Using IAC Networks to Model Countries

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1 Introduction

This project involves developing an Interactive Activation and Competition (IAC) network model to represent semantic knowledge about 15 different countries. IAC networks are neural network models that contain separate pools of nodes representing distinct concepts, with excitatory and inhibitory links between the nodes. When one node becomes active, it spreads activation to related nodes but also receives inhibition from nodes it is not related to, allowing the network to settle into a state where a subset of related nodes are active [1].

An IAC network is well-suited for representing semantic knowledge about countries because the distinct node pools can encode features and characteristics of each country, with bidirectional excitatory and inhibitory connections capturing the relationships between them. For example, activating the node for "France" could spread activation to related nodes like "Europe," "Unsafe," and "Romance languages," while inhibiting unrelated nodes like "Asia" Through this pattern of spreading activation and competition, the network can model the gist of knowledge about each country.

In this project, I develop an IAC network with 15 country nodes as the main representation. Each country node is connected to person, location, food, culture, and other category nodes that characterize that country. Additional connections between country nodes capture similarities and differences between them. By clamping external activation onto different country nodes and observing settling patterns, the network will demonstrate semantic knowledge for answering questions about country characteristics and relationships. This project will showcase the ability of IAC networks to concisely model rich real-world semantic domains.

The results will provide insight into effectively structuring IAC models for representing bodies of world knowledge. This could have implications for building more capable semantic agents and question answering systems.

2 Methodology

Interactive activation and competition (IAC) networks consist of pools of nodes representing distinct concepts, with bidirectional excitatory and inhibitory links between nodes capturing semantic relationships. Each node has an activation value a_i that changes over time according to input signals and lateral connections. The activation a_i of a node i is determined by the equation:

$$\frac{da_i}{dt} = -a_i + \sum_j W_{ij}\sigma(a_j) + I_i \tag{1}$$

Where:

- $-a_i$ is a decay term that causes activation to decay over time
- $\sum_j W_{ij}\sigma(a_j)$ represents input to node i from other nodes j, with W_{ij} as connection weights and $\sigma(a_j)$ typically a sigmoid function of node j's activation
- I_i is external input clamped onto node i

Nodes send excitatory activation to related nodes but compete via mutual inhibition with unrelated nodes. The net input to a node is determined by the equation:

$$net_i = \sum_j W_{ij}\sigma(a_j) + I_i - \sum_k S_{ik}\sigma(a_k) \qquad (2)$$

Where the last term represents lateral inhibition coming from nodes k that aren't related to node i, with S_{ik} as inhibitory connection weights.

Through cycles of activation spreading and competition, IAC network states settle into stable patterns where related node subsets remain active. This allows them to store semantic knowledge, complete patterns from partial inputs, and demonstrate inferences in their settled activation states.

The connections W_{ij} and S_{ik} are tuned through a training process to capture the desired semantic relationships between nodes for representing knowledge.

IND	Poor	Trop.	Asia	Indo	Okay	Big
KSA	Rich	Temp.	Asia	Semitic	Safe	Big
UK	Rich	Temp.	Eur.	Germanic	Okay	Small
USA	Rich	Temp.	Amer.	Germanic	Okay	Big
RUS	Mid	Temp.	Eur.	Slavic	Okay	Big
ITA	Rich	Temp.	Eur.	Romance	Okay	Small
MEX	Mid	Temp.	Amer.	Romance	Unsafe	Big
DEU	Rich	Temp.	Eur.	Germanic	Okay	Small
BRA	Mid	Trop.	Amer.	Romance	Unsafe	Big
JPN	Rich	Temp.	Asia	Japonic	Safe	Small
FRA	Rich	Temp.	Eur.	Romance	Unsafe	Small
CHI	Mid	Temp.	Asia	Sino	Okay	Big
NIG	Poor	Trop.	Africa	Afro	Unsafe	Small
EGY	Poor	Temp.	Africa	Semitic	Okay	Small
TUR	Mid	Temp.	Asia	Turkic	Okay	Small

Table 1: Countries and their attributes data table

An IAC network was developed to represent semantic knowledge about 15 countries across 6 key attributes:

- Economy: Based on income per capita of the country's population
- Climate: Dominant climate type of the geographic region
- Region: Continent where the majority of the country's population resides
- Language: Linguistic family of the primary language spoken in the country
- Crime level: Categorized as safe, unsafe, or okay
- Size: Land area classification of big or small

These 6 attributes constitute separate pools of nodes in the IAC network. Additional nodes represent the 15 countries modeled: India, Saudi Arabia, United Kingdom, United States, Canada, Russia, Italy, Mexico, Germany, Brazil, Japan, France, China, Nigeria, and Egypt. A decay rate of $a_i = 0.25$ was used for every node in the network.

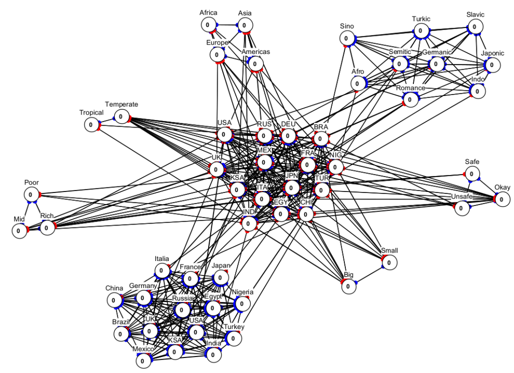

Figure 1: There are 8 pools of mutually inhibitory nodes including a pool of instance nodes in the center

3 Results

The interactive activation and competition (IAC) network was successfully developed to store structured knowledge about the 15 countries across the 6 attribute pools. The network appears to have adequately captured facts and relationships within the country domain.

To validate knowledge retrieval, individual country nodes were activated to observe spreading activation across attribute representations. Figure 2 provides an illustrative result of clamping a +1 input on the "KSA" (Saudi Arabia) node and evolving the network for 10 time steps.

As shown, stimulating the instance node for Saudi Arabia spreads activation to the corresponding attributes of Rich, Temperate, Asia, and so forth. This

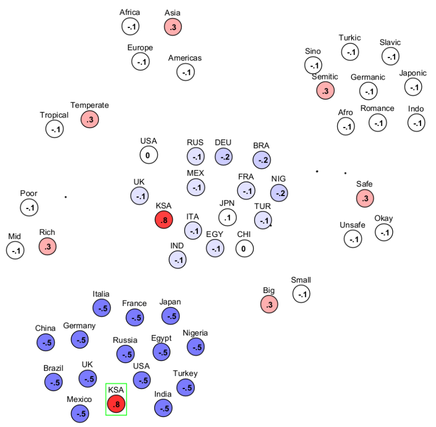

Figure 2: Activation state after clamping Saudi Arabia input.

demonstrates successful retrieval of stored knowledge about the country based on the tuned connectivity weights. In addition, the network showed an ability for retrieval based on partial attribute activation. As seen in Figure 3, clamping inputs for both Rich and Semitic led to inferred activation of Saudi Arabia after 10 cycles.

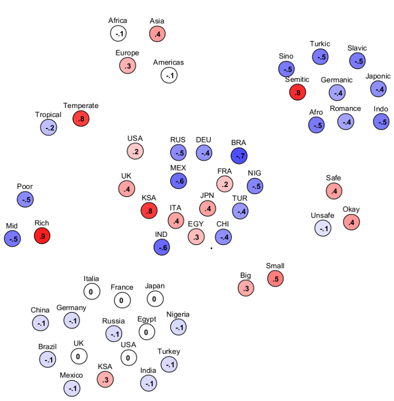

Figure 3: Inferred Saudi Arabia activation from partial attribute activation.

In addition to validation of accurate retrieval for known countries as shown, the model exhibits spontaneous generalization. As illustrated in Figure 4, clamping the Romance" language family node activates related attributes of Unsafe" crime, Temperate" climate, Rich/Mid" economy, Big/Small" size, and Europe/America" region.

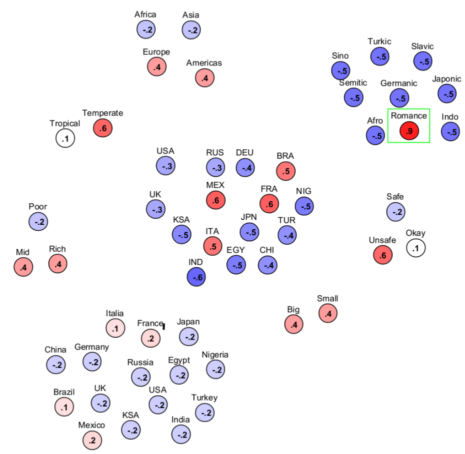

Figure 4: Inferred activations after clamping Romance language input.

4 Discussion

The interactive activation and competition (IAC) modeling approach demonstrated several useful capabilities for representing real-world semantic knowledge in an interconnected neural network architecture.

A key benefit is the graceful degradation in pattern completion. As shown in the partial matching results (Figure 3), the network can infer the most likely country target even given incomplete or degraded attribute input cues.

Additionally, content addressability was exhibited by the model's ability to retrieve category-level inferences (Figure 4) from stimulating shared attribute representations, without needing to stimulate unique entity names. This content-based inference through the learned weight structure avoids demanding exact address lookup.

Furthermore, training the model for a small set of countries enabled spontaneous generalization of properties to unseen countries sharing common features.

This indicates promising scalability by leveraging correlations and co-occurrences within the knowledge domain.

There are several worthwhile extensions to explore for enhancing model utility. Increasing the number of represented countries and adding more fine-grained attribute nodes would expand knowledge capacity. Additional connectivity to model higher-order constraints between attributes could improve reasoning.

In conclusion, the interactive activation principles achieved promising results for encoding structured, flexible knowledge in an efficient and generalizable neural framework amenable to expansion. The approach provides a neurocognitively grounded paradigm for developing more human-like semantic capabilities in machine learning systems.

References

[1] McClelland, J. L. and Rumelhart, D. E. (1981). An interactive activation model of context effects in letter perception: I. An account of basic findings. Psychological review, 88(5), 375.