A New Model for Artificial Intuition

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Abstract. The ability to inform and facilitate data-driven decisions is at the core of Data Science, AI, and general Machine Learning techniques. To achieve this, all possible scenarios must be considered, and their outcomes must be assessed logically and systematically to obtain accurate and applicable methods for knowledge discovery. There is compelling evidence from the cognitive sciences that intuition plays an important role in intelligence extraction and the associated decision-making process. As a consequence, the embedding of Artificial Intuition within AI would provide novel ways to identify and process information.

Keywords: Artificial Intuition · Artificial Intelligence · Network Theory · Decision Algorithms

1 Introduction

Artificial Intuition is becoming an increasingly relevant area in Computer Science as it could potentially lead to more efficient and fast problem-solving and decision-making approaches [4]. Artificial Intuition is the ability of a system to assess a problem context and identify novel links among the corresponding knowledge components to facilitate the decision process in an automated manner. Furthermore, intuition is dependent on past knowledge and experience for better recall of solutions to the given problems or normal logical process [2].
In this work, Artificial Creativity and Artificial Intuition refer to different, yet overlapping concepts. The former is associated with the automated creation and design of artefacts, objects, ideas, etc. which are regarded as (primarily) creatively 'beautiful'. They could, of course, be useful and have various applications. On the other hand, Artificial Intuition involves the automated identification of innovative solutions.

In this article, a rigorous approach to artificial intuition is proposed. The aim is to facilitate a comprehensive theory and subsequent implementations of Artificial Intuition to provide a better decision system, which mimics the agile and efficient intuitive processes extensively used by human agents.

The structure of the article is as follows: in Section 2, the state-of-the-art technology, methods and approaches of Artificial Intuition are presented and discussed, and Section 3 focuses on the necessary background information, which is at the core of the approach introduced in this article. Sections 4 and 5 provide the details of the Artificial Intuition model, and its development with respect to a decision system. The experimental evaluation is discussed in Sections 6 and 6.2. Finally, Section 7 concludes the article and prompts future research directions.

2 Related Work

The multi-disciplinary nature of Artificial Intuition is reflected by the extensive research carried out in several fields, such as Neuroscience, Business, Psychology and Computer Science, to name but a few.
In [4], a computational model of artificial intuition and decision making is discussed, which is achieved via the recognition of significant patterns and properties that are made available by prior knowledge and experience, given the domain of the problem.
From a cognitive research perspective, [9] presents a descriptive research on managerial decision-making and problem solving where insights into the nature of intuition are provided. It is argued that business executives who focus on real-time information aided by intuition, can react quickly and accurately to changing stimuli in their firm or its environment. Even though the available data is limited, executives who based their decision policies on real-time information were also most frequently described as being intuitive.
In [5], the authors have identified two fundamental and distinct modes of intuition based decision-making and reasoning, which are labelled as *System 1* (intuition) and *System 2* (logical reasoning). System 1 is an automated, fast and often unconscious way of thinking. It is autonomous and efficient, requiring little energy or attention and is dependent on some known information. System 2 is an effortful, slow and deliberately controlled way of thinking. Despite System 1 is likely to be affected by models of pattern recognition, System 2 is based on rational choices where humans use logic in its best sense to perform a cost/benefit analysis that will provide the best possible choice. Studies have shown that human beings do not have the natural ability to perform more than one cognitive process at the same time, hence it is argued that System 2 (rational and logic based reasoning) is less significant than System 1 (subconsciousness and intuition) [11]. However, this requires the agent/human to acquire considerable skills and experiences over a specific time period.

3 General Definitions and Background

The problems (or scenarios) which need to be assessed to reach a given solution will be referred to as *queries*.

Definition 1. *A* query *is a collection of semantically-linked concepts, which defines the main scenario or objective to be assessed. The* solution of a query *is a set of paths linking the query with suitably identified concepts.*
The concepts at the end of a path connected to a query are called the query leaf nodes*.*

Knowledge must be at the core of any Artificial Intuition approach, and the model proposed in this article will be based on three different types of knowledge as introduced in Definition 2.

Definition 2. *We define*

- Existing knowledge *as the information associated with specific and well-known (prior) knowledge,*
- Intuitive knowledge *as the information associated with more general (and potentially overlapping) knowledge, which might complement the above,*
- Contextualised knowledge *as the information associated with with individual experience and knowledge, if applicable.*

In this section, we shall describe the main mathematical concepts and algorithms, which will be evaluated and assessed in Section 6.

3.1 Network Theory

Let $G = G(V, E)$ be an undirected network, where $V = \{v_i\}_{i=1}^n$ is the *node set* and $E = \{e_{w_{i,j}}(v_i, v_j)\}_{v_i \neq v_j \in V}$ is the *edge set*. Note that each edge $e_{w_{i,j}}(v_i, v_j)$ is weighted by the parameter $w_{i,j} \in (0, 1]$, which is related to the type of relationship linking the two nodes v_i and v_j. We say that two nodes are *adjacent* if they are connected by an edge, and two edges are *incident* if they have a node in common. We define a *path* $P(v_a, v_b)$ between two nodes v_a and v_b a sequences of incident edges

$$e_{w_{a,k_1}}(v_a, v_{k_1}), e_{w_{k_1,k_2}}(v_{k_1}, v_{k_2}), \ldots, e_{w_{k_{n-1},k_n}}(v_{k_{n-1}}, v_{k_n}), e_{w_{k_n,b}}(v_{k_n}, v_b)$$

joining the two nodes. Note that if a network is not acyclic, then more than a path might exist between any two nodes.
In this article, as discussed in Definition 2, we shall consider the network generated by the union of three (usually overlapping) following networks

$$G = G_k \cup G_i \cup G_c \tag{1}$$

where

- G_k is the (semantic) network associated with existing knowledge within a specific setting,
- G_i is the (semantic) network associated with intuitive knowledge and
- G_c is the (semantic) network associated with contextualised knowledge.

As discussed above, each node is associated with a specific concept and the overall topology of the network G governs the way information is propagated across the network. More specifically, the overall information captured by the above (union of) networks must include

– The (perceived) probability of occurrence of each concept,
– Types of relationships associated with each edge, and
– Influence weight of each of them, which loosely speaking refers to the 'strength' of the corresponding relation.

4 Description of the Model

The mutual interactions within knowledge systems can be efficiently described as networks, where concepts correspond to nodes, linked by suitably defined edges. These contain the relevant information on the relationships joining any two nodes, which is assume to include the observed, estimated, or defined level of influence, as formalised in Definition 3.

Definition 3. *Each edge joining two nodes $x, y \in V$ has an associated* activation value $\alpha(x, y) \in (0, 1]$*, which is associated with the influence that x exerts on y.*

In this article, the activation value is deliberately defined in general terms. In fact, it should be learnt automatically based on the topology and the properties of the overall knowledge system. Future research will focus on a more comprehensive and robust investigation of its properties. The concepts and their mutual relations within a query are identified either manually, or via automated methods. In this article, only the former will be considered. This will create a semantic network which will be embedded into a suitably defined network generated by the corresponding existing, intuitive and contextualised knowledge. The topology of such network will be subsequently used to identify novel and potentially innovative solutions to a given query.

Each node $v \in V$ will be associated with a value $p(v) \in (0, 1]$. This can be interpreted as the (observed) probability of occurrence of the corresponding concept, which might refer to an actual or estimated assessment. Note that probability is closely related to the concept of information. In this article, the level of information captured by a node is regarded by its (observed) probability of occurrence. The authors are aware that this might not be appropriate in all theoretical scenarios. However, in line with this work, such distinction is deemed not to be significant. In the following definition, the *information propagation* will be introduced, which will be explicitly formulated in the following sections.

Definition 4. *The information propagation $I(x, y)$ between two nodes x and $y \in V$ is defined as a map*

$$I : V \times V \rightarrow [0, 1]. \tag{2}$$

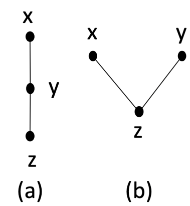

Fig. 1. Two simple networks as discussed in Section 4.1.

An important observation is that the information propagation from x to y might not necessarily coincide with the (observed) probability of y. Therefore, we define the *post node probability* of a node v with respect to one of its neighbours w as

$$\tilde{p}(v) = \min\{I(w,v), p(v)\}, \tag{3}$$

where $p(v)$ is the (observed) probability of v.

4.1 Combination of Edge Attributes

The information propagated along the edges feeds into the nodes in the corresponding paths. However, their topology can be interpreted in different ways. Consider, for example Figure 1 which depicts two very simple networks consisting of 3 nodes, namely x, y and z. These simple configurations might be associated with the following possibilities:

- Both x and y directly influence z, as depicted by Figure 1(a). In other words, they need to co-exist in order to have z.
- Figure 1(b) depicts a cumulative influence of x and y on z.

The above cases are formally written as

$$x \oplus y \to z \tag{4}$$
$$x \odot y \to z \tag{5}$$
$$x \not\leftrightarrow y \to z, \tag{6}$$

where '$\oplus$', '$\odot$' and '$\not\leftrightarrow$' refer to the disjoint, joint as information independence relationships. Note that the above expressions also include '$\to z$'. This refers (with a slight abuse of notation) to the fact that we are considering the information propagation of the nodes x and y into the node z. This notation will be dropped when such influence does not need to be emphasised.

Lemma 1. *Let x and y be two nodes. Then*

$$x \oplus y \to z \equiv x \not\leftrightarrow y \to z$$

if either $I(x,z) = 1$, or $I(y,z) = 1$

Proof. This is can be easily observed from the above. In fact, is the the disjoint relationship yields the the same influence on z as the information independence, then either the influence propagation $I(x,z) = 1$, or $I(y,z) = 1$. $\square$

4.2 Explicit Calculation of the Edge Attributes

Since the activation value associated with each edge joining two nodes x and y governs the information propagation, it will be an important parameter in the explicit formulation of Equations 4 and 5.
More specifically, for three nodes x, y, z we define $x \odot y (\to z)$ as

$$x \odot y = p(x)p(y)W_{x,y}W_{y,z}, \tag{7}$$

where

$$W_{x,y} = \tanh\left(\frac{k\,\alpha(x,y)}{2}\right), \tag{8}$$

where the choice of k depends on the required steepness of $W_{x,y}$. In this article, we shall assume that $k = 4$. Equation 8 is motivated by the sigmoid activation function widely used in Artificial Neural Networks [4].

Similarly, the disjoint relationship operation $x \oplus y \to z$ is defined as

$$x \oplus y = \begin{cases} p(x)W_{x,z} + p(y)W_{y,z}, & \text{if } p(x)W_{x,z} + p(y)W_{y,z} \leq 1 \\ 1, & \text{otherwise.} \end{cases} \tag{9}$$

Finally, we define the information independence relationship operation as

$$x \not\leftrightarrow y = \max\{p(x)W_{x,z}, p(y)W_{y,z}\} \tag{10}$$

5 The Assessment of Potential Solutions

In this work a solution is assumed to be based on the paths joining a set of nodes starting from a query and connecting all its neighbouring concepts. However, any such path needs to be assessed to determine whether it provides a viable solution.
Loosely speaking, an intuitive problem-solving process focuses on finding *different paths* to a solution, which might lead to a better solution compared to a 'conventional' one. In this section we will address the assessment and identification of the most suitable set of solutions via the *intuition* and *propagation indices*. In the rest of this section, for brevity we shall refer to a path $P(x_1, x_n) = \bigodot_{i=1}^{n} x_i$ as a vector $\underline{x} = [x_1, \ldots, x_n]$.

5.1 Intuition Index

Recall that knowledge is associated with the union of three different (knowledge) networks

$$G = G_k \cup G_i \cup G_c \tag{11}$$

where

- G_k is the (semantic) network associated with existing (prior) knowledge within a specific setting,
- G_i is the (semantic) network associated with intuitive knowledge and
- G_c is the (semantic) network associated with contextualised knowledge.

We can assume that a 'conventional' solution is embedded in G_k.

Definition 5. *We define the* innovation index *between the nodes x_s and x_e following the path $\underline{x}$, as*

$$i(\underline{x}) = \frac{|E(G \setminus G_k)(\underline{x})|}{|E_p(G)(\underline{x})|}, \tag{12}$$

where $E_p(G \setminus G_k)(\underline{x})$ and $E(G)(\underline{x})$ are the set of edges in $G \setminus G_k$ (that is the edges not in the 'common' knowledge) and the set of edges in G for a path $\underline{x}$ between the nodes x_s and x_e, respectively.

Hence, based on Equation 12, the overall innovation index between the nodes x_s and x_e, assuming there are n paths between them is

$$i(x_s, x_e) = \frac{1}{n} \sum_{j=1}^{n} i_{\underline{x}_j} \tag{13}$$

5.2 Propagation Index

As discussed in Section 4.2, the information is propagated based on specific rules, such as Equation 7 and more specifically, Equation 8. We define the *propagation index* associated with a path $\underline{x}$ as

$$\alpha(\underline{x}) = \prod_{x_i \in \underline{x}} \alpha(x_i). \tag{14}$$

The propagation index simply estimates how well information can spread along a specific path $\underline{x}$ and it will be used in conjunction with the innovation index to assess the suitability of paths related to a solution.

5.3 Edge Entropy

A network with very strong edge relations is optimal for reasoning as information is propagated more reliably and as such, the corresponding scenario can be modelled more efficiently. Therefore, we can use the concept of entropy to explore and assess how well a network with respect to a specific query-concept can be used to reason and find a solution. Note that high entropy values are also associated with very sparse networks. However, this corresponds to a trivial case, which will not be discussed in this article.

Definition 6. *Let $\underline{x}_t$ be a path at time t that is a sequence of incident edges $x_{i_1}, x_{i_2}, \ldots, x_{i_t}$. We define its entropy $H(\underline{x}_t)$ as*

$$H(\underline{x}_t) = -\alpha(\underline{x}_t) \log \alpha(\underline{x}_t). \tag{15}$$

The overall entropy from x_s is given by

$$H(x_s) = -\sum_{j=1}^{k} \alpha(\underline{x}_t^j) \log \alpha(\underline{x}_t^j), \tag{16}$$

for all the paths $\underline{x}_t^1, \ldots, \underline{x}_t^k$ originating from x_s.

The concept of entropy defined in Definition 6 will be used as an exploratory tool to assess whether a specific query (defined by one or more concepts) can be investigated based on a specific (knowledge) network and determine viable solutions. In other words, this will allow us to identify:

- Whether a given network can be used to identify one or more solutions from a query;
- How far we need to navigate into the network (by following paths originating from the query/concepts) to obtain a feasible solution.

It is straightforward to prove the following lemma.

Lemma 2. *Let $H(x_s)$ be defined as in Equation 16. If $\alpha(\underline{x}_t^j) = 1/e$ for all the paths $\underline{x}_t^1, \ldots, \underline{x}_t^k$ originating from x_s, then $H(x_s)$ is at its maximum value.*

The rest of the section will focus on defining a discovery algorithm to identify the best solution(s) for a query. The aim is to approximate the value of the entropy of the different paths, which are incrementally expanded during the discovery process as per the iteration time t. This will allow to automatically assess the most appropriate solution based on the edge properties of the corresponding paths.

As discussed above, it is clear that the best outcome in assessing a path $\underline{x}$ is when all the edges are associated with an activation index equal, or very close to 1. Let $0 \leq \epsilon \leq 1$ and consider the values of $H(\underline{x})$ for $\alpha(\underline{x}) = 1 - \epsilon$. In other words, ϵ can be regarded as a perturbation of $\alpha(\underline{x})$ for values close to 1.

Proposition 1. *Let $0 \leq \epsilon_i \leq 1$ for $i = 1, \ldots, k$. We have that the entropy of the path $\underline{x}_k$ is*

$$\begin{aligned} H(x_s) &= \sum_{i=1}^{k} H(\underline{x}_t^i) \approx \sum_{i=1}^{k} \left(\epsilon_i - \frac{\epsilon_i^2}{2} - \frac{\epsilon_i^3}{6} - \frac{\epsilon_i^4}{12} - \frac{\epsilon_i^5}{20} \right) \\ &\leq k \left(\bar{\epsilon} - \frac{\bar{\epsilon}^2}{2} - \frac{\bar{\epsilon}^3}{6} - \frac{\bar{\epsilon}^4}{12} - \frac{\bar{\epsilon}^5}{20} \right) \textit{ where } \bar{\epsilon} = \max_{i=1}^{k} \{\epsilon_i\}. \end{aligned} \tag{17}$$

Proof. The above can be obtained via Taylor's expansion of $x \log x$ at $x = 0.5$ and by substituting $x = 1/2 - \epsilon$, namely

$$\sum_{n \geq 2} \frac{(-1)^{1+n} 2^{-1+n} (-0.5 + \epsilon)^n}{(-1+n)n} + (\epsilon - 0.5)(\log(2) - 1) + \frac{\log(2)}{2} \tag{18}$$

Therefore, for all the paths discovered at time t, which originate at the node x_1, the result follows from Equation 16 . □

Note that if $\bar{\epsilon}$ is close to 0, then all the ϵ_i are also close to 0. When this happens, we say that the query has a *strong solution space* at time t.

Based on Definition 6, the overall entropy can be used to explore the query space. From Lemma 2, we therefore need to consider the entropy in the interval $[1/e, 1]$, which is equivalent to having $\alpha_k > 1/(ke)$

Algorithm 1 Solution Assessment

Let $t = 1$ and $D \leq 1$ be the threshold for the maximum entropy
Let $\underline{x}_t$ be a path connecting a query concept with one of its leaves leaf($\underline{x}$)
for path $\underline{x}$ **do**
  if $\alpha(\underline{x}_t) \geq 1/(t\,e)$ **and** $H(\underline{x}_t) \leq D$ **then**
    Continue
  else
    Stop
  end if
  if $\underline{x}_t != $ leaf($\underline{x}$) **then**
    $t = t + 1$
  else
    Stop
  end if
end for
return path $\underline{x}_t, H(\underline{x}_t)$

Algorithm 1 returns a path $\underline{x}_t$ and its entropy based on a query. However, it does not guarantee to identify the shortest path between the concept and leaf nodes which, based on the different parameters associated with the path, might not be reached by x_t. Despite such limitations, Algorithm 1 formalises an effective exploratory tool to assess a query. This will be further discussed in Section 6.2.

6 Experimental Results

This section presents an evaluation of the method introduced in this article based on semantic networks, generated by ConceptNet [6] and Wikipedia [7] as a corpus. Section 6.1 provides a description of their use in the context of this article [8].

6.1 ConceptNet and Wikipedia Datasets

ConceptNet is a semantic network of knowledge that consist of assertions of common sense knowledge encompassing the spatial, physical, social, temporal, and psychological aspects of everyday life. ConceptNet consists of information collected from many sources, including expert created resources and open Mind Common Sense corpus [6], a crowd-sourced knowledge project.

In this article, ConceptNet is used to identify suitable semantic networks as part of the validation process, via the following steps:

1. Identify specific concepts contained in a query;
2. Extract the relevant network defined by the main concepts related to the query and mutual relationships;
3. Merge the network with any other (semantic) network previously defined;
4. Navigate across the network to discover knowledge related to the query.

An important decision to make when building a knowledge graph from ConceptNet, is on what a node should represent, as this has significant effects on the graph that is retrieved and how the graph is used. Moreover, it also has implications on making linking and importing other resources non-trivial, as different resources are associated with different decisions about their representation [10]. Statements contain concepts, which are linked by a positive or negative weight. The higher values of the weights, the more likely that the assertion is reliable and true. On the other hand, a negative weight implies that the assertion may not be true [10].

Wikipedia is a multilingual online encyclopaedia created and maintained as an open collaboration project by a community of volunteer editors using a wiki-based editing system [7]. It is the largest and most popular general reference work on the World Wide Web and it features exclusively free content. SpaCy [1] was used to build an appropriate graph representation of knowledge from Wikipedia pages. See [12] for more technical details used in this work.

6.2 Evaluation Details

The validation process presented in this article, focuses on a query ‘weather forecast’. We retrieved the assertions associated with the following concepts: *weather, rain, rainfall, wind, temperature, cloud, cloudy, modelling, maths, statistics, sunshine, hot_weather, weather_forecast, weather_prediction predict_rainfall, wind_forecast, maths_statistics.*

More specifically, a total of 5495 relations from ConceptNet database were extracted. The lowest weight in the relations retrieved was 0.1 while the highest weight was 10.472. We noticed there were some repeating assertions which are due to data originating from various sources. In this work, this issue was addressed by ignoring all assertions with weight less than 1. The weights were subsequently normalised and grouped into 10 discrete categories

$$[0, 0.1), [0.1, 0.2), \ldots [0.9, 1].$$

This query identified the concepts: *aircraft, climate change, statistics* and *cattle*, as shown in Table 1. Note that despite a low propagation index for *aircraft*, its

	Path length	Propagation Index	Innovation Index
Aircraft	9	0.077	0.72
Climate Change	5	0.39	0.63
Statistics	3	0.64	0.39
Cattle	11	0.20	0.45

Table 1. The validation results as discussed in Section 6.2

innovation index is the highest. Interestingly, aircraft technology does contribute to weather forecast [3], despite not been fully captured in the dataset created for this validation. This suggests that using aircraft for weather forecast is a novel and intuitive solution with respect to the knowledge related to this context.

The validation discussed in this section has demonstrated the potential of this approach introduced in this article. In fact, this is far from being a comprehensive evaluation due to some obvious reasons. First of all, innovative and novel solutions can be complex to precisely pinpoint as this would require a manual comparison based on data that is currently either limited or non existent. Furthermore, ConceptNet and Wikipedia do not offer full semantic properties to create a fully implementable semantic network for artificial intuition.

7 Conclusion

Despite artificial intuition has drawn considerable attention from the research community, there has been limited effort in the creation of defining and investigating its mathematical concepts and properties. This work has addressed this by introducing a rigorous model to model and implement artificial intuition. The preliminary experimental results demonstrate the potential of this approach and motivate further work in this field. More specifically, future research will focus on a comprehensive mathematical analysis of the dynamical and algebraic properties of information aggregation and propagation. This will provide an in-depth analysis critical aspects and properties which can be applied to artificial intuition and its integration with AI systems. Furthermore, a collaborative research effort will focus on the creation a a large (semantic) dataset to complement and enhance the state-of-the-art data, which is currently available. This will enable a more comprehensive evaluation tools as well as training datasets to automatically identify some of the most important parameters related to artificial intuition.

Conflict of interest

The authors declare that they have no conflict of interest.

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