# Time Series and Data Analysis Based on Hybrid models of Deep Neural Networks and Neuro-Fuzzy Networks

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# Modular Neural Networks
# The Main Idea of Modularity

**Each modular system has a number of special modules that are working in small**

**main tasks. Each module has the following characteristics:**

**1. The domain modules are specific and have specialized computational architectures to recognize and respond to certain subsets of the overall task;**

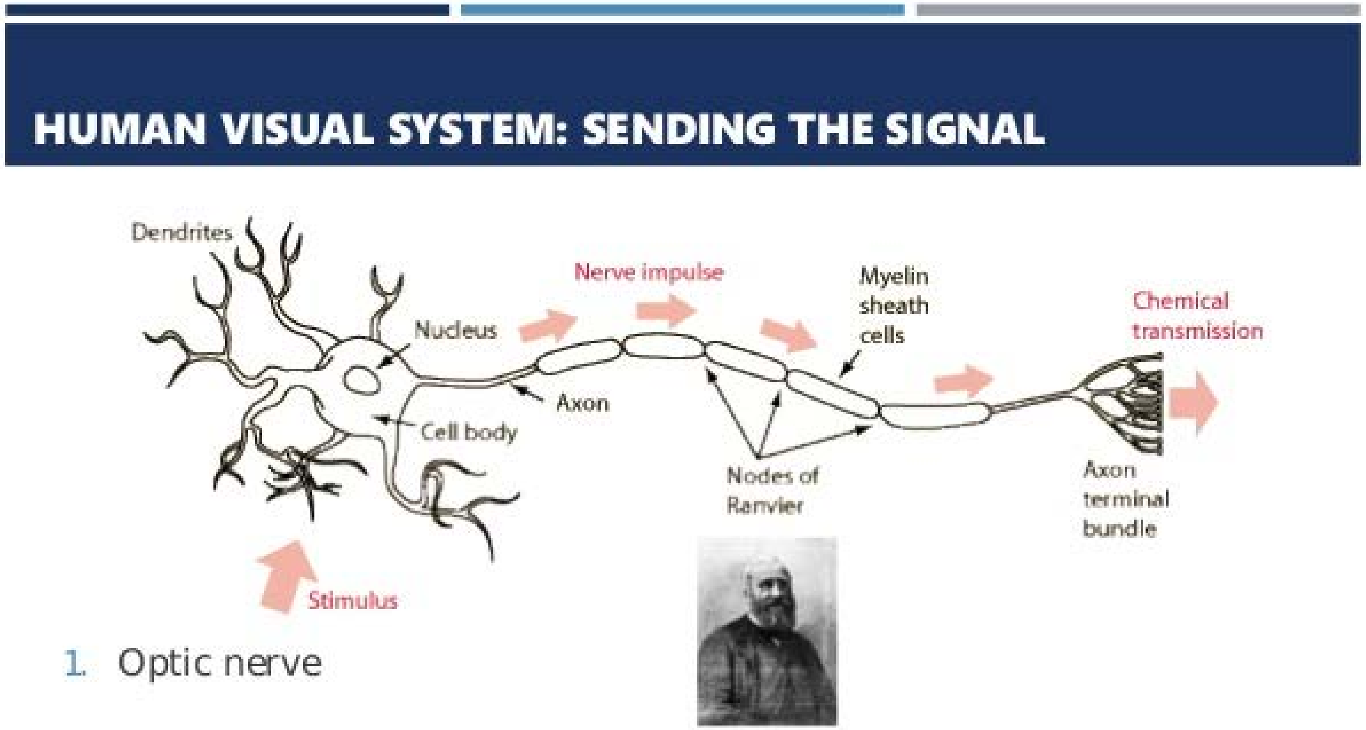
**2. Each module is typically independent of other modules in its functioning and does not influence or become influenced by other modules;**

**3. The modules generally have a simpler architecture as compared to the system as a whole.**

**Thus, a module can respond to given input faster than a complex monolithic system;**

**4. The responses of the individual modules are simple and have to combine by some integrating mechanism in order to generate the complex overall system response.**

# Modular Neural Networks
# The Main Idea of Modularity




The best example of modularity is human visual system. In this system, different modules are responsible for special tasks, like a motion detection, color recognition and shape. The central nervous system, upon receiving responses of the individual modules, develops a complete realization of the object which was processed by the visual system.

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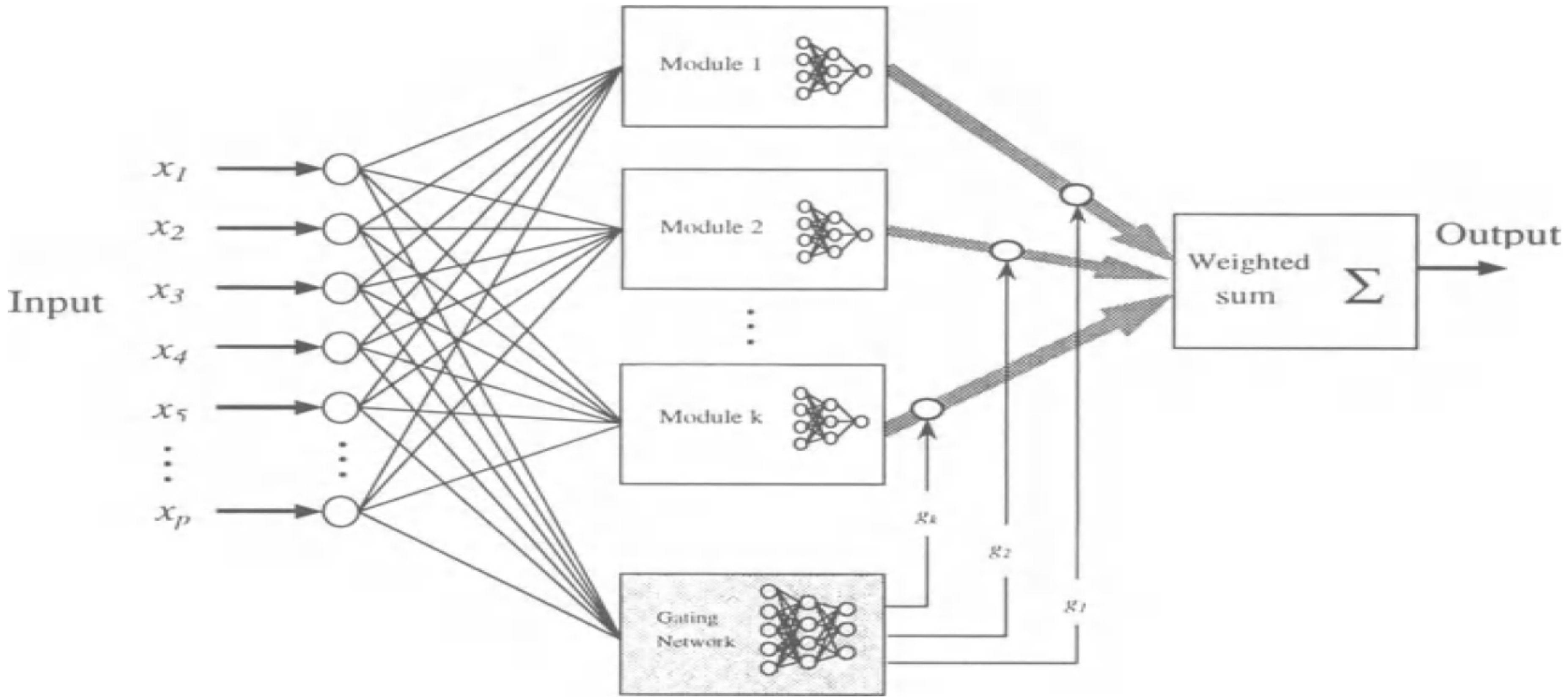
# Modular Neural Networks
# Advantages



# Modular Neural Networks Advantages

**Immunity**

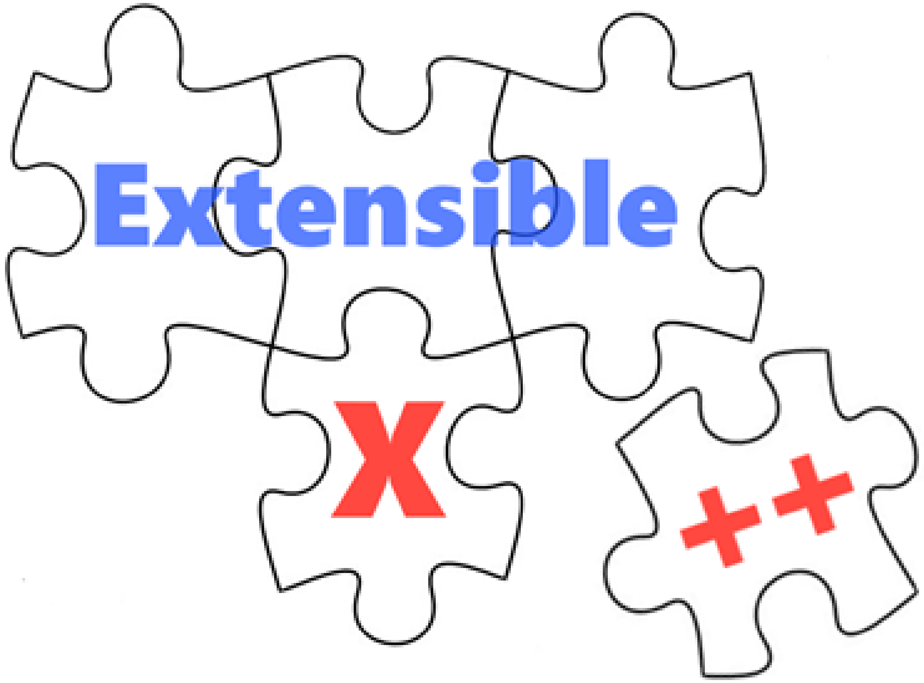
Homogeneous communication of traditional neural networks leads to poor stability and susceptibility to interference. Hybrid neural networks increase reliability and fault tolerance models.

Such properties have been observed in the structure of the visual system of the brain, which has a modular design and consists of separate, independent modules, which are interconnected.

Damage to one of the modules is not able to destroy the whole entire system.

# Modular Neural Networks Advantages

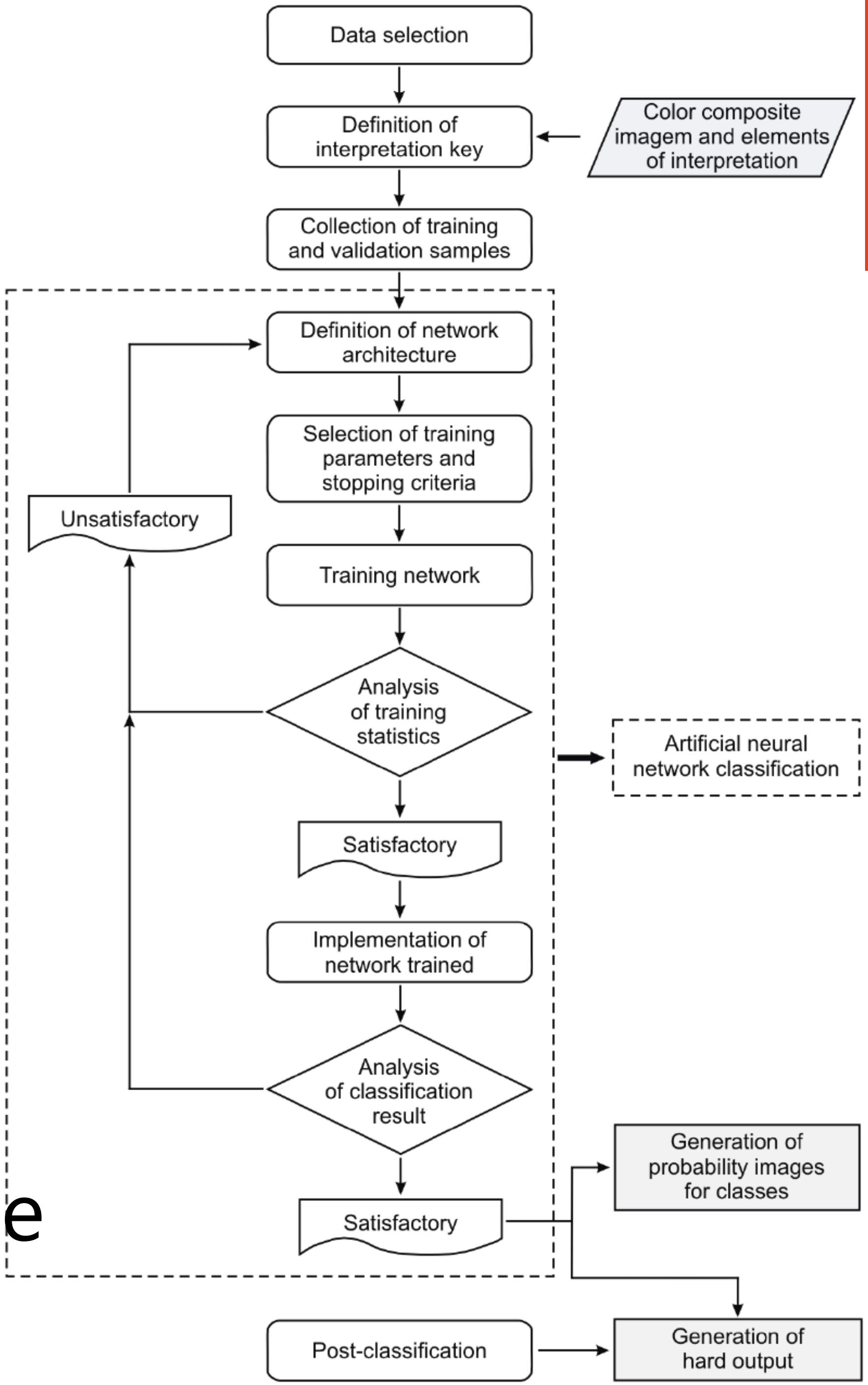
## Extensibility




Like in a puzzle, we can easily replace (module) or add one item to another

# Modular Neural Networks Advantages

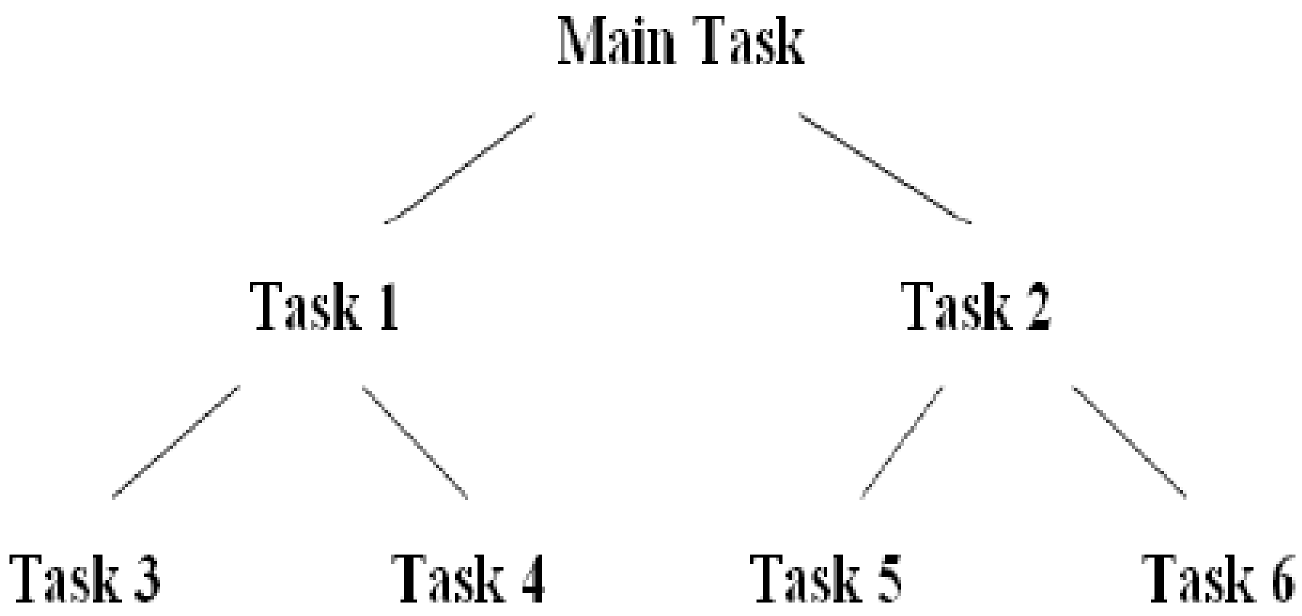
**Retraining is no longer needed**




ANN Training scheme

# Modular Neural Networks Advantages

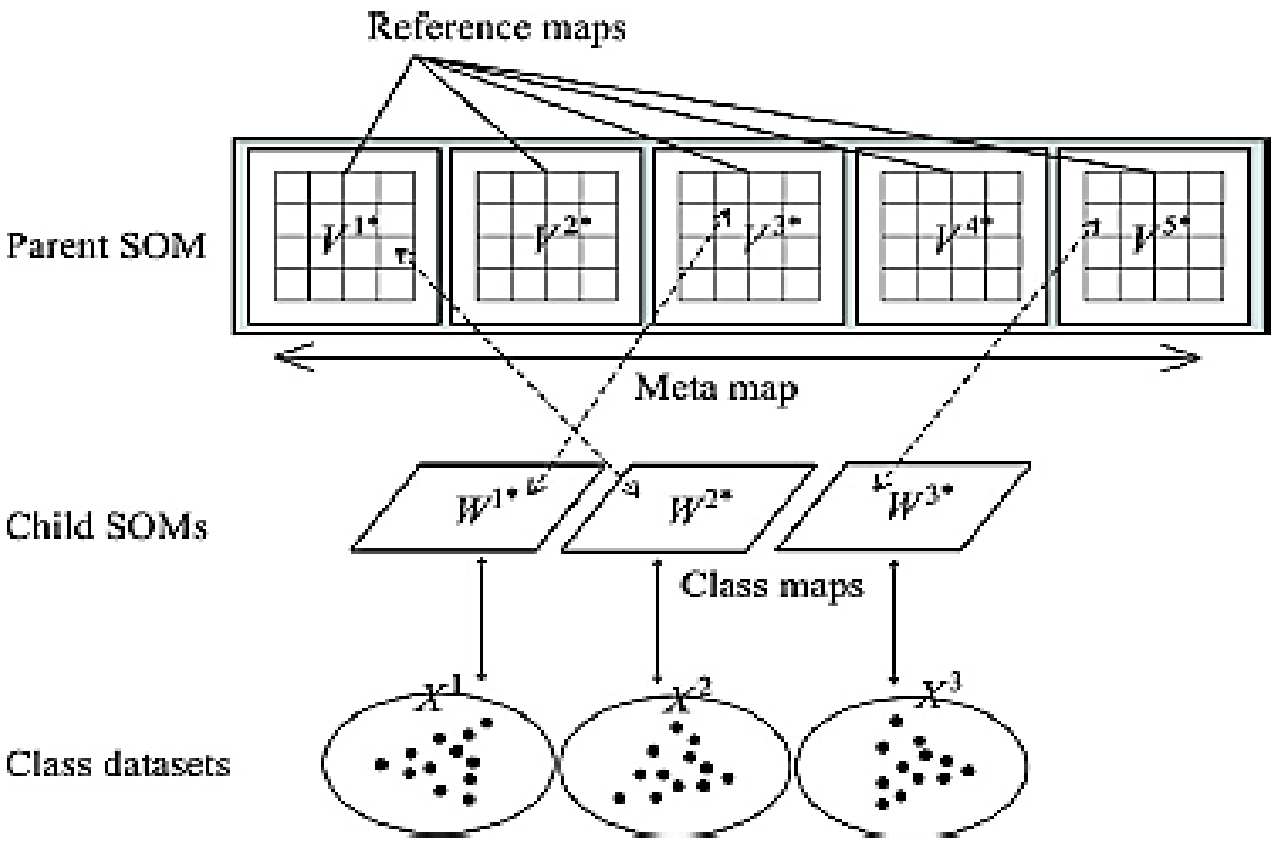
## **Efficiency**




Hybrid network have ability to decomposition of complex tasks into simple, thereby enhancing the learning ability and training time.

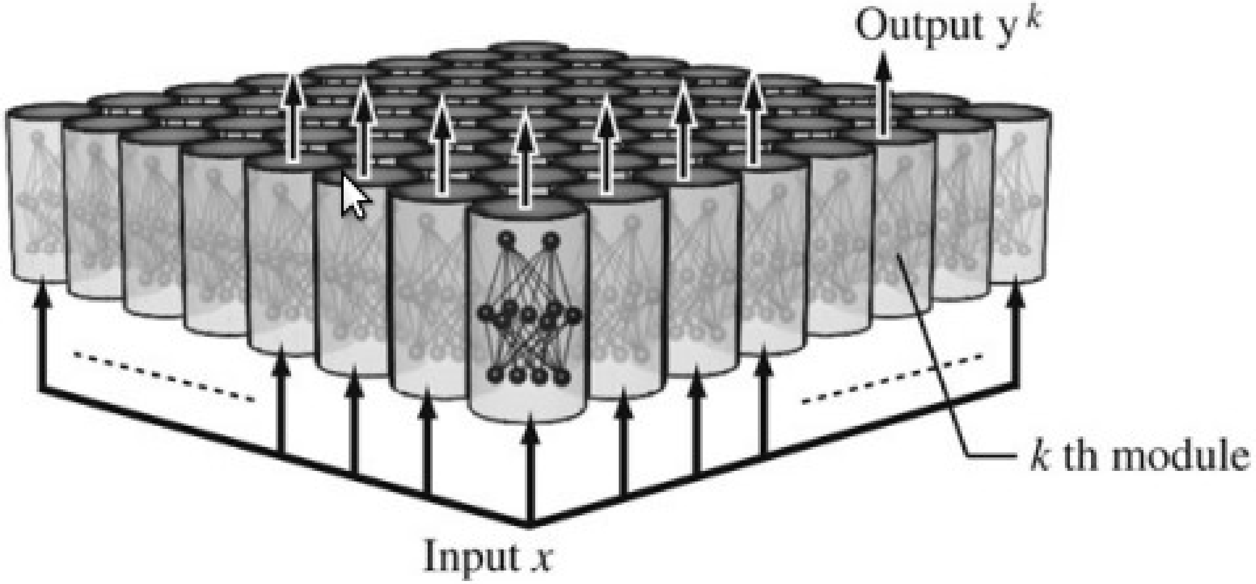
# SOM of SOMs (SOM²)

**Modular SOM are presented in a number of works by Tetsuo Furukawa.**
**SOM of SOMs is an extension of the self-organizing map (SOM), in which the mapping objects themselves are self-organizing maps. A SOM² has a hierarchical structure consisting of a single parent SOM and a set of child SOMs. Each child SOM is trained to represent the distribution of a data class in a manifold, while the parent SOM generates a self-organizing map of the group of manifolds modeled by the child SOMs.**




**SOM of SOMs architecture**

# Modular network SOM

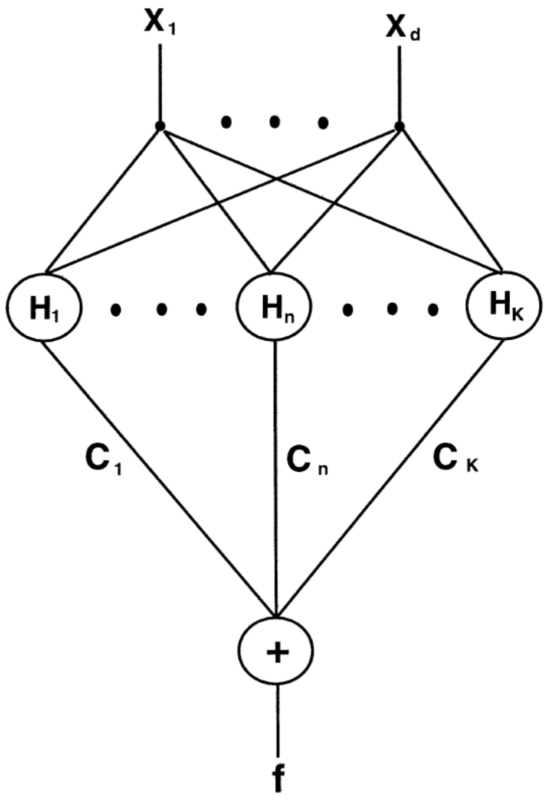


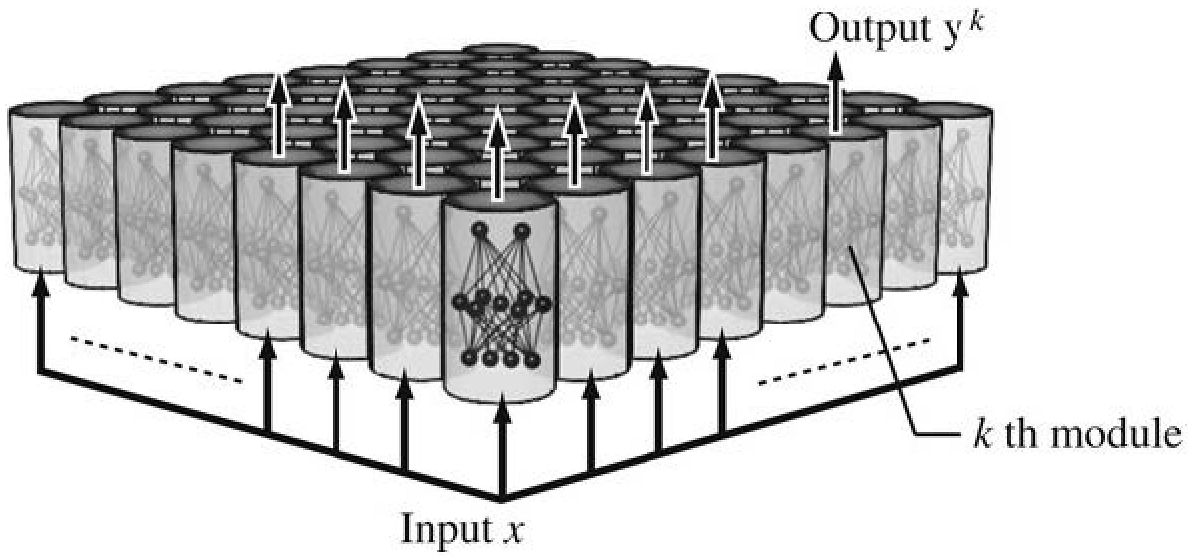

**The architecture of an mnSOM with MLP-modules**

Self organizing maps with functional modules – it's SOM where neurons replaced by more complex structures, for example – another NN.

# Modular neural networks

Modular neural network architecture for time series analysis and forecasting.




The architecture of an mnSOM with MLP-modules.

# SOM-VQTAM (SOM-Vector Quantized Associative Memory)

Input vector $u(t)$ has two parts:

$$x(t) = \begin{matrix} x^{in}(t) \\ x^{out}(t) \end{matrix}$$

$x^{in}(t)$ contains information about inputs of the dynamic object and it previous outputs:

$$x^{in}(t) = (y(t-1), \ldots, y(t-n_y), u(t), u(t-1), \ldots, u(t-n_u))$$

$x^{out}(t)$ contains information about the expected output of the dynamic object corresponding to the inputs $x^{in}(t)$

vector of the weights is divided in a similar way :

$$w_i(t) = \begin{matrix} w_i^{in}(t) \\ w_i^{out}(t) \end{matrix}$$

# SOM-VQTAM

The neuron-winner is determined only by the vector $x^{in}(t)$:

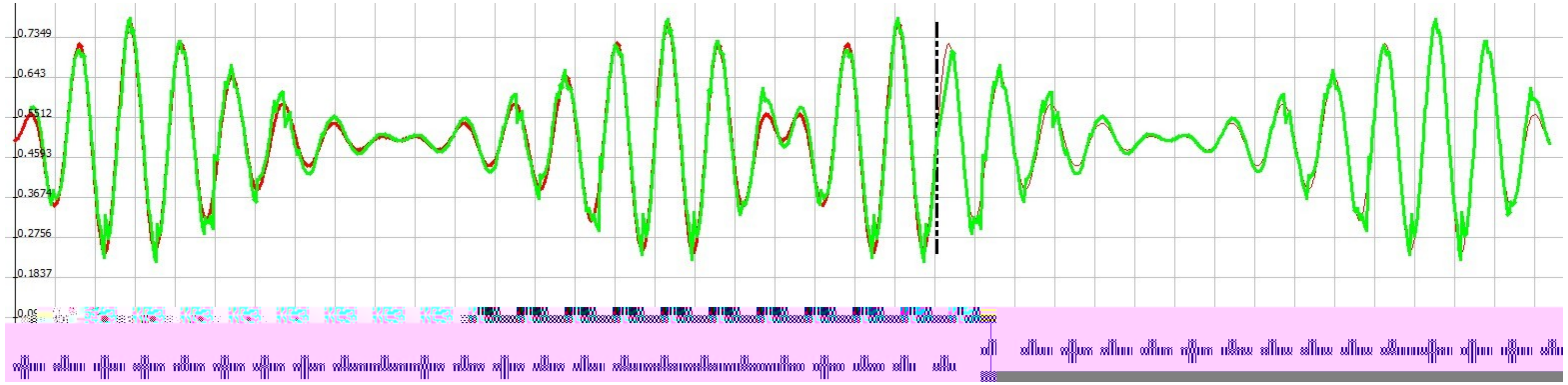
$$i^*(t) = \arg\min_i \| x^{in}(t) - w_i^{in}(t) \|$$

The change in weights follows the rules :

$$\Delta w_i^{in}(t) = \alpha(t) h(i^*, i, t)[x^{in}(t) - x_i^{in}(t)],$$

$$\Delta w_i^{out}(t) = \alpha(t) h(i^*, i, t)[x^{out}(t) - w_i^{out}(t)]$$

It is possible to improve the quality of the network when calculating the output of the network as a weighted mean of the outputs of several best neurons




Example of SOM-VQTAM working. Red color is data set and green color is result.

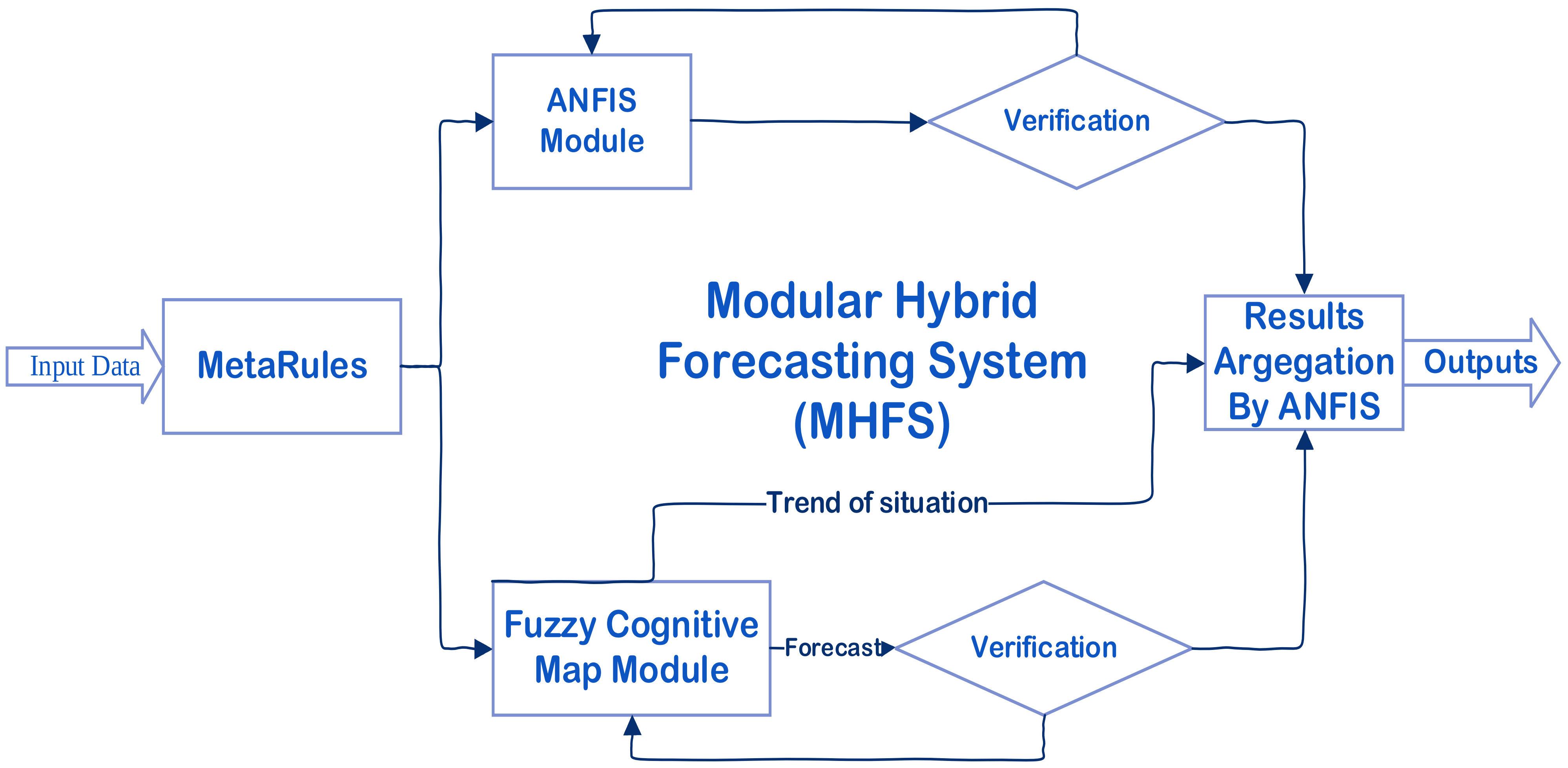
# Modular network SOM. Comparison with another algorithms

| № | Algorithm name | SMAPE | № | Algorithm name | SMAPE |
|---|---|---|---|---|---|
| 1 | Stat. Contender - Wildi | 14,84% | 17 | CI Benchmark - Naive SVR (Crone, Pietsch) | 18,60% |
| 2 | Stat. Benchmark - Theta Method (Nikolopoulos) | 14,89% | 18 | C49 | 18,72% |
| 3 | Illies, Jäger, Kosuchinas, Rincon, Sakenas, Vaskevcius | 15,18% | 19 | Perfilieva, Novak, Pavliska, Dvorak, Stepnicka | 18,81% |
| 4 | Stat. Benchmark - ForecastPro (Stellwagen) | 15,44% | 20 | Kurogi, Koyama, Tanaka, Sanuki | 19,00% |
| 5 | CI Benchmark - Theta AI (Nikolopoulos) | 15,66% | 21 | Stat. Contender - Beadle | 19,14% |
| 6 | Stat. Benchmark - Autobox (Reilly) | 15,95% | 22 | Stat. Contender - Lewicke | 19,17% |
| 7 | Adeodato, Vasconcelos, Arnaud, Chunha, Monteiro | 16,17% | 23 | Sorjamaa, Lendasse | 19,60% |
| 8 | Flores, Anaya, Ramirez, Morales | 16,31% | 24 | Isa | 20,00% |
| 9 | Chen, Yao | 16,55% | 25 | C28 | 20,54% |
| 10 | D’yakonov | 16,57% | 26 | Duclos-Gosselin | 20,85% |
| 11 | Kamel, Atiya, Gayar, El-Shishiny | 16,92% | – | SOMxRSOM | 21,64% |
| 12 | Abou-Nasr | 17,54% | 27 | Stat. Benchmark - Naive | 22,69% |
| 13 | Theodosiou, Swamy | 17,55% | 28 | Papadaki, Amaxopolous | 22,70% |
| – | VQTAM | 17,61% | 29 | Stat. Benchmark - Hazarika | 23,72% |
| – | SOMxVQTAM | 17,70% | 30 | C17 | 24,09% |
| 14 | CI Benchmark - Naive MLP (Crone) | 17,84% | 31 | Stat. Contender - Njimi, Mélard | 24,90% |
| – | RSOM | 17,94% | 32 | Pucheta, Patino, Kuchen | 25,13% |
| 15 | de Vos | 18,24% | 33 | Corzo, Hong | 27,53% |
| 16 | Yan | 18,58% | | | |

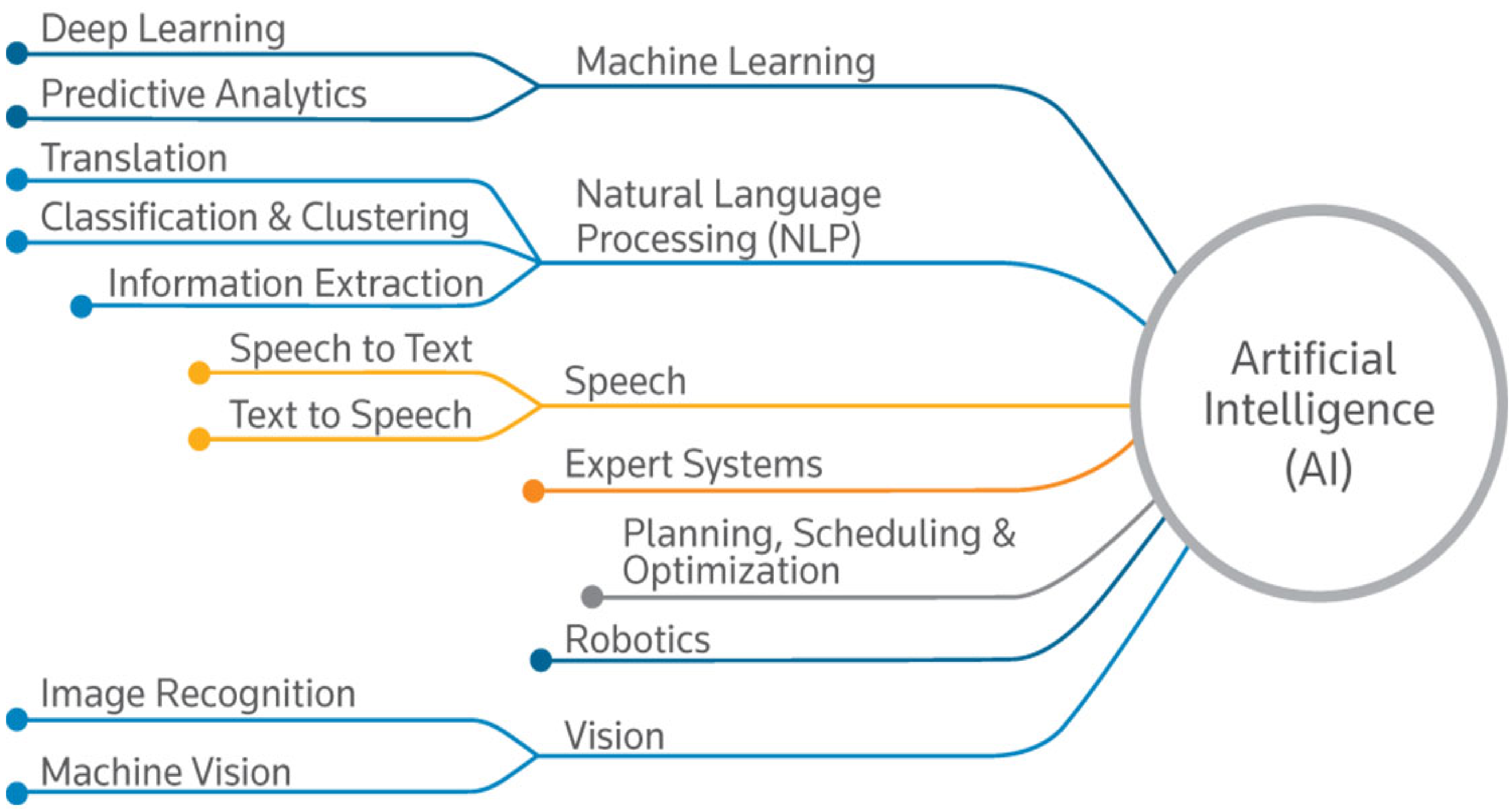
# Forecasting System Based on Modular Architecture
# Philosophy of this idea

- ❖Advantages of Biologically inspired modular architectures
- ❖Theory of Reflexivity from G. Soros to V. Lefebvre
- ❖Advantages of artificial intelligent in forecasting
- ❖Problems in time series forecasting area
- ❖Impact of the crisis on forecasting

# Forecasting System Based on Modular Architecture



# AI structure



# Embedding fuzzy inference systems into deep learning networks.

**Deep Learning has proven to be an effective method for making highly accurate predictions from complex data sources. Convolutional neural networks continue to dominate image classification problems and recursive neural networks have proven their utility in caption generation and language translations. While these approaches are powerful, they do not offer explanation for how the output is generated. Without understanding how deep learning arrives at a solution there is no guarantee that these networks will transition from controlled laboratory environments to field able systems. We present an approach for incorporating such rule based methodology into neural networks by embedding fuzzy inference systems into deep learning networks.**

# Hybrid models of Deep Neural Networks and Neuro-Fuzzy Networks

**Research can be conducted for the development of sensor fusion techniques between spectral and spatial information. This approach will use deep learning techniques to allow mid and high level sensor fusion between sensors enhancing the content derived from collected data. This information can be readily used by an analyst or an autonomous system to quickly and reliably make informed decisions.The features extracted from that data via DL will be further processed by ANFIS, allowing the system to model human reasoning and also provide a mechanism for biasing the system with feedback from an analyst . In order to train the system, both the feature vector inputs and the correct labeled output will be required. Such as system would have the flexibility to function either with rules defined by an expert, or optionally generate a reasonable set of rules on its own. Having an expert define the rules is desirable as it may bootstrap the learning process and allow the user of the system to define the features and relationships that are important for a specific application.**

# Conclusion

**The paper discusses various approaches to training ANFIS systems, a variety of brand architecture, including ensembles ANFIS.**

**The results of each study show ANFIS demonstrate excellence in predictive power compared to other systems, such as statistical models, etc. In particular, in addition to the prediction of the data architecture will work and much more convenient for understanding.**

**Based on the study, we can conclude about the effectiveness of the hybrid network architectures based on ANFIS models.**

**At the end we present an approach for incorporating such rule based methodology into neural networks by embedding fuzzy inference systems into deep learning networks.**