

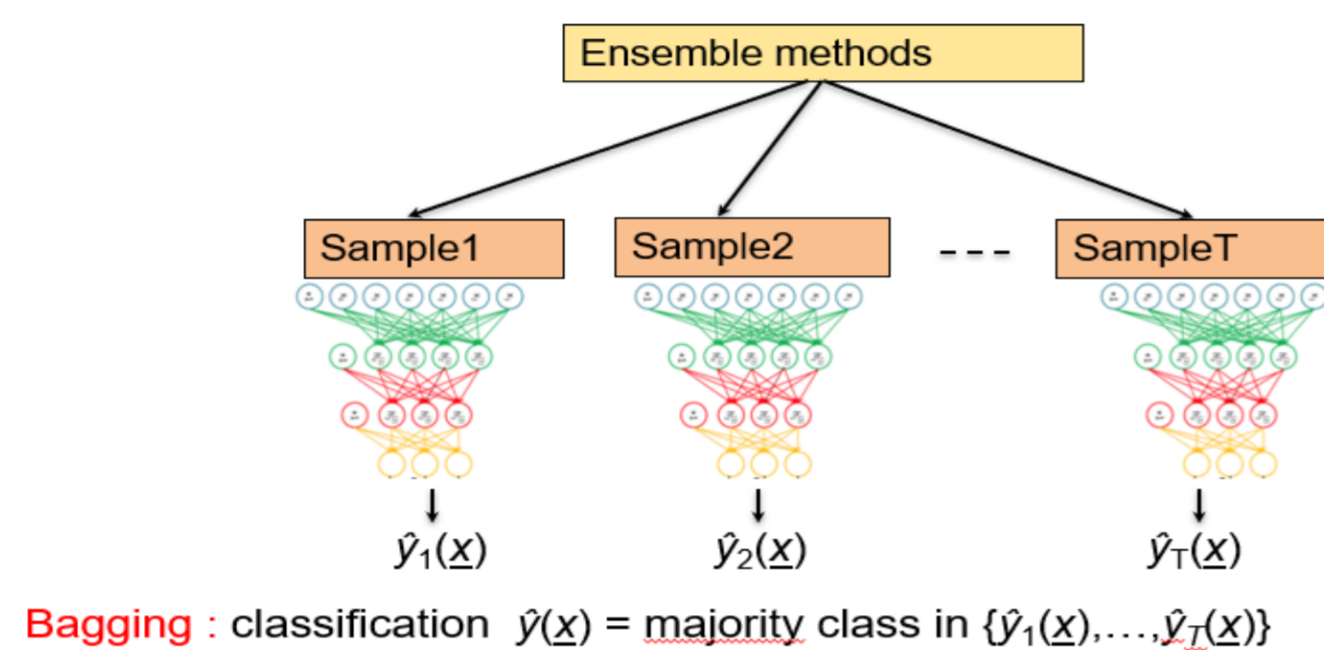
TransDeep: Transparent Deep ensemble method based on multiagent argumentation for classification

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Motivation

As the use of machine learning increases in critical areas like medicine, the explanation of classification results and the ability to introduce domain knowledge inside the learned models have become a necessity.

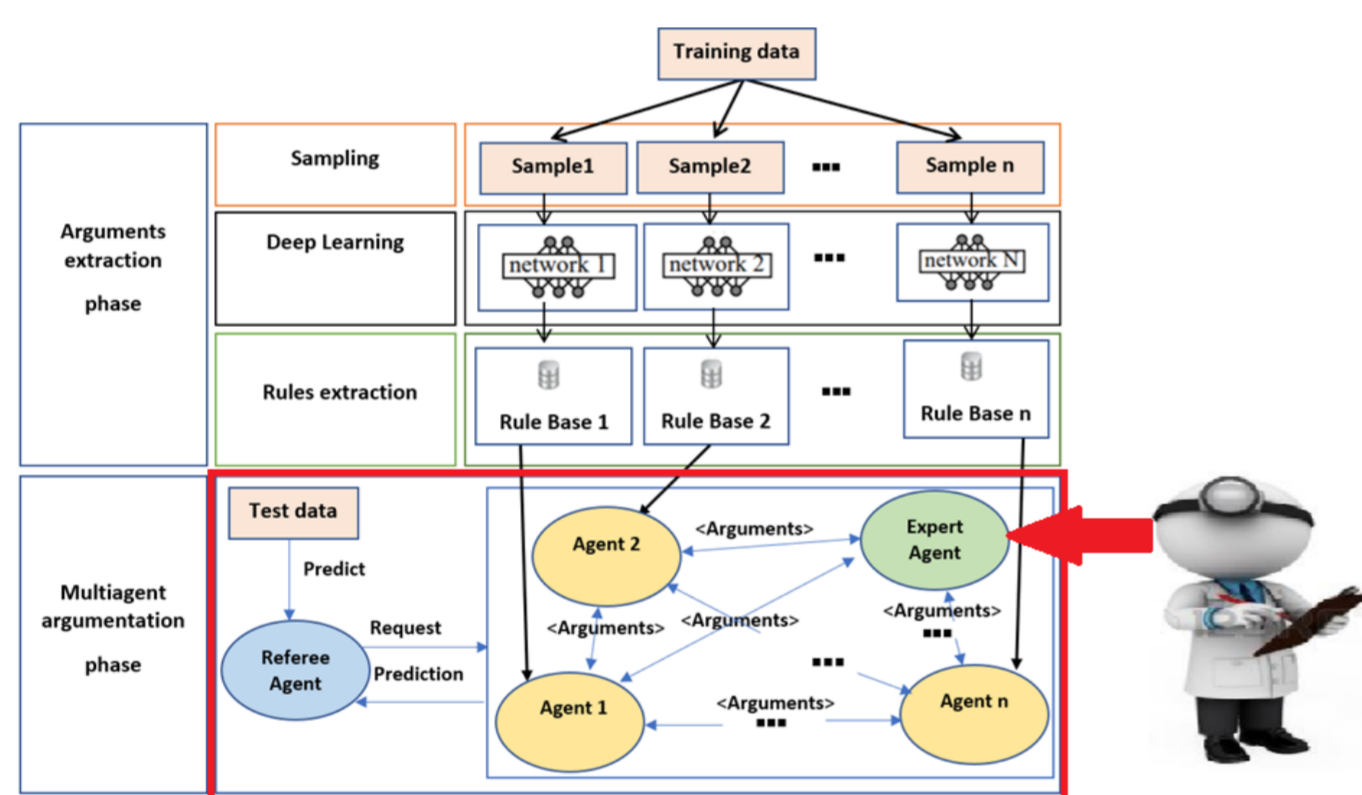
We present a new deep ensemble method based on multiagent argumentation (TransDeep) that combines machine learning algorithms with a multiagent system in order to explain the classification results and allow injecting prior knowledge. The idea is to extract arguments from classifiers and to provide the classification results (decisions) using argumentation. This allows to exploit the internal knowledge of each classifier, to provide an explanation for the decisions and facilitate integration of prior knowledge. The results demonstrate that our method effectively improves deep learning performance in addition to providing explanations and transparency of the predictions.



- ✓ Traditional Ensemble method integrate only classification results rather than internal classification knowledge,
- ✓ No explanation of the decision is given (black boxes).

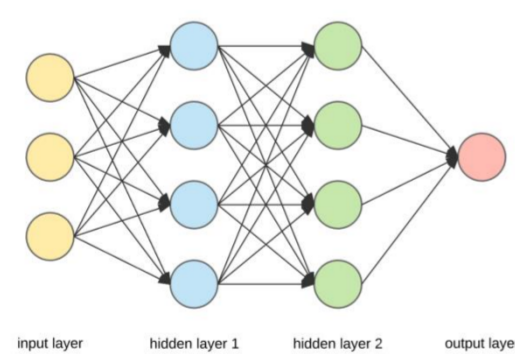
Method

TransDeep is a transparent deep ensemble method for explaining predictions. It proceeds in two main phases: arguments extraction phase and multiagent argumentation phase.

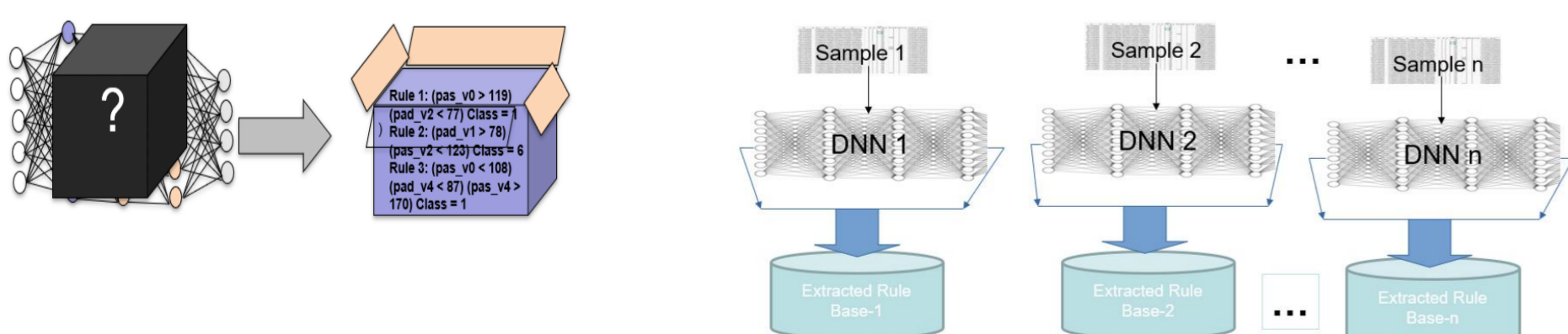


1. Arguments extraction step

- ❖ **Bootstrap Sampling** Each Classifier generates its training sample by sampling with replacement from the training data.
- ❖ **Deep Learning** a deep neural network is used, blessing to its power in machine learning.

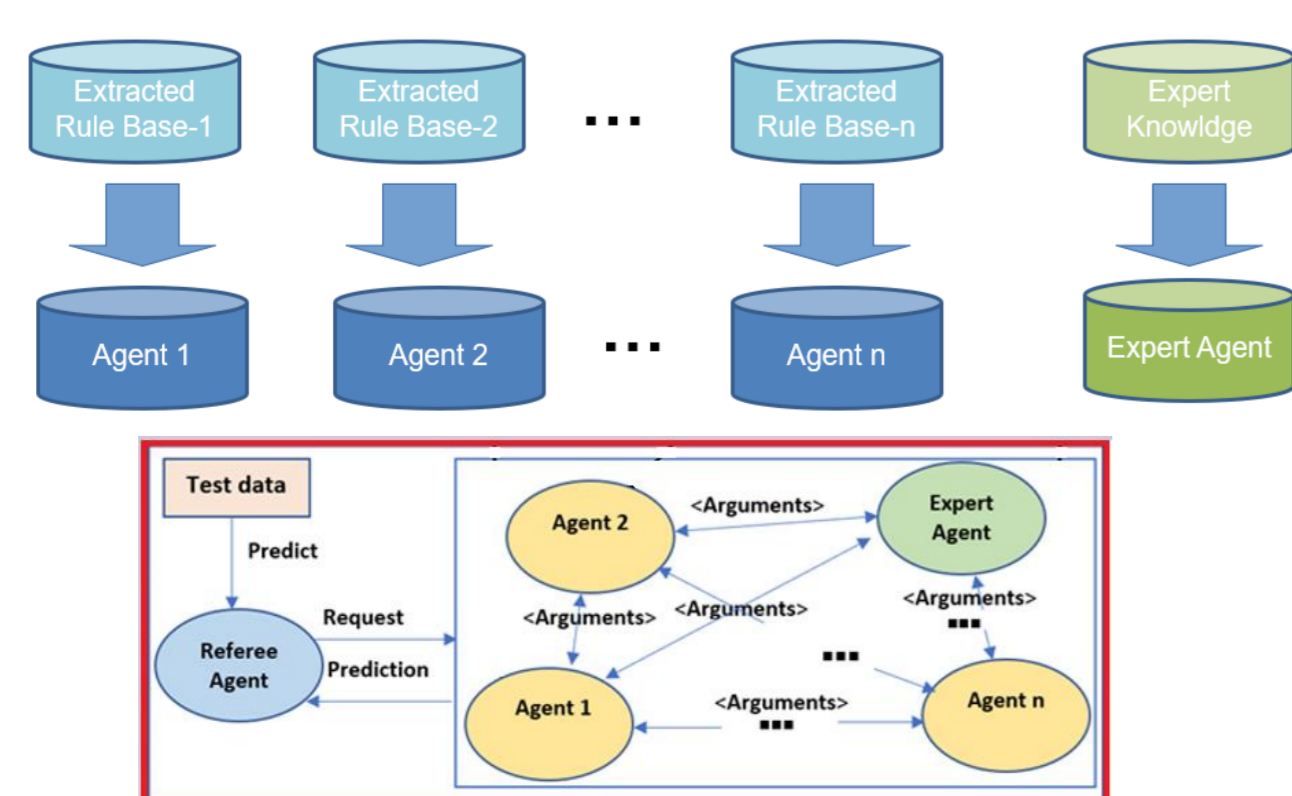


- ❖ **Rules extraction from Neural networks** in order to characterize and interpret black boxes, a rule base is generated from each deep neural network by using a rule extraction algorithm.



2. Argumentation step

Each rule base is integrated into an agent. Agents use individual knowledge, negotiate by exchanging their arguments to provide a prediction.



Results

A specific dataset that is a realistic virtual population is used:

- ✓ with the same age, sex and cardiovascular risk factors profile than the French population aged between 35 and 64 years old.
- ✓ 40000 individuals monitored for hypertension during 10 visits per patient.
- ✓ Each visit contains: the systolic blood pressure (SBP), diastolic blood pressure (DBP), etc.
- ✓ predict the optimal treatment.

• Improvement of predictions:

to validate the performance of our approach, we compared TransDeep to the most popular ensemble learning methods

- ✓ **Bagging**: combines multiple classifiers using weighted voting;
- ✓ **AdaBoost**: Predictions are made by calculating the weighted average of the weak classifiers;
- ✓ **DIMLP-B** : classification approach based on ensemble rule extraction that uses the deep multilayers perceptron (DIMLP) trained by bagging;
- ✓ **DIMLP-A** : classification approach based on ensemble rule extraction that uses the DIMLP trained by arcing.

	Adaboost	Bagging	Dimlp-B	Dimlp-A	TransDeep
Accuracy	0,79	0,76	0,79	0,85	0.89

The treatment for the patient x is class= beta blockers (BB)

R1: (age<50)(SBP3>137.027)(DBP3>83.85)->Class=BB(score=0.8)

or

hypertension treatment:

- If age < 50 year → Beta blockers
- If age > 50 year → diuretics

Results improvement /control



Conclusion

TransDeep allows:

1. **Transparency = Trust** :Expert can understand the reason behind a prediction
2. **Scalability = Control** : Expert can control the system

