

# Deep Learning in Storage

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**Deep Learning Applications in IT**



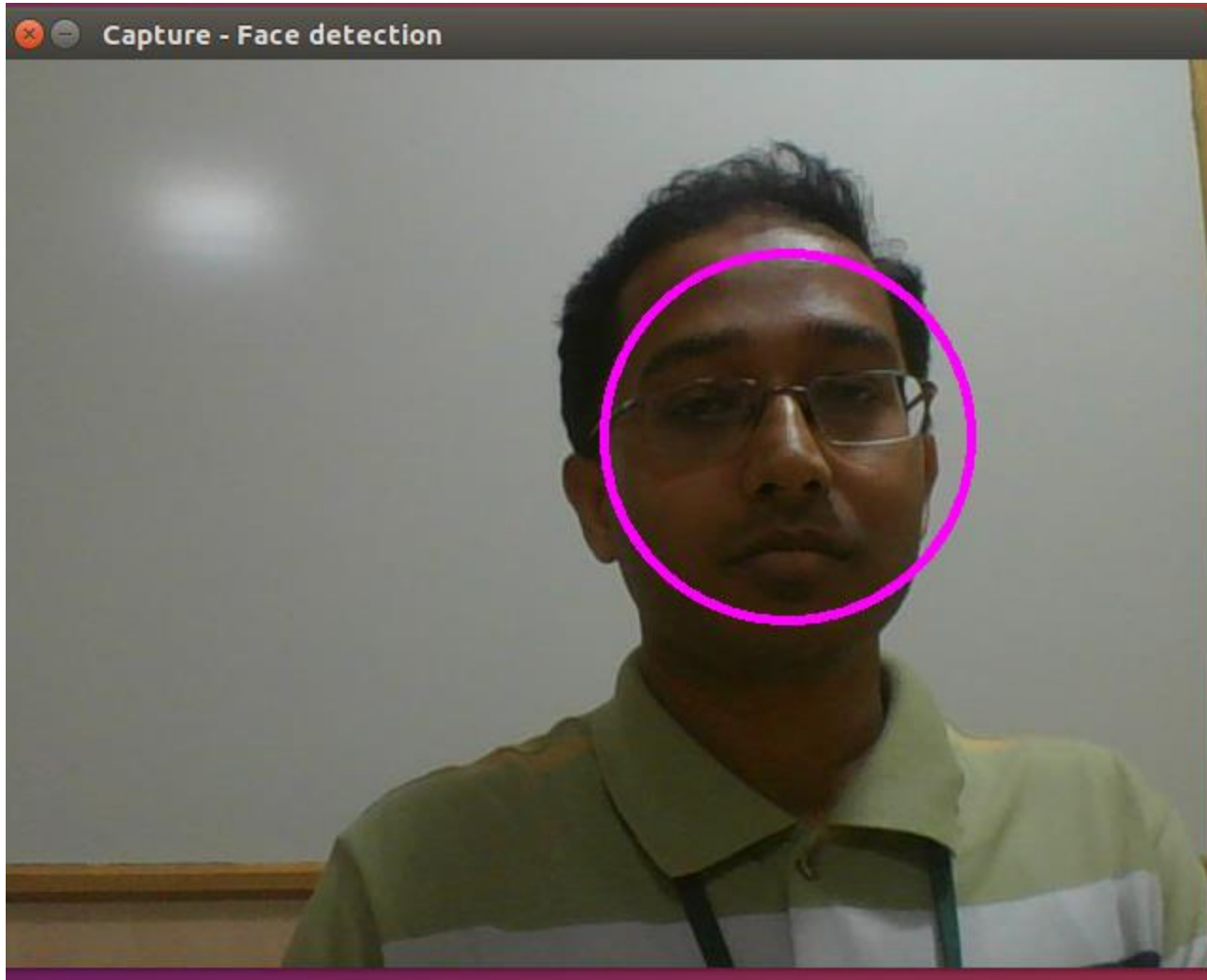
**Deep Learning Applications in Storage**

# Deep Learning Applications

IT - General

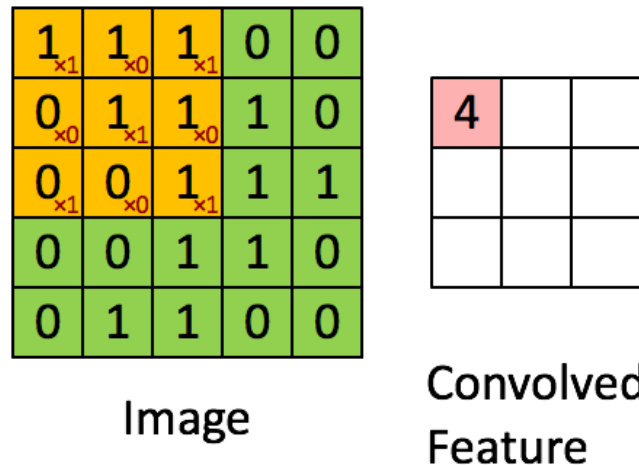


# Image Processing Example (CNN)



# Image Processing – Overview I

- The easiest way to understand a *convolution* is by thinking of it as a sliding window function applied to a matrix. It becomes quite clear looking at a visualization:

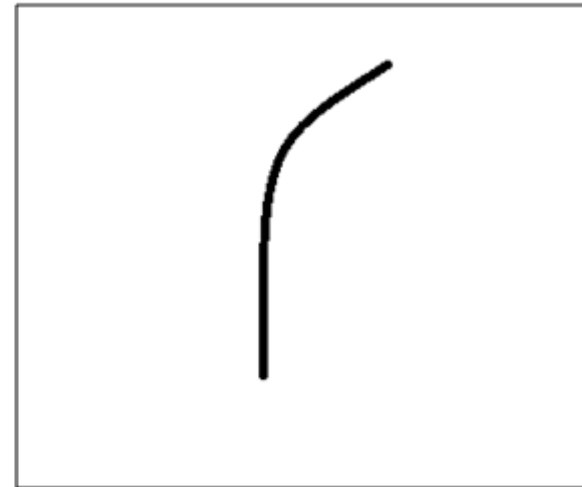


- The sliding window is called a *kernel*, *filter*, or *feature detector*. Here we use a 3×3 filter, multiply its values element-wise with the original matrix, then sum them up.

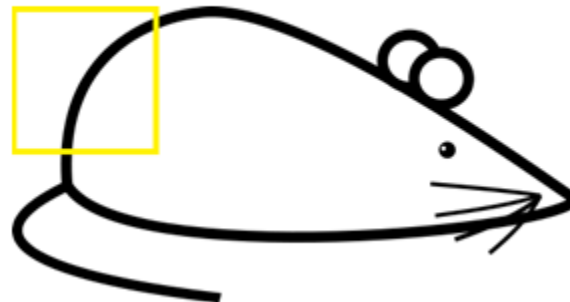
# Image Processing – Overview II

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

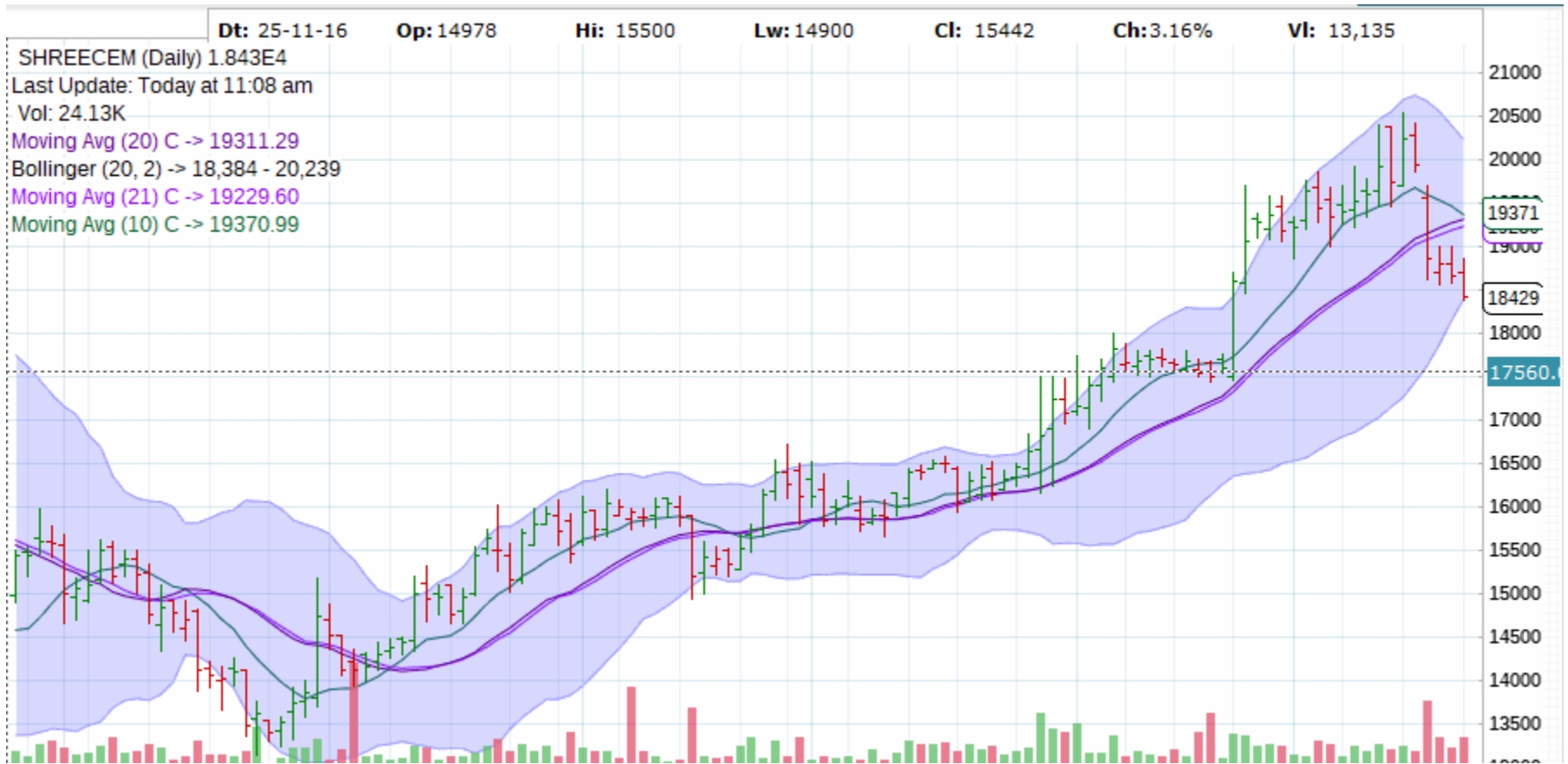


Visualization of a curve detector filter

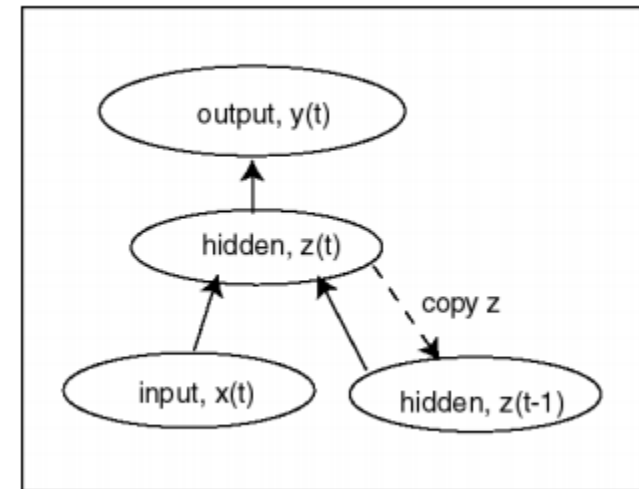
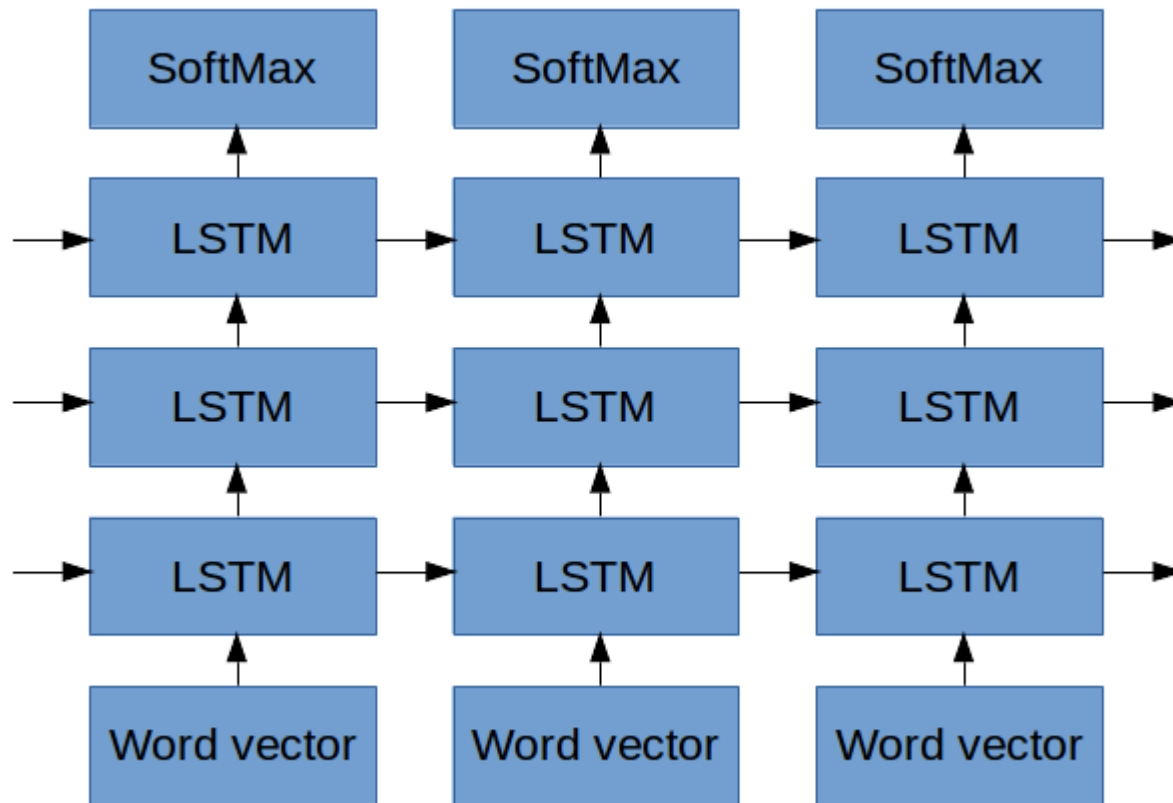


<https://adeshpande3.github.io/adeshpande3.github.io/A-Beginner's-Guide-To-Understanding-Convolutional-Neural-Networks/>

# Stock Prediction Example (RNN and LSTM)



# Stock Market Example - Process





# Person-Movie Relationship – RBM/Autoenc

	M1	M2	M3	M4	M5	M6	M7	M8
P1	1	1	1					
P2		1						
P3			1					
P4				1	1			
P5						1		
P6							1	

Person to Model, Model to Person, Model Strength  
SVD (Matrix representation)

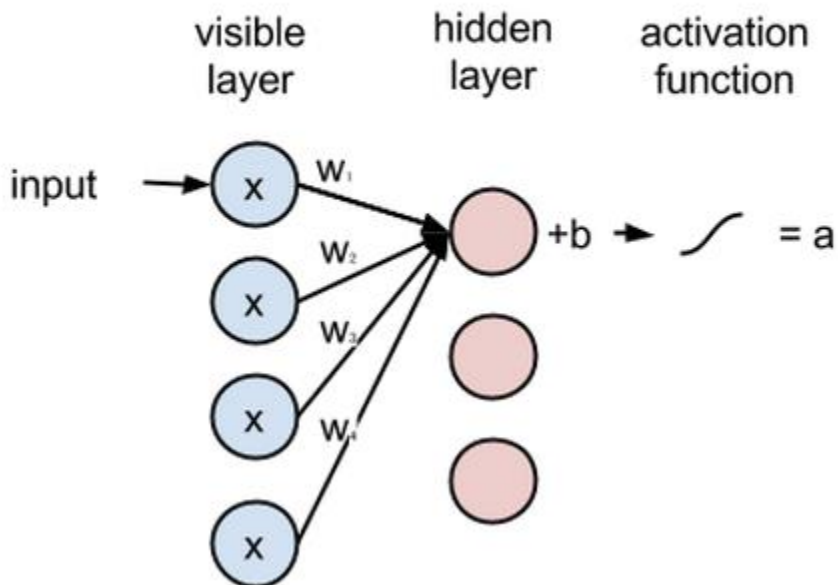
$$A = U\Sigma V^T$$

where  $U$  is an  $m \times m$  orthogonal matrix<sup>1</sup> whose columns are the eigenvectors of  $AA^T$ ,  $V$  is an  $n \times n$  orthogonal matrix whose columns are the eigenvectors of  $A^T A$ , and  $\Sigma$  is an  $m \times n$  diagonal matrix of the form

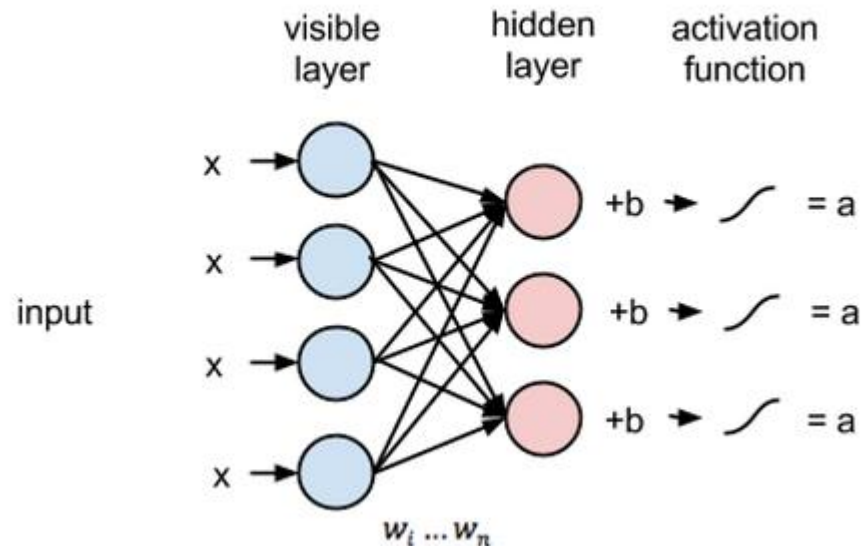
$$\Sigma = \begin{pmatrix} \sigma_1 & & & & & & & & & & & & 0 \\ & \ddots & & & & & & & & & & & 0 \\ & & & & \sigma_r & & & & & & & & 0 \\ & & & & & 0 & & & & & & & \\ & & & & & & & & & \ddots & & & \\ & & & & & & & & & & & & 0 \end{pmatrix}$$

# RBM

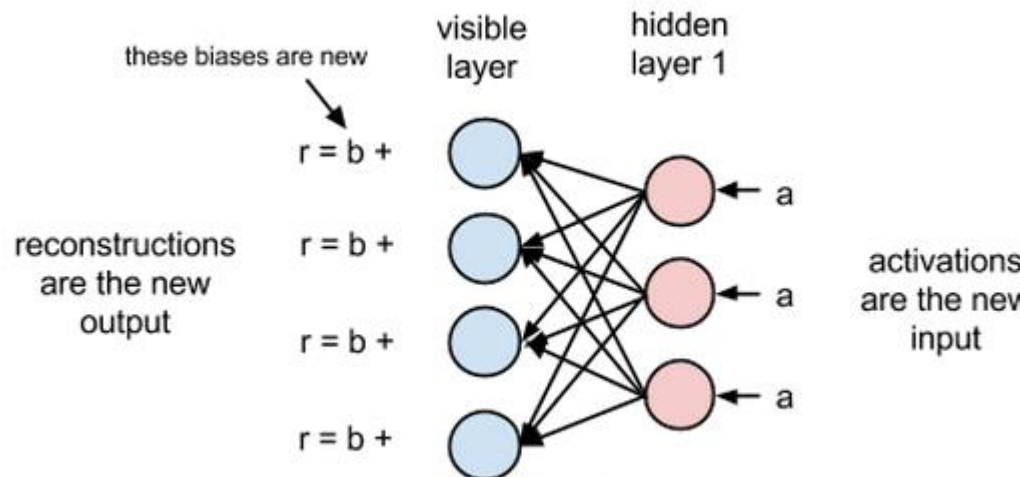
## Weighted Inputs Combine @Hidden Node



## Multiple Inputs



## Reconstruction



<https://deeplearning4j.org/restrictedboltzmannmachine>

# NLP Example

- Term Frequency, Inverse Document Frequency - tfidf

- Word Representation

- One hot: [1,0,0,0], [0,1,0,0], [0,0,1,0], [0,0,0,1]

- Vector Representation and Cosine Similarity

	King	Queen	Man	Woman
Familiarity	0.90	0.9	0.02	0.02
Wealth	0.90	0.99	0.5	0.5
Gender	....			
Other Attr				

- Word2Vec

$$P(w_t|h) = \text{softmax}(\text{score}(w_t, h))$$
$$= \frac{\exp\{\text{score}(w_t, h)\}}{\sum_{\text{Word } w' \text{ in Vocab}} \exp\{\text{score}(w', h)\}}$$

# Deep Learning Applications

IT - Storage

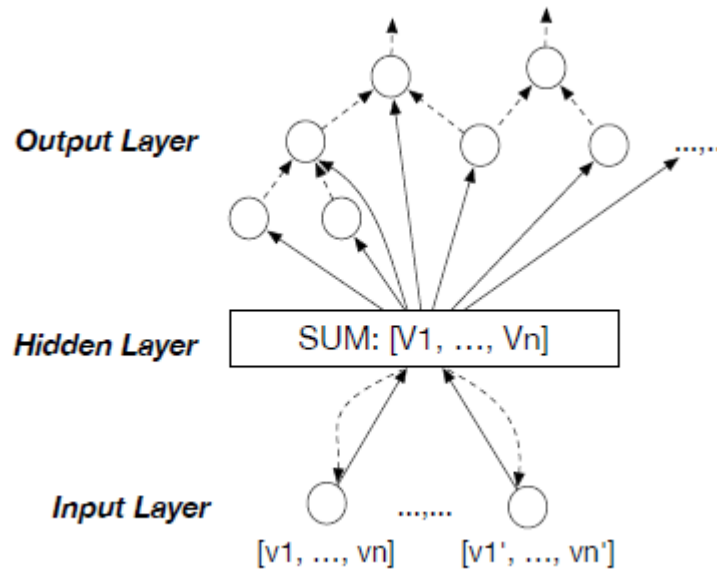


# Prefetching



# Vector Representation example

- Physical location of block
- File it belongs to
- User who owns the file
- Creation time
- Access time

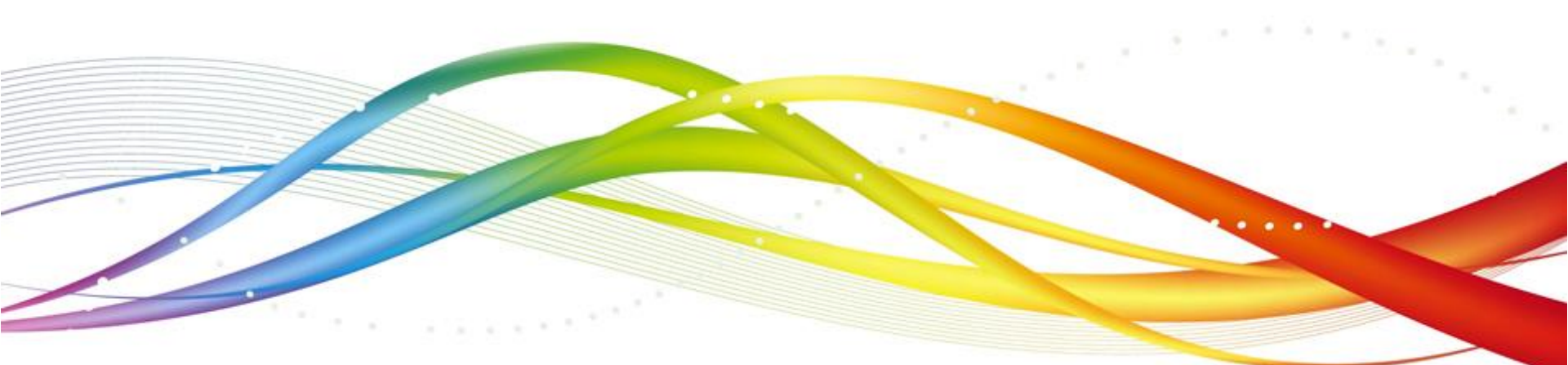


# Use Cases

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- VM Migration
    - PreCopy and Post Copy
    - PostCopy results in network fault and copies faulted data. Also prefetches pages
    - Vector representation – Pages belonging to schedulable processes
  - Tiering
    - Block movement between Tiers
    - Predicting blocks to be accessed in near future
  - NFS - 4.2 has application hint for caching
    - Cache or no cache
    - No application intelligence
- Local FS – Read ahead size

# Capacity/Performance





# Use cases

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- Power Consumption in Data Center – Historical Power consumption Data, CPU Memory Utilization, IO/Network Workload
- Performance Modelling and Prediction inter-arrival time, and sequential-scan run-length, queue time, seek and rotational latency, transfer time, sequential/random, read/write ratio – CART (Classification and Regression Tree) model
  - Parameter selection – additive and subtractive
    - CART model - CUT points are chosen
    - RBM to get latent features - subsequent regression can find the metric

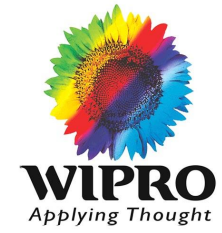
# Predictive Failure



# Use cases

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“Recently, **LSTM autoencoders and encoder-decoder frameworks** have been used as **reconstruction models** where some form of reconstruction error is used as a measure of anomaly. The idea behind such models is: autoencoder is trained to reconstruct the normal time-series and it is assumed that such a model would do badly to reconstruct the anomalous time-series having not seen them during training.”



# Miscellaneous



# Parameters

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- Load Balancing – some of the parameters
  - Latency
  - Response Time
  - Reject connection count
- Generalized Resource Management
  - Protocol Detection

# References

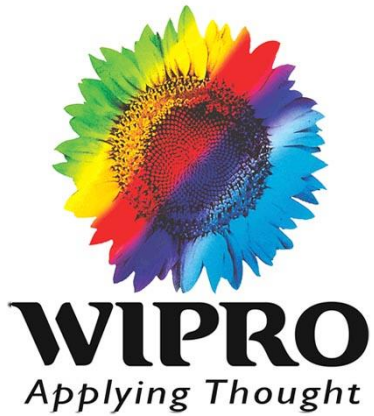
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<http://web.cs.iastate.edu/~cs577/handouts/svd.pdf>

<https://www.slideshare.net/ananth/word-representation-svd-lsa-word2vec>

<http://ieeexplore.ieee.org/document/7576472/>

<https://www.quora.com/How-do-I-use-LSTM-Networks-for-time-series-anomaly-detection>



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