White paper

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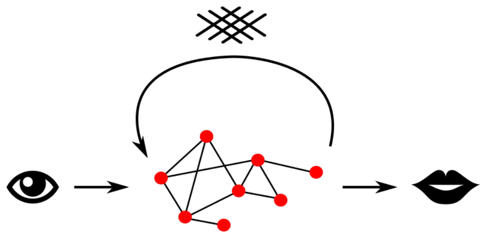
Abstract. This paper describes a cognitive architecture for common-sense reasoning.

0 Introduction

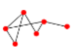
The architecture for **visual recognition** is:

 (1)

Our basic architecture is:

 (2)

 = [deep] neural network, trained via reinforcement learning

 = mental state / working memory

The main problems we need to solve:

(A) How to enable a neural network to act on a graph structure (that does not easily fit into a fixed-length vector)?

(B) How to achieve an ability that I call "learn by being told"?
This is related to the functional closure $\mathbb{X} \simeq \mathbb{X}^{\mathbb{X}}$ which gives a Cartesian-closed category

(C) How to incorporate **episodic memory** into the basic architecture (2)?
Episodic memory may be essential for the learning of common-sense (eg. the need to process **stories**).

Deep learning 所带来的好处是：它可以在 “multifarious”（「纷纭繁杂」）的资料中 factorize 出一些 intermediate features，从而将庞大的资料分类成数目较少的类别。这种分类法是旧式 AI 里没有的，例如 decision trees 的分类法，资料在切割之后不再相关。但神经网络像一些「拉面条」那样，在 hidden layers 中产生出 representation learning，这是以前的技术没有的。

The reason why I believe we can build AGI, is because we can use a deep network to emulate the following function:

 $\Longleftrightarrow \vdash^{\text{KB}}$ (3)

$\vdash^{\text{KB}}$ means to perform a **single step** of logical inference, ie, the **consequence operator**.

In the past, the learning of KB relied on **inductive logic learning**, based on combinatorial search, which was too slow. The new hope is for deep learning to learn this mapping in reasonable time.

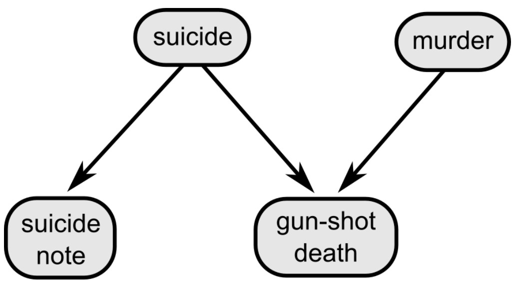
Deep learning 在 vision 中的成功，令我们相信它几乎可以 learn 出「任何 mapping」，除非那 mapping 具有 更深层 的结构；这时要用到 RNN。似乎 RNN 可以学习「任何结构」— “unreasonable effectiveness”。

An interesting idea is: would 2nd-order RNN’s have even more advantages?

1 Structure of memories

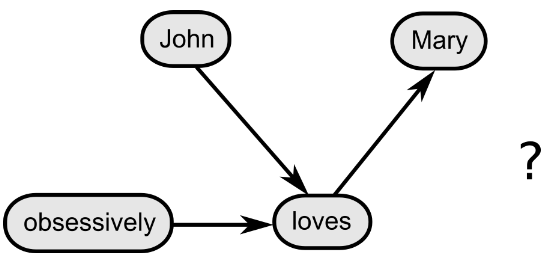
1.1 Working memory

At the proposition level, memory is organized as a **Bayesian network**, where each node is a proposition:



(4)

At the sub-propositional level, every proposition may be represented as an entity-relation graph, where each node is a **concept atom**:



(5)

but we are still unsure about the exact construction mechanism of sub-propostional graphs.

1.2 Episodic memory

Episodic memory = an even-bigger graph?

2 NN acting on graphs

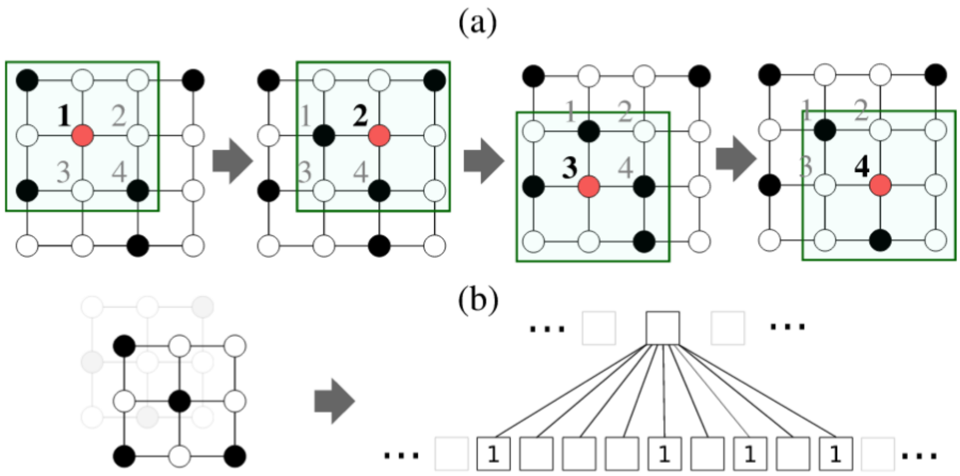
2.1 CNN

With this analogy:

$$\text{CNN for vision} \quad \Longleftrightarrow \quad \text{CNN for graphs} \tag{6}$$

a new breed of algorithms have been developed, eg: [1] [2] [3]. For a nice introduction see the blog entry: `https://tkipf.github.io/graph-convolutional-networks/`.

As explained in [1], a CNN works as if a "receptive field" moves over an image:



(7)

and the idea is to let a similar receptive field traverse a graph.

3 Cartesian closure

举例来说，「吃了污糟的食物会肚痛」是一个句子，它经由 进入 mental state $\boldsymbol{x}$ ，变成 proposition。但我们希望这逻辑命题变成 的一部分。With

$$\boldsymbol{x}' = \boldsymbol{f}(\boldsymbol{x}) \tag{8}$$

where

$$\boldsymbol{f} = \text{KB} = $$
$$\boldsymbol{x} = \text{state}$$

An individual logic rule is a restriction of $\boldsymbol{f}$ to a specific input.

$\boldsymbol{f} \equiv$ KB is the sum of restrictions:

$$\text{KB} = \bigcup \boldsymbol{f}_i \tag{9}$$

Or roughly speaking, $\boldsymbol{f}$ is the sum total of objects like $\boldsymbol{x}$:

$$\boldsymbol{f} = \bigcup \boldsymbol{x}_i \tag{10}$$

However, the problem is that the structure of $\boldsymbol{f}$ (as the neural network) is too complicated to be expressed as a sum of restricted functions. This remains an unsolved problem.

Acknowledgements

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Bibliography

[1] Mathias Niepert, Mohamed Ahmed, and Konstantin Kutzkov. Learning convolutional neural networks for graphs. 2016. URL `http://arxiv.org/abs/1605.05273`.

[2] Michaël Defferrard, Xavier Bresson, and Pierre Vandergheynst. Convolutional neural networks on graphs with fast localized spectral filtering. 2016. URL `http://arxiv.org/abs/1606.09375`.

[3] Thomas N. Kipf and Max Welling. Semi-supervised classification with graph convolutional networks. 2016. URL `http://arxiv.org/abs/1609.02907`.