

Introduction to Machine Learning

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ENCE 688P, Fall Semester 2021

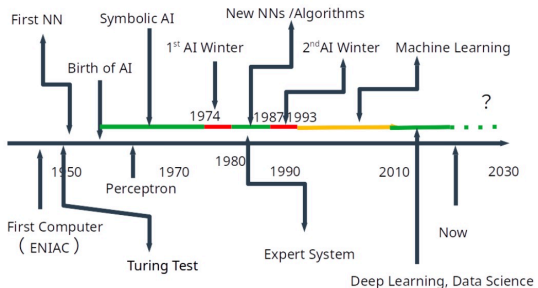
October 16, 2021

Overview

- 1 Quick Review
- 2 Artificial Intelligence and Machine Learning
- 3 Machine Learning Capabilities
- 4 Taxonomy of Machine Learning Problems
- 5 Types of Machine Learning Systems
- 6 Urban Applications
- 7 Recent Research at PEER and UMD

Part 02

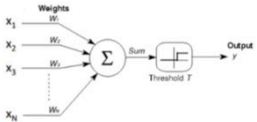
A Brief History



- 1943: First neural networks invented (McCulloch and Pitts)
- 1958-1969: Perceptrons (Rosenblatt, Minsky and Papert).
- 1980s-1990s: CNN, Back Propagation.
- 1990s-2010s: SVMs, decision trees and random forests.
- 2010s: Deep Neural Networks and deep learning.

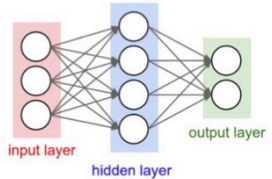
Machine Learning Capabilities (1980-1990)

Expressive Power of a Neural Network

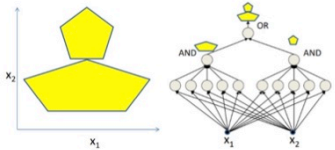
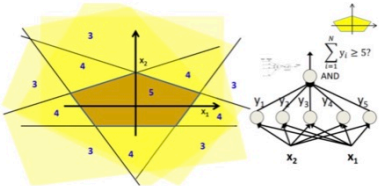


$$y = \begin{cases} 1 & \text{if } \sum_{i=1}^d w_i x_i \geq T \\ 0 & \text{else} \end{cases}$$

Neural Network with Single Hidden Layer

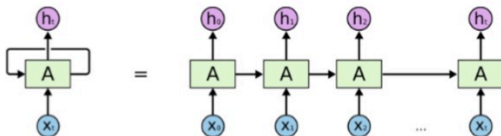


Approximation of Functions / Boolean Logic



Machine Learning Capabilities (1997-2014)

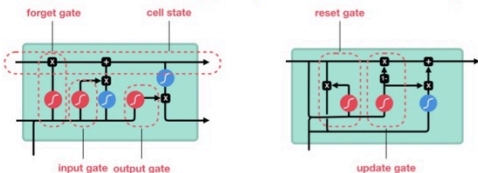
Recurrent Neural Networks (RNN): Learn sequences in data streams (text, speech)



Hidden state "h" serves two purposes:

- Make an output prediction.
- Represent features in the previous steps

Long Short-Term Memory (1997) Gated Recurrent Units (2014)



Key Features of LSTM:

- Standard RNN suffers from vanishing gradients for modeling of long-term dependencies.
- LSTM gives cells the ability to **remember values** for **long periods of time**.
- Gates regulate the flow of information in / out of the cell, and what should be remembered or discarded.



sigmoid



tanh



pointwise multiplication



pointwise addition



vector concatenation

Applications:

- Time series prediction.
- Time-series anomaly detection.

Machine Learning Capabilities (1997-2014)

Learning Streams of Text

- Download complete works of Shakespeare (5.4 million characters)
- Train machine to remember text.
- Write new Shakespeare!

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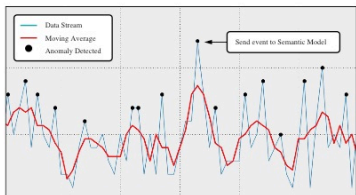
Sample after 1000 Iterations
-----
OTHERS. Allow up, whe, Will a moutice,
Reason thot boy Wokents allies; comn jusgius,
And encarembower hath leat)!
TASTOR. When no; devires at though me beligo jody?
NANCELOT. Trom juthar and bur itnot spock,
That as take have wendisho

Sample after 2000 Iterations
-----
VIBOTARD. Walk this boy and door as am 'stone!
NYRURLEN. Being entainure af Eaton.
Els that by much that, I mion's now, who make foll the Kid!!
CLOVE. Why which Hamm'd?
QUICKLY. And stand quast of I; this Fi

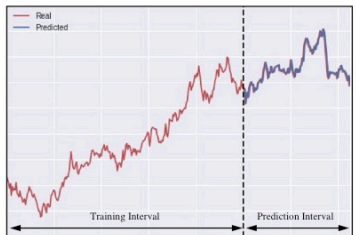
Sample after 2500 Iterations
-----
FORD. Nay, You're, excoun: and now did yet.
PAROLLES. Take DUTBY
This who is begin Cnoban a bows; but yet which that have be,
Oll, thou stan, and me not ready withered gids
And he in the pleassus or pardon us.
Mer. I pray you, how can, and tu

Sample after 3000 Iterations
-----
Rume, 'tignonig, gear?
By les, an hour, chork'd more in my grain,
I am thing forent inonion, nedam! I think I do speak you?
ARBESSTCHO. But his bosines, giving to know; foward to
the distvemail.' The to you well know yes, my lovi.
SECONO CMEOROR. He needs, for the refored are;
  
```

Time Series Anomaly Detection

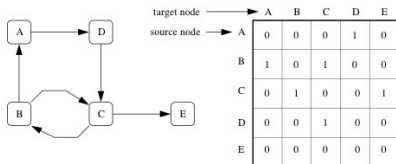


Time Series Prediction



Machine Learning Capabilities (2014-present)

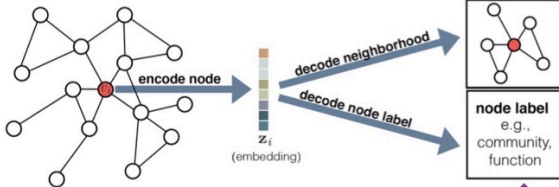
Traditional Approach to Graph Representation



Graph Analysis

- Connectivity / reachability analysis
- Cycle detection
- Traversal problems
- Shortest path problems
- Traceability problems (MBSE)
- Matching problems
- Topological sort problems
-

Graph Embedding Techniques



- Each **node** in the graph is **mapped** to a **low-dimensional space**.
- Goal is to **preserve local linkage structure** (not global structure).
- Each dimension corresponds to a **community** in the network.

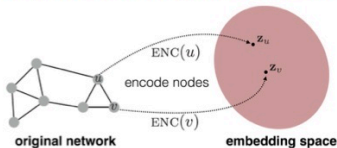
Graph Analytics

- Node Classification
- Node Clustering
- Anomaly Prediction
- Attribute Prediction
- Link Prediction
- Recommendation
- Etc ...

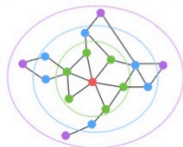
Captures **semantics**
in **domain application**

Machine Learning Capabilities (2014-present)

Graph-to-Embedding Space Transformation



Graph Reachability



- **Red:** Target node
- **Green:** 1-hop neighbors
 - A (i.e., adjacency matrix)
- **Blue:** 2-hop neighbors
 - A^2
- **Purple:** 3-hop neighbors
 - A^3

Goal: Design encoder so that similarity in embedding space is closely approximates similarity in original network.

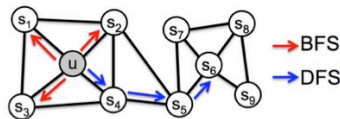
Graph Embedding Vector Design: node2vec, DeepWalk, ...

Node2vec: Combine two strategies:

BFS: Breadth First Search provides a local view of graph neighborhood.

DFS: Depth First Search provides a global view of the neighborhood.

Encoder is just a simple embedding vector lookup.



$$N_{BFS}(u) = \{s_1, s_2, s_3\}$$

Local microscopic view

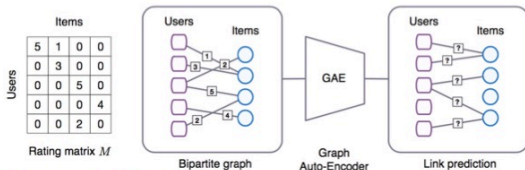
$$N_{DFS}(u) = \{s_4, s_5, s_6\}$$

Global macroscopic view

Machine Learning Capabilities (2014-present)

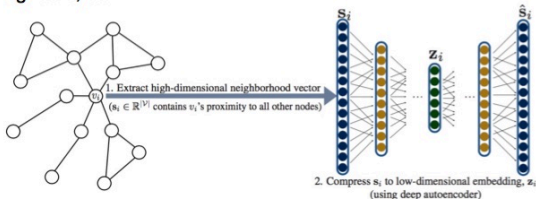
Graph Auto-encoder Link Prediction

Link prediction procedures can be used in new types of system validation / verification.



Deep Graph Auto-encoder Design

Requirements **traceability** needs **arbitrarily large levels of reachability** – first order neighbors, second-order neighbors, etc.



References

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