



Deep Learning for Cyber Security use cases

Vinayakumar R

PhD Student,

Centre for Computational Engineering and Networking, Amrita Vishwa Vidyapeetham,

Coimbatore

https://vinayakumarr.github.io/

Agenda





- Why deep learning?
- Deep Neural Networks
- Recurrent structures RNN, LSTM, GRU
- Bidirectional recurrent structures
- Cyber Security use case: Intrusion Detection
- Hands on tutorial on python numpy, scipy, matplotlib, pandas
- Hands on tutorial on TensorFlow and Keras

Deep Learning



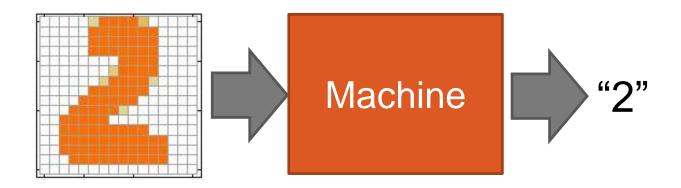
- Deep learning is kind of hard. Why bother with it?
- Amazing results... in speech, NLP, vision/multimodal work
- Does its own feature selection!
- The big players (Google, Facebook, Baidu, Microsoft, IBM…) are doing a lot of this
- The hot new thing?
- Actually, many of the architectures that we'll talk about were invented in the 1980s and 1990s
- What's new is hardware that can use these architectures at scale.





Example Application

Handwriting Digit Recognition

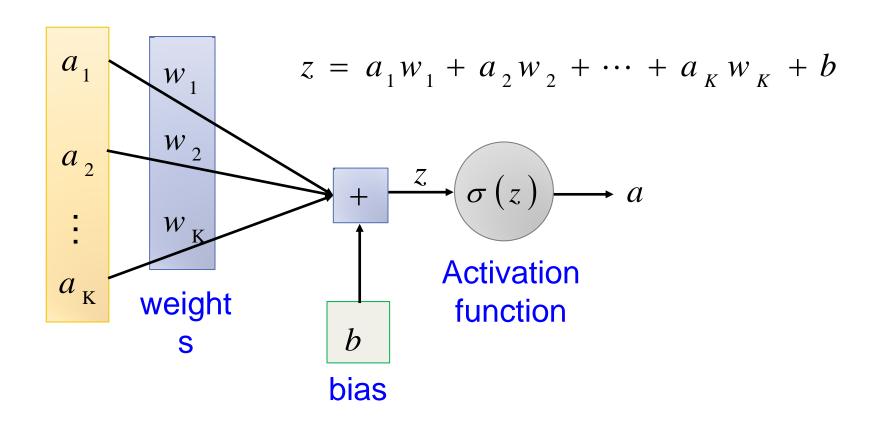






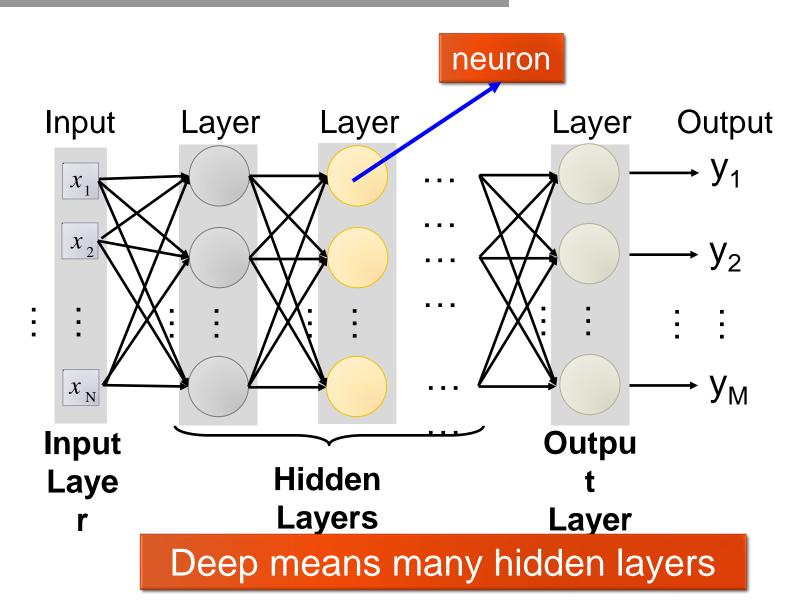
Element of Neural Network

Neuron $f: \mathbb{R}^K \to \mathbb{R}$



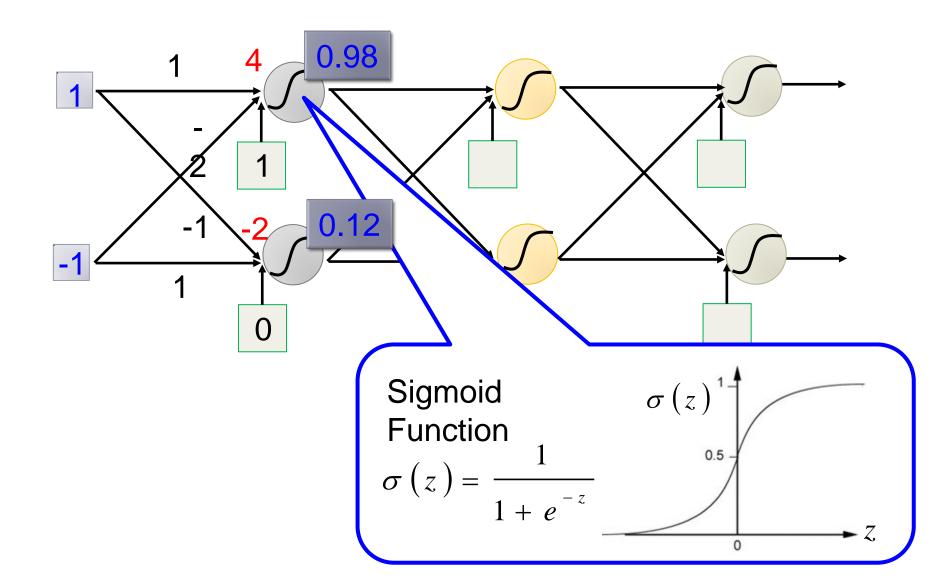






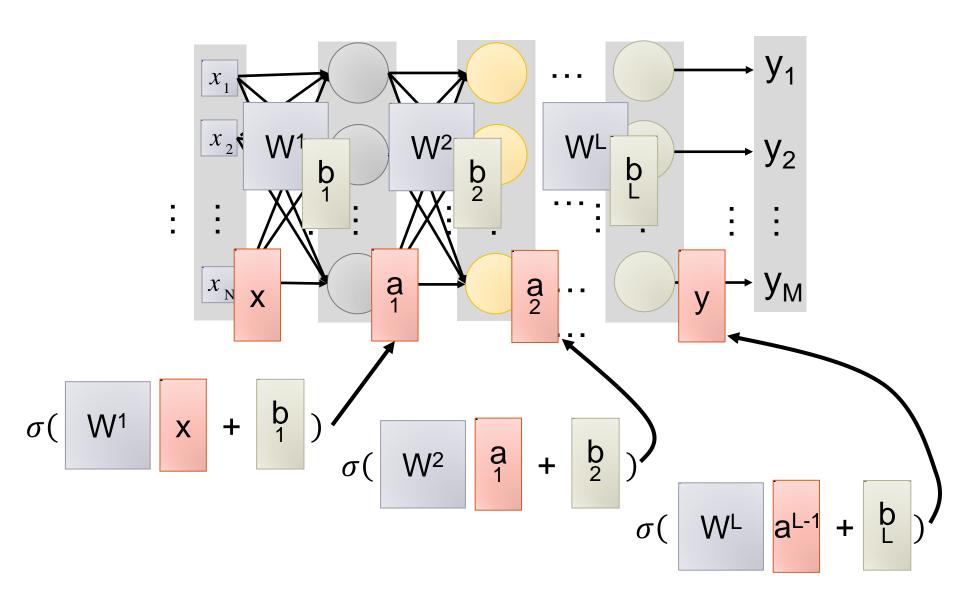
















Training DNN

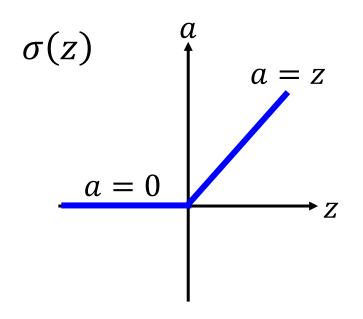
New Activation Function





ReLU

Rectified Linear Unit (ReLU)



Reason:

- 1. Fast to compute
- 2. Vanishing gradient problem

$$f'(x) = \begin{cases} 1 & \text{if } x > = 0 \\ 0 & \text{if } x < 0 \end{cases}$$

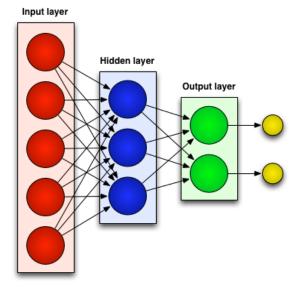
$$\sigma'(z) = \sigma(z) * (1 - \sigma(z))$$

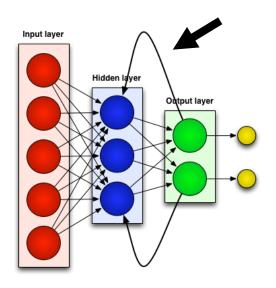




Generally there are two kinds of neural networks:

- > Feedforward Neural Networks:
 - ✓ connections between the units do not form a cycle





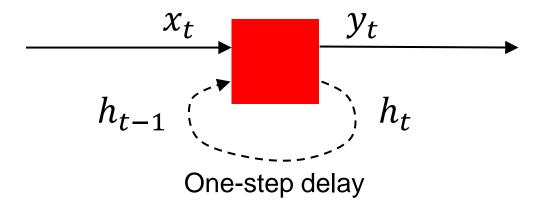
- Recurrent Neural Network:
 - ✓ connections between units form cyclic paths

Recurrent Neural Networks





Recurrent networks introduce cycles and a notion of time.



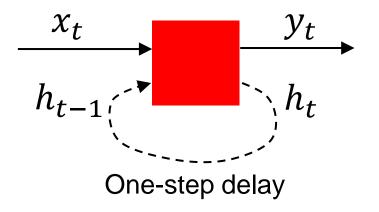
• They are designed to process sequences of data $x_1, ..., x_n$ and can produce sequences of outputs $y_1, ..., y_m$.

Unrolling RNNs



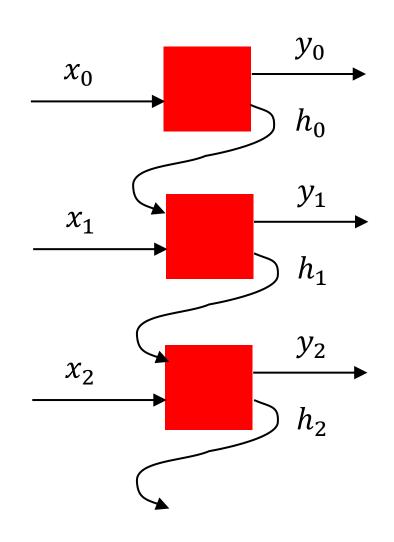


RNNs can be unrolled across multiple time steps.



This produces a DAG which supports backpropagation.

But its size depends on the input sequence length.

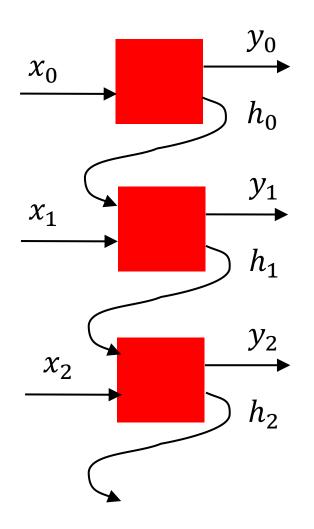


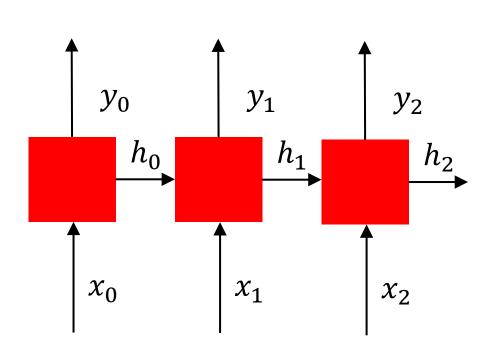
Unrolling RNNs





Usually drawn as:

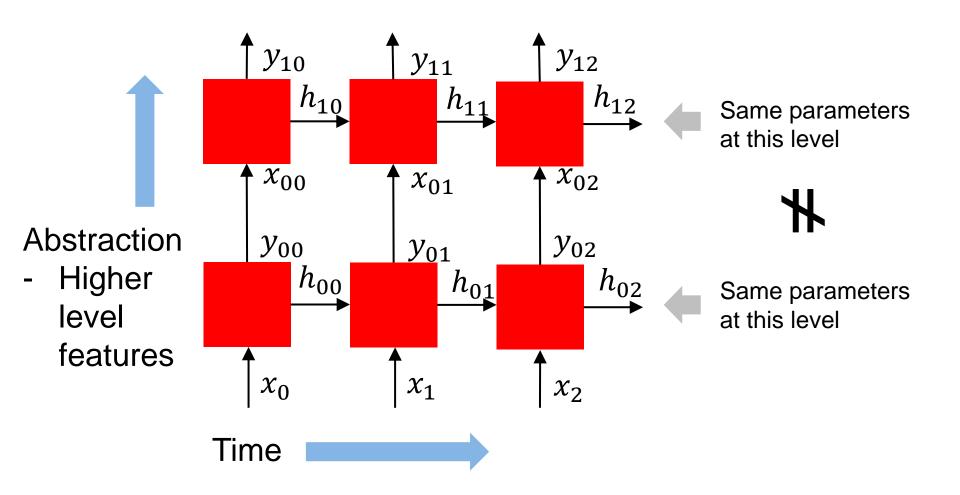






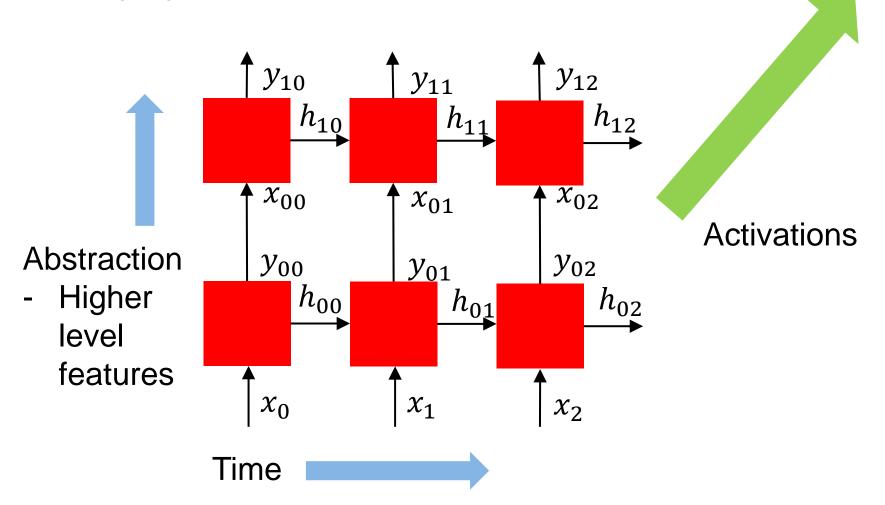


Often layers are stacked vertically (deep RNNs):



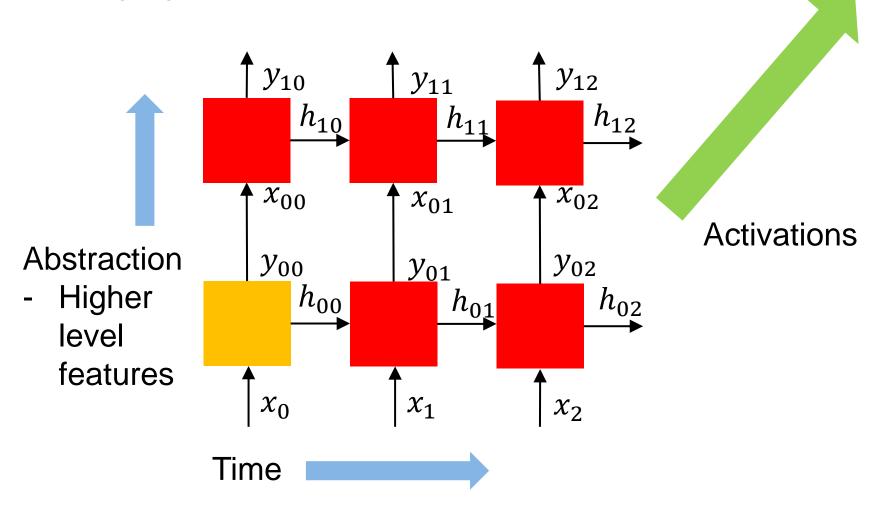






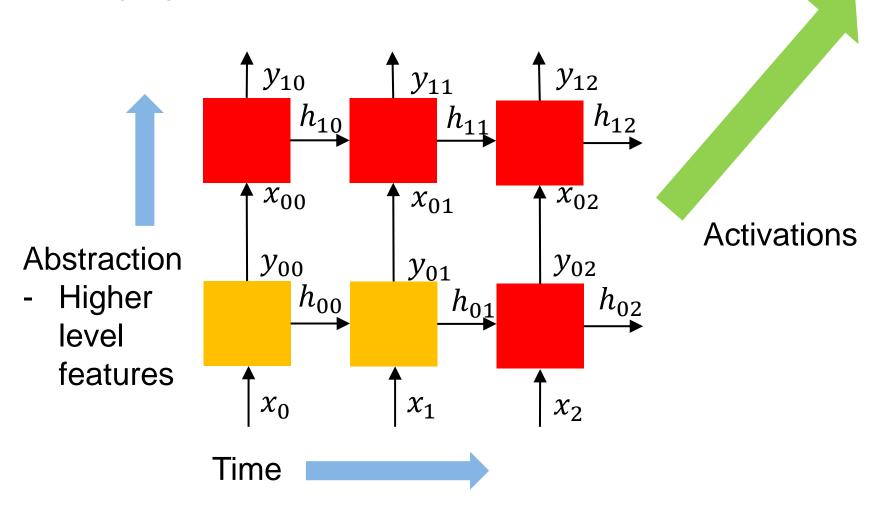






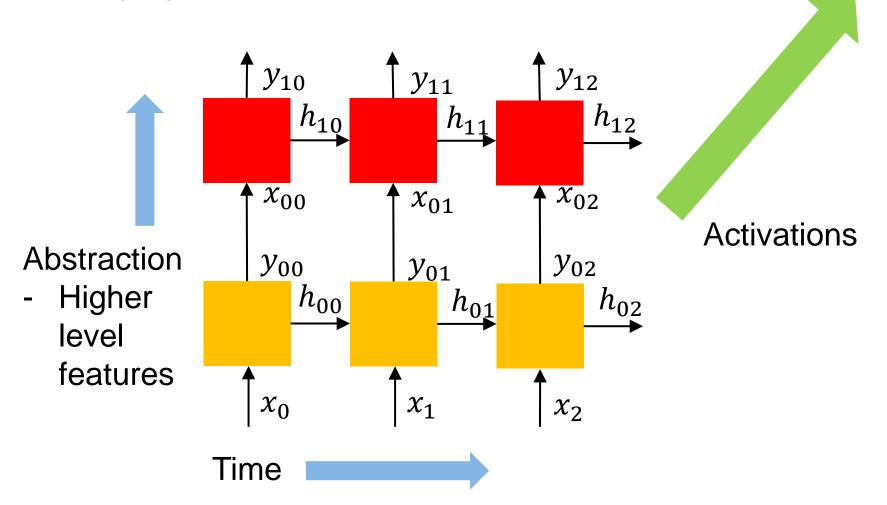






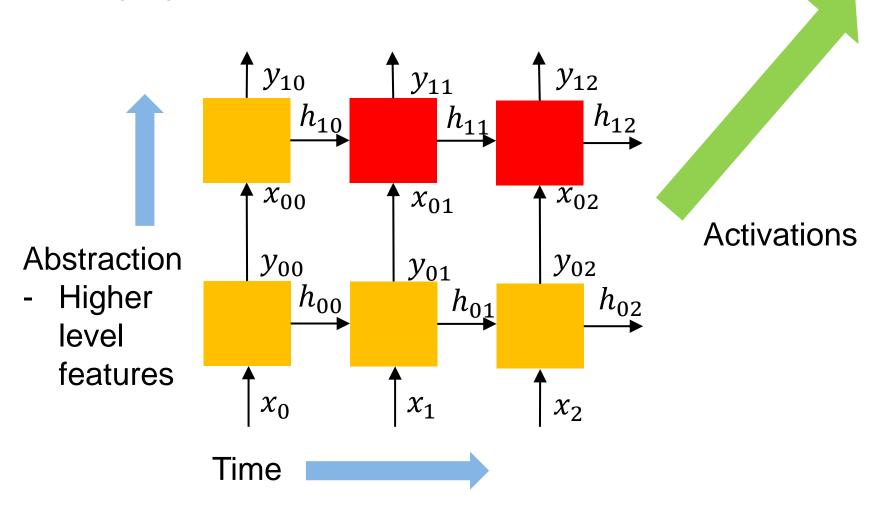






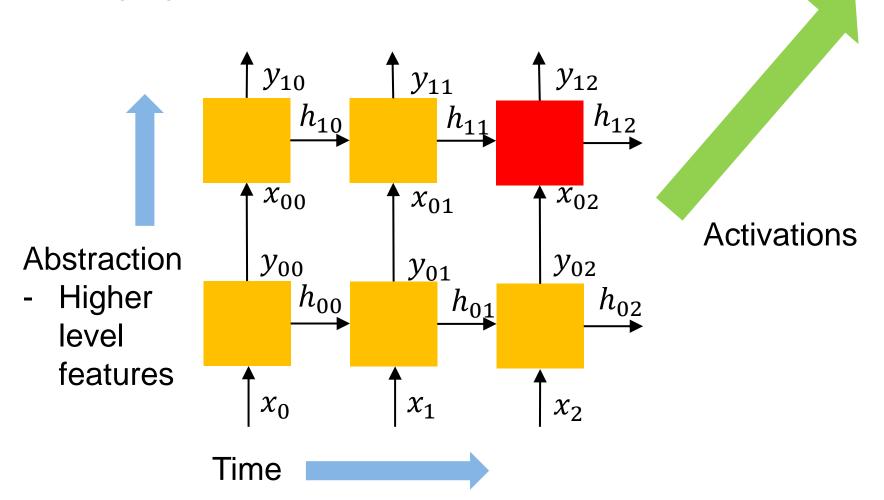






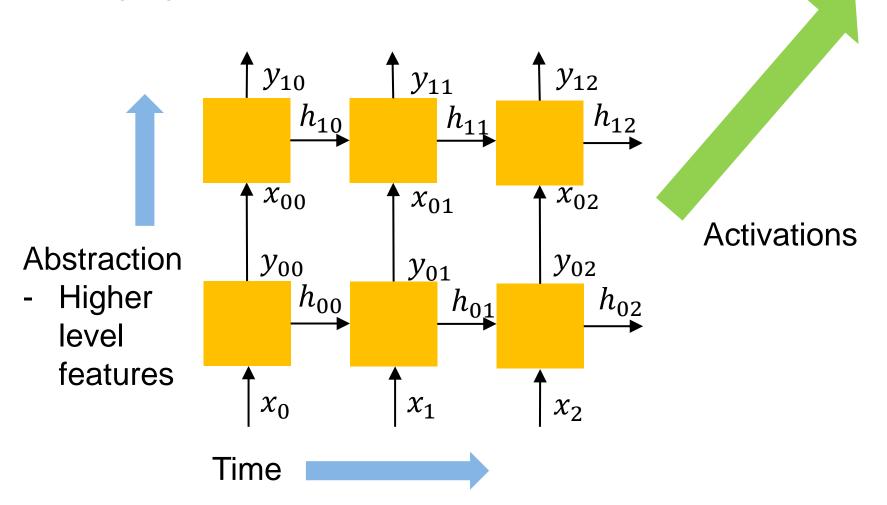






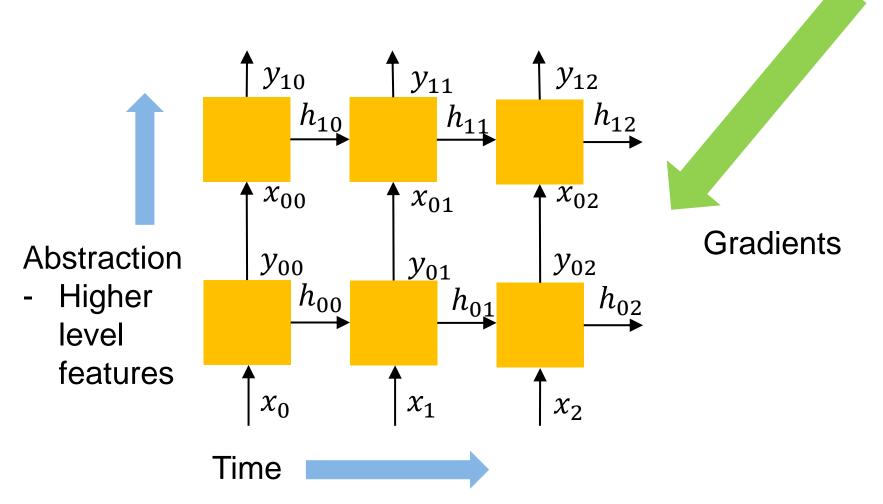






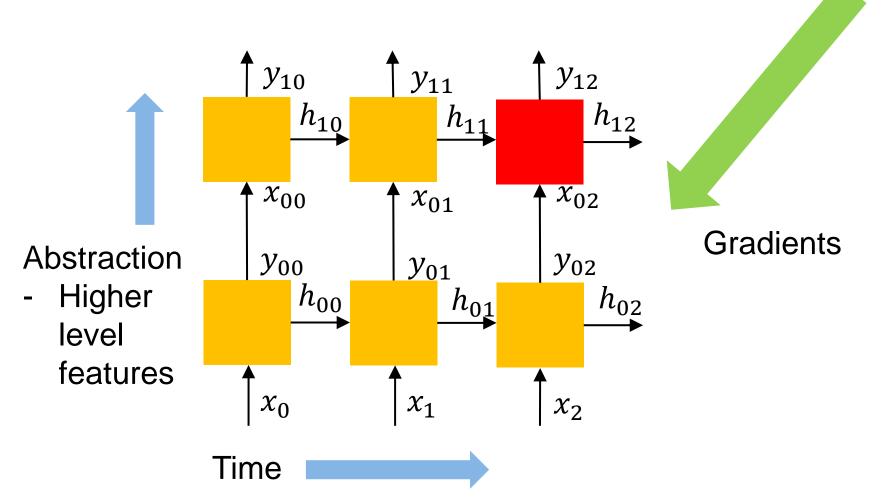






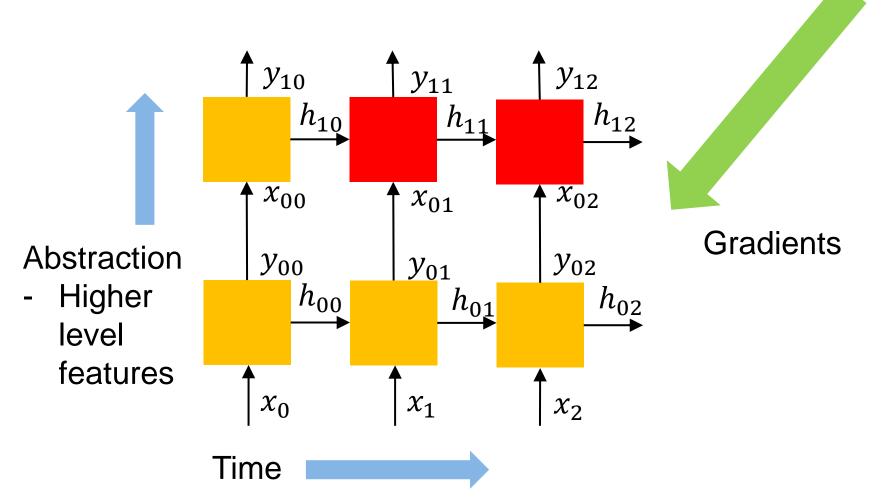






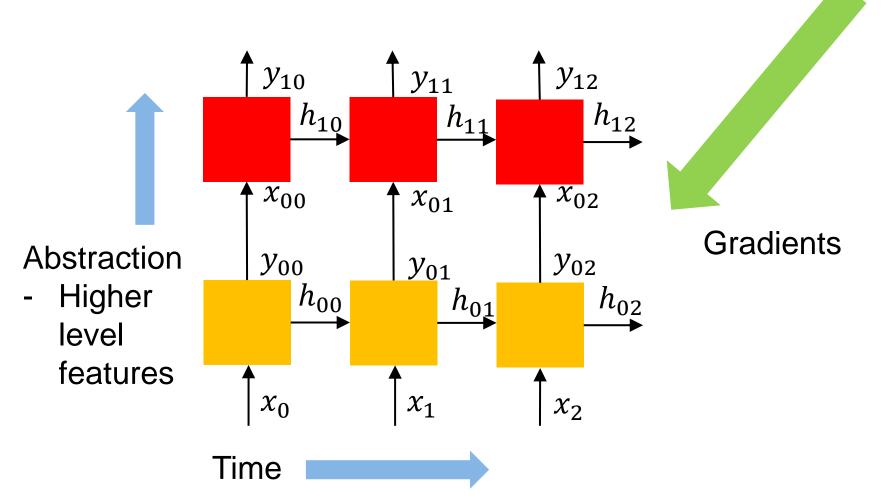






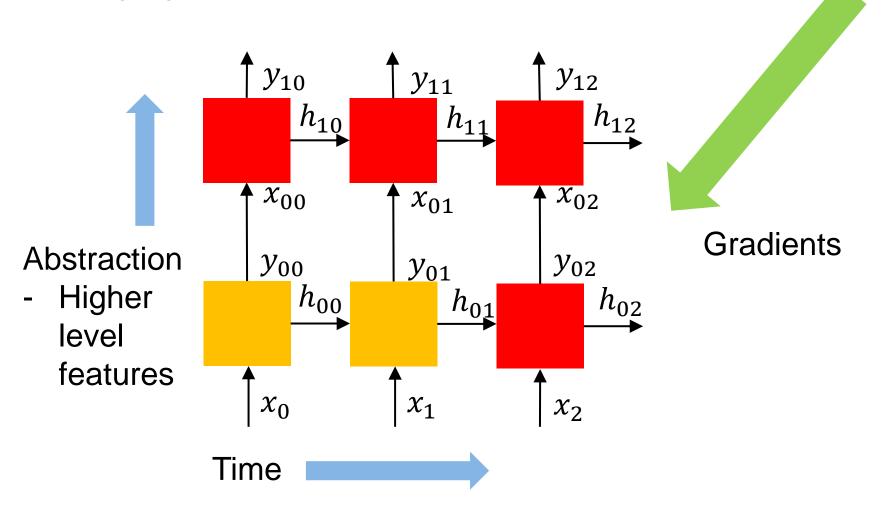






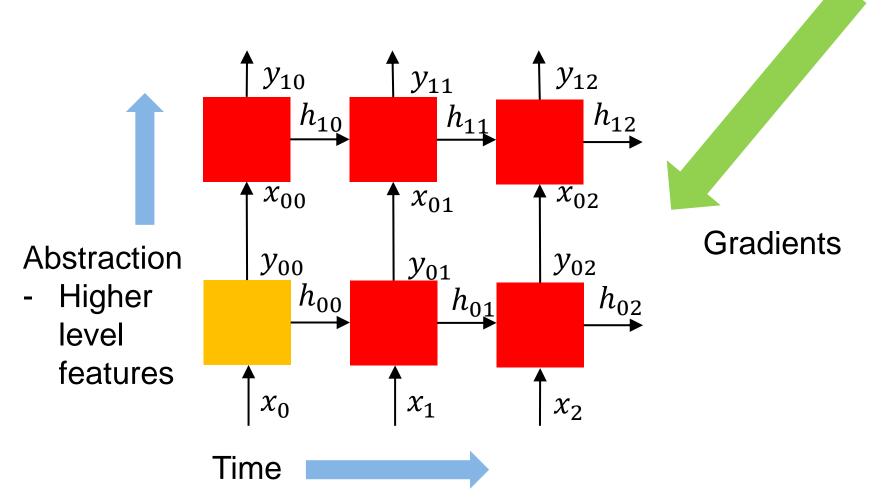






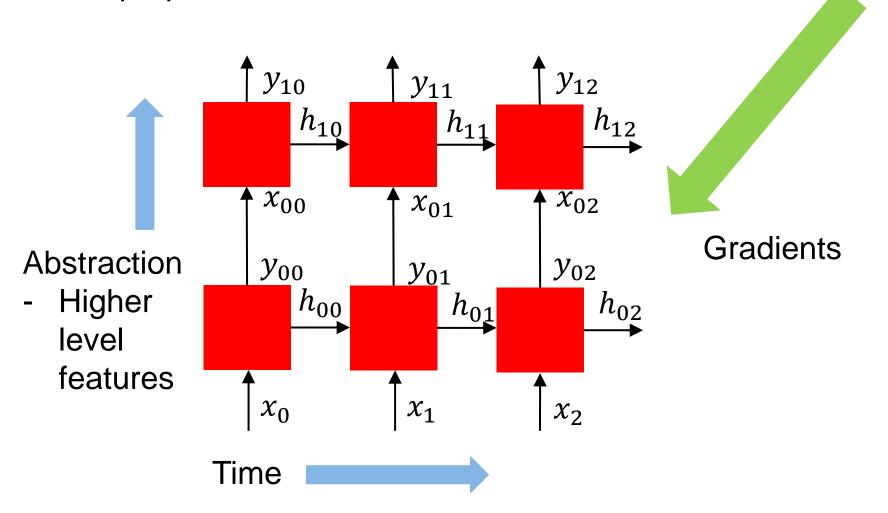










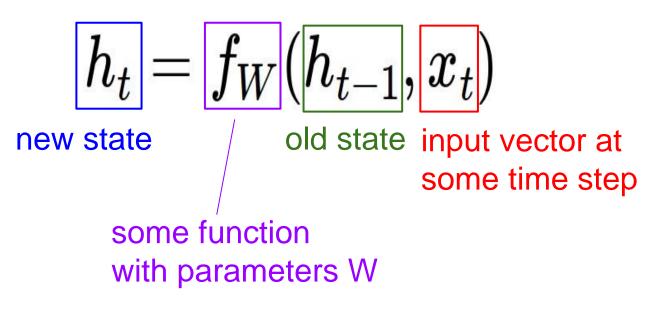


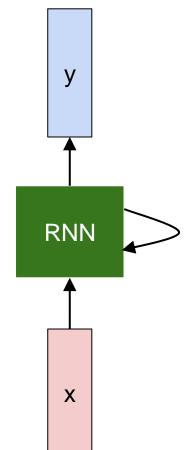
Recurrent Neural Network





We can process a sequence of vectors **x** by applying a recurrence formula at every time step:



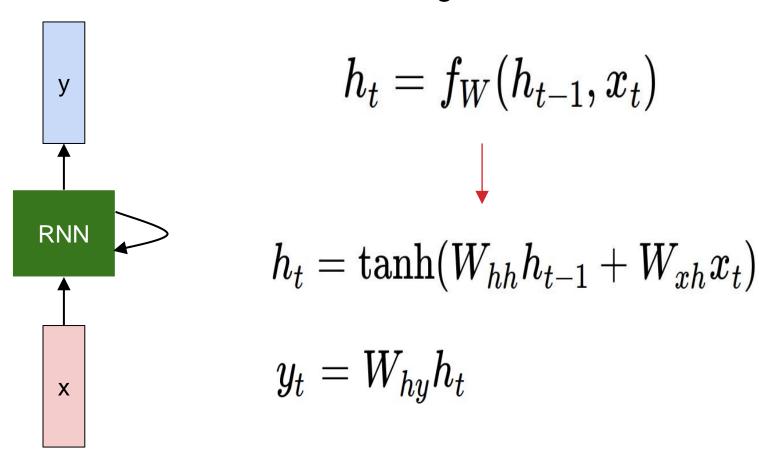


Recurrent Neural Network





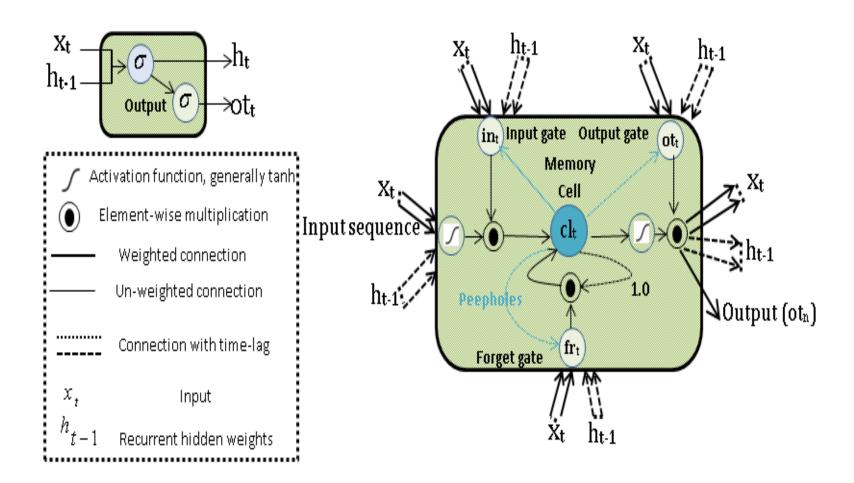
The state consists of a single "hidden" vector **h**:



Long short-term memory







Long short-term memory





$$x_t, h_{t-1}, cl_{t-1} \rightarrow h_t, cl_t$$

$$in_{t} = \sigma \left(w \underset{xin}{x} \underset{t}{t} + w \underset{hin}{h} \underset{t-1}{h} + w \underset{clin}{cl} \underset{t-1}{t} + b \underset{in}{l} \right)$$

$$fr_{t} = \sigma \left(w \underset{xfr}{x} \underset{t}{x} + w \underset{hifr}{h} \underset{t-1}{h} + w \underset{clfr}{cl} \underset{t-1}{t} + b \underset{fr}{} \right)$$

$$cl_t = fr_t \stackrel{\bigcirc}{\circ} cl_{t-1} + in_t \stackrel{\bigcirc}{\circ} \tanh(w_{xcl} x_t + w_{hcl} hi_{t-1} + b_{cl})$$

$$ot_{t} = \sigma \left(w_{xot} x_{t} + w_{hot} h i_{t-1} + w_{clot} c l_{t} + b_{ot} \right)$$

$$h_t = o t_t^{\odot} \tanh(c l_t)$$

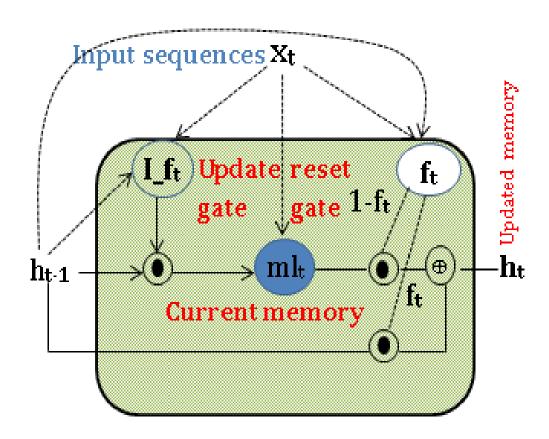
Gated Recurrent Unit





Gated recurrent unit (GRU) is an alternative to LSTM networks.

Formulae shows, unlike LSTM memory cell with a list of gates (input, output and forget), GRU only consist of gates (update and forget) that are collectively involve in balancing the interior flow of information of the unit.



Gated Recurrent Unit





$$x_t, h_{t-1} \to h_t$$

$$in_{-}fr_{t} = \sigma \left(w_{xin_{-}fr} x_{t} + w_{hiin_{-}fr} h_{t-1} + b_{in_{-}fr}\right)$$
 (Update gate)

$$fr_t = \sigma \left(w x f r^x t + w h i f r^h t - 1 + b f r^h \right)$$

(Forget or reset gate)

$$cl_{t} = \tanh(w_{xcl}x_{t} + w_{hcl}(fr^{\bigodot}hi_{t-1}) + b_{cl})$$

(Current memory)

$$h_t = f \odot h_{t-1} + (1-f) \odot cl$$

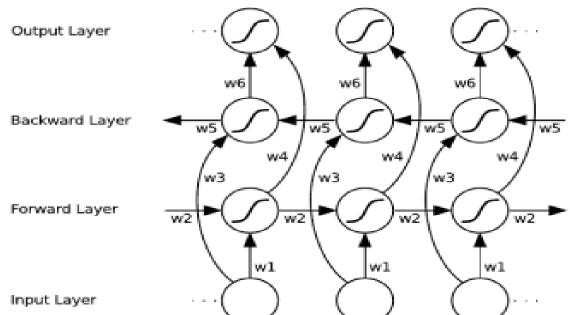
(Updated memory)

Extensions to LSTM architecture: Bidirectional RNN, LSTM, GRU





- Only the past information is taken into account in the training of a unidirectional RNN/LSTM
- Bidirectional architecture enables the use of future information
- Implementation with separate Forward-pass and Backwardpass specific layer weights
- Final output computed as the sum of forward and backward layer outputs



Summary





- RNNs allow a lot of flexibility in architecture design
- RNNs are simple but don't work very well
- Common to use LSTM or GRU: their additive interactions improve gradient flow
- Backward flow of gradients in RNN can explode or vanish. Exploding is controlled with gradient clipping. Vanishing is controlled with additive interactions (LSTM)
- Better/simpler architectures are a hot topic of current research
- Better understanding (both theoretical and empirical) is needed.

Case studies



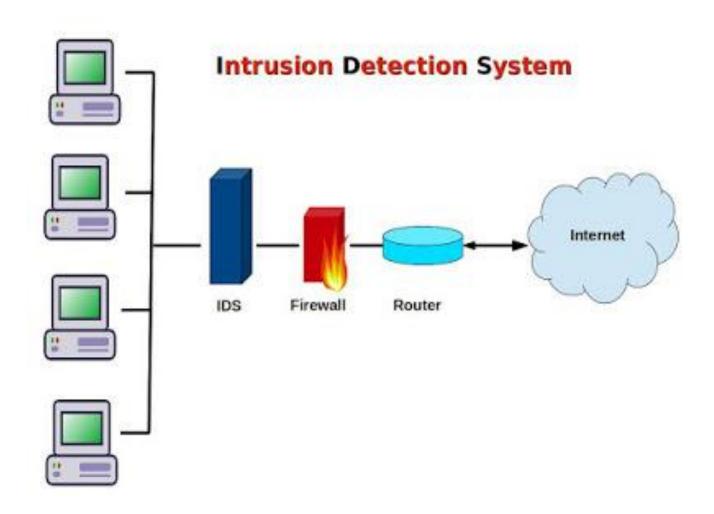


Cyber Security use case: Intrusion detection

Case studies











- Intrusion: Attempting to break into or misuse your system.
- Intruders may be from outside the network or legitimate users of the network.
- Intrusion can be a physical, system or remote intrusion.
- Intrusion Detection Systems look for attack signatures, which are specific patterns that usually indicate malicious or suspicious intent.
- anomaly detection, signature based, host based and network based are different IDS.
- There are various approaches to attack malicious activities, namely (1) static approaches: firewalls, encryption and decryption techniques of cryptography, software updates and many others and (2) dynamic approaches: anomaly and intrusion detection (ID).





- Intrusion detection is categorized in to 2 types based on the network behavior and network type.
- Network-based IDS (N-IDS): Most commonly used in both academia and industries, it analyzes all the network traffic by looking in packet level information to find the suspicious activity.
- Host-based IDS (H-IDS): focuses on the information of each particular system or host, heavily depends for data on the sources of log files such as sensors, system logs, software logs, file systems, disk resources and many more. Mostly, organizations used combination of both of them to get benefited largely in real-time IDS deployment.
- Lincoln Labs raw TCP dump data collected from a local-area network (LAN).





- The raw training data was about four gigabytes of compressed binary TCP dump data from seven weeks of network traffic. This was processed into about five million connection records. Similarly, the two weeks of test data yielded around two million connection records.
- A connection is a sequence of TCP packets starting and ending at some well defined times, between which data flows to and from a source IP address to a target IP address under some well defined protocol. Each connection is labeled as either normal, or as an attack, with exactly one specific attack type. Each connection record consists of about 100 bytes.
- DOS Intruder aims at making network resources down and consequently, resources are inaccessible to authorized users, e.g. syn flood.
- Probe acquiring statistics about the computer System or network e.g., port scanning.
- R2L Illegitimate access from remote computer, e.g. guessing password





Attack category	Full data set	10% data set	
	KDDCup '99'	KDDCup '99'	
	Train	Train	Test
Normal	972780	97278	60593
DoS	3883370	391458	229853
Probe	41102	4107	4166
R2L	1126	1126	16189
U2R	52	52	228
Total		494021	311029

Description of Data set





Demo





Thank you

Questions?

vinayakumarr77@gmail.com

https://vinayakumarr.github.io/





Hands on session on "Machine learning and Deep learning using Scikit-learn, Tensorflow and Keras"

Software Installation





- sudo apt-get install libatlas-base-dev gfortran python-dev
- sudo apt-get install python-pip
- sudo pip install --upgrade pip
- sudo pip install numpy
- sudo pip install scipy
- sudo pip install matplotlib
- Sudo pip install seaborn
- sudo pip install scikit-learn
- sudo pip install tensorflow
- sudo pip install theano
- sudo pip install keras
- sudo pip install pandas
- sudo pip install h5py
- sudo pip install jupyter
- sudo pip install ipython

Artificial Intelligence (AI) toolkits





Scikit-learn - Python library that implements a comprehensive range of machine learning algorithms.

- easy-to-use, general-purpose toolbox for machine learning in Python.
- supervised and unsupervised machine learning techniques.
- Utilities for common tasks such as model selection, feature extraction, and feature selection.
- Built on NumPy, SciPy, and matplotlib.
- Open source, commercially usable BSD license.

Artificial Intelligence (AI) toolkits





TensorFlow - library for numerical computation using data flow graphs / deep learning.

- Open source
- By Google
- used for both research and production
- Used widely for deep learning/neural nets
- But not restricted to just deep models
- Multiple GPU Support

Artificial Intelligence (AI) toolkits





Keras – It is a high-level neural networks API, written in Python and capable of running on top of TensorFlow, CNTK, or Theano. It was developed with a focus on enabling fast experimentation.

- Allows for easy and fast prototyping (through user friendliness, modularity, and extensibility).
- Runs seamlessly on CPU and GPU.

Supporting Libraries







NumPy Base N-dimensional array package



SciPy library Fundamental library for scientific computing



Matplotlib Comprehensive 2D Plotting



IPython Enhanced Interactive Console



Sympy Symbolic mathematics



pandas Data structures & analysis





Hands – on tutorial on supporting libraries





Hands – on tutorial on classical machine learning algorithms using scikit-learn





Hands – on tutorial on Tensorflow with Keras

References





- 1. R. Vinayakumar, K. P. Soman, Prabaharan Poornachandran: Applying convolutional neural network for network intrusion detection. ICACCI 2017: 1222-1228
- 2. R. Vinayakumar, K. P. Soman, Prabaharan Poornachandran: Evaluating effectiveness of shallow and deep networks to intrusion detection system. ICACCI 2017: 1282-1289
- 3. R. Vinayakumar, K. P. Soman, Prabaharan Poornachandran: Evaluation of Recurrent Neural Network and its variants for Intrusion Detection System (IDS)" has accepted in Special Issue On Big Data Searching, Mining, Optimization & Securing (BSMOS) Peer to Peer Cloud Based Networks in IJISMD (Accepted)