

Modeling Highly Interpretable Fuzzy Systems

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- Experimental Analysis
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Introduction Motivation

Comprehensible Intelligent Systems are on demand

- Humanistic systems: Those systems whose behavior is strongly influenced by human judgment, perception or emotions (Zadeh, 1975)
- Decision support systems: Medicine, Economics, Robotics, etc.

Fuzzy Systems (Zadeh 1965, Mamdani 1974)

- Universal Approximators (Accuracy)
 - \Rightarrow System identification
- Semantic expressivity (Interpretability)
 - \Rightarrow Knowledge extraction and representation

Introduction Accuracy vs. Interpretability

Accuracy

• How similar are the outputs of the model and the real system ?

Interpretability

- Comprehensibility, intelligibility, transparency, understandability, readability, etc.
- Is the model (description and behavior) understandable (to a human) ?
 - Description ⇒ System structure readability (transparency)
 - Explanation
 ⇒ System comprehensibility (understandability)



Introduction Accuracy vs. Interpretability (History)

Interpretability - Accuracy (Fuzzy Logic)

- [1965] Fuzzy Logic (Zadeh)
- [1965 1990] Interpretability (I)
 - Simple linguistic rules with high interpretability
 - Expert knowledge
- [1990 2000] Accuracy (A)
 - Complicated fuzzy rules with high accuracy
 - Induced knowledge
- [2000 2010] I-A Trade-off
 - Simple linguistic rules with high accuracy
 - Expert + Induced knowledge ?
 - Characterizing and assessing Interpretability
 - Looking for useful Interpretability indices

Introduction Regarding Interpretability in terms of complexity

Interpretability-Accuracy Trade-off

- Contradictory goals: Looking for a good compromise (multi-objective optimization techniques)
- As the complexity of a system increases, our ability to make precise and yet significant statements about its behavior diminishes until a threshold is reached beyond which precision and significance become almost mutually exclusive characteristics. The closer one looks at a real-world problem, the fuzzier becomes its solution (Principle of incompatibility, Zadeh 1973)



Introduction Regarding Interpretability in terms of complexity

Fuzzy Modeling (FM)

- Linguistic Fuzzy Modeling (LFM)
 - Maximizing Interpretability
 - Improving Accuracy
- Precise Fuzzy Modeling (PFM)
 - Maximizing Accuracy
 - Improving Interpretability
- Model Refining
 - Extending the modeling process

 (new algorithms for learning partitions and rules)
 - Extending the model structure (linguistics modifiers, weights, exceptions, etc.)

• How to characterize and evaluate Interpretability ?

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Intro Interp HILK Experiments Conclusions

Characterization Framework

Characterization of Interpretability

Definitions (I)

- Assuming T and S are formal theories, T is said to be interpretable in S ⇔ the language of T can be translated into the language of S in such a way that S proves the translation of every theorem of T (Tarski 1953)
- Interpretability means the possibility to estimate the system's behavior by reading and understanding its rule base (Bodenhofer and Bauer 2003)



Characterization of Interpretability

Definitions (II)

- Assessing Interpretability of a FS \equiv measuring the complexity of making the translation from L (model description based on FL) to L' (model explanation based on NL) (Mencar et al. 2005)
- Comprehensibility Postulate (Michalski 1983)
 - + Notion of Cointension (Zadeh 2005)
 - \Rightarrow Understandability of patterns (Mencar et al. 2007)
 - \Rightarrow Cointensive Interpretability (Mencar et al. 2009)

Interpretability must be a central point in system modeling

- PNL ⇒ Precisiated Natural Language
- **CWW** ⇒ Computing with Words
- HCC ⇒ Human Centric Computing

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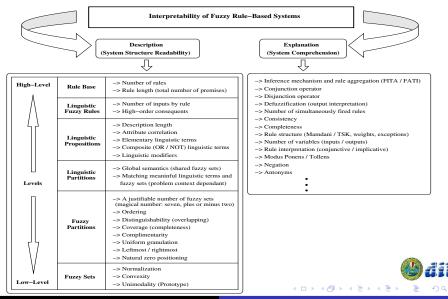
Conceptual Framework (I)

Two different points of view

- Description (system structure readability)
 - Number of variables, rules, linguistic terms, etc.
 - Regarding interpretability in terms of complexity:
 - \Rightarrow The more compact KB, the simpler its understanding
 - \Rightarrow Lower complexity means higher interpretability
- Explanation (system comprehension)
 - Inference level (fuzzy operators, rules fired at the same time, etc.)
 - Regarding interpretability in terms of complexity:
 - \Rightarrow The more compact KB, the more rules fired at the same time
 - \Rightarrow Lower complexity means lower interpretability
 - Contradictory goals
 - Cointensive Interpretability Logical View (Mencar et al. 2009)



Conceptual Framework (II)



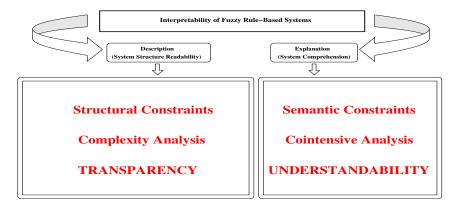
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Characterization Framework

Conceptual Framework (II)





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Starting point (I)

Proposal

- HILK: Highly Interpretable Linguistic Knowledge [IJIS 2008]
- Looking for a good interpretability-accuracy trade-off when modeling fuzzy rule-based classifiers (FRBCs)
 - KBCT

Knowledge Base Configuration Tool \Rightarrow freeSW

GUAJE

A Java Environment for Generating Understandable and Accurate Fuzzy Models \Rightarrow freeSW toolbox

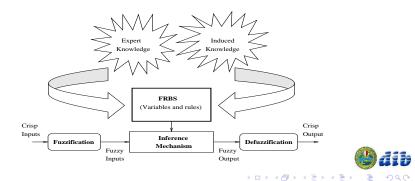
 HILKMO Embedding HILK into a Multi-objective evolutionary algorithm



Starting point (II)

HILK (Highly Interpretable Linguistic Knowledge) [IJIS 2008]

- Expert + Induced Knowledge
 - Partition design
 - Rule base learning
 - Knowledge base improvement



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Expert Knowledge

Advantages

- General knowledge
 - \Rightarrow Experience, education and training, several disciplines
- Global view of the problem
 - Most influential variables
 - Universal rules (involving a few variables)
- High Interpretability

Drawbacks

- Expert knowledge acquisition is a hard task (bottleneck)
- Interaction between variables is difficult to formalize

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Induced Knowledge

Advantages

- Automatic learning (knowledge discovery)
- Finding out interaction between variables
- High Accuracy

Drawbacks

- Specific knowledge
 - Rule generality depends on available data
 - Non-universal rules
- Interpretability depends on the learning technique
- Collecting representative data is expensive (time and money)



Expert + Induced Knowledge

Cooperation (Integration)

- Both kinds of knowledge convey complementary information
- Their combination is likely to yield compact and robust systems

Several options:

- First Expert ⇒ Then Data
- First Data ⇒ Then Expert
- Iterative approach



Intro Interp HILK Experiments Conclusions

HILK KBCT GUAJE HILKN

Expert + Induced Knowledge (Fuzzy Logic)

Cooperation (Framework)

Fuzzy Logic (FL) represents both kinds of knowledge under the same formalism

- Linguistic variables and rules (Mamdani)
- Comparison at linguistic level
- Automatic learning methods.

• FL semantic expressivity is close to natural language

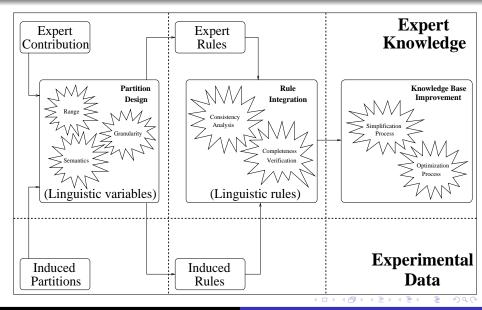
 FL favors the interpretability of the final model (but it is not enough to guarantee it)



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HILK KBCT GUAJE HILKMO

HILK (expert + data)



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Intro Interp HILK Experiments Conclusions

K **KBCT** GUAJE HILKM

KBCT (Knowledge Base Configuration Tool)

- Open-source (Free-software)
- Portable (Linux / Windows)
- User-friendly (Java Interface)
- Documentation
 - On-line documentation (HTML)
 - User Manual (PDF)
 - Java API
- KBCT
 - \Rightarrow FisPro C++ library
 - \Rightarrow Weka Java library
- Version 3 freely available at http://www.mat.upm.es/projects/advocate/kbct.htm

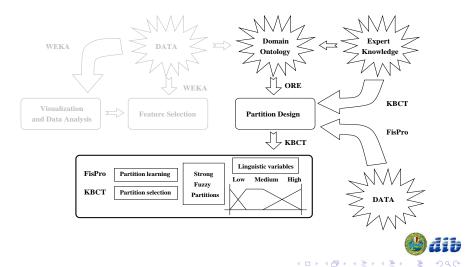


GUAJE (a Java Environment for Generating Understandable and Accurate Fuzzy Models)

- KBCT (Knowledge Base Configuration Tool)
- FisPro (Fuzzy Inference System Professional)
- ORE (Ontology Rule Editor)
- jMetal (Metaheuristic Algorithms in Java)
- Weka (Data Mining)
- Xfuzzy (Fuzzy Modeling)
- Matlab Fuzzy Toolbox

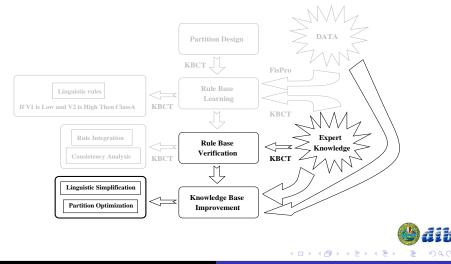


GUAJE Combining several tools (Partition Design)

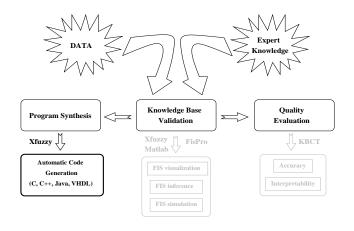


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GUAJE Combining several tools (RB verification and KB improvement)



GUAJE Combining several tools (KB validation)



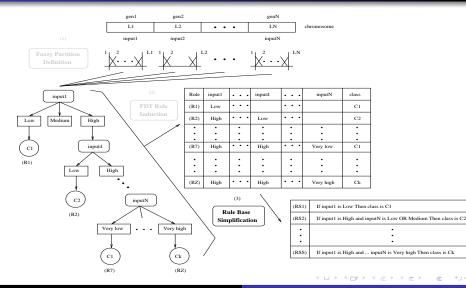
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HILKMO: Embedding HILK in a three-objective evolutionary algorithm



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HILKMO: Three-objective evolutionary algorithm

NSGA-II

- Initial population randomly generated
- Binary tournament selection
- Two point crossover and Thrift mutation
- Pareto ranking with crowding distance measure
- Elitist replacement update procedure

Objective functions

- Maximizing accuracy (classification rate)
- Maximizing interpretability
 - Maximizing readability (rule base complexity)
 - Maximizing comprehensibility (average fired rules)

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K KBCT GUAJE HILKMO

HILKMO: Experimentation (Problem description)

GLASS identification problem

Instances	Attributes	Classes	Class distribution
214	9	6	G1 (32.71%), G2 (35.51%), G3 (7.94%),
			G4 (6.074%), G5 (4.205%), G6 (13.561%)

- Attributes: RI, Na, Mg, AI, Si, K, Ca, Ba, Fe
- UCI: http://www.ics.uci.edu/-mlearn/MLSummary.html
- 5-fold cross-validation (5CV): 80% (training) 20% (test)



HILKMO: Experimentation (Parameter configuration)

HILKMO - NSGAII

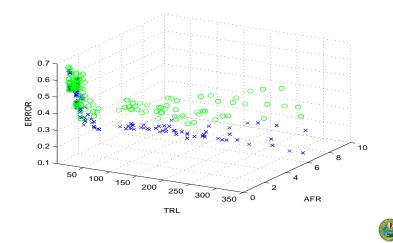
- Six runs for each training-test pair (6x5CV)
- P_s = 30 indviduals
- 12000 evaluations
- $P_c = 0.6$ (Two-point crossover)
- $P_m = 0.1$ (Thrift mutation)

HILKMO - FRBC

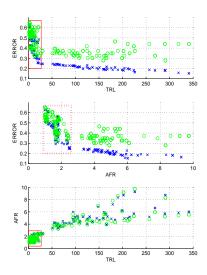
- Partition design: Uniform SFPs for all inputs
- Rule base definition: pruned FDT (tolerance 30%)
- Simplification: TRL <= 50

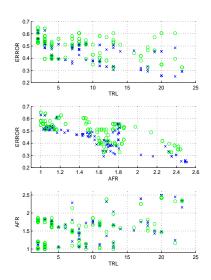
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HILKMO: Aggregated Pareto Front Approximation



HILKMO: Aggregated Pareto Front Approximation (Projection and Zoom)





HILKMO

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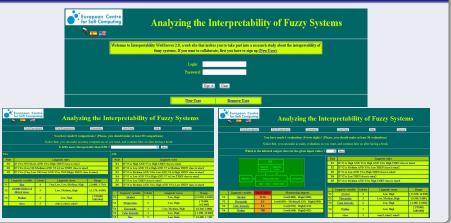
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GUAJEPOLL Analyzing the Interpretability of Fuzzy Systems https://apps.softcomputing.es/guajepoll/

Web poll



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 Modeling Higly Interpretable Fuzzy Systems

GUAJEPOLL

Analyzing the Interpretability of Fuzzy Systems https://apps.softcomputing.es/guajepoll/

Description of the experiments

- WINE problem: 13 inputs and 1 output (3 classes)
- HILK methodology (IJIS 2008)
 ⇒ six KBs of several sizes (with SFPs)
- Comparing several interpretability indices
- How to know which index is the best one ?
 - \Rightarrow ... asking people !
 - \Rightarrow The survey was addressed to

fuzzy experts (50%) and naive users (50%)

- How much interpretable are the analyzed KBs ?
- What is the best KB interpretability ranking ?
- What are the most relevant aspects when assessing interpretability ?

GUAJEPOLL

Analyzing the Interpretability of Fuzzy Systems https://apps.softcomputing.es/guajepoll/

Some preliminary conclusions (regarding readability)

- People get into difficulties giving numerical indices
- People find much more natural to make approximate reasoning based on the use of linguistic terms (*Highly interpretable*, *Moderately interpretable*, etc.)
- People feel much more confidence setting rankings than giving numerical values
- When two KBs are quite close regarding readability the final ranking choice depends in many subtle details, and as result, at the end there is a clearly subjective choice
- Because of this subjectivity there is a huge diversity of answers
- Objectivity (fair comparison) vs. Subjectivity (personalization)

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Pubs Concs

Publications Theoretical and experimental analysis

PhD dissertation (October 2007)

- Interpretable fuzzy systems modeling with cooperation between expert and induced knowledge
 - \Rightarrow http://oa.upm.es/588/

Fuzzy system modeling

- A new index easily adaptable to the context of each problem by means of incorporating user's preferences and quality criteria (WCCI 2010)
- Multiobjective fuzzy system modeling
 ⇒ interpretability vs. accuracy (GEFS 2010)
- Characterizing and measuring interpretability (IJAR 2009)
- HILK++: an enhanced version of HILK (SC 2010, ISDA09)

Pubs Concs

Publications Theoretical and experimental analysis

Fuzzy system modeling (Knowledge extraction and representation)

- Ontology (ESTYLF 2008)
- Consistency analysis (IJIS 2008)
- Accuracy improvement ⇒ Optimization (FUZZ-IEEE 2007)
- Interpretability improvement ⇒ Simplificationn (Mathware 2006)
- KBCT (FUZZIEEE 2004)



Publications Theoretical and experimental analysis

Real-world applications

- Human activity recognition fusing intensity of WiFi signal and accelerations (WCCI 2010)
- WiFi localization with robots (ECSC-UAH, EUROCAST 2009)
- An intelligent agent that analyzes data from medical devices for the management of Diabetes Mellitus patients (ECSC-GBT, AIME 2009)
- ADVOCATEII \Rightarrow Avoiding undetectable obstacles by robots (UPM-UAH, JRIS 2007)
- Real-Time System for Monitoring Driver Vigilance (UAH, IEEE Trans on ITS 2006)

Conclusions and Future Works

Conclusions

- Regarding interpretability in terms of readability (transparency) and comprehensibility (understandability)
- Quality-guided design of Highly Interpretable Fuzzy Systems
- Experimental analysis (web poll) https://apps.softcomputing.es/guajepoll/

Feature works (IFS \equiv Interpretable Fuzzy Systems)

- Organizing Panel Session and Special Session (July 21-22) during the IEEE WCCI 2010 (Barcelona, Spain)
- Editing a Journal Special Issue (Information Sciences, ELSEVIER)
- Writing a co-authored book (Authors: J. M. Alonso, C. Castiello, L. Magdalena, and C. Mencar)





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THANKS FOR LISTENING !



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