Fuzzy Logic and Fuzzy Systems

Guide to AI and Data Courses · Part II: Branches of AI

Fuzzy sets | Membership functions | Linguistic rules | Fuzzy inference | Fuzzy control | Neighboring courses

Sercan KÜLCÜ · Giresun University · Computer Engineering

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INTRODUCTION

What Question Does It Ask?

> **How do we reason with concepts like "hot" or "fast" that have no sharp boundary?**

Fuzzy logic drops the sharp line between belonging and not belonging to a set; it gives each element a **degree of membership** between 0 and 1. Rules can then be written with linguistic terms such as "hot" or "fairly fast", and these rules produce a numeric decision or control signal.

At a glance

APPROACH	INPUT	OUTPUT
partial membership and linguistic rules	measurements, expert rules	control signal or decision

SUCCESS MEASURE	MATH LOAD	DATA NEEDS
control quality, expert agreement	low-medium: set theory	little; expert knowledge

A Short History

1965
Zadeh publishes "Fuzzy Sets", introducing sets with partial membership.

1973
Zadeh introduces linguistic variables and approximate reasoning with fuzzy IF-THEN rules.

1975
Mamdani and Assilian control a steam engine with the first fuzzy controller.

1985
Takagi and Sugeno propose the fuzzy model whose rule outputs are functions (TS model).

1987
The Sendai subway in Japan opens, accelerating and braking under fuzzy control.

1993
Jang publishes ANFIS, which trains fuzzy rules like a neural network.

THE COURSE

Core Concepts

Fuzzy set
Each element has a membership degree between 0 and 1.

Membership function
Triangle, trapezoid, Gaussian: maps a value to a degree.

Linguistic variable
A variable whose values are words: low, medium, high.

Fuzzy operators
Minimum for AND, maximum for OR, 1-μ for NOT.

Rule base
Rules like IF temperature is high THEN fan is fast.

Mamdani inference
Rule outputs are fuzzy sets, later defuzzified.

Sugeno inference
Rule outputs are functions of the inputs; fast to compute.

Defuzzification
Reducing the fuzzy result to one number: the centroid.

THE COURSE

A Typical Workflow



Example: An air conditioner measures 27 °C in a room; this value belongs to "hot" with degree 0.7 and to "warm" with degree 0.3. The rules "if hot, cool strongly" and "if warm, cool moderately" fire with these degrees, their outputs are aggregated, and the centroid gives the compressor a single power value such as 72 percent.

THE COURSE

What Does the Course Cover?

1. Crisp and fuzzy sets; degree of membership
2. Membership functions: triangular, trapezoidal, Gaussian
3. Fuzzy set operations; t-norms and t-conorms
4. Fuzzy relations and max-min composition
5. The extension principle and fuzzy numbers
6. Linguistic variables and hedges
7. Fuzzy IF-THEN rules and approximate reasoning
8. Mamdani inference and defuzzification methods
9. Takagi-Sugeno inference
10. Fuzzy controller design; comparison with PID
11. Fuzzy clustering: fuzzy c-means
12. Neuro-fuzzy systems: ANFIS

Skills you will gain

building fuzzy systems with scikit-fuzzy

MATLAB Fuzzy Logic Toolbox

choosing and tuning membership functions

writing and testing a rule base

simulating closed-loop control

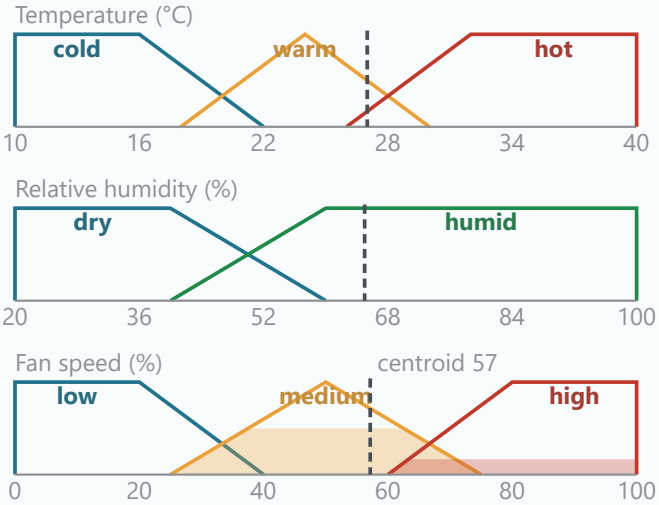
tuning rules from data with ANFIS

A typical semester; the order and coverage vary between universities.

TRY IT

Fuzzy Rules Run the Air Conditioner

The air conditioner follows verbal rules such as "if it is hot and humid, run the fan fast". Change temperature and humidity; watch how strongly each rule fires and the resulting fan speed.



Temperature = **27.0** °C

Relative humidity = **65%**

- 0 cold → low
- 0 warm ∧ dry → low
- **0.50** warm ∧ humid → medium
- 0 hot ∧ dry → medium
- **0.17** hot ∧ humid → high

Fan speed: **57%**

At 1 °C warmer: 65%. A crisp threshold rule would make the speed jump; fuzzy rules give a smooth transition.

Expert knowledge was written as verbal rules; fuzzy logic fires each rule **partially**, aggregates the outputs and turns them into one number with the centroid. No mathematical model is needed.

CONTEXT

Prerequisites

Courses worth knowing before this one, and why they are needed.

Course	Why it is needed
Artificial Intelligence	approximate reasoning
Discrete Mathematics	sets, relations and propositional logic
Programming	writing functions and building simple simulations
Control Systems	feedback and the PID controller

CONTEXT

Are You Ready for This Course?

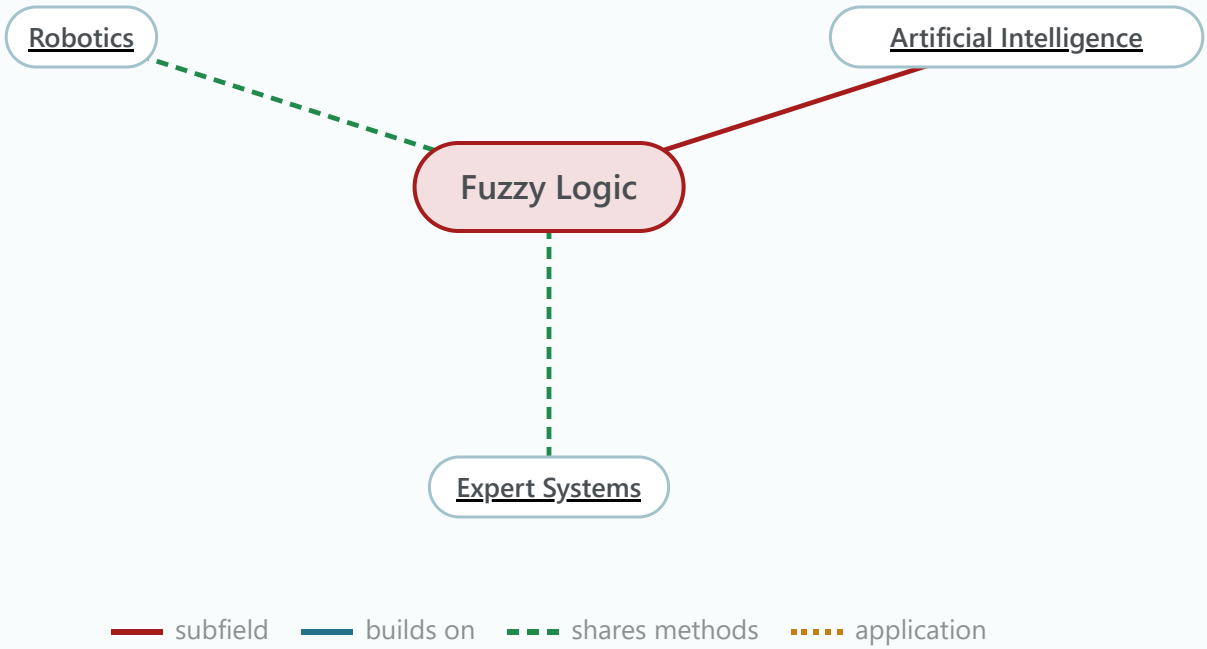
Ask yourself; for every "no", the right-hand column shows where to start.

Ask yourself	If not, start with
Can you explain union, intersection and complement of sets?	Sets and propositional logic from discrete mathematics
Can you compute the area under a piecewise-defined function?	Integrals and the centroid from calculus
Can you explain a feedback loop and what a PID controller does?	An intro to control systems: feedback and PID
Can you write Python functions and step through a simple simulation?	An intro programming course, then a short NumPy tutorial

If you can say "yes" to most of these, you are ready; one or two gaps can be closed during the semester.

CONTEXT

Neighbouring Courses



Overlapping Courses

Relation	Course	Shared ground
subfield	This course is a subfield of Artificial Intelligence	approximate reasoning
shares methods	Shares methods with Expert Systems and Knowledge Representation	IF-THEN rule base, inference engine
shares methods	Shares methods with Robotics and Robot Vision	fuzzy controllers

DIFFERENCES

Where It Differs (1/2)

Criterion	Fuzzy Logic	Probability & Statistics	Expert Systems
Core question	How do we reason with concepts like "hot" or "fast" that have no sharp boundary?	How is uncertainty measured, and how do we draw reliable conclusions from limited data?	How is an expert's knowledge written down and used for inference?
Approach	partial membership and linguistic rules	probability models and inference	symbolic logic and rules
Input	measurements, expert rules	sample data	facts and expert rules
Output	control signal or decision	estimate, confidence interval, test result	conclusion with justification
Success measure	control quality, expert agreement	unbiasedness, power, significance	expert agreement, explainability
Math load	low-medium: set theory	the theory itself	low: propositional and predicate logic
Data needs	little; expert knowledge	a sample	little; a knowledge base

- **Probability & Statistics:** Probability measures uncertainty about whether an event will happen; this course measures how far a concept applies, that is, a vague boundary.
- **Expert Systems:** Expert systems mostly run rules with crisp logic; this course builds approximate reasoning where rules can be partly true.

DIFFERENCES

Where It Differs (2/2)

Criterion	Fuzzy Logic	Robotics	Neural Networks
Core question	How do we reason with concepts like "hot" or "fast" that have no sharp boundary?	How does a machine sense the physical world, know where it is and move?	How do networks of simple units learn by adjusting their weights?
Approach	partial membership and linguistic rules	sense-plan-act loop	network of simple weighted units
Input	measurements, expert rules	sensor measurements	numeric feature vector
Output	control signal or decision	motor commands, path	class or numeric prediction
Success measure	control quality, expert agreement	task success, safety	loss and accuracy
Math load	low-medium: set theory	high: transformations, control	medium-high: derivatives, matrices
Data needs	little; expert knowledge	physical experiments and simulation	moderate

- **Robotics:** Robotics covers control as a whole; this course teaches the fuzzy controller as a model-free option.
- **Neural Networks:** Neural networks learn rules from data as unreadable weights; a fuzzy system's rules come from an expert and are readable.

PRACTICE

Applications

Home appliances
Washing machines, air conditioners, rice cookers.

Transportation
Subway acceleration and braking, automatic gearboxes.

Industrial control
Kiln temperature, cement and chemical processes.

Cameras
Autofocus and image stabilization.

Decision support
Risk assessment, supplier selection.

Medicine
Approximate diagnosis from symptoms, dose advice.

PRACTICE

Risks and Ethics

Arbitrary membership functions

Who placed the corners of a triangle, and why, is rarely documented; other shapes make the same rules decide differently.

Rule explosion

Rule count grows exponentially with inputs and terms; on combinations nobody wrote, the controller gives unforeseen outputs.

Stability without proof

A controller tuned by trial and error is seldom proven stable in closed loop, which is risky in systems such as brakes.

Subjectivity dressed as numbers

A fuzzy score in medicine or credit, presented as an exact measurement, turns an expert's bias into a scientific-looking number.

In depth: Explainable AI and AI Ethics.

PRACTICE

Tools and Datasets

Tools and libraries

MATLAB Fuzzy Logic Toolbox | scikit-fuzzy | jFuzzyLogic | fuzzylite | Simpful

Classic benchmark problems

Tipping problem | Inverted pendulum | Truck backer-upper | Washing machine control | Water tank level | Mackey-Glass time series

Fuzzy systems are usually built from **expert knowledge** rather than data; data is used to fine-tune the rules in methods such as ANFIS.

PRACTICE

Common Misconceptions

Common belief	In fact
Fuzzy logic is imprecise, sloppy logic.	Rules use vague concepts, but the computation is exact; the same input always gives the same output.
A membership degree is a probability.	0.7 is the degree of being "hot", not the chance of being hot; degrees need not sum to 1.
Fuzzy logic is an old, abandoned field.	It is widely used in appliances and industrial control, and its combination with neural networks continues.
A fuzzy system learns from data.	A basic fuzzy system takes its rules from an expert; learning is added by hybrid methods such as ANFIS.

NEXT STEPS

After This Course

Courses that build on or extend this one

This course is mostly an end point: it builds on the others.

Related careers

Control systems engineer

Embedded software engineer

Automation engineer

Decision support analyst

Fuzzy logic shares the rule base with expert systems and control with robotics. After this course you can move to neuro-fuzzy systems to learn rules from data, or to probabilistic graphical models to handle uncertainty with probability.

Further Reading

- Zadeh, "Fuzzy Sets", *Information and Control* 8(3), 1965.
- Klir and Yuan, *Fuzzy Sets and Fuzzy Logic: Theory and Applications*, Prentice Hall, 1995.
- Ross, *Fuzzy Logic with Engineering Applications*, 4th ed., Wiley, 2017.
- Jang, Sun and Mizutani, *Neuro-Fuzzy and Soft Computing*, Prentice Hall, 1997.

The End

Chapter 9: Fuzzy Logic and Fuzzy Systems

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