A cute teddy bear is reading Persian literature

A cute teddy bear is reading Persian literature

Encoder–Decoder Architecture

- Encoder (CNN): Encodes image into feature vector.
- Decoder (RNN/LSTM/Attention): Generates textual sequence.
- Key use: Image Captioning, VQA, Video Description.

References

- Guide to CNNs for CV – Khan et al. (2018)
- Deep Learning with Python – Chollet (2018)
- Deep Learning in Computer Vision – Awad & Hassaballah (2020)

- Deep Learning for Vision Systems by Mohamed Elgendy (2020)