LEARNING LIKE HUMANS WITH DEEP SYMBOLIC NETWORKS

Hybrid Machine Learning Approaches and Applications Seminar

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ARTIFICIAL INTELLIGENCE REPRESENTATIONS

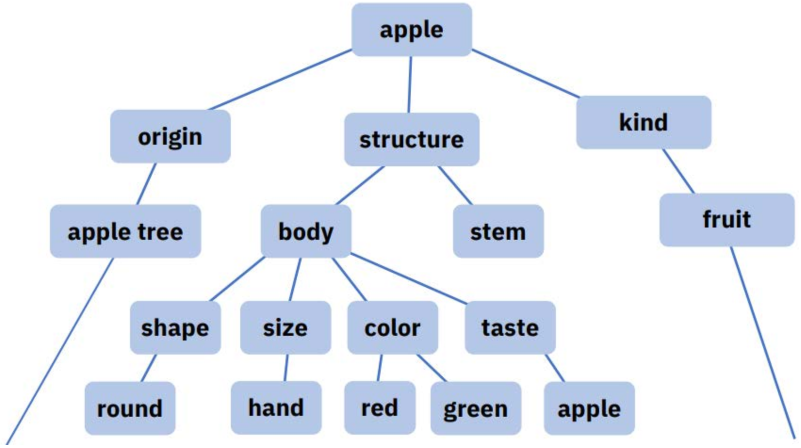
Symbolic AI (GOFAI)

- Expert Systems
- Planning, Inference, and Search Algorithms

Subsymbolic AI

- Machine Learning
  - Supervised
  - Unsupervised
  - Reinforcement
- Deep Learning
- Bayesian Learning

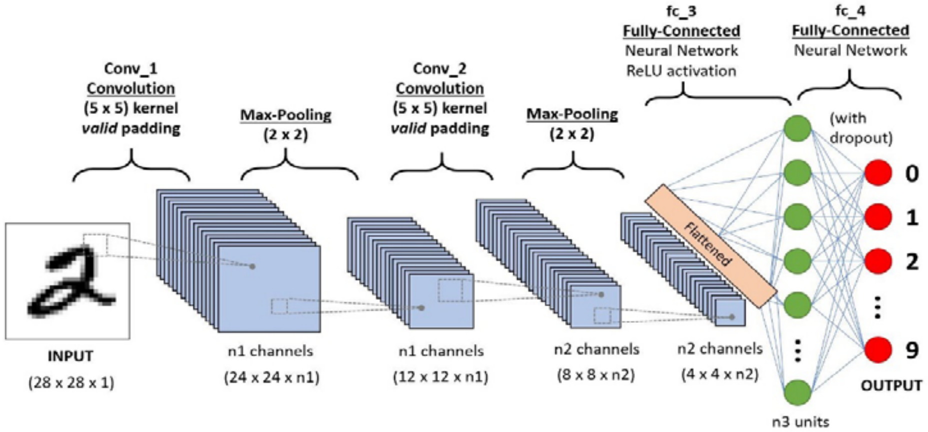
SYMBOLIC AI



Symbolic AI [1]

- Based on 'Symbolic' (human-readable) representation of problems & logic.
- Rules connect symbols in a relationship similar to an 'if-then' statement.
- Symbols & rules are fed explicitly.

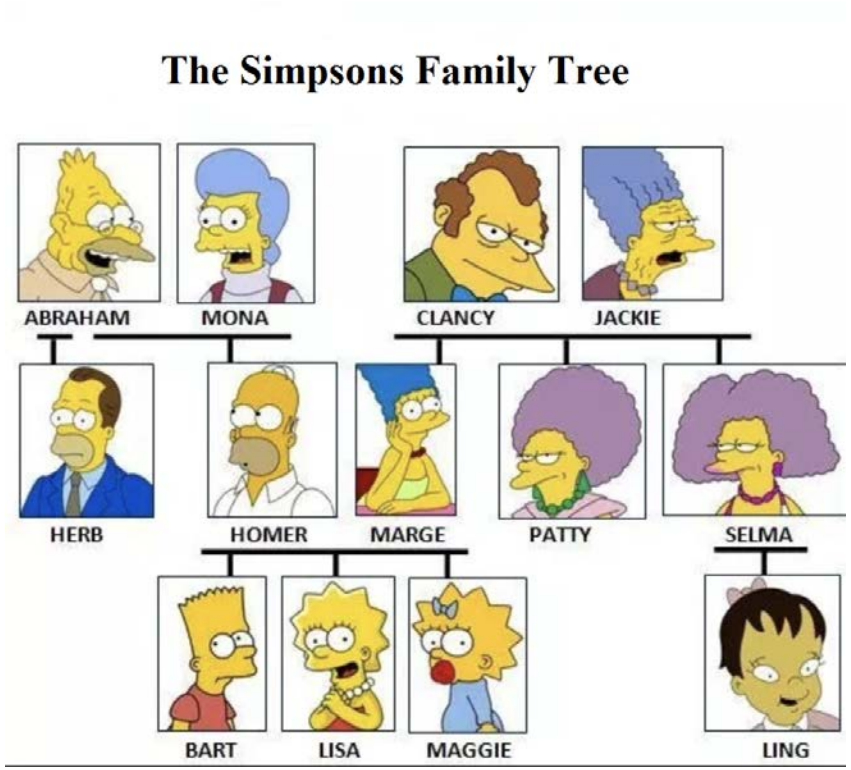
SUBSYMBOLIC AI (DEEP LEARNING)



Convolutional Neural Network [2]

- Inspired by the structure and function of neurons in the brain.
- Automatic feature extraction from raw data.
  - A neuron receives information from its neighbors.
  - Processes received information.
  - Sends processed info to other neurons.
- Continuously learn using objective functions.

THE PROBLEM



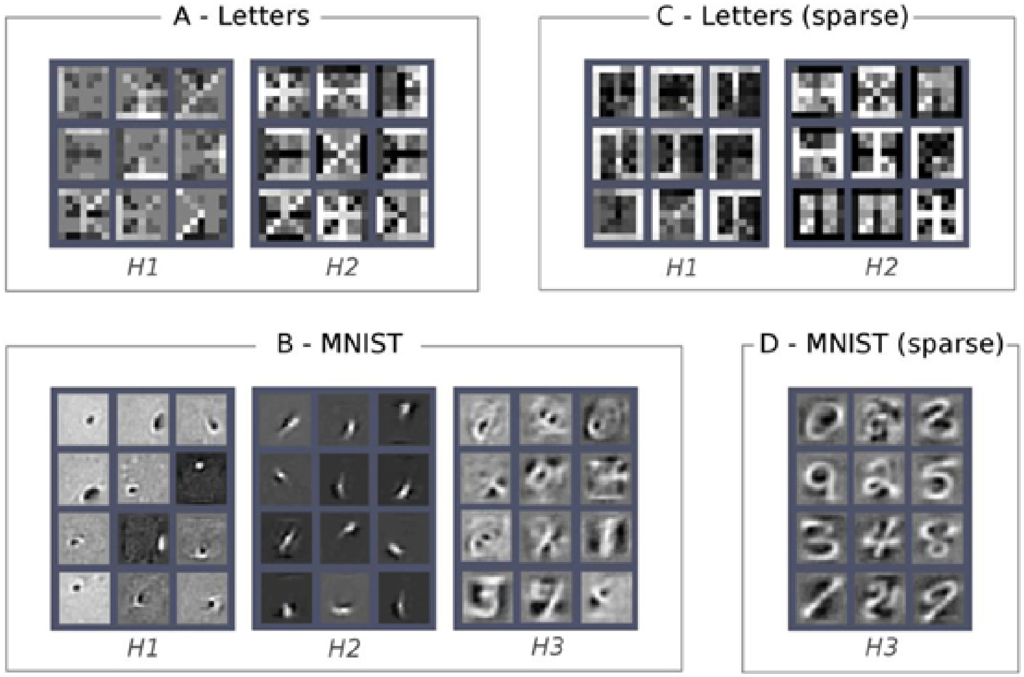
Information represented as symbols & rules [3]

Symbolic Methods

1. Advantages:
   - Excellent Reasoning & Logical Inferences.
   - Explainable decisions.
   - Can easily redefine propositional logic.
   - Expert Systems – can be deployed in critical environments.

2. Disadvantages:
   - Heavy reliance on rules & explicit symbolic representations.
   - Common sense knowledge problems.
   - Difficult to instil learning capabilities.

Subsymbolic Methods (Deep Learning)



Feature Maps at Hidden Layers [4]

1. Advantages:
   - Less upfront knowledge required.
   - Robust against noise.
   - Easier to scale.
   - Better performance on complex problems.

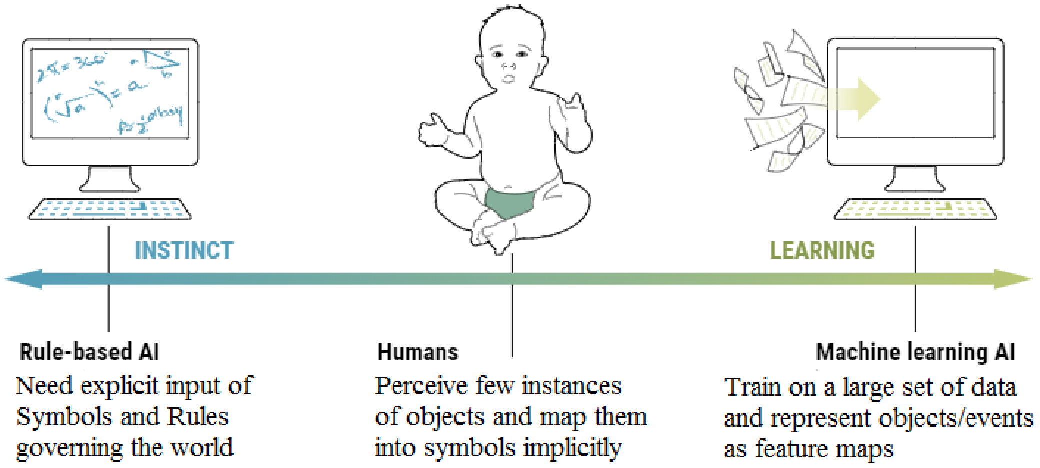
2. Disadvantages:
   - Require huge amounts of training data.
   - Computationally expensive.
   - Blackbox – risky to deploy in critical environments.

MOTIVATION

- Integrate Symbolic & Subsymbolic representations.
- Develop whitebox version of Deep Neural Networks (DNN).
- Learn representations of real-world objects like humans.
- Robust adaptation to both unstructured (data) and abstract problems.
- Learn with relatively small amounts of data.

WHAT DOES 'LEARN LIKE HUMANS' MEAN?

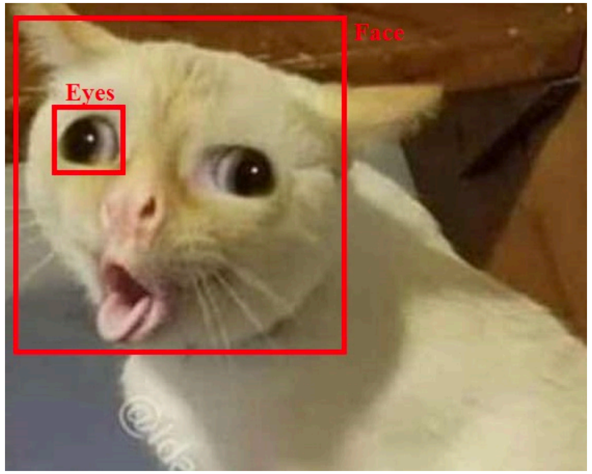
- In real-world, data is compositional (representable hierarchically).
- Humans learn to conceptualize knowledge as symbols and relations between them.
- Does not need thousand labelled instances of an object to recognize it.
- Strong Reasoning and Causal Inference.



Learning like human child [5]

WHY DO WE NEED IT?

- Implicit understanding of hierarchical representations in data.
- Less risk of Bias/Catastrophic failures.
- Reasoning and learning models of the world.
- Low reliance on expensive annotated datasets.



Facial features of a cat

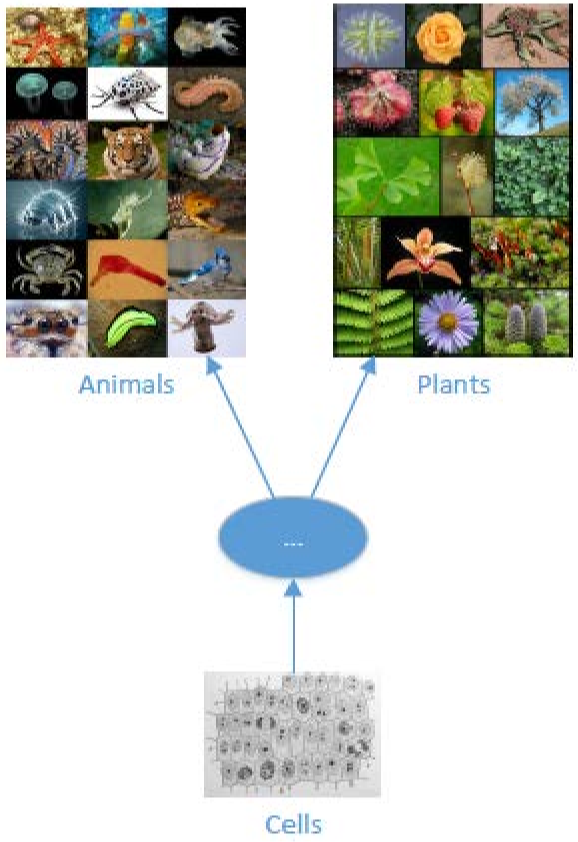
Car driving off a cliff

OVERVIEW

- Deep Symbolic Networks (DSN)
- Structure & Properties
- Training
- Uses
- Summary
- Limitations

DEEP SYMBOLIC NETWORKS

- Develop a recursive hierarchical structure (like DNN) to represent any knowledge of the world as symbols.
- Learn these symbols automatically using naturally occurring singularities (separators).
- Transparent representation of symbols.
- Refine the knowledge using optimization methods.



Hierarchical structure of symbols

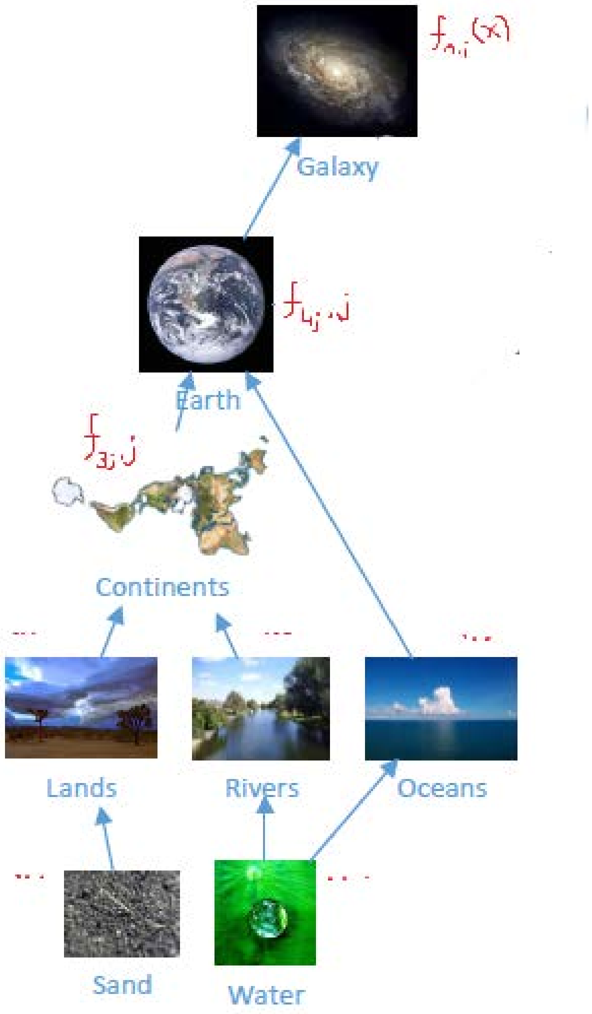
The Recursive Hierarchical Model

- Matter at higher layer is composed of matter at lower layers.
- No part of an object is made of itself.
- Identifying operators determine the symbol for new objects.

Deep Symbolic Network (DSN) formulation:

- Let ‘x’ be space the symbol occupies.
- f(x) approximates details at each point in space occupied.
- State parameters a, b, c represent magnitude, place & size.

$$f_{n,i}(x) + \epsilon_{f_{n,i}} = \sum_{j=1}^{k_{n,i}} (a_{n_j,j} + \epsilon_{a_{n_j,j}}) \left[f_{n_j,j}\left(\frac{x_j - (b_{n_j,j} + \epsilon_{b_{n_j,j}})}{c_{n_j,j} + \epsilon_{c_{n_j,j}}} \right) + \epsilon_{f_{n,j}} \right]$$



Deep Hierarchical Structure of Universe

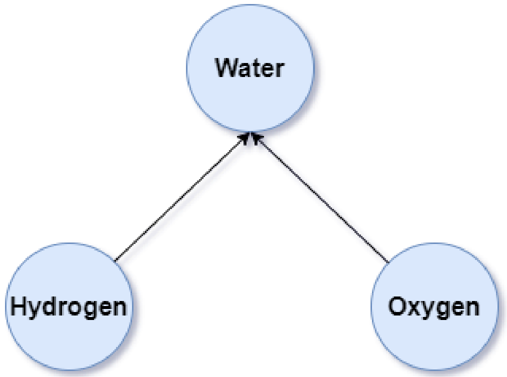
STRUCTURE & PROPERTIES

Deep Symbolic Networks has the following features:

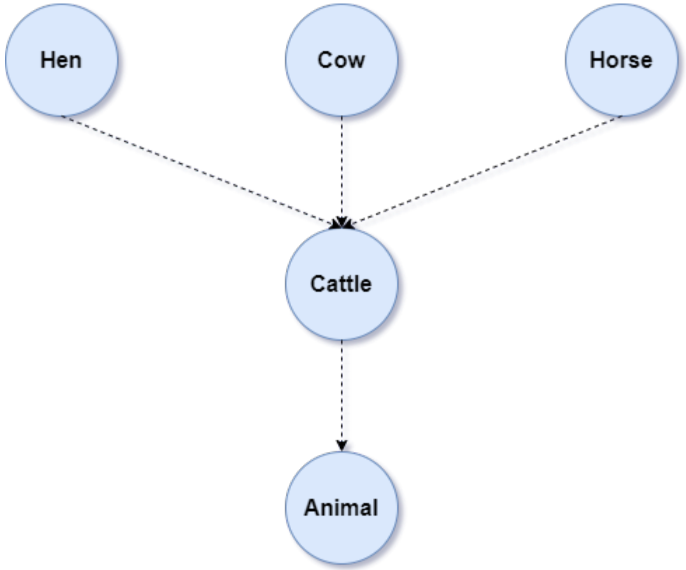
1. Links between symbols
   i. By Composition.
   ii. By Inheritance.
   iii. By Causality.
   iv. By Abstraction.

2. Interactions between symbols
3. Dynamics of symbols
4. Processes

1. Links between the symbols
   i. By Composition: Indicates the building blocks of higher-level symbols.
   ii. By Inheritance: Portrays that one kind of symbol belongs to another broader kind.



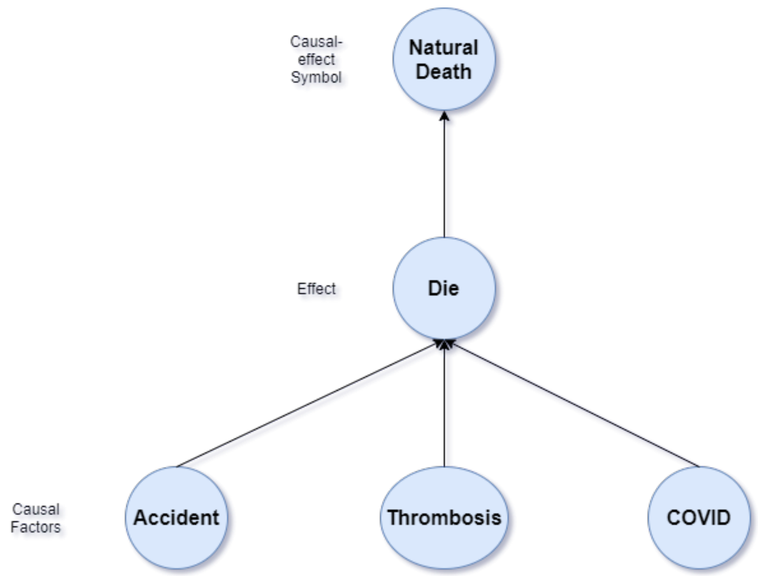
Composition



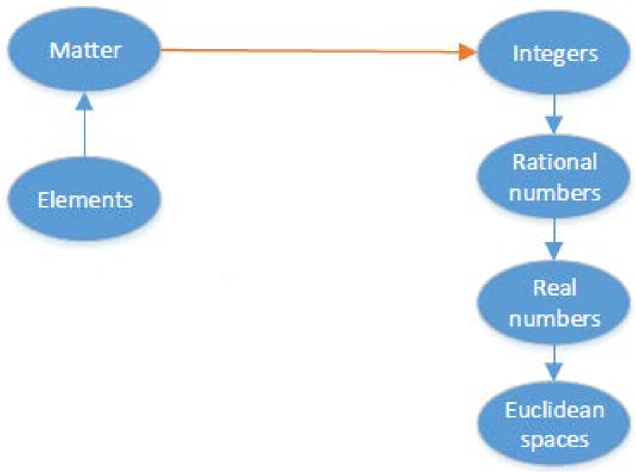
Inheritance

iii. By Causality: Generate a new symbol based on the pair of causal-effect symbols.

iv. By Abstraction: Parent symbol can be abstracted to a combination of child symbol.

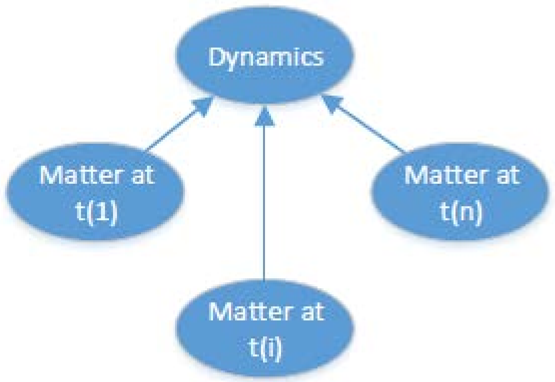


Causality

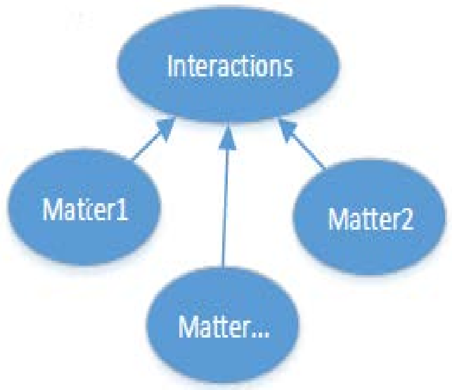


Abstraction

2. Interactions: has participants, outcomes and is linked with some dynamics.
3. Dynamics: represented by a symbol with its states changing with time.

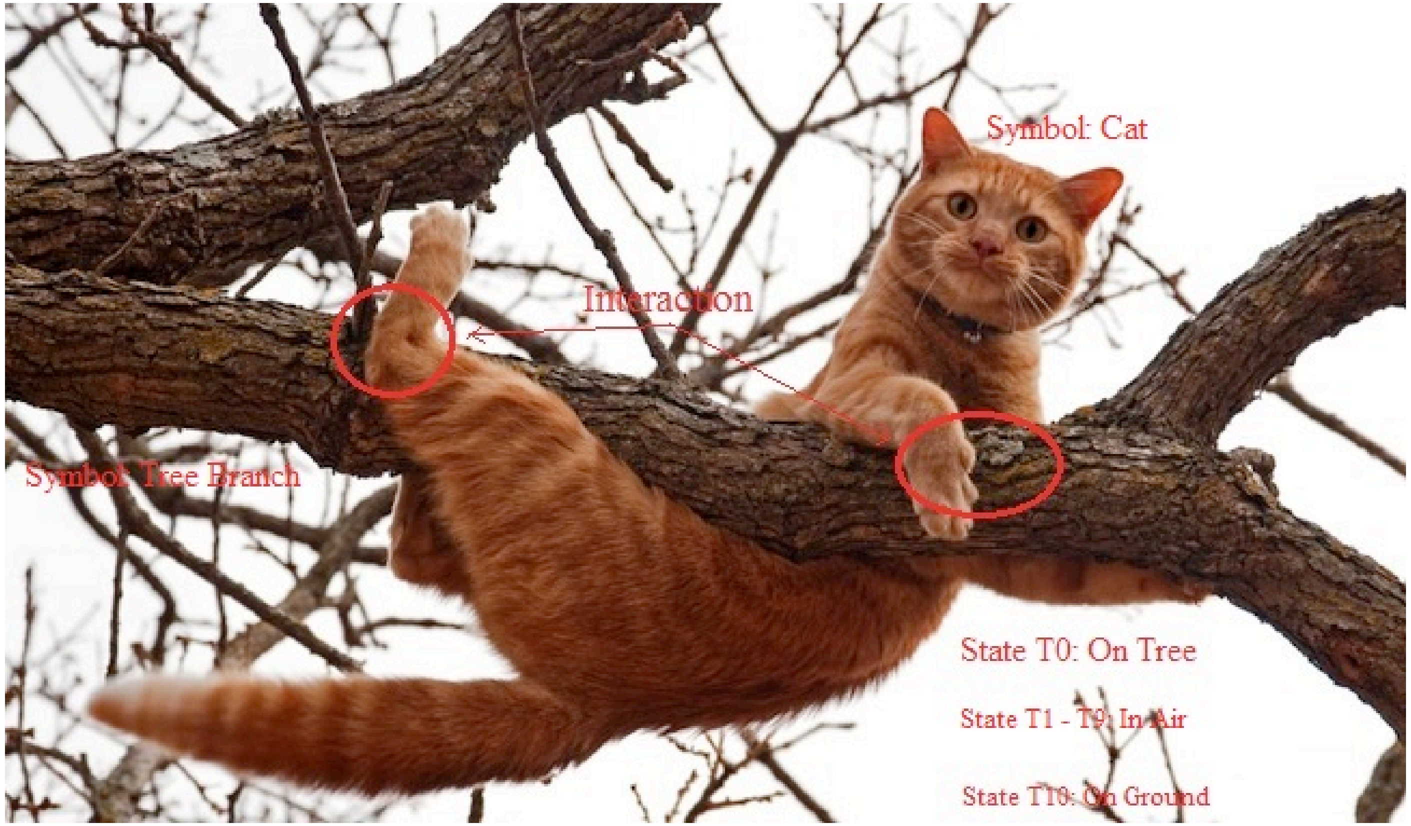


Dynamics



Interaction

3. Process: Produce output through a series of interactions & dynamics.



An illustration of interactions and dynamics between symbols

TRAINING DEEP SYMBOLIC NETWORKS

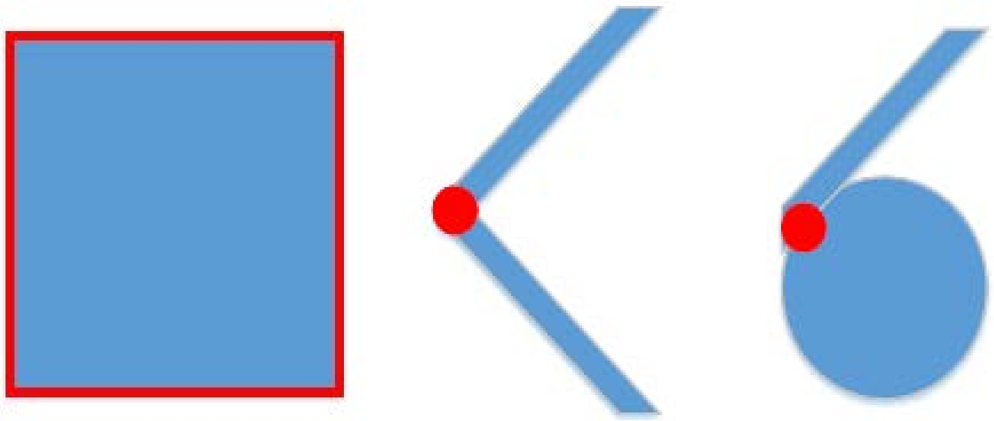
The training process involves 2 steps:

1. Identifying Operators
   i. Identify Singularities.
   ii. Extract First Layer Symbols.
   iii. Extract Higher Level Symbols.

2. Unsupervised Learning
   i. Cluster First Layer Symbols.
   ii. Cluster Higher Layer Symbols.

1. Identify Singularities

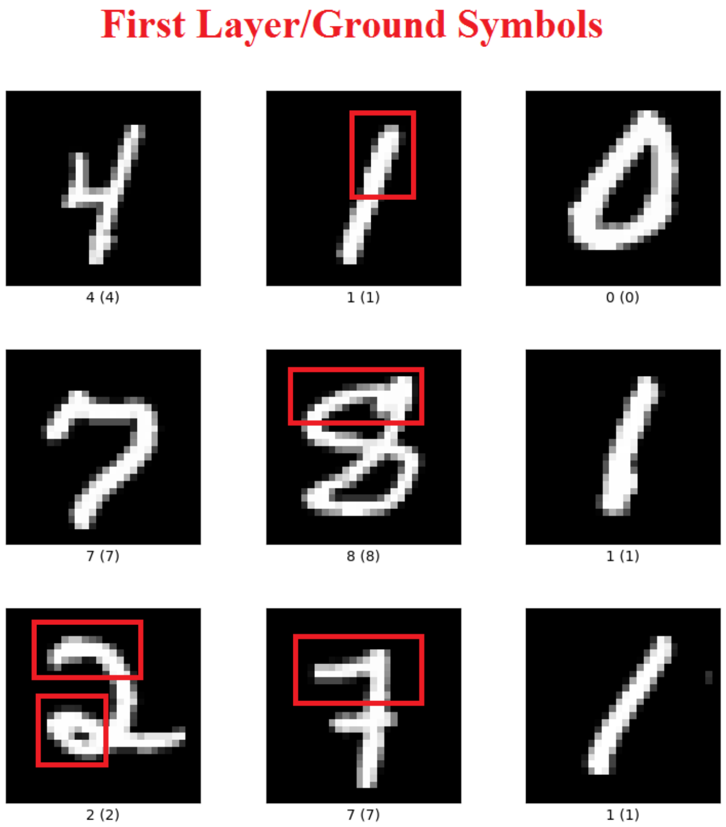
- Discontinuity in the color space.
- Discontinuity in the slopes.
- Discontinuity in the curvatures.



Examples of singularities separating different instances of different symbols.

2. Extract First Layer Symbols

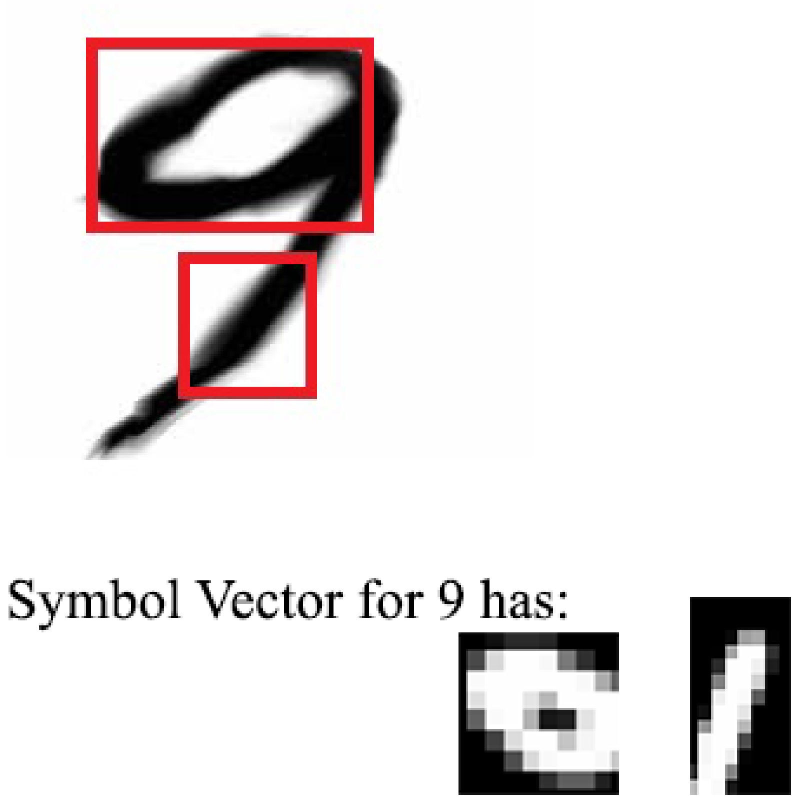
- Form the base of symbol space.
- Use themselves (normalized) as identifying operator.
- Identifying operator returns cosine similarity.
- Symbol selected if score above threshold.



Digit images from MNIST [6]

3. Extract Higher Level Symbols

- Represented by a set of first layer symbols.
- Use symbol vector (normalized) as identifying operator.
- Identifying operator returns cosine similarity.
- Symbol selected if score above threshold.
- Use State Parameter Identifier (ex: 6 & 9).

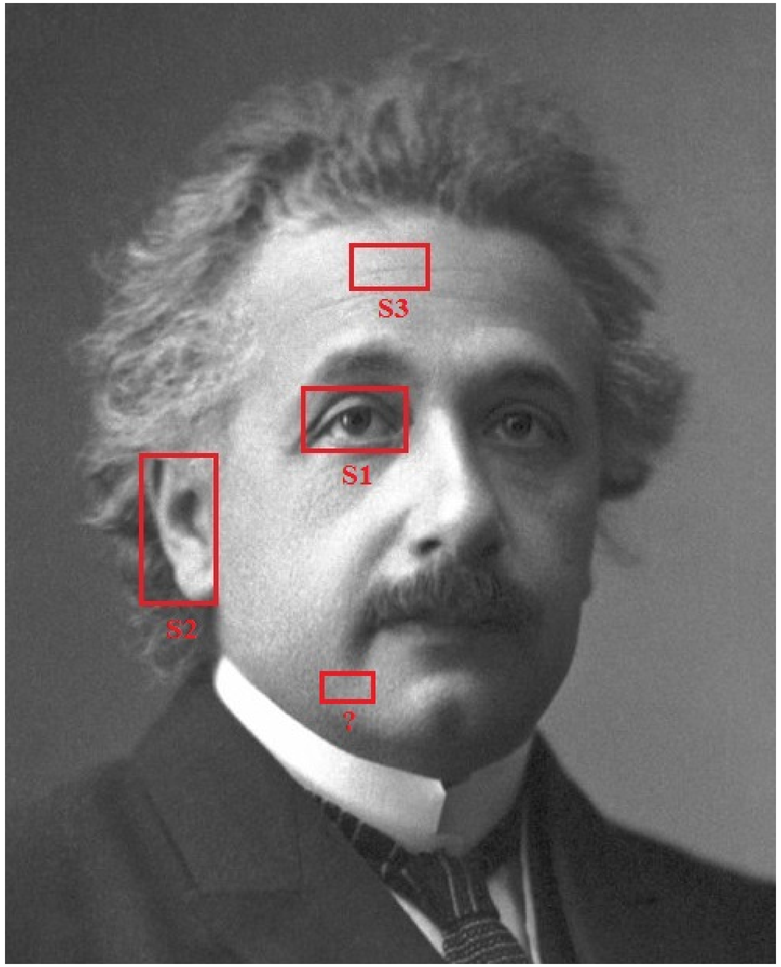


Higher-level symbol composition vector [6]

Unsupervised Learning

I. First Layer Symbols

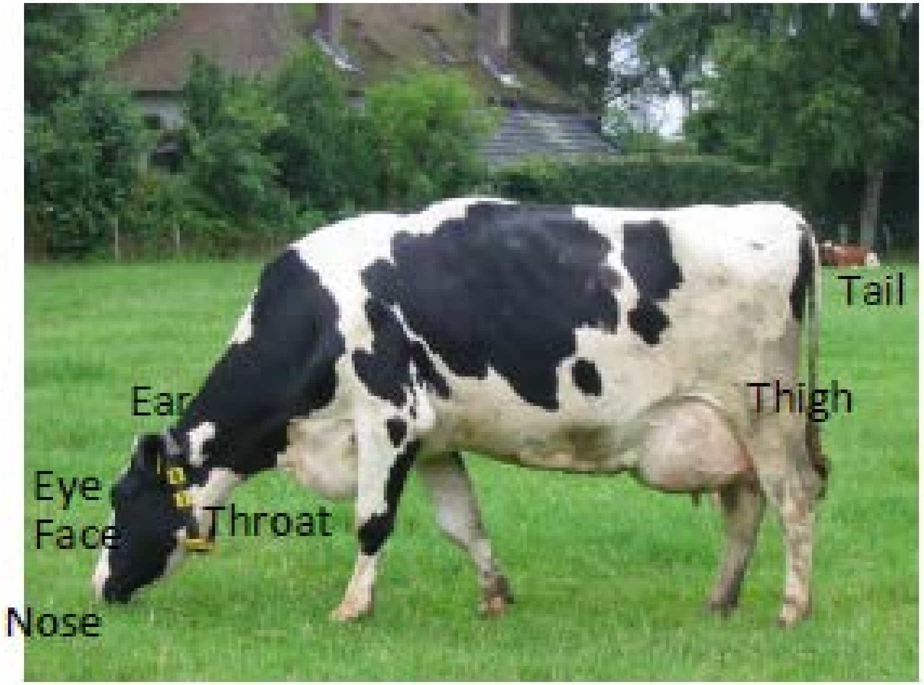
1. Detect singularities at all scales.
2. Extract data pieces using singularity bounding box.
3. Initially, add a data piece to new cluster.
4. Insert cluster into cluster list.
5. Generate identifying operator (kernel) to find ground symbol.
6. Match new data piece with existing clusters.
7. Threshold value to control number of clusters.



Lower-level facial symbols

II. Higher Layer Symbols

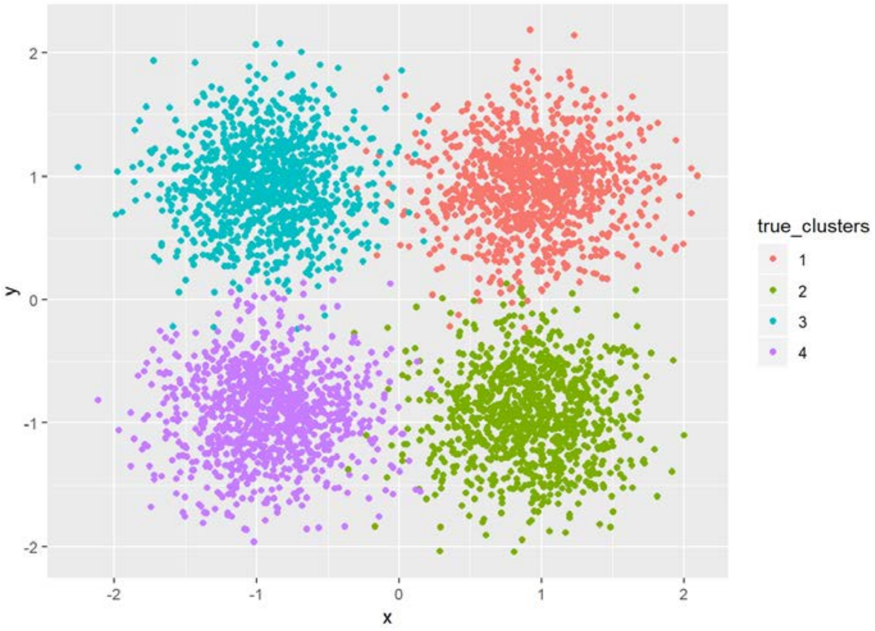
1. Data pieces represented by set of known ground symbols.
2. Repeat previous slide steps but at a bigger visual scope.
3. Decrease multi-layer noise.
4. Improve cluster accuracy with state parameter identifier.
5. Continue until no new symbols are identified.
6. Estimate best values of λ, μ.
7. Add composition links between symbols.
8. Record prior and posterior probabilities.



Lower levels symbols in a Cow symbol

Supervised Learning

1. Use Unsupervised learning to generate clusters as done previously.
2. Employ Supervised learning to find best values of cluster parameters: λ, μ.
3. Improve by optimizing the objective function.

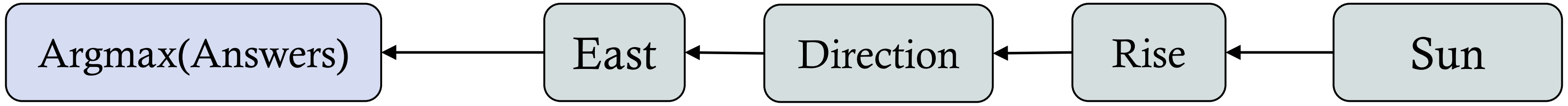


Clustering objects into symbol classes [7]

USES OF DEEP SYMBOLIC NETWORKS

1. Bayesian Decision Making

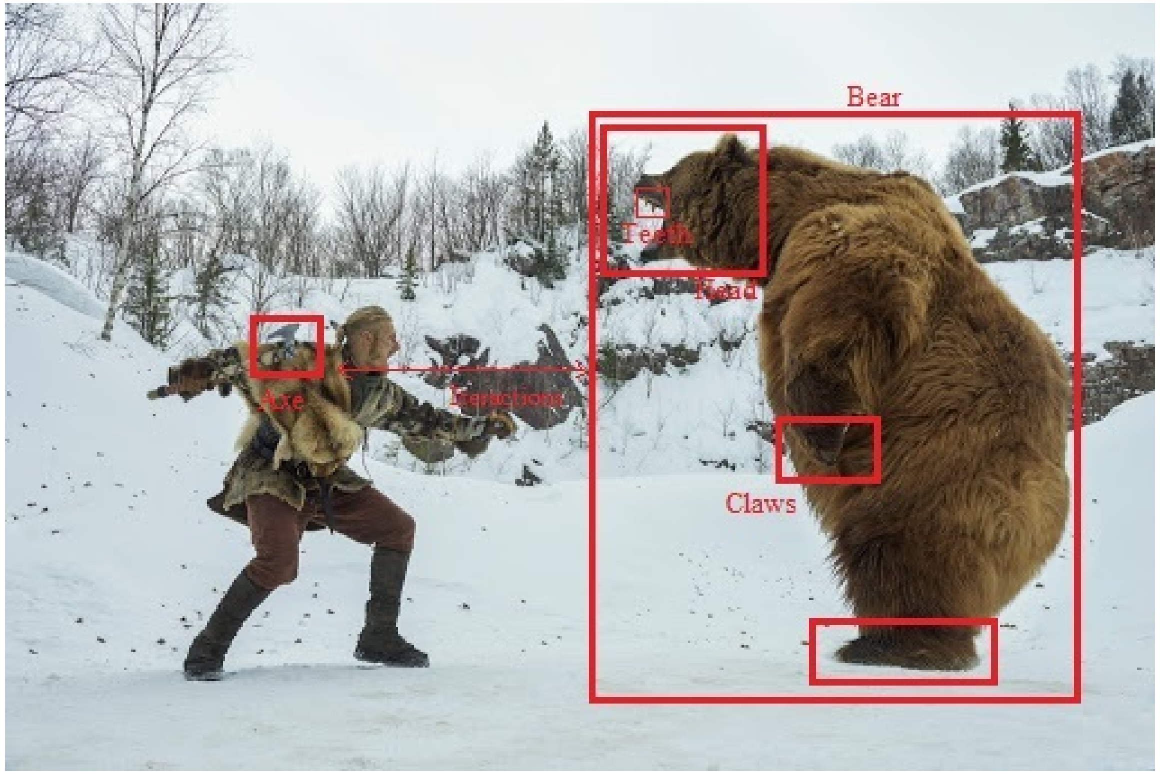
- Searching paths between links to find required output symbols.
- Ex: From which direction does the Sun rise?



$$\mathrm{P}(f_{m,j}|\underbrace{f_{n_1,1},...,f_{n_k,k}}_{\text{Input Symbols}}) = \sum_{f_{l_i,i}} \mathrm{P}(f_{m,j}|f_{l_1,1})\mathrm{P}(f_{l_1,1}|f_{l_2,2})...\mathrm{P}(f_{l_i,i}|f_{n_1,1},...,f_{n_k,k})$$

List of possible decisions

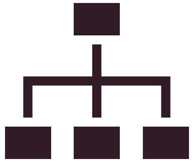
2. Cognitive tasks in critical environments
    - Use existing deep symbolic network aggregating all knowledge of the world.
    - DSN for perception and reasoning about the environment.
    - Ex: Hunter encountering a wild Bear.



Man fighting with a bear in the wild

SUMMARY

Develop whitebox versions of Deep Neural Networks



Represent deep hierarchical structures of the world in a human comprehensible format

Automatically learn knowledge representations from fuzzy and unstructured data

Singularities isolate symbols and naturally create symbol dictionary

LIMITATIONS

Training with Unsupervised Learning

- Unsupervised Learning assumes linear separability of symbols.
- Performs poorly with high amplitude of noises.
- Computationally intensive to estimate right cluster parameters.

Training with Supervised Learning

- Partial utilization of Supervised learning's benefits.
- No information about the training dataset.
- Incomplete information about evaluation metrics & model performance in both cases.

REFERENCES

1. Symbolic AI Symbol Representations
2. Convolution Neural Networks
3. Symbolic AI Symbols and Rules
4. Deep Learning Feature Maps
5. Learning like Human Child
6. MNIST Dataset Samples
7. Cluster Analysis & Parameter Approximation

QUESTIONS?